DATA 621: Homework 1 (Baseball Regression)

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Setup:

First, let's read in the provided dataset.

Data Exploration:

```
## The dataset consists of 2276 observations of 17 variables.
```

The variables and their definitions can be seen below:

Variable	Definition
INDEX	Identification variable
TARGET_WINS	Number of wins
TEAM_BATTING_H	Base hits by batters (1B, 2B, 3B, HR)
TEAM_BATTING_2B	Doubles by batters (2B)
TEAM_BATTING_3B	Triples by batters (3B)
TEAM_BATTING_HR	Homeruns by batters (4B)
TEAM_BATTING_BB	Walks by batters
TEAM_BATTING_HBP	Batters hit by pitch (get a free base)
TEAM_BATTING_SO	Strikeouts by batters
TEAM_BASERUN_SB	Stolen bases
TEAM_BASRUN_CS	Caught stealing
TEAM_FIELDING_E	Errors
TEAM_FIELDING_DP	Double plays
TEAM_PITCHING_BB	Walks allowed
TEAM_PITCHING_H	Hits allowed
TEAM_PITCHING_HR	Homeruns allowed
TEAM_PITCHING_SO	Strikeouts by pitchers

INDEX is an identifying feature and should not be included in the linear regression model.

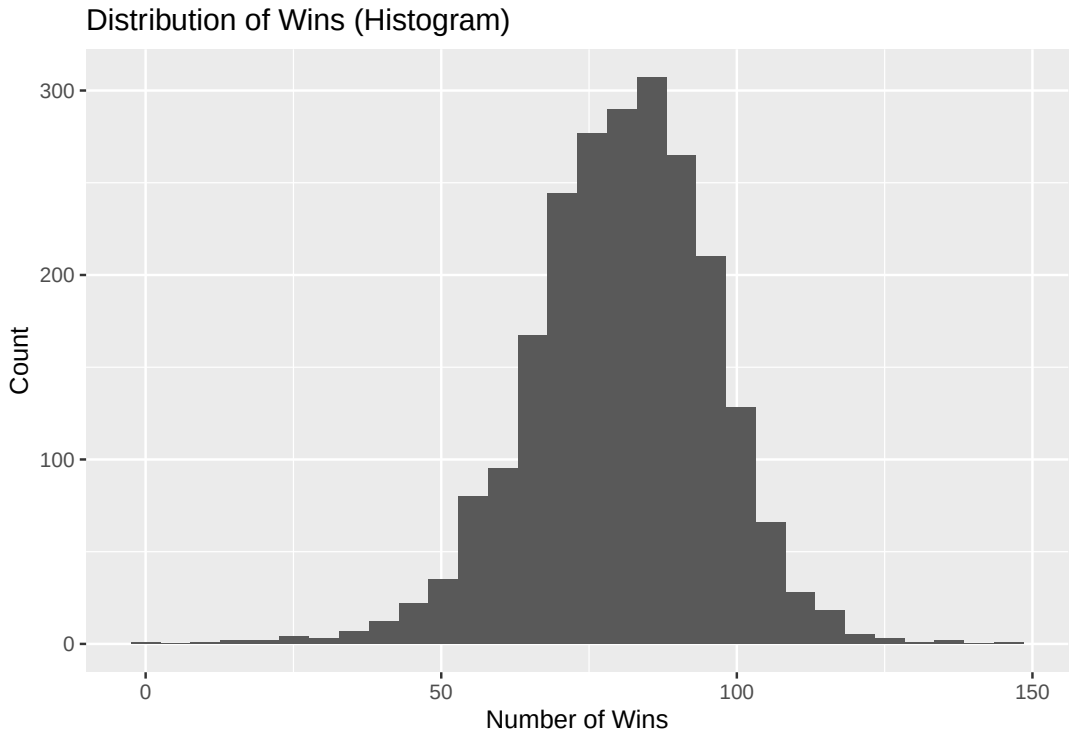
Next, let's print out some summary statistics. We're primarily interested in the TARGET_WINS variable, so we'll look at that first.

```
## The mean number of wins in a season is 80.79.
```

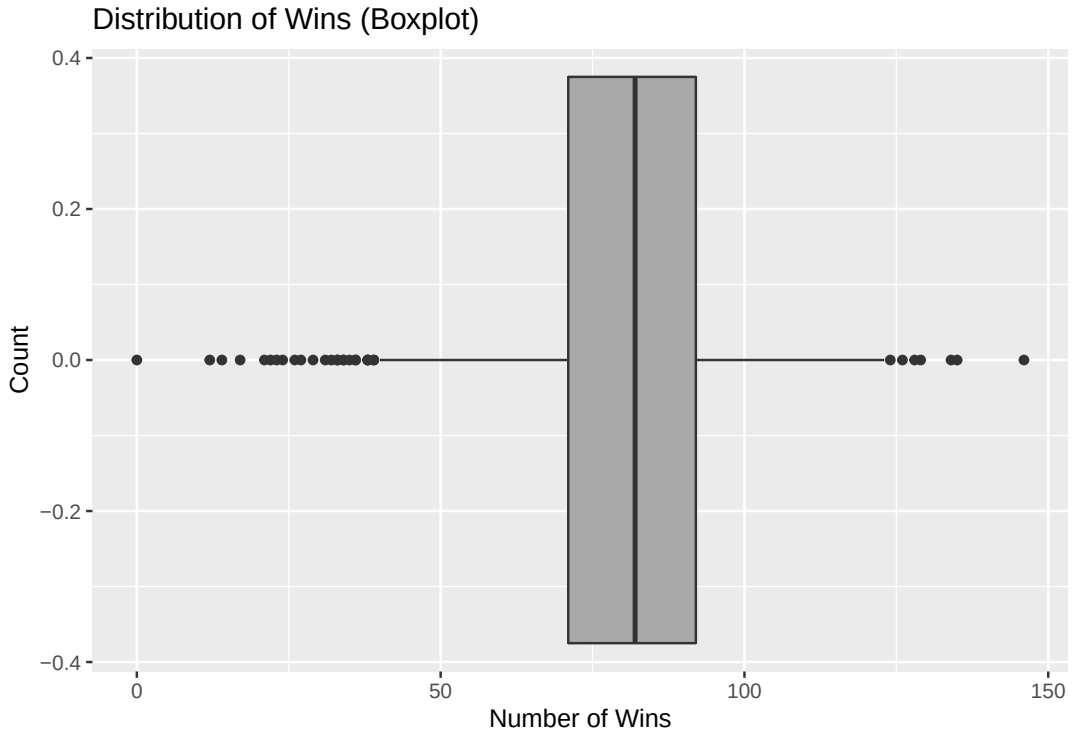
```
## The median number of wins in a season is 82.
```

```
## The standard deviation for number of wins in a season is 15.75.
```

Let's also make a 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. Looking at a boxplot helps to highlight the outliers.



We could describe the average team's season using the mean for all variables below:

TARGET_WINS	80.8
TEAM_BATTING_H	1469.3
TEAM_BATTING_2B	241.2
TEAM_BATTING_3B	55.2
TEAM_BATTING_HR	99.6
TEAM_BATTING_BB	501.6
TEAM_BATTING_SO	735.6
TEAM_BASERUN_SB	124.8
TEAM_BASERUN_CS	52.8
TEAM_BATTING_HBP	59.4
TEAM_PITCHING_H	1779.2
TEAM_PITCHING_HR	105.7
TEAM_PITCHING_BB	553.0
TEAM_PITCHING_SO	817.7
TEAM_FIELDING_E	246.5
TEAM_FIELDING_DP	146.4

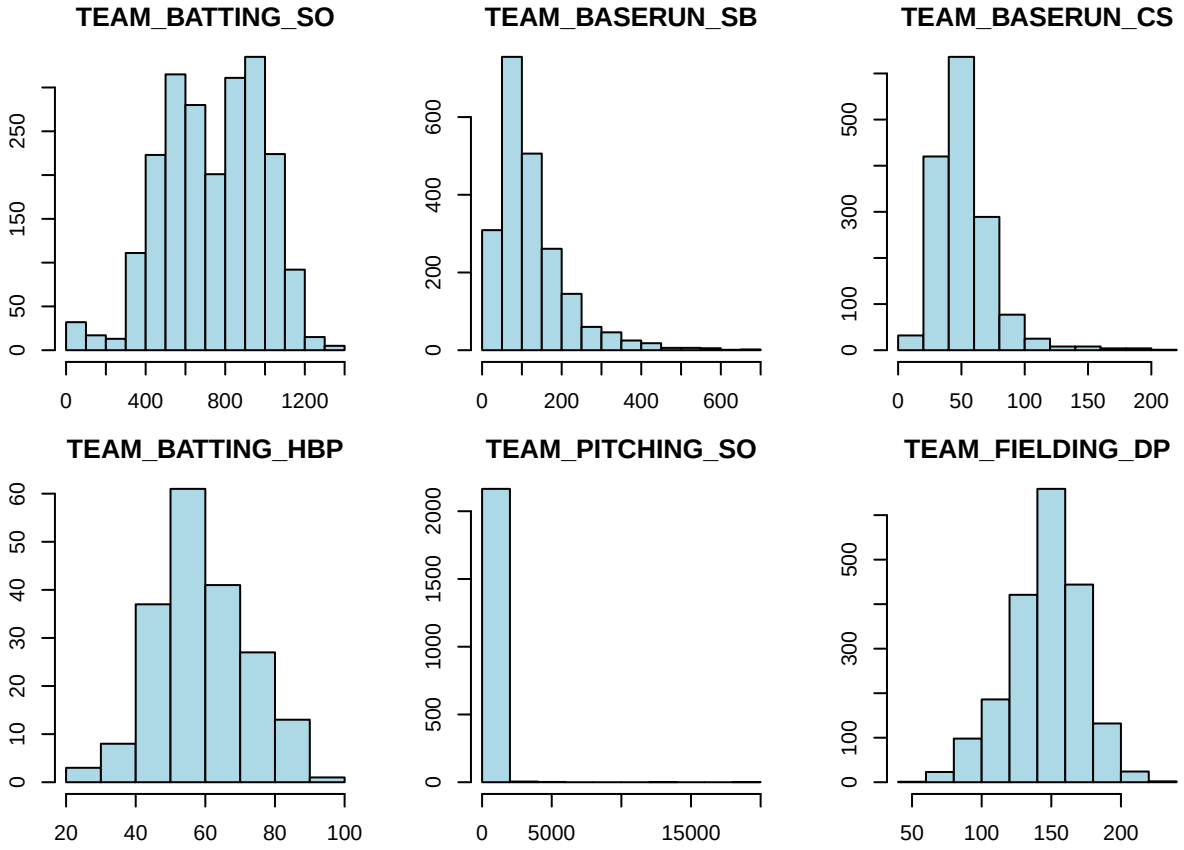
Data Preparation:

Let's take a closer look at all the summary statistics for these variables and identify any data completeness issues:

```
##   TARGET_WINS     TEAM_BATTING_H TEAM_BATTING_2B TEAM_BATTING_3B
##  Min.   :  0.00   Min.   : 891   Min.   : 69.0   Min.   :  0.00
##  1st Qu.: 71.00   1st Qu.:1383   1st Qu.:208.0   1st Qu.: 34.00
##  Median : 82.00   Median :1454   Median :238.0   Median : 47.00
##  Mean   : 80.79   Mean   :1469   Mean   :241.2   Mean   : 55.25
##  3rd Qu.: 92.00   3rd Qu.:1537   3rd Qu.:273.0   3rd Qu.: 72.00
##  Max.   :146.00   Max.   :2554   Max.   :458.0   Max.   :223.00
##
##  TEAM_BATTING_HR  TEAM_BATTING_BB TEAM_BATTING_SO  TEAM_BASERUN_SB
##  Min.   :  0.00   Min.   :  0.0   Min.   :   0.0   Min.   :  0.0
##  1st Qu.: 42.00   1st Qu.:451.0   1st Qu.: 548.0   1st Qu.: 66.0
##  Median :102.00   Median :512.0   Median : 750.0   Median :101.0
##  Mean   : 99.61   Mean   :501.6   Mean   : 735.6   Mean   :124.8
##  3rd Qu.:147.00   3rd Qu.:580.0   3rd Qu.: 930.0   3rd Qu.:156.0
##  Max.   :264.00   Max.   :878.0   Max.   :1399.0   Max.   :697.0
##                                   NA's   :102      NA's   :131
##  TEAM_BASERUN_CS TEAM_BATTING_HBP TEAM_PITCHING_H TEAM_PITCHING_HR
##  Min.   :  0.0   Min.   :29.00    Min.   : 1137   Min.   :  0.0
##  1st Qu.: 38.0   1st Qu.:50.50    1st Qu.: 1419   1st Qu.: 50.0
##  Median : 49.0   Median :58.00    Median : 1518   Median :107.0
##  Mean   : 52.8   Mean   :59.36    Mean   : 1779   Mean   :105.7
##  3rd Qu.: 62.0   3rd Qu.:67.00    3rd Qu.: 1682   3rd Qu.:150.0
##  Max.   :201.0   Max.   :95.00    Max.   :30132   Max.   :343.0
##  NA's   :772     NA's   :2085
##  TEAM_PITCHING_BB TEAM_PITCHING_SO  TEAM_FIELDING_E  TEAM_FIELDING_DP
##  Min.   :   0.0   Min.   :    0.0   Min.   :  65.0   Min.   : 52.0
##  1st Qu.: 476.0   1st Qu.:  615.0   1st Qu.: 127.0   1st Qu.:131.0
##  Median : 536.5   Median :  813.5   Median : 159.0   Median :149.0
```

```
##  Mean   : 553.0   Mean   :  817.7   Mean   : 246.5   Mean   :146.4
##  3rd Qu.: 611.0   3rd Qu.:  968.0   3rd Qu.: 249.2   3rd Qu.:164.0
##  Max.   :3645.0   Max.   :19278.0   Max.   :1898.0   Max.   :228.0
##                   NA's   :102                        NA's   :286
```

We can see quite a few NA values for `TEAM_BATTING_SO`, `TEAM_BASERUN_SB`, `TEAM_BASERUN_CS`, `TEAM_BATTING_HBP`, `TEAM_PITCHING_SO`, and `TEAM_FIELDING_DP`. Let's take a look at the distributions of these variables to see how to impute these missing values.



`TEAM_BASERUN_SB`, `TEAM_PITCHING_SO`, and `TEAM_BASERUN_CS` seem to be skewed to the right so we should probably impute the missing values using the median value for these variables. `TEAM_BATTING_HBP` and `TEAM_FIELDING_DP` seem basically normally distributed so we can use the mean here, although `TEAM_BATTING_HBP` has 2,085 NA values out of 2,276 observations so it may make sense to leave this variable out of our model entirely. `TEAM_BATTING_SO` is bimodally distributed, so we have decided to use KNN imputation, which does not rely on the shape of the distribution, for this variable.

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

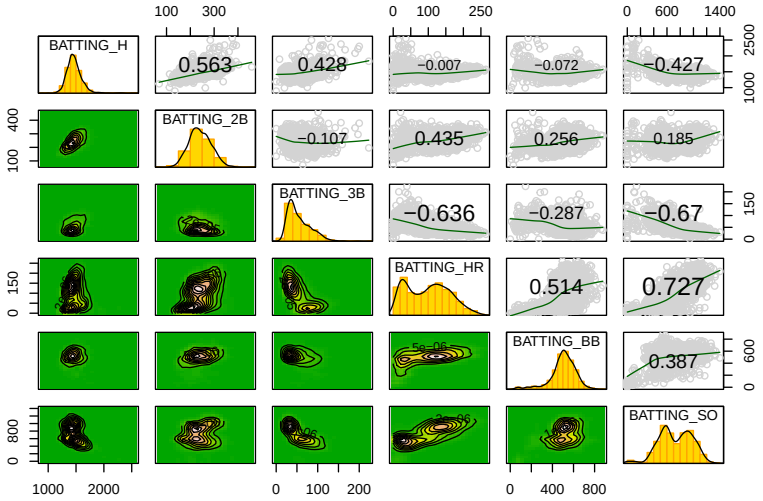
```
##                       [,1]
## TARGET_WINS       1.00000000
## TEAM_BATTING_H    0.38876752
## TEAM_BATTING_2B   0.28910365
## TEAM_BATTING_3B   0.14260841
## TEAM_BATTING_HR   0.17615320
## TEAM_BATTING_BB   0.23255986
## TEAM_BATTING_SO  -0.03606403
## TEAM_BASERUN_SB   0.12361087
## TEAM_BASERUN_CS   0.01595982
```

```
## TEAM_PITCHING_H  -0.10993705
## TEAM_PITCHING_HR  0.18901373
## TEAM_PITCHING_BB  0.12417454
## TEAM_PITCHING_SO -0.07579967
## TEAM_FIELDING_E  -0.17648476
## TEAM_FIELDING_DP -0.02884126
```

None of the independent variables seem to have such high correlation with `TARGET_WINS`. `TEAM_BATTING_H` is most highly correlated, with a correlation of 0.39. `TEAM_BATTING_H`, `TEAM_BATTING_2B`, `TEAM_BATTING_3B`, `TEAM_BATTING_HR`, `TEAM_BATTING_BB`, `TEAM_BASERUN_SB`, `TEAM_BASERUN_CS`, `TEAM_PITCHING_HR`, and `TEAM_PITCHING_BB` are all positively correlated with `TARGET_WINS` while `TEAM_BATTING_SO`, `TEAM_PITCHING_H`, `TEAM_PITCHING_SO`, `TEAM_FIELDING_E`, and `TEAM_FIELDING_DP` are negatively correlated.

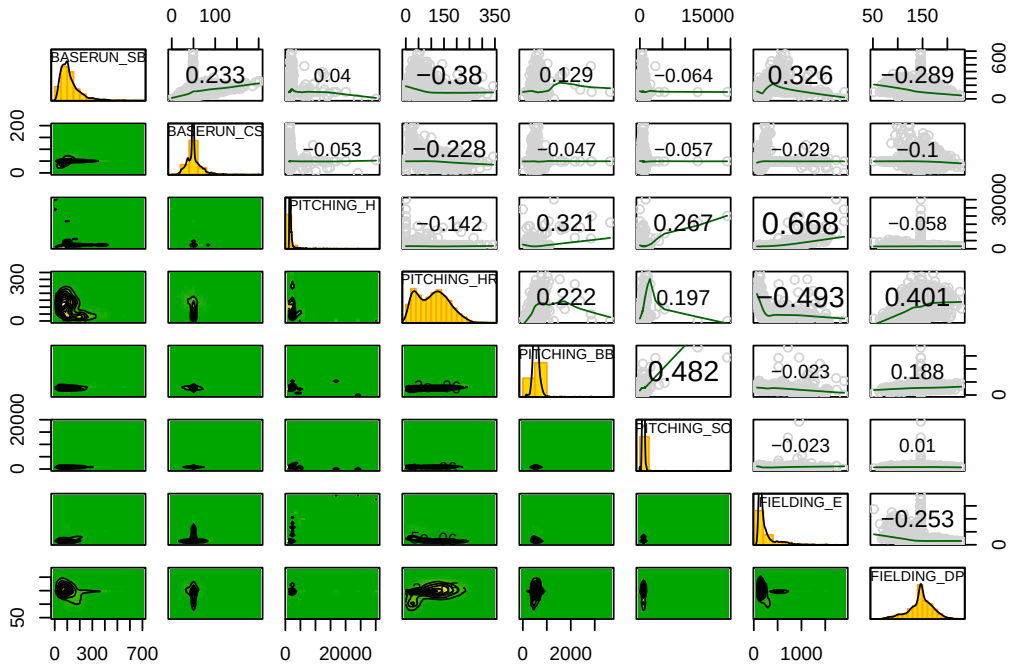
Some of these correlations are surprising, as we would have expected `TEAM_BASERUN_CS`, `TEAM_PITCHING_HR`, and `TEAM_PITCHING_BB` to be negatively correlated with `TARGET_WINS`, and we would have expected `TEAM_PITCHING_SO` and `TEAM_FIELDING_DP` to be positively correlated with `TARGET_WINS`. We won't exclude them from our models based solely on this surprise, however.

