WAR in Pieces: A Bottom-Up Approach to Player Evaluation in the NBA

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Introduction

Sports analytics is the application of data science and statistical analysis to the realm of sports to obtain some kind of competitive advantage. As an industry, it has exploded in recent years, growing at 31.2% per year and expected to reach $4.6 billion by 2025 [2]. As such, there have been increased efforts towards player evaluation for the countless situations that demand a quantitative and objective analysis or comparison of players. My work seeks to add to this literature by crafting my own statistic, which is originally inspired by the statistic of Wins Above Replacement (WAR) in baseball. In simplest terms, WAR is a singular value that estimates how many wins a player contributes to his team compared to if he was replaced by a player at a skill level that could be added to the team at any time. My goal is to apply this way of thinking to basketball and compute a value that numerically describes how each NBA player affects the most important part of the sport: winning.

Literature Review

- Adjusted Plus-Minus (APM) - estimates contribution to plus-minus
- Box Plus-Minus (BPM) - uses traditional box scores to estimate APM
- Value Over Replacement Player (VORP) - compares to BPM of -2.0
- Win Shares (WS) - assigns actual team wins to players based on plus-minus
- Wins Above Replacement Player (WARP) - linear combination formula
- RAPTOR (FiveThirtyEight) - proprietary formula

Areas for Improvement

- Treats game as a black box, so no basketball-specific knowledge incorporated that could add nuance and relevant information to the model
- Does not account for player-player interactions, which are much more prevalent in basketball; "invasion team sports" like basketball are "much more complex and hence the separability of individual player contributions is considerably more difficult" [1]

Data Sources

- Box Scores (Basketball Reference)
  - 2PA, 2P%, 3PA, 3P%, FTA, FT%, ORB, DRB, AST, STL, BLK, TOV, PF, PTS
- Individual Tracking Data (NBA, SAP)
  - DRIVES, PASSES, PTS_CREATED, CATCH
- Lineup Data (NBA) - describes Minutes Played, Offensive and Defensive Ratings

LINEUPS	TEAM	GP	MIN	OFFRTG	DEFRTG	NETRTG
J. Green - W. Barton - A. Gordon - N. Jokic - M. Morris	DEN	41	761	121.3	111.8	9.5
C. Paul - J. Crowder - D. Booker - M. Bridges - D. Ayton	PHX	38	754	116.4	109.0	7.4
M. Conley - B. Bogdanovic - R. Gobert - R. O'Neale - D. Mitchell	UTA	42	666	117.1	110.5	6.7
A. Horford - M. Smart - J. Brown - J. Tatum - R. Williams III	BOS	34	443	118.8	94.2	24.6
P. Beverley - D. Russell - K. Towns - J. Vanderbilt - A. Edwards	MIN	36	439	120.2	107.4	12.8

Methodology

Instead of a high-level approach of converting production (points, rebounds, assists) into value in wins, I will be using a **bottom-up approach** by examining the players on the court at each given minute. Once I can estimate how well lineups play using the five players' characteristics, I can use data on how often each lineup actually played to reconstruct the entire season and compute the expected offensive and defensive ratings and thus win percentage for each team that season.

1. Estimate offensive and defensive rating of each lineup using player characteristics.
2. Use minutes played of each lineup to reconstruct the season and estimate the ratings of the team as a whole.
3. Apply the Pythagorean Formula of sports to estimate win percentage:
$$\text{win\%} = \frac{(\text{offensive rating})^a}{(\text{offensive rating})^a + (\text{defensive rating})^a},$$
where a is an inherent property of the sport and for basketball is about 16.
4. Substitute replacement level player into previous steps to estimate replacement win percentage.
5. Take the difference as WAR.

Inference

Prior to this, a clever application of PCA is employed to embed each player into $\mathbf{R}^8$. In the past six season, there were 600 5-man lineups that played a sufficient number of minutes together, each of which I permute to get 72000 data points. For each data point, I concatenate the five player embeddings to get an $\mathbf{R}^{40}$ representation of each lineup, whose true offensive and defensive lineups as well as minutes played are known to me. For this application, I use two **neural networks each with four hidden layers**, which are deep enough to capture nonlinear relationships without expanding the parameter space by too much. After training the two models on the high-volume lineups, I feed in all lineups and group the outputs by team and season in order to compute their expected offensive and defensive ratings as well as implied win percentage.

