League of Legends players' performance analysis

Master Thesis

Data Science and Society

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Contents

Abstract

This thesis focuses on measuring the player performance in League of Legends, analyzing the professional players' Solo Queue and Tournament games. The general theories on this topic do not always take into consideration the differences between the various roles, however they validate the use of other useful metrics. To see which features are able to best calculate how well a player did in a match, a machine learning algorithm was applied, namely Random Forest. The results showed that 25 features are able to predict the role played in the observed match, therefore indicating which features could be used to measure the performance. Eventually, it was possible to indicate the differences between the Solo Queue and Tournament games, and to point out the features that made this distinction clear for each of the roles individuated. Since this study only dealt with numerical or boolean variables, additional research can be useful to individuate differences between regions, if there are any, or to take into consideration the Champion picked and the Items bought during a match.

1. Introduction

1.1 Background

Ways of calculating the overall team performance have already been uncovered, either through the notion of "Collective Intelligence" (Kim, Engel., Williams Woolley, Yu-Ting Lin, McArthur & Malone, 2017) or by analyzing the team's behavioral patterns by correlated evaluation metrics. Nonetheless, it is even easier to calculate the single-player performance: a very simple method is calculating the "KDA" for each game, which is the kill/assist to death ratio, a metric that every knowledgeable player can compute after each game. Another statistic that can be useful is CSPM, or creeper score per minute: this could also become relevant when calculating the amount of gold each player has accumulated through the game, but we have to consider that some items, especially for the Support role, can change this amount by quite a lot. However, pretty much anything correlates to the amount of gold gained through each phase of the game. I do not think this is necessarily true: the amount of gold each player gets also depends on the "team objectives". These can be divided into three distinct groups: "Rift Herald/Baron Nashor", "Dragon" and "Turret/Inhibitors". The first two do not have an immediate impact on the game but provide a buff to the entire team depending on the kind of objective that has been taken: the Rift herald summons a powerful ally that can deal massive damage to structures, while Dragons and Baron gift the players more or less powerful ability enhancements.

1.2 Motivation

Through this perspective, I would like to inquire about how professional League of Legends players perform differently in official tournaments and in "Solo Queue"; which is when a player gets matched with, and against, other casually selected players. That is because, during casual interviews with professional teams' coaches they all agreed that to run a successful team, its members not only have to be remarkably good at the game, but they necessarily have to perform well together. Being a good team player is not only a matter of individual skill, but other factors such as in-game communication and positive behavior do come into play when being assigned to play with a certain roster of players.

1.3 Problem statement and research questions

The League of Legends' community Includes a variety of people from different backgrounds; some of them can be defined as "casual players", others instead became famous for their skills at this game. However, there is one thing that they have in common: the desire to reach an even higher rank each season. League of Legends' rank system has just recently changed: now it counts nine Leagues, the lowest being "Iron" while the highest is "Challenger". While the majority of players are ranked between "Silver" and "Gold", only 0.1% of the players are able to reach "Master" and above (Rank Distribution, n.d.). In this thesis proposal, I

will be examining the different player performances at the highest two ranks in League of Legends, which are Grandmaster and Challenger, as well as the few people who made it into the competitive scene.
More specifically I will address the following problem statement:

- *To what extent are there differences in professional players performances between solo queue and tournaments?*

To find an informative answer to this problem, I will proceed using these research questions as steps to follow:

- *Can we create a reliable metric to predict player performance?*
- *Which features explain the differences in performance in solo queue and during tournaments?*
- *To what extent can we indicate the differences between Solo Queue and Tournaments?*

