# HW1

Team 1

September 13, 2020

1. The “moneyball” data set contains 2276 rows and 17 columns, including variables such as TARGET_WINS, TEAM_BATTING, TEAN_BASERUN, etc. Running a summary() function on the data set, we are able to get the mean, median, first and third quartile and the minimum and maximum values for each variable. We decided to use a scattered plot of base hit by batters (TEAM_BATTING_H) vs. number of wins (TARGET_WINS) for an overview of the relationship between wins and hits, the chart shows a
2. Data Preparation We addressed issues with imperfect data before building models or performing statistical analysis. We observed that several variables have high numbers of NA or missing values. EAM_BATTING_HBP has the highest number of missing cases i.e., 2085 (~ 90%). Before deleting this variable, we fit a model with all data then compared to after the variable is removed. The second model appeared to be a better fit with smaller standard error, more variables became significant predictors. M
3. Build models.

First we started a model with the backward elimination process with the data. In this process, we will be rejecting predictors with p-value greater than 0.05 with the backward elimination process. We will stop after all the predictors are less than 0.05. The second model we decided to go with the stepwise selection which includes a semi-automated process of building a model by adding or removing variables based solely on the t-statistics of their estimated coefficients.
For our third model we noticed one of the variables, TEAM_PITCHING_SO, have a p-value greater than 0.05 so we decided to investigate. When we removed the variable, TEAM_PITCHING_SO, and the R squared dropped slightly.

4. Out of the three models we created, the second model created with stepwise selection is the best of the three. The Adjusted R squared is 0.4098 which explains approximately 41% of variation in Target Wins can be explained by our model. This f statistic tells us if there is a relationship between the dependent and independent variables we are testing. Generally, a large F indicates a stronger relationship and here we have 113.9. The normal quantile quantile plot for residuals displays an approximately straight line so the residuals are approximately normally distributed. The MSE is 743.6606. Using this model we were able to make predictions for our evaluation data.

```
# load required packages
library(ggplot2)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
#library(tidyr)
library(corrplot)
```

```
## corrplot 0.84 loaded
```

```
library(MASS)
```

```
##
## Attaching package: 'MASS'
```

```
## The following object is masked from 'package:dplyr':
##
##     select
```

```
library(caret)
```

```
## Loading required package: lattice
```

```
library(RCurl)
```

```
# Loading the data
git_dir <- 'https://raw.github.com/odonnell31/data621-HW1/master/data'
train_df = read.csv(paste(git_dir, "/moneyball-training-data.csv", sep=""))
test_df = read.csv(paste(git_dir, "/moneyball-evaluation-data.csv", sep = ""))
```

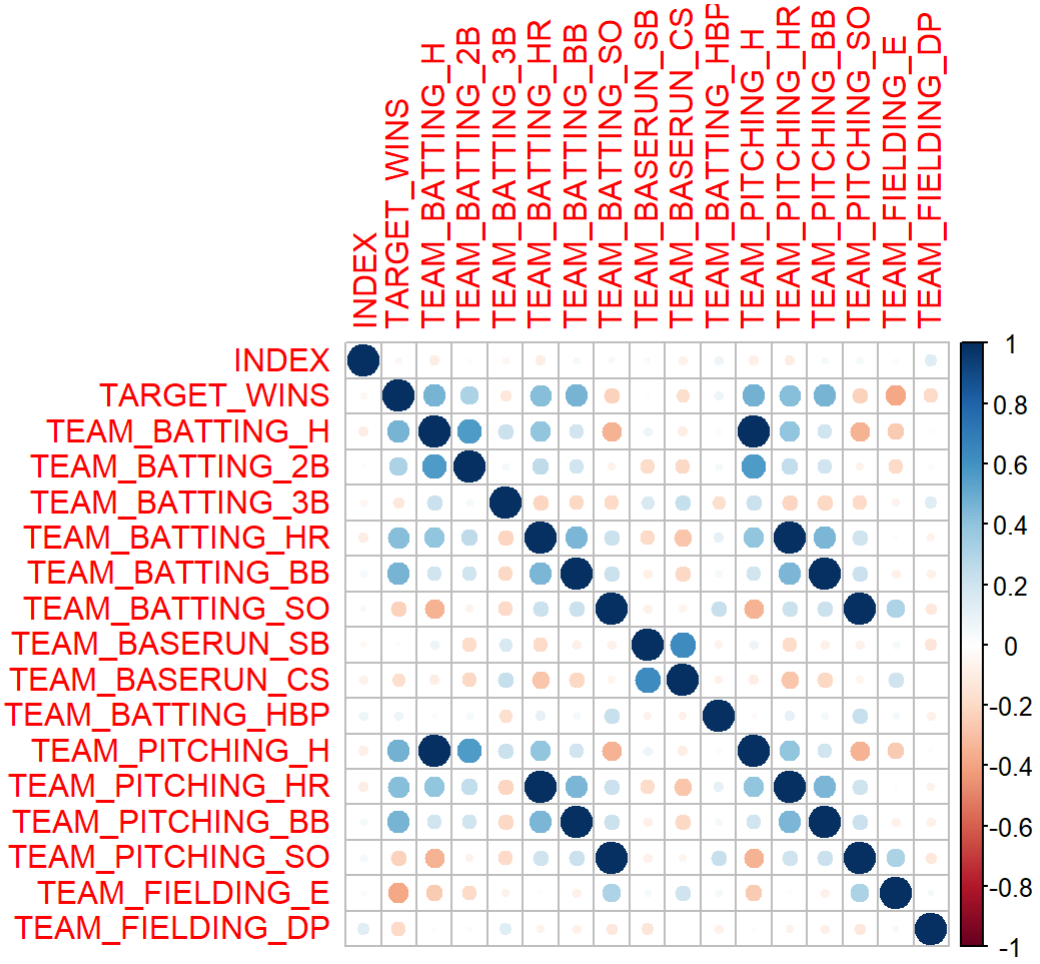
# 1. Data Exploration

See a summary of each column in the train_dfing set

```
# view a summary of all columns
summary(train_df)
```

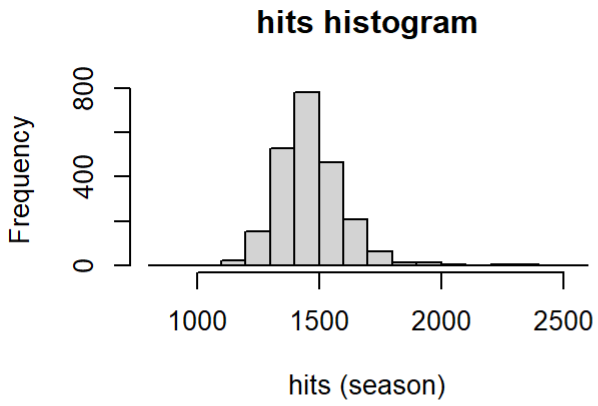
```
##      INDEX         TARGET_WINS     TEAM_BATTING_H TEAM_BATTING_2B
##  Min.   :   1.0   Min.   :  0.00   Min.   : 891   Min.   : 69.0
##  1st Qu.: 630.8   1st Qu.: 71.00   1st Qu.:1383   1st Qu.:208.0
##  Median :1270.5   Median : 82.00   Median :1454   Median :238.0
##  Mean   :1268.5   Mean   : 80.79   Mean   :1469   Mean   :241.2
##  3rd Qu.:1915.5   3rd Qu.: 92.00   3rd Qu.:1537   3rd Qu.:273.0
##  Max.   :2535.0   Max.   :146.00   Max.   :2554   Max.   :458.0
##
##  TEAM_BATTING_3B  TEAM_BATTING_HR  TEAM_BATTING_BB TEAM_BATTING_SO
##  Min.   :  0.00   Min.   :  0.00   Min.   :  0.0   Min.   :   0.0
##  1st Qu.: 34.00   1st Qu.: 42.00   1st Qu.:451.0   1st Qu.: 548.0
##  Median : 47.00   Median :102.00   Median :512.0   Median : 750.0
##  Mean   : 55.25   Mean   : 99.61   Mean   :501.6   Mean   : 735.6
##  3rd Qu.: 72.00   3rd Qu.:147.00   3rd Qu.:580.0   3rd Qu.: 930.0
##  Max.   :223.00   Max.   :264.00   Max.   :878.0   Max.   :1399.0
##                                                    NA's   :102
##  TEAM_BASERUN_SB TEAM_BASERUN_CS TEAM_BATTING_HBP TEAM_PITCHING_H
##  Min.   :  0.0   Min.   :  0.0   Min.   :29.00    Min.   : 1137
##  1st Qu.: 66.0   1st Qu.: 38.0   1st Qu.:50.50    1st Qu.: 1419
##  Median :101.0   Median : 49.0   Median :58.00    Median : 1518
##  Mean   :124.8   Mean   : 52.8   Mean   :59.36    Mean   : 1779
##  3rd Qu.:156.0   3rd Qu.: 62.0   3rd Qu.:67.00    3rd Qu.: 1682
##  Max.   :697.0   Max.   :201.0   Max.   :95.00    Max.   :30132
##  NA's   :131     NA's   :772     NA's   :2085
##  TEAM_PITCHING_HR TEAM_PITCHING_BB TEAM_PITCHING_SO  TEAM_FIELDING_E
##  Min.   :  0.0    Min.   :   0.0   Min.   :    0.0   Min.   :  65.0
##  1st Qu.: 50.0    1st Qu.: 476.0   1st Qu.:  615.0   1st Qu.: 127.0
##  Median :107.0    Median : 536.5   Median :  813.5   Median : 159.0
##  Mean   :105.7    Mean   : 553.0   Mean   :  817.7   Mean   : 246.5
##  3rd Qu.:150.0    3rd Qu.: 611.0   3rd Qu.:  968.0   3rd Qu.: 249.2
##  Max.   :343.0    Max.   :3645.0   Max.   :19278.0   Max.   :1898.0
##                                    NA's   :102
##  TEAM_FIELDING_DP
##  Min.   : 52.0
##  1st Qu.:131.0
##  Median :149.0
##  Mean   :146.4
##  3rd Qu.:164.0
##  Max.   :228.0
##  NA's   :286
```

