Predicting Win Shares in the NBA

By Anthony Le

Purpose

-Predicting the win shares statistic based on player's stats

- Find which stats are important for win shares

-Big fan of the NBA

-WIll help appreciate the game more.

-Find which model will be the best to predict the win shares

Win Shares

- player statistic which attempts to divvy up credit for team success to the individuals on the team
- An advanced statistic to see if the player is helping their team win.
- Add Offensive Win Shares and Defensive Win Shares together to get the total WIn Shares.
- The formula for the WIn Shares are from this source. (https://www.basketball-reference.com/about/ws.html)
- The data collected for this analysis are not related to the formula.

NBA Data

- Collected from the Basketball-Reference.com (https://www.basketball-reference.com/leagues/NBA_2019_advanced.html)
- Data collected website
- 2018-2019 NBA Season
- 708 players data collected (couple players played for multiple seasons)
- Used the Advanced Stats

Data Attributes

- 20 continuous variables
  - Age- Age; player age on February 1 of the given season.
  - G-Number of Games played
  - MP- Minutes Played
  - PER- Player Efficiency Rating
  - Ts%- True Shooting Percentage
  - 3PAr- 3-Point Field Goal Attempts Rate
  - FTr- Free Throw Attempts Rate
  - ORB%- Offensive Rebound Percentage
  - DRB%- Defensive Rebound Percentage
  - TRB%- Total Rebound Percentage
  - AST%- Assist Percentage
  - STL%- Steal Percentage

Data Attributes(Cont.)

- 20 continuous variables
  - BLK%- Block Percentage
  - TOV%- Turnover Percentage
  - USG%- Usage Percentage
  - OBPM- Offensive Box Plus/Minus
  - DBPM- Defensive Box Plus/ Minus
  - BPM- Box Plus/ Minus
  - VORP- Value over Replacement Player

Source-(https://www.basketball-reference.com/about/glossary.html)

Data Exploration

- Check to see any nulls in the dataset at all

```
nba_data.isnull().sum()*100/nba_data.isnull().count()
```

```
Player     0.000000
Age        0.000000
G          0.000000
MP         0.000000
PER        0.000000
TS%        0.847458
3PAr       0.847458
FTr        0.847458
ORB%       0.000000
DRB%       0.000000
TRB%       0.000000
AST%       0.000000
STL%       0.000000
BLK%       0.000000
TOV%       0.847458
USG%       0.000000
WS         0.000000
OBPM       0.000000
DBPM       0.000000
BPM        0.000000
VORP       0.000000
```

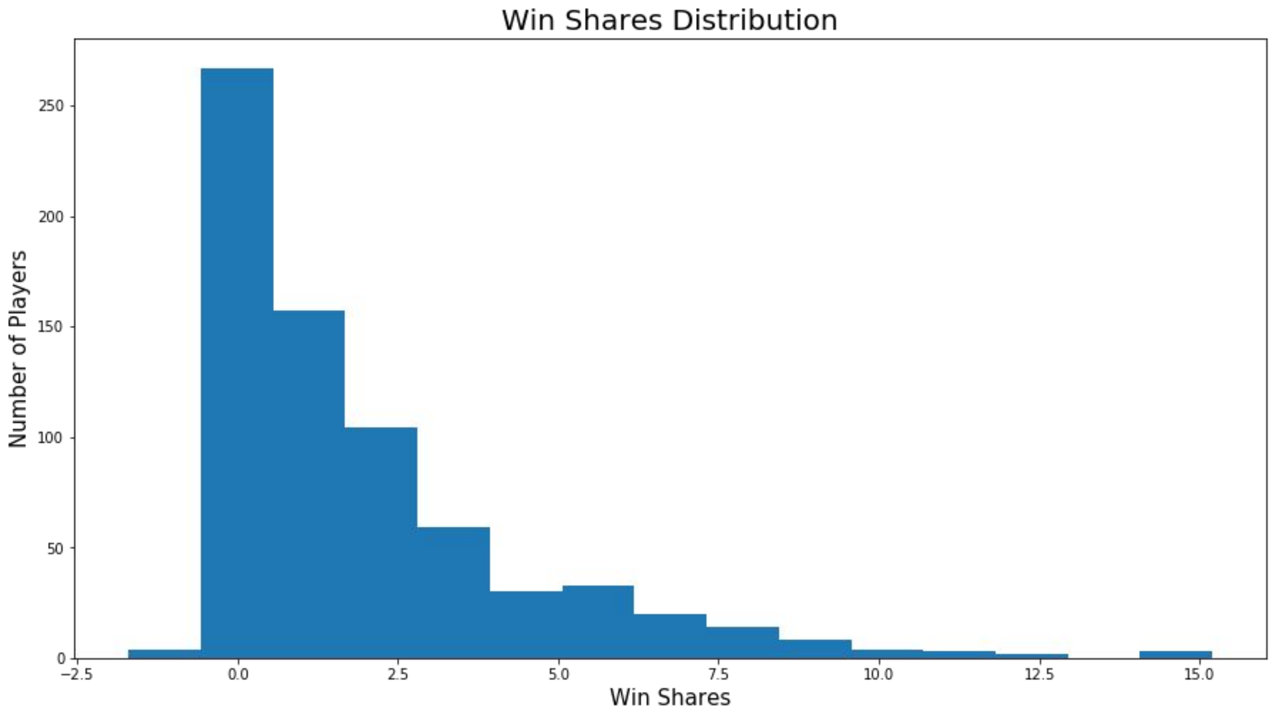
Null

- Replace the null with zero since the null is very low

```
nba_data["TS%"].fillna(0, inplace =True)
nba_data["3PAr"].fillna(0, inplace =True)
nba_data["FTr"].fillna(0, inplace =True)
nba_data["TOV%"].fillna(0, inplace =True)
```

Data Exploration

- Need to see what the Win Shares Distribution looks like.

