# STAT 425 Final Project

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# Abstract

In this study, we sought to determine how various conditions affect reaction times and to develop a predictive model that accurately forecasts these times. Our exploratory data analysis suggested minimal effects from variables such as sleep duration and caffeine, class and fatigue levels, leading to further model refinement. By employing backward and bidirectional elimination methods, we identified device usage, visual acuity, age and Wifi connectivity as significant predictors. We used model diagnostics and Box-Cox transformation, leading to a better prediction result.

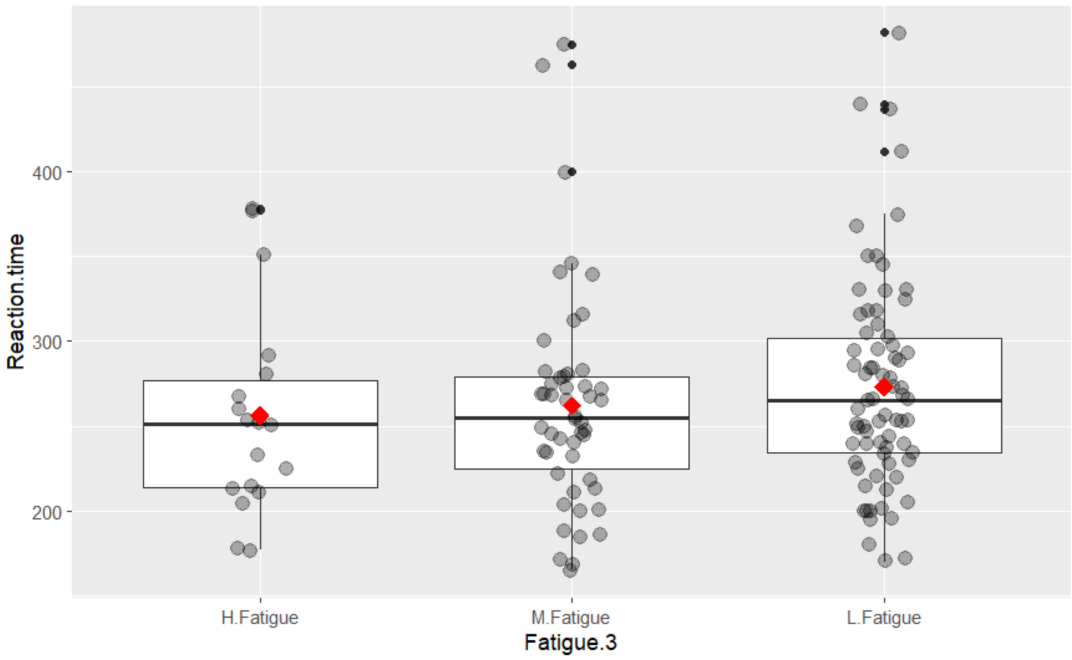
# Exploratory Data Analysis

Initially, we have an hypothesis that current condition, and relevant practice may affect the reaction time of a person.

## Tiredness

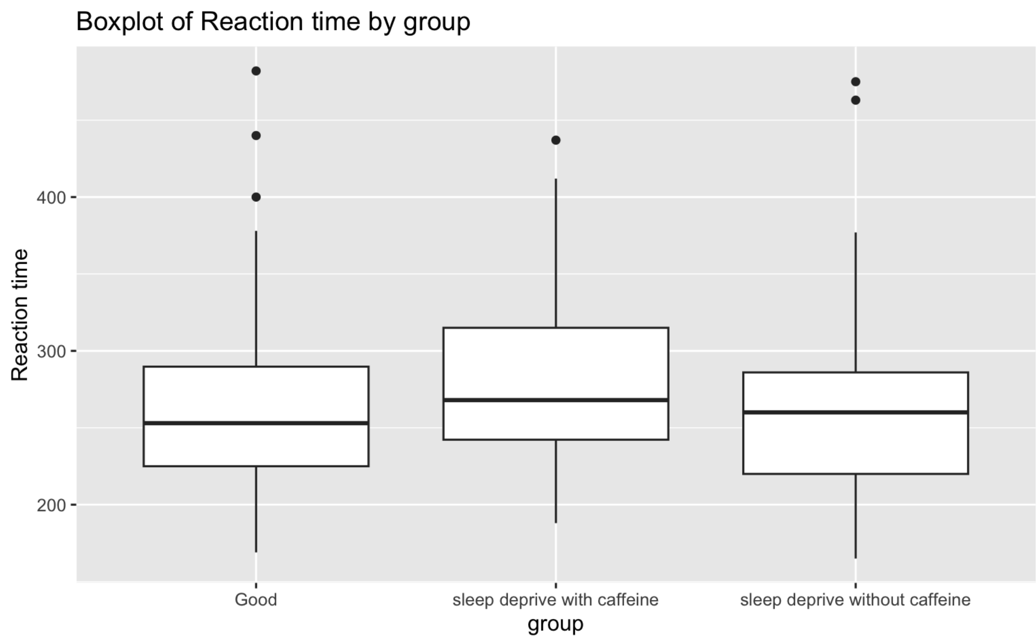
It is tempting to assume that tiredness will be an important factor for reaction time. In our research, Fatigue.level and lack of sleep are regarded as the main indicators of tiredness.

