DATA 621: Homework 1 (Group 2)

Moneyball Linear Regression

Contents

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0.1 Introduction

0.1.1 Assignment Objective

In this assignment, we analyze and model a baseball dataset containing multi-year game statistics for different teams. The objective is to build a multiple linear regression model on the training data to predict the number of wins for the team. We can only use the variables given to us (or variables that we derive from the variables provided).

0.1.1.1 Data

There are 2 datasets provided - The Moneyball training dataset contains 17 columns and 2276 rows. Each record in the Money Ball training dataset represents a professional baseball team from the years 1871 to 2006 inclusive. Each record has the performance of the team for the given year, with all of the statistics adjusted to match the performance of a 162 game season. For this assignment, the target variable in the dataset is TARGET_WINS.

On the nex page is a short description of the variables of interest in the data set:

0.1.2 Purpose of Analysis

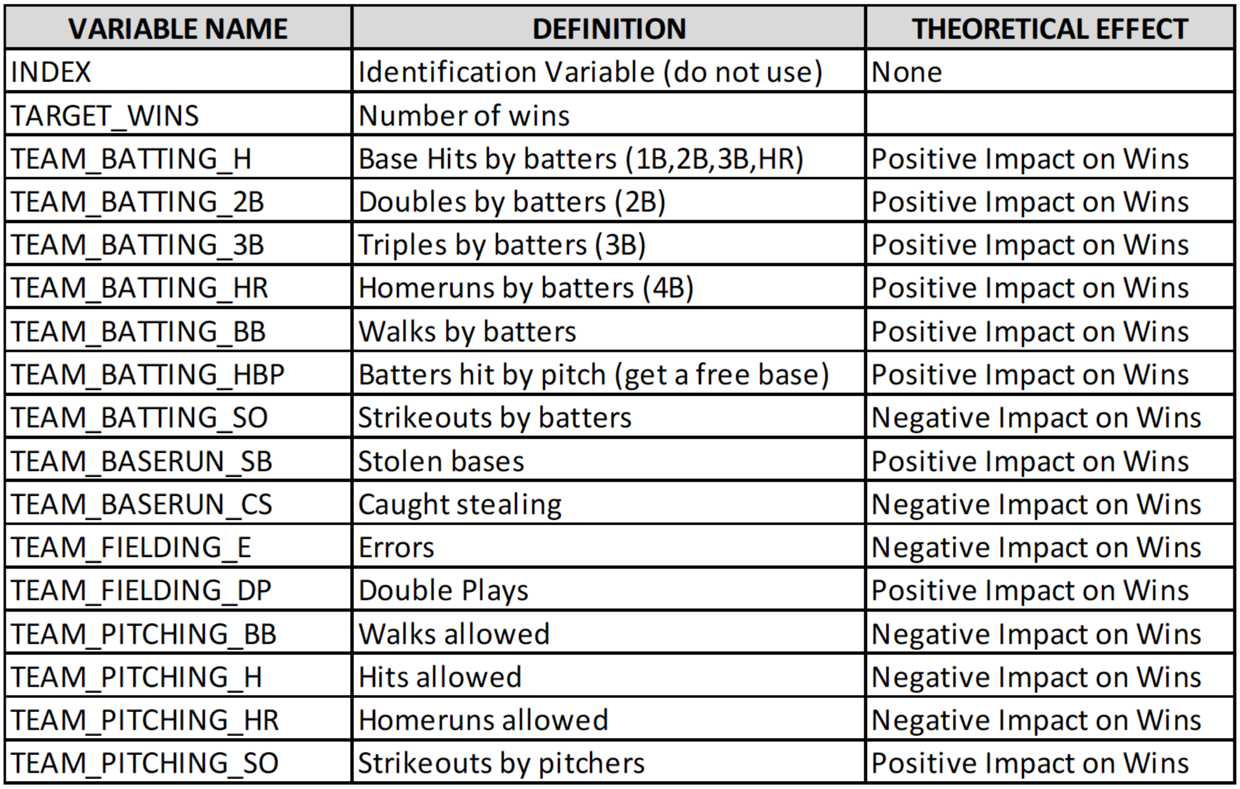
The purpose of the analysis is to find which of the predictors have significant ability to explain the variation in the response variable (number of wins by a team), and to make a prediction for all the records provided in the test data set.

0.1.3 Method

The method used is a multiple linear regression model on the training data to predict the number of wins for the team.

0.2 Data Exploration

The first variable in the above table (INDEX) was dropped from the dataset due to the fact that it is merely a row identifier, and has no impact on the target variable (TARGET_WINS).



VARIABLE NAME	DEFINITION	THEORETICAL EFFECT
INDEX	Identification Variable (do not use)	None
TARGET_WINS	Number of wins	
TEAM_BATTING_H	Base Hits by batters (1B,2B,3B,HR)	Positive Impact on Wins
TEAM_BATTING_2B	Doubles by batters (2B)	Positive Impact on Wins
TEAM_BATTING_3B	Triples by batters (3B)	Positive Impact on Wins
TEAM_BATTING_HR	Homeruns by batters (4B)	Positive Impact on Wins
TEAM_BATTING_BB	Walks by batters	Positive Impact on Wins
TEAM_BATTING_HBP	Batters hit by pitch (get a free base)	Positive Impact on Wins
TEAM_BATTING_SO	Strikeouts by batters	Negative Impact on Wins
TEAM_BASERUN_SB	Stolen bases	Positive Impact on Wins
TEAM_BASERUN_CS	Caught stealing	Negative Impact on Wins
TEAM_FIELDING_E	Errors	Negative Impact on Wins
TEAM_FIELDING_DP	Double Plays	Positive Impact on Wins
TEAM_PITCHING_BB	Walks allowed	Negative Impact on Wins
TEAM_PITCHING_H	Hits allowed	Negative Impact on Wins
TEAM_PITCHING_HR	Homeruns allowed	Negative Impact on Wins
TEAM_PITCHING_SO	Strikeouts by pitchers	Positive Impact on Wins

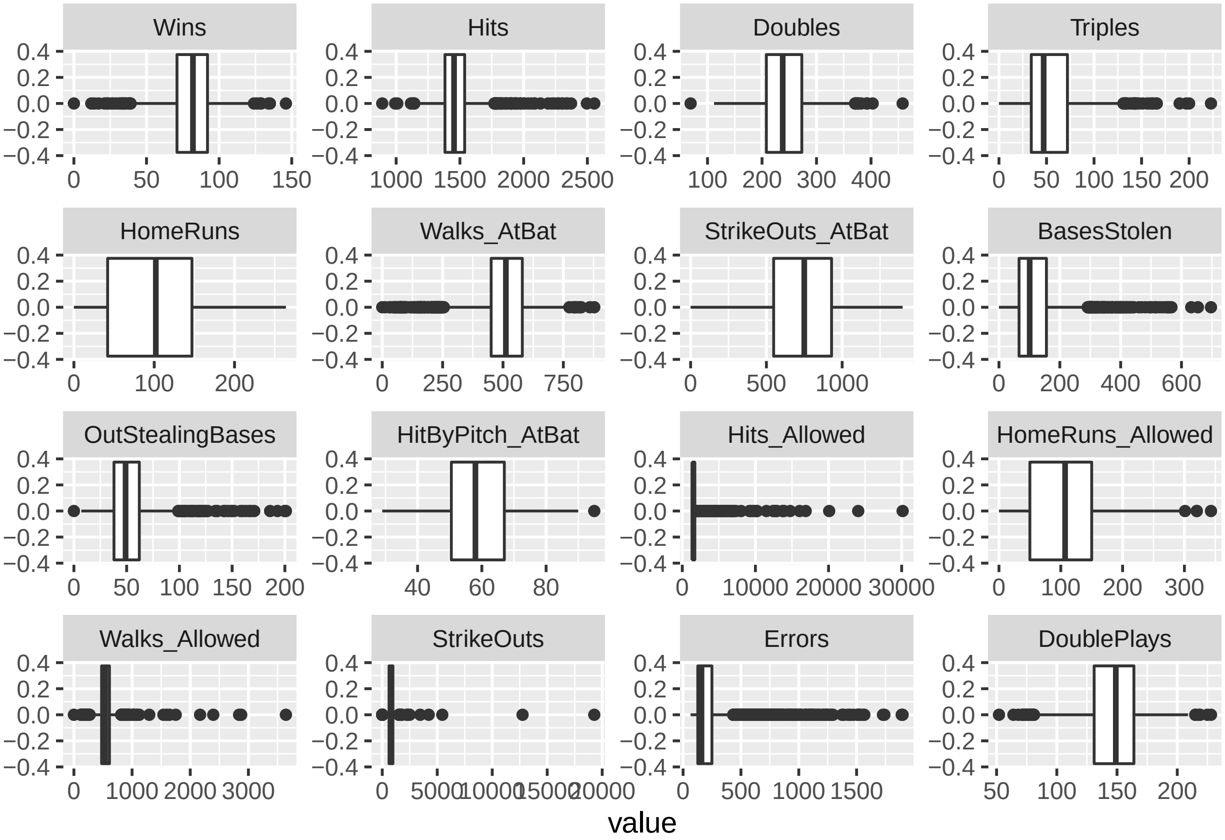
Figure 1: Variables of Interest

0.2.1 Summary Statistics

The first step in our data exploration was to compile summary statistics to give us some insight into the data prior to preparing the data for modeling. To make the variable names more readable, we removed the "TEAM_" prefix from each variable.

```
##       Wins            Hits         Doubles         Triples
##  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
##
##    HomeRuns       Walks_AtBat    StrikeOuts_AtBat  BasesStolen
##  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
##  OutStealingBases HitByPitch_AtBat  Hits_Allowed   HomeRuns_Allowed
##  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
##  Walks_Allowed      StrikeOuts          Errors        DoublePlays
##  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
```

