

**Author:** Brenda Gunderson, Ph.D., 2015

**License:** Unless otherwise noted, this material is made available under the terms of the Creative Commons Attribution-NonCommercial-Share Alike 3.0 Unported License: <http://creativecommons.org/licenses/by-nc-sa/3.0/>

The University of Michigan Open.Michigan initiative has reviewed this material in accordance with U.S. Copyright Law and have tried to maximize your ability to use, share, and adapt it. The attribution key provides information about how you may share and adapt this material.

Copyright holders of content included in this material should contact [open.michigan@umich.edu](mailto:open.michigan@umich.edu) with any questions, corrections, or clarification regarding the use of content.

For more information about how to attribute these materials visit: <http://open.umich.edu/education/about/terms-of-use>. Some materials are used with permission from the copyright holders. You may need to obtain new permission to use those materials for other uses. This includes all content from:

### Attribution Key

For more information see: <http://open.umich.edu/wiki/AttributionPolicy>

*Content the copyright holder, author, or law permits you to use, share and adapt:*



Creative Commons Attribution-NonCommercial-Share Alike License



Public Domain – Self Dedicated: Works that a copyright holder has dedicated to the public domain.

### *Make Your Own Assessment*

Content Open.Michigan believes can be used, shared, and adapted because it is ineligible for copyright.



Public Domain – Ineligible. Works that are ineligible for copyright protection in the U.S. (17 USC §102(b)) \*laws in your jurisdiction may differ.



Content Open.Michigan has used under a Fair Use determination  
Fair Use: Use of works that is determined to be Fair consistent with the U.S. Copyright Act (17 USC § 107)  
\*laws in your jurisdiction may differ.

Our determination DOES NOT mean that all uses of this third-party content are Fair Uses and we DO NOT guarantee that your use of the content is Fair. To use this content you should conduct your own independent analysis to determine whether or not your use will be Fair.

# Stat 250 Gunderson Lecture Notes

## 8: Learning about a Population Mean Difference

### Part 1: Distribution for a Sample Mean of Paired Differences

#### The Paired Data Scenario

An important special case of a single mean of a population occurs when two quantitative variables are **collected in pairs**, and we desire information about the **difference** between the two variables. Here are some ways that paired data can occur:

- Each person or unit is measured twice. The two measurements of the same characteristic or trait are made under different conditions. An example is measuring a quantitative response both before and after treatment.
- Similar individuals or units are paired prior to an experiment. During the experiment, each member of a pair receives a different treatment. The same quantitative response variable is measured for all individuals.

For paired data designs, it is the **differences** that we are interested in examining. By focusing on the differences we again have just one sample of observations (the differences). Sometimes you may see a “*d*” in the subscript of the mean to represent the **mean of the population of differences**:  $\mu_d$ ; and the data may be represented generically as:  $d_1, d_2, \dots, d_n$ .

#### Sampling Distribution for the Sample Mean of Paired Differences

The sampling distribution results for the mean of paired differences is really the same as that for a regular sample mean. Since the measurements are differences, the sample mean of the data,  $\bar{x}$ , is just written as  $\bar{d}$ , to emphasize that this is a paired design.

#### Freshmen Weight

A study was conducted to learn about the average weight gain in the first year of college for students. A sample of 60 students resulted in an average weight gain of 4.2 pounds (over the first 12 weeks of college).

Population =

Parameter =

Sample =

Statistic =

Can anyone say how close this observed sample mean difference  $\bar{d}$  of 4.2 pounds is to the true population mean difference  $\mu_d$ ? \_\_\_\_\_ If we were to take another random sample of the same size, would we get the same value for the sample mean difference? \_\_\_\_\_. So what are the possible values for the sample mean difference  $\bar{d}$  if we took many random samples of the same size from this population? What would the distribution of the possible  $\bar{d}$  values look like? What can we say about the **distribution of the sample mean difference**?



## Distribution of the Sample Mean Difference – Main Results

Let  $\mu_d$  = mean of the differences in the population of interest.

Let  $\sigma_d$  = standard deviation for the differences in the population of interest.

Let  $\bar{d}$  = the sample mean of the differences for a random sample of size  $n$ .

