Assignment #1- MSDS 411 Summer 2018
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Introduction
My complete work for this assignment can be found in the Jupyter Notebook file 411_Assignment_1_Knight.ipynb. All reference to the 'notebook' below refer to my work in this Jupyter Notebook file. **The file 411_Assignment_1_Knight_Notebook_Printout.pdf shows all code and output.**

In this assignment, we seek to build a predictive model using linear regression to predict the number of wins for each baseball team in the test dataset. The model will use the independent predictor variables and the dependent response variable 'TARGET_WINS' from the training dataset.

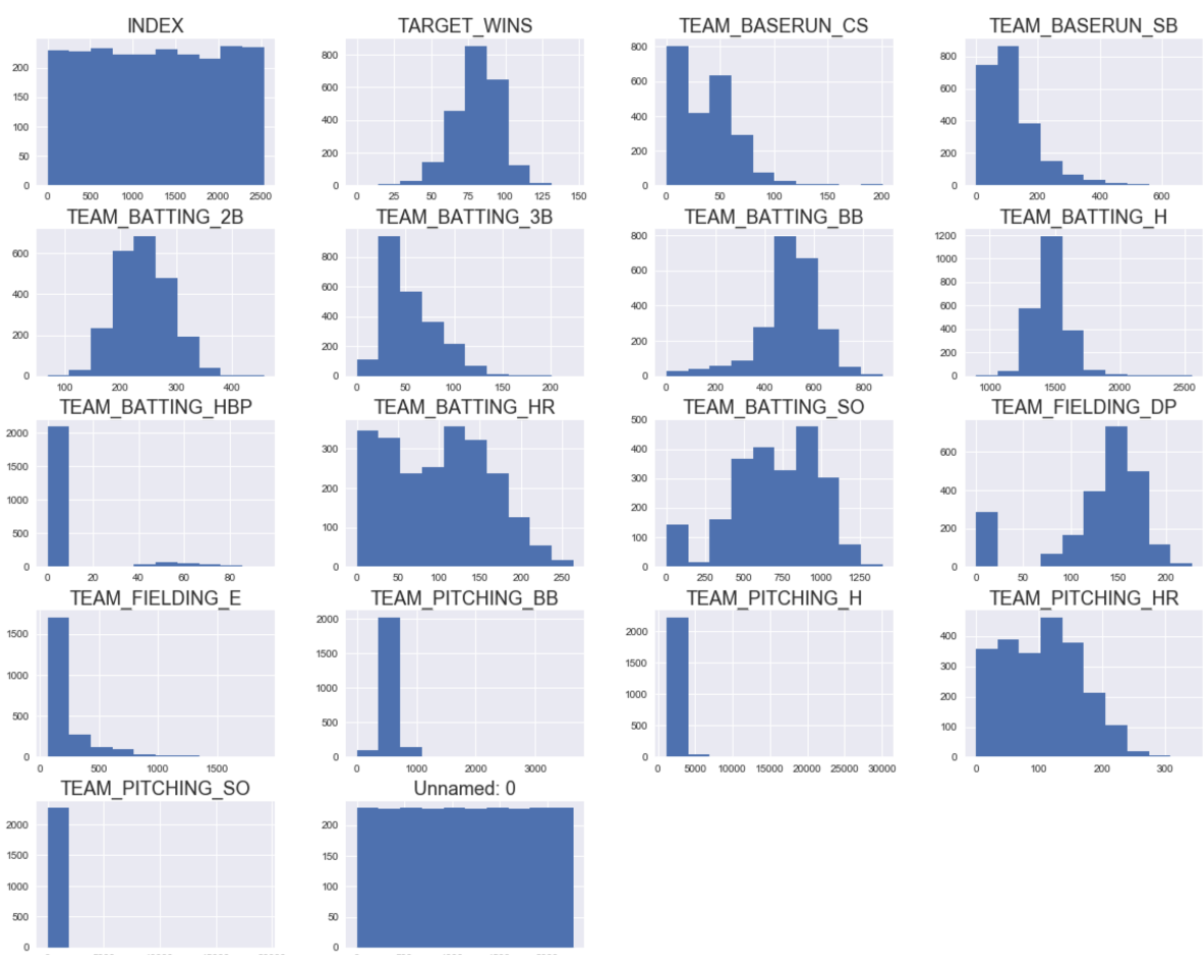
Data Exploration (EDA)
My goals for EDA focused on a few key areas. First, as with any EDA, I took some time to familiarize myself with the datasets. Several steps within the notebook dealt with understanding the structure and potential issues with the datasets. First some high-level basics.

There are 2276 records in the training dataset and 259 in the test dataset. Each observation (row) represents a single team for a whole season. There are 15 columns of independent variables and a response (TARGET_WINS) that can be used to build a predictive model. However, information that we are not given is which team is represented for each record, how many games were played that season or how many teams are represented for each season. There are 135 years represented in the data which we will use as the assumption that this is the number of seasons (ignoring war years and player strikes), dividing the records by 135 we get an average of 17 teams represented.

