Identifying and Evaluating Successful Non-meta Strategies in League of Legends

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ABSTRACT

League of Legends is a multiplayer online battle arena game where teams of five players compete against each other. Over the years, players (the crowd) have formed a metagaming strategy, which is widely adopted. This paper questions and answers whether the wisdom of the crowd defined the best strategy. We investigate players' choices of champions (and builds) and their team performance from matches in the North America and Western Europe regions, using the data gathered through the Riot Games official application program interface. We classify team compositions by players' spells and attributes of items, and identify several non-meta strategies that show a consistent advantage over the meta.

CCS CONCEPTS

• **Applied computing → Computer games**; • **Software and its engineering → Interactive games**; • **Information systems →** *Massively multiplayer online games*;

KEYWORDS

metagaming, league of legends, team composition

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1 INTRODUCTION

Video game genres such as Multiplayer Online Battle Arena (MOBA), First Person Shooter (FPS), and Real-Time Strategy (RTS) have started an era of electronic sports (e-sports), which is growing steadily over the past decade. PwC reports that e-sports is expected to bring in half a billion dollars in 2016 [7]. One of the most successful online video games is a MOBA called League of Legends (LoL) by Riot Games, and there are 64 million players worldwide, and 7.5 million players are active concurrently [10].

Players, also known as summoners, choose from 134 champions to form a team of five to play against another team. Competitive summoners, including e-sports cyberathletes, play in a map called Summoner's Rift[1]. The map consists of three lanes, and each team has 11 towers, 3 inhibitors, and a nexus, and the objective is to destroy the opponent team's nexus.

Riot Games developed the game but did not offer any official strategies other than classifying their champions into six categories: assassin, fighter, mage, support, tank, and marksman. Over the years, summoners have formulated a strategy, commonly referred to as *metagaming* [2] (also known as *meta*). The meta strategy is a product of the wisdom of the crowd, and it has stabilized to a team of five unique roles, which are different from Riot Games' categories: Top (T), Jungle (J), Mid (M), Attack damage carry (A), and Support (S). It is widely adopted by summoners, and most, if not all, champion guides explain how to play a champion in one of these meta roles. ChampionGG[2], an LoL fan site, suggests primary and secondary meta roles for all the champions, and provides their strategies and match statistics. While the meta strategy is widely accepted by the community, can we rely on the wisdom of the crowd for victory in LoL matches?

This paper presents results of collecting and analyzing data on League of Legends matches and their participants on the North America and Western Europe servers. Our data analyses show that: (1) the meta strategy is dominant and strong; (2) there are non-meta strategies that have a higher win rate than the meta strategy; and (3) non-meta strategies affect different match performance metrics positively and negatively with respect to the meta strategy.

The rest of this paper is organized as follows: Section 2 discusses some recent related work; Section 3 describes the data collection process, participant support vector construction and our data sets; Section 4 focuses on identifying team compositions via meta role predictions, and provides details of our analyses and observations of team performance based on compositions; and Section 5 summarizes our findings and considers future work.

2 RELATED WORK

Researchers have explored binary expertise, player styles, match outcome predictions, teamwork vs. skill level, and level of nonverbal communication in League of Legends. Donaldson explores binary elements in mechanical and metagame expertise [3]. Ong *et al.* perform a cluster analysis on match data to identify different player styles and develop a match outcome prediction model [8]. Their dataset consists of 10,000 matches in 2013-2014, while our dataset contains over 10,000,000 matches from 2014-2015. Kim *et al.* investigate the effect of team congruency (teamwork) and proficiency (expertise and skills) on team performance, and conclude that

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[1]http://leagueoflegends.wikia.com/wiki/Summoner's_Rift
[2]http://www.champion.gg/

