A Predictive to Prescriptive Analytics Approach for the League of Legends Team Selection Problem

Aaron K. Rush, Matthew A. Lanham, Andy Alexander
Purdue University Krannert School of Management
rush30@purdue.edu; lanhamm@purdue.edu: alexan11@purdue.edu

Abstract

In this study, we developed a model to assist competitive League of Legends (LoL) eSports players in their pre-game decision making process, particularly in how to select in-game characters, known as "champions", based on certain game-winning factors. We developed a predictive model that could estimate the probability of a character winning when playing a particular position and integrated that into a prescriptive/optimization model to support the team formation selection decision. The motivation for this study is that applications of analytics to support decision-making in eSports is sparse. Specifically, there has been little research to date in academic journals. Today, eSports is a massive industry that is estimated to generate $1.1 billion in 2019. Growing in popularity by the day, eSports, especially high stakes events with high prize pools, are proving to be a consistent cultural phenomenon, that could use analytics to improve outcomes.

Introduction

VIDEO MOTIVATION HERE

Primary Research Questions

1) Does a champion's potential have an observable impact on match outcomes?
2) Can we use previous match data from competitive competition events to predetermine game outcomes based on certain strategies?
3) How can prediction and optimization techniques be used together to support the team selection problem?

Literature Review

Study	Champions	Game Factors	5 Strategies	Drafting	Model	Player Data	Ensemble
(Summerville, 2016)	✓			✓			
(Yin, 2018)	✓	✓		✓			
(MOBA Champion, 2017)	✓			✓	✓		
(Randomonium, 2018)	✓	✓	✓		✓		
Our Study	✓	✓	✓	✓	✓	✓	✓

This study is novel as it provides a sophisticated yet usable analytics-based solution using predictive analytics and optimization to support team formation in competitive eSports matches such League of Legends. Other studies have focused on aspects of the game, but have not provided analytical decision-support models or tools to help top players.

Methodology

An Overview of Competitive League of Legends

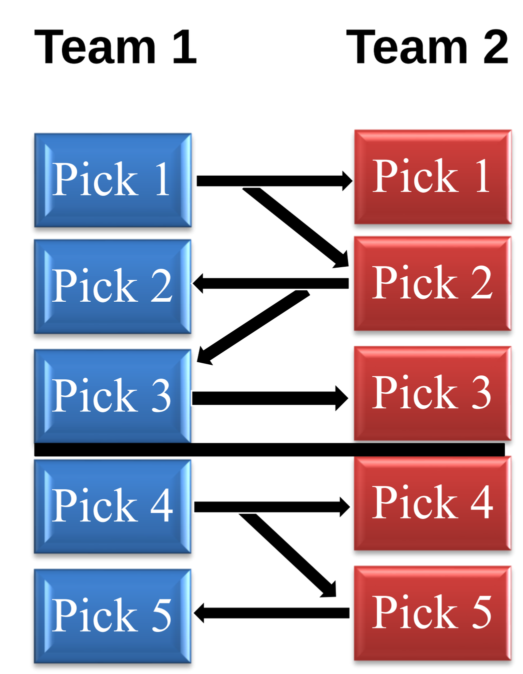


Figure 1. Competitive Pick System

Figure 2. Summoner's Rift

Data

Competitive League of Legends match data between the 2017 World Championships and the early 2018 season was provided by the Sportradar API. Primary research regarding champion competencies (Engage, Catch, Poke, Protect, Split) was also completed by interviewing high-ELO LoL players. We had 4,810 records where half were winners.

