Investigating the Impact of Game Features on Champion Usage in League of Legends

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ABSTRACT

League of Legends is a multiplayer online battle arena game where players typically form teams of five and play the role of a character (called a "champion") with certain in-game roles such as Assassin, Mage, or Tank. One of the major appeals of this game is that it follows a freemium model and the available in-game transactions do little to impact a player's performance or ability. Although champions can be purchased with actual (or in-game) money, another aspect of the game is a weekly rotation of ten (out of 123) free champions where players can test new champions before buying them. This project involves scraping champion usage data from online sources (e.g., from the LoL DB Gameguyz fansite) where we then analyze what impact the free rotation and other game features (such as the introduction of new champions and official game updates) have on champion usage. Additionally, we have also constructed a simple web application (*LoLNOVA*) that allows users to compare charts of usage statistics, perform simple data analyses, and download data for champions of their choice.

Categories and Subject Descriptors

Applied Computing [**Computers in other domains**]: Personal computers and PC applications – Computer games; Information Systems [**World Wide Web**]: Web Applications

General Terms

Game Design, Measurement, Human Factors

Keywords

League of Legends, Multiplayer Online Battle Arena, champion usage, statistics, time-series, LoLNOVA

1. INTRODUCTION

Online games have become more popular over the past decade, and the worldwide video game market was 93.3 billion dollars in 2012, with the projection of 111.0 billion dollars by 2015 [10]. One of the most successful online video games is a Multiplayer Online Battle Arena (MOBA) game called League of Legends by Riot Games. League of Legends was released in late 2009, and over 27 million players play it on a daily basis [9]. Riot Games uses a freemium model for League of Legends where players can download and play the game for free while there are champions and items that you can purchase with both in-game currency (Influence Points) and real currency (converted into "Riot Points"). Players gain more in-game currency as they engage in online matches.

League of Legends features four different game modes: Summoner's Rift, Twisted Treeline, All Random All Mid (ARAM), and Dominion. In each mode, a player chooses a champion to play and compete in a team typically consisting of five players against the other team. There are 123 champions in the game (as of Feb 2015), and each champion has different roles (Assassin, Fighter, Mage, Marksman, Support, Tank [1]) and features a different set of abilities. Riot Games continues to release patches to introduce new features as well as balance changes to the game. Balance changes include adjustments to champions' abilities as well as complete reworks of older champions which can lead to a huge impact on how players decide to use the champions in the matches. The freemium model Riot Games has adopted allows players to pick a champion that they bought or that is free for the week. Players tend to use the champions that are free more while they are free, and these trials lead to an increase in champion usage in the following weeks. For each champion that a player owns, he/she can customize the champion further by purchasing skins. Introductions of new skins for a champion can shift players' interest to the champion. Players can choose to play casually in the normal tier or competitively in ranked tiers (bronze, silver, gold, platinum, diamond, master, challenger). Due to the competitive nature of the ranked tiers, players tend to try out free champions in the normal tier more than the ranked tiers as wins and losses in the ranked tiers influence the players' standings in the competitive scene.

Researchers have investigated many different aspects of online video games, including MOBA games and League of Legends, but not directly at how game features affect the usage of champions in the game. Veron *et al.* discuss the de-

Champions list

Enter Champion Name

No.	Champion	Matches	Popularity ?	Wins	Losses
01		319,980	14.98%	152,063	167,917
02		297,885	13.94%	139,861	158,024
03		294,747	13.80%	142,341	152,406
04		274,720	12.86%	144,569	130,151
05		257,251	12.04%	123,114	134,137
06		243,587	11.40%	115,062	128,525
07		197,564	9.25%	95,886	101,678
08		162,637	7.61%	87,219	75,418
09		155,258	7.27%	81,875	73,383
10		151,740	7.10%	76,155	75,585

Figure 1: Sample Table from the Statistics Page on LoL DB

sign of matchmaking of players to improve their experience of playing the game [11]. Guo *et al.* analyze the characteristics of match-based games with regard to workload characteristics, win ratio, and player evolution [3]. Nuangjumnong examines the relationship between in-game roles of players and their leadership styles in MOBA games [5]. Suznjevic *et al.* evaluates the feasibility of porting online games to cloud gaming platforms by examining their network traffic patterns and players' quality of experience [8]. Carter *et al.* explores the modalities of game engagement to facilitate research in game design and player experience [2].

The rest of this paper is organized as follows: Section 2 describes the data collection process; Section 3 focuses on what metric we use, what analysis we performed, and what observations these analyses present; Section 4 describes the online tool to perform custom analysis based on the data set; and Section 5 summarizes our findings and considers future work.

