

**Math 180A, Fall 2005, Prof. Tesler – October 26, 2005**  
**Normal distribution and long-term averages or sums**

1. MEAN AND STANDARD DEVIATION OF SUMS OR AVERAGES OF I.I.D. VARIABLES

Let  $X$  be a random variable with  $\mu = E(X)$  and  $\sigma = \text{SD}(X)$ . Let  $X_1, \dots, X_n$  be  $n$  i.i.d. (independent identically distributed) random variables with the distribution of  $X$ .

Let  $S_n = X_1 + \dots + X_n$  be their sum and  $\bar{X}_n = (X_1 + \dots + X_n)/n = S_n/n$  be their average. Then

Sums	Averages
$E(S_n) = E(X_1) + \dots + E(X_n) = nE(X_1) = n\mu$	$E(\bar{X}_n) = \mu$
$\text{Var}(S_n) = \text{Var}(X_1) + \dots + \text{Var}(X_n) = n\text{Var}(X_1) = n\sigma^2$	$\text{Var}(\bar{X}_n) = \sigma^2/n$
$\text{SD}(S_n) = \sigma\sqrt{n}$	$\text{SD}(\bar{X}_n) = \sigma/\sqrt{n}$

To reduce confusion between the different types of standard deviation, we sometimes say “the *standard error* (SE) of the sum is  $\sigma\sqrt{n}$ ” and “the *standard error* (SE) of the average is  $\sigma/\sqrt{n}$ .”

2. LIMIT THEOREMS

When  $n$  is large enough, the sum or average of  $n$  i.i.d. random variables (for *any* distribution) closely resembles the normal curve! The details depend on the specific distribution. The proofs of the first 3 results below are in the book, and the 4th is beyond the scope of the book (but Chap. 2.3 has some details).

- (1) **Markov’s inequality (p. 174):** If  $X \geq 0$  then  $P(X \geq a) \leq E(X)/a$  for every  $a > 0$ .
- (a) **Example:** The average of three nonnegative numbers is 10. What’s the largest that any of them could be? Set two of them to 0 and the third one to 30.
- (b) Redo (a) if a weighted average were used instead of a regular average. Then you can make two numbers be 0, with combined probability  $1 - p$  (some  $0 \leq p \leq 1$ ), and set the third number to  $30/p$  with probability  $p$ . The third number can be as high as you want, at the expense of reducing its probability.
- (c) Instead of just 3 numbers, consider all distributions with  $X \geq 0$  and  $E(X) = 30$ . How large can  $P(X \geq 200)$  be?

$$\begin{aligned} E(X) &= \sum_{0 \leq x < 200} xP(X = x) + \sum_{x \geq 200} xP(X = x) \\ &\geq \sum_{0 \leq x < 200} 0P(X = x) + \sum_{x \geq 200} 200P(X = x) \geq 200P(X \geq 200) \end{aligned}$$

so  $P(X \geq 200) \leq E(X)/200 = 30/200 = 0.15$ .

- (2) **The Law of Large Numbers** (called “The Law of Averages” in our book, p. 195): Define  $\bar{X}_n$  as above. For any  $\epsilon > 0$ ,

$$\lim_{n \rightarrow \infty} P(|\bar{X}_n - \mu| < \epsilon) = 1$$

**Interpretation:** For either example on the back, pick a narrow interval of real numbers centered around the mean. For example, for the die, pick (3, 4) or (3.4, 3.6) or (3.49, 3.51) (corresponding to  $\epsilon = 1, 0.1, 0.01$ ). As  $n$  increases, notice the probability of the average being in that interval increases towards 1.

- (3) **Chebyshev’s inequality (p. 191):** For any random variable  $X$  and any (real)  $k > 0$ ,

$$P(|X - E(X)| \geq k \text{SD}(X)) \leq \frac{1}{k^2}$$

Or, in terms of the  $z$ -score  $Z = (X - E(X))/\text{SD}(X) = (X - \mu)/\sigma$ ,

$$P(|Z| \geq k) \leq \frac{1}{k^2} \quad \text{so, } P(|Z| \leq k) \geq 1 - \frac{1}{k^2}$$

So for *any* random variable, the probability of being between  $\mu \pm \sigma$  is at least  $1 - 1/1^2 = 0$ ; being within  $\mu \pm 2\sigma$  is at least  $1 - 1/2^2 = 0.75$ ; being within  $\mu \pm 3\sigma$  is at least  $1 - 1/3^2 \approx 0.88$ ; etc.

