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Regression Analysis of Success in Major League Baseball

Johnathon Tyler Clark
University of South Carolina - Columbia

Second Reader: James Harkey

Major League Baseball (MLB) is the oldest professional sports league in the United States and Canada. Not surprisingly, after surviving multiple world wars, the Great Depression, and over 125 years, it is commonly referred to as “America’s Past-time”.

Baseball is “A Thinking Man’s Game”, and arguably more than any other sport, a game of numbers. No other sport can be explained and studied as precisely with numbers. Indeed, some of the earliest attempts at using advanced metrics to study sports were performed in the mid-twentieth century in Earnshaw Cook’s *Percentage Baseball* (Cook). After failing to attract the attention of major sports organizations, Bill James introduced Sabermetrics in the late 1970s, which is the empirical analysis of athletic performance in baseball (Sabermetrics is named after SABR, or the Society for American Baseball Research). Perhaps the most famous use of a statistical approach to baseball is described in *Moneyball*, the 2003 book by Michael Lewis about Billy Beane, the manager of the Oakland A’s professional baseball team (Lewis). In an organization with minimal amounts of money to spend, Beane went against the grain of managerial baseball and used an analytical approach to finding the right players to help his team rise far above expectations and compete at the same level as the richest teams in the MLB.

This thesis is designed to explore whether a team’s success in any given season can be predicted or explained by any number of statistics in that season. There are thirty teams in the MLB; of these thirty, ten make the postseason bracket-style playoffs. The MLB is divided up into two leagues, the American League and the National League; these two leagues are then divided up into three divisions each, the West Division, the Central Division, and the East Division. To make the playoffs a team must either have the most wins in its division after the last game of the season is played, or it can obtain a Wild Card slot by having either the best or second best record among the non-divisional champions.

It is considered a great accomplishment for a team if it makes the postseason playoffs; indeed, since 1996, out of a 162-game season, the lowest number of wins a team has made the playoffs with is 82, with the average being just above 94. This thesis will investigate whether a team's likelihood of making the playoffs, as measured by their regular season win percentage, can be predicted by offensive and defensive statistics, and then investigate which of these offensive and defensive statistics have the most impact on win percentage.

Because baseball is so numbers-heavy, there are many different statistics to consider when searching for the best predictors of team success. There are offensive statistics (offense meaning when a team is batting) and defensive statistics (defense meaning when a team is in the field). These categories can be broken up into many more subcategories. However, for the purpose of this thesis, batting statistics, pitching statistics, and team statistics will be the only categories studied.

The batting statistics that will be used in this study are R/G, 1B, 2B, 3B, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, E, and DP. Below is a description of what each statistic means:

- R/G- Runs per game. Calculated by taking the total number of runs a team scores in its season divided by the number of games it plays.
- 1B- total singles for a team in a season. A single is defined as when a player hits the ball and arrives safely at first base on the play, assuming no errors by the fielding team. Denoted as 'X1B' in this study.
- 2B- total number of doubles for a team in a season. A double is defined as when a player hits the ball and arrives safely at second base on the play, assuming no errors by the fielding team. Denoted as 'X2B' in this study.

- 3B- total number of triples for a team in a season. A triple is defined as when a player hits the ball and arrives safely at third base on the play, assuming no errors by the fielding team. Denoted as ‘X3B’ in this study.
- HR- total number of home runs for a team in a season. A home run is defined as when a player either hits the ball over the outfield fence in the air or hits the ball and runs all the way around the bases back to home plate, assuming no errors by the fielding team.
- RBI- total number of runs batted in for a team in a season, calculated as runs a team scores that were the result of a hit.
- SB- total number of stolen bases for a team in a season, calculated as when a baserunner advances to the next base and not as a result of a hit.
- CS- total number of times a runner is tagged out attempting to steal a base for a team in a season.
- BB- total number of walks for a team in a season. A walk is defined as four balls thrown to a batter, with a ball being any pitch thrown outside the strike-zone.
- SO- total number of strikeouts for a team in a season. A strikeout is defined as three pitches thrown for strikes to a batter, with a strike being any pitch hit foul by a batter or thrown in the strike zone, and the third strike not tipped by the batter or it is tipped foul while attempting a bunt.
- BA- a team’s total batting average, calculated by dividing the total number of hits a team gets by its total number of at-bats (not including at-bats that result in walks).
- OBP- a team’s total on-base percentage, calculated by dividing the total number of times an at-bat results in the batter getting on base by the total number of at-bats.

- SLG- a team’s total slugging percentage, which weights hits for the number of bases that hit awards the batter. Calculated by dividing the total number of bases all batters are awarded over their at-bats by total at-bats.
- E- total number of errors all opposing teams commit in a season.
- DP- total number of double plays turned against a team in a season. A double play is when two outs are recorded in a single play.

The pitching statistics that will be used in this study are RA/G, ERA, CG, tSho, SV, IP, H, ER, HR, BB, SO, WHIP, E, DP, and Fld%. Below is a description of what each statistic means:

- RA/G- runs allowed per game, defined as the total number of runs a team allows in a season divided by the total number of games played.
- ERA- earned run average, or a team’s number of earned runs given up divided by total number of innings pitched.
- CG- complete games, or number of games in which the starting pitcher for a team pitches the entire game for that team.
- tSho- team shutouts, defined as the number of games a team does not allow a single run among all of its pitchers for that game.
- SV- total saves for a team. A save is defined as when a pitcher enters the game with a lead of no more than three runs and pitches for at least one inning and wins; or when a pitcher enters the game regardless of score, with the potential tying run either on base, at-bat, or next at-bat and wins; or a pitcher comes in and pitches for at least three innings and wins.

- IP- innings pitched, calculated as the total number of innings pitched by a team in a season.
- H- hits, calculated as total number of hits allowed by a team in a season. Denoted as ‘p_H’ in this study.
- ER- earned runs, calculated as total number of earned runs allowed by a team in a season. An earned run differs from a run in that the run has to be from a hit, and cannot be the result of an error.
- HR- home runs, calculated as total number of home runs allowed by a team in a season. Denoted as ‘p_HR’ in this study.
- BB- walks, calculated as total number of walks allowed by a team in a season. Denoted as ‘p_BB’ in this study.
- SO- strikeouts, calculated as total number of strikeouts by a team’s pitchers in a season. Denoted as ‘p_SO’ in this study.
- WHIP- walks and hits per inning pitched, calculated as the total number of walks and hits allowed by a team divided by the total number of innings pitched for the team.
- E- errors, calculated as total number of errors committed by a team in a season. Denoted as ‘p_E’ in this study.
- DP- double plays, calculated as total number of double plays a team makes in a season. Denoted as ‘p_DP’ in this study.
- Fld%- fielding percentage, defined as the percentage of times a defensive player properly handles a ball that has been put in play. It is calculated by dividing the sum of putouts and assists by the sum of putouts, assists, and errors; in other words, the percentage of time the team’s defense has a chance to make a play and does make the play.

The team statistics that will be used in this study are W, L, T, W-L%, Finish, GB, Playoffs, R, and RA. Below is a description of what each statistic means:

- W- wins, calculated as total number of wins by a team in a season.
- L- losses, calculated as total number of losses by a team in a season.
- T- ties, calculated as total number of ties by a team in a season. Note, only in extreme circumstances will regular season games end in a tie (playoff games will never end in a tie); such circumstances include if the game has been played at least half-way and the score is tied and the game cannot be finished due to weather and cannot be made up.
- W_L_pct- win/loss percentage, calculated by dividing total number of wins by a team in a season by the total number of games played by that team in that season, and then multiplying by 100 to get a true percent. Making it a true percent will make it easier to interpret the coefficients of the independent variables in the regression.
- Finish- this is the place in the team's respective division that the team ended at in a season; there are currently five teams in each division.
- GB- games behind, calculated as the number of wins the leading team got in a given team's division minus the number of wins the given team had.
- Playoffs- calculated as either a team made the playoffs in a given year or it did not make the playoffs in the given year.
- R- runs scored by a team in a season.
- RA- runs allowed by a team in a season.

All of the aforementioned statistics are taken from Baseball-Reference.com (Baseball Reference). The website has all of the hitting, pitching, and overall statistics for each team going back as far as the team has been in existence. Since 1961, the MLB has had 162-game seasons.

In 1994 and 1995, the MLB regular season was shortened due to strikes by the players. In 1996, the strikes ended and the 162-game seasons resumed, and this number of games per season has remained through today. In order to have seasonal data from only 162-game seasons, and to keep as many teams as possible in the study, data from the present day back until 1996 will be collected for each team. This will ensure that the statistics are comparable across season. Furthermore, all of the statistical analytics will be performed in the statistical software package R (R Core Team).

The first step in this study is to select the independent variables, or predictors, and the dependent variable. Once the variables are initially selected, a preliminary regression equation will be fit to the data in R. Then variable selection will be undertaken to determine which of the variables are necessary and which are not. Next, the assumptions of the model must be checked to make sure they hold for the data, we must check for multicollinearity, and we must check for outliers or influential observations.

Deciding on Candidate Independent Variables

The dependent variable, or regular season success, can be represented by the continuous W_L_pct variable (Win-Loss percentage), or be represented in the logistic transformation form of Yes/No for if the team in question made the playoffs that year or not (or 1/0, 1 if the team made the playoffs and 0 if the team did not make the playoffs). In the absence of evidence that a transformation of the dependent variable for regular season success is needed, we will use Win-Loss percentage.

Before the independent variables can be narrowed down from all of the available ones, it is a good idea to quickly plot all of the possible independent variables against Win-Loss percentage to check whether any of the independent variables need to be transformed, e.g., logarithmically or exponentially, etc. If the plot of a variable has a curved shape or any otherwise abnormal shape, as opposed to a scattered appearance or roughly linear shape, the variable might need to be transformed. To obtain the plot, an example code can be seen below, plotting the dependent variable W_L_pct against the independent variable of X2B:

```
>plot(X2B,W_L_pct)
```

To obtain the plot for every independent variable, one simply interchanges a new independent variable for ‘X2B’ in the code above. An examination of these plots shows that none of the independent variables have anything other than a scattered or linear shape, so no transformation should be necessary.

Once the independent variables have been initially checked, candidate independent variables can be selected. Baseball success certainly has many aspects and a team’s success cannot be boiled down to one or two statistics; however, it is the aim of this study to determine whether a relatively small number of statistics can give an accurate representation of how well a team does in a season, so the set of independent variables will have to be narrowed down.

