Critical Thinking Group 4 - HW1

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Purpose

The purpose of this experiment is to try to predict the amount of wins for a baseball team using the (modified) moneyball dataset. This dataset contains approximately 2200 observations with 17 variables. Each observation represents the performance of a professional baseball team from 1871 to 2006. The statistics have been adjusted to match the performance of a 162 game season.

Dataset:
Moneyball Training Data
Moneyball Evaluation Data

1. Data Exploration

The dependent (response) variable is *TARGET_WINS*. Excluding INDEX, the rest of the variables are the independent variables (predictors). Lets review how each of these independent variables are distributed & how each of these indepdent variable relates to the response variable 'TARGET_WINS'.

1.1 Missing Values

Review the *measure of the center* for the given variables. A quick look at the summary statistics indicate that there are missing values for some of the predictors.

```
##  TEAM_BATTING_H TEAM_BATTING_2B TEAM_BATTING_3B  TEAM_BATTING_HR
##  Min.   : 891   Min.   : 69.0   Min.   :  0.00   Min.   :  0.00
##  1st Qu.:1383   1st Qu.:208.0   1st Qu.: 34.00   1st Qu.: 42.00
##  Median :1454   Median :238.0   Median : 47.00   Median :102.00
##  Mean   :1469   Mean   :241.2   Mean   : 55.25   Mean   : 99.61
##  3rd Qu.:1537   3rd Qu.:273.0   3rd Qu.: 72.00   3rd Qu.:147.00
##  Max.   :2554   Max.   :458.0   Max.   :223.00   Max.   :264.00
##
##  TEAM_BATTING_BB TEAM_BATTING_SO  TEAM_BASERUN_SB TEAM_BASERUN_CS
##  Min.   :  0.0   Min.   :   0.0   Min.   :  0.0   Min.   :  0.0
##  1st Qu.:451.0   1st Qu.: 548.0   1st Qu.: 66.0   1st Qu.: 38.0
##  Median :512.0   Median : 750.0   Median :101.0   Median : 49.0
##  Mean   :501.6   Mean   : 735.6   Mean   :124.8   Mean   : 52.8
##  3rd Qu.:580.0   3rd Qu.: 930.0   3rd Qu.:156.0   3rd Qu.: 62.0
##  Max.   :878.0   Max.   :1399.0   Max.   :697.0   Max.   :201.0
##                  NA's   :102      NA's   :131     NA's   :772
##  TEAM_BATTING_HBP TEAM_PITCHING_H TEAM_PITCHING_HR TEAM_PITCHING_BB
##  Min.   :29.00    Min.   : 1137   Min.   :  0.0    Min.   :   0.0
##  1st Qu.:50.50    1st Qu.: 1419   1st Qu.: 50.0    1st Qu.: 476.0
##  Median :58.00    Median : 1518   Median :107.0    Median : 536.5
##  Mean   :59.36    Mean   : 1779   Mean   :105.7    Mean   : 553.0
##  3rd Qu.:67.00    3rd Qu.: 1682   3rd Qu.:150.0    3rd Qu.: 611.0
```

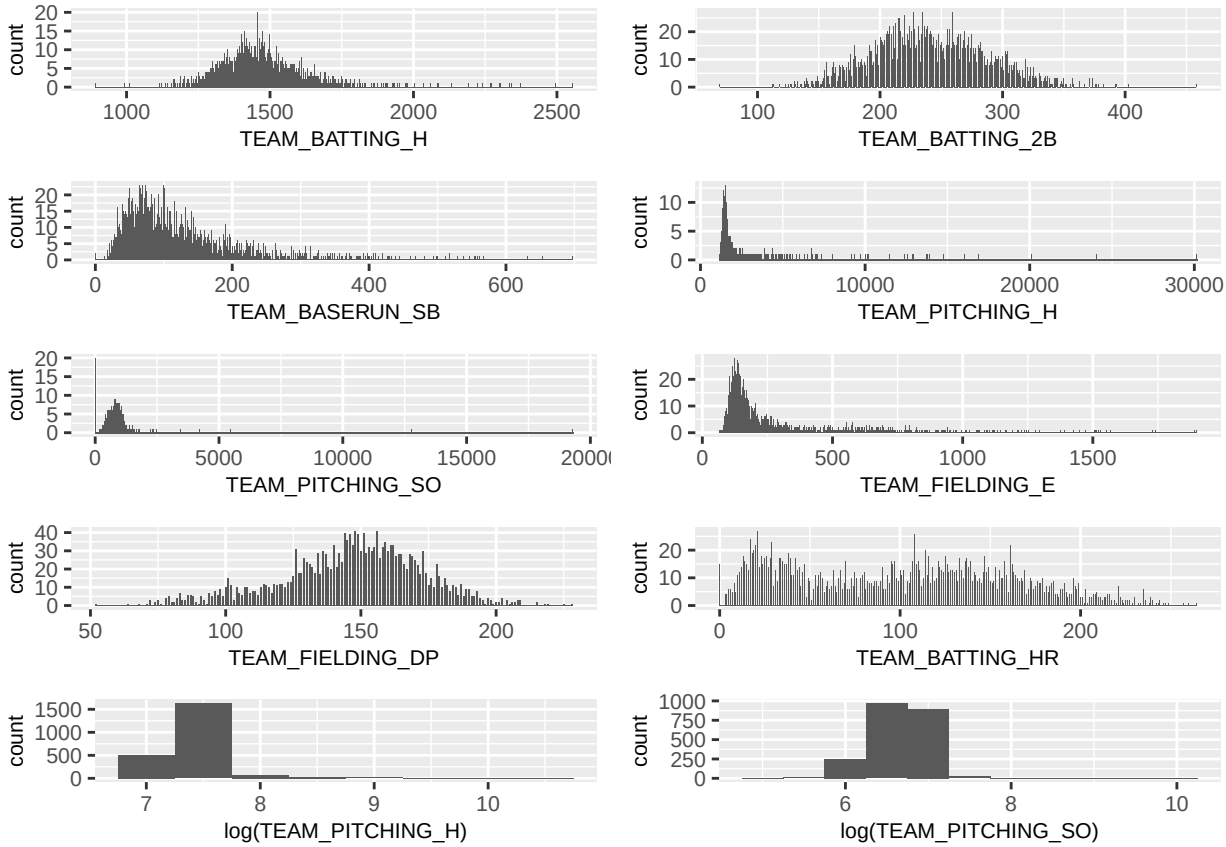
```
##  Max.   :95.00    Max.   :30132   Max.   :343.0    Max.   :3645.0
##  NA's   :2085
##  TEAM_PITCHING_SO  TEAM_FIELDING_E  TEAM_FIELDING_DP
##  Min.   :    0.0   Min.   :  65.0   Min.   : 52.0
##  1st Qu.:  615.0   1st Qu.: 127.0   1st Qu.:131.0
##  Median :  813.5   Median : 159.0   Median :149.0
##  Mean   :  817.7   Mean   : 246.5   Mean   :146.4
##  3rd Qu.:  968.0   3rd Qu.: 249.2   3rd Qu.:164.0
##  Max.   :19278.0   Max.   :1898.0   Max.   :228.0
##  NA's   :102                        NA's   :286
```

The list of predictor variables with missing data and their counts:

	Missing	Percentage
TEAM_BATTING_H	0	0.0000000
TEAM_BATTING_2B	0	0.0000000
TEAM_BATTING_3B	0	0.0000000
TEAM_BATTING_HR	0	0.0000000
TEAM_BATTING_BB	0	0.0000000
TEAM_BATTING_SO	102	0.0448155
TEAM_BASERUN_SB	131	0.0575571
TEAM_BASERUN_CS	772	0.3391916
TEAM_BATTING_HBP	2085	0.9160808
TEAM_PITCHING_H	0	0.0000000
TEAM_PITCHING_HR	0	0.0000000
TEAM_PITCHING_BB	0	0.0000000
TEAM_PITCHING_SO	102	0.0448155
TEAM_FIELDING_E	0	0.0000000
TEAM_FIELDING_DP	286	0.1256591

