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STAT 407-001

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Project Report

The experiment we chose for the project was seeing how brand of popcorn and microwave setting affect the number of unpopped kernels in a popped bag of microwave popcorn. Our research question was: "How do the brand of popcorn and microwave setting affect the number of unpopped kernels in a bag of microwave popcorn?"

Given the current state of the global COVID-19 pandemic, we were looking for a design experiment where obtaining materials and running the experiment would be convenient and the influence of external factors could be minimized. For this experiment, obtaining materials could be done in a single trip, and running the experiment did not require other human subjects or going out to collect data, which could be affected by closures, supply chain issues, or other unforeseen events. Additionally, the effects of the pandemic potentially confounding the data would be minimized.

The materials for the experiment consisted of 12 bags of microwave popcorn of similar size and price (six bags of Pop-Secret popcorn and six bags of Act II popcorn) and a single 1000-watt microwave. The bags of each brand were to be divided such that three bags each would be microwaved with the popcorn setting on the microwave enabled (hereafter referred to as "microwave setting") and three bags each would be microwaved with the microwave setting disabled. There were three main null hypotheses to be tested: (H_0 #1) whether there was a difference in the number of unpopped kernels between brands, (H_0 #2) whether there was a difference in the number of unpopped kernels among microwave setting, and (H_0 #3) whether there was a significant interaction between brand and microwave setting (Brand*Setting).

After some research and analysis of the experiment parameters, we observed that a two-factor factorial design would be the most appropriate for this experiment. The two factors were brand (with Pop-Secret and Act II as levels) and microwave setting as a binary categorical variable. The experimental units were the individual bags of popcorn and the response variable was the number of unpopped kernels in each bag. Our model for the design was in the form $y_{ijk} = \mu + \tau_i + \beta_j + (\tau\beta)_{ij} + \varepsilon_{ijk}$, where y is the response variable (number of unpopped kernels), μ is the intercept term, τ is the coded variable for brand, β is the coded variable for microwave setting, $\tau\beta$ is the interaction term, ε is the error term, i (brand levels) varies from 1 to 2, j (microwave setting levels) varies from 1 to 2, and k (replicates) varies from 1 to 3.

The order of the 12 runs were randomized to limit the influence of other variables, and all 12 bags of popcorn were checked before any runs were done to ensure they all had roughly the same weight and number of unpopped kernels. The experiment itself involved putting a bag of popcorn in the microwave and microwaving it for three minutes, recording the number of unpopped kernels in the bag, letting the microwave cool for five minutes, and repeating this process until all 12 runs were performed. The numbers of unpopped kernels would then be entered into R, with brand and microwave setting as factors with two levels each, where an ANOVA would be performed and a linear model would be generated.

Prior to conducting the experiment, we predicted there may be some difference in the number of unpopped kernels between brands, as there may be some differences in the harvesting, formulation, processing, and/or recipes of the popcorn between companies. However, the influence of the microwave setting was largely unknown as it was not known what exactly the microwave setting did. Logically, we could say the number of unpopped kernels would decrease if the microwave setting was enabled, as it would be reasonable to deduce that the microwave setting for which the button has the word “Popcorn” on it optimizes the microwaving of popcorn. However, without further details or explanation of the microwave setting, it was difficult to be fully confident of this prior to the experiment, especially at a level great enough to reject H_0 #2 and prove there is a significant difference. The gathered data can be found in Figure 1.

After conducting the ANOVA (seen in Figure 2), we saw that the p-values for brand, microwave setting, and the interaction term were $p = 0.000008$, $p = 0.000792$, and $p = 0.577085$, respectively. The linear model with the interaction term indicated the intercept ($p < 0.000001$) and coefficients for brand ($p = 0.000146$) and microwave setting ($p = 0.011055$) were all significant at the $\alpha = 0.05$ level, but the coefficient for the interaction term was not ($p = 0.577085$). Using the coefficient estimates provided by the linear model (Figure 3), our model was y = 48 - 13.667(Brand) - 6.667(Setting) - 1.667(Brand*Setting). This equation had an adjusted-r^2 of 0.9203, indicating that approximately 92.03 percent of the variation in the data was explained by the model.