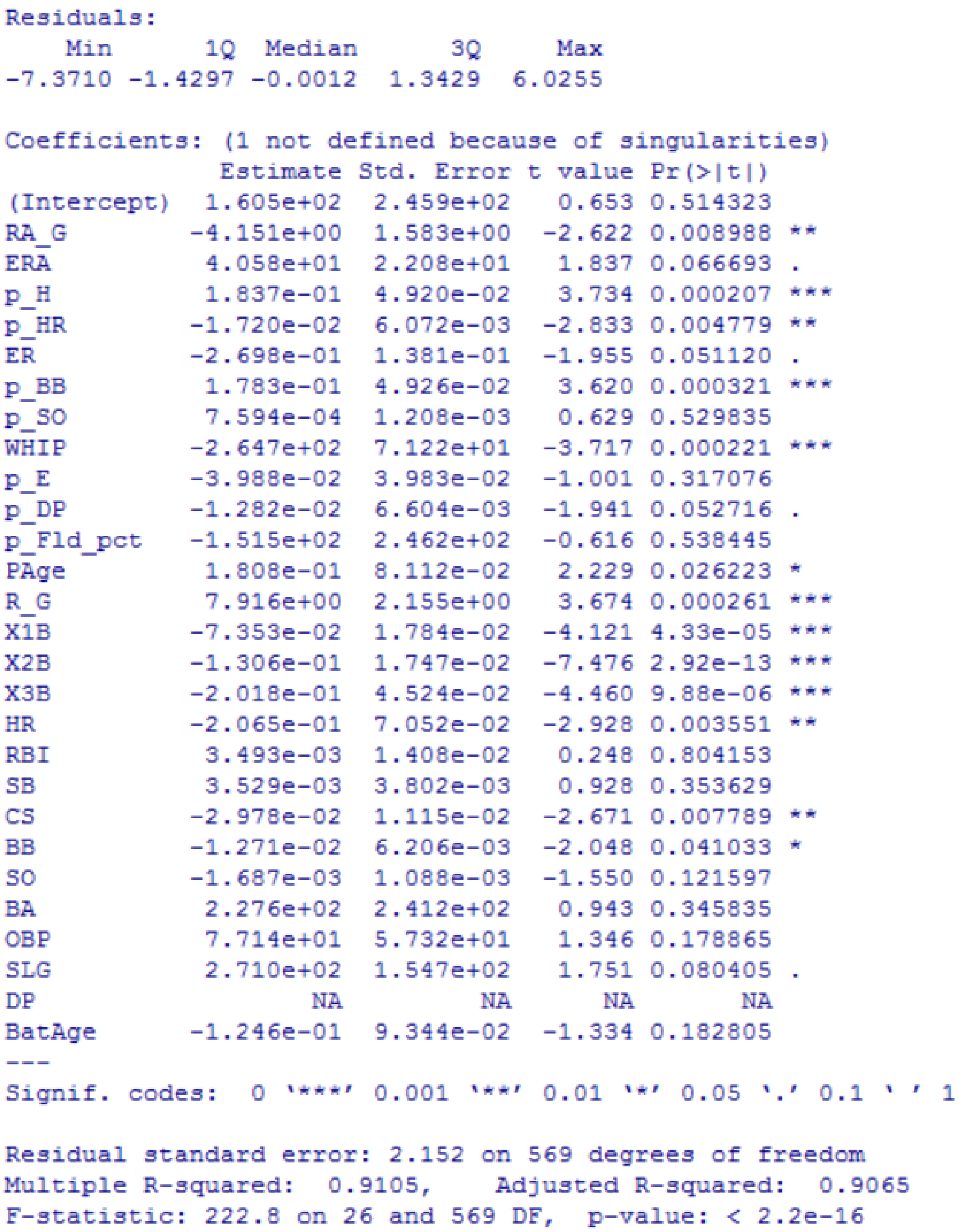
The hitting statistics that will be initially considered as predictors will be R_G, X1B, X2B, X3B, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, BatAge, and DP. The pitching statistics that will be initially considered as predictors will be RA_G, ERA, p_H, p_HR, ER, p_BB, p_SO, WHIP, p_E, p_DP, p_Fld_pct, and PAge.

Fitting the Preliminary Regression

Now that the variables have been selected, they can be fit into a linear regression. To do this, we use the following code in R:

```
> linreg_regseason <- lm(W_L_pct*100~RA_G + ERA + p_H + p_HR + ER + p_BB +
p_SO + WHIP + p_E + p_DP + p_Fld_pct + PAge + R_G + X1B + X2B + X3B + HR +
RBI + SB + CS + BB + SO + BA + OBP + SLG + DP + BatAge,
data=complete.data.used)
```

This linear regression produces the following coefficients for the respective independent variables, which are found in the ‘Estimate’ column:



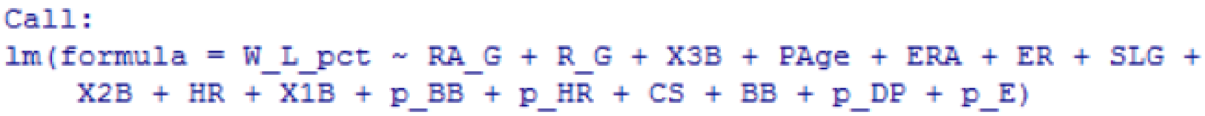
```
Residuals:
    Min      1Q  Median      3Q     Max 
-7.3710 -1.4297 -0.0012  1.3429  6.0255 

Coefficients: (1 not defined because of singularities)
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  1.605e+02  2.459e+02   0.653 0.514323    
RA_G        -4.151e+00  1.583e+00  -2.622 0.008988 ** 
ERA          4.058e+01  2.208e+01   1.837 0.066693 .  
p_H          1.837e-01  4.920e-02   3.734 0.000207 ***
p_HR        -1.720e-02  6.072e-03  -2.833 0.004779 ** 
ER          -2.698e-01  1.381e-01  -1.955 0.051120 .  
p_BB         1.783e-01  4.926e-02   3.620 0.000321 ***
p_SO         7.594e-04  1.208e-03   0.629 0.529835    
WHIP        -2.647e+02  7.122e+01  -3.717 0.000221 ***
p_E         -3.988e-02  3.983e-02  -1.001 0.317076    
p_DP        -1.282e-02  6.604e-03  -1.941 0.052716 .  
p_Fld_pct   -1.515e+02  2.462e+02  -0.616 0.538445    
PAge         1.808e-01  8.112e-02   2.229 0.026223 *  
R_G          7.916e+00  2.155e+00   3.674 0.000261 ***
X1B         -7.353e-02  1.784e-02  -4.121 4.33e-05 ***
X2B         -1.306e-01  1.747e-02  -7.476 2.92e-13 ***
X3B         -2.018e-01  4.524e-02  -4.460 9.88e-06 ***
HR          -2.065e-01  7.052e-02  -2.928 0.003551 ** 
RBI          3.493e-03  1.408e-02   0.248 0.804153    
SB           3.529e-03  3.802e-03   0.928 0.353629    
CS          -2.978e-02  1.115e-02  -2.671 0.007789 ** 
BB          -1.271e-02  6.206e-03  -2.048 0.041033 *  
SO          -1.687e-03  1.088e-03  -1.550 0.121597    
BA           2.276e+02  2.412e+02   0.943 0.345835    
OBP          7.714e+01  5.732e+01   1.346 0.178865    
SLG          2.710e+02  1.547e+02   1.751 0.080405 .  
DP                  NA         NA      NA       NA    
BatAge      -1.246e-01  9.344e-02  -1.334 0.182805    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.152 on 569 degrees of freedom
Multiple R-squared:  0.9105,	Adjusted R-squared:  0.9065 
F-statistic: 222.8 on 26 and 569 DF,  p-value: < 2.2e-16
```

Variable Selection

Now that we have a preliminary regression fit to the data, we can narrow down the variables in our model using tests that can shed light on which variables are unnecessary. We begin with a stepwise procedure. We call a ‘step’ function in R, which goes through the variables in the regression and through a series of additions or deletions of variables based on their values in the regression, and provides a list of necessary variables. To do this, we first use a step function that starts with no variables and works its way up until it reaches the correct number and combination of variables:

```
> step(null, scope=list(lower=null, upper=linreg_regseason), direction="both")
```

This function gives us the following regression fit:



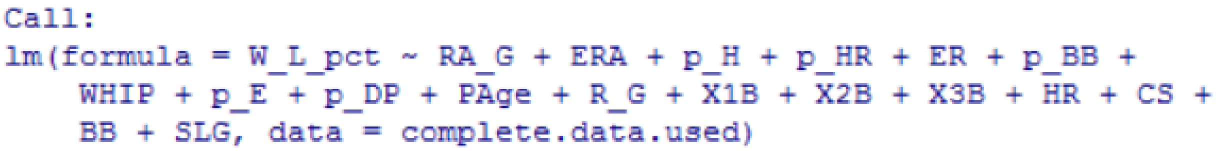
```
Call:
lm(formula = W_L_pct ~ RA_G + R_G + X3B + PAge + ERA + ER + SLG + 
    X2B + HR + X1B + p_BB + p_HR + CS + BB + p_DP + p_E)
```

As can be seen, the regression we originally chose has been narrowed down from 27 variables to 16.

Now, we use the same step function, but use backward elimination. This reverses directions so it starts with all the variables and whittles the regression down to the necessary number and combination, to compare the list of variables to the stepwise list:

```
> step(linreg_regseason, scope=list(lower=null, upper=linreg_regseason),
direction="backward")
```

This function gives us the following regression fit:



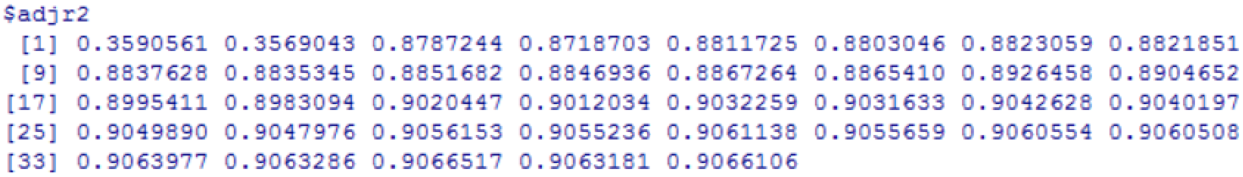
```
Call:
lm(formula = W_L_pct ~ RA_G + ERA + p_H + p_HR + ER + p_BB +
    WHIP + p_E + p_DP + PAge + R_G + X1B + X2B + X3B + HR + CS +
    BB + SLG, data = complete.data.used)
```

This time, the regression narrowed the 27 variables down to 18; the only difference between the two is the backward step function added p_H and WHIP. Thus, moving forward, we will keep all of the variables provided by either step function, or, essentially, the regression provided by the backward step function. Furthermore, CS was included in both but SB was not, so seemingly the number of times a team is caught stealing is more influential than the number of times it successfully steals a base. I would like to examine the effect of SB further, so I will add SB to the regression, giving us a total of 19 variables.

