Contents

Part Homework Problems:

-2  Math 280C Homework Problems
-2.1 Homework #1 (Due Friday, April 13, 2007)
-2.2 Homework #2 (Due Friday, April 20, 2007)
-2.3 Homework #3 (Due Friday, April 27, 2007)

-1  Math 280B Homework Problems
-1.1 Homework 1. Due Monday, January 22, 2007
-1.2 Homework 2. Due Monday, January 29, 2007
-1.3 Homework #3 Due Monday, February 5, 2007
-1.4 Homework #4 Due Friday, February 16, 2007
-1.5 Homework #5 Due Friday, February 23, 2007
-1.6 Homework #6 Due Monday, March 5, 2007
-1.7 Homework #7 Due Monday, March 12, 2007
-1.8 Homework #8 Due Wednesday, March 21, 2007 by 11:00AM!

0  Math 280A Homework Problems
0.1 Homework 1. Due Friday, September 29, 2006
0.2 Homework 2. Due Friday, October 6, 2006
0.3 Homework 3. Due Friday, October 13, 2006
0.4 Homework 4. Due Friday, October 20, 2006
0.5 Homework 5. Due Friday, October 27, 2006
0.6 Homework 6. Due Friday, November 3, 2006
0.7 Homework 7. Due Monday, November 13, 2006
  0.7.1 Corrections and comments on Homework 7 (280A)
0.8 Homework 8. Due Monday, November 27, 2006
0.9 Homework 9. Due Noon, on Wednesday, December 6, 2006
# Contents

**Part I Background Material**

1. **Limsups, Liminf s and Extended Limits** ................................................................. 11  
2. **Basic Probabilistic Notions** .................................................................................. 15  

**Part II Formal Development**

3. **Preliminaries** ........................................................................................................... 21  
   3.1 Set Operations ........................................................................................................... 21  
   3.2 Exercises .................................................................................................................. 23  
   3.3 Algebraic sub-structures of sets .............................................................................. 23  
4. **Finitely Additive Measures** ..................................................................................... 27  
   4.1 Finitely Additive Measures ..................................................................................... 27  
   4.2 Examples of Measures ............................................................................................ 28  
   4.3 Simple Integration .................................................................................................. 30  
   4.4 Simple Independence and the Weak Law of Large Numbers ............................... 32  
   4.5 Constructing Finitely Additive Measures ............................................................... 34  
5. **Countably Additive Measures** ................................................................................ 37  
   5.1 Distribution Function for Probability Measures on \((\mathbb{R}, \mathcal{B})\) .................... 37  
   5.2 Construction of Pre-measures ............................................................................... 37  
   5.3 Regularity and Uniqueness Results ...................................................................... 39  
   5.4 Construction of Measures ..................................................................................... 40  
   5.5 Completions of Measure Spaces .......................................................................... 43  
   5.6 A Baby Version of Kolmogorov’s Extension Theorem ......................................... 44  
6. **Random Variables** .................................................................................................. 45  
   6.1 Measurable Functions ............................................................................................ 45  
   6.2 Factoring Random Variables ................................................................................. 50  
7. **Independence** ......................................................................................................... 53  
   7.1 \(\pi \land \lambda\) and Monotone Class Theorems ......................................................... 53  
      7.1.1 The Monotone Class Theorem ....................................................................... 55  
   7.2 Basic Properties of Independence ...................................................................... 56  
      7.2.1 An Example of Ranks .................................................................................. 58  
   7.3 Borel-Cantelli Lemmas .......................................................................................... 61  
   7.4 Kolmogorov and Hewitt-Savage Zero-One Laws ................................................. 65
# Integration Theory

8.1 A Quick Introduction to Lebesgue Integration Theory .............................................. 69
8.2 Integrals of positive functions ..................................................................................... 72
8.3 Integrals of Complex Valued Functions ................................................................. 76
8.4 Densities and Change of Variables Theorems .......................................................... 80
8.5 Measurability on Complete Measure Spaces ............................................................ 83
8.6 Comparison of the Lebesgue and the Riemann Integral ............................................. 83
8.7 Exercises .................................................................................................................. 85
  8.7.1 Laws of Large Numbers Exercises .................................................................... 86

# Functional Forms of the \( \pi - \lambda \) Theorem

9.1 Modes of Convergence ............................................................................................... 113
9.2 Jensen’s, Hölder’s and Minkowski’s Inequalities ......................................................... 115
9.3 Completeness of \( L^p \) – spaces ................................................................................ 115
9.4 Relationships between different \( L^p \) – spaces ........................................................ 117
  9.4.1 Summary: ........................................................................................................... 117
9.5 Uniform Integrability ................................................................................................. 117
9.6 Exercises .................................................................................................................. 121
9.7 Appendix: Convex Functions .................................................................................... 121

### Part III: Convergence Results

12. Laws of Large Numbers .............................................................................................. 127
  12.1 Main Results ........................................................................................................... 128
  12.2 Examples ................................................................................................................ 130
    12.2.1 Random Series Examples ............................................................................... 130
    12.2.2 A WLLN Example .......................................................................................... 131
  12.3 Strong Law of Large Number Examples .................................................................. 132
  12.4 More on the Weak Laws of Large Numbers ........................................................... 134
  12.5 Maximal Inequalities .............................................................................................. 135
## Contents

1. **Hilbert Space Basics**
   - 16.1 Compactness Results for $L^p$ - Spaces .................................................. 199
   - 16.2 Exercises ........................................................................................................ 201

2. **The Radon-Nikodym Theorem** ............................................................................. 203

3. **Conditional Expectation**
   - 18.1 Examples ......................................................................................................... 209
   - 18.2 Additional Properties of Conditional Expectations ........................................ 212
   - 18.3 Regular Conditional Distributions .................................................................... 214
   - 18.4 Appendix: Standard Borel Spaces ..................................................................... 215

4. **Weak Convergence Results**
   - 13.1 Total Variation Distance .................................................................................. 145
   - 13.2 Weak Convergence ............................................................................................ 146
   - 13.3 “Derived” Weak Convergence ............................................................................ 149
   - 13.4 Skorohod and the Convergence of Types Theorems ........................................... 151
   - 13.5 Weak Convergence Examples ............................................................................ 154
   - 13.6 Compactness and Tightness .............................................................................. 158
   - 13.7 Weak Convergence in Metric Spaces ............................................................... 159

5. **Characteristic Functions (Fourier Transform)**
   - 14.1 Basic Properties of the Characteristic Function ............................................... 163
   - 14.2 Examples ........................................................................................................... 166
   - 14.3 Continuity Theorem .......................................................................................... 167
   - 14.4 A Fourier Transform Inversion Formula ............................................................ 171
   - 14.5 Exercises ........................................................................................................... 173
   - 14.6 Appendix: Bochner’s Theorem ......................................................................... 175
   - 14.7 Appendix: A Multi-dimensional Weirstrass Approximation Theorem ............. 178
   - 14.8 Appendix: Some Calculus Estimates ................................................................. 179

6. **Weak Convergence of Random Sums** .................................................................. 183
   - 15.1 Infinitely Divisible and Stable Symmetric Distributions ..................................... 187
     - 15.1.1 Stable Laws ................................................................................................. 191

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### Part IV Conditional Expectations and Martingales

7. **The Radon-Nikodym Theorem** ............................................................................. 203

8. **Conditional Expectation**
   - 18.1 Examples ......................................................................................................... 209
   - 18.2 Additional Properties of Conditional Expectations ........................................... 212
   - 18.3 Regular Conditional Distributions ...................................................................... 214
   - 18.4 Appendix: Standard Borel Spaces ................................................................. 215
Homework Problems:
Math 280C Homework Problems

-2.1 Homework #1 (Due Friday, April 13, 2007)

- Look at the following Exercises from the Lecture Notes: 19.4, 19.16
- Look at the following Exercises from Resnick Chapter 10: 19, 22-24,
- Hand in the following Exercises from the Lecture Notes: 19.7, 19.8, 19.9

-2.2 Homework #2 (Due Friday, April 20, 2007)

- Look at the following Exercises from the Lecture Notes: 19.12, 19.13, 19.14
- Hand in the following Exercises from the Lecture Notes: 19.6, 19.10, 19.11

-2.3 Homework #3 (Due Friday, April 27, 2007)

- Hand in the following Exercises from the Lecture Notes: 22.1, 22.2, 22.3

22.4
Math 280B Homework Problems

-1.1 Homework 1. Due Monday, January 22, 2007

- Hand in from p. 114 : 4.27
- Hand in from p. 196 : 6.5, 6.7
- Hand in from p. 234–246: 7.12, 7.16, 7.33, 7.36 (assume each \( X_n \) is integrable!), 7.42

Hints and comments.
1. For 6.7, observe that \( X_n \overset{d}{=} \sigma_n N(0,1) \).
2. For 7.12, let \( \{U_n : n = 0, 1, 2, \ldots\} \) be i.i.d. random variables uniformly distributed on \((0,1)\) and take \( X_0 = U_0 \) and then define \( X_n \) inductively so that \( X_{n+1} = X_n \cdot U_{n+1} \).
3. For 7.36; use the assumptions to bound \( \mathbb{E}[X_n] \) in terms of \( \mathbb{E}[X_n] : X_n \leq x \).
Then use the two series theorem.

-1.2 Homework 2. Due Monday, January 29, 2007

- Resnick Chapter 7: Hand in 7.9, 7.13.
- Resnick Chapter 7: look at 7.28. (For 28b, assume \( \mathbb{E}[X_i X_j] \leq \rho(i-j) \) for \( i \geq j \). Also you may find it easier to show \( \sum_n X_n \rightarrow 0 \) in \( L^2 \) rather than the weaker notion of in probability.)
- Hand in Exercise 13.2 from these notes.
- Resnick Chapter 8: Hand in 8.4a-d, 8.13 (Assume \( \text{Var}(N_n) > 0 \) for all \( n \).)

-1.3 Homework #3 Due Monday, February 5, 2007

- Resnick Chapter 8: Look at: 8.14, 8.20, 8.36
- Resnick Chapter 8: Hand in 8.7, 8.17, 8.31, 8.30* (Due 8.31 first), 8.34
*Ignore the part of the question referring to the moment generating function.
**Hint:** use problem 8.31 and the convergence of types theorem.
- Also hand in Exercise 13.3 from these notes.

-1.4 Homework #4 Due Friday, February 16, 2007

- Resnick Chapter 9: Look at: 9.22, 9.33
- Resnick Chapter 9: Hand in 9.5, 9.6, 9.9 a-e., 9.10
- Also hand in Exercise from these notes: 14.3, 14.3 and 14.4

-1.5 Homework #5 Due February 23, 2007

- Resnick Chapter 9: Look at: 8
- Resnick Chapter 9: Hand in 11, 28, 34 (assume \( \sum_n \sigma_n^2 > 0 \)), 35 (hint: show \( P[\xi_n \neq 0 \text{ i.o. }] = 0 \)), 38 (Hint: make use Proposition 7.25)

-1.6 Homework #6 Due Monday, March 5, 2007

- Look at Resnick Chapter 10: 11
- Hand in the following Exercises from the Lecture Notes: 12.1, 18.1, 18.2, 18.3, 18.4
- Resnick Chapter 10: Hand in 2\( ^\dagger \), 5\*, 7, 8\**
\( ^\dagger \)In part 2b, please explain what convention you are using when the denominator is 0.
\( ^\star \)A Poisson process, \( \{N(t)\}_{t \geq 0} \), with parameter \( \lambda \) satisfies (by definition): (i) \( N \) has independent increments, so that \( N(s) \) and \( N(t) - N(s) \) are independent; (ii) if \( 0 \leq u < v \) then \( N(v) - N(u) \) has the Poisson distribution with parameter \( \lambda(v-u) \).
\( ^\** \)Hint: use Exercise 12.1.

-1.7 Homework #7 Due Monday, March 12, 2007

- Hand in the following Exercises from the Lecture Notes: 18.5, 19.1, 19.2
- Hand in Resnick Chapter 10: 14 (take \( B_n := \sigma(Y_0, Y_1, \ldots, Y_n) \) for the filtration), 16
Look at the following Exercise from the Lecture Notes: 19.5.
Hand in the following Exercises from the Lecture Notes: 19.3.
For #28, let $B_n := \sigma(Y_1, \ldots, Y_n)$ define the filtration. Hint: for part b consider, $\ln X_n$. 
Math 280A Homework Problems

Unless otherwise noted, all problems are from Resnick, S. A Probability Path, Birkhauser, 1999.

0.1 Homework 1. Due Friday, September 29, 2006

- p. 20-27: Look at: 9, 12, 19, 27, 30, 36
- p. 20-27: Hand in: 5, 17, 18, 23, 40, 41

0.2 Homework 2. Due Friday, October 6, 2006

- p. 63-70: Look at: 18
- p. 63-70: Hand in: 3, 6, 7, 11, 13 and the following problem.

Exercise 0.1 (280A-2.1). Referring to the setup in Problem 7 on p. 64 of Resnick, compute the expected number of different coupons collected after buying \( n \) boxes of cereal.

0.3 Homework 3. Due Friday, October 13, 2006

- Look at from p. 63-70: 5, 14, 19
- Look at lecture notes: exercise 4.4 and read Section 5.5
- Hand in from p. 63-70: 16
- Hand in lecture note exercises: 4.1, 4.3, 5.1, and 5.2

0.4 Homework 4. Due Friday, October 20, 2006

- Look at from p. 85–90: 3, 7, 12, 17, 21
- Hand in from p. 85–90: 4, 6, 8, 9, 15
- Also hand in the following exercise.

Exercise 0.2 (280A-4.1). Suppose \( \{f_n\}_{n=1}^{\infty} \) is a sequence of Random Variables on some measurable space. Let \( B \) be the set of \( \omega \) such that \( f_n(\omega) \) is convergent as \( n \to \infty \). Show the set \( B \) is measurable, i.e. \( B \) is in the \( \sigma \)–algebra.

0.5 Homework 5. Due Friday, October 27, 2006

- Look at from p. 110–116: 3, 5
- Hand in from p. 110–116: 1, 6, 8, 18, 19

0.6 Homework 6. Due Friday, November 3, 2006

- Look at from p. 110–116: 3, 5, 28, 29
- Look at from p. 155–166: 6, 34
- Hand in from p. 110–116: 9, 11, 15, 25
- Hand in from p. 155–166: 7
- Hand in lecture note exercise: 7.1

0.7 Homework 7. Due Monday, November 13, 2006

- Look at from p. 155–166: 13, 16, 37
- Hand in from p. 155–166: 11, 21, 26
- Hand in lecture note exercises: 8.1, 8.2, 8.19, 8.20

0.7.1 Corrections and comments on Homework 7 (280A)

Problem 21 in Section 5.10 of Resnick should read,

\[
\frac{d}{ds} P(s) = \sum_{k=1}^{\infty} kp_k s^{k-1} \text{ for } s \in [0, 1].
\]

Note that \( P(s) = \sum_{k=0}^{\infty} p_k s^k \) is well defined and continuous (by DCT) for \( s \in [-1, 1] \). So the derivative makes sense to compute for \( s \in (-1, 1) \) with no qualifications. When \( s = 1 \) you should interpret the derivative as the one sided derivative

\[
\lim_{h \to 0^+} \frac{P(1) - P(1 - h)}{h}.
\]
and you will need to allow for this limit to be infinite in case \( \sum_{k=1}^{\infty} kp_k = \infty \).
In computing \( \frac{d}{ds}|_{s=1} P(s) \), you may wish to use the fact (draw a picture or give a calculus proof) that
\[
\frac{1 - s^k}{1 - s} \text{ increases to } k \text{ as } s \uparrow 1.
\]

**Hint for Exercise 8.20:** Start by observing that
\[
E \left( \frac{S_n}{n} - \mu \right)^4 \, d\mu = E \left( \frac{1}{n} \sum_{k=1}^{n} (X_k - \mu) \right)^4
\]
\[
= \frac{1}{n^k} \sum_{k,j,l,p=1}^{n} E [(X_k - \mu)(X_j - \mu)(X_l - \mu)(X_p - \mu)].
\]
Then analyze for which groups of indices \((k, j, l, p)\):
\[
E [(X_k - \mu)(X_j - \mu)(X_l - \mu)(X_p - \mu)] \neq 0.
\]

### 0.8 Homework 8. Due Monday, November 27, 2006
- Look at from p. 155–166: 19, 34, 38
- Look at from p. 195–201: 19, 24
- Hand in from p. 155–166: 14, 18 (Hint: see picture given in class.), 22a-b
- Hand in from p. 195–201: 1a,b,d, 12, 13, 33 and 18 (Also assume \( E X_n = 0 \))*
- Hand in lecture note exercises: 9.1

* For Problem 18, please add the missing assumption that the random variables should have mean zero. (The assertion to prove is false without this assumption.) With this assumption, \( \text{Var}(X) = E[X^2] \). Also note that \( \text{Cov}(X,Y) = 0 \) is equivalent to \( E[XY] = EX \cdot EY \).

### 0.9 Homework 9. Due Noon, on Wednesday, December 6, 2006
- Look at from p. 195–201: 3, 4, 14, 16, 17, 27, 30
- Hand in from p. 195–201: 15 (Hint: \(|a - b| = 2(a - b)^+ - (a - b). \)
- Hand in from p. 234–246: 1, 2 (Hint: it is just as easy to prove a.s. convergence), 15
Part I

Background Material
Lemma 1.2. Suppose \(\{a_n\}^\infty_{n=1}\) and \(\{b_n\}^\infty_{n=1}\) are convergent sequences in \(\overline{\mathbb{R}}\), then:

1. If \(a_n \leq b_n\) for a.a. \(n\) then \(\lim_{n \to \infty} a_n \leq \lim_{n \to \infty} b_n\).
2. If \(c \in \mathbb{R}\), \(\lim_{n \to \infty} (ca_n) = c \lim_{n \to \infty} a_n\).
3. If \(\{a_n + b_n\}^\infty_{n=1}\) is convergent and
\[
\lim_{n \to \infty} (a_n + b_n) = \lim_{n \to \infty} a_n + \lim_{n \to \infty} b_n
\]
provided the right side is not of the form \(\infty - \infty\).
4. \(\{a_n b_n\}^\infty_{n=1}\) is convergent and
\[
\lim_{n \to \infty} (a_n b_n) = \lim_{n \to \infty} a_n \cdot \lim_{n \to \infty} b_n
\]
provided the right hand side is not of the form \(\pm \infty \cdot 0\) or \(0 \cdot (\pm \infty)\).

Before going to the proof consider the simple example where \(a_n = n\) and \(b_n = -an\) with \(a > 0\). Then
\[
\lim (a_n + b_n) = \begin{cases} 
\infty & \text{if } a < 1 \\
0 & \text{if } a = 1 \\
-\infty & \text{if } a > 1
\end{cases}
\]
while
\[
\lim_{n \to \infty} a_n + \lim_{n \to \infty} b_n = "\infty - \infty."
\]
This shows that the requirement that the right side of Eq. (1.1) is not of form \(\infty - \infty\) is necessary in Lemma 1.2. Similarly by considering the examples \(a_n = n\) and \(b_n = n^{-\alpha}\) with \(\alpha > 0\) shows the necessity for assuming right hand side of Eq. (1.2) is not of the form \(\infty \cdot 0\).

Proof. The proofs of items 1. and 2. are left to the reader.

Proof of Eq. (1.1). Let \(a := \lim_{n \to \infty} a_n\) and \(b := \lim_{n \to \infty} b_n\). Case 1., suppose \(b = \infty\) in which case we must assume \(a > -\infty\). In this case, for every \(M > 0\), there exists \(N\) such that \(b_n \geq M\) and \(a_n \geq a - 1\) for all \(n \geq N\) and this implies
\[
a_n + b_n \geq M + a - 1\text{ for all } n \geq N.
\]
Since \(M\) is arbitrary it follows that \(a_n + b_n \to \infty\) as \(n \to \infty\). The cases where \(b = -\infty\) or \(a = \pm \infty\) are handled similarly. Case 2. If \(a, b \in \mathbb{R}\), then for every \(\varepsilon > 0\) there exists \(N \in \mathbb{N}\) such that
\[
|a - a_n| \leq \varepsilon\text{ and }|b - b_n| \leq \varepsilon\text{ for all } n \geq N.
\]
Therefore,
\[
|a + b - (a_n + b_n)| = |a - a_n + b - b_n| \leq |a - a_n| + |b - b_n| \leq 2\varepsilon
\]
for all \(n \geq N\). Since \(n\) is arbitrary, it follows that \(\lim_{n \to \infty} (a_n + b_n) = a + b\).

Proof of Eq. (1.2). It will be left to the reader to prove the case where \(\lim a_n\) and \(\lim b_n\) exist in \(\mathbb{R}\). I will only consider the case where \(a = \lim_{n \to \infty} a_n \neq 0\) and \(b = \lim_{n \to \infty} b_n = \infty\) here. Let us also suppose that \(a > 0\) (the case \(a < 0\) is handled similarly) and let \(\alpha := \min\left(\frac{\varepsilon}{2}, 1\right)\). Given any \(M < \infty\), there exists \(N \in \mathbb{N}\) such that \(a_n \geq \alpha\) and \(b_n \geq M\) for all \(n \geq N\) and for this choice of \(N\), \(a_n \geq M\alpha\) for all \(n \geq N\). Since \(\alpha > 0\) is fixed and \(M\) is arbitrary it follows that \(\lim_{n \to \infty} (a_n b_n) = \infty\) as desired. \(\square\)

For any subset \(\Lambda \subset \mathbb{R}\), let \(\sup\Lambda\) and \(\inf\Lambda\) denote the least upper bound and greatest lower bound of \(\Lambda\) respectively. The convention being that \(\sup\Lambda = \infty\) if \(\infty \in \Lambda\) or \(\Lambda\) is not bounded from above and \(\inf\Lambda = -\infty\) if \(-\infty \in \Lambda\) or \(\Lambda\) is not bounded from below. We will also use the conventions that \(\sup \emptyset = -\infty\) and \(\inf \emptyset = +\infty\).

Notation 1.3 Suppose that \(\{x_n\}^\infty_{n=1} \subset \mathbb{R}\) is a sequence of numbers. Then
\[
\liminf_{n \to \infty} x_n = \lim_{n \to \infty} \inf\{x_k : k \geq n\}\text{ and }\quad (1.3)
\]
\[
\limsup_{n \to \infty} x_n = \lim_{n \to \infty} \sup\{x_k : k \geq n\}.\quad (1.4)
\]
1 Limsups, Liminfs and Extended Limits

We will also write \( \lim \) for \( \lim \inf_{n \to \infty} \) and \( \varlimsup \) for \( \lim \sup \).

Remark 1.4. Notice that if \( a_k := \inf\{x_k : k \geq n\} \) and \( b_k := \sup\{x_k : k \geq n\} \), then \( \{a_k\} \) is an increasing sequence while \( \{b_k\} \) is a decreasing sequence. Therefore the limits in Eq. (1.3) and Eq. (1.4) always exist in \( \mathbb{R} \) and

\[
\lim_{n \to \infty} x_n = \sup_{n} \inf_{k} \{x_k : k \geq n\} \quad \text{and} \quad \lim_{n \to \infty} \sup_{n} \inf_{k} \{x_k : k \geq n\}.
\]

The following proposition contains some basic properties of liminfs and limsups.

**Proposition 1.5.** Let \( \{a_n\}_{n=1}^\infty \) and \( \{b_n\}_{n=1}^\infty \) be two sequences of real numbers. Then

1. \( \lim_{n \to \infty} \inf_{n \to \infty} a_n \leq \lim_{n \to \infty} \sup_{n \to \infty} a_n \) and \( \lim_{n \to \infty} \inf_{n \to \infty} a_n \) exists in \( \mathbb{R} \) iff

\[
\lim_{n \to \infty} \inf_{n \to \infty} a_n = \lim_{n \to \infty} \sup_{n \to \infty} a_n \in \mathbb{R}.
\]

2. There is a subsequence \( \{a_{n_k}\}_{k=1}^\infty \) of \( \{a_n\}_{n=1}^\infty \) such that \( \lim_{n \to \infty} \inf_{n \to \infty} a_{n_k} = \lim_{n \to \infty} \sup_{n \to \infty} a_n \). Similarly, there is a subsequence \( \{a_{n_k}\}_{k=1}^\infty \) of \( \{a_n\}_{n=1}^\infty \) such that \( \lim_{n \to \infty} \inf_{n \to \infty} a_{n_k} = \lim_{n \to \infty} \inf_{n \to \infty} a_n \).

3. \( \lim_{n \to \infty} (a_n + b_n) \leq \lim_{n \to \infty} a_n + \lim_{n \to \infty} b_n \) (1.5)

whenever the right side of this equation is not of the form \( \infty - \infty \).

4. If \( a_n \geq 0 \) and \( b_n \geq 0 \) for all \( n \in \mathbb{N} \), then

\[
\lim_{n \to \infty} \inf_{n \to \infty} (a_n b_n) \leq \lim_{n \to \infty} a_n \cdot \lim_{n \to \infty} b_n,
\]

provided the right hand side of (1.6) is not of the form \( 0 \cdot \infty \) or \( \infty \cdot 0 \).

**Proof.** Item 1. will be proved here leaving the remaining items as an exercise to the reader. Since

\[
\inf\{a_k : k \geq n\} \leq \sup\{a_k : k \geq n\} \quad \forall n,
\]

\[
\lim_{n \to \infty} \inf_{n \to \infty} a_n \leq \lim_{n \to \infty} \sup_{n \to \infty} a_n.
\]

Now suppose that \( \lim_{n \to \infty} \inf_{n \to \infty} a_n = \lim_{n \to \infty} \sup_{n \to \infty} a_n = a \in \mathbb{R} \). Then for all \( \varepsilon > 0 \), there is an integer \( N \) such that

\[
a - \varepsilon \leq \inf\{a_k : k \geq N\} \leq \sup\{a_k : k \geq N\} \leq a + \varepsilon,
\]

i.e.

\[
a - \varepsilon \leq a_k \leq a + \varepsilon \quad \text{for all} \quad k \geq N.
\]

Hence by the definition of the limit, \( \lim_{n \to \infty} a_k = a \). If \( \lim_{n \to \infty} a_n = \infty \), then we know for all \( M \in (0, \infty) \) there is an integer \( N \) such that

\[
M \leq \inf\{a_k : k \geq N\}
\]

and hence \( \lim_{n \to \infty} a_n = \infty \). The case where \( \lim_{n \to \infty} a_n = -\infty \) is handled similarly.

Conversely, suppose that \( \lim_{n \to \infty} a_n = A \in \mathbb{R} \) exists. If \( A \in \mathbb{R} \), then for every \( \varepsilon > 0 \) there exists \( N(\varepsilon) \in \mathbb{N} \) such that \( |A - a_n| \leq \varepsilon \) for all \( n \geq N(\varepsilon) \), i.e.

\[
A - \varepsilon \leq a_n \leq A + \varepsilon \quad \text{for all} \quad n \geq N(\varepsilon).
\]

From this we learn that

\[
A - \varepsilon \leq \lim_{n \to \infty} \inf_{n \to \infty} a_n \leq \lim_{n \to \infty} \sup_{n \to \infty} a_n \leq A + \varepsilon.
\]

Since \( \varepsilon > 0 \) is arbitrary, it follows that

\[
A \leq \lim_{n \to \infty} \inf_{n \to \infty} a_n \leq \lim_{n \to \infty} \sup_{n \to \infty} a_n \leq A,
\]

i.e. that \( A = \lim_{n \to \infty} \inf_{n \to \infty} a_n = \lim_{n \to \infty} \sup_{n \to \infty} a_n \). If \( A = \infty \), then for all \( M > 0 \) there exists \( N = N(M) \) such that \( a_n \geq M \) for all \( n \geq N \). This show that \( \lim_{n \to \infty} a_n \geq M \) and since \( M \) is arbitrary it follows that

\[
\infty \leq \lim_{n \to \infty} \inf_{n \to \infty} a_n \leq \lim_{n \to \infty} \sup_{n \to \infty} a_n.
\]

The proof for the case \( A = -\infty \) is analogous to the \( A = \infty \) case.

**Proposition 1.6 (Tonelli’s theorem for sums).** If \( \{a_{kn}\}_{k,n=1}^\infty \) is any sequence of non-negative numbers, then

\[
\sum_{k=1}^\infty \sum_{n=1}^\infty a_{kn} = \sum_{n=1}^\infty \sum_{k=1}^\infty a_{kn}.
\]

Here we allow for one and hence both sides to be infinite.

**Proof.** Let

\[
M := \sup \left\{ \sum_{k=1}^K \sum_{n=1}^N a_{kn} : K, N \in \mathbb{N} \right\} = \sup \left\{ \sum_{n=1}^N \sum_{k=1}^K a_{kn} : K, N \in \mathbb{N} \right\}
\]
and
\[ L := \sum_{k=1}^{\infty} \sum_{n=1}^{\infty} a_{kn}. \]

Since
\[ L = \sum_{k=1}^{\infty} \sum_{n=1}^{\infty} a_{kn} = \lim_{K \rightarrow \infty} \sum_{k=1}^{K} \sum_{n=1}^{\infty} a_{kn} = \lim_{K \rightarrow \infty} \lim_{N \rightarrow \infty} \sum_{k=1}^{K} \sum_{n=1}^{N} a_{kn} \]
and \( \sum_{k=1}^{K} \sum_{n=1}^{N} a_{kn} \leq M \) for all \( K \) and \( N \), it follows that \( L \leq M \). Conversely,
\[ \sum_{k=1}^{K} \sum_{n=1}^{N} a_{kn} \leq \sum_{k=1}^{K} \sum_{n=1}^{\infty} a_{kn} \leq \sum_{k=1}^{\infty} \sum_{n=1}^{\infty} a_{kn} = L \]
and therefore taking the supremum of the left side of this inequality over \( K \) and \( N \) shows that \( M \leq L \). Thus we have shown
\[ \sum_{k=1}^{\infty} \sum_{n=1}^{\infty} a_{kn} = M. \]

By symmetry (or by a similar argument), we also have that \( \sum_{n=1}^{\infty} \sum_{k=1}^{\infty} a_{kn} = M \) and hence the proof is complete. ■
Basic Probabilistic Notions

Definition 2.1. A sample space \( \Omega \) is a set which is to represent all possible outcomes of an “experiment.”

Example 2.2. 1. The sample space for flipping a coin one time could be taken to be, \( \Omega = \{0, 1\} \).
2. The sample space for flipping a coin \( N \)-times could be taken to be, \( \Omega = \{0, 1\}^N \) and for flipping an infinite number of times,
\[
\Omega = \{ \omega = (\omega_1, \omega_2, \ldots) : \omega_i \in \{0, 1\} \} = \{0, 1\}^\infty.
\]
3. If we have a roulette wheel with 40 entries, then we might take
\[
\Omega = \{00, 0, 1, 2, \ldots , 36\}
\]
for one spin, \( \Omega = \{00, 0, 1, 2, \ldots , 36\}^N \) for \( N \) spins, and
\[
\Omega = \{00, 0, 1, 2, \ldots , 36\}^\infty
\]
for an infinite number of spins.
4. If we throw darts at a board of radius \( R \), we may take
\[
\Omega = D_R := \{(x, y) \in \mathbb{R}^2 : x^2 + y^2 \leq R\}
\]
for one throw, \( \Omega = D_R^N \) for \( N \) throws, and
\[
\Omega = D_R^\infty
\]
for an infinite number of throws.
5. Suppose we release a perfume particle at location \( x \in \mathbb{R}^3 \) and follow its motion for all time, \( 0 \leq t < \infty \). In this case, we might take,
\[
\Omega = \{ \omega \in C([0, \infty), \mathbb{R}^3) : \omega(0) = x \}.
\]

Definition 2.3. An event is a subset of \( \Omega \).

Example 2.4. Suppose that \( \Omega = \{0, 1\}^N \) is the sample space for flipping a coin an infinite number of times. Here \( \omega_n = 1 \) represents the fact that a head was thrown on the \( n \text{th} \) toss, while \( \omega_n = 0 \) represents a tail on the \( n \text{th} \) toss.
1. \( A = \{ \omega \in \Omega : \omega_3 = 1 \} \) represents the event that the third toss was a head.
2. \( A = \bigcup_{n=1}^\infty \{ \omega \in \Omega : \omega_k = \omega_{k+1} = 1 \} \) represents the event that (at least) two heads are tossed twice in a row at some time.
3. \( A = \bigcap_{N=1}^\infty \bigcap_{n\geq N} \{ \omega \in \Omega : \omega_n = 1 \} \) is the event where there are infinitely many heads tossed in the sequence.
4. \( A = \bigcup_{N=1}^\infty \bigcap_{n\geq N} \{ \omega \in \Omega : \omega_n = 1 \} \) is the event where heads occurs from some time onwards, i.e. \( \omega \in A \) iff there exists, \( N = N(\omega) \) such that \( \omega_n = 1 \) for all \( n \geq N \).

Ideally we would like to assign a probability, \( P(A) \), to all events \( A \subset \Omega \). Given a physical experiment, we think of assigning this probability as follows. Run the experiment many times to get sample points, \( \omega(n) \in \Omega \) for each \( n \in \mathbb{N} \), then try to “define” \( P(A) \) by
\[
P(A) = \lim_{N \to \infty} \frac{1}{N} \# \{ 1 \leq k \leq N : \omega(k) \in A \}.
\]
That is we think of \( P(A) \) as being the long term relative frequency that the event \( A \) occurred for the sequence of experiments, \( \{\omega(k)\}_{k=1}^\infty \).

Similarly supposed that \( A \) and \( B \) are two events and we wish to know how likely the event \( A \) is given that we now that \( B \) has occurred. Thus we would like to compute:
\[
P(A|B) = \lim_{n \to \infty} \frac{\# \{k : 1 \leq k \leq n \text{ and } \omega_k \in A \cap B\}}{\# \{k : 1 \leq k \leq n \text{ and } \omega_k \in B\}},
\]
which represents the frequency that $A$ occurs given that we know that $B$ has occurred. This may be rewritten as

$$P(A|B) = \lim_{n \rightarrow \infty} \frac{\frac{1}{n} \# \{ k : 1 \leq k \leq n \text{ and } \omega_k \in A \cap B \}}{\frac{1}{n} \# \{ k : 1 \leq k \leq n \text{ and } \omega_k \in B \}} = \frac{P(A \cap B)}{P(B)}.$$  

**Definition 2.5.** If $B$ is a non-null event, i.e. $P(B) > 0$, define the *conditional probability of $A$ given $B$* by,

$$P(A|B) := \frac{P(A \cap B)}{P(B)}.$$ 

There are of course a number of problems with this definition of $P$ in Eq. (2.1) including the fact that it is not mathematical nor necessarily well defined. For example the limit may not exist. But ignoring these technicalities for the moment, let us point out three key properties that $P$ should have.

1. $P(A) \in [0,1]$ for all $A \subset \Omega$.
2. $P(\emptyset) = 1$ and $P(\Omega) = 1$.
3. **Additivity.** If $A$ and $B$ are disjoint event, i.e. $A \cap B = \emptyset$, then

$$P(A \cup B) = \lim_{N \rightarrow \infty} \frac{1}{N} \# \{ 1 \leq k \leq N : \omega(k) \in A \cup B \}$$

$$= \lim_{N \rightarrow \infty} \frac{1}{N} \left[ \# \{ 1 \leq k \leq N : \omega(k) \in A \} + \# \{ 1 \leq k \leq N : \omega(k) \in B \} \right]$$

$$= P(A) + P(B).$$

**Example 2.6.** Let us consider the tossing of a coin $N$ times with a fair coin. In this case we would expect that every $\omega \in \Omega$ is equally likely, i.e. $P(\{\omega\}) = \frac{1}{2N}$. Assuming this we are then forced to define

$$P(A) = \frac{1}{2^N} \# (A).$$

Observe that this probability has the following property. Suppose that $\sigma \in \{0,1\}^k$ is a given sequence, then

$$P(\{\omega : (\omega_1, \ldots, \omega_k) = \sigma \}) = \frac{1}{2^N} \cdot 2^{N-k} = \frac{1}{2^k}.$$ 

That is if we ignore the flips after time $k$, the resulting probabilities are the same as if we only flipped the coin $k$ times.

**Example 2.7.** The previous example suggests that if we flip a fair coin an infinite number of times, so that now $\Omega = \{0,1\}^\infty$, then we should define

$$P(\{\omega \in \Omega : (\omega_1, \ldots, \omega_k) = \sigma \}) = \frac{1}{2^k}$$

for any $k \geq 1$ and $\sigma \in \{0,1\}^k$. Assuming there exists a probability, $P : 2^\Omega \rightarrow [0,1]$ such that Eq. (2.2) holds, we would like to compute, for example, the probability of the event $B$ where an infinite number of heads are tossed. To try to compute this, let

$$A_n = \{ \omega \in \Omega : \omega_n = 1 \} = \{ \text{heads at time } n \}$$

and

$$B_N := \cup_{n \geq N} A_n = \{ \text{at least one heads at time } N \text{ or later} \}$$

Since

$$B_N^c = \cap_{n \geq N} A_n^c \subset \cap_{M \geq n \geq N} A_n^c = \{ \omega \in \Omega : \omega_N = \cdots = \omega_M = 1 \},$$

we see that

$$P(B_N^c) \leq \frac{1}{2^{M-N}} \rightarrow 0 \text{ as } M \rightarrow \infty.$$ 

Therefore, $P(B_N) = 1$ for all $N$. If we assume that $P$ is continuous under taking decreasing limits we may conclude, using $B_N \downarrow B$, that

$$P(B) = \lim_{N \rightarrow \infty} P(B_N) = 1.$$ 

Without this continuity assumption we would not be able to compute $P(B)$.

The unfortunate fact is that we can not always assign a desired probability function, $P(A)$, for all $A \subset \Omega$. For example we have the following negative theorem.

**Theorem 2.8 (No-Go Theorem).** Let $S = \{ z \in \mathbb{C} : |z| = 1 \}$ be the unit circle. Then there is no probability function, $P : 2^S \rightarrow [0,1]$ such that $P(S) = 1$, $P$ is invariant under rotations, and $P$ is continuous under taking decreasing limits.

**Proof.** We are going to use the fact proved below in Lemma 2, that the continuity condition on $P$ is equivalent to the $\sigma$–additivity of $P$. For $z \in S$ and $N \subset S$ let

$$zN := \{ zn \in S : n \in N \},$$

that is to say $e^{i\theta}N$ is the set $N$ rotated counter clockwise by angle $\theta$. By assumption, we are supposing that
\[ P(zN) = P(N) \] (2.4)

for all \( z \in S \) and \( N \subset S \).

Let
\[ R := \{ z = e^{i2\pi t} : t \in \mathbb{Q} \} = \{ z = e^{i2\pi t} : t \in [0,1) \cap \mathbb{Q} \} \]
– a countable subgroup of \( S \). As above \( R \) acts on \( S \) by rotations and divides \( S \) up into equivalence classes, where \( z, w \in S \) are equivalent if \( z = rw \) for some \( r \in R \). Choose (using the axiom of choice) one representative point \( n \) from each of these equivalence classes and let \( N \subset S \) be the set of these representative points. Then every point \( z \in S \) may be uniquely written as \( z = nr \) with \( n \in N \) and \( r \in R \). That is to say
\[ S = \sum_{r \in R} (rN) \] (2.5)

where \( \sum_\alpha A_\alpha \) is used to denote the union of pair-wise disjoint sets \( \{ A_\alpha \} \). By Eqs. (2.4) and (2.5),
\[ 1 = P(S) = \sum_{r \in R} P(rN) = \sum_{r \in R} P(N). \] (2.6)

We have thus arrived at a contradiction, since the right side of Eq. (2.6) is either equal to 0 or to \( \infty \) depending on whether \( P(N) = 0 \) or \( P(N) > 0 \).

To avoid this problem, we are going to have to relinquish the idea that \( P \) should necessarily be defined on all of \( 2^\Omega \). So we are going to only define \( P \) on particular subsets, \( B \subset 2^\Omega \). We will developed this below.
Formal Development
3 Preliminaries

3.1 Set Operations

Let \( \mathbb{N} \) denote the positive integers, \( \mathbb{N}_0 := \mathbb{N} \cup \{0\} \) be the non-negative integers and \( \mathbb{Z} = \mathbb{N}_0 \cup (-\mathbb{N}) \) – the positive and negative integers including 0, \( \mathbb{Q} \) the rational numbers, \( \mathbb{R} \) the real numbers, and \( \mathbb{C} \) the complex numbers. We will also use \( \mathbb{F} \) to stand for either of the fields \( \mathbb{R} \) or \( \mathbb{C} \).

**Notation 3.1** Given two sets \( X \) and \( Y \), let \( Y^X \) denote the collection of all functions \( f : X \to Y \). If \( X = \mathbb{N} \), we will say that \( f \in Y^\mathbb{N} \) is a sequence with values in \( Y \) and often write \( f_n \) for \( f(n) \) and express \( f \) as \( \{f_n\}_{n=1}^\infty \). If \( X = \{1, 2, \ldots, N\} \), we will write \( Y^N \) in place of \( Y^{\{1, 2, \ldots, N\}} \) and denote \( f \in Y^N \) by \( f = (f_1, f_2, \ldots, f_N) \) where \( f_n = f(n) \).

**Notation 3.2** More generally if \( \{X_\alpha : \alpha \in A\} \) is a collection of non-empty sets, let \( X_A = \prod_{\alpha \in A} X_\alpha \) and \( \pi_\alpha : X_A \to X_\alpha \) be the canonical projection map defined by \( \pi_\alpha(x) = x_\alpha \). If \( X_\alpha = X \) for some fixed space \( X \), then we will write \( \prod_{\alpha \in A} X_\alpha \) as \( X^A \) rather than \( X_A \).

Recall that an element \( x \in X_A \) is a “choice function,” i.e. an assignment \( x_\alpha := x(\alpha) \in X_\alpha \) for each \( \alpha \in A \). The axiom of choice states that \( X_A \neq \emptyset \) provided that \( X_\alpha \neq \emptyset \) for each \( \alpha \in A \).

**Notation 3.3** Given a set \( X \), let \( 2^X \) denote the power set of \( X \) – the collection of all subsets of \( X \) including the empty set.

The reason for writing the power set of \( X \) as \( 2^X \) is that if we think of 2 meaning \( \{0, 1\} \), then an element of \( a \in 2^X = \{0, 1\}^X \) is completely determined by the set

\[ A := \{x \in X : a(x) = 1\} \subset X. \]

In this way elements in \( \{0, 1\}^X \) are in one to one correspondence with subsets of \( X \).

For \( A \in 2^X \) let

\[ A^c := X \setminus A = \{x \in X : x \notin A\} \]

and more generally if \( A, B \subset X \) let

\[ B \setminus A := \{x \in B : x \notin A\} = A \cap B^c. \]

We also define the symmetric difference of \( A \) and \( B \) by

\[ A \triangle B := (B \setminus A) \cup (A \setminus B). \]

As usual if \( \{A_\alpha\}_{\alpha \in I} \) is an indexed collection of subsets of \( X \) we define the union and the intersection of this collection by

\[ \bigcup_{\alpha \in I} A_\alpha := \{x \in X : \exists \alpha \in I \ \exists x \in A_\alpha\} \quad \text{and} \quad \bigcap_{\alpha \in I} A_\alpha := \{x \in X : x \in A_\alpha \forall \alpha \in I\}. \]

**Notation 3.4** We will also write \( \sum_{\alpha \in I} A_\alpha \) for \( \bigcup_{\alpha \in I} A_\alpha \) in the case that \( \{A_\alpha\}_{\alpha \in I} \) are pairwise disjoint, i.e. \( A_\alpha \cap A_\beta = \emptyset \) if \( \alpha \neq \beta \).

Notice that \( \bigcup \) is closely related to \( \exists \) and \( \cap \) is closely related to \( \forall \). For example let \( \{A_n\}_{n=1}^\infty \) be a sequence of subsets from \( X \) and define

\[ \inf_{k \geq n} A_n := \bigcap_{k \geq n} A_k, \quad \sup_{k \geq n} A_n := \bigcup_{k \geq n} A_k, \quad \limsup_{n \to \infty} A_n := \{A_n \text{ i.o.}\} := \{x \in X : \# \{n : x \in A_n\} = \infty\} \]

and

\[ \liminf_{n \to \infty} A_n := \{A_n \text{ a.a.}\} := \{x \in X : x \in A_n \text{ for all } n \text{ sufficiently large}\}. \]

(One should read \( \{A_n \text{ i.o.}\} \) as \( A_n \) infinitely often and \( \{A_n \text{ a.a.}\} \) as \( A_n \) almost always.) Then \( x \in \{A_n \text{ i.o.}\} \) iff

\[ \forall N \in \mathbb{N} \exists n \geq N \exists x \in A_n \]

and this may be expressed as

\[ \{A_n \text{ i.o.}\} = \bigcap_{n=1}^\infty \bigcup_{n \geq N} A_n. \]

Similarly, \( x \in \{A_n \text{ a.a.}\} \) iff

\[ \exists N \in \mathbb{N} \forall n \geq N, \ x \in A_n \]

which may be written as

\[ \{A_n \text{ a.a.}\} = \bigcup_{n=1}^\infty \bigcap_{n \geq N} A_n. \]
Lemma 3.6. We have:

1. \( \{A_n \text{ i.o.}\}^c = \{A_n^c \text{ a.a.}\} \),
2. \( \limsup_{n \to \infty} A_n = \{x \in X : \sum_{n=1}^{\infty} 1_{A_n}(x) = \infty\} \),
3. \( \liminf_{n \to \infty} A_n = \{x \in X : \sum_{n=1}^{\infty} 1_{A_n}(x) < \infty\} \),
4. \( \sup_{k \geq n} 1_{A_k}(x) = 1_\bigcup_{k \geq n} A_k = \limsup_{n \to \infty} A_n \),
5. \( \inf_{k \geq n} 1_{A_k}(x) = 1_\bigcap_{k \geq n} A_k = \liminf_{n \to \infty} A_n \),
6. \( \limsup_{n \to \infty} A_n = \limsup_{n \to \infty} 1_{A_n} \), and
7. \( \liminf_{n \to \infty} A_n = \liminf_{n \to \infty} 1_{A_n} \).

Definition 3.7. A set \( X \) is said to be countable if it is empty or there is an injective function \( f : X \to \mathbb{N} \), otherwise \( X \) is said to be uncountable.

Lemma 3.8 (Basic Properties of Countable Sets).

1. If \( A \subset X \) is a subset of a countable set \( X \) then \( A \) is countable.
2. Any infinite subset \( A \subset \mathbb{N} \) is in one to one correspondence with \( \mathbb{N} \).
3. A non-empty set \( X \) is countable if there exists a surjective map, \( g : \mathbb{N} \to X \).
4. If \( X \) and \( Y \) are countable then \( X \times Y \) is countable.
5. Suppose for each \( m \in \mathbb{N} \) that \( A_m \) is a countable subset of a set \( X \), then \( A = \bigcup_{m=1}^{\infty} A_m \) is countable. In short, the countable union of countable sets is still countable.
6. If \( X \) is an infinite set and \( Y \) is a set with at least two elements, then \( Y^X \) is uncountable. In particular \( 2^X \) is uncountable for any infinite set \( X \).

Proof. 1. If \( f : X \to \mathbb{N} \) is an injective map then so is the restriction, \( f|_A \), of \( f \) to the subset \( A \). Let \( f(1) = \min A \) and define \( f \) inductively by

\[
f(n + 1) = \min \{ A \setminus \{ f(1), \ldots, f(n) \} \}.
\]

Since \( A \) is infinite the process continues indefinitely. The function \( f : \mathbb{N} \to A \) defined this way is a bijection.

3. If \( g : \mathbb{N} \to X \) is a surjective map, let

\[
f(x) = \min \{ n \in \mathbb{N} : f(n) = x \}.
\]

Then \( f : X \to \mathbb{N} \) is injective which combined with item 2. (taking \( A = f(X) \)) shows \( X \) is countable. Conversely if \( f : X \to \mathbb{N} \) is injective let \( x_0 \in X \) be a fixed point and define \( g : \mathbb{N} \to X \) by \( g(n) = f^{-1}(n) \) for \( n \in f(X) \) and \( g(n) = x_0 \) otherwise.

4. Let us first construct a bijection, \( h \), from \( \mathbb{N} \) to \( \mathbb{N} \times \mathbb{N} \). To do this put the elements of \( \mathbb{N} \times \mathbb{N} \) into an array of the form

\[
\begin{pmatrix}
1 & 1 & 2 & 1 & 2 & 2 & 3 & 1 & 3 & 2 & 3 & \ldots \\
2 & 1 & 2 & 2 & 3 & 3 & \ldots & & & & \\
3 & 1 & 3 & 2 & 3 & 3 & \ldots & & & &
\end{pmatrix}
\]

and then “count” these elements by counting the sets \( \{(i, j) : i + j = k\} \) one at a time. For example let \( h(1) = (1, 1), h(2) = (2, 1), h(3) = (1, 2), h(4) = (3, 1), h(5) = (2, 2), h(6) = (1, 3) \) and so on. If \( f : \mathbb{N} \to X \) and \( g : \mathbb{N} \to Y \) are surjective functions, then the function \( (f \times g) \circ h : \mathbb{N} \to X \times Y \) is surjective where \( (f \times g)(m, n) := (f(m), g(n)) \) for all \( (m, n) \in \mathbb{N} \times \mathbb{N} \).

5. If \( A = \emptyset \) then \( A \) is countable by definition so we may assume \( A \neq \emptyset \). With out loss of generality we may assume \( A_1 \neq \emptyset \) and by replacing \( A_m \) by \( A_1 \) if necessary we may also assume \( A_m \neq \emptyset \) for all \( m \). For each \( m \in \mathbb{N} \) let \( a_m : \mathbb{N} \to A_m \) be a surjective function and then define \( f : \mathbb{N} \times \mathbb{N} \to \bigcup_{m=1}^{\infty} A_m \) by \( f(m, n) := a_m(n) \). The function \( f \) is surjective and hence so is the composition, \( f \circ h : \mathbb{N} \to \bigcup_{m=1}^{\infty} A_m \), where \( h : \mathbb{N} \to \mathbb{N} \times \mathbb{N} \) is the bijection defined above.

6. Let us begin by showing \( 2^\mathbb{N} = \{0, 1\}^\mathbb{N} \) is uncountable. For sake of contradiction suppose \( f : \mathbb{N} \to \{0, 1\}^\mathbb{N} \) is a surjection and write \( f(n) \) as \( (f_1(n), f_2(n), f_3(n), \ldots) \). Now define \( a \in \{0, 1\}^\mathbb{N} \) by \( a_n := 1 - f(n) \). By construction \( f_n(n) \neq a_n \) for all \( n \) and so \( a \notin f(\mathbb{N}) \). This contradicts the assumption that \( f \) is surjective and shows \( 2^\mathbb{N} \) is uncountable. For the general case, since \( Y^X \subset Y^X \) for any subset \( Y_0 \subset Y \), if \( Y_0^X \) is uncountable then so is \( Y^X \). In this way we may assume \( Y_0 \) is a two point set which may as well be \( Y_0 = \{0, 1\} \). Moreover, since \( X \) is an infinite set we may find an injective map \( i : X \to \mathbb{N} \) and use this to set up an injection, \( i : 2^X \to 2^\mathbb{N} \) by setting \( i(A) := \{ x_n : x_n \in \mathbb{N} \} \subset X \) for all \( A \subset \mathbb{N} \). If \( 2^\mathbb{N} \) were countable we could find a surjective map \( f : 2^X \to \mathbb{N} \) in which case \( f \circ i : 2^X \to \mathbb{N} \) would be surjective as well. However this is impossible since we have already seed that \( 2^\mathbb{N} \) is uncountable.

We end this section with some notation which will be used frequently in the sequel.

Notation 3.9 If \( f : X \to Y \) is a function and \( \mathcal{E} \subset 2^Y \) let

\[
f^{-1}\mathcal{E} := f^{-1}(\mathcal{E}) := \{ f^{-1}(E) | E \in \mathcal{E} \}.
\]

If \( \mathcal{G} \subset 2^X \), let

\[
f_\mathcal{G} := \{ A \in 2^Y | f^{-1}(A) \in \mathcal{G} \}.
\]
Definition 3.10. Let $\mathcal{E} \subset 2^X$ be a collection of sets, $A \subset X$, $i_A : A \to X$ be the inclusion map ($i_A(x) = x$ for all $x \in A$) and

$$E_A = i_A^{-1}(\mathcal{E}) = \{ A \cap E : E \in \mathcal{E} \}.$$

3.2 Exercises

Let $f : X \to Y$ be a function and $\{ A_i \}_{i \in I}$ be an indexed family of subsets of $Y$, verify the following assertions.

Exercise 3.1. $(\bigcap_{i \in I} A_i)^c = \bigcup_{i \in I} A_i^c$.

Exercise 3.2. Suppose that $B \subset Y$, show that $B \setminus (\bigcup_{i \in I} A_i) = \bigcap_{i \in I} (B \setminus A_i)$.

Exercise 3.3. $f^{-1}(\bigcup_{i \in I} A_i) = \bigcup_{i \in I} f^{-1}(A_i)$.

Exercise 3.4. $f^{-1}(\bigcap_{i \in I} A_i) = \bigcap_{i \in I} f^{-1}(A_i)$.

Exercise 3.5. Find a counterexample which shows that $f(C \cap D) = f(C) \cap f(D)$ need not hold.

Example 3.11. Let $X = \{a, b, c\}$ and $Y = \{1, 2\}$ and define $f(a) = f(b) = 1$ and $f(c) = 2$. Then $\emptyset = f(\{a\} \cap \{b\}) \neq f(\{a\}) \cap f(\{b\}) = \{1\}$ and $\{1, 2\} = f(\{a\} \cap \{b\}) \neq f(\{a\})^c \cap f(\{b\})^c = \{2\}$.

3.3 Algebraic sub-structures of sets

Definition 3.12. A collection of subsets $\mathcal{A}$ of a set $X$ is a $\pi$-system or multiplicative system if $\mathcal{A}$ is closed under taking finite intersections.

Definition 3.13. A collection of subsets $\mathcal{A}$ of a set $X$ is an algebra (Field) if

1. $\emptyset, X \in \mathcal{A}$
2. $A \in \mathcal{A}$ implies that $A^c \in \mathcal{A}$
3. $\mathcal{A}$ is closed under finite unions, i.e. if $A_1, \ldots, A_n \in \mathcal{A}$ then $A_1 \cup \cdots \cup A_n \in \mathcal{A}$.

In view of conditions 1. and 2., 3. is equivalent to

3'. $\mathcal{A}$ is closed under finite intersections.

Definition 3.14. A collection of subsets $\mathcal{B}$ of $X$ is a $\sigma$-algebra (or sometimes called a $\sigma$-field) if $\mathcal{B}$ is an algebra which also closed under countable unions, i.e. if $\{A_i\}_{i=1}^\infty \subset \mathcal{B}$, then $\bigcup_{i=1}^\infty A_i \in \mathcal{B}$, (Notice that since $\mathcal{B}$ is also closed under taking complements, $\mathcal{B}$ is also closed under taking countable intersections.)

Example 3.15. Here are some examples of algebras.

1. $\mathcal{B} = 2^X$, then $\mathcal{B}$ is a $\sigma$-algebra.
2. $\mathcal{B} = \{\emptyset, X\}$ is a $\sigma$-algebra called the trivial $\sigma$-field.
3. Let $X = \{1, 2, 3\}$, then $\mathcal{A} = \{\emptyset, X, \{1\}, \{2, 3\}\}$ is an algebra while $\mathcal{S} := \{\emptyset, X, \{2, 3\}\}$ is not an algebra but is a $\pi$-system.

Proposition 3.16. Let $\mathcal{E}$ be any collection of subsets of $X$. Then there exists a unique smallest algebra $\mathcal{A}(\mathcal{E})$ and $\sigma$-algebra $\sigma(\mathcal{E})$ which contains $\mathcal{E}$.

Proof. Simply take

$$\mathcal{A}(\mathcal{E}) := \bigcap \{ \mathcal{A} : \mathcal{A} \text{ is an algebra such that } \mathcal{E} \subset \mathcal{A} \}$$

and

$$\sigma(\mathcal{E}) := \bigcap \{ \mathcal{M} : \mathcal{M} \text{ is a } \sigma \text{- algebra such that } \mathcal{E} \subset \mathcal{M} \}.$$

Example 3.17. Suppose $X = \{1, 2, 3\}$ and $\mathcal{E} = \{\emptyset, X, \{1, 2\}, \{1, 3\}\}$, see Figure 3.1. Then

![Figure 3.1](image-url)

Fig. 3.1. A collection of subsets.

$$\mathcal{A}(\mathcal{E}) = \sigma(\mathcal{E}) = 2^X.$$

On the other hand if $\mathcal{E} = \{\{1, 2\}\}$, then $\mathcal{A}(\mathcal{E}) = \{\emptyset, X, \{1, 2\}, \{3\}\}$.

Exercise 3.6. Suppose that $\mathcal{E}_i \subset 2^X$ for $i = 1, 2$. Show that $\mathcal{A}(\mathcal{E}_1) = \mathcal{A}(\mathcal{E}_2)$ iff $\mathcal{E}_1 \subset \mathcal{A}(\mathcal{E}_2)$ and $\mathcal{E}_2 \subset \mathcal{A}(\mathcal{E}_1)$. Similarly show, $\sigma(\mathcal{E}_1) = \sigma(\mathcal{E}_2)$ iff $\mathcal{E}_1 \subset \sigma(\mathcal{E}_2)$ and $\mathcal{E}_2 \subset \sigma(\mathcal{E}_1)$. Give a simple example where $\mathcal{A}(\mathcal{E}_1) = \mathcal{A}(\mathcal{E}_2)$ while $\mathcal{E}_1 \neq \mathcal{E}_2$. 


Definition 3.18. Let $X$ be a set. We say that a family of sets $\mathcal{F} \subset 2^X$ is a partition of $X$ if distinct members of $\mathcal{F}$ are disjoint and if $X$ is the union of the sets in $\mathcal{F}$.

Example 3.19. Let $X$ be a set and $\mathcal{E} = \{A_1, \ldots, A_n\}$ where $A_1, \ldots, A_n$ is a partition of $X$. In this case

$$A(\mathcal{E}) = \sigma(\mathcal{E}) = \{ \bigcup_{i \in A} A_i : A \subset \{1, 2, \ldots, n\} \}$$

where $\bigcup_{i \in A} A_i := \emptyset$ when $A = \emptyset$. Notice that

$$\#(A(\mathcal{E})) = \#(2^{\{1, 2, \ldots, n\}}) = 2^n.$$

Example 3.20. Suppose that $X$ is a finite set and that $A \subset 2^X$ is an algebra. For each $x \in X$ let

$$A_x = \bigcap \{ A \in A : x \in A \} \in A,$$

wherein we have used $A$ is finite to insure $A_x \in A$. Hence $A_x$ is the smallest set in $A$ which contains $x$. Let $C = A_x \cap A_y \in A$. I claim that if $C \neq \emptyset$, then $A_x = A_y$. To see this, let us first consider the case where $\{x, y\} \subset C$. In this case we must have $A_x \subset C$ and $A_y \subset C$ and therefore $A_x = A_y$. Now suppose either $x$ or $y$ is not in $C$. For definiteness, say $x \notin C$, i.e. $x \notin y$. Then $x \in A_x \setminus A_y \in A$ from which it follows that $A_x = A_x \setminus A_y$, i.e. $A_x \cap A_y = \emptyset$.

Let us now define $\{B_i\}_{i=1}^k$ to be an enumeration of $\{A_x\}_{x \in X}$. It is now a straightforward exercise to show

$$A = \{ \bigcup_{i \in A} B_i : A \subset \{1, 2, \ldots, k\} \}.$$

Proposition 3.21. Suppose that $B \subset 2^X$ is a $\sigma$– algebra and $B$ is at most a countable set. Then there exists a unique finite partition $\mathcal{F}$ of $X$ such that $\mathcal{F} \subset B$ and every element $B \in B$ is of the form

$$B = \bigcup \{ A \in \mathcal{F} : A \subset B \}.$$  \hspace{1cm} (3.1)

In particular $B$ is actually a finite set and $\#(B) = 2^n$ for some $n \in \mathbb{N}$.

Proof. We proceed as in Example 3.20. For each $x \in X$ let

$$A_x = \bigcap \{ A \in B : x \in A \} \in B,$$

wherein we have used $B$ is a countable $\sigma$– algebra to insure $A_x \in B$. Just as above either $A_x \cap A_y = \emptyset$ or $A_x = A_y$ and therefore $\mathcal{F} = \{A_x : x \in X\} \subset B$ is a (necessarily countable) partition of $X$ for which Eq. (3.1) holds for all $B \in B$.

Enumerate the elements of $\mathcal{F}$ as $\mathcal{F} = \{P_n\}_{n=1}^N$ where $N \in \mathbb{N}$ or $N = \infty$. If $N = \infty$, then the correspondence

$$a \in \{0, 1\}^N \rightarrow A_a = \bigcup \{P_n : a_n = 1\} \in B$$

is bijective and therefore, by Lemma 3.8, $B$ is uncountable. Thus any countable $\sigma$– algebra is necessarily finite. This finishes the proof modulo the uniqueness assertion which is left as an exercise to the reader. \hfill $\blacksquare$

Example 3.22 (Countable/Co-countable $\sigma$– Field). Let $X = \mathbb{R}$ and $\mathcal{E} := \{\{x\} : x \in \mathbb{R}\}$. Then $\sigma(\mathcal{E})$ consists of those subsets, $A \subset \mathbb{R}$, such that $A$ is countable or $A^c$ is countable. Similarly, $A(\mathcal{E})$ consists of those subsets, $A \subset \mathbb{R}$, such that $A$ is finite or $A^c$ is finite. More generally we have the following exercise.

Exercise 3.7. Let $X$ be a set, $I$ be an infinite index set, and $\mathcal{E} = \{A_i\}_{i \in I}$ be a partition of $X$. Prove the algebra, $A(\mathcal{E})$, and that $\sigma$– algebra, $\sigma(\mathcal{E})$, generated by $\mathcal{E}$ are given by

$$A(\mathcal{E}) = \{ \bigcup_{i \in A} A_i : A \subset I \text{ with } \#(A) < \infty \text{ or } \#(A^c) < \infty \}$$

and

$$\sigma(\mathcal{E}) = \{ \bigcup_{i \in A} A_i : A \subset I \text{ with } A \text{ countable or } A^c \text{ countable} \}$$

respectively. Here we are using the convention that $\bigcup_{i \in A} A_i := \emptyset$ when $A = \emptyset$.

Proposition 3.23. Let $X$ be a set and $\mathcal{E} \subset 2^X$. Let $\mathcal{E}^c := \{A^c : A \in \mathcal{E}\}$ and $\mathcal{E}_c := \mathcal{E} \cup \{X, \emptyset\} \cup \mathcal{E}^c$. Then

$$A(\mathcal{E}) := \{ \text{finite unions of finite intersections of elements from } \mathcal{E}_c \}.$$ \hspace{1cm} (3.2)

Proof. Let $A$ denote the right member of Eq. (3.2). From the definition of an algebra, it is clear that $\mathcal{E} \subset A \subset A(\mathcal{E})$. Hence to finish that proof it suffices to show $A$ is an algebra. The proof of these assertions are routine except for possibly showing that $A$ is closed under complementation. To check $A$ is closed under complementation, let $Z \in A$ be expressed as

$$Z = \bigcup_{i=1}^N \bigcap_{j=1}^K A_{ij}$$

where $A_{ij} \in \mathcal{E}_c$. Therefore, writing $B_{ij} = A_{ij}^c \in \mathcal{E}_c$, we find that

$$Z^c = \bigcap_{i=1}^N \bigcup_{j=1}^K B_{ij} = \bigcup_{j_1 \leq j_2 \leq \cdots \leq j_N} (B_{1j_1} \cap B_{2j_2} \cap \cdots \cap B_{Nj_N}) \in A$$

wherein we have used the fact that $B_{1j_1} \cap B_{2j_2} \cap \cdots \cap B_{Nj_N}$ is a finite intersection of sets from $\mathcal{E}_c$. \hfill $\blacksquare$
Remark 3.24. One might think that in general $\sigma(\mathcal{E})$ may be described as the countable unions of countable intersections of sets in $\mathcal{E}$. However this is in general false, since if

$$Z = \bigcup_{i=1}^{\infty} \bigcap_{j=1}^{\infty} A_{ij}$$

with $A_{ij} \in \mathcal{E}$, then

$$Z' = \bigcup_{j_1,i_1,j_2,\ldots,j_n=1}^{\infty} \left( \bigcap_{\ell=1}^{\infty} A_{i_{\ell}j_{\ell}} \right)$$

which is now an uncountable union. Thus the above description is not correct. In general it is complicated to explicitly describe $\sigma(\mathcal{E})$, see Proposition 1.23 on page 39 of Folland for details. Also see Proposition 3.21.

Exercise 3.8. Let $\tau$ be a topology on a set $X$ and $A = A(\tau)$ be the algebra generated by $\tau$. Show $A$ is the collection of subsets of $X$ which may be written as finite union of sets of the form $F \cap V$ where $F$ is closed and $V$ is open.

Solution to Exercise (3.8). In this case $\tau_c$ is the collection of sets which are either open or closed. Now if $V_i \subset_o X$ and $F_j \subset X$ for each $j$, then $(\bigcap_{i=1}^{m} V_i) \cap (\bigcap_{j=1}^{n} F_j)$ is simply a set of the form $V \cap F$ where $V \subset_o X$ and $F \subset X$. Therefore the result is an immediate consequence of Proposition 3.23.

Definition 3.25. The Borel $\sigma-$field, $B = B_\mathbb{R} = B(\mathbb{R})$, on $\mathbb{R}$ is the smallest $\sigma$-field containing all of the open subsets of $\mathbb{R}$.

Exercise 3.9. Verify the $\sigma-$algebra, $B_\mathbb{R}$, is generated by any of the following collection of sets:

1. $\{(a, \infty) : a \in \mathbb{R}\}$, 2. $\{(a, \infty) : a \in \mathbb{Q}\}$ or 3. $\{[a, \infty) : a \in \mathbb{Q}\}$.

Hint: make use of Exercise 3.6.

Exercise 3.10. Suppose $f : X \rightarrow Y$ is a function, $\mathcal{F} \subset 2^Y$ and $\mathcal{B} \subset 2^X$. Show $f^{-1}\mathcal{F}$ and $f_{*}\mathcal{B}$ (see Notation 3.9) are algebras ($\sigma-$algebras) provided $\mathcal{F}$ and $\mathcal{B}$ are algebras ($\sigma-$algebras).

Lemma 3.26. Suppose that $f : X \rightarrow Y$ is a function and $\mathcal{E} \subset 2^Y$ and $A \subset Y$ then

$$\sigma(\mathcal{E}^i) = f^{-1}(\sigma(\mathcal{E}))$$

(3.3)

(\sigma(\mathcal{E}))_A = \sigma(\mathcal{E}_A),

(3.4)

where $B_A := \{ B \cap A : B \in \mathcal{B} \}$. (Similar assertion hold with $\sigma(\cdot)$ being replaced by $A(\cdot)$.)

Proof. By Exercise 3.10 $f^{-1}(\sigma(\mathcal{E}))$ is a $\sigma-$algebra and since $\mathcal{E} \subset \mathcal{F}$, $f^{-1}(\mathcal{E}) \subset f^{-1}(\sigma(\mathcal{E}))$. It now follows that

$$\sigma(f^{-1}(\mathcal{E})) \subset f^{-1}(\sigma(\mathcal{E})).$$

For the reverse inclusion, notice that

$$f_*\sigma(f^{-1}(\mathcal{E})) := \{ B \subset Y : f^{-1}(B) \in \sigma(f^{-1}(\mathcal{E})) \}$$

is a $\sigma-$algebra which contains $\mathcal{E}$ and thus $\sigma(\mathcal{E}) \subset f_*\sigma(f^{-1}(\mathcal{E}))$. Hence for every $B \in \sigma(\mathcal{E})$ we know that $f^{-1}(B) \in \sigma(f^{-1}(\mathcal{E}))$ i.e.

$$f^{-1}(\sigma(\mathcal{E})) \subset \sigma(f^{-1}(\mathcal{E})).$$

Applying Eq. (3.3) with $X = A$ and $f = i_A$ being the inclusion map implies

$$\sigma(\mathcal{E})_A = i_A^{-1}(\sigma(\mathcal{E})) = \sigma(i_A^{-1}(\mathcal{E})) = \sigma(\mathcal{E}_A).$$

Example 3.27. Let $\mathcal{E} = \{(a, b) : -\infty < a < b < \infty\}$ and $\mathcal{B} = \sigma(\mathcal{E})$ be the Borel $\sigma-$field on $\mathbb{R}$. Then

$$\mathcal{E}_{[0,1]} = \{(a, b) : 0 \leq a < b \leq 1\}$$

and we have

$$\mathcal{B}_{[0,1]} = \sigma(\mathcal{E}_{[0,1]}).$$

In particular, if $A \subset \mathcal{B}$ such that $A \subset (0,1]$, then $A \in \sigma(\mathcal{E}_{[0,1]})$.

Definition 3.28. A function, $f : \Omega \rightarrow Y$ is said to be simple if $f(\Omega) \subset Y$ is a finite set. If $A \subset 2^\Omega$ is an algebra, we say that a simple function $f : \Omega \rightarrow Y$ is measurable if $\{ f = y \} := f^{-1}(\{ y \}) \in A$ for all $y \in Y$. A measurable simple function, $f : \Omega \rightarrow \mathbb{C}$, is called a simple random variable relative to $A$.

Notation 3.29 Given an algebra, $A \subset 2^\Omega$, let $\mathbb{S}(A)$ denote the collection of simple random variables from $\Omega$ to $\mathbb{C}$. For example if $A \subset A$, then $1_A \in \mathbb{S}(A)$ is a measurable simple function.

Lemma 3.30. For every algebra $A \subset 2^\Omega$, the set simple random variables, $\mathbb{S}(A)$, forms an algebra.

Proof. Let us observe that $1_\Omega = 1$ and $1_\emptyset = 0$ are in $\mathbb{S}(A)$. If $f, g \in \mathbb{S}(A)$ and $c \in \mathbb{C} \setminus \{ 0 \}$, then

$$\{ f + cg = \lambda \} = \bigcup_{a,b \in \mathbb{C}, a + cb = \lambda} \{ \{ f = a \} \cap \{ g = b \} \} \in A$$

(3.5)
and
\[ \{f \cdot g = \lambda\} = \bigcup_{a,b,c : a \cdot b = c = \lambda} \{(f = a) \cap \{g = b\}\} \in \mathcal{A} \] (3.6)
from which it follows that \( f + cg \) and \( f \cdot g \) are back in \( S(\mathcal{A}) \).

**Definition 3.31.** A *simple function algebra*, \( S \), is a subalgebra of the bounded complex functions on \( X \) such that \( 1 \in S \) and each function, \( f \in S \), is a simple function. If \( S \) is a simple function algebra, let
\[ \mathcal{A}(S) := \{ A \subset X : 1_A \in S \}. \]
(It is easily checked that \( \mathcal{A}(S) \) is a sub-algebra of \( 2^X \).)

**Lemma 3.32.** Suppose that \( S \) is a simple function algebra, \( f \in S \) and \( \alpha \in f(X) \). Then \( \{f = \alpha\} \in \mathcal{A}(S) \).

**Proof.** Let \( \{\lambda_i\}_{i=0}^n \) be an enumeration of \( f(X) \) with \( \lambda_0 = \alpha \). Then
\[ g := \left[ \prod_{i=1}^n (\alpha - \lambda_i) \right]^{-1} \prod_{i=1}^n (f - \lambda_i) \in S. \]
Moreover, we see that \( g = 0 \) on \( \cup_{i=1}^n \{f = \lambda_i\} \) while \( g = 1 \) on \( \{f = \alpha\} \). So we have shown \( g = 1_{f = \alpha} \in S \) and therefore that \( \{f = \alpha\} \in \mathcal{A} \).

**Exercise 3.11.** Continuing the notation introduced above:
1. Show \( \mathcal{A}(S) \) is an algebra of sets.
2. Show \( S(\mathcal{A}) \) is a simple function algebra.
3. Show that the map
\[ \mathcal{A} \in \{\text{Algebras} \subset 2^X\} \rightarrow S(\mathcal{A}) \in \{\text{simple function algebras on } X\} \]
is bijective and the map, \( S \rightarrow S(\mathcal{A}) \), is the inverse map.

**Solution to Exercise 3.11.**
1. Since \( 0 = 1_\emptyset, 1 = 1_X \in S \), it follows that \( 0 \) and \( X \) are in \( \mathcal{A}(S) \). If \( A \in \mathcal{A}(S) \), then \( 1_A = 1 - 1_A \in S \) and so \( A^c \in \mathcal{A}(S) \). Finally, if \( A, B \in \mathcal{A}(S) \) then \( 1_{A \cap B} = 1_A \cdot 1_B \in S \) and thus \( A \cap B \in \mathcal{A}(S) \).
2. If \( f, g \in S(\mathcal{A}) \) and \( c \in \mathbb{F} \), then
\[ \{f + cg = \lambda\} = \bigcup_{a,b,c : a \cdot b = c = \lambda} \{(f = a) \cap \{g = b\}\} \in \mathcal{A} \]
and
\[ \{f \cdot g = \lambda\} = \bigcup_{a,b,c : a \cdot b = c = \lambda} \{(f = a) \cap \{g = b\}\} \in \mathcal{A} \]
from which it follows that \( f + cg \) and \( f \cdot g \) are back in \( S(\mathcal{A}) \).

3. If \( f : \Omega \rightarrow \mathbb{C} \) is a simple function such that \( 1_{f = \lambda} \in S \) for all \( \lambda \in \mathbb{C} \), then \( f = \sum_{\lambda \in \mathbb{C}} 1_{f = \lambda} \in S \). Conversely, by Lemma 3.32, if \( f \in S \) then \( 1_{f = \lambda} \in S \) for all \( \lambda \in \mathbb{C} \). Therefore, a simple function, \( f : X \rightarrow \mathbb{C} \) is in \( S \) iff \( 1_{f = \lambda} \in S \) for all \( \lambda \in \mathbb{C} \). With this preparation, we are now ready to complete the verification.
First off,
\[ A \in \mathcal{A}(S(\mathcal{A})) \iff 1_A \in \mathcal{A}(S(\mathcal{A})) \iff A \in \mathcal{A} \]
which shows that \( \mathcal{A}(S(\mathcal{A})) = \mathcal{A} \). Similarly,
\[ f \in \mathcal{A}(S(\mathcal{A})) \iff \{f = \lambda\} \in \mathcal{A}(S(\mathcal{A})) \forall \lambda \in \mathbb{C} \]
\[ \iff 1_{\{f = \lambda\}} \in \mathcal{S} \forall \lambda \in \mathbb{C} \]
\[ \iff f \in S \]
which shows \( S(\mathcal{A}(S)) = S \).
Finitely Additive Measures

Definition 4.1. Suppose that $\mathcal{E} \subset 2^X$ is a collection of subsets of $X$ and $\mu : \mathcal{E} \to [0, \infty]$ is a function. Then

1. $\mu$ is monotonic if $\mu(A) \leq \mu(B)$ for all $A, B \in \mathcal{E}$ with $A \subset B$.
2. $\mu$ is sub-additive (finitely sub-additive) on $\mathcal{E}$ if
   \[ \mu(E) \leq \sum_{i=1}^{n} \mu(E_i) \]
   whenever $E = \bigcup_{i=1}^{n} E_i \in \mathcal{E}$ with $n \in \mathbb{N} \cup \{\infty\}$ ($n \in \mathbb{N}$).
3. $\mu$ is super-additive (finitely super-additive) on $\mathcal{E}$ if
   \[ \mu(E) \geq \sum_{i=1}^{n} \mu(E_i) \]
   whenever $E = \bigcap_{i=1}^{n} E_i \in \mathcal{E}$ with $n \in \mathbb{N} \cup \{\infty\}$ ($n \in \mathbb{N}$).
4. $\mu$ is additive or finitely additive on $\mathcal{E}$ if
   \[ \mu(E) = \sum_{i=1}^{n} \mu(E_i) \]
   whenever $E = \bigcup_{i=1}^{n} E_i \in \mathcal{E}$ with $E_i \in \mathcal{E}$ for $i = 1, 2, \ldots, n < \infty$.
5. If $\mathcal{E} = A$ is an algebra, $\mu(\emptyset) = 0$, and $\mu$ is finitely additive on $A$, then $\mu$ is said to be a finitely additive measure.
6. $\mu$ is $\sigma$-additive (or countable additive) on $\mathcal{E}$ if item 4. holds even when $n = \infty$.
7. If $\mathcal{E} = A$ is an algebra, $\mu(\emptyset) = 0$, and $\mu$ is $\sigma$-additive on $A$ then $\mu$ is called a premeasure on $A$.
8. A measure is a premeasure, $\mu : \mathcal{B} \to [0, \infty]$, where $\mathcal{B}$ is a $\sigma$-algebra. We say that $\mu$ is a probability measure if $\mu(X) = 1$.

4.1 Finitely Additive Measures

Proposition 4.2 (Basic properties of finitely additive measures). Suppose $\mu$ is a finitely additive measure on an algebra, $A \subset 2^X$, $E, F \in A$ with $E \subset F$ and $\{E_j\}_{j=1}^{\infty} \subset A$, then:

1. (\textit{\mu is monotone}) $\mu(E) \leq \mu(F)$ if $E \subset F$.
2. For $A, B \in A$, the following strong additivity formula holds;
   \[ \mu(A \cup B) + \mu(A \cap B) = \mu(A) + \mu(B). \] (4.3)
3. (\textit{\mu is finitely subadditive}) $\mu(\bigcap_{i=1}^{n} E_i) \leq \sum_{i=1}^{n} \mu(E_i)$. (4.1)
4. $\mu$ is sub-additive on $A$ iff
   \[ \mu(A) \leq \sum_{i=1}^{\infty} \mu(A_i) \text{ for } A = \bigcup_{i=1}^{\infty} A_i \] (4.4)
   where $A \in A$ and $\{A_i\}_{i=1}^{\infty} \subset A$ are pairwise disjoint sets.
5. (\textit{\mu is countably superadditive}) If $A = \bigcup_{i=1}^{\infty} A_i$ with $A_i \in A$, then
   \[ \mu\left(\bigcup_{i=1}^{\infty} A_i\right) \geq \sum_{i=1}^{\infty} \mu(A_i). \]
6. A finitely additive measure, $\mu$, is a premeasure iff $\mu$ is sub-additive.

Proof.

1. Since $F$ is the disjoint union of $E$ and $(F \setminus E)$ and $F \setminus E = F \cap E^c \in A$ it follows that
   \[ \mu(F) = \mu(E) + \mu(F \setminus E) \geq \mu(E). \]
2. Since
   \[ A \cup B = [A \setminus (A \cap B)] \cup [B \setminus (A \cap B)] \cup A \cap B, \]
   \[ \mu(A \cup B) = \mu(A \setminus (A \cap B)) + \mu(B \setminus (A \cap B)) + \mu(A \cap B) \]
   Adding $\mu(A \cap B)$ to both sides of this equation proves Eq. (4.3).
3. Let $\tilde{E}_j = E_j \setminus (E_1 \cup \cdots \cup E_{j-1})$ so that the $\tilde{E}_j$'s are pair-wise disjoint and $E = \bigcup_{j=1}^{\infty} \tilde{E}_j$. Since $\tilde{E}_j \subset E_j$ it follows from the monotonicity of $\mu$ that
   \[ \mu(E) = \sum \mu(\tilde{E}_j) \leq \sum \mu(E_j). \]
4. If $A = \bigcup_{i=1}^{\infty} B_i$ with $A \in \mathcal{A}$ and $B_i \in \mathcal{A}$, then $A = \sum_{i=1}^{\infty} A_i$ where $A_i := B_i \setminus (B_1 \cup \ldots \cup B_{i-1}) \in \mathcal{A}$ and $B_0 = \emptyset$. Therefore using the monotonicity of $\mu$ and Eq. \ref{eq:sum-measure}.

$$\mu(A) \leq \sum_{i=1}^{\infty} \mu(A_i) \leq \sum_{i=1}^{\infty} \mu(B_i).$$

5. Suppose that $A = \sum_{i=1}^{n} A_i$ with $A_i, A \in \mathcal{A}$, then $\sum_{i=1}^{n} A_i \subset A$ for all $n$ and so by the monotonicity and finite additivity of $\mu$, $\sum_{i=1}^{n} \mu(A_i) \leq \mu(A)$. Letting $n \to \infty$ in this equation shows $\mu$ is superadditive.

6. This is a combination of items 5. and 6.

**Proposition 4.3.** Suppose that $P$ is a finitely additive probability measure on an algebra, $A \subset 2^{\Omega}$. Then the following are equivalent:

1. $P$ is $\sigma$-additive on $A$.
2. For all $A_n \in A$ such that $A_n \uparrow A \in A$, $P(A_n) \uparrow P(A)$.
3. For all $A_n \in A$ such that $A_n \downarrow A \in A$, $P(A_n) \downarrow P(A)$.
4. For all $A_n \in A$ such that $A_n \uparrow \Omega$, $P(A_n) \uparrow 1$.
5. For all $A_n \in A$ such that $A_n \downarrow \Omega$, $P(A_n) \downarrow 1$.

**Proof.** We will start by showing $1 \iff 2 \iff 3$.

1 $\implies$ 2. Suppose $A_n \in A$ such that $A_n \uparrow A \in A$. Let $A'_n := A_n \setminus A_{n-1}$ with $A_0 := \emptyset$. Then $\{A'_n\}_{n=1}^{\infty}$ are disjoint, $A_n = \bigcup_{k=1}^{n} A'_k$ and $A = \bigcup_{k=1}^{\infty} A'_k$. Therefore,

$$P(A) = \sum_{k=1}^{\infty} P(A'_k) = \lim_{n \to \infty} \sum_{k=1}^{n} P(A'_k) = \lim_{n \to \infty} P(\bigcup_{k=1}^{n} A'_k) = \lim_{n \to \infty} P(A_n).$$

2 $\iff$ 1. If $\{A_n\}_{n=1}^{\infty}$ are disjoint and $A := \bigcup_{n=1}^{\infty} A_n \in A$, then $\bigcup_{n=1}^{\infty} A_n \uparrow A$. Therefore,

$$P(A) = \lim_{n \to \infty} P\left(\bigcup_{n=1}^{\infty} A_n\right) = \lim_{n \to \infty} \sum_{n=1}^{N} P(A_n) = \sum_{n=1}^{\infty} P(A_n).$$

2 $\implies$ 3. If $A_n \in A$ such that $A_n \downarrow A \in A$, then $A'_n \uparrow A^c$ and therefore,

$$\lim_{n \to \infty} \left(1 - P(A_n)\right) = \lim_{n \to \infty} P(A'_n) = P(A^c) = 1 - P(A).$$

3 $\implies$ 2. If $A_n \in A$ such that $A_n \uparrow A \in A$, then $A'_n \downarrow A^c$ and therefore we again have,

$$\lim_{n \to \infty} \left(1 - P(A_n)\right) = \lim_{n \to \infty} P(A'_n) = P(A^c) = 1 - P(A).$$

It is clear that 2 $\implies$ 4 and that 3 $\implies$ 5. To finish the proof we will show 5 $\implies$ 2 and 5 $\implies$ 3.

5 $\implies$ 2. If $A_n \in A$ such that $A_n \uparrow A \in A$, then $A \setminus A_n \downarrow \emptyset$ and therefore

$$\lim_{n \to \infty} [P(A) - P(A_n)] = \lim_{n \to \infty} P(A \setminus A_n) = 0.$$

5 $\implies$ 3. If $A_n \in A$ such that $A_n \downarrow A \in A$, then $A \setminus A_n \uparrow \emptyset$. Therefore,

$$\lim_{n \to \infty} [P(A_n) - P(A)] = \lim_{n \to \infty} P(A_n \setminus A) = 0.$$

**Remark 4.4.** Observe that the equivalence of items 1. and 2. in the above proposition hold without the restriction that $P(\Omega) = 1$ and in fact $P(\Omega) = \infty$ may be allowed for this equivalence.

**Definition 4.5.** Let $(\Omega, B)$ be a measurable space, i.e. $B \subset 2^{\Omega}$ is a $\sigma$-algebra. A probability measure on $(\Omega, B)$ is a finitely additive probability measure, $P : B \to [0,1]$ such that any and hence all of the continuity properties in Proposition 3.3 hold. We will call $(\Omega, B, P)$ a probability space.

**Lemma 4.6.** Suppose that $(\Omega, B, P)$ is a probability space, then $P$ is countably sub-additive.

**Proof.** Suppose that $A_n \in B$ and let $A'_n := A_n \setminus (A_1 \cup \ldots \cup A_{n-1}) \in B$. Then

$$P\left(\bigcup_{n=1}^{\infty} A_n\right) = P\left(\bigcup_{n=1}^{\infty} A'_n\right) = \sum_{n=1}^{\infty} P(A'_n) \leq \sum_{n=1}^{\infty} P(A_n).$$

**4.2 Examples of Measures**

Most $\sigma$-algebras and $\sigma$-additive measures are somewhat difficult to describe and define. However, there are a few special cases where we can describe explicitly what is going on.

**Example 4.7.** Suppose that $\Omega$ is a finite set, $B := 2^{\Omega}$, and $p : \Omega \to [0,1]$ is a function such that

$$\sum_{\omega \in \Omega} p(\omega) = 1.$$

Then

$$P(A) := \sum_{\omega \in A} p(\omega) \text{ for all } A \subset \Omega$$

defines a measure on $2^{\Omega}$.
Example 4.8. Suppose that $X$ is any set and $x \in X$ is a point. For $A \subset X$, let

$$\delta_x(A) = \begin{cases} 1 & \text{if } x \in A \\ 0 & \text{if } x \notin A. \end{cases}$$

Then $\mu = \delta_x$ is a measure on $X$ called the Dirac delta measure at $x$.

Example 4.9. Suppose that $\mu$ is a measure on $X$ and $\lambda > 0$, then $\lambda \cdot \mu$ is also a measure on $X$. Moreover, if $\{\mu_j\}_{j \in J}$ are all measures on $X$, then $\mu = \sum_{j=1}^{\infty} \mu_j$, i.e.

$$\mu(A) = \sum_{j=1}^{\infty} \mu_j(A)$$

is a measure on $X$. (See Section 3.1 for the meaning of this sum.) To prove this we must show that $\mu$ is countably additive. Suppose that $\{A_i\}_{i=1}^{\infty}$ is a collection of pairwise disjoint subsets of $X$, then

$$\mu(\bigcup_{i=1}^{\infty} A_i) = \sum_{i=1}^{\infty} \mu(A_i) = \sum_{i=1}^{\infty} \sum_{j=1}^{\infty} \mu_j(A_i)$$

is determined uniquely by its values on $\mathcal{F}$. Conversely, if we are given any function $\lambda : \mathcal{F} \to [0, \infty]$ we may define, for $A \in \mathcal{B}$,

$$\mu(A) = \sum_{\alpha \in \mathcal{F} \ni A} \lambda(\alpha) = \sum_{\alpha \in \mathcal{F}} \lambda(\alpha) 1_{\alpha \subset A}$$

where $1_{\alpha \subset A}$ is one if $\alpha \subset A$ and zero otherwise. We may check that $\mu$ is a measure on $\mathcal{B}$. Indeed, if $A = \bigcup_{i=1}^{\infty} A_i$ and $\alpha \in \mathcal{F}$, then $\alpha \subset A$ if and only if $\alpha \subset A_i$ for one and hence exactly one $A_i$. Therefore $1_{\alpha \subset A} = \sum_{i=1}^{\infty} 1_{\alpha \subset A_i}$ and hence

$$\mu(A) = \sum_{\alpha \in \mathcal{F}} \lambda(\alpha) 1_{\alpha \subset A} = \sum_{\alpha \in \mathcal{F}} \lambda(\alpha) \sum_{i=1}^{\infty} 1_{\alpha \subset A_i}$$

as desired. Thus we have shown that there is a one-to-one correspondence between measures $\mu$ on $\mathcal{B}$ and functions $\lambda : \mathcal{F} \to [0, \infty]$.

The following example explains what is going on in a more typical case of interest to us in the sequel.

Example 4.10. Suppose that $X : [0, \infty]$ is a function. Then

$$\mu := \sum_{x \in X} \lambda(x) \delta_x$$

is a measure, explicitly

$$\mu(A) = \sum_{x \in A} \lambda(x)$$

for all $A \subset X$.

Example 4.11. Suppose that $\mathcal{F} \subset 2^X$ is a countable or finite partition of $X$ and $\mathcal{B} \subset 2^X$ is the $\sigma$-algebra which consists of the collection of sets $A \subset X$ such that

$$A = \bigcup \{ \alpha \in \mathcal{F} : \alpha \subset A \}.$$  \hspace{1cm} (4.5)

Any measure $\mu : \mathcal{B} \to [0, \infty]$ is determined uniquely by its values on $\mathcal{F}$. Conversely, if we are given any function $\lambda : \mathcal{F} \to [0, \infty]$ we may define, for $A \in \mathcal{B}$,
4.3 Simple Integration

Definition 4.13 (Simple Integral). Suppose now that \( P \) is a finitely additive probability measure on an algebra \( \mathcal{A} \subset 2^\Omega \). For \( f \in \mathcal{S}(\mathcal{A}) \) the integral or expectation, \( \mathbb{E}(f) = \mathbb{E}_P(f) \), is defined by

\[
\mathbb{E}_P(f) = \sum_{y \in \mathcal{C}} y P(f = y). \tag{4.6}
\]

Example 4.14. Suppose that \( A \in \mathcal{A} \), then

\[
\mathbb{E}_1 A = 0 \cdot P(\lambda^c) + 1 \cdot P(\lambda) = P(\lambda). \tag{4.7}
\]

Remark 4.15. Let us recall that our intuitive notion of expectation, \( \mathbb{E} \) is defined by 
\[
P(A) = \lim_{N \to \infty} \frac{1}{N} \# \{1 \leq k \leq N : \omega(k) \in A\}
\]
where \( \omega(k) \in \Omega \) was the result of the \( k \)th “independent” experiment. If we use this interpretation back in Eq. (4.6), we arrive at

\[
\mathbb{E}(f) = \sum_{y \in \mathcal{C}} y P(f = y) = \lim_{N \to \infty} \frac{1}{N} \sum_{y \in \mathcal{C}} y \cdot \# \{1 \leq k \leq N : f(\omega(k)) = y\}
\]
\[
= \lim_{N \to \infty} \frac{1}{N} \sum_{y \in \mathcal{C}} y \cdot \sum_{k=1}^{N} 1_{f(\omega(k)) = y} = \lim_{N \to \infty} \frac{1}{N} \sum_{k=1}^{N} \sum_{y \in \mathcal{C}} f(\omega(k)) \cdot 1_{f(\omega(k)) = y}
\]
\[
= \lim_{N \to \infty} \frac{1}{N} \sum_{k=1}^{N} f(\omega(k)).
\]

Thus informally, \( \mathbb{E}f \) should represent the average of the values of \( f \) over many “independent” experiments.

Proposition 4.16. The expectation operator, \( \mathbb{E} = \mathbb{E}_P \), satisfies:

1. If \( f \in \mathcal{S}(\mathcal{A}) \) and \( \lambda \in \mathbb{C} \), then

\[
\mathbb{E}(\lambda f) = \lambda \mathbb{E}(f). \tag{4.8}
\]

2. If \( f, g \in \mathcal{S}(\mathcal{A}) \), then

\[
\mathbb{E}(f + g) = \mathbb{E}(g) + \mathbb{E}(f). \tag{4.9}
\]

3. \( \mathbb{E} \) is positive, i.e. \( \mathbb{E}(f) \geq 0 \) if \( f \) is a non-negative measurable simple function.

4. For all \( f \in \mathcal{S}(\mathcal{A}) \),

\[
|\mathbb{E}f| \leq \mathbb{E}|f|. \tag{4.10}
\]

Proof.

1. If \( \lambda \neq 0 \), then

\[
\mathbb{E}(\lambda f) = \sum_{y \in \mathcal{C} \cup \{\infty\}} y P(\lambda f = y) = \sum_{y \in \mathcal{C} \cup \{\infty\}} y P(f = y/\lambda).
\]

The case \( \lambda = 0 \) is trivial.

2. Writing \( \{f = a, g = b\} \) for \( f^{-1}\{a\} \cap g^{-1}\{b\} \), then

\[
\mathbb{E}(f + g) = \sum_{z \in \mathcal{C}} z P(f + g = z)
\]
\[
= \sum_{z \in \mathcal{C}} z P(\cup_{a+b=z} \{f = a, g = b\})
\]
\[
= \sum_{z \in \mathcal{C}} \sum_{a+b=z} (a+b) P(\{f = a, g = b\})
\]
\[
= \sum_{a,b} (a+b) P(\{f = a, g = b\}).
\]

But

\[
\sum_{a,b} a P(\{f = a, g = b\}) = \sum_{a} a \sum_{b} P(\{f = a, g = b\})
\]
\[
= \sum_{a} a P(\cup_{b} \{f = a, g = b\})
\]
\[
= \sum_{a} a P(\{f = a\}) = \mathbb{E}f
\]

and similarly,

\[
\sum_{a,b} b P(\{f = a, g = b\}) = \mathbb{E}g.
\]

Equation (4.9) is now a consequence of the last three displayed equations.

3. If \( f \geq 0 \) then

\[
\mathbb{E}(f) = \sum_{a \geq 0} a P(f = a) \geq 0.
\]
4. First observe that
\[ |f| = \sum_{\lambda \in \mathbb{C}} |\lambda| \, 1_{f=\lambda} \]
and therefore,
\[ E |f| = E \sum_{\lambda \in \mathbb{C}} |\lambda| \, 1_{f=\lambda} = \sum_{\lambda \in \mathbb{C}} |\lambda| \, E 1_{f=\lambda} = \sum_{\lambda \in \mathbb{C}} |\lambda| \, P(f = \lambda) \leq \max |f| . \]
On the other hand,
\[ |Ef| = \left| \sum_{\lambda \in \mathbb{C}} \lambda P(f = \lambda) \right| \leq \sum_{\lambda \in \mathbb{C}} |\lambda| \, P(f = \lambda) = E |f| . \]

Remark 4.17. Every simple measurable function, \( f : \Omega \to \mathbb{C} \), may be written as \( f = \sum_{j=1}^{N} \lambda_j 1_{A_j} \) for some \( \lambda_j \in \mathbb{C} \) and some \( A_j \in \mathcal{A} \). Moreover if \( f \) is represented this way, then
\[ Ef = E \left[ \sum_{j=1}^{N} \lambda_j 1_{A_j} \right] = \sum_{j=1}^{N} \lambda_j E 1_{A_j} = \sum_{j=1}^{N} \lambda_j P(A_j) . \]

Remark 4.18 (Chebyshev’s Inequality). Suppose that \( f \in \mathcal{S}(\mathcal{A}) \), \( \varepsilon > 0 \), and \( p > 0 \), then
\[ P\{ |f| \geq \varepsilon \} = E \left[ 1_{|f| \geq \varepsilon} \right] \leq \frac{\| f \|^p}{\varepsilon^p} E \left[ 1_{|f| \geq \varepsilon} \right] \leq \varepsilon^{-p} E |f|^p . \] (4.11)
Observe that
\[ |f|^p = \sum_{\lambda \in \mathbb{C}} |\lambda|^p \, 1_{f=\lambda} \]
is a simple random variable and \( \{ |f| \geq \varepsilon \} = \sum_{|\lambda| \geq \varepsilon} \{ f = \lambda \} \in \mathcal{A} \) as well. Therefore, \( |f|^p \, 1_{|f| \geq \varepsilon} \) is still a simple random variable.

Lemma 4.19 (Inclusion Exclusion Formula). If \( A_n \in \mathcal{A} \) for \( n = 1, 2, \ldots, M \) such that \( \mu (\bigcup_{n=1}^{M} A_n) \) is finite, then
\[ \mu (\bigcup_{n=1}^{M} A_n) = \sum_{k=1}^{M} (-1)^{k+1} \sum_{1 \leq n_1 < n_2 < \cdots < n_k \leq M} \mu (A_{n_1} \cap \cdots \cap A_{n_k}) . \] (4.12)

Proof. This may be proved inductively from Eq. 4.3. We will give a different and perhaps more illuminating proof here. Let \( A := \bigcup_{n=1}^{M} A_n \).
Since \( A^c = \left( \bigcup_{n=1}^{M} A_n \right)^c = \bigcap_{n=1}^{M} A_n^c \), we have
\[ 1 - 1_A = 1_{A^c} = \prod_{n=1}^{M} 1_{A_n^c} = \prod_{n=1}^{M} (1 - 1_{A_n}) \]
\[ = \sum_{k=0}^{M} \frac{(-1)^k}{k!} \sum_{0 \leq n_1 < n_2 \cdots < n_k \leq M} 1_{A_{n_1} \cap \cdots \cap A_{n_k}} \]
\[ = \sum_{k=0}^{M} (-1)^k \sum_{0 \leq n_1 < n_2 \cdots < n_k \leq M} 1_{A_{n_1} \cap \cdots \cap A_{n_k}} \]
from which it follows that
\[ 1_{\bigcup_{n=1}^{M} A_n} = 1_A = \sum_{k=1}^{M} (-1)^{k+1} \sum_{1 \leq n_1 < n_2 \cdots < n_k \leq M} 1_{A_{n_1} \cap \cdots \cap A_{n_k}} . \] (4.13)
Taking expectations of this equation then gives Eq. 4.12.

Remark 4.20. Here is an alternate proof of Eq. 4.13. Let \( \omega \in \Omega \) and by relabeling the sets \( \{ A_n \} \) if necessary, we may assume that \( \omega \in A_1 \cap \cdots \cap A_m \) and \( \omega \notin A_{m+1} \cup \cdots \cup A_M \) for some \( 0 \leq m \leq M \). (When \( m = 0 \), both sides of Eq. 4.13 are zero and so we will only consider the case where \( 1 \leq m \leq M \).) With this notation we have
\[ \sum_{k=1}^{M} (-1)^{k+1} \sum_{1 \leq n_1 < n_2 \cdots < n_k \leq M} 1_{A_{n_1} \cap \cdots \cap A_{n_k}} (\omega) \]
\[ = \sum_{k=1}^{m} (-1)^{k+1} \sum_{1 \leq n_1 < n_2 \cdots < n_k \leq m} 1_{A_{n_1} \cap \cdots \cap A_{n_k}} (\omega) \]
\[ = \sum_{k=1}^{m} (-1)^{k+1} \binom{m}{k} \]
\[ = 1 - \sum_{k=0}^{m} (-1)^k \binom{m}{k} \]
\[ = 1 - (1 - 1)^m = 1 . \]
This verifies Eq. 4.13 since \( 1_{\bigcup_{n=1}^{M} A_n} (\omega) = 1 \).

Example 4.21 (Coincidences). Let \( \Omega \) be the set of permutations (think of card shuffling), \( \omega : \{1, 2, \ldots, n\} \to \{1, 2, \ldots, n\} \), and define \( P(A) := \frac{\mu(A)}{n!} \) to be the uniform distribution (Haar measure) on \( \Omega \). We wish to compute the probability of the event, \( B \), that a random permutation fixes some index \( i \). To do this, let \( A_i := \{ \omega \in \Omega : \omega(i) = i \} \) and observe that \( B = \bigcup_{i=1}^{n} A_i \). So by the Inclusion Exclusion Formula, we have
4 Finitely Additive Measures

\[ P(B) = \sum_{k=1}^{n} (-1)^{k+1} \sum_{1 \leq i_1 < i_2 < \cdots < i_k \leq n} P(A_{i_1} \cap \cdots \cap A_{i_k}). \]

Since

\[ P(A_{i_1} \cap \cdots \cap A_{i_k}) = P(\{\omega \in \Omega : \omega(i_1) = i_1, \ldots, \omega(i_k) = i_k\}) = \frac{(n-k)!}{n!} \]

and

\[ \# \{1 \leq i_1 < i_2 < i_3 < \cdots < i_k \leq n\} = \binom{n}{k}, \]

we find

\[ P(B) = \sum_{k=1}^{n} (-1)^{k+1} \binom{n}{k} \frac{(n-k)!}{n!} = \sum_{k=1}^{n} (-1)^{k+1} \frac{1}{k!}. \]

For large \( n \) this gives,

\[ P(B) = -\sum_{k=1}^{n} \frac{(-1)^k}{k!} \cong -e^{-1} - 1 \cong 0.632. \]

**Example 4.22.** Continue the notation in Example 4.21. We now wish to compute the expected number of fixed points of a random permutation, \( \omega \), i.e. how many cards in the shuffled stack have not moved on average. To this end, let

\[ X_i = 1_{A_i}, \]

and observe that

\[ N(\omega) = \sum_{i=1}^{n} X_i(\omega) = \sum_{i=1}^{n} 1_{\omega(i) = i} = \# \{i : \omega(i) = i\}. \]

denote the number of fixed points of \( \omega \). Hence we have

\[ \mathbb{E}N = \sum_{i=1}^{n} \mathbb{E}X_i = \sum_{i=1}^{n} P(A_i) = \sum_{i=1}^{n} \frac{(n-1)!}{n!} = 1. \]

Let us check the above formula when \( n = 6 \). In this case we have

\[
\begin{array}{c|c|c}
\omega & N(\omega) \\
\hline
1 & 2 & 3 \\
1 & 3 & 2 \\
2 & 1 & 3 \\
2 & 3 & 1 \\
3 & 1 & 2 \\
3 & 2 & 1 \\
\end{array}
\]

and so

\[ P(\exists \text{ a fixed point}) = \frac{4}{6} = \frac{2}{3} \]

while

\[ \sum_{k=1}^{3} (-1)^{k+1} \frac{1}{k!} = 1 - \frac{1}{2} + \frac{1}{6} = \frac{2}{3} \]

and

\[ \mathbb{E}N = \frac{1}{6} (3 + 1 + 0 + 0 + 1) = 1. \]

### 4.4 Simple Independence and the Weak Law of Large Numbers

For the next two problems, let \( A \) be a finite set, \( n \in \mathbb{N} \), \( \Omega = A^n \), and \( X_i : \Omega \to A \) be defined by \( X_i(\omega) = \omega(i) \) for \( \omega \in \Omega \) and \( i = 1, 2, \ldots, n \). We further suppose \( p : \Omega \to [0, 1] \) is a function such that

\[ \sum_{\omega \in \Omega} p(\omega) = 1 \]

and \( P : 2^\Omega \to [0, 1] \) is the probability measure defined by

\[ P(A) := \sum_{\omega \in A} p(\omega) \text{ for all } A \subset 2^\Omega. \hspace{1cm} (4.14) \]

**Exercise 4.1 (Simple Independence 1.).** Suppose \( q_i : A \to [0, 1] \) are functions such that \( \sum_{\lambda \in A} q_i(\lambda) = 1 \) for \( i = 1, 2, \ldots, n \) and if \( p(\omega) = \prod_{i=1}^{n} q_i(\omega_i) \).

Show for any functions, \( f_i : A \to \mathbb{R} \) that

\[ \mathbb{E}P \left[ \prod_{i=1}^{n} f_i(X_i) \right] = \prod_{i=1}^{n} \mathbb{E}_P[f_i(X_i)] = \prod_{i=1}^{n} \mathbb{E}_{Q_i} f_i \]

where \( Q_i(\gamma) = \sum_{\lambda \in \gamma} q_i(\lambda) \) for all \( \gamma \subset A \).

**Exercise 4.2 (Simple Independence 2.).** Prove the converse of the previous exercise. Namely, if

\[ \mathbb{E}_P \left[ \prod_{i=1}^{n} f_i(X_i) \right] = \prod_{i=1}^{n} \mathbb{E}_P[f_i(X_i)] \hspace{1cm} (4.15) \]

for any functions, \( f_i : A \to \mathbb{R} \), then there exists functions \( q_i : A \to [0, 1] \) with \( \sum_{\lambda \in A} q_i(\lambda) = 1 \), such that \( p(\omega) = \prod_{i=1}^{n} q_i(\omega_i) \).
Exercise 4.3 (A Weak Law of Large Numbers). Suppose that $A \subset \mathbb{R}$ is a finite set, $n \in \mathbb{N}$, $\Omega = A^n$, $p(\omega) = \prod_{i=1}^{n} q(\omega_i)$ where $q : A \rightarrow [0,1]$ such that $\sum_{\lambda \in A} q(\lambda) = 1$, and let $P : 2^\Omega \rightarrow [0,1]$ be the probability measure defined as in Eq. (4.14). Further let $X_i(\omega) = \omega_i$ for $i = 1, 2, \ldots, n$, $\xi := EX_i$, $\sigma^2 := E(X_i - \xi)^2$, and

$$S_n = \frac{1}{n} (X_1 + \cdots + X_n).$$

1. Show, $\xi = \sum_{\lambda \in A} \lambda q(\lambda)$ and

$$\sigma^2 = \sum_{\lambda \in A} (\lambda - \xi)^2 q(\lambda) = \sum_{\lambda \in A} \lambda^2 q(\lambda) - \xi^2.$$  

(4.16)

2. Show, $E S_n = \xi$.

3. Let $\delta_{ij} = 1$ if $i = j$ and $\delta_{ij} = 0$ if $i \neq j$. Show

$$E[(X_1 - \xi)(X_j - \xi)] = \delta_{ij} \sigma^2.$$  

4. Using $S_n - \xi$ may be expressed as, $\frac{1}{n} \sum_{i=1}^{n} (X_i - \xi)$, show

$$E(S_n - \xi)^2 = \frac{1}{n} \sigma^2.$$  

(4.17)

5. Conclude using Eq. (4.17) and Remark 4.18 that

$$P(|S_n - \xi| \geq \varepsilon) \leq \frac{1}{n \varepsilon^2} \sigma^2.$$  

(4.18)

So for large $n$, $S_n$ is concentrated near $\xi = EX_i$, with probability approaching 1 for large. This is a version of the weak law of large numbers.

Exercise 4.4 (Bernoulli Random Variables). Let $A = \{0, 1\}$, $X : A \rightarrow \mathbb{R}$ be defined by $X(0) = 0$ and $X(1) = 1$, $x \in [0,1]$, and define $Q = x\delta_1 + (1-x) \delta_0$, i.e. $Q(\{0\}) = 1 - x$ and $Q(\{1\}) = x$. Verify,

$$\xi(x) := E_Q X = x$$

and

$$\sigma^2(x) := E_Q (X - x)^2 = (1-x)x \leq 1/4.$$  

Theorem 4.23 (Weierstrass Approximation Theorem via Bernstein’s Polynomials.). Suppose that $f \in C([0,1], \mathbb{C})$ and

$$p_n(x) := \sum_{k=0}^{n} \binom{n}{k} f \left( \frac{k}{n} \right) x^k (1-x)^{n-k}.$$  

Then

$$\lim_{n \rightarrow \infty} \sup_{x \in [0,1]} |f(x) - p_n(x)| = 0.$$  

(See Theorem 4.43 for a multi-dimensional generalization of this theorem.)

Proof. Let $x \in [0,1]$, $A = \{0, 1\}$, $q(0) = 1 - x$, $q(1) = x$, $\Omega = A^n$, and

$$P_x \{\omega\} = q(\omega_1) \cdots q(\omega_n) = x^{\sum_{i=1}^{n} \omega_i} \cdot (1-x)^{1-\sum_{i=1}^{n} \omega_i}.$$  

As above, let $S_n = \frac{1}{n} (X_1 + \cdots + X_n)$, where $X_i(\omega) = \omega_i$ and observe that

$$P_x \left(S_n = \frac{k}{n} \right) = \binom{n}{k} x^k (1-x)^{n-k}.$$  

Therefore, writing $E_x$ for $E_{P_x}$, we have

$$E_x [f(S_n)] = \sum_{k=0}^{n} f \left( \frac{k}{n} \right) \binom{n}{k} x^k (1-x)^{n-k} = p_n(x).$$  

Hence we find

$$\left| p_n(x) - f(x) \right| = \left| E_x [f(S_n) - f(x)] \right| = \left| E_x [f(S_n) - f(x)] \right|$$

$$\leq E_x |f(S_n) - f(x)|$$

$$= E_x \{|f(x) - f(y)| : |S_n - x| \geq \varepsilon\} + E_x \{|f(x) - f(y)| : |S_n - x| < \varepsilon\}$$

$$\leq 2M \cdot P_x (|S_n - x| \geq \varepsilon) + \delta(\varepsilon)$$

where

$$M := \max_{y \in [0,1]} |f(y)|$$

and

$$\delta(\varepsilon) := \sup \{|f(y) - f(x)| : x, y \in [0,1] \text{ and } |y - x| \leq \varepsilon\}$$

is the modulus of continuity of $f$. Now by the above exercises,

$$P_x (|S_n - x| \geq \varepsilon) \leq \frac{1}{4n \varepsilon^2}$$

and hence we may conclude that

$$\max_{x \in [0,1]} |p_n(x) - f(x)| \leq \frac{M}{2n \varepsilon^2} + \delta(\varepsilon)$$

and therefore, that

$$\limsup_{n \rightarrow \infty} \max_{x \in [0,1]} |p_n(x) - f(x)| \leq \delta(\varepsilon).$$

This completes the proof, since by uniform continuity of $f$, $\delta(\varepsilon) \downarrow 0$ as $\varepsilon \downarrow 0$. 

\[\square\]
4.5 Constructing Finitely Additive Measures

**Definition 4.24.** A set $S \subseteq 2^X$ is said to be an **semialgebra or elementary class** provided that

- $\emptyset \in S$
- $S$ is closed under finite intersections
- if $E \in S$, then $E^c$ is a finite disjoint union of sets from $S$. (In particular $X = \emptyset^c$ is a finite disjoint union of elements from $S$.)

**Example 4.25.** Let $X = \mathbb{R}$, then

$$S := \{(a, b] \cap \mathbb{R} : a, b \in \mathbb{R}\}$$

$$= \{(a, b] : a \in (-\infty, \infty) \text{ and } a < b < \infty\} \cup \{\emptyset, \mathbb{R}\}$$

is a semi-field.

**Exercise 4.5.** Let $A \subseteq 2^X$ and $B \subseteq 2^Y$ be semi-fields. Show the collection

$$\mathcal{E} := \{A \times B : A \in A \text{ and } B \in B\}$$

is also a semi-field.

**Proposition 4.26.** Suppose $S \subseteq 2^X$ is a semi-field, then $A = A(S)$ consists of sets which may be written as finite disjoint unions of sets from $S$.

**Proof.** Let $A$ denote the collection of sets which may be written as finite disjoint unions of sets from $S$. Clearly $S \subset A \subset A(S)$ so it suffices to show $A$ is an algebra since $A(S)$ is the smallest algebra containing $S$. By the properties of $S$, we know that $\emptyset, X \in A$. Now suppose that $A_i = \sum_{F \in A_i} F \in A$ where, for $i = 1, 2, \ldots, n$, $A_i$ is a finite collection of disjoint sets from $S$. Then

$$\bigcap_{i=1}^n A_i = \bigcap_{i=1}^n \left( \sum_{F \in A_i} F \right) = \bigcup_{(F_1, \ldots, F_n) \in A_1 \times \cdots \times A_n} (F_1 \cap F_2 \cap \cdots \cap F_n)$$

and this is a disjoint (you check) union of elements from $S$. Therefore $A$ is closed under finite intersections. Similarly, if $A = \sum_{F \in A} F$ with $A$ being a finite collection of disjoint sets from $S$, then $A^c = \bigcap_{F \in A} F^c$. Since by assumption $F^c \in A$ for $F \in A \subset S$ and $A$ is closed under finite intersections, it follows that $A^c \in A$.

**Example 4.27.** Let $X = \mathbb{R}$ and $S := \{(a, b] \cap \mathbb{R} : a, b \in \mathbb{R}\}$ be as in Example 4.25. Then $A(S)$ may be described as being those sets which are finite disjoint unions of sets from $S$.

**Proposition 4.28 (Construction of Finitely Additive Measures).** Suppose $S \subseteq 2^X$ is a semi-algebra (see Definition 4.24) and $A = A(S)$ is the algebra generated by $S$. Then every additive function $\mu : S \to [0, \infty]$ such that $\mu(\emptyset) = 0$ extends uniquely to an additive measure (which we still denote by $\mu$) on $A$.

**Proof.** Since (by Proposition 4.26) every element $A \in A$ is of the form $A = \sum_i E_i$ for a finite collection of $E_i \in S$, it is clear that if $\mu$ extends to a measure then the extension is unique and must be given by

$$\mu(A) = \sum_i \mu(E_i). \quad (4.19)$$

To prove existence, the main point is to show that $\mu(A)$ in Eq. (4.19) is well defined; i.e. if we also have $A = \sum_j F_j$ with $F_j \in S$, then we must show

$$\sum_i \mu(E_i) = \sum_j \mu(F_j). \quad (4.20)$$

But $E_i = \sum_j (E_i \cap F_j)$ and the additivity of $\mu$ on $S$ implies $\mu(E_i) = \sum_j \mu(E_i \cap F_j)$ and hence

$$\sum_i \mu(E_i) = \sum_i \sum_j \mu(E_i \cap F_j) = \sum_j \mu(E_i \cap F_j).$$

Similarly,
\[ \sum_j \mu(F_j) = \sum_{i,j} \mu(E_i \cap F_j) \]

which combined with the previous equation shows that Eq. (4.20) holds. It is now easy to verify that \( \mu \) extended to \( \mathcal{A} \) as in Eq. (4.19) is an additive measure on \( \mathcal{A} \).

\[ \sum j \mu(F_j) = \sum_{i,j} \mu(E_i \cap F_j) \]

**Proposition 4.29.** Let \( X = \mathbb{R} \), \( S \) be a semi-algebra

\[ S = \{ (a, b] \cap \mathbb{R} : -\infty \leq a \leq b \leq \infty \}, \]  

(4.21)

and \( \mathcal{A} = \mathcal{A}(S) \) be the algebra formed by taking finite disjoint unions of elements from \( S \), see Proposition 4.26. To each finitely additive probability measures \( \mu : \mathcal{A} \rightarrow [0, \infty) \), there is a unique increasing function \( F : \overline{\mathbb{R}} \rightarrow [0, 1] \) such that \( F(\infty) = 0 \), \( F(-\infty) = 1 \) and

\[ \mu((a, b] \cap \mathbb{R}) = F(b) - F(a) \quad \forall \ a \leq b \text{ in } \mathbb{R}. \]

(4.22)

Conversely, given an increasing function \( F : \overline{\mathbb{R}} \rightarrow [0, 1] \) such that \( F(\infty) = 0 \), \( F(-\infty) = 1 \) there is a unique finitely additive measure \( \mu = \mu_F \) on \( \mathcal{A} \) such that the relation in Eq. (4.22) holds.

**Proof.** Given a finitely additive probability measure \( \mu \), let

\[ F(x) := \mu((-\infty, x] \cap \mathbb{R}) \]  

for all \( x \in \overline{\mathbb{R}} \).

Then \( F(\infty) = 1 \), \( F(-\infty) = 0 \) and for \( b > a \),

\[ F(b) - F(a) = \mu((-\infty, b] \cap \mathbb{R}) - \mu((-\infty, a]) = \mu((a, b] \cap \mathbb{R}). \]

Conversely, suppose \( F : \overline{\mathbb{R}} \rightarrow [0, 1] \) as in the statement of the theorem is given. Define \( \mu \) on \( S \) using the formula in Eq. (4.22). The argument will be completed by showing \( \mu \) is additive on \( S \) and hence, by Proposition 4.28, has a unique extension to a finitely additive measure on \( \mathcal{A} \). Suppose that

\[ (a, b] = \sum_{i=1}^n (a_i, b_i]. \]

By reordering \( (a_i, b_i] \) if necessary, we may assume that

\[ a = a_1 < b_1 = a_2 < b_2 = a_3 < \cdots < b_{n-1} = a_n < b_n = b. \]

Therefore, by the telescoping series argument,

\[ \mu((a, b] \cap \mathbb{R}) = F(b) - F(a) = \sum_{i=1}^n [F(b_i) - F(a_i)] = \sum_{i=1}^n \mu((a_i, b_i] \cap \mathbb{R}). \]
Countably Additive Measures

5.1 Distribution Function for Probability Measures on \((\mathbb{R}, \mathcal{B}_\mathbb{R})\)

**Definition 5.1.** Given a probability measure, \(P\) on \(\mathcal{B}_\mathbb{R}\), the **cumulative distribution function** (CDF) of \(P\) is defined as the function, \(F = F_P : \mathbb{R} \to [0, 1]\) given as

\[
F(x) := P((-\infty, x]).
\]

**Example 5.2.** Suppose that

\[P = p\delta_{-1} + q\delta_1 + r\delta_\pi\]

with \(p, q, r > 0\) and \(p + q + r = 1\). In this case,

\[
F(x) = \begin{cases}
0 & \text{for } x < -1 \\
p & \text{for } -1 \leq x < 1 \\
p + q & \text{for } 1 \leq x < \pi \\
1 & \text{for } \pi \leq x < \infty
\end{cases}
\]

**Lemma 5.3.** If \(F = F_P : \mathbb{R} \to [0, 1]\) is a distribution function for a probability measure, \(P\), on \(\mathcal{B}_\mathbb{R}\), then:

1. \(F(-\infty) := \lim_{x \to -\infty} F(x) = 0\),
2. \(F(\infty) := \lim_{x \to \infty} F(x) = 1\),
3. \(F\) is non-decreasing, and
4. \(F\) is right continuous.

**Theorem 5.4.** To each function \(F : \mathbb{R} \to [0, 1]\) satisfying properties 1. – 4. in Lemma 5.3 there exists a unique probability measure, \(P_F\), on \(\mathcal{B}_\mathbb{R}\) such that

\[
P_F((a, b]) = F(b) - F(a) \text{ for all } -\infty < a \leq b < \infty.
\]

**Proof.** The uniqueness assertion in the theorem is covered in Exercise 5.1 below. The existence portion of the Theorem follows from Proposition 5.7 and Theorem 5.19 below.

**Example 5.5 (Uniform Distribution).** The function,

\[
F(x) := \begin{cases}
0 & \text{for } x \leq 0 \\
x & \text{for } 0 \leq x < 1 \\
1 & \text{for } 1 \leq x < \infty
\end{cases}
\]

is the distribution function for a measure, \(m\) on \(\mathcal{B}_\mathbb{R}\) which is concentrated on \((0, 1]\). The measure, \(m\) is called the uniform distribution or Lebesgue measure on \((0, 1]\).

Recall from Definition 3.14 that \(\mathcal{B} \subset 2^X\) is a \(\sigma\) – algebra on \(X\) if \(\mathcal{B}\) is an algebra which is closed under countable unions and intersections.

5.2 Construction of Premeasures

**Proposition 5.6.** Suppose that \(\mathcal{S} \subset 2^X\) is a semi-algebra, \(A = A(\mathcal{S})\) and \(\mu : A \to [0, \infty]\) is a finitely additive measure. Then \(\mu\) is a premeasure on \(A\) iff \(\mu\) is sub-additive on \(\mathcal{S}\).

**Proof.** Clearly if \(\mu\) is a premeasure on \(A\) then \(\mu\) is \(\sigma\) - additive and hence sub-additive on \(\mathcal{S}\). Because of Proposition 4.2, to prove the converse it suffices to show that the sub-additivity of \(\mu\) on \(\mathcal{S}\) implies the sub-additivity of \(\mu\) on \(A\).

So suppose \(A = \bigcup_{n=1}^{\infty} A_n\) with \(A \in A\) and each \(A_n \in A\) which we express as \(A = \bigcup_{j=1}^{k} E_j\) with \(E_j \in \mathcal{S}\) and \(A_n = \bigcup_{i=1}^{N_n} E_{n,i}\) with \(E_{n,i} \in \mathcal{S}\). Then

\[
E_j = A \cap E_j = \bigcup_{n=1}^{\infty} A_n \cap E_j = \bigcup_{n=1}^{\infty} \bigcup_{i=1}^{N_n} E_{n,i} \cap E_j
\]

which is a countable union and hence by assumption,

\[
\mu(E_j) \leq \sum_{n=1}^{\infty} \sum_{i=1}^{N_n} \mu(E_{n,i} \cap E_j).
\]

Summing this equation on \(j\) and using the finite additivity of \(\mu\) shows...
5 Countably Additive Measures

\[ \mu(A) = \sum_{j=1}^{k} \mu(E_j) \leq \sum_{j=1}^{k} \sum_{n=1}^{\infty} \sum_{i=1}^{N_n} \mu(E_{n,i} \cap E_j) \]

\[ = \sum_{n=1}^{\infty} \sum_{i=1}^{N_n} \sum_{j=1}^{k} \mu(E_{n,i} \cap E_j) = \sum_{n=1}^{\infty} \sum_{i=1}^{N_n} \mu(E_{n,i}) = \sum_{n=1}^{\infty} \mu(A_n), \]

which proves (using Proposition 4.2) the sub-additivity of \( \mu \) on \( \mathcal{A} \).

Now suppose that \( F : \mathbb{R} \to \mathbb{R} \) be an increasing function, \( F(\pm \infty) := \lim_{x \to \pm \infty} F(x) \) and \( \mu = \mu_F \) be the finitely additive measure on \((\mathbb{R}, \mathcal{A})\) described in Proposition 4.29. If \( \mu \) happens to be a premeasure on \( \mathcal{A} \), then, letting \( A_n = (a, b_n] \) with \( b_n \downarrow b \) as \( n \to \infty \), implies

\[ F(b_n) - F(a) = \mu((a, b_n]) \downarrow \mu((a, b]) = F(b) - F(a). \]

Since \( \{b_n\}_{n=1}^{\infty} \) was an arbitrary sequence such that \( b_n \downarrow b \), we have shown \( \lim_{y \downarrow b} F(y) = F(b) \), i.e. \( F \) is right continuous. The next proposition shows the converse is true as well. Hence premeasures on \( \mathcal{A} \) which are finite on bounded sets are in one to one correspondences with right continuous increasing functions which vanish at 0.

**Proposition 5.7.** To each right continuous increasing function \( F : \mathbb{R} \to \mathbb{R} \) there exists a unique premeasure \( \mu = \mu_F \) on \( \mathcal{A} \) such that

\[ \mu_F((a, b]) = F(b) - F(a) \quad \forall -\infty < a < b < \infty. \]

**Proof.** As above, let \( F(\pm \infty) := \lim_{x \to \pm \infty} F(x) \) and \( \mu = \mu_F \) be as in Proposition 4.29. Because of Proposition 5.6, to finish the proof it suffices to show \( \mu \) is sub-additive on \( \mathcal{S} \).

First suppose that \(-\infty < a < b < \infty\), \( J = (a, b], J_n = (a_n, b_n] \) such that \( J = \bigcup_{n=1}^{\infty} J_n \). We wish to show

\[ \mu(J) \leq \sum_{n=1}^{\infty} \mu(J_n). \]  

To do this choose numbers \( \tilde{a} > a, \tilde{b}_n > b_n \) in which case \( I := (\tilde{a}, b] \subset J \),

\[ \tilde{J}_n := (a_n, \tilde{b}_n] \supset \tilde{J}_n^o := (a_n, b_n] \supset J_n. \]

Since \( I = [\tilde{a}, b] \) is compact and \( \tilde{I} \subset J \subset \bigcup_{n=1}^{\infty} \tilde{J}_n^o \) there exists \( N < \infty \) such that

\[ I \subset \tilde{I} \subset J \subset \bigcup_{n=1}^{N} \tilde{J}_n^o \quad \forall n \in \mathbb{N}. \]

Hence by finite sub-additivity of \( \mu \),

\[ F(b) - F(\tilde{a}) = \mu(I) \leq \sum_{n=1}^{N} \mu(\tilde{J}_n^o) \leq \sum_{n=1}^{\infty} \mu(\tilde{J}_n^o). \]

Using the right continuity of \( F \) and letting \( \tilde{a} \downarrow a \) in the above inequality,

\[ \mu(J) = \mu((a, b]) = F(b) - F(a) \leq \sum_{n=1}^{\infty} \mu(\tilde{J}_n^o) \]

\[ = \sum_{n=1}^{\infty} \mu(J_n) + \sum_{n=1}^{\infty} \mu(\tilde{J}_n \setminus J_n). \]  

(5.2)

Given \( \varepsilon > 0 \), we may use the right continuity of \( F \) to choose \( \tilde{b}_n \) so that

\[ \mu(\tilde{J}_n \setminus J_n) = F(\tilde{b}_n) - F(b_n) \leq \varepsilon 2^{-n} \quad \forall n \in \mathbb{N}. \]

Using this in Eq. (5.2) shows

\[ \mu(J) = \mu((a, b]) \leq \sum_{n=1}^{\infty} \mu(J_n) + \varepsilon \]

which verifies Eq. (5.1) since \( \varepsilon > 0 \) was arbitrary.

The hard work is now done but we still have to check the cases where \( a = -\infty \) or \( b = \infty \). For example, suppose that \( b = \infty \) so that

\[ J = (a, \infty) = \bigcup_{n=1}^{\infty} J_n \]

with \( J_n = (a_n, b_n] \cap \mathbb{R} \). Then

\[ I_M := (a, M] = J \cap I_M = \bigcup_{n=1}^{\infty} J_n \cap I_M \]

and so by what we have already proved,

\[ F(M) - F(a) = \mu(I_M) \leq \sum_{n=1}^{\infty} \mu(J_n \cap I_M) \leq \sum_{n=1}^{\infty} \mu(J_n). \]

Now let \( M \to \infty \) in this last inequality to find that
\[ \mu((a, \infty)) = F(\infty) - F(a) \leq \sum_{n=1}^{\infty} \mu(J_n). \]

The other cases where \( a = -\infty \) and \( b \in \mathbb{R} \) and \( a = -\infty \) and \( b = \infty \) are handled similarly.

Before continuing our development of the existence of measures, we will pause to show that measures are often uniquely determined by their values on a generating sub-algebra. This detour will also have the added benefit of motivating Carathéodory’s existence proof to be given below.

### 5.3 Regularity and Uniqueness Results

**Definition 5.8.** Given a collection of subsets, \( \mathcal{E} \), of \( X \), let \( \mathcal{E}_\sigma \) denote the collection of subsets of \( X \) which are finite or countable unions of sets from \( \mathcal{E} \). Similarly let \( \mathcal{E}_\delta \) denote the collection of subsets of \( X \) which are finite or countable intersections of sets from \( \mathcal{E} \). We also write \( \mathcal{E}_{\sigma\delta} = (\mathcal{E}_\sigma)_\delta \) and \( \mathcal{E}_{\delta\sigma} = (\mathcal{E}_\delta)_\sigma \), etc.

**Lemma 5.9.** Suppose that \( A \subset 2^X \) is an algebra. Then:

1. \( A_\sigma \) is closed under taking countable unions and finite intersections.
2. \( A_\delta \) is closed under taking countable intersections and finite unions.
3. \( \{ A^c : A \in A_\sigma \} = A_\delta \) and \( \{ A^c : A \in A_\delta \} = A_\sigma \).

**Proof.** By construction \( A_\sigma \) is closed under countable unions. Moreover if \( A = \bigcup_{i=1}^{\infty} A_i \) and \( B = \bigcup_{j=1}^{\infty} B_j \) with \( A_i, B_j \in A \), then

\[ A \cap B = \bigcup_{i,j=1}^{\infty} A_i \cap B_j \in A_\sigma, \]

which shows that \( A_\sigma \) is also closed under finite intersections. Item 3. is straight forward and item 2. follows from items 1. and 3. \( \blacksquare \)

**Theorem 5.10 (Finite Regularity Result).** Suppose \( A \subset 2^X \) is an algebra, \( B = \sigma(A) \) and \( \mu : B \to [0,\infty) \) is a function. Then for every \( \varepsilon > 0 \), \( A \subset B \), \( \mu(X) \leq \infty \), \( \mu \in \mathcal{F} \), and \( \mu \) is a finite measure on \( X \). Therefore,

\[ \mu(C \setminus A) = \mu(\bigcup_{i=1}^{\infty} [C \setminus A_i]) \leq \sum_{i=1}^{\infty} \mu(C \setminus A_i) < \varepsilon. \]

Since \( C \setminus A \), it also follows that \( \mu(C \setminus A^c) < \varepsilon \) for sufficiently large \( N \) and this shows \( B = \bigcup_{n=1}^{\infty} B_n \in B_0 \). Hence \( B_0 = \sigma \) (A) contains \( A \), which shows \( B_0 = B \).

Many theorems in the sequel will require some control on the size of a measure \( \mu \). The relevant notion for our purposes (and most purposes) is that of a \( \sigma \) – finite measure defined next.

**Definition 5.11.** Suppose \( X \) is a set, \( \mathcal{E} \subset 2^X \) and \( \mu : B \to [0,\infty) \) is a function. The function \( \mu \) is \( \sigma \) – finite on \( \mathcal{E} \) if there exists \( E_n \in \mathcal{E} \) such that \( \mu(E_n) < \infty \) and \( X = \bigcup_{n=1}^{\infty} E_n \).

**Corollary 5.12 (\( \sigma \) – Finite Regularity Result).** Theorem 5.10 continues to hold under the weaker assumption that \( \mu : B \to [0,\infty) \) is a measure which is \( \sigma \) – finite on \( A \).

**Proof.** Let \( \mathcal{X} \subset F \) such that \( \bigcup_{n=1}^{\infty} \mathcal{X}_n = X \), then \( \mu(X) < \infty \).

Applying this result to \( B^c \) shows that it exists \( D \subset A_\sigma \) such that \( B^c \subset D \) and

\[ \mu(B^c \setminus D^c) = \mu(D \setminus B^c) < \varepsilon. \]

If we let \( \mathcal{X} = B^c \), then \( \mathcal{X} \cap B \subset C \), then \( \mathcal{X} \cap B \subset C \) and

\[ \mu(C \setminus A) \leq \mu(C \setminus A \cup [(C \setminus B) \setminus A]) \leq \mu(B \setminus A) + \mu(C \setminus B) < 2\varepsilon. \]

and the result is proved. \( \blacksquare \)
Exercise 5.1. Suppose \( A \subseteq 2^X \) is an algebra and \( \mu \) and \( \nu \) are two measures on \( B = \sigma(A) \).

a. Suppose that \( \mu \) and \( \nu \) are finite measures such that \( \mu = \nu \) on \( A \). Show \( \mu = \nu \).

b. Generalize the previous assertion to the case where you only assume that \( \mu \) and \( \nu \) are \( \sigma \)-finite on \( A \).

Corollary 5.13. Suppose \( A \subseteq 2^X \) is an algebra and \( \mu : B = \sigma(A) \rightarrow [0, \infty] \) is a measure which\( \sigma \)-finite on \( A \). Then for all \( B \in B \), there exists \( A \in \mathcal{A}_{\delta \sigma} \) and \( C \in \mathcal{A}_{\delta \nu} \) such that \( A \subseteq B \subseteq C \) and \( \mu(C \setminus A) = 0 \).

Proof. By Theorem 5.10, given \( B \in B \), we may choose \( A \in \mathcal{A}_\delta \) and \( C \in \mathcal{A}_\nu \) such that \( A \subseteq B \subseteq C \) and \( \mu(C \setminus B) \leq 1/\mu \) and \( \mu(B \setminus A) \leq 1/\mu \).

Exercise 5.2. Let \( B = B_{\mathbb{R}_+} = \sigma(\{ \text{open subsets of } \mathbb{R}^n \}) \) be the Borel \( \sigma \)-algebra on \( \mathbb{R}^n \) and \( \mu \) be a probability measure on \( B \). Further, let \( B_0 \) denote those sets \( B \in B \) such that for every \( \varepsilon > 0 \) there exists \( F \subseteq B \) such that \( F \) is closed, \( V \) is open, and \( \mu(V \setminus F) < \varepsilon \).

1. \( B_0 \) contains all closed subsets of \( B \). Hint: given a closed subset, \( F \subseteq \mathbb{R}^n \) and \( k \in \mathbb{N} \), let \( V_k := \cup_{x \in F} B(x, 1/k) \), where \( B(x, \delta) := \{ y \in \mathbb{R}^n : |y - x| < \delta \} \).

2. Show \( B_0 \) is a \( \sigma \)-algebra and use this along with the first part of this exercise to conclude \( B = B_0 \). Hint: follow closely the method used in the first step of the proof of Theorem 5.10.

3. Show for every \( \varepsilon > 0 \) and \( B \in B \), there exist a compact subset, \( K \subseteq \mathbb{R}^n \), such that \( K \subseteq B \) and \( \mu(B \setminus K) < \varepsilon \). Hint: take \( K := F \cap \{ x \in \mathbb{R}^n : |x| \leq n \} \) for some sufficiently large \( n \).

5.4 Construction of Measures

Remark 5.14. Let us recall from Proposition 4.4 and Remark 4.6 that a finitely additive measure \( \mu : A \rightarrow [0, \infty] \) is a premeasure on \( A \) if \( \mu(A_n) \uparrow \mu(A) \) for all \( \{ A_n \}_{n=1}^\infty \subseteq A \). Furthermore if \( \mu(X) < \infty \), then \( \mu \) is a premeasure on \( A \) if \( \mu(A_n) \downarrow 0 \) for all \( \{ A_n \}_{n=1}^\infty \subseteq A \) such that \( A_n \uparrow \emptyset \).

Proposition 5.15. Let \( \mu \) be a premeasure on an algebra \( A \), then \( \mu \) has a unique extension (still called \( \mu \)) to a function on \( \mathcal{A} \), satisfying the following properties.

1. (Continuity) If \( A_n \in A \) and \( A_n \uparrow A \in \mathcal{A} \), then \( \mu(A_n) \uparrow \mu(A) \) as \( n \rightarrow \infty \).  
2. (Monotonicity) If \( A, B \in \mathcal{A} \) with \( A \subseteq B \) then \( \mu(B) \leq \mu(A) \).
3. (Strong Additivity) If \( A, B \in \mathcal{A} \), then \( \mu(A \cup B) + \mu(A \cap B) = \mu(A) + \mu(B) \).  
4. (Sub-Additivity) If \( A \subseteq \mathcal{A} \) then \( \mu \) is sub-additive on \( \mathcal{A} \), i.e. if \( \{ A_n \}_{n=1}^\infty \subseteq \mathcal{A} \), then \( \mu(\bigcup_{n=1}^\infty A_n) \leq \sum_{n=1}^\infty \mu(A_n) \).  
5. (\( \sigma \)-Additivity) The function \( \mu \) is countably additive on \( \mathcal{A} \).

Proof. Let \( A, B \) be sets in \( \mathcal{A} \) such that \( A \subseteq B \) and suppose \( \{ A_n \}_{n=1}^\infty \) and \( \{ B_n \}_{n=1}^\infty \) are sequences in \( \mathcal{A} \) such that \( A_n \uparrow A \) and \( B_n \uparrow B \) as \( n \rightarrow \infty \). Since \( B_m \cap A_n \uparrow A_n \) as \( m \rightarrow \infty \), the continuity of \( \mu \) on \( A_n \) implies, \( \mu(A_n) = \lim_{m \rightarrow \infty} \mu(B_m \cap A_n) \leq \lim_{m \rightarrow \infty} \mu(B_m) \).

We may let \( n \rightarrow \infty \) in this inequality to find, \( \lim_{n \rightarrow \infty} \mu(A_n) \leq \lim_{m \rightarrow \infty} \mu(B_m) \).

Using this equation when \( B = A \), implies, \( \lim_{n \rightarrow \infty} \mu(A_n) = \lim_{m \rightarrow \infty} \mu(B_m) \) whenever \( A_n \uparrow A \) and \( B_n \uparrow A \). Therefore it is unambiguous to define \( \mu(A) \) by; \( \mu(A) = \lim_{n \rightarrow \infty} \mu(A_n) \).

for any sequence \( \{ A_n \}_{n=1}^\infty \subseteq A \) such that \( A_n \uparrow A \). With this definition, the continuity of \( \mu \) is clear and the monotonicity of \( \mu \) follows from Eq. (5.5).

Suppose that \( A, B \in \mathcal{A} \) and \( \{ A_n \}_{n=1}^\infty \) and \( \{ B_n \}_{n=1}^\infty \) are sequences in \( \mathcal{A} \) such that \( A_n \uparrow A \) and \( B_n \uparrow B \) as \( n \rightarrow \infty \). Then passing to the limit as \( n \rightarrow \infty \) in the identity, 

\[ \mu(A_n \cup B_n) + \mu(A_n \cap B_n) = \mu(A_n) + \mu(B_n) \]

proves Eq. (5.3). In particular, it follows that \( \mu \) is finitely additive on \( \mathcal{A} \).

Let \( \{ A_n \}_{n=1}^\infty \) be any sequence in \( \mathcal{A} \) and choose \( \{ A_n \}_{n=1}^\infty \subseteq A \) such that \( A_n \uparrow A \) as \( i \rightarrow \infty \). Then we have,

\[ \mu(\bigcup_{n=1}^N A_{n,N}) \leq \sum_{n=1}^N \mu(A_{n,N}) \leq \sum_{n=1}^N \mu(A_n) \leq \sum_{n=1}^\infty \mu(A_n) \].
Since \(\mathcal{A} \supseteq \bigcup_{n=1}^{\infty} A_n, N \uparrow \bigcup_{n=1}^{\infty} A_n \in \mathcal{A}_\sigma\), we may let \(N \to \infty\) in Eq. \((5.6)\) to conclude Eq. \((5.4)\) holds.

If we further assume that \(\{A_n\}_{n=1}^{\infty} \subset \mathcal{A}_\sigma\) is a disjoint sequence, by the finite additivity and monotonicity of \(\mu\) on \(\mathcal{A}_\sigma\), we have

\[
\begin{align*}
\lim_{N \to \infty} \sum_{n=1}^{N} \mu(A_n) &= \lim_{N \to \infty} \lim_{n \to \infty} \mu \left( \bigcup_{n=1}^{N} A_n \right) \\
&\leq \lim_{N \to \infty} \mu \left( \bigcup_{n=1}^{\infty} A_n \right).
\end{align*}
\]

The previous two inequalities show \(\mu\) is \(\sigma\)–additive on \(\mathcal{A}_\sigma\).

Lemma 5.16. Suppose \(\mu\) is a finite premeasure on an algebra, \(\mathcal{A} \subset 2^X\), and \(\mu\) has been extended to \(\mathcal{A}_\delta \cup \mathcal{A}_\sigma\) as described in Proposition \(5.15\) and Eq. \((5.7)\) above.

1. If \(A \in \mathcal{A}_\delta\) and \(A \in \mathcal{A}\) such that \(A_n \downarrow A\), then \(\mu(A) = \lim_{n \to \infty} \mu(A_n)\).
2. \(\mu\) is additive when restricted to \(\mathcal{A}_\delta\).
3. If \(A \in \mathcal{A}_\delta\) and \(C \in \mathcal{A}_\sigma\) such that \(A \subset C\), then \(\mu(C \setminus A) = \mu(C) - \mu(A)\).

Proof.

1. Since \(A_n \uparrow A^c \in \mathcal{A}_\sigma\), by the definition of \(\mu(A)\) and Proposition \(5.15\) it follows that

\[
\mu(A) = \mu(X) - \mu(A^c) = \mu(X) - \lim_{n \to \infty} \mu(A_n^c) = \lim_{n \to \infty} \mu \left( A_n^c \right) = \lim_{n \to \infty} \mu(A_n).
\]

2. Suppose \(A, B \in \mathcal{A}_\delta\) are disjoint sets and \(A_n, B_n \in \mathcal{A}\) such that \(A_n \downarrow A\) and \(B_n \downarrow B\) then \(A_n \cup B_n \downarrow A \cup B\) and therefore,

\[
\mu(A \cup B) = \lim_{n \to \infty} \mu(A_n \cup B_n) = \lim_{n \to \infty} \left[ \mu(A_n) + \mu(B_n) - \mu(A_n \cap B_n) \right] = \mu(A) + \mu(B)
\]

wherein the last equality we have used Proposition \(4.3\).

3. By assumption, \(X = A^c \cup C\). So applying the strong additivity of \(\mu\) on \(\mathcal{A}_\sigma\) in Eq. \((5.3)\) with \(A \to A^c \in \mathcal{A}_\sigma\) and \(B \to C \in \mathcal{A}_\sigma\) shows

\[
\mu(X) + \mu(C \setminus A) = \mu(A^c \cup C) + \mu(A^c \cap C) = \mu(A^c) + \mu(C) = \mu(X) - \mu(A) + \mu(C).
\]

Definition 5.17 (Measurable Sets). Suppose \(\mu\) is a finite premeasure on an algebra \(\mathcal{A} \subset 2^X\). We say that \(B \subset X\) is \(\text{measurable}\) if for all \(\varepsilon > 0\) there exists \(A \in \mathcal{A}_\delta\) and \(C \in \mathcal{A}_\sigma\) such that \(A \subset B \subset C\) and \(\mu(C \setminus A) < \varepsilon\). We will denote the collection of measurable subsets of \(X\) by \(\mathcal{B} = B(\mu)\). We also define \(\bar{\mu} : \mathcal{B} \to [0, \mu(X)]\) by

\[
\bar{\mu}(B) = \inf \{ \mu(C) : B \subset C \in \mathcal{A}_\sigma\}. \tag{5.8}
\]

Remark 5.18. If \(B \in \mathcal{B}, \varepsilon > 0, A \in \mathcal{A}_\delta\) and \(C \in \mathcal{A}_\sigma\) are such that \(A \subset B \subset C\) and \(\mu(C \setminus A) < \varepsilon\), then \(\mu(A) \leq \bar{\mu}(B) \leq \mu(C)\) and in particular,

\[
0 \leq \bar{\mu}(B) - \mu(A) < \varepsilon, \quad \text{and} \quad 0 \leq \mu(C) - \bar{\mu}(B) < \varepsilon. \tag{5.9}
\]

Indeed, if \(C' \in \mathcal{A}_\sigma\) with \(B \subset C'\), then \(A \subset C'\) and so by Lemma \(5.16\) we have

\[
\mu(A) \leq \mu(C' \setminus A) + \mu(A) = \mu(C'),
\]

from which it follows that \(\mu(A) \leq \bar{\mu}(B)\). The fact that \(\bar{\mu}(B) \leq \mu(C)\) follows directly from Eq. \((5.8)\).

Theorem 5.19 (Finite Premeasure Extension Theorem). Suppose \(\mu\) is a finite premeasure on an algebra \(\mathcal{A} \subset 2^X\). Then \(\mathcal{B}\) is a \(\sigma\)–algebra on \(X\) which contains \(\mathcal{A}\) and \(\bar{\mu}\) is a \(\sigma\)–additive measure on \(\mathcal{B}\). Moreover, \(\bar{\mu}\) is the unique measure on \(\mathcal{B}\) such that \(\bar{\mu}|\mathcal{A} = \mu\).

Proof. It is clear that \(\mathcal{A} \subset \mathcal{B}\) and that \(\mathcal{B}\) is closed under complementation. Now suppose that \(B_i \in \mathcal{B}\) for \(i = 1, 2\) and \(\varepsilon > 0\) is given. We may then choose \(A_i \subset B_i \subset C_i\) such that \(A_i \in \mathcal{A}_\delta, C_i \in \mathcal{A}_\sigma\), and \(\mu(C_i \setminus A_i) < \varepsilon\) for \(i = 1, 2\). Then with \(A = A_1 \cup A_2, B = B_1 \cup B_2\) and \(C = C_1 \cup C_2\), we have \(\mathcal{A}_\delta \ni A \subset B \subset C \in \mathcal{A}_\sigma\). Since

\[
C \setminus A = (C_1 \setminus A) \cup (C_2 \setminus A) \subset (C_1 \setminus A_1) \cup (C_2 \setminus A_2),
\]

it follows from the sub-additivity of \(\mu\) that with

\[
\mu(C \setminus A) \leq \mu(C_1 \setminus A_1) + \mu(C_2 \setminus A_2) < 2\varepsilon.
\]

Since \(\varepsilon > 0\) was arbitrary, we have shown that \(B \in \mathcal{B}\). Hence we now know that \(\mathcal{B}\) is an algebra.

Because \(\mathcal{B}\) is an algebra, to verify that \(\mathcal{B}\) is a \(\sigma\)–algebra it suffices to show that \(\mathcal{B} = \bigcup_{n=1}^{\infty} B_n \in \mathcal{B}\) whenever \(\{B_n\}_{n=1}^{\infty}\) is a disjoint sequence in \(\mathcal{B}\). To prove \(\mathcal{B} \ni B\), let \(\varepsilon > 0\) be given and choose \(A_i \subset B_i \subset C_i\) such that \(A_i \in \mathcal{A}_\delta, C_i \in \mathcal{A}_\sigma\), and \(\mu(C_i \setminus A_i) < \varepsilon 2^{-i}\) for all \(i\). Since the \(\{A_i\}_{i=1}^{\infty}\) are pairwise disjoint we may use Lemma \(5.16\) to show,
Therefore, using the sub-additivity of \( \varepsilon > 0 \) on \( A \) and the estimate \( (5.10) \),

\[
\mu ([C \setminus A^n]) = \mu (\bigcup_{i=1}^{n} (C_i \setminus A_i)) \\
= \mu (\bigcup_{i=1}^{n} (C_i \setminus A_i)) + \sum_{i=1}^{n} \mu (C_i \setminus A_i) \leq \mu (X) + \sum_{i=1}^{n} \varepsilon 2^{-i}.
\]

Passing to the limit, \( n \to \infty \), in this equation then shows

\[
\sum_{i=1}^{\infty} \mu (C_i) \leq \mu (X) + \varepsilon < \infty.
\]  
(5.10)

Let \( B = \bigcup_{i=1}^{\infty} B_i, C := \bigcup_{i=1}^{\infty} C_i \in \mathcal{A}_\sigma \) and for \( n \in \mathbb{N} \) let \( A_n := \bigcup_{i=1}^{n} A_i \in \mathcal{A}_\sigma \). Then \( \mathcal{A} \ni A^n \subset B \subset C \in \mathcal{A}_\sigma \), \( C \setminus A^n \in \mathcal{A}_\sigma \) and

\[
C \setminus A^n = \bigcup_{i=1}^{\infty} (C_i \setminus A^n) \subset \bigcup_{i=1}^{n} (C_i \setminus A_i) \cup \bigcup_{i=n+1}^{\infty} C_i \in \mathcal{A}_\sigma.
\]

Therefore, using the sub-additivity of \( \mu \) on \( \mathcal{A}_\sigma \) and the estimate \( (5.10) \),

\[
\mu (C \setminus A^n) = \mu (\bigcup_{i=1}^{n} (C_i \setminus A_i)) + \sum_{i=n+1}^{\infty} \mu (C_i) \leq \varepsilon + \sum_{i=n+1}^{\infty} \mu (C_i) \to \varepsilon \text{ as } n \to \infty.
\]

Since \( \varepsilon > 0 \) is arbitrary, it follows that \( B \in \mathcal{B} \). Moreover by repeated use of Remark 5.18, we find

\[
|\bar{\mu} (B) - \mu (A^n)| < \varepsilon + \sum_{i=n+1}^{\infty} \mu (C_i)
\]

and

\[
\left| \sum_{i=1}^{n} \bar{\mu} (B_i) - \mu (A^n) \right| = \left| \sum_{i=1}^{n} [\bar{\mu} (B_i) - \mu (A_i)] \right| \leq \sum_{i=1}^{n} |\bar{\mu} (B_i) - \mu (A_i)| \leq \varepsilon \sum_{i=1}^{n} 2^{-i} < \varepsilon.
\]

Combining these estimates shows

\[
|\bar{\mu} (B) - \sum_{i=1}^{n} \bar{\mu} (B_i)| < 2\varepsilon + \sum_{i=n+1}^{\infty} \mu (C_i)
\]

which upon letting \( n \to \infty \) gives,

\[
|\bar{\mu} (B) - \sum_{i=1}^{\infty} \bar{\mu} (B_i)| \leq 2\varepsilon.
\]

Since \( \varepsilon > 0 \) is arbitrary, we have shown \( \bar{\mu} (B) = \sum_{i=1}^{\infty} \bar{\mu} (B_i) \). This completes the proof that \( B \) is a \( \sigma \)-algebra and that \( \bar{\mu} \) is a measure on \( \mathcal{B} \).
set. For example if \( f \) and \( g \) are two measurable functions on \((X, B, \mu)\), \( f = g \) a.e. means that \( \mu(f \neq g) = 0 \).

\[ (0, 1] = \bigcup_{k=1}^{n} \left( \frac{k-1}{n}, \frac{k}{n} \right) = \bigcup_{k=1}^{n} \left( \frac{k-1}{n} + (0, 1/n) \right). \]

Therefore,

\[ 1 = m((0, 1]) = \sum_{k=1}^{n} m \left( \frac{k-1}{n} + (0, 1/n) \right) = \sum_{k=1}^{n} m((0, 1/n]) = n \cdot m((0, 1/n)). \]

That is to say

\[ m((0, 1/n]) = 1/n. \]

Similarly, \( m((0, \frac{1}{n}]) = l/n \) for all \( l, n \in \mathbb{N} \) and therefore by the translation invariance of \( m \),

\[ m((a, b]) = b - a \]

for all \( a, b \in \mathbb{Q} \) with \( a < b \).

Finally for \( a, b \in \mathbb{R} \) such that \( a < b \), choose \( a_n, b_n \in \mathbb{Q} \) such that \( b_n \downarrow b \) and \( a_n \uparrow a \), then \( (a_n, b_n] \downarrow (a, b] \) and thus

\[ m((a, b])] = \lim_{n \to \infty} m((a_n, b_n]) = \lim_{n \to \infty} (b_n - a_n) = b - a, \]

i.e. \( m \) is Lebesgue measure. To prove Eq. (5.13) we may assume that \( \lambda \neq 0 \) since this case is trivial to prove. Now let \( m_\lambda(B) := |\lambda|^{-1} m(\lambda B) \). It is easily checked that \( m_\lambda \) is again a measure on \( \mathcal{B} \) which satisfies

\[ m_\lambda((a, b]) = \lambda^{-1} m((\lambda a, \lambda b]) = \lambda^{-1}(\lambda b - \lambda a) = b - a \]

if \( \lambda > 0 \) and

\[ m_\lambda((a, b]) = |\lambda|^{-1} m((\lambda a, \lambda b]) = -|\lambda|^{-1}(\lambda b - \lambda a) = b - a \]

if \( \lambda < 0 \). Hence \( m_\lambda = m \).

5.5 Completions of Measure Spaces

**Definition 5.24.** A measure space \((X, B, \mu)\) is **complete** if every subset of a null set is in \( B \), i.e. for all \( F \subset X \) such that \( F \in \mathcal{B} \) with \( \mu(E) = 0 \) implies that \( F \in \mathcal{B} \).

**Proposition 5.25 (Completion of a Measure).** Let \((X, B, \mu)\) be a measure space. Set

\[ \bar{N} = N^n := \{ N \subset X : \exists F \in \mathcal{B} \text{ such that } N \subset F \text{ and } \mu(F) = 0 \} \]

\[ \bar{B} = \bar{B}^n := \{ A \cup N : A \in \mathcal{B} \text{ and } N \in \bar{N} \} \text{ and } \]

\[ \bar{\mu}(A \cup N) := \mu(A) \text{ for } A \in \mathcal{B} \text{ and } N \in \bar{N}, \]

see Fig. 5.1. Then \( \bar{B} \) is a \( \sigma \) – algebra, \( \bar{\mu} \) is a well defined measure on \( \bar{B} \), \( \bar{\mu} \) is the unique measure on \( \bar{B} \) which extends \( \mu \) on \( \mathcal{B} \), and \((X, \bar{B}, \bar{\mu})\) is complete measure space. The \( \sigma \)-algebra, \( \bar{B} \), is called the completion of \( \mathcal{B} \) relative to \( \mu \) and \( \bar{\mu} \), is called the completion of \( \mu \).

**Proof.** Clearly \( X, \emptyset \in \bar{B} \). Let \( A \in \mathcal{B} \) and \( N \in \bar{N} \) and choose \( F \in \mathcal{B} \) such that \( N \subset F \) and \( \mu(F) = 0 \). Since \( N^c = (F \setminus N) \cup F^c \),

\[ (A \cup N)^c = A^c \cap N^c = A^c \cap (F \setminus N \cup F^c) = [A^c \cap (F \setminus N)] \cup [A^c \cap F^c] \]

where \([A^c \cap (F \setminus N)] \in \bar{N} \) and \([A^c \cap F^c] \in \bar{B} \). Thus \( \bar{B} \) is closed under complements. If \( A_i \in \mathcal{B} \) and \( N_i \subset F_i \in \mathcal{B} \) such that \( \mu(F_i) = 0 \) then \( \bigcup (A_i \cup N_i) = (\bigcup A_i) \cup (\bigcup N_i) \in \bar{B} \) since \( \bigcup A_i \in \mathcal{B} \) and \( \bigcup N_i \subset \bigcup F_i \) and \( \mu(\bigcup F_i) = 0 \). Therefore, \( \bar{B} \) is a \( \sigma \) – algebra. Suppose \( A \cup N_1 = B \cup N_2 \) with \( A, B \in \mathcal{B} \) and \( N_1, N_2, \in \bar{N} \). Then \( A \subset A \cup N_1 \subset A \cup N_1 \cup F_2 = B \cup F_2 \) which shows that

\[ \mu(A) \leq \mu(B) + \mu(F_2) = \mu(B). \]
Similarly, we show that \( \mu(B) \leq \mu(A) \) so that \( \mu(A) = \mu(B) \) and hence \( \mu(A \cup N) := \mu(A) \) is well defined. It is left as an exercise to show \( \mu \) is a measure, i.e. that it is countable additive.

\[ \tag{5.15} \]

### 5.6 A Baby Version of Kolmogorov’s Extension Theorem

For this section, let \( A \) be a finite set, \( \Omega := A^\infty := A^N \), and let \( A \) denote the collection of cylinder subsets of \( \Omega \), where \( A \subset \Omega \) is a cylinder set if there exists \( n \in \mathbb{N} \) and \( B \subset A^n \) such that

\[ A = B \times A^\infty := \{ \omega \in \Omega : (\omega_1, \omega_2, \ldots, \omega_n) \in B \} . \]

Observe that we may also write \( A = B' \times A^\infty \) where \( B' = B \times A^k \subset A^{n+k} \) for any \( k \geq 0 \).

#### Exercise 5.3.
Show \( A \) is an algebra.

#### Lemma 5.26.
Suppose \( \{ A_n \}_{n=1}^\infty \subset A \) is a decreasing sequence of non-empty cylinder subsets, then \( \cap_{n=1}^\infty A_n \neq \emptyset \).

**Proof.** Since \( A_n \in A \), we may find \( N_n \in \mathbb{N} \) and \( B_n \subset A^{N_n} \) such that \( A_n = B_n \times A^\infty \). Using the observation just prior to this Lemma, we may assume that \( \{ N_n \}_{n=1}^\infty \) is a strictly increasing sequence.

By assumption, there exists \( \omega(n) = (\omega_1(n), \omega_2(n), \ldots) \in \Omega \) such that \( \omega(n) \in A_n \) for all \( n \). Moreover, since \( \omega(n) \in A_n \subset A_k \) for all \( n \leq k \), it follows that

\[ (\omega_1(n), \omega_2(n), \ldots, \omega_{N_k}(n)) \in B_k \]

for all \( k \leq n \). (5.14)

Since \( A \) is a finite set, we may find a \( \lambda_1 \in A \) and an infinite subset, \( \Gamma_1 \subset \mathbb{N} \) such that \( \omega_1(n) = \lambda_1 \) for all \( n \in \Gamma_1 \). Similarly, there exists \( \lambda_2 \in A \) and an infinite set, \( \Gamma_2 \subset \Gamma_1 \), such that \( \omega_2(n) = \lambda_2 \) for all \( n \in \Gamma_2 \). Continuing this procedure inductively, there exists (for all \( j \in \mathbb{N} \)) infinite subsets, \( \Gamma_j \subset \mathbb{N} \) and points \( \lambda_j \in A \) such that \( \Gamma_1 \supset \Gamma_2 \supset \Gamma_3 \supset \ldots \) and \( \omega_j(n) = \lambda_j \) for all \( n \in \Gamma_j \).

We are now going to complete the proof by showing that \( \lambda := (\lambda_1, \lambda_2, \ldots) \) is in \( \cap_{n=1}^\infty A_n \). By the construction above, for all \( N \in \mathbb{N} \) we have

\[ (\omega_1(n), \ldots, \omega_N(n)) = (\lambda_1, \ldots, \lambda_N) \]

for all \( n \in \Gamma_N \).

Taking \( N = N_k \) and \( n \in \Gamma_{N_k} \) with \( n \geq k \), we learn from Eq. (5.14) that

\[ (\lambda_1, \ldots, \lambda_{N_k}) = (\omega_1(n), \ldots, \omega_{N_k}(n)) \in B_k \]

But this is equivalent to showing \( \lambda \in A_k \). Since \( k \in \mathbb{N} \) was arbitrary it follows that \( \lambda \in \cap_{n=1}^\infty A_n \).

\[ \tag{5.15} \]

#### Theorem 5.27 (Kolmogorov’s Extension Theorem I). Continuing the notation above, every finitely additive probability measure, \( P : A \rightarrow [0,1] \), has a unique extension to a probability measure on \( \sigma(A) \).

