Regression Project

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What Data Set?

For our project, we are dealing with the GPA dataset. In this dataset, there is data from 366 college students, on 15 columns. These columns being,

- SAT Score
- Total Credit Hours Per Term
- **Cumulative GPA**
- Athletic Season
- First Semester
- Weighted GPA
- Verbal SAT to math ratio
- Term GPA
- High school class size
- Rank in high school class
- If they are female
- If they are black
- Percentile in high school
- If they play football

Description and Motivation of Analyses:

- We analyzed student data to see what factors influence cumulative GPA.
- Using regression models, we looked at how factors affects GPA, both individually and together, and whether some factors change the impact of others.
- The goal is to understand what drives academic performance and identify groups of students who may benefit from additional support.

Cleaning data

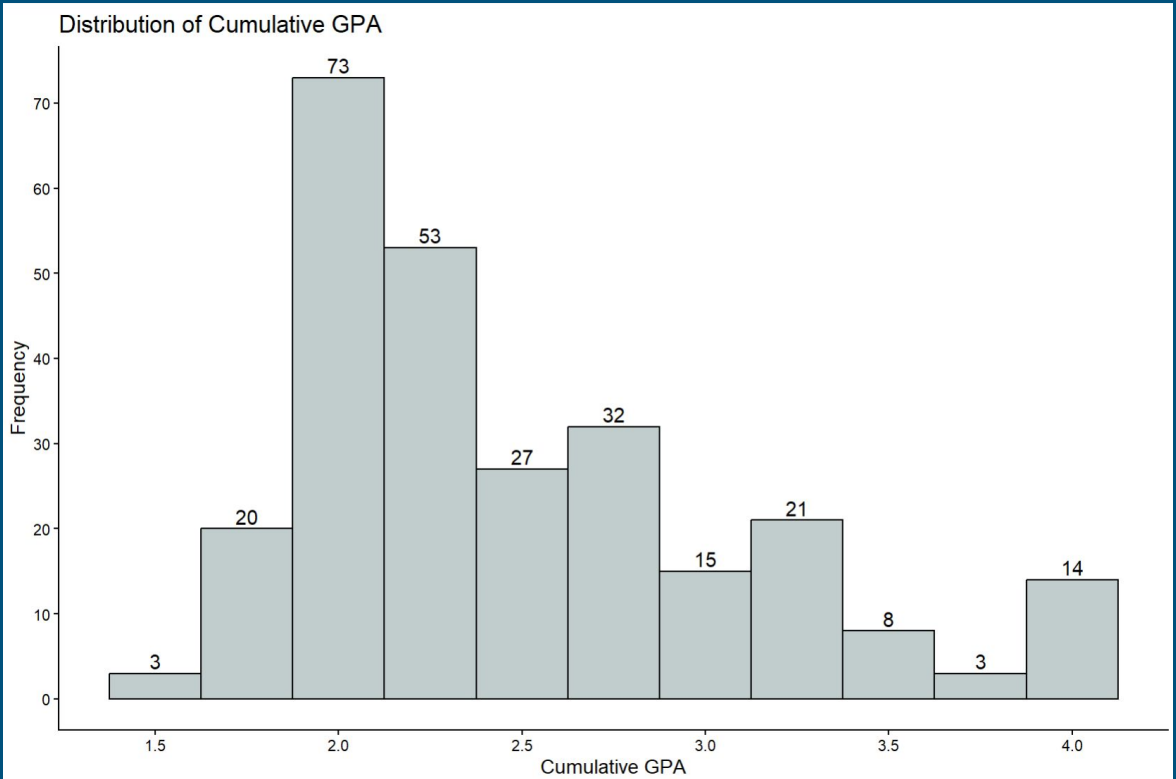
```r
# Check dataset
sum(is.na(GPA.data)) #0 NA's
view(GPA.data)
summary(GPA.data)
str(GPA.data) #all numeric

# Removes all 0 values in Cumulative GPA
Filtered_GPA_data <- GPA.data %>%
  filter(cumgpa != 0, !is.na(cumgpa))

# Convert categorical columns to factors
Filtered_GPA_data$season <- as.factor(Filtered_GPA_data$season)
Filtered_GPA_data$frstsem <- as.factor(Filtered_GPA_data$frstsem)
Filtered_GPA_data$female <- as.factor(Filtered_GPA_data$female)
