Can algorithms play Moneyball?

Zachary Agrue, Patricia Mills, and Charles Vanleuvan

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Introduction

The 2011 film, Moneyball, tells the story of how Billy Beane and Paul DePodesta found a way to help the Oakland A's improve their team with little money and a lot of data. Up to the A's in 2002, players' salaries and trade value were determined almost exclusively on the player's batting average, RBIs, and homeruns with a dose of "gut feeling" from the scouts and coaches. That year, the Yankees players earned a combined 125,928,583. The A's, by comparison, earned 39,679,746. Both teams were eliminated in the first round of the playoffs. Enter Sabermetrics.

Paul DePodesta did not think in terms of buy players but to buy runs. The three players that the A's got in the off season that year were sought out because they got on base, which is the first step to getting runs. This has completely changed the world of baseball over the 18 years since the A's did it.

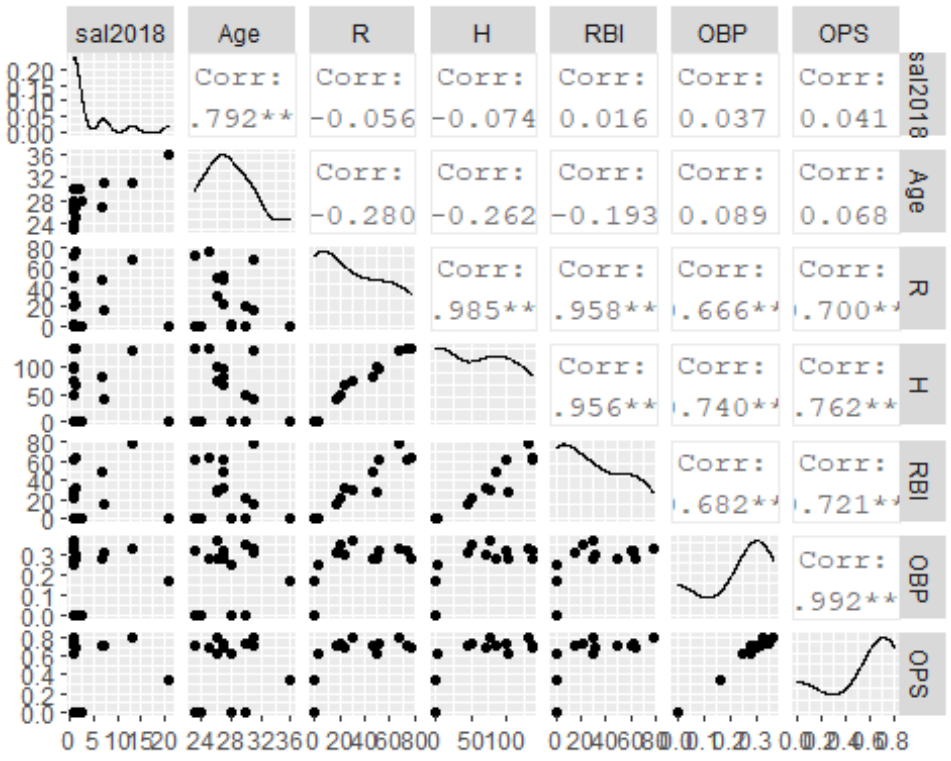
In 2018, the Chicago White Sox lost 100 games. In 2019, they lost 89. While still a losing season, the team made some changes in the off season. Meanwhile, in 2018 the Washington Nationals were barely above .500 but in 2019, they won the World Series. What did these teams change? Can machine learning algorithms identify who they should trade in order to play a little Moneyball?

Analysis and Models

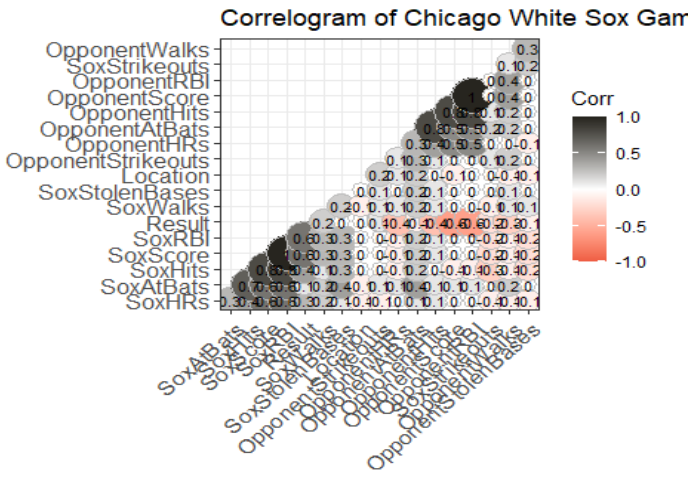
About the Data

Scatterplots are key visual tools that describe relationships between two categories. In this report, pitching and hitting metrics are compared against player salary. The fundamental relationship that needs to be understood is player performance and player salary. Anecdotal evidence suggests that the more a player is paid, the better their performance is.

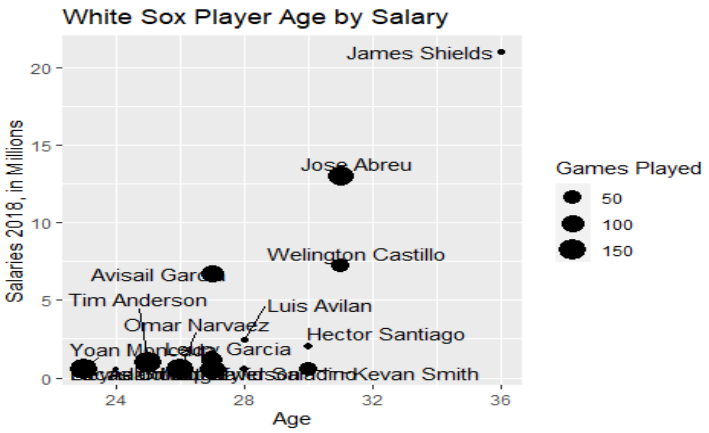
From the scatter plot matrix, pairs of features that show strong relationships can be observed.



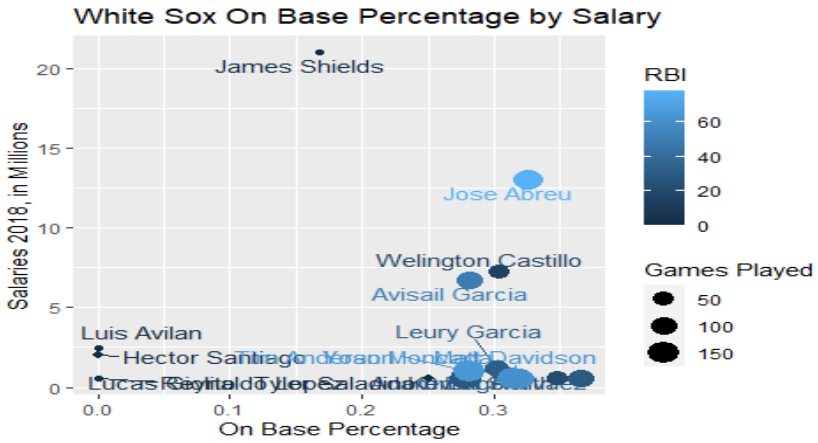
When considering game level data, the correlogram below shows high correlation for several statistics for the Chicago White Sox. Some are obvious correlations like the positive correlation between OpponentRBI and OpponentScore. Others seem less clear such as the slightly negative correlation between SoxHits and SoxStrikeouts. Interestingly, there is not the same correlation for OpponentHits and OpponentStrikeouts.



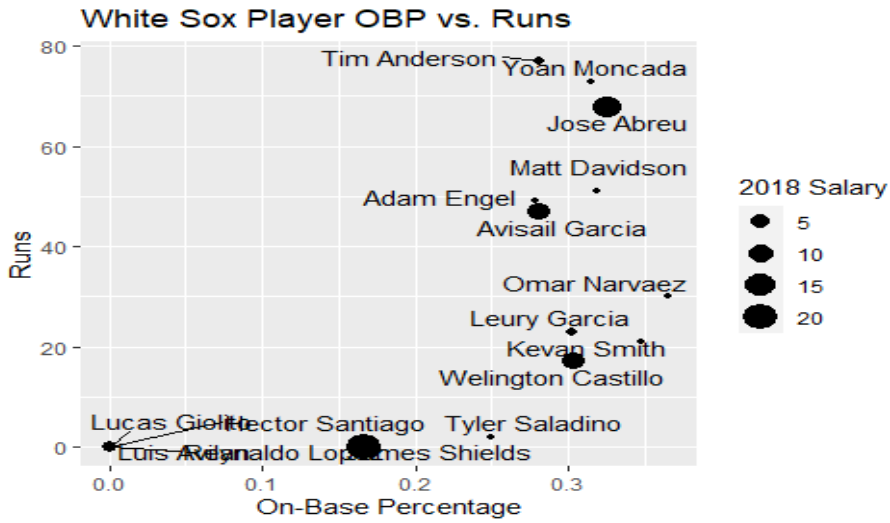
Older players are more established in the league and typically can negotiate higher salary on previous years' performance. However, age shows a weak correlation (max = 0.262 R) to most offensive statistics. The average salary of players over 28 years old is greater than 5 million, yet the average salary for players under 28 years is below 2 million. Salary does not have a R score greater than 0.1 for any of the offensive stats.



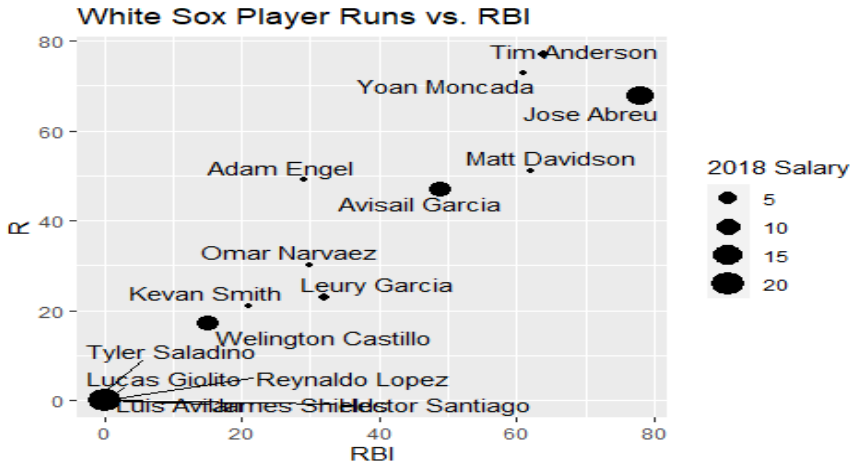
Excluding pitchers, the OBP for position players does not scale well with salary. Of the top 3 salary earners on the team, only 2 of those players reside in the top 5 players with highest OBP. On base percentage is a record of how often a player reaches base safely. In theory, these on base events should translate to more Runs. A player that scores many runs is directly contributing to a team's score and increases the chance of winning.



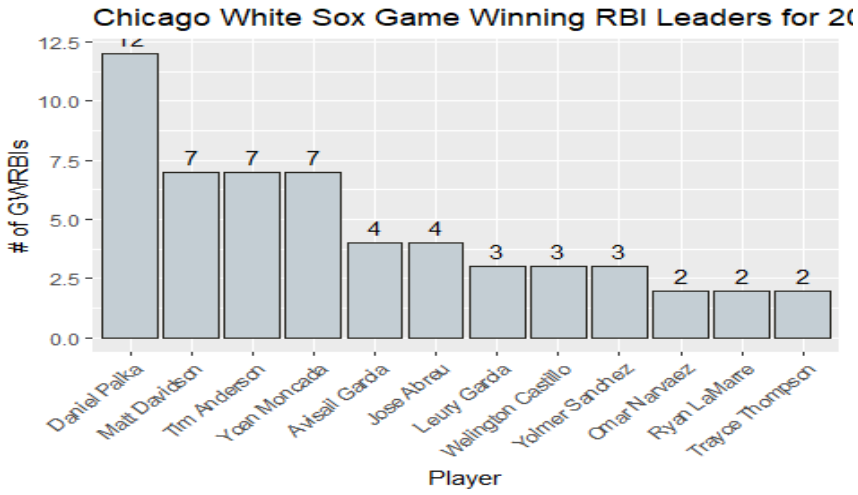
On the White Sox, it isn't necessarily true that higher OBP scales with runs. The R value for OBP by runs is 0.67, and yet the Tim Anderson, one of the lowest paid players, has the highest runs scored while nearly having the smallest OBP of the position players. If OBP is not a strong predictor for runs scored, then RBI might be.



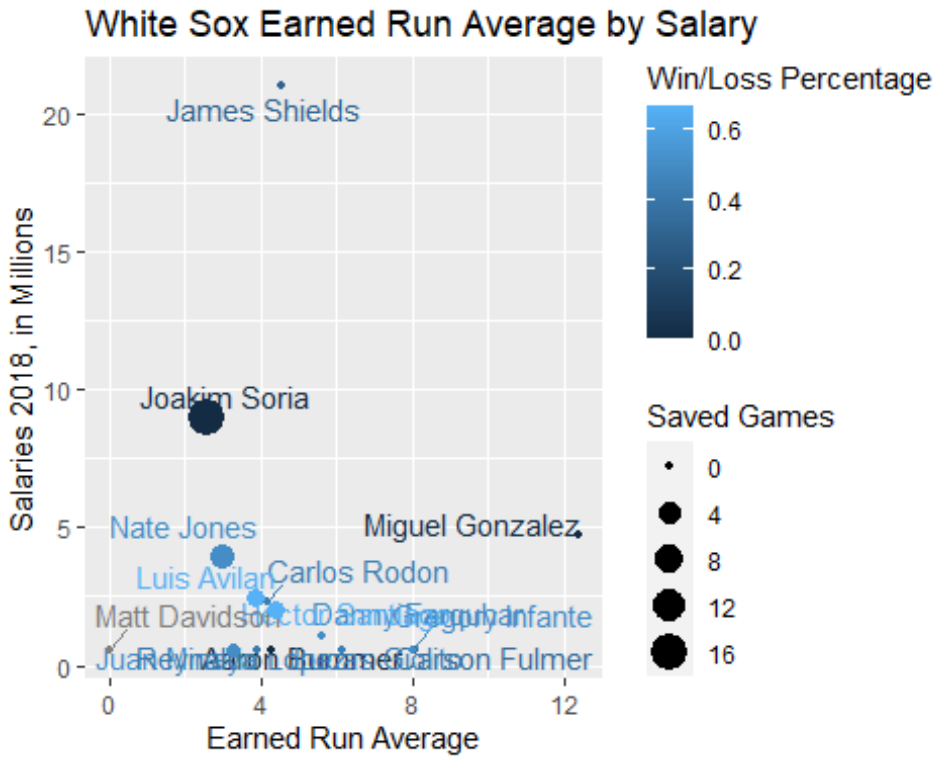
A strong R value (R = 0.958) between runs and RBI indicates that players who hit in more runs also individually contribute to the teams score by reaching homeplate safely themselves. Jose Abreu is the teams highest paid position player, has the most RBIs, and is third in runs scored. Two other players have similar performance to him, Tim Anderson and Yoan Moncada, yet they are paid significantly less than Abreu.



Game winning RBIs are runs that a player hits in that end up being the winning run for the game. In this study, this can be looked at as the “clutch performance factor”. Certain players show the tendency to perform well given a game-deciding situation. Daniel Palka, with 12 runs batted in, has approximately 40% more GWRBI’s than his closest teammate. This tendency can be a strong influencing factor in deciding to keep a player or update his contract.