Even though the interaction term did not appear to be significant, we still did an interaction plot (Figure 4) between brand and microwave setting to visualize this, and the plot confirmed there was very little to no interaction between the two factors as the two lines appeared to be almost completely parallel. In visualizing the difference between factors, an interval plot (Figure 5) confirmed the significance of the difference in unpopped kernels between brands, with no overlap between any of the displayed confidence intervals.

The residual plot (Figure 6) showed no signs of any pattern or clustering. The null hypothesis for the Shapiro-Wilk (Figure 7) test for normality on the residuals was also not rejected by a wide margin ($p = 0.9073$). The assumptions of normality and homoscedasticity were met fairly well and no transformation of the data or research into other models was necessary to proceed with interpretation and analysis of the results.

Because no transformation was necessary, we rejected H_0 #1 and H_0 #2, both at the $\alpha = 0.05$ level, and concluded there was a significant difference in unpopped kernels between both brand ($p = 0.000008$) and microwave setting ($p = 0.000792$). However, we failed to reject H_0 #3 at the $\alpha = 0.05$ level and concluded there was no significant interaction between brand and microwave setting ($p = 0.577085$).

Some of the challenges we faced throughout the course of the project included taking the class remotely. This led to some difficulty with communication and coordinating and slight difficulty in presenting the slideshow in fullscreen mode while simultaneously talking and monitoring the video/audio and chat for questions and comments. Additionally, since the class is designed to meet for only 50 minutes per day, three times per week (as opposed to most STAT classes that meet for 75 minutes per day, twice per week), there was less time allocated to each group to set up and present the project. Specifically, our group was the last scheduled presentation for the day, and we had to make sure the presentation did not exceed 6 minutes since class was scheduled to end and prior groups had taken more time on their presentations, as well as other students with several lengthy questions. However, the most important challenge faced (which applies universally to other assignments) was simply by virtue of being a college student in graduate school and having several other assignments simultaneously due and other non-academic commitments.

There are several potential modifications and variations of this experiment that could be made in a future trial. One of them is increasing the number of replicates to ensure a sufficient sample size for the statistical tests. Another is to use additional factors, including (but not limited to) microwave power, microwave time, and other brands and flavors, to measure the effects those have on the response variable. We could also increase the cooling time to reduce the influence it has on the response variable, as well as calculating the percentage or weight of unpopped kernels per bag instead of the number to ensure that varying numbers of unpopped kernels in the bag prior to microwaving do not unduly influence the number after the experiment.

Overall, the experiment was successful. We were able to deduce the usefulness of the Popcorn setting at least on the microwave that we used. We were also able to find that Pop Secret ended up with significantly less unpopped kernels when compared to Act II despite the two brands being of similar price and package size. In the end we were never able to deduce what the Popcorn button on the microwave actually did. Several sources on the internet claim that it listens to the pops and stops when the interval between pops becomes long enough however that was not the case for the microwave we used. But despite not knowing exactly what it does, it is clear to us that it has an impact in reducing the number of kernels left unpopped regardless of brand.

Output

Figure 1

	Brand	Setting	Unpopped
1	Pop	1	29
2	Pop	1	22
3	Act	0	50
4	Act	1	44
5	Act	1	41
6	Pop	0	35
7	Act	1	39
8	Pop	0	33
9	Pop	1	27
10	Act	0	46
11	Pop	0	35
12	Act	0	48

Figure 2

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Brand	1	630.7	630.7	102.284	7.8e-06
Setting	1	168.7	168.7	27.365	0.000792
Brand:Setting	1	2.1	2.1	0.338	0.577085
Residuals	8	49.3	6.2		

Figure 3

```
Call:
lm(formula = Unpopped ~ Brand + Setting + Brand * Setting, data = data)

Residuals:
    Min      1Q  Median      3Q     Max 
-4.0000 -1.5000  0.3333  1.2500  3.0000 

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)    
(Intercept)        48.000      1.434  33.479 6.92e-10 ***
BrandPop          -13.667      2.028  -6.740 0.000146 ***
Setting1           -6.667      2.028  -3.288 0.011055 *  
BrandPop:Setting1  -1.667      2.867  -0.581 0.577085    
```

