How Turnovers and Personal Fouls Per Game affect the Minutes Played conditioned on the players' Position in the basketball game?

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ABSTRACT

This study explores the nuanced impacts of turnovers (TOV) and personal fouls (PF) on the minutes played (MP) by NBA players, with a focus on how these effects vary according to the player's position on the court. Through a series of univariate, bivariate, and multivariate analyses, including correlation matrices and ANOVA tests, the research provides insights into the intricate relationships between TOV, PF, and MP across different positions. The findings suggest that the interaction between these variables is significantly influenced by the player's position, confirming the hypothesis that a player's position moderates the relationship between minutes played and turnovers/personal fouls. This is further substantiated by two-way ANOVA results, indicating significant differences across positions. The study employs various regression models, including XGBoost Tree Regressor and Random Forest Regressor, to predict minutes played, using metrics such as mean absolute error (MAE) and mean squared error (MSE) for model evaluation. A visualization dashboard is developed to present the findings interactively. This research contributes to the broader understanding of player performance in basketball, highlighting the importance of positional context in analyzing turnovers, personal fouls, and playing time.

INTODUCTION

- Disruptive technologies, notably AI and sports analytics, have revolutionized player evaluation and decision-making in basketball over the past decade.
- Drawing inspiration from sports analytics history, basketball has adopted innovative methodologies for player assessment, including advanced metrics like Player Efficiency Rating (PER).
- This research investigates the impact of turnovers and personal fouls per game on players' minutes, considering their positions on the court.
- The study aims to inform coaching strategies and player development, acknowledging the evolving nature of basketball positions.
- By exploring the interaction between these variables, the research contributes to optimal player utilization and strategic planning in basketball, showcasing the importance of data-driven approaches.

HYPOTHESIS TESTING

Input Parameters	F-Statistic	p-value	p-value<0.05
TOV	10838.09427	0	Yes
PF	6310.26834	0	Yes
Pos	157.113012	0	Yes
Pos:TOV	19.465898	4.02E-46	Yes
Pos:PF	17.896801	5.83E-42	Yes
TOV:PF	793.557187	4.90E-170	Yes
Pos:TOV:PF	3.239112	2.09E-05	Yes

Ho (Null Hypothesis) : The player's position does not moderate the relationship between minutes played and turnovers/personal fouls.

H1 (Alternate Hypothesis) : The player's position significantly moderates the relationship between minutes played and turnovers/personal fouls, with some positions showing stronger relationships than others.

METHODS

Data Sources: Utilized extensive datasets on NBA player statistics from the 1997-98 season to the 2021-22 season, with comprehensive coverage of metrics like turnovers (TOV), personal fouls (PF), and minutes played (MP).

Analytical Approach

Univariate: Analysis Examined the distribution of TOV, PF, and MP across different player positions to identify patterns and variances.

Bivariate Analysis: Explored relationships between two variables (e.g., MP vs. TOV, MP vs. PF) using scatter plots to assess correlation and trends specific to player positions.

Multivariate Analysis: Employed correlation matrices to evaluate how TOV, PF, and MP are interrelated across positions, indicating the complex dynamics influenced by player roles.

Statistical Testing:

ANOVA Tests: Conducted One-Way and Two-Way ANOVA to examine mean differences and interactions among TOV, PF, and MP across positions, forming a hypothesis on the moderating effect of player position on the relationship between minutes played and turnovers/personal fouls.

Modeling Techniques:

- Implemented regression models including XGBoost Tree Regressor, Random Forest Regressor, and Linear Regression to predict minutes played based on TOV, PF, and player position.
- Model performance evaluated using Mean Absolute Error (MAE) and Mean Squared Error (MSE).

Visualization: Developed an interactive dashboard to present findings, leveraging tools like Panel - Hvplot / Streamlit, allowing for an accessible and detailed exploration of player performance metrics.

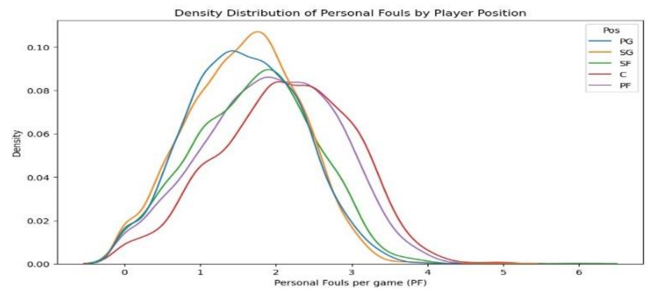
Key Tools and Libraries:

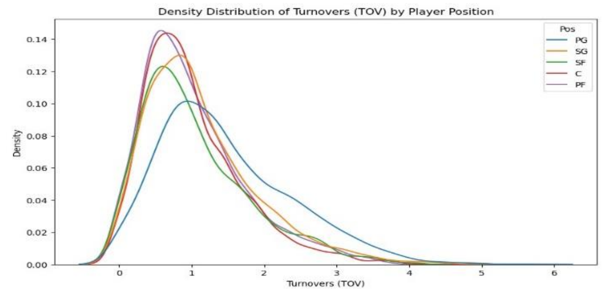
- Data Processing and Analysis: Python (Pandas, NumPy)
- Statistical Analysis: SciPy, StatsModels
- Machine Learning: XGBoost, sklearn
- Visualization: Panel - Hvplot, Streamlit