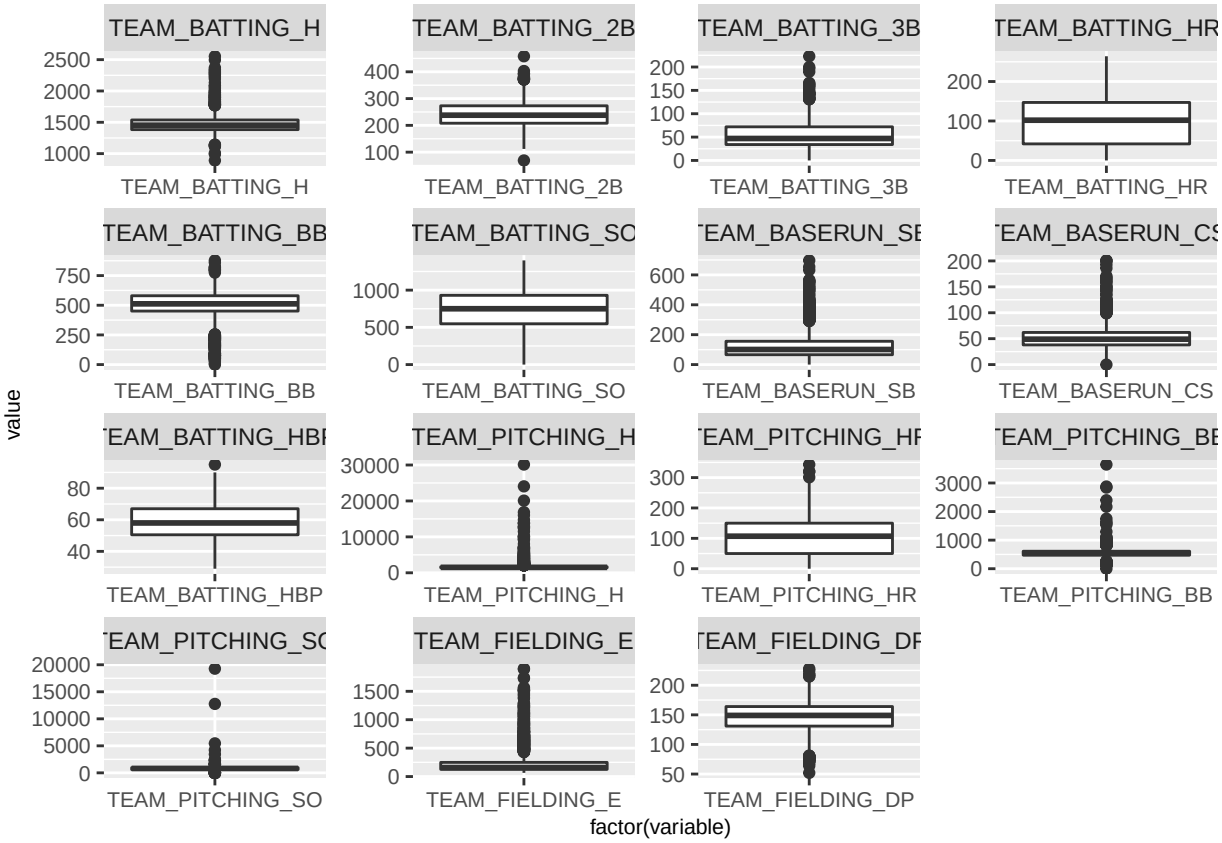
1.2 Distribution of predictors

Review the distributions of the predictors. Here are few histograms of the predictors.

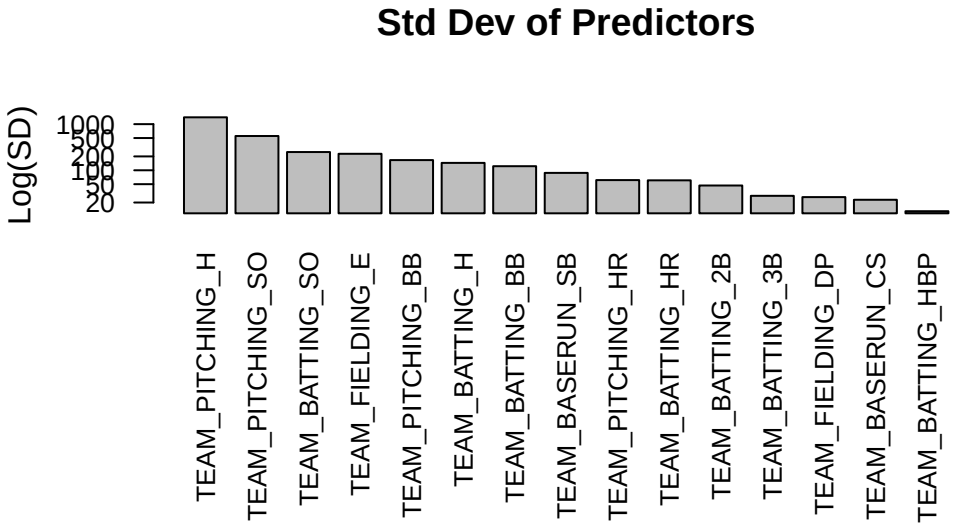


Based on the summary of the data, and the histograms, there are outliers and the distributions of the few of the predictors are skewed. Notice that *TEAM_PITCHING_H* and *TEAM_PICTCHING_SO* distributions are not visible at all in the above diagram, so the log transformation has been applied in the above.

Lets also review the box plot's of the predictors.


TEAM_BATTING_H
TEAM_BATTING_2B
TEAM_BATTING_3B
TEAM_BATTING_HR
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
value
factor(variable)

1.3 Standard Deviation



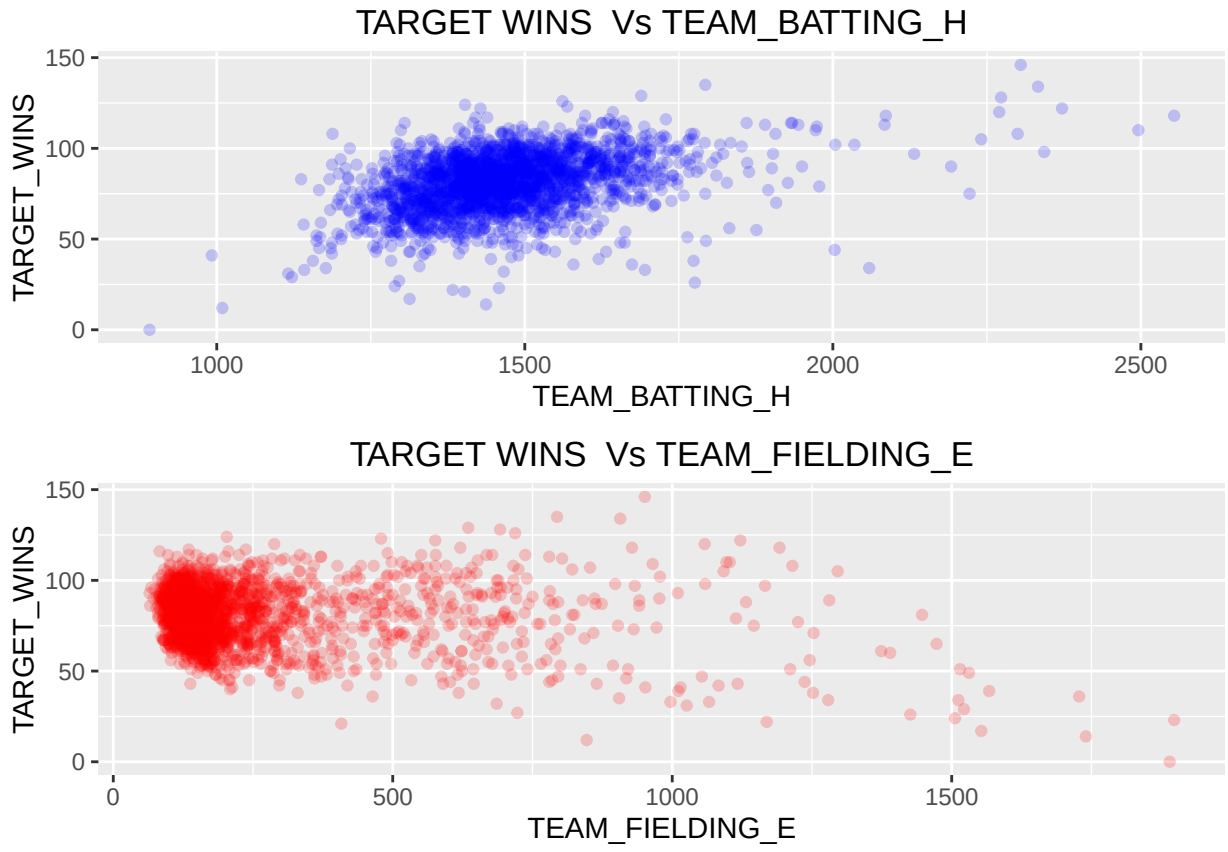
	std
TEAM_BATTING_H	144.59120
TEAM_BATTING_2B	46.80141
TEAM_BATTING_3B	27.93856
TEAM_BATTING_HR	60.54687
TEAM_BATTING_BB	122.67086
TEAM_BATTING_SO	248.52642
TEAM_BASERUN_SB	87.79117
TEAM_BASERUN_CS	22.95634
TEAM_BATTING_HBP	12.96712
TEAM_PITCHING_H	1406.84293
TEAM_PITCHING_HR	61.29875
TEAM_PITCHING_BB	166.35736
TEAM_PITCHING_SO	553.08503
TEAM_FIELDING_E	227.77097
TEAM_FIELDING_DP	26.22639

1.4 Correlation

Find correlation of Response variable with predictor variables

Variable	Correlation
TARGET_WINS	1.000
TEAM_BATTING_H	0.389
TEAM_BATTING_2B	0.289
TEAM_BATTING_3B	0.143
TEAM_BATTING_HR	0.176
TEAM_BATTING_BB	0.233
TEAM_BATTING_SO	NA
TEAM_BASERUN_SB	NA
TEAM_BASERUN_CS	NA
TEAM_BATTING_HBP	NA
TEAM_PITCHING_H	-0.110
TEAM_PITCHING_HR	0.189
TEAM_PITCHING_BB	0.124
TEAM_PITCHING_SO	NA
TEAM_FIELDING_E	-0.176
TEAM_FIELDING_DP	NA

From the above we can see that the *TEAM_BATTING_H* is high positively correlated, and *TEAM_FIELDING_E* has the negative corelation with the *TARGET_WINS*. Lets just visualize these two:



2. Data Preparation

2.1 Imputation of missing data

We have noticed that there are missing values for predictors, lets impute of missing values with mean.

