

621 HW1

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1. Data Exploration

The “moneyball” training data set contains 2276 rows and 17 columns, including variables such as TARGET_WINS, TEAM_BATTING, TEAM_BASERUN, etc. The variables are thought to have a positive or negative effect on the number of games the baseball team won during the season. 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 included a correlation plot and pairs plot to visualize the relationship among the variables. Histograms were created for each type of hits to observe the normality of the variables. We explored the structure of the variables for both the training and evaluation data sets and finally observed how TARGET_WINS are affected by other factors. Interestingly, the number of wins seems positively correlated with all hits by batters except triples by batters, which the correlation plot shows as slightly negatively correlated. One potential explanation may be that getting triples, while good, is actually always worse than getting homeruns, so having a large number of triples may actually mean the team is just barely falling short. Nothing from the correlation plot can be used to conclude this, but it is something that can be investigated further in the future. Also surprising is that stolen bases barely has any positive correlation with wins, but that may just be due to the rarity of the event (stolen bases). TEAM_PITCHING_H, TEAM_PITCHING_BB, and TEAM_PITCHING_HR surprisingly shows a positive correlation with team wins, but maybe this alludes to having good batters and getting runs being more important to winning than stopping the opponent from getting runs. Similarly, TEAM_PITCHING_SO and TEAM_PITCHING_DP are events of denying the opponent runs, but they show a negative correlation with number of wins and may also point to getting runs for your team as the key to winning.

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. TEAM_BATTING_HBP has the highest number of missing cases i.e., 2085 (~ 90%). Based on the variable definitions given in the assignment, it seemed reasonable that NA values meant that there were no occurrences of that event. So we chose to create additional columns flagging whether the original variable was NA or not (1 if NA, 0 if not NA), and then filled NAs with 0.

3. Build Models

First we built a model using the backward elimination process. In this process, we rejected predictors with p-value greater than 0.05 and stopped after all remaining model predictors had p-values of less than 0.05. For our second model we decided to use stepwise selection. Stepwise selection uses an automated process of building a model by adding or removing predictors repeatedly based on an improvement of a criterion (Akaike information criterion in our case). We noticed one of the variables, TEAM_PITCHING_SO, had a

p-value greater than 0.05 in the second model so we decided to build a third model using stepwise regression with the TEAM_PITCHING_SO predictor removed. The third model's R squared dropped slightly, so we decided to stick with our second model.

4. Select Models

Out of the three models we created, the second model with stepwise selection was the best of the three. The Adjusted R squared is 0.4098 which translates to approximately 41% of variation in Target Wins can be explained by our model. The 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 we have 113.9. The normal quantile quantile plot for residuals displays an approximately straight line so the residuals are approximately normally distributed. However, there is slight deviation at the extreme values, meaning our model does have a bit of trouble predicting a very high or low number of wins accurately. The MSE is 743.6606. Using this model we were able to make predictions for the test dataset. Finally, we made a histogram of wins from the training and evaluation set to see if the prediction distribution looked fairly similar to the training distribution, which it does.

Appendix

```
# 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.githubusercontent.com/san123i/CUNY/master/Semester4/621-BusinessAnalytics/HW1/d
```

```
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
```

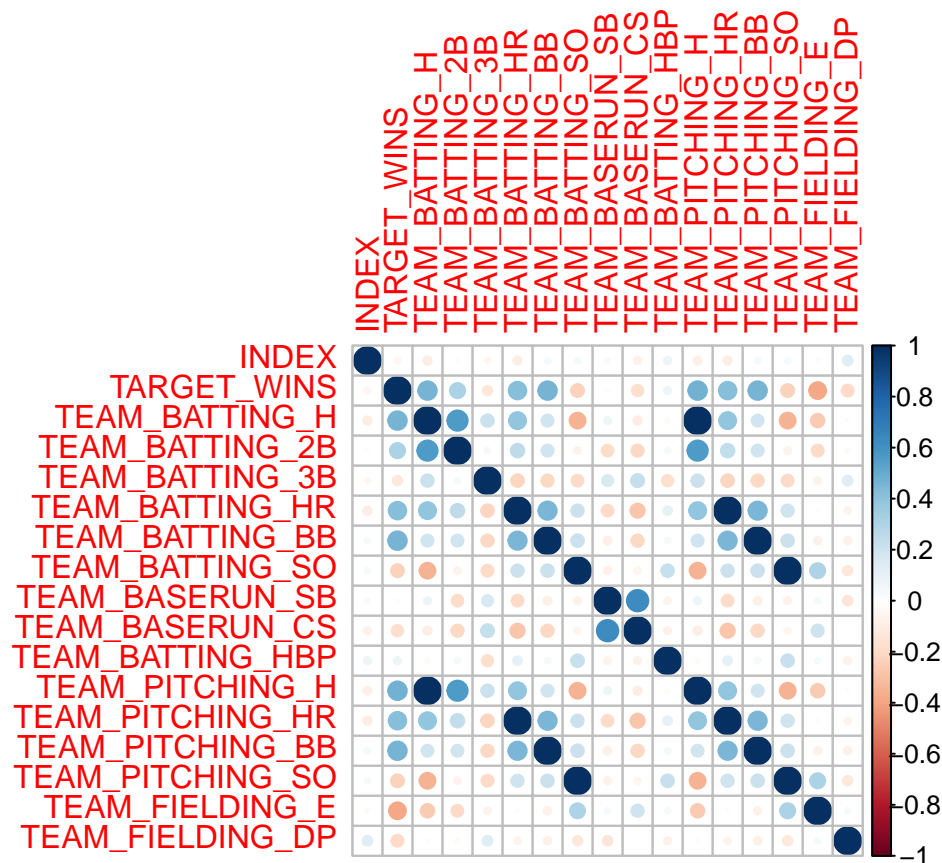
```
summary(train_df)
```

```
##      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
```