All variables were given as continuous numerics. Six of the 15 variables contained sme NaN values which had to be corrected. NA (null or NaN) values were initially replaced with zeros. Some of these would need to be further modified later. The six variables containing significant numbers of NA values for both training and test sets are given in the table below.

	TEAM_BATTING_HBP	TEAM_BASERUN_CS	TEAM_FIELDING_DP	TEAM_BATTING_SO	TEAM_PITCHING_SO	TEAM_BASERUN_SB
Train	2085	772	289	102	102	131
Test	240	87	31	13	13	13

After checking mean, median and standard deviation for each, I saved the resulting data frame (with NaN values replaced by zeros to new data frames named **train1** and **test1**. I checked the distribution of each variable provided and immediately began looking for things that could cause issues in my models. I started by looking at the minimum values (which for several variables was now zero) due to the fillna function used early on. Looking at a histogram of each I could tell when there were many ‘missing’ values that had been filled in a zeros. Two particularly high offenders in this area were TEAM_BATTING_HBP and TEAM_BASERUN_CS. Both of these had a high percentage of null values and as such I decided not to use either of these two variables in my models.



I also noticed some other opportunities to prepare these data for use in the model building process by applying transformations to several variables. For example, the histogram for some variables show they may be good candidates for a log transformation. These include variables like the TEAM_BASERUN_SB and TEAM_FIELDING_E. These transformations will be listed in detail below.
We also clearly see other variables have many zeros that need to be addressed because the are significantly skewing the data. This is a result of replacing NA values with zeros. Data cleaning described in the next section will handle this issue so that the resulting models perform better without removing rows of data.

Next, I focused on a the response variable. The distribution shows close similarity to normality and there are no NA values, and the mean, standard deviation, and max values all seem reasonable given basic knowledge of baseball. However, the min value displayed raises a flag. One single data point in the training set contained zero TARGET_WINS, which even in a short season of the 1800s, seems suspect. While the team was clearly bad with 24,057 TEAM_PITCHING_H and 1890 TEAM_FIELDING_E, ending a season with zero wins can't be accurate. I decided to remove this record only because I did not trust the validity of this observation. It was the only observation (row) that I completely removed.

```
# First lets see how many records contain zero wins
train1[train1['TARGET_WINS'] < 10]
```

	Unnamed: 0	INDEX	TARGET_WINS	TEAM_BATTING_H	TEAM_BATTING_2B	TEAM_BATTING_3B	TEAM_BATTING_HR
1210	1210	1347.0	0.0	891.0	135.0	0.0	0.0

Then using the describe() function, I noticed some extreme outliers in the training data. The TEAM_PITCHING_SO has some particularly high outliers (an order of magnitude higher than third quartile), as high as 19, 278 (shown in output below) when the mean value is 781. I decided to impute the outlier values with max values of three times the mean as a max value rather than replace them with the mean value.

	TEAM_PITCHING_HR	TEAM_PITCHING_BB	TEAM_PITCHING_SO	TEAM_FIELDING_E
count	2276.000000	2276.000000	2276.000000	2276.000000
mean	105.698594	553.007909	781.083480	246.480668
std	61.298747	166.357362	566.413951	227.770972
min	0.000000	0.000000	0.000000	65.000000
25%	50.000000	476.000000	587.750000	127.000000
50%	107.000000	536.500000	797.000000	159.000000
75%	150.000000	611.000000	957.000000	249.250000
max	343.000000	3645.000000	19278.000000	1898.000000

Many of the other variables that had null values replaced with zeros showed significant skew in their distributions due to these values. Looking through these variables, it became clear that when taken in context of a typical full season, the numbers simply did not make much sense when a little knowledge of baseball is applied. For example, team stats for a whole season with zero home runs, zero pitching strikeouts, zero batting walks, and others just doesn't make sense even for shorter seasons in the past. This is where more data would have been helpful such as actual number of games played in the season or perhaps an indicator about invalid data. However, given that my choice was to limit the number of observations that I am simply 'throwing out' was one of my primary objectives. So instead, I was forced to estimate the values. I chose to use the overall mean to replace them. The calculations in the notebook indicate exactly which were modified and how.

The other reason I did this was that based on initial analysis it seemed a log transformation may be useful for some predictors. As such, I wanted positive non-zero values to use for the np.log function.

I also tested creating a few new variables, both for clarifying given variables and for performing transformations to test in my model building process.
Because TEAM_BATTING_H (hits) includes singles, doubles, triples and home runs, I chose to create a new variable for singles by subtracting the other given values for HR, 2B, and 3B from it to arrive at the number of singles. I thought it would be better to have control over each metric separately during model selection.

I also tried creating a few variables for to test performance using LOG and SQRT of several predictor variables and the response in the training set. While the log-transformed variables improved several of my predictive models (using R-squared, AIC/BIC, etc) they did not seem to improve my submitted data score for the criteria in Kaggle.

Data Preparation

My data preparation for model testing was completed over many iterations. After checking for outliers of each of the variables, checking linearity, and normality assumptions using various plots shown in sections 2 and 3 in my notebook, I proceeded to testing models. With each model I typically referred back to the assumptions and when required performed additional tests moving between EDA, data preparation and model building with each iteration.

