Predicting the final seeds of National Basketball Association teams, a Machine Learning 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. 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 and Logistic Regression approach and a distinction will be made based on efficiency and accuracy and determine the most accurate model. It was then determined that the logistic regression model produced the most accurate result.**

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

I. 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.

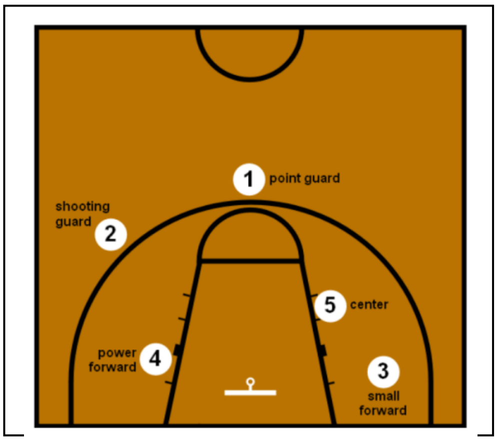


Figure 1.1. Traditional positions in basketball

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 defender's ability. The 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 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 evaluates the results of matches and values the strength of a team in comparison to other teams. Using this data, teams and coaches may then decide how to construct their teams, trade for players, rotate their roster, and draft future talent [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 model 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 model uses the decision tree classifier method but instead of creating a single tree, it creates multiple [10]. 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 [10]. 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].

The logistic regression model is used for classification and prediction analysis. It estimates the probability of an event occurring such as a win or a loss in this case. Since the result generated is a probability, the dependant variable is bound between 0 and 1 [15]. This model only uses the specified data to make a prediction without taking any other factors into account. Thus, removing all bias from the equation.

Based on the analysis of the possible advantages and drawbacks of all three approaches it can be assumed that the Elo based approach will produce the most accurate result as the plus-minus score depicts not only a player's impact on the game but their impact on their teammates as well.

II. Literature Review

Accurate predictions of a team's seed greatly influence 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 the Elo model, the Random Forest model and the Logistic Regression model will allow coaches and trainers to prepare for every likely outcome.

A. Elo Algorithm:

According to a fundamental premise of the Elo model, a metric's treatment of variation must coincide with the decision being made for it to be useful for that decision [1]. Even though we can separate some player, season, and team variation through data analysis and division, all measures we do are affected by chance's variability. 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 varying ratings [4]. 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]. This is the rationale behind modelling each player's contribution as a normally distributed random variable [4].

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 of 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 team's probable margin of victory if they win the game [9].

Building on previous work [4] where a modified version of the Elo algorithm using the plus-minus metric was created and analysed, this project sets out to create a model that can accurately predict each of the fifteen seeds in both conferences for a season by incorporating all traditional statistics available. An Elo based approach is employed to obtain probable wins in a head-to-head matchup between two teams based on player ratings to create a team rating, the player ratings are added together. The chance of each team winning during the season is then determined by comparing team ratings pairwise [4]. 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 comparing them to actual information from prior NBA seasons.

The largest noticeable drawback of the Elo algorithm is that two teams can have identical results but end up with different ratings because the ratings are calculated as a change to the current rating. In a practical sense it works as it is supposed to because a vast majority of teams improve at a very slow pace. However, the system can be seen as an unfair to teams that improve rapidly from a low starting point such as the 2022 Boston Celtics.

B. Random Forest Classifier:

Classification constitutes a large portion of machine learning. The ability to precisely classify observation is extremely important when it comes to making accurate predictions. Individual decision trees are combined to make a random forest. A decision tree is a flowchart-like structure, where each node denotes a test on an attribute, each branch represents an outcome or result, and each terminal node holds a class label [12]. The varying number of decision trees in the model operate as an ensemble. Each of the individual trees in the random forest then reports a class prediction and the class with the most words are taken as the model's prediction. The fundamental principle behind this approach is "A large number of relatively uncorrelated models operating as a group will outperform any of the individual constituent models" [13]. The randomness associated with generating the individual trees minimises the possibility for over-fitting and improves the overall accuracy of the model. This is primarily because the final prediction is deciphered by calculating the mean of the predictions of each individual tree, thus following the above-mentioned principle.