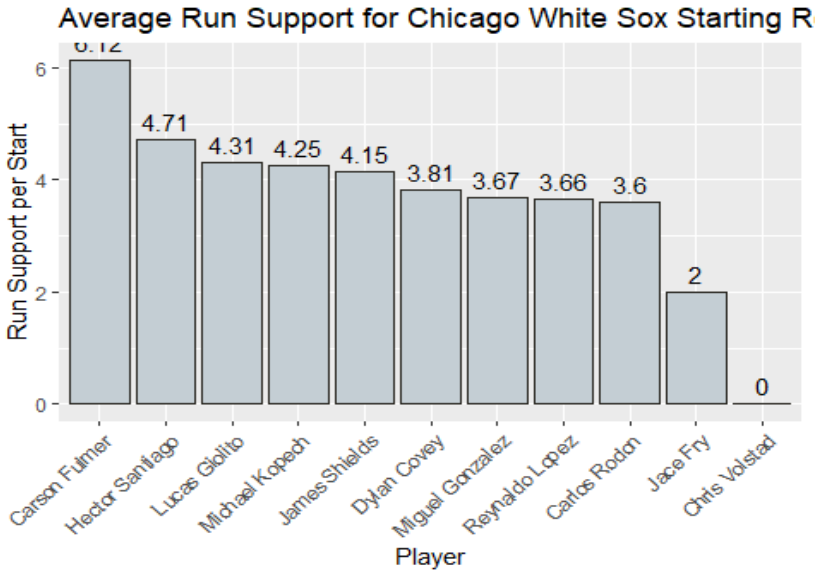


A pitcher's ERA is the gold standard for comparison between pitchers, where lower ERA is better. It is the total number of earned runs averaged out for every 9 innings pitched. The correlation between ERA and Salary suggests that ERA is a strong influence in a pitcher's salary. Barring outliers Matt Davidson and Miguel Gonzalez (G = 3), as ERA decreases, the pitcher salary increases. The same relationship is exhibited by salary and the number of saved games.

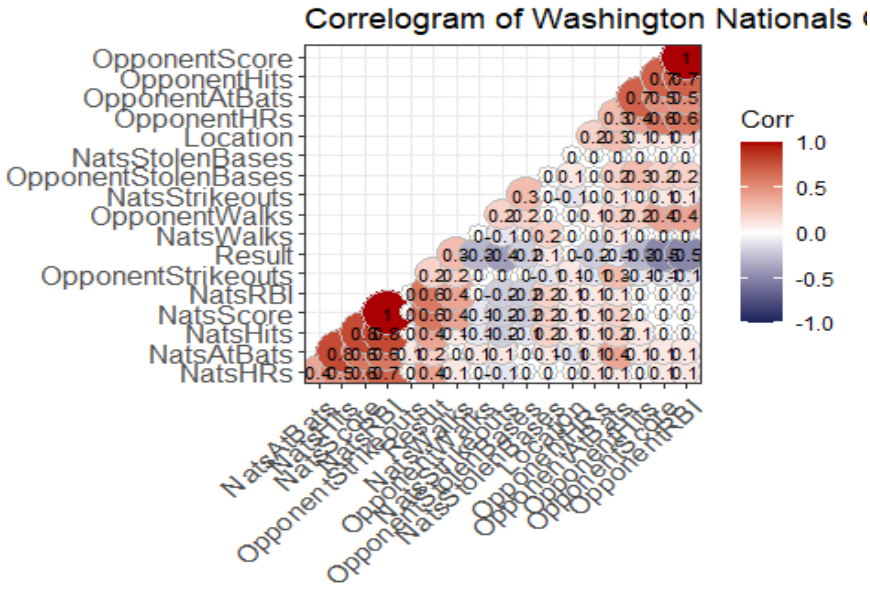


The Chicago White Sox pitching staff depend upon the batters to give run support to cover the pitcher's earned runs. While Carson Fulmer's run support average is over 6 runs per start, it does not counteract his Earned Run Average of 8.07. In fact, for the Sox pitching

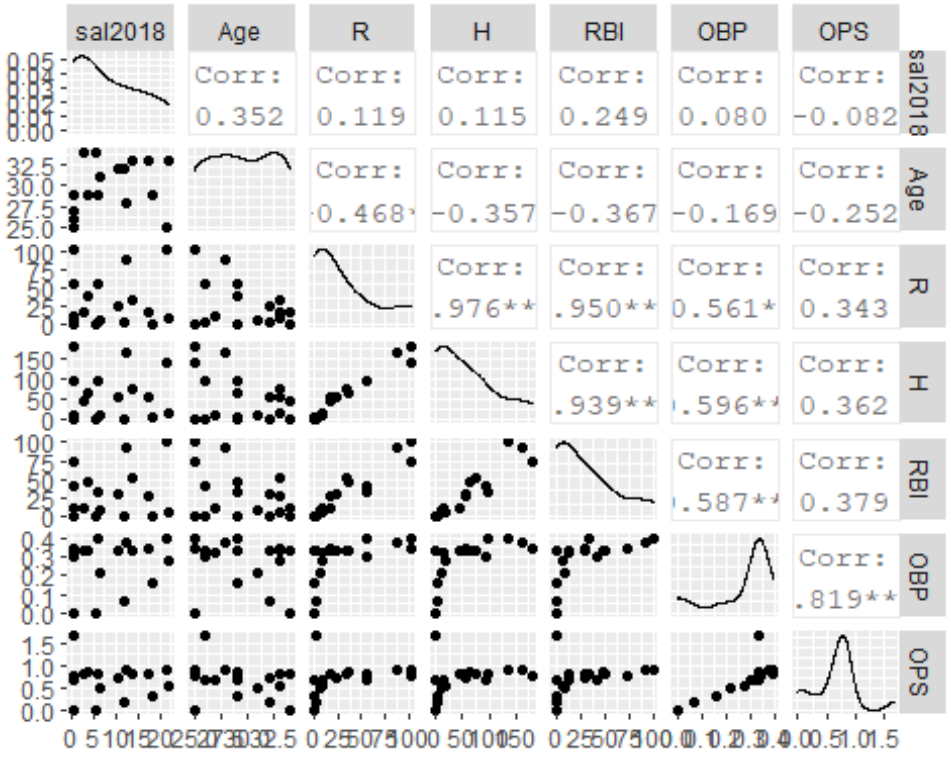
staff, Hector Santiago is the only pitcher whose average run support covers his ERA of 4.4, which explains why he has the highest win-loss percentage of the starting pitchers at 67%.



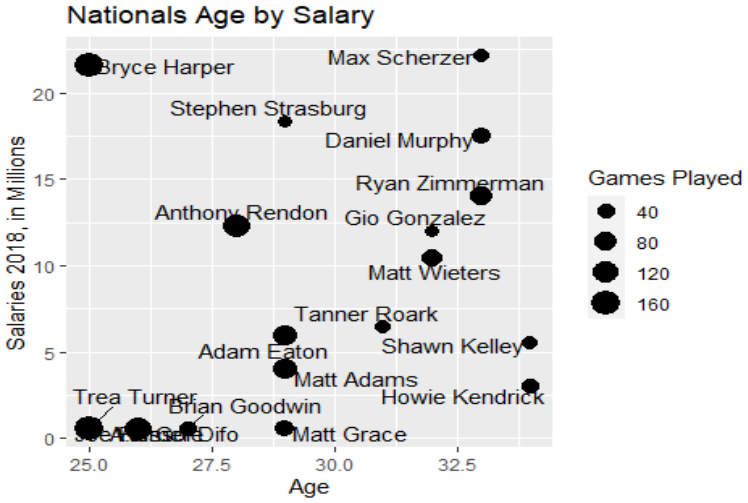
The correlogram of the Washington Nationals' game level statistics shows that there is a slight positive correlation between NatsWalks and NatsScore. With the rest of the correlations, there is not much that is not to be expected in baseball.



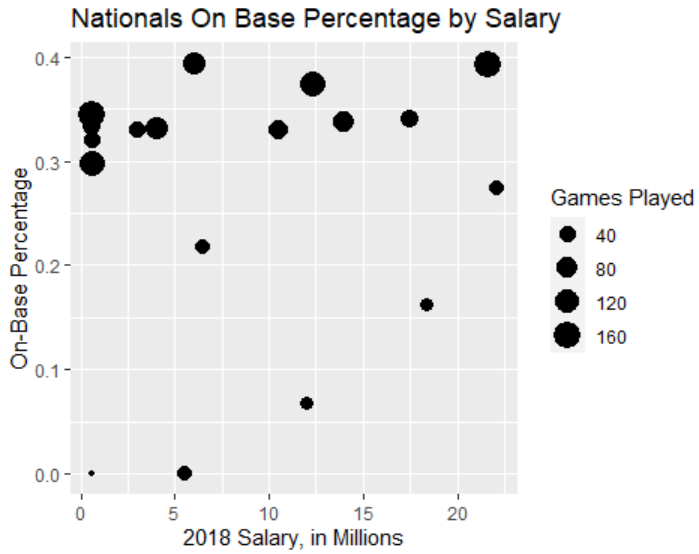
Similar to the White Sox, there is only a weak correlation between salary and most major offensive categories ($R < 0.25$). Stronger correlations exist within the offensive categories themselves ($R > 0.95$)



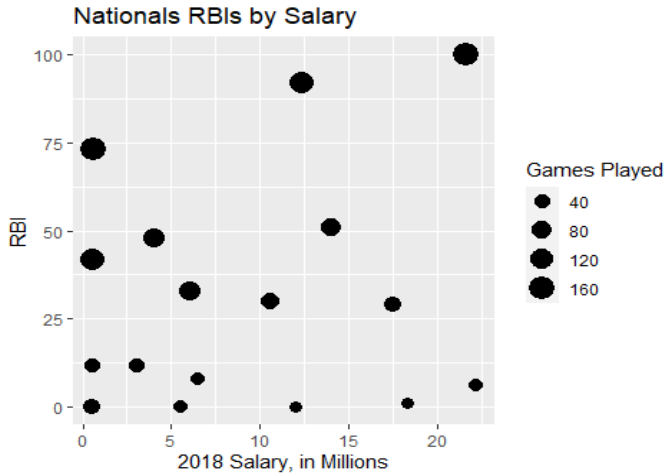
Another consistency between the two ball clubs is that older players have higher salaries, without necessarily providing better offense. Trea Turner's offensive stats were similar to Bryce Harper but was paid nearly 20 times less than Bryce.



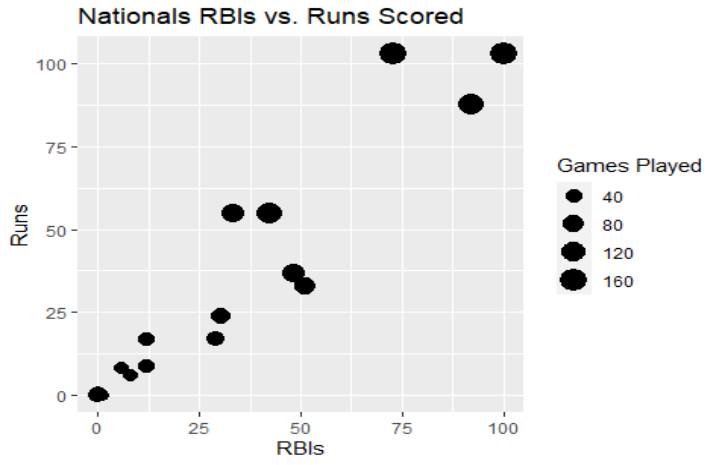
The Nationals have a higher OBP across their player salary range compared to the White Sox because they were a better offensive team. Still, however, the correlation between salary and OBP is $R < 0.1$.



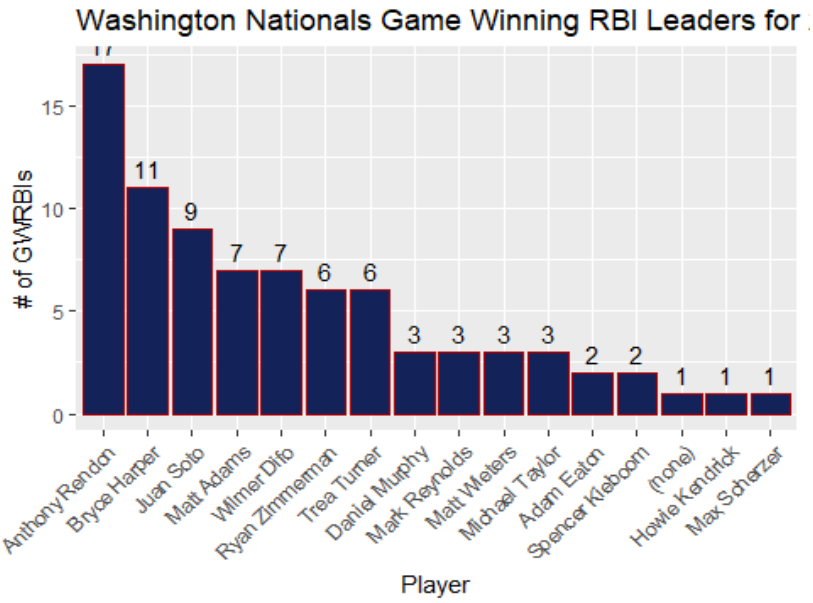
Runs batted in for the Nationals team show that the top three leaders in RBIs also played in the most games. However, it does not correlate to salary for all three. Two of the three are in the are amongst the high salary group while one is at or near the league minimum salary for 2018.



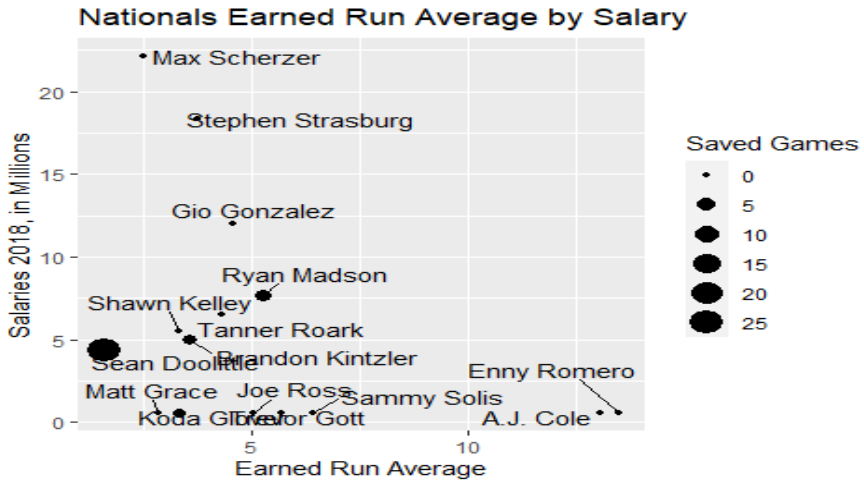
Like the White Sox, the Nationals players have a strong correlation between batting in runs and scoring runs (R = 0.95). Again, runs scored directly contribute to the teams score and thus increase the odds of winning the game. A player's RBIs should be taken into consideration by General Manager's deciding the team roster.



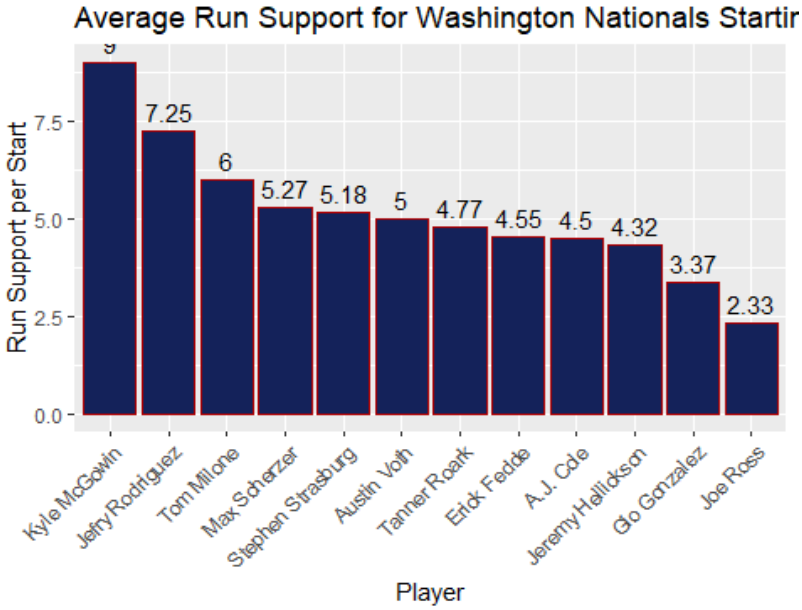
In terms of game winning performances, Anthony Rendon (3B) is paid almost $10 million less than Daniel Murphy (2B) but has 2.5 times the amount of game winning RBIs than Murphy (when averaged out for Game Winning RBIs per Game). Rendon also is 100 points higher than Murphy for OPS (On-base percentage plus slugging).



