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Week 11 Report

In this report, I evaluate the model approach and hyperparameters used in my fantasy football project to predict player fantasy points for the 2023 season. The goal of the project is to leverage historical performance data, including rushing yards, receiving yards, touchdowns, and other relevant metrics, to predict fantasy football outcomes. This report explores the model development process, hyperparameters evaluated, the performance metrics used for assessment, and the insights drawn from the model's results. The project code is structured to ensure clarity and reproducibility, with a focus on data preprocessing, feature engineering, and model evaluation. The dataset spans several years, with each year stored as a separate CSV file. After merging the data into a single cohesive dataset, extensive cleaning and preprocessing steps were applied. These included filling in missing values, removing duplicates, and standardizing columns to ensure consistency. Additionally, I created new features, such as total yards from scrimmage and touchdown efficiency, to provide the model with more meaningful inputs. Feature selection techniques were then applied to identify the most relevant predictors of fantasy points, streamlining the modeling process.

Key predictors in my model include rushing yards, receiving yards, total touchdowns, total yards from scrimmage, and games played. These features rank highest in importance because they directly correlate with fantasy points in most scoring systems. Other important predictors include average yards from scrimmage, receptions, and fantasy position, which provide additional context about a player’s role and performance consistency. This emphasis on core performance metrics ensures that the model aligns closely with real-world fantasy football scoring criteria. For example, rushing and receiving yards consistently drive predictions, as reflected in their top feature importance scores, while games played act as a stabilizing factor to gauge a player's availability and durability.

To further analyze the model’s predictions, I selected five random samples and explored how the model generated these outputs. In Sample 21, the model predicted 801.28 fantasy points compared to a true value of 868.0. This prediction was primarily influenced by the player’s rushing yards, receiving yards, and games played with touchdowns playing a secondary role. To achieve a closer match, the player’s receiving yards would need to increase by approximately 50 yards or their games played by one more. Similarly, in Sample 22, where the model predicted 353.29 versus a true value of 434.0, rushing yards and total touchdowns were key contributors, suggesting that adding one more touchdown or 70 additional rushing yards could significantly bridge the gap.

These analyses demonstrate the sensitivity of the model to variations in key predictors and provide actionable insights for refining predictions.

The dataset used in this project does not explicitly include protected categories such as race, gender, or age beyond a player's career stage (indirectly inferred from experience and age). However, it is worth noting that correlations may exist between player demographics and their performance metrics, which could inadvertently introduce biases. For example, positional tendencies in the NFL often align with specific demographic trends, potentially creating disparities in how certain positions are evaluated by the model. While these biases are not explicitly addressed in the dataset, their presence underscores the importance of scrutinizing feature correlations and the ethical implications of their inclusion in predictive models.

To mitigate potential biases, I explored bias removal strategies, including reweighting features and normalizing performance metrics across positions to ensure equitable evaluation. For instance, by standardizing predictions on a per-game basis, the model reduces the emphasis on cumulative totals that may penalize players with shorter seasons due to injury or other reasons. Additionally, I conducted a simulation to evaluate the impact of excluding games played from the feature set and observed that while the model's RMSE increased slightly, its bias toward availability decreased, offering a fairer assessment of player performance. Retraining the model with these adjustments revealed slightly reduced predictive power, as measured by a validation RMSE increase of 3.5%, but improved fairness metrics by accounting for variability in player availability.

Using this model in practice carries risks for stakeholders, particularly fantasy football managers. A key concern is the model's reliance on historical data, which may not capture emerging trends or outliers, such as a breakout season from a rookie or a player returning from injury. Additionally, overemphasis on games played could disadvantage managers who draft high-performing but injury-prone players, creating a bias toward durability over raw talent. Ethical considerations also arise when applying such models to broader contexts, such as player evaluations for contracts or public discourse, where predictions could inadvertently reinforce stereotypes or misrepresent individual potential. By addressing these risks and incorporating safeguards against bias, the model becomes a more responsible and accurate tool for its intended audience.

In conclusion, this report outlines the process of selecting and evaluating the best model for predicting fantasy football points using machine learning in Week 11. By focusing on relevant player statistics, adjusting key hyperparameters, and evaluating model performance through metrics like RMSE and R^2, I was able to identify the most accurate and generalizable model configuration. The insights gained from this analysis will be instrumental in improving future model development and can be applied to making more informed decisions in fantasy football leagues. Moving forward, additional refinements to the model, including feature engineering, per-game normalizations, and bias mitigation, may enhance its predictive power and reliability. I also believe that finding a way to number players, i.e. give each player a unique id, will help make this model extremely effective.