# Who is the Next Lebron James?

## Predicting NBA Player Impact with Advanced NBA Statistics


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Springboard

# Introduction

There has been a rise in the last ten years in interest in fantasy sports and online sports betting.

Often casual sports fans and professional analysts implement beliefs such as the Hot Hand fallacy to inform future decisions.

In 2011 the NBA began collecting Advanced Analytics, tracking hundreds of new individual player metrics using advanced camera technologies.

# Goal

To apply machine learning algorithms to this newly collected data to determine if new insights can be found and better predict NBA player performance.

# Business Application/ Stakeholders

This project could benefit NBA talent scouts, managers, and coaching staffs looking to forecast player performance to inform resigning current players, acquiring new players, or making trade decisions.

Additionally, individuals invested in fantasy sports or online sports betting could benefit as well by being able to find value players to add to their rosters.

# Data

- The data scraped from www.nba.com/stats/ from using Selenium and BeautifulSoup.

| | PLAYER | TEAM | AGE | GP | W | L | MIN | OFFRTG | DEFRTG | NETRTG | AST% | AST/TO | AST RATIO | OREB% | DREB% | REB% | TO RATIO | EFG% | TS% | USG% | PACE | PIE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | Giannis Antetokounmpo | MIL | 25 | 63 | 51 | 12 | 30.4 | 112.8 | 97.4 | 15.4 | 32.8 | 1.54 | 17.0 | 6.8 | 30.7 | 19.6 | 11.0 | 58.9 | 61.3 | 36.3 | 107.47 | 23.9 |
| 5 | LeBron James | LAL | 35 | 67 | 50 | 17 | 34.6 | 112.1 | 103.6 | 8.5 | 47.7 | 2.62 | 28.5 | 2.8 | 19.1 | 11.0 | 10.9 | 55.0 | 57.7 | 30.8 | 101.50 | 19.8 |
| 6 | Joel Embiid | PHI | 26 | 51 | 32 | 19 | 29.5 | 107.2 | 102.0 | 5.2 | 17.8 | 0.96 | 11.7 | 9.1 | 27.9 | 18.7 | 12.2 | 51.2 | 59.0 | 31.5 | 102.07 | 19.4 |
| 7 | Luka Doncic | DAL | 21 | 61 | 36 | 25 | 33.6 | 116.7 | 111.4 | 5.3 | 45.4 | 2.07 | 23.6 | 3.6 | 22.4 | 13.2 | 11.4 | 53.1 | 58.5 | 35.5 | 101.24 | 19.4 |
| 9 | Kawhi Leonard | LAC | 29 | 57 | 41 | 16 | 32.4 | 116.9 | 104.7 | 12.2 | 25.5 | 1.88 | 16.2 | 2.8 | 17.5 | 10.3 | 8.6 | 52.4 | 58.9 | 32.7 | 100.54 | 19.1 |

- **Explanatory Variables**: 118 unique player statistics from the 2017-2018 season.

- **Target Variable**: the Player Impact Estimate (PIE) in the 2018-2019 season, which is a calculation of what percent of game events (points, rebounds, etc.) did that player contribute to the team. This is an effective metric at comparing player value across all player positions.

# Explanatory Features (full names and formulas in glossary):

**Descriptive Stats:** Team, College, Country

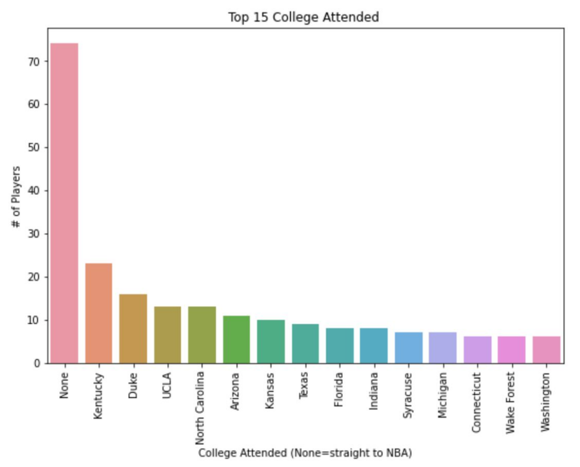
**Player Attributes:** Age, Height, Weight, Draft Number

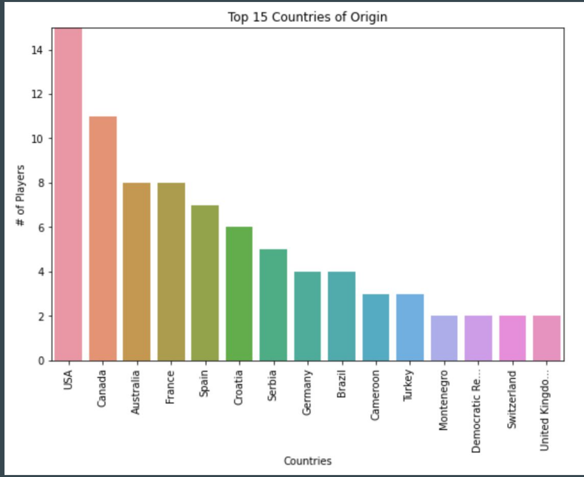
**Advanced Stats**: PassesMade, AST_PTS_Created, AdjustedREB_Chance%, AVG_REBDistance, %_Loose_BallsRecovered_OFF, Contested3PT_Shots,FG%_20_24ft, OPP_FG%_15_19ft