The Nationals starting rotation exhibit a clear and direct relationship between ERA and Salary for starting pitchers. Nationals pitchers with lower ERA in 2018 also had higher salaries. As with the White Sox pitchers, the ERA remains the gold standard in determining a pitcher's salary.



Unlike the Chicago White Sox, the Washington Nationals pitching staff enjoys high run support for most of the starting pitchers. For Washington, Austin Voth (6.57 ERA), Erick Fedde (5.54 ERA), AJ Cole (13.06 ERA), Gio Gonzalez (4.57 ERA), and Joe Ross (5.06 ERA) are the pitchers who draw less run support than their ERAs. The majority of the starting pitchers have far higher run support than needed.



Model 1

Association Rules Mining helped immensely to find trends for winning for each team. Two sets of rules were created for each team: winning games all data and winning batting lineups. For the all data rules, the parameters were set at a support of 15%, confidence of 50%, and a minimum length of 3. For the White Sox, this resulted in 42 rules. Meanwhile, 61 rules were generated for the Nationals.

The rules generated based on the batting lineups had parameters of support 15%, confidence 90%, and a minimum length of 3. This generated 24 rules for the White Sox and 103 rules for the Nationals.

Model 2

In order to determine which players were either being overpaid or underpaid by their team, players' salaries were grouped as low, mid, or high based on the mean salary for batters or pitchers for their team, based on position played. Then using random forest, each player's salary group was predicted based on comparisons to their batting or pitching stats, as appropriate.

Holdout testing was used to create as accurate a model as possible. Four folds were used for both team's batters. Five folds were used for pitchers. These folds resulted in groups of 4 players per holdout. Then a loop was written to create new test and train data frames. Each training group used all of the data in the salary and stats data frames. Once classification was made, each player's name, original salary range, and new salary range was added to a data frame of results for that team and that position – batters versus pitchers.

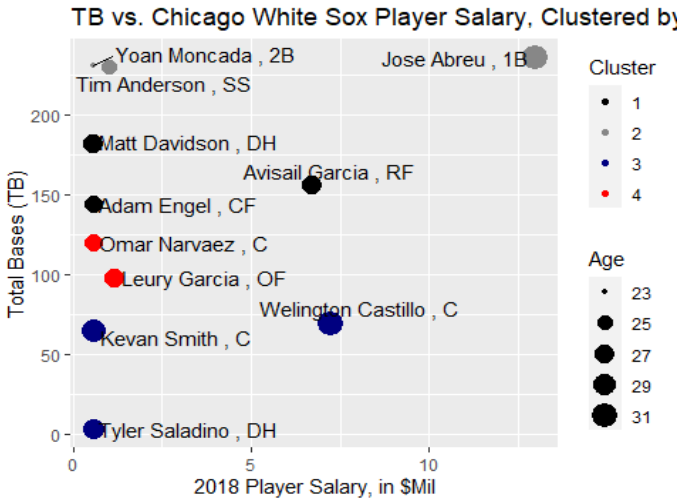
Model 3

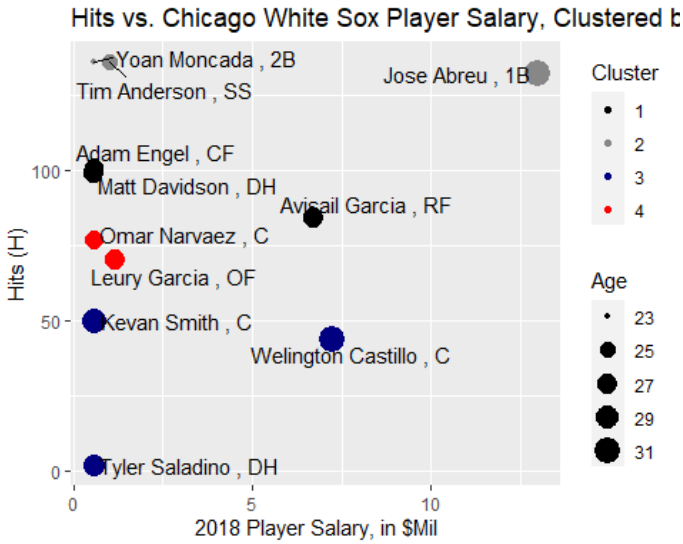
In order to optimize k value, the elbow method, looped through k values 1 to 10 which returns a rather interesting plot. The elbow where the Sum of Squared errors can be interpreted as any k value between k = 2 or k = 6, based on the shape of the plot.

```
##    Rk Pos             Player Age   G  PA  AB  R   H X2B X3B HR RBI SB CS B
B  SO
## 1   1   C       Omar Narvaez  26  97 322 280 30  77  14   1  9  30  0  2 3
8  65
## 2   2  1B         Jose Abreu  31 128 553 499 68 132  36   1 22  78  2  0 3
7 109
## 3   3  2B       Yoan Moncada  23 149 650 578 73 136  32   6 17  61 12  6 6
7 217
## 4   4  SS       Tim Anderson  25 153 606 567 77 136  28   3 20  64 26  8 3
0 149
## 5   5  3B     Yolmer Sanchez  26 155 662 600 62 145  34  10  8  55 14  6 4
9 138
## 6   6  LF    Nicky Delmonico  25  88 318 284 31  61  11   5  8  25  1  2 2
7  80
## 7   7  CF         Adam Engel  26 143 463 429 49 101  17   4  6  29 16  8 1
8 129
## 8   8  RF     Avisail Garcia  27  93 385 356 47  84  11   2 19  49  3  1 2
0 102
## 9   9  DH      Matt Davidson  27 123 496 434 51  99  23   0 20  62  0  0 5
2 165
## 10 10  OF       Daniel Palka  26 124 449 417 56 100  15   3 27  67  2  1 3
0 153
## 11 11  OF       Leury Garcia  27  82 275 258 23  70   7   4  4  32 12  1
```

```
9  69
## 12 12   C        Kevan Smith  30  52 187 171 21  50   6   0  3  21  1  0 1
0  18
## 13 13   C Welington Castillo  31  49 181 170 17  44   7   0  6  15  1  0
9  46
## 14 14  RF    Trayce Thompson  27  48 130 121 14  14   3   0  3   9  3  1
7  46
## 15 15  LF     Charlie Tilson  25  41 121 106  7  28   1   1  0  11  2  3 1
0  20
## 16 16  IF        Jose Rondon  24  42 107 100 15  23   6   0  6  14  2  1
7  30
## 17 17  LF       Ryan LaMarre  29  33  71  66  8  20   6   0  2  10  1  1
2  20
## 18 18  OF       Ryan Cordell  26  19  40  37  3   4   1   0  1   4  0  0
0  15
## 19 19  DH         Matt Skole  28   4  13  11  2   3   0   0  1   1  0  0
2   3
## 20 20   C   Alfredo Gonzalez  25   3   9   9  0   1   0   0  0   1  0  0
0   4
## 21 21  DH     Tyler Saladino  28   6   9   8  2   2   1   0  0   0  0  0
0   3
## 22 22   C     Dustin Garneau  30   1   3   2  0   1   0   0  0   1  0  0
1   0
## 23 23   P      James Shields  36   3   7   6  0   1   0   0  0   0  0  0
0   3
## 24 24   P      Lucas Giolito  23   3   6   6  0   0   0   0  0   0  0  0
0   4
## 25 25   P    Hector Santiago  30   5   4   4  0   0   0   0  0   0  0  0
0   2
## 26 26   P        Dylan Covey  26   1   1   1  0   0   0   0  0   0  0  0
0   1
## 27 27   P         Chris Beck  27   4   1   1  0   0   0   0  0   0  0  0
0   1
## 28 28   P        Luis Avilan  28   3   1   1  0   0   0   0  0   0  0  0
0   1
## 29 29   P     Reynaldo Lopez  24   1   1   1  0   0   0   0  0   0  0  0
0   1
##       BA   OBP   SLG   OPS OPS.  TB GDP HBP SH SF IBB   BATS
## 1  0.275 0.366 0.429 0.794  119 120   5   2  2  0   1   LEFT
## 2  0.265 0.325 0.473 0.798  117 236  14  11  0  6   7  RIGHT
## 3  0.235 0.315 0.400 0.714   96 231   4   1  2  2   1 SWITCH
## 4  0.240 0.281 0.406 0.687   87 230  15   4  2  3   2  RIGHT
## 5  0.242 0.306 0.372 0.678   87 223   9   8  2  3   0 SWITCH
## 6  0.215 0.296 0.373 0.669   84 106   7   6  0  1   1   LEFT
## 7  0.235 0.279 0.336 0.614   69 144   1   8  7  1   0  RIGHT
## 8  0.236 0.281 0.438 0.719   95 156   9   4  0  5   2  RIGHT
## 9  0.228 0.319 0.419 0.738  102 182   8   7  0  3   0  RIGHT
## 10 0.240 0.294 0.484 0.778  110 202   7   2  0  0   3   LEFT
## 11 0.271 0.303 0.376 0.679   87  97   2   3  4  1   0 SWITCH
## 12 0.292 0.348 0.380 0.728  102  65   5   5  0  1   0  RIGHT
```

```
## 13 0.259 0.304 0.406 0.710   94  69   7   2  0  0   0  RIGHT
## 14 0.116 0.163 0.215 0.378    4  26   0   0  1  1   1  RIGHT
## 15 0.264 0.331 0.292 0.623   75  31   2   1  2  1   0   LEFT
## 16 0.230 0.280 0.470 0.750  102  47   3   0  0  0   0  RIGHT
## 17 0.303 0.324 0.485 0.809  120  32   0   1  0  2   0  RIGHT
## 18 0.108 0.125 0.216 0.341   -8   8   0   1  0  2   0  RIGHT
## 19 0.273 0.385 0.545 0.930  154   6   0   0  0  0   0   LEFT
## 20 0.111 0.111 0.111 0.222  -38   1   0   0  0  0   0  RIGHT
## 21 0.250 0.250 0.375 0.625   70   3   0   0  1  0   0  RIGHT
## 22 0.500 0.667 0.500 1.167  232   1   0   0  0  0   0  RIGHT
## 23 0.167 0.167 0.167 0.333   -7   1   0   0  1  0   0  RIGHT
## 24 0.000 0.000 0.000 0.000 -100   0   0   0  0  0   0  RIGHT
## 25 0.000 0.000 0.000 0.000 -100   0   1   0  0  0   0  RIGHT
## 26 0.000 0.000 0.000 0.000 -100   0   0   0  0  0   0  RIGHT
## 27 0.000 0.000 0.000 0.000 -100   0   0   0  0  0   0  RIGHT
## 28 0.000 0.000 0.000 0.000 -100   0   0   0  0  0   0   LEFT
## 29 0.000 0.000 0.000 0.000 -100   0   0   0  0  0   0  RIGHT
```





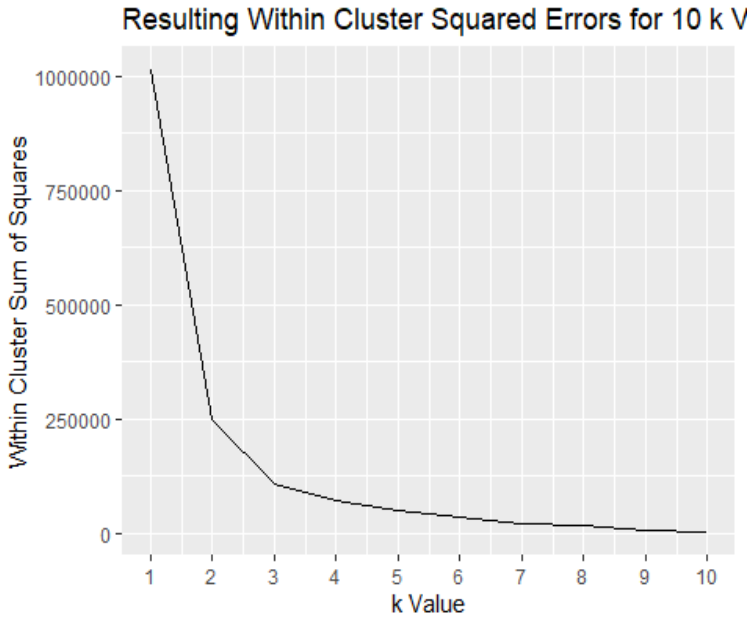
Using K-means clustering, we can group the players with similar performance together, and use the clusters to compare players. Using the elbow method, we can observe where the Within-Cluster Sum of Squares first starts to diminish, forming an "elbow" in the plot of k vs. WCSoS. From this, we see that the optimal k value is 3. When given business context, this can be construed to make sense. There are three categories of positions players: Outfielders, Infielders, and Catchers.