Let's review relationships between batting independent variables.



Most of the batting variables appear to be somewhat approximately normal although there are some cases of right skew. Overall, there aren't any very strong correlations between these statistics at least from a preliminary visual inspection. From the distributions of these variables, we can see some that require transforming to normalize them before we use them in our linear model.

Let's review relationships between other independent variables.



There isn't very strong correlation between the other independent variables similar to the batting statistics although there are more examples of skewed data with these inputs. Once again, we can see that we will need to transform some of these variables.

Model Development:

First, let's create a basic model with all untransformed variables:

```
##
## Call:
## lm(formula = TARGET_WINS ~ ., data = train_imputed)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -50.260  -8.612   0.151   8.425  59.018
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       2.657e+01  5.234e+00   5.078 4.14e-07 ***
## TEAM_BATTING_H    4.708e-02  3.699e-03  12.729  < 2e-16 ***
## TEAM_BATTING_2B  -1.788e-02  9.206e-03  -1.942 0.052245 .
## TEAM_BATTING_3B   6.137e-02  1.678e-02   3.657 0.000261 ***
## TEAM_BATTING_HR   5.752e-02  2.749e-02   2.093 0.036500 *
## TEAM_BATTING_BB   1.085e-02  5.816e-03   1.865 0.062310 .
## TEAM_BATTING_SO  -1.141e-02  2.579e-03  -4.427 1.00e-05 ***
## TEAM_BASERUN_SB   2.580e-02  4.317e-03   5.976 2.66e-09 ***
## TEAM_BASERUN_CS  -7.159e-03  1.577e-02  -0.454 0.649853
## TEAM_PITCHING_H  -8.980e-04  3.673e-04  -2.445 0.014562 *
## TEAM_PITCHING_HR  1.612e-02  2.431e-02   0.663 0.507243
## TEAM_PITCHING_BB -2.408e-05  4.124e-03  -0.006 0.995341
## TEAM_PITCHING_SO  3.201e-03  9.134e-04   3.505 0.000466 ***
```

```
## TEAM_FIELDING_E  -1.961e-02  2.448e-03  -8.011 1.80e-15 ***
## TEAM_FIELDING_DP -1.201e-01  1.293e-02  -9.290  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 13.05 on 2261 degrees of freedom
## Multiple R-squared:  0.3181, Adjusted R-squared:  0.3139
## F-statistic: 75.34 on 14 and 2261 DF,  p-value: < 2.2e-16
```

We can see that the R^2 value of a model that includes all the variables is not particularly high.

We can remove some variables that are not significant using backward step-wise elimination.

```
##
## Call:
## lm(formula = TARGET_WINS ~ TEAM_BATTING_H + TEAM_BATTING_2B +
##     TEAM_BATTING_3B + TEAM_BATTING_HR + TEAM_BATTING_BB + TEAM_BATTING_SO +
##     TEAM_BASERUN_SB + TEAM_PITCHING_H + TEAM_PITCHING_SO + TEAM_FIELDING_E +
##     TEAM_FIELDING_DP, data = train_imputed)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -50.201  -8.548   0.137   8.404  59.080
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)      25.5925419  5.0907238   5.027 5.36e-07 ***
## TEAM_BATTING_H    0.0473024  0.0036728  12.879  < 2e-16 ***
## TEAM_BATTING_2B  -0.0182083  0.0091927  -1.981 0.047742 *
## TEAM_BATTING_3B   0.0633643  0.0165996   3.817 0.000139 ***
## TEAM_BATTING_HR   0.0752404  0.0098361   7.649 2.97e-14 ***
## TEAM_BATTING_BB   0.0109356  0.0033639   3.251 0.001167 **
## TEAM_BATTING_SO  -0.0114146  0.0024962  -4.573 5.07e-06 ***
## TEAM_BASERUN_SB   0.0254110  0.0041873   6.069 1.51e-09 ***
## TEAM_PITCHING_H  -0.0008562  0.0003209  -2.669 0.007672 **
## TEAM_PITCHING_SO  0.0032329  0.0006703   4.823 1.51e-06 ***
## TEAM_FIELDING_E  -0.0192393  0.0023792  -8.086 9.91e-16 ***
## TEAM_FIELDING_DP -0.1201245  0.0129038  -9.309  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 13.04 on 2264 degrees of freedom
## Multiple R-squared:  0.3179, Adjusted R-squared:  0.3145
## F-statistic: 95.91 on 11 and 2264 DF,  p-value: < 2.2e-16
```

<<<<< HEAD The R^2 for this model is not much improved. Let's check for multicolinearity between variables.
======= The R^2 for this model is not much improved. Let's check for multicollinearity between variables.
>>>>> 3c1945e84a413cd7dc9c646dea0d7806941a8cdf

Reviewing the variance inflation factors:

```
##   TEAM_BATTING_H  TEAM_BATTING_2B  TEAM_BATTING_3B  TEAM_BATTING_HR
##         3.772304         2.475869         2.876917         4.744128
##  TEAM_BATTING_BB  TEAM_BATTING_SO  TEAM_BASERUN_SB  TEAM_PITCHING_H
```

```
##         2.277645         5.005090         1.710653         2.725441
## TEAM_PITCHING_SO  TEAM_FIELDING_E TEAM_FIELDING_DP
##         1.755773         3.928217         1.339341
```

The variance inflation factor for `TEAM_BATTING_SO` is greater than 5. We can remove this.

```
##
## Call:
## lm(formula = TARGET_WINS ~ TEAM_BATTING_H + TEAM_BATTING_2B +
##     TEAM_BATTING_3B + TEAM_BATTING_HR + TEAM_BATTING_BB + TEAM_BASERUN_SB +
##     TEAM_PITCHING_H + TEAM_PITCHING_SO + TEAM_FIELDING_E + TEAM_FIELDING_DP,
##     data = train_imputed)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -49.354  -8.637   0.046   8.422  56.185
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)      10.4516005  3.8837691   2.691  0.00717 **
## TEAM_BATTING_H    0.0543248  0.0033510  16.212  < 2e-16 ***
## TEAM_BATTING_2B  -0.0275776  0.0090008  -3.064  0.00221 **
## TEAM_BATTING_3B   0.0742212  0.0165010   4.498 7.21e-06 ***
## TEAM_BATTING_HR   0.0472798  0.0077385   6.110 1.17e-09 ***
## TEAM_BATTING_BB   0.0134412  0.0033335   4.032 5.71e-05 ***
## TEAM_BASERUN_SB   0.0204726  0.0040634   5.038 5.07e-07 ***
## TEAM_PITCHING_H  -0.0005109  0.0003132  -1.631  0.10300
## TEAM_PITCHING_SO  0.0020318  0.0006194   3.281  0.00105 **
## TEAM_FIELDING_E  -0.0186422  0.0023861  -7.813 8.48e-15 ***
## TEAM_FIELDING_DP -0.1165458  0.0129366  -9.009  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 13.1 on 2265 degrees of freedom
## Multiple R-squared:  0.3116, Adjusted R-squared:  0.3085
## F-statistic: 102.5 on 10 and 2265 DF,  p-value: < 2.2e-16
```

Let's remove `TEAM_PITCHING_H` as it is no longer significant.

```
##
## Call:
## lm(formula = TARGET_WINS ~ TEAM_BATTING_H + TEAM_BATTING_2B +
##     TEAM_BATTING_3B + TEAM_BATTING_HR + TEAM_BATTING_BB + TEAM_BASERUN_SB +
##     TEAM_PITCHING_SO + TEAM_FIELDING_E + TEAM_FIELDING_DP, data = train_imputed)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -51.785  -8.584   0.002   8.446  57.585
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)      12.1798845  3.7378157   3.259  0.00114 **
## TEAM_BATTING_H    0.0528676  0.0032309  16.363  < 2e-16 ***
```

```
## TEAM_BATTING_2B  -0.0272628  0.0090020  -3.029  0.00249 **
## TEAM_BATTING_3B   0.0787841  0.0162681   4.843 1.37e-06 ***
## TEAM_BATTING_HR   0.0481046  0.0077248   6.227 5.64e-10 ***
## TEAM_BATTING_BB   0.0133595  0.0033344   4.007 6.36e-05 ***
## TEAM_BASERUN_SB   0.0216382  0.0040015   5.408 7.06e-08 ***
## TEAM_PITCHING_SO  0.0016132  0.0005639   2.861  0.00426 **
## TEAM_FIELDING_E  -0.0208625  0.0019604 -10.642  < 2e-16 ***
## TEAM_FIELDING_DP -0.1173637  0.0129316  -9.076  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 13.1 on 2266 degrees of freedom
## Multiple R-squared:  0.3108, Adjusted R-squared:  0.308
## F-statistic: 113.5 on 9 and 2266 DF,  p-value: < 2.2e-16

##   TEAM_BATTING_H  TEAM_BATTING_2B  TEAM_BATTING_3B  TEAM_BATTING_HR
##         2.891551         2.351793         2.737074         2.898411
##  TEAM_BATTING_BB  TEAM_BASERUN_SB TEAM_PITCHING_SO  TEAM_FIELDING_E
##         2.216711         1.547476         1.230982         2.641838
## TEAM_FIELDING_DP
##         1.332410
```

Based on the definitions of `TEAM_BATTING_H`, `TEAM_BATTING_2B`, `TEAM_BATTING_3B`, and `TEAM_BATTING_HR`, there is probably some multicollinearity going on with these variables. Let's compare a model that uses just the total hits against a model using each individual type of hit.