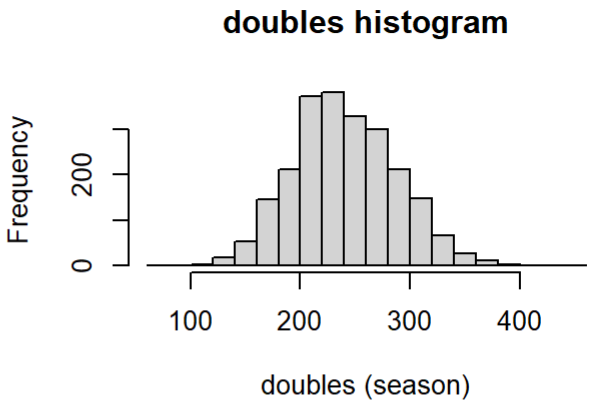
```
# Correlations
cor_train = cor(train_df,  use = "na.or.complete")
corrplot(cor_train)
```

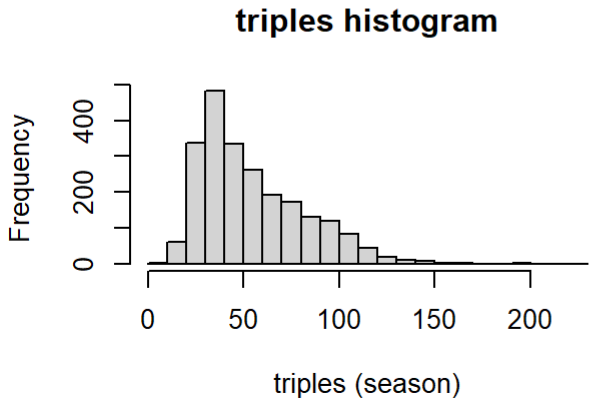


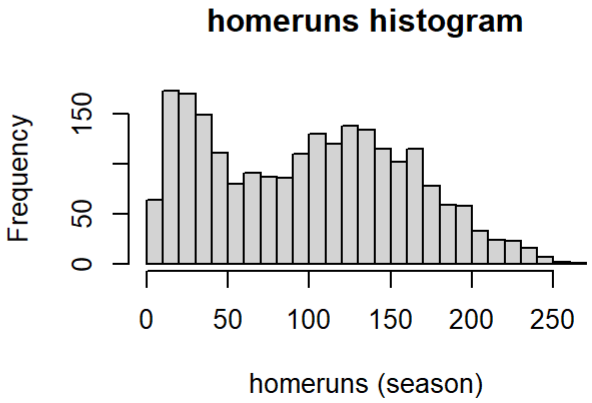

For types of hits, see a histogram of each

```
par(mfrow=c(2,2))
hist(train_df$TEAM_BATTING_H,
     main = "hits histogram", xlab = "hits (season)",
     breaks = 20)
hist(train_df$TEAM_BATTING_2B,
     main = "doubles histogram", xlab = "doubles (season)",
     breaks = 20)
hist(train_df$TEAM_BATTING_3B,
     main = "triples histogram", xlab = "triples (season)",
     breaks = 20)
hist(train_df$TEAM_BATTING_HR,
     main = "homeruns histogram", xlab = "homeruns (season)",
     breaks = 20)
```



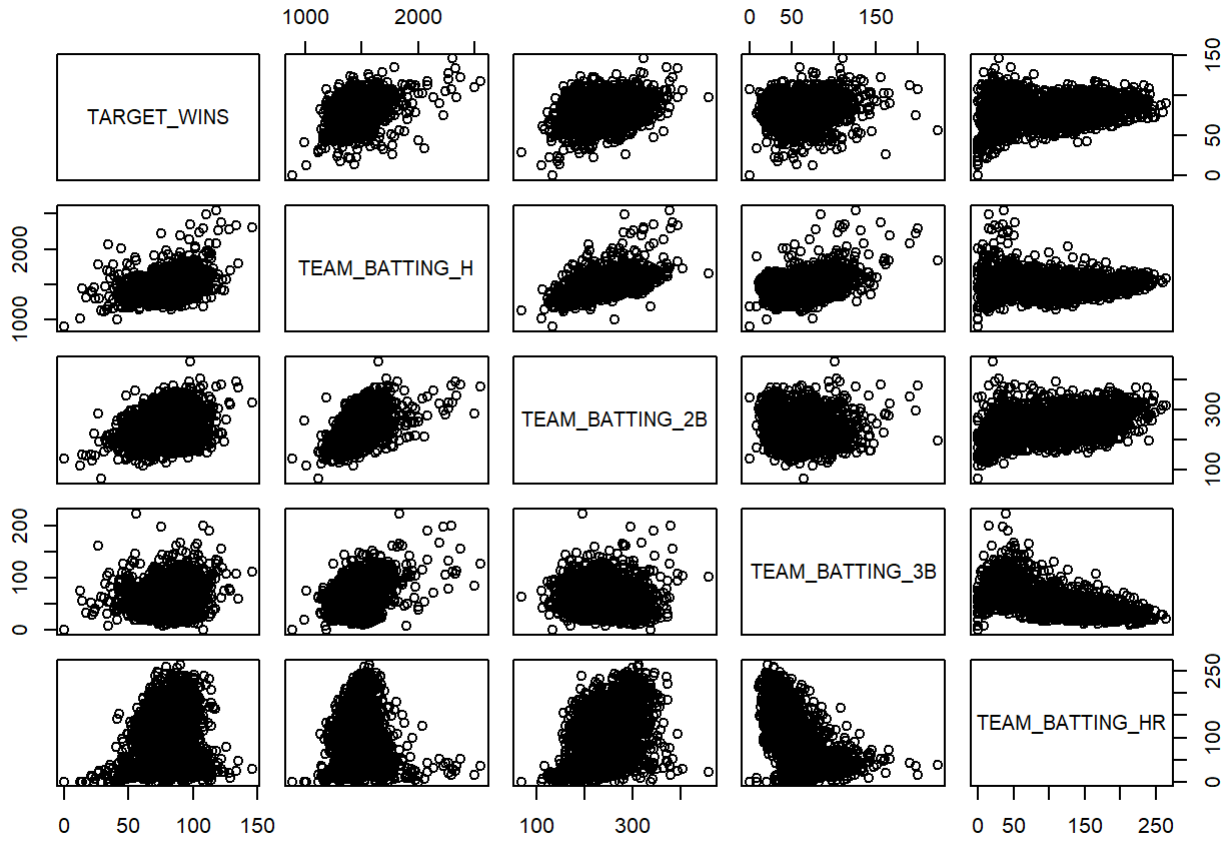




```
par(mfrow=c(1,1))
```

```
pairs(~ TARGET_WINS + TEAM_BATTING_H + TEAM_BATTING_2B
      + TEAM_BATTING_3B + TEAM_BATTING_HR, data = train_df)
```