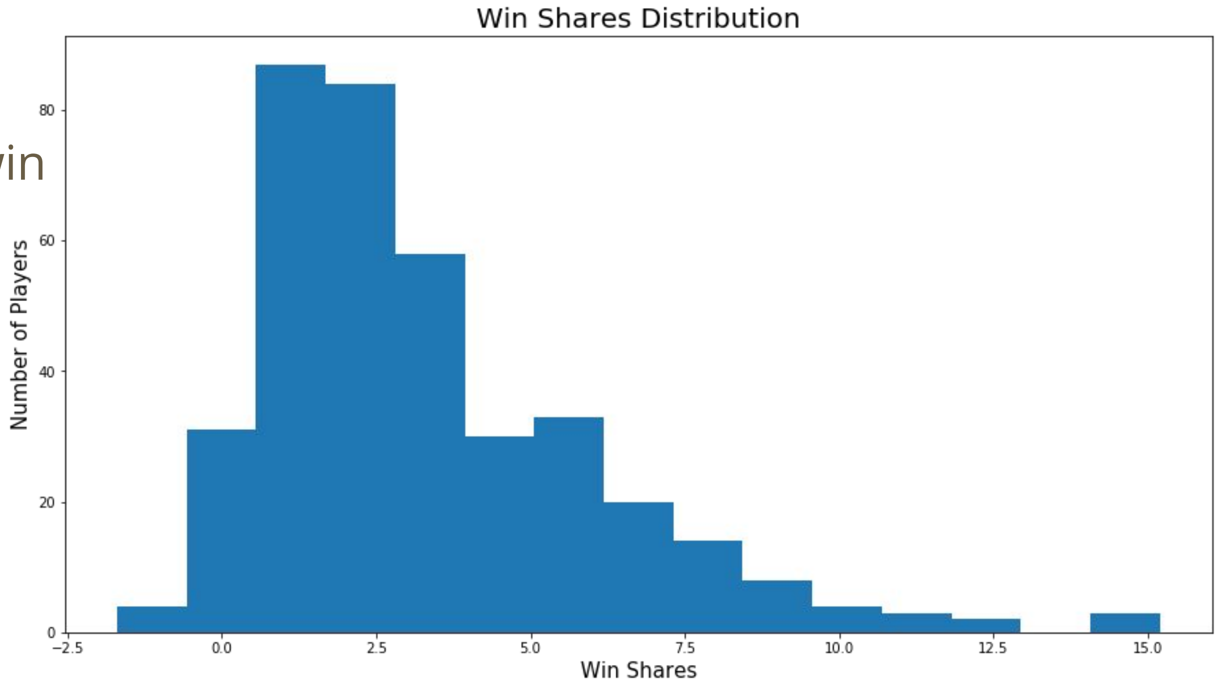


Data Transformation

- Decide to filter out players that barely played
  - 41 games or more
- There’s ton of player with 0 win shares.
- Only 15 players per team
  - Injuries, trades, etc. affects the data set

Data Transformation

- 381 players
- Less players with 0 win shares
- More normalized compared to the last distribution



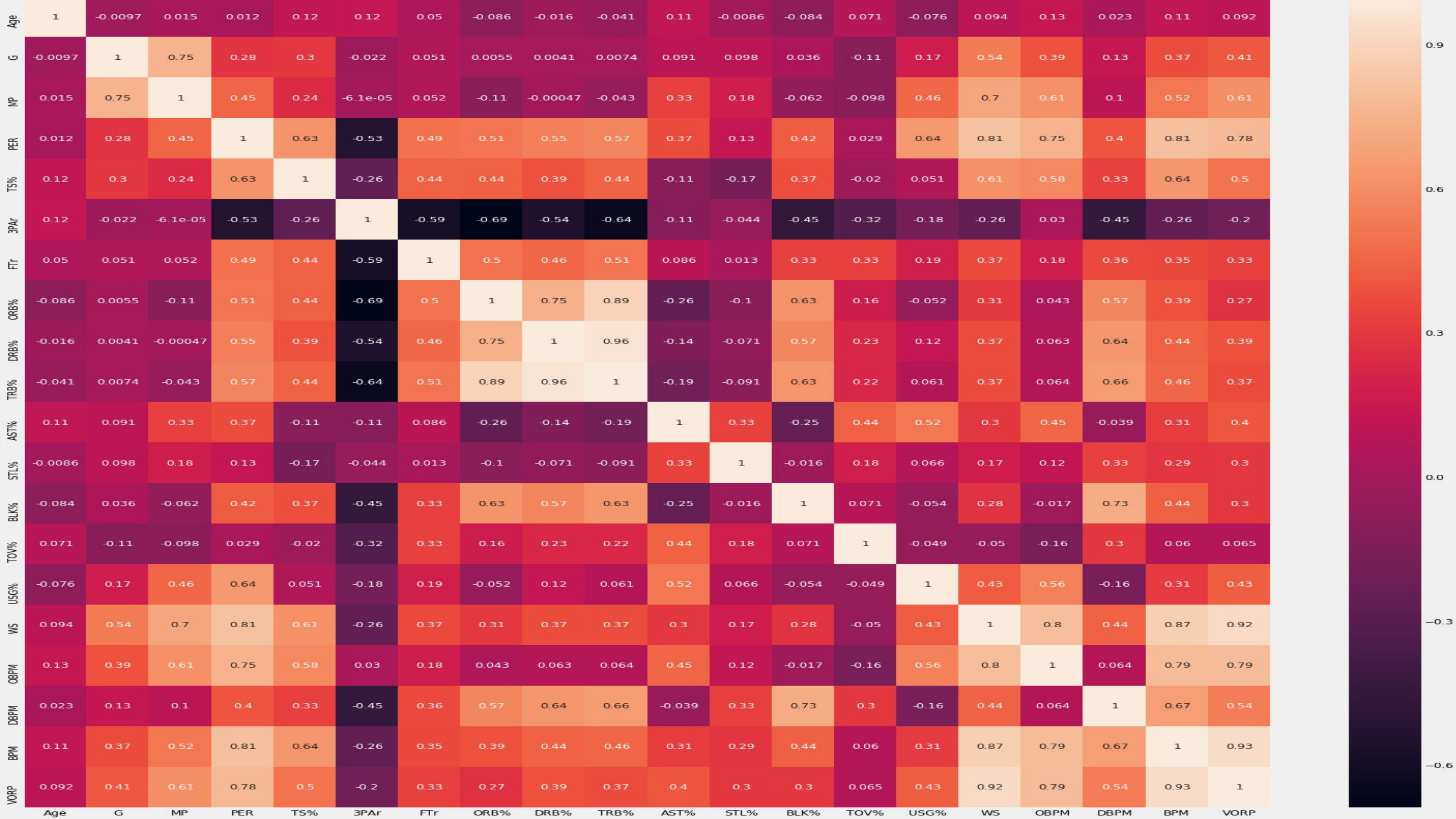
Correlation

- Finding which variables correlated well with WIn Shares.
- Use correlation function and heatmaps to determine correlation.

