

ISE 315: Engineering Statistics

Lecture 10: Hypothesis Testing for a Single Sample (cont'd)

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

Lecture 10

Hypothesis Testing: χ^2 -Test, Proportion Test, Type II Error, and Practice

Lecture 10 Outline

- Rule review: 1) test statistic vs critical value and 2) P-value vs α
- Chi-square (χ^2) test for the variance σ^2
- Z-test for a proportion p
- Type II error (β) and the α - β tradeoff
- Practice problems (Sets A–D)

Choosing the Right Test

Procedure 4.5; see also Table 4.9

Parameter	Condition	Test Statistic	Distribution	Book Eq.
μ	σ known	$Z_0 = \frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}}$	Standard Normal	(4.3)

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Today: the χ^2 row and the p row in detail, plus the α - β tradeoff.

Textbook: Chapter 4 ((4.7) and (4.8))

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- *For χ^2 tests, remember: the distribution is not symmetric.*

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Both methods lead to the same conclusion!

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Key difference from Z and t : The chi-square distribution is *not symmetric*, so critical values for left and right tails are different.

χ^2 -Test Decision Rules

Collected in Table 4.7

Test Type	H_1	Reject H_0 if
Two-tailed	$\sigma^2 \neq \sigma_0^2$	$\chi_0^2 < \chi_{1-\alpha/2, n-1}^2$ or $\chi_0^2 > \chi_{\alpha/2, n-1}^2$

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Left-tailed	$\sigma^2 < \sigma_0^2$	$\chi_0^2 < \chi_{1-\alpha, n-1}^2$

Important: $\chi_{\alpha, \nu}^2$ is the value such that $P(\chi_{\nu}^2 > \chi_{\alpha, \nu}^2) = \alpha$.

So $\chi_{0.05, 2}^2$ gives $P(\chi_2^2 > \chi_{0.05, 2}^2) = 0.05$, i.e. only 5% is in the left tail

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AI Safety Testing Context

An AV team wants to verify that the variance of sensor-fusion latency has been **reduced below** the legacy value $\sigma^2 = 0.25 \text{ ms}^2$ after a firmware patch. Data: $n = 20$ drives, $s^2 = 0.14 \text{ ms}^2$. Test at $\alpha = 0.05$.

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Conclusion: **Fail to reject H_0** . Not enough evidence at 5% that the latency variance has been reduced below 0.25 ms^2 .

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Note: the standard error uses p_0 (the H_0 value), *not* $\hat{p}$ — unlike the CI (3.7).

Type II Error (β) and The α - β Tradeoff

Recap: Two Types of Errors

Definitions in (4.2)

	H_0 True	H_0 False
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Fail to reject H_0	Correct!	Type II error (β)

- $\alpha = P(\text{reject } H_0 \mid H_0 \text{ is true})$ – **false alarm**
- $\beta = P(\text{fail to reject } H_0 \mid H_0 \text{ is false})$ – **missed detection**
- **Power** = $1 - \beta = P(\text{reject } H_0 \mid H_0 \text{ is false})$

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Get more evidence (i.e. increase the sample size n)

Example: Effect of Changing α

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Delivery route time test (Set A, later today): $n = 49$, $\sigma = 14$, $\mu_0 = 150$,
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Same data, same test statistic, **different conclusion!**

The stricter $\alpha = 0.01$ means we need stronger evidence to reject.

We claim β is now larger – but can we actually *calculate* β ?

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Yes! But we need to specify a particular “true” alternative value μ_{true} .

$$\beta(\mu_{\text{true}}) = P(\text{fail to reject } H_0 \mid \mu = \mu_{\text{true}})$$

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$$\beta(\mu_{\text{true}}) = P(\text{fail to reject } H_0 \mid \mu = \mu_{\text{true}})$$

Computing β for a Given μ_{true}

Procedure 4.4, Step 1: the Fail-to-Reject Interval

Recall: $n = 64$, known $\sigma = 16$ h, the operator claims $\mu_0 = 71$ h, and we observed $\bar{x} = 76$ h. The standard error is $SE = \frac{\sigma}{\sqrt{n}} = \frac{16}{8} = 2$ h.

Assume (for illustration) that the **true mean** is $\mu_{\text{true}} = 75$ h.

