CEE 260/MIE 273: Probability and Statistics in Civil Engineering

Lecture 6B: Inference for Two Samples

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Outline

1. CI for difference of two means
2. Hyp. Tests for difference of two means
3. Paired data
4. Outlook

Confidence intervals for difference of two means

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- You can easily derive the formulas for the upper/lower confidence bounds.

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(i.e. the smaller of the two)

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The void volume within a textile fabric affects comfort, flammability and insulation properties. Permeability of a fabric refers to the accessibility of void space to the flow of a gas or liquid. Consider the following permeability ($\text{cm}^3/\text{cm}^2/\text{sec}$) summary data on two different types of plain-weave fabric

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Fabric type	Sample size	Sample mean	Sample SD
Cotton	10	51.71	0.79
Triacetate	10	136.14	3.59

Assuming that the permeability distributions for both types of fabric are normal, calculate a CI for the difference between true average permeability for the cotton fabric and that for the triacetate fabric using a 95% confidence level.

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In this case, we can see that since $n_1 = n_2$, we ended up with $df = 10 - 1 = 9$.

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Key assumptions

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Key assumptions

- Normality: X_1 is a random normal sample; X_2 is a random normal sample

Comparing two populations: difference of two means

Example cases

- Is there any significant difference between the performances in the 2018 NY marathon and that of 2019?
- Is the hardness of heat-treated steel similar to that of cold-rolled steel?
- How can an engineer test if the proportion of defective batteries in a production batch is similar to that of another batch?

Key assumptions

- Normality: X_1 is a random normal sample; X_2 is a random normal sample
- Independence: X_1 and X_2 are independent of each other

Testing normal populations with known variances

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Null hypothesis:

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Often Δ_0 is often 0, in which case, $H_0 : \mu_1 = \mu_2$.

Test statistic:

$$z = \frac{\overline{x_1} - \overline{x_2} - \Delta_0}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}} \tag{9}$$

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where $\overline{x}_1$, $\overline{x}_2$ are the sample means, σ_1^2 σ_2^2 are the respective population variances, and n_1, n_2, the respective sample sizes.

Alternative Hypothesis	**Rejection Region for level α test**
$H_1 : \mu_1 - \mu_2 > \Delta_0$	$z \geq z_{1-\alpha}$ (upper-tailed)
$H_1 : \mu_1 - \mu_2 < \Delta_0$	$z \leq z_{\alpha}$ (lower-tailed)
$H_1 : \mu_1 - \mu_2 \neq \Delta_0$	$z \leq z_{\alpha/2}$ or $z \geq z_{(1-\alpha/2)}$ (both tails)

Difference between two population means

Example 1: Cold-rolled vs. galvanized steel

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Analysis of a random sample consisting of $n_1 = 20$ specimens of cold-rolled steel to determine yield strengths resulted in a sample average strength of $\overline{x} = 29.8$ ksi.

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A second random sample of $n_2 = 25$ two-sided galvanized steel specimens gave a sample average strength of $\overline{y} = 34.7$ ksi.

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Assuming that the two yield-strength distributions are normal with $\sigma_1 = 4.0$ and $\sigma_2 = 5.0$, do the data indicate that the corresonding true average yield strengths μ_1 and μ_2 are different?

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Carry out a test at significance level $\alpha = 0.01$.

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Step 1. Parameter of interest: $\mu_1 - \mu_2$ (difference between the true average strengths)

Step 2. Null hypothesis:

Difference between two population means

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Step 3. Alternative hypothesis:

Difference between two population means

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Difference between two population means

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Step 1. Parameter of interest: $\mu_1 - \mu_2$ (difference between the true average strengths)

Step 2. Null hypothesis: $H_0 : \mu_1 - \mu_2 = \Delta_0 = 0$

Step 3. Alternative hypothesis: $H_1 : \mu_1 - \mu_2 \neq 0$

Step 4. Formula for test statistic value:

Difference between two population means

Example 1: Cold-rolled vs. galvanized steel

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Step 3. Alternative hypothesis: $H_1 : \mu_1 - \mu_2 \neq 0$

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$$z = \frac{\overline{x} - \overline{y} - (0)}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}$$

Difference between two population means

Example 1: Cold-rolled vs. galvanized steel (cont.)

