NBA Player Positions

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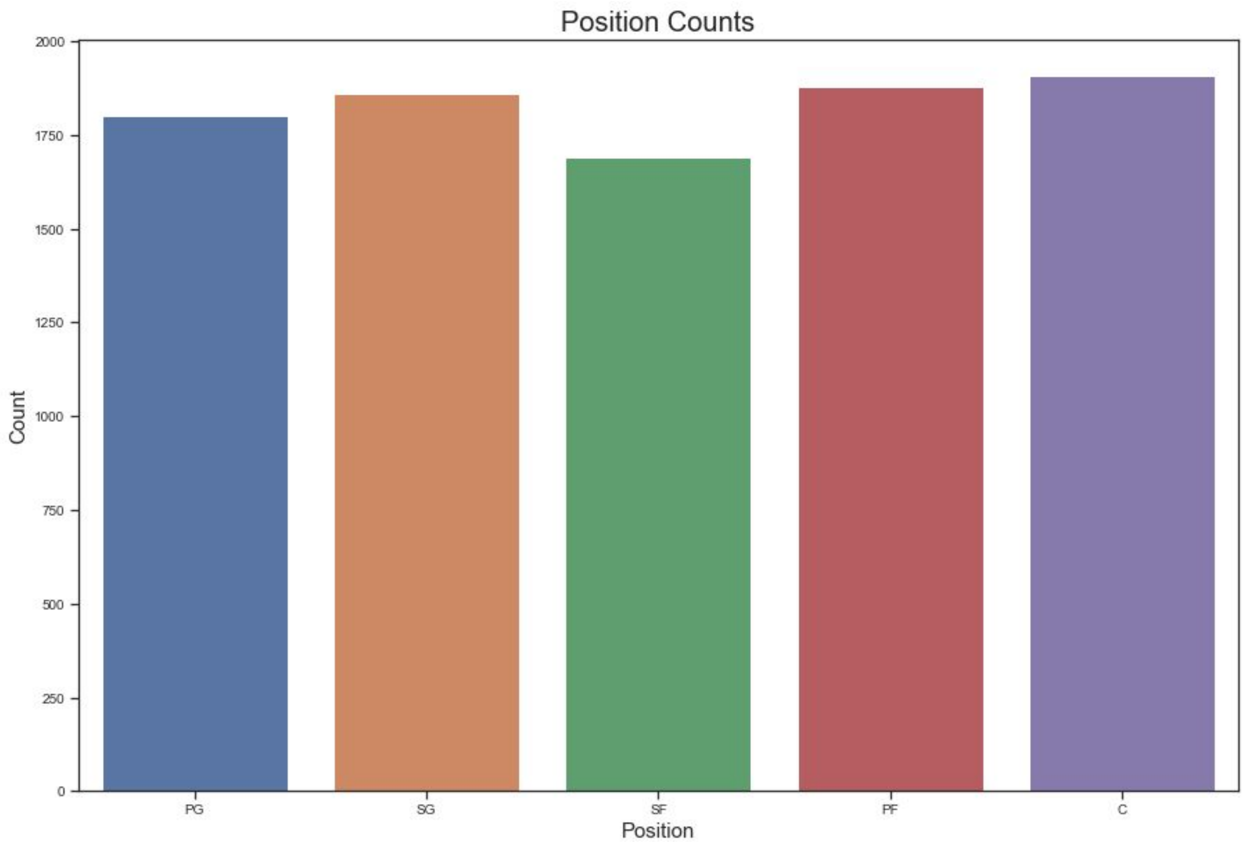
GitHub: https://github.com/jasonk33/nba-player-positions