As a subsequent method for variable selection, we run a 'leaps' function in R (Lumley). For our data, this gives us the best-fitting regression equations for any fixed number of variables we want to include. In this case, we give it a total of 19 variables to test, so it provides the two best-fitting one-variable regression equations, the two best-fitting two-variable regression equations, and so on, up to the two best-fitting 18-variable regression equations and then the lone 19-variable regression equation. It then provides the adjusted r-squared value for each regression equation. Adjusted r-squared is a measure of how well a regression equation fits its data, while penalizing the model for having a higher number of variables; in essence, a model is unlikely to have a high adjusted r-squared value if it fits the data well but has several unnecessary variables. The code for this test is:

```
> leaps(x = cbind(SB, RA_G, R_G, X3B, PAge, ERA ,ER, SLG, X2B, HR, X1B, p_BB, p_HR, CS, BB, p_DP, p_E, p_H, WHIP), y = W_L_pct*100, nbest = 2, method = "adjr2")
```

This code produces a very large table, but the adjusted r-squared values for the 37 different equations are:



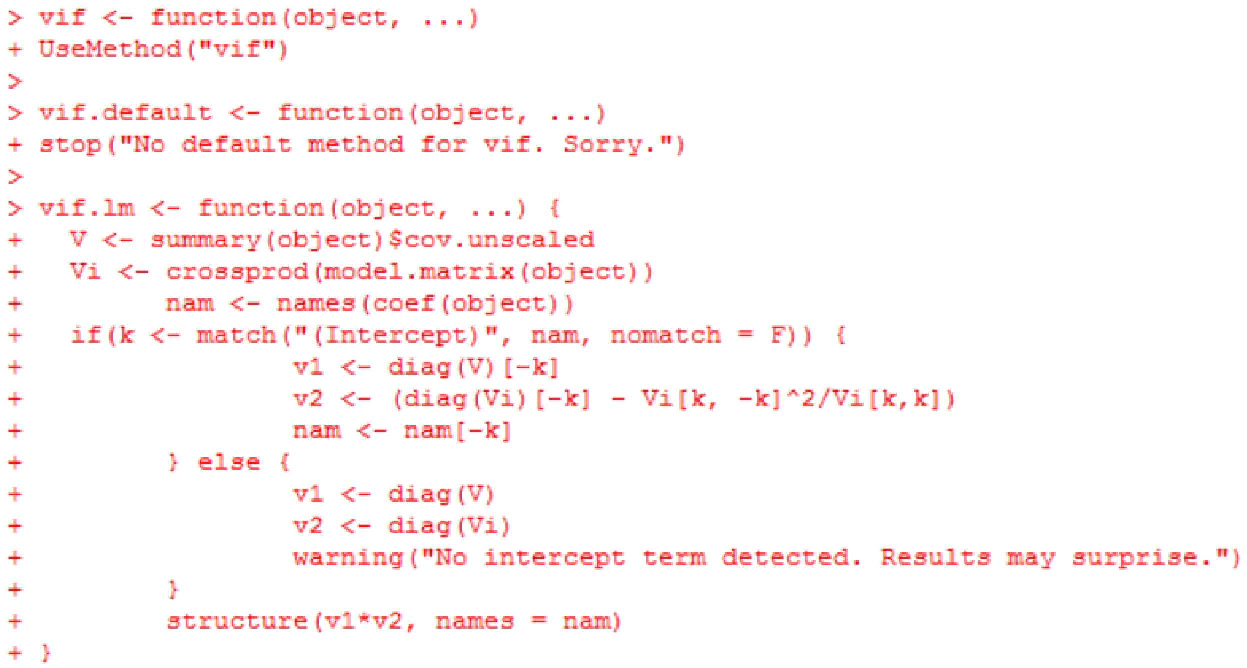
```
$adjr2
 [1] 0.3590561 0.3569043 0.8787244 0.8718703 0.8811725 0.8803046 0.8823059 0.8821851
 [9] 0.8837628 0.8835345 0.8851682 0.8846936 0.8867264 0.8865410 0.8926458 0.8904652
[17] 0.8995411 0.8983094 0.9020447 0.9012034 0.9032259 0.9031633 0.9042628 0.9040197
[25] 0.9049890 0.9047976 0.9056153 0.9055236 0.9061138 0.9055659 0.9060554 0.9060508
[33] 0.9063977 0.9063286 0.9066517 0.9063181 0.9066106
```

Note, adjusted r-squared values can be at most 1, so the highest value, .9066517, (value [35]) indicates that regression is a very good fit. This equation is one in which all the variables are used except SB; however, I am still interested in investigating its effects, so we will keep it in the model, and stay at 19 variables.

These 19 variables are then entered into a new regression:

```
> reg_better = lm(W_L_pct*100 ~ SB+ RA_G+ R_G+ X3B+ PAge+ ERA +ER+ SLG+ X2B+ HR+ X1B+ p_BB+ p_HR+ CS+ BB+ p_DP+ p_E+ p_H+ WHIP)
```

We also investigate multicollinearity. Multicollinearity is when some predictors are linear combinations of others; for example, the two variables ‘Height in feet’ and ‘Height in inches’ would be collinear, as ‘Height in feet’ can be expressed as (1/12)* ‘Height in inches’. When there is multicollinearity present, problems occur in the estimation of the coefficients of the linear regression. Next, we create a function that can take a regression equation and provide the VIF’s for the variables. VIF, or Variance Inflation Factor, is a test used to search for multicollinearity; that is, it compares the inflation of the variance of estimated regression coefficients in a linear relationship with the variance of estimated regression coefficients in a non-linear relationship. Lower values are desired, as it means variables most likely are not in a linear relationship with each other, and thus are necessary. The function can be seen below (Hitchcock):

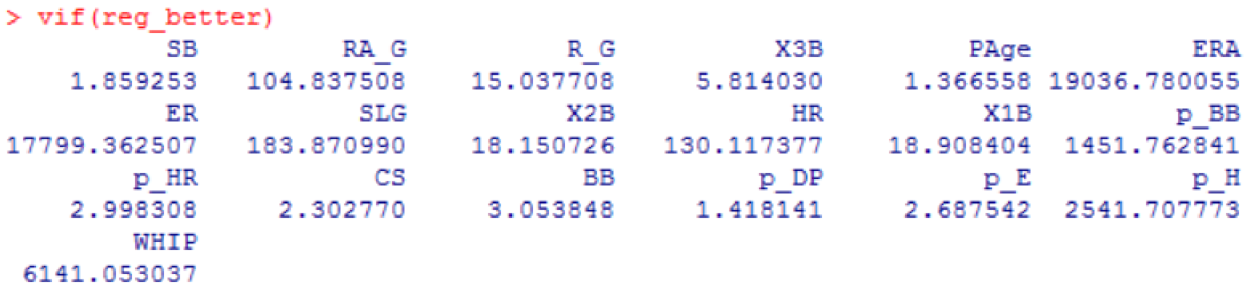


```
> vif <- function(object, ...)
+ UseMethod("vif")
>
> vif.default <- function(object, ...)
+ stop("No default method for vif. Sorry.")
>
> vif.lm <- function(object, ...) {
+   V <- summary(object)$cov.unscaled
+   Vi <- crossprod(model.matrix(object))
+         nam <- names(coef(object))
+   if(k <- match("(Intercept)", nam, nomatch = F)) {
+                 v1 <- diag(V)[-k]
+                 v2 <- (diag(Vi)[-k] - Vi[k, -k]^2/Vi[k,k])
+                 nam <- nam[-k]
+         } else {
+                 v1 <- diag(V)
+                 v2 <- diag(Vi)
+                 warning("No intercept term detected. Results may surprise.")
+         }
+         structure(v1*v2, names = nam)
+ }
```

Now, to view the VIFs of our regression equation, we type vif(*name of our equation), or:

> vif(reg_better)

and the VIFs are provided:

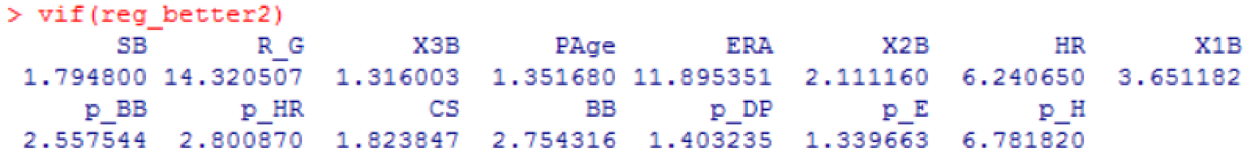


```
> vif(reg_better)
          SB          RA_G           R_G           X3B          PAge           ERA
    1.859253    104.837508     15.037708      5.814030      1.366558  19036.780055
          ER           SLG           X2B            HR           X1B          p_BB
17799.362507    183.870990     18.150726    130.117377     18.908404   1451.762841
        p_HR            CS            BB          p_DP           p_E           p_H
    2.998308      2.302770      3.053848      1.418141      2.687542   2541.707773
        WHIP
 6141.053037
```

Here, we can see RA_G, ERA, ER, SLG, HR, p_BB, p_H, and WHIP initially have incredibly high VIFs. This can be explained easily, as we would expect RA_G to be closely related to ERA and ER; SLG to be potentially related to HR; and p_H and p_BB to be closely related to WHIP.