For the data preparation section I was primarily interested in addressing outliers, checking linearity and normality assumptions for my linear model and creating additional variables. First, I reviewed outliers.
For the extreme outliers on the high end, I found several variables with data points exceeding three times the mean. Excluding the variables TEAM_BATTING_HBP and TEAM_BASERUN_CS which I had already determined lacked enough meaningful data points, the following variables had the highest number of extreme outliers.

Variable	**Mean**	**Number of Outliers > 3x Mean**
TEAM_FIELDING_E	246.48	102
TEAM_BASERUN_SB	117.58	63
TEAM_PITCHING_H	1779.21	37
TEAM_PITCHING_SO	781.08	7
TEAM_PTICHING_BB	553.01	6
TEAM_BATTING_3B	55.25	5
TEAM_PITCHING_HR	105.70	3

For these outliers, I decided to trim the max values to limit the values to 3 times the mean value. I replaced each value higher than this number with the value equal to the 3 times the previous original mean, shown in table above.

Next, I considered the zero values that were created for each variable to replace the NAs as an outlier on the low end. Because of the fact that several variables contained many zero values, the overall linear relationship was skewed on the low end. For the zero values in each, I made a decision to replace all zero values with the original mean value. This was done for both the training and the test sets. Afterwards, we have the following min values for each.

```
TRAIN DATA
------------
New TEAM_PITCHING_SO max values is: 2343.0
New TEAM_FIELDING_E max values is: 739.0
New TEAM_FIELDING_DP min value is: 52.0
New TEAM_PITCHING_BB min value is: 119.0
New TEAM_PITCHING_HR min value is: 3.0
New TEAM_BASERUN_SB min value is: 14.0
New TEAM_BATTING_3B min value is: 8.0
New TEAM_BATTING_BB min value is: 12.0
New TEAM_BATTING_SO min value is: 66.0
New TEAM_BATTING_HR min value is: 3.0
New TEAM_PITCHING_SO min value is: 181.0

TEST DATA
------------
New TEAM_PITCHING_SO max values is: 2232.0
New TEAM_FIELDING_E max values is: 749.0
New TEAM_FIELDING_DP min value is: 69.0
New TEAM_PITCHING_BB min value is: 136.0
New TEAM_PITCHING_HR min value is: 7.0
New TEAM_BASERUN_SB min value is: 14.0
New TEAM_BATTING_3B min value is: 14.0
New TEAM_BATTING_BB min value is: 15.0
New TEAM_BATTING_SO min value is: 44.0
New TEAM_BATTING_HR min value is: 3.0
New TEAM_PITCHING_SO min value is: 315.0
```

The new descriptive stats are given for each variable with the cleaned data.

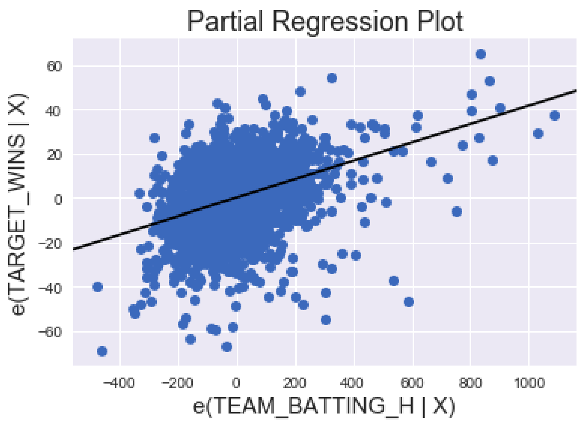
	Unnamed: 0	INDEX	TARGET_WINS	TEAM_BATTING_H	TEAM_BATTING_2B	\
count	2275.000000	2275.000000	2275.000000	2275.000000	2275.000000	
mean	1137.468132	1268.429011	80.826374	1469.523956	241.293626	
std	657.311649	736.509087	15.664221	144.113466	46.758628	
min	0.000000	1.000000	12.000000	992.000000	69.000000	
25%	568.500000	630.500000	71.000000	1383.000000	208.000000	
50%	1137.000000	1270.000000	82.000000	1454.000000	238.000000	
75%	1706.500000	1916.000000	92.000000	1537.500000	273.000000	
max	2275.000000	2535.000000	146.000000	2554.000000	458.000000	

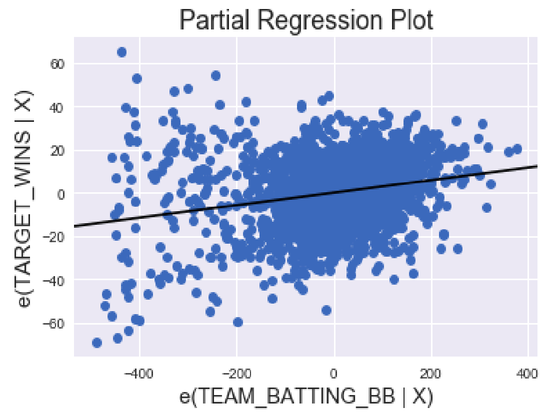
	TEAM_BATTING_3B	TEAM_BATTING_HR	TEAM_BATTING_BB	TEAM_BATTING_SO	\
count	2275.000000	2275.000000	2275.000000	2275.000000	
mean	55.298571	100.268821	501.779341	740.318813	
std	27.896579	60.013765	122.245998	233.020420	
min	8.000000	3.000000	12.000000	66.000000	
25%	34.000000	42.500000	451.000000	562.000000	
50%	47.000000	102.000000	512.000000	729.000000	
75%	72.000000	147.000000	580.000000	925.000000	
max	223.000000	264.000000	878.000000	1399.000000	