Table 1: Additional Participant Information from a Match

ID	Name	Description
	item0-6	Item ID in each slot (0-6)
	spell1Id, spell2Id	summoner spell IDs
1	kills	Number of kills
2	assists	Number of assists
3	deaths	Number of deaths
4	goldEarned	Gold earned
5	goldSpent	Gold spent
6	towerKills	Number of tower kills
7	inhibitorKills	Number of inhibitor kills
8	minionsKilled	Minions killed
9	neutralMinionsKilledEnemyJungle	Neutral jungle minions killed in the enemy team's jungle
10	neutralMinionsKilledTeamJungle	Neutral jungle minions killed in your team's jungle
11	physicalDamageDealt	Physical damage dealt
12	physicalDamageDealtToChampions	Physical damage dealt to champions
13	physicalDamageTaken	Physical damage taken
14	magicDamageDealt	Magical damage dealt
15	magicDamageDealtToChampions	Magical damage dealt to champions
16	magicDamageTaken	Magical damage taken
17	trueDamageDealt	True damage dealt
18	trueDamageDealtToChampions	True damage dealt to champions
19	trueDamageTaken	True damage taken
20	totalDamageDealt	Total damage dealt
21	totalDamageDealtToChampions	Total damage dealt to champions
22	totalDamageTaken	Total damage taken
23	totalHeal	Total heal amount
24	totalUnitsHealed	Total units healed
25	totalTimeCrowdControlDealt	Total dealt crowd control time
26	sightWardsBoughtInGame	Sight wards purchased
27	visionWardsBoughtInGame	Vision wards purchased
28	wardsKilled	Number of wards killed
29	wardsPlaced	Number of wards placed

team proficiency has a greater impact on the match outcomes than congruency [4]. Leavitt *et al.* show that the amount of non-verbal communication such as pings has a positive impact on match outcomes [5]. For another popular MOBA game called Defense of the Ancients 2 (DOTA2), Schubert *et al.* introduce an encounter-based analysis to predict win probabilities [9].

3 DATA COLLECTION AND SUMMARY

3.1 Data Collection

We collected a new dataset using a Python script based on [6], but with modifications to include key pieces of information we depend on to analyze team compositions and their performance. The Python script in [6] writes text files to store data from Riot Games' official API (application program interface)[3], and we made two modifications to the script: retrieval of additional match information and MySQL as the persistent storage. We expanded the set of match attributes (listed in Table 1) to enable our analyses in Section 4. Data exploration with MySQL is easier than text files, because we can execute queries while the data collection is ongoing.

Participants can purchase items during a match to enhance their champions, and thus their team's performance. Although the official API has an option to retrieve the timeline of a match, the timeline was coarse and did not provide enough details to reconstruct the item purchases, upgrades, and/or sales of the participants. As the next best alternative, our script records the items in each

[3]https://developer.riotgames.com/

Table 2: Item Attributes

Jungle Item	Ability Power
Armor	Armor Penetration
Attack Damage	Attack Speed
Bonus Gold per Large Monster Kill	Cooldown Reduction
Critical Strike	Damage taken from Critical Strikes
Gold per 10 seconds	Health
Health Regen	Life Steal
Magic Damage on Hit	Magic Penetration
Magic Resistance	Movement Speed
Mana	Mana Regen

participant's possession at the end of a match, but item identification numbers alone do not help us to understand how participants played their champions. Items come with a set of attributes, and our investigation into all the available items revealed 20 unique attributes listed in Table 2. For an item, we construct a vector of 20 components, each of which indicates the presence and absence of an attribute with one and zero respectively. Since a participant finishes a match with up to six items, each participant is assigned a vector of 20 components ranging from zero to six. For each component, zero indicates that the participant did not use any items that enhanced the corresponding attribute, while six shows that all six items boosted the attribute.

Participants are allowed to choose two from 11 spells at the beginning of each match. To represent participants' spell choices, we construct a vector of 11 components, each of which indicates if the corresponding spell is chosen. Therefore, a participant's spell vector consists of 9 zeroes and 2 ones, where the location of ones represents the spells chosen.

To represent a participant's strategy of building his/her champion, we concatenate vectors of item attributes and spells to form a support vector of 31 components. These vectors are used to identify a participant's strategy within a team, thus helping us to classify the meta role that he/she most likely played in a match. Section 4.1 provides the details on how these support vectors predict participants' roles in teams.

3.2 Dataset

We executed our data collection script for about 8 months from June 2015 until January 2016 on both North American (N. Amer) and Western European (EU West) servers. The focus of our investigation was for Preseason 5 and Season 5, which started on November 12, 2014 and lasted until November 11, 2015. The resulting dataset contained 2,337,595 and 3,520,308 unique summoners in North America and Western Europe regions respectively. Table 3 summarizes the match statistics for each region. The dataset is available at https://zenodo.org/record/582666.