- If the population of differences is normal (bell-shaped), and a random sample of any size is obtained, then the distribution of the sample mean difference  $\bar{d}$  is also normal, with a mean of  $\mu_d$  and a standard deviation of  $s.d.(\bar{d}) = \frac{\sigma_d}{\sqrt{n}}$ .
- If the population of differences is not normal (bell-shaped), but a *large* random sample of size  $n$  is obtained, then the distribution of the sample mean difference  $\bar{d}$  is *approximately* normal, with a mean of  $\mu_d$  and a standard deviation of  $s.d.(\bar{d}) = \frac{\sigma_d}{\sqrt{n}}$ .

### Notes:

- (1) An arbitrary level for what is 'large' enough has been 30. However, if any of the differences are extreme outliers, it is better to have a larger sample size.
- (2) The standard deviation of  $\bar{d}$  is a measure of the **accuracy of the process** of using a sample mean difference to estimate the population mean difference.

$$s.d.(\bar{d}) = \frac{\sigma_d}{\sqrt{n}}$$

- (3) In practice, the population standard deviation  $\sigma_d$  is rarely known, so the sample standard deviation  $s_d$  is used instead. When making this substitution we call the result a **standard error**.

**Standard error of the sample mean difference is given by:**

$$\text{s.e.}(\bar{d}) = \frac{s_d}{\sqrt{n}}$$

We can **interpret** the standard error of the sample mean difference as **estimating, approximately, the average distance** of the possible  $\bar{d}$  values (for repeated samples of the same size  $n$ ) from the **population mean difference**  $\mu_d$ .

Moreover, we can use this standard error of the sample mean difference to produce a range of values that we are very confident will contain the population mean difference  $\mu_d$ , namely,  $\bar{d} \pm (\text{a few})s.e.(\bar{d})$ . This is the basis for confidence interval for the population mean difference  $\mu_d$ , discussed in Part 2.

**Looking ahead:**

Do you think the 'few' in the expression  $\bar{d} \pm (\text{a few})\text{s.e.}(\bar{d})$  will be a  $z^*$  value or a  $t^*$  value?

What degrees of freedom will be used?

We will use the standard error of the sample mean difference to compute a standardized test statistic for testing hypotheses about the population mean difference  $\mu_d$ , namely,

**Sample statistic – Null value.**

**(Null) standard error**

This is the basis for testing about a population mean difference covered in Part 3.

**Looking ahead:**

Do you think the standardized test statistic will be a  $z$  statistic or a  $t$  statistic?

What do you think will be the most common null value?

$$H_0: \mu_d = \underline{\hspace{2cm}}$$

**Additional Notes**

A place to ... jot down questions you may have and ask during office hours, take a few extra notes, write out an extra problem or summary completed in lecture, create your own summary about these concepts.

# Stat 250 Gunderson Lecture Notes

## 8: Learning about a Population Mean Difference

### Part 2: Confidence Interval for a Population Mean of Paired Differences

#### Confidence Interval for the Population Mean of Paired Differences $\mu_d$

Recall that an important special case of a single mean of a population occurs when two quantitative variables are **collected in pairs**, and we desire information about the **difference** between the two variables. For paired data designs, it is the **differences** that we are interested in analyzing. By focusing on the differences we again have just one sample of observations (the differences) and are able to use the confidence interval for the population mean difference.

#### Notation:

Population Parameter:  $\mu_d$  = population mean difference

Data:  $d_1, d_2, \dots, d_n$

Sample Estimate:  $\bar{d}$  = sample mean difference

Standard Error:  $s.e.(\bar{d}) = \frac{s_d}{\sqrt{n}}$  ( $s_d$  = standard deviation of the sampled differences)

We use the sample estimate and its standard error to **form a confidence interval estimate** for the parameter using the following form:

$$\text{Sample Estimate} \pm \text{Multiplier} \times \text{Standard error}$$

The multiplier used will depend on the confidence level, the sample size, and the type of parameter being estimated. In this case, since we are estimating a single population mean, the multiplier will be a  $t^*$  value. Here is the summary for a paired data confidence interval:

#### One-sample $t$ Confidence Interval for the Population Mean Difference $\mu_d$

$$\bar{d} \pm t^* s.e.(\bar{d})$$

where  $t^*$  is the appropriate value for a  $t(n - 1)$  distribution.

Note that  $n$  is the number of pairs, or the number of differences. **This interval requires that the differences can be considered a random sample from a normal population.** If the sample size is large, the assumption of normality is not so crucial and the result is approximate.