The contribution of Fatigue level is studied after being divided into 3 categories, denoted as Fatigue.3. After sketching the boxplot of Reaction.time and Fatigue.3 and fitting the reference cell model, we observed that the variances of the data are big and the p-value of the F-test is 0.47 which is greater than 0.05, so we conclude that there is no significant difference between groups with different values of Fatigue.3.




To dig down deeper into the relation between tiredness, lack of sleep is studied.

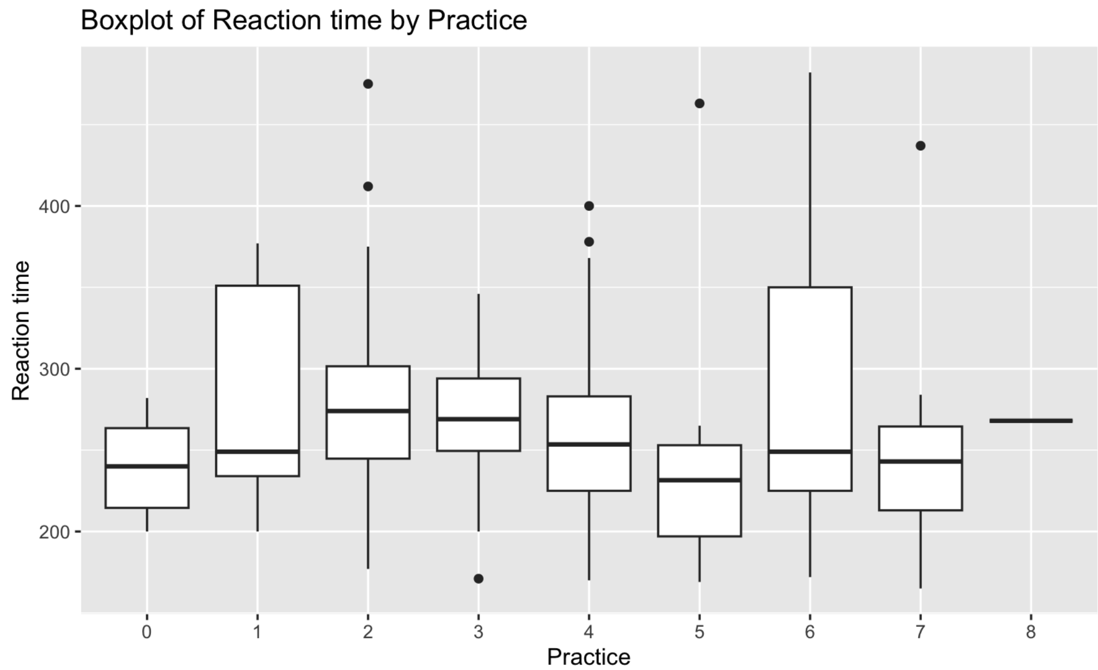
First, we examined the impact of sleep deprivation with boxplot. For improved data utilization, we converted sleep data into numeric values, where we use the minimum between 0 and the difference between last night sleep and average sleep time to determine the degree of sleep deprivation. In this way, we focus on sleep deprivation only. Additionally, to explore whether caffeine intake could mitigate the effects of sleep deprivation, we introduced a new variable that combines both sleep deprivation status and caffeine consumption.




Unfortunately, from the graph we cannot see any difference between the three groups. Further evaluation will be performed in model building.

