Prediction of NBA Player's Salary Based on Stepwise Regression Model

Hongye Xu

1 Introduction

1.1 Background

I have always felt that the NBA has the best data storage in the sport filed. In the beginning, I wanted to analyze the performance of the players by scrapping the data from the official NBA.stat website. However, since the NBA.stat table is in javascript format, and the official has canceled all the existing official APIs, no possible R-based crawler method has been found after the effort. Therefore, I chose an alternative, which is the basketball-reference website. This report is based on two data sources on the basketball-reference. My goal is to predict the player's salary for next season based on player performance this season.

1.2 Glossary

Abbreviation	Explanation
Pos	Position
Age	Age of Player at the start of February 1st of that season
Tm	Team
G	Games
GS	Games Started
MP	Minutes Played Per Game
FG	Field Goals Per Game
FGA	Field Goal Attempts Per Game
FG%	Field Goal Percentage
3P	3-Point Field Goals Per Game
3PA	3-Point Field Goal Attempts Per Game
3P%	FG% on 3-Pt FGAs.
2P	2-Point Field Goals Per Game
2PA	2-Point Field Goal Attempts Per Game
eFG%	Effective Field Goal Percentage
FT	Free Throws Per Game
FTA	Free Throw Attempts Per Game
FT%	Free Throw Percentage
ORB	Offensive Rebounds Per Game
DRB	Defensive Rebounds Per Game
TRB	Total Rebounds Per Game
AST	Assists Per Game
STL	Steals Per Game
BLK	Blocks Per Game
TOV	Turnovers Per Game
PF	Personal Fouls Per Game
PTS	Points Per Game

2 Preparation

2.1 Data Scraping and Cleaning

2.1.1 Players' Regular Season Data

My first data source came from https://www.basketball-reference.com/leagues/NBA_2019_per_game.html. Because all the data in the website is displayed in the form of HTML table, I can read the data in this table by reading the XPath('//*[@id="per_game_stats"]') of the table with Chrome browser. At the same time, because many NBA players transfer during the season, this data source records their data in many teams, and we just need to keep the data that represents their season average.In addition, I deleted those rows which do not contain 3 points field goals, 2 points field goals and free throw field goals.

```
##         Player Pos Age  Tm  G GS   MP  FG  FGA   FG%  3P 3PA   3P%  2P
## 1 Alex Abrines  SG  25 OKC 31  2 19.0 1.8  5.1 0.357 1.3 4.1 0.323 0.5
## 2   Quincy Acy  PF  28 PHO 10  0 12.3 0.4  1.8 0.222 0.2 1.5 0.133 0.2
## 3 Jaylen Adams  PG  22 ATL 34  1 12.6 1.1  3.2 0.345 0.7 2.2 0.338 0.4
## 4 Steven Adams   C  25 OKC 80 80 33.4 6.0 10.1 0.595 0.0 0.0 0.000 6.0
## 5  Bam Adebayo   C  21 MIA 82 28 23.3 3.4  5.9 0.576 0.0 0.2 0.200 3.4
## 6    Deng Adel  SF  21 CLE 19  3 10.2 0.6  1.9 0.306 0.3 1.2 0.261 0.3
##    2PA   2P%  eFG%  FT FTA   FT% ORB DRB TRB AST STL BLK TOV  PF  PTS
## 1  1.0 0.500 0.487 0.4 0.4 0.923 0.2 1.4 1.5 0.6 0.5 0.2 0.5 1.7  5.3
## 2  0.3 0.667 0.278 0.7 1.0 0.700 0.3 2.2 2.5 0.8 0.1 0.4 0.4 2.4  1.7
## 3  1.1 0.361 0.459 0.2 0.3 0.778 0.3 1.4 1.8 1.9 0.4 0.1 0.8 1.3  3.2
## 4 10.1 0.596 0.595 1.8 3.7 0.500 4.9 4.6 9.5 1.6 1.5 1.0 1.7 2.6 13.9
## 5  5.7 0.588 0.579 2.0 2.8 0.735 2.0 5.3 7.3 2.2 0.9 0.8 1.5 2.5  8.9
## 6  0.7 0.385 0.389 0.2 0.2 1.000 0.2 0.8 1.0 0.3 0.1 0.2 0.3 0.7  1.7
```