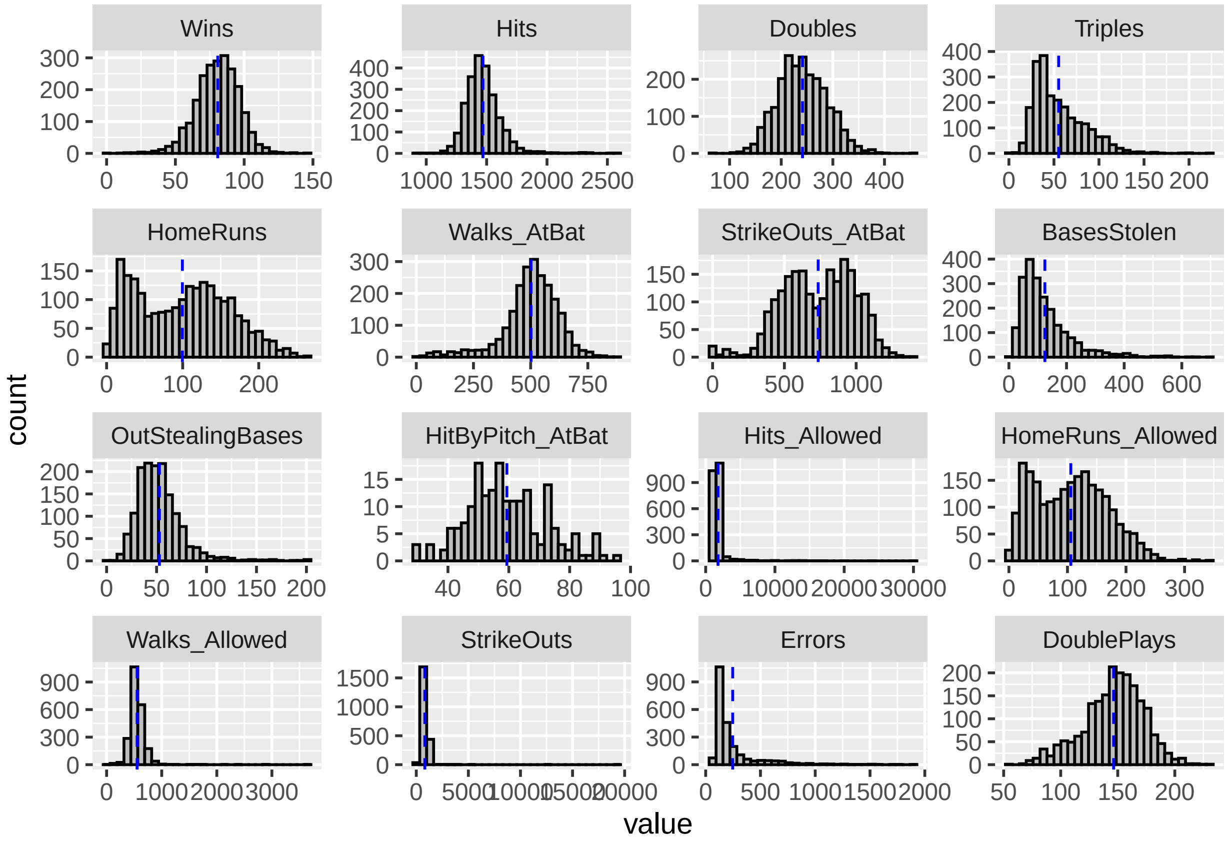
From the above, we see that there are 15 predictors and 1 response variable (Wins). Of the predictors, 6 have missing values. We then plotted boxplots for all the variables to get a sense of outliers.



From the box plots, we can see that quite a few predictors are very skewed in nature, such as Walks_Allowed and Hits_Allowed.

0.2.2 Variable Distributions

We created distribution plots for all the variables to check their shape visually and get a high-level, intuitive sense of normality.



The histograms provide additional confirmation that some of the variables are quite skewed. For example: Errors, Triples and Walks_AtBat. There are other variables with what look like bi-modal type of distributions. For example: StrikeOuts_AtBat. There are a couple of variables that look closer to the normal distribution. For example - the response variable Wins.

0.2.3 Feature Correlation

We now check which of the predictors are more correlated with the response variable as a mechanism to select which variables to include in the linear regression model. We also check the correlation between the predictors, since we'd like to avoid multi-collinearity.

Table 1: Correlation of Variables to Wins

	x
Hits	0.4699467
Doubles	0.3129840
Triples	-0.1243459
HomeRuns	0.4224168
Walks__AtBat	0.4686879
StrikeOuts__AtBat	-0.2288927
BasesStolen	0.0148364
OutStealingBases	-0.1787560
HitByPitch__AtBat	0.0735042
Hits__Allowed	0.4712343
HomeRuns__Allowed	0.4224668
Walks__Allowed	0.4683988
StrikeOuts	-0.2293648
Errors	-0.3866880
DoublePlays	-0.1958660

	Wins	Hits	Doubles	Triples	HomeRuns	Walks__AtBat	StrikeOuts__AtBat	BasesStoler
Wins	1.00	0.39	0.29	0.14	0.18	0.23	NA	NA
Hits	0.39	1.00	0.56	0.43	-0.01	-0.07	NA	NA
Doubles	0.29	0.56	1.00	-0.11	0.44	0.26	NA	NA
Triples	0.14	0.43	-0.11	1.00	-0.64	-0.29	NA	NA
HomeRuns	0.18	-0.01	0.44	-0.64	1.00	0.51	NA	NA
Walks__AtBat	0.23	-0.07	0.26	-0.29	0.51	1.00	NA	NA
StrikeOuts__AtBat	NA	NA	NA	NA	NA	NA	1	NA
BasesStolen	NA	NA	NA	NA	NA	NA	NA	1
OutStealingBases	NA	NA	NA	NA	NA	NA	NA	NA
HitByPitch__AtBat	NA	NA	NA	NA	NA	NA	NA	NA
Hits__Allowed	-0.11	0.30	0.02	0.19	-0.25	-0.45	NA	NA
HomeRuns__Allowed	0.19	0.07	0.45	-0.57	0.97	0.46	NA	NA
Walks__Allowed	0.12	0.09	0.18	0.00	0.14	0.49	NA	NA
StrikeOuts	NA	NA	NA	NA	NA	NA	NA	NA
Errors	-0.18	0.26	-0.24	0.51	-0.59	-0.66	NA	NA
DoublePlays	NA	NA	NA	NA	NA	NA	NA	NA

row	column	cor	p
Wins	Hits	0.3887675	0.0000000
Wins	Doubles	0.2891036	0.0000000
Wins	Walks_AtBat	0.2325599	0.0000000
Wins	HomeRuns_Allowed	0.1890137	0.0000000
Wins	Errors	-0.1764848	0.0000000
Wins	HomeRuns	0.1761532	0.0000000
Wins	Triples	0.1426084	0.0000000
Wins	BasesStolen	0.1351389	0.0000000
Wins	Walks_Allowed	0.1241745	0.0000000
Wins	Hits_Allowed	-0.1099371	0.0000001
Wins	StrikeOuts	-0.0784361	0.0002515
Wins	HitByPitch_AtBat	0.0735042	0.3122327
Wins	DoublePlays	-0.0348506	0.1201464
Wins	StrikeOuts_AtBat	-0.0317507	0.1388904
Wins	OutStealingBases	0.0224041	0.3852582

Based on the p-values, we could exclude the following variables from the regression model: StrikeOuts_AtBat, DoublePlays and OutStealingBases

