

# The 2019-20 NBA Season: What Could Have Been

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## Abstract

The COVID-19 pandemic has affected our society in various ways and has changed numerous events on schedule for 2020. One such event that we were looking forward to was the end of the 2019-20 NBA season as well as the 2020 NBA Playoffs. Since a large portion of the 2019-20 NBA regular season games have already been played, we utilized the data collected from these games to calculate Elo ratings for each team in order to predict the standings for 2019-20 as well as the matchups and results of the Playoffs. From our analysis, we found that ... **[NEED TO ADD MORE HERE]**.

## Introduction

Due to the widespread impact of the COVID-19 pandemic throughout the world, almost every company, organization, and public event has canceled or suspended any activities that involve interpersonal contact for the foreseeable future. Many of these activities are moving to a virtual format if possible, but several others have been forced to shut down.

As avid sports fans, the absence of the major sporting events during this time has hit us and many others around the world especially hard [1]. Some of the events that we particularly were looking forward to include the NBA, NCAA March Madness tournament, MLB, and the 2020 Summer Olympics.

In our curiosity, we decided to utilize this opportunity to exercise our data science and modeling skills in order to predict what could have been. Specifically, we focused on the NBA and the NBA Playoffs. Since the 2019-20 NBA season was suspended approximately one month prior to the end of the regular season (and the beginning of the playoffs), we used the 2019-20 season data accumulated from the games played before the suspension to predict how the season and the playoffs would have ended had everything gone according to schedule.

In this analysis, we will examine data from the 2019-20 NBA season as well as some data from previous NBA seasons in order to draw some meaningful conclusions about the remainder of the 2019-20 NBA season.

## Methods

### Predicting the 2019-20 NBA Season Standings

Since we missed one of the most exciting times of the year (the NBA Playoffs & Finals), we made some predictions on how the rest of the season might have played out using a popular methodology referred to as the Elo ratings system [2]. This tool, created by Hungarian-American physics professor Arpad Elo, was originally designed to rate chess players, but is now used for all sorts of competitions ranging anywhere from sports to video games. This is a methodology that FiveThirtyEight and many other popular sports analysts take advantage of due to its simplicity and effectiveness [3].

These ratings depend only on the final score of each game as well as where it was played (home-court advantage). In other words, this system is built on a Win/Loss basis. We will be analyzing the 2018-19 NBA Season in its entirety to validate its performance, then we will apply it to the 2019-20 regular season in order to predict the matchups for the Playoffs and the Finals and ultimately the NBA Champions. For this

project, we retrieved several types of data sources including game-by-game scores and schedules for several seasons from Basketball-Reference.com [4].

### How does Elo work?

The long-run average for an Elo score in the NBA sits around 1500. An Elo of 1500 means that the teams performance would be normally distributed around an average of 1500 with the chance of performing better or worse. For more detail, Figure 3 (Appendix) shows what an Elo rating tells us about a team and how it can convey the teams overall season record. A higher Elo rating indicates that the team has a high win-loss ratio and is more likely to play deeper into the season.

The formula for Elo below shows how the probability of one team beating another is calculated using the ratings. When Player  $A$  competes in a match against Player  $B$ , Player  $A$  has an expected outcome (probability or score) for Team  $A$  ( $E[A]$ ) where  $R_A$  is the rating for Team  $A$  and  $R_B$  is the rating for Team  $B$ . The expected outcome for Team  $A$  ( $E[A]$ ) can be calculated by the formula below:

$$E[A] = \frac{1}{1 + 10^{\frac{(R_B - R_A)}{400}}}$$

The same calculation ( $E[B]$ ) has to be done for Player  $B$ , but with  $R_A$  (current rating  $A$ ) and  $R_B$  (current rating  $B$ ) swapped so that  $E[A] + E[B] = 1$ . Once the match is played and  $S_A$  (actual outcome or score for Team  $A$ ) and  $S_B$  (actual outcome or score for Team  $B$ ) are determined,  $R'_A$  (the new rating for  $A$ ) and  $R'_B$  (the new rating for  $B$ ) are calculated with the formula below:

$$R'_A = R_A + K(S_A - E[A])$$

The  $S$  value in our case would either be 1 for a win, or 0 for a loss. This is because there are no ties in the NBA.

