

Ex of CLT  $\rightarrow$  Binomial distributi.

Ex 16 Bernoulli trials  $P = 0.5$ .  
Compute prob( # of successes) is 6, ~~7~~ 7 or 8.

Exact:  $P(6 \leq K \leq 8) = \sum_{k=6}^8 \binom{16}{k} P^k (1-P)^{16-k}$   
 $= 0.49$

Method 1 (Bad CLT Approx):  
 $P(6 \leq K \leq 8) \approx \Phi\left(\frac{8-8}{2}\right) - \Phi\left(\frac{6-8}{2}\right)$

Method 2 (good CLT approx)  $= \Phi\left(\frac{8\frac{1}{2}-8}{2}\right) - \Phi\left(\frac{6\frac{1}{2}-8}{2}\right)$   
 $\approx 0.34$

$$= 0.49306$$

much  
closer to  
exact.

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When does Gaussian Approx  
to Binomial fail

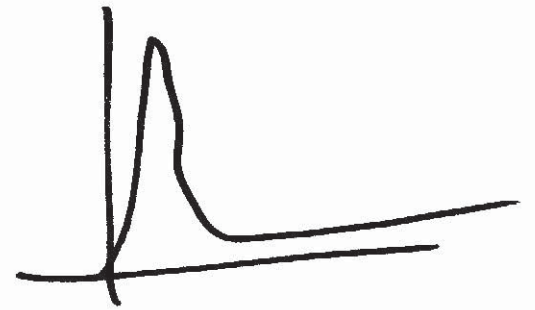
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If  $P$  is too close to 0 or to 1

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PMF Binomial  $\rightarrow$  too asymmetric

$\Rightarrow$  Much larger  $n$  for approx  
to hold.



# Poisson Approx To Binomial

- Recall. De Moivre-Laplace approx no good  
 $P \rightarrow 0$      $P \rightarrow 1$

- what approx does work?

$$P_K(k_0) = \binom{n}{k_0} p^{k_0} (1-p)^{n-k_0}$$

$$n \rightarrow \infty$$

$$P \rightarrow 0$$

$$nP = \mu$$

$$P_K(k_0) = \frac{n(n-1)\dots(n-k_0+1)}{\cancel{\dots} \cancel{\dots} k_0!} \left(\frac{\mu}{n}\right)^{k_0} \left(1 - \frac{\mu}{n}\right)^{n-k_0}$$

$$= \frac{n(n-1)\dots(n-k_0+1)}{n^{k_0}} \frac{\mu^{k_0}}{k_0!} \left(1 - \frac{\mu}{n}\right)^{n-k_0}$$

take

limit

$n \rightarrow \infty$

Poisson.

$$P_k(k_0) \underset{\text{lin } n \rightarrow \infty}{=} \frac{\mu^{k_0} e^{-\mu}}{k_0!}$$



~~do~~ 
$$\lim_{n \rightarrow \infty} \left(1 + \frac{a}{n}\right)^n = e^a.$$

Recall.



Words: as  $n \rightarrow \infty$   $p \rightarrow 0$   $np = \mu$

Binomial



Poisson.

$$P_k(k_0) \underset{\text{lin } n \rightarrow \infty}{=} \frac{(np)^{k_0} e^{-np}}{k_0!}$$

Ex

$n = 100$

$p = 0.01$

	$K_0 = 0$	$K_0 = 1$	$K_0 = 3$	$K_0 = 10$
Exact value $P_R(K_0)$	0.3660	0.3697	.0610	$7 \times 10^{-8}$
Poisson approx	.3679	0.3679	.0613	$10 \times 10^{-8}$
DeMoivre-Laplace approx.	0.2420	0.3850	.004	$< 2 \times 10^{-8}$

# Proof for CLT

- ①  $X_1, X_2, \dots, X_n$  iid.  
mean  $E(X)$   $\sigma_X^2 = \text{finite.}$

Define  $r = X_1 + X_2 + \dots + X_n$

→ show CDF  $P_{r <}(r_0)$  approaches CDF of a Gaussian R.V. as  $n \rightarrow \infty$ .