## Practice

We grouped sports and games together as indicators of practice to assess their impact on reaction time. We consolidated them into a single variable, representing the level of practice, where more frequent engagement in games or sports corresponds to a higher practice level. Specifically, "daily" activities were assigned a score of 4, while "never" was scored as 0. This combined score from both games and sports was then used as a singular variable in our data preprocessing efforts.



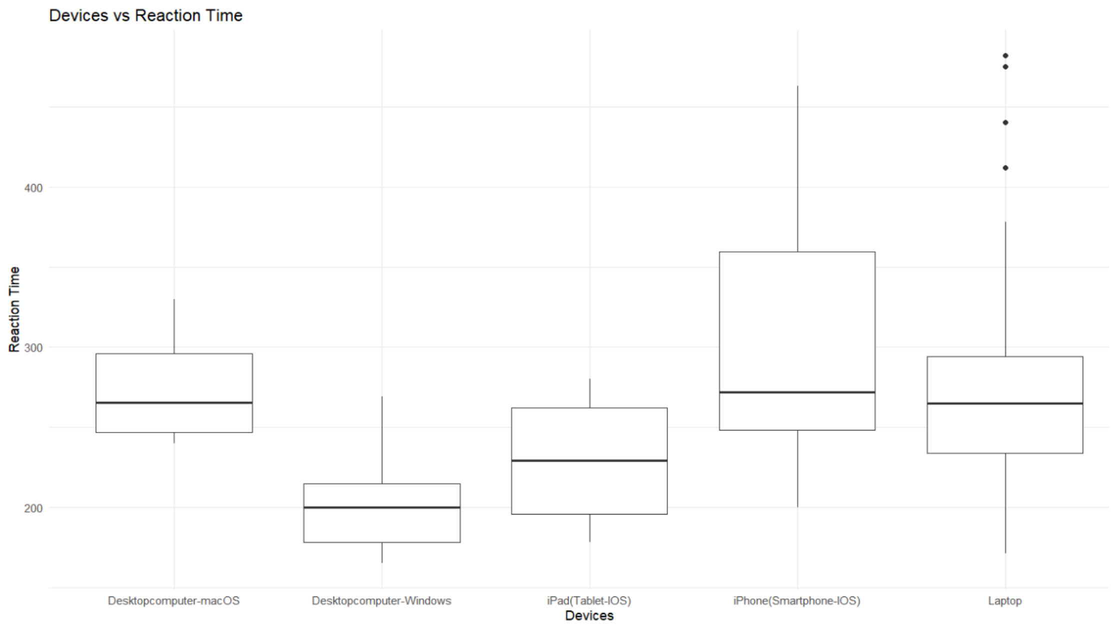
| 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| 7 | 5 | 46 | 16 | 34 | 12 | 13 | 7 | 1 |

the number of people for each level

Considering the distribution of participants across different levels, our analysis indicates a gradual decrease in mean reaction time from level 2 to 5, where the majority of participants are categorized. Which suggests that longer engagement in games and sports is associated with lower reaction time. This suits the intuition that practices that require involvement of reaction improve one's reaction time.

## Device

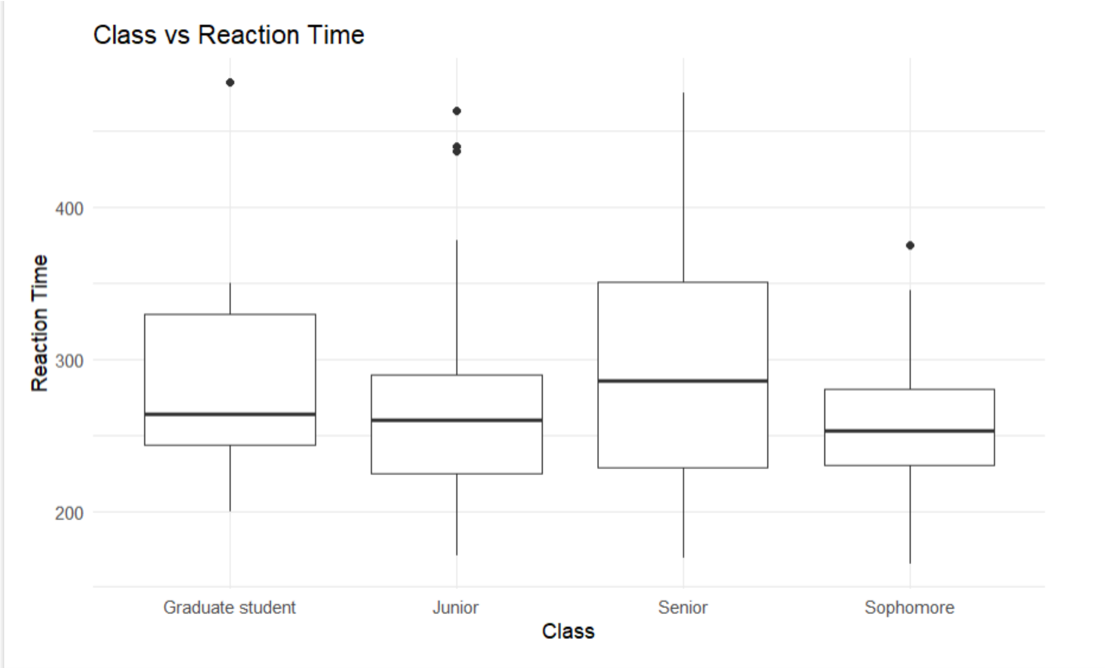
The boxplot reveals negligible differences in reaction time between users of Mac and Windows laptops, allowing us to combine these categories for simplicity. Additionally, we decided to exclude data from Android phone and Chromebook users due to their minimal sample size, each having only one data point.