2.1.2 Scale

Considering that regression analysis is mainly used in this report. In order to eliminate the inaccuracy of parameters caused by too large or too small data itself. I create a standardized version of the data.

```
##                     Age         MP         2P%        3P%         FT%
## Alex Abrines -0.2348656 -0.1678429 -0.05111731  0.1079674  1.30497350
## Quincy Acy    0.4772268 -0.9471834  2.01348589 -1.5619660 -0.28148044
## Jaylen Adams -0.9469579 -0.9122876 -1.76955950  0.2398043  0.27342273
## Steven Adams -0.2348656  1.5071577  1.13572046 -2.7309194 -1.70430908
## Bam Adebayo  -1.1843221  0.3323309  1.03681731 -0.9730947 -0.03248542
## Deng Adel    -1.1843221 -1.1914543 -1.47285006 -0.4369582  1.85276253
##                     TRB         AST        STL         BLK        TOV
## Alex Abrines -0.9119870 -0.81732136 -0.3701968 -0.49747590 -0.7975707
## Quincy Acy   -0.4970106 -0.70641502 -1.3498261  0.02415998 -0.9238106
## Jaylen Adams -0.7874941 -0.09643014 -0.6151041 -0.75829384 -0.4188509
## Steven Adams  2.4078238 -0.26278966  2.0788766  1.58906762  0.7173087
## Bam Adebayo   1.4948758  0.06992937  0.6094326  1.06743174  0.4648288
## Deng Adel    -1.1194751 -0.98368087 -1.3498261 -0.49747590 -1.0500506
##                      PF         PTS
## Alex Abrines -0.1395071 -0.64209057
## Quincy Acy    0.7994827 -1.23613639
## Jaylen Adams -0.6760726 -0.98861730
## Steven Adams  1.0677655  0.77701887
## Bam Adebayo   0.9336241 -0.04804476
## Deng Adel    -1.4809210 -1.23613639
```

2.1.3 Players' Salaries

The second data came from https://www.basketball-reference.com/contracts/players.html, and I imported it in the same way as I scrapped the first data. This data includes salary data for the next six seasons. But all we need is this season's data, so I filtered it and converted character data into numeric data. The result is as follow.

```
## [1] Player             Tm                 2018-19
## [4] duplicated(Player)
## <0 rows> (or 0-length row.names)
```

```
##              Player  Tm  2018-19
## 1     Stephen Curry GSW 37457154
## 2        Chris Paul HOU 35654150
## 3 Russell Westbrook OKC 35654150
## 4      LeBron James LAL 35654150
## 5     Blake Griffin DET 32088932
## 6    Gordon Hayward BOS 31214295
```

Finally, there is no duplicate player data.

2.1.4 Merging Data

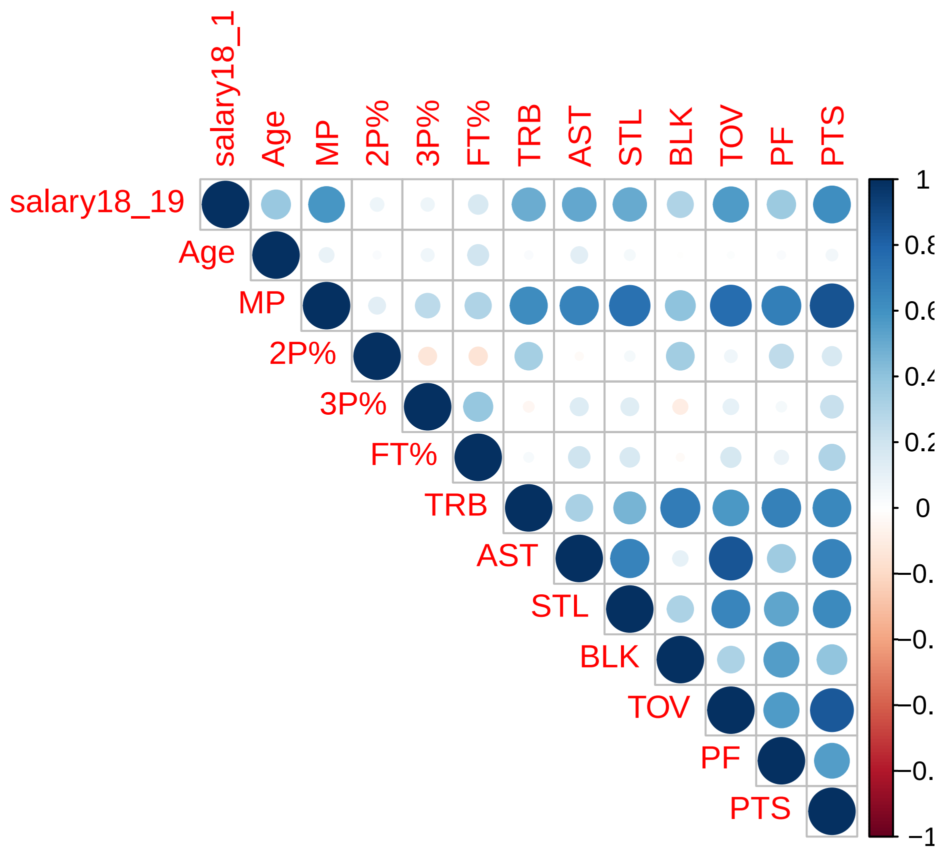
Merge standardized and non-standardized data with player salary data to get the final data we need.