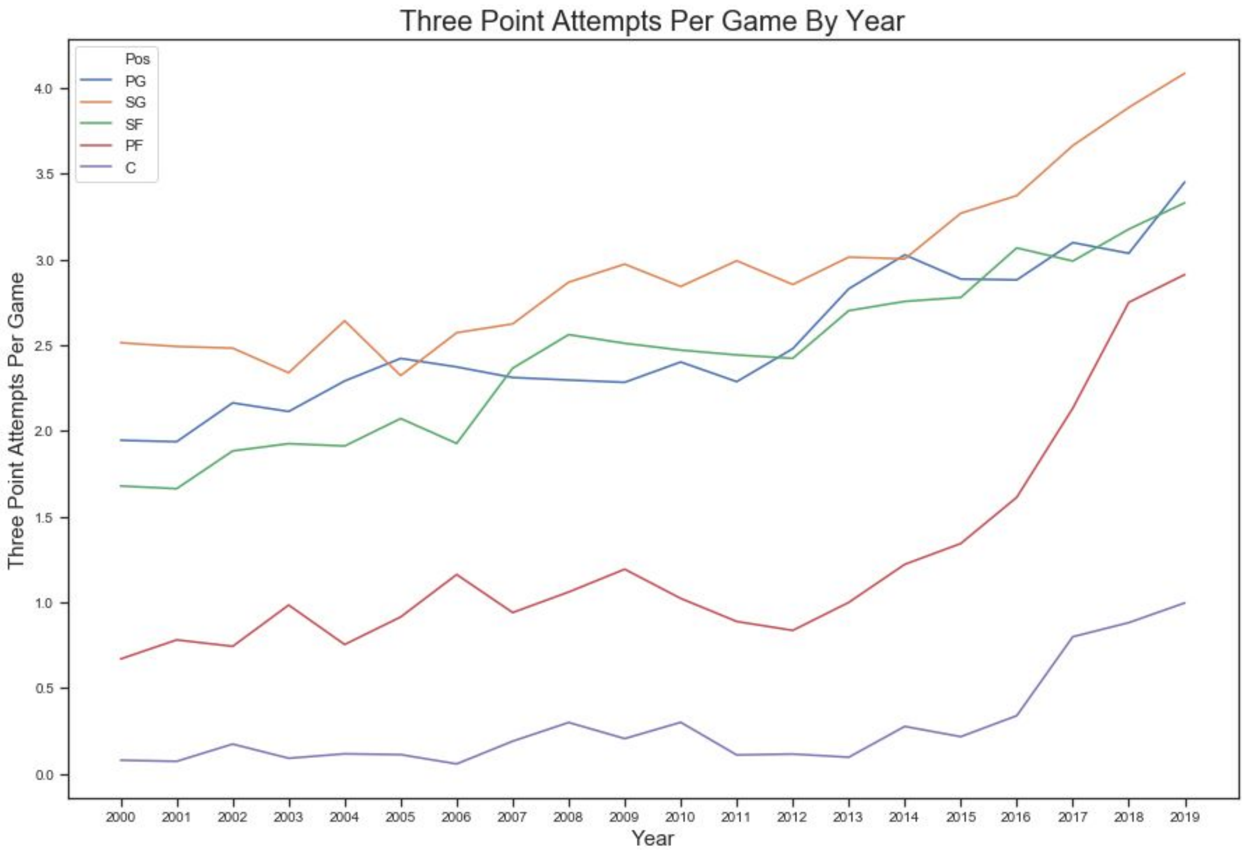
Introduction

For this project, I am trying to gain greater understanding into the different NBA positions. There are 5 positions in the NBA (point guard, shooting guard, small forward, power forward, and center). Each position has a unique skill set and it would be interesting to see which in game statistics contribute most to a player's position designation. This will be a classification task, where I predict a player's position based on their seasonal statistics. This is interesting because many NBA players are thought to be able to play different positions, and understanding what stats go into a player's position designation can give greater insight into the structure of NBA positions and how they have evolved over the years. The dataset for this project was scraped from basketball reference and contains around 10,000 total players from the 2000 through 2019.

