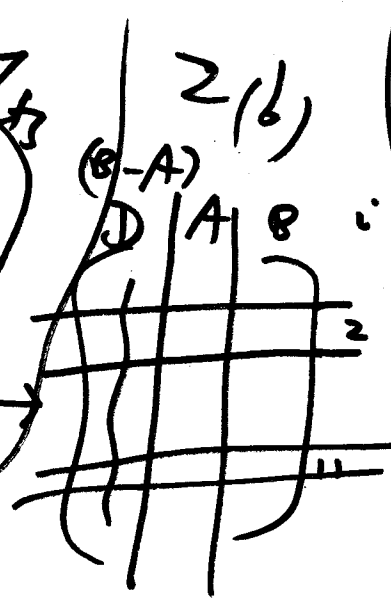


THT
3 #
2(9)

pop
all u.k. adults
7 parts
people
in early 1970s

like
IID

study
subjects
n=12



STAT 131
11 Jun 20
D) extra
office
1.5-hour
session

"representatively
chosen"

$$\hat{D}_h = \frac{1}{n} \sum_{i=1}^n D_i, \quad D_i = B_i - A_i$$

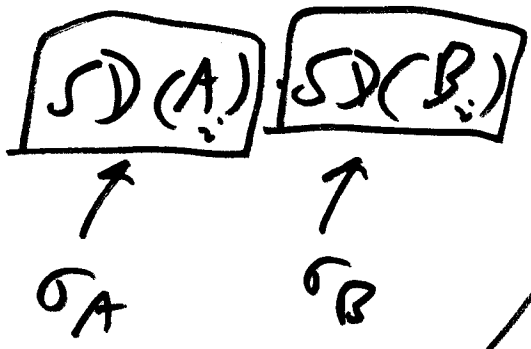
$$\begin{aligned} V_{RM}(\hat{D}_h) &= V_{RM}\left(\frac{1}{n} \sum_{i=1}^n D_i\right) \\ &= \frac{1}{n^2} V_{RM}\left(\sum_{i=1}^n D_i\right) \stackrel{\text{E}}{=} \frac{1}{n^2} \sum_{i=1}^n V_{RM}(D_i) \\ &= \frac{1}{n^2} \sum_{i=1}^n V_{RM}(B_i - A_i) \\ &= \frac{1}{n^2} \sum_{i=1}^n \left[V(B_i) + V(-A_i) + 2C(B_i, -A_i) \right] \end{aligned}$$

$$V(X + Y) = V(X) + V(Y) + 2C(X, Y)$$

$$= \frac{1}{n^2} \sum_{i=1}^n \left[\sigma_B^2 + (-1)^2 \sigma_A^2 - 2 \rho(A_i, B_i) \right]$$

(*)

$$\rho_{AB} \hat{=} \frac{C(A_i, B_i)}{\sigma(A_i) \sigma(B_i)} \rightarrow C(A_i, B_i) = \rho_{AB} \sigma_A \sigma_B$$



$$= V_{RM}(\bar{D}_n) = \frac{1}{n^2} \sum_{i=1}^n \left(\sigma_A^2 + \sigma_B^2 - 2\rho_{AB} \sigma_A \sigma_B \right)$$

$$= \frac{n \left(\sigma_A^2 + \sigma_B^2 - 2\rho_{AB} \sigma_A \sigma_B \right)}{n^2} = \frac{\sigma_A^2 + \sigma_B^2 - 2\rho_{AB} \sigma_A \sigma_B}{n}$$

3(b)(i) Support(X) = {0, 1, 2, ...}

$$P_X(x | s, \theta) = \binom{s+x-1}{x} \theta^s (1-\theta)^x \cdot \mathbb{I}_{\{0, 1, 2, \dots\}}(x)$$

N = # of trials needed to see s successes

fixed known

ex. $s=2$

FFFSFS $\left. \begin{array}{l} N=6 \\ X=4 \end{array} \right\}$

X = # failures needed to see s successes

$$N = X + s$$

$$n = x + s$$

$$x = n - s$$

$$P_N(n | s, \theta) =$$

$$\binom{n-x-1}{n-s} \cdot \theta^s \cdot (1-\theta)^{n-s}$$

$$\mathbb{I}_{\{s, s+1, \dots\}}(n)$$

$$P_X(x | s, \theta) =$$

$$\binom{s+x-1}{x} \theta^s (1-\theta)^x$$

$$\mathbb{I}_{\{0, 1, 2, \dots\}}(x)$$

$$\binom{5}{2} = \frac{5!}{2!3!} = \frac{5!}{\underline{3!2!}} = \binom{5}{3}$$

$$\binom{n}{k} = \binom{n}{n-k} \quad \begin{matrix} n = 1, 2, \dots \\ k = 0, 1, \dots, n \end{matrix}$$

$$\binom{n}{\begin{matrix} n-1 \\ n-s \end{matrix}} = \binom{\cancel{n-1}}{n-k} = \binom{n-1}{s-1}$$