There are six queue modes in the game: Artificial Intelligence (AI), Normal Blind (NB), Normal Draft (ND), Group Finder (GF), Ranked Solo (RS), and Ranked Team (RT). RS and RT are the competitive modes, where match outcomes affects summoners' rank. ND is the same as RS and RT except the summoners' rank is unaffected. Summoners can pick and play any champion of their choice in NB, while a group leader picks and chooses the composition in GF. AI is the only mode where summoners play against a team of bots, while all the other modes are players vs. players (PvP),

Table 3: Summary of the Dataset

Region	Queue	Matches	(%)	Participants	(%)
	Total	5,820,730	(100.00%)	57,103,460	(100.00%)
N. Amer	AI	220.768	(3.79%)	1,103,840	(1.93%)
	NB	2,311,456	(39.71%)	23,114,560	(40.48%)
	ND	498,270	(8.56%)	4,982,700	(8.73%)
	GF	633.867	(10.89%)	6,338,670	(11.10%)
	RS	2,044,068	(35.12%)	20,440,680	(35.80%)
	RT	112,301	(1.93%)	1,123,010	(1.97%)
	Total	4,598,994	(100.00%)	45,500,535	(100.00%)
EU West	AI	97,881	(2.13%)	489,405	(1.08%)
	NB	1,692,126	(36.79%)	16,921.260	(37.19%)
	ND	426,675	(9.28%)	4,266,750	(9.38%)
	GF	433,570	(9.43%)	4,335,700	(9.53%)
	RS	1,817,754	(39.53%)	18,177,540	(39.95%)
	RT	130,988	(2.85%)	1,309,880	(2.88%)
Total		10,419,724		102,603,995	(aggregate)
Total				5,857,903	(unique)

Table 4: Predicted role (rows) versus ChampionGG defined primary role (columns) for a random sample of 20,000 teams following a ChampionGG "primary meta composition" in the North American server and Ranked Team queue. The bottom row displays the percent of predicted roles that match the column's ChampionGG primary role.

		ChampionGG Primary Role				
		T	J	M	A	S
Pred. Role	T	18452	350	499	57	98
	J	446	19549	65	20	19
	M	914	63	19295	165	274
	A	20	15	57	19750	9
	S	168	23	84	8	19600
% Matching		92.3	97.7	96.5	98.8	98.0

4 DATA ANALYSIS

4.1 Predicting Build-Based Role

To better understand how participants deviate from the current meta, we first construct a support vector machine (SVM) model to classify the role based on the end match item attributes and spells. We train and tune the SVM using 20,000 randomly selected teams (100,000 participants) from the Ranked Team queue that followed the current meta (i.e., one of each of the five roles) according to the ChampionGG primary role designation. We refer to these team compositions as ChampionGG meta. As the goal is to learn what builds are consistent with each meta role, the support vectors were constructed based on the cumulative end match item attributes and spell selections as outlined in Section 3.1.

The rationale for limiting ourselves to only those in ChampionGG meta compositions is to find a subset of teams where the participants are likely to be following the meta closely. Further, participants involved in Ranked Team matches are presumably team oriented (and will often go into a match with a plan in mind). This helps limit the amount of noise that could occur from non-standard builds, and can help determine if certain styles that deviate from the meta are actually a feasible strategy.

For the training data, 96.6% of the predicted roles matched the ChampionGG primary role. Further, 87.2% of the teams had all five members match their predicted and primary roles. (Note that this is slightly above the expected 84.1% that would occur if individuals were making choices independent of their teammates.) These percentages indicate that both participants and teams consistently build items and choose spells according to the ChampionGG primary role. Table 4 displays the predicted classifications for each ChampionGG primary role.

As seen in the table, the only role that seems to exhibit a reasonable amount of variation in its build is the Top role (as about 4.6% and 2.2% were classified as the Mid and Jungle roles). This is not surprising as many champions that are typically considered Top champions can also be suitable in the Mid or Jungle role. In fact, many of these types of champions have secondary roles listed for them on the ChampionGG site. An example of this is the champion "Ekko" who, according to ChampionGG, has a primary role of Top, with both Middle and Jungle being listed as secondary roles. A quick online search for "example Ekko builds" shows that he is a versatile champion that has recommended builds in each of these three roles.