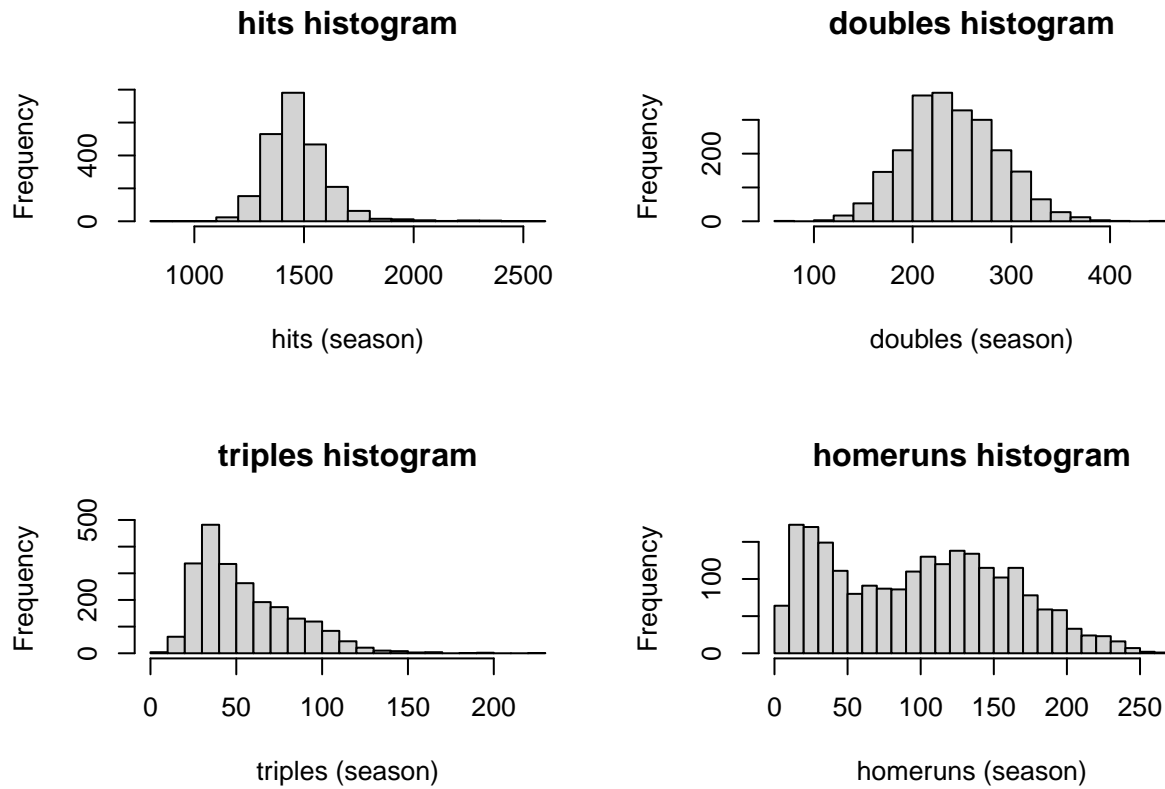
```
cor_train = cor(train_df, use = "na.or.complete")
corrplot(cor_train)
```



For types of hits, see a histogram of each

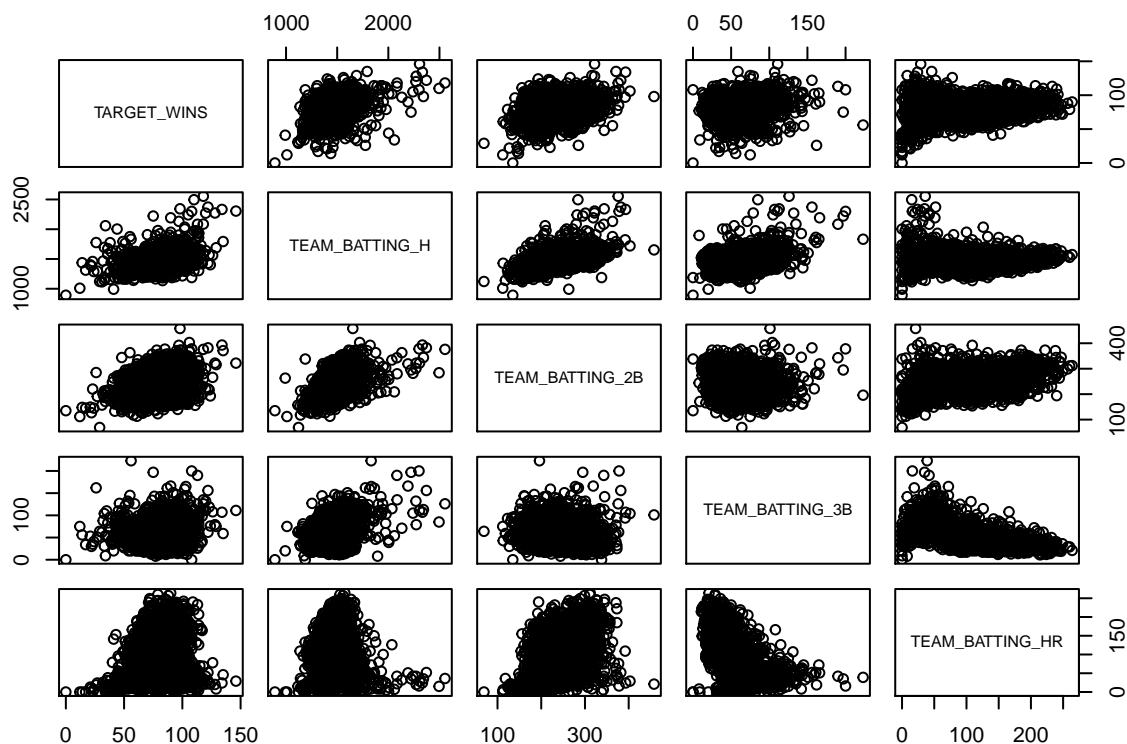
```
par(mfrow=c(2,2))
hist(train_df$TEAM_BATTING_H,
     main = "hits histogram", xlab = "hits (season)",
     breaks = 20)
hist(train_df$TEAM_BATTING_2B,
     main = "doubles histogram", xlab = "doubles (season)",
     breaks = 20)
hist(train_df$TEAM_BATTING_3B,
     main = "triples histogram", xlab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

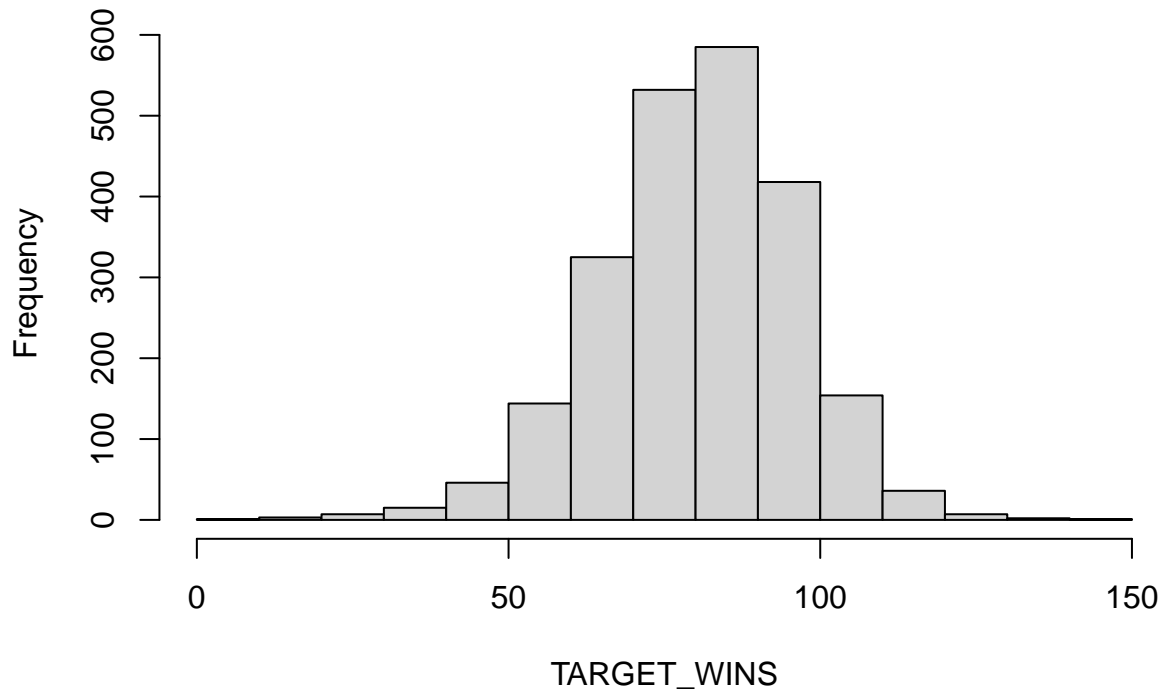
```
str(train_df)
```

