Predicting Champion Pick and Ban Sequences in League of Legends Drafting Phase

STUART LIN, Emory University, USA

Champion drafting plays a critical role in determining outcomes in competitive Multiplayer Online Battle Arena (MOBA) games, particularly in *League of Legends*, where teams must navigate a large and evolving champion pool under strict pick and ban constraints. Predicting draft decisions is challenging due to high dimensionality, data imbalance, and the influence of unobserved human factors such as player preference and strategic deception. In this work, I study the problem of champion pick and ban prediction during the drafting phase using over 101,000 match records. I first conduct exploratory analysis to examine champion presence rates and draft imbalance, then formulate the task as a supervised prediction problem with role- and side-aware feature representations. I compare the performance of multiple model families, including Random Forests, XGBoost, and Transformer-based sequence models. While exact top-1 prediction accuracy remains limited across all approaches, the results show consistent improvements over random baselines, with Transformer models achieving substantially higher top-k accuracy. These findings suggest that, although deterministic draft prediction is infeasible, machine learning models can capture meaningful structure in drafting behavior and provide useful insight into champion priority, role predictability, and meta-level trends. This work highlights both the limitations and practical value of data-driven draft analysis in competitive esports. Link to Code: https://github.com/Rheinixl/League-of-Legends-Ban-Pick-Predictor

Additional Key Words and Phrases: Esports Analytics, League of Legends, Draft Phase Prediction, Sequence Modeling, Machine Learning

ACM Reference Format:
Stuart Lin. 2025. Predicting Champion Pick and Ban Sequences in League of Legends Drafting Phase. 1, 1 (December 2025), 9 pages. https://doi.org/XXXXXXX.XXXXXXX

1 Introduction

Multiplayer online games have become a dominant force in the modern video game industry, with competitive multiplayer titles accounting for a substantial portion of active player bases and viewership worldwide. Among these, Multiplayer Online Battle Arena (MOBA) games and First-Person Shooter (FPS) games collectively occupy the majority of the competitive multiplayer market. These genres not only attract millions of daily players but also sustain large-scale professional esports ecosystems with global audiences.

Within the MOBA genre, *League of Legends* (LoL) holds a uniquely influential position. As the first widely successful modernized MOBA, League of Legends drew inspiration from the original *Defense of the Ancients* (DotA) mod while introducing a more structured competitive framework, streamlined mechanics, and consistent developer support. Since its release, League of Legends has accumulated the largest player base of any MOBA and has established one of the most mature professional scenes in esports. Its annual World Championship (Worlds) consistently ranks as the most anticipated and most-watched esports event each year, drawing tens of millions of concurrent viewers worldwide.

Author's Contact Information: Stuart Lin, xlin233@emory.edu, Emory University, Atlanta, Georgia, USA.

A standard League of Legends match consists of two teams of five players, each player occupying one of five predefined roles. Prior to gameplay, teams participate in a drafting phase in which they alternately ban and select champions from a roster that has grown to nearly 200 unique characters. This draft phase plays a critical role in determining match outcomes, as champion abilities, role assignments, and team composition synergies strongly influence both strategic options and in-game execution. Successful drafts must balance individual champion strength, role coverage, counter-picks, and team-level synergy, making drafting a complex and high-impact decision-making process in both casual and professional play.

The importance of drafting has become even more pronounced in recent professional seasons. In 2025, the professional League of Legends scene transitioned to a *fearless draft* format, in which teams are restricted from repeatedly selecting the same champions across a series. This change was introduced to increase strategic diversity and reduce repetitive optimal drafts, implicitly acknowledging that strong draft understanding alone can often determine match outcomes. While this format increases variability and strategic depth, it also significantly complicates meta analysis, especially under tight preparation schedules and limited scrim data.