Figure 4

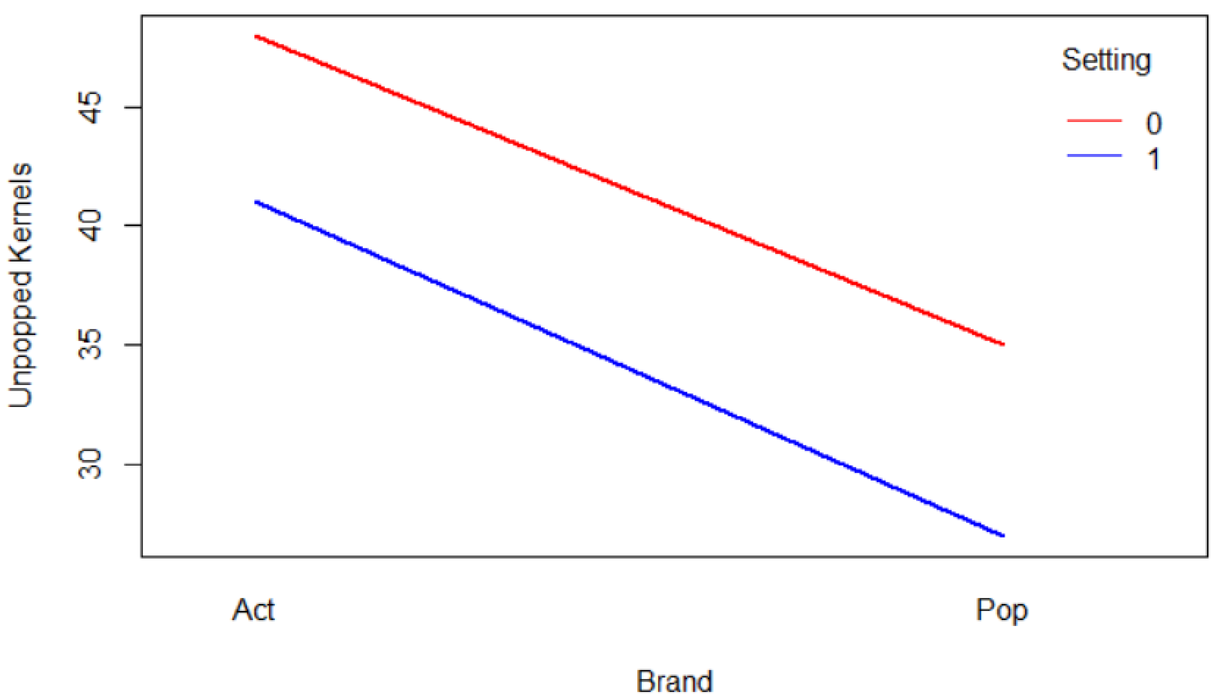


Figure 5

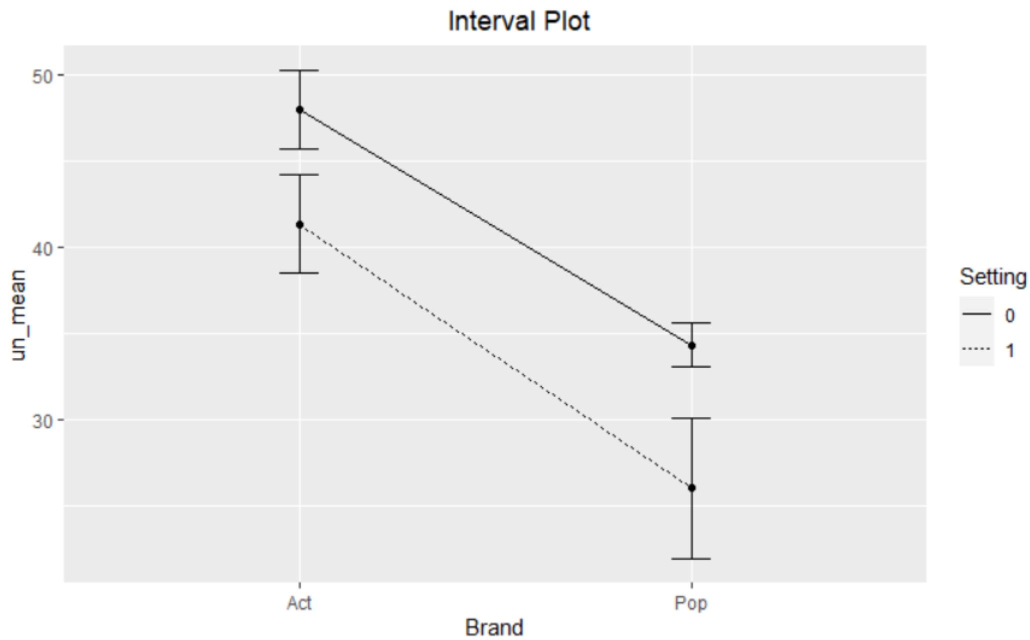


Figure 6

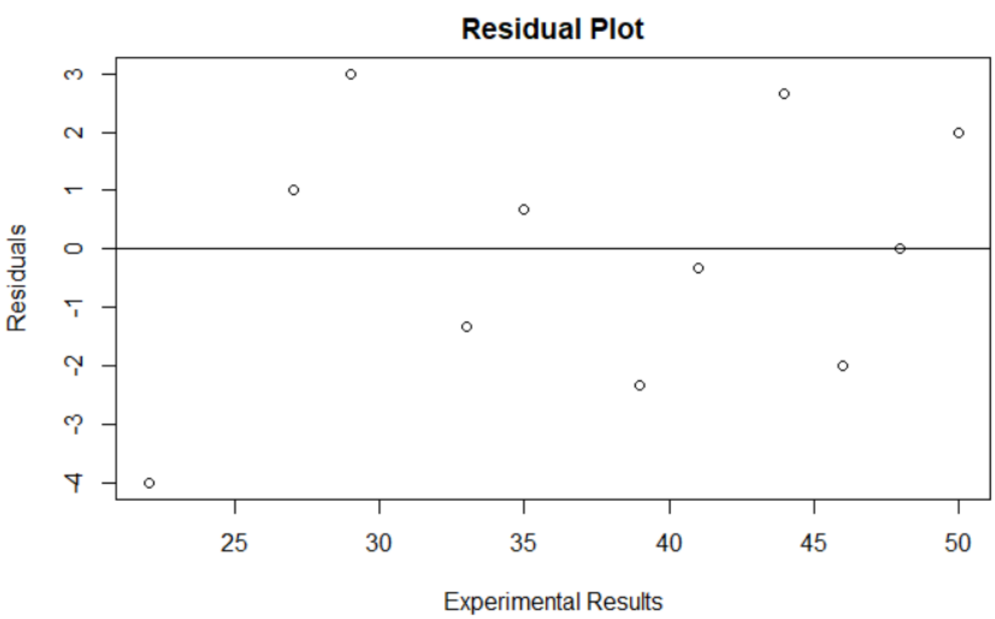


Figure 7

```
        Shapiro-Wilk normality test

data:  lm$residuals
W = 0.96967, p-value = 0.9073
```

Individual Contributions

Charles

- Proposed initial experiment idea and research question
- Created template for slides 1, 4-8, and 14-17 of presentation
- Presented slides 10-17 of presentation
- Wrote introduction, motivation, design, hypotheses, results, assumptions, analysis, challenges, and potential modifications in report

Aryan

- Gathered the materials and performed the experiment
- Wrote the code for the analysis in R
- Created the remainder of the slides and presented on slides 1-9
- Wrote the conclusion of the report

Design Report

```
library(ggplot2)
```

```
## Warning: package 'ggplot2' was built under R version 4.0.5
```

```
library(dplyr)
```

```
## Warning: package 'dplyr' was built under R version 4.0.5
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
data <- read.csv("C:/Users/Deepa/Desktop/Fall21/Consulting/data.csv")
```

```
data$Brand <- as.factor(data$Brand)
data$Setting <- as.factor(data$Setting)
```

