Predict NBA Regular Season MVP Winner

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Abstract

This project is to build a statistical model to predict who will win 2017 NBA Most Valuable Player (MVP) Award. The player statistics have been standardized to the Z scale in each player statistics category in order to remove any mean and standard deviation effect. The "MVP Index" has been derived from combining each player's Z statistics as a "Uniform" model. To evaluate the model accuracy, team has derived another "Accuracy Index" of predicting the top five MVP players recognized annually. The first "Uniform" model can predict the top five winners at 47% accuracy. Team has further derived the "Weighted" model by adding the weight factor. The "Weighted" model has further improved the Accuracy Index from 47% to 52%. Authors have added the "Team Winning" factor. Power transformation will improve the model accuracy but which may also create any over-fit concern when power level is getting higher. Based on the Power Model, team can improve the Accuracy Index to 70% at Power=3. Authors also used Data Mining Discriminant analysis to rank players into clusters. The Discriminant model accuracy is only 55%. Team will use the Power=3 model to predict 2017 MVP at the season end.

Keywords

Descriptive Statistics, Z Transformation, Power Model, Discriminant Cluster, Data Mining

1. Introduction

Sports are big part of our daily life. Every major city has their professional teams and local fans are very supportive to their local professional players as their heroes or role models. National Basketball Associate (NBA) is the largest basketball organization. Each year, in addition to the Regular Season Winner, NBA league would also announce the Regular Season Awards. Most Valuable Player (MVP) award is the most recognized award. In the past, some MVP winners like Michael Jordan were very obvious and consensus winners without any doubt. Though, some MVP winners were questionable. This paper would try to formulate what could be the most deciding factors to formulate the MVP ranking based on their individual season performance and their team performance.

In major professional sports, the coach and team management are looking for ways to win more games in order to attract more fans to support their business. Sports statistical modeling analytics[1, 2] is becoming a critical approach to uncover the winning patterns hidden in sports data collected during each game played. The objective of this paper is to build a statistical model based on the past NBA MVP Winners and their individual and team season performance in order to predict the NBA 2016-2017 Regular Season Most Valuable Player (MVP) in which official result will be released in June 2017.

There are several research talks presented in MIT Sloan Sports Analytics Conference[3-5]. These papers have used intensive Analytics to uncover players' playing patterns and help coach develop each player in order to create and maximize each player's values to their specific team. Our paper will provide the predictive methodology to be applied in the end of the regular season (April 2017). In below Figure 1[6], one Sports Analytics company has predicted the 2016-2017 MVP Award Odds in the early season. Our paper would build a predictive model to predict who will win the 2016-2017 MVP Award.

2016-17 NBA MOST VALUABLE PLAYER AWARD ODDS

› Odds as of November 18 at Sports Interaction

Russell Westbrook +200
James Harden +500
Kawhi Leonard +600
LeBron James +700
Stephen Curry +750
Kevin Durant +1200
Damian Lillard +1200
Anthony Davis +1200

Figure 1. MVP Award Odd

2. Data Collection, MVP Index and Model Accuracy Index

To start this project, author has laid out three subsections: (1) Data Collection, (2) Derive MVP Index to judge player performance, and (3) Derive Model Accuracy Index to assess model performance.

2.1 Data Collection

In order to predict the 2016-2017 season MVP, author has collected three raw data of the 2015-2016 season from the public Sports domain: (1) NBA player statistics in 2015-2016 season[7] as shown in Figure 2, (2) NBA team win% in 2015-2016 season record[8] as shown in Figure 3, and (3) historical MVP winners[9] as shown in Figure 4. Author has used these three data sets to derive the MVP Index and Predictive Model to predict 2016-2017 Season MVP winners. Figure 2 has shown the top 50 players statistics available in the website. Author has assumed the MVP winner should be included in the top 50 player statistics, and this assumption has been verified on the MVP winners in the past 15 seasons. Therefore, it's reliable to exclude the other MVP candidates if not listed in the top 50 players based on player statistics.