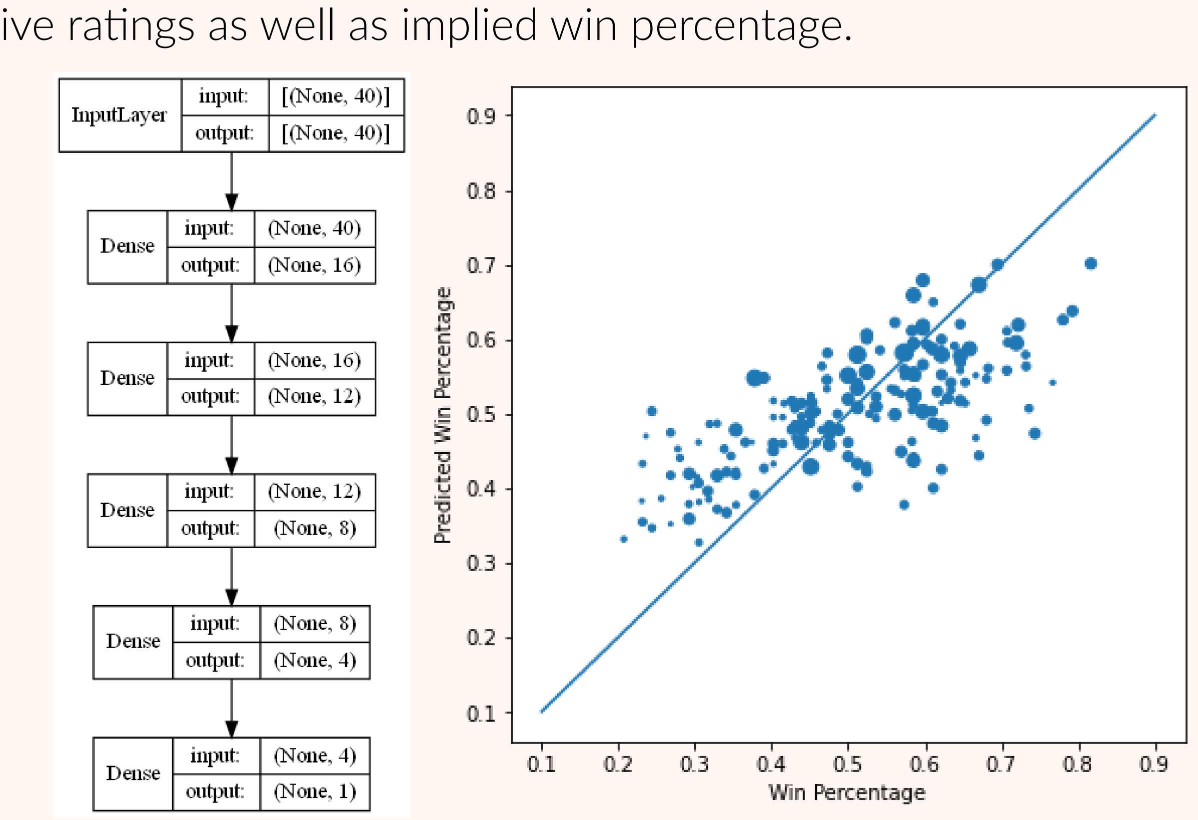


Figure 1. Win Percentage Predictions vs. True Values

Overall, this method works well, as the predicted win percentage values have a 0.72 correlation with the true values and an RMSE of 0.1021, or about 8 games per season. It is worth noting that the performance of the defensive rating model is noticeably worse than that of the offensive model, which is likely due to the bias towards offensive data used in this work. This is a promising area of improvement in future work.

Computing WAR

NBA rosters have 15 men, so I take the average of the 2701-2880th players by minutes played to be my replacement-level player. I can now compute the difference in expected wins after the substitution, as well as offensive and defensive WAR variants to isolate those two types of contributions.