Correlation-2

- Use variables that correlation that is .5 or higher

	index	WS
15	WS	1.000000
19	VORP	0.924396
18	BPM	0.868633
3	PER	0.813769
16	OBPM	0.795985
2	MP	0.698498
4	TS%	0.612444
1	G	0.537833
17	DBPM	0.441935
14	USG%	0.425792
9	TRB%	0.373042
8	DRB%	0.367111
6	FTr	0.365449
7	ORB%	0.305793
10	AST%	0.298471
12	BLK%	0.276973
11	STL%	0.172317
0	Age	0.094430
13	TOV%	-0.049696
5	3PAr	-0.255229


Age 1 -0.0097 0.015 0.012 0.12 0.12 0.05 -0.086 -0.016 -0.041 0.11 -0.0086 -0.084 0.071 -0.076 0.094 0.13 0.023 0.11 0.092
G -0.0097 1 0.75 0.28 0.3 -0.022 0.051 0.0055 0.0041 0.0074 0.091 0.098 0.036 -0.11 0.17 0.54 0.39 0.13 0.37 0.41
MP 0.015 0.75 1 0.45 0.24 -6.1e-05 0.052 -0.11 -0.00047 -0.043 0.33 0.18 -0.062 -0.098 0.46 0.7 0.61 0.1 0.52 0.61
PER 0.012 0.28 0.45 1 0.63 -0.53 0.49 0.51 0.55 0.57 0.37 0.13 0.42 0.029 0.64 0.81 0.75 0.4 0.81 0.78
TS% 0.12 0.3 0.24 0.63 1 -0.26 0.44 0.44 0.39 0.44 -0.11 -0.17 0.37 -0.02 0.051 0.61 0.58 0.33 0.64 0.5
3PAr 0.12 -0.022 -6.1e-05 -0.53 -0.26 1 -0.59 -0.69 -0.54 -0.64 -0.11 -0.044 -0.45 -0.32 -0.18 -0.26 0.03 -0.45 -0.26 -0.2
FTr 0.05 0.051 0.052 0.49 0.44 -0.59 1 0.5 0.46 0.51 0.086 0.013 0.33 0.33 0.19 0.37 0.18 0.36 0.35 0.33
ORB% -0.086 0.0055 -0.11 0.51 0.44 -0.69 0.5 1 0.75 0.89 -0.26 -0.1 0.63 0.16 -0.052 0.31 0.043 0.57 0.39 0.27
DRB% -0.016 0.0041 -0.00047 0.55 0.39 -0.54 0.46 0.75 1 0.96 -0.14 -0.071 0.57 0.23 0.12 0.37 0.063 0.64 0.44 0.39
TRB% -0.041 0.0074 -0.043 0.57 0.44 -0.64 0.51 0.89 0.96 1 -0.19 -0.091 0.63 0.22 0.061 0.37 0.064 0.66 0.46 0.37
AST% 0.11 0.091 0.33 0.37 -0.11 -0.11 0.086 -0.26 -0.14 -0.19 1 0.33 -0.25 0.44 0.52 0.3 0.45 -0.039 0.31 0.4
STL% -0.0086 0.098 0.18 0.13 -0.17 -0.044 0.013 -0.1 -0.071 -0.091 0.33 1 -0.016 0.18 0.066 0.17 0.12 0.33 0.29 0.3
BLK% -0.084 0.036 -0.062 0.42 0.37 -0.45 0.33 0.63 0.57 0.63 -0.25 -0.016 1 0.071 -0.054 0.28 -0.017 0.73 0.44 0.3
TOV% 0.071 -0.11 -0.098 0.029 -0.02 -0.32 0.33 0.16 0.23 0.22 0.44 0.18 0.071 1 -0.049 -0.05 -0.16 0.3 0.06 0.065
USG% -0.076 0.17 0.46 0.64 0.051 -0.18 0.19 -0.052 0.12 0.061 0.52 0.066 -0.054 -0.049 1 0.43 0.56 -0.16 0.31 0.43
WS 0.094 0.54 0.7 0.81 0.61 -0.26 0.37 0.31 0.37 0.37 0.3 0.17 0.28 -0.05 0.43 1 0.8 0.44 0.87 0.92
OBPM 0.13 0.39 0.61 0.75 0.58 0.03 0.18 0.043 0.063 0.064 0.45 0.12 -0.017 -0.16 0.56 0.8 1 0.064 0.79 0.79
DBPM 0.023 0.13 0.1 0.4 0.33 -0.45 0.36 0.57 0.64 0.66 -0.039 0.33 0.73 0.3 -0.16 0.44 0.064 1 0.67 0.54
BPM 0.11 0.37 0.52 0.81 0.64 -0.26 0.35 0.39 0.44 0.46 0.31 0.29 0.44 0.06 0.31 0.87 0.79 0.67 1 0.93
VORP 0.092 0.41 0.61 0.78 0.5 -0.2 0.33 0.27 0.39 0.37 0.4 0.3 0.3 0.065 0.43 0.92 0.79 0.54 0.93 1
Age G MP PER TS% 3PAr FTr ORB% DRB% TRB% AST% STL% BLK% TOV% USG% WS OBPM DBPM BPM VORP
0.9
0.6
0.3
0.0
−0.3
−0.6