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The fail-to-reject interval for H_0 (in terms of $\bar{X}$) is the book's acceptance region:

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At $\alpha = 0.05$: $71 - 1.96 \times 2 \leq \bar{X} \leq 71 + 1.96 \times 2 \Rightarrow 67.08 \leq \bar{X} \leq 74.92$

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The fail-to-reject interval for H_0 (in terms of $\bar{X}$) is the book's acceptance region:

$$\mu_0 - z_{\alpha/2} \frac{\sigma}{\sqrt{n}} \leq \bar{X} \leq \mu_0 + z_{\alpha/2} \frac{\sigma}{\sqrt{n}} \quad (4.9)$$

At $\alpha = 0.05$: $71 - 1.96 \times 2 \leq \bar{X} \leq 71 + 1.96 \times 2 \Rightarrow 67.08 \leq \bar{X} \leq 74.92$

Computing β for a Given μ_{true}

Procedure 4.4, Step 1: the Fail-to-Reject Interval

Recall: $n = 64$, known $\sigma = 16$ h, the operator claims $\mu_0 = 71$ h, and we observed $\bar{x} = 76$ h. The standard error is $SE = \frac{\sigma}{\sqrt{n}} = \frac{16}{8} = 2$ h.

Assume (for illustration) that the **true mean** is $\mu_{\text{true}} = 75$ h.

Scenario	Parameter Values	Interpretation
H_0 (Null hypothesis)	$\mu = \mu_0 = 71$ h	Assumed for testing
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Computing β for a Given μ_{true} (cont'd)

Procedure 4.4, Step 2: Probability under the Truth, via (4.10)

$$\text{If } \mu_{\text{true}} = 75 \text{ h, then } \beta(\mu_{\text{true}} = 75) = \overbrace{P(\bar{X} \in I_{H_0, \alpha} \mid \mu = 75)}^{\text{prob. } \bar{X} \text{ in the fail-to-reject region}}$$

Computing β for a Given μ_{true} (cont'd)

Procedure 4.4, Step 2: Probability under the Truth, via (4.10)

$$\text{If } \mu_{\text{true}} = 75 \text{ h, then } \beta(\mu_{\text{true}} = 75) = \overbrace{P(\bar{X} \in I_{H_0, \alpha} \mid \mu = 75)}^{\text{prob. } \bar{X} \text{ in the fail-to-reject region}}$$

- For $\alpha = 0.05$: $I_{H_0, \alpha=0.05} = [67.08, 74.92]$

$$\begin{aligned}\beta(\mu_{\text{true}} = 75) &= P(67.08 \leq \bar{X} \leq 74.92 \mid \mu = 75) = P\left(\frac{67.08 - 75}{2} \leq Z \leq \frac{74.92 - 75}{2}\right) \\ &= P(-3.96 \leq Z \leq -0.04) = \Phi(-0.04) - \Phi(-3.96) = 0.4840 - 0.0000 = \boxed{0.484}\end{aligned}$$

Computing β for a Given μ_{true} (cont'd)

Procedure 4.4, Step 2: Probability under the Truth, via (4.10)

If $\mu_{\text{true}} = 75$ h, then $\beta(\mu_{\text{true}} = 75) = \overbrace{P(\bar{X} \in I_{H_0, \alpha} \mid \mu = 75)}^{\text{prob. } \bar{X} \text{ in the fail-to-reject region}}$

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- For $\alpha = 0.01$: $I_{H_0, \alpha=0.01} = [65.85, 76.15]$

$$\begin{aligned}\beta(\mu_{\text{true}} = 75) &= P(65.85 \leq \bar{X} \leq 76.15 \mid \mu = 75) = P\left(\frac{65.85 - 75}{2} \leq Z \leq \frac{76.15 - 75}{2}\right) \\ &= P(-4.58 \leq Z \leq 0.58) = \Phi(0.58) - 0 = \boxed{0.719}\end{aligned}$$

Computing β for a Given μ_{true} (cont'd)

Procedure 4.4, Step 2: Probability under the Truth, via (4.10)

If $\mu_{\text{true}} = 75$ h, then $\beta(\mu_{\text{true}} = 75) = \overbrace{P(\bar{X} \in I_{H_0, \alpha} \mid \mu = 75)}^{\text{prob. } \bar{X} \text{ in the fail-to-reject region}}$

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By reducing α ($0.05 \rightarrow 0.01$), β increases $0.484 \rightarrow 0.719$.
fewer false alarms more failures to reject

What We Have So Far

- **Four test types:** Z -test (4.3), t -test (4.6), χ^2 -test (4.7), proportion Z -test (4.8)

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Now let's put it all together with practice problems.

