Analyzing the Impact of Predictable NFL Offenses

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Abstract

Predicting play calls in the National Football League (NFL) has long been a challenge for analysts and coaches alike. This study presents a novel approach to play prediction using Proximal Policy Optimization (PPO), a reinforcement learning algorithm, trained on historical NFL play-by-play data. The model was developed using data from the 2018-2024 seasons and evaluated on the 2016 season to assess its predictive accuracy across different game situations. Initially, with a binary action space (run/pass), the PPO agent achieved an overall play prediction accuracy of approximately 70%, with notable variations across different down situations. Specifically, the model demonstrated enhanced performance on third downs, with accuracy reaching 80%, while first down predictions were less reliable at 60%. This discrepancy suggested that play-calling patterns may be more consistent and thus more predictable in high-pressure situations like third downs. Subsequently, we expanded the action space to include 13 more nuanced play types, such as specific pass distances and run directions. With this expanded action space, the model achieved a play prediction accuracy of 23%. This significant decrease in accuracy highlights the increased complexity and reduced predictability when considering a more granular set of play options. To investigate the potential strategic implications of play predictability, we examined the correlation between a team's play-calling predictability and their winning percentage. Our analysis revealed a weak to moderate relationship between these factors. We found that the more predictable a team is in their play calling, there was a slight decrease in their winning percentage. These findings underscore the complexity of NFL play-calling and the challenges in accurately predicting specific play types. They also suggest that while general play patterns may be discernible, predicting exact play calls remains a formidable task, even with advanced machine learning techniques.

Introduction

The advent of big data in American football has revolutionized our ability to analyze and understand the intricacies of the game. This wealth of information allows for a more precise evaluation of decision-making processes and their outcomes, paving the way for the development of optimal strategies. The field of decision analysis in football has been a subject of extensive research, with numerous scholars contributing to our understanding of the game's strategic elements (Carter and Machol, 1971; Carroll, Palmer, and Thorn, 1988; Sahi and Shubi, 1988; Boronico and Newbert, 2007; Yam and Lopez, 2019).

While the initial aim of this study was to construct an agent capable of determining play optimality based on a set of features, time constraints necessitated a shift in focus. Instead, we developed a model using Proximal Policy Optimization (PPO) to predict the most likely play to be executed given specific game situations. This approach not only provides valuable insights into play-calling patterns but also lays the groundwork for future development of a comprehensive game simulator.

Background and Motivation

The National Football League (NFL) has seen a significant increase in the adoption of data analytics for decision-making in recent years. This trend has led to notable changes in game strategies, particularly in areas such as fourth-down decision-making and two-point conversion attempts. The integration of analytics into football operations has become so prevalent that even traditionally conservative teams are now recognizing its competitive advantages.

Relevance and Applications

The ability to predict plays accurately has several important applications in football:

- **Strategic Planning**: Teams can use play prediction models to anticipate opponent strategies and adjust their game plans accordingly.
- **Player Development**: Understanding play patterns can inform player training and preparation for specific game situations.
- **In-Game Decision Support**: Coaches can leverage predictive models to make more informed decisions during critical moments of the game.

Methodology Overview

Our study employs the PPO algorithm, a reinforcement learning technique, to train an agent on historical NFL play-by-play data. This approach allows the model to learn from past play-calling patterns and adapt its predictions based on various game features. The use of reinforcement learning in this context is particularly apt, as it mimics the decision-making process of coaches who learn and adjust their strategies based on past experiences and outcomes.

By focusing on play prediction rather than play optimality, we've created a foundation that can be expanded upon in future research. The probabilities generated by our model could be integrated into a more complex simulator that incorporates expected yardage gains, allowing for a comprehensive analysis of play effectiveness and strategic decision-making.

This research not only contributes to the growing field of sports analytics but also demonstrates the potential of machine learning techniques in deciphering the complex decision-making processes inherent in American football.