We can further evaluate the model by looking at the ratio of the estimated probability of the predicted role compared to the estimated probability of the ChampionGG primary role. Over 90% of time, if the two roles do not match, the predicted role's probability was at least twice that of the primary role (and in over 67% at least 10 times). This indicates that in most situations where the roles do not agree, the participants' item and spell choices match much more closely with the predicted role and not the ChampionGG primary role. (Another way of thinking of this is that these observations are not actually misclassified, but instead the build is very consistent with the predicted role.) This, combined with the very high overall matching rate, gives evidence that the item and spell choices of a participant can identify the role/build of a champion with high confidence.

Given this, we can then use the model to predict the role for every participant in our dataset and define the compositions of each team. For notational purposes, we define each team composition by the five roles predicted by the SVM model: T (Top), J (Jungle), M (Mid), A (Attack Damage Carry or ADC), and S (Support). Thus, a team following the meta would be abbreviated TJMAS, and an example non-meta team that replaces the Top build with an extra Mid would be JMMAS.

Figure 1 shows the "average team composition", defined here as the average number of champions appearing in each of the five meta roles, for the six queue modes (averaged across the two regions). When playing against AI, participants tend to focus on the roles that are more damage-oriented to be more aggressive against AI champions. It should be noted that AI opponents do not use a Jungle role - which may indicate why participants often do not play the Jungle role in this mode. Additionally, win rates against AI were over 99%, which indicates that regardless of team composition, participants have little difficulty defeating the AI.

As the competitiveness of the queue mode increases (i.e., moving from unranked - Normal based matches to Solo and Team Ranked), teams shift towards the meta with the Support role seemingly being the last to comply. In AI mode, less than 4% of teams build a TJMAS (i.e., meta) build, while this percent increases from about 48% in Normal Blind (NB) mode to over 70% in Ranked Team (RT) mode.

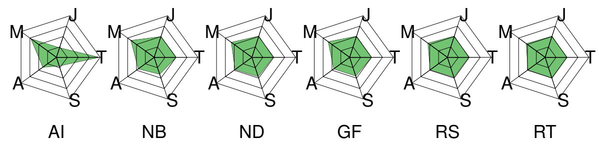

Figure 1: Illustration of average team composition by queue mode. Rings, from the inside moving out, represent an increase of 0.5 champions within the specific role (on average).

The $n\%$ column of Table 5 gives the exact percentage of TJMAS team compositions for each mode for the two regions.

Table 5: Summary of popularity and win rates for meta style team compositions (TJMAS). $n\%$ represents the percent of teams following the meta and $W\%$ is the overall win rate.

	North America		Europe West	
Queue mode	$n\%$	$W\%$	$n\%$	$W\%$
AI	3.7	99.5	2.6	99.5
NB	48.0	51.3	49.3	51.4
ND	63.2	50.9	64.0	50.8
GF	57.4	51.0	64.9	50.8
RS	69.7	50.4	73.1	50.3
RT	72.8	50.5	78.4	50.4

4.2 Successful Non-Meta Team Compositions

Regardless of region, across the queue modes, using the TJMAS (meta) build is generally a safe choice with win rates ($W\%$) that are consistently slightly above 50% (Table 5).

Table 6 displays the non-meta team compositions that have win rates ($W\%$) that are statistically significantly higher than 50% (at the 5% level of significance after adjusting for multiple comparisons using the Benjamini and Hochberg method [1]).

For both regions and all PvP queue modes, JMMAS (sixth row in Table 6) appears as a somewhat popular but slight variation from the TJMAS composition (appearing in at least 8% of teams across all PvP modes). It replaces the typical Top build with one more consistent with the Mid build. Given its resemblance to the meta, not surprisingly, its win rates are also slightly above 50%. When a JMMAS team competes against a TJMAS team, it tends to only have a slight (if any) advantage. This is seen in the $W_M\%$ values of Table 6 being slightly above 50% in most cases. Similarly, another semi-popular non-meta composition is TJMMA (seventh row). Again, this composition seems to perform pretty similar to the meta (i.e., a slightly above 50% overall win rate and approximately 50% win rate versus the meta).