An observable drawback of this model is that it is not easily interpretable. It provides feature importance, but it does not provide complete visibility into the coefficients. It is also computationally intensive for large datasets and the user has very little control over what the model does [14].

C. Logistic Regression:

This model allows its user to estimate the probability of a categorical response based on predictor variables. These responses are traditionally binary values but can even be categorical if required [16]. Logistic regression is an ideal choice because it tends to produce good accuracy for simple data sets and performs well when the dataset is linearly separable, and it can interpret model coefficients as a measure of feature significance.

The main disadvantage of logistic regression is the presupposition of linearity between the dependant and independent variables. Furthermore, logistic regression is bound to discrete number sets as it can only be used to predict discrete functions. The number of observations should always be greater than the number of features, otherwise, it can lead to overfitting i.e., the model won't be able to make accurate predictions about new data because it cannot distinguish between noise and essential data [17].

III. Methodology

A. Elo Approach

The Elo algorithm was developed initially to provide a useful chess player ranking system. 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. Rather, the team is regarded as a whole [4].

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 is made to monitor each basketball player's performance and aggregate their ratings to provide a team score that can be used to the simulations [4].

1) Plus-Minus Score (+/-)

The Plus-Minus score reflects how a team performed while a particular player was on the court. The introduction of the adjusted plus-minus score redefined the understanding of player value. The league wide statistic of adjusted plus-minus considers a player's marginal effect on the score per 100 possessions as compared to a league average player. This metric is widely used for comprehensive player analysis prior to a crucial matchup. Adjusted plus-minus is preferred over unadjusted plus-minus because in the latter each players rating is heavily influenced by the play of his on-court teammates [19]. A player's contribution to their team's performance is shown by a good score, and the opposite is also true.

2) Player Strength

Let p be the variable used to represent the number of points an NBA player contributes every minute. P thus evaluates a player's strength. Each member of a team is initialized with a p value of 1000 (normalizing constant a is multiplied) to make it easier to understand the data. An appropriate value of a is obtained empirically [4].

$$1000 = a \times p \tag{3.1.1}$$

3) 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 $Team_i$ plays, $Team_j$ then the rating is updated as [4]:

$$R_{i_{new}} = R_{i_{old}} + K(S_{ij} - x_{ij}) \tag{3.1.2}$$

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.

4) Actual Score (S)

The actual score being considered refers to the victory/defeat information acquired after a match.

The definition of S_{ij} is depicted as:

$$S_{ij} = \begin{cases} 1, if\ Team_i\ beats\ Team_j \\ 0, if\ Team_j\ beats\ Team\ _i \end{cases} \quad [4]$$

5) Expected Score (x)

Variable x_{ij} is used to denote the expected outcome of a match between $Team_i$ and $Team_j$. When two players are matched up with each other, the overall performance of the players is modelled as a normal random variable [20].

The probability that $Team_i$ wins against $Team_j$ is depicted as [4]:

$$P_r(i > j) = \frac{P_i}{P_i + P_j} \tag{3.1.3}$$

Where P_i and P_j are individual scores assigned to $Team_i$ and $Team_j$. The expression becomes a logistic function when an exponential score is considered [4]:

$$P_r(i > j) = \frac{e^{r_i}}{e^{r_i} + e^{r_j}} \tag{3.1.4}$$

Where r_i and r_j are the ratings of $Team_i$ and $Team_j$. The standard Elo algorithm is depicted as:

$$P_r(i > j) = \frac{1}{1 + 10^{\frac{r_j - r_i}{400}}} \tag{3.1.5}$$

Where 400 is the constant scale factor. Let x_{ij} be used to denote $P_r(i > j)$. Therefore x_{ij} is denoted as:

$$x_{ij} = \frac{1}{1 + 10^{\frac{r_j - r_i}{400}}} \tag{3.1.6}$$

A model is developed to predict a player's plus-minus score. Every time two teams compete; the individual player strengths are added up to provide a team's combined strength parameter [4]. The strength of $Team_i$ is depicted as:

$$m_i = \frac{\sum_{n=1}^{N} t_{in} p_{in}}{\sum_{n=1}^{N} t_{in}} \tag{3.1.7}$$

Where t_{in} denotes the minutes played by the nth player on the ith and p_{in} denotes the estimated strength of the nth player on $Team_i$. Furthermore, m_i denotes the average points scored per minute by $Team_i$ [4].