2. DATA COLLECTION

In this section, we provide the descriptions of the data collection process and the data collected. There are many fan-based websites that provide League of Legends news, guides, and video streams as well as data including popularity, kill-to-death ratio, and champion bans. We chose to use the LoL DB Gameguyz website[1] that offers champion data by popularity, win rate, Kill-Death-Assist (KDA) ratio, Penta-Kill-Ability (PKA), champion bans, items, and rating tiers for all player-versus-player games in the Summoner's Rift mode. The LoL DB Gameguyz website provides a full table of all champions in addition to summarized graphs, and we were able to gather a more complete picture of the data set compared to using other websites. Figure 1 depicts a sample table provided in the popularity section of the statistics page. The table provides the date of the data along with the number of matches in which the champion is picked, the "popularity score" computed by the website, the number of winning matches with the champion, and the number of losing matches with the champion. We note that we do not use the popularity scores reported by the website because it is unclear how it is computed. Section 3 describes the new metric we use to analyze champion usage.

We wrote a Python script to access this page directly to extract all the raw data from the table daily. Although the page is updated on a daily basis, we noticed that the time at which the data got updated was inconsistent. The server is set up to execute the script three times a day at 3am, 11am, and 7pm to ensure that we get the fresh data every day. In addition to the raw data from the table, we were also interested in which set of champions was free each week. Riot Games announces the free champion rotation every week, and we wrote another Python script to access the latest free champion rotation announcements to extract the ten champions free for the following week. The data collection started on 25 April 2014, and the scripts have been running steadily since then. There were a few incidents when the website changed the pages and the script failed to collect the data for a few days. The data on these days are shown as blank in graphs included in Section 3.

[1]http://loldb.gameguyz.com/

3. DATA ANALYSIS AND RESULT

Although LoL DB provides a "popularity score," it is unclear exactly how they calculate the score as the official description simply defines it as "The selection frequency of a Champion." Instead, we define the usage (U) for champion c, in tier t (normal, bronze, silver, gold, platinum, diamond), on day d (25 April 2014 to 02 January 2015) as

$$U_{ctd} = \frac{M_{ctd}}{\sum_{c=1}^{C} W_{ctd}/5} \cdot 100$$

where M_{ctd} is the number of matches in which champion c appears in tier t on day d and $\sum_{c=1}^{C} W_{ctd}/5$ represents the total number of wins in tier t on day d. Further, C represents the total number of champions played on day d in tier t. Typically this the total number of champions in the game (119 at the beginning of the study, 123 as of January 2015), but occasionally is it reduced if a champion is temporarily disabled due to game-crashing bugs. (Which are then typically fixed in the next patch.) We note that we exclude the master and challenger tiers of ranked play due to the extremely small number of players in each. We also note that while data for several different regions was collected (namely North America, Western Europe, and Korean servers) we elect to pool all regions together to simplify the analysis and generalize the results.

The usage score roughly translates to the percent of games in which a champion appears and allows for an increased score when popular champions appear on both teams (which can occur in the very popular normal tier using blind pick mode). Further, due to the possibility of having the same champion appear on each team, using the total number of wins provides a more robust way to count the total number of matches played each day. Finally, as the score is invariant to the total number of matches played in a tier each day, it can be used to provide a fair comparison across normal and ranked tiers (especially as the upper tiers, such as platinum and diamond, have far fewer total matches played than normal games and lower ranked tiers like silver and bronze).

In this section, the usage score is used in two main ways. The first is to investigate what impact the weekly free champion rotation has on champion usage. Second, we explore the impact that other features, such as releasing new champions, creating new "skins" for champions, and patches to the game (in particular those involving a change to a champion), have on the usage of specific champions.