The result suggests that there is a difference between observations with different devices.

## Class standing

We can see that there aren't significant differences between different classes for Reaction Time. We can try models with/without Class as factor to see which one is better.


Class vs Reaction Time
Reaction Time
400
300
200
Graduate student
Junior
Senior
Sophomore
Class

# Model Building

In this section, we use models both for comparison between groups and for predicting the reaction time.

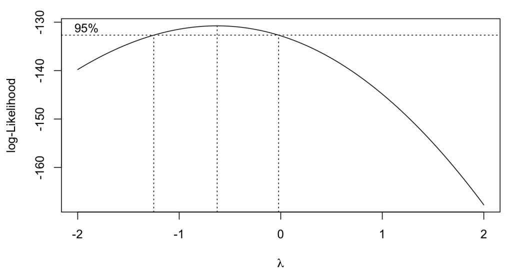
## Comparison

### Practice level

```
          Shapiro-Wilk normality test

data:  residuals(model)
W = 0.93001, p-value = 1.924e-06
```

We compare different practice levels to see if they have any differences in reaction time. The Shaprio-Wilk test of the mean model suggests non-normality between the residuals of data, thus, we perform box-plot transformation.




Based on the box-cox 95% log likelihood graphs, we choose lambda = -0.5.
After transformation, we passed the normality test

```
          Shapiro-Wilk normality test

data:  residuals(model_transformed)
W = 0.98723, p-value = 0.2191
```

```
  Posthoc multiple comparisons of means: Scheffe Test
    95% family-wise confidence level

$practice
                     diff      lwr.ci     upr.ci    pval
0,1,2,3-4,5,6,7 0.0109001 -0.0367739 0.0585741 0.9990
```

We perform Scheffe test to compare the mean between less practiced group (level 0 - level 3) with more practiced group (level 4 - level 7), but did not find any difference on reaction time.

### Caffeine intake and sleep deprivation

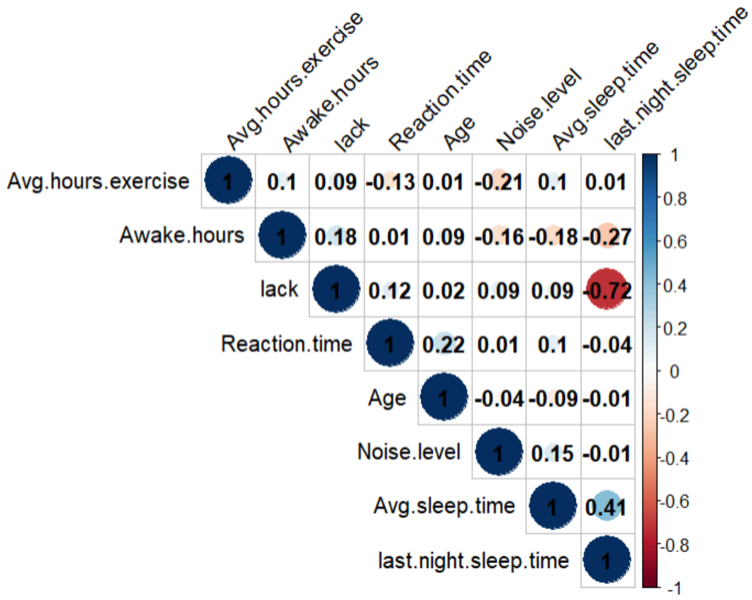
As the same issue also exists in groups of caffeine intake and sleep deprivation, we did the same transformation.
By performing the pairwise comparison, we show that there is no difference of reaction time between the three groups

```
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = y_transformed ~ group, data = data)

$group
                                                     diff          lwr         upr     p adj
deprive without caffeine-deprive with caffeine -0.0049667254 -0.015440964 0.005507513 0.5012847
Good-deprive with caffeine                     -0.0050701629 -0.015019343 0.004879017 0.4508252
Good-deprive without caffeine                  -0.0001034374 -0.006059111 0.005852236 0.9990669
```

