NBA MVP Comparisons - Part 2

Part 2

- 27th February 2019

In the previous post, Part 1 of the NBA MVP Comparison series, we gathered the relevant NBA MVP finalist data from basketball-reference.com and processed it.

Before going further, it is important to note that all analysis in Part 2 deals with MVP finalists from 1983 to the present (2018). This decision was made to separate the pre-3 point era from the post-3 point era which analytically and stylistically have different types of players.

Our goal with this blog post is to understand which MVP finalist, but non-MVP winner was most deserving of the award. To do this, we will predict the continuous dependent variable, vote share (ranging from 0 to 1), of a MVP finalist with a vector (list) of the following predictors (independent variables) from the processed MVP finalist data: age, games_played, avg_minutes, avg_points, avg_rebounds, avg_assists, avg_steals, avg_blocks, field_goal_pct, three_pt_pct, free_throw_pct, win_shares, win_shares_per_48.

The specific questions that will allow us to assess which finalist was most deserving of a MVP award are:

1. Which MVP winner(s) outperformed their predicted vote share?
2. Which MVP winner(s) should have finished second to another finalist in predicted vote share?

In this post, we will:

1. Compare machine learning (ML) models for selecting the MVP award
2. Identify the finalists deserving of a MVP award

While the language of statistical models deals more with over- and under-performance, I will interchange these terms with more colloquial language such as robbed/robbery.

Outline

1. Compare Machine Learning Regression Models
2. Determine Controversial MVPs
3. Choose New MVPs

Models Overview

- Which model did well?
- To predict MVP awards and vote share, I used machine learning (ML) regression models
- Machine learning refers to algorithms and models that perform predictions with advanced pattern recognition/correlations and are devoid of explicit human programming
- ML models were compared with the metric Root Mean Square Error (RMSE)

ML Regression Models

- Random Forest Regressor
  - Ensemble learning method that constructs decision trees and creates a mean prediction of the individual trees
- Latent Discriminant Analysis
  - Uses a linear combination of features to separate two or more classes
- Gradient Boost
  - Uses "weak learners", predicts loosely correlated with outcome variable, in an ensemble method to produced boosted "strong learners" with optimization
- XGBoost
  - Gradient boosting method "robust enough to support fine tuning and addition of regularization parameters"

Compare ML Regression Models

- To prepare the data for the ML models:
  - I split the MVP data into training (80%) and test datasets (20%)
  - The models are trained (learn the patterns) on the training set and then compared on how well they predict the MVPs in the test set
- Why Root Mean Square Error (RMSE)?

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Actual_i - Predicted_i)^2}$$

- RMSE is the square root of the average of squared differences between predicted values and actual observation. The RMSE ranges from 0 to ∞ and the direction (positive/negative) of the residual (Prediction - Actual) is inconsequential because the residual is squared. Lower RMSE correspond with better performing models.
- RMSE equation as a function in R:

```
RMSE = function(actual, predicted) {
  RMSE = sqrt(sum(mean(actual-predicted)^2))
  return(RMSE)
  }
```

Table 1: RMSE Table

Machine Learning Model	RMSE
Latent Discriminant Analysis	0.002
XGBoost - Linear	0.004
Random Forest Classifier	0.005
Gradient Boost	0.011
XGBoost - Tree	0.012

- The Latent Discriminant Analysis (LDA) was the best performing model
- Henceforth, "the model" will refer to the LDA model

Latent Discriminant Analysis (LDA)

Because our predicted variable, vote share, is continuous we need a rule to predict the binary (winner/loser(s)) MVP award. The rule we will use is the player with the maximum predicted vote share (LDA Prediction) for a given year will be awarded the MVP. This rule will need additional complexity to handle potential ties. The order of tiebreakers for playoff seeding is near the bottom of this article. Perhaps we could adopt similar rules for vote share ties; fortunately for this analysis, there were no ties.