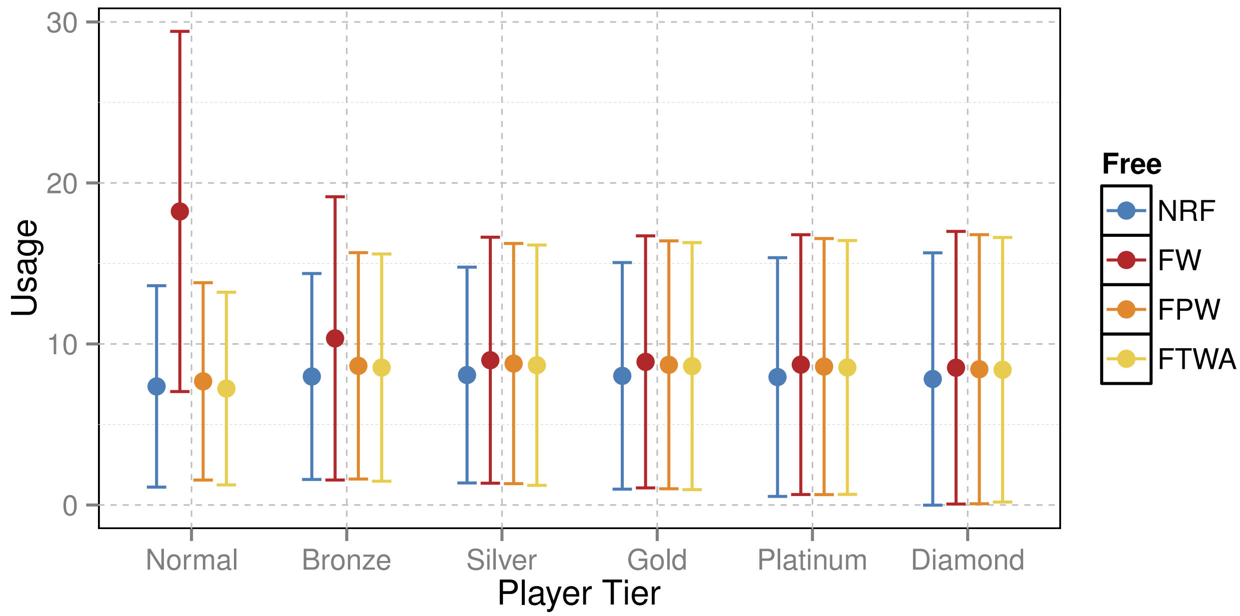

Figure 2: Mean champion usage (dots) with standard deviations (bars) comparing free zones for each player tier (normal and ranked).

Table 1: Average champion usage by player tier (normal and ranked tiers) and free week classification. Within each column, mean values for free zones with different letters are considered statistically significantly different (at the 1% level using the Holm-Bonferroni multiple comparisons adjustment).

Free Zone	Player Tier											
	Normal		Bronze		Silver		Gold		Platinum		Diamond	
Not Recently Free (NRF)	7.4	a	8.0	a	8.1	a	8.0	a	7.9	a	7.8	a
Free Current Week (FW)	18.2	b	10.3	b	9.0	b	8.9	b	8.7	b	8.5	b
Free Previous Week (FPW)	7.7	a	8.6	c	8.8	b	8.7	b	8.6	b	8.4	b
Free Two Weeks Ago (FTWA)	7.2	a	8.5	c	8.7	b	8.6	b	8.5	b	8.4	b

3.1 Trends in the Weekly Free Champion Rotation

To investigate the impact of the free week rotation on champion usage, we conduct an analysis of variance (ANOVA) on champion usage classifying a champion into one of three "Free Zone" categories for each day – not recently free (NRF), free during the current week (FW), free the previous week (FPW), and free two weeks ago (FTWA). These categories were chosen to see the direct impact on usage for free champions and to determine how players change their champion selection tendencies based on those that were recently free. Further, we investigate how champion usage is impacted by the free week changes

1. across normal and ranked tiers, and
2. within normal tier play,
   (a) based on the cost of the champion, and
   (b) based on the primary role of the champion.

More specifically, the ANOVA model for the first analysis was a two-factor model (free zone and player tier) with interaction and for the second, a three-factor ANOVA model (free zone, cost, and primary role) with pairwise interactions between free zone and each of cost and primary role. ANOVA models were fit using the statistical software package R [6] and, for each model, comparisons of usage scores for the free zone within the other factor's levels were based on a 1% statistical significance level after adjusting for multiple comparisons using the Holm-Bonferroni method [4]. Error degrees of freedom for the ANOVA model using all ranks (for analysis 1) was 173,555 (as there are 242 days used, 6 tiers used, and between 119 ad 123 for each day) and for the normal tier only model (for analyses 2a and 2b), 28,880 degrees of freedom.

As seen in Figure 2, while there is clear variability in popularity of different champions (as displayed in the standard deviation bars), there is a huge increase in average usage for free champions in normal tier play (an average increase in usage of approximately 11 points). This is no surprise as normal play is widely used by newer players that do not own as many champions as well as by experienced players to learn new champions before playing as them in ranked games. Further, for normal tier games, while there is the immediate increase in average usage while free, there is no lasting effect in the immediately following weeks (as the NRF, FPW, and