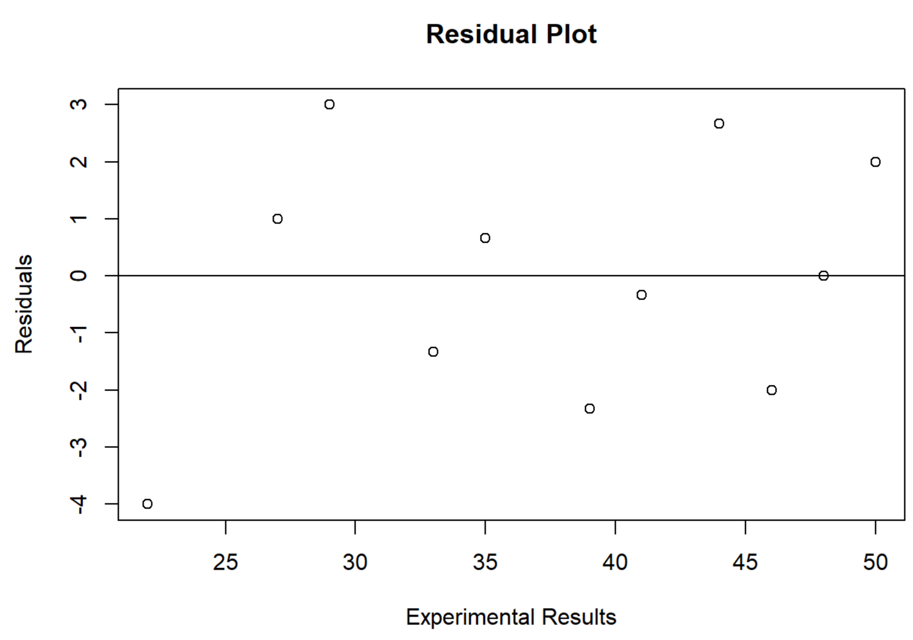
```
anova <- aov(Unpopped ~ Brand + Setting + Brand * Setting, data = data)
summary(anova)
```

```
##               Df Sum Sq Mean Sq F value   Pr(>F)
## Brand          1  630.7   630.7 102.284  7.8e-06 ***
## Setting        1  168.7   168.7  27.365 0.000792 ***
## Brand:Setting  1    2.1     2.1   0.338 0.577085
## Residuals      8   49.3     6.2
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
lm <- lm(Unpopped ~ Brand + Setting + Brand * Setting, data = data)
summary(lm)
```

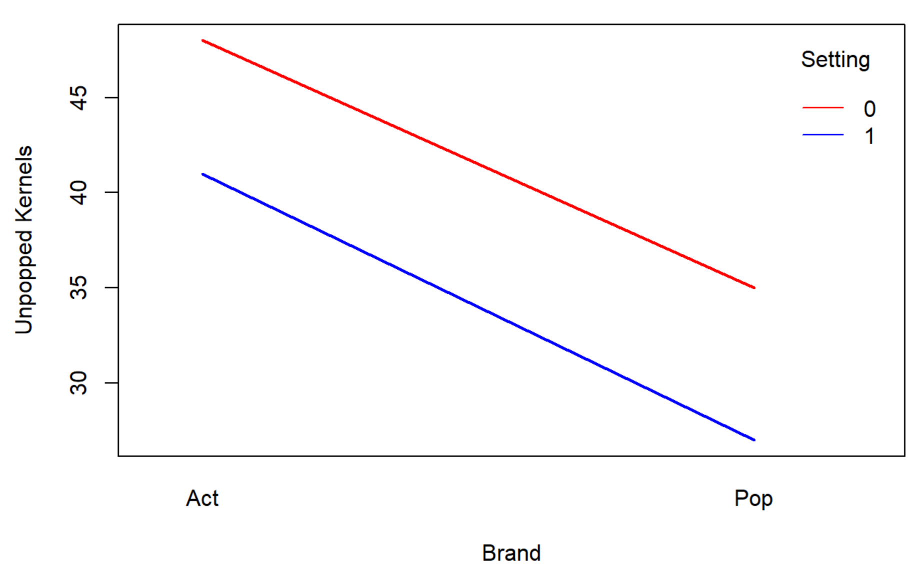
```
##
## Call:
## lm(formula = Unpopped ~ Brand + Setting + Brand * Setting, data = data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.0000 -1.5000  0.3333  1.2500  3.0000
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)         48.000      1.434  33.479 6.92e-10 ***
## BrandPop           -13.667      2.028  -6.740 0.000146 ***
## Setting1            -6.667      2.028  -3.288 0.011055 *
## BrandPop:Setting1   -1.667      2.867  -0.581 0.577085
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.483 on 8 degrees of freedom
## Multiple R-squared:  0.942,  Adjusted R-squared:  0.9203
## F-statistic: 43.33 on 3 and 8 DF,  p-value: 2.715e-05
```

```
plot(data$Unpopped, lm$residuals, xlab = "Experimental Results", ylab = "Residuals", main = 'Residual Plot') + ab
line(h = 0, col = 'black')
```




```
## integer(0)
```