In such environments, it becomes increasingly difficult for human analysts to accurately infer the evolving meta—commonly defined as the "most efficient tactic available"—within short time spans. This challenge motivates the application of machine learning methods, which can systematically analyze large volumes of historical match data and identify patterns that may not be immediately apparent through manual analysis alone. However, champion pick and ban prediction remains a fundamentally difficult problem. Even with a large dataset of over 101,000 professional matches, the data distribution is highly imbalanced: popular champions may appear in over half of all games (e.g., Yunara with a presence rate of 58%), while others appear extremely rarely (e.g., Kalista at approximately 1.2%). Such imbalance limits the amount of reliable signal available for less frequently selected champions.

Additionally, champion selection decisions depend on factors that are not captured in match datasets, including player-specific mastery, personal playstyle, psychological state, and even transient external influences such as recent strategy guides or professional matches viewed by players. Draft decisions are therefore inherently non-deterministic: given two identical draft states, the resulting pick or ban may still differ due to unobserved contextual factors. Prior work has demonstrated the difficulty of this task, with baseline guessing models achieving extremely low accuracy—for example, Inzitari et al. report a baseline accuracy of only 1.72% for pick-ban sequence prediction[1].

Given these challenges, this paper aims to take a systematic step toward understanding the feasibility and limitations of champion draft prediction. We compare the performance of several machine learning models with different inductive biases, including Random Forests, XGBoost, and Transformer-based sequence models, to evaluate their effectiveness in predicting champion pick and ban decisions during the drafting phase. Rather than claiming deterministic prediction of draft outcomes, our goal is to assess how well different model classes capture underlying drafting tendencies and to identify their respective strengths and weaknesses in this highly complex decision space.

2 Background

Champion drafting has long been recognized as a strategically important phase of competitive League of Legends play, leading to the development of numerous public-facing recommendation tools and analytics platforms. Popular websites and software such as *op.gg*, *u.gg*, and similar services provide tier lists, counter-pick suggestions, and role-based recommendations to players at all skill levels. These systems are typically driven by relatively simple statistics derived from match history, most commonly champion pick frequency, ban frequency, and win rate under specific conditions. While such approaches are effective for summarizing broad trends and providing intuitive guidance, they are fundamentally descriptive rather than predictive, and they do not explicitly model the sequential or strategic nature of the drafting process.

In contrast, recent academic research has explored more sophisticated machine learning approaches aimed at modeling champion pick and ban decisions as a structured prediction problem. Inzitari et al. [1] investigate champion draft prediction in League of Legends using a range of deep learning architectures, including Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, bi-directional LSTMs (BiLSTMs), and Convolutional LSTMs. Their work also evaluates a feature-augmented approach, in which additional contextual information is incorporated into the input representation. Among the tested models, a feature-augmented LSTM achieved the best performance, reaching an accuracy of 27.78%, substantially outperforming a weighted random guessing baseline. Despite this improvement, the authors emphasize that prediction accuracy remains limited due to the inherent complexity and stochasticity of draft decisions.

Similar challenges have been observed in studies of other MOBA titles, particularly *DotA 2*. Summerville et al. [2] present one of the earliest investigations into draft pick prediction in MOBA games, applying supervised machine learning techniques to model drafting behavior in professional DotA 2 matches. Their work highlights the difficulty of predicting individual draft choices with high accuracy, while also demonstrating that learned models can capture meaningful strategic tendencies and preferences present in historical data. More recently, Zhu et al. [3] propose a categorical learning-based approach for line-up prediction during the drafting process of MOBA games, further reinforcing the idea that draft prediction is best viewed as a structured, multi-step decision problem rather than a simple classification task.

Across these studies, a common conclusion emerges: achieving extremely high accuracy in champion pick or ban prediction is inherently difficult, even when using advanced models and large datasets. Draft decisions are influenced by incomplete information, evolving metas, player-specific preferences, and strategic deception, all of which introduce significant uncertainty. Nevertheless, these models consistently produce meaningful results in the sense that their predictions and learned representations provide insight into drafting patterns, strategic priorities, and meta-level tendencies.

As a result, the primary value of draft prediction models lies not solely in their raw predictive accuracy, but in the information they reveal about how teams and players approach the drafting process. Understanding which features, champions, or draft states drive model behavior can offer actionable insights for analysts, coaches, and researchers alike. This perspective motivates my work, which focuses on comparing different model families and evaluating what they learn about champion drafting dynamics, rather than framing the task as a pursuit of deterministic draft prediction.