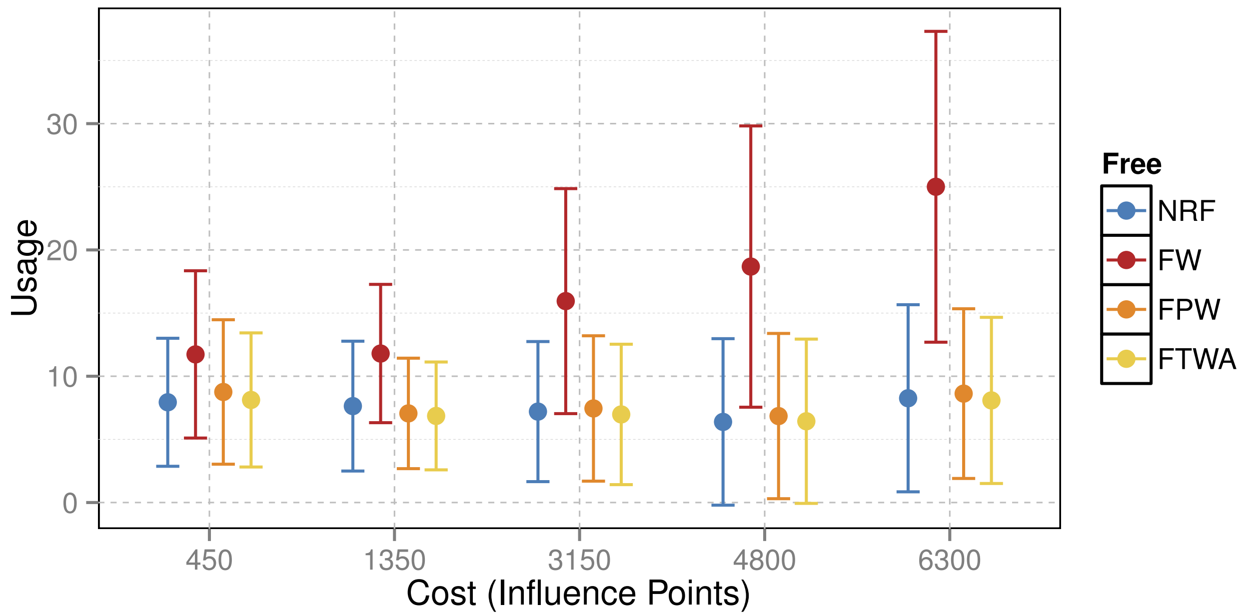

Figure 3: Mean champion usage (dots) with standard deviations (bars) by cost in influence points (IP) and free week classification for normal tier play.

Table 2: Average champion usage by cost in influence points (IP) and free week classification for normal tier play. Within each column, mean values for free zones with different letters are considered statistically significantly different (at the 1% level using the Holm-Bonferroni multiple comparisons adjustment).

Free Zone	450 IP		1350 IP		3150 IP		4800 IP		6300 IP	
Not Recently Free (NRF)	7.9	a	7.6	a	7.2	a	6.4	a	8.3	a
Free Current Week (FW)	11.7	b	11.8	b	15.9	b	18.7	b	25.0	b
Free Previous Week (FPW)	8.8	a	7.1	a	7.4	a	6.8	a	8.6	a
Free Two Weeks Ago (FTWA)	8.1	a	6.9	a	7.0	a	6.4	a	8.1	a

FTWA zones are not considered statistically significantly different from each other as indicated in Table 1).

More interesting is the free week impact in ranked tiers. For the bronze tier, there is a statistically significant increase in average usage when a champion becomes goes on free rotation (albeit smaller than in normal tier as it is only an average increase of about 2.3 points), and in the two weeks after they are free (FPW and FTWA) also have statistically significantly higher usage than prior to their free rotation (with average usage increasing by about 0.5 points as shown in Table 1). This impact is also seen at higher levels, though the increase during the free week (FW) itself is no longer statistically significantly higher than the two weeks afterwards. While we are unable to determine the direct cause for this increase in later weeks at the higher ranks, it is likely because players test out champions they do not own during the free week, purchase those that they like, and are then more likely to play them in the next few weeks given that they just purchased them (i.e., it is likely similar to “trying out a new toy” when you first purchase it).

Figure 3 and Table 2 show the average usage (with standard deviations included in the figure) for each of the cost tiers for champions (in Influence Points, or IP) in normal tier games. At all cost tiers, champions on free week (FW) show a significant increase in average usage with the more expensive champions displaying a much larger increase than the inexpensive ones – ranging from about only a four point increase for 450 IP and 1350 IP champions to nearly 17 points for 6300 IP champions. Although at most cost tiers (except 1350 IP) is a slight increase in the average usage in the week after a champion is free (FPW), at no cost tier level is it is large enough to be considered statistically significant (see letters in Table 2). Additionally, note that costs of champions are based on their price as of 02 January 2015. Thus all champions that had been added to the game since the beginning of the data collection are classified as 6300 IP champions (instead of including a separate category of 7800 IP for the first week in which a new champion is released).

This increase in the gap between a champion’s usage in free week and their cost is likely because the less expensive champions are already owned by many players (both because they are affordable for newer players and that they also tend to be older champions). Similarly, for the expensive champions players are likely to use those they may consider purchasing during the free week to help decide if they wish to commit the necessary IP later (as 6300 IP can take several weeks to obtain for the casual player).

