

- Last time Sec 2.2 Normal approx of binomial
- for  $\text{binomial}(n, p)$ ,  $\mu = np$
  - $\sigma = \sqrt{npq}$ ,  $q = 1-p$
  - when  $0 < \mu \pm 3\sigma < n$  and  $n$  large we can approx  $\text{binomial}(n, p)$  by normal.

Today

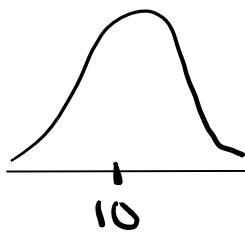
- 1) Finish sec 2.2 law of large numbers
- 2) Sec 2.4 (skip 2.3) Poisson approx.

### Law of large numbers (sec 2.4)

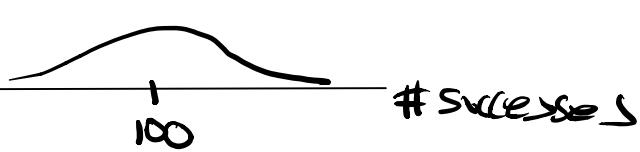
You roll a die with probability  $p = \frac{1}{6}$  of getting a six.  
Success = getting a six.

Pictures Which is law of large #'s?

$n=60$  rolls

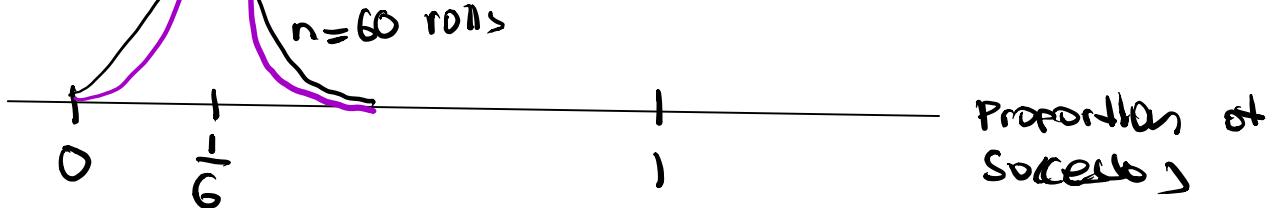


$n=600$  rolls



$n=600$  rolls

$n=60$  rolls



Proportion of Successes

Law of large #'s.

Law of large #'s says  
proportion of success  $\rightarrow p$  as  $n \rightarrow \infty$

You can see this in the bottom picture.  
As  $n$  gets large the distribution of the proportion of successes gets more concentrated around the  $\frac{1}{6}$  the true chance of a success.

To understand why, let's call the proportion of successes our estimate of  $p$ .

Then

$$\text{estimate} = \frac{\# \text{successes}}{n}$$

$$\text{avg}(\text{estimate}) = \frac{\text{avg}(\# \text{successes})}{n} = \frac{np}{n} = p$$

