Class 20

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Be The Difference.

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Final Exam

Thursday Dec 12, 8:00am – 10:00 pm Cudahy 001

[https://bulletin.marquette.edu/undergrad/academicregulations/#examination](https://bulletin.marquette.edu/undergrad/academicregulations/#examinations-midtermandfinal) [s-midtermandfinal](https://bulletin.marquette.edu/undergrad/academicregulations/#examinations-midtermandfinal)

"Final examinations are held in most subjects and must be held on the days/times, as published on the university calendar website. No final exam may be rescheduled for the convenience of the faculty or students."

"Students who miss a final examination risk receiving a failing grade for the course."

Agenda:

Recap Chapter 9.2 and 9.3

Lecture Chapter 10.1-10.2

Recap Chapter 9.2 and 9.3

9: Inferences Involving One Population 9.2 Inference about the Binomial Probability of Success Hypothesis Testing Procedure

We can perform hypothesis tests on the proportion $H_0: p \ge p_0$ vs. $H_a: p < p_0$ $H_0: p \le p_0$ vs. $H_a: p > p_0$ $H_0: p = p_0$ vs. $H_a: p \neq p_0$

Test Statistic for a Proportion *p* λ $\sqrt{\frac{p_0(1-p_0)}{p_0(1-p_0)}}$ with $\sqrt{\frac{10.00 \text{ m/s}}{n}}$ (9.9) 0 0 V^{\perp} P 0 ' $\star = \frac{P - P_0}{\sqrt{P_0(1 - p_0)}}$ *p* — *p z* p_{0} (1 – p *n* $=-\frac{p-1}{\sqrt{2\pi}}$ − '*x p* = *n*

Assume *n* large for CLT and *z*.

- **9: Inferences Involving One Population**
- **9.2 Inference about the Binomial Probability of Success**

Step 1:
$$
H_0: p=.61 \text{ (S) vs. } H_a: p > .61
$$

\n**Step 2:** $z^* = \frac{p' - p_0}{\sqrt{\frac{p_0(1 - p_0)}{n}}}$ $p' = \frac{x}{n}$ $p' = \frac{235}{350} = 0.671$
\n**Step 3:** $z^* = \frac{0.671 - 0.61}{\sqrt{\frac{0.61(1 - 0.61)}{350}}} = 2.34$
\n**Step 4:** $z(0.05) = 1.65$

Step 5: Since 2.34>1.65, Reject H_0 .

 \overline{z}

9: Inferences Involving One Population 9.3 Inference about the Variance and Standard Deviation

 Ω

We can perform hypothesis tests on the variance.

*H*₀: σ^2 ≥ σ_0^2 vs. *H_a*: σ^2 < σ_0^2 *H*₀: σ^2 ≤ σ_0^2 vs. *H_a*: σ^2 > σ_0^2 *H*₀: $\sigma^2 = \sigma_0^2$ vs. *H_a*: $\sigma^2 \neq \sigma_0^2$

For this hypothesis test, use the *χ*2 distribution

1. χ^2 is nonnegative 2. χ^2 is not symmetric, skewed to right 3. χ^2 is distributed to form a family each determined by *df=n-*1. $df = 1$ $df = 4$ $df = 10$ $df = 20$ χ^2 10 15 20 25 5 ∞

Figure from Johnson & Kuby, 2012.

- **9: Inferences Involving One Population**
- **9.3 Inference about the Variance and Standard Deviation**

Will also need critical values.

$$
P(\chi^2 > \chi^2(df,\alpha)) = \alpha
$$

Table 8 Appendix B Page 721

Marquette University Mathematic Contract Contract

 $\boldsymbol{\alpha}$

 χ^2

 χ^2 (df, α)

9: Inferences Involving One Pop. Example: Find $\chi^2(20,0.05)$. Table 8, Appendix B, Page 721.

a) Area to the Right

Figures from Johnson & Kuby, 2012.

Example:

A soft-drink bottling company wants to control variability by not allowing the variance to exceed 0.0004. A sample is taken, $n=28$, $s^2=0.0007$ and $\alpha=0.05$.

Chapter 9: Inferences Involving One Population

Questions?

Homework: Read Chapter 9.2-9.3 **WebAssign** Chapter 9 # 93, 95, 97, 119, 121, 129, 131, 135

Lecture Chapter 10

Chapter 10: Inference Involving Two Populations

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10: Inferences Involving Two Populations 10.1 Dependent and Independent Samples

In this chapter we will have samples from two populations.

The two populations can either be dependent or independent.

Dependent Samples: If samples have related pairs. Random sample of married couples. Male Height vs. Female Height \leftarrow

Independent Samples: If samples are unrelated. Random sample of males, Random Sample of females. Male Height vs. Female Height \leftarrow

not same

When we have dependent samples, there is a commonality between the two items in the pair. Quite often before and after.