2.1.5 Save No_scale Data Into CSV

I saved the merged non-standardized data to the working directory with the file name'18-19 players_stat.csv'.

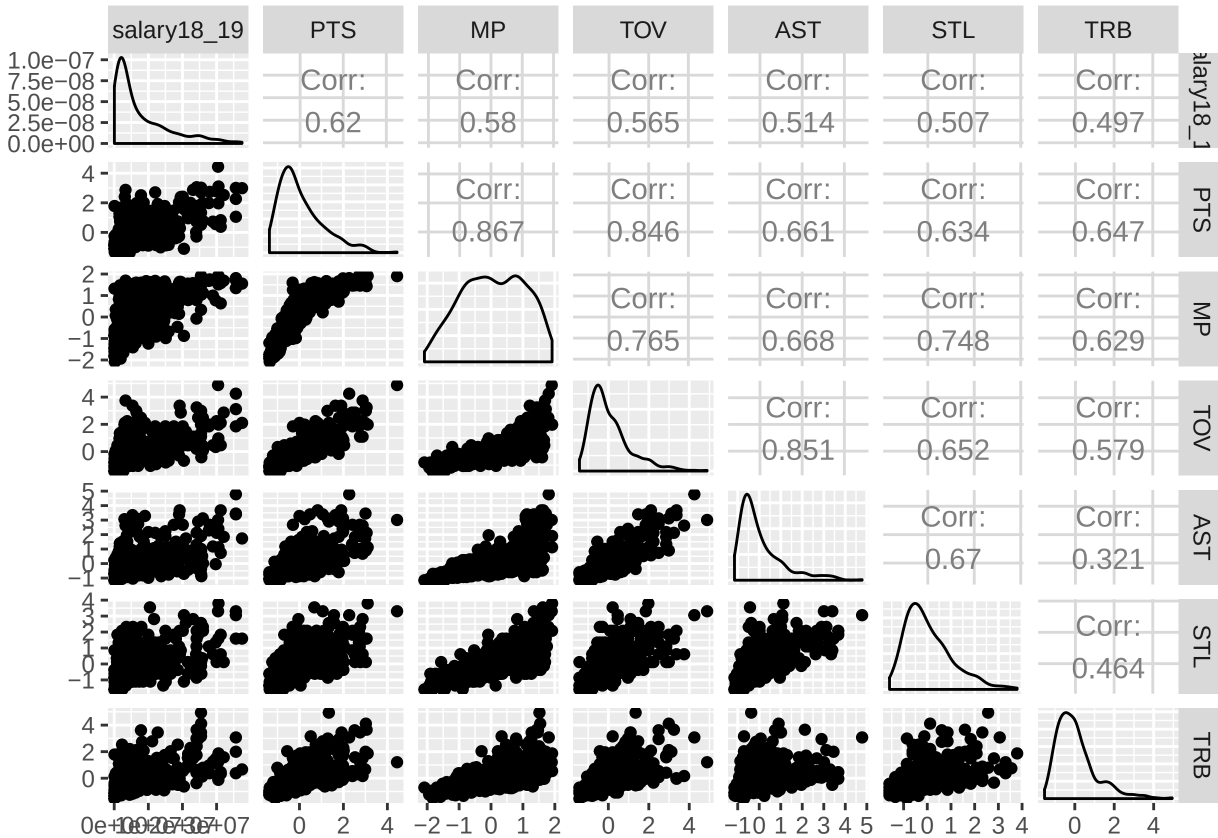
3 Correlation Check

3.1 Frist Check



The features that have strong correlation with salary are:PTS,TOV,STL,AST,TRB and MP. Besides, MP is strongly correlated with multiple features and may have multiple collinearities(This is in line with our common sense. The more time we play, the better the data will be). What I didn't expect was that the correlation between field goal and salary was not high, that is to say, the output of players influenced the salary of players more than efficiency.