0.2.4 Check for normality of predictors

```
##                  statistic
## Wins             0.988248
## Hits             0.9104077
## Doubles          0.9963224
## Triples          0.9179955
## HomeRuns         0.9619353
## Walks_AtBat      0.9378385
## StrikeOuts_AtBat 0.9809301
## BasesStolen      0.830944
## OutStealingBases 0.8696043
## HitByPitch_AtBat 0.9867283
## Hits_Allowed     0.2461101
## HomeRuns_Allowed 0.9715163
## Walks_Allowed    0.6605698
## StrikeOuts       0.3154772
## Errors           0.6271848
## DoublePlays      0.9875677
##                  p.value
## Wins             0.000000000001006842
## Hits             0.0000000000000000000000000000000001145863
## Doubles          0.00002408015
## Triples          0.00000000000000000000000000000000018063
## HomeRuns         0.000000000000000000000005232703
## Walks_AtBat      0.000000000000000000000000000007302396
## StrikeOuts_AtBat 0.0000000000000001807381
## BasesStolen      0.0000000000000000000000000000000000000000006620076
## OutStealingBases 0.000000000000000000000000000000001176157
## HitByPitch_AtBat 0.06996103
## Hits_Allowed     0.0000000000000000000000000000000000000000000000000000000000000000000003673509
## HomeRuns_Allowed 0.000000000000000000007284096
## Walks_Allowed    0.000000000000000000000000000000000000000000000000000000231042
## StrikeOuts       0.0000000000000000000000000000000000000000000000000000000000000000002960949
```

Table 2: Breakdown of Variables by Percentage of Missing Data

	x
HitByPitch_AtBat	91.61
OutStealingBases	33.92
DoublePlays	12.57
BasesStolen	5.76
StrikeOuts_AtBat	4.48
StrikeOuts	4.48
Wins	0.00
Hits	0.00
Doubles	0.00
Triples	0.00
HomeRuns	0.00
Walks_AtBat	0.00
Hits_Allowed	0.00
HomeRuns_Allowed	0.00
Walks_Allowed	0.00
Errors	0.00

```
## Errors           0.0000000000000000000000000000000000000000000000000000000521485
## DoublePlays      0.000000000004183658
```

From the above, it looks like most of the predictors are close to normality.

0.3 Data Preparation

0.3.1 Missing Data - Handling NA Values

We now dig deeper into the extent of missing data for the predictors.

91.61% percent of the rows are missing from the HitByPitch_AtBat variable, so we will remove this variable from the dataset completely. The percentage of missing data for the remaining variables with missing data is much less, and so excluding them from the final model could skew the results.

We now need to deal with 2 more data issues: 1) significant outliers 2) missing values

We could possibly drop rows with either of the 2 issues mentioned above, but then we may end up losing a fair amount of data. We therefore decided to remove the outliers for some of the more extreme cases, and then from the updated dataset, we imputed the missing values with the median of the respective predictor variable.

The following columns look like they have significant outliers: - Walks_Allowed - BasesStolen - StrikeOuts - Hits_Allowed - Errors - Triples

These are removed for the next analysis where they are greater than the IQR, with a summary of the updated data below.

```
##       Wins             Hits         Doubles         Triples
##  Min.   : 21.00   Min.   :1137   Min.   :130.0   Min.   : 11.0
##  1st Qu.: 72.00   1st Qu.:1385   1st Qu.:215.0   1st Qu.: 32.0
##  Median : 82.00   Median :1447   Median :244.0   Median : 42.0
##  Mean   : 80.77   Mean   :1457   Mean   :246.9   Mean   : 48.1
##  3rd Qu.: 90.00   3rd Qu.:1524   3rd Qu.:276.0   3rd Qu.: 60.0
##  Max.   :120.00   Max.   :1876   Max.   :392.0   Max.   :126.0
##     HomeRuns      Walks_AtBat    StrikeOuts_AtBat  BasesStolen
##  Min.   :  4.0   Min.   :273.0   Min.   : 268     Min.   : 18.0  
##  1st Qu.: 75.0   1st Qu.:472.0   1st Qu.: 598     1st Qu.: 62.0  
##  Median :118.0   Median :523.0   Median : 814     Median : 91.0  
##  Mean   :115.6   Mean   :527.9   Mean   : 783     Mean   :100.2  
##  3rd Qu.:156.0   3rd Qu.:585.0   3rd Qu.: 955     3rd Qu.:131.0  
##  Max.   :264.0   Max.   :775.0   Max.   :1399     Max.   :289.0  
##  OutStealingBases  Hits_Allowed  HomeRuns_Allowed Walks_Allowed  
##  Min.   : 11.00   Min.   :1137   Min.   :  4.0    Min.   :320.0  
##  1st Qu.: 41.00   1st Qu.:1407   1st Qu.: 79.0    1st Qu.:487.0  
##  Median : 49.00   Median :1490   Median :121.0    Median :537.0  
##  Mean   : 52.06   Mean   :1510   Mean   :118.4    Mean   :546.2  
##  3rd Qu.: 58.00   3rd Qu.:1590   3rd Qu.:158.0    3rd Qu.:601.0  
##  Max.   :201.00   Max.   :2069   Max.   :264.0    Max.   :810.0  
##    StrikeOuts         Errors       DoublePlays   
##  Min.   : 301.0   Min.   : 65.0   Min.   : 72.0  
##  1st Qu.: 639.0   1st Qu.:122.0   1st Qu.:136.0  
##  Median : 824.0   Median :144.0   Median :151.0  
##  Mean   : 805.5   Mean   :161.9   Mean   :150.4  
##  3rd Qu.: 962.0   3rd Qu.:184.0   3rd Qu.:165.0  
##  Max.   :1481.0   Max.   :430.0   Max.   :225.0  
```

0.4 Models

0.4.1 Model 1

Model 1 includes the remaining variables in the dataset except for the one dropped earlier due to lots of missing values (HitByPitch_AtBat).

0.4.1.0.1 Model 1 Statistics

Model 1 Summary Stats

```
## 
## Call:
## lm(formula = Wins ~ Hits + Doubles + Triples + HomeRuns + Walks_AtBat + 
##     BasesStolen + Hits_Allowed + HomeRuns_Allowed + Errors + 
##     Walks_Allowed + StrikeOuts + StrikeOuts_AtBat + OutStealingBases + 
##     DoublePlays, data = mb_training_updated)
## 
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -32.236  -7.006   0.134   6.904  29.838 
## 
## Coefficients:
##                   Estimate Std. Error t value             Pr(>|t|)    
## (Intercept)      57.033963   6.166067   9.250 < 0.0000000000000002 ***
## Hits             -0.035499   0.022113  -1.605              0.10860    
## Doubles          -0.054552   0.009026  -6.044        0.00000000183 ***
## Triples           0.186643   0.019712   9.468 < 0.0000000000000002 ***
## HomeRuns          0.241595   0.138884   1.740              0.08211 .  
## Walks_AtBat       0.200978   0.064606   3.111              0.00190 ** 
## BasesStolen       0.076969   0.006573  11.709 < 0.0000000000000002 ***
## Hits_Allowed      0.065127   0.020521   3.174              0.00153 ** 
## HomeRuns_Allowed -0.145831   0.134764  -1.082              0.27935    
## Errors           -0.124236   0.007365 -16.869 < 0.0000000000000002 ***
## Walks_Allowed    -0.159245   0.061932  -2.571              0.01021 *
## StrikeOuts        0.001674   0.032200   0.052              0.95854
## StrikeOuts_AtBat -0.023747   0.033436  -0.710              0.47765
## OutStealingBases -0.039104   0.014502  -2.696              0.00707 **
## DoublePlays      -0.109783   0.012606  -8.709 < 0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.26 on 1774 degrees of freedom
## Multiple R-squared:  0.4045, Adjusted R-squared:  0.3998
## F-statistic: 86.07 on 14 and 1774 DF,  p-value: < 0.00000000000000022
```

We see that the adjusted R-squared for this model is 0.40 i.e. these predictors explain about 40% of the variability in the response variable.

Model 1 R Squared

```
## [1] 0.4044997
```

Model 1 Coefficients

According to the model, there are 4 coefficients that are not as expected: `Hits`, `Doubles`, `Hits_Allowed`, and `DoublePlays`. If a team has a lot of hits, doubles, or double plays, it would be expected that such a team would win more games. Futhermore, if a team has a lot of hits allowed, it would be expected that such a team would lost more games. This can be due to skewed data since the skewness of `Hits_Allowed` is 0.8125714. Prior to removing outliers, the variable used to be heavily right skewed with a skewness of 10.3295111. It can also mean that there were some teams who had more hits and doubles than the average.

