Project1

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Contents

1. Introduction

An sports investor is interested in investing in the sport of baseball. The investor is looking at investments ranging from team ownership, collectibles, apparel and legal sports betting. There is interest in understanding what are factors that influence teams' winning and predicting the number of wins in a season, so that an informed decision is made on the investment. To enable decision making, historical performance of baseball teams from the year 1871 to 2006 is analyzed and modeled for predicting number of wins in a season. This report discusses the analysis and the predictive models developed using the historical data. It should be noted that the data scientist who analyzed the data does not have subject matter expertise in the area of baseball. It is expected that the model(s) may need fine tuning based on feedback from subject matter experts.

1.1 Analysis Process

The following process steps were used for building a predicitve models:

- Exploratory Data Analysis
  - Perform data quality checks, quantify missing data.
  - Check for systemic loss in data
  - Understand relationships amongst predictors and between target variables and predictors.
  - Create attribure or indicator variables to aid data cleaning.
  - Filter out clean data for feature selection and model building.
- Feature Selection
  - Subset complete records to model wins in season
  - Use different modeling techniques to select candidate predictors.
  - If data is missing for candidate predictors, identify imputing methods.
- Model Building
  - Test models that were build using complete records on the entire data set with imputed data.
  - Compare models based on Adjusted R squared, AIC, MAE
  - Check if models make physical sense.
- Initial model deployment
  - Deploy model to predict wins on out of sample data.
  - Discuss models and results with subject matter experts.
  - Fine tune model and re-test
- Final model deployment
  - Investment decisions.

1.2 Executive summary

The below model was chosen from a candidate pool of 10 models (7 models are discussed in this report) for its simplicity, interpretability and comparable mean absolute error.

TARGET_WINS = 34.12 + 0.01 * TEAM_BATTING_H + 0.1 * TEAM_BATTING_3B + 0.12 * TEAM_BATTING_HR + 0.04 * TEAM_BATTING_BB - 0.02 * TEAM_BATTING_SO + 0.07 * TEAM_BASERUN_SB - 5.49 * BatHR_Filter

The model has an average error (MAE) of $\pm$ 11 wins. The data scientist welcomes suggestions from subject matter expertise to further iterate on the model building process to produce a better model.

2. About the Data

The data provided has approximately 2300 rows, each representing a team's performance in the seasons during the years 1871 to 2006. The statistics are adjusted to match a performance of 162 game season. The

dictionary of the variables in the data are provided in appendix A.1. Table 1 below shows statistics of the variables in the data.

It can be seen that there are multiple variables with missing data. The systemic nature of missing data is discussed in the next section, the pattern in missing leads us to assume that the missing data is likely from the 18th and the early 19th century, where sophisticated data collection may not have existed. If the variables that contain missing data are deemed important for prediciting number of wins, then an appropriate method would be used for data imputation.

Table 1: Summary Stats and missing values

	min	Q1	median	Q3	max	mean	sd	n	missing	cv
INDEX	1	630.75	1270.5	1915.50	2535	1268.46	736.35	2276	0	0.58
TARGET_WINS	0	71.00	82.0	92.00	146	80.79	15.75	2276	0	0.19
TEAM_BATTING_H	891	1383.00	1454.0	1537.25	2554	1469.27	144.59	2276	0	0.10
TEAM_BATTING_2B	69	208.00	238.0	273.00	458	241.25	46.80	2276	0	0.19
TEAM_BATTING_3B	0	34.00	47.0	72.00	223	55.25	27.94	2276	0	0.51
TEAM_BATTING_HR	0	42.00	102.0	147.00	264	99.61	60.55	2276	0	0.61
TEAM_BATTING_BB	0	451.00	512.0	580.00	878	501.56	122.67	2276	0	0.24
TEAM_BATTING_SO	0	548.00	750.0	930.00	1399	735.61	248.53	2174	102	0.34
TEAM_BASERUN_SB	0	66.00	101.0	156.00	697	124.76	87.79	2145	131	0.70
TEAM_BASERUN_CS	0	38.00	49.0	62.00	201	52.80	22.96	1504	772	0.43
TEAM_BATTING_HBP	29	50.50	58.0	67.00	95	59.36	12.97	191	2085	0.22
TEAM_PITCHING_H	1137	1419.00	1518.0	1682.50	30132	1779.21	1406.84	2276	0	0.79
TEAM_PITCHING_HR	0	50.00	107.0	150.00	343	105.70	61.30	2276	0	0.58
TEAM_PITCHING_BB	0	476.00	536.5	611.00	3645	553.01	166.36	2276	0	0.30
TEAM_PITCHING_SO	0	615.00	813.5	968.00	19278	817.73	553.09	2174	102	0.68
TEAM_FIELDING_E	65	127.00	159.0	249.25	1898	246.48	227.77	2276	0	0.92
TEAM_FIELDING_DP	52	131.00	149.0	164.00	228	146.39	26.23	1990	286	0.18

3. Exploratory Data Analysis (EDA) & Data Preparation

3.1 Missing data

Figure 1, shows that the missing data is systematic and they correspond to the lower end of the distributions of home runs by batters and strike-outs. Its also seen that the home-runs and strike-outs are bi-modal in nature. The complete cases from the data are used to explore the relationship amongst the predictor variables and the relationship between Wins and the other predictors. The exploratory data analysis is used as a tool for feature selection for model building.

3.2 Correlations in the data

Figure 2 shows the correlation plot of the variables in the data. It is seen that team batting home runs and pitching home runs are strongly correlated amd so are walks by batters and walks allowed when pitching. Similary for the strike outs. The fielding errors and home runs are negatively correlated; so is triples with fielding errors. It will be interesting to understand the reason for this behaviour from the subject matter experts.

The target wins variable have weak correlations with many variables without a strong correlation with any of the variables in the data. The combined contributions of the predictor variables to explain the number of wins is explored in the sections below.

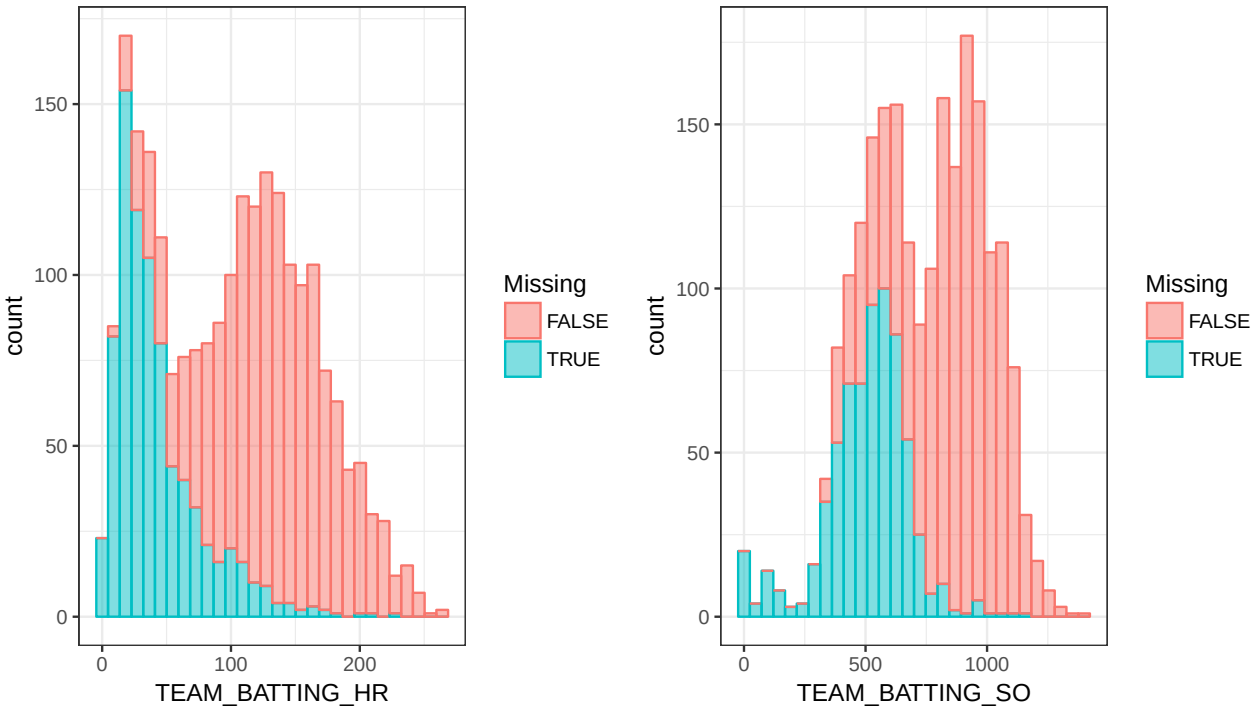


Figure 1: Rows with missing data is from the lower end of the distributions of Home runs and Strike outs

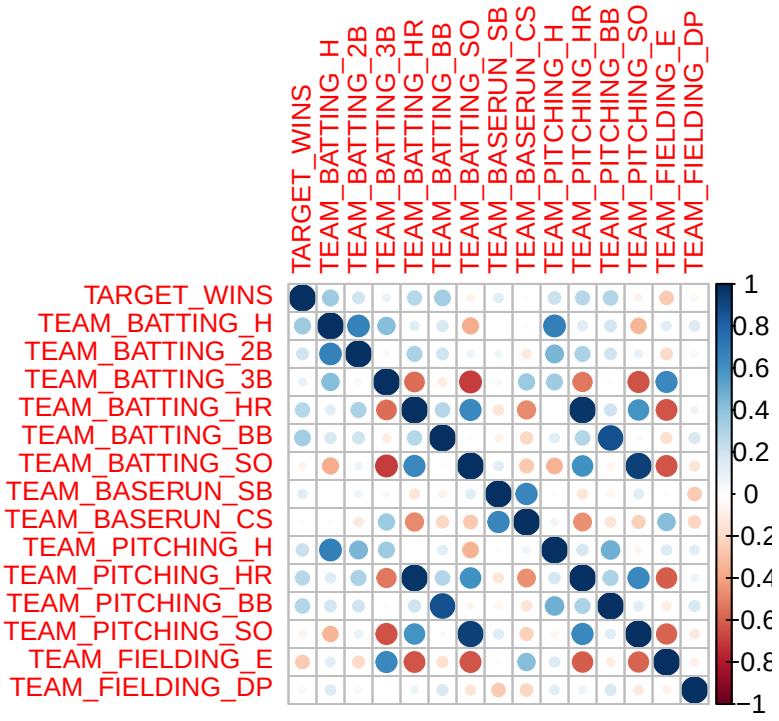


Figure 2: Correlation plot

3.3 Relationship between variables.

Left panel of Figure 3 shows the extreme values in hits allowed by teams and they correspond to rows where some variables have missing values. Zooming in on the set of data with complete cases (no missing data in any of the columns), it is seen that hits allowed has two contiguous distributions. The right panel of figure 3 shows the extreme values. Figure 4 shows the change in relationship amongst Base hits and hits allowed; strikeouts by pitcher; walks allowed by pitchers and walks by batters; is associated with the extreme values in hits allowed by pitchers.

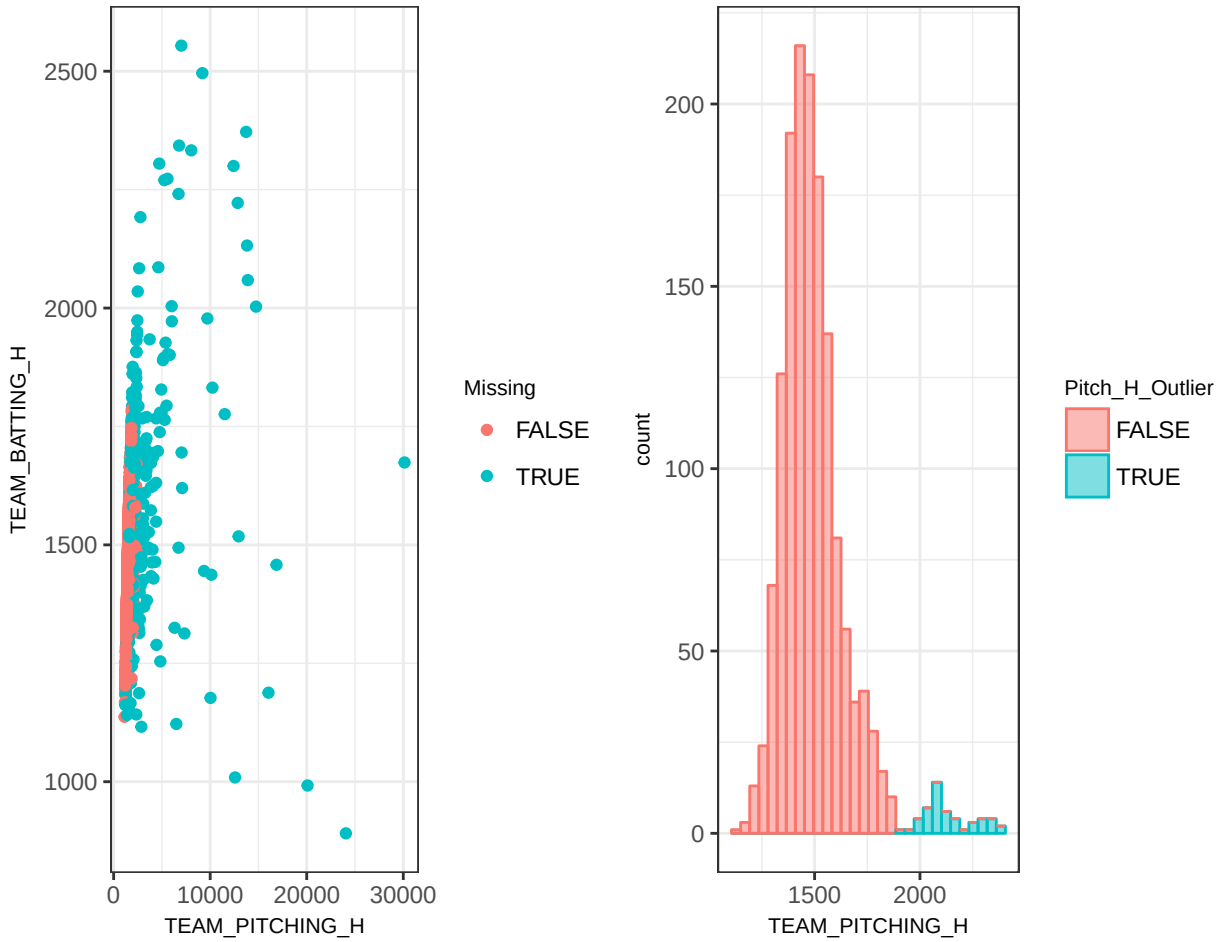


Figure 3: Extreme values in Hits allowed

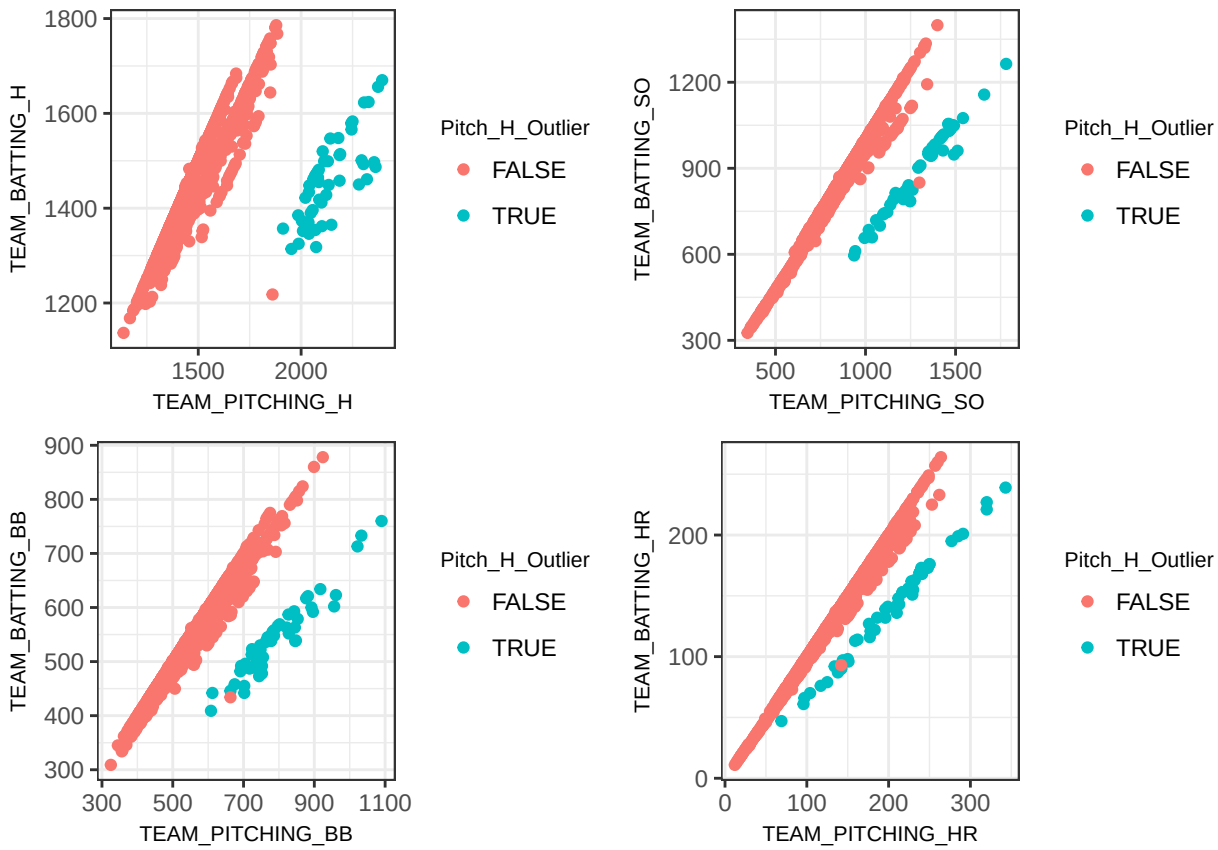


Figure 4: Distinct relationships between variables attributed to outliers in Hits allowed