**Proof.** From Theorem 5.19 it suffices to show \( \lim_{n \rightarrow \infty} P(A_n) = 0 \) whenever \( \{ A_n \}_{n=1}^\infty \subset A \) with \( A_n \uparrow N \). However, by Lemma 5.26 if \( A_n \in A \) and \( A_n \uparrow \emptyset \), we must have that \( A_n = \emptyset \) for a.a. \( n \) and in particular \( P(A_n) = 0 \) for a.a. \( n \). This certainly implies \( \lim_{n \rightarrow \infty} P(A_n) = 0 \).

Given a probability measure, \( P : \sigma(A) \rightarrow [0,1] \) and \( n \in \mathbb{N} \) and \( (\lambda_1, \ldots, \lambda_n) \in A^n \), let

\[ p_n(\lambda_1, \ldots, \lambda_n) := P(\{ \omega \in \Omega : \omega_1 = \lambda_1, \ldots, \omega_n = \lambda_n \}) . \]

#### Exercise 5.4 (Consistency Conditions).
If \( p_n \) is defined as above, show:

1. \( \sum_{\lambda \in A} p_1(\lambda) = 1 \)
2. for all \( n \in \mathbb{N} \) and \( (\lambda_1, \ldots, \lambda_n) \in A^n \),

\[ p_n(\lambda_1, \ldots, \lambda_n) = \sum_{\lambda \in A} p_{n+1}(\lambda, \lambda) . \]

#### Exercise 5.5 (Converse to 5.4).
Suppose for each \( n \in \mathbb{N} \) we are given functions, \( p_n : A^n \rightarrow [0,1] \) such that the consistency conditions in Exercise 5.4 hold. Then there exists a unique probability measure, \( P \) on \( \sigma(A) \) such that Eq. (5.15) holds for all \( n \in \mathbb{N} \) and \( (\lambda_1, \ldots, \lambda_n) \in A^n \).

#### Example 5.28 (Existence of iid simple R.V.s).
Suppose now that \( q : A \rightarrow [0,1] \) is a function such that \( \sum_{\lambda \in A} q(\lambda) = 1 \). Then there exists a unique probability measure \( P \) on \( \sigma(A) \) such that, for all \( n \in \mathbb{N} \) and \( (\lambda_1, \ldots, \lambda_n) \in A^n \), we have

\[ P(\{ \omega \in \Omega : \omega_1 = \lambda_1, \ldots, \omega_n = \lambda_n \}) = q(\lambda_1) \ldots q(\lambda_n) \]

This is a special case of Exercise 5.5 with \( p_n(\lambda_1, \ldots, \lambda_n) := q(\lambda_1) \ldots q(\lambda_n) \).
Random Variables

6.1 Measurable Functions

Definition 6.1. A measurable space is a pair \( (X, \mathcal{M}) \), where \( X \) is a set and \( \mathcal{M} \) is a \( \sigma \) – algebra on \( X \).

To motivate the notion of a measurable function, suppose \( (X, \mathcal{M}, \mu) \) is a measure space and \( f : X \to \mathbb{R}_+ \) is a function. Roughly speaking, we are going to define \( \int f \, d\mu \) as a certain limit of sums of the form,

\[
\sum_{0 < a_1 < a_2 < a_3 < \ldots} a_i \mu(f^{-1}(a_i, a_{i+1}]).
\]

For this to make sense we will need to require \( f^{-1}((a, b]) \in \mathcal{M} \) for all \( a < b \). Because of Corollary 6.7 below, this last condition is equivalent to the condition \( f^{-1}(\mathcal{B}_{\mathbb{R}}) \subset \mathcal{M} \).

Definition 6.2. Let \( (X, \mathcal{M}) \) and \( (Y, \mathcal{F}) \) be measurable spaces. A function \( f : X \to Y \) is measurable of more precisely, \( \mathcal{M}/\mathcal{F} \) – measurable or \( (\mathcal{M}, \mathcal{F}) \) – measurable, if \( f^{-1}(\mathcal{F}) \subset \mathcal{M} \), i.e. if \( f^{-1}(A) \in \mathcal{M} \) for all \( A \in \mathcal{F} \).

Remark 6.3. Let \( f : X \to Y \) be a function. Given a \( \sigma \) – algebra \( \mathcal{F} \subset 2^Y \), the \( \sigma \) – algebra \( \mathcal{M} := f^{-1}(\mathcal{F}) \) is the smallest \( \sigma \) – algebra on \( X \) such that \( f \) is \( (\mathcal{M}, \mathcal{F}) \) – measurable. Similarly, if \( \mathcal{M} \) is a \( \sigma \) – algebra on \( X \) then

\[
\mathcal{F} = f_* \mathcal{M} = \{ A \in 2^X | f^{-1}(A) \in \mathcal{M} \}
\]

is the largest \( \sigma \) – algebra on \( Y \) such that \( f \) is \( (\mathcal{M}, \mathcal{F}) \) – measurable.

Example 6.4 (Characteristic Functions). Let \( (X, \mathcal{M}) \) be a measurable space and \( A \subset X \). Then \( 1_A \) is \( (\mathcal{M}, \mathcal{B}_{\mathbb{R}}) \) – measurable if \( A \in \mathcal{M} \). Indeed, \( 1_A^{-1}(W) \) is either \( \emptyset \), \( X \), \( A \) or \( A^c \) for any \( W \subset \mathbb{R} \) with \( 1_A^{-1} \{ 1 \} = A \).

Example 6.5. Suppose \( f : X \to Y \) with \( Y \) being a finite set and \( \mathcal{F} = 2^Y \). Then \( f \) is measurable iff \( f^{-1}(\{ y \}) \in \mathcal{M} \) for all \( y \in Y \).

Proposition 6.6. Suppose that \( (X, \mathcal{M}) \) and \( (Y, \mathcal{F}) \) are measurable spaces and further assume \( \mathcal{E} \subset \mathcal{F} \) generates \( \mathcal{F} \), i.e. \( \mathcal{F} = \sigma(\mathcal{E}) \). Then a map, \( f : X \to Y \) is measurable iff \( f^{-1}(\mathcal{E}) \subset \mathcal{M} \).

Proof. If \( f \) is \( \mathcal{M}/\mathcal{F} \) measurable, then \( f^{-1}(\mathcal{E}) \subset f^{-1}(\mathcal{F}) \subset \mathcal{M} \). Conversely if \( f^{-1}(\mathcal{E}) \subset \mathcal{M} \), then, using Lemma 3.26

\[
f^{-1}(\mathcal{F}) = f^{-1}(\sigma(\mathcal{E})) = \sigma(f^{-1}(\mathcal{E})) \subset \mathcal{M}.
\]

Corollary 6.7. Suppose that \( (X, \mathcal{M}) \) is a measurable space. Then the following conditions on a function \( f : X \to \mathbb{R} \) are equivalent:

1. \( f \) is \( (\mathcal{M}, \mathcal{B}_{\mathbb{R}}) \) – measurable,
2. \( f^{-1}((a, \infty)) \in \mathcal{M} \) for all \( a \in \mathbb{R} \),
3. \( f^{-1}((a, \infty)) \in \mathcal{M} \) for all \( a \in \mathbb{Q} \),
4. \( f^{-1}((-\infty, a]) \in \mathcal{M} \) for all \( a \in \mathbb{R} \).


Exercise 6.2. If \( \mathcal{M} \) is the \( \sigma \) – algebra generated by \( \mathcal{E} \subset 2^X \), then \( \mathcal{M} \) is the union of the \( \sigma \) – algebras generated by countable subsets \( \mathcal{F} \subset \mathcal{E} \).

Exercise 6.3. Let \( (X, \mathcal{M}) \) be a measure space and \( f_n : X \to \mathbb{R} \) be a sequence of measurable functions on \( X \). Show that \( \{ x : \lim_{n \to \infty} f_n(x) \text{ exists in } \mathbb{R} \} \in \mathcal{M} \).

Exercise 6.4. Show that every monotone function \( f : \mathbb{R} \to \mathbb{R} \) is \( (\mathcal{B}_{\mathbb{R}}, \mathcal{B}_{\mathbb{R}}) \) – measurable.

Definition 6.8. Given measurable spaces \( (X, \mathcal{M}) \) and \( (Y, \mathcal{F}) \) and a subset \( A \subset X \). We say a function \( f : A \to Y \) is measurable iff \( f \) is \( \mathcal{M}_A/\mathcal{F} \) – measurable.

Proposition 6.9 (Localizing Measurability). Let \( (X, \mathcal{M}) \) and \( (Y, \mathcal{F}) \) be measurable spaces and \( f : X \to Y \) be a function.

1. If \( f \) is measurable and \( A \subset X \) then \( f\big|_A : A \to Y \) is measurable.
2. Suppose there exist \( A_n \in \mathcal{M} \) such that \( X = \bigcup_{n=1}^\infty A_n \) and \( f\big|_{A_n} \) is \( \mathcal{M}_{A_n} \) measurable for all \( n \), then \( f \) is \( \mathcal{M} \) – measurable.

Proof. 1. If \( f : X \to Y \) is measurable, \( f^{-1}(B) \in \mathcal{M} \) for all \( B \in \mathcal{F} \) and therefore

\[
f\big|_A^{-1}(B) = A \cap f^{-1}(B) \in \mathcal{M}_A \text{ for all } B \in \mathcal{F}.
\]
2. If \( B \in \mathcal{F} \), then
\[
f^{-1}(B) = \bigcup_{n=1}^{\infty} (f^{-1}(B) \cap A_n) = \bigcup_{n=1}^{\infty} f|_{A_n}^{-1}(B).
\]
Since each \( A_n \in \mathcal{M} \), \( M_{A_n} \subset \mathcal{M} \) and so the previous displayed equation shows \( f^{-1}(B) \in \mathcal{M} \).

**Proposition 6.10.** Let \((X, \mathcal{M}, \mu)\) be a measure space, \((Y, \mathcal{F})\) be a measurable space and \( f : X \to Y \) be a measurable map. Define a function \( \nu : \mathcal{F} \to [0, \infty] \) by \( \nu(A) := \mu(f^{-1}(A)) \) for all \( A \in \mathcal{F} \). Then \( \nu \) is a measure on \((Y, \mathcal{F})\). (In the future we will denote \( \nu \) by \( f_* \mu \) or \( \mu \circ f^{-1} \) and call \( f_* \mu \) the \textit{push-forward} of \( \mu \) by \( f \) or the \textit{law of} \( f \) \textit{under} \( \mu \).

**Theorem 6.11.** Given a distribution function, \( F : \mathbb{R} \to [0,1] \) let \( G : (0,1) \to \mathbb{R} \) be defined (see Figure 6.1) by,
\[
G(y) := \inf \{ x : F(x) \geq y \}.
\]
Then \( G : (0,1) \to \mathbb{R} \) is Borel measurable and \( G_* m = \mu_F \) where \( \mu_F \) is the unique measure on \((\mathbb{R}, \mathcal{B}_\mathbb{R})\) such that \( \mu_F ((a,b]) = F(b) - F(a) \) for all \(-\infty < a < b < \infty\).

![Fig. 6.1. A pictorial definition of \( G \).](image)

**Proof.** Since \( G : (0,1) \to \mathbb{R} \) is a non-decreasing function, \( G \) is measurable. We also claim that, for all \( x_0 \in \mathbb{R} \), that
\[
G^{-1}((0,x_0]) = \{ y : G(y) \leq x_0 \} = (0, F(x_0)] \cap \mathbb{R}, \tag{6.1}
\]
see Figure 6.2.

![Fig. 6.2. As can be seen from this picture, \( G(y) \leq x_0 \) iff \( y \leq F(x_0) \) and similarly, \( G(y) \leq x_1 \) iff \( y \leq x_1 \).](image)

To give a formal proof of Eq. (6.1), \( G(y) = \inf \{ x : F(x) \geq y \} \leq x_0 \), there exists \( x_n \geq x_0 \) with \( x_n \downarrow x_0 \) such that \( F(x_n) \geq y \). By the right continuity of \( F \), it follows that \( F(x_0) \geq y \). Thus we have shown
\[
\{ G \leq x_0 \} \subset (0, F(x_0)] \cap (0,1).
\]

For the converse, if \( y \leq F(x_0) \) then \( G(y) = \inf \{ x : F(x) \geq y \} \leq x_0 \), i.e. \( y \in \{ G \leq x_0 \} \). Indeed, \( y \in G^{-1}((\infty, x_0]) \) iff \( G(y) \leq x_0 \). Observe that
\[
G(F(x_0)) = \inf \{ x : F(x) \geq F(x_0) \} \leq x_0
\]
and hence \( G(y) \leq x_0 \) whenever \( y \leq F(x_0) \). This shows that
\[
(0, F(x_0)] \cap (0,1) \subset G^{-1}((0, x_0]).
\]

As a consequence we have \( G_* m = \mu_F \). Indeed,
\[
(G_* m)((\infty, x]) = m(G^{-1}((\infty, x])) = m(\{ y \in (0,1) : G(y) \leq x \}) = m((0, F(x)]) \cap (0,1)) = F(x).
\]

See section 2.5.2 on p. 61 of Resnick for more details.

**Theorem 6.12 (Durrett’s Version).** Given a distribution function, \( F : \mathbb{R} \to [0,1] \) let \( Y : (0,1) \to \mathbb{R} \) be defined (see Figure 6.3) by,
\[
Y(x) := \sup \{ y : F(y) < x \}.
\]
Then \( Y : (0,1) \to \mathbb{R} \) is Borel measurable and \( Y_* m = \mu_F \) where \( \mu_F \) is the unique measure on \((\mathbb{R}, \mathcal{B}_\mathbb{R})\) such that \( \mu_F ((a,b]) = F(b) - F(a) \) for all \(-\infty < a < b < \infty\).
**Lemma 6.13 (Composing Measurable Functions).** Suppose that \((X, \mathcal{M}), (Y, \mathcal{F})\) and \((Z, \mathcal{G})\) are measurable spaces. If \(f : (X, \mathcal{M}) \to (Y, \mathcal{F})\) and \(g : (Y, \mathcal{F}) \to (Z, \mathcal{G})\) are measurable functions then \(g \circ f : (X, \mathcal{M}) \to (Z, \mathcal{G})\) is measurable as well.

**Proof.** By assumption \(g^{-1}(\mathcal{G}) \subset \mathcal{F}\) and \(f^{-1}(\mathcal{F}) \subset \mathcal{M}\) so that

\[(g \circ f)^{-1}(\mathcal{G}) = f^{-1}(g^{-1}(\mathcal{G})) \subset f^{-1}(\mathcal{F}) \subset \mathcal{M}.\]

---

**Definition 6.14 (σ – Algebras Generated by Functions).** Let \(X\) be a set and suppose there is a collection of measurable spaces \(\{(Y_\alpha, \mathcal{F}_\alpha) : \alpha \in A\}\) and functions \(f_\alpha : X \to Y_\alpha\) for all \(\alpha \in A\). Let \(\sigma(f_\alpha : \alpha \in A)\) denote the smallest σ-algebra on \(X\) such that each \(f_\alpha\) is measurable, i.e.

\[\sigma(f_\alpha : \alpha \in A) = \sigma(\cup_{\alpha \in A} f_\alpha^{-1}(\mathcal{F}_\alpha)).\]

**Example 6.15.** Suppose that \(Y\) is a finite set, \(\mathcal{F} = 2^Y\), and \(X = Y^N\) for some \(N \in \mathbb{N}\). Let \(\pi_i : Y^N \to Y\) be the projection maps, \(\pi_i(y_1, \ldots, y_N) = y_i\). Then, as the reader should check,

\[\sigma(\pi_1, \ldots, \pi_n) = \{A \times A^{N-n} : A \subset A^n\}.\]

**Proposition 6.16.** Assuming the notation in Definition 6.14 and additionally let \((Z, \mathcal{M})\) be a measurable space and \(g : Z \to X\) be a function. Then \(g\) is \((\mathcal{M}, \sigma(f_\alpha : \alpha \in A))\)–measurable iff \(f_\alpha \circ g\) is \((\mathcal{M}, \mathcal{F}_\alpha)\)–measurable for all \(\alpha \in A\).

**Proof.** \((\Rightarrow)\) If \(g\) is \((\mathcal{M}, \sigma(f_\alpha : \alpha \in A))\)–measurable, then the composition \(f_\alpha \circ g\) is \((\mathcal{M}, \mathcal{F}_\alpha)\)–measurable by Lemma 6.13 \((\Leftarrow)\) Let

\[\mathcal{G} = \sigma(f_\alpha : \alpha \in A) = \sigma(\cup_{\alpha \in A} f_\alpha^{-1}(\mathcal{F}_\alpha)).\]

If \(f_\alpha \circ g\) is \((\mathcal{M}, \mathcal{F}_\alpha)\)–measurable for all \(\alpha\), then

\[g^{-1}(\cup_{\alpha \in A} f_\alpha^{-1}(\mathcal{F}_\alpha)) = \cup_{\alpha \in A} g^{-1} f_\alpha^{-1}(\mathcal{F}_\alpha) \subset \mathcal{M}.\]

and therefore

\[g^{-1}(\cup_{\alpha \in A} f_\alpha^{-1}(\mathcal{F}_\alpha)) = \cup_{\alpha \in A} g^{-1} f_\alpha^{-1}(\mathcal{F}_\alpha) \subset \mathcal{M}.\]

Hence

\[g^{-1}(\mathcal{G}) = g^{-1}(\sigma(\cup_{\alpha \in A} f_\alpha^{-1}(\mathcal{F}_\alpha))) = \sigma(g^{-1}(\cup_{\alpha \in A} f_\alpha^{-1}(\mathcal{F}_\alpha)) \subset \mathcal{M}\]

which shows that \(g\) is \((\mathcal{M}, \mathcal{G})\)–measurable.

**Definition 6.17.** A function \(f : X \to Y\) between two topological spaces is **Borel measurable** if \(f^{-1}(B_Y) \subset B_X\).

**Proposition 6.18.** Let \(X\) and \(Y\) be two topological spaces and \(f : X \to Y\) be a continuous function. Then \(f\) is Borel measurable.
Proof. Using Lemma 3.26 and $\mathcal{B}_Y = \sigma(\tau_Y)$,
\[ f^{-1}(\mathcal{B}_Y) = f^{-1}(\sigma(\tau_Y)) = \sigma(f^{-1}(\tau_Y)) \subset \sigma(\tau_X) = \mathcal{B}_X. \]

Example 6.19. For $i = 1, 2, \ldots, n$, let $\pi_i : \mathbb{R}^n \to \mathbb{R}$ be defined by $\pi_i(x) = x_i$. Then each $\pi_i$ is continuous and therefore $\mathcal{B}_{\mathbb{R}}/\mathcal{B}_{\mathbb{R}}$ – measurable.

Lemma 6.20. Let $\mathcal{E}$ denote the collection of open rectangle in $\mathbb{R}^n$, then $\mathcal{B}_{\mathbb{R}} = \sigma(\mathcal{E})$. We also have that $\mathcal{B}_{\mathbb{R}^n} = \sigma(\pi_1, \ldots, \pi_n)$ and in particular, $A_1 \times \cdots \times A_n \in \mathcal{B}_{\mathbb{R}^n}$ whenever $A_i \in \mathcal{B}_{\mathbb{R}}$ for $i = 1, 2, \ldots, n$. Therefore $\mathcal{B}_{\mathbb{R}^n}$ may be described as the algebra generated by $\{A_1 \times \cdots \times A_n : A_i \in \mathcal{B}_{\mathbb{R}}\}$.

Proof. Assertion 1. Since $\mathcal{E} \subset \mathcal{B}_{\mathbb{R}^n}$, it follows that $\sigma(\mathcal{E}) \subset \mathcal{B}_{\mathbb{R}^n}$. Let
\[ \mathcal{E}_0 := \{(a,b) : a,b \in \mathbb{Q}^n \ni a < b\}, \]
where, for $a,b \in \mathbb{R}^n$, we write $a < b$ iff $a_i < b_i$ for $i = 1, 2, \ldots, n$ and let
\[ (a,b) = (a_1,b_1) \times \cdots \times (a_n,b_n). \]  (6.3)
Since every open set, $V \subset \mathbb{R}^n$, may be written as a (necessarily) countable union of elements from $\mathcal{E}_0$, we have
\[ V \in \sigma(\mathcal{E}_0) \subset \sigma(\mathcal{E}), \]
i.e. $\sigma(\mathcal{E}_0)$ and hence $\sigma(\mathcal{E})$ contains all open subsets of $\mathbb{R}^n$. Hence we may conclude that
\[ \mathcal{B}_{\mathbb{R}^n} = \sigma(\text{open sets}) \subset \sigma(\mathcal{E}_0) \subset \sigma(\mathcal{E}) \subset \mathcal{B}_{\mathbb{R}^n}. \]

Assertion 2. Since each $\pi_i$ is $\mathcal{B}_{\mathbb{R}}/\mathcal{B}_{\mathbb{R}}$ – measurable, it follows that $\sigma(\pi_1, \ldots, \pi_n) \subset \mathcal{B}_{\mathbb{R}^n}$. Moreover, if $(a,b)$ is as in Eq. (6.3), then
\[ (a,b) = \cap_{i=1}^n \pi_i^{-1}((a_i,b_i)) \in \sigma(\pi_1, \ldots, \pi_n). \]
Therefore, $\mathcal{E} \subset \sigma(\pi_1, \ldots, \pi_n)$ and $\mathcal{B}_{\mathbb{R}^n} = \sigma(\mathcal{E}) \subset \sigma(\pi_1, \ldots, \pi_n)$.

Assertion 3. If $A_i \in \mathcal{B}_{\mathbb{R}}$ for $i = 1, 2, \ldots, n$, then
\[ A_1 \times \cdots \times A_n \cap \bigcap_{i=1}^n \pi_i^{-1}(A_i) \in \sigma(\pi_1, \ldots, \pi_n) = \mathcal{B}_{\mathbb{R}^n}. \]

Corollary 6.21. If $(X, \mathcal{M})$ is a measurable space, then
\[ f = (f_1, f_2, \ldots, f_n) : X \to \mathbb{R}^n \]
is $(\mathcal{M}, \mathcal{B}_{\mathbb{R}^n})$ – measurable iff $f_i : X \to \mathbb{R}$ is $(\mathcal{M}, \mathcal{B}_{\mathbb{R}})$ – measurable for each $i$.
In particular, a function $f : X \to \mathbb{C}$ is $(\mathcal{M}, \mathcal{B}_{\mathbb{C}})$ – measurable iff $\text{Re} f$ and $\text{Im} f$ are $(\mathcal{M}, \mathcal{B}_{\mathbb{R}})$ – measurable.

Proof. This is an application of Lemma 6.20 and Proposition 6.16.

Corollary 6.22. Let $(X, \mathcal{M})$ be a measurable space and $f, g : X \to \mathbb{C}$ be $(\mathcal{M}, \mathcal{B}_{\mathbb{C}})$ – measurable functions. Then $f \pm g$ and $f \cdot g$ are also $(\mathcal{M}, \mathcal{B}_{\mathbb{C}})$ – measurable.

Proof. Define $F : X \to \mathbb{C} \times \mathbb{C}$, $A_\pm : \mathbb{C} \times \mathbb{C} \to \mathbb{C}$ and $M : \mathbb{C} \times \mathbb{C} \to \mathbb{C}$ by $F(x) = (f(x), g(x))$, $A_\pm(w,z) = w \pm z$ and $M(w,z) = wz$. Then $A_\pm$ and $M$ are continuous and hence $(\mathcal{B}_{\mathbb{C}^2}, \mathcal{B}_{\mathbb{C}})$ – measurable. Also $F$ is $(\mathcal{M}, \mathcal{B}_{\mathbb{C}})$ – measurable since $\pi_1 \circ F = f$ and $\pi_2 \circ F = g$ are $(\mathcal{M}, \mathcal{B}_{\mathbb{C}})$ – measurable. Therefore $A_\pm \circ F = f \pm g$ and $M \circ F = f \cdot g$, being the composition of measurable functions, are also measurable.

Lemma 6.23. Let $\alpha \in \mathbb{C}$, $(X, \mathcal{M})$ be a measurable space and $f : X \to \mathbb{C}$ be a $(\mathcal{M}, \mathcal{B}_{\mathbb{C}})$ – measurable function. Then
\[ F(x) := \begin{cases} \frac{1}{\sqrt{\pi}} \text{ if } f(x) \neq 0 \\ \alpha \text{ if } f(x) = 0 \end{cases} \]
is measurable.

Proof. Define $i : \mathbb{C} \to \mathbb{C}$ by
\[ i(z) = \begin{cases} \frac{1}{z} \text{ if } z \neq 0 \\ 0 \text{ if } z = 0 \end{cases}. \]
For any open set $V \subset \mathbb{C}$ we have
\[ i^{-1}(V) = i^{-1}(V \setminus \{0\}) \cup i^{-1}(V \cap \{0\}) \]
Because $i$ is continuous except at $z = 0$, $i^{-1}(V \setminus \{0\})$ is an open set and hence in $\mathcal{B}_{\mathbb{C}}$. Moreover, $i^{-1}(V \cap \{0\}) \in \mathcal{B}_{\mathbb{C}}$ since $i^{-1}(V \cap \{0\})$ is either the empty set or the one point set $\{0\}$. Therefore $i^{-1}(\mathcal{B}_{\mathbb{C}}) \subset \mathcal{B}_{\mathbb{C}}$ and hence $i^{-1}(\mathcal{B}_{\mathbb{C}}) = i^{-1}(\sigma(\tau_{\mathbb{C}})) = \sigma(i^{-1}(\tau_{\mathbb{C}})) \subset \mathcal{B}_{\mathbb{C}}$ which shows that $i$ is Borel measurable. Since $F = i \circ f$ is the composition of measurable functions, $F$ is also measurable.

Remark 6.24. For the real case of Lemma 6.23, define $i$ as above but now take $z$ to real. From the plot of $i$, Figure 6.24, the reader may easily verify that $i^{-1}((\pm \infty, a])$ is an infinite half interval for all $a$ and therefore $i$ is measurable.
We will often deal with functions \( f : X \to \mathbb{R} = \mathbb{R} \cup \{ \pm \infty \} \). When talking about measurability in this context we will refer to the \( \sigma \)-algebra on \( \mathbb{R} \) defined by
\[
B_{\mathbb{R}} := \sigma \left( \{ [a, \infty] : a \in \mathbb{R} \} \right).
\] (6.4)

**Proposition 6.25 (The Structure of \( B_{\mathbb{R}} \)).** Let \( B_{\mathbb{R}} \) and \( B_\mathbb{R} \) be as above, then
\[
B_{\mathbb{R}} = \{ A \subset \{-\infty\} \cap \{ -\infty \} \in B_\mathbb{R} \}.
\] (6.5)

In particular \( \{ -\infty \} \in B_{\mathbb{R}} \) and \( B_{\mathbb{R}} \subset B_{\mathbb{R}} \).

**Proof.** Let us first observe that
\[
\{-\infty\} = \bigcap_{n=1}^{\infty} (-\infty, -n) = \bigcap_{n=1}^{\infty} [-n, \infty] \subset B_{\mathbb{R}},
\]
\[
\{ \infty \} = \bigcap_{n=1}^{\infty} [n, \infty] \in B_{\mathbb{R}} \quad \text{and} \quad \mathbb{R} = \mathbb{R} \setminus \{ \pm \infty \} \in B_{\mathbb{R}}.
\]

Letting \( i : \mathbb{R} \to B_\mathbb{R} \) be the inclusion map,
\[
i^{-1}(B_{\mathbb{R}}) = \sigma \left( i^{-1} \left( \{ [a, \infty] : a \in \mathbb{R} \} \right) \right) = \sigma \left( \{ i^{-1} ([a, \infty]) : a \in \mathbb{R} \} \right)
\]
\[
= \sigma \left( \{ [a, \infty] \cap \{ -\infty \} \cap \{ -\infty \} \in B_{\mathbb{R}} \} \right) = \sigma \left( \{ [a, \infty] : a \in \mathbb{R} \} \right) = B_{\mathbb{R}}.
\]

Thus we have shown
\[
B_{\mathbb{R}} = i^{-1}(B_{\mathbb{R}}) = \{ A \subset \mathbb{R} : A \cap \mathbb{R} \in B_{\mathbb{R}} \}.
\]

This implies:
1. \( A \subset B_{\mathbb{R}} \implies A \subset \mathbb{R} \in B_{\mathbb{R}} \) and
2. if \( A \subset \mathbb{R} \) is such that \( A \cap \mathbb{R} \in B_{\mathbb{R}} \) there exists \( B \in B_{\mathbb{R}} \) such that \( A \cap \mathbb{R} = B \cap \mathbb{R} \).

Because \( A \Delta B \subset \{ \pm \infty \} \) and \( \{ \infty \}, \{ -\infty \} \in B_{\mathbb{R}} \) we may conclude that \( A \in B_{\mathbb{R}} \) as well.

This proves Eq. (6.5). 

The proofs of the next two corollaries are left to the reader, see Exercises 6.5 and 6.6.

**Corollary 6.26.** Let \( (X, \mathcal{M}) \) be a measurable space and \( f : X \to \mathbb{R} \) be a function. Then the following are equivalent
1. \( f \) is \( (\mathcal{M}, B_{\mathbb{R}}) \) - measurable,
2. \( f^{-1}([a, \infty]) \in \mathcal{M} \) for all \( a \in \mathbb{R} \),
3. \( f^{-1}((-\infty, a]) \in \mathcal{M} \) for all \( a \in \mathbb{R} \),
4. \( f^{-1}([-\infty)) \in \mathcal{M}, f^{-1}([\infty)) \in \mathcal{M} \) and \( f^0 : X \to \mathbb{R} \) defined by
\[
f^0 (x) := 1_{\mathbb{R}} (f (x)) = \begin{cases} f (x) & \text{if } f (x) \in \mathbb{R} \\ 0 & \text{if } f (x) \in \{ \pm \infty \} \end{cases}
\]
is measurable.

**Corollary 6.27.** Let \( (X, \mathcal{M}) \) be a measurable space, \( f, g : X \to \mathbb{R} \) be functions and define \( f \cdot g : X \to \mathbb{R} \) and \( f + g : X \to \mathbb{R} \) using the conventions, \( 0 \cdot \infty = 0 \) and \( (f + g)(x) = 0 \) if \( f (x) = \infty \) and \( g (x) = -\infty \) or \( f (x) = -\infty \) and \( g (x) = \infty \). Then \( f \cdot g \) and \( f + g \) are measurable functions on \( X \) if both \( f \) and \( g \) are measurable.

**Exercise 6.5.** Prove Corollary 6.26 noting that the equivalence of items 1. - 3. is a direct analogue of Corollary 6.7. Use Proposition 6.25 to handle item 4.

**Exercise 6.6.** Prove Corollary 6.27.

**Proposition 6.28 (Closure under sups, infs and limits).** Suppose that \( (X, \mathcal{M}) \) is a measurable space and \( f_j : (X, \mathcal{M}) \to \mathbb{R} \), \( j \in \mathbb{N} \) is a sequence of \( \mathcal{M}/B_\mathbb{R} \) - measurable functions. Then
\[
\sup_j f_j, \quad \inf_j f_j, \quad \limsup_{j \to \infty} f_j \quad \text{and} \quad \liminf_{j \to \infty} f_j
\]
are all \( \mathcal{M}/B_\mathbb{R} \) - measurable functions. (Note that this result is in generally false when \( (X, \mathcal{M}) \) is a topological space and measurable is replaced by continuous in the statement.)

**Proof.** Define \( g_+ (x) := \sup_j f_j (x) \), then
\[
\{ x : g_+ (x) \leq a \} = \{ x : f_j (x) \leq a \forall j \}
\]
\[
= \cap_j \{ x : f_j (x) \leq a \} \in \mathcal{M}
\]
so that \( g_+ \) is measurable. Similarly if \( g_- (x) = \inf_j f_j (x) \) then
\[
\{ x : g_- (x) \geq a \} = \cap_j \{ x : f_j (x) \geq a \} \in \mathcal{M}.
\]
Since
\[
\limsup_{j \to \infty} f_j = \inf_n \{ f_j : j \geq n \} \quad \text{and} \quad \liminf_{j \to \infty} f_j = \sup_n \{ f_j : j \geq n \}
\]
we are done by what we have already proved.

**Definition 6.29.** Given a function \( f : X \to \mathbb{R} \) let \( f_+ (x) := \max \{ f (x), 0 \} \) and \( f_- (x) := \min (f (x), 0) \). Notice that \( f = f_+ - f_- \).

**Corollary 6.30.** Suppose \( (X, \mathcal{M}) \) is a measurable space and \( f : X \to \mathbb{R} \) is a function. Then \( f \) is measurable iff \( f_\pm \) are measurable.

**Proof.** If \( f \) is measurable, then Proposition 6.28 implies \( f_\pm \) are measurable. Conversely if \( f_\pm \) are measurable then so is \( f = f_+ - f_- \).
\textbf{Definition 6.31.} Let \((X, \mathcal{M})\) be a measurable space. A function \(\varphi : X \to \mathbb{F}\) (\(\mathbb{F}\) denotes either \(\mathbb{R}, \mathbb{C}\) or \([0, \infty] \subset \mathbb{R}\)) is a \textit{simple function} if \(\varphi\) is \(\mathcal{M} - \mathcal{B}_{\mathbb{F}}\) measurable and \(\varphi(X)\) contains only finitely many elements.

Any such simple functions can be written as

\[
\varphi = \sum_{i=1}^{n} \lambda_i 1_{A_i} \text{ with } A_i \in \mathcal{M} \text{ and } \lambda_i \in \mathbb{F}. \tag{6.6}
\]

Indeed, take \(\lambda_1, \lambda_2, \ldots, \lambda_n\) to be an enumeration of the range of \(\varphi\) and \(A_i = \varphi^{-1}((\lambda_i))\). Note that this argument shows that any simple function may be written intrinsically as

\[
\varphi = \sum_{y \in \mathbb{F}} y 1_{\varphi^{-1}((y))}. \tag{6.7}
\]

The next theorem shows that simple functions are “pointwise dense” in the space of measurable functions.

\textbf{Theorem 6.32 (Approximation Theorem).} Let \(f : X \to [0, \infty] \) be measurable and define, see Figure 6.4,

\[
\varphi_n(x) := \sum_{k=0}^{n2^n-1} \frac{k}{2^n} f^{-1}(\left(\frac{n}{2^n}, \frac{n+1}{2^n}\right))(x) + n1_{f^{-1}(n2^n, \infty]}(x)
\]

\[
= \sum_{k=0}^{n2^n-1} \frac{k}{2^n} \{\frac{n}{2^n} < x \leq \frac{n+1}{2^n}\} + n1_{\{f > n2^n\}}(x)
\]

then \(\varphi_n \leq f\) for all \(n\), \(\varphi_n(x) \uparrow f(x)\) for all \(x \in X\) and \(\varphi_n \uparrow f\) uniformly on the sets \(X_M := \{x \in X : f(x) \leq M\}\) with \(M < \infty\).

Moreover, if \(f : X \to \mathbb{C}\) is a measurable function, then there exists simple functions \(\varphi_n\) such that \(\lim_{n \to \infty} \varphi_n(x) = f(x)\) for all \(x\) and \(|\varphi_n| \uparrow |f|\) as \(n \to \infty\).

\textbf{Proof.} Since

\[
\left(\frac{k}{2^n}, \frac{k+1}{2^n}\right) = \left(\frac{2k}{2^n+1}, \frac{2k+1}{2^n+1}\right) \cup \left(\frac{2k+1}{2^n+1}, \frac{2k+2}{2^n+1}\right),
\]

if \(x \in f^{-1}\left(\left(\frac{2k}{2^n+1}, \frac{2k+1}{2^n+1}\right)\right)\) then \(\varphi_n(x) = \varphi_{n+1}(x) = \frac{2k}{2^n+1}\) and if \(x \in f^{-1}\left(\left(\frac{2k+1}{2^n+1}, \frac{2k+2}{2^n+1}\right)\right)\) then \(\varphi_n(x) = \frac{2k+1}{2^n+1} < \frac{2k+1}{2^n+1} = \varphi_{n+1}(x)\). Similarly

\[(2^n, \infty) = (2^n, 2^{n+1}) \cup (2^{n+1}, \infty),\]

and so for \(x \in f^{-1}(2^n, \infty)\), \(\varphi_n(x) = 2^n < 2^{n+1} = \varphi_{n+1}(x)\) and for \(x \in f^{-1}(2^n, 2^{n+1}]\), \(\varphi_{n+1}(x) \geq 2^n = \varphi_n(x)\). Therefore \(\varphi_n \leq \varphi_{n+1}\) for all \(n\). It is clear by construction that \(\varphi_n(x) \leq f(x)\) for all \(x\) and that \(0 \leq f(x) - \varphi_n(x) \leq 2^{-n}\) if \(x \in X_{2^n}\). Hence we have shown that \(\varphi_n(x) \uparrow f(x)\) for all \(x \in X\) and \(\varphi_n \uparrow f\) uniformly on bounded sets. For the second assertion, first assume that \(f : X \to \mathbb{R}\) is a measurable function and choose \(\varphi_n\) to be simple functions such that \(\varphi_n \uparrow f\) as \(n \to \infty\) and define \(\varphi_n = \varphi_n^+ - \varphi_n^-\). Then

\[
|\varphi_n| = \varphi_n^+ + \varphi_n^- \leq \varphi_{n+1}^+ + \varphi_{n+1}^- = |\varphi_{n+1}|
\]

and clearly \(|\varphi_n| = \varphi_n^+ + \varphi_n^- \uparrow f_+ + f_- = |f|\) and \(\varphi_n = \varphi_n^+ - \varphi_n^- \downarrow f_+ - f_- = f\) as \(n \to \infty\). Now suppose that \(f : X \to \mathbb{C}\) is measurable. We may now choose simple function \(u_n\) and \(v_n\) such that \(|u_n| \uparrow |\text{Re } f|\), \(|v_n| \uparrow |\text{Im } f|\), \(u_n \to \text{Re } f\) and \(v_n \to \text{Im } f\) as \(n \to \infty\). Let \(\varphi_n = u_n + iv_n\), then

\[
|\varphi_n|^2 = u_n^2 + v_n^2 \uparrow |\text{Re } f|^2 + |\text{Im } f|^2 = |f|^2
\]

and \(\varphi_n \equiv u_n + iv_n \to \text{Re } f + i \text{Im } f = f\) as \(n \to \infty\).

\textbf{6.2 Factoring Random Variables}

\textbf{Lemma 6.33.} Suppose that \((\mathcal{Y}, \mathcal{F})\) is a measurable space and \(Y : \Omega \to \mathbb{Y}\) is a map. Then to every \((\sigma(Y), \mathcal{B}_{\mathbb{Y}})\) - measurable function, \(H : \Omega \to \mathbb{R}\), there is a \((\mathcal{F}, \mathcal{B}_{\mathbb{R}})\) - measurable function \(h : \mathbb{Y} \to \mathbb{R}\) such that \(H = h \circ Y\).

\textbf{Proof.} First suppose that \(H = 1_A\) where \(A \in \sigma(Y) = Y^{-1}(\mathcal{F})\). Let \(B \in \mathcal{F}\) such that \(A = Y^{-1}(B)\) then \(1_A = 1_{Y^{-1}(B)} = 1_B \circ Y\) and hence the lemma is valid in this case with \(h = 1_B\). More generally if \(H = \sum a_i 1_{A_i}\) is a simple
function, then there exists $B_i \in \mathcal{F}$ such that $1_{A_i} = 1_{B_i} \circ Y$ and hence $H = h \circ Y$ with $h := \sum a_i 1_{B_i}$ - a simple function on $\bar{\mathbb{R}}$.

For a general $(\mathcal{F}, \mathcal{B}_{\bar{\mathbb{R}}})$ - measurable function, $H$, from $\Omega \to \bar{\mathbb{R}}$, choose simple functions $H_n$ converging to $H$. Let $h_n : \mathcal{Y} \to \bar{\mathbb{R}}$ be simple functions such that $H_n = h_n \circ Y$. Then it follows that

$$H = \lim_{n \to \infty} H_n = \limsup_{n \to \infty} H_n = \limsup_{n \to \infty} h_n \circ Y = h \circ Y$$

where $h := \limsup_{n \to \infty} h_n$ - a measurable function from $\mathcal{Y}$ to $\bar{\mathbb{R}}$.

The following is an immediate corollary of Proposition 6.16 and Lemma 6.33.

**Corollary 6.34.** Let $X$ and $A$ be sets, and suppose for $\alpha \in A$ we are give a measurable space $(\mathcal{Y}_\alpha, \mathcal{F}_\alpha)$ and a function $f_\alpha : X \to \mathcal{Y}_\alpha$. Let $Y := \prod_{\alpha \in A} \mathcal{Y}_\alpha$, $\mathcal{F} := \bigotimes_{\alpha \in A} \mathcal{F}_\alpha$ be the product $\sigma$-algebra on $Y$ and $\mathcal{M} := \sigma(f_\alpha : \alpha \in A)$ be the smallest $\sigma$-algebra on $X$ such that each $f_\alpha$ is measurable. Then the function $F : X \to Y$ defined by $[F(x)]_\alpha := f_\alpha(x)$ for each $\alpha \in A$ is $(\mathcal{M}, \mathcal{F})$ - measurable and a function $H : X \to \bar{\mathbb{R}}$ is $(\mathcal{M}, \mathcal{B}_{\bar{\mathbb{R}}})$ - measurable iff there exists a $(\mathcal{F}, \mathcal{B}_{\bar{\mathbb{R}}})$ - measurable function $h$ from $Y$ to $\bar{\mathbb{R}}$ such that $H = h \circ F$. 


### Independence

#### 7.1 $\pi - \lambda$ and Monotone Class Theorems

**Definition 7.1.** Let $\mathcal{C} \subset 2^\Omega$ be a collection of sets.

1. $\mathcal{C}$ is a monotone class if it is closed under countable increasing unions and countable decreasing intersections.
2. $\mathcal{C}$ is a $\pi - \text{class}$ if it is closed under finite intersections and
3. $\mathcal{C}$ is a $\lambda - \text{class}$ if $\mathcal{C}$ satisfies the following properties:
   a) $X \in \mathcal{C}$
   b) If $A, B \in \mathcal{C}$ and $A \subset B$, then $B \setminus A \in \mathcal{C}$. (Closed under proper differences.)
   c) If $A_n \in \mathcal{C}$ and $A_n \uparrow A$, then $A \in \mathcal{C}$. (Closed under countable increasing unions.)

**Remark 7.2.** If $\mathcal{C}$ is a collection of subsets of $\Omega$ which is both a $\lambda - \text{class}$ and a $\pi - \text{system}$ then $\mathcal{C}$ is a $\sigma - \text{algebra}$. Indeed, since $A^c = X \setminus A$, we see that any $\lambda - \text{system}$ is closed under complementation. If $\mathcal{C}$ is also a $\pi - \text{system}$, it is closed under intersections and therefore $\mathcal{C}$ is an algebra. Since $\mathcal{C}$ is also closed under increasing unions, $\mathcal{C}$ is a $\sigma - \text{algebra}.

**Lemma 7.3 (Alternate Axioms for a $\lambda - \text{System}^*$).** Suppose that $\mathcal{L} \subset 2^\Omega$ is a collection of subsets $\Omega$. Then $\mathcal{L}$ is a $\lambda - \text{class}$ iff $\lambda$ satisfies the following postulates:

1. $X \in \mathcal{L}$
2. $A \in \mathcal{L}$ implies $A^c \in \mathcal{L}$. (Closed under complementation.)
3. If $\{A_n\}_{n=1}^\infty \subset \mathcal{L}$ are disjoint, then $\bigcup_{n=1}^\infty A_n \in \mathcal{L}$. (Closed under disjoint unions.)

**Proof.** Suppose that $\mathcal{L}$ satisfies a. – c. above. Clearly then postulates 1. and 2. hold. Suppose that $A, B \in \mathcal{L}$ such that $A \cap B = \emptyset$, then $A \subset B^c$ and

$$A^c \cap B^c = B^c \setminus A \in \mathcal{L}.$$ 

Taking compliments of this result shows $A \cup B \in \mathcal{L}$ as well. So by induction, $B_m := \sum_{n=1}^m A_n \in \mathcal{L}$. Since $B_m \uparrow \sum_{n=1}^\infty A_n$ it follows from postulate c. that $\sum_{n=1}^\infty A_n \in \mathcal{L}$. 

Now suppose that $\mathcal{L}$ satisfies postulates 1. – 3. above. Notice that $\emptyset \in \mathcal{L}$ and by postulate 3., $\mathcal{L}$ is closed under finite disjoint unions. Therefore if $A, B \in \mathcal{L}$ with $A \subset B$, then $B^c \in \mathcal{L}$ and $A \cap B^c = \emptyset$ allows us to conclude that $A \cup B^c \in \mathcal{L}$. Taking complements of this result shows $B \setminus A = A^c \cap B \in \mathcal{L}$ as well, i.e. postulate b. holds. If $A_n \in \mathcal{L}$ with $A_n \uparrow A$, then $B_n := A_n \setminus A_{n-1} \in \mathcal{L}$ for all $n$, where by convention $A_0 = \emptyset$. Hence it follows by postulate 3 that $\bigcup_{n=1}^\infty A_n = \sum_{n=1}^\infty B_n \in \mathcal{L}$. 

**Theorem 7.4 (Dynkin’s $\pi - \lambda$ Theorem).** If $\mathcal{L}$ is a $\lambda - \text{class}$ which contains a contains a $\pi - \text{class}$, $\mathcal{P}$, then $\sigma(\mathcal{P}) \subset \mathcal{L}$.

**Proof.** We start by proving the following assertion; for any element $C \in \mathcal{L}$, the collection of sets,

$$\mathcal{L}^C := \{D \in \mathcal{L} : C \cap D \in \mathcal{L}\},$$

is a $\lambda - \text{system}$. To prove this claim, observe that: a. $X \in \mathcal{L}^C$, b. if $A \subset B$ with $A, B \in \mathcal{L}^C$, then $A \cap C, B \cap C \in \mathcal{L}$ with $A \cap C \subset B \cap C$ and

$$(B \setminus A) \cap C = [B \cap C] \setminus [A \cap C] \subset \mathcal{L}^C.$$

Therefore $\mathcal{L}^C$ is closed under proper differences. Finally, c. if $A_n \in \mathcal{L}^C$ with $A_n \uparrow A$, then $A_n \cap C \in \mathcal{L}^C$ and $A_n \cap C \uparrow A \cap C \in \mathcal{L}^C$, i.e. $A \in \mathcal{L}^C$. Hence we have verified $\mathcal{L}^C$ is still a $\lambda - \text{system}$. 

For the rest of the proof, we may assume with out loss of generality that $\mathcal{L}$ is the smallest $\lambda - \text{class}$ containing $\mathcal{P}$ – if not just replace $\mathcal{L}$ by the intersection of all $\lambda - \text{classes}$ containing $\mathcal{P}$. Then for $C \in \mathcal{P}$ we know that $\mathcal{L}^C \subset \mathcal{L}$ is a $\lambda - \text{class}$ containing $\mathcal{P}$ and hence $\mathcal{L}^C = \mathcal{L}$. Since $C \in \mathcal{P}$ was arbitrary, we have shown, $C \cap D \in \mathcal{L}$ for all $C, D \in \mathcal{P}$ and $D \in \mathcal{L}$. We may now conclude that if $C \in \mathcal{L}$, then $\mathcal{P} \subset \mathcal{L}^C \subset \mathcal{L}$ and hence again $\mathcal{L}^C = \mathcal{L}$. Since $C \in \mathcal{L}$ is arbitrary, we have shown $C \cap D \in \mathcal{L}$ for all $C, D \in \mathcal{L}$, i.e. $\mathcal{L}$ is a $\pi - \text{system}$. So by Remark 7.2. $\mathcal{L}$ is a $\sigma - \text{algebra}$. Since $\sigma(\mathcal{P})$ is the smallest $\sigma - \text{algebra}$ containing $\mathcal{P}$ it follows that $\sigma(\mathcal{P}) \subset \mathcal{L}$.

As an immediate corollary, we have the following uniqueness result.

**Proposition 7.5.** Suppose that $\mathcal{P} \subset 2^\Omega$ is a $\pi - \text{system}$. If $P$ and $Q$ are two probability measures on $\sigma(\mathcal{P})$ such that $P = Q$ on $\mathcal{P}$, then $P = Q$ on $\sigma(\mathcal{P})$.

\[1\] More generally, $P$ and $Q$ could be two measures such that $P(\Omega) = Q(\Omega) < \infty.$
Definition 7.8. Let \( \mathcal{L} := \{ A \in \sigma(\mathcal{P}) : P(A) = Q(A) \} \). One easily shows \( \mathcal{L} \) is a \( \lambda \)–class which contains \( \mathcal{P} \) by assumption. Indeed, \( \Omega \in \mathcal{P} \subset \mathcal{L} \), if \( A, B \in \mathcal{L} \) with \( A \subset B \), then
\[
P(B \setminus A) = P(B) - P(A) = Q(B) - Q(A) = Q(B \setminus A)
\]
so that \( B \setminus A \in \mathcal{L} \), and if \( A_n \in \mathcal{L} \) with \( A_n \uparrow A \), then \( P(A) = \lim_{n \to \infty} P(A_n) = \lim_{n \to \infty} Q(A_n) = Q(A) \) which shows \( A \in \mathcal{L} \). Therefore \( \sigma(\mathcal{P}) \subset \mathcal{L} = \sigma(\mathcal{P}) \) and the proof is complete. \( \blacksquare \)

Example 7.6. Let \( \Omega := \{ a, b, c, d \} \) and let \( \mu \) and \( \nu \) be the probability measure on \( 2^{\Omega} \) determined by, \( \mu(\{ x \}) = \frac{1}{2} \) for all \( x \in \Omega \) and \( \nu(\{ a \}) = \nu(\{ d \}) = \frac{1}{3} \) and \( \nu(\{ b \}) = \nu(\{ c \}) = \frac{5}{6} \). In this example, \( \mathcal{L} := \{ A \in 2^{\Omega} : P(A) = Q(A) \} \)
is \( \lambda \)–system which is not an algebra. Indeed, \( A = \{ a, b \} \) and \( B = \{ a, c \} \) are in \( \mathcal{L} \) but \( A \cap B \notin \mathcal{L} \).

Exercise 7.1. Suppose that \( \mu \) and \( \nu \) are two measure on a measure space, \((\Omega, \mathcal{B})\) such that \( \mu = \nu \) on a \( \pi \)–system, \( \mathcal{P} \). Further assume \( \mathcal{B} = \sigma(\mathcal{P}) \) and there exists \( \Omega_n \in \mathcal{P} \) such that: i) \( \mu(\Omega_n) = \nu(\Omega_n) < \infty \) for all \( n \) and ii) \( \Omega_n \uparrow \Omega \) as \( n \uparrow \infty \). Show \( \mu = \nu \) on \( \mathcal{B} \).

Hint: Consider the measures, \( \mu_n(A) := \mu(A \cap \Omega_n) \) and \( \nu_n(A) = \nu(A \cap \Omega_n) \).

Solution to Exercise (7.1). Let \( \mu_n(A) := \mu(A \cap \Omega_n) \) and \( \nu_n(A) = \nu(A \cap \Omega_n) \) for all \( A \in \mathcal{B} \). Then \( \mu_n \) and \( \nu_n \) are finite measure such \( \mu_n(\Omega) = \nu_n(\Omega) \) and \( \mu_n = \nu_n \) on \( \mathcal{P} \). Therefore by Proposition 7.3, \( \mu_n = \nu_n \) on \( \mathcal{B} \). So by the continuity properties of \( \mu \) and \( \nu \), it follows that
\[
\mu(A) = \lim_{n \to \infty} \mu(A \cap \Omega_n) = \lim_{n \to \infty} \mu_n(A) = \lim_{n \to \infty} \nu_n(A) = \lim_{n \to \infty} \nu(A \cap \Omega_n) = \nu(A)
\]
for all \( A \in \mathcal{B} \).

Corollary 7.9. The joint distribution, \( \mu \) is uniquely determined from the knowledge of
\[
P((X_1, \ldots, X_n) \in A_1 \times \cdots \times A_n) \text{ for all } A_i \in \mathcal{B}_\mathbb{R}
\]
or from the knowledge of
\[
P(X_1 \leq x_1, \ldots, X_n \leq x_n) \text{ for all } A_i \in \mathcal{B}_\mathbb{R}
\]
for all \( x = (x_1, \ldots, x_n) \in \mathbb{R}^n \).

Proof. Apply Proposition 7.3 with \( \mathcal{P} \) being the \( \pi \)–systems defined by
\[
\mathcal{P} := \{ A_1 \times \cdots \times A_n \in \mathcal{B}_\mathbb{R}^n : A_i \in \mathcal{B}_\mathbb{R} \}
\]
for the first case and
\[
\mathcal{P} := \{ (-\infty, x_1] \times \cdots \times (-\infty, x_n] \in \mathcal{B}_\mathbb{R}^n : x_i \in \mathbb{R} \}
\]
for the second case. \( \blacksquare \)

Definition 7.10. Suppose that \( \{ X_i \}_{i=1}^n \) and \( \{ Y_i \}_{i=1}^n \) are two finite sequences of random variables on two probability spaces, \((\Omega, \mathcal{B}, P)\) and \((X, \mathcal{F}, Q)\) respectively. We write \( (X_1, \ldots, X_n) \overset{d}{=} (Y_1, \ldots, Y_n) \) if \((X_1, \ldots, X_n)\) and \((Y_1, \ldots, Y_n)\) have the same distribution, i.e. if
\[
P((X_1, \ldots, X_n) \in B) = Q((Y_1, \ldots, Y_n) \in B) \text{ for all } B \in \mathcal{B}_\mathbb{R}^n.
\]
More generally, if \( \{ X_i \}_{i=1}^\infty \) and \( \{ Y_i \}_{i=1}^\infty \) are two sequences of random variables on two probability spaces, \((\Omega, \mathcal{B}, P)\) and \((X, \mathcal{F}, Q)\) we write \( \{ X_i \}_{i=1}^\infty \overset{d}{=} \{ Y_i \}_{i=1}^\infty \) iff \( (X_1, \ldots, X_n) \overset{d}{=} (Y_1, \ldots, Y_n) \) for all \( n \in \mathbb{N} \).

Exercise 7.2. Let \( \{ X_i \}_{i=1}^\infty \) and \( \{ Y_i \}_{i=1}^\infty \) be two sequences of random variables such that \( \{ X_i \}_{i=1}^\infty \overset{d}{=} \{ Y_i \}_{i=1}^\infty \). Let \( \{ S_n \}_{n=1}^\infty \) and \( \{ T_n \}_{n=1}^\infty \) be defined by, \( S_n := X_1 + \cdots + X_n \) and \( T_n := Y_1 + \cdots + Y_n \). Prove the following assertions.

1. Suppose that \( f : \mathbb{R}^n \to \mathbb{R}^k \) is a \( \mathcal{B}_\mathbb{R}^n / \mathcal{B}_\mathbb{R}^k \) measurable function, then \( f(X_1, \ldots, X_n) \overset{d}{=} f(Y_1, \ldots, Y_n) \).

2. Use your result in item 1. to show \( \{ S_n \}_{n=1}^\infty \overset{d}{=} \{ T_n \}_{n=1}^\infty \).

Hint: apply item 1. with \( k = n \) and a judiciously chosen function, \( f : \mathbb{R}^n \to \mathbb{R}^n \).

3. Show \( \limsup_{n \to \infty} X_n \overset{d}{=} \limsup_{n \to \infty} Y_n \) and similarly that \( \liminf_{n \to \infty} X_n \overset{d}{=} \liminf_{n \to \infty} Y_n \).

Hint: with the aid of the set identity,
\begin{align*}
\left\{ \limsup_{n \to \infty} X_n \geq x \right\} &= \{ X_n \geq x \text{ i.o.} \},
\end{align*}

show

\begin{align*}
P \left( \limsup_{n \to \infty} X_n \geq x \right) &= \lim_{n \to \infty} \lim_{m \to \infty} P \left( \bigcup_{k=n}^{m} \{ X_k \geq x \} \right).
\end{align*}

To use this identity you will also need to find \( B \in \mathcal{B}_2 \) such that

\[ \bigcup_{k=n}^{m} \{ X_k \geq x \} = \{(X_1, \ldots, X_m) \in B\}. \]

7.1.1 The Monotone Class Theorem

This subsection may be safely skipped!

**Lemma 7.11 (Monotone Class Theorem**\(^*\)). Suppose \( A \subset 2^X \) is an algebra and \( C \) is the smallest monotone class containing \( A \). Then \( C = \sigma(A) \).

**Proof.** For \( C \in C \) let

\[ \mathcal{C}(C) = \{ B \in \mathcal{C} : C \cap B, C \cap B^c, B \cap C^c \in \mathcal{C} \}, \]

then \( \mathcal{C}(C) \) is a monotone class. Indeed, if \( B_n \in \mathcal{C}(C) \) and \( B_n \uparrow B \), then \( B_n^c \downarrow B^c \) and so

\[ \mathcal{C} \ni C \cap B_n \uparrow C \cap B \]

\[ \mathcal{C} \ni C \cap B_n \downarrow C \cap B^c \]

\[ \mathcal{C} \ni B_n \cap C^c \uparrow B \cap C^c. \]

Since \( \mathcal{C} \) is a monotone class, it follows that \( C \cap B, C \cap B^c, B \cap C^c \in \mathcal{C} \), i.e. \( B \in \mathcal{C}(C) \). This shows that \( \mathcal{C}(C) \) is closed under increasing limits and a similar argument shows that \( \mathcal{C}(C) \) is closed under decreasing limits. Thus we have shown that \( \mathcal{C}(C) \) is a monotone class for all \( C \in \mathcal{C} \). If \( A \in \mathcal{A} \subset \mathcal{C} \), then \( A \cap B, A \cap B^c, B \cap A^c \in \mathcal{C} \) for all \( B \in \mathcal{A} \) and hence it follows that \( A \in \mathcal{C}(A) \subset \mathcal{C} \). Since \( C \) is the smallest monotone class containing \( A \) and \( \mathcal{C}(A) \) is a monotone class containing \( A \), we conclude that \( \mathcal{C}(A) = C \) for any \( A \in \mathcal{A} \). Let \( B \in \mathcal{C} \) and notice that \( A \in \mathcal{C}(B) \) happens iff \( B \in \mathcal{C}(A) \). This observation and the fact that \( \mathcal{C}(A) = C \) for all \( A \in \mathcal{A} \) implies \( A \subset \mathcal{C}(B) \subset \mathcal{C} \) for all \( B \in \mathcal{C} \). Again since \( \mathcal{C} \) is the smallest monotone class containing \( A \) and \( \mathcal{C}(B) \) is a monotone class we conclude that \( \mathcal{C}(B) = C \) for all \( B \in \mathcal{C} \). That is to say, if \( A, B \in \mathcal{C} \) then \( A \in \mathcal{C} \cap C \) and hence \( A \cap B, A \cap B^c, A^c \cap B \in \mathcal{C} \). So \( \mathcal{C} \) is closed under complements (since \( X \in \mathcal{A} \subset \mathcal{C} \)) and finite intersections and increasing unions from which it easily follows that \( \mathcal{C} \) is a \( \sigma \)-algebra. \( \Box \)

**Exercise 7.3.** Suppose that \( A \subset 2^\Omega \) is an algebra, \( B := \sigma(A) \), and \( P \) is a probability measure on \( B \). Show, using the \( \pi - \lambda \) theorem, that for every \( B \in B \) there exists \( A \in \mathcal{A} \) such that that \( P(A \triangle B) < \varepsilon \). Here

\[ A \triangle B := (A \setminus B) \cup (B \setminus A) \]

is the symmetric difference of \( A \) and \( B \).

**Hints:**

1. It may be useful to observe that

\[ 1_{A \triangle B} = |1_A - 1_B| \]

so that \( P(A \triangle B) = \mathbb{E} |1_A - 1_B| \).

2. Also observe that if \( B = \bigcup B_i \) and \( A = \bigcup A_i \), then

\[ B \setminus A \subset \bigcup B_i \setminus A_i \subset \bigcup B_i \setminus A_i \triangle B_i \]

so that

\[ A \setminus B \subset \bigcup A_i \setminus B_i \subset \bigcup A_i \setminus B_i \triangle A_i \]

3. We also have

\[ (B_2 \setminus B_1) \setminus (A_2 \setminus A_1) = B_2 \cap B_1^c \setminus (A_2 \setminus A_1)^c \]

\[ = B_2 \cap B_1^c \setminus (A_2 \setminus A_1)^c \]

\[ = B_2 \cap B_1^c \setminus (A_2 \setminus A_1) \]

\[ \subset (B_2 \setminus A_2) \cup (A_1 \setminus B_1) \]

and similarly,

\[ (A_2 \setminus A_1) \setminus (B_2 \setminus B_1) \subset (A_2 \setminus A_2) \cup (A_1 \setminus B_1) \]

so that

\[ (A_2 \setminus A_1) \triangle (B_2 \setminus B_1) \subset (A_2 \setminus A_2) \cup (A_1 \setminus B_1) \cup (A_2 \setminus A_2) \cup (B_1 \setminus A_1) \]

\[ = (A_1 \triangle B_1) \cup (A_2 \triangle B_2). \]

4. Observe that \( A_n \in B \) and \( A_n \uparrow A \), then

\[ P(B \triangle A_n) = P(B \setminus A_n) + P(A_n \setminus B) \to P(B \setminus A) + P(A \setminus B) = P(A \triangle B). \]

5. Let \( \mathcal{L} \) be the collection of sets \( B \) for which the assertion of the theorem holds. Show \( \mathcal{L} \) is a \( \lambda \)-system which contains \( \mathcal{A} \).
Solution to Exercise 7.3]. Since $\mathcal{L}$ contains the $\pi$–system, it suffices by the $\pi$–$\lambda$ theorem to show $\mathcal{L}$ is a $\lambda$–system. Clearly, $\Omega \in \mathcal{L}$ since $\Omega \in A \subseteq \mathcal{L}$.

If $B_1 \subset B_2$ with $B_i \in \mathcal{L}$ and $\varepsilon > 0$, there exists $A_i \in \mathcal{A}$ such that $P(B_i \setminus A_i) = \varepsilon |A_i - B_i| < \varepsilon/2$ and therefore,

$$P((B_2 \setminus B_1) \cup (A_2 \setminus A_1)) \leq P((A_1 \setminus B_1) \cup (A_2 \setminus B_2)) \leq P((A_1 \setminus B_1)) + P((A_2 \setminus B_2)) < \varepsilon.$$ 

Moreover, if $B_n \uparrow B$ with $B_n \in \mathcal{L}$, there exists $A_n \in \mathcal{A}$ such that $P(B_n \setminus A_n) < \varepsilon 2^{-n}$ and therefore,

$$P([\cup_i B_n] \setminus [\cup_i A_n]) \leq \sum_{i=1}^{\infty} P(B_n \setminus A_n) < \varepsilon.$$ 

Also if $B_n \uparrow B$ with $B_n \in \mathcal{L}$, there exists $A_n \in \mathcal{A}$ such that $P(B_n \setminus A_n) < \varepsilon 2^{-n}$ and therefore,

$$P([\cup_i B_n] \setminus [\cup_i A_n]) \leq \sum_{i=1}^{\infty} P(B_n \setminus A_n) < \varepsilon.$$ 

Moreover, if we let $B := \cup_n B_n$ and $A^N := \cup_{n=1}^{\infty} A_n$, then

$$P(B \setminus A^N) = P(B \setminus A^N) + P(A^N \setminus B) = P(B \setminus A) + P(A \setminus B) = P(B \setminus A)$$

where $A := \cup_n A_n$. Hence it follows for $N$ large enough that $P(B \setminus A^N) < \varepsilon$.

### 7.2 Basic Properties of Independence

For this section we will suppose that $(\Omega, B, P)$ is a probability space.

**Definition 7.12.** We say that $A$ is independent of $B$ is $P(A|B) = P(A)$ or equivalently that

$$P(A \cap B) = P(A) P(B).$$

We further say a finite sequence of collection of sets, $\{C_i\}_{i=1}^{n}$, are independent if

$$P(\cap_{i=1}^{n} A_j) = \prod_{j=1}^{n} P(A_j)$$

for all $A_i \in \mathcal{C}_i$ and $J \subseteq \{1, 2, \ldots, n\}$. 

Observe that if $\{C_i\}_{i=1}^{n}$ are independent classes then so are $\{C_i \cup \{X\}\}_{i=1}^{n}$. Moreover, if we assume that $X \in \mathcal{C}_i$ for each $i$, then $\{C_i\}_{i=1}^{n}$ are independent if

$$P(\cap_{j=1}^{n} A_j) = \prod_{j=1}^{n} P(A_j)$$

for all $(A_1, \ldots, A_n) \in \mathcal{C}_1 \times \cdots \times \mathcal{C}_n$.

**Theorem 7.13.** Suppose that $\{C_i\}_{i=1}^{n}$ is a finite sequence of independent $\pi$–classes. Then $\{\sigma(C_i)\}_{i=1}^{n}$ are also independent.

**Proof.** As mentioned above, we may always assume with out loss of generality that $X \in \mathcal{C}_i$. Fix, $A_j \in \mathcal{C}_j$ for $j = 2, 3, \ldots, n$. We will begin by showing that

$$P(A \cap A_2 \cap \cdots \cap A_n) = P(A) P(A_2) \cdots P(A_n) \quad \text{for all } A \in \sigma(\mathcal{C}_1).$$

(7.1)

Since it is clear that this identity holds if $P(A_j) = 0$ for some $j = 2, \ldots, n$, we may assume that $P(A_j) > 0$ for $j \geq 2$. In this case we may define,

$$Q(A) = \frac{P(A \cap A_2 \cap \cdots \cap A_n)}{P(A \cap A_2 \cap \cdots \cap A_n)} = \frac{P(A \cap A_2 \cap \cdots \cap A_n)}{P(A \cap A_2 \cap \cdots \cap A_n)}$$

for all $A \in \sigma(\mathcal{C}_1)$.

Then equation Eq. (7.1) is equivalent to $P(A) = Q(A)$ on $\sigma(\mathcal{C}_1)$. But this is true by Proposition 7.5 using the fact that $Q = P$ on the $\pi$–system, $\mathcal{C}_1$.

Since $(A_2, \ldots, A_n) \in C_2 \times \cdots \times C_n$ were arbitrary we may now conclude that $\sigma(C_1), C_2, \ldots, C_n$ are independent.

By applying the result we have just proved to the sequence, $C_2, \ldots, C_n, \sigma(C_1)$ shows that $\sigma(C_2), \sigma(C_3), \ldots, \sigma(C_n), \sigma(C_1)$ are independent. Similarly we show inductively that

$$\sigma(C_j), \sigma(C_{j+1}), \ldots, \sigma(C_n), \sigma(C_1), \ldots, \sigma(C_{j-1})$$

are independent for each $j = 1, 2, \ldots, n$. The desired result occurs at $j = n$. 

**Definition 7.14.** A collection of subsets of $\mathcal{B}$, $\{C_t\}_{t \in T}$ is said to be independent iff $\{C_t\}_{t \in A}$ are independent for all finite subsets, $A \subset T$. More explicitly, we are requiring

$$P(\cap_{t \in A} C_t) = \prod_{t \in A} P(C_t)$$

whenever $A$ is a finite subset of $T$ and $C_t \in C_t$ for all $t \in A$.

**Corollary 7.15.** If $\{C_t\}_{t \in T}$ is a collection of independent classes such that each $C_t$ is a $\pi$–system, then $\{\sigma(C_t)\}_{t \in T}$ are independent as well.

**Example 7.16.** Suppose that $\Omega = \mathbb{N}$ where $\Omega$ is a finite set, $B = 2^\Omega, P(\{\omega\}) = \prod_{j=1}^{\Omega} q_j(\omega)$ where $q_j : A \rightarrow [0, 1]$ are functions such that $\sum_{j \in \Omega} q_j(\lambda) = 1$. Let $C_t := \{A^{t-1} \times A \times A^{n-t-1} : A \subset A \}$. Then $\{C_t\}_{t=1}^{n}$ are independent. Indeed, if $B_i := A^{t-1} \times A_t \times A^{n-t}$, then

$$\n \cap B_i = \prod_{i=1}^{n} P(A_i)$$

and we have

$$P(\cap B_i) = \sum_{\omega \in \cap A_i} \prod_{i=1}^{n} q_i(\omega_i) = \prod_{i=1}^{n} \sum_{\lambda \in \cap A_i} q_i(\lambda)$$
Definition 7.17. A collection of random variables, \( \{X_t : t \in T\} \) are independent iff \( \sigma (X_t) : t \in T \) are independent.

Theorem 7.18. Let \( \mathcal{X} := \{X_t : t \in T\} \) be a collection of random variables. Then the following are equivalent:

1. The collection \( \mathcal{X} \),
2. \[ P(\bigcap_{t \in A} \{X_t \in A_t\}) = \prod_{t \in A} P(X_t \in A_t) \]
   for all finite subsets, \( A \subset T \), and all \( A_t \in \mathcal{B}_R \) for \( t \in A \).
3. \[ P(\bigcap_{t \in A} \{X_t \leq x_t\}) = \prod_{t \in A} P(X_t \leq x_t) \]
   for all finite subsets, \( A \subset T \), and all \( x_t \in \mathbb{R} \) for \( t \in A \).

Proof. The equivalence of 1. and 2. follows almost immediately form the definition of independence and the fact that \( \sigma (X_t) = \{\{X_t \in A\} : A \in \mathcal{B}_R\} \).

Clearly 2. implies 3. holds. Finally, 3. implies 2. is an application of Corollary 7.15 with \( \mathcal{C}_t := \{\{X_t \leq \alpha\} : \alpha \in \mathbb{R}\} \) and making use the observations that \( \mathcal{C}_t \) is a \( \pi \) system for all \( t \) and that \( \sigma (\mathcal{C}_t) = \sigma (X_t) \).

Example 7.19. Continue the notation of Example 7.16 and further assume that \( A \subset \mathbb{R} \) and let \( X_t : \Omega \rightarrow A \) be defined by, \( X_t (\omega) = \omega \). Then \( \{X_t\}_{t=1}^n \) are independent random variables. Indeed, \( \sigma (X_t) = \mathcal{C}_t \) with \( \mathcal{C}_t \) as in Example 7.16.

Alternatively, from Exercise 4.1, we know that

\[ \mathbb{E}_P \left[ \prod_{i=1}^n f_i (X_i) \right] = \prod_{i=1}^n \mathbb{E}_P [f_i (X_i)] \]

for all \( f_i : A \rightarrow \mathbb{R} \). Taking \( A_t \subset A \) and \( f_i := 1_{A_t} \) in the above identity shows that

\[ P(X_1 \in A_1, \ldots, X_n \in A_n) = \mathbb{E}_P \left[ \prod_{i=1}^n 1_{A_i} (X_i) \right] = \prod_{i=1}^n \mathbb{E}_P [1_{A_i} (X_i)] = \prod_{i=1}^n P(X_i \in A_i) \]

as desired.

Corollary 7.20. A sequence of random variables, \( \{X_j\}_{j=1}^k \) with countable ranges are independent iff

\[ P(\bigcap_{j=1}^k \{X_j = x_j\}) = \prod_{j=1}^k P(X_j = x_j) \tag{7.2} \]

for all \( x_j \in \mathbb{R} \).

Proof. Observe that both sides of Eq. (7.2) are zero unless \( x_j \) is in the range of \( X_j \) for all \( j \). Hence it suffices to verify Eq. (7.2) for those \( x_j \in \text{Ran}(X_j) =: R_j \) for all \( j \). Now if \( \{X_j\}_{j=1}^k \) are independent, then \( \{X_j = x_j\} \in \sigma (X_j) \) for all \( x_j \in \mathbb{R} \) and therefore Eq. (7.2) holds.

Conversely if Eq. (7.2) and \( V_j \in \mathcal{B}_R \), then

\[ P(\bigcap_{j=1}^k \{X_j \in V_j\}) = P \left( \bigcap_{j=1}^k \sum_{x_j \in V_j \cap R_j} \{X_j = x_j\} \right) \]

\[ = P \left( \sum_{(x_1, \ldots, x_k) \in \bigcap_{j=1}^k V_j \cap R_j} \prod_{j=1}^k P(X_j = x_j) \right) \]

\[ = \prod_{j=1}^k \sum_{x_j \in V_j \cap R_j} P(X_j = x_j) = \prod_{j=1}^k \sum_{x_j \in V_j} P(X_j = x_j) \]

\[ = \prod_{j=1}^k \sum_{x_j \in V_j} P(X_j = x_j) = \prod_{j=1}^k P(X_j \in V_j) \]

Definition 7.21. As sequences of random variables, \( \{X_n\}_{n=1}^{\infty} \), on a probability space, \((\Omega, \mathcal{B}, P)\), are i.i.d. (= independent and identically distributed) if they are independent and \( (X_n)_n P = (X_k)_k P \) for all \( k, n \). That is we should have

\[ P(X_n \in A) = P(X_k \in A) \text{ for all } k, n \in \mathbb{N} \text{ and } A \in \mathcal{B}_R. \]

Observe that \( \{X_n\}_{n=1}^{\infty} \) are i.i.d. random variables iff

\[ P(X_1 \in A_1, \ldots, X_n \in A_n) = \prod_{j=1}^n P(X_1 \in A_i) = \prod_{j=1}^n P(X_1 \in A_i) = \prod_{j=1}^n \mu (A_i) \tag{7.3} \]
where \( \mu = (X_1)_* P \). The identity in Eq. (7.3) is to hold for all \( n \in \mathbb{N} \) and all \( A_i \in \mathcal{B}_R \).

**Theorem 7.22 (Existence of i.i.d simple R.V.’s).** Suppose that \( \{q_i\}_{i=0}^n \) is a sequence of positive numbers such that \( \sum_{i=0}^n q_i = 1 \). Then there exists a sequence \( \{X_k\}_{k=1}^\infty \) of simple random variables taking values in \( \Lambda = \{0, 1, 2, \ldots, n\} \) on \( ((0, 1), \mathcal{B}, m) \) such that

\[
m(\{X_1 = i_1, \ldots, X_k = i_k\}) = q_{i_1} \cdots q_{i_k}
\]

for all \( i_1, i_2, \ldots, i_k \in \{0, 1, 2, \ldots, n\} \) and all \( k \in \mathbb{N} \). (See Theorem 7.27 below for the general case of this theorem.)

**Proof.** For \( i = 0, 1, \ldots, n \), let \( \sigma_{-1} = 0 \) and \( \sigma_j := \sum_{i=0}^j q_i \) and for any interval, \( (a, b] \), let

\[
T_i ((a, b]) := (a + \sigma_{i-1} (b - a), a + \sigma_i (b - a)).
\]

Given \( i_1, i_2, \ldots, i_k \in \{0, 1, 2, \ldots, n\} \), let

\[
J_{i_1, i_2, \ldots, i_k} := T_{i_k} (T_{i_{k-1}} (\ldots T_{i_1} ((0, 1])))
\]

and define \( \{X_k\}_{k=1}^\infty \) on \( (0, 1] \) by

\[
X_k := \sum_{i_1, i_2, \ldots, i_k \in \{0, 1, \ldots, n\}} i_k J_{i_1, i_2, \ldots, i_k},
\]

see Figure 7.1. Repeated applications of Corollary 6.22 shows the functions, \( X_k : (0, 1] \to \mathbb{R} \) are measurable.

Observe that

\[
m(T_i ((a, b])) = q_i (b - a) = q_i m((a, b]), \tag{7.4}
\]

and so by induction,

\[
m(J_{i_1, i_2, \ldots, i_k}) = q_{i_1} q_{i_{k-1}} \ldots q_{i_k}.
\]

The reader should convince herself/himself that

\[
\{X_1 = i_1, \ldots, X_k = i_k\} = J_{i_1, i_2, \ldots, i_k}
\]

and therefore, we have

\[
m(\{X_1 = i_1, \ldots, X_k = i_k\}) = m(J_{i_1, i_2, \ldots, i_k}) = q_{i_1} q_{i_{k-1}} \ldots q_{i_k}
\]
as desired.

---

**Corollary 7.23 (Independent variables on product spaces).** Suppose \( \Lambda = \{0, 1, 2, \ldots, n\} \), \( q_i > 0 \) with \( \sum_{i=0}^n q_i = 1 \), \( \Omega = \Lambda^\infty = \Lambda^n \), and for \( i \in \mathbb{N} \), let \( Y_i : \Omega \to \mathbb{R} \) be defined by \( Y_i (\omega) = \omega_i \) for all \( \omega \in \Omega \). Further let \( \mathcal{B} := \sigma (Y_1, Y_2, \ldots, Y_n, \ldots) \). Then there exists a unique probability measure, \( P : \mathcal{B} \to [0, 1] \) such that

\[
P(\{Y_1 = i_1, \ldots, Y_k = i_k\}) = q_{i_1} \ldots q_{i_k}.
\]

**Proof.** Let \( \{X_i\}_{i=1}^n \) be as in Theorem 7.22 and define \( T : (0, 1] \to \Omega \) by

\[
T (x) = (X_1 (x), X_2 (x), \ldots, X_k (x), \ldots).
\]

Observe that \( T \) is measurable since \( Y_i \circ T = X_i \) is measurable for all \( i \). We now define, \( P := T_* m \). Then we have

\[
P(\{Y_1 = i_1, \ldots, Y_k = i_k\}) = m(T^{-1}(\{Y_1 = i_1, \ldots, Y_k = i_k\}))
\]

\[
= m(\{Y_1 \circ T = i_1, \ldots, Y_k \circ T = i_k\})
\]

\[
= m(\{X_1 = i_1, \ldots, X_k = i_k\}) = q_{i_1} \ldots q_{i_k}.
\]

---
Theorem 7.24. Given a finite subset, $A \subset \mathbb{R}$ and a function $q : A \to [0,1]$ such that $\sum_{\lambda \in A} q(\lambda) = 1$, there exists a probability space, $(\Omega, \mathcal{B}, P)$ and an independent sequence of random variables, $\{ X_n \}_{n=1}^{\infty}$ such that $P(X_n = \lambda) = q(\lambda)$ for all $\lambda \in A$.

Proof. Use Corollary 7.20 to show that random variables constructed in Example 5.28 or Theorem 7.22 fit the bill. ■

Proposition 7.25. Suppose that $\{ X_n \}_{n=1}^{\infty}$ is a sequence of i.i.d. random variables with distribution, $P(X_n = 0) = P(X_n = 1) = \frac{1}{2}$. If we let $U := \sum_{n=1}^{\infty} 2^{-n} X_n$, then $P(U \leq x) = (0 \vee x) \wedge 1$, i.e. $U$ has the uniform distribution on $[0,1]$.

Proof. Let us recall that $P(X_n = 0 \text{ a.a.}) = P(X_n = 1 \text{ a.a.})$. Hence we may, by shrinking $\Omega$ if necessary, assume that $\{ X_n = 0 \text{ a.a.} \} = \emptyset = \{ X_n = 1 \text{ a.a.} \}$. With this simplification, we have

\[
\begin{aligned}
\{ U < \frac{1}{2} \} &= \{ X_1 = 0 \}, \\
\{ U < \frac{1}{4} \} &= \{ X_1 = 0, X_2 = 0 \} \text{ and} \\
\{ \frac{1}{2} \leq U < \frac{3}{4} \} &= \{ X_1 = 1, X_2 = 0 \}
\end{aligned}
\]

and hence that

\[
\begin{aligned}
\{ U < \frac{3}{4} \} &= \left\{ U < \frac{1}{2} \right\} \cup \left\{ \frac{1}{2} \leq U < \frac{3}{4} \right\} \\
&= \{ X_1 = 0 \} \cup \{ X_1 = 1, X_2 = 0 \}.
\end{aligned}
\]

From these identities, it follows that

\[
P(U < 0) = 0, \quad P \left( U < \frac{1}{4} \right) = \frac{1}{4}, \quad P \left( U < \frac{1}{2} \right) = \frac{1}{2}, \quad \text{and} \quad P \left( U < \frac{3}{4} \right) = \frac{3}{4}.
\]

More generally, we claim that if $x = \sum_{j=1}^{n} \varepsilon_j 2^{-j}$ with $\varepsilon_j \in \{0,1\}$, then

\[
P(U \leq x) = x.
\]

(7.5)

The proof is by induction on $n$. Indeed, we have already verified (7.5) when $n = 1, 2$. Suppose we have verified (7.5) up to some $n \in \mathbb{N}$ and let $x = \sum_{j=1}^{n+1} \varepsilon_j 2^{-j}$ and consider

\[
P \left( U \leq x + 2^{-(n+1)} \right) = P(U \leq x) + P \left( x \leq U < x + 2^{-(n+1)} \right) = x + P \left( x \leq U < x + 2^{-(n+1)} \right).
\]

Since $\{ x \leq U < x + 2^{-(n+1)} \} = \left[ \bigcap_{j=1}^{n} \{ X_j = \varepsilon_j \} \right] \cap \{ X_{n+1} = 0 \}$ we see that

\[
P \left( x \leq U < x + 2^{-(n+1)} \right) = 2^{-n+1}
\]

and hence

\[
P \left( U < x + 2^{-(n+1)} \right) = x + 2^{-(n+1)}
\]

which completes the induction argument.

Since $x \to P(U < x)$ is left continuous we may now conclude that $P(U \leq x) = x$ for all $x \in (0,1)$ and since $x \to x$ is continuous we may also deduce that $P(U \leq x) = x$ for all $x \in (0,1)$. Hence we may conclude that

\[
P(U \leq x) = (0 \vee x) \wedge 1.
\]

Lemma 7.26. Suppose that $\{ B_t : t \in T \}$ is an independent family of $\sigma$-fields. And further assume that $T = \sum_{s \in S} T_s$ and let

\[
B_{T_s} = \bigvee_{t \in T_s} B_s = \sigma(\bigcup_{t \in T_s} B_s).
\]

Then $\{ B_{T_s} \}_{s \in S}$ is an independent family of $\sigma$ fields.

Proof. Let $C_s = \{ \cap_{\alpha \in K} B_{n} : B_n \in B_n, \ K \subset T_s \}$. It is now easily checked that $\{ C_s \}_{s \in S}$ is an independent family of $\pi$-systems. Therefore $\{ B_{T_s} = \sigma(C_s) \}_{s \in S}$ is an independent family of $\sigma$-algebras. ■

We may now show the existence of independent random variables with arbitrary distributions.

Theorem 7.27. Suppose that $\{ \mu_n \}_{n=1}^{\infty}$ are a sequence of probability measures on $(\mathbb{R}, \mathcal{B}_{\mathbb{R}})$. Then there exists a probability space, $(\Omega, \mathcal{B}, P)$ and a sequence $\{ Y_n \}_{n=1}^{\infty}$ independent random variables with Law$(Y_n) := P \circ Y_n^{-1} = \mu_n$ for all $n$.

Proof. By Theorem 7.24, there exists a sequence of i.i.d. random variables, $\{ Z_i \}_{i=1}^{\infty}$, such that $P(Z_i = 1) = P(Z_i = 0) = \frac{1}{2}$. These random variables may be put into a two dimensional array, $\{ X_{i,j} : i,j \in \mathbb{N} \}$, see the proof of Lemma 3.8. For each $i$, let $U_i := \sum_{j=1}^{\infty} 2^{-j} X_{i,j} \in \sigma(\{ X_{i,j} \}_{j=1}^{\infty})$ measurable random variable. According to Proposition 7.25, $U_i$ is uniformly distributed on $[0,1]$. Moreover by the grouping Lemma 7.26, $\sigma(\{ X_{i,j} \}_{j=1}^{\infty})$ are independent $\sigma$
Finally, let \( F_i(x) := \mu((\infty, x]) \) for all \( x \in \mathbb{R} \) and let \( G_i(y) = \inf \{ x : F_i(x) \geq y \} \). Then according to Theorem 6.11, \( Y_i := G_i(U_i) \) has \( \mu_i \) as its distribution. Moreover each \( Y_i \) is \( \sigma \left( \{ X_{ij} \}_{j=1}^{\infty} \right) \)-measurable and therefore the \( \{ Y_i \}_{i=1}^{\infty} \) are independent random variables.

### 7.2.1 An Example of Ranks

Let \( \{ X_n \}_{n=1}^{\infty} \) be i.i.d. with common continuous distribution function, \( F \). In this case we have, for any \( i \neq j \), that

\[
P(X_i = X_j) = \mu_F \otimes \mu_F (\{(x, x) : x \in \mathbb{R}\}) = 0.
\]

This may be proved directly with some work or will be an easy consequence of Fubini’s theorem to be considered later, see Example 10.11 below. For the direct proof, let \( \{ a_l \}_{l=1}^{\infty} \) be a sequence such that, \( a_l < a_{l+1} \) for all \( l \in \mathbb{Z} \), \( \lim_{l \to -\infty} a_l = \infty \) and \( \lim_{l \to +\infty} a_l = -\infty \). Then

\[
\{ (x, x) : x \in \mathbb{R} \} \subseteq \cup_{l \in \mathbb{Z}} [(a_l, a_{l+1}] \times (a_l, a_{l+1}]
\]

and therefore,

\[
P(X_i = X_j) \leq \sum_{l \in \mathbb{Z}} P(X_i \in (a_l, a_{l+1}], X_j \in (a_l, a_{l+1}]) = \sum_{l \in \mathbb{Z}} |F(a_{l+1}) - F(a_l)|^2
\]

\[
\leq \sup_{l \in \mathbb{Z}} |F(a_{l+1}) - F(a_l)| \sum_{l \in \mathbb{Z}} |F(a_{l+1}) - F(a_l)| = \sup_{l \in \mathbb{Z}} |F(a_{l+1}) - F(a_l)|.
\]

Since \( F \) is continuous and \( F(\infty+) = 1 \) and \( F(\infty-) = 0 \), it is easily seen that \( F \) is uniformly continuous on \( \mathbb{R} \). Therefore, if we choose \( a_l = \frac{l}{N} \), we have

\[
P(X_i = X_j) \leq \lim_{N \to \infty} \sup_{l \in \mathbb{Z}} \left[ F\left( \frac{l+1}{N} \right) - F\left( \frac{l}{N} \right) \right] = 0.
\]

Let \( R_n \) denote the “rank” of \( X_n \) in the list \( (X_1, \ldots, X_n) \), i.e.

\[
R_n := \sum_{j=1}^{n} 1_{X_j > X_n} = \# \{ j \leq n : X_j > X_n \}.
\]

For example if \( (X_1, X_2, X_3, X_4, X_5, \ldots) = (9, -8, 3, 7, 23, \ldots) \), we have \( R_1 = 1, R_2 = 2, R_3 = 2, \) and \( R_4 = 2, R_5 = 1 \). Observe that rank order, from lowest to highest, of \( (X_1, X_2, X_3, X_4, X_5) \) is \( (X_2, X_3, X_4, X_1, X_5) \). This can be determined by the values of \( R_i \) for \( i = 1, 2, \ldots, 5 \) as follows. Since \( R_5 = 1 \), we must have \( X_5 \) in the last slot, i.e. \( (\ast, \ast, \ast, \ast, X_5) \). Since \( R_4 = 2 \), we know out of the remaining slots, \( X_4 \) must be in the second from the far most right, i.e. \( (\ast, \ast, X_4, \ast, X_5) \). Since \( R_3 = 2 \), we know that \( X_3 \) is again the second from the right of the remaining slots, i.e. we now know, \((\ast, X_3, X_4, \ast, X_5) \). Similarly, \( R_2 = 2 \) implies \((X_2, X_3, X_4, \ast, X_5) \) and finally \( R_1 = 1 \) gives, \((X_2, X_3, X_4, X_1, X_5) \). As another example, if \( R_i = i \) for \( i = 1, 2, \ldots, n \), then \( X_n < X_{n-1} < \cdots < X_1 \).

**Theorem 7.28 (Renyi Theorem).** Let \( \{ X_n \}_{n=1}^{\infty} \) be i.i.d. and assume that \( F(x) := P(X_n \leq x) \) is continuous. The \( \{ R_n \}_{n=1}^{\infty} \) is an independent sequence,

\[
P(R_n = k) = \frac{1}{n} \quad \text{for} \quad k = 1, 2, \ldots, n,
\]

and the events, \( A_n = \{ X_n \text{ is a record} \} = \{ R_n = 1 \} \) are independent as \( n \) varies and

\[
P(A_n) = P(R_n = 1) = \frac{1}{n}.
\]

**Proof.** By Problem 6 on p. 110 of Resnick, \((X_1, \ldots, X_n)\) and \((X_{\sigma_1}, \ldots, X_{\sigma_n})\) have the same distribution for any permutation \( \sigma \).

Since \( F \) is continuous, it now follows that up to a set of measure zero,

\[
\Omega = \sum_{\sigma} \{ X_{\sigma_1} < X_{\sigma_2} < \cdots < X_{\sigma_n} \}
\]

and therefore

\[
1 = P(\Omega) = \sum_{\sigma} P(\{ X_{\sigma_1} < X_{\sigma_2} < \cdots < X_{\sigma_n} \})
\]

Since \( P(\{ X_{\sigma_1} < X_{\sigma_2} < \cdots < X_{\sigma_n} \}) \) is independent of \( \sigma \) we may now conclude that

\[
P(\{ X_{\sigma_1} < X_{\sigma_2} < \cdots < X_{\sigma_n} \}) = \frac{1}{n!}
\]

for all \( \sigma \). As observed before the statement of the theorem, to each realization \((\varepsilon_1, \ldots, \varepsilon_n)\), (here \( \varepsilon_i \in \mathbb{N} \) with \( \varepsilon_i \leq i \) of \((R_1, \ldots, R_n)\) there is a permutation, \( \sigma = \sigma(\varepsilon_1, \ldots, \varepsilon_n) \) such that \( X_{\sigma_1} < X_{\sigma_2} < \cdots < X_{\sigma_n} \). From this it follows that

\[
\{(R_1, \ldots, R_n) = (\varepsilon_1, \ldots, \varepsilon_n)\} = \{ X_{\sigma_1} < X_{\sigma_2} < \cdots < X_{\sigma_n} \}
\]

and therefore,

\[
P(\{(R_1, \ldots, R_n) = (\varepsilon_1, \ldots, \varepsilon_n)\}) = P(X_{\sigma_1} < X_{\sigma_2} < \cdots < X_{\sigma_n}) = \frac{1}{n!}.
\]

Since
\[ P \left( \{ R_n = \varepsilon_n \} \right) = \sum_{(\varepsilon_1, \ldots, \varepsilon_{n-1})} P \left( \{(R_1, \ldots, R_n) = (\varepsilon_1, \ldots, \varepsilon_n)\} \right) \]
\[ = \sum_{(\varepsilon_1, \ldots, \varepsilon_{n-1})} \frac{1}{n!} = (n-1)! \cdot \frac{1}{n!} = \frac{1}{n} \]

we have shown that
\[ P \left( \{(R_1, \ldots, R_n) = (\varepsilon_1, \ldots, \varepsilon_n)\} \right) = \frac{1}{n} = \prod_{j=1}^{n-1} \frac{1}{j} = \prod_{j=1}^{n} P \left( \{R_j = \varepsilon_j\} \right). \]

### 7.3 Borel-Cantelli Lemmas

**Lemma 7.29 (First Borel Cantelli-Lemma).** Suppose that \( \{A_n\}_{n=1}^{\infty} \) are measurable sets. If
\[ \sum_{n=1}^{\infty} P \left( A_n \right) < \infty, \]  \hfill (7.6)
then
\[ P \left( \{A_n \text{ i.o.}\} \right) = 0. \]

**Proof. First Proof.** We have
\[ P \left( \{A_n \text{ i.o.}\} \right) = P \left( \bigcap_{n=1}^{\infty} \bigcup_{k \geq n} A_k \right) = \lim_{n \to \infty} P \left( \bigcup_{k \geq n} A_k \right) \leq \lim_{n \to \infty} \sum_{k \geq n} P \left( A_k \right) = 0. \]  \hfill (7.7)

**Second Proof.** (Warning: this proof requires integration theory which is developed below.) Equation (7.6) is equivalent to
\[ E \left[ \sum_{n=1}^{\infty} 1_{A_n} \right] < \infty \]
from which it follows that
\[ \sum_{n=1}^{\infty} 1_{A_n} < \infty \text{ a.s.} \]
which is equivalent to \( P \left( \{A_n \text{ i.o.}\} \right) = 0. \]

**Example 7.30.** Suppose that \( \{X_n\} \) are Bernoulli random variables with \( P \left( X_n = 1 \right) = p_n \) and \( P \left( X_n = 0 \right) = 1 - p_n \). If
\[ \sum p_n < \infty \]
then
\[ P \left( X_n = 1 \text{ i.o.} \right) = 0 \]
and hence
\[ P \left( X_n = 0 \text{ a.a.} \right) = 1. \]

In particular,
\[ P \left( \lim_{n \to \infty} X_n = 0 \right) = 1. \]

Figure 7.2 below serves as motivation for the following elementary lemma on convex functions.

![Fig. 7.2. A convex function, \( \varphi \), along with a cord and a tangent line. Notice that the tangent line is always below \( \varphi \) and the cord lies above \( \varphi \) between the points of intersection of the cord with the graph of \( \varphi \).](image)

**Lemma 7.31 (Convex Functions).** Suppose that \( \varphi \in PC^2 ((a, b) \to \mathbb{R}) \) with \( \varphi''(x) \geq 0 \) for almost all \( x \in (a, b) \). Then \( \varphi \) satisfies;
1. for all \( x_0, x \in (a, b) \),
\[ \varphi(x_0) + \varphi'(x_0)(x - x_0) \leq \varphi(x) \]
and
2. \( PC^2 \) denotes the space of piecewise \( C^2 \) functions, i.e. \( \varphi \in PC^2 ((a, b) \to \mathbb{R}) \) means the \( \varphi \) is \( C^1 \) and there are a finite number of points,
\[ \{a = a_0 < a_1 < a_2 < \cdots < a_{n-1} < a_n = b\}, \]
such that \( \varphi|_{[a_{j-1}, a_j]} \cap (a, b) \) is \( C^2 \) for all \( j = 1, 2, \ldots, n \).
2. for all \( u \leq v \) with \( u, v \in (a, b) \),

\[
\varphi (u + t(v - u)) \leq \varphi (u) + t(\varphi (v) - \varphi (u)) \quad \forall \ t \in [0, 1].
\]

(This lemma applies to the functions, \( e^{\lambda x} \) for all \( \lambda \in \mathbb{R} \), \( |x|^\alpha \) for \( \alpha > 1 \), and \(-\ln x\) to name a few examples. See Appendix II.7 below for much more on convex functions.)

**Proof.** 1. Let

\[
f(x) := \varphi (x) - [\varphi (x_0) + \varphi' (x_0)(x - x_0)].
\]

Then \( f(x_0) = f'(x_0) = 0 \) while \( f''(x) \geq 0 \) a.e. and so by the fundamental theorem of calculus,

\[
f'(x) = \varphi'(x) - \varphi'(x_0) = \int_{x_0}^{x} \varphi''(y) \, dy.
\]

Hence it follows that \( f'(x) \geq 0 \) for \( x > x_0 \) and \( f'(x) \leq 0 \) for \( x < x_0 \) and therefore, \( f(x) \geq 0 \) for all \( x \in (a, b) \).

2. Let

\[
f(t) := \varphi (u) + t(\varphi (v) - \varphi (u)) - \varphi (u + t(v - u)).
\]

Then \( f(0) = f(1) = 0 \) with \( f(t) = -(v - u)^2 \varphi''(u + t(v - u)) \) \( \leq 0 \) for almost all \( t \). By the mean value theorem, there exists, \( t_0 \in (0, 1) \) such that \( f(t_0) = 0 \) and then by the fundamental theorem of calculus it follows that

\[
\dot{f}(t) = \int_{t_0}^{t} \ddot{f}(\tau) \, d\tau.
\]

In particular, \( \dot{f}(t) \leq 0 \) for \( t > t_0 \) and \( \dot{f}(t) \geq 0 \) for \( t < t_0 \) and hence \( f(t) \geq f(1) = 0 \) for \( t \geq t_0 \) and \( f(t) \geq f(0) = 0 \) for \( t \leq t_0 \), i.e. \( f(t) \geq 0 \).

**Example 7.32.** Taking \( \varphi(x) := e^{-x} \), we learn (see Figure 7.3),

\[
1 - x \leq e^{-x} \quad \text{for all } x \in \mathbb{R}
\]

and taking \( \varphi(x) = e^{-2x} \) we learn that

\[
1 - x \geq e^{-2x} \quad \text{for } 0 \leq x \leq 1/2.
\]

**Exercise 7.4.** For \( \{a_n\}_{n=1}^{\infty} \subset [0, 1] \), let

\[
\prod_{n=1}^{\infty} (1 - a_n) := \lim_{N \to \infty} \prod_{n=1}^{N} (1 - a_n).
\]

(The limit exists since, \( \prod_{n=1}^{N} (1 - a_n) \downarrow \) as \( N \uparrow \).) Show that if \( \{a_n\}_{n=1}^{\infty} \subset [0, 1] \), then

\[
\prod_{n=1}^{\infty} (1 - a_n) = 0 \iff \sum_{n=1}^{\infty} a_n = \infty.
\]

**Solution to Exercise (7.4).** On one hand we have

\[
\prod_{n=1}^{N} (1 - a_n) \leq \prod_{n=1}^{N} e^{-a_n} = \exp \left(-\sum_{n=1}^{N} a_n \right).
\]
which upon passing to the limit as \( N \to \infty \) gives
\[
\prod_{n=1}^{\infty} (1 - a_n) \leq \exp \left( -\sum_{n=1}^{\infty} a_n \right).
\]

Hence if \( \sum_{n=1}^{\infty} a_n = \infty \) then \( \prod_{n=1}^{\infty} (1 - a_n) = 0 \).

Conversely, suppose that \( \sum_{n=1}^{\infty} a_n < \infty \). In this case \( a_n \to 0 \) as \( n \to \infty \) and so there exists an \( m \in \mathbb{N} \) such that \( a_n \in [0, 1/2] \) for all \( n \geq m \). With this notation we then have for \( N \geq m \) that
\[
\prod_{n=1}^{N} (1 - a_n) = \prod_{n=1}^{m} (1 - a_n) \cdot \prod_{n=m+1}^{N} (1 - a_n)
\geq \prod_{n=1}^{m} (1 - a_n) \cdot \prod_{n=m+1}^{N} e^{-2a_n} = \prod_{n=1}^{m} (1 - a_n) \cdot \exp \left( -2 \sum_{n=m+1}^{N} a_n \right)
\geq \prod_{n=1}^{m} (1 - a_n) \cdot \exp \left( -2 \sum_{n=m+1}^{\infty} a_n \right).
\]

So again letting \( N \to \infty \) shows,
\[
\prod_{n=1}^{\infty} (1 - a_n) \geq \prod_{n=1}^{m} (1 - a_n) \cdot \exp \left( -2 \sum_{n=m+1}^{\infty} a_n \right) > 0.
\]

**Lemma 7.33 (Second Borel-Cantelli Lemma).** Suppose that \( \{A_n\}_{n=1}^{\infty} \) are independent sets. If
\[
\sum_{n=1}^{\infty} P(A_n) = \infty,
\tag{7.10}
\]

then
\[
P(\{A_n \text{ i.o.}\}) = 1. \tag{7.11}
\]

Combining this with the first Borel Cantelli Lemma gives the (Borel) Zero-One law,
\[
P(A_n \text{ i.o.}) = \begin{cases} 0 & \text{if } \sum_{n=1}^{\infty} P(A_n) < \infty, \\ 1 & \text{if } \sum_{n=1}^{\infty} P(A_n) = \infty. \end{cases}
\]

**Proof.** We are going to prove Eq. (7.11) by showing,
\[
0 = P(\{A_n \text{ i.o.}\}^{c}) = P(\{A_n^{c} \text{ a.a.}\}) = P(\cup_{n=1}^{\infty} \cap_{k \geq n} A_k^{c}).
\]

Since \( \cap_{k \geq n} A_k^{c} \uparrow \cup_{n=1}^{\infty} \cap_{k \geq n} A_k^{c} \) as \( n \to \infty \) and \( \cap_{n=m}^{\infty} A_k^{c} \downarrow \cup_{n=1}^{m} \cup_{k \geq n} A_k \) as \( m \to \infty \),

\[
P(\cup_{n=1}^{\infty} \cap_{k \geq n} A_k^{c}) = \lim_{n \to \infty} P(\cap_{k \geq n} A_k^{c}) = \lim_{n \to \infty} \lim_{m \to \infty} P(\cap_{m \geq k \geq n} A_k^{c}).
\]

Making use of the independence of \( \{A_k\}_{k=1}^{\infty} \) and hence the independence of \( \{A_k^{c}\}_{k=1}^{\infty} \), we have
\[
P(\cap_{m \geq k \geq n} A_k^{c}) = \prod_{m \geq k \geq n} P(A_k^{c}) = \prod_{m \geq k \geq n} (1 - P(A_k)). \tag{7.12}
\]

Using the simple inequality in Eq. (7.8) along with Eq. (7.12) shows
\[
P(\cap_{m \geq k \geq n} A_k^{c}) \leq \prod_{m \geq k \geq n} e^{-P(A_k)} = \exp \left( -\sum_{k=m}^{\infty} P(A_k) \right).
\]

Using Eq. (7.10), we find from the above inequality that
\[
\lim_{m \to \infty} P(\cap_{m \geq k \geq n} A_k^{c}) = 0 \quad \text{and hence}
\]
\[
P(\cup_{n=1}^{\infty} \cap_{k \geq n} A_k^{c}) = \lim_{n \to \infty} \lim_{m \to \infty} P(\cap_{m \geq k \geq n} A_k^{c}) = \lim_{n \to \infty} 0 = 0
\]
as desired.

**Example 7.34 (Example 7.30 continued).** Suppose that \( \{X_n\} \) are now independent Bernoulli random variables with \( P(X_n = 1) = p_n \) and \( P(X_n = 0) = 1 - p_n \). Then
\[
P(\lim_{n \to \infty} X_n = 0) = 1 \iff \sum_{n=1}^{\infty} p_n < \infty.
\]
Indeed, \( P(\lim_{n \to \infty} X_n = 0) = 1 \iff P(X_n = 0 \text{ a.a.}) = 1 \iff P(X_n = 1 \text{ i.o.}) = 0 \iff \sum_{n=1}^{\infty} P(X_n = 1) < \infty.
\]

**Proposition 7.35 (Extremal behavior of i.i.d. random variables).** Suppose that \( \{X_n\}_{n=1}^{\infty} \) is a sequence of i.i.d. random variables and \( c_n \) is an increasing sequence of positive real numbers such that for all \( \alpha > 1 \) we have
\[
\sum_{n=1}^{\infty} P(X_1 > \alpha^{-1} c_n) = \infty \tag{7.13}
\]

while
\[
\sum_{n=1}^{\infty} P(X_1 > \alpha c_n) < \infty. \tag{7.14}
\]

Then
\[
\lim_{n \to \infty} \sup_{c_n} X_n = 1 \text{ a.s.} \tag{7.15}
\]

**Proof.** By the second Borel-Cantelli Lemma, Eq. (7.13) implies
\[
P(X_n > \alpha^{-1} c_n \text{ i.o.}) = 1
\]

from which it follows that
\[
P(X_n > \alpha^{-1} c_n \text{ i.o.}) = 1
\]
That is to say, or equivalently, 

\[
\alpha > 0 \quad \text{and hence working as above,}
\]

\[
\limsup_{n \to \infty} \frac{X_n}{c_n} \geq \alpha^{-1} \quad \text{a.s.}.
\]

Taking \(\alpha = \alpha_k = 1 + 1/k\), we find

\[
P \left( \limsup_{n \to \infty} \frac{X_n}{c_n} \geq 1 \right) = P \left( \bigcap_{k=1}^{\infty} \left\{ \limsup_{n \to \infty} \frac{X_n}{c_n} \geq \frac{1}{\alpha_k} \right\} \right) = 1.
\]

Similarly, by the first Borel-Cantelli lemma, Eq. (7.14) implies

\[
P \left( X_n > \alpha c_n \text{ i.o.} \right) = 0
\]
or equivalently,

\[
P \left( X_n \leq \alpha c_n \text{ a.a.} \right) = 1.
\]

That is to say,

\[
\limsup_{n \to \infty} \frac{X_n}{c_n} \leq \alpha \quad \text{a.s.}
\]

and hence working as above,

\[
P \left( \limsup_{n \to \infty} \frac{X_n}{c_n} = 1 \right) = P \left( \bigcap_{k=1}^{\infty} \left\{ \limsup_{n \to \infty} \frac{X_n}{c_n} \leq \frac{1}{\alpha_k} \right\} \right) = 1.
\]

Hence,

\[
P \left( \limsup_{n \to \infty} \frac{X_n}{c_n} = 1 \right) = P \left( \left\{ \limsup_{n \to \infty} \frac{X_n}{c_n} \geq 1 \right\} \cap \left\{ \limsup_{n \to \infty} \frac{X_n}{c_n} \leq 1 \right\} \right) = 1.
\]

**Example 7.36.** Let \(\{E_n\}_{n=1}^{\infty}\) be a sequence of independent random variables with exponential distributions determined by

\[
P(E_n > x) = e^{-\alpha x} \quad \text{or} \quad P(E_n \leq x) = 1 - e^{-\alpha x}.
\]

(Observe that \(P(E_n \leq 0) = 0\)) so that \(E_n > 0\) a.s. Then for \(c_n > 0\) and \(\alpha > 0\), we have

\[
\sum_{n=1}^{\infty} P(E_n > \alpha c_n) = \sum_{n=1}^{\infty} e^{-\alpha c_n} = \sum_{n=1}^{\infty} (e^{-c_n})^\alpha.
\]

Hence if we choose \(c_n = \ln n\) so that \(e^{-c_n} = 1/n\), then we have

\[
\sum_{n=1}^{\infty} P(E_n > \alpha \ln n) = \sum_{n=1}^{\infty} \left( \frac{1}{n^\alpha} \right)
\]

which is convergent iff \(\alpha > 1\). So by Proposition 7.35, it follows that

\[
\limsup_{n \to \infty} \frac{E_n}{\ln n} = 1 \quad \text{a.s.}
\]

**Example 7.37.** Suppose now that \(\{X_n\}_{n=1}^{\infty}\) are i.i.d. distributed by the Poisson distribution with intensity, \(\lambda\), i.e.

\[
P(X_1 = k) = \frac{\lambda^k}{k!} e^{-\lambda}.
\]

In this case we have

\[
P(X_1 \geq n) = e^{-\lambda} \sum_{k=n}^{\infty} \frac{\lambda^k}{k!} \geq \frac{\lambda^n}{n!} e^{-\lambda}
\]

and

\[
\sum_{k=n}^{\infty} \frac{\lambda^k}{k!} e^{-\lambda} = \frac{\lambda^n}{n!} e^{-\lambda} \sum_{k=n}^{\infty} \frac{n!}{k!(k+n)!} \lambda^{-n} \leq \frac{\lambda^n}{n!} e^{-\lambda} \sum_{k=0}^{\infty} \frac{1}{k!} \lambda^k = \frac{\lambda^n}{n!}.
\]

Thus we have shown that

\[
\frac{\lambda^n}{n!} e^{-\lambda} \leq P(X_1 \geq n) \leq \frac{\lambda^n}{n!}.
\]

Thus in terms of convergence issues, we may assume that

\[
P(X_1 \geq x) \sim \frac{\lambda^x}{x!} \sim \frac{\lambda^x}{\sqrt{2\pi xe^{-x}x^x}}
\]

wherein we have used Stirling’s formula,

\[
x! \sim \sqrt{2\pi xe^{-x}x^x}.
\]

Now suppose that we wish to choose \(c_n\) so that

\[
P(X_1 \geq c_n) \sim 1/n.
\]

This suggests that we need to solve the equation, \(x^x = n\). Taking logarithms of this equation implies that

\[
x = \frac{\ln n}{\ln x}
\]

and upon iteration we find,

\[
x = \frac{\ln n}{\ln (\frac{\ln n}{\ln x})} = \frac{\ln n}{\ell_2(n) - \ell_2(x)} = \frac{\ln n}{\ell_2(n) - \ell_2(\frac{\ln n}{\ln x})}
\]

\[
= \frac{\ln n}{\ell_2(n) - \ell_3(n) + \ell_3(x)}.
\]
where $\ell_k = \ln \ln \cdots \ln$. Since, $x \leq \ln (n)$, it follows that $\ell_3 (x) \leq \ell_3 (n)$ and hence that
\[ x = \frac{\ln (n)}{\ell_2 (n) + O (\ell_3 (n))} = \frac{\ln (n)}{\ell_2 (n)} \left( 1 + O \left( \frac{\ell_3 (n)}{\ell_2 (n)} \right) \right). \]

Thus we are lead to take $c_n := \frac{\ln (n)}{\ell_2 (n)}$. We then have, for $\alpha \in (0, \infty)$ that
\[(\alpha c_n)^{\alpha c_n} = \exp (\alpha c_n [\ln (\alpha + \ln c_n)]) = \exp \left( \alpha \frac{\ln (n)}{\ell_2 (n)} [\ln \alpha + \ell_2 (n) - \ell_3 (n)] \right) = \exp \left( \alpha \frac{\ln \alpha - \ell_3 (n)}{\ell_2 (n)} + 1 \right) \ln (n) \]
\[= n \alpha (1 + \varepsilon_n (\alpha)). \]

Hence we have
\[ P \left( X_1 \geq \alpha c_n \right) \sim \frac{\lambda^{\alpha c_n}}{\sqrt{2 \pi \alpha c_n} e^{-\alpha c_n}} (\alpha c_n)^{\alpha c_n} \sim \frac{1}{\sqrt{2 \pi \alpha c_n} n^{\alpha (1 + \varepsilon_n (\alpha))}}. \]

Since \( \ln (\lambda/e)^{\alpha c_n} = \alpha c_n \ln (\lambda/e) = \alpha \frac{\ln n}{\ell_2 (n)} \ln (\lambda/e) = n^\alpha \frac{\ln (\lambda/e)}{\ell_2 (n)}, \)

it follows that
\[(\lambda/e)^{\alpha c_n} = n^\alpha \frac{\ln (\lambda/e)}{\ell_2 (n)}. \]

Therefore,
\[ P \left( X_1 \geq \alpha c_n \right) \sim \frac{n^\alpha \frac{\ln (\lambda/e)}{\ell_2 (n)}}{\sqrt{\ln (n)} \frac{\ln (n)}{\ell_2 (n)}} \frac{1}{n^{\alpha (1 + \varepsilon_n (\alpha))}} = \frac{\ell_2 (n)}{\ln (n)} \frac{1}{n^{\alpha (1 + \delta_n (\alpha))}} \]

where $\delta_n (\alpha) \to 0$ as $n \to \infty$. From this observation, we may show,
\[ \sum_{n=1}^{\infty} P \left( X_1 \geq \alpha c_n \right) < \infty \text{ if } \alpha > 1 \]
\[ \sum_{n=1}^{\infty} P \left( X_1 \geq \alpha c_n \right) = \infty \text{ if } \alpha < 1 \]

and so by Proposition 7.35 we may conclude that
\[ \limsup_{n \to \infty} \frac{X_n}{\ln (n) / \ell_2 (n)} = 1 \text{ a.s.} \]

7.4 Kolmogorov and Hewitt-Savage Zero-One Laws

Let $\{X_n\}_{n=1}^{\infty}$ be a sequence of random variables on a measurable space, $(\Omega, \mathcal{B})$. Let $\mathcal{B}_n := \sigma (X_1, \ldots, X_n), \mathcal{B}_\infty := \sigma (X_1, X_2, \ldots), \mathcal{T}_n := \sigma (X_{n+1}, X_{n+2}, \ldots)$, and $\mathcal{T} := \cap_{n=1}^{\infty} \mathcal{T}_n \subset \mathcal{B}_\infty$. We call $\mathcal{T}$ the tail $\sigma$-field and events, $A \in \mathcal{T}$, are called tail events.

**Example 7.38.** Let $S_n := X_1 + \cdots + X_n$ and $\{b_n\}_{n=1}^{\infty} \subset (0, \infty)$ such that $b_n \uparrow \infty$. Here are some examples of tail events and tail measurable random variables:

1. $\{\sum_{n=1}^{\infty} X_n \text{ converges} \} \in \mathcal{T}_n$.
2. both $\limsup_{n \to \infty} X_n$ and $\liminf_{n \to \infty} X_n$ are $\mathcal{T}$-measurable as are $\limsup_{n \to \infty} \frac{S_n}{b_n}$ and $\liminf_{n \to \infty} \frac{S_n}{b_n}$.
3. $\{\lim X_n \text{ exists in } \mathbb{R}\} = \{\limsup_{n \to \infty} X_n = \liminf_{n \to \infty} X_n\} \in \mathcal{T}$ and similarly,
\[ \left\{ \limsup_{n \to \infty} \frac{S_n}{b_n} \text{ exists in } \mathbb{R}\right\} = \left\{ \limsup_{n \to \infty} \frac{S_n}{b_n} = \liminf_{n \to \infty} \frac{S_n}{b_n} \right\} \in \mathcal{T} \]

and
\[ \left\{ \liminf_{n \to \infty} \frac{S_n}{b_n} = 0 \right\} \in \mathcal{T}. \]

Indeed, for any $k \in \mathbb{N}$,
\[ \lim_{n \to \infty} \frac{S_n}{b_n} = \lim_{n \to \infty} \frac{X_{k+1} + \cdots + X_n}{b_n} \]

from which it follows that $\left\{ \lim_{n \to \infty} \frac{S_n}{b_n} = 0 \right\} \in \mathcal{T}_k$ for all $k$.

**Definition 7.39.** Let $(\Omega, \mathcal{B}, P)$ be a probability space. A $\sigma$-field, $\mathcal{F} \subset \mathcal{B}$ is almost trivial iff $P (\mathcal{F}) = \{0, 1\}$, i.e. $P (A) \in \{0, 1\}$ for all $A \in \mathcal{F}$.

**Lemma 7.40.** Suppose that $X : \Omega \to \mathbb{R}$ is a random variable which is $\mathcal{F}$ measurable, where $\mathcal{F} \subset \mathcal{B}$ is almost trivial. Then there exists $c \in \mathbb{R}$ such that $X = c$ a.s.
Proof. Since \( \{X = \infty\} \) and \( \{X = -\infty\} \) are in \( \mathcal{F} \), if \( P(X = \infty) > 0 \) or \( P(X = -\infty) > 0 \), then \( P(X = \infty) = 1 \) or \( P(X = -\infty) = 1 \) respectively. Hence, it suffices to finish the proof under the added condition that \( P(X \in \mathbb{R}) = 1 \).

For each \( x \in \mathbb{R}, \{X \leq x\} \in \mathcal{F} \) and therefore, \( P(X \leq x) \) is either 0 or 1. Since the function, \( F(x) := P(X \leq x) \in \{0, 1\} \) is right continuous, non-decreasing and \( F(-\infty) = 0 \) and \( F(+\infty) = 1 \), there is a unique point \( c \in \mathbb{R} \) where \( F(c) = 1 \) and \( F(c-) = 0 \). At this point, we have \( P(X = c) = 1 \).

Proposition 7.41 (Kolmogorov’s Zero-One Law). Suppose \( P \) is a probability measure on \((\Omega, \mathcal{B})\) such that \( X_n \) \( n \geq 1 \) are independent random variables. Then \( \mathcal{T} \) is almost trivial, i.e. \( P(A) \in \{0, 1\} \) for all \( A \in \mathcal{T} \).

Proof. Let \( A \in \mathcal{T} \subset \mathcal{B}_\infty \). Since \( A \in \mathcal{T}_n \) for all \( n \) and \( \mathcal{T}_n \) is independent of \( \mathcal{B}_n \), it follows that \( A \) is independent of \( \cup_{n=1}^\infty \mathcal{B}_n \) for all \( n \). Since the latter set is a multiplicative set, it follows that \( A \) is independent of \( \mathcal{B}_\infty = \sigma(\cup_{n=1}^\infty \mathcal{B}_n) \). But \( A \in \mathcal{B}_1 \) and hence \( A \) is independent of itself, i.e.

\[
P(A) = P(A \cap A) = P(A)P(A)
\]

Since the only \( x \in \mathbb{R} \), such that \( x = x^2 = 0 \) or \( x = 0 \), the result is proved. In particular the tail events in Example 7.38 have probability either 0 or 1.

Corollary 7.42. Keeping the assumptions in Proposition 7.41 and let \( \{b_n\}_{n=1}^\infty \subset (0, \infty) \) such that \( b_n \uparrow \infty \). Then \( \lim_{n \to \infty} X_n = \lim_{n \to \infty} \frac{S_n}{b_n} \) and \( \lim_{n \to \infty} \frac{S_n}{b_n} \) are constant almost surely. In particular, either \( P\left(\lim_{n \to \infty} \frac{S_n}{b_n} \text{ exists}\right) = 0 \) or \( P\left(\lim_{n \to \infty} \frac{S_n}{b_n} \text{ exists}\right) = 1 \) and in the latter case \( \lim_{n \to \infty} \frac{S_n}{b_n} = c \) a.s. for some \( c \in \mathbb{R} \).

Let us now suppose that \( \Omega := \mathbb{R}^\infty = \mathbb{R}^{\mathbb{N}}, X_n(\omega) = \omega_n \) for all \( \omega \in \Omega \), and \( \mathcal{B} := \sigma(X_1, X_2, \ldots) \). We say a permutation (i.e. a bijective map on \( \mathbb{N} \), \( \pi : \mathbb{N} \to \mathbb{N} \) is finite if \( \pi(n) = n \) for a.a. \( n \). Define \( T_\pi : \Omega \to \Omega \) by \( T_\pi(\omega) = (\omega_1, \omega_{\pi(2)}, \ldots) \).

Definition 7.43. The permutation invariant \( \sigma \)-field, \( \mathcal{S} \subset \mathcal{B} \), is the collection of sets, \( A \in \mathcal{B} \) such that \( T_\pi^{-1}(A) = A \) for all finite permutations \( \pi \).

In the proof below we will use the identities,

\[
1_{A \triangle B} = |1_A - 1_B| \quad \text{and} \quad P(A \triangle B) = \mathbb{E}|1_A - 1_B|.
\]

Proposition 7.44 (Hewitt-Savage Zero-One Law). Let \( P \) be a probability measure on \((\Omega, \mathcal{B})\) such that \( X_n \) \( n \geq 1 \) is an i.i.d. sequence. Then \( \mathcal{S} \) is almost trivial.

Proof. Let \( \mathcal{B}_0 := \cup_{n=1}^\infty \pi(X_1, X_2, \ldots, X_n) \). Then \( \mathcal{B}_0 \) is an algebra and \( \sigma(\mathcal{B}_0) = \mathcal{B} \). By the regularity Theorem 5.10, for any \( B \in \mathcal{B} \) and \( \varepsilon > 0 \), there exists \( A_n \in \mathcal{B}_0 \) such that \( A_n \uparrow C \subset (B)_\varepsilon \), \( B \subset C \), and \( P(C \setminus B) < \varepsilon \).

\[
P(A_n \triangle B) = P(A_n \setminus B \cup B \setminus A_n) = P(A_n \setminus B) + P(B \setminus A_n)
\]

\[
\rightarrow P(C \setminus B) + P(B \setminus C) < \varepsilon,
\]

for sufficiently large \( n \), we have \( P(A_n \Delta B) < \varepsilon \) where \( A = A_n \in \mathcal{B}_0 \).

Now suppose that \( B \in \mathcal{S}, \varepsilon > 0 \), and \( A \in \sigma(X_1, X_2, \ldots, X_n) \subset \mathcal{B}_0 \) such that \( P(A \Delta B) < \varepsilon \). Let \( \pi : \mathbb{N} \to \mathbb{N} \) be the permutation defined by \( \pi(j) = j + n \), \( \pi(j + n) = j \) for \( j = 1, 2, \ldots, n \), and \( \pi(j + 2n) = j + 2n \) for all \( j \in \mathbb{N} \). Since \( B = \{(X_1, \ldots, X_n) \in B'\} = \{\omega : (\omega_1, \ldots, \omega_n) \in B'\} \)

for some \( B' \in \mathcal{B}_\mathbb{N} \), we have

\[
T_\pi^{-1}(B) = \{\omega : ((T_\pi(\omega))_1, \ldots, (T_\pi(\omega))_n) \in B'\}
\]

\[
= \{\omega : (\omega_1, \ldots, \omega_n) \in B'\}
\]

\[
= \{(X_{n+1}, \ldots, X_{n+n}) \in B'\} \in \sigma(X_{n+1}, \ldots, X_{n+n})
\]

it follows that \( B \) and \( T_\pi^{-1}(B) \) are independent with \( P(B) = P(T_\pi^{-1}(B)) \).

Therefore \( P(B \cap T_\pi^{-1}B) = P(B)^2 \). Combining this observation with the identity, \( P(A) = P(A \cap A) = P(A \cap T_\pi^{-1}A) \), we find

\[
|P(A) - P(B)|^2 = |P(A \cap T_\pi^{-1}A) - P(B \cap T_\pi^{-1}B)| = |P[A \cap T_\pi^{-1}A - B \cap T_\pi^{-1}B]|
\]

\[
\leq |P[A \cap T_\pi^{-1}A - B \cap T_\pi^{-1}B]|
\]

\[
= |P[1A \cap T_\pi^{-1}A - 1B \cap T_\pi^{-1}B]|
\]

\[
= |P[1A - 1B]1T_\pi^{-1}A - 1B[1T_\pi^{-1}A - 1T_\pi^{-1}B]|
\]

\[
\leq |P[1A - 1B]| + |P[1T_\pi^{-1}A - 1T_\pi^{-1}B]|
\]

\[
= P(A \Delta B) + P(T_\pi^{-1}A \Delta T_\pi^{-1}B) < 2\varepsilon.
\]

Since \(|P(A) - P(B)| \leq P(A \Delta B) < \varepsilon\), it follows that

\[
|P(A) - P(A) + O(\varepsilon)|^2 < \varepsilon.
\]

Since \( \varepsilon > 0 \) was arbitrary, we may conclude that \( P(A) = P(A)^2 \) for all \( A \in \mathcal{S} \).
Example 7.45 (Some Random Walk $0 - 1$ Law Results). Continue the notation in Proposition 7.44 

1. As above, if $S_n = X_1 + \cdots + X_n$, then $P(S_n \in B \ i.o.) \in \{0, 1\}$ for all $B \in \mathcal{B}_\mathbb{R}$. Indeed, if $\pi$ is a finite permutation,

$$T^{-1}_\pi \left( \{S_n \in B \ i.o.\} \right) = \{S_n \circ T_\pi \in B \ i.o.\} = \{S_n \in B \ i.o.\}.$$ 

Hence $\{S_n \in B \ i.o.\}$ is in the permutation invariant $\sigma$-field. The same goes for $\{S_n \in B \ a.a.\}$.

2. If $P(X_1 \neq 0) > 0$, then $\limsup_{n \to \infty} S_n = \infty$ a.s. or $\limsup_{n \to \infty} S_n = -\infty$ a.s. Indeed,

$$T^{-1}_\pi \left\{ \limsup_{n \to \infty} S_n \leq x \right\} = \left\{ \limsup_{n \to \infty} S_n \circ T_\pi \leq x \right\} = \left\{ \limsup_{n \to \infty} S_n \leq x \right\}$$

which shows that $\limsup_{n \to \infty} S_n$ is $\mathcal{S}$-measurable. Therefore, $\limsup_{n \to \infty} S_n = c$ a.s. for some $c \in \mathbb{R}$. Since, a.s.,

$$c = \limsup_{n \to \infty} S_{n+1} = \limsup_{n \to \infty} (S_n + X_1) = \limsup_{n \to \infty} S_n + X_1 = c + X_1,$$

we must have either $c \in \{\pm \infty\}$ or $X_1 = 0$ a.s. Since the latter is not allowed, $\limsup_{n \to \infty} S_n = \infty$ or $\limsup_{n \to \infty} S_n = -\infty$ a.s.

3. Now assume that $P(X_1 \neq 0) > 0$ and $X_1 \overset{d}{=} -X_1$, i.e. $P(X_1 \in A) = P(-X_1 \in A)$ for all $A \in \mathcal{B}_\mathbb{R}$. From item 2, we know that and from what we have already proved, we know $\limsup_{n \to \infty} S_n = c$ a.s. with $c \in \{\pm \infty\}$.

Since $\{X_n\}_{n=1}^\infty$ and $\{-X_n\}_{n=1}^\infty$ are i.i.d. and $X_n \overset{d}{=} X_n$, it follows that $\{X_n\}_{n=1}^\infty \overset{d}{=} \{-X_n\}_{n=1}^\infty$. The results of Exercise 7.2 then imply that $\limsup_{n \to \infty} S_n = \limsup_{n \to \infty} (-S_n)$ and in particular $\limsup_{n \to \infty} (-S_n) = c$ a.s. as well.

Thus we have

$$c = \limsup_{n \to \infty} (-S_n) = -\liminf_{n \to \infty} S_n \geq -\limsup_{n \to \infty} S_n = -c.$$ 

Since the $c = -\infty$ does not satisfy, $c \geq -c$, we must $c = \infty$. Hence in this symmetric case we have shown,

$$\limsup_{n \to \infty} S_n = \infty \text{ and } \limsup_{n \to \infty} (-S_n) = \infty \text{ a.s.}$$

or equivalently that

$$\limsup_{n \to \infty} S_n = \infty \text{ and } \liminf_{n \to \infty} S_n = -\infty \text{ a.s.}$$
Integration Theory

In this chapter, we will greatly extend the “simple” integral or expectation which was developed in Section 4.3 above. Recall there that if $(\Omega, \mathcal{B}, \mu)$ was measurable space and $f : \Omega \to [0, \infty]$ was a measurable simple function, then we let

$$E_\mu f := \sum_{\lambda \in [0, \infty]} \lambda \mu(f = \lambda).$$

8.1 A Quick Introduction to Lebesgue Integration Theory

Theorem 8.1 (Extension to positive functions). For a positive measurable function, $f : \Omega \to [0, \infty]$, the integral of $f$ with respect to $\mu$ is defined by

$$\int_X f(x) \, d\mu(x) := \sup \{E_\mu \varphi : \varphi \text{ is simple and } \varphi \leq f\}.$$

This integral has the following properties.

1. This integral is linear in the sense that

$$\int_\Omega (f + \lambda g) \, d\mu = \int_\Omega f \, d\mu + \lambda \int_\Omega g \, d\mu$$

whenever $f, g \geq 0$ are measurable functions and $\lambda \in [0, \infty)$.

2. The integral is continuous under increasing limits, i.e. if $0 \leq f_n \uparrow f$, then

$$\int_\Omega f \, d\mu = \lim_{n \to \infty} \int_\Omega f_n \, d\mu = \lim_{n \to \infty} \int_\Omega f_n \, d\mu.$$

See the monotone convergence Theorem 8.15 below.

Remark 8.2. Given $f : \Omega \to [0, \infty]$ measurable, we know from the approximation Theorem 6.32, $\varphi_n \uparrow f$ where

$$\varphi_n := \sum_{k=0}^{2^n-1} \frac{k}{2^n} 1_{\{ \frac{k}{2^n} < f \leq \frac{k+1}{2^n} \}} + n 1_{\{ f > n2^n \}}.$$

Therefore by the monotone convergence theorem,

$$\int_\Omega f \, d\mu = \lim_{n \to \infty} \int_\Omega \varphi_n \, d\mu = \lim_{n \to \infty} \sum_{k=0}^{2^n-1} \frac{k}{2^n} \mu\left( \frac{k}{2^n} < f \leq \frac{k+1}{2^n} \right) + n \mu(f > n2^n).$$

We call a function, $f : \Omega \to \mathbb{R}$, integrable if it is measurable and $\int_\Omega |f| \, d\mu < \infty$. We will denote the space of $\mu$–integrable functions by $L^1(\mu)$.

Theorem 8.3 (Extension to integrable functions). The integral extends to a linear function from $L^1(\mu) \to \mathbb{R}$. Moreover this extension is continuous under dominated convergence (see Theorem 8.34). That is if $f_n \in L^1(\mu)$ and there exists $g \in L^1(\mu)$ such that $|f_n| \leq g$ and $f := \lim_{n \to \infty} f_n$ exists pointwise, then

$$\int_\Omega f \, d\mu = \int_\Omega \lim_{n \to \infty} f_n \, d\mu = \lim_{n \to \infty} \int_\Omega f_n \, d\mu.$$

Notation 8.4 We write $\int_A f \, d\mu := \int_\Omega 1_A f \, d\mu$ for all $A \in \mathcal{B}$ where $f$ is a measurable function such that $1_A f$ is either non-negative or integrable.

Notation 8.5 If $m$ is Lebesgue measure on $\mathbb{R}$, $f$ is a non-negative Borel measurable function and $a < b$ with $a, b \in \mathbb{R}$, we will often write $\int_a^b f(x) \, dx$ or $\int_a^b f \, dm$ for $\int_{[a,b] \cap \mathbb{R}} f \, dm$.

Example 8.6. Suppose $-\infty < a < b < \infty$, $f \in C([a, b], \mathbb{R})$ and $m$ be Lebesgue measure on $\mathbb{R}$. Given a partition,

$$\pi = \{ a = a_0 < a_1 < \cdots < a_n = b \},$$

let

$$\text{mesh}(\pi) := \max\{|a_j - a_{j-1}| : j = 1, \ldots, n\}$$

and

$$f_\pi(x) := \sum_{i=0}^{n-1} f(a_i) 1_{(a_i, a_{i+1})}(x).$$

Then

$$\int_\pi f \, dm = \lim_{n \to \infty} \int_\pi \varphi_n \, dm = \lim_{n \to \infty} \sum_{k=0}^{2^n-1} \frac{k}{2^n} m\left( \frac{k}{2^n} < f \leq \frac{k+1}{2^n} \right) + n m(f > n2^n).$$
Simple manipulations show, 

$$\int_a^b f(x) \, dm = \sum_{i=0}^{n-1} f(a_i) m((a_i, a_{i+1})) = \sum_{i=0}^{n-1} f(a_i) (a_{i+1} - a_i)$$

is a Riemann sum. Therefore if \( \{\pi_k\}_{k=1}^\infty \) is a sequence of partitions with \( \lim_{k \to \infty} \text{mesh}(\pi_k) = 0 \), we know that

$$\lim_{k \to \infty} \int_a^b f_{\pi_k} \, dm = \int_a^b f(x) \, dx \quad (8.1)$$

where the latter integral is the Riemann integral. Using the (uniform) continuity of \( f \) on \((a, b)\), it easily follows that \( \lim_{k \to \infty} f_{\pi_k}(x) = f(x) \) and that \( |f_{\pi_k}(x)| \leq g(x) := M_{(a,b)}(x) \) for all \( x \in (a, b) \) where \( M := \max_{x \in [a,b]} |f(x)| < \infty \). Since \( \int_a g dm = M(b-a) < \infty \), we may apply D.C.T. to conclude,

$$\lim_{k \to \infty} \int_a^b f_{\pi_k} \, dm = \int_a^b \lim_{k \to \infty} f_{\pi_k} \, dm = \int_a^b f \, dm.$$

This equation with Eq. (8.1) shows

$$\int_a^b f(x) \, dm = \int_a^b f(x) \, dx$$

whenever \( f \in C([a, b], \mathbb{R}) \), i.e. the Lebesgue and the Riemann integral agree on continuous functions. See Theorem 8.51 below for a more general statement along these lines.

**Theorem 8.7 (The Fundamental Theorem of Calculus).** Suppose \(-\infty < a < b < \infty \), \( f \in C([a, b], \mathbb{R}) \cap C^1((a, b), \mathbb{R}) \) and \( F(x) := \int_a^x f(y) \, dy \). Then

1. \( F \in C([a, b], \mathbb{R}) \cap C^1((a, b), \mathbb{R}) \).
2. \( F'(x) = f(x) \) for all \( x \in (a, b) \).
3. If \( G \in C([a, b], \mathbb{R}) \cap C^1((a, b), \mathbb{R}) \) is an anti-derivative of \( f \) on \((a, b)\) (i.e. \( f = G'|_{(a,b)} \) then

$$\int_a^b f(x) dm(x) = G(b) - G(a).$$

**Proof.** Since \( F(x) := \int_a^x f(y) \, dy \), \( \lim_{x \to z} 1_{(a,x)}(y) f(y) \, dy \) is \( 1_{(a,x)}(y) f(y) \) for \( m \)-a.e. \( y \) and \( |1_{(a,x)}(y) f(y)| \leq 1_{(a,b)}(y) |f(y)| \) is an \( L^1 \)-function, it follows from the dominated convergence Theorem 8.34 that \( F \) is continuous on \((a, b]\). Simple manipulations show,

$$\left| \frac{F(x+h) - F(x)}{h} - f(x) \right| = \frac{1}{|h|} \begin{cases} \int_{x+h}^{x} [f(y) - f(x)] \, dy \, dm(y) & \text{if } h > 0 \\ \int_{x}^{x+h} [f(y) - f(x)] \, dy \, dm(y) & \text{if } h < 0 \end{cases}$$

$$\leq \frac{1}{|h|} \begin{cases} \int_{x+h}^{x} |f(y) - f(x)| \, dy \, dm(y) & \text{if } h > 0 \\ \int_{x}^{x+h} |f(y) - f(x)| \, dy \, dm(y) & \text{if } h < 0 \end{cases}$$

$$\leq \sup \{|f(y) - f(x)| : y \in [x-|h|, x+|h|]\}$$

and the latter expression, by the continuity of \( f \), goes to zero as \( h \to 0 \). This shows \( F' = f \) on \((a, b] \).

For the converse direction, we have by assumption that \( G'(x) = F'(x) \) for \( x \in (a, b) \). Therefore by the mean value theorem, \( F-G = C \) for some constant \( C \). Hence

$$\int_a^b f(x) dm(x) = F(b) = F(b) - F(a) = (G(b) + C) - (G(a) + C) = G(b) - G(a).$$

[\( \blacksquare \)]

We can use the above results to integrate some non-Riemann integrable functions:

**Example 8.8.** For all \( \lambda > 0 \),

$$\int_0^\infty e^{-\lambda x} \, dx = \lambda^{-1} \quad \text{and} \quad \int_R \frac{1}{1 + x^2} \, dx = \pi.$$

The proof of these identities are similar. By the monotone convergence theorem, Example 8.6 and the fundamental theorem of calculus for Riemann integrals (or Theorem 8.7 below),

$$\int_0^\infty e^{-\lambda x} \, dx = \lim_{N \to \infty} \int_0^N e^{-\lambda x} \, dx = \lim_{N \to \infty} \int_0^N e^{-\lambda x} \, dx = \lim_{N \to \infty} \frac{1}{\lambda} e^{-\lambda x} \bigg|_0^N = \lambda^{-1}$$

and

$$\int_R \frac{1}{1 + x^2} \, dx = \lim_{N \to \infty} \int_{-N}^N \frac{1}{1 + x^2} \, dx = \lim_{N \to \infty} \int_{-N}^N \frac{1}{1 + x^2} \, dx = \lim_{N \to \infty} \left[ \tan^{-1}(N) - \tan^{-1}(-N) \right] = \pi.$$

Let us also consider the functions \( x^{-p} \),

$$\int_{(0,1]} \frac{1}{x^p} \, dx = \lim_{N \to \infty} \int_0^1 \frac{1}{x^p} \, dx = \lim_{N \to \infty} \frac{1}{N^{1-p}} \left[ \frac{x^{1-p}}{1-p} \right]_0^1 = \begin{cases} \frac{1}{1-p} & \text{if } p < 1 \\ \infty & \text{if } p > 1 \end{cases}$$
If \( p = 1 \) we find
\[
\int_{(0,1]} \frac{1}{x^p} \, dm(x) = \lim_{n \to \infty} \int_{1/n}^1 \frac{1}{x} \, dx = \lim_{n \to \infty} \ln(x)|_{1/n}^1 = \infty.
\]

**Exercise 8.1.** Show
\[
\int_1^\infty \frac{1}{x^p} \, dm(x) = \begin{cases} \infty & \text{if } p \leq 1 \\ \frac{1}{p-1} & \text{if } p > 1. \end{cases}
\]

**Example 8.9.** The following limit holds,
\[
\lim_{n \to \infty} \int_0^n \left( 1 - \frac{x}{n} \right)^n \, dm(x) = 1.
\]
To verify this, let \( f_n(x) := \left( 1 - \frac{x}{n} \right)^n \). Then \( \lim_{n \to \infty} f_n(x) = e^{-x} \) for all \( x \geq 0 \) and by taking logarithms of Eq. (7.8),
\[
\ln (1 - x) \leq -x \text{ for } x < 1.
\]
Therefore, for \( x < n \), we have
\[
\left( 1 - \frac{x}{n} \right)^n = e^{n \ln(1 - \frac{x}{n})} \leq e^{-n(\frac{x}{n})} = e^{-x}
\]
from which it follows that
\[
0 \leq f_n(x) \leq e^{-x} \text{ for all } x \geq 0.
\]
From Example 8.8 we know
\[
\int_0^\infty e^{-x} \, dm(x) = 1 < \infty,
\]
so that \( e^{-x} \) is an integrable function on \([0, \infty)\). Hence by the dominated convergence theorem,
\[
\lim_{n \to \infty} \int_0^n \left( 1 - \frac{x}{n} \right)^n \, dm(x) = \lim_{n \to \infty} \int_0^\infty f_n(x) \, dm(x)
= \int_0^\infty \lim_{n \to \infty} f_n(x) \, dm(x) = \int_0^\infty e^{-x} \, dm(x) = 1.
\]

The limit in the above example may also be computed using the monotone convergence theorem. To do this we must show that \( n \to f_n(x) \) is increasing in \( n \) for each \( x \) and for this it suffices to consider \( n > x \). But for \( n > x \),
\[
\frac{d}{dn} \ln f_n(x) = \frac{d}{dn} \left[ n \ln \left( 1 - \frac{x}{n} \right) \right] = \ln \left( 1 - \frac{x}{n} \right) + \frac{n}{1 - n} \frac{x}{n^2}
= \ln \left( 1 - \frac{x}{n} \right) + \frac{x}{1 - \frac{x}{n}} = h(x/n)
\]
where, for \( 0 \leq y < 1 \),
\[
h(y) := \ln(1 - y) + \frac{y}{1 - y}.
\]
Since \( h(0) = 0 \) and
\[
h'(y) = -\frac{1}{1 - y} + \frac{1}{1 - y} + \frac{y}{(1 - y)^2} > 0
\]
it follows that \( h \geq 0 \). Thus we have shown, \( f_n(x) \uparrow e^{-x} \) as \( n \to \infty \) as claimed.

**Example 8.10 (Jordan’s Lemma).** In this example, let us consider the limit;
\[
\lim_{n \to \infty} \int_0^\pi \cos \left( \frac{\sin \theta}{n} \right) e^{-n \sin(\theta)} \, d\theta.
\]
Let
\[
f_n(\theta) := \begin{cases} 1_{(0,\pi]}(\theta) \cos \left( \frac{\theta}{n} \right) e^{-n \sin(\theta)} & \text{if } \theta \in (0,\pi] \\ 0 & \text{otherwise} \end{cases}
\]
Then
\[
|f_n| \leq 1_{(0,\pi]} \in L^1(m)
\]
and
\[
\lim_{n \to \infty} f_n(\theta) = 1_{(0,\pi]}(\theta) 1_{(\pi)}(\theta) = 1_{(\pi)}(\theta).
\]
Therefore by the D.C.T.,
\[
\lim_{n \to \infty} \int_0^\pi \cos \left( \frac{\theta}{n} \right) e^{-n \sin(\theta)} \, d\theta = \int_\pi 1_{(\pi)}(\theta) \, d\theta = m \{\pi\} = 0.
\]

**Exercise 8.2** (Folland 2.28 on p. 60.). Compute the following limits and justify your calculations:

1. \( \lim_{n \to \infty} \int_0^\infty \frac{\sin(\frac{\theta}{n})}{(1 + \frac{x}{n})^n} \, dx \)
2. \( \lim_{n \to \infty} \int_0^1 \frac{1 + nx^2}{(1 + x^2)^n} \, dx \)
3. \( \lim_{n \to \infty} \int_0^\infty \frac{n \sin(x/n)}{x(1+x^2)} \, dx \)
4. For all \( a \in \mathbb{R} \) compute,
\[
f(a) := \lim_{n \to \infty} \int_a^\infty n(1 + n^2 x^2)^{-1} \, dx.
\]
Now that we have an overview of the Lebesgue integral, let us proceed to the formal development of the facts stated above.
8.2 Integrals of positive functions

**Definition 8.11.** Let \( L^+ = L^+(\mathcal{B}) = \{f : X \to [0, \infty] : f \text{ is measurable}\}. \)

Define
\[
\int_X f(x) \, d\mu(x) = \int_X f \, d\mu := \sup \{E_{\mu} \varphi : \varphi \text{ is simple and } \varphi \leq f\}.
\]

We say the \( f \in L^+ \) is **integrable** if \( \int_X f \, d\mu < \infty \). If \( A \in \mathcal{B} \), let
\[
\int_A f(x) \, d\mu(x) = \int_A f \, d\mu := \int_X 1_A f \, d\mu.
\]

**Remark 8.12.** Because of item 3. of Proposition 4.16 if \( f \) is a non-negative simple function, \( \int_X \varphi d\mu = E_{\mu} \varphi \) so that \( \int_X \) is an extension of \( E_{\mu} \).

**Lemma 8.13.** Let \( f, g \in L^+(\mathcal{B}) \). Then:

1. if \( \lambda \geq 0 \), then
\[
\int_X \lambda f \, d\mu = \lambda \int_X f \, d\mu.
\]
   wherein \( \lambda \int_X f \, d\mu \equiv 0 \) if \( \lambda = 0 \), even if \( \int_X f \, d\mu = \infty \).
2. if \( 0 \leq f \leq g \), then
\[
\int_X f \, d\mu \leq \int_X g \, d\mu. \tag{8.2}
\]
3. For all \( \varepsilon > 0 \) and \( p > 0 \),
\[
\mu(f \geq \varepsilon) \leq \frac{1}{\varepsilon^p} \int_X f^p 1_{\{f \geq \varepsilon\}} \, d\mu \leq \frac{1}{\varepsilon^p} \int_X f^p \, d\mu. \tag{8.3}
\]

The inequality in Eq. \([8.3] \) is called Chebyshev’s Inequality for \( p = 1 \) and Markov’s inequality for \( p = 2 \).

4. If \( \int_X f \, d\mu < \infty \) then \( \mu(f = \infty) = 0 \) (i.e. \( f < \infty \) a.e.) and the set \( \{f > 0\} \)
   is \( \sigma \) - finite.

**Proof.** 1. We may assume \( \lambda > 0 \) in which case,
\[
\int_X \lambda f \, d\mu = \sup \{E_{\mu} \varphi : \varphi \text{ is simple and } \varphi \leq \lambda f\}
= \sup \{E_{\mu} \varphi : \varphi \text{ is simple and } \lambda^{-1} \varphi \leq f\}
= \sup \{E_{\mu} [\lambda \psi] : \psi \text{ is simple and } \psi \leq f\}
= \sup \{\lambda E_{\mu} [\psi] : \psi \text{ is simple and } \psi \leq f\}
= \lambda \int_X f \, d\mu.
\]

2. Since
\[
\{\varphi \text{ is simple and } \varphi \leq f\} \subset \{\varphi \text{ is simple and } \varphi \leq g\},
\]
Eq. \([8.2] \) follows from the definition of the integral.

3. Since \( 1_{\{f \geq \varepsilon\}} \leq 1_{\{f \geq \varepsilon\}} \frac{1}{\varepsilon} f \leq \frac{1}{\varepsilon} f \) we have
\[
1_{\{f \geq \varepsilon\}} \leq 1_{\{f \geq \varepsilon\}} \left( \frac{1}{\varepsilon} f \right) \leq \left( \frac{1}{\varepsilon} f \right)^p
\]
and by monotonicity and the multiplicative property of the integral,
\[
\mu(f \geq \varepsilon) = \int_X 1_{\{f \geq \varepsilon\}} \, d\mu \leq \left( \frac{1}{\varepsilon} \right)^p \int_X 1_{\{f \geq \varepsilon\}} f^p \, d\mu \leq \left( \frac{1}{\varepsilon} \right)^p \int_X f^p \, d\mu.
\]

4. If \( \mu(f = \infty) > 0 \), then \( \varphi_n := n1_{\{f = \infty\}} \) is a simple function such that \( \varphi_n \leq f \) for all \( n \) and hence
\[
n\mu(f = \infty) = E_{\mu} (\varphi_n) \leq \int_X f \, d\mu
\]
for all \( n \). Letting \( n \to \infty \) shows \( \int_X f \, d\mu = \infty \). Thus if \( \int_X f \, d\mu < \infty \) then
\( \mu(f = \infty) = 0 \).

Moreover,
\[
\{f > 0\} = \bigcup_{n=1}^{\infty} \{f > 1/n\}
\]
with \( \mu(f > 1/n) \leq n \int_X f \, d\mu < \infty \) for each \( n \).

**Lemma 8.14 (Sums as Integrals).** Let \( X \) be a set and \( \rho : X \to [0, \infty] \) be a function, let \( \mu = \sum_{x \in X} \rho(x) \delta_x \) on \( \mathcal{B} = 2^X \), i.e.
\[
\mu(A) = \sum_{x \in A} \rho(x).
\]

If \( f : X \to [0, \infty] \) is a function (which is necessarily measurable), then
\[
\int_X f \, d\mu = \sum_X f \rho.
\]

**Proof.** Suppose that \( \varphi : X \to [0, \infty] \) is a simple function, then \( \varphi = \sum_{z \in [0, \infty]} z 1_{(\varphi = z)} \) and
\[
\sum_X \varphi \rho = \sum_{x \in X} \rho(x) \sum_{z \in [0, \infty]} z 1_{(\varphi = z)}(x) = \sum_{z \in [0, \infty]} z \sum_{x \in X} \rho(x) 1_{(\varphi = z)}(x) = \sum_{z \in [0, \infty]} z \mu(\{\varphi = z\}) = \int_X \varphi \, d\mu.
\]
So if \( \varphi : X \to [0, \infty) \) is a simple function such that \( \varphi \leq f \), then
\[
\int_X \varphi d\mu = \sum_X \varphi \rho \leq \sum_X f \rho.
\]
Taking the sup over \( \varphi \) in this last equation then shows that
\[
\int_X f d\mu \leq \sum_X f \rho.
\]
For the reverse inequality, let \( A \subseteq X \) be a finite set and \( N \in (0, \infty) \). Set
\( f^N(x) = \min \{N, f(x)\} \) and let \( \varphi_{N,A} \) be the simple function given by \( \varphi_{N,A}(x) := 1_A(x) f^N(x) \). Because \( \varphi_{N,A}(x) \leq f(x) \),
\[
\sum_A f^N \rho = \sum_X \varphi_{N,A} \rho = \int_X \varphi_{N,A} d\mu \leq \int_X f d\mu.
\]
Since \( f^N \uparrow f \) as \( N \to \infty \), we may let \( N \to \infty \) in this last equation to conclude
\[
\sum_A f \rho \leq \int_X f d\mu.
\]
Since \( A \) is arbitrary, this implies
\[
\sum_X f \rho \leq \int_X f d\mu.
\]

**Theorem 8.15 (Monotone Convergence Theorem).** Suppose \( f_n \in L^+ \) is a sequence of functions such that \( f_n \uparrow f \) \( (f \) is necessarily in \( L^+ \)) then
\[
\int f_n \uparrow \int f \text{ as } n \to \infty.
\]

**Proof.** Since \( f_n \leq f_m \leq f \), for all \( n \leq m < \infty \),
\[
\int f_n \leq \int f_m \leq \int f
\]
from which if follows \( \int f_n \) is increasing in \( n \) and
\[
\lim_{n \to \infty} \int f_n \leq \int f. \tag{8.4}
\]
For the opposite inequality, let \( \varphi : X \to [0, \infty) \) be a simple function such that \( 0 \leq \varphi \leq f \), \( \alpha \in (0,1) \) and \( X_\alpha := \{f \geq \alpha \varphi \} \). Notice that \( X_\alpha \uparrow X \) and
\( f_n \geq \alpha_1 X_n \varphi \) and so by definition of \( \int f_n \),
\[
\int f_n \geq \alpha \mu [\alpha_1 X_n \varphi] = \alpha \mu [1_{X_n} \varphi]. \tag{8.5}
\]
Then using the continuity of \( \mu \) under increasing unions,
\[
\lim_{n \to \infty} \mu [1_{X_n} \varphi] = \lim_{n \to \infty} \int 1_{X_n} \sum_{y > 0} y 1_{\varphi = y} \\
= \lim_{n \to \infty} \sum_{y > 0} y \mu (X_n \cap \{ \varphi = y \}) \\
= \sum_{y > 0} \lim_{n \to \infty} \mu (X_n \cap \{ \varphi = y \}) \\
= \sum_{y > 0} y \lim_{n \to \infty} \mu (\{ \varphi = y \}) = \mu [\varphi]
\]
This identity allows us to let \( n \to \infty \) in Eq. (8.5) to conclude \( \lim_{n \to \infty} \int f_n \geq \alpha \mu [\varphi] \) and since \( \alpha \in (0,1) \) was arbitrary we may further conclude \( \mu [\varphi] \leq \lim_{n \to \infty} \int f_n \). The latter inequality being true for all simple functions \( \varphi \leq f \) then implies that
\[
\int f \leq \lim_{n \to \infty} \int f_n,
\]
which combined with Eq. (8.4) proves the theorem. \( \blacksquare \)

**Corollary 8.16.** If \( f_n \in L^+ \) is a sequence of functions then
\[
\int \sum_{n=1}^\infty f_n = \sum_{n=1}^\infty \int f_n.
\]
In particular, if \( \sum_{n=1}^\infty \int f_n < \infty \) then \( \sum_{n=1}^\infty f_n < \infty \) a.e.

**Proof.** First off we show that
\[
\int (f_1 + f_2) = \int f_1 + \int f_2
\]
by choosing non-negative simple function \( \varphi_n \) and \( \psi_n \) such that \( \varphi_n \uparrow f_1 \) and \( \psi_n \uparrow f_2 \). Then \( (\varphi_n + \psi_n) \) is simple as well and \( (\varphi_n + \psi_n) \uparrow (f_1 + f_2) \) so by the monotone convergence theorem,
\[
\int (f_1 + f_2) = \lim_{n \to \infty} \int (\varphi_n + \psi_n) = \lim_{n \to \infty} \left( \int \varphi_n + \int \psi_n \right) \\
= \lim_{n \to \infty} \int \varphi_n + \lim_{n \to \infty} \int \psi_n = \int f_1 + \int f_2.
\]
Now to the general case. Let $g_N := \sum_{n=1}^{N} f_n$ and $g = \sum_{n=1}^{\infty} f_n$, then $g_N \uparrow g$ and so again by monotone convergence theorem and the additivity just proved,

$$
\sum_{n=1}^{\infty} \int f_n := \lim_{N \to \infty} \sum_{n=1}^{N} \int f_n = \lim_{N \to \infty} \int \sum_{n=1}^{N} f_n \\
= \lim_{N \to \infty} \int g_N = \int g =: \int \sum_{n=1}^{\infty} f_n.
$$

\[ \square \]

**Remark 8.17.** It is in the proof of this corollary (i.e. the linearity of the integral) that we really make use of the assumption that all of our functions are measurable. In fact the definition $\int f d\mu$ makes sense for all functions $f : X \to [0, \infty]$ not just measurable functions. Moreover the monotone convergence theorem holds in this generality with no change in the proof. However, in the proof of Corollary 8.16 we use the approximation Theorem 6.32 which relies heavily on the measurability of the functions to be approximated.

**Example 8.18.** Suppose, $\Omega = \mathbb{N}$, $\mathcal{B} := 2^{\mathbb{N}}$, and $\mu(A) = \#(A)$ for $A \subset \Omega$ is the counting measure on $\mathcal{B}$. Then for $f : \mathbb{N} \to [0, \infty)$, the function

$$
f_N(\cdot) := \sum_{n=1}^{N} f(n) 1_{\{n\}}
$$

is a simple function with $f_N \uparrow f$ as $N \to \infty$. So by the monotone convergence theorem,

$$
\int f d\mu = \lim_{N \to \infty} \int f_N d\mu = \lim_{N \to \infty} \sum_{n=1}^{N} f(n) \mu(\{n\}) \\
= \lim_{N \to \infty} \sum_{n=1}^{N} f(n) = \sum_{n=1}^{\infty} f(n).
$$

**Exercise 8.3.** Suppose that $\mu_n : \mathcal{B} \to [0, \infty]$ are measures on $\mathcal{B}$ for $n \in \mathbb{N}$. Also suppose that $\mu_n(A)$ is increasing in $n$ for all $A \in \mathcal{B}$. Prove that $\mu : \mathcal{B} \to [0, \infty]$ defined by $\mu(A) := \lim_{n \to \infty} \mu_n(A)$ is also a measure. Hint: use Example 8.18 and the monotone convergence theorem.

**Proposition 8.19.** Suppose that $f \geq 0$ is a measurable function. Then $\int_X f d\mu = 0$ iff $f = 0$ a.e. Also if $f, g \geq 0$ are measurable functions such that $f \leq g$ a.e. then $\int f d\mu \leq \int g d\mu$. In particular if $f = g$ a.e. then $\int f d\mu = \int g d\mu$.

**Proof.** If $f = 0$ a.e. and $\varphi \leq f$ is a simple function then $\varphi = 0$ a.e. This implies that $\mu(\varphi^{-1}(\{y\})) = 0$ for all $y > 0$ and hence $\int_X \varphi d\mu = 0$ and therefore $\int_X f d\mu = 0$. Conversely, if $\int f d\mu = 0$, then by (Lemma 8.21),

$$
\mu(f \geq 1/n) \leq n \int f d\mu = 0 \text{ for all } n.
$$

Therefore, $\mu(f > 0) \leq \sum_{n=1}^{\infty} \mu(f \geq 1/n) = 0$, i.e. $f = 0$ a.e. For the second assertion let $E$ be the exceptional set where $f > g$, i.e. $E := \{x \in X : f(x) > g(x)\}$. By assumption $E$ is a null set and $1_{E^c} f \leq 1_{E^c} g$ everywhere. Because $g = 1_{E^c} g + 1_E g$ and $1_E g = 0$ a.e.,

$$
\int g d\mu = \int 1_{E^c} g d\mu + \int 1_E g d\mu = \int 1_{E^c} g d\mu
$$

and similarly $\int f d\mu = \int 1_{E^c} f d\mu$. Since $1_{E^c} f \leq 1_{E^c} g$ everywhere,

$$
\int f d\mu \leq \int 1_{E^c} f d\mu \leq \int 1_{E^c} g d\mu = \int g d\mu.
$$

\[ \square \]

**Corollary 8.20.** Suppose that $\{f_n\}$ is a sequence of non-negative measurable functions and $f$ is a measurable function such that $f_n \uparrow f$ off a null set, then

$$
\int f_n \uparrow \int f \text{ as } n \to \infty.
$$

**Proof.** Let $E \subset X$ be a null set such that $f_n 1_{E^c} \uparrow f 1_{E^c}$ as $n \to \infty$. Then by the monotone convergence theorem and Proposition 8.19

$$
\int f_n = \int f_n 1_{E^c} \uparrow \int f 1_{E^c} = \int f \text{ as } n \to \infty.
$$

\[ \square \]

**Lemma 8.21 (Fatou's Lemma).** If $f_n : X \to [0, \infty]$ is a sequence of measurable functions then

$$
\int \lim inf_{n \to \infty} f_n \leq \lim inf_{n \to \infty} \int f_n
$$

**Proof.** Define $g_k := \inf_{n \geq k} f_n$ so that $g_k \uparrow \lim inf_{n \to \infty} f_n$ as $k \to \infty$. Since $g_k \leq f_n$ for all $k \leq n$,

$$
\int g_k \leq \int f_n \text{ for all } n \geq k
$$

and therefore

$$
\int g_k \leq \lim inf_{n \to \infty} \int f_n
$$
\[ \int g_k \leq \lim_{n \to \infty} \inf \int f_n \text{ for all } k. \]

We may now use the monotone convergence theorem to let \( k \to \infty \) to find
\[ \int \lim_{n \to \infty} f_n = \int \lim_{k \to \infty} g_k = \int g_k \leq \lim_{n \to \infty} \inf \int f_n. \]

The following Lemma and the next Corollary are simple applications of Corollary 8.16.