After imputation, the missing values should not be there.

	mb.imp
TEAM_BATTING_H	0
TEAM_BATTING_2B	0
TEAM_BATTING_3B	0
TEAM_BATTING_HR	0
TEAM_BATTING_BB	0
TEAM_BATTING_SO	0
TEAM_BASERUN_SB	0
TEAM_BASERUN_CS	0
TEAM_BATTING_HBP	0
TEAM_PITCHING_H	0
TEAM_PITCHING_HR	0
TEAM_PITCHING_BB	0
TEAM_PITCHING_SO	0
TEAM_FIELDING_E	0
TEAM_FIELDING_DP	0

Correlation of response variable to predictor variable after imputing data

Variable	Correlation
TARGET_WINS	1.000
TEAM_BATTING_H	0.389
TEAM_BATTING_2B	0.289
TEAM_BATTING_3B	0.143
TEAM_BATTING_HR	0.176
TEAM_BATTING_BB	0.233
TEAM_BATTING_SO	-0.031
TEAM_BASERUN_SB	0.123
TEAM_BASERUN_CS	0.016
TEAM_BATTING_HBP	0.016
TEAM_PITCHING_H	-0.110
TEAM_PITCHING_HR	0.189
TEAM_PITCHING_BB	0.124
TEAM_PITCHING_SO	-0.076
TEAM_FIELDING_E	-0.176
TEAM_FIELDING_DP	-0.029

3. Build Models

Lets try to build different models to predict the *TARTGET_WINS*. The first thing we would like to do is to split our given dataset into 'training' and 'test' datasets.

Lets take sample of 75% observations into *training* bucket, which we will use for the model building, and the remaining 25% into *test* bucket, which can be used to compare the model predictions with the actuals.

Number of observations in *training* dataset is 1707 Number of observations in *test* dataset is 409

The below are the few different approaches we will try to build the models:

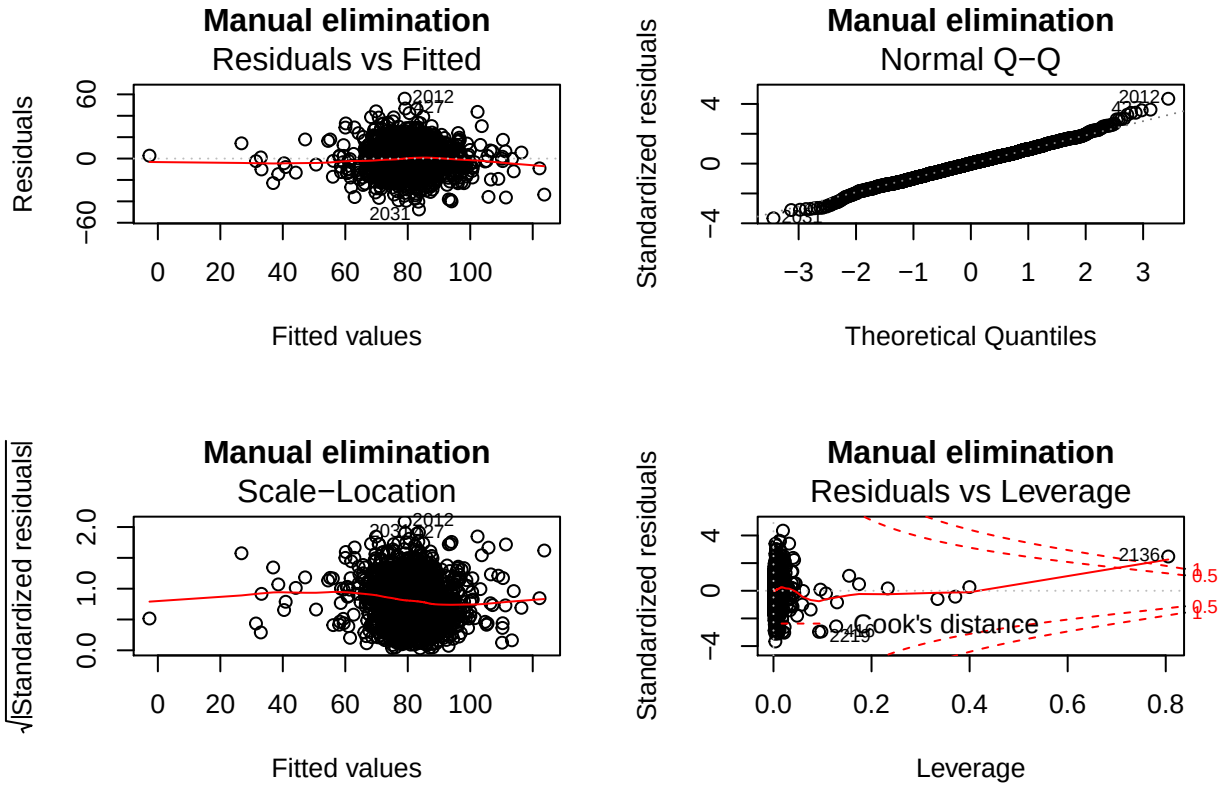
1. Manual elimination
2. Stepwise Regression
3. Stepwise Backward
4. Stepwise Forward
5. High Variance Inflation Factor (VIF) , high p-value predictors elimination.

3.1 Manual elimination

Lets try to fit a multiple linear regression model with TARGET_WINS as the response variable all the other predictors as the explanatory variables except 'TEAM BASERUN CS','TEAM BATTING HBP','TEAM BATTING SO' as they have very low correlation with Wins: (Note: Since we do not need INDEX field, We will be removing INDEX data element from the model building)

The coefficients are:

```
##      (Intercept)   TEAM_BATTING_H  TEAM_BATTING_2B  TEAM_BATTING_3B
##     5.826962e-04     1.214980e-35     7.589261e-02     1.278705e-04
##  TEAM_BATTING_HR  TEAM_BATTING_BB  TEAM_BASERUN_SB  TEAM_PITCHING_H
##     4.651885e-01     1.499784e-01     1.193355e-07     3.816406e-01
## TEAM_PITCHING_HR TEAM_PITCHING_BB TEAM_PITCHING_SO  TEAM_FIELDING_E
##     3.337000e-01     9.055960e-01     9.934444e-01     8.507711e-12
## TEAM_FIELDING_DP
##     3.188035e-12
```



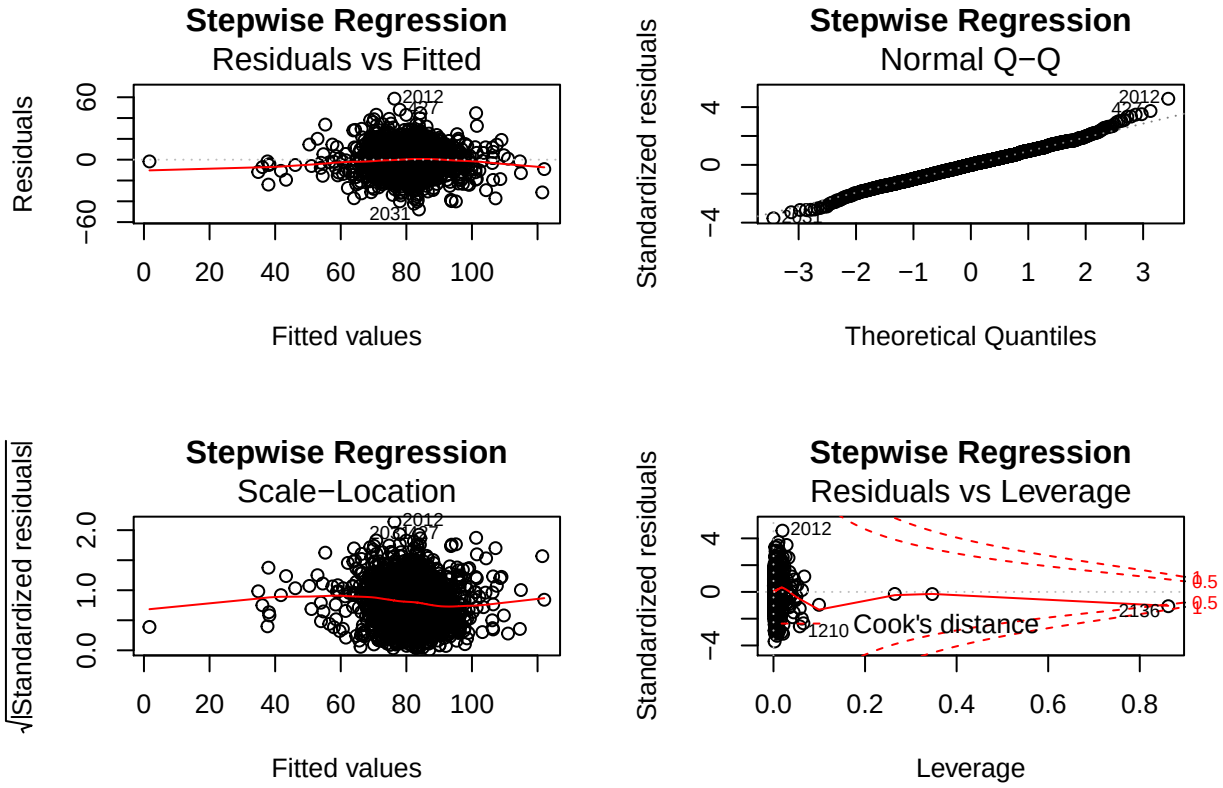
The adjusted r-squared values is 0.3108851

3.2 Stepwise Regression

Here, we will be selecting the predictors based on stepwise regression.