Background

To understand the context of play prediction in the National Football League (NFL), it's essential to be familiar with some basic rules:

1. **Downs:** Teams have four attempts (downs) to advance the ball 10 yards. If successful, they receive a new set of downs.
2. **Play types:** Offensive plays are broadly categorized into running plays (where the ball is handed off or run by a player) and passing plays (where the ball is thrown forward).
3. **Field position:** The 100-yard field is divided into zones, with each team defending one end zone. The offense aims to move towards their opponent's end zone.
4. **Game situations:** Factors such as the current down, yards to go for a first down, score, and time remaining all influence play-calling decisions.
5. **Play clock:** Teams have a limited time (usually 40 seconds) to start the next play after the previous one ends.
6. **Communication:** In the NFL, one player (usually the quarterback) is allowed radio contact with the sidelines for a defined interval before each play to receive play calls.

Understanding these rules provides the necessary context for analyzing and predicting play-calling patterns in NFL games.

Related Work

The play prediction model developed in this study could serve as a foundation for creating a rough football simulator. By providing a probability distribution over possible plays for a given set of features (e.g., down, distance to go, formation), this model could be extended to include expected yardage gains. Such a simulator could then be used to train more complex RL algorithms to optimize game strategies, although this was beyond the scope of the current project due to time constraints.

Comparison with Traditional Machine Learning Approaches

While play prediction is fundamentally a classification problem that could be addressed using traditional machine learning algorithms, the decision to use reinforcement learning, specifically PPO, for this study was motivated by several factors:

1. **Probability distribution output:** PPO naturally produces a probability distribution over the action space (in this case, the possible plays), which aligns well with the goal of predicting play probabilities rather than just the most likely play.
2. **Online learning capability:** Although not fully utilized in this study, PPO's ability to learn in an online manner could be beneficial for adapting to changing play-calling patterns throughout a season or even within a game.
3. **Flexibility for future extensions:** By using an RL framework, the model can be more easily extended in the future to incorporate sequential decision-making aspects of football strategy.
4. **Handling of large action spaces:** PPO can efficiently handle large discrete action spaces, which is useful when dealing with the numerous possible plays in football.
5. **Exploration during training:** The exploration mechanisms in PPO can help in discovering less obvious patterns in play-calling that might be missed by more straightforward classification algorithms.

It's important to note that while these are potential advantages of using PPO, the primary use in this study was for classification rather than for determining play optimality or sequential decision-making.

Project Details

The Markov Decision Process (MDP) for this project was structured as follows:

State The state space comprised a set of features including:

- Down
- Distance to go
- Yardline
- Score differential
- Time left on field
- Offensive formation
- Whether it was the second or fourth quarter

To manage the state space complexity and improve data robustness, state aggregation was performed on the time and yardline features. This aggregation helped balance the trade-off between state granularity and data sparsity, ensuring that the model remained responsive without becoming overly volatile due to limited data.

Action The action space was initially kept simple, consisting of two primary actions:

- Run
- Pass

As the research progressed, the action space was significantly expanded to include more nuanced play types. The expanded action space now consists of the following 13 actions:

Pass Actions	Run Actions
short right	left end
short left	right end
deep left	left guard
short middle	left tackle
deep right	right guard
deep middle	right tackle
	middle run

Table 1: Football Play Actions

This expanded action space allows for a more detailed analysis of play types, incorporating variations in pass distance (short and deep), run directions (left, right, and middle), and specific offensive line positions for running plays. While the initial analysis focused on the binary classification of run versus pass, this enhanced action space provides a foundation for more sophisticated strategic analysis and decision-making in football play prediction and planning.

Transition Function The transition function was implemented as a random selection process. This approach was chosen over sequential sampling to avoid oversampling specific play sequences, which could lead to biased learning.

Reward Function The reward function was designed to capture multiple aspects of play prediction accuracy:

1. A baseline reward for correctly predicting the primary play type (run vs. pass)
2. An additional reward for correctly predicting the play depth (short vs. long)
3. A smaller reward for correctly predicting the play direction (right vs. middle vs. left)

This tiered reward structure was implemented to prioritize learning the most crucial aspects of play prediction while still incentivizing finer-grained accuracy.