**Lemma 8.22 (The First Borell–Carnelli Lemma).** Let \((X, \mathcal{B}, \mu)\) be a measure space, \(A_n \in \mathcal{B}\), and set
\[ \{A_n \text{ i.o.}\} = \{x \in X : x \in A_n \text{ for infinitely many } n\}'s = \bigcap_{N=1}^{\infty} \bigcup_{n \geq N} A_n. \]

If \( \sum_{n=1}^{\infty} \mu(A_n) < \infty \) then \( \mu(\{A_n \text{ i.o.}\}) = 0. \)

**Proof.** (First Proof.) Let us first observe that
\[ \{A_n \text{ i.o.}\} = \left\{ x \in X : \sum_{n=1}^{\infty} 1_{A_n}(x) = \infty \right\}. \]

Hence if \( \sum_{n=1}^{\infty} \mu(A_n) < \infty \) then
\[ \infty > \sum_{n=1}^{\infty} \mu(A_n) = \sum_{n=1}^{\infty} \int_X 1_{A_n} d\mu = \int_X \sum_{n=1}^{\infty} 1_{A_n} d\mu \]
implies that \( \sum_{n=1}^{\infty} 1_{A_n}(x) < \infty \) for \( \mu \) a.e. \( x \). That is to say \( \mu(\{A_n \text{ i.o.}\}) = 0. \)

(Second Proof.) Of course we may give a strictly measure theoretic proof of this fact:
\[ \mu(\{A_n \text{ i.o.}\}) = \lim_{N \to \infty} \mu(\bigcup_{n \geq N} A_n) \leq \lim_{N \to \infty} \sum_{n \geq N} \mu(A_n) \]
and the last limit is zero since \( \sum_{n=1}^{\infty} \mu(A_n) < \infty. \)

**Corollary 8.23.** Suppose that \((X, \mathcal{B}, \mu)\) is a measure space and \(\{A_n\}_{n=1}^{\infty} \subset \mathcal{B}\) is a collection of sets such that \(\mu(A_i \cap A_j) = 0\) for all \(i \neq j\), then
\[ \mu(\bigcup_{n=1}^{\infty} A_n) = \sum_{n=1}^{\infty} \mu(A_n). \]

**Proof.** Since
\[ \mu(\bigcup_{n=1}^{\infty} A_n) = \int_X 1_{\bigcup_{n=1}^{\infty} A_n} d\mu \]
and
\[ \sum_{n=1}^{\infty} \mu(A_n) = \int_X \sum_{n=1}^{\infty} 1_{A_n} d\mu \]
it suffices to show
\[ \sum_{n=1}^{\infty} 1_{A_n} = 1_{\bigcup_{n=1}^{\infty} A_n} \mu \text{ a.e.} \]

Now \( \sum_{n=1}^{\infty} 1_{A_n} \geq 1_{\bigcup_{n=1}^{\infty} A_n} \) and \( \sum_{n=1}^{\infty} 1_{A_n}(x) \neq 1_{\bigcup_{n=1}^{\infty} A_n}(x) \) iff \( x \in A_i \cap A_j \) for some \( i \neq j \), that is
\[ \left\{ x : \sum_{n=1}^{\infty} 1_{A_n}(x) \neq 1_{\bigcup_{n=1}^{\infty} A_n}(x) \right\} = \bigcup_{i<j} A_i \cap A_j \]
and the latter set has measure zero. This proves Eq. (8.6) and hence the corollary.

**Example 8.24.** Let \( \{r_n\}_{n=1}^{\infty} \) be an enumeration of the points in \( \mathbb{Q} \cap [0,1] \) and define
\[ f(x) = \sum_{n=1}^{\infty} 2^{-n} \frac{1}{\sqrt{|x-r_n|}} \]
with the convention that
\[ \frac{1}{\sqrt{|x-r_n|}} = 5 \text{ if } x = r_n. \]

Since, By Theorem 8.7,
\[ \int_0^1 \frac{1}{\sqrt{|x-r_n|}} \, dx = \int_{r_n}^1 \frac{1}{\sqrt{x-r_n}} \, dx + \int_0^r \frac{1}{\sqrt{r_n-x}} \, dx \]
\[ = 2\sqrt{x-r_n} \bigg|_0^{r_n} = 2(\sqrt{1-r_n} - \sqrt{r_n}) \leq 4, \]
we find
\[ \int_{[0,1]} f(x) \, dm(x) = \sum_{n=1}^{\infty} 2^{-n} \int_{[0,1]} \frac{1}{\sqrt{|x-r_n|}} \, dx \leq \sum_{n=1}^{\infty} 2^{-n} 4 = 4 < \infty. \]

In particular, \( m(f = \infty) = 0 \), i.e. that \( f < \infty \) for almost every \( x \in [0,1] \) and this implies that
This result is somewhat surprising since the singularities of the summands form a dense subset of \([0, 1]\).

8.3 Integrals of Complex Valued Functions

Definition 8.25. A measurable function \(f : X \to \mathbb{R}\) is integrable if \(f_+ := f 1_{f \geq 0}\) and \(f_- := -f 1_{f \leq 0}\) are integrable. We write \(L^1 (\mu; \mathbb{R})\) for the space of real valued integrable functions. For \(f \in L^1 (\mu; \mathbb{R})\), let

\[
\int f \, d\mu = \int f_+ \, d\mu - \int f_- \, d\mu
\]

Convention: If \(f, g : X \to \mathbb{R}\) are two measurable functions, let \(f + g\) denote the collection of measurable functions \(h : X \to \mathbb{R}\) such that \(h(x) = f(x) + g(x)\) whenever \(f(x) + g(x)\) is well defined, i.e. is not of the form \(\infty - \infty\) or \(-\infty + \infty\). We use a similar convention for \(f - g\). Notice that if \(f, g \in L^1 (\mu; \mathbb{R})\) and \(h_1, h_2 \in f + g\), then \(h_1 = h_2\) a.e. because \(|f| < \infty\) and \(|g| < \infty\) a.e.

Notation 8.26 (Abuse of notation) We will sometimes denote the integral \(\int_X f \, d\mu\) by \(\mu(f)\). With this notation we have \(\mu(A) = \mu(1_A)\) for all \(A \in \mathcal{B}\).

Remark 8.27. Since

\[
f_\pm \leq |f| \leq f_+ + f_-,
\]
a measurable function \(f\) is integrable iff \(\int |f| \, d\mu < \infty\). Hence

\[
L^1 (\mu; \mathbb{R}) := \left\{ f : X \to \mathbb{R} : f \text{ is measurable and } \int_X |f| \, d\mu < \infty \right\}.
\]

If \(f, g \in L^1 (\mu; \mathbb{R})\) and \(f = g\) a.e. then \(f_\pm = g_\pm\) a.e. and so it follows from Proposition 8.19 that \(\int f \, d\mu = \int g \, d\mu\). In particular if \(f, g \in L^1 (\mu; \mathbb{R})\) we may define

\[
\int_X (f + g) \, d\mu = \int_X h \, d\mu
\]
where \(h\) is any element of \(f + g\).

Proposition 8.28. The map

\[
f \in L^1 (\mu; \mathbb{R}) \mapsto \int_X f \, d\mu \in \mathbb{R}
\]
is linear and has the monotonicity property: \(\int f \, d\mu \leq \int g \, d\mu\) for all \(f, g \in L^1 (\mu; \mathbb{R})\) such that \(f \leq g\) a.e.

Proof. Let \(f, g \in L^1 (\mu; \mathbb{R})\) and \(a, b \in \mathbb{R}\). By modifying \(f\) and \(g\) on a null set, we may assume that \(f, g\) are real valued functions. We have \(af + bg \in L^1 (\mu; \mathbb{R})\) because

\[
|af + bg| \leq |a||f| + |b||g| \in L^1 (\mu; \mathbb{R})
\]

If \(a < 0\), then

\[
(af)_+ = -af_- \text{ and } (af)_- = -af_+
\]

so that

\[
\int af = -a \int f_- + a \int f_+ = a(\int f_+ - \int f_-) = a \int f.
\]

A similar calculation works for \(a > 0\) and the case \(a = 0\) is trivial so we have shown that

\[
\int af = a \int f.
\]

Now set \(h = f + g\). Since \(h = h_+ - h_-\),

\[
h_+ - h_- = f_+ - f_- + g_+ - g_-
\]
or

\[
h_+ + f_- + g_- = h_+ + f_+ + g_+.
\]

Therefore,

\[
\int h_+ + \int f_- + \int g_- = \int h_- + \int f_+ + \int g_
\]
and hence

\[
\int h = \int h_+ - \int h_- = \int f_+ + \int g_+ - \int f_- - \int g_- = \int f + \int g.
\]

Finally if \(f_+ - f_- \leq g \leq g_+ - g_-\) then \(f_+ + g_- \leq g_+ + f_-\) which implies that

\[
\int f_+ + \int g_- \leq \int g_+ + \int f_-
\]
or equivalently that

\[
\int f = \int f_+ - \int f_- \leq \int g_+ - \int g_- = \int g.
\]

The monotonicity property is also a consequence of the linearity of the integral, the fact that \(f \leq g\) a.e. implies \(0 \leq g - f\) a.e. and Proposition 8.19.

Definition 8.29. A measurable function \(f : X \to \mathbb{C}\) is integrable if \(\int_X |f| \, d\mu < \infty\). Analogously to the real case, let

\[
L^1 (\mu; \mathbb{C}) := \left\{ f : X \to \mathbb{C} : f \text{ is measurable and } \int_X |f| \, d\mu < \infty \right\}.
\]
denote the complex valued integrable functions. Because, \( \max(|\text{Re} f|, |\text{Im} f|) \leq |f| \leq \sqrt{2} \max(|\text{Re} f|, |\text{Im} f|) \), \( \int |f| \, d\mu < \infty \) iff
\[
\int |\text{Re} f| \, d\mu + \int |\text{Im} f| \, d\mu < \infty.
\]

For \( f \in L^1(\mu; \mathbb{C}) \) define
\[
\int f \, d\mu = \int \text{Re} f \, d\mu + i \int \text{Im} f \, d\mu.
\]

It is routine to show the integral is still linear on \( L^1(\mu; \mathbb{C}) \) (prove!). In the remainder of this section, let \( L^1(\mu) \) be either \( L^1(\mu; \mathbb{C}) \) or \( L^1(\mu; \mathbb{R}) \). If \( A \in \mathcal{B} \) and \( f \in L^1(\mu; \mathbb{C}) \) or \( f : X \to [0, \infty] \) is a measurable function, let
\[
\int_A f \, d\mu := \int_X 1_A f \, d\mu.
\]

**Proposition 8.30.** Suppose that \( f \in L^1(\mu; \mathbb{C}) \), then
\[
\left| \int_X f \, d\mu \right| \leq \int_X |f| \, d\mu.
\]  

**Proof.** Start by writing \( \int_X f \, d\mu = \text{Re}^i \) with \( R \geq 0 \). We may assume that \( R = |\int_X f \, d\mu| > 0 \) since otherwise there is nothing to prove. Since
\[
R = e^{-i\theta} \int_X f \, d\mu = \int_X e^{-i\theta} f \, d\mu = \int_X \text{Re}(e^{-i\theta} f) \, d\mu + i \int_X \text{Im}(e^{-i\theta} f) \, d\mu,
\]
it must be that \( \int_X \text{Im}[e^{-i\theta} f] \, d\mu = 0 \). Using the monotonicity in Proposition 8.19
\[
\left| \int_X f \, d\mu \right| = \int_X \text{Re}(e^{-i\theta} f) \, d\mu \leq \int_X |\text{Re}(e^{-i\theta} f)| \, d\mu \leq \int_X |f| \, d\mu.
\]

**Proposition 8.31.** Let \( f, g \in L^1(\mu) \), then
1. The set \( \{f \neq 0\} \) is \( \sigma \) finite, in fact \( \{|f| \geq \frac{1}{n}\} \} \) \( \{f \neq 0\} \) and \( \mu(|f| \geq \frac{1}{n}) < \infty \) for all \( n \).
2. The following are equivalent
   a) \( \int_E f = \int_E g \) for all \( E \in \mathcal{B} \)
   b) \( \int_X |f - g| = 0 \)
   c) \( f = g \) a.e.

**Proof.** 1. By Chebyshev’s inequality, Lemma 8.13
\[
\mu(|f| \geq \frac{1}{n}) \leq n \int_X |f| \, d\mu < \infty
\]
for all \( n \).
2. (a) \( \Rightarrow \) (c) Notice that
\[
\int_E f = \int_E g \Leftrightarrow \int_E (f - g) = 0
\]
for all \( E \in \mathcal{B} \). Taking \( E = \{\text{Re}(f - g) > 0\} \) and using \( \text{Re}(f - g) \geq 0 \), we learn that
\[
0 = \text{Re} \int_E (f - g) \, d\mu = \int_E \text{Re}(f - g) \Rightarrow \int_E \text{Re}(f - g) = 0 \text{ a.e.}
\]
This implies that \( \int_E = 0 \) a.e. which happens iff
\[
\mu(\{\text{Re}(f - g) > 0\}) = \mu(E) = 0.
\]
Similar \( \mu(\text{Re}(f - g) < 0) = 0 \) so that \( \text{Re}(f - g) = 0 \) a.e. Similarly, \( \text{Im}(f - g) = 0 \) a.e and hence \( f - g = 0 \) a.e., i.e. \( f = g \) a.e. (c) \( \Rightarrow \) (b) is clear and so is (b) \( \Rightarrow \) (a) since
\[
\int_E f - \int_E g \leq \int_X |f - g| = 0.
\]  

**Definition 8.32.** Let \( (X, \mathcal{B}, \mu) \) be a measurable space and \( L^1(\mu) = L^1(X, \mathcal{B}, \mu) \) denote the set of \( L^1(\mu) \) functions modulo the equivalence relation; \( f \sim g \) iff \( f = g \) a.e. We make this into a normed space using the norm
\[
\|f - g\|_{L^1} = \int_X |f - g| \, d\mu
\]
and into a metric space using \( p_1(f, g) = \|f - g\|_{L^1} \).

**Warning:** in the future we will often not make much of a distinction between \( L^1(\mu) \) and \( L^1(\mu) \). On occasion this can be dangerous and this danger will be pointed out when necessary.

**Remark 8.33.** More generally we may define \( L^p(\mu) = L^p(X, \mathcal{B}, \mu) \) for \( p \in [1, \infty) \) as the set of measurable functions \( f \) such that
\[
\int_X |f|^p \, d\mu < \infty
\]
modulo the equivalence relation; \( f \sim g \) iff \( f = g \) a.e.
We will see in later that
\[
\|f\|_{L^p} = \left( \int |f|^p \, d\mu \right)^{1/p}
\]
for \( f \in L^p(\mu) \)
is a norm and \((L^p(\mu), \|\cdot\|_{L^p})\) is a Banach space in this norm.

**Theorem 8.34 (Dominated Convergence Theorem).** Suppose \( f_n, g_n, g \in L^1(\mu) \), \( f_n \to f \) a.e., \( |f_n| \leq g_n \in L^1(\mu) \), \( g_n \to g \) a.e. and \( \int_X g_n \, d\mu \to \int_X g \, d\mu \). Then \( f \in L^1(\mu) \) and
\[
\int_X f \, d\mu = \lim_{n \to \infty} \int_X f_n \, d\mu.
\]
(In most typical applications of this theorem \( g_n = g \in L^1(\mu) \) for all \( n \).)

**Proof.** Notice that \( |f| = \lim_{n \to \infty} |f_n| \leq \lim_{n \to \infty} |g_n| \leq g \) a.e. so that \( f \in L^1(\mu) \). By considering the real and imaginary parts of \( f \) separately, it suffices to prove the theorem in the case where \( f \) is real. By Fatou’s Lemma,
\[
\int_X (g \pm f) \, d\mu = \int_X \lim_{n \to \infty} (g_n \pm f) \, d\mu \leq \liminf_{n \to \infty} \int_X (g_n \pm f_n) \, d\mu
\]
\[
= \lim_{n \to \infty} \int_X g_n \, d\mu + \liminf_{n \to \infty} \left( \pm \int_X f_n \, d\mu \right)
\]
\[
= \int_X g \, d\mu + \liminf_{n \to \infty} \left( \pm \int_X f_n \, d\mu \right)
\]
Since \( \liminf_{n \to \infty} (-a_n) = -\limsup_{n \to \infty} a_n \), we have shown,
\[
\int_X g \, d\mu + \int_X f \, d\mu \leq \int_X g \, d\mu + \left\{ \liminf_{n \to \infty} \int_X f_n \, d\mu \right\} - \limsup_{n \to \infty} \int_X f_n \, d\mu
\]
and therefore
\[
\limsup_{n \to \infty} \int_X f_n \, d\mu \leq \int_X f \, d\mu \leq \liminf_{n \to \infty} \int_X f_n \, d\mu.
\]
This shows that \( \lim_{n \to \infty} \int_X f_n \, d\mu \) exists and is equal to \( \int_X f \, d\mu \). \( \square \)

**Exercise 8.4.** Give another proof of Proposition 8.30 by first proving Eq. 8.7 with \( f \) being a simple function in which case the triangle inequality for complex numbers will do the trick. Then use the approximation Theorem 8.32 along with the dominated convergence Theorem 8.34 to handle the general case.

**Proposition 8.35.** Suppose that \((\Omega, \mathcal{B}, P)\) is a probability space and \( \{Z_j\}_{j=1}^n \) are independent integrable random variables. Then \( \prod_{j=1}^n Z_j \) is also integrable and
\[
E \left[ \prod_{j=1}^n Z_j \right] = \prod_{j=1}^n E[Z_j].
\]

**Proof.** By definition, \( \{Z_j\}_{j=1}^n \) are independent iff \( \{\sigma(Z_j)\}_{j=1}^n \) are independent. Then as we have seen in a homework problem,
\[
E[1_{A_1} \ldots 1_{A_n}] = E[1_{A_1}] \ldots E[1_{A_n}] \quad \text{when} \quad A_i \in \sigma(Z_i) \quad \text{for each} \quad i.
\]
By multi-linearity it follows that
\[
E[\varphi_1 \ldots \varphi_n] = E[\varphi_1] \ldots E[\varphi_n]
\]
whenever \( \varphi_i \) are bounded \( \sigma(Z_i) \) – measurable simple functions. By approximation by simple functions and the monotone and dominated convergence theorem,
\[
E[Y_1 \ldots Y_n] = E[Y_1] \ldots E[Y_n]
\]
whenever \( Y_i \) is \( \sigma(Z_i) \) – measurable and either \( Y_i \geq 0 \) or \( Y_i \) is bounded. Taking \( Y_i = |Z_i| \) then implies that
\[
E \left[ \prod_{j=1}^n |Z_j| \right] = \prod_{j=1}^n E[|Z_j|] < \infty
\]
so that \( \prod_{j=1}^n Z_j \) is integrable. Moreover, for \( K > 0 \), let \( Z_j^K = Z_j 1_{|Z_j| \leq K} \), then
\[
E \left[ \prod_{j=1}^n Z_j 1_{|Z_j| \leq K} \right] = \prod_{j=1}^n E[Z_j 1_{|Z_j| \leq K}].
\]
Now apply the dominated convergence theorem, \( n+1 \) – times, to conclude
\[
E \left[ \prod_{j=1}^n Z_j \right] = \lim_{K \to \infty} E \left[ \prod_{j=1}^n Z_j 1_{|Z_j| \leq K} \right] = \prod_{j=1}^n \lim_{K \to \infty} E[Z_j 1_{|Z_j| \leq K}] = \prod_{j=1}^n E[Z_j].
\]
The dominating functions used here are \( \prod_{j=1}^n |Z_j| \), and \( \{|Z_j|\}_{j=1}^n \) respectively.

**Corollary 8.36.** Let \( \{f_n\}_{n=1}^\infty \subset L^1(\mu) \) be a sequence such that \( \sum_{n=1}^\infty \|f_n\|_{L^1(\mu)} < \infty \), then \( \sum_{n=1}^\infty f_n \) is convergent a.e. and
\[
\int_X \left( \sum_{n=1}^\infty f_n \right) \, d\mu = \sum_{n=1}^\infty \int_X f_n \, d\mu.
\]
Proof. The condition $\sum_{n=1}^{\infty} ||f_n||_{L^1(\mu)} < \infty$ is equivalent to $\sum_{n=1}^{\infty} |f_n| \in L^1(\mu)$. Hence $\sum_{n=1}^{\infty} f_n$ is almost everywhere convergent and if $S_N := \sum_{n=1}^{N} f_n$, then

$$|S_N| \leq \sum_{n=1}^{N} |f_n| \leq \sum_{n=1}^{\infty} |f_n| \in L^1(\mu).$$

So by the dominated convergence theorem,

$$\int_{X} \left( \sum_{n=1}^{\infty} f_n \right) d\mu = \int_{X} \lim_{N \to \infty} S_N d\mu = \lim_{N \to \infty} \int_{X} S_N d\mu = \lim_{N \to \infty} \sum_{n=1}^{N} \int_{X} f_n d\mu = \sum_{n=1}^{\infty} \int_{X} f_n d\mu.$$

\[\Box\]

Example 8.37 (Integration of Power Series). Suppose $R > 0$ and $\{a_n\}_{n=0}^{\infty}$ is a sequence of complex numbers such that $\sum_{n=0}^{\infty} |a_n| r^n < \infty$ for all $r \in (0, R)$. Then

$$\int_{\alpha}^{\beta} \left( \sum_{n=0}^{\infty} a_n x^n \right) \, dm(x) = \sum_{n=0}^{\infty} a_n \int_{\alpha}^{\beta} x^n \, dm(x) = \sum_{n=0}^{\infty} a_n \frac{\beta^{n+1} - \alpha^{n+1}}{n+1}
$$

for all $-R < \alpha < \beta < R$. Indeed this follows from Corollary 8.36 since

$$\sum_{n=0}^{\infty} \int_{\alpha}^{\beta} |a_n| |x|^n \, dm(x) \leq \sum_{n=0}^{\infty} \left( \int_{0}^{|\beta|} |a_n| |x|^n \, dm(x) + \int_{0}^{|\alpha|} |a_n| |x|^n \, dm(x) \right) \leq 2r \sum_{n=0}^{\infty} |a_n| r^n < \infty$$

where $r = \max(|\beta|, |\alpha|)$.

Corollary 8.38 (Differentiation Under the Integral). Suppose that $J \subset \mathbb{R}$ is an open interval and $f : J \times X \to \mathbb{C}$ is a function such that

1. $x \to f(t, x)$ is measurable for each $t \in J$.
2. $f(t_0, \cdot) \in L^1(\mu)$ for some $t_0 \in J$.
3. $\frac{\partial f}{\partial t}(t, x)$ exists for all $(t, x)$.
4. There is a function $g \in L^1(\mu)$ such that $|\frac{\partial f}{\partial t}(t, \cdot)| \leq g$ for each $t \in J$.

Then $f(t, \cdot) \in L^1(\mu)$ for all $t \in J$ (i.e. $\int_X |f(t, x)| \, d\mu(x) < \infty$), $t \to \int_X f(t, x) \, d\mu(x)$ is a differentiable function on $J$ and

$$\frac{d}{dt} \int_X f(t, x) \, d\mu(x) = \int_X \frac{\partial f}{\partial t}(t, x) \, d\mu(x).$$

Proof. By considering the real and imaginary parts of $f$ separately, we may assume that $f$ is real. Also notice that

$$\frac{\partial f}{\partial t}(t, x) = \lim_{n \to \infty} n(f(t + n^{-1}, x) - f(t, x))$$

and therefore, for $x \to \frac{\partial f}{\partial t}(t, x)$ is a sequential limit of measurable functions and hence is measurable for all $t \in J$. By the mean value theorem,

$$|f(t, x) - f(t_0, x)| \leq g(x) |t - t_0| \quad \text{for all } t \in J \quad (8.8)$$

and hence

$$|f(t, x)| \leq |f(t, x) - f(t_0, x)| + |f(t_0, x)| \leq g(x) |t - t_0| + |f(t_0, x)|.$$

This shows $f(t, \cdot) \in L^1(\mu)$ for all $t \in J$. Let $G(t) := \int_X f(t, x) \, d\mu(x)$, then

$$\frac{G(t) - G(t_0)}{t - t_0} = \int_X \frac{f(t, x) - f(t_0, x)}{t - t_0} \, d\mu(x).$$

By assumption,

$$\lim_{t \to t_0} \frac{f(t, x) - f(t_0, x)}{t - t_0} = \frac{\partial f}{\partial t}(t, x) \quad \text{for all } x \in X$$

and by Eq. (8.8),

$$\left| \frac{f(t, x) - f(t_0, x)}{t - t_0} \right| \leq g(x) \quad \text{for all } t \in J \text{ and } x \in X.$$
8 Integration Theory

Example 8.39. Recall from Example 8.8 that

\[ \lambda^{-1} = \int_{[0, \infty)} e^{-\lambda x} \, dm(x) \] for all \( \lambda > 0 \).

Let \( \varepsilon > 0 \). For \( \lambda \geq 2\varepsilon > 0 \) and \( n \in \mathbb{N} \) there exists \( C_n(\varepsilon) < \infty \) such that

\[ 0 \leq \left( -\frac{d}{d\lambda} \right)^n e^{-\lambda x} = x^n e^{-\lambda x} \leq C(\varepsilon) e^{-\varepsilon x}. \]

Using this fact, Corollary 8.38 and induction gives

\[ n! \lambda^{-n-1} = \left( -\frac{d}{d\lambda} \right)^n \lambda^{-1} = \int_{[0, \infty)} \left( -\frac{d}{d\lambda} \right)^n e^{-\lambda x} \, dm(x) \]

\[ = \int_{[0, \infty)} x^n e^{-\lambda x} \, dm(x). \]

That is \( n! = \lambda^n \int_{[0, \infty)} x^n e^{-\lambda x} \, dm(x) \). Recall that

\[ \Gamma(t) := \int_{[0, \infty)} x^{t-1} e^{-x} \, dx \] for \( t > 0 \).

(The reader should check that \( \Gamma(t) < \infty \) for all \( t > 0 \).) We have just shown that \( \Gamma(n + 1) = n! \) for all \( n \in \mathbb{N} \).

Remark 8.40. Corollary 8.38 may be generalized by allowing the hypothesis to hold for \( x \in X \setminus E \) where \( E \in \mathcal{B} \) is a fixed null set, i.e. \( E \) must be independent of \( t \). Consider what happens if we formally apply Corollary 8.38 to \( g(t) := \int_0^\infty 1_{x \leq t} \, dm(x) \),

\[ \dot{g}(t) = \frac{d}{dt} \int_0^\infty 1_{x \leq t} \, dm(x) \overset{?}{=} \int_0^\infty \frac{d}{dt} 1_{x \leq t} \, dm(x). \]

The last integral is zero since \( \frac{d}{dt} 1_{x \leq t} = 0 \) unless \( t = x \) in which case it is not defined. On the other hand \( g(t) = t \) so that \( \dot{g}(t) = 1 \). (The reader should decide which hypothesis of Corollary 8.38 has been violated in this example.)

8.4 Densities and Change of Variables Theorems

Exercise 8.5. Let \((X, \mathcal{M}, \mu)\) be a measure space and \( \rho : X \to [0, \infty] \) be a measurable function. For \( A \in \mathcal{M} \), set \( \nu(A) := \int_A \rho \, d\mu \).

1. Show \( \nu : \mathcal{M} \to [0, \infty] \) is a measure.

2. Let \( f : X \to [0, \infty] \) be a measurable function, show

\[ \int_X f \, d\nu = \int_X f \rho \, d\mu. \] (8.9)

Hint: first prove the relationship for characteristic functions, then for simple functions, and then for general positive measurable functions.

3. Show that a measurable function \( f : X \to \mathbb{C} \) is in \( L^1(\nu) \) iff \( |f| \rho \in L^1(\mu) \) and if \( f \in L^1(\nu) \) then Eq. (8.9) still holds.

Solution to Exercise 8.5. The fact that \( \nu \) is a measure follows easily from Corollary 8.16. Clearly Eq. (8.9) holds when \( f = 1_A \) by definition of \( \nu \). It then holds for positive simple functions, \( f \), by linearity. Finally for general \( f \in L^1(\nu) \), choose simple functions, \( \varphi_n \), such that \( 0 \leq \varphi_n \uparrow f \). Then using MCT twice we find

\[ \int_X f \, d\nu = \lim_{n \to \infty} \int_X \varphi_n \, d\nu = \lim_{n \to \infty} \int_X \varphi_n \rho \, d\mu = \int_X \lim_{n \to \infty} \varphi_n \rho \, d\mu = \int_X f \rho \, d\mu. \]

By what we have just proved, for all \( f : X \to \mathbb{C} \) we have

\[ \int_X |f| \, d\nu = \int_X |f| \rho \, d\mu \]

so that \( f \in L^1(\mu) \) iff \( |f| \rho \in L^1(\mu) \). If \( f \in L^1(\mu) \) and \( f \) is real,

\[ \int_X f \, d\nu = \int_X f^+ \, d\nu - \int_X f^- \, d\nu = \int_X f^+ \rho \, d\mu - \int_X f^- \rho \, d\mu \]

\[ = \int_X [f^+ \rho - f^- \rho] \, d\mu = \int_X f \rho \, d\mu. \]

The complex case easily follows from this identity.

Notation 8.41. It is customary to informally describe \( \nu \) defined in Exercise 8.5 by writing \( d\nu = \rho \, d\mu \).

Exercise 8.6. Let \((X, \mathcal{M}, \mu)\) be a measure space, \((Y, \mathcal{F})\) be a measurable space and \( f : X \to Y \) be a measurable map. Define a function \( \nu : \mathcal{F} \to [0, \infty] \) by \( \nu(A) := \mu(f^{-1}(A)) \) for all \( A \in \mathcal{F} \).

1. Show \( \nu \) is a measure. (We will write \( \nu = f_* \mu \) or \( \nu = \mu \circ f^{-1} \).)

2. Show

\[ \int_Y g \, d\nu = \int_X (g \circ f) \, d\mu \] (8.10)

for all measurable functions \( g : Y \to [0, \infty] \). Hint: see the hint from Exercise 8.5.
3. Show a measurable function $g : Y \to \mathbb{C}$ is in $L^1(\nu)$ iff $g \circ f \in L^1(\mu)$ and that Eq. \((8.10)\) holds for all $g \in L^1(\nu)$.

**Solution to Exercise (8.6).** The fact that $\nu$ is a measure is a direct check which will be left to the reader. The key computation is to observe that if $A \subseteq \mathcal{F}$ and $g = 1_A$, then

$$\int_{Y} g \, d\nu = \int_{Y} 1_{A} \, d\nu = \nu(A) = \mu(f^{-1}(A)) = \int_{X} 1_{f^{-1}(A)} \, d\mu.$$ 

Moreover, $1_{f^{-1}(A)}(x) = 1$ iff $x \in f^{-1}(A)$ which happens iff $f(x) \in A$ and hence $1_{f^{-1}(A)}(x) = 1_{A}(f(x)) = g(f(x))$ for all $x \in X$. Therefore we have

$$\int_{Y} g \, d\nu = \int_{X} (g \circ f) \, d\mu$$

whenever $g$ is a characteristic function. This identity now extends to non-negative simple functions by linearity and then to all non-negative measurable functions by MCT. The statements involving complex functions follows as in the solution to Exercise 8.5.

**Remark 8.42.** If $X$ is a random variable on a probability space, $(\Omega, \mathcal{B}, P)$, and $F(x) := P(X \leq x)$. Then

$$\mathbb{E}[f(X)] = \int_{\mathbb{R}} f(x) \, dF(x) \tag{8.11}$$

where $dF$ is shorthand for $d\mu_F(x)$ and $\mu_F$ is the unique probability measure on $(\mathbb{R}, \mathcal{B}_{\mathbb{R}})$ such that $\mu_F((\infty, x]) = F(x)$ for all $x \in \mathbb{R}$. Moreover if $F : \mathbb{R} \to [0,1]$ happens to be $C^1$-function, then

$$d\mu_F(x) = F'(x) \, dm(x) \tag{8.12}$$

and Eq. \((8.11)\) may be written as

$$\mathbb{E}[f(X)] = \int_{\mathbb{R}} f(x) \, F'(x) \, dm(x). \tag{8.13}$$

To verify Eq. \((8.12)\) it suffices to observe, by the fundamental theorem of calculus, that

$$\mu_F([a,b]) = F(b) - F(a) = \int_{a}^{b} F'(x) \, dx = \int_{[a,b]} F' \, dm.$$ 

From this equation we may deduce that $\mu_F(A) = \int_{A} F' \, dm$ for all $A \subseteq \mathcal{B}_{\mathbb{R}}$.

**Exercise 8.7.** Let $F : \mathbb{R} \to \mathbb{R}$ be a $C^1$-function such that $F'(x) > 0$ for all $x \in \mathbb{R}$ and $\lim_{x \to \pm \infty} F(x) = \pm \infty$. (Notice that $F$ is strictly increasing so that $F^{-1} : \mathbb{R} \to \mathbb{R}$ exists and moreover, by the inverse function theorem that $F^{-1}$ is a $C^1$ function.) Let $m$ be Lebesgue measure on $\mathcal{B}_{\mathbb{R}}$ and

$$\nu(A) = m(F(A)) = m((F^{-1})^{-1}(A)) = (F^{-1}m)(A)$$

for all $A \subseteq \mathcal{B}_{\mathbb{R}}$. Show $d\nu = F' \, dm$. Use this result to prove the change of variable formula,

$$\int_{\mathbb{R}} h \circ F \cdot F' \, dm = \int_{\mathbb{R}} h \circ dm \tag{8.14}$$

which is valid for all Borel measurable functions $h : \mathbb{R} \to [0, \infty]$. 

**Hint:** Start by showing $d\nu = F' \, dm$ on sets of the form $A = (a,b]$ with $a,b \in \mathbb{R}$ and $a < b$. Then use the uniqueness assertions in Exercise 5.1 to conclude $d\nu = F' \, dm$ on all of $\mathcal{B}_{\mathbb{R}}$. To prove Eq. \((8.14)\) apply Exercise 8.6 with $g = h \circ F$ and $f = F^{-1}$.

**Solution to Exercise (8.7).** Let $d\mu = F' \, dm$ and $A = (a,b]$, then

$$\nu((a,b]] = m(F((a,b]]) = m((F(a), F(b)]) = F(b) - F(a)$$

while

$$\mu((a,b]) = \int_{[a,b]} F' \, dm = \int_{a}^{b} F'(x) \, dx = F(b) - F(a).$$

It follows that both $\mu = \nu = \mu_F$ – where $\mu_F$ is the measure described in Proposition 5.7. By Exercise 8.6 with $g = h \circ F$ and $f = F^{-1}$, we find

$$\int_{\mathbb{R}} h \circ F \cdot F' \, dm = \int_{\mathbb{R}} h \circ F \, d\nu = \int_{\mathbb{R}} h \circ F \circ (F^{-1}m) = \int_{\mathbb{R}} (h \circ F) \circ F^{-1} \, dm$$

$$= \int_{\mathbb{R}} h \circ dm.$$ 

This result is also valid for all $h \in L^1(m)$.

**Lemma 8.43.** Suppose that $X$ is a standard normal random variable, i.e.

$$P(X \in A) = \frac{1}{\sqrt{2\pi}} \int_{A} e^{-x^2/2} \, dx \text{ for all } A \subseteq \mathcal{B}_{\mathbb{R}},$$

then

$$P(X \geq x) \leq \frac{1}{\sqrt{2\pi}} e^{-x^2/2} \tag{8.15}$$

and

Proof. We begin by observing that

\[ P(X \geq x) = \int_x^\infty \frac{1}{\sqrt{2\pi}} e^{-y^2/2} dy \leq \int_x^\infty \frac{1}{\sqrt{2\pi}} \frac{1}{2\pi x} e^{-y^2/2} dy = -\frac{1}{\sqrt{2\pi}} \frac{1}{2\pi x} e^{-y^2/2} |_{x}^{\alpha} \]

from which Eq. (8.15) follows. To prove Eq. (8.16), let \( \alpha > 0 \), then

\[ P(X \geq x) = \int_x^\infty \frac{1}{\sqrt{2\pi}} e^{-y^2/2} dy \geq \int_x^{\alpha x} \frac{1}{\sqrt{2\pi}} e^{-y^2/2} dy \]

\[ \geq \int_x^{\alpha x} \frac{1}{\sqrt{2\pi}} \frac{1}{\alpha x} e^{-y^2/2} dy = -\frac{1}{\sqrt{2\pi}} \frac{1}{\alpha x} e^{-y^2/2} |_{x}^{\alpha x} \]

\[ = -\frac{1}{\sqrt{2\pi}} \frac{1}{\alpha x} \left[ e^{-x^2/2} - e^{-\alpha x^2/2} \right]. \]

Hence

\[ P(X \geq x) \geq \int_x^{\alpha x} \frac{1}{\sqrt{2\pi}} \frac{1}{\alpha x} e^{-y^2/2} dy \geq \frac{1}{\alpha} \left[ e^{-x^2/2} - e^{-\alpha x^2/2} \right] = \frac{1}{\alpha} \left[ 1 - e^{-(\alpha - 1)x^2/2} \right]. \]

From this equation it follows that

\[ \liminf_{x \to \infty} \frac{1}{\sqrt{2\pi}} \frac{1}{\alpha} P(X \geq x) \geq \frac{1}{\alpha}. \]

Since \( \alpha > 1 \) was arbitrary, it follows that

\[ \liminf_{x \to \infty} \frac{1}{\sqrt{2\pi}} P(X \geq x) = 1. \]

Since Eq. (8.15) implies that

\[ \limsup_{x \to \infty} \frac{1}{\sqrt{2\pi}} P(X \geq x) = 1 \]

we are done.

Additional information: Suppose that now we take

\[ \alpha = 1 + x^{-p} = \frac{1 + x^p}{x^p}. \]

Then

\[ (\alpha^2 - 1)x^2 = (x^{-2p} + 2x^{-p})x^2 = (x^{2-2p} + 2x^{-2p}) \]

Hence if \( p = 2 - \delta \), we find

\[ (\alpha^2 - 1)x^2 = (x^{2(-1+\delta)} + 2x^{\delta}) \leq 3x^{\delta} \]

so that

\[ 1 \geq \frac{P(X \geq x)}{\frac{1}{x^2} \frac{1}{\sqrt{2\pi}} e^{-x^2/2}} \geq \frac{1}{1 + x^{-(2-\delta)}} \left[ 1 - e^{-3x^{\delta}/2} \right] \]

for \( x \) sufficiently large.

Example 8.44. Let \( \{X_n\}_{n=1}^\infty \) be i.i.d. standard normal random variables. Then

\[ P(X_n \geq \alpha c_n) \sim \frac{1}{\alpha c_n} \frac{1}{\sqrt{2\pi}} \frac{1}{\alpha} e^{-\alpha^2 c_n^2/2}. \]

Now, suppose that we take \( c_n \) so that

\[ e^{-c_n^2/2} = \frac{C}{n} \]

or equivalently,

\[ c_n^2/2 = \ln(n/C) \]

or

\[ c_n = \sqrt{2\ln(n) - 2\ln(C)}. \]

(We now take \( C = 1 \).) It then follows that

\[ P(X_n \geq \alpha c_n) \sim \frac{1}{\alpha \sqrt{2\ln(n)}} e^{-\alpha^2 \ln(n)} = \frac{1}{\alpha \sqrt{2\ln(n)}} \frac{1}{n^{-\alpha^2}} \]

and therefore

\[ \sum_{n=1}^{\infty} P(X_n \geq \alpha c_n) = \infty \text{ if } \alpha < 1 \]

and

\[ \sum_{n=1}^{\infty} P(X_n \geq \alpha c_n) < \infty \text{ if } \alpha > 1. \]

Hence an application of Proposition 7.35 shows

\[ \limsup_{n \to \infty} \frac{X_n}{\sqrt{2\ln(n)}} = 1 \text{ a.s.}. \]
8.5 Measurability on Complete Measure Spaces

In this subsection we will discuss a couple of measurability results concerning completions of measure spaces.

**Proposition 8.45.** Suppose that \((X, \mathcal{B}, \mu)\) is a complete measure space\(^2\) and \(f : X \to \mathbb{R}\) is measurable.

1. If \(g : X \to \mathbb{R}\) is a function such that \(f(x) = g(x)\) for \(\mu\) - a.e. \(x\), then \(g\) is measurable.
2. If \(f_n : X \to \mathbb{R}\) are measurable and \(f : X \to \mathbb{R}\) is a function such that \(\lim_{n \to \infty} f_n = f\), \(\mu\) - a.e., then \(f\) is measurable as well.

**Proof.** 1. Let \(E = \{x : f(x) \neq g(x)\}\) which is assumed to be in \(B\) and \(\mu(E) = 0\). Then \(g = 1_{E^c}f + 1_Eg\) since \(f = g\) on \(E^c\). Now \(1_{E^c}f\) is measurable so \(g\) will be measurable if we show \(1_Eg\) is measurable. For this consider,

\[
(1_Eg)^{-1}(A) = \begin{cases} E^c \cup (1_Eg)^{-1}(A \setminus \{0\}) & \text{if } 0 \in A \\ (1_Eg)^{-1}(A) & \text{if } 0 \notin A \end{cases} \tag{8.17}
\]

Since \((1_Eg)^{-1}(B) \subset E\) if \(0 \notin B\) and \(\mu(E) = 0\), it follow by completeness of \(B\) that \((1_Eg)^{-1}(B) \in B\) if \(0 \notin B\). Therefore Eq. 8.17 shows that \(1_Eg\) is measurable. 2. Let \(E = \{x : \lim_{n \to \infty} f_n(x) \neq f(x)\}\) by assumption \(E \in \mathcal{B}\) and \(\mu(E) = 0\). Since \(g := \lim_{n \to \infty} f_n = 1_{E^c}f_n\), \(g\) is measurable. Because \(f = g\) on \(E^c\) and \(\mu(E) = 0\), \(g = f\) a.e. so by part 1, \(f\) is also measurable.

The above results are in general false if \((X, \mathcal{B}, \mu)\) is not complete. For example, let \(X = \{0, 1, 2\}, \mathcal{B} = \{\{0\}, \{1, 2\}, X, \varnothing\}\) and \(\mu = \delta_0\). Take \(g(0) = 0, g(1) = 1, g(2) = 2\), then \(g = 0\) a.e. yet \(g\) is not measurable.

**Lemma 8.46.** Suppose that \((X, \mathcal{M}, \mu)\) is a measurable space and \(\tilde{\mathcal{M}}\) is the completion of \(\mathcal{M}\) relative to \(\mu\) and \(\tilde{\mu}\) is the extension of \(\mu\) to \(\tilde{\mathcal{M}}\). Then a function \(f : X \to \mathbb{R}\) is \((\tilde{\mathcal{M}}, \tilde{\mathcal{B}})\) – measurable iff there exists a function \(g : X \to \mathbb{R}\) that is \((\mathcal{M}, \mathcal{B})\) – measurable such \(E = \{x : f(x) \neq g(x)\}\) in \(\mathcal{M}\) and \(\tilde{\mu}(E) = 0\), i.e. \(f(x) = g(x)\) for \(\tilde{\mu}\) – a.e. \(x\). Moreover for such a pair \(f\) and \(g\), \(f \in L^1(\tilde{\mu})\) iff \(g \in L^1(\mu)\) and in which case

\[
\int_X f d\tilde{\mu} = \int_X g d\mu. \tag{8.18}
\]

**Proof.** Suppose first that such a function \(g\) exists so that \(\tilde{\mu}(E) = 0\). Since \(g\) is also \((\mathcal{M}, \mathcal{B})\) – measurable, we see from Proposition 8.45 that \(f\) is \((\mathcal{M}, \mathcal{B})\) – measurable. Conversely if \(f\) is \((\tilde{\mathcal{M}}, \tilde{\mathcal{B}})\) – measurable, by considering \(f_+\) we may assume that \(f \geq 0\). Choose \((\mathcal{M}, \mathcal{B})\) – measurable simple function \(\varphi_n \geq 0\) such that \(\varphi_n \uparrow f\) as \(n \to \infty\). Writing

\[
\varphi_n = \sum a_k 1_{A_k}
\]

with \(A_k \in \mathcal{M}\), we may choose \(B_k \in \mathcal{M}\) such that \(B_k \subset A_k\) and \(\tilde{\mu}(A_k \setminus B_k) = 0\). Letting

\[
\tilde{\varphi}_n := \sum a_k 1_{B_k}
\]

we have produced a \((\mathcal{M}, \mathcal{B})\) – measurable simple function \(\tilde{\varphi}_n \geq 0\) such that \(E_n := \{\varphi_n \neq \tilde{\varphi}_n\}\) has zero \(\tilde{\mu}\) – measure. Since \(\tilde{\mu}(\cup_n E_n) \leq \sum_n \tilde{\mu}(E_n)\), there exists \(F \in \mathcal{M}\) such that \(\cup_n E_n \subset F\) and \(\mu(F) = 0\). It now follows that

\[
1_F \cdot \tilde{\varphi}_n = 1_F \cdot \varphi_n \uparrow g := 1_F f \text{ as } n \to \infty.
\]

This shows that \(g = 1_F f\) is \((\mathcal{M}, \mathcal{B})\) – measurable and that \(\{f \neq g\} \subset F\) has \(\tilde{\mu}\) – measure zero. Since \(f = g\), \(\tilde{\mu}\) – a.e., \(\int_X f d\tilde{\mu} = \int_X g d\mu\) so to prove Eq. 8.18 it suffices to prove

\[
\int_X g d\tilde{\mu} = \int_X g d\mu. \tag{8.18}
\]

Because \(\tilde{\mu} = \mu\) on \(\mathcal{M}\), Eq. 8.18 is easily verified for non-negative \(\mathcal{M}\) – measurable simple functions. Then by the monotone convergence theorem and the approximation Theorem 6.32 it holds for all \(\mathcal{M}\) – measurable functions \(g : X \to [0, \infty]\). The rest of the assertions follow in the standard way by considering \((\text{Re}g)_\pm\) and \((\text{Im}g)_\pm\). \(\blacksquare\)

8.6 Comparison of the Lebesgue and the Riemann Integral

For the rest of this chapter, let \(-\infty < a < b < \infty\) and \(f : [a, b] \to \mathbb{R}\) be a bounded function. A partition of \([a, b]\) is a finite subset \(\pi \subset [a, b]\) containing \([a, b]\). To each partition

\[
\pi = \{a = t_0 < t_1 < \cdots < t_n = b\}, \tag{8.19}
\]

of \([a, b]\) let

\[
\text{mesh}(\pi) := \max \{|t_j - t_{j-1}| : j = 1, \ldots, n\},
\]

\[
M_j = \sup \{f(x) : t_j \leq x \leq t_{j-1}\}, \quad m_j = \inf \{f(x) : t_j \leq x \leq t_{j-1}\}
\]

\[
G_\pi = f(a)1_{\{a\}} + \sum_{j=1}^{n} M_j 1_{[t_{j-1}, t_j]}, \quad g_\pi = f(a)1_{\{a\}} + \sum_{j=1}^{n} m_j 1_{[t_{j-1}, t_j]}\]

and
\[ S_\pi f = \sum M_j(t_j - t_{j-1}) \text{ and } s_\pi f = \sum m_j(t_j - t_{j-1}). \]

Notice that
\[ S_\pi f = \int_a^b G_\pi dm \text{ and } s_\pi f = \int_a^b g_\pi dm. \]
The upper and lower Riemann integrals are defined respectively by
\[ \int_a^b f(x)dx = \inf_{\pi} S_\pi f \text{ and } \int_a^b f(x)dx = \sup_{\pi} s_\pi f. \]

**Definition 8.47.** The function \( f \) is **Riemann integrable** iff \( \overline{\int_a^b} f = \int_a^b f \in \mathbb{R} \) and which case the Riemann integral \( \int_a^b f \) is defined to be the common value:
\[ \int_a^b f(x)dx = \int_a^b f(x)dx = \int_a^b f(x)dx. \]

The proof of the following Lemma is left to the reader as Exercise 8.18.

**Lemma 8.48.** If \( \pi' \) and \( \pi \) are two partitions of \([a,b]\) and \( \pi \subset \pi' \) then
\[ G_\pi \geq G_{\pi'} \geq f \geq g_{\pi'} \geq g_\pi \text{ and } S_\pi f \geq S_{\pi'} f \geq s_{\pi'} f \geq s_\pi f. \]
There exists an increasing sequence of partitions \( \{\pi_k\}_{k=1}^\infty \) such that \( \text{mesh}(\pi_k) \downarrow 0 \) and
\[ S_{\pi_k} f \downarrow \int_a^b f \text{ and } s_{\pi_k} f \uparrow \int_a^b f \text{ as } k \to \infty. \]

If we let
\[ G := \lim_{k \to \infty} G_{\pi_k} \text{ and } g := \lim_{k \to \infty} g_{\pi_k} \]
then by the dominated convergence theorem,
\[ \int_{[a,b]} g dm = \lim_{k \to \infty} \int_{[a,b]} g_{\pi_k} = \lim_{k \to \infty} s_{\pi_k} f = \int_a^b f(x)dx \]
and
\[ \int_{[a,b]} G dm = \lim_{k \to \infty} \int_{[a,b]} G_{\pi_k} = \lim_{k \to \infty} S_{\pi_k} f = \int_a^b f(x)dx. \]

**Notation 8.49.** For \( x \in [a,b] \), let
\[ H(x) = \limsup_{y \to x} f(y) := \lim_{\varepsilon \downarrow 0} \sup \{ f(y) : |y - x| \leq \varepsilon, y \in [a,b] \} \]
and
\[ h(x) = \liminf_{y \to x} f(y) := \lim_{\varepsilon \downarrow 0} \inf \{ f(y) : |y - x| \leq \varepsilon, y \in [a,b] \}. \]

**Lemma 8.50.** The functions \( H, h : [a,b] \to \mathbb{R} \) satisfy:
1. \( h(x) \leq f(x) \leq H(x) \) for all \( x \in [a,b] \) and \( h(x) = H(x) \) iff \( f \) is continuous at \( x \).
2. If \( \{\pi_k\}_{k=1}^\infty \) is any increasing sequence of partitions such that \( \text{mesh}(\pi_k) \downarrow 0 \) and \( G \) and \( g \) are defined as in Eq. (8.20), then
\[ G(x) = H(x) \geq f(x) \geq h(x) = g(x) \quad \forall x \notin \pi := \bigcup_{k=1}^\infty \pi_k. \]  
(8.23)

(Note \( \pi \) is a countable set.)

3. \( H \) and \( h \) are Borel measurable.

**Proof.** Let \( G_k := G_{\pi_k} \downarrow G \) and \( g_k := g_{\pi_k} \uparrow g \).
1. It is clear that \( h(x) \leq f(x) \leq H(x) \) for all \( x \) and \( H(x) = h(x) \) iff \( \lim_{y \to x} f(y) \) exists and is equal to \( f(x) \). That is \( H(x) = h(x) \) iff \( f \) is continuous at \( x \).
2. For \( x \notin \pi \),
\[ G_k(x) \geq H(x) \geq f(x) \geq h(x) \geq g_k(x) \quad \forall k \]
and letting \( k \to \infty \) in this equation implies
\[ G(x) \geq H(x) \geq f(x) \geq h(x) \geq g(x) \quad \forall x \notin \pi. \]  
(8.24)
Moreover, given \( \varepsilon > 0 \) and \( x \notin \pi \),
\[ \sup \{ f(y) : |y - x| \leq \varepsilon, y \in [a,b] \} \geq G_k(x) \]
for all \( k \) large enough, since eventually \( G_k(x) \) is the supremum of \( f(y) \) over some interval contained in \([x - \varepsilon, x + \varepsilon]\). Again letting \( k \to \infty \) implies \( \sup \{ f(y) \} \geq G(x) \) and therefore, that
\[ H(x) = \limsup_{y \to x} f(y) \geq G(x) \]
for all \( x \notin \pi \). Combining this equation with Eq. (8.24) then implies \( H(x) = G(x) \) if \( x \notin \pi \). A similar argument shows that \( h(x) = g(x) \) if \( x \notin \pi \) and hence Eq. (8.23) is proved.

3. The functions \( G \) and \( g \) are limits of measurable functions and hence measurable. Since \( H = G \) and \( h = g \) except possibly on the countable set \( \pi \), both \( H \) and \( h \) are also Borel measurable. (You justify this statement.)

**Theorem 8.51.** Let \( f : [a,b] \to \mathbb{R} \) be a bounded function. Then
\[ \overline{\int_a^b} f = \int_{[a,b]} H dm \text{ and } \int_a^b f = \int_{[a,b]} h dm \]
(8.25)
and the following statements are equivalent:
1. $H(x) = h(x)$ for $m$-a.e. $x$.
2. the set $E := \{x \in [a, b] : f \text{ is discontinuous at } x\}$ is an $\bar{m} –$ null set.
3. $f$ is Riemann integrable.

If $f$ is Riemann integrable then $f$ is Lebesgue measurable, i.e. $f \in \mathcal{L}/\mathcal{B}$ – measurable where $\mathcal{L}$ is the Lebesgue $\sigma$ – algebra and $\mathcal{B}$ is the Borel $\sigma$ – algebra on $[a, b]$. Moreover if we let $\bar{m}$ denote the completion of $m$, then

$$\int_{[a, b]} H d\bar{m} = \int_{[a, b]} f(x) dx = \int_{[a, b]} f d\bar{m} = \int_{[a, b]} h d\bar{m}. \quad (8.26)$$

**Proof.** Let $\{\pi_k\}_{k=1}^\infty$ be an increasing sequence of partitions of $[a, b]$ as described in Lemma 8.48 and let $G$ and $g$ be defined as in Lemma 8.50. Since $m(\pi) = 0$, $H = G$ a.e., Eq. (8.25) is a consequence of Eqs. (8.21) and (8.22). From Eq. (8.25), $f$ is Riemann integrable iff

$$\int_{[a, b]} H d\bar{m} = \int_{[a, b]} h d\bar{m}$$

and because $h \leq f \leq H$ this happens iff $h(x) = H(x)$ for $m$ - a.e. $x$. Since $E = \{x : H(x) \neq h(x)\}$, this last condition is equivalent to $E$ being a $m$ – null set. In light of these results and Eq. (8.23), the remaining assertions including Eq. (8.26) are now consequences of Lemma 8.46.

**Notation 8.52** In view of this theorem we will often write $\int_a^b f(x)dx$ for $\int_a^b f(x) d\bar{m}$.

### 8.7 Exercises

**Exercise 8.8.** Let $\mu$ be a measure on an algebra $\mathcal{A} \subset 2^X$, then $\mu(A) + \mu(B) = \mu(A \cup B) + \mu(A \cap B)$ for all $A, B \in \mathcal{A}$.

**Exercise 8.9 (From problem 12 on p. 27 of Folland.)** Let $(X, \mathcal{M}, \mu)$ be a finite measure space and for $A, B \in \mathcal{M}$ let $\rho(A, B) = \mu(A \Delta B)$ where $A \Delta B = (A \setminus B) \cup (B \setminus A)$; It is clear that $\rho(A, B) = \rho(B, A)$. Show:

1. $\rho$ satisfies the triangle inequality:
   $$\rho(A, C) \leq \rho(A, B) + \rho(B, C) \text{ for all } A, B, C \in \mathcal{M}.$$

2. Define $A \sim B$ iff $\mu(A \Delta B) = 0$ and notice that $\rho(A, B) = 0$ iff $A \sim B$. Show “$\sim$” is an equivalence relation.
3. Let $\mathcal{M}/\sim$ denote $\mathcal{M}$ modulo the equivalence relation, $\sim$, and let $[A] := \{B \in \mathcal{M} : B \sim A\}$. Show that $\tilde{\rho}([A], [B]) := \rho(A, B)$ is a well defined metric on $\mathcal{M}/\sim$.
4. Similarly show $\tilde{\mu}([A]) = \mu(A)$ is a well defined function on $\mathcal{M}/\sim$ and show $\tilde{\mu} : (\mathcal{M}/\sim) \to \mathbb{R}_+$ is $\tilde{\rho}$ – continuous.

**Exercise 8.10.** Suppose that $\mu_n : \mathcal{M} \to [0, \infty]$ are measures on $\mathcal{M}$ for $n \in \mathbb{N}$. Also suppose that $\mu_n(A)$ is increasing in $n$ for all $A \in \mathcal{M}$. Prove that $\mu : \mathcal{M} \to [0, \infty]$ defined by $\mu(A) := \lim_{n \to \infty} \mu_n(A)$ is also a measure.

**Exercise 8.11.** Now suppose that $\mathcal{A}$ is some index set and for each $\lambda \in \mathcal{A}$, $\mu_\lambda : \mathcal{M} \to [0, \infty]$ is a measure on $\mathcal{M}$. Define $\mu : \mathcal{M} \to [0, \infty]$ by $\mu(A) = \sum_{\lambda \in \mathcal{A}} \mu_\lambda(A)$ for each $A \in \mathcal{M}$. Show that $\mu$ is also a measure.

**Exercise 8.12.** Let $(X, \mathcal{M}, \mu)$ be a measure space and $\{A_n\}_{n=1}^\infty \subset \mathcal{M}$, show

$$\mu(\{A_n \text{ a.a.}\}) \leq \liminf_{n \to \infty} \mu(A_n)$$

and if $\mu(\cup_{m \geq n} A_m) < \infty$ for some $n$, then

$$\mu(\{A_n \text{ i.o.}\}) \geq \limsup_{n \to \infty} \mu(A_n).$$

**Exercise 8.13 (Folland 2.13 on p. 52.)** Suppose that $\{f_n\}_{n=1}^\infty$ is a sequence of non-negative measurable functions such that $f_n \to f$ pointwise and

$$\lim_{n \to \infty} \int f_n = \int f < \infty.$$

Then

$$\int f = \lim_{n \to \infty} \int f_n$$

for all measurable sets $E \in \mathcal{M}$. The conclusion need not hold if $\lim_{n \to \infty} \int f_n = \int f$. Hint: “Fatou times two.”

**Exercise 8.14.** Give examples of measurable functions $\{f_n\}$ on $\mathbb{R}$ such that $f_n$ decreases to 0 uniformly yet $\int f_n dm = \infty$ for all $n$. Also give an example of a sequence of measurable functions $\{g_n\}$ on $[0, 1]$ such that $g_n \to 0$ while $\int g_n dm = 1$ for all $n$.

**Exercise 8.15.** Suppose $\{a_n\}_{n=-\infty}^{\infty} \subset \mathbb{C}$ is a summable sequence (i.e. $\sum_{n=-\infty}^{\infty} |a_n| < \infty$), then $f(\theta) := \sum_{n=-\infty}^{\infty} a_n e^{in\theta}$ is a continuous function for $\theta \in \mathbb{R}$ and

$$a_n = \frac{1}{2\pi} \int_{-\pi}^{\pi} f(\theta) e^{-in\theta} d\theta.$$
Exercise 8.16. For any function \( f \in L^1(m) \), show \( x \rightarrow \int_{(-\infty, x]} f(t) \, d\mu(t) \) is continuous in \( x \). Also find a finite measure, \( \mu \), on \( \mathcal{B}_\mathbb{R} \) such that \( x \rightarrow \int_{(-\infty, x]} f(t) \, d\mu(t) \) is not continuous.

Exercise 8.17. Folland 2.31b and 2.31e on p. 60. (The answer in 2.13b is wrong by a factor of \(-1\) and the sum is on \( k = 1 \) to \( \infty \). In part (e), \( s \) should be taken to be \( a \). You may also freely use the Taylor series expansion

\[
(1 - z)^{-1/2} = \sum_{n=0}^{\infty} \frac{(2n - 1)!!}{2^n n!} z^n = \sum_{n=0}^{\infty} \frac{(2n)!}{4^n (n!)^2} z^n \quad \text{for} \quad |z| < 1.
\]


8.7.1 Laws of Large Numbers Exercises

For the rest of the problems of this section, let \((\Omega, \mathcal{B}, P)\) be a probability space, \(\{X_n\}_{n=1}^{\infty}\) be a sequence of i.i.d. random variables, and \(S_n := \sum_{k=1}^{n} X_k\). If \(E|X_n| = E|X_1| < \infty\) let

\[
\mu := E\mu_n = \text{be the mean of } X_n,
\]

if \(E[X_n^2] = E[X_1^2] < \infty\), let

\[
\sigma^2 := E[(X_n - \mu)^2] = E[X_n^2] - \mu^2 = \text{be the standard deviation of } X_n
\]

and if \(E[|X_n|^4] < \infty\), let

\[
\gamma := E[|X_n - \mu|^4].
\]

Exercise 8.19 (A simple form of the Weak Law of Large Numbers). Assume \(E[|X_1|^2] < \infty\). Show

\[
E\left[\frac{S_n}{n}\right] = \mu,
\]

\[
E\left(\frac{S_n}{n} - \mu\right)^2 = \frac{\sigma^2}{n}, \quad \text{and}
\]

\[
P\left(\left|\frac{S_n}{n} - \mu\right| > \varepsilon\right) \leq \frac{\sigma^2}{n^2 \varepsilon^2}
\]

for all \(\varepsilon > 0\) and \(n \in \mathbb{N}\).

Exercise 8.20 (A simple form of the Strong Law of Large Numbers). Suppose now that \(E\left[|X_1|^4\right] < \infty\). Show for all \(\varepsilon > 0\) and \(n \in \mathbb{N}\) that

\[
E\left[\left(\frac{S_n}{n} - \mu\right)^4\right] = \frac{1}{n^4} \left(n\gamma + 3n(n-1)\sigma^4\right)
\]

\[
= \frac{1}{n^2} \left[n^{-1}\gamma + 3 \left(1 - n^{-1}\right) \sigma^4\right]
\]

and use this along with Chebyshev’s inequality to show

\[
P\left(\left|\frac{S_n}{n} - \mu\right| > \varepsilon\right) \leq \frac{n^{-1}\gamma + 3 \left(1 - n^{-1}\right) \sigma^4}{\varepsilon^4 n^2}.
\]

Conclude from the last estimate and the first Borel Cantelli Lemma that \(\lim_{n \to \infty} \frac{S_n}{n} = \mu\) a.s.
Functional Forms of the $\pi - \lambda$ Theorem

**Notation 9.1.** Let $\Omega$ be a set and $\mathbb{H}$ be a subset of the bounded real valued functions on $\mathbb{H}$. We say that $\mathbb{H}$ is **closed under bounded convergence** if, for every sequence, $\{f_n\}_{n=1}^{\infty} \subseteq \mathbb{H}$, satisfying:

1. there exists $M < \infty$ such that $|f_n(\omega)| \leq M$ for all $\omega \in \Omega$ and $n \in \mathbb{N}$,
2. $f(\omega) := \lim_{n \to \infty} f_n(\omega)$ exists for all $\omega \in \Omega$,

then $f \in \mathbb{H}$. Similarly we say that $\mathbb{H}$ is **closed under monotone convergence** if, for every sequence, $\{f_n\}_{n=1}^{\infty} \subseteq \mathbb{H}$, satisfying:

1. there exists $M < \infty$ such that $0 \leq f_n(\omega) \leq M$ for all $\omega \in \Omega$ and $n \in \mathbb{N}$,
2. $f(\omega)$ is increasing in $n$ for all $\omega \in \Omega$,

then $f := \lim_{n \to \infty} f_n \in \mathbb{H}$.

Clearly if $\mathbb{H}$ is closed under bounded convergence then it is also closed under monotone convergence.

**Proposition 9.2.** Let $\Omega$ be a set. Suppose that $\mathbb{H}$ is a vector subspace of bounded real valued functions from $\Omega$ to $\mathbb{R}$ which is closed under monotone convergence. Then $\mathbb{H}$ is closed under uniform convergence. as well, i.e. $\{f_n\}_{n=1}^{\infty} \subseteq \mathbb{H}$ with $\sup_{n \in \mathbb{N}} \sup_{\omega \in \Omega} |f_n(\omega)| < \infty$ and $f_n \to f$, then $f \in \mathbb{H}$.

**Proof.** Let us first assume that $\{f_n\}_{n=1}^{\infty} \subseteq \mathbb{H}$ such that $f_n$ converges uniformly to a bounded function, $f : \Omega \to \mathbb{R}$. Let $\|f\|_{\infty} := \sup_{\omega \in \Omega} |f(\omega)|$. Let $\varepsilon > 0$ be given. By passing to a subsequence if necessary, we may assume $\|f - f_n\|_{\infty} \leq \varepsilon 2^{-(n+1)}$. Let

$$g_n := f_n - \delta_n + M$$

with $\delta_n$ and $M$ constants to be determined shortly. We then have

$$g_{n+1} - g_n = f_{n+1} - f_n + \delta_n - \delta_{n+1} \geq -\varepsilon 2^{-(n+1)} + \delta_n - \delta_{n+1}.$$ 

Taking $\delta_n := \varepsilon 2^{-n}$, then $\delta_n - \delta_{n+1} = \varepsilon 2^{-n} (1 - 1/2) = \varepsilon 2^{-(n+1)}$ in which case $g_{n+1} - g_n \geq 0$ for all $n$. By choosing $M$ sufficiently large, we will also have $g_n \geq 0$ for all $n$. Since $\mathbb{H}$ is a vector space containing the constant functions, $g_{n} \in \mathbb{H}$ and since $g_n \uparrow f + M$, it follows that $f = f + M - M \in \mathbb{H}$. So we have shown that $\mathbb{H}$ is closed under uniform convergence. \hfill $\Box$

**Theorem 9.3 (Dynkin’s Multiplicative System Theorem).** Suppose that $\mathbb{H}$ is a vector subspace of bounded functions from $\Omega$ to $\mathbb{R}$ which contains the constant functions and is closed under monotone convergence. If $\mathcal{M}$ is **multiplicative system** (i.e. $\mathcal{M}$ is a subset of $\mathbb{H}$ which is closed under pointwise multiplication), then $\mathbb{H}$ contains all bounded $\sigma(\mathcal{M})$ – measurable functions.

**Proof.** Let

$$\mathcal{L} := \{A \subseteq \Omega : 1_A \in \mathbb{H}\}.$$ 

We then have $\Omega \in \mathcal{L}$ since $\{1\} = 1 \in \mathbb{H}$, if $A, B \in \mathcal{L}$ with $A \subseteq B$ then $B \setminus A \in \mathcal{L}$ since $1_B \setminus 1_A = 1_B - 1_A \in \mathbb{H}$, and if $A_n \in \mathcal{L}$ with $A_n \uparrow A$, then $A \in \mathcal{L}$ because $1_{A_n} \in \mathbb{H}$ and $1_A \uparrow 1_A \in \mathbb{H}$. Therefore $\mathcal{L}$ is $\lambda -$ system.

Let $\varphi_n(x) = 0 \lor \lceil nx \rceil 1$ (see Figure 9.1 below) so that $\varphi_n(x) \uparrow 1_{x > 0}$. Given $f_1, f_2, \ldots, f_k \in M$ and $a_1, \ldots, a_k \in \mathbb{R}$, let

$$F_n := \prod_{i=1}^{k} \varphi_n(f_i - a_i)$$

and let

$$M := \sup_{i=1}^{k} \sup_{\omega \in \Omega} |f_i(\omega) - a_i|.$$ 

By the Weierstrass approximation Theorem 4.2, we may find polynomial functions, $p_i(x)$ such that $p_i \to \varphi_n$ uniformly on $[-M, M]$. Since $p_i$ is a polynomial it is easily seen that $\prod_{i=1}^{k} p_i \circ (f_i - a_i) \in \mathbb{H}$. Moreover,

$$\prod_{i=1}^{k} p_i \circ (f_i - a_i) \to F_n \text{ uniformly as } l \to \infty,$$

from with it follows that $F_n \in \mathbb{H}$ for all $n$. Since,

$$F_n \uparrow \prod_{i=1}^{k} 1_{\{f_i > a_i\}} = 1_{\bigcap_{i=1}^{k} \{f_i > a_i\}}$$

it follows that $1_{\bigcap_{i=1}^{k} \{f_i > a_i\}} \in \mathbb{H}$ or equivalently that $\bigcap_{i=1}^{k} \{f_i > a_i\} \in \mathcal{L}$. Therefore $\mathcal{L}$ contains the $\pi -$ system, $\mathcal{P}$, consisting of finite intersections of sets of the form, $\{f > a\}$ with $f \in \mathcal{M}$ and $a \in \mathbb{R}$.
As a consequence of the above paragraphs and the \( \pi - \lambda \) Theorem \[7,4\] \( \mathcal{L} \) contains \( \sigma (P) = \sigma (M) \). In particular it follows that \( 1_A \in H \) for all \( A \in \sigma (M) \). Since any positive \( \sigma (M) \) \- measurable function may be written as an increasing limit of simple functions, it follows that \( H \) contains all non-negative bounded \( \sigma (M) \) \- measurable functions. Finally, since any bounded \( \sigma (M) \) \- measurable functions may be written as the difference of two such non-negative simple functions, it follows that \( H \) contains all bounded \( \sigma (M) \) \- measurable functions.

**Corollary 9.4.** Suppose that \( H \) is a vector subspace of bounded functions from \( \Omega \) to \( \mathbb{R} \) which contains the constant functions and is closed under bounded convergence. If \( M \) is a subset of \( H \) which is closed under pointwise multiplication, then \( H \) contains all bounded \( \sigma (M) \) \- measurable functions.

**Proof.** This is of course a direct consequence of Theorem \[9.3\]. Moreover, under the assumptions here, the proof of Theorem \[9.3\] simplifies in that Proposition \[9.2\] is no longer needed. For fun, let us give another self-contained proof of this corollary which does not even refer to the \( \pi - \lambda \) theorem.

In this proof, we will assume that \( H \) is the smallest subspace of bounded functions on \( \Omega \) which contains the constant functions, contains \( M \), and is closed under bounded convergence. (As usual such a space exists by taking the intersection of all such spaces.)

For \( f \in H \), let \( \mathbb{H}^f := \{ g \in H : fg \in H \} \). The reader will now easily verify that \( \mathbb{H}^f \) is a linear subspace of \( H \), \( 1 \in \mathbb{H}^f \), and \( \mathbb{H}^f \) is closed under bounded convergence. Moreover if \( f \in M \), then \( M \subset \mathbb{H}^f \) and so by the definition of \( H \), \( \mathbb{H} = \mathbb{H}^f \), i.e. \( fg \in H \) for all \( f \in M \) and \( g \in H \). Having proved this it now follows for any \( f \in H \) that \( M \subset \mathbb{H}^f \) and therefore \( fg \in H \) whenever \( f, g \in H \), i.e. \( H \) is now an algebra of functions.

We will now show that \( B := \{ A \subset \Omega : 1_A \in H \} \) is \( \sigma \) \- algebra. Using the fact that \( H \) is an algebra containing constants, the reader will easily verify that \( B \) is closed under complementation, finite intersections, and contains \( \Omega \), i.e. \( B \) is an algebra. Using the fact that \( H \) is closed under bounded convergence, it follows that \( B \) is closed under increasing unions and hence that \( B \) is \( \sigma \) \- algebra.

Since \( H \) is a vector space, \( H \) contains all \( B \) \- measurable simple functions. Since every bounded \( B \) \- measurable function may be written as a bounded limit of such simple functions, it follows that \( H \) contains all bounded \( B \) \- measurable functions. The proof is now completed by showing \( B \) contains \( \sigma (M) \) as was done in second paragraph of the proof of Theorem \[9.3\].

**Exercise 9.1.** Let \( (\Omega, B, P) \) be a probability space and \( X, Y : \Omega \rightarrow \mathbb{R} \) be a pair of random variables such that

\[
\mathbb{E} [f(X)g(Y)] = \mathbb{E} [f(X)g(X)]
\]

for every pair of bounded measurable functions, \( f, g : \mathbb{R} \rightarrow \mathbb{R} \). Show \( P(X = Y) = 1 \). Hint: Let \( H \) denote the bounded Borel measurable functions, \( h : \mathbb{R}^2 \rightarrow \mathbb{R} \) such that

\[
\mathbb{E} [h(X,Y)] = \mathbb{E} [h(X,X)] .
\]

Use Corollary \[9.4\] to show \( H \) is the vector space of all bounded Borel measurable functions. Then take \( h(x,y) = 1_{\{x=y\}} \).

**Corollary 9.5.** Suppose \( H \) is a real subspace of bounded functions such that \( 1 \in H \) and \( H \) is closed under bounded convergence. If \( \mathcal{P} \subset 2^{\mathbb{R}} \) is a multiplicative class such that \( 1_A \in H \) for all \( A \in \mathcal{P} \), then \( H \) contains all bounded \( \sigma (\mathcal{P}) \) \- measurable functions.

**Proof.** Let \( \mathbb{M} = \{1\} \cup \{1_A : A \in \mathcal{P} \} \). Then \( \mathbb{M} \subset H \) is a multiplicative system and the proof is completed with an application of Theorem \[9.3\].

**Example 9.6.** Suppose \( \mu \) and \( \nu \) are two probability measure on \( (\Omega, B) \) such that

\[
\int_{\Omega} f d\mu = \int_{\Omega} f d\nu \quad \text{(9.1)}
\]

for all \( f \) in a multiplicative subset, \( \mathbb{M} \), of bounded measurable functions on \( \Omega \). Then \( \mu = \nu \) on \( \sigma (M) \). Indeed, apply Theorem \[9.3\] with \( H \) being the bounded measurable functions on \( \Omega \) such that Eq. (9.1) holds. In particular if \( \mathbb{M} = \{1\} \cup \{1_A : A \in \mathcal{P} \} \) with \( \mathcal{P} \) being a multiplicative class we learn that \( \mu = \nu \) on \( \sigma (M) = \sigma (\mathcal{P}) \).

**Corollary 9.7.** The smallest subspace of real valued functions, \( H \), on \( \mathbb{R} \) which contains \( C_b(\mathbb{R}, \mathbb{R}) \) \( \text{(the space of continuous functions on } \mathbb{R} \text{ with compact support)} \) is the collection of bounded Borel measurable function on \( \mathbb{R} \).
Proof. By a homework problem, for $-\infty < a < b < \infty$, $1_{(a,b]}$ may be written as a bounded limit of continuous functions with compact support from which it follows that $\sigma(C_c(\mathbb{R}, \mathbb{R})) = \mathcal{B}_\mathbb{R}$. It is also easy to see that $1$ is a bounded limit of functions in $C_c(\mathbb{R}, \mathbb{R})$ and hence $1 \in \mathcal{H}$. The corollary now follows by an application of Theorem 9.9 with $\mathcal{M} := C_c(\mathbb{R}, \mathbb{R})$.

For the rest of this chapter, recall for $p \in [1, \infty)$ that $L^p(\mu) = L^p(X, \mathcal{B}, \mu)$ is the set of measurable functions $f : \Omega \to \mathbb{R}$ such that $\|f\|_{L^p} := (\int |f|^p \, d\mu)^{1/p} < \infty$. It is easy to see that $\|xf\|_{L^p} = |x| \|f\|_p$ for all $x \in \mathbb{R}$ and we will show below that
\[
\|f + g\|_p \leq \|f\|_p + \|g\|_p \quad \text{for all } f, g \in L^p(\mu),
\]
i.e. $\|\cdot\|_p$ satisfies the triangle inequality.

**Theorem 9.8 (Density Theorem).** Let $p \in [1, \infty)$, $(\Omega, \mathcal{B}, \mu)$ be a measure space and $\mathcal{M}$ be an algebra of bounded $\mathbb{R}$ - valued measurable functions such that

1. $\mathcal{M} \subset L^p(\mu, \mathbb{R})$ and $\sigma(\mathcal{M}) = \mathcal{B}$.
2. There exists $\psi_k \in \mathcal{M}$ such that $\psi_k \to 1$ boundedly.

Then to every function $f \in L^p(\mu, \mathbb{R})$, there exist $\varphi_n \in \mathcal{M}$ such that $\lim_{n \to \infty} \|f - \varphi_n\|_{L^p(\mu)} = 0$, i.e. $\mathcal{M}$ is dense in $L^p(\mu, \mathbb{R})$.

**Proof.** Fix $k \in \mathbb{N}$ for the moment and let $\mathbb{H}$ denote those bounded $\mathbb{B}$ - measurable functions, $f : \Omega \to \mathbb{R}$, for which there exists $\{\varphi_n\}_{n=1}^\infty \subset \mathcal{M}$ such that $\lim_{n \to \infty} \|\psi_k f - \varphi_n\|_{L^p(\mu)} = 0$. A routine check shows $\mathbb{H}$ is a subspace of the bounded measurable $\mathbb{R}$ - valued functions on $\Omega$, i.e. $\mathbb{H} \subset \mathcal{H}$ and $\mathbb{H}$ is closed under bounded convergence. To verify the latter assertion, suppose $f_n \in \mathbb{H}$ and $f_n \to f$ boundedly. Then, by the dominated convergence theorem, $\lim_{n \to \infty} \|\psi_k f - f\|_{L^p(\mu)} = 0$. (Take the dominating function to be $g = [2C |f|]^p$ where $C$ is a constant bounding all of the $\{f_n\}_{n=1}^\infty$.) We may now choose $\varphi_n \in \mathcal{M}$ such that $\|\varphi_n - \psi_k f_n\|_{L^p(\mu)} \leq \frac{1}{n}$ then
\[
\lim_{n \to \infty} \sup \|\psi_k f - \varphi_n\|_{L^p(\mu)} \leq \lim_{n \to \infty} \sup \|\psi_k (f - f_n)\|_{L^p(\mu)} + \lim_{n \to \infty} \|\psi_k f_n - \varphi_n\|_{L^p(\mu)} = 0
\]
(9.2)
which implies $f \in \mathbb{H}$.

An application of Dynkin’s Multiplicative System Theorem 9.3 now shows $\mathbb{H}$ contains all bounded measurable functions on $\Omega$. Let $f \in L^p(\mu)$ be given. The dominated convergence theorem implies $\lim_{n \to \infty} \|\psi_k 1_{\{|f| \leq k\}} f - f\|_{L^p(\mu)} = 0$.

(Take the dominating function to be $g = [2C |f|]^p$ where $C$ is a bound on all of the $\{\psi_k\}$.) Using this and what we have just proved, there exists $\varphi_k \in \mathcal{M}$ such that
\[
\|\psi_k 1_{\{|f| \leq k\}} f - \varphi_k\|_{L^p(\mu)} \leq \frac{1}{k}
\]
The same line of reasoning used in Eq. (9.2) now implies $\lim_{k \to \infty} \|f - \varphi_k\|_{L^p(\mu)} = 0$.

**Example 9.9.** Let $\mu$ be a measure on $(\mathbb{R}, \mathcal{B}_\mathbb{R})$ such that $\mu([-\infty, M]) < \infty$ for all $M < \infty$. Then $C_c(\mathbb{R}, \mathbb{R})$ (the space of continuous functions on $\mathbb{R}$ with compact support) is dense in $L^p(\mu)$ for all $1 \leq p < \infty$. To see this, apply Theorem 9.8, with $\mathcal{M} = C_c(\mathbb{R}, \mathbb{R})$ and $\psi_k := 1_{[-k,k]}$.

**Theorem 9.10.** Suppose $p \in [1, \infty)$, $\mathcal{A} \subset \mathcal{B} \subset 2^\Omega$ is an algebra such that $\sigma(\mathcal{A}) = \mathcal{B}$ and $\mu$ is $\sigma$ - finite on $\mathcal{A}$. Let $\mathcal{S}(\mathcal{A}, \mu)$ denote the measurable simple functions, $\varphi : \Omega \to \mathbb{R}$ such $\{\varphi = y\} \in \mathcal{A}$ for all $y \in \mathbb{R}$ and $\mu(\{\varphi \neq 0\}) < \infty$. Then $\mathcal{S}(\mathcal{A}, \mu)$ is dense subspace of $L^p(\mu)$.

**Proof.** Let $\mathcal{M} := \mathcal{S}(\mathcal{A}, \mu)$. By assumption there exists $\Omega_k \in \mathcal{A}$ such that $\mu(\Omega_k) < \infty$ and $\Omega_k \uparrow \Omega$ as $k \to \infty$. If $A \in \mathcal{A}$, then $\Omega_k \cap A \in \mathcal{A}$ and $\mu(\Omega_k \cap A) < \infty$ so that $\Omega_k \cap A \in \mathcal{M}$. Therefore $1_A = \lim_{k \to \infty} 1_{\Omega_k \cap A}$ is $\sigma(\mathcal{M})$ - measurable for every $A \in \mathcal{A}$. So we have shown that $\mathcal{A} \subset \sigma(\mathcal{M}) \subset \mathcal{B}$ and therefore $\mathcal{B} = \sigma(\mathcal{A}) \subset \sigma(\mathcal{M}) \subset \mathcal{B}$, i.e. $\sigma(\mathcal{M}) = \mathcal{B}$. The theorem now follows from Theorem 9.8 after observing $\psi_k := 1_{\Omega_k} \in \mathcal{M}$ and $\psi_k \to 1$ boundedly.

**Theorem 9.11 (Separability of $L^p$ - Spaces).** Suppose, $p \in [1, \infty)$, $\mathcal{A} \subset \mathcal{B}$ is a countable algebra such that $\sigma(\mathcal{A}) = \mathcal{B}$ and $\mu$ is $\sigma$ - finite on $\mathcal{A}$. Then $L^p(\mu)$ is separable and
\[
\mathcal{D} = \{ \sum a_j 1_{A_j} : a_j \in \mathbb{Q} + i\mathbb{Q}, A_j \in \mathcal{A} \text{ with } \mu(A_j) < \infty \}
\]
is a countable dense subset.

**Proof.** It is left to reader to check $\mathcal{D}$ is dense in $\mathcal{S}(\mathcal{A}, \mu)$ relative to the $L^p(\mu)$ - norm. Once this is done, the proof is then complete since $\mathcal{S}(\mathcal{A}, \mu)$ is a dense subspace of $L^p(\mu)$ by Theorem 9.10.

**Notation 9.12** Given a collection of bounded functions, $\mathcal{M}$, from a set, $\Omega$, to $\mathbb{R}$, let $\mathcal{M}_1$ ($\mathcal{M}_+^1$) denote the bounded monotone increasing (decreasing) limits of functions from $\mathcal{M}$. More explicitly a bounded function, $f : \Omega \to \mathbb{R}$ is in $\mathcal{M}_1$ respectively $\mathcal{M}_+^1$ iff there exists $f_n \in \mathcal{M}$ such that $f_n \uparrow f$ respectively $f_n \downarrow f$.

**Theorem 9.13 (Bounded Approximation Theorem).** Let $(\Omega, \mathcal{B}, \mu)$ be a finite measure space and $\mathcal{M}$ be an algebra of bounded $\mathbb{R}$ - valued measurable functions such that:

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1. It is at this point that the proof would break down if $p = \infty$. 

1. $\sigma(M) = B$.
2. $1 \in M$ and 
3. $|f| \in M$ for all $f \in M$.

Then for every bounded $\sigma(M)$ measurable function, $g : \Omega \to \mathbb{R}$, and every $\varepsilon > 0$, there exists $f \in M_1$ and $h \in M_1$ such that $f \leq g \leq h$ and $\mu(h - f) < \varepsilon$.

**Proof.** Let us begin with a few simple observations.

1. $M$ is a “lattice” – if $f, g \in M$ then
   
   $$f \lor g = \frac{1}{2}(f + g + |f - g|) \in M$$
   
   and
   
   $$f \land g = \frac{1}{2}(f + g - |f - g|) \in M.$$  

2. If $f, g \in M_1$ then $f + g \in M_1$ or $f + g \in M_1$ respectively.
3. If $\lambda \geq 0$ and $f, g \in M_1$, then $\lambda f \in M_1$ ($\lambda f \in M_1$).
4. If $f \in M_1$, then $-f \in M_1$ and visa versa.
5. If $f_n \in M_1$ and $f_n \uparrow f$ where $f : \Omega \to \mathbb{R}$ is a bounded function, then $f \in M_1$.

Indeed, by assumption there exist $f_{n,i} \in M$ such that $f_{n,i} \uparrow f_n$ as $i \to \infty$. By observation (1), $g_n := \max\{f_{i,j} : i, j \leq n\} \in M$. Moreover it is clear that $g_n \leq \max\{f_k : k \leq n\} = f_n \leq f$ and hence $g_n \uparrow g := \lim_{n \to \infty} g_n \leq f$. Since $f_{i,j} \leq g$ for all $i, j$, it follows that $f_n = \lim_{n \to \infty} f_{i,j} \leq g$ and consequently that $f = \lim_{n \to \infty} f_n \leq g \leq f$. So we have shown that $g_n \uparrow f \in M_1$.

Now let $\mathbb{H}$ denote the collection of bounded measurable functions which satisfy the assertion of the theorem. Clearly, $M \subset \mathbb{H}$ and in fact it is also easy to see that $M_1$ and $M_2$ are contained in $\mathbb{H}$ as well. For example, if $f \in M_1$, by definition, there exist $f_n \in M \subset M_1$ such that $f_n \uparrow f$. Since $M_1 \ni f_n \leq f \in M_1$ and $\mu(f - f_n) \to 0$ by the dominated convergence theorem, it follows that $f \in \mathbb{H}$. As similar argument shows $M_1 \subset \mathbb{H}$. We will now show $\mathbb{H}$ is a vector sub-space of the bounded $\mathcal{B} = \sigma(M)$ – measurable functions.

$\mathbb{H}$ is closed under addition. If $g_i \in \mathbb{H}$ for $i = 1, 2$, and $\varepsilon > 0$ is given, we may find $f_i \in M_1$ and $h_i \in M_1$ such that $f_i \leq g_i \leq h_i$ and $\mu(h_i - f_i) < \varepsilon/2$ for $i = 1, 2$. Since $h = h_1 + h_2 \in M_1$, $f := f_1 + f_2 \in M_1$, $f \leq g_1 + g_2 \leq h$, and

$$\mu(h - f) = \mu(h_1 - f_1) + \mu(h_2 - f_2) < \varepsilon,$$

it follows that $g_1 + g_2 \in \mathbb{H}$.

$\mathbb{H}$ is closed under scalar multiplication. If $g \in \mathbb{H}$ then $\lambda g \in \mathbb{H}$ for all $\lambda \in \mathbb{R}$. Indeed suppose that $\varepsilon > 0$ is given and $f \in M_1$ and $h \in M_1$ such that $f \leq g \leq h$ and $\mu(h - f) < \varepsilon$. Then for $\lambda \geq 0$, $\lambda f \leq \lambda g \leq \lambda h \in M_1$ and

$$\mu(\lambda h - \lambda f) = \lambda \mu(h - f) < \lambda \varepsilon.$$

Since $\varepsilon > 0$ was arbitrary, it follows that $\lambda g \in \mathbb{H}$ for $\lambda \geq 0$. Similarly, $M_1 \ni -h \leq -g \leq -f \in M_1$ and

$$\mu(-f - (-h)) = \mu(h - f) < \varepsilon.$$

which shows $-g \in \mathbb{H}$ as well.

Because of Theorem 9.3 to complete this proof, it suffices to show $\mathbb{H}$ is closed under monotone convergence. So suppose that $g_n \in \mathbb{H}$ and $g_n \uparrow g$, where $g : \Omega \to \mathbb{R}$ is a bounded function. Since $\mathbb{H}$ is a vector space, it follows that $0 \leq \delta_n := g_{n+1} - g_n \in \mathbb{H}$ for all $n \in \mathbb{N}$. If $\varepsilon > 0$ is given, we can find, $M_1 \ni u_n \leq \delta_n \leq \delta_n \leq u_n \in M_1$, such that $\mu(u_n - u_n) \leq 2^{-n}\varepsilon$ for all $n$. By replacing $u_n$ by $u_n \vee 0 \in M_1$ (by observation 1), we may further assume that $u_n \geq 0$. Let

$$v := \sum_{n=1}^{\infty} u_n = \lim_{N \to \infty} \sum_{n=1}^{N} u_n \in M_1 \quad \text{(using observations 2. and 5.)}$$

and for $N \in \mathbb{N}$, let

$$u_N := \sum_{n=1}^{N} u_n \in M_1 \quad \text{(using observation 2)}.$$

Then

$$\sum_{n=1}^{\infty} \delta_n = \lim_{N \to \infty} \sum_{n=1}^{N} \delta_n = \lim_{N \to \infty} (g_{N+1} - g_1) = g - g_1$$

and $u_N \leq g - g_1 \leq v$. Moreover,

$$\mu(v - u_N) = \sum_{n=1}^{N} \mu(v_n) \leq \sum_{n=1}^{\infty} \mu(v_n) + \sum_{n=N+1}^{\infty} \mu(v_n) \leq \varepsilon + \sum_{n=N+1}^{\infty} \mu(v_n).$$

However, since

$$\sum_{n=1}^{\infty} \mu(v_n) \leq \sum_{n=1}^{\infty} \mu(\delta_n + \varepsilon 2^{-n}) = \sum_{n=1}^{\infty} \mu(\delta_n) + \varepsilon \mu(\Omega) = \sum_{n=1}^{\infty} \mu(g - g_1) + \varepsilon \mu(\Omega) < \infty,$$

it follows that for $N \in \mathbb{N}$ sufficiently large that $\sum_{n=N+1}^{\infty} \mu(v_n) < \varepsilon$. Therefore, for this $N$, we have $\mu(v - u_N) < 2\varepsilon$ and since $\varepsilon > 0$ is arbitrary, it follows that $g - g_1 \in \mathbb{H}$. Since $g_1 \in \mathbb{H}$ and $\mathbb{H}$ is a vector space, we may conclude that $g = (g - g_1) + g_1 \in \mathbb{H}$. Q.E.D
**Theorem 9.14 (Complex Multiplicative System Theorem).** Suppose \( \mathbb{H} \) is a complex linear subspace of the bounded complex functions on \( \Omega \), \( 1 \in \mathbb{H} \), \( \mathbb{H} \) is closed under complex conjugation, and \( \mathbb{H} \) is closed under bounded convergence. If \( \mathcal{M} \subset \mathbb{H} \) is multiplicative system which is closed under conjugation, then \( \mathbb{H} \) contains all bounded complex valued \( \sigma(\mathcal{M}) \)-measurable functions.

**Proof.** Let \( \mathbb{M}_0 = \text{span}_c(\mathcal{M} \cup \{1\}) \) be the complex span of \( \mathcal{M} \). As the reader should verify, \( \mathbb{M}_0 \) is an algebra, \( \mathbb{M}_0 \subset \mathbb{H} \), \( \mathbb{M}_0 \) is closed under complex conjugation and \( \sigma(\mathbb{M}_0) = \sigma(\mathcal{M}) \). Let

\[
\mathbb{H}^R := \{ f \in \mathbb{H} : f \text{ is real valued} \} \quad \text{and} \quad \mathbb{M}_0^R := \{ f \in \mathbb{M}_0 : f \text{ is real valued} \}.
\]

Then \( \mathbb{H}^R \) is a real linear space of bounded real valued functions which is closed under bounded convergence and \( \mathbb{M}_0^R \subset \mathbb{H}^R \). Moreover, \( \mathbb{M}_0^R \) is a multiplicative system (as the reader should check) and therefore by Theorem 9.3, \( \mathbb{H}^R \) contains all bounded \( \sigma(\mathbb{M}_0^R) \)-measurable real valued functions. Since \( \mathbb{H} \) and \( \mathbb{M}_0 \) are complex linear spaces closed under complex conjugation, for any \( f \in \mathbb{H} \) or \( f \in \mathbb{M}_0 \), the functions \( \text{Re} \, f = \frac{1}{2} (f + \bar{f}) \) and \( \text{Im} \, f = \frac{1}{2} (f - \bar{f}) \) are in \( \mathbb{H} \) or \( \mathbb{M}_0 \) respectively. Therefore \( \mathbb{M}_0 = \mathbb{M}_0^R + i\mathbb{M}_0^R \), \( \sigma(\mathbb{M}_0^R) = \sigma(\mathbb{M}_0) = \sigma(\mathcal{M}) \), and \( \mathbb{H} = \mathbb{H}^R + i\mathbb{H}^R \). Hence if \( f : \Omega \to \mathbb{C} \) is a bounded \( \sigma(\mathcal{M}) \)-measurable function, then \( f = \text{Re} \, f + i \text{Im} \, f \in \mathbb{H} \) since \( \text{Re} \, f \) and \( \text{Im} \, f \) are in \( \mathbb{H}^R \). \( \blacksquare \)
Multiple and Iterated Integrals

10.1 Iterated Integrals

**Notation 10.1** (Iterated Integrals) If \((X, \mathcal{M}, \mu)\) and \((Y, \mathcal{N}, \nu)\) are two measure spaces and \(f : X \times Y \to \mathbb{C}\) is a \(\mathcal{M} \otimes \mathcal{N}\) - measurable function, the **iterated integrals** of \(f\) (when they make sense) are:

\[
\int_X \, d\mu(x) \int_Y \, d\nu(y) f(x,y) := \int_X \left[ \int_Y \, f(x,y) \, d\nu(y) \right] \, d\mu(x)
\]

and

\[
\int_Y \, d\nu(y) \int_X \, d\mu(x) f(x,y) := \int_Y \left[ \int_X \, f(x,y) \, d\mu(x) \right] \, d\nu(y).
\]

**Notation 10.2** Suppose that \(f : X \to \mathbb{C}\) and \(g : Y \to \mathbb{C}\) are functions, let \(f \otimes g\) denote the function on \(X \times Y\) given by

\[
f \otimes g(x,y) = f(x)g(y).
\]

Notice that if \(f, g\) are measurable, then \(f \otimes g\) is \((\mathcal{M} \otimes \mathcal{N}, \mathcal{B}_{\mathbb{C}})\) - measurable.

To prove this let \(F(x,y) = f(x)\) and \(G(x,y) = g(y)\) so that \(f \otimes g = F \cdot G\) will be measurable provided that \(F\) and \(G\) are measurable. Now \(F = f \circ \pi_1\) where \(\pi_1 : X \times Y \to X\) is the projection map. This shows that \(F\) is the composition of measurable functions and hence measurable. Similarly one shows that \(G\) is measurable.

10.2 Tonelli’s Theorem and Product Measure

**Theorem 10.3.** Suppose \((X, \mathcal{M}, \mu)\) and \((Y, \mathcal{N}, \nu)\) are \(\sigma\)-finite measure spaces and \(f\) is a nonnegative \((\mathcal{M} \otimes \mathcal{N}, \mathcal{B}_{\mathbb{R}})\) - measurable function, then for each \(y \in Y\),

\[
x \to f(x, y) \text{ is } \mathcal{M} - \mathcal{B}_{[0, \infty]} \text{ measurable}, \quad (10.1)
\]

for each \(x \in X\),

\[
y \to f(x, y) \text{ is } \mathcal{N} - \mathcal{B}_{[0, \infty]} \text{ measurable}, \quad (10.2)
\]

\[
x \to \int_Y f(x, y) \, d\nu(y) \text{ is } \mathcal{M} - \mathcal{B}_{[0, \infty]} \text{ measurable,} \quad (10.3)
\]

\[
y \to \int_X f(x, y) \, d\mu(x) \text{ is } \mathcal{N} - \mathcal{B}_{[0, \infty]} \text{ measurable,} \quad (10.4)
\]

and

\[
\int_Y \, d\nu(y) \int_X \, d\mu(x) f(x,y) = \int_X \, d\mu(x) \int_Y \, d\nu(y) f(x,y). \quad (10.5)
\]

**Proof.** Suppose that \(E = A \times B \in \mathcal{E} := \mathcal{M} \times \mathcal{N}\) and \(f = 1_E\). Then

\[
f(x, y) = 1_{A \times B}(x,y) = 1_A(x)1_B(y)
\]

and one sees that Eqs. (10.1) and (10.2) hold. Moreover

\[
\int_Y f(x,y) \, d\nu(y) = \int_Y 1_A(x)1_B(y) \, d\nu(y) = 1_A(x)\nu(B),
\]

so that Eq. (10.3) holds and we have

\[
\int_X d\mu(x) \int_Y d\nu(y) f(x,y) = \nu(B)\mu(A). \quad (10.6)
\]

Similarly,

\[
\int_Y d\nu(y) \int_X d\mu(x) f(x,y) = \nu(B)\mu(A)
\]

from which it follows that Eqs. (10.4) and (10.5) hold in this case as well.

For the moment let us now further assume that \(\mu(X) < \infty\) and \(\nu(Y) < \infty\) and let \(\mathcal{H}\) be the collection of all bounded \((\mathcal{M} \otimes \mathcal{N}, \mathcal{B}_{\mathbb{R}})\) - measurable functions on \(X \times Y\) such that Eqs. (10.1) – (10.5) hold. Using the fact that measurable functions are closed under pointwise limits and the dominated convergence theorem (the dominating function always being a constant), one easily shows that \(\mathcal{H}\) closed under bounded convergence. Since we have just verified that \(1_E \in \mathcal{H}\) for all \(E\) in the \(\pi\) - class, \(\mathcal{E}\), it follows by Corollary 9.5 that \(\mathcal{H}\) is the space...
of all bounded \((\mathcal{M} \otimes \mathcal{N}, B_{\mathbb{R}})\) – measurable functions on \(X \times Y\). Moreover, if \(f : X \times Y \to [0, \infty]\) is a \((\mathcal{M} \otimes \mathcal{N}, B_{\mathbb{R}})\) – measurable function, let \(f_M = M \land f\) so that \(f_M \uparrow f\) as \(M \to \infty\). Then Eqs. (10.1) – (10.5) hold with \(f\) replaced by \(f_M\) for all \(M \in \mathbb{N}\). Repeated use of the monotone convergence theorem allows us to pass to the limit \(M \to \infty\) in these equations to deduce the theorem in the case \(\mu\) and \(\nu\) are finite measures.

For the \(\sigma\) – finite case, choose \(X_n \in \mathcal{M}, Y_n \in \mathcal{N}\) such that \(X_n \uparrow X, Y_n \uparrow Y, \mu(X_n) < \infty\) and \(\nu(Y_n) < \infty\) for all \(n \in \mathbb{N}\). Then define \(\mu_m(A) = \mu(X_m \cap A)\) and \(\nu_n(B) = \nu(Y_n \cap B)\) for all \(A \in \mathcal{M}\) and \(B \in \mathcal{N}\) or equivalently \(d\mu_m = 1_{X_m} \, d\mu\) and \(d\nu_n = 1_{Y_n} \, d\nu\). By what we have just proved Eqs. (10.1) – (10.5) then follow by passing to the limits \(m \to \infty\) and then \(n \to \infty\) making use of the monotone convergence theorem in the following context. For all \(u \in L^+(X, \mathcal{M})\),

\[
\int_X u \, d\mu_m = \int_X u \, 1_{X_m} \, d\mu \uparrow \int_X u \, d\mu \quad \text{as} \quad m \to \infty,
\]

and for all \(v \in L^+(Y, \mathcal{N})\),

\[
\int_Y v \, d\nu_m = \int_Y v \, 1_{Y_m} \, d\nu \uparrow \int_Y v \, d\nu \quad \text{as} \quad n \to \infty.
\]

\[\text{Corollary 10.4.} \quad \text{Suppose} \quad (X, \mathcal{M}, \mu) \quad \text{and} \quad (Y, \mathcal{N}, \nu) \quad \text{are} \quad \sigma\quad \text{– finite measure spaces. Then there exists a unique measure} \ \pi \quad \text{on} \quad \mathcal{M} \otimes \mathcal{N} \quad \text{such that} \quad \pi(A \times B) = \mu(A) \nu(B) \quad \text{for all} \ A \in \mathcal{M} \quad \text{and} \ B \in \mathcal{N}. \quad \text{Moreover} \ \pi \quad \text{is given by}
\]

\[
\pi(E) = \int_X \mu(x) \int_Y \nu(y) 1_E(x, y) \, d\mu(x) \, d\nu(y) = \int_Y \nu(y) \int_X \mu(x) 1_E(x, y) \, d\mu(x) \, d\nu(y) \quad \text{(10.7)}
\]

\[\text{for all} \ E \in \mathcal{M} \otimes \mathcal{N} \quad \text{and} \ \pi \quad \text{is} \ \sigma\quad \text{– finite.}
\]

\[\text{Proof.} \quad \text{Notice that any measure} \ \pi \quad \text{such that} \ \pi(A \times B) = \mu(A) \nu(B) \quad \text{for all} \ A \in \mathcal{M} \quad \text{and} \ B \in \mathcal{N} \quad \text{is necessarily} \ \sigma\quad \text{– finite. Indeed, let} \ X_n \in \mathcal{M} \quad \text{and} \ Y_n \in \mathcal{N} \quad \text{be chosen so that} \ \mu(X_n) < \infty, \ \nu(Y_n) < \infty, \ X_n \uparrow X \quad \text{and} \ Y_n \uparrow Y; \ \text{then} \ X_n \times Y_n \in \mathcal{M} \otimes \mathcal{N}, \ X_n \times Y_n \uparrow X \times Y \quad \text{and} \ \pi(X_n \times Y_n) < \infty \quad \text{for all} \ n. \ \text{The uniqueness assertion is a consequence of the combination of Exercises 1.5 and 5.1 Proposition 4.26 with} \ \mathcal{E} = \mathcal{M} \otimes \mathcal{N}. \ \text{For the existence,} \ \text{it suffices to observe, using the monotone convergence theorem, that} \ \pi \quad \text{defined in Eq. (10.7)} \quad \text{is a measure on} \ \mathcal{M} \otimes \mathcal{N}. \ \text{Moreover this measure satisfies} \ \pi(A \times B) = \mu(A) \nu(B) \quad \text{for all} \ A \in \mathcal{M} \quad \text{and} \ B \in \mathcal{N} \quad \text{from Eq. (10.6).}
\]

\[\text{Notation 10.5} \quad \text{The measure} \ \pi \quad \text{is called the product measure of} \ \mu \quad \text{and} \ \nu \quad \text{and} \ \text{will be denoted by} \ \mu \otimes \nu.
\]

\[\text{Theorem 10.6 (Tonelli’s Theorem).} \quad \text{Suppose} \quad (X, \mathcal{M}, \mu) \quad \text{and} \quad (Y, \mathcal{N}, \nu) \quad \text{are} \ \sigma\quad \text{– finite measure spaces and} \ \pi = \mu \otimes \nu \quad \text{is the product measure on} \ \mathcal{M} \otimes \mathcal{N}. \quad \text{If} \ f \quad \text{is} \mathcal{M} \otimes \mathcal{N} \quad \text{measurable,} \ \text{then} \ f(\cdot, y) \quad \text{is} \mathcal{L}(X, \mathcal{M}) \quad \text{for all} \ y \in Y, \ f(x, \cdot) \quad \text{is} \mathcal{L}(Y, \mathcal{N}) \quad \text{for all} \ x \in X,
\]

\[
\int_Y f(\cdot, y) \, d\nu(y) \in \mathcal{L}(X, \mathcal{M}), \quad \int_X f(x, \cdot) \, d\mu(x) \in \mathcal{L}(Y, \mathcal{N})
\]

\[\text{and}
\]

\[
\int_{X \times Y} f \, d\pi = \int_X f(x) \, d\mu(x) \int_Y f(x, y) \, d\nu(y) = \int_Y f(y) \, d\nu(y) \int_X f(x) \, d\mu(x).
\]

\[\text{Proof.} \quad \text{By Theorem 10.3 and Corollary 10.4 the theorem holds when} \ f = 1_E \quad \text{with} \ E \in \mathcal{M} \otimes \mathcal{N}. \ \text{Using the linearity of all of the statements, the theorem is also true for non-negative simple functions. Then using the monotone convergence theorem repeatedly along with the approximation Theorem 6.32 one deduces the theorem for general} \ f \in \mathcal{L}^+(X \times Y, \mathcal{M} \otimes \mathcal{N}).
\]

\[\text{Example 10.7.} \quad \text{In this example we are going to show} \ I := \int_{\mathbb{R}} e^{-x^2/2} \, dm(x) = \sqrt{2\pi}. \ \text{To this end} \ \text{we observe, using Tonelli’s theorem, that}
\]

\[
I^2 = \left[ \int_{\mathbb{R}} e^{-x^2/2} \, dm(x) \right]^2 = \int_{\mathbb{R}} e^{-y^2/2} \left[ \int_{\mathbb{R}} e^{-x^2/2} \, dm(x) \right] \, dm(y)
\]

\[
= \int_{\mathbb{R}^2} e^{-(x^2+y^2)/2} \, dm^2(x, y)
\]

\[\text{where} \ m^2 = m \otimes m \ \text{is “Lebesgue measure” on} \ \left(\mathbb{R}^2, B_{\mathbb{R}^2} = B_\mathbb{R} \otimes B_\mathbb{R}\right). \ \text{From the monotone convergence theorem,}
\]

\[
I^2 = \lim_{R \to \infty} \int_{D_R} e^{-(x^2+y^2)/2} \, d\pi(x, y)
\]

\[\text{where} \ D_R = \left\{(x, y) : x^2 + y^2 < R^2\right\}. \ \text{Using the change of variables theorem described in Section 10.5 below we find}
\]

\[
\int_{D_R} e^{-(x^2+y^2)/2} \, d\pi(x, y) = \int_{(0,R) \times (0,2\pi)} e^{-r^2/2} \, r \, dr \, d\theta = 2\pi \int_0^R e^{-r^2/2} \, r \, dr = 2\pi \left(1 - e^{-R^2/2}\right).
\]

\[1 \text{Alternatively, you can easily show that the integral} \ \int_{D_R} f \, dm^2 \ \text{agrees with the multiple integral in undergraduate analysis when} \ f \ \text{is continuous. Then use the change of variables theorem from undergraduate analysis.}
\]
From this we learn that
\[ I^2 = \lim_{R \to \infty} 2\pi \left(1 - e^{-R^2/2}\right) = 2\pi \]
as desired.

### 10.3 Fubini’s Theorem

The following convention will be in force for the rest of this section.

**Convention:** If \((X, \mathcal{M}, \mu)\) is a measure space and \(f : X \to \mathbb{C}\) is a measurable but non-integrable function, i.e. \(\int_X |f| d\mu = \infty\), by convention we will define \(\int_X f d\mu := 0\). However if \(f\) is a non-negative function (i.e. \(f : X \to [0, \infty]\)) is a non-integrable function we will still write \(\int_X f d\mu = \infty\).

**Theorem 10.8 (Fubini’s Theorem).** Suppose \((X, \mathcal{M}, \mu)\) and \((Y, \mathcal{N}, \nu)\) are \(\sigma\)–finite measure spaces, \(\pi = \mu \otimes \nu\) is the product measure on \(\mathcal{M} \otimes \mathcal{N}\) and \(f : X \times Y \to \mathbb{C}\) is a \(\mathcal{M} \otimes \mathcal{N}\)–measurable function. Then the following three conditions are equivalent:

\[
\begin{align*}
\int_{X \times Y} |f| \, d\pi &< \infty, \text{ i.e. } f \in L^1(\pi), \tag{10.10} \\
\int_X \left(\int_Y |f(x,y)| \, d\nu(y)\right) \, d\mu(x) &< \infty \text{ and } \\
\int_Y \left(\int_X |f(x,y)| \, d\mu(x)\right) \, d\nu(y) &< \infty. \tag{10.12}
\end{align*}
\]

If any one (and hence all) of these condition hold, then \(f(x, \cdot) \in L^1(\nu)\) for \(\mu\)-a.e. \(x\), \(f(\cdot, y) \in L^1(\mu)\) for \(\nu\)-a.e. \(y\), \(\int_X f(x, \cdot) \, d\mu(x) = \int_Y f(\cdot, y) \, d\nu(y) = \int_{X \times Y} f \, d\pi\), and Eqs. (10.8) and (10.9) are still valid.

**Proof.** The equivalence of Eqs. (10.10) – (10.12) is a direct consequence of Tonelli’s Theorem 10.6. Now suppose \(f \in L^1(\pi)\) is a real valued function and let
\[ E := \left\{ x \in X : \int_Y |f(x,y)| \, d\nu(y) = \infty \right\}. \tag{10.13} \]
Then by Tonelli’s theorem, \(x \mapsto \int_Y |f(x,y)| \, d\nu(y)\) is measurable and hence \(E \in \mathcal{M}\). Moreover Tonelli’s theorem implies
\[
\int_X \left[ \int_Y |f(x,y)| \, d\nu(y) \right] \, d\mu(x) = \int_{X \times Y} |f(x,y)| \, d\pi < \infty
\]
which implies that \(\mu(E) = 0\). Let \(f_\pm\) be the positive and negative parts of \(f\), then using the above convention we have

\[
\int_Y f(x,y) \, d\nu(y) = \int_Y 1_{E^c}(x) f(x,y) \, d\nu(y)
= \int_Y 1_{E^c}(x) \left[ f_+(x,y) - f_-(x,y) \right] \, d\nu(y)
= \int_Y 1_{E^c}(x) f_+(x,y) \, d\nu(y) - \int_Y 1_{E^c}(x) f_-(x,y) \, d\nu(y).
\]

Noting that \(1_{E^c}(x) f_+(x,y) = (1_{E^c} \otimes 1_Y \cdot f_+)(x,y)\) is a positive \(\mathcal{M} \otimes \mathcal{N}\)–measurable function, it follows from another application of Tonelli’s theorem that \(x \mapsto \int_Y f(x,y) \, d\nu(y)\) is \(\mathcal{M}\)–measurable, being the difference of two measurable functions. Moreover
\[
\int_X \left[ \int_Y f(x,y) \, d\nu(y) \right] \, d\mu(x) \leq \int_X \left[ \int_Y |f(x,y)| \, d\nu(y) \right] \, d\mu(x) < \infty,
\]
which shows \(\int_Y f(\cdot,y) \, d\nu(y) \in L^1(\mu)\). Integrating Eq. (10.14) on \(x\) and using Tonelli’s theorem repeatedly implies,
\[
\int_X \left[ \int_Y f(x,y) \, d\nu(y) \right] \, d\mu(x)
= \int_X d\mu(x) \int_Y \left[ \int_Y f(x,y) \, d\nu(y) \right] \, d\nu(y) = \int_X \left[ \int_Y f(x,y) \, d\nu(y) \right] \, d\mu(x)\]
\[
= \int_X \int_Y d\mu(x) \int_Y f_+(x,y) \, d\nu(y) - \int_X \int_Y d\mu(x) \int_Y f_-(x,y) \, d\nu(y)
= \int_X \int_Y d\mu(x) f_+(x,y) \, d\nu(y) - \int_X \int_Y d\mu(x) f_-(x,y) \, d\nu(y)
= \int_{X \times Y} f_+ \, d\pi - \int_{X \times Y} f_- \, d\pi = \int_{X \times Y} (f_+ - f_-) \, d\pi = \int_{X \times Y} f \, d\pi \tag{10.15}
\]
which proves Eq. (10.8) holds.

Now suppose \(f = u + iv\) is complex valued and again let \(E\) be as in Eq. (10.13). Just as above we still have \(E \in \mathcal{M}\) and \(\mu(E) = 0\). By our convention,
\[
\int_Y f(x,y) \, d\nu(y) = \int_Y 1_{E^c}(x) f(x,y) \, d\nu(y) = \int_Y 1_{E^c}(x) \left[ u(x,y) + iv(x,y) \right] \, d\nu(y)
= \int_Y 1_{E^c}(x) u(x,y) \, d\nu(y) + i \int_Y 1_{E^c}(x) v(x,y) \, d\nu(y)
\]
which is measurable in \(x\) by what we have just proved. Similarly one shows \(\int_Y f(\cdot,y) \, d\nu(y) \in L^1(\mu)\) and Eq. (10.8) still holds by a computation similar to that done in Eq. (10.15). The assertions pertaining to Eq. (10.9) may be proved in the same way.

The previous theorems have obvious generalizations to products of any finite number of \(\sigma\)–finite measure spaces. For example the following theorem holds.
Theorem 10.9. Suppose \( \{ (X_i, \mathcal{M}_i, \mu_i) \}_{i=1}^n \) are \( \sigma \)-finite measure spaces and \( X := X_1 \times \cdots \times X_n \). Then there exists a unique measure, \( \pi \), on \( (X, \mathcal{M}_1 \otimes \cdots \otimes \mathcal{M}_n) \) such that
\[
\pi(A_1 \times \cdots \times A_n) = \mu_1(A_1) \cdots \mu_n(A_n) \text{ for all } A_i \in \mathcal{M}_i.
\]
(This measure and its completion will be denoted by \( \mu_1 \otimes \cdots \otimes \mu_n \).) If \( f : X \to [0, \infty] \) is a \( \mathcal{M}_1 \otimes \cdots \otimes \mathcal{M}_n \) measurable function then
\[
\int_X f(x) d\pi = \int_{X_{\sigma(1)}} d\mu_{\sigma(1)}(x_{\sigma(1)}) \cdots \int_{X_{\sigma(n)}} d\mu_{\sigma(n)}(x_{\sigma(n)}) f(x_{\sigma(1)}, \ldots, x_{\sigma(n)}) 
\tag{10.16}
\]
where \( \sigma \) is any permutation of \( \{1, 2, \ldots, n\} \). This equation also holds for any \( f \in L^1(\pi) \) iff
\[
\left| \int_{X_{\sigma(1)}} d\mu_{\sigma(1)}(x_{\sigma(1)}) \cdots \int_{X_{\sigma(n)}} d\mu_{\sigma(n)}(x_{\sigma(n)}) f(x_{\sigma(1)}, \ldots, x_{\sigma(n)}) \right| < \infty
\]
for some (and hence all) permutations, \( \sigma \).

This theorem can be proved by the same methods as in the two factor case, see Exercise [10.4]. Alternatively, one can use the theorems already proved and induction on \( n \), see Exercise [10.5] in this regard.

Proposition 10.10. Suppose that \( \{ X_k \}_{k=1}^n \) are random variables on a probability space \( (\Omega, \mathcal{B}, P) \) and \( \mu_k = P \circ X_k^{-1} \) is the distribution for \( X_k \) for \( k = 1, 2, \ldots, n \), and \( \pi := P \circ (X_1, \ldots, X_n)^{-1} \) is the joint distribution of \( (X_1, \ldots, X_n) \). Then the following are equivalent,

1. \( \{ X_k \}_{k=1}^n \) are independent,
2. for all bounded measurable functions, \( f : (\mathbb{R}^n, \mathcal{B}_{\mathbb{R}^n}) \to (\mathbb{R}, \mathcal{B}_{\mathbb{R}}) \),
\[
\mathbb{E} f(X_1, \ldots, X_n) = \int_{\mathbb{R}^n} f(x_1, \ldots, x_n) d\mu_1(x_1) \cdots d\mu_n(x_n), \text{ (taken in any order)}
\tag{10.17}
\]
and
3. \( \pi = \mu_1 \otimes \mu_2 \otimes \cdots \otimes \mu_n \).

Proof. (1 \( \implies \) 2) Suppose that \( \{ X_k \}_{k=1}^n \) are independent and let \( \mathbb{H} \) denote the set of bounded measurable functions, \( f : (\mathbb{R}^n, \mathcal{B}_{\mathbb{R}^n}) \to (\mathbb{R}, \mathcal{B}_{\mathbb{R}}) \) such that Eq. \[10.17\] holds. Then it is easily checked that \( \mathbb{H} \) is a vector space which contains the constant functions and is closed under bounded convergence. Moreover, if \( f = 1_{A_1 \times \cdots \times A_n} \) where \( A_i \in \mathcal{B}_{\mathbb{R}} \), we have
\[
\mathbb{E} f(X_1, \ldots, X_n) = P((X_1, \ldots, X_n) \in A_1 \times \cdots \times A_n)
= \prod_{j=1}^n P(X_j \in A_j) = \prod_{j=1}^n \mu_j(A_j)
= \int_{\mathbb{R}^n} f(x_1, \ldots, x_n) d\mu_1(x_1) \cdots d\mu_n(x_n).
\]
Therefore, \( \mathbb{H} \) contains the multiplicative system, \( \mathcal{M} := \{ 1_{A_1 \times \cdots \times A_n} : A_i \in \mathcal{B}_{\mathbb{R}} \} \) and so by the multiplicative systems theorem, \( \mathbb{H} \) contains all bounded \( \sigma (\mathcal{M}) = \mathcal{B}_{\mathbb{R}} \) measurable functions.

(2 \( \implies \) 3) Let \( A \in \mathcal{B}_{\mathbb{R}^n} \) and \( f = 1_A \) in Eq. \[10.17\] to conclude that
\[
\pi(A) = P((X_1, \ldots, X_n) \in A) = \mathbb{E} 1_A(X_1, \ldots, X_n)
= \int_{\mathbb{R}^n} 1_A(x_1, \ldots, x_n) d\mu_1(x_1) \cdots d\mu_n(x_n) = (\mu_1 \otimes \cdots \otimes \mu_n)(A).
\]

(3 \( \implies \) 1) This follows from the identity,
\[
P((X_1, \ldots, X_n) \in A_1 \times \cdots \times A_n) = \pi(A_1 \times \cdots \times A_n) = \prod_{j=1}^n \mu_j(A_j)
= \prod_{j=1}^n P(X_j \in A_j),
\]
which is valid for all \( A_j \in \mathcal{B}_{\mathbb{R}} \).

Example 10.11 (No Ties). Suppose that \( X \) and \( Y \) are independent random variables on a probability space \( (\Omega, \mathcal{B}, P) \). If \( F(x) := P(X \leq x) \) is continuous, then \( P(X = Y) = 0 \). To prove this, let \( \mu(A) := P(X \in A) \) and \( \nu(A) = P(Y \in A) \). Because \( F \) is continuous, \( \mu(\{y\}) = F(y) - F(y^-) = 0 \), and hence
\[
P(X = Y) = \mathbb{E} [1_{\{X = Y\}}] = \int_{\mathbb{R}^2} 1_{\{x = y\}} d(\mu \otimes \nu)(x, y)
= \int_{\mathbb{R}} d\nu(y) \int_{\mathbb{R}} d\mu(x) 1_{\{x = y\}} = \int_{\mathbb{R}} \mu(\{y\})\, d\nu(y)
= \int_{\mathbb{R}} 0 \, d\nu(y) = 0.
\]

Example 10.12. In this example we will show
\[
\lim_{M \to \infty} \int_0^M \frac{\sin x}{x} dx = \pi/2.
\tag{10.18}
\]
To see this write \( \frac{1}{x} = \int_0^\infty e^{-tx} dt \) and use Fubini-Tonelli to conclude that
\[
\int_0^M \frac{\sin x}{x} \, dx = \int_0^M \left[ \int_0^\infty e^{-tx} \sin x \, dt \right] \, dx \\
= \int_0^\infty \left[ \int_0^M e^{-tx} \sin x \, dx \right] \, dt \\
= \int_0^\infty \frac{1}{1 + t^2} (1 - te^{-Mt} \sin M - e^{-Mt} \cos M) \, dt \\
\rightarrow \int_0^\infty \frac{1}{1 + t^2} \, dt = \frac{\pi}{2} \text{ as } M \rightarrow \infty,
\]

wherein we have used the dominated convergence theorem (for instance, take \(g(t) := \frac{1}{1 + t^2} (1 + te^{-t} + e^{-t})\)) to pass to the limit.

The next example is a refinement of this result.

**Example 10.13.** We have

\[
\int_0^\infty \frac{\sin x}{x} e^{-Ax} \, dx = \frac{1}{2} \pi - \arctan A \text{ for all } A > 0 \tag{10.19}
\]

and for \(A, M \in [0, \infty)\),

\[
\left| \int_0^M \frac{\sin x}{x} e^{-Ax} \, dx - \frac{1}{2} \pi + \arctan A \right| \leq C \frac{e^{-MA}}{M} \tag{10.20}
\]

where \(C = \max_{x \geq 0} \frac{1+x}{1+x^2} = \frac{1}{2\sqrt{2} - 2} \approx 1.2\). In particular Eq. (10.18) is valid.

To verify these assertions, first notice that by the fundamental theorem of calculus,

\[
|\sin x| = \left| \int_0^x \cos y \, dy \right| \leq \int_0^x |\cos y| \, dy \leq \int_0^x 1 \, dy = |x|
\]

so \(\left| \frac{\sin x}{x} \right| \leq 1\) for all \(x \neq 0\). Making use of the identity

\[
\int_0^\infty e^{-tx} \, dt = \frac{1}{x}
\]

and Fubini’s theorem,

\[
\int_0^M \frac{\sin x}{x} e^{-Ax} \, dx = \int_0^M \frac{dx \sin x}{x} e^{-Ax} \int_0^\infty e^{-tx} \, dt \\
= \int_0^\infty dt \int_0^M \frac{dx \sin x}{e^{-tx} e^{(A+t)x}} \\
= \int_0^\infty 1 - (\cos M + (A+t) \sin M) e^{M(A+t)} \, dt \\
(\Lambda + t)^2 + 1 \\
= \int_0^\infty \frac{1}{(A+t)^2 + 1} \, dt - \int_0^\infty \cos M + (A+t) \sin M \, dt \\
= \frac{1}{2} \pi - \arctan A - \varepsilon(M, A) \tag{10.21}
\]

where

\[
\varepsilon(M, A) = \int_0^\infty \frac{\cos M + (A+t) \sin M}{(A+t)^2 + 1} e^{-M(A+t)} \, dt.
\]

Since

\[
\left| \frac{\cos M + (A+t) \sin M}{(A+t)^2 + 1} \right| \leq \frac{1 + (A+t)}{(A+t)^2 + 1} \leq C,
\]

\[
|\varepsilon(M, A)| \leq \int_0^\infty e^{-M(A+t)} \, dt = C e^{-MA}.
\]

This estimate along with Eq. (10.21) proves Eq. (10.20) from which Eq. (10.18) follows (using the dominated convergence theorem again) by letting \(M \rightarrow \infty\).

Note: you may skip the rest of this chapter!

### 10.4 Fubini’s Theorem and Completions

**Notation 10.14** Given \(E \subset X \times Y\) and \(x \in X\), let

\[
_xE := \{ y \in Y : (x, y) \in E \}.
\]

Similarly if \(y \in Y\) is given let

\[
_yE := \{ x \in X : (x, y) \in E \}.
\]

If \(f : X \times Y \rightarrow \mathbb{C}\) is a function let \(f_x = f(x, \cdot)\) and \(f^y = f(\cdot, y)\) so that \(f_x : Y \rightarrow \mathbb{C}\) and \(f^y : X \rightarrow \mathbb{C}\).
Suppose \((X, \mathcal{M}, \mu)\) and \((Y, \mathcal{N}, \nu)\) are complete \(\sigma\)-finite measure spaces. Let \((X \times Y, \mathcal{L}, \lambda)\) be the completion of \((X \times Y, \mathcal{M} \otimes \mathcal{N}, \mu \otimes \nu)\). If \(f\) is \(\mathcal{L}\) measurable and (a) \(f \geq 0\) or (b) \(f \in L^1(\lambda)\) then \(f_x\) is \(\mathcal{N}\) measurable for \(\mu\) a.e. \(x\) and \(f^y\) is \(\mathcal{L}\) measurable for \(\nu\) a.e. \(y\) and in case (b) \(f_x \in L^1(\nu)\) and \(f^y \in L^1(\mu)\) for \(\mu\) a.e. \(x\) and \(\nu\) a.e. \(y\) respectively. Moreover,

\[
(x \to \int_Y f_x d\nu) \in L^1(\mu) \quad \text{and} \quad (y \to \int_X f^y d\mu) \in L^1(\nu)
\]

and

\[
\int_{X \times Y} f d\lambda = \int_Y d\nu \int_X d\mu f = \int_X d\mu \int_Y d\nu f.
\]

**Proof.** If \(E \in \mathcal{M} \otimes \mathcal{N}\) is a \(\mu \otimes \nu\) null set (i.e. \((\mu \otimes \nu)(E) = 0\)), then

\[
0 = (\mu \otimes \nu)(E) = \int_X \nu(\cdot | E) d\mu(x) = \int_X \mu(E_y) d\nu(y).
\]

This shows that

\[
\mu\{x : \nu(\cdot | E) \neq 0\} = 0 \quad \text{and} \quad \nu\{y : \mu(E_y) \neq 0\} = 0,
\]

i.e. \(\nu(\cdot | E) = 0\) for \(\mu\) a.e. \(x\) and \(\mu(E_y) = 0\) for \(\nu\) a.e. \(y\). If \(h\) is \(\mathcal{L}\) measurable and \(h = 0\) for \(\lambda\)-a.e., then there exists \(E \in \mathcal{M} \otimes \mathcal{N}\) such that \(\{(x, y) : h(x, y) \neq 0\} \subset E\) and \((\mu \otimes \nu)(E) = 0\). Therefore \(|h(x, y)| \leq 1_E(x, y)\) and \((\mu \otimes \nu)(E) = 0\).

Since

\[
\{h_x \neq 0\} = \{y \in Y : h(x, y) \neq 0\} \subset E_Y
\]

and

\[
\{h_y \neq 0\} = \{x \in X : h(x, y) \neq 0\} \subset Y_E
\]

we learn that for \(\mu\) a.e. \(x\) and \(\nu\) a.e. \(y\) that \(\{h_x \neq 0\} \in \mathcal{M}\), \(\{h_y \neq 0\} \in \mathcal{N}\), \(\nu(\{h_x \neq 0\}) = 0\) and \(\mu(\{h_y \neq 0\}) = 0\). This implies \(\int_Y h(x, y) d\nu(y)\) exists and equals \(0\) for \(\mu\) a.e. \(x\) and similarly that \(\int_X h(x, y) d\mu(x)\) exists and equals \(0\) for \(\nu\) a.e. \(y\). Therefore

\[
0 = \int_{X \times Y} h d\lambda = \int_Y \int_X h d\mu d\nu = \int_X \int_Y h d\nu d\mu.
\]

For general \(f \in L^1(\lambda)\), we may choose \(g \in L^1(\mathcal{M} \otimes \mathcal{N}, \mu \otimes \nu)\) such that \(f(x, y) = g(x, y)\) for \(\lambda\)-a.e. \((x, y)\). Define \(h := f - g\). Then \(h = 0\), \(\lambda\)-a.e. Hence by what we have just proved and Theorem \([\text{10.6}]\) \(f = g + h\) has the following properties:

1. For \(\mu\) a.e. \(x, y \to f(x, y) = g(x, y) + h(x, y)\) is in \(L^1(\nu)\) and
   \[
   \int_Y f(x, y) d\nu(y) = \int_Y g(x, y) d\nu(y).
   \]
2. For \(\nu\) a.e. \(y, x \to f(x, y) = g(x, y) + h(x, y)\) is in \(L^1(\mu)\) and
   \[
   \int_X f(x, y) d\mu(x) = \int_X g(x, y) d\mu(x).
   \]

From these assertions and Theorem \([\text{10.6}]\) it follows that

\[
\int_{X \times Y} \nu(f(x, y)) = \int_{X \times Y} \mu(f(x, y)) = \int_{X \times Y} \nu(g(x, y)) = \int_{X \times Y} \mu(g(x, y))
\]

Similarly it is shown that

\[
\int_Y \nu(f(x, y)) = \int_X \nu(f(x, y)) = \int_X \nu(g(x, y)) = \int_X \nu(g(x, y)).
\]

\[\blacksquare\]

### 10.5 Lebesgue Measure on \(\mathbb{R}^d\) and the Change of Variables Theorem

**Notation 10.16** Let

\[
m^d := m \otimes \cdots \otimes m \quad \text{on } B_{\mathbb{R}^d} = B_{\mathbb{R}} \otimes \cdots \otimes B_{\mathbb{R}}
\]

be the \(d\)-fold product of Lebesgue measure \(m\) on \(B_{\mathbb{R}}\). We will also use \(m^d\) to denote its completion and let \(\mathcal{L}_d\) be the completion of \(B_{\mathbb{R}^d}\) relative to \(m^d\). A subset \(A \in \mathcal{L}_d\) is called a Lebesgue measurable set and \(m^d\) is called \(d\)-dimensional Lebesgue measure, or just Lebesgue measure for short.

**Definition 10.17.** A function \(f : \mathbb{R}^d \to \mathbb{R}\) is Lebesgue measurable if \(f^{-1}(B_{\mathbb{R}}) \subset \mathcal{L}_d\).

**Definition 10.18** I will often be sloppy in the sequel and write \(m\) for \(m^d\) and \(dx\) for \(dm(x) = dm^d(x)\), i.e.

\[
\int_{\mathbb{R}^d} f(x) \, dx = \int_{\mathbb{R}^d} f \, dm = \int_{\mathbb{R}^d} f \, dm^d.
\]

Hopefully the reader will understand the meaning from the context.
Theorem 10.19. Lebesgue measure $m^d$ is translation invariant. Moreover $m^d$ is the unique translation invariant measure on $B_{\mathbb{R}^d}$ such that $m^d((0,1]^d) = 1$.

Proof. Let $A = J_1 \times \cdots \times J_d$ with $J_i \in B_{\mathbb{R}}$ and $x \in \mathbb{R}^d$. Then
\[ x + A = (x_1 + J_1) \times (x_2 + J_2) \times \cdots \times (x_d + J_d) \]
and therefore by translation invariance of $m$ on $B_{\mathbb{R}}$ we find that
\[ m^d(x + A) = m(x_1 + J_1) \cdots m(x_d + J_d) = m(J_1) \cdots m(J_d) = m^d(A) \]
and hence $m^d(x + A) = m^d(A)$ for all $A \in B_{\mathbb{R}^d}$ since it holds for $A$ in a multiplicative system which generates $B_{\mathbb{R}^d}$. From this fact we see that the measure $m^d(x + \cdot)$ and $m^d(\cdot)$ have the same null sets. Using this it is easily seen that $m(x + A) = m(A)$ for all $A \in \mathcal{L}_d$. The proof of the second assertion is Exercise H16.

Exercise 10.1. In this problem you are asked to show there is no reasonable notion of Lebesgue measure on an infinite dimensional Hilbert space. To be more precise, suppose $H$ is an infinite dimensional Hilbert space and $m$ is a countably additive measure on $B_H$ which is invariant under translations and satisfies, $m(B_0(\varepsilon)) > 0$ for all $\varepsilon > 0$. Show $m(V) = \infty$ for all non-empty open subsets $V \subset H$.

Theorem 10.20 (Change of Variables Theorem). Let $\Omega \subset \mathbb{R}^d$ be an open set and $T : \Omega \to T(\Omega) \subset \mathbb{R}^d$ be a $C^1$–diffeomorphism. \[ \text{see Figure 10.1.} \] Then for any Borel measurable function, $f : T(\Omega) \to [0, \infty]$,\[ \int_{\Omega} f(T(x)) \det T'(x) \, dx = \int_{T(\Omega)} f(y) \, dy, \tag{10.22} \]
where $T'(x)$ is the linear transformation on $\mathbb{R}^d$ defined by $T'(x)v := \frac{d}{dt} \big|_{t=0} T(x + tv)$. More explicitly, viewing vectors in $\mathbb{R}^d$ as columns, $T'(x)$ may be represented by the matrix
\[ T'(x) = \begin{bmatrix} \partial_1 T_1(x) & \cdots & \partial_d T_1(x) \\ \vdots & \ddots & \vdots \\ \partial_1 T_d(x) & \cdots & \partial_d T_d(x) \end{bmatrix}, \tag{10.23} \]
i.e. the $i$–$j$–matrix entry of $T'(x)$ is given by $T'(x)_{ij} = \partial_i T_j(x)$ where $T(x) = (T_1(x), \ldots, T_d(x))^t$ and $\partial_i = \partial / \partial x_i$.

Remark 10.21. Theorem 10.20 is best remembered as the statement: if we make the change of variables $y = T(x)$, then $dy = |\det T'(x)| \, dx$. As usual, you must also change the limits of integration appropriately, i.e. if $x$ ranges through $\Omega$ then $y$ must range through $T(\Omega)$.

Proof. The proof will be by induction on $d$. The case $d = 1$ was essentially done in Exercise 9.7. Nevertheless, for the sake of completeness let us give a proof here. Suppose $d = 1$, $a < \alpha < \beta < b$ such that $[a, b]$ is a compact subinterval of $\Omega$. Then $|\det T'| = |T'|$ and
\[ \int_{[a,b]} 1_{(\alpha, \beta)}(T(x)) \, T'(x) \, dx = \int_{[a,b]} 1_{(\alpha, \beta)}(x) \, |T'(x)| \, dx = \int_{\alpha}^{\beta} |T'(x)| \, dx. \]
If $T'(x) > 0$ on $[a, b]$, then
\[ \int_{\alpha}^{\beta} |T'(x)| \, dx = \int_{\alpha}^{\beta} T'(x) \, dx = T(\beta) - T(\alpha) \]
\[ = m(T((\alpha, \beta])) = \int_{T([a,b])} 1_{T((\alpha, \beta))} \, dy \]
while if $T'(x) < 0$ on $[a, b]$, then
Summing this equality on \( n \), as in Eq. (10.23), the matrix associated to the differential, \( \mathbf{u} \) write vectors in \( \mathbb{R}^n \) theorem is valid with \( d \) captures with \( \Omega \) Recall that \( f \) holds for every bounded measurable function \( f : T((a, b]) \rightarrow \mathbb{R} \) (Observe that \( [T'(x)] \) is continuous and hence bounded for \( x \) in the compact interval, \( [a, b] \).) Theorem 9.3 then implies that Eq. (10.24) whenever \( \beta \). Hence if \( f : T(\Omega) \rightarrow \mathbb{R}^+ \) is a Borel measurable function and \( a_n < \alpha_k < \beta_k < b_n \) with \( \alpha_k \downarrow a_n \) and \( \beta_k \uparrow b_n \), then by what we have already proved and the monotone convergence theorem

\[
\int_{\Omega} 1_{(a_n, b_n)} \cdot (f \circ T) \cdot |T'| dm = \int_{\Omega} 1_{T((a_n, b_n))} \cdot f \circ T \cdot |T'| dm \\
= \lim_{k \to \infty} \int_{\Omega} 1_{T((a_k, b_k))} \cdot f \circ T \cdot |T'| dm \\
= \lim_{k \to \infty} \int_{T(\Omega)} 1_{T((a_k, b_k))} \cdot f \cdot dm \\
= \int_{T(\Omega)} 1_{T((a_n, b_n))} \cdot f \cdot dm.
\]

Summing this equality on \( n \), then shows Eq. (10.22) holds.

To carry out the induction step, we now suppose \( d > 1 \) and suppose the theorem is valid with \( d \) being replaced by \( d-1 \). For notational compactness, let us write vectors in \( \mathbb{R}^d \) as row vectors rather than column vectors. Nevertheless, the matrix associated to the differential, \( T'(x) \), will always be taken to be given as in Eq. (10.23).

**Case 1.** Suppose \( T(x) \) has the form

\[
T(x) = (x_1, T_2(x), \ldots, T_d(x)) \tag{10.25}
\]

or

\[
T(x) = (T_1(x), \ldots, T_{d-1}(x), x_d) \tag{10.26}
\]

for some \( i \in \{1, \ldots, d\} \). For definiteness we will assume \( T \) is as in Eq. (10.25), the case of \( T \) in Eq. (10.26) may be handled similarly. For \( t \in \mathbb{R} \), let \( \iota_t : \mathbb{R}^{d-1} \to \mathbb{R}^d \) be the inclusion map defined by

\[
\iota_t(w) := \omega_t := (w_1, \ldots, w_{i-1}, t, w_{i+1}, \ldots, w_{d-1}),
\]

\( \Omega_t \) be the (possibly empty) open subset of \( \mathbb{R}^{d-1} \) defined by

\[
\Omega_t := \{ w \in \mathbb{R}^{d-1} : (w_1, \ldots, w_{i-1}, t, w_{i+1}, \ldots, w_{d-1}) \in \Omega \}
\]

and \( T_t : \Omega_t \to \mathbb{R}^{d-1} \) be defined by

\[
T_t(w) := (T_2(w), \ldots, T_d(w))
\]

see Figure 10.2 Expanding \( \det T'(w_i) \) along the first row of the matrix \( T'(w_i) \)

![Fig. 10.2](image-url)

**Fig. 10.2.** In this picture \( d = i = 3 \) and \( \Omega \) is an egg-shaped region with an egg-shaped hole. The picture indicates the geometry associated with the map \( T \) and slicing the set \( \Omega \) along planes where \( x_3 = t \).

shows

\[
|\det T'(w_i)| = |\det T'_t(w)|.
\]

Now by the Fubini-Tonelli Theorem and the induction hypothesis,
\[
\int_{\Omega} f \circ T \, |\det T'| \, dm = \int_{\Omega} 1_{\Omega} \cdot f \circ T \, |\det T'| \, dm
\]

\[
= \int_{\mathbb{R}^d} 1_{\Omega}(w_t) \cdot (f \circ T)(w_t) \cdot |\det (w_t)| \, dw \, dt
\]

\[
= \int_{\mathbb{R}} \left[ \int_{T_t} (f \circ T)(w_t) \cdot |\det T'(w_t)| \, dw \right] \, dt
\]

\[
= \int_{\mathbb{R}} \left[ \int f(t, T_t(w)) \cdot |\det T'_t(w)| \, dw \right] \, dt
\]

\[
= \int_{\mathbb{R}} \left[ \int f(t, z) \, dz \right] \, dt = \int_{\mathbb{R}} \left[ \int 1_{T(\Omega)}(t, z) \cdot f(t, z) \, dz \right] \, dt
\]

\[
= \int_{T(\mathbb{R})} f(y) \, dy
\]

wherein the last two equalities we have used Fubini-Tonelli along with the identity:

\[
T(\Omega) = \sum_{t \in \mathbb{R}} T(i_t(\Omega)) = \sum_{t \in \mathbb{R}} \{(t, z) : z \in T_t(i_t(\Omega))\}.
\]

**Case 2.** (Eq. [10.22] is true locally.) Suppose that \( T : \Omega \to \mathbb{R}^d \) is a general map as in the statement of the theorem and \( x_0 \in \Omega \) is an arbitrary point. We will now show there exists an open neighborhood \( W \subset \Omega \) of \( x_0 \) such that

\[
\int_{W} f \circ T \, |\det T'| \, dm = \int_{T(W)} f \, dm
\]

holds for all Borel measurable function, \( f : T(W) \to [0, \infty) \). Let \( M_i \) be the \( i\)-th minor of \( T'(x_0) \), i.e. the determinant of \( T'(x_0) \) with the first row and \( i\)-th column removed. Since

\[
0 \neq \det T'(x_0) = \sum_{i=1}^{d} (-1)^{i+1} \partial_i T_j(x_0) \cdot M_i,
\]

there must be some \( i \) such that \( M_i \neq 0 \). Fix an \( i \) such that \( M_i \neq 0 \) and let,

\[
S(x) := (x_1, T_2(x), \ldots, T_d(x)).
\]

(10.27)

Observe that \(|\det S'(x_0)| = |M_i| \neq 0\). Hence by the inverse function Theorem, there exist an open neighborhood \( W \) of \( x_0 \) such that \( W \subset \Omega \) and \( S(W) \subset \mathbb{R}^d \).

and \( S : W \to S(W) \) is a \( C^1 \) – diffeomorphism. Let \( R : S(W) \to T(W) \subset \mathbb{R}^d \) to be the \( C^1 \) – diffeomorphism defined by

\[
R(z) := T \circ S^{-1}(z) \text{ for all } z \in S(W).
\]

Because

\[
(T_1(x), \ldots, T_d(x)) = T(x) = R(S(x)) = R((x_1, T_2(x), \ldots, T_d(x)))
\]

for all \( x \in W \), if

\[
(z_1, z_2, \ldots, z_d) = S(x) = (x_1, T_2(x), \ldots, T_d(x))
\]

then

\[
R(z) = (T_1(S^{-1}(z)), z_2, \ldots, z_d).
\]

(10.28)

Observe that \( S \) is a map of the form in Eq. [10.25], \( R \) is a map of the form in Eq. [10.26], \( T'(x) = R'(S(x)) \cdot S'(x) \) (by the chain rule) and (by the multiplicative property of the determinant)

\[
|\det T'(x)| = |\det R'(S(x))| \cdot |\det S'(x)| \quad \forall \ x \in W.
\]

So if \( f : T(W) \to [0, \infty) \) is a Borel measurable function, two applications of the results in Case 1. shows,

\[
\int_{W} f \circ T \cdot |\det T'| \, dm = \int_{W} (f \circ R \cdot |\det R'|) \circ S \cdot |\det S'| \, dm
\]

\[
= \int_{W} f \circ R \cdot |\det R'| \, dm = \int_{S(W)} f \, dm
\]

\[
= \int_{T(W)} f \, dm
\]

and Case 2. is proved.

**Case 3.** (General Case.) Let \( f : \Omega \to [0, \infty] \) be a general non-negative Borel measurable function and let

\[
K_n := \{x \in \Omega : \text{dist}(x, \Omega^c) \geq 1/n \text{ and } |x| \leq n\}.
\]

Then each \( K_n \) is a compact subset of \( \Omega \) and \( K_n \uparrow \Omega \) as \( n \to \infty \). Using the compactness of \( K_n \) and case 2, for each \( n \in \mathbb{N} \), there is a finite open cover \( \mathcal{W}_n \) of \( K_n \) such that \( W \subset \Omega \) and Eq. [10.22] holds with \( \Omega \) replaced by \( W \) for each \( W \in \mathcal{W}_n \). Let \( \{W_i\}_{i=1}^{\infty} \) be an enumeration of \( \cup_{n=1}^{\infty} \mathcal{W}_n \) and set \( \tilde{W}_1 = W_1 \) and

\[
\tilde{W}_i := W_i \setminus (W_1 \cup \cdots \cup W_{i-1}) \quad \text{for all } i \geq 2.
\]

Then \( \Omega = \sum_{i=1}^{\infty} \tilde{W}_i \) and by repeated use of case 2.,
Then by the chain rule and the fundamental theorem of calculus,
\[ \int_{a}^{b} f \circ T \cdot |\det T'| \, dm = \sum_{i=1}^{\infty} \int_{1_i \Omega} 1_{T(W_i)} \cdot (f \circ T) \cdot |\det T'| \, dm \]
\[ = \sum_{i=1}^{\infty} \int_{1_i \Omega} \left[(1_{T(W_i)} f) \circ T\right] \cdot |\det T'| \, dm \]
\[ = \sum_{i=1}^{\infty} \int_{T(W_i)} 1_{T(W_i)} \cdot f \, dm = \sum_{i=1}^{\infty} \int_{T(W_i)} 1_{T(W_i)} \cdot f \, dm \]
\[ = \int_{T(\Omega)} f \, dm. \]

Remark 10.22. When \( d = 1 \), one often learns the change of variables formula as
\[ \int_{a}^{b} f(T(x)) T'(x) \, dx = \int_{T(a)}^{T(b)} f(y) \, dy \tag{10.29} \]
where \( f : [a, b] \to \mathbb{R} \) is a continuous function and \( T \) is \( C^1 \) - function defined in a neighborhood of \([a, b]\). If \( T' > 0 \) on \((a, b)\) then \( T((a, b)) = (T(a), T(b)) \) and Eq. (10.29) implies Eq. (10.22) with \( \Omega = (a, b) \). On the other hand if \( T' < 0 \) on \((a, b)\) then \( T((a, b)) = (T(b), T(a)) \) and Eq. (10.29) is equivalent to
\[ \int_{(a, b)} f(T(x)) \cdot |T'(x)| \, dx = -\int_{T(b)}^{T(a)} f(y) \, dy = -\int_{T(a)}^{T(b)} f(y) \, dy \]
which is again implies Eq. (10.22). On the other hand Eq. (10.29) is more general than Eq. (10.22) since it does not require \( T \) to be injective. The standard proof of Eq. (10.29) is as follows. For \( z \in T([a, b]) \), let
\[ F(z) := \int_{T(a)}^{z} f(y) \, dy. \]
Then by the chain rule and the fundamental theorem of calculus,
\[ \int_{a}^{b} f(T(x)) T'(x) \, dx = \int_{a}^{b} F'(T(x)) T'(x) \, dx = \int_{a}^{b} \frac{d}{dx} [F(T(x))] \, dx \]
\[ = F(T(x)) \bigg|_{a}^{b} = \int_{T(a)}^{T(b)} f(y) \, dy. \]

An application of Dynkin’s multiplicative systems theorem now shows that Eq. (10.29) holds for all bounded measurable functions \( f \) on \((a, b)\). Then by the usual truncation argument, it also holds for all positive measurable functions on \((a, b)\).

Example 10.23. Continuing the setup in Theorem [10.20], if \( A \in \mathcal{B}_\Omega \), then
\[ m(T(A)) = \int_{\mathbb{R}^d} 1_{T(A)} (y) \, dy = \int_{\mathbb{R}^d} 1_{T(A)} (T x) \cdot |\det T'(x)| \, dx \]
\[ = \int_{\mathbb{R}^d} 1_A (x) \cdot |\det T'(x)| \, dx \]
wherein the second equality we have made the change of variables, \( y = T(x) \).
Hence we have shown
\[ d(m \circ T) = |\det T'(\cdot)| \, dm. \]
In particular if \( T \in GL(d, \mathbb{R}) = GL(\mathbb{R}^d) \) - the space of \( d \times d \) invertible matrices, then \( m \circ T = |\det T| \cdot m \), i.e.
\[ m(T(A)) = |\det T| \cdot m(A) \quad \text{for all} \quad A \in \mathcal{B}_{\mathbb{R}^d}. \tag{10.30} \]
This equation also shows that \( m \circ T \) and \( m \) have the same null sets and hence the equality in Eq. (10.30) is valid for any \( A \in \mathcal{L}_d \).

Exercise 10.2. Show that \( f \in L^1 (T(\Omega), m^d) \) iff
\[ \int_{\Omega} |f \circ T| \cdot |\det T'| \, dm < \infty \]
and if \( f \in L^1 (T(\Omega), m^d) \), then Eq. (10.22) holds.

Example 10.24 (Polar Coordinates). Suppose \( T : (0, \infty) \times (0, 2\pi) \to \mathbb{R}^2 \) is defined by
\[ x = T(r, \theta) = (r \cos \theta, r \sin \theta), \]
i.e. we are making the change of variable,
\[ x_1 = r \cos \theta \quad \text{and} \quad x_2 = r \sin \theta \quad \text{for} \quad 0 < r < \infty \quad \text{and} \quad 0 < \theta < 2\pi. \]
In this case
\[ T'(r, \theta) = \begin{pmatrix} \cos \theta & -r \sin \theta \\ \sin \theta & r \cos \theta \end{pmatrix} \]
and therefore
\[ dx = |\det T'(r, \theta)| \, dr \, d\theta = r \, dr \, d\theta. \]

Observing that
\[ \mathbb{R}^2 \setminus T((0, \infty) \times (0, 2\pi)) = \ell := \{(x, 0) : x \geq 0\} \]
has \( m^2 \) - measure zero, it follows from the change of variables Theorem 10.20 that
\[ \int_{\mathbb{R}^2} f(x) \, dx = \int_{0}^{2\pi} d\theta \int_{0}^{\infty} r \cdot f(r \cos \theta, r \sin \theta) \, dr \]
for any Borel measurable function \( f : \mathbb{R}^2 \to [0, \infty] \).
Example 10.25 (Holomorphic Change of Variables). Suppose that $f : \Omega \subset \mathbb{C} \rightarrow \mathbb{R}^2$ is an injective holomorphic function such that $f'(z) \neq 0$ for all $z \in \Omega$. We may express $f$ as

$$f(x + iy) = U(x, y) + iV(x, y)$$

for all $z = x + iy \in \Omega$. Hence if we make the change of variables,

$$w = u + iv = f(x + iy) = U(x, y) + iV(x, y)$$

then

$$dudv = \left| \det \begin{bmatrix} U_x & U_y \\ V_x & V_y \end{bmatrix} \right| dxdy = |U_x V_y - U_y V_x| dxdy.$$

Recalling that $U$ and $V$ satisfy the Cauchy Riemann equations, $U_x = V_y$ and $U_y = -V_x$ with $f' = U_x + iV_x$, we learn

$$U_x V_y - U_y V_x = U_x^2 + V_y^2 = |f'|^2.$$

Therefore

$$dudv = |f'(x + iy)|^2 dxdy.$$

Exercise 10.3 (Spherical Coordinates). Let $T : (0, \infty) \times (0, \pi) \times (0, 2\pi) \rightarrow \mathbb{R}^3$ be defined by

$$T(r, \varphi, \theta) = (r \sin \varphi \cos \theta, r \sin \varphi \sin \theta, r \cos \varphi)$$

see Figure 10.4. By making the change of variables $x = T(r, \varphi, \theta)$, show

$$T(r, \varphi, \theta) = (r \sin \varphi \cos \theta, r \sin \varphi \sin \theta, r \cos \varphi).$$

The function $T$ is not injective on $\Omega$ but it is injective on each of its connected components. Let $D$ be the connected component in the first quadrant so that $\Omega = -D \cup D$ and $T(\pm D) = (1, 2) \times (0, 1)$. The change of variables theorem then implies

$$I_\pm := \int\int_{\pm D} (x^4 - y^4) dxdy = \frac{1}{2} \int\int_{(1, 2) \times (0, 1)} u^2 dudv = \frac{1}{2} \frac{u^2}{2} \cdot 1 = \frac{3}{4}$$

and therefore $I = I_+ + I_- = 2 \cdot (3/4) = 3/2.$
are continuous, they are both Borel measurable. For 

\[ E \]

So it suffices to compute:

\[ \Phi \]

\[ R \]

\[ R \]

This shows that

\[ I \]

Using polar coordinates, see Eq. (10.31), we find,

\[ I \]

\[ 10.6 \]

Then \( I_\alpha(a) = (\pi/a)^{d/2} \).

**Proof.** By Tonelli’s theorem and induction,

\[ I_\alpha(a) = \int_{\mathbb{R}^d \times \mathbb{R}} e^{-a|y|^2} e^{-at^2} m_{d-1} (dy) \; dt \]

\[ = I_{d-1}(a) I_1(a) = I_1^d (a). \quad (10.32) \]

So it suffices to compute:

\[ I_2(a) = \int_{\mathbb{R}^2} e^{-a|x|^2} dm(x) = \int_{\mathbb{R}^2 \setminus \{0\}} e^{-a(x_1^2 + x_2^2)} dx_1 dx_2. \]

Using polar coordinates, see Eq. (10.31), we find,

\[ I_2(a) = \int_0^\infty dr r^{2\pi} e^{-ar^2} = 2\pi \int_0^\infty r e^{-ar^2} dr \]

\[ = 2\pi \lim_{M \to \infty} \int_0^M r e^{-ar^2} dr = 2\pi \lim_{M \to \infty} \frac{e^{-ar^2}}{2a} \int_0^M = \frac{2\pi}{2a} = \pi/a. \]

This shows that \( I_2(a) = \pi/a \) and the result now follows from Eq. (10.32). □

**10.6 The Polar Decomposition of Lebesgue Measure**

Let

\[ S^{d-1} = \{ x \in \mathbb{R}^d : |x|^2 = \sum_{i=1}^d x_i^2 = 1 \} \]

be the unit sphere in \( \mathbb{R}^d \) equipped with its Borel \( \sigma \)-algebra, \( \mathcal{B}_{S^{d-1}} \) and \( \Phi : \mathbb{R}^d \setminus \{0\} \to (0, \infty) \times S^{d-1} \) be defined by \( \Phi(x) := (|x|, x^{-1} x) \). The inverse map, \( \Phi^{-1} : (0, \infty) \times S^{d-1} \to \mathbb{R}^d \setminus \{0\} \), is given by \( \Phi^{-1}(r, \omega) = r\omega \). Since \( \Phi \) and \( \Phi^{-1} \) are continuous, they are both Borel measurable. For \( E \in \mathcal{B}_{S^{d-1}} \) and \( a > 0 \), let

\[ E_a := \{ r\omega : r \in (0, a] \text{ and } \omega \in E \} = \Phi^{-1}((0, a] \times E) \in \mathcal{B}_{\mathbb{R}^d}. \]

**Definition 10.28.** For \( E \in \mathcal{B}_{S^{d-1}} \), let \( \sigma(E) := d \cdot m(E_1) \). We call \( \sigma \) the surface measure on \( S^{d-1} \).

It is easy to check that \( \sigma \) is a measure. Indeed if \( E \in \mathcal{B}_{S^{d-1}} \), then \( E_1 = \Phi^{-1}((0, 1] \times E) \in \mathcal{B}_{\mathbb{R}^d} \) so that \( m(E_1) \) is well defined. Moreover if \( E = \sum_{i=1}^\infty E_i \), then \( E_1 = \sum_{i=1}^\infty (E_i)_1 \) and

\[ \sigma(E) = d \cdot m(E_1) = \sum_{i=1}^\infty m((E_i)_1) = \sum_{i=1}^\infty \sigma(E_i). \]

The intuition behind this definition is as follows. If \( E \subset S^{d-1} \) is a set and \( \varepsilon > 0 \) is a small number, then the volume of

\[ (1, 1 + \varepsilon] \cdot E = \{ r\omega : r \in (1, 1 + \varepsilon] \text{ and } \omega \in E \} \]

should be approximately given by \( m ((1, 1 + \varepsilon] \cdot E) \equiv \sigma(E)\varepsilon \), see Figure 10.5 below. On the other hand

![Fig. 10.5. Motivating the definition of surface measure for a sphere.](image)

\[ m ((1, 1 + \varepsilon] \cdot E) = m (E_1 + \varepsilon) \cdot E_1 = \{(1 + \varepsilon) \cdot 1 \} \cdot m(E_1). \]

Therefore we expect the area of \( E \) should be given by

\[ \sigma(E) = \lim_{\varepsilon \downarrow 0} \frac{\{(1 + \varepsilon) \cdot 1 \} \cdot m(E_1)}{\varepsilon} = d \cdot m(E_1). \]

The following theorem is motivated by Example 10.24 and Exercise 10.3.

**Theorem 10.29 (Polar Coordinates).** If \( f : \mathbb{R}^d \to [0, \infty] \) is a \( (\mathcal{B}_{\mathbb{R}^d}, \mathcal{B}) \)-measurable function then
\[
\int_{\mathbb{R}^d} f(x)dm(x) = \int_{(0, \infty) \times S^{d-1}} f(r\omega) r^{d-1} \, dr \, d\sigma(\omega).
\] (10.33)

In particular if \( f : \mathbb{R}_+ \to \mathbb{R}_+ \) is measurable then

\[
\int_{\mathbb{R}^d} f(|x|)dx = \int_0^\infty f(r) dV(r)
\] (10.34)

where \( V(r) = m(B(0, r)) = r^d m(B(0, 1)) = d^{-1} \sigma(S^{d-1}) r^d \).

**Proof.** By Exercise 8.6,

\[
\int_{\mathbb{R}^d} fdm = \int_{\mathbb{R}^d \setminus \{0\}} (f \circ \Phi^{-1}) \circ \Phi \, dm = \int_{(0, \infty) \times S^{d-1}} (f \circ \Phi^{-1}) \, d(\Phi_*m)
\] (10.35)

and therefore to prove Eq. (10.33) we must work out the measure \( \Phi_*m \) on \( B_{(0,\infty)} \otimes B_{S^{d-1}} \) defined by

\[
\Phi_*m(A) := m(\Phi^{-1}(A)) \quad A \in B_{(0,\infty)} \otimes B_{S^{d-1}}.
\] (10.36)

If \( A = (a, b] \times E \) with \( 0 < a < b \) and \( E \in B_{S^{d-1}} \), then

\[
\Phi^{-1}(A) = \{r\omega : r \in (a, b] \text{ and } \omega \in E\} = bE_1 \setminus aE_1
\]

wherein we have used \( E_a = aE_1 \) in the last equality. Therefore by the basic scaling properties of \( m \) and the fundamental theorem of calculus,

\[
(\Phi_*m)((a, b] \times E) = m(bE_1 \setminus aE_1) = m(bE_1) - m(aE_1)
\]

\[
= b^d m(E_1) - a^d m(E_1) = d \cdot m(E_1) \int_a^b r^{d-1}dr.
\] (10.37)

Letting \( d\rho(r) = r^{d-1}dr \), i.e.

\[
\rho(J) = \int_J r^{d-1}dr \quad \forall J \in B_{(0,\infty)},
\] (10.38)

Eq. (10.37) may be written as

\[
(\Phi_*m)((a, b] \times E) = \rho((a, b]) \cdot \sigma(E) = (\rho \otimes \sigma)((a, b] \times E).
\] (10.39)

Since

\[
\mathcal{E} = \{(a, b] \times E : 0 < a < b \text{ and } E \in B_{S^{d-1}}\},
\]

is a \( \pi \) class (in fact it is an elementary class) such that \( \sigma(\mathcal{E}) = B_{(0,\infty)} \otimes B_{S^{d-1}} \), it follows from the \( \pi - \lambda \) Theorem and Eq. (10.39) that \( \Phi_*m = \rho \otimes \sigma \). Using this result in Eq. (10.35) gives

\[
\int_{\mathbb{R}^d} fdm = \int_{(0, \infty) \times S^{d-1}} (f \circ \Phi^{-1}) \, d(\rho \otimes \sigma)
\]

which combined with Tonelli’s Theorem 10.6 proves Eq. (10.33).

**Corollary 10.30.** The surface area \( \sigma(S^{d-1}) \) of the unit sphere \( S^{d-1} \subset \mathbb{R}^d \) is

\[
\sigma(S^{d-1}) = \frac{2\pi^{d/2}}{\Gamma(d/2)}
\] (10.40)

where \( \Gamma \) is the gamma function given by

\[
\Gamma(x) := \int_0^\infty u^{x-1}e^{-u}du
\] (10.41)

Moreover, \( \Gamma(1/2) = \sqrt{\pi}, \Gamma(1) = 1 \) and \( \Gamma(x+1) = x\Gamma(x) \) for \( x > 0 \).