	TEAM_BASERUN_SB	TEAM_BASERUN_CS	TEAM_BATTING_HBP	TEAM_PITCHING_H	\
count	2275.000000	2275.000000	2275.000000	2275.000000	
mean	124.454801	34.908571	4.983297	1769.418022	
std	85.181498	31.197593	16.885607	1327.302422	
min	14.000000	0.000000	0.000000	1137.000000	
25%	67.000000	0.000000	0.000000	1419.000000	
50%	106.000000	38.000000	0.000000	1518.000000	
75%	151.000000	54.500000	0.000000	1682.000000	
max	697.000000	201.000000	95.000000	30132.000000	

	TEAM_PITCHING_HR	TEAM_PITCHING_BB	TEAM_PITCHING_SO	TEAM_FIELDING_E	\
count	2275.000000	2275.000000	2275.000000	2275.00000	
mean	106.395508	553.250989	807.404630	230.34022	
std	60.704264	165.989151	247.339494	168.05354	
min	3.000000	119.000000	181.000000	65.00000	
25%	52.000000	476.000000	633.000000	127.00000	
50%	107.000000	537.000000	797.000000	159.00000	
75%	150.000000	611.000000	957.000000	249.00000	
max	343.000000	3645.000000	2343.000000	697.00000	

I also plotted the partial regression line for each variable against the response TARGET_WINS to check the linear relationship. I verified that variables associated with positive influence on wins like team batting hits as shown below showed a strong positive trend. More details for this were performed in the model building section that follows.





Finally, I considered new variables before moving on to the model selection process. Because many of the distributions provided in the training dataset did not closely resemble normality, I thought introducing log-transformed variable may help. I was especially interested in testing log-transformed variables for the team baserun and team pitching variables because these were so highly skewed due to the many low values shown in the histogram plots above. In addition I also tried created a new variable just for singles from the hits variable. I really focused on utilizing the log values to try to get a closer approximation to the normal distribution, however this did not ultimately increase my final score of my model in Kaggle. All new variables added to both training and test datasets can be found in the notebook. Partial regression plots were done as well to compare with the OLS regression summary. With each new variable test, I compared the P values for each coefficient as well as the overall F-statistic to determine statistical significance.

Build Models

The first thing I did for the model building process was write a function to be able to quickly build and analyze the model from a single string definition. I could then define a list for the exact variables I wanted to test for each iteration and run each test without a code change. I kept a record of each trial run by defining new variables for each test to correspond with the resulting output data file to be scored in Kaggle. I then used the **smf.ols()** function from the statsmodels package to fit the full model and view the results summary for each trial.

I employed a few different methods for building and testing the models. The full list of all models tested and submitted can be found in my notebook file. First, I programmed a way to build the model string that I wanted to test so that it could be broken down into individual components. To test different models, I simply had to provide the full model string and use the cells below it to perform analysis on the full and reduced models. The primary metrics used for determining the accuracy of the model were Adjusted R-Squared, AIC and BIC values. The statsmodel package was used to quickly perform the calculations and provide a table output of the summary. To compare different models I started with the Adjusted R-Squared values provided for each model string to determine the relative accuracy of the model. However, I also chose to use AIC and BIC with a step-wise iterative approach to determine which predictor variables gave the best fit. Because AIC will continue to get smaller as I add variables, I used BIC to penalized overly complex models with too many variables. The combination of the lowest AIC and BIC scored gave me insight as to which specific variables gave the best performing model.

