Predictive Analytics for the Fantasy Football Draft

Team 127 - Alex Haan, Venkata Ale, Brent Speelman, Jesse Keith, Nandhini Soundaiah

Introduction

Fantasy Football (FF) is a game in which players act as virtual general managers and owners of National Football League (NFL) teams. Competitors select virtual teams from within the actual player-pool of the NFL and score points corresponding to the actual performance of their selected players during the NFL season. FF is a very popular game and the ability to gain a competitive advantage is potentially lucrative to competitors. For reference, 45.9 million adult Americans are estimated to have participated in the game in 2019 [1], and in the same year the size of the American and Canadian fantasy sport industry was estimated to be $7 billion [2]. The goal of this project is to leverage the power of data and machine learning to develop a tool that will give FF competitors a competitive advantage when selecting players by better predicting the performance of football players during the upcoming season.

Problem definition

Jargon-free Definition: To start each season in FF, all entrants in a fantasy league conduct a live draft to select their players for the upcoming season. During the draft, competitors generally have 1 to 2 minutes to make a selection, and each competitor will be expected to make approximately 16 selections over the course of the draft. Each selection will be influenced by the selections made by preceding competitors, each of which reduces the remaining player-pool. The competitors who are able to select the football players who subsequently perform the best during the NFL season will have a winning advantage. This means FF competitors are attempting to make a number of predictions of future player performance in a shifting and time-constrained environment. In this situation, the computation speed of a computer-based tool and the predictive capabilities of machine learning algorithms could provide a competitive advantage against human players.

Formal Definition: The goal of FF competitors is to select the set of players that will have the best performance statistics in the upcoming NFL season, with the competitor whose set of players achieves the best performance statistics winning the pool. Therefore, the goal of the competitors is to have the highest level of prediction accuracy of future football player performance statistics. This accuracy can be measured in absolute terms by using metrics that compare predicted performance against actual performance, such as mean absolute percentage error (MAPE), but also in relative terms which compare the performance of one predictive method against another. For example, ESPN provides NFL player rankings that competitors can use to select their fantasy team. For a machine learning model to be useful it would need to provide higher accuracy beyond these existing and readily available methods. The goal of this project is to develop a machine learning model and visual interface that provides competitors with that advantage. Our methodology for design and validation is detailed in this report.

Literature Survey

To determine the best approach for this project, our group conducted a survey of the literature for predicting professional sports statistics, and for ranking fantasy sports players. Several approaches to selecting fantasy players have been proposed. Linear optimization methods using fantasy website rankings have been used for selections. However, the algorithm did not incorporate historical player data [*3*] while another did not use modern programming platforms [*4*]. However, these studies did show the utility of analytic approaches to player selection, and their shortcomings point to improvements that our project will incorporate. Gradient boosting techniques have been used for fantasy soccer [*5*] using multiple datasets (which our proposed method will incorporate), but this study was evaluated against purely random player selection rather than the method more commonly used by competitors, such as ESPN player rankings. Player recommendations have been determined by investigating correlations between complimentary players [*6*]; an approach we hope to investigate during the modeling phase of our project. Although we propose to visually show choices of players to draft, we propose a more varied dataset, rather than proprietary rankings from a single site. Variance of provided rankings has been used to optimize player selection [*7*], and this derivative feature may show utility for our study. This study, though, showed only marginal improvement of a random team, in contrast to our proposed use of historical data (rather than fantasy league data alone).

Objective information for competitors playing FF is crucial for engagement and enjoyment [*8, 9*], as with applications beyond sports in the real world [*10*]. Still, our project proposes more robust procedures, rather than presupposed distributions or vague approaches to algorithmic player selection, which we hope to enable competitors to visualize. The strength of schedule during a season for an NFL team was used in one study to assign the expected value of each play of a game [*11*]. Although this approach used video game simulations to calculate some transition probabilities, the strength of schedule could be incorporated as a feature for our investigation. Linear regression was used to determine the value of rookie players in the actual NFL draft [*12*]. Our proposal could also use similar methods for evaluation of rookies for the draft, although the study was not optimized for fantasy points. Also, the environment that a player finds himself in can be crucial to performance, whether for choosing players for fantasy soccer [*13*] or measuring overall productivity of NFL players [*14*]. However, these studies lacked rigorous machine learning modalities. Hockey players were placed in performance tiers rather than given individual rankings [*15*]. Six machine learning methods were used with the Bayesian method performing the best. However, defensive players were not amenable to accurate classification. The position and movement data of NFL players was used to evaluate quarterback decision making at the point of pass release [*16*]. Although innovative, this data is proprietary and not available for predictive studies. The effects of injury were also investigated

[17], particularly concussions. This will also be investigated in our study, although this paper focused on the prevalence of machine learning methods rather than the performance.

Plan of Activities

Our team has progressed the project according to the plan of activities outlined in our project proposal. The project team has been meeting 1-2 times per week to coordinate activities. Both our original(left) and final(right) activity plans are shown below to quantify progress and distribution of work.