SCORING	GP	GS	MPG	PPG ▾	PTS/48	PTS	FGM/G	FGA/G	FG%	3FGM/G	3FGA/G	3FG%	FTM/G	FTA/G	FT%	HIGH	PPS
1 Davis, Anthony NO	18	18	37.5	32.1	41.1	578	11.3	21.7	.519	0.7	2.4	.279	8.9	10.9	.816	50	1.48
2 Westbrook, Russell OKC	19	19	35.4	30.9	41.9	588	10.3	23.7	.432	1.8	5.3	.347	8.6	10.5	.819	51	1.30
3 DeRozan, DeMar TOR	17	17	36.4	29.2	38.6	497	10.6	22.0	.481	0.5	1.8	.258	7.6	9.3	.816	40	1.33
4 Harden, James HOU	18	18	36.9	28.7	37.3	517	8.6	18.9	.452	3.1	8.4	.362	8.6	10.3	.832	41	1.52
4 Cousins, DeMarcus SAC	18	18	34.1	28.7	40.5	517	9.8	20.8	.472	1.7	4.3	.390	7.4	9.9	.743	38	1.38
6 Lillard, Damian POR	19	19	35.7	28.2	37.9	536	8.9	19.3	.463	2.6	7.1	.366	7.7	8.6	.896	42	1.46
7 Durant, Kevin GS	18	18	34.4	27.1	37.7	487	9.7	16.9	.570	2.1	4.8	.442	5.6	6.6	.849	39	1.60
8 Curry, Stephen GS	18	18	33.6	26.6	38.1	479	8.8	17.8	.494	4.2	9.9	.421	4.9	5.3	.917	46	1.50
9 Thomas, Isaiah BOS	17	17	33.2	26.0	37.6	442	7.9	18.6	.423	2.2	6.9	.325	8.0	9.1	.883	37	1.39
10 Butler, Jimmy CHI	16	16	35.2	25.8	35.2	413	8.0	16.3	.490	1.4	3.4	.426	8.4	9.4	.887	40	1.58

Figure 2. Top 50 Player Statistics in 2015-2016 Season.

Figure 3 has sown the NBA Team regular season record in 2015-2016. Author in this paper will use the W/L% column data to study whether the team record will influence the voting of selecting MVP winner. Basketball sport is a team sport. Therefore, the team performance should be equivalently important as individual player contribution when selecting the MVP winner who has created the most values and contribution to team performance.

Conference Standings * Playoff teams

Eastern Conference	W	L	W/L%	GB	PS/G	PA/G	SRS
Cleveland Cavaliers* (1)	57	25	.695	—	104.3	98.3	5.45
Toronto Raptors* (2)	56	26	.683	1.0	102.7	98.2	4.08
Miami Heat* (3)	48	34	.585	9.0	100.0	98.4	1.50
Atlanta Hawks* (4)	48	34	.585	9.0	102.8	99.2	3.49
Boston Celtics* (5)	48	34	.585	9.0	105.7	102.5	2.84
Charlotte Hornets* (6)	48	34	.585	9.0	103.4	100.7	2.36
Indiana Pacers* (7)	45	37	.549	12.0	102.2	100.5	1.62
Detroit Pistons* (8)	44	38	.537	13.0	102.0	101.4	0.43
Chicago Bulls (9)	42	40	.512	15.0	101.6	103.1	-1.46
Washington Wizards (10)	41	41	.500	16.0	104.1	104.6	-0.50
Orlando Magic (11)	35	47	.427	22.0	102.1	103.7	-1.68
Milwaukee Bucks (12)	33	49	.402	24.0	99.0	103.2	-3.98
New York Knicks (13)	32	50	.390	25.0	98.4	101.1	-2.74
Brooklyn Nets (14)	21	61	.256	36.0	98.6	106.0	-7.12
Philadelphia 76ers (15)	10	72	.122	47.0	97.4	107.6	-9.92

