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# **Module 3 Lecture - Transformations and Non-parametric Comparisons for Two Groups**

Analysis of Variance

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# 1 Overview and Introduction

## 1.1 Objectives

- In module 2, we discussed the intricacies of avoiding I and II errors in hypothesis testing, the connection to statistical power, and how assumption violations can create problems in Type II errors
- In this module, students should be able to:
  - Understand the different possible options to pursue in light of assumption violations
  - Appreciate the use of variable transformations in addressing problems in skew, and using trimming/winsorizing to address kurtosis, i.e., solving problems in normality
  - Understand non-parametric tests as viable alternative to our usual parametric tests, with certain nuances to be aware of in application.

## 1.2 Introduction

- Previously, we talked about \_\_\_\_\_ problems in 3 types of common assumptions:
  - \_\_\_\_\_
  - \_\_\_\_\_ of variances
  - \_\_\_\_\_ of sampling variables
- Now we will go through the [Solutions for Assumption Violations](#), and how they may (or may not) solve our problems
  - Our data is \_\_\_\_\_ ideal! We might need to readily consider these options

 Discuss: Of the top of your head, try to remember the different methods of identifying the above assumption violations

## 2 Solutions for Assumption Violations

### 2.1 3 General Strategies

#### ! Important

There is considerable controversy and conflicting ideas in this area, as to 'what should we do' - take non-parametric class for more fun!

- We need a way to \_\_\_\_\_ assumption violations when they occur (well mostly - see **Do Nothing!**)
  - As mentioned before, the main \_\_\_\_\_ of assumption violations, is that they reduce power and raise Type \_\_\_\_\_ error rate
  - Since we are coming into most studies with a hypothesis of differences \_\_\_\_\_, we want to plan an analysis that has the sufficient power to detect that hypothesized difference
- We have 3 \_\_\_\_\_ for approaching assumption violations:
  - **Do Nothing!**
  - **Correct for Violations in Data**
  - **Use Non-parametric Tests**
- Before we go through those, lets talk about some reasonable advice for working through these:

### 2.2 Advice in 'Fixing' Assumption Violations

- First, always \_\_\_\_\_ checks/tests for assumptions of the test you are using
  - E.g., \_\_\_\_\_ tests like Kolmogorov-Smirnov and Shapiro-Wilk; \_\_\_\_\_ to examine skew and kurtosis; Levene's test for homogeneity of \_\_\_\_\_, etc.
  - Review notes from module 2 for more details on each of those
- Second, you should report assumption checks both \_\_\_\_\_ AND \_\_\_\_\_ you attempt a fix
  - I.e., If you \_\_\_\_\_ /trim a variable, you should check assumption both before AND after the transformation/trim
  - Re-check \_\_\_\_\_ assumptions, not just the ones you attempted to fix with the transformation or \_\_\_\_\_

- Third, be \_\_\_\_\_ and transparent when it seems like a solution does not work or when the downsides outweigh the results
  - We'll talk about different \_\_\_\_\_ when using each strategy
  - It's good practice to always be straightforward about \_\_\_\_\_ of our analyses

❗ Important

The emphasis is always on transparently reporting results!

## 2.3 Do Nothing!

- Without going into too much detail, we are concerned with how robust a test is, or how \_\_\_\_\_ a test is to assumption violations, and how well it works under less-than-ideal circumstances
- Some researcher's hold that many commonly used tests, i.e., t-tests are reasonably \_\_\_\_\_ at baseline to assumption violations
  - This becomes even more true at large  $n$  size (See discussion in Sample Size section in module 2 notes)
  - However, when samples are small or the groups being compared are \_\_\_\_\_
    - this route cannot be recommended

🔊 Discuss: How often do you think this option is taken in 'real' research?