```
## '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="")
```

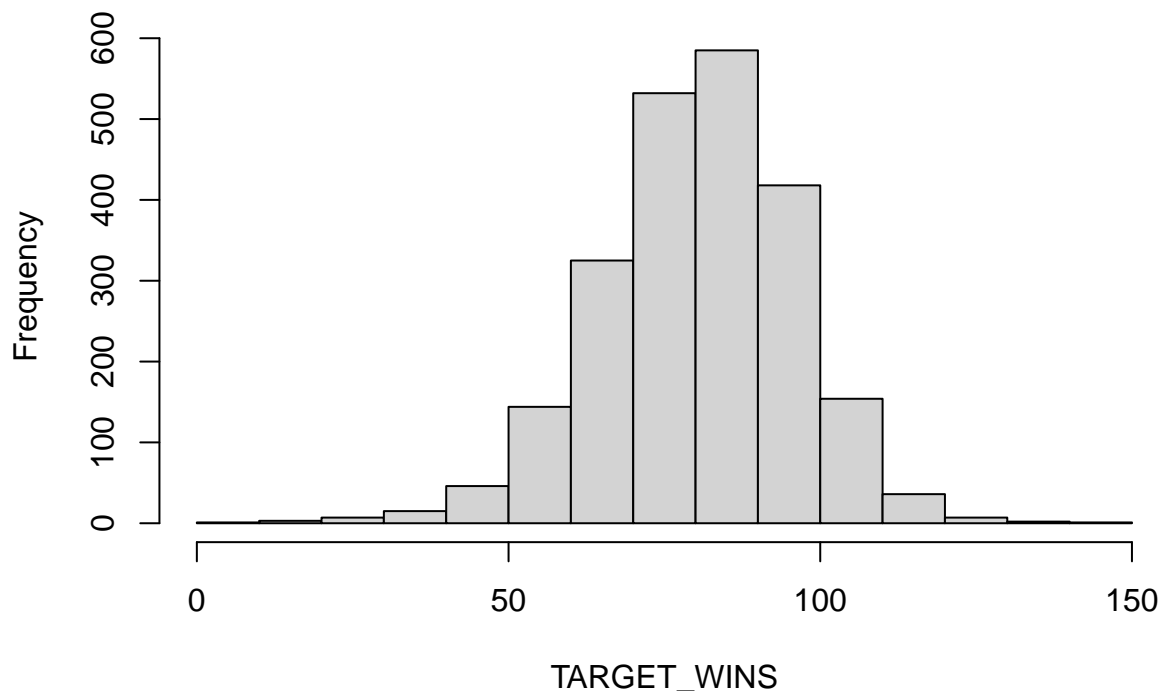


```
# we have no TARGET_WINS from eval  
# hist(eval$TARGET_WINS,xlab="TARGET_WINS",main="")
```

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_SO + TEAM_BATTING_BB + TEAM_BATTING_SB + TEAM_BATTING_CS + TEAM_BATTING_HBP + TEAM_PITCHING_H + TEAM_PITCHING_HR + TEAM_PITCHING_BB + TEAM_PITCHING_SO + TEAM_FIELDING_E)
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
```