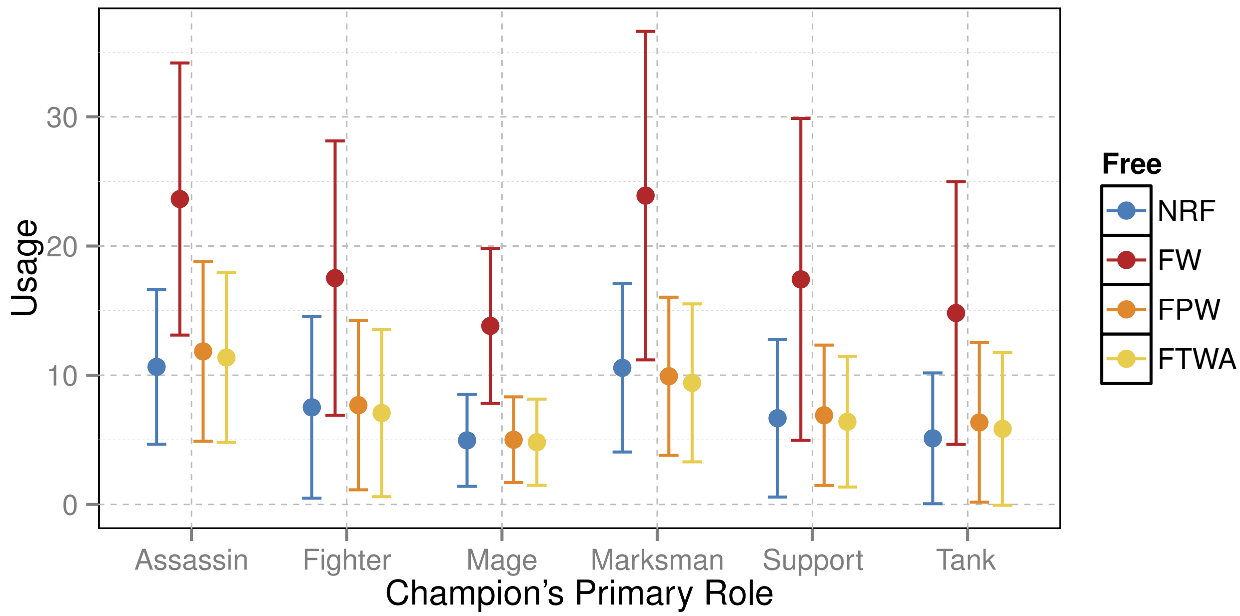

Figure 4: Mean champion usage (dots) with standard deviations (bars) comparing free zones for primary role for Normal tier games.

Table 3: Average champion usage by primary role and free week classification for normal tier play. Within each column, mean values for free zones with different letters are considered statistically significantly different (at the 1% level using the Holm-Bonferroni multiple comparisons adjustment).

Free Zone	Primary Role											
	Assassin		Fighter		Mage		Marksman		Support		Tank	
Not Recently Free (NRF)	10.7	a	7.5	a	5.0	a	10.6	a	6.7	a	5.1	a
Free Current Week (FW)	23.6	b	17.5	b	13.8	b	23.9	b	17.4	b	14.8	b
Free Previous Week (FPW)	11.8	a	7.7	a	5.0	a	9.9	ac	6.9	a	6.3	c
Free Two Weeks Ago (FTWA)	11.4	a	7.1	a	4.8	a	9.4	c	6.4	a	5.9	ac

Finally, we compare the free week impact on champion usage across the champion's primary role (Assassin, Fighter, Mage, Marksman, Support, or Tank) for normal tier matches. As seen in Figure 4 and Table 3, all roles see a substantial (and statistically significant) increase in the champion's average usage while free ranging from about 9 points for mages to more than 13 points for Marksmen. Assassins, Fighters, Mages, and Supports see only the temporary boost in usage during their free week (as FPW and FTWA are not significantly different from NRF for these roles). Tanks show a small, but statistically significant, increase in their average usage the week after they are free when compared to their usage when not recently free (6.3 points in FPW versus 5.1 points in NRF). This further supports the idea seen in the usage impact across the ranked tiers (displayed in Figure 2) that players tend to purchase a champion shortly after they become familiar with them during the champion's free week and then use their new champion in the following week.

Interestingly, Marksmen see a slight, but statistically significant, decrease in the average usage between their typical usage when not recently free (10.6 points) and their usage two weeks after they are free (9.4 points). While it is not entirely clear why this would occur, one possibility is perhaps that generally there is at least one free Marksmen each week, and as these champions are "auto-attack" based, many have similar playing styles and could be more easily interchanged. This then allows players to quickly adjust to playing the free Marksmen for that week instead of purchasing one that they had just recently played.