The reward function can be represented as:

$$R(s, a, s') = w_1 \cdot r_{\text{play type}} + w_2 \cdot r_{\text{depth}} + w_3 \cdot r_{\text{direction}} \quad (1)$$

where w_1, w_2, and w_3 are weight parameters, and $r_{\text{play type}}$, r_{depth}, and $r_{\text{direction}}$ are the individual rewards for correctly predicting each aspect.

Data Collection and Preprocessing

Data from the 2018-2024 NFL seasons was collected using the nfl_data_py package. Preprocessing steps included:

- Data normalization
- Encoding categorical variables (e.g., teams) using LabelEncoders
- Scaling numerical variables (e.g., yardline) using MinMaxScalers

Model Architecture and Training

A custom Proximal Policy Optimization (PPO) algorithm was implemented for this project. The choice of PPO was motivated by its simplicity and its focus on optimizing over actions, which aligns well with the goal of generating action distributions for potential use in future simulators.

The policy network architecture consisted of:

- 3 layers
- 64 units per layer
- ReLU activation function
- 13 action dimensions (corresponding to the actions)

The training process utilized the Adam optimizer for gradient descent. The algorithm followed standard PPO practices for trajectory collection and network updates, involving iterative sampling of the environment and policy improvement steps.

Model Evaluation and Hyperparameter Tuning

A predict_play function was developed to return the action distribution for a given state, with the highest probability action selected as the prediction.

Hyperparameter tuning involved experimenting with:

- Learning rates
- Number of training epochs
- Batch sizes
- Feature selection

These experiments led to significant improvements in model accuracy, increasing from approximately 60% to 70%. Notably, it was observed that training beyond 100 epochs yielded diminishing returns, likely due to the limited size of the dataset.

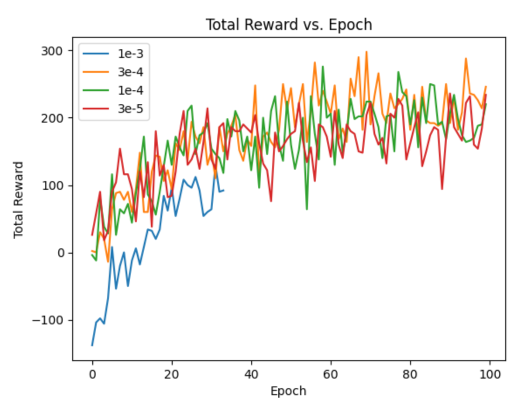


Figure 1: Effects of different hyperparameters on model performance

This project structure demonstrates a systematic approach to applying reinforcement learning techniques to the challenge of NFL play prediction, with careful consideration given to data preprocessing, model architecture, and performance optimization.

Experiments and Results

After successfully training the agent, we conducted a series of experiments to analyze the model's performance and investigate our initial hypotheses.

Feature Importance Analysis

To understand which features were most crucial in predicting whether a play would be a pass or a run, we extracted the feature weights from the trained model and visualized them.

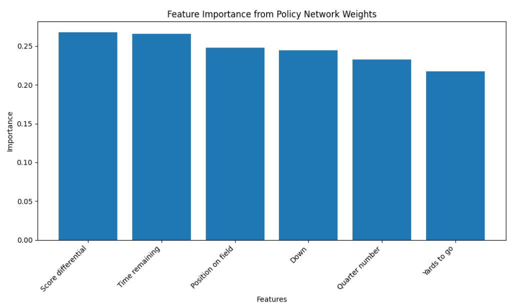
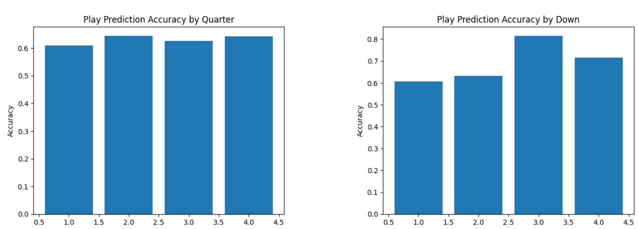


Figure 2: Relative importance of features in play prediction

Accuracy Analysis by Game Situation

We examined how the model's accuracy varied across different game situations, specifically focusing on accuracy per quarter and per down. Our hypothesis was that the model would show higher accuracy in situations where play-calling tends to be more predictable, such as third downs or late in each half.