## 3 Correct for Violations in Data

### 3.1 Transformations / Dealing with Skewness

- There are several options for selectively \_\_\_\_\_ and or \_\_\_\_\_ our data to correct for certain patterns of skewness, kurtosis, or \_\_\_\_\_

- However, be aware these are not panaceas - they come with their own issues
- Making mathematical **variable transformations** is largely used to address the Normality Assumption, but maybe indirectly solve other issues as well
- The exact transformation is dependent on the type of problem, specifically the:
  - \_\_\_\_\_ /right skew: Logarithmic (Severe) or Square Root (Moderate)
    - \* Logarithmic method:  $\log_{10}(X)$
    - \* Square root method:  $\sqrt{X}$
    - \*  $X$  is the variable of interest
  - \_\_\_\_\_ /left skew: Reflect and Logarithmic (Severe) or Reflect and Square Root (Moderate)
    - \* Logarithmic method:  $\log_{10}(K - X)$
    - \* Square root method:  $\sqrt{K - X}$
    - \*  $K$  is a constant from which each score is subtracted, so that the smallest score is equal to 1
- Advantages:
  - Makes use of \_\_\_\_\_ available data
  - Allows for use of a \_\_\_\_\_ well-known technique.
- Disadvantages:
  - \_\_\_\_\_ can be questionable
  - Fixing one assumption violation can \_\_\_\_\_ others

? I have a variable of numeric test scores, in which a histogram shows that there is severe bunching of scores to the left, with a tail off to the right. Which of the above transformation might be the best to try first?

- A) Log
- B) Square Root
- C) Reflect and Log
- D) Reflect and Square Root

Explanation:

### 3.2 Trimming and Winsorizing / Dealing with Kurtosis

- Another option, particularly useful for kurtotic (platykurtic) distributions (relatively flat distributions with an unusual number of observations in the tails) is to use **variable trimming**.
- A trimmed sample is a sample where a \_\_\_\_\_ percentage of extreme values is removed from each tail.
  - Of course, if you are comparing groups, you would want to trim the same percentage from the tails of \_\_\_\_\_ groups to be fair.
  - \_\_\_\_\_ percent or 0.10 from each tail is the most common amount to trim
  - Example Mean:  $((6.0 + 8.1 + 8.3 + 9.1 + 9.9)/5) = 8.28$
  - Example 20% Trimmed Mean:  $(8.1 + 8.3 + 9.1)/3 = 8.50$
- Another related option is using **winsorizing**
  - A Winsorized sample replaces the trimmed values by the most \_\_\_\_\_ value remaining in each tail.
  - Example Dataset: 2, 4, 7, 8, 11, 14, 18, 23, 23, 27, 35, 40, 49, 50, 55, 60, 61, 61, 62, 75
  - Example 20% Winsorized Dataset: 7, 7, 7, 8, 11, 14, 18, 23, 23, 27, 35, 40, 49, 50, 55, 60, 61, 61, 61, 61
  - Note: \_\_\_\_\_ of freedom (df) for a test on a trimmed or Winsorized sample must be adjusted for the data trimming. For both, you would subtract your total N by the number of trimmed cases to get a new value for N. (We do this even for Winsorized samples b/c the added values are really pseudovalues.)
- Advantages:
  - Allows for use of a \_\_\_\_\_ well-known technique.
  - Interpretability of variable remains \_\_\_\_\_
- Disadvantages:
  - Loss of information - what if those \_\_\_\_\_ were an important part of the phenomenon

🔊 Discuss: Using the variable data 1, 2, 3, 4, 5, try 20 percent trimming and winsorizing this data

## 4 Use Non-parametric Tests

### 4.1 Introduction

- Non-parametric test are \_\_\_\_\_ -free statistical tests that are not based on \_\_\_\_\_ (i.e., means or standard deviations) or assumptions about the normality underlying data distribution.
- They do still have some \_\_\_\_\_, just not about normality! More on that in [Assumptions of Non-parametric Tests](#).
- Instead, non-parametric tests are based on amounts such as percentages (Chi-square) or ranks, i.e., \_\_\_\_\_ or \_\_\_\_\_ - transformed data
- Non-parametric tests are just as \_\_\_\_\_ as traditional tests, and under situations of violated assumptions can be much more \_\_\_\_\_
- We'll discuss the [Wilcoxon Rank Sum Test](#) and the [Mann Whitney U Test](#) as they are non-parametric tests comparing the \_\_\_\_\_ orderings of two independent samples
  - These can be thought of as the non-parametric versions of the \_\_\_\_\_ samples t-test
- We'll also cover the [Wilcoxon Matched Pairs Signed Rank Test](#), sort of an analog to the dependent-samples t-test
- Because these test use ranks, they can actually use \_\_\_\_\_ data, unlike the t-test!