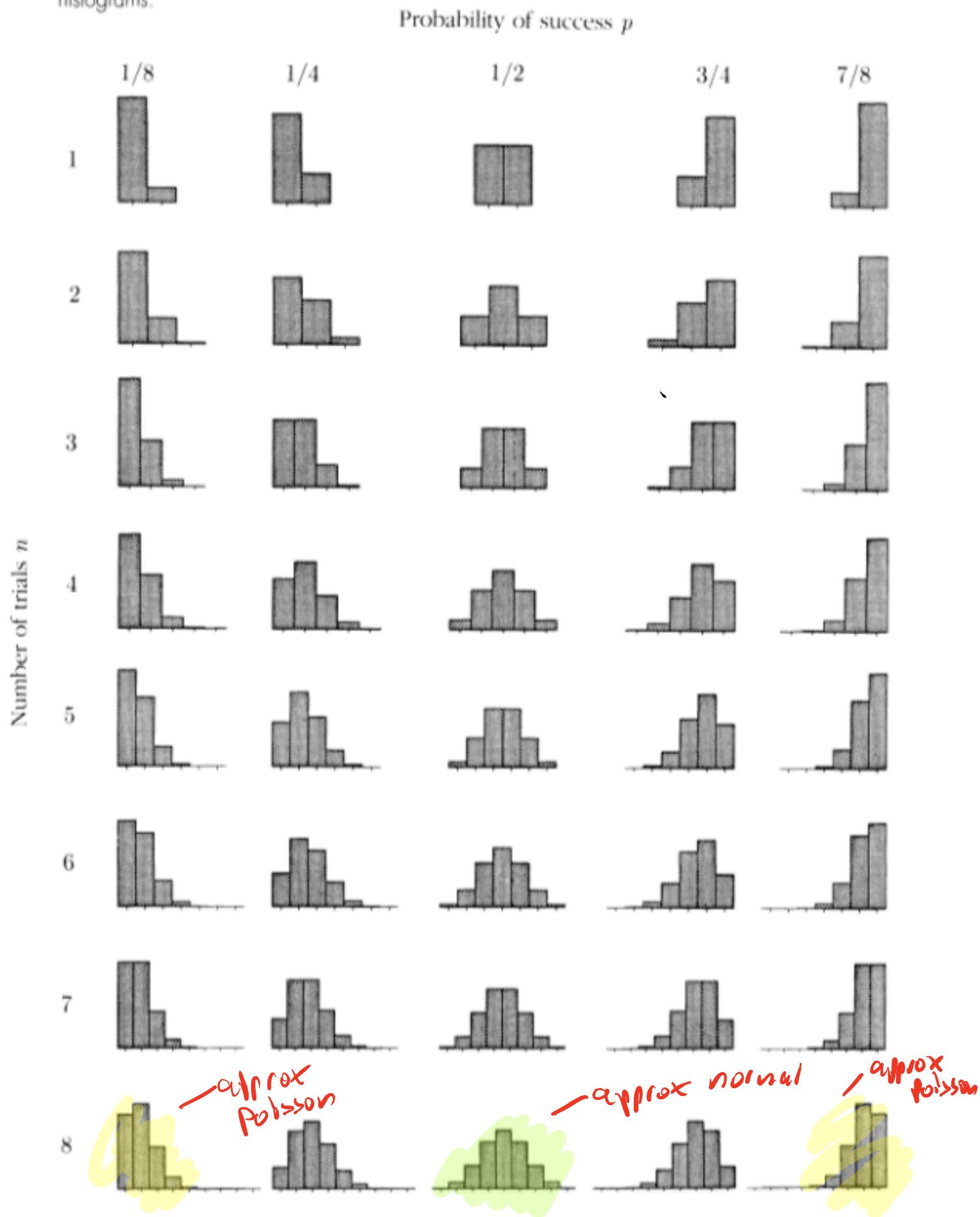
$$\sigma(\text{estimate}) = \frac{\sigma(\# \text{successes})}{n} = \frac{\sqrt{npq}}{\sqrt{n}} = \frac{\sqrt{pq}}{\sqrt{n}}$$

$\text{avg}(\text{estimate}) = p$  says that the center of our distribution of our estimate is  $p$  independent of what  $n$  is.

$\sigma(\text{estimate}) = \frac{\sqrt{pq}}{\sqrt{n}}$  is called the square root

law and says that the distribution of our estimate gets steeper as  $n$  gets bigger since  $\sqrt{n}$  is in the denominator.

**FIGURE 3. Histograms of some binomial distributions.** The histogram in row  $n$ , column  $p$  shows the binomial  $(n, p)$  distribution for the number of successes in  $n$  independent trials, each with success probability  $p$ . In row  $n$ , the range of values shown is 0 to  $n$ . The horizontal scale changes from one row to the next, but equal probabilities are represented by equal areas, even in different histograms.



## Sec 2.4 (skip 2.5) Poisson approx.

The normal approx has about 100% of data  $\pm 3\sigma$  from mean  $\mu$ .

For this reason we approximated binomial w/ normal only when  $\mu \pm 3\sigma$  is between 0 and  $n$ .