6) *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 is initialized as a 1000 prior to execution for each team.

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%.

7) *Match Outcome*

Utilizing (3.1.7), the overall team rating is obtained based on the strengths of the individual players on the team. Consider that the team ratings of $Team_i$ and $Team_j$ are denoted as r_i and r_j respectively. The probability that $Team_i$ wins a matchup against $Team_j$ is derived using (1.5.3). For the simulations being considered in these particular instances, a win is predicted if $Team_i$ has a higher overall rating than $Team_j$.

8) *Seed Outcome*

A seed in basketball represents a number which correlates to a team's ranking. In the NBA seeds are determined based on a teams win record or win rate. The team which finishes the season with the best record is awarded the first seed, the second-best team gets the next seed and so on. In each conference i.e., Eastern and Western, the top 8 seeds advance to the playoffs and the higher seeds are awarded home court advantage. The match results correlated above are recorded and teams are ordered based on their win rate.

9) *Algorithms*

a) *Update Team Rating [4]*

```
Algorithm 1: Update Team Ratings according to Elo Algorithm
Initialize all team ratings to a 1000.

for all matches between two teams $Team_i$ and $Team_j$ do

        Calculate $x_{ij}$ and $x_{ji}$ which corresponds to the probability of $Team_i$ and $Team_j$ winning respectively

        Update rating for $Team_i$ and $Team_j$ according to equation 3.1.2

end for
```

b) *Predict Match Winner [4]*

```
Algorithm 2: Predict the winner of match between $Team_i$ and $Team_j$
Determine the functional strength of $Team_i$ based on (3.1.7)

Determine the functional strength of $Team_j$ based on (3.1.7)

It is anticipated that the team with the better strength of the two will prevail.
```

10) *Datasets*

a) *Data:*

Basketball Reference and the NBA website are used to scrape the necessary datasets. The regular seasons of 2018–19, 2019–2020, and 2020–2021 are used to collect the data. There are records for both the team and the player box score.

b) *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. To extract the necessary statistics from online tables, a Python programme was created, and the results were saved locally as a CSV file.

c) *Metric Calculation*

Here, the plus-minus score is calculated using the same mathematical formula as in (1.2.1). The two teams' respective effective strengths are computed using (3.1.7). The winning team is the one with the highest strength.

B. *Random Forest Approach*

The objective is to create predictive models that can predict if the home team will win an NBA regular season basketball game. After that, the models' performance will be assessed, and the wins will be aggregated to obtain a seed. The 2017–18, 2018–19, and 2020–21 NBA season's data were used.

1) *Dataset*

The required dataset was obtained from Basketball reference [21] and the NBA website [8] and stored locally as a CSV file. The source is extensive and consists of vast statistics related to player and team statistics over a 40-year period. The chosen dataset consists of regular season standings and regular season results for 2018-2019, 2019-2020 and 2020-2021.

2) *Data Cleaning*

Data cleaning is the process of eliminating or changing data that is inaccurate, lacking, unnecessary, duplicated, or formatted incorrectly in order to prepare it for analysis [24]. For this particular case, games that ended after regulation time were left blank in the overtime column.

3) *Pandas*[1]

The most often used open-source Python library for data science, data analysis, and machine learning activities is called Pandas. It is constructed on top of NumPy, a different package that supports multi-dimensional arrays. Pandas is one of the most widely used data wrangling tools, and it normally comes with every Python distribution. Pandas integrates nicely with many other data science modules in the Python ecosystem [22].

4) *Scikit-Learn*[2]

The most reliable and effective Python machine learning package is called Skearn (Skit-Learn). Through a Python consistency interface, it offers several effective tools for statistical modelling and machine learning, including classification, regression, clustering, and dimensionality reduction. This library is built on NumPy, SciPy, and Matplotlib[3], and was primarily developed in Python. [23].