Filtered_GPA_data$black <- as.factor(Filtered_GPA_data$black)
Filtered_GPA_data$white <- as.factor(Filtered_GPA_data$white)
Filtered_GPA_data$football <- as.factor(Filtered_GPA_data$football)

# Check for columns with only 1 value
sapply(Filtered_GPA_data, function(x) length(unique(x)))

# because frstsem has one 1 value, remove it from the data set
Master.GPA.data <- Filtered_GPA_data %>% select(-frstsem)

# Check filtered data
view(Master.GPA.data)
str(Master.GPA.data)
summary(Master.GPA.data)
```

```
> str(Filtered_GPA_data)
tibble [269 × 15] (S3: tbl_df/tbl/data.frame)
 $ sat     : num [1:269] 920 780 960 820 820 730 780 830 710 980 ...
 $ tothrs  : num [1:269] 31 28 91 25 30 34 59 62 120 35 ...
 $ cumgpa  : num [1:269] 2.25 2.03 2.35 2.12 1.93 ...
 $ season  : Factor w/ 2 levels "0","1": 1 1 2 2 2 2 2 2 2 2 ...
 $ frstsem : Factor w/ 1 level "0": 1 1 1 1 1 1 1 1 1 1 ...
 $ crsgpa  : num [1:269] 2.65 2.87 2.85 2.63 2.61 ...
 $ verbmath: num [1:269] 0.484 0.814 1 0.783 0.907 ...
 $ trmgpa  : num [1:269] 1.5 2.2 2.8 1.5 2.5 ...
 $ hssize  : num [1:269] 10 123 383 344 228 482 78 196 300 152 ...
 $ hsrank  : num [1:269] 4 102 66 36 155 273 17 54 226 45 ...
 $ female  : Factor w/ 2 levels "0","1": 2 1 1 2 1 1 1 1 1 1 ...
 $ black   : Factor w/ 2 levels "0","1": 1 1 1 2 1 2 1 2 2 2 ...
 $ white   : Factor w/ 2 levels "0","1": 1 2 2 1 2 1 2 1 1 1 ...
 $ hsperc  : num [1:269] 40 82.9 17.2 10.5 68 ...
 $ football: Factor w/ 2 levels "0","1": 1 1 1 1 1 2 2 1 2 2 ...
```