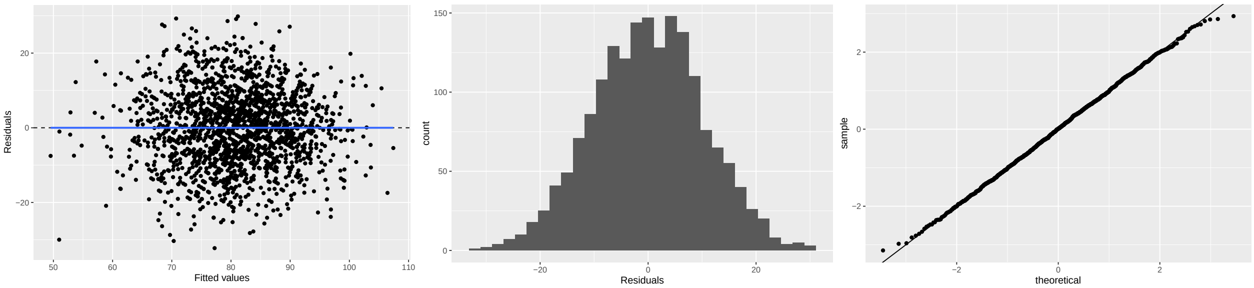
Model 1 Confidence Intervals

We calculate the 95% confidence intervals for each of the co-efficients and the intercept for this model.

```
##                         2.5 %       97.5 %
## (Intercept)      44.94044362 69.127482832
## Hits             -0.07886950  0.007872103
## Doubles          -0.07225451 -0.036849474
## Triples           0.14798073  0.225304552
## HomeRuns         -0.03079800  0.513988472
## Walks_AtBat       0.07426677  0.327689717
## BasesStolen       0.06407675  0.089861282
## Hits_Allowed      0.02487963  0.105374808
## HomeRuns_Allowed -0.41014380  0.118482229
## Errors           -0.13868039 -0.109790758
## Walks_Allowed    -0.28071180 -0.037777706
## StrikeOuts       -0.06148025  0.064828416
## StrikeOuts_AtBat -0.08932553  0.041830860
## OutStealingBases -0.06754688 -0.010661147
## DoublePlays      -0.13450771 -0.085058563
```

0.4.1.0.2 Model 1 Plots

We plot the residuals versus the fitted values - it shows that the residuals are scattered fairly evenly and there doesn't seem to be a trend. The distribution of the residuals does not seem very skewed. The same can be seen through the qq-plot as well.



0.4.1.1 Model 2

Model 2 uses stepwise regression on the variables in Model 1 to create the best performing model.

Model 2 Summary Stats

```
##
## Call:
## lm(formula = Wins ~ Hits + Doubles + Triples + HomeRuns + Walks_AtBat +
##     BasesStolen + Hits_Allowed + HomeRuns_Allowed + Errors +
##     Walks_Allowed + StrikeOuts_AtBat + OutStealingBases + DoublePlays,
##     data = mb_training_updated)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -32.235  -7.017   0.138   6.908  29.818
##
## Coefficients:
##                   Estimate Std. Error t value             Pr(>|t|)
## (Intercept)      57.054236   6.151995   9.274 < 0.0000000000000002 ***
## Hits             -0.035845   0.021081  -1.700             0.089244 .
## Doubles          -0.054553   0.009023  -6.046        0.00000000181 ***
## Triples           0.186556   0.019637   9.500 < 0.0000000000000002 ***
## HomeRuns          0.236397   0.096373   2.453             0.014264 *
## Walks_AtBat       0.200201   0.062835   3.186             0.001467 **
## BasesStolen       0.076979   0.006568  11.720 < 0.0000000000000002 ***
## Hits_Allowed      0.065450   0.019551   3.348             0.000832 ***
## HomeRuns_Allowed -0.140764   0.093058  -1.513             0.130547
## Errors           -0.124249   0.007359 -16.885 < 0.0000000000000002 ***
## Walks_Allowed    -0.158502   0.060243  -2.631             0.008586 **
## StrikeOuts_AtBat -0.022013   0.002395  -9.192 < 0.0000000000000002 ***
## OutStealingBases -0.039065   0.014479  -2.698             0.007039 **
## DoublePlays      -0.109815   0.012588  -8.724 < 0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.26 on 1775 degrees of freedom
## Multiple R-squared:  0.4045, Adjusted R-squared:  0.4001
## F-statistic: 92.74 on 13 and 1775 DF,  p-value: < 0.00000000000000022
```

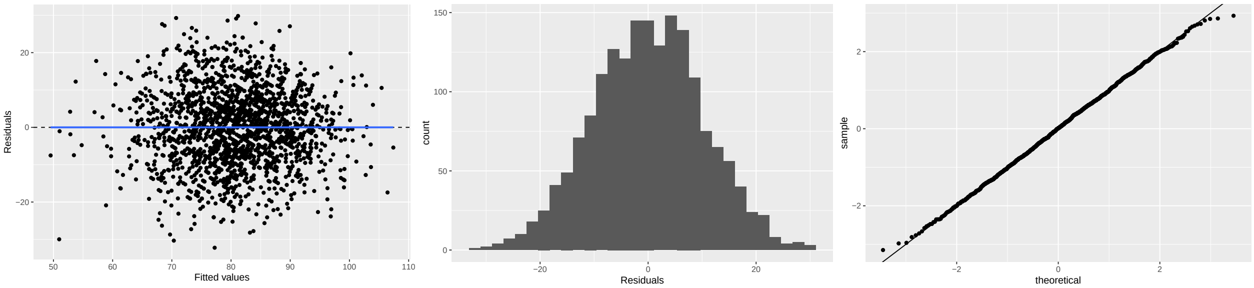
However we see minimal impact to the R-squared value, which remains around 0.40.

Model 2 Coefficients

According to this model, there are again 4 coefficients that are not as expected: `Hits`, `Doubles`, `Hits_Allowed`, and `DoublePlays`. We expect these variables to have the opposite effect on the target wins. Similarly to

Model 1, this can be due to skewed data and there could have been some teams who either performed better or worse than the average.

0.4.1.1.1 Model 2 Plots



Wins = Target__wins, Hits = Batting__h, Doubles = Batting__2b, Triples = Batting__3b, HomeRuns = Batting__hr, Walks__AtBat = Batting__bb, StrikeOuts__AtBat = Batting__so, BasesStolen = Baserun__sb, OutStealingBases = Baserun__cs, Hits__Allowed = Pitching__h, HitByPitch__AtBat = Batting__hbp, Errors = Fielding__e, HomeRuns__Allowed = Pitching__hr, Walks__Allowed = Pitching__bb, StrikeOuts = Pitching__so, DoublePlays = Fielding__dp

0.4.1.1.2 Model 3

For Model 3, we create a new dataframe and derive some new variables by transforming existing predictors to include in this dataframe: - Singles is derived as the difference between all Hits and Doubles, Triples and Home Runs - Homeruns difference is the difference between home runs scored and allowed.

We also include certain variables derived on the fly in the model - for example: the ratio between Home runs allowed and scores, the product of home runs allowed and scored, the reciprocal of Double plays and the cube of the stolen basis variable.

Model 3 Summary Stats

```
##
## Call:
## lm(formula = Wins ~ Hits + Doubles + Triples + Walks_AtBat +
##     BasesStolen + Hits_Allowed + Errors + Walks_Allowed + StrikeOuts +
##     Singles + Homeruns_diff + StrikeOuts_AtBat + I(HomeRuns_Allowed/HomeRuns) +
##     I(HomeRuns_Allowed * HomeRuns) + I(1/DoublePlays) + I(OutStealingBases^3),
##     data = mb_training_new)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -31.826  -7.049   0.066   6.960  31.025
##
## Coefficients:
##                                     Estimate      Std. Error t value
## (Intercept)                     109.9453169993   40.2856609726   2.729
## Hits                              0.0281580282    0.0440891477   0.639
## Doubles                          -0.1735673380    0.0277600015  -6.252
## Triples                           0.0602076781    0.0303537212   1.984
## Walks_AtBat                       0.1904325935    0.0648354833   2.937
## BasesStolen                       0.0687665386    0.0060907199  11.290
## Hits_Allowed                      0.1198392065    0.0310629804   3.858
## Errors                           -0.1235278847    0.0075827849 -16.291
## Walks_Allowed                    -0.1489662240    0.0621728192  -2.396
## StrikeOuts                        0.0166499515    0.0340842858   0.488
## Singles                           -0.1206931596    0.0272655274  -4.427
## Homeruns_diff                     -0.2229976419    0.1427124139  -1.563
## StrikeOuts_AtBat                  -0.0391231155    0.0354323522  -1.104
## I(HomeRuns_Allowed/HomeRuns)     -85.2314174131   37.8641514196  -2.251
## I(HomeRuns_Allowed * HomeRuns)    -0.0000688546    0.0000877940  -0.784
## I(1/DoublePlays)                2390.0964728930  257.2489261894   9.291
## I(OutStealingBases^3)              0.0000001113    0.0000004862   0.229
##                                             Pr(>|t|)
## (Intercept)                               0.006413 **
## Hits                                      0.523126
## Doubles                             0.000000000505 ***
## Triples                                   0.047462 *
## Walks_AtBat                               0.003355 **
## BasesStolen                   < 0.0000000000000002 ***
## Hits_Allowed                              0.000118 ***
## Errors                        < 0.0000000000000002 ***
## Walks_Allowed                             0.016678 *
## StrikeOuts                                0.625261
## Singles                             0.000010157283 ***
## Homeruns_diff                             0.118333
## StrikeOuts_AtBat                          0.269672
## I(HomeRuns_Allowed/HomeRuns)              0.024509 *
## I(HomeRuns_Allowed * HomeRuns)            0.432984
## I(1/DoublePlays)               < 0.0000000000000002 ***
## I(OutStealingBases^3)                     0.819000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.25 on 1772 degrees of freedom
## Multiple R-squared:  0.4069, Adjusted R-squared:  0.4015
## F-statistic: 75.97 on 16 and 1772 DF,  p-value: < 0.00000000000000022
```

We don't see much change to the R-squared value.

