Predicting the final seeds of National Basketball Association teams, an Elo based approach

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*Abstract*—The introduction of statistical analysis into the National Basketball Association has radically changed the way basketball shot selection and plays are thought about. The Elo algorithm is a popular ranking algorithm used to rank players in a competitive setting. The Elo algorithm is often associated with chess as it is used extensively by FIDE (the governing body of international chess) to determine world rankings of chess players. For the model being considered here, the Elo rating will depend on the players +/- for each game. The model will include only regular season games as they are defining factor when it comes to a team’s final seed. Teams will gain points after winning matches and lose points post defeat. Finally, teams will be seeded from one to fifteen in each conference based on their Elo scores. The generated seeds will be validated by creating the model for a previous season and cross-checking its accuracy with real world results. This model will then be compared with a Random Forest Classifier approach and a distinction will be made based on efficiency and accuracy.

Keywords—plays, Elo algorithm, playoffs, seeded, Random Forest Classifier.

# Introduction

The National Basketball Association (NBA) is a men’s professional basketball league in North America, composed of thirty teams divided into western and eastern conferences. Each NBA team has a maximum of fifteen players, out of which thirteen are allowed to be active in each game. Players on a basketball court position themselves in five locations as shown in Figure 1.1. Each of these positions require distinct abilities and physical attributes.

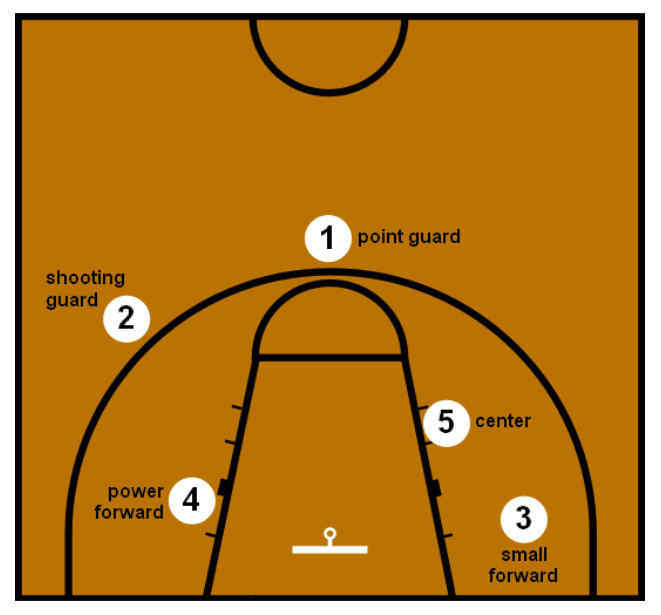


Figure 1.1. Traditional positions in basketball

At the highest level of professional basketball, every play is executed by a team is carefully devised by a team of coaches. Basic plays such as a switch or a give-and-go are widely used and can be situational. However, particular plays such as those centred around off ball movement in order to ensure that a particular player loses their defender are drawn up after taking into consideration the player as well as the defenders ability. The ultimate goal of the offense is to shoot the ball, the strategy lies in devising plays to create good shot opportunities. Defensive plays on the other hand are often drawn up to restrict the movement and ability of one particular player or a set of players. These types of plays are often drawn up after watching a particular player over multiple games and analysing their offensive and defensive capabilities.

General managers such as Darryl Morey set out to prove that data driven decisions would result in a competitive edge. Previously implemented conventional methods used to simulate gameplay and deduce plays have ignored that in a sport such as basketball the dynamics of movement and cohesiveness are unique from line-up to line-up and do not depend solely on individual offensive and defensive ability.

The Elo rating system is popular and widely used, this is mainly because it is elegant yet simple in its execution. A rating system analyses the outcomes of matches and assigns a value to the strength of a team relative to others. This information then allows teams and coaches to make beneficial long term decisions regarding team formation, trades, player rotations and drafts [4]. The performance in the Elo system is not measured in absolute terms. It is inferred from wins and losses.

The Random Forest Classifier is a flexible and intuitive algorithm that can be used for both classification and regression tasks and tends to produce an accurate result. It is widely used due to its simplicity and effectiveness. This algorithm uses the decision tree classifier method but instead of creating a single tree, it creates multiple. This gives it the opportunity of random sampling of data as each individual tree learns from a random sample of data points which are drawn without replacement. This then minimizes the possibility of over-fitting and improves overall predictive accuracy of the model. This is because the final predictions will be made by computing the mean of the predictions of each individual tree. Using this particular model should also give us the ability to extract feature importance which tells us which variable or variables contribute the final result the most. One foreseeable drawback is that this model may be difficult to interpret in comparison to a single decision tree because of the complexity involved with combining multiple trees. Finally, the results obtained from both models will be compared for accuracy and efficiency [10].

# Literature Review

Accurate predictions of a team’s seed greatly influences a team’s chances of winning prior to the playoffs. The ability to discern a potential round one matchup at the least will give coaching staff the opportunity to condition players and design game plans specifically suited to their opponents. The Elo model when run through the course of a season should analyse various strengths and weaknesses when it comes to likely matchups. Comparing the outcomes of both the Elo model and the Random Forest model will allow coaches and trainers to prepare for every likely outcome.

## Elo Algorithm:

A base understanding of the Elo model indicates that for a metric to be useful for a particular decision, its treatment of variation needs to match up with the decision that is being made [1]. While we can isolate some player, season, and team variation by analysing and dividing the data, all measurements that we take are confounded with the randomness of chance. The main feature of the Elo rating system is that performance is not measured in absolute terms but is derived from wins and losses against other players with different ratings. In other words, player ratings depend on both their performance and the ratings of their opponents [11]. This ensures that an effective comparison can be made with other Machine Learning models.