Proposal Plan / Completed Plan

TASK	ASSIGNED TO	PROGRESS	START	END
Research and Planning				
Project Ideas Brainstorm	All	100%	2-1-22	2-10-22
Project and Data Source Research	All	100%	2-10-22	2-24-22
Project Proposal	All	50%	2-24-22	3-4-22
Proposal Presentation	Alex	20%	2-24-22	3-4-22
Data Gathering & Design				
Data Gathering	Alex	0%	3-5-22	3-15-22
Data Cleaning	Venkata	0%	3-16-22	3-21-22
Create sample vizualizations and app layout	Alex	0%	3-16-22	3-21-22
Progress Report	Brent	0%	3-25-22	4-1-22
Implementation				
Build and test algorithm(s)	Nandhini	0%	3-22-22	3-27-22
Link algorithms to vizualization in app	Jesse	0%	3-28-22	4-2-22
Run test draft	Venkata	0%	4-3-22	4-5-22
Adjust and Revise	Nandhini, Brent	0%	4-6-22	4-11-22
Poster Presentation Video	Jesse, Alex	0%	4-12-22	4-22-22
Final Report	Brent, Satwik	0%	4-12-22	4-22-22

TASK	ASSIGNED TO	PROGRESS	START	END
Research and Planning				
Project Ideas Brainstorm	All	100%	2-1-22	2-10-22
Project and Data Source Research	All	100%	2-10-22	2-24-22
Project Proposal	All	100%	2-24-22	3-4-22
Proposal Presentation	Alex, Nandhini	100%	2-24-22	3-4-22
Data Gathering & Design				
Data Gathering	Alex	100%	3-5-22	3-15-22
Data Cleaning	Venkata, Alex Jesse	100%	3-16-22	3-21-22
Create sample vizualizations and app layout	Alex	100%	3-16-22	3-21-22
Progress Report	Jesse, Brent	100%	3-25-22	4-1-22
Implementation				
Build and test algorithm(s)	All	100%	3-22-22	3-27-22
Link algorithms to vizualization in app	Alex	100%	3-28-22	4-2-22
Run test draft	Jesse	100%	4-3-22	4-5-22
Adjust and Revise	All	100%	4-6-22	4-11-22
Poster Presentation Video	Venkata	100%	4-12-22	4-22-22
Final Report	Brent, All	100%	4-12-22	4-22-22

Note: all members have contributed a similar amount of work.

Proposed method

As outlined in the Literature Survey, our group has proposed to go beyond other fantasy ranking methods in several key areas. Our proposed method is outlined below.

Data

One area where our method has improved upon other existing FF ranking methods is in the use of a more expansive dataset. Our approach has focused on using past player performance to predict future player performance. To achieve this, we gathered a comprehensive dataset of NFL player statistics from 2010-2021. This data gathering was done using a combination of downloading available datasets from FF Data Pros [*18*] and scraping from online sites including Strength of Schedule [*19*], Average Draft Position [*20*], Player Age [*21*], 2021 Stats [*22*], and 2021 Targets [*23*]. The scraping scripts were written in Python using the Beautiful Soup library. Once the data was gathered, our group used Python along with the Pandas library to prepare the data for modeling. Our data sources are listed below in the Data References section.

Modeling

Another key innovation of our approach to fantasy ranking is the investigation of custom metrics for cross-validation and testing. The primary goal of this study is to provide a ranking of players, not necessarily to predict the overall fantasy points for the season (although this is used to perform the ranking). Consequently, a custom metric derived from normalized discounted cumulative gain (NDCG) that evaluates the quality of the ranking, is used for optimizing the hyperparameters of each method. In some cases, the 5-fold cross-validation (CV) is also evaluated with mean absolute percentage error (MAPE) rather than mean squared error. Since MAPE is a percentage, it is useful for comparing models using datasets of different sizes. Our training set consists of years 2010 to 2020, our test set uses 2021, and our final validation will be for the future 2022 season. Additionally, we investigate a *hyper*-grid search using different data preprocessing steps: Cook's distance for outlier removal, the Box-Cox transformation of the response, principal component analysis (PCA) of the features, a minimum fantasy point cutoff (to filter data points with a low response value), and a filter to evaluate one year of past data rather than three years. First the preprocessing steps are set and then CV is performed for each modeling method. We investigated elastic net regression, random forest and gradient boosting using the preprocessing grid search.

Not only is the quality-of-ranking metric used for cross-validation, it is also used for evaluating the 2021 test data with the following: abs($rank_{actual} - rank_{predicted}$)$/log_{10}(w + 1)$. The w represents weights (1st-5th: 1, 6th-10th: 2, 11th-15th: 4, 16th-20th: 8, and >20th: 16) and reduces the error for lower rank positions while rewarding correct predictions for the top players.

