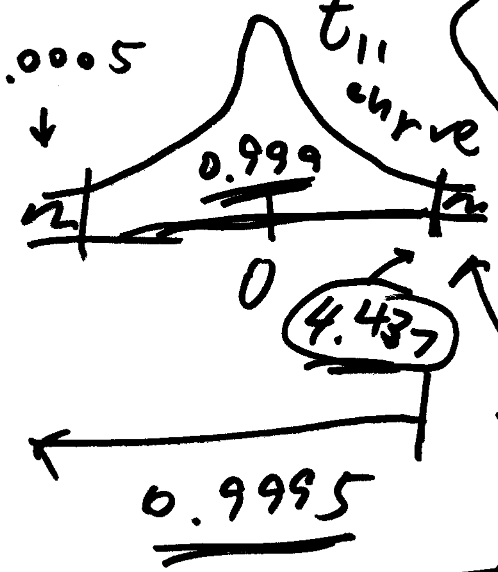


PDF of $\dfrac{\bar{D}_n - \Delta}{S_D/\sqrt{n}}$

THT 3 2 (a)

STAT 131 10 Jun 20

DD extra office 1.5-hour session

99.9% CI for Δ: middle 0.999 (t_{11}^{-1})

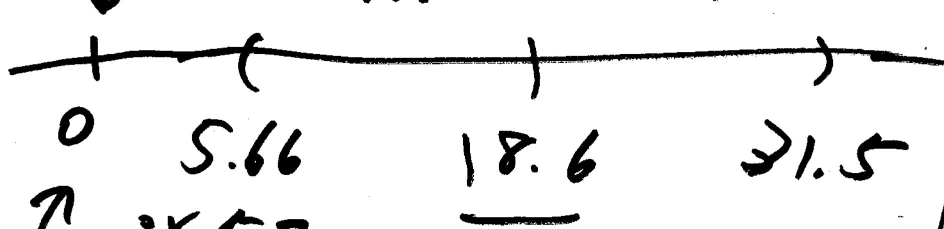
$$\hat{\Delta} \pm 4.437 \cdot \left(\frac{S_D}{\sqrt{n}} \right)$$

18.6 10.1 12

$$S_D = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (d_i - \bar{d})^2}$$

d.f.

99.9% CI for Δ



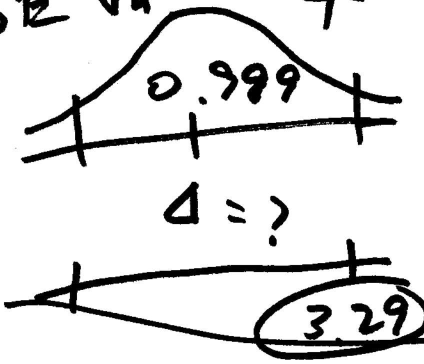
$\hat{\Delta}$

null $(\Delta_0 = 0)$ (devil's advocate) (no average effect) value of Δ

Since 0 is not in 99.9% CI for Δ, the difference between $\hat{\Delta} \doteq 19$ and 0 is statsig

$\hat{SE}$ $\frac{SD}{\sqrt{n}}$ α_T

PDF of $\bar{D}_n$



$\hat{SE}(\bar{D}_n) = \frac{SD}{\sqrt{n}} =$ [illegible]

estimated $\hat{SE}$

$n = 12$

$= 2.9$

THT 3 3(a)

Bernoulli process: $\begin{pmatrix} 1 & \text{success} & \text{w.p. } \theta \\ 0 & \text{failure} & \text{w.p. } (1-\theta) \end{pmatrix}$

$I_1, I_2, \ldots$

$(I_i \mid \theta) \stackrel{IID}{\sim} \text{Bernoulli}(\theta)$ $(i = 1, \ldots, n)$

discrete

$\text{Support}(I_i) = \{0, 1\}$

Binomial sampling: fix n; observe $I_1, \ldots, I_n$; define $S = \sum_{i=1}^{n} I_i$

discrete; PMF?

Negative Binomial Sampling: fix s; observe $I_1, I_2, \ldots,$ until s successes at trial N

$\text{Support}(S) = \{0, 1, \dots, n\}$

PMF of S : Binomial(n, θ)

$$f_S(s \mid \theta) = \begin{cases} \binom{n}{s} \theta^s (1-\theta)^{n-s} & \text{for } s = 0, 1, \dots, n \\ 0 & \text{else} \end{cases}$$

$$= \binom{n}{s} \theta^s (1-\theta)^{n-s} I_{\{0,1,\dots,n\}}(s)$$

$E(S) = n\theta$ | $V(S) = n\theta(1-\theta)$

S = # of successes in n IID Bernoulli(θ) trials

ex. $n = 20$; $S = 17$; $\hat{\theta}_B = \frac{17}{20} = \frac{S}{n}$

$$E(\underline{\hat{\theta}_B}) = E\Big(\frac{\overset{\text{r.v.}}{S}}{\underset{\text{constant}}{n}}\Big) = \frac{1}{n} E(S) = \frac{n\theta}{n} = \theta$$

$\therefore\ \hat{\theta}_B$ is $\left\{ \begin{array}{l} \text{unbiased for } \theta \quad \text{good} \\ \text{an unbiased estimator of } \theta \end{array} \right\}$

$$V(\hat{\theta}_B) = V\left(\frac{S}{n}\right) = \frac{1}{n^2} V(S) = \frac{n\theta(1-\theta)}{n^2}$$

$$= \frac{\theta(1-\theta)}{n} \quad \& \quad SD(\hat{\theta}_B) = SE(\hat{\theta}_B)$$

want small SD = SE = uncertainty

$$= \sqrt{V(\hat{\theta}_B)}$$

$$= \sqrt{\frac{\theta(1-\theta)}{n}}$$

$\to 0$ as $n \uparrow \infty$ (good)

CLT

PMF of $\hat{\theta}_B$

$V(Y_i) = \theta(1-\theta) < \infty$

part 1 CLT

as long as $V(Y_i) < \infty$ and n is big, the sum $S = \sum_{i=1}^{n} Y_i$ of n IID Y_i will have a PMF/PDF that's close to normal: same result for $\frac{S}{n} = \hat{\theta}_B$