**Proof.** Using Theorem 10.29 we find

\[
I_d(1) = \int_0^\infty dr \cdot r^{d-1}e^{-r^2} \int_{S^{d-1}} d\sigma = \sigma(S^{d-1}) \int_0^\infty r^{d-1}e^{-r^2}dr.
\]

We simplify this last integral by making the change of variables \( u = r^2 \) so that \( r = u^{1/2} \) and \( dr = \frac{1}{2}u^{-1/2}du \). The result is

\[
\int_0^\infty r^{d-1}e^{-r^2}dr = \int_0^\infty u^{d/2-1}e^{-u}\frac{1}{2}u^{-1/2}du = \frac{1}{2} \int_0^\infty u^{d-1}e^{-u}du = \frac{1}{2}\Gamma(d/2).
\] (10.42)

Combining the last two equations with Lemma 10.27 which states that \( I_d(1) = \pi^{d/2} \), we conclude that

\[
\pi^{d/2} = I_d(1) = \frac{1}{2}\sigma(S^{d-1}) \Gamma(d/2)
\]

which proves Eq. (10.40). Example 8.8 implies \( \Gamma(1) = 1 \) and from Eq. (10.42),

\[
\Gamma(1/2) = 2 \int_0^\infty e^{-r^2}dr = \int_{-\infty}^\infty e^{-r^2}dr = \Gamma(1) = \sqrt{\pi}.
\]

The relation, \( \Gamma(x+1) = x\Gamma(x) \) is the consequence of the following integration by parts argument:

\[
\Gamma(x+1) = \int_0^\infty e^{-u}u^{x+1}\frac{du}{u} = \int_0^\infty u^x \left( -\frac{d}{du} e^{-u} \right) du = x \int_0^\infty u^{x-1}e^{-u}du = x \Gamma(x).
\]
10.7 More Spherical Coordinates

In this section we will define spherical coordinates in all dimensions. Along the way we will develop an explicit method for computing surface integrals on spheres. As usual when \( n = 2 \) define spherical coordinates \( (r, \theta) \in (0, \infty) \times [0, 2\pi) \) so that

\[
\begin{pmatrix}
    x_1 \\
    x_2 \\
    x_3
\end{pmatrix} = \begin{pmatrix}
    r \cos \theta \\
    r \sin \theta
\end{pmatrix} = T_2(\theta, r).
\]

For \( n = 3 \) we let \( x_3 = r \cos \varphi_1 \) and then

\[
\begin{pmatrix}
    x_1 \\
    x_2
\end{pmatrix} = T_2(\theta, r \sin \varphi_1),
\]

as can be seen from Figure 10.6 so that

![Figure 10.6. Setting up polar coordinates in two and three dimensions.](image)

and more generally,

\[
\begin{align*}
    x_1 &= r \sin \varphi_{n-2} \ldots \sin \varphi_2 \sin \varphi_1 \cos \theta \\
    x_2 &= r \sin \varphi_{n-2} \ldots \sin \varphi_2 \sin \varphi_1 \sin \theta \\
    x_3 &= r \sin \varphi_{n-2} \ldots \sin \varphi_2 \cos \varphi_1 \\
    &\vdots \\
    x_{n-2} &= r \sin \varphi_{n-2} \sin \varphi_{n-3} \cos \varphi_{n-4} \\
    x_{n-1} &= r \sin \varphi_{n-2} \cos \varphi_{n-3} \\
    x_n &= r \cos \varphi_{n-2}.
\end{align*}
\]

By the change of variables formula,

\[
\begin{align*}
    \int_{\mathbb{R}^n} f(x)dm(x) &= \int_0^\infty dr \int_{0 \leq \rho \leq \infty} \int_{0 \leq \theta \leq 2\pi} d\varphi_1 \ldots d\varphi_{n-2} d\theta \left[ \Delta_n(\theta, \varphi_1, \ldots, \varphi_{n-2}, r) \times f(T_n(\theta, \varphi_1, \ldots, \varphi_{n-2}, r)) \right] \\
    &= \int_{0 \leq \rho \leq \infty} \int_{0 \leq \varphi_1 \leq \pi, 0 \leq \theta \leq 2\pi} f(T_n(\theta, \varphi_1, \ldots, \varphi_{n-2}, r)) \Delta_n(\theta, \varphi_1, \ldots, \varphi_{n-2}, r) d\varphi_1 \ldots d\varphi_{n-2} d\theta.
\end{align*}
\]

where

\[
\Delta_n(\theta, \varphi_1, \ldots, \varphi_{n-2}, r) := |\det T'_n(\theta, \varphi_1, \ldots, \varphi_{n-2}, r)|.
\]

**Proposition 10.31.** The Jacobian, \( \Delta_n \) is given by

\[
\Delta_n(\theta, \varphi_1, \ldots, \varphi_{n-2}, r) = r^{n-1} \sin^{n-2} \varphi_{n-2} \ldots \sin^2 \varphi_2 \sin \varphi_1.
\]

If \( f \) is a function on \( rS^{n-1} \) – the sphere of radius \( r \) centered at \( 0 \) inside of \( \mathbb{R}^n \), then

\[
\int_{rS^{n-1}} f(x)d\sigma(x) = r^{n-1} \int_{S^{n-1}} f(r\omega)d\sigma(\omega)
\]

\[
= \int_{0 \leq \rho \leq \infty, 0 \leq \theta \leq 2\pi} f(T_n(\theta, \varphi_1, \ldots, \varphi_{n-2}, r)) \Delta_n(\theta, \varphi_1, \ldots, \varphi_{n-2}, r) d\varphi_1 \ldots d\varphi_{n-2} d\theta.
\]

**Proof.** We are going to compute \( \Delta_n \) inductively. Letting \( \rho := r \sin \varphi_{n-1} \) and writing \( \frac{\partial T_n}{\partial \phi_1} \) for \( \frac{\partial T_n}{\partial \phi}(\theta, \varphi_1, \ldots, \varphi_{n-2}, \rho) \) we have

\[
\Delta_{n+1}(\theta, \varphi_1, \ldots, \varphi_{n-2}, \varphi_{n-1}, r) = |\begin{vmatrix}
    \frac{\partial T_n}{\partial \varphi_1} & \frac{\partial T_n}{\partial \varphi_2} & \cdots & \frac{\partial T_n}{\partial \varphi_{n-2}} & \frac{\partial T_n}{\partial \varphi_{n-1}} & \frac{\partial T_n}{\partial \rho} \sin \varphi_{n-1} \\
    0 & 0 & \cdots & 0 & -r \sin \varphi_{n-1} & \cos \varphi_{n-1}
\end{vmatrix}|.
\]

\[
= r \left( \cos^2 \varphi_{n-1} + \sin^2 \varphi_{n-1} \right) \Delta_n(\theta, \varphi_1, \ldots, \varphi_{n-2}, \rho) = r \Delta_n(\theta, \varphi_1, \ldots, \varphi_{n-2}, r \sin \varphi_{n-1}),
\]
i.e.
\[ \Delta_{n+1}(\theta, \varphi_1, \ldots, \varphi_{n-2}, \varphi_{n-1}, r) = r \Delta_n(\theta, \varphi_1, \ldots, \varphi_{n-2}, r \sin \varphi_{n-1}). \]  
\[ (10.47) \]

To arrive at this result we have expanded the determinant along the bottom row. Staring with \(\Delta_2(\theta, r) = r\) already derived in Example \[10.24\] Eq. \[10.47\] implies,
\[ \Delta_3(\theta, \varphi_1, r) = r \Delta_2(\theta, r \sin \varphi_1) = r^2 \sin \varphi_1 \]
\[ \Delta_4(\theta, \varphi_1, \varphi_2, r) = r \Delta_3(\theta, \varphi_1, r \sin \varphi_2) = r^3 \sin^2 \varphi_2 \sin \varphi_1 \]
\[ \vdots \]
\[ \Delta_n(\theta, \varphi_1, \ldots, \varphi_{n-2}, r) = r^{n-1} \sin^{n-2} \varphi_{n-2} \ldots \sin^2 \varphi_2 \varphi_1 \]
which proves Eq. \[10.45\]. Equation \[10.46\] now follows from Eqs. \[10.33\], \[10.44\] and \[10.45\].

As a simple application, Eq. \[10.46\] implies
\[ \sigma(S^{n-1}) = 2 \pi \prod_{k=1}^{n-2} \gamma_k = \sigma(S^{n-2}) \gamma_{n-2} \]
\[ (10.48) \]

where \(\gamma_k := \int_0^\pi \sin^k \varphi d \varphi\). If \(k \geq 1\), we have by integration by parts that,
\[ \gamma_k = \int_0^\pi \sin^k \varphi d \varphi = - \int_0^\pi \sin^{k-1} \varphi \cos \varphi d \varphi = 2 \delta_{k,1} + (k-1) \int_0^\pi \sin^{k-2} \varphi \cos^2 \varphi d \varphi \]
\[ = 2 \delta_{k,1} + (k-1) \int_0^\pi \sin^{k-2} \varphi (1- \sin^2 \varphi) d \varphi = 2 \delta_{k,1} + (k-1) [\gamma_{k-2} - \gamma_k] \]
and hence \(\gamma_k\) satisfies \(\gamma_0 = \pi, \gamma_1 = 2\) and the recursion relation
\[ \gamma_k = \frac{k-1}{k} \gamma_{k-2} \text{ for } k \geq 2. \]

Hence we may conclude
\[ \gamma_0 = \pi, \gamma_1 = 2, \gamma_2 = \frac{1}{2} \pi, \gamma_3 = \frac{2}{3} \pi, \gamma_4 = \frac{3}{4} \pi, \gamma_5 = \frac{4}{5} \pi, \gamma_6 = \frac{5}{6} \pi \]
and more generally by induction that
\[ \gamma_{2k} = \frac{2k}{(2k)} \pi (2k-1)!! \text{ and } \gamma_{2k+1} = \frac{2}{(2k+1)} \pi (2k)!! \]

Indeed,
\[ \gamma_{2(k+1)+1} = \frac{2k + 2}{2k + 3} \gamma_{2k+1} = \frac{2k + 2}{2k + 3} \frac{(2k)!!}{(2k+1)!!} = \frac{2}{(2k+1)} \pi (2k+1)!! \]
and
\[ \gamma_{2(k+1)} = \frac{2k + 1}{2k + 2} \gamma_{2k} = \frac{2k + 1}{2k + 2} \pi (2k-1)!! = \pi (2k+1)!! \]

The recursion relation in Eq. \[10.48\] may be written as
\[ \sigma(S^n) = \sigma(S^{n-1}) \gamma_{n-1} \]
\[ (10.49) \]
which combined with \(\sigma(S^1) = 2\pi\) implies
\[ \sigma(S^1) = 2\pi, \]
\[ \sigma(S^2) = 2\pi \cdot \gamma_1 = 2\pi \cdot 2, \]
\[ \sigma(S^3) = 2\pi \cdot 2 \cdot \gamma_2 = 2\pi \cdot 2 \cdot \frac{1}{2} \pi \]
\[ = \frac{2^2 \pi^2}{2!!}, \]
\[ \sigma(S^4) = \frac{2^2 \pi^2}{2!!} \cdot \gamma_3 = \frac{2^2 \pi^2}{2!!} \cdot 2 \cdot \frac{1}{3} \]
\[ = \frac{2^3 \pi^3}{3!!}, \]
\[ \sigma(S^5) = 2\pi \cdot 2 \cdot \frac{1}{2} \pi \cdot \frac{2}{3} \cdot \frac{3}{4} \pi \]
\[ = \frac{2^3 \pi^3}{4!!}, \]
\[ \sigma(S^6) = 2\pi \cdot 2 \cdot \frac{1}{2} \pi \cdot \frac{2}{3} \cdot \frac{3}{4} \pi \cdot \frac{4}{5} \pi \cdot \frac{5}{6} \pi = \frac{2^4 \pi^3}{5!!} \]

and more generally that
\[ \sigma(S^{2n}) = \frac{2 (2\pi)^n}{(2n-1)!!} \text{ and } \sigma(S^{2n+1}) = \frac{(2\pi)^{n+1}}{(2n)!!} \]
\[ (10.50) \]
which is verified inductively using Eq. \[10.49\]. Indeed,
\[ \sigma(S^{2n+1}) = \sigma(S^{2n}) \gamma_{2n} = \frac{2 (2\pi)^n}{(2n-1)!!} \frac{(2n-1)!!}{(2n)!!} = \frac{(2\pi)^{n+1}}{(2n)!!} \]
and
\[ \sigma(S^{n+1}) = \sigma(S^{2n+2}) = \sigma(S^{2n+1}) \gamma_{2n+1} = \frac{(2\pi)^{n+1}}{(2n)!!} \frac{2}{(2n+1)!!} = 2 \frac{(2\pi)^{n+1}}{(2n+1)!!} \]

Using
\[ (2n)!! = 2n (2n-1) \ldots (2 \cdot 1) = 2^n n! \]
we may write \(\sigma(S^{2n+1}) = \frac{2^n \pi^{n+1}}{(n+1)!!}\) which shows that Eqs. \[10.33\] and \[10.50\] are in agreement. We may also write the formula in Eq. \[10.50\] as
\[ \sigma(S^n) = \begin{cases} \frac{2 (2\pi)^n}{(n-1)!!} & \text{for } n \text{ even} \\ \frac{(2\pi)^{n+1}}{(n-1)!!} & \text{for } n \text{ odd} \end{cases} \]
10.8 Exercises

Exercise 10.4. Prove Theorem \[10.9\] Suggestion, to get started define

\[\pi (A) := \int_{X_1} d\mu (x_1) \cdots \int_{X_n} d\mu (x_n) 1_A (x_1, \ldots , x_n)\]

and then show Eq. \[10.16\] holds. Use the case of two factors as the model of your proof.

Exercise 10.5. Let \((X_j, M_j, \mu_j)\) for \(j = 1, 2, 3\) be \(\sigma\) – finite measure spaces. Let \(F: (X_1 \times X_2) \times X_3 \to X_1 \times X_2 \times X_3\) be defined by

\[F((x_1, x_2), x_3) = (x_1, x_2, x_3).\]

1. Show \(F\) is \((M_1 \otimes M_2) \otimes M_3, M_1 \otimes M_2 \otimes M_3)\) – measurable and \(F^{-1}\) is \((M_1 \otimes M_2 \otimes M_3)\) – measurable. That is

\[F: ((X_1 \times X_2) \times X_3, (M_1 \otimes M_2) \otimes M_3) \to (X_1 \times X_2 \times X_3, M_1 \otimes M_2 \otimes M_3)\]

is a “measure theoretic isomorphism.”

2. Let \(\pi := F_* [(\mu_1 \otimes \mu_2) \otimes \mu_3]\), i.e. \(\pi (A) = [(\mu_1 \otimes \mu_2) \otimes \mu_3] (F^{-1} (A))\) for all \(A \in (M_1 \otimes M_2) \otimes M_3\). Then \(\pi\) is the unique measure on \(M_1 \otimes M_2 \otimes M_3\) such that

\[\pi (A_1 \times A_2 \times A_3) = \mu_1 (A_1) \mu_2 (A_2) \mu_3 (A_3)\]

for all \(A_i \in M_i\). We will write \(\pi := \mu_1 \otimes \mu_2 \otimes \mu_3\).

3. Let \(f: X_1 \times X_2 \times X_3 \to [0, \infty)\) be a \((M_1 \otimes M_2) \otimes M_3, B_{\mathbb{R}})\) – measurable function. Verify the identity,

\[\int_{X_1 \times X_2 \times X_3} f d\pi = \int_{X_3} d\mu_3 (x_3) \int_{X_2} d\mu_2 (x_2) \int_{X_1} d\mu_1 (x_1) f(x_1, x_2, x_3),\]

makes sense and is correct.

4. (Optional.) Also show the above identity holds for any one of the six possible orderings of the iterated integrals.

Exercise 10.6. Prove the second assertion of Theorem \[10.19\] That is show \(m^d\) is the unique translation invariant measure on \(B_{\mathbb{R}^d}\) such that \(m^d ((0, 1]^d) = 1\).

Hint: Look at the proof of Theorem \[5.22\]

Exercise 10.7. (Part of Folland Problem 2.46 on p. 69.) Let \(X = [0, 1], M = B_{[0,1]}\) be the Borel \(\sigma\) – field on \(X\), \(m\) be Lebesgue measure on \([0, 1]\) and \(\nu\) be counting measure, \(\nu (A) = \# (A)\). Finally let \(D = \{(x, x) \in X^2 : x \in X\}\) be the diagonal in \(X^2\). Show

\[\int_X \left[ \int_X 1_D (x, y) d\nu (y) \right] dm (x) \neq \int_X \left[ \int_X 1_D (x, y) dm (x) \right] d\nu (y)\]

by explicitly computing both sides of this equation.

Exercise 10.8. Folland Problem 2.48 on p. 69. (Counter example related to Fubini Theorem involving counting measures.)

Exercise 10.9. Folland Problem 2.50 on p. 69 pertaining to area under a curve. (Note the \(M \times B_{\mathbb{R}}\) should be \(M \otimes B_{\mathbb{R}}\) in this problem.)

Exercise 10.10. Folland Problem 2.55 on p. 77. (Explicit integrations.)

Exercise 10.11. Folland Problem 2.56 on p. 77. Let \(f \in L^1 ((0, a), dm), g(x) = \int_x^a f(t) \frac{dt}{t}\) for \(x \in (0, a),\) show \(g \in L^1 ((0, a), dm)\) and

\[\int_0^a g(x) dx = \int_0^a f(t) dt.\]

Exercise 10.12. Show \(\int_0^\infty |\sin \frac{x}{x}| dm (x) = \infty\). So \(\sin \frac{x}{x} \notin L^1 ([0, \infty), m)\) and \(\int_0^\infty \sin \frac{x}{x} dm (x)\) is not defined as a Lebesgue integral.


Exercise 10.15. Folland Problem 2.60 on p. 77. Properties of the \(\Gamma\) – function.

Exercise 10.16. Folland Problem 2.61 on p. 77. Fractional integration.

Exercise 10.17. Folland Problem 2.62 on p. 80. Rotation invariance of surface measure on \(S^{n-1}\).

Exercise 10.18. Folland Problem 2.64 on p. 80. On the integrability of \(|x|^n \log |x|\) for \(x\) near \(0\) and \(x\) near \(\infty\) in \(\mathbb{R}^n\).

Exercise 10.19. Show, using Problem \[10.17\] that

\[\int_{S^{d-1}} \omega_i \omega_j d\sigma (\omega) = \frac{1}{d} \delta_{ij} \sigma (S^{d-1}).\]

Hint: show \(\int_{S^{d-1}} \omega_i^2 d\sigma (\omega)\) is independent of \(i\) and therefore

\[\int_{S^{d-1}} \omega_i^2 d\sigma (\omega) = \frac{1}{d} \sum_{j=1}^d \int_{S^{d-1}} \omega_j^2 d\sigma (\omega).\]
Let \((\Omega, B, \mu)\) be a measure space and for \(0 < p < \infty\) and a measurable function \(f : \Omega \to \mathbb{C}\) let
\[
\|f\|_p := \left(\int_{\Omega} |f|^p \, d\mu\right)^{1/p}
\tag{11.1}
\]
and when \(p = \infty\), let
\[
\|f\|_\infty = \inf \{a > 0 : \mu(|f| > a) = 0\}
\tag{11.2}
\]
For \(0 < p \leq \infty\), let
\[
L^p(\Omega, B, \mu) = \{f : \Omega \to \mathbb{C} : f \text{ is measurable and } \|f\|_p < \infty\}/\sim
\]
where \(f \sim g\) iff \(f = g\) a.e. Notice that \(\|f - g\|_p = 0\) iff \(f \sim g\) and if \(f \sim g\) then \(\|f\|_p = \|g\|_p\). In general we will (by abuse of notation) use \(f\) to denote both the function \(f\) and the equivalence class containing \(f\).

**Remark 11.1.** Suppose that \(\|f\|_\infty \leq M\), then for all \(a > M\), \(\mu(|f| > a) = 0\) and therefore \(\mu(|f| > M) = \lim_{n \to \infty} \mu(|f| > M + 1/n) = 0\), i.e. \(|f(\omega)| \leq M\) for \(\mu\) a.e. \(\omega\). Conversely, if \(|f| \leq M\) a.e. and \(a > M\) then \(\mu(|f| > a) = 0\) and hence \(\|f\|_\infty \leq M\). This leads to the identity:
\[
\|f\|_\infty = \inf \{a > 0 : |f(\omega)| \leq a\ \text{for} \ \mu - \text{a.e.} \ \omega\}.
\]

### 11.1 Modes of Convergence

Let \(\{f_n\}_{n=1}^\infty \cup \{f\}\) be a collection of complex valued measurable functions on \(\Omega\). We have the following notions of convergence and Cauchy sequences.

**Definition 11.2.**
1. \(f_n \to f\) a.e. if there is a set \(E \in B\) such that \(\mu(E) = 0\) and \(\lim_{n \to \infty} 1_{E^c} f_n = 1_{E^c} f\).
2. \(f_n \to f\) in \(\mu\) - measure if \(\lim_{n \to \infty} \mu(|f_n - f| > \varepsilon) = 0\) for all \(\varepsilon > 0\). We will abbreviate this by saying \(f_n \to f\) in \(L^0\) or by \(f_n \overset{\mu}{\to} f\).
3. \(f_n \to f\) in \(L^p\) iff \(f_n \in L^p\) for all \(n\), and \(\lim_{n \to \infty} \|f_n - f\|_p = 0\).

**Definition 11.3.**
1. \(\{f_n\}\) is a.e. Cauchy if there is a set \(E \in B\) such that \(\mu(E) = 0\) and \(1_{E^c} f_n \to 1_{E^c} f\) is a pointwise Cauchy sequences.
2. \(\{f_n\}\) is Cauchy in \(\mu\) - measure (or \(L^0\) - Cauchy) if \(\lim_{m,n \to \infty} \mu(|f_n - f_m| > \varepsilon) = 0\) for all \(\varepsilon > 0\).
3. \(\{f_n\}\) is Cauchy in \(L^p\) if \(\lim_{m,n \to \infty} \|f_n - f_m\|_p = 0\).

When \(\mu\) is a probability measure, we describe, \(f_n \overset{\mu}{\to} f\) as \(f_n\) converging to \(f\) in probability. If a sequence \(\{f_n\}_{n=1}^\infty\) is \(L^p\) - convergent, then it is \(L^p\) - Cauchy. For example, when \(p \in [1, \infty)\) and \(f_n \to f\) in \(L^p\), we have
\[
\|f_n - f_m\|_p \leq \|f_n - f\|_p + \|f - f_m\|_p \to 0 \text{ as } m, n \to \infty.
\]
The case where \(p = 0\) will be handled in Theorem 11.7 below.

**Lemma 11.4 (\(L^p\) - convergence implies convergence in probability).** Let \(p \in [1, \infty)\). If \(\{f_n\} \subset L^p\) is \(L^p\) - convergent (Cauchy) then \(\{f_n\}\) is also convergent (Cauchy) in measure.

**Proof.** By Chebyshev’s inequality (8.3),
\[
\mu(|f| \geq \varepsilon) = \mu(|f|^p \geq \varepsilon^p) \leq \frac{1}{\varepsilon^p} \int_{\Omega} |f|^p \, d\mu = \frac{1}{\varepsilon^p} \|f\|_p^p
\]
and therefore if \(\{f_n\}\) is \(L^p\) - Cauchy, then
\[
\mu(|f_n - f_m| \geq \varepsilon) \leq \frac{1}{\varepsilon^p} \|f_n - f_m\|_p \to 0 \text{ as } m, n \to \infty
\]
showing \(\{f_n\}\) is \(L^0\) - Cauchy. A similar argument holds for the \(L^p\) - convergent case.

Here is a sequence of functions where \(f_n \to 0\) a.e., \(f_n \overset{\mu}{\to} 0\) in \(L^1\), \(f_n \overset{\mu}{\to} 0\).
Above is a sequence of functions where \( f_n \to 0 \) a.e., yet \( f_n \not\to 0 \) in \( L^1 \).

Here is a sequence of functions where \( f_n \to 0 \) a.e., \( f_n \not\to 0 \) in \( L^1 \).

Above is a sequence of functions where \( f_n \to 0 \) in \( L^1 \), \( f_n \not\to 0 \) a.e., and \( f_n m \to 0 \).

Theorem 11.5 (Egoroff’s Theorem: almost sure convergence implies convergence in probability).

Suppose \( \mu(\Omega) = 1 \) and \( f_n \to f \) a.s. Then for all \( \varepsilon > 0 \) there exists \( E = E_\varepsilon \in \mathcal{B} \) such that \( \mu(E) < \varepsilon \) and \( f_n \to f \) uniformly on \( E^c \). In particular \( f_n \overset{\mu}{\to} f \) as \( n \to \infty \).

**Proof.** Let \( f_n \to f \) a.e. Then for all \( \varepsilon > 0 \),

\[
0 = \mu(\{|f_n - f| > \varepsilon \text{ i.o. } n\}) \\
= \lim_{N \to \infty} \mu\left(\bigcup_{n \geq N} \{|f_n - f| > \varepsilon\}\right) \\
\geq \limsup_{N \to \infty} \mu(\{|f_N - f| > \varepsilon\})
\]

from which it follows that \( f_n \overset{\mu}{\to} f \) as \( n \to \infty \). To get the uniform convergence off a small exceptional set, the equality in Eq. (11.3) allows us to choose an increasing sequence \( \{N_k\}_{k=1}^\infty \), such that, if

\[
E_k := \bigcup_{n \geq N_k} \left\{|f_n - f| > \frac{1}{k}\right\}, \text{ then } \mu(E_k) < \varepsilon 2^{-k}.
\]

The set, \( E := \bigcup_{k=1}^\infty E_k \), then satisfies the estimate, \( \mu(E) < \sum_k \varepsilon 2^{-k} = \varepsilon \). Moreover, for \( \omega \notin E \), we have \( |f_n(\omega) - f(\omega)| \leq \frac{1}{k} \) for all \( n \geq N_k \) and all \( k \). That is \( f_n \to f \) uniformly on \( E^c \).
Lemma 11.6. Suppose \( a_n \in \mathbb{C} \) and \( |a_{n+1} - a_n| \leq \varepsilon_n \) and \( \sum_{n=1}^{\infty} \varepsilon_n < \infty \). Then
\[
\lim_{n \to \infty} a_n = a \in \mathbb{C} \quad \text{exists and} \quad |a - a_n| \leq \delta_n := \sum_{k=n}^{\infty} \varepsilon_k.
\]

Proof. Let \( m > n \) then
\[
|a_m - a_n| = \left| \sum_{k=n}^{m-1} (a_{k+1} - a_k) \right| \leq \sum_{k=n}^{m-1} |a_{k+1} - a_k| \leq \sum_{k=n}^{\infty} \varepsilon_k := \delta_n. \tag{11.4}
\]
So we have \( |a_m - a_n| \leq \delta_{\min(m,n)} \to 0 \) as \( m, n \to \infty \), i.e. \( \{a_n\} \) is Cauchy. Let \( m \to \infty \) in (11.4) to find \( |a - a_n| \leq \delta_n \). \[\square\]

Theorem 11.7. Let \((\Omega, \mathcal{B}, \mu)\) be a measure space and \( \{f_n\}_{n=1}^{\infty} \) be a sequence of measurable functions on \( \Omega \).

1. If \( f \) and \( g \) are measurable functions and \( f_n \overset{\mu}{\to} f \) and \( f_n \overset{\mu}{\to} g \) then \( f = g \) a.e.
2. If \( f_n \overset{\mu}{\to} f \) then \( \{f_n\}_{n=1}^{\infty} \) is Cauchy in measure.
3. If \( \{f_n\}_{n=1}^{\infty} \) is Cauchy in measure, there exists a measurable function, \( f \), and a subsequence \( g_j = f_{n_j} \) of \( \{f_n\} \) such that \( \lim_{j \to \infty} g_j := f \) exists a.e.
4. If \( \{f_n\}_{n=1}^{\infty} \) is Cauchy in measure and \( f \) is as in item 3, then \( f_n \overset{\mu}{\to} f \).
5. Let us now further assume that \( \mu(\Omega) < \infty \). In this case, a sequence of functions, \( \{f_n\}_{n=1}^{\infty} \), converges to \( f \) in probability if every subsequence, \( \{f'_n\}_{n=1}^{\infty} \) of \( \{f_n\}_{n=1}^{\infty} \) has a further subsequence, \( \{f''_n\}_{n=1}^{\infty} \), which is almost surely convergent to \( f \).

Proof.

1. Suppose that \( f \) and \( g \) are measurable functions such that \( f_n \overset{\mu}{\to} g \) and \( f_n \overset{\mu}{\to} f \) as \( n \to \infty \) and \( \varepsilon > 0 \) is given. Since
\[
\{ |f - g| > \varepsilon \} = \{ |f - f_n + f_n - g| > \varepsilon \} \subset \{ |f - f_n| + |f_n - g| > \varepsilon \} \subset \{ |f - f_n| > \varepsilon/2 \} \cup \{ |g - f_n| > \varepsilon/2 \},
\]
we have
\[
\mu(|f - g| > \varepsilon) \leq \mu(|f - f_n| > \varepsilon/2) + \mu(|g - f_n| > \varepsilon/2) \to 0 \quad \text{as} \quad n \to \infty.
\]
Hence
\[
\mu(|f - g| > 0) = \mu \left( \bigcup_{n=1}^{\infty} \left\{ |f - g| > \frac{1}{n} \right\} \right) \leq \sum_{n=1}^{\infty} \mu \left( |f - g| > \frac{1}{n} \right) = 0,
\]
i.e. \( f = g \) a.e.

2. Suppose \( f_n \overset{\mu}{\to} f, \varepsilon > 0 \) and \( m, n \in \mathbb{N} \) and \( \omega \in \Omega \) are such that \( |f_n(\omega) - f_m(\omega)| > \varepsilon \). Then
\[
\varepsilon < |f_n(\omega) - f_m(\omega)| = |f_n(\omega) - f(\omega)| + |f(\omega) - f_m(\omega)|
\]
from which it follows that either \( |f_n(\omega) - f(\omega)| > \varepsilon/2 \) or \( |f(\omega) - f_m(\omega)| > \varepsilon/2 \). Therefore we have shown,
\[
\{ |f_n - f_m| > \varepsilon \} \subset \{ |f_n - f| > \varepsilon/2 \} \cup \{ |f_m - f| > \varepsilon/2 \}
\]
and hence
\[
\mu(|f_n - f_m| > \varepsilon) \leq \mu(|f_n - f| > \varepsilon/2) + \mu(|f_m - f| > \varepsilon/2) \to 0 \quad \text{as} \quad m, n \to \infty.
\]
3. Suppose \( \{f_n\} \) is \( L^0(\mu) \)-Cauchy and let \( \varepsilon_n > 0 \) such that \( \sum_{n=1}^{\infty} \varepsilon_n < \infty \) (\( \varepsilon_n = 2^{-n} \) would do) and set \( \delta_n = \sum_{k=n}^{\infty} \varepsilon_k \). Choose \( g_j = f_{n_j} \) where \( \{n_j\} \) is a subsequence of \( \mathbb{N} \) such that
\[
\mu(\{|g_{j+1} - g_j| > \varepsilon_j\}) \leq \varepsilon_j.
\]
Let \( F_N := \bigcup_{j \geq N} \{|g_{j+1} - g_j| > \varepsilon_j\} \) and
\[
E := \bigcap_{N=1}^{\infty} F_N = \{|g_{j+1} - g_j| > \varepsilon_j \text{ i.o.}\}
\]
and observe that \( \mu(F_N) \leq \delta_N < \infty \). Since
\[
\sum_{j=1}^{\infty} \mu(\{|g_{j+1} - g_j| > \varepsilon_j\}) \leq \sum_{j=\infty}^{\infty} \varepsilon_j < \infty,
\]
it follows from the first Borel-Cantelli lemma that
\[
0 = \mu(E) = \lim_{N \to \infty} \mu(F_N).
\]
For \( \omega \notin E, |g_{j+1}(\omega) - g_j(\omega)| \leq \varepsilon_j \) for a.a. \( j \) and so by Lemma 11.6, \( f(\omega) := \lim_{j \to \infty} g_j(\omega) \) exists. For \( \omega \in E \) we may define \( f(\omega) \equiv 0 \).

4. Next we will show \( g_N \overset{\mu}{\to} f \) as \( N \to \infty \) where \( f \) and \( g_N \) are as above. If \( \omega \in F_N^c = \bigcap_{j \geq N} \{|g_{j+1} - g_j| \leq \varepsilon_j\} \),
\[
\omega \in F_N^c = \bigcap_{j \geq N} \{|g_{j+1} - g_j| \leq \varepsilon_j\},
\]
then
\[
|g_{j+1}(\omega) - g_j(\omega)| \leq \varepsilon_j \quad \text{for all} \quad j \geq N.
\]
Another application of Lemma 11.6 shows \( |f(\omega) - g_j(\omega)| \leq \delta_j \) for all \( j \geq N \), i.e.
Corollary 11.8 (Dominated Convergence Theorem). Let $(\Omega, \mathcal{B}, \mu)$ be a measure space. Suppose $\{f_n\}$, $\{g_n\}$, and $g$ are in $L^1$ and $f \in L^0$ are functions such that

$$|f_n| \leq g_n \text{ a.e., } f_n \overset{\mu}{\longrightarrow} f, \quad g_n \overset{\mu}{\longrightarrow} g, \quad \text{and } \int g_n \to \int g \text{ as } n \to \infty.$$ 

Then $f \in L^1$ and $\lim_{n \to \infty} \|f - f_n\|_1 = 0$, i.e. $f_n \to f$ in $L^1$. In particular $\lim_{n \to \infty} \int f_n = \int f$.

Proof. First notice that $|f| \leq g$ a.e. and hence $f \in L^1$ since $g \in L^1$. To see that $|f| \leq g$, use Theorem 11.7 to find subsequences $\{f_{n_k}\}$ and $\{g_{n_k}\}$ of $\{f_n\}$ and $\{g_n\}$ respectively which are almost everywhere convergent. Then

$$|f| = \lim_{k \to \infty} |f_{n_k}| \leq \lim_{k \to \infty} g_{n_k} = g \text{ a.e.}$$

If (for sake of contradiction) $\lim_{n \to \infty} \|f - f_n\|_1 \neq 0$ there exists $\varepsilon > 0$ and a subsequence $\{f_{n_k}\}$ of $\{f_n\}$ such that

$$\int |f - f_{n_k}| \geq \varepsilon \text{ for all } k.$$  

(11.5)

Using Theorem 11.7 again, we may assume (by passing to a further subsequences if necessary) that $f_{n_k} \to f$ and $g_{n_k} \to g$ almost everywhere. Noting, $|f - f_{n_k}| \leq g + g_{n_k} \to 2g$ and $\int (g + g_{n_k}) \to 2g$, an application of the dominated convergence Theorem 8.32 implies $\lim_{k \to \infty} \int |f - f_{n_k}| = 0$ which contradicts Eq. (11.5).

Exercise 11.1 (Fatou’s Lemma). Let $(\Omega, \mathcal{B}, \mu)$ be a measure space. If $f_n \geq 0$ and $f_n \to f$ in measure, then $\int f_n d\mu \leq \liminf_{n \to \infty} \int f_n d\mu$.

Exercise 11.2. Let $(\Omega, \mathcal{B}, \mu)$ be a measure space, $p \in [1, \infty)$, $\{f_n\} \subset L^p(\mu)$ and $f \in L^p(\mu)$. Then $f_n \to f$ in $L^p(\mu)$ if $f_n \overset{\mu}{\longrightarrow} f$ and $\int |f_n|^p \to \int |f|^p$.

Solution to Exercise 11.2. By the triangle inequality, $\|f - f_n\|_p \leq \|f - f_n\|_p$ which shows $\int |f_n|^n \to \int |f|^p$ if $f_n \to f$ in $L^p$. Moreover Chebyshev’s inequality implies $f_n \overset{\mu}{\longrightarrow} f$ if $f_n \to f$ in $L^p$.

For the converse, let $F_n := |f - f_n|^p$ and $G_n := 2^{p-1} (|f|^p + |f_n|^p)$. Then $F_n \overset{\mu}{\longrightarrow} 0$, $F_n \leq G_n \in L^1$, and $\int G_n \to \int G$ where $G := 2^{p-1} |f|^p \in L^1$. Therefore, by Corollary 11.8 $\int |f - f_n|^p = \int F_n \to 0 = 0$.

Corollary 11.9. Suppose $(\Omega, \mathcal{B}, \mu)$ is a probability space, $f_n \overset{\mu}{\rightarrow} f$ and $g_n \overset{\mu}{\rightarrow} g$ and $\varphi : \mathbb{R} \to \mathbb{R}$ and $\psi : \mathbb{R}^2 \to \mathbb{R}$ are continuous functions. Then

1. $\varphi(f_n) \overset{\mu}{\rightarrow} \varphi(f)$,
2. $\psi(f_n, g_n) \overset{\mu}{\rightarrow} \psi(f, g)$,
3. $f_n + g_n \overset{\mu}{\rightarrow} f + g$, and
4. $f_n \cdot g_n \overset{\mu}{\rightarrow} f \cdot g$.

Proof. Item 1., 3. and 4. all follow from item 2. by taking $\psi(x, y) = \varphi(x)$, $\psi(x, y) = x + y$, and $\psi(x, y) = x \cdot y$ respectively. So it suffices to prove item 2. To do this we will make repeated use of Theorem 11.7.
11.2 Jensen’s, Hőlder’s and Minkowski’s Inequalities

Theorem 11.10 (Jensen’s Inequality). Suppose that $(\Omega, \mathcal{B}, \mu)$ is a probability space, i.e. $\mu$ is a positive measure and $\mu(\Omega) = 1$. Also suppose that $f \in L^1(\mu)$, $f : \Omega \rightarrow (a, b)$, and $\varphi : (a, b) \rightarrow \mathbb{R}$ is a convex function, (i.e. $\varphi''(x) \geq 0$ on $(a,b)$.) Then

$$\varphi\left(\int_{\Omega} f d\mu\right) \leq \int_{\Omega} \varphi(f) d\mu$$

where if $\varphi \circ f \not\in L^1(\mu)$, then $\varphi \circ f$ is integrable in the extended sense and $\int_{\Omega} \varphi(f) d\mu = \infty$.

Proof. Let $t = \int_{\Omega} f d\mu \in (a, b)$ and let $\beta \in \mathbb{R}$ ($\beta = \varphi(t)$ when $\varphi(t)$ exists), be such that $\varphi(s) - \varphi(t) \geq \beta(s-t)$ for all $s \in (a, b)$. (See Lemma 7.31 and Figure 7.2 when $\varphi$ is $C^1$ and Theorem 11.35 below for the existence of such a $\beta$ in the general case.) Then integrating the inequality, $\varphi(f) - \varphi(t) \geq \beta(f-t)$, implies that

$$0 \leq \int_{\Omega} \varphi(f) d\mu - \varphi(t) = \int_{\Omega} \varphi(f) d\mu - \varphi\left(\int_{\Omega} f d\mu\right).$$

Moreover, if $\varphi(f)$ is not integrable, then $\varphi(f) \geq \varphi(t) + \beta(f-t)$ which shows that negative part of $\varphi(f)$ is integrable. Therefore, $\int_{\Omega} \varphi(f) d\mu = \infty$ in this case.

Example 11.11. Since $e^x$ for $x \in \mathbb{R}$, $-\ln x$ for $x > 0$, and $x^p$ for $x \geq 0$ and $p \geq 1$ are all convex functions, we have the following inequalities

$$\exp\left(\int_{\Omega} f d\mu\right) \leq \int_{\Omega} e^{f} d\mu, \quad \int_{\Omega} \log(|f|) d\mu \leq \log\left(\int_{\Omega} |f| d\mu\right)$$

and for $p \geq 1,$

$$\left|\int_{\Omega} f d\mu\right|^{p} \leq \left(\int_{\Omega} |f| d\mu\right)^{p} \leq \int_{\Omega} |f|^{p} d\mu.$$  

As a special case of Eq. (11.6), if $p_i, s_i > 0$ for $i = 1, 2, \ldots, n$ and $\sum_{i=1}^{n} \frac{1}{p_i} = 1$, then

$$s_1 \ldots s_n = e^\sum_{i=1}^{n} \ln s_i = e^\sum_{i=1}^{n} \frac{1}{p_i} \ln s_i^{p_i} \leq \sum_{i=1}^{n} \frac{1}{p_i} e^{\ln s_i^{p_i}} = \sum_{i=1}^{n} \frac{s_i^{p_i}}{p_i}. \quad (11.7)$$

Indeed, we have applied Eq. (11.6) with $\Omega = \{1, 2, \ldots, n\}$, $\mu = \sum_{i=1}^{n} \frac{1}{p_i} \delta_i$ and $f(i) := \ln s_i^{p_i}$. As a special case of Eq. (11.7), suppose that $s, t, p, q \in (1, \infty)$ with $q = \frac{p}{p-1}$ (i.e. $\frac{1}{p} + \frac{1}{q} = 1$) then

$$st \leq \frac{1}{p} s^p + \frac{1}{q} t^q. \quad (11.8)$$

(When $p = q = 1/2$, the inequality in Eq. (11.8) follows from the inequality, $0 \leq (s - t)^2$.)

As another special case of Eq. (11.7), take $p_i = n$ and $s_i = a_i^{1/n}$ with $a_i > 0$, then we get the arithmetic geometric mean inequality,

$$\sqrt[n]{a_1 \ldots a_n} \leq \frac{1}{n} \sum_{i=1}^{n} a_i. \quad (11.9)$$

Theorem 11.12 (Hőlder’s Inequality). Suppose that $1 \leq p \leq \infty$ and $q := \frac{p}{p-1},$ or equivalently $p^{-1} + q^{-1} = 1$. If $f$ and $g$ are measurable functions then

$$\|fg\|_1 \leq \|f\|_p \cdot \|g\|_q. \quad (11.10)$$

Assuming $p \in (1, \infty)$ and $\|f\|_p \cdot \|g\|_q < \infty$, equality holds in Eq. (11.10) iff $|f|^p$ and $|g|^q$ are linearly dependent as elements of $L^1$ which happens iff

$$|g|^q \|f\|^p_p = \|g\|^q_\|f\|_p \ a.e. \quad (11.11)$$

Proof. The cases $p = 1$ and $q = \infty$ or $p = \infty$ and $q = 1$ are easy to deal with and will be left to the reader. So we now assume that $p, q \in (1, \infty)$. If $\|f\|_q = 0$ or $\|g\|_p = 0$ or $\|f\|_p = \infty$, Eq. (11.10) is again easily verified. So we will now assume that $0 < \|f\|_q, \|g\|_p < \infty$. Taking $s = |f|/\|f\|_p$ and $t = |g|/\|g\|_q$ in Eq. (11.8) gives,

$$\frac{|fg|}{\|f\|_p \|g\|_q} \leq \frac{1}{p} \|f\|_p^p + \frac{1}{q} \|g\|_q^q$$

with equality iff $|g|/\|g\|_q = |f|/(\|f\|_p^{p-1}) = |f|^{p-1}/\|f\|_p^{(p-1)}$, i.e. $|g|^q \|f\|_p^p = \|g\|^q |f|^{p^2}$. Integrating Eq. (11.12) implies...
with equality iff Eq. (11.11) holds. The proof is finished since it is easily checked that equality holds in Eq. (11.10) when \(|f|^p = c |g|^q\) of \(|g|^q = c |f|^p\) for some constant \(c\).

**Example 11.13.** Suppose that \(a_k \in \mathbb{C}\) for \(k = 1, 2, \ldots, n\) and \(p \in [1, \infty)\), then

\[
\left| \sum_{k=1}^{n} a_k \right|^p \leq \left( \sum_{k=1}^{n} |a_k|^p \right)^{1/p} \left( \sum_{k=1}^{n} 1^q \right)^{1/q} = n^{1/q} \left( \sum_{k=1}^{n} |a_k|^p \right)^{1/p} .
\]

Indeed, by Hölder’s inequality applied using the measure space, \{1, 2, \ldots, n\} equipped with counting measure, we have

\[
\sum_{k=1}^{n} a_k = \sum_{k=1}^{n} a_k \cdot 1 \leq \left( \sum_{k=1}^{n} |a_k|^p \right)^{1/p} \left( \sum_{k=1}^{n} 1^q \right)^{1/q} = n^{1/q} \left( \sum_{k=1}^{n} |a_k|^p \right)^{1/p} .
\]

where \(q = \frac{p}{p-1}\). Taking the \(p^{th}\) power of this inequality then gives, Eq. (11.14).

**Theorem 11.14 (Generalized Hölder’s inequality).** Suppose that \(f_i : \Omega \rightarrow \mathbb{C}\) are measurable functions for \(i = 1, \ldots, n\) and \(p_1, \ldots, p_n\) and \(r\) are positive numbers such that \(\sum_{i=1}^{n} p_i^{-1} = r^{-1}\), then

\[
\left\| \prod_{i=1}^{n} f_i \right\|_r \leq \prod_{i=1}^{n} \left\| f_i \right\|_{p_i} .
\]

**Proof.** One may prove this theorem by induction based on Hölder’s Theorem 11.12 above. Alternatively we may give a proof along the lines of the proof of Theorem 11.12 which is what we will do here.

Since Eq. (11.14) is easily seen to hold if \(\|f_i\|_{p_i}^r = 0\) for some \(i\), we will assume that \(\|f_i\|_{p_i} > 0\) for all \(i\). By assumption, \(\sum_{i=1}^{n} \frac{p_i}{p_i} = 1\), hence we may replace \(s_i\) by \(s_i^r\) and \(p_i\) by \(p_i/r\) for each \(i\) in Eq. (11.7) to find

\[
s_1^r \ldots s_n^r \leq \sum_{i=1}^{n} \left( \frac{s_i^r}{p_i} \right)^{p_i/r} = r \sum_{i=1}^{n} \frac{s_i^r}{p_i} .
\]

Now replace \(s_i\) by \(|f_i| / \|f_i\|_{p_i}\) in the previous inequality and integrate the result to find

\[
\frac{1}{\prod_{i=1}^{n} \|f_i\|_{p_i}} \left\| \prod_{i=1}^{n} f_i \right\|_r \leq r \sum_{i=1}^{n} \frac{1}{p_i} \left\| f_i \right\|_{p_i} \int_{\Omega} |f_i|^{p_i} d\mu = \sum_{i=1}^{n} \frac{r}{p_i} = 1 .
\]

\[\text{Note:} \quad 1 \text{ of Example 11.13 gives } \|f + g\|_{p} \leq \|f\|_{p} + \|g\|_{p} .\]

**Theorem 11.15 (Minkowski’s Inequality).** If \(1 \leq p \leq \infty\) and \(f, g \in L^p\) then

\[
\|f + g\|_p \leq \|f\|_p + \|g\|_p .
\]

**Proof.** When \(p = \infty\), \(|f| \leq \|f\|_{\infty}\) a.e. and \(|g| \leq \|g\|_{\infty}\) a.e. so that \(|f + g| \leq |f| + |g| \leq \|f\|_{\infty} + \|g\|_{\infty}\) a.e. and therefore

\[
\|f + g\|_{\infty} \leq \|f\|_{\infty} + \|g\|_{\infty} .
\]

When \(p < \infty\),

\[
|f + g|^p \leq (2 \max(|f|, |g|))^p = 2^p \max(|f|^p, |g|^p) \leq 2^p (|f|^p + |g|^p) ,
\]

which implies \(f + g \in L^p\) since

\[
\|f + g\|^p \leq 2^p (\|f\|^p + \|g\|^p) < \infty .
\]

Furthermore, when \(p = 1\) we have

\[
\|f + g\|_1 = \int_{\Omega} |f + g| d\mu \leq \int_{\Omega} |f| d\mu + \int_{\Omega} |g| d\mu = \|f\|_1 + \|g\|_1 .
\]

We now consider \(p \in (1, \infty)\). We may assume \(\|f + g\|_p, \|f\|_p\) and \(\|g\|_p\) are all positive since otherwise the theorem is easily verified. Integrating

\[
|f + g|^p = |f + g| |f + g|^{p-1} \leq (|f| + |g|) |f + g|^{p-1}
\]

and then applying Hölder’s inequality with \(q = p/(p-1)\) gives

\[
\int_{\Omega} |f + g|^p d\mu \leq \int_{\Omega} |f| |f + g|^{p-1} d\mu \leq (\|f\|_p + \|g\|_p) \|f + g|^{p-1} \|_q ,
\]

where

\[
\|f + g|^{p-1} \|_q = \int_{\Omega} (|f + g|^{p-1})^q d\mu = \int_{\Omega} |f + g|^p d\mu = \|f + g\|_p^p .
\]

Combining Eqs. (11.16) and (11.17) implies

\[
\|f + g\|_p^p \leq \|f\|_p^p |f + g|^{p-1} + \|g\|_p^p |f + g|^{p-1} \|_q
\]

Solving this inequality for \(\|f + g\|_p\) gives Eq. (11.15).
11.3 Completeness of $L^p$ – spaces

**Theorem 11.16.** Let $\|\|_\infty$ be as defined in Eq. (11.3), then $(L^\infty(\Omega, \mathcal{B}, \mu), \|\|_\infty)$ is a Banach space. A sequence $\{f_n\}_{n=1}^\infty \subset L^\infty$ converges to $f \in L^\infty$ iff there exists $E \in \mathcal{B}$ such that $\mu(E) = 0$ and $f_n \to f$ uniformly on $E^c$. Moreover, bounded simple functions are dense in $L^\infty$.

**Proof.** By Minkowski’s Theorem\[11.15] $\|\|_\infty$ satisfies the triangle inequality. The reader may easily check the remaining conditions that ensure $\|\|_\infty$ is a norm. Suppose that $\{f_n\}_{n=1}^\infty \subset L^\infty$ is a sequence such $f_n \to f \in L^\infty$, i.e. $\|f_n - f\|_\infty \to 0$ as $n \to \infty$. Then for all $k \in \mathbb{N}$, there exists $N_k < \infty$ such that $\mu(\{|f_n - f| > k^{-1}\}) = 0$ for all $n \geq N_k$.

Let $E = \bigcup_{k=1}^\infty \bigcap_{n \geq N_k} \{|f_n - f| > k^{-1}\}$.

Then $\mu(E) = 0$ and for $x \in E^c$, $|f(x) - f_n(x)| \leq k^{-1}$ for all $n \geq N_k$. This shows that $f_n \to f$ uniformly on $E^c$. Conversely, if there exists $E \in \mathcal{B}$ such that $\mu(E) = 0$ and $f_n \to f$ uniformly on $E^c$, then for any $\varepsilon > 0$,

$$\mu(|f_n - f| \geq \varepsilon) = \mu(\{|f_n - f| \geq \varepsilon\} \cap E^c) = 0$$

for all $n$ sufficiently large. That is to say $\lim_{j \to \infty} \|f_n - f\|_\infty \leq \varepsilon$ for all $\varepsilon > 0$.

The density of simple functions follows from the approximation Theorem\[6.32].

So the last item to prove is the completeness of $L^\infty$.

Suppose $\varepsilon_{m,n} := \|f_m - f_n\|_\infty \to 0$ as $m, n \to \infty$. Let $E_{m,n} = \{|f_n - f_m| > \varepsilon_{m,n}\}$ and $E := \cup E_{m,n}$, then $\mu(E) = 0$ and

$$\sup_{x \in E^c} |f_m(x) - f_n(x)| \leq \varepsilon_{m,n} \to 0$$

as $m, n \to \infty$.

Therefore, $f := \lim_{m \to \infty} f_m$ exists on $E^c$ and the limit is uniform on $E^c$. Letting $f = \lim_{m \to \infty} 1_{E^c} f_m$, it then follows that $\lim_{m \to \infty} \|f_m - f\|_\infty = 0$.

**Theorem 11.17 (Completeness of $L^p(\mu)$).** For $1 \leq p \leq \infty$, $L^p(\mu)$ equipped with the $L^p$ – norm, $\|\|_p$ (see Eq. (11.4)), is a Banach space.

**Proof.** By Minkowski’s Theorem\[11.15] $\|\|_p$ satisfies the triangle inequality. As above the reader may easily check the remaining conditions that ensure $\|\|_p$ is a norm. So we are left to prove the completeness of $L^p(\mu)$ for $1 \leq p < \infty$, the case $p = \infty$ being done in Theorem 11.16.

Let $\{f_n\}_{n=1}^\infty \subset L^p(\mu)$ be a Cauchy sequence. By Chebyshev’s inequality (Lemma\[11.4]), $\{f_n\} \subset L^p$-Cauchy (i.e. Cauchy in measure) and by Theorem 11.7 there exists a subsequence $\{g_j\}$ of $\{f_n\}$ such that $g_j \to f$ a.e. By Fatou’s Lemma, $\lim_{j \to \infty} \int |g_j - g_k|^p d\mu \leq \lim_{j \to \infty} \int |g_j|^p d\mu = \lim_{j \to \infty} \|g_j\|_p^p \to 0$ as $j \to \infty$.

In particular, $\|f\|_p \leq \|g_j - f\|_p + \|g_j\|_p \to 0$ so the $f \in L^p$ and $g_j \underset{L^p}{\to} f$. The proof is finished because,

$$\|f - g\|_p \leq \|f - g_j\|_p + \|g_j - f\|_p \to 0$$

as $j, n \to \infty$.

See Proposition\[12.5] for an important example of the use of this theorem.

11.4 Relationships between different $L^p$ – spaces

The $L^p(\mu)$ – norm controls two types of behaviors of $f$, namely the “behavior at infinity” and the behavior of “local singularities.” So in particular, if $f$ blows up at a point $x_0 \in \Omega$, then locally near $x_0$ it is harder for $f$ to be in $L^p(\mu)$ as $p$ increases. On the other hand a function $f \in L^p(\mu)$ is allowed to decay at “infinity” slower and slower as $p$ increases. With these insights in mind, we should not in general expect $L^p(\mu) \subset L^q(\mu)$ or $L^q(\mu) \subset L^p(\mu)$. However, there are two notable exceptions. (1) If $\mu(\Omega) < \infty$, then there is no behavior at infinity to worry about and $L^q(\mu) \subset L^p(\mu)$ for all $q \geq p$ as is shown in Corollary\[11.18] below. (2) If $\mu$ is counting measure, i.e. $\mu(A) = \#(A)$, then all functions in $L^p(\mu)$ for any $p$ can not blow up on a set of positive measure, so there are no local singularities. In this case $L^p(\mu) \subset L^q(\mu)$ for all $q \geq p$, see Corollary\[11.23] below.

**Corollary 11.18.** If $\mu(\Omega) < \infty$ and $0 < p < q \leq \infty$, then $L^p(\mu) \subset L^q(\mu)$, the inclusion map is bounded and in fact

$$\|f\|_q \leq \mu(\Omega)^{(\frac{1}{p} - \frac{1}{q})} \|f\|_p.$$  

**Proof.** Take $a \in [1, \infty]$ such that

$$\frac{1}{p} = \frac{1}{a} + \frac{1}{q}, \text{ i.e. } a = \frac{pq}{q - p}.$$  

Then by Theorem 11.14

$$\|f\|_p = \|f \cdot 1\|_p \leq \|f\|_q \cdot \|1\|_a = \mu(\Omega)^{1/a} \|f\|_q = \mu(\Omega)^{(\frac{1}{p} - \frac{1}{q})} \|f\|_q.$$  

The reader may easily check this final formula is correct even when $q = \infty$ provided we interpret $1/p - 1/\infty$ to be $1/p$.  


The rest of this section may be skipped.

**Example 11.19 (Power Inequalities).** Let \( a := (a_1, \ldots, a_n) \) with \( a_i > 0 \) for \( i = 1, 2, \ldots, n \) and for \( p \in \mathbb{R} \setminus \{0\} \), let

\[
\|a\|_p := \left( \frac{1}{n} \sum_{i=1}^{n} a_i^p \right)^{1/p}.
\]

Then by Corollary 11.18 \( p \to \|a\|_p \) is increasing in \( p \) for \( p > 0 \). For \( p = -q < 0 \), we have

\[
\|a\|_{-q} := \left( \frac{1}{n} \sum_{i=1}^{n} a_i^{-q} \right)^{-1/q} = \left( \frac{1}{n} \sum_{i=1}^{n} (\frac{1}{a_i})^q \right)^{1/q} = \frac{1}{a^{1/q}}
\]

where \( \frac{1}{q} := (1/a_1, \ldots, 1/a_n) \). So for \( p < 0 \), as \( p \) increases, \( q = -p \) decreases, so that \( \|a\|^q_q \) is decreasing and hence \( \|a\|^{-1}_q \) is increasing. Hence we have shown that \( p \to \|a\|_p \) is increasing for \( p \in \mathbb{R} \setminus \{0\} \).

We now claim that \( \lim_{p \to 0} \|a\|_p = \sqrt[n]{a_1 \cdots a_n} \). To prove this, write \( a_i^p = e^{p \ln a_i} = 1 + p \ln a_i + O(p^2) \) for \( p \) near zero. Therefore,

\[
\frac{1}{n} \sum_{i=1}^{n} a_i = 1 + p \sum_{i=1}^{n} \ln a_i + O(p^2).
\]

Hence it follows that

\[
\lim_{p \to 0} \|a\|_p = \lim_{p \to 0} \left( \frac{1}{n} \sum_{i=1}^{n} a_i^p \right)^{1/p} = \lim_{p \to 0} \left( 1 + p \sum_{i=1}^{n} \ln a_i + O(p^2) \right)^{1/p} = e^{\frac{1}{n} \sum_{i=1}^{n} \ln a_i} = \sqrt[n]{a_1 \cdots a_n}.
\]

So if now we define \( \|a\|_0 := \sqrt[n]{a_1 \cdots a_n} \), the map \( p \in \mathbb{R} \to \|a\|_p \in (0, \infty) \) is continuous and increasing in \( p \).

We will now show that \( \lim_{p \to \infty} \|a\|_p = \max_i a_i =: M \) and \( \lim_{p \to -\infty} \|a\|_p = \min_i a_i =: m \). Indeed, for \( p > 0 \),

\[
\frac{1}{n} M^p \leq \frac{1}{n} \sum_{i=1}^{n} a_i^p \leq M^p
\]

and therefore,

\[
(\frac{1}{n})^{1/p} M \leq \|a\|_p \leq M.
\]

Since \( (\frac{1}{n})^{1/p} \to 1 \) as \( p \to \infty \), it follows that \( \lim_{p \to \infty} \|a\|_p = M \). For \( p = -q < 0 \), we have

\[
\lim_{p \to -\infty} \|a\|_p = \lim_{q \to \infty} \left( \frac{1}{a^{1/q}} \right) = \frac{1}{\max_i (1/a_i)} = \frac{1}{1/m} = m = \min_i a_i.
\]

**Conclusion.** If we extend the definition of \( \|a\|_p \) to \( p = \infty \) and \( p = -\infty \) by \( \|a\|_{\infty} = \max_i a_i \) and \( \|a\|_{-\infty} = \min_i a_i \), then \( \mathbb{R} \ni p \to \|a\|_p \in (0, \infty) \) is a continuous non-decreasing function of \( p \).

**Proposition 11.20.** Suppose that \( 0 < p_0 < p_1 \leq \infty \), \( \lambda \in (0,1) \) and \( p_\lambda \in (p_0, p_1) \) be defined by

\[
\frac{1}{p_\lambda} = \frac{1 - \lambda}{p_0} + \frac{\lambda}{p_1} \tag{11.19}
\]

with the interpretation that \( \lambda/p_1 = 0 \) if \( p_1 = \infty \). Then \( L^{p_\lambda} \subset L^{p_0} + L^{p_1} \), i.e. every function \( f \in L^{p_\lambda} \) may be written as \( f = g + h \) with \( g \in L^{p_0} \) and \( h \in L^{p_1} \). For \( 1 \leq p_0 < p_1 \leq \infty \) and \( f \in L^{p_0} + L^{p_1} \) let

\[
\|f\| := \inf \left\{ \|g\|_{p_0} + \|h\|_{p_1} : f = g + h \right\}.
\]

Then \( (L^{p_0} + L^{p_1}, \|\cdot\|) \) is a Banach space and the inclusion map from \( L^{p_\lambda} \to L^{p_0} + L^{p_1} \) is bounded; in fact \( \|f\| \leq 2 \|f\|_{p_\lambda} \) for all \( f \in L^{p_\lambda} \).

**Proof.** Let \( M > 0 \), then the local singularities of \( f \) are contained in the set \( E := \{|f| > M\} \) and the behavior of \( f \) at “infinity” is solely determined by \( f \) on \( \mathcal{E} \). Hence \( g = f|_E \) and \( h = f|_{E^c} \) so that \( f = g + h \). By our earlier discussion we expect that \( g \in L^{p_0} \) and \( h \in L^{p_1} \) and this is the case since

\[
\|g\|_{p_0} = \int |f|_{p_0} 1_{|f| > M} = M^{p_0} \int \left| \frac{f}{M} \right|_{p_0} 1_{|f| > M} 
\]

\[
\leq M^{p_0} \int \left| \frac{f}{M} \right|_{p_0} 1_{|f| > M} \leq M^{p_{0} - p_{\lambda}} \|f\|_{P_{\lambda}} < \infty
\]

and

\[
\|h\|_{p_1} = \|f 1_{|f| \leq M}\|_{p_1} = \int |f|_{p_1} 1_{|f| \leq M} = M^{p_1} \int \left| \frac{f}{M} \right|_{p_1} 1_{|f| \leq M} 
\]

\[
\leq M^{p_1} \int \left| \frac{f}{M} \right|_{p_1} 1_{|f| \leq M} \leq M^{p_{1} - p_{\lambda}} \|f\|_{P_{\lambda}} < \infty.
\]

\(^2\) A little algebra shows that \( \lambda \) may be computed in terms of \( p_0 \), \( p_\lambda \) and \( p_1 \) by

\[
\lambda = \frac{p_0}{p_\lambda} \cdot \frac{p_1 - p_\lambda}{p_1 - p_0}.
\]
Moreover this shows
\[ \|f\| \leq M^{1-p_\lambda/p_0} \|f\|_{p_\lambda}^{p_\lambda/p_0} + M^{1-p_\lambda/p_1} \|f\|_{p_\lambda}^{p_\lambda/p_1}. \]
Taking \( M = \lambda \|f\|_{p_\lambda} \) then gives
\[ \|f\| \leq (\lambda^{1-p_\lambda/p_0} + \lambda^{1-p_\lambda/p_1}) \|f\|_{p_\lambda}, \]
and then taking \( \lambda = 1 \) shows \( \|f\| \leq 2 \|f\|_{p_\lambda} \). The proof that \((L^{p_0} + L^{p_1}, \|\cdot\|)\) is a Banach space is left as Exercise 11.6 to the reader.

**Corollary 11.21 (Interpolation of \( L^p \) – norms).** Suppose that \( 0 < p_0 < p_1 \leq \infty \), \( \lambda \in (0, 1) \) and \( p_\lambda \in (p_0, p_1) \) be defined as in Eq. (11.19), then \( L^{p_\lambda} \subset L^{p_0} \cap L^{p_1} \subset L^{p_\lambda} \) and
\[ \|f\|_{p_\lambda} \leq \|f\|_{p_0}^{\lambda} \|f\|_{p_1}^{1-\lambda}. \]  
(11.20)

Further assume \( 1 \leq p_0 < p_\lambda < p_1 \leq \infty \), and for \( f \in L^{p_0} \cap L^{p_1} \) let
\[ \|f\| := \|f\|_{p_0} + \|f\|_{p_1}. \]
Then \((L^{p_0} \cap L^{p_1}, \|\cdot\|)\) is a Banach space and the inclusion map of \( L^{p_\lambda} \cap L^{p_0} \) into \( L^{p_\lambda} \) is bounded, in fact
\[ \|f\|_{p_\lambda} \leq \max (\lambda^{-1}, (1-\lambda)^{-1}) \left( \|f\|_{p_0} + \|f\|_{p_1} \right). \]  
(11.21)

The heuristic explanation of this corollary is that if \( f \in L^{p_0} \cap L^{p_1} \), then \( f \) has local singularities no worse than an \( L^{p_\lambda} \) function and behavior at infinity no worse than an \( L^{p_0} \) function. Hence \( f \in L^{p_\lambda} \) for any \( p_\lambda \) between \( p_0 \) and \( p_1 \).

**Proof.** Let \( \lambda \) be determined as above, \( a = p_0/\lambda \) and \( b = p_1/(1-\lambda) \), then by Theorem 11.14
\[ \|f\|_{p_\lambda} = \left\| \|f\|^{\lambda} \right\|_{p_\lambda} \leq \left\| \|f\|^{\lambda} \right\|_{a} \left\| \|f\|^{1-\lambda} \right\|_{b} = \|f\|_{p_0} \|f\|_{p_1}^{1-\lambda}. \]
It is easily checked that \( \|\cdot\| \) is a norm on \( L^{p_0} \cap L^{p_1} \). To show this space is complete, suppose that \( \{f_n\} \subset L^{p_0} \cap L^{p_1} \) is a \( \|\cdot\| \) – Cauchy sequence. Then \( \{f_n\} \) is both \( L^{p_0} \) and \( L^{p_1} \) – Cauchy. Hence there exist \( f \in L^{p_0} \) and \( g \in L^{p_1} \) such that \( \lim_{n \to \infty} \|f - f_n\|_{p_\lambda} = 0 \) and \( \lim_{n \to \infty} \|g - f_n\|_{p_\lambda} = 0 \). By Chebyshev’s inequality (Lemma 11.14) \( f_n \to f \) and \( f_n \to g \) in measure and therefore by Theorem 11.7 \( f = g \) a.e. It now is clear that \( \lim_{n \to \infty} \|f - f_n\| = 0 \). The estimate in Eq. (11.21) is left as Exercise 11.5 to the reader.

**Remark 11.22.** Combining Proposition 11.20 and Corollary 11.21 gives
\[ L^{p_0} \cap L^{p_1} \subset L^{p_\lambda} \subset L^{p_0} + L^{p_1} \]
for \( 0 < p_0 < p_1 \leq \infty \), \( \lambda \in (0, 1) \) and \( p_\lambda \in (p_0, p_1) \) as in Eq. (11.19).

**Corollary 11.23.** Suppose now that \( \mu \) is counting measure on \( \Omega \). Then \( L^p(\mu) \subset L^q(\mu) \) for all \( 0 < p < q \leq \infty \) and \( \|f\|_q \leq \|f\|_p \).

**Proof.** Suppose that \( 0 < p < q = \infty \), then
\[ \|f\|_q^\alpha = \sup \{ |f(x)|^p : x \in \Omega \} \leq \sum_{x \in \Omega} |f(x)|^p = \|f\|_p^\alpha, \]
i.e. \( \|f\|_\infty \leq \|f\|_p \) for all \( 0 < p < \infty \). For \( 0 < p \leq q \leq \infty \), apply Corollary 11.21 with \( p_0 = p \) and \( p_1 = \infty \) to find
\[ \|f\|_q \leq \|f\|_p^{p/q} \|f\|_\infty^{1-p/q} \leq \|f\|_p^{p/q} \|f\|_p^{1-p/q} = \|f\|_p, \]

**11.4.1 Summary:**
1. \( L^{p_0} \cap L^{p_1} \subset L^q \subset L^{p_0} + L^{p_1} \) for any \( q \in (p_0, p_1) \).
2. If \( p < q \), then \( \ell^p \subset \ell^q \) and \( \|f\|_q \leq \|f\|_p \).
3. Since \( \mu([f] > \varepsilon) \leq \varepsilon^{-p} \|f\|_p^p \), \( L^p \) – convergence implies \( L^0 \) – convergence.
4. \( L^p \) – convergence implies almost everywhere convergence for some subsequence.
5. If \( \mu(\Omega) < \infty \) then almost everywhere convergence implies uniform convergence off certain sets of small measure and in particular we have \( L^0 \) – convergence.
6. If \( \mu(\Omega) < \infty \), then \( L^q \subset L^p \) for all \( p \leq q \) and \( L^q \) – convergence implies \( L^p \) – convergence.

**11.5 Uniform Integrability**

This section will address the question as to what extra conditions are needed in order that an \( L^0 \) – convergent sequence is \( L^p \) – convergent. This will lead us to the notion of uniform integrability. To simplify matters a bit here, it will be assumed that \((\Omega, \mathcal{B}, \mu)\) is a finite measure space for this section.

**Notation 11.24** For \( f \in L^1(\mu) \) and \( E \in \mathcal{B} \), let
\[ \mu(f : E) := \int_E f \, d\mu. \]
and more generally if \( A, B \in \mathcal{B} \) let
\[ \mu(f : A, B) := \int_{A \cap B} f \, d\mu. \]
When \( \mu \) is a probability measure, we will often write \( \mathbb{E}[f : E] \) for \( \mu(f : E) \) and \( \mathbb{E}[f : A, B] \) for \( \mu(f : A, B) \).
\textbf{Definition 11.25.} A collection of functions, \( \Lambda \subset L^1(\mu) \) is said to be \textbf{uniformly integrable} if,
\[
\lim_{a \to \infty} \sup_{f \in A} \mu(|f| : |f| \geq a) = 0. \tag{11.22}
\]

The condition in Eq. (11.22) implies \( \sup_{f \in A} \|f\|_1 < \infty \). Indeed, choose \( a \) sufficiently large so that \( \sup_{f \in A} \mu(|f| : |f| \geq a) \leq 1 \), then for \( f \in A \)
\[
\|f\|_1 = \mu(|f| : |f| \geq a) + \mu(|f| : |f| < a) \leq 1 + a \mu(\Omega).
\]

Let us also note that if \( \Lambda = \{f\} \) with \( f \in L^1(\mu) \), then \( \Lambda \) is uniformly integrable. Indeed, \( \lim_{n \to \infty} \mu(|f| : |f| \geq a) = 0 \) by the dominated convergence theorem.

\textbf{Definition 11.26.} A collection of functions, \( \Lambda \subset L^1(\mu) \) is said to be \textbf{uniformly absolutely continuous} if for all \( \varepsilon > 0 \) there exists \( \delta > 0 \) such that
\[
\sup_{f \in A} \mu(|f| : E) < \varepsilon \text{ whenever } \mu(E) < \delta. \tag{11.23}
\]

\textbf{Remark 11.27.} It is not in general true that if \( \{f_n\} \subset L^1(\mu) \) is uniformly absolutely continuous implies \( \sup_n \|f_n\|_1 < \infty \). For example take \( \Omega = \{\ast\} \) and \( \mu(\{\ast\}) = 1 \). Let \( f_n(\ast) = n \). Since for \( \delta < 1 \) a set \( E \subset \Omega \) such that \( \mu(E) < \delta \) is in fact the empty set and hence \( \{f_n\}_{n=1}^\infty \) is uniformly absolutely continuous. However, for finite measure spaces without “atoms”, for every \( \delta > 0 \) we may find a finite partition of \( \Omega \) by sets \( \{E_i\}_{i=1}^k \) with \( \mu(E_i) < \delta \). If Eq. (11.23) holds with \( \varepsilon = 1 \), then
\[
\mu(|f_n|) = \sum_{i=1}^k \mu(|f_n| : E_i) \leq k,
\]
showing that \( \mu(|f_n|) \leq k \) for all \( n \).

\textbf{Lemma 11.28 (This lemma may be skipped.)} For any \( g \in L^1(\mu) \), \( \Lambda = \{g\} \) is uniformly absolutely continuous.

\textbf{Proof. First Proof.} If the Lemma is false, there would exist \( \varepsilon > 0 \) and sets \( E_n \) such that \( \mu(E_n) \to 0 \) while \( \mu(|g| : E_n) \geq \varepsilon \) for all \( n \). Since \( |1_{E_n}| \leq |g| \in L^1 \) and for any \( \delta > 0 \), \( \nu(1_{E_n} |g|) < \delta \) is \( \mu(E_n) \to 0 \) as \( n \to \infty \), the dominated convergence theorem of Corollary 11.18 implies \( \lim_{n \to \infty} \mu(|g| : E_n) = 0 \). This contradicts \( \mu(|g| : E_n) \geq \varepsilon \) for all \( n \) and the proof is complete.

\textbf{Second Proof.} Let \( \varphi = \sum_{i=1}^n c_i 1_{B_i} \) be a simple function such that
\[
\|g - \varphi\|_1 < \varepsilon/2.
\]

\textbf{Proposition 11.29.} A subset \( \Lambda \subset L^1(\mu) \) is uniformly integrable if and only if \( \Lambda \subset L^1(\mu) \) is uniformly absolutely continuous.

\textbf{Proof.} (\( \Rightarrow \)) We have already seen that uniformly integrable subsets, \( \Lambda \), are bounded in \( L^1(\mu) \). Moreover, for \( f \in \Lambda \) and \( E \in B \),
\[
\mu(|f| : E) = \mu(|f| : |f| \geq M, E) + \mu(|f| : |f| < M, E) 
\leq \sup_n \mu(|f| : |f| \geq M) + M \mu(E).
\]

So given \( \varepsilon > 0 \) choose \( M \) so large that \( \sup_{f \in \Lambda} \mu(|f| : |f| \geq M) < \varepsilon/2 \) and then take \( \delta = \frac{\varepsilon}{2M} \) to verify that \( \Lambda \) is uniformly absolutely continuous.

(\( \Leftarrow \)) Let \( K := \sup_{f \in \Lambda} \|f\|_1 < \infty \). Then for \( f \in \Lambda \), we have
\[
\mu(|f| \geq a) \leq \|f\|_1 / a \leq K/a \text{ for all } a > 0.
\]

Hence given \( \varepsilon > 0 \) and \( \delta > 0 \) as in the definition of uniform absolute continuity, we may choose \( a = K/\delta \) in which case
\[
\sup_{f \in A} \mu(|f| : |f| \geq a) < \varepsilon.
\]

Since \( \varepsilon > 0 \) was arbitrary, it follows that \( \lim_{n \to \infty} \sup_{f \in \Lambda} \mu(|f| : |f| \geq a) = 0 \) as desired.

\textbf{Corollary 11.30.} Suppose \( \{f_n\}_{n=1}^\infty \) and \( \{g_n\}_{n=1}^\infty \) are two uniformly integrable sequences, then \( \{f_n + g_n\}_{n=1}^\infty \) is also uniformly integrable.

\textbf{Proof.} By Proposition 11.29 \( \{f_n\}_{n=1}^\infty \) and \( \{g_n\}_{n=1}^\infty \) are both bounded in \( L^1(\mu) \) and are both uniformly absolutely continuous. Since \( \|f_n + g_n\|_1 \leq \|f_n\|_1 + \|g_n\|_1 \) it follows that \( \{f_n + g_n\}_{n=1}^\infty \) is bounded in \( L^1(\mu) \) as well. Moreover, for \( \varepsilon > 0 \) we may choose \( \delta > 0 \) such that \( \mu(|f_n| : E) < \varepsilon \) and \( \mu(|g_n| : E) < \varepsilon \) whenever \( \mu(E) < \delta \). For this choice of \( \varepsilon \) and \( \delta \), we then have
\[
\mu(|f_n + g_n| : E) \leq \mu(|f_n| + |g_n| : E) < 2\varepsilon \text{ whenever } \mu(E) < \delta,
\]
showing \( \{f_n + g_n\}_{n=1}^\infty \) uniformly absolutely continuous. Another application of Proposition 11.29 completes the proof.
Exercise 11.3 (Problem 5 on p. 196 of Resnick). Suppose that \( \{X_n\}_{n=1}^{\infty} \) is a sequence of integrable and i.i.d random variables. Then \( \{ \frac{X_n}{n} \}_{n=1}^{\infty} \) is uniformly integrable.

Theorem 11.31 (Vitali Convergence Theorem). Let \((\Omega, \mathcal{B}, \mu)\) be a finite measure space, \(A := \{f_n\}_{n=1}^{\infty} \) be a sequence of functions in \(L^1(\mu)\), and \(f : \Omega \to \mathbb{C} \) be a measurable function. Then \(f \in L^1(\mu)\) and \(\|f - f_n\|_1 \to 0\) as \(n \to \infty\) if \(f_n \to f\) in \(\mu\) measure and \(A\) is uniformly integrable.

Proof. \((\leftarrow \rightarrow)\) If \(f_n \to f\) in \(\mu\) measure and \(A = \{f_n\}_{n=1}^{\infty}\) is uniformly integrable then we know \(M := \sup_{n} \|f_n\|_1 < \infty\). Hence and application of Fatou’s lemma, see Exercise 11.1,

\[
\int |f| d\mu \leq \liminf_{n \to \infty} \int |f_n| d\mu \leq M < \infty,
\]
i.e. \(f \in L^1(\mu)\). One now easily checks that \(A_0 := \{f - f_n\}_{n=1}^{\infty}\) is bounded in \(L^1(\mu)\) and (using Lemma 11.28 and Proposition 11.29) \(A_0\) is uniformly absolutely continuous and hence \(A_0\) is uniformly integrable. Therefore,

\[
\|f - f_n\|_1 = \mu(\{|f - f_n| \geq \alpha\}) + \mu(\{|f - f_n| < \alpha\}) \leq \varepsilon(\alpha) + \int_{\Omega \setminus \{|f - f_n| < \alpha\}} |f - f_n| d\mu,
\]
where

\[
\varepsilon(\alpha) := \sup_{m} \mu(\{|f - f_m| \geq \alpha\}) \to 0 \text{ as } \alpha \to \infty.
\]

Since \(1_{\{|f - f_n| < \alpha\}}|f - f_n| \leq \alpha \in L^1(\mu)\) and

\[
\mu(1_{\{|f - f_n| < \alpha\}}|f - f_n| > \varepsilon) \leq \mu(|f - f_n| > \varepsilon) \to 0 \text{ as } n \to \infty,
\]
we may pass to the limit in Eq. (11.24), with the aid of the dominated convergence theorem (see Corollary 11.8), to find

\[
\lim_{n \to \infty} \sup \|f - f_n\|_1 \leq \varepsilon(\alpha) \to 0 \text{ as } \alpha \to \infty.
\]

\((\leftarrow \rightarrow)\) If \(f_n \to f\) in \(L^1(\mu)\), then by Chebyshev’s inequality it follows that \(f_n \to f\) in \(\mu\) measure. Since convergent sequences are bounded, to show \(A\) is uniformly integrable it suffices to show \(A\) is uniformly absolutely continuous. Now for \(E \in \mathcal{B}\) and \(n \in \mathbb{N}\),

\[
\mu(\{|f_n| : E\}) \leq \mu(\{|f - f_n| : E\}) + \mu(\{|f| : E\}) \leq \|f - f_n\|_1 + \mu(|f| : E).
\]

Let \(\varepsilon_N := \sup_{n>N} \|f - f_n\|_1\), then \(\varepsilon_N \downarrow 0\) as \(N \uparrow \infty\) and

\[
\sup \mu(\{|f_n| : E\}) \leq \sup \mu(\{|f_n| : E\}) \vee (\varepsilon_N + \mu(|f| : E)) \leq \varepsilon_N + \mu(\{g_N : E\}),
\]
where \(g_N = |f| + \sum_{n=1}^{N} |f_n| \in L^1\). Given \(\varepsilon > 0\) fix \(N\) large so that \(\varepsilon_N < \varepsilon/2\) and then choose \(\delta > 0\) (by Lemma 11.28) such that \(\mu(\{g_N : E\}) < \varepsilon\) if \(\mu(E) < \delta\).

It then follows from Eq. (11.25) that

\[
\sup \mu(\{|f_n| : E\}) < \varepsilon/2 + \varepsilon/2 = \varepsilon \text{ when } \mu(E) < \delta.
\]

\(\blacksquare\)

Example 11.32. Let \(\Omega = [0, 1], \mathcal{B} = \mathcal{B}_{[0, 1]}\) and \(P = m\) be Lebesgue measure on \(\mathcal{B}\). Then the collection of functions, \(f_x(x) := \frac{1}{x+\varepsilon}\) for \(\varepsilon \in (0, 1)\), is bounded in \(L^1(P)\), \(f_x \to 0\) a.e. as \(\varepsilon \downarrow 0\) but

\[
0 = \lim_{\varepsilon \downarrow 0} \int f_x dP \neq \lim_{\varepsilon \downarrow 0} \int f_x dP = 1.
\]

This is a typical example of a bounded and pointwise convergent sequence in \(L^1\) which is not uniformly integrable.

Example 11.33. Let \(\Omega = [0, 1], \mathcal{B} = \mathcal{B}_{[0, 1]}\), and for \(\varepsilon \in (0, 1)\) let \(a_\varepsilon > 0\) with \(\lim_{\varepsilon \downarrow 1} a_\varepsilon = \infty\) and let \(f_{\varepsilon} := a_\varepsilon 1_{[0,\varepsilon]}\). Then \(E f_{\varepsilon} = \varepsilon a_\varepsilon\) and so \(\sup_{\varepsilon > 0} \|f_{\varepsilon}\|_1 =: K < \infty\) if \(\varepsilon a_\varepsilon \leq K\) for all \(\varepsilon\). Since

\[
\sup_{\varepsilon} \varepsilon f_{\varepsilon} \geq M = \sup_{\varepsilon} \varepsilon a_\varepsilon \cdot 1_{a_\varepsilon \geq M},
\]
if \(\{f_{\varepsilon}\}\) is uniformly integrable and \(\delta > 0\) is given, for large \(M\) we have \(\varepsilon a_\varepsilon \leq \delta\) for \(\varepsilon\) small enough so that \(a_\varepsilon \geq M\). From this we conclude that \(\lim_{\varepsilon \downarrow 0} \varepsilon a_\varepsilon = \delta\) and since \(\delta > 0\) was arbitrary, \(\lim_{\varepsilon \downarrow 0} a_\varepsilon = 0\) if \(\{f_{\varepsilon}\}\) is uniformly integrable. By reversing these steps one sees the converse is also true.

Alternatively. No matter how \(a_\varepsilon > 0\) is chosen, \(\lim_{\varepsilon \downarrow 0} f_{\varepsilon} = 0\) a.s.. So from Theorem 11.31 if \(\{f_{\varepsilon}\}\) is uniformly integrable we would have to have

\[
\lim_{\varepsilon \downarrow 0} (\varepsilon a_\varepsilon) = \lim_{\varepsilon \downarrow 0} E f_{\varepsilon} = E 0 = 0.
\]

Corollary 11.34. Let \((\Omega, \mathcal{B}, \mu)\) be a finite measure space, \(p \in [1, \infty), \{f_n\}_{n=1}^{\infty}\) be a sequence of functions in \(L^p(\mu)\), and \(f : \Omega \to \mathbb{C}\) be a measurable function. Then \(f \in L^p(\mu)\) and \(\|f - f_n\|_p \to 0\) as \(n \to \infty\) if \(f_n \to f\) in \(\mu\) measure and \(A := \{|f_n|^{p}\}_{n=1}^{\infty}\) is uniformly integrable.

Proof. \((\leftarrow \rightarrow)\) Suppose that \(f_n \to f\) in \(\mu\) measure and \(A := \{|f_n|^{p}\}_{n=1}^{\infty}\) is uniformly integrable. By Corollary 11.9 \(f_n^{p} \to f^{p}\) in \(\mu\) measure, and \(h_n := |f - f_n|^{p}_{\mu} \to 0\), and by Theorem 11.31 \(|f|^{p} \in L^1(\mu)\) and \(|f_n|^{p} \to |f|^{p}\) in \(L^1(\mu)\). Since
A typical example for \( \varphi \) in item 1. is \( \varphi(x) = x^p \) for some \( p > 1 \).

**Proof.** Let \( \varphi \) be as in item 1. above and set \( \varepsilon_a := \sup_{x \geq a} \frac{\varphi(x)}{x} \rightarrow 0 \) as \( a \rightarrow \infty \) by assumption. Then for \( f \in A \)

\[
\mu(|f| : |f| \geq a) = \mu \left( \frac{|f|}{\varphi(|f|)} \varphi(|f|) : |f| \geq a \right) \leq \mu(\varphi(|f|)) \varepsilon_a \\
\leq \mu(\varphi(|f|)) \varepsilon_a \leq K \varepsilon_a
\]

and hence

\[
\lim_{a \rightarrow \infty} \sup_{f \in A} \mu \left( |f| : |f| \geq a \right) \leq \lim_{a \rightarrow \infty} K \varepsilon_a = 0.
\]

2. By assumption, \( \varepsilon_a := \sup_{f \in A} \mu \left( |f| : |f| \geq a \right) \rightarrow 0 \) as \( a \rightarrow \infty \). Therefore we may choose \( a_n \uparrow \infty \) such that

\[
\sum_{n=0}^{\infty} (n+1) \varepsilon_{a_n} < \infty
\]

where by convention \( a_0 := 0 \). Now define \( \varphi \) so that \( \varphi(0) = 0 \) and

\[
\varphi(x) = \sum_{n=0}^{\infty} (n+1) 1_{[a_n,a_{n+1})}(x),
\]

i.e.

\[
\varphi(x) = \int_0^x \varphi(y)dy = \sum_{n=0}^{\infty} (n+1) (x \wedge a_{n+1} - x \wedge a_n).
\]

By construction \( \varphi \) is continuous, \( \varphi(0) = 0 \), \( \varphi'(x) \) is increasing (so \( \varphi \) is convex) and \( \varphi'(x) \geq (n+1) \) for \( x \geq a_n \). In particular

\[
\frac{\varphi(x)}{x} \geq \frac{\varphi(a_n) + (n+1)x}{x} \geq n+1 \text{ for } x \geq a_n
\]

from which we conclude \( \lim_{x \rightarrow \infty} \varphi(x)/x = \infty \). We also have \( \varphi'(x) \leq (n+1) \) on \([0,a_{n+1})\] and therefore

\[
\varphi(x) \leq (n+1)x \text{ for } x \leq a_{n+1}.
\]

So for \( f \in A \),

\[
\mu(\varphi(|f|)) = \sum_{n=0}^{\infty} \mu(\varphi(|f|)1_{[a_n,a_{n+1})}(|f|)) \\
\leq \sum_{n=0}^{\infty} (n+1) \mu(1_{[a_n,a_{n+1})}(|f|)) \\
\leq \sum_{n=0}^{\infty} (n+1) \mu(|f| : |f| \geq a_n) \leq \sum_{n=0}^{\infty} (n+1) \varepsilon_{a_n}
\]
and hence
\[
\sup_{f \in A} \mu(\varphi(|f|)) \leq \sum_{n=0}^{\infty} (n + 1) \varepsilon_n < \infty.
\]

11.6 Exercises

Exercise 11.4. Let \( f \in L^p \cap L^\infty \) for some \( p < \infty \). Show \( \|f\|_\infty = \lim_{q \to \infty} \|f\|_q \). If we further assume \( \mu(X) < \infty \), show \( \|f\|_\infty = \lim_{q \to \infty} \|f\|_q \) for all measurable functions \( f : X \to \mathbb{C} \). In particular, \( f \in L^p \) iff \( \lim_{q \to \infty} \|f\|_q < \infty \).

Hints: Use Corollary 11.21 to show \( \limsup_{q \to \infty} \|f\|_q \leq \|f\|_\infty \) and to show \( \liminf_{q \to \infty} \|f\|_q \geq \|f\|_\infty \), let \( M < \|f\|_\infty \) and make use of Chebyshev’s inequality.

Exercise 11.5. Prove Eq. (11.21) in Corollary 11.21 (Part of Folland 6.3 on p. 186.) Hint: Use the inequality, with \( a, b \geq 1 \) with \( a^{-1} + b^{-1} = 1 \) chosen appropriately,
\[
st \leq \frac{s^a}{a} + \frac{t^b}{b}
\]
applied to the right side of Eq. (11.20).

Exercise 11.6. Complete the proof of Proposition 11.20 by showing \( (L^p + L^\infty, \|\|) \) is a Banach space.

11.7 Appendix: Convex Functions

Reference; see the appendix (page 500) of Revuz and Yor.

Definition 11.36. A function \( \varphi : (a, b) \to \mathbb{R} \) is convex if for all \( a < x < y < b \) and \( t \in [0, 1] \) \( \varphi(tx_1 + (1-t)x_0) \leq t \varphi(x_1) + (1-t)\varphi(x_0) \) where \( x_t = tx_1 + (1-t)x_0 \), see Figure ?? below.

Example 11.37. The functions \( \exp(x) \) and \( -\log(x) \) are convex and \( |x|^p \) is convex if \( p \geq 1 \) as follows from Lemma 7.31 for \( p > 1 \) and by inspection of \( p = 1 \).

Theorem 11.38. Suppose that \( \varphi : (a, b) \to \mathbb{R} \) is convex and for \( x, y \in (a, b) \) with \( x < y \), let
\[
F(x, y) := \frac{\varphi(y) - \varphi(x)}{y - x}.
\]

Then:
\[\text{\footnote{The same formula would define} } F(x, y) \text{ for } x \neq y. \text{ However, since } F(x, y) = F(y, x), \text{ we would gain no new information by this extension.} \]
Therefore Eq. (11.30) holds for $y$. Inequality in Eq. (11.31) shows $a < u < v < w < b$, these inequalities may be written more compactly as 
and convexity also implies 
and convexity of $\varphi$ is equivalent to 
and to 
and convexity also implies 
These inequalities may be written more compactly as, 
valid for all $a < u < v < w < b$, again see Figure 11.1. The first (second) inequality in Eq. (11.31) shows $F(x,y)$ is increasing in $y$ (x). This then implies the limits in item 2. are monotone and hence exist as claimed.

3. Let $a < x < y < b$. Using the increasing nature of $F$, 
and
as desired.

4. Let $t \in [\varphi'_-(x), \varphi'_+(x)]$. Then 

\[ t \leq \varphi'_+(x) = F(x,x+) \leq F(x,y) = \frac{\varphi(y) - \varphi(x)}{y-x} \]
or equivalently, 

\[ \varphi(y) \geq \varphi(x) + t(y-x) \] 

for $y \geq x$. Therefore Eq. (11.30) holds for $y \geq x$. Similarly, for $y < x$,

\[ t \geq \varphi'_-(x) = F(x-,x) \geq F(y,x) = \frac{\varphi(x) - \varphi(y)}{x-y} \]
or equivalently,

\[ \varphi(y) \geq \varphi(x) - t(y-x) = \varphi(x) + t(y-x) \] 

for $y \leq x$.

Hence we have proved Eq. (11.30) for all $x,y \in (a,b)$.

5. For $a < \alpha \leq x < y \leq \beta < b$, we have 

\[ \varphi'_+(\alpha) \leq \varphi'_+(x) = F(x,x+) \leq F(x,y) \leq F(y-,y) = \varphi'_-(y) \leq \varphi'_-(\beta) \]

and in particular,

\[ -K \leq \varphi'_+(\alpha) \leq \varphi(y) - \varphi(x) \leq \varphi'_-(\beta) \leq K. \]

This last inequality implies, $|\varphi(y) - \varphi(x)| \leq K (y-x)$ which is the desired Lipschitz bound.

6. For $a < c < x < y < b$, we have 

\[ \varphi'_+(x) = F(x,x+) \leq F(x,y) \] 

and letting 

\[ y \downarrow c \quad \text{(using the continuity of $F$)} \]

we learn $\varphi'_+(c) = \varphi'_+(c-)$ and hence that $\varphi'_+$ is right continuous.

Similarly, for $a < x < y < c < b$, we have 

\[ \varphi'_-(y) \geq \varphi(y) \] 

and letting 

\[ x \uparrow c \quad \text{(using the continuity of $F$)} \]

we learn $\varphi'_-(c) = \varphi'_-(c-)$ and hence that $\varphi'_-$ is left continuous.

7. Since $\varphi'_\pm$ are increasing functions, they have at most countably many points of discontinuity. Letting 

\[ x \uparrow y \quad \text{in Eq. (11.29), using the left continuity of $\varphi'_-$,} \]

shows $\varphi'_-(y) = \varphi'_-(y-)$, hence if $\varphi'_-$ is continuous at $y$, 

\[ \varphi'_-(y) = \varphi'_-(y+) = \varphi'_+(y) \]

and $\varphi$ is differentiable at $y$. Conversely if $\varphi$ is differentiable at $y$, then 

\[ \varphi'_+(y-) = \varphi'_+(y) = \varphi'_+(y) \]

which shows $\varphi'_+$ is continuous at $y$. Thus we have shown that set of points of discontinuity of $\varphi'_+$ is the same as the set of points of non-differentiability of $\varphi$. That the discontinuity set of $\varphi'_-$ is the same as the non-differentiability set of $\varphi$ is proved similarly.

\[ \textbf{Corollary 11.39.} \text{ If } \varphi : (a,b) \to \mathbb{R} \text{ is a convex function and } D \subset (a,b) \text{ is a dense set, then} \]

\[ \varphi(y) = \sup_{x \in D} [\varphi(x) + \varphi'_+(x)(y-x)] \quad \text{for all } x, y \in (a,b). \]
Proof. Let $\psi_{\pm}(y) := \sup_{x \in D} [\varphi(x) + \varphi_{\pm}(x)(y - x)]$. According to Eq. (11.30) above, we know that $\varphi(y) \geq \psi_{\pm}(y)$ for all $y \in (a, b)$. Now suppose that $x \in (a, b)$ and $x_n \in A$ with $x_n \uparrow x$. Then passing to the limit in the estimate,

$$\psi_{-}(y) \geq \varphi(x_n) + \varphi'_{-}(x_n)(y - x_n),$$

shows $\psi_{-}(y) \geq \varphi(x) + \varphi'_{-}(x)(y - x)$. Since $x \in (a, b)$ is arbitrary we may take $x = y$ to discover $\psi_{-}(y) \geq \varphi(y)$ and hence $\varphi(y) = \psi_{-}(y)$. The proof that $\varphi(y) = \psi_{+}(y)$ is similar. □
Part III

Convergence Results
Laws of Large Numbers

In this chapter \( \{X_k\}_{k=1}^\infty \) will be a sequence of random variables on a probability space, \((\Omega, \mathcal{B}, P)\), and we will set \( S_n := X_1 + \cdots + X_n \) for all \( n \in \mathbb{N} \).

**Definition 12.1.** The covariance, \( \text{Cov}(X, Y) \) of two square integrable random variables, \( X \) and \( Y \), is defined by

\[
\text{Cov}(X, Y) = \mathbb{E}[(X - a_X)(Y - a_Y)] = \mathbb{E}[XY] - \mathbb{E}X \cdot \mathbb{E}Y
\]

where \( a_X := \mathbb{E}X \) and \( a_Y := \mathbb{E}Y \). The variance of \( X \),

\[
\text{Var}(X) := \text{Cov}(X, X) = \mathbb{E}[X^2] - (\mathbb{E}X)^2 \quad (12.1)
\]

We say that \( X \) and \( Y \) are uncorrelated if \( \text{Cov}(X, Y) = 0 \), i.e., \( \mathbb{E}[XY] = \mathbb{E}X \cdot \mathbb{E}Y \). More generally we say \( \{X_k\}_{k=1}^n \subset L^2(P) \) are uncorrelated iff \( \text{Cov}(X_i, X_j) = 0 \) for all \( i \neq j \).

Notice that if \( X \) and \( Y \) are independent random variables, then \( f(X), g(Y) \) are independent and hence uncorrelated for any choice of Borel measurable functions, \( f, g : \mathbb{R} \to \mathbb{R} \) such that \( f(X) \) and \( g(X) \) are square integrable. It also follows from Eq. (12.1) that

\[
\text{Var}(X) \leq \mathbb{E}[X^2] \quad \text{for all } X \in L^2(P). \quad (12.2)
\]

**Lemma 12.2.** The covariance function, \( \text{Cov}(X, Y) \) is bilinear in \( X \) and \( Y \) and \( \text{Cov}(X, Y) = 0 \) if either \( X \) or \( Y \) is constant. For any constant \( k \), \( \text{Var}(X + k) = \text{Var}(X) \) and \( \text{Var}(kX) = k^2 \text{Var}(X) \). If \( \{X_k\}_{k=1}^n \) are uncorrelated \( L^2(P) \)-random variables, then

\[
\text{Var}(S_n) = \sum_{k=1}^n \text{Var}(X_k).
\]

**Proof.** We leave most of this simple proof to the reader. As an example of the type of argument involved, let us prove \( \text{Var}(X + k) = \text{Var}(X) \);

\[
\text{Var}(X + k) = \text{Cov}(X + k, X + k) = \text{Cov}(X + k, X) + \text{Cov}(X, X + k) = \text{Cov}(X + k, X) + \text{Cov}(X, X) = \text{Cov}(X, X) = \text{Var}(X).
\]

**Exercise 12.1 (A correlation inequality).** Suppose that \( X \) is a random variable and \( f, g : \mathbb{R} \to \mathbb{R} \) are two increasing functions such that both \( f(X) \) and \( g(X) \) are square integrable. Show \( \text{Cov}(f(X), g(X)) \geq 0 \). **Hint:** let \( Y \) be another random variable which has the same law as \( X \) and is independent of \( X \). Then consider

\[
\mathbb{E}[(f(Y) - f(X)) \cdot (g(Y) - g(X))].
\]

**Theorem 12.3 (An \( L^2 \)-Weak Law of Large Numbers).** Let \( \{X_n\}_{n=1}^\infty \) be a sequence of uncorrelated square integrable random variables, \( \mu_n = \mathbb{E}X_n \) and \( \sigma_n^2 = \text{Var}(X_n) \). If there exists an increasing positive sequence, \( \{a_n\} \) and \( \mu \in \mathbb{R} \) such that

\[
\frac{1}{a_n} \sum_{j=1}^n \mu_j \to \mu \text{ as } n \to \infty \quad \text{and} \quad \frac{1}{a_n^2} \sum_{j=1}^n \sigma_j^2 \to 0 \text{ as } n \to \infty,
\]

then \( S_n/a_n \to \mu \) in \( L^2(P) \) and also in probability.

**Proof.** We first observe that \( \mathbb{E}S_n = \sum_{j=1}^n \mu_j \) and

\[
\mathbb{E} \left( S_n - \sum_{j=1}^n \mu_j \right)^2 = \text{Var}(S_n) = \sum_{j=1}^n \text{Var}(X_j) = \sum_{j=1}^n \sigma_j^2.
\]

Hence

\[
\mathbb{E}S_n = \frac{1}{a_n} \sum_{j=1}^n \mu_j \to \mu
\]

and

\[
\mathbb{E} \left( \frac{S_n - \sum_{j=1}^n \mu_j}{a_n} \right)^2 = \frac{1}{a_n^2} \sum_{j=1}^n \sigma_j^2 \to 0.
\]

Hence,
\[ \left\| \frac{S_n - \mu}{a_n} \right\|_{L^2(P)} = \left\| \frac{S_n - \sum_{j=1}^{n} \mu_j}{a_n} + \sum_{j=1}^{n} \frac{\mu_j}{a_n} - \mu \right\|_{L^2(P)} \leq \left\| \frac{S_n - \sum_{j=1}^{n} \mu_j}{a_n} \right\|_{L^2(P)} + \left\| \sum_{j=1}^{n} \frac{\mu_j}{a_n} - \mu \right\| \rightarrow 0. \]

**Example 12.4.** Suppose that \( \{X_k\}_{k=1}^{\infty} \subset L^2(P) \) are uncorrelated identically distributed random variables. Then \( \frac{S_n}{n} \rightarrow \mu = \mathbb{E}X_1 \) as \( n \rightarrow \infty \).

To see this, simply apply Theorem 12.3 with \( a_n = n \).

**Proposition 12.5 (\( L^2 \) - Convergence of Random Sums).** Suppose that \( \{X_k\}_{k=1}^{\infty} \subset L^2(P) \) are uncorrelated. If \( \sum_{k=1}^{\infty} \text{Var}(X_k) < \infty \) then

\[ \sum_{k=1}^{\infty} (X_k - \mu_k) \text{ converges in } L^2(P) \]

where \( \mu_k := \mathbb{E}X_k \).

**Proof.** Letting \( S_n := \sum_{k=1}^{n} (X_k - \mu_k) \), it suffices by the completeness of \( L^2(P) \) (see Theorem 11.17) to show \( \|S_n - S_m\|_2 \rightarrow 0 \) as \( m, n \rightarrow \infty \). Supposing \( n > m \), we have

\[ \|S_n - S_m\|_2^2 = \mathbb{E} \left( \sum_{k=m+1}^{n} (X_k - \mu_k) \right)^2 = \sum_{k=m+1}^{n} \text{Var}(X_k) = \sum_{k=m+1}^{n} \sigma_k^2 \rightarrow 0 \text{ as } m, n \rightarrow \infty. \]

**Note well:** since \( L^2(P) \) convergence implies \( L^p(P) \) – convergence for \( 0 \leq p \leq 2 \), where by \( L^0(P) \) – convergence we mean convergence in probability. The remainder of this chapter is mostly devoted to proving \( a.s. \) convergence for the quantities in Theorem 11.17 and Proposition 12.5 under various assumptions. These results will be described in the next section.

### 12.1 Main Results

The proofs of most of the theorems in this section will be the subject of later parts of this chapter.

---

**Theorem 12.6 (Khintchin’s WLLN).** If \( \{X_n\}_{n=1}^{\infty} \) are i.i.d. \( L^1(P) \) – random variables, then \( \frac{1}{n} S_n \rightarrow \mu = \mathbb{E}X_1 \).

**Proof.** Letting

\[ S_n' := \sum_{i=1}^{n} X_i |X_i| \leq n, \]

we have \( \{S'_n \neq S_n\} \subset \bigcup_{i=1}^{n} \{|X_i| > n\} \). Therefore, using Chebyshev’s inequality along with the dominated convergence theorem, we have

\[ P(S'_n \neq S_n) \leq \sum_{i=1}^{n} P(|X_i| > n) = nP(|X_1| > n) \leq \mathbb{E}|X_1| : |X_1| > n \rightarrow 0. \]

Hence it follows that

\[ P \left( \left| \frac{S_n}{n} - \frac{S'_n}{n} \right| > \varepsilon \right) \leq P(S'_n \neq S_n) \rightarrow 0 \text{ as } n \rightarrow \infty, \]

i.e. \( \frac{S_n}{n} - \frac{S'_n}{n} \rightarrow 0 \). So it suffices to prove \( \frac{S'_n}{n} \rightarrow \mu \).

We will now complete the proof by showing that, in fact, \( \frac{S'_n}{n} \rightarrow \mu \) in \( L^2(P) \). To this end, let

\[ \mu_n := \frac{1}{n} \mathbb{E}S'_n = \frac{1}{n} \sum_{i=1}^{n} \mathbb{E}[X_i 1_{|X_i| \leq n}] = \mathbb{E}[X_1 1_{|X_1| \leq n}] \]

and observe that \( \lim_{n \rightarrow \infty} \mu_n = \mu \) by the DCT. Moreover,

\[ \mathbb{E} \left| \frac{S'_n}{n} - \mu_n \right|^2 = \text{Var} \left( \frac{S'_n}{n} \right) = \frac{1}{n^2} \text{Var} (S'_n) \]

where

\[ \text{Var} (S'_n) = \frac{1}{n^2} \sum_{i=1}^{n} \text{Var} (X_1 1_{|X_1| \leq n}) \leq \frac{1}{n} \text{Var} (X_1 1_{|X_1| \leq n}) \leq \mathbb{E} |X_1| 1_{|X_1| \leq n} \]

and so again by the DCT, \( \left\| \frac{S'_n}{n} - \mu_n \right\|_{L^2(P)} \rightarrow 0 \). This completes the proof since,

\[ \left\| \frac{S'_n}{n} - \mu \right\|_{L^2(P)} \leq \left\| \frac{S'_n}{n} - \mu_n \right\|_{L^2(P)} + |\mu_n - \mu| \rightarrow 0 \text{ as } n \rightarrow \infty. \]

In fact we have the stronger result.
Theorem 12.7 (Kolmogorov’s Strong Law of Large Numbers). Suppose that \( \{X_n\}_{n=1}^{\infty} \) are i.i.d. random variables and let \( S_n := X_1 + \cdots + X_n \). Then there exists \( \mu \in \mathbb{R} \) such that \( \frac{1}{n} S_n \to \mu \) a.s. iff \( X_n \) is integrable and in which case \( \mathbb{E} X_n = \mu \).

Remark 12.8. If \( \mathbb{E} |X_1| = \infty \) but \( \mathbb{E} X_1^- < \infty \), then \( \frac{1}{n} S_n \to \infty \) a.s. To prove this, for \( M > 0 \) let \( X_n^M := X_n \wedge M \) and \( S_n^M := \sum_{i=1}^{n} X_i^M \). It follows from Theorem 12.7 that \( \frac{1}{n} S_n^M \to \mu^M := \mathbb{E} X_1^M \) a.s. Since \( S_n \geq S_n^M \), we may conclude that

\[
\liminf_{n \to \infty} \frac{S_n}{n} \geq \liminf_{n \to \infty} \frac{1}{n} S_n^M = \mu^M \text{ a.s.}
\]

Since \( \mu^M \to \infty \) as \( M \to \infty \), it follows that \( \liminf_{n \to \infty} \frac{S_n}{n} = \infty \) a.s. and hence that \( \lim_{n \to \infty} \frac{S_n}{n} = \infty \) a.s.

One proof of Theorem 12.7 is based on the study of random series. Theorem 12.11 and 12.12 are standard convergence criteria for random series.

Definition 12.9. Two sequences, \( \{X_n\} \) and \( \{X_n'\} \), of random variables are tail equivalent if

\[
\mathbb{E} \left[ \sum_{n=1}^{\infty} 1_{X_n \neq X_n'} \right] = \sum_{n=1}^{\infty} P( X_n \neq X_n') < \infty.
\]

Proposition 12.10. Suppose \( \{X_n\} \) and \( \{X_n'\} \) are tail equivalent. Then

1. \( \sum (X_n - X_n') \) converges a.s.
2. The sum \( \sum X_n \) is convergent a.s. iff the sum \( \sum X_n' \) is convergent a.s. More generally we have

\[
P \left( \left\{ \sum X_n \text{ is convergent} \right\} \triangle \left\{ \sum X_n' \text{ is convergent} \right\} \right) = 1
\]

3. If there exists a random variable, \( X \), and a sequence \( a_n \to \infty \) such that

\[
\lim_{n \to \infty} \frac{1}{a_n} \sum_{k=1}^{n} X_k = X \text{ a.s}
\]

then

\[
\lim_{n \to \infty} \frac{1}{a_n} \sum_{k=1}^{n} X_k' = X \text{ a.s}
\]

Proof. If \( \{X_n\} \) and \( \{X_n'\} \) are tail equivalent, we know, for a.e. \( \omega \), \( X_n(\omega) = X_n'(\omega) \) for a.a. \( n \). The proposition is an easy consequence of this observation.

Theorem 12.11 (Kolmogorov’s Convergence Criteria). Suppose that \( \{Y_n\}_{n=1}^{\infty} \) are independent square integrable random variables. If \( \sum_{j=1}^{\infty} \mathbb{Var}(Y_j) < \infty \), then \( \sum_{j=1}^{\infty} (Y_j - \mathbb{E} Y_j) \) converges a.s.

Proof. One way to prove this is to appeal Proposition 12.5 above and Lévy’s Theorem 12.31 below. As second method is to make use of Kolmogorov’s inequality. We will give this second proof below.

The next theorem generalizes the previous theorem by giving necessary and sufficient conditions for a random series of independent random variables to converge.

Theorem 12.12 (Kolmogorov’s Three Series Theorem). Suppose that \( \{X_n\}_{n=1}^{\infty} \) are independent random variables. Then the random series, \( \sum_{j=1}^{\infty} X_j \), is almost surely convergent iff there exists \( c > 0 \) such that

1. \( \sum_{n=1}^{\infty} P( |X_n| > c) < \infty \),
2. \( \sum_{n=1}^{\infty} \mathbb{Var}(X_n 1_{|X_n| \leq c}) < \infty \), and
3. \( \sum_{n=1}^{\infty} \mathbb{E} (X_n 1_{|X_n| \leq c}) \) converges.

Moreover, if the three series above converge for some \( c > 0 \) then they converge for all values of \( c > 0 \).

Proof. Proof of sufficiency. Suppose the three series converge for some \( c > 0 \). If we let \( X_n' := X_n 1_{|X_n| \leq c} \), then

\[
\sum_{n=1}^{\infty} P(X_n' \neq X_n) = \sum_{n=1}^{\infty} P(|X_n| > c) < \infty.
\]

Hence \( \{X_n\} \) and \( \{X_n'\} \) are tail equivalent and so it suffices to show \( \sum_{n=1}^{\infty} X_n' \) is almost surely convergent. However, by the convergence of the second series we learn

\[
\sum_{n=1}^{\infty} \mathbb{Var}(X_n') = \sum_{n=1}^{\infty} \mathbb{Var}(X_n 1_{|X_n| \leq c}) < \infty
\]

and so by Kolmogorov’s convergence criteria,

\[
\sum_{n=1}^{\infty} (X_n' - \mathbb{E} X_n') \text{ is almost surely convergent.}
\]

Finally, the third series guarantees that \( \sum_{n=1}^{\infty} \mathbb{E} X_n' = \sum_{n=1}^{\infty} \mathbb{E} (X_n 1_{|X_n| \leq c}) \) is convergent, therefore we may conclude \( \sum_{n=1}^{\infty} X_n' \) is convergent. The proof of the reverse direction will be given in Section 12.8 below.
12.2 Examples

12.2.1 Random Series Examples

Example 12.13 (Kolmogorov’s Convergence Criteria Example). Suppose that \( \{Y_n\}_{n=1}^\infty \) are independent square integrable random variables, such that \( \sum_{j=1}^\infty \text{Var}(Y_j) < \infty \) and \( \sum_{j=1}^\infty \mathbb{E}Y_j \) converges a.s., then \( \sum_{j=1}^\infty Y_j \) converges a.s.

**Definition 12.14.** A random variable, \( Y \), is normal with mean \( \mu \) standard deviation \( \sigma^2 \) iff

\[
P(Y \in B) = \frac{1}{\sqrt{2\pi}\sigma^2} \int_B e^{-\frac{(y-\mu)^2}{2\sigma^2}} dy \quad \text{for all } B \in \mathcal{B}_\mathbb{R}.
\]

We will abbreviate this by writing \( Y \overset{d}{=} N(\mu, \sigma^2) \). When \( \mu = 0 \) and \( \sigma^2 = 1 \) we will simply write \( N \) for \( N(0, 1) \) and if \( Y \overset{d}{=} N \), we will say \( Y \) is a standard normal random variable.

Observe that Eq. (12.3) is equivalent to writing

\[
\mathbb{E}[f(Y)] = \frac{1}{\sqrt{2\pi}\sigma^2} \int_{\mathbb{R}} f(y) e^{-\frac{(y-\mu)^2}{2\sigma^2}} dy
\]

for all bounded measurable functions, \( f : \mathbb{R} \to \mathbb{R} \). Also observe that \( Y \overset{d}{=} N(\mu, \sigma^2) \) is equivalent to \( Y \overset{d}{=} \sigma N + \mu \). Indeed, by making the change of variable, \( y = \sigma x + \mu \), we find

\[
\mathbb{E}[f(\sigma N + \mu)] = \frac{1}{\sqrt{2\pi}\sigma} \int_{\mathbb{R}} f(\sigma x + \mu) e^{-\frac{x^2}{2}} dx = \frac{1}{\sqrt{2\pi}\sigma^2} \int_{\mathbb{R}} f(y) e^{-\frac{(y-\mu)^2}{2\sigma^2}} dy
\]

**Lemma 12.15.** Suppose that \( \{Y_n\}_{n=1}^\infty \) are independent square integrable random variables such that \( Y_n \overset{d}{=} N(\mu_n, \sigma_n^2) \). Then \( \sum_{j=1}^\infty \sigma_j^2 < \infty \) and \( \sum_{j=1}^\infty \mu_j \) converges a.s. iff \( \sum_{j=1}^\infty \sigma_j^2 < \infty \) and \( \sum_{j=1}^\infty \mu_j \) converges.

**Proof.** The implication \( \Rightarrow \) is true without the assumption that the \( Y_n \) are normal random variables as pointed out in Example 12.13. To prove the converse directions we will make use of the Kolmogorov’s three series theorem. Namely, if \( \sum_{j=1}^\infty Y_j \) converges a.s. then the three series in Theorem 12.12 converge for all \( c > 0 \).

1. Since \( Y_n \overset{d}{=} \sigma_n N + \mu_n \), we have for any \( c > 0 \) that

\[
\infty > \sum_{n=1}^\infty P(|\sigma_n N + \mu_n| > c) = \sum_{n=1}^\infty \frac{1}{\sqrt{2\pi}} \int_{B_n} e^{-\frac{x^2}{2}} dx
\]

where

\[
B_n = (-\infty, -\frac{c + \mu_n}{\sigma_n}) \cup \left( -\frac{c - \mu_n}{\sigma_n}, \infty \right).
\]

If \( \lim_{n \to \infty} \mu_n \neq 0 \) then there is a \( c > 0 \) such that either \( \mu_n \geq c \) i.o. or \( \mu_n \leq -c \) i.o. In the first case in which case \( (0, \infty) \subset B_n \) and in the second \( (-\infty, 0) \subset B_n \) and in either case we will have \( \frac{1}{\sqrt{2\pi}} \int_{B_n} e^{-\frac{x^2}{2}} dx \geq 1/2 \) i.o. which would contradict Eq. (12.4). Hence we may concluded that \( \lim_{n \to \infty} \mu_n = 0 \). Similarly if \( \lim_{n \to \infty} \sigma_n \neq 0 \), then we may conclude that \( B_n \) contains a set of the form \( [\alpha, \infty) \) i.o. for some \( \alpha < \infty \) and so

\[
\frac{1}{\sqrt{2\pi}} \int_{B_n} e^{-\frac{x^2}{2}} dx \geq \frac{1}{\sqrt{2\pi}} \int_{\alpha}^\infty e^{-\frac{x^2}{2}} dx \text{ i.o.}
\]

which would again contradict Eq. (12.4). Therefore we may conclude that \( \lim_{n \to \infty} \mu_n = \lim_{n \to \infty} \sigma_n = 0 \).

2. The convergence of the second series for all \( c > 0 \) implies

\[
\infty > \sum_{n=1}^\infty \text{Var}(Y_n 1_{|Y_n| \leq c}) = \sum_{n=1}^\infty \text{Var}([\sigma_n N + \mu_n] 1_{|\sigma_n N + \mu_n| \leq c}), \text{ i.e.}
\]

\[
\infty > \sum_{n=1}^\infty [\sigma_n^2 \text{Var}(N 1_{|N| \leq c}) + \mu_n^2 \text{Var}(1_{|\sigma_n N + \mu_n| \leq c})] \geq \sum_{n=1}^\infty \sigma_n^2 \alpha_n.
\]

where \( \alpha_n := \text{Var}(N 1_{|N| \leq c}) \). As the reader should check, \( \alpha_n \to 1 \) as \( n \to \infty \) and therefore we may conclude \( \sum_{n=1}^\infty \sigma_n^2 < \infty \). It now follows by Kolmogorov’s convergence criteria that \( \sum_{n=1}^\infty (Y_n - \mu_n) \) is almost surely convergent and therefore

\[
\sum_{n=1}^\infty \mu_n = \infty \sum_{n=1}^\infty Y_n - \sum_{n=1}^\infty (Y_n - \mu_n)
\]

converges as well.

**Alternatively:** we may also deduce the convergence of \( \sum_{n=1}^\infty \mu_n \) by the third series as well. Indeed, for all \( c > 0 \) implies

\[
\sum_{n=1}^\infty \mathbb{E}([\sigma_n N + \mu_n] 1_{|\sigma_n N + \mu_n| \leq c}) \text{ is convergent, i.e.}
\]

\[
\sum_{n=1}^\infty [\sigma_n \delta_n + \mu_n \beta_n] \text{ is convergent.}
\]
where $\delta_n := \mathbb{E} \left( N \cdot 1_{|\sigma_n N + \mu_n| \leq c} \right)$ and $\beta_n := \mathbb{E} \left( 1_{|\sigma_n N + \mu_n| \leq c} \right)$. With a little effort one can show,

$$\delta_n \sim e^{-k/\sigma_n^2} \text{ and } 1 - \beta_n \sim e^{-k/\sigma_n^2} \text{ for large } n.$$ 

Since $e^{-k/\sigma_n^2} \leq C\sigma_n^2$ for large $n$, it follows that $\sum_{n=1}^{\infty} |\sigma_n \delta_n| \leq C \sum_{n=1}^{\infty} \sigma_n^3 < \infty$ so that $\sum_{n=1}^{\infty} \mu_n \beta_n$ is convergent. Moreover, 

$$\sum_{n=1}^{\infty} |\mu_n (\beta_n - 1)| \leq C \sum_{n=1}^{\infty} |\mu_n| \sigma_n^2 < \infty$$

and hence 

$$\sum_{n=1}^{\infty} \mu_n = \sum_{n=1}^{\infty} \mu_n \beta_n - \sum_{n=1}^{\infty} \mu_n (\beta_n - 1)$$

must also be convergent. \(\blacksquare\)

**Example 12.16 (Brownian Motion).** Let $\{N_n\}_{n=1}^{\infty}$ be i.i.d. standard normal random variable, i.e.

$$P(N_n \in A) = \int_{A} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx \text{ for all } A \in \mathcal{B}_\mathbb{R}.$$ 

Let $\{\omega_n\}_{n=1}^{\infty} \subset \mathbb{R}$, $\{a_n\}_{n=1}^{\infty} \subset \mathbb{R}$, and $t \in \mathbb{R}$, then 

$$\sum_{n=1}^{\infty} a_nN_n \sin \omega_n t \text{ converges a.s.}$$

provided $\sum_{n=1}^{\infty} a_n^2 < \infty$. This is a simple consequence of Kolmogorov’s convergence criteria, Theorem 12.11 and the facts that $\mathbb{E}[a_n N_n \sin \omega_n t] = 0$ and 

$$\text{Var}(a_n N_n \sin \omega_n t) = a_n^2 \sin^2 \omega_n t \leq a_n^2.$$ 

As a special case, if we take $\omega_n = (2n-1) \frac{\pi}{2}$ and $a_n = \frac{\sqrt{2}}{\pi(2n-1)}$, then it follows that 

$$B_t := \frac{2\sqrt{2}}{\pi} \sum_{k=1,3,5,\ldots}^{\infty} \frac{N_k}{k} \sin \left( k \frac{\pi t}{2} \right)$$

is a.s. convergent for all $t \in \mathbb{R}$. The factor $\frac{2\sqrt{2}}{\pi}$ has been determined by requiring,

$$\int_{0}^{t} \left[ \frac{d}{dt} \frac{2\sqrt{2}}{\pi k} \sin (k\pi t) \right]^2 dt = 1$$

as seen by,

$$\int_{0}^{t} \left[ \frac{d}{dt} \frac{2\sqrt{2}}{\pi k} \sin (k\pi t) \right]^2 dt = \frac{k^2 \pi^2}{2^2} \int_{0}^{t} \left[ \frac{1}{2} \cos \left( \frac{k\pi t}{2} \right) \right]^2 dt$$

$$= \frac{k^2 \pi^2}{2^2} \frac{2}{k\pi} \left[ \frac{k\pi t}{4} + \frac{1}{4} \sin (k\pi t) \right]_0^t = \frac{k^2 \pi^2}{2^2}.$$ 

**Fact:** Wiener in 1923 showed the series in Eq. (12.5) is in fact almost surely uniformly convergent. Given this, the process, $t \rightarrow B_t$ is almost surely continuous. The process $\{B_t : 0 \leq t \leq 1\}$ is **Brownian Motion**.

**Example 12.17.** As a simple application of Theorem 12.12 we will now use Theorem 12.12 to give a proof of Theorem 12.11. We will apply Theorem 12.12 with $X_n := Y_n - \mathbb{E}Y_n$. We need to then check the three series in the statement of Theorem 12.12 converge. For the first series we have by the Markov inequality,

$$\sum_{n=1}^{\infty} P(|X_n| > c) \leq \sum_{n=1}^{\infty} \frac{1}{c^2} \mathbb{E}|X_n|^2 = \frac{1}{c^2} \sum_{n=1}^{\infty} \text{Var}(Y_n) < \infty.$$ 

For the second series, observe that 

$$\sum_{n=1}^{\infty} \text{Var}(X_n 1_{|X_n| \leq c}) \leq \sum_{n=1}^{\infty} \mathbb{E}
\left( (X_n 1_{|X_n| \leq c})^2 \right) \leq \sum_{n=1}^{\infty} \mathbb{E}[X_n^2] = \sum_{n=1}^{\infty} \text{Var}(Y_n) < \infty$$

and for the third series (by Jensen’s or Hölder’s inequality)

$$\sum_{n=1}^{\infty} \left| \mathbb{E}(X_n 1_{|X_n| \leq c}) \right| \leq \sum_{n=1}^{\infty} \mathbb{E}(X_n^2 1_{|X_n| \leq c}) \leq \sum_{n=1}^{\infty} \text{Var}(Y_n) < \infty.$$ 

**12.2.2 A WLLN Example**

Let $\{X_n\}_{n=1}^{\infty}$ be i.i.d. random variables with common distribution function, $F(x) := P(X_n \leq x)$. For $x \in \mathbb{R}$ let $F_n(x)$ be the **empirical distribution function** defined by,

$$F_n(x) := \frac{1}{n} \sum_{j=1}^{n} 1_{X_j \leq x} = \left( \frac{1}{n} \sum_{j=1}^{n} \delta_{X_j} \right)(-\infty,x].$$

Since $\mathbb{E}1_{X_j \leq x} = F(x)$ and $\{1_{X_j \leq x}\}_{j=1}^{\infty}$ are Bernoulli random variables, the weak law of large numbers implies $F_n(x) \xrightarrow{p} F(x)$ as $n \rightarrow \infty$. As usual, for $p \in (0,1)$ let 

$$F^- (p) := \inf \{ x : F(x) \geq p \}$$

and recall that $F^- (p) \leq x$ iff $F(x) \geq p$. Let us notice that
then probability, the \( \bar{\Phi} \) of Proposition 12.18.

\[
P \left( F^{-} (p) - F_{\bar{n}}^{-} (p) \geq \varepsilon \right) = P \left( F_{\bar{n}}^{-} (p) - \varepsilon - F (F^{-} (p) - \varepsilon) \geq p - F (F^{-} (p) - \varepsilon) \right) \]
\[
= P \left( F_{\bar{n}}^{-} (p) - \varepsilon - F (F^{-} (p) - \varepsilon) \geq \delta \varepsilon \right) \to 0 \text{ as } n \to \infty.
\]

Thus we have shown that \( X_{[np]}^{(n)} \to F^{-} (p) \) as \( n \to \infty. \]

\subsection*{12.3 Strong Law of Large Number Examples}

\textbf{Example 12.19 (Renewal Theory).} Let \( \{X_i\}_{i=1}^{\infty} \) be i.i.d. random variables with \( 0 < X_i < \infty \) a.s. Think of the \( X_i \) as the time that bulb number \( i \) burns and \( T_n := X_1 + \cdots + X_n \) is the time that the \( n \)-th bulb burns out. (We assume the bulbs are replaced immediately on burning out.) Further let \( N_t := \{ \{ n \geq 0 : T_n \leq t \} \} \) denote the number of bulbs which have burned out up to time \( n \). By convention, we set \( T_0 = 0. \) Letting \( \mu := \mathbb{E}X_1 \in (0, \infty) \), we have \( \mathbb{E}T_n = n\mu \) – the expected time the \( n \)-th bulb burns out. On these grounds we expect \( N_t \sim t/\mu \) and hence
\[
\frac{1}{t} N_t \to \frac{1}{\mu} \text{ a.s.} \quad (12.6)
\]

To prove Eq. (12.6), by the SSLN, if \( \Omega_0 := \{ \lim_{n \to \infty} N_t / n = \mu \} \) then \( P (\Omega_0) = 1. \) From the definition of \( N_t, T_N \leq t < T_{N+1} \) and so
\[
\frac{T_N}{N_t} \leq \frac{t}{N_t} < \frac{T_{N+1}}{N_t}.
\]

Since \( X_i > 0 \) a.s., \( \Omega_1 := \{ N_t \uparrow \infty \text{ as } t \uparrow \infty \} \) also has full measure and for \( \omega \in \Omega_0 \cap \Omega_1 \) we have
\[
\mu = \lim_{t \to \infty} \frac{T_N (\omega)}{N_t (\omega)} \leq \lim_{t \to \infty} \frac{t}{N_t (\omega)} \leq \lim_{t \to \infty} \frac{T_{N+1} (\omega) - N_t (\omega) + 1}{N_t (\omega)} = \mu.
\]

\textbf{Example 12.20 (Renewal Theory II).} Let \( \{X_i\}_{i=1}^{\infty} \) be i.i.d. and \( \{Y_i\}_{i=1}^{\infty} \) be i.i.d. with \( \{X_i\}_{i=1}^{\infty} \) being independent of the \( \{Y_i\}_{i=1}^{\infty} \). Also again assume that \( 0 < X_i < \infty \) and \( 0 < Y_i < \infty \) a.s. We will interpret \( Y_i \) to be the amount of time the \( i \)-th bulb remains out after burning out before it is replaced by bulb number \( i+1 \). Let \( R_t \) be the amount of time that we have a working bulb in the time interval \([0, t]\). We are now going to show
\[
\lim_{t \to \infty} \frac{1}{t} R_t = \frac{\mathbb{E}X_1}{\mathbb{E}X_1 + \mathbb{E}Y_1}.
\]
To prove this, now let \( T_n := \sum_{i=1}^{n} (X_i + Y_i) \) be the time that the \( n \)th bulb is replaced and
\[
N_t := \sup \{ n \geq 0 : T_n \leq t \}
\]
denote the number of bulbs which have burned out up to time \( n \). Then \( R_t = \sum_{i=1}^{N_t} X_i \). Setting \( \mu = \mathbb{E}X_1 \) and \( \nu = \mathbb{E}Y_1 \), we now have \( \frac{1}{t} N_t \to \frac{\nu}{\mu + \nu} \) a.s.
so that \( N_t = \frac{\nu}{\mu + \nu} t + o(t) \) a.s. Therefore, by the strong law of large numbers,
\[
\frac{1}{t} R_t = \frac{1}{t} \sum_{i=1}^{N_t} X_i = \frac{N_t}{t} \sum_{i=1}^{N_t} X_i \to \frac{1}{\mu + \nu} \cdot \mu \text{ a.s.}
\]

**Theorem 12.21 (Glivenko-Cantelli Theorem).** Suppose that \( \{X_n\}_{n=1}^{\infty} \) are i.i.d. random variables and \( F(x) := P(X_1 \leq x) \). Further let \( \mu_n := \frac{1}{n} \sum_{i=1}^{n} \delta_{X_i} \)
be the empirical distribution with empirical distribution function,
\[
F_n(x) := \mu_n((-\infty,x]) = \frac{1}{n} \sum_{i=1}^{n} 1_{X_i \leq x}.
\]

Then
\[
\lim_{n \to \infty} \sup_{x \in \mathbb{R}} |F_n(x) - F(x)| = 0 \text{ a.s.}
\]

**Proof.** Since \( \{1_{X_1 \leq x}\}_{i=1}^{\infty} \) are i.i.d random variables with \( \mathbb{E}1_{X_1 \leq x} = P(X_1 \leq x) = F(x) \), it follows by the strong law of large numbers the \( \lim_{n \to \infty} F_n(x) = F(x) \) a.s. for each \( x \in \mathbb{R} \). Our goal is to now show that this convergence is uniform. To do this we will use one more application of the strong law of large numbers applied to \( \{1_{X_i \leq x}\} \) which allows us to conclude, for each \( x \in \mathbb{R} \), that
\[
\lim_{n \to \infty} F_n(x^-) = F(x^-) \text{ a.s. (the null set depends on } x \).
\]

Given \( k \in \mathbb{N} \), let \( A_k := \{ \frac{i}{k} : i = 1,2,\ldots,k-1 \} \) and let \( x_i := \inf \{ x : F(x) \geq i/k \} \) for \( i = 1,2,\ldots,k-1 \). Let us further set \( x_k = \infty \). Observe that if \( F \) is continuous then, by what we have just shown, there is a set \( \Omega_0 \subset \Omega \) such that \( P(\Omega_0) = 1 \) and on \( \Omega_0, F_n(r) \to F(r) \) for all \( r \in \mathbb{Q} \). Moreover on \( \Omega_0, \) if \( x \in \mathbb{R} \) and \( r \leq x \leq s \) with \( r, s \in \mathbb{Q} \), we have
\[
F(r) = \lim_{n \to \infty} F_n(r) \leq \liminf_{n \to \infty} F_n(x) \leq \limsup_{n \to \infty} F_n(x) = \lim_{n \to \infty} F_n(s) = F(s).
\]

We may now let \( s \downarrow x \) and \( r \uparrow x \) to conclude, on \( \Omega_0 \), on
\[
F(x) \leq \liminf_{n \to \infty} F_n(x) \leq \limsup_{n \to \infty} F_n(x) \leq F(x) \text{ for all } x \in \mathbb{R},
\]
\[\text{i.e. on } \Omega_0, \lim_{n \to \infty} F_n(x) = F(x). \]

Now suppose \( i \) has been chosen so that \( x_i < x_{i+1} \) and let \( x \in (x_i,x_{i+1}) \). Further let \( N(\omega) \in \mathbb{N} \) be chosen so that
\[
|F_n(x_i) - F(x)| < 1/k \text{ and } |F_n(x_{i+1}) - F(x)| < 1/k
\]
for \( n \geq N(\omega) \) and \( i = 1,2,\ldots,k-1 \) and \( \omega \in \Omega_k \) with \( P(\Omega_k) = 1 \). We then have
\[
F_n(x) \leq F_n(x_{i+1}) - 1/k \leq F(x_{i+1}) - 1/k \leq F(x) + 2/k
\]
and
\[
F_n(x) \geq F_n(x_i) \geq F(x_i) - 1/k \geq F(x_{i+1}) - 2/k \geq F(x) - 2/k.
\]

From this it follows that \( |F(x) - F_n(x)| \leq 2/k \) and we have shown for \( \omega \in \Omega_k \) and \( n \geq N(\omega) \) that
\[
\sup_{x \in \mathbb{R}} |F(x) - F_n(x)| \leq 2/k.
\]

Hence it follows on \( \Omega_0 := \cap_{k=1}^{\infty} \Omega_k \) (a set with \( P(\Omega_0) = 1 \)) that
\[
\lim_{n \to \infty} \sup_{x \in \mathbb{R}} |F_n(x) - F(x)| = 0.
\]

and \( x_0 = -\infty \). Observe that it is possible that \( x_i = x_{i+1} \) for some of the \( i \). This can occur when \( F \) has jumps of size greater than \( 1/k \).
Example 12.22 (Shannon’s Theorem). Let \( \{X_i\}_{i=1}^{\infty} \) be a sequence of i.i.d. random variables with values in \( \{1, 2, \ldots, r\} \subset \mathbb{N} \). Let \( p(k) := P(X_i = k) > 0 \) for \( 1 \leq k \leq r \). Further, let \( \pi_n(\omega) = p(X_1(\omega)) \ldots p(X_n(\omega)) \) be the probability of the realization, \( (X_1(\omega), \ldots, X_n(\omega)) \). Since \( \{\ln p(X_i)\}_{i=1}^{\infty} \) are i.i.d.,
\[
-\frac{1}{n} \ln \pi_n = -\frac{1}{n} \sum_{i=1}^{n} \ln p(X_i) \to -\mathbb{E}[\ln p(X_1)] = -\sum_{k=1}^{r} p(k) \ln p(k) =: H(p).
\]
In particular if \( \varepsilon > 0 \), \( P(H - \frac{1}{n} \ln \pi_n > \varepsilon) \to 0 \) as \( n \to \infty \). Since
\[
\left\{ H + \frac{1}{n} \ln \pi_n > \varepsilon \right\} = \left\{ H + \frac{1}{n} \ln \pi_n > \varepsilon \right\} \cup \left\{ H + \frac{1}{n} \ln \pi_n < -\varepsilon \right\}
\]
\[
= \left\{ \frac{1}{n} \ln \pi_n > -H + \varepsilon \right\} \cup \left\{ \frac{1}{n} \ln \pi_n < -H - \varepsilon \right\}
\]
\[
= \left\{ \pi_n > e^{n(-H + \varepsilon)} \right\} \cup \left\{ \pi_n < e^{n(-H - \varepsilon)} \right\}
\]
and
\[
\left\{ H - \frac{1}{n} \ln \pi_n > \varepsilon \right\} = \left\{ \pi_n > e^{n(-H + \varepsilon)} \right\} \cap \left\{ \pi_n < e^{n(-H - \varepsilon)} \right\}
\]
\[
= \left\{ \pi_n \leq e^{n(H + \varepsilon)} \right\} \cap \left\{ \pi_n \geq e^{n(-H - \varepsilon)} \right\}
\]
\[
= \left\{ e^{-n(H + \varepsilon)} \leq \pi_n \leq e^{-n(H - \varepsilon)} \right\},
\]
it follows that
\[
P(e^{-n(H + \varepsilon)} \leq \pi_n \leq e^{-n(H - \varepsilon)}) \to 1 \text{ as } n \to \infty.
\]
Thus the probability, \( \pi_n \), that the random sample \( \{X_1, \ldots, X_n\} \) should occur is approximately \( e^{-nH} \) with high probability. The number \( H \) is called the entropy of the distribution, \( \{p(k)\}_{k=1}^{\infty} \).

12.4 More on the Weak Laws of Large Numbers

Theorem 12.23 (Weak Law of Large Numbers). Suppose that \( \{X_n\}_{n=1}^{\infty} \) is a sequence of independent random variables. Let \( S_n := \sum_{j=1}^{n} X_j \) and \( a_n := \sum_{k=1}^{n} E(X_k : |X_k| \leq n) = nE(X_1 : |X_1| \leq n) \).

If
\[
\sum_{k=1}^{n} P(|X_k| > n) \to 0 \quad (12.7)
\]
and
\[
\frac{1}{n^2} \sum_{k=1}^{n} E(X_k^2 : |X_k| \leq n) \to 0, \quad (12.8)
\]
then
\[
\frac{S_n - a_n}{n} \to P. \to 0.
\]

Proof. A key ingredient in this proof and proofs of other versions of the law of large numbers is to introduce truncations of the \( \{X_k\} \). In this case we consider
\[
S_n' := \sum_{k=1}^{n} X_k 1_{X_k \leq n}.
\]
Since \( \{S_n' \neq S_n'\} \subset \bigcup_{k=1}^{n} \{|X_k| > n\} \),
\[
P \left( \frac{S_n - a_n}{n} - \frac{S_n' - a_n}{n} \right) > \varepsilon \right) = P \left( \frac{S_n - S_n'}{n} \right) > \varepsilon \right)
\]
\[
\leq P(S_n \neq S_n') \leq \sum_{k=1}^{n} P(|X_k| > n) \to 0 \text{ as } n \to \infty.
\]
Hence it suffices to show \( \frac{S_n - a_n}{n} \to 0 \) as \( n \to \infty \) and for this it suffices to show,
\[
\frac{S_n' - a_n}{n} \overset{L^2(P)}{\to} 0 \text{ as } n \to \infty.
\]
Observe that \( E(S_n') = a_n \) and therefore,
\[
E \left( \left[ \frac{S_n' - a_n}{n} \right]^2 \right) = \frac{1}{n^2} \text{Var}(S_n') = \frac{1}{n^2} \sum_{k=1}^{n} \text{Var}(X_k 1_{X_k \leq n})
\]
\[
\leq \frac{1}{n^2} \sum_{k=1}^{n} E(X_k^2 1_{X_k \leq n}) \to 0 \text{ as } n \to \infty.
\]

We now verify the hypothesis of Theorem 12.23 in three situations.

Corollary 12.24. If \( \{X_n\}_{n=1}^{\infty} \) are i.i.d. \( L^2(P) \) random variables, then
\[
\frac{1}{n}S_n \overset{P}{\to} \mu = E(X_1).
\]

Proof. By the dominated convergence theorem,
\[
\frac{a_n}{n} := \frac{1}{n} \sum_{k=1}^{n} E(X_k : |X_k| \leq n) = E(X_1 : |X_1| \leq n) \to \mu. \quad (12.9)
\]
Moreover,
\[
\frac{1}{n^2} \sum_{k=1}^{n} \mathbb{E} \left( X_k^2 : |X_k| \leq n \right) = \frac{1}{n} \mathbb{E} \left( X_1^2 : |X_1| \leq n \right) \leq \frac{1}{n} \mathbb{E} (X_1^2) \to 0 \text{ as } n \to \infty
\]
and by Chebyshev’s inequality,
\[
\sum_{k=1}^{n} P (|X_k| > n) = n P (|X_1| > n) \leq n \frac{1}{n^2} \mathbb{E} |X_1|^2 \to 0 \text{ as } n \to \infty.
\]

With these observations we may now apply Theorem [12.23] to complete the proof. \(\blacksquare\)

**Corollary 12.25 (Khintchin’s WLLN).** If \( \{X_n\}_{n=1}^{\infty} \) are i.i.d. \( L^1 \) \( (P) \) random variables, then \( \frac{1}{n} S_n \to \mu = \mathbb{E} X_1 \).

**Proof.** Again we have by Eq. (12.9), Chebyshev’s inequality, and the dominated convergence theorem, that
\[
\sum_{k=1}^{n} P (|X_k| > n) = n P (|X_1| > n) \leq n \frac{1}{n} \mathbb{E} [X_1 : |X_1| > n] \to 0 \text{ as } n \to \infty.
\]

Also
\[
\frac{1}{n^2} \sum_{k=1}^{n} \mathbb{E} (X_k^2 : |X_k| \leq n) = \frac{1}{n} \mathbb{E} \left[ X_1^2 : |X_1| \leq n \right] = \mathbb{E} \left| X_1 \right| \frac{|X_1|}{n} 1_{|X_1| \leq n}
\]
and the latter expression goes to zero as \( n \to \infty \) by the dominated convergence theorem, since
\[
|X_1| \frac{|X_1|}{n} 1_{|X_1| \leq n} \leq |X_1| \in L^1 (P)
\]
and \( \lim_{n \to \infty} |X_1| \frac{|X_1|}{n} 1_{|X_1| \leq n} = 0 \). Hence again the hypothesis of Theorem [12.23] have been verified. \(\blacksquare\)

**Lemma 12.26.** Let \( X \) be a random variable such that \( \tau (x) := x P (|X| \geq x) \to 0 \text{ as } x \to \infty \), then
\[
\lim_{n \to \infty} \frac{1}{n} \mathbb{E} \left[ X^2 : |X| \leq n \right] = 0.
\] (12.10)

**Note:** If \( X \in L^1 (P) \), then by Chebyshev’s inequality and the dominated convergence theorem,
\[
\tau (x) \leq \mathbb{E} [X : |X| \geq x] \to 0 \text{ as } x \to \infty.
\]

**Proof.** To prove this we observe that
\[
\mathbb{E} (X^2 : |X| \leq n) = \mathbb{E} \left[ \frac{2}{n} \int_{1}^{n} x \mathbb{P} (|X| \leq x) \, dx \right] \geq 2 \int_{0}^{n} P (0 \leq x \leq |X| \leq n) \, dx
\]
\[
\leq 2 \int_{0}^{n} x \mathbb{P} (|X| \geq x) \, dx = \mathbb{E} \left[ \frac{1}{n} \sum_{k=1}^{n} X_k^2 \right].
\]

Now given \( \varepsilon > 0 \), let \( M = M (\varepsilon) \) be chosen so that \( \tau (x) \leq \varepsilon \) for \( x \geq M \). Then
\[
\mathbb{E} (X^2 : |X| \leq n) = 2 \int_{M}^{n} \tau (x) \, dx + 2 \int_{0}^{M} \tau (x) \, dx \leq 2KM + (n - M) \varepsilon
\]
where \( K = \sup \{ \tau (x) : x \geq 0 \} \). Dividing this estimate by \( n \) and then letting \( n \to \infty \) shows
\[
\lim_{n \to \infty} \frac{1}{n} \mathbb{E} \left[ X^2 : |X| \leq n \right] \leq 2\varepsilon.
\]
Since \( \varepsilon > 0 \) was arbitrary, the proof is complete. \(\blacksquare\)

**Corollary 12.27 (Feller’s WLLN).** If \( \{X_n\}_{n=1}^{\infty} \) are i.i.d. and \( \tau (x) := x P (|X_1| > x) \to 0 \text{ as } x \to \infty \), then the hypothesis of Theorem [12.23] are satisfied.

**Proof.** Since
\[
\sum_{k=1}^{n} P (|X_k| > n) = n P (|X_1| > n) = \tau (n) \to 0 \text{ as } n \to \infty,
\]
Eq. (12.7) is satisfied. Eq. (12.8), follows from Lemma [12.26] and the identity,
\[
\frac{1}{n^2} \sum_{k=1}^{n} \mathbb{E} (X_k^2 : |X_k| \leq n) = \frac{1}{n} \mathbb{E} \left[ X_1^2 : |X_1| \leq n \right].
\] \(\blacksquare\)

### 12.5 Maximal Inequalities

**Theorem 12.28 (Kolmogorov’s Inequality).** Let \( \{X_n\} \) be a sequence of independent random variables with mean zero, \( S_n := X_1 + \cdots + X_n \), and \( S_n^* = \max_{j \leq n} |S_j| \). Then for any \( \alpha > 0 \) we have
\[
P (S_n^* \geq \alpha) \leq \frac{1}{\alpha^2} \mathbb{E} \left[ S_n^2 : S_n^* \geq \alpha \right].
\]

(See Proposition [19.38] and Example [19.40] below for generalizations of this inequality.)
Proof. Let \( J = \inf \{ j : |S_j| \geq \alpha \} \) with the infimum of the empty set being taken to be equal to \( \infty \). Observe that
\[
\{J = j\} = \{|S_1| < \alpha, \ldots, |S_{j-1}| < \alpha, |S_j| \geq \alpha\} \in \sigma (X_1, \ldots, X_j).
\]

Now
\[
E \left[ S_N^2 : |S_N| > \alpha \right] = E \left[ S_N^2 : J \leq N \right] = \sum_{j=1}^{N} E \left[ S_N^2 : J = j \right]
\]
\[
= \sum_{j=1}^{N} E \left[ (S_j + S_N - S_j)^2 : J = j \right]
\]
\[
= \sum_{j=1}^{N} E \left[ S_j^2 + (S_N - S_j)^2 + 2S_j (S_N - S_j) : J = j \right]
\]
\[
= \sum_{j=1}^{N} E \left[ S_j^2 + (S_N - S_j)^2 : J = j \right]
\]
\[
\geq \sum_{j=1}^{N} \alpha^2 P (J = j) = \alpha^2 P (|S_N| > \alpha).
\]

The equality, (\( \ast \)), is a consequence of the observations: 1) \( 1_{J=j}S_j \) is \( \sigma (X_1, \ldots, X_j) \) - measurable, 2) \( S_N - S_j \) is \( \sigma (X_{j+1}, \ldots, X_n) \) - measurable and hence \( 1_{J=j}S_j \) and \( S_N - S_j \) are independent, and so 3)
\[
E \left[ S_j (S_N - S_j) : J = j \right] = E \left[ S_j 1_{J=j} (S_N - S_j) \right] = E \left[ S_j 1_{J=j} \right] \cdot E \left[ S_N - S_j \right] = E \left[ S_j 1_{J=j} \right] \cdot 0 = 0.
\]

\[\square\]

Corollary 12.29 (\( L^2 \) - SSLN). Let \( \{X_n\} \) be a sequence of independent random variables with mean zero, and \( \sigma^2 = E \sum_k X_k^2 < \infty \). Letting \( S_n = \sum_{k=1}^{n} X_k \) and \( p > 1/2 \), we have
\[
\frac{1}{n^p} S_n \to 0 \text{ a.s.}
\]

If \( \{Y_n\} \) is a sequence of independent random variables \( EY_n = \mu \) and \( \sigma^2 = \text{Var} (X_n) < \infty \), then for any \( \beta \in (0, 1/2) \),
\[
\frac{1}{n^\beta} \sum_{k=1}^{n} Y_k - \mu = O \left( \frac{1}{n^{\beta}} \right).
\]

Proof. (The proof of this Corollary may be skipped. We will give another proof in Corollary [12.36] below.) From Theorem 12.28 we have for every \( \varepsilon > 0 \) that
\[
P \left( \frac{S_N^*}{N^p} \geq \varepsilon \right) = P \left( S_N^* \geq \varepsilon N^p \right) \leq \frac{1}{\varepsilon^2 N^{2p}} E \left[ S_N^* \right] = \frac{C}{\varepsilon^2 N^{2p}}.
\]
Hence if we suppose that \( N_n = n^\alpha \) with \( \alpha (2p-1) > 1 \), then we have
\[
\sum_{n=1}^{\infty} P \left( \frac{S_N^*}{N_n^p} \geq \varepsilon \right) \leq \sum_{n=1}^{\infty} \frac{C}{\varepsilon^2 N^{(2p-1)}} < \infty
\]
and so by the first Borel – Cantelli lemma we have
\[
P \left( \frac{S_N^*}{N_n^p} \geq \varepsilon \text{ for } n \text{ i.o.} \right) = 0.
\]
From this it follows that \( \lim_{n \to \infty} \frac{S_n^*}{N_n^p} = 0 \text{ a.s.} \).
To finish the proof, for \( m \in \mathbb{N} \), we may choose \( n = n \left( m \right) \) such that
\[
n^\alpha = N_n \leq m < N_{n+1} = \left( n + 1 \right)^\alpha.
\]
Since
\[
\frac{S_{n(m)}^*}{N_{n(m)}^{p+1}} \leq \frac{S_m^*}{m^{p}} \leq \frac{S_{n(m)+1}^*}{N_{n(m)}^p}
\]
and
\[
N_{n+1}/N_n \to 1 \text{ as } n \to \infty,
\]
it follows that
\[
0 = \lim_{m \to \infty} \frac{S_{n(m)}^*}{N_{n(m)}^{p+1}} = \lim_{m \to \infty} \frac{S_{n(m)}^*}{N_{n(m)}^p} \leq \lim_{m \to \infty} \frac{S_m^*}{m^p}
\]
\[
\leq \lim_{m \to \infty} \frac{S_{n(m)+1}^*}{N_{n(m)}^p} = \lim_{m \to \infty} \frac{S_{n(m)+1}^*}{N_{n(m)}^{p+1}} = 0 \text{ a.s.}
\]
That is \( \lim_{m \to \infty} \frac{S_m^*}{m^p} = 0 \text{ a.s.} \).

\[\square\]

Theorem 12.30 (Skorohod’s Inequality). Let \( \{X_n\} \) be a sequence of independent random variables and let \( \alpha > 0 \). Let \( S_n := X_1 + \cdots + X_n \). Then for all \( \alpha > 0 \),
\[
P (|S_n| > \alpha) \geq (1 - c_N (\alpha)) P \left( \max_{j \leq n} |S_j| > 2\alpha \right),
\]
where
\[
c_N (\alpha) := \max_{j \leq n} P (|S_N - S_j| > \alpha).
\]
Proof. Our goal is to compute
\[ P \left( \max_{j \leq N} |S_j| > 2\alpha \right). \]

To this end, let \( J = \inf \{ j : |S_j| > 2\alpha \} \) with the infimum of the empty set being taken to be equal to \( \infty \). Observe that
\[ \{ J = j \} = \{ |S_1| \leq 2\alpha, \ldots, |S_{j-1}| \leq 2\alpha, |S_j| > 2\alpha \}, \]
and therefore
\[ \left\{ \max_{j \leq N} |S_j| > 2\alpha \right\} = \sum_{j=1}^{\infty} \{ J = j \}. \]

Also observe that on \( \{ J = j \} \),
\[ |S_N| = |S_N - S_j + S_j| \geq |S_j| - |S_N - S_j| > 2\alpha - |S_N - S_j|, \]
Hence on the \( \{ J = j, |S_N - S_j| \leq \alpha \} \) we have \( |S_N| > \alpha \), i.e.
\[ \{ J = j, |S_N - S_j| \leq \alpha \} \subset \{ |S_N| > \alpha \} \text{ for all } j \leq N. \]

Hence it follows from this identity and the independence of \( \{ X_n \} \) that
\[ P(|S_N| > \alpha) \geq \sum_{j=1}^{N} P(J = j, |S_N - S_j| \leq \alpha) \]
\[ = \sum_{j=1}^{N} P(J = j) P(|S_N - S_j| \leq \alpha). \]

Under the assumption that \( P(|S_N - S_j| > \alpha) \leq c \) for all \( j \leq N \), we find
\[ P(|S_N - S_j| \leq \alpha) \geq 1 - c \]
and therefore,
\[ P(|S_N| > \alpha) \geq \sum_{j=1}^{N} P(J = j) (1 - c) = (1 - c) P \left( \max_{j \leq N} |S_j| > 2\alpha \right). \]

As an application of Theorem 12.30 we have the following convergence result.

Theorem 12.31 (Lévy’s Theorem). Suppose that \( \{ X_n \}_{n=1}^{\infty} \) are i.i.d. random variables then \( \sum_{n=1}^{\infty} X_n \) converges in probability iff \( \sum_{n=1}^{\infty} X_n \) converges a.s.

Proof. Let \( S_n := \sum_{k=1}^{n} X_k \). Since almost sure convergence implies convergence in probability, it suffices to show: if \( S_n \) is convergent in probability then \( S_n \) is almost surely convergent. Given \( M \in \mathbb{N} \), let \( Q_M := \sup_{n \geq M} |S_n - S_M| \) and for \( M < N \), let \( Q_{M,N} := \sup_{M \leq n \leq N} |S_n - S_M| \). Given \( \varepsilon \in (0, 1) \), by assumption, there exists \( M = M(\varepsilon) \in \mathbb{N} \) such that \( \max_{M \leq j \leq N} P(|S_N - S_j| > \varepsilon) < \varepsilon \) for all \( N \geq M \). An application of Skorohod’s inequality, then shows
\[ P(Q_{M,N} \geq 2\varepsilon) \leq \frac{P(|S_N - S_M| > \varepsilon)}{1 - \max_{M \leq j \leq N} P(|S_N - S_j| > \varepsilon)} \leq \frac{\varepsilon}{1 - \varepsilon}. \]

Since \( Q_{M,N} \uparrow Q_M \) as \( N \to \infty \), we may conclude
\[ P(Q_M \geq 2\varepsilon) \leq \frac{\varepsilon}{1 - \varepsilon}. \]

Since,
\[ \delta_M := \sup_{m,n \geq M} |S_n - S_m| \leq \sup_{m,n \geq M} |S_n - S_M| + |S_M - S_m| = 2Q_M \]
we may further conclude, \( P(\delta_M > 4\varepsilon) \leq \frac{\varepsilon}{1 - \varepsilon} \) and since \( \varepsilon > 0 \) is arbitrary, it follows that \( \delta_M \overset{P}{\to} 0 \) as \( M \to \infty \). Moreover, since \( \delta_M \) is decreasing in \( M \), it follows that \( \lim_{M \to \infty} \delta_M =: \delta \) exists and because \( \delta_M \overset{P}{\to} 0 \) we may concluded that \( \delta = 0 \) a.s. Thus we have shown
\[ \lim_{m,n \to \infty} |S_n - S_m| = 0 \text{ a.s.} \]
and therefore \( \{ S_n \}_{n=1}^{\infty} \) is almost surely Cauchy and hence almost surely convergent.

Proposition 12.32 (Reflection Principle). Let \( X \) be a separable Banach space and \( \{ \xi_i \}_{i=1}^{N} \) be independent symmetric (i.e. \( \xi_i \equiv -\xi_i \)) random variables with values in \( X \). Let \( S_k := \sum_{i=1}^{k} \xi_i \) and \( S_k^* := \sup_{j \leq k} \| S_j \| \) with the convention that \( S_0^* = 0 \). Then
\[ P(S_N^* \geq r) \leq 2P(\| S_N \| \geq r). \] (12.11)

Proof. Since
\[ \{ S_N^* \geq r \} = \sum_{j=1}^{N} \{ \| S_j \| \geq r, S_{j-1}^* < r \}, \]
\[ P(S_N^* \geq r) = P(S_N^* \geq r, \| S_N \| \geq r) + P(S_N^* \geq r, \| S_N \| < r) \]
\[ = P(\| S_N \| \geq r) + P(S_N^* \geq r, \| S_N \| < r). \] (12.12)

where
\[ P(S^*_N \geq r, \|S_N\| < r) = \sum_{j=1}^{N} P(||S_j|| \geq r, S^*_{j-1} < r, \|S_N\| < r) \quad (12.13) \]

By symmetry and independence we have

\[ P(||S_j|| \geq r, S^*_{j-1} < r, \|S_N\| < r) = P(||S_j|| \geq r, S^*_{j-1} < r, \left\| S_j + \sum_{k>j} \xi_k \right\| < r) \]

\[ = P(||S_j|| \geq r, S^*_{j-1} < r, \left\| S_j - \sum_{k>j} \xi_k \right\| < r) \]

\[ = P(||S_j|| \geq r, S^*_{j-1} < r, \|2S_j - S_N\| < r). \]

If \( ||S_j|| \geq r \) and \( 2S_j - S_N \) then

\[ r > \|2S_j - S_N\| \geq 2\|S_j\| - \|S_N\| \geq 2r - \|S_N\| \]

and hence \( ||S_N|| > r \). This shows,

\[ \{ ||S_j|| \geq r, S^*_{j-1} < r, \|2S_j - S_N\| < r \} \subset \{ ||S_j|| \geq r, S^*_{j-1} < r, \|S_N\| > r \} \]

and therefore,

\[ P(||S_j|| \geq r, S^*_{j-1} < r, \|S_N\| < r) \leq P(||S_j|| \geq r, S^*_{j-1} < r, \|S_N\| > r). \]

Combining the estimate with Eq. (12.13) gives

\[ P(S^*_N \geq r, \|S_N\| < r) \leq \sum_{j=1}^{N} P(||S_j|| \geq r, S^*_{j-1} < r, \|S_N\| > r) \]

\[ = P(S^*_N \geq r, \|S_N\| > r) \leq P(||S_N|| \geq r). \]

This estimate along with the estimate in Eq. (12.12) completes the proof of the theorem. \( \blacksquare \)

### 12.6 Kolmogorov’s Convergence Criteria and the SSLN

We are now in a position to prove Theorem 12.11 which we restate here.

**Theorem 12.33 (Kolmogorov’s Convergence Criteria).** Suppose that \( \{Y_n\}_{n=1}^\infty \) are independent square integrable random variables. If \( \sum_{j=1}^{\infty} \text{Var}(Y_j) < \infty \), then \( \sum_{j=1}^{\infty} (Y_j - EY_j) \) converges a.s.

**Proof. First proof.** By Proposition 12.5 the sum, \( \sum_{j=1}^{\infty} (Y_j - EY_j) \), is \( L^2(P) \) convergent and hence convergent in probability. An application of Lévy’s Theorem 12.31 then shows \( \sum_{j=1}^{\infty} (Y_j - EY_j) \) is almost surely convergent.

**Second proof.** Let \( S_n := \sum_{j=1}^{n} X_j \) where \( X_j := Y_j - EY_j \). According to Kolmogorov’s inequality, Theorem 12.28, for all \( M < N \),

\[ P \left( \max_{M \leq j \leq N} |S_j - S_M| \geq \alpha \right) \leq \frac{1}{\alpha^2} \mathbb{E} \left[ (S_N - S_M)^2 \right] = \frac{1}{\alpha^2} \sum_{j=M+1}^{N} \mathbb{E} [X_j^2] \]

\[ = \frac{1}{\alpha^2} \sum_{j=M+1}^{N} \text{Var}(X_j). \]

Letting \( N \to \infty \) in this inequality shows, with \( Q_M := \sup_{j \geq M} |S_j - S_M| \),

\[ P(Q_M \geq \alpha) \leq \frac{1}{\alpha^2} \sum_{j=M+1}^{\infty} \text{Var}(X_j). \]

Since

\[ \delta_M := \sup_{j,k \geq M} |S_j - S_k| \leq \sup_{j,k \geq M} (|S_j - S_M| + |S_M - S_k|) \leq 2Q_M \]

we may further conclude,

\[ P(\delta_M \geq 2\alpha) \leq \frac{1}{\alpha^2} \sum_{j=M+1}^{\infty} \text{Var}(X_j) \to 0 \text{ as } M \to \infty, \]

i.e. \( \delta_M \overset{P}{\to} 0 \text{ as } M \to \infty \). Since \( \delta_M \) is decreasing in \( M \), it follows that \( \lim_{M \to \infty} \delta_M =: \delta \) exists and because \( \delta_M \overset{P}{\to} 0 \text{ we may conclude that } \delta = 0 \) a.s. Thus we have shown

\[ \lim_{n,m \to \infty} |S_n - S_m| = 0 \text{ a.s.} \]

and therefore \( \{S_n\}_{n=1}^\infty \) is almost surely Cauchy and hence almost surely convergent. \( \blacksquare \)

**Lemma 12.34 (Kronecker’s Lemma).** Suppose that \( \{x_k\} \subset \mathbb{R} \) and \( \{a_k\} \subset (0, \infty) \) are sequences such that \( a_k \uparrow \infty \) and \( \sum_{k=1}^{\infty} \frac{x_k}{a_k} \) exists. Then

\[ \lim_{n \to \infty} \frac{1}{a_n} \sum_{k=1}^{n} x_k = 0. \]
Proof. Before going to the proof, let us warm-up by proving the following continuous version of the lemma. Let \( a(s) \in (0, \infty) \) and \( x(s) \in \mathbb{R} \) be continuous functions such that \( a(s) \uparrow \infty \) as \( s \to \infty \) and \( \int_1^\infty \frac{x(s)}{a(s)} ds \) exists. We are going to show

\[
\lim_{n \to \infty} \frac{1}{a(n)} \int_1^n x(s) ds = 0.
\]

Let \( X(s) := \int_0^s x(u) du \) and

\[
r(s) := \int_s^\infty \frac{X'(u)}{a(u)} du = \int_s^\infty \frac{x(u)}{a(u)} du.
\]

Then by assumption, \( r(s) \to 0 \) as \( s \to 0 \) and \( X'(s) = -a(s) r'(s) \). Integrating this equation shows

\[
X(s) - X(s_0) = -\int_{s_0}^s a(u) r'(u) du = -a(u) r(u) \bigg|_{u=s_0}^{u=s} + \int_{s_0}^s r(u) a'(u) du.
\]

Dividing this equation by \( a(s) \) and then letting \( s \to \infty \) gives

\[
\limsup_{s \to \infty} \frac{|X(s)|}{a(s)} = \limsup_{s \to \infty} \left[ \frac{a(s_0) r(s_0) - a(s) r(s)}{a(s)} + \frac{1}{a(s)} \int_{s_0}^s r(u) a'(u) du \right]
\]

\[
\leq \limsup_{s \to \infty} \left[ -r(s) + \frac{1}{a(s)} \int_{s_0}^s |r(u)| a'(u) du \right]
\]

\[
\leq \limsup_{s \to \infty} \left[ a(s) - a(s_0) \sup_{u \geq s_0} |r(u)| \right] = \sup_{u \geq s_0} |r(u)| \to 0 \quad \text{as} \quad s_0 \to \infty.
\]

With this as warm-up, we go to the discrete case.