## Prediction




From the correlation matrix, we see that there is little correlation between predictors, which ensures us to naively construct a model with all the predictors at first. The only term with high correlation is the correlation between last.night.sleep.time and lack, which is a predictor we added. When we fit models, we ensure that lack and last.night.sleep are not included at the same time to prohibit the problems of collinearity when studying the significance of each predictors.

## Full Model

We fit the full model. From the t-table, we see that there are just few predictors that are significant, and the R-square is not too high.

```
## Call:
## lm(formula = Reaction.time ~ . - lack, data = survey)
## last.night.sleep.time              -8.4802     3.4057  -2.490 0.014721 *
## Multiple R-squared:  0.5772, Adjusted R-squared:  0.3036
```

## Model with low sleep but with coffee

To further study the relationship between lack of sleep and reaction time, we create a new variable that highlights the lack of sleep. We first take the difference between Avg.sleep.time and last.night.sleep.time. Then, we take the product of the absolute value of this difference and itself, and denote it as lack.

lack = |Avg.sleep.time - last.night.sleep.time|*(Avg.sleep.time - last.night.sleep.time)

This predictor has a higher emphasis on larger differences and it tells the difference between lack of sleep and sleeping more than average, which makes it superior to just taking the square of the differences.
We also took into account the effect of Caffeine.intake because we believe that

caffeine can balance the effect of lack.

The outcome shows that lack is significant with the parameter estimated as 0.86, and the model has a better R-square compared with the one with last.night.sleep.time even though with an interaction term.

```
## lm(formula = Reaction.time ~ . - lack + last.night.sleep.time *
##     Caffein.intake, data = survey)
```

```
## Multiple R-squared:  0.5772, Adjusted R-squared:  0.2954
```

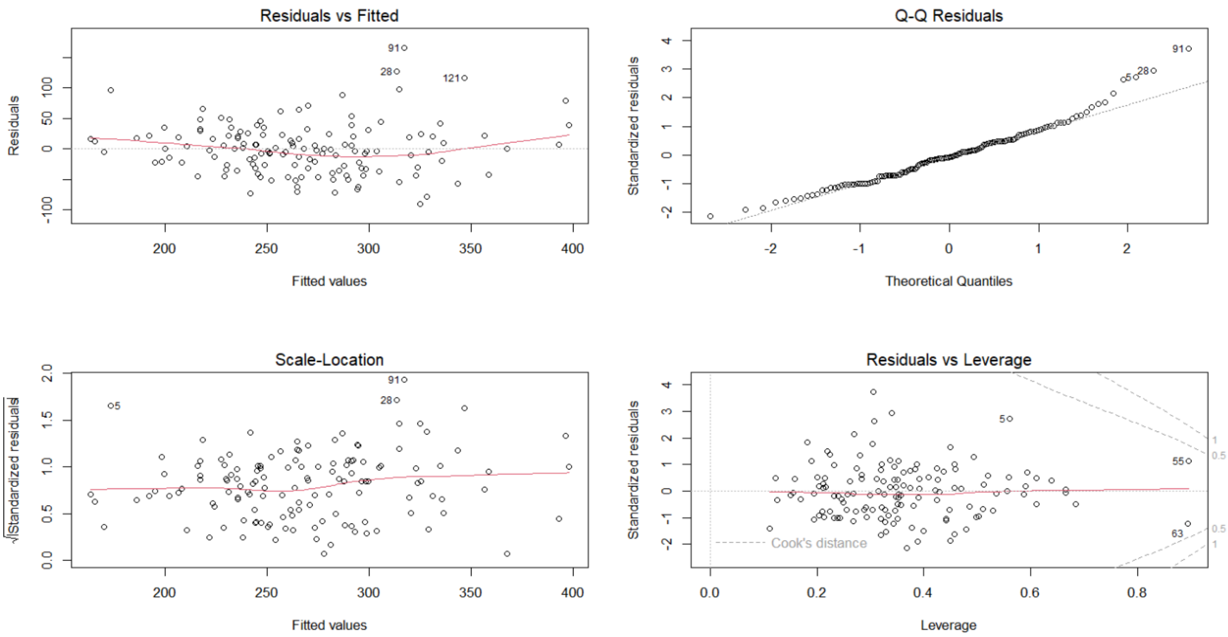
```
## lm(formula = Reaction.time ~ . - last.night.sleep.time + lack *
##     Caffein.intake, data = survey)
```

```
## lack                              0.8632     0.4100   2.105 0.038237 *
```