Predictive Model

A logistic regression model was used to estimate the parameter coefficients of winning versus losing a game.

$$P(Winning) = \beta_0 + \beta_i(Player) + \beta_j(Player * Position) + \beta_k(Kills) + \beta_a(Assists) + \beta_d(Deaths) + \beta_l(Level) + \beta_m(Minions) + \beta_e(Engage) + \beta_{pr}(Protect) + \beta_c(Catch) + \beta_{po}(Poke) + \beta_s(Split)$$

Optimization Model

The logistic regression model parameters are used in the objective function of the optimization model. The objective is to select the top five players for the available five positions that lead to a greater expecting winning score than your competitor's team. Let,

- x_i := decision to draft the *i*'th LoL champion in one of their typically played positions
- $P(Winning) = P_i$:= be the amount of win percentage a champion is predicted to add to a competitive LoL team. This is the predictive model.
- Let C_i denote whether the *i*'th champion is typically drafted as an AD Carry in competitive play. Similarly, S_i, M_i, T_i, J_i: whether the *i*'th champion is typically drafted as Support, Mid Lane, Top Lane, or Jungle, respectively.
- Let Pk_j denote the *j*'th pick in the champion selection process

Maximize:

$$\sum_i P_i x_i$$

Subject To:

$\sum_i C_i x_i = 1, i = 1,..,82$ (One player to AD Carry lane)
$\sum_i S_i x_i = 1, i = 1,..,82$ (One player to Support lane)
$\sum_i M_i x_i = 1, i = 1,..,82$ (One player to Mid lane)
$\sum_i T_i x_i = 1, i = 1,..,82$ (One player to Top lane)
$\sum_i J_i x_i = 1, i = 1,..,82$ (One player to Jungle lane)
$Pk_j x_i = 1, j = 1,2,3$ (Locked picks for selection stages 1, 2, and 3)
$x_i \in \{0,1\}$

Results

The logistic regression model was trained and evaluated using 5-fold cross-validation. The model was **91.05% accurate** on the test set with a **97.14% AUC**. The training data was 89.7% accurate providing evidence that our model is indeed generalizable to future competitive matches.

There were 128 unique champions in the metagame. However, we only considered the top 82. These **82 champions historically account for 96%** of all champion selections in competitive play.

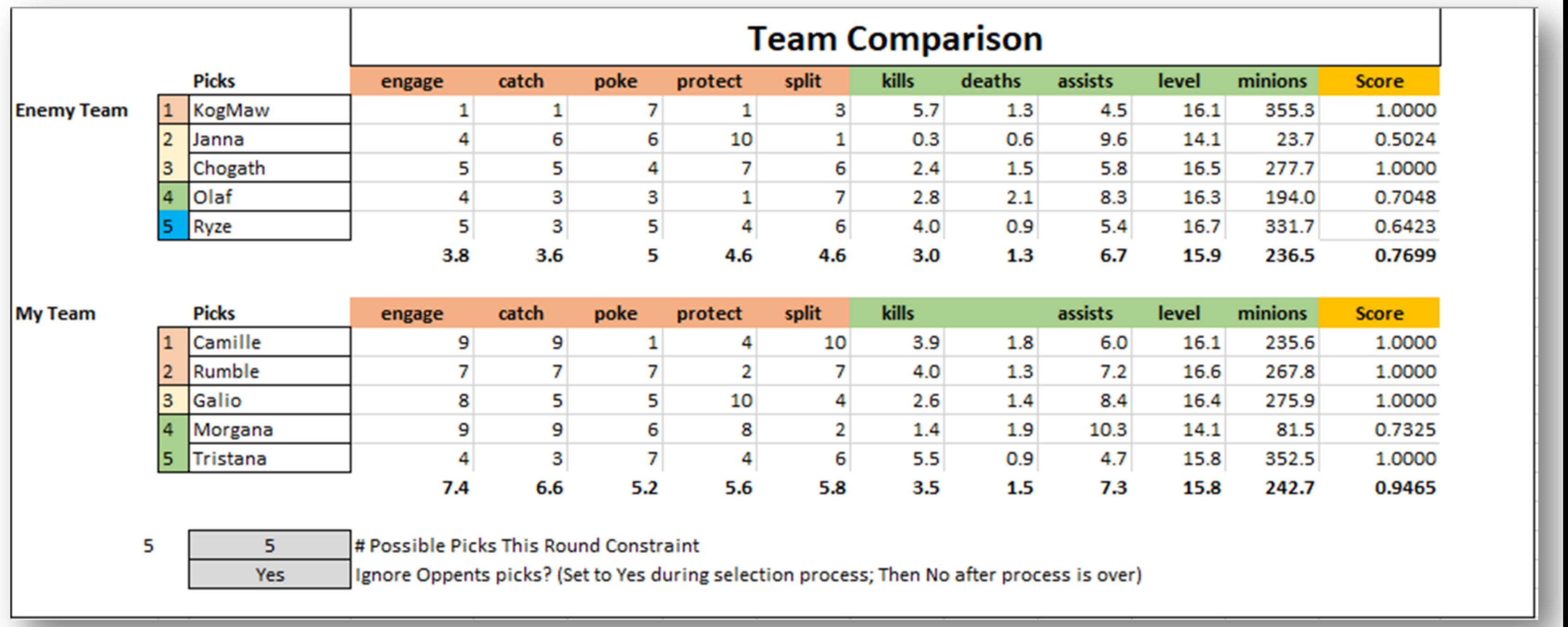
Result 1: We were able to estimate the impact of winning for each champion, although the estimate effect was not statistically significant ($\alpha = .05$) for all 82 champions.