Let

\[
S_k := \sum_{j=1}^k x_j \quad \text{and} \quad r_k := \sum_{j=k}^\infty \frac{x_j}{a_j},
\]

so that \( r_k \to 0 \) as \( k \to \infty \) by assumption. Since \( x_k = a_k (r_k - r_{k+1}) \), we find

\[
\frac{S_n}{a_n} = \frac{1}{a_n} \sum_{k=1}^n a_k (r_k - r_{k+1}) = \frac{1}{a_n} \left[ \sum_{k=1}^n a_k r_k - \sum_{k=2}^{n+1} a_{k-1} r_k \right]
\]

\[
= \frac{1}{a_n} \left[ a_1 r_1 - a_n r_{n+1} + \sum_{k=2}^n (a_k - a_{k-1}) r_k \right]. \quad \text{(summation by parts)}
\]

Using the fact that \( a_k - a_{k-1} \geq 0 \) for all \( k \geq 2 \), and

\[
\lim_{n \to \infty} \frac{1}{a_n} \sum_{k=2}^m (a_k - a_{k-1}) |r_k| = 0
\]

for any \( m \in \mathbb{N} \); we may conclude

\[
\limsup_{n \to \infty} \frac{\left| \frac{S_n}{a_n} \right|}{b_n} \leq \limsup_{n \to \infty} \frac{1}{a_n} \sum_{k=2}^n \frac{(a_k - a_{k-1}) |r_k|}{b_n} \leq \limsup_{n \to \infty} \frac{1}{a_n} \sum_{k=2}^n \frac{(a_k - a_{k-1}) r_k}{b_n}
\]

\[
= \sup_{k \geq m} |r_k| \limsup_{n \to \infty} \frac{1}{a_n} \sum_{k=m}^n \frac{(a_k - a_{k-1})}{b_n} = \sup_{k \geq m} |r_k|.
\]

This completes the proof since \( \sup_{k \geq m} |r_k| \to 0 \) as \( m \to \infty \).

\[\mathbf{Corollary \ 12.35.} \text{ Let } \{X_n\} \text{ be a sequence of independent square integrable random variables and } b_n \text{ be a sequence such that } b_n \uparrow \infty. \text{ If}
\]

\[
\sum_{k=1}^\infty \frac{\text{Var} (X_k)}{b_k^2} < \infty
\]

\[
\text{then }
\frac{S_n - \mathbb{E}S_n}{b_n} \to 0 \text{ a.s.}
\]

\[\mathbf{Proof.} \text{ By Kolmogorov's Convergence Criteria, Theorem 12.33}
\]

\[
\sum_{k=1}^\infty \frac{X_k - \mathbb{E}X_k}{b_k}
\]

is convergent a.s.

Therefore an application of Kronecker’s Lemma implies

\[
0 = \lim_{n \to \infty} \frac{1}{b_n} \sum_{k=1}^n (X_k - \mathbb{E}X_k) = \lim_{n \to \infty} \frac{S_n - \text{ES}_n}{b_n}.
\]

\[\mathbf{Corollary \ 12.36 \ (L^2 - \text{SSLN}).} \text{ Let } \{X_n\} \text{ be a sequence of independent random variables such that } \sigma^2 = \mathbb{E}X_n^2 < \infty. \text{ Letting } S_n = \sum_{k=1}^n X_k \text{ and } \mu := \mathbb{E}X_n, \text{ we have}
\]

\[
\frac{1}{b_n} (S_n - n\mu) \to 0 \text{ a.s.} \quad \text{(12.14)}
\]

\[\text{provided } b_n \uparrow \infty \text{ and } \sum_{k=1}^\infty \frac{1}{b_n^2} < \infty. \text{ For example, we could take } b_n = n \text{ or } b_n = n^p \text{ for any } p > 1/2, \text{ or } b_n = n^{1/2} (\ln n)^{1/2 + \varepsilon} \text{ for any } \varepsilon > 0. \text{ We may rewrite Eq. (12.14) as}
\]

\[\]
or equivalently,
\[
\frac{S_n}{n} - \mu = o(1) \frac{b_n}{n}.
\]

**Proof.** This corollary is a special case of Corollary 12.35. Let us simply observe here that
\[
\sum_{n=2}^{\infty} \frac{1}{n^{1/2} (\ln n)^{1/2+\varepsilon}} = \sum_{n=2}^{\infty} \frac{1}{n (\ln n)^{1+2\varepsilon}}
\]
by comparison with the integral
\[
\int_{2}^{\infty} \frac{1}{x \ln^{1+2\varepsilon}} \, dx = \int_{\ln 2}^{\infty} \frac{1}{y \ln^{1+2\varepsilon}} e^y \, dy = \int_{\ln 2}^{\infty} \frac{1}{y^{1+2\varepsilon}} \, dy < \infty,
\]
wherein we have made the change of variables, \( y = \ln x \). □

**Fact 12.37** Under the hypothesis in Corollary 12.36
\[
\lim_{n \to \infty} \frac{S_n - n \mu}{n^{1/2} (\ln \ln n)^{1/2}} = \frac{\sqrt{2\pi}}{\sigma} \text{ a.s.}
\]

Our next goal is to prove the Strong Law of Large numbers (in Theorem 12.7) under the assumption that \( \mathbb{E} |X_1| < \infty \).

### 12.7 Strong Law of Large Numbers

**Lemma 12.38.** Suppose that \( X : \Omega \to \mathbb{R} \) is a random variable, then
\[
\mathbb{E} |X|^p = \int_{0}^{\infty} p s^{p-1} P(|X| \geq s) \, ds = \int_{0}^{\infty} p s^{p-1} P(|X| > s) \, ds.
\]

**Proof.** By the fundamental theorem of calculus,
\[
|X|^p = \int_{0}^{\frac{|X|}{p}} p s^{p-1} \, ds = p \int_{0}^{\infty} 1_{s \leq |X|} \cdot s^{p-1} \, ds = p \int_{0}^{\infty} 1_{s < |X|} \cdot s^{p-1} \, ds.
\]
Taking expectations of this identity along with an application of Tonelli’s theorem completes the proof. □

**Lemma 12.39.** If \( X \) is a random variable and \( \varepsilon > 0 \), then
\[
\sum_{n=1}^{\infty} P(|X| \geq n \varepsilon) \leq \frac{1}{\varepsilon} \mathbb{E} |X| \leq \sum_{n=0}^{\infty} P(|X| \geq n \varepsilon).
\]

**Proof.** First observe that for all \( y \geq 0 \) we have,
\[
\sum_{n=1}^{y} \frac{1}{n} \leq \sum_{n=1}^{\infty} \frac{1}{n} \leq \sum_{n=0}^{\infty} \frac{1}{n} = \infty.
\]
Taking \( y = \frac{|X|}{\varepsilon} \) in Eq. (12.16) and then take expectations gives the estimate in Eq. (12.15). □

**Proposition 12.40.** Suppose that \( \{X_n\}_{n=1}^{\infty} \) are i.i.d. random variables, then the following are equivalent:

1. \( \mathbb{E}|X_1| < \infty \).
2. There exists \( \varepsilon > 0 \) such that \( \sum_{n=1}^{\infty} P(|X_1| \geq \varepsilon n) < \infty \).
3. For all \( \varepsilon > 0 \), \( \sum_{n=1}^{\infty} P(|X_1| \geq \varepsilon n) < \infty \).
4. \( \lim_{n \to \infty} \frac{|X_n|}{n} = 0 \) a.s.

**Proof.** The equivalence of items 1., 2., and 3. easily follows from Lemma 12.39. So to finish the proof it suffices to show 3. is equivalent to 4. To this end we start by noting that \( \lim_{n \to \infty} \frac{|X_n|}{n} = 0 \) a.s. iff
\[
0 = P \left( \frac{|X_n|}{n} \geq \varepsilon \text{ i.o.} \right) = P \left( \frac{|X_n|}{n} \geq n \varepsilon \text{ i.o.} \right) \text{ for all } \varepsilon > 0. \tag{12.17}
\]
However, since \( \{|X_n| \geq n \varepsilon\}_{n=1}^{\infty} \) are independent sets, Borel zero-one law shows the statement in Eq. (12.17) is equivalent to \( \sum_{n=1}^{\infty} P(|X_1| \geq \varepsilon n) < \infty \) for all \( \varepsilon > 0 \). □

**Corollary 12.41.** Suppose that \( \{X_n\}_{n=1}^{\infty} \) are i.i.d. random variables such that \( \frac{1}{n} S_n \to c \in \mathbb{R} \) a.s., then \( X_n \in L^1(P) \) and \( \mu := \mathbb{E} X_n = c \).

**Proof.** If \( \frac{1}{n} S_n \to c \) a.s. then \( \varepsilon_n := \frac{S_{n+1}}{n+1} - \frac{S_n}{n} \to 0 \) a.s. and therefore,
\[
\frac{X_{n+1}}{n+1} = \frac{S_{n+1}}{(n+1)^2} - \frac{S_n}{n+1} = \varepsilon_n + \frac{S_n}{n+1} \left[ \frac{1}{n+1} - \frac{1}{n} \right] = \varepsilon_n + \frac{1}{(n+1)^2} \frac{S_n}{n} \to 0 + 0 \cdot c = 0.
\]
Hence an application of Proposition 12.40 shows \( X_n \in L^1(P) \). Moreover by Exercise 11.3 \( \{\frac{1}{n} S_n\}_{n=1}^{\infty} \) is a uniformly integrable sequenced and therefore,
\[
\mu = \mathbb{E} \left[ \frac{1}{n} S_n \right] \to \mathbb{E} \left[ \lim_{n \to \infty} \frac{1}{n} S_n \right] = \mathbb{E}[c] = c.
\]

Lemma 12.42. For all $x \geq 0$, $\varphi(x) := \sum_{n=1}^{\infty} \frac{1}{n^2} 1_{x \leq n} = \sum_{n \geq x} \frac{1}{n^2} \leq 2 \cdot \min \left( \frac{1}{x}, 1 \right)$.

Proof. The proof will be by comparison with the integral, $\int_a^\infty \frac{1}{t^2} dt = 1/a$.

For example, $\sum_{n=1}^{\infty} \frac{1}{n^2} \leq 1 + \int_1^\infty \frac{1}{t^2} dt = 1 + 1 = 2$

and so $\sum_{n \geq x} \frac{1}{n^2} = \sum_{n=1}^{\infty} \frac{1}{n^2} \geq 2 \frac{1}{x}$ for $0 < x \leq 1$.

Similarly, for $x > 1$,

$\sum_{n \geq x} \frac{1}{n^2} \leq \frac{1}{x^2} + \int_x^\infty \frac{1}{t^2} dt = \frac{1}{x^2} + \frac{1}{x} = \frac{1}{x} \left( 1 + \frac{1}{x} \right) \leq \frac{2}{x}$,

see Figure 12.7 below.

\[ \sum_{n=1}^{\infty} \frac{1}{n^2} \mathbb{E} \left[ |X|^2 : 1_{|X| \leq n} \right] = \mathbb{E} \left[ |X|^2 \sum_{n=1}^{\infty} \frac{1}{n^2} 1_{|X| \leq n} \right] = \mathbb{E} \left[ |X|^2 \varphi(|X|) \right] \leq 2 \mathbb{E} \left[ |X|^2 \left( \frac{1}{|X|} \wedge 1 \right) \right] \leq 2 \mathbb{E} |X|.

Lemma 12.43. Suppose that $X : \Omega \to \mathbb{R}$ is a random variable, then

$$\sum_{n=1}^{\infty} \frac{1}{n^2} \mathbb{E} \left[ |X|^2 : 1_{|X| \leq n} \right] \leq 2 \mathbb{E} |X|.$$
So to finish the proof, it only remains to observe
\[
\lim_{n \to \infty} \frac{1}{n} \sum_{k=1}^{n} \mathbb{E}X_k = \lim_{n \to \infty} \frac{1}{n} \sum_{k=1}^{n} \mathbb{E}[X_n 1_{|X_n| \leq n}] = \lim_{n \to \infty} \frac{1}{n} \sum_{k=1}^{n} \mathbb{E}[X_1 1_{|X_1| \leq n}] = \lim_{n \to \infty} \mathbb{E}[X_1 1_{|X_1| \leq n}] = \mu.
\]

Here we have used the dominated convergence theorem to see that \( a_n := \mathbb{E}[X_1 1_{|X_1| \leq n}] \to \mu \) as \( n \to \infty \). It is now easy (and standard) to check that
\[
\lim_{n \to \infty} \frac{1}{n} \sum_{k=1}^{n} a_k = \lim_{n \to \infty} a_n = \mu \text{ as well.}
\]

We end this section with another example of using Kolmogorov’s convergence criteria in conjunction with Kronecker’s lemma. We now assume that \( \{X_n\}_{n=1}^{\infty} \) are i.i.d. random variables with a continuous distribution function and let \( A_j \) denote the event when \( X_j \) is a record, i.e.
\[
A_j := \{X_j > \max \{X_1, X_2, \ldots, X_{k-1}\}\}.
\]

Recall from Renyi Theorem 7.28 that \( \{A_j\}_{j=1}^{\infty} \) are independent and \( P(A_j) = \frac{1}{j} \) for all \( j \).

**Proposition 12.45.** Keeping the preceding notation and let \( \mu_N := \sum_{j=1}^{N} 1_{A_j} \) denote the number of records in the first \( N \) observations. Then \( \lim_{N \to \infty} \frac{\mu_N}{N} = 1 \) a.s.

**Proof.** Since \( 1_{A_j} \) are Bernoulli random variables, \( \mathbb{E}1_{A_j} = \frac{1}{j} \) and
\[
\text{Var}(1_{A_j}) = \mathbb{E}(1_{A_j})^2 - (\mathbb{E}1_{A_j})^2 = \frac{1}{j} - \frac{1}{j^2} = \frac{j-1}{j^2}.
\]

Observing that
\[
\sum_{j=1}^{n} \mathbb{E}1_{A_j} = \sum_{j=1}^{N} \frac{1}{j} \sim \int_{1}^{N} \frac{1}{x} dx = \ln N
\]
we are lead to try to normalize the sum \( \sum_{j=1}^{N} 1_{A_j} \) by \( \ln N \). So in the spirit of the proof of the strong law of large numbers let us compute;
\[
\sum_{j=2}^{\infty} \text{Var} \left( \frac{1_{A_j}}{\ln j} \right) = \sum_{j=2}^{\infty} \frac{1}{\ln^2 j} \frac{j-1}{j^2} \sim \int_{2}^{\infty} \frac{1}{\ln^2 x} \frac{1}{x} dx = \int_{\ln 2}^{\infty} \frac{1}{y^2} dy < \infty.
\]

Therefore by Kolmogorov’s convergence criteria we may conclude
\[
\sum_{j=2}^{\infty} \frac{1_{A_j}}{\ln j} - \frac{\mu}{\ln j} = \sum_{j=2}^{\infty} \left[ \frac{1_{A_j}}{\ln j} - \mathbb{E} \left( \frac{1_{A_j}}{\ln j} \right) \right]
\]
is almost surely convergent. An application of Kronecker’s Lemma then implies
\[
\lim_{n \to \infty} \frac{\sum_{j=1}^{N} \left( 1_{A_j} - \frac{1}{j} \right)}{\ln N} = 0 \text{ a.s.}
\]
So to finish the proof it only remains to show
\[
\lim_{n \to \infty} \frac{\sum_{j=1}^{N} \frac{1}{j}}{\ln N} = 1.
\]

(12.18)

To see this write
\[
\ln (N + 1) = \int_{1}^{N+1} \frac{1}{x} dx = \sum_{j=1}^{N} \int_{j}^{j+1} \frac{1}{x} dx
\]
\[
= \sum_{j=1}^{N} \int_{j}^{j+1} \left( \frac{1}{x} - \frac{1}{j} \right) dx + \sum_{j=1}^{N} \frac{1}{j} = \rho_N + \sum_{j=1}^{N} \frac{1}{j}
\]
where
\[
|\rho_N| = \sum_{j=1}^{N} \left| \ln \left( \frac{j+1}{j} \right) - \frac{1}{j} \right| = \sum_{j=1}^{N} \left| \ln (1 + 1/j) - \frac{1}{j} \right| \sim \sum_{j=1}^{N} \frac{1}{j^2}
\]
and hence we conclude that \( \lim_{N \to \infty} \rho_N < \infty \). So dividing Eq. (12.19) by \( \ln N \) and letting \( N \to \infty \) gives the desired limit in Eq. (12.18).

12.8 Necessity Proof of Kolmogorov’s Three Series Theorem

This section is devoted to the necessity part of the proof of Kolmogorov’s Three Series Theorem [12.12] We start with a couple of lemmas.

**Lemma 12.46.** Suppose that \( \{Y_n\}_{n=1}^{\infty} \) are independent random variables such that there exists \( c < \infty \) such that \( |Y_n| \leq c < \infty \) a.s. and further assume \( \mathbb{E}Y_n = 0 \). If \( \sum_{n=1}^{\infty} \mathbb{E}Y_n^2 < \infty \). More precisely the following estimate holds,
\[
\sum_{j=1}^{\infty} \mathbb{E}Y_j^2 \leq \frac{(\lambda + c)^2}{P(\sup_{n} |S_n| \leq \lambda)} \text{ for all } \lambda > 0,
\]
where as usual, \( S_n := \sum_{j=1}^{n} Y_j \).
Remark 12.47. It follows from Eq. (12.20) that if $P \left( \sup_n |S_n| < \infty \right) > 0$, then $\sum_{j=1}^{\infty} E Y_j^2 < \infty$ and hence by Kolmogorov’s Theorem, $\sum_{j=1}^{\infty} Y_j = \lim_{n \to \infty} S_n$ exists a.s. and in particular, $P \left( \sup_n |S_n| < \infty \right)$.

**Proof.** Let $\lambda > 0$ and $\tau$ be the first time $|S_n| > \lambda$, i.e. let $\tau$ be the “stopping time” defined by,

$$\tau = \tau_\lambda := \inf \left\{ n \geq 1 : |S_n| > \lambda \right\}.$$

As usual, $\tau = \infty$ if $\{ n \geq 1 : |S_n| > \lambda \} = \emptyset$. Then for $N \in \mathbb{N}$,

$$E \left[ S_N^2 : \tau \leq N \right] = \sum_{j=1}^{N} E \left[ S_N^2 : \tau = j \right] = \sum_{j=1}^{N} \left[ E \left[ |S_j + S_N - S_j|^2 : \tau = j \right] \right].$$

Moreover,

$$E \left[ S_N^2 : \tau \leq N \right] = \sum_{j=1}^{N} E \left[ S_N^2 : \tau = j \right] = \sum_{j=1}^{N} E \left[ \left( S_j + S_N - S_j \right)^2 : \tau = j \right] = \sum_{j=1}^{N} \left[ S_j^2 + 2S_j (S_N - S_j) + (S_N - S_j)^2 : \tau = j \right]$$

$$= \sum_{j=1}^{N} E \left[ S_j^2 : \tau = j \right] + \sum_{j=1}^{N} E \left[ (S_N - S_j)^2 : \tau = j \right]$$

$$\leq \sum_{j=1}^{N} \left[ (S-j-1 + Y_j)^2 : \tau = j \right] + \sum_{j=1}^{N} \left[ (\lambda + c)^2 : \tau = j \right] = \left[ (\lambda + c)^2 + E[S_n^2] \right] \tau \leq N].$$

Putting this all together then gives,

$$E \left[ S_N^2 \right] \leq \left[ (\lambda + c)^2 + E[S_n^2] \right] P \left[ \tau \leq N \right] + \lambda^2 P \left[ \tau > N \right]$$

$$\leq \left[ (\lambda + c)^2 + E[S_n^2] \right] P \left[ \tau \leq N \right] + (\lambda + c)^2 \left[ \tau > N \right]$$

$$= (\lambda + c)^2 + P \left[ \tau \leq N \right] \cdot E[S_n^2]$$

form which it follows that

$$E \left[ S_N^2 \right] \leq \frac{(\lambda + c)^2}{1 - P \left[ \tau \leq N \right]} \leq \frac{(\lambda + c)^2}{1 - P \left[ \tau < \infty \right]} = \frac{(\lambda + c)^2}{P \left[ \tau = \infty \right]}$$

$$= \frac{(\lambda + c)^2}{P \left( \sup_n |S_n| \leq \lambda \right)}.$$
2. $\sum_{n=1}^{\infty} \text{Var} \left( X_n 1_{|X_n| \leq c} \right) < \infty$, and
3. $\sum_{n=1}^{\infty} E \left( X_n 1_{|X_n| \leq c} \right)$ converges.

Since $\sum_{n=1}^{\infty} X_n$ is almost surely convergent, it follows that $\lim_{n \to \infty} X_n = 0$ a.s. and hence for every $c > 0$, $P \left( \{|X_n| \geq c \text{ i.o.} \} \right) = 0$. According the Borel zero one law this implies for every $c > 0$ that $\sum_{n=1}^{\infty} P \left( |X_n| > c \right) < \infty$. Given this, we now know that $\{X_n\}$ and $\{X_n^c := X_n 1_{|X_n| \leq c}\}$ are tail equivalent for all $c > 0$ and in particular $\sum_{n=1}^{\infty} X_n^c$ is almost surely convergent for all $c > 0$. So according to Lemma 12.48 (with $Y_n = X_n^c$),

$$\sum_{n=1}^{\infty} E X_n^c = \sum_{n=1}^{\infty} E \left( X_n 1_{|X_n| \leq c} \right)$$

converges.

Letting $Y_n := X_n^c - E X_n^c$, we may now conclude that $\sum_{n=1}^{\infty} Y_n$ is almost surely convergent. Since $\{Y_n\}$ is uniformly bounded and $E Y_n = 0$ for all $n$, an application of Lemma 12.46 allows us to conclude

$$\sum_{n=1}^{\infty} \text{Var} \left( X_n 1_{|X_n| \leq c} \right) = \sum_{n=1}^{\infty} E Y_n^2 < \infty.$$
Weak Convergence Results

Suppose \( \{X_n\}_{n=1}^{\infty} \) is a sequence of random variables and \( X \) is another random variable (possibly defined on a different probability space). We would like to understand when, for large \( n \), \( X_n \) and \( X \) have nearly the “same” distribution. Alternatively put, if we let \( \mu_n (A) := P (X_n \in A) \) and \( \mu (A) := P (X \in A) \), when is \( \mu_n \) close to \( \mu \) for large \( n \). This is the question we will address in this chapter.

13.1 Total Variation Distance

**Definition 13.1.** Let \( \mu \) and \( \nu \) be two probability measure on a measurable space, \((\Omega, \mathcal{B})\). The total variation distance, \( d_{TV} (\mu, \nu) \), is defined as

\[
  d_{TV} (\mu, \nu) := \sup_{A \in \mathcal{B}} |\mu (A) - \nu (A)|.
\]

**Remark 13.2.** The function, \( \lambda : \mathcal{B} \to \mathbb{R} \) defined by, \( \lambda (A) := \mu (A) - \nu (A) \) for all \( A \in \mathcal{B} \), is an example of a “signed measure.” For signed measures, one usually defines

\[
  ||\lambda||_{TV} := \sup \left\{ \sum_{i=1}^{n} |\lambda (A_i)| : n \in \mathbb{N} \text{ and partitions, } \{A_i\}_{i=1}^{n} \subset \mathcal{B} \text{ of } \Omega \right\}.
\]

You are asked to show in Exercise [13.1] below, that when \( \lambda = \mu - \nu \), \( d_{TV} (\mu, \nu) = \frac{1}{2} ||\mu - \nu||_{TV} \).

**Lemma 13.3 (Scheffé’s Lemma).** Suppose that \( m \) is another positive measure on \((\Omega, \mathcal{B})\) such that there exists measurable functions, \( f, g : \Omega \to [0, \infty) \), such that \( dm = fdm \) and \( dv = gdm \).[1] Then

\[
  d_{TV} (\mu, \nu) = \frac{1}{2} \int_{\Omega} |f - g| dm.
\]

Moreover, if \( \{\mu_n\}_{n=1}^{\infty} \) is a sequence of probability measure of the form, \( dm = f_n dm \) with \( f_n : \Omega \to [0, \infty) \), and \( f_n \rightarrow g \), \( m \)-a.e., then \( d_{TV} (\mu_n, \nu) \rightarrow 0 \) as \( n \rightarrow \infty \).

**Proof.** Let \( \lambda = \mu - \nu \) and \( h := f - g : \Omega \to \mathbb{R} \) so that \( d\lambda = hd\mu \). Since

\[
  \lambda (\Omega) = \mu (\Omega) - \nu (\Omega) = 1 - 1 = 0,
\]

if \( A \in \mathcal{B} \) we have

\[
  \lambda (A) + \lambda (A^c) = \lambda (\Omega) = 0.
\]

In particular this shows \( |\lambda (A)| = |\lambda (A^c)| \) and therefore,

\[
  |\lambda (A)| = \frac{1}{2} [|\lambda (A)| + |\lambda (A^c)|] = \frac{1}{2} \left[ \int_A hd\mu + \int_{A^c} hd\mu \right] \tag{13.1}
\]

\[
  \leq \frac{1}{2} \left[ \int_A |h| dm + \int_{A^c} |h| dm \right] = \frac{1}{2} \int_{\Omega} |h| dm.
\]

This shows

\[
  d_{TV} (\mu, \nu) = \sup_{A \in \mathcal{B}} |\lambda (A)| \leq \frac{1}{2} \int_{\Omega} |h| dm.
\]

To prove the converse inequality, simply take \( A = \{h > 0\} \) (note \( A^c = \{h \leq 0\} \)) in Eq. (13.1) to find

\[
  |\lambda (A)| = \frac{1}{2} \left[ \int_A hd\mu - \int_{A^c} hd\mu \right] = \frac{1}{2} \left[ \int_A |h| dm + \int_{A^c} |h| dm \right] = \frac{1}{2} \int_{\Omega} |h| dm.
\]

For the second assertion, let \( G_n := f_n + g \) and observe that \( |f_n - g| \rightarrow 0 \) \( m \)-a.e., \( |f_n - g| \leq G_n \in L^1 (m) \), \( G_n \rightarrow G := 2g \) a.e. and \( \int_{\Omega} G_n dm = 2 \rightarrow 2 = \int_{\Omega} G dm \) and \( n \rightarrow \infty \). Therefore, by the dominated convergence theorem 8.34

\[
  \lim_{n \to \infty} d_{TV} (\mu_n, \nu) = \frac{1}{2} \lim_{n \to \infty} \int_{\Omega} |f_n - g| dm = 0.
\]

For a concrete application of Scheffé’s Lemma, see Proposition [13.35] below.

**Corollary 13.4.** Let \( ||h||_{\infty} := \sup_{\omega \in \Omega} |h (\omega)| \) when \( h : \Omega \to \mathbb{R} \) is a bounded random variable. Continuing the notation in Scheffé’s lemma above, we have...
the latter implies Eq. (13.4). Moreover, from the proof of Scheffé's Lemma 13.3, we have

\[ \int h \, d\mu_n \to \int h \, d\nu \text{ if } d_{TV}(\mu_n, \nu) \to 0. \]  

(13.4)

**Proof.** We begin by observing that

\[ \left| \int \Omega h \, d\mu - \int \Omega h \, d\nu \right| = \left| \int \Omega h (f - g) \, dm \right| \leq \int \left| h \right| |f - g| \, dm \leq \|h\|_\infty \int \Omega |f - g| \, dm = 2d_{TV}(\mu, \nu) \|h\|_\infty. \]

Moreover, from the proof of Scheffé's Lemma \[13.3\] we have

\[ d_{TV}(\mu, \nu) = \frac{1}{2} \left| \int \Omega h \, d\mu - \int \Omega h \, d\nu \right| \]

when \( h := 1_{f \geq g} - 1_{f \leq g} \). These two equations prove Eqs. (13.2) and (13.3) and the latter implies Eq. (13.4). \( \square \)

**Exercise 13.1.** Under the hypothesis of Scheffé's Lemma [13.3] show

\[ \|\mu - \nu\|_{TV} = \int \left| f - g \right| \, dm = 2d_{TV}(\mu, \nu). \]

**Exercise 13.2.** Suppose that \( \Omega \) is a (at most) countable set, \( B := 2^\Omega \), and \( \{\mu_n\}_{n=0}^\infty \) are probability measures on \( (\Omega, B) \). Let \( f_n(\omega) := \mu_n(\{\omega\}) \) for \( \omega \in \Omega \). Show

\[ d_{TV}(\mu_n, \mu_0) = \frac{1}{2} \sum_{\omega \in \Omega} \left| f_n(\omega) - f_0(\omega) \right| \]

and \( \lim_{n \to \infty} d_{TV}(\mu_n, \mu_0) = 0 \) iff \( \lim_{n \to \infty} \mu_n(\{\omega\}) = \mu_0(\{\omega\}) \) for all \( \omega \in \Omega \).

**Notation 13.5** Suppose that \( X \) and \( Y \) are random variables, let

\[ d_{TV}(X, Y) := d_{TV}(\mu_X, \mu_Y) = \sup_{A \in B_\mathbb{R}} |P(X \in A) - P(Y \in A)|, \]

where \( \mu_X = P \circ X^{-1} \) and \( \mu_Y = P \circ Y^{-1} \).

### 13.2 Weak Convergence

**Example 13.6.** Suppose that \( P(X_n = \frac{i}{n}) = \frac{1}{n} \) for \( i \in \{1, 2, \ldots, n\} \) so that \( X_n \) is a discrete “approximation” to the uniform distribution, i.e. to \( U \) where \( P(U \in A) = m(A \cap [0,1]) \) for all \( A \in B_\mathbb{R} \). We let \( A_n = \left\{ \frac{i}{n} : i = 1, 2, \ldots, n \right\} \), then \( P(X_n \in A_n) = 1 \) while \( P(U \in A_n) = 0 \). Therefore, it follows that

\[ d_{TV}(X_n, U) = 1 \text{ for all } n. \]

Nevertheless we would like \( X_n \) to be close to \( U \) in distribution. Let us observe that if we let \( F_n(y) := P(X_n \leq y) \) and \( F(y) := P(U \leq y) \), then

\[ F_n(y) = P(X_n \leq y) = \frac{1}{n} \# \left\{ i \in \{1, 2, \ldots, n\} : \frac{i}{n} \leq y \right\} \]

and

\[ F(y) := P(U \leq y) = (y \wedge 1) \vee 0. \]

From these formula, it easily follows that \( F(y) = \lim_{n \to \infty} F_n(y) \) for all \( y \in \mathbb{R} \). This suggest that we should say that \( X_n \) converges in distribution to \( U \) if \( P(X_n \leq y) \to P(X \leq y) \) for all \( y \in \mathbb{R} \). However, the next simple example shows this definition is also too restrictive.

**Example 13.7.** Suppose that \( P(X_n = 1/n) = 1 \) for all \( n \) and \( P(X_0 = 0) = 1 \). Then it is reasonable to insist that \( X_n \) converges of \( X_0 \) in distribution. However, \( F_n(y) = 1_{y \geq 1/n} \to 1_{y \geq 0} = F_0(y) \) for all \( y \in \mathbb{R} \) except for \( y = 0 \). Observe that \( y \) is the only point of discontinuity of \( F_0 \).

**Notation 13.8** Let \( (X, d) \) be a metric space, \( f : X \to \mathbb{R} \) be a function. The set \( x \in X \) where \( f \) is continuous (discontinuous) at \( x \) will be denoted by \( C(f)(D(f)) \).

Observe that if \( F : \mathbb{R} \to [0,1] \) is a non-decreasing function, then \( C(F) \) is at most countable. To see this, suppose that \( \varepsilon > 0 \) is given and let \( C_\varepsilon := \{ y \in \mathbb{R} : F(y+) - F(y-) \geq \varepsilon \} \). If \( y < y' \) with \( y, y' \in C_\varepsilon \), then \( F(y+) < F(y-) \) and \((F(y-), F(y+))\) and \((F(y'-), F(y'+))\) are disjoint intervals of length greater that \( \varepsilon \). Hence it follows that

\[ 1 = m([0,1]) \geq \sum_{y \in C_\varepsilon} m((F(y-), F(y+))) \geq \varepsilon \cdot \#(C_\varepsilon) \]

and hence that \( \#(C_\varepsilon) \leq \varepsilon^{-1} < \infty \). Therefore \( C := \bigcup_{k=1}^\infty C_{1/k} \) is at most countable.

\(^2\) More generally, if \( \mu \) and \( \nu \) are two probability measure on \( (\mathbb{R}, B_\mathbb{R}) \) such that \( \mu(\{x\}) = 0 \) for all \( x \in \mathbb{R} \) while \( \nu \) concentrates on a countable set, then \( d_{TV}(\mu, \nu) = 1 \).
Definition 13.9. Let \( \{F, F_n : n = 1, 2, \ldots \} \) be a collection of right continuous non-increasing functions from \( \mathbb{R} \) to \([0, 1]\) and by abuse of notation let us also denote the associated measures, \( \mu_F \) and \( \mu_{F_n} \) by \( F \) and \( F_n \) respectively. Then

1. \( F_n \) converges to \( F \) vaguely and write, \( F_n \xrightarrow{v} F \), iff \( F_n ((a, b]) \to F ((a, b]) \)
   for all \( a, b \in C(F) \).
2. \( F_n \) converges to \( F \) weakly and write, \( F_n \xrightarrow{w} F \), iff \( F_n (x) \to F (x) \)
   for all \( x \in C(F) \).
3. We say \( F \) is proper, if \( F \) is a distribution function of a probability measure,
   i.e. if \( F(\infty) = 1 \) and \( F(-\infty) = 0 \).

Example 13.10. If \( X_n \) and \( U \) are as in Example 13.6 and \( F_n (y) := P(X_n \leq y) \)
and \( F(y) := P(Y \leq y) \), then \( F_n \xrightarrow{v} F \) and \( F_n \xrightarrow{w} F \).

Lemma 13.11. Let \( \{F, F_n : n = 1, 2, \ldots \} \) be a collection of proper distribution functions.
Then \( F_n \xrightarrow{v} F \) iff \( F_n \xrightarrow{w} F \). In the case where \( F_n \) and \( F \) are proper and \( F_n \xrightarrow{w} F \),
we will write \( F_n \Longrightarrow F \).

Proof. If \( F_n \xrightarrow{w} F \), then \( F_n ((a, b]) = F_n (b) - F_n (a) \to F (b) - F (a) = F ((a, b]) \)
for all \( a, b \in C(F) \) and therefore \( F_n \xrightarrow{v} F \). So now suppose \( F_n \xrightarrow{v} F \) and let \( a < x \) with \( a, x \in C(F) \). Then
\[
F(x) = F(a) + \lim_{n \to \infty} [F_n(x) - F_n(a)] \leq F(a) + \liminf_{n \to \infty} F_n(x).
\]
Letting \( a \downarrow -\infty \), using the fact that \( F \) is proper, implies
\[
F(x) \leq \liminf_{n \to \infty} F_n(x).
\]
Likewise,
\[
F(x) - F(a) = \lim_{n \to \infty} [F_n(x) - F_n(a)] \geq \limsup_{n \to \infty} [F_n(x) - 1] = \limsup_{n \to \infty} F_n(x) - 1
\]
which upon letting \( a \uparrow \infty \), (so \( F(a) \uparrow 1 \)) allows us to conclude,
\[
F(x) \geq \limsup_{n \to \infty} F_n(x).
\]

Definition 13.12. A sequence of random variables, \( \{X_n\}_{n=1}^{\infty} \) is said to converge weakly or to converge in distribution to a random variable \( X \) (written \( X_n \Longrightarrow X \)) iff \( F_n(y) := P(X_n \leq y) \Longrightarrow F(y) := P(X \leq y) \).

Example 13.13 (Central Limit Theorem). The central limit theorem (see the next chapter) states; if \( \{X_n\}_{n=1}^{\infty} \) are i.i.d. \( L^2(P) \) random variables with \( \mu := \mathbb{E}X_1 \) and \( \sigma^2 = \text{Var}(X_1) \), then
\[
\frac{S_n - n\mu}{\sqrt{n}} \Rightarrow N(0, \sigma) \quad \text{d} = \sigma N(0, 1).
\]
Written out explicitly we find
\[
\lim_{n \to \infty} P \left( a < \frac{S_n - n\mu}{\sigma\sqrt{n}} \leq b \right) = P(a < N(0, 1) \leq b) = \frac{1}{\sqrt{2\pi}} \int_a^b e^{-\frac{1}{2}x^2} \, dx
\]
or equivalently put
\[
\lim_{n \to \infty} P \left( n\mu + \sigma\sqrt{n}a < S_n \leq n\mu + \sigma\sqrt{nb} \right) = \frac{1}{\sqrt{2\pi}} \int_a^b e^{-\frac{1}{2}x^2} \, dx.
\]
More intuitively, we have
\[
S_n \overset{d}{=} n\mu + \sqrt{n}\sigma N(0, 1) \overset{d}{=} N(n\mu, n\sigma^2).
\]

Lemma 13.14. Suppose \( X \) is a random variable, \( \{c_n\}_{n=1}^{\infty} \subset \mathbb{R} \), and \( X_n = X + c_n \). If \( c := \lim_{n \to \infty} c_n \) exists, then \( X_n \Longrightarrow X + c \).

Proof. Let \( F(x) := P(X \leq x) \) and
\[
F_n(x) := P(X_n \leq x) = P(X + c_n \leq x) = F(x - c_n).
\]
Clearly, if \( c_n \to c \) as \( n \to \infty \), then for all \( x \in C(F(-c)) \) we have \( F_n(x) \to F(x - c) \). Since \( F(x - c) = P(X + c \leq x) \), we see that \( X_n \Longrightarrow X + c \).

Example 13.15. Suppose that \( P(X_n = n) = 1 \) for all \( n \), then \( F_n(y) = 1 \) for \( y \geq n \to 0 = F(y) \) as \( n \to \infty \). Notice that \( F \) is not a distribution function because all of the mass went off to \( +\infty \). Similarly, if we suppose, \( P(X_n = \pm n) = \frac{1}{2} \) for all \( n \), then \( F_n = \frac{1}{2}1_{[\pm n, n]} + 1_{[n, \infty)} \to \frac{1}{2} = F(y) \) as \( n \to \infty \). Again, \( F \) is not a distribution function on \( \mathbb{R} \) since half the mass went to \( -\infty \) while the other half went to \( +\infty \).

Example 13.16. Suppose \( X \) is a non-zero random variables such that \( X \overset{d}{=} -X \),
then \( X_n := (-1)^nX \overset{d}{=} X \) for all \( n \) and therefore, \( X_n \Longrightarrow X \) as \( n \to \infty \). On the other hand, \( X_n \) does not converge to \( X \) almost surely or in probability.
The next theorem summarizes a number of useful equivalent characterizations of weak convergence. (The reader should compare Theorem 13.17 with Corollary 13.18) In this theorem we will write $BC(\mathbb{R})$ for the bounded continuous functions, $f : \mathbb{R} \to \mathbb{R}$ (or $f : \mathbb{R} \to \mathbb{C}$) and $C_c(\mathbb{R})$ for those $f \in C(\mathbb{R})$ which have compact support, i.e. $f(x) \equiv 0$ if $|x|$ is sufficiently large.

**Theorem 13.17.** Suppose that $\{\mu_n\}_{n=0}^{\infty}$ is a sequence of probability measures on $(\mathbb{R}, \mathcal{B})$ and for each $n$, let $F_n(y) := \mu_n(\{\infty, y\})$ be the (proper) distribution function associated to $\mu_n$. Then the following are equivalent.

1. For all $f \in BC(\mathbb{R})$,
   \[ \int_{\mathbb{R}} f \, d\mu_n \to \int_{\mathbb{R}} f \, d\mu_0 \quad \text{as} \quad n \to \infty. \]  
   (13.5)

2. Eq. (13.5) holds for all $f \in BC(\mathbb{R})$ which are uniformly continuous.

3. Eq. (13.5) holds for all $f \in C_c(\mathbb{R})$.

4. $F_n \Rightarrow F$.

5. There exists a probability space $(\Omega, \mathcal{B}, P)$ and random variables, $Y_n$, on this space such that $P \circ Y_n^{-1} = \mu_n$ for all $n$ and $Y_n \to Y_0$ a.s.

**Proof.** Clearly 1. $\Rightarrow$ 2. $\Rightarrow$ 3. and 5. $\Rightarrow$ 1. by the dominated convergence theorem. Indeed, we have

\[ \int_{\mathbb{R}} f \, d\mu_n = \mathbb{E}[f(Y_n)] \xrightarrow{\text{D.C.T.}} \mathbb{E}[f(Y)] = \int_{\mathbb{R}} f \, d\mu_0 \]

for all $f \in BC(\mathbb{R})$. Therefore it suffices to prove 3. $\Rightarrow$ 4. and 4. $\Rightarrow$ 5. The proof of 4. $\Rightarrow$ 5. will be the content of Skorohod’s Theorem 13.28 below. Given Skorohod’s Theorem, we will now complete the proof.

(3. $\Rightarrow$ 4.) Let $-\infty < a < b < \infty$ with $a, b \in \mathcal{C}(F_0)$ and for $\varepsilon > 0$, let $f_\varepsilon(x) \geq 1_{[a,b]}$ and $g_\varepsilon(x) \leq 1_{[a,b]}$ be the functions in $C_c(\mathbb{R})$ pictured in Figure 13.1. Then

\[ \limsup_{n \to \infty} \mu_n((a, b]) \leq \limsup_{n \to \infty} \int_{\mathbb{R}} f_\varepsilon \, d\mu_n = \int_{\mathbb{R}} f_\varepsilon \, d\mu_0 \]  
   (13.6)

and

\[ \liminf_{n \to \infty} \mu_n((a, b]) \geq \liminf_{n \to \infty} \int_{\mathbb{R}} g_\varepsilon \, d\mu_n = \int_{\mathbb{R}} g_\varepsilon \, d\mu_0. \]  
   (13.7)

Since $f_\varepsilon \to 1_{[a,b]}$ and $g_\varepsilon \to 1_{[a,b]}$ as $\varepsilon \downarrow 0$, we may use the dominated convergence theorem to pass to the limit as $\varepsilon \downarrow 0$ in Eqs. (13.6) and (13.7) to conclude,

\[ \limsup_{n \to \infty} \mu_n((a, b]) \leq \mu_0((a, b]) \]

and

\[ \liminf_{n \to \infty} \mu_n((a, b]) \geq \mu_0((a, b]) \]

where the second equality in each of the equations holds because $a$ and $b$ are points of continuity of $F_0$. Hence we have shown that $\lim_{n \to \infty} \mu_n((a, b])$ exists and is equal to $\mu_0((a, b])$.

![Fig. 13.1. The picture definition of the trapezoidal functions, $f_\varepsilon$ and $g_\varepsilon.$](image)

**Corollary 13.18.** Suppose that $\{X_n\}_{n=0}^{\infty}$ is a sequence of random variables, such that $X_n \xrightarrow{P} X_0$, then $X_n \Rightarrow X_0$. (Recall that example 13.16 shows the converse is in general false.)

**Proof.** Let $g \in BC(\mathbb{R})$, then by Corollary 11.9 $g(X_n) \xrightarrow{P} g(X_0)$ and since $g$ is bounded, we may apply the dominated convergence theorem (see Corollary 11.8) to conclude that $\mathbb{E}[g(X_n)] \to \mathbb{E}[g(X_0)]$.

**Lemma 13.19.** Suppose $\{X_n\}_{n=1}^{\infty}$ is a sequence of random variables on a common probability space and $c \in \mathbb{R}$. Then $X_n \Rightarrow c$ iff $X_n \xrightarrow{P} c$.

**Proof.** Recall that $X_n \xrightarrow{P} c$ iff for all $\varepsilon > 0$, $P(|X_n - c| > \varepsilon) \to 0$. Since

\[ \{|X_n - c| > \varepsilon\} = \{X_n > c + \varepsilon\} \cup \{X_n < c - \varepsilon\} \]

it follows $X_n \xrightarrow{P} c$ iff $P(X_n > x) \to 0$ for all $x > c$ and $P(X_n < x) \to 0$ for all $x < c$. These conditions are also equivalent to $P(X_n \leq x) \to 1$ for all $x > c$ and $P(X_n \leq x) \to P(X_n \leq x') \to 0$ for all $x < c$ (where $x < x'$). So $X_n \xrightarrow{P} c$ iff
such that $P(0 < x < c) = F(x)$, and so by Fatou's lemma, \[ \lim_{n \to \infty} P(X_n \leq x) = \begin{cases} 0 & \text{if } x < c \\ 1 & \text{if } x > c \end{cases} = F(x) \]

where $F(x) = P(c \leq x) = 1_{x \geq c}$. Since $C(F) = \mathbb{R} \setminus \{c\}$, we have shown $X_n \overset{d}{\rightarrow} c$ iff $X_n \overset{a.s.}{\rightarrow} c$.

We end this section with a few more equivalent characterizations of weak convergence. The combination of Theorem 13.17 and 13.20 is often called the Portmanteau Theorem.

**Theorem 13.20 (The Portmanteau Theorem).** Suppose $\{F_n\}_{n=0}^{\infty}$ are proper distribution functions. By abuse of notation, we will denote $\mu_{F_n}(A)$ simply by $F_n(A)$ for all $A \in \mathcal{B}_{\mathbb{R}}$. Then the following are equivalent.

1. $F_n \overset{a.s.}{\rightarrow} F_0$.
2. $\liminf_{n \to \infty} F_n(U) \geq F_0(U)$ for open subsets, $U \subset \mathbb{R}$.
3. $\limsup_{n \to \infty} F_n(C) \leq F_0(C)$ for all closed subsets, $C \subset \mathbb{R}$.
4. $\lim_{n \to \infty} F_n(A) = F_0(A)$ for all $A \in \mathcal{B}_{\mathbb{R}}$ such that $F_0(\partial A) = 0$.

**Proof.** (1. $\implies$ 2.) By Theorem 13.20, we may choose random variables, $Y_n$, such that $P(Y_n \leq y) = F_n(y)$ for all $y \in \mathbb{R}$ and $n \in \mathbb{N}$, and $Y_n \overset{a.s.}{\rightarrow} Y_0$. Since $U$ is open, it follows that

$$1_U(Y) \leq \liminf_{n \to \infty} 1_U(Y_n) \text{ a.s.}$$

and so by Fatou's lemma,

$$F(U) = P(Y \in U) = \mathbb{E}[1_U(Y)] \leq \liminf_{n \to \infty} \mathbb{E}[1_U(Y_n)] = \liminf_{n \to \infty} P(Y_n \in U) = \liminf_{n \to \infty} F_n(U).$$

(2. $\implies$ 3.) This follows from the observations: 1) $C \subset \mathbb{R}$ is closed iff $U = C^c$ is open, 2) $F(U) = 1 - F(C)$, and 3) $\limsup_{n \to \infty} (-F_n(C)) = -\liminf_{n \to \infty} F_n(C)$.

(2. and 3. $\implies$ 4.) If $F_0(\partial A) = 0$, then $A^c \subset A \subset \bar{A}$ with $F_0(\bar{A} \setminus A^c) = 0$. Therefore

$$F_0(A) = F_0(A^c) = \liminf_{n \to \infty} F_n(A^c) \leq \limsup_{n \to \infty} F_n(\bar{A}) \leq F_0(\bar{A}) = F_0(A).$$

(4. $\implies$ 1.) Let $a, b \in C(F_0)$ and take $A := (a, b]$. Then $F_0(\partial A) = F_0(\{a, b\}) = 0$ and therefore, $\lim_{n \to \infty} F_n((a, b]) = F_0((a, b])$, i.e. $F_n \overset{a.s.}{\rightarrow} F_0$.

**Exercise 13.3.** Suppose that $F$ is a continuous proper distribution function. Show,

1. $F: \mathbb{R} \to [0, 1]$ is uniformly continuous.
2. If $\{F_n\}_{n=1}^{\infty}$ is a sequence of distribution functions converging weakly to $F$, then $F_n$ converges to $F$ uniformly on $\mathbb{R}$, i.e.

$$\lim_{n \to \infty} \sup_{x \in \mathbb{R}} |F(x) - F_n(x)| = 0.$$
is closed for all \( a ∈ \mathbb{R} \), i.e. \( f_δ \) is upper semi-continuous. Moreover, \( f_δ ≤ f ≤ f^\delta \) for all \( δ > 0 \) and \( f^\delta ↓ f^\delta \) and \( f_δ ↑ f_0 \) as \( δ ↓ 0 \), where \( f_0 ≤ f ≤ f^0 \) and \( f_0 : X → \mathbb{R} \cup \{-∞\} \) and \( f^0 : X → \mathbb{R} \cup \{∞\} \) are measurable functions. The proof is now complete since it is easy to see that

\[
\mathcal{D}(f) = \{f^0 > f_0\} = \{f^0 - f_0 ≠ 0\} ∈ \mathcal{B}_X.
\]

\[\Box\]

**Remark 13.22.** Suppose that \( x_n → x \) with \( x ∈ \mathcal{C}(f) := \mathcal{D}(f)^c \). Then \( f(x_n) → f(x) \) as \( n → ∞ \).

**Theorem 13.23 (Continuous Mapping Theorem).** Let \( f : \mathbb{R} → \mathbb{R} \) be a Borel measurable functions. If \( X_n → X_0 \) and \( P(X_0 ∈ \mathcal{D}(f)) = 0 \), then \( f(X_n) → f(X_0) \). If in addition, \( f \) is bounded, \( E[f(X_n)] → E[f(X_0)] \).

**Proof.** Let \( \{Y_n\}_{n=0}^∞ \) be random variables on some probability space as in Theorem 13.28. For \( g ∈ BC(\mathbb{R}) \) we observe that \( \mathcal{D}(g ∘ f) ⊂ \mathcal{D}(f) \) and therefore,

\[
P(Y_0 ∈ \mathcal{D}(g ∘ f)) ≤ P(Y_0 ∈ \mathcal{D}(f)) = P(X_0 ∈ \mathcal{D}(f)) = 0.
\]

Hence it follows that \( g ∘ f \) is bounded a.s. So an application of the dominated convergence theorem (see Corollary 11.8) implies

\[
E[g(f(X_n))] = E[g(f(Y_n))] → E[g(f(Y_0))] = E[g(f(X_0))]. \tag{13.8}
\]

This proves the first assertion. For the second assertion we take \( g(x) = (x ∧ M) ∨ (-M) \) in Eq. 13.8 where \( M \) is a bound on \( |f| \).

**Theorem 13.24 (Slutzky’s Theorem).** Suppose that \( X_n → X \) and \( Y_n → c \) where \( c \) is a constant. Then \( (X_n, Y_n) → (X, c) \) in the sense that \( E[f(X_n, Y_n)] → E[f(X, c)] \) for all \( f ∈ BC(\mathbb{R}^2) \). In particular, by taking \( f(x, y) = g(x + y) \) and \( f(x, y) = g(x · y) \) with \( g ∈ BC(\mathbb{R}) \), we learn \( X_n + Y_n → X + c \) and \( X_n · Y_n → X · c \) respectively.

**Proof.** First suppose that \( f ∈ C_∞(\mathbb{R}^2) \), and for \( ε > 0 \), let \( δ := δ(ε) \) be chosen so that

\[
|f(x, y) - f(x', y')| ≤ ε \text{ if } \|(x, y) - (x', y')\| ≤ δ.
\]

Then

\[
E[f(X_n, Y_n) - f(X_n, c)] ≤ E[|f(X_n, Y_n) - f(X_n, c)| : |Y_n - c| ≤ δ]
+ E[|f(X_n, Y_n) - f(X_n, c)| : |Y_n - c| > δ]
≤ ε + 2MP(|Y_n - c| > δ) → ε \text{ as } n → ∞,
\]

where \( M = \sup |f| \). Since, \( X_n → X \), we know \( E[f(X_n, c)] → E[f(X, c)] \) and hence we have shown,

\[
\limsup_{n → ∞} E[f(X_n, Y_n) - f(X_n, c)] ≤ \limsup_{n → ∞} |E[f(X_n, Y_n) - f(X_n, c)]| + \limsup_{n → ∞} |E[f(X_n, c) - f(X, c)]| ≤ ε.
\]

Since \( ε > 0 \) was arbitrary, we learn that \( \lim_{n → ∞} E[f(X_n, Y_n)] = E[f(X, c)] \).

Now suppose \( f ∈ BC(\mathbb{R}^2) \) with \( f ≥ 0 \) and let \( φ_k(x, y) ∈ [0, 1] \) be continuous functions with compact support such that \( φ_k(x, y) = 1 \) if \( |x| ∨ |y| ≤ k \) and \( φ_k(x, y) ↑ 1 \) as \( k → ∞ \). Then applying what we have just proved to \( f_k := φ_k f \), we find

\[
E[f_k(X, c)] = \lim_{n → ∞} E[f_k(X_n, Y_n)] \leq \liminf_{n → ∞} E[f(X_n, Y_n)].
\]

Letting \( k → ∞ \) in this inequality then implies that

\[
E[f(X, c)] ≤ \liminf_{n → ∞} E[f(X_n, Y_n)].
\]

This inequality with \( f \) replaced by \( M - f ≥ 0 \) then shows,

\[
M - E[f(X, c)] ≤ \liminf_{n → ∞} E[M - f(X_n, Y_n)] = M - \limsup_{n → ∞} E[f(X_n, Y_n)].
\]

Hence we have shown,

\[
\limsup_{n → ∞} E[f(X_n, Y_n)] ≤ E[f(X, c)] ≤ \liminf_{n → ∞} E[f(X_n, Y_n)]
\]

and therefore \( \lim_{n → ∞} E[f(X_n, Y_n)] = E[f(X, c)] \) for all \( f ∈ BC(\mathbb{R}^2) \) with \( f ≥ 0 \). This completes the proof since any \( f ∈ BC(\mathbb{R}^2) \) may be written as a difference of its positive and negative parts.

**Theorem 13.25 (δ-method).** Suppose that \( \{X_n\}_{n=1}^∞ \) are random variables, \( b ∈ \mathbb{R}, a_n ∈ \mathbb{R} \setminus \{0\} \) with \( \lim_{n → ∞} a_n = 0 \), and

\[
\frac{X_n - b}{a_n} → Z.
\]

If \( g : \mathbb{R} → \mathbb{R} \) be a measurable function which is differentiable at \( b \), then

\[
g(X_n) - g(b) = \frac{X_n - b}{a_n} → g'(b) Z.
\]

**Proof.** Observe that

\[
X_n - b = a_n \frac{X_n - b}{a_n} → 0 \cdot Z = 0
\]
so that \( X_n \Rightarrow b \) and hence \( X_n \overset{d}{\to} b \). By definition of the derivative of \( g \) at \( b \), we have
\[
g(x + \Delta) = g(b) + g'(b) \Delta + \varepsilon(\Delta) \Delta
\]
where \( \varepsilon(\Delta) \to 0 \) as \( \Delta \to 0 \). Let \( Y_n \) and \( Y \) be random variables on a fixed probability space such that \( Y_n \overset{d}{=} \frac{X_n - b}{a_n} \) and \( Y \overset{d}{=} Z \) with \( Y_n \to Y \) a.s. Then
\[
X_n = a_n Y_n + b, \text{ so that}
\]
\[
\frac{g(X_n) - g(b)}{a_n} = \frac{g(a_n Y_n + b) - g(b)}{a_n} = g'(b) Y_n + \frac{a_n Y_n \varepsilon(a_n Y_n)}{a_n} = g'(b) Y_n + Y_n \varepsilon(a_n Y_n) \to g'(b) Y \text{ a.s.}
\]
This completes the proof since \( g'(b) Y \overset{d}{=} g'(b) Z \). 

**Example 13.26.** Suppose that \( \{U_n\}_{n=1}^{\infty} \) are i.i.d. random variables which are uniformly distributed on \([0, 1]\) and let \( Y_n := \prod_{j=1}^{n} U_j^{\Delta} \). Our goal is to find \( a_n \) and \( b_n \) such that \( Y_n \overset{a.s.}{\to} b \), \( a_n \) is weakly convergent to a non-constant random variable. To this end, let
\[
X_n := \ln Y_n = \frac{1}{n} \sum_{j=1}^{n} \ln U_j.
\]
By the strong law of large numbers,
\[
\lim_{n \to \infty} X_n \overset{a.s.}{=} E[\ln U_1] = \int_{0}^{1} \ln x \, dx = [x \ln x - x]_0^1 = -1
\]
and therefore, \( \lim_{n \to \infty} Y_n \overset{a.s.}{=} e^{-1} \).

Let us further observe that
\[
E[\ln^2 U_1] = \int_{0}^{1} \ln^2 x \, dx = 2
\]
so that \( \text{Var}(\ln U_1) = 2 - (-1)^2 = 1 \). Hence by the central limit theorem,
\[
\frac{X_n - (-1)}{\sqrt{n}} = \sqrt{n} (X_n + 1) \Rightarrow N(0, 1).
\]
Therefore the \( \delta \) – method implies,
\[
g(X_n) - g(-1) \overset{1}{\sqrt{n}} \Rightarrow g'(-1) N(0, 1).
\]
Taking \( g(x) := e^x \) using \( g(X_n) = e^{X_n} = Y_n \), then implies

\[
\frac{Y_n - e^{-1}}{\sqrt{n}} \Rightarrow e^{-1} N(0, 1) \overset{d}{=} N(0, e^{-2}).
\]
Hence we have shown,
\[
\sqrt{n} \left( \prod_{j=1}^{n} U_j^{\Delta} - e^{-1} \right) \Rightarrow N(0, e^{-2}).
\]

**Exercise 13.4.** Given a function, \( f : X \to \mathbb{R} \) and a point \( x \in X \), let
\[
\begin{align*}
\lim \inf_{y \to x} f(y) &:= \lim \inf_{y \to x} \inf_{\varepsilon \in B_x^{'(*)}} f(y) \text{ and } \quad (13.9) \\
\lim \sup_{y \to x} f(y) &:= \lim \sup_{y \to x} \sup_{\varepsilon \in B_x^{'(*)}} f(y), \quad (13.10)
\end{align*}
\]
where
\[
B_x^{'(*)} := \{ y \in X : 0 < d(x, y) < \delta \}.
\]
Show \( f \) is lower (upper) semi-continuous iff \( \lim \inf_{y \to x} f(y) \geq f(x) \) (\( \lim \sup_{y \to x} f(y) \leq f(x) \)) for all \( x \in X \).

**Solution to Exercise (13.4).** Suppose Eq. (13.9) holds, \( a \in \mathbb{R} \), and \( x \in X \) such that \( f(x) > a \). Since,
\[
\lim \inf_{y \to x} f(y) = \lim \inf_{\varepsilon \in B_x^{'(*)}} f(y) \overset{\overset{1}{\overset{g}{\to}}}{=} f(x) > a,
\]
it follows that \( \inf_{y \in B_x^{'(*)}} f(y) > a \) for some \( \delta > 0 \). Hence we may conclude that \( B_x(\delta) \subset \{ f > a \} \) which shows \( \{ f > a \} \) is open.

Conversely, suppose now that \( \{ f > a \} \) is open for all \( a \in \mathbb{R} \). Given \( x \in X \) and \( a < f(x) \), there exists \( \delta > 0 \) such that \( B_x(\delta) \subset \{ f > a \} \). Hence it follows that \( \lim \inf_{y \to x} f(y) \geq a \) and then letting \( a \uparrow f(x) \) then implies \( \lim \inf_{y \to x} f(y) \geq f(x) \).

### 13.4 Skorohod and the Convergence of Types Theorems

**Notation 13.27** Given a proper distribution function, \( F : \mathbb{R} \to [0, 1] \), let \( Y = F^{-} : (0, 1) \to \mathbb{R} \) be the function defined by
\[
Y(x) = F^{-}(x) = \sup \{ y \in \mathbb{R} : F(y) < x \}.
\]
Similarly, let
\[
Y^{+}(x) := \inf \{ y \in \mathbb{R} : F(y) > x \}.
\]
We will need the following simple observations about \( Y \) and \( Y^+ \) which are easily understood from Figure 13.4.

1. \( Y(x) \leq Y^+(x) \) and \( Y(x) < Y^+(x) \) iff \( x \) is the height of a “flat spot” of \( F \).
2. The set, \( E := \{ x \in (0,1) : Y(x) < Y^+(x) \} \), of flat spot heights is at most countable. This is because, \( \{(Y(x), Y^+(x))\}_{x \in E} \) is a collection of pairwise disjoint intervals which is necessarily countable. (Each such interval contains a rational number.)
3. The following inequality holds,

\[
F(Y(x) -) \leq x \leq F(Y(x)) \quad \text{for all } x \in (0,1). \tag{13.11}
\]

Indeed, if \( y > Y(x) \), then \( F(y) \geq x \) and by right continuity of \( F \) it follows that \( F(Y(x)) \geq x \). Similarly, if \( y < Y(x) \), then \( F(y) < x \) and hence \( F(Y(x) -) \leq x \).

4. \( \{ x \in (0,1) : Y(x) \leq y_0 \} = (0, F(y_0)] \cap (0,1) \). To prove this assertion first suppose that \( Y(x) \leq y_0 \), then according to Eq. (13.11) we have \( x \leq F(Y(x)) \leq F(y_0) \), i.e. \( x \in (0, F(y_0)] \cap (0,1) \). Conversely, if \( x \in (0,1) \) and \( x \leq F(y_0) \), then \( Y(x) \leq y_0 \) by definition of \( Y \).
5. As a consequence of item 4, we see that \( Y \) is \( B_{(0,1)}/B_\mathbb{R} \) - measurable and \( m \circ Y^{-1} = F \), where \( m \) is Lebesgue measure on \( ((0,1), B_{(0,1)}) \).

**Theorem 13.28 (Baby Skorohod Theorem).** Suppose that \( \{ F_n \}_{n=0}^\infty \) is a collection of distribution functions such that \( F_n \Rightarrow F_0 \). Then there exists a probability space, \( (\Omega, \mathcal{B}, P) \) and random variables, \( \{ Y_n \}_{n=1}^\infty \) such that \( P(Y_n \leq y) = F_n(y) \) for all \( n \in \mathbb{N} \cup \{ \infty \} \) and \( \lim_{n \to \infty} F_n = \lim_{n \to \infty} Y_n = Y \) \( F^{-} \) a.s.

**Proof.** We will take \( \Omega := (0,1), \mathcal{B} = B_{(0,1)}, \) and \( P = m \) - Lebesgue measure on \( \Omega \) and let \( Y_n := F_n^{-} \) and \( Y := F_0^{-} \) as in Notation 13.27. Because of the above comments, \( P(Y_n \leq y) = F_n(y) \) and \( P(Y \leq y) = F_0(y) \) for all \( y \in \mathbb{R} \). So in order to finish the proof it suffices to show, \( Y_n(x) \to Y(x) \) for all \( x \notin E \), where \( E \) is the countable null set defined as above, \( E := \{ x \in (0,1) : Y(x) < Y^+(x) \} \).

We now suppose \( x \notin E \). If \( y \in C(F_0) \) with \( y < Y(x) \), we have \( \lim_{n \to \infty} F_n(y) = F_0(y) < x \) and in particular, \( F_n(y) < x \) for almost all \( n \). This implies that \( Y_n(x) \geq y \) for a.a. \( n \) and hence that \( \liminf_{n \to \infty} Y_n(x) \geq y \). Letting \( y \uparrow Y(x) \) with \( y \in C(F_0) \) then implies

\[
\liminf_{n \to \infty} Y_n(x) \geq Y(x).
\]

Similarly, for \( x \notin E \) and \( y \in C(F_0) \) with \( Y(x) = Y^+(x) < y \), we have \( \lim_{n \to \infty} F_n(y) = F_0(y) > x \) and in particular, \( F_n(y) > x \) for almost all \( n \). This implies that \( Y_n(x) \leq y \) for a.a. \( n \) and hence that \( \limsup_{n \to \infty} Y_n(x) \leq y \).

Letting \( y \downarrow Y(x) \) with \( y \in C(F_0) \) then implies

\[
\limsup_{n \to \infty} Y_n(x) \leq Y(x).
\]

Hence we have shown, for \( x \notin E \), that

\[
\limsup_{n \to \infty} Y_n(x) \leq Y(x) \leq \liminf_{n \to \infty} Y_n(x)
\]

which shows

\[
\lim_{n \to \infty} F_n^{-}(x) = \lim_{n \to \infty} Y_n(x) = Y(x) = F^{-}(x) \quad \text{for all } x \notin E. \tag{13.12}
\]

**Definition 13.29.** Two random variables, \( Y \) and \( Z \), are said to be of the same type if there exists constants, \( A > 0 \) and \( B \in \mathbb{R} \) such that

\[
Z \overset{d}{=} AY + B. \tag{13.13}
\]

Alternatively put, if \( U(y) := P(Y \leq y) \) and \( V(y) := P(Z \leq y) \), then \( U \) and \( V \) should satisfy,

\[
U(y) = P(Y \leq y) = P(Z \leq Ay + B) = V(Ay + B).
\]

For the next theorem we will need the following elementary observation.

**Lemma 13.30.** If \( Y \) is non-constant (a.s.) random variable and \( U(y) := P(Y \leq y) \), then \( U^{-} \) \( \gamma_1 \) \( U^{-} \) \( \gamma_2 \) for all \( \gamma_1 \) sufficiently close to \( 0 \) and \( \gamma_2 \) sufficiently close to \( 1 \).

**Proof.** Observe that \( Y \) is constant iff \( U(y) = 1_{y > c} \) for some \( c \in \mathbb{R} \), i.e. if \( U \) only takes on the values, \( \{0,1\} \). So since \( Y \) is not constant, there exists \( y \in \mathbb{R} \) such that \( 0 < U(y) < 1 \). Hence if \( \gamma_2 > U(y) \) then \( U^{-} \) \( \gamma_2 \geq y \) and if \( \gamma_1 < U(y) \) then \( U^{-} \) \( \gamma_1 \leq y \). Moreover, if we suppose that \( \gamma_1 \) is not the height of a flat spot of \( U \), then in fact, \( U^{-} \) \( \gamma_1 \) \( U^{-} \) \( \gamma_2 \). This inequality then remains valid as \( \gamma_1 \) decreases and \( \gamma_2 \) increases.
Theorem 13.31 (Convergence of Types). Suppose \( \{X_n\}_{n=1}^{\infty} \) is a sequence of random variables and \( a_n, \alpha_n \in (0, \infty) \), \( b_n, \beta_n \in \mathbb{R} \) are constants and \( Y \) and \( Z \) are non-constant random variables. Then

1. if \( \frac{X_n - b_n}{a_n} \xrightarrow{\text{d}} Y \) \hspace{2cm} (13.14)

and \( \frac{X_n - \beta_n}{\alpha_n} \xrightarrow{\text{d}} Z \), \hspace{2cm} (13.15)

then \( Y \) and \( Z \) are of the same type. Moreover, the limits,

\[
A = \lim_{n \to \infty} \frac{\alpha_n}{a_n} \in (0, \infty) \quad \text{and} \quad B := \lim_{n \to \infty} \frac{\beta_n - b_n}{a_n}
\]

(13.16)

exists and \( Y \overset{\text{d}}{=} AZ + B \).

2. If the relations in Eq. [13.16] hold then either of the convergences in Eqs. [13.14] or [13.15] implies the others with \( Z \) and \( Y \) related by Eq. [13.13].

3. If there are some constants, \( a_n > 0 \) and \( b_n \in \mathbb{R} \) and a non-constant random variable \( Y \), such that Eq. (13.14) holds, then Eq. (13.15) holds using \( \alpha_n \) and \( \beta_n \) of the form,

\[
\alpha_n := F_n^-(\gamma_2) - F_n^-(\gamma_1) \quad \text{and} \quad \beta_n := F_n^-(\gamma_1)
\]

(13.17)

for some \( 0 < \gamma_1 < \gamma_2 < 1 \). If the \( F_n \) are invertible functions, Eq. (13.17) may be written as

\[
F_n(\beta_n) = \gamma_1 \quad \text{and} \quad F_n(\alpha_n + \beta_n) = \gamma_2.
\]

(13.18)

**Proof.** (2) Assume the limits in Eq. [13.16] hold. If Eq. (13.14) is satisfied, then by Slutsky’s Theorem [13.20]

\[
\frac{X_n - \beta_n}{\alpha_n} = \frac{X_n - b_n + b_n - \beta_n}{a_n} \xrightarrow{\text{d}} \frac{\alpha_n}{a_n} \quad \Rightarrow \quad A^{-1}(Y - B) =: Z
\]

Similarly, if Eq. (13.15) is satisfied, then

\[
\frac{X_n - b_n}{a_n} = \frac{X_n - \beta_n}{\alpha_n} + \frac{\beta_n - b_n}{a_n} \xrightarrow{\text{d}} AZ + B = Y.
\]

(1) If \( F_n(y) := P(X_n \leq y) \), then

\[
P\left( \frac{X_n - b_n}{\alpha_n} \leq y \right) = F_n(\alpha_n y + b_n) \quad \text{and} \quad P\left( \frac{X_n - \beta_n}{\alpha_n} \leq y \right) = F_n(\alpha_n y + \beta_n).
\]

By assumption we have

\[
F_n(\alpha_n y + b_n) \implies U(y) \quad \text{and} \quad F_n(\alpha_n y + \beta_n) \implies V(y).
\]

If \( w := \sup \{y : F_n(\alpha_n y + b_n) < x\} \), then \( a_n w + b_n = F_n^-(x) \) and hence

\[
\sup \{y : F_n(\alpha_n y + b_n) < x\} = \frac{F_n^-(x) - b_n}{\alpha_n}.
\]

Similarly,

\[
\sup \{y : F_n(\alpha_n y + \beta_n) < x\} = \frac{F_n^-(x) - \beta_n}{\alpha_n}.
\]

With these identities, it now follows from the proof of Skorohod’s Theorem [13.28] (see Eq. (13.12)) that there exists an at most countable subset, \( A \), of \( (0, 1) \) such that,

\[
\frac{F_n^-(x) - b_n}{\alpha_n} = \sup \{y : F_n(\alpha_n y + b_n) < x\} \to U^-(x) \quad \text{and} \quad \frac{F_n^-(x) - \beta_n}{\alpha_n} = \sup \{y : F_n(\alpha_n y + \beta_n) < x\} \to V^-(x)
\]

for all \( x \notin A \). Since \( Y \) and \( Z \) are not constants a.s., we can choose, by Lemma \( 13.30 \) \( \gamma_1 \neq \gamma_2 \) not in \( A \) such that \( U^-(\gamma_1) < U^-(\gamma_2) \) and \( V^-(\gamma_1) < V^-(\gamma_2) \). In particular it follows that

\[
\frac{F_n^-(\gamma_2) - F_n^-(\gamma_1)}{\alpha_n} = \frac{F_n^-(\gamma_2) - b_n}{\alpha_n} - \frac{F_n^-(\gamma_1) - b_n}{\alpha_n} \to U^-(\gamma_2) - U^-(\gamma_1) > 0
\]

(13.19)

and similarly

\[
\frac{F_n^-(\gamma_2) - F_n^-(\gamma_1)}{\alpha_n} \to V^-(\gamma_2) - V^-(\gamma_1) > 0.
\]

Taking ratios of the last two displayed equations shows,

\[
\frac{\alpha_n}{a_n} \to A := \frac{U^-(\gamma_2) - U^-(\gamma_1)}{V^-(\gamma_2) - V^-(\gamma_1)} \in (0, \infty).
\]

Moreover,

\[
\frac{F_n^-(\gamma_1) - b_n}{\alpha_n} \to U^-(\gamma_1) \quad \text{and} \quad \frac{F_n^-(\gamma_1) - \beta_n}{\alpha_n} \to AV^-(\gamma_1)
\]

(13.20)
and therefore,
\[
\beta_n - b_n = \frac{F_n^- (\gamma_1) - \beta_n}{a_n} - \frac{F_n^- (\gamma_1) - b_n}{a_n} \to AV^- (\gamma_1) - U^- (\gamma_1) := B.
\]

(3) Now suppose that we define \( \alpha_n := F_n^- (\gamma_2) - F_n^- (\gamma_1) \) and \( \beta_n := F_n^- (\gamma_1) \), then according to Eqs. (13.19) and (13.20) we have
\[
\alpha_n/a_n \to U^- (\gamma_2) - U^- (\gamma_1) \in (0, 1) \quad \text{and}
\]
\[
\beta_n - b_n/a_n \to U^- (\gamma_1) \quad \text{as} \quad n \to \infty.
\]

Thus we may always center and scale the \( \{X_n\} \) using \( \alpha_n \) and \( \beta_n \) of the form described in Eq. (13.17).

\section{13.5 Weak Convergence Examples}

\textbf{Example 13.32.} Suppose that \( \{X_n\}_{n=1}^\infty \) are i.i.d. \( \exp (\lambda) \) random variables, i.e. \( X_n \geq 0 \) a.s. and \( P (X_n \geq x) = e^{-\lambda x} \) for all \( x \geq 0 \). In this case
\[
F (x) := P (X_1 \leq x) = 1 - e^{-\lambda x (x \geq 0)}
\]

Consider \( M_n := \max (X_1, \ldots, X_n) \). We have, for \( x \geq 0 \) and \( c_n \in (0, \infty) \) that
\[
F_n (x) := P (M_n \leq x) = P \left( \bigcap_{j=1}^n \{X_j \leq x\} \right) = \prod_{j=1}^n P (X_j \leq x) = [F (x)]^n = (1 - e^{-\lambda x})^n.
\]

We now wish to find \( a_n \geq 0 \) and \( b_n \in \mathbb{R} \) such that \( M_n - b_n/a_n \Rightarrow Y \).  

1. To this end we note that
\[
P \left( \frac{M_n - b_n}{a_n} \leq x \right) = P (M_n \leq a_n x + b_n) = F_n (a_n x + b_n) = [F (a_n x + b_n)]^n.
\]

If we demand (c.f. Eq. (13.18) above)
\[
P \left( \frac{M_n - b_n}{a_n} \leq 0 \right) = F_n (b_n) = [F (b_n)]^n \to \gamma_1 \in (0, 1),
\]
then \( b_n \to \infty \) and we find
\[
\ln \gamma_1 \sim n \ln F (b_n) = n \ln (1 - e^{-\lambda b_n}) \sim -n e^{-\lambda b_n}.
\]

From this it follows that \( b_n \sim \lambda^{-1} \ln n \). Given this, we now try to find \( a_n \) by requiring,
\[
P \left( \frac{M_n - b_n}{a_n} \leq 1 \right) = F_n (a_n + b_n) = [F (a_n + b_n)]^n \to \gamma_2 \in (0, 1).
\]

However, by what we have done above, this requires \( a_n + b_n \sim \lambda^{-1} \ln n \). Hence we may as well take \( a_n \) to be constant and for simplicity we take \( a_n = 1 \).

2. We now compute
\[
\lim_{n \to \infty} P (M_n - \lambda^{-1} \ln n \leq x) = \lim_{n \to \infty} \left( 1 - e^{-\lambda (x + \lambda^{-1} \ln n)} \right)^n
\]
\[
= \lim_{n \to \infty} \left( 1 - \frac{e^{-\lambda x}}{n} \right)^n = \exp (-e^{-\lambda x}).
\]

Notice that \( F (x) \) is a distribution function for some random variable, \( Y \), and therefore we have shown
\[
M_n - \frac{1}{\lambda} \ln n \Rightarrow Y \quad \text{as} \quad n \to \infty
\]

where \( P (Y \leq x) = \exp (-e^{-\lambda x}) \).

\textbf{Example 13.33.} For \( p \in (0, 1) \), let \( X_p \) denote the number of trials to get success in a sequence of independent trials with success probability \( p \). Then \( P (X_p > n) = (1 - p)^n \) and therefore for \( x > 0 \),
\[
P (p X_p > x) = P \left( X_p > \frac{x}{p} \right) = (1 - p)^x \left[ \frac{x}{p} \right] = e \left[ \frac{x}{p} \right] (1 - p)^{\ln (1 - p)}
\]
\[
\sim e^{-n \left[ \frac{x}{p} \right]} \to e^{-x} \quad \text{as} \quad p \to 0.
\]

Therefore \( p X_p \Rightarrow T \) where \( T \overset{d}{=} \exp (1) \), i.e. \( P (T > x) = e^{-x} \) for \( x \geq 0 \) or alternatively, \( P (T \leq y) = 1 - e^{-y} \).

\textbf{Remarks on this example.} Let us see in a couple of ways where the appropriate centering and scaling of the \( X_p \) come from in this example. For this let \( q = 1 - p \), then \( P (X_p = n) = (1 - p)^n q^{n-1} p = q^{n-1} p \) for \( n \in \mathbb{N} \). Also let
\[
F_p (x) = P (X_p \leq x) = P (X_p \leq \lfloor x \rfloor) = 1 - q^{\lfloor x \rfloor}
\]

where \( \lfloor x \rfloor := \sum_{n=1}^{x} n \cdot 1_{[n,n+1)} \).

\textbf{Method 1.} Our goal is to choose \( a_p > 0 \) and \( b_p \in \mathbb{R} \) such that \( \lim_{p \to 0} F_p (a_p x + b_p) \) exists. As above, we first demand (taking \( x = 0 \)) that
\[
\lim_{p \to 0} F_p (b_p) = \gamma_1 \in (0, 1).
\]
Since, $\gamma_1 \sim F_p(b_p) \sim 1 - q^{b_p}$ we require, $q^{b_p} \sim 1 - \gamma_1$ and hence, $c \sim b_p \ln q = b_p \ln (1 - p) \sim -b_p p$. This suggests that we take $b_p = 1/p$ say. Having done this, we would like to choose $a_p$ such that

$$F_0(x) := \lim_{p \to 0} F_p(a_p x + b_p) \text{ exists.}$$

Since,

$$F_0(x) \sim F_p(a_p x + b_p) \sim 1 - q^{a_p x + b_p}$$

this requires that

$$(1 - p)^{a_p x + b_p} = q^{a_p x + b_p} \sim 1 - F_0(x)$$

and hence that

$$\ln(1 - F_0(x)) = (a_p x + b_p) \ln q \sim (a_p x + b_p) (-p) = -pa_p x - 1.$$ From this (setting $x = 1$) we see that $pa_p \sim c > 0$. Hence we might take $a_p = 1/p$ as well. We then have

$$F_p(a_p x + b_p) = F_p(p^{-1} x + p^{-1}) = 1 - (1 - p)^{p^{-1}(x + 1)}$$

which is equal to 0 if $x \leq -1$, and for $x > -1$ we find

$$(1 - p)^{p^{-1}(x + 1)} = \exp\left(\left[p^{-1}(x + 1)\right] \ln(1 - p)\right) \to \exp(- (x + 1)).$$

Hence we have shown,

$$\lim_{p \to 0} F_p(a_p x + b_p) = [1 - \exp(- (x + 1))]_x \geq -1$$

$$\frac{X_p - 1/p}{1/p} = pX_p - 1 \Rightarrow T - 1$$

or again that $pX_p \to T$.

**Method 2.** (Center and scale using the first moment and the variance of $X_p$) The generating function is given by

$$f(z) := \mathbb{E}\left[z^{X_p}\right] = \sum_{n=1}^{\infty} z^n q^{n-1} = \frac{pz}{1 - qz}.$$ Observe that $f(z)$ is well defined for $|z| < \frac{1}{q}$ and that $f(1) = 1$, reflecting the fact that $P(X_p \in \mathbb{N}) = 1$, i.e. a success must occur almost surely. Moreover, we have

$$f'(z) = \mathbb{E}\left[X_p z^{X_p-1}\right], \quad f''(z) = \mathbb{E}\left[X_p (X_p - 1) z^{X_p-2}\right], \ldots,$$

$$f^{(k)}(z) = \mathbb{E}\left[X_p (X_p - 1) \ldots (X_p - k + 1) z^{X_p-k}\right]$$

and in particular,

$$\mathbb{E}[X_p (X_p - 1) \ldots (X_p - k + 1)] = f^{(k)}(1) = \left(\frac{d}{dz}\right)_{z=1} \frac{pz}{p - qz}.$$ Since

$$\frac{d}{dz} \frac{pz}{1 - qz} = \frac{p(1 - qz) + qpz}{(1 - qz)^2} = \frac{p}{(1 - qz)^2}$$

and

$$\frac{d^2}{dz^2} \frac{pz}{1 - qz} = 2 \frac{pq}{(1 - qz)^3},$$

it follows that

$$\mu_p := \mathbb{E}X_p = \frac{p}{(1 - q)^2} = \frac{1}{p}$$

and

$$\mathbb{E}[X_p (X_p - 1)] = 2 - \frac{pq}{(1 - q)^3} = \frac{2q}{p^2}.$$ Therefore,

$$\sigma_p^2 = \text{Var}(X_p) = \mathbb{E}X_p^2 - (\mathbb{E}X_p)^2 = \frac{2q}{p^2} + \frac{1}{p} - \left(\frac{1}{p}\right)^2$$

$$= \frac{2q + p - 1}{p^2} = \frac{q}{p^2} = \frac{1 - p}{p^2}.$$ Thus, if we had used $\mu_p$ and $\sigma_p$ to center and scale $X_p$ we would have considered,

$$\frac{X_p - \frac{1}{p}}{\sqrt{\frac{1 - p}{p}}} = pX_p - 1 \to T - 1$$

instead.

**Theorem 13.34.** Let $\{X_n\}_{n=1}^{\infty}$ be i.i.d. random variables such that $P(X_n = \pm 1) = 1/2$ and let $S_n := X_1 + \cdots + X_n$ – the position of a drunk after $n$ steps. Observe that $|S_n|$ is an odd integer if $n$ is odd and an even integer if $n$ is even. Then $\frac{S_n}{\sqrt{n}} \to N(0, 1)$ as $m \to \infty$.

**Proof.** (Sketch of the proof.) We start by observing that $S_{2n} = 2k$ iff

$$\# \{i \leq 2n : X_i = 1\} = n + k \text{ while}$$

$$\# \{i \leq 2n : X_i = -1\} = 2n - (n + k) = n - k$$

and therefore,
13 Weak Convergence Results

\[
P(S_{2n} = 2k) = \left(\frac{2n}{n+k}\right) \left(\frac{1}{2}\right)^{2n} \frac{(2n)!}{(n+k)! \cdot (n-k)!} \left(\frac{1}{2}\right)^{2n}.
\]

Recall Stirling’s formula states,

\[n! \sim n^n e^{-n} \sqrt{2\pi n} \text{ as } n \to \infty\]

and therefore,

\[
P(S_{2n} = 2k)
\sim \frac{(2n)^{2n} e^{-2n} \sqrt{4\pi n}}{(n+k)^{(n+k)} \sqrt{2\pi (n+k)}} \cdot \frac{(n-k)^{n-k} e^{-(n-k)} \sqrt{2\pi (n-k)}}{(n-k)^{(n-k)}} \left(\frac{1}{2}\right)^{2n}
\]

\[= \frac{n^{n} e^{-n} \sqrt{2\pi n}}{(n+k)(n-k)} \left(\frac{1}{2}\right)^{2n} \cdot \left(\frac{1}{n}\right)^{k} \cdot \left(\frac{1}{n}\right)^{k}
\]

\[= \frac{n^{n} e^{-n} \sqrt{2\pi n}}{(n+k)(n-k)} \left(\frac{1}{2}\right)^{2n} \cdot \left(\frac{1}{n}\right)^{k} \cdot \left(\frac{1}{n}\right)^{k}
\]

So if we let \(x := 2k/\sqrt{2n}\), i.e. \(k = x \sqrt{n/2}\) and \(k/n = \frac{x}{\sqrt{2n}}\), we have

\[
P\left(S_{2n}/\sqrt{2n} = x\right)
\sim \frac{n^{n} e^{-n} \sqrt{2\pi n}}{\sqrt{2\pi n}} \left(\frac{1}{2}\right)^{2n} \cdot \left(\frac{1}{n}\right)^{k} \cdot \left(\frac{1}{n}\right)^{k}
\]

\[= \frac{n^{n} e^{-n} \sqrt{2\pi n}}{\sqrt{2\pi n}} \left(\frac{1}{2}\right)^{2n} \cdot \left(\frac{1}{n}\right)^{k} \cdot \left(\frac{1}{n}\right)^{k}
\]

\[= \frac{n^{n} e^{-n} \sqrt{2\pi n}}{\sqrt{2\pi n}} \left(\frac{1}{2}\right)^{2n} \cdot \left(\frac{1}{n}\right)^{k} \cdot \left(\frac{1}{n}\right)^{k}
\]

where the sum is over \(x\) of the form, \(x = \frac{2k}{\sqrt{2n}}\) with \(k \in \{0, \pm 1, \ldots, \pm n\}\). Since \(\frac{2}{\sqrt{2n}}\) is the increment of \(x\) as \(k\) increases by 1, we see the latter expression in Eq. (13.21) is the Riemann sum approximation to

\[\frac{1}{\sqrt{2\pi}} \int_{a}^{b} e^{-x^2/2} dx.
\]

This proves \(S_{2n}/\sqrt{2n} \Rightarrow N(0, 1)\). Since

\[
S_{2n+1}/\sqrt{2n+1} = S_{2n} + X_{2n+1} = \frac{S_{2n}}{\sqrt{2n}} \left(1 + \frac{k}{n}\right) + X_{2n+1}/\sqrt{2n+1}
\]

it follows directly (or see Slutsky’s Theorem 13.20) that \(S_{2n+1}/\sqrt{2n+1} \Rightarrow N(0, 1)\) as well.

**Proposition 13.35.** Suppose that \(\{U_n\}_{n=1}^{\infty}\) are i.i.d. random variables which are uniformly distributed in \((0, 1)\). Let \(U(k,n)\) denote the position of the \(k\)-th largest number from the list, \(\{U_1, U_2, \ldots, U_n\}\). Further let \(k(n)\) be chosen so that \(\lim_{n \to \infty} k(n) / n = \infty\) while \(\lim_{n \to \infty} k(n)/n = 0\) and let

\[X_n := U(k(n), n) - k(n)/n \frac{\sqrt{k(n)}}{\sqrt{n}}.
\]

Then \(d_{TV}(X_n, N(0, 1)) \to 0\) as \(n \to \infty\).

**Proof.** (Sketch only. See Resnick, Proposition 8.2.1 for more details.) Observe that, for \(x \in (0, 1)\), that

\[
P(U(k,n) \leq x) = P\left(\sum_{i=1}^{n} X_i \geq k\right) = \sum_{l=k}^{n} \left(\begin{array}{c} n \\ l \end{array}\right) x^l (1-x)^{n-l}.
\]

From this it follows that \(\rho_n(x) = 1_{(0,1)}(x) \frac{k}{n} P(U(k,n) \leq x)\) is the probability density for \(U(k,n)\). It now turns out that \(\rho_n(x)\) is a Beta distribution,

\[\rho_n(x) = \left(\begin{array}{c} n \\ k \end{array}\right) k \cdot x^{k-1} (1-x)^{n-k}.
\]

Giving a direct computation of this result is not so illuminating. So let us go another route. To do this we are going to estimate, \(P(U(k,n) \in (x, x+\Delta))\), for \(\Delta \in (0, 1)\). Observe that if \(U(k,n) \in (x, x+\Delta)\), then there must be at least one \(U_i \in (x, x+\Delta)\), for otherwise, \(U(k,n) \leq x + \Delta\) would imply \(U(k,n) \leq x\) as well and hence \(U(k,n) \notin (x, x+\Delta)\). Let
$\Omega_i := \{ U_i \in (x, x + \Delta) \text{ and } U_j \notin (x, x + \Delta) \text{ for } j \neq i \}.
$

Since

$$P(U_i, U_j \in (x, x + \Delta) \text{ for } i \neq j \text{ with } i, j \leq n) \leq \sum_{i<j \leq n} P(U_i, U_j \in (x, x + \Delta)) \leq \frac{n^2 - n}{2} \Delta^2,$$

we see that

$$P(U_{(k, n)} \in (x, x + \Delta)) = \sum_{i=1}^{n} P(U_{(k, n)} \in (x, x + \Delta), \Omega_i) + O(\Delta^2) = nP(U_{(k, n)} \in (x, x + \Delta), \Omega_i) + O(\Delta^2).$$

Now on the set, $\Omega_1; U_{(k, n)} \in (x, x + \Delta)$ iff there are exactly $k - 1$ of $U_2, \ldots, U_n$ in $[0, x]$ and $n - k$ of these in $[x + \Delta, 1]$. This leads to the conclusion that

$$P(U_{(k, n)} \in (x, x + \Delta)) = n \left( \frac{n - 1}{k - 1} \right) x^{k-1} (1 - (x + \Delta))^{n-k} + O(\Delta^2)$$

and therefore,

$$\rho_n(x) = \lim_{\Delta \to 0} \frac{P(U_{(k, n)} \in (x, x + \Delta))}{\Delta} = \frac{n!}{(k - 1)! \cdot (n - k)!} x^{k-1} (1 - x)^{n-k}.$$

By Stirling’s formula,

$$\frac{n!}{(k - 1)! \cdot (n - k)!} \sim \frac{n^ne^{-n}\sqrt{2\pi n}}{(k - 1)^{(k-1)}e^{-(k-1)}\sqrt{2\pi (k - 1)}(n - k)^{(n-k)}e^{-(n-k)}\sqrt{2\pi (n - k)}}$$

$$= \frac{\sqrt{n}e^{-1}}{\sqrt{2\pi}} \frac{1}{\left( \frac{k - 1}{n} \right)^{(k-1)} \sqrt{\frac{k-1}{n}}} \left( \frac{n-k}{n} \right)^{(n-k)} \sqrt{n-k}$$

$$= \frac{\sqrt{n}e^{-1}}{\sqrt{2\pi}} \frac{1}{\left( \frac{k - 1}{n} \right)^{(k-1/2)} \left( 1 - \frac{k}{n} \right)^{(n-k+1/2)}}.$$

Since

$$\left( \frac{k - 1}{n} \right)^{(k-1/2)} = \left( \frac{k}{n} \right)^{(k-1/2)} \cdot \left( 1 - \frac{k}{n} \right)^{(k-1/2)}$$

$$= \left( \frac{k}{n} \right)^{(k-1/2)} \cdot \left( 1 - \frac{1}{k} \right)^{(k-1/2)}$$

$$\sim e^{-1} \left( \frac{k}{n} \right)^{(k-1/2)}$$

we arrive at

$$\frac{n!}{(k - 1)! \cdot (n - k)!} \sim \frac{\sqrt{n}}{\sqrt{2\pi}} \left( \frac{k}{n} \right)^{(k-1/2)} \left( 1 - \frac{k}{n} \right)^{(n-k+1/2)}.$$

By the change of variables formula, with

$$x = \frac{u - k(n)/n}{\sqrt{k(n)}},$$

on noting the $du = \frac{\sqrt{k(n)}}{n} dx, x = -\sqrt{k(n)}$ at $u = 0$, and

$$x = \frac{1 - k(n)/n}{\sqrt{k(n)}} = -\frac{k(n)}{\sqrt{k(n)}},$$

$$= \frac{n}{\sqrt{k(n)}} \left( 1 - \frac{k(n)}{n} \right) = \sqrt{n} \frac{\sqrt{n}}{\sqrt{k(n)}} \left( 1 - \frac{k(n)}{n} \right) =: b_n,$$

$$E[F(X_n)] = \int_{0}^{1} \rho_n(u) F \left( \frac{u - k(n)/n}{\sqrt{k(n)}} \right) du$$

$$= \int_{-\sqrt{k(n)}}^{b_n} \frac{\sqrt{k(n)}}{n} \rho_n \left( \frac{\sqrt{k(n)}}{n} x + k(n)/n \right) F(x) du.$$

Using this information, it is then shown in Resnick that

$$\frac{\sqrt{k(n)}}{n} \rho_n \left( \frac{\sqrt{k(n)}}{n} x + k(n)/n \right) \to e^{-a^2/2}$$

which upon an application of Scheffé’s Lemma completes the proof. ■

Remark 13.36. It is possible to understand the normalization constants in the definition of $X_n$ by computing the mean and the variance of $U_{(n,k)}$. After some computations (see Chapter ??), one arrives at
Suppose that $\Lambda \subset \mathbb{R}$ is a dense set and $F$ and $\tilde{F}$ are two right continuous functions. If $F = \tilde{F}$ on $\Lambda$, then $F = \tilde{F}$ on $\mathbb{R}$. Indeed, for $x \in \mathbb{R}$ we have

$$F(x) = \lim_{\Lambda \ni \lambda \downarrow x} F(\lambda) = \lim_{\Lambda \ni \lambda \uparrow x} \tilde{F}(\lambda) = \tilde{F}(x).$$

**Lemma 13.37.** If $G : \Lambda \rightarrow \mathbb{R}$ is a non-decreasing function, then

$$F(x) := G_+(x) := \inf \{ G(\lambda) : x < \lambda \in \Lambda \}$$

is a non-decreasing right continuous function.

**Proof.** To show $F$ is right continuous, let $x \in \mathbb{R}$ and $\lambda \in \Lambda$ such that $\lambda > x$. Then for any $y \in (x, \lambda)$,

$$F(x) \leq F(y) = G_+(y) \leq G(\lambda)$$

and therefore,

$$F(x) \leq F(x+) := \lim_{y \downarrow x} F(y) \leq G(\lambda).$$

Since $\lambda > x$ with $\lambda \in \Lambda$ is arbitrary, we may conclude, $F(x) \leq F(x+) \leq G_+(x) = F(x)$, i.e. $F(x+) = F(x)$.

**Proposition 13.38.** Suppose that $\{F_n\}_{n=1}^\infty$ is a sequence of distribution functions and $\Lambda \subset \mathbb{R}$ is a dense set such that $G(\lambda) := \lim_{n \rightarrow \infty} F_n(\lambda) \in [0,1]$ exists for all $\lambda \in \Lambda$. If, for all $x \in \mathbb{R}$, we define $F = G_+$ as in Eq. (13.22), then $F_n(x) \rightarrow F(x)$ for all $x \in \mathcal{C}(F)$. (Note well; as we have already seen, it is possible that $F(\infty) < 1$ and $F(-\infty) > 0$ so that $F$ need not be a distribution function for a measure on $(\mathbb{R}, \mathcal{B}_R)$.)

**Proof.** Suppose that $x, y \in \mathbb{R}$ with $x < y$ and and $s, t \in \Lambda$ are chosen so that $s < y < t$. Then passing to the limit in the inequality,

$$F_n(s) \leq F_n(y) \leq F_n(t)$$

implies

$$F(x) = G_+(x) \leq G(s) \leq \liminf_{n \rightarrow \infty} F_n(y) \leq \limsup_{n \rightarrow \infty} F_n(y) \leq G(t).$$

Taking the infimum over $t \in \Lambda \cap (y, \infty)$ and then letting $x \in \mathbb{R}$ tend up to $y$, we may conclude

$$F(y-) \leq \liminf_{n \rightarrow \infty} F_n(y) \leq \limsup_{n \rightarrow \infty} F_n(y) \leq F(y)$$

for all $y \in \mathbb{R}$.

This completes the proof, since $F(y-) = F(y)$ for $y \in \mathcal{C}(F)$.

The next theorem deals with weak convergence of measures on $(\mathbb{R}, \mathcal{B}_R)$. So as not have to introduce any new machinery, the reader should identify $\mathbb{R}$ with $[-1,1] \subset \mathbb{R}$ via the map,

$$[-1,1] \ni x \rightarrow \tan \left( \frac{\pi x}{2} \right) \in \mathbb{R}.$$ 

Hence a probability measure on $(\mathbb{R}, \mathcal{B}_R)$ may be identified with a probability measure on $(\mathbb{R}, \mathcal{B}_{\mathbb{R}})$ which is supported on $[-1,1]$. Using this identification, we see that a $-\infty$ should only be considered a point of continuity of a distribution function, $F : \mathbb{R} \rightarrow [0,1]$ iff and only if $F(-\infty) = 0$. On the other hand, $\infty$ is always a point of continuity.

**Theorem 13.39 (Helly’s Selection Theorem).** Every sequence of probability measures, $\{\mu_n\}_{n=1}^\infty$, on $(\mathbb{R}, \mathcal{B}_{\mathbb{R}})$ has a sub-sequence which is weakly convergent to a probability measure, $\mu_0$ on $(\mathbb{R}, \mathcal{B}_{\mathbb{R}})$.

**Proof.** Using the identification described above, rather than viewing $\mu_n$ as probability measures on $(\mathbb{R}, \mathcal{B}_{\mathbb{R}})$, we may view them as probability measures on $(\mathbb{R}, \mathcal{B}_{\mathbb{R}})$ which are supported on $[-1,1]$; i.e. $\mu_n([1,1]) = 1$. As usual, let

$$F_n(x) := \mu_n((-\infty,x]) = \mu_n((x,\infty] \cap [-1,1]).$$

Since $\{F_n(x)\}_{n=1}^\infty \subset [0,1]$ and $[0,1]$ is compact, for each $x \in \mathbb{R}$ we may find a convergence subsequence of $\{F_n(x)\}_{n=1}^\infty$. Hence by Cantor’s diagonalization
argument we may find a subsequence, \( \{G_k := F_{n_k}\}_{k=1}^\infty \) of the \( \{F_n\}_{n=1}^\infty \) such that \( G(x) := \lim_{k \to \infty} G_k(x) \) exists for all \( x \in \Lambda := \mathbb{Q} \).

Letting \( F(x) := G(x^+) \) as in Eq. (13.22), it follows from Lemma 13.37 and Proposition 13.38 that \( G_k = F_{n_k} \implies F_0 \). Moreover, since \( G_k(x) = 0 \) for all \( x \in \mathbb{Q} \cap (-\infty, -1) \) and \( G_k(x) = 1 \) for all \( x \in \mathbb{Q} \cap [1, \infty) \). Therefore, \( F_0(x) = 1 \) for all \( x > 1 \) and \( F_0(x) = 0 \) for all \( x < -1 \) and the corresponding measure, \( \mu_0 \) is supported on \([-1, 1]\). Hence \( \mu_0 \) may now be transferred back to a measure on \((\overline{\mathbb{R}}, B_{\overline{\mathbb{R}}} ) \).

\[ \]

**Example 13.40.** Suppose \( \delta_{-n} \implies \delta_{-\infty} \) and \( \delta_n \implies \delta_{\infty} \) and \( \frac{1}{2} (\delta_n + \delta_{-n}) \implies \frac{1}{2} (\delta_{\infty} + \delta_{-\infty}) \). This shows that probability may indeed transfer to the points at \( \pm \infty \).

The next question we would like to address is when is the limiting measure, \( \mu_0 \) on \((\overline{\mathbb{R}}, B_{\overline{\mathbb{R}}} ) \) concentrated on \( \mathbb{R} \). The following notion of tightness is the key to answering this question.

**Definition 13.41.** A collection of probability measures, \( \Gamma \), on \((\mathbb{R}, B_{\mathbb{R}})\) is **tight** if for every \( \varepsilon > 0 \) there exists \( M_\varepsilon < \infty \) such that

\[
\inf_{\mu \in \Gamma} \mu([-M_\varepsilon, M_\varepsilon]) \geq 1 - \varepsilon. \tag{13.23}
\]

We further say that a collection of random variables, \( \{X_\lambda : \lambda \in \Lambda\} \) is **tight** if the collection probability measures, \( \{P \circ X_\lambda^{-1} : \lambda \in \Lambda\} \) is tight. Equivalently, put, \( \{X_\lambda : \lambda \in \Lambda\} \) is tight iff

\[
\lim_{M \to \infty} \sup_{\lambda \in \Lambda} P(|X_\lambda| \geq M) = 0. \tag{13.24}
\]

Observe that the definition of uniform integrability (see Definition 11.25) is considerably stronger than the notion of tightness. It is also worth observing that if \( \alpha > 0 \) and \( C := \sup_{\lambda \in \Lambda} \mathbb{E}|X_\lambda|^{\alpha} < \infty \), then by Chebyshev’s inequality,

\[
\sup_{\lambda} P(|X_\lambda| \geq M) \leq \sup_{\lambda} \left[ \frac{1}{M^\alpha} \mathbb{E}|X_\lambda|^{\alpha} \right] \leq \frac{C}{M^\alpha} \to 0 \text{ as } M \to \infty
\]

and therefore \( \{X_\lambda : \lambda \in \Lambda\} \) is tight.

**Theorem 13.42.** Let \( \Gamma := \{\mu_n\}_{n=1}^\infty \) be a sequence of probability measures on \((\mathbb{R}, B_{\mathbb{R}})\). Then \( \Gamma \) is tight if every subsequently limit measure, \( \mu_0 \), on \((\overline{\mathbb{R}}, B_{\overline{\mathbb{R}}} ) \) is supported on \( \mathbb{R} \). In particular if \( \Gamma \) is tight, there is a weakly convergent subsequence of \( \Gamma \) converging to a probability measure on \((\overline{\mathbb{R}}, B_{\overline{\mathbb{R}}} ) \).

**Proof.** Suppose that \( \mu_{n_k} \implies \mu_0 \) with \( \mu_0 \) being a probability measure on \((\overline{\mathbb{R}}, B_{\overline{\mathbb{R}}} ) \). As usual, let \( F_0(x) := \mu_0([\infty, x]) \). If \( \Gamma \) is tight and \( \varepsilon > 0 \) is given, we may find \( M_\varepsilon < \infty \) such that \( M_\varepsilon, -M_\varepsilon \in \mathcal{C}(F_0) \) and \( \mu_n([-M_\varepsilon, M_\varepsilon]) \geq 1 - \varepsilon \) for all \( n \). Hence it follows that

\[
\mu_0([-M_\varepsilon, M_\varepsilon]) = \lim_{k \to \infty} \mu_{n_k}([-M_\varepsilon, M_\varepsilon]) \geq 1 - \varepsilon
\]

and by letting \( \varepsilon \downarrow 0 \) we conclude that \( \mu_0(\mathbb{R}) = \lim_{k \to 0} \mu_0([-M_\varepsilon, M_\varepsilon]) = 1 \).

Conversely, suppose there is a subsequence \( \{\mu_{n_k}\}_{k=1}^\infty \) such that \( \mu_{n_k} \implies \mu_0 \) with \( \mu_0 \) being a probability measure on \((\overline{\mathbb{R}}, B_{\overline{\mathbb{R}}} ) \) such that \( \mu_0(\mathbb{R}) < 1 \). In this case \( \varepsilon_0 := \mu_0(\{\infty, -\infty\}) > 0 \) and hence for all \( M < \infty \) we have

\[
\mu_0([-M, M]) \leq \mu_0(\mathbb{R}) - \mu_0(\{\infty, -\infty\}) = 1 - \varepsilon_0.
\]

By choosing \( M \) so that \( -M \) and \( M \) are points of continuity of \( F_0 \), it then follows that

\[
\lim_{k \to \infty} \mu_{n_k}([-M, M]) = \mu_0([-M, M]) \leq 1 - \varepsilon_0.
\]

Therefore,

\[
\inf_{n \in \mathbb{N}} \mu_n([-M, M]) \leq 1 - \varepsilon_0 \text{ for all } M < \infty
\]

and \( \{\mu_n\}_{n=1}^\infty \) is not tight.

---

### 13.7 Weak Convergence in Metric Spaces

(This section may be skipped.)

**Definition 13.43.** Let \( X \) be a metric space. A sequence of probability measures \( \{P_n\}_{n=1}^\infty \) is said to converge weakly to a probability \( P \) if \( \lim_{n \to \infty} P_n(f) = P(f) \) for all \( f \in \mathcal{B}(X) \). This is actually weak-* convergence when viewing \( P_n \in \mathcal{B}(X)^* \).

For simplicity we will now assume that \( X \) is a complete metric space throughout this section.

**Proposition 13.44.** The following are equivalent:

1. \( P_n \xrightarrow{w} P \) as \( n \to \infty \), i.e. \( P_n(f) \to P(f) \) for all \( f \in \mathcal{B}(X) \).
2. \( P_n(f) \to P(f) \) for every \( f \in \mathcal{B}(X) \) which is uniformly continuous.
3. \( \lim \sup_{n \to \infty} P_n(F) \leq P(F) \) for all \( F \subseteq X \).
4. \( \lim \inf_{n \to \infty} P_n(G) \geq P(G) \) for all \( G \subseteq X \).
5. \( \lim_{n \to \infty} P_n(A) = P(A) \) for all \( A \in \mathcal{B} \) such that \( P(\text{bd}(A)) = 0 \).
Proof. 1. \(\implies\) 2. is obvious. For 2. \(\implies\) 3., let
\[
\varphi(t) := \begin{cases} 1 & \text{if } t \leq 0 \\ 1-t & \text{if } 0 \leq t \leq 1 \\ 0 & \text{if } t \geq 1 \end{cases}
\] (13.25)
and let \(f_n(x) := \varphi(n \delta(x, F))\). Then \(f_n \in BC(X, [0, 1])\) is uniformly continuous, \(0 \leq 1_F \leq f_n\) for all \(n\) and \(f_n \downarrow 1_F\) as \(n \to \infty\). Passing to the limit \(n \to \infty\) in the equation
\[
0 \leq P_n(F) \leq P_n(f_m)
\]
gives
\[
0 \leq \limsup_{n \to \infty} P_n(F) \leq P(f_m)
\]
and then letting \(m \to \infty\) in this inequality implies item 3. 3. \(\iff\) 4. Assuming item 3., let \(F = G^c\), then
\[
1 - \liminf_{n \to \infty} P_n(G) = \limsup_{n \to \infty} (1 - P_n(G)) = \limsup_{n \to \infty} P_n(G^c) \leq P(G^c) = 1 - P(G)
\]
which implies 4. Similarly 4. \(\implies\) 3. 3. \(\iff\) 5. Recall that \(bd(A) = \bar{A} \setminus A^o\), so if \(P(bd(A)) = 0\) and 3. (and hence also 4. holds) we have
\[
\limsup_{n \to \infty} P_n(A) = \limsup_{n \to \infty} P_n(\bar{A}) \leq P(\bar{A}) = P(A) \text{ and}
\liminf_{n \to \infty} P_n(A) = \liminf_{n \to \infty} P_n(A^o) \geq P(A^o) = P(A)
\]
from which it follows that \(\lim_{n \to \infty} P_n(A) = P(A)\). Conversely, let \(F \subset X\) and set \(F_\delta := \{x \in X : \rho(x, F) \leq \delta\}\). Then
\[
bd(F_\delta) \subset F_\delta \setminus \{x \in X : \rho(x, F) < \delta\} = A_\delta
\]
where \(A_\delta := \{x \in X : \rho(x, F) = \delta\}\). Since \(\{A_\delta\}_{\delta > 0}\) are all disjoint, we must have
\[
\sum_{\delta > 0} P(A_\delta) \leq P(X) \leq 1
\]
and in particular the set \(A := \{\delta > 0 : P(A_\delta) > 0\}\) is at most countable. Let \(\delta_n \notin A\) be chosen so that \(\delta_n \downarrow 0\) as \(n \to \infty\), then
\[
P(F_{\delta_n}) = \lim_{n \to \infty} P_n(F_{\delta_n}) \geq \limsup_{n \to \infty} P_n(F).
\]
Let \(m \to \infty\) in this equation to conclude \(P(F) \geq \limsup_{n \to \infty} P_n(F)\) as desired.
To finish the proof we will now show 3. \(\implies\) 1. By an affine change of variables it suffices to consider \(f \in C(X, (0, 1))\) in which case we have
\[
\sum_{i=1}^{k} \frac{(i-1)}{k} \{1 \leq x \leq \frac{i}{k}\} \leq f \leq \sum_{i=1}^{k} \frac{i}{k} \{\frac{i-1}{k} \leq x < \frac{i}{k}\}.
\] (13.26)
Let \(F_i := \{\frac{i}{k} \leq f\}\) and notice that \(F_k = \emptyset\). Then for any probability \(P_{\infty}\)
\[
\sum_{i=1}^{k} \frac{(i-1)}{k} [P(F_{i-1}) - P(F_i)] \leq P(f) \leq \sum_{i=1}^{k} \frac{i}{k} [P(F_{i-1}) - P(F_i)].
\] (13.27)
Since
\[
\sum_{i=1}^{k} \frac{(i-1)}{k} [P(F_{i-1}) - P(F_i)] = \sum_{i=1}^{k} \frac{(i-1)}{k} P(F_{i-1}) - \sum_{i=1}^{k} \frac{i}{k} P(F_i) = \frac{1}{k} \sum_{i=1}^{k-1} P(F_i)
\]
and
\[
\sum_{i=1}^{k} \frac{i}{k} [P(F_{i-1}) - P(F_i)] = \sum_{i=1}^{k} \frac{i}{k} P(F_{i-1}) - \sum_{i=1}^{k} \frac{1}{k} [P(F_{i-1}) - P(F_i)] = \sum_{i=1}^{k-1} P(F_i) + 1/k.
\]
Eq. (13.27) becomes,
\[
\frac{1}{k} \sum_{i=1}^{k-1} P(F_i) \leq P(f) \leq \frac{1}{k} \sum_{i=1}^{k-1} P(F_i) + 1/k.
\]
Using this equation with \(P = P_n\) and then with \(P = P\) we find
\[
\limsup_{n \to \infty} P_n(f) \leq \limsup_{n \to \infty} \left[ \frac{1}{k} \sum_{i=1}^{k-1} P_n(F_i) + 1/k \right] \leq \frac{1}{k} \sum_{i=1}^{k-1} P(F_i) + 1/k \leq P(f) + 1/k.
\]
since $k$ is arbitrary, $\limsup_{n \to \infty} P_n(f) \leq P(f)$. Replacing $f$ by $1 - f$ in this inequality also gives $\liminf_{n \to \infty} P_n(f) \geq P(f)$ and hence we have shown $\lim_{n \to \infty} P_n(f) = P(f)$ as claimed. ■

Theorem 13.45 (Skorohod Theorem). Let $(X, d)$ be a separable metric space and $\{\mu_n\}^\infty_{n=0}$ be probability measures on $(X, B_X)$ such that $\mu_n \Rightarrow \mu_0$ as $n \to \infty$. Then there exists a probability space, $(\Omega, B, P)$ and measurable functions, $Y_n : \Omega \to X$, such that $\mu_n = P \circ Y_n^{-1}$ for all $n \in \mathbb{N}_0 := \mathbb{N} \cup \{0\}$ and $\lim_{n \to \infty} Y_n = Y$ a.s.

Proof. See Theorem 4.30 on page 79 of Kallenberg [7]. ■

Definition 13.46. Let $X$ be a topological space. A collection of probability measures $\Lambda$ on $(X, B_X)$ is said to be tight if for every $\varepsilon > 0$ there exists a compact set $K_\varepsilon \subset B_X$ such that $P(K_\varepsilon) \geq 1 - \varepsilon$ for all $P \in \Lambda$.

Theorem 13.47. Suppose $X$ is a separable metrizable space and $\Lambda = \{P_n\}^\infty_{n=1}$ is a tight sequence of probability measures on $B_X$. Then there exists a subsequence $\{P_{n_k}\}^\infty_{k=1}$ which is weak convergent to a probability measure $P$ on $B_X$.

Proof. First suppose that $X$ is compact. In this case $C(X)$ is a Banach space which is separable by the Stone – Weierstrass theorem, see Exercise 2?. By the Riesz theorem, Corollary 2?, we know that $C(X)^*$ is in one to one correspondence with the complex measures on $(X, B_X)$. We have also seen that $C(X)^*$ is metrizable and the unit ball in $C(X)^*$ is weak - * compact, see Theorem 2?. Hence there exists a subsequence $\{P_{n_k}\}^\infty_{k=1}$ which is weak - * convergent to a probability measure $P$ on $X$. Alternatively, use the cantor’s diagonalization procedure on a countable dense set $\Gamma \subset C(X)$ so find $\{P_{n_k}\}^\infty_{k=1}$ such that $A(f) := \lim_{k \to \infty} P_{n_k}(f)$ exists for all $f \in \Gamma$. Then for $g \in C(X)$ and $f \in \Gamma$, we have

$$|P_{n_k}(g) - P_{n_l}(g)| \leq |P_{n_k}(g) - P_{n_k}(f)| + |P_{n_l}(f) - P_{n_l}(f)|$$

$$+ |P_{n_l}(f) - P_{n_l}(g)| \leq 2\|g - f\|_\infty + |P_{n_k}(f) - P_{n_l}(f)|$$

which shows

$$\limsup_{n \to \infty} |P_{n_k}(g) - P_{n_l}(g)| \leq 2\|g - f\|_\infty.$$  

Letting $f \in \Lambda$ tend to $g$ in $C(X)$ shows $\limsup_{n \to \infty} |P_{n_k}(g) - P_{n_l}(g)| = 0$ and hence $A(g) := \lim_{k \to \infty} P_{n_k}(g)$ for all $g \in C(X)$. It is now clear that $A(g) \geq 0$ for all $g \geq 0$ so that $A$ is a positive linear functional on $X$ and thus there is a probability measure $P$ such that $A(g) = P(g)$.

General case. By Theorem 18.38 we may assume that $X$ is a subset of a compact metric space which we will denote by $\bar{X}$. We now extend $P_n$ to $\bar{X}$ by setting $\tilde{P}_n(A) := P_n(A \cap X)$ for all $A \in B_X$. By what we have just proved, there is a subsequence $\{P_k' := P_{n_k}\}^\infty_{k=1}$ such that $P_k'$ converges weakly to a probability measure $\tilde{P}$ on $X$. The main thing we now have to prove is that “$\tilde{P}(X) = 1,”$ this is where the tightness assumption is going to be used. Given $\varepsilon > 0$, let $K_\varepsilon \subset X$ be a compact set such that $\tilde{P}_n(K_\varepsilon) \geq 1 - \varepsilon$ for all $n$. Since $K_\varepsilon$ is compact in $X$ it is compact in $\bar{X}$ as well and in particular a closed subset of $\bar{X}$. Therefore by Proposition 13.44

$$\tilde{P}(K_\varepsilon) \geq \limsup_{k \to \infty} \tilde{P}_k(K_\varepsilon) = 1 - \varepsilon.$$

Since $\varepsilon > 0$ is arbitrary, this shows with $X_0 := \bigcup_{n=1}^\infty K_{1/n}$ satisfies $\tilde{P}(X_0) = 1$.

Because $X_0 \in B_X \cap B_\bar{X}$, we may view $\tilde{P}$ as a measure on $B_X$ by letting $P(A) := \tilde{P}(A \cap X_0)$ for all $A \in B_X$. Given a closed subset $F \subset X$, choose $\tilde{F} \subset \bar{X}$ such that $F = \tilde{F} \cap X$. Then

$$\limsup_{k \to \infty} P_k'(F) = \limsup_{k \to \infty} P_k'(\tilde{F}) \leq \tilde{P}(\tilde{F}) = \tilde{P}(\tilde{F} \cap X_0) = P(F),$$

which shows $P_k' \Rightarrow P$. ■
Characteristic Functions (Fourier Transform)

Definition 14.1. Given a probability measure, \( \mu \) on \( (\mathbb{R}^n, \mathcal{B}_{\mathbb{R}^n}) \), let

\[
\hat{\mu}(\lambda) := \int_{\mathbb{R}^n} e^{i\lambda \cdot x} d\mu(x)
\]

be the Fourier transform or characteristic function of \( \mu \). If \( X = (X_1, \ldots, X_n) : \Omega \rightarrow \mathbb{R}^n \) is a random vector on some probability space \((\Omega, \mathcal{B}, P)\), then we let \( f(\lambda) := f_X(\lambda) := \mathbb{E}[e^{i\lambda \cdot X}] \). Of course, if \( \mu := P \circ X^{-1} \), then \( f_X(\lambda) = \hat{\mu}(\lambda) \).

Notation 14.2. Given a measure \( \mu \) on a measurable space, \((\Omega, \mathcal{B})\) and a function, \( f \in L^1(\mu) \), we will often write \( \mu(f) \) for \( \int_\Omega f d\mu \).

Definition 14.3. Let \( \mu \) and \( \nu \) be two probability measure on \((\mathbb{R}^n, \mathcal{B}_{\mathbb{R}^n})\). The convolution of \( \mu \) and \( \nu \), denoted \( \mu \ast \nu \), is the measure, \( P \circ (X + Y)^{-1} \) where \( \{X, Y\} \) are two independent random vectors such that \( P \circ X^{-1} = \mu \) and \( P \circ Y^{-1} = \nu \).

Of course we may give a more direct definition of the convolution of \( \mu \) and \( \nu \) by observing for \( A \in \mathcal{B}_{\mathbb{R}^n} \) that

\[
\mu \ast \nu(A) = P(X + Y \in A)
\]

\[
= \int_{\mathbb{R}^n} d\mu(x) \int_{\mathbb{R}^n} d\nu(y) 1_A(x + y) \quad (14.1)
\]

\[
= \int_{\mathbb{R}^n} \nu(A - x) d\mu(x)
\]

\[
= \int_{\mathbb{R}^n} \mu(A - x) d\nu(x). \quad (14.2)
\]

Remark 14.4. Suppose that \( d\mu(x) = u(x) dx \) where \( u(x) \geq 0 \) and \( \int_{\mathbb{R}^n} u(x) dx = 1 \). Then using the translation invariance of Lebesgue measure and Tonelli’s theorem, we have

\[
\mu \ast \nu(f) = \int_{\mathbb{R}^n \times \mathbb{R}^n} f(x + y) u(x) dy dx = \int_{\mathbb{R}^n \times \mathbb{R}^n} f(x) u(x - y) dy dx
\]

from which it follows that

\[
d(\mu \ast \nu)(x) = \left[ \int_{\mathbb{R}^n} u(x - y) d\nu(y) \right] dx.
\]

If we further assume that \( d\nu(x) = v(x) dx \), then we have

\[
d(\mu \ast \nu)(x) = \left[ \int_{\mathbb{R}^n} u(x - y) v(y) dy \right] dx.
\]

To simplify notation we write,

\[
u * v(x) = \int_{\mathbb{R}^n} u(x - y) v(y) dy = \int_{\mathbb{R}^n} v(x - y) u(y) dy.
\]

Example 14.5. Suppose that \( n = 1 \), \( d\mu(x) = 1_{[0,1]}(x) dx \) and \( d\nu(x) = 1_{[-1,0]}(x) dx \) so that \( \nu(A) = \mu(-A) \). In this case

\[
d(\mu \ast \nu)(x) = \left( 1_{[0,1]} * 1_{[-1,0]} \right)(x) dx
\]

where

\[
(1_{[0,1]} * 1_{[-1,0]})(x) = \int_{\mathbb{R}} 1_{[-1,0]}(x - y) 1_{[0,1]}(y) dy
\]

\[
= \int_{\mathbb{R}} 1_{[0,1]}(y - x) 1_{[0,1]}(y) dy
\]

\[
= \int_{\mathbb{R}} 1_{[0,1]}(y) 1_{[0,1]}(y) dy
\]

\[
= m([0,1] \cap (x + [0,1])) = (1 - |x|)_+.
\]

14.1 Basic Properties of the Characteristic Function

Definition 14.6. A function \( f : \mathbb{R}^n \rightarrow \mathbb{C} \) is said to be positive definite, iff \( f(-\lambda) = \overline{f(\lambda)} \) for all \( \lambda \in \mathbb{R}^n \) and for all \( m \in \mathbb{N} \), \( \{\lambda_j\}_{j=1}^m \subset \mathbb{R}^n \) the matrix, \( \{f(\lambda_j - \lambda_k)\}_{j,k=1}^m \) is non-negative. More explicitly we require,

\[
\sum_{j,k=1}^m f(\lambda_j - \lambda_k) \xi_j \xi_k \geq 0 \text{ for all } (\xi_1, \ldots, \xi_m) \in \mathbb{C}^m.
\]
Notation 14.7 For \( l \in \mathbb{N} \cup \{0\} \), let \( C^l (\mathbb{R}^n, \mathbb{C}) \) denote the vector space of functions, \( f : \mathbb{R}^n \to \mathbb{C} \) which are \( l \)-time continuously differentiable. More explicitly, if \( \partial_j := \frac{\partial}{\partial x_j} \), then \( f \in C^l (\mathbb{R}^n, \mathbb{C}) \) if the partial derivatives, \( \partial_{j_1} \ldots \partial_{j_k} f \), exist and are continuous for \( k = 1, 2, \ldots, l \) and all \( j_1, \ldots, j_k \in \{1, 2, \ldots, n\} \).

Proposition 14.8 (Basic Properties of \( \hat{\mu} \)). Let \( \mu \) and \( \nu \) be two probability measures on \( (\mathbb{R}^n, B_{\mathbb{R}^n}) \), then:

1. \( \hat{\mu} (0) = 1 \), and \( |\hat{\mu} (\lambda)| \leq 1 \) for all \( \lambda \).
2. \( \hat{\mu} (\lambda) \) is continuous.
3. \( \hat{\mu} (\lambda) = \hat{\mu} (-\lambda) \) for all \( \lambda \in \mathbb{R}^n \) and in particular, \( \hat{\mu} \) is real valued iff \( \mu \) is symmetric, i.e. iff \( \mu (-A) = \mu (A) \) for all \( A \in B_{\mathbb{R}^n} \). (If \( \mu = P \circ X^{-1} \) for some random vector \( X \), then \( \mu \) is symmetric iff \( X \overset{d}{=} -X \).)
4. \( \hat{\mu} \) is a positive definite function. (For the converse of this result, see Bochner’s Theorem 14.41 below.
5. If \( \int_{\mathbb{R}^n} \| x \|^l \, d\mu (x) < \infty \), then \( \hat{\mu} \in C^l (\mathbb{R}^n, \mathbb{C}) \) and \( \partial_{j_1} \ldots \partial_{j_m} \hat{\mu} (\lambda) = \int_{\mathbb{R}^n} (ix_{j_1} \ldots ix_{j_m}) e^{i\lambda \cdot x} \, d\mu (x) \) for all \( m \leq l \).
6. If \( X \) and \( Y \) are independent random vectors then \( f_{X+Y} (\lambda) = f_X (\lambda) f_Y (\lambda) \) for all \( \lambda \in \mathbb{R}^n \).

This may be alternatively expressed as \( \hat{\mu} * \hat{\nu} (\lambda) = \hat{\mu} (\lambda) \hat{\nu} (\lambda) \) for all \( \lambda \in \mathbb{R}^n \).

7. If \( a \in \mathbb{R}, \, b \in \mathbb{R}^n, \) and \( X : \Omega \to \mathbb{R}^n \) is a random vector, then \( f_{aX+b} (\lambda) = e^{i\lambda \cdot b} f_{X} (a\lambda) . \)

**Proof.** The proof of items 1., 2., 6., and 7. are elementary and will be left to the reader. It also easy to see that \( \hat{\mu} (\lambda) = \hat{\mu} (-\lambda) \) and \( \hat{\mu} (\lambda) = \hat{\mu} (-\lambda) \) if \( \mu \) is symmetric. Therefore if \( \mu \) is symmetric, then \( \hat{\mu} (\lambda) \) is real. Conversely if \( \hat{\mu} (\lambda) \) is real then \( \hat{\mu} (\lambda) = \hat{\mu} (-\lambda) = \int_{\mathbb{R}^n} e^{i\lambda \cdot x} \, d\nu (x) = \hat{\nu} (\lambda) \)

where \( \nu (A) := \mu (-A) \). The uniqueness Proposition 14.10 below then implies \( \mu = \nu \), i.e. \( \mu \) is symmetric. This proves item 3.

Item 5 follows by induction using Corollary 8.38. For item 4. let \( m \in \mathbb{N}, \{\lambda_j\}_{j=1}^m \subset \mathbb{R}^n \) and \( (\xi_1, \ldots, \xi_m) \in \mathbb{C}^m \). Then

\[
\sum_{j=1}^m \hat{\mu} (\lambda_j - \lambda_k) \xi_j \xi_k = \int_{\mathbb{R}^n} \sum_{j=1}^m e^{i(\lambda_j - \lambda_k) \cdot x} \xi_j \xi_k \, d\mu (x) \\
= \int_{\mathbb{R}^n} \sum_{j=1}^m e^{i\lambda_j \cdot x} \xi_j e^{i\lambda_k \cdot x} \xi_k \, d\mu (x) \\
= \int_{\mathbb{R}^n} \sum_{j=1}^m e^{i\lambda_j \cdot x} \xi_j \, d\mu (x) \geq 0.
\]

Example 14.9 (Example 14.5 continued.). Let \( d\mu (x) = 1_{[0,1]} (x) \, dx \) and \( \nu (A) = \mu (-A) \). Then

\[
\hat{\mu} (\lambda) = \int_0^1 e^{i\lambda x} \, dx = \frac{e^{i\lambda} - 1}{i\lambda},
\]

\[
\nu (\lambda) = \hat{\mu} (-\lambda) = \frac{e^{-i\lambda} - 1}{-i\lambda}, \quad \text{and}
\]

\[
\hat{\mu} * \nu (\lambda) = \hat{\mu} (\lambda) \nu (\lambda) = |\hat{\mu} (\lambda)|^2 = \frac{\left| e^{i\lambda} - 1 \right|^2}{|i\lambda|^2} = \frac{2}{\lambda^2} \left| 1 - \cos \lambda \right|.
\]

According to example 14.5 we also have \( d (\mu * \nu) (x) = (1 - |x|)_+ \, dx \) and so directly we find

\[
\hat{\mu} * \nu (\lambda) = \int_{\mathbb{R}} e^{i\lambda x} (1 - |x|)_+ \, dx = \int_{\mathbb{R}} \cos (\lambda x) (1 - |x|)_+ \, dx \\
= 2 \int_0^1 (1-x) \cos \lambda x \, dx = 2 \int_0^1 (1-x) \frac{\sin \lambda x}{\lambda} \, dx \\
= -2 \int_0^1 (1-x) \frac{\sin \lambda x}{\lambda} \, dx = 2 \int_0^1 \sin \lambda x \, dx = \frac{2 \sin \lambda x}{\lambda^2} \bigg|_{x=1}^{x=0} \\
= 2 \frac{1 - \cos \lambda}{\lambda^2}.
\]

**Proposition 14.10 (Injectivity of the Fourier Transform).** If \( \mu \) and \( \nu \) are two probability measure on \( (\mathbb{R}^n, B_{\mathbb{R}^n}) \) such that \( \hat{\mu} = \hat{\nu} \), then \( \mu = \nu \).

**Proof.** Let \( \mathbb{H} \) be the subspace of bounded measurable complex functions, \( f : \mathbb{R}^n \to \mathbb{C}, \) such that \( \mu (f) = \nu (f) \). Then \( \mathbb{H} \) is closed under bounded convergence and complex conjugation. Suppose that \( A \subset \mathbb{Z}^d \) is a finite set, \( L > 0 \) and

\[
p (x) = \sum_{\lambda \in A} a_\lambda e^{i\lambda \cdot x/(2\pi L)}
\]
with $\alpha \in \mathbb{C}$. Then by assumption,

$$
\mu(p) = \sum_{\lambda \in A} a_\lambda \mu\left(\frac{\lambda}{2\pi L}\right) = \sum_{\lambda \in A} a_\lambda \hat{\nu}\left(\frac{\lambda}{2\pi L}\right) = \nu(p)
$$

so that $p \in \mathbb{H}$. From the Stone-Weierstrass theorem (see Exercise 14.47 below) or the theory of the Fourier series, any $f \in C(\mathbb{R}^n, \mathbb{C})$ which is $L$-periodic, (i.e. $f(x + Lc) = f(x)$ for all $x \in \mathbb{R}^n$ and $i = 1, 2, \ldots, n$) may be uniformly approximated by a trigonometric polynomial of the form in Eq. (14.4), see Exercise 14.8 below. Hence it follows from the bounded convergence theorem that $f \in \mathbb{H}$ for all $f \in C(\mathbb{R}^n, \mathbb{C})$ which are $L$-periodic. Now suppose $f \in C_c(\mathbb{R}^n, \mathbb{C})$. Then for $L > 0$ sufficiently large the function,

$$
f_L(x) := \sum_{\lambda \in \mathbb{Z}^n} f(x + L\lambda),
$$

is continuous and $L$ periodic and hence $f_L \in \mathbb{H}$. Since $f_L \to f$ boundedly as $L \to \infty$, we may further conclude that $f \in \mathbb{H}$ as well, i.e. $C_c(\mathbb{R}^n, \mathbb{C}) \subset \mathbb{H}$. An application of the multiplicative system Theorem (see either Theorem 9.3 or Theorem 9.14) implies $\mathbb{H}$ contains all bounded $\sigma(C_c(\mathbb{R}^n, \mathbb{R})) = B_{\mathbb{R}^n}$ measurable functions and this certainly implies $\mu = \nu$.

For the most part we are now going to stick to the one dimensional case, i.e. $X$ will be a random variable and $\mu$ will be a probability measure on $(\mathbb{R}, B_\mathbb{R})$. The following Lemma is a special case of item 4. of Proposition 14.8.

**Lemma 14.11.** Suppose $n \in \mathbb{N}$ and $X$ is random variables such that $E[|X|^n] < \infty$. If $\mu = P \circ X^{-1}$ is the distribution of $X$, then $\hat{\mu}(\lambda) := E[e^{i\lambda X}]$ is $C^m$-differentiable and

$$
\hat{\mu}^{(l)}(\lambda) = E[(iX)^l e^{i\lambda X}] = \int_\mathbb{R} (ix)^l e^{i\lambda x} d\mu(x) \quad \text{for } l = 0, 1, 2, \ldots, n.
$$

In particular it follows that

$$
E[X^l] = \frac{\hat{\mu}^{(l)}(0)}{i^l}.
$$

The following theorem is a partial converse to this lemma. Hence the combination of Lemma 14.11 and Theorem 14.12 (see also Corollary 14.34 below) shows that there is a correspondence between the number of moments of $X$ and the differentiability of $f_X$.

**Theorem 14.12.** Let $X$ be a random variable, $m \in \{0, 1, 2, \ldots\}$, $f(\lambda) = E[e^{i\lambda X}]$. If $f \in C^{2m}(\mathbb{R}, \mathbb{C})$ such that $g := f^{(2m)}$ is differentiable in a neighborhood of 0 and $g''(0) = f^{(2m+2)}(0)$ exists. Then $E[X^{2m+2}] < \infty$ and $f \in C^{2m+2}(\mathbb{R}, \mathbb{C})$.

**Proof.** This will be proved by induction on $m$. We start with $m = 0$ in which case we automatically we know by Proposition 14.8 or Lemma 14.11 that $f \in C(\mathbb{R}, \mathbb{C})$. Since

$$
u(\lambda) := \Re f(\lambda) = E[\cos(\lambda X)],
$$

it follows that $u$ is an even function of $\lambda$ and hence $u' = \Re f'$ is an odd function of $\lambda$ and in particular, $u'(0) = 0$. By the mean value theorem, to each $\lambda > 0$ with $\lambda$ near 0, there exists $0 < c_\lambda < \lambda$ such that

$$
\frac{u(\lambda) - u(0)}{\lambda} = u'(c_\lambda) = u'(\lambda) - u'(0).
$$

Therefore,

$$
\frac{u(0) - u(\lambda)}{\lambda c_\lambda} = \frac{-u'(c_\lambda)}{c_\lambda} \to -u''(0) \quad \text{as } \lambda \downarrow 0.
$$

Since

$$
E\left[\frac{1 - \cos(\lambda X)}{\lambda^2}\right] \leq E\left[\frac{1 - \cos(\lambda X)}{\lambda c_\lambda}\right] = \frac{u(0) - u(\lambda)}{\lambda c_\lambda}
$$

and $\lim_{\lambda \to 0} \frac{1 - \cos(\lambda X)}{\lambda^2} = \frac{1}{2} X^2$, we may apply Fatou’s lemma to conclude,

$$
\frac{1}{2} E[X^2] \leq \liminf_{\lambda \to 0} E\left[\frac{1 - \cos(\lambda X)}{\lambda^2}\right] \leq -u''(0) < \infty.
$$

An application of Lemma 14.11 then implies that $f \in C^2(\mathbb{R}, \mathbb{C})$.

For the general induction step we assume the truth of the theorem at level $m$ in which case we know by Lemma 14.11 that

$$f^{(2m)}(\lambda) = (-1)^m E[X^{2m} e^{i\lambda X}] = (-1)^m g(\lambda).
$$

By assumption we know that $g$ is differentiable in a neighborhood of 0 and that $g''(0)$ exists. We now proceed exactly as before but now with $u := \Re g$. So for each $\lambda > 0$ near 0, there exists $c_\lambda \in (0, \lambda)$ such that

$$
\frac{u(0) - u(\lambda)}{\lambda c_\lambda} \to -u''(0) \quad \text{as } \lambda \downarrow 0
$$

and

$$
E\left[X^{2m+2} \frac{1 - \cos(\lambda X)}{\lambda^2}\right] \leq E\left[X^{2m} \frac{1 - \cos(\lambda X)}{\lambda c_\lambda}\right] = \frac{u(0) - u(\lambda)}{\lambda c_\lambda}.
$$

Another use of Fatou’s lemma gives,

$$
\frac{1}{2} E[X^{2m+2}] \leq \liminf_{\lambda \to 0} E\left[X^{2m+2} \frac{1 - \cos(\lambda X)}{\lambda^2}\right] \leq -u''(0) < \infty
$$

from which Lemma 14.11 may be used to show $f \in C^{2m+2}(\mathbb{R}, \mathbb{C})$. This completes the induction argument.

\[\text{Page: 165} \quad \text{job: prob} \quad \text{macro: svmobob.cls} \quad \text{date/time: 17-Apr-2007/22:02}\]
14.2 Examples

Example 14.13. If \(-\infty < a < b < \infty\) and \(d\mu (x) = \frac{1}{b-a} \mathbb{1}_{[a,b]} (x) \, dx\) then
\[
\hat{\mu} (\lambda) = \frac{1}{b-a} \int_a^b e^{i\lambda x} \, dx = \frac{e^{i\lambda b} - e^{i\lambda a}}{i\lambda (b-a)}.
\]
If \(a = -c\) and \(b = c\) with \(c > 0\), then
\[
\hat{\mu} (\lambda) = \frac{\sin \lambda c}{\lambda c}.
\]
Observe that
\[
\hat{\mu} (\lambda) = 1 - \frac{1}{3!} \lambda^2 c^2 + \ldots
\]
and therefore, \(\hat{\mu}' (0) = 0\) and \(\hat{\mu}'' (0) = -\frac{1}{3} c^2\) and hence it follows that
\[
\int_{\mathbb{R}} x \, d\mu (x) = 0 \quad \text{and} \quad \int_{\mathbb{R}} x^2 \, d\mu (x) = \frac{1}{3} c^2.
\]

Example 14.14. Suppose \(Z\) is a Poisson random variable with mean \(a > 0\), i.e.
\[P (Z = n) = e^{-a} \frac{a^n}{n!}.\]
Then
\[
f_Z (\lambda) = \mathbb{E} [e^{i\lambda Z}] = e^{-a} \sum_{n=0}^\infty e^{i\lambda n} \frac{a^n}{n!} = e^{-a} \sum_{n=0}^\infty \left(\frac{ae^{i\lambda}}{n!}\right)^n = \exp \left(a \left(e^{i\lambda} - 1\right)\right).
\]
Differentiating this result gives,
\[
f'_Z (\lambda) = iae^{i\lambda} \exp \left(a \left(e^{i\lambda} - 1\right)\right) \quad \text{and} \quad f''_Z (\lambda) = \left(-a^2 e^{2i\lambda} - ae^{i\lambda}\right) \exp \left(a \left(e^{i\lambda} - 1\right)\right)
\]
from which we conclude,
\[
\mathbb{E}Z = \frac{1}{i} f'_Z (0) = a \quad \text{and} \quad \mathbb{E}Z^2 = -f''_Z (0) = a^2 + a.
\]
Therefore,
\[
\mathbb{E}Z = a = \text{Var} (Z).
\]

Example 14.15. Suppose \(T\) is a positive random variable such that
\[P (T \leq t + s | T \geq s) = P (T \leq t)\] for all \(s, t \geq 0\), or equivalently
\[P (T \geq t + s) = P (T \geq t) P (T \geq s)\] for all \(s, t \geq 0,
\]
then \(P (T \geq t) = e^{-at}\) for some \(a > 0\). (Such exponential random variables are often used to model “waiting times.”) The distribution function for \(T\) is
\[F_T (t) := P (T \leq t) = 1 - e^{-a(t+0)}.\] Since \(F_T (t)\) is piecewise differentiable, the law of \(T\), \(\mu := P \circ T^{-1}\), has a density,
\[
d\mu (t) = F'_T (t) \, dt = ae^{-at} \mathbb{1}_{[0, \infty)} (t) \, dt.
\]
Therefore,
\[
\mathbb{E} [e^{iaT}] = \int_0^\infty ae^{-at} e^{it} \, dt = \frac{a}{a - i\lambda} = \hat{\mu} (\lambda).
\]
Since
\[
\hat{\mu}' (\lambda) = i \frac{a}{(a - i\lambda)^2} \quad \text{and} \quad \hat{\mu}'' (\lambda) = -2 \frac{a}{(a - i\lambda)^3}
\]
it follows that
\[
\mathbb{E}T = \frac{\hat{\mu}' (0)}{i} = a^{-1} \quad \text{and} \quad \mathbb{E}T^2 = \frac{\hat{\mu}'' (0)}{i^2} = \frac{2}{a^2}
\]
and hence \(\text{Var} (T) = \frac{2}{a^2} - \left(\frac{1}{a}\right)^2 = a^{-2}.
\]

Proposition 14.16. If \(d\mu (x) := \frac{1}{\sqrt{2\pi}} e^{-x^2/2} \, dx\), then \(\hat{\mu} (\lambda) = e^{-\lambda^2/2}\). In particular we have
\[
\int_{\mathbb{R}} x \, d\mu (x) = 0 \quad \text{and} \quad \int_{\mathbb{R}} x^2 \, d\mu (x) = 1.
\]

Proof. Differentiating the formula,
\[
\hat{\mu} (\lambda) = \frac{1}{\sqrt{2\pi}} \int_{\mathbb{R}} e^{-x^2/2} e^{i\lambda x} \, dx,
\]
for \(\hat{\mu}\) with respect to \(\lambda\) and then integrating by parts implies,
\[
\hat{\mu}' (\lambda) = \frac{1}{\sqrt{2\pi}} \int_{\mathbb{R}} ixe^{-x^2/2} e^{i\lambda x} \, dx
\]
\[
= \frac{i}{\sqrt{2\pi}} \int_{\mathbb{R}} \left[-\frac{d}{dx} e^{-x^2/2}\right] e^{i\lambda x} \, dx
\]
\[
= \frac{i}{\sqrt{2\pi}} \int_{\mathbb{R}} e^{-x^2/2} \frac{d}{dx} e^{i\lambda x} \, dx = -\lambda \hat{\mu} (\lambda).
\]
Solving this equation of \(\hat{\mu} (\lambda)\) then implies
\[
\hat{\mu} (\lambda) = e^{-\lambda^2/2} \hat{\mu} (0) = e^{-\lambda^2/2} \hat{\mu} (\mathbb{R}) = e^{-\lambda^2/2}.
\]
Example 14.17. If \( \mu \) is a probability measure on \((\mathbb{R}, \mathcal{B}_\mathbb{R})\) and \( n \in \mathbb{N} \), then \( \hat{\mu}^n \) is the characteristic function of the probability measure, namely the measure

\[
\hat{\mu}^n := \underbrace{\mu \ast \cdots \ast \mu}_{n \text{ times}}.
\]

(14.5)

Alternatively put, if \( \{X_k\}_{k=1}^n \) are i.i.d. random variables with \( \mu = P \circ X_k^{-1} \), then

\[
f_{X_1 + \cdots + X_n} (\lambda) = f_X^n (\lambda).
\]

Example 14.18. Suppose that \( \{\mu_n\}_{n=0}^\infty \) are probability measure on \((\mathbb{R}, \mathcal{B}_\mathbb{R})\) and \( \{p_n\}_{n=0}^\infty \subset [0, 1] \) such that \( \sum_{n=0}^\infty p_n = 1 \). Then \( \sum_{n=0}^\infty p_n \mu_n \) is the characteristic function of the probability measure,

\[
\mu := \sum_{n=0}^\infty p_n \mu_n.
\]

Here is a more interesting interpretation of \( \mu \). Let \( \{X_n\}_{n=0}^\infty \cup \{T\} \) be independent random variables with \( P \circ X_n^{-1} = \mu_n \) and \( P \{ T = n \} = p_n \) for all \( n \in \mathbb{N}_0 \). Then \( \mu (A) = P (X_T \in A) \), where \( X_T (\omega) := X_{T(\omega)} \). Indeed,

\[
\mu (A) = P (X_T \in A) = \sum_{n=0}^\infty P (X_T \in A, T = n) = \sum_{n=0}^\infty P (X_n \in A, T = n) = \sum_{n=0}^\infty P (X_n \in A, T = n) = \sum_{n=0}^\infty p_n \mu_n (A).
\]

Let us also observe that

\[
\hat{\mu} (\lambda) = \mathbb{E} [e^{i\lambda X_T}] = \sum_{n=0}^\infty \mathbb{E} [e^{i\lambda X_T} : T = n] = \sum_{n=0}^\infty \mathbb{E} [e^{i\lambda X_n} : T = n] = \sum_{n=0}^\infty \mathbb{E} [e^{i\lambda X_n}] P (T = n) = \sum_{n=0}^\infty p_n \hat{\mu}_n (\lambda).
\]

Example 14.19. If \( \mu \) is a probability measure on \((\mathbb{R}, \mathcal{B}_\mathbb{R})\) then \( \sum_{n=0}^\infty p_n \hat{\mu}^n \) is the characteristic function of a probability measure, \( \nu \), on \((\mathbb{R}, \mathcal{B}_\mathbb{R})\). In this case, \( \nu := \sum_{n=0}^\infty p_n \hat{\mu}^n \) where \( \hat{\mu}^n \) is defined in Eq. (14.5). As an explicit example, if \( a > 0 \) and \( p_n = \frac{a^n}{n!} e^{-a} \), then

\[
\sum_{n=0}^\infty p_n \hat{\mu}_n = \sum_{n=0}^\infty a^n n! e^{-a} \hat{\mu}_n = e^{-a} e^{a \hat{\mu}} = e^{a \hat{\mu} - a} \hat{\mu} = \mu (\hat{\mu}^{-1})
\]

is the characteristic function of a probability measure. In other words,

\[
f_{X_T} (\lambda) = \mathbb{E} [e^{i\lambda X_T}] = \exp (a (f_X (\lambda) - 1)).
\]

14.3 Continuity Theorem

Lemma 14.20 (Tail Estimate). Let \( X : (\Omega, \mathcal{B}, P) \to \mathbb{R} \) be a random variable and \( f_X (\lambda) := \mathbb{E} [e^{i\lambda X}] \) be its characteristic function. Then for \( a > 0 \),

\[
P (|X| \geq a) \leq \frac{a}{2} \int_{-2/a}^{2/a} (1 - f_X (\lambda)) d\lambda = \frac{a}{2} \int_{-2/a}^{2/a} (1 - \Re f_X (\lambda)) d\lambda
\]

(14.6)

Proof. Recall that the Fourier transform of the uniform distribution on \([-c, c]\) is \( \frac{\sin \lambda c}{\lambda c} \) and hence

\[
\frac{1}{2c} \int_{-c}^{c} f_X (\lambda) d\lambda = \frac{1}{2c} \int_{-c}^{c} \mathbb{E} [e^{i\lambda X}] d\lambda = \mathbb{E} \left[ \frac{\sin \lambda c}{\lambda c} \right].
\]

Therefore,

\[
\frac{1}{2c} \int_{-c}^{c} (1 - f_X (\lambda)) d\lambda = 1 - \mathbb{E} \left[ \frac{\sin \lambda c}{\lambda c} \right] = \mathbb{E} [Y_c]
\]

(14.7)

where

\[
Y_c := 1 - \frac{\sin \lambda c}{\lambda c}.
\]

Notice that \( Y_c \geq 0 \) (see Eq. (14.47)) and moreover, \( Y_c \geq 1/2 \) if \( |c| \geq 2 \). Hence we may conclude

\[
\mathbb{E} [Y_c] \geq \mathbb{E} [Y_c : |c| \geq 2] \geq \mathbb{E} \left[ \frac{1}{2} : |c| \geq 2 \right] = \frac{1}{2} P (|X| \geq 2/c).
\]

Combining this estimate with Eq. (14.7) shows,

\[
\frac{1}{2c} \int_{-c}^{c} (1 - f_X (\lambda)) d\lambda \geq \frac{1}{2} P (|X| \geq 2/c).
\]

Taking \( a = 2/c \) in this estimate proves Eq. (14.6).

Theorem 14.21 (Continuity Theorem). Suppose that \( \{\mu_n\}_{n=1}^\infty \) is a sequence of probability measure on \((\mathbb{R}, \mathcal{B}_\mathbb{R})\) and suppose that \( f (\lambda) := \lim_{n \to \infty} \hat{\mu}_n (\lambda) \) exists for all \( \lambda \in \mathbb{R} \). If \( f \) is continuous at \( \lambda = 0 \), then \( f \) is the characteristic function of a unique probability measure, \( \mu \), on \( \mathcal{B}_\mathbb{R} \) and \( \mu_n \Rightarrow \mu \) as \( n \to \infty \).

Proof. By the continuity of \( f \) at \( \lambda = 0 \), for every \( \varepsilon > 0 \) we may choose \( a_\varepsilon \) sufficiently large so that

\[
\frac{1}{2} a_\varepsilon \int_{-2/a_\varepsilon}^{2/a_\varepsilon} (1 - \Re f (\lambda)) d\lambda \leq \varepsilon / 2.
\]
According to Lemma 14.20 and the DCT,
\[ \mu_n \left( \{ x : |x| \geq a \varepsilon \} \right) \leq \frac{1}{2} a \varepsilon \int_{-a\varepsilon}^{a\varepsilon} (1 - \text{Re} \hat{\mu}_n (\lambda)) d \lambda \]
\[ \to \frac{1}{2} a \varepsilon \int_{-a\varepsilon}^{a\varepsilon} (1 - \text{Re} f (\lambda)) d \lambda \leq \varepsilon / 2. \]

Hence \( \mu_n \left( \{ x : |x| \geq a \varepsilon \} \right) \leq \varepsilon \) for all sufficiently large \( n \), say \( n \geq N \). By increasing \( a \varepsilon \) if necessary we can assure that \( \mu_n \left( \{ x : |x| \geq a \varepsilon \} \right) \leq \varepsilon \) for all \( n \) and hence \( \Gamma := \left\{ \mu_n \right\}_{n=1}^{\infty} \) is tight.

By Theorem 13.42 we may find a subsequence, \( \{\mu_{n_k}\}_{k=1}^{\infty} \) and a probability measure \( \mu \) on \( \mathbb{B} \) such that \( \mu_{n_k} \rightharpoonup \mu \) as \( k \to \infty \). Since \( \mu \) is the characteristic function of a probability measure, \( \mu \), and \( f \) is a bounded and continuous function, it follows that
\[ \hat{\mu} (\lambda) = \lim_{k \to \infty} \mu_{n_k} (\lambda) = f (\lambda) \]
for all \( \lambda \in \mathbb{R} \), that is \( f \) is the characteristic function of a probability measure, \( \mu \).

We now claim that \( \mu \rightharpoonup \mu \) as \( n \to \infty \). If not, we could find a bounded continuous function, \( g \), such that \( \lim_{n \to \infty} \mu_n (g) \neq \mu (g) \) or equivalently, there would exist \( \varepsilon > 0 \) and a subsequence \( \{\mu'_{n_k}\} \) such that
\[ |\mu (g) - \mu'_{n_k} (g)| \geq \varepsilon \]
for all \( k \in \mathbb{N} \).

However by Theorem 13.42 again, there is a further subsequence, \( \mu''_{n_k} = \mu'_{n_{k_l}} \) of \( \mu''_{n_k} \) such that \( \mu''_{n_{k_l}} \rightharpoonup \nu \) for some probability measure \( \nu \). Since \( \hat{\nu} (\lambda) = \lim_{n \to \infty} \hat{\mu''_{n}} (\lambda) = f (\lambda) = \hat{\mu} (\lambda) \), it follows that \( \mu = \nu \). This leads to a contradiction since
\[ \varepsilon \leq \lim_{l \to \infty} |\mu (g) - \mu''_{n} (g)| = |\mu (g) - \nu (g)| = 0. \]

Remark 14.22. One could also use Bochner’s Theorem 14.41 to conclude; if \( f (\lambda) = \lim_{n \to \infty} \hat{\mu}_n (\lambda) \) is continuous then \( f \) is the characteristic function of a probability measure. Indeed, the condition of a function being positive definite is preserved under taking pointwise limits.

Exercise 14.1. Suppose now \( X : (\Omega, \mathcal{B}, P) \to \mathbb{R}^d \) is a random vector and \( f_X (\lambda) := \mathbb{E} [e^{i\lambda X}] \) is its characteristic function. Show for \( a > 0 \),
\[ P(\|X\| \geq a) \leq 2 \left( \frac{a}{4} \right)^d \int_{[-a/2,a/2]^d} (1 - f_X (\lambda)) d \lambda = 2 \left( \frac{a}{4} \right)^d \int_{[-a/2,a/2]^d} (1 - \text{Re} f_X (\lambda)) d \lambda \]
where \( |X| = \max_i |X_i| \) and \( d \lambda = d \lambda_1 \ldots, d \lambda_d \).

Solution to Exercise (14.1). Working as above, we have
\[ \left( \frac{1}{2c} \right)^d \int_{[-c,c]^d} (1 - e^{i\lambda \cdot X}) d \lambda = 1 - \prod_{j=1}^d \sin \frac{c X_j}{c \lambda} =: Y_c, \]
for all \( c > 0 \) and \( c \geq 1/2 \) if \( c |X_j| \geq 2 \) for some \( j \), i.e. if \( c |X| \geq 2 \).

Therefore taking expectations of Eq. (14.9) implies,
\[ \left( \frac{1}{2c} \right)^d \int_{[-c,c]^d} (1 - f_X (\lambda)) d \lambda = \mathbb{E} [Y_c] \geq \mathbb{E} [Y_c : |X| \geq 2/c] \]
\[ \geq \mathbb{E} \left[ \left( \frac{1}{2} : |X| \geq 2/c \right) \right] = \frac{1}{2} P(|X| \geq 2/c). \]
Taking \( c = 2/a \) in this expression implies Eq. (14.8).

The following lemma will be needed before giving our first applications of the continuity theorem.

Lemma 14.23. Suppose that \( \{z_n\}_{n=1}^{\infty} \subset \mathbb{C} \) satisfies, \( \lim_{n \to \infty} n z_n = \xi \in \mathbb{C} \), then
\[ \lim_{n \to \infty} (1 + z_n)^n = e^\xi. \]

Proof. Since \( n z_n \to \xi \), it follows that \( z_n \sim \xi / n \to 0 \) as \( n \to \infty \) and therefore by Lemma 14.23 below, \( (1 + z_n)^n = e^{nx(nz_n)} \) and
\[ \ln (1 + z_n) = z_n + O \left( \frac{z_n^2}{n^2} \right). \]

Therefore,
\[ (1 + z_n)^n = \left[ e^{nx(nz_n)} \right]^n = e^{nx(nz_n)} = e^{n(z_n + O(\frac{1}{n}))} \to e^\xi \text{ as } n \to \infty. \]

Proposition 14.24 (Weak Law of Large Numbers revisited). Suppose that \( \{X_n\}_{n=1}^{\infty} \) are i.i.d. integrable random variables. Then \( \frac{S_n}{n} \to \mathbb{E} X_1 : = \mu \).

Proof. Let \( f (\lambda) := f_{X_1} (\lambda) = \mathbb{E} [e^{i\lambda X_1}] \). Then by Taylor’s theorem, \( f (\lambda) = 1 + i \mu \lambda + o (\lambda) \). Since,
\[ f_{S_n} (\lambda) = \left[ f \left( \frac{\lambda}{n} \right) \right]^n = \left[ 1 + i \mu \frac{\lambda}{n} + o \left( \frac{1}{n} \right) \right]^n \]

it follows from Lemma 14.23 that
which is the characteristic function of the constant random variable, $\mu$. By the continuity Theorem 14.21, it follows that $\frac{S_n}{\sqrt{n}} \implies \mu$ and since $\mu$ is constant we may apply Lemma 13.19 to conclude $\frac{S_n}{\sqrt{n}} \xrightarrow{p} \mu$. \hfill $\blacksquare$

**Theorem 14.25 (The Basic Central Limit Theorem).** Suppose that $(X_n)_{n=1}^\infty$ are i.i.d. square integrable random variables such that $E X_1 = 0$ and $E X_1^2 = 1$. Then $\frac{S_n}{\sqrt{n}} \implies N(0, 1)$.

**Proof.** By Theorem 14.21 and Proposition 14.10 it suffices to show

$$\lim_{n \to \infty} E \left[ e^{i\lambda \frac{S_n}{\sqrt{n}}} \right] = e^{-\lambda^2/2}$$

for all $\lambda \in \mathbb{R}$.

Letting $f(\lambda) := E \left[ e^{i\lambda X_1} \right]$, we have by Taylor’s theorem (see Eq. (14.43) and (14.46)) that

$$f(\lambda) = 1 - \frac{1}{2} \left( 1 + \varepsilon(\lambda) \right) \lambda^2$$

where $\varepsilon(\lambda) \to 0$ as $\lambda \to 0$. Therefore,

$$f_{\frac{S_n}{\sqrt{n}}}(\lambda) = E \left[ e^{i\lambda \frac{S_n}{\sqrt{n}}} \right] = \left[ f \left( \frac{\lambda}{\sqrt{n}} \right) \right]^n$$

wherein we have used Lemma 14.23 with

$$z_n = -\frac{1}{2} \left( 1 + \varepsilon \left( \frac{\lambda}{\sqrt{n}} \right) \right) \frac{\lambda^2}{n}.$$

**Alternative proof.** This proof uses Lemma 15.6 below as follows:

$$\left| f_{\frac{S_n}{\sqrt{n}}}(\lambda) - e^{-\lambda^2/2} \right| = \left| \left[ f \left( \frac{\lambda}{\sqrt{n}} \right) \right]^n - \left[ e^{-\lambda^2/2n} \right]^n \right|$$

$$\leq n \left| f \left( \frac{\lambda}{\sqrt{n}} \right) - e^{-\lambda^2/2n} \right|$$

$$= n \left| 1 - \frac{1}{2} \left( 1 + \varepsilon \left( \frac{\lambda}{\sqrt{n}} \right) \right) \frac{\lambda^2}{n} - \left( 1 - \frac{\lambda^2}{2n} + O \left( \frac{1}{n^2} \right) \right) \right|$$

$$\to 0 \text{ as } n \to \infty.$$
Theorem 14.28 (A Non-Characteristic Proof of the CLT). Suppose that 
\( \{X_n\}_{n=1}^{\infty} \) are mean zero variance one i.i.d random variables such that \( \mathbb{E}|X_1|^3 < \infty \). Then for \( f \in C^3 (\mathbb{R}) \) with \( M := \sup_{x \in \mathbb{R}} |f^{(3)}(x)| < \infty \),
\[
\left| \mathbb{E} \left[ f \left( \frac{S_n}{\sqrt{n}} \right) \right] - \mathbb{E} f(N) \right| \leq \frac{1}{\sqrt{n}} \frac{M}{3!} \mathbb{E} \left[ |N|^3 + |X_1|^3 \right] 
\]  
(14.13)
where \( S_n := X_1 + \cdots + X_n \) and \( N \overset{d}{=} N(0,1) \).

Proof. Let \( \{\tilde{X}_n, N_n\}_{n=1}^{\infty} \) be independent random variables such that \( N_n \overset{d}{=} N(0,1) \) and \( \tilde{X}_n \overset{d}{=} X_1 \). To simplify notation, we will denote \( \tilde{X}_n \) by \( X_n \). Let \( T_n := N_1 + \cdots + N_n \) and for \( 0 \leq k \leq n \), let
\[
V_k := (N_1 + \cdots + N_k + X_{k+1} + \cdots + X_n) / \sqrt{n}
\]
with the convention that \( V_n = S_n / \sqrt{n} \) and \( V_0 = T_n / \sqrt{n} \). Then by a telescoping series argument, it follows that
\[
f \left( \frac{S_n}{\sqrt{n}} \right) - f \left( \frac{T_n}{\sqrt{n}} \right) = f \left( V_n \right) - f \left( V_0 \right) = \sum_{k=1}^{n} [f \left( V_k \right) - f \left( V_{k-1} \right)] .
\]  
(14.14)
We now make use of Taylor’s theorem with integral remainder the form,
\[
f (x + \Delta) - f(x) = f'(x) \Delta + \frac{1}{2} f''(x) \Delta^2 + r(x, \Delta) \Delta^3
\]  
(14.15)
where
\[
r(x, \Delta) := \frac{1}{2} \int_{0}^{1} f'''(x + t\Delta) (1-t)^2 \, dt.
\]
Taking Eq. (14.15) with \( \Delta \) replaced by \( \delta \) and subtracting the results then implies
\[
f (x + \delta) - f(x + \Delta) = f'(x) (\Delta - \delta) + \frac{1}{2} f''(x) (\Delta^2 - \delta^2) + r(x, \Delta),
\]  
(14.16)
where
\[
|\rho(x, \Delta)| = |r(x, \Delta)| \Delta^3 - r(x, \delta) \delta^3 \leq \frac{M}{3!} \left[ |\Delta|^3 + |\delta|^3 \right],
\]  
(14.17)
wherein we have used the simple estimate, \( |r(x, \Delta)| \leq M/3! \).

