Predictive Analysis of Player Performance in Sports Betting with Singular Value Decomposition

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1 Introduction

Sports betting relies heavily on predictive analysis of player performance. In a sport like basketball, where 82 games are played each season, there is ample data to assess player performance over time to predict future outcomes. This paper focuses on props for players, specifically points (PTS), rebounds (REB), and assists (AST) over the course of a full game, with the goal of predicting these statistics.

Various factors influence the performance of the player on any given day, including rest days, opponent strength, pace of play, and recent form. However, different players are affected by these factors to varying degrees. Some players maintain consistent performance regardless of opponent strength, while others may struggle against strong defensive teams. Fatigue also affects players differently. Instead of using the same predictive features for all players, identifying latent factors that affect individual player performance can improve predictive accuracy for betting decisions. This paper utilizes Singular Value Decomposition (SVD) to identify patterns in player performance and weights these patterns to predict next-game performance.

2 Data Collection

Data on player performance were collected from the current NBA seasons (2024-25) and the previous season (2023-24) using the NBA API. For each statistic (PTS, REB, AST), potential predictive factors were considered. Although this paper focuses on PTS, the same methodology applies to REB and AST.

The following factors were considered to predict PTS:

- **Historical patterns:** $\text{PTS}_{L5_{\text{AVG}}}$, $\text{PTS}_{L5_{\text{STD}}}$, $\text{PTS}_{L5_{\text{TREND}}}$

- **Shooting efficiency:** $\text{FG\%}_{L5_{\text{AVG}}}$, $\text{FG\%}_{L5_{\text{STD}}}$, $\text{FG\%}_{L5_{\text{TREND}}}$, $\text{FG3\%}_{L5_{\text{AVG}}}$, $\text{FG3\%}_{L5_{\text{STD}}}$, $\text{FG3\%}_{L5_{\text{TREND}}}$, $\text{TS\%}_{L5_{\text{AVG}}}$, $\text{FGA}_{L5_{\text{AVG}}}$
- **Usage/minutes:** $\text{USG\%}_{L5_{\text{AVG}}}$, PREV_GAME_MIN
- **Game context:** Home game, Days rest, Back-to-back
- **Opponent context:** Defensive rating, Pace, Team strength, Schedule difficulty

Each game in the data set corresponds to a row in the feature matrix X, which is an $m \times n$ matrix, where m is the number of games and n is the number of features. Games in which players recorded zero minutes were excluded.

3 Methods

After constructing the feature matrix X, it was standardized before applying Singular Value Decomposition (SVD). SVD decomposes X into three matrices:

$$X = U\Sigma V^T, \tag{1}$$

where:

- U is an $m \times r$ matrix (game representation in reduced space),
- Σ is an $r \times r$ diagonal matrix containing singular values,
- V^T is an $r \times n$ matrix (feature patterns).

For this analysis, three principal components were retained ($r = 3$). The rows of V^T represent the impact of each feature on each pattern. For example, the transposed V matrix for Jalen Green is presented below.

- Pattern 1 was heavily influenced by $\text{PTS}_{L5_{\text{AVG}}}$, $\text{FG\%}_{L5_{\text{AVG}}}$, opponent defensive rating, team strength, and schedule difficulty, suggesting that this pattern represents the context of the game and recent form.
- Pattern 2 was strongly correlated with $\text{FG\%}_{L5_{\text{TREND}}}$, $\text{FG3\%}_{L5_{\text{AVG}}}$, $\text{PTS}_{L5_{\text{TREND}}}$, rest days, previous game minutes, and pace, indicating a dependence on shooting efficiency (hot/cold streaks), fatigue, and game pace.
- Pattern 3 was primarily associated with the context and momentum of the game.

The matrix U represents the strength of these patterns in each game, and the diagonal matrix Σ contains singular values, which quantify the importance of each pattern.

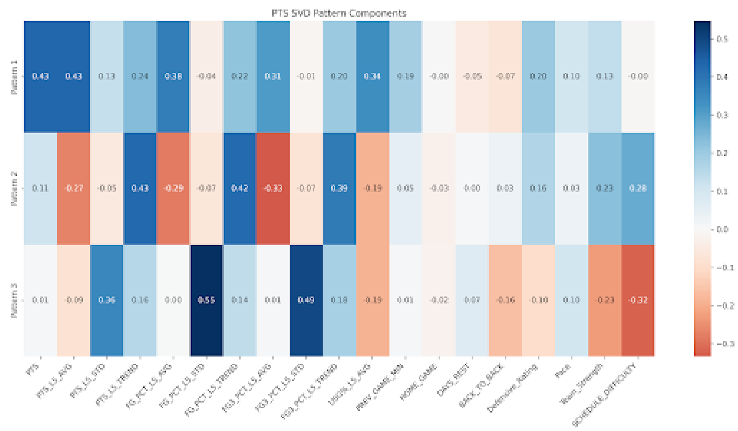

Figure 1: Transposed V matrix for Jalen Green

3.1 Prediction Process

To predict the performance of a player in the next game, we construct a new standardized feature vector $x_{\text{new}} \in \mathbb{R}^{1\times n}$, which contains opponent rating, pace, $\text{PTS}_{L5_{\text{AVG}}}$, etc. We then project x_{new} onto V:

$$x' = x_{\text{new}} V, \tag{2}$$

producing a 1×3 matrix, which represents the predicted strength of each pattern in the upcoming game. We then weight these components using Σ:

$$x'' = x'\Sigma, \tag{3}$$

and project back onto the feature space using V^T:

$$\hat{x} = x'' V^T. \tag{4}$$

The PTS value from $\hat{x}$ represents the standardized predicted points for the next game. Converting this back to the original scale using the player's mean and standard deviation yields the final points prediction:

$$\hat{y} = \mu_{\text{PTS}} + \sigma_{\text{PTS}} \cdot \hat{x}_{\text{PTS}}. \tag{5}$$

4 Results and Conclusions

With past odds/player prop lines being difficult to access, the model was tested on future odds which were available, running on March 12, 13, and 14. Thresholds for deciding whether to take the over or under were hard coded as 2.5 for points, 1.5 for rebounds and assists. The model would recommend the under if below the line minus the threshold, and the over if higher than the line plus

	Points	Rebounds	Assists
Correct Bets	90	56	40
Incorrect Bets	80	44	40
Accuracy	0.529	0.56	0.50

Table 1: Model prediction accuracy for different player props.

the threshold. If the prediction was in between, the model would choose not to take the bet.

These results do not show significant accuracy, indicating that SVD alone is insufficient for predicting player prop decisions. However, SVD's pattern recognition capability may still be valuable. By understanding key factors that correlate with player performance, additional tools such as Markov matrices could be used to improve predictions. Incorporating more factors, such as player-specific matchup difficulty, historical performance against specific teams, and accounting for injuries, could enhance predictive accuracy as well. While SVD can be useful for assessing the factors influencing player performance, a more comprehensive approach is required for making betting predictions.