Western Conference	W	L	W/L%	GB	PS/G	PA/G	SRS
Golden State Warriors* (1)	73	9	.890	—	114.9	104.1	10.38
San Antonio Spurs* (2)	67	15	.817	6.0	103.5	92.9	10.28
Oklahoma City Thunder* (3)	55	27	.671	18.0	110.2	102.9	7.09
Los Angeles Clippers* (4)	53	29	.646	20.0	104.5	100.2	4.13
Portland Trail Blazers* (5)	44	38	.537	29.0	105.1	104.3	0.98
Dallas Mavericks* (6)	42	40	.512	31.0	102.3	102.6	-0.02
Memphis Grizzlies* (7)	42	40	.512	31.0	99.1	101.3	-2.14
Houston Rockets* (8)	41	41	.500	32.0	106.5	106.4	0.34
Utah Jazz (9)	40	42	.488	33.0	97.7	95.9	1.84
Sacramento Kings (10)	33	49	.402	40.0	106.6	109.1	-2.32
Denver Nuggets (10)	33	49	.402	40.0	101.9	105.0	-2.81
New Orleans Pelicans (12)	30	52	.366	43.0	102.7	106.5	-3.56
Minnesota Timberwolves (13)	29	53	.354	44.0	102.4	106.0	-3.38
Phoenix Suns (14)	23	59	.280	50.0	100.9	107.5	-6.32
Los Angeles Lakers (15)	17	65	.207	56.0	97.3	106.9	-8.92

Figure 3. Team Winning% in 2015-2016 Season

Figure 4 has shown the NBA most valuable player award for top 5 candidates. Our predictive model will not just predict the winner but also the other winners in top the 5 list. In some year, the top winner may be obvious. It may be even more difficult to predict the other winners in the top 5 list.


NBA OFFICIAL

Third: Nikola Jokic, Denver Nuggets

Kia NBA Most Valuable Player Award

COMPLETE VOTING RESULTS | PRESS RELEASE

Winner: Stephen Curry, Golden State Warriors
Second: Kawhi Leonard, San Antonio Spurs
Third: LeBron James, Cleveland Cavaliers
Fourth: Russell Westbrook, Oklahoma City Thunder
Fifth: Kevin Durant, Oklahoma City Thunder

Figure 4. NBA MVP Award Winner.

2.2 Derive MVP Index

Before building the proto model, the player statistics have been standardized to the Z scale in each player statistics category in order to remove any mean and standard deviation bias effect. This Z transformation can eliminate any statistics bias or domination from any particular player statistics category. The Z scale will also analyze each player's performance as compared to the other top 50 NBA players in the same regular season. The "MVP Index" has been derived from summing each player's Z statistics as shown in Figure 5 and extended to the past 2003-2016 seasons. The higher MVP index means a higher chance to win the MVP Award. Though, can the MVP Index formula sufficiently predict the MVP winner in the same season?

