Fantasy Football Predictions

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***Abstract*—Picking the best Fantasy Football players is high stakes for many individuals. With the increasing popularity of punishments for the worst players in each league, it is more important now than ever to pick the best team. The goal of this paper is to outline a machine learning model that can accurately predict the best fantasy players for each week.**

I. OBJECTIVE

The primary goal of this project is to develop a machine learning model that can analyze historical and current NFL player data to predict the top Fantasy Football performers for each week. We plan to achieve this by obtaining game statistics for each current NFL player and defense. Initially, we aimed to use a dataset from Kaggle, but we later switched to using the nfl-data-py API as our main data source. After we obtain the data, we will clean it by removing players that we don't need. This will likely be defensive players, non-skill players, and retired players.

Once we sufficiently clean and format the data, we will apply it to various machine learning models to predict the top fantasy performers for each week and evaluate their performance. The models will take into account historical player data, the strength of the opposition's defense, and historical matchup performances. Once we find the best approach, we will spend the remaining time fine-tuning that model to try to achieve the best results.

We are able to examine the performance of our model by comparing it to the current NFL season, which will benefit our improvements process. Highlighting any shortcomings of changes that could improve the model performance and reliability.

II. MOTIVATION

Selecting Fantasy Football players each week holds a great deal of risk and can quickly become overwhelming for some players to do successfully. Augmenting Fantasy Football players with a machine learning model can greatly improve safety and chances of success. Helping players be safer and more confident in their choices can increase enjoyment as increased success rate is expected.

Furthermore, most Fantasy Football players are a part of Fantasy Football leagues, which often carry punishments for any players with underperforming rosters. Helping players be more competitive with the help of our model means that these punishments are avoided.

III. TECHNOLOGIES USED

There are several data processing and machine learning python libraries available that we leveraged for this project. We utilized `scikit-learn` to select and implement our machine learning algorithm. Given the extensive availability of good data, we will be opting to create a supervised model. After extensive testing, we decided to use a `Random Forest Regressor` due to its ability to handle complex data.

Additionally, we relied on data processing libraries such as `pandas` for its ease of use and modularity. We also utilized `Google Collab` for its free computational resources.

IV. DATASET AND PROCESSING

Data is gathered using a Python library dataset called `nfl-data-py`, which contains NFL statistics from the 1999 season to present. This dataset contains all statistics that are used in Fantasy Football, as well as detailed player and team information. It is continually updated, ensuring that the statistics are never out of data. A significant amount of data cleaning was required to make this dataset viable, because there were a lot of useless and outdated statistics.

We decided to use data from the 2022 to 2024 seasons, since statistics before that had no relevance to modern day Fantasy Football. Additionally, a substantial amount of data unrelated to Fantasy Football had to be filtered out. We also had to consider data values, as not every statistic is worth the same in Fantasy Football, such as rushing and receiving touchdowns being worth more than passing touchdowns.

We also wanted to incorporate non statistical metrics. The opposition team and the coaches are all used. This allows for more information about strategic tendencies or possible matchups to be incorporated.

After processing the data, each of our data entries includes the player, their statistics for that game, information about the game itself, and team-specific details (e.g., coaches). In total, we included 447 active players and 735 games.

Additionally, two embeddings were created. The first, a player embedding, is used to capture player-specific performance trends and context. The second, a team embedding, which helps represent team-level performances and strategies. We chose to use two embeddings to allow the model to distinguish between player performances and how well they do in certain situations.

V. Model

Our model is trained using a Random Forest regressor with 100 trees using the processed game data and both embeddings. We then save this model to be used for our predictor.

The predictor then automates a lot of the information needed to use our model. It takes advantage of embeddings, saved information about the schedule, and coaches. A user can input which week they want to see predictions for in the current NFL season, then top predictions for each position will be given, and a CSV file of all active player predictions can be made. This is the main use case right now, but it is possible to make shell scripts or modifications to the code to help get the desired information.

VI. Results

Overall, when evaluating using normal metrics, the results were average, showing both signs of promise and disappointment. From the MAE, we expect that the predictions will be about three points off their real value. However, this changes from position to position. This is because some positions, like QB and WR, have a higher variance and standard deviation from player to player and week to week.