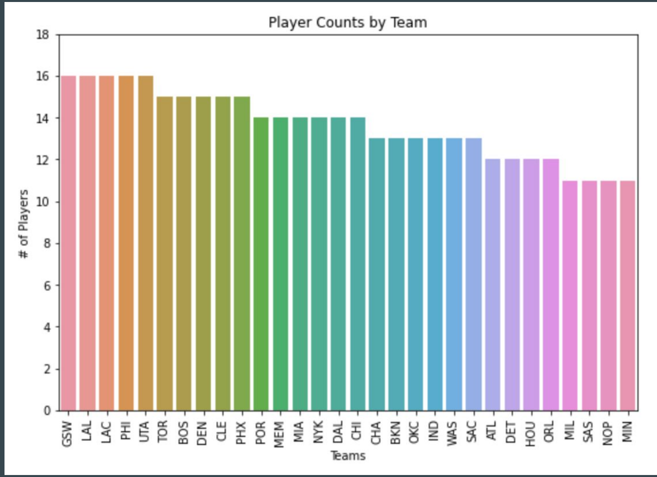
```
['Player', 'TEAM', 'College', 'Country', 'MIN_2017', 'MIN_2018', 'AGE', 'Height', 'Weight', 'Draft_Number', 'GP',
'W', 'L', 'PTS', 'FGM', 'FGA', 'FG%', '3PM', '3PA', '3P%', 'FTM', 'FTA', 'FT%', 'OREB', 'DREB', 'REB', 'AST', 'TOV',
'STL', 'BLK', 'PF', 'FP', 'DD2', 'TD3', '+/-', 'Box_Outs', 'OFF_Box_Outs', 'DEF_Box_Outs', 'Team_RebOn_Box_Outs', 'Pl
ayer_RebOn_Box_Outs', '%_Box_Outs_Off', '%_Box_Outs_Def', '%_Team_RebWhen_Box_Out', '%_Player_RebWhen_Box_Out', 'Cont
estedREB', 'ContestedREB%', 'REBChances', 'REBChance%', 'DeferredREB_Chances', 'AdjustedREB_Chance%', 'AVG_REBDistanc
e', 'PassesMade', 'PassesReceived', 'SecondaryAST', 'PotentialAST', 'AST_PTS_Created', 'ASTAdj', 'AST_ToPass%', 'AST_
ToPass%_Adj', 'ScreenAssists', 'ScreenAssists_PTS', 'Deflections', 'OFF_Loose_BallsRecovered', 'DEF_Loose_BallsRecove
red', 'Loose_BallsRecovered', '%_Loose_BallsRecovered_OFF', '%_Loose_BallsRecovered_DEF', 'ChargesDrawn', 'Contested2
PT_Shots', 'Contested3PT_Shots', 'ContestedShots', 'FGM_und_5ft', 'FGA_und_5ft', 'FG%_und_5ft', 'FGM_5_9ft', 'FGA_5_9
ft', 'FG%_5_9ft', 'FGM_10_14ft', 'FGA_10_14ft', 'FG%_10_14ft', 'FGM_15_19ft', 'FGA_15_19ft', 'FG%_15_19ft', 'FGM_20_2
4ft', 'FGA_20_24ft', 'FG%_20_24ft', 'FGM_25_29ft', 'FGA_25_29ft', 'FG%_25_29ft', 'OPP_FGM_und_5ft', 'OPP_FGA_und_5f
t', 'OPP_FG%_und_5ft', 'OPP_FGM_5_9ft', 'OPP_FGA_5_9ft', 'OPP_FG%_5_9ft', 'OPP_FGM_10_14ft', 'OPP_FGA_10_14ft', 'OPP_
FG%_10_14ft', 'OPP_FGM_15_19ft', 'OPP_FGA_15_19ft', 'OPP_FG%_15_19ft', 'OPP_FGM_20_24ft', 'OPP_FGA_20_24ft', 'OPP_FG%
_20_24ft', 'OPP_FGM_25_29ft', 'OPP_FGA_25_29ft', 'OPP_FG%_25_29ft', 'DEFRTG', 'NETRTG', 'AST%', 'OREB%', 'DREB%', 'RE
B%', 'eFG%', 'TS%', 'USG%', 'PACE', 'PIE']
```

