DATA 608: Homework 1 (Baseball Regression)

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First, let's read in the provided dataset

Data Exploration

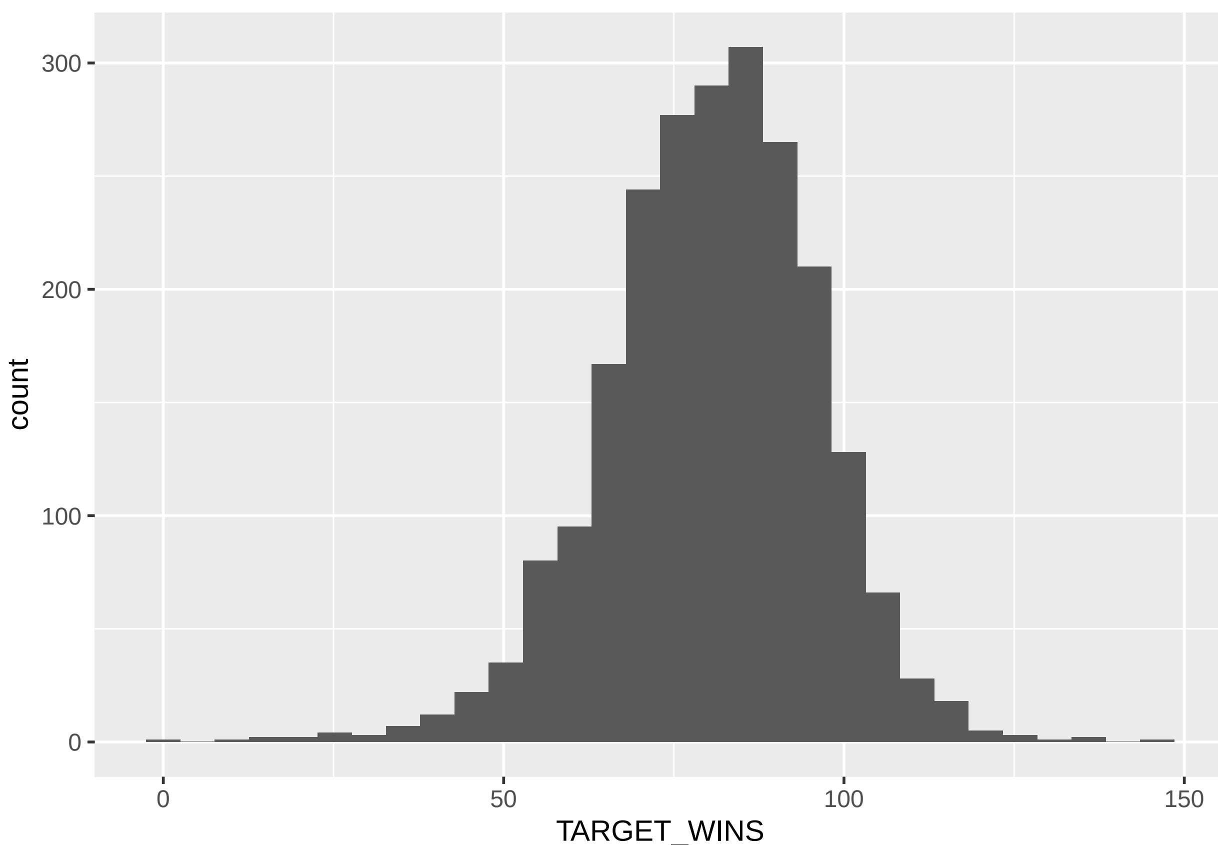
First, let's print out some summary statistics. We're primarily interested in the `TARGET_WINS` feature, so we'll look at that first

```
## The mean number of wins in a season is 80.7908611599297
```

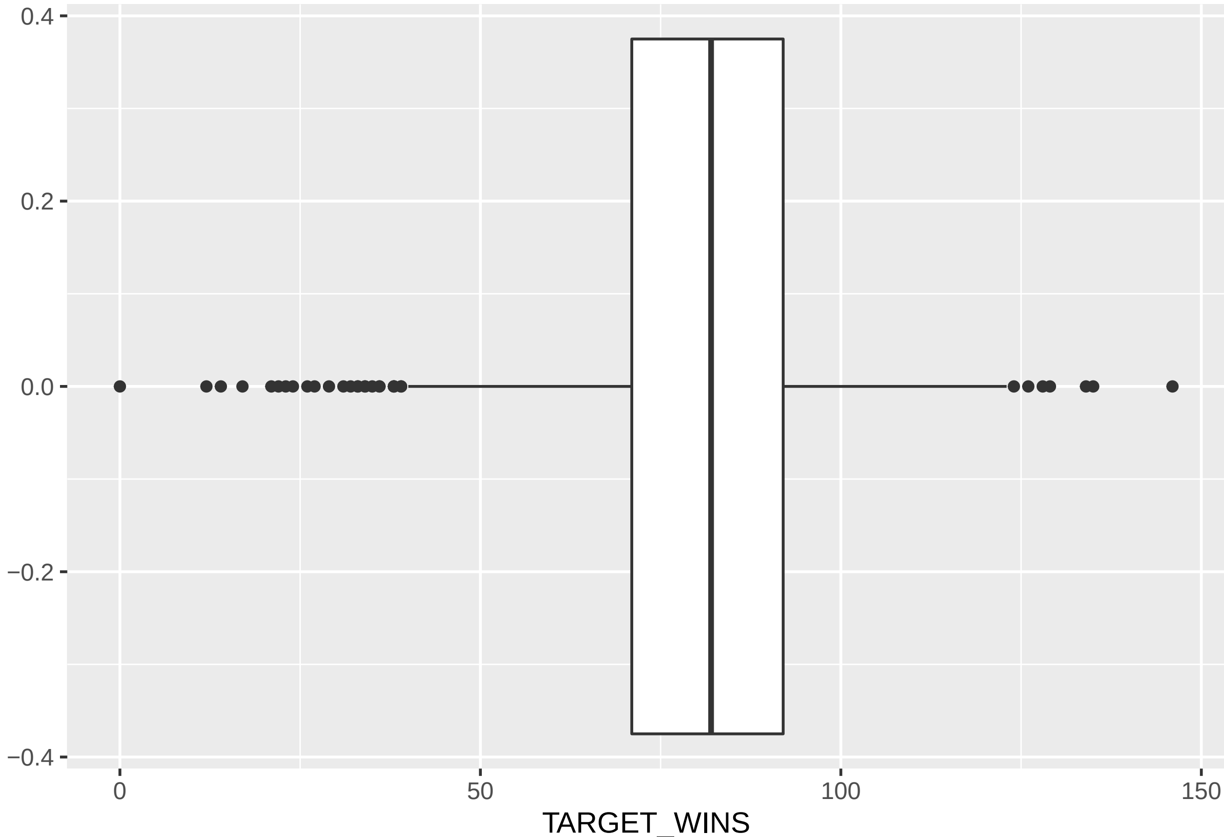
```
## The median number of wins in a season is 82
```

```
## The standard deviation for number of wins in a season is 15.7521524768421
```

Let's also make a boxplot and histogram of the `TARGET_WINS` variable. This should give us a sense of the distribution of wins for teams/seasons in our population



Overall, the number of wins in a season for a given baseball team looks fairly normally distributed. We can also plot this distribution via a boxplot, which helps to highlight outliers.