The coefficients we obtained here are:

```
##      (Intercept)   TEAM_BATTING_H  TEAM_BATTING_3B  TEAM_BATTING_HR
##     3.093915e-09     5.706711e-35     3.874854e-04     5.755982e-13
##  TEAM_BATTING_BB  TEAM_BATTING_SO  TEAM_BASERUN_SB  TEAM_PITCHING_H
##     6.395560e-02     7.608175e-06     1.160772e-10     1.295941e-01
## TEAM_PITCHING_SO  TEAM_FIELDING_E TEAM_FIELDING_DP
##     8.623681e-02     5.443116e-13     2.175865e-14
```

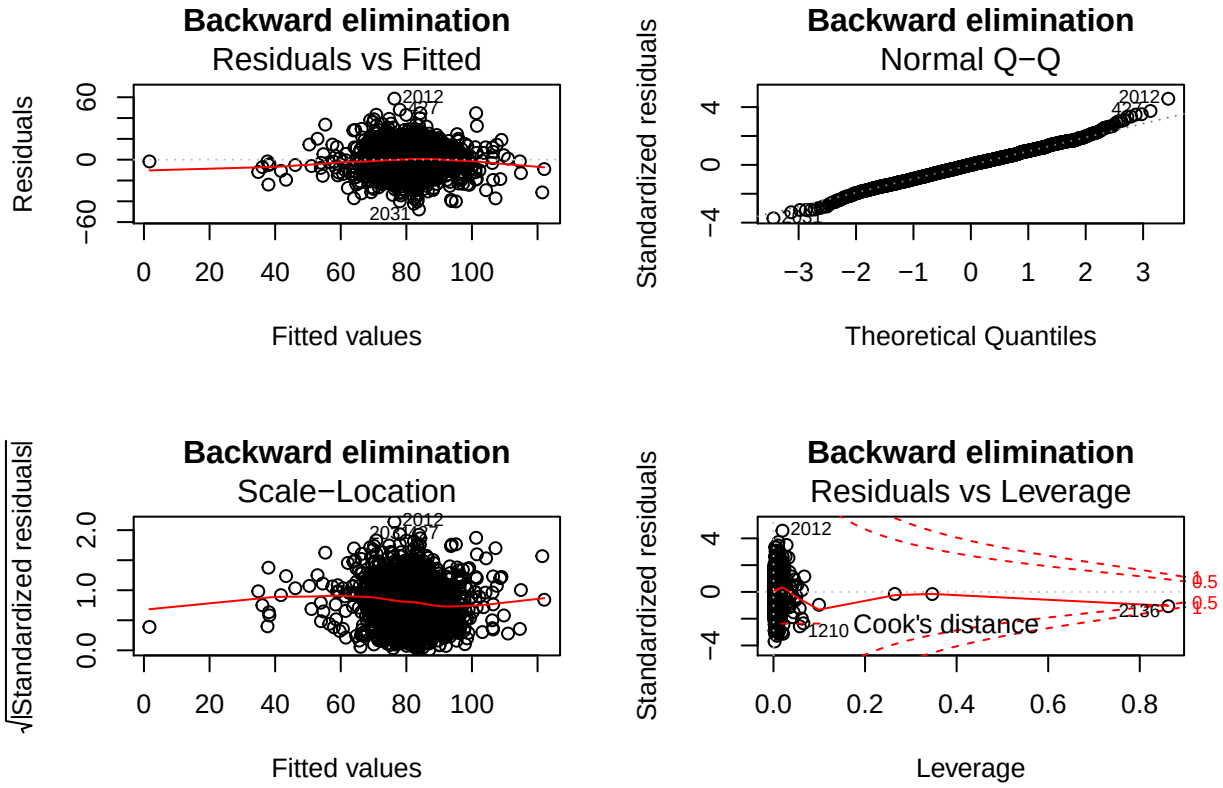


And the adjusted r-squared value is 0.3177756

3.3 Stepwise Backward

The coefficients we obtained here are:

```
##      (Intercept)   TEAM_BATTING_H  TEAM_BATTING_3B  TEAM_BATTING_HR
##     3.093915e-09     5.706711e-35     3.874854e-04     5.755982e-13
##  TEAM_BATTING_BB  TEAM_BATTING_SO  TEAM_BASERUN_SB  TEAM_PITCHING_H
##     6.395560e-02     7.608175e-06     1.160772e-10     1.295941e-01
## TEAM_PITCHING_SO  TEAM_FIELDING_E TEAM_FIELDING_DP
##     8.623681e-02     5.443116e-13     2.175865e-14
```

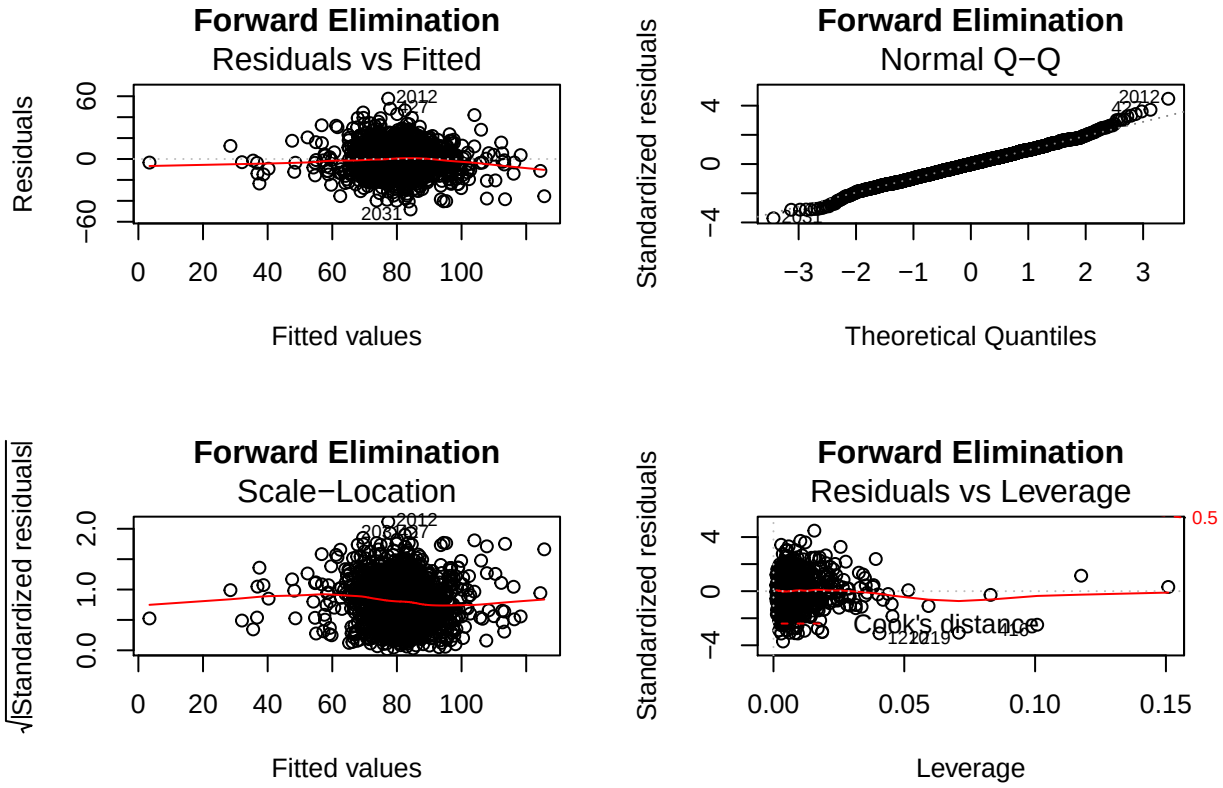


The adjusted r-squared value in the stepwise backward model is 0.3177756

3.4 Stepwise Forward

The coefficients we obtained here are:

```
##   TEAM_BATTING_H  TEAM_FIELDING_E  TEAM_BASERUN_SB TEAM_FIELDING_DP
##     3.568358e-47     6.665677e-20     9.139606e-10     1.390602e-11
##  TEAM_BATTING_BB TEAM_PITCHING_HR TEAM_BATTING_HBP  TEAM_BATTING_3B
##     3.162675e-03     4.421072e-01     4.257336e-05     5.214172e-04
##  TEAM_BATTING_2B  TEAM_BATTING_SO  TEAM_BATTING_HR
##     7.360106e-02     4.512284e-02     9.833910e-02
```



The adjusted r-squared value in the stepwise backward model is 0.9752137

3.5 Remove VIF, and high p value predictors manually.

In this model we would be removing the multi-collinear predictors - basically removing the excessive correlation among the explanatory variables. And then try removing the high p value predictors (> 0.05)

The below is the VIF values, lets get rid of those that has got VIF > 5.