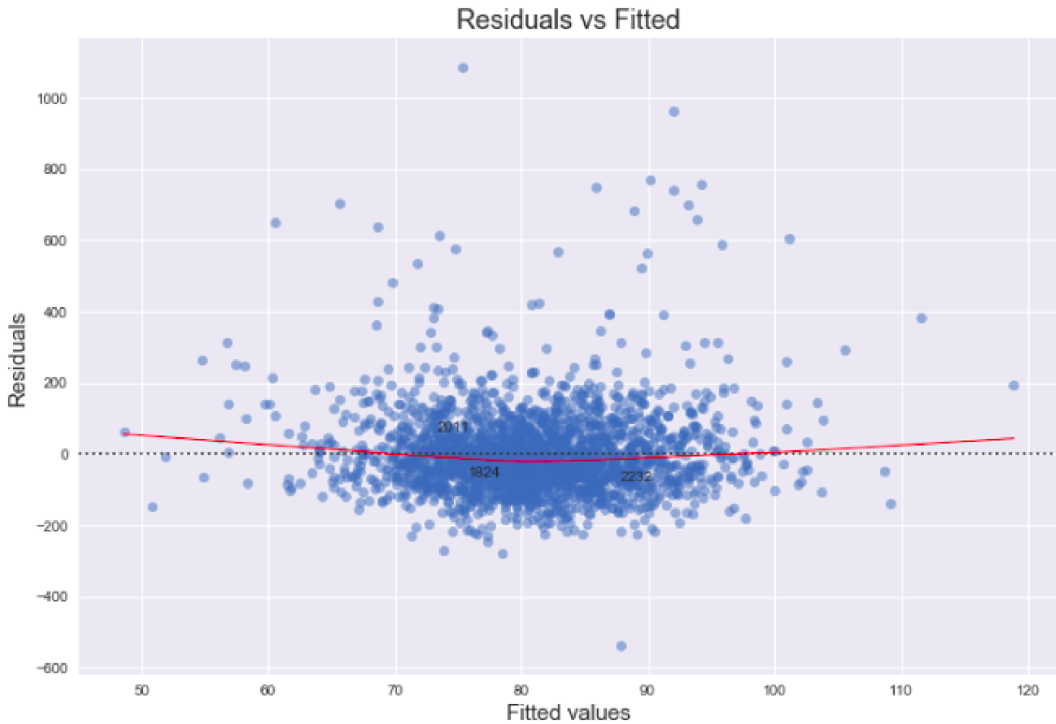
The first metric I was looking for in each was the p-value to determine the statistical significance of each coefficient included in the model. When comparing each variable for a given trial model, the first thing I looked as was the p-value to determine if the data given in that variable provided enough statistical significance to be considered as a reliable predictor of the response. A p-value of less than 0.5 indicates the variable is statistically significant so I started by removing variables like TEAM_PITCHING_SO and TEAM_BATTING_SO which gave p-values of .9 or higher. This indicates the t-test for the error between the observed and the predicted values failed. However, as I found after running several trials the resulting p-values changed depending on the variables included in the model. So, we also need to look at the relative fit of the model using the R-squared value.
The r-squared value provides a metric to determine the accuracy of the model. For the model I ultimately submitted, the R-squared was 0.220 and the Adjusted R-squared was 0.216. I found that when I used models that used the log-transformed variables I saw a higher R-squared value in general. For example, by modifying only the three TEAM_PITCHING_ variables in my same model as my selected, I saw the R-squared and Adjusted R-squared values increase to 0.232 and 0.228 respectively. However, I noticed that my public score in the Kaggle competition decreased as a result of using the log-transformed values. After trial several variations without a decreasing score I decided to omit the log values in my models altogether.
The next metric I reviewed with each trial was the skewness and kurtosis. These are useful to determine the relative location and variability in any model. We generally want to see skewness around zero and kurtosis near 3 and again I noticed the log-values tended to perform better in this regard. I noticed that for most of the models I tested, the values for these were not significantly impacted by the inclusion or exclusion of one or two variables.
Finally, in each linear regression result obtained for a given trial model, I was interested in the AIC and BIC values reported in the summary. I wanted to use this information to determine how many variables as well as which variables to include in my model.

I search for an R-like package that would given me a step-wise forward selection process that compared AIC and BIC values at each step to determine the right set of variables. Finding no such package for Python I tried to write my own. My function stepwise_fwd_selection was used for this. I included BIC because I know that AIC will continue to increase as we add more variables and concluded that finding the point where BIC values began decreasing should offer clues about stopping point. So for example in my model that included the following predictors:
TARGET_WINS ~ TEAM_BATTING_HR + TEAM_BATTING_2B + TEAM_BATTING_3B + TEAM_BATTING_BB + TEAM_FIELDING_DP + TEAM_PITCHING_SO + TEAM_BATTING_SO + TEAM_BASERUN_CS + TEAM_FIELDING_E + **LOG_TEAM_PITCHING_BB + LOG_TEAM_PITCHING_H + LOG_TEAM_PITCHING_HR**