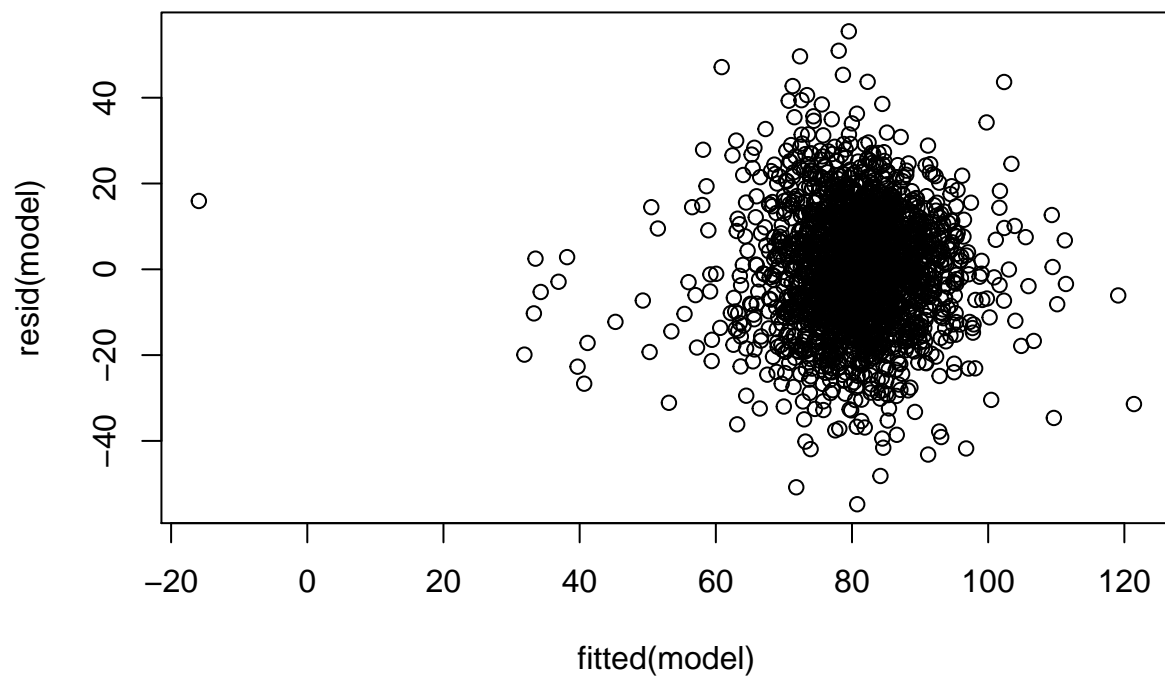
```
model <- update(model, ~. - TEAM_BATTING_BB, data=train_df)
summary(model)
```

```
##
## 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)
```

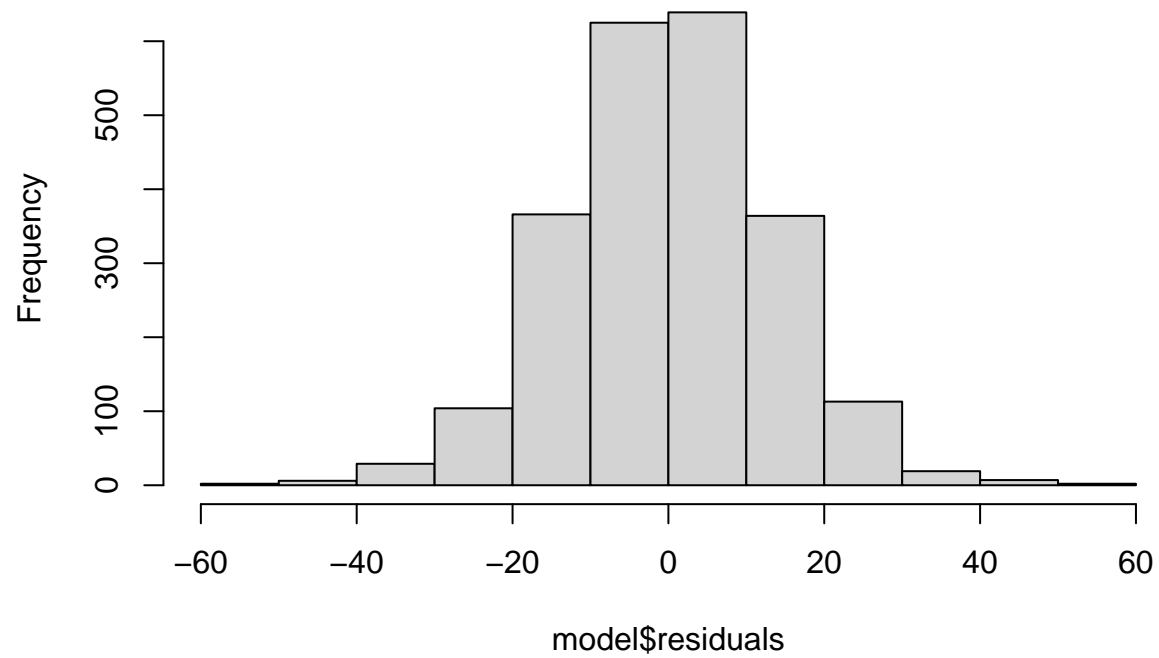
```
##
## Call:
## lm(formula = TARGET_WINS ~ TEAM_BATTING_H + TEAM_BATTING_2B +
##     TEAM_BATTING_3B + TEAM_BATTING_HR + TEAM_PITCHING_H + TEAM_PITCHING_BB +
##     TEAM_FIELDING_E, data = train_df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -54.763  -8.861   0.095   8.860  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))
```