We believe that the best way to see how it works is in real time. Luckily, the NFL season is taking place over the course of this project, so this can be used to test its effectiveness. The following section examines the performance of our model for week 12 of the 2024 NFL season.

VII. Prediction vs. Actual

To evaluate the performance of our model, we compare the predicted values for various players to their actual performance in week 12 of the 2024 NFL season. This comparison allows us to assess the actual performance and reliability of our model. By examining these results, we can assess how well our model performs in a variety of circumstances.

```
Position: WR
           player_name team opponent_team  predicted_ppr
8         Keenan Allen  CHI           MIN      32.687064
143   Justin Jefferson  MIN           CHI      26.164850
146        CeeDee Lamb  DAL           WAS      22.404945
97        Jakobi Meyers   LV           DEN      20.985893
72         Cooper Kupp   LA           PHI      18.850612
```

Fig. I: WR Predicted Labels 2024 Week 12

Player	Points
Kennen Allen	23.6
Justin Jefferson	4.7
CeeDee Lamb	16.8
Jakobi Meyers	22.1
Cooper Kupp	20.0

TABLE I. WR Actual Results 2024 Week 12

```
Position: QB
         player_name team opponent_team  predicted_ppr
148      Jalen Hurts  PHI            LA      25.789552
327           Bo Nix  DEN            LV      21.121433
90     Lamar Jackson  BAL           LAC      19.915757
67   Patrick Mahomes   KC           CAR      18.158727
105     Kyler Murray  ARI           SEA      17.343212
```

Fig. II: QB Predicted Labels 2024 Week 12

Player	Points
Jalen Hurts	15.1
Bo Nix	19.4
Lamar Jackson	22.6
Patrick Mahomes	28.8
Kyler Murray	10.3

TABLE II. QB Actual Results 2024 Week 12

```
Position: RB
        player_name team opponent_team  predicted_ppr
58     James Conner  ARI           SEA      25.263900
36    Derrick Henry  BAL           LAC      21.847417
50      Aaron Jones  MIN           CHI      21.813655
199     Jerome Ford  CLE           PIT      20.074600
122     Josh Jacobs   GB            SF      19.859817
```

Fig. III: RB Predicted Labels 2024 Week 12

Player	Points
James Conner	9.9
Derrick Henry	14.0
Aaron Jones	19.9
Jerome Ford	3.7
Josh Jacobs	DNP

TABLE III. RB Actual Results 2024 Week 12

```
Position: TE
         player_name team opponent_team  predicted_ppr
307     Brock Bowers   LV           DEN      22.443000
80    Dallas Goedert  PHI            LA      18.608708
10      Travis Kelce   KC           CAR      15.900848
68      David Njoku  CLE           PIT      14.304217
83   Dalton Schultz  HOU           TEN      13.175133
```

Fig. IV: TE Predicted Labels 2024 Week 12

Player	Points
Brock Bowers	7.8
Dallas Godert	5.9
Travis Kelce	12.2
David Njoku	3.9
Dalton Schults	4.0

TABLE IV. Tight End (TE) Actual Results 2024 Week 12

In general, the predictor gives mixed results. Player predictions vary from week to week, indicating that the model is adjusting based on matchups, which is ideal. The model exhibits enough accuracy and insight that should help provide value to fantasy managers. Helping them decide whether to start or sit a particular player.

However, there are clear issues. The model struggles to account for a team's offense not performing for a week, which was evident in the case of Justin Jefferson, who underperformed. It also struggles to predict the impact of injuries, as seen with Josh Jacobs, who was marked as `"Did Not Play" (DNP)` and thus could not contribute. In addition, the model has difficulty accounting for player regressions of the season. Ezekiel Elliot, who was predicted to score 12 points but ended up with 0.6, exemplifies this. Backup players who may start due to injuries on the team are also difficult to predict and are ignored by the model.