3 System Design and Methodology

This section describes the overall system pipeline used in this study, including exploratory analysis, data preprocessing, feature engineering, and model training. My design follows a staged approach, beginning with statistical analysis to understand the data distribution and progressing toward increasingly expressive machine learning models.

3.1 Exploratory Data Analysis

Before model training, I conducted exploratory statistical analysis to better understand champion selection dynamics within the dataset. Specifically,I computed champion pick, ban, and overall presence rates across all matches to identify highly frequent and rarely selected champions. This analysis highlights the strong imbalance inherent in champion selection data and provides context for downstream modeling challenges.

3.2 Data Preprocessing

Raw match data contains a large number of features that are not informative for draft prediction. As a result, I performed aggressive feature pruning to remove fields unrelated to the drafting phase. This included identifiers such as match IDs, player IDs, timestamps of in-game events, and ingame-dependent features such as nexus destruction. Removing these features reduces noise and prevents data leakage from post-draft information into the prediction task.

3.3 Champion Identifier Normalization

Champion identifiers present a non-trivial preprocessing challenge due to changes in Riot Games' internal champion IDs across different patches. To address this issue, I implemented a normalization step that maps all champion IDs to canonical champion names using patch-specific lookup tables. These names were then re-encoded into a consistent internal name-to-ID mapping used throughout the dataset. This process ensures that champion representations remain stable across patches and prevents inconsistencies during training.

3.4 Encoding and Feature Engineering

Since champion identities are categorical variables with no inherent ordinal relationship, I applied one-hot encoding to all champion-related features. Beyond simple champion identity, I further enriched the feature representation by incorporating both role and side information. Each champion pick feature encodes not only the selected champion, but also the role (e.g., top, jungle, mid, ADC, support) and the team side (blue or red). For example, a champion selected as the blue-side ADC is treated as a distinct feature from the same champion selected in a different role or on the opposing side. This representation allows models to capture role-specific and side-dependent drafting patterns.

3.5 Model Training

I trained and evaluated several models with increasing expressive capacity. As a baseline, I first trained a Random Forest classifier using default hyperparameters. I then applied Randomized Search Cross-Validation to optimize the Random Forest model, using accuracy as the evaluation metric during hyperparameter selection.

Next, I trained an XGBoost model, which is well-suited for high-dimensional sparse feature spaces and has demonstrated strong performance in structured tabular prediction tasks. Finally, I implemented a Transformer-based model to explicitly model the sequential nature of the drafting process. Unlike tree-based models, the Transformer treats draft picks as ordered sequences and is capable of capturing long-range dependencies between earlier and later draft decisions.

For the Transformer model, training proceeded over multiple epochs, and model selection was based on identifying the epoch with the most balanced training and validation loss, rather than simply minimizing training error. This approach helps mitigate overfitting in a task with high stochasticity and class imbalance.

3.6 Evaluation and Comparison

Model performance was evaluated using prediction accuracy, consistent with prior work in draft prediction. After training, I compared the performance of all models under identical evaluation conditions to assess the trade-offs between model complexity, predictive accuracy, and stability. In addition to raw accuracy, I examine qualitative differences in model behavior in the Results section to better understand what each model learns about champion drafting dynamics.

4 Results and Analysis

This section presents the results of the exploratory analysis and model evaluations. I begin by examining champion presence rates to contextualize the drafting landscape, followed by a comparison of model performance across Random Forest, XGBoost, and Transformer-based approaches.