3.2 Individual Champions

Since April 2014, a total of four champions (Braum, Gnar, Azir, Kalista, and Rek'Sai) have been added to League of Legends. To investigate the impact of a new champion, we chose Braum as he is the first champion to have been released since we began collecting data (as Braum was released in May 2014). Figure 5 depicts the usage for Braum in normal tier games over time. Upon release, Braum draws players' interest as indicated by a huge spike. Interest in Braum continues as shown by the spikes during the free weeks as many players want to try out the "new champion." Over time, we see that the usage of Braum gradually stabilizes during the times he is not free as his role in the game has become more established. While not shown, a similar, but smaller, spike in his usage occurs in ranked play with the effect lessening as the tier increases. Additionally, the other

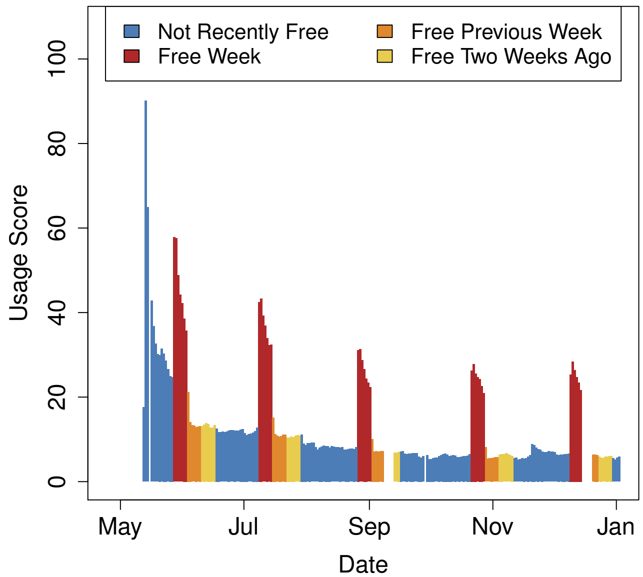

Figure 5: Usage for Braum in normal tier games. Illustrates the impact of a new champion being introduced into the game.

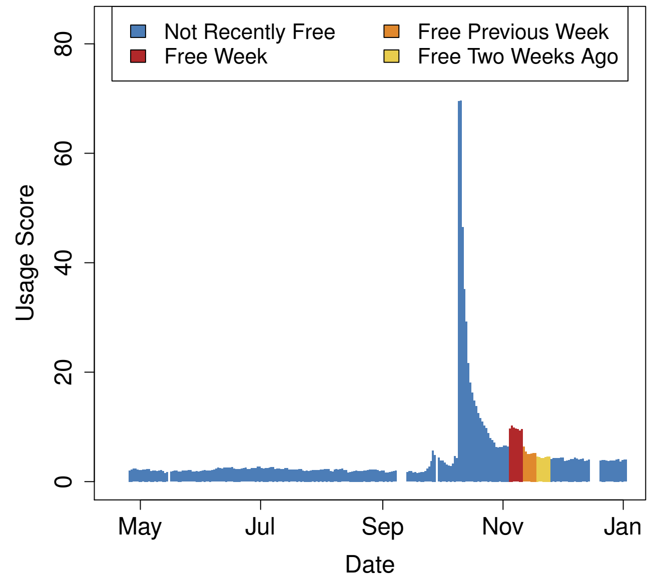

Figure 6: Usage for Sion in normal tier games. Illustrates the impact that a major reworking of a champion has on the game.

new champions exhibit a similar trend of a huge usage spike upon release and in their free weeks, but for most it is still too early to tell if their usage has stabilized during non-free weeks.

In addition to new champions, Riot Games occasionally does major reworking of older champions which can have a huge impact on champion usage. During the period of our data collection, Riot Games have reworked a few champions including Sion, Soraka, and Cassiopeia. Figure 6 demonstrates the usage for Sion in normal tier games. Sion is one of the original champions that launched with the game in February 2009. Before Patch 4.18, Sion was unpopular due to his mechanics and age. The reworking of Sion in Patch 4.18 basically relaunched Sion as a new champion and we see a tremendous increase in usage in October 2014 when Patch 4.18 was released. The usage stabilizes quickly over time, and it remains mostly unaffected during his free week because many players already own Sion (due to his age) and inexpensiveness (only 1350 IP). Even with a complete reworking of Sion, he remains only slightly more popular than before (moving from a usage score of approximately 2 points to about 5 points).

Riot Games continuously releases patches to tweak champions and items to balance the game and to fix the current bugs in the game. Figure 7 depicts how the usage for Kha'Zix responds to the changes in the games in the bronze and diamond tier games, noting that the large spike in Kha'Zix's usage in the bronze tier in May coincides with him being free that week. In general, before Patch 4.9, players considered Kha'Zix to be a strong assassin champion. In June 2014, Patch 4.9 implemented damage reduction to Kha'Zix's abilities, and these changes discouraged players from using him as shown by a sudden drop as well as a continuous gradual drop all the way through July. Towards the end of July, players start to adapt to the changes as we observe a small increase in the usage for Kha'Zix. Since Patch 4.13, we see a rapid increase in diamond tier games and a following slower increase in the bronze tier games. Although there were no changes to Kha'Zix in Patch 4.13, there were significant tweaks that diminished the effectiveness of Lee Sin and Elise. Lee Sin and Elise are popular champions that assume the same role as Kha'Zix in the game, and more significantly, Lee Sin was considered as a counter pick against Kha'Zix. As a result, players in the diamond tier started picking up Kha'Zix again quickly. We also observe that players in the bronze tier are following the trend in the diamond tier because many players learn how to play better by watching players of higher caliber on streaming services. At Patch 4.18, there is a slow decline in usage in both diamond and bronze tiers due to a small change that weakened Kha'Zix again. Finally, Patch 4.20 introduced many new items that apply to the role that Kha'Zix is usually picked for, and we see that players chose not to play Kha'Zix, avoiding the steep learning curve to adapt to the major changes. A similar decrease in usage occurred with many of the champions used in the same role as Kha'Zix due to the introduction of these new items.