# Exploratory Data Analysis

## Trends with Categorical Variables

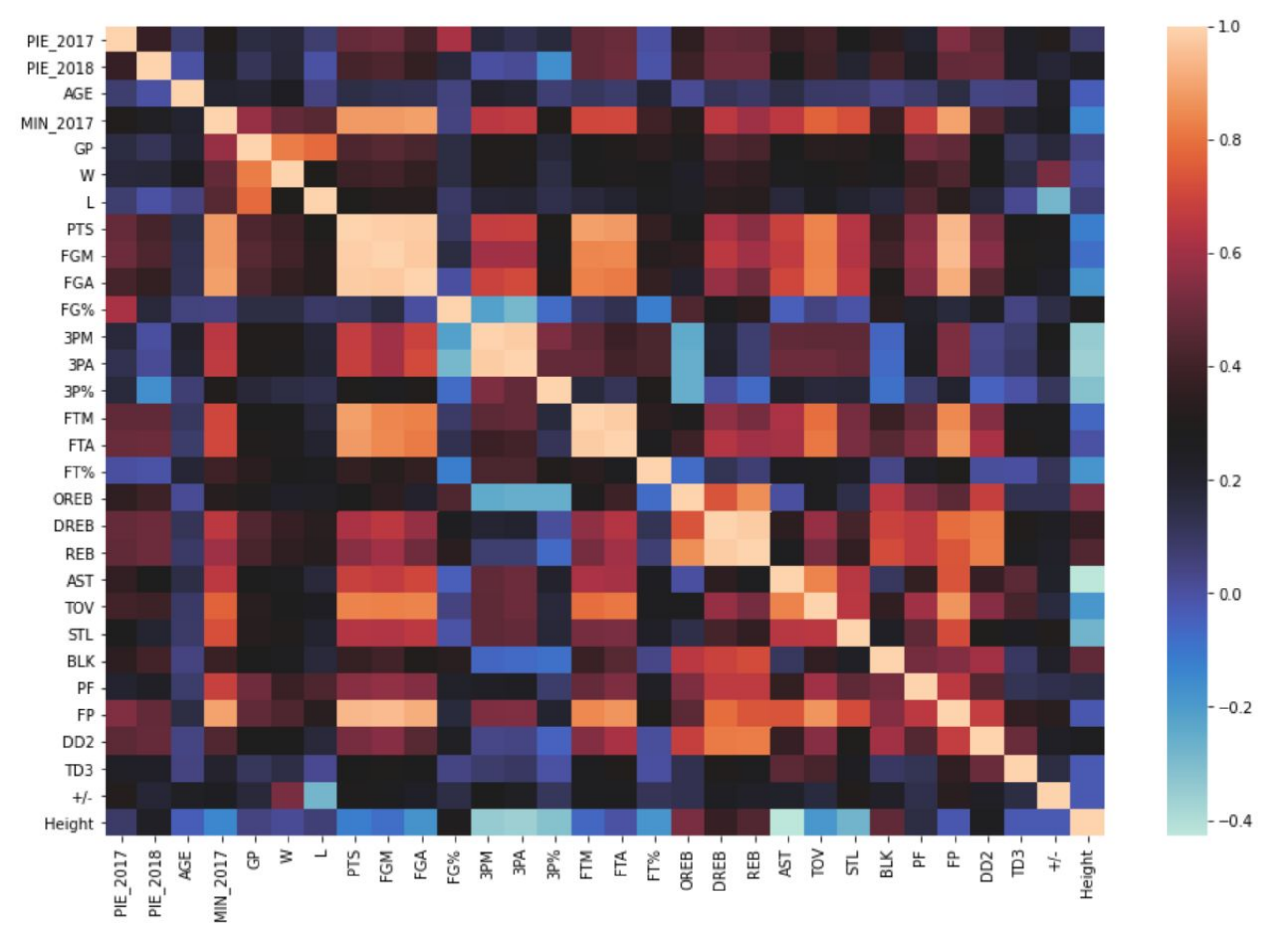


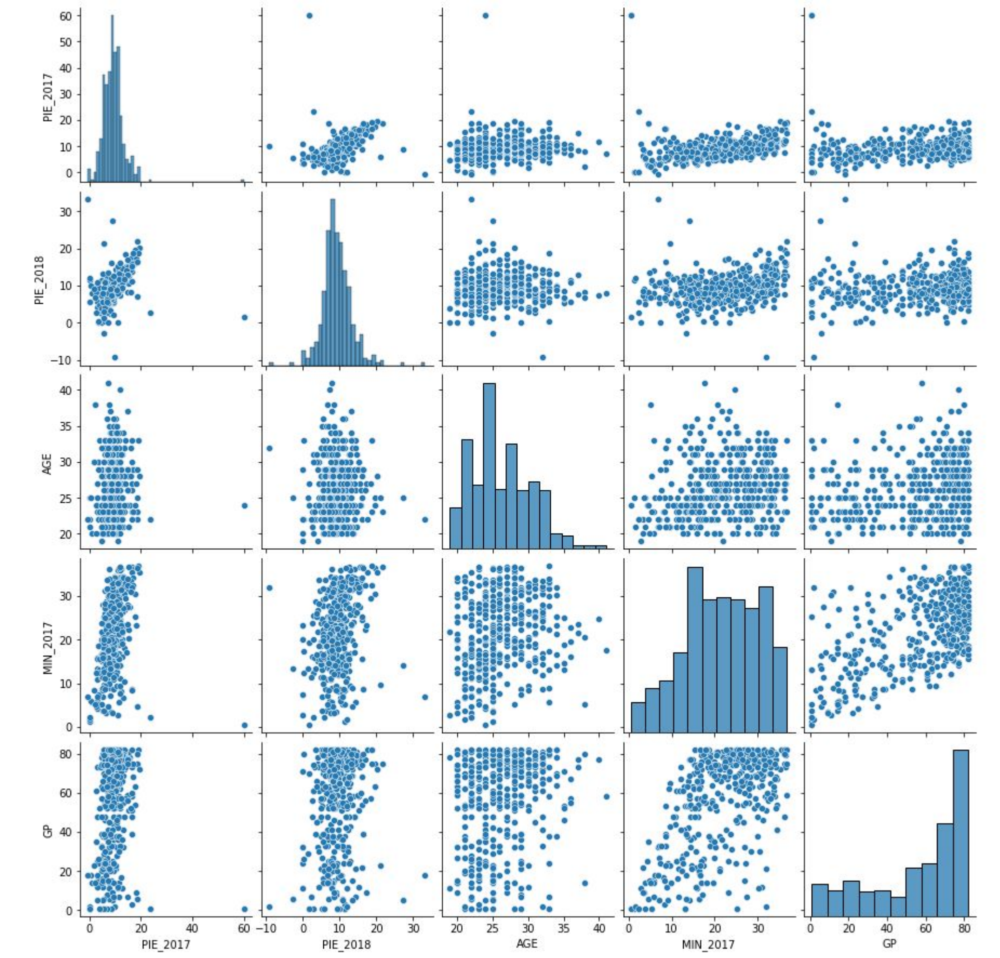
# EDA

Correlation Heat Map of first 30 numeric features:



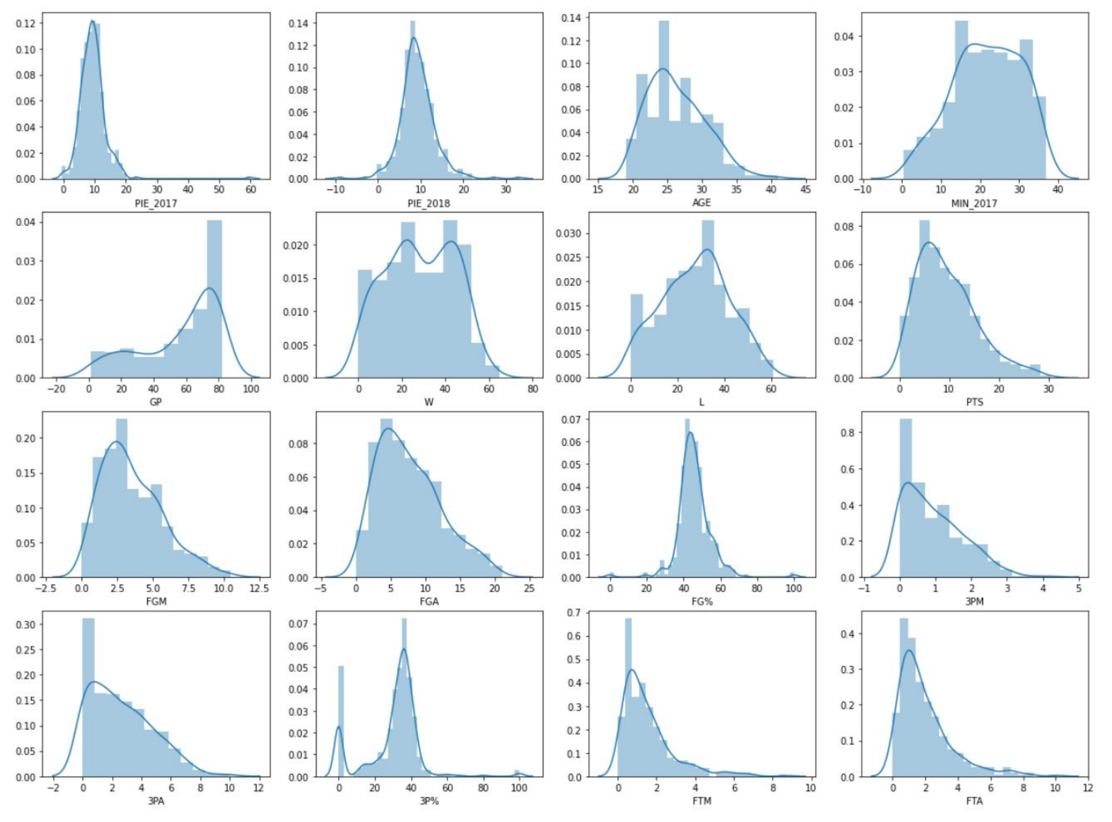
# EDA

## Scatter Plot Matrix of First 5 Numeric Features:



# EDA

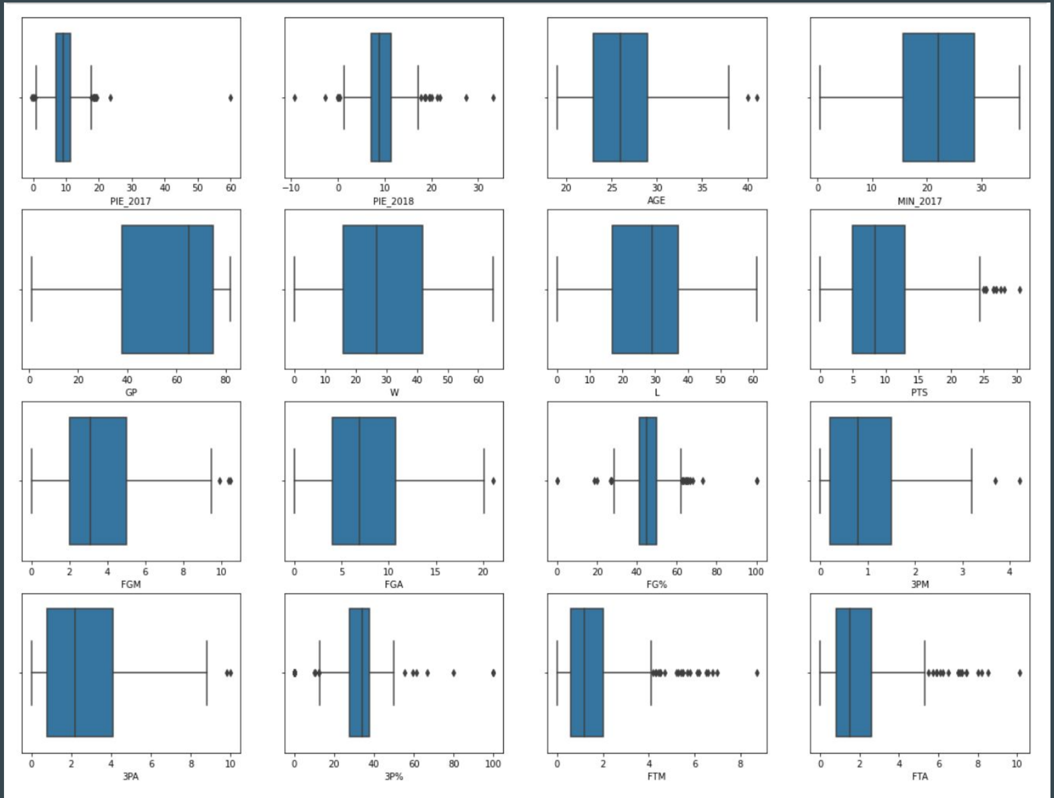
Examining distributions of first 16 numeric features.




Note: many are not normally distributed. To optimize model performance, we will use the Yeo-Johnson transformation to normalize the distributions before standardizing them.