One general trend that seems apparent is that some non-meta compositions seem to become more viable in the Ranked Team mode where teamwork is essential to victory. For example, compositions such as TTMAS, TMMAS, TTJSM, and JJMAS are all fairly uncommon, but seem to hold an advantage over the meta - winning more than 53% of the time. (TTMAS seems to be of particular interest given its appearance in several modes, Normal Draft, Ranked

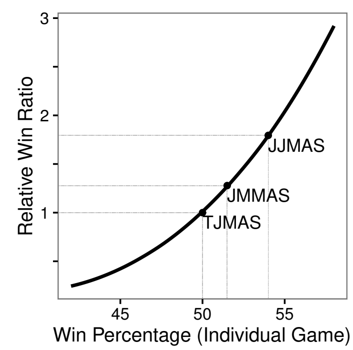

Figure 2: Illustration of compounding effect of how a relatively small increase in winning percentage of each game can influence the chance of winning a tournament.

Solo, and Ranked Team, and with high win rates against the meta.) This trend may be due to participants needing to become comfortable with a non-standard composition, but after learning the style, can use it to their advantage.

Digging deeper into the TTMAS composition for Ranked Team matches in Europe West (which had a win percentage of 56.5%) showed that the champion “Kayle" was used 67% of the time. In each case, the participant using Kayle was classified as a Top role based on the item and spell builds in every case. According to ChampionGG, Kayle is a multipurpose champion with a primary role of Top and both Mid and Jungle secondary roles. Further investigation into these matches indicated that Kayle, while finishing with a “Top consistent build", seemingly still played the Jungle position as she finished with the most number of jungle minion kills on the team (attributes 9 and 10 in Table 1). Further, in the matches that Kayle was involved with, the team won 65.5% of the time - which is substantially larger than the 48.7% win rate for TJMAS teams (in Europe West Ranked Team queue) where Kayle is built (and classified) as a Jungler.

Each queue mode also have non-meta team compositions that perform poorly (with win rates well below 50%). While these are too numerous to list, one of the more popular poor compositions was TTJAS (which appeared in just under 6% of teams in ranked matches) and had win rates ranging from 46% to 48%. Typically, team compositions that are very imbalanced tended to perform poorly (with win rates below 30% in many cases).

We note that with the extremely large sample sizes for some team compositions (especially in the Ranked Solo mode where $n\% < 1$ can still be more than 10,000 teams), the statistical power to detect win rates above 50% is quite large, and even small increases (such as 51%) can be detected with relative ease. While this may seem a trivial increase, its compounding effect through repeated play should not be underestimated. Similar to the idea of compounding interest, a slight increase in win percentage can have substantial benefits in the long run. To illustrate this, we simulate how a team would perform in the tournament format used for the 2015 League of Legends World Championship. The tournament is composed of a group stage and a knockout stage. In the group stage, 16 teams are divided into four groups, in which each team plays all the other teams twice. After all the matches in the group stage, the top two teams in each group advance to the knockout stage. In the knockout stage, each round is played as a best of five, all the way to the grand final. Our simulation assumes that a meta team has 50% chance of winning against another meta team. For our non-meta team with the winning chance of p, a meta team has a winning chance of $1 - p$. We count the number of times the non-meta team wins the tournament after 100,000 runs for each p ranging from 0.4 up to 0.6 in increments of 0.005. Based on these simulated tournaments, we use least squares regression to model the relative win ratio (y) as a third order polynomial with respect to p with estimated form: $y = 18.45p - 93.64p^2 + 121.57p^3$ (noting that the model had an $R^2 = 0.999$). This equation, illustrated in Figure 2, shows how even small advantages can be extremely beneficial. For example, team compositions such as JMMAS (which has a win rate of just above 51% versus the meta in ranked play) would be approximately 1.18 times more likely to win the tournament than a meta team. For the JJMAS composition (which when averaged over the two regions has about a 54% win rate over the meta in ranked play) is 1.8 times more likely to win. The opposite holds true as well and shows how inferior team compositions can further disadvantage them.

