

# MATH 180A: Introduction to Probability

Lecture B00 (Nemish)

[www.math.ucsd.edu/~ynemish/teaching/180a](http://www.math.ucsd.edu/~ynemish/teaching/180a)

Lecture C00 (Au)

[www.math.ucsd.edu/~bau/f20.180a](http://www.math.ucsd.edu/~bau/f20.180a)

Today: Independence of random variables. Convolutions

Next: ASV 8.2-8.3

Video: Prof. Todd Kemp, Fall 2019

Week 9:

- Homework 7 (due Friday, December 4, 11:59 PM)
- Regrades for Homework 6 (until Wednesday, December 2, 11 PM)

# Joint Distributions & Independence

6.3

Suppose  $\underline{X} = (X_1, \dots, X_n)$  is jointly continuous. Then

$X_1, \dots, X_n$  are independent iff  $f_{\underline{X}}(x_1, \dots, x_n) = f_{X_1}(x_1) \dots f_{X_n}(x_n)$ .

( $\Rightarrow$ ) (Special case  $n=2$ )

Suppose  $X, Y$  are independent.  $f_X, f_Y$ .

$$P(X \leq s, Y \leq t) = P(X \leq s) P(Y \leq t)$$

$$\begin{aligned} P((X, Y) \in (-\infty, s] \times (-\infty, t]) &= \int_{-\infty}^s \int_{-\infty}^t f_{X,Y}(x, y) dx dy \\ &\stackrel{\text{equal for all } s, t}{=} \int_{-\infty}^s f_X(x) dx \cdot \int_{-\infty}^t f_Y(y) dy \\ &= \int_{-\infty}^s \int_{-\infty}^t f_X(x) f_Y(y) dx dy \end{aligned}$$

Now take  $\frac{\partial^2}{\partial s \partial t}$  of both sides.

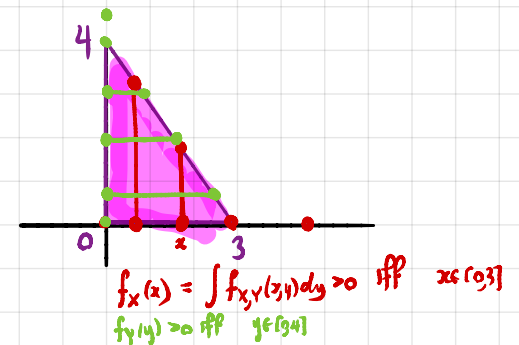
$$f_{X,Y}(s, t) = f_X(s) f_Y(t). \quad //$$

Eg. Multivariate standard normal  $\frac{1}{(2\pi)^{n/2}} e^{-\|x\|^2/2}$   
 $= \left(\frac{1}{\sqrt{2\pi}} e^{-x^2/2}\right) \dots \left(\frac{1}{\sqrt{2\pi}} e^{-x_n^2/2}\right)$

Since the joint density is a product of single-variable densities, the components of the random vector are independent, with those densities as marginals:

I.e. if  $\underline{X}$  is a multivariate standard normal,  $\underline{X} = (X_1, \dots, X_n)$  then  $X_1, \dots, X_n$  are independent  $N(0,1)$ 's.

Q: Suppose  $\underline{X}$  is uniform on the triangle  $(x, y)$  Are  $X, Y$  independent?



No!

$f_{(X,Y)}(x,y) = f_X(x) f_Y(y)$

$\begin{cases} 1/6 & \text{on } \triangle \\ 0 & \text{off } \triangle \end{cases}$

$\text{Support}(f_X) = \{x : f_X(x) \neq 0\} = [0, 3]$

$\text{Support}(f_Y) = \{y : f_Y(y) \neq 0\} = [0, 4]$

$\therefore \text{supp } f_{X,Y} = [0, 3] \times [0, 4]$



Example. Suppose  $X \sim \text{Exp}(\lambda)$ ,  $Y \sim \text{Exp}(\mu)$ , and  $X, Y$  independent.