3.3.1 Indicator variables

To effectively capture the various phenomena (such as the difference in slopes in Fig 4) either attributed to or associated with various sections in the data, indicator variables are used. Indicator variables can be used as dummy variables in regression models to model the change in behaviors. The following table lists the indicator variables created for effective modeling. Figure 5 and 6 shows the indicator variables capturing the intended section of the population.

Table 2: Indicator variables description

Name	Purpose	Criteria
Pitch_H_Outlier	Outlier filter	TEAM_PITCHING_H >= 1890
BatHR_Filter	bimodal capture	TEAM_BATTING_HR <= 59
BatSO_Filter	Outlier filter	TEAM_BATTING_SO <= 250
PitSO_Filter	Outlier filter	TEAM_PITCHING_SO
AltSlope	Capture parallel slope	setdiff(setdiff(Pitch_H_outlierT,BatSO_Filter_T), PitSOFilter_T)

Figure 5: indicator variables

3.3.2 Target Wins Vs Potential predictors

The effect of indicator variables on relationship between Target Wins and potential predictors is showm in figure 7. The data is subsetted to exclude outliers in strike-outs by batters and pitchers.

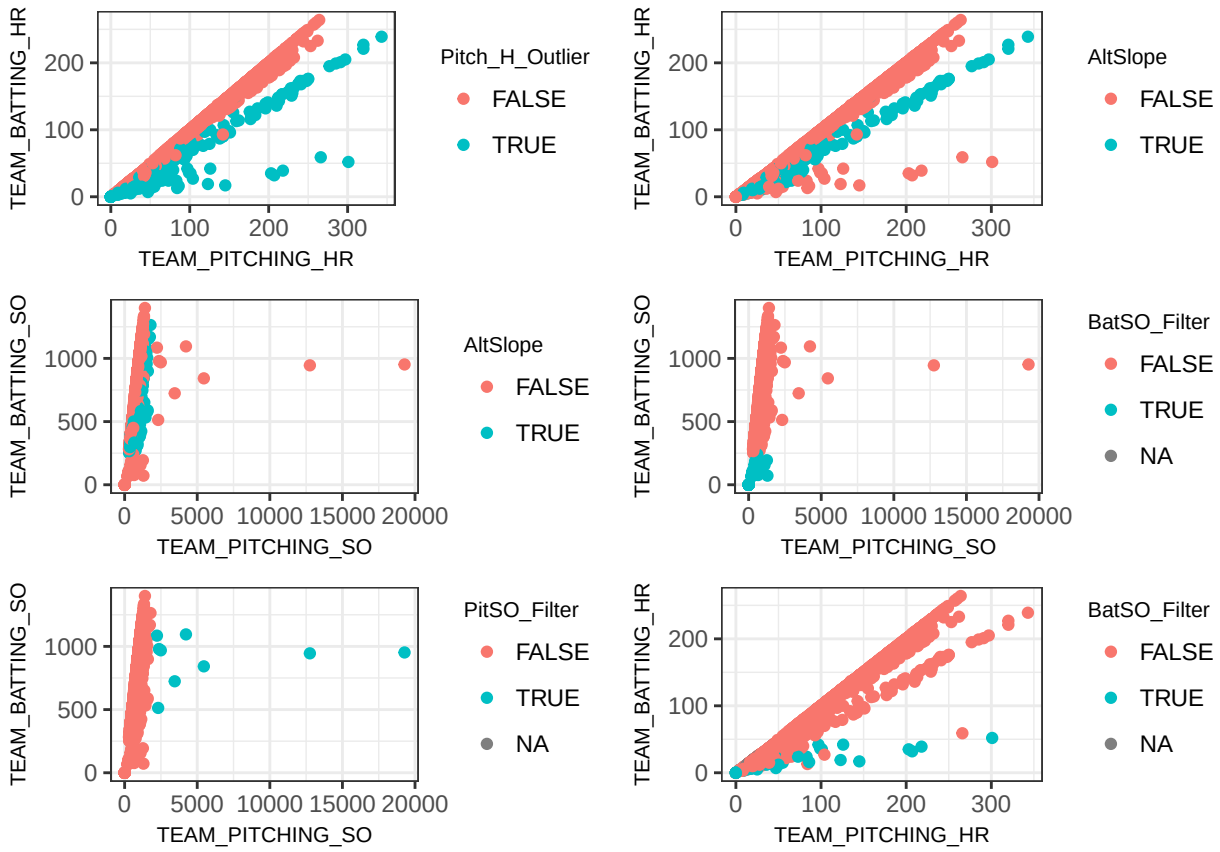


Figure 6: Indicator variables contd

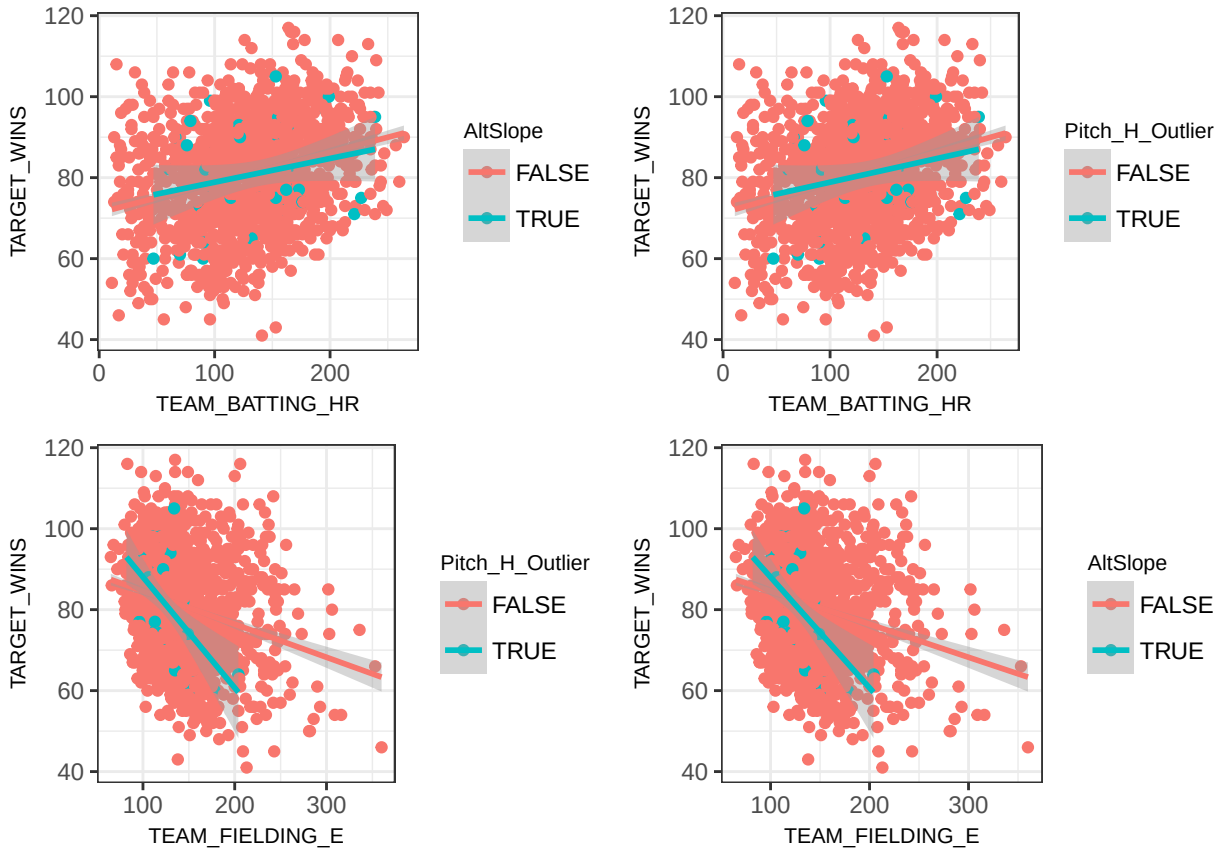


Figure 7: Target Wins Vs Predictors by AltSlope and Pitch_H_Outlier

4. Feature selections & Model building

The feature selections and Model building steps of the analysis process are iterative. The modeling process begins with a selection of subset of variables that are theoretically correlated with wins. When predictors are related or correalted to eachother, refer figure 2, only one of the predictors from the pair of correlated variables is selected for modeling. The feature selection and model building process is initially built on complete cases or records. Then model is then tested on the entire data set after filling in the missing values (if needed) by imputation.

In the sections below, several models are discussed such as:

1. Simple multiple regression models, with manual feature selection (2 nos).
2. Stepwise automated variable selection.
3. Principle components regression (PCR).
4. Lasso regression variable selection and OLS regression.
5. Partial Least Squares regression (PLS).
6. Random forest feature selection and OLS regression.

4.1 Multiple linear regression (Simple models)

The following model was fit with manual choice of variables by refering the correlation plot in figure 2. When manual choice of features/ variables were made, the theoretical effect was born in mind. However, no subject matter expertise was used in selection.

TARGET_WINS = 31.39 + 0.03 * TEAM_BATTING_H - 0.05 * TEAM_BATTING_2B + 0.08 * TEAM_BATTING_3B + 0.11 * TEAM_BATTING_HR + 0.04 * TEAM_BATTING_BB - 0.02 * TEAM_BATTING_SO + 0.07 * TEAM_BASERUN_SB - 0.01 * TEAM_BASERUN_CS - 0.09 * TEAM_FIELDING_DP - 0.87 * Pitch_H_Outlier - 5.4 * BatHR_Filter

It is found that "BASERUN_CS" and "PITCH_H_Outlier" variables were statistically not significant from zero. Also the model meshes with theoretical effect for most part except that the coefficent for FIELDING_DP is negative, counter to expectation. The adjusted R-squared of 35% leaves room for improvement. The assumption of OLS regression have been satisfied.

```
##
## Call:
## lm(formula = TARGET_WINS ~ ., data = cordata[, simple.Pred])
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -38.789  -7.134   0.131   7.060  29.210
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      31.387639   6.988558   4.491 7.63e-06 ***
## TEAM_BATTING_H    0.032833   0.005038   6.517 9.83e-11 ***
## TEAM_BATTING_2B  -0.051953   0.010036  -5.177 2.57e-07 ***
## TEAM_BATTING_3B   0.075513   0.023054   3.276  0.00108 **
## TEAM_BATTING_HR   0.111551   0.010290  10.841  < 2e-16 ***
## TEAM_BATTING_BB   0.039478   0.003606  10.948  < 2e-16 ***
## TEAM_BATTING_SO  -0.017120   0.002589  -6.611 5.31e-11 ***
## TEAM_BASERUN_SB   0.066541   0.009068   7.338 3.58e-13 ***
## TEAM_BASERUN_CS  -0.013322   0.019192  -0.694  0.48770
## TEAM_FIELDING_DP -0.091301   0.014024  -6.511 1.02e-10 ***
## Pitch_H_Outlier  -0.866432   1.475723  -0.587  0.55721
```

```
## BatHR_FilterTRUE -5.402819   1.259058  -4.291 1.89e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.27 on 1474 degrees of freedom
## Multiple R-squared:  0.3505, Adjusted R-squared:  0.3456
## F-statistic: 72.31 on 11 and 1474 DF,  p-value: < 2.2e-16
```

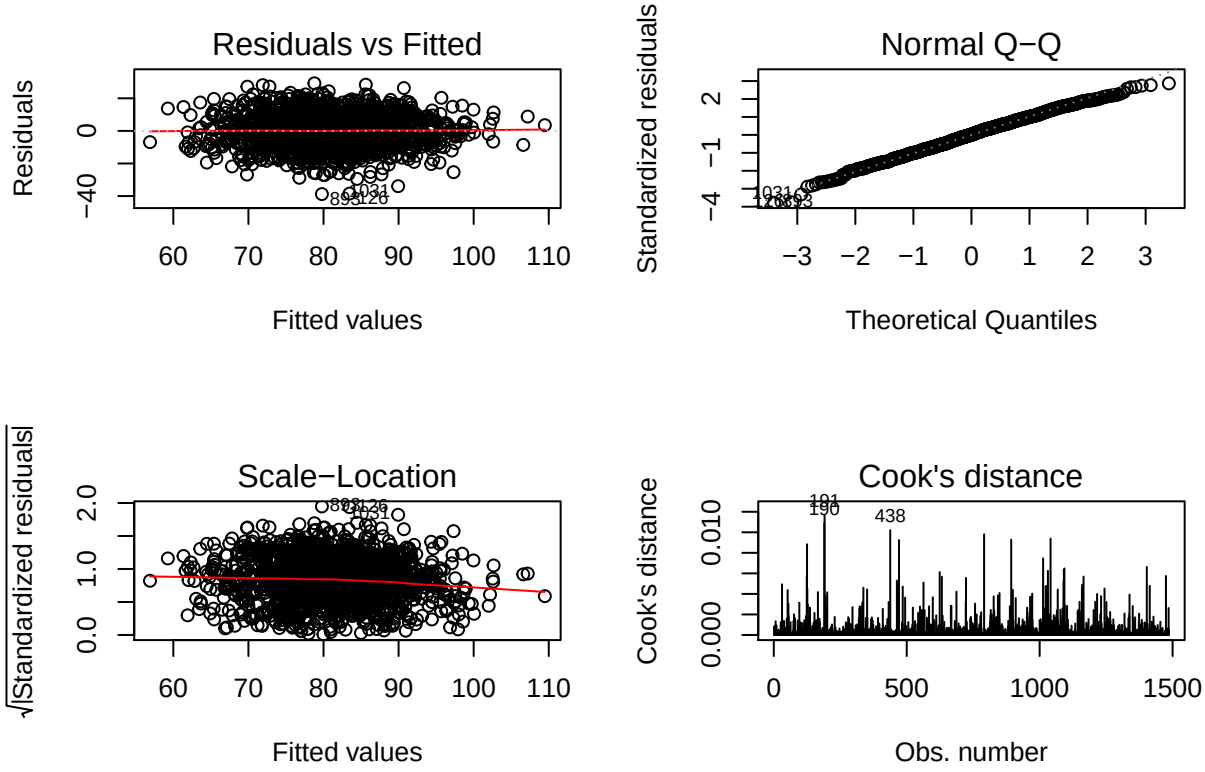


Figure 8: Simple model results

4.2 Revisied simple multiple linear regression model

From the above model, the variables "BASERUN_CS" and "PITCH_H_Outlier" are removed and a revised model is fit as below:

TARGET_WINS = 34.12 + 0.01 * TEAM_BATTING_H + 0.1 * TEAM_BATTING_3B + 0.12 * TEAM_BATTING_HR + 0.04 * TEAM_BATTING_BB - 0.02 * TEAM_BATTING_SO + 0.07 * TEAM_BASERUN_SB - 5.49 * BatHR_Filter

This model is interpretable and is in line with theoretical expectations. The indicator variable correctly identifies the effect of low values of home runs leading up to fewer predicted wins. However adjusted R-Squared value of 32% leaves room for improvement. The assumptions of OLS regression is satisfied and multicollinearity is satisfactory.

```
##
## Call:
## lm(formula = TARGET_WINS ~ ., data = cordata[, simple.rev.Pred])
##
## Residuals:
```

```
##     Min      1Q  Median      3Q     Max
## -37.318  -7.166   0.248   7.110  32.629
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      34.124308   5.721631   5.964 3.07e-09 ***
## TEAM_BATTING_H    0.012656   0.003639   3.478  0.00052 ***
## TEAM_BATTING_3B   0.099892   0.023008   4.342 1.51e-05 ***
## TEAM_BATTING_HR   0.116681   0.010430  11.187  < 2e-16 ***
## TEAM_BATTING_BB   0.035491   0.003624   9.794  < 2e-16 ***
## TEAM_BATTING_SO  -0.019570   0.002469  -7.926 4.43e-15 ***
## TEAM_BASERUN_SB   0.070751   0.006691  10.574  < 2e-16 ***
## BatHR_FilterTRUE -5.489045   1.245679  -4.406 1.13e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.48 on 1478 degrees of freedom
## Multiple R-squared:  0.321,  Adjusted R-squared:  0.3178
## F-statistic: 99.81 on 7 and 1478 DF,  p-value: < 2.2e-16
```

```
##  TEAM_BATTING_H TEAM_BATTING_3B TEAM_BATTING_HR TEAM_BATTING_BB
##        1.947511        2.486960        3.472341        1.151583
## TEAM_BATTING_SO TEAM_BASERUN_SB    BatHR_Filter
##        3.306176        1.189305        1.686170
```

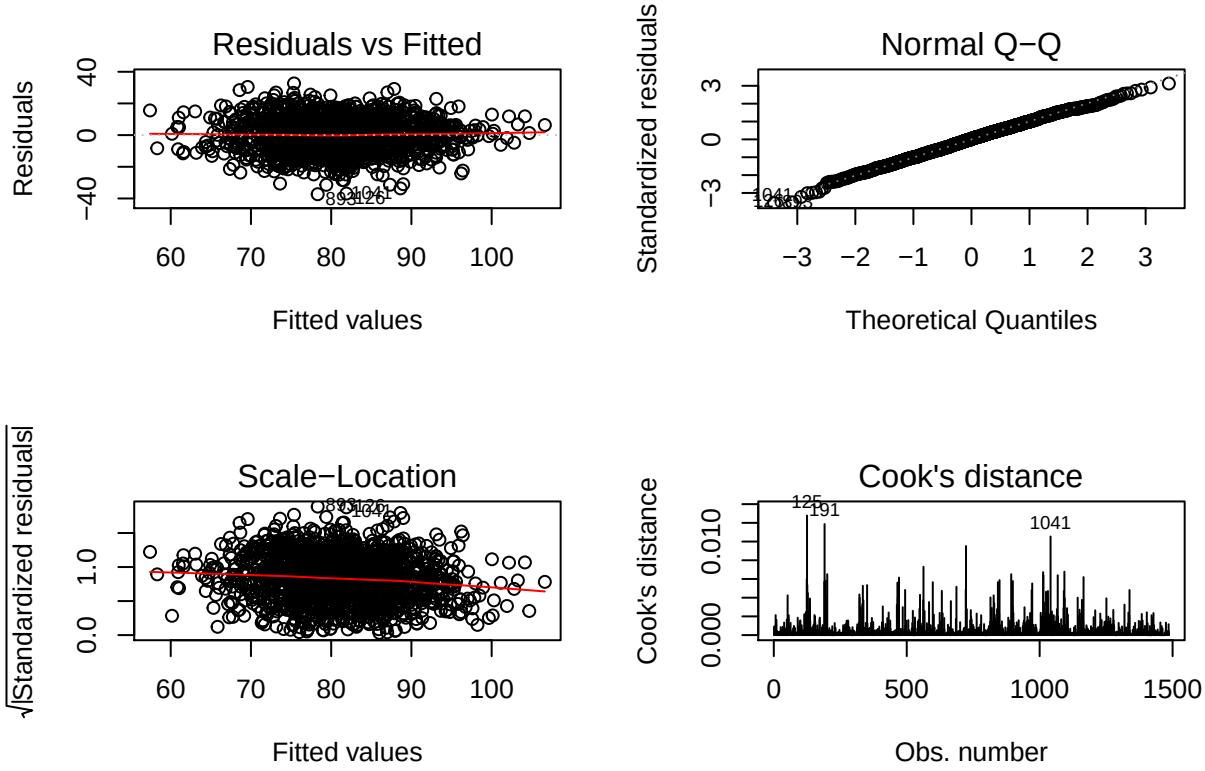


Figure 9: Revised Simple model results

4.3 Automated Variable selection

Automated stepwise variable selection method was employed with a search range between full model (all variables) and intercept only variables. The resulting model had high multicollinearity and the model is not shown in this report. However, automated variable selection was used to search within the manually chosen variables used in the above two models. The following model was fit as a result:

TARGET_WINS = 34.12 + 0.01 * TEAM_BATTING_H + 0.1 * TEAM_BATTING_3B + 0.12 * TEAM_BATTING_HR + 0.04 * TEAM_BATTING_BB - 0.02 * TEAM_BATTING_SO + 0.07 * TEAM_BASERUN_SB - 5.49 * BatHR_Filter

The resulting model was identical to the revised simple model.

```
##
## Call:
## lm(formula = TARGET_WINS ~ TEAM_BATTING_H + TEAM_BATTING_3B +
##     TEAM_BATTING_HR + TEAM_BATTING_BB + TEAM_BATTING_SO + TEAM_BASERUN_SB +
##     BatHR_Filter, data = cordata[, simple.rev.Pred])
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -37.318  -7.166   0.248   7.110  32.629
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      34.124308   5.721631   5.964 3.07e-09 ***
## TEAM_BATTING_H    0.012656   0.003639   3.478  0.00052 ***
## TEAM_BATTING_3B   0.099892   0.023008   4.342 1.51e-05 ***
## TEAM_BATTING_HR   0.116681   0.010430  11.187  < 2e-16 ***
## TEAM_BATTING_BB   0.035491   0.003624   9.794  < 2e-16 ***
## TEAM_BATTING_SO  -0.019570   0.002469  -7.926 4.43e-15 ***
## TEAM_BASERUN_SB   0.070751   0.006691  10.574  < 2e-16 ***
## BatHR_FilterTRUE -5.489045   1.245679  -4.406 1.13e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.48 on 1478 degrees of freedom
## Multiple R-squared:  0.321,  Adjusted R-squared:  0.3178
## F-statistic: 99.81 on 7 and 1478 DF,  p-value: < 2.2e-16
```

3.2 PCA

```
## Importance of components:
##                            Comp.1    Comp.2    Comp.3     Comp.4     Comp.5
## Standard deviation     2.2961654 1.8549068 1.5203573 1.27137742 1.15632108
## Proportion of Variance 0.3101397 0.2023929 0.1359698 0.09508239 0.07865167
## Cumulative Proportion  0.3101397 0.5125326 0.6485024 0.74358479 0.82223647
##                            Comp.6     Comp.7     Comp.8     Comp.9
## Standard deviation     0.91188783 0.75215016 0.72295091 0.61905022
## Proportion of Variance 0.04891408 0.03327823 0.03074459 0.02254254
## Cumulative Proportion  0.87115055 0.90442878 0.93517337 0.95771591
##                           Comp.10    Comp.11     Comp.12     Comp.13
## Standard deviation     0.55246457 0.45403972 0.402273828 0.201145815
## Proportion of Variance 0.01795395 0.01212659 0.009519073 0.002379979
## Cumulative Proportion  0.97566985 0.98779644 0.997315517 0.999695496
```

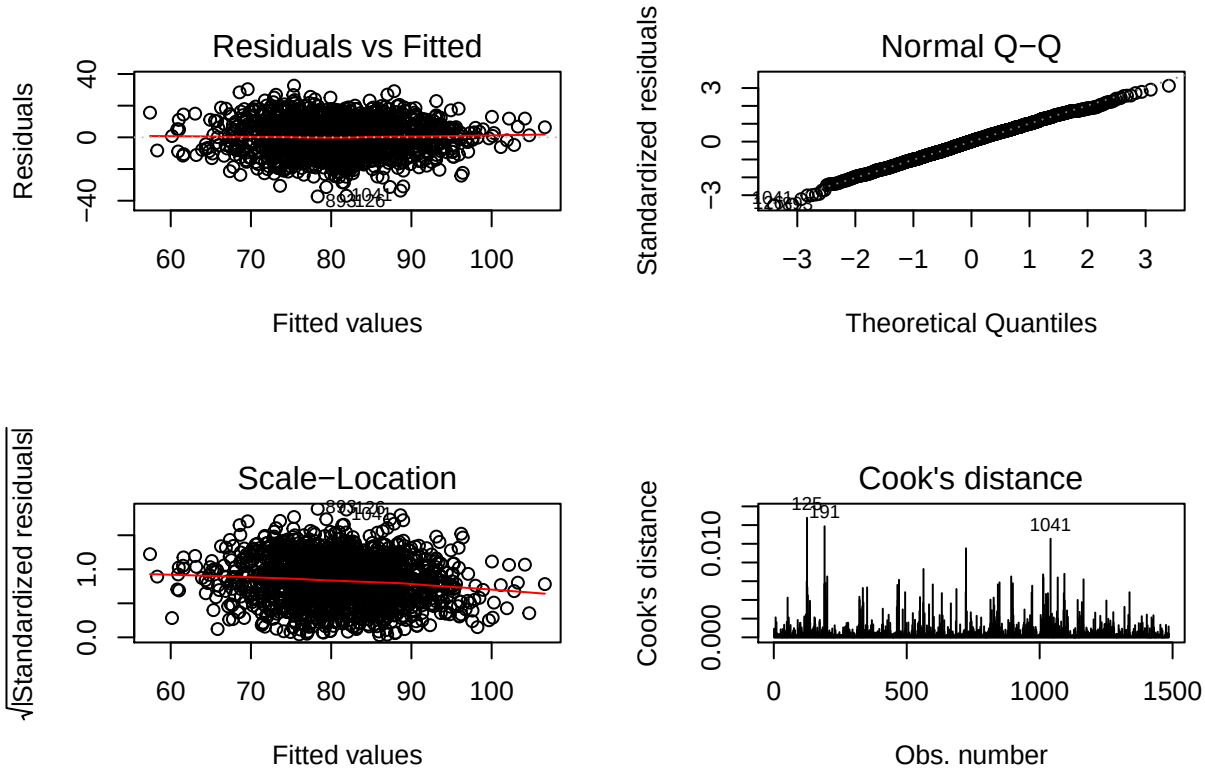
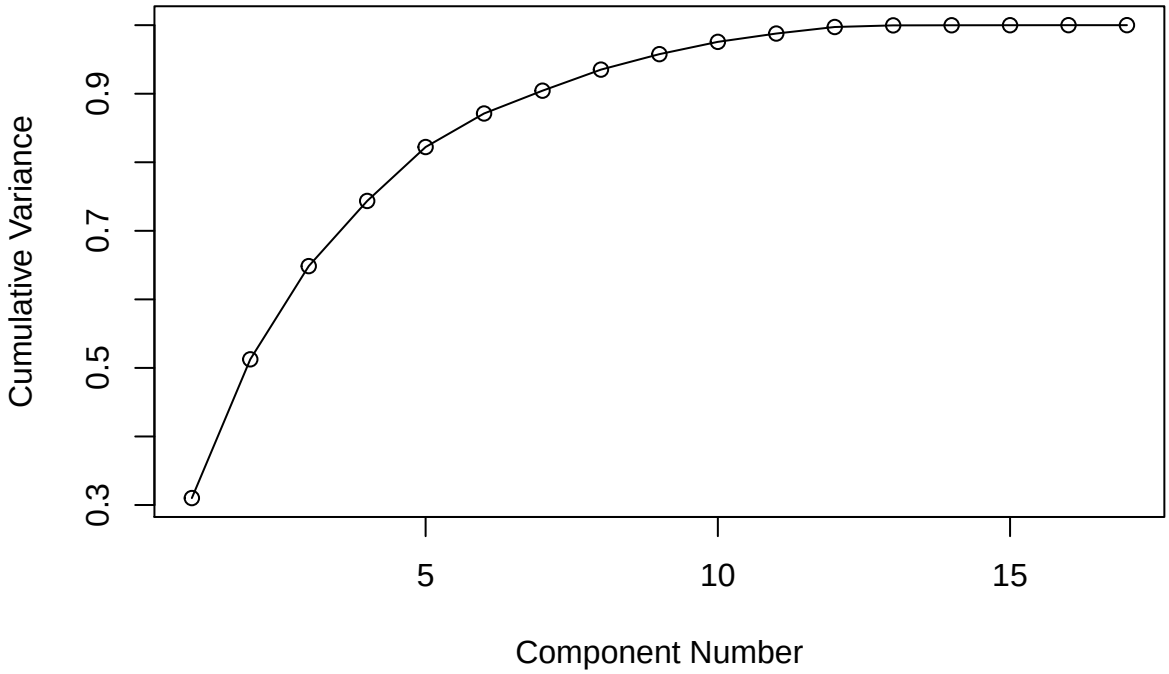
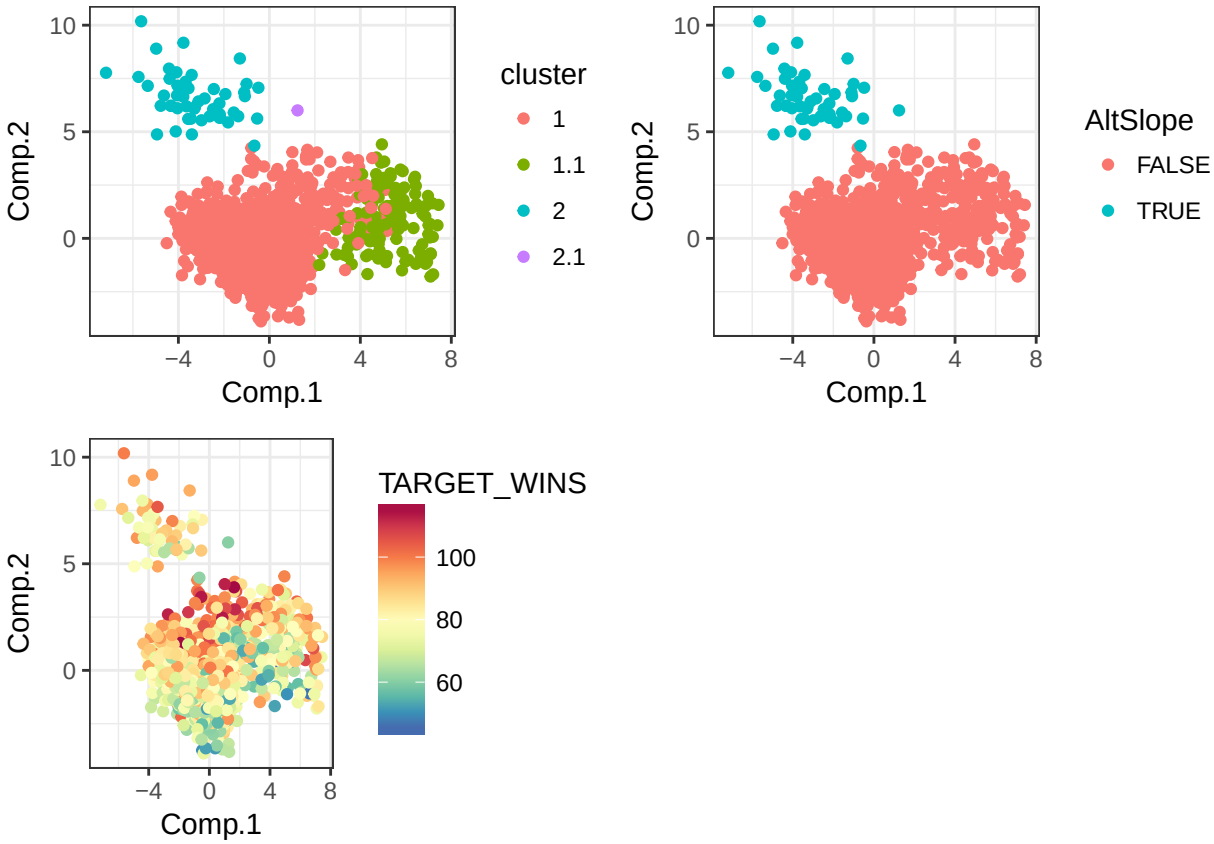