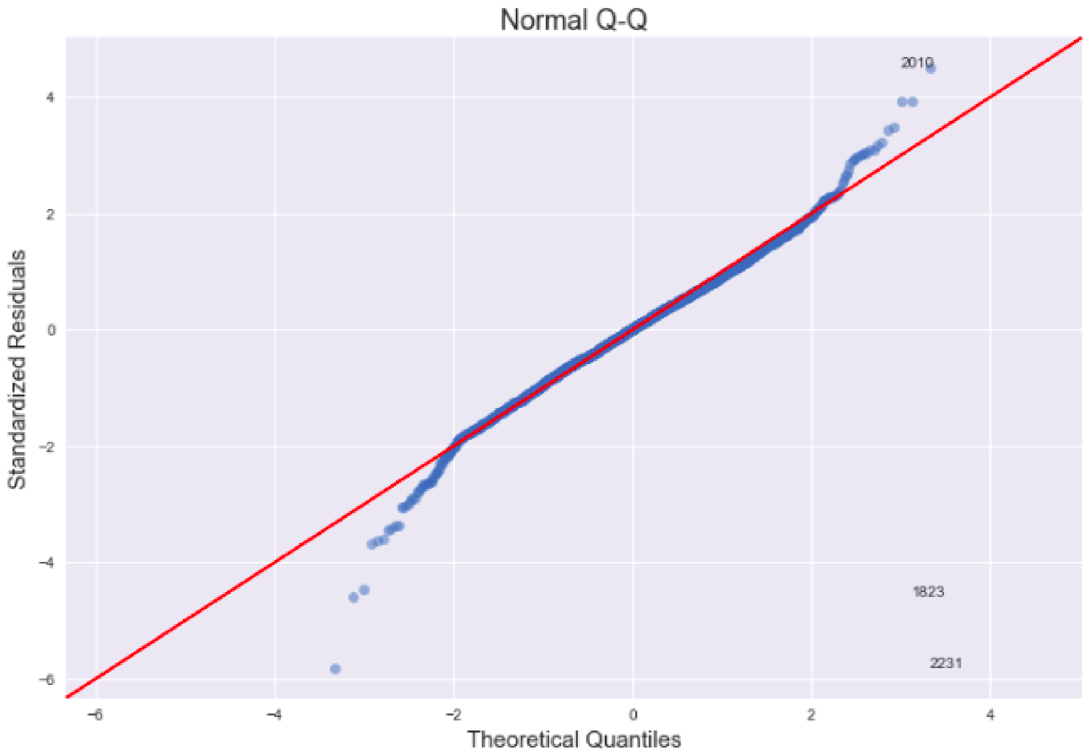
I obtained the following printed results indicating that I should try a model without the last LOG_TEAM_PITCHING_HR variable. The counts listed at the end give the max values for R-squared (11), AIC (11) and BIC (10) respectively. If BIC max value is less than AIC, it indicates my model is being penalized for being more compless. In other words, more variables may not be a good thing despite the higher R-squared value and I should try fewer, or different variables.

```
TEAM_BATTING_HR + TEAM_BATTING_2B + TEAM_BATTING_3B + TEAM_BATTING_BB + TEAM_FIELDING_DP + TEAM_PITCHING_SO + TEAM_BATTING_SO + TEAM_BASERUN_CS + TEAM_FIELDING_E + LOG_TEA
M_PITCHING_BB + LOG_TEAM_PITCHING_H + LOG_TEAM_PITCHING_HR
[0.022626330782965054, 0.0820139521697234, 0.15017217966990348, 0.174143726940155, 0.1957303173617687, 0.20731936097751102, 0.20717386050460318, 0.20688571801327804, 0.212
61405176216486, 0.2166807424867654, 0.22741230496242015, 0.22791186096443516]
11
11
10
```

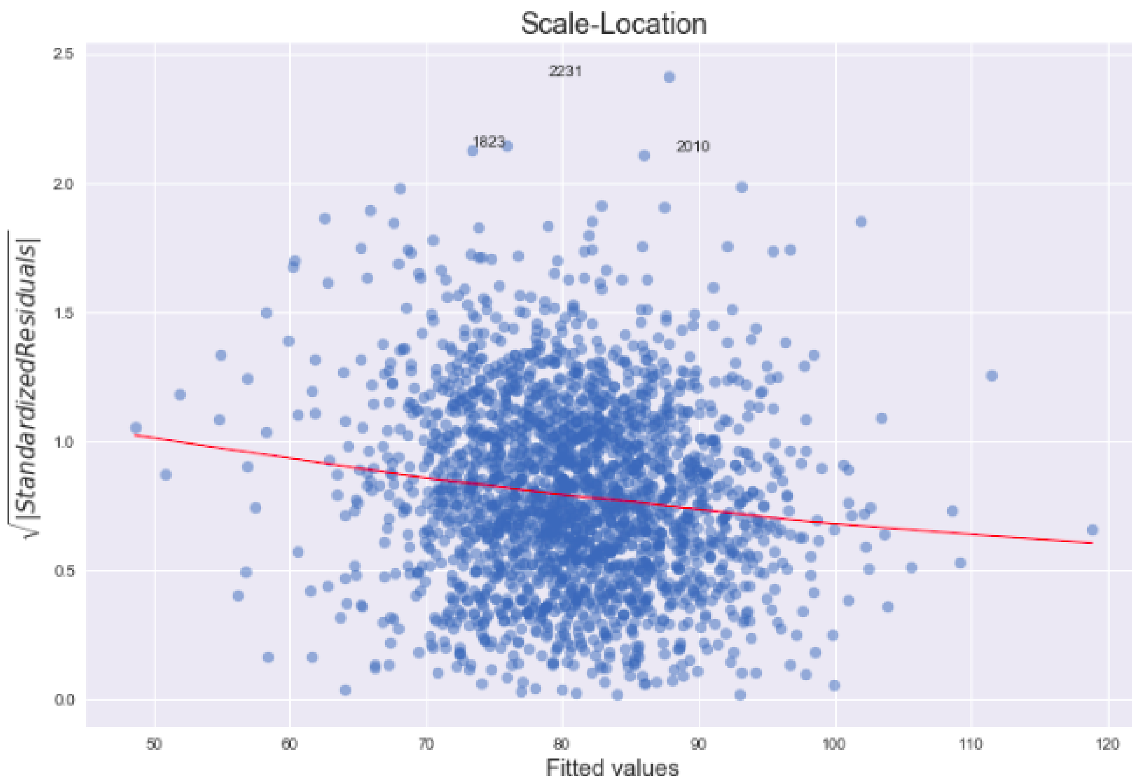
The next portion of my tests in the model building process followed the R-like plots of the OLS regression plots. These were done to verify model assumptions. The first was a plot of the residuals versus fitted values for individual single variables used in my model. While it can be time consuming to check many variables one by one, it was useful to verify the residual plot. For example, the TEAM_BATTING_H plot is shown here.