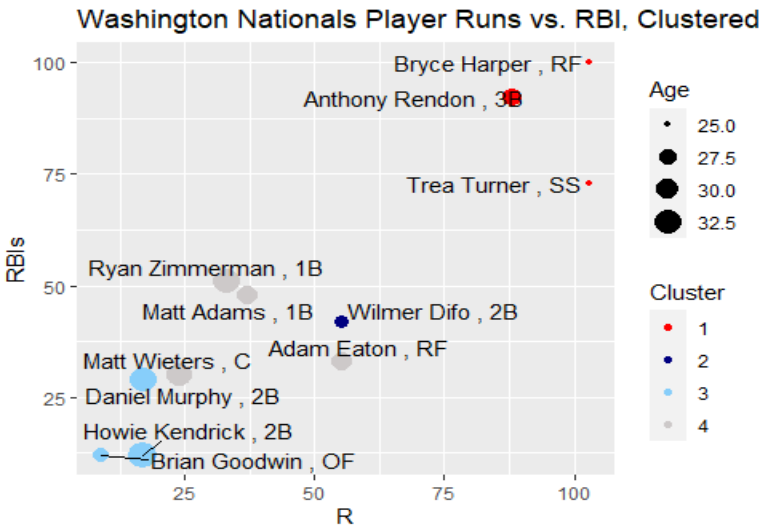
```
#clustering players
WashingtonNationals2018Batting # WAS batting stats for 2018
```

```
##    Rk Pos            Player Age   G  PA  AB   R   H X2B X3B HR RBI SB CS
BB
## 1   1   C      Matt Wieters  32  76 271 235  24  56   8   0  8  30  0  1
30
## 2   2  1B    Ryan Zimmerman  33  85 323 288  33  76  21   2 13  51  1  1
30
## 3   3  2B       Wilmer Difo  26 148 456 408  55  94  14   7  7  42 10  3
39
## 4   4  SS       Trea Turner  25 162 740 664 103 180  27   6 19  73 43  9
69
## 5   5  3B    Anthony Rendon  28 136 597 529  88 163  44   2 24  92  2  1
55
## 6   6  LF         Juan Soto  19 116 494 414  77 121  25   1 22  70  5  2
79
## 7   7  CF Michael A. Taylor  27 134 385 353  46  80  22   3  6  28 24  6
29
## 8   8  RF      Bryce Harper  25 159 695 550 103 137  34   0 34 100 13  3 1
30
## 9   9  RF        Adam Eaton  29  95 370 319  55  96  18   1  5  33  9  1
38
## 10 10  1B        Matt Adams  29  94 277 249  37  64   9   0 18  48  0  0
24
## 11 11  1B     Mark Reynolds  34  86 235 206  26  51   8   0 13  40  0  0
24
## 12 12   C    Pedro Severino  24  70 213 190  14  32   9   0  2  15  1  0
18
## 13 13  2B     Daniel Murphy  33  56 205 190  17  57   9   0  6  29  1  0
13
## 14 14  2B    Howie Kendrick  34  40 160 152  17  46  14   0  4  12  1  1
5
## 15 15   C   Spencer Kieboom  27  52 143 125  16  29   5   0  2  13  0  0
16
## 16 16  OF  Andrew Stevenson  24  57  86  75   9  19   2   0  1  13  1  1
6
## 17 17  OF     Brian Goodwin  27  48  79  65   9  13   1   0  3  12  3  1
10
## 18 18  OF     Victor Robles  21  21  66  59   8  17   3   1  3  10  3  2
4
## 19 19  OF     Moises Sierra  29  27  60  54   4   9   2   0  0   4  1  1
2
```

```
## 20 20  IF    Adrian Sanchez  27  28  59  58   8  16   2   1  0   3  0  0
1
## 21 21  3B     Matt Reynolds  27  12  14  13   1   2   0   0  0   1  0  0
1
## 22 22   C    Miguel Montero  34   4  13  11   0   0   0   0  0   0  0  0
2
## 23 23  OF   Rafael Bautista  25   9   6   6   1   0   0   0  0   0  0  0
0
## 24 24   P      Max Scherzer  33  32  78  70   8  17   2   0  0   6  1  0
1
## 25 25   P      Tanner Roark  31  29  65  58   6  11   2   1  0   8  0  0
1
## 26 26   P Stephen Strasburg  29  22  51  41   0   5   0   0  0   1  0  0
2
## 27 27   P      Gio Gonzalez  32  24  47  44   1   3   1   0  0   0  0  0
0
## 28 28   P Jeremy Hellickson  31  18  35  32   0   2   1   0  0   1  0  0
0
## 29 29   P   Jefry Rodriguez  24  14  18  16   2   3   1   0  0   1  0  0
0
## 30 30   P       Erick Fedde  25  10  17  16   1   1   0   0  0   0  0  0
1
## 31 31   P      Tommy Milone  31   5   9   7   0   0   0   0  0   0  0  0
1
## 32 32   P          Joe Ross  25   3   5   5   0   0   0   0  0   0  0  0
0
## 33 33   P         A.J. Cole  26   4   4   3   1   1   0   0  1   1  0  0
0
## 34 34   P      Wander Suero  26  38   3   3   0   0   0   0  0   0  0  0
0
## 35 35   P        Matt Grace  29  54   3   3   0   1   0   0  0   0  0  0
0
## 36 36   P      Kyle McGowin  26   5   2   2   1   0   0   0  0   0  0  0
0
## 37 37   P       Austin Voth  26   4   2   2   0   0   0   0  0   0  0  0
0
## 38 38   P      Shawn Kelley  34  32   1   1   0   0   0   0  0   0  0  0
0
## 39 39   P     Justin Miller  31  46   1   1   0   0   0   0  0   0  0  0
0
##     SO    BA   OBP   SLG   OPS OPS.  TB GDP HBP SH SF IBB   BATS
## 1   45 0.238 0.330 0.374 0.704   86  88   5   3  1  2   3 SWITCH
## 2   55 0.264 0.337 0.486 0.824  114 140  10   3  0  2   1  RIGHT
## 3   82 0.230 0.298 0.350 0.649   71 143   8   2  3  4   5 SWITCH
## 4  132 0.271 0.344 0.416 0.760  100 276   7   5  2  0   3  RIGHT
## 5   82 0.308 0.374 0.535 0.909  137 283   5   5  0  8   5  RIGHT
## 6   99 0.292 0.406 0.517 0.923  142 214   9   0  1  0  10   LEFT
## 7  116 0.227 0.287 0.357 0.644   69 126   9   1  2  0   2  RIGHT
## 8  169 0.249 0.393 0.496 0.889  133 273   7   6  0  9  16   LEFT
## 9   64 0.301 0.394 0.411 0.805  114 131   2  11  2  0   0   LEFT
```

```
## 10  55 0.257 0.332 0.510 0.842  118 127   6   4  0  0   2   LEFT
## 11  64 0.248 0.328 0.476 0.803  109  98   8   2  0  3   1  RIGHT
## 12  47 0.168 0.254 0.247 0.501   34  47   3   4  0  1   4  RIGHT
## 13  17 0.300 0.341 0.442 0.784  105  84   4   0  0  2   2   LEFT
## 14  29 0.303 0.331 0.474 0.805  110  72   6   2  0  1   1  RIGHT
## 15  28 0.232 0.322 0.320 0.642   71  40   2   1  0  1   0  RIGHT
## 16  23 0.253 0.306 0.320 0.626   66  24   0   1  1  3   0   LEFT
## 17  26 0.200 0.321 0.354 0.674   78  23   0   2  1  1   0   LEFT
## 18  12 0.288 0.348 0.525 0.874  127  31   2   2  0  1   0  RIGHT
## 19  20 0.167 0.217 0.204 0.420   12  11   2   2  0  2   0  RIGHT
## 20   8 0.276 0.288 0.345 0.633   67  20   0   0  0  0   0  RIGHT
## 21   4 0.154 0.214 0.154 0.368    0   2   0   0  0  0   0  RIGHT
## 22   3 0.000 0.154 0.000 0.154  -54   0   0   0  0  0   1   LEFT
## 23   1 0.000 0.000 0.000 0.000 -100   0   1   0  0  0   0  RIGHT
## 24  14 0.243 0.274 0.271 0.545   45  19   1   2  5  0   0  RIGHT
## 25  19 0.190 0.217 0.259 0.475   25  15   1   1  5  0   0  RIGHT
## 26  12 0.122 0.163 0.122 0.285  -23   5   3   0  8  0   0  RIGHT
## 27  27 0.068 0.068 0.091 0.159  -58   4   0   0  3  0   0  RIGHT
## 28  13 0.063 0.063 0.094 0.156  -59   3   0   0  3  0   0  RIGHT
## 29   8 0.188 0.188 0.250 0.438   14   4   0   0  2  0   0  RIGHT
## 30   5 0.063 0.118 0.063 0.180  -50   1   1   0  0  0   0  RIGHT
## 31   3 0.000 0.125 0.000 0.125  -63   0   0   0  1  0   0   LEFT
## 32   3 0.000 0.000 0.000 0.000 -100   0   1   0  0  0   0  RIGHT
## 33   1 0.333 0.333 1.333 1.667  311   4   0   0  1  0   0  RIGHT
## 34   1 0.000 0.000 0.000 0.000 -100   0   0   0  0  0   0  RIGHT
## 35   0 0.333 0.333 0.333 0.667   77   1   0   0  0  0   0   LEFT
## 36   0 0.000 0.000 0.000 0.000 -100   0   0   0  0  0   0  RIGHT
## 37   1 0.000 0.000 0.000 0.000 -100   0   0   0  0  0   0  RIGHT
## 38   1 0.000 0.000 0.000 0.000 -100   0   0   0  0  0   0  RIGHT
## 39   0 0.000 0.000 0.000 0.000 -100   0   1   0  0  0   0  RIGHT
```





Model 4

kMeans clustering provided a method for unsupervised pattern recognition within the White Sox and Nationals datasets. There are also supervised learning methods that utilize the same basic principles of determining similarity between data points based on distance between all vectors of the examples. One such method is kNN, which is an abbreviation for k-Nearest Neighbors. The term "k" acts in kNN similar to the "k" in kMeans, where it can be arbitrarily decided by the model user. In kNN, k represents the number of neighbors, or closest data points, to a test record example that will be used to calculate the majority classification voting that will determine the predicted class. If k is small, then the model is very sensitive to noise, and if k is large, then the neighborhood is too large and the estimated class will be generalized. A unique feature of kNN modeling is there is no standard training and testing split. The algorithm function takes both a training and testing input simultaneously, and the user denotes the training data set's classification labels.

To run kNN modeling, all players needed to be classified based on their salary in three distinct groups. Players with salaries under 3 million in 2018 were labeled as "low", players with salaries over $11 million in 2018 were labelled as "high", and the rest were labeled as "mid". The goal in this analysis is to find the number k that provides the best accuracy in the kNN model, when attempting to label players salaries based on their performance.

The Nationals and White Sox player data sets were relatively small. To create more data, sampling with replacement was done to fabricate more data that was identical to the original data set. This method of sampling simulated a player being compared to different teammates in different sampling cycles, so it strained the model to provide consistent accuracy feedback.

The process for running kNN with the player datasets was an iterative one. After identifying the optimal k value for batters and pitchers data sets, 3-fold cross validation was repeated and the accuracy score was calculated for each iteration.

```
## [1] 16
```

```
## Warning in split.default(sample(1:nrow(CWSsalbatstats18reduced2)), 1:k_fol
ds):
## data length is not a multiple of split variable

## [1] "K-Fold Iteration:  1     Accuracy:  0.491"
## [1] "K-Fold Iteration:  2     Accuracy:  0.212"
## [1] "K-Fold Iteration:  3     Accuracy:  0.35"

## [1] 15

## [1] "K-Fold Iteration:  1     Accuracy:  0.208"
## [1] "K-Fold Iteration:  2     Accuracy:  0.215"
## [1] "K-Fold Iteration:  3     Accuracy:  0.589"
```

The Washington Nationals batter's dataset was used to determine the optimal k value for batters. Using 3-fold cross validation to collect accuracy scores, k values were iterated from 1 to 5, and the accuracies plotted below. K was set to 5 for model testing as the accuracy plateaued for values larger than 5.

```
## [1] 19

## Warning in split.default(sample(1:nrow(WASsalbatstats18reduced2)), 1:k_fol
ds):
## data length is not a multiple of split variable

## [1] "K-Fold Iteration:  1     Accuracy:  0.462"
## [1] "K-Fold Iteration:  2     Accuracy:  0.489"
## [1] "K-Fold Iteration:  3     Accuracy:  0.142"

## [1] 15

## [1] "K-Fold Iteration:  1     Accuracy:  0.598"
## [1] "K-Fold Iteration:  2     Accuracy:  0.199"
## [1] "K-Fold Iteration:  3     Accuracy:  0.8"
```

Results

Model 1

A couple of the more interesting rules generated for the White Sox is if they're playing at night, and the opponents don't hit any home runs (or have any stolen bases), they are more likely to win, as well as if they're playing a home game and don't hit any home runs themselves, they're more likely to lose. This gives insight as to how schedule factors into overall performance, as well as how important defense is. But those rules don't give any insight to player performance, so we generated rules based on the winning batting lineup of each game.

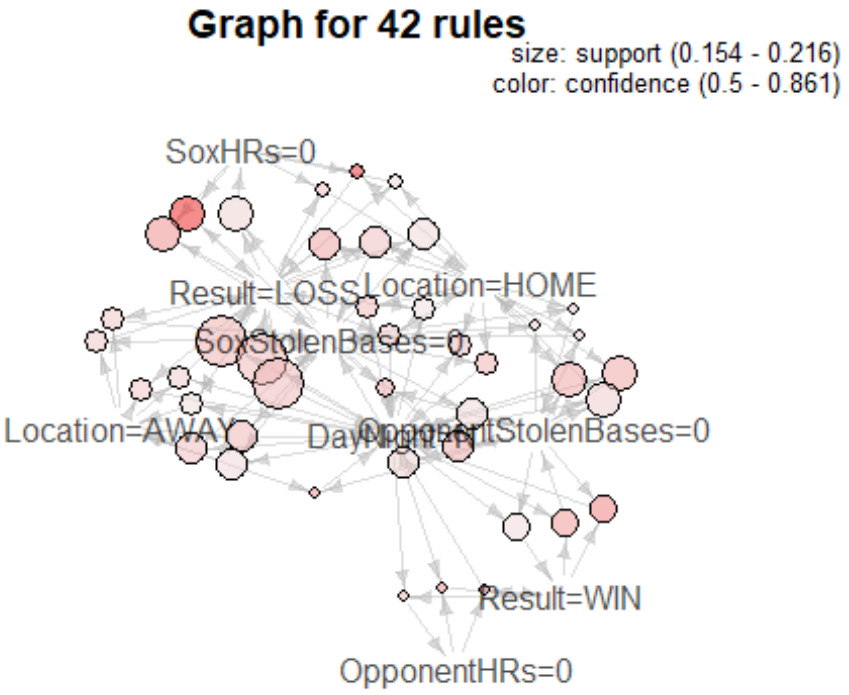
```
##     lhs                                    rhs                 support
## [1] {SoxHRs=0,SoxStolenBases=0}        => {Result=LOSS}      0.1913580
## [2] {Location=HOME,SoxHRs=0}           => {Result=LOSS}      0.1604938
```

```
## [3] {Result=WIN,OpponentHRs=0}         => {DayNight=N}       0.1543210
## [4] {Result=WIN,OpponentStolenBases=0} => {DayNight=N}       0.1790123
## [5] {Result=LOSS,SoxHRs=0}             => {SoxStolenBases=0} 0.1913580
## [6] {DayNight=N,OpponentHRs=0}         => {Result=WIN}       0.1543210
##     confidence lift     count
## [1] 0.8611111  1.395000 31
## [2] 0.8387097  1.358710 26
## [3] 0.7352941  1.215486 25
## [4] 0.7250000  1.198469 29
## [5] 0.7045455  1.214217 31
## [6] 0.6944444  1.814516 25

##      lhs                          rhs                        support confiden
ce      lift count
## [1]  {SoxHRs=0,
##       SoxStolenBases=0}      => {Result=LOSS}           0.1913580  0.86111
11 1.3950000    31
## [2]  {Location=HOME,
##       SoxHRs=0}              => {Result=LOSS}           0.1604938  0.83870
97 1.3587097    26
## [3]  {Result=WIN,
##       OpponentHRs=0}         => {DayNight=N}            0.1543210  0.73529
41 1.2154862    25
## [4]  {Result=WIN,
##       OpponentStolenBases=0} => {DayNight=N}            0.1790123  0.72500
00 1.1984694    29
## [5]  {Result=LOSS,
##       SoxHRs=0}              => {SoxStolenBases=0}      0.1913580  0.70454
55 1.2142166    31
## [6]  {DayNight=N,
##       OpponentHRs=0}         => {Result=WIN}            0.1543210  0.69444
44 1.8145161    25
## [7]  {Location=AWAY,
##       OpponentStolenBases=0} => {DayNight=N}            0.1543210  0.69444
44 1.1479592    25
## [8]  {Result=WIN,
##       DayNight=N}            => {OpponentStolenBases=0} 0.1790123  0.69047
62 1.3476764    29
## [9]  {Location=HOME,
##       SoxStolenBases=0}      => {Result=LOSS}           0.1851852  0.66666
67 1.0800000    30
## [10] {Location=HOME,
##       OpponentStolenBases=0} => {DayNight=N}            0.1913580  0.65957
45 1.0903170    31
## [11] {Location=HOME,
##       DayNight=N}            => {OpponentStolenBases=0} 0.1913580  0.65957
45 1.2873622    31
## [12] {SoxStolenBases=0,
##       OpponentStolenBases=0} => {DayNight=N}            0.1851852  0.63829
79 1.0551455    30
```

```
## [13] {Result=LOSS,
##       OpponentStolenBases=0} => {DayNight=N}            0.1666667  0.62790
70 1.0379687    27
## [14] {Result=LOSS,
##       DayNight=N}            => {SoxStolenBases=0}      0.2160494  0.62500
00 1.0771277    35
## [15] {Location=HOME,
##       SoxStolenBases=0}      => {DayNight=N}            0.1728395  0.62222
22 1.0285714    28
## [16] {Location=AWAY,
##       SoxStolenBases=0}      => {DayNight=N}            0.1851852  0.61224
49 1.0120783    30
## [17] {DayNight=N,
##       SoxStolenBases=0}      => {Result=LOSS}           0.2160494  0.60344
83 0.9775862    35
## [18] {Result=LOSS,
##       SoxStolenBases=0}      => {DayNight=N}            0.2160494  0.60344
83 0.9975369    35
## [19] {Location=HOME,
##       DayNight=N}            => {SoxStolenBases=0}      0.1728395  0.59574
47 1.0267089    28
## [20] {Location=HOME,
##       DayNight=N}            => {Result=LOSS}           0.1728395  0.59574
47 0.9651064    28
## [21] {Result=WIN,
##       DayNight=N}            => {OpponentHRs=0}         0.1543210  0.59523
81 1.8543956    25
## [22] {Result=LOSS,
##       SoxHRs=0}              => {Location=HOME}         0.1604938  0.59090
91 1.1818182    26
## [23] {Location=AWAY,
##       DayNight=N}            => {SoxStolenBases=0}      0.1851852  0.58823
53 1.0137672    30
## [24] {Location=HOME,
##       Result=LOSS}           => {SoxStolenBases=0}      0.1851852  0.58823
53 1.0137672    30
## [25] {Location=AWAY,
##       SoxStolenBases=0}      => {Result=LOSS}           0.1728395  0.57142
86 0.9257143    28
## [26] {Location=AWAY,
##       Result=LOSS}           => {SoxStolenBases=0}      0.1728395  0.57142
86 0.9848024    28
## [27] {Location=AWAY,
##       Result=LOSS}           => {DayNight=N}            0.1728395  0.57142
86 0.9446064    28
## [28] {Location=HOME,
##       SoxStolenBases=0}      => {OpponentStolenBases=0} 0.1543210  0.55555
56 1.0843373    25
## [29] {DayNight=N,
##       OpponentStolenBases=0} => {Location=HOME}         0.1913580  0.55357
```