# EDA

Examining boxplots of first 16 numeric features, with whiskers = 1.5*IQR.



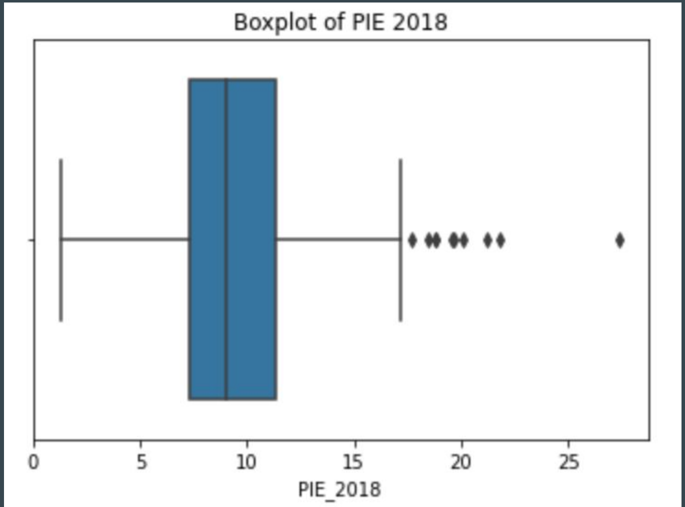

Note: there are a minimal number of outliers. Some of these outliers with be filtered out by excluding players with essentially zero playing time in the 2018-2019 season.

