

## Module 8: Introduction to the $t$ tests

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Introduction to Statistics for the Social Sciences



# The RSS short courses

The Research and Statistical Support (RSS) office at the University of North Texas hosts a number of “Short Courses”. A list of them is available at:

<http://www.unt.edu/rss/Instructional.htm>

# Outline

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  - Using delta ( $\delta$ ) for Statistical Power
  - Calculating Confidence Interval Limits ( $CI_{95}$ )
  - Summary of Section 1

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- Continued on the next slide.



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  - Therefore, less correction is needed as sample size increases.

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$$S_M^2 = \frac{S^2}{n} \qquad S_M = \sqrt{S_M^2}$$

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  - But, you must take into account sample size; meaning, the  $df$  in order to find  $t_{crit}$

# An Excerpt from the $t$ distribution table

Table 1:  $t$  Critical Values

1-tailed	$df$	.10	.05	.025	.01
2-tailed	$df$	.20	.10	.05	.02
	1	3.078	6.314	12.710	31.821
	2	1.886	2.920	4.303	6.965
	3	1.638	2.353	3.182	4.541
	4	1.533	2.132	2.776	3.747
	5	1.476	2.015	2.571	3.365
	6	1.440	1.943	2.447	3.143
	etc.				

Degrees of freedom in the left column and significance level along the top rows.

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- Note, the Alternative hypothesis ( $H_1$ ) is directional: one-tailed test.

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Table 2: Comparison dist. (estimate  $\sigma$  with  $S_M$ )

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- Critical  $t$  value is 2.353
- Which means, we need  $t_{calc}$  to be greater than  $|2.353|$  (absolute value of 2.353) to find a significant difference.

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$$t_{calc} = \frac{\bar{X} - \mu}{S_M} = \frac{4.00 - 6.08}{0.912} = \frac{-2.08}{0.912} = -2.28$$

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- Do not be tempted to say something like; nearly significant, just missed significance, etc.
  - Although the sample mean is numerically smaller, it is not statistically significantly smaller.
  - Remember, we have a *very* small sample size, so we would need a *very* large mean difference to achieve significance (or a larger sample).

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$$d = \frac{\bar{X} - \mu}{S} = \frac{4 - 6.08}{\sqrt{3.33}} = \frac{-2.08}{1.82} = 1.143$$

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# Effect Size

- The appropriate effect size measure for the one sample  $t$  test is Cohen's  $d$ .
- Calculation of  $d$  in its general form (as it was with the Z-test) is:

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- So, although we have a large effect size (standardized difference), we did not achieve statistical significance. However, keep in mind that with a larger sample, this amount of mean difference may have been significant.
  - Statistical significance is **directly** tied to sample size, effect size is not.

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  - Where  $n = (\delta/d)^2$
  - This type of power calculation (figuring a-priori sample size) is **very** useful.

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- If we were to take an infinite number of samples of students in this class, 95% of those samples' means would be between 6.146 and 1.854 hours of sleep.
  - Remember, the population mean is fixed (but unknown); while each sample has its own mean (sample means fluctuate).



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- Important: the interval is **not** interpreted as “we are 95% confident that population 1’s mean is between 6.146 and 1.854.”
  - We are dealing with a sample; we do not know what  $\mu_1$  is; so, we can not know what that interval would be

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- Instead, as we will see; we estimate population values with sample statistics and compare samples to *infer* effects in the general population(s) of interest.
  - The  $t$  distribution is used for other types of  $t$  tests which will be covered shortly.

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- Calculation of Confidence Intervals.

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- Essentially, it compares two sample means which are known to be related in some way.

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Gist: There is some sort of known meaningful relationship between the two groups of scores.

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- Then, after they have spent the first semester at colleges/universities (away from their sweat-heart), they again rate their relationship satisfaction.



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Same critical value we used with the One Sample  $t$  Test.

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$$t = \frac{\bar{D} - \mu_D}{S_M} = \frac{8 - 0}{1.08} = 7.41$$

- So, our  $t_{calc} = 7.41$  which is fairly large.

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- At this point in the course, you should be able to calculate the means and standard deviations of each group of scores; however the exact  $p$  value was obtained by verifying the results above in SPSS (see below).

**Paired Samples Statistics**

	Mean	N	Std. Deviation	Std. Error Mean
Pair 1 before	39.0000	4	2.58199	1.29099
after	31.0000	4	.81650	.40825

**Paired Samples Correlations**

	N	Correlation	Sig.
Pair 1 before & after	4	.632	.368

**Paired Samples Test**

	Paired Differences					t	df	Sig. (2-tailed)
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
				Lower	Upper			
Pair 1 before - after	8.00000	2.16025	1.08012	4.56257	11.43743	7.407	3	.005

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- A large effect size.



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- Since our  $\delta$  table shows that anything with a  $\delta > 5.00$  equates to power greater than 0.99, we can safely assume we have at least a power of 0.99.

[http://www.unt.edu/rss/class/Jon/ISSS\\_SC/Module008/](http://www.unt.edu/rss/class/Jon/ISSS_SC/Module008/) Research and Statistical Support

**RSS**  
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- If we drew an infinite number of samples of young adults' relationship satisfaction ratings, 95% of those samples' difference score means would be between 5.459 and 10.541.

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$$LL = -2.353 * 1.08 + 8 = 5.459$$

$$UL = +2.353 * 1.08 + 8 = 10.541$$

- If we drew an infinite number of samples of young adults' relationship satisfaction ratings, 95% of those samples' difference score means would be between 5.459 and 10.541.
  - Remember, the population difference score mean is fixed (but unknown); while each sample has its own difference score mean (samples fluctuate).