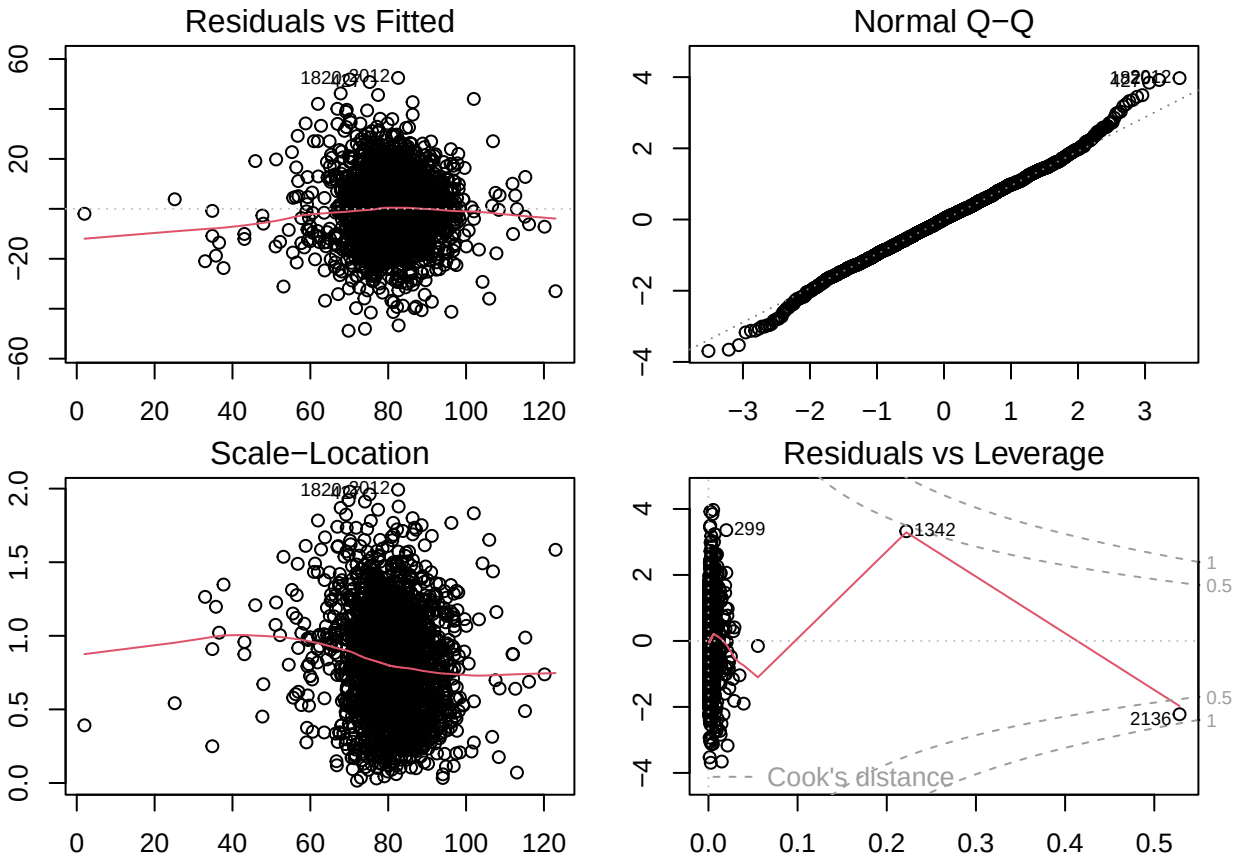
```
##
## Call:
## lm(formula = TARGET_WINS ~ TEAM_BATTING_H + TEAM_BATTING_BB +
##     TEAM_BASERUN_SB + TEAM_PITCHING_SO + TEAM_FIELDING_E + TEAM_FIELDING_DP,
##     data = train_imputed)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -48.823  -8.638   0.156   8.473  52.443
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       9.7032191  3.5315442   2.748  0.00605 **
## TEAM_BATTING_H    0.0542548  0.0021078  25.740  < 2e-16 ***
## TEAM_BATTING_BB   0.0171889  0.0032588   5.275 1.46e-07 ***
## TEAM_BASERUN_SB   0.0237070  0.0037196   6.374 2.23e-10 ***
## TEAM_PITCHING_SO  0.0015116  0.0005316   2.844  0.00450 **
## TEAM_FIELDING_E  -0.0210881  0.0018286 -11.532  < 2e-16 ***
## TEAM_FIELDING_DP -0.1107454  0.0128421  -8.624  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 13.24 on 2269 degrees of freedom
## Multiple R-squared:  0.2955, Adjusted R-squared:  0.2936
## F-statistic: 158.6 on 6 and 2269 DF,  p-value: < 2.2e-16


##
```

```
## Call:
## lm(formula = TARGET_WINS ~ TEAM_BATTING_2B + TEAM_BATTING_3B +
##     TEAM_BATTING_HR + TEAM_BATTING_BB + TEAM_BASERUN_SB + TEAM_PITCHING_SO +
##     TEAM_FIELDING_E + TEAM_FIELDING_DP, data = train_imputed)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -61.232  -8.904   0.069   8.910  65.787
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)      55.5049520  2.7892547  19.900  < 2e-16 ***
## TEAM_BATTING_2B   0.0694280  0.0071795   9.670  < 2e-16 ***
## TEAM_BATTING_3B   0.1953241  0.0154629  12.632  < 2e-16 ***
## TEAM_BATTING_HR   0.0748393  0.0079819   9.376  < 2e-16 ***
## TEAM_BATTING_BB   0.0103989  0.0035199   2.954  0.00317 **
## TEAM_BASERUN_SB   0.0221969  0.0042302   5.247 1.69e-07 ***
## TEAM_PITCHING_SO -0.0012958  0.0005657  -2.291  0.02208 *
## TEAM_FIELDING_E  -0.0110738  0.0019737  -5.611 2.26e-08 ***
## TEAM_FIELDING_DP -0.0947871  0.0135932  -6.973 4.05e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 13.85 on 2267 degrees of freedom
## Multiple R-squared:  0.2293, Adjusted R-squared:  0.2266
## F-statistic: 84.31 on 8 and 2267 DF,  p-value: < 2.2e-16
```

The model using `TEAM_BATTING_HITS` has a higher R^2 so it accounts for more variability. Let's use this variable in our model.

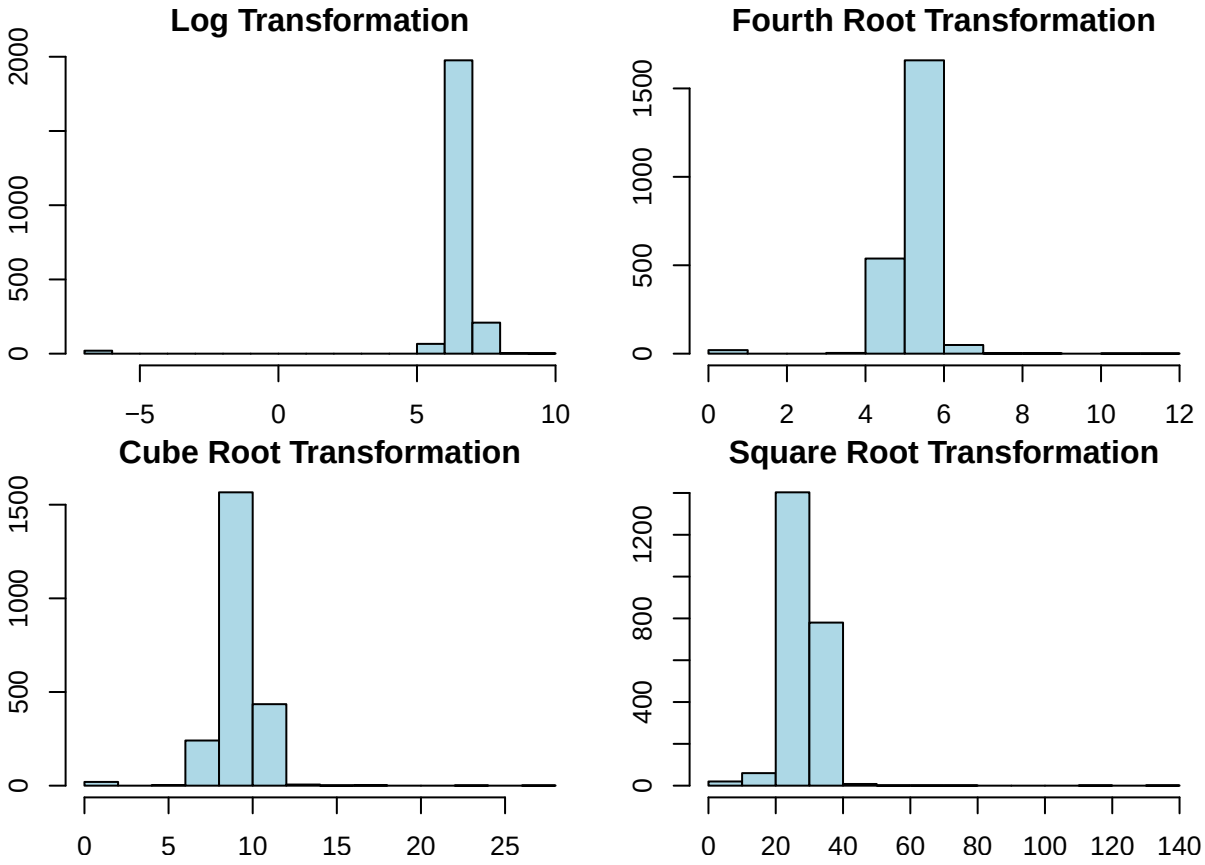
We can make some plots to help test our assumptions of our basic model using the `plot` function on our model variable:



The Q-Q plot shows that the residuals of this model are fairly normally distributed. The residuals vs. fitted plot shows a cluster of residuals and a seeming outlying point. There is no general pattern seen here and the cluster of points seems to indicate that homoscedasticity is satisfied for this model.

Let's try transforming some of our variables to come up with a more accurate model.

`TEAM_PITCHING_SO` is a right-skewed variable with very large outliers. Let's compare how four common transformations (log, fourth root, cube root, and square root) would normalize the distribution of this variable (after adding a small constant since the variable includes accurate values of 0).