Figure 10: Stepwise automated variable selection

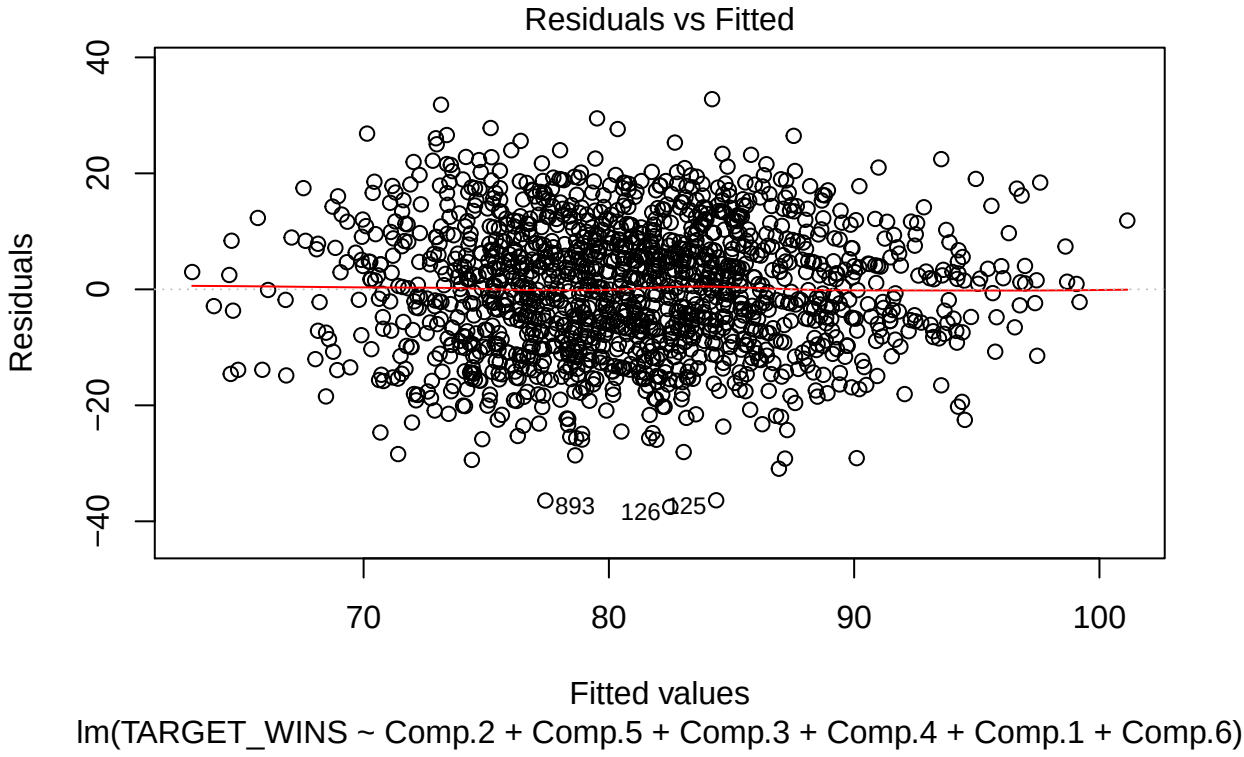
```
##                             Comp.14      Comp.15      Comp.16 Comp.17
## Standard deviation     0.0518176699 3.903839e-02 3.110471e-02       0
## Proportion of Variance 0.0001579453 8.964682e-05 5.691192e-05       0
## Cumulative Proportion  0.9998534413 9.999431e-01 1.000000e+00       1
```

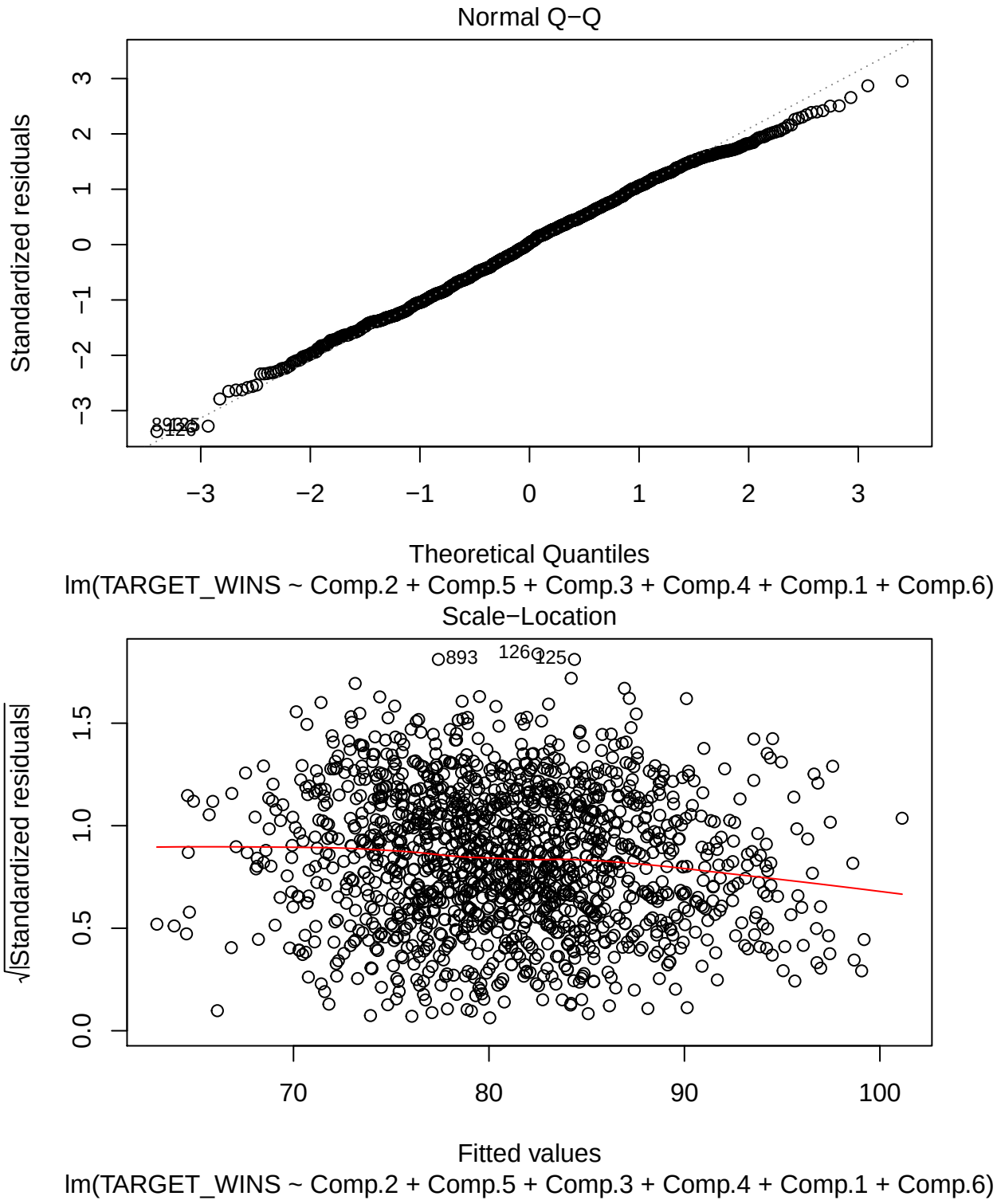


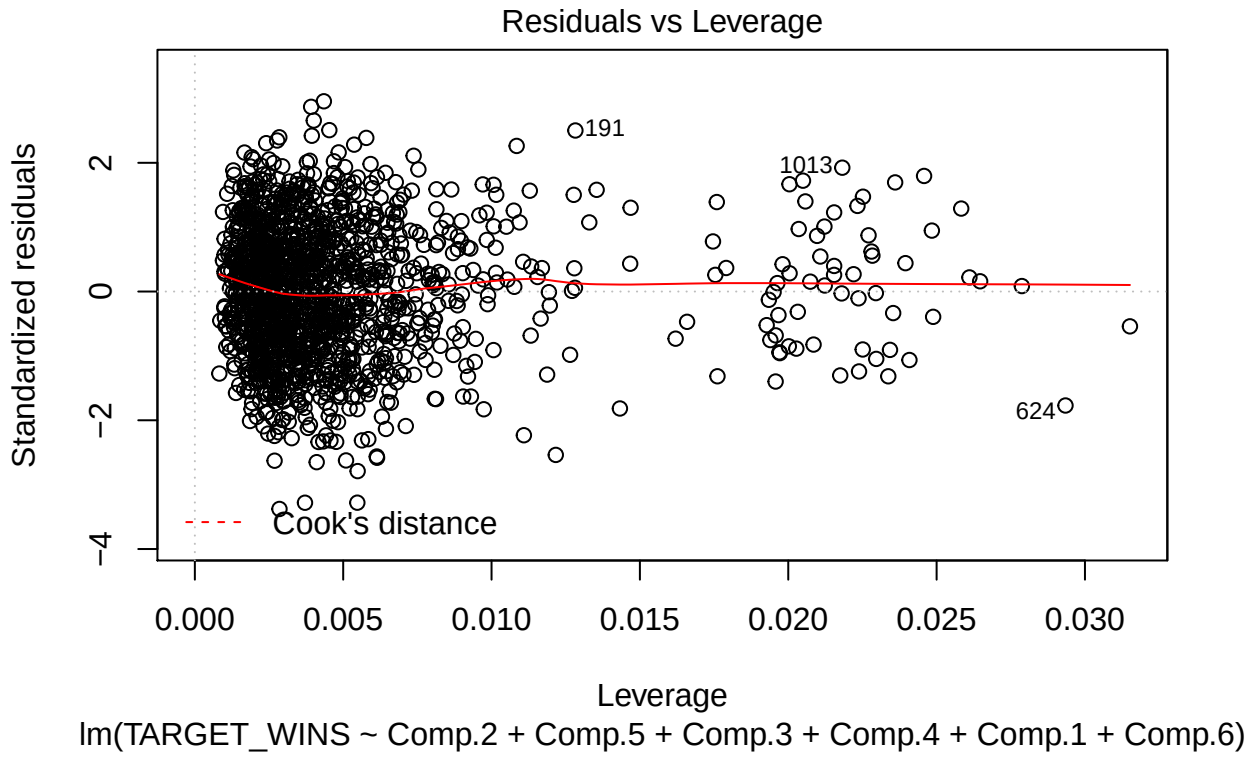



```
##
## Call:
## lm(formula = TARGET_WINS ~ Comp.2 + Comp.5 + Comp.3 + Comp.4 +
##     Comp.1 + Comp.6, data = dfclust[, c(1:6, 10)])
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -37.505  -7.796   0.259   7.867  32.792
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  80.9966     0.2885 280.778  < 2e-16 ***
## Comp.2        1.8439     0.1555  11.856  < 2e-16 ***
## Comp.5       -2.4834     0.2495  -9.954  < 2e-16 ***
## Comp.3        1.7658     0.1897   9.306  < 2e-16 ***
## Comp.4        2.0729     0.2269   9.136  < 2e-16 ***
## Comp.1       -0.8234     0.1256  -6.554 7.73e-11 ***
## Comp.6       -0.5721     0.3163  -1.808   0.0708 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 11.12 on 1479 degrees of freedom
## Multiple R-squared:  0.2356, Adjusted R-squared:  0.2325
## F-statistic: 75.99 on 6 and 1479 DF,  p-value: < 2.2e-16

## Analysis of Variance Table
##
```