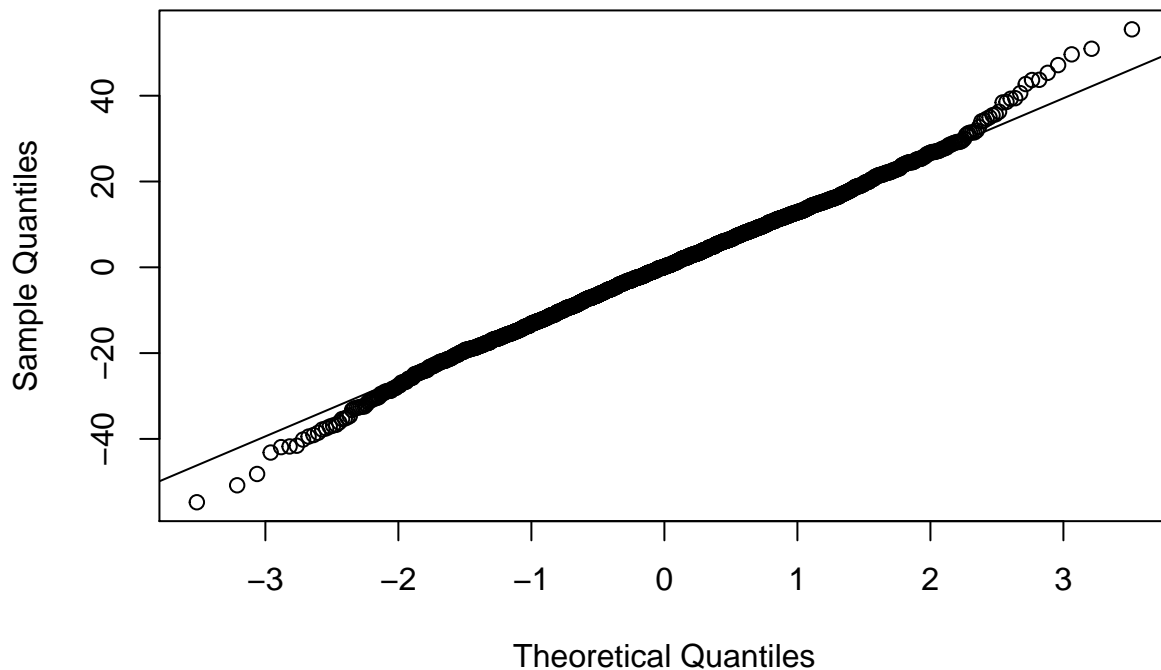
```
hist(model$residuals)
```

Histogram of model\$residuals



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

Normal Q-Q Plot



```
#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_BB, TEAM_BATTING_SO, TEAM_BASERUN_SB, TEAM_BASERUN_CS, TEAM_BATTING_HBP, TEAM_PITCHING_H, TEAM_PITCHING_HR, TEAM_PITCHING_BB, TEAM_PITCHING_SO, TEAM_FIELDING_E, TEAM_FIELDING_DP, TEAM_BATTING_SO_NA, TEAM_BASERUN_SB_NA, TEAM_BASERUN_CS_NA, TEAM_BATTING_HBP_NA, TEAM_PITCHING_SO_NA, TEAM_FIELDING_DP_NA))
# 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-selection-essentials/
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
```

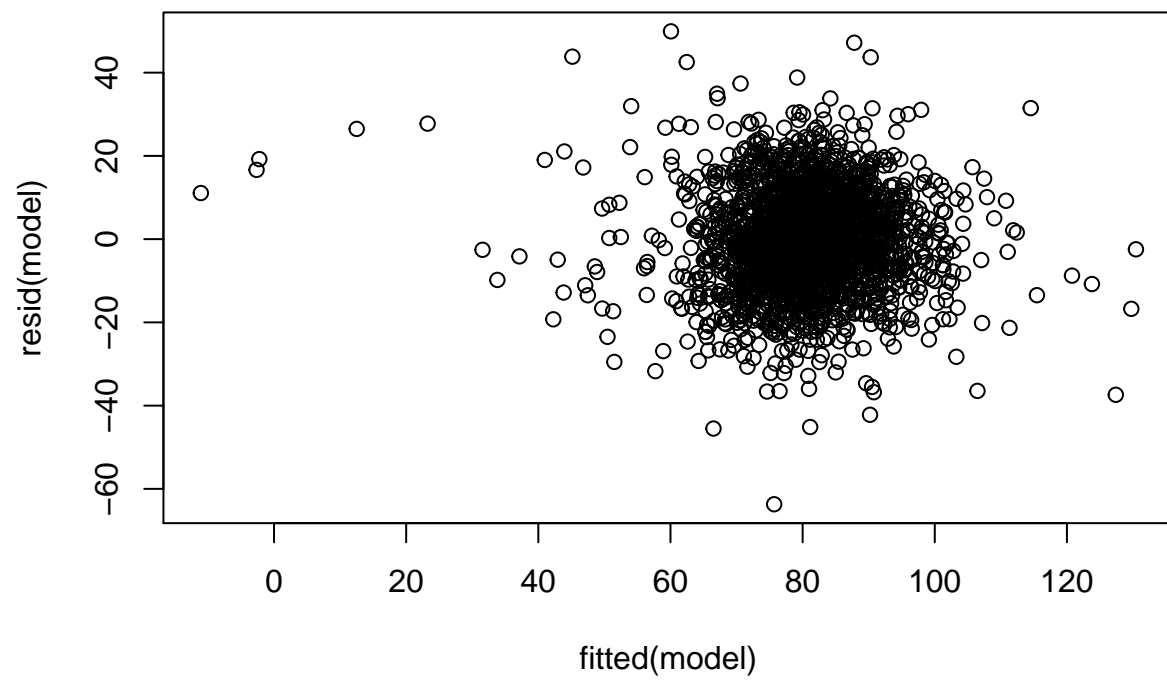
```
##
## Call:
## lm(formula = .outcome ~ TEAM_BATTING_H + TEAM_BATTING_2B + TEAM_BATTING_3B +
##   TEAM_BATTING_HR + TEAM_BATTING_BB + TEAM_BATTING_SO + TEAM_BASERUN_SB +
##   TEAM_PITCHING_H + TEAM_PITCHING_SO + TEAM_FIELDING_E + TEAM_FIELDING_DP +
##   TEAM_BASERUN_SB_NA + TEAM_BATTING_HBP_NA + TEAM_FIELDING_DP_NA,
##   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
```

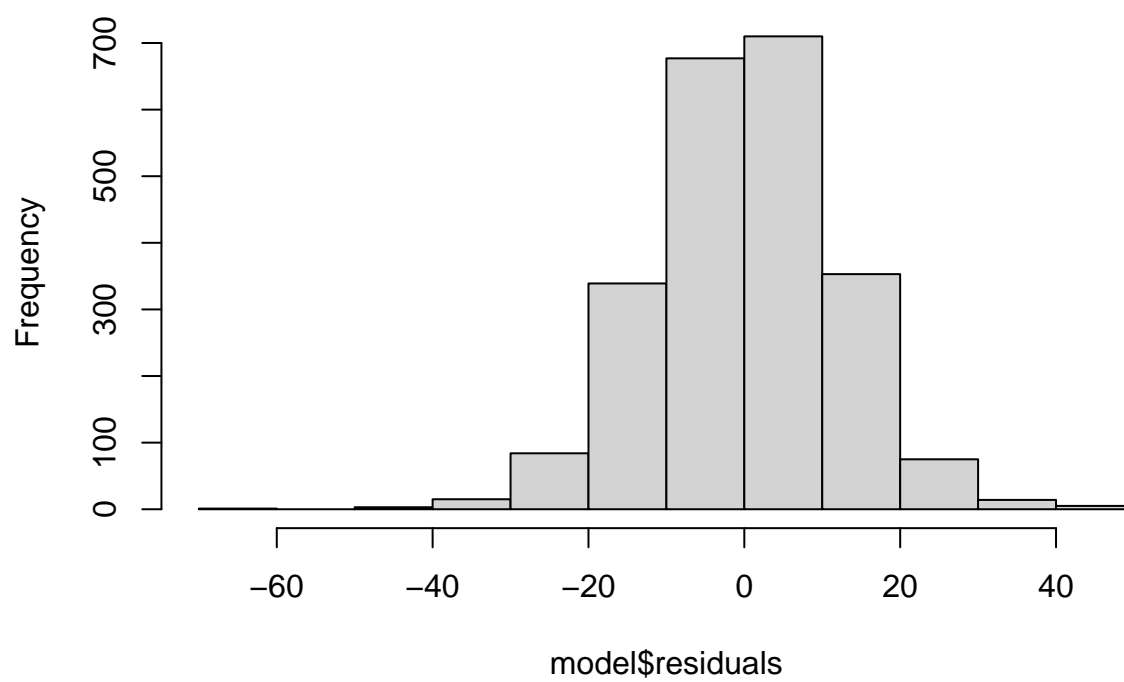
```
##
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1.820e+01  4.192e+00   4.340 1.49e-05 ***
## TEAM_BATTING_H    4.682e-02  3.212e-03  14.578 < 2e-16 ***
## TEAM_BATTING_2B  -2.757e-02  8.973e-03  -3.073 0.002147 **
## TEAM_BATTING_3B    5.424e-02  1.547e-02   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))
```