Result 2: Certain champions do lead a noticeable change in game winning probability. It turns out the composition of certain teams tend to beat other team compositions as shown in Figure 3.

Win Rates	L_Engage	L_Catch	L_Protect	L_Poke	L_Split
W_Engage	0.60	0.39	0.55	0.52	-
W_Catch	0.61	0.58	0.38	0.56	-
W_Protect	0.45	0.62	-	0.53	-
W_Poke	0.48	0.44	0.47	-	-
W_Split	-	-	-	-	-

Figure 3. Win Rates By Strategy

Result 3: Integrating the predictive model into a formal integer programming (IP) model can give you a better chance of winning almost every time. Here is a demonstration in Excel.



Team Comparison

Enemy Team	Picks	engage	catch	poke	protect	split	kills	deaths	assists	level	minions	Score
	1 KogMaw	1	1	7	1	3	5.7	1.3	4.5	16.1	355.3	1.0000
	2 Janna	4	6	6	10	1	0.3	0.6	9.6	14.1	23.7	0.5024
	3 Chogath	5	5	4	7	6	2.4	1.5	5.8	16.5	277.7	1.0000
	4 Olaf	4	3	3	1	7	2.8	2.1	8.3	16.3	194.0	0.7048
	5 Ryze	5	3	5	4	6	4.0	0.9	5.4	16.7	331.7	0.6423
		3.8	**3.6**	**5**	**4.6**	**4.6**	**3.0**	**1.3**	**6.7**	**15.9**	**236.5**	**0.7699**

My Team	Picks	engage	catch	poke	protect	split	kills		assists	level	minions	Score
	1 Camille	9	9	1	4	10	3.9	1.8	6.0	16.1	235.6	1.0000
	2 Rumble	7	7	7	2	7	4.0	1.3	7.2	16.6	267.8	1.0000
	3 Galio	8	5	5	10	4	2.6	1.4	8.4	16.4	275.9	1.0000
	4 Morgana	9	9	6	8	2	1.4	1.9	10.3	14.1	81.5	0.7325
	5 Tristana	4	3	7	4	6	5.5	0.9	4.7	15.8	352.5	1.0000
		7.4	**6.6**	**5.2**	**5.6**	**5.8**	**3.5**	**1.5**	**7.3**	**15.8**	**242.7**	**0.9465**

5 | 5 | # Possible Picks This Round Constraint
Yes | Ignore Oppents picks? (Set to Yes during selection process; Then No after process is over)

Figure 4. Team Selection Optimization Model

Conclusions

With League of Legends leading the charge in eSports, a decision-making tool for one of the most critical aspects of the game, champion selection, could serve as a useful asset to crack this highly-observed, multimillion dollar game. We discovered that teams that have equal or superior pre-game team compositions have roughly a 57% win-rate (given that League is an 50/50 game ideally). Additionally, we found that previous match data could be utilized to predict future winners with **91% accuracy**. Integrating this accurate predictive model into prescriptive decision-making has the potential to change the way competitive League of Legends is viewed by providing teams a decision support edge.

Acknowledgements

We thank Jack Holt for providing avenues to high-ELO perspectives on LoL.