

3236 Statistical Theory

3/28/23

Confidence intervals.

Assume that X_i is a random sample from a Normal population with μ and σ^2 unknown.

$$s' = \left(\frac{1}{N-1} \sum_{i=1}^N (X_i - \bar{X})^2 \right)^{1/2}$$

$$\bar{X} = \frac{1}{N} \sum_{i=1}^N X_i$$

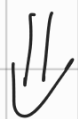
$$U = \frac{N^{1/2} (\bar{X}_n - \mu)}{s'}$$

U is a T r.v. with $N-1$

d.o.f.

Find c such that

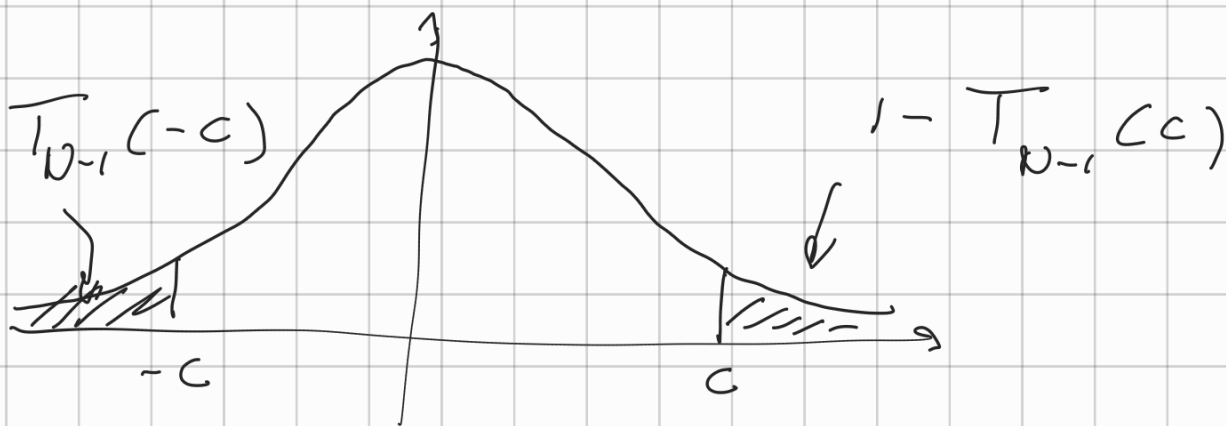
$$P(-c \leq U \leq c) \Rightarrow \gamma$$



$$IP \left(\bar{X} - \frac{c \hat{\sigma}'}{\sqrt{N}} \leq \mu \leq \bar{X} + \frac{c \hat{\sigma}'}{\sqrt{N}} \right) = \gamma$$

$$IP \left(-c \leq U \leq c \right) = T_{N-1}(c) - T_{N-1}(-c)$$

$T_{N-1}(x)$ is the c.d.f. of a
T r.v. with $N-1$ d.o.f.



$$T_{N-1}(-c) = 1 - T_{N-1}(c)$$

$$\gamma = 2 T_{N-1}(c) - 1$$



$$IP \left(-c \leq U \leq c \right) = \gamma$$

$$C = T_{N-1}^{-1} \left((1+\gamma)/2 \right) = t_{N-1, \gamma/2}$$

for N large

$$t_{N, \gamma} \rightarrow z_{\gamma}$$

With probability $1-\gamma$

$$\bar{X} - T_{N-1}^{-1} \left((1+\gamma)/2 \right) \frac{\hat{\sigma}}{\sqrt{N}} \leq \mu \leq \bar{X} + T_{N-1}^{-1} \left((1+\gamma)/2 \right) \frac{\hat{\sigma}}{\sqrt{N}}$$

coefficient γ confidence interval
for μ .

100 γ percent confidence interval

$$\gamma = 0.95, 0.98, 0.99$$

Def: Confidence Interval.

If we have two statistics

$A(\underline{X})$ and $B(\underline{X})$ such that

$$P(A(\underline{X}) \leq g(\underline{\theta}) \leq B(\underline{X})) \geq \gamma$$

for every value of $\underline{\theta}$

Then

$$[A(\underline{X}), B(\underline{X})]$$

is a coeff. γ conf. inter for

$g(\underline{\theta})$. If we have

$$P(A(\underline{X}) \leq g(\underline{\theta}) \leq B(\underline{X})) = \gamma$$

exact conf. inter.