4.3 Performance attributes of viable non-meta compositions

Having identified several non-meta team compositions that are seemingly viable, we further investigate what aspects of the match they tend to focus on. To do so, we compare the attributes listed in Table 1 from the identified non-meta compositions in Table 6 to meta teams. More specifically, for each of the 28 non-meta compositions identified in Table 6 (keeping queue mode and region separate), we

(1) consider only matches in which the non-meta team defeats a TJMAS team,
(2) calculate the average duration and the average of each of the 29 numbered attributes in Table 1 (scaled by the duration of the match), and,
(3) find the difference between these averages and a control group represented by the similarly calculated values obtained when a TJMAS plays another TJMAS.

These differences in averages are then scaled by their root mean square error (centered around zero) to provide a standardized effect than can be easily compared across match attributes that are on widely different scales. We used *gplots*[4] to plot Figure 3 which displays these standardized effects. We use hierarchical clustering (based on Ward's D linkage) to separately group both the team compositions and game attributes. The resulting hierarchical trees were used to order the match attributes and team compositions to more easily detect patterns in the compositions. To further ease in detecting patterns, we split the standardized effect scale into a "low" (white cells), "medium" (lightly shaded), and "high" (darkest shade) categories. Blue coloring indicates the team composition had a higher average than the typical winning meta team, while red coloring indicates it was lower (on average) than a winning meta team. Last, note that to better separate jungle and lane performance,

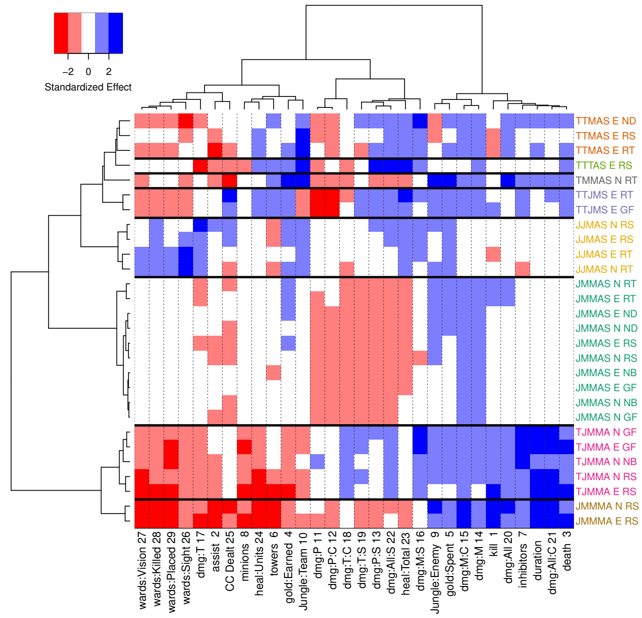

Figure 3: Cluster dendrogram and heatmap of standardized effect scores the 30 match attributes for each of the 28 viable non-meta compositions. Along the row labels, the first five letters represent the team composition, the next is the region (N = N. Amer, E = EU West), and the last two the queue mode. Numbers next to attribute names (column labels) can be mapped to Table 1 for details. For damage (dmg) type variables, P, M, and T stand for Physical, Magic, and True damage respectively. C is damage dealt to opposing champions, and S is damage taken to one's self.

we redefine attribute 8 - "minionsKilled", to be the non-jungle minions killed (labeled "minions" in Figure 3).

The largest group (JMMAS - sixth group from the top in Figure 3) also exhibits the most similarities to the current meta. This is seen by noticing the large number of white and lightly shaded cells in Figure 3. The main areas in which winning JMMAS teams differ from winning meta teams is that they deal (and take) physical damage at a slightly lower rate and deal magic damage at a slightly higher rate. Similarly, the JJMAS composition (fifth group from the top) only slightly differs from meta teams and seem to focus on wards (both placing wards and destroying the opposition's wards).

Both the TJMMA and JMMMA compositions (bottom two groups) tend to be rather aggressive towards opposing champions. They accrue kills and deaths, deal more damage (magic and overall), and invade the enemy's jungle at a faster rate than winning meta teams. On the flip side, they largely ignore wards, have lower assists rates, and have fewer lane minion kills per minute.