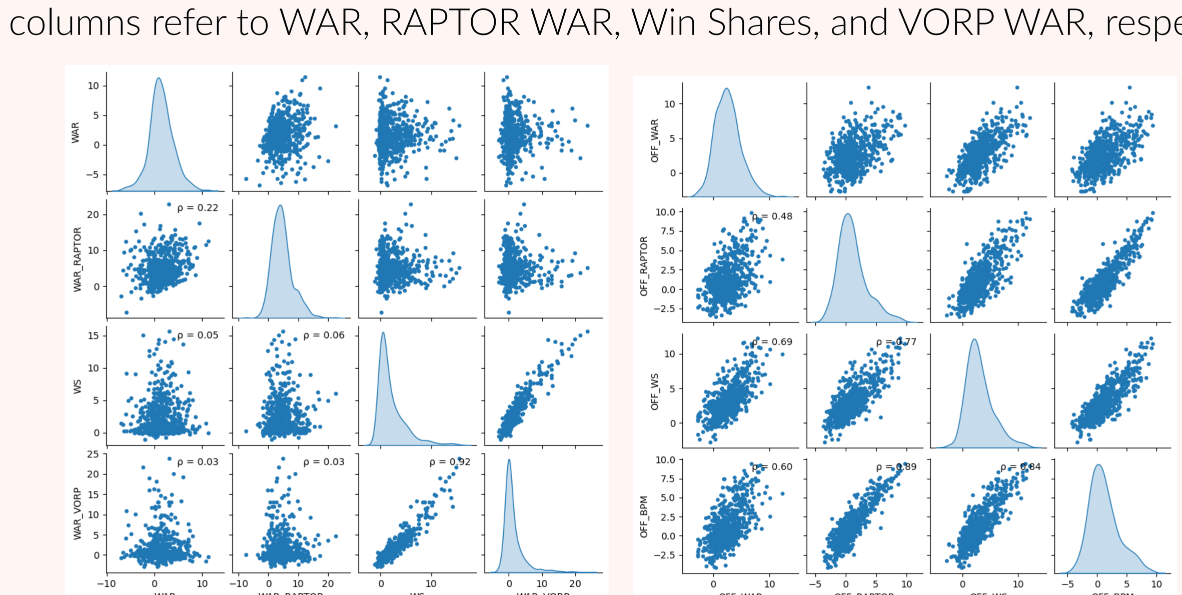
$$\text{WAR} = 82 \times \left(W(o_{off}, o_{def}) - W(r_{off}, r_{def})\right)$$
$$\text{WAR\_OFF} = 82 \times \left(W(o_{off}, r_{def}) - W(r_{off}, r_{def})\right)$$
$$\text{WAR\_DEF} = 82 \times \left(W(r_{off}, o_{def}) - W(r_{off}, r_{def})\right)$$

Results

The resulting WAR values are as follows. For comparison, the correlation plots between WAR and the other metrics listed are below, as well as those of offensive WAR with the respective offensive variants.

	PLAYER	WAR		RAPTOR		WS		VORP	
		Value	Perc	Value	Perc	Value	Perc	Value	Perc
2016	DeAndre Jordan	9.0	100	7.8	84	11.8	96	9.5	85
	Ricky Rubio	8.1	-	5.8	71	6.1	67	4.9	61
	Hassan Whiteside	7.4	-	4.7	58	9.5	90	5.9	69
2017	Paul George	7.5	100	8.8	87	8.9	88	9.7	86
	Steven Adams	7.2	-	6.8	79	9.7	91	5.4	66
	Kyle Lowry	6.8	-	10.7	93	10.2	93	12.2	91
2018	Rudy Gobert	10.9	100	11.4	95	14.4	99	13.0	93
	Paul George	9.5	-	17.4	100	11.9	96	17.8	98
	Ben Simmons	8.7	-	3.0	35	8.2	84	10.3	88
2019	Rudy Gobert	8.4	100	10.6	93	10.7	94	8.9	83
	Hassan Whiteside	7.5	-	6.1	74	8.5	85	7.0	76
	Damian Lillard	6.6	-	11.9	96	11.6	96	15.9	97
2020	Rudy Gobert	11.4	100	12.4	97	11.3	95	10.3	88
	Draymond Green	7.2	-	7.5	84	4.6	47	5.1	63
	Clint Capela	6.9	-	8.8	87	8.2	84	5.9	69
2021	Rudy Gobert	8.6	100	10.8	94	11.7	96	9.7	86
	Clint Capela	8.1	-	5.7	70	8.3	85	5.7	67
	Mitchell Robinson	8.0	-	5.3	65	8.5	85	5.4	66

The columns refer to WAR, RAPTOR WAR, Win Shares, and VORP WAR, respectively.



Overall, the WAR metrics agree with a weak correlation, with a higher correlation among the offensive variants. However, the goal of my thesis is not to recreate existing work, but rather capture new information using my own novel and intuitive methodology. When used in conjunction, this set of metrics can tell a compelling story and reveal truths otherwise unseen.

References

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