Thus, we will eliminate RA_G, ER, SLG, and WHIP, as they can be expressed by the remaining variables. We then create a new regression analysis, and find the VIFs of this new equation:

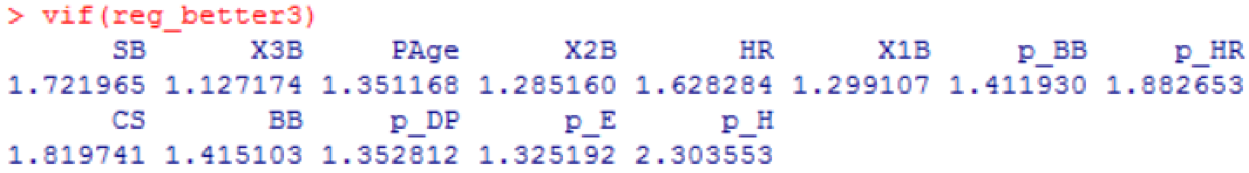
> reg_better2 = lm(W_L_pct*100 ~ SB+ R_G+ X3B+ PAge+ ERA + X2B+ HR+ X1B+ p_BB+ p_HR+ CS+ BB+ p_DP+ p_E+ p_H)



```
> vif(reg_better2)
       SB       R_G       X3B      PAge       ERA       X2B        HR       X1B 
 1.794800 14.320507  1.316003  1.351680 11.895351  2.111160  6.240650  3.651182 
     p_BB      p_HR        CS        BB      p_DP       p_E       p_H 
 2.557544  2.800870  1.823847  2.754316  1.403235  1.339663  6.781820 
```

These VIFs are much more manageable; however, the VIFs of R_G and ERA are still a little too high to be accepted and these predictors could be related to other variables, so we will eliminate them from the regression analysis, and repeat the steps:

> reg_better3 = lm(W_L_pct*100 ~ SB+ X3B+ PAge + X2B+ HR+ X1B+ p_BB+ p_HR+ CS+ BB+ p_DP+ p_E+ p_H)



```
> vif(reg_better3)
      SB      X3B     PAge      X2B       HR      X1B     p_BB     p_HR 
1.721965 1.127174 1.351168 1.285160 1.628284 1.299107 1.411930 1.882653 
      CS       BB     p_DP      p_E      p_H 
1.819741 1.415103 1.352812 1.325192 2.303553 
```

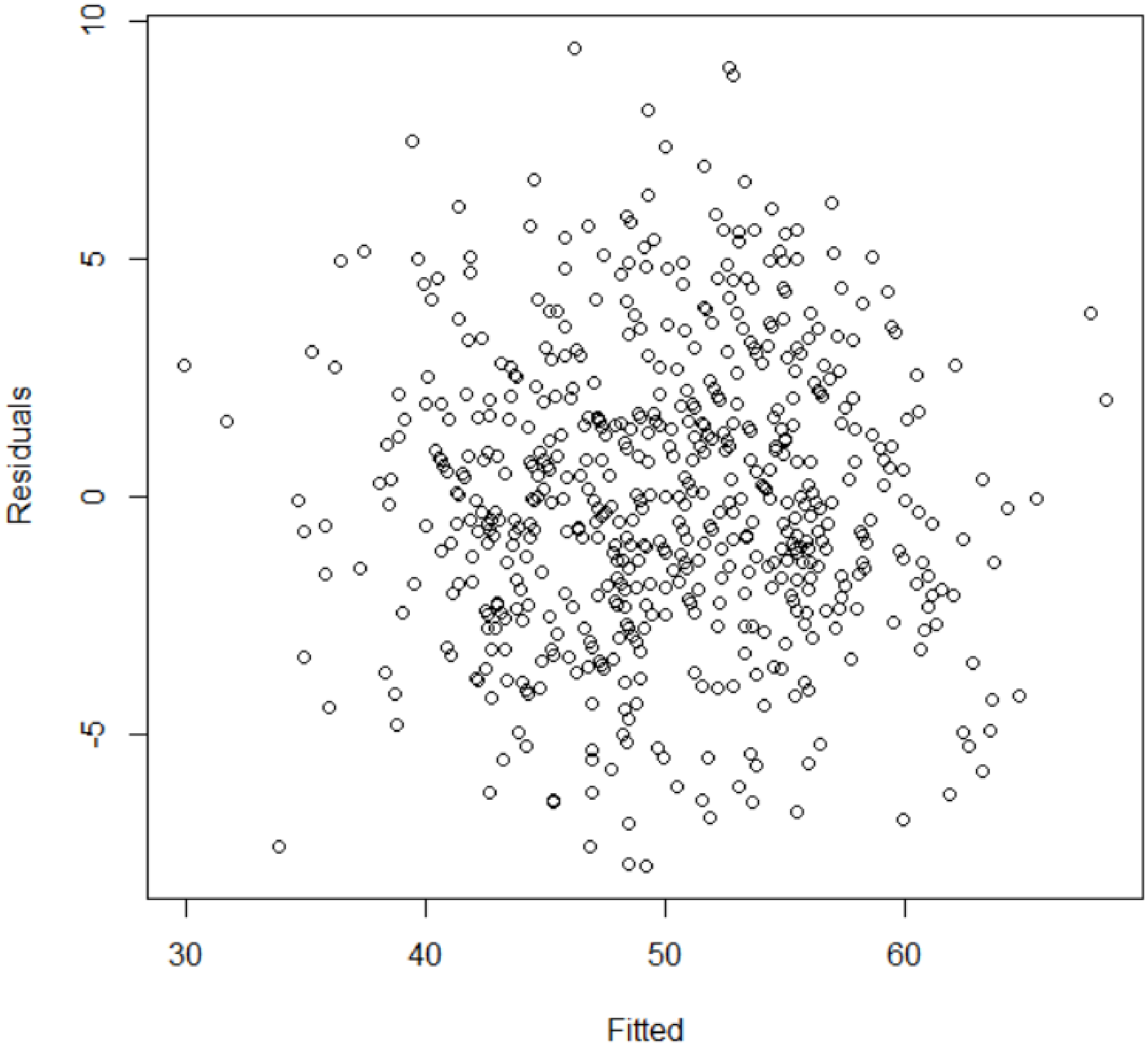
These VIFs are very small, within the acceptable range, so we move on to check the model assumptions for our regression.

Checking Model Assumptions

When checking to see whether our model assumptions hold for the data, we need to check for constant error variance (is the variance of the errors a constant value or does it depend on some variable?); model specification (is the data best represented by a linear or nonlinear regression?); normality of errors (do the errors closely follow a normal distribution or are they distributed irregularly?); and independent errors (are the errors independent of one another or are they related?).

An initial test for these assumptions is to plot the residuals of the linear regression against the fitted values of the observations. To do this, the following code is used, and the following chart produced:

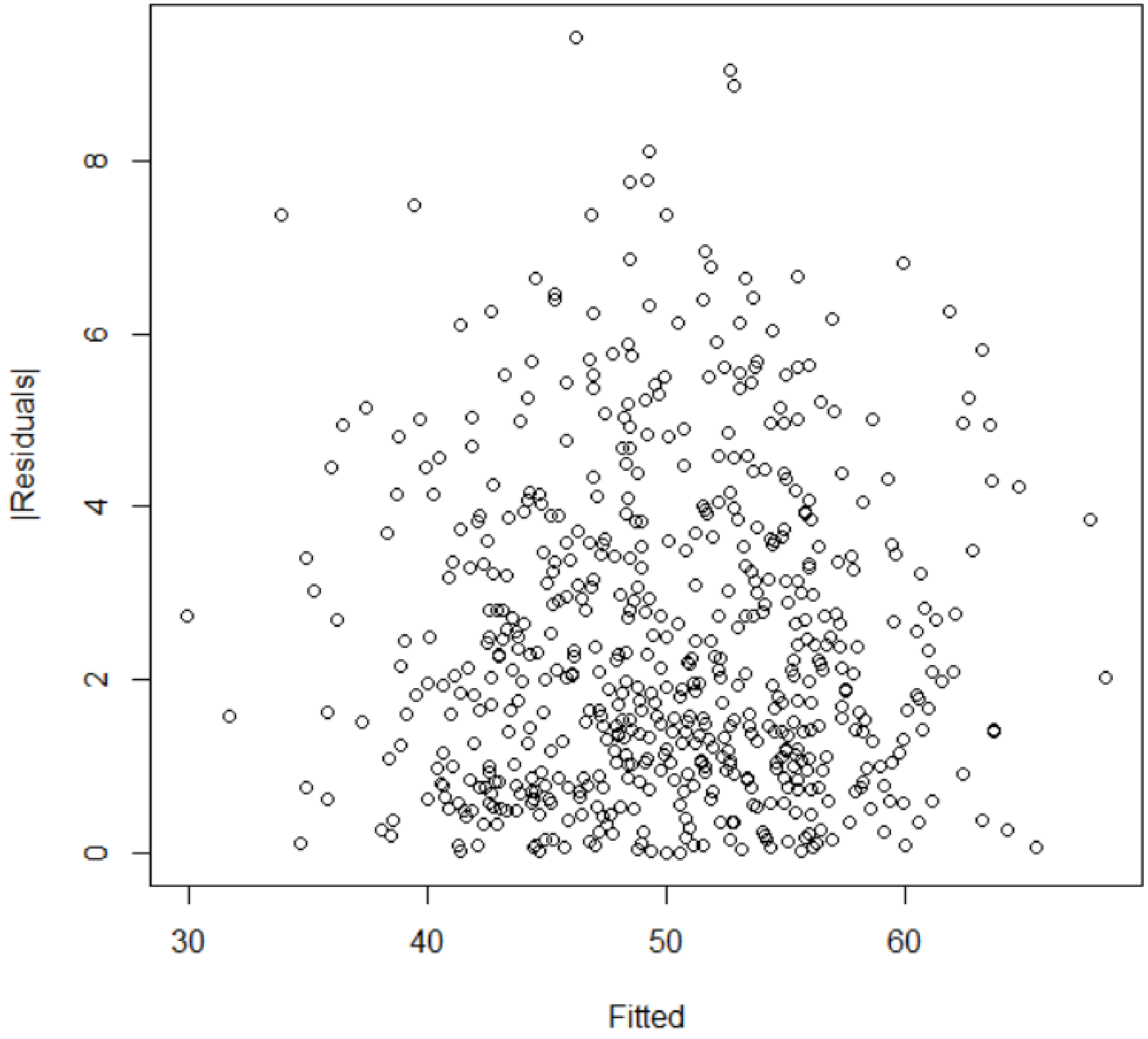
```
>plot(fitted(reg_better3),residuals(reg_better3),xlab="Fitted",ylab="Residuals”)
```



This plot tells us a few things about the data. First of all, because the spread of the residuals does not increase or decrease with the fitted values, there is not an issue of heteroscedasticity (heteroscedasticity meaning the variance of the regression changes for larger or smaller fitted values). This means the error variance of the data is constant, meeting the constant error variance assumption. Additionally, because the plot displays random scatter, there is no indication that the regression relationship is nonlinear (as opposed to if the plot had, say, a parabolic shape), so a linear regression is the appropriate model specification for this data.