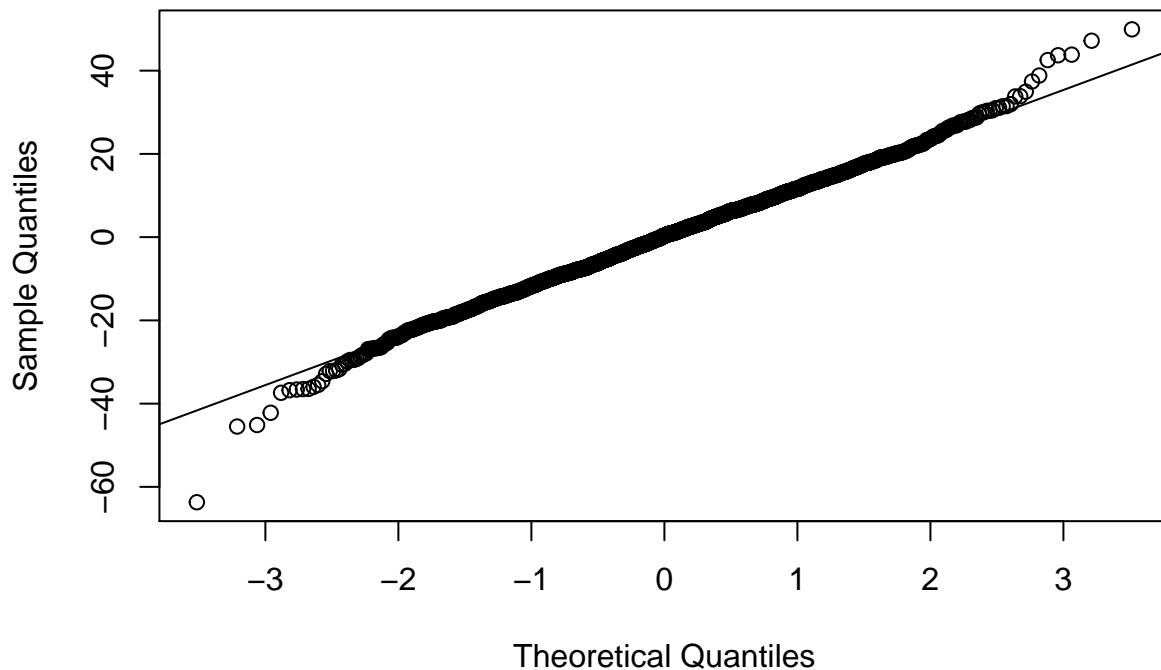
```
hist(model$residuals)
```

Histogram of model\$residuals



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

Normal Q-Q Plot



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

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

```
# 743.6606
```

Model 3 - Try removing TEAM_PITCHING_SO

```
# Train model without TEAM_PITCHING_SO since it has a relatively high p-value
train_control = trainControl(method = "cv", number = 10)
no_TPS = subset(train_df, select=-c(Team_Pitching_SO))
step_model_noTPS = train(TARGET_WINS ~ ., data=no_TPS,
                          method = "lmStepAIC",
                          trControl = train_control,
                          trace=FALSE)

# Model accuracy
step_model_noTPS$results
```

```
## parameter RMSE Rsquared MAE RMSESD RsquaredSD MAESD
## 1 none 12.2715 0.3955766 9.654802 0.559686 0.04342146 0.3603521
```

```
# Final model coefficients
step_model_noTPS$finalModel
```