5) *Baseline*

A random prediction of all games results in rough accuracy of 50% correct predictions. A more accurate baseline in sports is home win percentage. In most sports the home team has a higher chance of winning a match as is depicted in Fig 2.4.1. In order for the model to be practical it has to have an accuracy rate greater than the baseline.

6) *Basic Classification with Decsion Tree*

Two additional features are added which are checks to see if the home team and the visitor team won their last game and also checks if the team in consideration is on a winning streak. The addition of these features aims to improve the F1 score slightly.

C. *Logistic Regression*

In order to forecast the outcome of an NBA game, the model uses eight variables that were scraped from the league's website [8]. To guarantee that pace has no bearing on the forecasts, each stat is converted to per 100 possessions. For the sake of visibility, it is also possible to see predictions for a single day period along with a past set of dates. The factors being considered are:

1) *Variables*

a) *Home Team*

As noted above, the most accurate baseline in most sports is home team win rate as home court advantage plays a major role in match outcomes. The NBA's home court advantage lends itself incredibly nicely to study. The impact is significant. The average point differential between home and away teams is usually around 3.5 points, and the home side typically wins roughly 60% of the games [25].

b) *Win Percentage*

Win percentage is obtained by multiplying the teams current win-loss record by a 100. The calculated metric is then utilized to calculate the effective probability of the outcome of a particular matchup.

c) *Rebounds*

An effective center can position themselves optimally either to retrieve a rebound or in order to box out an opponent which will then allow their teammate to obtain the rebound. The offensive and defensive rebounds gained and lost each possession directly influence the number of points score. Hence, making them a crucial metric.

d) *Turnovers*

A turnover cost your team the opportunity to obtain a shot at the hoop since it gives the opposition another possession, which they can turn into another shooting attempt. The team with more possessions will score more points if we assume that all the other specified elements are fairly equal. If a team has a lot of turnovers, it will be seen when it is near to a team that shoots at a higher % and has a low shooting percentage. Turnovers become a significant metric as a result.

e) *Plus-Minus*

As mentioned in an earlier section, the plus-minus rating shows how a team fared with a certain player on the floor. This measure is frequently employed for thorough player evaluation before a major matchup. A player's contribution to their team's success while they are on the court is shown by a good score, and the opposite is also true [19].

f) *Offensive Rating*

The number of points a player score for every 100 total individual possessions is known as individual offensive rating. Individual Total Possessions and Individual Points Produced serve as the fundamental building elements in the calculation of the Offensive Rating [21].

g) *Defensive Rating*

The number of points a player concedes per 100 total individual possessions is known as their individual defensive rating. The idea of the individual Defensive Stop is the basis of the calculation of Defensive Rating. Stops include both an estimate of the number of forced turnovers and forced misses

[1] Pandas - https://pandas.pydata.org/docs/

[2] Sklearn - https://scikit-learn.org/stable/

[3] Matplotlib - https://matplotlib.org/stable/users/project/

by the player that aren't recorded by steals and blocks, as well as instances of a player terminating an opponent's possession that are marked in the box score (blocks, steals, and defensive rebounds).

h) True Shooting Percentage

The shooting percentage, which calculates a player's shooting efficiency by adjusting it for three-pointers and free throws, is known as the true shooting percentage. True shooting percentage is calculated by dividing the number of field goals and free throws attempted by the total number of points scored.

2) Dataset

The required dataset was acquired from the NBA's website [8]. The factors mentioned above are collected from the 2018-2019, 2019-2020 and 2020-2021 seasons during the execution of the model. The data was obtained by scraping it directly from the website.

IV. RESULTS

All the above-mentioned models were executed on data pertaining to the NBA 2018-2019 season and the following results were observed. The datasets required were obtained from the NBA's official website [8] and Basketball Reference [21]. The main metrics analyzed for the results are the accuracy, precision, and recall which are calculated using the True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) obtained from the confusion matrix [27]. The formulae for which are depicted in equations 4.1.1, 4.1.2 and 4.1.3.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + FP} \tag{4.1.1}$$

$$Precision = \frac{TP}{TP + FP} \tag{4.1.2}$$

$$Recall = \frac{TP}{TP + FN} \tag{4.1.3}$$

A. Individual Analysis

1) Elo Algorithm

The results displayed in Table 4.1.1 indicate the final Elo ratings for all 30 NBA teams at the end of the 2018-19 season. These ratings are further analyzed to predict playoff matchup winners and ultimately the NBA champion.