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  - Robust (in this situation) means, even with moderate departures from normality we can be confident in our results.

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- Use subscripts to identify each group with either a 1 or a 2 subscript.

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<http://www.math.unb.ca/~knight/utility/t-table.htm>

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- Assess their knowledge of Current World Events using the CWE questionnaire, which has a range of 1 to 10.

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- In terms of knowledge about current events.
- Notice the directional alternative hypothesis ( $H_1$ ) which indicates a one-tailed test.

# The Daily show group's data

Table 3: Daily Show Group

$X_1$	$\bar{X}_1$	$X_1 - \bar{X}_1$	$(X_1 - \bar{X}_1)^2$
6	6.75	-0.750	0.563
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9	6.75	2.250	5.063
8	6.75	1.250	1.563
4	6.75	-2.275	7.563
6	6.75	-0.750	0.563
7	6.75	0.250	0.063
8	6.75	1.250	1.563
$54 = \sum X_1$		$SOS_1 = 17.50$	

$$8 = n_1$$

$$S_1^2 = \frac{\sum (X_1 - \bar{X}_1)^2}{n_1 - 1} = \frac{SOS_1}{df_1} = \frac{17.50}{8 - 1} = \frac{17.50}{7} = 2.50$$

# The Factor show group's data

Table 4: Factor Show Group

$X_2$	$\bar{X}_2$	$X_2 - \bar{X}_2$	$(X_2 - \bar{X}_2)^2$
5	3.875	1.125	1.266
4	3.875	0.125	0.016
3	3.875	-0.875	0.766
1	3.875	-2.875	8.266
5	3.875	1.125	1.266
6	3.875	2.125	4.516
3	3.875	-0.875	0.766
4	3.875	0.125	0.016
$31 = \sum X_2$		$SOS_2 = 16.875$	

$$8 = n_2$$

$$S_2^2 = \frac{\sum (X_2 - \bar{X}_2)^2}{n_2 - 1} = \frac{SOS_2}{df_2} = \frac{16.875}{8 - 1} = \frac{16.875}{7} = 2.411$$

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- 2. Determine the characteristics of the comparison distribution.
- $df_t = df_1 + df_2 = n_1 + n_2 - 2 = 8 + 8 - 2 = 14$
- And from above,  $S_1^2 = 2.500$  and  $S_2^2 = 2.411$

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- Please note; if the groups were different sizes, the variances of each distribution of means would be different.

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- Because;  $t_{calc} = 3.69 > 1.761 = t_{crit}$  we reject the null hypothesis and conclude there was a statistically significant difference between the two show groups.
  - But, you should know by now, that's not the whole story.



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- So, the effect size is fairly large;  $d = 1.83$

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- The  $\delta$  table shows that with a  $\delta = 3.60$  (note: it is best to round down) we have a power of 0.98.

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- As you can see, this is exactly as we did for the dependent samples situation. Just remember that the  $n$  refers to the number of **each group**.

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- The dependent samples design has greater power (all else being equal, such as sample size, effect size, etc.) than the independent samples design.
- And, as always, the larger the sample size, the greater the power.



# Calculating a Confidence Interval

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$$UL = (+t_{crit}) * (S_{dif}) + (\bar{X}_1 - \bar{X}_2) = +1.761 * 0.78 + (6.75 - 3.875) = +1.374 + 2.875 = 4.249$$

$$LL = 1.50$$
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- So, if we drew an infinite number of random samples of viewers of each show, 95% of the differences between means would be between 1.50 and 4.25.
  - Remember, the mean of the population of differences between means is fixed (but unknown); while each sample has its own differences between means (samples fluctuate).

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- Calculation of Confidence Intervals.

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- The  $t$  tests can tolerate some deviation from normality, but if skewness and/or kurtosis are greater than  $|1.0|$  in the sample(s) then you should be cautious about proceeding.

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  - Use a corrected  $t$  test formula, such as  $t$  prime ( $t'$ ):

# Homogeneity of Variances (HOV) assumption

- Does not apply to the one sample  $t$  test, but does with the dependent and independent tests.
- This assumption states that each of the two populations (represented by our two sample groups) have equal (homogeneous) variances.
  - As the definition implies, the variance of one group should be very similar to the variance of the other group.
  - There are empirical tests for this assumption in virtually all statistical software packages.
- If the assumption is violated, there are options available.
  - Use trimmed samples; trimming 10 or 20% of the extreme scores (from each group) to make them more homogeneous.
  - Use a corrected  $t$  test formula, such as  $t$  prime ( $t'$ ):

$$t' = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}}$$

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- If your study did not use random sampling, then you may have a problem with biased results.
  - For instance, if you offer compensation for participation (i.e. paying people to be in your study) and an entire community of underprivileged folks show up, then your results are not likely to be applicable to a larger population (i.e. more privileged folks).

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    - In the ANOVA situation  $t$  tests can be used for discovering pair-wise differences among multiple groups.
    - In the Regression situation  $t$  tests are used to evaluate the significance of the weights associated with predictors in a model.
- The bottom line is this,  $t$  tests are important and are frequently used; and the issue of cumulative error rates is important.

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A firm understanding of the topics covered here and previously will be necessary for understanding future topics.

# This concludes Module 8

Next time Module 9.

- Next time we'll begin covering Introduction to Analysis of Variance.
- Until next time; have a nice day.

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