In The case of normal sample

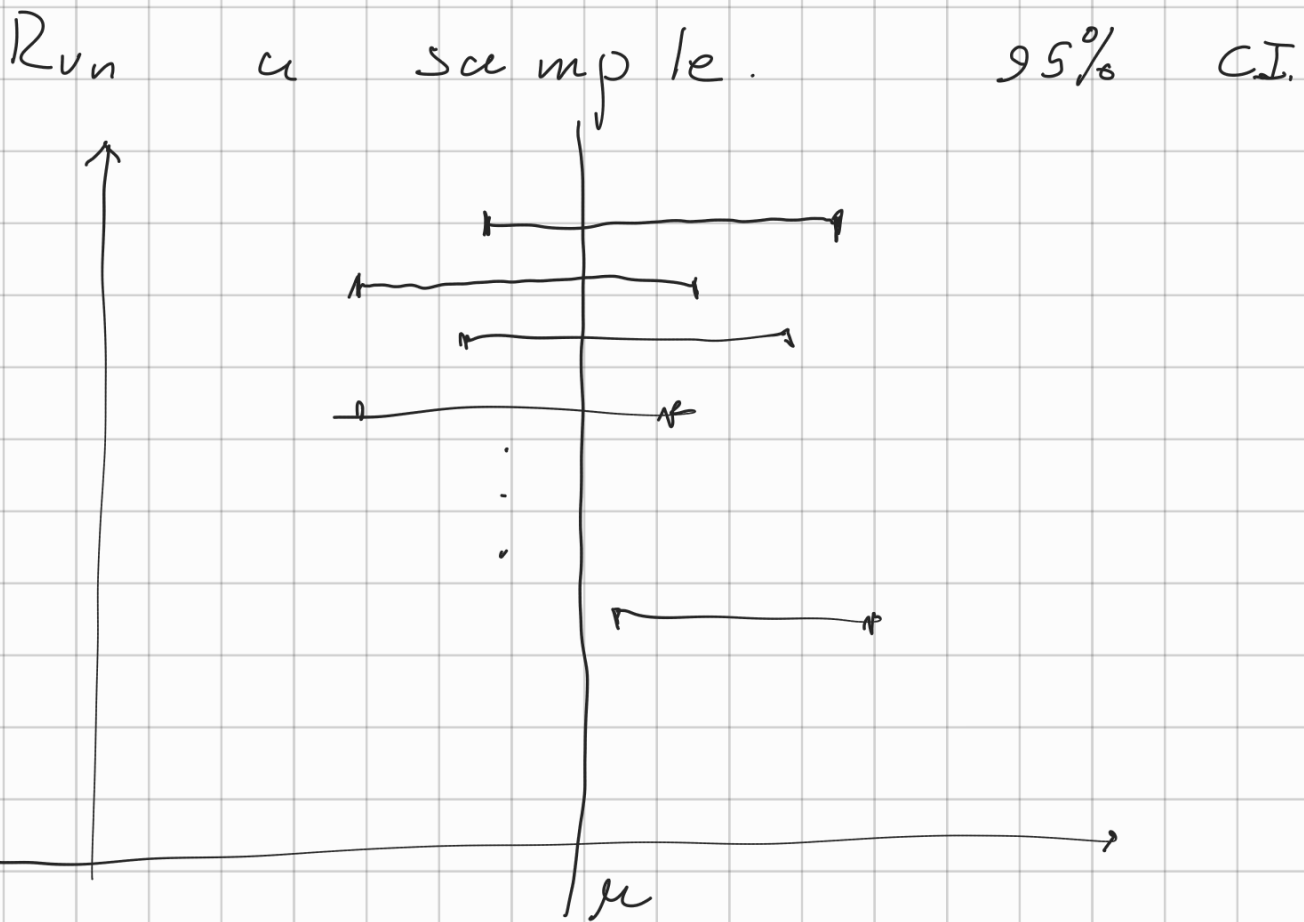
we have

$$\underline{\theta} = (\mu, \sigma) \quad g(\underline{\theta}) = \mu$$

$$A(\underline{X}) = \bar{X} - \frac{1}{T_{n-1}}^{-1} \left((1+\gamma)/2 \right) \frac{\hat{\sigma}}{\sqrt{n}}$$

$$B(\underline{X}) = \bar{X} + \frac{1}{T_{n-1}}^{-1} \left((1+\gamma)/2 \right) \frac{\hat{\sigma}}{\sqrt{n}}$$

Exact.



$$x_i \quad i = 1 \dots n$$

$$\bar{x} = \frac{1}{n} \sum_i x_i \quad s' = \left(\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2 \right)^{\frac{1}{2}}$$

$$\bar{x} - t_{n-1}^{-1} \left((1+\gamma)/2 \right) \frac{s'}{\sqrt{n}} \leq \mu \leq$$

$$\bar{x} + t_{n-1}^{-1} \left((1+\gamma)/2 \right) \frac{s'}{\sqrt{n}}$$

If n is large enough

$$t_{n-1}^{-1} \left((1+\gamma)/2 \right) \rightarrow \Phi^{-1} \left((1+\gamma)/2 \right)$$

What if X_i are not Normal?

$$E(X_i) = \mu$$

$$\text{Var}(X_i) = \sigma^2$$

↑
Known

If N is small, ...