(a) Accuracy per quarter

(b) Accuracy per down

Figure 3: Model accuracy across different game situations

The results aligned with our expectations, showing increased accuracy on third downs and during the second and fourth quarters. This pattern likely reflects the tendency for teams to pass more in these situations, making play-calling more predictable.

Team Predictability and Win Percentage

To address our initial research question, we investigated the relationship between a team's predictability and their winning percentage. We calculated each team's winning percentage over the training data period (2018-2024) and their predictability score, defined as the percentage of plays correctly predicted by our model.

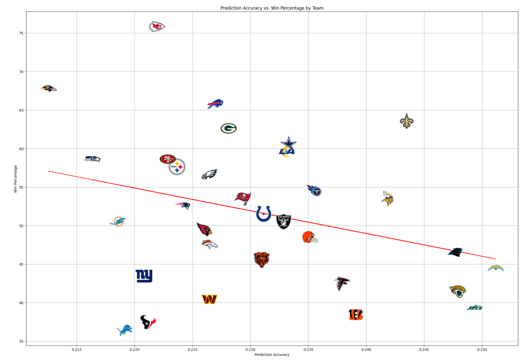


Figure 4: Team predictability vs. win percentage (2018-2024)

Analysis of the scatter plot revealed a weak to moderate negative correlation between team predictability and win percentage, with a correlation coefficient of -0.30. This finding suggests that teams with more predictable play-calling tendencies tend to have slightly lower winning percentages, although the relationship is not strong. The negative correlation of -0.30 indicates that:

- There is an inverse relationship between predictability and winning percentage.
- As a team's play-calling becomes more predictable, there is a slight tendency for their winning percentage to decrease.
- Approximately 9% of the variance in winning percentage can be explained by play-calling predictability (calculated as the square of the correlation coefficient: $0.30^2 = 0.09$).

This result, obtained using our expanded action space model with 13 distinct play types, provides more nuanced insights compared to our initial binary (run/pass) prediction model. It suggests that teams with less predictable play-calling strategies may have a slight advantage in terms of overall success. However, while this correlation is noteworthy, it does not imply causation. Other factors, such as team talent, coaching strategies, and opponent quality, likely play more significant roles in determining a team's success. These findings underscore the potential value of strategic unpredictability in NFL play-calling, while also highlighting the multifaceted nature of factors contributing to team success. Further research could explore how this relationship varies across different game situations, such as down and distance, score differential, or time remaining in the game.

Limitations and Future Work

While our experiments provided valuable insights, there are several limitations to consider:

- Limited features: Additional contextual features, such as player personnel or weather conditions, could potentially improve prediction accuracy.
- Time frame: The analysis covers only the 2018-2024 seasons, which may not capture longer-term trends in NFL strategy.

Future work could address these limitations by:

- Incorporating additional features, including real-time game statistics and player-specific data.
- Extending the analysis to cover a longer time period and investigate how predictability and its impact on success have evolved over time.
- Developing a full game simulator using the predictive model to explore optimal play-calling strategies.

These enhancements could provide deeper insights into the relationship between play predictability, strategic decision-making, and team success in the NFL.

Conclusion

This study applied Proximal Policy Optimization (PPO) to NFL play prediction, yielding several key findings:

1. The initial binary (run/pass) model achieved 70% accuracy, while the expanded 13-play model reached 23% accuracy, highlighting the increased complexity of more granular predictions.
2. Both models showed higher accuracy on third downs and in the second and fourth quarters, consistent with established play-calling patterns.
3. With the expanded model, a weak to moderate negative correlation ($r = -0.30$) was found between play-calling predictability and win percentage, suggesting slightly lower success rates for more predictable teams.
4. Feature importance analysis provided insights into key factors influencing play-calling decisions.
5. The study demonstrated the adaptability of PPO to classification tasks and emphasized the importance of thorough data preprocessing and hyperparameter tuning.

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