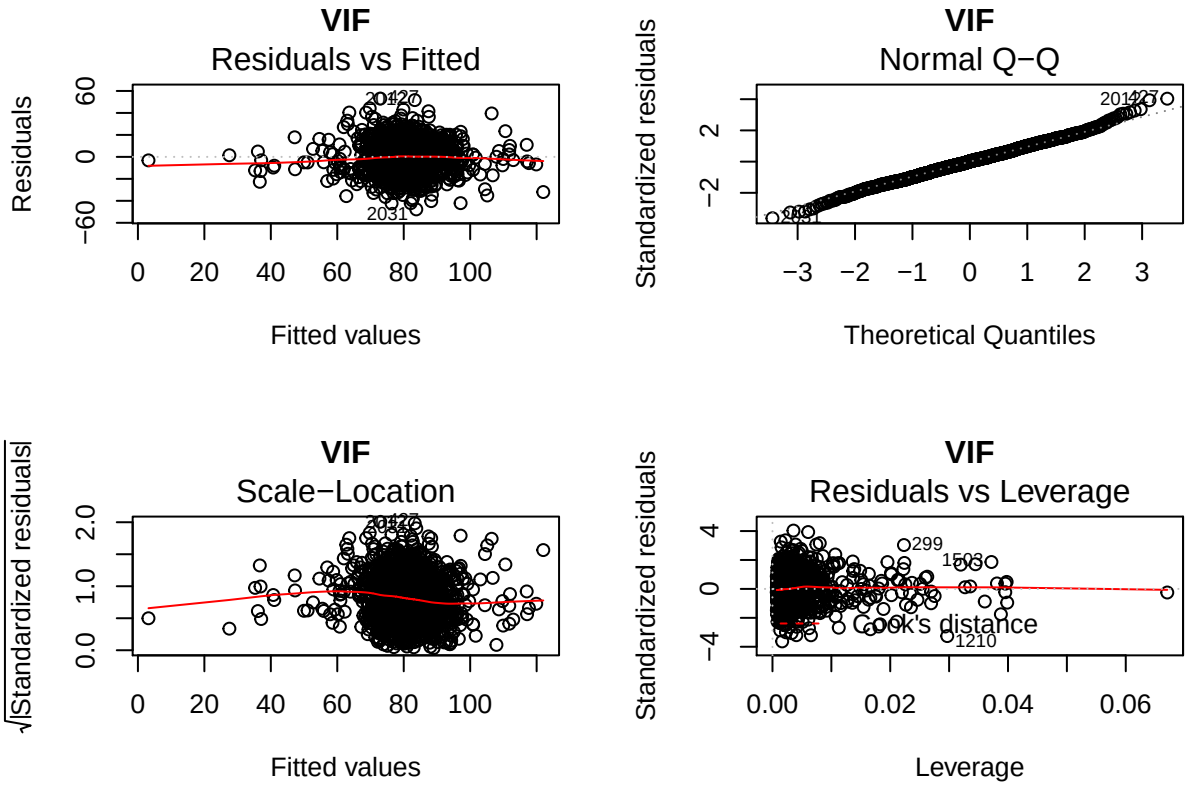
	VIF
TEAM_BATTING_HR	40.345137
TEAM_PITCHING_HR	32.787751
TEAM_BATTING_BB	6.930289
TEAM_PITCHING_BB	6.330015
TEAM_BATTING_SO	5.056772
TEAM_FIELDING_E	4.350257
TEAM_BATTING_H	3.873960
TEAM_PITCHING_H	3.609783
TEAM_BATTING_3B	2.956973
TEAM_PITCHING_SO	2.627914
TEAM_BATTING_2B	2.463035
TEAM_BASERUN_SB	1.932703
TEAM_FIELDING_DP	1.374783
TEAM_BASERUN_CS	1.205459
TEAM_BATTING_HBP	1.002919

Lets remove *TEAM_BATTING_HR TEAM_PITCHING_HR TEAM_BATTING_BB TEAM_PITCHING_BB* , these highly corelated, which results in multi-colineary among these variables, lets get rid of these from the model building.

These predictors: *TEAM_BATTING_3B, TEAM_BATTING_2B, TEAM_BATTING_SO, TEAM_BATTING_HBP, TEAM_PITCHING_H, TEAM_PITCHING_SO* has got high p value, so, lets try removing and re-build the model:

Here are the final co-efficients we got:

```
##      (Intercept)   TEAM_BATTING_H  TEAM_BASERUN_SB  TEAM_BASERUN_CS
##     6.637961e-07    1.108413e-103     2.109642e-14     2.040959e-02
##  TEAM_FIELDING_E TEAM_FIELDING_DP
##     5.296020e-62     1.058256e-08
```



The adjusted r-squared value we got from the above model is 0.2920768

4. Selection

Lets now check to see how each model performed, by looking at the adjusted r-sqaured, RMSE values.

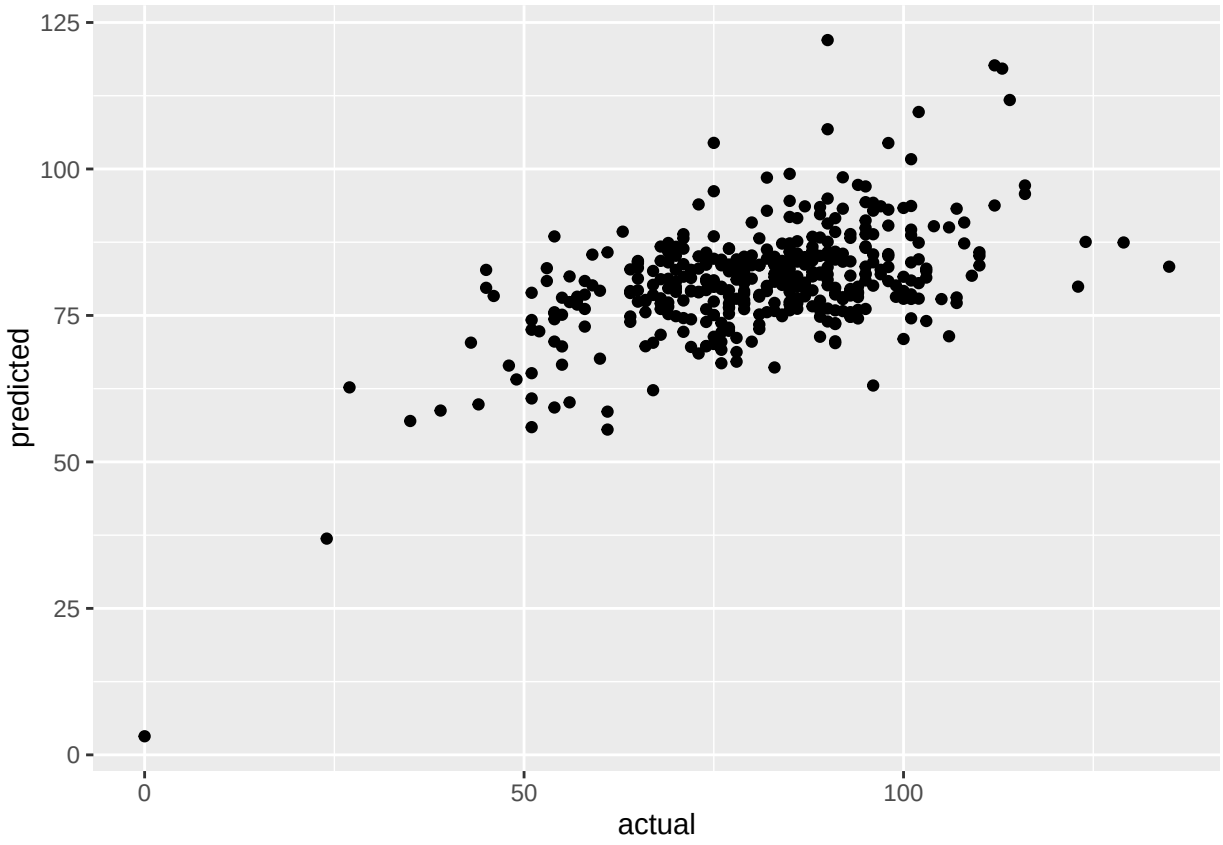
Here is the adjusted R-Sqaured values from different model above:

Method	Adj R Squared
Manual Elimination	31.09

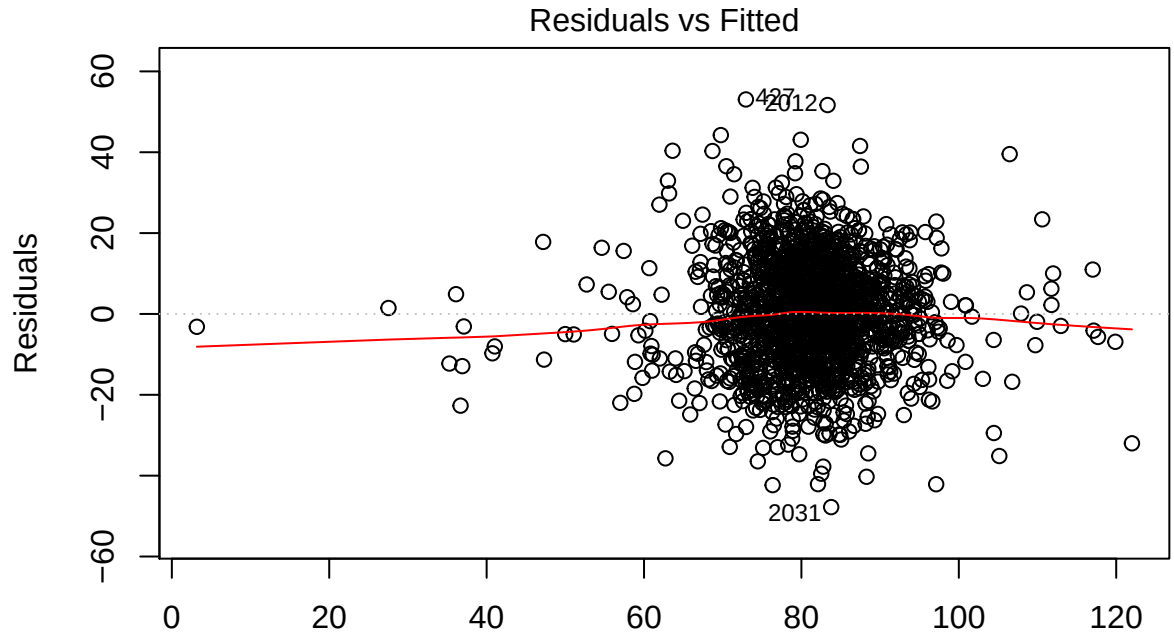
Method	Adj R Squared
Stepwise Regression	31.78
Stepwise Backward	31.78
Stepwise Forward	97.52
VIF Elimination	29.21

4.1. RMSE - Root Mean Sqared Error (verification with test data)

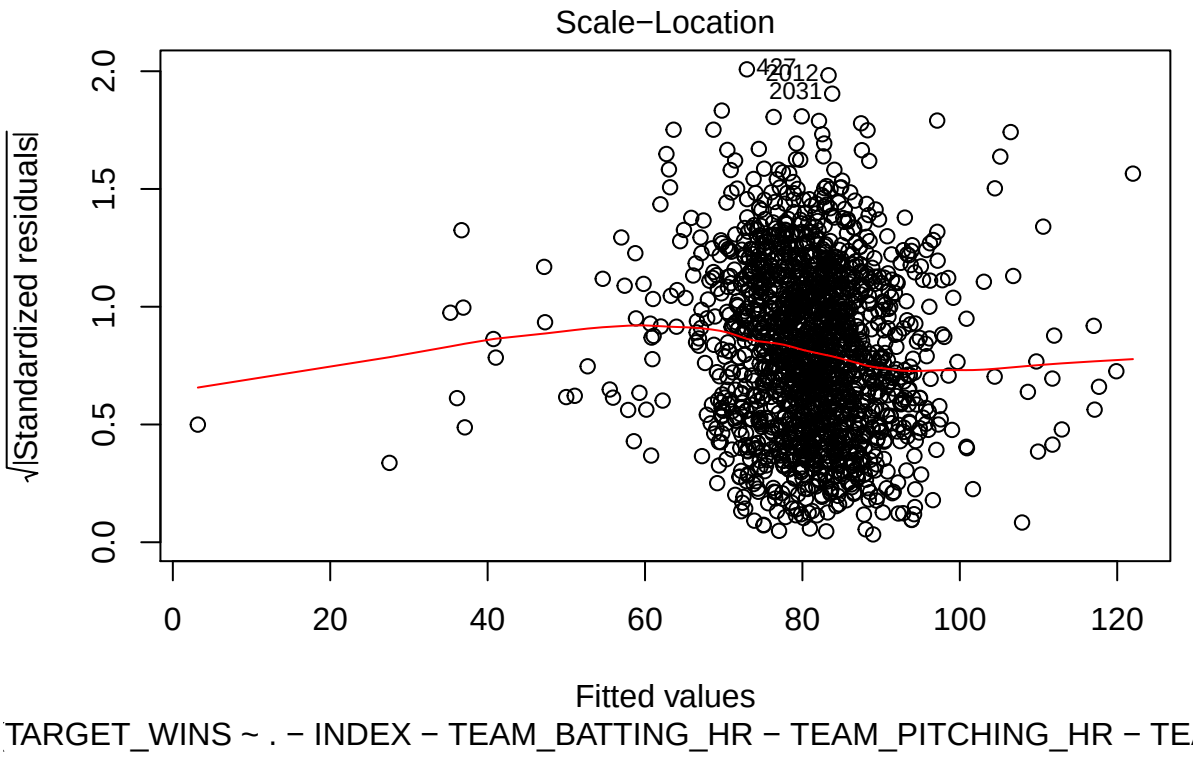
```
## [1] 13.95157
```



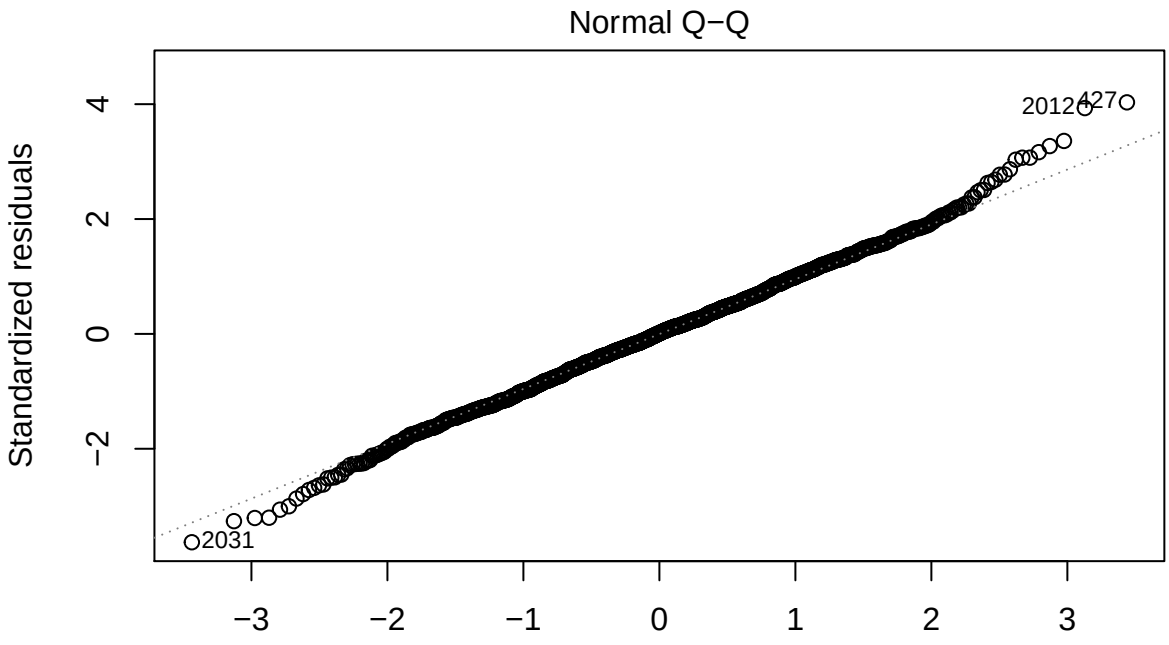
3.5.2 Diagnostic plots, check for linearity, normality is justified for residuals . . .