- (4) **Central Limit Theorem (p. 196):** For  $n$  i.i.d. random variables with sum  $S_n$  and average  $\bar{X}_n$  as defined above, and any real numbers  $a < b$ ,

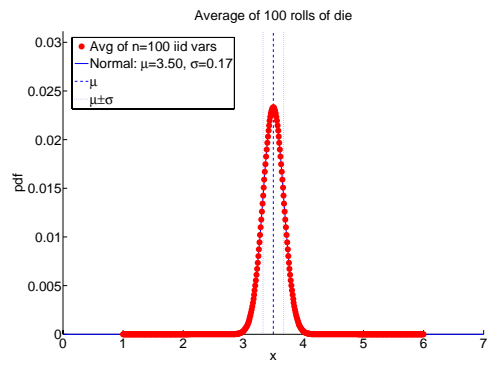
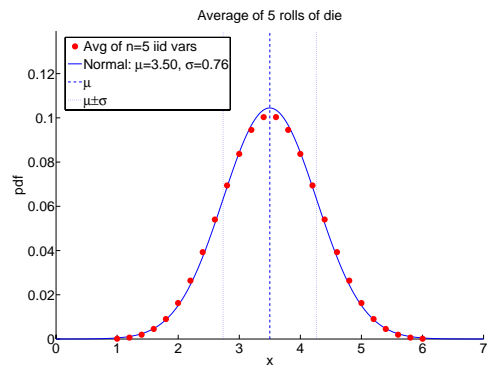
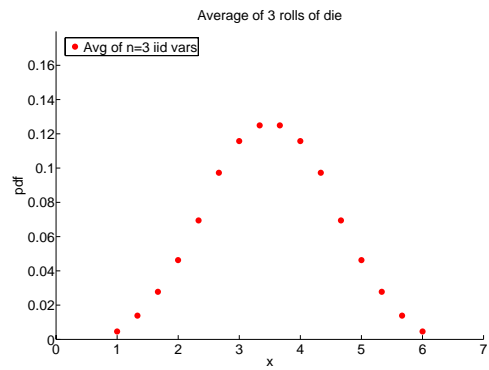
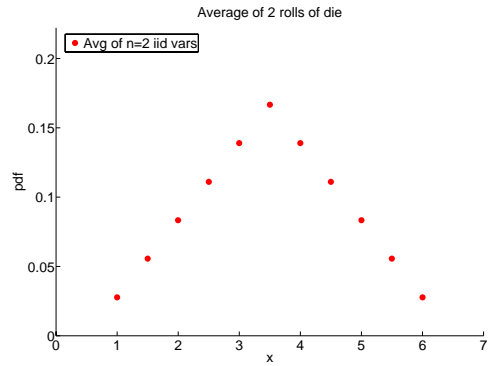
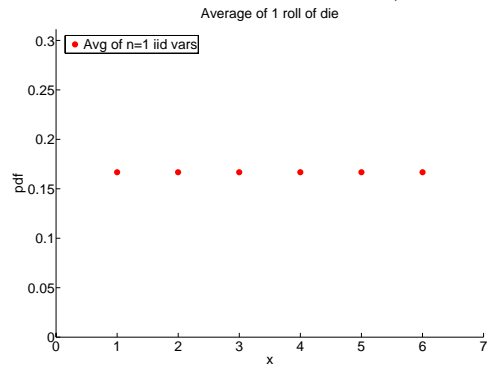
$$P\left(a \leq \frac{S_n - n\mu}{\sigma\sqrt{n}} \leq b\right) = P\left(a \leq \frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}} \leq b\right) \approx \Phi(b) - \Phi(a)$$

As  $n \rightarrow \infty$ , the approximation becomes exact equality.

**Interpretation:** Notice in the two examples on the back, that as  $n$  increases, the pdf more and more closely resembles the normal curve. The mean of  $\bar{X}_n$  stays the same as for  $X$ , while the standard deviation shrinks by the formula  $\text{SD}(\bar{X}_n) = \text{SD}(X)/\sqrt{n}$ .

## Repeated rolls of a die

Initial distribution  $\mu = 3.5$ ,  $\sigma = \sqrt{35/12} \approx 1.71$



## Repeated trials of "sawtooth" distribution

Initial distribution  $\mu = 4$ ,  $\sigma \approx 2.24$