If N is large, we can use
The CLT.

$$\bar{X} = \frac{1}{N} \sum_i X_i \approx N\left(\mu, \frac{\sigma^2}{N}\right)$$

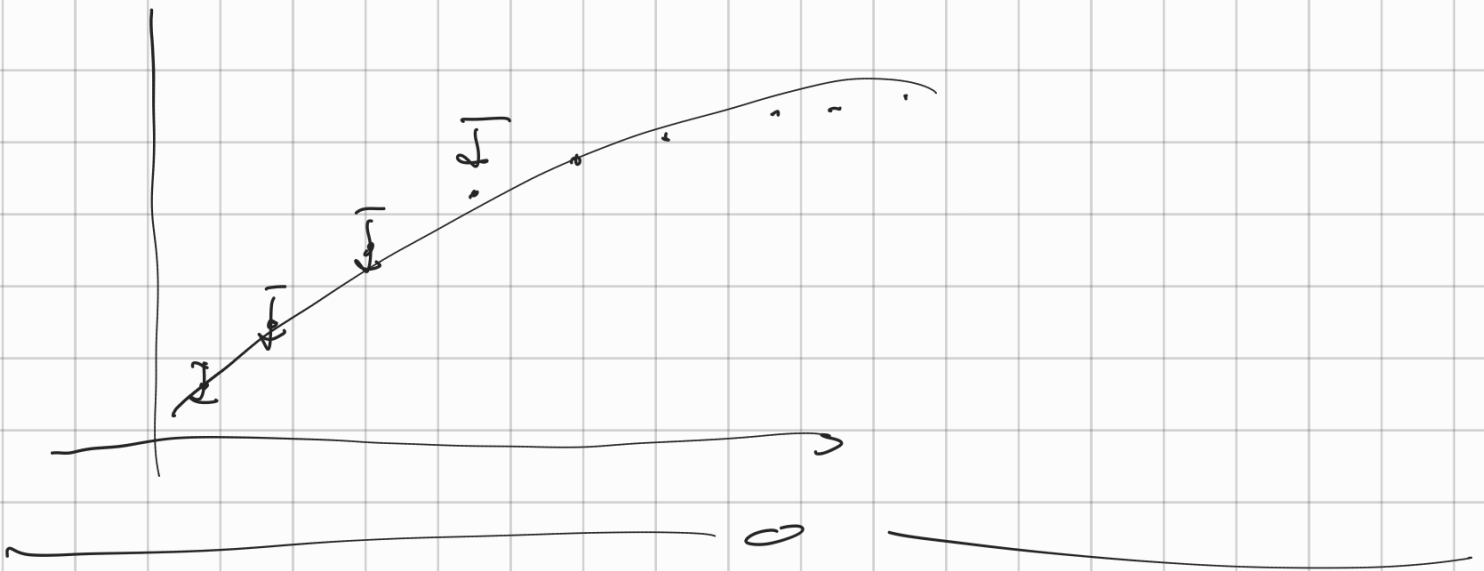
$$P\left(\bar{X} - \phi^{-1}\left(\frac{1+\gamma}{2}\right) \frac{\sigma}{\sqrt{N}} \leq \mu \leq \bar{X} + \phi^{-1}\left(\frac{1+\gamma}{2}\right) \frac{\sigma}{\sqrt{N}}\right) \approx \gamma$$

$N > 40$ mean N large.

$$r = 0.95$$

$$\Phi^{-1}\left(\frac{(1+r)/2}{2}\right) = 1.96$$

$$\bar{x} - 1.96 \frac{\sigma}{\sqrt{N}} \leq \mu \leq \bar{x} + 1.96 \frac{\sigma}{\sqrt{N}}$$