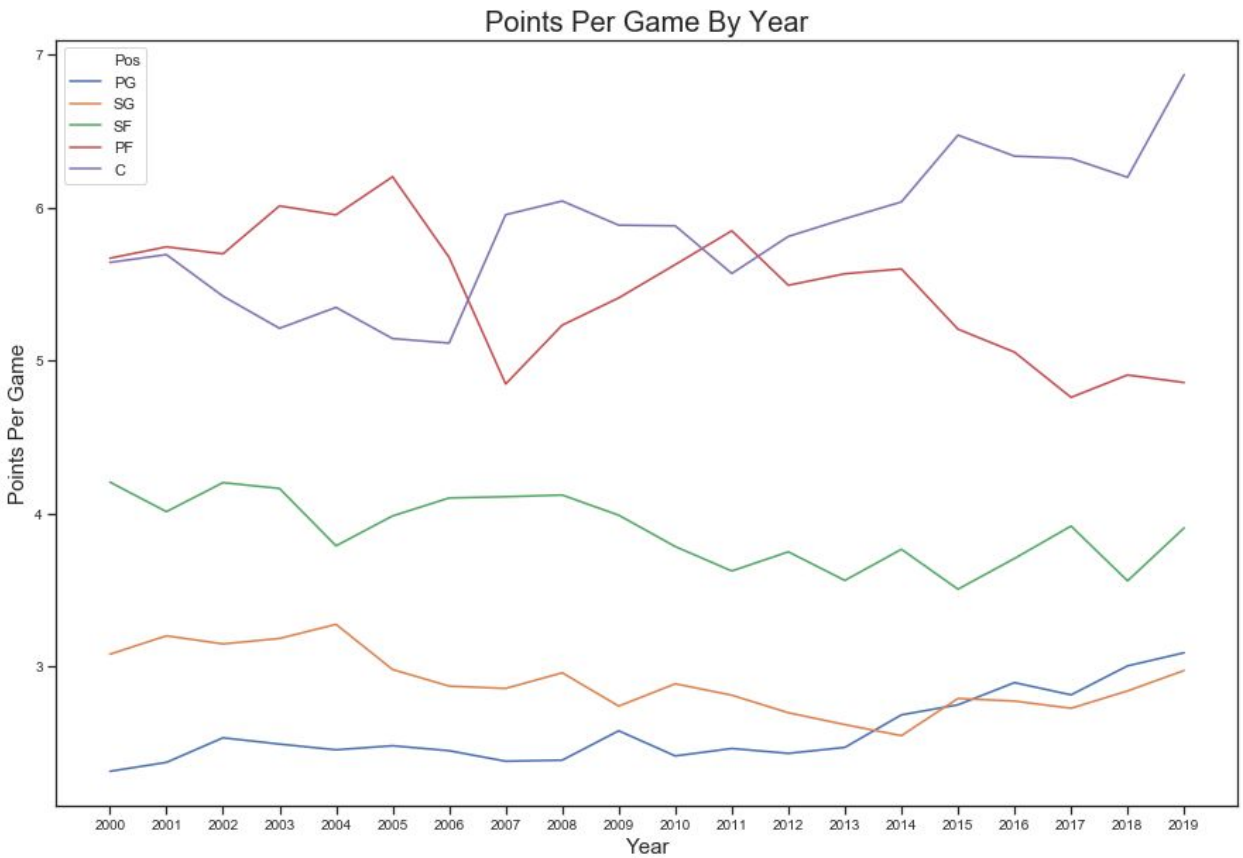
EDA



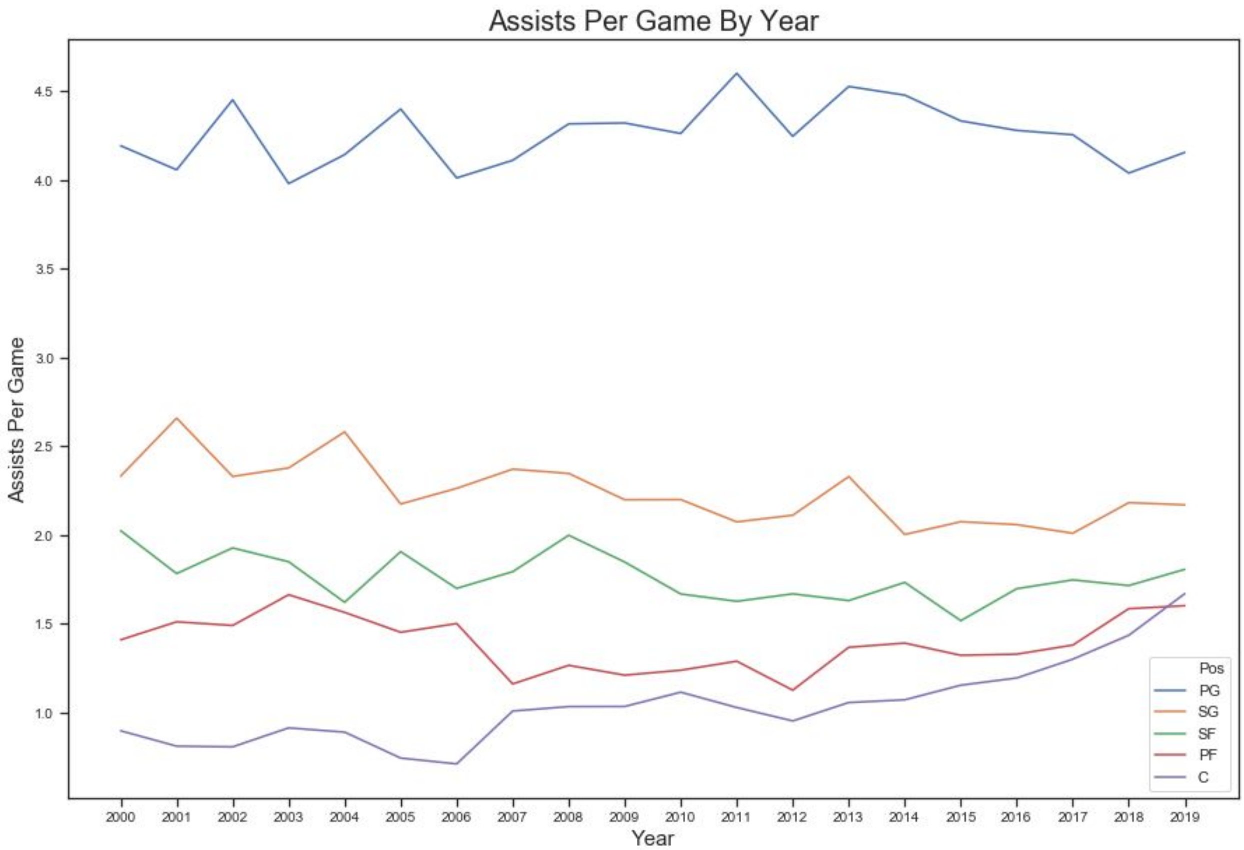
This figure shows the breakdown of number of players for each position in the entire dataset