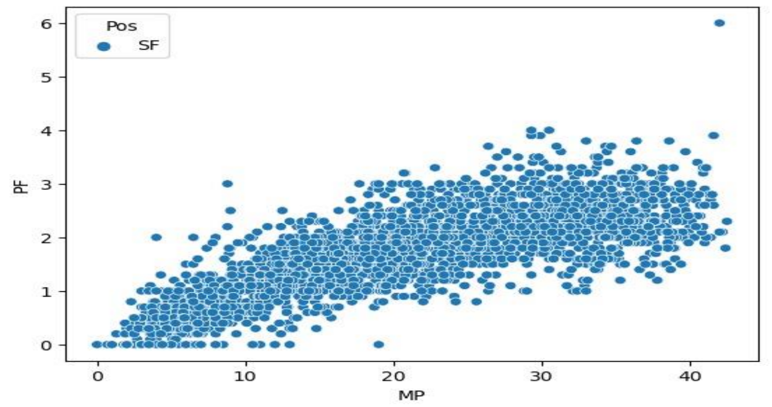
Steps followed : Data Collection → Data Preprocessing → Exploratory Data Analysis → Statistical Analysis and Regression Analysis → Predictive modelling → Testing and Validation → Data Visualization and Reporting

Results

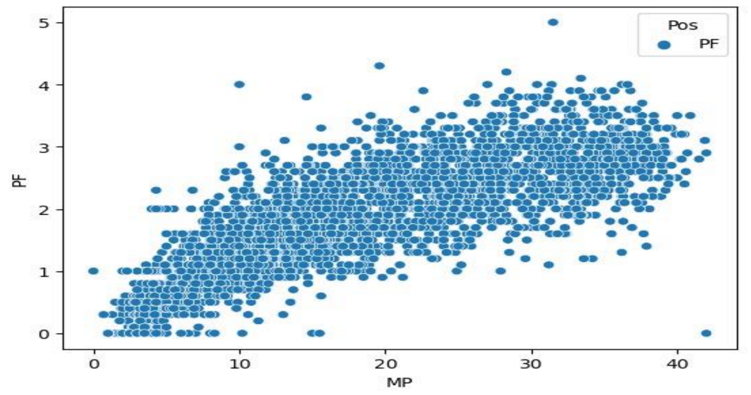
Graphs showcasing the univariate analysis results, including the distribution of TOV and PF across positions, and how MP varies by position.



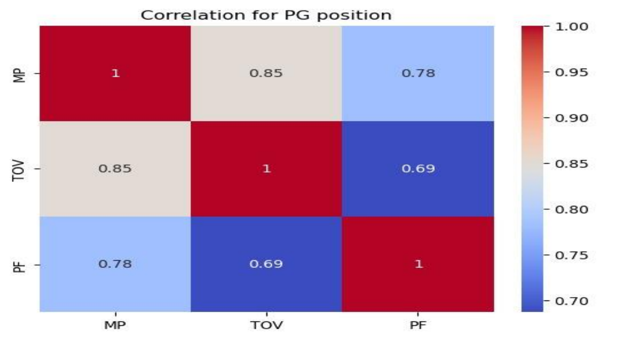


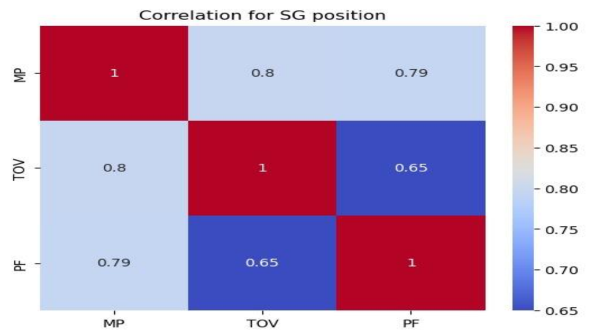


Scatter plots from the bivariate analysis, illustrating the positive relationships between MP and TOV, as well as MP and PF for each position.

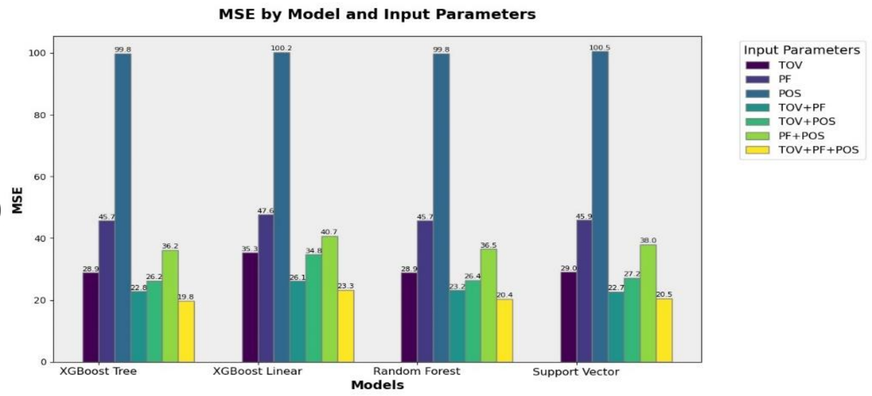


Visual representation of the correlation matrices, highlighting the strong correlations between TOV, PF, and MP, differentiated by player positions.





This chart displays the predictive accuracy of four machine learning models in estimating NBA players' minutes played. The models—XGBoost Tree, XGBoost Linear, Random Forest, and Support Vector—are evaluated by Mean Squared Error (MSE), with lower scores indicating better accuracy. Results show that combining turnovers (TOV) personal fouls (PF), and player positions (POS) as input factors yields the most accurate predictions across all models.



CONCLUSION

The study on the impact of turnovers and personal fouls on minutes played by position in basketball has provided valuable insights. Here are the key findings: Point guards are more likely to accumulate turnovers due to their ball-handling responsibilities, which can lead to decreased playing time. Centers tend to commit more personal fouls due to their defensive role, resulting in potential bench time. Shooting guards and small forwards have a relatively lower impact of turnovers and personal fouls on their playing time.

These findings highlight the importance of minimizing turnovers and personal fouls in order to maximize playing time and contribute effectively to the team's success.

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