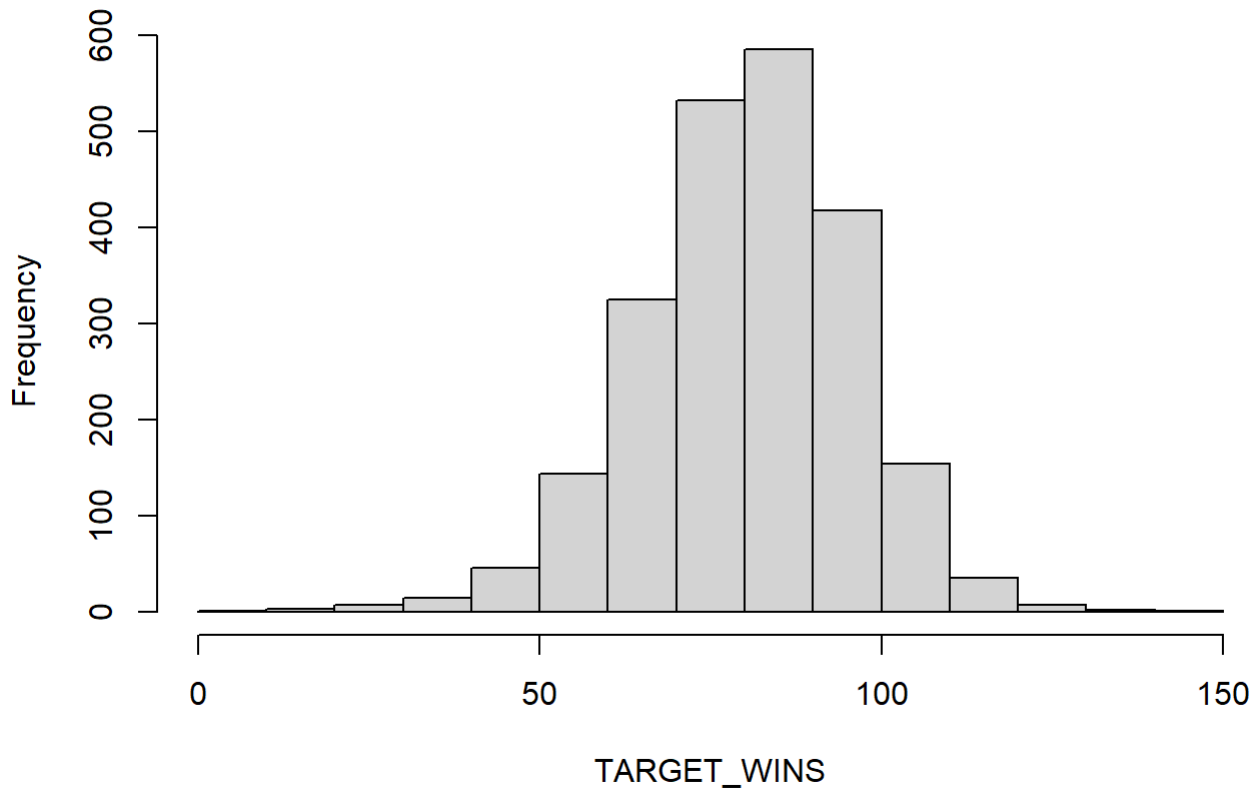

```
# look at the structure of the variables
str(train_df)
```

```
## 'data.frame':    2276 obs. of  17 variables:
##  $ INDEX           : int  1 2 3 4 5 6 7 8 11 12 ...
##  $ TARGET_WINS     : int  39 70 86 70 82 75 80 85 86 76 ...
##  $ TEAM_BATTING_H  : int  1445 1339 1377 1387 1297 1279 1244 1273 1391 1271 ...
##  $ TEAM_BATTING_2B : int  194 219 232 209 186 200 179 171 197 213 ...
##  $ TEAM_BATTING_3B : int  39 22 35 38 27 36 54 37 40 18 ...
##  $ TEAM_BATTING_HR : int  13 190 137 96 102 92 122 115 114 96 ...
##  $ TEAM_BATTING_BB : int  143 685 602 451 472 443 525 456 447 441 ...
##  $ TEAM_BATTING_SO : int  842 1075 917 922 920 973 1062 1027 922 827 ...
##  $ TEAM_BASERUN_SB : int  NA 37 46 43 49 107 80 40 69 72 ...
##  $ TEAM_BASERUN_CS : int  NA 28 27 30 39 59 54 36 27 34 ...
##  $ TEAM_BATTING_HBP: int  NA NA NA NA NA NA NA NA NA NA ...
##  $ TEAM_PITCHING_H : int  9364 1347 1377 1396 1297 1279 1244 1281 1391 1271 ...
##  $ TEAM_PITCHING_HR: int  84 191 137 97 102 92 122 116 114 96 ...
##  $ TEAM_PITCHING_BB: int  927 689 602 454 472 443 525 459 447 441 ...
##  $ TEAM_PITCHING_SO: int  5456 1082 917 928 920 973 1062 1033 922 827 ...
##  $ TEAM_FIELDING_E : int  1011 193 175 164 138 123 136 112 127 131 ...
##  $ TEAM_FIELDING_DP: int  NA 155 153 156 168 149 186 136 169 159 ...
```

```
str(eval)
```

```
## function (expr, envir = parent.frame(), enclos = if (is.list(envir) ||
##     is.pairlist(envir)) parent.frame() else baseenv())
```

```
# lets observe how targets_win are effected by other factors
hist(train_df$TARGET_WINS,xlab="TARGET_WINS",main="")
```

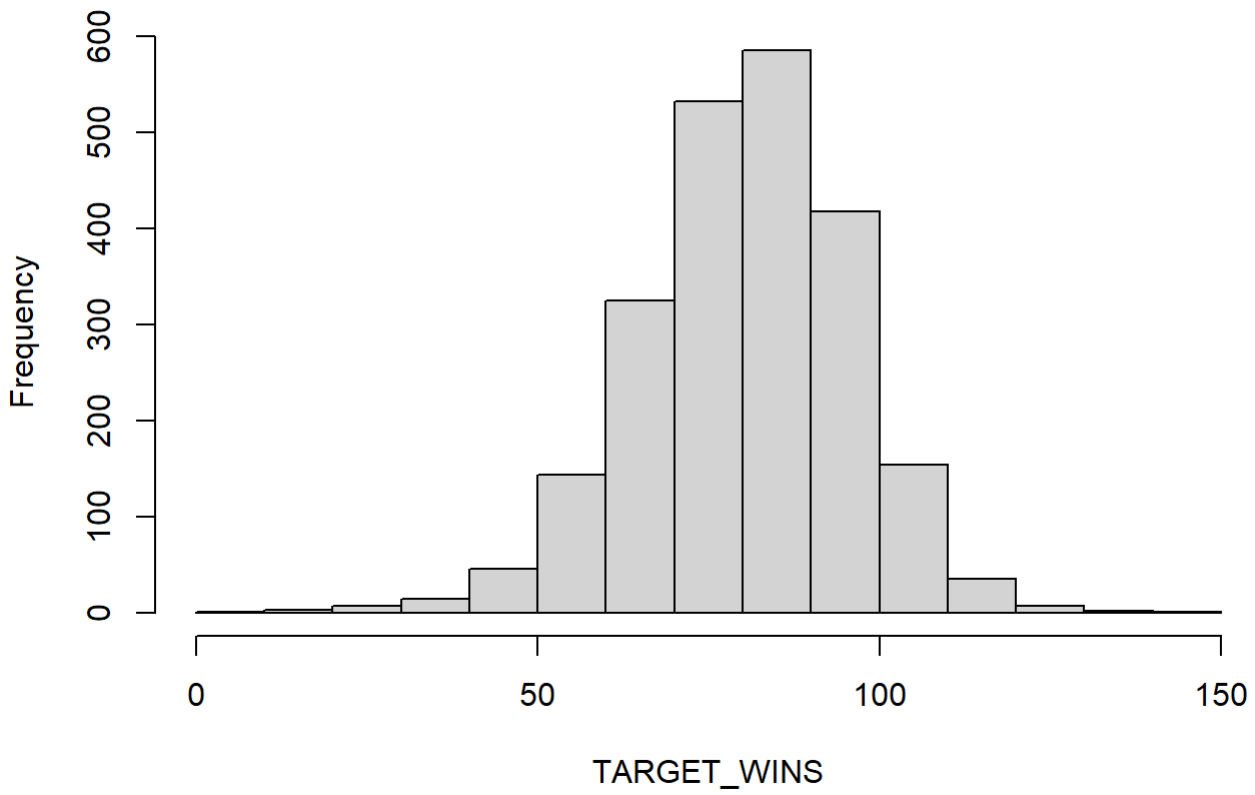



```
# we have no TARGET_WINS from eval
# hist(eval$TARGET_WINS,xlab="TARGET_WINS",main="")
```