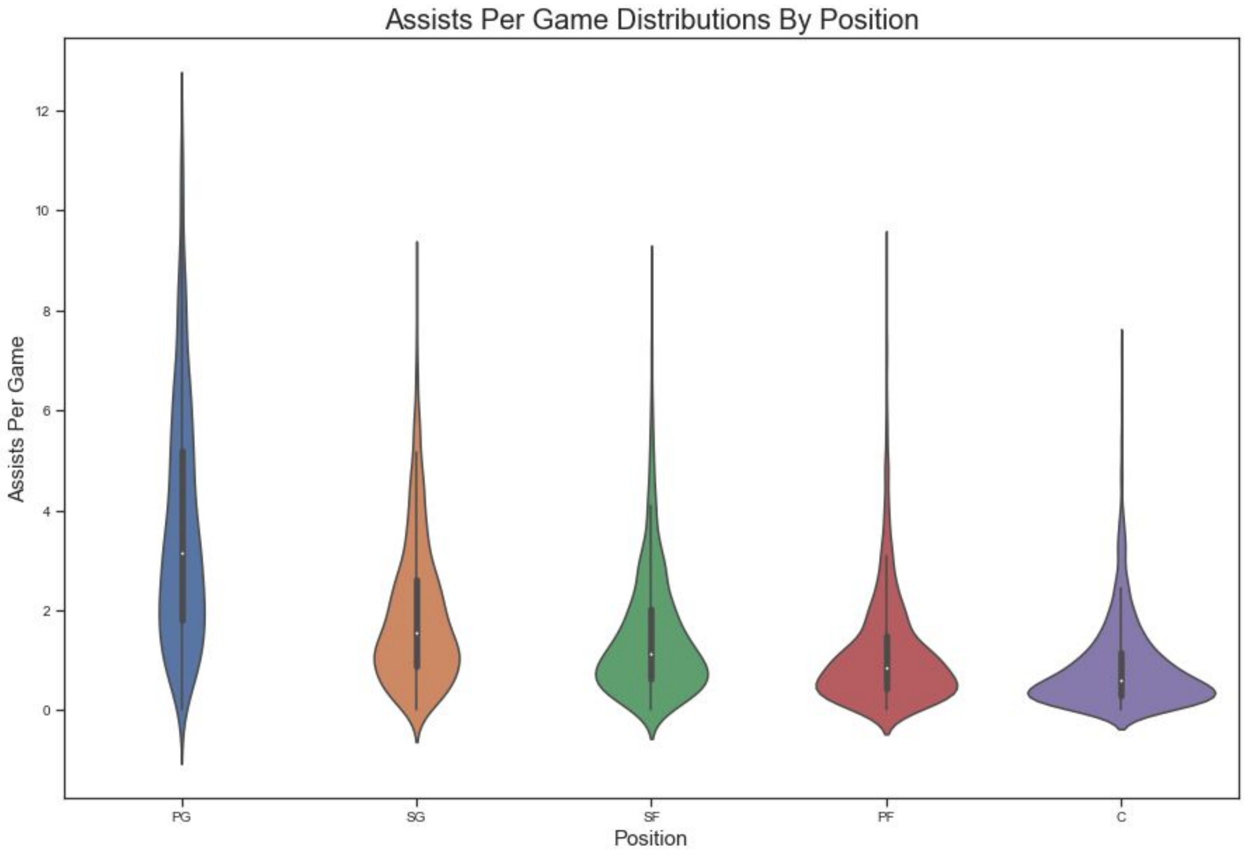
This figure shows how the number of three pointers taken per game has been rising over the years, especially for PF