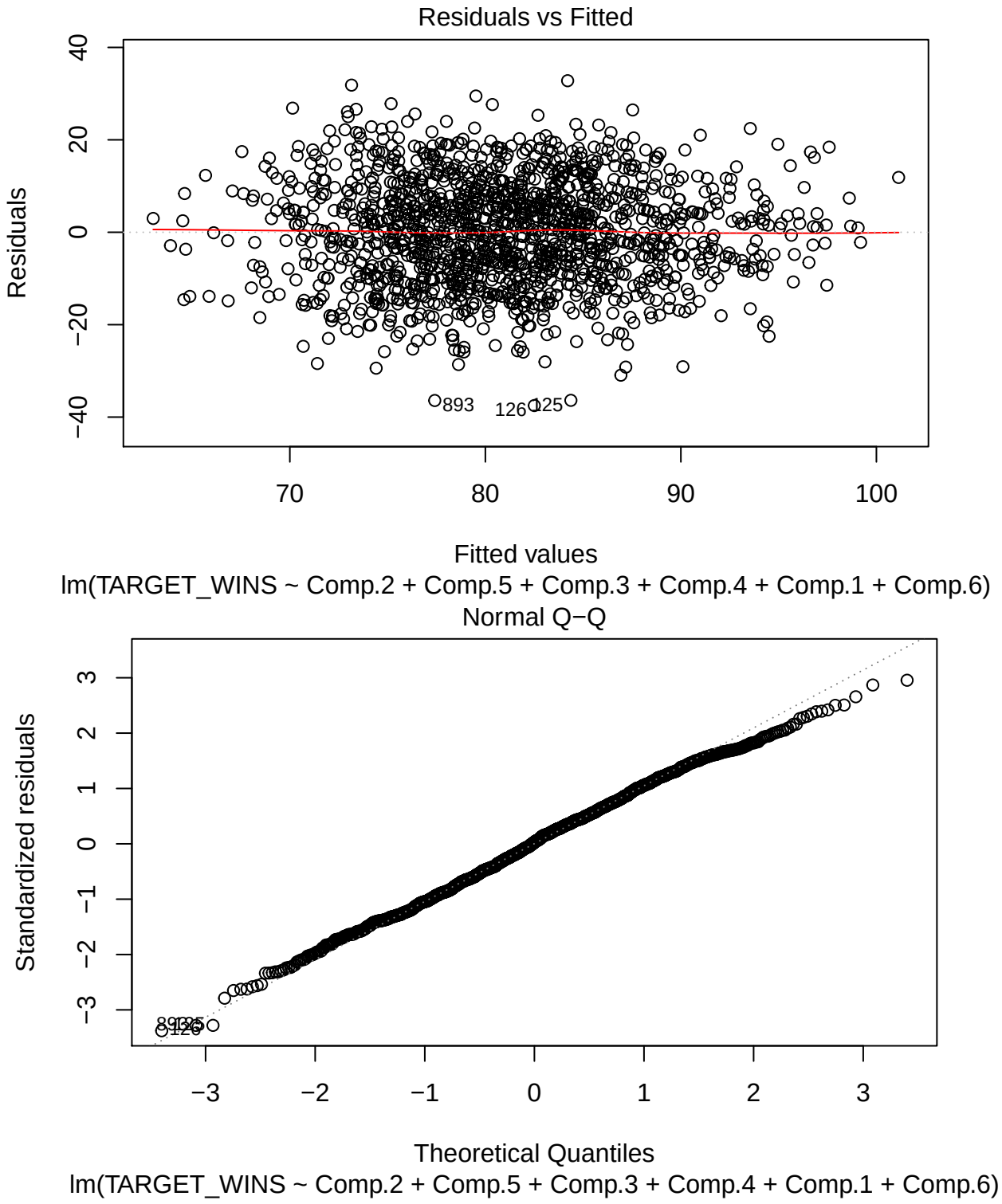
```
## Response: TARGET_WINS
##              Df Sum Sq Mean Sq  F value    Pr(>F)
## Comp.2        1  17383 17383.4 140.5754 < 2.2e-16 ***
## Comp.5        1  12253 12253.4  99.0902 < 2.2e-16 ***
## Comp.3        1  10710 10709.5  86.6055 < 2.2e-16 ***
## Comp.4        1  10321 10321.3  83.4662 < 2.2e-16 ***
## Comp.1        1   5311  5311.4  42.9521 7.726e-11 ***
## Comp.6        1    404   404.4   3.2702   0.07075 .
## Residuals  1479 182892   123.7
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

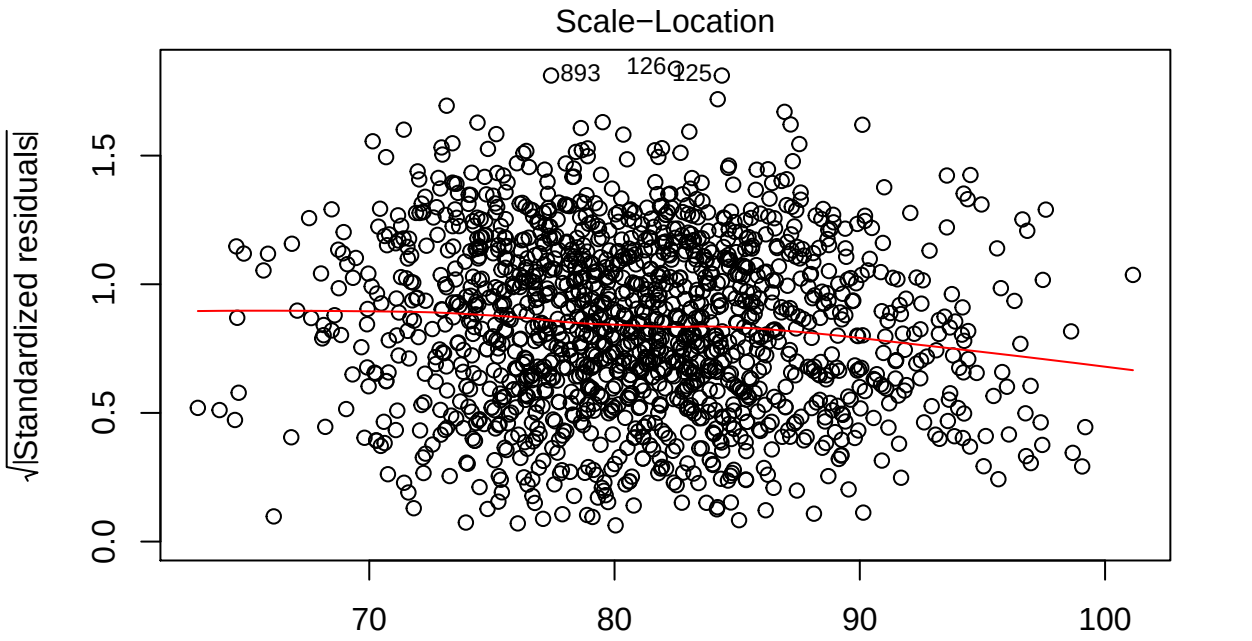


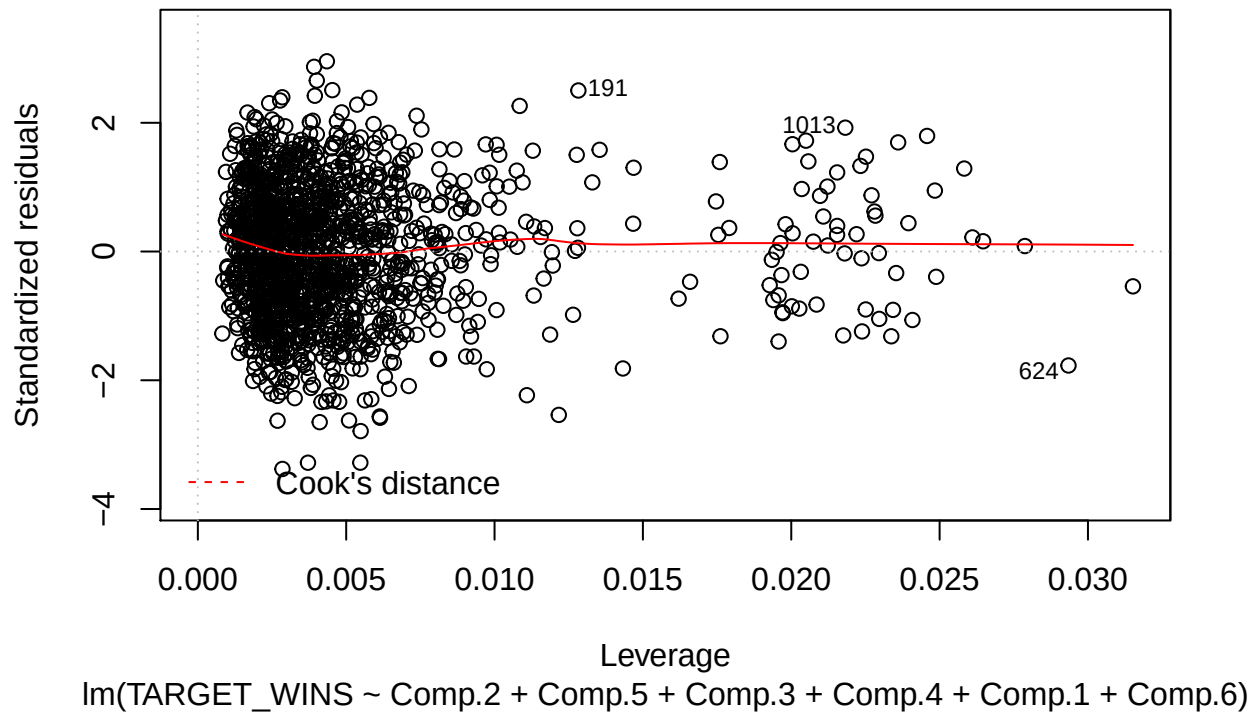

Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(TARGET_WINS ~ Comp.2 + Comp.5 + Comp.3 + Comp.4 + Comp.1 + Comp.6)
Scale−Location
√|Standardized residuals|
893
1260
125
Fitted values
lm(TARGET_WINS ~ Comp.2 + Comp.5 + Comp.3 + Comp.4 + Comp.1 + Comp.6)




```
##
## Call:
## lm(formula = TARGET_WINS ~ Comp.2 + Comp.5 + Comp.3 + Comp.4 +
##     Comp.1 + Comp.6, data = dfclust[, c(1:6, 10)])
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -37.505  -7.796   0.259   7.867  32.792
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  80.9966     0.2885 280.778  < 2e-16 ***
## Comp.2        1.8439     0.1555  11.856  < 2e-16 ***
## Comp.5       -2.4834     0.2495  -9.954  < 2e-16 ***
## Comp.3        1.7658     0.1897   9.306  < 2e-16 ***
## Comp.4        2.0729     0.2269   9.136  < 2e-16 ***
## Comp.1       -0.8234     0.1256  -6.554 7.73e-11 ***
## Comp.6       -0.5721     0.3163  -1.808   0.0708 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 11.12 on 1479 degrees of freedom
## Multiple R-squared:  0.2356, Adjusted R-squared:  0.2325
## F-statistic: 75.99 on 6 and 1479 DF,  p-value: < 2.2e-16
```

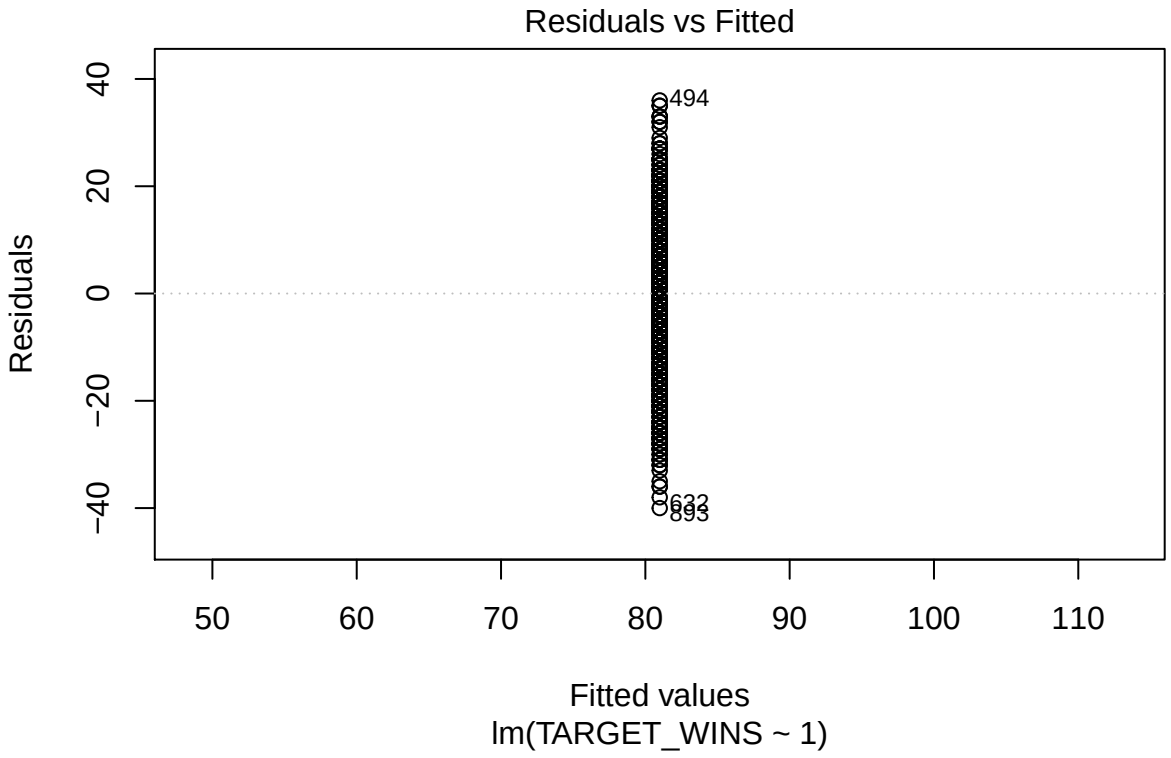

Residuals vs Fitted
Residuals
40
20
0
−20
−40
893
126
125
70
80
90
100
Fitted values
lm(TARGET_WINS ~ Comp.2 + Comp.5 + Comp.3 + Comp.4 + Comp.1 + Comp.6)
Normal Q−Q
Standardized residuals
3
2
1
0
−1
−2
−3
−3
−2
−1
0
1
2
3
Theoretical Quantiles
lm(TARGET_WINS ~ Comp.2 + Comp.5 + Comp.3 + Comp.4 + Comp.1 + Comp.6)

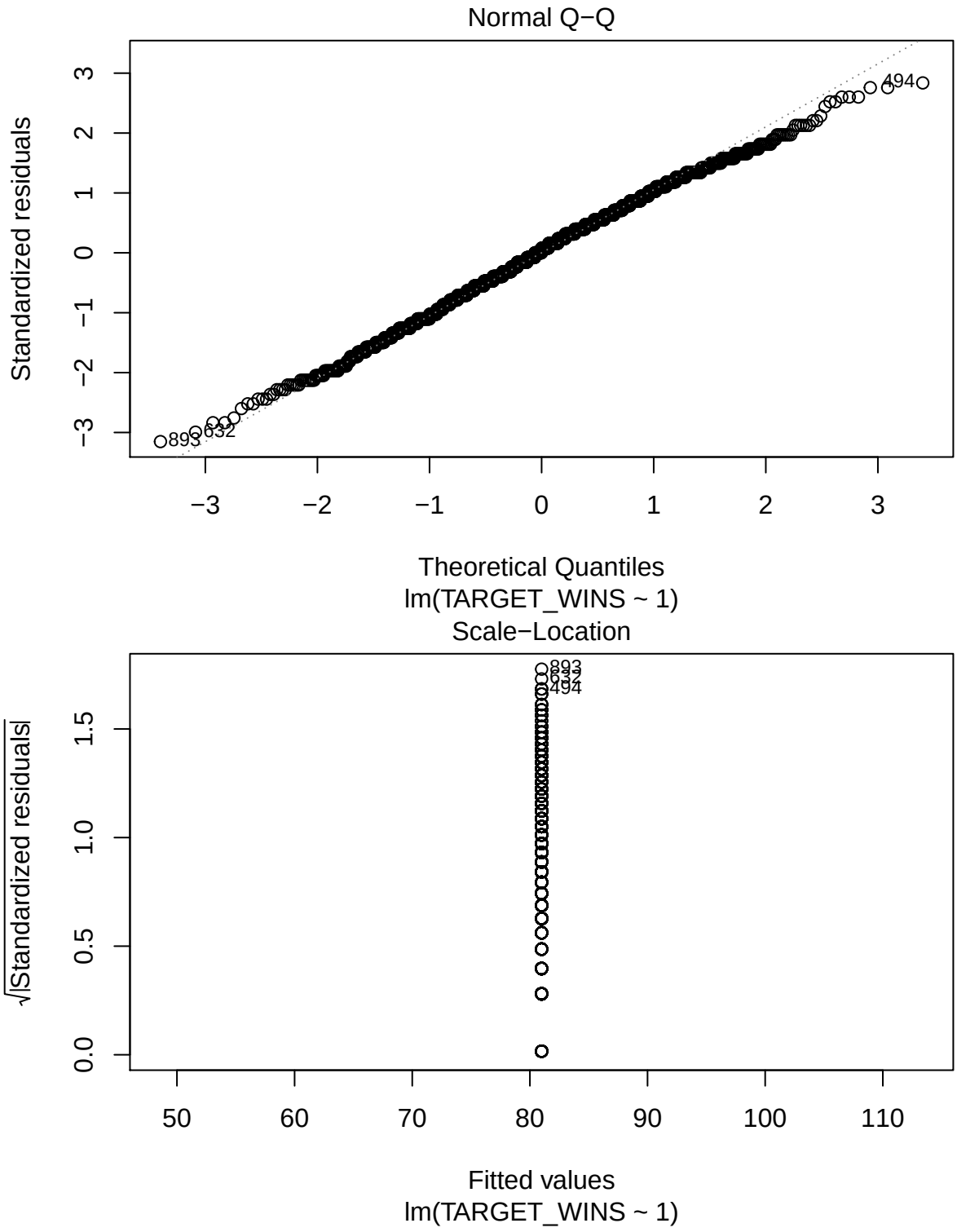




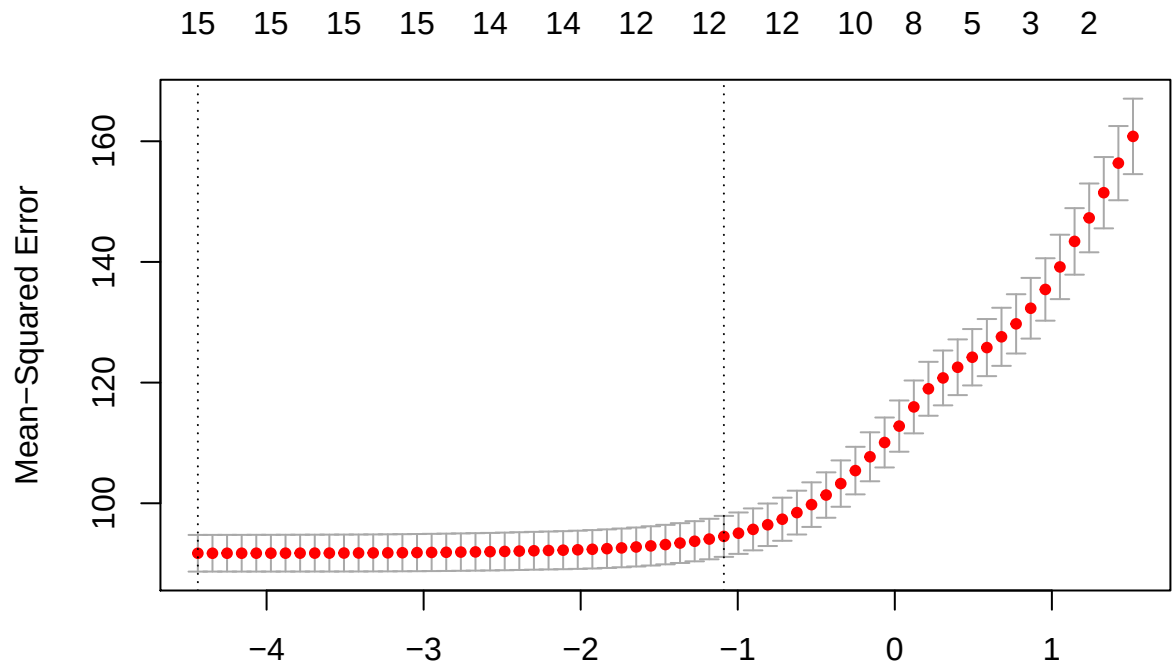