3.2 Second Check

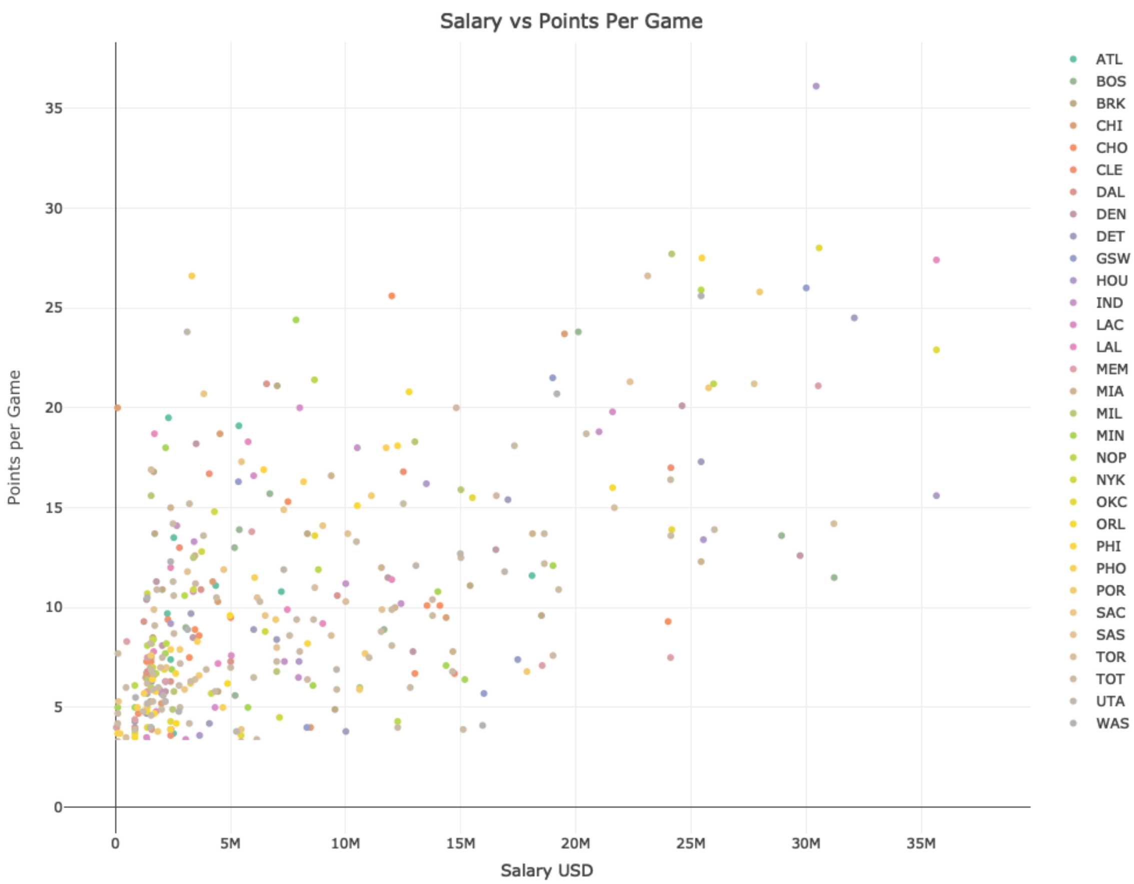



```
## salary18_19         PTS          MP         TOV         AST         STL
##   1.0000000   0.6198192   0.5803967   0.5645525   0.5142283   0.5066299
##         TRB
##   0.4972563
```