1.4 Evaluation Method

The first step in this analysis, and the answer to the first research question, would be to compute a useful evaluation metric to calculate the individual player performance. In recent works (Do Nascimento Jr., Da Costa Melo, Da Costa & Marinho, 2017), the features that have more impact on a player's performance seem to be the number of consecutive kills obtained, minion score (the terms "minion" or "creeper" can be used interchangeably), number of neutral monster kills (also referred as "jungle" minions), total healing done and number of wards placed. However, these variables come into play only because the amount of gold earned has been removed due to being strongly correlated to a high number of other variables. Besides, I think that taking only the gold earned by each player does not give us an informative view of the aforementioned player's overall performance: gold can be earned also with team objectives such as slaying the Baron or destroying a Turret. Since I am also trying to figure out which features are more relevant in explaining the differences in performance, the following step is to use the average of said variables to compute the baseline of the initial metric needed to evaluate a player's performance. However, I have to take into consideration some factors before proceeding with the next step: this metric will differ from role to role and will depend on the team strategy. Specifically, in League of Legends there can be identified five different roles: Top, Jungle, Mid, ADC (Ad Carry) and Support. These different roles cannot be measured using the same metrics due to the fact that each role has a specific function: Junglers and Support function as "enablers" for the other lanes: Junglers will have a higher count of Neutral Monster Killed while a Support will place more Wards throughout the game. Regarding the team strategy, my sample for the eSport dataset is big enough to assume that these will be evened out, meaning that each team will eventually adopt strategies employed already by other teams. To see to what extent I can distinguish players performances, I will compare the new found metrics for a set of players from the eSport scene, in official tournaments and during solo queue. During this phase I will have to create a metric for each of the roles present in the game; this will allow me to look for more evident patterns in the data. If these are not visibly clear at this point, I would need to take into consideration some external aspects such as the role of tacit communication or decision making (Ji Kim, Engel, Williams Woolley, Yu-Ting Lin, McArthur & Malone, 2017).

1.5 Dataset Description

Most of the datasets that will be consulted during this research are available on the Oracle's Elixir website, which collects data from all the official tournaments from 2016 onwards; these will be used to track individual player performance through various competitive Seasons (a Season usually corresponds to a calendar year, but the starting and ending date differ from season to season). In these files I can both assess a player's performance, by checking his KDA ratio, gold and experience, and the overall team performance with shared team objectives, as team kills, total gold collected or even team dragon kills. Other data related to a player's solo queue will be collected manually, since there is no known repository for such information; the website that will be consulted during this task is "op.gg". The only real problem with this kind of data is that it is possible to collect the necessary features only from the most recent games player; there is no known way at the moment to access the match history of past Seasons.

1.6 Algorithms and Software

After this data collection phase, I will conduct the analysis mainly using R. Since the performance will be mainly calculated with a numerical formula for the most part, the type of statistical analysis I will conduct can be observed with the help of different learning algorithm, depending on the type of data at my disposal. If the features in the dataset will not be sufficient to discover a clear pattern between the performances in professional tournaments and in solo queue, I will create additional ones to see if a deeper analysis shows any further differences. The baseline data will be calculated using the Spring and Summer regular season data set from the LCS scene (LCS stands for "League of Legends Championship Series" in North America and Canada, also known as NA LCS); from this data, I will compare all the successive performance metrics.

1.7 Structure

The remaining of this study is structured as follows. Chapter 2 presents a review of previous literature on player performances and team behavior in videogames. Chapter 3 describes the experimental setup, the feature selection process and the evaluation criteria used for the analysis. Chapter 4 shows the results obtained, with the help of graphs and tables. Finally, Chapter 5 discusses the answer to the research questions, the limitations of this research and future improvements and recommendations.

2. Related Work

In this chapter, the previous relevant literature works will be discussed. In the first two paragraphs, there is a review of the general state of the art regarding how to measure player performance. In the third and fourth paragraphs, the focus will move to the effect of teamwork in a virtual environment and videogames, since it could help to explain some of the underlying differences between Solo Queue and Tournaments. A review of these topics is useful to understand the main factors that influence the "individual performance" as academically described. In addition, previous literature can be insightful when dealing with how analyses have been conducted and to which conclusions they led.

2.1 Player Performance in video games

Shim, Sharan & Srivastava (2010) applied baseball home run prediction to player performance evaluation in Everquest, an old MMORPG. Starting from two different methods of home run prediction, PECOTA and MARCEL, they individuated various individual "achievements" in Everquest to be of similar function to those in baseball. One of their main findings was that most of the players do not lower their performance in the short period so that the most recent performance should be the most informative to predict the performance at the current level.

In another report by Shim, Hsu, Damania, DeLong & Srivastava (2011), they inquired about players and team performance in multiplayer first-person shooter games. To measure the player performance, they used two similar metrics, KDA (kill/death/assist) and KD (kill/death) ratio. They stated that the KDA ratio is helpful when determining which role has been selected by the player, while the KD ratio only measures how well that player has been doing. For the team performance, they computed the same two metrics using the team scores, and the WL ratio (win/loss) for each team. Then, using these metrics, they added the possibility of a player switching teams during a competitive season, and how this influences the team's performances. As expected, the results found show that changing players, the impact is greater for the teams rather than the individuals playing; the WL ratio is much more negatively impacted than the KD or KDA ratio.