```
##
## Call:
## lm(formula = TARGET_WINS ~ 1, data = dfclust[, c(1:6, 10)])
##
## Residuals:
##     Min      1Q  Median      3Q     Max
```

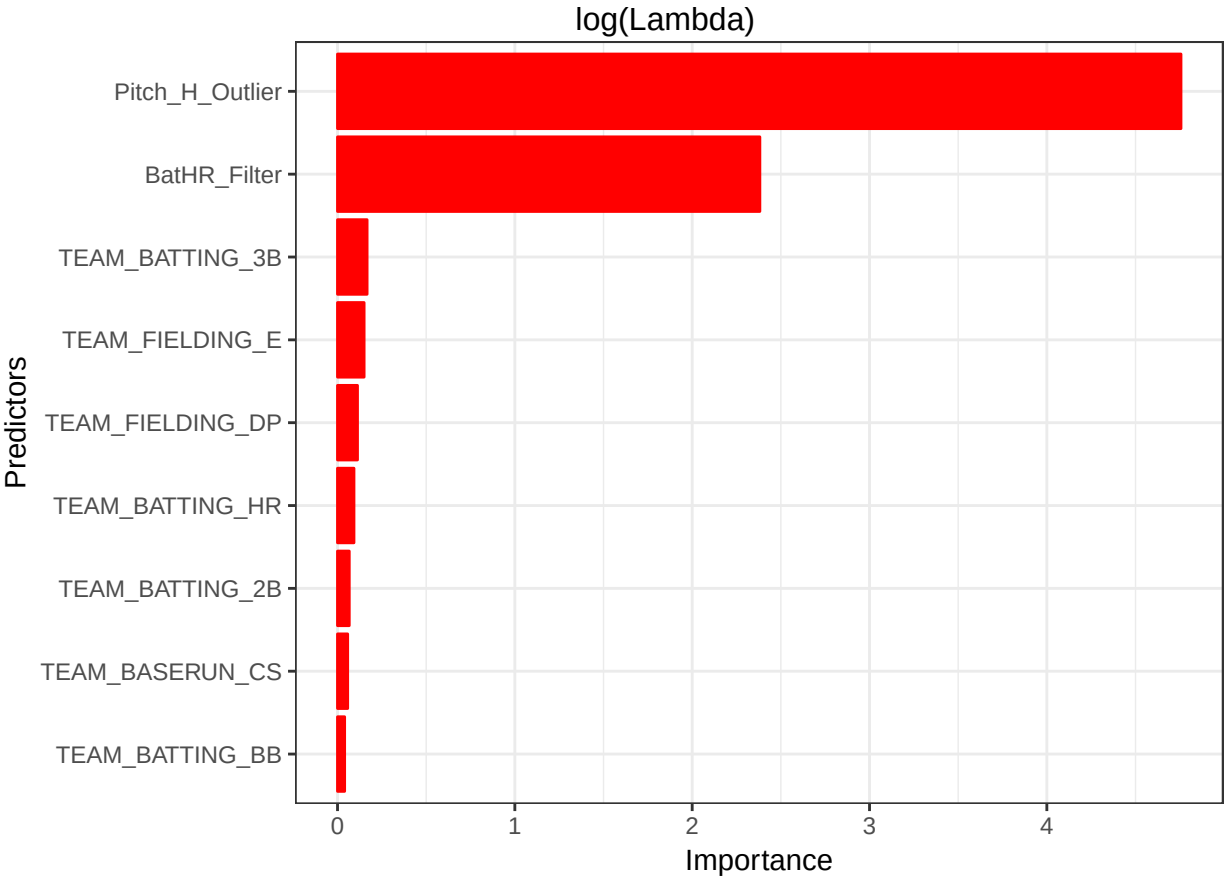
```
## -39.997  -8.997   0.503   9.003  36.003
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  80.9966     0.3293     246   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 12.69 on 1485 degrees of freedom
```



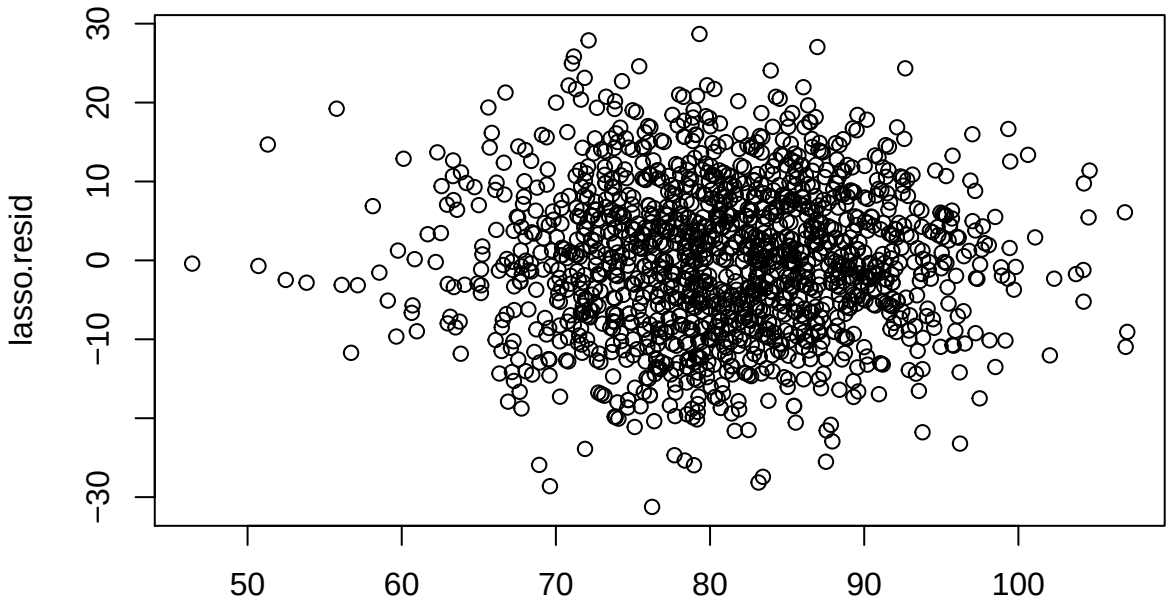

Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(TARGET_WINS ~ 1)
Scale−Location
√|Standardized residuals|
Fitted values
lm(TARGET_WINS ~ 1)

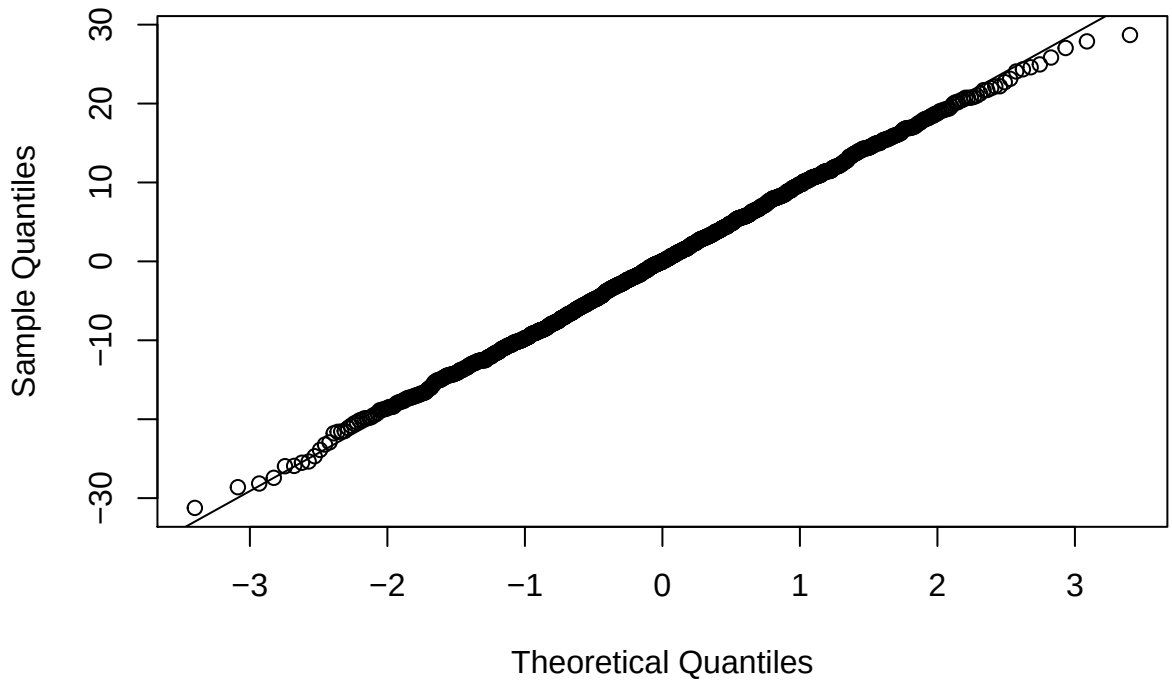
3.2 Lasso






```
## [1] 0.4405071
```

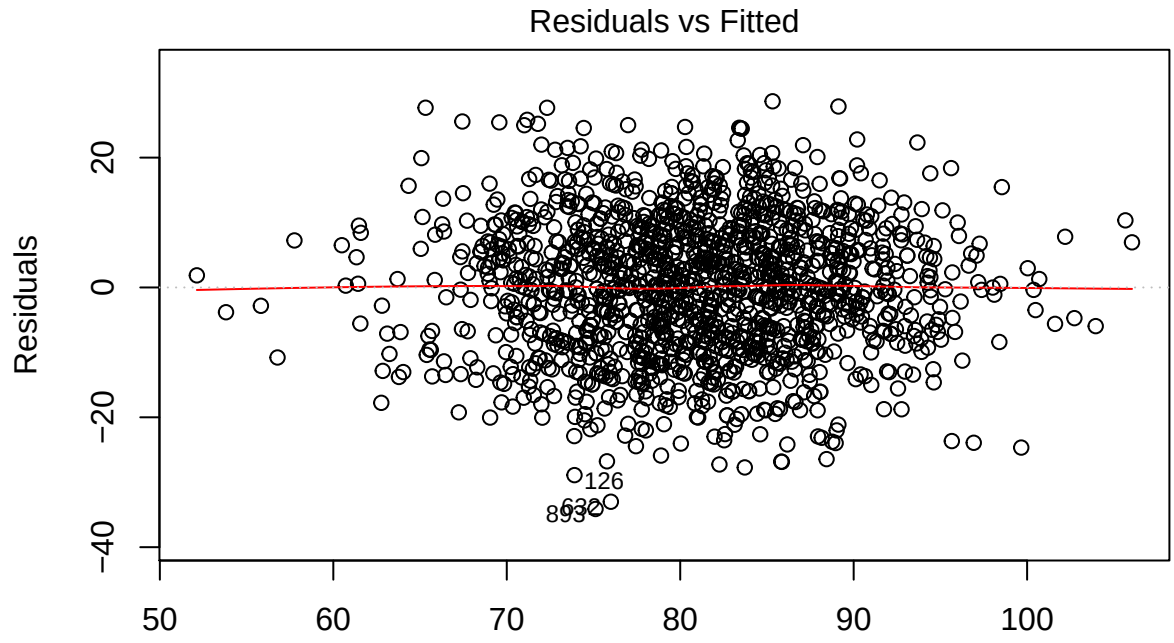


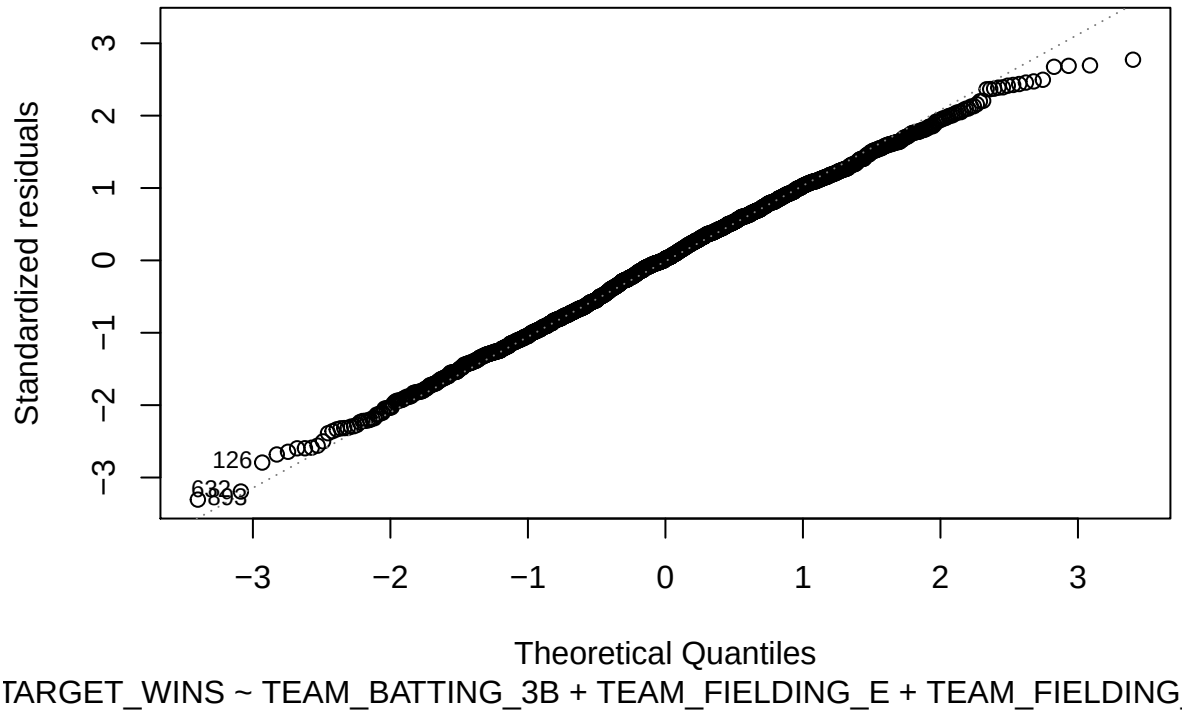


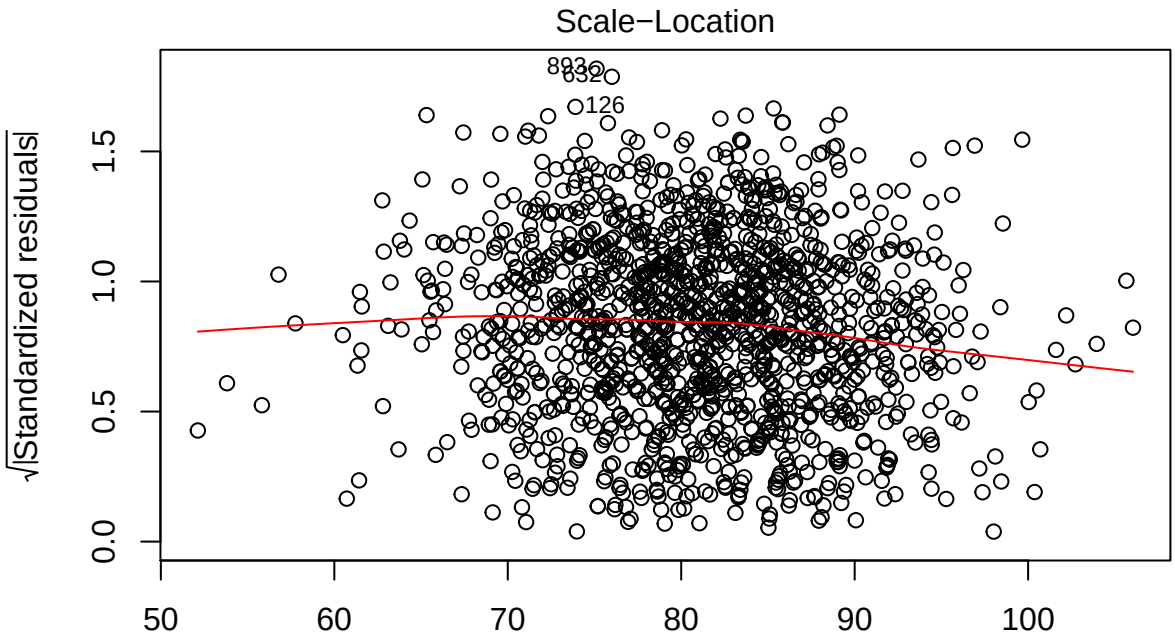