② Apply iid →  $M_r(s) = [M_X(s)]^n$

③ Reminder: if  $Y = ar + b$   
how is  $M_Y(s)$  related to  $M_X(s)$ ?

$$\begin{aligned}
 M_Y(s) &= E(e^{-sY}) = E\left[ e^{-ars} e^{-bs} \right] \\
 &= e^{-sb} \int_{-\infty}^{+\infty} e^{-ars} f_r(r_0) dr_0 \\
 M_Y(s) &= e^{-sb} M_r(as) = e^{-sb} [M_x(as)]^n
 \end{aligned}$$

$$y = \frac{r - E(r)}{\sigma_r}$$


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$$r - nE(x)$$

$$\Rightarrow a = \frac{1}{\sqrt{n} \sigma_x}$$

$$b = \frac{-\sqrt{n} E(x)}{\sigma_x}$$

$$M_y(s) = e^{+s \frac{\sqrt{n} E(x)}{G_x}} \left[ M_x \left( \frac{s}{\sqrt{n} G_x} \right) \right]^n$$

$$M_y(s) = \left[ e^{s \frac{E(x)}{\sqrt{n} G_x}} M_x \left( \frac{s}{\sqrt{n} G_x} \right) \right]^n$$

Transformation of  $y$  when

$$y = \frac{x_1 + x_2 + x_3 + \dots + x_n - n E(x)}{\sqrt{n} G_x}$$

(4) approx  $e^{\dots}$ ,  $M_x$  near  $s \approx 0$



$$e^x \approx 1 + x + \frac{x^2}{2}$$

$$e^{\frac{s E(x)}{6x \sqrt{n}}} \approx 1 + \frac{E(x)}{6x} \left( \frac{s}{\sqrt{n}} \right) + \frac{[E(x)]^2}{2 \cdot 6x^2} \left( \frac{s}{\sqrt{n}} \right)^2$$

$$M_x \left( \frac{s}{\sqrt{n} \cdot 6x} \right)$$

$$M_x(s) = E[e^{-sx}] \approx E \left[ 1 - sx + \frac{s^2 x^2}{2} \right]$$

$$= 1 - s E(x) + \frac{1}{2} s^2 E[x^2]$$

$$\Rightarrow M_x(s) \approx 1 - s E(x) + \frac{1}{2} s^2 E[x^2]$$

$$M_x \left( \frac{s}{\sqrt{n} \cdot 6x} \right) \approx 1 - \frac{E(x)}{6x} \left( \frac{s}{\sqrt{n}} \right) + \frac{E(x^2)}{2 \cdot 6x^2} \left( \frac{s}{\sqrt{n}} \right)^2$$