Players can buy skins (using Riot Points) for the champions they own to customize their looks in the game. Skins boost interest in champions because players can boast the distinguished looks of their champions. Introduction of new skins to a champion can generate a temporary interest and usage boost to the champion. The effect is more subtle compared to other features discussed above because players can only buy skins for champions they own. Figure 8 depicts the usage for Veigar in normal tier games. Riot Games started

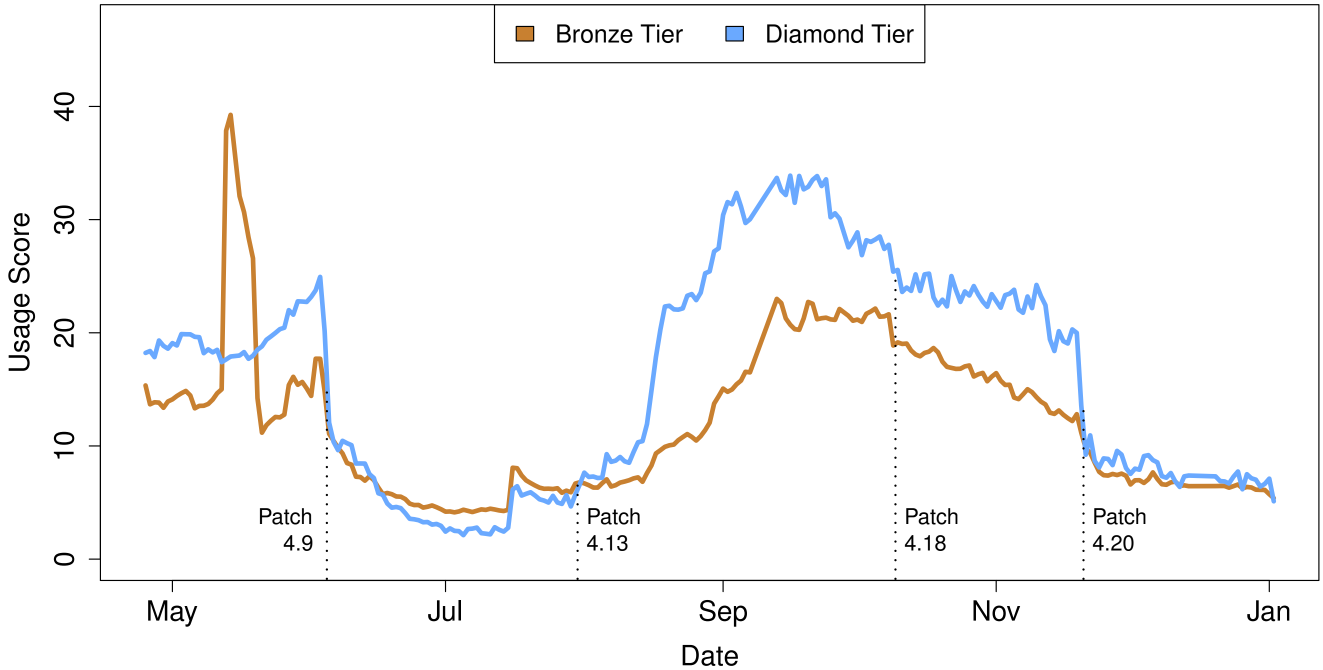

Figure 7: Usage for Kha'Zix in bronze and diamond tier games. Illustrates the impact that official game patches can have on a champion affected by the patch.

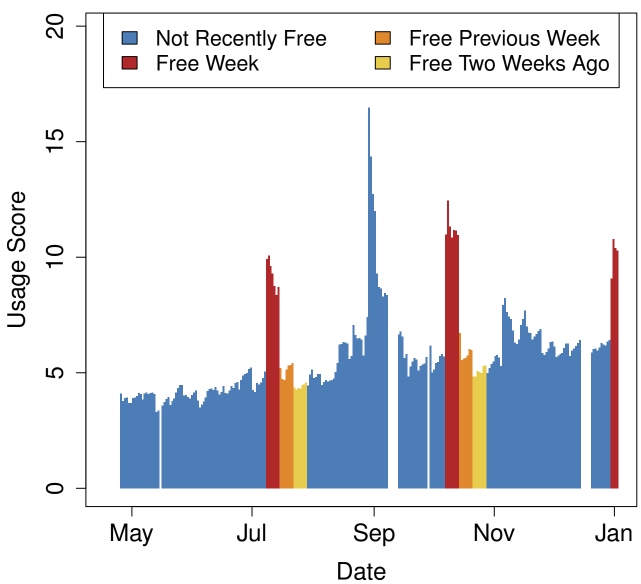

Figure 8: Usage for Veigar in normal tier games. Illustrates the temporary impact introducing a new skin for a champion has on the game.

releasing new skins for Hecarim, Miss Fortune, Sona, and Veigar as an Arcade series. Veigar's "Final Boss" skin was released on 28 August 2014, and we observe an immediate increase for a few days after the release. However, the effect is temporary, and the usage for Veigar stabilizes soon afterwards. A similar pattern occurs in the ranked tiers as well as for other champions when skins are released for them.

