

ISE 315: Engineering Statistics

Lecture 6: Statistical Intervals for a Single Sample (Part 2)

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Based on Montgomery & Runger, Applied Statistics and Probability for Engineers, 6th Ed.

Lecture 6

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Lecture 6 Outline (Textbook Chapter 3)

- Announcements:
 - HW #2 due next week
 - Major Exam 1 in Week 8 (Textbook Chapters 2–5)
 - Quiz #2 next Wednesday (up to 5 questions about Chapter 3)
- Z Table and Problem Examples
- CI for Mean (σ^2 unknown), Variance, and Proportion

How to Read the Z-Table (Table B.1 in the textbook appendix)

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z	0.00	0.01	0.02	...	0.05	0.06	...
...	...	...	...	...	...	...	...
1.6	0.9452	0.9463	0.9474	...	0.9505	0.9515	...
...	...	...	...	...	...	...	...
1.9	0.9713	0.9719	0.9726	...	0.9744	0.9750	...
2.0	0.9772	0.9778	0.9783	...	0.9798	0.9803	...
...	...	...	...	...	...	...	...

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Example: $\Phi(1.96) = P(Z \leq 1.96) = 0.9750$

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1.9	0.9713	...	0.9744	0.9750	0.9756	...
2.0	0.9772	...	0.9798	0.9803	0.9808	...
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Common Critical Values (Table 3.1 in the textbook)

Conf. Level	α	Two-sided (CI)		One-sided	
		$\Phi(z_{\alpha/2})$	$z_{\alpha/2}$	$\Phi(z_{\alpha})$	z_{α}
90%	0.10	0.95	1.645	0.90	1.282
95%	0.05	0.975	1.960	0.95	1.645
99%	0.01	0.995	2.576	0.99	2.326

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Example 1 (Review): Port Container Dwell Time

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Plan: Two-sided z-interval, (3.1) via Procedure 3.1

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$$\begin{aligned} n &= \left(\frac{z_{\alpha/2} \sigma}{E} \right)^2 = \left(\frac{1.96 \times 12}{3} \right)^2 \\ &= \left(\frac{23.52}{3} \right)^2 = (7.84)^2 = 61.47 \approx 62 \text{ users (round up!)} \end{aligned}$$

An AV safety team measures the pedestrian-detection distance of a perception model in $n = 16$ test runs. Sample mean $\bar{x} = 185.0$ m, known $\sigma = 10$ m. Find a 95% lower confidence bound for the true mean detection distance.

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4. Sample Proportion:

- $\hat{p} = X/n$ where $X =$ successes
- Estimates proportion p
- Uses Normal approximation (if some conditions are met)

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As $df \rightarrow \infty$: $t \rightarrow z$ and $\chi^2/df \rightarrow 1$

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When in doubt about assumptions, use larger sample sizes!

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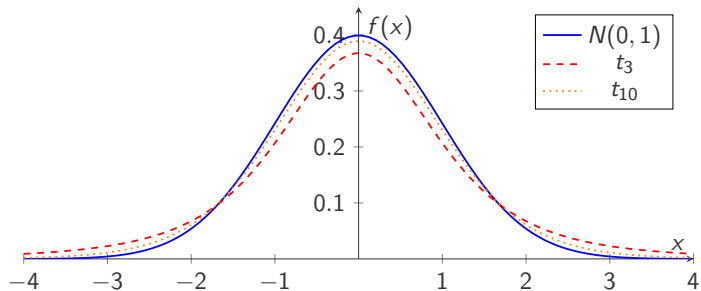
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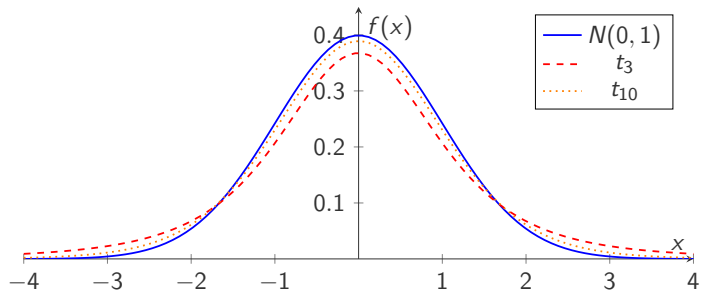
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- As $n \rightarrow \infty$: $t_{n-1} \rightarrow N(0, 1)$