## Try It! Changes in Reasoning Scores

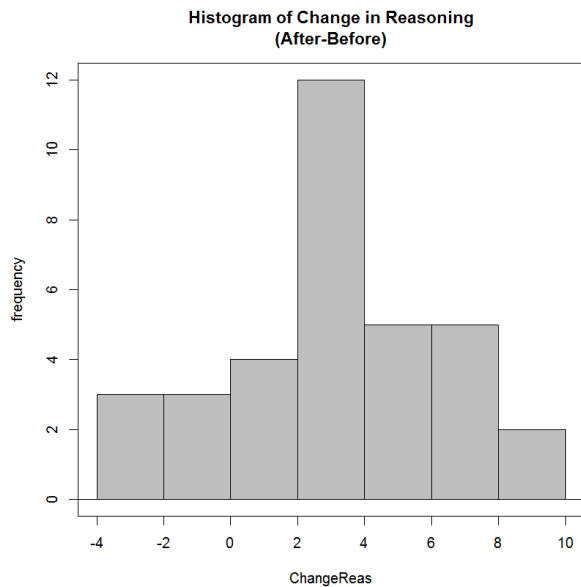
### Do piano lessons improve spatial-temporal reasoning of preschool children?

**Data:** The change in reasoning score, after piano lessons - before piano lessons, with larger values indicating better reasoning, for a random sample of  $n = 34$  preschool children.

2	5	7	-2	2	7	4	1	0	7	3	4
3	4	9	4	5	2	9	6	0	3	6	-1
3	4	6	7	-2	7	-3	3	4	4		

(a) Display the data, summarize the distribution.

These data were entered into R to produce the following histogram.



#### Notes:

1. Diff = after – before so ...

2. Sample mean difference = \_\_\_\_\_

3. Normality of the response  
(the difference) for the population?

Some summary measures were obtained using R Commander and entered into the table:

```
> numSummary(Dataset[, "ChangeReas"], statistics=c("mean", "sd", "IQR",
+ "quantiles"), quantiles=c(0, .25, .5, .75, 1))
  mean      sd IQR 0% 25% 50% 75% 100%  n
3.617647 3.055196  4 -3  2  4  6  9 34
```

Summary Statistics			
Mean diff ( $\bar{d}$ )	Std. Dev ( $s_d$ )	Sample size (n)	Std. Error
3.62	3.06	34	0.52

(b) Give a 95% confidence interval for the population mean improvement in reasoning scores.

(c) What value is of particular interest to see whether or not it is in the interval?

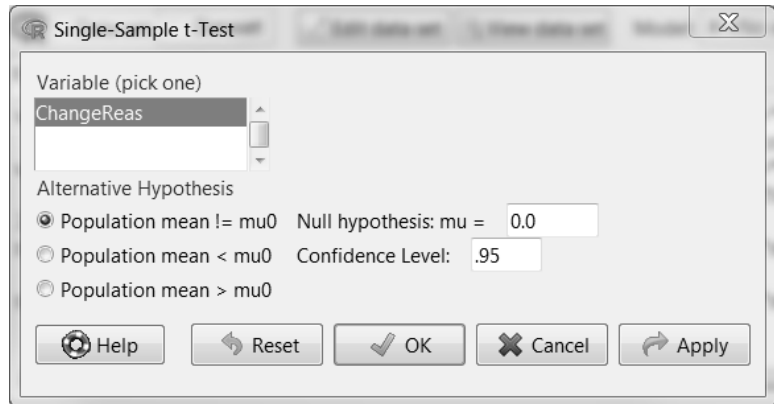


(d) A student in your class wrote the following interpretation about the 95% confidence level used in making the interval. Is it a correct interpretation? If not, update it to make it correct.

***“If this study were repeated many times, we would expect 95% of the resulting confidence intervals to contain the sample mean improvement in reasoning scores.”***

**R Note:**

The differences were already computed and entered as the data. So to make a confidence interval with R Commander we would need to perform a single-sample t-Test on the differences (and leave the null hypothesis value the default of 0). Be sure the confidence level is the one you want, namely .95.



```
> with(Dataset, (t.test(ChangeReas, alternative='two.sided', mu=0.0,
+   conf.level=.95)))

One sample t-test

data:  ChangeReas
t = 6.9044, df = 33, p-value = 6.919e-08
alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
 2.551639 4.683655
sample estimates:
mean of x
 3.617647
```

<i>Paired T Results</i>			
<b>Mean diff (<math>\bar{d}</math>)</b>	<b>df</b>	<b>95% CI Lower</b>	<b>95% CI Upper</b>
3.62	33	2.55	4.68

If the before and after scores were entered into R, then we would use a paired t-test option. R would compute the differences for us and provide the confidence interval results. Details of the R steps for analyzing paired data can be found in your Lab Workbook.