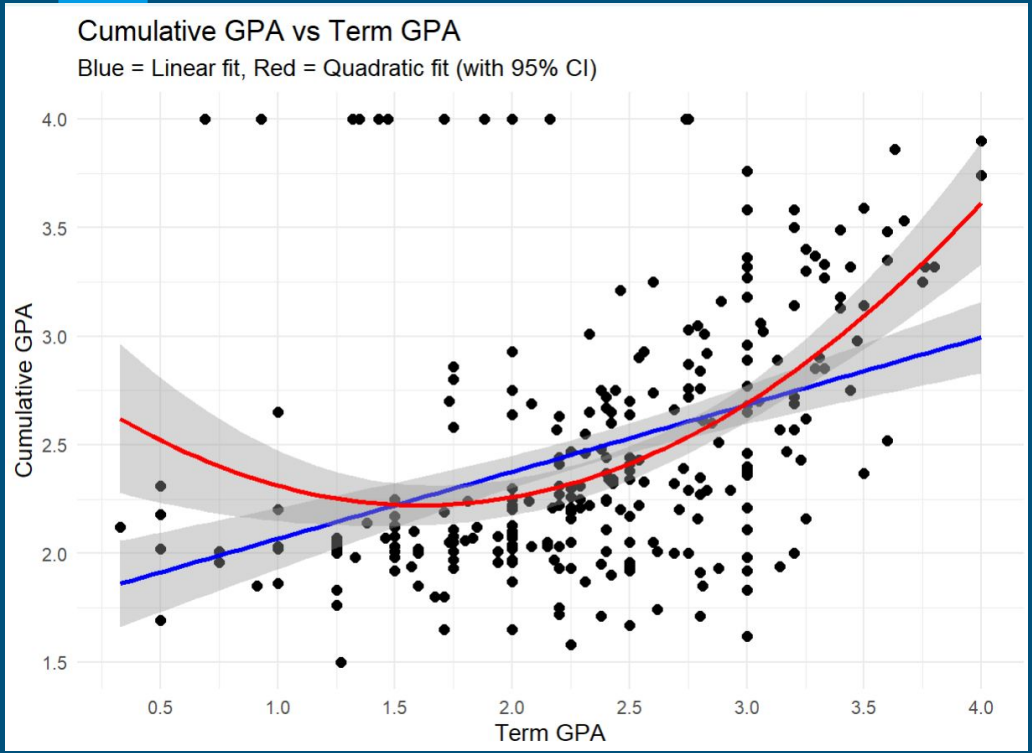
Identify Significant Variables

```
> summary(Everything_reg)

Call:
lm(formula = cumgpa ~ ., data = Master.GPA.data)

Residuals:
     Min       1Q   Median       3Q      Max
-1.28390 -0.31150 -0.02194  0.26339  1.78888

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.0621163  0.5772294   1.840 0.066927 .
sat          0.0006074  0.0002410   2.520 0.012349 *
tothrs      -0.0066636  0.0010888  -6.120 3.51e-09 ***
season      -0.0860712  0.0980053  -0.878 0.380645
crsgpa       0.2174252  0.1696083   1.282 0.201033
verbmath    -0.2787843  0.2067879  -1.348 0.178801
trmgpa       0.2253863  0.0575872   3.914 0.000117 ***
hssize       0.0003838  0.0003066   1.252 0.211746
hsrank      -0.0013537  0.0007361  -1.839 0.067058 .
female       0.3074157  0.0878382   3.500 0.000549 ***
black        0.3445385  0.1922989   1.792 0.074370 .
white        0.2342521  0.1829093   1.281 0.201462
hsperc       0.0003432  0.0029561   0.116 0.907668
football     0.3003614  0.0815191   3.685 0.000280 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4971 on 255 degrees of freedom
Multiple R-squared:  0.3453,    Adjusted R-squared:  0.3119
F-statistic: 10.35 on 13 and 255 DF,  p-value: < 2.2e-16
```