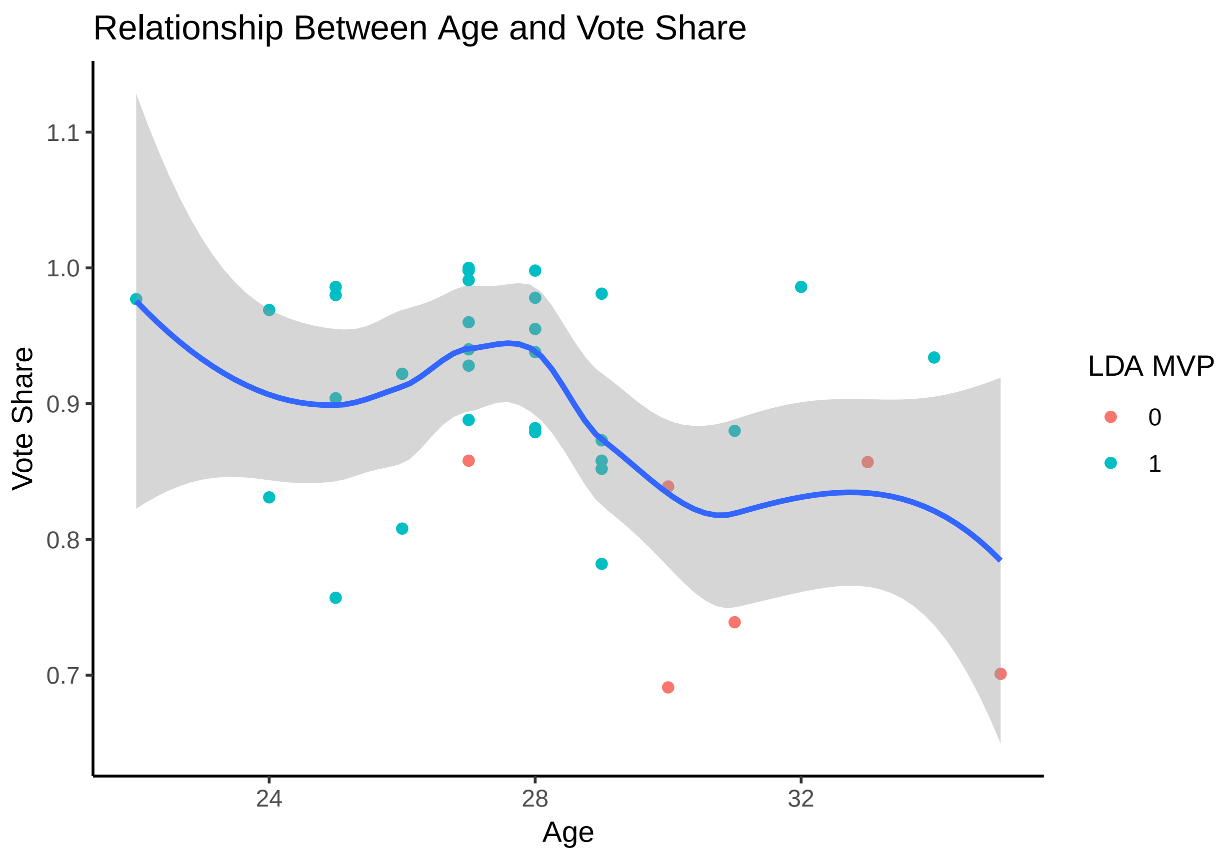
- Use `dplyr` library and `ifelse` function within `mutate`
  - Create the binary LDA MVP variable based on our rule

```
mvp_finalist_data = mvp_finalist_data %>%
  group_by(Year) %>%
  mutate(`LDA MVP` = ifelse(`LDA Prediction` == max(`LDA Prediction`), 1,
                     ifelse(`LDA Prediction` != max(`LDA Prediction`), 0,0)))
```

- What did the LDA model do well?
  - 30 of 36 MVPs accurately predicted with LDA vote share model
- How do we find where the model "struggled"?
  - LDA unsuccessfully predicts MVP
  - LDA predicts another player that year with higher vote share as a better candidate for the MVP

Table 2: LDA Correct MVP Predictions

Player	Age	Year	Team	Rank	Vote Share	MVP	LDA MVP
Moses Malone	27	1983	PHI	1	0.96	1	1
Larry Bird	28	1985	BOS	1	0.978	1	1
Larry Bird	29	1986	BOS	1	0.981	1	1
Magic Johnson	27	1987	LAL	1	0.94	1	1
Michael Jordan	24	1988	CHI	1	0.831	1	1
Magic Johnson	29	1989	LAL	1	0.782	1	1
Michael Jordan	27	1991	CHI	1	0.928	1	1
Michael Jordan	28	1992	CHI	1	0.938	1	1
Charles Barkley	29	1993	PHO	1	0.852	1	1
Hakeem Olajuwon	31	1994	HOU	1	0.88	1	1
David Robinson	29	1995	SAS	1	0.858	1	1
Michael Jordan	32	1996	CHI	1	0.986	1	1
Michael Jordan	34	1998	CHI	1	0.934	1	1
Shaquille O'Neal	27	2000	LAL	1	0.998	1	1
Allen Iverson	25	2001	PHI	1	0.904	1	1
Tim Duncan	25	2002	SAS	1	0.757	1	1
Tim Duncan	26	2003	SAS	1	0.808	1	1
Kevin Garnett	27	2004	MIN	1	0.991	1	1
Dirk Nowitzki	28	2007	DAL	1	0.882	1	1
Kobe Bryant	29	2008	LAL	1	0.873	1	1
LeBron James	24	2009	CLE	1	0.969	1	1
LeBron James	25	2010	CLE	1	0.98	1	1
Derrick Rose	22	2011	CHI	1	0.977	1	1
LeBron James	27	2012	MIA	1	0.888	1	1
LeBron James	28	2013	MIA	1	0.998	1	1
Kevin Durant	25	2014	OKC	1	0.986	1	1
Stephen Curry	26	2015	GSW	1	0.922	1	1
Stephen Curry	27	2016	GSW	1	1	1	1
Russell Westbrook	28	2017	OKC	1	0.879	1	1
James Harden	28	2018	HOU	1	0.955	1	1