	GP-N	Min-N	FG%-N	3pt%-N	FT%-N	RB-N	AST-N	STL-N	BLK-N	PPG-N	RB/MIN-N	AST/MIN-N	A/T-N	PPG/MIN-N	MVP Index
3	0.10	-0.12	0.85	0.63	1.04	0.69	0.47	-0.43	0.83	2.08	0.66	0.45	-0.21	2.43	13.6397
4	-0.44	-0.41	-0.19	0.17	-0.67	1.89	-0.33	0.86	1.16	1.74	1.94	-0.24	-1.04	2.32	10.9282
5	0.41	-0.17	1.14	-0.03	-0.54	0.40	1.32	0.43	-0.14	1.32	0.40	1.26	0.73	1.61	11.8496
6	0.33	-0.14	-0.81	0.53	0.98	-0.83	1.32	-0.64	-0.47	1.27	-0.78	1.25	0.83	1.53	7.0714
7	-0.75	-0.19	0.62	0.10	-0.29	1.46	-1.00	0.22	2.13	1.07	1.42	-0.90	-0.92	1.33	6.1905
8	0.71	-0.46	-0.14	-0.14	0.23	0.55	3.03	1.71	-0.63	0.86	0.64	3.00	1.26	1.32	14.9505
9	0.56	-0.09	-0.29	0.22	0.59	-0.65	-0.00	-0.43	-0.63	0.86	-0.62	0.01	0.37	1.01	3.0789
10	0.79	-0.36	-0.83	0.49	0.68	0.26	0.05	1.50	-0.47	0.75	0.32	0.11	-0.49	1.11	6.4032
11	0.87	-0.99	-0.64	0.39	0.78	-1.19	1.04	-0.21	-0.95	0.52	-1.02	1.28	1.08	1.38	5.2135
12	0.71	-0.72	0.17	0.95	0.80	-0.90	-0.90	-0.86	-0.14	0.49	-0.76	-0.75	-0.50	1.11	0.9823
13	0.10	-0.29	-0.52	0.22	0.39	0.51	0.09	-0.64	-0.30	0.42	0.55	0.14	0.27	0.65	2.6984
14	-2.74	-0.70	0.74	0.17	-0.58	0.77	0.42	-0.86	-0.30	0.31	0.94	0.56	0.70	0.86	-0.6220
15	0.48	0.17	-0.66	0.64	0.22	-0.58	1.14	1.93	-0.47	0.26	-0.60	0.97	0.95	0.14	5.2764
16	0.10	-0.79	0.87	1.10	0.81	0.19	-0.67	1.29	0.51	0.26	0.38	-0.50	0.24	0.88	5.8932
17	0.79	-0.17	-0.66	0.49	0.56	-0.69	0.57	0.86	-0.30	0.18	-0.64	0.55	1.35	0.29	4.2466
18	-0.29	0.15	-0.14	-0.00	0.42	-0.36	0.38	0.86	-0.14	0.18	-0.39	0.30	1.24	0.07	1.9540
19	0.71	-0.38	-0.25	0.88	0.37	-1.12	0.14	0.00	-0.63	0.16	-1.03	0.20	0.22	0.42	0.9892

Figure 5. Z Transformation and MVP Index

2.3 Derive Model Accuracy Index

To evaluate the MVP index model accuracy, author has also derived another "Model Accuracy Index" of predicting the top five MVP players (shown in Figure 4) recognized annually. MVP index of each top player was sorted and then mapped to the actual top 5 MVP winners in that particular season. Model accuracy will be determined on how the MVP Index ranking matches the actual MVP winners in the same regular season (2003-2016). Accuracy Index is a percentage of the mapping result. The model accuracy is an accumulated index which include the Accuracy-X (x= 1 to 5). For example, accuracy-3 index is how accurately the model can match the actual winners in the top 3 spots. The Accuracy Index will be the average of the five sub accuracy-x (1-5).

3. Build Statistical Modeling Algorithms

Based on the derived MVP index and Model Accuracy index defined in section 2, author has further derived and compared four statistical models: (1) Uniform Model, (2) Weighted Model, (3) Power Model, and (4) Discriminant Clustering Model. These models are compared in order to find the optimum model which can match the previous 2003-2016 seasons' MVP winners and also to predict the coming 2016-2017 season MVP winners.

3.1 Uniform Model

In the Uniform model, the "MVP Index" has been derived from combining each player's Z statistics evenly with equal weight as shown in Figure 6. The accuracy-x index will get higher from Accuracy-1 to Accuracy-5. The Uniform model can predict the top winners in 2003-2016 seasons about 38%, and top two winners about 38%. The accuracy is getting much higher and about 58% for predicting the accumulated Accuracy-5. Overall, the "Uniform" model can predict the MVP winners at 47% accuracy. Author won't be satisfied with the 47% accuracy based on the Uniform Model. Uniform model is a very simple proto model to demonstrate and define the MVP Index, and Accuracy Index. Though, this Uniform Model did not consider which player statistics categories are more critical to judge MVPs' values or contributions.