To provide added clarity for detecting nonconstant variance, the predicted values of the regression are plotted against the absolute value of the residuals. This folds up the bottom half of the above plot to help provide insight into any patterns that could be missed in the above plot. This is done with the following code, and produces the following plot:

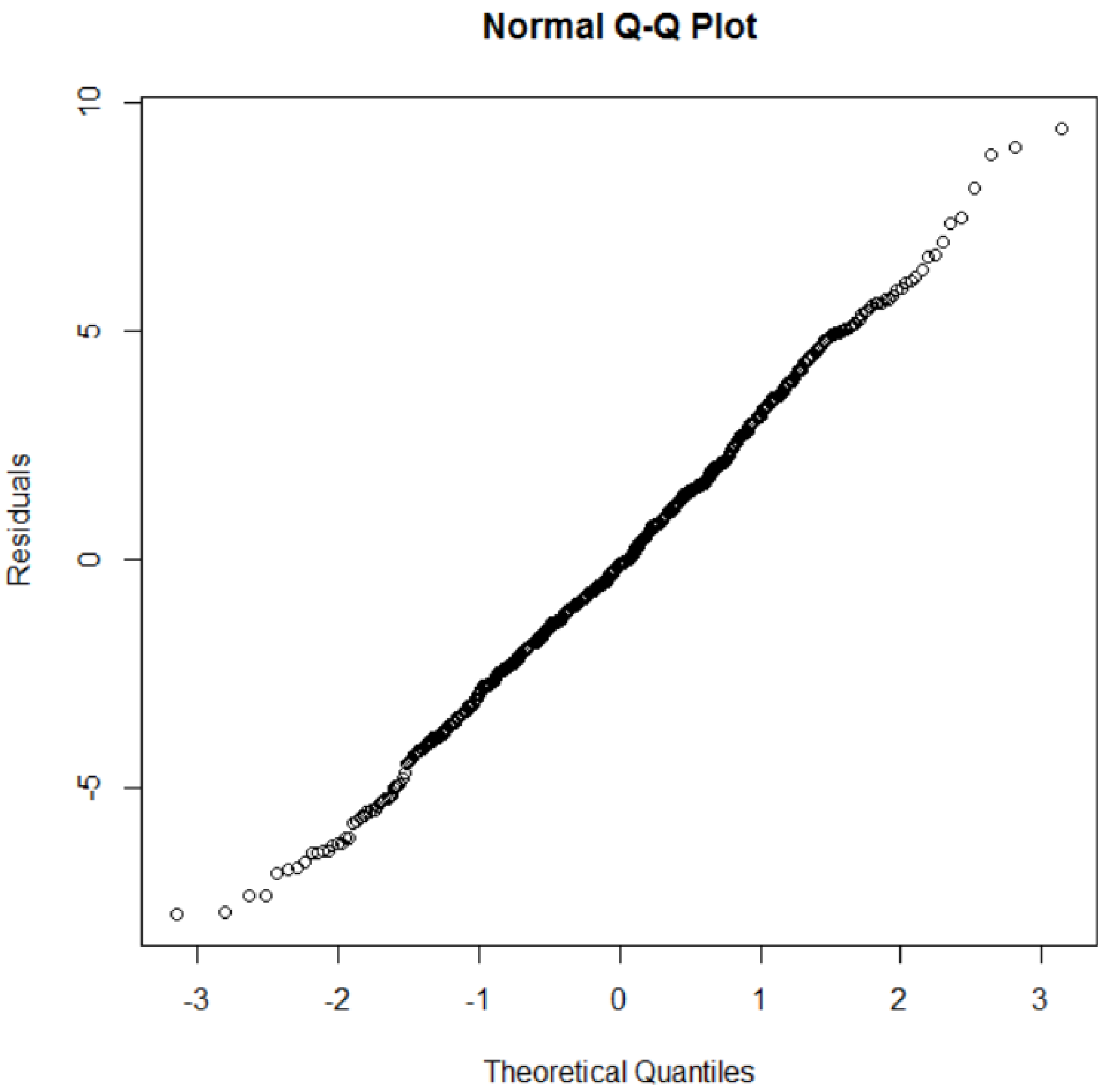
```
>plot(fitted(reg_better3),abs(residuals(reg_better3)),xlab="Fitted",ylab="|Residuals|")
```



Again, there does not seem to be any sort of heteroscedastic or nonlinear issue with this plot, and thus there does not seem to be an issue with nonconstant variance.

The testing that we are using assumes the errors are normally distributed. To check for this, a Q-Q plot is created, which compares the residuals with what we would expect as normal observations. To do this, the following code is used and the following plot is produced:

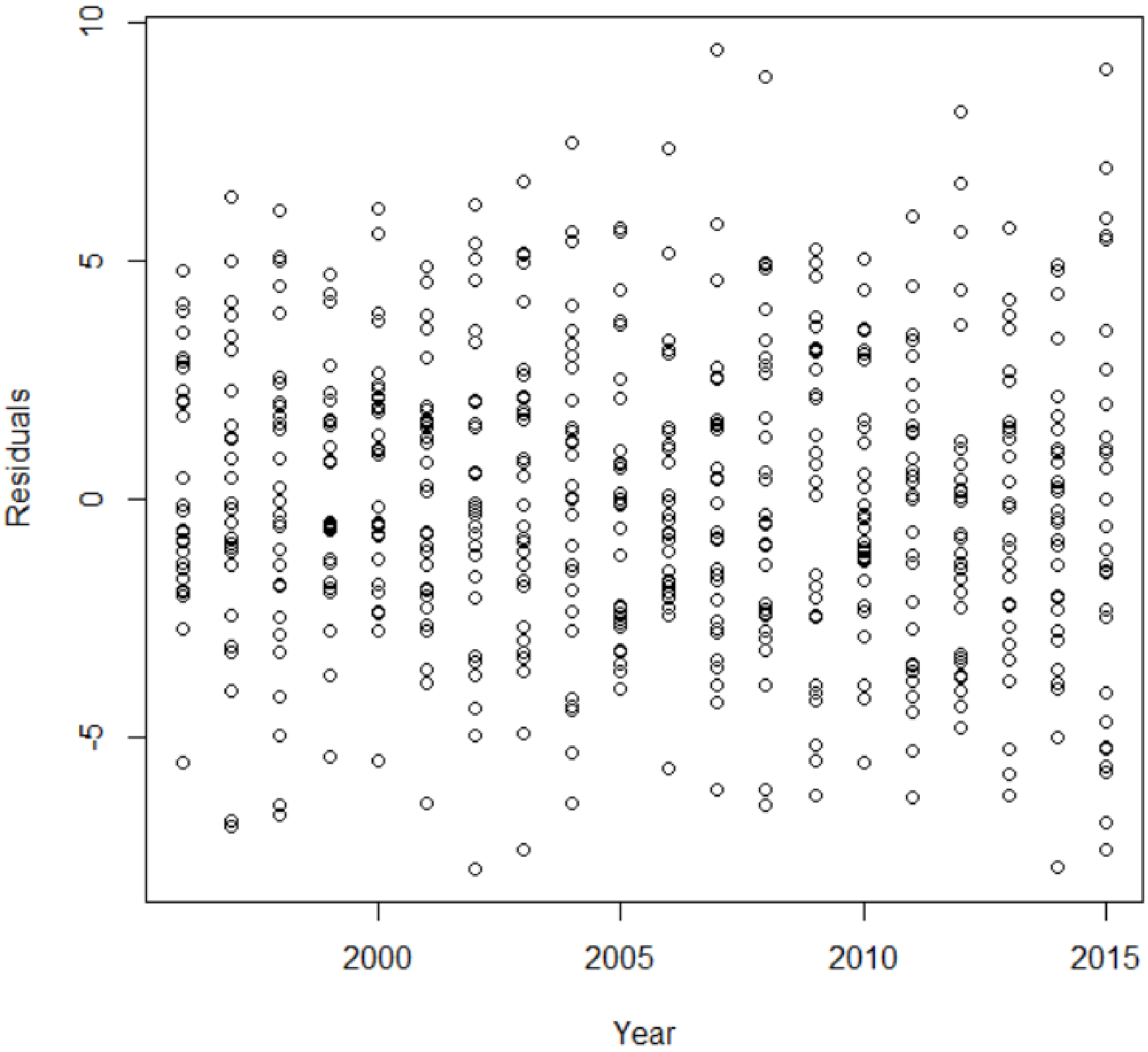
```
> qqnorm(residuals(reg_better3),ylab="Residuals")
```



If the errors are indeed normally distributed, then the plot should produce a relatively straight line of observations. Because the plot above approximately can be seen to follow a straight line, the residuals meet the normality assumption.

Lastly, the tests assume the errors are uncorrelated; however, for time-based data, there may be some correlation. To check for this, the residuals will be plotted against time, using the following R code and producing the following plot:

```
> plot(Year,residuals(reg_better3),xlab="Year",ylab="Residuals")
```



Because there is no change in the pattern of residuals over the years, the errors can be assumed to be uncorrelated, meeting the last test assumption.

Checking for Outliers or Influential Observations

An outlier is a data observation that does not fit with the regression; if the linear regression accurately predicts 99 out of 100 data observations but the last prediction is far from the observed value, that point is an outlier. If an observation has an unduly strong effect on the regression fit, it is called influential. Testing for outliers and influential observations is important because if present, they may affect the fit of a regression.

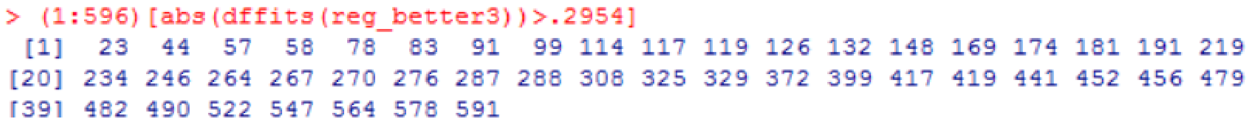
To check for influential observations, we use the code:

```
>influence.measures(reg_better3)
```

This produces a very large table that gives several measures of how influential each observation is (with each observation being a specific year for a specific team). We will look more closely at the measure ‘dffits’; if dffits is greater than twice the square root of one plus the number of variables in the regression divided by the total number of observations, it can be considered an influential observation. To test for this, and knowing that after working out the numbers we are looking for dffits with absolute values greater than .2954 (m=12, n=596), we use the following code:

```
> (1:596)[abs(dffits(reg_better3))>.2954]
```

This gives us the following specific observations which have been, by our criteria, defined as influential observations:

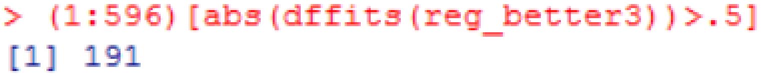


```
> (1:596)[abs(dffits(reg_better3))>.2954]
 [1]  23  44  57  58  78  83  91  99 114 117 119 126 132 148 169 174 181 191 219
[20] 234 246 264 267 270 276 287 288 308 325 329 372 399 417 419 441 452 456 479
[39] 482 490 522 547 564 578 591
```

This is a fairly long list of influential observations, so we can narrow it down and see how many are exceptionally influential:

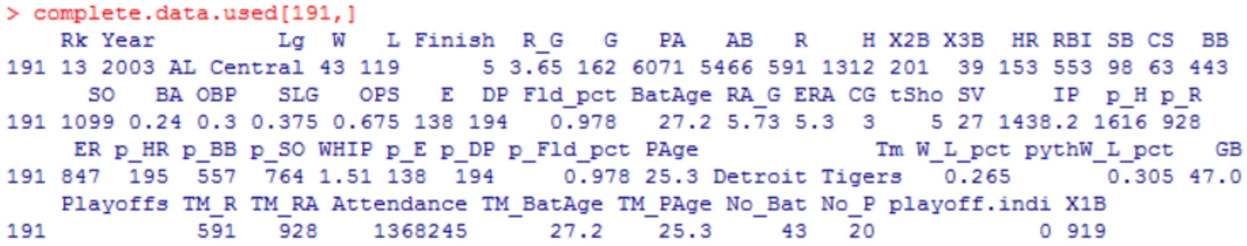
```
> (1:596)[abs(dffits(reg_better3))>.5]
```

This tells us that there is one exceptionally influential observation:



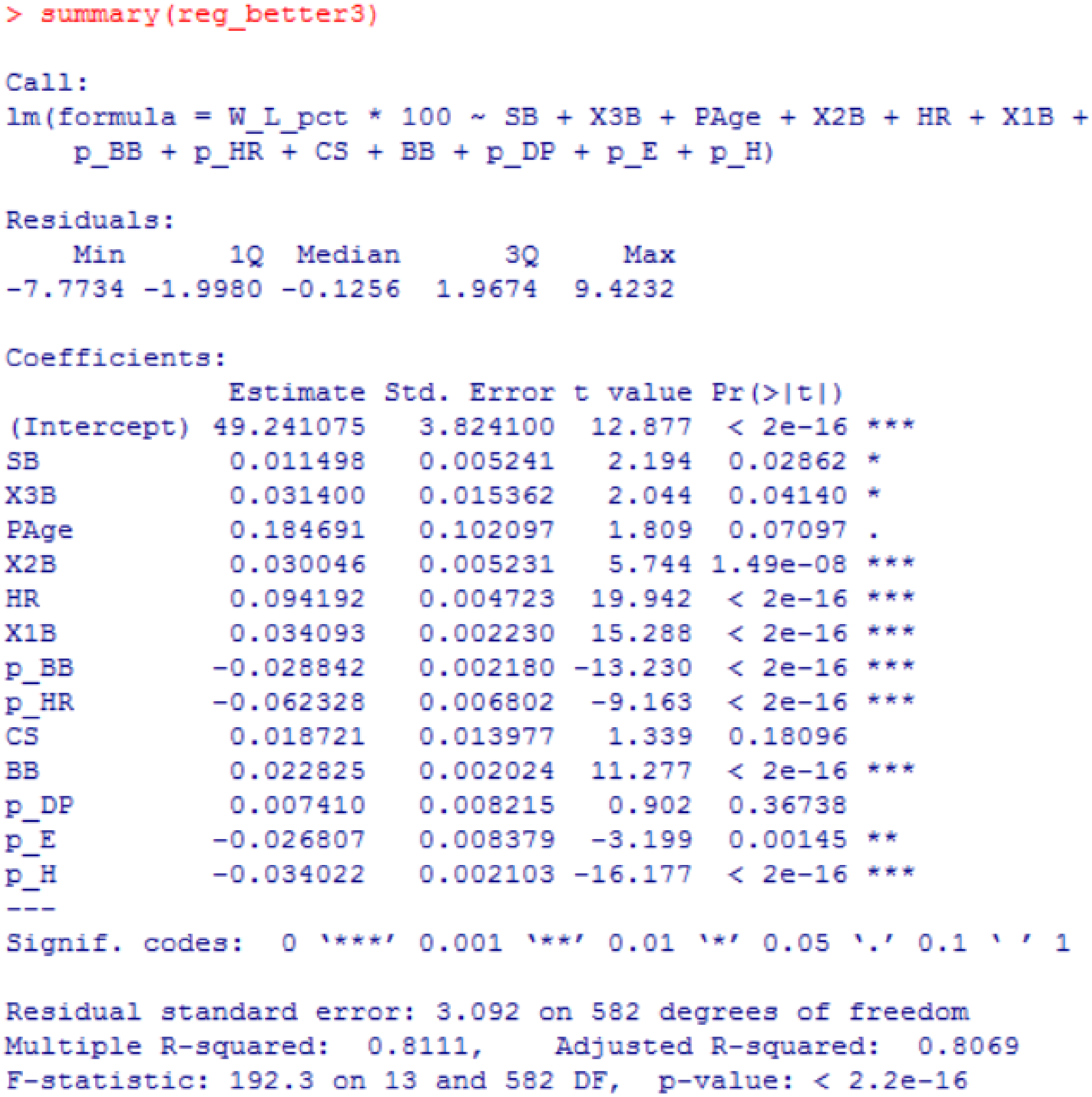
```
> (1:596)[abs(dffits(reg_better3))>.5]
[1] 191
```

The observation ‘191’ is the 2003 Detroit Tigers, who finished 5th in the American League Central Division:



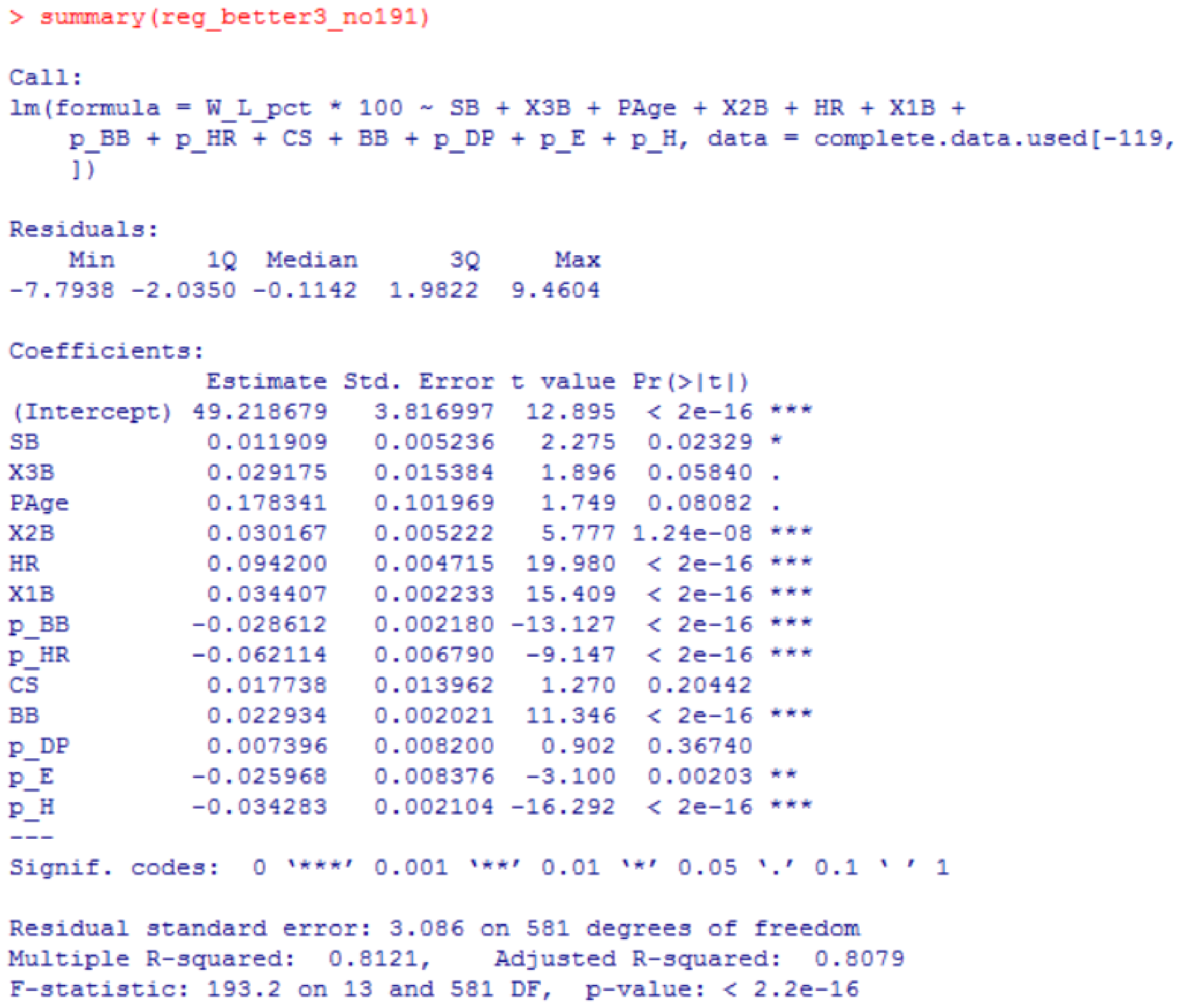
```
> complete.data.used[191,]
    Rk Year         Lg  W   L Finish  R_G   G   PA   AB   R    H X2B X3B  HR RBI SB CS  BB
191 13 2003 AL Central 43 119      5 3.65 162 6071 5466 591 1312 201  39 153 553 98 63 443
      SO   BA OBP   SLG   OPS   E  DP Fld_pct BatAge RA_G ERA CG tSho SV     IP  p_H p_R
191 1099 0.24 0.3 0.375 0.675 138 194   0.978   27.2 5.73 5.3  3    5 27 1438.2 1616 928
     ER p_HR p_BB p_SO WHIP p_E p_DP p_Fld_pct PAge             Tm W_L_pct pythW_L_pct   GB
191 847  195  557  764 1.51 138  194     0.978 25.3 Detroit Tigers   0.265       0.305 47.0
    Playoffs TM_R TM_RA Attendance TM_BatAge TM_PAge No_Bat No_P playoff.indi X1B
191           591   928    1368245      27.2    25.3     43   20            0 919
```

To figure out if this observation negatively affects our regression, we will compare a statistical summary of the regression with the observation included against a summary without it. If the observation is very influential, then the coefficients of the variables will have a significant change when the observation is left out of the regression.



```
> summary(reg_better3)

Call:
lm(formula = W_L_pct * 100 ~ SB + X3B + PAge + X2B + HR + X1B +
    p_BB + p_HR + CS + BB + p_DP + p_E + p_H)

Residuals:
    Min      1Q  Median      3Q     Max
-7.7734 -1.9980 -0.1256  1.9674  9.4232

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 49.241075   3.824100  12.877  < 2e-16 ***
SB           0.011498   0.005241   2.194  0.02862 *
X3B          0.031400   0.015362   2.044  0.04140 *
PAge         0.184691   0.102097   1.809  0.07097 .
X2B          0.030046   0.005231   5.744 1.49e-08 ***
HR           0.094192   0.004723  19.942  < 2e-16 ***
X1B          0.034093   0.002230  15.288  < 2e-16 ***
p_BB        -0.028842   0.002180 -13.230  < 2e-16 ***
p_HR        -0.062328   0.006802  -9.163  < 2e-16 ***
CS           0.018721   0.013977   1.339  0.18096
BB           0.022825   0.002024  11.277  < 2e-16 ***
p_DP         0.007410   0.008215   0.902  0.36738
p_E         -0.026807   0.008379  -3.199  0.00145 **
p_H         -0.034022   0.002103 -16.177  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.092 on 582 degrees of freedom
Multiple R-squared:  0.8111,    Adjusted R-squared:  0.8069
F-statistic: 192.3 on 13 and 582 DF,  p-value: < 2.2e-16
```