- Green dots represent MVP winners successfully predicted by the model
- Red dots represent MVP winners the model missed
- MVP winners are clustered between ages 27 and 29
- Older winners average lower vote share
- The model struggled with predicting older MVP winners

Controversial MVPs

1. Which MVP winner(s) outperformed their predicted vote share?
2. Which MVP winner(s) should have finished second to another finalist in predicted vote share?

Identify controversial MVPs

- Select MVPs that the LDA model missed
- Create additional column for residual or error
  - Absolute value of the difference between actual and predicted vote share for a MVP finalist
- Residuals help us determine how much a player over- or under-performed relative to our model

```r
mvp_finalist_data = mvp_finalist_data %>%
  mutate(Residual = abs(`Vote Share`-`LDA Prediction`))
```

Table 3: Controversial MVPs

Player	Age	Year	Team	Vote Share	LDA Prediction	Residual	LDA MVP
Larry Bird	27	1984	BOS	0.858	0.347	0.511	0
Magic Johnson	30	1990	LAL	0.691	0.518	0.173	0
Karl Malone	33	1997	UTA	0.857	0.857	0	0
Karl Malone	35	1999	UTA	0.701	0.701	0	0
Steve Nash	30	2005	PHO	0.839	0.739	0.1	0
Steve Nash	31	2006	PHO	0.739	0.739	0	0

- Steve Nash (2005, 2006) and Karl Malone (1997, 1999) are repeat offenders!
- A quick note on Larry in 1984 and Magic in 1990:
  - Larry had the highest residual (0.511), overperformance, of any MVP winner
  - Magic Johnson owns the second highest winner residual of 0.173.
  - Can't tell a story of basketball without tying Larry and Magic together.
- The controversial MVP discussion will focus on Malone and Nash
- Whom did the models prefer in 1984, 1990, 1997, 1999, 2005, and 2006?

Table 4: LDA Preferred MVPs

Player	Age	Year	Team	Rank	Vote Share	LDA Prediction	Residual	LDA MVP
Bernard King	27	1984	NYK	2	0.491	0.491	0	1
Charles Barkley	26	1990	PHI	2	0.667	0.667	0	1
Michael Jordan	33	1997	CHI	2	0.832	0.934	0.102	1
Shaquille O'Neal	26	1999	LAL	6	0.075	0.888	0.813	1
Shaquille O'Neal	32	2005	MIA	2	0.813	0.813	0	1
Chauncey Billups	29	2006	DET	5	0.344	0.977	0.633	1

- The model preferred 2nd place finishers in 4 of 6 controversial MVP years
- 1984 projects as the only year a potential MVP (Bernard King) would not have a vote share majority

The Robbers

- Although Karl Malone and Steve Nash both "stole" 2 MVPs, I'm going to focus on Steve Nash
- Steve Nash draws more scrutiny because Malone's predicted vote share in our model doesn't change
  - Our model predicts that two players were overlooked in his winning years
- One such overlooked player was Michael Jordan in 1997
  - Jordan would go on to win the 1998 MVP award
  - If Jordan had won the 1997 award, his legacy could have spanned seven MVPs
  - Maybe voter fatigue was a factor in denying Jordan his 6^{th} MVP (at that time) for Malone's first
- Contrastingly, our model shows that Steve Nash overperformed in one year
  - Nash also should have faced a finalist with better vote share en route to his second MVP
- Our model suggests that Steve Nash overperformed in 2005 by 0.1where Malone never overperformed

The Robbed

- Shaq and Chauncey Billups wildly underperformed in 2 years the model had them as clear favorites
- Shaq has the most beef as the only player robbed of two potential MVPs
- Shaq recorded the highest residual prediction value (0.813)
  - Shaq was the most underrated MVP finalist ever in his 1999 campaign
- Shaq also loses a MVP in 2005 when our model suggests that Steve Nash overperformed
- Chauncey in 2006 had the second highest residual of 0.633 and could be the rightful owner of Steve Nash's second MVP

Review

- We compared multiple machine learning regression models to determine MVP/MVP vote share
- Concluded that Steve Nash and Karl Malone repeatedly robbed deserving MVP candidates
- Predicted that Larry Bird had the most over-inflated vote share of any MVP winner
- Voters may have corrected for failing to give MVP awards to Jordan and Shaq in 1997 and 1999, respectively, by rewarding the players with the MVP in the subsequent year