From a general understanding of most sports, it can be discerned that better statistics do not always infer a win. In most cases an athlete will perform at their average level throughout their career. Deviations from this do occur, large deviations occur less frequently than smaller ones. Hence, it was assumed that “the many performances of an individual will be normally distributed, when evaluated on an appropriate scale [2].” It is for this reason that the contribution of each player is modelled as a normally distributed random variable.

Another reason for the selection of the Elo model is that it can account for the margin of victory. Teams will gain rating points after wins and lose the same after losses, but they also gain or lose more points based on margin on victory i.e., a blowout win, or loss is more consequential to a team’s rating. This can be implemented by assigning a multiplier to each match and dividing it by the teams probable margin of victory if they win the game [9].

Building on previous work [4], this project sets out to create a model that can accurately predict each of the fifteen seeds in both conferences for a season. An Elo based approach is employed to obtain probable wins in a head-to-head matchup between two teams based on player ratings. The individual player ratings are combined to obtain a team rating. Team ratings are then compared pairwise to obtain the probability of a win by each of the teams during the season. The probable wins are then cumulated, and a seed is calculated for each team. Each of the fifteen teams in each conference are then ordered based on their win to loss ratio. The rating system is validated by running them over real-life data from previous NBA seasons.

## Random Forest Classifier:

# Methodology

The original purpose of the Elo algorithm was to develop a viable rating system for chess players. As the popularity of the algorithm increased, analysts and statisticians began modifying the algorithm so it could be applied to various other sports. In the simulations being considered here, players alone are not given individual attention when it comes to win prediction. Instead, the team is considered as a single entity.

The true value of a player is not specifically quantifiable and therefore, cannot be measured and analysed. Hence, we depend on the observable metrics of the sport such as points scored, rebounds, assists and so on. The primary statistic being considered in the algorithm is the plus-minus score. The algorithm as a whole is designed to track the performance of individual basketball players and combine their ratings in order to obtain a team score which can then be used in the simulations.

## Plus-Minus Score (+/-)

The Plus-Minus score reflects how the team did while a particular player was on the court.

## Elo Approach

### Player Strength

### Estimate

In the algorithm, it is assumed that each team's actual strength is derived from a normally distributed random variable, with the team's actual strength being represented by the mean. A team that maintains the same lineup every game should perform at the same strength. Due to this reason a normal distribution is chosen. The rating of a team is updated continuously based on observed wins and losses. If plays, then the rating is updated as:

[3]

Where *R* refers to the rating, *K* refers to the K factor, *S* refers to the actual score and *x* refers to the expected score.

### Actual Score (S)

The definition of is depicted as:

[3]

### Expected Score (x)

Variable is used to denote the expected outcome of a match between and .

### K Factor (K)

The K-factor determines how quickly the rating reacts to new game results [9]. A high K value allows the estimate to adapt quickly, however if K is set to high it will result in the large variations in the estimate. On the other hand, if the K value is set too low then the estimate will take too long to recognize important changes. The K factor being selected here depends on the total number of minutes being played by each individual player.

There are still multiple cases where the algorithm is too slow to catch up to major trades or signings like when Lebron James was signed by the Lakers or when Kevin Durant left the Golden State Warriors. Furthermore, a bad start to the season could result in extremely low team rating, however the team may go on to finish the season with a win rate of greater than 50%.

### F(x)

### Match Outcome

### Seed Outcome

## Algorithms

### Algorithm 1: Update Team Rating

### Algorithm 2: Update Player Ratings

### Algorithm 3: Predict Match Winner

## Datasets

### Physical Data:

The required datasets are obtained by scraping data from the NBA website. The data is obtained from the 2017-2018, 2018-2019 and 2020-2021 regular seasons. Both the player box score and the team box score are recorded.

### Data Scraping

Data or web scraping refers to the process of importing information from a web page, typically written in HTML or XHTML, into a locally saved spreadsheet. A Python program was written to extract the required statistics from online tables and is stored locally as a CSV file.

### Synthetic Data

### Initialization

### Metric Calculation

# Results

## Testing on the NBA 2018-19 Season

Algorithms 1 and 3, as depicted above, are used to predict the outcome of a match for the base Elo algorithm and the modified algorithm, respectively. During the testing phase the ratings of both players and teams are updated repeatedly even as results are predicted.

# Discussion

# Conclusion

The Elo algorithm is a widely used rating system due to its simplicity and the fact that it offers relatively high prediction accuracy. The main reason it was selected is because the algorithm considers the whole team as a fundamental unit. In the models being discussed above, a modified version of the Elo algorithm is used where a team’s performance is modelled using the +/- metric of individual players. Individual player ratings are combined to obtain a team rating which is then used to predict the outcome of matches. The chosen algorithm is compared with the base Elo algorithm by analyzing the implementation of the algorithms over real-world and synthetic data. From the above simulations it is observed that the base algorithm is more accurate than its modified version. This is largely due to the fact that the addition of individual player ratings increases the complexity of the algorithm. The model does however offer additional insight into player strengths which further enable the analysis of injuries and possible transfers. This particular factor should allow teams to better quantify a players worth and overall trade value.

# Future Work

Analysis of test results indicate that further modifications to the algorithm may result in further understanding of individual player strengths and susceptibility to injuries. This may be able to aid front office management when it comes to player transfers and contract extensions.

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