# 2. Data Preparation

1. We are told everything is standardized to match a 162 game season, so it is my preference to make TARGET_WINS a decimal of 162

```
train_target_wins = train_df$TARGET_WINS
#train_df$TARGET_WINS = train_df$TARGET_WINS/162.
# TARGET_WINS now a decimal of games won in 162 game season
hist(train_df$TARGET_WINS,xlab="TARGET_WINS",main="")
```




```
str(train_df)
```

```
## 'data.frame':    2276 obs. of  17 variables:
##  $ INDEX           : int  1 2 3 4 5 6 7 8 11 12 ...
##  $ TARGET_WINS     : int  39 70 86 70 82 75 80 85 86 76 ...
##  $ TEAM_BATTING_H  : int  1445 1339 1377 1387 1297 1279 1244 1273 1391 1271 ...
##  $ TEAM_BATTING_2B : int  194 219 232 209 186 200 179 171 197 213 ...
##  $ TEAM_BATTING_3B : int  39 22 35 38 27 36 54 37 40 18 ...
##  $ TEAM_BATTING_HR : int  13 190 137 96 102 92 122 115 114 96 ...
##  $ TEAM_BATTING_BB : int  143 685 602 451 472 443 525 456 447 441 ...
##  $ TEAM_BATTING_SO : int  842 1075 917 922 920 973 1062 1027 922 827 ...
##  $ TEAM_BASERUN_SB : int  NA 37 46 43 49 107 80 40 69 72 ...
##  $ TEAM_BASERUN_CS : int  NA 28 27 30 39 59 54 36 27 34 ...
##  $ TEAM_BATTING_HBP: int  NA NA NA NA NA NA NA NA NA NA ...
##  $ TEAM_PITCHING_H : int  9364 1347 1377 1396 1297 1279 1244 1281 1391 1271 ...
##  $ TEAM_PITCHING_HR: int  84 191 137 97 102 92 122 116 114 96 ...
##  $ TEAM_PITCHING_BB: int  927 689 602 454 472 443 525 459 447 441 ...
##  $ TEAM_PITCHING_SO: int  5456 1082 917 928 920 973 1062 1033 922 827 ...
##  $ TEAM_FIELDING_E : int  1011 193 175 164 138 123 136 112 127 131 ...
##  $ TEAM_FIELDING_DP: int  NA 155 153 156 168 149 186 136 169 159 ...
```

2. Assuming that everything that is NA can be filled by 0 based on the description of variables, create columns flagging if original values were NA (e.g. create TEAM_BATTING_HBP_NA column and value is 1 if TEAM_BATTING_HBP is NA and 0 otherwise meaning it wasn't NA and had a value. Do this for all columns)

```
#
has_NA = names(which(sapply(train_df, anyNA)))
for (col in has_NA)
{
   new_col = (paste(col,"_NA", sep=""))
   train_df[,new_col] = as.numeric(is.na(train_df[,col]))
   test_df[,new_col] = as.numeric(is.na(test_df[,col]))
}
train_df[is.na(train_df)] = 0
test_df[is.na(test_df)] = 0
```

# 3. Build Models

```
# set seed for reproducibility
n_records = nrow(train_df)
set.seed(1)
```

# Model 1 - Backward Elimination Process

We will be rejecting predictors with p-value greater than 0.05 with the backward elimination process. We will stop after all the predictors are less than 0.05

```
model <- lm(TARGET_WINS ~ TEAM_BATTING_H + TEAM_BATTING_2B + TEAM_BATTING_3B + TEAM_BATTING_HR +
TEAM_BATTING_BB + TEAM_PITCHING_H + TEAM_PITCHING_HR + TEAM_PITCHING_BB + TEAM_FIELDING_E, data=
train_df)
summary(train_df)
```

```
##      INDEX         TARGET_WINS     TEAM_BATTING_H TEAM_BATTING_2B
##  Min.   :   1.0   Min.   :  0.00   Min.   : 891   Min.   : 69.0
##  1st Qu.: 630.8   1st Qu.: 71.00   1st Qu.:1383   1st Qu.:208.0
##  Median :1270.5   Median : 82.00   Median :1454   Median :238.0
##  Mean   :1268.5   Mean   : 80.79   Mean   :1469   Mean   :241.2
##  3rd Qu.:1915.5   3rd Qu.: 92.00   3rd Qu.:1537   3rd Qu.:273.0
##  Max.   :2535.0   Max.   :146.00   Max.   :2554   Max.   :458.0
##  TEAM_BATTING_3B  TEAM_BATTING_HR  TEAM_BATTING_BB TEAM_BATTING_SO
##  Min.   :  0.00   Min.   :  0.00   Min.   :  0.0   Min.   :   0.0
##  1st Qu.: 34.00   1st Qu.: 42.00   1st Qu.:451.0   1st Qu.: 524.0
##  Median : 47.00   Median :102.00   Median :512.0   Median : 728.0
##  Mean   : 55.25   Mean   : 99.61   Mean   :501.6   Mean   : 702.6
##  3rd Qu.: 72.00   3rd Qu.:147.00   3rd Qu.:580.0   3rd Qu.: 925.0
##  Max.   :223.00   Max.   :264.00   Max.   :878.0   Max.   :1399.0
##  TEAM_BASERUN_SB TEAM_BASERUN_CS  TEAM_BATTING_HBP TEAM_PITCHING_H
##  Min.   :  0.0   Min.   :  0.00   Min.   : 0.000   Min.   : 1137
##  1st Qu.: 60.0   1st Qu.:  0.00   1st Qu.: 0.000   1st Qu.: 1419
##  Median : 97.0   Median : 38.00   Median : 0.000   Median : 1518
##  Mean   :117.6   Mean   : 34.89   Mean   : 4.981   Mean   : 1779
##  3rd Qu.:151.0   3rd Qu.: 54.25   3rd Qu.: 0.000   3rd Qu.: 1682
##  Max.   :697.0   Max.   :201.00   Max.   :95.000   Max.   :30132
##  TEAM_PITCHING_HR TEAM_PITCHING_BB TEAM_PITCHING_SO  TEAM_FIELDING_E
##  Min.   :  0.0    Min.   :   0.0   Min.   :    0.0   Min.   :  65.0
##  1st Qu.: 50.0    1st Qu.: 476.0   1st Qu.:  587.8   1st Qu.: 127.0
##  Median :107.0    Median : 536.5   Median :  797.0   Median : 159.0
##  Mean   :105.7    Mean   : 553.0   Mean   :  781.1   Mean   : 246.5
##  3rd Qu.:150.0    3rd Qu.: 611.0   3rd Qu.:  957.0   3rd Qu.: 249.2
##  Max.   :343.0    Max.   :3645.0   Max.   :19278.0   Max.   :1898.0
##  TEAM_FIELDING_DP TEAM_BATTING_SO_NA TEAM_BASERUN_SB_NA TEAM_BASERUN_CS_NA
##  Min.   :  0.0    Min.   :0.00000    Min.   :0.00000    Min.   :0.0000
##  1st Qu.:118.0    1st Qu.:0.00000    1st Qu.:0.00000    1st Qu.:0.0000
##  Median :145.0    Median :0.00000    Median :0.00000    Median :0.0000
##  Mean   :128.0    Mean   :0.04482    Mean   :0.05756    Mean   :0.3392
##  3rd Qu.:161.2    3rd Qu.:0.00000    3rd Qu.:0.00000    3rd Qu.:1.0000
##  Max.   :228.0    Max.   :1.00000    Max.   :1.00000    Max.   :1.0000
##  TEAM_BATTING_HBP_NA TEAM_PITCHING_SO_NA TEAM_FIELDING_DP_NA
##  Min.   :0.0000      Min.   :0.00000     Min.   :0.0000
##  1st Qu.:1.0000      1st Qu.:0.00000     1st Qu.:0.0000
##  Median :1.0000      Median :0.00000     Median :0.0000
##  Mean   :0.9161      Mean   :0.04482     Mean   :0.1257
##  3rd Qu.:1.0000      3rd Qu.:0.00000     3rd Qu.:0.0000
##  Max.   :1.0000      Max.   :1.00000     Max.   :1.0000
```