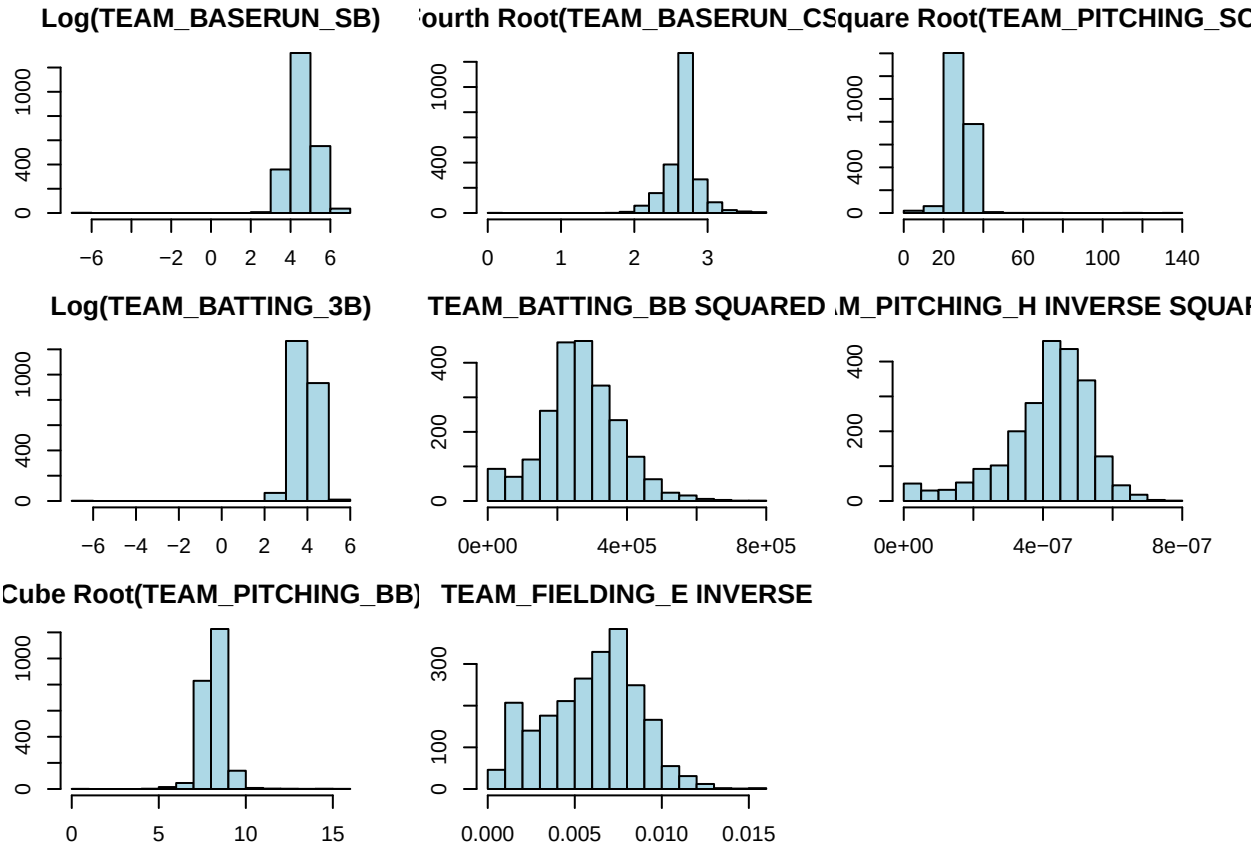


The square root transformation appears to normalize the data best. Let's confirm the ideal lambda proposed by the boxcox function from the MASS library is similar to to the square root transformation lambda (0.5) we assume will work best for this data.

```
## [1] 0.45
```

The proposed lambda of 0.45 is in fact very close to 0.5, so we will go with the easier to understand square root transformation. We will follow a similar process to find reasonable transformations for several other variables in our model without showing the process repeatedly.

variables	lambdas	adj
TEAM_BASERUN_SB	0.2	log
TEAM_BASERUN_CS	0.3	fourth root
TEAM_PITCHING_SO	0.45	square root
TEAM_BATTING_3B	0.3	log
TEAM_BATTING_BB	1.75	square
TEAM_PITCHING_H	-2	square inverse
TEAM_PITCHING_BB	0.35	cube root
TEAM_FIELDING_E	-0.95	inverse



Adjusting the ideal lambdas proposed for several variables to commonly understood transformations, we see mixed results on normalizing the distributions. Let's use the same variables from our final untransformed model above to see if we can improve the model using transformations.

```
##
## Call:
## lm(formula = TARGET_WINS ~ TEAM_BATTING_H + TEAM_BATTING_BB +
##     I(TEAM_BATTING_BB^2) + log(TEAM_BASERUN_SB + 1e-04) + I(TEAM_PITCHING_SO^0.5) +
##     I(TEAM_FIELDING_E^-1) + TEAM_FIELDING_DP, data = train_imputed)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -59.340  -8.557   0.113   8.603  55.118
##
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                  -3.404e+00  4.958e+00  -0.686   0.4925
## TEAM_BATTING_H                4.868e-02  2.173e-03  22.405  < 2e-16 ***
## TEAM_BATTING_BB               5.538e-03  1.068e-02   0.518   0.6042
## I(TEAM_BATTING_BB^2)          2.482e-05  1.131e-05   2.195   0.0283 *
## log(TEAM_BASERUN_SB + 1e-04)  3.037e+00  4.263e-01   7.125 1.39e-12 ***
## I(TEAM_PITCHING_SO^0.5)      -1.991e-02  5.392e-02  -0.369   0.7119
## I(TEAM_FIELDING_E^-1)         1.411e+03  1.427e+02   9.885  < 2e-16 ***
## TEAM_FIELDING_DP             -1.270e-01  1.313e-02  -9.672  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

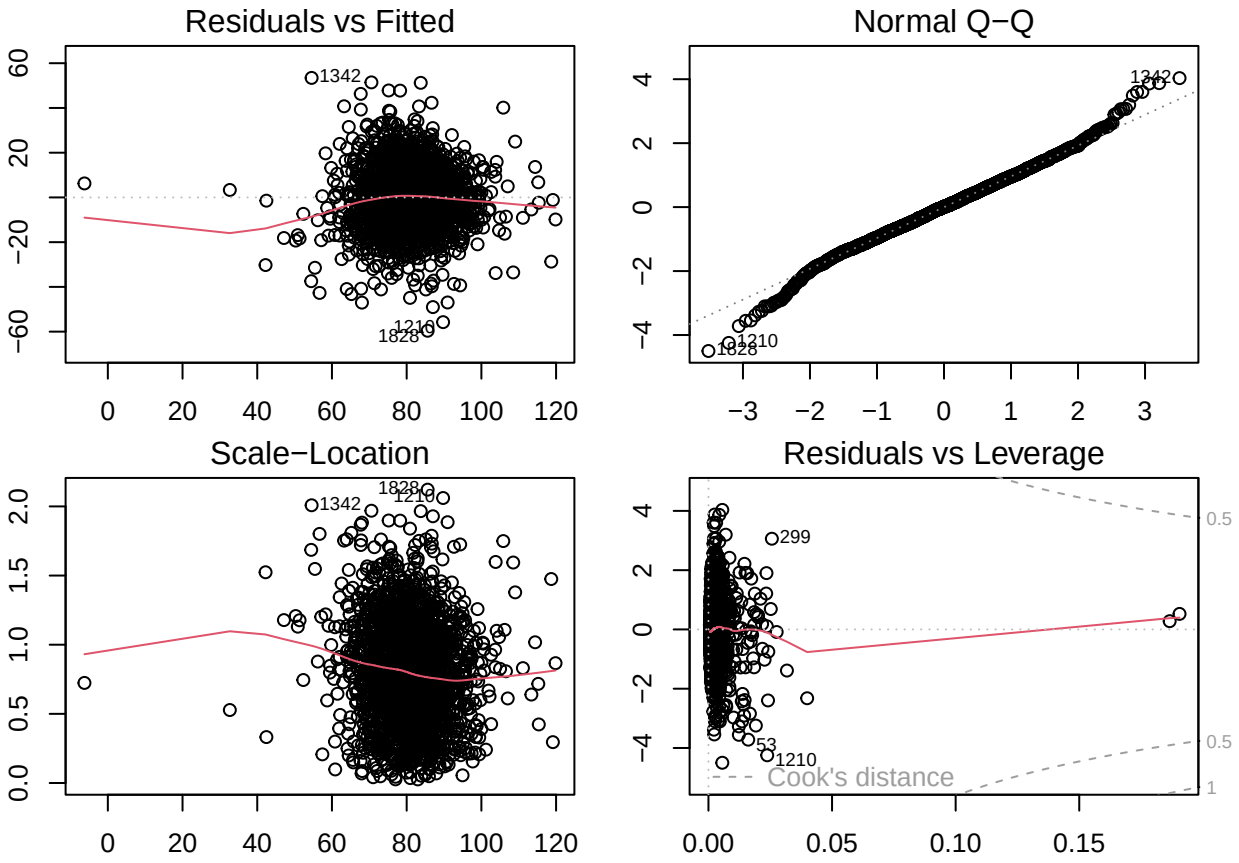
```
## Residual standard error: 13.29 on 2268 degrees of freedom
## Multiple R-squared:  0.2905, Adjusted R-squared:  0.2883
## F-statistic: 132.7 on 7 and 2268 DF,  p-value: < 2.2e-16
```

Note: There are instances of `TEAM_BASERUN_SB` where the value is zero. Because of this, a log transformation creates an error. To account for this we increment by a small number (0.0001) so that the log transformation can be applied.

The transformed `TEAM_PITCHING_SO` is no longer significant, let's remove it.