Model 3 R-Squared

```
## [1] 0.4068615
```

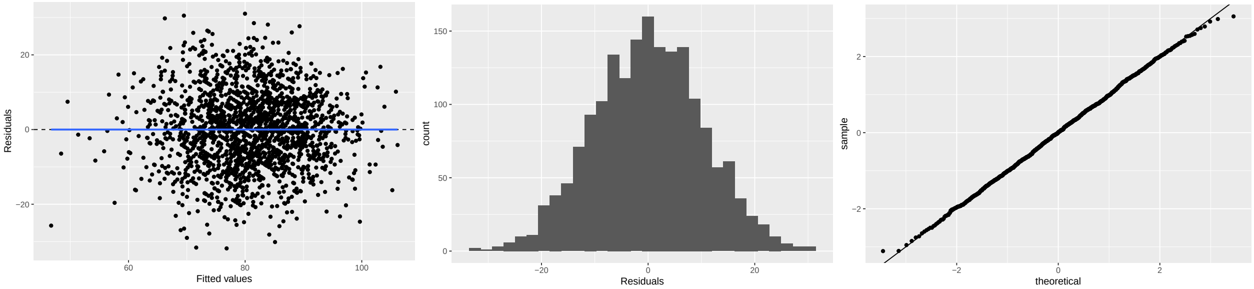
Model 3 Coefficients

According to this model, there are 2 coefficients that are not as expected: `Doubles` and `Hits_Allowed`. We expect these variables to have the opposite effect on the target wins. Similarly to Model 1, this can be due to skewed data and there could have been some teams who either performed better or worse than the average. Also the effect of `DoublePlays` effect is worsened as it is given a greater weight compared to all the other variables. The coefficients gives a greater weight to those who have less double plays. It would not be the most efficient model to use because double plays occur nearly one time each game by each team. Also the coefficient is unreasonable since each team only plays 162 games a season.

Model 3 Confidence Intervals

```
##                                              2.5 %           97.5 %
## (Intercept)                     30.9329035984562 188.957730400225
## Hits                            -0.0583141776004   0.114630233945
## Doubles                         -0.2280131298677  -0.119121546135
## Triples                          0.0006748143466   0.119740541945
## Walks_AtBat                      0.0632705241893   0.317594662719
## BasesStolen                      0.0568207875157   0.080712289602
## Hits_Allowed                          0.0589152700712    0.180763142896
## Errors                               -0.1384000282943   -0.108655741084
## Walks_Allowed                        -0.2709060004136   -0.027026447629
## StrikeOuts                           -0.0501996822336    0.083499585329
## Singles                              -0.1741691375868   -0.067217181579
## Homeruns_diff                        -0.5029000183358    0.056904734612
## StrikeOuts_AtBat                     -0.1086167168480    0.030370485818
## I(HomeRuns_Allowed/HomeRuns)   -159.4945153196878  -10.968319506518
## I(HomeRuns_Allowed * HomeRuns)   -0.0002410453595    0.000103336128
## I(1/DoublePlays)               1885.5532182390721 2894.639727546878
## I(OutStealingBases^3)            -0.0000008422653    0.000001064801
```

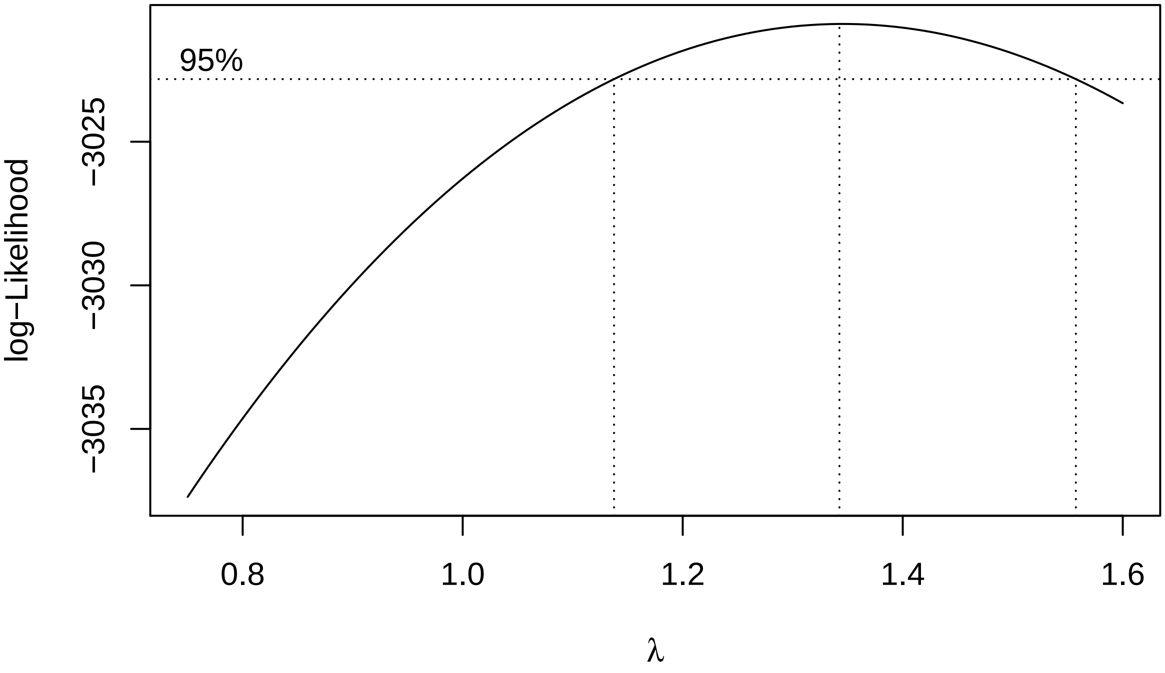
0.4.1.1.3 Model 3 Plots



There is not much change in the scatter plot of the residuals with the fitted values, and the distribution of errors does not seem to have changed much.

0.4.1.2 Model 4 - Box Cox transformation

For our final model (Model 4), we do a Box Cox transformation on the response variable from Model 1 to see if it provides a better-fitting model. We plot the lambda and based on the plot, a lambda value of around 1.35 seems like the best value.



0.4.1.2.1 Model 4 Statistics

Model 4 Summary Stats

```
##
## Call:
## lm(formula = (((Wins^1.35) - 1)/1.35) ~ Hits + Doubles + Triples +
##     HomeRuns + Walks_AtBat + BasesStolen + Hits_Allowed + HomeRuns_Allowed +
##     Errors + Walks_Allowed + StrikeOuts + StrikeOuts_AtBat +
##     OutStealingBases + DoublePlays, data = mb_training_updated)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -138.325  -33.262   -0.183   31.243  143.981
##
## Coefficients:
##                    Estimate Std. Error t value             Pr(>|t|)
## (Intercept)      169.730793  28.446990   5.967        0.00000000292 ***
## Hits              -0.160624   0.102019  -1.574              0.11556
## Doubles           -0.251500   0.041641  -6.040        0.00000000188 ***
## Triples            0.859596   0.090943   9.452 < 0.0000000000000002 ***
## HomeRuns           1.088291   0.640737   1.698              0.08959 .
## Walks_AtBat        0.922916   0.298057   3.096              0.00199 **
## BasesStolen        0.351828   0.030326  11.602 < 0.0000000000000002 ***
## Hits_Allowed       0.296026   0.094672   3.127              0.00180 **
## HomeRuns_Allowed  -0.640745   0.621730  -1.031              0.30288
## Errors            -0.560633   0.033978 -16.500 < 0.0000000000000002 ***
## Walks_Allowed     -0.729399   0.285721  -2.553              0.01077 *
## StrikeOuts         0.007101   0.148555   0.048              0.96188
## StrikeOuts_AtBat  -0.110581   0.154256  -0.717              0.47355
## OutStealingBases  -0.183480   0.066905  -2.742              0.00616 **
## DoublePlays       -0.502375   0.058158  -8.638 < 0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 47.33 on 1774 degrees of freedom
## Multiple R-squared:  0.4028, Adjusted R-squared:  0.3981
## F-statistic: 85.46 on 14 and 1774 DF,  p-value: < 0.00000000000000022
```

Model 4 R Squared

```
## [1] 0.4027743
```

We don't see much impact on R-squared, possibly because the response variable was close to normal to begin with.