Team	Team Rating
Atlanta Hawks	936
Boston Celtics	1062
Brooklyn Nets	1030
Charlotte Hornets	998
Chicago Bulls	845
Cleveland Cavaliers	824
Dallas Mavericks	917
Denver Nuggets	1096
Detroit Pistons	1000
Golden State Warriors	1129
Houston Rockets	1136
Indiana Pacers	1019
Los Angeles Clippers	1065
Los Angeles Lakers	950
Memphis Grizzlies	926
Miami Heat	988
Milwaukee Bucks	1139
Minnesota Timberwolves	950
New Orleans Pelicans	905
New York Knicks	800
Oklahoma City Thunder	1068
Orlando Magic	1051
Philadelphia 76ers	1063
Phoenix Suns	830
Portland Trailblazers	1127
Sacramento Kings	955
San Antonio Spurs	1073
Toronto Raptors	1117
Utah Jazz	1097
Washington Wizards	900

Table 4.1.1 Elo ratings for the 2018-2019 season

The results visible in Table 4.1.1 are used to order each individual team into a seed based on their final Elo rating, the outcome of which is visible in Table 4.1.2.

	Easter Conference		Western Conference	
Seed	Team	Elo Rating	Team	Elo Rating
1	Milwaukee Bucks	1139	Houston Rockets	1136
2	Toronto Raptors	1117	Golden State Warriors	1129
3	Philadelphia 76ers	1063	Portland Trailblazers	1127
4	Boston Celtics	1062	Utah Jazz	1097
5	Orlando Magic	1051	Denver Nuggets	1096
6	Brooklyn Nets	1030	San Antonio Spurs	1073
7	Indiana Pacers	1019	Oklahoma City Thunder	1068
8	Detroit Pistons	1000	Los Angeles Clippers	1065
9	Charlotte Hornets	998	Sacramento Kings	955
10	Miami Heat	988	Minnesota Timberwolves	950
11	Atlanta Hawks	936	Los Angeles Lakers	950
12	Washington Wizards	900	Memphis Grizzlies	926
13	Chicago Bulls	845	Dallas Mavericks	917
14	Cleveland Cavaliers	824	New Orleans Pelicans	905
15	New York Knicks	800	Phoenix Suns	830

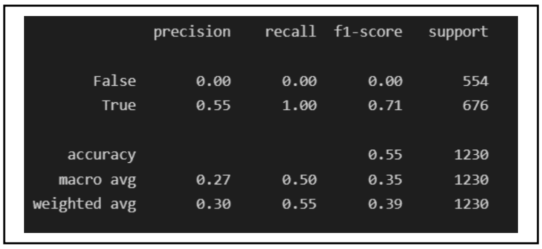
Table 4.1.2 Final Seed results for the 2018-2019 NBA Season

2) *Random Forest Classifier*

The final result for the Random Forest model contains a F1 score. The F1 score is a metric which is obtained by combining the precision and recall scores obtained using the formula visible below.

$$F1 = 2 \times \frac{Precision\ \times Recall}{Precision + Recall} \tag{4.1.4}$$

The results observed in our case is:

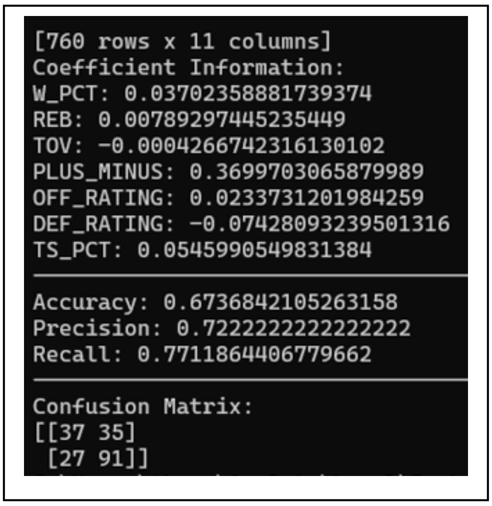


```
              precision    recall  f1-score   support

       False       0.00      0.00      0.00       554
        True       0.55      1.00      0.71       676

    accuracy                           0.55      1230
   macro avg       0.27      0.50      0.35      1230
weighted avg       0.30      0.55      0.39      1230
```