Practice Problems

Sets A–D, each with the seven steps of Procedure 4.2

Set A: Z-Test, Two-Tailed (Delivery Route Time)

Supply Chain Context

A logistics planner tests whether the mean delivery route time differs from the scheduled 150 minutes. $n = 49$ routes, $\bar{x} = 154$ min, $\sigma = 14$ min, $\alpha = 0.05$.

Set A: Z-Test, Two-Tailed (Delivery Route Time)

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Steps 1–3: Parameter: μ , σ known. $H_0 : \mu = 150$ vs $H_1 : \mu \neq 150$ (two-tailed).

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Steps 4–5: Z-test (4.3); reject if $|Z_0| > z_{0.025} = 1.96$.

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Step 6: $Z_0 = \frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}} = \frac{154 - 150}{14/\sqrt{49}} = \frac{4}{2} = 2.00$; P-value (4.5) $= 2(1 - \Phi(2.00)) = 2(0.0228) = 0.0455$

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Step 7: $|2.00| = 2.00 > 1.96 \Rightarrow$ **Reject H_0** .

Sufficient evidence at 5% that the mean route time differs from 150 minutes.

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Step 7: $|2.00| = 2.00 > 1.96 \Rightarrow$ **Reject H_0** .

Sufficient evidence at 5% that the mean route time differs from 150 minutes.

α - β : At $\alpha = 0.01$: P-value $= 0.0455 > 0.01 \Rightarrow$ fail to reject. β increases.

Set B: t -Test, Right-Tailed (Feature Activations)

Startup Context

A startup founder claims the new onboarding flow pushes the mean number of first-week feature activations above 10.0 per user. $n = 16$ pilot users, $\bar{x} = 10.8$, $s = 1.2$, $\alpha = 0.05$.

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Steps 4–5: t -test (4.6), $df = 15$; reject if $t_0 > t_{0.05, 15} = 1.753$.

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Steps 4–5: t -test (4.6), $df = 15$; reject if $t_0 > t_{0.05, 15} = 1.753$.

Step 6: $t_0 = \frac{10.8 - 10.0}{1.2/\sqrt{16}} = \frac{0.8}{0.3} = 2.67$; P-value bounds (Procedure 4.3):

$t_{0.01, 15} = 2.602 < 2.67 < 2.947 = t_{0.005, 15}$, so $0.005 < P < 0.01$ (≈ 0.0088)

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Step 7: $2.67 > 1.753 \Rightarrow$ **Reject H_0** .

Sufficient evidence at 5% that the mean activations exceed 10.0 per user.

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Step 7: $2.67 > 1.753 \Rightarrow$ **Reject H_0** .

Sufficient evidence at 5% that the mean activations exceed 10.0 per user.

α - β : At $\alpha = 0.01$: $t_{0.01, 15} = 2.602$. Since $2.67 > 2.602$, still reject. β increases but the conclusion holds.

Set C: χ^2 -Test, Left-Tailed (Sensor-Fusion Latency Variance)

AI Safety Testing Context

The AV team tests whether the latency variance has been reduced below 0.25 ms^2 after the firmware patch. $n = 20$ drives, $s^2 = 0.14 \text{ ms}^2$, $\alpha = 0.05$.

Set C: χ^2 -Test, Left-Tailed (Sensor-Fusion Latency Variance)

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Steps 1–3: Parameter: σ^2 , Normal population. $H_0 : \sigma^2 = 0.25$ vs $H_1 : \sigma^2 < 0.25$ (left-tailed).

Set C: χ^2 -Test, Left-Tailed (Sensor-Fusion Latency Variance)

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Steps 4–5: χ^2 -test (4.7), $\text{df} = 19$; reject if $\chi_0^2 < \chi_{0.95, 19}^2 = 10.117$.

Set C: χ^2 -Test, Left-Tailed (Sensor-Fusion Latency Variance)

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Steps 4–5: χ^2 -test (4.7), $df = 19$; reject if $\chi_0^2 < \chi_{0.95, 19}^2 = 10.117$.

Step 6: $\chi_0^2 = \frac{19 \times 0.14}{0.25} = \frac{2.66}{0.25} = 10.64$; P-value = $P(\chi_{19}^2 < 10.64) \approx 0.065$

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The AV team tests whether the latency variance has been reduced below 0.25 ms^2 after the firmware patch. $n = 20$ drives, $s^2 = 0.14 \text{ ms}^2$, $\alpha = 0.05$.