Find the distribution of  $\min(X, Y)$ .

$$F_{\min(X, Y)}(t) = P(\min(X, Y) \leq t) = 1 - P(\min(X, Y) > t)$$

$$\downarrow$$
$$\therefore = 1 - e^{-(\lambda + \mu)t}$$

$$= F_Z(t)$$

where  $Z \sim \text{Exp}(\lambda + \mu)$

$$\{ \min(X, Y) > t \}$$
$$= \{ X > t, Y > t \}$$

$$\therefore P(X > t, Y > t)$$

$$= P(X > t)P(Y > t)$$

$$= e^{-\lambda t} e^{-\mu t}$$

$$= e^{-(\lambda + \mu)t}$$

Theorem. Suppose  $\underline{X} = (X_1, \dots, X_n)$  is a random vector, with  $X_1, \dots, X_n$  independent.

E.g.  $X, Y$  indep.

$$\mathbb{E}(X^2 Y)$$

$$= \mathbb{E}(X^2) \mathbb{E}(Y)$$

For any functions  $g_1, g_2, \dots, g_n: \mathbb{R} \rightarrow \mathbb{R}$ ,

$$\mathbb{E}(g_1(X_1) g_2(X_2) \dots g_n(X_n)) = \mathbb{E}(g_1(X_1)) \cdot \mathbb{E}(g_2(X_2)) \cdot \dots \cdot \mathbb{E}(g_n(X_n))$$

Pf. ( $n=2$ , jointly continuous)

$$\mathbb{E}(g(X)h(Y)) = \iint_{\mathbb{R}^2} g(x)h(y) \underbrace{f_{(X,Y)}(x,y)}_{f_X(x) f_Y(y)} dx dy$$

$$= \int_{-\infty}^{\infty} g(x) f_X(x) dx \cdot \int_{-\infty}^{\infty} h(y) f_Y(y) dy = \mathbb{E}(g(X)) \cdot \mathbb{E}(h(Y)).$$

In particular,  $\mathbb{E}(X_1 X_2 \dots X_n) = \mathbb{E}(X_1) \mathbb{E}(X_2) \dots \mathbb{E}(X_n)$ .

Actually, the last theorem is iff.

↳ Suppose we know

$$\mathbb{E}(g_1(X_1)g_2(X_2)\dots g_n(X_n)) = \mathbb{E}(g_1(X_1))\mathbb{E}(g_2(X_2))\dots\mathbb{E}(g_n(X_n))$$

for all functions  $g_1, g_2, \dots, g_n$ . Fix  $A_1, \dots, A_n \subseteq \mathbb{R}$ .

Just take  $g_1 = \mathbb{1}_{A_1} \dots g_n = \mathbb{1}_{A_n}$

$$\mathbb{E}(g_1(X_1)) = \mathbb{E}(\mathbb{1}_{A_1}(X_1)) = \mathbb{P}(X_1 \in A_1).$$

↳  $\text{Ber}(p)$  where  $p = \mathbb{P}(X_1 \in A_1)$

$$g_1(X_1)g_2(X_2) = \mathbb{1}_{A_1}(X_1)\mathbb{1}_{A_2}(X_2)$$

$$= \begin{cases} 0 & \text{if } X_1 \notin A_1 \\ 1 & \text{if } X_1 \in A_1 \end{cases} \cdot \begin{cases} 0 & \text{if } X_2 \notin A_2 \\ 1 & \text{if } X_2 \in A_2 \end{cases} = \begin{cases} 0 & \text{otherwise} \\ 1 & \underline{X_1 \in A_1 \ \& \ X_2 \in A_2} \end{cases}$$

$$\therefore \mathbb{E}(\text{" "}) = \mathbb{P}(X_1 \in A_1, X_2 \in A_2)$$

# Convolution

Let  $X, Y$  be independent random variables. What can we say about the distribution of  $X+Y$ ?

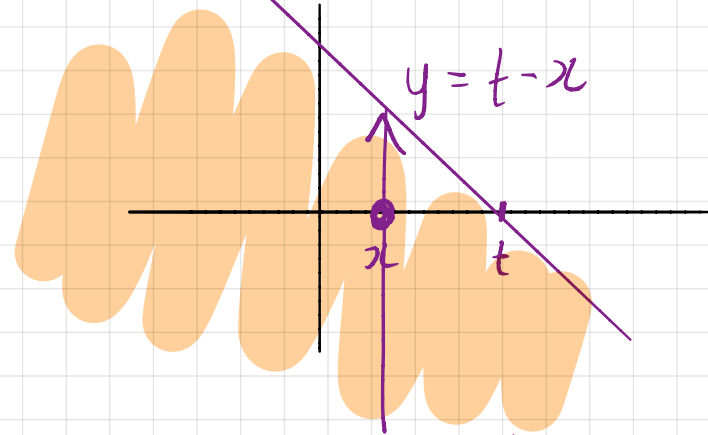
$$F_{X+Y}(t) = P(X+Y \leq t) \\ = P((X, Y) \in T_t)$$

