

Lecture 12

Inlec 10;

$$\frac{\hat{\theta} - \theta}{SE[\hat{\theta}]} \xrightarrow{d} N(0,1) \Rightarrow \frac{\hat{\theta} - \theta}{SE[\hat{\theta}]} \xrightarrow{d} N(0,1)$$

We can use this now in our situation:

$$\frac{\hat{\theta}_1 - \hat{\theta}_2}{SE[\hat{\theta}_1 - \hat{\theta}_2]} \xrightarrow{d} N(0,1) \Rightarrow \frac{\hat{\theta}_1 - \hat{\theta}_2}{SE[\hat{\theta}_1 - \hat{\theta}_2]} \xrightarrow{d} N(0,1)$$

$$SE[\hat{\theta}_1 - \hat{\theta}_2] = \sqrt{\theta_{\text{shared}}(1 - \theta_{\text{shared}}) \left(\frac{1}{n_1} + \frac{1}{n_2} \right)}$$

$$SE[\hat{\theta}_1 - \hat{\theta}_2] = \sqrt{\hat{\theta}_{\text{shared}}(1 - \hat{\theta}_{\text{shared}}) \left(\frac{1}{n_1} + \frac{1}{n_2} \right)} \quad \text{if } \hat{\theta}_{\text{shared}} \text{ is consistent}$$

$\hat{\theta}_{\text{shared}}$ = avg. over both samples

$$= \frac{\sum x_{1i} + \sum x_{2i}}{n_1 + n_2}$$

$$\Rightarrow \frac{\hat{\theta}_1 - \hat{\theta}_2}{\sqrt{\frac{\sum x_{1i} + \sum x_{2i}}{n_1 + n_2} \left(1 - \frac{\sum x_{1i} + \sum x_{2i}}{n_1 + n_2} \right) \left(\frac{1}{n_1} + \frac{1}{n_2} \right)}} \xrightarrow{d} N(0,1)$$

e.g. $H_a: \theta_1 - \theta_2 \neq 0$, $H_0: \theta_1 - \theta_2 = 0$, $\alpha = 5\%$

Control | $n_1 = 81$, $\sum X_{1i} = 27 \Rightarrow \hat{\theta}_1 = \frac{27}{81} = 0.333$

Experimental | $n_2 = 79$, $\sum X_{2i} = 12 \Rightarrow \hat{\theta}_2 = \frac{12}{79} = 0.152$

$$\hat{\theta}_{\text{shared}} = \frac{27 + 12}{81 + 79} = 0.244$$

$$\begin{aligned} (\hat{\theta}_1 - \hat{\theta}_2)_{\text{std}} &= \frac{0.333 - 0.152}{\sqrt{0.244(1-0.244)\left(\frac{1}{81} + \frac{1}{79}\right)}} \\ &= 2.66 \notin [-1.96, +1.96] \\ &\Rightarrow \text{Reject } H_0. \end{aligned}$$

Another (obvious) Wald Test: let X_1, \dots, X_n

iid DGP with mean θ and variance (sigma-squared) (σ^2) and the estimator $\hat{\theta}$ is \bar{X} , then the

CLT implies that:

$$\frac{\hat{\theta} - \theta}{\frac{\sigma}{\sqrt{n}}} \xrightarrow{d} N(0, 1) \quad \text{if } \sigma \text{ is known}$$

if σ is unknown... I can replace
Sigma with any consistent estimator
eg. S , Sigma-hat and

$$\frac{1}{n} \sum (x_i - \theta)^2$$

$$\Rightarrow \frac{\hat{\theta} - \theta}{\frac{S}{\sqrt{n}}} \xrightarrow{d} N(0,1)$$

Are you allowed to just use the T-test
~~test~~ here? Many people just use
the T-test here. Technically it's
wrong because you need the OAP
to be normal iid. But if you use the
T-test... it's "not so bad" I did this
on problem 11 of the midterm:

$$H_a: \theta > 2, n=30, \bar{X}=2.57, S=1.00$$

$$\hat{\theta}_{std} = \frac{2.57 - 2}{\frac{1.00}{\sqrt{30}}} = 3.12 \notin [-\infty, 1.645]$$

\Rightarrow Reject H_0

* Another Wald test for two independent samples with unknown variances and you wish to test a difference in means.

$$\frac{\hat{\theta}_1 - \hat{\theta}_2}{\sqrt{\frac{\hat{\sigma}_1^2}{n_1} + \frac{\hat{\sigma}_2^2}{n_2}}} \xrightarrow[\text{from last class}]{d} N(0,1) \Rightarrow \frac{\hat{\theta}_1 - \hat{\theta}_2}{\sqrt{\frac{\hat{\sigma}_1^2}{n_1} + \frac{\hat{\sigma}_2^2}{n_2}}} \xrightarrow{d} N(0,1)$$

if you use the Satterthwaite t-test,

it "wouldn't be so bad" because unless your population distributions were so very skewed it should be fine.

Let's use the asymptotic normality of the MLE thm (last class) to do a Wald Test.