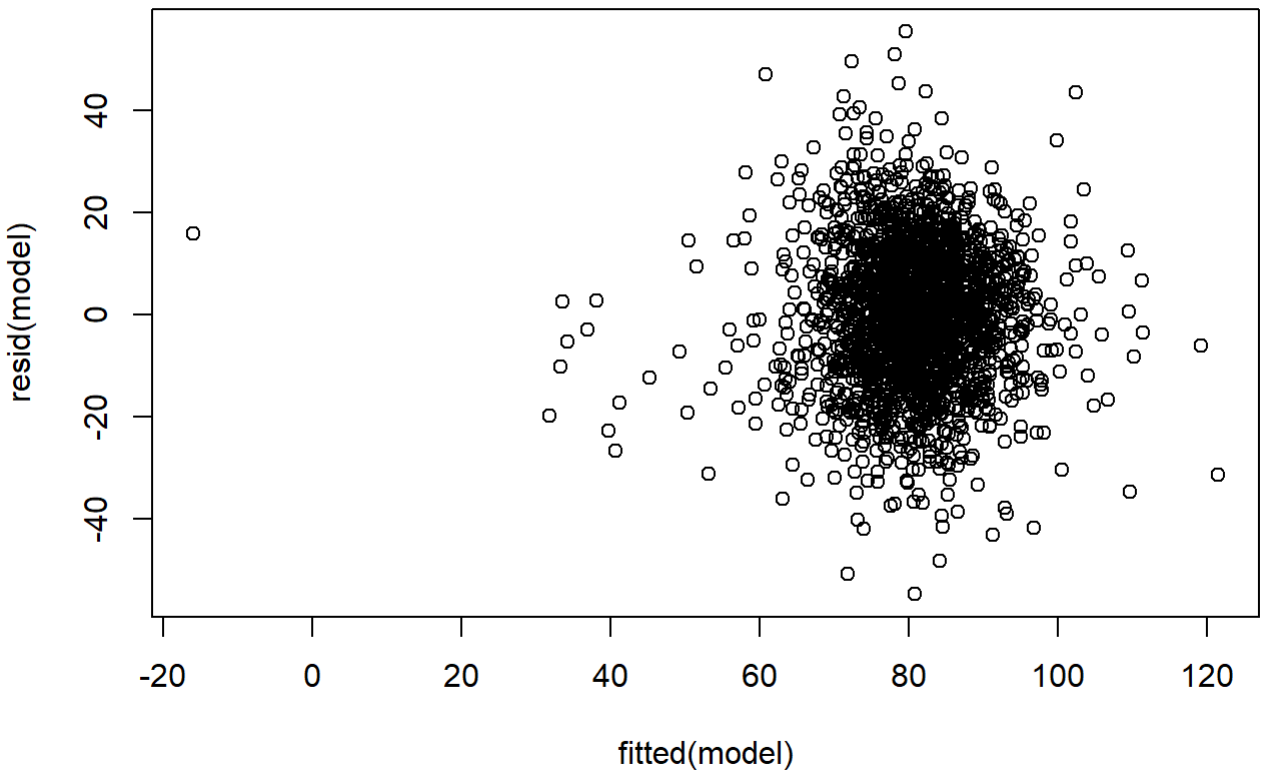
```
model <- update(model, .~. - TEAM_BATTING_BB, data=train_df)
summary(model)
```

```
##
## Call:
## lm(formula = TARGET_WINS ~ TEAM_BATTING_H + TEAM_BATTING_2B +
##     TEAM_BATTING_3B + TEAM_BATTING_HR + TEAM_PITCHING_H + TEAM_PITCHING_HR +
##     TEAM_PITCHING_BB + TEAM_FIELDING_E, data = train_df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -54.273  -8.832   0.127   8.886  55.587
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)       6.526453   3.423988   1.906   0.0568 .
## TEAM_BATTING_H    0.048766   0.003208  15.200  < 2e-16 ***
## TEAM_BATTING_2B  -0.026072   0.009050  -2.881   0.0040 **
## TEAM_BATTING_3B   0.102196   0.016708   6.116 1.12e-09 ***
## TEAM_BATTING_HR   0.054383   0.024691   2.203   0.0277 *
## TEAM_PITCHING_H  -0.001282   0.000327  -3.922 9.05e-05 ***
## TEAM_PITCHING_HR -0.016991   0.022575  -0.753   0.4517
## TEAM_PITCHING_BB  0.010755   0.002036   5.283 1.40e-07 ***
## TEAM_FIELDING_E  -0.016351   0.002287  -7.149 1.18e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 13.48 on 2267 degrees of freedom
## Multiple R-squared:  0.2702, Adjusted R-squared:  0.2677
## F-statistic: 104.9 on 8 and 2267 DF,  p-value: < 2.2e-16
```

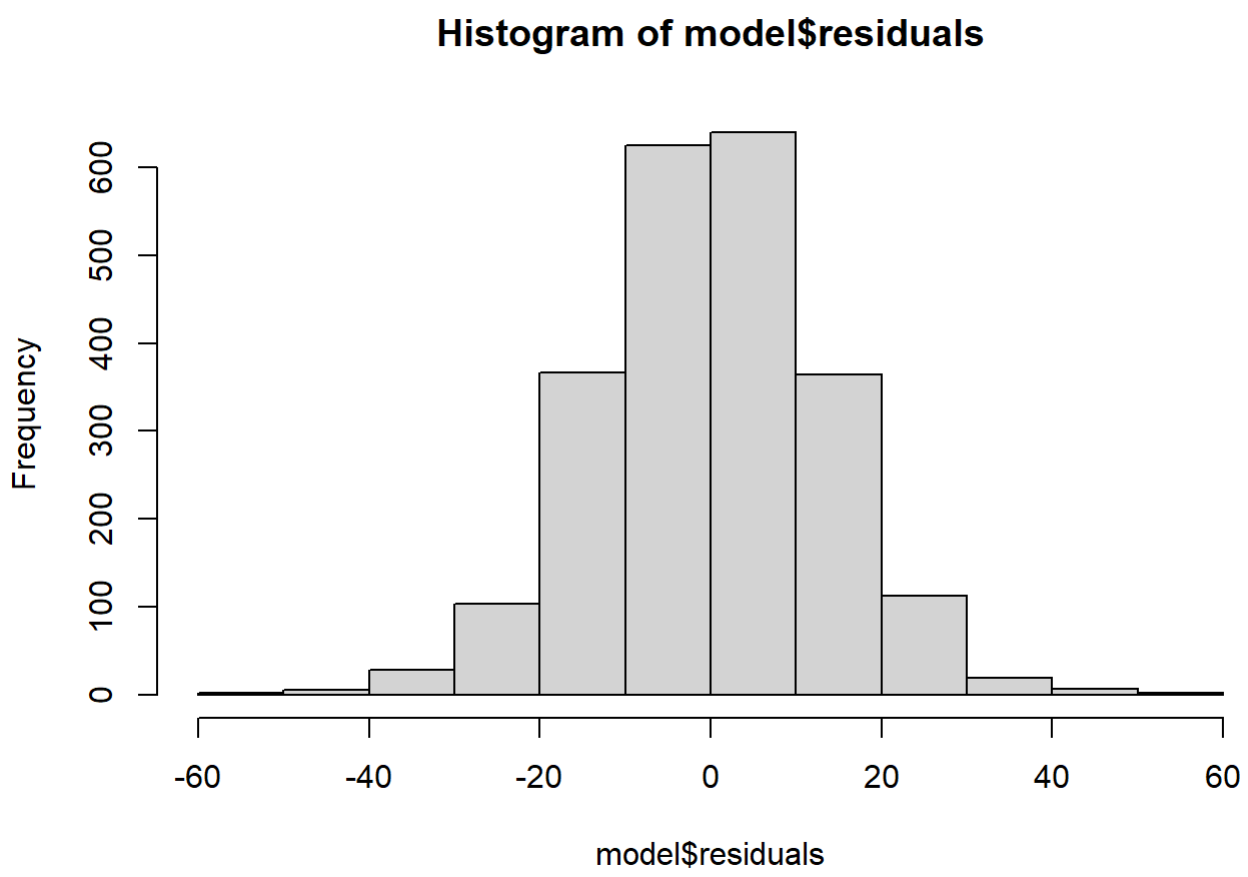
```
model <- update(model, .~. - TEAM_PITCHING_HR, data=train_df)
summary(model)
```

```
##
## Call:
## lm(formula = TARGET_WINS ~ TEAM_BATTING_H + TEAM_BATTING_2B +
##     TEAM_BATTING_3B + TEAM_BATTING_HR + TEAM_PITCHING_H + TEAM_PITCHING_BB +
##     TEAM_FIELDING_E, data = train_df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -54.763  -8.861   0.095   8.860  55.469
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       7.2713462  3.2775220   2.219  0.02662 *
## TEAM_BATTING_H    0.0484775  0.0031849  15.221  < 2e-16 ***
## TEAM_BATTING_2B  -0.0258127  0.0090430  -2.854  0.00435 **
## TEAM_BATTING_3B   0.1010776  0.0166406   6.074 1.46e-09 ***
## TEAM_BATTING_HR   0.0366916  0.0075591   4.854 1.29e-06 ***
## TEAM_PITCHING_H  -0.0013088  0.0003251  -4.026 5.87e-05 ***
## TEAM_PITCHING_BB  0.0103207  0.0019522   5.287 1.36e-07 ***
## TEAM_FIELDING_E  -0.0166263  0.0022577  -7.364 2.48e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 13.48 on 2268 degrees of freedom
## Multiple R-squared:   0.27,  Adjusted R-squared:  0.2678
## F-statistic: 119.9 on 7 and 2268 DF,  p-value: < 2.2e-16
```