4.1 Champion Presence and Draft Distribution

I first analyze champion pick, ban, and overall presence rates across the dataset, summarized in Figure 1 and Figure 2. The results show that champion selection is highly imbalanced. A small subset of champions dominates the drafting phase, while many others appear only rarely. For example, Yunara exhibits an overall presence rate exceeding 58%, reflecting her high priority in both picks and bans, whereas champions such as Kalista appear in fewer than 2% of matches.

	pick_count	pick_rate	ban_count	ban_rate	presence_count	presence_rate
Yunara	26210	0.257357	33129	0.325295	59339	0.582652
Pyke	6093	0.059827	31444	0.308750	37537	0.368577
Zed	10082	0.098996	26417	0.259389	36499	0.358385
Draven	5199	0.051049	30183	0.296368	35382	0.347417
Yasuo	10466	0.102766	22811	0.223982	33277	0.326748
Shaco	6179	0.060672	26823	0.263376	33002	0.324048
Mel	7572	0.074350	25078	0.246242	32650	0.320591
Lulu	12729	0.124986	16781	0.164773	29510	0.289760
Pantheon	11095	0.108942	16439	0.161415	27534	0.270357
Belveth	3876	0.038059	22166	0.217649	26042	0.255707
Nautilus	11204	0.110012	14150	0.138939	25354	0.248952
Viego	13137	0.128993	11526	0.113174	24663	0.242167
Sylas	11155	0.109531	12423	0.121982	23578	0.231513
Gwen	7303	0.071708	14802	0.145341	22105	0.217050
Jax	8446	0.082932	13592	0.133460	22038	0.216392
Lucian	11634	0.114235	10374	0.101863	22008	0.216097
Blitzcrank	4607	0.045236	16752	0.164488	21359	0.209725
Caitlyn	9432	0.092613	10805	0.106095	20237	0.198708
Leblanc	4498	0.044166	15429	0.151498	19927	0.195664
Fiora	5714	0.056106	13650	0.134030	19364	0.190136

Fig. 1. Champion pick, ban, and overall presence rates across the dataset.

	pick_count	pick_rate	ban_count	ban_rate	presence_count	presence_rate
Kalista	1047	0.010281	193	0.001895	1240	0.012176
Skarner	1202	0.011802	402	0.003947	1604	0.015750
Shyvana	1753	0.017213	253	0.002484	2006	0.019697
Taric	1799	0.017664	355	0.003486	2154	0.021150
Renata	2019	0.019825	199	0.001954	2218	0.021779
Sejuani	2371	0.023281	193	0.001895	2564	0.025176
Maokai	2512	0.024665	222	0.002180	2734	0.026845
Gnar	2456	0.024116	408	0.004006	2864	0.028122
Rammus	1257	0.012343	1854	0.018204	3111	0.030547
Heimerdinger	2005	0.019687	1255	0.012323	3260	0.032010
Cassiopeia	1989	0.019530	1438	0.014120	3427	0.033650
AurelionSol	2592	0.025451	840	0.008248	3432	0.033699
Lissandra	3012	0.029575	731	0.007178	3743	0.036753
Olaf	2621	0.025736	1210	0.011881	3831	0.037617
Xayah	3408	0.033463	472	0.004635	3880	0.038098
RekSai	2877	0.028249	1041	0.010222	3918	0.038471
Rumble	3080	0.030243	864	0.008484	3944	0.038726
Velkoz	3299	0.032393	769	0.007551	4068	0.039944
Zeri	3713	0.036458	440	0.004320	4153	0.040778
Singed	3193	0.031352	990	0.009721	4183	0.041073

Fig. 2. Champion pick, ban, and overall presence rates across the dataset.

This imbalance highlights a core challenge of draft prediction: models receive substantially more training signal for popular champions than for niche or situational picks. Moreover, high ban rates often reflect perceived threat rather than intrinsic champion strength, further complicating the relationship between presence and match outcome. These observations motivate the need for models that can generalize beyond simple frequency-based heuristics.

4.2 Baseline Random Forest Performance

As an initial baseline, I trained a Random Forest model with 200 trees, a maximum depth of 30, and a minimum of two samples per leaf. Prediction accuracy varied substantially by role. Bottom lane and support roles achieved notably higher accuracy (14.3% and 11.8%, respectively), while top, jungle, and mid lane predictions remained below 8%.

This discrepancy likely reflects structural differences in drafting behavior. Bottom lane and support champions are often selected in more constrained role pairings and exhibit stronger meta stability, whereas solo lanes and jungle roles tend to allow for greater flexibility and counter-pick variation.