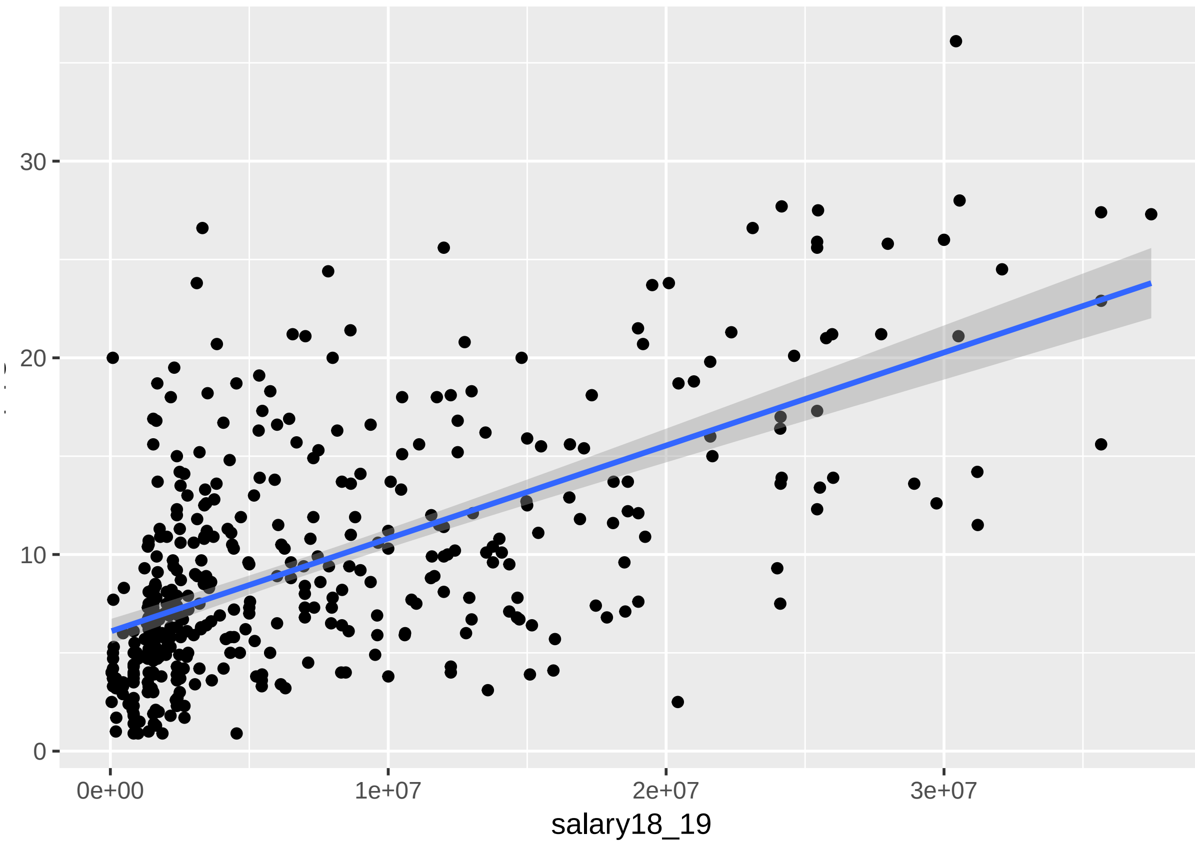
Correlation strength is: PTS > MP > TOV > AST > STL > TRB There's also one thing that surprises me: the number of players'turnivers is positively correlated with their salaries. I mean, generally speaking, assuming that a player's turnover rate is constant, the total number of turnovers will increase as his minutes played increases, and important players will have higher minutes played and higher salaries.

4 Data Visualization

4.1 Interactive Plot



4.2 Scatter Plot With Regression Line



Under the simple linear model, we can understand that the fitted curve represents the average level of the league, and the player below the curve performs worse than the expected performance corresponding to the salary. We can check their name by hovering on the points in the interactive plot(only in HTML form file). It includes a lot of All-Star players, such as Chris Paul, Kyle Lowry, Al Horford, Gordon Haywood(The Celtics are unlucky) and etc. However, it only considers the scoring feature, and does not fully reflect the players'influence on the field.