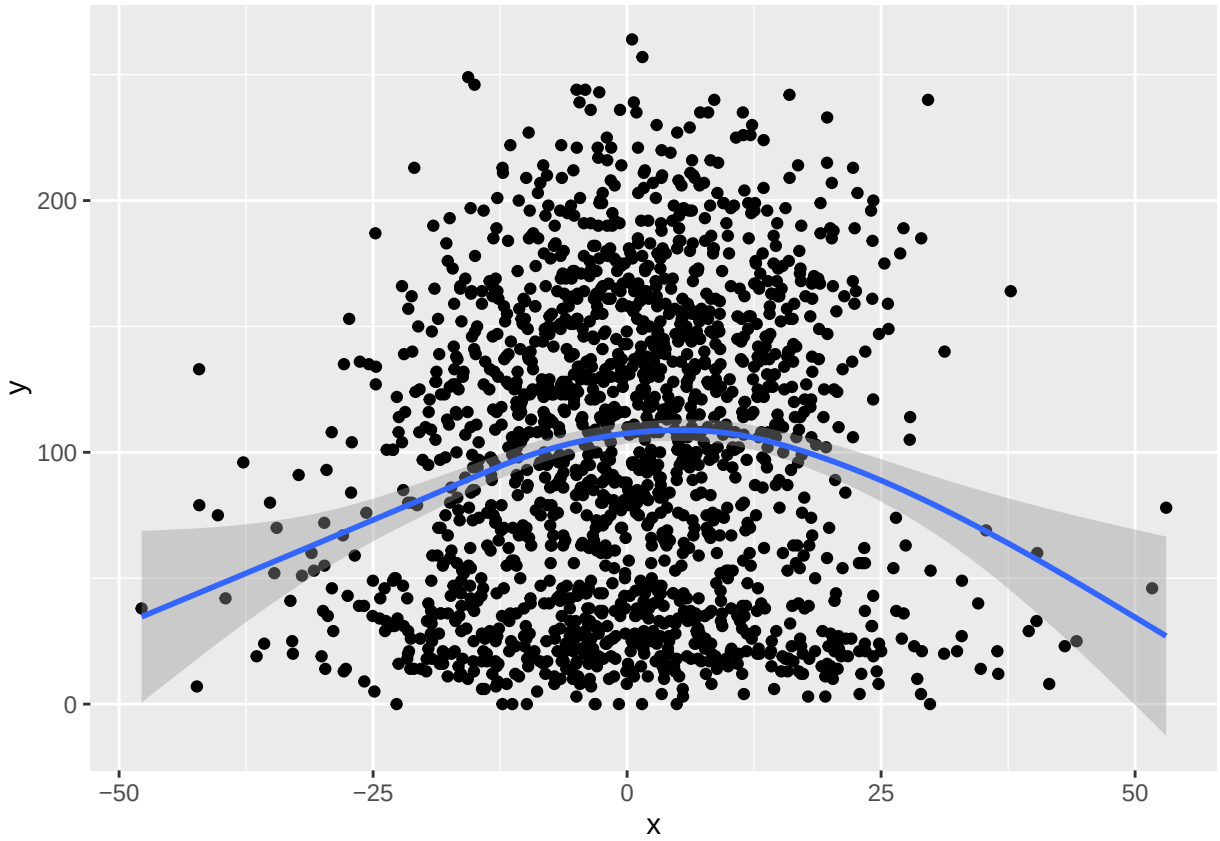
TARGET_WINS ~ . − INDEX − TEAM_BATTING_HR − TEAM_PITCHING_HR − TEAM_



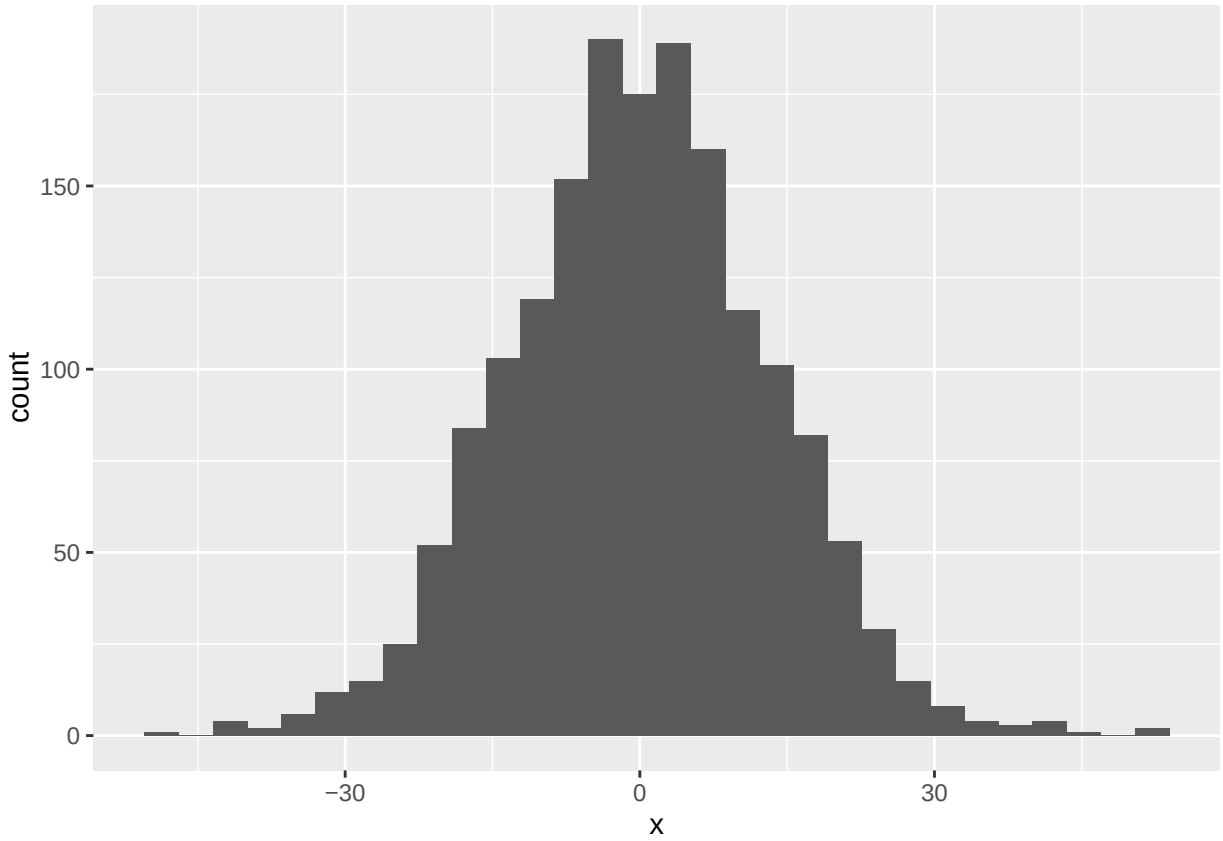
TARGET_WINS ~ . − INDEX − TEAM_BATTING_HR − TEAM_PITCHING_HR − TEAM_

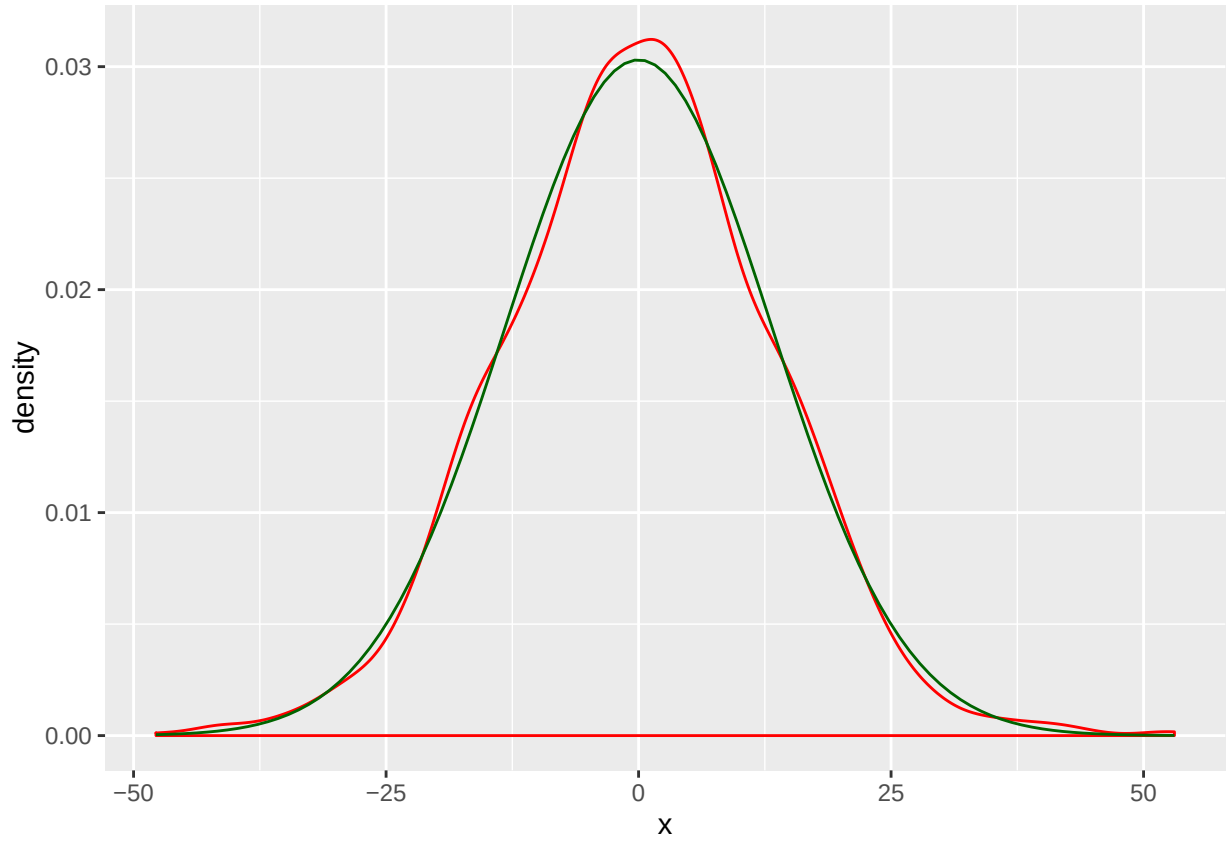


TARGET_WINS ~ . − INDEX − TEAM_BATTING_HR − TEAM_PITCHING_HR − TEAM_




```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```


150
100
50
0
count
−30
0
30
x



5. Evaluation