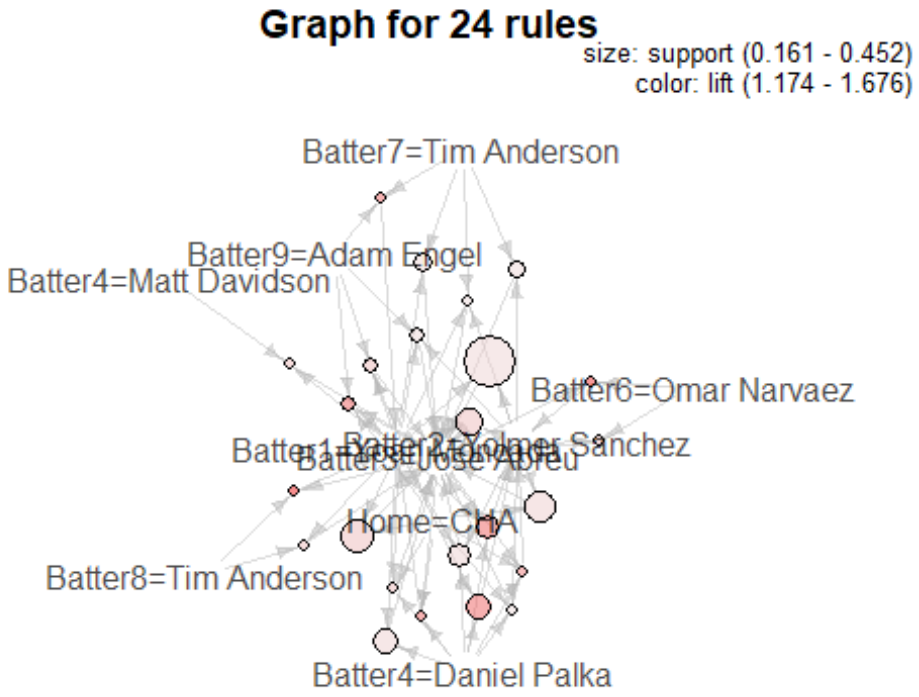
```
14 1.1071429    31
## [30] {Location=AWAY,
##       DayNight=N}            => {Result=LOSS}           0.1728395  0.54901
96 0.8894118    28
## [31] {Location=HOME,
##       Result=LOSS}           => {DayNight=N}            0.1728395  0.54901
96 0.9075630    28
## [32] {DayNight=N,
##       OpponentStolenBases=0} => {SoxStolenBases=0}      0.1851852  0.53571
43 0.9232523    30
## [33] {Result=LOSS,
##       SoxStolenBases=0}      => {SoxHRs=0}              0.1913580  0.53448
28 1.5742947    31
## [34] {Location=HOME,
##       OpponentStolenBases=0} => {SoxStolenBases=0}      0.1543210  0.53191
49 0.9167044    25
## [35] {SoxStolenBases=0,
##       OpponentStolenBases=0} => {Location=HOME}         0.1543210  0.53191
49 1.0638298    25
## [36] {DayNight=N,
##       OpponentStolenBases=0} => {Result=WIN}            0.1790123  0.51785
71 1.3531106    29
## [37] {DayNight=N,
##       SoxStolenBases=0}      => {Location=AWAY}         0.1851852  0.51724
14 1.0344828    30
## [38] {Result=LOSS,
##       SoxStolenBases=0}      => {Location=HOME}         0.1851852  0.51724
14 1.0344828    30
## [39] {DayNight=N,
##       SoxStolenBases=0}      => {OpponentStolenBases=0} 0.1851852  0.51724
14 1.0095555    30
## [40] {Location=HOME,
##       Result=LOSS}           => {SoxHRs=0}              0.1604938  0.50980
39 1.5016043    26
## [41] {Result=LOSS,
##       DayNight=N}            => {Location=AWAY}         0.1728395  0.50000
00 1.0000000    28
## [42] {Result=LOSS,
##       DayNight=N}            => {Location=HOME}         0.1728395  0.50000
00 1.0000000    28
```



Those results were mostly centered around Jose Abreu being third in the lineup, but Adam Engel being ninth in the lineup, as well as Yoan Moncada being leadoff, and Yolmer Sanchez being second seem to be the only other consistencies withing the winning batting lineups. The more variable ones (the ones that didn't have any rules generated about them), the players can be assessed to determine if their performance for the season merits them remaining on the team.

```
##      lhs                           rhs                          support confid
ence     lift count
## [1]  {Batter1=Yoan Moncada,
##       Batter8=Tim Anderson}   => {Batter3=Jose Abreu}     0.1612903  1.000
0000 1.291667    10
## [2]  {Batter3=Jose Abreu,
##       Batter8=Tim Anderson}   => {Batter1=Yoan Moncada}   0.1612903  1.000
0000 1.675676    10
## [3]  {Batter2=Yolmer Sanchez,
##       Batter6=Omar Narvaez}   => {Batter3=Jose Abreu}     0.1612903  1.000
0000 1.291667    10
## [4]  {Batter3=Jose Abreu,
##       Batter6=Omar Narvaez}   => {Batter2=Yolmer Sanchez} 0.1612903  1.000
0000 1.631579    10
## [5]  {Batter1=Yoan Moncada,
##       Batter4=Matt Davidson}  => {Batter3=Jose Abreu}     0.1612903  1.000
0000 1.291667    10
## [6]  {Home=CHA,
##       Batter1=Yoan Moncada}   => {Batter3=Jose Abreu}     0.3225806  1.000
```

```
0000 1.291667    20
## [7]  {Home=CHA,
##       Batter1=Yoan Moncada,
##       Batter4=Daniel Palka}   => {Batter3=Jose Abreu}     0.1612903  1.000
0000 1.291667    10
## [8]  {Home=CHA,
##       Batter1=Yoan Moncada,
##       Batter9=Adam Engel}     => {Batter3=Jose Abreu}     0.1774194  1.000
0000 1.291667    11
## [9]  {Home=CHA,
##       Batter1=Yoan Moncada,
##       Batter2=Yolmer Sanchez} => {Batter3=Jose Abreu}     0.2741935  1.000
0000 1.291667    17
## [10] {Home=CHA,
##       Batter2=Yolmer Sanchez} => {Batter3=Jose Abreu}     0.3064516  0.950
0000 1.227083    19
## [11] {Batter1=Yoan Moncada,
##       Batter4=Daniel Palka}   => {Batter2=Yolmer Sanchez} 0.2580645  0.941
1765 1.535604    16
## [12] {Batter1=Yoan Moncada,
##       Batter4=Daniel Palka}   => {Batter3=Jose Abreu}     0.2580645  0.941
1765 1.215686    16
## [13] {Batter1=Yoan Moncada,
##       Batter2=Yolmer Sanchez,
##       Batter4=Daniel Palka}   => {Batter3=Jose Abreu}     0.2419355  0.937
5000 1.210938    15
## [14] {Batter1=Yoan Moncada,
##       Batter3=Jose Abreu,
##       Batter4=Daniel Palka}   => {Batter2=Yolmer Sanchez} 0.2419355  0.937
5000 1.529605    15
## [15] {Batter1=Yoan Moncada,
##       Batter2=Yolmer Sanchez} => {Batter3=Jose Abreu}     0.4516129  0.933
3333 1.205556    28
## [16] {Batter1=Yoan Moncada,
##       Batter7=Tim Anderson}   => {Batter3=Jose Abreu}     0.2096774  0.928
5714 1.199405    13
## [17] {Batter2=Yolmer Sanchez,
##       Batter7=Tim Anderson}   => {Batter3=Jose Abreu}     0.1935484  0.923
0769 1.192308    12
## [18] {Home=CHA,
##       Batter3=Jose Abreu,
##       Batter9=Adam Engel}     => {Batter1=Yoan Moncada}   0.1774194  0.916
6667 1.536036    11
## [19] {Batter1=Yoan Moncada,
##       Batter2=Yolmer Sanchez,
##       Batter9=Adam Engel}     => {Batter3=Jose Abreu}     0.1774194  0.916
6667 1.184028    11
## [20] {Batter7=Tim Anderson,
##       Batter9=Adam Engel}     => {Batter1=Yoan Moncada}   0.1612903  0.909
0909 1.523342    10
```



For the Nationals, perhaps the most interesting rule is that if they don't hit any HR's and have no stolen bases, they're 1.58 times more likely to lose. Looking at their 2018 record being mostly wins and the support of this being 15% (good for the amount of data), this indicates that they're mostly an offensive team, and that players with lower overall performance should be assessed for a spot on the team next season.

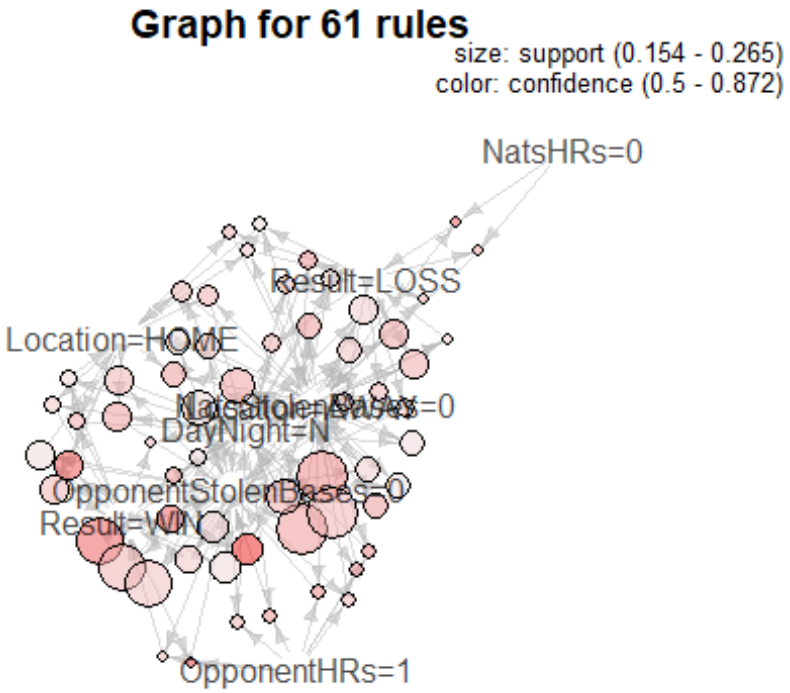
```
##     lhs                     rhs                       support confidence
lift count
## [1] {Result=WIN,
##      NatsStolenBases=0} => {OpponentStolenBases=0} 0.2098765  0.8717949 1.
295695    34
## [2] {Result=WIN,
##      OpponentHRs=1}     => {OpponentStolenBases=0} 0.1543210  0.8333333 1.
238532    25
## [3] {Location=HOME,
##      Result=WIN}        => {OpponentStolenBases=0} 0.2037037  0.8048780 1.
196241    33
## [4] {Result=WIN,
##      DayNight=N}        => {OpponentStolenBases=0} 0.2530864  0.7884615 1.
171842    41
## [5] {NatsHRs=0,
##      NatsStolenBases=0} => {Result=LOSS}          0.1543210  0.7812500 1.
582031    25
## [6] {Location=AWAY,
##      Result=WIN}        => {OpponentStolenBases=0} 0.1975309  0.7804878 1.
159991    32
```

```
##      lhs                          rhs                          support confiden
ce      lift count
## [1]  {Result=WIN,
##       NatsStolenBases=0}     => {OpponentStolenBases=0} 0.2098765  0.87179
49 1.2956951    34
## [2]  {Result=WIN,
##       OpponentHRs=1}         => {OpponentStolenBases=0} 0.1543210  0.83333
33 1.2385321    25
## [3]  {Location=HOME,
##       Result=WIN}            => {OpponentStolenBases=0} 0.2037037  0.80487
80 1.1962408    33
## [4]  {Result=WIN,
##       DayNight=N}            => {OpponentStolenBases=0} 0.2530864  0.78846
15 1.1718419    41
## [5]  {NatsHRs=0,
##       NatsStolenBases=0}     => {Result=LOSS}           0.1543210  0.78125
00 1.5820312    25
## [6]  {Location=AWAY,
##       Result=WIN}            => {OpponentStolenBases=0} 0.1975309  0.78048
78 1.1599910    32
## [7]  {NatsStolenBases=0,
##       OpponentHRs=1}         => {DayNight=N}            0.1604938  0.72222
22 1.1584158    26
## [8]  {NatsStolenBases=0,
##       OpponentHRs=1}         => {OpponentStolenBases=0} 0.1604938  0.72222
22 1.0733945    26
## [9]  {DayNight=N,
##       NatsStolenBases=0}     => {OpponentStolenBases=0} 0.2654321  0.71666
67 1.0651376    43
## [10] {DayNight=N,
##       OpponentHRs=1}         => {NatsStolenBases=0}     0.1604938  0.70270
27 1.2648649    26
## [11] {DayNight=N,
##       OpponentHRs=1}         => {OpponentStolenBases=0} 0.1604938  0.70270
27 1.0443838    26
## [12] {Location=AWAY,
##       Result=LOSS}           => {DayNight=N}            0.1728395  0.70000
00 1.1227723    28
## [13] {NatsStolenBases=0,
##       OpponentStolenBases=0} => {DayNight=N}            0.2654321  0.69354
84 1.1124241    43
## [14] {Result=WIN,
##       NatsStolenBases=0}     => {DayNight=N}            0.1666667  0.69230
77 1.1104341    27
## [15] {Location=AWAY,
##       NatsStolenBases=0}     => {DayNight=N}            0.1913580  0.68888
89 1.1049505    31
## [16] {Location=AWAY,
##       NatsStolenBases=0}     => {OpponentStolenBases=0} 0.1913580  0.68888
89 1.0238532    31
```

```
## [17] {Location=HOME,
##       NatsStolenBases=0}     => {OpponentStolenBases=0} 0.1913580  0.68888
89 1.0238532    31
## [18] {Location=HOME,
##       DayNight=N}            => {OpponentStolenBases=0} 0.2037037  0.68750
00 1.0217890    33
## [19] {Location=AWAY,
##       DayNight=N}            => {OpponentStolenBases=0} 0.2222222  0.67924
53 1.0095205    36
## [20] {Result=LOSS,
##       DayNight=N}            => {NatsStolenBases=0}     0.2037037  0.67346
94 1.2122449    33
## [21] {Location=HOME,
##       Result=WIN}            => {DayNight=N}            0.1666667  0.65853
66 1.0562666    27
## [22] {Result=LOSS,
##       NatsHRs=0}             => {NatsStolenBases=0}     0.1543210  0.65789
47 1.1842105    25
## [23] {Location=HOME,
##       Result=LOSS}           => {NatsStolenBases=0}     0.1604938  0.65000
00 1.1700000    26
## [24] {Result=LOSS,
##       NatsStolenBases=0}     => {DayNight=N}            0.2037037  0.64705
88 1.0378567    33
## [25] {Location=HOME,
##       NatsStolenBases=0}     => {DayNight=N}            0.1790123  0.64444
44 1.0336634    29
## [26] {Location=AWAY,
##       OpponentStolenBases=0} => {DayNight=N}            0.2222222  0.64285
71 1.0311174    36
## [27] {Result=LOSS,
##       OpponentStolenBases=0} => {NatsStolenBases=0}     0.1728395  0.63636
36 1.1454545    28
## [28] {Result=LOSS,
##       OpponentStolenBases=0} => {DayNight=N}            0.1728395  0.63636
36 1.0207021    28
## [29] {Result=WIN,
##       OpponentStolenBases=0} => {DayNight=N}            0.2530864  0.63076
92 1.0117289    41
## [30] {Location=AWAY,
##       Result=LOSS}           => {NatsStolenBases=0}     0.1543210  0.62500
00 1.1250000    25
## [31] {DayNight=N,
##       OpponentStolenBases=0} => {NatsStolenBases=0}     0.2654321  0.62318
84 1.1217391    43
## [32] {Location=HOME,
##       OpponentStolenBases=0} => {Result=WIN}            0.2037037  0.62264
15 1.2300966    33
## [33] {Location=HOME,
##       OpponentStolenBases=0} => {DayNight=N}            0.2037037  0.62264
```

```
15 0.9986923    33
## [34] {OpponentHRs=1,
##       OpponentStolenBases=0} => {NatsStolenBases=0}     0.1604938  0.61904
76 1.1142857    26
## [35] {OpponentHRs=1,
##       OpponentStolenBases=0} => {DayNight=N}            0.1604938  0.61904
76 0.9929279    26
## [36] {Location=AWAY,
##       Result=WIN}            => {DayNight=N}            0.1543210  0.60975
61 0.9780246    25
## [37] {Location=HOME,
##       DayNight=N}            => {NatsStolenBases=0}     0.1790123  0.60416
67 1.0875000    29
## [38] {OpponentHRs=1,
##       OpponentStolenBases=0} => {Result=WIN}            0.1543210  0.59523
81 1.1759582    25
## [39] {DayNight=N,
##       OpponentStolenBases=0} => {Result=WIN}            0.2530864  0.59420
29 1.1739130    41
## [40] {Location=AWAY,
##       DayNight=N}            => {NatsStolenBases=0}     0.1913580  0.58490
57 1.0528302    31
## [41] {Location=HOME,
##       OpponentStolenBases=0} => {NatsStolenBases=0}     0.1913580  0.58490
57 1.0528302    31
## [42] {Location=HOME,
##       NatsStolenBases=0}     => {Result=LOSS}           0.1604938  0.57777
78 1.1700000    26
## [43] {Result=LOSS,
##       DayNight=N}            => {Location=AWAY}         0.1728395  0.57142
86 1.1428571    28
## [44] {Result=LOSS,
##       DayNight=N}            => {OpponentStolenBases=0} 0.1728395  0.57142
86 0.8492792    28
## [45] {Location=AWAY,
##       OpponentStolenBases=0} => {Result=WIN}            0.1975309  0.57142
86 1.1289199    32
## [46] {Location=HOME,
##       DayNight=N}            => {Result=WIN}            0.1666667  0.56250
00 1.1112805    27
## [47] {Location=AWAY,
##       NatsStolenBases=0}     => {Result=LOSS}           0.1543210  0.55555
56 1.1250000    25
## [48] {Location=AWAY,
##       OpponentStolenBases=0} => {NatsStolenBases=0}     0.1913580  0.55357
14 0.9964286    31
## [49] {DayNight=N,
##       NatsStolenBases=0}     => {Result=LOSS}           0.2037037  0.55000
00 1.1137500    33
## [50] {Result=LOSS,
```

```
##       NatsStolenBases=0}     => {OpponentStolenBases=0} 0.1728395  0.54901
96 0.8159741    28
## [51] {NatsStolenBases=0,
##       OpponentStolenBases=0} => {Result=WIN}            0.2098765  0.54838
71 1.0833989    34
## [52] {Location=AWAY,
##       DayNight=N}            => {Result=LOSS}           0.1728395  0.52830
19 1.0698113    28
## [53] {Result=WIN,
##       OpponentStolenBases=0} => {NatsStolenBases=0}     0.2098765  0.52307
69 0.9415385    34
## [54] {DayNight=N,
##       OpponentStolenBases=0} => {Location=AWAY}         0.2222222  0.52173
91 1.0434783    36
## [55] {Result=WIN,
##       DayNight=N}            => {Location=HOME}         0.1666667  0.51923
08 1.0384615    27
## [56] {Result=WIN,
##       DayNight=N}            => {NatsStolenBases=0}     0.1666667  0.51923
08 0.9346154    27
## [57] {DayNight=N,
##       NatsStolenBases=0}     => {Location=AWAY}         0.1913580  0.51666
67 1.0333333    31
## [58] {Result=LOSS,
##       NatsStolenBases=0}     => {Location=HOME}         0.1604938  0.50980
39 1.0196078    26
## [59] {Result=WIN,
##       OpponentStolenBases=0} => {Location=HOME}         0.2037037  0.50769
23 1.0153846    33
## [60] {NatsStolenBases=0,
##       OpponentStolenBases=0} => {Location=AWAY}         0.1913580  0.50000
00 1.0000000    31
## [61] {NatsStolenBases=0,
##       OpponentStolenBases=0} => {Location=HOME}         0.1913580  0.50000
00 1.0000000    31
```