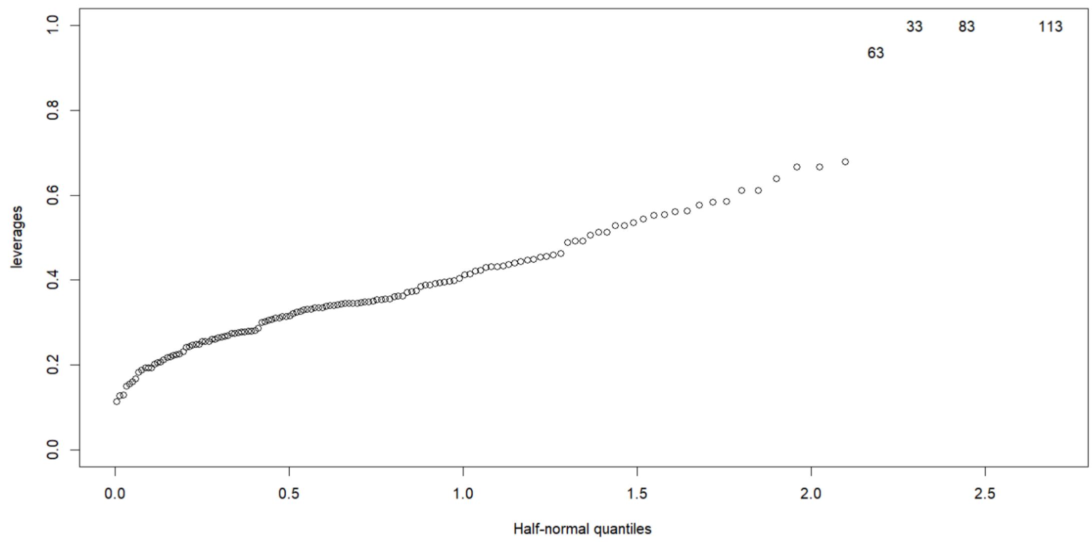
```
## Multiple R-squared:  0.5795, Adjusted R-squared:  0.2991
```

So the modification of lack indeed improves the model, which supports our viewpoint that the relationship between lack of sleep and reaction time is not linear, instead, as the lack of sleep gets more significant, it increases the reaction time much more significantly. In other words, when you sleep a little less than usual, it is not a big deal, however, as you sleep a lot less than usual, you are gonna be slowed down a lot.