Multicollinearity

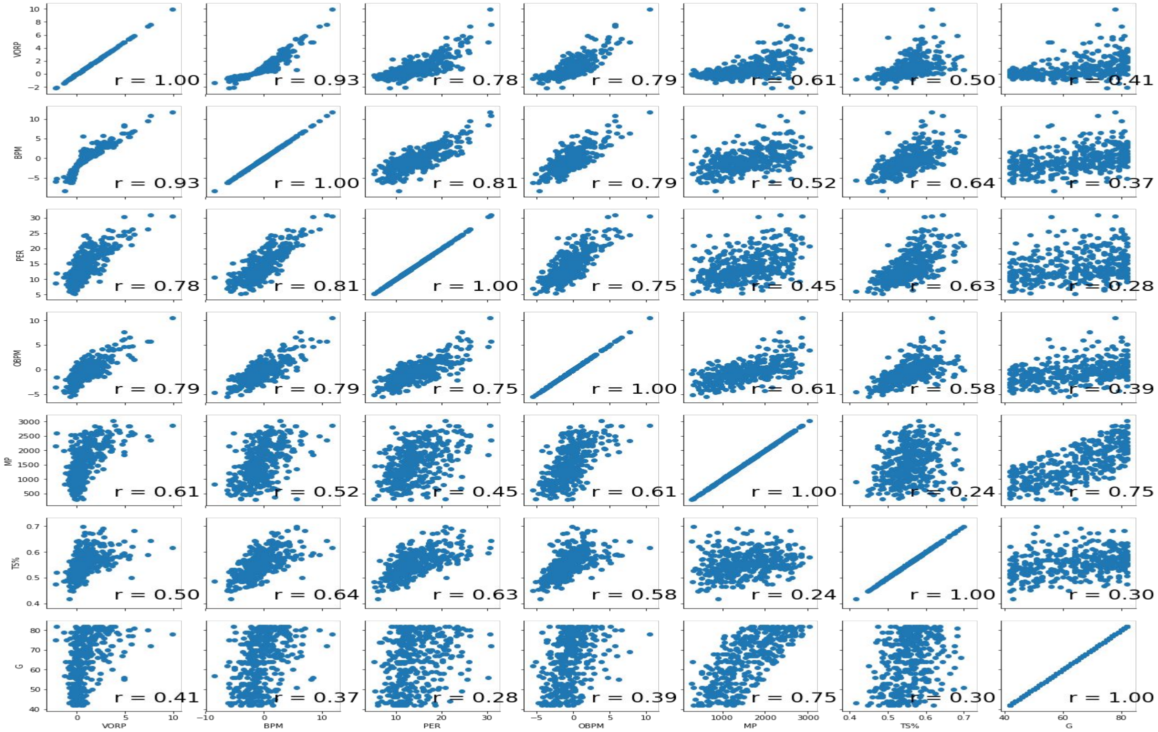
- Need to check that other variables correlated with each too closely.
- Won’t skew the model
- Use graphs and table to check

Multicollinearity

- VORP and BPM have a correlation of .93
- BPM would be dropped because VORP used BPM in their formula

	VORP	BPM	PER	OBPM	MP	TS%	G
VORP	1.000000	0.929908	0.779450	0.794319	0.606268	0.504991	0.408920
BPM	0.929908	1.000000	0.806153	0.785744	0.521236	0.637544	0.371151
PER	0.779450	0.806153	1.000000	0.749606	0.448797	0.625866	0.281484
OBPM	0.794319	0.785744	0.749606	1.000000	0.612428	0.581164	0.387401
MP	0.606268	0.521236	0.448797	0.612428	1.000000	0.235015	0.749390
TS%	0.504991	0.637544	0.625866	0.581164	0.235015	1.000000	0.296773
G	0.408920	0.371151	0.281484	0.387401	0.749390	0.296773	1.000000