If we define \( U_k := (N_1 + \cdots + N_{k-1} + X_{k+1} + \cdots + X_n) / \sqrt{n} \), then \( V_k = U_k + N_k / \sqrt{n} \) and \( V_{k-1} = U_k + X_k / \sqrt{n} \). Hence, using Eq. (14.16) with \( x = U_k \), \( \Delta = N_k / \sqrt{n} \) and \( \delta = X_k / \sqrt{n} \), it follows that
\[
f (V_k) - f (V_{k-1}) = f (U_k + N_k / \sqrt{n}) - f (U_k + X_k / \sqrt{n})
\]
\[
= \frac{1}{\sqrt{n}} f' (U_k) (N_k - X_k) + \frac{1}{2n} f'' (U_k) (N_k - X_k)^2 + R_k
\]  
(14.18)
where
\[
|R_k| \leq \frac{M}{3! \cdot n^{3/2}} \left[ |N_k|^3 + |X_k|^3 \right].
\]  
(14.19)
Taking expectations of Eq. (14.18) using Eq. (14.19), \( \mathbb{E} N_k = 1 = \mathbb{E} X_k \), \( \mathbb{E} N_k^2 = 1 = \mathbb{E} X_k^2 \) and the fact that \( U_k \) is independent of both \( X_k \) and \( N_k \), we find
\[
|\mathbb{E} [f (V_k) - f (V_{k-1})]| \leq |\mathbb{E} R_k| \leq \frac{M}{3! \cdot n^{3/2}} \mathbb{E} \left[ |N_k|^3 + |X_k|^3 \right]
\]
\[
\leq \frac{M}{3! \cdot n^{3/2}} \mathbb{E} \left[ |N_k|^3 + |X_k|^3 \right].
\]
Combining this estimate with Eq. (14.14) shows,
\[
|\mathbb{E} [f (S_n / \sqrt{n}) - f (T_n / \sqrt{n})]| \leq \sum_{k=1}^{n} \mathbb{E} |R_k| \leq \frac{1}{\sqrt{n}} \frac{M}{3!} \mathbb{E} \left[ |N_1|^3 + |X_1|^3 \right].
\]
This completes the proof of Eq. (14.13) since \( T_n \overset{d}{=} N(0,1) \).

\[
f_{X_n} (\lambda) = \left[ f_N \left( \frac{\lambda}{\sqrt{n}} \right) \right]^n = \exp \left( -\frac{1}{2} \lambda^2 / n \right) = \exp \left( -\lambda^2 / 2 \right) = f_N (\lambda).
\]

For more in this direction the reader is advised to look up “Stein’s method.”
14.4 A Fourier Transform Inversion Formula

Proposition [14.10] guarantees the injectivity of the Fourier transform on the space of probability measures. Our next goal is to find an inversion formula for the Fourier transform. To motivate the construction below, let us first recall a few facts about Fourier series. To keep our exposition as simple as possible, we now restrict ourselves to the one dimensional case.

For \( f \in L^2([-\pi L, \pi L], dx) \), then suggests that \( \hat{f}(\lambda) = \frac{1}{\pi L} \int_{-\pi L}^{\pi L} f(y) e^{-i\lambda y} dy \) \( e^{-i\frac{\pi}{L} x} \) and we are lead to expect, \( f(x) = \frac{1}{\pi L} \int_{-\pi}^{\pi} \hat{f}(\lambda) e^{-i\lambda x} d\lambda \)

This should provide some motivation for Theorem 14.30 below. The following lemma is needed in the proof of the inversion Theorem 14.30 below.

**Lemma 14.29.** For \( c > 0 \), let

\[
S(c) := \frac{1}{2\pi} \int_{-c}^{c} \frac{\sin \lambda}{\lambda} d\lambda.
\]

Then \( S(c) \to \pi \) boundedly as \( c \to \infty \) and

\[
\int_{-c}^{c} \frac{\sin \lambda y}{\lambda} d\lambda = \text{sgn}(y) S(c |y|) \quad \text{for all } y \in \mathbb{R}.
\]

where

\[
\text{sgn}(y) = \begin{cases} 
1 & \text{if } y > 0 \\
-1 & \text{if } y < 0 \\
0 & \text{if } y = 0 
\end{cases}
\]

**Proof.** The first assertion has already been dealt with in Example [10.12]. We will repeat the argument here for the reader’s convenience. By symmetry and Fubini’s theorem,

\[
S(c) = \frac{1}{\pi} \int_{0}^{c} \frac{\sin \lambda}{\lambda} d\lambda = \frac{1}{\pi} \int_{0}^{c} \sin \lambda \left( \int_{0}^{\infty} e^{-\lambda t} dt \right) d\lambda
\]

and we are lead to expect,

\[
\int_{-c}^{c} \frac{\sin \lambda y}{\lambda} d\lambda = \text{sgn}(y) S(c |y|) \quad \text{for all } y \in \mathbb{R}.
\]

Hence if we now think that \( f(x) \) is a probability density and let \( d\mu(x) := f(x) dx \) so that \( \hat{\mu}(\lambda) = \hat{f}(\lambda) \), we should expect

\[
\mu([a, b]) = \int_{a}^{b} f(x) dx = \int_{a}^{b} \left[ \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{\mu}(\lambda) e^{-i\lambda x} d\lambda \right] dx.
\]

This yields

\[
= \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{\mu}(\lambda) \left( \int_{a}^{b} e^{-i\lambda x} dx \right) d\lambda
\]

and we have used

\[
\int_{0}^{c} \lambda \sin \lambda e^{-\lambda t} = \text{Im} \int_{0}^{c} \lambda e^{i\lambda t} e^{-\lambda t} = \text{Im} \int_{0}^{c} \lambda e^{i\lambda t} dt
\]

wherein we have used

\[
= \text{Im} \left( \frac{(e^{i\lambda t}) e^{-1}}{i - t} \right) = \frac{1}{1 + t^2} \text{Im} \left( e^{i\lambda t} - 1 \right) (-i - t)
\]

and we have used

\[
\int_{a}^{b} e^{-i\lambda x} dx = \frac{1}{i\lambda} \left( e^{-i\lambda b} - e^{-i\lambda a} \right).
\]
Theorem 14.30 (Fourier Inversion Formula). If \( \mu \) is a probability measure on \((\mathbb{R}, B_\mathbb{R})\) and \(-\infty < a < b < \infty\), then
\[
\lim_{c \to \infty} \frac{1}{2\pi} \int_{-c}^{c} \hat{\mu} (\lambda) \left( \frac{e^{-i\lambda a} - e^{-i\lambda b}}{i\lambda} \right) d\lambda = \mu ((a, b)) + \frac{1}{2} (\mu (\{a\}) + \mu (\{b\})).
\]

Proof. By Fubini’s theorem and Lemma 14.29,
\[
I (c) := \int_{-c}^{c} \hat{\mu} (\lambda) \left( \frac{e^{-i\lambda a} - e^{-i\lambda b}}{i\lambda} \right) d\lambda
\]
\[
= \int_{-c}^{c} \left( \int_{\mathbb{R}} e^{i\lambda x} d\mu (x) \right) \left( \frac{e^{-i\lambda a} - e^{-i\lambda b}}{i\lambda} \right) d\lambda
\]
\[
= \int_{\mathbb{R}} d\mu (x) \int_{-c}^{c} e^{i\lambda x} \left( \frac{e^{-i\lambda a} - e^{-i\lambda b}}{i\lambda} \right) d\lambda
\]
\[
= \int_{\mathbb{R}} d\mu (x) \int_{-c}^{c} \frac{e^{-i\lambda (a-x)} - e^{-i\lambda (b-x)}}{i\lambda} d\lambda.
\]
Since
\[
\text{Im} \left( \frac{e^{-i\lambda (a-x)} - e^{-i\lambda (b-x)}}{i\lambda} \right) = - \left( \cos \left( \lambda (a-x) \right) - \cos \left( \lambda (b-x) \right) \right)
\]
is an odd function of \( \lambda \) it follows that
\[
I (c) = \int_{\mathbb{R}} d\mu (x) \int_{-c}^{c} d\lambda \text{Re} \left( \frac{e^{-i\lambda (a-x)} - e^{-i\lambda (b-x)}}{i\lambda} \right)
\]
\[
= \int_{\mathbb{R}} d\mu (x) \int_{-c}^{c} d\lambda \left( \sin \lambda (x-a) - \sin \lambda (x-b) \right)
\]
\[
= 2\pi \int_{\mathbb{R}} d\mu (x) \left[ \text{sgn} (x-a) S (c \{x-a\}) - \text{sgn} (x-b) S (c \{x-b\}) \right].
\]
Now letting \( c \to \infty \) in this expression (using the DCT) shows
\[
\lim_{c \to \infty} \frac{1}{2\pi} I (c) = \frac{1}{2} \int_{\mathbb{R}} d\mu (x) \left[ \text{sgn} (x-a) - \text{sgn} (x-b) \right]
\]
\[
= \frac{1}{2} \int_{\mathbb{R}} d\mu (x) \left[ 2 \cdot 1_{(a,b)} (x) + 1_{\{a\}} (x) + 1_{\{b\}} (x) \right]
\]
\[
= \mu ((a, b)) + \frac{1}{2} \left( \mu (\{a\}) + \mu (\{b\}) \right).
\]

Corollary 14.31. Suppose that \( \mu \) is a probability measure on \((\mathbb{R}, B_\mathbb{R})\) such that \( \hat{\mu} \in L^1 (m) \), then \( d\mu = \rho dm \) where \( \rho \) is a continuous density on \( \mathbb{R} \).

Proof. The function,
\[
\rho (x) := \frac{1}{2\pi} \int_{\mathbb{R}} \hat{\mu} (\lambda) e^{-i\lambda x} d\lambda,
\]
is continuous by the dominated convergence theorem. Moreover,
\[
\int_{a}^{b} \rho (x) dx = \frac{1}{2\pi} \int_{\mathbb{R}} d\lambda \hat{\mu} (\lambda) e^{-i\lambda x}
\]
\[
= \frac{1}{2\pi} \int_{\mathbb{R}} d\lambda \hat{\mu} (\lambda) \left[ \frac{e^{-i\lambda a} - e^{-i\lambda b}}{i\lambda} \right]
\]
\[
= \frac{1}{2\pi} \int_{\mathbb{R}} d\lambda \hat{\mu} (\lambda) \left[ e^{-i\lambda a} - e^{-i\lambda b} \right] d\lambda
\]
\[
= \mu ((a, b)) + \frac{1}{2} \left( \mu (\{a\}) + \mu (\{b\}) \right).
\]

Letting \( a \uparrow b \) over \( a \in \mathbb{R} \) such that \( \mu (\{a\}) = 0 \) in this identity shows \( \mu (\{b\}) = 0 \) for all \( b \in \mathbb{R} \). Therefore we have shown
\[
\mu ((a, b)) = \int_{a}^{b} \rho (x) dx \text{ for all } -\infty < a < b < \infty.
\]

Using one of the multiplicative systems theorems, it is now easy to verify that \( \mu (A) = \int_{A} \rho (x) dx \) for all \( A \in B_\mathbb{R} \) or \( \int_{A} h dm = \int_{A} h \rho d\mu \) for all bounded measurable functions \( h : \mathbb{R} \to \mathbb{R} \). This then implies that \( \rho \geq 0, m \text{ a.e.} \), and the \( d\mu = \rho dm \).

Example 14.32. Recall from Example 14.9 that
\[
\int_{\mathbb{R}} e^{i\lambda x} \left( 1 - |x| \right)_{+} dx = 2 \frac{1 - \cos \lambda}{\lambda^2}.
\]

Hence it follows\(^\dagger\) from Corollary 14.31 that
\[
(1 - |x|)_{+} = \frac{1}{4\pi} \int_{\mathbb{R}} \left( 1 - \frac{\cos \lambda}{\lambda^2} \right) e^{-i\lambda x} d\lambda.
\]

\(^\dagger\) This identity could also be verified directly using residue calculus techniques from complex variables.
Corollary 14.33. For all random variables, $X$, we have

$$E|X| = \frac{1}{\pi} \int_R \frac{1 - \Re f_X(\lambda)}{\lambda^2} d\lambda. \quad (14.25)$$

**Proof.** Evaluating Eq. (14.24) at $x = 0$ implies

$$1 = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{1 - \cos \lambda}{\lambda^2} d\lambda.$$

Making the change of variables, $\lambda \rightarrow M\lambda$, in the above integral then shows

$$M = \frac{1}{\pi} \int_R \frac{1 - \cos (\lambda M)}{\lambda^2} d\lambda.$$

Now let $M = |X|$ in this expression and then take expectations to find

$$E|X| = \frac{1}{\pi} \int_R \frac{1 - \cos \lambda X}{\lambda^2} d\lambda = \frac{1}{\pi} \int_R \frac{1 - \Re f_X(\lambda)}{\lambda^2} d\lambda.$$

Suppose that we did not know the value of $c := \int_{-\infty}^{\infty} \frac{1 - \cos \lambda}{\lambda^2} d\lambda$ is $\pi$, we could still proceed as above to learn

$$E|X| = \frac{1}{c} \int_R \frac{1 - \Re f_X(\lambda)}{\lambda^2} d\lambda.$$

We could then evaluate $c$ by making a judicious choice of $X$. For example if $X \sim N(0,1)$, we would have on one hand

$$E|X| = \frac{1}{\sqrt{2\pi}} \int_R e^{-x^2/2} dx = \frac{2}{\sqrt{2\pi}} \int_0^{\infty} e^{-x^2/2} dx = \sqrt{\frac{2}{\pi}}.$$

On the other hand, $f_X(\lambda) = e^{-\lambda^2/2}$ and so

$$\sqrt{\frac{2}{\pi}} = \frac{1}{c} \int_R \left(1 - e^{-\lambda^2/2}\right) d\lambda = \frac{1}{c} \int_R d \left(1 - e^{-\lambda^2/2}\right) \lambda^{-1} = \frac{1}{c} \int_R e^{-\lambda^2/2} d\lambda = \frac{\sqrt{2\pi}}{c},$$

from which it follows, again, that $c = \pi$.

**Corollary 14.34.** Suppose $X$ is a random variable such that $u(\lambda) := f_X(\lambda)$ continuously differentiable for $\lambda \in (-\varepsilon, \varepsilon)$ for some $\varepsilon > 0$. We further assume

$$\int_{|\lambda|<\varepsilon} \left|u'(\lambda)\right| \lambda d\lambda < \infty. \quad (14.26)$$

Then $E|X| < \infty$ and $f_X \in C^1(\mathbb{R}, \mathbb{C})$. (Since $u$ is even, $u'$ is odd and $u'(0) = 0$. Hence if $u'(\lambda)$ were $\alpha$–Hölder continuous for some $\alpha > 0$, then Eq. (14.26) would hold.)

**Proof.** Let $u(\lambda) := \Re f_X(\lambda) = E \cos \lambda X$ and assume that $u \in C^1((-\varepsilon,\varepsilon), \mathbb{C})$. Then according to Eq. (14.25)

$$\pi \cdot E|X| = \int_R \frac{1 - u(\lambda)}{\lambda^2} d\lambda = \int_{|\lambda|\leq\varepsilon} \frac{1 - u(\lambda)}{\lambda^2} d\lambda + \int_{|\lambda|>\varepsilon} \frac{1 - u(\lambda)}{\lambda^2} d\lambda.$$

Since $0 \leq 1 - u(\lambda) \leq 2$ and $2/\lambda^2$ is integrable for $|\lambda| > \varepsilon$, it suffices to show

$$\infty \geq \int_{|\lambda|\leq\varepsilon} \frac{1 - u(\lambda)}{\lambda^2} d\lambda = \lim_{\delta \downarrow 0} \int_{\delta \leq |\lambda| \leq \varepsilon} \frac{1 - u(\lambda)}{\lambda^2} d\lambda.$$

By an integration by parts we find

$$\int_{\delta \leq |\lambda| \leq \varepsilon} \frac{1 - u(\lambda)}{\lambda^2} d\lambda = \int_{\delta \leq |\lambda| \leq \varepsilon} (1 - u(\lambda)) d(-\lambda^{-1})$$

$$= \frac{u(\delta) - 1}{\lambda} + \int_{\delta}^{\varepsilon} \frac{u(\lambda) - 1}{\lambda} - \int_{\delta}^{\varepsilon} \lambda^{-1} u'(\lambda) d\lambda$$

$$= -\left[\int_{\delta \leq |\lambda| \leq \varepsilon} \lambda^{-1} u'(\lambda) d\lambda + \frac{u(\varepsilon) - 1}{\varepsilon} - \frac{u(-\varepsilon) - 1}{-\varepsilon}\right]$$

$$= -\lim_{\delta \downarrow 0} \int_{\delta \leq |\lambda| \leq \varepsilon} \lambda^{-1} u'(\lambda) d\lambda + \frac{u(\varepsilon) + u(-\varepsilon)}{\varepsilon} + u'(0) - u'(0)$$

$$\leq \int_{|\lambda| \leq \varepsilon} \left|\frac{u'(\lambda)}{\lambda}\right| d\lambda + \frac{u(\varepsilon) + u(-\varepsilon)}{\varepsilon}$$

$$= 2 \int_{\varepsilon}^{\varepsilon} \frac{\left|u'(\lambda)\right|}{\lambda} d\lambda + \frac{u(\varepsilon) + u(-\varepsilon)}{\varepsilon} < \infty.$$

Passing the limit as $\delta \downarrow 0$ using the fact that $u'(\lambda)$ is an odd function, we learn

$$\int_{|\lambda| \leq \varepsilon} \frac{1 - u(\lambda)}{\lambda^2} d\lambda = \lim_{\delta \downarrow 0} \int_{\delta \leq |\lambda| \leq \varepsilon} \lambda^{-1} u'(\lambda) d\lambda + \frac{u(\varepsilon) + u(-\varepsilon)}{\varepsilon}$$

$$\leq 2 \int_{\varepsilon}^{\varepsilon} \frac{\left|u'(\lambda)\right|}{\lambda} d\lambda + \frac{u(\varepsilon) + u(-\varepsilon)}{\varepsilon} < \infty.$$

**14.5 Exercises**

**Exercise 14.2.** For $x, \lambda \in \mathbb{R}$, let
Exercise 14.3. To each finite and compactly supported measure, \( \nu \), on \((\mathbb{R}, B_\mathbb{R})\) show there exists a sequence \( \{\nu_n\}_{n=1}^\infty \) of finitely supported finite measures on \((\mathbb{R}, B_\mathbb{R})\) such that \( \nu_n \rightarrow \nu \). Here we say \( \nu \) is compactly supported if there exists \( M < \infty \) such that \( \nu(\{x : x \geq M\}) = 0 \) and we say \( \nu \) is finitely supported if there exists a finite subset, \( A \subset \mathbb{R} \) such that \( \nu(\mathbb{R} \setminus A) = 0 \). Please interpret \( \nu_n \rightarrow \nu \) to mean,

\[
\int f \, d\nu_n \rightarrow \int f \, d\nu \quad \text{for all} \quad f \in BC(\mathbb{R}).
\]

Exercise 14.4. Show that if \( \nu \) is a finite measure on \((\mathbb{R}, B_\mathbb{R})\), then

\[
f(\lambda) := \exp \left( \int_\mathbb{R} \varphi(\lambda, x) \, d\nu(x) \right)
\]

is the characteristic function of a probability measure on \((\mathbb{R}, B_\mathbb{R})\). Here is an outline to follow. (You may find the calculus estimates in Section 14.8 to be of help.)

1. Show \( f(\lambda) \) is continuous.
2. Now suppose that \( \nu \) is compactly supported. Show, using Exercises 14.3 and the continuity Theorem 14.2 that \( \exp \left( \int_\mathbb{R} \varphi(\lambda, x) \, d\nu(x) \right) \) is the characteristic function of a probability measure on \((\mathbb{R}, B_\mathbb{R})\).
3. For the general case, approximate \( \nu \) by a sequence of finite measures with compact support as in item 2.

Exercise 14.5 (Exercise 2.3 in [10]). Let \( \mu \) be the probability measure on \((\mathbb{R}, B_\mathbb{R})\), such that \( \mu]\{n\}\) = \( p(n) = c_{p,1} \ln |n| \) with \( c \) chosen so that \( \sum_{n \in \mathbb{Z}} p(n) = 1 \). Show that \( \hat{\mu} \in C^1(\mathbb{R}, \mathbb{C}) \) even though \( \int_\mathbb{R} |x| \, d\mu(x) = \infty \). To do this show,

\[
g(t) := \sum_{n \geq 2} \frac{1 - \cos nt}{n^2 \ln n}
\]

is continuously differentiable.

Exercise 14.6 (Polya’s Criterion [1, Problem 26.3 on p. 305.] and [3, p. 104-107]). Suppose \( \varphi(\lambda) \) is a non-negative symmetric continuous function such that \( \varphi(0) = 1, \varphi(\lambda) \) is non-increasing and convex for \( \lambda \geq 0 \). Show \( \varphi(\lambda) = \hat{\nu}(\lambda) \) for some probability measure, \( \nu \), on \((\mathbb{R}, B_\mathbb{R})\).

Solution to Exercise 14.6. Because of the continuity theorem and some simple limiting arguments, it suffices to prove the result for a function \( \varphi \) as pictured in Figure 14.1. From Example 14.32 we know that \((1 - |\lambda|)_+ = \hat{\mu}(\lambda)

where \( \mu \) is the probability measure,

\[
d\mu(x) := \frac{1}{\pi} \frac{1 - \cos x}{x^2} \, dx.
\]

For \( a > 0 \), let \( \mu_a(A) = \mu(aA) \) in which case \( \mu_a(f) = \mu(f(a^{-1})) \) for all bounded measurable \( f \) and in particular, \( \hat{\mu}_a(\lambda) = \hat{\mu}(a^{-1}\lambda) \). To finish the proof it suffices to show that \( \varphi(\lambda) \) may be expressed as
where the last equality follows from Eq. (14.30). Working backwards with \( \nu \) we must require,

\[ 0 = \varphi(a_N) = 1 - \sum_{n=1}^{N} d_n s_n. \] (14.30)

Notice that \( s_n = 0 \) for all \( n > N \).

Since

\[ \varphi'(\lambda) = -\sum_{n=k}^{\infty} p_n \frac{1}{a_n} \text{ when } a_{k-1} < \lambda < a_k \]

we must require,

\[ s_k = \sum_{n=k}^{\infty} p_n \frac{1}{a_n} \text{ for all } k \]

which then implies \( p_k \frac{1}{a_k} = s_k - s_{k+1} \) or equivalently that

\[ p_k = a_k (s_k - s_{k+1}). \] (14.31)

Since \( \varphi \) is convex, we know that \(-s_k \leq -s_{k+1} \) or \( s_k \geq s_{k+1} \) for all \( k \) and therefore \( p_k \geq 0 \) and \( p_k = 0 \) for all \( k > N \). Moreover,

\[ \sum_{k=1}^{\infty} p_k = \sum_{k=1}^{\infty} a_k (s_k - s_{k+1}) = \sum_{k=1}^{\infty} a_k s_k - \sum_{k=2}^{\infty} a_{k-1} s_k \]

\[ = a_1 s_1 + \sum_{k=2}^{\infty} s_k (a_k - a_{k-1}) = d_1 s_1 + \sum_{k=2}^{\infty} s_k d_k \]

\[ = \sum_{k=1}^{\infty} s_k d_k = 1 \]

where the last equality follows from Eq. (14.30). Working backwards with \( p_k \) defined as in Eq. (14.31) it is now easily shown that \( \frac{d}{d\lambda} \sum_{n=1}^{\infty} p_n \left( 1 - \left| \frac{\lambda}{a_n} \right| \right) \bigg|_{\lambda = 0} = \varphi'(\lambda) \) for \( \lambda \notin \{a_1, a_2, \ldots \} \) and since both functions are equal to 1 at \( \lambda = 0 \) we may conclude that Eq. (14.29) is indeed valid.

### 14.6 Appendix: Bochner’s Theorem

**Definition 14.35.** A function \( f \in C(\mathbb{R}^n, \mathbb{C}) \) is said to have **rapid decay** or **rapid decrease** if

\[
\sup_{x \in \mathbb{R}^n} (1 + |x|)^N |f(x)| < \infty \text{ for } N = 1, 2, \ldots.
\]

Equivalently, for each \( N \in \mathbb{N} \) there exists constants \( C_N < \infty \) such that

\[
|f(x)| \leq C_N (1 + |x|)^{-N} \text{ for all } x \in \mathbb{R}^n.
\]

A function \( f \in C(\mathbb{R}^n, \mathbb{C}) \) is said to have (at most) **polynomial growth** if there exists \( N < \infty \) such that

\[
\sup_{x \in \mathbb{R}^n} (1 + |x|)^{-N} |f(x)| < \infty,
\]

i.e. there exists \( N \in \mathbb{N} \) and \( C < \infty \) such that

\[
|f(x)| \leq C (1 + |x|)^N \text{ for all } x \in \mathbb{R}^n.
\]

**Definition 14.36 (Schwartz Test Functions).** Let \( S \) denote the space of functions \( f \in C^\infty(\mathbb{R}^n) \) such that \( f \) and all of its partial derivatives have rapid decay and let

\[
\|f\|_{N, \alpha} = \sup_{x \in \mathbb{R}^n} (1 + |x|)^{N} |\partial^\alpha f(x)|
\]

so that

\[
S = \left\{ f \in C^\infty(\mathbb{R}^n) : \|f\|_{N, \alpha} < \infty \text{ for all } N \text{ and } \alpha \right\}.
\]

Also let \( P \) denote those functions \( g \in C^\infty(\mathbb{R}^n) \) such that \( g \) and all of its derivatives have at most polynomial growth, i.e. \( g \in C^\infty(\mathbb{R}^n) \) is in \( P \) iff for all multi-indices \( \alpha \), there exists \( N_\alpha < \infty \) such that

\[
\sup_{x \in \mathbb{R}^n} (1 + |x|)^{-N_\alpha} |\partial^\alpha g(x)| < \infty.
\]

(Notice that any polynomial function on \( \mathbb{R}^n \) is in \( P \).

**Definition 14.37.** A function \( \chi : \mathbb{R}^n \to \mathbb{C} \) is said to be **positive (semi) definite** iff the matrices \( A := \{ \chi(x_k - x_j) \}_{k,j=1}^{m} \) are positive definite for all \( m \in \mathbb{N} \) and \( \{x_j\}_{j=1}^{m} \subset \mathbb{R}^n \).

**Proposition 14.38.** Suppose that \( \chi : \mathbb{R}^n \to \mathbb{C} \) is said to be positive definite with \( \chi(0) = 1 \). If \( \chi \) is continuous at 0 then in fact \( \chi \) is uniformly continuous on all of \( \mathbb{R}^n \).

**Proof.** Taking \( \xi_1 = x \), \( \xi_2 = y \) and \( \xi_3 = 0 \) in Definition 14.37 we conclude that

\[
A := \begin{bmatrix}
1 & \chi(x-y) & \chi(x) \\
\chi(y-x) & 1 & \chi(y) \\
\chi(-x) & \chi(-y) & 1
\end{bmatrix} = \begin{bmatrix}
1 & \chi(x-y) & \chi(x) \\
\bar{\chi}(x-y) & 1 & \chi(y) \\
\bar{\chi}(x) & \bar{\chi}(y) & 1
\end{bmatrix}
\]
is positive definite. In particular,
\[
0 \leq \det A = 1 + \chi(x-y)\chi(y)\bar{x}(x) + \chi(x)\bar{x}(y) + \chi(x)\bar{y}(y) - |\chi(x)|^2 - |\chi(y)|^2 - |\chi(x-y)|^2.
\]
Combining this inequality with the identity,
\[
|\chi(x) - \chi(y)|^2 = |\chi(x)|^2 + |\chi(y)|^2 - \chi(x)\bar{y}(y) - \chi(y)\bar{x}(x),
\]
gives
\[
0 \leq 1 - |\chi(x-y)|^2 + \chi(x-y)\chi(y)\bar{x}(x) + \chi(x)\bar{y}(y) - \chi(x)\bar{x}(y)
- \left\{|\chi(x) - \chi(y)|^2 + \chi(x)\bar{y}(y) + \chi(y)\bar{x}(x)\right\}
= 1 - |\chi(x-y)|^2 - |\chi(x) - \chi(y)|^2 + \chi(x-y)\chi(y)\bar{x}(x)
+ \chi(x)\bar{x}(y) - \chi(y)\bar{y}(y) - \chi(x)\bar{x}(y)
= 1 - |\chi(x-y)|^2 - |\chi(x) - \chi(y)|^2 + 2\Re(\chi(x-y) - 1)\chi(y)\bar{x}(x)
\leq 1 - |\chi(x-y)|^2 - |\chi(x) - \chi(y)|^2 + 2|\chi(x-y) - 1|.
\]
Hence we have
\[
|\chi(x) - \chi(y)|^2 \leq 1 - |\chi(x-y)|^2 + 2|\chi(x-y) - 1|
= (1 - |\chi(x-y)|^2)(1 + |\chi(x-y)|^2) + 2|\chi(x-y) - 1|
\leq 4|1 - \chi(x-y)|
\]
which completes the proof. □

**Lemma 14.39.** If \( \chi \in C(\mathbb{R}^n, \mathbb{C}) \) is a positive definite function, then

1. \( \chi(0) \geq 0 \).
2. \( \chi(-\xi) = \overline{\chi(\xi)} \) for all \( \xi \in \mathbb{R}^n \).
3. \( \chi(\xi) \leq \chi(0) \) for all \( \xi \in \mathbb{R}^n \).
4. For all \( f \in \mathcal{S}(\mathbb{R}^n) \),
\[
\int_{\mathbb{R}^n \times \mathbb{R}^n} \chi(\xi - \eta) f(\xi) \overline{f(\eta)} d\xi d\eta \geq 0. \tag{14.32}
\]

**Proof.** Taking \( m = 1 \) and \( \xi_1 = 0 \) we learn \( \chi(0)|\lambda|^2 \geq 0 \) for all \( \lambda \in \mathbb{C} \) which proves item 1. Taking \( m = 2, \xi_1 = \xi \) and \( \xi_2 = \eta \), the matrix
\[
A := \begin{bmatrix}
\chi(0) & \chi(\xi - \eta) \\
\chi(\eta - \xi) & \chi(0)
\end{bmatrix}
\]
is positive definite from which we conclude \( \chi(\xi - \eta) = \overline{\chi(\eta - \xi)} \) (since \( A = A^* \) by definition) and
\[
0 \leq \det \begin{bmatrix}
\chi(0) & \chi(\xi - \eta) \\
\chi(\eta - \xi) & \chi(0)
\end{bmatrix} = |\chi(0)|^2 - |\chi(\xi - \eta)|^2.
\]
and hence \( |\chi(\xi)| \leq \chi(0) \) for all \( \xi \). This proves items 2. and 3. Item 4. follows by approximating the integral in Eq. (14.32) by Riemann sums,
\[
\int_{\mathbb{R}^n \times \mathbb{R}^n} \chi(\xi - \eta) f(\xi) \overline{f(\eta)} d\xi d\eta
= \lim_{\varepsilon \to 0} \int_{|\xi,\eta| < (\varepsilon,\varepsilon)} \chi(\xi - \eta) f(\xi) \overline{f(\eta)} d\xi d\eta \geq 0.
\]
The details are left to the reader. □

**Lemma 14.40.** If \( \mu \) is a finite positive measure on \( \mathcal{B}_{\mathbb{R}^n} \), then \( \chi := \hat{\mu} \in C(\mathbb{R}^n, \mathbb{C}) \) is a positive definite function.

**Proof.** As has already been observed after Definition ??, the dominated convergence theorem implies \( \hat{\mu} \in C(\mathbb{R}^n, \mathbb{C}) \). Since \( \mu \) is a positive measure (and hence real),
\[
\hat{\mu}(-\xi) = \int_{\mathbb{R}^n} e^{i\xi \cdot x} d\mu(x) = \int_{\mathbb{R}^n} e^{-i\xi \cdot x} d\mu(x) = \overline{\hat{\mu}(-\xi)}.
\]
From this it follows that for any \( m \in \mathbb{N} \) and \( \{\xi_j\}_{j=1}^m \subset \mathbb{R}^n \), the matrix \( A := \{\hat{\mu}(\xi_k - \xi_j)\}_{k,j=1}^m \) is self-adjoint. Moreover if \( \lambda \in \mathbb{C}^m \),
\[
\sum_{k,j=1}^m \hat{\mu}(\xi_k - \xi_j) \lambda_k \lambda_j = \int_{\mathbb{R}^n} \sum_{k,j=1}^m e^{i(\xi_k - \xi_j) \cdot x} \lambda_k \lambda_j d\mu(x)
= \int_{\mathbb{R}^n} \sum_{k,j=1}^m e^{-i(\xi_k - \xi_j) \cdot x} \lambda_k \lambda_j d\mu(x)
= \int_{\mathbb{R}^n} \left| \sum_{k=1}^m e^{-i\xi_k \cdot x} \lambda_k \right|^2 d\mu(x) \geq 0
\]
showing \( A \) is positive definite. □

**Theorem 14.41 (Bochner’s Theorem).** Suppose \( \chi \in C(\mathbb{R}^n, \mathbb{C}) \) is positive definite function, then there exists a unique positive measure \( \mu \) on \( \mathcal{B}_{\mathbb{R}^n} \) such that \( \chi = \hat{\mu} \).

**Proof.** If \( \chi(\xi) = \hat{\mu}(\xi) \), then for \( f \in \mathcal{S} \) we would have
\[
\int_{\mathbb{R}^n} f d\mu = \int_{\mathbb{R}^n} (f^\vee) \cdot d\mu = \int_{\mathbb{R}^n} f^\vee(\xi) \hat{\mu}(\xi) d\xi.
\]
This suggests that we define
\[ I(f) := \int_{\mathbb{R}^n} \chi(\xi) f(\xi) d\xi \] for all \( f \in \mathcal{S} \).

We will now show \( I \) is positive in the sense if \( f \in \mathcal{S} \) and \( f \geq 0 \) then \( I(f) \geq 0 \). For general \( f \in \mathcal{S} \) we have
\[
I(|f|^2) = \int_{\mathbb{R}^n} \chi(\xi) (|f|^2)(\xi) d\xi = \int_{\mathbb{R}^n} \chi(\xi) (f^\vee f^\vee)(\xi) d\xi \\
= \int_{\mathbb{R}^n} \chi(\xi) f^\vee(\xi - \eta) f^\vee(\eta) d\eta d\xi = \int_{\mathbb{R}^n} \chi(\xi) f^\vee(\xi - \eta) f^\vee(-\eta) d\eta d\xi \\
= \int_{\mathbb{R}^n} \chi(\xi - \eta) f^\vee(\xi) f(\eta) d\eta d\xi \geq 0.
\] (14.33)

For \( t > 0 \) let \( p_t(x) := t^{-n/2} e^{-|x|^2/2t} \in \mathcal{S} \) and define
\[ I_t(x) := I \circ p_t(x) := I(p_t(x - \cdot)) = I(\sqrt{p_t(x - \cdot)}^2) \]
which is non-negative by Eq. (14.33) and the fact that \( \sqrt{p_t(x - \cdot)} \in \mathcal{S} \). Using
\[
[p_t(x - \cdot)]^\vee(\xi) = \int_{\mathbb{R}^n} p_t(x - y) e^{iy \cdot \xi} dy = \int_{\mathbb{R}^n} p_t(y) e^{iy \cdot (x - \xi)} dy \\
= e^{ix \cdot \xi} p_t(\xi) = e^{ix \cdot \xi} t^{-n/2}|\xi|^2/2,
\]
\[ \langle I_t, \psi \rangle = \int_{\mathbb{R}^n} I_t(x - \cdot) \psi(x) dx \]
\[ = \int_{\mathbb{R}^n} \left( \int_{\mathbb{R}^n} \chi(\xi) [p_t(x - \cdot)]^\vee(\xi) \psi(x) d\xi \right) dx \\
= \int_{\mathbb{R}^n} \left( \int_{\mathbb{R}^n} \chi(\xi) e^{ix \cdot \xi} e^{-t|\xi|^2/2} \psi(x) d\xi \right) dx \\
= \int_{\mathbb{R}^n} \chi(\xi) \psi^\vee(\xi) e^{-t|\xi|^2/2} d\xi \\
\] which coupled with the dominated convergence theorem shows
\[ \langle I \circ p_t, \psi \rangle \rightarrow \int_{\mathbb{R}^n} \chi(\xi) \psi^\vee(\xi) d\xi = I(\psi) \] as \( t \downarrow 0 \).

Hence if \( \psi \geq 0 \), then \( I(\psi) = \lim_{t \downarrow 0} \langle I_t, \psi \rangle \geq 0 \).

Let \( K \subset \mathbb{R} \) be a compact set and \( \psi \in C_c(\mathbb{R}, [0, \infty)) \) be a function such that \( \psi = 1 \) on \( K \). If \( f \in C_c^\infty(\mathbb{R}, \mathbb{R}) \) is a smooth function with \( \text{supp}(f) \subset K \), then \( 0 \leq \|f\|_\infty \psi - f \in \mathcal{S} \) and hence
\[
0 \leq \langle I, f \rangle = \|f\|_\infty \langle I, \psi \rangle = \|f\|_\infty \langle I, f \rangle - \langle I, f \rangle
\]
and therefore \( \langle I, f \rangle \leq \|f\|_\infty \langle I, \psi \rangle \). Replacing \( f \) by \( -f \) implies, \( -\langle I, f \rangle \leq \|f\|_\infty \langle I, \psi \rangle \) and hence we have proved
\[
\langle I, f \rangle \leq C(\text{supp}(f)) \|f\|_\infty
\] (14.34)
for all \( f \in D_{\mathbb{R}^n} := C_c^\infty(\mathbb{R}^n, \mathbb{R}) \) where \( C(K) \) is a finite constant for each compact subset of \( \mathbb{R}^n \). Because of the estimate in Eq. (14.34), it follows that \( I|_{D_{\mathbb{R}^n}} \) has a unique extension \( I \) to \( C_c(\mathbb{R}^n, \mathbb{R}) \) still satisfying the estimates in Eq. (14.34) and moreover this extension is still positive. So by the Riesz – Markov Theorem ??, there exists a unique Radon – measure \( \mu \) on \( \mathbb{R}^n \) such that such that \( \langle I, f \rangle = \mu(f) \) for all \( f \in C_c(\mathbb{R}^n, \mathbb{R}) \).

To finish the proof we must show \( \hat{\mu}(\eta) = \chi(\eta) \) for all \( \eta \in \mathbb{R}^n \) given
\[
\mu(f) = \int_{\mathbb{R}^n} \chi(\xi) f^\vee(\xi) d\xi \] for all \( f \in C_c^\infty(\mathbb{R}^n, \mathbb{R}) \). (14.35)

Let \( f \in L_1(\mathbb{R}^n, \mathbb{R}_+) \) be a radial function such \( f(0) = 1 \) and \( f(x) \) is decreasing as \( |x| \) increases. Let \( f_\varepsilon(x) := f(\varepsilon x) \), then by Theorem ??,
\[
\mathcal{F}^{-1}[e^{-i\eta \xi} f_\varepsilon(x)] \langle \xi \rangle = \varepsilon^{-n} f^\vee(\frac{\xi - \eta}{\varepsilon})
\]
and therefore, from Eq. (14.35),
\[
\int_{\mathbb{R}^n} e^{-i\eta \xi} f_\varepsilon(x) d\mu(x) = \int_{\mathbb{R}^n} \chi(\xi) \varepsilon^{-n} f^\vee(\frac{\xi - \eta}{\varepsilon}) d\xi.
\] (14.36)

Because \( \int_{\mathbb{R}^n} f^\vee(\xi) d\xi = \mathcal{F} f^\vee(0) = f(0) = 1 \), we may apply the approximate \( \delta – \) function Theorem ?? to Eq. (14.36) to find
\[
\int_{\mathbb{R}^n} e^{-i\eta \xi} f_\varepsilon(x) d\mu(x) \rightarrow \chi(\eta) \varepsilon \downarrow 0.
\] (14.37)

On the other hand, when \( \eta = 0 \), the monotone convergence theorem implies \( \mu(f_\varepsilon) \uparrow \mu(1) = \mu(\mathbb{R}^n) \) and therefore \( \mu(\mathbb{R}^n) = \mu(1) = \chi(0) < \infty \) now knowing the \( \mu \) is a finite measure we may use the dominated convergence theorem to concluded
\[
\mu(e^{-i\eta \xi} f_\varepsilon(x)) \rightarrow \mu(e^{-i\eta \xi}) = \hat{\mu}(\eta) \varepsilon \downarrow 0
\]
for all \( \eta \). Combining this equation with Eq. (14.37) shows \( \hat{\mu}(\eta) = \chi(\eta) \) for all \( \eta \in \mathbb{R}^n \). \[ \blacksquare \]
14.7 Appendix: A Multi-dimensional Weierstrass Approximation Theorem

The following theorem is the multi-dimensional generalization of Theorem 4.23.

**Theorem 14.42 (Weierstrass Approximation Theorem).** Suppose that $K = [a_1, b_1] \times \ldots \times [a_d, b_d]$ with $-\infty < a_i < b_i < \infty$ is a compact rectangle in $\mathbb{R}^d$. Then for every $f \in C(K, \mathbb{C})$, there exists polynomials $p_n$ on $\mathbb{R}^d$ such that $p_n \rightarrow f$ uniformly on $K$.

**Proof.** By a simple scaling and translation of the arguments of $f$ we may assume without loss of generality that $K = [0, 1]^d$. By considering the real and imaginary parts of $f$ separately, it suffices to assume $f \in C([0, 1], \mathbb{R})$.

Given $x \in K$, let $\{X_n = (X_n^1, \ldots, X_n^d)\}_{n=1}^{\infty}$ be i.i.d. random vectors with values in $\mathbb{R}^d$ such that

$$ P(X_n = \varepsilon) = \prod_{i=1}^{d} (1 - x_i)^{1 - \varepsilon_i} x_i^{\varepsilon_i} $$

for all $\varepsilon = (\varepsilon_1, \ldots, \varepsilon_d) \in \{0, 1\}^d$. Since each $X_n^j$ is a Bernoulli random variable with $P(X_n^j = 1) = x_j$, we know that

$$ \mathbb{E}X_n = x \quad \text{and} \quad \text{Var}(X_n^j) = x_j - x_j^2 = x_j(1 - x_j). $$

As usual let $S_n = S_n := X_1 + \cdots + X_n \in \mathbb{R}^d$, then

$$ \mathbb{E} \left[ \frac{S_n}{n} \right] = x \quad \text{and} \quad \mathbb{E} \left[ \left\| \frac{S_n}{n} - x \right\|^2 \right] = \sum_{j=1}^{d} \mathbb{E} \left( \frac{S_n^j}{n} - x_j \right)^2 = \sum_{j=1}^{d} \text{Var} \left( \frac{S_n^j}{n} - x_j \right) = \frac{d}{n^2} \sum_{j=1}^{d} \sum_{k=1}^{n} \text{Var} \left( X_k^j \right) = \frac{1}{n} \sum_{j=1}^{d} x_j(1 - x_j) \leq \frac{d}{4n}. $$

This shows $S_n/n \rightarrow x$ in $L^2(P)$ and hence by Chebyshev’s inequality, $S_n/n \xrightarrow{P} x$ in and by a continuity theorem, $f \left( \frac{S_n}{n} \right) \xrightarrow{P} f(x)$ as $n \rightarrow \infty$. This along with the dominated convergence theorem shows

$$ p_n(x) := \mathbb{E} \left[ f \left( \frac{S_n}{n} \right) \right] \xrightarrow{} f(x) \quad \text{as} \quad n \rightarrow \infty, \quad (14.38) $$

where

$$ p_n(x) = \sum_{\varepsilon(\cdot) \in \{0, 1\}^d} f \left( \frac{\varepsilon(1) + \cdots + \varepsilon(d)}{n} \right) P(X_1 = \varepsilon(1), \ldots, X_n = \varepsilon(n)) $$

$$ = \sum_{\varepsilon(\cdot) \in \{0, 1\}^d} f \left( \frac{\varepsilon(1) + \cdots + \varepsilon(d)}{n} \right) \prod_{k=1}^{d} (1 - x_i)^{1 - \varepsilon_i(k)} x_i^{\varepsilon_i(k)} $$

is a polynomial of degree $nd$. In fact more is true.

Suppose $\varepsilon > 0$ is given, $M = \sup \{ |f(x)| : x \in K \}$, and

$$ \delta_\varepsilon = \sup \{ |f(y) - f(x)| : x, y \in K \quad \text{and} \quad \|y - x\| \leq \varepsilon \}. $$

By uniform continuity of $f$ on $K$, $\lim_{\varepsilon \downarrow 0} \delta_\varepsilon = 0$. Therefore,

$$ |f(x) - p_n(x)| = \left| \mathbb{E} \left( f(x) - f \left( \frac{S_n}{n} \right) \right) \right| \leq \mathbb{E} \left| f(x) - f \left( \frac{S_n}{n} \right) \right| $$

$$ \leq \mathbb{E} \left[ \left| f(x) - f \left( \frac{S_n}{n} \right) \right| : \|S_n - x\| > \varepsilon \right] + \mathbb{E} \left[ \left| f(x) - f \left( \frac{S_n}{n} \right) \right| : \|S_n - x\| \leq \varepsilon \right] $$

$$ \leq 2MP \left( \|S_n - x\| > \varepsilon \right) + \delta_\varepsilon. \quad (14.39) $$

By Chebyshev’s inequality,

$$ P \left( \|S_n - x\| > \varepsilon \right) \leq \frac{1}{\varepsilon^2} \mathbb{E} \left( \|S_n - x\|^2 \right) = \frac{d}{4n \varepsilon^2}, $$

and therefore, Eq. (14.39) yields the estimate

$$ \sup_{x \in K} |f(x) - p_n(x)| \leq \frac{2dM}{n \varepsilon^2} + \delta_\varepsilon $$

and hence

$$ \lim_{n \rightarrow \infty} \sup_{x \in K} |f(x) - p_n(x)| \leq \delta_\varepsilon \rightarrow 0 \quad \text{as} \quad \varepsilon \downarrow 0. \quad \blacksquare $$

Here is a version of the complex Weierstrass approximation theorem.

**Theorem 14.43 (Complex Weierstrass Approximation Theorem).** Suppose that $K \subset \mathbb{C}^d \cong \mathbb{R}^d \times \mathbb{R}^d$ is a compact rectangle. Then there exists polynomials in $(z = x + iy, \bar{z} = x - iy)$, $p_n(z, \bar{z})$ for $z \in \mathbb{C}^d$, such that

$$ \sup_{z \in K} |g_n(z, \bar{z}) - f(z)| \rightarrow 0 \quad \text{as} \quad n \rightarrow \infty \quad \text{for every} \quad f \in C(K, \mathbb{C}). \quad \blacksquare
Theorem 14.42. Conversely a polynomial \( q \) in \((z, \bar{z})\) may be written as a polynomial \( p \) in \((x, y)\), namely \( p(x, y) = q(x + iy, x - iy) \). Hence the result now follows from Theorem 14.44.

Example 14.44. Let \( K = S^1 = \{z \in C : |z| = 1\} \) and \( A \) be the set of polynomials in \((z, \bar{z})\) restricted to \( S^1 \). Then \( A \) is dense in \( C(S^1) \). To prove this first observe if \( f \in C(S^1) \) then \( F(z) = |z|^2 f\left(\frac{z}{|z|}\right) \) for \( z \neq 0 \) and \( F(0) = 0 \) defines \( F \in C(C) \) such that \( F|_{S^1} = f \). By applying Theorem 14.43 to \( F \) restricted to a compact rectangle containing \( S^1 \) we may find \( q_n(z, \bar{z}) \) converging uniformly to \( F \) on \( K \) and hence on \( S^1 \). Since \( \bar{z} = z^{-1} \) on \( S^1 \), we have shown polynomials in \( z \) and \( z^{-1} \) are dense in \( C(S^1) \). This example generalizes in an obvious way to \( K = (S^1)^d \subset C^d \).

Exercise 14.7. Use Example 14.44 to show that any \( 2\pi \)–periodic continuous function, \( g : \mathbb{R}^d \to \mathbb{C} \), may be uniformly approximated by a trigonometric polynomial of the form

\[
p(x) = \sum_{\lambda \in A} a_{\lambda} e^{i\lambda \cdot x},
\]

where \( A \) is a finite subset of \( \mathbb{Z}^d \) and \( a_{\lambda} \in \mathbb{C} \) for all \( \lambda \in A \). Hint: start by showing there exists a unique continuous function, \( f : (S^1)^d \to \mathbb{C} \) such that \( f(e^{i\lambda_1}, \ldots, e^{i\lambda_d}) = F(x) \) for all \( x = (x_1, \ldots, x_d) \in \mathbb{R}^d \).

Solution to Exercise 14.7. I will write out the solution when \( d = 1 \). For \( z \in S^1 \), define \( F(z) := f(e^{i\theta}) \) where \( \theta \in \mathbb{R} \) is chosen so that \( z = e^{i\theta} \). Since \( f \) is \( 2\pi \)–periodic, \( F \) is well defined since if \( \theta \) solves \( e^{i\theta} = z \) then all other solutions are of the form \( \{\theta + 2\pi n : n \in \mathbb{Z}\} \). Since the map \( \theta \to e^{i\theta} \) is a local homeomorphism, i.e. for any \( J = (a, b) \) with \( b - a < 2\pi \), the map \( \theta \in J \mapsto \tilde{J} := \{e^{i\theta} : \theta \in J\} \subset S^1 \) is a homeomorphism, it follows that \( F(z) = f \circ \phi^{-1}(z) \) for \( z \in \tilde{J} \). This shows \( F \) is continuous when restricted to \( \tilde{J} \). Since such sets cover \( S^1 \), it follows that \( F \) is continuous. It now follows from Example 14.44 that polynomials in \( z \) and \( z^{-1} \) are dense in \( C(S^1) \). Hence for any \( \varepsilon > 0 \) there exists

\[
p(z, \bar{z}) = \sum_{m,n} a_{m,n} z^m \bar{z}^n = \sum_{m,n} a_{m,n} z^m z^{-n} = \sum_{m,n} a_{m,n} z^{m-n}
\]

such that \( |F(z) - p(z, \bar{z})| \leq \varepsilon \) for all \( z \). Taking \( z = e^{i\theta} \) then implies there exists \( b_n \in \mathbb{C} \) and \( N \in \mathbb{N} \) such that

14.8 Appendix: Some Calculus Estimates

We end this section by gathering together a number of calculus estimates that we will need in the future.

1. Taylor’s theorem with integral remainder states, if \( f \in C^k(\mathbb{R}) \) and \( z, \Delta \in \mathbb{R} \), \( f \) be holomorphic in a neighborhood of \( z \in \mathbb{C} \) and \( \Delta \in \mathbb{C} \) be sufficiently small so that \( f(z + t\Delta) \) is defined for \( t \in [0, 1] \), then

\[
f(z + \Delta) = \sum_{k=0}^{k-1} f^{(n)}(z) \frac{\Delta^n}{n!} + \Delta^k r_k(z, \Delta) \quad (14.42)
\]

\[
= \sum_{k=0}^{k-1} f^{(n)}(z) \frac{\Delta^n}{n!} + \Delta^k \left[ \frac{1}{k!} f^{(k)}(z) + \varepsilon(z, \Delta) \right] \quad (14.43)
\]
Alternatively, 
and for \( y \) and \( z, \Delta \)

\[
r_k (z, \Delta) = \frac{1}{(k-1)!} \int_0^1 f^{(k)} (z + t\Delta) (1 - t)^{k-1} \ dt = \frac{1}{k!} f^{(k)} (z) + \varepsilon (z, \Delta)
\]  

(14.45)

and

\[
\varepsilon (z, \Delta) = \frac{1}{(k-1)!} \int_0^1 \left[ f^{(k)} (z + t\Delta) - f^{(k)} (z) \right] (1 - t)^{k-1} \ dt \to 0 \text{ as } \Delta \to 0.
\]  

(14.46)

To prove this, use integration by parts to show,

\[
r_k (z, \Delta) = \frac{1}{k!} \int_0^1 f^{(k)} (z + t\Delta) \left( -\frac{d}{dt} \right) (1 - t)^k \ dt \\
= -\frac{1}{k!} \left[ f^{(k)} (z + t\Delta) (1 - t)^k \right]_{t=0}^{1} + \frac{1}{k!} \int_0^1 f^{(k+1)} (z + t\Delta) (1 - t)^k \ dt
\]  

(14.47)

\[
= \frac{1}{k!} f^{(k)} (z) + \Delta r_{k+1} (z, \Delta),
\]

i.e.

\[
\Delta^k r_k (z, \Delta) = \frac{1}{k!} f^{(k)} (z) \Delta^k + \Delta^{k+1} r_{k+1} (z, \Delta).
\]

The result now follows by induction.

2. For \( y \in \mathbb{R} \), sin \( y = y \int_0^1 \cos (ty) \ dt \) and hence

\[
|\sin y| \leq |y|.
\]  

(14.47)

3. For \( y \in \mathbb{R} \) we have

\[
\cos y = 1 + y^2 \int_0^1 -\cos (ty) (1 - t) \ dt \geq 1 + y^2 \int_0^1 - (1 - t) \ dt = 1 - \frac{y^2}{2}.
\]

Equivalently put\(^2\)

\[
|\cos y| \leq 1 - \frac{y^2}{2}.
\]

Alternatively,

\[
|\sin y| = \left| \int_0^y \cos x \ dx \right| \leq \int_0^y |\cos x| \ dx \leq |y|
\]

and for \( y \geq 0 \) we have,

\[
\cos y - 1 = \int_0^y -\sin x \ dx \geq \int_0^y -x \ dx = -\frac{y^2}{2}.
\]

This last inequality may also be proved as a simple calculus exercise following from;

\[
g (\pm \infty) = \infty \text{ and } g' (y) = 0 \text{ iff } \sin y = y \text{ which happens iff } y = 0.
\]

4. Since

\[
|e^z - 1 - z| = |z^2 \int_0^1 e^{tz} (1 - t) \ dt| \leq |z|^2 \int_0^1 e^{\Re z} (1 - t) \ dt,
\]

if \( \Re z \leq 0 \), then

\[
|e^z - 1 - z| \leq |z|^2 / 2
\]  

(14.49)

and if \( \Re z > 0 \) then

\[
|e^z - 1 - z| \leq e^{\Re z} |z|^2 / 2.
\]

Combining these into one estimate gives,

\[
|e^z - 1 - z| \leq e^{\Re z} \frac{|z|^2}{2}.
\]  

(14.50)

5. Since \( e^{iy} - 1 = iy \int_0^1 e^{ity} \ dt \), \( |e^{iy} - 1| \leq |y| \) and hence

\[
|e^{iy} - 1| \leq 2 \wedge |y| \text{ for all } y \in \mathbb{R}.
\]  

(14.51)

**Lemma 14.45.** For \( z = re^{i\theta} \) with \( -\pi < \theta < \pi \) and \( r > 0 \), let \( \ln z = \ln r + i\theta \). Then \( \ln : \mathbb{C} \setminus (-\infty, 0] \to \mathbb{C} \) is a holomorphic function such that \( e^{\ln z} = z \) and if \( |z| < 1 \) then

\[
|\ln (1 + z) - z| \leq |z|^2 \left( \frac{1}{1 - |z|^2} \right) \text{ for } |z| < 1.
\]  

(14.52)

**Proof.** Clearly \( e^{\ln z} = z \) and \( \ln z \) is continuous. Therefore by the inverse function theorem for holomorphic functions, \( \ln z \) is holomorphic and

\[
z \frac{d}{dz} \ln z = e^{\ln z} \frac{d}{dz} \ln z = 1.
\]

\(^3\) For the purposes of this lemma it suffices to define \( \ln (1 + z) = -\sum_{n=1}^{\infty} (-z)^n / n \) and to then observe: 1)

\[
\frac{d}{dz} \ln (1 + z) = \sum_{n=0}^{\infty} (-z)^n = \frac{1}{1 + z}
\]

and 2) the functions \( 1 + z \) and \( e^{\ln (1 + z)} \) both solve

\[
f' (z) = \frac{1}{1 + z} f (z) \text{ with } f (0) = 1
\]

and therefore \( e^{\ln (1 + z)} = 1 + z. \)
Therefore, $\frac{d}{dz} \ln z = \frac{1}{z}$ and $\frac{d^2}{dz^2} \ln z = -\frac{1}{z^2}$. So by Taylor’s theorem,

$$\ln (1 + z) = z - z^2 \int_0^1 \frac{1}{(1 + tz)^2} (1 - t) \, dt. \quad (14.53)$$

If $t \geq 0$ and $|z| < 1$, then

$$\left| \frac{1}{(1 + tz)} \right| \leq \sum_{n=0}^{\infty} |tz|^n \leq \frac{1}{1 - |z|} \quad \text{and therefore,}$$

and therefore,

$$\left| \int_0^1 \frac{1}{(1 + tz)^2} (1 - t) \, dt \right| \leq \frac{1}{2 (1 - |z|)^2}.$$  \quad (14.54)

Eq. (14.52) is now a consequence of Eq. (14.53) and Eq. (14.54).

Lemma 14.46. For all $y \in \mathbb{R}$ and $n \in \mathbb{N} \cup \{0\}$,

$$\left| e^{iy} - \sum_{k=0}^{n} \frac{(iy)^k}{k!} \right| \leq \frac{|y|^{n+1}}{(n+1)!} \quad (14.55)$$

and in particular,

$$\left| e^{iy} - \left( 1 + iy - \frac{y^2}{2!} \right) \right| \leq y^2 \wedge \frac{|y|^3}{3!}.$$  \quad (14.56)

More generally for all $n \in \mathbb{N}$ we have

$$\left| e^{iy} - \sum_{k=0}^{n} \frac{(iy)^k}{k!} \right| \leq \frac{|y|^{n+1}}{(n+1)!} \wedge \frac{2 |y|^n}{n!}.$$  \quad (14.57)

Proof. By Taylor’s theorem (see Eq. (14.42) with $f(y) = e^{iy}, x = 0$ and $\Delta = y$) we have

$$\left| e^{iy} - \sum_{k=0}^{n} \frac{(iy)^k}{k!} \right| = \frac{|y|^{n+1}}{n!} \left| \int_0^1 i^{n+1} e^{ity} (1 - t)^n \, dt \right| \leq \frac{|y|^{n+1}}{n!} \int_0^1 (1 - t)^n \, dt = \frac{|y|^{n+1}}{(n+1)!},$$

which is Eq. (14.55). Using Eq. (14.55) with $n = 1$ implies

$$\left| e^{iy} - \left( 1 + iy - \frac{y^2}{2!} \right) \right| \leq \left| e^{iy} - (1 + iy) \right| + \frac{|y|^2}{2} \leq \frac{|y|^2}{2} + \frac{|y|^2}{2} = y^2$$

and using Eq. (14.55) with $n = 2$ implies

$$\left| e^{iy} - \left( 1 + iy - \frac{y^2}{2!} \right) \right| \leq \frac{|y|^3}{3!}.$$ Combining the last two inequalities completes the proof of Eq. (14.56).

Equation (14.57) is proved similarly and hence will be omitted. \quad $\blacksquare$

Lemma 14.47. If $X$ is a square integrable random variable, then

$$f(\lambda) := \mathbb{E} [e^{i\lambda X}] = 1 + i\lambda \mathbb{E} X - \frac{\lambda^2}{2!} \mathbb{E} [X^2] + r(\lambda)$$

where

$$r(\lambda) := \lambda^2 \mathbb{E} \left[ X^2 \wedge \frac{|\lambda| |X|^3}{3!} \right] = \lambda^2 \mathbb{E} (\lambda)$$

and

$$\mathbb{E} (\lambda) := \mathbb{E} \left[ X^2 \wedge \frac{|\lambda| |X|^3}{3!} \right] \rightarrow 0 \text{ as } \lambda \rightarrow 0.$$  \quad (14.58)

Proof. Using Eq. (14.56) with $y = \lambda X$ and taking expectations implies,

$$\left| f(\lambda) - \left( 1 + i\lambda \mathbb{E} X - \frac{\lambda^2}{2!} \mathbb{E} [X^2] \right) \right| \leq \mathbb{E} \left| e^{i\lambda X} - \left( 1 + i\lambda X - \frac{\lambda^2}{2!} X^2 \right) \right| \leq \lambda^2 \mathbb{E} \left[ X^2 \wedge \frac{|\lambda| |X|^3}{3!} \right] =: \lambda^2 \mathbb{E} (\lambda).$$

The DCT, with $X^2 \in L^1 (P)$ being the dominating function, allows us to conclude that $\lim_{\lambda \rightarrow 0} \mathbb{E} (\lambda) = 0$. \quad $\blacksquare$
Weak Convergence of Random Sums

Throughout this chapter, we will assume the following standing notation unless otherwise stated. For each \( n \in \mathbb{N} \), let \( \{X_{n,k}\}_{k=1}^{n} \) be independent random variables and let
\[
S_n := \sum_{k=1}^{n} X_{n,k}.
\] (15.1)

Until further notice we are going to assume \( \mathbb{E}[X_{n,k}] = 0 \), \( \sigma_{n,k}^2 = \mathbb{E}[X_{n,k}^2] < \infty \), and \( \text{Var}(S_n) = \sum_{k=1}^{n} \sigma_{n,k}^2 = 1 \). Also let
\[
f_{nk}(\lambda) := \mathbb{E}[e^{i\lambda X_{n,k}}]
\] (15.2)
denote the characteristic function of \( X_{n,k} \).

**Example 15.1.** Suppose \( \{X_n\}_{n=1}^{\infty} \) are mean zero square integrable random variables with \( \sigma_n^2 = \text{Var}(X_n) \). If we let \( s_n^2 := \sum_{k=1}^{n} \text{Var}(X_k) = \sum_{k=1}^{n} \sigma_k^2 \), \( \sigma_{n,k}^2 := \sigma_k^2/s_n^2 \), and \( X_{n,k} := X_k/s_n \), then \( \{X_{n,k}\}_{k=1}^{n} \) satisfy the above hypothesis and \( S_n = \frac{1}{s_n^2} \sum_{k=1}^{n} X_k \).

Our main interest in this chapter is to consider the limiting behavior of \( S_n \) as \( n \to \infty \). In order to do this, it will be useful to put conditions on the \( \{X_{n,k}\} \) such that no one term dominates sum defining the sum defining \( S_n \) in Eq. (15.1) in the limit as \( n \to \infty \).

**Definition 15.2.** We say that \( \{X_{n,k}\} \) satisfies the **Lindeberg Condition (LC)** iff
\[
\lim_{n \to \infty} \sum_{k=1}^{n} \mathbb{E}[X_{n,k}^2 : |X_{n,k}| > t] = 0 \text{ for all } t > 0.
\] (15.3)
We say \( \{X_{n,k}\} \) satisfies condition \( (M) \) if
\[
D_n := \max \{ \sigma_{n,k}^2 : k \leq n \} \to 0 \text{ as } n \to \infty,
\] (15.4)
and we say \( \{X_{n,k}\} \) is **uniformly asymptotic negligibility (UAN)** if for all \( \varepsilon > 0 \),
\[
\lim_{n \to \infty} \max_{k \leq n} P(|X_{n,k}| > \varepsilon) = 0.
\] (15.5)

**Remark 15.3.** The reader should observe that in order for condition \((M)\) to hold in the setup in Example 15.1 it is necessary that \( \lim_{n \to \infty} s_n^2 = \infty \).

**Lemma 15.4.** Let us continue the notation in Example 15.1. Then \( \{X_{n,k} := X_k/s_{n}\} \) satisfies (LC) if either of two conditions hold;
1. \( \{X_n\}_{n=1}^{\infty} \) are i.i.d.
2. The \( \{X_n\}_{n=1}^{\infty} \) satisfy Liapunov condition; there exists some \( \alpha > 2 \) such that
\[
\lim_{n \to \infty} \frac{\sum_{k=1}^{n} \mathbb{E}[|X_k|^\alpha]}{s_n^2} = 0.
\] (15.6)
More generally, if \( \{X_{n,k}\} \) satisfies the Liapunov condition,
\[
\lim_{n \to \infty} \sum_{k=1}^{n} \mathbb{E}[X_{n,k}^2 \varphi(|X_{n,k}|)] = 0
\]
where \( \varphi : [0, \infty) \to [0, \infty) \) is a non-decreasing function such that \( \varphi(t) > 0 \) for all \( t > 0 \), then \( \{X_{n,k}\} \) satisfies (LC).

**Proof.** 1. If \( \{X_n\}_{n=1}^{\infty} \) are i.i.d., then \( s_n = \sqrt{n}\sigma \) where \( \sigma^2 = \mathbb{E}X_1^2 \) and
\[
\sum_{k=1}^{n} \mathbb{E}[X_{n,k}^2 : |X_{n,k}| > t] = \frac{1}{s_n^2} \sum_{k=1}^{n} \mathbb{E}[X_k^2 : |X_k| > s_n t] = \frac{1}{\sigma^2} \mathbb{E}[X_1^2 : |X_1| > \sqrt{n}\sigma t]
\] (15.7)
which, by DCT, tends to zero as \( n \to \infty \).

2. Assuming Eq. (15.6), then for any \( t > 0 \),
\[
\sum_{k=1}^{n} \mathbb{E}[X_{n,k}^2 : |X_{n,k}| > t] \leq \sum_{k=1}^{n} \mathbb{E}[X_{n,k}^2 : |X_{n,k}|^\alpha^{2} : |X_{n,k}| > t] \leq \frac{1}{t^{\alpha-2}} \sum_{k=1}^{n} \mathbb{E}[X_{n,k}]^\alpha \to 0.
\]
For the last assertion, working as above we have
\[
\sum_{k=1}^{n} \mathbb{E} \left[ X_{n,k}^2 : |X_{n,k}| > t \right] \leq \sum_{k=1}^{n} \mathbb{E} \left[ X_{n,k}^2 \frac{\varphi(|X_{n,k}|)}{\varphi(t)} : |X_{n,k}| > t \right] \\
\leq \frac{1}{\varphi(t)} \sum_{k=1}^{n} \mathbb{E} \left[ X_{n,k}^2 \varphi(|X_{n,k}|) \right] \to 0
\]
as \( n \to \infty \).

**Lemma 15.5.** Let \( \{X_{n,k}\}_{n=1}^{\infty} \) be as above, then \((LC) \implies (M) \implies (UAN)\).

**Proof.** For \( k \leq n \),
\[
\sigma_{n,k}^2 = \mathbb{E} \left[ X_{n,k}^2 \right] = \mathbb{E} \left[ X_{n,k}^2 1_{|X_{n,k}| \leq t} \right] + \mathbb{E} \left[ X_{n,k}^2 1_{|X_{n,k}| > t} \right] \\
\leq t^2 + \mathbb{E} \left[ X_{n,k}^2 1_{|X_{n,k}| > t} \right] \leq t^2 + \sum_{m=1}^{n} \mathbb{E} \left[ X_{n,m}^2 1_{|X_{n,m}| > t} \right]
\]
and therefore using \((LC)\) we find
\[
\lim_{n \to \infty} \max_{k \leq n} \sigma_{n,k}^2 \leq t^2 \text{ for all } t > 0.
\]
This clearly implies \((M)\) holds. The assertion that \((M)\) implies \((UAN)\) follows by Chebyshev’s inequality,
\[
\max_{k \leq n} P \left( |X_{n,k}| > \varepsilon \right) \leq \max_{k \leq n} \frac{1}{\varepsilon^2} \mathbb{E} \left[ |X_{n,k}|^2 : |X_{n,k}| > \varepsilon \right] \\
\leq \frac{1}{\varepsilon^2} \sum_{k=1}^{n} \mathbb{E} \left[ |X_{n,k}|^2 : |X_{n,k}| > \varepsilon \right] \to 0.
\]
In fact the same argument shows that \((M)\) implies
\[
\sum_{k=1}^{n} P \left( |X_{n,k}| > \varepsilon \right) \leq \frac{1}{\varepsilon^2} \sum_{k=1}^{n} \mathbb{E} \left[ |X_{n,k}|^2 : |X_{n,k}| > \varepsilon \right] \to 0.
\]

We will need the following lemma for our subsequent applications of the continuity theorem.

**Lemma 15.6.** Suppose that \( a_i, b_i \in \mathbb{C} \) with \( |a_i|, |b_i| \leq 1 \) for \( i = 1, 2, \ldots, n \). Then
\[
\left| \prod_{i=1}^{n} a_i - \prod_{i=1}^{n} b_i \right| \leq \sum_{i=1}^{n} |a_i - b_i|.
\]

**Proof.** Let \( a := \prod_{i=1}^{n-1} a_i \) and \( b := \prod_{i=1}^{n-1} b_i \) and observe that \( |a|, |b| \leq 1 \) and that
\[
|a_{n} a - b_{n} b| \leq |a_{n} a - a_{n} b| + |a_{n} b - b_{n} b| \\
= |a_{n}| |a - b| + |a_{n} - b_{n}| |b| \\
\leq |a - b| + |a_{n} - b_{n}|.
\]
The proof is now easily completed by induction on \( n \).

**Theorem 15.7 (Lindeberg-Feller CLT (I)).** Suppose \( \{X_{n,k}\} \) satisfies \((LC)\), then
\[
S_n \implies N(0,1).
\]
(See Theorem 15.11 for a converse to this theorem.)

To prove this theorem we must show
\[
\mathbb{E} \left[ e^{\lambda S_n} \right] \to e^{-\lambda^2/2} \text{ as } n \to \infty.
\]
Before starting the formal proof, let me give an informal explanation for Eq. (15.9). Using
\[
f_{n,k}(\lambda) \sim 1 - \frac{\lambda^2}{2} \sigma_{n,k}^2,
\]
we might expect
\[
\mathbb{E} \left[ e^{\lambda S_n} \right] = \prod_{k=1}^{n} f_{n,k}(\lambda) = e^{\sum_{k=1}^{n} \ln f_{n,k}(\lambda)} \\
= e^{\sum_{k=1}^{n} \ln(1+f_{n,k}(\lambda)-1)} \\
= e^{\sum_{k=1}^{n} f_{n,k}(\lambda)-1} \\
= \prod_{k=1}^{n} e^{f_{n,k}(\lambda)-1} \\
= e^{\sum_{k=1}^{n} \lambda^2 \sigma_{n,k}^2} = e^{-\lambda^2/2}.
\]
The question then becomes under what conditions are these approximations valid. It turns out that approximation \((A)\), namely that
\[
\lim_{n \to \infty} \left| \prod_{k=1}^{n} f_{n,k}(\lambda) - \exp \left( \sum_{k=1}^{n} (f_{n,k}(\lambda)-1) \right) \right| = 0,
\]
is valid if condition \((M)\) holds, see Lemma 15.5 below. It is shown in the estimate Eq. (15.11) below that the approximation \((B)\) is valid, i.e.
\[
\lim_{n \to \infty} \sum_{k=1}^{n} (f_{n,k}(\lambda)-1) = -\frac{1}{2} \lambda^2.
\]
if (LC) is satisfied. These observations would then constitute a proof of Theorem 15.7. The proof given below of Theorem 15.7 will not quite follow this route and will not use Lemma 15.9 directly. However, this lemma will be used in the proofs of Theorems 15.11 and 15.14.

**Proof.** Now on to the formal proof of Theorem 15.7. Since

\[
\mathbb{E} \left[ e^{i\lambda S_n} \right] = \prod_{k=1}^{n} f_{n,k}(\lambda) \quad \text{and} \quad e^{-\lambda^2/2} = \prod_{k=1}^{n} e^{-\lambda^2 \sigma_{n,k}^2/2},
\]

we may use Lemma 15.6 to conclude,

\[
\left| \mathbb{E} \left[ e^{i\lambda S_n} \right] - e^{-\lambda^2/2} \right| \leq \sum_{k=1}^{n} \left| f_{n,k}(\lambda) - e^{-\lambda^2 \sigma_{n,k}^2/2} \right| = \sum_{k=1}^{n} (A_{n,k} + B_{n,k})
\]

where

\[
A_{n,k} := \left| f_{n,k}(\lambda) - \left( 1 - \frac{\lambda^2 \sigma_{n,k}^2}{2} \right) \right|
\]

and

\[
B_{n,k} := \left| \left( 1 - \frac{\lambda^2 \sigma_{n,k}^2}{2} \right) - e^{-\lambda^2 \sigma_{n,k}^2/2} \right|.
\]

Now, using Lemma 14.47,

\[
A_{n,k} = \left| \mathbb{E} \left[ e^{i\lambda X_{n,k}} \right] - 1 + \frac{\lambda^2}{2} X_{n,k} \right| \leq \mathbb{E} \left| e^{i\lambda X_{n,k}} - 1 + \frac{\lambda^2}{2} X_{n,k} \right| \leq \lambda^2 \mathbb{E} \left[ X_{n,k} \right] \frac{|\lambda|^3}{3!} \leq \lambda^2 \mathbb{E} \left[ X_{n,k} \right] \frac{|\lambda|^3}{3!} : |X_{n,k}| \leq \varepsilon + \lambda^2 \mathbb{E} \left[ X_{n,k} \right] \frac{|\lambda|^3}{3!} : |X_{n,k}| > \varepsilon
\]

\[
\leq \lambda^2 \mathbb{E} \left[ |X_{n,k}|^3 \right] \frac{3!}{3!} : |X_{n,k}| \leq \varepsilon + \lambda^2 \mathbb{E} \left[ X_{n,k} : |X_{n,k}| > \varepsilon \right]
\]

\[
\leq \lambda^2 \mathbb{E} \left[ |X_{n,k}|^3 \right] \frac{3!}{3!} : |X_{n,k}| \leq \varepsilon + \lambda^2 \mathbb{E} \left[ X_{n,k} : |X_{n,k}| > \varepsilon \right]
\]

\[
\leq \lambda^2 \mathbb{E} \left[ |X_{n,k}|^3 \right] \frac{3!}{3!} : |X_{n,k}| \leq \varepsilon + \lambda^2 \mathbb{E} \left[ X_{n,k} \right] \frac{3!}{3!} : |X_{n,k}| > \varepsilon
\]

\[
= \left( \frac{\lambda^2}{6} \sigma_{n,k}^2 + \frac{\lambda^2}{6} \mathbb{E} \left[ X_{n,k}^2 : |X_{n,k}| > \varepsilon \right] \right).
\]

From this estimate and (LC) it follows that

\[
\limsup_{n \to \infty} \frac{1}{n} \sum_{k=1}^{n} A_{n,k} \leq \limsup_{n \to \infty} \left( \frac{\lambda^2}{6} \sigma_{n,k}^2 + \frac{\lambda^2}{6} \mathbb{E} \left[ X_{n,k}^2 : |X_{n,k}| > \varepsilon \right] \right) = \frac{\lambda^2 \varepsilon}{6},
\]

and since \( \varepsilon > 0 \) is arbitrary, we may conclude that \( \limsup_{n \to \infty} \sum_{k=1}^{n} A_{n,k} = 0 \).

To estimate \( \sum_{k=1}^{n} B_{n,k} \), we use the estimate, \( |e^{-u} - 1 + u| \leq u^2/2 \) valid for \( u \geq 0 \) (see Eq. 14.49 with \( z = -u \)). With this estimate we find,

\[
\sum_{k=1}^{n} B_{n,k} = \sum_{k=1}^{n} \left[ 1 - \frac{\lambda^2 \sigma_{n,k}^2}{2} \right] - e^{-\lambda^2 \sigma_{n,k}^2/2} \leq \sum_{k=1}^{n} \frac{1}{2} \frac{\lambda^2 \sigma_{n,k}^2}{2} \leq \frac{\lambda^4}{8} \sum_{k=1}^{n} \sigma_{n,k}^4 \leq \frac{\lambda^4}{8} \max_{1 \leq k \leq n} \sigma_{n,k}^4 \sigma_{n,k}^2 \to 0,
\]

wherein we have used (M) (which is implied by (LC)) in taking the limit as \( n \to \infty \).

As an application of Theorem 15.7 we can give half of the proof of Theorem 12.12.

**Theorem 15.8 (Converse assertion in Theorem 12.12).** If \( \{X_n\}_{n=1}^{\infty} \) are independent random variables and the random series, \( \sum_{n=1}^{\infty} X_n \), is almost surely convergent, then for all \( c > 0 \) the following three series converge:

1. \( \sum_{n=1}^{\infty} P \left( |X_n| > c \right) < \infty \),
2. \( \sum_{n=1}^{\infty} \text{Var} \left( X_n | X_n \leq c \right) < \infty \), and
3. \( \sum_{n=1}^{\infty} \mathbb{E} \left( X_n | X_n \leq c \right) \) converges.

**Proof.** Since \( \sum_{n=1}^{\infty} X_n \) is almost surely convergent, it follows that \( \lim_{n \to \infty} X_n = 0 \) a.s. and hence for every \( c > 0 \), \( P \left( |X_n| \geq c \right) = 0 \). According the Borel zero one law this implies for every \( c > 0 \) that \( \sum_{n=1}^{\infty} P \left( |X_n| > c \right) < \infty \). Since \( X_n \to 0 \) a.s., \( \{X_n\} \) and \( \{X^c_n := X_n | X_n \leq c\} \) are tail equivalent for all \( c > 0 \). In particular \( \sum_{n=1}^{\infty} X^c_n \) is almost surely convergent for all \( c > 0 \).

Fix \( c > 0 \), let \( Y_n := X^c_n - \mathbb{E} [X^c_n] \) and let

\[
s_n^2 = \text{Var} (Y_1 + \cdots + Y_n) = \sum_{k=1}^{n} \text{Var} (Y_k) = \sum_{k=1}^{n} \text{Var} (Y_n^c) = \sum_{k=1}^{n} \text{Var} (X_k | X_k \leq c).
\]

For the sake of contradictions, suppose \( s_n^2 \to \infty \) as \( n \to \infty \). Since \( |Y_k| \leq 2c \), it follows that \( \sum_{k=1}^{n} \mathbb{E} \left[ Y_k^2 | X_k > s_n \right] \to 0 \) for all sufficiently large \( n \) and hence

\[
\lim_{n \to \infty} \frac{1}{s_n^2} \sum_{k=1}^{n} \mathbb{E} \left[ Y_k^2 | X_k > s_n \right] = 0,
\]

i.e. \( \{Y_{nk} := Y_k/s_n\}_{n=1}^{\infty} \) satisfies (LC) – see Examples 15.1 and Remark 15.3. So by the central limit Theorem 15.7 it follows that
Since we already know that
\[ \frac{1}{s^2_n} \sum_{k=1}^{n} (X^c_n - E [X^c_n]) = \frac{1}{s^2_n} \sum_{k=1}^{n} Y_k \implies N (0, 1). \]

On the other hand we know
\[ \lim_{n \to \infty} \frac{1}{s^2_n} \sum_{k=1}^{n} X^c_n = \frac{\sum_{k=1}^{\infty} X^c_k}{\lim_{n \to \infty} s^2_n} = 0 \text{ a.s.} \]

and so by Slutsky’s theorem,
\[ \frac{1}{s^2_n} \sum_{k=1}^{n} E [X^c_n] = \frac{1}{s^2_n} \sum_{k=1}^{n} X^c_n - \frac{1}{s^2_n} \sum_{k=1}^{n} Y_k \implies N (0, 1). \]

But it is not possible for constant (i.e. non-random) variables, \(c_n := \frac{1}{s^2_n} \sum_{k=1}^{n} E [X^c_n]\), to converge to a non-degenerate limit. (Think about this either in terms of characteristic functions or in terms of distribution functions.)

Thus we must conclude that
\[ \sum_{n=1}^{\infty} \text{Var} (X_n | |X_n| \leq c) = \sum_{n=1}^{\infty} \text{Var} (X_n) = \lim_{n \to \infty} s^2_n < \infty. \]

An application of Kolmogorov’s convergence criteria (Theorem 12.11) implies that
\[ \sum_{n=1}^{\infty} (X^c_n - E [X^c_n]) \text{ is convergent a.s.} \]

Since we already know that \(\sum_{n=1}^{\infty} X^c_n\) is convergent almost surely we may now conclude \(\sum_{n=1}^{\infty} E (X_n | |X_n| \leq c)\) is convergent.

Let us now turn to the converse of Theorem 15.7, see Theorem 15.11 below.

**Lemma 15.9.** Suppose that \(\{X_{n,k}\}\) satisfies property \((M)\), i.e. \(D_n := \max_{k \leq n} \sigma^2_{n,k} \to 0\). If we define,
\[ \varphi_{n,k} (\lambda) := f_{n,k} (\lambda) - 1 = E \left[ e^{i \lambda X_{n,k}} - 1 \right], \]
then:
1. \(\lim_{n \to \infty} \max_{k \leq n} |\varphi_{n,k} (\lambda)| = 0\) and
2. \(f_{S_n} (\lambda) = \prod_{k=1}^{n} e^{\varphi_{n,k}(\lambda)} \to 0\) as \(n \to \infty\), where
\[ f_{S_n} (\lambda) = E \left[ e^{i \lambda S_n} \right] = \prod_{k=1}^{n} f_{n,k} (\lambda). \]

**Proof.** For the first item we estimate,
\[ |E e^{i \lambda X} - 1| \leq E |e^{i \lambda X} - 1| \leq E [2 \land |\lambda X|] = E [2 \land |\lambda X| : |X| \geq \varepsilon] + E [2 \land |\lambda X| : |X| < \varepsilon] \]
\[ \leq 2P (|X| \geq \varepsilon) + |\lambda| \varepsilon \leq \frac{2}{\varepsilon^2} E |X|^2 + |\lambda| \varepsilon. \]

Replacing \(X\) by \(X_{n,k}\) and in the above inequality shows
\[ |\varphi_{n,k} (\lambda)| = |f_{n,k} (\lambda) - 1| \leq \frac{2}{\varepsilon^2} E |X_{n,k}|^2 + |\lambda| \varepsilon = \frac{2 \sigma^2_{n,k}}{\varepsilon^2} + |\lambda| \varepsilon. \]

Therefore,
\[ \lim sup \max_{n \to \infty} |\varphi_{n,k} (\lambda)| \leq \lim sup \max_{n \to \infty} \left[ \frac{2D_n}{\varepsilon^2} + |\lambda| \varepsilon \right] = |\lambda| \varepsilon \to 0 \text{ as } \varepsilon \downarrow 0. \]

For the second item, observe that \(\text{Re} \varphi_{n,k} (\lambda) = \text{Re} f_{n,k} (\lambda) - 1 \leq 0\) and hence
\[ |e^{\varphi_{n,k}(\lambda)}| = e^{\text{Re} \varphi_{n,k}(\lambda)} \leq e^0 = 1 \]
and hence we have from Lemma 15.6 and the estimate (14.49),
\[ \left| \prod_{k=1}^{n} f_{n,k} (\lambda) - \prod_{k=1}^{n} e^{\varphi_{n,k}(\lambda)} \right| \leq \sum_{k=1}^{n} \left| f_{n,k} (\lambda) - e^{\varphi_{n,k}(\lambda)} \right| \leq \sum_{k=1}^{n} \left| e^{\varphi_{n,k}(\lambda)} - 1 - \varphi_{n,k} (\lambda) \right| \leq \frac{1}{2} \sum_{k=1}^{n} |\varphi_{n,k} (\lambda)|^2 \leq \frac{1}{2} \max_{k \leq n} |\varphi_{n,k} (\lambda)| \cdot \sum_{k=1}^{n} |\varphi_{n,k} (\lambda)|. \]

Moreover since \(E X_{n,k} = 0\), the estimate in Eq. (14.49) implies
\[ \sum_{k=1}^{n} |\varphi_{n,k} (\lambda)| = \sum_{k=1}^{n} |E \left[ e^{i \lambda X_{n,k}} - 1 - i \lambda X_{n,k} \right]| \leq \sum_{k=1}^{n} \left| E \left[ \frac{1}{2} (\lambda X_{n,k})^2 \right] \right| \leq \frac{1}{2} \lambda^2 \sum_{k=1}^{n} \sigma^2_{n,k} = \frac{\lambda^2}{2}. \]

Thus we have shown,
In particular if we choose

\[
\text{Theorem 15.11 (Lindeberg-Feller CLT (II)).}
\]

Suppose

\[
\text{Suppose that } \lambda X \rightarrow \infty \text{ and } \lambda X = 0.
\]

Further let \( f (\lambda) := \mathbb{E} [e^{i \lambda X}] \) and \( u (\lambda) := \text{Re} (f (\lambda) - 1). \) Then for all \( c > 0, \)

\[
u (\lambda) + \frac{\lambda^2}{2} \mathbb{E} [X^2] \geq \mathbb{E} \left[ X^2 \left( \frac{\lambda^2}{2} - \frac{2}{c^2} \right) : |X| > c \right]
\]

(15.12)
or equivalently

\[
\mathbb{E} \left[ \cos \lambda X - 1 + \frac{\lambda^2}{2} X^2 \right] \geq \mathbb{E} \left[ X^2 \left( \frac{\lambda^2}{2} - \frac{2}{c^2} \right) : |X| > c \right].
\]

(15.13)

In particular if we choose \(|\lambda| \geq \sqrt{6}/|c|, \)

then

\[
\mathbb{E} \left[ \cos \lambda X - 1 + \frac{\lambda^2}{2} X^2 \right] \geq \frac{1}{c^2} \mathbb{E} \left[ X^2 : |X| > c \right].
\]

(15.14)

**Proof.** For all \( \lambda \in \mathbb{R}, \) we have (see Eq. (14.48)) \( \cos \lambda X - 1 + \frac{\lambda^2}{2} X^2 \geq 0 \) and \( \cos \lambda X - 1 \geq -2. \) Therefore,

\[
u (\lambda) + \frac{\lambda^2}{2} \mathbb{E} [X^2] = \mathbb{E} \left[ \cos \lambda X - 1 + \frac{\lambda^2}{2} X^2 \right]
\]

\[
\geq \mathbb{E} \left[ \cos \lambda X - 1 + \frac{\lambda^2}{2} X^2 : |X| > c \right]
\]

\[
\geq \mathbb{E} \left[ -2 + \frac{\lambda^2}{2} X^2 : |X| > c \right]
\]

\[
\geq \mathbb{E} \left[ -2 \frac{|X|^2}{c^2} + \frac{\lambda^2}{2} X^2 : |X| > c \right]
\]

which gives Eq. (15.12).

**Theorem 15.11 (Lindeberg-Feller CLT (II)).** Suppose \( \{X_{n,k}\} \) satisfies (M) and also the central limit theorem in Eq. (15.8) holds, then \( \{X_{n,k}\} \) satisfies (LC). So under condition (M), \( S_n \) converges to a normal random variable iff (LC) holds.

**Proof.** By assumption we have

\[
\lim_{n \to \infty} \max_{1 \leq k \leq n} \sigma_{n,k}^2 = 0 \quad \text{and} \quad \lim_{n \to \infty} \prod_{k=1}^{n} f_{n,k} (\lambda) = e^{-\lambda^2/2}.
\]

The second inequality combined with Lemma 15.9 implies,

\[
\lim_{n \to \infty} e^{\sum_{k=1}^{n} \varphi_{n,k} (\lambda)} = \lim_{n \to \infty} \prod_{k=1}^{n} e^{\varphi_{n,k} (\lambda)} = e^{-\lambda^2/2}.
\]

Taking the modulus of this equation then implies,

\[
\lim_{n \to \infty} e^{\sum_{k=1}^{n} \text{Re} \varphi_{n,k} (\lambda)} = \lim_{n \to \infty} \left| e^{\sum_{k=1}^{n} \varphi_{n,k} (\lambda)} \right| = e^{-\lambda^2/2}
\]

from which we may conclude

\[
\lim_{n \to \infty} \sum_{k=1}^{n} \text{Re} \varphi_{n,k} (\lambda) = -\lambda^2/2.
\]

We may write this last limit as

\[
\lim_{n \to \infty} \sum_{k=1}^{n} \mathbb{E} \left[ \cos (\lambda X_{n,k}) - 1 + \frac{\lambda^2}{2} X_{n,k}^2 \right] = 0
\]

which by Lemma 15.10 implies

\[
\lim_{n \to \infty} \sum_{k=1}^{n} \mathbb{E} \left[ X_{n,k}^2 : |X_{n,k}| > c \right] = 0
\]

for all \( c > 0 \) which is (LC).

**15.1 Infinitely Divisible and Stable Symmetric Distributions**

To get some indication as to what we might expect to happen when the Lindeberg condition is relaxed, we consider the following Poisson limit theorem.

**Theorem 15.12 (A Poisson Limit Theorem).** For each \( n \in \mathbb{N}, \) let \( \{X_{n,k}\}_{k=1}^{n} \) be independent Bernoulli random variables with \( P(X_{n,k} = 1) = p_{n,k} \) and \( P(X_{n,k} = 0) = q_{n,k} := 1 - p_{n,k}. \) Suppose;

1. \( \lim_{n \to \infty} \sum_{k=1}^{n} p_{n,k} = a \in (0, \infty) \) and 
2. \( \lim_{n \to \infty} \max_{1 \leq k \leq n} p_{n,k} = 0. \) (So no one term is dominating the sums in item 1.)

Then \( S_n = \sum_{k=1}^{n} X_{n,k} \implies Z \) where \( Z \) is a Poisson random variable with mean \( a. \) (See Section 2.6 of Durrett[3] for more on this theorem.)
Since $1 + p_{n,k} (e^{i\lambda} - 1)$ lies on the line segment joining 1 to $e^{i\lambda}$, it follows that

$$|1 + p_{n,k} (e^{i\lambda} - 1)| \leq 1.$$ 

Hence we may apply Lemma 15.6 to find

$$\left| \prod_{k=1}^{n} \exp \left( p_{n,k} \left( e^{i\lambda} - 1 \right) \right) - \prod_{k=1}^{n} \left[ 1 + p_{n,k} \left( e^{i\lambda} - 1 \right) \right] \right| \leq \sum_{k=1}^{n} \left| \exp \left( p_{n,k} \left( e^{i\lambda} - 1 \right) \right) - \left[ 1 + p_{n,k} \left( e^{i\lambda} - 1 \right) \right] \right| = \sum_{k=1}^{n} |\exp (z_{n,k}) - [1 + z_{n,k}]|$$

where

$$z_{n,k} = p_{n,k} (e^{i\lambda} - 1).$$

Since $\text{Re} z_{n,k} = p_{n,k} (\cos \lambda - 1) \leq 0$, we may use the calculus estimate in Eq. (15.49) to conclude,

$$\left| \prod_{k=1}^{n} \exp \left( p_{n,k} \left( e^{i\lambda} - 1 \right) \right) - \prod_{k=1}^{n} \left[ 1 + p_{n,k} \left( e^{i\lambda} - 1 \right) \right] \right| \leq \frac{1}{2} \sum_{k=1}^{n} |z_{n,k}|^2 \leq \frac{1}{2} \max_{1 \leq k \leq n} |z_{n,k}| \sum_{k=1}^{n} |z_{n,k}| \leq 2 \max_{1 \leq k \leq n} p_{n,k} \sum_{k=1}^{n} p_{n,k}.$$ 

Using the assumptions, we may conclude

$$\left| \prod_{k=1}^{n} \exp \left( p_{n,k} \left( e^{i\lambda} - 1 \right) \right) - \prod_{k=1}^{n} \left[ 1 + p_{n,k} \left( e^{i\lambda} - 1 \right) \right] \right| \to 0 \text{ as } n \to \infty.$$ 

Since

$$\prod_{k=1}^{n} \exp \left( p_{n,k} \left( e^{i\lambda} - 1 \right) \right) = \exp \left( \sum_{k=1}^{n} p_{n,k} \left( e^{i\lambda} - 1 \right) \right) \to \exp \left( a \left( e^{i\lambda} - 1 \right) \right),$$

we have shown

$$\lim_{n \to \infty} \mathbb{E} \left[ e^{i\lambda S_n} \right] = \lim_{n \to \infty} \prod_{k=1}^{n} \left[ 1 + p_{n,k} \left( e^{i\lambda} - 1 \right) \right] = \lim_{n \to \infty} \prod_{k=1}^{n} \exp \left( p_{n,k} \left( e^{i\lambda} - 1 \right) \right) = \exp \left( a \left( e^{i\lambda} - 1 \right) \right).$$

The result now follows by an application of the continuity Theorem 14.21.

\begin{remark}
Keeping the notation in Theorem 15.12, we have

$$\mathbb{E} [X_{n,k}] = p_{n,k} \text{ and } \text{Var} (X_{n,k}) = p_{n,k} (1 - p_{n,k})$$

and

$$s_n^2 := \sum_{k=1}^{n} \text{Var} (X_{n,k}) = \sum_{k=1}^{n} p_{n,k} (1 - p_{n,k}).$$

Under the assumptions of Theorem 15.12 we see that $s_n^2 \to a$ as $n \to \infty$. Let $Y_{n,k} := \frac{X_{n,k} - p_{n,k}}{s_n}$, so that $\mathbb{E} [Y_{n,k}] = 0$ and $\sigma_{n,k}^2 := \text{Var} (Y_{n,k}) = \frac{1}{s_n^2} \text{Var} (X_{n,k}) = \frac{1}{s_n^2} p_{n,k} (1 - p_{n,k})$ which satisfies condition (M). Let us observe that, for large

\end{remark}
Suppose Theorem 15.14. We assume

$$f$$ is a normal random variable. 

where

$$\exp \left( \int \frac{e^{i \lambda x} - 1 - i \lambda x}{x^2} d\nu (x) \right)$$

from which it follows that

$$\lim_{n \to \infty} \sum_{k=1}^{n} \mathbb{E} \left[ Y_{n,k}^2 : |Y_{n,k}| > t \right] = \lim_{n \to \infty} \sum_{k=1}^{n} \frac{p_{n,k}}{s_n} \left( 1 - \frac{p_{n,k}}{s_n} \right)^2 = a.$$ 

Therefore $$\{Y_{n,k}\}$$ do not satisfy (LC). Nevertheless we have

$$\sum_{k=1}^{n} Y_{n,k} = \sum_{k=1}^{n} X_{n,k} - \sum_{k=1}^{n} p_{n,k} \Rightarrow Z - a \frac{Z}{a}$$

where $$Z$$ is a Poisson random variable with mean $$a$$. Notice that the limit is not a normal random variable.

We wish to characterize the possible limiting distributions of sequences $$\{S_n\}_{n=1}^{\infty}$$ when we relax the Lindeberg condition (LC) to condition (M). We have the following theorem.

**Theorem 15.14.** Suppose $$\{X_{n,k}\}_{k=1}^{n}$$ satisfy property (M) and $$S_n := \sum_{k=1}^{n} X_{n,k} \Rightarrow L$$ for some random variable $$L$$. Then the characteristic function $$f_L (\lambda) := \mathbb{E} \left[ e^{i \lambda L} \right]$$ must be of the form,

$$f_L (\lambda) = \exp \left( \int \frac{e^{i \lambda x} - 1 - i \lambda x}{x^2} d\nu (x) \right)$$

where $$\nu$$ is a finite positive measure on $$\mathbb{R}$$ such that $$\nu (\mathbb{R}) \leq 1$$. (Recall that you proved in Exercise 14.4 that $$\exp \left( \int \frac{e^{i \lambda x} - 1 - i \lambda x}{x^2} d\nu (x) \right)$$ is always the characteristic function of a probability measure.)

**Proof.** As before, let $$f_{n,k} (\lambda) = \mathbb{E} \left[ e^{i \lambda X_{n,k}} \right]$$ and $$\varphi_{n,k} (\lambda) := f_{n,k} (\lambda) - 1$$. By the continuity theorem we are assuming

$$\lim_{n \to \infty} f_{S_n} (\lambda) = \lim_{n \to \infty} \prod_{k=1}^{n} f_{n,k} (\lambda) = f (\lambda)$$

where $$f (\lambda)$$ is continuous at $$\lambda = 0$$. We are also assuming property (M), i.e.

$$\lim_{n \to \infty} \max_{1 \leq k \leq n} \sigma_{n,k}^2 = 0.$$ 

Under condition (M), we expect $$f_{n,k} (\lambda) \approx 1$$ for $$n$$ large. Therefore we expect

$$f_{n,k} (\lambda) = e^{i \lambda f_{n,k} (\lambda)} = e^{i \lambda (f_{n,k} (\lambda) - 1)} \approx e^{(f_{n,k} (\lambda) - 1)}$$

and hence that

$$\mathbb{E} \left[ e^{i \lambda S_n} \right] = \prod_{k=1}^{n} f_{n,k} (\lambda) \approx \prod_{k=1}^{n} e^{(f_{n,k} (\lambda) - 1)} = \exp \left( \sum_{k=1}^{n} (f_{n,k} (\lambda) - 1) \right). \quad (15.15)$$

This is in fact correct, since Lemma 15.9 indeed implies

$$\lim_{n \to \infty} \left[ \mathbb{E} \left[ e^{i \lambda S_n} \right] - \exp \left( \sum_{k=1}^{n} (f_{n,k} (\lambda) - 1) \right) \right] = 0. \quad (15.16)$$

Since $$\mathbb{E} \left[ X_{n,k} \right] = 0$$,

$$f_{n,k} (\lambda) - 1 = \mathbb{E} \left[ e^{i \lambda X_{n,k}} - 1 \right] = \mathbb{E} \left[ e^{i \lambda X_{n,k}} - 1 - i \lambda X_{n,k} \right]$$

$$= \int_{\mathbb{R}} \left( e^{i \lambda x} - 1 - i \lambda x \right) d\mu_{n,k} (x)$$

where $$\mu_{n,k} := P \circ X_{n,k}^{-1}$$ is the law of $$X_{n,k}$$. Therefore we have

$$\exp \left( \sum_{k=1}^{n} (f_{n,k} (\lambda) - 1) \right) = \exp \left( \sum_{k=1}^{n} \int_{\mathbb{R}} \left( e^{i \lambda x} - 1 - i \lambda x \right) d\mu_{n,k} (x) \right)$$

$$= \exp \left( \int_{\mathbb{R}} \left( e^{i \lambda x} - 1 - i \lambda x \right) d\nu_n (x) \right) \quad (15.17)$$

where $$\nu_n := \sum_{k=1}^{n} \mu_{n,k}$$. Let us further observe that

$$\int_{\mathbb{R}} x^2 d\nu_n (x) = \sum_{k=1}^{n} \int_{\mathbb{R}} x^2 d\mu_{n,k} (x) = \sum_{k=1}^{n} \sigma_{n,k}^2 = 1.$$ 

Hence if we define $$d\nu_n (x) := x^2 d\nu_n (x)$$, then $$\nu_n$$ is a probability measure and we have from Eqs. (15.16) and Eq. (15.17) that

$$\left| f_{S_n} (\lambda) - \exp \left( \int_{\mathbb{R}} \frac{e^{i \lambda x} - 1 - i \lambda x}{x^2} d\nu_n (x) \right) \right| \to 0. \quad (15.18)$$
Corollary 15.15. Suppose \( h(x) := \frac{e^{\lambda x} - 1 - i \lambda x}{x^2} \) is a continuous function of \( \mathbb{R} \) with \( h(\pm \infty) = 0 \), there is a subsequence, \( \{n_i\} \) of \( \{n\} \) such that \( \nu_{n_i}(h) \to \tilde{\nu}(h) \) for some probability measure on \( (\mathbb{R}, \mathcal{B}_\mathbb{R}) \). Combining this with Eq. (15.18) allows us to conclude,

\[
f_L(\lambda) = \lim_{l \to \infty} \mathbb{E}[e^{\lambda S_n}] = \lim_{l \to \infty} \left( \int_{\mathbb{R}} (e^{i\lambda x} - 1 - i \lambda x) \, d\nu_{n_i}(x) \right)
= \exp \left( \int_{\mathbb{R}} \frac{e^{i\lambda x} - 1 - i \lambda x}{x^2} \, d\nu(x) \right).
\]

Definition 15.15. We say that \( \{X_{n,k}\}_{k=1}^n \) has bounded variation (BV) iff

\[
\sup_n \text{Var}(S_n) = \sup_n \sum_{k=1}^n \sigma_{n,k}^2 < \infty. \tag{15.19}
\]

Corollary 15.16. Suppose \( \{X_{n,k}\}_{k=1}^n \) satisfy properties (M) and (BV). If \( S_n := \sum_{k=1}^n X_{n,k} \implies L \) for some random variable \( L \), then

\[
f_L(\lambda) = \exp \left( \int_{\mathbb{R}} \frac{e^{i\lambda x} - 1 - i \lambda x}{x^2} \, d\nu(x) \right) \tag{15.20}
\]

where \( \nu \) is a finite positive measure on \((\mathbb{R}, \mathcal{B}_\mathbb{R})\).

Proof. Let \( s^2_n := \text{Var}(S_n) \). If \( \lim_{n \to \infty} s_n = 0 \), then \( S_n \to 0 \) in \( L^2 \) and hence weakly, therefore Eq. (15.20) holds with \( \nu \equiv 0 \). So let us now suppose \( \lim_{n \to \infty} s_n \neq 0 \). Since \( \{s_n\}_{n=1}^\infty \) is bounded, we may by passing to a subsequence if necessary, assume \( \lim_{n \to \infty} s_n = s > 0 \). By replacing \( X_{n,k} \) by \( X_{n,k}/s_n \) and hence \( S_n \) by \( S_n/s_n \), we then know by Slutsky’s theorem that \( S_n/s_n \implies L/s \). Hence by an application of Theorem 15.14 we may conclude

\[
f_L(\lambda/s) = f_{L/s}(\lambda) = \exp \left( \int_{\mathbb{R}} \frac{e^{i\lambda x} - 1 - i \lambda x}{x^2} \, d\nu(x) \right)
\]

where \( \nu \) is a finite positive measure on \((\mathbb{R}, \mathcal{B}_\mathbb{R})\) such that \( \nu(\mathbb{R}) \leq 1 \). Letting \( \lambda \to s\lambda \) in this expression then implies

\[
f_L(\lambda) = \exp \left( \int_{\mathbb{R}} \frac{e^{i\lambda x} - 1 - i \lambda x}{x^2} \, d\nu(x) \right)
= \exp \left( \int_{\mathbb{R}} \frac{e^{i\lambda x} - 1 - i \lambda x}{s^2x^2} \, d\nu(x) \right)
= \exp \left( \int_{\mathbb{R}} \frac{e^{i\lambda x} - 1 - i \lambda x}{x^2} \, d\nu_s(x) \right)
\]

where \( \nu_s \) is the finite measure on \((\mathbb{R}, \mathcal{B}_\mathbb{R})\) defined by

\[
\nu_s(A) := s^2\nu(s^{-1}A) \text{ for all } A \in \mathcal{B}_\mathbb{R}.
\]

The reader should observe that

\[
\frac{e^{i\lambda x} - 1 - i \lambda x}{x^2} = \frac{1}{x^2} \sum_{k=2}^\infty \frac{(i\lambda x)^k}{k!} = \frac{1}{x^2} \sum_{k=2}^\infty \frac{i^k \lambda^k x^{k-2}}{k!}
\]

due to \( (\lambda, x) \to \frac{e^{i\lambda x} - 1 - i \lambda x}{x^2} \) is smooth. Moreover,

\[
\frac{d}{d\lambda} \frac{e^{i\lambda x} - 1 - i \lambda x}{x^2} = ixe^{i\lambda x} - ix = i \frac{e^{i\lambda x} - 1}{x}
\]
and

\[
\frac{d^2}{d\lambda^2} \frac{e^{i\lambda x} - 1 - i \lambda x}{x^2} = ix^2e^{i\lambda x} = -i e^{i\lambda x}.
\]

Using these remarks and the fact that \( \nu(\mathbb{R}) < \infty \), it is easy to see that

\[
f'_L(\lambda) = \left( \int_{\mathbb{R}} \frac{e^{i\lambda x} - 1}{x} \, d\nu_s(x) \right) f_L(\lambda)
\]
and

\[
f''_L(\lambda) = \left( \int_{\mathbb{R}} -e^{i\lambda x} \, d\nu_s(x) + \left( \int_{\mathbb{R}} \frac{e^{i\lambda x} - 1}{x} \, d\nu_s(x) \right)^2 \right) f_L(\lambda)
\]

and in particular, \( f'_L(0) = 0 \) and \( f''_L(0) = -\nu_s(\mathbb{R}) \). Therefore the probability measure, \( \mu \), on \((\mathbb{R}, \mathcal{B}_\mathbb{R})\) such that \( \mu(\lambda) = f_L(\lambda) \) has mean zero and variance, \( \nu_s(\mathbb{R}) < \infty \).

Definition 15.17. A probability distribution, \( \mu \), on \((\mathbb{R}, \mathcal{B}_\mathbb{R})\) is infinitely divisible iff for all \( n \in \mathbb{N} \) there exists i.i.d. nondegenerate random variables, \( \{X_{n,k}\}_{k=1}^n \), such that \( X_{n,1} + \cdots + X_{n,n} \overset{d}{=} \mu \). This can be formulated in the following two equivalent ways. For all \( n \in \mathbb{N} \) there should exists a non-degenerate probability measure, \( \mu_n \), on \((\mathbb{R}, \mathcal{B}_\mathbb{R})\) such that \( \mu^n_n = \mu \). For all \( n \in \mathbb{N} \), \( \mu(\lambda) = [g(\lambda)]^n \) for some non-constant characteristic function, \( g \).

Theorem 15.18. The following class of symmetric distributions on \((\mathbb{R}, \mathcal{B}_\mathbb{R})\) are equal;

1. \( C_1 \) - all possible limiting distributions under properties (M) and (BV).
2. \( C_2 \) - all distributions with characteristic functions of the form given in Corollary 15.16.
3. \( C_3 \) – all infinitely divisible distributions with mean zero and finite variance.

**Proof.** The inclusion, \( C_1 \subset C_2 \), is the content of Corollary 15.16. For \( C_2 \subset C_3 \), observe that if

\[
\hat{\mu}(\lambda) = \exp \left( \int_{\mathbb{R}} \frac{e^{i\lambda x} - 1 - i\lambda x}{x^2} d\nu(x) \right)
\]

then \( \hat{\mu}(\lambda) = [\hat{\mu}_n(\lambda)]^n \) where \( \mu_n \) is the unique probability measure on \((\mathbb{R}, \mathcal{B}_\mathbb{R})\) such that

\[
\hat{\mu}_n(\lambda) = \exp \left( \int_{\mathbb{R}} \frac{e^{i\lambda x} - 1 - i\lambda x}{n} d\nu(x) \right).
\]

For \( C_3 \subset C_1 \), simply define \( \{X_{n,k}\}_{k=1}^n \) to be i.i.d with \( \mathbb{E}[e^{i\lambda X_{n,k}}] = \hat{\mu}_n(\lambda) \). In this case \( S_n = \sum_{k=1}^n X_{n,k} \overset{d}{=} \mu \).

**15.1.1 Stable Laws**

See the file, dynkin-stable-infinitely-divs.pdf, and Durrett Example 3.10 on p. 106 and Section 2.7.].
Conditional Expectations and Martingales
Hilbert Space Basics

Definition 16.1. Let $H$ be a complex vector space. An inner product on $H$ is a function, $\langle \cdot | \cdot \rangle : H \times H \to \mathbb{C}$, such that

1. $\langle ax + by | z \rangle = a \langle x | z \rangle + b \langle y | z \rangle$ i.e. $x \to \langle x | z \rangle$ is linear.
2. $\langle x | y \rangle = \overline{\langle y | x \rangle}$.
3. $\| x \|^2 := \langle x | x \rangle \geq 0$ with equality $\| x \|^2 = 0$ iff $x = 0$.

Notice that combining properties (1) and (2) that $x \to \langle z | x \rangle$ is conjugate linear for fixed $z \in H$, i.e.

$$\langle z | ax + by \rangle = \overline{a} \langle z | x \rangle + \overline{b} \langle z | y \rangle.$$ 

The following identity will be used frequently in the sequel without further mention,

$$\| x + y \|^2 = \langle x + y | x + y \rangle = \| x \|^2 + \| y \|^2 + \langle x | y \rangle + \langle y | x \rangle$$

$$= \| x \|^2 + \| y \|^2 + 2 \Re \langle x | y \rangle.$$  \hspace{1cm} (16.1)

Theorem 16.2 (Schwarz Inequality). Let $(H, \langle \cdot | \cdot \rangle)$ be an inner product space, then for all $x, y \in H$

$$\| x \|^2 \leq \langle x | y \rangle \| y \|$$

and equality holds iff $x$ and $y$ are linearly dependent.

Proof. If $y = 0$, the result holds trivially. So assume that $y \neq 0$ and observe; if $x = \alpha y$ for some $\alpha \in \mathbb{C}$, then $\langle x | y \rangle = \overline{\alpha} \| y \|^2$ and hence

$$\| x \| = | \alpha | \| y \|^2 = \| x \| \| y \|.$$ 

Now suppose that $x \in H$ is arbitrary, let $z := x - \| y \|^{-2} \langle x | y \rangle y$. (So $z$ is the “orthogonal projection” of $x$ onto $y$, see Figure 16.1) Then

$$0 \leq \| z \|^2 = \left\| x - \frac{\langle x | y \rangle y}{\| y \|^2} \right\|^2$$

$$= \| x \|^2 + \frac{\| x \|^2}{\| y \|^4} \| y \|^2 - 2 \Re \frac{\langle x | y \rangle \langle x | y \rangle}{\| y \|^2}$$

$$= \| x \|^2 - \frac{\| x \|^2}{\| y \|^2} \| y \|^2$$

from which it follows that $0 \leq \langle x | y \rangle \| y \|^2 - \| x \|^2$ with equality iff $z = 0$ or equivalently iff $x = \| y \|^{-2} \langle x | y \rangle y$.

Corollary 16.3. Let $(H, \langle \cdot | \cdot \rangle)$ be an inner product space and $\| x \| := \sqrt{\langle x | x \rangle}$. Then the Hilbertian norm, $\| \cdot \|$, is a norm on $H$. Moreover $\langle \cdot | \cdot \rangle$ is continuous on $H \times H$, where $H$ is viewed as the normed space $(H, \| \cdot \|)$.

Proof. If $x, y \in H$, then, using Schwarz’s inequality,

$$\| x + y \|^2 = \| x \|^2 + \| y \|^2 + 2 \Re \langle x | y \rangle$$

$$\leq \| x \|^2 + \| y \|^2 + 2 \| x \| \| y \| = (\| x \| + \| y \|)^2.$$ 

Taking the square root of this inequality shows $\| \cdot \|$ satisfies the triangle inequality.

Checking that $\| \cdot \|$ satisfies the remaining axioms of a norm is now routine and will be left to the reader. If $x, x', y, y' \in H$, then

$$\| x + \Delta x \| y + \Delta y \| - \| x \| y \| = \| x \| \Delta y \| + \langle x | y \rangle + \langle \Delta x | y \rangle$$

$$\leq \| x \| \| y \| \| \Delta y \| + \| x \| \| \Delta x \| + \| \Delta x \| \| \Delta y \|$$

$$\to 0$$

as $\Delta x, \Delta y \to 0$.

from which it follows that $\langle \cdot | \cdot \rangle$ is continuous.

Definition 16.4. Let $(H, \langle \cdot | \cdot \rangle)$ be an inner product space, we say $x, y \in H$ are orthogonal and write $x \perp y$ iff $\langle x | y \rangle = 0$. More generally if $A \subset H$ is a set, $x \in H$ is orthogonal to $A$ (write $x \perp A$) iff $\langle x | y \rangle = 0$ for all $y \in A$. Let

![Fig. 16.1. The picture behind the proof of the Schwarz inequality.](image-url)
\( A^\perp = \{ x \in H : x \perp A \} \) be the set of vectors orthogonal to \( A \). A subset \( S \subset H \) is an orthogonal set if \( x \perp y \) for all distinct elements \( x, y \in S \). If \( S \) further satisfies, \( \| x \| = 1 \) for all \( x \in S \), then \( S \) is said to be an orthonormal set.

**Proposition 16.5.** Let \(( H, \langle \cdot | \cdot \rangle )\) be an inner product space then

1. (Parallelogram Law)
   \[ \| x + y \|^2 + \| x - y \|^2 = 2 \| x \|^2 + 2 \| y \|^2 \quad (16.2) \]
   for all \( x, y \in H \).

2. (Pythagorean Theorem) If \( S \subset H \) is a finite orthogonal set, then
   \[ \left\| \sum_{x \in S} x \right\|^2 = \sum_{x \in S} \| x \|^2. \quad (16.3) \]

3. If \( A \subset H \) is a set, then \( A^\perp \) is a closed linear subspace of \( H \).

**Proof.** I will assume that \( H \) is a complex Hilbert space, the real case being easier. Items 1. and 2. are proved by the following elementary computations;

\[ \| x + y \|^2 + \| x - y \|^2 = \| x \|^2 + \| y \|^2 + 2\Re(x|y) + \| x \|^2 + \| y \|^2 - 2\Re(x|y) \]

\[ = 2 \| x \|^2 + 2 \| y \|^2, \]

and

\[ \left\| \sum_{x \in S} x \right\|^2 = \left( \sum_{x \in S} \sum_{y \in S} (x|y) \right) = \sum_{x,y \in S} (x|y) \]

\[ = \sum_{x \in S} \sum_{y \in S} (x|y) = \sum_{x \in S} \| x \|^2. \]

Item 3. is a consequence of the continuity of \( \langle \cdot | \cdot \rangle \) and the fact that

\[ A^\perp = \bigcap_{x \in A} \text{Null}(\langle \cdot | x \rangle) \]

where \( \text{Null}(\langle \cdot | x \rangle) = \{ y \in H : \langle y|x \rangle = 0 \} \) – a closed subspace of \( H \).

**Definition 16.6.** A Hilbert space is an inner product space \(( H, \langle \cdot | \cdot \rangle )\) such that the induced Hilbertian norm is complete.

**Example 16.7.** For any measure space, \(( \Omega, B, \mu ), \ H := L^2(\mu) \) with inner product,

\[ \langle f | g \rangle = \int_{\Omega} f(\omega) \overline{g}(\omega) \, d\mu(\omega) \]

is a Hilbert space – see Theorem 11.17 for the completeness assertion.

**Definition 16.8.** A subset \( C \) of a vector space \( X \) is said to be convex if for all \( x, y \in C \) the line segment \( [x,y] := \{ tx + (1-t)y : 0 \leq t \leq 1 \} \) joining \( x \) to \( y \) is contained in \( C \) as well. (Notice that any vector subspace of \( X \) is convex.)

**Theorem 16.9 (Best Approximation Theorem).** Suppose that \( H \) is a Hilbert space and \( M \subset H \) is a closed convex subset of \( H \). Then for any \( x \in H \) there exists a unique \( y \in M \) such that

\[ \| x - y \| = d(x,M) = \inf_{z \in M} \| x - z \|. \]

Moreover, if \( M \) is a vector subspace of \( H \), then the point \( y \) may also be characterized as the unique point in \( M \) such that \( (x-y) \perp M \).

**Proof. Uniqueness.** By replacing \( M \) by \( M - x := \{ m - x : m \in M \} \) we may assume \( x = 0 \). Let \( \delta := d(0,M) = \inf_{m \in M} \| m \| \) and \( y, z \in M \), see Figure 16.2.

![Fig. 16.2. The geometry of convex sets.](image)

By the parallelogram law and the convexity of \( M \),

\[ 2 \| y \|^2 + 2 \| z \|^2 = \| y + z \|^2 + \| y - z \|^2 \]

\[ = 4 \left\| \frac{y + z}{2} \right\|^2 + \| y - z \|^2 \geq 4 \delta^2 + \| y - z \|^2. \quad (16.4) \]

Hence if \( \| y \| = \| z \| = \delta \), then \( 2 \delta^2 + 2 \delta^2 \geq 4 \delta^2 + \| y - z \|^2 \), so that \( \| y - z \|^2 = 0 \). Therefore, if a minimizer for \( d(0,\cdot)|_M \) exists, it is unique.

**Existence.** Let \( y_n \in M \) be chosen such that \( \| y_n \| = \delta_n \to \delta = d(0,M) \). Taking \( y = y_m \) and \( z = y_n \) in Eq. 16.4 shows

\[ 2 \delta^2_m + 2 \delta^2_n \geq 4 \delta^2 + \| y_n - y_m \|^2. \]
Passing to the limit \(m,n \to \infty\) in this equation implies,
\[
2\delta^2 + 2\delta^2 \geq 4\delta^2 + \limsup_{m,n \to \infty} \|y_n - y_m\|^2,
\]
i.e. \(\limsup_{m,n \to \infty} \|y_n - y_m\|^2 = 0\). Therefore, by completeness of \(H\), \(\{y_n\}_{n=1}^\infty\) is convergent. Because \(M\) is closed, \(y := \lim_{n \to \infty} y_n \in M\) and because the norm is continuous,
\[
\|y\| = \lim_{n \to \infty} \|y_n\| = \delta = d(0, M).
\]
So \(y\) is the desired point in \(M\) which is closest to \(0\).

Now suppose \(M\) is a closed subspace of \(H\) and \(x \in H\). Let \(y \in M\) be the closest point in \(M\) to \(x\). Then for \(w \in M\), the function
\[
g(t) := \|x - (y + tw)\|^2 = \|x - y\|^2 - 2t \Re \langle x - y, w \rangle + t^2 \|w\|^2
\]
has a minimum at \(t = 0\) and therefore \(0 = g'(0) = -2\Re \langle x - y, w \rangle\). Since \(w \in M\) is arbitrary, this implies that \((x - y) \perp M\).

Finally suppose \(y \in M\) is any point such that \((x - y) \perp M\). Then for \(z \in M\), by Pythagorean’s theorem,
\[
\|x - z\|^2 = \|x - y - z\|^2 = \|x - y\|^2 + \|y - z\|^2 \geq \|x - y\|^2
\]
which shows \(d(x, M)^2 \geq \|x - y\|^2\). That is to say \(y\) is the point in \(M\) closest to \(x\).

**Definition 16.10.** Suppose that \(A : H \to H\) is a bounded operator, i.e.
\[
\|A\| := \sup \{\|Ax\| : x \in H \text{ with } \|x\| = 1\} < \infty.
\]
The **adjoint** of \(A\), denoted \(A^* : H \to H\) such that \(\langle Ax, y \rangle = \langle x, A^*y \rangle\). (The proof that \(A^*\) exists and is unique will be given in Proposition [16.15](#).) A bounded operator \(A : H \to H\) is **self-adjoint** or **Hermitian** if \(A = A^*\).

**Definition 16.11.** Let \(H\) be a Hilbert space and \(M \subset H\) be a closed subspace. The orthogonal projection of \(H\) onto \(M\) is the function \(P_M : H \to H\) such that for \(x \in H\), \(P_M(x)\) is the unique element in \(M\) such that \((x - P_M(x)) \perp M\), i.e. \(P_M(x)\) is the unique element in \(M\) such that
\[
\langle x | m \rangle = \langle P_M(x) | m \rangle \quad \text{for all } m \in M.
\]

**Theorem 16.12 (Projection Theorem).** Let \(H\) be a Hilbert space and \(M \subset H\) be a closed subspace. The orthogonal projection \(P_M\) satisfies:

1. \(P_M\) is linear and hence we will write \(P_Mx\) rather than \(P_M(x)\).
2. \(P_M^2 = P_M\) (\(P_M\) is a projection).
3. \(P_M^* = P_M\) (\(P_M\) is self-adjoint).
4. \(\operatorname{Ran}(P_M) = M\) and \(\operatorname{Null}(P_M) = M^\perp\).
5. If \(N \subset M \subset H\) is another closed subspace, the \(P_N P_M = P_M P_N = P_N\).

**Proof.**

1. Let \(x_1, x_2 \in H\) and \(\alpha, \beta \in \mathbb{C}\), then \(P_Mx_1 + \alpha P_Mx_2 \in M\) and
\[
P_M(x_1 + \alpha x_2) = [P_Mx_1 - x_1 + \alpha(P_Mx_2 - x_2)] \in M^\perp
\]
showing \(P_M(x_1 + \alpha P_Mx_2 = P_M(x_1 + \alpha x_2)\), i.e. \(P_M\) is linear.
2. Obviously \(\operatorname{Ran}(P_M) = M\) and \(P_Mx = x\) for all \(x \in M\). Therefore \(P_M^2 = P_M\).
3. Let \(x, y \in H\), then since \((x - P_Mx)\) and \((y - P_My)\) are in \(M^\perp\),
\[
\langle P_Mx | y \rangle = \langle P_Mx | P_My + y - P_My \rangle = \langle P_Mx | P_My \rangle = \langle P_Mx + (x - P_Mx) | P_My \rangle = \langle x | P_My \rangle.
\]
4. We have already seen, \(\operatorname{Ran}(P_M) = M\) and \(P_Mx = 0\) if \(x = 0 \in M^\perp\), i.e. \(\operatorname{Null}(P_M) = M^\perp\).
5. If \(N \subset M \subset H\) it is clear that \(P_MP_N = P_N\) since \(P_M = \operatorname{Id}\) on \(N = \operatorname{Ran}(P_M) \subset M\). Taking adjoints gives the other identity, namely that \(P_N P_M = P_N\). More directly, if \(x \in H\) and \(n \in N\), we have
\[
\langle P_N P_Mx | n \rangle = \langle P_Mx | P_N n \rangle = \langle P_Mx | n \rangle = \langle x | P_Mn \rangle = \langle x | n \rangle.
\]
Since this holds for all \(n\) we may conclude that \(P_N P_Mx = P_Nx\).

**Corollary 16.13.** If \(N \subset H\) is a proper closed subspace of a Hilbert space \(H\), then \(H = M \oplus M^\perp\).

**Proof.** Given \(x \in H\), let \(y = P_Mx\) so that \((x - y) \in M^\perp\). Then \(x = y + (x - y) \in M + M^\perp\). If \(x \in M \cap M^\perp\), then \(x = x \perp x\), i.e. \(\|x\|^2 = \langle x | x \rangle = 0\). So \(M \cap M^\perp = \{0\}\).

**Exercise 16.1.** Suppose \(M\) is a subset of \(H\), then \(M^\perp = \overline{\langle M \rangle}\).

**Theorem 16.14 (Riesz Theorem).** Let \(H^*\) be the dual space of \(H\) (i.e. that linear space of continuous linear functionals on \(H\)). The map
\[
z \in H \quad \mapsto \quad \langle \cdot | z \rangle \in H^*
\]
is a conjugate linear isometric isomorphism.

\[1\] Recall that \(j\) is conjugate linear if
\[
j(z_1 + \alpha z_2) = jz_1 + \overline{\alpha}jz_2
\]
for all \(z_1, z_2 \in H\) and \(\alpha \in \mathbb{C}\).
Proof. The map \( j \) is conjugate linear by the axioms of the inner products. Moreover, for \( x, z \in H \),

\[
|\langle x | z \rangle| \leq \|x\| \|z\| \quad \text{for all } x \in H
\]

with equality when \( x = z \). This implies that \( \|jz\|_{H^*} = \|\langle \cdot | z \rangle\|_{H^*} = \|z\| \). Therefore \( j \) is isometric and this implies \( j \) is injective. To finish the proof we must show that \( j \) is surjective. So let \( f \in H^* \) which we assume, with out loss of generality, is non-zero. Then \( M = \text{Null}(f) \) – a closed proper subspace of \( H \). Since, by Corollary 16.13 \( H = M \oplus M^\perp \), \( f : H/M \cong M^\perp \to F \) is a linear isomorphism. This shows that \( \dim(M^\perp) = 1 \) and hence \( H = M \oplus Fx_0 \) where \( x_0 \in M^\perp \setminus \{0\} \).

Choose \( z = \lambda x_0 \in M^\perp \) such that \( f(x_0) = \langle x_0 | z \rangle \), i.e. \( \lambda = \|f(x_0)/\|x_0\|^2 \). Then for \( x = m + \lambda x_0 \) with \( m \in M \) and \( \lambda \in F \),

\[
f(x) = \lambda f(x_0) = \lambda\langle x_0 | z \rangle = \langle \lambda x_0 | z \rangle = \langle m + \lambda x_0 | z \rangle = \langle x | z \rangle
\]

which shows that \( f = jz \).

Proposition 16.15 (Adjoints). Let \( H \) and \( K \) be Hilbert spaces and \( A : H \to K \) be a bounded operator. Then there exists a unique bounded operator \( A^* : K \to H \) such that

\[
\langle Ax | y \rangle_K = \langle x | A^* y \rangle_H \quad \text{for all } x \in H \quad \text{and} \quad y \in K. \tag{16.7}
\]

Moreover, for all \( A, B \in L(H, K) \) and \( \lambda \in \mathbb{C} \),

1. \( (A + \lambda B)^* = A^* + \lambda B^* \),
2. \( A^{**} = (A^*)^* = A \),
3. \( \|A^*\| = \|A\| \quad \text{and} \quad \|A\| \in L(H, K) \) has a bounded inverse if \( A \) has a bounded and \( (A^*)^{-1} = (A^{-1})^* \).
4. \( \|A^*A\| = \|A\|^2 \).
5. If \( K = H \), then \( (AB)^* = B^*A^* \). In particular \( A \in L(H) \) has a bounded inverse if \( A^* \) has a bounded inverse and \( (A^*)^{-1} = (A^{-1})^* \).

Proof. For each \( y \in K \), the map \( x \to \langle Ax | y \rangle_K \) is in \( H \) and therefore there exists, by Theorem 16.14, a unique vector \( z \in H \) (we will denote this \( z \) by \( A^*(y) \)) such that

\[
\langle Ax | y \rangle_K = \langle x | z \rangle_H \quad \text{for all } x \in H.
\]

This shows there is a unique map \( A^* : K \to H \) such that \( \langle Ax | y \rangle_K = \langle x | A^*(y) \rangle_H \) for all \( x \in H \) and \( y \in K \).

To see \( A^* \) is linear, let \( y_1, y_2 \in K \) and \( \lambda \in \mathbb{C} \), then for any \( x \in H \),

\[
(Ax|y_1 + \lambda y_2) = \langle Ax | y_1 \rangle_K + \lambda \langle Ax | y_2 \rangle_K
\]

and by the uniqueness of \( A^*(y_1 + \lambda y_2) \) we find

\[
A^*(y_1 + \lambda y_2) = A^*(y_1) + \lambda A^*(y_2).
\]

This shows \( A^* \) is linear and so we will now write \( A^* y \) instead of \( A^*(y) \).

Since

\[
\langle A^* y | x \rangle_H = \langle A y | x \rangle_K = \langle y | A^* x \rangle_K
\]

it follows that \( A^{**} = A \). The assertion that \( (A + \lambda B)^* = A^* + \lambda B^* \) is Exercise 16.2.

Items 3. and 4. Making use of Schwarz’s inequality (Theorem 16.2), we have

\[
\|A^*\| = \sup_{k \in K: \|k\|=1} \|A^* k\|
\]

and

\[
\|A\|^2 = \sup_{h \in H: \|h\|=1} \|Ah\|^2 = \sup_{h \in H: \|h\|=1} \langle Ah | h \rangle
\]

so that \( \|A^*\| = \|A\| \). Since

\[
\|A^*A\| \leq \|A^*\| \|A\| = \|A\|^2
\]

and

\[
\|A\|^2 = \sup_{h \in H: \|h\|=1} \|Ah\|^2 = \sup_{h \in H: \|h\|=1} \langle Ah | h \rangle
\]

we also have \( \|A^*A\| \leq \|A\|^2 \leq \|A^* A\| \) which shows \( \|A\|^2 = \|A^* A\| \).

Alternatively, from Eq. (16.8),

\[
\|A\|^2 \leq \|A^* A\| \leq \|A\| \|A^*\| \quad \tag{16.9}
\]

which then implies \( \|A\| \leq \|A^*\| \). Replacing \( A \) by \( A^* \) in this last inequality shows \( \|A^*\| \leq \|A\| \) and hence that \( \|A^*\| = \|A\| \). Using this identity back in Eq. (16.9) proves \( \|A\|^2 = \|A^* A\| \).

Now suppose that \( K = H \). Then

\[
\langle Ah | k \rangle = \langle Bh | A^* k \rangle = \langle h | B A^* k \rangle
\]
which shows $(AB)^* = B^* A^*$. If $A^{-1}$ exists then
\[
(A^{-1})^* A^* = (AA^{-1})^* = I^* = I \quad \text{and} \quad A^* (A^{-1})^* = (A^{-1} A)^* = I^* = I.
\]
This shows that $A^*$ is invertible and $(A^*)^{-1} = (A^{-1})^*$. Similarly if $A^*$ is invertible then so is $A = A^{**}$.

**Exercise 16.2.** Let $H, K, M$ be Hilbert spaces, $A, B \in L(H, K)$, $C \in L(K, M)$ and $A \in \mathbb{C}$. Show $(A + \lambda B)^* = A^* + \lambda B^*$ and $(CA)^* = A^* C^* \in L(M, H)$.

**Exercise 16.3.** Let $H = \mathbb{C}^n$ and $K = \mathbb{C}^m$ equipped with the usual inner products, i.e. $(z|w)_H = z \cdot w$ for $z, w \in H$. Let $A$ be an $m \times n$ matrix thought of as a linear operator from $H$ to $K$. Show the matrix associated to $A^*: K \to H$ is the conjugate transpose of $A$.

**Lemma 16.16.** Suppose $A: H \to K$ is a bounded operator, then:

1. $\text{Nul}(A^*) = \text{Ran}(A)^\perp$.
2. $\text{Ran}(A) = \text{Nul}(A^*)^\perp$.
3. If $K = H$ and $V \subset H$ is an $A$-invariant subspace (i.e. $A(V) \subset V$), then $V^\perp$ is $A^*$-invariant.

**Proof.** An element $y \in K$ is in $\text{Nul}(A^*)$ iff $0 = (A^* y| x) = (y| A x)$ for all $x \in H$ which happens if $y \in \text{Ran}(A)^\perp$. Because, by Exercise 16.1, $\text{Ran}(A) = \text{Ran}(A)^\perp \perp$, and so by the first item, $\text{Ran}(A) = \text{Nul}(A^*)^\perp$. Now suppose $A(V) \subset V$ and $y \in V^\perp$, then
\[
(A^* y|x) = (y| A x) = 0 \quad \text{for all } x \in V
\]
which shows $A^* y \in V^\perp$.

The next elementary theorem (referred to as the bounded linear transformation theorem, or B.L.T. theorem for short) is often useful.

**Theorem 16.17 (B.L.T. Theorem).** Suppose that $Z$ is a normed space, $X$ is a Banach[¹] space, and $S \subset Z$ is a dense linear subspace of $Z$. If $T: S \to X$ is a bounded linear transformation (i.e. there exists $C < \infty$ such that $\|Tz\| \leq C \|z\|$ for all $z \in S$), then $T$ has a unique extension to an element $\bar{T} \in L(Z, X)$ and this extension still satisfies
\[
\|\bar{T}z\| \leq C \|z\| \quad \text{for all } z \in \tilde{S}.
\]

[¹] A Banach space is a complete normed space. The main examples for us are Hilbert spaces.

**Proof.** Let $z \in Z$ and choose $z_n \in S$ such that $z_n \to z$. Since
\[
\|Tz_n - Tz\| \leq C \|z_n - z\| \to 0 \quad \text{as } m, n \to \infty,
\]
it follows by the completeness of $X$ that $\lim_{n \to \infty} Tz_n =: \bar{T}z$ exists. Moreover, if $w_n \in S$ is another sequence converging to $z$, then
\[
\|Tz_n - Tw_n\| \leq C \|z_n - w_n\| \to C \|z - z\| = 0
\]
and therefore $\bar{T}z$ is well defined. It is now a simple matter to check that $\bar{T}: Z \to X$ is still linear and that
\[
\|\bar{T}z\| = \lim_{n \to \infty} \|Tz_n\| \leq \lim_{n \to \infty} C \|z_n\| = C \|z\| \quad \text{for all } x \in Z.
\]
Thus $\bar{T}$ is an extension of $T$ to all of $Z$. The uniqueness of this extension is easy to prove and will be left to the reader.

### 16.1 Compactness Results for $L^p$ – Spaces

In this section we are going to identify the sequentially “weak” compact subsets of $L^p(\Omega, B, P)$ for $1 \leq p < \infty$, where $(\Omega, B, P)$ is a probability space. The key to our proofs will be the following Hilbert space compactness result.

**Theorem 16.18.** Suppose $\{x_n\}_{n=1}^\infty$ is a bounded sequence in $H$ (i.e. $C = \sup_{n} \|x_n\| < \infty$), then there exists a sub-sequence, $y_k := x_{n_k}$ and an $x \in H$ such that $\lim_{k \to \infty} \langle y_k| h \rangle = \langle x| h \rangle$ for all $h \in H$. We say that $y_k$ converges to $x$ weakly in this case and denote this by $y_k \rightharpoonup x$.

**Proof.** Let $H_0 := \text{span}\{x_k : k \in \mathbb{N}\}$. Then $H_0$ is a closed separable Hilbert subspace of $H$ and $\{x_k\}_{k=1}^\infty \subset H_0$. Let $\{h_n\}_{n=1}^\infty$ be a countable dense subset of $H_0$. Since $\|x_k| h_n\| \leq \|x_k\| \|h_n\| \leq C \|h_n\| < \infty$, the sequence, $\{x_k| h_n\}_{k=1}^\infty \subset C$, is bounded and hence has a convergent sub-sequence for all $n \in \mathbb{N}$. By the Cantor’s diagonalization argument we can find a a sub-sequence, $y_k := x_{n_k}$, of $\{x_n\}$ such that $\lim_{k \to \infty} \langle y_k| h_n \rangle$ exists for all $n \in \mathbb{N}$.

We now show $\varphi(z) := \lim_{k \to \infty} \langle y_k| z \rangle$ exists for all $z \in H_0$. Indeed, for any $k, l, n \in \mathbb{N}$, we have
\[
\|y_k - y_l\| = \|y_k - y_l | h_n\| \leq \|y_k - y_l| h_n\| + \|y_k - y_l| z - h_n\| \\
\leq \|y_k - y_l| h_n\| + 2C \|z - h_n\|
\]
Letting $k, l \to \infty$ in this estimate then shows
\[
\lim_{k, l \to \infty} \|y_k - y_l\| \leq 2C \|z - h_n\|
\]
Since we may choose $n \in \mathbb{N}$ such that $\|z - h_n\|$ is as small as we please, we may conclude that $\limsup_{k \to \infty} |\langle y_k | z \rangle - \langle y | z \rangle|$, i.e. $\varphi(z) := \lim_{k \to \infty} \langle y_k | z \rangle$ exists.

The function, $\varphi(z) = \lim_{k \to \infty} \langle z | y_k \rangle$ is a bounded linear functional on $H$ because

$$|\varphi(z)| = \liminf_{k \to \infty} |\langle z | y_k \rangle| \leq C \|z\|.$$ 

Therefore by the Riesz Theorem (16.14) there exists $x \in H_0$ such that $\varphi(z) = \langle z | x \rangle$ for all $z \in H_0$. Thus, for this $x \in H_0$ we have shown

$$\lim_{k \to \infty} \langle y_k | z \rangle = \langle x | z \rangle \quad \text{for all } z \in H_0. \quad (16.10)$$

To finish the proof we need only observe that Eq. (16.10) is valid for all $z \in H$. Indeed if $z \in H$, then $z = z_0 + z_1$, where $z_0 = P_{H_0} z \in H_0$ and $z_1 = z - P_{H_0} z \in H_0^\perp$. Since $y_k, x \in H_0$, we have

$$\lim_{k \to \infty} \langle y_k | z \rangle = \lim_{k \to \infty} \langle y_k | z_0 \rangle = \langle x | z_0 \rangle = \langle z | x \rangle \quad \text{for all } z \in H.$$  \hfill \blacksquare

Since unbounded subsets of $H$ are clearly not sequentially weakly compact, the previous states that a set is sequentially precompact in $H$ iff it is bounded. Let us now use Theorem (16.18) to identify the sequentially compact subsets of $L^p(\Omega, \mathcal{B}, P)$ for all $1 \leq p < \infty$. We begin with the case $p = 1$.

**Theorem 16.19.** If $(X_n)_{n=1}^\infty \subseteq L^1(\Omega, \mathcal{B}, P)$ is a uniformly integrable subset of $L^1(\Omega, \mathcal{B}, P)$, there exists a subsequence $Y_k := X_{n_k}$ of $(X_n)_{n=1}^\infty$ and $X \in L^1(\Omega, \mathcal{B}, P)$ such that

$$\lim_{k \to \infty} E[Y_k h] = E[X h] \quad \text{for all } h \in B_0. \quad (16.11)$$

**Proof.** For each $m \in \mathbb{N}$ let $X_m := X_n 1_{|X_n| \leq m}$. The truncated sequence $(X_m)_{n=1}^\infty$ is a bounded subset of the Hilbert space, $L^2(\Omega, \mathcal{B}, P)$, for all $m \in \mathbb{N}$. Therefore by Theorem 16.18, $(X_n)_{n=1}^\infty$ has a weakly convergent sub-sequence for all $m \in \mathbb{N}$. By Cantor’s diagonalization argument, we can find $Y_m := X_{n_k}$ and $X \in L^2(\Omega, \mathcal{B}, P)$ such that $Y_m \overset{\text{w}}{\to} X$ as $m \to \infty$ and in particular

$$\lim_{k \to \infty} E[Y_{n_k} h] = E[X h] \quad \text{for all } h \in B_0.$$  

Our next goal is to show $X_m \to X$ in $L^1(\Omega, \mathcal{B}, P)$. To this end, for $m < M$ and $h \in B_0$ we have

$$E[(X^M - X^m) h] = \lim_{k \to \infty} E[(Y_k^M - Y_k^m) h] \leq \liminf_{k \to \infty} E[Y_k^M - Y_k^m | h] \leq \|h\|_{\infty} \liminf_{k \to \infty} E|Y_k| : M \geq |Y_k| > M| \leq \|h\|_{\infty} \liminf_{k \to \infty} E|Y_k| : |Y_k| > M|.$$ 

Taking $h = \text{sgn}(X^M - X^m)$ in this inequality shows

$$E[(X^M - X^m)] \leq \liminf_{k \to \infty} E[|Y_k| : |Y_k| > M]$$

with the right member of this inequality going to zero as $m, M \to \infty$ with $M \leq m$ by the assumed uniform integrability of the $(X_n)$. Therefore there exists $X \in L^1(\Omega, \mathcal{B}, P)$ such that $\lim_{m \to \infty} E[|X - X^m|] = 0$.

We are now ready to verify Eq. (16.11) is valid. For $h \in B_0$,

$$E[|X - Y_k| h] \leq E[|X^M - Y_k^m| h] + E[|X - X^m| h] + E[|Y_k - Y_k^m| h] \leq E[|X^M - Y_k^m| h] + \|h\|_{\infty} \cdot (E[|X - X^m|] + E[|Y_k| : |Y_k| > M]).$$

Passing to the limit as $k \to \infty$ in the above inequality shows

$$\limsup_{k \to \infty} E[|X - Y_k| h] \leq \|h\|_{\infty} \cdot \left( E[|X - X^m|] + \sup_{l} E[|Y_l| : |Y_l| > M] \right).$$

Since $X^m \to X$ in $L^1$ and sup$_l E[|Y_l| : |Y_l| > M] \to 0$ by uniform integrability, it follows that, $\limsup_{k \to \infty} E[|X - Y_k| h] = 0.$

**Example 16.20.** Let $(\Omega, \mathcal{B}, P) = (\{0, 1\}, B_{\{0,1\}}, m)$ where $m$ is Lebesgue measure and let $X_n(\omega) = 2^n 1_{0 \leq \omega < 2^{-n}}$. Then $E[X_n] = 1$ for all $n$ and hence $(X_n)_{n=1}^\infty$ is bounded in $L^1(\Omega, \mathcal{B}, P)$ (but is not uniformly integrable). Suppose for sake of contradiction that there existed $X \in L^1(\Omega, \mathcal{B}, P)$ and subsequence, $Y_k := X_{n_k}$ such that $Y_k \overset{\text{w}}{\to} X$. Then for $h \in B_0$ and any $\varepsilon > 0$ we would have

$$E[X h 1_{(\varepsilon, 1)}] = \lim_{k \to \infty} E[Y_k h 1_{(\varepsilon, 1)}] = 0.$$ 

Then by DCT it would follow that $E[X 1] = 0$ for all $h \in B_0$ and hence that $X \equiv 0$. On the other hand we would also have

$$0 \leq E[X 1] = \lim_{k \to \infty} E[Y_k 1] = 1$$

and we have reached the desired contradiction. Hence we must conclude that bounded subset of $L^1(\Omega, \mathcal{B}, P)$ need not be weakly compact and thus we can not drop the uniform integrability assumption made in Theorem 16.19.

When $1 < p < \infty$, the situation is simpler.

**Theorem 16.21.** Let $p \in (1, \infty)$ and $q = p (p - 1)^{-1} \in (1, \infty)$ be its conjugate exponent. If $(X_n)_{n=1}^\infty$ is a bounded sequence in $L^p(\Omega, \mathcal{B}, P)$, there exists $X \in L^q(\Omega, \mathcal{B}, P)$ and a subsequence $Y_k := X_{n_k}$ of $(X_n)_{n=1}^\infty$ such that

$$\lim_{k \to \infty} E[Y_k h] = E[X h] \quad \text{for all } h \in L^p(\Omega, \mathcal{B}, P). \quad (16.12)$$
Proof. Let \( C := \sup_{n \in \mathbb{N}} \|X_n\|_p < \infty \) and recall that Lemma 16.19 guarantees that \( \{X_n\}_{n=1}^{\infty} \) is a uniformly integrable subset of \( L^1(\Omega, \mathcal{B}, P) \). Therefore by Theorem 16.16 there exists \( X \in L^1(\Omega, \mathcal{B}, P) \) and a subsequence, \( Y_k := X_{n_k} \), such that Eq. (16.11) holds. We will complete the proof by showing; a) \( X \in L^p(\Omega, \mathcal{B}, P) \) and b) Eq. (16.12) is valid.

a) For \( h \in \mathcal{B}_b \) we have

\[
|E[|X|h]| \leq \liminf_{k \to \infty} |E[Y_kh]| \leq \liminf_{k \to \infty} \|Y_k\|_p \cdot \|h\|_q \leq C \|h\|_q.
\]

For \( M < \infty \), taking \( \bar{h} = \text{sgn}(X)|X|^{p-1} 1_{|X| \leq M} \) in the previous inequality shows

\[
E\left[|X|^p 1_{|X| \leq M}\right] \leq C \left\| \text{sgn}(X)|X|^{p-1} 1_{|X| \leq M}\right\|_q
= C \left( E\left[|X|^{p-1} 1_{|X| \leq M}\right]\right)^{1/q} \leq C \left( E\left[|X|^p 1_{|X| \leq M}\right]\right)^{1/q}
\]

from which it follows that

\[
\left( E\left[|X|^p 1_{|X| \leq M}\right]\right)^{1/p} \leq \left( E\left[|X|^p 1_{|X| \leq M}\right]\right)^{1-1/q} \leq C.
\]

Using the monotone convergence theorem, we may let \( M \to \infty \) in this equation to find \( \|X\|_p = (E\left[|X|^p\right])^{1/p} \leq C < \infty \).

b) Now that we know \( X \in L^p(\Omega, \mathcal{B}, P) \), in make sense to consider \( E[|X-Y_k|h]\) for all \( h \in L^p(\Omega, \mathcal{B}, P) \). For \( M < \infty \), let \( h := h_{1_{|h| \leq M}} \), then

\[
E[|X-Y_k|h] \leq |E[(X-Y_k)\cdot h_M]| + \|X-Y_k\|_p \cdot \|h_M\|_q
\]

\[
\leq \|X-Y_k\|_q \cdot \|h_M\|_q + 2C \|h_{1_{|h| \leq M}}\|_q.
\]

Since \( h_M \in \mathcal{B}_b \), we may pass to the limit \( k \to \infty \) in the previous inequality to find,

\[
\limsup_{k \to \infty} |E[(X-Y_k)h]| \leq 2C \|h\|_{L^\infty}.
\]

This completes the proof, since \( \|h\|_{L^\infty} \to 0 \) as \( M \to \infty \) by DCT.  

16.2 Exercises

Exercise 16.4. Suppose that \( \{M_n\}_{n=1}^{\infty} \) is an increasing sequence of closed subspaces of a Hilbert space, \( H \). Let \( M \) be the closure of \( M_0 := \bigcup_{n=1}^{\infty} M_n \). Show \( \lim_{n \to \infty} P_{M_n}x = P_Mx \) for all \( x \in H \). Hint: first prove this for \( x \in M_0 \) and then for \( x \in M \). Also consider the case where \( x \in M^\perp \).

Solution to Exercise (16.4). Let \( P_n := P_{M_n} \) and \( P = P_M \). If \( y \in M_0 \), then \( P_ny = y = Py \) for all \( n \) sufficiently large, and therefore, \( \lim_{n \to \infty} P_ny = Py \). Now suppose that \( x \in M \) and \( y \in M_0 \). Then

\[
|P_nx - Py| \leq |P_nx - Py| + |Py - P_ny| + |P_ny - Py|
\]

\[
\leq 2|y - y| + |P_ny - Py|
\]

and passing to the limit as \( n \to \infty \) then shows

\[
\limsup_{n \to \infty} |P_nx - Py| \leq 2|y - y|.
\]

The left hand side may be made as small as we like by choosing \( y \in M_0 \) arbitrarily close to \( x \in M = M_0 \).

For the general case, if \( x \in H \), then \( x = Px + y \) where \( y = x - Px \in M^\perp \subset M_{n_{\infty}}^\perp \) for all \( n \). Therefore,

\[
P_nx = P_nPx + P_ny \quad \text{as} \quad n \to \infty
\]

by what we have just proved.

Exercise 16.5 (The Mean Ergodic Theorem). Let \( U : H \to H \) be a unitary operator on a Hilbert space \( H = \text{null}(U-I) \), \( P = P_M \) be orthogonal projection onto \( M \), and \( S_n = \frac{1}{n} \sum_{k=1}^{n-1} U_k \). Show \( S_n \to P_M \) strongly by which we mean \( \lim_{n \to \infty} S_nx = Px \) for all \( x \in H \).

Hints: 1. Show \( H \) is the orthogonal direct sum of \( M \) and \( \text{null}(U-I) \) by first showing \( \text{null}(U^*-I) = \text{null}(U-I) \) and then using Lemma 16.16. 2. Verify the result for \( x \in \text{null}(U-I) \) and \( x \in \text{ran}(U-I) \). 3. Use a limiting argument to verify the result for \( x \in \text{ran}(U-I) \).

Solution to Exercise (16.5). Let \( M = \text{null}(U-I) \), then \( S_nx = x \) for all \( x \in M \). Notice that \( x \in \text{null}(U^* - I) \) if \( x = U^*x \) if \( Ux = UU^*x = x \), if \( x \in \text{null}(U-I) = M \). Therefore

\[
\text{null}(U-I) = \text{null}(U^* - I)^\perp = \text{null}(U-I)^\perp = M^\perp.
\]

Suppose that \( x = Uy - y \in \text{ran}(U-I) \) for some \( y \in H \), then

\[
S_nx = \frac{1}{n} (U^n y - y) \to 0 \quad \text{as} \quad n \to \infty.
\]

Finally, if \( x \in M^\perp \) and \( y \in \text{ran}(U-I) \), we have

\[
\|S_nx - S_ny\| \leq \|x - y\|
\]

and hence
\[
\lim \sup_{n \to \infty} \|S_n x - S_n y\| \leq \|x - y\|
\]
from which it follows that \(\limsup_{n \to \infty} \|S_n x\| \leq \|x - y\|\). Letting \(y \to x\) shows that \(\limsup_{n \to \infty} \|S_n x\| = 0\) for all \(x \in M^\perp\). Therefore if \(x \in H\) and \(x = m + m^\perp \in M \oplus M^\perp\), then

\[
\lim_{n \to \infty} S_n x = \lim_{n \to \infty} S_n m + \lim_{n \to \infty} S_n m^\perp = m + 0 = P_M x.
\]
The Radon-Nikodym Theorem

**Theorem 17.1 (A Baby Radon-Nikodym Theorem).** Suppose \((X, \mathcal{M})\) is a measurable space, \(\lambda\) and \(\nu\) are two finite positive measures on \(\mathcal{M}\) such that \(\nu(A) \leq \lambda(A)\) for all \(A \in \mathcal{M}\). Then there exists a measurable function, \(\rho : X \to [0,1]\) such that \(d\nu = \rho d\lambda\).

**Proof.** If \(f\) is a non-negative simple function, then
\[
\nu(f) = \sum_{a \geq 0} a \nu(f = a) \leq \sum_{a \geq 0} a \lambda(f = a) = \lambda(f).
\]
In light of Theorem 6.32 and the MCT, this inequality continues to hold for all non-negative measurable functions. Furthermore if \(f \in L^1(\lambda)\), then \(\nu(|f|) \leq \lambda(|f|) < \infty\) and hence \(f \in L^1(\nu)\) and
\[
|\nu(f)| \leq \nu(|f|) \leq \lambda(|f|) \leq \lambda(X)^{1/2} \cdot \|f\|_{L^2(\lambda)}.
\]
Therefore, \(L^2(\lambda) \ni f \to \nu(f) \in \mathbb{C}\) is a continuous linear functional on \(L^2(\lambda)\). By the Riesz representation Theorem 16.14 there exists a unique \(\rho \in L^2(\lambda)\) such that
\[
\nu(f) = \int_X f \rho d\lambda \text{ for all } f \in L^2(\lambda).
\]
In particular this equation holds for all bounded measurable functions, \(f : X \to \mathbb{R}\) and for such a function we have
\[
\nu(f) = \text{Re} \nu(f) = \text{Re} \int_X f \rho d\lambda = \int_X f \text{Re} \rho \ d\lambda. \tag{17.1}
\]
Thus by replacing \(\rho\) by \(\text{Re} \rho\) if necessary we may assume \(\rho\) is real.

Taking \(f = 1_{\rho < 0}\) in Eq. (17.1) shows
\[
0 \leq \nu(\rho < 0) = \int_X 1_{\rho < 0} \rho \ d\lambda \leq 0,
\]
from which we conclude that \(1_{\rho < 0} \rho = 0\), \(\lambda\) - a.e., i.e. \(\lambda(\rho < 0) = 0\). Therefore \(\rho \geq 0\), \(\lambda\) - a.e. Similarly for \(\alpha > 1\),
\[
\lambda(\rho > \alpha) \geq \nu(\rho > \alpha) = \int_X 1_{\rho > \alpha} \rho \ d\lambda \geq \alpha \lambda(\rho > \alpha)
\]
which is possible iff \(\lambda(\rho > \alpha) = 0\). Letting \(\alpha \downarrow 1\), it follows that \(\lambda(\rho > 1) = 0\) and hence \(0 \leq \rho \leq 1\), \(\lambda\) - a.e.

**Definition 17.2.** Let \(\mu\) and \(\nu\) be two positive measure on a measurable space, \((X, \mathcal{M})\). Then:
1. \(\mu\) and \(\nu\) are mutually singular (written as \(\mu \perp \nu\)) if there exists \(A \in \mathcal{M}\) such that \(\nu(A) = 0\) and \(\mu(A^c) = 0\). We say that \(\nu\) lives on \(A\) and \(\mu\) lives on \(A^c\).
2. The measure \(\nu\) is absolutely continuous relative to \(\mu\) (written as \(\nu \ll \mu\)) provided \(\nu(A) = 0\) whenever \(\mu(A) = 0\).

As an example, suppose that \(\mu\) is a positive measure and \(\rho \geq 0\) is a measurable function. Then the measure, \(\nu := \rho \mu\) is absolutely continuous relative to \(\mu\). Indeed, if \(\mu(A) = 0\) then
\[
\nu(A) = \int_A \rho d\mu = 0.
\]
We will eventually show that if \(\mu\) and \(\nu\) are \(\sigma\) – finite and \(\nu \ll \mu\), then \(d\nu = \rho d\mu\) for some measurable function, \(\rho \geq 0\).

**Definition 17.3 (Lebesgue Decomposition).** Let \(\mu\) and \(\nu\) be two positive measure on a measurable space, \((X, \mathcal{M})\). Two positive measures \(\nu_a\) and \(\nu_s\) form a Lebesgue decomposition of \(\nu\) relative to \(\mu\) if \(\nu = \nu_a + \nu_s\), \(\nu_a \ll \mu\), and \(\nu_s \perp \mu\).

**Lemma 17.4.** If \(\mu_1, \mu_2\) and \(\nu\) are positive measures on \((X, \mathcal{M})\) such that \(\mu_1 \perp \nu\) and \(\mu_2 \perp \nu\), then \((\mu_1 + \mu_2) \perp \nu\). More generally if \(\{\mu_i\}_{i=1}^\infty\) is a sequence of positive measures such that \(\mu_i \perp \nu\) for all \(i\) then \(\mu = \sum_{i=1}^\infty \mu_i\) is singular relative to \(\nu\).

**Proof.** It suffices to prove the second assertion since we can then take \(\mu_j \equiv 0\) for all \(j \geq 3\). Choose \(A_i \in \mathcal{M}\) such that \(\nu(A_i) = 0\) and \(\mu_i(A_i^c) = 0\) for all \(i\). Letting \(A := \cup_i A_i\) we have \(\nu(A) = 0\). Moreover, since \(A^c = \cap_i A_i^c \subset A_i^c\) for all \(m\), we have \(\mu_i(A^c) = 0\) for all \(i\) and therefore, \(\mu(A^c) = 0\). This shows that \(\mu \perp \nu\).

**Lemma 17.5.** Let \(\nu\) and \(\mu\) be positive measures on \((X, \mathcal{M})\). If there exists a Lebesgue decomposition, \(\nu = \nu_s + \nu_a\), of the measure \(\nu\) relative to \(\mu\) then this decomposition is unique. Moreover: if \(\nu\) is a \(\sigma\) – finite measure then so are \(\nu_s\) and \(\nu_a\).
Theorem 17.8 (Radon-Nikodym Theorem for Positive Measures). Suppose that \( \mu \) and \( \nu \) are \( \sigma \)-finite positive measures on \((X, \mathcal{M})\). Then \( \nu \) has a unique Lebesgue decomposition \( \nu = \nu_a + \nu_s \) relative to \( \mu \) and there exists a unique (modulo sets of \( \mu \)-measure 0) function \( \rho : X \to [0, \infty) \) such that \( d\nu_a = \rho d\mu \). Moreover, \( \nu_s = 0 \) iff \( \nu \ll \mu \).

Proof. The uniqueness assertions follow directly from Lemmas 17.5 and 17.6.

Existence when \( \mu \) and \( \nu \) are both finite measures. (Von-Neumann’s Proof. See Remark 17.9 for the motivation for this proof.) First suppose that \( \mu \) and \( \nu \) are finite measures and let \( \lambda = \mu + \nu \). By Theorem 17.1 \( d\nu = h d\lambda \). Then by what we have just proved there exists \( \rho = \mu(g) \) such that

\[
\nu(f) = \lambda(fh) = \mu(fh) + \nu(fh)
\]

or equivalently

\[
\nu(f(1-h)) = \mu(fh).
\]

Taking \( f = 1_{\{h=1\}} \) in Eq. (17.6) shows that

\[
\mu(\{h=1\}) = \nu(1_{\{h=1\}}(1-h)) = 0,
\]

i.e. \( 0 \leq h(x) < 1 \) for \( \mu \)-a.e. \( x \). Let

\[
\rho := 1_{\{h<1\}} \frac{h}{1-h}
\]

and then take \( g = 1_{\{h<1\}}(1-h)^{-1} \) with \( g \geq 0 \) in Eq. (17.6) to learn

\[
\nu(g1_{\{h<1\}}) = \mu(g1_{\{h<1\}}(1-h)^{-1}h) = \mu(\rho g).
\]

Hence if we define

\[
\nu_a := 1_{\{h<1\}} \nu \text{ and } \nu_s := 1_{\{h=1\}} \nu,
\]

we then have \( \nu_s \perp \mu \) (since \( \nu_s \) “lives” on \( \{h=1\} \)) while \( \mu(h=1) = 0 \) and \( \nu_a = \rho \mu \) and in particular \( \nu_a \ll \mu \). Hence \( \nu = \nu_a + \nu_s \) is the desired Lebesgue decomposition of \( \nu \). If we further assume that \( \nu \ll \mu \), then \( \mu(h=1) = 0 \) implies \( \nu(h=1) = 0 \) and hence that \( \nu_s = 0 \) and we conclude that \( \nu = \nu_a \).