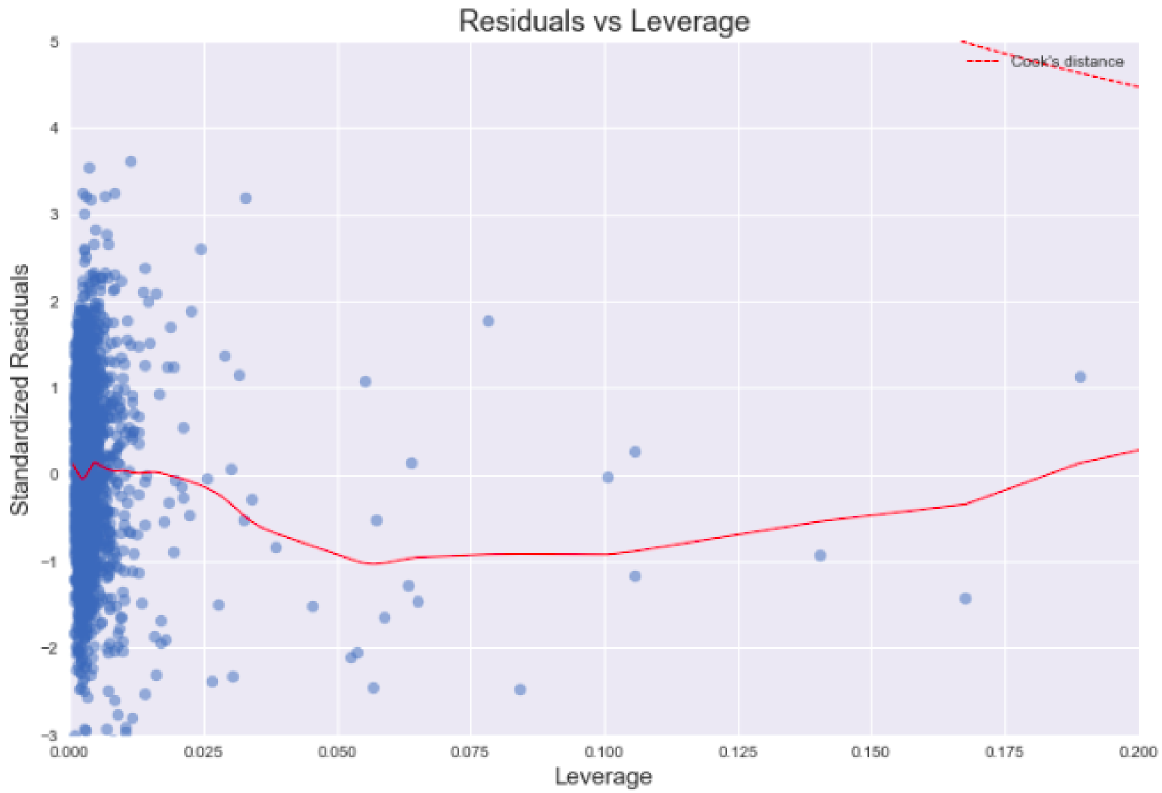
The next plot that is useful to check is the Q-Q plot of the normalized residuals shown below. This is useful for validating the common distribution assumption and for observing the ‘tail behavior’ to see effects. Here is the Q-Q plot for the same model.



The third visual item that was checked is the Scale-Location plot. Similar to the residuals plot, here again we are looking for any patterns that would indicate these residuals do not come from the normal distribution. The ideal plot shows uniform residuals versus fitted values. This is shown below.



Finally, the fourth item useful for validating model assumptions is the leverage plot. This shows the residuals versus leverage to detect the ‘pull’ of outliers within the data. The Cook’s Distance values can be used to determine any outliers that have too much leverage on the resulting fit. This is shown below.