Let's look at raw correlations between our other included variables and a team's win total for a season:

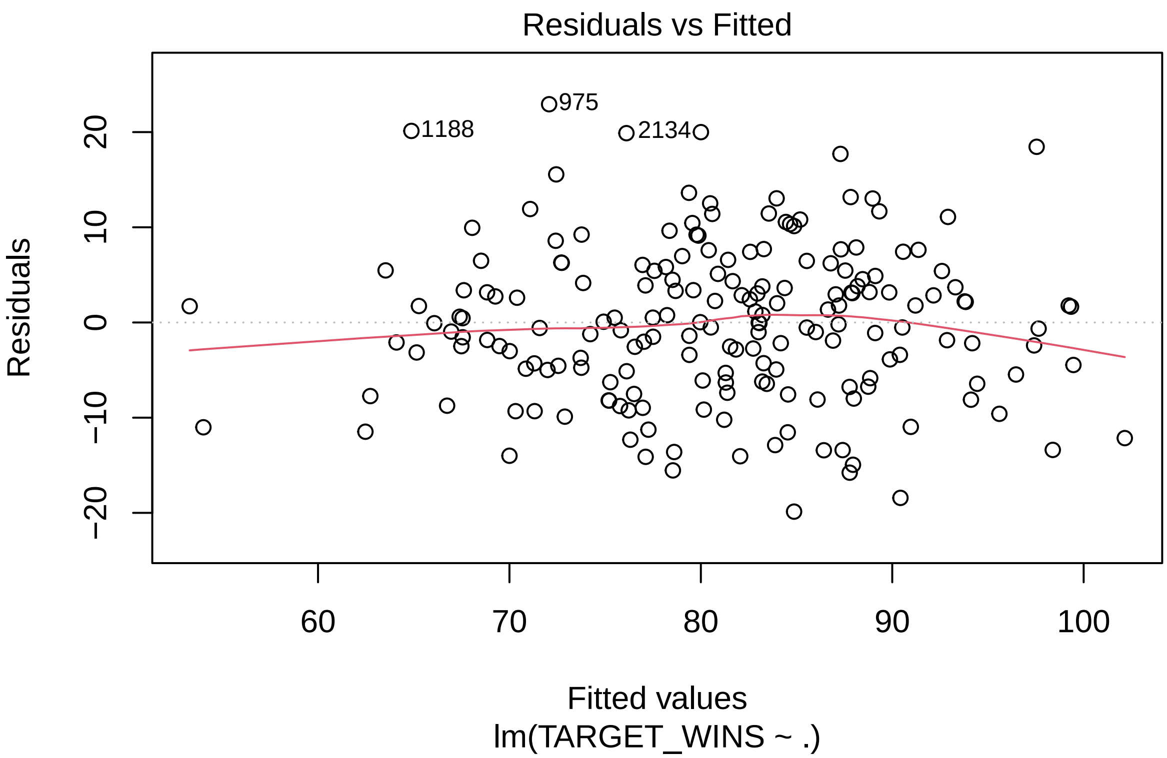
```
##                        [,1]
## TARGET_WINS       1.0000000
## TEAM_BATTING_H    0.3887675
## TEAM_BATTING_2B   0.2891036
## TEAM_BATTING_3B   0.1426084
## TEAM_BATTING_HR   0.1761532
## TEAM_BATTING_BB   0.2325599
## TEAM_BATTING_SO          NA
## TEAM_BASERUN_SB          NA
## TEAM_BASERUN_CS          NA
## TEAM_BATTING_HBP         NA
## TEAM_PITCHING_H  -0.1099371
## TEAM_PITCHING_HR  0.1890137
## TEAM_PITCHING_BB  0.1241745
## TEAM_PITCHING_SO         NA
## TEAM_FIELDING_E  -0.1764848
## TEAM_FIELDING_DP         NA
```

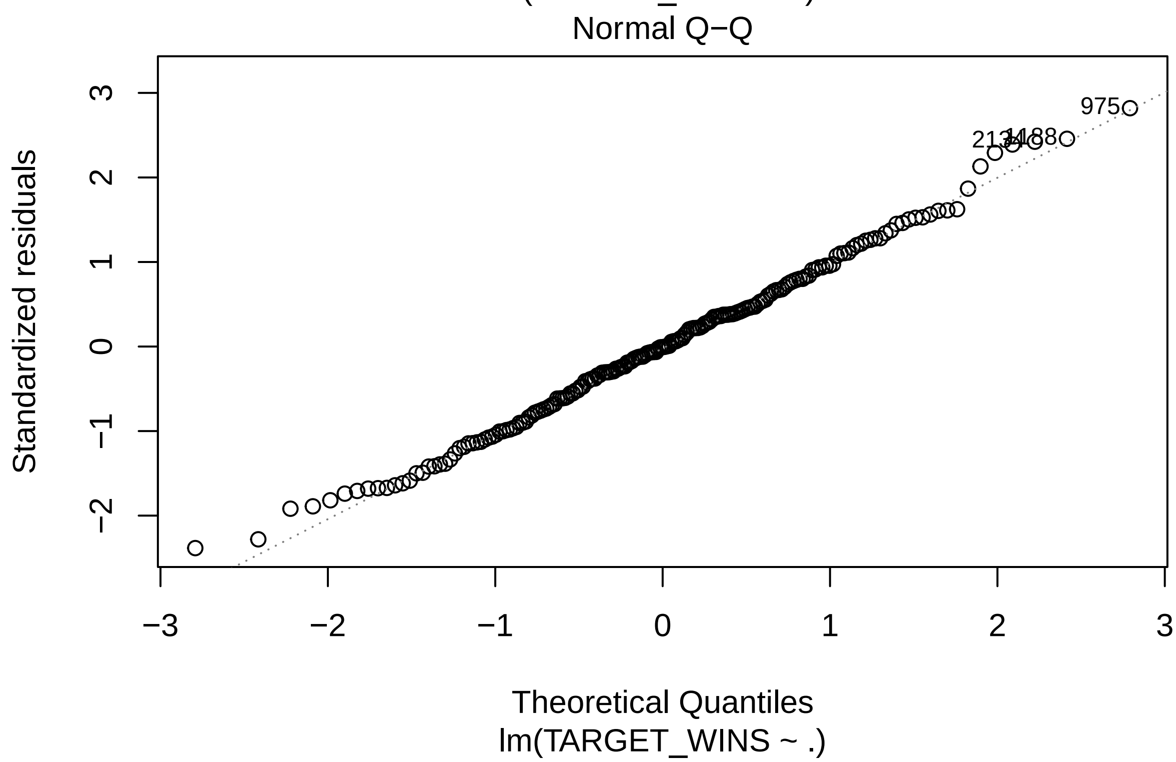
Let's make a basic model with some offensive inputs (hits, 2B, 3B, Home Runs)