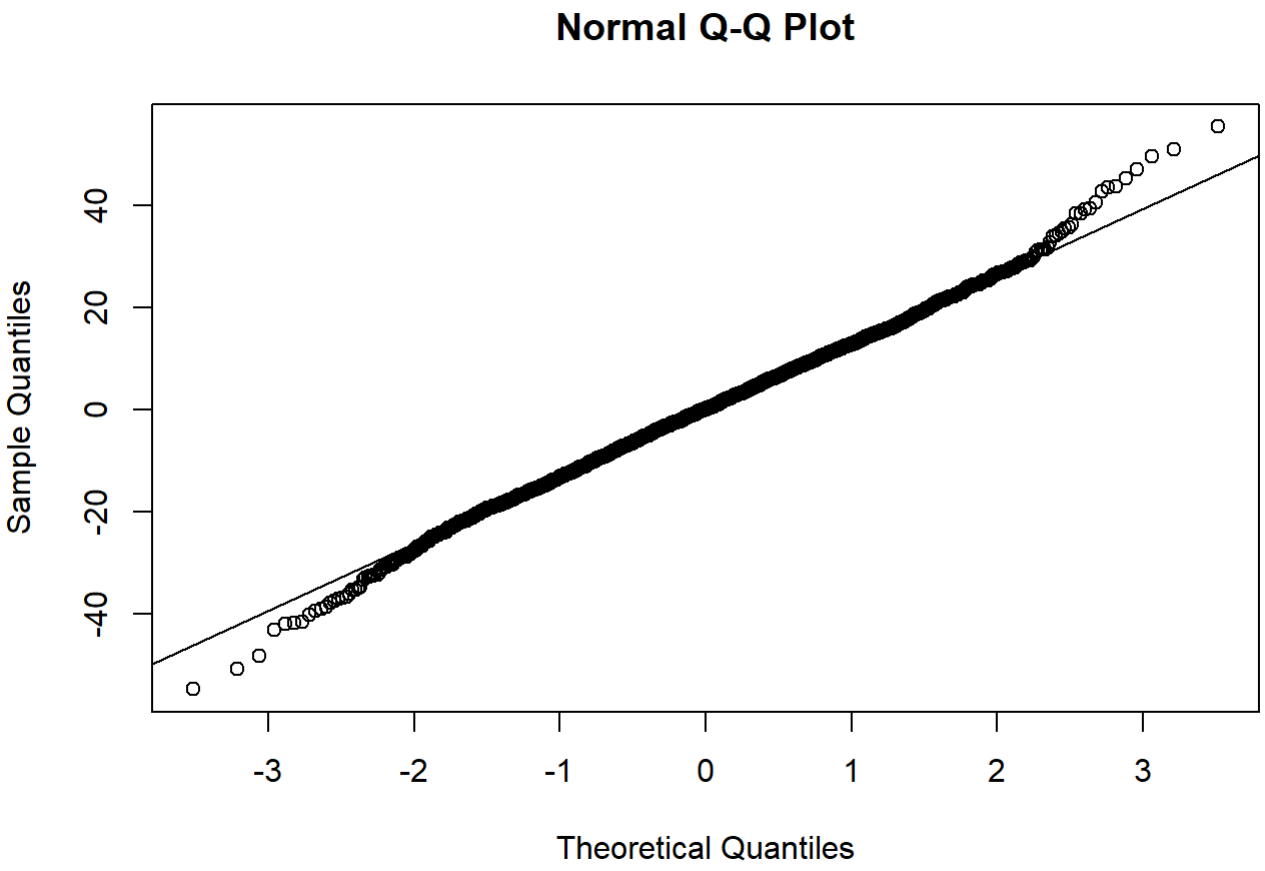
```
plot(fitted(model), resid(model))
```




```
hist(model$residuals)
```




```
qqnorm(resid(model))
qqline(resid(model))
```




```
#predict the model on the eval
colnames(test_df)
```

```
##  [1] "INDEX"               "TEAM_BATTING_H"      "TEAM_BATTING_2B"
##  [4] "TEAM_BATTING_3B"     "TEAM_BATTING_HR"     "TEAM_BATTING_BB"
##  [7] "TEAM_BATTING_SO"     "TEAM_BASERUN_SB"     "TEAM_BASERUN_CS"
## [10] "TEAM_BATTING_HBP"    "TEAM_PITCHING_H"     "TEAM_PITCHING_HR"
## [13] "TEAM_PITCHING_BB"    "TEAM_PITCHING_SO"    "TEAM_FIELDING_E"
## [16] "TEAM_FIELDING_DP"    "TEAM_BATTING_SO_NA"  "TEAM_BASERUN_SB_NA"
## [19] "TEAM_BASERUN_CS_NA"  "TEAM_BATTING_HBP_NA" "TEAM_PITCHING_SO_NA"
## [22] "TEAM_FIELDING_DP_NA"
```

```
#remove the predictors that have negative effect to the target wins

new_eval_model = subset(test_df, select=c(TEAM_BATTING_H, TEAM_BATTING_2B, TEAM_BATTING_3B, TEAM
_BATTING_HR, TEAM_PITCHING_H, TEAM_PITCHING_BB, TEAM_FIELDING_E))
# Turn the NA values in 0
new_eval_model[is.na(new_eval_model)] = 0

# prediction model
prediction_model <- predict(model, newdata=new_eval_model)
prediction_model
```

```
##        1        2        3        4        5        6        7        8
##  68.57679  70.20767  77.35107  83.60728  66.44188  67.44392  74.01699  72.52290
##        9       10       11       12       13       14       15       16
##  72.07908  75.86204  76.14127  85.66302  84.25863  82.11244  79.28366  80.65313
##       17       18       19       20       21       22       23       24
##  72.72498  80.73209  68.24429  93.15727  84.03790  86.72537  83.94422  76.45507
##       25       26       27       28       29       30       31       32
##  82.33443  84.46690  53.99437  77.34772  83.55037  76.54752  89.64897  87.49762
##       33       34       35       36       37       38       39       40
##  86.39979  88.63464  83.07959  82.97654  76.59917  90.98962  88.25264  89.93392
##       41       42       43       44       45       46       47       48
##  81.06430  86.65244  32.00565  93.94542  84.49850  91.12091  95.25990  72.55215
##       49       50       51       52       53       54       55       56
##  70.71842  77.42567  80.56279  86.18097  79.54452  75.66770  76.77920  78.91475
##       57       58       59       60       61       62       63       64
##  87.00232  70.24445  62.43238  76.94456  85.57690  82.32992  84.10415  84.08464
##       65       66       67       68       69       70       71       72
##  81.72510  88.61128  77.01994  84.45808  75.03575  84.58887  93.11545  78.11656
##       73       74       75       76       77       78       79       80
##  83.60987  87.48446  83.25982  87.59647  81.10361  79.45530  69.17038  75.34361
##       81       82       83       84       85       86       87       88
##  86.58620  91.02278  98.65784  83.24041  86.29588  81.38914  77.81345  83.29427
##       89       90       91       92       93       94       95       96
##  82.14307  85.78844  77.31626  90.17090  74.92238  80.27929  76.63840  76.41073
##       97       98       99      100      101      102      103      104
##  83.76351 101.49146  90.66066  91.80633  85.67709  75.74458  85.85636  82.51112
##      105      106      107      108      109      110      111      112
##  80.28514  75.74648  59.21657  80.05705  83.36447  63.89810  81.69559  80.89442
##      113      114      115      116      117      118      119      120
##  90.51339  88.42404  82.00004  79.88766  89.12636  79.28716  78.32773  70.56117
##      121      122      123      124      125      126      127      128
##  88.18073  64.83877  68.79647  62.89740  70.53486  89.14903  93.52098  77.13546
##      129      130      131      132      133      134      135      136
##  89.76420  96.00349  87.87496  79.55286  74.18762  83.65916  84.63120  67.92567
##      137      138      139      140      141      142      143      144
##  76.76088  79.31622  80.25903  79.00221  65.97271  70.88566  93.96534  80.09868
##      145      146      147      148      149      150      151      152
##  75.63502  76.66057  79.09194  81.58381  85.45157  81.03183  83.18578  79.69117
##      153      154      155      156      157      158      159      160
##  32.00533  74.74922  76.72696  73.53798  83.62346  70.38656  90.86799  71.82949
##      161      162      163      164      165      166      167      168
## 103.86302 102.94796  91.40787 103.43996  96.25437  92.15061  87.44536  83.28689
##      169      170      171      172      173      174      175      176
##  73.88550  80.44850  87.53529  83.90489  81.81791  91.73197  83.62750  78.62979
##      177      178      179      180      181      182      183      184
##  78.72177  78.62720  77.61974  80.23747  75.75891  82.42463  82.50687  83.40560
##      185      186      187      188      189      190      191      192
##  93.86719  84.08224  84.88270  59.90440  62.71131 106.61875  70.30532  79.80179
##      193      194      195      196      197      198      199      200
##  77.50981  80.91032  82.33698  71.26555  77.85090  81.87750  80.77272  86.39044
##      201      202      203      204      205      206      207      208
##  80.67028  82.42010  76.24716  85.64095  77.63218  78.86158  80.18659  76.75479
##      209      210      211      212      213      214      215      216
```

```
##  78.45877  74.04968 102.73424  94.95937  83.50166  71.04174  76.47425  88.75922
##       217       218       219       220       221       222       223       224
##  87.14607  86.32952  77.07959  76.85061  79.78128  75.26852  82.97115  79.90219
##       225       226       227       228       229       230       231       232
##  88.18673  76.73958  79.38705  80.08819  80.21071  76.68290  71.78995  94.28243
##       233       234       235       236       237       238       239       240
##  83.96099  86.59268  79.03424  74.35427  81.44309  78.25418  92.42152  75.30730
##       241       242       243       244       245       246       247       248
##  90.78059  88.86296  85.17144  83.49939  63.68535  86.98493  79.74425  82.77956
##       249       250       251       252       253       254       255       256
##  76.14821  84.12894  82.43395  59.19506  90.43189  46.23627  70.80823  77.18288
##       257       258       259
##  75.82183  77.87520  77.54615
```