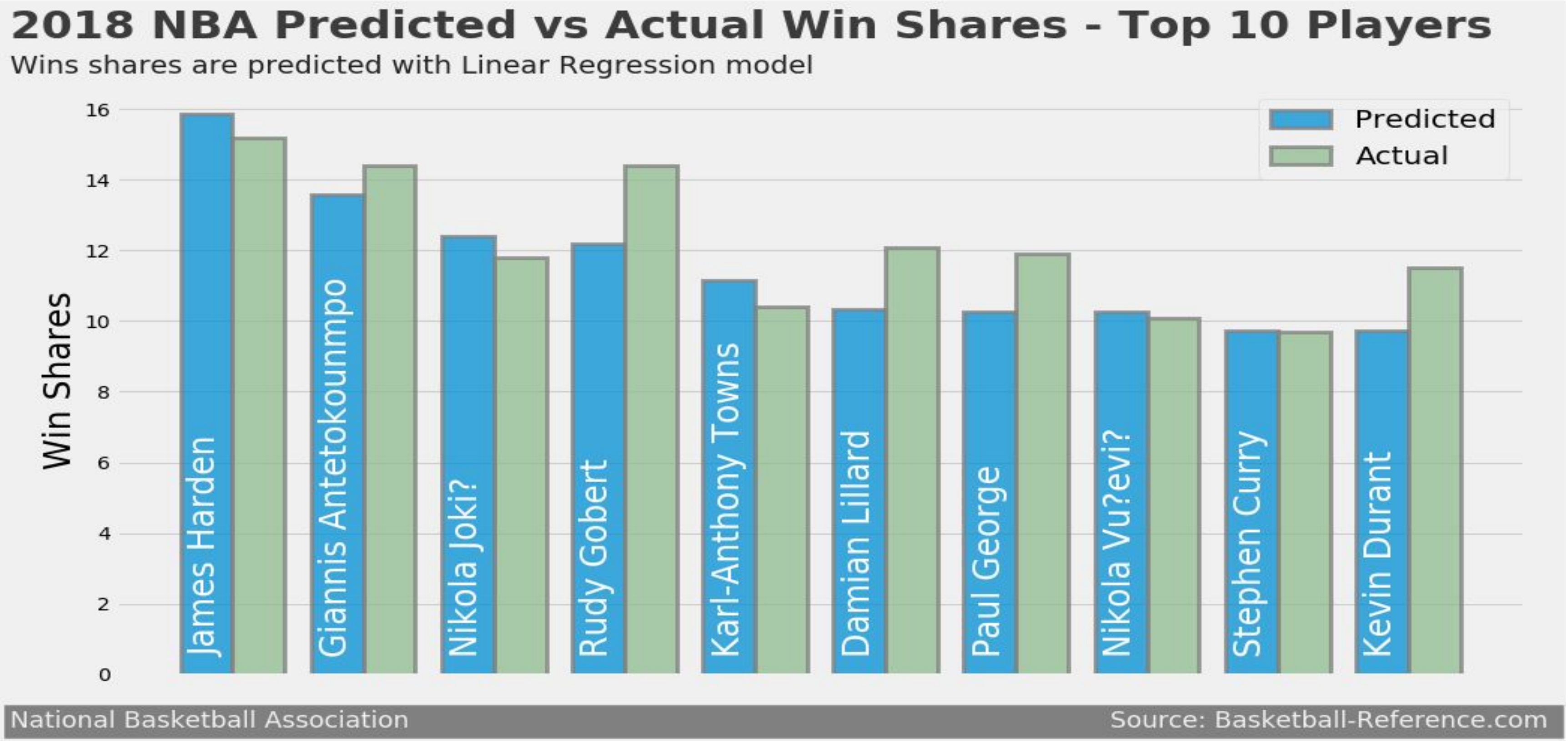
Multicollinearity



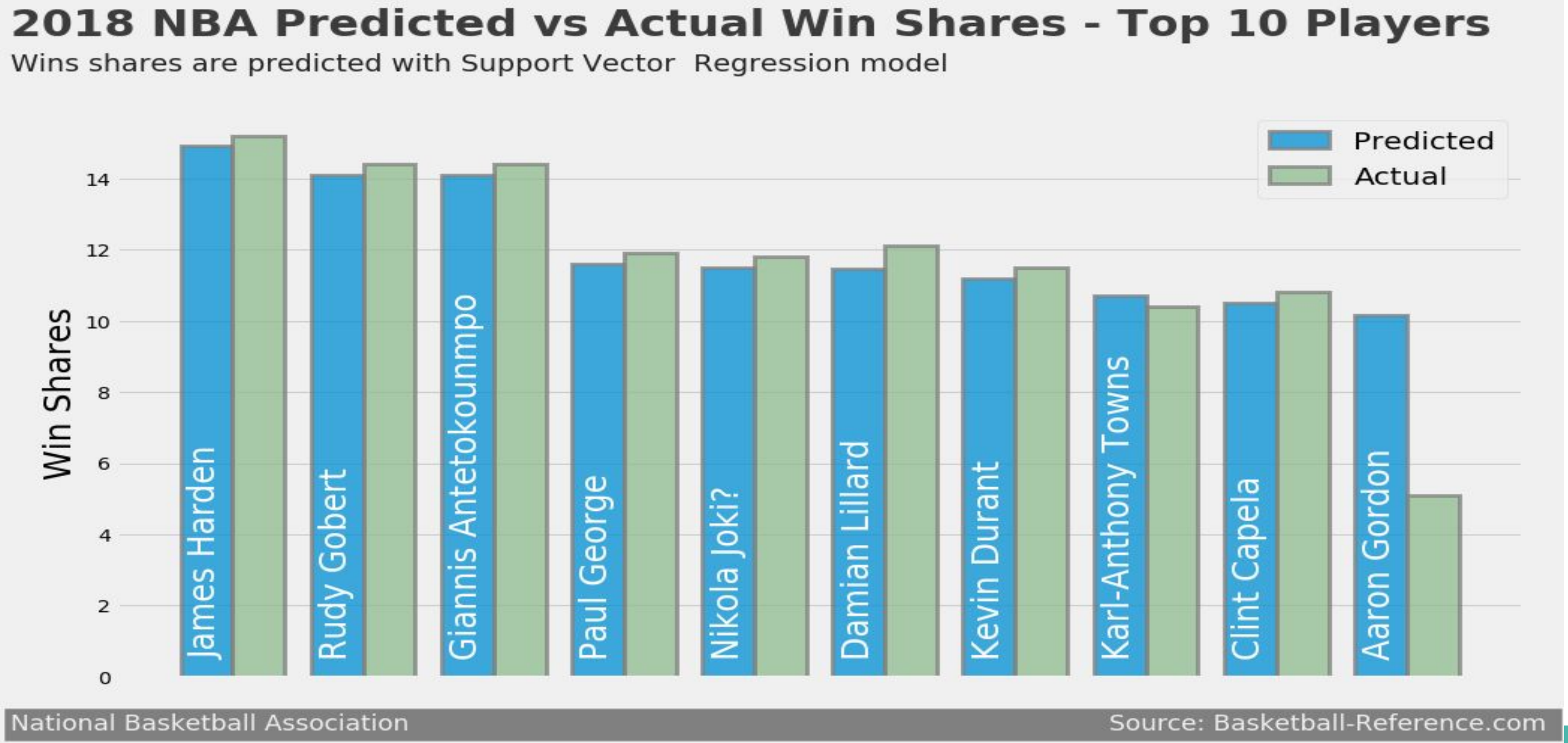
Chosen Features

- VORP
- PER
- OBPM
- MP
- TS%
- G
- 20% tested and 80% trained

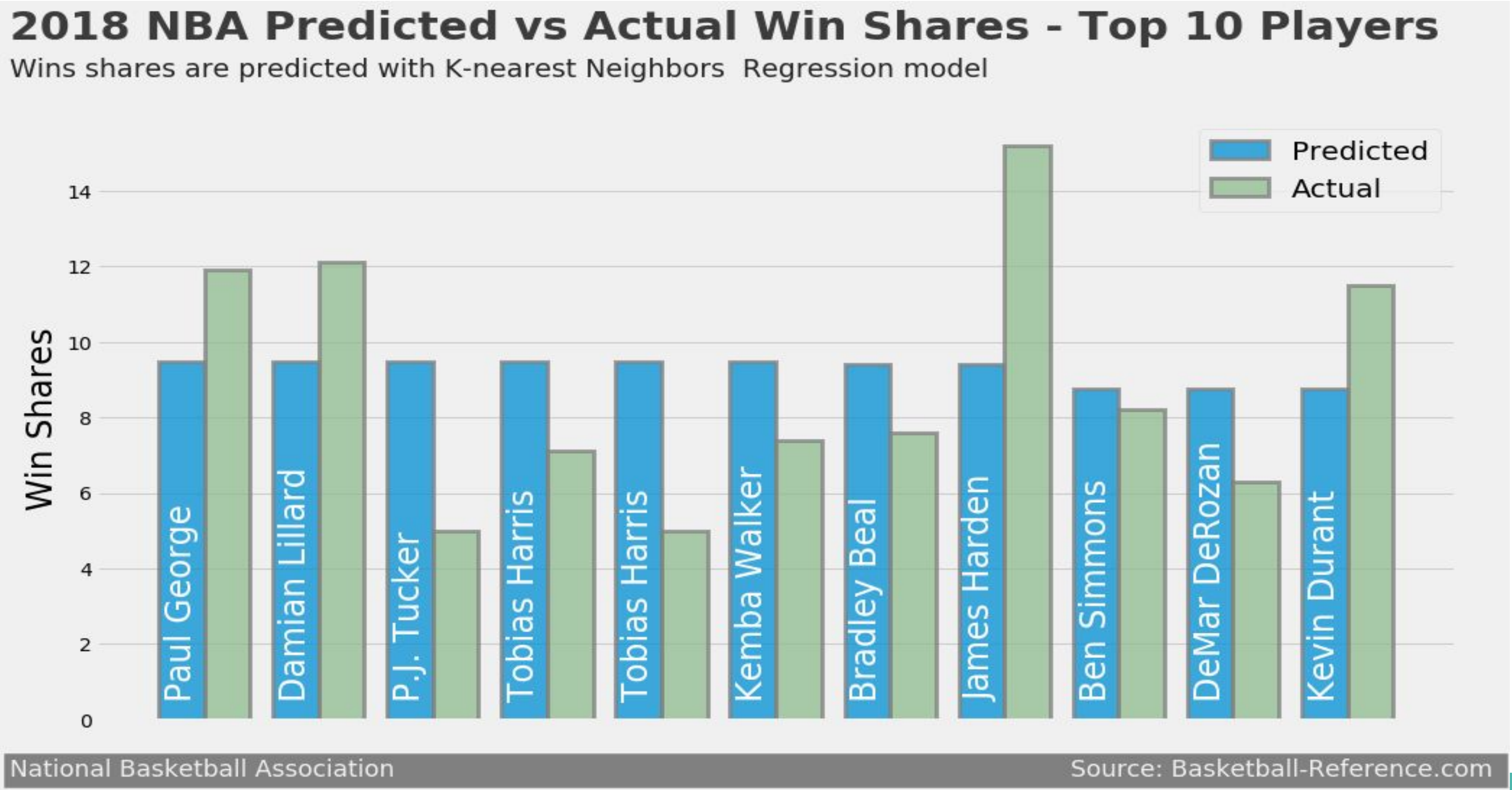
Model 1- Linear Regression



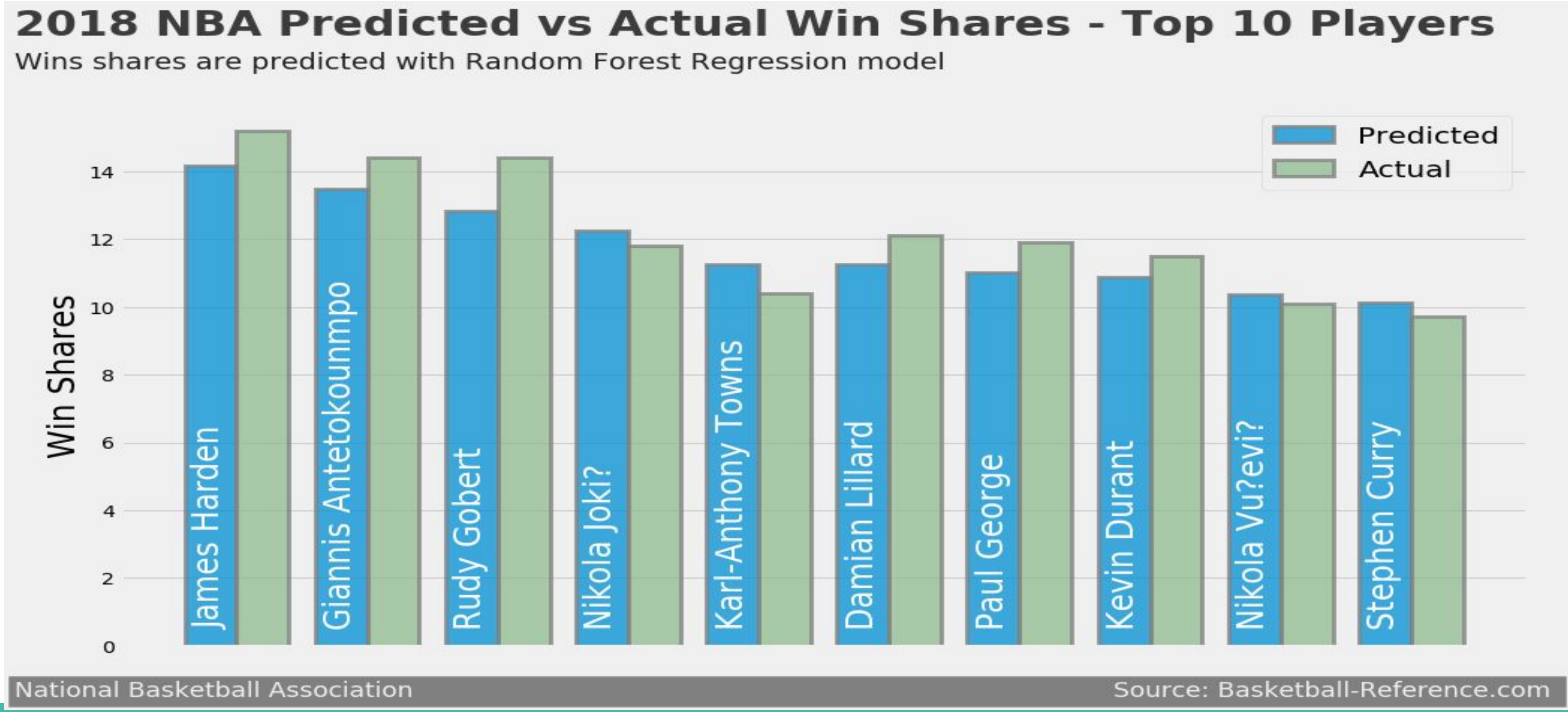
Model 2- Support Vector Regression



Model 3- K-Nearest Neighbors Regression



Model 4- Random Forest Regression



Performance Evaluation

Model	Mean Squared Error	Mean Absolute Error	Variance Score
Linear	0.360	0.448	0.926
Support Vector	2.878	1.270	0.406
k-Nearest Neighbors	3.560	1.332	0.265
Random Forest	0.331	0.451	0.932

