NFL Fantasy League Draft Optimizer

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1 Introduction

Drafting in fantasy football is traditionally guided by lists derived from consensus rankings, Average Draft Position (ADP) values, and Value Over Replacement Player (VORP) metrics. These methods, however, treat the draft as a static process, ignoring the impact of opponent strategies and the multidimensional risks associated with player performance. The goal of this project is to develop an adaptive, data-driven NFL Fantasy Draft Optimizer that captures dynamic drafting behavior and uncertainty. By combining predictive modeling, behavioral insights, and interactive visualization, the system aims to assist users in making more informed and competitive draft decisions.

2 Problem Definition

The central question is how to improve fantasy football drafting by utilizing machine learning at a holistic level of the game. The goal is to account for both the uncertainty in player performance and the strategies employed by opponents, thereby constructing teams that maximize expected value while satisfying positional and roster constraints. Let $\mathcal{P}$ be the set of all draftable players, and Π the set of valid drafting strategies. The goal is to select a strategy $\pi^* \in \Pi$ that maximizes the expected team utility:

$$\pi^* = \arg\max_{\pi \in \Pi} E[U(T(\pi), O, I)]$$

where:

- $T(\pi)$ is the team constructed under strategy π.
- O represents opponent behaviors.
- I represents stochastic factors such as injuries or performance variance.
- $U(T, O, I)$ is a utility function combining projected points, positional balance, and risk-adjusted value.

The strategy must satisfy roster constraints:

$$T(\pi) \subseteq \mathcal{P}, \quad |T(\pi)| = N, \quad \text{Positional requirements satisfied.}$$

This formalization captures the sequential, stochastic, and constrained nature of fantasy football drafts, explicitly modeling round-by-round dependencies, opponent strategies, and uncertainty in player outcomes.

3 Literature Survey

Prior research in fantasy football analytics has explored a variety of predictive, optimization, and behavioral techniques. Romer [1] demonstrated decision-making inefficiencies in professional football, highlighting the limitations of heuristic strategies. Yurko et al. [2] introduced *nflWAR*, a wins-above-replacement metric derived from play-by-play data using regression-based approaches, which outperforms expert consensus rankings in player projection accuracy but primarily focuses on team-level aggregation.

Predictive modeling for fantasy points has employed multiple machine learning techniques. Lutz [3] applied Support Vector Regression and Neural Networks to forecast quarterback performance, while Morgan et al. [4] used Lasso and Random Forests to identify undervalued players, incorporating salary considerations. Landers and Duperrouzel [5] extended decision-tree and perceptron-based models to all positions, though without explicit attention to draft order. Paramarti and Li [6] demonstrated that collaborative filtering improves quarterback predictions, but their scope was position-specific.

Optimization studies have incorporated draft dynamics and constraints. Becker and Sun [7] formulated a mixed-integer optimization model considering draft order and positional requirements, though excluding injury risk. Fry, Lundberg, and Ohlmann [8] proposed a dynamic stochastic programming approach for competitive drafting, albeit under simplifying assumptions. Behavioral analyses reveal systematic biases in drafting: Lee and Liu [9] documented herding behavior and positional preferences, while Burgess et al. [10] linked medical data, such as ACL reconstruction outcomes, to fantasy performance.

Foundational methodology for this project is drawn from the Mixture of Experts (MoE) framework [11], wherein specialized models are coordinated by a gating network to handle heterogeneous tasks more effectively than a single monolithic model. Perin et al. [12] explored interactive visualizations for sports analytics, informing ways to incorporate user feedback and interactivity into modeling.

4 Proposed Method

Our draft optimizer advances the state of the art by integrating position-specific expert models, a gating network for dynamic expert selection. The system is built upon a Mixture of Experts (MoE) architecture. Each expert is trained on position-specific data using Random Forest and various regression techniques, while the gating network outputs weights determining the influence of each expert based on contextual inputs such as the current draft stage, positional scarcity, and opponent tendencies. The overall prediction for a player is computed as a weighted sum of expert outputs:

$$y = \sum_i G_i(x)E_i(x)$$

where $G_i(x)$ are the gating weights and $E_i(x)$ the expert predictions. The optimizer dynamically updates as players are drafted, maintaining projections for the remaining options.

Data integration extends previous work by combining player performance statistics, medical data including injury history and recovery metrics, and behavioral tendencies. Unlike static approaches, our model dynamically adjusts injury risk estimates in response to draft context.

The user interface provides visual dashboards, following the approach of Perin et al., that illustrate team composition, positional scarcity, and real-time draft recommendations, while alerting users to herding effects or gaps in player value all while providing the commonly found statistics of other draft tools available. If time allows, we will expand to aim for other projects past fantasy points accrued such as yardage, interceptions, etc.