Visualization

Our project aims to improve on existing fantasy draft methods by providing competitors with an interactive visualization interface that provides key data insights for making the best choices, as well as a tool that adjusts in real-time to the draft selections made by other competitors [24]. Our team has chosen to use Tableau as our visualization platform since, as our medium for visualization, it allows for high levels of customizability; we can present the view we think will be most useful in a time-sensitive process such as the FF draft. We wanted users to be able to quickly identify the information they might need and facilitate faster decisions.

Experiments/ Evaluation

Table 1 shows the characteristics of the best performing models for each position. Elastic Net (EN) and Random Forest (RF) are represented, each with different preprocessing and filters. This displays the utility of investigating multiple models–models custom fit for each position.

Table 1: Best Models, Metrics, Preprocessing, and Filters for each Position

Position	Preprocessing			Filters		Model
	Cook's	Box-Cox	PCA	Years past data	Point cutoff	
QB	False	False	True	1	150	EN
RB	True	False	True	1	50	RF
WR	False	False	False	3	150	RF
TE	True	True	False	3	9*	EN

*for the position of TE, the average fantasy points per game were used rather than the total

Perhaps the most common selection method for FF competitors is to use the rankings provided by online resources, with the most popular of those being ESPN. In order to quantify the upside of our methodology, our final ranking algorithm was tested against the ESPN and FantasyNerds ranking for the recently completed 2021 NFL season as shown in Tables 2 and 3.

Table 2: Comparison to ESPN and FantasyNerds–Sum of 2021 Season Points

Position	Grouping	Team 127 Points	ESPN Points	Fantasy Nerds Points
Running Back	T12	2,734	2,735	2,681
	T24	4,728	4,631	4,526
Quarter Back	T12	4,254	4,478	4,073
	T24	6,841	6,863	7,114
Wide Receiver	T12	3,042	2,613	2,616
	T24	5,391	5,237	5,103
Tight End	T12	1,945	1,803	1,999
	T24	2,889	2,933	2,933

Table 3: Comparison to ESPN and FantasyNerds–2021 Ranking Error

Position	Grouping	Team 127 Error	ESPN Error	Fantasy Nerds Error
Running Back	Top 12	193.50	320.49	346.40
	Top 13:24	142.18	186.73	186.10
Quarter Back	Top 12	234.39	157.98	154.55
	Top 13:24	80.46	80.04	75.35
Wide Receiver	Top 12	298.33	486.12	454.44
	Top 13:24	92.36	197.87	210.67
Tight End	Top 12	126.95	153.69	146.13
	Top 13:24	149.66	109.96	114.20

Table 2 shows the sum of the top 12 or 24 players' fantasy points for the season (larger values are better). Table 3 uses the quality-of-ranking method discussed above to calculate an error value. Considering the actual ranking order, Table 3 shows that our modeling outperformed ESPN and FantasyNerds for running back (RB), wide receiver (WR) and tight end (TE) . In fact, RB and WR had at least a 40% reduction of error when compared to the other online resources with the top 12 players considered. Table 2 (considering the sum of player's points) shows that our model outperformed ESPN for 24 players and FantasyNerds for 12 and 24 players at RB. For WR, Table 2 shows outperformance of both ESPN and FantasyNerds. Both Tables show that our model did not perform as well for QB; however, accurate predictions for RB and WR are most critical to a successful fantasy football draft given they generally have higher draft positions [20]. To enhance the user-experience of this data during a fantasy football draft, a Tableau dashboard was created. Our tool conveys powerful decision-making insight to users: top picks for each position and tooltips with relevant player statistics. Given the tight timelines of a FF draft, the dashboard allows intuitive player exclusion (as they are drafted) and quick, one-on-one, player comparisons.

Conclusions & Discussion

One novel finding is that for each position the best performing models seem to require different amounts of historical data. The position QB and RB only needed one season of statistics to create the model—the initial model started with approximately one-third of the statistical features. It seems to be analogous to a memoryless process, where the fantasy points for these positions only depend on one season's performance with memory of prior seasons having diminutive relevance. However, WR and TE (both positions gain fantasy points similarly) used models requiring the past three seasons of data.

The common theme among all of these techniques is to strive for the simplest model possible to optimize predictive performance while avoiding overfitting. For the running back random forest model, PCA was used as a preprocessing step. PCA, by finding the linear combinations of features with the maximum variance, provides to the random forest algorithm new features ready made for efficient splitting. Additionally, when PCA was incorporated, only the 15 features with the largest variance were used, a reduction of features from 165 to 15. The random forest method additionally reduces complexity by constraining the depth of each tree. The fantasy point cutoff for data points also acted to simplify the dataset by filtering noisy (insignificant to the top ranks) players from the models.

Both the quarterback and tight end models used Elastic Net, a technique using regularization to simplify overly complex models. The geometry of the constraint in parameter space allows for feature reduction as the coefficients of some features go to zero; however, Elastic Net's combination of Lasso and Ridge regression gives better results with possibly correlated features.

Note: all team members have contributed a similar amount of effort.

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