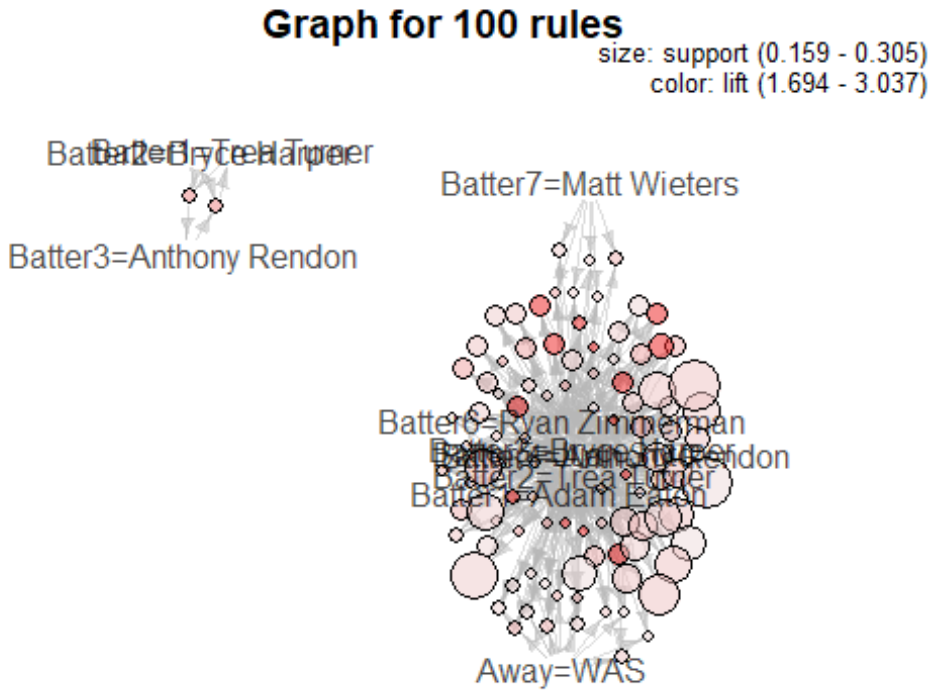


Trea Turner was in 12 of the top 20 rules for the winning batting lineups at either first or second in the lineup, indicating that a strong leadoff is necessary for a win. Juan Soto made a difference when they brought him up from the minors, with 8 of the top 20 rules having him batting at fifth. Like with the White Sox, the remaining players' performance should be assessed for a remaining spot on the team.

```
##      lhs                           rhs                          support confid
ence     lift count
## [1]  {Batter2=Bryce Harper,
##       Batter3=Anthony Rendon} => {Batter1=Trea Turner}    0.1707317
1 2.484848    14
## [2]  {Batter1=Adam Eaton,
##       Batter6=Ryan Zimmerman} => {Batter4=Anthony Rendon} 0.1707317
1 3.037037    14
## [3]  {Batter5=Juan Soto,
##       Batter6=Ryan Zimmerman} => {Batter4=Anthony Rendon} 0.1951220
1 3.037037    16
## [4]  {Batter4=Anthony Rendon,
##       Batter6=Ryan Zimmerman} => {Batter2=Trea Turner}    0.2073171
1 1.952381    17
## [5]  {Batter2=Trea Turner,
##       Batter6=Ryan Zimmerman} => {Batter4=Anthony Rendon} 0.2073171
1 3.037037    17
## [6]  {Batter3=Bryce Harper,
##       Batter6=Ryan Zimmerman} => {Batter4=Anthony Rendon} 0.1951220
1 3.037037    16
```

```
## [7]  {Batter1=Adam Eaton,
##       Batter6=Ryan Zimmerman} => {Batter2=Trea Turner}    0.1707317
1 1.952381    14
## [8]  {Batter5=Juan Soto,
##       Batter6=Ryan Zimmerman} => {Batter2=Trea Turner}    0.1951220
1 1.952381    16
## [9]  {Batter5=Juan Soto,
##       Batter6=Ryan Zimmerman} => {Batter3=Bryce Harper}   0.1951220
1 1.863636    16
## [10] {Batter3=Bryce Harper,
##       Batter6=Ryan Zimmerman} => {Batter5=Juan Soto}      0.1951220
1 2.277778    16
## [11] {Batter3=Bryce Harper,
##       Batter6=Ryan Zimmerman} => {Batter2=Trea Turner}    0.1951220
1 1.952381    16
## [12] {Batter4=Anthony Rendon,
##       Batter7=Matt Wieters}   => {Batter2=Trea Turner}    0.1585366
1 1.952381    13
## [13] {Batter5=Juan Soto,
##       Batter7=Matt Wieters}   => {Batter3=Bryce Harper}   0.1707317
1 1.863636    14
## [14] {Batter1=Adam Eaton,
##       Batter4=Anthony Rendon} => {Batter2=Trea Turner}    0.2682927
1 1.952381    22
## [15] {Batter4=Anthony Rendon,
##       Batter5=Juan Soto}      => {Batter2=Trea Turner}    0.2560976
1 1.952381    21
## [16] {Batter4=Anthony Rendon,
##       Batter5=Juan Soto}      => {Batter3=Bryce Harper}   0.2560976
1 1.863636    21
## [17] {Home=WAS,
##       Batter4=Anthony Rendon} => {Batter2=Trea Turner}    0.1585366
1 1.952381    13
## [18] {Away=WAS,
##       Batter4=Anthony Rendon} => {Batter2=Trea Turner}    0.1707317
1 1.952381    14
## [19] {Batter3=Bryce Harper,
##       Batter4=Anthony Rendon} => {Batter2=Trea Turner}    0.3048780
1 1.952381    25
## [20] {Batter1=Adam Eaton,
##       Batter5=Juan Soto,
##       Batter6=Ryan Zimmerman} => {Batter4=Anthony Rendon} 0.1585366
1 3.037037    13

## Warning: plot: Too many rules supplied. Only plotting the best 100 rules u
sing
## 'support' (change control parameter max if needed)
```



Model 2

Each team and each position results, batters versus pitchers, were added to a confusion matrix. For the Chicago White Sox batters, all three high salary players were classified as low salaried. One low salaried player was ranked as high salaried while three were classified as mid salaried. The remaining six were correctly classified. All three mid salaried players were ranked as low salaried. At 37.5% accurate, this model is not accurate as many low paid players play as well or better than the higher paid players.

```
## [1] "Chicago White Sox Batter Salary Prediction Accuracy"

##
##        high low mid
##   high    0   3   0
##   low     2   6   2
##   mid     0   3   0

## [1] 37.5
```

For the Chicago White Sox pitchers, both high salary players were classified as low salaried. Two low salaried players were ranked as mid salaried while the remaining six were correctly classified. One mid salaried pitcher was correctly classified and the other four were classified as low salaried. At 46.67% accurate, this model is not accurate either. A case can be made that the White Sox were undervaluing several players and overvaluing others.

```
## [1] "Chicago White Sox Pitcher Salary Prediction Accuracy"
```

```
##
##        high low mid
##   high    0   2   0
##   low     0   7   1
##   mid     0   4   1

## [1] 53.33333
```

The Washington Nationals batters have a more mixed prediction with lower accuracy at just 21.05%. For the Nationals, there is a better mix between low, mid, and high salaried players where the White Sox, for the most part, either paid their players close to the league minimum, 545,000, or a very high salary, 7 million or more. Only four players were accurately predicted for salary, 2 high and 2 low. Three high paid players were ranked as low while two were raked as mid. Of the misclassified low paid players, two were ranked as high and three were ranked as mid. The mid salaried players were mostly classified as high with one classified as low.

```
## [1] "Washington Nationals Batter Salary Prediction Accuracy"

##
##        high low mid
##   high    0   5   2
##   low     3   2   2
##   mid     2   2   1

## [1] 15.78947
```

The best prediction accuracy was the pitching staff of the Washington Nationals at 53.33%. Two of the four high paid pitchers were misclassified as mid salary while the other two were accurately predicted. Two of the seven low salaried pitchers were misclassified as mid salary. The other five low salaried pitchers were accurately predicted. For the mid salary group, two of four were classified as low. Of the remaining two pitchers, one was correctly classified as mid-range. Unlike the White Sox, the Nationals are not overwhelmingly under- or over-valuing their pitching staff. However, for batters it appears that the Nationals are consistent in mis-valuing their players.

```
## [1] "Washington Nationals Pitcher Salary Prediction Accuracy"

##
##        high low mid
##   high    3   0   1
##   low     1   5   1
##   mid     1   3   0

## [1] 53.33333
```

Model 3

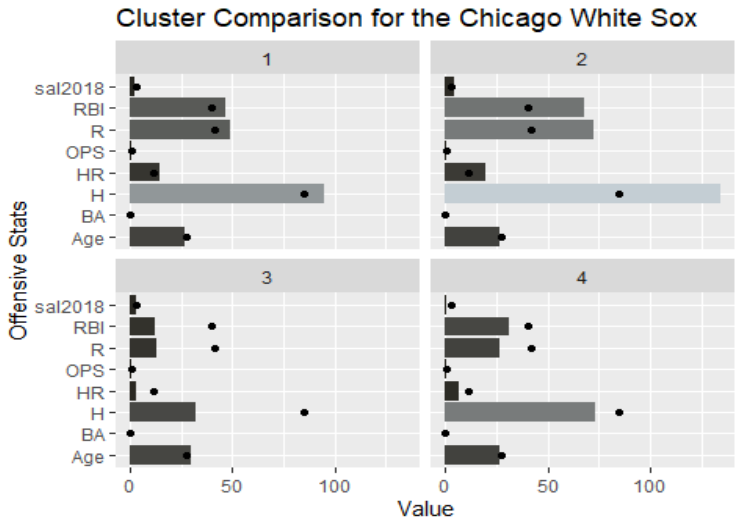
When k = 2, the clusters are split based where cluster 1 has scored greater than 45 runs, and cluster 2 has scored less than 45 runs. There is slight overlap with 3 players (Adam

Engel, Leury Garcia, Omar Narvaez) in terms of separating them into clusters based on RBIs. Overall, cluster two offensively performs better than cluster 1.

K=4 provides a more detailed breakdown of the runs scored by the White Sox players, where the players can be visually grouped into 4 offensive tiers: High Performing Tier, Upper Middle Performing Tier, Lower Middle Performing Tier, Lower Performing Tier.

K=6 follows upon the 4-means clustering above and further separates players based on offensive performance. Tim Anderson and Yoan Moncada form the new cluster 5, while Avisail Garcia and Adam Engel form the new cluster 6. Matt Davidson remain. With 6 centroids, Matt Davidson and Jose Abreu form the first cluster, whereas in earlier k-means models (k=4) Matt Davidson was not with Jose Abreu. Both Matt Davidson and Jose Abreu had higher OPS and OBP compared to Tim Anderson and Yoan Moncada.