VIII. Challenges

There are many challenges that we encountered when attempting a project like this, which are faced by many other Fantasy Football prediction systems. The most significant challenge lies in the inherent unpredictable nature of football that makes predicting statistics exceptionally difficult. There are many minute factors and situations in football that can drastically alter a player's performance. An unexpected bounce of the ball, a gust of wind affecting a pass, or even a questionable referee call can all play a role in a player's performance. These seemingly insignificant and unpredictable events make it nearly impossible to accurately forecast performance across the board.

Another challenge we faced early on was balancing the use of historical data and current trends. The nature of Fantasy Football forces us to strive for a perfect balance between understanding historical performances of players and recognizing the evolving state of the game. Our dataset spans back until 1999, which means that there is a great deal of noise that is of no real use to the model. The game has evolved greatly since 1999 and finding the right amount of past seasons to include required some testing. After considerable deliberation, we decided to include only the previous three seasons in our model. We felt that any data prior to this window were simply not relevant enough and would negatively impact our model's performance and reliability. However, limiting our dataset in this way introduced its own challenges. Identifying trends and patterns is simply more difficult with less data, but our model performed better with these settings. With exceptions such as Ezekiel Elliot, whose performance has rapidly decreased over the last three seasons.

Finally, it is impossible for our model to account for unpredictable events. Injuries, changes in team's dynamics, and new coaching staff are all incredibly difficult to predict and contribute to the challenge of building a truly accurate Fantasy Football prediction system.

IX. Responsibilities

- **Fort Hunter: Data collector** — Responsible for collecting raw data and developing the methods to store it.
- **Dillon Frankenstein: Data Cleaner** — Responsible for cleaning the data, which includes removing unnecessary statistics and players, as well as formatting the data for compatibility for the model.
- **Vincent Broda: Model Creator** — Responsible for designing the machine learning model to calculate statistics and generate an accurate fantasy score prediction.
- **Austin Smith: Model Optimizer** — Responsible for optimizing the machine learning model and ensuring it is effective and efficient.

X. Future Work

There are several avenues for improving the model that could improve its accuracy. One key area is incorporating additional game data such as location, weather, and officiating. Originally, we even had officials included in the embeddings, but this was removed as there were complications with this prediction step and a time constraint. Future work could revisit this area and potentially refine the approach.

Injuries also represent a significant gap in the current model. Currently, the model does not account for players who are inactive, leading to false predictions. Additionally, backup players for injured players are underestimated. A potential solution to this may be adding an additional step to the prediction process that considers both previously predicted scores and adjusts for backup players' usage. This adjustment would benefit the reliability of the model and would better reflect players' statistics.

Another important improvement is the inclusion of kicker and defensive point predictions. The idea for this is straightforward, but challenges arise due to lack of direct kicker statistics in the API we currently use. Further development in this area could turn out to be very fruitful for a more expansive prediction system.

To address the issue of balancing between historical and current trends, we also plan to experiment with creating embeddings for historical and current season data. This approach would allow us to further tune the relative weight of each data type, allowing us to optimize for a more current balance. By adjusting these weights, we hope to improve the model's adaptability to player performance changes over time.

Finally, enhancing the overall usability of our model remains paramount. Currently, our pipeline is easy to use and provides useful information to users. However, repeated and prolonged use can be a bit tedious. To address this, we plan to implement features that streamline the process and align more with our original goal of delivering a user-friendly application.

XI. Organization Chart

October 20 — Initial exploration of Kaggle data and an early model was created. This phase primarily served as a test and practice run, focusing on identifying key features that could be refined later on.

October 22 — A transition to using nfl-data-py as the primary data source. A new predictor script was created to show a proof of concept, showcasing how this data source could be used.

November 14 — Significant progress on the pipeline and model was made. This period included evaluating relevant statistics and determining useful data points.

November 17 — The pipeline was finalized. This includes data collection from the API, data processing (up to the embeddings), model training, and predictions.

November19 — Final round of smaller fixes and refinements were made to the pipeline. Focus on polishing the system and preparing it for the presentation.

November 21 — Presentation of the project.

December 7 — Final Paper was Finalized.

REFERENCES

[1] Funk Monarch, "NFL statistics 2012-2023," Kaggle, https://www.kaggle.com/datasets/philiphyde1/nfl-statistics-1999-2022 (accessed Sep. 26, 2024).