We have had significant challenges in gathering behavioral data for draft fantasy applications, although we can approximate using other behavioral studies and data that are relevant. We have also struggled with comprehensive injury data. The few datasets readily available are limited in scope or length, and the websites with detailed databases over the course of many years have advanced bot detection and prevention measures built in to prevent scraping the data. We have reached out requesting the data for educational purposes, but none have responded positively thus far. We plan to compile a few years worth of data manually to compensate.

All team members contributed a similar amount of effort to this project.

5 Evaluation

Evaluation will be conducted using historical and current NFL fantasy drafts. Metrics to evaluate the optimizer include projected points, playoff qualification rates, win rates, and championship outcomes. User satisfaction and perceived fairness will also be evaluated during interactive testing among ourselves and peers. We are also exploring simulating NFL seasons, effectively creating synthetic data to use for testing. The experimental design includes comparing drafts guided by the optimizer against baseline strategies derived from ADP and consensus rankings and assembling teams at random. Monte Carlo simulations will test robustness against injuries, trades, and breakout performances. Additionally, ablation studies will measure the individual contributions of the gating network and behavioral modeling components. Results are pending full implementation.

6 Conclusions and Discussion

This project proposes an adaptive NFL Fantasy Draft Optimizer that integrates predictive modeling, behavioral analytics, and user interactivity into a unified system. The approach advances the field by modeling opponent dynamics and injury risk in real time, leveraging a Mixture of Experts architecture to enhance predictive flexibility, and combining statistical optimization with user-centered design. Limitations include potential sensitivity to unpredictable injuries, trades, or emergent breakout players. Future work could incorporate reinforcement learning for strategy optimization or integration with live fantasy draft APIs, advanced injury data and using player tracking data that is currently not publicly available.

Project Title	NFL Fantasy League Draft Optimizer Using Mixture of Experts				
Interface & UX	Seth Shirley (Team Contact)				
Data Engineers	Mac Sanders, TJ McCoy				
Analysts	Rich Yones				
Milestone	**Task**	**Owner**	**Start**	**End**	**% Complete**
1	**Project Initation & Proposal**				
1.1	Team Formation	Seth	8/20	9/19	100%
1.1.1	Dataset Selection	Team	8/26	9/1	100%
1.2	Scope & Timeline	Team	9/1	9/15	100%
1.3	Proposal Draft & Slides	Team	9/15	10/1	100%
1.4	Prop. Recording & Submission	Seth	10/1	10/3	100%
2	**Data Exploration & Inital Analytics**				
2.1	Explore & Cleansing	Mac & TJ	9/23	10/10	50%
2.2	Analysis & Early Modeling	Rich & Seth	10/1	10/15	15%
2.3	Stakeholder Assessment 1	Team	10/20	11/1	0%
2.4	User Interface Framework	Seth & Rich	10/27	11/2	0%
2.5	Progress Update & Submission	Team	10/23	10/26	0%
3	**UX/UI & Model Finalization**				
3.1	Data Cleansing Finalized	Mac & TJ	11/3	11/9	0%
3.2	Data Modeling Finalized	Rich, Mac, TJ	11/7	11/12	0%
3.2.1	User Interface & Viz Finalized	Seth & Rich	11/7	11/12	0%
3.2.2	Stakeholder Assessment 2	Team	11/12	11/13	0%
3.3	End to End Test & Review	Team	11/13	11/14	0%
4	**Final Presentation & Submission**				
4.1	Poster & Report Creation	Team	11/2	11/11	0%
4.2	Presentation Recording	Team	11/11	11/14	0%
4.3	Final Submission	Seth	11/14	11/14	0%
4.4	Project Review	Team	12/2	12/5	0%

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2	**Data Exploration & Inital Analytics**				
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2.2	Analysis & Early Modeling	Rich & Seth	10/1	10/15	100%
2.3	Stakeholder Assessment 1	Team	10/20	11/1	100%
2.4	User Interface Framework	Seth & Rich	10/27	11/2	85%
2.5	Progress Update & Submission	Team	10/23	10/26	100%
3	**UX/UI & Model Finalization**				
3.1	Data Cleansing Finalized	Mac & TJ	11/3	11/9	95%
3.2	Data Modeling Finalized	Rich, Mac, TJ	11/7	11/12	75%
3.2.1	User Interface & Viz Finalized	Seth & Rich	11/7	11/12	50%
3.2.2	Stakeholder Assessment 2	Team	11/12	11/13	0%
3.3	End to End Test & Review	Team	11/13	11/14	0%
4	**Final Presentation & Submission**				
4.1	Poster & Report Creation	Team	11/2	11/11	20%
4.2	Presentation Recording	Team	11/11	11/14	0%
4.3	Final Submission	Seth	11/14	11/14	0%
4.4	Project Review	Team	12/2	12/5	0%

Figure 1: Plans of Activities: (Top) Original, (Bottom) Updated

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