Model 4 Coefficients

According to this model, there are 4 coefficients that are not as expected: `Hits`, `Doubles`, `Hits_Allowed` and `DoublePlays`. We expect these variables to have the opposite effect on the target wins. This can be attributed to skewed data and the missing values that were imputed. The intercept is also unreasonable since it can be interpreted that a team scores on average 169 wins, given that everything else is 0 and there is a 162 game season.

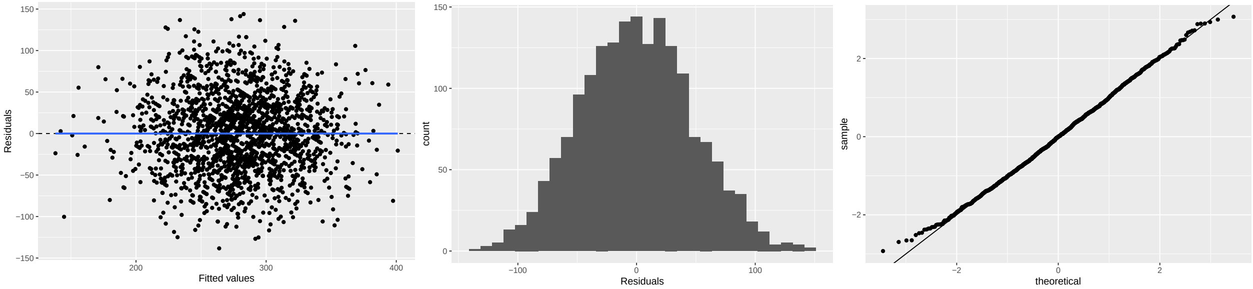
Model 4 Confidence Intervals

We calculate the 95% confidence intervals for each of the co-efficients and the intercept for this model.

```
##                        2.5 %       97.5 %
## (Intercept)      113.9376512 225.52393496
## Hits              -0.3607137   0.03946645
## Doubles           -0.3331698  -0.16982958
## Triples            0.6812301   1.03796157
## HomeRuns          -0.1683880   2.34497038
## Walks_AtBat        0.3383354   1.50749568
## BasesStolen        0.2923498   0.41130605
## Hits_Allowed       0.1103447   0.48170712
## HomeRuns_Allowed  -1.8601466   0.57865598
## Errors            -0.6272741  -0.49399258
## Walks_Allowed     -1.2897845  -0.16901436
## StrikeOuts        -0.2842602   0.29846157
## StrikeOuts_AtBat  -0.4131244   0.19196222
## OutStealingBases  -0.3147009  -0.05225998
## DoublePlays       -0.6164411  -0.38830872
```

0.4.1.2.2 Model 4 Plots

We plot the residuals versus the fitted values - it shows that the residuals are scattered fairly evenly and there doesn't seem to be a trend. The distribution of the residuals does not seem very skewed. The same can be seen through the qq-plot as well.



The residuals for this model behave similarly to the residuals from the previous model.

0.5 Model Selection

We decide to use model one for making predictions for the test dataset, since the other models do not provide a sgnificant improvement over it.

0.5.0.1 Predicting the response variable for the test dataset

We now predict the number of wins for the test data using model one.

```
##  TEAM_BATTING_H TEAM_BATTING_2B TEAM_BATTING_3B  TEAM_BATTING_HR
##  Min.   : 819   Min.   : 44.0   Min.   : 14.00   Min.   :  0.00
##  1st Qu.:1387   1st Qu.:210.0   1st Qu.: 35.00   1st Qu.: 44.50
##  Median :1455   Median :239.0   Median : 52.00   Median :101.00
##  Mean   :1469   Mean   :241.3   Mean   : 55.91   Mean   : 95.63
##  3rd Qu.:1548   3rd Qu.:278.5   3rd Qu.: 72.00   3rd Qu.:135.50
##  Max.   :2170   Max.   :376.0   Max.   :155.00   Max.   :242.00
##
##  TEAM_BATTING_BB TEAM_BATTING_SO  TEAM_BASERUN_SB TEAM_BASERUN_CS
##  Min.   : 15.0   Min.   :   0.0   Min.   :  0.0   Min.   :  0.00
##  1st Qu.:436.5   1st Qu.: 545.0   1st Qu.: 59.0   1st Qu.: 38.00
##  Median :509.0   Median : 686.0   Median : 92.0   Median : 49.50
##  Mean   :499.0   Mean   : 709.3   Mean   :123.7   Mean   : 52.32
##  3rd Qu.:565.5   3rd Qu.: 912.0   3rd Qu.:151.8   3rd Qu.: 63.00
##  Max.   :792.0   Max.   :1268.0   Max.   :580.0   Max.   :154.00
##                  NA's   :18       NA's   :13      NA's   :87
##  TEAM_BATTING_HBP TEAM_PITCHING_H TEAM_PITCHING_HR TEAM_PITCHING_BB
##  Min.   :42.00    Min.   : 1155   Min.   :  0.0    Min.   : 136.0
##  1st Qu.:53.50    1st Qu.: 1426   1st Qu.: 52.0    1st Qu.: 471.0
##  Median :62.00    Median : 1515   Median :104.0    Median : 526.0
##  Mean   :62.37    Mean   : 1813   Mean   :102.1    Mean   : 552.4
##  3rd Qu.:67.50    3rd Qu.: 1681   3rd Qu.:142.5    3rd Qu.: 606.5
##  Max.   :96.00    Max.   :22768   Max.   :336.0    Max.   :2008.0
##  NA's   :240
##  TEAM_PITCHING_SO TEAM_FIELDING_E  TEAM_FIELDING_DP
##  Min.   :   0.0   Min.   :  73.0   Min.   : 69.0
##  1st Qu.: 613.0   1st Qu.: 131.0   1st Qu.:131.0
##  Median : 745.0   Median : 163.0   Median :148.0
##  Mean   : 799.7   Mean   : 249.7   Mean   :146.1
##  3rd Qu.: 938.0   3rd Qu.: 252.0   3rd Qu.:164.0
##  Max.   :9963.0   Max.   :1568.0   Max.   :204.0
##  NA's   :18                        NA's   :31
```