Population 1:
$$
\mu_1 = \mu_c + \mu_{before}
$$

\nCommon or baseline mean
\nPopulation 2: $\mu_2 = \mu_c + \mu_{after}$
\nCommon or baseline mean

But we're interested in the difference in means:

$$
\mu_1 - \mu_2 = (\mu_c + \mu_{before}) - (\mu_c + \mu_{after})
$$

 $=\mu_{before}-\mu_{after}$

common mean subtracts out

Paired Difference

10: Inferences Involving Two Populations 10.2 Inference for Mean Difference Two Dependent Samples

We form a paired difference from the data

This means that we are subtracting the sample value from

a $d = x_1 - x_2$ (10.1)

population 2 from the sample value from population 1.

Imagine that we have paired data $(x_{1,1}, x_{2,1}),..., (x_{1,n}, x_{2,n})$ $x_{j,i}$, population *j*, observation *i* where $j=1,2$ $i=1,\ldots,n$. *x*

We form a paired difference from the data: $d_{i} = x_{1,i} - x_{2,i}$ $d_1 = x_{1,1} - x_{2,1}, \ d_2 = x_{1,2} - x_{2,2}, \ldots, \ d_n = x_{1,n} - x_{2,n}$

When paired observations are randomly selected from normal populations, the paired difference, $d_i = x_{1,i} - x_{2,i}$ will be approximately normally distributed about a mean $\mu_{\scriptscriptstyle d}$ with a standard deviation $\sigma_{_d}$.

> Is actually exactly normally distributed if the populations are (dependent) normally distributed.

With the d_i 's being sampled from populations

with a mean of μ_d and a standard deviation of σ_d , then

 $i\,d = -\sum d_i$ is approximately normally distributed (recall CLT) 1 1 *n i i* $d = \rightarrow d$ $n_{\,\,\overline{}\,}$ = $=\frac{1}{\pi}\sum$

with a mean $\mu_{\bar{d}} = \mu_d\,$, and standard deviation $\sigma_{\bar{d}} = \frac{\sigma_d}{\sqrt{\sigma}}\,$. *d d n* = σ σ

This would allow us to form a *z* statistic for the mean of

differences d, $z = \frac{u - \mu_d}{\sqrt{n}}$ with a standard normal distribution. We can then look up probabilities in the table, *d* / *d d d z n* $=\frac{u \mu_{\text{}}$ σ assuming known

find critical values *z*(*α*/2), construct confidence intervals

$$
\bar{d} \pm z(\alpha/2) \frac{\sigma_d}{\sqrt{n}}
$$

and test hypotheses using
$$
z^* = \frac{\overline{d} - \mu_{0d}}{\sigma_d / \sqrt{n}}
$$
.

Figure from Johnson & Kuby, 2012.

However, as in Inferences for One Population, we never

know the true value of σ_d . So we estimate it with sample

standard deviation *s^d* . This changes / *d d d z n* $=\frac{u \mu_{\text{c}}$ σ

to $t = \frac{a^2 - a^2}{\sqrt{a^2}}$ and the distribution from standard normal / *d d d t* $s_{\scriptscriptstyle A}$ / \sqrt{n} − = μ_{c}

to Student *t* with
$$
df=n-1
$$
 where $s_d^2 = \frac{1}{n-1} \sum_{i=1}^n (d_i - \overline{d})^2$.

10: Inferences Involving Two Populations 10.2 Inference for Mean Difference Two Dependent Samples Confidence Interval Procedure

With σ_d unknown, a 1- α confidence interval for μ_d is:

Confidence Interval for Mean Difference (Dependent Samples)

$$
\overline{d} - t(df, \alpha/2) \frac{s_d}{\sqrt{n}} \quad \text{to} \quad \overline{d} + t(df, \alpha/2) \frac{s_d}{\sqrt{n}} \quad \text{where } df = n-1
$$
 (10.2)

$$
\overline{d} = \frac{1}{n} \sum_{i=1}^{n} d_i \qquad (10.3) \qquad \qquad s_d^2 = \frac{1}{n-1} \sum_{i=1}^{n} (d_i - \overline{d})^2 \qquad (10.4)
$$

10.2 Inference for Mean Difference Two Dependent Samples

Example:

Construct a 95% CI for mean difference in Brand B – A tire wear. *d*_{*i*}[']**s**: 8, 1, 9, −1, 12, 9

$$
n=6 \qquad \qquad df=5 \qquad t(df,\alpha/2)=
$$

$$
\overline{d}=\qquad \qquad \alpha=0.05
$$

$$
s_d = \overline{d} \pm t(df, \alpha/2) \frac{s_d}{\sqrt{n}} \longrightarrow
$$

$$
\overline{d} = \frac{1}{n} \sum_{i=1}^{n} d_i
$$

$$
s_d^2 = \frac{1}{n-1} \sum_{i=1}^{n} (d_i - \overline{d})^2
$$

Figure from Johnson & Kuby, 2012.