In this equation,  $K$  is an optimization constant that usually takes different values according the sport and the amount of games available. In other words, this value is the maximum amount by which a score can change in one match. If  $K$  is set too high, the ratings will jump around too much; if  $K$  is set too low, Elo will take too long to recognize important changes in team quality. Determining the right value of  $K$  is an entirely different and more complicated topic, so for this experiment we will be using  $K = 20$ , the optimal  $K$  for the NBA determined by FiveThirtyEight [3]. This is higher than most other sports and can likely be attributed to the fact that the NBA plays more games (81 games per team) and is subject to relatively little randomness.

Home-court advantage is set as equivalent to 100 Elo rating points. One hundred Elo points is equivalent to about 3.5 NBA points, so it can also be interpreted as the home team being favored by 3 to 4 points if the teams were otherwise evenly matched (obviously this value fluctuates from season to season). Since every team plays about half of their games at home and the other half away, a change in the home-court advantage value does not produce a significant difference in the ratings, but is still an important factor to consider.

Elo strikes a nice balance between ratings systems that account for margin of victory and those that do not. While teams always gain Elo points after wins and lose Elo points after losses, they also gain or lose more with larger margins of victory.

This works by assigning a multiplier to each game based on the final score and dividing it by a team's projected margin of victory conditional upon having won the game. For instance, the Golden State Warriors' 4-point margin over the Houston Rockets in Game 1 of the 2018-19 Western Conference finals was lower than Elo would expect for a Warriors win. So the Warriors gain Elo points, but not as many as if they'd won by a larger margin. The formula accounts for diminishing returns; going from a 5-point win to a 10-point win matters more than going from a 25-point win to a 30-point win. For the exact formula, see the footnotes.

Instead of resetting each team's rating when a new season begins, Elo carries over a portion of a team's rating from one season to the next. This is to account for any momentum that a team may build from season-to-season (i.e. sports dynasties). In NBA ratings, three-quarters of the previous score are kept. The high fraction reflects the fact that NBA teams are more consistent from year to year. For example, the Miami Heat ended the 2012-13 NBA season with an Elo rating of 1754. The team's Elo rating for the start of the 2013-14 season is calculated as follows:

$$(0.75 * 1754) + (0.25 * 1500) = 1692$$

Since this is a consistent method, we will also initialize the Elo scores for the 2019-20 NBA Season using the Elo scores from the 2018-19 season.

After incorporating a constant for home court advantage, our formula is as follows with  $A = 100$  points (the value we previously determined represents a home-court advantage):

$$P(\text{Home team wins}) = \frac{1}{1 + 10^{-\frac{(H-R+A)}{400}}}$$

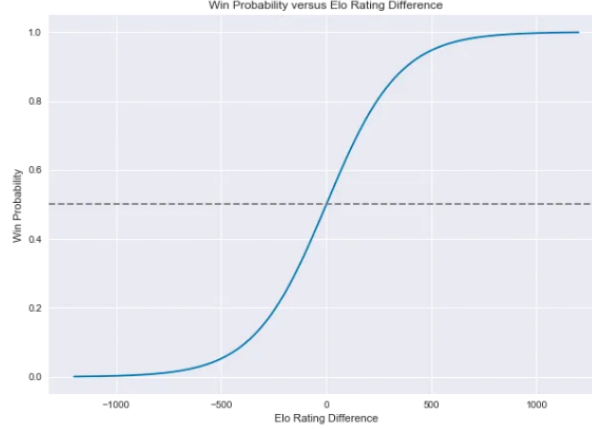


Figure 1: Logistic Function of Win Probability by Elo Rating Difference

In Figure 1, we see an example of a logistic function for win probability by Elo rating difference.

## Predicting the 2019-20 NBA Season Award Winners

Another interesting part of any NBA season is the awards given to the players and teams based on their regular season performances. Some key awards that catch headlines every year include Most Valuable Player (MVP), Defensive Player of the Year (DPOY), and Rookie of the Year (ROY). In addition to predicting the end-of-season standings, we decided that any analysis of the remainder of the 2019-20 NBA season would be incomplete unless it discussed award winners in the major categories. In particular, we sought to predict the MVP and

In order to predict award winners at the end of the season, we needed to predict the leaders of some of the crucial statistical categories at the end of the season. To predict these players, we analyzed some significant statistics and identified the optimal regression model to predict these statistics. Some of the statistics we utilized in building this model include true shooting percentage (TS%), total rebound percentage (TRB%), assist percentage (AST%), and block percentage (BLK%) among 22 total recorded categories. For additional information on the exact statistics that were used in these predictions, refer to Table 3 (Appendix).