```
##
## Call:
## lm(formula = TARGET_WINS ~ ., data = cordata[, c("TARGET_WINS",
##     Candidate_Lasso)])
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -34.266  -7.471   0.105   7.259  28.584
```

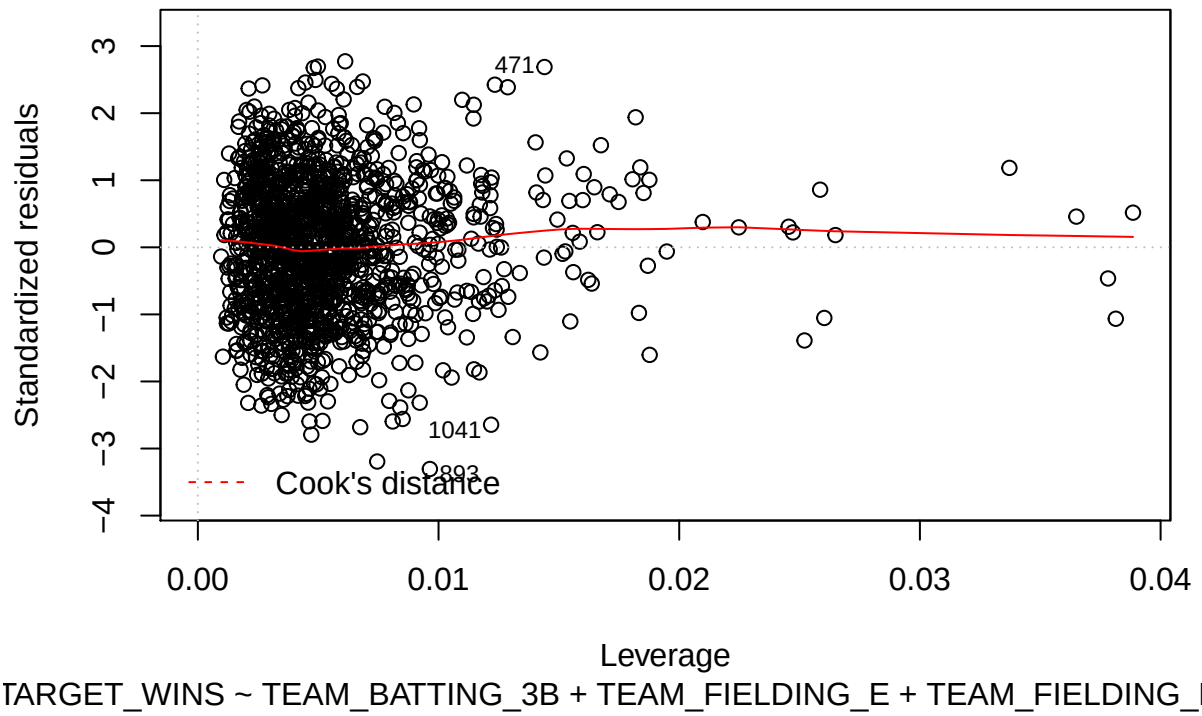
```
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)      60.955332   3.948154  15.439  < 2e-16 ***
## Pitch_H_Outlier  -1.529950   1.491255  -1.026    0.305
## BatHR_FilterTRUE -1.718587   1.282512  -1.340    0.180
## TEAM_BATTING_3B   0.337979   0.020725  16.308  < 2e-16 ***
## TEAM_FIELDING_E  -0.133816   0.010366 -12.909  < 2e-16 ***
## TEAM_FIELDING_DP -0.076028   0.013759  -5.526 3.87e-08 ***
## TEAM_BATTING_HR   0.076531   0.008587   8.913  < 2e-16 ***
## TEAM_BATTING_2B  -0.010047   0.007205  -1.395    0.163
## TEAM_BASERUN_CS   0.093695   0.014230   6.584 6.33e-11 ***
## TEAM_BATTING_BB   0.047501   0.003567  13.317  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.37 on 1476 degrees of freedom
## Multiple R-squared:  0.3367, Adjusted R-squared:  0.3327
## F-statistic: 83.25 on 9 and 1476 DF,  p-value: < 2.2e-16