5 Multiple Regression

```
##
## Call:
## lm(formula = salary18_19 ~ PTS + MP + TOV + AST + STL + TRB,
##     data = regression)
##
## Coefficients:
## (Intercept)          PTS           MP          TOV          AST
##     7114340      3626578      -546186     -2022044      2571555
##         STL          TRB
##      833962      1888579
```

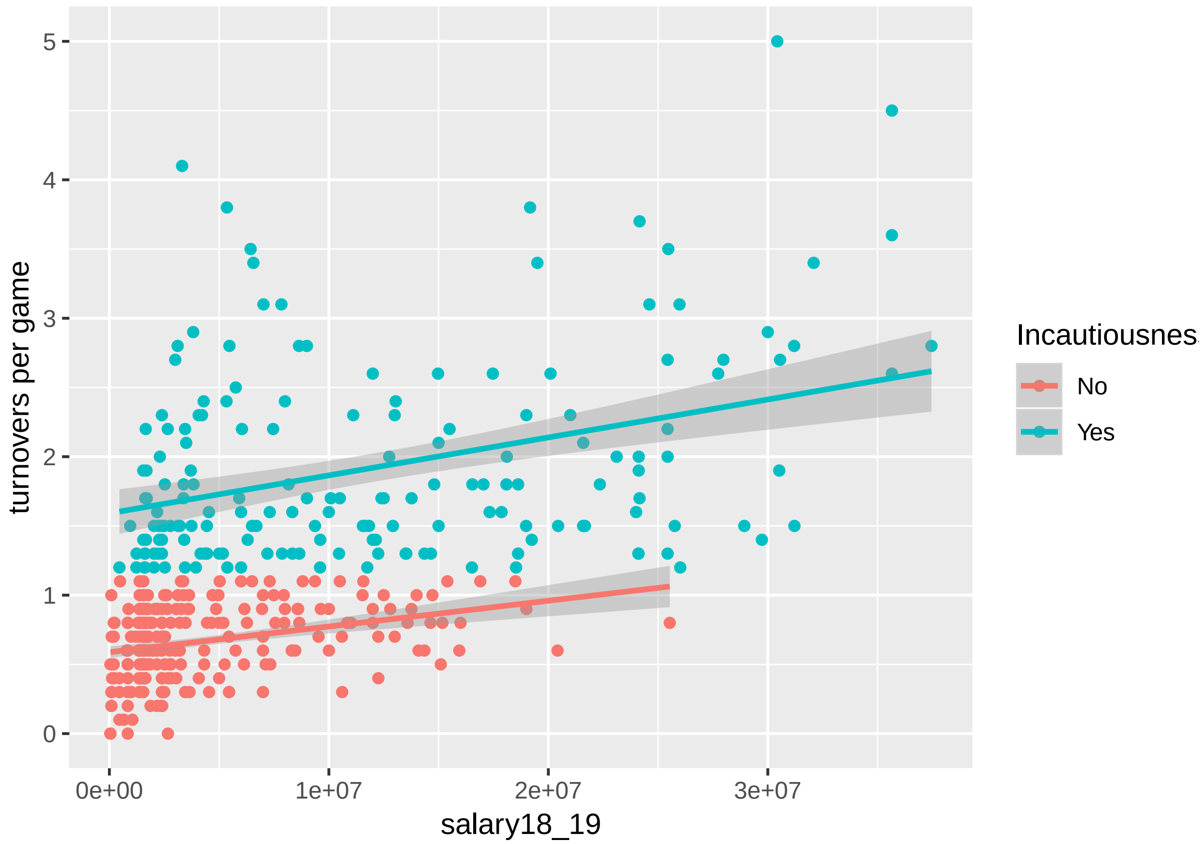
From here, we can see that points per game is the most significant feature of positive impact, while turnovers per game is the most significant feature of negative impact. However, simple multiple regression also has some problems, that is, there are multiple collinearities.

5.1 Player 's Importance And Incautiousness

Here we make two definitions that a player is "important" if his minutes played is above average and is "incautious" if his turnover per game is above average.

5.2 Prallel Slope Model

5.2.1 Incautiousness Comparision



The plot shows that the number of turnovers of the players with higher salaries will increase correspondingly, but the magnitude is not large. We can think that it is a natural phenomenon caused by the increase of playing time. Then I do a regression analysis of Importance and Incautiousness. The result is as follow

```
##
## Call:
## lm(formula = salary18_19 ~ Importance * Incautiousness, data = regression)
##
## Coefficients:
##                       (Intercept)                      ImportanceYes
##                           3275995                            3754147
##                  IncautiousnessYes  ImportanceYes:IncautiousnessYes
##                           3048670                            3017297
```

We can assume that the impact of A and B is close to synchronization, which confirms my previous view that players with higher salaries have more playing time, which leads to more turnovers, rather than higher salaries because of higher turnovers.