Accordingly, we examined different types of regression models in order to identify which type of model best predicted some of the major statistics. These include win shares (WS), value over replacement player (VORP), player efficiency rating (PER), usage percentage (USG%), offensive box plus/minus (OBPM), and defensive box plus/minus (DBPM).

To identify the best prediction model, we first predicted WS from the current 2019-20 season statistics using 4 different regression models: linear, lasso, ridge, and logistic. We measured the performance of every model with the actual WS values for each player using RMSE (root mean squared error) to determine which had the least error with smaller RMSE values indicating higher accuracy. In order to reduce Monte Carlo variability, we used 200 repeated random samples of the data for each model to find the true RMSE values.

We then used this to predict the MVP and DPOY by looking at the leaders at the end of the season in WS, VORP, PER, OBPM, and DBPM because these categories carried significant weighting in determining

Table 1: Elo Ratings for Every NBA Team (Descending)

Team	Elo Rating		Team	Elo Rating
Milwaukee Bucks	1628.4919	16	Sacramento Kings	1496.7678
Los Angeles Lakers	1627.8301	17	Brooklyn Nets	1491.0335
Toronto Raptors	1601.2836	18	Orlando Magic	1490.3970
Los Angeles Clippers	1588.4583	19	Portland Trail Blazers	1478.5000
Oklahoma City Thunder	1582.6036	20	San Antonio Spurs	1478.2600
Boston Celtics	1569.6068	21	Phoenix Suns	1453.5151
Denver Nuggets	1560.4563	22	Washington Wizards	1446.2512
Utah Jazz	1559.3314	23	Charlotte Hornets	1435.6679
Houston Rockets	1546.1499	24	New York Knicks	1430.9475
Indiana Pacers	1544.9614	25	Atlanta Hawks	1424.2177
Philadelphia 76ers	1536.7509	26	Cleveland Cavaliers	1412.5029
Miami Heat	1531.0399	27	Chicago Bulls	1410.1883
Dallas Mavericks	1530.4395	28	Minnesota Timberwolves	1391.4969
Memphis Grizzlies	1512.1054	29	Golden State Warriors	1387.3738
New Orleans Pelicans	1507.3374	30	Detroit Pistons	1383.5339

the respective awards. In order to produce statistics that would reflect the end-of-season data, we updated each player’s stats based on their team, schedule matchups, and usage percentage. We weighted each of these features by category and used the current player statistics to simulate the expected statistics for every player at the end of the 2019-20 season. We chose these specific features because a player’s team and schedule can heavily influence their output and their usage percentage indicates how heavily their team relies on that specific player (which correlates to more playing time).

## Results

**[Tables, figures, and text that illustrate your findings. Keep the focus on the numbers here. You will interpret your results in the next section.]**

First, we calculated the Elo ratings for each team for the games played so far in the 2019-20 season. As explained earlier, we incorporated 25% of the previous season’s Elo ratings with 75% of this season’s current Elo ratings. Table 1 shows the Elo ratings we derived for each team when the NBA season was suspended. ... **[NEED TO ADD MORE HERE]**

After simulating how the 2019-20 NBA season and Playoffs would have ended, we tested several regression models to determine the best model to predict end-of-season WS. By testing linear, lasso, ridge, and logistic regression models, found that the lasso model provided the lowest RMSE value (0.26059111) with the linear model (0.34488769) and logistic models (0.34454006) providing slightly higher RMSE values.

Then, we predicted the season leaders for the various principal categories of WS, VORP, PER, OBPM, and DBPM. We utilized a logistic regression model for predicting the stat leaders due to its relative simplicity and clarity. We verified that this logistic regression model was appropriate by measuring its RMSE values and plotting actual vs. predicted for each category for the current 2019-20 season data (Figure 2). These plots verify that the predicted stats fall within a very small margin of the actual stats and thus have small residual values.