Step 5. Calculate test statistic value:

Difference between two population means

Example 1: Cold-rolled vs. galvanized steel (cont.)

Step 5. Calculate test statistic value:

$$z = \frac{29.8 - 34.7}{\sqrt{\frac{16.0}{20} + \frac{25.0}{25}}} =$$

Difference between two population means

Example 1: Cold-rolled vs. galvanized steel (cont.)

Step 5. Calculate test statistic value:

$$z = \frac{29.8 - 34.7}{\sqrt{\frac{16.0}{20} + \frac{25.0}{25}}} = \frac{-4.90}{1.34} =$$

Difference between two population means

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Step 6. Find the critical values (two-tailed test):

$$\alpha/2 = 0.01/2 = 0.005$$
$$z^* = z_{(1-\alpha/2)} = z_{0.995} = 2.58 \quad (\texttt{norm.ppf(0.995)})$$

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Step 7. Conclude:

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Since $-3.66 < -2.58$, z falls in the lower tail of the rejection region.

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Since $-3.66 < -2.58$, z falls in the lower tail of the rejection region. H_0 is therefore rejected in favor of the conclusion that $\mu_1 \neq \mu_2$.

Furthermore, the p-value is $2(1 - \Phi(3.66)) \approx 2(1 - 1) = 0$.

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Furthermore, the p-value is $2(1 - \Phi(3.66)) \approx 2(1 - 1) = 0$.

So, H_0 should be rejected at any reasonable significance level.

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- n independently selected pairs of observations: $\mathbb{E}(X_i) = \mu_1, \mathbb{E}(Y_i) = \mu_2$.

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- Differences betweeen pairs $D_i = X_i - Y_i$ are normally distributed with mean μ_D and variance σ_D^2

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    - If n is small, conduct t-test
    - If n is large, conduct z-test

Paired t-test

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where $\overline{d}$ is the sample difference, μ_0 is the null difference and s_D is the sample standard deviation

Alternative Hypothesis	Rejection Region for level α test
$H_1 : \mu_D > \mu_0$	$t \geq t_{\alpha,n-1}$ (upper-tailed)
$H_1 : \mu_D < \mu_0$	$t \leq t_{\alpha,n-1}$ (lower-tailed)
$H_1 : \mu_D \neq \mu_0$	$t \leq t_{\alpha/2,n-1}$ or $t \geq t_{(1-\alpha/2),n-1}$ (both tails)

Paired t-test example

Example 2: Intervention for ergonomic improvements

Musculoskeletal neck-and-shoulder disorders are all too common among office staff who perform repetitive tasks using visual display units. A study was conducted to determine whether more varied work conditions would have any impact on arm movement.[a]

Paired t-test example

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The accompanying data was obtained from a sample of $n = 16$ subjects. Each observation is the amount of time, expressed as a proportion of total time observed, during which arm elevation was 30°. The two measurements from each subject were obtained 18 months apart.

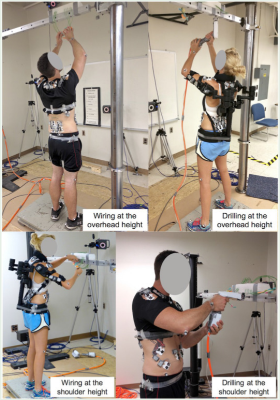

Illustration of upper-arm elevation. Source: https://www.sciencedirect.com/science/article/pii/S0003687018300590

[a] "Upper-Arm Elevation During Office Work" (*Ergonomics*, 1996: 1221-1230)

Paired t-test in practice

Example 2: Intervention for ergonomic improvements (cont.)

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During this period, work conditions were changed, and subjects were allowed to engage in a wider variety of work tasks. Do the data suggest that true average time during which elevation is below 30° differs after the change from what it was before the change?