5.3 Stepwise Regression

Considering that the data of NBA players will increase with the increase of playing time, there must be multiple collinearity among the features. So stepwise regression is the more accurate method.

```
##
## Call:
## lm(formula = salary18_19 ~ PTS + TOV + AST + STL + TRB, data = regression)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -15540227  -3515763   -874394   3138553  20906046
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  7101619     295954  23.996  < 2e-16 ***
## PTS          3284754     601916   5.457 8.34e-08 ***
## TOV         -1924931     847259  -2.272 0.023600 *
## AST          2488319     653919   3.805 0.000163 ***
## STL           679543     437411   1.554 0.121052
## TRB          1820063     421730   4.316 1.99e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6057000 on 415 degrees of freedom
## Multiple R-squared:  0.4391, Adjusted R-squared:  0.4323
## F-statistic: 64.97 on 5 and 415 DF,  p-value: < 2.2e-16
```

Here I use k-fold cross-validation to test the error of the models that have different number of variate.

```
##   nvmax    RMSE  Rsquared     MAE   RMSESD RsquaredSD    MAESD
## 1     1 6477031 0.3656265 4841275 740066.8  0.1181143 489025.3
## 2     2 6394271 0.3803728 4800648 640458.4  0.1150337 384294.5
## 3     3 6113242 0.4295432 4634334 621821.6  0.1299230 442098.5
## 4     4 6082951 0.4340008 4636211 662992.5  0.1335307 493985.8
## 5     5 6157695 0.4198971 4707174 644375.1  0.1258431 498597.2
## 6     6 6142967 0.4211164 4689635 668283.2  0.1298739 503369.9
## 7     7 6118851 0.4262623 4685282 678915.2  0.1321880 539508.8
## 8     8 6116129 0.4267740 4683816 673996.1  0.1312854 541582.6
## 9     9 6116129 0.4267740 4683816 673996.1  0.1312854 541582.6
```

From the result we can see that three-variable model's RMSE is the smallest and Rsquared is second largest. So the three-variable model is the best one. Let us find out the order in which variables are added to the model.

```
## Subset selection object
## 8 Variables  (and intercept)
##                   Forced in Forced out
## PTS                   FALSE      FALSE
## MP                    FALSE      FALSE
## TOV                   FALSE      FALSE
## AST                   FALSE      FALSE
## STL                   FALSE      FALSE
## TRB                   FALSE      FALSE
## ImportanceYes         FALSE      FALSE
## IncautiousnessYes     FALSE      FALSE
## 1 subsets of each size up to 4
```

```
## Selection Algorithm: backward
##          PTS MP  TOV AST STL TRB ImportanceYes IncautiousnessYes
## 1  ( 1 ) "*" " " " " " " " " " " " "           " "
## 2  ( 1 ) "*" " " " " "*" " " " " " "           " "
## 3  ( 1 ) "*" " " " " "*" " " "*" " "           " "
## 4  ( 1 ) "*" " " "*" "*" " " "*" " "           " "
```

```
## (Intercept)         PTS         AST         TRB
##     7095995     2678780     1764352     1642389
```

The best model is salary18_19 ~ PTS + AST + TRB

6 Conclusion

6.1 What i want to predict

As Lebron James fan, I am concerned about the new contract for the Lakers who may stay next season. Let's find them first.

```
## # A tibble: 8 x 1
## # Groups:   Player [8]
##   Player
##   <chr>
## 1 Kentavious Caldwell-Pope
## 2 Rajon Rondo
## 3 Mike Muscala
## 4 Lance Stephenson
## 5 Reggie Bullock
## 6 JaVale McGee
## 7 Andre Ingram
## 8 Scott Machado
```

6.2 Analysis conclusion

```
## [1] "Expected Salary: $6,771,542"
```

```
## [1] "Expected Salary: $7,275,901"
```

```
## [1] "Expected Salary: $5,902,181"
```

Here I choose three players who are more likely to stay next season to make predictions.The result shows that salaries for Pope, Bullock and Stephenson for next season are $6,771,542, $7,275,901 and $5,902,181

7 Github Link

https://github.com/szxuhongye/NBA-Player-Salary-Predicton.git