Hw 4.1.1 has DUP: X_1, \dots, X_n iid Gumbel(0,1)

The Gumbel is a rv model for "extreme events"

think maximum rainfall per month.

$$l'(\theta; x_1, \dots, x_n) = n - e^\theta \sum_{i=1}^n e^{-x_i} \stackrel{!}{=} 0 \Rightarrow \hat{\theta}^{MLE} = \ln\left(\frac{n}{\sum_{i=1}^n e^{-x_i}}\right)$$

$$l'(\theta; x) = 1 - e^\theta e^{-x} \Rightarrow l''(\theta; x) = -e^\theta e^{-x} ?$$

$$I(\theta) = E[-l''(\theta; x)] \\ = E[e^\theta e^{-x}] = e^\theta E[e^{-x}] = e^{2\theta}$$

$$\frac{\hat{\theta}^{MLE} - \theta}{\frac{\sqrt{I(\theta)^{-1}}}{n}} = \frac{\hat{\theta}^{MLE} - \theta}{\frac{e^\theta}{\sqrt{n}}}$$

$$= \frac{\ln\left(\frac{n}{\sum_{i=1}^n e^{-x_i}}\right) - \theta}{\frac{e^\theta}{\sqrt{n}}} \xrightarrow{d} N(0,1)$$

$$X_1 = 2.15, X_2 = 1.91, 3.66, 4.85, 3.03, 1.03, 3.58$$

$$n = 7$$

$$\hat{\theta}^{MLE} = 2.26$$

$$\text{Test } H_0: \theta \leq 2 \quad \alpha = 5\%$$

$$\hat{\theta}_{std}^{MLE} = \frac{2.26 - 2}{\frac{e^2}{\sqrt{7}}} = \frac{0.26}{2.79} = 0.09 \in [-1.64, 1.64] \Rightarrow \text{Retain } H_0$$

Next unit

There are three goals of statistical inference

(1) Point Estimation

Goal here is to provide a best guess, $\hat{\theta}$ of the value of θ . You don't know if your specific guess is good, is close, is bad, is far ... How do we

ask the question "is it good/bad"? We imagined

$\hat{\theta}$ coming from a distribution $\hat{\theta}$, the

"sampling distribution". There are properties

about the sampling distribution e.g. Some good

properties are unbiasedness, consistency,

low MSE, low risk (for general loss functions)

(2) Testing:

Goal Here is to test a theory about a specific

θ , we used hypothesis testing. What makes

a "good test"? One property is "power". There

are other properties we did not discuss.

(3) Confidence Sets

The "Goal" here is to create a set of values for θ that you are "Confident in". The approach we use here is the "Confidence interval".

Definition: an "interval estimate" are two statistics:

$W_L(x_1, \dots, x_n)$ & $W_U(x_1, \dots, x_n)$ s.t. $W_L < W_U$ for all data sets.

estimate
is a
number

Combined in an interval: $[W_L(x_1, \dots, x_n), W_U(x_1, \dots, x_n)]$

e.g. $[1.789, 2.463]$

estimator
is a
random
Variable.

and of course, the "interval estimator" is:

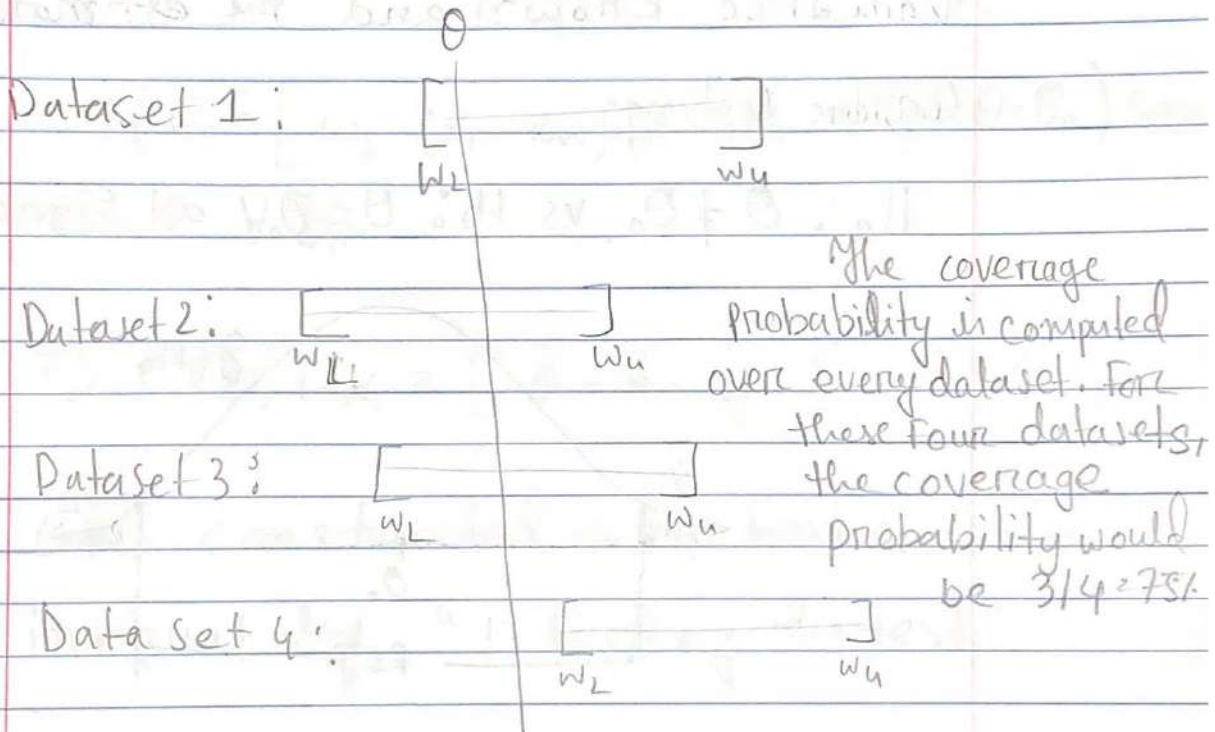
$[W_L(X_1, \dots, X_n), W_U(X_1, \dots, X_n)]$

