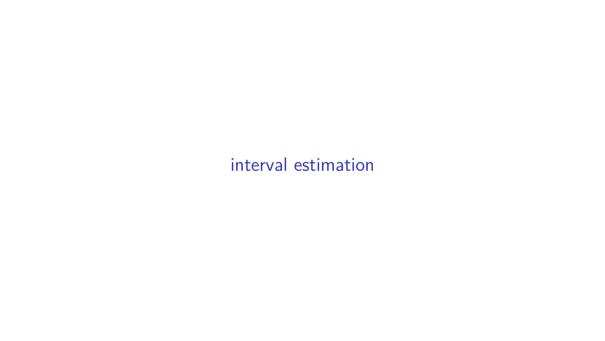
STA286 Lecture 24

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It is possible to have $\hat{\theta}_L = -\infty$ or $\hat{\theta}_U = \infty$

When $\alpha = 0.05$ (as usual), we have a 95% confidence interval.

(artifical) example of a confidence interval

Suppose the underlying population is $N(\mu, \sigma_0)$ with σ_0 (magically) known.

We plan to gather a sample X_1, \ldots, X_n . There are *lots* of 95% confidence intervals for μ , obtained by isolating μ in the middle of:

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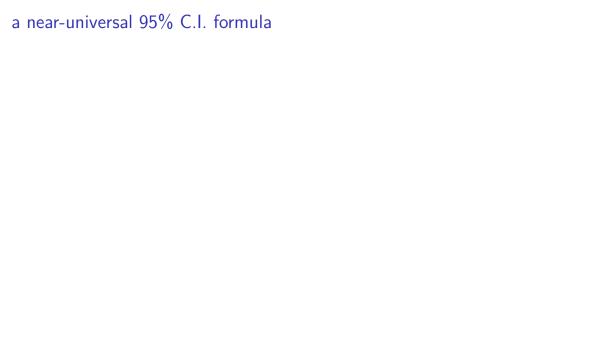
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Define z_{α} as the solution of $P(Z \leq z_{\alpha}) = 1 - \alpha$, where $Z \sim N(0, 1)$. The shortest possible 95% confidence interval for μ comes from:

$$P\left(\overline{X} - z_{0.025} \frac{\sigma_0}{\sqrt{n}} < \mu < \overline{X} + z_{0.025} \frac{\sigma_0}{\sqrt{n}}\right) = 0.95$$



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estimator \pm "2"s.e.(estimator)

"Two" is in quotation marks because the precise value will vary a little over and under 2, but it will always be close to 2 (for a 95% interval).

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The statement is nonsense. Either μ is between 4.2 and 6.8, or it isn't.

The (artificial) example is nevertheless characteristic:

$$\overline{X} \pm z_{\alpha/2} \frac{\sigma_0}{\sqrt{n}}$$

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The larger the α , the narrower the C.I. (But α is arbitrary.)

The larger the n, the narrower the C.I. (The sample size is under your control.)

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In the current (artificial) situation, to produce a $(1 - \alpha) \cdot 100\%$ confidence interval of width 2e, the sample size needs to be:

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▶ collect a "pilot sample" of some moderate size (30 to 50, say), to get an estimate of σ .

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- use prior knowledge of the value of σ
- ▶ if the population is plausibly normal, use prior knowledge of the minimum m and maximum M plausible values you might ever see, and use (M m)/6 as a rough guesstimate for σ .

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Define $t_{n-1,\alpha}$ as the solution of $P(t_{n-1} \leqslant t_{n-1,\alpha}) = 1 - \alpha$. The new interval will be based on:

$$P\left(-t_{n-1,\alpha/2} < \frac{\overline{X} - \mu}{S/\sqrt{n}} < t_{n-1,\alpha/2}\right) = 1 - \alpha$$

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The value $\frac{S}{\sqrt{n}}$ is (also) called the (estimated) standard error for \overline{X} , or s.e.(\overline{X}), and we end up with another example of the universal formula:

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That's because t calculations aren't wildly different from N(0,1) calculations as long as n-1 isn't tiny.

 $t_{n-1,0.025}$ for some non-insane sample sizes

t	n	
2.131449	15	
2.042273	30	
2.021075	40	
2.008559	50	
2.000298	60	
1.975905	150	

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So, for example, consider textbook question 9.14, which gives 15 values for the drying time, in hours, of a brand of latex paint.

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So, for example, consider textbook question 9.14, which gives 15 values for the drying time, in hours, of a brand of latex paint.

x_bar	S	n
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The 95% confidence interval for the mean drying time is:

conf.low	conf.high
3.248994	4.324339