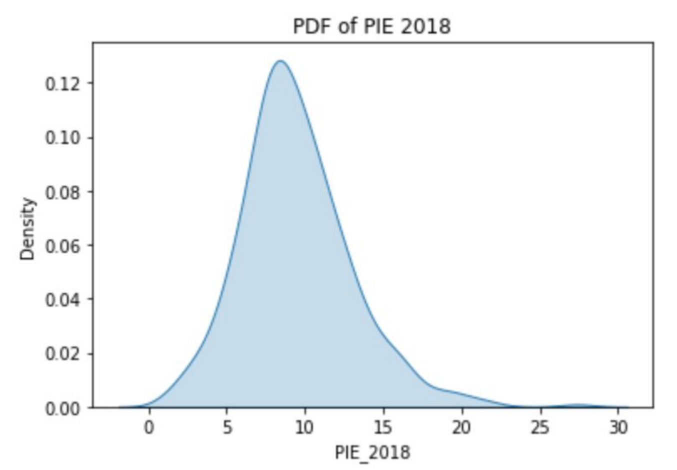
# EDA: Closer Look at Target Variable

Looking at the summary statistics for PIE_2018, there is a relatively small interquartile range around the mean PIE value of 9.44. The boxplot also reflects this displaying a small but notable number of outliers beyond the plot's whiskers. The PDF show that by visual analysis the PIE scores are normally distributed.

```
df.PIE_2018.describe()

count    399.000000
mean       9.444862
std        3.549127
min        1.300000
25%        7.300000
50%        9.000000
75%       11.300000
max       27.400000
Name: PIE_2018, dtype: float64
```



# Pre-Processing

- Normalized and standardized the data.

- created an additional feature with K-Nearest Neighbors to create 5 players clusters.

- Converted categorical features into dummy variables.

- Split training and testing data (60/40)

- Used a 5 fold cross validation when tuning hyper-parameters

# Modeling Overview

Type: Multivariate Linear Regression

Scoring Metric: RMSE

Algorithms: OLS, Lasso, Ridge, Elastic Net, Random Forest, XGBoost

Hyper-parameter Tuning: Grid Search, Random Grid Search, Bayesian Optimization

Tools/Libraries: Statsmodels, Scikit-Learn, xgBoost, BayesOpt

# Model Comparison

- XGBoost and Random Forest had the lowest RMSE, but their results are less interpretable

- The most accurate model was Elastic Net and with additional hyperparameter tuning it had a comparable RMSE with Random Forest.

| | RMSE | R-Squared | Hyperparameters |
|---|---|---|---|
| **XGBoost** | 2.20 | 0.53 | Default |
| **Random_Forest** | 2.26 | 0.50 | Default |
| **Elastic_Net** | 2.28 | 0.49 | Bayesian Optimization |
| **Elastic_Net** | 2.36 | 0.45 | Grid Search |
| **Elastic_Net** | 2.36 | 0.45 | Grid Search |
| **Lasso** | 2.36 | 0.45 | Grid Search |
| **Ridge** | 2.36 | 0.45 | Grid Search |
| **Elastic_Net** | 2.38 | 0.44 | Random Grid Search |
| **SmOLS** | 3.02 | 0.10 | Default |

# Model Predictions: What Went Wrong?

10 LEAST Accurate Predictions

Themes between these players:

- Changed teams

- No regression towards mean

- Large change in PIE score

| Player | PIE_2017 | PIE_2018 | predictions | pred_error | AGE | MIN_2017 | true_change_in_PIE | diff_team |
|---|---|---|---|---|---|---|---|---|
| Wade Baldwin IV | 9.4 | 2.1 | 9.142897 | 7.042897 | 22 | 11.5 | -7.3 | False |
| James Harden | 19.4 | 20.1 | 13.754321 | 6.345679 | 28 | 35.4 | 0.7 | False |
| Andrew Harrison | 8.3 | 2.5 | 8.453300 | 5.953300 | 23 | 23.7 | -5.8 | True |
| Nikola Vucevic | 13.9 | 18.5 | 13.312251 | 5.187749 | 27 | 29.5 | 4.6 | False |
| Anthony Davis | 18.8 | 19.7 | 14.630221 | 5.069779 | 25 | 36.4 | 0.9 | False |
| Paul George | 12.0 | 16.1 | 11.068824 | 5.031176 | 28 | 36.6 | 4.1 | False |
| Mike Conley | 10.9 | 15.1 | 10.366519 | 4.733481 | 30 | 31.1 | 4.2 | False |
| Tyrone Wallace | 6.0 | 4.3 | 8.926866 | 4.626866 | 24 | 28.4 | -1.7 | False |
| Jeremy Lin | 7.1 | 10.0 | 5.511644 | 4.488356 | 29 | 25.2 | 2.9 | True |
| Walt Lemon Jr. | 3.0 | 10.9 | 6.474474 | 4.425526 | 25 | 7.0 | 7.9 | True |