### Additional Notes

A place to ... jot down questions you may have and ask during office hours, take a few extra notes, write out an extra problem or summary completed in lecture, create your own summary about these concepts.

<b>Population Mean</b>	
<b>Parameter</b>	$\mu$
<b>Statistic</b>	$\bar{x}$
<b>Standard Error</b>	
$\text{s.e.}(\bar{x}) = \frac{s}{\sqrt{n}}$	
<b>Confidence Interval</b>	
$\bar{x} \pm t^* \text{s.e.}(\bar{x})$	df = n - 1
<b>Paired Confidence Interval</b>	
$\bar{d} \pm t^* \text{s.e.}(\bar{d})$	df = n - 1
<b>One-Sample t-Test</b>	
$t = \frac{\bar{x} - \mu_0}{\text{s.e.}(\bar{x})} = \frac{\bar{x} - \mu_0}{s/\sqrt{n}}$	df = n - 1
<b>Paired t-Test</b>	
$t = \frac{\bar{d} - 0}{\text{s.e.}(\bar{d})} = \frac{\bar{d}}{s_d/\sqrt{n}}$	df = n - 1



### Try It! Knob Turning

A study involved  $n=25$  right-handed students and a device with two different knobs (right-hand thread and left-hand thread). The **response** of interest is the time it takes to move knob indicator a fixed distance. The **question** of interest is to assess if right-hand threads are easier to turn on average. Use a 5% significance level.

- Why is this a paired design and how should randomization be used in the experiment?
- State the hypotheses.  $H_0$ : \_\_\_\_\_ versus  $H_a$ : \_\_\_\_\_

Here are a few summaries of each set of responses separately and then of the paired data:

**Paired Samples Statistics**

		Mean	N	Std. Deviation	Std. Error Mean
Pair	RTHREAD	104.00	25	15.93	3.19
1	LTHREAD	117.44	25	27.26	5.45

Below are the  $t$ -test results generated using **R Commander** and selecting **Statistics > Means > Paired T Test** and the correct direction for the alternative hypothesis. Notice that a 95% one-sided confidence bound is provided since our test alternative was one-sided to the left. If you wanted to also report a regular 95% confidence interval, you would run a two-sided hypothesis test in R.

**Summary Statistics**

Mean diff ( $\bar{d}$ )	Std. Dev ( $s_d$ )	Sample size (n)	Std. Error
-13.44	23.06	25	4.61

**Paired T Results**

$t$	$df$	$p$ -value	95% CI Lower	95% CI Upper
-2.914	24	0.004	***	-5.55

- Perform the test.
- Which are assumptions required for performing the paired  $t$ -test?
    - the turning times for the right-hand threaded knob are independent of the turning times for the left-hand threaded knob.
    - the turning times for the right-hand threaded knob are normally distributed.
    - the difference in turning times ( $\text{diff} = \text{RT} - \text{LT}$ ) is normally distributed.

### Additional Notes

A place to ... jot down questions you may have and ask during office hours, take a few extra notes, write out an extra problem or summary completed in lecture, create your own summary about these concepts.

Population Mean	
<b>Parameter</b>	$\mu$
<b>Statistic</b>	$\bar{x}$
<b>Standard Error</b>	$\text{s.e.}(\bar{x}) = \frac{s}{\sqrt{n}}$
<b>Confidence Interval</b>	$\bar{x} \pm t^* \text{s.e.}(\bar{x}) \quad \text{df} = n - 1$
<b>Paired Confidence Interval</b>	$\bar{d} \pm t^* \text{s.e.}(\bar{d}) \quad \text{df} = n - 1$
<b>One-Sample <i>t</i>-Test</b>	$t = \frac{\bar{x} - \mu_0}{\text{s.e.}(\bar{x})} = \frac{\bar{x} - \mu_0}{s/\sqrt{n}} \quad \text{df} = n - 1$
<b>Paired <i>t</i>-Test</b>	$t = \frac{\bar{d} - 0}{\text{s.e.}(\bar{d})} = \frac{\bar{d}}{s_d/\sqrt{n}} \quad \text{df} = n - 1$