In addition to being more likely to win against a meta team, TTMAS, TTTAS, TMMAS, and TTJMS (the top four groups in Figure 3) all have several match attributes that differ quite a bit from the typical meta team. For example, TTMAS teams have relatively high rates of magic damage dealt, but also tend to take damage at

[4] https://www.rdocumentation.org/packages/gplots/versions/3.0.1

Table 6: Summary of non-meta team compositions with overall win rates statistically significantly higher than 50% (within a region and queue mode). Within each region and queue mode, $n\%$ represents the percent of teams with the specified composition, $W\%$ is the overall win percentage for the composition, and $W_M\%$ is the win percentage against a meta composition.

		Normal Blind			Normal Draft			Group Finder			Ranked Solo			Ranked Team		
Composition	Region	$n\%$	$W\%$	$W_M\%$	$n\%$	$W\%$	$W_M\%$	$n\%$	$W\%$	$W_M\%$	$n\%$	$W\%$	$W_M\%$	$n\%$	$W\%$	$W_M\%$
TTMAS	N. Amer															
	EU West				0.3	56.6	54.7				0.3	57.1	57.2	0.2	56.5	55.8
TTTAS	N. Amer															
	EU West										0.1	57.1	55.5			
TMMAS	N. Amer													0.9	53.9	53.4
	EU West															
TTJMS	N. Amer															
	EU West							1.8	52.0	51.4				0.8	54.5	54.5
JJMAS	N. Amer										1.1	50.8	50.5	1.3	52.6	53.4
	EU West										0.9	50.9	50.8	1.2	54.1	54.8
JMMAS	N. Amer	10.2	51.5	50.2	10.5	51.3	50.1	8.3	50.6	49.6	9.5	52.1	51.8	9.0	52.0	51.6
	EU West	11.1	51.8	50.4	12.0	51.5	50.7	10.1	50.8	50.0	9.8	52.0	51.7	8.1	51.7	51.5
JMMMA	N. Amer										0.4	51.8	51.2			
	EU West										0.4	51.2	51.1			
TJMMA	N. Amer	6.9	50.7	48.9				5.5	51.2	50.0	3.4	51.5	51.1			
	EU West							5.0	50.6	49.8	3.4	51.0	50.4			

a high rate. (This likely results in somewhat higher kill and death rates too.) All four of these compositions also have a lower rate of physical damage dealt and tend to have slightly lower emphasis on wards. Interestingly, even though TTMAS does not have a champion that is built in the traditional Jungle style, they kill jungle minions in their own jungle at a substantially higher rate than meta teams. (This trend is also shared by both the TTTAS and TMMAS.)

5 CONCLUSION AND FUTURE WORK

In this paper, we have collected a massive number of participant statistics and information to predict different types of builds in League of Legends. Based on the meta strategy of having one of each of the five roles (TJMAS), we train an SVM to use in-match item attributes and spell selections to identify successful "non-meta" team compositions. Across PvP queue modes on both North American and Western Europe regions, the majority of teams follow the established meta, and win just over 50% of matches. We also identified 28 non-meta compositions that have a statistically significant win rate above 50%. Additionally, for the ranked queue modes, many of the non-meta builds show a small (but consistent) advantage over the meta teams. Within winning teams of these non-meta compositions, we also investigate which match statistics they tend to excel (or ignore) when compared to a typical winning meta team.

One of the main contributions of this work is collecting and making available the dataset. Its extremely large number of matches provide enough samples to discover uncommon team compositions with their above-50% win ratio. As this is an observational study, we cannot directly state that these team compositions are the sole reason of their victories, but it can establish a more systematic way to discover what tactics these teams use. For example, as indicated in Section 4.2, the champion Kayle was heavily involved in the success of the TTMAS (Ranked Team queue in Europe West) matches by having an end-game build consistent with a Top role while seemingly playing the Jungle position. If in-match information could become available, future work could then focus on the match IDs for these teams, obtain the match timeline, and further analyze their tactics (such as through the methods described by [9]). Alternatively, participants already familiar with Kayle could experiment with a Top build in the Jungle position to see if they can reverse engineer the successful tactics of these teams.

Many of the concepts and statistical techniques used in this paper could be applied to other maps in League of Legends (such as Twisted Treeline), to other MOBAs (such as Heroes of the Storm or DOTA2), and to other team-based games (such as Overwatch). These can again lead to a better understanding of uncommon (but potentially advantageous) team compositions that deviate from the accepted norm.

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