Table 1. Top-1 prediction accuracy (%) for each role across different models.

Role	RF (CV)	XGBoost (CV)	Transformer
Top Lane	8.2	9.2	9.5
Jungle	7.4	8.3	8.2
Mid Lane	6.8	8.2	8.5
Bottom Lane	17.7	18.7	18.7
Support	12.5	13.1	13.5

4.3 Random Forest with Hyperparameter Optimization

Applying randomized search cross-validation improved performance across all roles. Optimized Random Forest models achieved accuracy gains of approximately 1–3 percentage points depending on role, with bottom lane accuracy increasing to 17.7% and support accuracy to 12.5%. Optimal configurations generally favored deeper trees or unrestricted depth for roles with higher variability, while limiting depth for others to reduce overfitting.

Despite these improvements, Random Forest performance appears to plateau relatively quickly, suggesting limited capacity to capture complex interactions in the high-dimensional, sparse feature space.

4.4 XGBoost Results

XGBoost models trained with randomized hyperparameter search consistently outperformed Random Forest baselines across all roles. The strongest gains were again observed in bottom lane and support predictions, achieving accuracies of 18.7% and 13.1%, respectively. Notably, XGBoost also improved performance for top, jungle, and mid roles, narrowing the performance gap between roles.

These results suggest that gradient-boosted decision trees are better suited to modeling non-linear interactions among champion-role-side features, particularly in imbalanced settings. However, improvements remain incremental rather than transformative, reinforcing the inherent difficulty of deterministic pick prediction.

4.5 Transformer-Based Sequence Modeling

The Transformer model achieved the strongest overall performance, particularly when evaluated beyond top-1 accuracy. While top-1 accuracy remained modest (ranging from 8.2% to 18.7%), top-3 and top-5 accuracies increased substantially across all roles. For example, bottom lane predictions reached 36.4% top-3 accuracy and 48.2% top-5 accuracy, indicating that the correct champion frequently appears among the model's highest-confidence predictions even when not ranked first.

These results highlight an important distinction between strict classification accuracy and practical utility. In realistic drafting scenarios, analysts and players often consider a small set of likely options rather than a single deterministic outcome. From this perspective, the Transformer's ability to model draft sequences and capture long-range dependencies provides meaningful insight into drafting tendencies, even when exact prediction remains uncertain.

4.6 Comparative Analysis

Across all experiments, several consistent trends emerge. First, bottom lane and support roles are consistently easier to predict than other roles, likely due to stronger role constraints, duo synergies, and meta stability. Second, tree-based ensemble models benefit significantly from hyperparameter tuning but remain limited in expressive capacity. Finally,

Table 2. Transformer performance using ranked accuracy metrics.

Role	Top-1 Acc	Top-3 Acc	Top-5 Acc
Top Lane	9.5	21.2	29.6
Jungle	8.2	19.9	29.0
Mid Lane	8.5	19.5	27.8
Bottom Lane	18.7	36.4	48.2
Support	13.5	29.0	39.7

sequence-based models such as Transformers offer the most informative predictions when evaluated using ranked metrics rather than strict top-1 accuracy.

Overall, these findings support prior conclusions in the literature: champion pick and ban prediction is not well-suited to deterministic modeling, but machine learning approaches can nevertheless capture meaningful structure in drafting behavior. The value of these models lies less in exact prediction and more in the strategic insights they provide into champion priority, role interaction, and meta dynamics.

5 Improvement, Applications, and Future Pathways

Although exact champion pick and ban prediction remains difficult, the results demonstrate several practical applications and highlight promising directions for future research.

5.1 Applications

One of the most immediate and practical applications of this work lies in ranked prediction rather than strict top-1 accuracy. While exact prediction accuracy remains modest, top-3 and top-5 accuracy is substantially higher across all roles, indicating that the model frequently identifies a small set of highly likely picks. In realistic drafting scenarios, this set of likely options is often more valuable than a single deterministic prediction, making ranked outputs meaningful advisory signals rather than definitive answers.