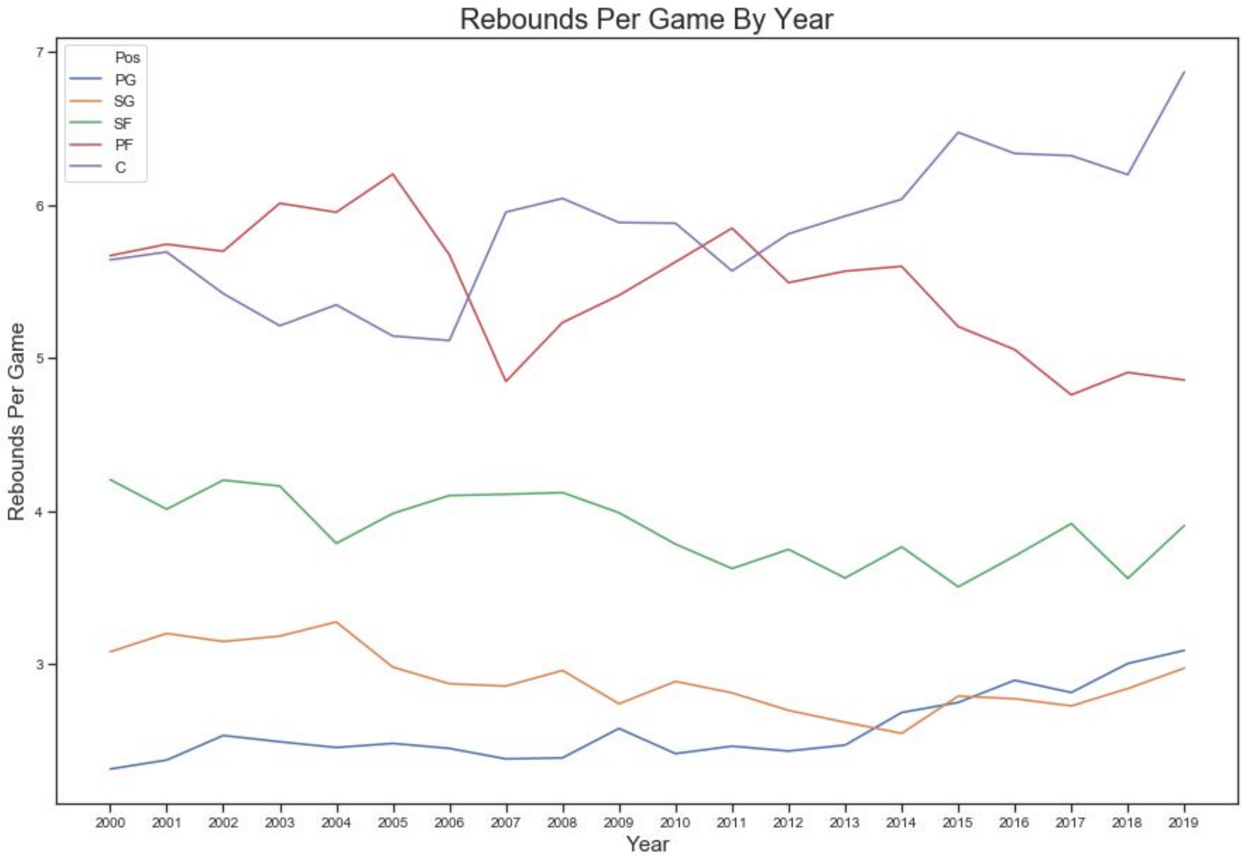
This figure shows how points per game has changed over the years for each position