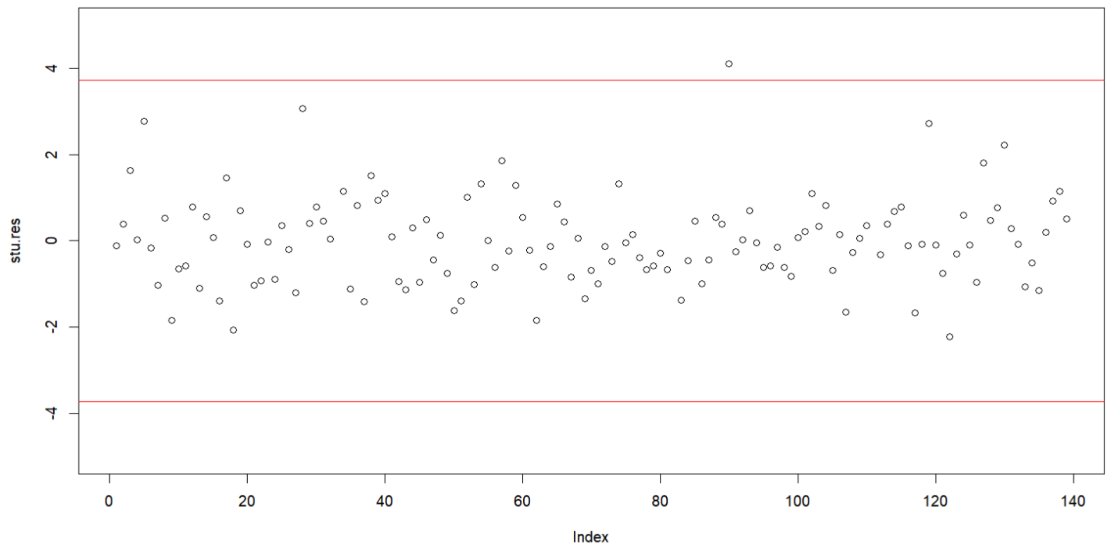
## Model Diagnostics for Full Model




We can see that the residual plot has a slightly curvy distribution, and the Q-Q plot also shows that some residuals does not follows a normal distribution.




The graph indicates that we need to drop one outlier.




## Variable Selection

- Predictors selected based on both AIC/BIC and OLS backward/both side elimination

Both the AIC/BIC and OLS results suggest we choose the same variables as below. Although the ANOVA results suggest that the original full model is better, the adjusted R^2 is actually about the same as the main model, and based on the principle of parsimoniousness, it is probably better to have the reduced one, as the main model has too many useless variables.

```
Call:
lm(formula = Reaction.time ~ Age + Visual.acuity + Device.OS +
    WiFi.stable, data = survey)

Residuals:
    Min      1Q  Median      3Q     Max
-94.471 -35.925  -6.979  21.512 190.496

Coefficients:
                                 Estimate Std. Error t value Pr(>|t|)
(Intercept)                       199.919     59.637   3.352 0.001054 **
Age                                 6.508      2.603   2.500 0.013678 *
Visual.acuityExcellent            -59.032     15.834  -3.728 0.000288 ***
Visual.acuityGood                 -51.430     15.891  -3.236 0.001541 **
Visual.acuityPoor                 -12.502     30.139  -0.415 0.678968
Visual.acuityVery Poor           -162.780     56.554  -2.878 0.004687 **
Device.OSDesktopcomputer-Windows  -79.942     26.899  -2.972 0.003536 **
Device.OSiPad(Tablet-IOS)         -43.949     34.460  -1.275 0.204499
Device.OSiPhone(Smartphone-IOS)    19.684     27.120   0.726 0.469280
Device.OSLaptop                   -13.178     22.544  -0.585 0.559872
WiFi.stableUnstable               -88.831     32.550  -2.729 0.007246 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 53.37 on 128 degrees of freedom
Multiple R-squared:  0.3235,    Adjusted R-squared:  0.2707
F-statistic: 6.121 on 10 and 128 DF,  p-value: 1.395e-07
```

# Discussion of Results and Conclusions

Our initial hypothesis posited that sleep duration and caffeine intake were primary predictors of reaction time. However, our findings contradicted this hypothesis, showing that these factors were not as influential as anticipated.

In conclusion, the choice of participation devices has a significant effect on reaction time, particularly for those who are using Windows desktops to complete the test. This result may be attributed to the fact that the majority of individuals prefer to use a desktop for gaming, particularly a desktop with a Windows system, rather than a laptop. Many video games necessitate that their players have a fast reaction time in order to gain an advantage during gaming matches.

Another noteworthy aspect is that visual acuity also has a considerable influence on reaction time. Higher visual acuity may allow for more rapid and precise detection of visual stimuli. The ability to see something clearly allows for a faster reaction time.

Other significant predictors, such as age, can be explained by the fact that as people age, they require more time to react than younger people. It is also apparent that individuals with poor WiFi connections will have a greater time lag, which will result in a higher reaction time during the test.

## Challenges

This project faced several challenges, including the small sample sizes for certain groups including device types, alcohol level and so on, which limited the generalizability of our findings. Additionally, isolating the impact of individual variables on reaction times proved complex due to the intertwined nature of factors like sleep, caffeine intake, and device usage.

## Future Prospect

We hypothesize that individual differences in reaction time are more significant than other factors. Therefore, we propose using paired data from the same individuals under different conditions as this approach may yield more accurate comparisons and results.