Distribution of Cumulative GPA

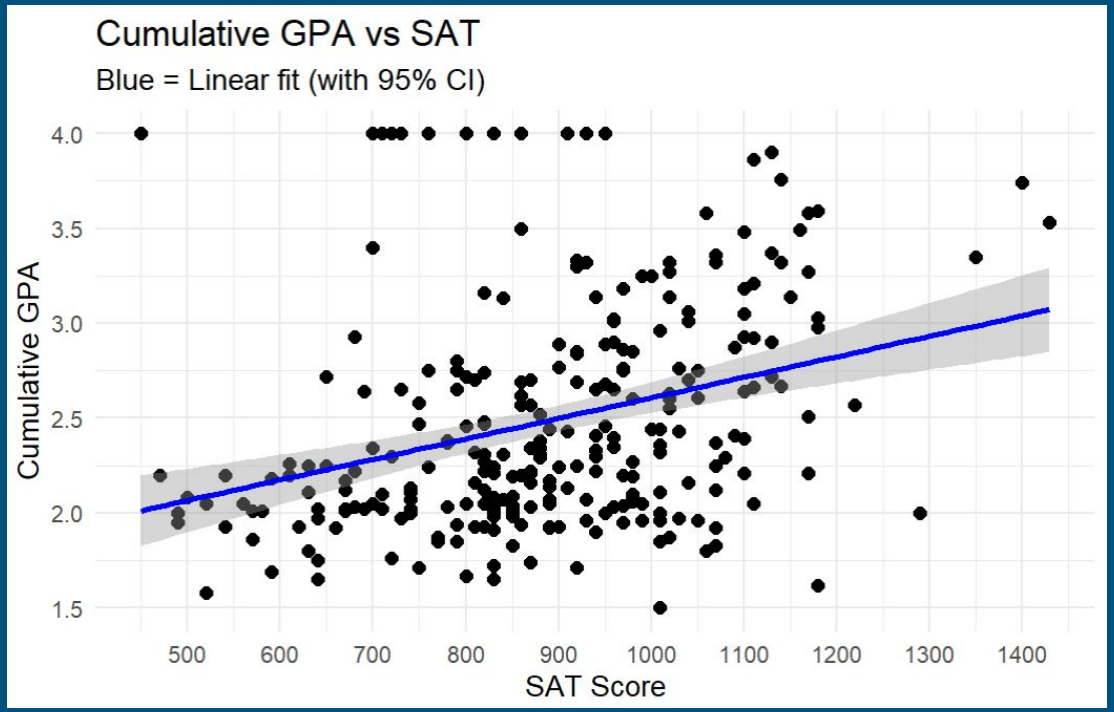


Simple Linear Regression - Cumulative GPA vs Term GPA



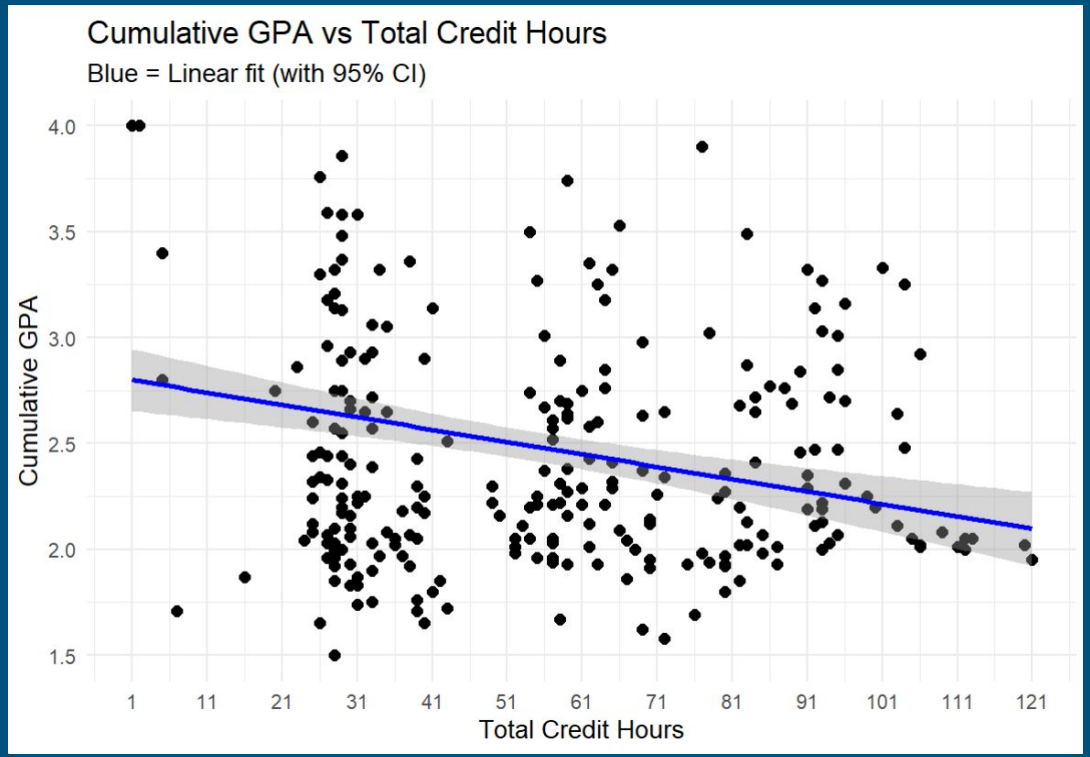

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.75821    0.11494  15.297  < 2e-16 ***
trmgpa       0.30892    0.04658   6.633 1.82e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5563 on 267 degrees of freedom
Multiple R-squared:  0.1415,    Adjusted R-squared:  0.1382
F-statistic: 43.99 on 1 and 267 DF,  p-value: 1.825e-10
```

Simple Linear Regression - Cumulative GPA vs SAT scores