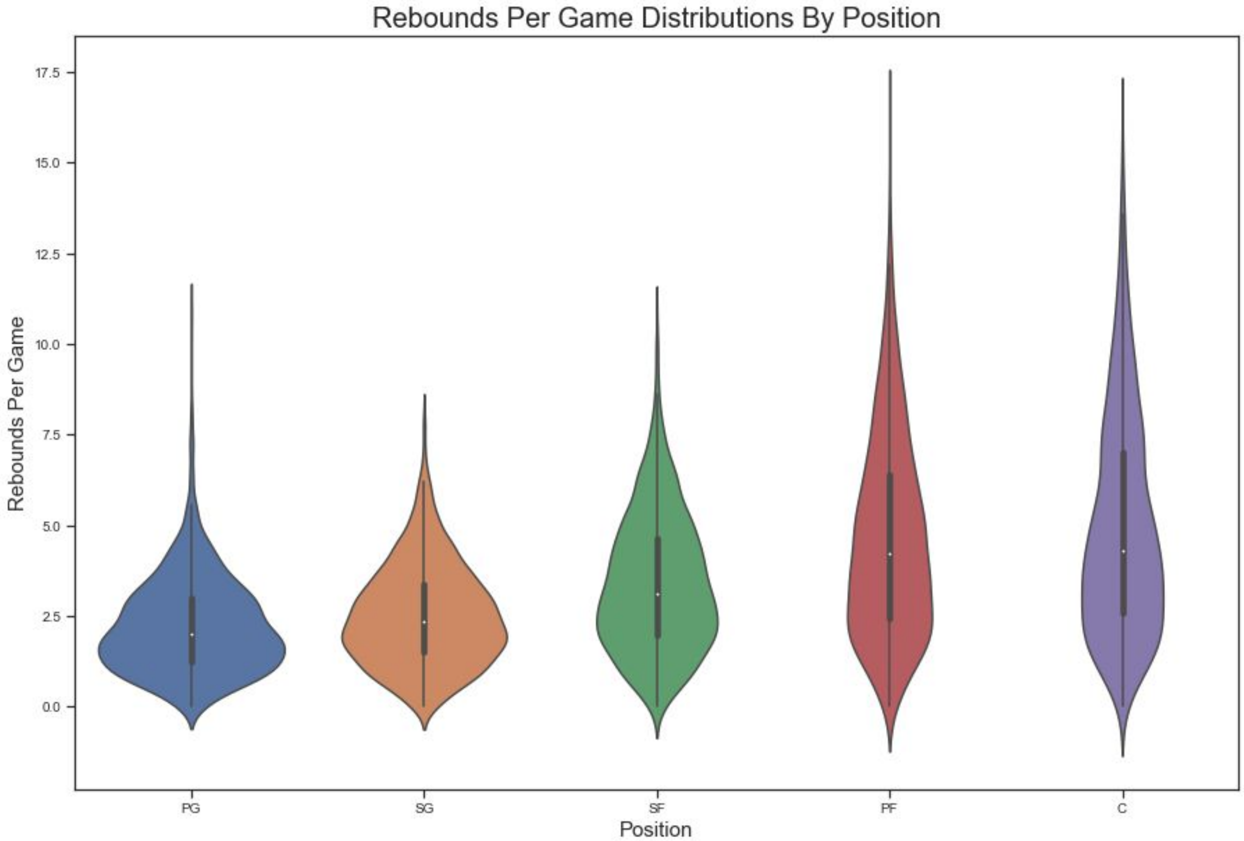
This figure shows assists per game by position over the years, note how point guards have the most, but centers have started to rise in recent years