Beyond individual predictions, the models can be used as analytical tools to generate likely draft trajectories given partial draft states. By conditioning on early picks and bans, the system can propose plausible future draft paths, offering insight into how drafts tend to evolve under similar conditions. Additionally, performance degradation across unseen patches may serve as a weak signal for meta shifts. If model accuracy drops sharply on matches from newer patches, this may indicate that the underlying drafting dynamics have changed, providing a data-driven mechanism for detecting patch-induced meta transitions.

Several extensions naturally follow from this work. Draft prediction models could be combined with win/loss classifiers to jointly recommend champions that are not only likely to be selected, but also associated with higher win rates in a given draft context. Such a system could be deployed as a real-time drafting assistant, providing context-aware recommendations during live matches. Furthermore, training on more focused datasets—such as professional games from a single patch or tournament—may reduce noise and yield higher predictive accuracy by constraining the strategic space.

5.2 Limitations

This study is subject to several important limitations. First, the feature set is intentionally minimal and does not include higher-level strategic information such as champion playstyle archetypes, counter relationships, or synergy graphs.

While such features could significantly improve model performance, engineering them reliably would require additional models or external knowledge bases, which was beyond the scope of this work.

Second, rare champions present a persistent challenge. Champions with low pick and ban rates contribute disproportionately to prediction error due to insufficient training signal. While larger datasets may partially alleviate this issue, rarity is an inherent property of evolving metas and cannot be fully eliminated.

Finally, ranked and public match data is inherently noisy. Players do not always draft optimally or rationally, and champion selection may be influenced by factors entirely absent from match records, such as personal preference or experimentation. A sufficiently large, patch-aligned dataset consisting solely of professional matches would likely reduce this noise and provide a cleaner signal for modeling draft behavior.

5.3 Future Pathways

The results suggest that traditional tree-based models such as Random Forests and XGBoost are approaching their performance ceiling for this task, as diminishing returns are observed during hyperparameter optimization. In contrast, neural and deep learning approaches appear more promising. Prior work by Inzitari et al. [1] demonstrates that sequence-aware neural architectures can achieve substantially higher accuracy under more constrained datasets, suggesting that representation learning plays a critical role in draft modeling.

Future work may benefit significantly from expanded feature engineering, alternative input representations, or hybrid models that combine learned embeddings with features. Additionally, explicitly modeling uncertainty—rather than optimizing solely for classification accuracy—may better reflect the inherently stochastic nature of champion selection.

5.4 Summary

In summary, although champion drafting is influenced by noisy and partially unobserved factors, the models explored in this work achieve between four and eleven times the accuracy of random guessing and consistently capture meaningful structure in drafting behavior. Rather than enabling deterministic prediction, these models provide valuable insight into role predictability, champion priority, and the fundamental limits of data-only draft modeling. These findings highlight both the challenges and opportunities of applying machine learning to strategic decision-making in competitive esports.

Acknowledgments

I would like to thank Dr. Li Xiong for her guidance in CS 334, under which this project was conducted. I am also grateful to Dr. Davide Fossati, my research advisor, for providing valuable feedback and discussion when I shared ideas and progress related to this work. In addition, I acknowledge the use of AI-assisted tools to help refine grammar and improve wording clarity throughout the writing process.

References

[1] Tim Inzitari, Benjamin Lyons, and Md Nafee Al Islam. 2022. Predicting Pick-Ban Sequence in League of Legends Games. ACM, New York, NY, USA, 7 pages. doi:10.1145/1122445.1122456

[2] Adam Summerville, Michael Cook, and Ben Steenhuisen. 2016. Draft-Analysis of the Ancients: Predicting Draft Picks in DotA 2 Using Machine Learning. In *Proceedings of the AAAI Conference Workshops*. AAAI Press.

[3] Run-Lu Zhu, Jie Wang, and Sheng-Jie Zhao. 2023. Categorical Learning-based Line-up Prediction in the Drafting Process of MOBA Games. *Journal of Information Technology and Applications* (2023).

Received 13 December 2025