K=4 did not have the smallest sum of squared errors (as shown in the elbow plot) but showed the best separation between high performing and low performing White Sox players. It also provided the best business context sense that is easy to interpret.

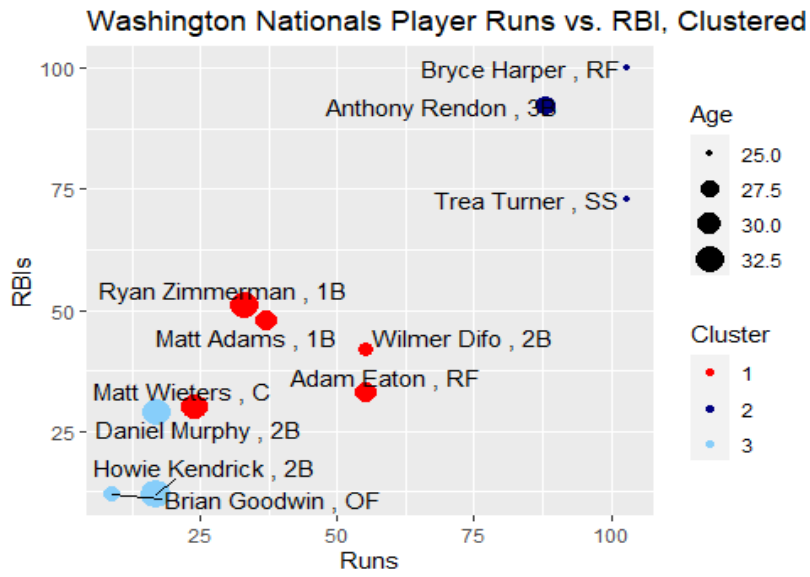



```
##                Player             Player2       X1        X2 Position MLSR
V
## 3          Jose Abreu         Abreu, Jose    Abreu      Jose       1b 4.00
0
## 10 Welington Castillo Castillo, Welington Castillo Welington        c 6.00
9
## 2      Avisail Garcia     Garcia, Avisail   Garcia   Avisail       rf 4.16
7
## 5        Leury Garcia       Garcia, Leury   Garcia     Leury    cf-2b 3.02
5
## 8        Tim Anderson       Anderson, Tim Anderson       Tim       ss 1.11
5
## 6       Matt Davidson      Davidson, Matt Davidson      Matt    dh-3b 1.14
5
## 9      Tyler Saladino     Saladino, Tyler Saladino     Tyler       2b 2.08
7
```

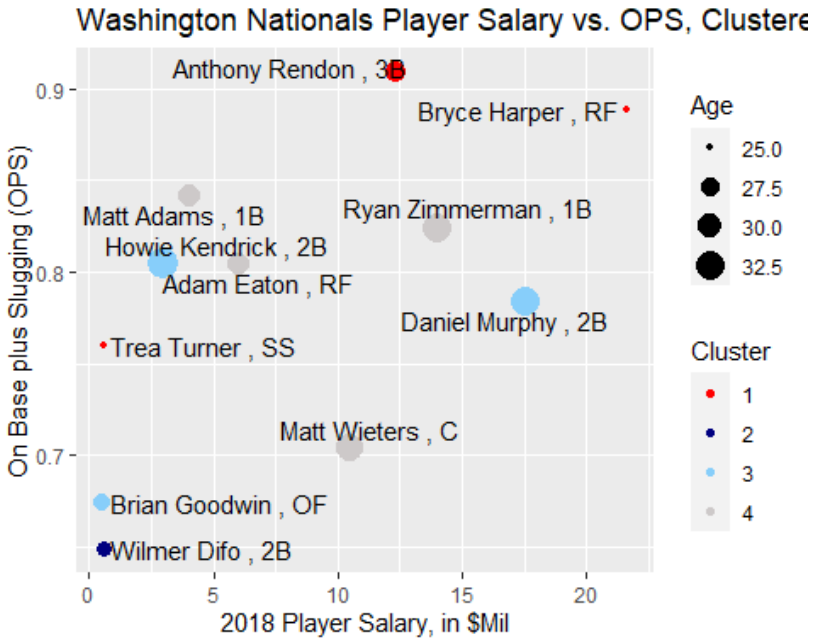
```
## 4         Kevan Smith        Smith, Kevan    Smith     Kevan        c 1.04
3
## 7        Omar Narvaez       Narvaez, Omar  Narvaez      Omar        c 1.08
9
## 11       Yoan Moncada       Moncada, Yoan  Moncada      Yoan    2b-3b 0.10
6
## 1          Adam Engel         Engel, Adam    Engel      Adam       of 0.11
8
##              Agent            Length.TotalValue sal2018 Rk Pos Age   G  PA
AB
## 3     ISE Baseball               1 yr/$13M (18)  13.000  2  1B  31 128 553
499
## 10            ACES  2 yr/$15M (18-19)+20 cl opt   7.250 13   C  31  49 181
170
## 2        Gene Mato              1 yr/$6.7M (18)   6.700  8  RF  27  93 385
356
## 5   Rep 1 Baseball            1 yr/$1.175M (18)   1.175 11  OF  27  82 275
258
## 8  Reynolds Sports 6 yr/$25M (17-22)+23-24 opts   1.000  4  SS  25 153 606
567
## 6       MVP Sports             1 yr/$0.57M (18)   0.570  9  DH  27 123 496
434
## 9                              1 yr/$0.565M (18)   0.565 21  DH  28   6   9
8
## 4     Pro Star Mgt             1 yr/$0.56M (18)   0.560 12   C  30  52 187
171
## 7                              1 yr/$0.56M (18)   0.560  1   C  26  97 322
280
## 11  David Hastings             1 yr/$0.555M (18)   0.555  3  2B  23 149 650
578
## 1                              1 yr/$0.552M (18)   0.552  7  CF  26 143 463
429
##     R   H X2B X3B HR RBI SB CS BB  SO    BA   OBP   SLG   OPS OPS.  TB GDP
HBP
## 3  68 132  36   1 22  78  2  0 37 109 0.265 0.325 0.473 0.798  117 236  14
11
## 10 17  44   7   0  6  15  1  0  9  46 0.259 0.304 0.406 0.710   94  69   7
2
## 2  47  84  11   2 19  49  3  1 20 102 0.236 0.281 0.438 0.719   95 156   9
4
## 5  23  70   7   4  4  32 12  1  9  69 0.271 0.303 0.376 0.679   87  97   2
3
## 8  77 136  28   3 20  64 26  8 30 149 0.240 0.281 0.406 0.687   87 230  15
4
## 6  51  99  23   0 20  62  0  0 52 165 0.228 0.319 0.419 0.738  102 182   8
7
## 9   2   2   1   0  0   0  0  0  0   3 0.250 0.250 0.375 0.625   70   3   0
0
## 4  21  50   6   0  3  21  1  0 10  18 0.292 0.348 0.380 0.728  102  65   5
5
```

```
## 7  30  77  14   1  9  30  0  2 38  65 0.275 0.366 0.429 0.794  119 120   5
2
## 11 73 136  32   6 17  61 12  6 67 217 0.235 0.315 0.400 0.714   96 231   4
1
## 1  49 101  17   4  6  29 16  8 18 129 0.235 0.279 0.336 0.614   69 144   1
8
##    SH SF IBB   BATS salCategory cws_four_clusters.cluster
## 3   0  6   7  RIGHT        high                         2
## 10  0  0   0  RIGHT        high                         3
## 2   0  5   2  RIGHT         mid                         1
## 5   4  1   0 SWITCH         low                         4
## 8   2  3   2  RIGHT         low                         2
## 6   0  3   0  RIGHT         low                         1
## 9   1  0   0  RIGHT         low                         3
## 4   0  1   0  RIGHT         low                         3
## 7   2  0   1   LEFT         low                         4
## 11  2  2   1 SWITCH         low                         2
## 1   7  1   0  RIGHT         low                         1
```

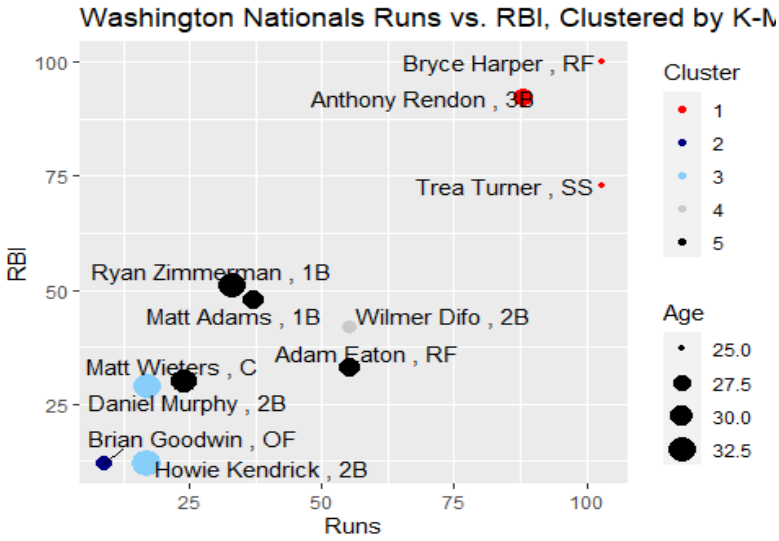
K=3 is given as the optimal k value via the Elbow Method, and clear separation between clusters is seen when viewing RBIs against Runs. The three players with the most RBIs, Turner, Rendon, and Harper, are all members of the 2nd cluster, while the 3rd cluster contains the players with the least RBIs.



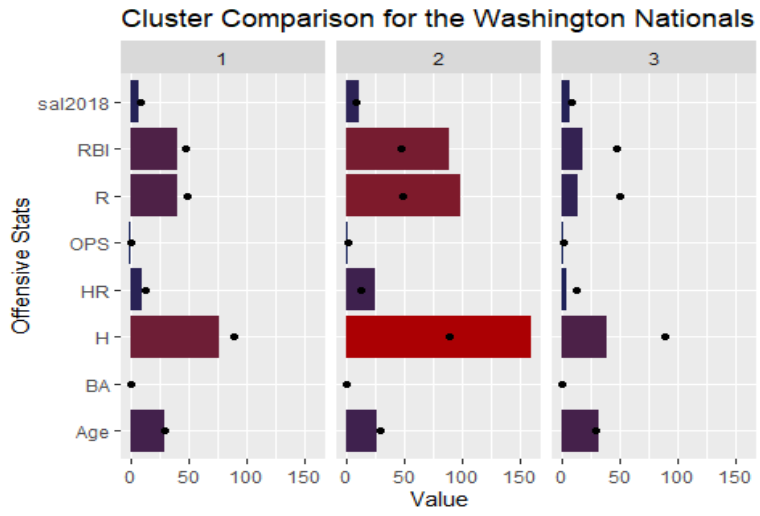
When the kmeans algorithm uses 4 clusters, Wilmer Difo is separated from cluster 1 and forms his own new cluster. However, he still has similar Runs and RBIs to Matt Adams and Adam Eaton, who are in cluster two. At this k value, we can begin to see the individual examples become their own clusters, as k approaches the number of samples.



With 5 clusters, Wilmer Difo is still isolated in a separate cluster, and Daniel Murphy and Howie Kendrick both leave cluster 3 to form their own. Brian Goodwin also forms a solitary cluster as well. The k-means algorithm continues to create single unit clusters as k approaches the number of samples.



K = 3 provided the best delineation between players, although 4 and 5 had lower Within cluster sum of squared errors. As k approaches n, the number of samples in the dataset, individual players will begin forming solitary clusters. Ultimately, when k = n, each player will have his own cluster. This type of clustering is analogous to overfitting in other predictive models.




```
##             Player          Player2        X1      X2 Position  MLSRV
## 4    Bryce Harper   Harper, Bryce    Harper   Bryce       rf  5.159
## 5   Daniel Murphy  Murphy, Daniel    Murphy  Daniel       2b  8.109
## 9  Ryan Zimmerman Zimmerman, Ryan Zimmerman    Ryan       1b 12.032
## 2  Anthony Rendon Rendon, Anthony    Rendon Anthony       3b  4.130
## 8    Matt Wieters   Wieters, Matt   Wieters    Matt        c  8.129
## 1      Adam Eaton     Eaton, Adam     Eaton    Adam       cf  5.030
## 7      Matt Adams     Adams, Matt     Adams    Matt       1b  5.033
## 6  Howie Kendrick Kendrick, Howie  Kendrick   Howie       lf 11.091
## 10    Trea Turner    Turner, Trea    Turner    Trea       ss  1.135
## 11    Wilmer Difo    Difo, Wilmer      Difo  Wilmer       ss  1.110
## 3   Brian Goodwin  Goodwin, Brian   Goodwin   Brian       of  1.019
##               Agent               Length.TotalValue sal2018 Rk Pos Age   G
PA
## 4      Boras Corp.             1 yr/$21.625M (18) 21.6250  8  RF  25 159 6
95
## 5             ACES            3 yr/$37.5M (16-18) 17.5000 13  2B  33  56 2
05
## 9       CAA Sports      6 yr/$100M (14-19)+20 opt 14.0000  2  1B  33  85 3
23
## 2      Boras Corp.               1 yr/$12.3M (18) 12.3000  5  3B  28 136 5
97
## 8      Boras Corp.      1 yr/$10.5M (17)+18 p opt 10.5000  1   C  32  76 2
71
## 1     Diamond Spts 5 yr/$23.5M (15-19)+20-21 opts  6.0000  9  RF  29  95 3
70
## 7  Wasserman Media                 1 yr/$4M (18)  4.0000 10  1B  29  94 2
77
## 6  Reynolds Sports               2 yr/$7M (18-19)  3.0000 14  2B  34  40 1
60
## 10      CAA Sports             1 yr/$0.5772M (18)  0.5772  4  SS  25 162 7
40
## 11                             1 yr/$0.5579M (18)  0.5579  3  2B  26 148 4
56
```

```
## 3      Boras Corp.             1 yr/$0.5539M (18)  0.5539 17  OF  27  48
79
##     AB   R   H X2B X3B HR RBI SB CS  BB  SO    BA   OBP   SLG   OPS OPS.
TB
## 4  550 103 137  34   0 34 100 13  3 130 169 0.249 0.393 0.496 0.889  133 2
73
## 5  190  17  57   9   0  6  29  1  0  13  17 0.300 0.341 0.442 0.784  105
84
## 9  288  33  76  21   2 13  51  1  1  30  55 0.264 0.337 0.486 0.824  114 1
40
## 2  529  88 163  44   2 24  92  2  1  55  82 0.308 0.374 0.535 0.909  137 2
83
## 8  235  24  56   8   0  8  30  0  1  30  45 0.238 0.330 0.374 0.704   86
88
## 1  319  55  96  18   1  5  33  9  1  38  64 0.301 0.394 0.411 0.805  114 1
31
## 7  249  37  64   9   0 18  48  0  0  24  55 0.257 0.332 0.510 0.842  118 1
27
## 6  152  17  46  14   0  4  12  1  1   5  29 0.303 0.331 0.474 0.805  110
72
## 10 664 103 180  27   6 19  73 43  9  69 132 0.271 0.344 0.416 0.760  100 2
76
## 11 408  55  94  14   7  7  42 10  3  39  82 0.230 0.298 0.350 0.649   71 1
43
## 3   65   9  13   1   0  3  12  3  1  10  26 0.200 0.321 0.354 0.674   78
23
##    GDP HBP SH SF IBB   BATS salCategory three_clusters.cluster
## 4    7   6  0  9  16   LEFT        high                       2
## 5    4   0  0  2   2   LEFT        high                       3
## 9   10   3  0  2   1  RIGHT        high                       1
## 2    5   5  0  8   5  RIGHT        high                       2
## 8    5   3  1  2   3 SWITCH         mid                       1
## 1    2  11  2  0   0   LEFT         mid                       1
## 7    6   4  0  0   2   LEFT         mid                       1
## 6    6   2  0  1   1  RIGHT         low                       3
## 10   7   5  2  0   3  RIGHT         low                       2
## 11   8   2  3  4   5 SWITCH         low                       1
## 3    0   2  1  1   0   LEFT         low                       3
```

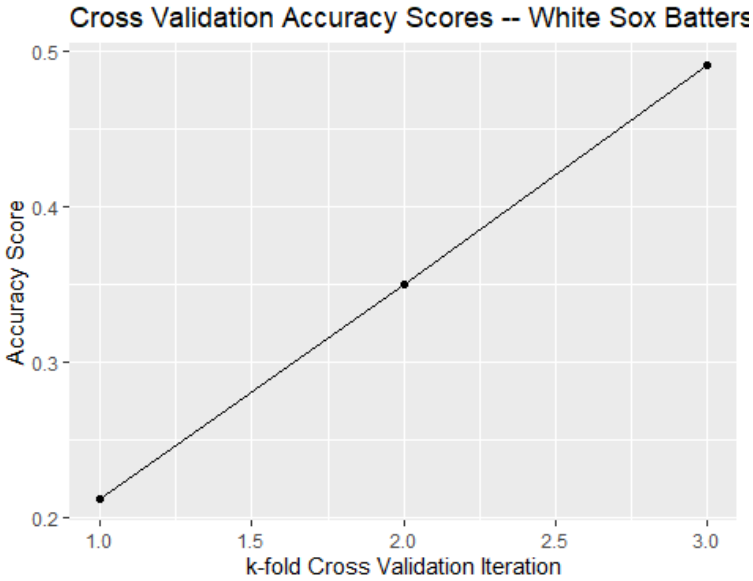
The second Cluster was the highest performing for all offensive categories. The greatest difference is observed in the sum total stats, rather than the calculated stats. (i.e., Hits and Runs rather than OPS and BA). This suggest that a general manager should aim to use the pure stats to review player performance and make comparisons rather than the calculated stats (assuming equal number of games played).