10.2 Inference for Mean Difference Two Dependent Samples

Example:

Construct a 95% CI for mean difference in Brand B – A tire wear. *d*_{*i*}[']**s**: 8, 1, 9, −1, 12, 9

$$
n=6
$$
 $df = 5$ $t(df, \alpha / 2) = 2.57$
 $\overline{d} = 6.3$ $\alpha = 0.05$

$$
\overline{d} = \frac{1}{n} \sum_{i=1}^{n} d_i
$$

$$
s_d^2 = \frac{1}{n-1} \sum_{i=1}^{n} (d_i - \overline{d})^2
$$

1

i

 $n-1$ $\overline{I_{i-1}}$

−

 $s_{d} = 5.1$ $(df, \alpha / 2) \frac{s_d}{f}$ $d \pm t (df)$ *n* $\pm t(df, \alpha/2) \frac{d}{dx} \longrightarrow (0.090, 11.7)$

Figure from Johnson & Kuby, 2012.

10: Inferences Involving Two Populations 10.2 Inference for Mean Difference Two Dependent Samples Hypothesis Testing Procedure

We can test for differences in the population means:

$$
H_0: \mu_1 \ge \mu_2 \text{ vs. } H_a: \mu_1 < \mu_2 \longrightarrow H_0: \mu_1 - \mu_2 \ge 0 \text{ vs. } H_a: \mu_1 - \mu_2 < 0
$$
\n
$$
H_0: \mu_1 \le \mu_2 \text{ vs. } H_a: \mu_1 > \mu_2 \longrightarrow H_0: \mu_1 - \mu_2 \le 0 \text{ vs. } H_a: \mu_1 - \mu_2 > 0
$$
\n
$$
H_0: \mu_1 = \mu_2 \text{ vs. } H_a: \mu_1 \ne \mu_2 \longrightarrow H_0: \mu_1 - \mu_2 = 0 \text{ vs. } H_a: \mu_1 - \mu_2 \ne 0
$$

10: Inferences Involving Two Populations 10.2 Inference for Mean Difference Two Dependent Samples Hypothesis Testing Procedure

We can test for differences in the population means:

$$
H_0: \mu_1 \ge \mu_2 \text{ vs. } H_a: \mu_1 < \mu_2 \longrightarrow H_0: \mu_1 \cdot \mu_2 \ge 0 \text{ vs. } H_a: \mu_1 \cdot \mu_2 < 0
$$
\n
$$
H_0: \mu_1 \le \mu_2 \text{ vs. } H_a: \mu_1 > \mu_2 \longrightarrow H_0: \mu_1 \cdot \mu_2 \le 0 \text{ vs. } H_a: \mu_1 \cdot \mu_2 > 0
$$
\n
$$
H_0: \mu_1 = \mu_2 \text{ vs. } H_a: \mu_1 \ne \mu_2 \longrightarrow H_0: \mu_1 \cdot \mu_2 = 0 \text{ vs. } H_a: \mu_1 \cdot \mu_2 \ne 0
$$
\n
$$
\mu_d = \mu_1 \cdot \mu_2 \longrightarrow H_0: \mu_d \ge 0 \text{ vs. } H_a: \mu_d < 0
$$

$$
(\mu_d = \mu_{before} - \mu_{after}) \qquad H_0: \mu_d \le 0 \text{ vs. } H_a: \mu_d > 0
$$

 $H_0: \mu_d = 0$ vs. $H_a: \mu_d \neq 0$

10: Inferences Involving Two Populations 10.2 Inference for Mean Difference Two Dependent Samples Hypothesis Testing Procedure

With σ_d unknown, the test statistic for μ_d is:

Go through the same five hypothesis testing steps.

9: Inferences Involving One Population 9.2 Inference about the Binomial Probability of Success

There are three possible hypothesis pairs for the proportion.

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There are three possible hypothesis pairs for the proportion.

 $H_0: \mu_d \leq \mu_{d0}$ vs. $H_a: \mu_d > \mu_{d0}$ Non-Critical Region Fail to Reject **Critical** Region Reject Ω *CV t* * Reject H_0 if greater then data indicates $\mu_d > \mu_{d0}$ because d is "a lot" smaller than μ_{d0} $t(df, \alpha)$ $* = \frac{a - \mu_{d0}}{s + \sqrt{n}}$ *d d d t s n* $=\frac{d-\mu_a}{l}$

9: Inferences Involving One Population 9.2 Inference about the Binomial Probability of Success

There are three possible hypothesis pairs for the proportion.