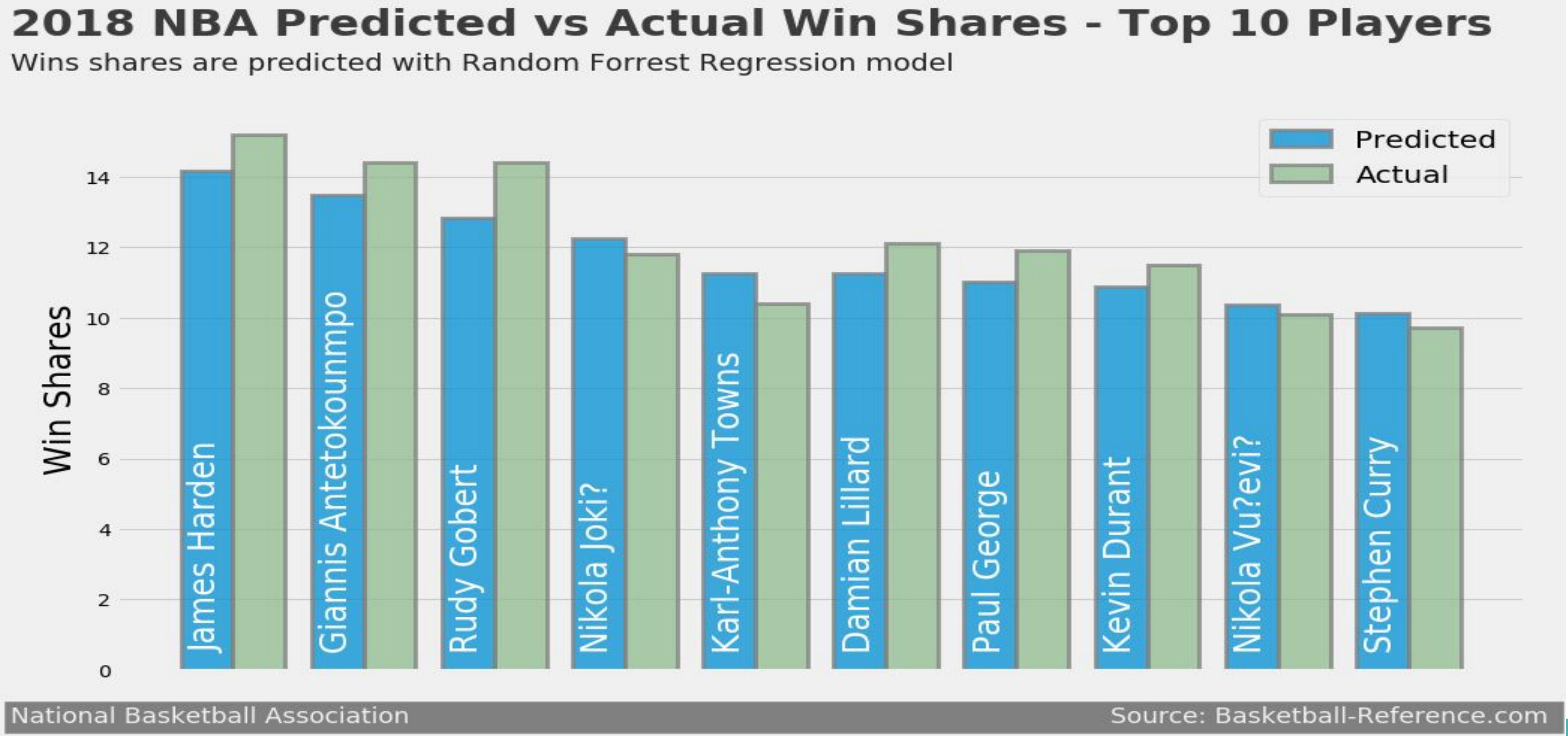
Best Model

- Random Forest proven to be the best model
- Predict the top ten players accurately
- Has the lowest value of Mean Squared Error and Mean Absolute Error
- Has the highest value of Variance score.

Random Forest

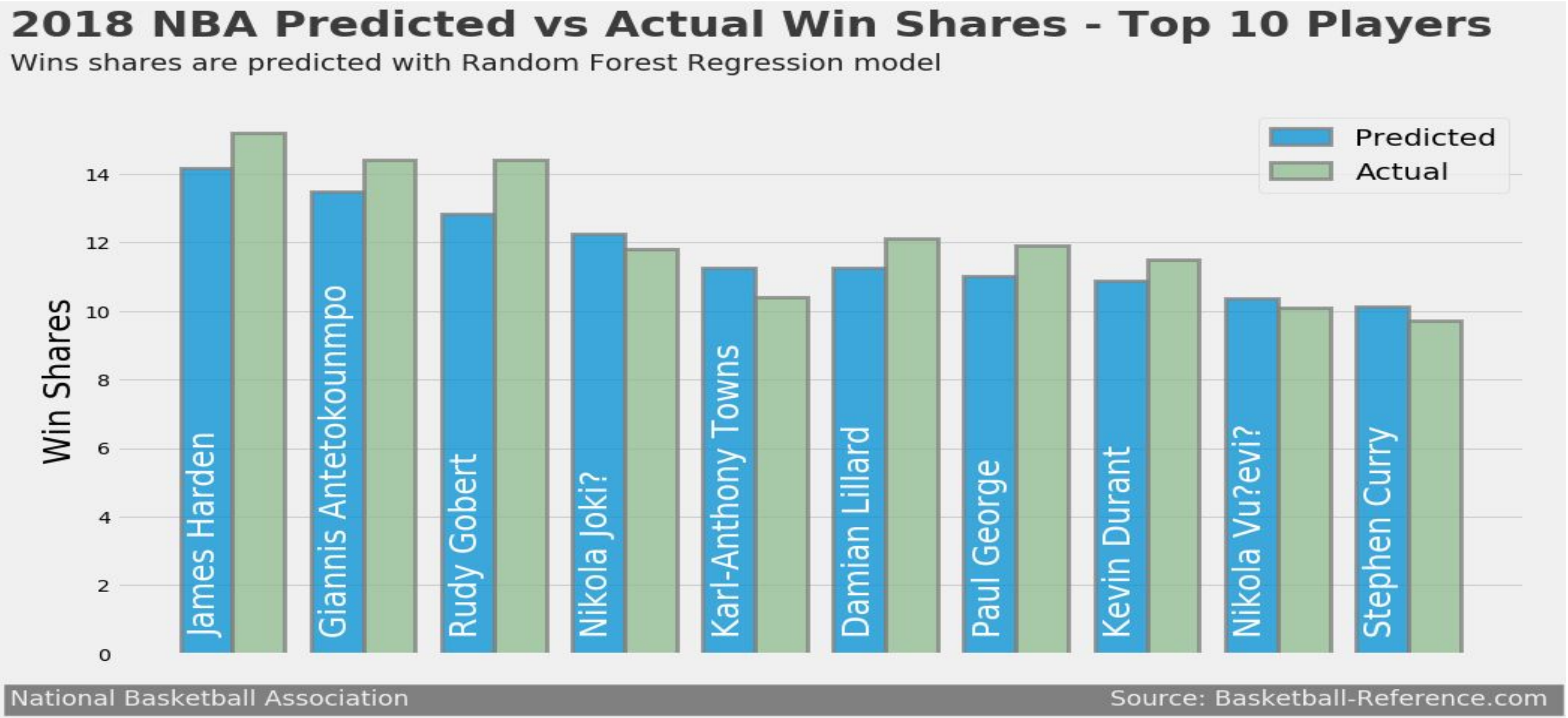
- Need to see the Random Forest was overfitted or not
- To see there was a good generalization or not.