Using these accumulated season statistics, we determined the end-of-season statistics by updating each player’s stats based on their team, schedule matchups, and usage percentage. We updated the statistics to arrive at the end-of-season statistics using these factors because a player’s team and schedule can heavily influence their output and their usage percentage indicates how heavily their team relies on that specific player (which correlates to more playing time).

The final season stat leaders for each of the categories is shown in Table 2. We verified these predictions by limiting the qualifiers for each category and comparing with each player’s previous performance history. We narrowed the pool of players down by only considering players with more than 25 games played and 1200

Table 2: End-of-Season 2019-20 Predicted Stat Leaders with Logistic Regression Model

Player	Predicted WS	Player	Predicted VORP
Giannis Antetokounmpo	14.478185	Giannis Antetokounmpo	6.1347205
James Harden	13.220107	James Harden	5.4737304
Anthony Davis	11.621329	LeBron James	5.1022434
LeBron James	11.523466	Luka Dončić	4.9062273
Damian Lillard	11.128818	Kawhi Leonard	4.7994347
Player	Predicted PER	Player	Predicted USG%
Giannis Antetokounmpo	30.804962	James Harden	36.049086
James Harden	27.917457	Damian Lillard	35.627054
Anthony Davis	27.608894	Giannis Antetokounmpo	35.228546
Luka Dončić	27.482960	Luka Dončić	35.016353
Kawhi Leonard	27.058236	Bradley Beal	34.273879
Player	Predicted OBPM	Player	Predicted DBPM
James Harden	8.8580677	Giannis Antetokounmpo	3.3616434
Damian Lillard	8.4996834	Kris Dunn	2.9598130
Giannis Antetokounmpo	7.9153899	Anthony Davis	2.8100089
Luka Dončić	7.4550437	Nikola Jokić	2.6709743
LeBron James	7.3032265	Bam Adebayo	2.5195388

minutes played because this reflects the criteria that the NBA Season Awards use to nominate qualifying players. By inspecting the top five players in each category, we noticed several household names and early season favorites for MVP and DPOY including Giannis Antetokounmpo, James Harden, LeBron James, and Anthony Davis.