10.2 Inference for Mean Difference Two Dependent Samples

n = 6 8, 1, 9, -1, 12, 9

Step 2

Step 3

Step 4

Figures from Johnson & Kuby, 2012.

10.2 Inference for Mean Difference Two Dependent Samples

n = 6 8, 1, 9, -1, 12, 9

Test mean difference of Brand B minus Brand A is zero.

 $H_0: \mu_d = 0$ vs. $H_a: \mu_d \neq 0$ **Step 2 Step 5**

Step 3

Step 4

Figures from Johnson & Kuby, 2012.

10.2 Inference for Mean Difference Two Dependent Samples

 $n=6$ 8, 1, 9, -1, 12, 9

Step 5

Test mean difference of Brand B minus Brand A is zero.

 $H_0: \mu_d = 0$ vs. $H_a: \mu_d \neq 0$ $df = 5$ $t^* = \frac{u - \mu_{d0}}{s + \sqrt{n}}$ **Step 2** *d d d t s n* $=\frac{d-\mu_a}{l}$

Step 3

Step 4

Figures from Johnson & Kuby, 2012.

10.2 Inference for Mean Difference Two Dependent Samples

 $n = 6$ 8, 1, 9, -1, 12, 9

Test mean difference of Brand B minus Brand A is zero.

 $H_0: \mu_d = 0$ vs. $H_a: \mu_d \neq 0$ $d = 6.3$ $s_{d} = 5.1$ $df = 5$ $t^* = \frac{u - \mu_{d0}}{s + \sqrt{n}}$ **Example:** $\frac{\text{Brand A}}{\text{Brand B}} = \frac{125}{133} = \frac{64}{65} = \frac{94}{103} = \frac{3}{3}$
 Example: $\frac{\text{Brand B}}{\text{Bend B}} = \frac{125}{133} = \frac{64}{65} = \frac{94}{103} = \frac{3}{3}$
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 Exam $* = \frac{6.3 - 0}{\sqrt{ }} = 3.03$ $5.1/\sqrt{6}$ *t* $=\frac{0.5-0}{\sqrt{2}}$ **Step 2 Step 3 Step 5** *d d d t s n* $=\frac{d-\mu_a}{l}$

Step 4

Figures from Johnson & Kuby, 2012.

10.2 Inference for Mean Difference Two Dependent Samples

 $n=6$ 8, 1, 9, -1, 12, 9

Test mean difference of Brand B minus Brand A is zero.

 $H_0: \mu_d = 0$ vs. $H_a: \mu_d \neq 0$ $d = 6.3$ $s_{d} = 5.1$ $df = 5$ $t^* = \frac{u - \mu_{d0}}{s + \sqrt{n}}$ **Example:** $\frac{\text{Brand A}}{\text{Brand B}} = \frac{125}{133} = \frac{64}{65} = \frac{94}{103} = \frac{3}{3}$
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Figures from Johnson & Kuby, 2012.

10.2 Inference for Mean Difference Two Dependent Samples

 $n = 6$ 8, 1, 9, -1, 12, 9

Test mean difference of Brand B minus Brand A is zero.

 $H_0: \mu_d = 0$ vs. $H_a: \mu_d \neq 0$ $d = 6.3$ $s_{d} = 5.1$ $df = 5$ $t^* = \frac{u - \mu_{d0}}{s + \sqrt{n}}$ **Example:** $\frac{\text{Brand A}}{\text{Brand B}} = \frac{125}{133} = \frac{64}{65} = \frac{94}{103} = \frac{3}{3}$
 Example: $\frac{\text{Brand B}}{\text{Brand B}} = \frac{125}{133} = \frac{64}{65} = \frac{94}{103} = \frac{3}{3}$
 Fest mean difference of Brand B minus Brand
 Step 1 $H_0: \mu_d=0$ vs. $H_a: \mu_d\$ $* = \frac{6.3 - 0}{\sqrt{ }} = 3.03$ $5.1/\sqrt{6}$ *t* $=\frac{0.5-0}{\sqrt{2}}$ **Step 2 Step 3 Step 4** $t(df, \alpha / 2) = 2.57$ *d d d t s n* $=\frac{d-\mu_a}{l}$

Conclusion: Significant difference in tread wear at .05 level.

Figures from Johnson & Kuby, 2012.

Chapter 10: Inferences Involving Two Populations

Questions?

Homework:Read Chapter 10.1-10.2 WebAssign Chapter 10 #13, 15, 23, 25, 29, 31, 35