10%



2018 NBA Predicted vs Actual Win Shares - Top 10 Players
Wins shares are predicted with Random Forrest Regression model
Predicted
Actual
Win Shares
0
2
4
6
8
10
12
14
James Harden
Giannis Antetokounmpo
Rudy Gobert
Nikola Joki?
Karl-Anthony Towns
Damian Lillard
Paul George
Kevin Durant
Nikola Vu?evi?
Stephen Curry
National Basketball Association
Source: Basketball-Reference.com

50%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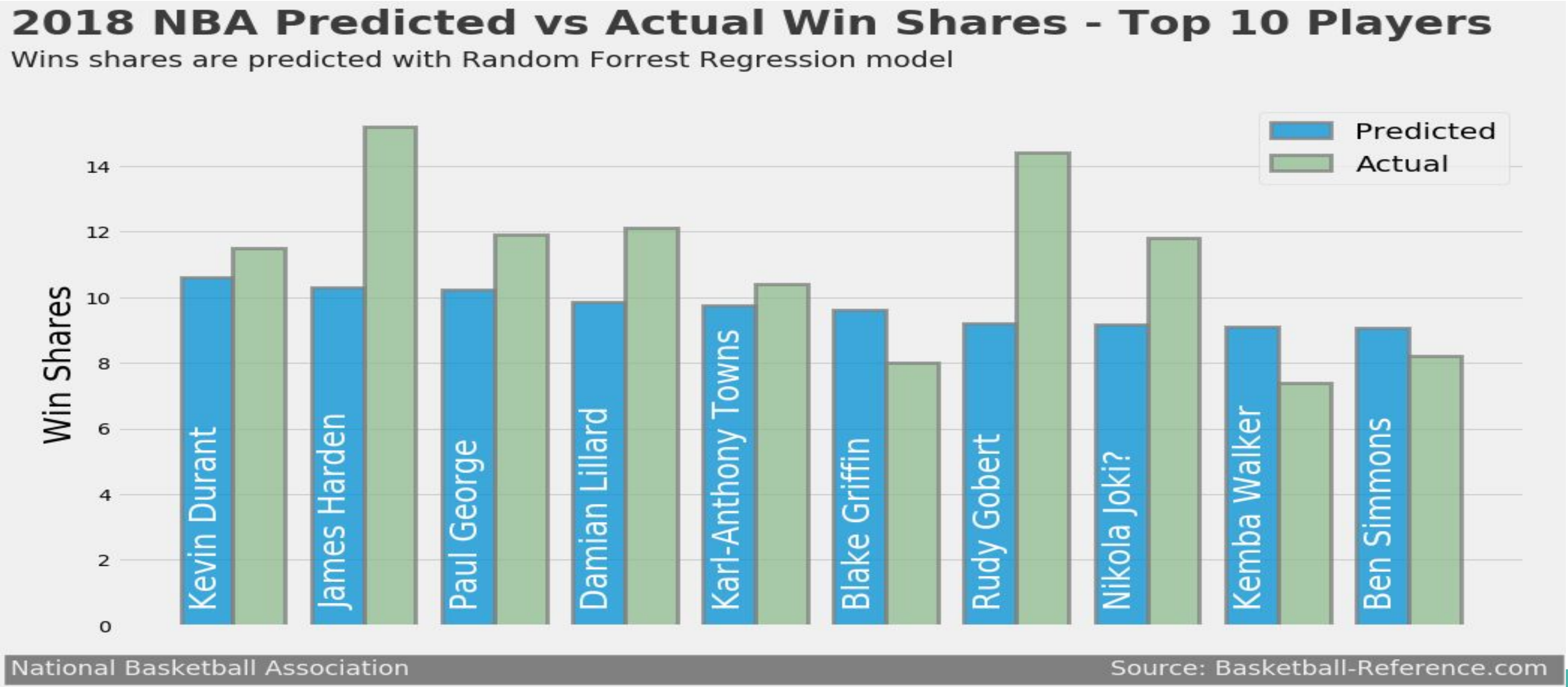
Nikola Vu?evi?
Stephen Curry
National Basketball Association
Source: Basketball-Reference.com

90%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Kevin Durant
James Harden
Paul George
Damian Lillard
Karl-Anthony Towns
Blake Griffin
Rudy Gobert
Nikola Joki?
Kemba Walker
Ben Simmons
National Basketball Association
Source: Basketball-Reference.com

Random Forest

Test	Mean Squared Error	Mean Absolute Error	Variance Score
10%	0.319	0.471	0.940
50%	0.689	0.567	.0902
90%	1.020	0.713	0.863

Random Forest

- At 10% seem to be the closest for performance for 20%
- 10% and 50% have similar results for top ten players
- 50% has higher error though
- This shows that the random forest wasn’t overfitted for 20% because 90% would have similar results.

Conclusion

- Random Forest best model for this dataset based on performance
- VORP has the most correlation
- Age didn’t have an impact
- Not the best stat to judge individuals’ performance
    - Team fit and player personnel
- Need more datasets
    - Used past seasons
    - Used more features