Model 4

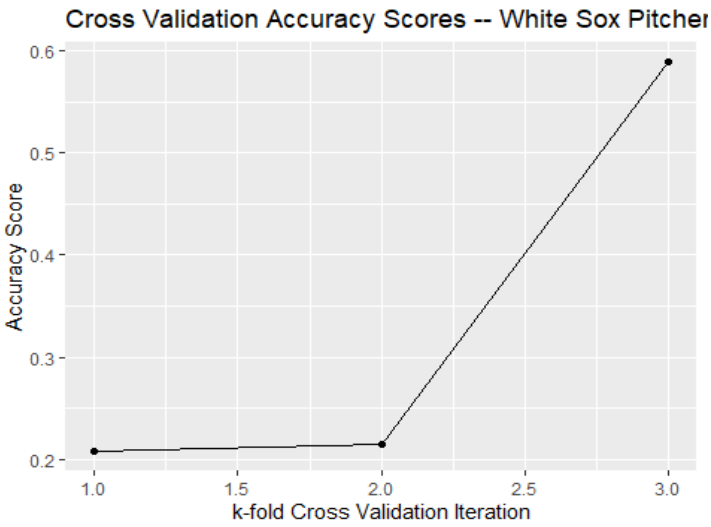
True accuracy scores were measured to test model validity. True accuracy is represented as: (Count(Total Correct Predictions))/(Count(All Predictions))

The 3-fold CV resulted in an average accuracy of 36.1% for the Chicago White Sox batters. For their pitchers, the 3-fold CV resulted in an average accuracy of 46.7%.

```
## [1] "Average Accuracy:  0.351"
```

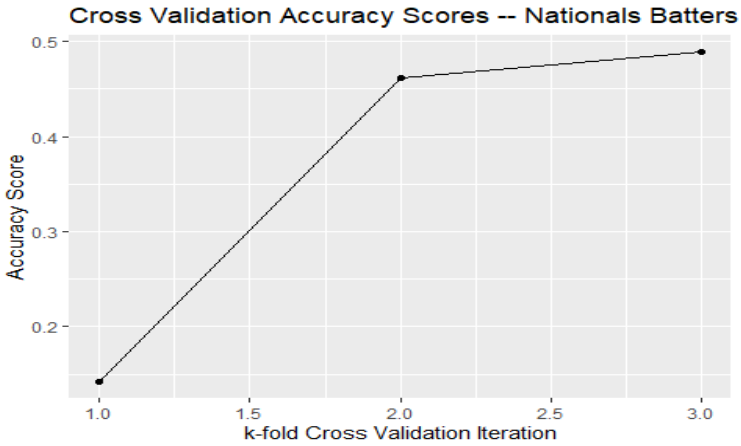



```
## [1] "Average Accuracy:  0.337333333333333"
```

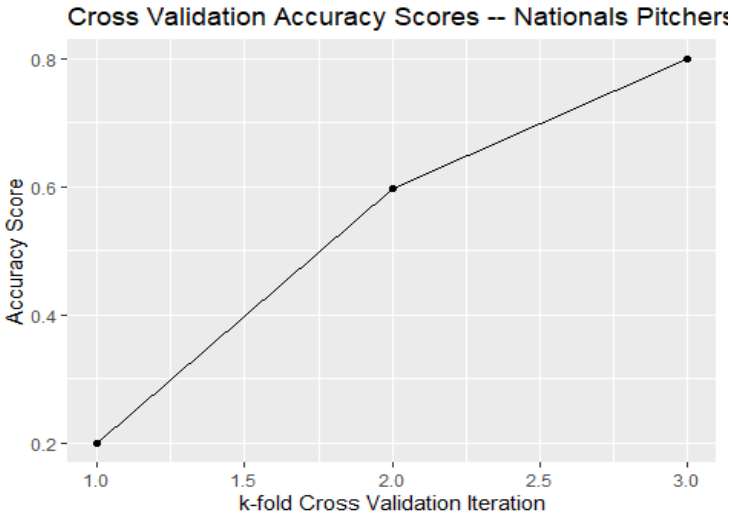


The 3-fold CV resulted in an average accuracy of 26.1% for the Washington Nationals batters. The 3-fold CV resulted in an average accuracy of 45.2% for their pitchers.

```
## [1] "Average Accuracy:  0.364333333333333"
```




```
## [1] "Average Accuracy:  0.532333333333333"
```



Conclusions

Can machine learning algorithms identify who they should trade in order to play a little Moneyball? The answer is a qualified yes. The algorithms definitely help to identify players whose salary does not match other players with similar records. However, even with the identification, there needs to be human interpretation of the results.

The Chicago White Sox pay Jose Abreu handsomely, but random forest assigned him to the low salary group. Why? It is not because he is not a good player as his offensive power statistic (OPS), RBIs, and slugging (SLG) are the highest on the team and he is among the highest for on-base percentage (OBP) and batting average. What is discovered through K-Means clustering is that many of the low paid players are similar to Abreu.

Based on statistics and identification by the different models, the team would be best served by trading the following position players: Adam Engel and Welington Castillo. Castillo is the clearest case as he is high salary but made few appearances with few RBIs

and a mediocre batting average. Adam Engel is not on the mismatched salary list however, his batting average amongst the lowest on the team when looking at players with more than 150 at bats. He also has low OBP, SLG, and OPS.

```
##                Player2 orig pred Rk  AB RBI    BA   OBP   SLG   OPS
## 1          Abreu, Jose high  low  2 499  78 0.265 0.325 0.473 0.798
## 2         Avilan, Luis  mid  low 28   1   0 0.000 0.000 0.000 0.000
## 3  Castillo, Welington high  low 13 170  15 0.259 0.304 0.406 0.710
## 4      Garcia, Avisail  mid  low  8 356  49 0.236 0.281 0.438 0.719
## 5       Giolito, Lucas  low  mid 24   6   0 0.000 0.000 0.000 0.000
## 6      Lopez, Reynaldo  low  mid 29   1   0 0.000 0.000 0.000 0.000
## 7      Saladino, Tyler  low high 21   8   0 0.250 0.250 0.375 0.625
## 8     Santiago, Hector  mid  low 25   4   0 0.000 0.000 0.000 0.000
## 9       Shields, James high  low 23   6   0 0.167 0.167 0.167 0.333
## 10        Smith, Kevan  low high 12 171  21 0.292 0.348 0.380 0.728

##           Player2 orig pred Rk Pos  AB  R RBI    BA   OBP   SLG   OPS
## 1  Anderson, Tim  low  low  4  SS 567 77  64 0.240 0.281 0.406 0.687
## 2 Davidson, Matt  low  low  9  DH 434 51  62 0.228 0.319 0.419 0.738
## 3    Engel, Adam  low  low  7  CF 429 49  29 0.235 0.279 0.336 0.614
## 4  Garcia, Leury  low  low 11  OF 258 23  32 0.271 0.303 0.376 0.679
## 5  Moncada, Yoan  low  low  3  2B 578 73  61 0.235 0.315 0.400 0.714
## 6  Narvaez, Omar  low  low  1   C 280 30  30 0.275 0.366 0.429 0.794
```

For the Chicago pitchers, the trade recommendations are more obvious. Both earned run average ERA and fielding independent percentage (FIP) are the best metrics for pitchers and should be low. Miguel Gonzalez has the highest ERA and FIP. Even more glaring for Gonzalez, he has won no games. Both and Carlos Rodon are in the mid-salary range but do not have the statistics to support such pay. Rodon has a losing record, an ERA over the league average of 4.15, and a FIP of nearly 5. Both Carson Fulmer and Lucas Giolito are low paid pitchers but it is still recommended to trade them as they have a losing record with high ERAs and high FIPS.

```
##            Player2 orig pred Rk  W.L.   ERA SV  FIP
## 1     Avilan, Luis  mid  low 10 0.667  3.86  2 2.71
## 2    Bummer, Aaron  low  mid 13 0.000  4.26  0 2.40
## 3 Gonzalez, Miguel  mid  low 21 0.000 12.41  0 8.02
## 4      Jones, Nate  mid  low 14 0.500  3.00  5 4.56
## 5    Rodon, Carlos  mid  low  5 0.429  4.18  0 4.95
## 6   Shields, James high  low  1 0.304  4.53  0 5.09
## 7    Soria, Joakim high  low  6 0.000  2.56 16 2.15

##            Player2 orig pred Rk  W.L.  ERA SV  FIP
## 1   Davidson, Matt  low  low 30 0.000 0.00  0 2.83
## 2  Farquhar, Danny  low  low 25 0.500 5.63  0 5.79
## 3   Fulmer, Carson  low  low 12 0.333 8.07  0 7.27
## 4   Giolito, Lucas  low  low  3 0.435 6.13  0 5.56
## 5 Infante, Gregory  low  low 23 0.500 8.00  0 4.49
## 6  Lopez, Reynaldo  low  low  2 0.412 3.91  0 4.63
```

```
## 7     Minaya, Juan  low  low  9 0.500 3.28  1 3.57
## 8 Santiago, Hector  mid  mid  7 0.667 4.41  2 5.09
```

The Washington Nationals should look into trading Wilmer Difo, Brian Goodwin, and Matt Wieters. Of these, only Matt Wieters is paid over $2 million dollars. Brian Goodwin has the lowest batting average of any position player and the second lowest OBP, SLG, and OPS of any position player. Difo holds the lowest OBP, SLG, and OPS of the position players and the second worst batting average. Wieters is the third worst position player for all four of those statistics.

```
##               Player2 orig pred Rk  AB RBI    BA   OBP   SLG   OPS
## 1         Adams, Matt  mid high 10 249  48 0.257 0.332 0.510 0.842
## 2        Difo, Wilmer  low  mid  3 408  42 0.230 0.298 0.350 0.649
## 3         Eaton, Adam  mid  low  9 319  33 0.301 0.394 0.411 0.805
## 4       Gonzalez, Gio high  low 27  44   0 0.068 0.068 0.091 0.159
## 5      Goodwin, Brian  low high 17  65  12 0.200 0.321 0.354 0.674
## 6       Harper, Bryce high  low  8 550 100 0.249 0.393 0.496 0.889
## 7       Kelley, Shawn  mid  low 38   1   0 0.000 0.000 0.000 0.000
## 8     Kendrick, Howie  low high 14 152  12 0.303 0.331 0.474 0.805
## 9      Murphy, Daniel high  low 13 190  29 0.300 0.341 0.442 0.784
## 10    Rendon, Anthony high  low  5 529  92 0.308 0.374 0.535 0.909
## 11      Roark, Tanner  mid high 25  58   8 0.190 0.217 0.259 0.475
## 12          Ross, Joe  low  mid 32   5   0 0.000 0.000 0.000 0.000
## 13      Scherzer, Max high  mid 24  70   6 0.243 0.274 0.271 0.545
## 14 Strasburg, Stephen high  low 26  41   1 0.122 0.163 0.122 0.285
## 15       Turner, Trea  low high  4 664  73 0.271 0.344 0.416 0.760
## 16    Zimmerman, Ryan high  mid  2 288  51 0.264 0.337 0.486 0.824

##         Player2 orig pred Rk  AB RBI    BA   OBP   SLG   OPS
## 1    Cole, A.J.  low  low 33   3   1 0.333 0.333 1.333 1.667
## 2   Grace, Matt  low  low 35   3   0 0.333 0.333 0.333 0.667
## 3 Wieters, Matt  mid  mid  1 235  30 0.238 0.330 0.374 0.704
```

With the Washington Nationals pitching staff, Ryan Madson, Tanner Roark, Sammy Solis, AJ Cole, Gio Gonzalez, Trevor Gott, and Enny Romero should all be under consideration for trades. Madson, who earns a high salary, has four saves which is the second highest on the team but, as a reliever, he is the losing pitcher almost as often as he either wins or gets a save. His ERA and FIP are also above the league average. Roark is a mid-salary pitcher, but he is often credited with the loss. Additionally, his ERA and FIP are slightly higher than the league average. Solis has the third highest ERA and a high FIP. His losing record does not show any saves. Cole and Romero duked it out to see who could get the highest ERA and highest FIP. In both cases, Romero “won”. With ERAs over 13, both Cole and Romero should be looking for new teams. Gio Gonzalez, despite having an ERA that is only slightly above the league average, had an incredibly bad win-loss record. As he earns a high salary, it is necessary for the team to look for a pitcher that can bring the wins at a lower cost. Gott has no wins, no saves, and an ERA above the league average. It may have been a fluke season but there is nothing to recommend him to not be traded.

```
##             Player2 orig pred Rk  W.L.  ERA SV  FIP
## 1   Doolittle, Sean  mid  low  7 0.500 1.60 25 1.89
## 2       Grace, Matt  low  mid  8 0.500 2.87  0 3.39
## 3     Kelley, Shawn  mid  low 15 1.000 3.34  0 4.55
## 4 Kintzler, Brandon  mid  low 14 0.333 3.59  2 3.44
## 5      Madson, Ryan high  mid 10 0.286 5.28  4 4.36
## 6     Roark, Tanner  mid high  2 0.375 4.34  0 4.27
## 7      Solis, Sammy  low high 11 0.333 6.41  0 4.91
```

```
##              Player2 orig pred Rk  W.L.   ERA SV   FIP
## 1         Cole, A.J.  low  low 25 0.500 13.06  0 10.51
## 2       Glover, Koda  low  low 22 0.250  3.31  1  4.69
## 3      Gonzalez, Gio high high  3 0.389  4.57  0  4.25
## 4       Gott, Trevor  low  low 19 0.000  5.68  0  6.21
## 5       Romero, Enny  low  low 29 0.000 13.50  0 10.66
## 6          Ross, Joe  low  low 23 0.000  5.06  0  5.85
## 7      Scherzer, Max high high  1 0.720  2.53  0  2.65
## 8 Strasburg, Stephen high high  4 0.588  3.74  0  3.62
```

Of all the position players trade recommendations for either team, only Brian Goodwin and Matt Wieters appear to have been traded between the 2018 and 2019 seasons. The pitcher recommendations were followed by the Washington Nationals to the man. The Chicago White Sox did not follow any of the recommendations. It is not hard to see why the Nationals won the World Series in 2019 while the White Sox continued to lose more than they won.