```
##
## Call:
## lm(formula = TARGET_WINS ~ TEAM_BATTING_H + TEAM_BATTING_BB +
##     I(TEAM_BATTING_BB^2) + log(TEAM_BASERUN_SB + 1e-04) + I(TEAM_FIELDING_E^-1) +
##     TEAM_FIELDING_DP, data = train_imputed)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -59.611  -8.620   0.107   8.597  53.441
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 -4.223e+00  4.433e+00  -0.953   0.3409
## TEAM_BATTING_H               4.893e-02  2.059e-03  23.771  < 2e-16 ***
## TEAM_BATTING_BB              5.693e-03  1.067e-02   0.533   0.5938
## I(TEAM_BATTING_BB^2)         2.473e-05  1.131e-05   2.188   0.0288 *
## log(TEAM_BASERUN_SB + 1e-04)  3.019e+00  4.233e-01   7.132 1.33e-12 ***
## I(TEAM_FIELDING_E^-1)        1.394e+03  1.354e+02  10.297  < 2e-16 ***
## TEAM_FIELDING_DP            -1.269e-01  1.312e-02  -9.668  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 13.29 on 2269 degrees of freedom
## Multiple R-squared:  0.2905, Adjusted R-squared:  0.2886
## F-statistic: 154.8 on 6 and 2269 DF,  p-value: < 2.2e-16
```

The adjusted R^2 is slightly less for this model than for the untransformed one. Let's take a look at the diagnostic plots for this transformed model.



Once again, the Q-Q plot shows that the residuals are fairly normally distributed. From the plot of Cook's distance, it seems there are fewer possible leverage points. The residuals vs. fitted plot also seems to indicate that homoscedasticity is satisfied.

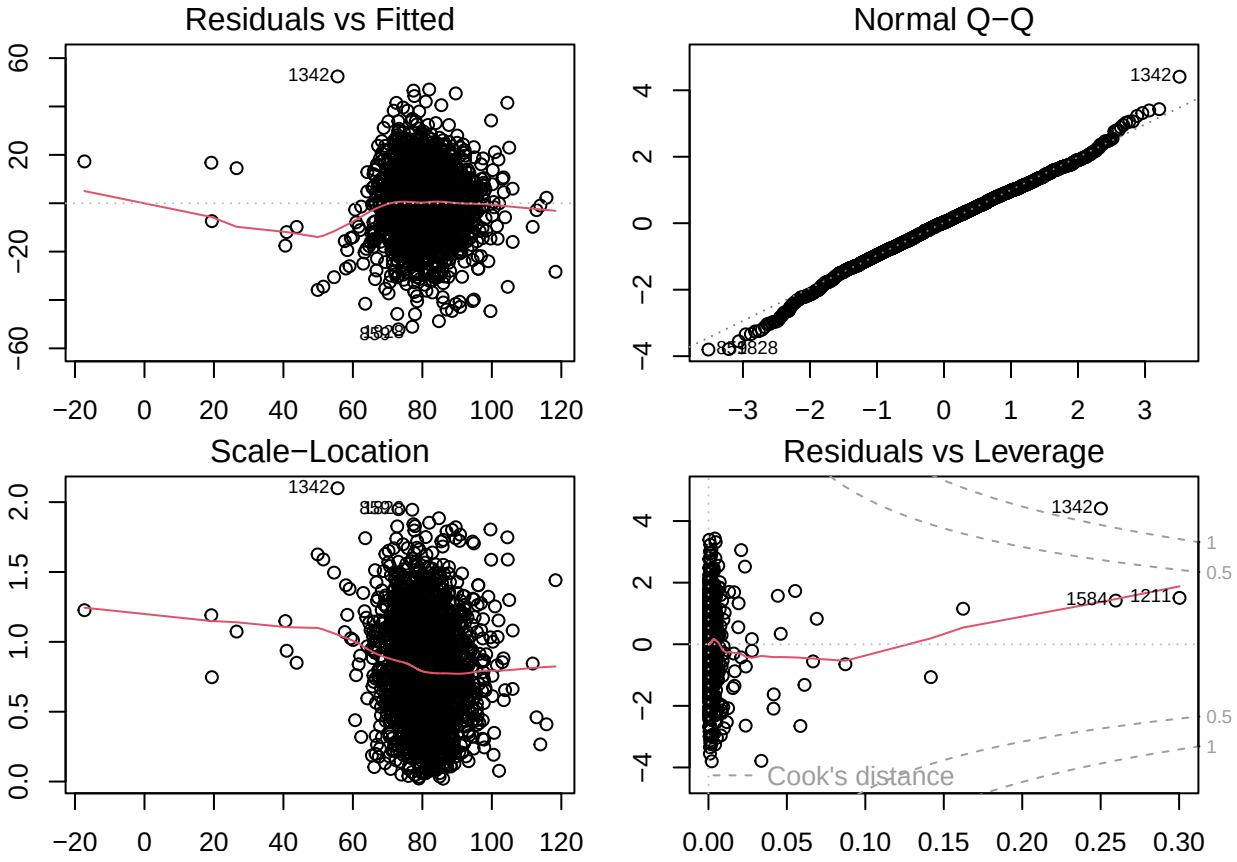
Now we can make a model with inputs that we know from baseball.

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

We chose these variables based on our understanding that good teams generally tend to get on base more frequently (positive predictor variables `TEAM_BATTING_HITS` and `TEAM_BATTING_BB`) while allowing *fewer* runners on base (negative predictor variables `TEAM_PITCHING_H` and `TEAM_PITCHING_BB`).

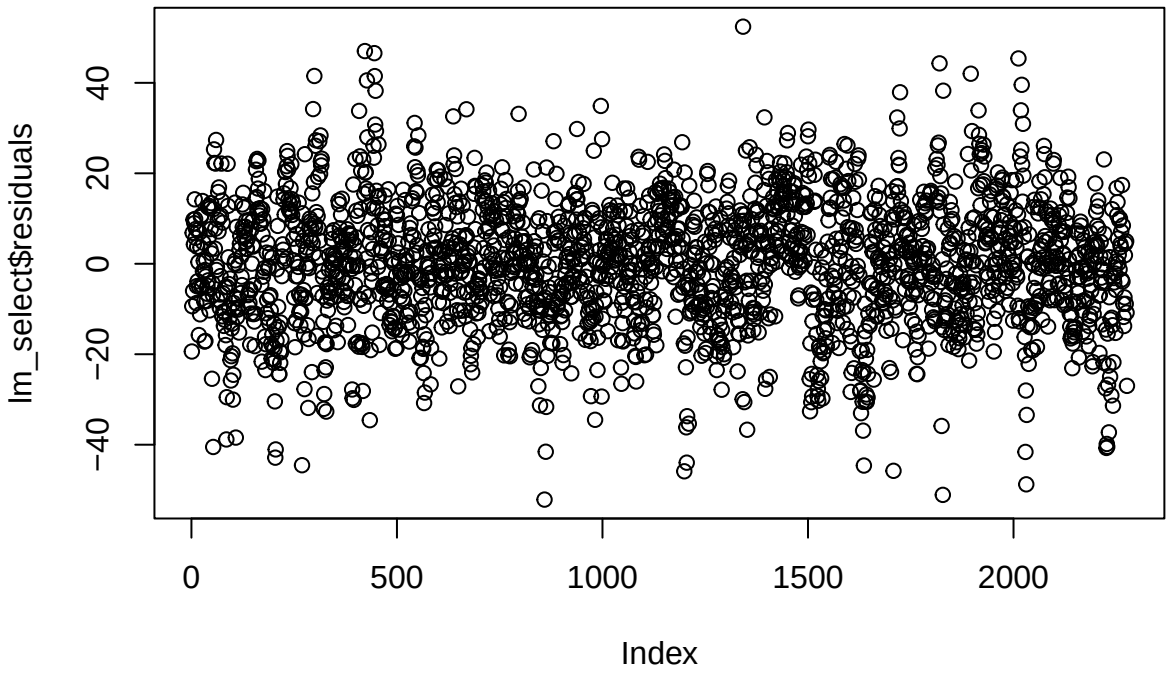
```
##
## Call:
## lm(formula = TARGET_WINS ~ TEAM_BATTING_H + TEAM_BATTING_BB +
##     TEAM_PITCHING_H + TEAM_PITCHING_BB, data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -52.133  -8.860   0.379   9.373  52.416
##
## Coefficients:
##                    Estimate Std. Error 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
```

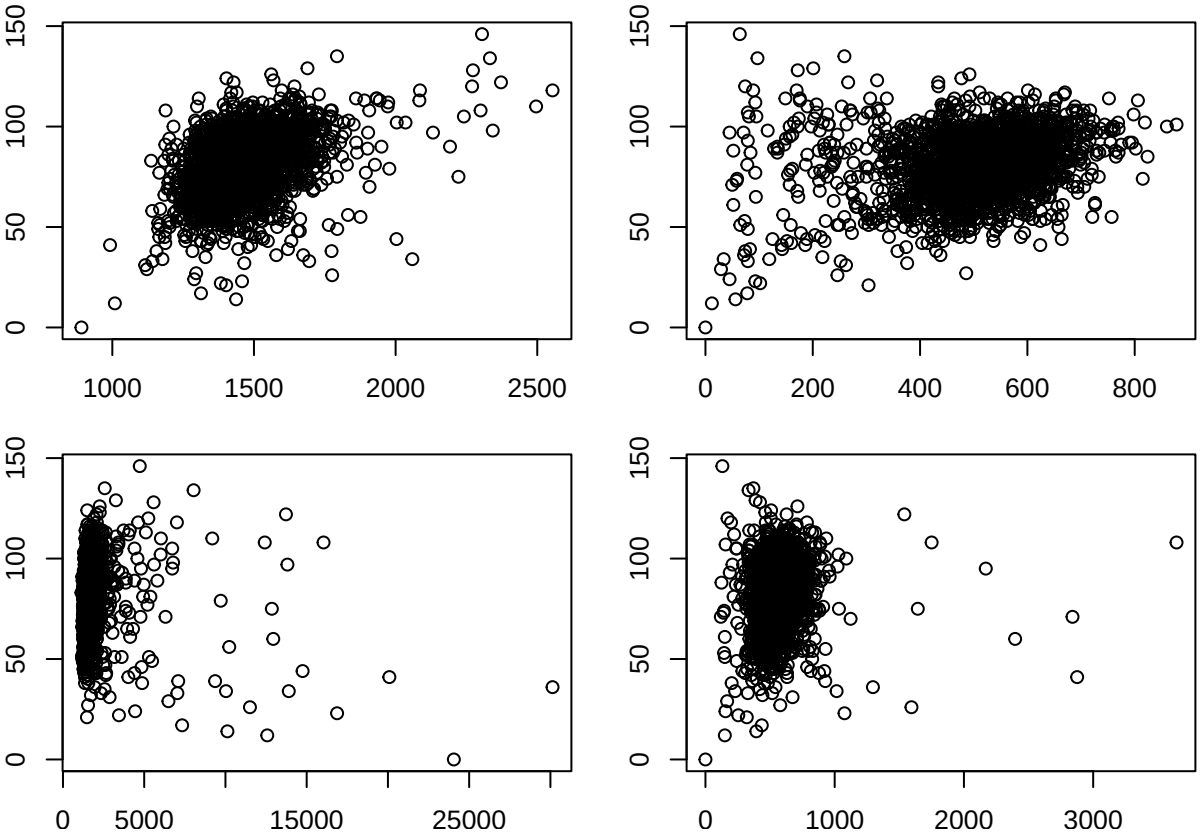


It's interesting to note that with selected variables (walks and hits gained/allowed per team) that our adjusted R^2 actually went *down*, indicating the amount of variability in `TARGET_WINS` explained by our more selective walks/hits model is *less* than the model including all variables.

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.



«««< HEAD ## Model Evaluation/Selection

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

Discussion Missing

Model Evaluation/Selection:

First we read in our evaluation data.

Now we can make some predictions on the test holdout data and compare results from our models before we select the best model to use on the evaluation data.

Writing a quick RMSE function

We can use the Root-mean Squared Error (RMSE) (from the `modelr` package) to analyze our models from above. This is one way to measure the performance of a model. In simple terms, a smaller RMSE value indicates better model performance when predicting on new data.