This figure shows the distribution of assists per game by position, point guards have a very narrow distribution compared to the other positions



This figure shows rebounds per game by position over the years, note how centers have overtaken power forwards



This figure shows the distributions of rebounds per game by position, note how the power forward and center distributions are very narrow compared to the other three positions

Methods

For preprocessing, most of the features were continuous, so standard scaling was applied. One hot encoding was applied to the single categorical feature. The label had multiple values, so a label encoder was used. After preprocessing, there were 22 features and 10,000 data points. For the labels, almost every player has one of the 5 main position designations (PG, SG, SF, PF, C), but a select few players are listed under multiple positions. Since the number of players listed under multiple positions is small, those were removed from the dataset. Players who were traded during the season, were listed more than once, with statistics for each team they played for, as well as their total stats combined for the year. For players that were traded, the rows representing their total stats combined for both teams were kept, and the other rows for them were removed. There were some missing values for field goal percentage statistics when a player had not attempted any shots. Since field goal percentages can be calculated directly from field goal makes and attempts, the percentage features were removed.

For the machine learning pipeline, I used repeated k fold stratified cross validation. I chose to use stratification to make sure the classes for each of the five positions were balanced. I used five folds and three repeats for the cross validation. I tried four different kinds of models and tuned the hyperparameters using a grid search. For logistic regression I tuned the value C and tried the range 0.1 to 1.0. For random forest, I tuned the maximum depth and the minimum number of samples for a split, I tried the ranges of 5 to 10 and 3 to 11 respectively. For support vector machines I tuned C and gamma, trying the ranges of 150 to 250 and 0.001 to 0.1 respectively. For k nearest neighbors, I tuned the number of neighbors, trying the range 25 to 75. I used both accuracy and logistic loss to evaluate the models' performance. I used accuracy as the main metric because it is easily understood, but also made sure to watch logistic loss to ensure the predicted probabilities were reasonable outside of pure class prediction. I used the same random seed for splitting and non deterministic models to ensure all results were reproducible.

Results

The baseline model for this five class classification task was .209. Out of all the models, the one that performed the best was the support vector machine, with an accuracy of .664. The top 5 features were assists, three point attempts, blocks, total rebounds, and offensive rebounds with values of .253, .148, .126, .097, and .092 respectively. These all make sense as important features as high assists normally indicate a point guard, high three point attempts indicate it is not a big man, and high blocks and rebounds indicate it is a big man. These results fit into a human context, as the most important features all pass the eye test and the ability to make a good predictor reinforce the idea that there is a fundamental difference between the five different positions in what they do on court from a stats perspective.

Outlook

To improve the model, I would experiment with other types of models, such as gradient boosting or neural networks. I would also see if there are any other hyperparameters I could tune, possibly different types of kernels for the support vector machine model. I could also acquire more data in addition to seasonal statistics, such as salary information or player details such as height and weight.

References

Data was scraped from basketball reference. While doing research for the project, I found three other people who performed similar work, trying to predict player positions:
Predicting NBA Player Positions
NBA Position Predictor
Predicting NBA players positions using Keras