# Model Predictions: What Went Right?

10 MOST Accurate Predictions

Themes between these players:

- Did not changed teams

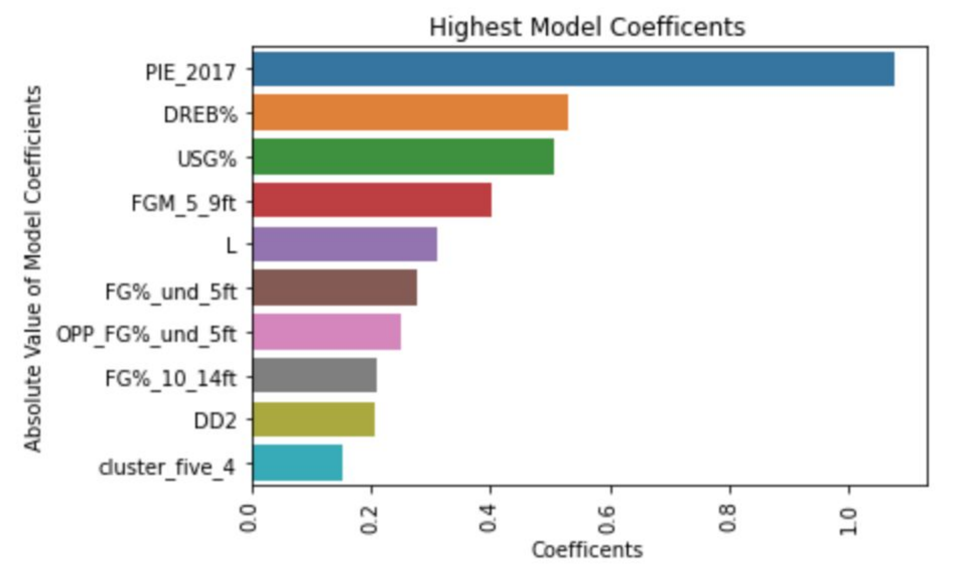
- Small change in PIE

- General regression towards the mean.

| Player | PIE_2017 | PIE_2018 | predictions | pred_error | AGE | MIN_2017 | true_change_in_PIE | diff_team |
|---|---|---|---|---|---|---|---|---|
| Davis Bertans | 9.2 | 8.2 | 8.193908 | 0.006092 | 25 | 14.1 | -1.0 | False |
| Kyle Lowry | 13.6 | 11.5 | 11.488014 | 0.011986 | 32 | 32.2 | -2.1 | False |
| JaMychal Green | 10.1 | 10.3 | 10.324258 | 0.024258 | 28 | 28.0 | 0.2 | True |
| Jon Leuer | 7.0 | 9.1 | 9.052195 | 0.047805 | 29 | 17.1 | 2.1 | False |
| Ante Zizic | 13.2 | 10.3 | 10.354570 | 0.054570 | 21 | 6.7 | -2.9 | False |
| Doug McDermott | 6.9 | 7.5 | 7.415245 | 0.084755 | 26 | 21.8 | 0.6 | True |
| Terry Rozier | 11.8 | 10.3 | 10.432317 | 0.132317 | 24 | 25.9 | -1.5 | False |
| Tyler Dorsey | 7.0 | 7.2 | 7.061712 | 0.138288 | 22 | 17.4 | 0.2 | True |
| Udonis Haslem | 2.1 | 6.7 | 6.849273 | 0.149273 | 38 | 5.1 | 4.6 | False |
| Fred VanVleet | 11.1 | 9.5 | 9.292208 | 0.207792 | 24 | 20.0 | -1.6 | False |

# Analysis: Most Impactful Coefficients

| | Absolute Value of Model Coefficients | +/- Corr. |
|---|---|---|
| **PIE_2017** | 1.074437 | + |
| **DREB%** | 0.531392 | + |
| **USG%** | 0.507683 | + |
| **FGM_5_9ft** | 0.402081 | + |
| **L** | 0.312532 | - |
| **FG%_und_5ft** | 0.278564 | + |
| **OPP_FG%_und_5ft** | 0.249301 | - |
| **FG%_10_14ft** | 0.210631 | - |
| **DD2** | 0.207227 | + |
| **cluster_five_4** | 0.153731 | + |