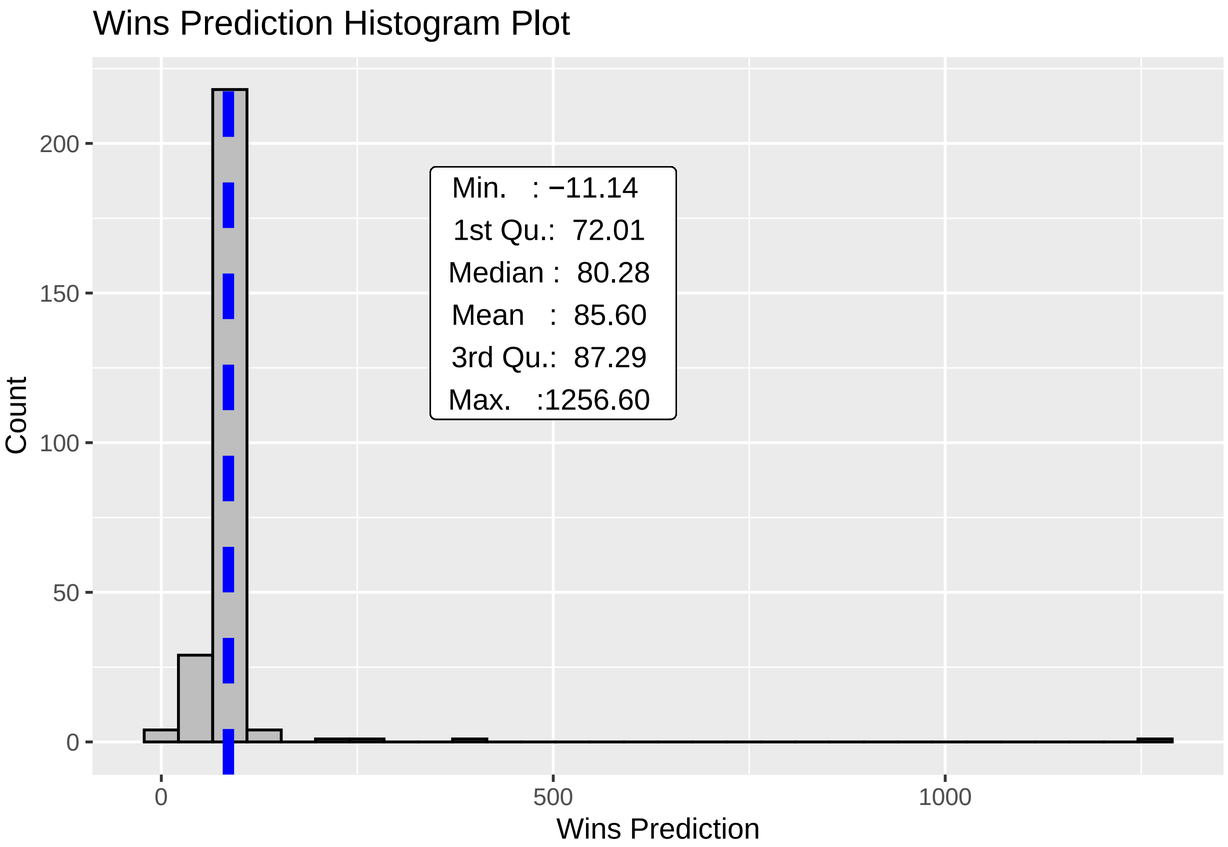
0.5.1 Data Preparation, Test Data

The test data is prepared similarly to the training data, with columns renamed and missing values assigned an imputed value of the median.

```
##       Hits          Doubles         Triples          HomeRuns
##  Min.   : 819   Min.   : 44.0   Min.   : 14.00   Min.   :  0.00
##  1st Qu.:1387   1st Qu.:210.0   1st Qu.: 35.00   1st Qu.: 44.50
##  Median :1455   Median :239.0   Median : 52.00   Median :101.00
##  Mean   :1469   Mean   :241.3   Mean   : 55.91   Mean   : 95.63
##  3rd Qu.:1548   3rd Qu.:278.5   3rd Qu.: 72.00   3rd Qu.:135.50
##  Max.   :2170   Max.   :376.0   Max.   :155.00   Max.   :242.00
##   Walks_AtBat    StrikeOuts_AtBat  BasesStolen    OutStealingBases
##  Min.   : 15.0   Min.   :   0.0   Min.   :  0.0   Min.   :  0.00
##  1st Qu.:436.5   1st Qu.: 565.0   1st Qu.: 60.5   1st Qu.: 44.00
##  Median :509.0   Median : 686.0   Median : 92.0   Median : 49.50
##  Mean   :499.0   Mean   : 707.7   Mean   :122.1   Mean   : 51.37
##  3rd Qu.:565.5   3rd Qu.: 904.5   3rd Qu.:149.0   3rd Qu.: 56.00
##  Max.   :792.0   Max.   :1268.0   Max.   :580.0   Max.   :154.00
##  HitByPitch_AtBat  Hits_Allowed   HomeRuns_Allowed Walks_Allowed
##  Min.   :42.00    Min.   : 1155   Min.   :  0.0    Min.   : 136.0
##  1st Qu.:62.00    1st Qu.: 1426   1st Qu.: 52.0    1st Qu.: 471.0
##  Median :62.00    Median : 1515   Median :104.0    Median : 526.0
##  Mean   :62.03    Mean   : 1813   Mean   :102.1    Mean   : 552.4
##  3rd Qu.:62.00    3rd Qu.: 1681   3rd Qu.:142.5    3rd Qu.: 606.5
##  Max.   :96.00    Max.   :22768   Max.   :336.0    Max.   :2008.0
##    StrikeOuts         Errors        DoublePlays
##  Min.   :   0.0   Min.   :  73.0   Min.   : 69.0
##  1st Qu.: 622.5   1st Qu.: 131.0   1st Qu.:134.5
##  Median : 745.0   Median : 163.0   Median :148.0
##  Mean   : 795.9   Mean   : 249.7   Mean   :146.3
##  3rd Qu.: 927.5   3rd Qu.: 252.0   3rd Qu.:160.5
##  Max.   :9963.0   Max.   :1568.0   Max.   :204.0
```

0.5.2 Predicting Wins

We will look at the distribution of the predicted test data and create a table for the predicted wins.



fit	lwr	upr
60.80215	40.58776	81.01653
67.69641	47.50656	87.88625
72.45775	52.28529	92.63021
83.37307	63.20421	103.54192
145.16145	68.69661	221.62629
75.81520	41.43534	110.19506

0.6 Conclusion

We conclude that model one which includes a majority of the predictors except one provides the best overall fit. While we did try additional models based on transformed variables, they did not provide a significant improvement, so we decided to go with model one. This model does not seem to violate the assumptions of linear regression.

0.7 References

Sellmair, Reinhard. "How to handle correlated Features?" June 25, 2018. https://www.kaggle.com/reisel/how-to-handle-correlated-features

Xie, Yihui, J. J. Allaire, and Garrett Grolemund, *R Markdown: The Definitive Guide*, CRC PressDecember 14, 2020 https://bookdown.org/yihui/rmarkdown/r-code.html.

https://rstatisticsblog.com/data-science-in-action/data-preprocessing/six-amazing-function-to-create-train-test-split-in-r/