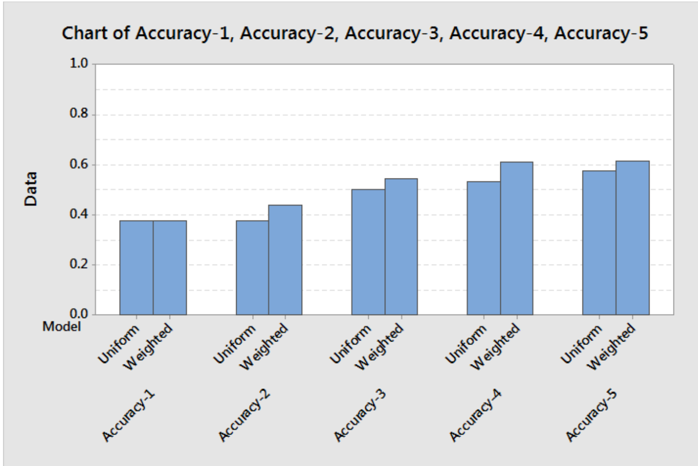

Figure 6. Model Accuracy: Uniform model vs. Weighted model.

3.2 Weighted Model

In order to overcome the drawback of the Uniform Model, the "Weighted" model has added the Statistics Weight factor. The weight factor would reflect which player Z scale statistics categories are more critically contributed to the MVP Award selection process. To determine the weight factor level, the descriptive dispersion "Median" statistics between the top 5 MVP winners and the remaining players not in top 5 were calculated for each Z scale statistics. Author used Median instead of mean in order to prevent the outlier and skewness impact on defining the weight formula. The weight factor coefficients are determined by the delta of two medians (from top 5 players, non-top five players) to differentiate which Player Z statistics are more critical to select the MVP winners. Also, author has used these weight coefficients to screen out the less significant player Z statistics categories. These weight coefficients have been implemented to the previous Uniform Model and which become the new Weighted Model and the Weighted MVP Index. The weighted MVP index formula is shown below:

Weighted MVP Index = 1.03*'GP-N'+0.73*'Min-N'+**1.71***'FG%-N'+0.61*'3pt%-N'+0.67*'FT%-N'+**1.17***'RB-N'+**1.66***'AST-N'+1.5*'STL-N'+1.16*'BLK-N'+**2.7***'PPG-N'+0.89*'RB/MIN-N'+1.3*'AST/MIN-N'+0.96*'A/T-N'+**3.13***'PPG/MIN-N'

The top four weighted items are: (1) Point per Minute (PPG/MIN-N), (2) Point per Game (PPG-N), (3) Field Goal % (FG%-N), (4) Assist (AST-N), and (5) Rebound (RB-N). The "Weighted" model has slightly improved the Accuracy Index from 47% to 52% shown in Figure 6 above. Both the Uniform Model and the Weighted Model are assuming the MVP winner selection is purely based on the individual Player Statistics, not considering the Team Performance. Since MVP is the most valuable player, their teams should do well in the regular season. Therefore, the team record should be included in the MVP selection process significantly in order to demonstrate the MVPs' values and contribution to their teams. Authors also used the Best Subset algorithm[10] to select the most critical input variables which will impact the MVP selection. The best subset algorithm is taking the Feature Selection concept which is popularly used to improve model such as Fisher-Markov[11] method. The present algorithm is very efficient and it selects the best subset without exhaustive search.

A feature subset selection algorithm is developed to select the best subset of m features from an n-feature set. In the Weighted Model, authors would like to subset 3-7 features from an 14-feature set by using the Best-Subset method shown in Figure 7. The top four statistics categories identified from the Best Subset algorithm are: (1) Field Goal %, (2) 3-Point %, (3) Rebound, (4) Games Played, and (5) Point per Minute. This ranking list is slightly different from the previous list ranked based on the Weighted Coefficients.