For the cases when  $p$  is small or  $p$  is close to 1 and  $n$  is large, we approximate

(See picture  
of binomial  
histograms above)

Binomial ( $n, p$ ) by Poisson ( $\mu = np$ )

Def<sup>n</sup> Poisson ( $\mu$ )

Outcomes 0, 1, 2, ..., ...

infinitely many  
possible outcomes

$$P_m(k) = \frac{e^{-m} m^k}{k!}$$

Ex Bet ~~small~~<sup>large</sup> times, independently, on a bet with  $\frac{1}{1000}$ <sup>small</sup> chance of winning.

$$P(\text{win} \geq 1 \text{ bet})$$

$$P(k \geq 1) = 1 - P(0)$$

exactly (binomial)

$$1 - P(0) = 1 - \binom{500}{0} \left(\frac{1}{1000}\right)^0 \left(\frac{999}{1000}\right)^{500}$$

$$= 1 - \left(\frac{999}{1000}\right)^{500} = .3936$$

approximately (Poisson)

$$1 - P(0) = 1 - \frac{e^{-\lambda} (\frac{\lambda}{e})^0}{0!} = 1 - e^{-\lambda} = .3943$$

What about those binomials with  $P$  close to 1?

$P$  = chance of success

$q$  = chance of failure

if  $P \approx 1$  then  $q = 1 - P \approx 0$

Binomial ( $n, q$ )  $\approx$  Poisson ( $\mu = nq$ ) for large  $n$ , small  $q$

Ex 97.8% of approx 30 million poor families in US have a fridge.

If you randomly sample 100 of these families roughly what is the chance 98 or more have a fridge?

$P$  = Prob have a fridge = .978 close to 1

$n = 100$  — large. success

Find  $P(98 \text{ or more have a } \frac{\text{fridge}}{\text{failure}})$

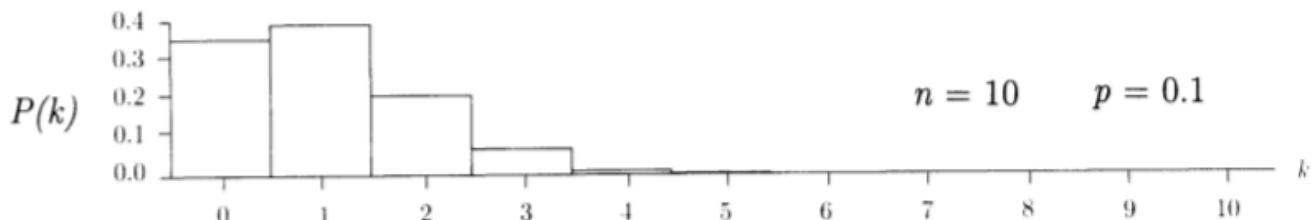
 $= P(2 \text{ or less } \frac{\text{don't have a } \frac{\text{fridge}}{\text{failure}}}{q = .022})$ 
 $\quad q = .022$ 
 $n = 100$ 
 $\mu = 2.2$ 

$$= P(0) + P(1) + P(2)$$
 $\approx e^{-2.2} + e^{-2.2} (2.2) + \frac{e^{-2.2} (2.2)^2}{2!}$ 
 $= e^{-2.2} \left(1 + 2.2 + \frac{2.2^2}{2}\right) = .6227$

Here is a picture of how Poisson(1)  
is a limit of binomials as  $p \rightarrow 0$  and  
 $n \rightarrow \infty$  and  $np \rightarrow 1$

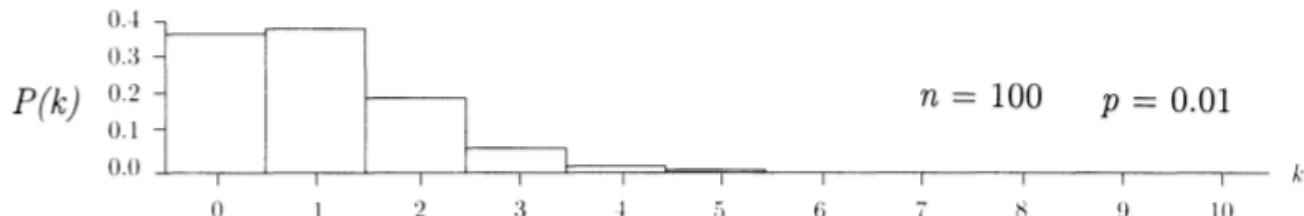
### **Example 1. The binomial (10, 1/10) distribution.**

This is the distribution of the number of black balls obtained in 10 random draws with replacement from a box containing 1 black ball and 9 white ones.