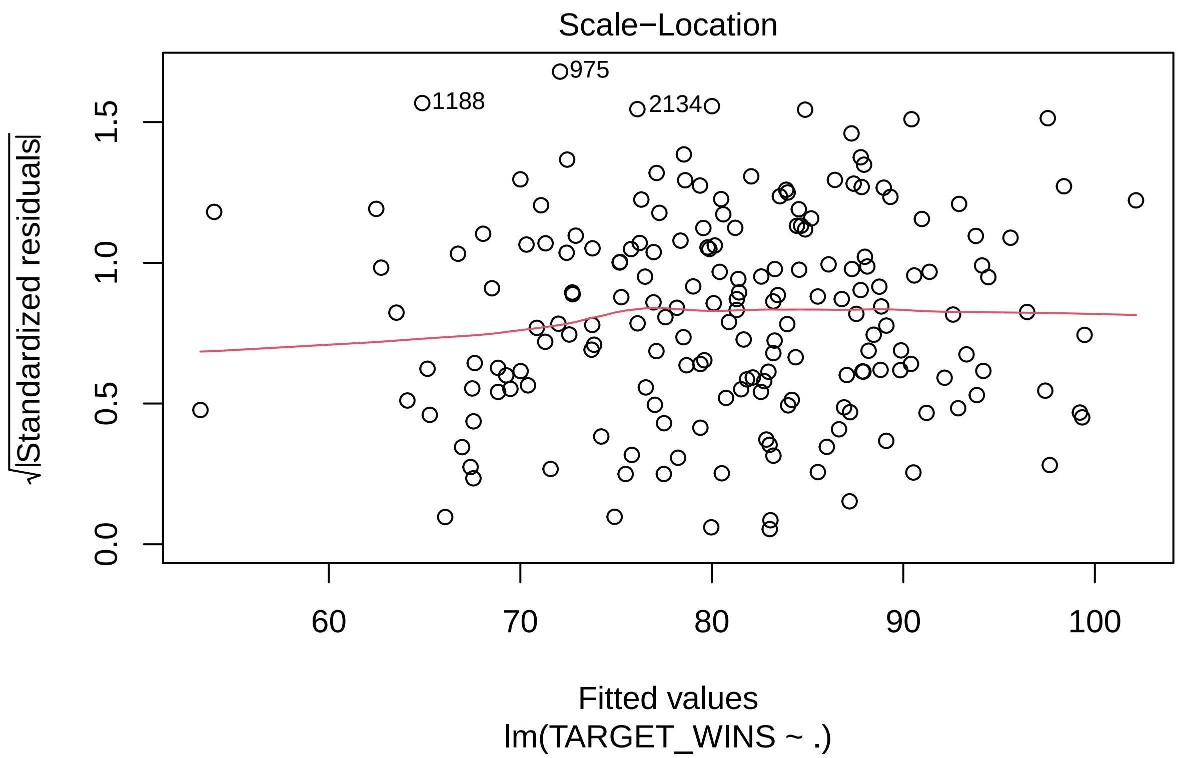
```
##
## Call:
```

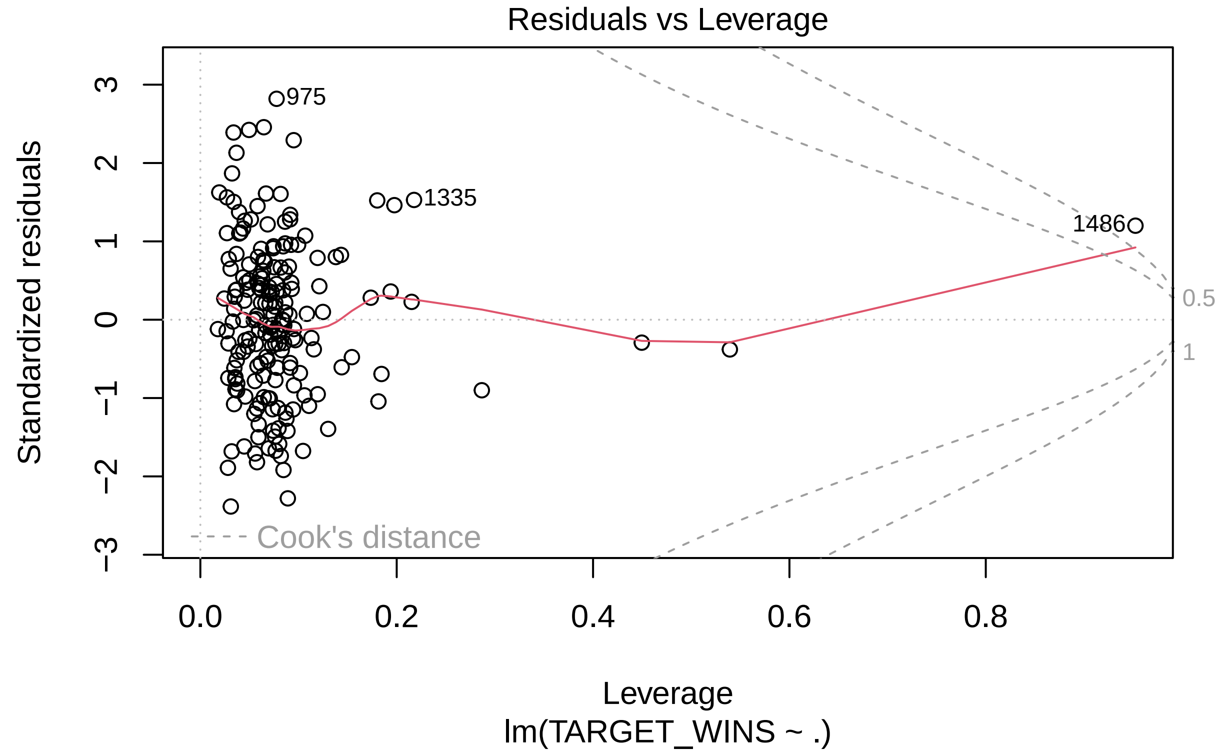
```
## lm(formula = TARGET_WINS ~ ., data = train)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -19.8708  -5.6564  -0.0599   5.2545  22.9274
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)       60.28826   19.67842   3.064  0.00253 **
## TEAM_BATTING_H     1.91348    2.76139   0.693  0.48927
## TEAM_BATTING_2B    0.02639    0.03029   0.871  0.38484
## TEAM_BATTING_3B   -0.10118    0.07751  -1.305  0.19348
## TEAM_BATTING_HR   -4.84371   10.50851  -0.461  0.64542
## TEAM_BATTING_BB   -4.45969    3.63624  -1.226  0.22167
## TEAM_BATTING_SO    0.34196    2.59876   0.132  0.89546
## TEAM_BASERUN_SB    0.03304    0.02867   1.152  0.25071
## TEAM_BASERUN_CS   -0.01104    0.07143  -0.155  0.87730
## TEAM_BATTING_HBP   0.08247    0.04960   1.663  0.09815 .
## TEAM_PITCHING_H   -1.89096    2.76095  -0.685  0.49432
## TEAM_PITCHING_HR   4.93043   10.50664   0.469  0.63946
## TEAM_PITCHING_BB   4.51089    3.63372   1.241  0.21612
## TEAM_PITCHING_SO  -0.37364    2.59705  -0.144  0.88577
## TEAM_FIELDING_E   -0.17204    0.04140  -4.155 5.08e-05 ***
## TEAM_FIELDING_DP  -0.10819    0.03654  -2.961  0.00349 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 8.467 on 175 degrees of freedom
##   (2085 observations deleted due to missingness)
## Multiple R-squared:  0.5501, Adjusted R-squared:  0.5116
## F-statistic: 14.27 on 15 and 175 DF,  p-value: < 2.2e-16
```