Paired t-test in practice

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Step 1. $H_0 : \mu_D = 0$

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$$n = 16$$

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$$\begin{aligned} n &= 16 \\ \sum d_i &= 108 \end{aligned}$$

Paired t-test in practice

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Step 3. Compute the parameters:

$$
\begin{aligned}
n &= 16 \\
\sum d_i &= 108 \\
\sum d_i^2 &= 1746
\end{aligned}
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Paired t-test in practice

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$$\begin{aligned} n &= 16 \\ \sum d_i &= 108 \\ \sum d_i^2 &= 1746 \\ \overline{d} &= 6.75 \end{aligned}$$

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$$
\begin{aligned}
n &= 16 \\
\sum d_i &= 108 \\
\sum d_i^2 &= 1746 \\
\overline{d} &= 6.75 \\
s_D &= 8.234
\end{aligned}
$$

Paired t-test in practice

Example 2: Intervention for ergonomic improvements (cont.)

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Step 5. Compute the T-statistic:

Paired t-test in practice

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$$t = \frac{\overline{d} - 0}{s_D/\sqrt{n}}$$

Paired t-test in practice

Example 2: Intervention for ergonomic improvements (cont.)

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$$
\begin{aligned}
t &= \frac{\overline{d} - 0}{s_D/\sqrt{n}} \\
&= \frac{6.75}{8.234/\sqrt{16}}
\end{aligned}
$$

Paired t-test in practice

Example 2: Intervention for ergonomic improvements (cont.)

Step 5. Compute the T-statistic:

$$
\begin{aligned}
t &= \frac{\overline{d} - 0}{s_D/\sqrt{n}} \\
&= \frac{6.75}{8.234/\sqrt{16}} = 3.28 \approx 3.3
\end{aligned}
$$

Paired t-test in practice

Example 2: Intervention for ergonomic improvements (cont.)

Step 5. Compute the T-statistic:

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Step 6. Find the p-value:

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Step 6. Find the p-value:

$$p\text{-value} \;=\; 2 \cdot (1 - F_T(3.3, 15)) \quad (2 * \texttt{t.sf}(3.3, 15))$$

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Example 2: Intervention for ergonomic improvements (cont.)

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$$\begin{aligned} p\text{-value} &= 2 \cdot (1 - F_T(3.3, 15)) \quad (2 * \texttt{t.sf}(3.3, 15)) \\ &= 2(0.0024) \end{aligned}$$

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$$\begin{aligned} t &= \frac{\overline{d} - 0}{s_D/\sqrt{n}} \\ &= \frac{6.75}{8.234/\sqrt{16}} = 3.28 \approx 3.3 \end{aligned}$$

Step 6. Find the p-value:

$$\begin{aligned} p\text{-value} &= 2 \cdot (1 - F_T(3.3, 15)) \quad (2 * \texttt{t.sf}(3.3, 15)) \\ &= 2(0.0024) \approx 0.005 \end{aligned}$$

Paired t-test in practice

Example 2: Intervention for ergonomic improvements (cont.)

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Paired t-test in practice

Example 2: Intervention for ergonomic improvements (cont.)

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Since $0.005 < 0.01$, the null hypothesis can be rejected at either significance level 0.05 or 0.01.Thus, this test indicates that the true average time after the change is different from that before the change.

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- When population variances are unknown, we use the t-distribution with degrees of freedom computed using a complicated formula or a simple shortcut.
- Paired data arise when two different observations are made on the same set of individuals in a sample.
- The paired t-test is used to test hypotheses about the mean difference between paired observations.

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- Two-sample z-test (known variances):

$$z = \frac{\overline{x_1} - \overline{x_2} - \Delta_0}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}$$

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- Paired data differences $D_i = X_i - Y_i$ are normally distributed with mean μ_D and variance σ_D^2.
- Paired t-test:

$$t = \frac{\overline{d} - \mu_0}{s_D/\sqrt{n}}$$

where $\overline{d} = \overline{x_1} - \overline{x_2}$ is the sample mean difference and s_D is the sample standard deviation of differences