0.7.1 R Code

```
# =============================================================================
# Load Libraries and Disable Scientific Notation for Readability Purposes
# =====================================================================================

knitr::opts_chunk$set(echo = TRUE)
# Disable scientific numbers for readability purposes.
options(scipen = 999)

library(MASS)
library(tidyverse)
library(dplyr)
library(reshape2)
library(kableExtra)
library(corrplot)
library(ggplot2)
library(Hmisc)
library(PerformanceAnalytics)
library(GGally)
library(ggpubr)
library(car)


# =====================================================================================
# Load The Dataset and Summarize the Data
# =====================================================================================

# Load in the training data.
url = "https://raw.githubusercontent.com/Jagdish16/CUNY_DATA_621/main/project_1/moneyball-training-data
mb_training <- read.csv(url)

# Remove the INDEX variable as it is of no value in the data evaluation.
mb_training <- subset(mb_training, select = -c(INDEX))

# Summarize the test data.
summary(mb_training)


# =====================================================================================
# Rename the Variables to be More Intuitive
# =====================================================================================

# Rename the columns to be more intuitive.
mb_training <- mb_training %>%
  rename_with(~ gsub("TEAM_", "", .x)) %>%
  rename_with(stringr::str_to_title) %>%
  dplyr::rename(
    Wins = Target_wins,
    Hits = Batting_h,
    Doubles = Batting_2b,
    Triples = Batting_3b,
    HomeRuns = Batting_hr,
    Walks_AtBat = Batting_bb,
    StrikeOuts_AtBat = Batting_so,
    BasesStolen = Baserun_sb,
    OutStealingBases = Baserun_cs,
    Hits_Allowed = Pitching_h,
    HitByPitch_AtBat = Batting_hbp,
    Errors = Fielding_e,
    HomeRuns_Allowed = Pitching_hr,
    Walks_Allowed = Pitching_bb,
    StrikeOuts = Pitching_so,
    DoublePlays = Fielding_dp
  )


# =====================================================================================
# Box Plots
# =====================================================================================

# Plot boxplots for all variables.
long <- mb_training %>% as.data.frame() %>% melt()

long %>%
  ggplot(aes(x=value)) + geom_boxplot() + facet_wrap(~variable, scales = 'free')


# =====================================================================================
# Distribution Plots
# =====================================================================================

# mean_data <- long %>% na.omit() %>% #omits na values only, not full cases
#  group_by(variable) %>%
#  summarise(mean = mean(value))

# long %>%
#  ggplot(aes(x=value)) +
#  geom_histogram(color = 'black', fill = 'gray', bins = 30) +
#  geom_vline(data = mean_data, aes(xintercept = mean), linetype = 'dashed', color = 'blue') +
#  facet_wrap(~variable, scales = 'free')


# =====================================================================================
# Missing Data
# =====================================================================================

# Create a table of variables sorted by percentage of missing data.
missing_data <- colSums(mb_training %>% sapply(is.na))
percentage_missing <- round(missing_data / nrow(mb_training) * 100, 2)
missing_values_table <- sort(percentage_missing, decreasing = TRUE)

missing_values_table %>%
  kable(caption = 'Breakdown of Variables by Percentage of Missing Data') %>%
  kable_styling()

# Drop the HitByPitch_AtBat variable from the dataset.
mb_training <- mb_training %>% dplyr::select(-HitByPitch_AtBat)

# =====================================================================================
# Handle Outliers
# ==========================================================================================

# Remove outlier rows for the 6 predictor variables.
mb_training_updated <- mb_training

# Remove outliers - Method 2.
for (n in c("Walks_Allowed", "BasesStolen", "StrikeOuts", "Hits_Allowed", "Errors", "Triples")) {
  Q <- quantile(mb_training[,n], probs = c(.25, .75), na.rm = TRUE)
  iqr <- IQR(mb_training[,n], na.rm = TRUE)
  # Upper Range.
  up <- Q[2] + 1.5 * iqr
  # Lower Range.
  low <- Q[1] - 1.5 * iqr
  mb_training_updated <- subset(mb_training_updated, mb_training_updated[,n] > (Q[1]-1.5 * iqr)&mb_trai
}

# Check the summary for the updated dataframe.
summary(mb_training_updated)

# Impute missing values with the median value for each remaining column.
mb_training_updated <- data.frame(sapply(mb_training_updated, function(x) ifelse(is.na(x), median(x, na

# Check the summary for the updated dataframe.
summary(mb_training_updated)

# ==========================================================================================
# Data Correlation
# ==========================================================================================

# Perform a correlation analysis on the data. In this analysis, we are only interested in the
# correlation of the predicter variables and the "TARGET_WINS" variable.
correlation_table <- cor(mb_training_updated, method = 'pearson', use = 'complete.obs')[,1]

# Remove the TARGET_WINS variable from the correlation table as it is redundant
# within the context of of our correlation analysis.
correlation_table <- correlation_table[-c(1)]

correlation_table %>%
  kable(caption = 'Correlation of Variables to Wins') %>% kable_styling()

# Calculate correlation between variables.
mb_training_updated_corr_matrix <- mb_training_updated %>% cor() %>% round(2) %>% as.matrix()
mb_training_updated_corr_matrix %>% kable() %>% kable_styling()

# flattenCorrMatrix
# cormat : matrix of the correlation coefficients.
# pmat : matrix of the correlation p-values.
flattenCorrMatrix <- function(cormat, pmat) {
  ut <- upper.tri(cormat)
  data.frame(
    row = rownames(cormat)[row(cormat)[ut]],
    column = rownames(cormat)[col(cormat)[ut]],
    cor  =(cormat)[ut],
    p = pmat[ut]
    )
}

# Another method to check correlations and their significance.
corr.mat<-rcorr(as.matrix(mb_training_updated))

flattenCorrMatrix(corr.mat$r, corr.mat$P)%>% filter(row=='Wins') %>% arrange(-abs(cor))


# ==================================================================================
# Check Normality of Predictors
# ==================================================================================

# Run the Shapiro wilkes test for normality.
do.call(rbind, lapply(mb_training_updated, function(x) shapiro.test(x)[c("statistic", "p.value")]))


# ==================================================================================
# Model 1
# ==================================================================================

model_one <- lm(Wins ~ Hits + Doubles + Triples + HomeRuns +
                Walks_AtBat + BasesStolen + Hits_Allowed +
                HomeRuns_Allowed + Errors + Walks_Allowed + StrikeOuts +
                StrikeOuts_AtBat + OutStealingBases + DoublePlays,
                mb_training_updated)

# Model 1 summary stats.
summary(model_one)

# Model 1 R Squared.
summary(model_one)$r.squared

# Model 1 Confidence Intervals.
confint(model_one)

# Model 1 plots - residuals vs fitted values, residuals distribution.
ggplot(data = model_one, aes(x = .fitted, y = .resid)) +
  geom_point() + geom_hline(yintercept = 0, linetype = "dashed") +
  geom_smooth(se = FALSE) + xlab("Fitted values") + ylab("Residuals")

ggplot(data = model_one, aes(x = .resid)) + geom_histogram() + xlab("Residuals")

ggplot(data = model_one) + stat_qq(aes(sample = .stdresid)) + geom_abline()


# ==================================================================================
# Model 2
# ==================================================================================

# Model 2 uses stepwise regression on the variables in Model 1.
model_two <- stepAIC(model_one, direction = 'both', trace = FALSE)

# Model 2 summary stats.
```

```
summary(model_two)

# Model 2 plots - residuals vs fitted values, residuals distribution.
ggplot(data = model_two, aes(x = .fitted, y = .resid)) +
  geom_point() + geom_hline(yintercept = 0, linetype = "dashed") +
  geom_smooth(se = FALSE) + xlab("Fitted values") + ylab("Residuals")

ggplot(data = model_two, aes(x = .resid)) + geom_histogram() + xlab("Residuals")

ggplot(data = model_two) + stat_qq(aes(sample = .stdresid)) + geom_abline()


# ==================================================================================
# Model 3
# ==================================================================================

# Derive 2 new variables for Singles and Home run difference.
mb_training_new <- mb_training_updated %>% mutate(Singles = Hits - Doubles - Triples - HomeRuns)
mb_training_new <- mb_training_new %>% mutate(Homeruns_diff = HomeRuns_Allowed - HomeRuns)

model_three <- lm(Wins ~ Hits + Doubles + Triples + Walks_AtBat +
                  BasesStolen + Hits_Allowed + Errors + Walks_Allowed +
                  StrikeOuts + Singles + Homeruns_diff + StrikeOuts_AtBat +
                  I(HomeRuns_Allowed/HomeRuns) + I(HomeRuns_Allowed*HomeRuns) +
                  I(1/DoublePlays) + I(OutStealingBases^3),
                  mb_training_new)

# Model 3 summary stats.
summary(model_three)

# Model 3 R-Squared.
summary(model_three)$r.squared

# Model 3 confidence intervals.
confint(model_three)


# Model 3 plots - residuals vs fitted values, residuals distribution.
ggplot(data = model_three, aes(x = .fitted, y = .resid)) +
  geom_point() + geom_hline(yintercept = 0, linetype = "dashed") +
  geom_smooth(se = FALSE) + xlab("Fitted values") + ylab("Residuals")

ggplot(data = model_three, aes(x = .resid)) + geom_histogram() + xlab("Residuals")

ggplot(data = model_three) + stat_qq(aes(sample = .stdresid)) + geom_abline()


# ==================================================================================
# Model 4
# ==================================================================================

# Model 4 - Box Cox method.
MASS::boxcox(model_one, lambda = seq(0.75, 1.6, by = 0.05), plotit = TRUE)
```

```
# Fit a model using a lambda value of 1.35 for the response variable.
model_cox = lm((((Wins ^ 1.35) - 1)/ 1.35) ~ Hits + Doubles + Triples + HomeRuns + Walks_AtBat +
    BasesStolen + Hits_Allowed + HomeRuns_Allowed + Errors +
    Walks_Allowed + StrikeOuts + StrikeOuts_AtBat + OutStealingBases +
    DoublePlays,
    mb_training_updated)

# Model 4 summary stats.
summary(model_cox)

# Model 4 R Squared.
summary(model_cox)$r.squared

# Model 4 confidence intervals.
confint(model_cox)


# Model 4 plots - residuals vs fitted values, residuals distribution.
ggplot(data = model_cox, aes(x = .fitted, y = .resid)) +
  geom_point() + geom_hline(yintercept = 0, linetype = "dashed") +
  geom_smooth(se = FALSE) + xlab("Fitted values") + ylab("Residuals")

ggplot(data = model_cox, aes(x = .resid)) + geom_histogram() + xlab("Residuals")

ggplot(data = model_cox) + stat_qq(aes(sample = .stdresid)) + geom_abline()


# =====================================================================================
# Model Selection
# =====================================================================================

# Predict the number of wins for the test data using model one.

# Load in the test data.
url2 <- 'https://raw.githubusercontent.com/Jagdish16/CUNY_DATA_621/main/project_1/moneyball-evaluation-
mb_test <- read.csv(url2)

# Remove the INDEX variable as it is of no value in the data evaluation.
mb_test <- subset(mb_test, select = -c(INDEX))

# Summarize the test data.
summary(mb_test)

# Rename the test data variables to be more intuitive.
mb_test <- mb_test %>%
  rename_with(~ gsub("TEAM_", "", .x)) %>%
  rename_with(stringr::str_to_title) %>%
  dplyr::rename(
    Hits = Batting_h,
    Doubles = Batting_2b,
    Triples = Batting_3b,
    HomeRuns = Batting_hr,
    Walks_AtBat = Batting_bb,
    StrikeOuts_AtBat = Batting_so,
    BasesStolen = Baserun_sb,
    OutStealingBases = Baserun_cs,
    Hits_Allowed = Pitching_h,
    HitByPitch_AtBat = Batting_hbp,
    Errors = Fielding_e,
    HomeRuns_Allowed = Pitching_hr,
    Walks_Allowed = Pitching_bb,
    StrikeOuts = Pitching_so,
    DoublePlays = Fielding_dp
  )

# Impute missing values with the median value for each column.
mb_test_updated <- data.frame(sapply(mb_test, function(x) ifelse(is.na(x), median(x, na.rm = TRUE), x)))

# Summarize the test data.
summary(mb_test_updated)

# Predicting Wins in the test data and looking at the distribution.
mb_test_updated$predicted_wins <- predict(model_one, type = 'response', newdata = mb_test_updated)

ggplot(data = mb_test_updated, aes(x = predicted_wins))  +
  geom_histogram( color = 'black', fill =  'gray') +
  geom_vline(aes(xintercept = mean(predicted_wins)), linetype = 'dashed', size = 2, color = 'blue') +
  geom_label(aes(x = 500, y = 150,label= str_replace_all(toString(summary(mb_test_updated['predicted_win
  labs(title = 'Wins Prediction Histogram Plot', y = 'Count', x = 'Wins Prediction')

# Create a table of prediction and confidence intervals.
test_data <- predict(model_one, newdata = mb_test_updated, interval = 'prediction')
summary(test_data)
```