\uparrow \uparrow
 k $(n-1) - (n-s)$

$$f_N(n|s, \theta) = \binom{n-1}{s-1} \theta^s (1-\theta)^{n-s}$$

neg. bin $I_{\{s, s+1, \dots\}}(n)$

$$\rightarrow f_S(s|n, \theta) = \binom{n}{s} \theta^s (1-\theta)^{n-s}$$

bin. $I_{\{0, 1, \dots, n\}}(s)$

$$f_X(x | r, p) = \binom{r+x-1}{x} p^r (1-p)^x$$

$$I \{0, 1, \dots\} (x)$$

DS def.
of neg. bin.

who	count	prob.
us	s	θ
DS	r	p

DS

us

$$DS: E(X) = \frac{r(1-p)}{p}$$

$$\frac{s(1-\theta)}{\theta}$$

$$V(X) = \frac{r(1-p)}{p^2}$$

$$\frac{s(1-\theta)}{\theta^2}$$

$N = X + s$

$$E(N) = E(X + s) = s + E(X) = s + \frac{s(1-\theta)}{\theta}$$

$$= \frac{s + s - s\theta}{\theta} = \frac{s}{\theta}$$

$$V(N) = V(X + s)$$

$$= V(X) = \frac{s(1-\theta)}{\theta^2}$$

$$\vec{\theta}_B = \frac{\sum}{n} \leftarrow \text{rv.}$$

↑
const.

$$E(\vec{\theta}_B) = \theta, \quad V(\vec{\theta}_B) = \frac{\theta(1-\theta)}{n}$$

(easier) exact unbiasedness

$$\vec{\theta}_{MB} = \frac{s}{N}$$

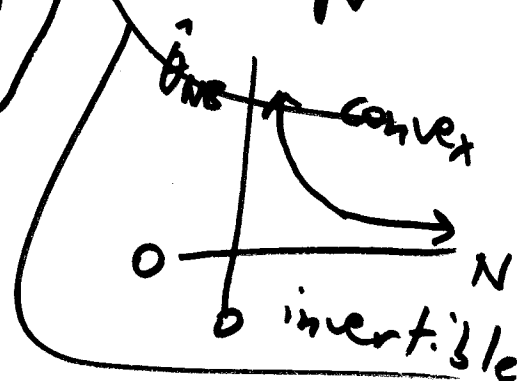
Delta method

$$\vec{\theta}_{MB} = g(N) = \frac{s}{N}$$

(harder)

$$E(\vec{\theta}_{MB}) = E\left(\frac{s}{N}\right)$$

$$E[g(N)] = g[E(N)]$$



$$E\left(N = \frac{s}{\theta}\right) = \frac{s}{\theta} = \theta$$

$$E(\vec{\theta}_{MB}) = \theta$$

approximate unbiasedness

$$V[g(N)] = \left\{g'(E(N))\right\}^2 \cdot V(N)$$

$$g(N) = \frac{s}{N} = s \cdot N^{-1}$$

$$V(N) = \frac{s(1-\theta)}{\theta^2}$$

$$g'(N) = -\frac{s}{N^2}$$

$$g'(E(N)) = \frac{-s}{[E(N)]^2} = \frac{-s}{\left(\frac{s}{\theta}\right)^2} = -\frac{\theta^2}{s}$$

So $V[g(N)] = V(\hat{\theta}_{NB})$

$$= \left(-\frac{\theta^2}{s}\right)^2 \frac{s(1-\theta)}{\theta^2} = \frac{\theta^4 s(1-\theta)}{s^2 \theta^2} = \frac{\theta^2(1-\theta)}{s}$$

$$= \frac{\theta(1-\theta)}{\left(\frac{s}{\theta}\right)} = \frac{\theta(1-\theta)}{\sqrt{E(N)}}$$