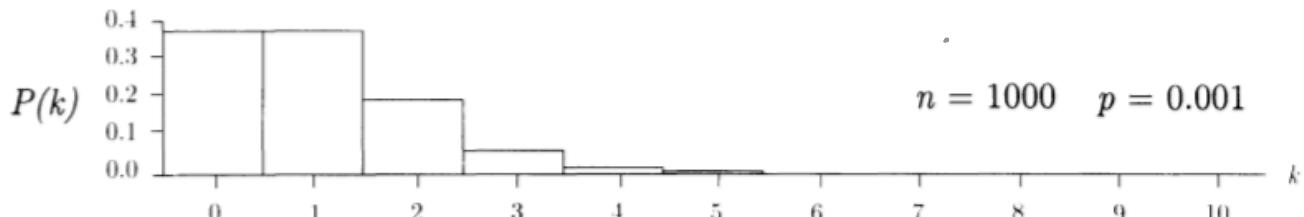
### **Example 2. The binomial (100, 1/100) distribution.**

This is the distribution of the number of black balls obtained in 100 random draws with replacement from a box containing 1 black ball and 99 white ones.



### **Example 3. The binomial (1000, 1/1000) distribution.**

Now take 1000 random draws with replacement from a box with 1 black ball and 999 white ones. This is the distribution of the number of black balls drawn:



As these examples show, binomial distributions with parameters  $n$  and  $1/n$  are always concentrated on a small number of values near the mean value  $\mu = 1$ , with a

Why

$$P(k) = \binom{n}{k} p^k (1-p)^{n-k} \rightarrow \frac{e^{-\mu} \mu^k}{k!} \text{ as } n \rightarrow \infty \text{ and } p \rightarrow 0 \text{ with } np = \mu ?$$

Facts

$$\textcircled{1} \quad P_n(0) \approx e^{-\mu}$$

$$\textcircled{2} \quad P_n(k) = P_n(k-1) \frac{\mu}{k}$$

$$\text{so } P_n(1) = e^{-\mu} \frac{\mu}{1}$$

$$P_n(2) = P_n(1) \frac{\mu}{2} = e^{-\mu} \frac{\mu}{1} \cdot \frac{\mu}{2} = e^{-\mu} \frac{\mu^2}{2!}$$

etc

Proof of fact  $\textcircled{1}$ :

Remember from Calculus  $\log(1+x) \approx x$  for  $x$  small

let  $P_n(k) = \binom{n}{k} p^k (1-p)^{n-k}$  binomial formula

$$P_n(0) = (1-p)^n \quad \begin{matrix} p \text{ small} \\ np = \mu \end{matrix}$$

$$\Rightarrow \log P_n(0) = n \log(1-p) \approx n(-p) = -\mu$$

$$\Rightarrow P_n(0) = e^{-\mu}$$

□

Proof of fact  $\textcircled{2}$ :

Remember from Sec 2.1 p85,  $\frac{P_n(k)}{P_n(k-1)} = \left[ \frac{n-k+1}{k} \right] \frac{p}{q}$

$$\Rightarrow P_n(k) = P_n(k-1) \left[ \frac{n-(k-1)}{k} \right] \frac{p}{q}$$

$$= P_n(k-1) \left[ \frac{np - (k-1)p}{k} \right] \frac{1}{2} \approx P_n(k-1) \frac{\mu}{k}$$

□

## Stat 134

Chapter 2   Wednesday September 5 2018

1. Recall that  $np + p$  is used to test for the mode of a binomial. The mode of Poisson(5) is:

- a 5  
b 4,5  
c 0,1

d none of the above

*For binomial,*  
 $m = \lfloor np + p \rfloor$  ← floor of  $np + p$   
 $\text{mode} = \begin{cases} m & \text{if } K \neq np + p \\ m-1, m & \text{if } K = np + p \end{cases}$

as  $p \rightarrow 0$  and  $np \rightarrow 5$

only  $M=5$  is necessary  
to find the mode.

For Poisson( $\mu$ ), let

$$m = \lfloor \mu \rfloor$$

$\text{mode} = \begin{cases} m & \text{if } K \neq \mu \\ m+1, m & \text{if } K = \mu \end{cases}$

we have  $\lfloor 5 \rfloor = 5$  so mode = 4, 5