This Best Subset algorithm can minimize the Multi-Collinearity (shown in Mallows Cp coefficient) among the linearly dependent factors. For example, the Point per Minute is selected and the Point per Game is not selected since both have high dependency if playing minutes are similar to each other. The limitation of the Best Subset model is which could not quantify the weighted coefficients to be placed in the weighted model. The alternative choice is to keep these subset items and run the uniform model. Authors decided to keep the previous Weighted Model for simplicity.

Vars	R-Sq	R-Sq (adj)	R-Sq (pred)	Mallows Cp	S	GP - N	Min - N	FG% - N	3pt% - N	FT% - N	RB - N	AST - N	STL - N	BLK - N	PPG - N	RB/MIN - N	AST/MIN - N	A/T - N	PPG/MIN - N
3	16.1	12.7	6.7	-0.2	1.3300	X		X	X										
3	15.8	12.3	6.4	0.1	1.3329			X	X		X								
3	14.9	11.4	5.4	0.8	1.3398			X	X							X			
4	18.0	13.4	6.2	0.2	1.3241	X		X	X		X								
4	17.6	13.0	6.2	0.6	1.3277	X		X	X										X
4	17.6	13.0	5.3	0.6	1.3277	X		X	X					X					
5	19.4	13.7	5.3	1.1	1.3219	X		X	X		X								X
5	19.2	13.5	5.5	1.2	1.3238			X	X		X				X		X		
5	19.2	13.5	5.1	1.3	1.3239			X	X		X						X		X
6	21.3	14.5	4.9	1.5	1.3158	X		X	X		X						X		X
6	21.1	14.3	4.6	1.7	1.3174			X	X	X	X				X		X		
6	21.1	14.3	4.9	1.7	1.3174	X		X	X		X	X							X
7	22.4	14.6	3.2	2.6	1.3154	X		X	X	X	X						X		X
7	22.4	14.5	3.3	2.6	1.3161	X		X	X	X	X	X							X
7	22.2	14.3	3.2	2.8	1.3177	X		X	X	X	X				X		X		

Figure 7. Best Subset of Statistics Categories

3.3. Power Model

To further optimize the prediction accuracy, author has added the "Team Winning" factor. Most historical MVP winners were from the teams with best or better regular season records. Author has assessed the team winning factor based on the “Power” model from power= 0 (equivalent to the Weighted Model), Power=1, 2, 3, 4, 5, 6 to power= infinity (pick MVP from the best Team). In the Power Model, the previous weighted MVP Index will be multiplied by the power (from power order of 0,1,.., to infinity) of the team winning% as power base. For example, the power=2 model, the MVP Index= Weighted Index * (team winning%)^2. Power transformation will improve the model accuracy but which may also create any power over-fit concern when power level is getting higher. Based on the Power Model shown in Figure 8, team can further improve the Accuracy Index to 60% at Power=1, 67% at Power=2, and 70% at Power=3. The Power model has significantly indicated the importance of team winning % on the MVP selection process. Though, beyond Power=3, there is little benefit but more over-fit concern. It should be wisely to choose and stop at Power= 3. It should not put too much weight on the Team Winning %. Otherwise, as the extreme case (Power= Infinity), the top MVP winners will be purely determined on the team record. The best player of the best teams in the regular season will always win the MVP awards based on the ranking of the season team record.