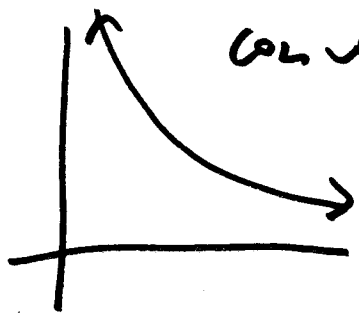
$\text{SE}(\hat{\theta}_{NB}) =$

$$\sqrt{\frac{\theta(1-\theta)}{E(N)}}$$

$$V(\hat{\theta}_B) = \frac{\theta(1-\theta)}{n}$$

$$\text{SE}(\hat{\theta}_B) = \sqrt{\frac{\theta(1-\theta)}{n}}$$

Jensen's \neq



convex

if g is convex then

$$E[g(X)] \geq g[E(X)]$$

with equality only if $g(x) = a + bx$

$V(X) = E(X^2) - (E(X))^2 \geq 0$ so $E(X^2) \geq (E(X))^2$

So here $E(\hat{\theta}_{NB}) = E\left[g(N)\right] > g\left[E(N)\right]$

$$g(N) = \frac{S}{N} \quad g\left[E(N)\right] = \frac{S}{E(N)} = \frac{S}{\frac{S}{\theta}} = \theta, \text{ i.e.,}$$

$$E(N) = \frac{S}{\theta}$$

$$\underline{E(\hat{\theta}_{NB})} > \theta, \text{ i.e.,}$$

$\hat{\theta}_{NB}$ is biased on the high side

can show that

$$E\left(\frac{S-1}{N-1}\right) = \theta$$

$$\text{bias}(\hat{\theta}_{NB}) \stackrel{\Delta}{=} E(\hat{\theta}_{NB}) - \theta > 0$$

So

$$\begin{aligned} E(\hat{\theta}_{NB}) - \theta &= E\left(\frac{S}{N}\right) - E\left(\frac{S-1}{N-1}\right) \\ &= E\left(\frac{S}{N} - \frac{S-1}{N-1}\right) = E\left(\frac{S(N-1) - (S-1)N}{N(N-1)}\right) \end{aligned}$$

~~bias~~ bias($\vec{\theta}_{NB}$) = $E(\vec{\theta}_{NB}) - \theta$ ($\frac{s}{N} \rightarrow \theta$)

= $E\left(\frac{N-s}{N(N-1)}\right)$; $\frac{N-s}{N(N-1)} = \frac{0}{N(N-1)} = \frac{0}{N} = 0$

" = $P\left(\frac{1}{N}\right)$

for large N

$\frac{N - N\theta}{N(N-1)} = \frac{N(1-\theta)}{N(N-1)}$

THF3
#4(b)

name	control # of syringes	years

1954
401,974

4(c) practicing?) statistics?
yes

keep prob./stat. inf. model

T

pop. U.S. children who might get polio in early 1950s

(T)

Sample the observed children (V)

P.S. data set (all) possible $\theta_{T,S}$

polio? $\begin{pmatrix} 1 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{pmatrix}$

actual like IID

$y=1$
 $N=0$
polio?
 $\begin{pmatrix} 1 \\ 1 \\ 2 \\ 0 \end{pmatrix}$

$n_T = 201229$

mean $\bar{\theta}_T = \frac{33}{\dots}$

$\begin{pmatrix} .0001640 \\ .0001807 \\ \vdots \\ \vdots \end{pmatrix}$
long run mean
 $E(\bar{\theta}_T)$
M \downarrow B
(VLLN)

mean $\theta_T = ?$

$n_T = 201229$
lowest est. $\hat{SE}(\bar{\theta}_T)$
mean $\bar{\theta}_T = ?$ (ex. 0001907)

2 - independent samples

pop. some kids except (C)

(C)

sample different kids (C)

P.S. dataset

$\begin{pmatrix} \vdots \\ \vdots \\ \vdots \end{pmatrix}$

like IID

polio?
 $\begin{pmatrix} 1 \\ 1 \\ \vdots \\ 0 \end{pmatrix}$
 $n_C = 200745$

mean $\bar{\theta}_C = \frac{115}{\dots}$

diff (C)

mean $\theta_C = ?$

inferential summary

pop.	unknown pop qty. of main interest	$(\theta_C - \theta_T) =$	prop. weat diff. in polio incidence (C-T)
sample	estimate of $(\theta_C - \theta_T)$	$(\hat{\theta}_C - \hat{\theta}_T) =$	0.0005729 - 0.0001640 <hr style="width: 50%; margin: 0 auto;"/> 0.0004089
R.S. target	give or take for $(\hat{\theta}_C - \hat{\theta}_T)$ or est. of $(\theta_C - \theta_T)$	\uparrow $SE(\hat{\theta}_C - \hat{\theta}_T) =$	0.00006055
	99.9% CI for $(\theta_C - \theta_T)$	$(.00021, .00061)$	