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Step 6: $\chi_0^2 = \frac{19 \times 0.14}{0.25} = \frac{2.66}{0.25} = 10.64$; P-value = $P(\chi_{19}^2 < 10.64) \approx 0.065$

Step 7: $10.64 > 10.117$ (not in rejection region) $\Rightarrow$ **Fail to reject H_0** .

Not enough evidence at 5% that the variance is below 0.25 ms^2 .

Set C: χ^2 -Test, Left-Tailed (Sensor-Fusion Latency Variance)

AI Safety Testing Context

The AV team tests whether the latency variance has been reduced below 0.25 ms^2 after the firmware patch. $n = 20$ drives, $s^2 = 0.14 \text{ ms}^2$, $\alpha = 0.05$.

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Step 7: $10.64 > 10.117$ (not in rejection region) $\Rightarrow$ **Fail to reject H_0** .

Not enough evidence at 5% that the variance is below 0.25 ms^2 .

α - β : At $\alpha = 0.10$: $\chi_{0.90, 19}^2 = 11.651$. Since $10.64 < 11.651$, now reject. β decreases.

Set D: Proportion Z-Test, Right-Tailed (Late Deliveries)

Supply Chain Context

A carrier's contract requires at most 5% late arrivals. An audit samples $n = 400$ shipments and finds 28 late, so $\hat{p} = 28/400 = 0.07$. Is the late rate **above** the contract level? $\alpha = 0.05$.

Set D: Proportion Z-Test, Right-Tailed (Late Deliveries)

Supply Chain Context

A carrier's contract requires at most 5% late arrivals. An audit samples $n = 400$ shipments and finds 28 late, so $\hat{p} = 28/400 = 0.07$. Is the late rate **above** the contract level? $\alpha = 0.05$.

Steps 1–3: Parameter: p . $H_0 : p = 0.05$ vs $H_1 : p > 0.05$ (right-tailed). Check: $np_0 = 20 \geq 5$, $n(1 - p_0) = 380 \geq 5$. ✓

Set D: Proportion Z-Test, Right-Tailed (Late Deliveries)

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Steps 4–5: Proportion Z-test (4.8); reject if $Z_0 > z_{0.05} = 1.645$.

Set D: Proportion Z-Test, Right-Tailed (Late Deliveries)

Supply Chain Context

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Step 6: $Z_0 = \frac{0.07 - 0.05}{\sqrt{0.05 \times 0.95/400}} = \frac{0.02}{0.01090} = 1.84$; P-value (4.5) = $1 - \Phi(1.84) = 0.0329$

Set D: Proportion Z-Test, Right-Tailed (Late Deliveries)

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Step 7: $1.84 > 1.645 \Rightarrow$ **Reject H_0** .

Sufficient evidence at 5% that the late-delivery rate exceeds the 5% contract level.

Set D: Proportion Z-Test, Right-Tailed (Late Deliveries)

Supply Chain Context

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Step 7: $1.84 > 1.645 \Rightarrow$ **Reject H_0** .

Sufficient evidence at 5% that the late-delivery rate exceeds the 5% contract level.

α - β : At $\alpha = 0.01$: $z_{0.01} = 2.326$. Since $1.84 < 2.326$, fail to reject. β increases.

Summary: Comparing the Four Sets

See Table 4.10 in the textbook

	Set A	Set B	Set C	Set D
Parameter	μ	μ	σ^2	p

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Test	Z (4.3)	t (4.6)	χ^2 (4.7)	Z (4.8)
Tail	Two	Right	Left	Right
Decision	Reject H_0	Reject H_0	Fail to reject	Reject H_0

Summary: Comparing the Four Sets

See Table 4.10 in the textbook

	Set A	Set B	Set C	Set D
Parameter	μ	μ	σ^2	p
σ known?	Yes	No	N/A	N/A
Test	Z (4.3)	t (4.6)	χ^2 (4.7)	Z (4.8)
Tail	Two	Right	Left	Right
Decision	Reject H_0	Reject H_0	Fail to reject	Reject H_0
P-value	0.0455	0.0088	0.065	0.0329

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Same seven-step procedure (Procedure 4.2), only the test statistic and distribution change!

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- **Next:** Chapter 5 – Hypothesis testing for two samples

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