```
##            INDEX   TEAM_BATTING_H  TEAM_BATTING_2B  TEAM_BATTING_3B
##                0                0                0                0
##  TEAM_BATTING_HR  TEAM_BATTING_BB  TEAM_BATTING_SO  TEAM_BASERUN_SB
##                0                0               18               13
##  TEAM_BASERUN_CS TEAM_BATTING_HBP  TEAM_PITCHING_H TEAM_PITCHING_HR
##               87              240                0                0
## TEAM_PITCHING_BB TEAM_PITCHING_SO  TEAM_FIELDING_E TEAM_FIELDING_DP
##                0               18                0               31
```

```
##            INDEX   TEAM_BATTING_H  TEAM_BATTING_2B  TEAM_BATTING_3B
##                0                0                0                0
##  TEAM_BATTING_HR  TEAM_BATTING_BB  TEAM_BATTING_SO  TEAM_BASERUN_SB
##                0                0                0                0
##  TEAM_BASERUN_CS TEAM_BATTING_HBP  TEAM_PITCHING_H TEAM_PITCHING_HR
##                0                0                0                0
## TEAM_PITCHING_BB TEAM_PITCHING_SO  TEAM_FIELDING_E TEAM_FIELDING_DP
##                0                0                0                0
```

```
##        1        2        3        4        5        6
## 67.15349 67.48693 76.94324 87.98109 70.82748 73.26754
```

A. Appendix

```
library(RCurl)
library(dplyr)
library(ggplot2)
library(gridExtra)
library(gridExtra)
library(psych)
library(reshape)
library(MASS)
library(car)
library(recommenderlab)
library(knitr)
# opts_chunk$set(tidy.opts=list(width.cutoff=80),tidy=TRUE)

moneyballTraining <- read.csv("https://raw.githubusercontent.com/Nguyver/DATA621-HW/master/HW1/moneyball
    header = TRUE, sep = ",", stringsAsFactors = FALSE)

summary(moneyballTraining[3:17])

moneyball.NA <- apply(moneyballTraining[3:17], 2, function(x) sum(is.na(x)))
moneyball.missing <- cbind(moneyball.NA, moneyball.NA/nrow(moneyballTraining))
colnames(moneyball.missing) <- c("Missing", "Percentage")
kable(moneyball.missing)

# Explore independent variable TEAM_BATTING_H
g_tbh <- ggplot(data = moneyballTraining) + geom_histogram(aes(x = TEAM_BATTING_H),
    binwidth = 0.5) + theme(axis.text = element_text(size = 8),
    axis.title = element_text(size = 8))

g_b2b <- ggplot(data = moneyballTraining) + geom_histogram(aes(x = TEAM_BATTING_2B),
    binwidth = 0.5) + theme(axis.text = element_text(size = 8),
    axis.title = element_text(size = 8))

g_brsb <- ggplot(data = moneyballTraining) + geom_histogram(aes(x = TEAM_BASERUN_SB),
    binwidth = 0.5) + theme(axis.text = element_text(size = 8),
    axis.title = element_text(size = 8))

g_tph <- ggplot(data = moneyballTraining) + geom_histogram(aes(x = TEAM_PITCHING_H),
    binwidth = 0.5) + theme(axis.text = element_text(size = 8),
    axis.title = element_text(size = 8))

g_tps <- ggplot(data = moneyballTraining) + geom_histogram(aes(x = TEAM_PITCHING_SO),
    binwidth = 0.5) + theme(axis.text = element_text(size = 8),
    axis.title = element_text(size = 8))

g_tfe <- ggplot(data = moneyballTraining) + geom_histogram(aes(x = TEAM_FIELDING_E),
    binwidth = 0.5) + theme(axis.text = element_text(size = 8),
    axis.title = element_text(size = 8))

g_tfd <- ggplot(data = moneyballTraining) + geom_histogram(aes(x = TEAM_FIELDING_DP),
    binwidth = 0.5) + theme(axis.text = element_text(size = 8),
    axis.title = element_text(size = 8))
```

```
g_tbhr <- ggplot(data = moneyballTraining) + geom_histogram(aes(x = TEAM_BATTING_HR),
    binwidth = 0.5) + theme(axis.text = element_text(size = 8),
    axis.title = element_text(size = 8))

g_tphLg <- ggplot(data = moneyballTraining) + geom_histogram(aes(x = log(TEAM_PITCHING_H)),
    binwidth = 0.5) + theme(axis.text = element_text(size = 8),
    axis.title = element_text(size = 8))

g_tpsLg <- ggplot(data = moneyballTraining) + geom_histogram(aes(x = log(TEAM_PITCHING_SO)),
    binwidth = 0.5) + theme(axis.text = element_text(size = 8),
    axis.title = element_text(size = 8))

grid.arrange(g_tbh, g_b2b, g_brsb, g_tph, g_tps, g_tfe, g_tfd,
    g_tbhr, g_tphLg, g_tpsLg, ncol = 2)

meltMoneyBallTraining <- melt(moneyballTraining[3:17])
ggplot(meltMoneyBallTraining, aes(factor(variable), value)) +
    geom_boxplot() + facet_wrap(~variable, scale = "free") +
    theme(axis.text = element_text(size = 8), axis.title = element_text(size = 8))

getStandardDev <- function(moneyballTraining) {
    stdDevs <- SD(moneyballTraining[3:17])
    par(mai = c(3, 1.2, 1, 1))

    # transformed the y, due to high variances.
    barplot(stdDevs[order(stdDevs, decreasing = T)], log = "y",
        las = 2, main = "Std Dev of Predictors", xlab = "", ylab = "Log(SD)",
        cex.axis = 0.8, cex.names = 0.8)

    return(stdDevs)
}

std <- getStandardDev(moneyballTraining)
kable(as.data.frame(std))

corData <- round(cor(moneyballTraining), 3)  # rounding makes it easier to look at
t.corData <- t(corData[2, c(2:17)])  # we are only interested on correlation of Team win against all ot
moneyballTraining.cor <- melt(t.corData)  # convert the wide format to long form for ease of read
moneyballTraining.cor <- moneyballTraining.cor[, 2:3]
colnames(moneyballTraining.cor) <- c("Variable", "Correlation")

kable(moneyballTraining.cor)

g1 = ggplot(data = moneyballTraining) + geom_point(aes(x = TEAM_BATTING_H,
    y = TARGET_WINS), alpha = 0.2, color = "blue") + ggtitle("TARGET WINS  Vs TEAM_BATTING_H")

g2 = ggplot(data = moneyballTraining) + geom_point(aes(x = TEAM_FIELDING_E,
    y = TARGET_WINS), alpha = 0.2, color = "red") + ggtitle("TARGET WINS  Vs TEAM_FIELDING_E")

grid.arrange(g1, g2, nrow = 2)
# similarly other specific independent variables Vs target
# wins correlation diagram
```

```r
# Replacing Missing Values In dataset with column mean
for (i in 1:ncol(moneyballTraining)) {
    moneyballTraining[is.na(moneyballTraining[, i]), i] <- mean(moneyballTraining[,
        i], na.rm = TRUE)
}

mb.imp <- apply(moneyballTraining[3:17], 2, function(x) sum(is.na(x)))
# colnames(mb.imp) <- c('# Missing')
kable(as.data.frame(mb.imp))

corData.imp <- round(cor(moneyballTraining), 3)  # rounding makes it easier to look at
t.corData.imp <- t(corData.imp[2, c(2:17)])  # we are only interested on correlation of Team win agains
moneyballTraining.cor.imp <- melt(t.corData.imp)  # convert the wide format to long form for ease of re
moneyballTraining.cor.imp <- moneyballTraining.cor.imp[, 2:3]

colnames(moneyballTraining.cor.imp) <- c("Variable", "Correlation")
kable(moneyballTraining.cor.imp)
```