$$E_{IID}(\hat{\theta}_T) = \theta_T$$

$$E_{IID}(\hat{\theta}_C) = \theta_C$$

$$E(\hat{\theta}_C - \hat{\theta}_T) = \theta_C - \theta_T$$

$$SE(\hat{\theta}_C - \hat{\theta}_T) =$$

$$\sqrt{V_{IID}(\hat{\theta}_C - \hat{\theta}_T)}$$

$$\begin{aligned} \underline{V_{IID}}(\hat{\theta}_C - \hat{\theta}_T) &= V(\hat{\theta}_C) + V(-\hat{\theta}_T) \\ &= V(\hat{\theta}_C) + V(\hat{\theta}_T) \end{aligned}$$

$$V(\hat{\theta}_T) = V\left(\frac{S_T}{n_T}\right) = \frac{1 \cdot \theta_T(1-\theta_T) \cdot h_T}{n_T^2}$$

$$V(\hat{\theta}_c) = \frac{\theta_c(1-\theta_c)}{n_c}$$

$$= \frac{\theta_T(1-\theta_T)}{n_T}$$

$(S_T | \theta_T) \sim \text{Binomial}(n_T, \theta_T)$

$S_T = \# \text{ (T)}$
 kids with polio
 $(S_T = 33)$

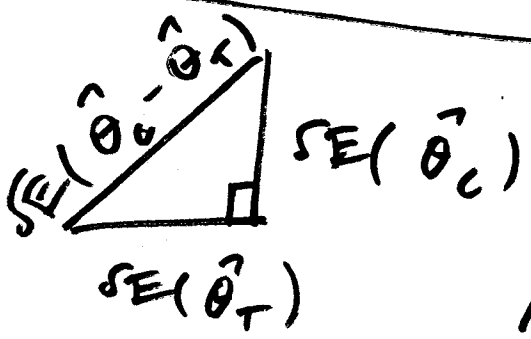
so $V(\hat{\theta}_c - \hat{\theta}_T) = V(\hat{\theta}_c) + V(\hat{\theta}_T)$

$$= \frac{\theta_c(1-\theta_c)}{n_c} + \frac{\theta_T(1-\theta_T)}{n_T}$$

and $SD(\hat{\theta}_c - \hat{\theta}_T) \triangleq SE(\hat{\theta}_c - \hat{\theta}_T)$

$$= \sqrt{\left(\frac{\hat{\theta}_c(1-\hat{\theta}_c)}{n_c}\right)^2 + \left(\frac{\hat{\theta}_T(1-\hat{\theta}_T)}{n_T}\right)^2}$$

$SE(\hat{\theta}_T) = \sqrt{\frac{\theta_T(1-\theta_T)}{n_T}}$



$= .00006055$

$\hat{SE} = 0.00006$

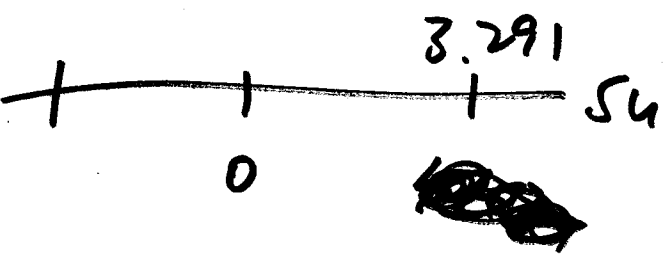
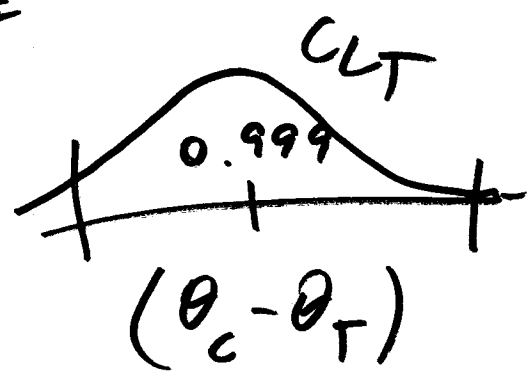
P.D.F./P.M.F