We can make some plots to help test our assumptions of our basic model using the `plot` function on our model variable


Residuals vs Fitted
975
1188
2134
Residuals
20
10
0
−10
−20
60
70
80
90
100
Fitted values
lm(TARGET_WINS ~ .)


Normal Q−Q
975
2134
1188
Standardized residuals
3
2
1
0
−1
−2
−3
−2
−1
0
1
2
3
Theoretical Quantiles
lm(TARGET_WINS ~ .)



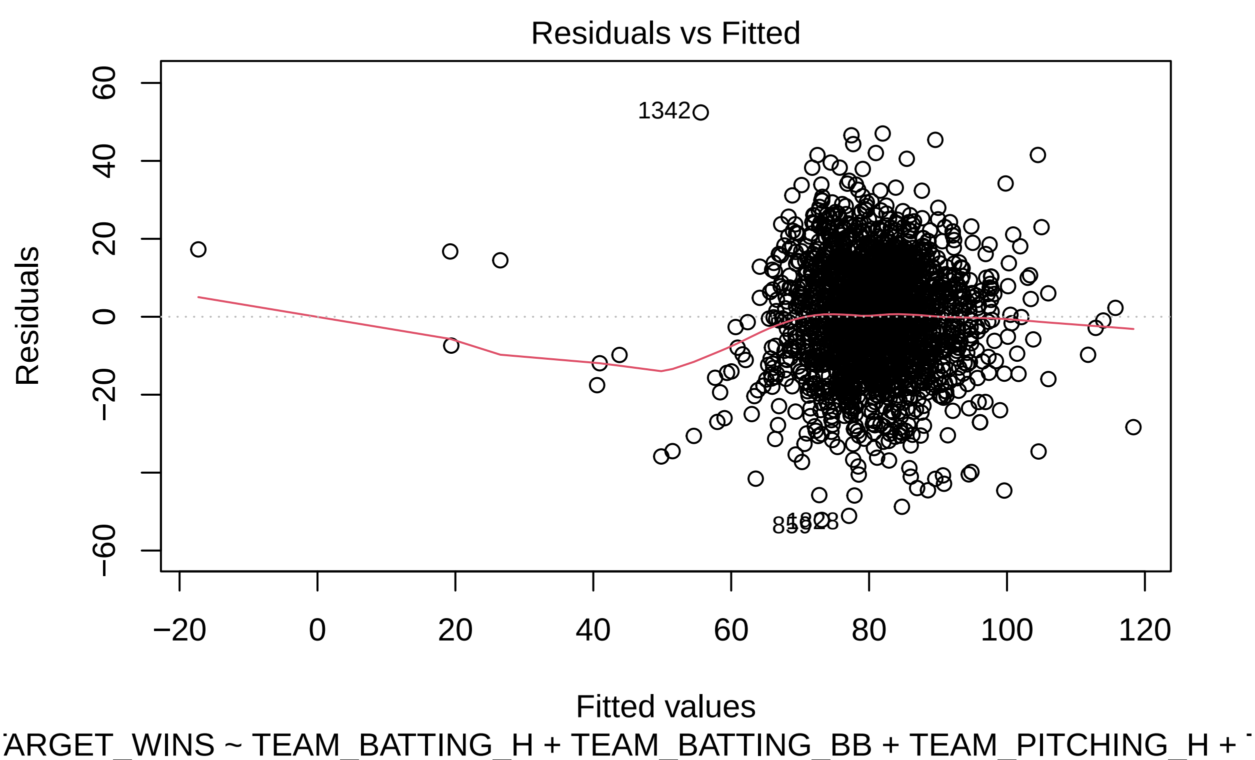


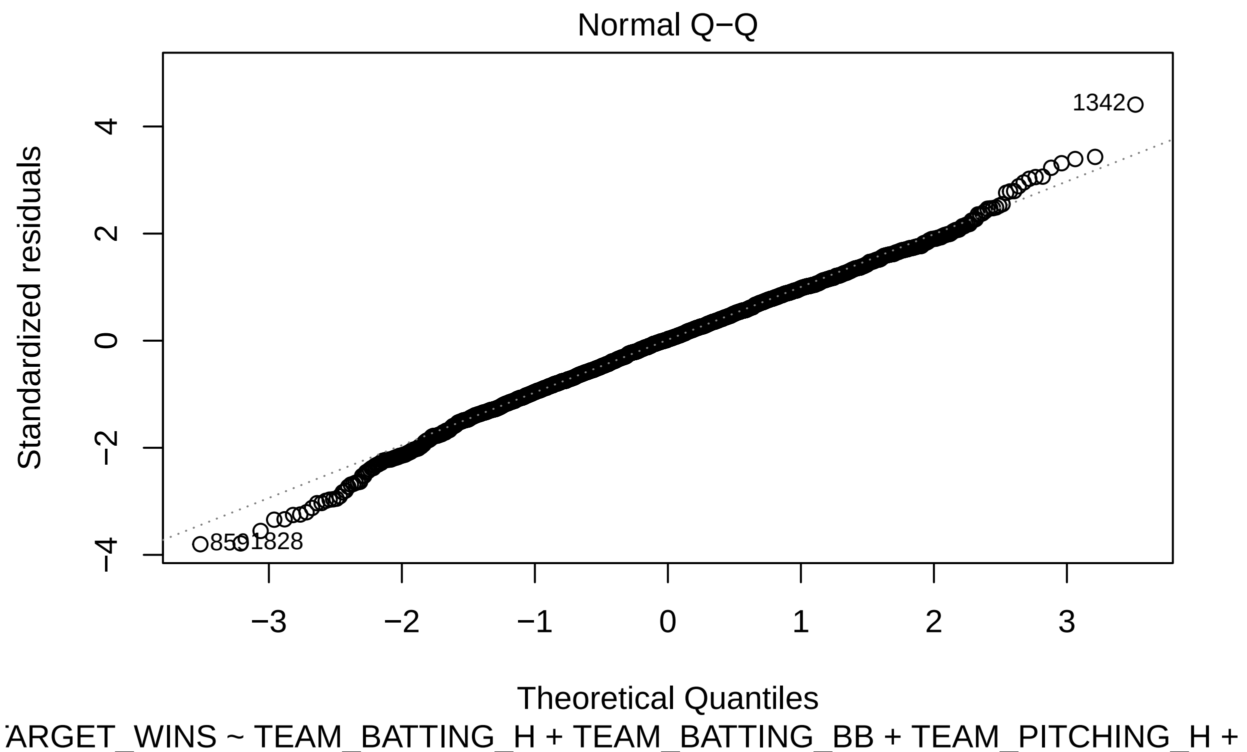
Now we can make a model with inputs that we know from baseball.

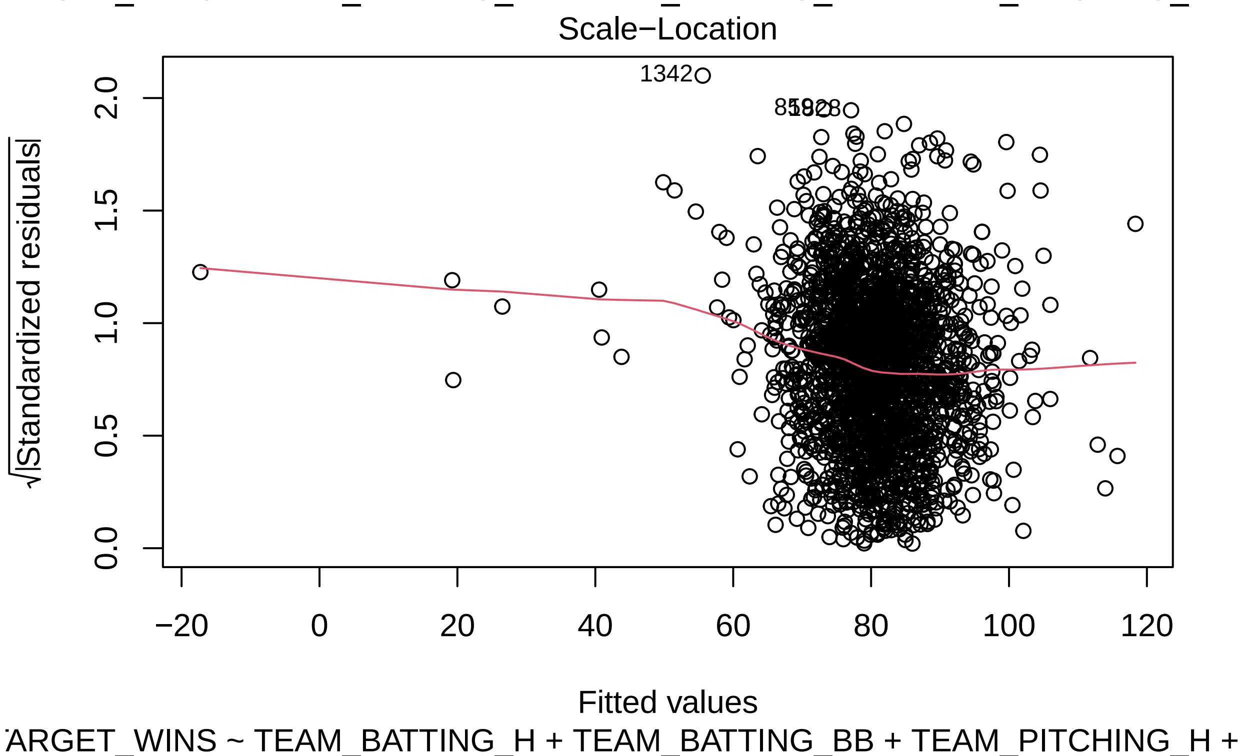
- Total hits (`TEAM_BATTING_H`)
- Total walks gained (`TEAM_BATTING_BB`)
- Total hits allowed (`TEAM_PITCHING_H`)
- Total walks allowed (`TEAM_PITCHING_BB`)