# Model 2 - Stepwise Regression

```
# Try stepwise regression as mentioned in http://www.sthda.com/english/articles/37-model-selecti
on-essentials-in-r/154-stepwise-regression-essentials-in-r/
full_model = lm(TARGET_WINS ~ ., data=train_df)
step.model <- stepAIC(full_model, direction = "both",
                      trace = FALSE)
summary(step.model)
```

```
##
## 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 + TEAM_BASERUN_SB_NA + TEAM_BATTING_HBP_NA +
##     TEAM_FIELDING_DP_NA, data = train_df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -63.693  -8.067   0.330   7.875  49.924
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)          1.820e+01  4.192e+00   4.340 1.49e-05 ***
## TEAM_BATTING_H       4.682e-02  3.212e-03  14.578  < 2e-16 ***
## TEAM_BATTING_2B     -2.757e-02  8.973e-03  -3.073 0.002147 **
## TEAM_BATTING_3B      5.424e-02  1.547e-02   3.507 0.000461 ***
## TEAM_BATTING_HR      7.549e-02  8.642e-03   8.736  < 2e-16 ***
## TEAM_BATTING_BB      2.398e-02  3.239e-03   7.404 1.86e-13 ***
## TEAM_BATTING_SO     -1.025e-02  1.776e-03  -5.771 8.97e-09 ***
## TEAM_BASERUN_SB      5.014e-02  4.457e-03  11.249  < 2e-16 ***
## TEAM_PITCHING_H      1.980e-03  3.339e-04   5.930 3.49e-09 ***
## TEAM_PITCHING_SO    -1.096e-03  6.613e-04  -1.657 0.097666 .
## TEAM_FIELDING_E     -5.685e-02  3.370e-03 -16.873  < 2e-16 ***
## TEAM_FIELDING_DP    -1.045e-01  1.309e-02  -7.985 2.21e-15 ***
## TEAM_BASERUN_SB_NA   3.969e+01  2.048e+00  19.385  < 2e-16 ***
## TEAM_BATTING_HBP_NA  3.277e+00  1.071e+00   3.059 0.002244 **
## TEAM_FIELDING_DP_NA -1.073e+01  1.948e+00  -5.507 4.07e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 12.1 on 2261 degrees of freedom
## Multiple R-squared:  0.4135, Adjusted R-squared:  0.4098
## F-statistic: 113.9 on 14 and 2261 DF,  p-value: < 2.2e-16
```

```
# Train model
train_control = trainControl(method = "cv", number = 10)
step_model = train(TARGET_WINS ~ ., data=train_df,
                   method = "lmStepAIC",
                   trControl = train_control,
                   trace=FALSE)
# Model accuracy
step_model$results
```

```
##   parameter    RMSE  Rsquared     MAE    RMSESD RsquaredSD     MAESD
## 1      none 12.2621 0.3901083 9.64169 0.5608981 0.06517879 0.3265393
```

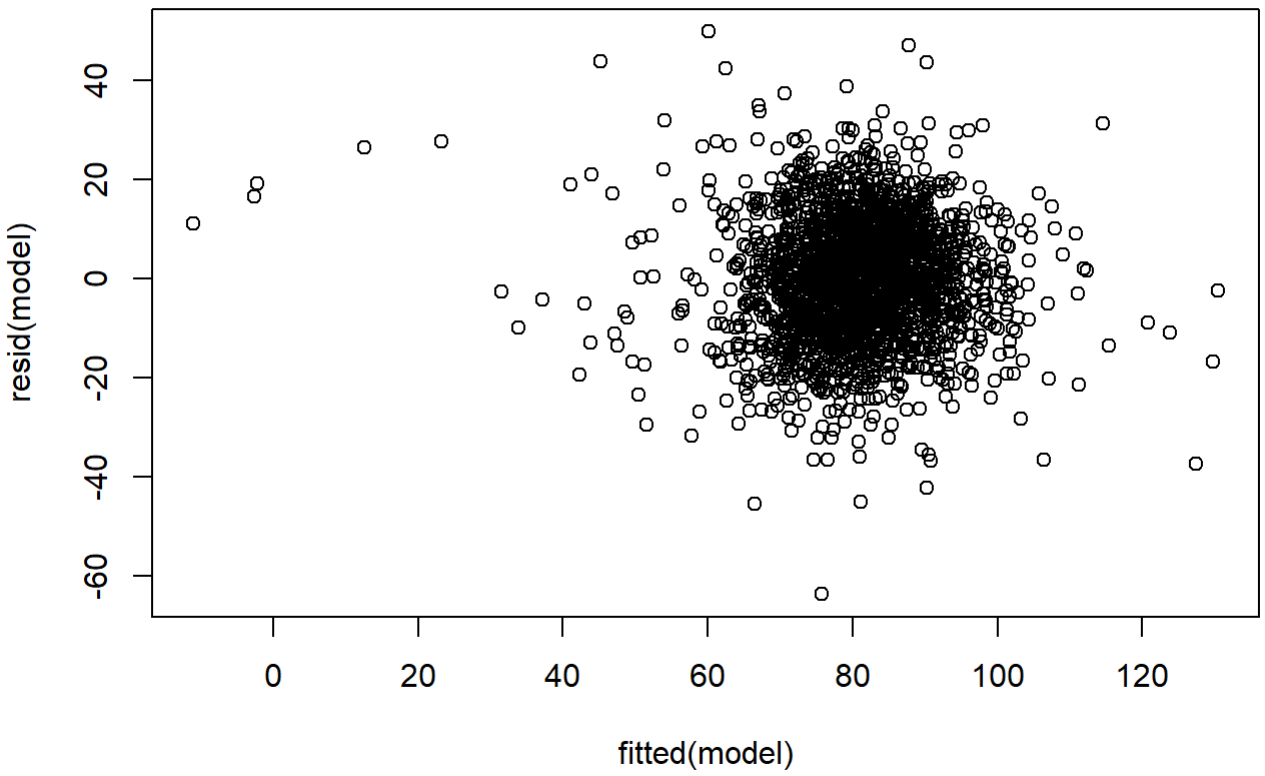
```
# Final model coefficients
step_model$finalModel
```

```
##
## Call:
## lm(formula = .outcome ~ 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 +
##     TEAM_BASERUN_SB_NA + TEAM_BATTING_HBP_NA + TEAM_FIELDING_DP_NA,
##     data = dat)
##
## Coefficients:
##         (Intercept)       TEAM_BATTING_H      TEAM_BATTING_2B
##           18.196340             0.046820            -0.027572
##     TEAM_BATTING_3B      TEAM_BATTING_HR      TEAM_BATTING_BB
##            0.054244             0.075494             0.023983
##     TEAM_BATTING_SO      TEAM_BASERUN_SB      TEAM_PITCHING_H
##           -0.010247             0.050139             0.001980
##    TEAM_PITCHING_SO      TEAM_FIELDING_E     TEAM_FIELDING_DP
##           -0.001096            -0.056855            -0.104532
##  TEAM_BASERUN_SB_NA  TEAM_BATTING_HBP_NA  TEAM_FIELDING_DP_NA
##           39.693780             3.277467           -10.727882
```