Fig 4.1.2 Random Forest results for the 2018-2019 season

3) *Logistic Regression*

The results displayed in Figure 4.1.2 are also stored in the “gamesWithInfo.csv” file generated. The accuracy, precision and recall are calculated using equations 4.1.1, 4.1.2 and 4.1.3. The heatmap depicted in Figure 4.1.4 is provided to allow for a better understanding of the final result.



```
[760 rows x 11 columns]
Coefficient Information:
W_PCT: 0.03702358881739374
REB: 0.00789297445235449
TOV: -0.0004266742316130102
PLUS_MINUS: 0.3699703065879989
OFF_RATING: 0.0233731201984259
DEF_RATING: -0.07428093239501316
TS_PCT: 0.0545990549831384

Accuracy: 0.6736842105263158
Precision: 0.7222222222222222
Recall: 0.7711864406779662

Confusion Matrix:
[[37 35]
 [27 91]]
```

Fig 4.1.3 Logistic Regression results for the 2018-2019 season

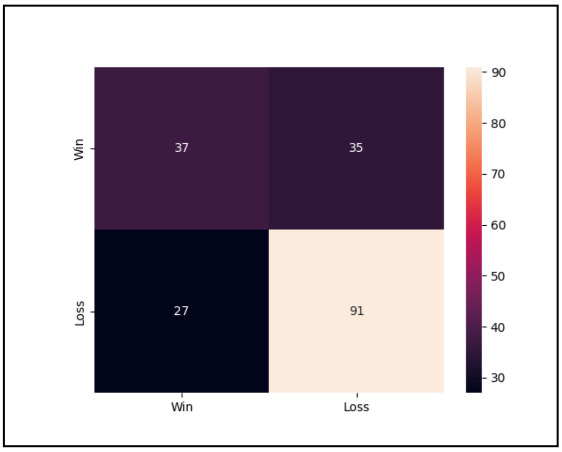


Fig 4.1.4 Confusion matrix for the results depicted above

B. *Final Analysis*

Algorithm/Model	Accuracy
Elo Algorithm	0.63
Random Forest Classifier	0.55
Logistic Regression	0.67

Table 4.2.1 Final Results for all three models

V. Discussion

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 when the main metric being considered is the plus-minus score. A team rating is created by adding the individual player ratings, and this rating is then used to forecast the results of games.

Table 4.2.1 indicates that the Elo algorithm performed relatively poorly in a minor sense when compared to the logistic regression model. The most likely reason that the logistic regression approach outperformed the Elo approach is because of the number of variables or factors being considered in the model's analysis. The greater the number of variables being considered, the more accurately a model can assess a team's overall performance. The random forest approach considered multiple records from the league standings as well as the regular season results, the logistic regression approach considered eight unique factors during its execution, whereas the Elo algorithms main metric for calculation was the combined plus-minus scores of multiple players belonging to a single team. The over dependance on a single metric may have resulted in a less accurate score when the model is run over the course of an entire season's statistics. From the results provided it can be inferred that when all the given models are considered in their current state, the logistic regression model provides a more accurate result over the course of a regular season.

Overall, the hypothesis stated during the introduction of this paper appears incorrect as the logistic regression approach produced the most accurate result and not the Elo approach as originally anticipated.

VI. Future Work

A. *Elo Algorithm*

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. Considering additional metrics in the calculation of the rating may result in a more accurate prediction.

B. *Random Forest Classifier*

The analysis above can be improved by incorporating match odds from an external source. This should allow a user to analyze the outcome and place accurate bets. The result can be further improved by incorporating per-player data such as offensive and defensive ratings.