```
## [1] 10.2899
```

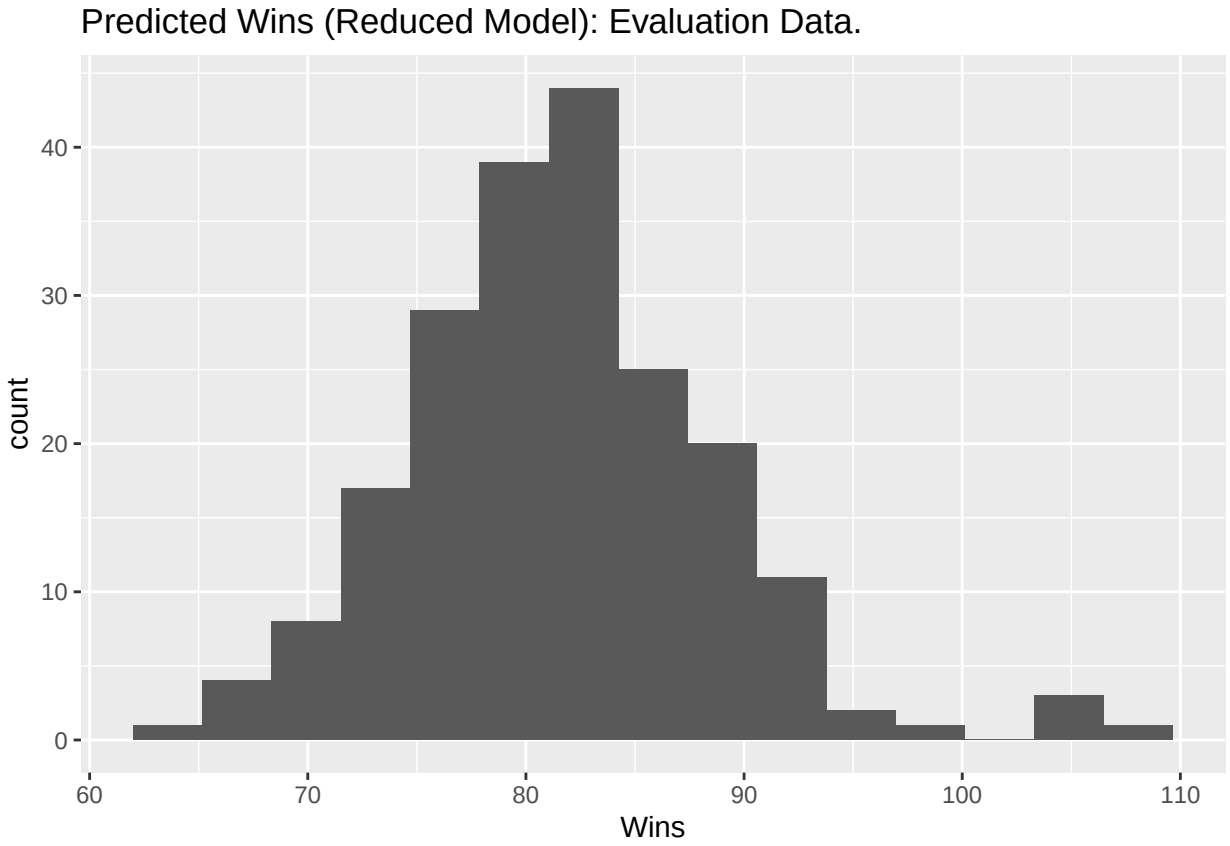
```
## [1] 10.56701
```

```
## [1] 10.60202
```

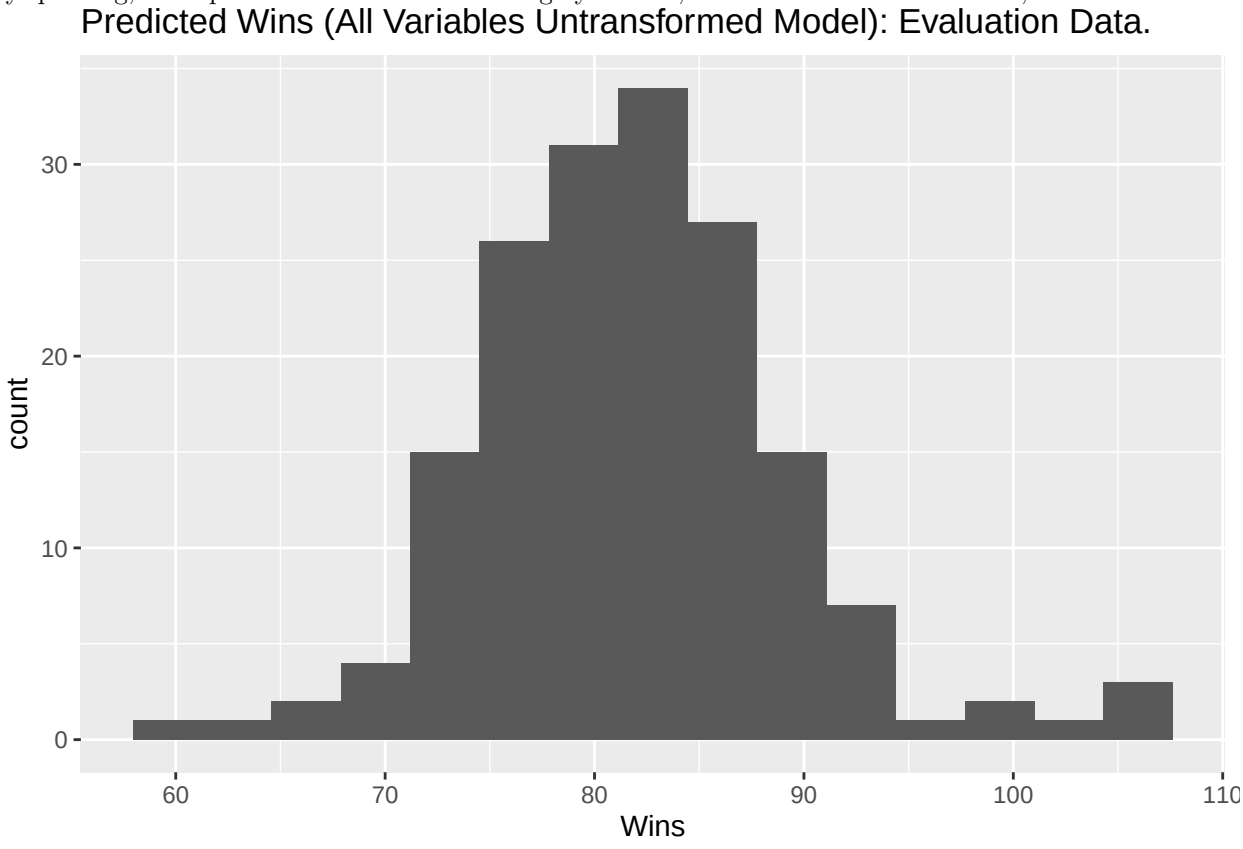
Lastly, we can predict on our `eval` data based on the best RMSE value coming from our *reduced* model. Since we don't have `TARGET_WINS` in our evaluation data, we won't be able to evaluate the model performance against actual win totals.

The model with the lowest RMSE is our all variable model without transformations, so we will make predictions on the evaluation data using this model. Since we don't have `TARGET_WINS` in our evaluation data, we won't be able to evaluate the model performance against actual win totals.

However, we can look at the distribution of predicted wins to make sure our model predicts reasonable values. Knowing what we know about baseball, average teams tend to win 80 games in a season (out of 162 total regular season games).



Roughly speaking, these predicted win totals look roughly normal, and centered around 80 wins, which is ex-



pected

Conclusions:

Discussion Missing

Appendix: Report Code

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

```
knitr::opts_chunk$set(echo = FALSE, warning = FALSE, message = FALSE)
library(glue)
library(tidyverse)
library(car)
library(ResourceSelection)
library(VIM)
library(pracma)
library(MASS)
select <- dplyr::select
library(knitr)
library(modelr)
df <- read.csv("https://raw.githubusercontent.com/andrewbowen19/businessAnalyticsDataMiningDATA621/main/
df <- data.frame(df)
dim = dim(df)

print(glue("The dataset consists of {dim[1]} observations of {dim[2]} variables."))
set.seed(42)