of $(\vec{\theta}_C - \vec{\theta}_T)$

99.9% CI

for

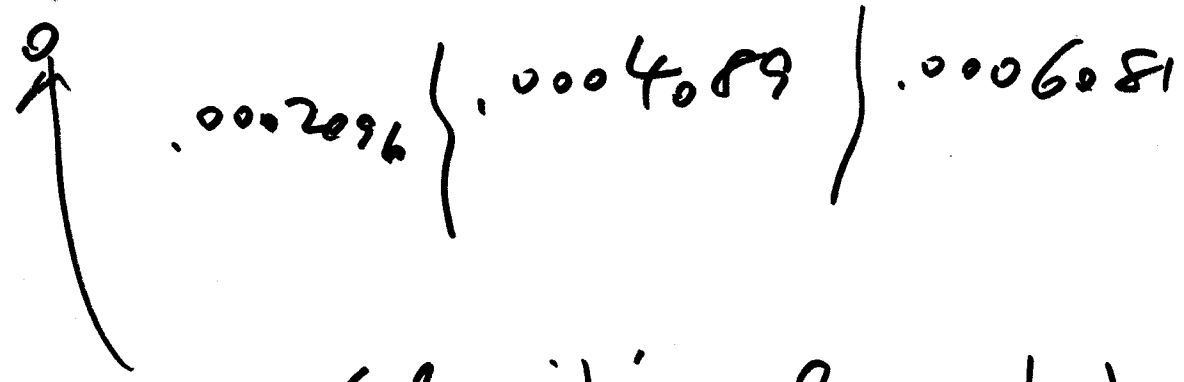
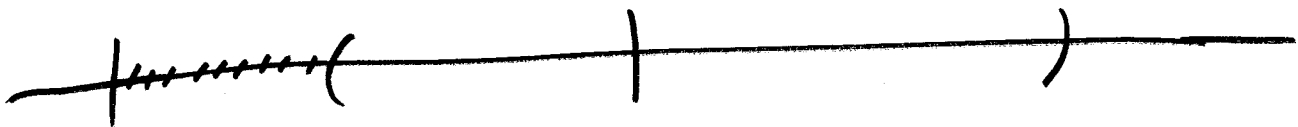
$(\theta_C - \theta_T)$



$$(\vec{\theta}_C - \vec{\theta}_T) \pm$$

$$(3.291) \hat{SE} (\vec{\theta}_C - \vec{\theta}_T)$$

99.9% CI for $(\theta_C - \theta_T)$



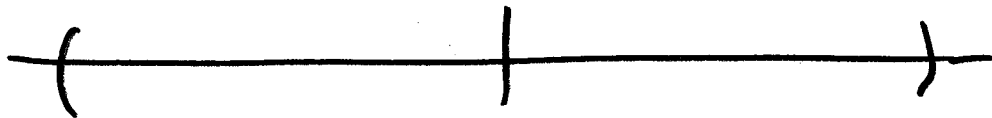
hull (devil's advocate)

story (science not effective)

0 is not in 99.9% CI, so d.f. between $(\vec{\theta}_C - \vec{\theta}_T)$ and 0 is statis

99.9% CI

(14)



$\hat{\theta}_c - \hat{\theta}_r$
(0.0004)

$$(\hat{\theta}_c - \hat{\theta}_r) - 3.291 \sqrt{E} (\hat{\theta}_c - \hat{\theta}_r) = 0$$

$$n = n_c + n_T$$

\downarrow \downarrow
 $\frac{n}{2}$ $\frac{n}{2}$

$$(\hat{\theta}_c - \hat{\theta}_r) = 3.291 \sqrt{E}$$

$$\sqrt{E} (\hat{\theta}_c - \hat{\theta}_r) =$$

$$\frac{\hat{\theta}_c - \hat{\theta}_r}{3.291}$$

$$\sqrt{\frac{2 \cdot \hat{\theta}_c (1 - \hat{\theta}_c)}{\frac{n}{2}} + \frac{2 \cdot \hat{\theta}_r (1 - \hat{\theta}_r)}{\frac{n}{2}}} =$$

$$\frac{2 \left[\hat{\theta}_c (1 - \hat{\theta}_c) + \hat{\theta}_r (1 - \hat{\theta}_r) \right]}{n} = \frac{\hat{\theta}_c - \hat{\theta}_r}{3.291}$$

$$\frac{2 [\dots]}{n} = \left(\frac{\vec{\theta}_C - \vec{\theta}_T}{3.291} \right)^2$$

$$n = \frac{3.291^2 \cdot 2 \cdot (\vec{\theta}_C(1-\vec{\theta}_C) + \vec{\theta}_T(1-\vec{\theta}_T))}{(\vec{\theta}_C - \vec{\theta}_T)^2}$$