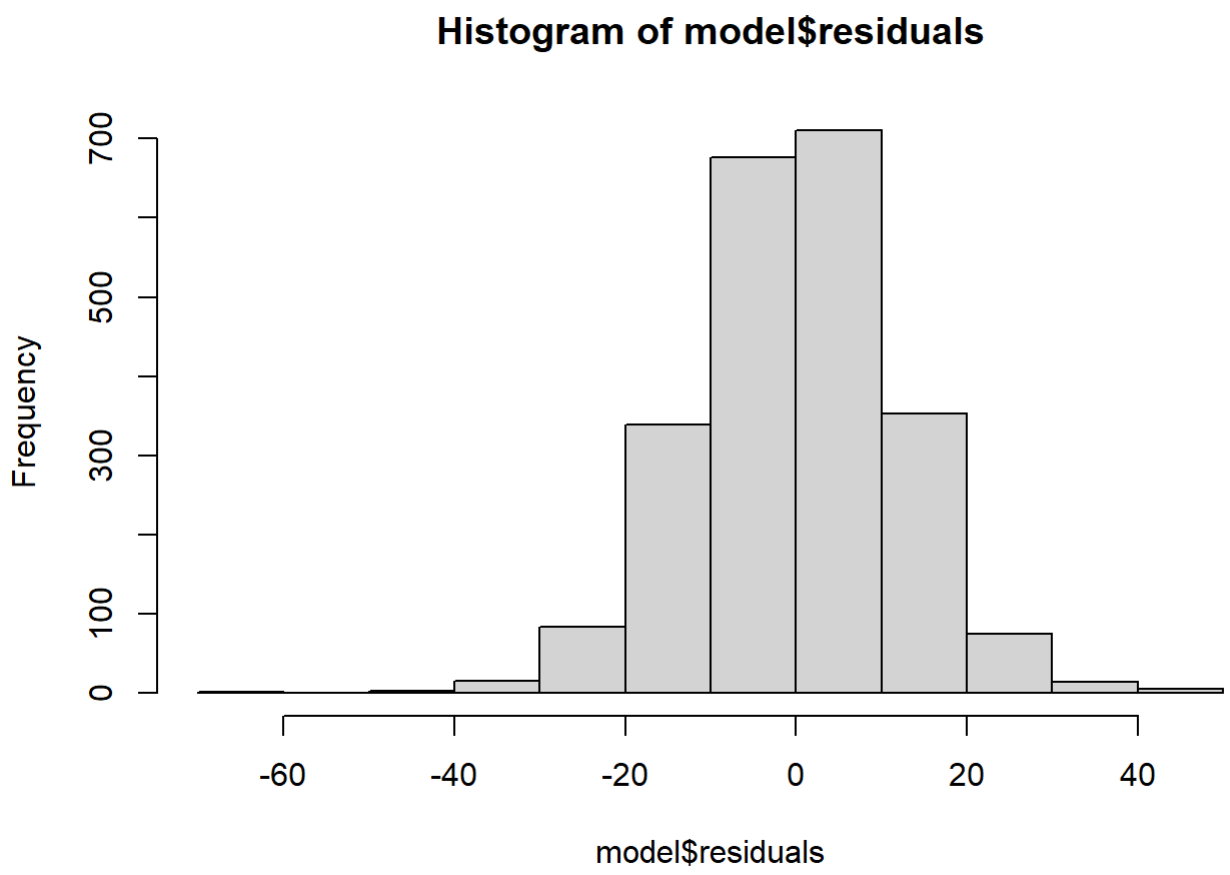
```
# Summary of model
summary(step_model$finalModel)
```

```
##
## Call:
## lm(formula = .outcome ~ 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 +
##     TEAM_BASERUN_SB_NA + TEAM_BATTING_HBP_NA + TEAM_FIELDING_DP_NA,
##     data = dat)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -63.693  -8.067   0.330   7.875  49.924
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)          1.820e+01  4.192e+00   4.340 1.49e-05 ***
## TEAM_BATTING_H       4.682e-02  3.212e-03  14.578  < 2e-16 ***
## TEAM_BATTING_2B     -2.757e-02  8.973e-03  -3.073 0.002147 **
## TEAM_BATTING_3B      5.424e-02  1.547e-02   3.507 0.000461 ***
## TEAM_BATTING_HR      7.549e-02  8.642e-03   8.736  < 2e-16 ***
## TEAM_BATTING_BB      2.398e-02  3.239e-03   7.404 1.86e-13 ***
## TEAM_BATTING_SO     -1.025e-02  1.776e-03  -5.771 8.97e-09 ***
## TEAM_BASERUN_SB      5.014e-02  4.457e-03  11.249  < 2e-16 ***
## TEAM_PITCHING_H      1.980e-03  3.339e-04   5.930 3.49e-09 ***
## TEAM_PITCHING_SO    -1.096e-03  6.613e-04  -1.657 0.097666 .
## TEAM_FIELDING_E     -5.685e-02  3.370e-03 -16.873  < 2e-16 ***
## TEAM_FIELDING_DP    -1.045e-01  1.309e-02  -7.985 2.21e-15 ***
## TEAM_BASERUN_SB_NA   3.969e+01  2.048e+00  19.385  < 2e-16 ***
## TEAM_BATTING_HBP_NA  3.277e+00  1.071e+00   3.059 0.002244 **
## TEAM_FIELDING_DP_NA -1.073e+01  1.948e+00  -5.507 4.07e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 12.1 on 2261 degrees of freedom
## Multiple R-squared:  0.4135, Adjusted R-squared:  0.4098
## F-statistic: 113.9 on 14 and 2261 DF,  p-value: < 2.2e-16
```

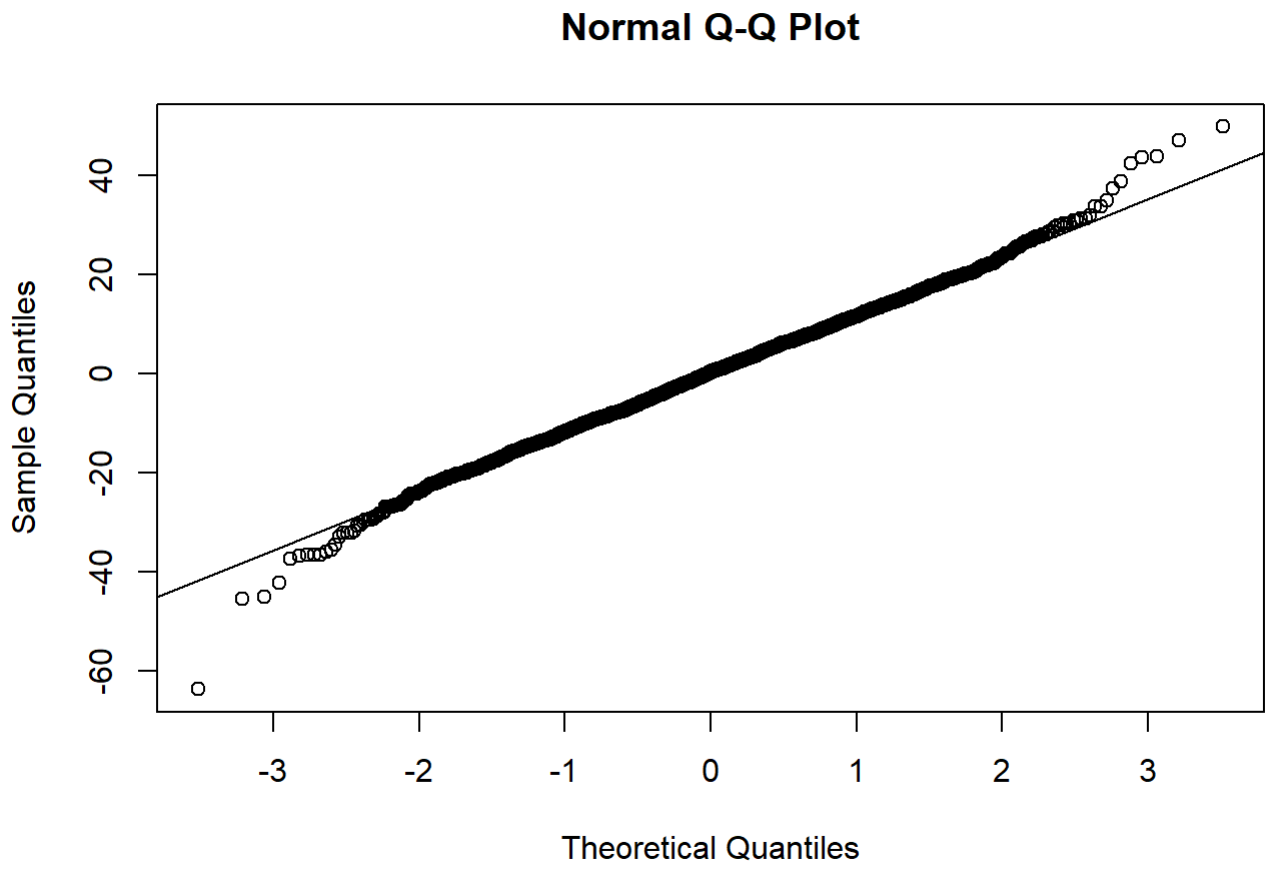
```
model = step_model$finalModel
plot(fitted(model), resid(model))
```




```
hist(model$residuals)
```




```
qqnorm(resid(model))
qqline(resid(model))
```




```
# Check MSE
mean(summary(model$residuals^2))
```

```
## [1] 743.6606
```

```
# 743.6606
```

# Model 3 - Try removing TEAM_PITCHING_SO