```
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 1.5259990  0.1805214   8.453 1.86e-15 ***
sat         0.0010812  0.0001994   5.423 1.32e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5698 on 267 degrees of freedom
Multiple R-squared:  0.0992,    Adjusted R-squared:  0.09583
F-statistic:  29.4 on 1 and 267 DF,  p-value: 1.316e-07
```

Simple Linear Regression - Cumulative GPA vs Total Credit hours

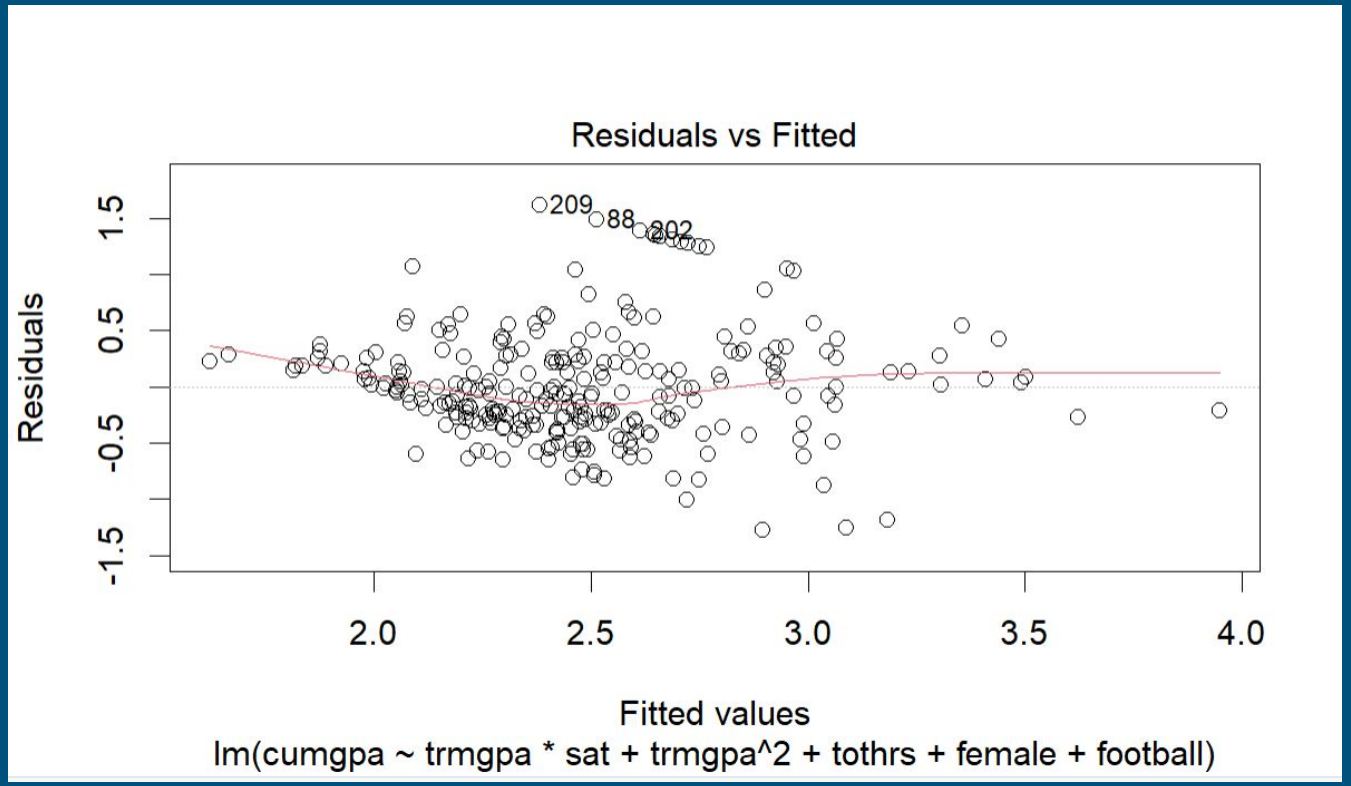



```
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.805473   0.075242  37.286  < 2e-16 ***
tothrs      -0.005852   0.001221  -4.792 2.74e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5761 on 267 degrees of freedom
Multiple R-squared:  0.07921,   Adjusted R-squared:  0.07576
F-statistic: 22.97 on 1 and 267 DF,  p-value: 2.737e-06
```

Create our Best Fit Model

```
> summary(best_fit_model)

Call:
lm(formula = cumgpa ~ trmgpa * sat + trmgpa^2 + tothrs + female +
    football, data = Master.GPA.data)

Residuals:
    Min      1Q  Median      3Q     Max
-1.2749 -0.2988 -0.0371  0.2563  1.6164