Discuss: Think of a hypothesis/scenario in which you'd use the independent samples t-test

## 4.2 Wilcox Rank Sum Test

- The Wilcox Rank Sum Test is based on the logic that if there truly is a significant difference between two groups, the \_\_\_\_\_ from one group should generally be lower than the \_\_\_\_\_ from the other group.
- Following from that, if the groups are different, the \_\_\_\_\_ of one group should be lower than the \_\_\_\_\_ of the ranks from the other group.
  - If the sum of the one group is too small relative to the other sum we will reject the null hypothesis.

### 4.2.1 Calculating Test Statistic

- First, combine both groups and \_\_\_\_\_ their values from smallest (starting at 1) to largest
  - In the scenario of \_\_\_\_\_, you can assign them all the mean rank or assign adjacent ranks at random

Group A Scores ( $n_1 = 4$ )	Group B Scores ( $n_2 = 5$ )
85	70
92	82
88	75
95	78
	80

Score	Group	Rank
70	B	1

Score	Group	Rank
75	B	2
78	B	3
80	B	4
82	B	5
85	A	6
88	A	7
92	A	8
95	A	9

- Second, calculate the \_\_\_\_\_ of the ranks of the smaller group, also called  $W_s$ .
  - The “smaller” group is the one with a smaller  $n$

Group A Ranks	Group B Ranks
6	1
7	2
8	3
9	4
	5
<b>Sum (<math>W_A</math>) = 30   Sum (<math>W_B</math>) = 15</b>	

- Third, compare  $W_s$  against \_\_\_\_\_ value table, which is derived from sample \_\_\_\_\_ from the smaller and larger groups
  - Realistically, we’ll use SPSS for this

**!** Discuss: Try calculating the rank sums for groups of data: A: 23, 34, 89; B: 16, 12, 40, 50; which of these is  $W_s$ ?

### ! Important

Contrary to what we are used to, we want our test statistic to be \*less\* than the critical value

- This is a \_\_\_\_\_ -tailed test that tests to see if the ranks of the smaller group are sufficiently smaller than the larger group.

### 4.2.2 When Smaller Group Has Larger Ranks

- A problem we may run into in the above process is if the smaller group (by  $n$ ) actually has the \_\_\_\_\_ ranks
  - To solve for this, we can backwards rank the data, i.e., start with the value as 1
- We can check for that possibility by calculating  $W'_s$  or the compliment of  $W_s$ 
  - $W'_s = 2\bar{W} - W_s$  where
- Where:
  - $2\bar{W} = n_1(n_1 + n_2 + 1)$
  - $n_1$ : sample size of smaller sample
  - $n_2$ : sample size of the larger sample

**!** Important

So effectively, we have to consider the statistic both ways to account for both directions. This gets covered by our next test.

### 4.3 Mann Whitney U Test

- The **Mann Whitney U Test** is a test completely \_\_\_\_\_ to the Wilcoxon Rank Sum, however, it is slightly more \_\_\_\_\_ in order to eliminate the need to compute  $W'_s$ .

**!** Important

For this reason, it tends to be a bit more immediately useful, because it doesn't require going through the equation twice.

- The Mann Whitney U, like the Wilcoxon Rank Sum, is based on ranked data.

#### 4.3.1 Calculating Test Statistic

- We start with the exact same steps as the **Wilcoxon Rank Sum Test**, calculating  $W_s$
- The we calculate the  $U$  statistic:

$$U = \frac{n_1(n_1 + 2n_2 + 1)}{2} - W_s$$

- Where:

- $n_1$ : sample size of smaller sample
- $n_2$ : sample size of the larger sample

**!** Important

SPSS will only calculate Mann Whitney U, but because these tests are equivalent, that is fine!

## 4.4 Wilcoxon Matched Pairs Signed Rank Test

- The **Wilcoxon Matched Pairs Signed Rank Test** is a non-parametric test testing the null hypothesis that two \_\_\_\_\_ samples were drawn from identical populations with the same mean.
  - This is a non-parametric version of the \_\_\_\_\_ /paired samples t-test.
- The logic of the Signed Ranks Test rests on measuring the direction and of change.