Which is a "random interval".

Definition: An interval estimator has
"Coverage probability"

$$P(\theta \in [w_L(x_1, \dots, x_n), w_U(x_1, \dots, x_n)] | \theta).$$

An illustration:



We define the "Confidence interval"

with the coverage probability $1 - \alpha$ for

parameter θ as this interval estimate and interval estimator (depending on context)

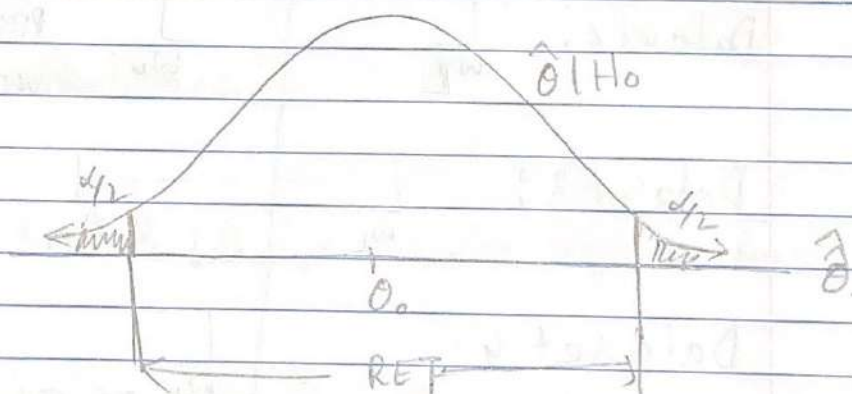
Demoset

$(1-\alpha)$

Given α , how do we find the confidence interval? let's begin with the DHP iid normal mean θ , variance σ^2 and Variance known and the estimator \bar{X}

Consider testing:

$H_a: \theta \neq \theta_0$ vs $H_0: \theta = \theta_0$ at size α



$$P(\hat{\theta} \in \text{RET} | H_0) = 1 - \alpha \quad z_{1-\frac{\alpha}{2}} = z_{\frac{1-\alpha}{2}}$$

||

$$P(\hat{\theta} \in [\theta_0 - z_{1-\frac{\alpha}{2}} \cdot \frac{\sigma}{\sqrt{n}}, \theta_0 + z_{1-\frac{\alpha}{2}} \cdot \frac{\sigma}{\sqrt{n}}] | \theta_0, \theta_0)$$

$$= P(\hat{\theta} - \theta_0 \in [-z_{1-\frac{\alpha}{2}} \cdot \frac{\sigma}{\sqrt{n}}, +z_{1-\frac{\alpha}{2}} \cdot \frac{\sigma}{\sqrt{n}}] \mid \theta = \theta_0)$$

$$= P(\theta_0 - \hat{\theta} \in [-z_{1-\frac{\alpha}{2}} \cdot \frac{\sigma}{\sqrt{n}}, +z_{1-\frac{\alpha}{2}} \cdot \frac{\sigma}{\sqrt{n}}] \mid \theta = \theta_0)$$

$$= P(\theta_0 \in [\underbrace{\hat{\theta} - z_{1-\frac{\alpha}{2}} \cdot \frac{\sigma}{\sqrt{n}}}_{w_L}, \underbrace{\hat{\theta} + z_{1-\frac{\alpha}{2}} \cdot \frac{\sigma}{\sqrt{n}}}_{w_U}] \mid \theta = \theta_0)$$

$$= P(\theta_0 \in [w_L(x_1, \dots, x_n), w_U(x_1, \dots, x_n)] \mid \theta = \theta_0) \text{ Since valid } \forall \theta_0.$$

$$\Rightarrow CI_{\theta, 1-\alpha} = [\hat{\theta} - z_{1-\frac{\alpha}{2}} \cdot \frac{\sigma}{\sqrt{n}}, \hat{\theta} + z_{1-\frac{\alpha}{2}} \cdot \frac{\sigma}{\sqrt{n}}]$$

We constructed our first confidence interval by "inverting the test".