# Adding a 20% holdout of our input data for model evaluation later
train <- subset(df[sample(1:nrow(df)), ], select=-c(TEAM_BATTING_HBP))%>%
          sample_frac(0.7)

test  <- dplyr::anti_join(df, train, by = 'INDEX')

train = subset(df, select=-c(INDEX))
mean_wins <- mean(train$TARGET_WINS)
median_wins <- median(train$TARGET_WINS)
sd_wins <- sd(train$TARGET_WINS)

# Print summary stats
print(glue("The mean number of wins in a season is {round(mean_wins,2)}."))
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 {round(sd_wins,2)}."))
ggplot(train, aes(x=TARGET_WINS)) +
  geom_histogram() +
  labs(title = "Distribution of Wins (Histogram)", x = "Number of Wins", y = "Count")
ggplot(train, aes(x=TARGET_WINS)) +
  geom_boxplot(fill="darkgrey") +
  labs(title = "Distribution of Wins (Boxplot)", x = "Number of Wins", y = "Count")
cMeans <- as.data.frame(round(colMeans(train, na.rm = TRUE), 1))
colnames(cMeans) <- NULL
kable(cMeans, format = "simple")

summary(train)
```

```r
par(mfrow=c(2,3))
par(mai=c(.3,.3,.3,.3))

variables <- c("TEAM_BATTING_SO", "TEAM_BASERUN_SB", "TEAM_BASERUN_CS", "TEAM_BATTING_HBP", "TEAM_PITCH

for (i in 1:(length(variables))) {
    hist(train[[variables[i]]], main = variables[i], col = "lightblue")
}
train_imputed <- train |>
    mutate(TEAM_BASERUN_SB = replace(TEAM_BASERUN_SB, is.na(TEAM_BASERUN_SB),
                                     median(TEAM_BASERUN_SB, na.rm=T)),
           TEAM_BASERUN_CS = replace(TEAM_BASERUN_CS, is.na(TEAM_BASERUN_CS),
                                     median(TEAM_BASERUN_CS, na.rm=T)),
           TEAM_PITCHING_SO = replace(TEAM_PITCHING_SO, is.na(TEAM_PITCHING_SO),
                                      median(TEAM_PITCHING_SO, na.rm=T)),
           TEAM_FIELDING_DP = replace(TEAM_FIELDING_DP, is.na(TEAM_FIELDING_DP),
                                      mean(TEAM_FIELDING_DP, na.rm=T))) |>
    select(-TEAM_BATTING_HBP)


train_imputed <- train_imputed |>
    VIM::kNN(variable = "TEAM_BATTING_SO", k = 15, numFun = weighted.mean,
             weightDist = TRUE) |>
    select(-TEAM_BATTING_SO_imp)

cor(train_imputed, df$TARGET_WINS)
train_cleaned <- train_imputed |> rename_all(~stringr::str_replace(.,"^TEAM_",""))
subset_batting <- train_cleaned |> select(contains('batting'))
kdepairs(subset_batting)
subset_pitching <- train_cleaned |> select(!contains('batting'), -TARGET_WINS)
kdepairs(subset_pitching)
lm_all <- lm(TARGET_WINS~., train_imputed)
summary(lm_all)
lm_all_reduced <- step(lm_all, direction="backward", trace = 0)
summary(lm_all_reduced)
vif(lm_all_reduced)
lm_all_reduced <- update(lm_all_reduced, .~. - TEAM_BATTING_SO)
summary(lm_all_reduced)
lm_all_reduced <- update(lm_all_reduced, .~. - TEAM_PITCHING_H)
summary(lm_all_reduced)
vif(lm_all_reduced)
lm_all_reduced_hits <- update(lm_all_reduced, .~. - TEAM_BATTING_2B - TEAM_BATTING_3B - TEAM_BATTING_HR
summary(lm_all_reduced_hits)
lm_all_reduced_others <- update(lm_all_reduced, .~. - TEAM_BATTING_H)
summary(lm_all_reduced_others)
par(mfrow=c(2,2))
par(mai=c(.3,.3,.3,.3))
plot(lm_all_reduced_hits)
train_imputed_transformed <- train_imputed
#Add a small constant to TEAM_PITCHING_SO so there are no 0 values.
train_imputed_transformed$TEAM_PITCHING_SO <- train_imputed_transformed$TEAM_PITCHING_SO + 0.001
par(mfrow=c(2,2))
par(mai=c(.3,.3,.3,.3))
```

```r
#Compare how easy to understand transformations alter the distribution
hist(log(train_imputed_transformed$TEAM_PITCHING_SO),
     main = "Log Transformation", col="lightblue")
hist(nthroot(train_imputed_transformed$TEAM_PITCHING_SO, 4),
     main = "Fourth Root Transformation", col="lightblue")
hist(nthroot(train_imputed_transformed$TEAM_PITCHING_SO, 3),
     main = "Cube Root Transformation", col="lightblue")
hist(sqrt(train_imputed_transformed$TEAM_PITCHING_SO),
     main = "Square Root Transformation", col="lightblue")
bc <- boxcox(lm(train_imputed_transformed$TEAM_PITCHING_SO ~ 1),
             lambda = seq(-2, 2, length.out = 81),
             plotit = FALSE)
lambda <- bc$x[which.max(bc$y)]
lambda
variables <- c("TEAM_BASERUN_SB", "TEAM_BASERUN_CS", "TEAM_PITCHING_SO",
               "TEAM_BATTING_3B", "TEAM_BATTING_BB", "TEAM_PITCHING_H",
               "TEAM_PITCHING_BB", "TEAM_FIELDING_E")
for (i in 1:(length(variables))){
    #Add a small constant to columns with any 0 values
    if (sum(train_imputed_transformed[[variables[i]]] == 0) > 0){
        train_imputed_transformed[[variables[i]]] <-
            train_imputed_transformed[[variables[i]]] + 0.001
    }
}
for (i in 1:(length(variables))){
    if (i == 1){
        lambdas <- c()
    }
    bc <- boxcox(lm(train_imputed_transformed[[variables[i]]] ~ 1),
                 lambda = seq(-2, 2, length.out = 81),
                 plotit = FALSE)
    lambda <- bc$x[which.max(bc$y)]
    lambdas <- append(lambdas, lambda)
}
lambdas <- as.data.frame(cbind(variables, lambdas))
adj <- c("log", "fourth root", "square root", "log", "square", "square inverse", "cube root", "inverse")
lambdas <- cbind(lambdas, adj)
kable(lambdas, format = "simple")
par(mfrow=c(3, 3))
par(mai=c(.3,.3,.3,.3))
#Compare how easy to understand transformations alter the distribution
hist(log(train_imputed_transformed$TEAM_BASERUN_SB),
     main = "Log(TEAM_BASERUN_SB)", col="lightblue")
hist(nthroot(train_imputed_transformed$TEAM_BASERUN_CS, 4),
     main = "Fourth Root(TEAM_BASERUN_CS)", col="lightblue")
hist(sqrt(train_imputed_transformed$TEAM_PITCHING_SO),
     main = "Square Root(TEAM_PITCHING_SO)", col="lightblue")
hist(log(train_imputed_transformed$TEAM_BATTING_3B),
     main = "Log(TEAM_BATTING_3B)", col="lightblue")
hist(train_imputed_transformed$TEAM_BATTING_BB^2,
     main = "TEAM_BATTING_BB SQUARED", col="lightblue")
hist(train_imputed_transformed$TEAM_PITCHING_H^-2,
     main = "TEAM_PITCHING_H INVERSE SQUARED", col="lightblue")
```

```
hist(nthroot(train_imputed_transformed$TEAM_PITCHING_BB, 3),
     main = "Cube Root(TEAM_PITCHING_BB)", col="lightblue")
hist(train_imputed_transformed$TEAM_FIELDING_E^-1,
     main = "TEAM_FIELDING_E INVERSE", col="lightblue")

lm_trans <- lm(TARGET_WINS ~ TEAM_BATTING_H + TEAM_BATTING_BB + I(TEAM_BATTING_BB**2) + log(TEAM_BASERU
summary(lm_trans)
lm_trans_reduced <- update(lm_trans, .~. - I(TEAM_PITCHING_SO**.5), train_imputed)
summary(lm_trans_reduced)
par(mfrow=c(2,2))
par(mai=c(.3,.3,.3,.3))
plot(lm_trans_reduced)
# 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)
par(mfrow=c(2,2))
par(mai=c(.3,.3,.3,.3))
plot(lm_select)
# Plot selective model residuals
plot(lm_select$residuals)
par(mfrow=c(2,2))
par(mai=c(.3,.3,.3,.3))
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

eval <- read.csv(eval_data_url)
test <- drop_na(test)

# Predict using the model using all input variables
predict_all <- predict(lm_all, test)
predict_reduced <- predict(lm_all_reduced, test)

predict_all_transformed <- predict(lm_trans, test)
rmse <- function(c1, c2){
  sqrt(mean((c1 - c2)^2))
}
# Calcualte RMSE and print to screen
rmse_all <- modelr::rmse(lm_all, test)
rmse_reduced <- modelr::rmse(lm_all_reduced, test)
rmse_all_transformed <- modelr::rmse(lm_trans, test)

print(rmse_all)
print(rmse_reduced)
print(rmse_all_transformed)
# Predict and plot on evaluation data (no wins listed)
prediction_reduced <- predict(lm_all_reduced, eval)
predict_reduced_eval <- as.data.frame(prediction_reduced)

# Plot reduced model evaluation
ggplot(predict_reduced_eval,
       aes(x = prediction_reduced)) +
       geom_histogram(bins=15) +
```

```
       labs(x="Wins",
            title="Predicted Wins (Reduced Model): Evaluation Data.")
predict_all_eval <- as.data.frame(predict(lm_all, eval))

ggplot(as.data.frame(predict_all_eval), aes(x = predict(lm_all, eval))) + geom_histogram(bins=15) + labs
```