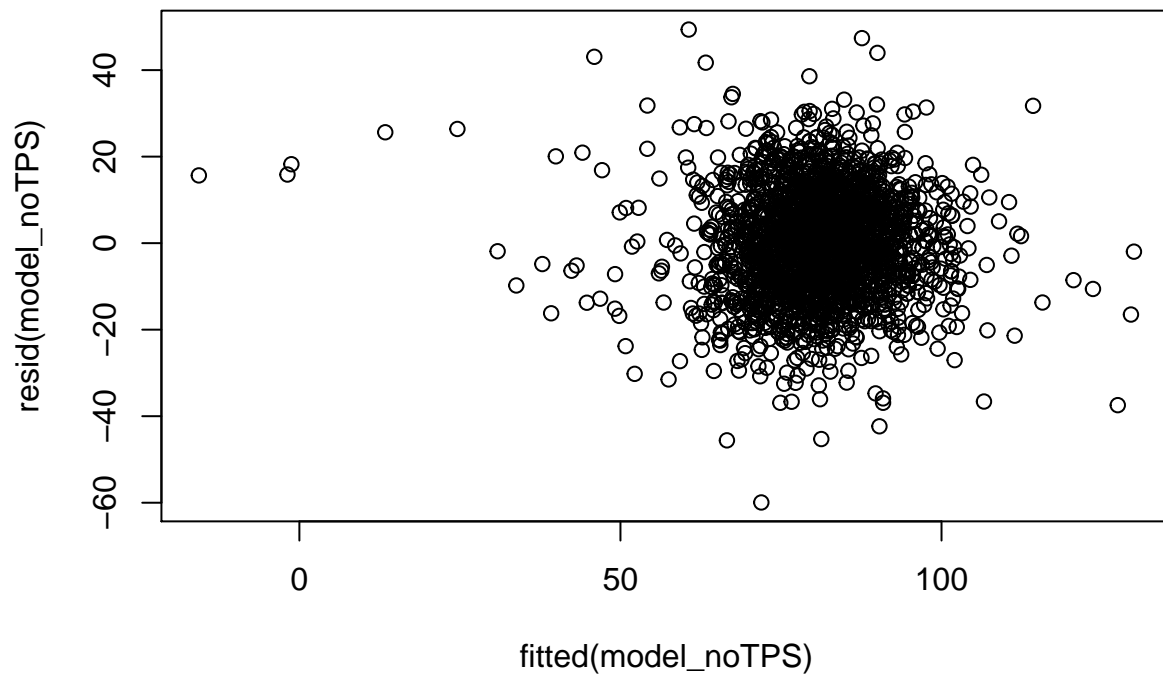
```
##
## Call:
## lm(formula = .outcome ~ TEAM_BATTING_H + TEAM_BATTING_2B + TEAM_BATTING_3B +
##     TEAM_BATTING_HR + TEAM_BATTING_BB + TEAM_BATTING_SO + TEAM_BASERUN_SB +
##     TEAM_PITCHING_H + TEAM_FIELDING_E + TEAM_FIELDING_DP + TEAM_BASERUN_SB_NA +
##     TEAM_BATTING_HBP_NA + TEAM_FIELDING_DP_NA, data = dat)
##
## Coefficients:
##      (Intercept)      TEAM_BATTING_H      TEAM_BATTING_2B
##      17.475160         0.047857        -0.029176
##     TEAM_BATTING_3B     TEAM_BATTING_HR     TEAM_BATTING_BB
##      0.053032         0.076969         0.023764
##     TEAM_BATTING_SO     TEAM_BASERUN_SB     TEAM_PITCHING_H
##     -0.011516         0.049503         0.001683
##     TEAM_FIELDING_E     TEAM_FIELDING_DP     TEAM_BASERUN_SB_NA
##     -0.055278        -0.104090         38.683727
## TEAM_BATTING_HBP_NA  TEAM_FIELDING_DP_NA
##      3.170394        -11.012818
```

```
# Summary of model
summary(step_model_noTPS$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_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
## -59.938  -8.049   0.369   7.904  49.371
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.748e+01  4.171e+00   4.189 2.91e-05 ***
## TEAM_BATTING_H    4.786e-02  3.151e-03  15.187 < 2e-16 ***
## TEAM_BATTING_2B  -2.918e-02  8.924e-03  -3.269 0.001094 **
## TEAM_BATTING_3B    5.303e-02  1.545e-02   3.432 0.000611 ***
## TEAM_BATTING_HR    7.697e-02  8.599e-03   8.951 < 2e-16 ***
## TEAM_BATTING_BB    2.376e-02  3.238e-03   7.339 2.98e-13 ***
## TEAM_BATTING_SO   -1.152e-02  1.603e-03  -7.185 9.12e-13 ***
## TEAM_BASERUN_SB    4.950e-02  4.442e-03  11.144 < 2e-16 ***
## TEAM_PITCHING_H    1.683e-03  2.817e-04   5.974 2.68e-09 ***
## TEAM_FIELDING_E   -5.528e-02  3.234e-03 -17.095 < 2e-16 ***
## TEAM_FIELDING_DP  -1.041e-01  1.309e-02  -7.950 2.92e-15 ***
## TEAM_BASERUN_SB_NA  3.868e+01  1.956e+00  19.782 < 2e-16 ***
## TEAM_BATTING_HBP_NA 3.170e+00  1.070e+00   2.964 0.003072 **
## TEAM_FIELDING_DP_NA -1.101e+01  1.941e+00  -5.673 1.58e-08 ***
## ---
```

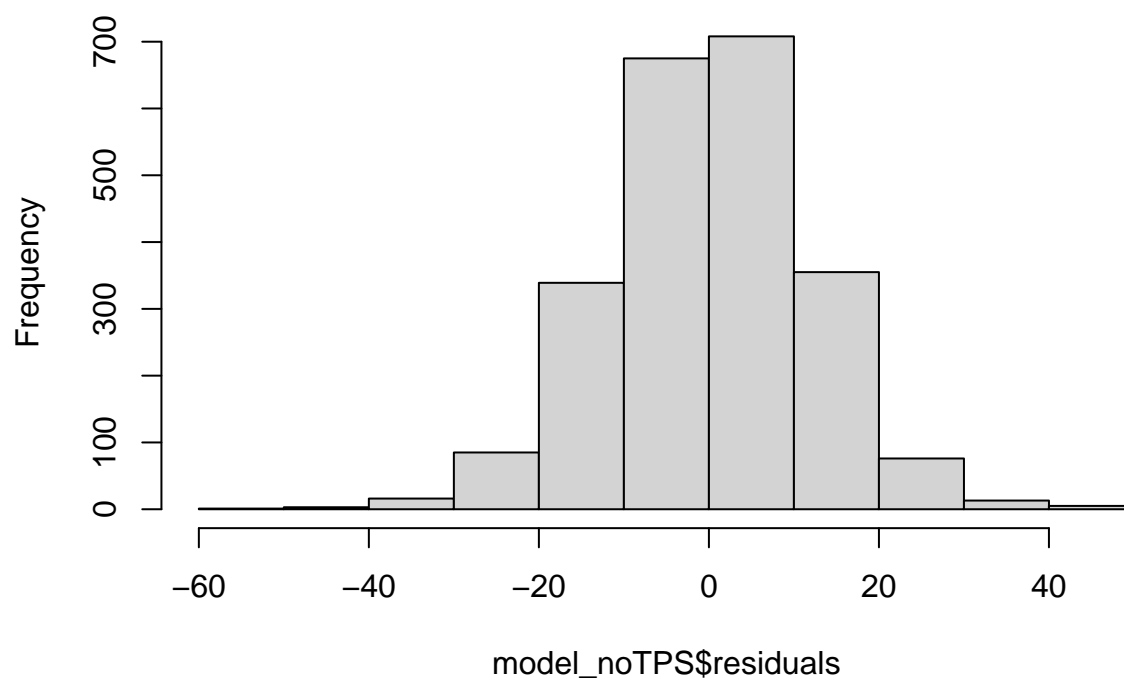
```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## Residual standard error: 12.11 on 2262 degrees of freedom  
## Multiple R-squared:  0.4128, Adjusted R-squared:  0.4094  
## F-statistic: 122.3 on 13 and 2262 DF,  p-value: < 2.2e-16
```

```
model_noTPS = step_model_noTPS$finalModel  
plot(fitted(model_noTPS), resid(model_noTPS))
```