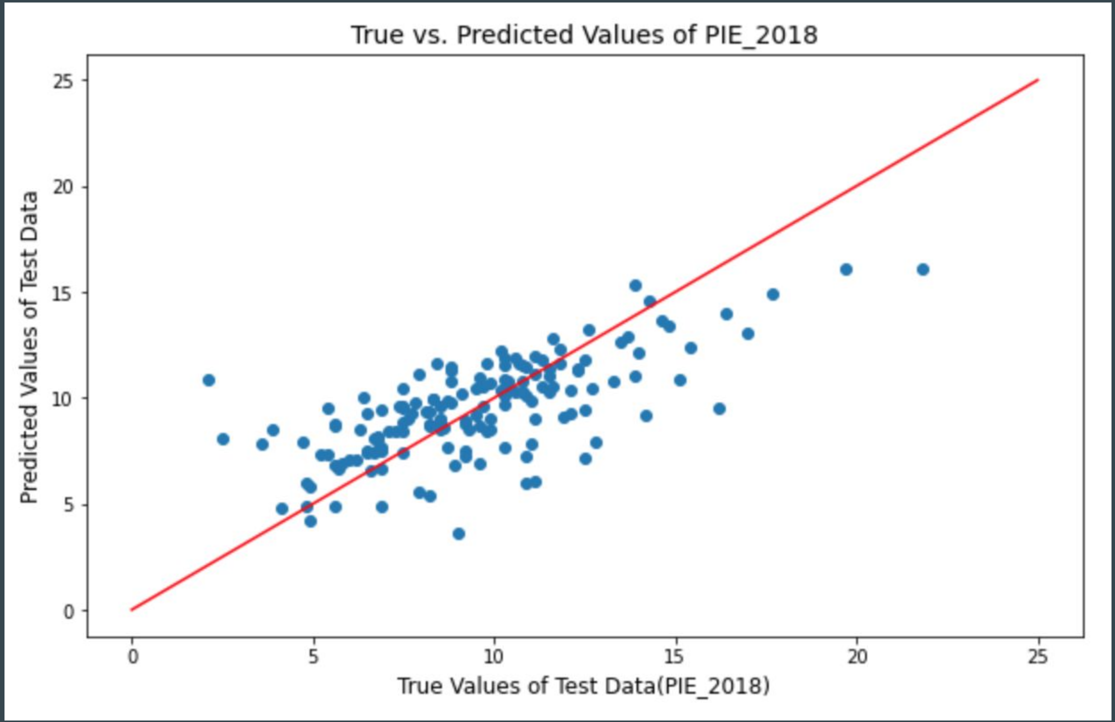

- DREB%, USG%, FGM_5_ft are surprisingly most impactful positive coefficients
- FG%_10_14ft is surprisingly negatively correlated with Player Impact

# Analysis: Residuals

- The model underestimated higher true values and overestimated lower true values.

- The model was more accurate in predicting the general trend of a Regression Towards the mean.

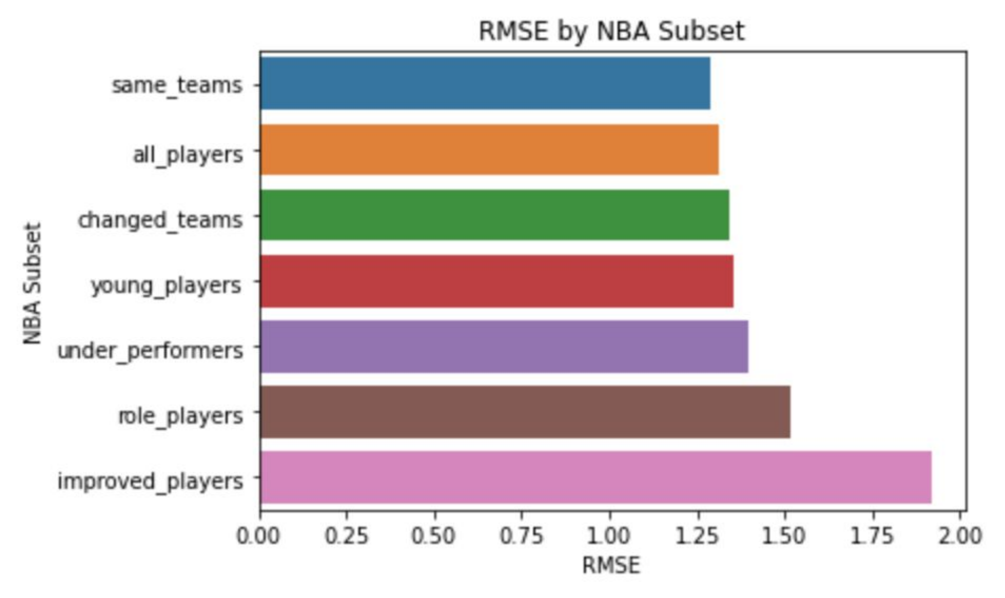
- The model was less accurate at capturing outlier player progress between seasons.



# Analysis: On Which Subsets was More/Less Accurate?

-Most accurate predictions with players who did not change teams.

-Least accurate predictions on most improved players, less able to identify outliers.



# Next Steps

- Add additional seasons into the training set to improve model performance and hopefully the additional data would better capture the unique progression and growth of superstar players.

- Build this regression model into a Flask app where a user could select a target feature and a player of their choice and see a prediction for that feature in the upcoming season.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