Existence when \( \mu \) and \( \nu \) are \( \sigma \)-finite measures. Write \( X = \sum_{n=1}^{\infty} X_n \) where \( X_n \in \mathcal{M} \) are chosen so that \( \mu(X_n) < \infty \) and \( \nu(X_n) < \infty \) for all \( n \). Let \( d\mu_n = 1_{X_n} d\mu \) and \( d\nu_n = 1_{X_n} d\nu \). Then by what we have just proved there exists \( \rho_n \in L^1(X_n, \mu_n) \subseteq L^1(X, \mu) \) and measure \( \nu_n^a \) such that \( d\nu_n = \rho_n d\mu_n + d\nu_n^a \) with \( \nu_n^a \perp \mu_n \). Since \( \mu_n \) and \( \nu_n^a \) “live” on \( X_n \) there exists \( A_n \in \mathcal{M}_{X_n} \) such that \( \mu(A_n) = \mu_n(A_n) = 0 \) and

\[
\nu_n^a = 1_{\{h<1\}} \nu_n \text{ and } \nu_n^s := 1_{\{h=1\}} \nu_n,
\]

we then have \( \nu_n^s \perp \mu_n \) (since \( \nu_n^s \) “lives” on \( \{h=1\} \)) while \( \mu_n(h=1) = 0 \) and \( \nu_n^a = \rho_n \mu_n \) and in particular \( \nu_n^a \ll \mu_n \). Hence \( \nu_n = \nu_n^a + \nu_n^s \) is the desired Lebesgue decomposition of \( \nu_n \).

Remark 17.7. Lemma 17.6 is in general false without the \( \sigma \)-finiteness assumption. A trivial counterexample is to take \( \mathcal{M} = 2^X \), \( \mu(A) = \infty \) for all non-empty \( A \in \mathcal{M} \), \( f = 1_X \) and \( g = 2 \cdot 1_X \). Then Eq. (17.4) holds yet \( f \neq g \).
\[ \nu_n^a (X \setminus A_n) = \nu_n^a (X_n \setminus A_n) = 0. \]

This shows that \( \nu_n^a \perp \mu \) for all \( n \) and so by Lemma 17.4 \( \nu_s := \sum_{n=1}^{\infty} \nu_n^a \) is singular relative to \( \mu \). Since

\[ \nu = \sum_{n=1}^{\infty} \nu_n = \sum_{n=1}^{\infty} (\rho_n \nu_n + \nu_n^a) = \sum_{n=1}^{\infty} (\rho_n 1_{X_n} \mu + \nu_n^a) = \rho \mu + \nu_s, \quad (17.7) \]

where \( \rho := \sum_{n=1}^{\infty} 1_{X_n} \rho_n \), it follows that \( \nu = \nu_a + \nu_s \) with \( \nu_a = \rho \mu \). Hence this is the desired Lebesgue decomposition of \( \nu \) relative to \( \mu \).

**Remark 17.9.** Here is the motivation for the above construction. Suppose that \( d\nu = d\nu_s + \rho d\mu \) is the Radon-Nikodym decomposition and \( X = A \sum B \) such that \( \nu_s (B) = 0 \) and \( \mu (A) = 0 \). Then we find

\[ \nu_s (f) + \mu (\rho f) = \nu (f) = \lambda (hf) = \nu (hf) + \mu (hf). \]

Letting \( f \to 1_A f \) then implies that

\[ \nu (1_A f) = \nu_s (1_A f) = \nu (1_A hf) \]

which show that \( h = 1, \nu \) - a.e. on \( A \). Also letting \( f \to 1_B f \) implies that

\[ \mu (\rho 1_B f) = \nu (h 1_B f) + \mu (h 1_B f) = \mu (\rho h 1_B f) + \mu (h 1_B f) \]

which implies, \( \rho = \rho h + h, \mu \) - a.e. on \( B \), i.e.

\[ \rho (1 - h) = h, \mu \) - a.e. on \( B. \]

In particular it follows that \( h < 1, \mu = \nu \) - a.e. on \( B \) and that \( \rho = \frac{h}{1-h} 1_{h < 1} \), \( \mu \) - a.e. So up to sets of \( \nu \) - measure zero, \( A = \{ h = 1 \} \) and \( B = \{ h < 1 \} \) and therefore,

\[ d\nu = 1_{\{h=1\}} d\nu + 1_{\{h<1\}} d\nu = 1_{\{h=1\}} d\nu + \frac{h}{1-h} 1_{h < 1} d\mu. \]
Conditional Expectation

In this section let \((\Omega, \mathcal{B}, P)\) be a probability space and \(\mathcal{G} \subset \mathcal{B}\) be a sub-sigma algebra of \(\mathcal{B}\). We will write \(f \in \mathcal{G}_0\) iff \(f : \Omega \to \mathbb{C}\) is bounded and \(f\) is \((\mathcal{G}, \mathcal{B}_\mathbb{C})\) – measurable. If \(A \in \mathcal{B}\) and \(P(A) > 0\), we will let

\[
E[X|A] := \frac{E[X : A]}{P(A)} \quad \text{and} \quad P(B|A) := E[1_B|A] := \frac{P(A \cap B)}{P(A)}
\]

for all integrable random variables, \(X\), and \(B \in \mathcal{B}\). We will often use the factorization Lemma in this section. Because of this let us repeat it here.

**Lemma 18.1.** Suppose that \((\mathbb{Y}, \mathcal{F})\) is a measurable space and \(Y : \Omega \to \mathbb{Y}\) is a map. Then to every \((\sigma(Y), \mathcal{B}_\mathbb{Y})\) – measurable function, \(H : \Omega \to \mathbb{R}\), there is a \((\mathcal{F}, \mathcal{B}_\mathbb{R})\) – measurable function \(h : \mathbb{Y} \to \mathbb{R}\) such that \(H = h \circ Y\).

**Proof.** First suppose that \(H = 1_A\) where \(A \in \sigma(Y) = Y^{-1}(\mathcal{F})\). Let \(B \in \mathcal{F}\) such that \(A = Y^{-1}(B)\) then \(1_A = 1_{Y^{-1}(B)} = 1_B \circ Y\) and hence the lemma is valid in this case with \(h = 1_B\). More generally if \(H = \sum a_i 1_{A_i}\) is a simple function, then there exists \(B_i \in \mathcal{F}\) such that \(A_i = 1_{B_i} \circ Y\) and hence \(H = h \circ Y\) with \(h := \sum a_i 1_{B_i}\) – a simple function on \(\mathbb{R}\).

For a general \((\mathcal{F}, \mathcal{B}_\mathbb{R})\) – measurable function, \(H\), from \(\Omega \to \mathbb{R}\), choose simple functions \(H_n\) converging to \(H\). Let \(h_n : \mathbb{Y} \to \mathbb{R}\) be simple functions such that \(H_n = h_n \circ Y\). Then it follows that

\[
H = \lim_{n \to \infty} H_n = \limsup_{n \to \infty} h_n = \limsup_{n \to \infty} h_n \circ Y = h \circ Y
\]

where \(h := \limsup_{n \to \infty} h_n\) – a measurable function from \(\mathbb{Y}\) to \(\mathbb{R}\).

**Lemma 18.2 (Integral Comparison).** Suppose that \(F, G : \Omega \to [0, \infty]\) are \(\mathcal{B}\) – measurable functions. Then \(F \geq G\) a.s. iff

\[
E[F] \geq E[G] \quad \text{for all } A \in \mathcal{B}\tag{18.1}
\]

In particular \(F = G\) a.s. iff equality holds in Eq. (18.1). Moreover, for \(F \in L^1(\Omega, \mathcal{B}, P)\), \(F = 0\) a.s. iff \(E[F : A] = 0\) for all \(A \in \mathcal{B}\).

**Proof.** It is clear that \(F \geq G\) a.s. implies Eq. (18.1). For the converse assertion, if we take \(A = \{F = 0\}\) in Eq. (18.1) we learn that

\[
0 = E[F : F = 0] \geq E[G : F = 0]
\]

and hence that \(G1_{F=0} = 0\) a.s., i.e.

\[
G = 0 \text{ a.s. on } \{F = 0\}\tag{18.2}
\]

Similarly if \(A := \{G > \alpha F\}\) with \(\alpha > 1\) in Eq. (18.1), then

\[
E[F : G > \alpha F] \geq E[G : G > \alpha F] \geq \alpha E[F : G > \alpha F] \equiv \alpha E[F : G > \alpha F].
\]

Since \(\alpha > 1\), the only way this can happen is if \(E[F : G > \alpha F] = 0\). By the MCT we may now let \(\alpha \downarrow 1\) to conclude, \(0 = E[F : G > F]\). This implies \(F1_{G > F} = 0\) a.s. or equivalently

\[
G \leq F \text{ a.s. on } \{F > 0\}.	ag{18.3}
\]

Since \(\Omega = \{F = 0\} \cup \{F > 0\}\) and on both sets, by Eqs. (18.2) and (18.3) we have \(G \leq F\) a.s. we may conclude that \(G \leq F\) a.s. on \(\Omega\) as well. If equality holds in Eq. (18.1), then we know that \(G \leq F\) and \(F \leq G\) a.s., i.e. \(F = G\) a.s.

If \(F \in L^1(\Omega, \mathcal{B}, P)\) and \(E[F : A] = 0\) for all \(A \in \mathcal{B}\), we may conclude by a simple limiting argument that \(E[Fh] = 0\) for all \(h \in \mathcal{B}_\mathbb{R}\). Taking \(h := \text{sgn}(F) := \frac{F}{|F|} 1_{|F|>0}\) in this identity then implies

\[
0 = E[Fh] = E \left[ \frac{F}{|F|} 1_{|F|>0} \right] = E \left[ |F| 1_{|F|>0} \right] = E(|F|)
\]

which implies that \(F = 0\) a.s. \(\blacksquare\)

**Definition 18.3 (Conditional Expectation).** Let \(E_\mathcal{G} : L^2(\Omega, \mathcal{B}, P) \to L^2(\Omega, \mathcal{G}, P)\) denote orthogonal projection of \(L^2(\Omega, \mathcal{B}, P)\) onto the closed subspace \(L^2(\Omega, \mathcal{G}, P)\). For \(f \in L^2(\Omega, \mathcal{B}, P)\), we say that \(E_\mathcal{G}f \in L^2(\Omega, \mathcal{G}, P)\) is the conditional expectation of \(f\).

**Remark 18.4 (Basic Properties of \(E_\mathcal{G}\)).** Let \(f \in L^2(\Omega, \mathcal{B}, P)\). By the orthogonal projection Theorem we know that \(F \in L^2(\Omega, \mathcal{G}, P)\) is the conditional expectation of \(f\).

1. \(\|f - F\|_2 \leq \|f - g\|_2\) for all \(g \in L^2(\Omega, \mathcal{G}, P)\) or
2. \(E[fh] = E[Fh]\) for all \(h \in L^2(\Omega, \mathcal{G}, P)\).
Moreover if \( G_0 \subset G_1 \subset B \) then \( L^2(\Omega, G_0, P) \subset L^2(\Omega, G_1, P) \subset L^2(\Omega, B, P) \) and therefore,
\[
E_{G_0} E_{G_1} f = E_{G_1} E_{G_0} f = E_{G_0} f \quad \text{a.s. for all } f \in L^2(\Omega, B, P). \tag{18.4}
\]

It is also useful to observe that condition 2. above may expressed as
\[
E[f : A] = E[F : A] \quad \text{for all } A \in G \tag{18.5}
\]
or
\[
E[f] = E[F] \quad \text{for all } h \in G_0. \tag{18.6}
\]

Indeed, if Eq. (18.5) holds then by linearity we have \( E[fh] = E[Fh] \) for all \( G - \) measurable simple functions, \( h \) and hence by the approximation Theorem 6.32 and the DCT for all \( h \in G_0 \). Therefore Eq. (18.5) implies Eq. (18.6). If Eq. (18.6) holds and \( h \in L^2(\Omega, G, P) \), we may use DCT to show
\[
E[fh] = \lim_{n \to \infty} E[fh1_{|h| \leq n}] = E[Fh],
\]
which is condition 2. in Remark 18.4. Taking \( h = 1_A \) with \( A \in G \) in condition 2. or Remark 18.4 we learn that Eq. (18.5) is satisfied as well.

**Theorem 18.5.** Let \( (\Omega, B, P) \) and \( G \subset B \) be as above and let \( f, g \in L^1(\Omega, B, P) \). The operator \( E_G : L^2(\Omega, B, P) \to L^2(\Omega, G, P) \) extends uniquely to a linear contraction from \( L^1(\Omega, B, P) \) to \( L^1(\Omega, G, P) \). This extension enjoys the following properties:

1. If \( f \geq 0 \), \( P - a.e. \) then \( E_G f \geq 0 \), \( P - a.e. \).
2. **Monotonicity.** If \( f \geq g \), \( P - a.e. \) there \( E_G f \geq E_G g \), \( P - a.e. \).
3. **L∞ - contraction property.** \( |E_G f| \leq E_G |f| \), \( P - a.e. \).
4. **Averaging Property.** If \( f \in L^1(\Omega, B, P) \) then \( F = E_G f \) iff \( F \in L^1(\Omega, G, P) \) and
\[
E(Fh) = E(fh) \quad \text{for all } h \in G_0. \tag{18.7}
\]

5. **Pull out property or product rule.** If \( g \in G_0 \) and \( f \in L^1(\Omega, B, P) \), then
\[
E_G (gf) = g \cdot E_G f, \quad P - a.e.
\]
6. **Tower or smoothing property.** If \( G_0 \subset G_1 \subset B \). Then
\[
E_{G_0} E_{G_1} f = E_{G_1} E_{G_0} f = E_{G_0} f \quad a.s. \quad \text{for all } f \in L^1(\Omega, B, P). \tag{18.8}
\]

**Proof.** By the definition of orthogonal projection, \( f \in L^2(\Omega, B, P) \) and \( h \in G_0 \),
\[
E(fh) = E(f \cdot E_G h) = E(E_G f \cdot h). \tag{18.9}
\]
Taking
\[
h = \text{sgn}(E_G f) := \frac{E_G f}{|E_G f|} 1_{|E_G f| > 0}
\]
in Eq. (18.9) shows
\[
E(|E_G f|) = E(E_G f \cdot h) = E(fh) \leq E(|fh|) \leq E(|f|). \tag{18.10}
\]

It follows from this equation and the BLT (Theorem 16.17) that \( E_G \) extends uniquely to a contraction form \( L^1(\Omega, B, P) \) to \( L^1(\Omega, G, P) \). Moreover, by a simple limiting argument, Eq. (18.9) remains valid for all \( f \in L^1(\Omega, B, P) \) and \( h \in G_0 \). Indeed, (with out reference to Theorem 16.17) if \( f_n := f1_{|f| \leq n} \in L^2(\Omega, B, P) \), then \( f_n \to f \) in \( L^1(\Omega, B, P) \) and hence
\[
E(|E_G f_n - E_G f_m|) = E(|E_G (f_n - f_m)|) \to 0 \quad \text{as } m, n \to \infty.
\]

By the completeness of \( L^1(\Omega, G, P) \), \( F := L^1(\Omega, G, P)\text{-lim}_{n \to \infty} E_G f_n \) exists. Moreover the function \( F \) satisfies,
\[
E(F \cdot h) = E(\lim_{n \to \infty} E_G f_n \cdot h) = \lim_{n \to \infty} E(f_n \cdot h) = E(f \cdot h) \tag{18.11}
\]
for all \( h \in G_0 \) and by Lemma 18.2 there is at most one, \( F \in L^1(\Omega, G, P) \), which satisfies Eq. (18.12). We will again denote \( F \) by \( E_G f \). This proves the existence and uniqueness of \( F \) satisfying the defining relation in Eq. (18.7) of item 4. The same argument used in Eq. (18.11) again shows \( E(F^2) \leq E(|f|) \) and therefore that \( E_G : L^1(\Omega, B, P) \to L^1(\Omega, G, P) \) is a contraction.

Items 1 and 2. If \( f \in L^1(\Omega, B, P) \) with \( f \geq 0 \), then
\[
E(E_G f \cdot h) = E(fh) \geq 0 \quad \forall \ h \in G_0 \text{ with } h \geq 0. \tag{18.12}
\]

An application of Lemma 18.2 then shows that \( E_G f \geq 0 \quad a.e. \) The proof of item 2. follows by applying item 1. with \( f \) replaced by \( f - g \geq 0 \).

Item 3. If \( f \) is real, \( \pm f \leq |f| \) and so by Item 2., \( \pm E_G f \leq E_G |f| \), i.e. \( |E_G f| \leq E_G |f| \), \( P - a.e. \). For complex \( f \), let \( h \geq 0 \) be a bounded and \( G - \) measurable function. Then
\[
E(|E_G f| |h|) = E \left[ E_G f \cdot \text{sgn}(E_G f) |h| \right] = E \left[ f \cdot \text{sgn}(E_G f) |h| \right] \leq E(|f| |h|) = E[|E_G f| |h|].
\]
Since \( h \geq 0 \) is an arbitrary \( G - \) measurable function, it follows, by Lemma 18.2 that \( |E_G f| \leq E_G |f| \), \( P - a.e. \). Recall the item 4. has already been proved.

Item 5. If \( h \in G_0 \) and \( f \in L^1(\Omega, B, P) \), then
\[
E(g1_{E_G f} h) = E(E_G f \cdot h) = E[f \cdot h] = E[|g f \cdot h|] = E[|E_G (g f)|] \cdot h.
\]

Thus \( E_G (g f) = g \cdot E_G f, \quad P - a.e. \).

This can also easily be proved directly here by taking \( h = 1_{E_G f < 0} \) in Eq. (18.13).
Example 18.8. Suppose $G$ is the trivial $\sigma$-algebra, i.e. $G = \{\emptyset, \Omega\}$. In this case $E_G f = E f$ a.s.

Example 18.9. On the opposite extreme, if $G = B$, then $E_G f = f$ a.s.

**Lemma 18.10.** Suppose $(X, M)$ is a measurable space, $X : \Omega \to X$ is a measurable function, and $G$ is a sub-$\sigma$-algebra of $B$. If $X$ is independent of $G$ and $f : X \to \mathbb{R}$ is a measurable function such that $f(X) \in L^1(\Omega, B, P)$, then $E_G [f(X)] = E[f(X)]$ a.s. Conversely if $E_G [f(X)] = E[f(X)]$ a.s. for all bounded measurable functions, $f : X \to \mathbb{R}$, then $X$ is independent of $G$.

**Proof.** Suppose that $X$ is independent of $G$, $f : X \to \mathbb{R}$ is a measurable function such that $f(X) \in L^1(\Omega, B, P)$, $\mu := E[f(X)]$, and $A \in G$. Then, by independence,

$$E[f(X) : A] = E[f(X) 1_A] = E[f(X)] E[1_A] = E[\mu 1_A] = E[\mu : A].$$

Therefore $E_G [f(X)] = \mu = E[f(X)]$ a.s.

Conversely if $E_G [f(X)] = E[f(X)]$ a.s. and $A \in G$, then

$$E[f(X) 1_A] = E[f(X) : A] = E[\mu : A] = \mu E[1_A] = E[f(X)] E[1_A].$$

Since the last equation is assumed to hold true for all $A \in G$ and all bounded measurable functions, $f : X \to \mathbb{R}$, $X$ is independent of $G$.

The following remark is often useful in computing conditional expectations. The following Exercise should help you gain some more intuition about conditional expectations.

**Remark 18.11 (Note well.)** According to Lemma 18.1, $E(f|X) = \tilde{f}(X)$ a.s. for some measurable function, $\tilde{f} : X \to \mathbb{R}$. So computing $E(f|X) = \tilde{f}(X)$ is equivalent to finding a function, $\tilde{f} : X \to \mathbb{R}$, such that

$$E [f \cdot h(X)] = E [\tilde{f} (X) h(X)]$$

for all bounded and measurable functions, $h : X \to \mathbb{R}$.

**Exercise 18.2.** Suppose $(\Omega, B, P)$ is a probability space and $\mathcal{P} := \{A_i\}_{i=1}^{\infty} \subseteq B$ is a partition of $\Omega$. (Recall this means $\Omega = \bigcup_{i=1}^{\infty} A_i$.) Let $G$ be the $\sigma$-algebra generated by $\mathcal{P}$. Show:

1. $B \in G$ iff $B = \bigcup_{i \in A} A_i$ for some $A \subseteq \mathbb{N}$.
2. $g : \Omega \to \mathbb{R}$ is $G$-measurable iff $g = \sum_{i=1}^{\infty} \lambda_i 1_{A_i}$ for some $\lambda_i \in \mathbb{R}$.
3. For $f \in L^1(\Omega, B, P)$, let $E[f|A_i] := E[1_{A_i} f] / P(A_i)$ if $P(A_i) \neq 0$ and $E[f|A_i] = 0$ otherwise. Show

$$E_G f = \sum_{i=1}^{\infty} E[f|A_i] 1_{A_i}, \text{ a.s.}$$

18.1 Examples

**Example 18.8.** Suppose $G$ is the trivial $\sigma$-algebra, i.e. $G = \emptyset, \Omega\}$. In this case $E_G f = E f$ a.s.

Example 18.9. On the opposite extreme, if $G = B$, then $E_G f = f$ a.s.
Solution to Exercise \textbf{(18.2)}. We will only prove part 3. here. To do this, suppose that $E_g f = \sum_{i=1}^{\infty} \lambda_i A_i$ for some $\lambda_i \in \mathbb{R}$. Then

$$E[f : A_j] = E[E_g f : A_j] = E \left[ \sum_{i=1}^{\infty} \lambda_i 1_{A_i} : A_j \right] = \lambda_j P(A_j)$$

which holds automatically if $P(A_j) = 0$ no matter how $\lambda_j$ is chosen. Therefore, we must take

$$\lambda_j = \frac{E[f : A_j]}{P(A_j)} = E[f | A_j]$$

which verifies Eq. \textbf{(18.15)}.

**Proposition 18.12.** Suppose that $(\Omega, \mathcal{B}, P)$ is a probability space, $(\mathcal{X}, \mathcal{M}, \mu)$ and $(\mathcal{Y}, \mathcal{N}, \nu)$ are two $\sigma$–finite measure spaces, $X: \Omega \to \mathcal{X}$ and $Y: \Omega \to \mathcal{Y}$ are measurable functions, and there exists $0 \leq \rho \in L^1(\Omega, \mathcal{B}, \mu \otimes \nu)$ such that $P((X,Y)\in U) = \int_U \rho(x,y) \, d\mu(x) \, d\nu(y)$ for all $U \in \mathcal{M} \otimes \mathcal{N}$. Let

$$\bar{\rho}(x) := \int_Y \rho(x,y) \, d\nu(y)$$

and $x \in \mathcal{X}$ and $B \in \mathcal{N}$, let

$$Q(x, B) := \begin{cases} \frac{1}{\rho(x)} \int_B \rho(x,y) \, d\nu(y) & \text{if} \ \rho(x) \in (0, \infty) \\ \delta_{y_0}(B) & \text{if} \ \rho(x) \in \{0, \infty\} \end{cases}$$

where $y_0$ is some arbitrary but fixed point in $Y$. Then for any bounded (or non-negative) measurable function, $f: \mathcal{X} \times \mathcal{Y} \to \mathbb{R}$, we have

$$E[f(X,Y) | X] = Q(X,f(X,\cdot)) = \int_Y f(x,y) \, Q(X,dy) = g(X) \text{ a.s.} \tag{18.18}$$

where,

$$g(x) := \int_Y f(x,y) \, Q(X,dy) = Q(x,f(x,\cdot)).$$

As usual we use the notation,

$$Q(x, v) := \int_Y v(y) \, Q(x,dy) = \begin{cases} \frac{1}{\rho(x)} \int_Y v(y) \, \rho(x,y) \, d\nu(y) & \text{if} \ \bar{\rho}(x) \in (0, \infty) \\ \delta_{y_0}(v) = v(y_0) & \text{if} \ \bar{\rho}(x) \in \{0, \infty\}. \end{cases}$$

for all bounded measurable functions, $v: \mathcal{Y} \to \mathbb{R}$.

**Proof.** Our goal is to compute $E[f(X,Y) | X]$. According to Remark \textbf{(18.11)} we are searching for a bounded measurable function, $g : \mathcal{X} \to \mathbb{R}$, such that

$$E[f(X,Y)h(X)] = E[g(X)h(X)] \text{ for all } h \in \mathcal{M}_b.$$  \tag{18.19}  

(Throughout this argument we are going to repeatedly use the Tonelli - Fubini theorems.) We now explicitly write out both sides of Eq. \textbf{(18.19)}:

$$E[f(X,Y)h(X)] = \int_{\mathcal{X} \times \mathcal{Y}} h(x,f(x,y)) \, \rho(x,y) \, d\mu(x) \, d\nu(y)$$

$$= \int_{\mathcal{X}} h(x) \left[ \int_{\mathcal{Y}} f(x,y) \rho(x,y) \, d\nu(y) \right] \, d\mu(x) \tag{18.20}$$

$$E[g(X)h(X)] = \int_{\mathcal{X} \times \mathcal{Y}} h(x) \int_{\mathcal{Y}} g(x,y) \, \rho(x,y) \, d\nu(y) \, d\mu(x)$$

$$= \int_{\mathcal{X}} h(x) \rho(x) \, d\mu(x) \tag{18.21}.$$  

Since the right sides of Eqs. \textbf{(18.20)} and \textbf{(18.21)} must be equal for all $h \in \mathcal{M}_b$, we must demand,

$$\int_{\mathcal{Y}} f(x,y) \rho(x,y) \, d\nu(y) = g(x) \rho(x) \text{ for } \mu - \text{a.e. } x. \tag{18.22}$$

There are two possible problems in solving this equation for $g(x)$ at a particular point $x$; the first is when $\bar{\rho}(x) = 0$ and the second is when $\bar{\rho}(x) = \infty$. Since

$$\int_{\mathcal{X}} \bar{\rho}(x) \, d\mu(x) = \int_{\mathcal{X}} \left[ \int_{\mathcal{Y}} \rho(x,y) \, d\nu(y) \right] \, d\mu(x) = 1,$$

we know that $\bar{\rho}(x) < \infty$ for $\mu$ – a.e. $x$ and therefore

$$P(X \in \{\bar{\rho} = 0\}) = P(\bar{\rho}(X) = 0) = \int_{\mathcal{X}} 1_{\bar{\rho}=0} \bar{\rho} \, d\mu = 0.$$  

Hence the points where $\bar{\rho}(x) = \infty$ will not cause any problems.

For the first problem, namely points $x$ where $\bar{\rho}(x) = 0$, we know that $\rho(x,y) = 0$ for $\nu$ – a.e. $y$ and therefore

$$\int_{\mathcal{Y}} f(x,y) \rho(x,y) \, d\nu(y) = 0. \tag{18.23}$$

Hence at such points, $x$ where $\bar{\rho}(x) = 0$, Eq. \textbf{(18.22)} will be valid no matter how we choose $g(x)$. Therefore, if we let $y_0 \in \mathcal{Y}$ be an arbitrary but fixed point and then define

$$g(x) := \begin{cases} \frac{1}{\rho(x)} \int_{\mathcal{Y}} f(x,y) \rho(x,y) \, d\nu(y) & \text{if} \ \bar{\rho}(x) \in (0, \infty) \\ f(x,y_0) & \text{if} \ \bar{\rho}(x) \in \{0, \infty\}. \end{cases}$$
then we have shown \( \mathbb{E} [ f (X, Y) | X] = g(X) = Q(X, f) \) a.s. as desired. (Observe where that when \( \bar{\rho}(x) < \infty, \rho(x, \cdot) \in L^1(\nu) \) and hence the integral in the definition of \( g \) is well defined.)

Just for added security, let us check directly that \( g(X) = \mathbb{E} [ f (X, Y) | X] \) a.s.. According to Eq. (18.21) we have

\[
\mathbb{E} [g(X) h(X)] = \int_X h(x) g(x) \bar{\rho}(x) d\mu(x) = \int_{\mathbb{R} \cap (0, \infty)} h(x) \bar{\rho}(x) \frac{1}{\bar{\rho}(x)} \int_Y f(x, y) \rho(x, y) d\nu(y) d\mu(x)
\]

wherein we have repeatedly used \( \mu(\bar{\rho} = \infty) = 0 \) and Eq. (18.23) holds when \( \bar{\rho}(x) = 0 \). This completes the verification that \( g(X) = \mathbb{E} [ f (X, Y) | X] \) a.s. ■

This proposition shows that conditional expectation is a generalization of the notion of performing integration over a partial subset of the variables in the integrand. Whereas to compute the expectation, one should integrate over all of the variables. It also gives an example of regular conditional probabilities.

**Definition 18.13.** Let \((X, \mathcal{M})\) and \((Y, \mathcal{N})\) be measurable spaces. A function, \(Q : X \times N \to [0,1]\) is a *probability kernel on \(X \times Y\) iff*

1. \(Q(x, \cdot) : N \to [0,1]\) is a probability measure on \((Y, \mathcal{N})\) for each \(x \in X\) and
2. \(\mathcal{Q}(\cdot, B) : X \to [0,1]\) is \(\mathcal{M}/\mathcal{B}_R\) – measurable for all \(B \in \mathcal{N}\).

If \(Q\) is a probability kernel on \(X \times Y\) and \(f : Y \to \mathbb{R}\) is a bounded measurable function or a positive measurable function, then \(x \to Q(x, f) := \int_Y f(y) Q(x, dy)\) is \(\mathcal{M}/\mathcal{B}_R\) – measurable. This is clear for simple functions and then for general functions via simple limiting arguments.

**Definition 18.14.** Let \((X, \mathcal{M})\) and \((Y, \mathcal{N})\) be measurable spaces and \(X : \Omega \to X\) and \(Y : \Omega \to Y\) be measurable functions. A probability kernel, \(Q\), on \(X \times Y\) is said to be a *regular conditional distribution of \(Y\) given \(X\) iff* \(Q(X, B)\) is a version of \(P(Y \in B | X)\) for each \(B \in \mathcal{N}\). Equivalently, we should have \(Q(X, f) = \mathbb{E} [f(Y) | X] \) a.s. for all \(f \in \mathcal{N}_B\). When \(X = \Omega\) and \(\mathcal{M} = \mathcal{G}\) is a sub-\(\sigma\)-algebra of \(\mathcal{B}\), we say that \(Q\) is the *regular conditional distribution of \(Y\) given \(G\).*

The probability kernel, \(Q\), defined in Eq. (18.17) is an example of a regular conditional distribution of \(Y\) given \(X\). In general if \(\mathcal{G}\) is a sub-\(\sigma\)-algebra of \(\mathcal{B}\), Letting \(P_\mathcal{G}(A) = P(A | \mathcal{G}) := \mathbb{E} [1_A | \mathcal{G}] \in L^2(\Omega, \mathcal{G}, P)\) for all \(A \in \mathcal{B}\), then \(P_\mathcal{G} : B \to L^2(\Omega, \mathcal{G}, P)\) is a map such that whenever \(A, A_n \in \mathcal{B}\) with \(A = \sum_{n=1}^\infty A_n\), we have (by cDCT) that

\[
P_\mathcal{G}(A) = \sum_{n=1}^\infty P_\mathcal{G}(A_n) \text{ (equality in } L^2(\mathcal{G}, P)\).
\]

Now suppose that we have chosen a representative, \(P_\mathcal{G}(A) : \Omega \to [0,1]\), of \(P_\mathcal{G}(A)\) for each \(A \in \mathcal{B}\). From Eq. (18.24) it follows that

\[
P_\mathcal{G}(A)(\omega) = \sum_{n=1}^\infty P_\mathcal{G}(A_n)(\omega) \text{ for } P \text{-a.e. } \omega.
\]

However, note well, the exceptional set of \(\omega\)’s depends on the sets \(A, A_n \in \mathcal{B}\). The goal of regular conditioning is to carefully choose the representative, \(P_\mathcal{G}(A) : \Omega \to [0,1]\), such that Eq. (18.25) holds for all \(\omega \in \Omega\) and all \(A, A_n \in \mathcal{B}\) with \(A = \sum_{n=1}^\infty A_n\).

**Remark 18.15.** Unfortunately, regular conditional distributions do not always exist. However, if we require \(\mathfrak{Y}\) to be a “standard Borel space,” (i.e. \(\mathfrak{Y}\) is isomorphic to a Borel subset of \(\mathbb{R}\), then a conditional distribution of \(Y\) given \(X\) will always exists. See Theorem 18.25 below for more details. So in most instances of interest a regular conditional distribution of \(Y\) given \(X\) will exist.

**Exercise 18.3.** Suppose that \((X, \mathcal{M})\) and \((Y, \mathcal{N})\) are measurable spaces, \(X : \Omega \to X\) and \(Y : \Omega \to Y\) are measurable functions, and there exists a regular conditional distribution, \(Q\), of \(Y\) given \(X\). Show:

1. For all bounded measurable functions, \(f : (X \times Y, \mathcal{M} \otimes \mathcal{N}) \to \mathbb{R}\), the function \(X \ni x \to Q(x, f(x, \cdot))\) is measurable and

\[
Q(X, f(X, \cdot)) = \mathbb{E} [f(Y) | X] \text{ a.s. \ (18.26)}
\]

**Hint:** let \(\mathbb{H}\) denote the set of bounded measurable functions, \(f\), on \(X \times Y\) such that the two assertions are valid.

2. If \(A \in \mathcal{M} \otimes \mathcal{N}\) and \(\mu := P \circ X^{-1}\) be the law of \(X\), then

\[
P((X, Y) \in A) = \int_X Q(x, 1_A(x, \cdot)) d\mu(x) = \int_X d\mu(x) \int_Y 1_A(x, y) Q(x, dy).
\]

(18.27)
Exercise 18.4. Keeping the same notation as in Exercise 18.3 and further assume that \( X \) and \( Y \) are independent. Find a regular conditional distribution of \( Y \) given \( X \) and prove
\[
\mathbb{E}[f(X,Y)|X] = h_f(X) \text{ a.s. for all } x \in X,
\]
where
\[
h_f(x) := \mathbb{E}[f(x,Y)] \text{ for all } x \in X,
\]
i.e.
\[
\mathbb{E}[f(X,Y)|X] = \mathbb{E}[f(x,Y)|X]|_{x=x} \text{ a.s.}
\]

Exercise 18.5. Suppose \((\Omega, \mathcal{B}, P)\) and \((\Omega', \mathcal{B}', P')\) are two probability spaces, \((\mathcal{X}, \mathcal{M})\) and \((\mathcal{Y}, \mathcal{N})\) are measurable spaces, \(X : \Omega \to \mathcal{X}, X' : \Omega' \to \mathcal{X}, Y : \Omega \to \mathcal{Y},\) and \(Y' : \Omega \to \mathcal{Y}\) are measurable functions such that \(P \circ (X,Y)^{-1} = P' \circ (X',Y')\), i.e. \((X,Y) \overset{d}{=} (X',Y')\). If \(f : (\mathcal{X} \times \mathcal{Y}, \mathcal{M} \otimes \mathcal{N}) \to \mathbb{R}\) is a bounded measurable function and \(\bar{f} : (\mathcal{X}, \mathcal{M}) \to \mathbb{R}\) is a measurable function such that \(\bar{f}(X) = \mathbb{E}[f(X,Y)|X] \text{ P - a.s. then}
\]
\[
\mathbb{E}'[f(X',Y')|X'] = \bar{f}(X') \text{ P' a.s.}
\]

18.2 Additional Properties of Conditional Expectations

The next theorem is devoted to extending the notion of conditional expectations to all non-negative functions and to proving conditional versions of the MCT, DCT, and Fatou’s lemma.

Theorem 18.16 (Extending \(\mathbb{E}_{\mathcal{G}}\)). If \(F : \Omega \to [0, \infty]\) is \(\mathcal{B}\) - measurable, the function \(F := \lim_{n \to \infty} \mathbb{E}_{\mathcal{G}}[f \land n]\) exists a.s. and is, up to sets of measure zero, uniquely determined by as the \(\mathcal{G}\) - measurable function, \(F : \Omega \to [0, \infty]\), satisfying
\[
\mathbb{E}[f : A] = \mathbb{E}[F : A] \text{ for all } A \in \mathcal{G}.
\]
Hence it is consistent to denote \(F\) by \(\mathbb{E}_{\mathcal{G}}f\). In addition we now have;

1. Properties 2., 5. (with \(0 \leq g \in \mathcal{G}_0\)), and 6. of Theorem 18.5 still hold for any \(\mathcal{B}\) - measurable functions such that \(0 \leq f \leq g\). Namely:
   a) Order Preserving. \(\mathbb{E}_{\mathcal{G}}f \leq \mathbb{E}_{\mathcal{G}}g\) a.s. when \(0 \leq f \leq g\),
   b) Pull out Property. \(\mathbb{E}_{\mathcal{G}}[hf] = h\mathbb{E}_{\mathcal{G}}[f]\) a.s. for all \(h \geq 0\) and \(\mathcal{G}\) - measurable.
   c) Tower or smoothing property. If \(\mathcal{G}_0 \subset \mathcal{G}_1 \subset \mathcal{B}\). Then
   \[
   \mathbb{E}_{\mathcal{G}_0} \mathbb{E}_{\mathcal{G}_1} f = \mathbb{E}_{\mathcal{G}_1} \mathbb{E}_{\mathcal{G}_0} f = \mathbb{E}_{\mathcal{G}_0} f \text{ a.s.}
   \]

2. Conditional Monotone Convergence (cMCT). Suppose that, almost surely, \(0 \leq f_n \leq f_{n+1}\) for all \(n\), then \(\lim_{n \to \infty} \mathbb{E}_{\mathcal{G}}f_n = \mathbb{E}_{\mathcal{G}}[\lim_{n \to \infty} f_n]\) a.s.

3. Conditional Fatou’s Lemma (cFatou). Suppose again that \(0 \leq f_n \leq f_{n+1}\) for all \(n\) in \(L^1(\Omega, \mathcal{B}, P)\) a.s., then
\[
\mathbb{E}_{\mathcal{G}} \left[ \liminf_{n \to \infty} f_n \right] \leq \liminf_{n \to \infty} \mathbb{E}_{\mathcal{G}}[f_n] \text{ a.s. (18.29)}
\]

4. Conditional Dominated Convergence (cDCT). If \(f_n \to f\) a.s. and \(|f_n| \leq g \in L^1(\Omega, \mathcal{B}, P)\), then \(\mathbb{E}_{\mathcal{G}}f_n \to \mathbb{E}_{\mathcal{G}}f\) a.s.

Remark 18.17. Regarding item 4. above. Suppose that \(f_n \overset{P}{\to} f, |f_n| \leq g \in L^1(\Omega, \mathcal{B}, P)\), \(g, f \overset{P}{\to} f \in L^1(\Omega, \mathcal{B}, P)\) and \(\mathbb{E}g_n \to \mathbb{E}g\). Then by the DCT in Corollary 11.8 we know that \(f_n \to f\) in \(L^1(\Omega, \mathcal{B}, P)\). Since \(\mathbb{E}_{\mathcal{G}}\) is a contraction, it follows that \(\mathbb{E}_{\mathcal{G}}f_n \to \mathbb{E}_{\mathcal{G}}f\) in \(L^1(\Omega, \mathcal{B}, P)\) and hence in probability.

Proof. Since \(f \land n \in L^1(\Omega, \mathcal{B}, P)\) and \(f \land n\) is increasing, it follows that \(F := \lim_{n \to \infty} \mathbb{E}_{\mathcal{G}}[f \land n]\) exists a.s. Moreover, by two applications of the standard MCT, we have for any \(A \in \mathcal{G}\), that
\[
\mathbb{E}[F : A] = \lim_{n \to \infty} \mathbb{E}[\mathbb{E}_{\mathcal{G}}[f \land n] : A] = \lim_{n \to \infty} \mathbb{E}[f \land n : A] = \lim_{n \to \infty} \mathbb{E}[f : A].
\]
Thus Eq. (18.28) holds and this uniquely determines \(F\) follows from Lemma 18.2.

Item 1. a) If \(0 \leq f \leq g\), then
\[
\mathbb{E}_{\mathcal{G}}f = \lim_{n \to \infty} \mathbb{E}_{\mathcal{G}}[f \land n] \leq \lim_{n \to \infty} \mathbb{E}_{\mathcal{G}}[g \land n] = \mathbb{E}_{\mathcal{G}}g \text{ a.s.}
\]
and so \(\mathbb{E}_{\mathcal{G}}\) still preserves order. We will prove items 1b and 1c at the end of this proof.

Item 2. Suppose that, almost surely, \(0 \leq f_n \leq f_{n+1}\) for all \(n\), then \(\mathbb{E}_{\mathcal{G}}f_n\) is a.s. increasing in \(n\). Hence, again by two applications of the MCT, for any \(A \in \mathcal{G}\), we have
\[
\mathbb{E} \left[ \lim_{n \to \infty} \mathbb{E}_{\mathcal{G}}f_n : A \right] = \lim_{n \to \infty} \mathbb{E}[\mathbb{E}_{\mathcal{G}}f_n : A] = \lim_{n \to \infty} \mathbb{E}[f_n : A] = \mathbb{E} \left[ \lim_{n \to \infty} f_n : A \right] = \mathbb{E} \left[ \mathbb{E}_{\mathcal{G}} \left[ \lim_{n \to \infty} f_n \right] : A \right]
\]
from which it follows that \(\lim_{n \to \infty} \mathbb{E}_{\mathcal{G}}f_n = \mathbb{E}_{\mathcal{G}}[\lim_{n \to \infty} f_n]\) a.s.

Item 3. For \(0 \leq f_n\), let \(g_k := \inf_{n \geq k} f_n\). Then \(g_k \leq f_k\) for all \(k\) and \(g_k \uparrow \liminf_{n \to \infty} f_n\) and hence by cMCT and item 1.,
\[
\mathbb{E}_{\mathcal{G}} \left[ \liminf_{n \to \infty} f_n \right] = \liminf_{k \to \infty} \mathbb{E}_{\mathcal{G}}g_k \leq \liminf_{k \to \infty} \mathbb{E}_{\mathcal{G}}f_k \text{ a.s.}
\]
Item 4. As usual it suffices to consider the real case. Let $f_n \to f$ a.s. and $|f_n| \leq g$ a.s. with $g \in L^1(\Omega, B, P)$. Then following the proof of the Dominated convergence theorem, we start with the fact that $0 \leq g \pm f_n$ a.s. for all $n$. Hence by cFatou,

$$E_g (g \pm f) = E_g \left[ \liminf_{n \to \infty} (g \pm f_n) \right]$$

$$\leq \liminf_{n \to \infty} E_g (g \pm f_n) = E_g g + \left\{ \begin{array}{ll}
\liminf_{n \to \infty} E_g (f_n) & \text{in } + \text{ case,}
\limsup_{n \to \infty} E_g (f_n) & \text{in } - \text{ case},
\end{array} \right.$$  

where the above equations hold a.s. Cancelling $E_g g$ from both sides of the equation then implies

$$\limsup_{n \to \infty} E_g (f_n) \leq E_g f \leq \liminf_{n \to \infty} E_g (f_n) \text{ a.s.}$$

Item 1. b) If $h \geq 0$ is a $\mathcal{G}$–measurable function and $f \geq 0$, then by cMCT,

$$E_g \left[ hf \right] = \lim_{n \to \infty} E_g \left[ (h \wedge n) \right] = \lim_{n \to \infty} (h \wedge n) E_g \left[ f \wedge n \right] = h E_g f \text{ a.s.}$$

Item 1. c) Similarly by multiple uses of cMCT,

$$E_{g_1} E_{g_1} f = E_{g_1} \lim_{n \to \infty} E_{g_1} (f \wedge n) = \lim_{n \to \infty} E_{g_1} E_{g_1} (f \wedge n) = \lim_{n \to \infty} E_{g_1} (f \wedge n) = E_{g_1} f$$

and

$$E_{g_2} E_{g_2} f = E_{g_2} \lim_{n \to \infty} E_{g_2} (f \wedge n) = \lim_{n \to \infty} E_{g_2} E_{g_2} (f \wedge n) = \lim_{n \to \infty} E_{g_2} (f \wedge n) = E_{g_2} f.$$  

The next result in Lemma 18.19 shows how to localize conditional expectations. We first need the following definition.

**Definition 18.18.** Suppose that $\mathcal{F}$ and $\mathcal{G}$ are sub-sigma-fields of $B$ and $A \in B$. We say that $\mathcal{F} = \mathcal{G}$ on $A$ iff $A \in \mathcal{F} \cap \mathcal{G}$ and $\mathcal{F}_A = \mathcal{G}_A$. Recall that $\mathcal{F}_A = \{ B \cap A : B \in \mathcal{F} \}$.

Notice that if $\mathcal{F} = \mathcal{G}$ on $A$ then $\mathcal{F} = \mathcal{G} = \mathcal{F} \cap \mathcal{G}$ on $A$ as well. Indeed, if $B \in \mathcal{F}_A$ then $B \in \mathcal{G}_A$ and so $B \cap A \in \mathcal{F} \cap \mathcal{G}$ and hence $B \cap A = (B \cap A) \cap A \in \mathcal{F} \cap \mathcal{G}_A$. Moreover, because $[\mathcal{F} \cap \mathcal{G}]_A \subset \mathcal{F}_A$ we have $\mathcal{F}_A = \mathcal{G}_A$ implies

$$\mathcal{F}_A = \mathcal{G}_A = [\mathcal{F} \cap \mathcal{G}]_A.$$  

**Lemma 18.19 (Localizing Conditional Expectations).** Let $(\Omega, B, P)$ be a probability space, $\mathcal{F}$ and $\mathcal{G}$ be sub-sigma-fields of $B$, $X, Y \in L^1(\Omega, B, P)$ or $X, Y : (\Omega, B) \to [0, \infty]$ are measurable, and $A \in \mathcal{F} \cap \mathcal{G}$. If $\mathcal{F} = \mathcal{G}$ on $A$ and $X = Y$ a.s. on $A$, then

$$\mathbb{E}_{\mathcal{F}} X = \mathbb{E}_{\mathcal{F} \cap \mathcal{G}} X = \mathbb{E}_{\mathcal{F} \cap \mathcal{G}} Y = \mathbb{E}_{\mathcal{G}} Y \text{ a.s. on } A.$$  

Alternatively put, if $A \in \mathcal{F} \cap \mathcal{G}$ and $\mathcal{F}_A = \mathcal{G}_A$ then

$$1 A \mathbb{E}_{\mathcal{F}} = 1 A \mathbb{E}_{\mathcal{F} \cap \mathcal{G}} = 1 A \mathbb{E}_{\mathcal{G}}.$$  

**Proof.** Let us start with the observation that if $X$ is an $\mathcal{F}$–measurable random variable, then $1 A X$ is $\mathcal{F} \cap \mathcal{G}$ measurable. This can be checked directly (see Remark 18.20 below) or as follows. If $X = 1 B$ with $B \in \mathcal{F}$, then $1 A 1 B = 1 A \cap B$ and $A \cap B \in \mathcal{F}_A = \mathcal{G}_A = [\mathcal{F} \cap \mathcal{G}]_A \subset \mathcal{F} \cap \mathcal{G}$ and so $1 A 1 B$ is $\mathcal{F} \cap \mathcal{G}$–measurable. The general $X$ case now follows by linearity and then passing to the limit.

Suppose $X \in L^1(\Omega, B, P)$ or $X \geq 0$ and let $\bar{X}$ be a representative of $\mathbb{E}_{\mathcal{F}} X$. By the previous observation, $1 A \bar{X}$ is $\mathcal{F} \cap \mathcal{G}$–measurable. Therefore,

$$1 A \bar{X} = 1 A \mathbb{E}_{\mathcal{F} \cap \mathcal{G}} [1 A \bar{X}] = 1 A \mathbb{E}_{\mathcal{F} \cap \mathcal{G}} [\bar{X}] = 1 A \mathbb{E}_{\mathcal{F} \cap \mathcal{G}} \mathbb{E}_{\mathcal{F}} X = 1 A \mathbb{E}_{\mathcal{F} \cap \mathcal{G}} \mathbb{E}_{\mathcal{F}} X \text{ a.s.},$$

i.e. $1 A \mathbb{E}_{\mathcal{F}} X = 1 A \mathbb{E}_{\mathcal{F} \cap \mathcal{G}} X$ a.s. This proves the first equality in Eq. (18.31) while the second follows by interchanging the roles of $\mathcal{F}$ and $\mathcal{G}$.

Equation (18.31) is now easily verified. First notice that $X = Y$ a.s. on $A$ iff $1 A X = 1 A Y$ a.s. Now from Eq. (18.32), the tower property of conditional expectation, and the fact that $1 A = 1 A \cdot 1 A$, we find

$$1 A \mathbb{E}_{\mathcal{F}} X = 1 A \mathbb{E}_{\mathcal{F}} [1 A \mathbb{E}_{\mathcal{F}} X] = 1 A \mathbb{E}_{\mathcal{F}} [1 A Y] = 1 A \mathbb{E}_{\mathcal{F}} Y = 1 A \mathbb{E}_{\mathcal{F} \cap \mathcal{G}} Y$$

from which it follows that $\mathbb{E}_{\mathcal{F}} X = \mathbb{E}_{\mathcal{F} \cap \mathcal{G}} Y$ a.s. on $A$.  

**Remark 18.20.** For the direct verification that $1 A X$ is $\mathcal{F} \cap \mathcal{G}$ measurable, we have,

$$\{ 1 A X \neq 0 \} = A \cap \{ X \neq 0 \} \in \mathcal{F}_A = \mathcal{G}_A = [\mathcal{F} \cap \mathcal{G}]_A \subset \mathcal{F} \cap \mathcal{G}.$$  

So for $B \in \mathcal{B}_B$,

$$\{ 1 A X \in B \} = A \cap \{ X \in B \} \in \mathcal{F}_A \subset \mathcal{F} \cap \mathcal{G} \text{ if } 0 \notin B$$

while if $0 \in B$,

$$\{ 1 A X \in B \} = \{ 1 A X = 0 \}^c \cup A \cap \{ X \in (B \setminus \{ 0 \}) \} = \{ 1 A X \neq 0 \}^c \cup A \cap \{ X \in (B \setminus \{ 0 \}) \} \in \mathcal{F} \cap \mathcal{G}.$$
Theorem 18.21 (Conditional Jensen’s inequality). Let \((\Omega, B, P)\) be a probability space, \(-\infty \leq a < b \leq \infty\), and \(\varphi : (a, b) \to \mathbb{R}\) be a convex function. Assume \(f \in L^1(\Omega, B, P; \mathbb{R})\) is a random variable satisfying, \(f \in (a, b)\) a.s. and \(\varphi(f) \in L^1(\Omega, B, P; \mathbb{R})\). Then \(\varphi(E_G f) \in L^1(\Omega, G, P)\),

\[
\varphi(E_G f) \leq E_G [\varphi(f)] \ \text{a.s.} \tag{18.33}
\]

and

\[
E [\varphi(E_G f)] \leq E [\varphi(f)] \tag{18.34}
\]

**Proof.** Let \(A := Q \cap (a, b)\) – a countable dense subset of \((a, b)\). By Theorem 11.38 (also see Lemma 7.31 and Figure 7.2 when \(\varphi\) is \(C^1\))

\[
\varphi(y) \geq \varphi(x) + \varphi'(x)(y-x) \quad \text{for all } x, y \in (a, b),
\]

where \(\varphi'(x)\) is the left hand derivative of \(\varphi\) at \(x\). Taking \(y = f\) and then taking conditional expectations imply,

\[
E_G [\varphi(f)] \geq E_G [\varphi(x) + \varphi'(x)(f-x)] = \varphi(x) + \varphi'(x)(E_G f - x) \ \text{a.s.} \tag{18.35}
\]

Since this is true for all \(x \in (a, b)\) (and hence all \(x\) in the countable set, \(A\)) we may conclude that

\[
E_G [\varphi(f)] \geq \sup_{x \in A} [\varphi(x) + \varphi'(x)(E_G f - x)] \ \text{a.s.}
\]

By Exercise 18.1 \(E_G f \in (a, b)\), and hence it follows from Corollary 11.39 that

\[
\sup_{x \in A} [\varphi(x) + \varphi'(x)(E_G f - x)] = \varphi(E_G f) \ \text{a.s.}
\]

Combining the last two estimates proves Eq. (18.33).

From Eqs. (18.33) and (18.35) we infer,

\[
|\varphi(E_G f)| \leq |E_G [\varphi(f)]| \vee [\varphi(x) + \varphi'(x)(E_G f - x)] \in L^1(\Omega, G, P)
\]

and hence \(\varphi(E_G f) \in L^1(\Omega, G, P)\). Taking expectations of Eq. (18.33) is now allowed and immediately gives Eq. (18.34).

**Corollary 18.22.** The conditional expectation operator, \(E_G\) maps \(L^p(\Omega, B, P)\) into \(L^p(\Omega, G, P)\) and the map remains a contraction for all \(1 \leq p \leq \infty\).

**Proof.** The case \(p = \infty\) and \(p = 1\) have already been covered in Theorem 18.3. So now suppose, \(1 < p < \infty\), and apply Jensen’s inequality with \(\varphi(x) = |x|^p\) to find \(|E_G f|^p \leq E_G |f|^p\) a.s. Taking expectations of this inequality gives the desired result.

### 18.3 Regular Conditional Distributions

**Lemma 18.23.** Suppose that \((X, M)\) is a measurable space and \(F : X \times \mathbb{R} \to \mathbb{R}\) is a function such that; 1) \(F(t, \cdot) : X \to \mathbb{R}\) is \(M/B_R\) measurable for all \(t \in \mathbb{R}\), and 2) \(F(x, \cdot) : \mathbb{R} \to \mathbb{R}\) is continuous for all \(x \in X\). Then \(F = M \otimes B_R / B_R\) measurable.

**Proof.** For \(n \in \mathbb{N}\), the function,

\[
F_n(x, t) := \sum_{k=-\infty}^{\infty} F(x, (k+1)2^{-n}) 1_{(k2^{-n},(k+1)2^{-n})}(t),
\]

is \(M \otimes B_R / B_R\) measurable. Using the right continuity assumption, it follows that \(F(x, t) = \lim_{n \to \infty} F_n(x, t)\) for all \((x, t) \in X \times \mathbb{R}\) and therefore \(F\) is also \(M \otimes B_R / B_R\) measurable.

**Theorem 18.24.** Suppose that \((X, M)\) is a measurable space, \(X : \Omega \to X\) is a measurable function and \(Y : \Omega \to \mathbb{R}\) is a random variable. Then there exists a probability kernel, \(Q\), on \(X \times \mathbb{R}\) such that \(E[f(Y) | X] = Q(X, f)\), \(P\) a.s., for all bounded measurable functions, \(f : \mathbb{R} \to \mathbb{R}\).

**Proof.** For each \(r \in \mathbb{Q}\), let \(q_r : X \to [0, 1]\) be a measurable function such that

\[
E[1_{Y \leq r}|X] = q_r(X) \ \text{a.s.}
\]

Let \(\nu := P \circ X^{-1}\) be the law of \(X\). Then using the basic properties of conditional expectation, \(q_r \leq q_s\), \(\nu\) a.s. for all \(r \leq s\), \(\lim_{r \to \infty} q_r = 1\) and \(\lim_{r \to -\infty} q_r = 0\), \(\nu\) a.s. Hence the set, \(X_0 \subset X\) where \(q_r(x) \leq q_s(x)\) for all \(r \leq s\), \(\lim_{r \to \infty} q_r = 1\), and \(\lim_{r \to -\infty} q_r = 0\) satisfies, \(\nu(X_0) = P(X \in X_0) = 1\). For \(t \in \mathbb{R}\), let

\[
F(x, t) := 1_{X_0}(x) \cdot \inf \{q_r(x) : r > t\} + 1_{X \setminus X_0}(x) \cdot 1_{t < 0}.
\]

Then \(F(t, \cdot) : X \to \mathbb{R}\) is measurable for each \(t \in \mathbb{R}\) and \(F(x, \cdot)\) is a distribution function on \(\mathbb{R}\) for each \(x \in X\). Hence an application of Lemma 18.23 shows \(F : X \times \mathbb{R} \to [0, 1]\) is measurable.

For each \(x \in X\) and \(B \in B_R\), let \(Q(x, B) = \mu_{F(x, \cdot)}(B)\) where \(\mu_F\) denotes the probability measure on \(\mathbb{R}\) determined by a distribution function, \(F : \mathbb{R} \to [0, 1]\).

We will now show that \(Q\) is the desired probability kernel. To prove this, let \(\mathbb{H}\) be the collection of bounded measurable functions, \(f : \mathbb{R} \to \mathbb{R}\), such that \(X \ni x \to Q(x, f) \in \mathbb{R}\) is measurable and \(E[f(Y) | X] = Q(X, f)\), \(P\) a.s. It is easily seen that \(\mathbb{H}\) is a linear subspace which is closed under bounded convergence. We will finish the proof by showing that \(\mathbb{H}\) contains the multiplicative class, \(M = \{1_{(-\infty, t]} : t \in \mathbb{R}\}\).

Notice that \(Q(x, 1_{(-\infty, t]}) = F(x, t)\) is measurable. Now let \(r \in \mathbb{Q}\) and \(g : X \to \mathbb{R}\) be a bounded measurable function, then
Let us now define $E\{1_{Y \leq r} \cdot g(X)\} = E\{E\{1_{Y \leq r} | X\} \cdot g(X)\} = E\{q_r(X) \cdot g(X)\} = E\{q_r(X) \cdot 1_{X_0}(X) \cdot g(X)\}$.

For $t \in \mathbb{R}$, we may let $r \uparrow t$ in the above equality (use DCT) to learn,

$E\{1_{Y \leq t} \cdot g(X)\} = E\{F(X, t) \cdot 1_{X_0}(X) \cdot g(X)\} = E\{F(X, t) \cdot g(X)\}$.

Since $g$ was arbitrary, we may conclude that

$Q(X, 1_{(-\infty, t]}) = F(X, t) = E\{1_{Y \leq t} | X\}$ a.s.

This completes the proof.

This result leads fairly immediately to the following far reaching generalization.

**Theorem 18.25.** Suppose that $(\mathcal{X}, \mathcal{M})$ is a measurable space and $(\mathcal{Y}, \mathcal{N})$ is a standard Borel space, see Appendix 18.4 below. Suppose that $X : \Omega \to \mathcal{X}$ and $Y : \Omega \to \mathcal{Y}$ are measurable functions. Then there exists a probability kernel, $Q$, on $\mathcal{X} \times \mathcal{Y}$ such that $E[f(Y) | X] = Q(X, f)$, $P$ – a.s., for all bounded measurable functions, $f : \mathcal{Y} \to \mathbb{R}$.

**Proof.** By definition of a standard Borel space, we may assume that $\mathcal{Y} \in \mathcal{B}_\mathbb{R}$ and $\mathcal{N} = \mathcal{B}_\mathbb{R}$. In this case $Y$ may also be viewed to be a measurable map form $\Omega \to \mathbb{R}$ such that $Y(\Omega) \subset \mathcal{Y}$. By Theorem 18.24 we may find a probability kernel, $Q_0$, on $\mathcal{X} \times \mathbb{R}$ such that

$E[f(Y) | X] = Q_0(X, f)$, $P$ – a.s.,

for all bounded measurable functions, $f : \mathbb{R} \to \mathbb{R}$.

Taking $f = 1_Y$ in Eq. (18.36) shows

$1 = E\{1_Y(Y) | X\} = Q_0(X, Y)$ a.s.

Thus if we let $X_0 := \{x \in \mathcal{X} : Q_0(x, Y) = 1\}$, we know that $P(X \in X_0) = 1$.

Let us now define

$Q(x, B) := 1_{X_0}(x) \cdot Q_0(x, B) + 1_{X \setminus X_0}(x) \cdot 1_B$ for $(x, B) \in \mathcal{X} \times \mathcal{B}_\mathbb{R}$,

where $y$ is an arbitrary but fixed point in $Y$. Then and hence $Q$ is a probability kernel on $\mathcal{Y} \times \mathbb{R}$. Moreover if $B \in \mathcal{B}_\mathbb{R} \subset \mathcal{B}_\mathbb{R}$, then

$Q(X, B) = 1_{X_0}(X) \cdot Q_0(X, B) + 1_{X \setminus X_0}(X) \cdot E[1_B(Y) | X] = E[1_B(Y) | X]$ a.s.

This shows that $Q$ is the desired regular conditional probability.

**Corollary 18.26.** Suppose $\mathcal{G}$ is a sub-$\sigma$ – algebra, $(\mathcal{Y}, \mathcal{N})$ is a standard Borel space, and $Y : \Omega \to \mathcal{Y}$ is a measurable function. Then there exists a probability kernel, $Q$, on $(\Omega, \mathcal{G}) \times (\mathcal{Y}, \mathcal{N})$ such that $E[f(Y) | \mathcal{G}] = Q(\cdot, f)$, $P$ – a.s. for all bounded measurable functions, $f : \mathcal{Y} \to \mathbb{R}$.

**Proof.** This is a special case of Theorem 18.25 applied with $(\mathcal{X}, \mathcal{M}) = (\Omega, \mathcal{G})$ and $Y : \Omega \to \Omega$ being the identity map which is $\mathcal{B}/\mathcal{G}$ – measurable.

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**18.4 Appendix: Standard Borel Spaces**

For more information along the lines of this section, see Royden [9].

**Definition 18.27.** Two measurable spaces, $(X, \mathcal{M})$ and $(Y, \mathcal{N})$ are said to be **isomorphic** if there exists a bijective map, $f : X \to Y$ such that $f(\mathcal{M}) = \mathcal{N}$ and $f^{-1}(\mathcal{N}) = \mathcal{M}$, i.e. both $f$ and $f^{-1}$ are measurable. In this case we say $f$ is a measure theoretic isomorphism and we will write $X \cong Y$.

**Definition 18.28.** A measurable space, $(X, \mathcal{M})$ is said to be a **standard Borel space** if $(X, \mathcal{M}) \cong (B, \mathcal{B}_B)$ where $B$ is a Borel subset of $((0,1), \mathcal{B}_{(0,1)})$.

**Definition 18.29 (Polish spaces).** A **Polish space** is a separable topological space $(X, \tau)$ which admits a complete metric, $\rho$, such that $\tau = \tau \rho$.

The main goal of this chapter is to prove every Borel subset of a Polish space is a standard Borel space, see Corollary 18.39 below. Along the way we will show a number of spaces, including $[0,1]$, $(0,1]$, $[0,1]^d$, $\mathbb{R}^d$, and $\mathbb{R}^N$, are all isomorphic to $(0,1)$. Moreover we also will see that the a countable product of standard Borel spaces is again a standard Borel space, see Corollary 18.36.

On first reading, you may wish to skip the rest of this section.

**Lemma 18.30.** Suppose $(X, \mathcal{M})$ and $(Y, \mathcal{N})$ are measurable spaces such that $X = \bigcap_{n=1}^\infty X_n$, $Y = \bigcap_{n=1}^\infty Y_n$, with $X_n \in \mathcal{M}$ and $Y_n \in \mathcal{N}$. If $(X_n, \mathcal{M}_{X_n})$ is isomorphic to $(Y_n, \mathcal{N}_{Y_n})$ for all $n$ then $X \cong Y$. Moreover, if $(X_n, \mathcal{M}_n)$ and $(Y_n, \mathcal{N}_n)$ are isomorphic measure spaces, then $(X := \bigcap_{n=1}^\infty X_n, \otimes_{n=1}^\infty \mathcal{M}_n)$ are isomorphic.

**Proof.** For each $n \in \mathbb{N}$, let $f_n : X_n \to Y_n$ be a measure theoretic isomorphism. Then define $f : X \to Y$ by $f = f_n$ on $X_n$. Clearly, $f : X \to Y$ is a bijection and if $B \in \mathcal{N}$, then

$f^{-1}(B) = \bigcup_{n=1}^\infty f_n^{-1}(B \cap Y_n) = \bigcup_{n=1}^\infty f_n^{-1}(B \cap Y_n) \in \mathcal{M}$.

This shows $f$ is measurable and by similar considerations, $f^{-1}$ is measurable as well. Therefore, $f : X \to Y$ is the desired measure theoretic isomorphism.

For the second assertion, let $f_n : X_n \to Y_n$ be a measure theoretic isomorphism of all $n \in \mathbb{N}$ and then define

$f(x) = (f_1(x_1), f_2(x_2), \ldots)$ with $x = (x_1, x_2, \ldots) \in X$.

Again it is clear that $f$ is bijective and measurable, since
Proposition 18.31. Let $-\infty < a < b < \infty$. The following measurable spaces equipped with there Borel $\sigma$-algebras are all isomorphic: $(0,1), [0,1), (0,1], [0,1), (a,b), [a,b), [a,b), \mathbb{R}$, and $(0,1) \cup A$ where $A$ is a finite or countable subset of $\mathbb{R} \setminus (0,1)$.

Proof. It is easy to see by that any bounded open, closed, or half open interval is isomorphic to any other such interval using an affine transformation. Let us now show $(-1,1) \cong [-1,1]$. To prove this it suffices, by Lemma 18.30, to observe that

$$(-1,1) = \{0\} \cup \sum_{n=0}^{\infty} (-2^{-n}, -2^{-n}] \cup [2^{-n-1}, 2^{-n})$$

and

$$[-1,1] = \{0\} \cup \sum_{n=0}^{\infty} (-2^{-n}, -2^{-n-1}) \cup [2^{-n-1}, 2^{-n}) \cup [2^{-n}, 2^{-n-1}).$$

Similarly $(0,1)$ is isomorphic to $(0,1)$ because

$$(0,1) = \sum_{n=0}^{\infty} (2^{-n-1}, 2^{-n}) \text{ and } (0,1) = \sum_{n=0}^{\infty} (2^{-n-1}, 2^{-n}).$$

The assertion involving $\mathbb{R}$ can be proved using the bijection, tan : $(-\pi/2, \pi/2) \rightarrow \mathbb{R}$.

If $A = \{1\}$, then by Lemma 18.30 and what we have already proved, $(0,1) \cup \{1\} \cong (0,1)$. Similarly if $N \in \mathbb{N}$ with $N \geq 2$ and $A = \{2, \ldots, N+1\}$, then

$$(0,1) \cup A \cong (0,1) \cup A = (0,2^{-N+1}] \cup \sum_{n=1}^{N-1} (2^{-n}, 2^{-n-1}) \cup A$$

while

$$(0,1) = (0,2^{-N+1}] \cup \sum_{n=1}^{N-1} (2^{-n}, 2^{-n-1}) \cup \sum_{n=1}^{2^{-n}, n = 1, 2, \ldots, N}$$

and so again it follows from what we have proved and Lemma 18.30 that $(0,1) \cong (0,1) \cup A$. Finally if $A = \{2,3,4,\ldots\}$ is a countable set, we can show $(0,1) \cong (0,1) \cup A$ with the aid of the identities,

$$(0,1) = \left[ \sum_{n=1}^{\infty} (2^{-n}, 2^{-n-1}) \right] \cup \{2^{-n} : n \in \mathbb{N}\}$$

and

$$(0,1) \cup A \cong (0,1) \cup A = \left[ \sum_{n=1}^{\infty} (2^{-n}, 2^{-n-1}) \right] \cup A.$$
By construction,
\[ x = \sum_{j=1}^{k} 2^{-j} \gamma_j(x) + r_{k+1}(x) \]
and \( r_{k+1}(x) \to 0 \) as \( k \to \infty \), therefore
\[ x = \sum_{j=1}^{\infty} 2^{-j} \gamma_j(x) \quad \text{and} \quad r_{k+1}(x) = \sum_{j=k+1}^{\infty} 2^{-j} \gamma_j(x). \quad (18.38) \]

Hence if we define \( f : \Omega \to [0,1] \) by \( f = \sum_{j=1}^{\infty} 2^{-j} \pi_j \), then \( f(g(x)) = x \) for all \( x \in [0,1] \). This shows \( g \) is injective, \( f \) is surjective, and \( f \) in injective on the range of \( g \).

We now claim that \( \Omega_0 := g([0,1)) \), the range of \( g \), consists of those \( \omega \in \Omega \) such that \( \omega_i = 0 \) for infinitely many \( i \). Indeed, if there exists an \( k \in \mathbb{N} \) such that \( \gamma_j(x) = 1 \) for all \( j \geq k \), then (by Eq. \((18.38)) \) \( r_{k+1}(x) = 2^{-k} \) which would contradict Eq. \((18.37)) \). Hence \( g([0,1)) \subseteq \Omega_0 \). Conversely if \( \omega \in \Omega_0 \) and \( x = f(\omega) \in [0,1] \), it is not hard to show inductively that \( \gamma_j(x) = \omega_j \) for all \( j \), i.e. \( g(x) = \omega \). For example, if \( \omega_1 = 1 \) then \( x \geq 2^{-1} \) and hence \( \gamma_1(x) = 1 \). Alternatively, if \( \omega_1 = 0 \), then
\[ x = \sum_{j=2}^{\infty} 2^{-j} \omega_j \sum_{j=1}^{\infty} 2^{-j} = 2^{-1} \]
so that \( \gamma_1(x) = 0 \). Hence it follows that \( r_2(x) = \sum_{j=2}^{\infty} 2^{-j} \omega_j \) and by similar reasoning we learn \( r_2(x) \geq 2^{-2} \) iff \( \omega_2 = 1 \), i.e. \( \gamma_2(x) = 1 \) iff \( \omega_2 = 1 \). The full induction argument is now left to the reader.

Since single point sets are in \( \mathcal{B} \) and
\[ A := \Omega \setminus \Omega_0 = \cup_{n=1}^{\infty} \{ \omega \in \Omega : \omega_j = 1 \text{ for } j \geq n \} \]
is a countable set, it follows that \( A \in \mathcal{B} \) and therefore \( \Omega_0 = \Omega \setminus A \in \mathcal{B} \).

Hence we may now conclude that \( g : ([0,1), \mathcal{B}_{[0,1)}) \to (\Omega_0, \mathcal{B}_{\Omega_0}) \) is a measurable bijection with measurable inverse given by \( f|_{\Omega_0} \), i.e. \( ([0,1), \mathcal{B}_{[0,1)}) \cong (\Omega_0, \mathcal{B}_{\Omega_0}) \).

An application of Lemma \((18.30)) \) and Proposition \((18.31)) \) now implies
\[ \Omega = \Omega_0 \cup A \cong [0,1) \cup \mathbb{N} \cong [0,1) \cong (0,1). \]

Corollary 18.35. The following spaces are all isomorphic to \( ([0,1), \mathcal{B}_{[0,1)}) \); \( (0,1)^d \) and \( \mathbb{R}^d \) for any \( d \in \mathbb{N} \) and \( [0,1]^{\mathbb{N}} \) and \( \mathbb{R}^{\mathbb{N}} \) where both of these spaces are equipped with their natural product \( \sigma \)-algebras.
where $B_n = \tilde{B}_n \cap A_n$ is the generic element in $B_{A_n}$, we see that $\otimes_{n=1}^\infty B_{A_n}$ and $M_A$ can both be generated by the same collections of sets, we may conclude that $\otimes_{n=1}^\infty B_{A_n} = M_A$.

Our next goal is to show that any Polish space with its Borel $\sigma$–algebra is a standard Borel space.

**Notation 18.37** Let $Q := [0,1]^\mathbb{N}$ denote the (infinite dimensional) unit cube in $\mathbb{R}^\mathbb{N}$. For $a,b \in Q$ let

$$d(a,b) := \sum_{n=1}^\infty \frac{1}{2^n} |a_n - b_n| = \sum_{n=1}^\infty \frac{1}{2^n} |\pi_n(a) - \pi_n(b)|.$$  \hspace{1cm} (18.39)

**Exercise 18.6.** Show $d$ is a metric and that the Borel $\sigma$–algebra on $(Q,d)$ is the same as the product $\sigma$–algebra.

**Solution to Exercise 18.6.** It is easily seen that $d$ is a metric on $Q$ which, by Eq. (18.39), is measurable relative to the product $\sigma$–algebra, $\mathcal{M}_Q$. Therefore, $\mathcal{M}_Q$ contains all open balls and hence contains the Borel $\sigma$–algebra, $\mathcal{B}$.

Conversely, since

$$|\pi_n(a) - \pi_n(b)| \leq 2^n d(a,b),$$

each of the projection operators, $\pi_n : Q \to [0,1]$ is continuous. Therefore each $\pi_n$ is $\mathcal{B}$–measurable and hence $\mathcal{M}_Q = \sigma(\{\pi_n\}_{n=1}^\infty) \subset \mathcal{B}$.

**Theorem 18.38.** To every separable metric space $(X,\rho)$, there exists a continuous injective map $G : X \to Q$ such that $G : X \to G(X) \subset Q$ is a homeomorphism. Moreover if the metric, $\rho$, is also complete, then $G(X)$ is a $G_\delta$–set, i.e. the $G(X)$ is the countable intersection of open subsets of $(Q,d)$. In short, any separable metrizable space $X$ is homeomorphic to a subset of $(Q,d)$ and if $X$ is a Polish space then $X$ is homeomorphic to a $G_\delta$–subset of $(Q,d)$.

**Proof.** (This proof follows that in Rogers and Williams [3] Theorem 82.5 on p. 106.) By replacing $\rho$ by $\frac{\rho}{\tau_\rho}$ if necessary, we may assume that $0 \leq \rho < 1$.

Let $D = \{a_n\}_{n=1}^\infty$ be a countable dense subset of $X$ and define

$$G(x) = (\rho(x,a_1), \rho(x,a_2), \rho(x,a_3), \ldots ) \in Q$$

and

$$\gamma(x,y) = d(G(x),G(y)) = \sum_{n=1}^\infty \frac{1}{2^n} |\rho(x,a_n) - \rho(y,a_n)|$$

for $x,y \in X$. To prove the first assertion, we must show $G$ is injective and $\gamma$ is a metric on $X$ which is compatible with the topology determined by $\rho$.

If $G(x) = G(y)$, then $\rho(x,a) = \rho(y,a)$ for all $a \in D$. Since $D$ is a dense subset of $X$, we may choose $a_k \in D$ such that

$$0 = \lim_{k \to \infty} \rho(x,a_k) = \lim_{k \to \infty} \rho(y,a_k) = \rho(y,x)$$

and therefore $x = y$. A simple argument using the dominated convergence theorem shows $y \to \gamma(x,y)$ is $\rho$–continuous, i.e. $\gamma(x,y)$ is small if $\rho(x,y)$ is small. Conversely,

$$\rho(x,y) \leq \rho(x,a_n) + \rho(y,a_n) + 2\rho(x,a_n) + \rho(y,a_n) - \rho(x,a_n)$$

$$\leq 2\rho(x,a_n) + \rho(y,a_n) \leq 2\rho(x,a_n) + 2^n \gamma(x,y).$$

Hence if $\varepsilon > 0$ is given, we may choose $n$ so that $2\rho(x,a_n) < \varepsilon/2$ and so if $\gamma(x,y) < 2^{-(n+1)} \varepsilon$, it will follow that $\rho(x,y) < \varepsilon$. This shows $\tau_\gamma = \tau_\rho$. Since $G : (X,\gamma) \to (Q,d)$ is isometric, $G$ is a homeomorphism.

Now suppose that $(X,\rho)$ is a complete metric space. Let $S := G(X)$ and $\sigma$ be the metric on $S$ defined by $\sigma(G(x),G(y)) = \rho(x,y)$ for all $x,y \in X$. Then $(S,\sigma)$ is a complete metric (being the isometric image of a complete metric space) and by what we have just proved, $\tau_\sigma = \tau_{d_S}$. Consequently, if $u \in S$ and $\varepsilon > 0$ is given, we may find $\delta'(\varepsilon)$ such that $B_{\delta'}(u) \subset B_d(u,\varepsilon)$. Taking $\delta(\varepsilon) = \min(\delta'(\varepsilon),\varepsilon)$, we have $\text{diam}_\delta(B_d(u,\delta(\varepsilon))) < \varepsilon$ and $\text{diam}_\sigma(B_d(u,\delta(\varepsilon))) < \varepsilon$ where

$$\text{diam}_\sigma(A) := \{\sup u,v : u,v \in A\}$$

and

$$\text{diam}_\delta(A) := \{\sup d(u,v) : u,v \in A\}.$$
(Sub and Super) Martingales

Notation 19.1 A **filtered probability space** is a probability space, \((\Omega, \mathcal{B}, \mathbb{P})\) endowed with a sequence of sub-\(\sigma\)-algebras, \(\{\mathcal{B}_n\}_{n=0}^\infty\) such that \(\mathcal{B}_n \subset \mathcal{B}_{n+1} \subset \mathcal{B}\) for all \(n = 0, 1, 2, \ldots\). We further define

\[
\mathcal{B}_\infty := \bigvee_{n=0}^\infty \mathcal{B}_n := \sigma(\cup_{n=0}^\infty \mathcal{B}_n) \subset \mathcal{B}.
\] (19.1)

Through out this chapter, we will assume \((\Omega, \mathcal{B}, \{\mathcal{B}_n\}_{n=0}^\infty, \mathbb{P})\) is a filtered probability space and \(\mathcal{B}_\infty\) is defined as in Eq. (19.1).

**Definition 19.2.** A sequence of random variables, \(\{Y_n\}_{n=0}^\infty\) are **adapted** to the filtration if \(Y_n\) is \(\mathcal{B}_n\) – measurable for all \(n\). We say \(\{Z_n\}_{n=1}^\infty\) is **predictable** if each \(Z_n\) is \(\mathcal{B}_{n-1}\) – measurable for all \(n \in \mathbb{N}\).

A typical example is when \(\{X_n\}_{n=0}^\infty\) is a sequence of random variables on a probability space \((\Omega, \mathcal{B}, \mathbb{P})\) and \(\mathcal{B}_n := \sigma(X_0, \ldots, X_n)\). An application of Lemma [18.1] shows that \(\{Y_n\}\) is adapted to the filtration if there are measurable functions, \(f_n : \mathbb{R}^{n+1} \to \mathbb{R}\) such that \(Y_n = f_n(X_0, \ldots, X_n)\) for all \(n \in \mathbb{N}_0\) and \(\{Z_n\}_{n=1}^\infty\) is predictable iff there exists, there are measurable functions, \(f_n : \mathbb{R}^n \to \mathbb{R}\) such that \(Z_n = f_n(X_0, \ldots, X_{n-1})\) for all \(n \in \mathbb{N}\).

**Definition 19.3.** Let \(\mathcal{X} := \{X_n\}_{n=0}^\infty\) be an adapted sequence of integrable random variables. Then;

1. \(\mathcal{X}\) is a \(\{\mathcal{B}_n\}_{n=0}^\infty\) – **martingale** if \(\mathbb{E}[X_{n+1}|\mathcal{B}_n] = X_n\) a.s. for all \(n \in \mathbb{N}_0\).
2. \(\mathcal{X}\) is a \(\{\mathcal{B}_n\}_{n=0}^\infty\) – **submartingale** if \(\mathbb{E}[X_{n+1}|\mathcal{B}_n] \geq X_n\) a.s. for all \(n \in \mathbb{N}_0\).
3. \(\mathcal{X}\) is a \(\{\mathcal{B}_n\}_{n=0}^\infty\) – **supermartingale** if \(\mathbb{E}[X_{n+1}|\mathcal{B}_n] \leq X_n\) a.s. for all \(n \in \mathbb{N}_0\).

By induction one shows that \(\mathcal{X}\) is a supermartingale, martingale, or submartingale if

\[
\mathbb{E}[X_m|\mathcal{B}_n] \leq X_n \text{ a.s. for all } m \geq n,
\] (19.2)

to be read from top to bottom respectively. This last equation may also be expressed as

\[
\mathbb{E}[X_n|\mathcal{B}_m] \leq X_{m \wedge n} \text{ a.s. for all } m, n \in \mathbb{N}_0.
\] (19.3)

The reader should also note that \(\mathbb{E}[X_n]\) is decreasing, constant, or increasing respectively. The next lemma shows that we may shrink the filtration, \(\{\mathcal{B}_n\}_{n=0}^\infty\), within limits and still have \(\mathcal{X}\) retain the property of being a supermartingale, martingale, or submartingale.

**Lemma 19.4 (Shrinking the filtration).** Suppose that \(\mathcal{X}\) is a \(\{\mathcal{B}_n\}_{n=0}^\infty\) – supermartingale, martingale, submartingale respectively and \(\{\mathcal{B}'_n\}_{n=0}^\infty\) is another filtration such that \(\sigma(X_0, \ldots, X_n) \subset \mathcal{B}'_n \subset \mathcal{B}_n\) for all \(n\). Then \(\mathcal{X}\) is a \(\{\mathcal{B}'_n\}_{n=0}^\infty\) – supermartingale, martingale, submartingale respectively.

**Proof.** Since \(\{X_n\}_{n=0}^\infty\) is adapted to \(\{\mathcal{B}_n\}_{n=0}^\infty\) and \(\sigma(X_0, \ldots, X_n) \subset \mathcal{B}'_n \subset \mathcal{B}_n\), for all \(n\),

\[
\mathbb{E}_{\mathcal{B}'_n}[X_{n+1}] = \mathbb{E}_{\mathcal{B}'_n}[X_{n+1}] \leq \mathbb{E}_{\mathcal{B}_n}[X_n] = X_n,
\]

when \(\mathcal{X}\) is a \(\{\mathcal{B}'_n\}_{n=0}^\infty\) – supermartingale, martingale, submartingale respectively – read from top to bottom. 

Enlarging the filtration is another matter all together. In what follows we will simply say \(\mathcal{X}\) is a supermartingale, martingale, submartingale if it is a \(\{\mathcal{B}_n\}_{n=0}^\infty\) – supermartingale, martingale, submartingale.

19.1 (Sub and Super) Martingale Examples

**Example 19.5.** Suppose that \((\Omega, \mathcal{B}, \{\mathcal{B}_n\}_{n=0}^\infty, \mathbb{P})\) is a filtered probability space and \(X \in L^1(\Omega, \mathcal{B}, \mathbb{P})\). Then \(X_n := \mathbb{E}[X|\mathcal{B}_n]\) is a martingale. Indeed, by the tower property of conditional expectations,

\[
\mathbb{E}[X_{n+1}|\mathcal{B}_n] = \mathbb{E}[\mathbb{E}[X|\mathcal{B}_{n+1}]|\mathcal{B}_n] = \mathbb{E}[X|\mathcal{B}_n] = X_n \text{ a.s.}
\]

**Example 19.6.** Suppose that \(\Omega = [0, 1], \mathcal{B} = \mathcal{B}_{[0, 1]}, \mathbb{P} = m – \text{Lebesgue measure}\). Let \(\mathcal{P}_n = \{(k/2^n, k+1/2^n)\}_{k=1}^{2^n-1} \cup \{(0, 1/2^n)\}\) and \(\mathcal{B}_n := \sigma(\mathcal{P}_n)\) for each \(n \in \mathbb{N}\). Then \(M_n := 2^n \chi_{(0, 2^{-n})}\) for \(n \in \mathbb{N}\) is a martingale such that \(\mathbb{E}[M_n] = 1\) for all \(n\). However, there is no \(X \in L^1(\Omega, \mathcal{B}, \mathbb{P})\) such that \(M_n = \mathbb{E}[X|\mathcal{B}_n]\). To verify this last assertion, suppose such an \(X\) existed. Let \(\mathcal{C}\). We would then have for \(2^n > k > 0\) and any \(m > n\), that
220 19 (Sub and Super) Martingales

\[ \mathbb{E} \left[ X : \left( \frac{k}{2^n}, \frac{k + 1}{2^n} \right) \right] = \mathbb{E} \left[ \mathbb{E}_{B_n} X : \left( \frac{k}{2^n}, \frac{k + 1}{2^n} \right) \right] = \mathbb{E} \left[ M_m : \left( \frac{k}{2^n}, \frac{k + 1}{2^n} \right) \right] = 0. \]

Using \( \mathbb{E}[X : A] = 0 \) for all \( A \) in the \( \pi \) system, \( \mathcal{Q} := \bigcup_{n=1}^{\infty} \left\{ \left( \frac{k}{2^n}, \frac{k + 1}{2^n} \right) : 0 < k < 2^n \right\} \), an application of the \( \pi - \lambda \) theorem shows \( \mathbb{E}[X : A] = 0 \) for all \( A \in \sigma(\mathcal{Q}) = \mathcal{B} \). Therefore \( X = 0 \) a.s. by Lemma 18.2. But this is impossible since \( 1 = EM_n \neq EX \).

**Moral:** not all \( L^1 \) bounded martingales are of the form in Example 19.5. Proposition 19.7 shows what is missing from this martingale in order for it to be of the form in Example 19.5.

**Proposition 19.7.** Suppose \( 1 \leq p < \infty \) and \( X \in L^p(\Omega, \mathcal{B}, P) \). Then the collection of random variables, \( \Gamma := \{ \mathbb{E}[X|\mathcal{G}] : \mathcal{G} \subset \mathcal{B} \} \) is a bounded subset of \( L^p(\Omega, \mathcal{B}, P) \) which is also uniformly integrable.

**Proof.** Since \( \mathbb{E}_\mathcal{G} \) is a contraction on all \( L^p \) spaces it follows that \( \Gamma \) is bounded in \( L^p \) with

\[ \sup_{\mathcal{G} \subset \mathcal{B}} ||\mathbb{E}[X|\mathcal{G}]||_p \leq ||X||_p. \]

For the \( p > 1 \) the uniform integrability of \( \Gamma \) follows directly from Lemma 11.35.

We now concentrate on the \( p = 1 \) case. Recall that \( ||\mathbb{E}_\mathcal{G} X|| \leq \mathbb{E}_\mathcal{G} ||X|| \) a.s. and therefore,

\[ \mathbb{E}[||\mathbb{E}_\mathcal{G} X|| : ||\mathbb{E}_\mathcal{G} X|| \geq a] \leq \mathbb{E}[||X|| : ||\mathbb{E}_\mathcal{G} X|| \geq a] \text{ for all } a > 0. \]

But by Chebyshev’s inequality,

\[ P(||\mathbb{E}_\mathcal{G} X|| \geq a) \leq \frac{1}{a} \mathbb{E}[||\mathbb{E}_\mathcal{G} X||] \leq \frac{1}{a} \mathbb{E}[||X||]. \]

Since \( \{||X||\} \) is uniformly integrable, it follows from Proposition 11.29 that, by choosing \( a \) sufficiently large, \( \mathbb{E}[||\mathbb{E}_\mathcal{G} X|| \geq a] \) is as small as we please uniformly in \( \mathcal{G} \subset \mathcal{B} \) and therefore,

\[ \lim_{a \to \infty} \sup_{\mathcal{G} \subset \mathcal{B}} \mathbb{E}[||\mathbb{E}_\mathcal{G} X|| : ||\mathbb{E}_\mathcal{G} X|| \geq a] = 0. \]

**Example 19.8.** This example generalizes Example 19.6. Suppose \( (\Omega, \mathcal{B}, \{\mathcal{B}_n\}_{n=0}^{\infty}, P) \) is a filtered probability space and \( Q \) is another probability measure on \( (\Omega, \mathcal{B}) \). Let us assume that \( Q|_{\mathcal{B}_n} \ll P|_{\mathcal{B}_n} \) for all \( n \), which by the Raydon-Nikodym Theorem 17.8 implies there exists \( 0 \leq X_n \in L^1(\Omega, \mathcal{B}_n, P) \) with \( \mathbb{E}X_n = 1 \) such that \( dQ|_{\mathcal{B}_n} = X_n dP|_{\mathcal{B}_n} \), or equivalently, put, for any \( B \in \mathcal{B}_n \) we have

\[ Q(B) = \int_B X_n dP = \mathbb{E}[X_n : B]. \]

Since \( B \in \mathcal{B}_n \subset \mathcal{B}_{n+1} \), we also have \( \mathbb{E}[X_{n+1} : B] = Q(B) = \mathbb{E}[X_n : B] \) for all \( B \in \mathcal{B}_n \) and hence \( \mathbb{E}[X_{n+1}|\mathcal{B}_n] = X_n \) a.s., i.e. \( X = \{X_n\}_{n=0}^{\infty} \) is a positive martingale.

Example 19.6 is of this form with \( Q = \delta_0 \). Notice that \( \delta_0|_{\mathcal{B}_n} \ll m|_{\mathcal{B}_n} \) for all \( n < \infty \) while \( \delta_0 \perp m \) on \( \mathcal{B}_{[0,1]} = \mathcal{B}_\infty \). See Section 20.3 for more in the direction of this example.

It is often fruitful to view \( X_n \) as your earnings at time \( n \) while playing some game of chance. In this interpretation, your expected earnings at time \( n + 1 \) given the history of the game up to time \( n \) is the same, greater than, less than your earnings at time \( n \) if \( X = \{X_n\}_{n=0}^{\infty} \) is a martingale, submartingale or supermartingale respectively. In this interpretation, martingales are fair games, submartingales are favorable games, and supermartingales are unfavorable games.

**Example 19.9.** Suppose at each time \( n \), we flip a fair coin and record the value, \( X_n \in \{0,1\} \). Let us suppose that a gambler is going to bet one dollar between flips that either a 0 or a 1 is going to occur and if she is correct she will be paid \( 1 + \alpha \) dollars in return, otherwise she loses his dollar to the house. Let us say \( Y_{n+1} \) is the gambler’s prediction for the value of \( X_{n+1} \) at time \( n \). Hence if we let \( M_n \) denote the gamblers fortune at time \( n \) we have

\[ M_{n+1} = M_n - 1 + (1 + \alpha) 1_{Y_{n+1} = X_{n+1}}. \]

Assuming the gambler can not see into the future, his/her prediction at time \( n \) can only depend on the game up to time \( n \), i.e. we should have \( Y_{n+1} = f_{n+1}(X_0, \ldots, X_n) \) or equivalently, \( Y_{n+1} \) is \( \mathcal{B}_n = \sigma(X_0, \ldots, X_n) \) measurable. In this situation \( \{M_n\}_{n=1}^{\infty} \) is an adapted process and moreover,

\[ \mathbb{E}[M_{n+1}|\mathcal{B}_n] = \mathbb{E}[M_n - 1 + (1 + \alpha) 1_{Y_{n+1} = X_{n+1}}|\mathcal{B}_n] = M_n - 1 + (1 + \alpha) \mathbb{E}[1_{Y_{n+1} = X_{n+1}}|\mathcal{B}_n] = M_n - 1 + (1 + \alpha) \frac{1}{2} = M_n + \frac{1}{2} (\alpha - 1) \]

wherein we have used Exercise 18.4 in the last line. Hence we see that \( \{M_n\}_{n=1}^{\infty} \) is a martingale if \( \alpha = 1 \), a sub-martingale of \( \alpha > 1 \) and as supermartingale of \( \alpha < 1 \).

**Exercise 19.1.** Suppose that \( \{X_n\}_{n=1}^{\infty} \) are i.i.d. random functions taking values in a finite set, \( S \), and let \( p(s) := P(X_n = s) \) for all \( s \in S \) and assume
Also let \( s \), \( \alpha \), and \( \beta \) be measurable random variables with the convention that \( \mathbb{B}_0 = \{ \emptyset, \Omega \} \). Let \( Y_n \) be the predictions of a gambler as to the value of \( X_n \) based on the values of \( \{ X_1, \ldots, X_{n-1} \} \), i.e., \( Y_n \in \mathbb{S} \) is a \( \mathbb{S}_{n-1} \) measurable random variable with the convention that \( \mathbb{B}_0 = \{ \emptyset, \Omega \} \). Also let \( M_n \) be the gambler’s fortune at time \( n \). Assuming the gambler always wages one dollar and receives a pay off of \( 1 + \alpha(s) \) if \( Y_{n+1} = s = X_{n+1} \) for some \( s \in \mathbb{S} \), then

\[
M_{n+1} = M_n - 1 + \sum_{s \in \mathbb{S}} (1 + \alpha(s) \mathbbm{1}_{Y_{n+1} = s = X_{n+1}}.
\]

Show \( \{ M_n \} \) is a martingale, submartingale, supermartingale, if \( \alpha = \frac{1-p}{p} \alpha \geq \frac{1-p}{p} \) or \( \alpha = \frac{1-p}{p} \) respectively.

**Lemma 19.10.** Let \( X := \{ X_n \}_{n=0}^{\infty} \) be an adapted process of integrable random variables on a filtered probability space, \( (\Omega, \mathcal{B}, \{ \mathcal{B}_n \}_{n=0}^{\infty}, P) \) and let \( d_n := X_n - X_{n-1} \) with \( X_n := \mathbb{E}X_0 \). Then \( X \) is a martingale (respectively submartingale or supermartingale) if \( \mathbb{E}[d_{n+1}|\mathcal{B}_n] = 0 \), \( \mathbb{E}[d_{n+1}|\mathcal{B}_n] \geq 0 \) or \( \mathbb{E}[d_{n+1}|\mathcal{B}_n] \leq 0 \) respectively for all \( n \in \mathbb{N} \).

Conversely if \( \{ d_n \}_{n=1}^{\infty} \) is an adapted sequence of integrable random variables and \( X_0 \) is a \( \mathbb{B}_0 \) measurable integral random variable. Then \( X_n = X_0 + \sum_{j=1}^{n} d_j \) is a martingale (respectively submartingale or supermartingale) if \( \mathbb{E}[d_{n+1}|\mathcal{B}_n] = 0 \), \( \mathbb{E}[d_{n+1}|\mathcal{B}_n] \geq 0 \) or \( \mathbb{E}[d_{n+1}|\mathcal{B}_n] \leq 0 \) respectively for all \( n \in \mathbb{N} \).

**Proof.** We prove the assertions for martingales only, the other all being similar. Clearly \( X \) is a martingale iff

\[
0 = \mathbb{E}[X_{n+1}|\mathcal{B}_n] - X_n = \mathbb{E}[X_{n+1} - X_n|\mathcal{B}_n] = \mathbb{E}[d_{n+1}|\mathcal{B}_n].
\]

The second assertion is an easy consequence of the first assertion. \( \blacksquare \)

**Example 19.11.** Suppose that \( \{ X_n \}_{n=0}^{\infty} \) is a sequence of independent random variables, \( S_n = X_0 + \cdots + X_n \), and \( \mathcal{B}_n := \sigma(X_0, \ldots, X_n) = \sigma(S_0, \ldots, S_n) \). Then

\[
\mathbb{E}[S_{n+1}|\mathcal{B}_n] = \mathbb{E}[S_n + X_{n+1}|\mathcal{B}_n] = S_n + \mathbb{E}[X_{n+1}].
\]

Therefore \( \{ S_n \}_{n=0}^{\infty} \) is a martingale respectively submartingale or supermartingale if \( \mathbb{E}X_n = 0 \) \( \mathbb{E}X_n \geq 0 \) or \( \mathbb{E}X_n \leq 0 \) respectively for all \( n \in \mathbb{N} \).

**Example 19.12.** Suppose that \( \{ Z_n \}_{n=0}^{\infty} \) is a sequence of independent integrable random variables, \( X_n = Z_0 \cdots Z_n \), and \( \mathcal{B}_n := \sigma(Z_0, \ldots, Z_n) \). (Observe that

\[
\mathbb{E}|X_n| = \prod_{k=0}^{n} \mathbb{E}|Z_k| < \infty. \) If \( \mathbb{E}Z_n = 1 \) for all \( n \) then \( X \) is a martingale while if \( Z_n \geq 0 \) and \( \mathbb{E}Z_n \leq 1 \) \( \mathbb{E}Z_n \geq 1 \) for all \( n \) then \( X \) is a supermartingale (submartingale). Indeed, this follows from the simple identity:

\[
\mathbb{E}[X_{n+1}|\mathcal{B}_n] = \mathbb{E}[X_n Z_{n+1}|\mathcal{B}_n] = X_n \mathbb{E}[Z_{n+1}|\mathcal{B}_n] = X_n \cdot \mathbb{E}[Z_{n+1}] \quad \text{a.s.}
\]

**Proposition 19.13.** Suppose that \( X = \{ X_n \}_{n=0}^{\infty} \) is a martingale and \( \varphi \) is a convex function such that \( \varphi(X_n) \in L^1 \) for all \( n \). Then \( \varphi(X) = \{ \varphi(X_n) \}_{n=0}^{\infty} \) is a submartingale. If \( \varphi \) is also assumed to be increasing, it suffices to assume that \( X \) is a submartingale in order to conclude that \( \varphi(X) \) is a submartingale. (For example if \( X \) is a positive submartingale, \( p \in (1, \infty) \), and \( \mathbb{E}X_n < \infty \) for all \( n \), then \( X^p := \{ X_n^p \}_{n=0}^{\infty} \) is another positive submartingale.

**Proof.** When \( X \) is a martingale, by the conditional Jensen’s inequality

\[
\varphi(X_n) = \varphi(\mathbb{E}_{\mathbb{B}_n} X_{n+1}) \leq \mathbb{E}_{\mathbb{B}_n} [\varphi(X_{n+1})]
\]

which shows \( \varphi(X) \) is a submartingale. Similarly, if \( X \) is a submartingale and \( \varphi \) is convex and increasing, then \( \varphi \) preserves the inequality, \( X_n \leq \mathbb{E}X_n \), and hence

\[
\varphi(X_n) \leq \mathbb{E}_{\mathbb{B}_n} [\varphi(X_{n+1})]
\]

so again \( \varphi(X) \) is a submartingale. \( \blacksquare \)

**19.2 Decompositions**

**Notation 19.14** Given a sequence \( \{ Z_k \}_{k=0}^{\infty} \), let \( \Delta_k Z := Z_k - Z_{k-1} \) for \( k = 1, 2, \ldots \).

**Lemma 19.15 (Doob Decomposition).** To each adapted sequence, \( \{ Z_n \}_{n=0}^{\infty} \), of integrable random variables has a unique decomposition,

\[
Z_n = M_n + A_n \quad (19.4)
\]

where \( \{ M_n \}_{n=0}^{\infty} \) is a martingale and \( A_n \) is a predictable process such that \( A_0 = 0 \). Moreover this decomposition is given by \( A_0 = 0 \),

\[
A_n := \sum_{k=1}^{n} \mathbb{E}_{\mathbb{B}_{k-1}} [\Delta_k Z] \quad \text{for } n \geq 1
\]

and

\[
M_n = Z_n - A_n = Z_n - \sum_{k=1}^{n} \mathbb{E}_{\mathbb{B}_{k-1}} [\Delta_k Z] \quad (19.5)
\]

\[
= Z_0 + \sum_{k=1}^{n} (Z_k - \mathbb{E}_{\mathbb{B}_{k-1}} Z_k). \quad (19.6)
\]
In particular, \( \{Z_i\}_{i=0}^\infty \) is a submartingale (supermartingale) iff \( A_n \) is increasing (decreasing) almost surely.

**Proof.** Assuming \( Z_n \) has a decomposition as in Eq. (19.4), then

\[
\mathbb{E}_B_n \left[ \Delta_{n+1} Z \right] = \mathbb{E}_B_n \left[ \Delta_{n+1} M + \Delta_{n+1} A \right] = \Delta_{n+1} A
\]

wherein we have used \( M \) is a martingale and \( A \) is predictable so that \( \mathbb{E}_B_n \left[ \Delta_{n+1} M \right] = 0 \) and \( \mathbb{E}_B_n \left[ \Delta_{n+1} A \right] = \Delta_{n+1} A \). Hence we must define, for \( m \geq 1 \),

\[
A_n := \sum_{k=1}^{n} \Delta_k A = \sum_{k=1}^{n} \mathbb{E}_{B_{k-1}} \left[ \Delta_k Z \right]
\]

which is a predictable process. This proves the uniqueness of the decomposition and the validity of Eq. (19.5).

For existence, from Eq. (19.5) it follows that

\[
\mathbb{E}_B_n \left[ \Delta_{n+1} M \right] = \mathbb{E}_B_n \left[ \Delta_{n+1} A - \Delta_{n+1} A \right] = 0
\]

and hence \( \{M_n\}_{n=0}^\infty \) is a martingale. Moreover, Eq. (19.6) follows from Eq. (19.7) since,

\[
M_n = Z_0 + \sum_{k=1}^{n} (\Delta_k Z - \mathbb{E}_{B_{k-1}} [\Delta_k Z])
\]

and

\[
\Delta_k Z - \mathbb{E}_{B_{k-1}} [\Delta_k Z] = Z_k - Z_{k-1} - \mathbb{E}_{B_{k-1}} [Z_k - Z_{k-1}]
\]

\[
= Z_k - Z_{k-1} - (\mathbb{E}_{B_{k-1}} Z_k - Z_{k-1}) = Z_k - \mathbb{E}_{B_{k-1}} Z_k.
\]

**Remark 19.16.** Suppose that \( X = \{X_n\}_{n=0}^\infty \) is a submartingale and \( X_n = M_n + A_n \) is it Doob decomposition. Then \( A_n = \| \mathbb{E}_{[X_n]} \mathbb{E}_{X_n - X_0} \| \) and hence by MCT,

\[
\mathbb{E}_A_n = \mathbb{E} [X_n - M_n] = \mathbb{E}_X X_n - \mathbb{E}_M M_n = \mathbb{E} [X_n - X_0]
\]

**Example 19.17.** Suppose that \( N = \{N_n\}_{n=0}^\infty \) is a square integrable martingale, i.e. \( \mathbb{E}N_n^2 < \infty \) for all \( n \). Then from Proposition 19.13

\[
X := \{X_n = N_n^2\}_{n=0}^\infty
\]

is a positive submartingale. In this case

\[
\mathbb{E}_{B_{k-1}} [\Delta_k X] = \mathbb{E}_{B_{k-1}} (N_k^2 - N_{k-1}^2) = \mathbb{E}_{B_{k-1}} [(N_k - N_{k-1}) (N_k + N_{k-1})]
\]

\[
= \mathbb{E}_{B_{k-1}} [(N_k - N_{k-1}) (N_k - N_{k-1})]
\]

\[
= \mathbb{E}_{B_{k-1}} (N_k - N_{k-1})^2
\]

wherein the second to last equality we have used

\[
\mathbb{E}_{B_{k-1}} [(N_k - N_{k-1}) (N_k - N_{k-1})] = 0 \text{ a.s.}
\]

in order to change \((N_k + N_{k-1})\) to \((N_k - N_{k-1})\). Hence the increasing predictable process, \( A_n \), in the Doob decomposition may be written as

\[
A_n = \sum_{k=n}^{\infty} \mathbb{E}_{B_{k-1}} [\Delta_k X] = \sum_{k=n}^{\infty} \mathbb{E}_{B_{k-1}} [(\Delta_k N)^2].
\]

**Remark 19.18.** If \( X \) is a real valued random variable, then \( X = X^+ - X^- \), \( |X| = X^+ + X^- \), \( X^+ \leq |X| = 2X^+ - X \), so that

\[
\mathbb{E}X^+ \leq \mathbb{E}|X| = 2\mathbb{E}X^+ - \mathbb{E}X.
\]

Hence if \( \{X_n\}_{n=0}^\infty \) is a submartingale then

\[
\mathbb{E}X_n^+ \leq \mathbb{E}|X_n| = 2\mathbb{E}X_n^+ - \mathbb{E}X_n \leq 2\mathbb{E}X_n^+ - \mathbb{E}X_0
\]

from which it follows that

\[
\sup_n \mathbb{E}X_n^+ \leq \sup_n \mathbb{E}|X_n| \leq 2 \sup_n \mathbb{E}X_n^+ - \mathbb{E}X_0.
\]

**Theorem 19.19 (Krickeberg Decomposition).** Suppose that \( X \) is an integrable submartingale such that \( C := \sup_n \mathbb{E}[X_n^+] < \infty \) or equivalently \( \sup_n \mathbb{E}[|X_n|] < \infty \), see Eq. (19.12). Then

\[
M_n := \lim_{p \to \infty} \mathbb{E} \left[ X_n^+ | B_n \right] \text{ exists a.s.,}
\]

\( M = \{M_n\}_{n=0}^\infty \) is a positive martingale, \( Y = \{Y_n\}_{n=0}^\infty \) with \( Y_n := X_n - M_n \) is a positive supermartingale, and hence \( X_n = M_n - Y_n \). So \( X \) can be decomposed into the difference of a positive martingale and a positive supermartingale.
Lemma 19.21. \( \tau \) a.s.

Moreover if any of these conditions hold for \( n \in \mathbb{N}_0 \) then they also hold for \( n = \infty \).

Proof. (1. \( \iff \) 2.) Observe that if \( \{ \tau \leq n \} \in \mathcal{B}_n \) for all \( n \in \mathbb{N}_0 \), then \( \{ \tau < \infty \} = \bigcup_{n=1}^{\infty} \{ \tau \leq n \} \in \mathcal{B}_\infty \) and therefore \( \{ \tau = \infty \} = \{ \tau < \infty \}^c \in \mathcal{B}_\infty \) and hence \( \{ \tau \leq \infty \} = \{ \tau < \infty \} \cup \{ \tau = \infty \} \in \mathcal{B}_\infty \). Hence in order to check that \( \tau \) is a stopping time, it suffices to show \( \{ \tau \leq n \} \in \mathcal{B}_n \) for all \( n \in \mathbb{N}_0 \).

The equivalence of 2., 3., and 4. follows from the identities

\[
\begin{align*}
\{ \tau > n \}^c &= \{ \tau \leq n \}, \\
\{ \tau = n \} &= \{ \tau \leq n \} \setminus \{ \tau \leq n - 1 \}, \quad \text{and} \\
\{ \tau \leq n \} &= \bigcup_{k=0}^{n} \{ \tau = k \}.
\end{align*}
\]

from which we conclude that 2. \( \implies \) 3. \( \implies \) 4. \( \implies \) 1.

Clearly any constant function, \( \tau : \Omega \rightarrow \mathbb{N} \), is a stopping time. The reader should also observe that if \( B_n = \sigma (X_0, \ldots, X_n) \), then \( \tau : \Omega \rightarrow \mathbb{N} \) is a stopping time iff, for each \( n \in \mathbb{N}_0 \), there exists a measurable function \( f_n : \mathbb{R}^{n+1} \rightarrow \mathbb{R} \) such that \( 1_{\{\tau = n\}} = f_n (X_0, \ldots, X_n) \). Here is another common example of a stopping time.

Example 19.22 (First hitting times). Suppose that \( X := \{ X_n \}_{n=0}^{\infty} \) is an adapted process on the filtered space, \( (\Omega, \mathcal{B}, \mathcal{B}_n) \) and \( A \in \mathcal{B}_0 \). Then the first hitting time of \( A \),

\[
\tau := \inf \{ n \in \mathbb{N}_0 : X_n \in A \},
\]

(with convention that \( \inf \emptyset = \infty \)) is a stopping time. To see this, observe that

\[
\{ \tau = n \} = \{ X_0 \in A^c, \ldots, X_{n-1} \in A^c, X_n \in A \} \in \sigma (X_0, \ldots, X_n) \subset \mathcal{B}_n.
\]

More generally if \( \sigma \) is a stopping time, then the first hitting time after \( \sigma \),

\[
\tau := \inf \{ k \geq \sigma : X_k \in A \},
\]

is also a stopping time. Indeed,

\[
\{ \tau = n \} = \{ \sigma \leq n \} \cap \{ X_0 \notin A, \ldots, X_{n-1} \notin A, X_n \in A \} = \bigcup_{0 \leq k \leq n} \{ \sigma = k \} \cap \{ X_k \notin A, \ldots, X_{n-1} \notin A, X_n \in A \}
\]

which is in \( \mathcal{B}_n \) for all \( n \). Here we use the convention that

\[
\{ X_k \notin A, \ldots, X_{n-1} \notin A, X_n \in A \} = \{ X_n \in A \} \text{ if } k = n.
\]
On the other hand the last hitting time, $\tau = \sup \{n \in \mathbb{N}_0 : X_n \in A\}$, of a set $A$ is typically not a stopping time. Indeed, in this case

$$\{\tau = n\} = \{X_n \in A, X_{n+1} \notin A, X_{n+2} \notin A, \ldots \} \in \sigma (X_n, X_{n+1}, \ldots)$$

which typically will not be in $\mathcal{B}_n$.

**Proposition 19.23 (New Stopping Times from Old).** Let $(\Omega, \mathcal{B}, \{\mathcal{B}_n\}_{n=0}^{\infty})$ be a filtered measure space and suppose $\sigma, \tau$, and $\{\tau_n\}_{n=1}^{\infty}$ are all stopping times. Then

1. $\sigma \wedge \tau, \sigma \vee \tau, \tau + \sigma$ are all stopping times.
2. If $\tau_k \uparrow \tau_\infty$ or $\tau_k \downarrow \tau_\infty$, then $\tau_\infty$ is a stopping time.
3. In general, $\sup_k \tau_k = \lim_{k \to \infty} \max \{\tau_1, \ldots, \tau_k\}$ and $\inf_k \tau_k = \lim_{k \to \infty} \min \{\tau_1, \ldots, \tau_k\}$ are also stopping times.

**Proof.**

1. Since $\{\tau \wedge \sigma > n\} = \{\tau > n\} \cap \{\sigma > n\} \in \mathcal{B}_n$, $\{\tau \vee \sigma \leq n\} \subseteq \{\tau \leq n\} \cap \{\sigma \leq n\} \in \mathcal{B}_n$ for all $n$, and

$$\{\tau + \sigma = n\} = \bigcup_{k=0}^{n} \{\tau = k, \sigma = n-k\} \in \mathcal{B}_n$$

for all $n, \tau \wedge \sigma, \tau \vee \sigma, \tau + \sigma$ are all stopping times.

2. If $\tau_k \uparrow \tau_\infty$, then $\{\tau_\infty \leq n\} = \bigcap_k \{\tau_k \leq n\} \in \mathcal{B}_n$ and so $\tau_\infty$ is a stopping time. Similarly, if $\tau_k \downarrow \tau_\infty$, then $\{\tau_\infty > n\} = \bigcap_k \{\tau_k > n\} \in \mathcal{B}_n$ and so $\tau_\infty$ is a stopping time. (Recall that $\{\tau_\infty > n\} = \{\tau_\infty \geq n+1\}$.)

3. This follows from items 1. and 2.

**Lemma 19.24.** If $\tau$ is a stopping time, then the processes, $f_n := 1_{\{\tau \leq n\}}$, and $f_n := 1_{\{\tau = n\}}$ are adapted and $f_n := 1_{\{\tau < n\}}$ is predictable. Moreover, if $\sigma$ and $\tau$ are two stopping times, then $f_n := 1_{\sigma < n \leq \tau}$ is predictable.

**Proof.** These are all trivial to prove. For example, if $f_n := 1_{\sigma < n \leq \tau}$, then $f_n$ is $\mathcal{B}_{n-1}$ measurable since,

$$\{\sigma < n \leq \tau\} = \{\sigma < n\} \cap \{n \leq \tau\} = \{\sigma < n\} \cap \{\tau < n\} \in \mathcal{B}_{n-1}.$$

**Notation 19.25 (Stochastic intervals)** If $\sigma, \tau : \Omega \to \overline{\mathbb{N}}$, let

$$(\sigma, \tau) := \{(\omega, n) \in \Omega \times \overline{\mathbb{N}} : \sigma (\omega) < n \leq \tau (\omega)\}$$

and we will write $1_{(\sigma, \tau)}$ for the process, $1_{\sigma < n \leq \tau}$.

Our next goal is to define the “stopped” $\sigma$ – algebra, $\mathcal{B}_\tau$. To motivate the upcoming definition, suppose $X_n : \Omega \to \mathbb{R}$ are given functions for all $n \in \mathbb{N}_0$, $\mathcal{B}_n := \sigma (X_0, \ldots, X_n)$, and $\tau : \Omega \to \mathbb{N}_0$ is a $\mathcal{B}_\tau$ – stopping time. Recalling that a function $Y : \Omega \to \mathbb{R}$ is $\mathcal{B}_n$ measurable iff $Y (\omega) = f_n (X_0 (\omega), \ldots, X_n (\omega))$ for some measurable function, $f_n : \mathbb{R}^{n+1} \to \mathbb{R}$, it is reasonable to suggest that $Y$ is $\mathcal{B}_\tau$ measurable iff $Y (\omega) = f_\tau (\omega) (X_0 (\omega), \ldots, X_n (\omega))$, where $f_\tau \mathbb{R}^{n+1} \to \mathbb{R}$ are measurable random variables. If this is the case, then we would have $1_{\tau=n} Y = f_n (X_0, \ldots, X_n)$ is $\mathcal{B}_n$ – measurable for all $n$. Hence we should define $A \subset \Omega$ to be in $\mathcal{B}_\tau$ iff $1_A$ is $\mathcal{B}_\tau$ measurable if $1_{\tau=n} 1_A$ is $\mathcal{B}_n$ measurable for all which happens if $\{\tau = n\} \cap A \in \mathcal{B}_n$ for all $n$.

**Definition 19.26 (Stopped $\sigma$ – algebra).** Given a stopping time $\tau$ on a filtered measure space $(\Omega, \mathcal{B}, \{\mathcal{B}_n\}_{n=0}^{\infty})$ with $\mathcal{B}_{\infty} := \cap_{n=0}^{\infty} \mathcal{B}_n := \sigma (\cup_{n=0}^{\infty} \mathcal{B}_n)$, let

$$\mathcal{B}_\tau := \{A \subset \Omega : \{\tau = n\} \cap A \in \mathcal{B}_n \text{ for all } n \leq \infty\}.$$  

**Lemma 19.27.** Suppose $\sigma$ and $\tau$ are stopping times.

1. A set, $A \subset \Omega$ is in $\mathcal{B}_\tau$ iff $A \cap \{\tau \leq n\} \in \mathcal{B}_n$ for all $n \leq \infty$.
2. $\mathcal{B}_\tau$ is a sub-$\sigma$-algebra of $\mathcal{B}_\infty$.
3. If $\sigma \leq \tau$, then $\mathcal{B}_\sigma \subset \mathcal{B}_\tau$.

**Proof.** 1. Since

$$A \cap \{\tau \leq n\} = \bigcup_{k \leq n} \{A \cap \{\tau \leq k\}\}$$

and

$$A \cap \{\tau = n\} = \{A \cap \{\tau \leq n\}\} \setminus \{A \cap \{\tau \leq n-1\}\},$$

it easily follows that $A \subset \Omega$ is in $\mathcal{B}_\tau$ iff $A \cap \{\tau \leq n\} \in \mathcal{B}_n$ for all $n \leq \infty$.

2. Since $\Omega \cap \{\tau \leq n\} = \{\tau \leq n\} \in \mathcal{B}_n$ for all $n$, it follows that $\Omega \in \mathcal{B}_\tau$. If $A \in \mathcal{B}_\tau$, then, for all $n \in \mathbb{N}_0$,

$$A^{\infty} \cap \{\tau \leq n\} = \{\tau \leq n\} \setminus \{A \cap \{\tau \leq n\}\} \subseteq \mathcal{B}_n.$$  

This shows $A^{\infty} \in \mathcal{B}_\tau$. Similarly if $\{A_k\}_{k=1}^{\infty} \subset \mathcal{B}_\tau$, then

$$\{\tau \leq n\} \cap (\cap_{k=1}^{\infty} A_k) = \cap_{k=1}^{\infty} \{\{\tau \leq n\} \cap A_k\} \subseteq \mathcal{B}_n$$

and hence $\cap_{k=1}^{\infty} A_k \subset \mathcal{B}_\tau$. This completes the proof the $\mathcal{B}_\tau$ is a $\sigma$ – algebra. Since $A = A \cap \{\tau \leq \infty\}$, it also follows that $\mathcal{B}_\tau \subset \mathcal{B}_\infty$.

3. Now suppose that $\sigma \leq \tau$ and $A \in \mathcal{B}_\sigma$. Since $A \cap \{\sigma \leq n\}$ and $\{\tau \leq n\}$ are in $\mathcal{B}_n$ for all $n \leq \infty$, we find

$$A \cap \{\tau \leq n\} = \{A \cap \{\sigma \leq n\}\} \cap \{\tau \leq n\} \in \mathcal{B}_n \ \forall \ n \leq \infty$$

which shows $A \in \mathcal{B}_\tau$.  

**Page: 224**
Proposition 19.28 ($\mathcal{B}_\tau$ – measurable random variables). Let $(\Omega, \mathcal{B}, \{\mathcal{B}_n\}_{n=0}^\infty)$ be a filtered measure space. Let $\tau$ be a stopping time and $Z : \Omega \to \mathbb{R}$ be a function. Then the following are equivalent:

1. $Z$ is $\mathcal{B}_\tau$ – measurable,
2. $1_{\{\tau \leq n\}} Z$ is $\mathcal{B}_n$ – measurable for all $n \leq \infty$,
3. $1_{\{\tau = n\}} Z$ is $\mathcal{B}_n$ – measurable for all $n \leq \infty$.
4. There exists, $Y_n : \Omega \to \mathbb{R}$ which are $\mathcal{B}_n$ – measurable for all $n \leq \infty$ such that

$$Z = Y_\tau = \sum_{n \in \mathbb{N}} 1_{\{\tau = n\}} Y_n.$$

**Proof.** 1. $\implies$ 2. By definition, if $A \in \mathcal{B}_\tau$, then $1_{\{\tau \leq n\}} 1_A = 1_{\{\tau \leq n\} \cap A}$ is $\mathcal{B}_n$ – measurable for all $n \leq \infty$. Consequently any simple $\mathcal{B}_\tau$ – measurable function, $Z$, satisfies $1_{\{\tau \leq n\}} Z$ is $\mathcal{B}_n$ – measurable for all $n$. So by the usual limiting argument (Theorem 6.32), it follows that $1_{\{\tau \leq n\}} Z$ is $\mathcal{B}_n$ – measurable for all $n$ for any $\mathcal{B}_\tau$ – measurable function, $Z$.

2. $\implies$ 3. This property follows from the identity,

$$1_{\{\tau = n\}} Z = 1_{\{\tau \leq n\}} Z - 1_{\{\tau < n\}} Z.$$

3. $\implies$ 4. Simply take $Y_n = 1_{\{\tau = n\}} Z$.

4. $\implies$ 1. Since $Z = \sum_{n \in \mathbb{N}} 1_{\{\tau = n\}} Y_n$, it suffices to show $1_{\{\tau = n\}} Y_n$ is $\mathcal{B}_\tau$ – measurable if $Y_n$ is $\mathcal{B}_n$ – measurable. Further, by the usual limiting arguments using Theorem 6.32 it suffices to assume that $Y_n = 1_A$ for some $A \in \mathcal{B}_n$. In this case $1_{\{\tau = n\}} Y_n = 1_{A \cap \{\tau = n\}}$. Hence we must show $A \cap \{\tau = n\} \in \mathcal{B}_\tau$ which indeed is true because

$$A \cap \{\tau = n\} \cap \{\tau = k\} = \begin{cases} \emptyset \in \mathcal{B}_k & \text{if } k \neq n \\ A \cap \{\tau = n\} \in \mathcal{B}_k & \text{if } k = n. \end{cases}$$

**Alternatively proof for 1. $\implies$ 2.** If $Z$ is $\mathcal{B}_\tau$ measurable, then $\{Z \in B\} \cap \{\tau \leq n\} \in \mathcal{B}_n$ for all $n \leq \infty$ and $B \in \mathcal{B}_\tau$. Hence if $B \in \mathcal{B}_\tau$ with $0 \notin B$, then

$$\{1_{\{\tau \leq n\}} Z \in B\} = \{Z \in B\} \cap \{\tau \leq n\} \in \mathcal{B}_n$$

and similarly,

$$\{1_{\{\tau \leq n\}} Z = 0\}^c = \{\{\tau \leq n\} Z \neq 0\} = \{Z \neq 0\} \cap \{\tau \leq n\} \in \mathcal{B}_n$$

From these two observations, it follows that $\{1_{\{\tau \leq n\}} Z \in B\} \in \mathcal{B}_n$ for all $B \in \mathcal{B}_\tau$ and therefore, $1_{\{\tau \leq n\}} Z$ is $\mathcal{B}_n$ – measurable. 

**Lemma 19.29 ($\mathcal{B}_\tau$ – conditioning).** Suppose $\sigma$ is a stopping time and $Z \in L^1(\Omega, \mathcal{B}, P)$ or $Z \geq 0$, then

$$E[Z|\mathcal{B}_\sigma] = \sum_{n \leq \infty} 1_{\sigma = n} E[Z|\mathcal{B}_n] = Y_\sigma$$

where

$$Y_n := E[Z|\mathcal{B}_n] \text{ for all } n \in \mathbb{N}.$$ 

**Proof.** By Proposition 19.28 $Y_\sigma$ is $\mathcal{B}_\sigma$ – measurable. Moreover if $Z$ is integrable, then

$$\sum_{n \leq \infty} E[1_{\{\sigma = n\}}|Y_n] = \sum_{n \leq \infty} E1_{\{\sigma = n\}} |E[Z|\mathcal{B}_n]|$$

$$\leq \sum_{n \leq \infty} E[1_{\{\sigma = n\}}|E[Z|\mathcal{B}_n]|]$$

$$= \sum_{n \leq \infty} E[|1_{\{\sigma = n\}}|Z|\mathcal{B}_n]|]$$

$$= \sum_{n \leq \infty} E[1_{\{\sigma = n\}}|Z|] = E|Z| < \infty$$

and therefore

$$E|Y_\sigma| = E\left|\sum_{n \leq \infty} 1_{\{\sigma = n\}} Y_n \right|$$

$$\leq \sum_{n \leq \infty} E[1_{\{\sigma = n\}}|Y_n]| \leq E|Z| < \infty.$$ 

Furthermore if $A \in \mathcal{B}_\sigma$, then

$$E[Z : A] = \sum_{n \leq \infty} E[Z : A \cap \{\sigma = n\}] = \sum_{n \leq \infty} E[Y_n : A \cap \{\sigma = n\}]$$

$$= \sum_{n \leq \infty} E[1_{\{\sigma = n\}} Y_n : A] = E\left[\sum_{n \leq \infty} 1_{\{\sigma = n\}} Y_n : A\right]$$

$$= E[Y_\sigma : A],$$

wherein the interchange of the sum and the expectation in the second to last equality is justified by the estimate in 19.16 or by the fact that everything is positive when $Z \geq 0$. 

**Exercise 19.2.** Suppose $\sigma$ and $\tau$ are two stopping times. Show:

1. $\{\sigma < \tau\}, \{\sigma = \tau\}$, and $\{\sigma \leq \tau\}$ are all in $\mathcal{B}_\sigma \cap \mathcal{B}_\tau$,
2. $\mathcal{B}_{\sigma \wedge \tau} = \mathcal{B}_\sigma \cap \mathcal{B}_\tau$, 

3. \( B_{\sigma \vee \tau} = B_{\sigma} \lor B_{\tau} := \sigma (B_{\sigma} \cup B_{\tau}) \), and
4. \((B_{\sigma})(\sigma \leq \tau) \subset B_{\sigma \wedge \tau} \) and \((B_{\sigma})(\sigma < \tau) \subset B_{\sigma \land \tau} \).

Recall that \((B_{\sigma})(\sigma \leq \tau) = \{A \cap \{\sigma \leq \tau\} : A \in B_{\sigma}\} \).

**Exercise 19.3 (Tower Property II).** Let \( X \in L^1(\Omega, \mathcal{B}, P) \) or \( X : \Omega \to [0, \infty) \) be a \( \mathcal{B} \)-measurable function. Then given any two stopping times, \( \sigma \) and \( \tau \), show
\[
E_{B_\sigma}E_{B_\tau}X = E_{B_\sigma}E_{B_\tau}X = E_{B_{\sigma \wedge \tau}}X.
\]
(19.17)

**Hints:** 1. It suffices to consider the case where \( X \geq 0 \). 2. Make use of Exercise 19.2 Lemma 19.29 and the basic properties of conditional expectations. If you want to be sophistcated you may also want to use the localization Lemma 18.19 – but it can be avoided if you choose.

**Exercise 19.4.** Show, by example, that it is not necessarily true that
\[
E_{\mathcal{G}_1}E_{\mathcal{G}_2} = E_{\mathcal{G}_1 \wedge \mathcal{G}_2}
\]
for arbitrary \( \mathcal{G}_1 \) and \( \mathcal{G}_2 \) – sub-sigma algebras of \( \mathcal{B} \).

**Hint:** it suffices to take \((\Omega, \mathcal{B}, \mathcal{P}) \) with \( \Omega = \{1, 2, 3\}, \mathcal{B} = 2^\Omega \), and \( \mathcal{P}(\{j\}) = \frac{1}{3} \) for \( j = 1, 2, 3 \).

### 19.4 Stochastic Integrals and Optional Stopping

**Notation 19.30** Suppose that \( \{u_n\}_{n=1}^\infty \) and \( \{x_n\}_{n=0}^\infty \) are two sequences of numbers, let \( udx \) denote the sequence of numbers defined by
\[
( u \cdot \Delta x )_n = \sum_{j=1}^n u_j (x_j - x_{j-1}) = \sum_{j=1}^n u_j \Delta_j x \ l for \ n \geq 1.
\]

For a gambling interpretation of \(( u \cdot \Delta x )_n \), let \( x_j \) represent the price of a stock at time \( j \). Suppose that you, the investor, then buys \( u_{j-1} \) shares at time \( j-1 \) and then sells these shares back at time \( j \). With this interpretation, \( u_{j-1} \Delta_j x \) represents your profit (or loss if negative) in the time interval form \( j-1 \) to \( j \) and \(( u \cdot \Delta x )_n \) represents your profit (or loss) from time \( 0 \) to time \( n \). By the way, if you want to buy 5 shares of the stock at time \( n = 0 \) and then sell them all at time \( n \), you would take \( u_k = 5 \cdot 1_{k < n} \).

**Example 19.31.** Suppose that \( 0 \leq \sigma \leq \tau \) where \( \sigma, \tau \in \bar{\mathbb{N}}_0 \) and let \( u_n := 1_{\sigma < n \leq \tau} \). Then
\[
( u \cdot \Delta x )_n = \sum_{j=1}^n 1_{\sigma < j \leq \tau}(x_j - x_{j-1}) = \sum_{j=1}^\infty 1_{\sigma < j \leq \tau \land n}(x_j - x_{j-1})
\]
\[
= x_{\tau \land n} - x_{\sigma \land n}.
\]

**Proposition 19.32 (The Discrete Stochastic Integral).** Let \( X = \{X_n\}_{n=0}^\infty \) be an adapted integrable process, i.e. \( \mathbb{E}[X_n] < \infty \) for all \( n \). If \( X \) is a martingale and \( \{U_n\}_{n=1}^\infty \) is a predictable sequence of bounded random variables, then \((U \cdot \Delta X)_n\) is a martingale. If \( X := \{X_n\}_{n=0}^\infty \) is a submartingale (supermartingale) (necessarily real valued) and \( U_n \geq 0 \), then \((U \cdot \Delta X)_n\) is a submartingale (supermartingale).

Conversely if \( X \) is an adapted process of integrable functions such that \( \mathbb{E}[(U \cdot \Delta X)_n] = 0 \) for all bounded predictable processes, \( \{U_n\}_{n=1}^\infty \), then \( X \) is a martingale. Similarly if \( X \) is real valued adapted process such that
\[
\mathbb{E}[(U \cdot \Delta X)_n] \leq 0
\]
for all \( n \) and for all bounded, non-negative predictable processes, \( U \), then \( X \) is a supermartingale, martingale, or submartingale respectively.

**Proof.** For any adapted process \( X \), we have
\[
\mathbb{E}[(U \cdot \Delta X)_{n+1}] = \mathbb{E}[(U \cdot \Delta X)_n + U_{n+1}(X_{n+1} - X_n)]_{\mathcal{B}_n}
\]
\[
= (U\cdot \Delta X)_n + U_{n+1}\mathbb{E}[(X_{n+1} - X_n)]_{\mathcal{B}_n}.
\]
(19.19)
The first assertions easily follow from this identity.

Now suppose that \( X \) is an adapted process of integrable functions such that \( \mathbb{E}[(U \cdot \Delta X)_n] = 0 \) for all bounded predictable processes, \( \{U_n\}_{n=1}^\infty \). Taking expectations of Eq. (19.19) then allows us to conclude that
\[
\mathbb{E}[U_{n+1}\mathbb{E}[(X_{n+1} - X_n)]_{\mathcal{B}_n}] = 0
\]
for all bounded \( \mathcal{B}_n \) measurable random variables, \( U_{n+1} \). Taking \( U_{n+1} := \text{sgn} \mathbb{E}[(X_{n+1} - X_n)]_{\mathcal{B}_n} \) shows \( \mathbb{E}[(X_{n+1} - X_n)]_{\mathcal{B}_n} = 0 \) a.s. and hence \( X \) is a martingale. Similarly, if for all non-negative, predictable \( U \), Eq. (19.18) holds for all \( n \geq 1 \), and \( U_n \geq 0 \), then taking \( A \in \mathcal{B}_n \) and \( U_k = \delta_{k,n+1}A \) in Eq. (19.18) allows us to conclude that
\[
\mathbb{E}[X_{n+1} - X_n : A] = \mathbb{E}[(U \cdot \Delta X)_{n+1}] \leq 0,
\]
i.e. \( X \) is a supermartingale, martingale, or submartingale respectively.

**Example 19.33.** Suppose that \( \{X_n\}_{n=0}^\infty \) are mean zero independent integrable random variables and \( f_n : \mathbb{R}^n \to \mathbb{R} \) are bounded measurable functions. Then
\[
Y_n := \sum_{j=1}^n f_n(X_0, \ldots, X_{n-1})(X_n - X_{n-1})
\]
(19.20)
defines a martingale sequence.
Notation 19.34 Given an adapted process, $X$, and a stopping time $\tau$, let $X^n_\tau := X_\tau \wedge n$. We call $X^n_\tau := \{X^n_\tau\}_{n=0}^\infty$ the process $X$ stopped by $\tau$.

Theorem 19.35 (Optional stopping theorem). Suppose $X = \{X_n\}_{n=0}^\infty$ is a supermartingale, martingale, or submartingale and $\tau$ is a stopping time, then $X^\tau$ is a $\{B_n\}_{n=0}^\infty$- supermartingale, martingale, or submartingale respectively. This is the natural generalization of Eq. (19.3) to the stopping time setting.

Proof. First proof. Since $1_{\tau \leq n} X_\tau = \sum_{k=0}^n 1_{\tau = n} X_n$ is $B_n$ measurable, $\{\tau > n\} \in B_n$, and

$$X^{\tau \wedge (n+1)}_\tau = 1_{\tau \leq n} X_\tau + 1_{\tau > n} X_{n+1},$$

we have

$$E_{B_n} \left[ X^{\tau \wedge (n+1)}_\tau \right] = 1_{\tau \leq n} X_\tau + 1_{\tau > n} E_{B_n} X_{n+1} \leq 1_{\tau \leq n} X_\tau + 1_{\tau > n} X_n = X^{\tau \wedge n}_\tau.$$  

Second proof in case $E|X_n| < \infty$. Let $U_k := 1_{0 < k \leq \tau}$ for $k = 1, 2, \ldots, \tau$. Then $U$ is a bounded predictable process and

$$(U \cdot \Delta X)_n = \sum_{k=0}^n \Delta_k X = \sum_{0 < k \leq \tau \wedge n} \Delta_k X = X^{\tau \wedge n}_\tau - X_0.$$ 

Therefore, by Proposition 19.32, $X^\tau_\tau = X_0 + (U \cdot \Delta X)_n$ is (respectively) a supermartingale, martingale, or submartingale.

Third proof. See Remark 19.37 below.

Theorem 19.36 (Optional sampling theorem I). Suppose that $\sigma$ and $\tau$ are two stopping times and $\tau$ is bounded, i.e. there exists $N \in \mathbb{N}$ such that $\tau \leq N < \infty$ a.s. If $X = \{X_n\}_{n=0}^\infty$ is integrable and $\sigma < \tau$ a.s.

$$E[|X_\tau|] \leq \sum_{0 \leq k \leq \tau} 1_{\tau = k}|X_k| \leq \sum_{0 \leq k \leq N} |X_k|,$$

from top to bottom. Moreover, Eq. (19.21) is valid with no integrability assumptions on $X$ provided $X_n \geq 0$ a.s. for all $n < \infty$.

Proof. Since

if $X_n \in L^1(\Omega, \mathcal{B}, P)$ for all $n$ we see that $E|X_\tau| \leq \sum_{0 \leq k \leq N} E|X_k| < \infty$. Hence it remains to prove Eq. (19.21) in case $X_n \geq 0$ or $X_n \in L^1(\Omega, \mathcal{B}, P)$ for all $n$.

According to Lemma 19.29

$$E[|X_\sigma|] = \sum_{n=0}^\infty 1_{\sigma = n} E[|X_\tau|] = \sum_{n=0}^\infty 1_{\sigma = n} E[X_n] = E[X_\sigma].$$  

On the other hand we know $X^\tau$ is a supermartingale, martingale, or submartingale respectively and therefore, for any $n < \infty$ and $\tau \leq N$ we have

$$E[X_\tau] = E[X_n] \leq E[X^\tau_\tau] = E[X^\tau_n] = X^\tau_n \geq X^\tau_n \geq X_\tau \wedge n.$$ 

Combining this equation with Eq. (19.22) shows

$$E[X_\tau] = \sum_{n=0}^\infty 1_{\sigma = n} E[X_\tau] = \sum_{n=0}^\infty 1_{\sigma = n} X_\tau \wedge n = X_\tau \wedge \sigma.$$ 

This completes the proof. Nevertheless we will give two more proofs of Eq. (19.22) under the assumption that $X_n \in L^1(\Omega, \mathcal{B}, P)$ for all $n$.

First alternative proof. First suppose $X$ is a martingale in which case $X_n = E_{B_n} X_N$ for all $n \leq N$ and hence

$$X_\tau = \sum_{n \leq N} 1_{\tau = n} X_n = \sum_{n \leq N} 1_{\tau = n} E_{B_n} X_N = \sum_{n \leq N} 1_{\tau = n} E_{B_n} X_N = E_{B_{\tau \wedge n}} X_N.$$ 

Therefore, by Exercise 19.3

$$E_{B_\tau} X_\tau = E_{B_\tau} E_{B_{\tau \wedge n}} X_N = E_{B_{\tau \wedge n}} X_N = X_\tau \wedge \tau.$$ 

Now suppose that $X$ is a submartingale. By the Doob decomposition (Lemma 19.15), $X_n = M_n + A_n$ where $M$ is a martingale and $A$ is an increasing predictable process. In this case we have

$$E_{B_\tau} X_\tau = E_{B_\tau} M_\tau + E_{B_\tau} A_\tau = M_\tau \wedge \tau + E_{B_\tau} A_\tau \geq M_\tau \wedge \tau + E_{B_\tau} A_\tau \wedge \tau = X_\tau \wedge \tau.$$ 

The submartingale case follows from the submartingale result just proved applied to $-X$.

Second alternative proof. Let $A \in \mathcal{B}_\sigma$ and $U_n := 1_A \cdot 1_{\sigma < n \leq \tau}$. Then $U$ is predictable since

$$A \cap \{\sigma < n \leq \tau\} = (A \cap \{\sigma < n\}) \cap \{n \leq \tau\} \in B_{n-1} \text{ for all } n.$$ 

Let us also observe that

2 This is the natural generalization of Eq. (19.3) to the stopping time setting.
\[ (U \cdot \Delta X)_n = \sum_{k \leq n} 1_{A} \cdot 1_{\sigma < k \leq \tau} \Delta_k X = \sum_{1 \leq k \leq n} 1_{A} \cdot 1_{\sigma \land k \leq \tau \land \Delta_k X} = 1_{A} (X_{\tau \land n} - X_{\sigma \land \tau}) \]

By Proposition 19.32, \((U \cdot \Delta X)\) is a supermartingale, martingale, or submartingale respectively and hence

\[ E[1_{A} (X_{\tau} - X_{\sigma \land \tau})] = E[1_{A} (X_{\tau \land n} - X_{\sigma \land \tau})] = E[(U \cdot \Delta X)_n] \leq 0 \]

respectively.

Since \(A \in B_{\sigma}\) is arbitrary and \(X_{\sigma \land \tau}\) is \(B_{\sigma} -\) measurable (in fact \(B_{\sigma \land \tau} -\) measurable), Eq. (19.21) has been proved.

**Remark 19.37.** Theorem 19.36 can be used to give a simple proof of the Optional stopping Theorem 19.35. For example, if \(X = \{X_n\}_{n=0}^{\infty}\) is a submartingale and \(\tau\) is a stopping time, then

\[ E_a X_{\tau \land (n+1)} \geq X_{\tau \land (n+1)} \land n = X_{\tau \land n} \]

i.e. \(X_{\tau}\) is a submartingale.

### 19.5 Submartingale Inequalities

For a process, \(X = \{X_n\}_{n=0}^{\infty}\) let

\[ X_N := \max\{|X_0|, \ldots, |X_N|\}. \tag{19.23} \]

#### 19.5.1 Maximal Inequalities

**Proposition 19.38 (Maximal Inequalities of Bernstein and Lévy).** Let \(\{X_n\}\) be a submartingale on a filtered probability space, \((\Omega, \mathcal{B}, \{\mathcal{B}_n\}_{n=0}^{\infty}, P)\). Then for any \(a \geq 0\) and \(N \in \mathbb{N}\),

\[ aP(\max_{n \leq N} X_n \geq a) \leq E\left[X_N : \max_{n \leq N} X_n \geq a \right] \leq E[X_N^+], \tag{19.24} \]

\[ aP(\min_{n \leq N} X_n \leq -a) \leq E\left[X_N : \min_{k \leq N} X_k > -a \right] - E[X_0] \leq E[X_N^+] - E[X_0], \tag{19.25} \]

and

\[ aP(X_N^+ \geq a) \leq 2E [X_N^+] - E[X_0]. \tag{19.27} \]

Proof. Initially let \(X\) be any integrable adapted process and \(\tau\) be the stopping time defined by, \(\tau := \inf \{n : X_n \geq a\}\). Since \(X_{\tau} \geq a\) on \(\{\tau \leq N\} = \left\{\max_{n \leq N} X_n \geq a\right\}\),

\[ aP\left(\max_{n \leq N} X_n \geq a\right) = E[a : \tau \leq N] \leq E[X_{\tau} : \tau \leq N] \tag{19.29} \]

\[ = E[X_N : \tau \leq N] - E[X_N - X_{\tau} : \tau \leq N] = E[X_N : \tau \leq N] - E[X_N - X_{\tau \land N}]. \tag{19.30} \]

Let me emphasize again that in deriving Eq. (19.30), we have not used any special properties (not even adaptedness) of \(X\).

If \(X\) is now assumed to be a submartingale, by the optional sampling Theorem 19.36 \(E_{\tau \land N} X_N \geq X_{\tau \land N}\) and in particular \(E[X_N - X_{\tau \land N}] \geq 0\). Combining this observation with Eq. (19.30) and Eq. (19.28) gives Eq. (19.24).

(Alternatively, since \(\tau \land N \in B_{\tau \land N}\), it follows by optional sampling that

\[ E[X_{\tau} : \tau \leq N] = E[X_{\tau \land N} : \tau \leq N] \leq E[X_N : \tau \leq N] \]

which combined with Eq. (19.29) gives Eq. (19.24).)

Secondly we may apply Eq. (19.30) with \(X_n\) replaced by \(-X_n\) to find

\[ aP\left(\min_{n \leq N} X_n \leq -a\right) = aP\left(-\min_{n \leq N} X_n \geq a\right) = aP\left(\max_{n \leq N} (-X_n) \geq a\right) \leq -E[X_N : \tau \leq N] + E[X_N - X_{\tau \land N}] \tag{19.31} \]

where now,

\[ \tau := \inf \{n : -X_n \geq a\} = \inf \{n : X_n \leq -a\}. \]

By the optional sampling Theorem 19.36 \(E[X_{\tau \land N} - X_0] \geq 0\) and adding this to right side of Eq. (19.31) gives the estimate

\[ aP\left(\min_{n \leq N} X_n \leq -a\right) \leq -E[X_N : \tau \leq N] + E[X_N - X_{\tau \land N}] + E[X_{\tau \land N} - X_0] \leq E[X_N - X_0] - E[X_N : \tau \leq N] = E[X_N : \tau > N] - E[X_0] = E[X_N : \min_{k \leq N} X_k > -a] - E[X_0] \]

which proves Eq. (19.25) and hence Eq. (19.26). Adding Eqs. (19.24) and (19.26) gives the estimate in Eq. (19.27).
Remark 19.39. It is of course possible to give a direct proof of Proposition 19.38. For example,

\[ \mathbb{E} \left[ X_N : \max_{n \leq N} X_n \geq a \right] = \sum_{k=1}^{N} \mathbb{E} \left[ X_N : X_1 < a, \ldots, X_{k-1} < a, X_k \geq a \right] \]

\[ \geq \sum_{k=1}^{N} \mathbb{E} \left[ X_k : X_1 < a, \ldots, X_{k-1} < a, X_k \geq a \right] \]

\[ \geq \sum_{k=1}^{N} \mathbb{E} \left[ a : X_1 < a, \ldots, X_{k-1} < a, X_k \geq a \right] \]

\[ = a P \left( \max_{n \leq N} X_n \geq a \right) \]

which proves Eq. (19.24).

Example 19.40. Let \( \{X_n\} \) be a sequence of independent random variables with mean zero, \( S_n := X_1 + \cdots + X_n \), and \( S_n^* = \max_{j \leq n} |S_j| \). Since \( \{S_n\}_{n=1}^{\infty} \) is a martingale and \( \{|S_n|^p\}_{n=1}^{\infty} \) is an (possibly extended) submartingale for any \( p \in [1, \infty) \). Therefore an application of Eq. (19.24) of Proposition 19.38 show

\[ P \left( S_n^* \geq a \right) = P \left( S_n^p \geq a^p \right) \leq \frac{1}{a^p} \mathbb{E} \left[ |S_n|^p : S_n^* \geq a \right]. \]

When \( p = 2 \), this is Kolmogorov’s Inequality, see Theorem 12.28.

Lemma 19.41. Suppose that \( X \) and \( Y \) are two non-negative random variables such that \( P (Y \geq y) \leq \frac{1}{y} \mathbb{E} [X : Y \geq y] \) for all \( y > 0 \). Then for all \( p \in (1, \infty) \),

\[ \mathbb{E} Y^p \leq \left( \frac{p}{p-1} \right)^p \mathbb{E} X^p. \quad (19.32) \]

Proof. We will begin by proving Eq. (19.32) under the additional assumption that \( Y \in L^p (\Omega, \mathcal{B}, \mathbb{P}) \). Since

\[ \mathbb{E} Y^p = p \mathbb{E} \int_0^{\infty} 1_{y \leq Y} \cdot y^{p-1} dy = p \int_0^{\infty} 1_{y \leq \frac{1}{Y}} \cdot y^{p-1} dy \]

\[ = p \int_0^{\infty} P (Y \geq y) \cdot y^{p-1} dy \leq p \int_0^{\infty} \frac{1}{y} \mathbb{E} [X : Y \geq y] \cdot y^{p-1} dy \]

\[ = p \mathbb{E} \int_0^{\infty} X 1_{y \leq Y} \cdot y^{p-2} dy = \frac{p}{p-1} \mathbb{E} [XY^{p-1}]. \]

Now apply Hölder’s inequality, with \( q = p (p-1)^{-1} \), to find

\[ \mathbb{E} [XY^{p-1}] \leq \|X\|_p \cdot \|Y^{p-1}\|_{\frac{q}{p}} = \|X\|_p \cdot \|\mathbb{E} [Y]^{p-1}\|_{\frac{q}{p}}. \]

Combining these two inequalities shows and solving for \( \|Y\|_p \),

\[ \mathbb{E} [Y] \leq \left( \frac{p}{p-1} \right)^{\frac{q}{p}} \mathbb{E} X^p. \quad (19.33) \]

We may now use the MCT to pass to the limit, \( M \uparrow \infty \), and hence conclude that Eq. (19.32) holds in general.

Corollary 19.42 (Doob’s Inequality). If \( X = \{X_n\}_{n=0}^{\infty} \) be a non-negative submartingale and \( 1 < p < \infty \), then

\[ \mathbb{E} X_n^p \leq \left( \frac{p}{p-1} \right)^p \mathbb{E} X_0^p. \quad (19.33) \]


Corollary 19.43 (Doob’s Inequality). If \( \{M_n\}_{n=0}^{\infty} \) is a martingale and \( 1 < p < \infty \), then for all \( a > 0 \),

\[ P (M_n^* \geq a) \leq \frac{1}{a} \mathbb{E} [\|M\| : M_n^* \geq a] \leq \frac{1}{a} \mathbb{E} [\|M_n\|]. \quad (19.34) \]

and

\[ \mathbb{E} M_n^p \leq \left( \frac{p}{p-1} \right)^p \mathbb{E} |M_n|^p. \quad (19.35) \]

Proof. By the conditional Jensen’s inequality, it follows that \( X_n := |M_n| \) is a submartingale. Hence Eq. (19.34) follows from Eq. (19.24) and Eq. (19.35) follows from Eq. (19.33).
19.5.2 Upcrossing Inequalities and Convergence Results

Given a function, \( \mathbb{N}_0 \ni n \to X_n \in \mathbb{R} \) and \( -\infty < a < b < \infty \), let

\[ \tau_0 = 0, \quad \tau_1 = \inf \{ n \geq \tau_0 : X_n \leq a \}, \quad \tau_2 = \inf \{ n \geq \tau_1 : X_n \geq b \}, \quad \tau_3 = \inf \{ n \geq \tau_2 : X_n \leq a \}, \ldots \]

\[ \tau_{2k} = \inf \{ n \geq \tau_{2k-1} : X_n \geq b \}, \quad \tau_{2k+1} = \inf \{ n \geq \tau_{2k} : X_n \leq a \} \]

(19.36)

with the usual convention that \( \inf \emptyset = \infty \) in the definitions above, see Figures 19.1 and 19.2.

Observe that \( \tau_{n+1} \geq \tau_n + 1 \) for all \( n \geq 1 \) and hence \( \tau_n \geq n - 1 \) for all \( n \geq 1 \). Further, for each \( N \in \mathbb{N} \) let

\[ U_N^X(a, b) = \max \{ k : \tau_{2k} \leq N \} \]

be the number of upcrossings of \( X \) across \([a, b]\) in the time interval, \([0, N]\).

**Lemma 19.44.** Suppose \( X = \{X_n\}_{n=0}^{\infty} \) is a sequence of extended real numbers such that \( U_N^X(a, b) < \infty \) for all \( a, b \in \mathbb{Q} \) with \( a < b \). Then \( X_\infty := \lim_{n \to \infty} X_n \) exists in \( \mathbb{R} \).

**Proof.** If \( \lim_{n \to \infty} X_n \) does not exist in \( \mathbb{R} \), then there would exists \( a, b \in \mathbb{Q} \) such that

\[ \liminf_{n \to \infty} X_n < a < b < \limsup_{n \to \infty} X_n \]

and for this choice of \( a \) and \( b \), we must have \( X_n < a \) and \( X_n > b \) infinitely often. Therefore, \( U_N^X(a, b) = \infty \).

**Theorem 19.45 (Doob’s Upcrossing Inequality – buy low sell high).** If \( \{X_n\}_{n=0}^{\infty} \) is a submartingale and \( -\infty < a < b < \infty \), then for all \( N \in \mathbb{N} \),

\[ \mathbb{E} \left[ U_N^X(a, b) \right] \leq \frac{1}{b - a} \left[ \mathbb{E} (X_N - a)_+ - \mathbb{E} (X_0 - a)_+ \right]. \]

**Proof.** We first suppose that \( X_n \geq 0, a = 0 \) and \( b > 0 \). Let

\[ \tau_0 = 0, \quad \tau_1 = \inf \{ n \geq \tau_0 : X_n = 0 \}, \quad \tau_2 = \inf \{ n \geq \tau_1 : X_n \geq b \}, \quad \tau_3 = \inf \{ n \geq \tau_2 : X_n = 0 \}, \ldots \]

\[ \tau_{2k} = \inf \{ n \geq \tau_{2k-1} : X_n \geq b \}, \quad \tau_{2k+1} = \inf \{ n \geq \tau_{2k} : X_n = 0 \}, \ldots \]

(19.37)

Note that if \( \tau_{2n-1} \geq N \), then \( X_{\tau_{2n}^\prime} - X_{\tau_{2n-1}^\prime} \geq b \) if there were an upcrossing in the interval \([\tau_{2n-1}^\prime, \tau_{2n}^\prime]\) and \( X_{\tau_{2n}^\prime} - X_{\tau_{2n-1}^\prime} \geq 0 \) otherwise. Taking expectations of Eq. (19.37) implies

\[ X_N - X_0 = \sum_{n=1}^{2k} (X_{\tau_n^\prime} - X_{\tau_{n-1}^\prime}) \]

\[ \geq b \sum_{n=1}^{k} \left( X_{\tau_{2n}^\prime} - X_{\tau_{2n-1}^\prime} \right) + \sum_{n=1}^{k} \left( X_{\tau_{2n-1}^\prime} - X_{\tau_{2n-2}^\prime} \right), \]

If \( \tau_{2n-1} \geq N \), then \( X_{\tau_{2n}^\prime} - X_{\tau_{2n-1}^\prime} = X_N - X_N = 0 \), while if \( \tau_{2n-1} < N \), \( X_{\tau_{2n}^\prime} - X_{\tau_{2n-1}^\prime} = X_{\tau_{2n}^\prime} - 0 = b \).
and therefore inequality that  

\[ \text{wherein we have used the optional sampling theorem to guarantee,} \]

\[ \begin{align*}
\mathbb{E} & \left( X_{\tau_{2n-1}} - X_{\tau_{2n-2}} \right) \\
& \geq 0.
\end{align*} \]

If \( X \) is a general submartingale and \(-\infty < a < b < \infty\), we know by Jensen’s inequality that \( (X_n - a)_+ \) is still a submartingale and moreover

\[ U_N^X (a, b) = U^{(X-a)_+} (0, b-a) \]

and therefore

\[ (b-a) \mathbb{E} \left[ U_N^X (a, b) \right] = (b-a) \mathbb{E} \left[ U^{(X-a)_+} (0, b-a) \right] \]

\[ \leq \mathbb{E} (X_N - a)_+ - \mathbb{E} (X_0 - a)_+ . \]

It is worth contemplating a bit how is that \( \mathbb{E} \left( X_{\tau_{2n-1}} - X_{\tau_{2n-2}} \right) \geq 0 \) given that are strategy is to buy high and sell low. On the \( \{ \tau_{2n-1} \leq N \} \), \( X_{\tau_{2n-1}} - X_{\tau_{2n-2}} \leq 0 \) and \( -b = \bar{b} \) and therefore,

\[ 0 \leq \mathbb{E} \left( X_{\tau_{2n-1}} - X_{\tau_{2n-2}} \right) \]

\[ = \mathbb{E} \left( X_{\tau_{2n-1}} - X_{\tau_{2n-2}} : \tau_{2n-1} \leq N \right) + \mathbb{E} \left( X_{\tau_{2n-1}} - X_{\tau_{2n-2}} : \tau_{2n-1} > N \right) \]

\[ \leq -b \mathbb{P} (\tau_{2n-1} \leq N) + \mathbb{E} \left( X_N - X_{\tau_{2n-2}} : \tau_{2n-1} > N \right) . \]

Therefore we must have

\[ \mathbb{E} \left( X_N - X_{\tau_{2n-2} \wedge N} : \tau_{2n-1} > N \right) \geq b \mathbb{P} (\tau_{2n-1} \leq N) \]

so that \( X_N \) must be sufficiently large sufficiently often on the set where \( \tau_{2n-1} > N \).

\textbf{Corollary 19.46.} Suppose \( \{X_n\}_{n=0}^{\infty} \) is an integrable submartingale such that \( \sup_n \mathbb{E} X_n^+ < \infty \) (or equivalently \( C := \sup_n \mathbb{E} \left| X_n \right| < \infty \), see Remark 19.18), then \( X_{\infty} := \lim_{n \to \infty} X_n \) exists in \( \mathbb{R} \) a.s. and moreover, \( X_{\infty} \in L^1 (\Omega, \mathcal{B}, \mathbb{P}) \).

\textbf{Proof.} For any \(-\infty < a < b < \infty\), by Doob’s upcrossing inequality (Theorem 19.45) and the MCT,

\[ \mathbb{E} \left[ U_N^X (a, b) \right] \leq \frac{1}{b-a} \left[ \sup_N \mathbb{E} (X_N - a)_+ - \mathbb{E} (X_0 - a)_+ \right] < \infty \]

where

\[ U_N^X (a, b) := \lim_{N \to \infty} U_N^X (a, b) \]

is the total number of upcrossings of \( X \) across \([a, b]\). In particular it follows that

\[ \Omega_0 := \cap \{ U_N^X (a, b) < \infty : a, b \in \mathbb{Q} \text{ with } a < b \} \]

has probability one. Hence by Lemma 19.44 for \( \omega \in \Omega_0 \) we have \( X_{\infty} (\omega) := \lim_{n \to \infty} X_n (\omega) \) exists in \( \mathbb{R} \). By Fatou’s lemma we know that

\[ \mathbb{E} \left[ |X_{\infty}| \right] = \mathbb{E} \left[ \liminf_{n \to \infty} |X_n| \right] \leq \liminf_{n \to \infty} \mathbb{E} \left[ |X_n| \right] \leq C < \infty \]

(19.38)

and therefore that \( X_{\infty} \in \mathbb{R} \) a.s.
Second Proof. We may also give another proof based on the Krickeberg Decomposition Theorem \[19.19\] and the supermartingale convergence Corollary \[19.54\] below. Indeed, by Theorem \[19.19\] $X_n = M_n - Y_n$ where $M$ is a positive martingale and $Y$ is a positive supermartingale. Hence by two applications of Corollary \[19.54\] we may conclude that

$$X_\infty = \lim_{n \to \infty} X_n = \lim_{n \to \infty} M_n - \lim_{n \to \infty} Y_n$$

exists in $\mathbb{R}$ almost surely.

**Notation 19.47** Given a probability space, $(\Omega, \mathcal{B}, P)$ and $A, B \in \mathcal{B}$, we say $A = B$ a.s. iff $P(A \triangle B) = 0$.

**Corollary 19.48 (Localizing Corollary Eq. \[19.46\]).** Suppose $M = \{M_n\}_{n=0}^\infty$ is a martingale and $c < \infty$ such that $\Delta_n M \leq c$ a.s. for all $n$. Then

$$\left\{ \lim_{n \to \infty} M_n \text{ exists in } \mathbb{R} \right\} = \left\{ \sup_n M_n < \infty \right\} \text{ a.s.}$$

**Proof.** Let $\tau_m := \inf\{n : M_n \geq m\}$ for all $m \in \mathbb{N}$. Then by the optional stopping theorem, $n \to M_{\tau_m}$ is still a martingale. Since $M_{\tau_m} \leq m + c$, it follows that $\mathbb{E}(M_{\tau_m})_+ \leq m + c < \infty$ for all $n$. Hence we may apply Corollary \[19.46\] to conclude, $\lim_{n \to \infty} M_n = M_{\tau_m}$ exists in $\mathbb{R}$ almost surely. Therefore $n \to M_n$ is convergent in $\mathbb{R}$ almost surely on the set

$$\bigcup_m \{M_{\tau_m} = M\} = \left\{ \sup_n M_n < \infty \right\}.$$

Conversely if $n \to M_n$ is convergent in $\mathbb{R}$, then $\sup_n M_n < \infty$.

**Corollary 19.49.** Suppose $M = \{M_n\}_{n=0}^\infty$ is a martingale, and $c < \infty$ such that $|\Delta_n M| \leq c$ a.s. for all $n$. Let

$$C := \left\{ \lim_{n \to \infty} M_n \text{ exists in } \mathbb{R} \right\} \quad \text{and} \quad D := \left\{ \lim_{n \to \infty} \sup M_n = \infty \right\} \cap \left\{ \lim_{n \to \infty} \inf M_n = -\infty \right\}.$$

Then, $P(C \cup D) = 1$.

**Proof.** Since both $M$ and $-M$ satisfy the hypothesis of Corollary \[19.48\] we may conclude that almost surely,

$$C = \left\{ \sup_n M_n < \infty \right\} = \left\{ \inf_n M_n > -\infty \right\} \quad \text{and hence almost surely,}$$

$$C^c = \left\{ \sup_n M_n = \infty \right\} = \left\{ \inf_n M_n = -\infty \right\} = D.$$

**Corollary 19.50.** Suppose $(\Omega, \mathcal{B}, \{B_n\}_n, P)$ is a filtered probability space and $A_n \in B_n$ for all $n$. Then

$$\{A_n \text{ i.o.}\} = \left\{ \sum_n \mathbb{E}[1_{A_n} | B_n] = 1 \right\} \text{ a.s.} \quad (19.39)$$

**Proof.** Let $\Delta_n M := 1_{A_n} - \mathbb{E}[1_{A_n} | B_n]$ and then set $M_n := \sum_{k \leq n} \Delta_n M$. Then $M$ is a martingale with $|\Delta_n M| \leq 1$ for all $n$. Since

$$\{A_n \text{ i.o.}\} = \left\{ \sum_n 1_{A_n} = \infty \right\},$$

it follows that on $C$ we have $\{A_n \text{ i.o.}\} = \left\{ \sum_n \mathbb{E}[1_{A_n} | B_n] = 1 \right\}$ a.s. Moreover, on $D$, we must have $\sum_n 1_{A_n} = \infty$ and $\sum_n \mathbb{E}[1_{A_n} | B_n] = \infty$ and hence again it follows that Eq. \[19.39\] holds. Since $C \cup D = \Omega$ a.s., the proof is complete.

See Durrett [3 Chapter 4.3] for more in this direction.