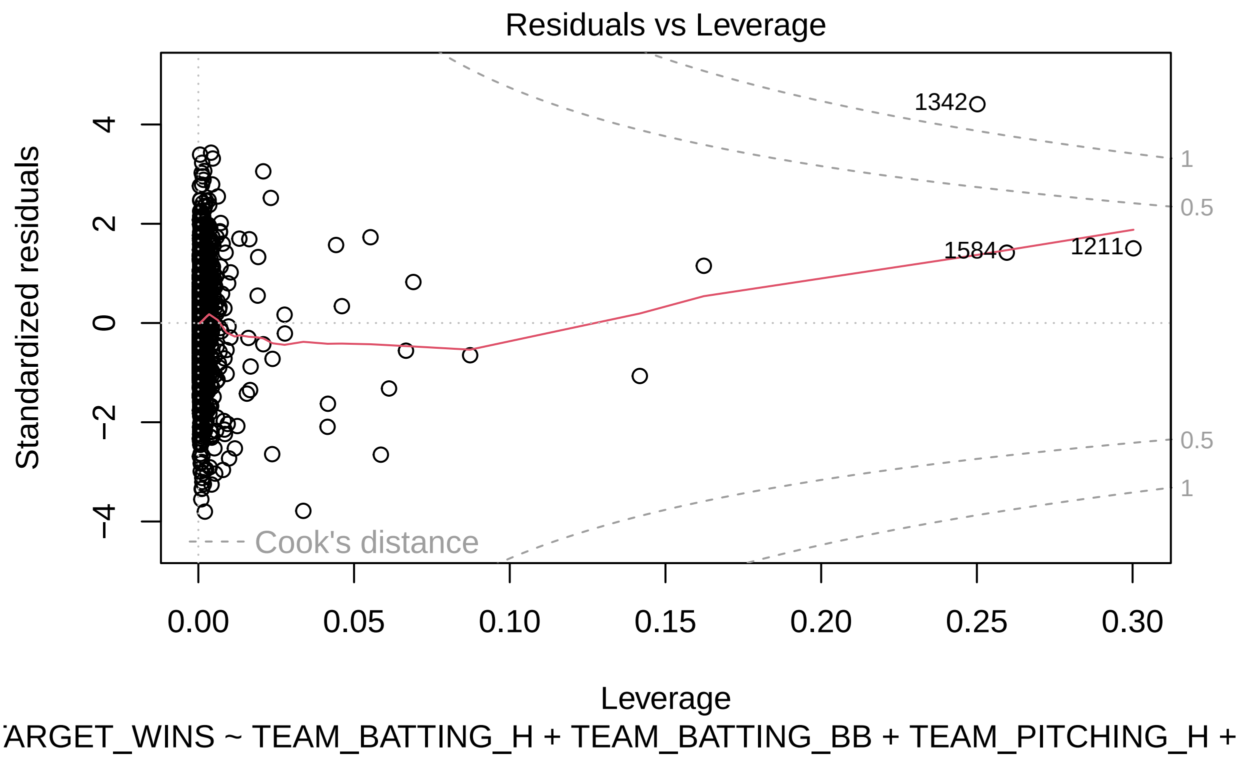
The thinking being here that good teams generally tend to get on base more frequently (`TEAM_BATTING_HITS` and `TEAM_BATTING_BB`) while allowing *fewer* runners on base (Negative predictor variables `TEAM_PITCHING_H` and `TEAM_PITCHING_BB`)

```
##
## Call:
## lm(formula = TARGET_WINS ~ TEAM_BATTING_H + TEAM_BATTING_BB +
##     TEAM_PITCHING_H + TEAM_PITCHING_BB, data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -52.133  -8.860   0.379   9.373  52.416
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -0.3518000  3.2552864  -0.108 0.913949
## TEAM_BATTING_H    0.0497667  0.0021032  23.663  < 2e-16 ***
## TEAM_BATTING_BB   0.0148499  0.0039923   3.720 0.000204 ***
## TEAM_PITCHING_H  -0.0025469  0.0003317  -7.679 2.36e-14 ***
## TEAM_PITCHING_BB  0.0092317  0.0027681   3.335 0.000867 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 13.73 on 2271 degrees of freedom
## Multiple R-squared:  0.2416, Adjusted R-squared:  0.2403
## F-statistic: 180.9 on 4 and 2271 DF,  p-value: < 2.2e-16
```



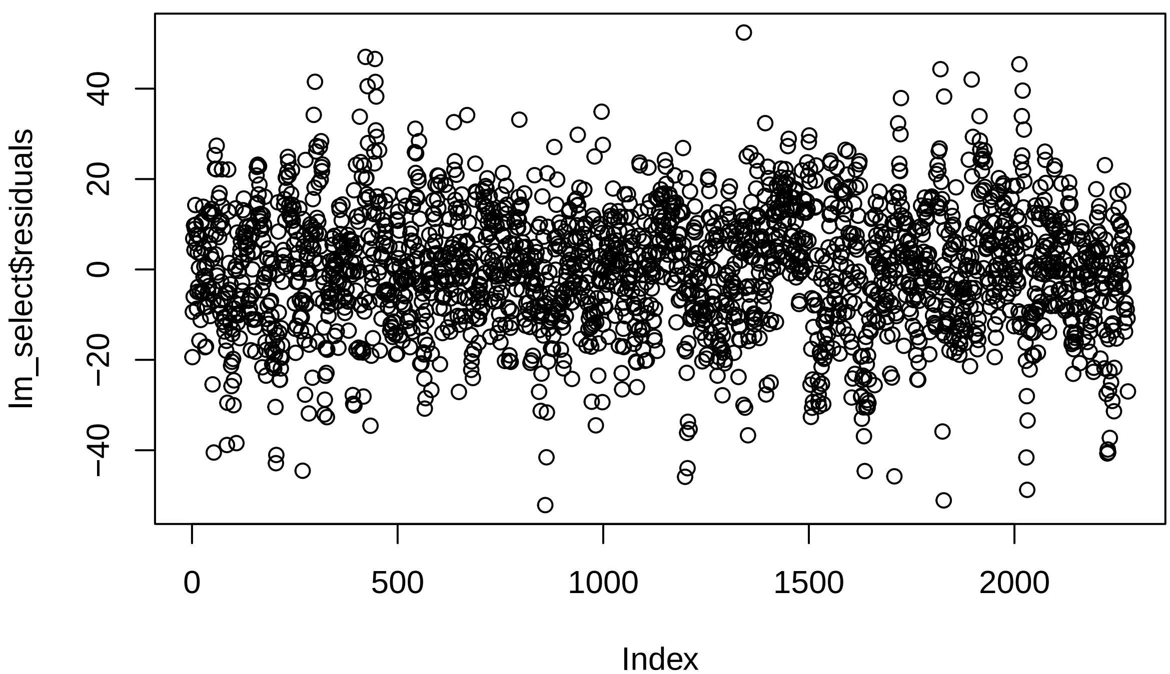

Normal Q−Q
Standardized residuals
Theoretical Quantiles
ARGET_WINS ~ TEAM_BATTING_H + TEAM_BATTING_BB + TEAM_PITCHING_H +
1342
1828


Scale−Location
√|Standardized residuals|
Fitted values
ARGET_WINS ~ TEAM_BATTING_H + TEAM_BATTING_BB + TEAM_PITCHING_H +
1342