4. LoLNOVA APPLICATION

There are various ways to analyze the data collected, and we are unable to report all findings due to space limitation. We introduce a new tool called *LoLNOVA* that can access the data collected continuously to perform data analyses that are both similar to ones in this paper and new. *LoLNOVA* is based on Shiny, a web application framework that uses the statistical software package R [7]. *LoLNOVA* is available on the web at `http://tinyurl.com/pr75d8y` and provides data sets for download and basic ANOVA based custom analyses. Figure 9 shows an example analysis of Kha'Zix and Veigar. The *LoLNOVA* application allows you to select two champions, two regions, two tiers, and a date range. While all these selections can be independent of one another, the ANOVA and mean usage score reports are only available when all categories except one (excluding date range) are different. The selected data can also be downloaded as a comma separated file for further, independent, data analysis.

5. CONCLUSION AND FUTURE WORK

In this paper, we have analyzed the impact that the free rotation and other game features, such as the introduction of new champions and official game updates, have on champion usage. There is a huge increase in average usage for free champions in normal tier play while the impact diminishes as it gets to higher ranked tiers. However, in ranked play the impact persists through to the two weeks following the week that the champion is free. At all cost tiers, champions on free week show a significant increase in average usage with the more expensive champions are the larger increase

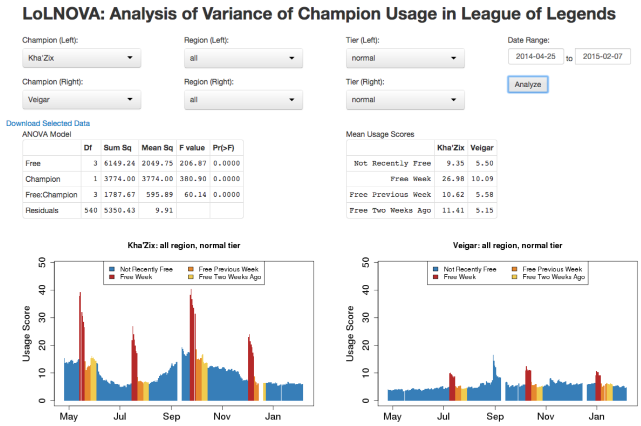

Figure 9: LoLNOVA: Analysis of Variance of Champion Usage in League of Legends

in average usage. Across the primary roles of champions, there is a major increase in the average usage of champions, although the impact does not tend to persist through the following weeks. In addition to the free champion week, the introduction of new champions and skins, and major and minor changes to champions also have an impact on champion usage. When a new champion is introduced the champion usage starts at an extremely high level, and the champion usage stabilizes over the following months – although the champion usage remains high during the free weeks. Major changes to existing champions mimic the impact of new champions but the increase during the free weeks are not as extreme. Minor tweaks to existing champions also have an impact on the affected champion usage as well as on related champions. Depending on the changes, it can either increase or decrease the champion usage. The impact of the introduction of new skins is not as large as other feature changes as they only affect the players who own the champions first, and it only persists for a few days.

We developed a web application called *LoLNOVA* where interested parties can perform their own analyses and download the data set based on the parameters. *LoLNOVA* allows visitors to analyze the data based on two champions, two regions, two tiers, and a date range. The application provides the ANOVA model and mean usage scores if and only if one category has different values. The two graphs are always plotted based on the parameters selected on the website.

Further analysis based on player defined roles in the game (e.g., jungler, top lane, and bottom lane), interactions in usage between champions of similar roles, and how champion usage in the world championship tournaments affects players' selection will be investigated. Riot Games provides difficulty ratings for all the champions, and it is another factor to investigate using a similar analysis described in Section 3. As mentioned in Section 2, the LoL DB Gameguyz fansite provides other data of interest for analysis such as champion bans, player profiles, and players' match histories. Data on champion bans can be examined using the same technique as champion usage. New champions, major reworking, and/or minor tweaks will affect players' choice on which champion to ban. Some players decide to run an illicit "bot" which allows them to increase their in-game time without having to play the game themselves, and they affect legitimate players' experience negatively. Analyzing data on both player profiles and their match histories may provide more ideas on bot detection and their presence in matches.

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