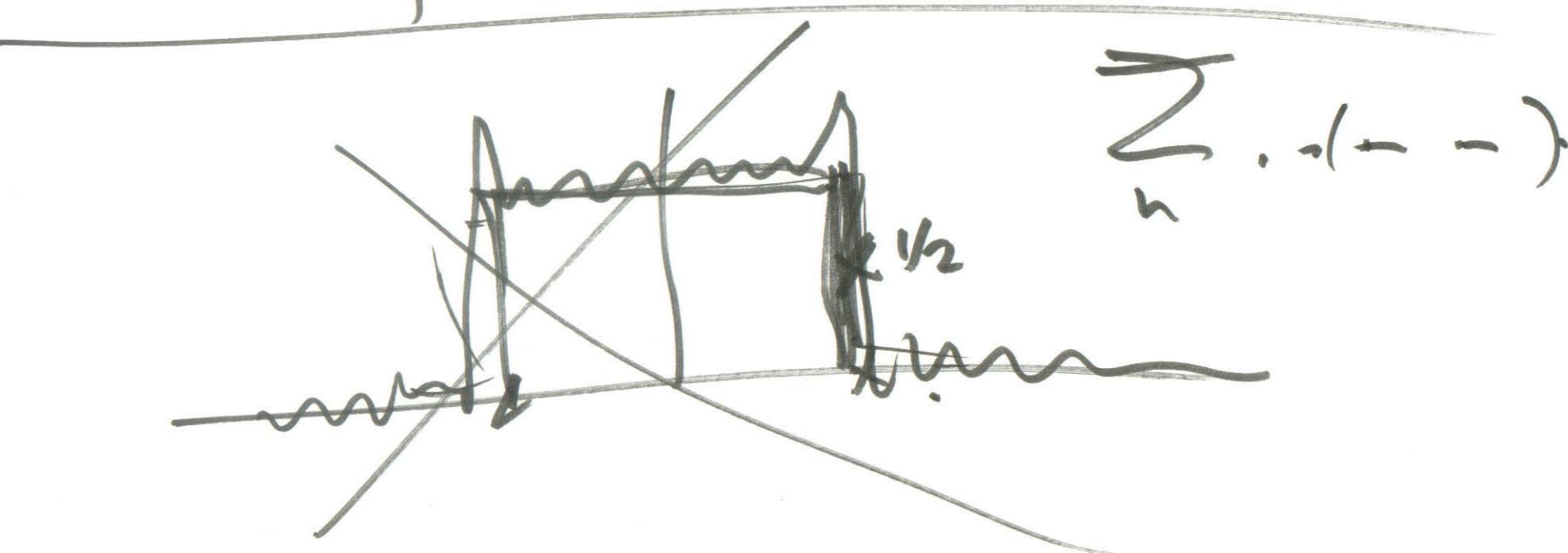
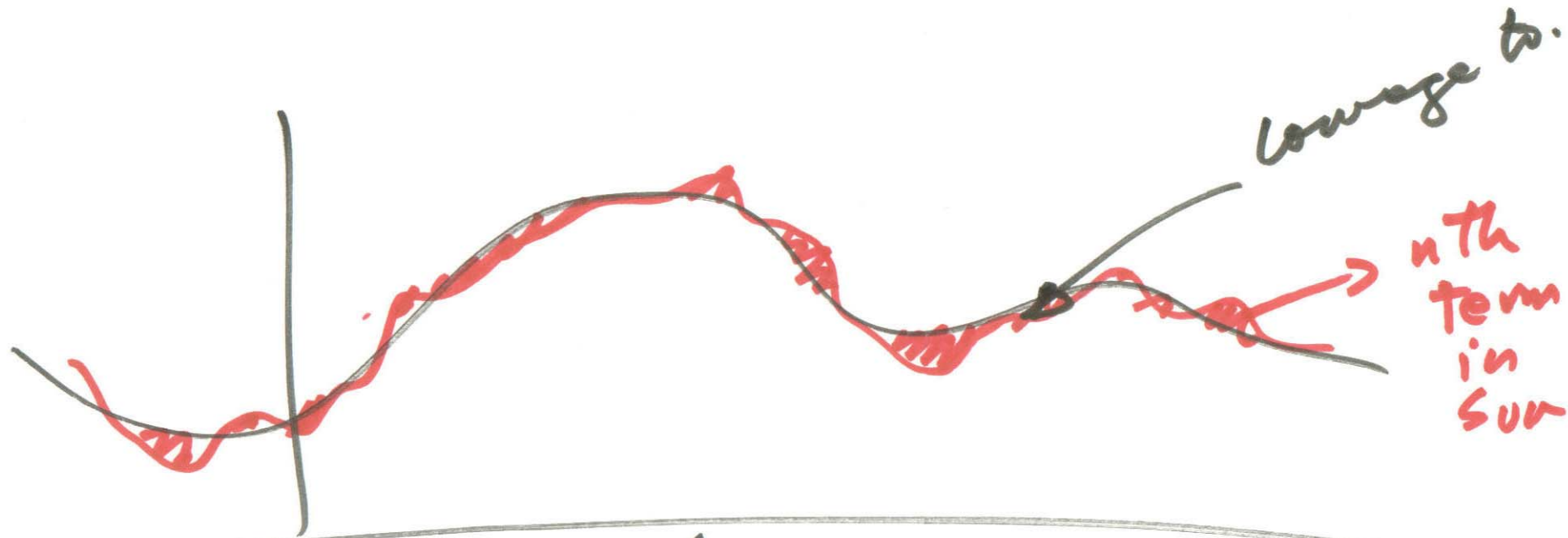
⑤ multiply approx for  $e^{\dots}$   
 and  $M_r$ , collect Terms. plug it  
 into  $M_y(s) = \left[ e^{\dots} M_r(\dots) \right]^n$

$$M_y(s) = \left( 1 + \frac{1}{2} \frac{s^2}{n} \right)^n \quad \frac{s^2}{2}$$

⑥ take  $\lim_{n \rightarrow \infty} M_y(s) = e$

Tracer of a gaussian  
 mean 0, s.d 1

This does not assume point by point  
 convergence yet!



(7) Invoke: Continuity thm of  
Xform theory:

if  $\lim_{n \rightarrow \infty} M_{Y_n}(s) = M_W(s)$  and if

$M_W(s)$  is continuous function Then

CDF of R.V  $Y_n$  converges to CDF of  
R.V  $W$ , on a point by point  
basis.

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$$\lim_{n \rightarrow \infty} F_{Y_n}(y_0) = F_W(y_0)$$

# CLT

$$r = x_1 + x_2 + \dots + x_n$$

$$x_1, x_2, \dots, x_n \quad \text{IID.}$$

$E(x)$        $\sigma_x^2$

lim  
 $n \rightarrow \infty$

$$P_{r \leq r_0} = \Phi\left(\frac{r - E(r)}{\sigma_r}\right)$$

$$E(r) = n E(x)$$

$$\sigma_r = \sqrt{n} \sigma_x$$

# Statistics

- Statistician

Statistician

infer from data.

Build Probabilistic models  
of reality :

- prediction
- gain ~~into~~ insight  
into behavior
- decisions.

# Question to answer

(1) Based on observed exp data,  
does this Prob. model seem  
reasonable?

→ significance Testing  
Given data, how to  
choose among Prob models?

⇒ Hypothesis Testing.

③

Given. postulated model of  
a phys. system + exp data  
how to establish the most  
desirable value of parameters  
for that prob. model.

⇒ estimation.

④

how to combine Apriori info  
with exp. data

⇒ Bayesian Analysis.