Nonparametric Rating and Speed Analysis

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Non-Parametric Testing Procedures

Describe the differences between a parametric and a non-parametric statistical approach.

Non-parametric tests are distribution free because unlike parametric analysis, they do not assume that your data follow a specific distribution. To put in laymen's terms, parametric analysis uses the mean to determine insights on group data that is normally distributed; nonparametric analysis uses the median in order to control more easily for non-normal distributions of group data.

What are the advantages of a parametric approach over a non-parametric approach on regression?

Parametric tests can perform well with continuous data that are non-normal if you can satisfy sample guidelines, such as samples of 20 for 1 sample t-test and 15 per group for 2 sample t tests. For non-parametric tests that compare groups, a common assumption is that the data for all groups must have the same spread.

At the end of the day, parametric tests usually have more statistical power, while non-parametric tests, though less predictive overall, do a much better job working with messier, non-normally distributions of data.

What are the disadvantages of a parametric approach?

Nonparametric tests use the median as the best measure of central tendency, thus dealing best with non-normal distributions, small sample size and non-continuous data. Typical parametrics can be significantly affected by outliers. Conversely, some nonparametric tests can handle ordinal data, ranked data, and not be seriously affected by outliers. If your groups have different spread, datatypes, and insufficient sample size the nonparametric tests might not provide valid results.

Souperb: Wilcoxon Signed-Rank Test

Using the Wilcoxon Signed-Rank Test, we will decide whether the corresponding data population distributions are identical without assuming them to follow the normal distribution.

We observe 15 observations from a population of survey responders.

Assumptions:

- n observations are independent
- The observations come from a continuous population which as a median and which is symmetric

Souperb Import Data

Souperb EDA

```
glimpse(souperb)
```

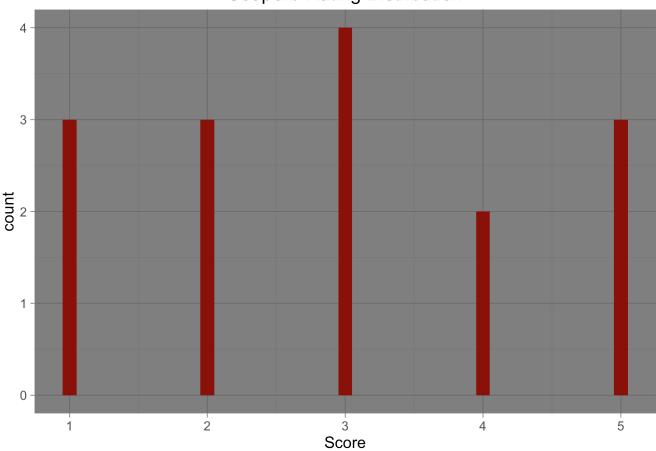
```
## Observations: 15
## Variables: 2
## $ Person <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15
## $ Score <dbl> 5, 3, 2, 1, 4, 3, 5, 1, 5, 2, 3, 4, 2, 1, 3
```

```
summary(souperb$Score)
```

```
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 1.000 2.000 3.000 2.933 4.000 5.000
```

```
ggplot(data=souperb, aes(Score)) +
    geom_histogram(binwidth = .1, fill = "#8b0000") +
    theme_dark() +
    ggtitle("Souperb Rating Distribution")
```

Souperb Rating Distribution



Souperb Hypothesis

 H^0 : Median is greater than or equal to 3

 H^1 : Median is less than 3

Souperb Hypothesis Testing

```
SIGN.test(souperb$Score, md = 3, y = NULL, alternative = "less", conf.level = 0.95)
```

```
##
## One-sample Sign-Test
##
## data: souperb$Score
## s = 5, p-value = 0.5
## alternative hypothesis: true median is less than 3
## 95 percent confidence interval:
## -Inf 4
## sample estimates:
## median of x
## 3
```

```
## Conf.Level L.E.pt U.E.pt
## Lower Achieved CI 0.9408 -Inf 4
## Interpolated CI 0.9500 -Inf 4
## Upper Achieved CI 0.9824 -Inf 4
```

Souperb Conclusion

Given our alternative hypothesis of the median being lower than 3, we have computed a one sided sign test, at a 95% confidence interval. The S statistic tells us the number of positive differences between the data and the hypothesized median, in this case 5. The p-value of 0.5 is greater than the 0.05 p-value, we therefore cannot reject the null hypothesis that the median is less than 3.

Operating System Rates: Wilcoxon Rank Sum Test

To best test the difference in two population means I will use the Wilcoxon Rank-Sum Test. We will obtain n + m observations from two groups and compare their medians.

Assumptions:

- Samples from each population were random samples
- · Samples are independent
- · Both populations are continuous

OS Import Data

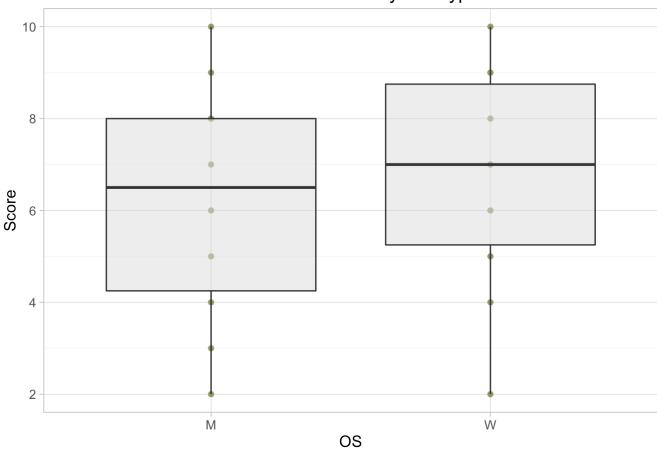
OS EDA

```
glimpse(os_rates)
```

```
summary(os_rates$Score)
```

```
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 2.00 4.75 7.00 6.45 8.25 10.00
```

Score Distribution by OS Type



OS Hypothesis

 H^0 : The populations of M and W Operating systems are the same

 ${\cal H}^1$: The operating system W has a higher median than the M operating system

OS Hypothesis Testing

```
os_rates1 <- os_rates %>% group_by(OS)

M <- as.numeric(os_rates$Score[1:10])

W <- as.numeric(os_rates$Score[11:20])

os_rates2 <- as.data.frame(cbind(M,W), row.names = c("M","W"))

wilcox.test(data = os_rates, x = M, y = W, paired = FALSE, alternative = "greater")</pre>
```

```
## Warning in wilcox.test.default(data = os_rates, x = M, y = W, paired =
## FALSE, : cannot compute exact p-value with ties
```

```
##
## Wilcoxon rank sum test with continuity correction
##
## data: M and W
## W = 44.5, p-value = 0.676
## alternative hypothesis: true location shift is greater than 0
```

OS Conclusion

Given our alternative hypothesis of the median value of W being higher than M, we have computed a one sided sign test, with the desire of a 0.05 p value. The p-value of 0.676 is greater than the 0.05 p-value, we therefore cannot reject the null hypothesis that the median W is more than M. This number is additionally affirmed by a high value of the W (or U) statisti of 44.5.