Now, we create a new regression, without the influential observation:



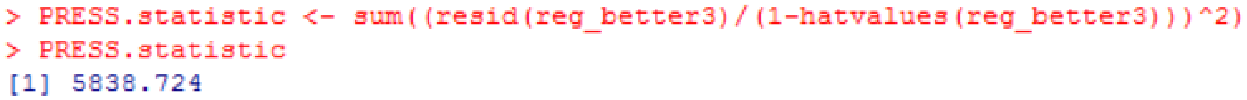
```
> summary(reg_better3_no191)

Call:
lm(formula = W_L_pct * 100 ~ SB + X3B + PAge + X2B + HR + X1B +
    p_BB + p_HR + CS + BB + p_DP + p_E + p_H, data = complete.data.used[-119,
    ])

Residuals:
    Min      1Q  Median      3Q     Max
-7.7938 -2.0350 -0.1142  1.9822  9.4604

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 49.218679   3.816997  12.895  < 2e-16 ***
SB           0.011909   0.005236   2.275  0.02329 *
X3B          0.029175   0.015384   1.896  0.05840 .
PAge         0.178341   0.101969   1.749  0.08082 .
X2B          0.030167   0.005222   5.777 1.24e-08 ***
HR           0.094200   0.004715  19.980  < 2e-16 ***
X1B          0.034407   0.002233  15.409  < 2e-16 ***
p_BB        -0.028612   0.002180 -13.127  < 2e-16 ***
p_HR        -0.062114   0.006790  -9.147  < 2e-16 ***
CS           0.017738   0.013962   1.270  0.20442
BB           0.022934   0.002021  11.346  < 2e-16 ***
p_DP         0.007396   0.008200   0.902  0.36740
p_E         -0.025968   0.008376  -3.100  0.00203 **
p_H         -0.034283   0.002104 -16.292  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 3.086 on 581 degrees of freedom
Multiple R-squared:  0.8121,    Adjusted R-squared:  0.8079
F-statistic: 193.2 on 13 and 581 DF,  p-value: < 2.2e-16
```

As can be seen in comparing the two regression summaries, including the influential observation has a very minimal effect on the coefficients themselves and on their significance (as defined by their p-values). Thus, we will keep the observation in our regression.

We can further validate the model by checking the PRESS, or predictive residual sum of squares. This function goes through the regression and for each observation in the data set, removes that observation, fits a new regression with one less observation, and measures how closely the removed observation would have been predicted by the new regression. We can compare it to the SSE, or sum of squared residuals; we expect the PRESS to be slightly larger than SSE, and hope that it is not too much larger:

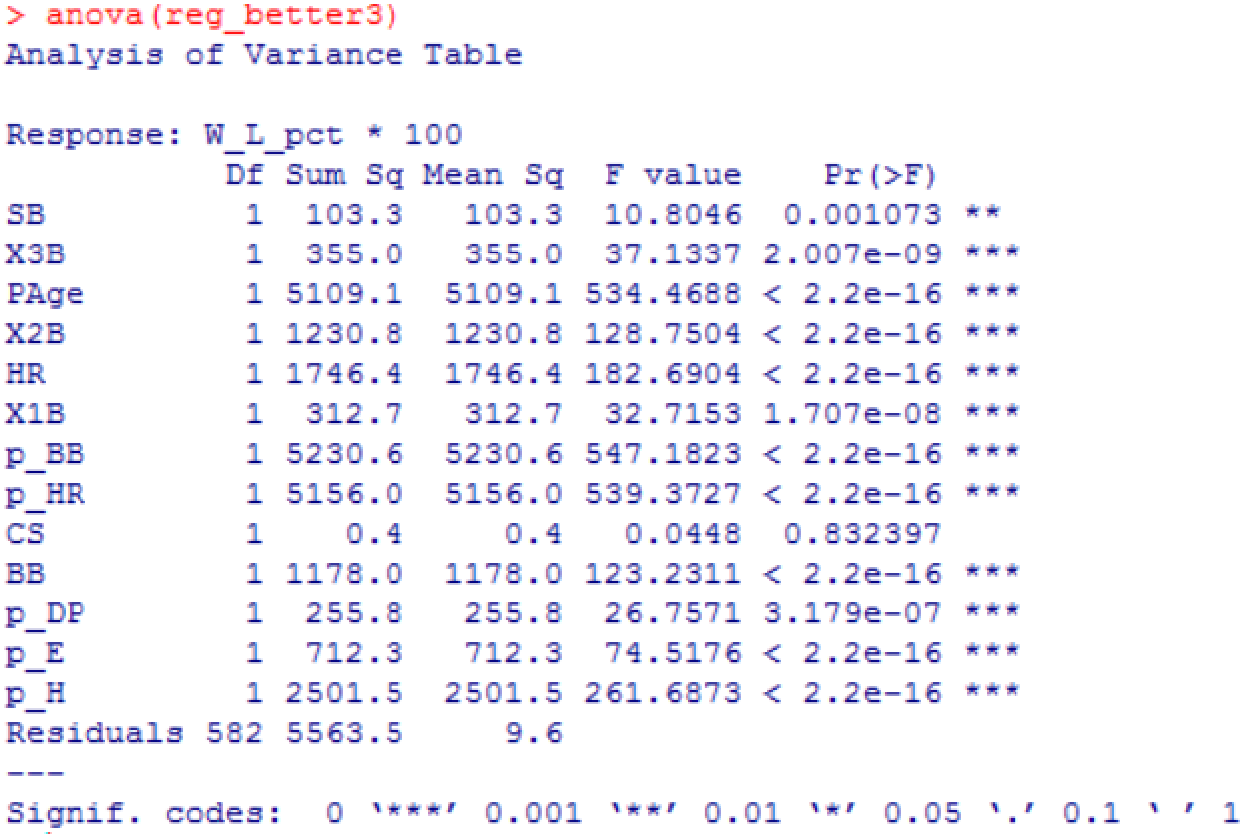
> PRESS.statistic <- sum((resid(reg_better3)/(1-hatvalues(reg_better3)))^2)

Doing this gives us a value of 5838.724, as can be seen below:



```
> PRESS.statistic <- sum((resid(reg_better3)/(1-hatvalues(reg_better3)))^2)
> PRESS.statistic
[1] 5838.724
```

The anova, or analysis of variance for our chosen regression model, shows we get a SSE of 5563.5, which can be seen below:



```
> anova(reg_better3)
Analysis of Variance Table

Response: W_L_pct * 100
           Df Sum Sq Mean Sq  F value    Pr(>F)    
SB          1  103.3   103.3  10.8046  0.001073 ** 
X3B         1  355.0   355.0  37.1337 2.007e-09 ***
PAge        1 5109.1  5109.1 534.4688 < 2.2e-16 ***
X2B         1 1230.8  1230.8 128.7504 < 2.2e-16 ***
HR          1 1746.4  1746.4 182.6904 < 2.2e-16 ***
X1B         1  312.7   312.7  32.7153 1.707e-08 ***
p_BB        1 5230.6  5230.6 547.1823 < 2.2e-16 ***
p_HR        1 5156.0  5156.0 539.3727 < 2.2e-16 ***
CS          1    0.4     0.4   0.0448  0.832397    
BB          1 1178.0  1178.0 123.2311 < 2.2e-16 ***
p_DP        1  255.8   255.8  26.7571 3.179e-07 ***
p_E         1  712.3   712.3  74.5176 < 2.2e-16 ***
p_H         1 2501.5  2501.5 261.6873 < 2.2e-16 ***
Residuals 582 5563.5     9.6                       
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

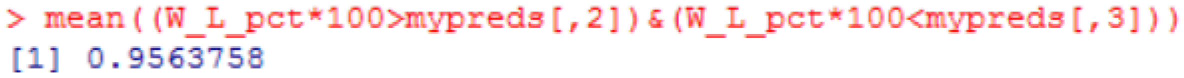
Because 5838.724 is not much larger than 5563.5, we further accept that the regression fits the data well.

Prediction Intervals

Prediction intervals can be handy for measuring intervals where future observations will fall, given certain predictors; in this case, we could use them to predict an interval for a team's winning percentage given certain factors, such as Batting Average, Hits, etc. However, we can also use prediction intervals to see how well our model fits the data; we can estimate prediction intervals for our data, and hope to see a large portion of our response values fall within their respective intervals.

To do this, we first create the prediction intervals at a 95% level; this means we hope to see at least 95% of our response values fall in the prediction intervals. Next, we calculate in R the percent of winning percentages that do fall in the prediction intervals.