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.5762417  0.5330073   6.710 1.20e-10 ***
trmgpa      -0.5892897  0.2084249  -2.827 0.005056 **
sat         -0.0017641  0.0005997  -2.941 0.003560 **
tothrs      -0.0062564  0.0010545  -5.933 9.36e-09 ***
female       0.2942832  0.0812793   3.621 0.000353 ***
football     0.2183923  0.0759206   2.877 0.004351 **
trmgpa:sat   0.0009552  0.0002275   4.199 3.68e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.491 on 262 degrees of freedom
Multiple R-squared:  0.3435,    Adjusted R-squared:  0.3285
F-statistic: 22.85 on 6 and 262 DF,  p-value: < 2.2e-16
```

Test for Linearity of expectations



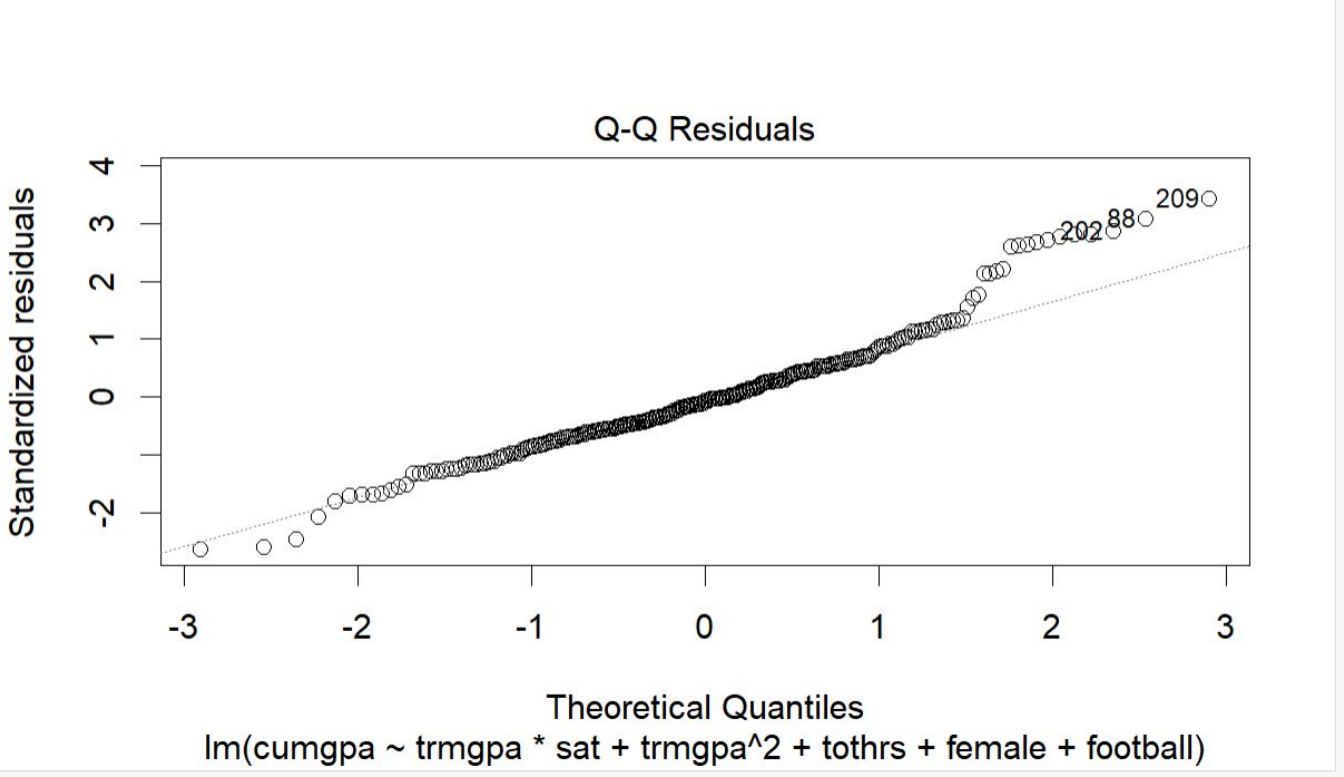
Test for Independence of Errors

```
> # test for independence of errors
> dwtest(best_fit_model) #dw is close to 2, no autocorrelation

        Durbin-Watson test

data:  best_fit_model
DW = 2.184, p-value = 0.9342
alternative hypothesis: true autocorrelation is greater than 0
```

Test for Heteroskedasticity

```
> # test for heteroskedasticity
> bptest(best_fit_model) # P-value < 0.05, we reject null, heteroskedasticity is present

        studentized Breusch-Pagan test

data:  best_fit_model
BP = 57.823, df = 6, p-value = 1.244e-10
```

Test for Normality



Test for Multicollinearity

```
> # Test for Multicollinearity
> vif(signif_reg)
     sat   tothrs   trmgpa   female footbal
1.447371 1.020858 1.652858 1.281310 1.378340
```

The best fit model, was not used to test multicollinearity

Conclusion/Next Steps/Recommendations

- Term GPA, SAT scores, and Total Credit Hours are the strongest predictors of cumulative GPA, with their effects varying across students, yet by themselves, they are not a strong predictor of the entire GPA.
- Determine the effects Gender and football has on GPA, then build models to visualize those effects.
- Collect more data/variables to build a better model, ex: Hours Spent studying, Time spent working, Household Income, Neighborhood location, etc...