X_i are not Normal

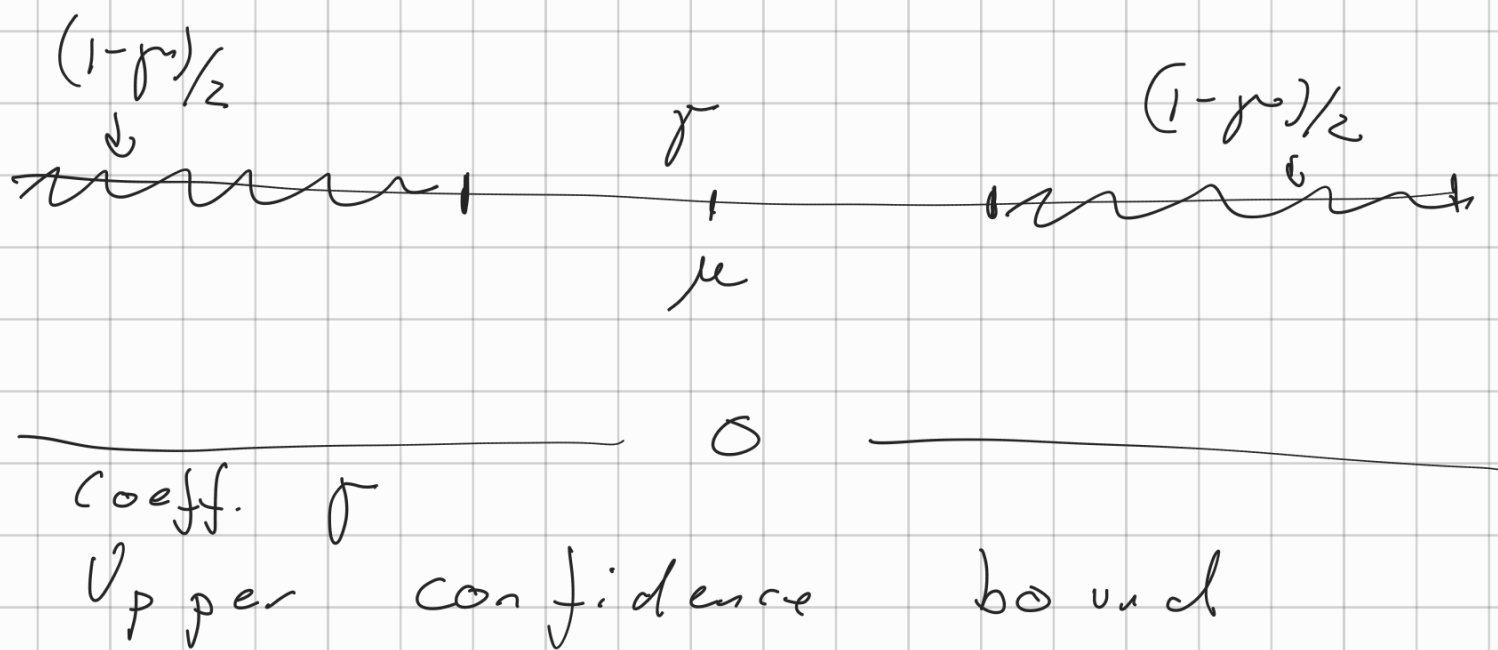
both σ and μ are
unknown.

$$\frac{\sqrt{N}(\bar{X} - \mu)}{\hat{\sigma}}$$

$$\xrightarrow{d} N(0, 1)$$

$$N \rightarrow \infty$$

$$P\left(\bar{X} - \Phi^{-1}\left(\frac{1+\gamma}{2}\right) \frac{\hat{\sigma}}{\sqrt{n}} \leq \mu \leq \bar{X} + \Phi^{-1}\left(\frac{1+\gamma}{2}\right) \frac{\hat{\sigma}}{\sqrt{n}}\right) = \gamma$$



$$P(g(\underline{X}) \leq B(\underline{X})) \geq \gamma$$

Lower confidence bound

$$P(A(\underline{X}) \leq g(\underline{X})) \geq \gamma$$

If X_i are Normal

$$P\left(\mu \leq \bar{X} + \frac{1}{n} T_{n-1}^{-1}(\gamma) \frac{\hat{\sigma}}{\sqrt{n}}\right) = \gamma$$

$$\underline{X} = X_1, X_2, \dots, X_n$$

$V(\underline{X}, \theta)$ whose distribution does not depend on θ .

$$V(\underline{X}, \theta) = \frac{n^{1/2} (\bar{X} - \mu)}{\hat{\sigma}} \sim T_{n-1} \quad \text{Normal}$$

$V(\underline{X}, \theta)$ pivotal quantity

There exists r

$$r(V(\underline{X}, \theta), \underline{X}) = g(\theta)$$

Fix

$$A(\underline{X}) = r(G^{-1}(\gamma), \underline{X})$$

$$B(X) = r(G^{-1}(r_2), \underline{X})$$

where $r_2 > r_1$ $r_2 - r_1 = r$

and G is the c.d.f. of $V(X, \theta)$. Then we have

$$\mathbb{P}(A(X) \leq \underset{0}{g(\theta)} \leq B(X)) = r$$

if X_i are exp. with
 par μ μX_i is

exp par $\frac{1}{\mu}$.

$\mu \sum_{i=1}^n X_i = \mu T_0$ has $\Gamma(n, 1)$