```
> mypreds=predict(reg_better3,interval="prediction",level=0.95)
```



```
> mean((W_L_pct*100>mypreds[,2])&(W_L_pct*100<mypreds[,3]))
[1] 0.9563758
```

We are further satisfied with our model, having 95.6378% of our response values fall within the prediction intervals.

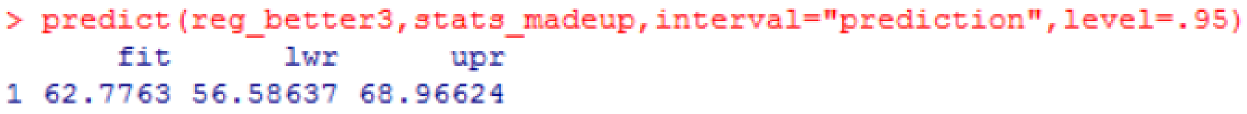
Sample Predictions

Now that we have our regression, and have validated the model and checked to ensure the model assumptions hold, we can use it to predict the winning percentage of teams with specific statistics; for example, we can predict the winning percentage of a team with hypothetical statistics, and we can predict the winning percentage of a team in a long ago season to see how it would fare in today's world of baseball based on its statistics back then. This is significant because the game of baseball, like everything else in life, changes over time, and what may have been key for winning games 40 years ago might not be key for winning games today.

First, we will make up a team's statistics, and create a dataframe with these statistics:

```
> stats_madeup <-
data.frame(cbind(SB=70,X3B=30,PAge=27,X2B=375,HR=215,X1B=1000,p_BB=450,p_HR=160,CS=38,BB=525,p_DP=165,p_E=80,p_H=1400))
```

We then predict the hypothetical team's winning percentage for those given statistics:

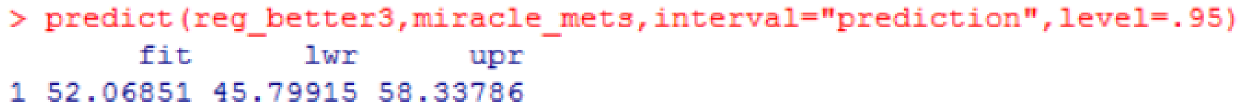


```
> predict(reg_better3,stats_madeup,interval="prediction",level=.95)
      fit      lwr      upr
1 62.7763 56.58637 68.96624
```

So by the calculations in R, the team with the given statistics is predicted to win 62.77% of their games; and if there were many, many teams with those given statistics, 95% of the teams would be predicted to have a winning percentage between 56.58% and 68.97%.

Now, we can predict the winning percentage of a historical team; for example, the 1969 "Miracle Mets". The New York Mets surprised the country and overcame a late-season divisional gap between them and the divisional leaders, the Chicago Cubs, and ended up winning the World Series. They ended the regular season with a 61.7% winning percentage. To calculate the Miracle Mets' predicted winning percentage, we repeat the above steps using the Mets' stats from that year:

```
> miracle_mets <-
data.frame(cbind(SB=66,X3B=41,PAge=25.8,X2B=184,HR=109,X1B=977,p_BB=517,p_HR=119,BB=527,p_DP=146,p_E=122,p_H=1217,CS=43))
```

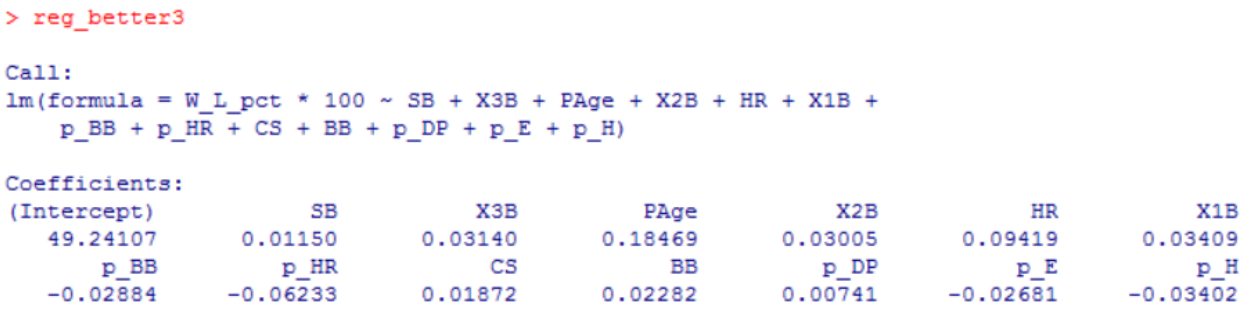


```
> predict(reg_better3,miracle_mets,interval="prediction",level=.95)
       fit      lwr      upr
1 52.06851 45.79915 58.33786
```

Thus, based on our regression, we would have predicted the Mets' winning percentage to be 52.06%; given the statistics, if there were many identical teams, 95% of the teams would have a winning percentage between 45.8% and 58.34%. The fact that the actual winning percentage of the team was much higher either means the statistics that helped them win that year are not as significant in this time period, or they had a lucky season, as their nickname suggests.

Interpretation of Regression

The final regression that we came up with, along with the coefficients, is:



```
> reg_better3

Call:
lm(formula = W_L_pct * 100 ~ SB + X3B + PAge + X2B + HR + X1B + 
    p_BB + p_HR + CS + BB + p_DP + p_E + p_H)

Coefficients:
(Intercept)           SB          X3B         PAge          X2B           HR          X1B  
   49.24107      0.01150      0.03140      0.18469      0.03005      0.09419      0.03409  
       p_BB         p_HR           CS           BB         p_DP          p_E          p_H  
   -0.02884     -0.06233      0.01872      0.02282      0.00741     -0.02681     -0.03402  
```

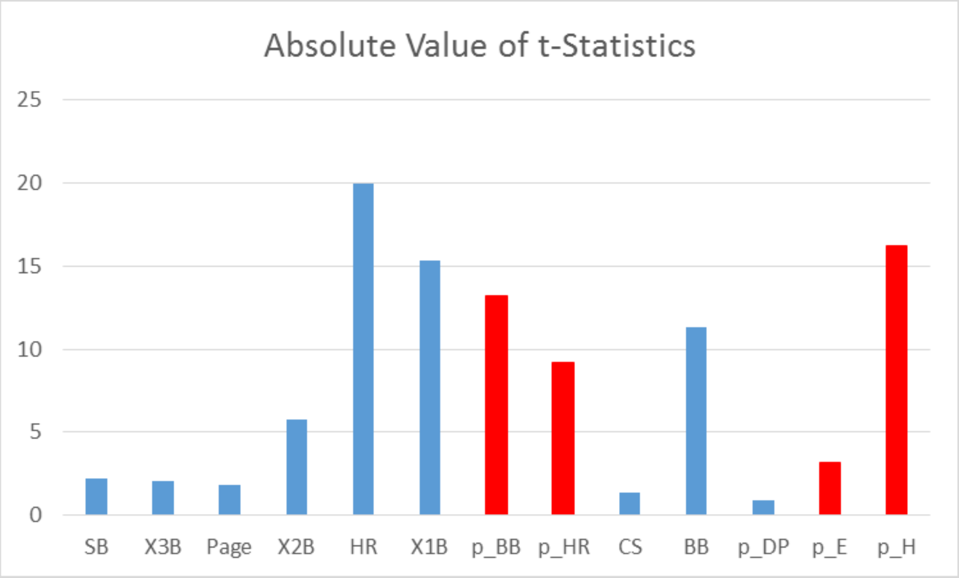
Below is a concise list of the variables that were included:

- SB- stolen bases for a team in a season. The coefficient can be interpreted as for each additional stolen base, a team's winning percentage can be expected to increase .0115%, adjusting for the other predictors in the model.
- X3B- triples hit for a team in a season. The coefficient can be interpreted as for each additional triple hit, a team's winning percentage can be expected to increase .0314%, adjusting for the other predictors in the model.

- PAge- average pitcher age on a team. The coefficient can be interpreted as for each additional year in average pitcher age, a team's winning percentage can be expected to increase .18469%, adjusting for the other predictors in the model.
- X2B- doubles hit for a team in a season. The coefficient can be interpreted as for each additional double hit, a team's winning percentage can be expected to increase .03005%, adjusting for the other predictors in the model.
- HR- home runs hit for a team in a season. The coefficient can be interpreted as for each additional home run hit, a team's winning percentage can be expected to increase .09419%, adjusting for the other predictors in the model.
- X1B- singles hit for a team in a season. The coefficient can be interpreted as for each additional single hit, a team's winning percentage can be expected to increase .03409%, adjusting for the other predictors in the model.
- P_BB- walks allowed by a team in a season. The coefficient can be interpreted as for each additional walk allowed, a team's winning percentage can be expected to decrease .02884%, adjusting for the other predictors in the model.
- P_HR- home runs allowed by a team in a season. The coefficient can be interpreted as for each additional home run allowed, a team's winning percentage can be expected to decrease .06233%, adjusting for the other predictors in the model.
- CS- number of times a team gets caught stealing in a season. The coefficient can be interpreted as for each additional time a team gets caught stealing, a team's winning percentage can be expected to increase .01872%, adjusting for the other predictors in the model.

- BB- walks for a team in a season. The coefficient can be interpreted as for each additional walk earned, a team's winning percentage can be expected to increase .02282%, adjusting for the other predictors in the model.
- P_DP- double plays turned by a team in a season. The coefficient can be interpreted as for each additional double play turned, a team's winning percentage can be expected to increase .00741%, adjusting for the other predictors in the model.
- P_E- errors by a team's defense in a season. The coefficient can be interpreted as for each additional error, a team's winning percentage can be expected to decrease .02681%, adjusting for the other predictors in the model.
- P_H- hits given up by a team in a season. The coefficient can be interpreted as for each additional hit allowed, a team's winning percentage can be expected to decrease .03402%, adjusting for the other predictors in the model.

Below is a graph of the predictor variables in the regression and their corresponding t-statistics. The t-statistic measures how significant that variable is in predicting win percentage, being measured by dividing the estimated coefficient by the standard error of that coefficient. (The blue bars are positive t-statistics and the red bars are negative t-statistics).



The coefficients, for the most part, make sense. All of the variables have the same sign (positive or negative) as what would be expected; all except CS, or caught stealing. One would think that the more times a team gets caught stealing, the less baserunners would score, and the less wins a team would get. However, the coefficient having a positive sign means the more times a team gets caught stealing the more wins it gets. Perhaps this is because more times caught stealing implies more aggressive base-running and more runners on base to begin with, and thus perhaps more runs scored and more wins, but this is mere speculation. However, an examination of the t-test about the coefficient of CS shows that it is not significantly different from zero (P-value=0.18), so little importance should be assigned to its positive estimated coefficient.

Furthermore, while PAge, for example, has a positive coefficient, this does not mean that steadily increasing a team's average pitcher age will steadily increase the team's winning percentage. At some point increasing the average age by another year will not result in a higher winning percentage, and will obviously start to negatively affect the winning percentage as the pitchers get older and older (while a 35-year old pitcher might be argued to be more beneficial to a team than a 32-year old pitcher, a 70-year old pitcher will undoubtedly be much worse for a team than a 35-year old pitcher). Looking at the positive coefficient and assuming this implies that increasing the average age will always increase the winning percentage is called extrapolation. We cannot assume that what we know about relationships between variables applies to data outside that range. Such an erroneous assumption is illustrated by the simple example above about a 70-year old pitcher.

Conclusion

In completing this regression analysis, I was able to put together skills I learned from my statistics courses to investigate something that is interesting to me. From start to finish, I pulled statistics from a database, edited them into a form that I could use, and manipulated statistical software to answer the research questions I was interested in learning about.

I learned how to research in textbooks and online, and how to use all of the resources available to me to both learn technical skills and then use them to accomplish a goal. Being able to use statistical software to learn about trends in data, and being able to learn new procedures in statistical software, is important to me going into a career as an actuary. With this experience, I was able to put to use my education in mathematics and statistics in the culmination of my time as a student of USC, and gain experience that will greatly benefit me in my career in the workplace.

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