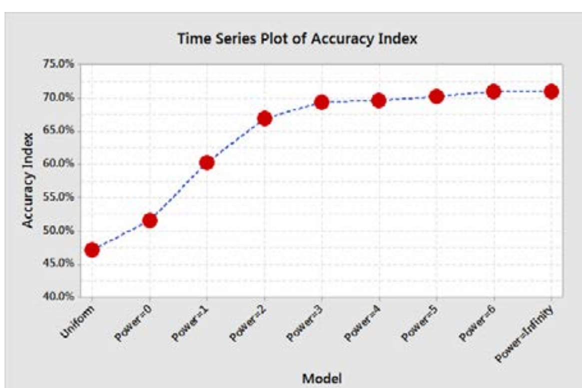

Figure 8. Model Accuracy: compare all models

3.4. Data Mining Discriminant Model

Data Mining Discriminant analysis[12] has been utilized to identify the basketball performance indicators in regular season and playoff games. Discriminant analysis was used to split the actual winners (true groups) into 5 discriminant clusters based on the Z Scale Statistics. The discriminant analysis like affinity analysis can group the similar players together based on their statistics purely with equal weight. It's interesting to apply Data Mining algorithms on this MVP case study. The Discriminant model accuracy is at 54.5% not better than Power model shown in Table 1. The Discriminant model is not considering the team record factor. There are still some values in this Discriminant model since which is still better than the Uniform Model and Weighted Model without considering the Team factor.

Table 1. Accuracy of Discriminant Analysis.

		Discriminant Clusters				
		1	**2**	**3**	**4**	**5**
True Group	**1**	**9**	**3**	**3**	**0**	**1**
	2	**3**	**8**	**3**	**0**	**3**
	3	**1**	**1**	**5**	**4**	**1**
	4	**1**	**1**	**2**	**9**	**0**
	5	**1**	**2**	**3**	**2**	**11**
	Total N	15	15	16	15	16
	N correct	9	8	5	9	11
	Sub-Accuracy	60%	53%	31%	60%	69%
	Accuracy	**54.5%**				

4 Results and Conclusions

Author has utilized JMP statistics software Z transformation, Descriptive statistics, Power Transformation, Best Subset, and Data Mining Discriminant analysis to build four different predictive models to predict the NBA MVP winners. Table 2 has shown the model algorithm and accuracy comparison. Power=3 model has shown the better prediction capability which has indicated the importance of team performance on the MVP selection process. Power=3 model will be utilized to predict the 2017 MVP winner in mid-April 2017 when the MVP regular season will be ended.

Table 2. Comparison of Model Algorithm and Accuracy

Algorithm	Accuracy
Uniform Model	47%
Weighted Model	52%
Power=3 Model	69%
Discriminant Model	55%

If not considering the Team Factor, the Data Mining Discriminant Model has outperformed the Uniform Model and Weighted Model. The Sports Analytics can help MVP award selection process. The Power=3 model can predict the past top 5 MVP winners at 70% accuracy. This model can demonstrate the potential to make the MVP selection process more objective and transparent than current more subjective methodology (voting). This modeling concept can be also applied to Olympic Event and other Professional Sports such as Football, Baseball, and Soccer.

The Power model has shown the Team Record should be a dominant factor when deciding which player has truly contributed to team success. The MVP selection should weight more on Team Performance over Individual Achievement.

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Biography

Mason Chen is student in Stanford On-Line High School Program. Mason has certified Lean Six Sigma Black Belt through IASSC (International Associate of Six Sigma Certification), and also certified IBM SPSS/Modeler Statistics and Data Mining Certificates. Mr. Chen has been invited to several conferences like IEOM, ASQ, AQI, ASA, JMP/SAS and local ASQ SV statistics group to present his STEM Projects. His STEM projects have drawn interest in Robotics/EV3, JAVA Science, Poker Probability, Powerball Lottery, Sports Analytics, Biostatistics and Healthcare Statistics… Mason is familiar with Lean Six Sigma DMAIC, DFSS, and Minitab 17, JMP 13, SPSS 24, and Modeler 18 Statistics Software. Mason has also been learning Data Mining and Big Data Analytics through several STEM Projects. As a Stanford High School Student, he has published several Conference Papers in IEOM, IWSM, FSDM conferences.