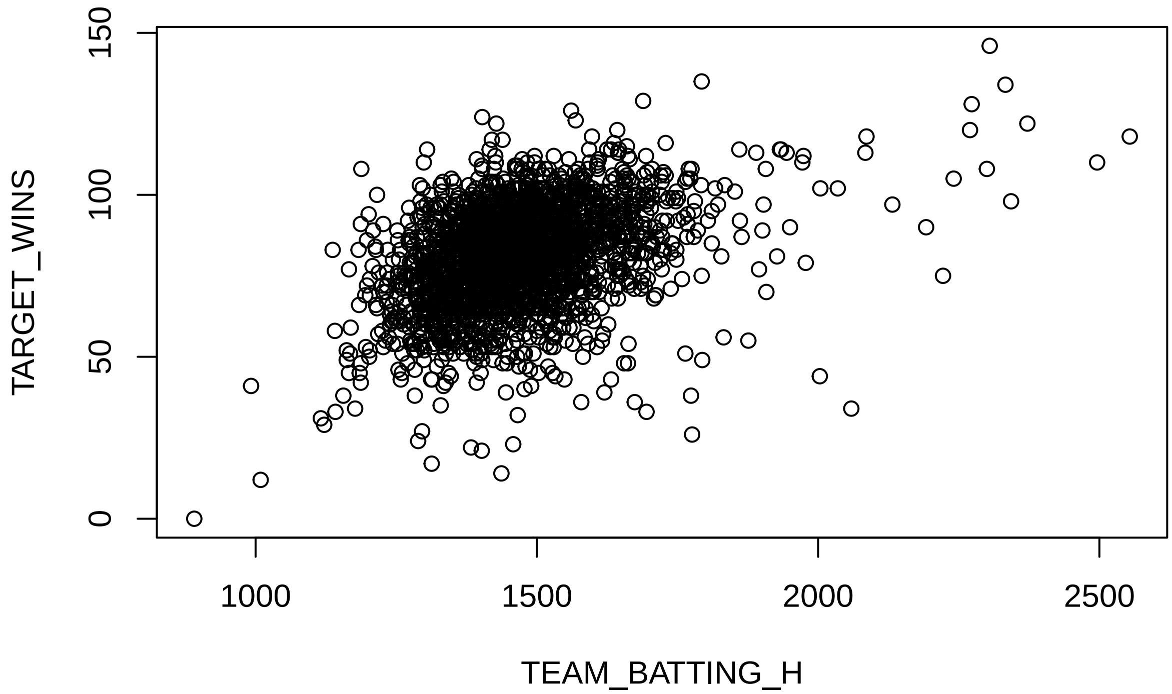


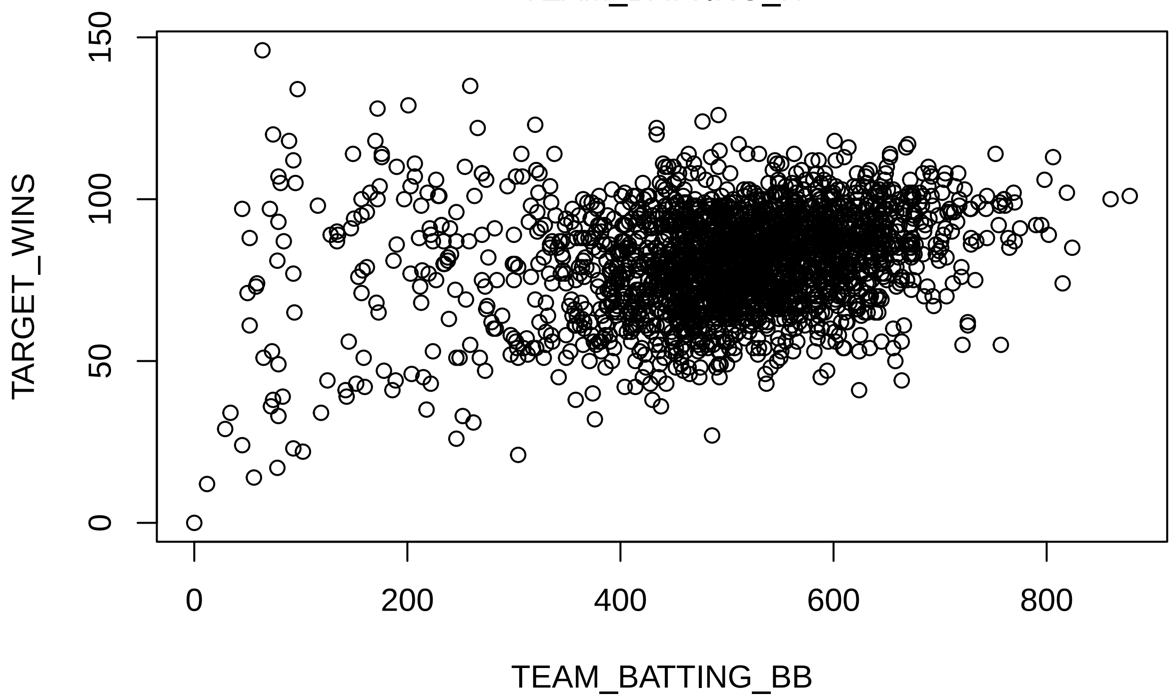
It's interesting to not that with selected variables (walks and hits gained/allowed per team) that our adjusted R^2 actually went *down*, indicating the amount of variability in `TARGET_WINS` explained by our more selective walks/hits model is *less* than the model including all variables.