### 19.6 Supermartingale inequalities

As the optional sampling theorem was our basic tool for deriving submartingale inequalities, the following switching lemma will be our basic tool for deriving positive supermartingale inequalities.

**Lemma 19.51 (Switching Lemma).** Suppose that $X$ and $Y$ are two supermartingales and $\tau$ is a stopping time such that $X_\tau \geq Y_\tau$ on $\{\tau < \infty\}$. Then

$$Z_n = 1_{n < \tau} X_n + 1_{n \geq \tau} Y_n = \begin{cases} X_n & \text{if } n < \tau \\ Y_n & \text{if } n \geq \tau \end{cases}$$

is again a supermartingale. (In short we can switch from $X$ to $Y$ at time $\tau$, provided $Y \leq X$ at the switching time, $\tau$.) This lemma is valid if $X_n, Y_n \in L^1(\Omega, B_n, P)$ for all $n$ or if both $X_n, Y_n \geq 0$ for all $n$. In the latter case, we should be using the extended notion of conditional expectations.
Proof. We begin by observing,

\[
Z_{n+1} = 1_{n+1<\tau}X_{n+1} + 1_{n+1\geq\tau}Y_{n+1} \\
= 1_{n+1<\tau}X_{n+1} + 1_{n\geq\tau}Y_{n+1} + 1_{\tau=n+1}Y_{n+1} \\
\leq 1_{n+1<\tau}X_{n+1} + 1_{n\geq\tau}Y_{n+1} + 1_{\tau=n+1}X_{n+1} \\
= 1_{n<\tau}X_n + 1_{n\geq\tau}Y_n.
\]

Since \( \{ n < \tau \} \) and \( \{ n \geq \tau \} \) are \( \mathcal{B}_n \) - measurable, it now follows from the supermartingale property of \( X \) and \( Y \) that

\[
\mathbb{E}_{\mathcal{B}_n} Z_{n+1} \leq \mathbb{E}_{\mathcal{B}_n} [1_{n<\tau}X_{n+1} + 1_{n\geq\tau}Y_{n+1}] \\
= 1_{n<\tau}\mathbb{E}_{\mathcal{B}_n} [X_{n+1}] + 1_{n\geq\tau}\mathbb{E}_{\mathcal{B}_n} [Y_{n+1}] \\
\leq 1_{n<\tau}X_n + 1_{n\geq\tau}Y_n = Z_n.
\]

\[\blacksquare\]

19.6.1 Maximal Inequalities

Theorem 19.52 (Supermartingale maximal inequality). Let \( X \) be a positive supermartingale (in the extended sense) and \( a \in \mathcal{B}_0 \) with \( a \geq 0 \), then

\[
aP \left[ \sup_n X_n \geq a | \mathcal{B}_0 \right] \leq a \wedge X_0 \tag{19.40}
\]

and moreover

\[
P \left[ \sup_n X_n = \infty | \mathcal{B}_0 \right] = 0 \text{ on } \{ X_0 < \infty \}. \tag{19.41}
\]

In particular if \( X_0 < \infty \) a.s. then \( \sup_n X_n < \infty \) a.s.

Proof. Let \( \tau := \inf \{ n : X_n \geq a \} \) which is a stopping time since,

\[
\{ \tau \leq n \} = \{ X_n \geq a \} \in \mathcal{B}_n \text{ for all } n.
\]

Since \( X_\tau \geq a \) on \( \{ \tau < \infty \} \) and \( Y_n := a \) is a supermartingale, it follows by the switching Lemma \[19.51\] that

\[
Z_n := 1_{n<\tau}X_n + a1_{n\geq\tau}
\]

is a supermartingale (in the extended sense). In particular it follows

\[
aP (\tau \leq n | \mathcal{B}_0) = \mathbb{E}_{\mathcal{B}_0} [a1_{n\geq\tau}] \leq \mathbb{E}_{\mathcal{B}_0} Z_n \leq Z_0,
\]

and

\[
Z_0 = 1_{0<\tau}X_0 + a1_{\tau=0} = 1_{X_0<a}X_0 + 1_{X_0\geq a}a = a \wedge X_0.
\]

Therefore, using the cMCT,

\[
aP \left[ \sup_n X_n \geq a | \mathcal{B}_0 \right] = aP [\tau < \infty | \mathcal{B}_0] = \lim_{n \to \infty} aP (\tau \leq n | \mathcal{B}_0) \leq Z_0 = a \wedge X_0
\]

which proves Eq. \[19.40\].

For the last assertion, take \( a > 0 \) to be constant in Eq. \[19.40\] and then use the cDCT to let \( a \uparrow \infty \) to conclude

\[
P \left[ \sup_n X_n = \infty | \mathcal{B}_0 \right] = \lim_{a \to \infty} P \left[ \sup_n X_n \geq a | \mathcal{B}_0 \right] \leq \lim_{a \to \infty} 1 \wedge \frac{X_0}{a} = 1_{X_0=\infty}.
\]

Multiplying this equation by \( 1_{X_0<\infty} \) and then taking expectations implies

\[
\mathbb{E} \left[ 1_{\sup_n X_n=\infty} 1_{X_0<\infty} \right] = \mathbb{E} \left[ 1_{X_0=\infty} 1_{X_0<\infty} \right] = 0
\]

which implies \( \sup_n X_n = \infty \) \( a.s. \), i.e. \( \sup_n X_n < \infty \) a.s. on \( \{ X_0 < \infty \} \).

\[\blacksquare\]

19.6.2 The upcrossing inequality and convergence result

Theorem 19.53 (Dubin’s Upcrossing Inequality). Suppose \( X = \{ X_n \}_{n=0}^\infty \) is a positive supermartingale and \( 0 < a < b < \infty \). Then

\[
P \left[ U^X_{\infty} (a, b) \geq k | \mathcal{B}_0 \right] \leq \left( \frac{a}{b} \right)^k \left( 1 \wedge \frac{X_0}{a} \right), \text{ for } k \geq 1 \tag{19.42}
\]

and \( U^X_{\infty} (a, b) < \infty \) a.s. and in fact

\[
\mathbb{E} \left[ U^X_{\infty} (a, b) \right] \leq \frac{1}{b/a - 1} = \frac{a}{b-a} < \infty.
\]

Proof. Since \( U^X_{N} (a, b) = U^X_{N/a} (1, b/a) \),

it suffices to consider the case where \( a = 1 \) and \( b > 1 \). Let \( \tau_n \) be the stopping times defined in Eq. \[19.30\] with \( a = 1 \) and \( b > 1 \), i.e.

\[
\tau_0 = 0, \quad \tau_1 = \inf \{ n \geq \tau_0 : X_n \leq 1 \}
\]

\[
\tau_2 = \inf \{ n \geq \tau_1 : X_n \geq 2 \}, \quad \tau_3 := \inf \{ n \geq \tau_2 : X_n \leq 1 \}
\]

\[
\vdots
\]

\[
\tau_{2k} = \inf \{ n \geq \tau_{2k-1} : X_n \geq b \}, \quad \tau_{2k+1} := \inf \{ n \geq \tau_{2k} : X_n \leq 1 \},
\]

\[
\vdots
\]
see Figure 19.1.

Let $k \geq 1$ and use the switching Lemma 19.51 repeatedly to define a new positive supermartingale $Y_n = Y_n^{(k)}$ (see Exercise 19.5 below) as follows,

\[
Y_n^{(k)} = 1_{n < \tau_1} + 1_{\tau_1 \leq n < \tau_2} X_n + b_1 1_{\tau_2 \leq n < \tau_3} + b X_n 1_{\tau_3 \leq n < \tau_4} + b^2 1_{\tau_4 \leq n < \tau_5} + b^2 X_n 1_{\tau_5 \leq n < \tau_6} + \ldots + b^{k-1} 1_{\tau_{2k-2} \leq n < \tau_{2k-1}} + b^{k-1} X_n 1_{\tau_{2k-1} \leq n < \tau_{2k}} + b^k 1_{\tau_{2k} \leq n}.
\]

(19.43)

Since $\mathbb{E}[Y_n|B_0] \leq Y_0$ a.s., $Y_n \geq b^k 1_{\tau_{2k} \leq n}$, and

\[
Y_0 = 1_{0 < \tau_1} + 1_{\tau_1 = 0} X_0 = 1_{X_0 > 1} + 1_{X_0 \leq 1} X_0 = 1 \land X_0,
\]

we may infer that

\[
b^k P(\tau_{2k} \leq n|B_0) = \mathbb{E}\left[b^k 1_{\tau_{2k} \leq n}|B_0\right] \leq \mathbb{E}[Y_n|B_0] \leq 1 \land X_0 \text{ a.s.}
\]

Using cMCT, we may now let $n \to \infty$ to conclude

\[
P\left(U^X_\infty(1,b) \geq k|B_0\right) \leq P(\tau_{2k} < \infty|B_0) \leq \frac{1}{b^k} (1 \land X_0) \text{ a.s.}
\]

which is Eq. (19.42). Using cDCT, we may let $k \uparrow \infty$ in this equation to discover $P\left(U^X_\infty(1,b) = \infty|B_0\right) = 0$ a.s. and in particular, $U^X_\infty(1,b) < \infty$ a.s. In fact we have

\[
\mathbb{E}\left[U^X_\infty(1,b)\right] = \sum_{k=1}^\infty P\left(U^X_\infty(1,b) \geq k\right) \leq \sum_{k=1}^\infty \mathbb{E}\left[\frac{1}{b^k} (1 \land X_0)\right]
\]

\[
= \frac{1}{b} \frac{1}{1 - 1/b} \mathbb{E}\left[(1 \land X_0)\right] \leq \frac{1}{b - 1} < \infty.
\]

\[\]

Exercise 19.5. In this exercise you are asked to fill in the details showing $Y_n$ in Eq. (19.43) is still a supermartingale. To do this, define $Y_n^{(k)}$ via Eq. (19.43) and then show (making use of the switching Lemma 19.51) that $Y_n^{(k+1)}$ is a submartingale under the assumption that $Y_n^{(k)}$ is a submartingale. Finish off the induction argument by observing that the constant process, $U_n := 1$ and $V_n = 0$ are supermartingales such that $U_{\tau_1} = 1 \geq 0 = V_{\tau_1}$ on $\{\tau_1 < \infty\}$, and therefore by the switching Lemma 19.51

\[
Y_n^{(1)} = 1_{0 \leq n < \tau_1} U_n + 1_{\tau_1 \leq n} V_n = 1_{0 \leq n < \tau_1}
\]

is also a supermartingale.

Corollary 19.54 (Positive Supermartingale convergence). Suppose $X = \{X_n\}_{n=0}^\infty$ is a positive supermartingale (possibly in the extended sense), then $X_\infty = \lim_{n \to \infty} X_n$ exists a.s. and we have

\[
\mathbb{E}[X_\infty|B_n] \leq X_n \text{ for all } n \in \mathbb{N}.
\]

(19.44)

In particular,

\[
\mathbb{E}X_\infty \leq \mathbb{E}X_n \leq \mathbb{E}X_0 \text{ for all } n < \infty.
\]

(19.45)

Proof. The set,

\[
\Omega_0 := \cap \left\{U^X_\infty(a,b) < \infty : a, b \in \mathbb{Q} \text{ with } a < b\right\},
\]

has full measure $(P(\Omega_0) = 1)$ by Dubin’s upcrossing inequality in Theorem 19.53. So by Lemma 19.44 for $\omega \in \Omega_0$ we have $X_\infty(\omega) := \lim_{n \to \infty} X_n(\omega)$ exists a.s. in $[0, \infty]$. For definiteness, let $X_\infty = 0$ on $\Omega_0$. Equation (19.44) is now a consequence of cFatou;

\[
\mathbb{E}[X_\infty|B_n] = \mathbb{E}\left[\lim_{m \to \infty} X_n|B_n\right] \leq \liminf_{m \to \infty} \mathbb{E}[X_n|B_n] \leq \liminf_{m \to \infty} X_n = X_n \text{ a.s.}
\]

The supermartingale property guarantees that $\mathbb{E}X_n \leq \mathbb{E}X_0$ for all $n < \infty$ while taking expectations of Eq. (19.44) implies $\mathbb{E}X_\infty \leq \mathbb{E}X_n$.

Theorem 19.55 (Optional sampling II – Positive supermartingales). Suppose that $X = \{X_n\}_{n=0}^\infty$ is a positive supermartingale, $X_\infty := \lim_{n \to \infty} X_n$ (which exists a.s. by Corollary 19.54), and $\sigma$ and $\tau$ are arbitrary stopping times. Then $X_\tau^n := X_{\tau \land n}$ is a positive $\{B_n\}_{n=0}^\infty –$ supermartingale, $X_\infty^n = \lim_{n \to \infty} X_\tau^n$, and

\[
\mathbb{E}[X_{\tau^n}|B_n] \leq X_{\sigma \land \tau} \text{ a.s.}
\]

(19.46)

Moreover, if $\mathbb{E}X_0 < \infty$, then $\mathbb{E}[X_\tau] = \mathbb{E}[X_\infty] < \infty$.

Proof. We already know that $X^n$ is a positive supermartingale by optional stopping Theorem 19.35. Hence an application of Corollary 19.54 implies that $\lim_{n \to \infty} X^n_\tau = \lim_{n \to \infty} X_{\tau \land n}$ is convergent and

\[
\mathbb{E}\left[\lim_{n \to \infty} X^n_\tau|B_m\right] \leq X_m^n = X_{\tau \land m} \text{ for all } m < \infty.
\]

(19.47)

On the set $\{\tau < \infty\}$, $\lim_{n \to \infty} X^n_{\tau \land n} = X_\tau$ and on the set $\{\tau = \infty\}$, $\lim_{n \to \infty} X^n_{\tau \land n} = \lim_{n \to \infty} X_n = X_\infty = X_\tau$ a.s. Therefore it follows that $\lim_{n \to \infty} X^n_{\tau} = X_\tau$ and Eq. (19.47) may be expressed as

\[
\mathbb{E}[X_{\tau^n}|B_m] \leq X_{\tau \land m} \text{ for all } m < \infty.
\]

(19.48)

An application of Lemma 19.29 now implies

\[
\mathbb{E}[X_{\tau^n}|B_\sigma] = \sum_{m \leq \infty} 1_{\sigma = m} \mathbb{E}[X_{\tau^n}|B_m] \leq \sum_{m \leq \infty} 1_{\sigma = m} X_{\tau \land m} = X_{\tau \land \sigma} \text{ a.s.}
\]

\[5\] If $\mathbb{E}X_0 < \infty$, this may also be deduced by applying Corollary 19.46 to $(-X_n)_{n=0}^\infty$. 

---
19.7 Martingale Closure and Regularity Results

Theorem 19.56. Let $M := \{M_n\}_{n=0}^\infty$ be an $L^1$ - bounded martingale, i.e. $C := \sup_n E |M_n| < \infty$ and let $M_\infty := \lim_{n \to \infty} M_n$ which exists a.s. and satisfies, $E |M_\infty| < \infty$ by Corollary 19.46. Then the following are equivalent:

1. There exists $X \in L^1(\Omega, \mathcal{B}, P)$ such that $M_n = E[X|\mathcal{B}_n]$ for all $n$.
2. $\{M_n\}_{n=0}^\infty$ is uniformly integrable.
3. $M_n \to M_\infty$ in $L^1(\Omega, \mathcal{B}, P)$.

Moreover, if any of the above equivalent conditions hold we may take $X = M_\infty$.

Proof. 1. $\implies$ 2. was already proved in Proposition 19.7. 2. $\implies$ 3. follows from Theorem 11.31.
3. $\implies$ 2. If $M_n \to M_\infty$ in $L^1(\Omega, \mathcal{B}, P)$ and $A \in \mathcal{B}_m$, then $E[M_n : A] = E[M_m : A]$ for all $n \geq m$ and

$$E[M_\infty : A] = \lim_{n \to \infty} E[M_n : A] = E[M_m : A].$$

Since $A \in \mathcal{B}_m$ was arbitrary, it follows that $M_n = E[M_\infty|\mathcal{B}_n]$. $\blacksquare$

Definition 19.57. A martingale satisfying any and all of the equivalent statements in Theorem 19.56 is said to be regular.

Theorem 19.58. Suppose $1 < p < \infty$ and $M := \{M_n\}_{n=0}^\infty$ is an $L^p$ - bounded martingale. Then $M_n \to M_\infty$ almost surely and in $L^p$.

Proof. Again, the almost sure convergence follows from Corollary 19.46. So, because of Corollary 11.34 to finish the proof it suffices to show $\{|M_n|^p\}_{n=0}^\infty$ is uniformly integrable. But by Doob’s inequality, Corollary 19.43 and the MCT, we find

$$E\left[\sup_n |M_n|^p\right] \leq \left(\frac{p}{p-1}\right)^p \sup_n E[|M_n|^p] < \infty.$$}

It now follows by an application of Proposition 11.29 that $\{|M_n|^p\}_{n=0}^\infty$ is uniformly integrable. $\blacksquare$

Theorem 19.59 (Optional sampling III – regular martingales). Suppose that $M = \{M_n\}_{n=0}^\infty$ is a regular martingale, $\alpha$ and $\tau$ are arbitrary stopping times. Define $M_\infty := \lim_{n \to \infty} M_n$ a.s.. Then $M_\infty \in L^1(P)$,

$$M_\tau = E[M_\infty|\mathcal{B}_\tau], \quad E|M_\tau| < \infty$$

and

$$E[M_\tau|\mathcal{B}_\sigma] = M_{\sigma \land \tau} \text{ a.s.}$$

Proof. By Theorem 19.56, $M_\infty \in L^1(\Omega, \mathcal{B}, P)$ and $M_n := E_{\mathcal{B}_n} M_\infty$ a.s. for all $n \leq \infty$. By Lemma 19.29,

$$E_{\mathcal{B}_n} M_\infty = \sum_{n \leq \tau} 1_{\tau = n} E_{\mathcal{B}_n} M_\infty = \sum_{n \leq \tau} 1_{\tau = n} M_n = M_\tau.$$

Hence we have $|M_\tau| = |E_{\mathcal{B}_n} M_\infty| \leq E_{\mathcal{B}_n} |M_\infty|$ a.s. and $E|M_\tau| \leq E|M_\infty| < \infty$. An application of Exercise 19.3 now concludes the proof;

$$E_{\mathcal{B}_n} M_\tau = E_{\mathcal{B}_n} E_{\mathcal{B}_n} M_\infty = E_{\mathcal{B}_n} E_{\mathcal{B}_\tau} M_\infty = M_{\sigma \land \tau}.$$

Definition 19.60. Let $M = \{M_n\}_{n=0}^\infty$ be a martingale. We say that $\tau$ is a regular stopping time for $M$ if $M^\tau$ is a regular martingale.

Remark 19.61. If $\tau$ is regular for $M$, then $\lim_{n \to \infty} M_n^\tau := M_\infty^\tau$ exists a.s. and hence

$$\lim_{n \to \infty} M_n = M_\infty \text{ a.s. on } \{\tau = \infty\}.$$ (19.51)

Thus if $\tau$ is regular for $M$, we may define $M_{\tau}$ as,

$$M_{\tau} := M_\infty^\tau = \lim_{n \to \infty} M_n^\tau.$$ (19.52)

Also observe by Fatou’s lemma that,

$$E|M_\tau| \leq \lim \inf_{n \to \infty} E|M_n^\tau| \leq \sup_n E|M_n^\tau|.$$ (19.53)

Theorem 19.62. Suppose $M = \{M_n\}_{n=0}^\infty$ is a martingale and $\alpha, \tau$, are stopping times such that $\tau$ is a regular stopping time for $M$. Then

1. $E_{\mathcal{B}_n} M_\tau = M_{\tau \land \sigma}$. (19.52)
2. If $\sigma \leq \tau$ a.s. then $M_n^\tau = E_{\mathcal{B}_n} [E_{\mathcal{B}_\tau} M_\tau]$ and $\sigma$ is regular for $M$.

Proof. By assumption, $M_\tau = \lim_{n \to \infty} M_n^\tau$ exists almost surely and in $L^1(P)$ and $M_n^\tau = E[M_\tau|\mathcal{B}_n]$ for $n \leq \infty$.

1. Equation (19.52) is a consequence of;

$$E_{\mathcal{B}_n} M_\tau = \sum_{n \leq \tau} 1_{\tau = n} E_{\mathcal{B}_n} M_\tau = \sum_{n \leq \tau} 1_{\tau = n} M_n^\tau = M_{\sigma \land \tau}. $$

2. By Theorem 19.59 and Exercise 19.3

$$M_n^\sigma = M_{\sigma \land n} = E_{\mathcal{B}_n} M_\infty = E_{\mathcal{B}_n} E_{\mathcal{B}_\tau} M_\infty = E_{\mathcal{B}_n} E_{\mathcal{B}_\tau} M_\tau = \sum_{n \leq \tau} 1_{\tau = n} M_n^\tau = M_{\sigma \land \tau}.$$ from which it follows that $M^\sigma$ is a regular martingale. $\blacksquare$
Proposition 19.63. Suppose that $M$ is a martingale and $\tau$ is a stopping time. Then the $\tau$ is regular for $M$ iff:

1. $\mathbb{E}[|M_\tau| : \tau < \infty] < \infty$ and
2. $\{M_n 1_{\tau < n}\}_{n=0}^\infty$ is a uniformly integrable sequence of random variables.

Moreover, condition 1. is automatically satisfied if $M$ is $L^1$ bounded, i.e. if $C := \sup_n \mathbb{E}[|M_n|] < \infty$.

Proof. ($\Rightarrow$) If $\tau$ is regular for $M$, $M_\tau \in L^1(P)$ and $M_n = \mathbb{E}_n M_\tau$. In particular it follows that

$$\mathbb{E}[|M_\tau| : \tau < \infty] \leq \mathbb{E}|M_\tau| < \infty.$$ 

Moreover,

$$|M_n 1_{\tau < n}| \leq |\mathbb{E}_n M_\tau 1_{\tau < n} - \mathbb{E}_n|M_\tau| \text{ a.s.}$$

from which it follows that $\{M_n 1_{\tau < n}\}_{n=0}^\infty$ is uniformly integrable.

($\Leftarrow$) Our goal is to show $\{M_n\}_{n=0}^\infty$ is uniformly integrable. We begin with the identity;

$$\mathbb{E}[|M_\tau| : |M_\tau|^a \leq a] = \mathbb{E}[|M_\tau| : |M_\tau|^a \leq a, \tau \leq n] + \mathbb{E}[|M_n| : |M_n|^a \geq a, \tau < n].$$

Since (by assumption 1.) $\mathbb{E}[|M_\tau| : \tau < \infty] < \infty$ and

$$\mathbb{E}[|M_\tau| : |M_\tau|^a \leq a, \tau \leq n] \leq \mathbb{E}[M_\tau 1_{\tau < \infty}] : |M_\tau 1_{\tau < \infty}| \geq a],$$

if follows that

$$\lim_{n \to \infty} \sup_{a \leq n} \mathbb{E}[|M_\tau| : |M_\tau|^a \leq a, \tau \leq n] = 0.$$ 

Moreover,

$$\sup_n \mathbb{E}[|M_n| : |M_n|^a \geq a, n < \tau] = \sup_n \mathbb{E}[|M_n 1_{\tau < n}| : |M_n 1_{\tau < n}| \geq a]$$

goes to zero as $n \to \infty$ by assumption 2. Hence we have shown,

$$\lim_{a \to \infty} \sup_n \mathbb{E}[|M_n| : |M_n|^a \geq a] = 0$$

as desired.

For the last assertion, by Corollary 19.64, $M_{\infty} := \lim_{n \to \infty} M_n$ a.s. and $\mathbb{E}|M_{\infty}| < \infty$. Therefore,

$$\mathbb{E}[|M_\tau| : \tau < \infty] \leq \mathbb{E}|M_\tau| = \mathbb{E}\left[\lim_{n \to \infty} |M_{\tau \wedge n}|\right]$$

$$\leq \liminf_{n \to \infty} \mathbb{E}[|M_{\tau \wedge n}|] \leq \liminf_{n \to \infty} \mathbb{E}[|M_n|] < \infty$$

wherein we have used the optional sampling theorem ($M_{\tau \wedge n} = \mathbb{E}_{\tau \wedge n} M_n$) and Jensen to conclude $|M_{\tau \wedge n}| \leq \mathbb{E}_{\tau \wedge n}|M_n|$. ■

Corollary 19.64. Suppose that $M$ is an $L^1$ bounded martingale and $J \subset \mathbb{R}$ is a bounded set, then $\tau := \inf\{n : M_n \notin J \}$ is a regular stopping time for $M$.

Proof. According to Proposition 19.63, it suffices to show $\{M_n 1_{n < \tau}\}_{n=0}^\infty$ is a uniformly integrable sequence of random variables. However, if we choose $A < \infty$ such that $J \subset [-A, A]$, since $M_n 1_{n < \tau} \in J$ we have $|M_n 1_{n < \tau}| \leq A$ which is sufficient to complete the proof. ■

Exercise 19.6. Suppose $\{M_n\}_{n=0}^\infty$ is a square integrable martingale. Show;

1. $\mathbb{E}[M_{n+1}^2 - M_n^2 | \mathcal{B}_n] = \mathbb{E}[(M_{n+1} - M_n)^2 | \mathcal{B}_n]$. Conclude from this that the Doob decomposition of $M_n^2$ is of the form,

$$M_n^2 = N_n + A_n$$

where

$$A_n := \sum_{1 \leq k \leq n} \mathbb{E}[(M_k - M_{k-1})^2 | \mathcal{B}_{k-1}].$$

2. If we further assume that $M_k - M_{k-1}$ is independent of $\mathcal{B}_{k-1}$ for all $k = 1, 2, \ldots$, explain why,

$$A_n = \sum_{1 \leq k \leq n} \mathbb{E}(M_k - M_{k-1})^2.$$ 

For the next four exercises, let $\{Z_n\}_{n=1}^\infty$ be a sequence of Bernoulli random variables with $P(Z_n = \pm 1) = \frac{1}{2}$ and let $S_0 = 0$ and $S_n := Z_1 + \cdots + Z_n$. Then $S$ becomes a martingale relative to the filtration, $\mathcal{B}_n := \sigma(Z_1, \ldots, Z_n)$ with $\mathcal{B}_0 := \{\emptyset, \Omega\}$ – of course $S_n$ is the (fair) simple random walk on $\mathbb{Z}$. For any $a \in \mathbb{Z}$, let

$$\sigma_a := \inf\{n : S_n = a\}.$$ 

Exercise 19.7. For $a < 0 < b$ with $a, b \in \mathbb{Z}$, let $\tau = \sigma_a \land \sigma_b$. Explain why $\tau$ is regular for $S$. Use this to show $P(\tau = \infty) = 0$. Hint: make use of Remark 19.61 and the fact that $|S_n - S_{n-1}| = |Z_n| = 1$ for all $n$.

Exercise 19.8. In this exercise, you are asked to give a central limit theorem argument for the result, $P(\tau = \infty) = 0$, Exercise 19.7. Hints: Use the central limit theorem to show

$$\frac{1}{\sqrt{2\pi}} \int_{\mathbb{R}} f(x) e^{-x^2/2} dx \geq f(0) P(\tau = \infty)$$

for all bounded continuous functions, $f : \mathbb{R} \to [0, \infty)$. Use this inequality to conclude that $P(\tau = \infty) = 0$. 

Exercise 19.9. Show
\[ P(\sigma_b < \sigma_a) = \frac{|a|}{b + |a|} \]  
(19.54)
and use this to conclude \( P(\sigma_b < \infty) = 1 \), i.e. every \( b \in \mathbb{N} \) is almost surely visited by \( S_n \). (This last result also follows by the Hewitt-Savage Zero-One Law, see Example 7.45 where it is shown \( b \) is visited infinitely often.)

**Hint:** Using properties of martingales and Exercise 19.7 compute \( \lim_{n \to \infty} \mathbb{E}[S_n^{\sigma_b \wedge \sigma_a}] \) in two different ways.

Exercise 19.10. Let \( \tau := \sigma_a \wedge \sigma_b \). In this problem you are asked to show \( \mathbb{E}[\tau] = |a|/b \) with the aid of the following outline.

1. Use Exercise 19.6 above to conclude \( N_n := S_n^2 - n \) is a martingale.
2. Now show
\[ 0 = \mathbb{E}N_0 = \mathbb{E}N_{\tau \wedge n} = \mathbb{E}S_{\tau \wedge n}^2 - \mathbb{E}[(\tau \wedge n)^2] \]  
(19.55)
3. Now use DCT and MCT along with Exercise 19.9 to compute the limit as \( n \to \infty \) in Eq. (19.55) to find
\[ \mathbb{E}[\sigma_a \wedge \sigma_b] = \mathbb{E}[\tau] = b|a| \]  
(19.56)
4. By considering the limit, \( a \to -\infty \) in Eq. (19.56), show \( \mathbb{E}[\sigma_b] = \infty \).

### 19.7.1 More Random Walk Exercises

Suppose now that \( P(Z_n = 1) = p > 1/2 \) and \( P(Z_n = -1) = q = 1 - p < 1/2 \). As before let \( B_n = \sigma(Z_1, \ldots, Z_n) \), \( S_0 = 0 \) and \( S_n = Z_1 + \cdots + Z_n \) for \( n \in \mathbb{N} \). In order to follow the procedures above, we start by looking for a function, \( \varphi \), such that \( \varphi(S_n) \) is a martingale. Such a function must satisfy,
\[ \varphi(S_n) = \mathbb{E}B_n \varphi(S_{n+1}) = \varphi(S_n + 1) p + \varphi(S_n - 1) q, \]
and this then leads us to try to solve the following difference equation for \( \varphi \);
\[ \varphi(x) = px \varphi(x + 1) + qx \varphi(x - 1) \quad \text{for all } x \in \mathbb{Z}. \]  
(19.57)

Similar to the theory of second order ODE’s this equation has two linearly independent solutions which could be found by solving Eq. (19.57) with initial conditions, \( \varphi(0) = 1 \) and \( \varphi(1) = 0 \) and then with \( \varphi(0) = 0 \) and \( \varphi(1) = 1 \) for example. Rather than doing this, motivated by second order constant coefficient ODE’s, let us try to find solutions of the form \( \varphi(x) = \lambda^x \) with \( \lambda \) to be determined. Doing so leads to the equation, \( \lambda x = p\lambda x+1 + q\lambda x-1 \), or equivalently to the **characteristic equation**, \( p\lambda^2 - \lambda + q = 0 \).

The solutions to this equation are
\[ \lambda = \frac{1 \pm \sqrt{1 - 4pq}}{2p} = \frac{1 \pm \sqrt{1 - 4p(1 - p)}}{2p} \]
\[ = \frac{1 \pm \sqrt{4p^2 - 4p + 1}}{2p} = \frac{1 \pm \sqrt{(2p - 1)^2}}{2p} = \{1, (1 - p)/p\} = \{1, q/p\}. \]
The most general solution to Eq. (19.57) is then given by
\[ \varphi(x) = A + B(q/p)^x. \]
Below we will take \( A = 0 \) and \( B = 1 \). As before let \( \sigma_a = \inf\{n \geq 0 : S_n = a\} \).

Exercise 19.11. Let \( a < 0 < b \) and \( \tau := \sigma_a \wedge \sigma_b \).

1. Apply the method in Exercise 19.7 with \( S_n \) replaced by \( M_n := (q/p)^{S_n} \) to show \( P(\tau = \infty) = 0 \).
2. Now use the method in Exercise 19.9 to show
\[ P(\sigma_a < \sigma_b) = \frac{(q/p)^b - 1}{(q/p)^b - (q/p)^a}. \]  
(19.58)
3. By letting \( a \to -\infty \) in Eq. (19.58), conclude \( P(\sigma_b = \infty) = 0 \).
4. By letting \( b \to \infty \) in Eq. (19.58), conclude \( P(\sigma_a < \infty) = (q/p)^{|a|} \).

Exercise 19.12. Verify,
\[ M_n := S_n - n(p - q) \]
and
\[ N_n := M_n^2 - \sigma^2 n \]
are martingales, where \( \sigma^2 = 1 - (p - q)^2 \).

\[ \mathbb{E}(\sigma_a \wedge \sigma_b) = \left(\frac{b[1 - (q/p)^a] + a[(q/p)^b - 1]}{(q/p)^b - (q/p)^a}\right)(p - q)^{-1}. \]  
(19.59)
By considering the limit of this equation as \( a \to -\infty \), show
\[ \mathbb{E}[\sigma_b] = \frac{b}{p - q} \]  
and by considering the limit as \( b \to \infty \), show \( \mathbb{E}[\sigma_a] = \infty \).
19.8 More Exercises:

Exercise 19.14. Let \((M_n)_{n=0}^\infty\) be a martingale with \(M_0 = 0\) and \(E[M_n^2] < \infty\) for all \(n\). Show that for all \(\lambda > 0\),

\[
P \left( \max_{1 \leq m \leq n} M_m \geq \lambda \right) \leq \frac{E[M_n^2]}{E[M_n^2] + \lambda^2}.
\]

Hints: First show that for any \(c > 0\) that \(\{X_n := (M_n + c^2)_{n=0}^\infty\) is a submartingale and then observe,

\[
\left\{ \max_{1 \leq m \leq n} M_m \geq \lambda \right\} \subset \left\{ \max_{1 \leq m \leq n} X_n \geq (\lambda + c)^2 \right\}.
\]

Now use Doob’ Maximal inequality to estimate the probability of the last set and then choose \(c\) so as to optimize the resulting estimate you get for \(P(\max_{1 \leq m \leq n} M_m \geq \lambda)\).

Exercise 19.15. Let \(\{Z_n\}_{n=1}^\infty\) be independent random variables, \(S_0 = 0\) and \(S_n := Z_1 + \cdots + Z_n\), and \(f_n(\lambda) := \mathbb{E}[e^{\lambda Z_n}]\). Suppose \(\mathbb{E}e^{\lambda S_n} = \prod_{n=1}^{\infty} f_n(\lambda)\) converges to a continuous function, \(F(\lambda)\), as \(N \to \infty\). Show for each \(\lambda \in \mathbb{R}\) that

\[
P \left( \lim_{n \to \infty} e^{\lambda S_n} \right) = 1. \tag{19.60}
\]

Hints:

1. Show it is enough to find an \(\varepsilon > 0\) such that Eq. (19.60) holds for \(|\lambda| \leq \varepsilon\).
2. Choose \(\varepsilon > 0\) such that \(|F(\lambda) - 1| < 1/2\) for \(|\lambda| \leq \varepsilon\). For \(|\lambda| \leq \varepsilon\), show

\[M_n(\lambda) := \frac{e^{\lambda Z_n}}{\mathbb{E}e^{\lambda Z_n}}\]

is a bounded complex martingale relative to the filtration, \(\mathcal{F}_n = \sigma(Z_1, \ldots, Z_n)\).

Exercise 19.16 (Continuation of Exercise 19.15). Let \(\{Z_n\}_{n=1}^\infty\) be independent random variables. Prove the series, \(\sum_{n=1}^{\infty} Z_n\), converges in \(\mathbb{R}\) a.s. iff \(\prod_{n=1}^{\infty} f_n(\lambda)\) converges to a continuous function, \(F(\lambda)\) as \(N \to \infty\). Conclude from this that \(\sum_{n=1}^{\infty} Z_n\) is a.s. convergent iff \(\sum_{n=1}^{\infty} Z_n\) is convergent in distribution. (See Doob [2] Chapter VII.5.)

6 Please use the obvious generalization of a martingale for complex valued processes. It will be useful to observe that the real and imaginary parts of a complex martingales are real martingales.

19.9 Backwards Submartingales

In this section we will consider submartingales indexed by \(\mathbb{Z}_- := \{\ldots, -n, -n+1, \ldots, -2, -1\}\). So again we assume that we have an increasing filtration, \(\{\mathcal{B}_n : n \leq 0\}\), i.e., \(\cdots \subset \mathcal{B}_{-2} \subset \mathcal{B}_{-1} \subset \mathcal{B}_0 \subset \mathcal{B}\). As usual, we say an adapted process \(\{X_n\}_{n \leq 0}\) is a submartingale (martingale) provided \(\mathbb{E}[X_m - X_n | \mathcal{B}_n] \geq 0\) for all \(m \geq n\). Observe that \(\mathbb{E}X_n \geq \mathbb{E}X_0\) for \(m \geq n\), so that \(\mathbb{E}X_n\) decreases as \(n\) increases. Also observe that \((X_n, X_{n-1}, \ldots, X_0)\) is a “finite string” submartingale relative to the filtration, \(\mathcal{B}_n \subset \mathcal{B}_{n-1} \subset \cdots \subset \mathcal{B}_{-1} \subset \mathcal{B}_0\).

Theorem 19.65 (Backwards Submartingale Convergence). Let \(\{\mathcal{B}_n : n \leq 0\}\) be a reverse filtration, \(\{X_n\}_{n \leq 0}\) is a backwards submartingale. Then \(X_\infty = \lim_{n \to \infty} X_n\) exists a.s. in \(-\infty \cup \mathbb{R}\) and \(X_\infty^+ \in L^1(\Omega, \mathcal{B}, \mathbb{P})\).

If we further assume that

\[
C := \lim_{n \to \infty} \mathbb{E}X_n = \inf_{n \leq 0} \mathbb{E}X_n > -\infty, \tag{19.61}
\]

then \(\{X_n\}_{n \leq 0}\) uniformly integrable, \(X_\infty \in L^1(\Omega, \mathcal{B}, \mathbb{P})\), and

\[
\lim_{n \to \infty} \mathbb{E}[X_n - X_\infty] = 0.
\]

Proof. The number of downcrossings of \((X_0, X_{-1}, \ldots, X_{-(n-1)}, X_{-n})\) across \([a, b]\), (denoted by \(D_n(a, b)\)) is equal to the number of upcrossings, \((X_n, X_{n-1}, \ldots, X_{1}, X_0)\) across \([a, b]\). Since \((X_n, X_{n-1}, \ldots, X_{1}, X_0)\) is a submartingale relative to the filtration, \(\mathcal{B}_n \subset \mathcal{B}_{n-1} \subset \cdots \subset \mathcal{B}_{-1} \subset \mathcal{B}_0\), we may apply Doob’s upcrossing inequality (Theorem 19.45) to find;

\[
(b - a) \mathbb{E}[D_n(a, b)] \leq \mathbb{E}(X_0 - a)^+ - \mathbb{E}(X_n - a)^+ \\
\leq \mathbb{E}(X_0 - a)^+ < \infty. \tag{19.62}
\]

Letting \(D_\infty(a, b) := \lim_{n \to \infty} D_n(a, b)\) be the total number of downcrossing of \((X_0, X_{-1}, \ldots, X_{-n}, \ldots)\), using the MCT to pass to the limit in Eq. (19.62), we have

\[
(b - a) \mathbb{E}[D_\infty(a, b)] \leq \mathbb{E}(X_0 - a)^+ < \infty.
\]

In particular it follows that \(D_\infty(a, b) < \infty\) a.s. for all \(a < b\). As in the proof of Corollary 19.44 (making use of the obvious downcrossing analogue of Lemma 19.44), it follows that \(X_\infty := \lim_{n \to \infty} X_n\) exists in \(\mathbb{R}\) a.s. At the end of the proof, we will show that \(X_\infty\) takes values in \(-\infty \cup \mathbb{R}\) almost surely.

Now suppose that \(C > -\infty\). We begin by computing the Doob decomposition of \(X_n\) as \(X_n = M_n + A_n\) with \(A_n\) being predictable, increasing and satisfying, \(A_\infty = \lim_{n \to \infty} A_n = 0\). If such an \(A\) is to exist, following Lemma 19.13, we should define
$A_n = \sum_{k \leq n} \mathbb{E} [\Delta_k X | B_{k-1}]$. 

This is a well defined increasing predictable process since that submartingale property implies $\mathbb{E} [\Delta_k X | B_{k-1}] \geq 0$. Moreover we have 

$$
\mathbb{E} A_0 = \sum_{k \leq 0} \mathbb{E} [\mathbb{E} [\Delta_k X | B_{k-1}]] = \sum_{k \leq 0} \mathbb{E} [\Delta_k X] = \lim_{N \to -\infty} (\mathbb{E} X_0 - \mathbb{E} X_{-N}) = \mathbb{E} X_0 - \inf_{n \leq 0} \mathbb{E} X_n = \mathbb{E} X_0 - C < \infty.
$$

As $0 \leq A_n \leq A_n^*$, $A_0 \in L^1 (P)$, it follows that $\{A_n\}_{n \leq 0}$ is uniformly integrable. Moreover if we define $M_n := X_n - A_n$, then

$$
\mathbb{E} [\Delta_n M | B_{n-1}] = \mathbb{E} [\Delta_n X - \Delta_n A | B_{n-1}] = \mathbb{E} [\Delta_n X | B_{n-1}] - \Delta_n A = 0 \text{ a.s.}
$$

Thus $M$ is a martingale and therefore, $M_n = \mathbb{E} [M_0 | B_n]$ with $M_0 = X_0 - A_0 \in L^1 (P)$. An application of Proposition 19.7 implies $\{M_n\}_{n \leq 0}$ is uniformly integrable and hence $X_n = M_n + A_n$ is uniformly integrable as well. (See Remark 19.66 for an alternate proof of the uniform integrability of $X$.) Therefore $X_\infty \in L^1 (\Omega, B, P)$ and $X_n \to X_\infty$ in $L^1 (\Omega, B, P)$ as $n \to \infty$.

To finish the proof we must show, with out assumptions on $C > -\infty$, that $X_\infty^+ \in L^1 (\Omega, B, P)$ which will certainly imply $P (X_\infty = \infty) = 0$. To prove this, notice that $X_\infty^+ = \lim_{n \to -\infty} X_n^+$ and that by Jensen's inequality, $\{X_n^+\}_{n \leq -1}$ is a non-negative backwards submartingale. Since $\inf \mathbb{E} X_n^+ \geq 0 > -\infty$, it follows by what we have just proved that $X_\infty^+ \in L^1 (\Omega, B, P)$.

**Remark 19.66.** Let us give a direct proof of the fact that $X$ is uniformly integrable if $C > -\infty$. We begin with Jensen's inequality;

\[
\mathbb{E} |X_n| = 2 \mathbb{E} X_n^+ - \mathbb{E} X_n \leq 2 \mathbb{E} X_0^+ - \mathbb{E} X_n \leq 2 \mathbb{E} X_0^+ - C = K < \infty,
\]

which shows that $\{X_n\}_{n \leq 1}$ is $L^1$-bounded. For uniform integrability we will use the following identity;

\[
\mathbb{E} [\mathbb{E} [X] : |X| \geq \lambda] = \mathbb{E} [\mathbb{E} [X : X \geq \lambda]] - \mathbb{E} [\mathbb{E} [X : X \leq -\lambda]] \\
= \mathbb{E} [\mathbb{E} [X : X = \lambda]] - (\mathbb{E} X - \mathbb{E} [\mathbb{E} [X : X > -\lambda]]) \\
= \mathbb{E} [\mathbb{E} [X : X \geq \lambda]] + \mathbb{E} [\mathbb{E} [X : X > -\lambda]] - \mathbb{E} X.
\]

Taking $X = X_n$ and $k \geq n$, we find

\[
\mathbb{E} [\mathbb{E} [X_n] : |X_n| \geq \lambda] = \mathbb{E} [X_n : X_n \geq \lambda] + \mathbb{E} [X_n : X_n > -\lambda] - \mathbb{E} X_n \\
\leq \mathbb{E} [X_k : X_k \geq \lambda] + \mathbb{E} [X_k : X_k > -\lambda] - \mathbb{E} X_k + (\mathbb{E} X_k - \mathbb{E} X_n) \\
= \mathbb{E} [X_k : X_k \geq \lambda] - \mathbb{E} [X_k : X_k \leq -\lambda] + (\mathbb{E} X_k - \mathbb{E} X_n) \\
= \mathbb{E} [\mathbb{E} [X_k] : |X_k| \geq \lambda] + (\mathbb{E} X_k - \mathbb{E} X_n).
\]

Given $\varepsilon > 0$ we may choose $k = k_\varepsilon$ so that if $n \leq k$, $0 \leq \mathbb{E} X_n - \mathbb{E} X_n \leq \varepsilon$ and hence

\[
\lim \sup \sup_{n \leq k} \mathbb{E} [\mathbb{E} [X_n] : |X_n| \geq \lambda] \leq \lim \sup \mathbb{E} [\mathbb{E} [X_n] : |X_n| \geq \lambda] + \varepsilon \leq \varepsilon
\]

wherein we have used Eq. (19.63). Chebyshev's inequality to conclude $P (|X_n| \geq \lambda) \leq K / \lambda$ and then the uniform integrability of the singleton set, $\{|X_k|\} \in L^1 (\Omega, B, P)$. From this it now easily follows that $\{X_n\}_{n \leq 0}$ is a uniformly integrable.

**Corollary 19.67.** Suppose $1 \leq p < \infty$ and $M_n$ in Theorem 19.65 is an $L^p$-bounded martingale. Then $M_n \to M_\infty$ in $L^p (P)$. Moreover $M_\infty = \mathbb{E} [M_0 | B_\infty]$.

**Proof.** Since $M_n = \mathbb{E} [M_0 | B_n]$ for all $n$, it follows by Jensen that $|M_n|^p \leq \mathbb{E} [|M_0|^p | B_n]$ for all $n$. By Proposition 19.7, $\{\mathbb{E} [M_0^p | B_n]\}_{n \leq 0}$ is uniformly integrable and so is $\{M_n|^p\}_{n \leq 0}$. By Theorem 19.65, $M_n \to M_\infty$ a.s. Hence we may now apply Corollary 11.34 to see that $M_n \to M_\infty$ in $L^p (P)$.

**Example 19.68 (SLLN).** In this example we are going to give another proof of the strong law of large numbers in Theorem 12.44. Let $\{X_n\}_{n \leq 1}$ be i.i.d. random variables such that $\mathbb{E} X_n = 0$ and let $S_n := X_1 + \cdots + X_n$ and $B_n = \sigma (S_n, S_{n+1}, S_{n+2}, \ldots)$ so that $S_n$ is $B_n$ measurable for all $n$.

1. For any permutation $\sigma$ of the set $\{1, 2, \ldots, n\}$,

\[
(X_1, \ldots, X_n, S_n^*, S_{n+1}^*, S_{n+2}^*, \ldots) \overset{d}{=} (X_1, \ldots, X_n, S_n, S_{n+1}, S_{n+2}, \ldots)
\]

and in particular

\[
(X_j, S_n, S_{n+1}, S_{n+2}, \ldots) \overset{d}{=} (X_1, S_n, S_{n+1}, S_{n+2}, \ldots) \text{ for all } j \leq n.
\]

2. By Exercise 18.8 we may conclude that

\[
\mathbb{E} [X_j | S_n, S_{n+1}, S_{n+2}, \ldots] = \mathbb{E} [X_1 | S_n, S_{n+1}, S_{n+2}, \ldots] \text{ for all } j \leq n.
\]

3. Summing Eq. (19.64) over $j = 1, 2, \ldots, n$ gives,

\[
S_n = \mathbb{E} [S_n | S_n, S_{n+1}, S_{n+2}, \ldots] = n \mathbb{E} [X_1 | S_n, S_{n+1}, S_{n+2}, \ldots]
\]

from which it follows that

\[
M_n := \frac{S_n}{n} := \mathbb{E} [X_1 | S_n, S_{n+1}, S_{n+2}, \ldots]
\]

and hence $\{M_n = \frac{1}{n} S_n\}$ is a backwards martingale.
4. By Theorem 19.65 we know;
\[ \lim_{n \to \infty} \frac{S_n}{n} = \lim_{n \to \infty} M_n \text{ exists a.s.} \]

5. By Kolmogorov’s zero one law (Proposition 7.41) we know that
\[ \lim_{n \to \infty} \frac{S_n}{n} = c \text{ a.s. for some constant } c. \]

6. Equation (19.65) along with Proposition 19.7 shows \( \{ \frac{S_n}{n} \}_{n=1}^\infty \) is uniformly integrable. Therefore,
\[ \lim_{n \to \infty} \frac{S_n}{n} \text{ a.s.} = c = E \left[ \lim_{n \to \infty} \frac{S_n}{n} \right] = \lim_{n \to \infty} E \left[ \frac{S_n}{n} \right] = E X_1 \]

wherein we have use Theorem [1.31] to justify the interchange of the limit with the expectation. This shows \( c = E X_1 \).

We have proved the strong law of large numbers.

19.10 Appendix: Some Alternate Proofs

This section may be safely omitted.

**Proof. Alternate proof of Theorem 19.36** Let \( A \in \mathcal{B}_\sigma \). Then
\[ E [X_\tau - X_\sigma : A] = E \left[ \sum_{k=0}^{N-1} 1_{\sigma \leq k < \tau} \Delta_{k+1} X : A \right] \]
\[ = E \left[ \sum_{k=1}^N \Delta_k X : A \cap \{ \sigma \leq k < \tau \} \right]. \]

Since \( A \in \mathcal{B}_\sigma \), \( A \cap \{ \sigma \leq k \} \in \mathcal{B}_k \) and since \( \{ k < \tau \} = \{ \tau \leq k \}^c \in \mathcal{B}_k \), it follows that \( A \cap \{ \sigma \leq k < \tau \} \in \mathcal{B}_k \). Hence we know that
\[ E [\Delta_{k+1} X : A \cap \{ \sigma \leq k < \tau \}] \leq 0 \text{ respectively.} \]

and hence that
\[ E [X_\tau - X_\sigma : A] \geq 0 \text{ respectively.} \]

Since this true for all \( A \in \mathcal{B}_\sigma \), Eq. (19.21) follows.

**Lemma 19.69.** Suppose \( (\Omega, \mathcal{B}, \{ \mathcal{B}_n \}_{n=0}^\infty, P) \) is a filtered probability space, \( 1 \leq p < \infty \), and let \( \mathcal{B}_\infty := \bigvee_{n=1}^\infty \mathcal{B}_n := \sigma (\bigcup_{n=1}^\infty \mathcal{B}_n) \). Then \( \bigcup_{n=1}^\infty L^p (\Omega, \mathcal{B}_n, P) \) is dense in \( L^p (\Omega, \mathcal{B}_\infty, P) \).

**Proof.** Let \( M_n := L^p (\Omega, \mathcal{B}_n, P) \), then \( M_n \) is an increasing sequence of closed subspaces of \( M_\infty = L^p (\Omega, \mathcal{B}_\infty, P) \). Further let \( \mathcal{A} \) be the algebra of functions consisting of those \( f \in \bigcup_{n=1}^\infty M_n \) such that \( f \) is bounded. As a consequence of the density Theorem 9.8 we know that \( \mathcal{A} \) and hence \( \bigcup_{n=1}^\infty M_n \) is dense in \( M_\infty = L^p (\Omega, \mathcal{B}_\infty, P) \). This completes the proof. However for the readers convenience let us quickly review the proof of Theorem 9.8 in this context.

Let \( \mathcal{H} \) denote those bounded \( \mathcal{B}_\infty \) – measurable functions, \( f : \Omega \to \mathbb{R} \), for which there exists \( \{ \varphi_n \}_{n=1}^\infty \subset \mathcal{A} \) such that \( \lim_{n \to \infty} \| f - \varphi_n \|_{L^p (\mathcal{P})} = 0 \). A routine check shows \( \mathcal{H} \) is a subspace of the bounded \( \mathcal{B}_\infty \) – measurable \( \mathbb{R} \) – valued functions on \( \Omega \), \( 1 \in \mathcal{H} \), \( \mathcal{A} \subset \mathcal{H} \) and \( \mathcal{H} \) is closed under bounded convergence. To verify the latter assertion, suppose \( f_n \in \mathcal{H} \) and \( f_n \to f \) boundedly. Then, by the dominated (or bounded) convergence theorem, \( \lim_{n \to \infty} \| f - f_n \|_{L^p (\mathcal{P})} = 0 \).

We may now choose \( \varphi_n \in \mathcal{A} \) such that \( \| f - f_n \|_{L^p (\mathcal{P})} \leq \frac{1}{n} \) then
\[ \limsup_{n \to \infty} \| f - \varphi_n \|_{L^p (\mathcal{P})} \leq \limsup_{n \to \infty} \| (f - f_n) \|_{L^p (\mathcal{P})} = 0 + \limsup_{n \to \infty} \| f_n - \varphi_n \|_{L^p (\mathcal{P})} = 0, \]

which implies \( f \in \mathcal{H} \).

An application of Dynkin’s Multiplicative System Theorem 9.3 now shows \( \mathcal{H} \) contains all bounded \( \sigma (\mathcal{A}) = \mathcal{B}_\infty \) – measurable functions on \( \Omega \). Since for any \( f \in L^p (\Omega, \mathcal{B}, P) \), \( 1_{|f| \leq \varphi} \in \mathcal{H} \) there exists \( \varphi_n \in \mathcal{A} \) such that \( \| f_n - \varphi_n \|_p \leq n^{-1} \). Using the DCT we know that \( f_n \to f \) in \( L^p \) and therefore by Minikowski’s inequality it follows that \( \varphi_n \to f \) in \( L^p \).

**Theorem 19.70.** Suppose \( (\Omega, \mathcal{B}, \{ \mathcal{B}_n \}_{n=0}^\infty, P) \) is a filtered probability space, \( 1 \leq p < \infty \), and let \( \mathcal{B}_\infty := \bigvee_{n=1}^\infty \mathcal{B}_n := \sigma (\bigcup_{n=1}^\infty \mathcal{B}_n) \). Then for every \( X \in L^p (\Omega, \mathcal{B}, P) \), \( X = E [X | \mathcal{B}] \) is a martingale and \( X_n \to X_\infty := E [X | \mathcal{B}_\infty] \) in \( L^p (\Omega, \mathcal{B}_\infty, P) \) as \( n \to \infty \).

**Proof.** We have already seen in Example 19.5 that \( X_n = E [X | \mathcal{B}_n] \) is always a martingale. Since conditional expectation is a contraction on \( L^p \) it follows that \( E [X_n]^p \leq E [X]^p < \infty \) for all \( n \in \mathbb{N} \setminus \{ \infty \} \). So to finish the proof we need to show \( X_n \to X_\infty \) in \( L^p (\Omega, \mathcal{B}, P) \) as \( n \to \infty \).

Let \( M_n := L^p (\Omega, \mathcal{B}_n, P) \) and \( M_\infty = L^p (\Omega, \mathcal{B}_\infty, P) \). If \( X \in \bigcup_{n=1}^\infty M_n \), then \( X_n = X \) for sufficiently large \( n \) and for \( n = \infty \). Now suppose that \( X \in M_\infty \) and \( Y \in \bigcup_{n=1}^\infty M_n \). Then
\[ \| E_{\mathcal{B}_\infty} X - E_{\mathcal{B}_n} X \|_p \leq \| E_{\mathcal{B}_\infty} X - E_{\mathcal{B}_\infty} Y \|_p + \| E_{\mathcal{B}_\infty} Y - E_{\mathcal{B}_n} Y \|_p + \| E_{\mathcal{B}_n} Y - E_{\mathcal{B}_n} X \|_p \leq 2 \| X - Y \|_p + \| E_{\mathcal{B}_\infty} Y - E_{\mathcal{B}_n} Y \|_p \]

and hence

\[ \text{7 It is at this point that the proof would break down if } p = \infty. \]

\[ \]
\[ \limsup_{n \to \infty} \|E_{B_n} X - E_{B_n} X \|_p \leq 2 \|X - Y\|_p. \]

Using the density Lemma 19.69 we may choose \( Y \in \bigcup_{n=1}^{\infty} M_n \) as close to \( X \in M_\infty \) as we please and therefore it follows that \( \limsup_{n \to \infty} \|E_{B_n} X - E_{B_n} X \|_p = 0 \).

For general \( X \in L^p (\Omega, \mathcal{B}, P) \) it suffices to observe that \( X_\infty := \mathbb{E} [X | \mathcal{B}_\infty] \in L^p (\Omega, \mathcal{B}_\infty, P) \) and by the tower property of conditional expectations,

\[ \mathbb{E} [X | \mathcal{B}_n] = \mathbb{E} [\mathbb{E} [X | \mathcal{B}_\infty] | \mathcal{B}_n] = \mathbb{E} [X | \mathcal{B}_n] = X_n. \]

So again \( X_n \to X_\infty \) in \( L^p \) as desired.

We are now ready to prove the converse of Theorem 19.70.

**Theorem 19.71.** Suppose \((\Omega, \mathcal{B}, \{\mathcal{B}_n\}_{n=0}^{\infty}, P)\) is a filtered probability space, \(1 \leq p < \infty\), \(\mathcal{B}_\infty := \bigvee_{n=1}^{\infty} \mathcal{B}_n := \sigma (\bigcup_{n=1}^{\infty} \mathcal{B}_n)\), and \(\{X_n\}_{n=0}^{\infty} \subset L^p (\Omega, \mathcal{B}, P)\) is a martingale. Further assume that \( \sup_n \|X_n\|_p < \infty \) and that \( \{X_n\}_{n=0}^{\infty} \) is uniformly integrable if \( p = 1 \). Then there exists \( X_\infty \in L^p (\Omega, \mathcal{B}_\infty, P) \) such that \( X_n := \mathbb{E} [X | \mathcal{B}_\infty] \). Moreover by Theorem 19.70 we know that \( X_n \to X_\infty \) in \( L^p (\Omega, \mathcal{B}_\infty, P) \) as \( n \to \infty \) and hence \( X_\infty \) is uniquely determined by \( \{X_n\}_{n=0}^{\infty} \).

**Proof.** By Theorems 16.19 and 16.21 there exists \( X_n \in L^p (\Omega, \mathcal{B}_\infty, P) \) and a subsequence, \( Y_k = X_{n_k} \), such that

\[ \lim_{k \to \infty} \mathbb{E} [Y_k h] = \mathbb{E} [X h] \text{ for all } h \in L^q (\Omega, \mathcal{B}_\infty, P), \]

where \( q := (p - 1)^{-1} \). Using the martingale property, if \( h \in (\mathcal{B}_n) \) for some \( n \), it follows that \( \mathbb{E} [Y_k h] = \mathbb{E} [X h] \) for all large \( k \) and therefore that

\[ \mathbb{E} [X h] = \mathbb{E} [X h] \text{ for all } h \in (\mathcal{B}_n). \]

This implies that \( X_n = \mathbb{E} [X | \mathcal{B}_n] \) as desired.

**Theorem 19.72 (Almost sure convergence).** Suppose \((\Omega, \mathcal{B}, \{\mathcal{B}_n\}_{n=0}^{\infty}, P)\) is a filtered probability space, \(1 \leq p < \infty\), and let \(\mathcal{B}_\infty := \bigvee_{n=1}^{\infty} \mathcal{B}_n := \sigma (\bigcup_{n=1}^{\infty} \mathcal{B}_n). Then for every \( X \in L^1 (\Omega, \mathcal{B}, P)\) , the martingale, \( X_n = \mathbb{E} [X | \mathcal{B}_n] \), converges almost surely to \( X_\infty := \mathbb{E} [X | \mathcal{B}_\infty] \).

Before starting the proof, recall from Proposition 1.5 if \( \{a_n\}_{n=1}^{\infty} \) and \( \{b_n\}_{n=1}^{\infty} \) are two bounded sequences, then

\[ \limsup_{n \to \infty} (a_n + b_n) - \liminf_{n \to \infty} (a_n + b_n) \]

\[ \leq \limsup_{n \to \infty} a_n + \limsup_{n \to \infty} b_n - \left( \liminf_{n \to \infty} a_n + \liminf_{n \to \infty} b_n \right) \]

\[ = \limsup_{n \to \infty} a_n - \liminf_{n \to \infty} a_n + \limsup_{n \to \infty} b_n - \liminf_{n \to \infty} b_n. \] (19.66)

**Proof.** Since

\[ X_n = \mathbb{E} [X | \mathcal{B}_n] = \mathbb{E} [\mathbb{E} [X | \mathcal{B}_\infty] | \mathcal{B}_n] = \mathbb{E} [X | \mathcal{B}_\infty], \]

there is no loss in generality in assuming \( X = X_\infty \). If \( X \in M_n := L^1 (\Omega, \mathcal{B}_n, P) \), then \( X_n = X_\infty \) a.s. for all \( m \geq n \) and hence \( X_m \to X_\infty \) a.s. Therefore the theorem is valid for any \( X \) in the dense (by Lemma 19.69) of \( L^1 (\Omega, \mathcal{B}_\infty, P) \).

For general \( X \in L^1 (\Omega, \mathcal{B}_\infty, P) \), let \( Y_j \in \mathcal{B}_n \) such that \( Y_j \to X \in L^1 (\Omega, \mathcal{B}_\infty, P) \) and let \( Y_{j,n} := \mathbb{E} [Y_j | \mathcal{B}_n] \) and \( X_n := \mathbb{E} [X | \mathcal{B}_n] \). We know that \( Y_{j,n} \to Y_{j,\infty} \) a.s. for each \( j \in \mathbb{N} \) and our goal is to show \( X_n \to X_\infty \) a.s. By Doob’s inequality in Corollary 19.43 and the \( L^1 \) contraction property of conditional expectation we know that

\[ P \left( \sup_n |X_n| \geq a \right) \leq \frac{1}{a} \mathbb{E} [X | X] \leq \frac{1}{a} \mathbb{E} [X] \]

and so passing to the limit as \( N \to \infty \) we learn that

\[ P \left( \sup_n |X_n| \geq a \right) \leq \frac{1}{a} \mathbb{E} [X] \text{ for all } a > 0. \] (19.67)

Letting \( a \uparrow \infty \) then shows \( P (\sup_n |X_n| = \infty) = 0 \) and hence \( \sup_n |X_n| < \infty \) a.s. Hence we may use Eq. (19.66) with \( a_n = X_n - Y_{j,n} \) and \( b_n = Y_{j,n} \) to find

\[ D = \limsup_{n \to \infty} X_n - \liminf_{n \to \infty} X_n \]

\[ \leq \limsup_{n \to \infty} a_n - \liminf_{n \to \infty} a_n + \limsup_{n \to \infty} b_n - \liminf_{n \to \infty} b_n \]

\[ = \limsup_{n \to \infty} a_n - \liminf_{n \to \infty} a_n \leq 2 \sup_n |a_n| \]

\[ = 2 \sup_n |X_n - Y_{j,n}|, \]

wherein we have used \( \limsup_{n \to \infty} b_n - \liminf_{n \to \infty} b_n = 0 \) a.s. since \( Y_{j,n} \to Y_{j,\infty} \) a.s. We now apply Doob’s inequality one more time, i.e. use Eq. (19.67) with \( X_n \to X_n - Y_{j,n} \) and \( X \to X - Y_j \), to conclude,

\[ P (D \geq a) \leq P \left( \sup_n |X_n - Y_{j,n}| \geq a \right) \leq \frac{2}{a} \mathbb{E} [X - Y_j] \to 0 \text{ as } j \to \infty. \]

Since \( a > 0 \) is arbitrary here, it follows that \( D = 0 \) a.s., i.e. \( \limsup_{n \to \infty} X_n = \liminf_{n \to \infty} X_n \) and hence \( \lim_{n \to \infty} X_n \) exists in \( \mathbb{R} \) almost surely. Since we already know that \( X_n \to X_\infty \) in \( L^1 (\Omega, \mathcal{B}, P) \), we may conclude that \( \lim_{n \to \infty} X_n = X_\infty \) a.s.
Some Martingale Examples and Applications

**Exercise 20.1.** Let $S_n$ be the total assets of an insurance company in year $n$. Assume that for all $n$, we have $S_n = S_{n-1} + \xi_n$, where $\xi_n = c - Z_n$ and $Z_1, Z_2, \ldots$ are i.i.d. random variables having the normal distribution with mean $\mu < c$ and variance $\sigma^2$. (The number $c$ is to be interpreted as the yearly premium.) Let $R$ be the event that $S_n \leq 0$ for some $n$. Show that if $S_0 > 0$ is constant, then

$$P(\text{Ruin}) = P(R) \leq e^{-2(c-\mu)\sigma^2/\sigma^2}.$$ 

**Solution to Exercise [20.1].** Let us first fine $\lambda$ such that $1 = E[e^{\lambda\xi_n}]$. To do this let $N$ be a standard normal random variable in which case,

$$1 = \mathbb{E} e^{\lambda(c-\mu-\sigma N)} = e^\lambda(c-\mu) (\sigma^2 \lambda^2)/2,$$

leads to the equation for $\lambda$;

$$\frac{\sigma^2}{2} \lambda^2 + \lambda (c - \mu) = 0.$$ 

Hence we should take $\lambda = -2(c-\mu)/\sigma^2$ – the other solution, $\lambda = 0$, is uninteresting. Since $\mathbb{E} e^{\lambda\xi_n} = 1$, we know from Example [19.12] that

$$Y_n := e^{S_0} \prod_{j=1}^n e^{\lambda \xi_j} = \exp(\lambda S_n)$$

is a non-negative $\mathcal{B} = \sigma(Z_1, \ldots, Z_n)$ martingale. By the super-martingale or the sub-martingale convergence theorem, it follows that $\lim_{n \to \infty} Y_n = Y_\infty$ exists and $\tau$ is any stopping time,

$$E Y_\tau = E \lim_{n \to \infty} Y_{\tau \wedge n} \leq \lim_{n \to \infty} E Y_{\tau \wedge n} = E Y_0 = e^{-\lambda S_0}$$

as follows from Fatou’s Lemma and the optional sampling theorem.

Let us now take $\tau = \inf\{n : S_n \leq 0\}$ and observe that $S_\tau \leq 0$ on $R = \{\tau < \infty\}$. Because $\lambda < 0$, it follows that $Y_\tau = e^{\lambda S_\tau} \geq 1$ on $R$ and therefore,

$$P(R) \leq E Y_\tau \leq e^{-\lambda S_0} = e^{-2(c-\mu)\sigma^2/\sigma^2}.$$ 

**20.1 A Polya Urn Model**

Suppose that an urn contains $r$ red balls and $g$ green balls. At each time we draw a ball out, then replace it and add $c$ more balls of the color drawn. Let $(r_n, g_n)$ be the number of red and green balls in the urn at time $n$. Then we have

$$P((r_{n+1}, g_{n+1}) = (r+c, g)) = \frac{r}{r+g} \quad \text{and} \quad P((r_{n+1}, g_{n+1}) = (r, g+c)) = \frac{g}{r+g}.$$ 

Let us observe that $r_n + g_n = r_0 + g_0 + nc$ and hence

$$X_n := \frac{g_n}{r_n + g_n} = \frac{g_n}{r_0 + g_0 + nc}.$$ 

We now claim that $\{X_n\}_{n=0}^\infty$ is a martingale. Indeed,

$$E[X_{n+1} | X_n] = \frac{\frac{r_n}{r_n + g_n} \cdot \frac{g_n}{r_n + g_n + c} + \frac{g_n}{r_n + g_n} \cdot \frac{g_n + c}{r_n + g_n + c}}{\frac{r_n}{r_n + g_n} \cdot \frac{g_n}{r_n + g_n + c} + \frac{g_n + c}{r_n + g_n + c}} = X_n.$$ 

Since $X_\infty \geq 0$, we know that $X_\infty := \lim_{n \to \infty} X_n$ exists a.s. Our next goal is to prove the following theorem.

**Theorem 20.1.** Let $\gamma := g/c$ and $\rho := r/c$ and $P, X_\infty^{-1}$ be the law of $X_\infty$. Then $X_\infty$ is distributed according to the beta distribution on $[0, 1]$ with parameters, $\gamma, \rho$, i.e.

$$d(P \circ X_\infty^{-1})(dx) = \frac{\Gamma(\rho + \gamma)}{\Gamma(\rho) \Gamma(\gamma)} x^{\rho-1}(1-x)^{\gamma-1} dx \text{ for } x \in [0, 1].$$ 

**Proof.** We will begin by computing the distribution of $X_n$. As an example, the probability of drawing 3 greens and then 2 reds is

$$\frac{g}{r+g} \cdot \frac{g+c}{r+g+c} \cdot \frac{g+2c}{r+g+2c} \cdot \frac{r}{r+g+3c} \cdot \frac{r+c}{r+g+4c}.$$
More generally, the probability of first drawing \( m \) greens and then \( n - m \) reds is
\[
g \cdot (g + c) \cdots (g + (n - 1) c) \cdot r \cdot (r + c) \cdots (r + (n - m - 1) c) \\
(r + g) \cdot (r + g + c) \cdots (r + g + (n - 1) c)
\]
Since this is the same probability for any on of the \( \binom{n}{m} \) - ways of drawing \( m \) greens and \( n - m \) reds in \( n \) draws we have
\[
P(\text{Draw} \ m \ - \ \text{greens}) = \binom{n}{m} \frac{g \cdot (g + c) \cdots (g + (n - 1) c) \cdot r \cdot (r + c) \cdots (r + (n - m - 1) c) \\
(r + g) \cdot (r + g + c) \cdots (r + g + (n - 1) c)}{(r + g) \cdot (r + g + c) \cdots (r + g + (n - 1) c)}.
\]
Before going to the general case let us warm up with the special case, \( g = r = c = 1 \). In this case Eq. (20.1) becomes,
\[
P(\text{Draw} \ m \ - \ \text{greens}) = \binom{n}{m} \frac{1 \cdot 2 \cdot \cdots \cdot m \cdot 1 \cdot 2 \cdots \cdot (n - m)}{2 \cdot 3 \cdots \cdot (n + 1)} = \frac{1}{n + 1}.
\]
On the set, \{Draw \ \text{m} \ - \ \text{greens}\}, we have \( X_n = \frac{1 + m}{2 + n} \) and hence it follows that,
\[
E[f(X_n)] = \sum_{m=0}^{n} P(\text{Draw} \ m \ - \ \text{greens}) \\
= \sum_{m=0}^{n} f\left(\frac{1 + m}{2 + n}\right) \frac{1}{n + 1} - \int_{0}^{1} f(x) \, dx
\]
from which it follows that \( X_{\infty} \) has the uniform distribution on \([0,1] \).

For the general case, recall from Example 8.39 that \( n! = \Gamma(n+1) \) where
\[
\Gamma(t) := \int_{[0,\infty)} x^{t-1} e^{-x} \, dx \text{ for } t > 0.
\]
Moreover we have
\[
\Gamma(t+1) = \int_{[0,\infty)} e^{-x} x^t \, dx = -\int_{[0,\infty)} \frac{d}{dx} e^{-x} x^t \, dx = \int_{[0,\infty)} e^{-x} \cdot \frac{d}{dx} x^t \, dx
\]
and therefore for \( m \in \mathbb{N} \),
\[
\Gamma(x + m) = (x + m - 1)(x + m - 2) \ldots (x + 1)x^\gamma(x).
\]

Another key fact about the \( \Gamma \) function is Sterling’s formula which states
\[
\Gamma(x) = \sqrt{2\pi x^{x-1/2}} e^{-x} [1 + r(x)]
\]
where \( |r(x)| \to 0 \) as \( x \to \infty \).

On the set, \( \{\text{Draw} \ m \ - \ \text{greens}\} \), we have
\[
X_n = \frac{g + mc}{r + g + nc} = \frac{\gamma + m}{\rho + \gamma + n} =: x_m,
\]
where \( \rho := r/c \) and \( \gamma := g/c \). For later notice that \( \Delta_m x = \frac{\gamma}{\rho + \gamma + n} \).

Using this notation we may rewrite Eq. (20.1) as
\[
P(\text{Draw} \ m \ - \ \text{greens}) = \binom{n}{m} \frac{\Gamma(\gamma + m) \cdot \Gamma(\rho + n - m)}{\Gamma(\gamma) \cdot \Gamma(\rho + n - m)}.
\]
Now by Sterling’s formula,
\[
\frac{\Gamma(\gamma + m)}{\Gamma(\gamma)} = \frac{(\gamma + m)^{\gamma + m - 1/2} e^{-\gamma + m}}{(1 + m)^{m + 1/2 - (\gamma + m)/2}} \left[ 1 + \frac{r(\gamma + m)}{1 + (r + 1)(m + 1)} \right]
\]
\[
= (\gamma + m)^{\gamma - 1} \left( \frac{\gamma + m}{m + 1} \right)^{m + 1/2} e^{-\gamma - 1} \left( 1 + \frac{r(\gamma + m)}{1 + (r + 1)(m + 1)} \right)
\]
\[
= (\gamma + m)^{\gamma - 1} \left( \frac{1 + \gamma/m}{1 + 1/m} \right)^{m + 1/2} e^{-\gamma - 1} \left( 1 + \frac{r(\gamma + m)}{1 + (r + 1)(m + 1)} \right)
\]
We will keep \( m \) fairly large, so that
\[
\left( \frac{1 + \gamma/m}{1 + 1/m} \right)^{m + 1/2} = \exp \left( (m + 1/2) \ln \left( \frac{1 + \gamma/m}{1 + 1/m} \right) \right)
\]
\[
\cong \exp \left( (m + 1/2) (\gamma/m - 1) \right) \cong e^{\gamma - 1}.
\]
Hence we have
\[
\frac{\Gamma(\gamma + m)}{\Gamma(\gamma + m)} \approx (\gamma + m)^{\gamma - 1}.
\]
Similarly, keeping \( n - m \) fairly large, we also have
\[ \frac{\Gamma(\rho + n - m)}{\Gamma(n + 1)} \leq (\rho + n - m)^{\rho - 1} \quad \text{and} \quad \frac{\Gamma(\rho + \gamma + n)}{\Gamma(n + 1)^{\rho + \gamma - 1}}. \]

Combining these estimates with Eq. (20.4) gives,

\[ P(\text{Draw } m - \text{greens}) \leq \frac{\Gamma(\rho + \gamma)}{\Gamma\big(\rho\big) \Gamma\big(\gamma\big)} \fi(\rho + \gamma + \gamma + n)^{\rho - 1} \]
\[ = \frac{\Gamma(\rho + \gamma)}{\Gamma\big(\rho\big) \Gamma\big(\gamma\big)} (x_m)^{\gamma - 1} \cdot (1 - x_m)^{\rho - 1} \Delta \mu x. \]

Therefore it follows that

\[ E[f(X_{\infty})] = \lim_{n \to \infty} E[f(X_n)] \]
\[ = \lim_{n \to \infty} \sum_{m=0}^{n} f(x_m) \frac{\Gamma(\rho + \gamma)}{\Gamma\big(\rho\big) \Gamma\big(\gamma\big)} (x_m)^{\gamma - 1} \cdot (1 - x_m)^{\rho - 1} \Delta \mu x \]
\[ = \int_{0}^{1} f(x) \mu(x) \, dx \]

where

\[ \mu(x) := \frac{\Gamma(\rho + \gamma)}{\Gamma\big(\rho\big) \Gamma\big(\gamma\big)} x^{\gamma - 1} (1 - x)^{\rho - 1}. \]

\[ 20.2 \text{ Galton Watson Branching Process} \]

See p. 245 –249 in Durrett.

Let \( \{\xi_i^n : i, n \geq 0\} \) be a sequence of i.i.d. non-negative integer valued random variables. Suppose that \( Z_n \) is the number of people in the \( n \)-th generation and \( \xi_1^{n+1}, \ldots, \xi_n^{n+1} \) are the number of offsprings of the \( Z_n \) people of generation \( n \). Then

\[ Z_{n+1} = \xi_1^{n+1} + \cdots + \xi_n^{n+1} \]

represents the number of people present in generation, \( n + 1 \). We complete the description of the process, \( Z_n \) by setting \( Z_0 = 1 \) and \( Z_{n+1} = 0 \) if \( Z_n = 0 \), i.e. once the population dies out it remains extinct forever after. The process \( \{Z_n\}_{n \geq 0} \) is called a Galton-Watson process.

Let \( \xi \overset{d}{=} \xi_i^n \), \( p_k := P(\xi = k) \) be the off-spring distribution,

\[ \mu := E\xi = \sum_{k=0}^{\infty} kp_k, \]

and

\[ B_n := \sigma(\xi_i^n : i \geq 1 \text{ and } 1 \leq m \leq n). \]

On the set \( \{Z_n = k\} \), \( Z_{n+1} = \xi_1^{n+1} + \cdots + \xi_k^{n+1} \) and therefore, on \( \{Z_n = k\} \),

\[ E[Z_{n+1}|B_n] = E[\xi_1^{n+1} + \cdots + \xi_k^{n+1}|B_n] = E[\xi_1^{n+1} + \cdots + \xi_k^{n+1}] = \mu k = \mu Z_n. \]

Since this is true for all \( k \), it follows that

\[ E[Z_{n+1}|B_n] = \mu Z_n \text{ a.s.} \quad (20.5) \]

So we have shown, \( M_n := Z_n/\mu^n \) is a martingale in the extended sense. From this observation it follows that

\[ 1 = EM_0 = EM_n = \frac{EZ_n}{\mu^n}, \]

i.e. \( EZ_n = \mu^n < \infty \).

**Theorem 20.2.** If \( \mu < 1 \), then, almost surely, \( Z_n = 0 \) a.a.

**Proof.** When \( \mu < 1 \), we have

\[ E \sum_{n=0}^{\infty} Z_n = \sum_{n=0}^{\infty} \mu^n = \frac{1}{1 - \mu} < \infty \]

and therefore that

\[ \sum_{n=0}^{\infty} Z_n < \infty \text{ a.s.} \]

But this can only happen if \( Z_n = 0 \) a.a. \[ \blacksquare \]

**Theorem 20.3.** If \( \mu = 1 \) and \( P(\xi_i^n = 1) < 1 \), then again, almost surely, \( Z_n = 0 \) a.a.
Proof. In this case \( \{Z_n\}_{n=1}^{\infty} \) is a martingale which, being positive, is \( L^1 \) bounded. Therefore, \( \lim_{n \to \infty} Z_n =: Z_\infty \) exists. Because \( Z_n \) is integer valued, it must happen that \( Z_n = Z_\infty ~ a.a. \) If \( k \in \mathbb{N} \), since
\[
\{Z_\infty = k\} = \{Z_n = k ~ a.s.\} = \cup_{n=1}^{\infty} \{Z_n = k \text{ for all } n \geq N\},
\]
we have
\[
P(Z_\infty = k) = \lim_{N \to \infty} P(Z_n = k \text{ for all } n \geq N).
\]
However,
\[
P(Z_n = k \text{ for all } n \geq N) = P(\xi_1^n + \cdots + \xi_k^n = k \text{ for all } n \geq N)
\]
\[
= [P(\xi_1^n + \cdots + \xi_k^n = k)]^\infty = 0,
\]
because,
\[
P(\xi_1^n + \cdots + \xi_k^n = k) < 1.
\]
(Note that the only way \( P(\xi_1^n + \cdots + \xi_k^n = k) = 1 \) would be for \( P(\xi_i^n = 1) \), but we assumed \( P(\xi_i^n = 1) < 1 \). Therefore we have shown \( P(Z_\infty = k) = 0 \) for all \( k > 0 \) and therefore, \( Z_\infty = 0 ~ a.s. \) and hence almost surely, \( Z_n = 0 \) for a.a. \( n \).

Remark 20.4. By the way, the branching process, \( \{Z_n\}_{n=0}^{\infty} \) with \( \mu = 1 \) and \( P(\xi = 1) < 1 \) gives a nice example of a non regular martingale. Indeed, if \( Z \) were regular, we would have
\[
Z_n = \mathbb{E} \left[ \lim_{m \to \infty} Z_m | \mathcal{B}_n \right] = \mathbb{E} [0 | \mathcal{B}_n] = 0
\]
which is clearly false.

We now wish to consider the case where \( \mu := \mathbb{E} [\xi_1^n] > 1 \). Let \( \xi \overset{d}{=} \xi_1^n \) and for \( s \in (-\infty, \infty) \), let
\[
\varphi(s) := \mathbb{E} [s^k] = \sum_{k \geq 0} p_k s^k.
\]
Then if \( |s| < 1 \), we have
\[
\varphi'(s) = \sum_{k \geq 0} kp_k s^{k-1} \text{ and } \varphi''(s) = \sum_{k \geq 0} k(k-1) p_k s^{k-2}
\]
with
\[
\lim_{s \downarrow 1} \varphi'(s) = \sum_{k \geq 0} kp_k = \mathbb{E} [\xi] =: \mu \text{ and }
\]
\[
\lim_{s \downarrow 1} \varphi''(s) = \sum_{k \geq 0} k(k-1) p_k = \mathbb{E} [\xi(\xi - 1)].
\]

Fig. 20.1. Figure associated to \( \varphi(s) = \frac{1}{s} (1 + 3s + 3s^2 + s^3) \) which is relevant for Exercise 3.13 of Durrett on p. 249. In this case \( \rho \approx 0.23607 \).

Lemma 20.5. If \( \mu = \varphi'(1) > 1 \), there exists a unique \( \rho < 1 \) so that \( \varphi(\rho) = \rho \).

Proof. See Figure 20.1 below.

Theorem 20.6 (See Durrett, p. 247-248.). If \( \mu > 1 \), then
\[
P(\{Z_n = 0 \text{ for some } n\}) = \rho.
\]

Proof. Since \( \{Z_m = 0\} \subset \{Z_{m+1} = 0\} \), it follows that \( \{Z_m = 0\} \uparrow \{Z_n = 0 \text{ for some } n\} \) and therefore if
\[
\theta_m := P(Z_m = 0),
\]
then
\[
P(\{Z_n = 0 \text{ for some } n\}) = \lim_{m \to \infty} \theta_m.
\]
We now show: \( \theta_m = \varphi(\theta_{m-1}) \). To see this, conditioned on the set \( \{Z_1 = k\} \), \( Z_m = 0 \) iff all \( k \) - families die out in the remaining \( m - 1 \) time units. Since each family evolves independently, the probability of this event is \( \theta_{m-1}^k \). Combining this with, \( P(\{Z_1 = k\}) = P(\xi_1^k = k) = p_k \), allows us to conclude,
\[
\theta_m = P(Z_m = 0) = \sum_{k=0}^{\infty} P(Z_m = 0, Z_1 = k)
\]
\[
= \sum_{k=0}^{\infty} P(Z_m = 0 | Z_1 = k) P(Z_1 = k) = \sum_{k=0}^{\infty} p_k \theta_{m-1}^k = \varphi(\theta_{m-1}).
\]
20.3 Kakutani’s Theorem

Proposition 20.7. Suppose that \( \mu \) and \( \nu \) are \( \sigma \)-finite positive measures on \((X, M)\), \( \nu = \nu_a + \nu_s \) is the Lebesgue decomposition of \( \nu \) relative to \( \mu \), and \( \rho : X \to [0, \infty) \) is a measurable function such that \( d\nu_a = \rho d\mu \) so that

\[
    dv = d\nu_a + d\nu_s = \rho d\mu + dv_s.
\]

If \( g : X \to [0, \infty) \) is another measurable function such that \( gd\mu \leq dv \), (i.e. \( \int_B gd\mu \leq \nu(B) \) for all \( B \in \mathcal{M} \)), then \( g \leq \rho \), \( \mu \) a.e.

Proof. Let \( A \in \mathcal{M} \) be chosen so that \( \mu(A^c) = 0 \) and \( \nu_s(A) = 0 \). Then, for all \( B \in \mathcal{M} \),

\[
    \int_B gd\mu = \int_{B \cap A} gd\mu \leq \nu(B \cap A) = \int_{B \cap A} \rho \mu = \int_B \rho d\mu.
\]

So by the comparison Lemma 18.2, \( g \leq \rho \).

Example 20.8. This example generalizes Example 19.8 Suppose \((\Omega, \mathcal{B}, \{\mathcal{B}_n\}_{n=0}^\infty, P)\) is a filtered probability space and \( Q \) is any another probability measure on \((\Omega, \mathcal{B})\). By the Raydon-Nikodym Theorem 17.8 for each \( n \in \mathbb{N} \) we may write

\[
    dQ|_{\mathcal{B}_n} = X_n dP|_{\mathcal{B}_n} + dr_n
\]

where \( r_n \) is a measure on \((\Omega, \mathcal{B}_n)\) which is singular relative to \( P|_{\mathcal{B}_n} \) and \( 0 \leq X_n \leq \infty \). In this case the most we can say in general is that \( X := \{X_n\}_{n \leq \infty} \) is a positive supermartingale. To verify this assertion, for \( B \in \mathcal{B}_n \) and \( n \leq m \leq \infty \), we have

\[
    Q(B) = E[X_m : B] + R_m(B) \geq E[X_m : B] = E[E_{\mathcal{B}_n}(X_m) : B]
\]

from which it follows that \( E_{\mathcal{B}_n}(X_m) \cdot dP|_{\mathcal{B}_n} \leq dQ|_{\mathcal{B}_n} \). So according to Proposition 20.7,

\[
    E_{\mathcal{B}_n}(X_m) \leq X_n \text{ (P - a.s.) for all } n \leq m \leq \infty. \tag{20.6}
\]

Proposition 20.9. Keeping the assumptions and notation used in Example 20.8, then \( \lim_{n \to \infty} X_n = X_\infty \) a.s. and in particular the Lebesgue decomposition of \( Q|_{\mathcal{B}_\infty} \) relative to \( P|_{\mathcal{B}_\infty} \) may be written as

\[
    dQ|_{\mathcal{B}_\infty} = \left( \lim_{n \to \infty} X_n \right) \cdot dP|_{\mathcal{B}_\infty} + dr_\infty. \tag{20.7}
\]

Proof. By Example 20.8 we know that \( \{X_n\}_{n=1}^\infty \) is a positive supermartingale and by letting \( m = \infty \) in Eq. (20.6), we know

\[
    E_{\mathcal{B}_n} X_\infty \leq X_n \text{ a.s.}. \tag{20.8}
\]

By the supermartingale convergence Corollary 19.54 or by the submartingale convergence Corollary 19.46 applied to \( -X_n \) we know that \( X_0 := \lim_{n \to \infty} X_n \) exists almost surely. From the regular martingale convergence Theorem 19.36 we also know that \( \lim_{n \to \infty} E_{\mathcal{B}_n} X_\infty = X_\infty \) a.s. as well. So passing to the limit in Eq. (20.8) implies \( X_\infty \leq X_0 \) a.s.

To prove the reverse inequality, \( X_0 \leq X_\infty \) a.s., let \( B \in \mathcal{B}_m \) and \( n \geq m \). Then

\[
    Q(B) = E[X_n : B] + R_n(B) \geq E[X_n : B]
\]

and so by Fatou’s lemma,

\[
    E[X_0 : B] = E\left[\liminf_{n \to \infty} X_n : B\right] \leq \liminf_{n \to \infty} E[X_n : B] \leq Q(B). \tag{20.9}
\]

Since \( m \in \mathbb{N} \) was arbitrary, we have proved \( E[X_0 : B] \leq Q(B) \) for all \( B \) in the algebra, \( \mathcal{A} := \cup_{m \in \mathbb{N}} \mathcal{B}_m \). As a consequence of the regularity Theorem 5.10, it follows that

\[
    Q(B) = E[X_\infty : B] + dr_\infty. \tag{20.10}
\]
Recall from Exercise 7.4, that if 0

Theorem 20.10. Let \( (\Omega, \mathcal{B}, \{B_n\}_{n=0}^{\infty}, P) \) be a filtered probability space and \( Q \) be a probability measure on \( (\Omega, \mathcal{B}) \) such that \( Q|_{B_n} \ll P|_{B_n} \) for all \( n \in \mathbb{N} \). Let \( M_n := \frac{dQ|_{B_n}}{dP|_{B_n}} \) be a version of the Raydon-Nikodym derivative of \( Q|_{B_n} \) relative to \( P|_{B_n} \), see Theorem 17.8. Recall from Example 19.8 that \( \{M_n\}_{n=1}^{\infty} \) is a positive martingale and let \( M_\infty = \lim_{n \to \infty} M_n \) which exists a.s. Then the following are equivalent:

1. \( Q|_{B_\infty} \ll P|_{B_\infty} \)
2. \( E_P M_\infty = 1 \)
3. \( M_n \to M_\infty \) in \( L^1(\Omega, \mathcal{B}, P) \), and
4. \( \{M_n\}_{n=1}^{\infty} \) is uniformly integrable.

**Proof.** Recall from Proposition 20.9 (where \( X_n \) is now \( M_n \)) that in general,

\[
dQ|_{B_\infty} = M_\infty \circ dP|_{B_\infty} + dR_\infty
\]

where \( R_\infty \) is singular relative to \( P|_{B_\infty} \). Therefore, \( Q|_{B_\infty} \ll P|_{B_\infty} \) iff \( R_\infty = 0 \) which happens iff \( \Omega Q \) is empty, i.e. iff

\[
1 = Q(\Omega) = \int_{\Omega} M_\infty \circ dP|_{B_\infty} = E_P M_\infty.
\]

This proves the equivalence of items 1 and 2. If item 2 holds, then \( M_n \to M_\infty \) by the DCT, Corollary 11.8 with \( g_n = f_n = M_n \) and \( g = f = M_\infty \) and so item 3 hold. The implication of 3. \( \implies \) 2. is easy and the equivalence of items 3 and 4 follows from Theorem 11.31. \( \blacksquare \)

**Remark 20.11.** Recall from Exercise 7.4 that if \( 0 < a_n \leq 1 \), \( \prod_{n=1}^{\infty} a_n > 0 \) iff \( \sum_{n=1}^{\infty} (1 - a_n) < \infty \). Indeed, \( \prod_{n=1}^{\infty} a_n > 0 \) iff

\[-\infty < \ln \left( \prod_{n=1}^{\infty} a_n \right) = \sum_{n=1}^{\infty} \ln a_n = \sum_{n=1}^{\infty} \ln (1 - (1 - a_n)) \]

and

\[\sum_{n=1}^{\infty} \ln (1 - (1 - a_n)) > -\infty \text{ iff } \sum_{n=1}^{\infty} (1 - a_n) < \infty.\]

Recall that \( \ln(1 - (1 - a_n)) \approx (1 - a_n) \) for \( a_n \) near 1.

Theorem 20.12 (Kakutani’s Theorem). Let \( \{X_n\}_{n=1}^{\infty} \) be independent non-negative random variables with \( E X_n = 1 \) for all \( n \). Further, let \( M_0 = 1 \) and \( M_n := X_1 \cdot X_2 \cdots \cdot X_n \) - a martingale relative to the filtration, \( E_n := \sigma(X_1, \ldots, X_n) \) as was shown in Example 19.12. According to Corollary 19.54, \( M_\infty := \lim_{n \to \infty} M_n \) exists a.s. and \( E M_\infty \leq 1 \). The following statements are equivalent;

1. \( E M_\infty = 1 \)
2. \( M_n \to M_\infty \) in \( L^1(\Omega, \mathcal{B}, P) \),
3. \( \{M_n\}_{n=1}^{\infty} \) is uniformly integrable,
4. \( \prod_{n=1}^{\infty} E \left( \sqrt{X_n} \right) > 0 \),
5. \( \sum_{n=1}^{\infty} (1 - E (\sqrt{X_n})) < \infty. \)

Moreover, if any one, and hence all of the above statements, fails to hold, then \( P(M_\infty = 0) = 1 \).

**Proof.** If \( a_n := E (\sqrt{X_n}) \), then \( 0 < a_n \) and \( a_n^2 \leq E X_n = 1 \) with equality iff \( X_n = 1 \) a.s. So Remark 20.11 gives the equivalence of items 4 and 5.

The equivalence of items 1., 2. and 3. follow by the same techniques used in the proof of Theorem 20.10 above. We will now complete the proof by showing 4. \( \implies \) 3. and not(4) \( \implies P(M_\infty = 0) = 1 \) which clearly implies not(1). For both parts of the argument, let \( N_0 = 1 \) and \( N_n \) be the martingale (again see Example 19.12) defined by

\[
N_n := \prod_{k=1}^{n} \frac{\sqrt{X_k}}{a_k} = \frac{\sqrt{M_n}}{\prod_{k=1}^{n} a_k}. \tag{20.11}
\]

Further observe that, in all cases, \( N_\infty = \lim_{n \to \infty} N_n \) exists in \([0, \infty)\) \( \mu \)-a.s., see Corollary 19.46 or Corollary 19.54.

4. \( \implies \) 3. Since

\[
N_n^2 = \prod_{k=1}^{n} \frac{X_k}{a_k} = \frac{M_n}{(\prod_{k=1}^{n} a_k)^2},
\]

\[
E [N_n^2] = \frac{E M_n}{(\prod_{k=1}^{n} a_k)^2} \leq \frac{1}{(\prod_{k=1}^{\infty} a_k)^2} < \infty,
\]

and hence \( \{N_n\}_{n=1}^{\infty} \) is bounded in \( L^2 \). Therefore, using

\[
M_n = \left( \prod_{k=1}^{n} a_k \right)^2 N_n^2 \leq N_n^2 \tag{20.12}
\]

and Doob’s inequality in Corollary 19.43 we find

\[
E \left[ \sup_n M_n \right] = E \left[ \sup_n N_n^2 \right] \leq 4 \sup_n E [N_n^2] < \infty. \tag{20.13}
\]
Equation Eq. (20.13) certainly implies \( \{M_n\}_{n=1}^{\infty} \) is uniformly integrable, see Proposition 11.29.

Not(4.) \( \implies P(M_{\infty} = 0) = 1 \). If

\[
\prod_{n=1}^{\infty} E \left( \sqrt{X_n} \right) = \lim_{n \to \infty} \prod_{k=1}^{n} a_k = 0,
\]

we may pass to the limit in Eq. (20.12) to find

\[
M_\infty = \lim_{n \to \infty} M_n = \lim_{n \to \infty} \left[ \left( \prod_{k=1}^{n} a_k \right)^2 \cdot N_n^2 \right] = 0 \cdot \left( \lim_{n \to \infty} N_n \right)^2 = 0 \text{ a.s.}
\]

Definition 20.13. Two probability measures, \( \mu \) and \( \nu \) on a measure space, \((\Omega, \mathcal{B})\) are said to be equivalent (written \( \mu \sim \nu \)) if \( \mu \ll \nu \) and \( \nu \ll \mu \), i.e., if \( \mu \) and \( \nu \) are absolutely continuous relative to one another. The Hellinger integral of \( \mu \) and \( \nu \) is defined as

\[
H(\mu, \nu) := \int_{\Omega} \sqrt{\frac{d\mu}{d\lambda}} \cdot \frac{d\nu}{d\lambda} d\lambda = \sqrt{\int_{\Omega} d\mu \cdot d\nu}
\]

where \( \lambda \) is any measure (for example \( \lambda = \frac{1}{2} (\mu + \nu) \) would work) on \((\Omega, \mathcal{B})\) such that there exists, \( \frac{d\mu}{d\lambda} \) and \( \frac{d\nu}{d\lambda} \) in \( L^1(\Omega, \mathcal{B}, \lambda) \) such that \( d\mu = \frac{d\mu}{d\lambda} d\lambda \) and \( d\nu = \frac{d\nu}{d\lambda} d\lambda \).

Proposition 20.14. The Hellinger integral, \( H(\mu, \nu) \), of two probability measures, \( \mu \) and \( \nu \), is well defined. Moreover \( H(\mu, \nu) \) satisfies;

1. \( 0 \leq H(\mu, \nu) \leq 1 \)
2. \( H(\mu, \nu) = 1 \iff \mu = \nu \)
3. \( H(\mu, \nu) = 0 \iff \mu \perp \nu \), and
4. If \( \mu \sim \nu \) or more generally if \( \nu \ll \mu \), then \( H(\mu, \nu) > 0 \).

Furthermore\(^3\)

\[
H(\mu, \nu) = \inf \left\{ \sum_{i=1}^{n} \sqrt{\mu(A_i) \nu(A_i)} : \Omega = \sum_{i=1}^{n} A_i \text{ and } n \in \mathbb{N} \right\}.
\]

Proof. Let \( \lambda' \) be another measure such that \( \mu, \nu \ll \lambda' \) and let \( \gamma := \lambda + \lambda' \). Then \( \lambda', \lambda \ll \gamma \) and therefore, \( d\lambda = p d\gamma \) for some \( p \geq 0 \). Moreover, \( \frac{d\mu}{d\lambda} = \frac{d\mu}{d\lambda} \frac{d\lambda}{d\lambda'} \frac{d\lambda'}{d\gamma} \) and \( d\nu = \frac{d\nu}{d\lambda} d\lambda = \frac{d\nu}{d\lambda} \frac{d\lambda}{d\lambda'} \frac{d\lambda'}{d\gamma} \) and hence

\[
\int_{\Omega} \sqrt{\frac{d\mu}{d\gamma} \cdot \frac{d\nu}{d\gamma} d\gamma} = \int_{\Omega} \sqrt{\frac{d\mu}{d\lambda} \cdot \frac{d\nu}{d\lambda} d\lambda} = \int_{\Omega} \sqrt{\frac{d\mu}{d\lambda} \cdot \frac{d\nu}{d\lambda} d\lambda}.
\]

By symmetry we also have

\[
\int_{\Omega} \sqrt{\frac{d\mu}{d\lambda} \cdot \frac{d\nu}{d\lambda} d\lambda'} = \int_{\Omega} \sqrt{\frac{d\mu}{d\gamma} \cdot \frac{d\nu}{d\gamma} d\gamma} = \int_{\Omega} \sqrt{\frac{d\mu}{d\lambda} \cdot \frac{d\nu}{d\lambda} d\lambda}
\]

which shows \( H(\mu, \nu) \) is well defined.

Items 1. and 2. are both an easy consequence of the Schwarz inequality and its converse. For item 3., if \( H(\mu, \nu) = 0 \), then \( \frac{d\mu}{d\lambda} = \frac{d\nu}{d\lambda} = 0 \), \( \lambda \) - a.e.. Therefore, if we let

\[
A := \left\{ \frac{d\mu}{d\lambda} \neq 0 \right\},
\]

then \( \frac{d\mu}{d\lambda} = 1_A \frac{d\mu}{d\lambda} - \lambda \) - a.e. and \( \frac{d\nu}{d\lambda} 1_A \frac{d\nu}{d\lambda} = \frac{d\nu}{d\lambda} - \lambda \) - a.e. Hence it follows that \( \mu(A^c) = 0 \) and \( \nu(A) = 0 \) and hence \( \mu \perp \nu \).

If \( \nu \sim \mu \) and in particular, \( \nu \ll \mu \), then

\[
H(\mu, \nu) = \int_{\Omega} \sqrt{\frac{d\nu}{d\mu} \cdot \frac{d\mu}{d\mu} d\mu} = \int_{\Omega} \sqrt{\frac{d\nu}{d\mu} d\mu}.
\]

For sake of contradiction, if \( H(\mu, \nu) = 0 \) then \( \sqrt{\frac{d\nu}{d\mu}} = 0 \) and hence \( \frac{d\nu}{d\mu} = 0 \), \( \mu \) - a.e. The later would imply \( \nu = 0 \) which is impossible. Therefore, \( H(\mu, \nu) > 0 \) if \( \nu \ll \mu \). The last statement is left to the reader as Exercise 20.3.

Exercise 20.2. Find a counter example to the statement that \( H(\mu, \nu) > 0 \) implies \( \nu \ll \mu \).

Exercise 20.3. Prove Eq. (20.15).

Corollary 20.15 (Kakutani [9]). Let \( \Omega = \mathbb{R}^n \), \( Y_n(\omega) = \omega_n \) for all \( \omega \in \Omega \) and \( n \in \mathbb{N} \), and \( \mathcal{B} := \mathcal{B}_\infty = \sigma(Y_n : n \in \mathbb{N}) \) be the product \( \sigma \) - algebra on \( \Omega \). Further, let \( \mu := \otimes_{n=1}^{\infty} \mu_n \) and \( \nu := \otimes_{n=1}^{\infty} \nu_n \) be product measures on \((\Omega, \mathcal{B}_\infty)\) associated to two sequences of probability measures, \( \{\mu_n\}_{n=1}^{\infty} \) and \( \{\nu_n\}_{n=1}^{\infty} \) on \((\mathbb{R}, \mathcal{B})\), see Theorem 3.27 (take \( \mu := P \circ (Y_1, Y_2, \ldots)^{-1} \)). Let us further assume that \( \nu_n \ll \mu_n \) for all \( n \) so that

\[
0 < H(\mu_n, \nu_n) = \int_{\mathbb{R}} \frac{d\nu_n}{d\mu_n} d\mu_n \leq 1.
\]

Then precisely one of the two cases below hold;
1. \( \sum_{n=1}^{\infty} (1 - H(\mu_n, \nu_n)) < \infty \) which happens iff \( \prod_{n=1}^{\infty} H(\mu_n, \nu_n) > 0 \) which happens iff \( \nu \ll \mu \)

or
2. \( \sum_{n=1}^{\infty} (1 - H(\mu_n, \nu_n)) < \infty \) which happens iff \( \prod_{n=1}^{\infty} H(\mu_n, \nu_n) = 0 \) which happens iff \( \mu \perp \nu \).

In case 1. where \( \nu \ll \mu \) we have
\[
\frac{d\nu}{d\mu} = \prod_{n=1}^{\infty} \frac{d\nu_n}{d\mu_n}(Y_n), \quad \mu\text{-a.s.}
\]
and in all cases we have
\[
H(\mu, \nu) = \prod_{n=1}^{\infty} H(\mu_n, \nu_n).
\]

Proof. Let \( P = \mu, Q = \nu, \mathcal{B}_n := \sigma(Y_1, \ldots, Y_n), X_n := \frac{d\nu}{d\mu_n}(Y_n), \) and
\[
M_n := X_1 \cdots X_n = \frac{d\nu_1}{d\mu_1}(Y_1) \cdots \frac{d\nu_n}{d\mu_n}(Y_n).
\]
If \( f : \mathbb{R}^n \to \mathbb{R} \) is a bounded measurable function, then
\[
E_{\nu}(f(Y_1, \ldots, Y_n)) = \int_{\mathbb{R}^n} f(y_1, \ldots, y_n) d\nu_1(y_1) \cdots d\nu_n(y_n) = \int_{\mathbb{R}^n} f(y_1, \ldots, y_n) \frac{d\nu_1}{d\mu_1}(y_1) \cdots \frac{d\nu_n}{d\mu_n}(y_n) d\mu_1(y_1) \cdots d\mu_n(y_n)
\]
\[
= \mathbb{E}_{\mu} \left[ f(Y_1, \ldots, Y_n) \frac{d\nu_1}{d\mu_1}(Y_1) \cdots \frac{d\nu_n}{d\mu_n}(Y_n) \right] = \mathbb{E}_{\mu}[f(Y_1, \ldots, Y_n) M_n]
\]
from which it follows that
\[
d\nu|_{\mathcal{B}_n} = M_n d\mu|_{\mathcal{B}_n}.
\]
Hence by Theorem 20.10 \( M_n := \lim_{n \to \infty} M_n \) exists a.s. and the Lebesgue decomposition of \( \nu \) is given by
\[
d\nu = M_\infty d\mu + dR_\infty
\]
where \( R_\infty \perp \mu \). Moreover \( \nu \ll \mu \) iff \( R_\infty = 0 \) which happens iff \( \mathbb{E}M_\infty = 1 \) and \( \nu \perp \mu \) iff \( R_\infty = 0 \) which happens iff \( M_\infty = 0 \). From Theorem 20.12
\[
\mathbb{E}_{\mu} M_\infty = 1 \text{ iff } 0 < \prod_{n=1}^{\infty} \mathbb{E}_{\mu}(\sqrt{X_n}) = \prod_{n=1}^{\infty} \int_{\mathbb{R}} \frac{d\nu_n}{d\mu_n}(y) d\mu_n = \prod_{n=1}^{\infty} H(\mu_n, \nu_n)
\]
and in this case
\[
d\nu = M_\infty d\mu = \left( \prod_{k=1}^{\infty} X_k \right) d\mu = \left( \prod_{n=1}^{\infty} \frac{d\nu_n}{d\mu_n}(Y_n) \right) d\mu.
\]
On the other hand, if
\[
\prod_{n=1}^{\infty} \mathbb{E}_{\mu}(\sqrt{X_n}) = \prod_{n=1}^{\infty} H(\mu_n, \nu_n) = 0,
\]
Theorem 20.12 implies \( M_\infty = 0, \mu \) - a.s. in which case Theorem 20.10 implies \( \nu \perp \mu \).

(The rest of the argument may be safely omitted.) For the last assertion, if \( \prod_{n=1}^{\infty} H(\mu_n, \nu_n) = 0 \) then \( \nu \perp \mu \) and hence \( H(\mu, \nu) = 0 \). Conversely if \( \prod_{n=1}^{\infty} H(\mu_n, \nu_n) > 0 \), then \( M_n \to M_\infty \) in \( L^1(\mu) \) and therefore
\[
\mathbb{E}_{\mu} \left[ \left| \sqrt{M_n} - \sqrt{M_\infty} \right|^2 \right] = \mathbb{E}_{\mu} \left[ \left| \sqrt{M_n} - \sqrt{M_\infty} \right| \cdot \sqrt{M_n} + \sqrt{M_\infty} \right]
\]
\[
= \mathbb{E}_{\mu} \left[ |M_n - M_\infty| \right] \to 0 \text{ as } n \to \infty.
\]
Since \( d\nu = M_\infty d\mu \) in this case, it follows that
\[
H(\mu, \nu) = \mathbb{E}_{\mu} \left[ \sqrt{M_\infty} \right] = \lim_{n \to \infty} \mathbb{E}_{\mu} \left[ \sqrt{M_n} \right] = \lim_{n \to \infty} \prod_{k=1}^{n} H(\mu_k, \nu_k) = \prod_{k=1}^{\infty} H(\mu_k, \nu_k).
\]

Example 20.16. Suppose that \( \nu_n = \delta_1 \) for all \( n \) and \( \mu_n = (1 - p_n^2) \delta_0 + p_n^2 \delta_1 \) with \( p_n \in (0, 1) \). Then \( \nu_n \ll \mu_n \) with
\[
\frac{d\nu_n}{d\mu_n} = 1_{(1)} p_n^{-2}
\]
and
\[
H(\mu_n, \nu_n) = \int_{\mathbb{R}} \sqrt{1_{(1)} p_n^{-2}} d\mu_n = \sqrt{p_n^{-2}} = p_n.
\]
So in this case \( \nu \ll \mu \) iff \( \sum_{n=1}^{\infty} (1 - p_n) < \infty \). Observe that \( \mu \) is never absolutely continuous relative to \( \nu \).

On the other hand; if we further assume in Corollary 20.15 that \( \mu_n \sim \nu_n \), then either; \( \mu \sim \nu \) or \( \mu \perp \nu \) depending on whether \( \prod_{n=1}^{\infty} H(\mu_n, \nu_n) > 0 \) or \( \prod_{n=1}^{\infty} H(\mu_n, \nu_n) = 0 \) respectively.

For broad generalizations of the results in this section, see Chapter IV of [4] or [5]. In the next group of problems you will be given probability measures, \( \mu_n \) and \( \nu_n \) on \( \mathbb{R} \) and you will be asked to decide if \( \mu := \otimes_{n=1}^{\infty} \mu_n \) and \( \nu := \otimes_{n=1}^{\infty} \nu_n \) are equivalent.
Exercise 20.4 (A Discrete Cameron-Martin Theorem). Suppose $t > 0$, 
\( \{a_n\} \subset \mathbb{R} \), 
\( d\mu_n (x) = \frac{1}{\sqrt{2\pi t}} e^{-x^2/2t} dx \) and 
\( d\nu_n (x) = \frac{1}{\sqrt{2\pi t}} e^{-(x+a_n)^2/2t} dx \). Show 
\( \mu \sim \nu \) if \( \sum_{k=1}^{\infty} a_k^2 < \infty \).

Exercise 20.5. Suppose \( s, t > 0 \), \( \{a_n\} \subset \mathbb{R} \), 
\( d\mu_n (x) = \frac{1}{\sqrt{2\pi t}} e^{-x^2/2t} dx \) and 
\( d\nu_n (x) = \frac{1}{\sqrt{2\pi s}} e^{-(x+a_n)^2/2s} dx \). Show \( \mu \perp \nu \) if \( s \neq t \).

Exercise 20.6. Suppose \( \{t_n\} \subset (0, \infty) \), 
\( d\mu_n (x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2t_n} dx \) and 
\( d\nu_n (x) = \frac{1}{\sqrt{2\pi t_n}} e^{-(x+a_n)^2/2t_n} dx \). If 
\( \sum_{n=1}^{\infty} (t_n - 1)^2 < \infty \) then \( \mu \sim \nu \).

20.3.1 For the Future

1. See Section 15 on p.153 of Williams for more applications.
2. Exchangeable Random Variables, see Durrett and Fitzsimmons notes.
3. Kolmogorov’s 0-1 law, see p. 148 of Roger and Williams, Volume I.
5. Random walk applications in Resnick
6. Option Pricing schemes.

The following have already been done.

1. Kakutani’s theorem and more general differentiation theorems. See Resnick
Random Fields and Continuous Time Processes
Kolmogorov’s Theorems

Theorem 21.1 (Inner-Outer Regularity). Suppose \( \mu \) is a probability measure on \((\mathbb{R}^N, B_{\mathbb{R}^N})\), then for all \( B \in B_{\mathbb{R}^N} \) we have

\[
\mu (B) = \inf \{ \mu (V) : B \subset V \text{ and } V \text{ is open} \} \tag{21.1}
\]

and

\[
\mu (B) = \sup \{ \mu (K) : K \subset B \text{ with } K \text{ compact} \} . \tag{21.2}
\]

Proof. In this proof, \( C \) and \( C_i \) will always denote a closed subset of \( \mathbb{R}^N \) and \( V, V_i \) will always be open subsets of \( \mathbb{R}^N \). Let \( \mathcal{F} \) be the collection of sets, \( A \in \mathcal{B} \), such that for all \( \varepsilon > 0 \) there exists an open set \( V \) and a closed set, \( C \), such that \( C \subset A \subset V \) and \( \mu (V \setminus C) < \varepsilon \). The key point of the proof is to show \( \mathcal{F} = \mathcal{B} \) for this certainly implies Equation \((21.1)\) and also that

\[
\mu (B) = \sup \{ \mu (C) : C \subset B \text{ with } C \text{ closed} \} . \tag{21.3}
\]

Moreover, by MCT, we know that if \( C \) is closed and \( K_n := C \cap \{ x \in \mathbb{R}^N : |x| \leq n \} \), then \( \mu (K_n) \uparrow \mu (C) \). This observation along with Eq. \((21.3)\) shows Eq. \((21.2)\) is valid as well.

To prove \( \mathcal{F} = \mathcal{B} \), it suffices to show \( \mathcal{F} \) is a \( \sigma \)– algebra which contains all closed subsets of \( \mathbb{R}^N \). To prove the latter assertion, given a closed subset, \( C \subset \mathbb{R}^N \), and \( \varepsilon > 0 \), let

\[
C_\varepsilon := \cup_{x \in C} B (x, \varepsilon)
\]

where \( B (x, \varepsilon) := \{ y \in \mathbb{R}^N : |y - x| < \varepsilon \} \). Then \( C_\varepsilon \) is an open set and \( C_\varepsilon \downarrow C \) as \( \varepsilon \downarrow 0 \). (You prove.) Hence by the DCT, we know that \( \mu (C \setminus C_\varepsilon) \downarrow 0 \) from which it follows that \( C \in \mathcal{F} \).

We now show that \( \mathcal{F} \) is an algebra. Clearly \( \mathcal{F} \) contains the empty set and if \( A \in \mathcal{F} \) with \( C \subset A \subset V \) and \( \mu (V \setminus C) < \varepsilon \), then \( V' \subset A \subset C' \) with \( \mu (C' \setminus V') = \mu (V \setminus C) < \varepsilon \). This shows \( A' \in \mathcal{F} \). Similarly if \( A_i \in \mathcal{F} \) for \( i = 1, 2 \) and \( C_i \subset A_i \subset V_i \) with \( \mu (V_i \setminus C_i) < \varepsilon \), then

\[
C := C_1 \cup C_2 \subset A_1 \cup A_2 \subset V_1 \cup V_2 =: V
\]

and

\[
\mu (V \setminus C) \leq \mu (V_1 \setminus C) + \mu (V_2 \setminus C) \\
\leq \mu (V_1 \setminus C_1) + \mu (V_2 \setminus C_2) < 2\varepsilon.
\]

This implies that \( A_1 \cup A_2 \in \mathcal{F} \) and we have shown \( \mathcal{F} \) is an algebra.

We now show that \( \mathcal{F} \) is a \( \sigma \) – algebra. To do this it suffices to show \( A := \sum_{n=1}^{\infty} A_n \in \mathcal{F} \) if \( A_n \in \mathcal{F} \) with \( A_n \cap A_{m} = \emptyset \) for \( m \neq n \). Let \( C_n \in \mathcal{A} \subset V_n \) with \( \mu (V_n \setminus C_n) < \varepsilon 2^{-n} \) for all \( n \) and let \( C := \bigcup_{n=1}^{\infty} C_n \) and \( V := \bigcap_{n=1}^{\infty} V_n \). Then \( C \subset A \subset V \) and

\[
\mu (V \setminus C) \leq \sum_{n=0}^{\infty} \mu (V_n \setminus C) \leq \sum_{n=0}^{N} \mu (V_n \setminus C_n) + \sum_{n=N+1}^{\infty} \mu (V_n)
\]

\[
\leq \sum_{n=0}^{N} \varepsilon 2^{-n} + \sum_{n=N+1}^{\infty} [\mu (A_n) + \varepsilon 2^{-n}]
\]

\[
= \varepsilon + \sum_{n=N+1}^{\infty} \mu (A_n).
\]

The last term is less that \( 2\varepsilon \) for \( N \) sufficiently large because \( \sum_{n=1}^{\infty} \mu (A_n) = \mu (A) < \infty \).

Lemma 21.2 (Baby Tychonoff’s Theorem). Suppose that for each \( m \in \mathbb{N} \) we are given

\[
K^m := K^m_1 \times K^m_2 \times \cdots \times K^m_n \times \cdots \subset \mathbb{R}^N
\]

where \( \{ K^m_i : i, n \in \mathbb{N} \} \) are compact subsets of \( \mathbb{R} \). If \( \cap_{n=1}^{\infty} K^n \neq \emptyset \) for all \( m \in \mathbb{N} \), then \( \cap_{n=1}^{\infty} K^n \neq \emptyset \).

Proof. By assumption, for each \( m \in \mathbb{N} \) there exists \( x(m) = (x_1(m), x_2(m), \ldots) \in \cap_{n=1}^{\infty} K^n \). Since \( x_i(m) \in K^m_i \) for all \( m \) and \( K^m_i \) is compact, there \( \{ x_i(m) \}_{m=1}^{\infty} \) has a convergent subsequence for each \( i \). By Cantor’s diagonalization method, we may find a subsequence, \( m_1 < m_2 < m_3 < \cdots \) such that

\[
y_i := \lim_{k \to \infty} x_i (m_k) \text{ exists in } K^m_i \text{ for all } i \in \mathbb{N}.
\]

Since \( x_i (m_k) \in \cap_{n=1}^{\infty} K^n_i \) for all \( k \) large and \( \cap_{n=1}^{\infty} K^n \) is closed, it follows that \( y_i \in \cap_{n=1}^{\infty} K^n_i \) for all \( m \). Because this is true for all \( i \), it follows that \( y := (y_1, y_2, \ldots) \in \cap_{n=1}^{\infty} K^n \) for all \( m \) and hence \( y \in \cap_{n=1}^{\infty} K^n \).

Theorem 21.3 (Kolmogorov’s Extension Theorem). Let \( I := [0, 1] \). For each \( n \in \mathbb{N} \), let \( \mu_n \) be a probability measure on \((I^n, B_{I^n})\) such that
\[ \mu_{n+1}(A \times I) = \mu_n(A). \] Then there exists a unique measure, \( P \) on \((I^n, B_I^n)\) such that
\[ P(A \times I^n) = \mu_n(A) \]
for all \( A \in B_I^n \) and \( n \in \mathbb{N} \).

**Proof.** Let \( A := \cup B_n \) where \( B_n := \{ A \times I^n : A \in B_I^n \} \), where \( \pi_i(x) = x_i \) if \( x = (x_1, x_2, \ldots) \). Then define \( P \) on \( A \) by Eq. (21.4), which is easily seen (Exercise 21.1) to be a well defined finitely additive measure on \( A \). To finish the proof it suffices to show if \( B_n \in A \) is a decreasing sequence such that
\[ \inf_n P(B_n) = \lim_{n \to \infty} P(B_n) = \varepsilon > 0, \]
then \( B := \cap B_n \neq \emptyset \).

To simplify notation, we may reduce to the case where \( B_n \in B_n \) for all \( n \). To see this is permissible, let us choose \( 1 \leq n_1 < n_2 < n_3 < \ldots \) such that \( B_n \in B_n \) for all \( k \). (This is possible since \( B_n \) is increasing in \( n \).) We now define a new decreasing sequence of sets, \( \{ \tilde{B}_k \}_{k=1}^\infty \) as follows,
\[ (\tilde{B}_1, \tilde{B}_2, \ldots) = \left( \underbrace{I^n \times \cdots \times I^n}_{n-1 \text{ times}}, \underbrace{B_1, \ldots, B_1}_{n_2 \text{ times}}, \underbrace{B_2, \ldots, B_2}_{n_3 \text{ times}}, \ldots, \underbrace{B_3, \ldots, B_3}_{n_4 \text{ times}} \right). \]

We then have \( \tilde{B}_n \in B_n \) for all \( n \), \( \lim_{n \to \infty} P(\tilde{B}_n) = \varepsilon > 0 \), and \( B = \cap_{n=1}^\infty \tilde{B}_n \).

Hence we may replace \( B_n \) by \( \tilde{B}_n \) if necessary so as to have \( B_n \in B_n \) for all \( n \).

Since \( B_n \in B_n \), there exists \( B'_n \in B_I^n \) such that \( B_n = B'_n \times I^n \) for all \( n \). Using the regularity Theorem 21.1 there are compact sets, \( K'_n \subseteq B'_n \subseteq I^n \), such that \( \mu_n(B'_n \setminus K'_n) \leq \varepsilon 2^{-n-1} \) for all \( n \in \mathbb{N} \).

\[ K'_n := \cap_{k \leq n} \left( K''_k \times I^{n-k} \right) \text{ and } K_n := K'_n \times I^n \quad \forall n \in \mathbb{N}, \]
then \( K'_n \) is still compact, \( K_n \subseteq B_n \), and \( K_n \) is decreasing. Since
\[ B_n \setminus K_n = \cup_{k \leq n} B_n \setminus \left( K''_k \times I^{n-k} \times I^n \right) \subset \cup_{k \leq n} B_k \setminus \left( K''_k \times I^n \right) = \cup_{k \leq n} \left( B'_k \setminus K''_k \right) \times I^n \]
it follows that
\[ P(B_n \setminus K_n) \leq \sum_{k \leq n} P \left( \left( B'_k \setminus K''_k \right) \times I^n \right) = \sum_{k \leq n} \mu_k \left( B'_k \setminus K''_k \right) \leq \varepsilon \sum_{k=1}^\infty 2^{-k-1} = \varepsilon/2 \text{ for all } n. \]

Therefore,
\[ P(K_n) = P(B_n) - P(B_n \setminus K_n) \geq \varepsilon - \varepsilon/2 = \varepsilon/2 \text{ for all } n. \]

In particular, \( K_n \neq \emptyset \) for all \( n \) and so by Lemma 21.2, \( \emptyset \neq \cap_n K_n \subset \cap_n B_n \).

**Exercise 21.1.** Show that Eq. (21.4) defines a well defined finitely additive measure on \( A := \cup B_n \).

The next result is an easy corollary of Theorem 21.3.

**Theorem 21.4.** Suppose \( \{(X_n, \mathcal{M}_n)\}_{n \in \mathbb{N}} \) are standard Borel spaces, \( X := \prod_{n \in \mathbb{N}} X_n \), \( \pi_n : X \to X_n \) be the \( n^{th} \) projection map, \( B_n := \sigma(\pi_k : k \leq n) \), \( B = \sigma(\pi_n : n \in \mathbb{N}) \), and \( T_n := X_{n+1} \times X_{n+2} \times \ldots \). Further suppose that for each \( n \in \mathbb{N} \) we are given a probability measure, \( \mu_n \) on \( \mathcal{M}_1 \otimes \cdots \otimes \mathcal{M}_n \) such that
\[ \mu_{n+1}(A \times X_{n+1}) = \mu_n(A) \quad \text{for all } n \in \mathbb{N} \text{ and } A \in \mathcal{M}_1 \otimes \cdots \otimes \mathcal{M}_n. \]

Then there exists a unique probability measure, \( P \), on \((X, B)\) such that \( P(A \times T_n) = \mu_n(A) \) for all \( A \in \mathcal{M}_1 \otimes \cdots \otimes \mathcal{M}_n \).

**Proof.** Since each \( (X_n, \mathcal{M}_n) \) is measure theoretic isomorphic to a Borel subset of \( I \), we may assume that \( X_n \in B_I \) and \( \mathcal{M}_n = (B_I^n)_{X_n} \) for all \( n \). Given \( A \in B_I^n \), let \( \bar{\mu}_n(A) := \mu_n(A \cap [X_1 \times \cdots \times X_n]) \) — a probability measure on \( B_I^n \). Furthermore,
\[ \bar{\mu}_{n+1}(A \times I) = \mu_{n+1} \left( (A \times I) \cap [X_1 \times \cdots \times X_{n+1}] \right) = \mu_{n+1} \left( (A \cap [X_1 \times \cdots \times X_n]) \times X_{n+1} \right) = \mu_n \left( (A \cap [X_1 \times \cdots \times X_n]) \right) = \bar{\mu}_n(A). \]

Hence by Theorem 21.3 there is a unique probability measure, \( \bar{P} \), on \( I^n \) such that
\[ \bar{P} \left( A \times I^n \right) = \bar{\mu}_n(A) \quad \text{for all } n \in \mathbb{N} \text{ and } A \in B_I^n. \]

We will now check that \( P := \bar{P} \otimes \bar{\mu}_n \) is the desired measure. First off we have
\[ P(X) = \lim_{n \to \infty} \bar{P} \left( X_1 \times \cdots \times X_n \times I^n \right) = \lim_{n \to \infty} \bar{\mu}_n(X_1 \times \cdots \times X_n) = \lim_{n \to \infty} \mu_n(X_1 \times \cdots \times X_n) = 1. \]

Secondly, if \( A \in \mathcal{M}_1 \otimes \cdots \otimes \mathcal{M}_n \), we have
\[ P(A \times T_n) = \bar{P}(A \times T_n) = \bar{P} \left( (A \times I^n) \cap X \right) = \bar{P} \left( A \times I^n \right) = \bar{\mu}_n(A) = \mu_n(A). \]
Theorem 21.5 (Kolmogorov). For each $\pi$, verify Eq. (21.6) by showing

$$\mu := \otimes_{t \in T} M_t,$$

and for $A \subset T$ let

$$\left( X_A := \prod_{t \in A} X_t, M_A := \otimes_{t \in A} M_t \right)$$

Theorem 21.5 (Kolmogorov). For each $A \subset T$ (i.e. $A \subset T$ and $\#(A) < \infty$), let $\mu_A$ be a probability measure on $(X_A, M_A)$. We further suppose $\{\mu_A\}_{A \subset T}$ satisfy the following compatibility relations:

$$\mu_A \circ \pi^{-1}_{A,A'} = \mu_A$$

Then there exists a unique probability measure, $P$, on $(X, M)$ such that $P \circ \pi^{-1}_{A} = \mu_A$ for all $A \subset T$.

Proof. Let

$$A := \bigcup_{A \subset T} \pi^{-1}_A (M_A)$$

and for $A = \pi^{-1}_A (A') \in A$, let $P(A) := \mu_A(A')$. The compatibility conditions in Eq. (21.5) imply $P$ is a well defined finitely additive measure on the algebra, $A$. We now complete the proof by showing $P$ is continuous on $A$.

To this end, suppose $A_n := \pi^{-1}_A (A'_n) \in A$ with $A_n \downarrow \emptyset$ as $n \to \infty$. Let $A := \bigcup_{n=1}^{\infty} A_n - A$ be a countable subset of $T$. Owing to Theorem 21.4, there is a unique probability measure, $P_A$, on $(X_A, M_A)$ such that $P_A (\pi^{-1}_A (A)) = \mu_A (A)$ for all $\Gamma \subset T$ and $A \in M_{\Gamma}$. Hence if we let $\hat{A}_n := \pi^{-1}_A (A_n)$, we then have

$$P(A_n) = \mu_A (A'_n) = P_A (\hat{A}_n)$$

with $\hat{A}_n \downarrow \emptyset$ as $n \to \infty$. Since $P_A$ is a measure, we may conclude

$$\lim_{n \to \infty} P(A_n) = \lim_{n \to \infty} P_A (\hat{A}_n) = 0.$$

Exercise 21.2. Let us write $A \subset c T$ to mean $A \subset T$ and $A$ is at most countable. Show

$$M := \bigcup_{A \subset c T} \pi^{-1}_A (M_A).$$

Hint: Verify Eq. (21.6) by showing $M_0 := \bigcup_{A \subset c T} \pi^{-1}_A (M_A)$ is a $\sigma$–algebra.

\section{1 Kolmogorov’s Continuity Criterion}

For this section, let $D$ be a bounded open subset of $\mathbb{R}^d$ and $(E, \rho)$ be a complete metric space.

Proposition 21.6. Suppose that $X_t : \Omega \to E$ is a process for $t \in D$. Assume there exists positive constants, $\varepsilon$, $\beta$, and $C$, such that

$$E[\rho(X_t, X_s)^\gamma] \leq C|t - s|^1 + \beta$$

for all $s,t \in D$. Then for any $\alpha \in (0, \beta/\varepsilon)$ there is a modification of $X$ of which $\alpha$–Hölder continuous. Moreover, there is a random variable $K_\alpha$ such that

$$\rho(X_t, X_s) \leq K_\alpha|\alpha - s|^{\alpha} \text{ for all } s,t \in D$$

and $EK_\alpha^p < \infty$ for all $p < \frac{\beta - \alpha}{\varepsilon}$. Before giving the proof of this proposition it will be useful to make a couple of remarks. First assume that $x$ is a continuous function such that $\rho(x(t), x(\nu)) \leq K|t - \nu|^{\gamma}$ for all $s,t \in D$ where $\alpha < \gamma$. Then

$$\rho \left( x \left( i + \frac{1}{2^n} \right), x \left( i + \frac{1}{2^n} \right) \right) \leq K2^{-n\gamma} \leq K2^{-n(\gamma - \alpha)}2^{-\alpha} \leq 2^{-\alpha n}$$

for $n$ sufficiently large, i.e. for $n \geq \frac{\log K}{\gamma - \alpha}$. Conversely we have the following lemma.

Lemma 21.7. Suppose that $x : D \cap \mathbb{D} \to E$ ($\mathbb{D}$ denotes the dyadic rationales) is a given function. Assume there exists $\nu \in \mathbb{N}$ such that

$$\rho \left( x \left( i + \frac{1}{2^n} \right), x \left( i + \frac{1}{2^n} \right) \right) \leq 2^{-\alpha n} \text{ for all } n \geq \nu$$

then there is a constant

$$C = C(\alpha) = \left( 1 + \frac{2}{2^\alpha - 1} \right) 2^\alpha$$

such that for all $s, t \in D \cap \mathbb{D}$,

$$\rho(x(s), x(t)) \leq C|s - t|^{\alpha} \text{ if } |s - t| \leq 2^{-\nu}.$$

In particular $x$ uniquely extends to a continuous function on $D$ which is $\alpha$–Hölder continuous. Moreover, the following estimate holds,

$$\rho(x(s), x(t)) \leq \tilde{C}2^{\nu(1 - \alpha)} \text{ for all } s,t \in D \cap \mathbb{D}$$

where $\tilde{C}$ is a constant which only depends on $\alpha$ and the diameter of $D$.\]
Proof. Let \(n \geq \nu\) and \(s \in \mathbb{D} \cap D\). Write \(s = \frac{i}{2^n} + \sum_{k=1}^{\infty} \frac{a_k}{2^{mk}}\) where \(a_k = 0\) or 1. Set \(S_m = \frac{i}{2^n} + \sum_{k=1}^{m} \frac{a_k}{2^{mk}}\) and notice that \(S_0 = \frac{i}{2^n}\) and \(S_m = s\) for all \(m\) sufficiently large. Therefore with \(m_0\) sufficiently large, we have

\[
\rho \left( x(s), x \left( \frac{i}{2^n} \right) \right) = \rho \left( x(S_{m_0}), x(S_0) \right) \leq \sum_{k=0}^{m_0-1} \rho \left( x(S_{k+1}), x(S_k) \right).
\]

Since \(S_{k+1} - S_k = \frac{a_{k+1}}{2^{k+1}} \leq 2^{-\nu}\), we have by Eq. (21.9) that

\[
\rho \left( x(s), x \left( \frac{i}{2^n} \right) \right) \leq \sum_{k=0}^{\infty} \left( \frac{1}{2^n + k} \right)^\alpha = 2^{-\alpha(n+1)} \frac{1}{1 - 2^{-\alpha}}
\]

\[
= 2^{-\alpha} \frac{1}{(2^n - 1)}.
\]

Therefore, if \(|s - t| \leq 2^{-\nu}\) then \(2^{-\nu} - 2^{-n} = 2^{-(n+1)} < |s - t| \leq 2^{-n}\) for some \(n \geq \nu\). So there exists \(i, j \in \mathbb{N}\) with \(|i - j| \leq 1\) such that \(|s - i2^{-n}| \leq 2^{-n}\) and \(|s - j2^{-n}| \leq 2^{-n}\).

\[
\rho(x(s), x(t)) \leq \rho(x(s), x(i2^{-n})) + \rho(x(i2^{-n}), x(j2^{-n})) + \rho(x(j2^{-n}), x(t))
\]

\[
\leq 2^{-\alpha_n} + \frac{2 \cdot 2^{-\alpha_n}}{2^n - 1} = \left( 1 + \frac{2}{2^n - 1} \right) 2^n |s - t|^{\alpha} =: C|s - t|^\alpha.
\]

From this estimate it follows that \(x\) has an \(\alpha\)-Hölder continuous extension to \(D\). We will continue to denote this extension by \(x\).

If \(|s - t| > 2^{-\nu}\), choose \(k \in \mathbb{N} \setminus \{0\}\) such that \(|s - t| = 2^{-k} - \delta\) with \(0 \leq \delta < 2^{-\nu}\). By repeated use of the triangle inequality, we find that

\[
\rho(x(s), x(t)) \leq C(k2^{-\nu} + \delta^\alpha) \leq 2C2^{-\nu} \leq 2C2^{-\nu} \frac{|s - t|}{2^{-\nu}} = 2C2^{\nu(1 - \alpha)} |s - t|.
\]

Hence

\[
\frac{\rho(x(s), x(t))}{|s - t|^\alpha} \leq 2C2^\nu |s - t|^\alpha \leq \tilde{C}2^{\nu(1 - \alpha)},
\]

where \(\tilde{C}\) is a constant which only depends on \(\alpha\) and the diameter of \(D\). \(\Box\)

Proof. Using Chebyshev’s inequality,

\[
P \left( \rho \left( X \left( \frac{i}{2^n} \right), X \left( \frac{i}{2^n} \right) \right) \geq 2^{-\alpha_n} \right) \leq 2^{\alpha_n} E \rho \left( X \left( \frac{i}{2^n} \right), X \left( \frac{i}{2^n} \right) \right)^\nu \leq C2^{\alpha_n} 2^{-\nu(1 + \beta)}.
\]

Let

\[
A_n := \left\{ \max_{0 \leq i \leq 2^n - 1} \rho \left( X \left( \frac{i + 1}{2^n} \right), X \left( \frac{i}{2^n} \right) \right) \geq 2^{-\alpha_n} \right\}.
\]

Then by Eq. (21.11)

\[
P(A_n) \leq 2^n C2^{\alpha_n} 2^{-n(1 + \beta)} = C2^{-n(\beta - \alpha)}.
\]

Define \(\nu(\omega) = N\) if \(\omega \in A_{N-1}\) and \(\omega \notin A_n\) for all \(n \geq N\) with \(\nu(\omega) = \infty\) is no such \(N\) exists. Notice that \(\{\nu \leq N\} = \cap_{n \geq N} A_n^c\). Using this observation and Eq. (21.12), we learn that

\[
P(\{\nu > N\}) = \sum_{n \geq N} P(\{\nu \leq N\}) = \sum_{n \geq N} \frac{1}{1 - 2^{-\nu(\beta - \alpha)}}.
\]

In particular, it follows that \(P(\nu = \infty) = 0\).

Hence on the set, \(\{\nu < \infty\}\), we have shown that \(\rho \left( X \left( \frac{i}{2^n} \right), X \left( \frac{i}{2^n} \right) \right) < 2^{-\alpha_n}\) for all \(n \geq \nu\). So by Lemma 21.7

\[
\rho(X_t, X_s) \leq |t - s|^\alpha \text{ when } |t - s| \leq 2^{-\nu}.
\]

It clearly follows from this last inequality that there exists a \(\alpha\)-Hölder continuous process \(X\) such \(\tilde{X}_t = X_t\) for \(t \in \mathbb{D} \cap D\) on \(\{\nu < \infty\}\). Moreover, for \(t \in D\) and \(s \in D \cap \mathbb{D}\), we have that

\[
\rho(\tilde{X}_t, X_t) \leq \rho(\tilde{X}_t, \tilde{X}_s) + \rho(\tilde{X}_s, X_s) + \rho(X_s, X_t) = \rho(\tilde{X}_t, \tilde{X}_s) + \rho(X_s, X_t) \text{ a.e.}
\]

By continuity, \(\lim_{s \to t} \tilde{X}_s = \tilde{X}_t\) a.e. and by Eq. (21.7) it follows that \(\lim_{s \to t} X_s = X_t\) in measure. Hence, \(X_t = \tilde{X}_t\) a.e. and \(\tilde{X}\) is a version of \(X\).

It is only left to prove the quantitative estimate in Eq. (21.8). Because of Eq. (21.10) we have the following estimate:

\[
\rho(\tilde{X}_t, \tilde{X}_s) \leq K_\alpha \text{ for all } s \neq t \in D,
\]

where \(K_\alpha = \tilde{C}2^{\nu(1 - \alpha)}\) and \(\tilde{C}\) is a constant which depends on \(\alpha\) and the diameter of \(D\). We estimate the \(p\)-norm of \(K_\alpha\) using Eq. (21.13) as follows:

\[
E K_\alpha^p = \tilde{C}^p \sum_{n=0}^{\infty} 2^{(1 - \alpha)p} P(\{\nu = n\})
\]

\[
\leq \tilde{C}^p \cdot (1 + \sum_{n=1}^{\infty} 2^{(1 - \alpha)p} P(\{\nu > n - 1\}))
\]

\[
\leq \tilde{C}^p \cdot (1 + \frac{C}{1 - 2^{-(\beta - \alpha)}} \sum_{n=1}^{\infty} 2^{(1 - \alpha)p} 2^{-n(\beta - \alpha)}) < \infty
\]

provided that \((1 - \alpha)p - (\beta - \alpha) \epsilon < 0\). \(\Box\)
Gaussian Fields and Poisson Point Processes

**Definition 22.1.** A random variable, \( Y : \Omega \rightarrow \mathbb{R} \) is said to be **Gaussian** if
\[
\mathbb{E} e^{i \lambda Y} = \exp \left( -\frac{1}{2} \lambda^2 \text{Var} (Y) + i \lambda \mathbb{E} Y \right)
\]
for all \( \lambda \in \mathbb{R} \).

**Definition 22.2.** A random vector, \( X : \Omega \rightarrow \mathbb{R}^N \), is said to be **Gaussian** if \( \lambda \cdot X \) is a Gaussian random variable for all \( \lambda \in \mathbb{R}^N \). Equivalently put, \( X : \Omega \rightarrow \mathbb{R}^N \) is Gaussian provided
\[
\mathbb{E} \left[ e^{i \lambda \cdot X} \right] = \exp \left( -\frac{1}{2} \text{Var} (\lambda \cdot X) + i \lambda \mathbb{E} (\lambda \cdot X) \right), \quad \forall \lambda \in \mathbb{R}^N. \tag{22.1}
\]

**Definition 22.3.** The mean and the covariance matrix
\[
c = \begin{bmatrix} c_1 \\ \vdots \\ c_N \end{bmatrix} \quad \text{and} \quad Q := \begin{bmatrix} Q_{11} & \cdots & Q_{1N} \\ \vdots & \ddots & \vdots \\ Q_{N1} & \cdots & Q_{NN} \end{bmatrix}
\]

of a random vector, \( X : \Omega \rightarrow \mathbb{R}^N \), are defined by
\[
c_i := \mathbb{E} [X_i] \quad \text{and} \quad Q_{ij} := \text{Cov} (X_i, X_j) = \mathbb{E} [(X_i - c_i) (X_j - c_j)]. \tag{22.2}
\]

We will abbreviate Eq. (22.2) by writing,
\[
c := \mathbb{E} X \quad \text{and} \quad Q := \mathbb{E} [X - c] (X - c)^\text{tr}, \quad \text{where} \quad [\mathbb{E} A]_{ij} := \mathbb{E} A_{ij}, \quad \text{when} \quad A : \Omega \rightarrow \mathbb{R}^{m \times n} \text{ is a random matrix.}
\]

Therefore Eq. (22.1) becomes,
\[
\mathbb{E} e^{i \lambda \cdot X} = \exp \left( -\frac{1}{2} Q \lambda \cdot \lambda + i \lambda \cdot c \right). \tag{22.4}
\]

**Definition 22.4.** Given a Gaussian random vector, \( X \), we call the pair \((Q, c) = (\text{cov. matrix, mean}) \), the **characteristics** of \( X \). We will also abbreviate this by writing \( X \triangleq N (Q, c) \).

**Example 22.5.** Suppose \( \{X_i\}_{i=1}^N \) are i.i.d. standard normal random variables, then \( X := (X_1, \ldots, X_N)^\text{tr} \) is Gaussian with characteristics, \((I, 0)\). Indeed,
\[
\mathbb{E} [e^{i \lambda \cdot X}] = \prod_{j=1}^N \mathbb{E} [e^{i \lambda_j X_j}] = \prod_{j=1}^N e^{-\frac{1}{2} \lambda_j^2} = \exp \left( -\frac{1}{2} \lambda \cdot \lambda \right).
\]

**Lemma 22.6.** If \( X \in \mathbb{R}^N \) is a Gaussian random vector with characteristics, \((Q, c), A : \mathbb{R}^N \rightarrow \mathbb{R}^M \) is a linear transformation (i.e. a \( M \times N \) matrix), and \( b \in \mathbb{R}^M \) then \( AX + b \) is a Gaussian random vector in \( \mathbb{R}^M \) with characteristics, \((AQA^\text{tr}, b + Ac\), i.e. if \( X \triangleq N (Q, c) \) then \( AX + b \triangleq N (AQA^\text{tr}, b + Ac) \). In particular if \( X \triangleq N (I, 0) \), then \( AX + b \triangleq N (AA^\text{tr}, b) \).

**Proof.** The result is a consequence of the following computation:
\[
\mathbb{E} \left[ e^{i \lambda \cdot (AX + b)} \right] = e^{i \lambda \cdot b} \mathbb{E} \left[ e^{i \lambda A^\text{tr} X} \right] = e^{i \lambda \cdot b} \exp \left( -\frac{1}{2} QA^\text{tr} \lambda \cdot A^\text{tr} \lambda + i A^\text{tr} \lambda \cdot c \right) = \exp \left( -\frac{1}{2} AQA^\text{tr} \lambda \cdot \lambda + i \lambda \cdot Ac + i \lambda \cdot b \right).
\]

**Remark 22.7.** Recall that if \( Q \) is a real symmetric \( N \times N \) matrix, then the spectral theorem asserts there exists an orthonormal basis, \( \{u_j\}_{j=1}^N \), such that \( Qu_j = \lambda_j u_j \) for some \( \lambda_j \in \mathbb{R} \). Moreover, \( \lambda_j \geq 0 \) for all \( j \) is equivalent to \( Q \) being non-negative. Hence if \( Q \geq 0 \) and \( f : \{\lambda_j : j = 1, 2, \ldots, N\} \rightarrow \mathbb{R} \), we may define \( f (Q) \) to be the unique linear transformation on \( \mathbb{R}^N \) such that \( f (Q) u_j = \lambda_j u_j \).
Notice that $Q^{1/2} \geq 0$ and $Q = Q^{1/2}Q^{1/2}$.

**Example 22.8.** When $Q \geq 0$ and $f(x) := \sqrt{x}$, we write $Q^{1/2}$ or $\sqrt{Q}$ for $f(Q)$.

**Example 22.9.** When $Q$ is symmetric and

$$f(x) = \begin{cases} \frac{1}{x} & \text{if } x \neq 0 \\ 0 & \text{if } x = 0 \end{cases}$$

we will denote $f(Q)$ by $Q^{-1}$. As the notation suggests, $f(Q)$ is the inverse of $Q$ when $Q$ is invertible which happens iff $\lambda_i \neq 0$ for all $i$. When $Q$ is not invertible,

$$Q^{-1} := f(Q) = Q^{\text{Ran}(Q)} P,$$  \hfill (22.5)

where $P : \mathbb{R}^n \rightarrow \mathbb{R}^n$ be orthogonal projection onto the Ran $(Q)$. Observe that $P = g(Q)$ where $g(x) = 1_{x \neq 0}$.

**Lemma 22.10.** For any $Q \geq 0$ we can find a matrix, $A$, such that $Q = AA^T$. In fact it suffices to take $A = Q^{1/2}$.

**Corollary 22.11.** Given a $N \times N$ symmetric non-negative matrix, $Q$, and a point, $c \in \mathbb{R}^N$, there exists a Gaussian random vector, $X$, with characteristics, $(Q,c)$. In particular, the laws of Gaussian random vectors (called **Gaussian measures**) are in one to one correspondance with pairs, $(Q,c)$, where $Q \geq 0$ and $c \in \mathbb{R}^N$.

**Proof.** By Example 22.5 there exists a Gaussian random vector, $Y : \Omega \rightarrow \mathbb{R}^N$ such that $Y \overset{d}{=} N(I,0)$. Then according to Lemma 22.6 we may take

$$X = Q^{1/2}Y + c.$$

**Proposition 22.12.** Suppose $X \overset{d}{=} N(Q,c)$ where $c \in \mathbb{R}^N$ and $Q$ is a $N \times N$ symmetric positive definite matrix. If $\mu = \mu_{(Q,c)} = P \circ X^{-1}$ then

$$d\mu(x) := \frac{1}{\sqrt{\det(2\pi Q)}} \exp(-\frac{1}{2}Q^{-1}(x-c) \cdot (x-c)) \, dx.$$  \hfill (22.7)

**Proof.** If $f : \mathbb{R}^N \rightarrow \mathbb{R}$ be a bounded measurable function and $Y \overset{d}{=} N(I,0)$, then according to Example 22.5 and Eq. (22.6),

$$\int_{\mathbb{R}^N} f(x) \, d\mu(x) = \mathbb{E}[f(Y)] = E\left[f\left(Q^{1/2}Y + c \right)\right] = \int_{\mathbb{R}^N} f\left(Q^{1/2}y + c \right) \left(\frac{1}{2\pi}\right)^{N/2} e^{-\frac{1}{2}|y|^2} \, dy.$$

Making the change of variables, $x = Q^{1/2}y + c$, using

$$dx = \det Q^{1/2} \, dy = \sqrt{\det Q} \, dy,$$

we conclude

$$\int_{\mathbb{R}^N} f(x) \, d\mu(x) = \int_{\mathbb{R}^N} f(x) \left(\frac{1}{2\pi}\right)^{N/2} e^{-\frac{1}{2}|x-c|^2} \, dx \sqrt{\det Q}$$

$$= \int_{\mathbb{R}^N} f(x) \left(\frac{1}{2\pi}\right)^{N/2} \exp\left(-\frac{1}{2}Q^{-1}(x-c) \cdot (x-c)\right) \, dx$$

which gives Eq. (22.7).

We can find a similar formula for $P \circ X^{-1}$ when $Q$ is degenerate. In order to do this, $k := \dim \text{Ran}(Q)$ and let $U : \mathbb{R}^k \rightarrow \mathbb{R}^N$ be a linear transformation such that $\text{Ran}(U) = \text{Ran}(Q)$ and $U : \mathbb{R}^k \rightarrow \text{Ran}(Q)$ is an isometric isomorphism. Letting $A := Q^{1/2}U$, we again have

$$AA^T = Q^{1/2}UU^TQ^{1/2} = Q^{1/2}P_{\text{Ran}(Q)}Q^{1/2} = Q.$$  

Therefore, if $Y = N(I_k \times 0)$, then $X = AY + c \overset{d}{=} N(Q,c)$. Observe that $X-c$ necessarily takes values in $\text{Ran}(Q) + c$.

**Proposition 22.13.** Suppose $X \overset{d}{=} N(Q,c)$ with $k = \dim \text{Ran}(Q)$. If $\mu = \mu_{(Q,c)} = P \circ X^{-1}$, then

$$\int_{\mathbb{R}^N} f(x) \, d\mu(x) = \int_{\text{Ran}(Q)+c} f(x) \exp\left(-\frac{1}{2}Q^{-1}(x-c) \cdot (x-c)\right) \, dx$$

where $dx$ is now “Lebesgue measure” on $\text{Ran}(Q) + c$.

**Proof.** Proceeding as in the proof of Proposition 22.12,

$$\int_{\mathbb{R}^N} f(x) \, d\mu(x) = \int_{\mathbb{R}^k} f\left(Ay + c\right) \left(\frac{1}{2\pi}\right)^{k/2} e^{-\frac{1}{2}|y|^2} \, dy$$

$$= \int_{\mathbb{R}^k} f\left(Q^{1/2}Uy + c\right) \left(\frac{1}{2\pi}\right)^{k/2} e^{-\frac{1}{2}|y|^2} \, dy.$$
and
\[ |y|^2 = \left( U^\intercal Q^{1/2} U \right)^{-1} \left( U^\intercal Q^{1/2} U \right) = \left( Q^{-1/2} U, Q^{-1/2} U \right)_N \]

and because \( x \) and \( y \) were arbitrary, we may conclude from this that \( X \) and \( Y \) are independent.

**Theorem 22.15.** Suppose that \( Z = (X,Y)^\intercal \) is a mean zero Gaussian random vector with \( X \in \mathbb{R}^k \) and \( Y \in \mathbb{R}^l \). Let \( Q = \begin{bmatrix} X X^\intercal \end{bmatrix} \) and then let

\[ W := Y - \mathbb{E} [Y X^\intercal] Q^{-1} X \]

where \( Q^{-1} \) is as in Example 22.9. Then \( (X,W)^\intercal \) is again a Gaussian random vector and moreover \( W \) is independent of \( X \). The covariance matrix for \( W \) is

\[ \mathbb{E} [W W^\intercal] = \mathbb{E} [Y Y^\intercal] - \mathbb{E} [Y X^\intercal] Q^{-1} \mathbb{E} [X Y^\intercal]. \]  

**Proof.** Let \( A \) be any \( k \times l \) matrix and let \( W := Y - A X \). Since

\[ \begin{bmatrix} X \\ W \end{bmatrix} = \begin{bmatrix} I & 0 \end{bmatrix} \begin{bmatrix} X \\ Y \end{bmatrix}, \]

according to Lemma 22.6, \( (X,W)^\intercal \) is still Gaussian. So in order to make \( W \) independent of \( X \) it suffices to choose \( A \) so that \( W \) and \( X \) are uncorrelated, i.e.

\[ 0 = \text{Cov} (W_j, X_i) = \text{Cov} \left( Y_j - \sum_k A_{jk} X_k, X_i \right) = \mathbb{E} [Y_j X_i] - \sum_k A_{jk} \mathbb{E} [X_k X_i] \]

or in matrix notation, we want to choose \( A \) so that

\[ \mathbb{E} [Y X^\intercal] = A \mathbb{E} [X X^\intercal]. \] (22.9)

In the case \( Q := \mathbb{E} [X X^\intercal] \) is non-degenerate, we see that \( A := \mathbb{E} [Y X^\intercal] Q^{-1} \) is the desired solution. In fact this works for general \( Q \) where \( Q^{-1} \) is defined in Example 22.9. To see this is correct, recall

\[ v \cdot Q v = v \cdot \mathbb{E} [X X^\intercal] v = \mathbb{E} [v \cdot X]^2 \]

from which it follows that

\[ \text{Nul} (Q) = \left\{ v \in \mathbb{R}^k : v \cdot X = 0 \right\}. \]

Hence it follows that

\[ \mathbb{E} [Y X^\intercal] v = A \mathbb{E} [X X^\intercal] v \quad \text{for all} \quad v \in \text{Nul} (Q) \]

no matter how \( A \) is chosen. On the other hand if \( v \in \text{Ran} (Q) = \text{Nul} (Q)^\perp \),\n
\[ A \mathbb{E} [X X^\intercal] v = \mathbb{E} [Y X^\intercal] Q^{-1} Q v = \mathbb{E} [Y X^\intercal] v \]
We then have
\[ W := Y - BQ^{-1}X. \]

We have then
\[
\mathbb{E} [WW^{tr}] = \mathbb{E} \left[ (Y - BQ^{-1}X) (Y - BQ^{-1}X)^{tr} \right] \\
= \mathbb{E} \left[ (Y - BQ^{-1}X) (Y^{tr} - X^{tr}Q^{-1}B^{tr}) \right] \\
= \mathbb{E} [YY^{tr} - YX^{tr}Q^{-1}B^{tr} - BQ^{-1}XY^{tr} + BQ^{-1}X^{tr}Q^{-1}B^{tr}] \\
= \mathbb{E} [YY^{tr}] - BQ^{-1}B^{tr} - BQ^{-1}B^{tr} + BQ^{-1}Q^{-1}B^{tr} \\
= \mathbb{E} [YY^{tr}] - BQ^{-1}B^{tr} \\
= \mathbb{E} [YY^{tr}] - \mathbb{E} [YX^{tr}] Q^{-1} \mathbb{E} [XY^{tr}].
\]

**Corollary 22.16.** Suppose that \( Z = (X,Y)^{tr} \) is a mean zero Gaussian random vector with \( X \in \mathbb{R}^k \) and \( Y \in \mathbb{R}^l \),
\[
A := \mathbb{E} [Y^{tr}] Q^{-1}, \\
Q_W := \mathbb{E} [YY^{tr}] - \mathbb{E} [YX^{tr}] Q^{-1} \mathbb{E} [XY^{tr}],
\]
and suppose \( W \overset{d}{=} N(Q_W,0) \). If \( f : \mathbb{R}^k \times \mathbb{R}^l \rightarrow \mathbb{R} \) is a bounded measurable function, then
\[ \mathbb{E} [f(X,Y) | X] = \mathbb{E} [f(x,AX + W) | x=X]. \]

As an important special case, if \( x \in \mathbb{R}^k \) and \( y \in \mathbb{R}^l \), then
\[
\mathbb{E} \left[ e^{i(xX+yY)} | X \right] = e^{i(xX+yAX)} e^{-i \frac{1}{2} \text{Var}(W)} = e^{i(xX+yAX)} e^{-i \frac{1}{2} Q_W y}. 
\] (22.10)

**Proof.** Using the notation in Theorem 22.15,
\[ \mathbb{E} [f(X,Y) | X] = \mathbb{E} [f(X,AX + W) | X] \]
where \( W \overset{d}{=} N(Q_W,0) \) and \( W \) is independent of \( X \). The result now follows by an application of Exercise 18.4. Let us now specialize to the case where \( f(X,Y) = e^{i(xX+yY)} \) in which case
\[
\mathbb{E} \left[ e^{i(xX+yY)} | X \right] = \mathbb{E} \left[ e^{i(x'X+(y(Ax'+W))} | X \right] | x'=x \\
= e^{i(xX+yAX)} e^{-i \frac{1}{2} \text{Var}(W)} = e^{i(xX+yAX)} e^{-i \frac{1}{2} Q_W y}. 
\]

**Exercise 22.1.** Suppose now that \((X,Y,Z)^{tr}\) is a mean zero Gaussian random vector with \( X \in \mathbb{R}^k \), \( Y \in \mathbb{R}^l \), and \( Z \in \mathbb{R}^m \). Show for all \( y \in \mathbb{R}^l \) and \( z \in \mathbb{R}^m \) that
\[
\mathbb{E} [\exp (i(y \cdot Y + z \cdot Z)) | X] = \exp (- \text{Cov}(y \cdot W_1, z \cdot W_2)) \cdot \mathbb{E} [\exp (iy \cdot Y) | X] \cdot \mathbb{E} [\exp (iz \cdot Z) | X].
\]

In performing these computations please use the following definitions,
\[
Q := Q_X := \mathbb{E} [X^{tr}] , \\
A := \mathbb{E} [[Y]^{tr} X^{tr}] Q^{-1} = \mathbb{E} [Y^{tr} X^{tr}] Q^{-1} = \begin{bmatrix} A_1 \\ A_2 \end{bmatrix},
\]
and
\[
W := \begin{bmatrix} W_1 \\ W_2 \end{bmatrix} = \begin{bmatrix} Y \\ Z \end{bmatrix} - AX = \begin{bmatrix} Y - A_1X \\ Z - A_2X \end{bmatrix}.
\]

**Definition 22.17 (Conditional Independence).** Let \((\Omega,\mathcal{B},\mathbb{P})\) be a probability space and \(\mathcal{B}_i \subset \mathcal{B}\) be a sub-sigma algebra of \(\mathcal{B}\) for \(i = 1,2,3\). We say that \(\mathcal{B}_1\) is independent of \(\mathcal{B}_3\) conditioned on \(\mathcal{B}_2\) (written \(\mathcal{B}_1 \perp \perp \mathcal{B}_3\) given \(\mathcal{B}_2\)) if
\[ P(A \cap B | \mathcal{B}_2) = P(A | \mathcal{B}_2) \cdot P(B | \mathcal{B}_2) \ a.s. \]
for all \(A \in \mathcal{B}_1\) and \(B \in \mathcal{B}_3\). This can be equivalently stated as
\[
\mathbb{E} (f \cdot g | \mathcal{B}_2) = \mathbb{E} (f | \mathcal{B}_2) \cdot \mathbb{E} (g | \mathcal{B}_2) \ a.s.
\]
for all \(f \in (\mathcal{B}_1)_b\) and \(g \in (\mathcal{B}_3)_b\), where \(\mathcal{B}_b\) denotes the bounded \(\mathcal{B} -\) measurable functions. If \(X,Y,Z\) are measurable functions on \((\Omega,\mathcal{B})\), we say that \(X\) is independent of \(Z\) conditioned on \(Y\) provided \(\sigma(X) \perp \perp \sigma(Z)\).

**Exercise 22.2.** Suppose \(M_i \subset (\mathcal{B}_i)_b\) for \(i = 1\) and \(i = 3\) are multiplicative systems such that \(\mathcal{B}_1 = \sigma (M_1)\). Show \(\mathcal{B}_1 \perp \perp \mathcal{B}_3\) iff
\[
\mathbb{E} (f \cdot g | \mathcal{B}_2) = \mathbb{E} (f | \mathcal{B}_2) \cdot \mathbb{E} (g | \mathcal{B}_2) \ a.s. \\forall f \in M_1 \text{ and } g \in M_3. \tag{22.11}
\]

**Hint:** Do this by two applications of the functional form of the multiplicative systems theorem. For the first application, fix an \(f \in M_1\) and let
\[
\mathbb{H} := \{g \in (\mathcal{B}_3)_b : \mathbb{E} (f \cdot g | \mathcal{B}_2) = \mathbb{E} (f | \mathcal{B}_2) \cdot \mathbb{E} (g | \mathcal{B}_2) \ a.s. \}.
\]

**Exercise 22.3.** Keeping the same notation as in Exercise 22.1 show \(Y \perp \perp Z\) iff
\[
\mathbb{E} [Y^{Z^{tr}}] = \mathbb{E} [Y^{X^{tr}}] Q^{-1} \mathbb{E} [X^{Z^{tr}}].
\]

where
\[ Q = Q_X := \mathbb{E} [X^{tr}]. \]
**Definition 22.18.** Let $T$ be a set. A Gaussian random field indexed by $T$ is a collection of random variables, $\{X_t\}_{t \in T}$, on some probability space $(\Omega, \mathcal{B}, P)$ such that for any finite subset, $\Lambda \subset T$, $\{X_t : t \in \Lambda\}$ is a Gaussian random vector.

Associated to a Gaussian random field, $\{X_t\}_{t \in T}$, are the two functions,

$$c : T \to \mathbb{R} \text{ and } Q : T \times T \to \mathbb{R}$$

defined by $c(t) := \mathbb{E}X_t$ and $Q(s, t) := \text{Cov}(X_s, X_t)$. By the previous results, the functions $(Q, c)$ uniquely determine the finite dimensional distributions of $\{X_t : t \in \Lambda\}$ for all $\Lambda \subset T$.

**Definition 22.19.** Suppose $T$ is a set and $\{X_t : t \in T\}$ is a random field. For any $\Lambda \subset T$, let $\mathcal{B}_\Lambda := \sigma(\{X_t : t \in \Lambda\})$.

**Exercise 22.4.** Suppose $T = [0, \infty)$ and $\{X_t : t \in T\}$ is a mean zero Gaussian random field (process). Show that $\mathcal{B}_{[0, \sigma]} \perp \perp \mathcal{B}_{[\sigma, \infty)}$ for all $0 \leq \sigma < \infty$ iff

$$Q(s, \sigma)Q(\sigma, t) = Q(\sigma, \sigma)Q(s, t) \quad \forall \ 0 \leq s \leq \sigma \leq t < \infty.$$  

(22.12)
References