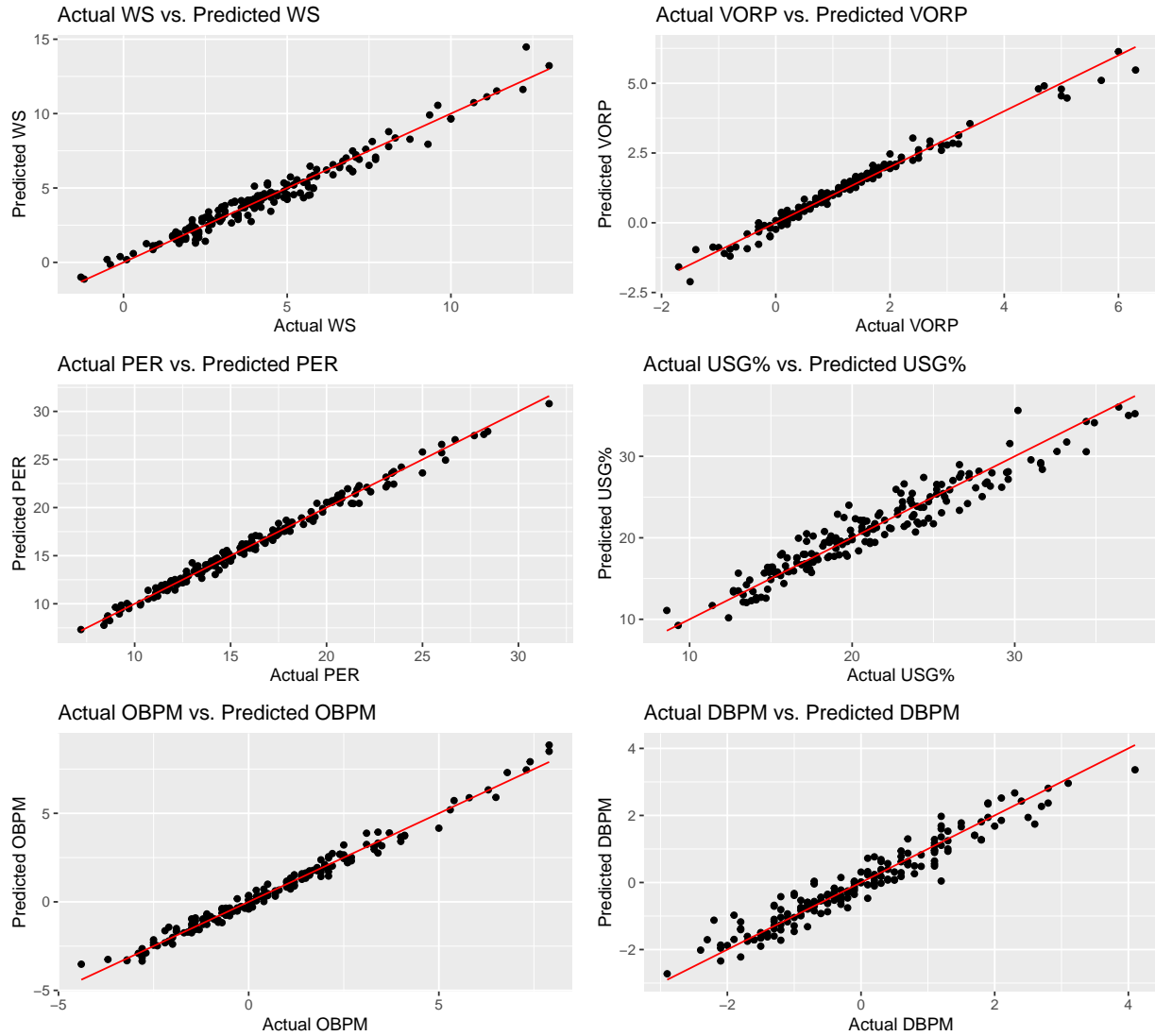


Figure 2: End-of-Season Predictions of Key Statistics with Logistic Regression Model

## Conclusion

[Interpret what you found. What are the main lessons we should take away from your report?]

## Shortcomings/Drawbacks

### Appendix

ELO	EQUIVALENT RECORD	TEAM DESCRIPTION
1800	67-15	All-time great
1700	60-22	Title contender
1600	51-31	Playoff bound
1500	41-41	<b>Average</b>
1400	31-51	In the lottery
1300	22-60	LOL
1200	15-67	Historically awful

Figure 3: Breakdown of Elo Rating

Statistics	Meaning
G	Num. games played
MP	Num. minutes played
PER	Measure of per-minute production
TS.	Overall shooting efficiency
X3PAr	% of field goal attempts from 3-point range
FTr	Num. free throw attempts per field goal attempt
ORB.	% of available offensive rebounds that a player grabbed
DRB.	% of available defensive rebounds that a player grabbed
TRB.	% of available total rebounds that a player grabbed
AST.	% of teammate field goals that a player assisted
STL.	% of opponent possessions that were stolen by a player
BLK.	% of opponent field goals attempts that were blocked by a player
TOV.	Num. turnovers committed per 100 plays
USG.	% of team plays used by a player
OWS	Num. wins contributed by a player from his offense
DWS	Num. wins contributed by a player from his defense
WS	Num. wins contributed by a player
WS.48	Num. wins contributed by a player per 48 minutes
OBPM	Offensive points per 100 possessions above a league-average player
DBPM	Defensive points per 100 possessions above a league-average player
BPM	Total points per 100 possessions above a league-average player
VORP	Points per 100 team possessions contributed by a player above a replacement-level player

## References

- [1] List of all sporting events canceled around the world during the coronavirus pandemic ([https://www.espn.com/olympics/story/\\_/id/28824781/list-sporting-events-canceled-coronavirus](https://www.espn.com/olympics/story/_/id/28824781/list-sporting-events-canceled-coronavirus))
- [2] Elo ratings system ([https://en.wikipedia.org/wiki/Elo\\_rating\\_system](https://en.wikipedia.org/wiki/Elo_rating_system))
- [3] FiveThirtyEight NBA Elo Ratings (<https://fivethirtyeight.com/features/how-we-calculate-nba-elo-ratings/>)
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