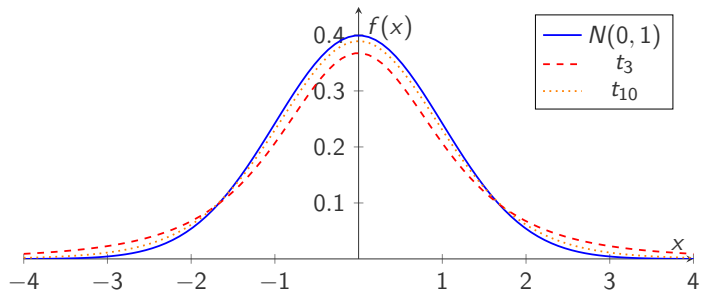
Comparing t and Normal Distributions



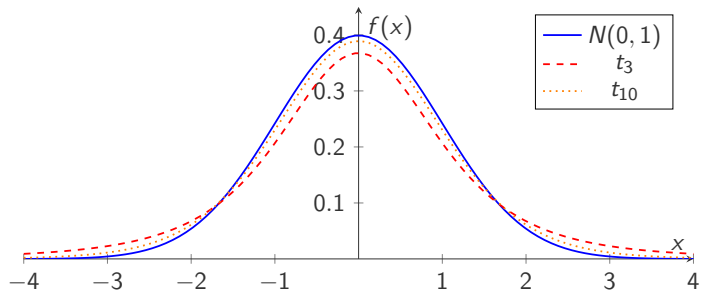
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Key point: Lower df $\Rightarrow$ heavier tails $\Rightarrow$ larger critical values $\Rightarrow$ wider CI

CI Formulas: Mean (σ unknown) and Variance

CI for Mean μ (σ unknown) — the t -interval, Procedure 3.2:

$$\bar{x} - t_{\alpha/2, n-1} \frac{s}{\sqrt{n}} \leq \mu \leq \bar{x} + t_{\alpha/2, n-1} \frac{s}{\sqrt{n}} \quad (3.5)$$

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CI for Mean μ (σ unknown) — the t -interval, Procedure 3.2:

$$\bar{x} - t_{\alpha/2, n-1} \frac{s}{\sqrt{n}} \leq \mu \leq \bar{x} + t_{\alpha/2, n-1} \frac{s}{\sqrt{n}} \quad (3.5)$$

CI for Variance σ^2 — the χ^2 -interval, Procedure 3.3:

$$\frac{(n-1)s^2}{\chi_{\alpha/2, n-1}^2} \leq \sigma^2 \leq \frac{(n-1)s^2}{\chi_{1-\alpha/2, n-1}^2} \quad (3.6)$$

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For a CI on σ , take square roots of both endpoints of (3.6).

CI Formulas: Proportion

CI for Proportion p (large sample) — Procedure 3.4:

$$\hat{p} - z_{\alpha/2} \sqrt{\frac{\hat{p}(1 - \hat{p})}{n}} \leq p \leq \hat{p} + z_{\alpha/2} \sqrt{\frac{\hat{p}(1 - \hat{p})}{n}} \quad (3.7)$$

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Sample Size for Proportion:

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If no prior $\hat{p}$ is available, use $\hat{p} = 0.5$ — the conservative version, (3.9) in the textbook.

t -Distribution Critical Values, Table 3.3 ($t_{\alpha,\nu}$ = value where $P(T > t_{\alpha,\nu}) = \alpha$)

df (ν)	Upper-tail probability α			
	0.10	0.05	0.025	0.01
1	3.078	6.314	12.706	31.821
2	1.886	2.920	4.303	6.965
3	1.638	2.353	3.182	4.541
5	1.476	2.015	2.571	3.365
10	1.372	1.812	2.228	2.764
15	1.341	1.753	2.131	2.602
20	1.325	1.725	2.086	2.528
30	1.310	1.697	2.042	2.457
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Example: For 95% two-sided CI with $n = 11$ samples ($df = 10$): Use $t_{0.025,10} = 2.228$

χ^2 -Distribution Critical Values, Table 3.4 ($\chi^2_{\alpha,\nu}$ = value s.t. $P(\chi^2 > \chi^2_{\alpha,\nu}) = \alpha$)

df (ν)	Upper-tail probability α			
	0.975	0.95	0.05	0.025
1	0.001	0.004	3.841	5.024
2	0.051	0.103	5.991	7.378
5	0.831	1.145	11.070	12.833
9	2.700	3.325	16.919	19.023
10	3.247	3.940	18.307	20.483
19	8.907	10.117	30.144	32.852
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Example: For 95% CI for σ^2 with $n = 10$ ($df = 9$): Use $\chi_{0.975,9}^2 = 2.700$ and $\chi_{0.025,9}^2 = 19.023$

Summary

- When σ is **unknown**, use the *t*-**distribution** (3.5):
 - Replace σ with s
 - Replace $z_{\alpha/2}$ with $t_{\alpha/2, n-1}$
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- For **variance** σ^2 , use the **χ^2 -distribution** (3.6):
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- For **proportion** p , use **Normal approximation** (3.7):
 - Requires large sample: $n\hat{p} \geq 10$ and $n(1 - \hat{p}) \geq 10$
 - Standard error: $\sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$

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 - Check: $n\hat{p} \geq 10$ and $n(1 - \hat{p}) \geq 10$?
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 - Use $\hat{p} = 0.5$ (conservative, maximizes $\hat{p}(1 - \hat{p})$, (3.9))

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