NFL Fantasy League Draft Optimizer Using Mixture of Experts

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Introduction and Background [HQ1, HQ2]

Drafting in fantasy football is currently dominated by lists derived from consensus rankings and Average Draft Position (ADP) values and Value Over Replacement Player (VORP). These methods treat the draft as a static process, ignoring both opponent strategy and multidimensional risk. Research in decision-making highlights the limitations of such heuristics. Romer [1] demonstrated that even professional coaches often fail to maximize value when compared to data-driven strategies, but limited scope to only options during fourth down. Yurko, Ventura, and Horowitz [2] introduced nflWAR, a wins-above-replacement metric derived from play-by-play data by focusing on Regression based approaches, which have been shown to outperform expert consensus rankings in player projection accuracy, but failed to measure individual performances in certain aspects of the game and focused on team aggregation. Lutz [3] tries to predict Quarterback Fantasy points via Support Vector Regression and Neural Networks, while Morgan et al. [4] employed Lasso and Random Forest regression to identify undervalued players integrating a player salary component; however, each restricted research to a subset of all draftable positions. Landers and Duperrouzel [5] applied decision trees and perceptron-based models holistically to all draftable positions, but without explicit attention to draft order dynamics. Paramarti and Li [6] demonstrated that collaborative filtering improved fantasy point predictions for quarterbacks specifically, again, reducing scope to one position only. Optimization studies by Becker and Sun [7] utilized mixed-integer optimization that took into account all positions and draft dynamics, but suffers from not including injury risk. Fry, Lundberg and Ohlmann [8] created a competitive drafting strategy via a dynamic stochastic program, but introduced many restrictions and assumptions into their work in order to solve it. Lee and Liu [9] revealed that drafters generally follow predictable positional patterns, with evidence of herding behavior when early picks influence subsequent selections, but they did not take into account draft order. Meanwhile, Burgess et al. [10] directly linked ACL reconstruction outcomes to fantasy production, establishing how medical data can be mapped onto fantasy scoring, but constrained their research to a specific injury type.

Proposed Approach [HQ3]

Our contribution is the development of an adaptive NFL Fantasy Draft Optimizer based on the Mixture of Experts framework. Bishop [11] formalized MoE architectures as ensembles of specialized models coordinated by a gating network and how they can outperform singular models. We plan to train position-specific experts with each model learning distinctive attributes such as yardage projections, touchdown likelihood, volatility, and injury sensitivity. A gating network then selects the appropriate expert given the draft context, enabling heterogeneous tasks to be handled more effectively than a monolithic recommendation model.

The optimizer will also be based on a more comprehensive dataset that aims to capture as much complexity in NFL games and drafting dynamics as possible. First, it incorporates medical

data into projections by extending prior retrospective analyses of injury outcomes into dynamic forecasts that adjust player risk over the course of a season. Second, it leverages behavioral findings by detecting herd effects and alerting users when opponents' strategies follow predictable biases. Third, it employs interactive visualizations, building on the work of Perin et al. [12], to present users a method of providing the optimizer with real-time feedback that reflects league-specific scoring formats, draft rules, and evolving pick sequences. This combination of statistical rigor, behavioral awareness, and interactivity is designed to make the optimizer uniquely successful.

Impact, Risks, and Evaluation [HQ4–HQ9]

With a projected cost of $0, this project advances the state of fantasy football analytics by introducing a Mixture of Experts–based optimizer that combines player projections, injury forecasting, and behavioral insights into a single adaptive framework. By situating itself at the intersection of predictive modeling, cognitive-behavioral analysis, and interactive visualization, it addresses the shortcomings of static ranking systems and establishes a pathway for future applications of optimization under uncertainty in sports.

The success of the system will be measured quantitatively through large-scale simulations comparing optimizer-guided drafts against ADP- and consensus-based drafts, using metrics such as projected points, playoff qualification rates, and championship outcomes. Qualitative evaluation will include user studies of draft satisfaction and perceived fairness. Finally, ground-truth validation will involve testing model outputs against real-world outcomes in the ongoing 2025 NFL season.

Risks include uncertainty from injuries, trades, and breakout performances that can disrupt projections, as well as computational overhead associated with training multiple expert models and a gating network. Nonetheless, the potential payoff is significant: a tool that consistently outperforms expert consensus rankings, democratizes advanced strategies, and contributes to the literature on applied optimization under uncertainty.

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%

Statement of effort: All team members have contributed a similar amount of work.

References

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