C. *Logistic Regression*

The same elements affect each NBA player differently and have an impact on their game in different ways. Some players perform noticeably better at home or when playing their former team. Some people don't do well in certain time zones or on the second night of a back-to-back. By virtue of this variance, each NBA club will have its own logistic regression model for determining whether they will prevail in a forthcoming contest. We could add more variables from additional datasets or increase the number of observations by incorporating more players in order to improve accuracy.

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MSc Project - Reflective Essay

Project Title:	Predicting the final seeds of National Basketball Association teams, a Machine Learning approach
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Programme of Study:	MSc Computer Science (FT)

This research sought to analyse the widely available National Basketball Association (NBA) statistics and attempt to predict the final seeds or ranking of each team at the end of the regular season. The main algorithm being considered here is the Elo algorithm which is a popular rating system. It assesses the outcomes of games and values a team's strength in relation to other teams. Teams and coaches can use this information to make decisions about how to put their teams together, trade for players, rotate their roster, and select future prospects. The Elo system does not use an absolute metric to assess performance. It can be deduced based on wins and losses. As you can see in the paragraphs below, I first provide a brief explanation of the rationale behind the chosen strategy before going into detail about the project's advantages and disadvantages in relation to earlier research, as well as potential areas for future study and its practical difficulties and solutions.

Approach:

The data chosen for the required analysis was obtained from the NBA’s official website and Basketball Reference. For the execution of both the Elo algorithm and the Logistic Regression model, the data was scraped directly from the site and stored locally as CSV files. The Random Forest model was executed on Jupyter Notebook and data obtained was exported to the required format directly from Basketball Reference.

The genuine value of a player is not exactly quantifiable in a dynamic sport like basketball where teams and players have different playing styles, hence it cannot be evaluated or analysed. Therefore, we rely on the sport's observable measurements, such points scored, offensive and defensive rebounds, assists, turnovers, and so forth. The plus-minus score is the main statistic taken into account by the Elo approach. The plus-minus rating shows how a team performed collectively when a certain player was on the court. The advanced adjusted plus-minus metric used by the NBA takes into account a player's marginal impact on the score per 100 possessions in comparison to the league average player. Unadjusted plus-minus is typically favoured to adjusted plus-minus because the latter heavily influences each player's score based on his on-court teammates' talent and abilities (Ghimire S. et al.,2020). A player's contribution to their team's success while they are on the court is shown by a good score, and the opposite is also true. Each individual players plus-minus score is aggregated to provide a team rating which was then used in the required simulations. One of the major reasons for selecting the Elo algorithm is that it can account for margin of victory. Teams will receive more rating points for victories and fewer rating points for defeats, but they will gain or lose more rating points depending on the margin of victory, i.e., a lopsided win or loss has a higher impact on the team's total rating. This was done by giving each game a multiplier and dividing it by the team's expected margin of victory.

The Random Forest Classifier was selected as a comparative model due to its adaptability, simplicity, and suitability for both classification and regression problems. A decision tree is a structure that resembles a flowchart, in which each node represents a test on an attribute, each branch a possible conclusion, and each terminal node a class label. Each decision tree in this model learns from a random sample of data points that are drawn without replacement, giving it the option for random sampling of data. As a result, the likelihood of overfitting is reduced, and overall predicted accuracy is increased. This methodology is based on the core tenet that "a large number of relatively uncorrelated models working as a group will outperform any of the individual constituent models." The practical objective during the implementation of this approach was to create a predictive model that can foresee if the home team in a particular matchup will win. This was done by taking the teams home win-loss record, road win-loss record and points scored per match. Additional features such as winning streaks and previous match wins were added directly on Jupyter Notebook to further increase accuracy. The data for the 2018-2019, 2019-2020 and 2020-2021 NBA season were exported directly from Basketball Reference. A baseline of home team victories was selected and the python libraries Pandas and Scikit-Learn were utilized for implementation and analysis. The ultimate aim was to obtain an accuracy score higher than the chosen baseline.