$$= \iint_{T_t} f_{(X, Y)}(x, y) dx dy$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{t-x} f_{(X, Y)}(x, y) dy dx$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{t-x} f_X(x) f_Y(y) dy dx$$

$$T_t = \{(x, y) : x+y \leq t\}$$



$$= \int_{-\infty}^{\infty} f_X(x) \int_{-\infty}^{t-x} f_Y(y) dy$$

$$\therefore f_{X+Y}(t) = \frac{d}{dt}(\text{" "}) = \int_{-\infty}^{\infty} f_X(x) f_Y(t-x) dx$$

The convolution of two prob. densities is  $(f * g)(t) = \int_{-\infty}^{\infty} f_X(x) f_Y(t-x) dx$

Eg.  $X, Y \sim \text{Exp}(\lambda)$ , independent. Find  $f_{X+Y}$ .

$$f_{X+Y}(t) = f_X * f_Y(t) = \int_{-\infty}^{\infty} f_X(x) f_Y(t-x) dx$$

$$\lambda e^{-\lambda x} \quad \lambda e^{-\lambda(t-x)}$$

$x \geq 0$        $t-x \geq 0$

$0 \leq x \leq t$

$$X+Y \sim \Gamma(2, \lambda).$$

$$= \int_0^t \lambda e^{-\lambda x} \cdot \lambda e^{-\lambda(t-x)} dx$$

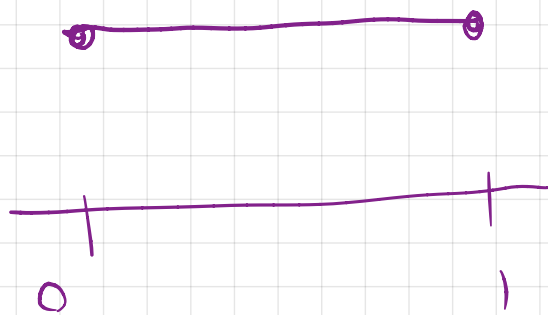
$e^{-\lambda t} \cdot e^{\lambda x}$

$$= \int_0^t \lambda^2 e^{-\lambda t} dx = \lambda^2 t e^{-\lambda t} \quad t \geq 0$$

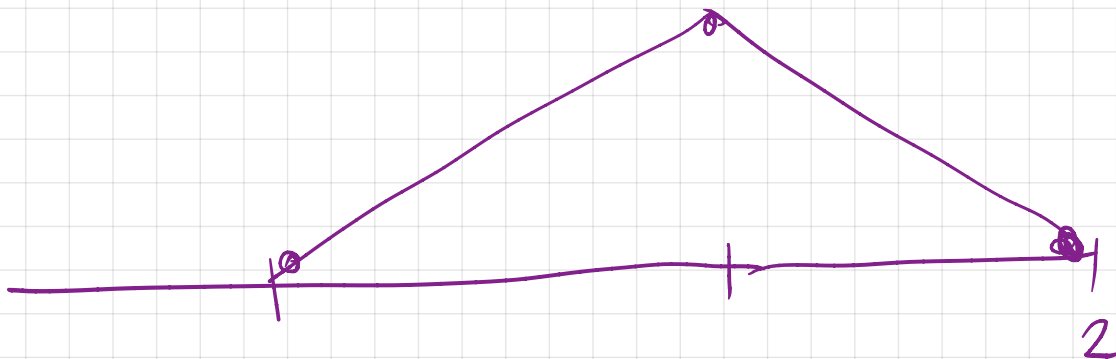


E.g.  $X, Y \sim \text{Unif}([0,1])$ , independent.

$f_X, f_Y$



$f_{X+Y}$



$$\mathbb{1}_A(x) = \begin{cases} 1 & x \in A \\ 0 & x \notin A \end{cases}$$

E.g.  $X \sim \text{Unif}[0,1]$ ,  $f_X(x) = \mathbb{1}_{[0,1]}(x)$