Throughout the model building and validation process I ran several visual analyses similar to the output provided from the lm() function in R, which I had used in the past to validate model parameter selection. Using the four primary components of this aside from viewing the model results summary were the Residuals vs Fitted Values plot, the Q-Q Plot, the Scale-Location plot, and the Leverage and Cook's D plots show in the notebook output. Ultimately, these are all just tools to determine the best model and the ability of that model to accurately predict the response. The linear model summary for the final model used is given here.

```
TARGET_WINS ~ TEAM_BATTING_H + TEAM_BATTING_BB + TEAM_FIELDING_DP + TEAM_PITCHING_SO + TEAM_BATTING_SO + TEAM_FIELDIN
G_E + TEAM_PITCHING_BB + TEAM_PITCHING_H + TEAM_PITCHING_HR
                            OLS Regression Results
==============================================================================
Dep. Variable:            TARGET_WINS   R-squared:                       0.276
Model:                            OLS   Adj. R-squared:                  0.274
Method:                 Least Squares   F-statistic:                     96.17
Date:                Sun, 15 Jul 2018   Prob (F-statistic):          3.16e-152
Time:                        21:15:10   Log-Likelihood:                -9118.8
No. Observations:                2275   AIC:                         1.826e+04
Df Residuals:                    2265   BIC:                         1.831e+04
Df Model:                           9
Covariance Type:            nonrobust
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
Intercept           15.9986      5.093      3.141      0.002       6.010      25.987
TEAM_BATTING_H       0.0545      0.003     20.547      0.000       0.049       0.060
TEAM_BATTING_BB      0.0077      0.006      1.362      0.173      -0.003       0.019
TEAM_FIELDING_DP    -0.1465      0.014    -10.839      0.000      -0.173      -0.120
TEAM_PITCHING_SO    -0.0002      0.003     -0.057      0.955      -0.007       0.006
TEAM_BATTING_SO      0.0003      0.004      0.089      0.929      -0.007       0.008
TEAM_FIELDING_E     -0.0129      0.003     -4.388      0.000      -0.019      -0.007
TEAM_PITCHING_BB     0.0133      0.004      3.570      0.000       0.006       0.021
TEAM_PITCHING_H     -0.0028      0.000     -7.101      0.000      -0.004      -0.002
TEAM_PITCHING_HR     0.0224      0.008      2.681      0.007       0.006       0.039
==============================================================================
Omnibus:                       17.570   Durbin-Watson:                   1.070
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               24.991
Skew:                          -0.062   Prob(JB):                     3.74e-06
Kurtosis:                       3.498   Cond. No.                     5.17e+04
==============================================================================
```

Select Model

The model I ultimately selected was one of the simpler models based on the performance score in Kaggle. This ended up being one of my first models submitted. This model was used for submission #3 with a public score of 13.2. The final model string is as follows.

'TARGET_WINS ~ TEAM_BATTING_H + TEAM_BATTING_BB + TEAM_FIELDING_DP + TE AM_PITCHING_SO + TEAM_BATTING_SO + TEAM_FIELDING_E + TEAM_PITCHING_BB + TEAM_PITCHING_H + TEAM_PITCHING_HR'

Based on the summary table above this full model could be written as,
TARGET_WINS = 15.9986 + 0.0545 * TEAM_BATTING_H + 0.0077 * TEAM_BATTING_BB - 0.1465 * TEAM_FIELDING_DP - 0.0002 * TEAM_PITCHING_SO + 0.0003 * TEAM_BATTING_SO - 0.0129 * TEAM_FIELDING_E + 0.0133 * TEAM_PITCHING_BB - 0.0028 * TEAM_PITCHING_H + 0.0224 * TEAM_PITCHING_HR

While this formula is mostly intuitive, a couple components are a little odd like the negative coefficient value on team fielding double plays and the positive value on the team pitching home runs. Most coefficients showed positive values that would be expected based on things that contribute to good baseball, like hits, walks and good pitching. But a few seemed the opposite as expected such as positive values for things that contribute to bad baseball like bad pitching and bad defensive fielding. The model is relatively simple using nine predictors out of the possible 15 and without employing transformations. As compared to other models the AIC and BIC values of **18,260 and 18,310** were respectively lower and the R-squared value of **0.276** is reasonably high as well.

The independent variables were chosen to based on various tests performed in EDA and model validation test. First, the variable TEAM_BATTING_H showed a strong positive relationship to the number of TARGET_WINS and due to the fact that it includes all hits (singles, doubles, triples and home runs), I chose to simplify the model and use this over separating out the individual elements and risk multicollinearity issues by overlapping variables that were highly correlated in their contributions to the response variable. Also, after trying log- and sqrt-transformed variables on both predictors and the dependent response variable, these results showed that transforming the variables generally did not improve my performance. This was all surprising as many of the tests I performed which I thought would help improve the score did not. For example, standardizing data, imputing extreme outliers, taking actions to improve collinearity and transformations of the predictors all did not seem to provide a significant improvement.

Scored Data File

The final scored data file that had the best overall score ended up being **andrew_knight_predictions3.csv** on Kaggle. It is also included in the final submission files for the assignment in Canvas.

Conclusion

In conclusion, I enjoyed this assignment and the practice of performing the EDA, Data Prep and Model Building process. I would have liked to have seen a better improvement in the public score on Kaggle based on the many tests in my analysis. The Jupyter Notebook file should show the depth of the analysis that went into my final result and much effort went into clearly explaining my approach, calculations and graphical results throughout.