The likelihood of an event occurring is estimated by the logistic regression model. The main justification for choosing this model is because it just uses the supplied data to generate a forecast and ignores all other outside influences. Consequently, all bias is taken out of the equation. The approach is an effective choice since it usually yields good accuracy for straightforward data sets and performs well when the dataset can be linearly separated. Eight factors were chosen based on their ability to influence game wins and losses. The factors selected were home court, previous win percentage, rebounds, turnovers, plus-minus, offensive rating, defensive rating, and true shooting percentage. These eight variables were utilised to forecast game outcomes after being directly scraped from the NBA's official website. To guarantee that pace has no bearing on the forecasts, each stat is converted to per 100 possessions.

Finally, all three models were run over past NBA seasons, and they were compared based on overall prediction accuracy. The main aim was to identify an effective machine learning algorithm for NBA match prediction while also taking into account the various features that the models are utilizing and identifying which of these variables is best suited for analysis.

Contribution and Further Work:

The likelihood that a club will succeed before the postseason depends heavily on accurate projections about its seed. Ideally, being able to predict a first-round opponent will allow a team's coaches and trainers to prepare players and create offensive and defensive plays specifically for those opponents. The ability to compare the results of all three models will provide players the chance to get ready for any possible scenario going into the postseason. For this reason, the primary contribution of this project was to identify the most accurate model which can be used for predictive analysis of an NBA season.

This research aimed to develop a model that can precisely forecast each of the fifteen seeds in both conferences for a season by building on earlier work (M. Richard Einstein Doss, 2018) where a modified version of the Elo algorithm was constructed where the plus-minus metric was given the utmost importance. Using all available traditional team statistics, the Elo ratings are calculated and then used to order the teams and thereby identify their individual seed. Then, team ratings are compared pairwise to calculate the likelihood of each team winning during the season. These wins and losses are combined and assigned to each team as a season record, this record is then used to determine the team’s seed. The seed is ultimately used to determine round one playoff matchups.

According to an analysis of the test findings, additional adjustments to the Elo algorithm may lead to a better understanding of each player's capabilities and injury susceptibility. The front office management may benefit from this when it comes to player trades and contract extensions. If time permitted, a more accurate and consistent prediction might be obtained by including more criteria such as offensive rating, defensive rating, and true shooting percentage in the Elo rating calculation. Incorporating match odds from an external source could provide a new dimension to this research, thereby giving it an additional purpose.

In order to increase accuracy, more variables from more datasets may be included if there was more time. Incorporating advanced statistics such as defensive rating, offensive rating and true shooting percentage may generate standings for a season with greater accuracy. Additionally, the models specified can be tested on various leagues such as the National Collegiate Athletic Association and the National Basketball League to ensure its usability.

Limitations and Practical Challenges:

The main constraints of this work were time and computational resources, which made it more difficult to complete follow-up analyses to expand on the above contributions. Additional challenges faced during the execution of the predictive analysis involved the drawbacks of the individual models which will be elaborated on below. Apart from those, recent changes to the python NBA API caused errors during code execution and consequentially required debugging of the code related to all three models.

The Elo algorithm's biggest observable flaw is the possibility of two teams having equal results but different ratings because the ratings are determined as a shift from the present ranking. Practically speaking, it functions as it should because the vast majority of teams advance extremely slowly. The approach, meanwhile, may appear unfair to teams that advance quickly after a poor start.

The Random Forest model has the observable flaw of being difficult to interpret. However, it does not offer total visibility into the coefficients; it only shows feature importance. Large datasets require a lot of work, and the user has limited influence over the model's behaviour.

The presumption of linearity between the independent and dependent variables is the main downside of logistic regression. Furthermore, as logistic regression can only be used to estimate discrete functions, it is confined to discrete number sets. The number of observations should always be higher than the number of features to prevent overfitting, which hinders the model from correctly predicting new data since it is unable to distinguish between noise and essential information.

Legal, Social and Ethical Challenges:

There are no known legal, social, or ethical challenges as all required metrics were obtained either from the National Basketball Association’s official website or Basketball-Reference. This data is available freely to the public as is stated in the Terms of Use for both the NBA [8] and Basketball-Reference [9].

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