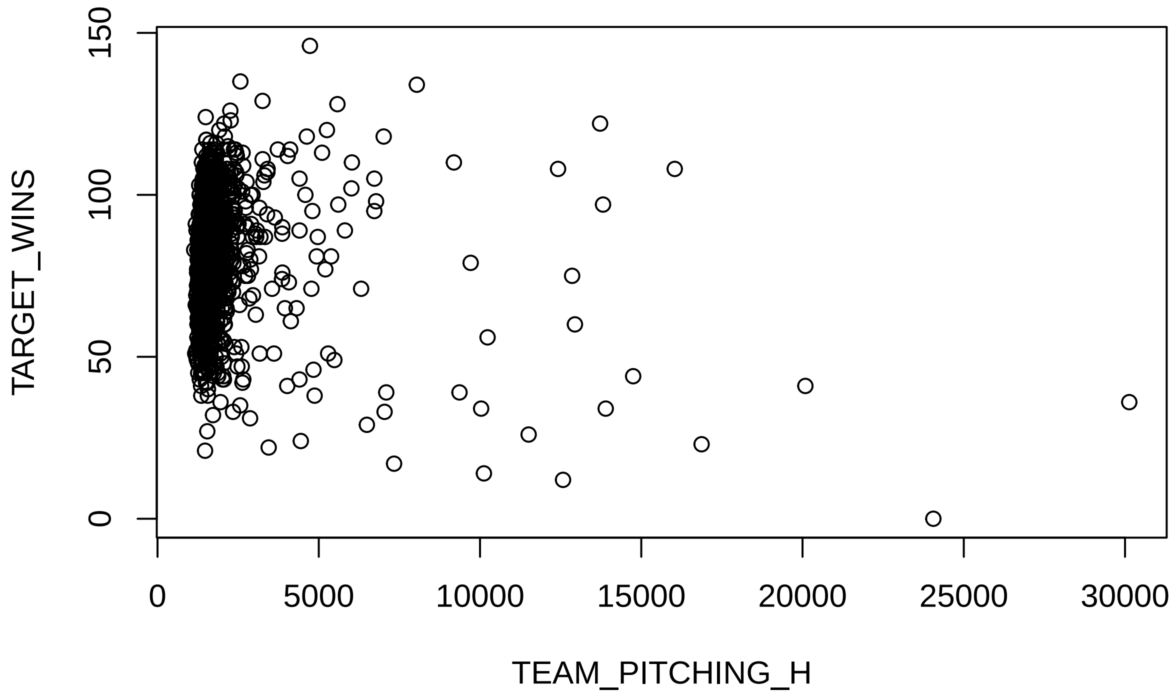
Looking at our residual plot above, there seems to be a clustering of residuals along the x-axis at $X \approx 80$. This shows a pattern in our residuals

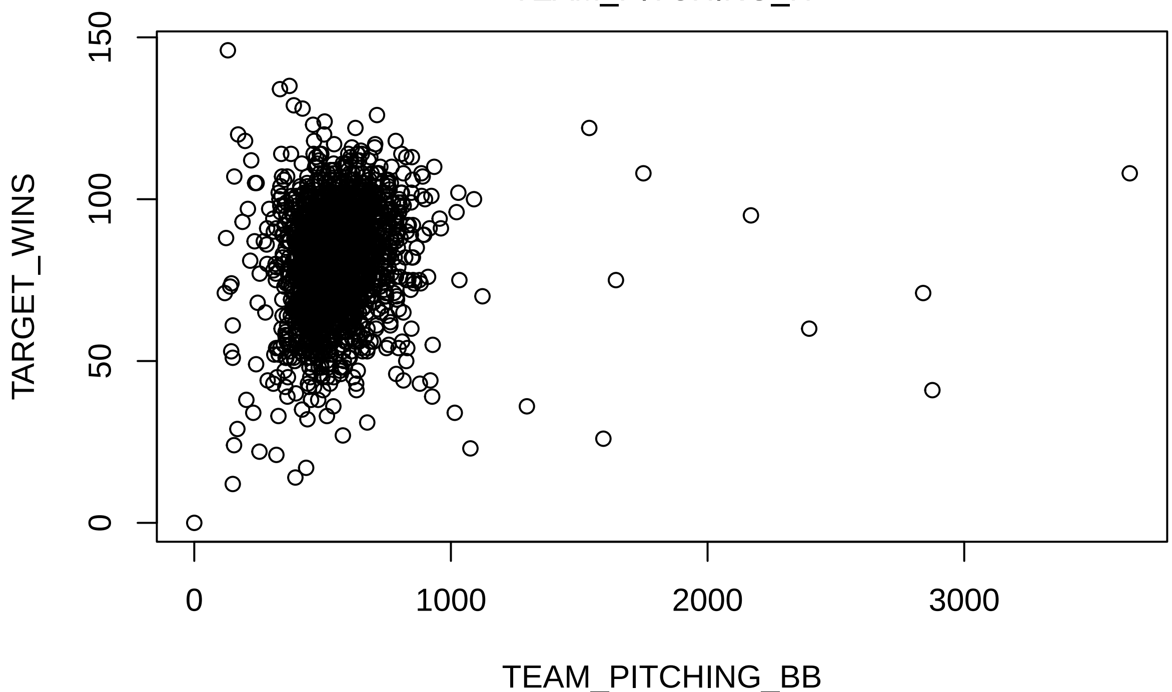


Let's plot our response variable (*Total Wins*) versus each of our predictor variables to get a sense of linear relationships


TARGET_WINS
TEAM_BATTING_H
0
50
100
150
1000
1500
2000
2500


TARGET_WINS
TEAM_BATTING_BB
0
50
100
150
0
200
400
600
800





Model Evaluation

We'll need to read in our evaluation data, which is hosted on GitHub for reproduceability.

Appendix: Report Code

Below is the code for this report to generate the models and charts above

```r
knitr::opts_chunk$set(echo = TRUE)
library(glue)
library(tidyverse)
library(car)
df <- read.csv("https://raw.githubusercontent.com/andrewbowen19/businessAnalyticsDataMiningDATA621/main/
df <- data.frame(df)
mean_wins <- mean(df$TARGET_WINS)
median_wins <- median(df$TARGET_WINS)
sd_wins <- sd(df$TARGET_WINS)

# Print summary stats
print(glue("The mean number of wins in a season is {mean_wins}"))
print(glue("The median number of wins in a season is {median_wins}"))
print(glue("The standard deviation for number of wins in a season is {sd_wins}"))
ggplot(df, aes(x=TARGET_WINS)) + geom_histogram()
ggplot(df, aes(x=TARGET_WINS)) + geom_boxplot()
train <- subset(df, select=-c(INDEX))
cor(train, df$TARGET_WINS)
lm_all <- lm(TARGET_WINS~., train)
summary(lm_all)
plot(lm_all)

# Create model with select inputs (walks and hits allowed/gained)
lm_select <- lm(TARGET_WINS ~ TEAM_BATTING_H + TEAM_BATTING_BB + TEAM_PITCHING_H + TEAM_PITCHING_BB, tra

summary(lm_select)
plot(lm_select)

# Plot selective model residuals
plot(lm_select$residuals)


# Plot our response variable for each predictor variable to get a sense of
plot(TARGET_WINS ~ TEAM_BATTING_H + TEAM_BATTING_BB + TEAM_PITCHING_H + TEAM_PITCHING_BB, data=train)

eval_data_url <- "https://raw.githubusercontent.com/andrewbowen19/businessAnalyticsDataMiningDATA621/ma

test <- read.csv(eval_data_url)
```