## Start:  AIC=6961.08
## TARGET_WINS ~ Pitch_H_Outlier + BatHR_Filter + TEAM_BATTING_3B +
##     TEAM_FIELDING_E + TEAM_FIELDING_DP + TEAM_BATTING_HR + TEAM_BATTING_2B +
##     TEAM_BASERUN_CS + TEAM_BATTING_BB
##
##                     Df Sum of Sq    RSS    AIC
## - Pitch_H_Outlier    1     113.2 158822 6960.1
## - BatHR_Filter       1     193.1 158902 6960.9
## - TEAM_BATTING_2B    1     209.1 158918 6961.0
## <none>                           158709 6961.1
## - TEAM_FIELDING_DP   1    3283.2 161992 6989.5
## - TEAM_BASERUN_CS    1    4661.9 163371 7002.1
## - TEAM_BATTING_HR    1    8541.2 167250 7037.0
## - TEAM_FIELDING_E    1   17917.2 176626 7118.0
## - TEAM_BATTING_BB    1   19068.9 177778 7127.7
## - TEAM_BATTING_3B    1   28596.5 187306 7205.3
##
## Step:  AIC=6960.14
## TARGET_WINS ~ BatHR_Filter + TEAM_BATTING_3B + TEAM_FIELDING_E +
##     TEAM_FIELDING_DP + TEAM_BATTING_HR + TEAM_BATTING_2B + TEAM_BASERUN_CS +
##     TEAM_BATTING_BB
##
##                     Df Sum of Sq    RSS    AIC
## - BatHR_Filter       1     185.1 159007 6959.9
## <none>                           158822 6960.1
## - TEAM_BATTING_2B    1     228.9 159051 6960.3
## + Pitch_H_Outlier    1     113.2 158709 6961.1
## - TEAM_FIELDING_DP   1    3290.3 162113 6988.6
## - TEAM_BASERUN_CS    1    4575.9 163398 7000.4
## - TEAM_BATTING_HR    1    8609.8 167432 7036.6
## - TEAM_FIELDING_E    1   17808.0 176630 7116.1
## - TEAM_BATTING_BB    1   19079.2 177901 7126.7
## - TEAM_BATTING_3B    1   28724.1 187546 7205.2
##
```

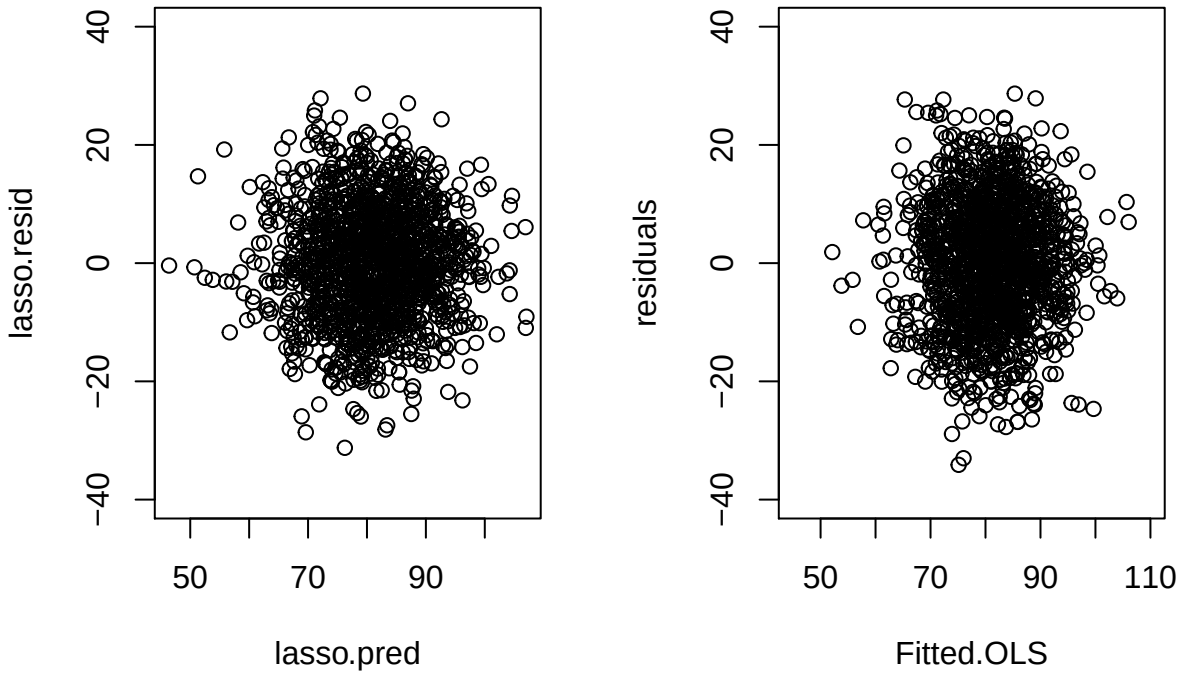
```
## Step:  AIC=6959.87
## TARGET_WINS ~ TEAM_BATTING_3B + TEAM_FIELDING_E + TEAM_FIELDING_DP +
##     TEAM_BATTING_HR + TEAM_BATTING_2B + TEAM_BASERUN_CS + TEAM_BATTING_BB
##
##                     Df Sum of Sq    RSS    AIC
## <none>                           159007 6959.9
## + BatHR_Filter       1     185.1 158822 6960.1
## - TEAM_BATTING_2B    1     295.3 159303 6960.6
## + Pitch_H_Outlier    1     105.2 158902 6960.9
## - TEAM_FIELDING_DP   1    3253.3 162261 6988.0
## - TEAM_BASERUN_CS    1    4395.6 163403 6998.4
## - TEAM_BATTING_HR    1   10413.5 169421 7052.1
## - TEAM_BATTING_BB    1   18980.1 177987 7125.4
## - TEAM_FIELDING_E    1   19384.3 178392 7128.8
## - TEAM_BATTING_3B    1   28554.7 187562 7203.3
##
## Call:
## lm(formula = TARGET_WINS ~ TEAM_BATTING_3B + TEAM_FIELDING_E +
##     TEAM_FIELDING_DP + TEAM_BATTING_HR + TEAM_BATTING_2B + TEAM_BASERUN_CS +
##     TEAM_BATTING_BB, data = cordata[, c("TARGET_WINS", Candidate_Lasso)])
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -34.118  -7.411   0.201   7.152  28.674
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      59.812925   3.627653  16.488  < 2e-16 ***
## TEAM_BATTING_3B   0.335779   0.020610  16.292  < 2e-16 ***
## TEAM_FIELDING_E  -0.135922   0.010126 -13.423  < 2e-16 ***
## TEAM_FIELDING_DP -0.075655   0.013758  -5.499 4.49e-08 ***
## TEAM_BATTING_HR   0.080295   0.008161   9.838  < 2e-16 ***
## TEAM_BATTING_2B  -0.011802   0.007124  -1.657   0.0978 .
## TEAM_BASERUN_CS   0.089381   0.013983   6.392 2.19e-10 ***
## TEAM_BATTING_BB   0.047367   0.003566  13.282  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.37 on 1478 degrees of freedom
## Multiple R-squared:  0.3355, Adjusted R-squared:  0.3323
## F-statistic: 106.6 on 7 and 1478 DF,  p-value: < 2.2e-16
```


Residuals vs Fitted
Residuals
20
0
−20
−40
126
632
893
50
60
70
80
90
100
Fitted values
lm(TARGET_WINS ~ TEAM_BATTING_3B + TEAM_FIELDING_E + TEAM_FIELDING_DP)


Normal Q−Q
Standardized residuals
3
2
1
0
−1
−2
−3
126
632
893
−3
−2
−1
0
1
2
3
Theoretical Quantiles
lm(TARGET_WINS ~ TEAM_BATTING_3B + TEAM_FIELDING_E + TEAM_FIELDING_DP)

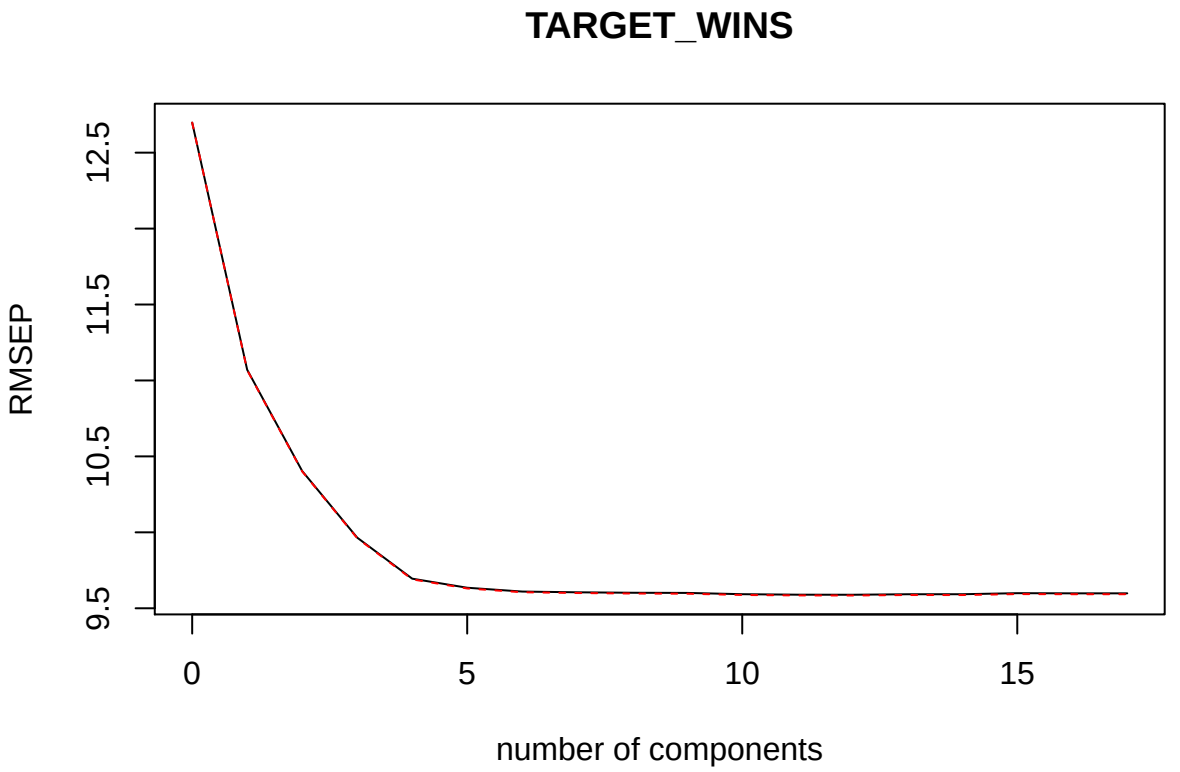

Scale−Location
893
632
126
√|Standardized residuals|
0.0
0.5
1.0
1.5
50
60
70
80
90
100
Fitted values
TARGET_WINS ~ TEAM_BATTING_3B + TEAM_FIELDING_E + TEAM_FIELDING_DP


Residuals vs Leverage
471
1041
893
Cook's distance
Standardized residuals
−4
−3
−2
−1
0
1
2
3
0.00
0.01
0.02
0.03
0.04
Leverage
TARGET_WINS ~ TEAM_BATTING_3B + TEAM_FIELDING_E + TEAM_FIELDING_DP



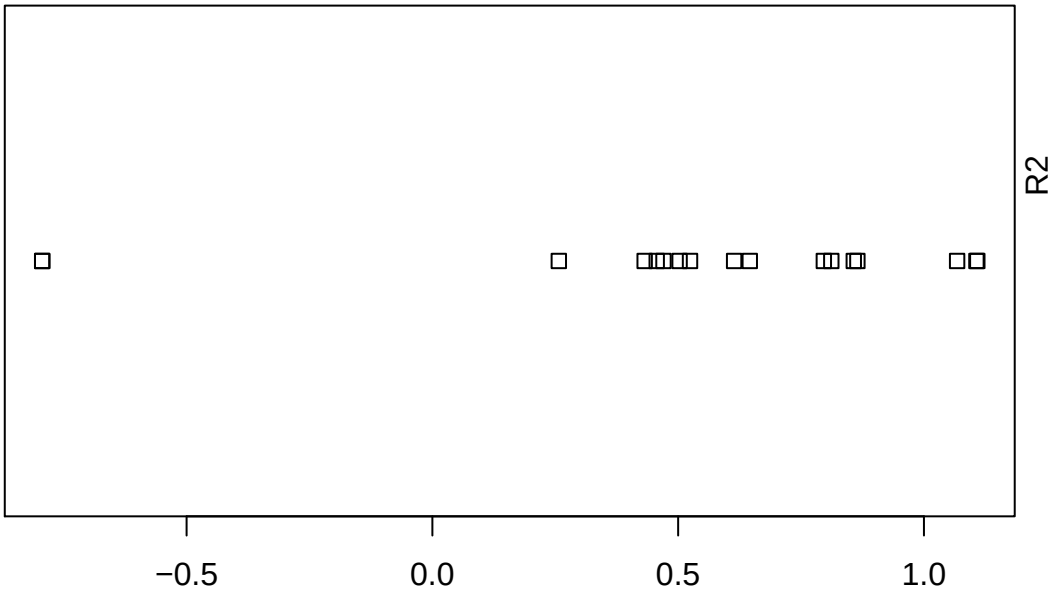
3.3 Partial Least Squares (PLS) Regression

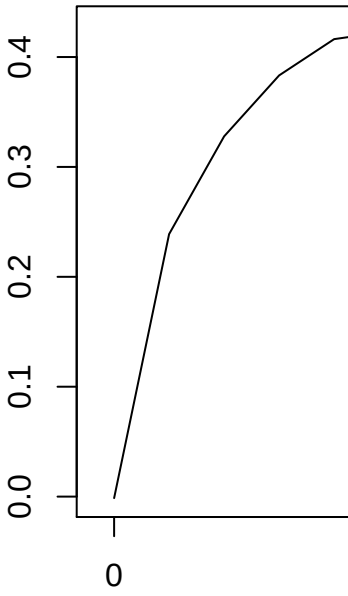
How to add indicator variables to the model?

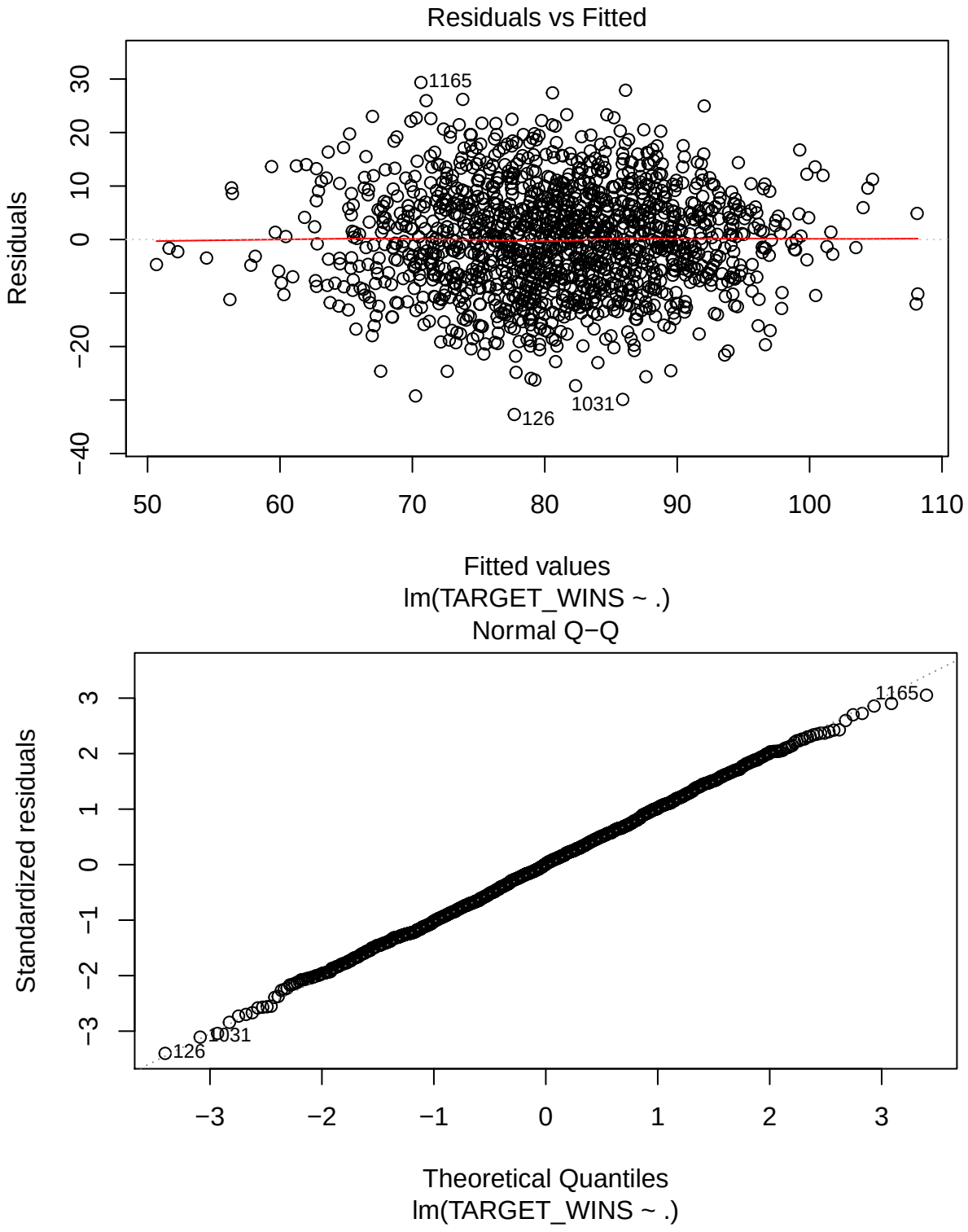


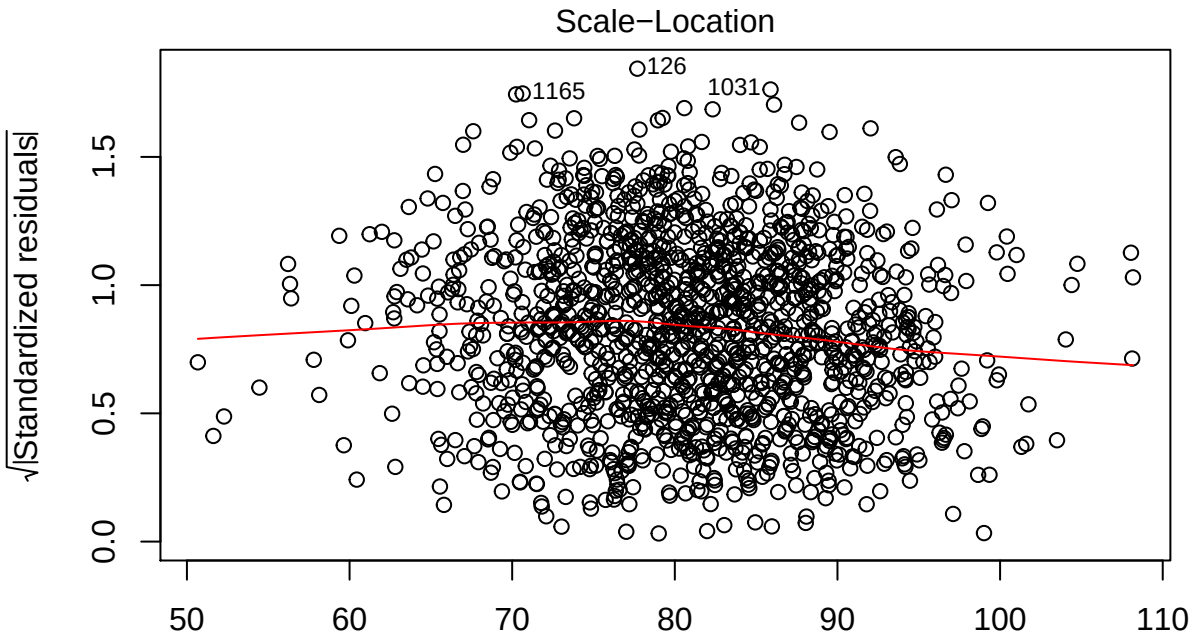

```
## Data:    X dimension: 1486 17
##  Y dimension: 1486 1
## Fit method: kernelpls
```

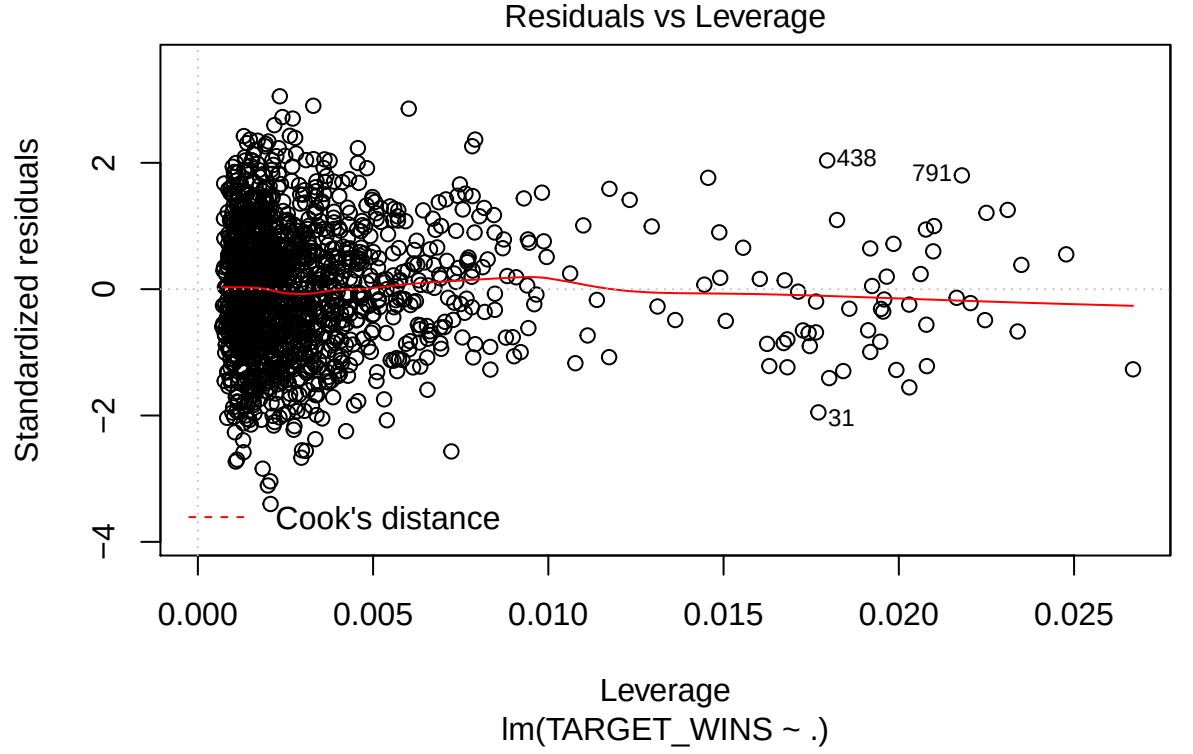
```
## Number of components considered: 17
##
## VALIDATION: RMSEP
## Cross-validated using 10 random segments.
##        (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## CV            12.7    11.07     10.4    9.965    9.695    9.635    9.610
## adjCV         12.7    11.07     10.4    9.962    9.690    9.630    9.605
##        7 comps  8 comps  9 comps  10 comps  11 comps  12 comps  13 comps
## CV       9.605    9.602    9.601     9.593     9.589     9.589     9.592
## adjCV    9.600    9.597    9.596     9.588     9.585     9.584     9.587
##        14 comps  15 comps  16 comps  17 comps
## CV        9.592     9.599     9.598     9.598
## adjCV     9.587     9.593     9.592     9.592
##
## TRAINING: % variance explained
##              1 comps  2 comps  3 comps  4 comps  5 comps  6 comps  7 comps
## X              21.27    40.91    56.24    65.64    75.42    80.57    87.18
## TARGET_WINS    24.72    33.68    39.26    42.66    43.42    43.71    43.79
##              8 comps  9 comps  10 comps  11 comps  12 comps  13 comps
## X              89.66    92.85     94.64     96.31     98.85     99.84
## TARGET_WINS    43.87    43.94     43.99     44.00     44.01     44.02
##              14 comps  15 comps  16 comps  17 comps
## X               99.98     99.99    100.00    100.12
## TARGET_WINS     44.08     44.09     44.09     44.09
```






Residuals vs Fitted
Residuals
Fitted values
lm(TARGET_WINS ~ .)
1165
1031
126
Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(TARGET_WINS ~ .)
1165
1031
126






```
##
## Call:
## lm(formula = TARGET_WINS ~ ., data = pls.df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
```

```
## -32.697  -6.743   0.106   6.336  29.356
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  80.9966     0.2497  324.38   <2e-16 ***
## Comp.1        3.7604     0.1488   25.27   <2e-16 ***
## Comp.2        2.5600     0.1683   15.21   <2e-16 ***
## Comp.3        2.2174     0.1848   12.00   <2e-16 ***
## Comp.4        2.0707     0.2210    9.37   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.625 on 1481 degrees of freedom
## Multiple R-squared:  0.4266, Adjusted R-squared:  0.425
## F-statistic: 275.4 on 4 and 1481 DF,  p-value: < 2.2e-16
```

```
## Analysis of Variance Table
##
## Response: TARGET_WINS
##             Df Sum Sq Mean Sq F value    Pr(>F)
## Comp.1       1  59149   59149 638.425 < 2.2e-16 ***
## Comp.2       1  21439   21439 231.398 < 2.2e-16 ***
## Comp.3       1  13343   13343 144.013 < 2.2e-16 ***
## Comp.4       1   8133    8133  87.789 < 2.2e-16 ***
## Residuals 1481 137212      93
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

3.4 Random forest

4. Imputing and Data Prep for testing

5. Model Selection

6. Prediction