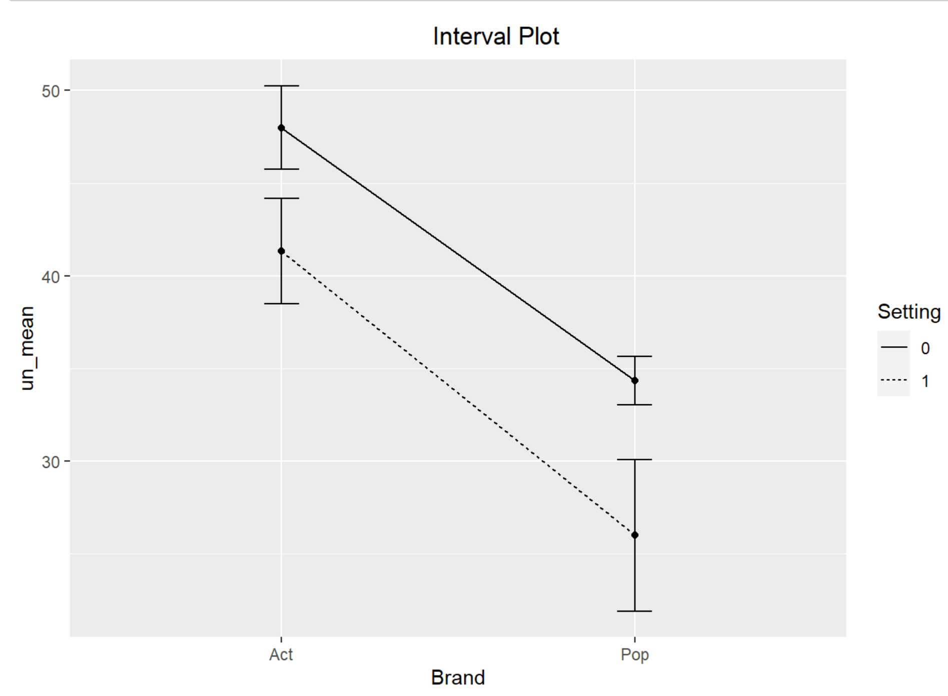
```
interaction.plot(x.factor = data$Brand, #x-axis variable
                 trace.factor = data$Setting, #variable for lines
                 response = data$Unpopped, #y-axis variable
                 fun = median, #metric to plot
                 ylab = "Unpopped Kernels",
                 xlab = "Brand",
                 col = c("red", "blue"),
                 lty = 1, #line type
                 lwd = 2, #line width
                 trace.label = "Setting"
                 )
```




```
sum_d <- data %>%
          group_by(Brand, Setting) %>%
          summarise(un_mean = mean(Unpopped),
                    un_ci   = 1.96 * sd(Unpopped)/sqrt(n()))
```

```
## `summarise()` has grouped output by 'Brand'. You can override using the `.groups` argument.
```

```
sum_d %>%
  ggplot(aes(x = Brand, y = un_mean, group = Setting)) +
  geom_point()+
  geom_line(aes(linetype = Setting)) +
  geom_errorbar(aes(ymin = un_mean - un_ci, ymax = un_mean + un_ci), width = 0.1) +
  labs(title = paste("                                                   Interval Plot"))
```




```
shapiro.test(lm$residuals)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  lm$residuals
## W = 0.96967, p-value = 0.9073
```