### 4.4.1 Calculating Test Statistic

- Compute difference scores ( $d$ ) between time 1 ( $t_1$ ) and time 2 ( $t_2$ )

Participant	Before	After	Difference ( $d_i$ )
1	120	115	-5
2	135	130	-5
3	110	120	+10
4	145	145	0
5	130	110	-20
6	125	122	-3

- Next, rank *regardless of sign*

$ d_i $	Absolute Rank	Sign
3	1	Negative
5	2.5	Negative
5	2.5	Negative
10	4	Positive
20	5	Negative

- There are two kinds of \_\_\_\_\_ possible this time:

- Like before, you can have rank ties which you would handle by either random ranks or tied ranks.
- Now, though, you have the possibility for paired values to be equal (difference = 0). When this happens do not rank that case, and \_\_\_\_\_ it from your sample.
- Next, Sum positive and negative ranks

Absolute Rank	Positive Ranks ( $R^+$ )	Negative Ranks ( $R^-$ )
1		1
2.5		2.5
2.5		2.5
4	4	
5		5
<b>Sum (<math>W</math>)</b>	$W^+ = 4$	$W^- = 11$

- Our test statistic is  $T$ , which is the smaller of the two \_\_\_\_\_ sums

## 4.5 Assumptions of Non-parametric Tests

- These mentioned non-parametric tests allow us to ignore \_\_\_\_\_ problems in our data
  - However, we still need to test for and address problems in homogeneity of \_\_\_\_\_
  - See prior module lecture on examining \_\_\_\_\_ and \_\_\_\_\_ test to help identify these issues

## 4.6 Effect Size Under Non-parametric Tests

- We can use this quick equation and rule-of-thumb for effect \_\_\_\_\_ under these tests

$$r = \frac{z}{\sqrt{n}}$$

- Where:
  - $z$  is the \_\_\_\_\_ test value
  - $n$  is the sample size
- Interpretation
  - \_\_\_\_\_ : 0.1
  - \_\_\_\_\_ : 0.2
  - \_\_\_\_\_ : 0.3

**!** Important

Like with many statistics, there are \*many\* other ways of calculating effect size, some with much more complex equations - but for the scope of this class, we'll use this

## 4.7 Advantages and Disadvantages of Non-parametric Tests

- Advantages of Non-Parametrics
  - \_\_\_\_\_ of variables remains intact
  - Makes use of all available data
  - We still have good options for statistical \_\_\_\_\_ testing, \_\_\_\_\_ size, and other normal comforts of parametric tests
- Disadvantages
  - Non-parametric tests are relatively \_\_\_\_\_. Many researchers would not know how to \_\_\_\_\_ them, and thus, may prefer just to see the parametric version, regardless of issues

**!** Discuss: Do you think this is disadvantage is a sufficient reason to avoid these tests? What issues (if any) do you have with this view?

## 5 Conclusion

### 5.1 Recap

- We have now discussed various methods we may pursue when dealing with oddities in our data that result in assumption violations
- Some of these strategies involve carefully modifying our data with transforming, trimming, or winsorizing; some strategies involve alternative selection of tests;

and then finally, we may do nothing (mindfully)

- Each of our options result in some new things to be careful about, like transformation changing the scale of our data, trimming removing data, or non-parametric tests changing interpretation of results
- Our discussion of the non-parametric analogs for the t-test will help lead us into a similar discussion on alternative tests to the one-way ANOVA (and others) later in the semester
- Paramount to all of these things, we must be mindful of transparency when working through assumption problems

## Key Terms

### M

**Mann Whitney U Test** A non-parametric test similar to the Wilcoxon Rank Sum Test, but used for the purpose of doing the test 'both ways'; preferred over Wilcoxon Rank Sum, and equivalent to it [10](#)

### N

**Non-parametric test** Tests without normality assumptions and without mean or standard deviation parameters [7](#)

### R

**robust** A description of how resilient a test is to assumption violations, and how well it works under less-than-ideal circumstances [4](#)

### V

**variable transformations** Mathematical transformations usually used to counteract skew, to try and meet the normality assumption [5](#)

**variable trimming** Removing a certain amount of variables at the high and low end of a variable, usually to solve for platykurtic-ness [6](#)

### W

**Wilcoxon Matched Pairs Signed Rank Test** A non-parametric test used to compare dependent-samples, i.e., those that are the same individuals taken at two times points [11](#)

**Wilcoxon Rank Sum Test** A non-parametric test for testing whether the ranks of one group are significantly smaller than another; akin to a independent-samples t-test [8](#)

**winsorizing** A process of replacing the most extreme values of a variable with the last remaining one [6](#)

*The instructor-provided glossary may not include all terms worth memorizing, make sure you consider using the vocabulary list in your book and your own judgment to make sure you have all relevant terms*