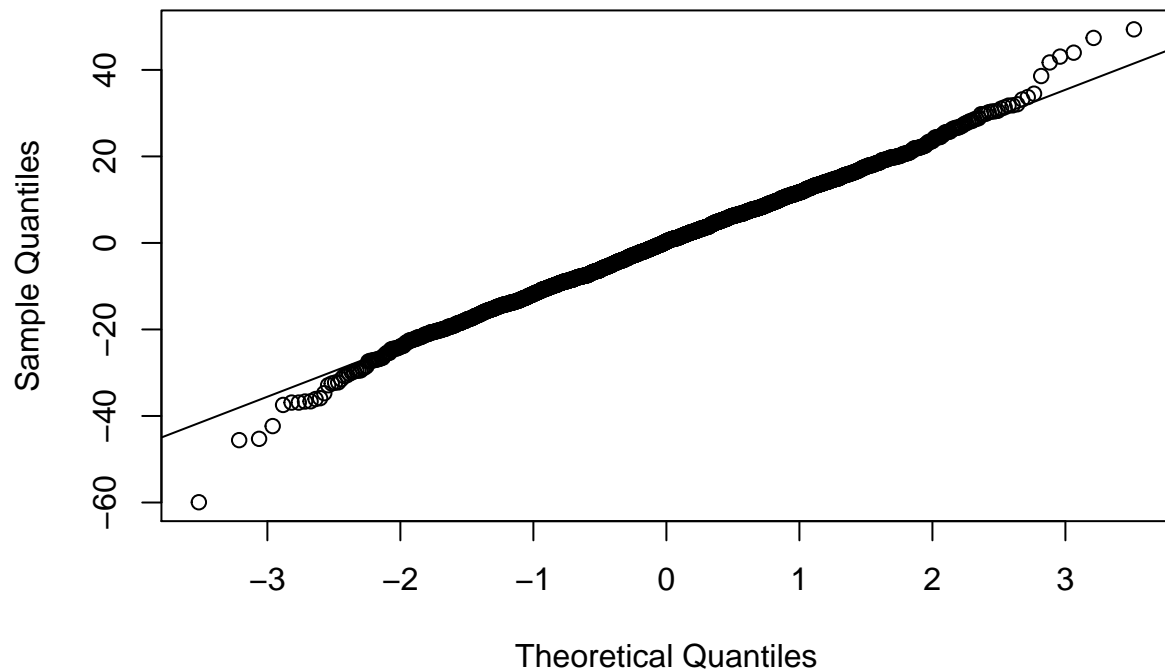
```
hist(model_noTPS$residuals)
```

Histogram of model_noTPS\$residuals



```
qqnorm(resid(model_noTPS))  
qqline(resid(model_noTPS))
```


Normal Q-Q Plot

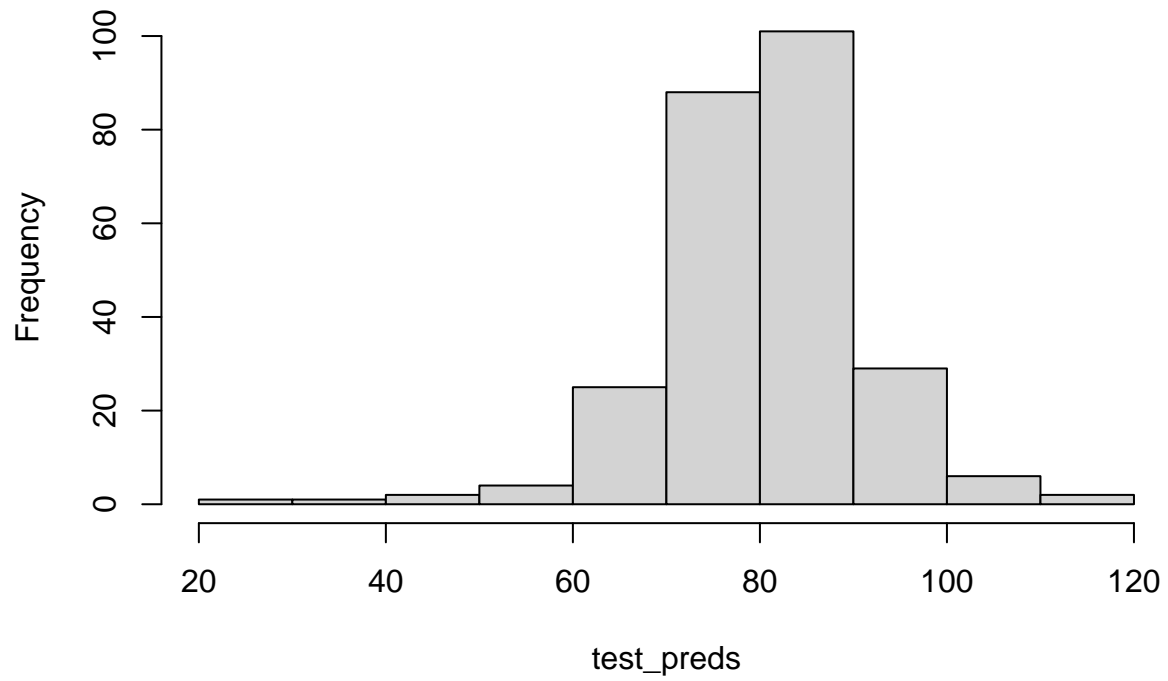


Predictions on Evaluation Set

```
# convert decimals of wins back to number of wins, rounded
test_preds = round(predict(model, newdata=test_df)) ##162
test_df$PRED_TARGET_WINS = test_preds
# write out evaluation data with predictions
write.csv(test_df, 'datasets/eval_with_preds.csv')

# visually inspect the distribution of predictions for test and wins from the training set
hist(test_preds)
```

Histogram of test_preds



```
hist(train_target_wins)
```