In a research conducted on the “Comebacks” in MOBA games, Li et al. (2017) indentify several key factors that can be used to understand this situation. The first feature that they individuate is the kind of Towers, or Turrets, destroyed; not only the number of objective taken is shown to be impactful, but also the different kind of *takeaway*, as named in the report, seems to be relevant. Another cause to the *snowballing* occurrence is given by the gap between the two teams: the first one that can get the better equipment or items has a higher chance of winning the match. However, one of the main reason behind the snowballing occurrence is the presence of an outstanding performance by one, or more, of the players. This eventuality can be reduced by finding a better algorithm to calculate the ELO or MMR ratings.

2.2 Player performance in League of Legends

In a study by Novak, Bennett, Pluss & Fransen (2019b), they researched the relationship between 43 in-game features and match outcomes in the 2018 League of Legends World Championship tournament. With the help of some professional coaches and video footage of the games played, they found evidence of the importance of Team Objectives such as Turrets and Inhibitors, while implementing a new feature called Tower Percentage. The Tower Percentage measures the number of enemy Turrets destroyed related to the own team's Turrets still standing. However, according to the coaches' opinion, the most informative variable to predict the match outcome remains the number of Turrets destroyed.

Wang (2018) discussed the possibilities of predictive analytics on eSport games, testing how champion selection, in-game factors, and player performance are tied to the match outcome. For the in-game features, he found that amongst all the available ones, the Turret kills, First Blood, First Turret and Baron Kills are the most significant ones, especially the first two. A similar this happened for the player performance feature when only four variables are closely related to the match outcome. In this case, Wang is referring to the KDA ratio and the difference between teams in Gold Earned, Minions killed and Experience gained.

Sapienza, Zeng, Bessi, Lerman & Ferrara (2018) researched short-term and long-term performance in League of Legends. For the long-term term performance calculation, they hypothesize that it would positively increase with time due to players getting more experienced at the game, however, their findings show the opposite behavior where "the longer the users play, the more the performance related to their teams reverts to the mean, which is approximately 0.5", This is caused by the fact that if a player keeps on winning, it will be matched against other players of increasingly higher ELO/MMR ratings. For the short-term performance, Sapienza et al. (2018) found that it decreases over time during a single session (for a number of games between 1 and 5). This decrease is more significant for the win rate rather than for the KDA ratio, especially from the third game onwards.

2.3 Team behaviors in video games

Qiu, Tay & Wu (2009) speculate that the use of teamwork in a virtual environment is useful to develop a common group identity. This situation produces both positives and negatives effects: as expected from the "offline" world, the creation of strong group identities affects different aspects such as trust and cooperation amongst members of the same team, while encouraging discriminatory behaviors between members of different team categories. Ultimately, their study shows that even without practical communication, teamwork that happens in virtual environments has a positive interaction with problem-solving and creativity.

Badatala, Leddo, Islam, Patel & Surapaneni (2017) researched a correlation between aggressive behavior and teamwork in videogames and the Prisoner's Dilemma. While tracing the steps of a similar experiment conducted by Ewoldsen, Eno, Okdie, Velez, Guadagno & DeCoster (2012), they investigated whether playing video games can have an impact on subsequent teamwork performance. In this research, it is eventually shown that the most important skill is the capability to think in terms of overall team performance, rather than individual performance. This finding translates into a change of behavior in the Prisoner's Dilemma, especially for those who were not acquainted with video games since there is an improvement in the cooperation condition and a decline in the competition condition.

2.4 Teamwork and League of Legends

Ji Kim, Engel, Williams Woolley, Yu-Ting Lin, McArthur, & Malone (2017) started their research by examining the role of Collective Intelligence (referenced as CI from now on) in MOBA videogames. By definition, CI is the "team's ability to perform a wide variety of tasks", however, they stated that some of its predictors do not apply in virtual environments. Following this assumption, their research shows that lasting teams in League of Legends (i.e. active for at least 6 months) are more likely to improve their performance. The last helpful conclusion that is shown in this paper is that communication through the in-game chat is not substantially correlated with CI.

The topic of League of Legends' ranking system has been discussed by Kou & Gui (2014), specifically on the formation of social stratification and stereotypes. For the interviewed players, the in-game rank means more than just a skill level; these stereotypes do not only reflect the virtual behavior, but they are transposed outside the game and create a sort of parallel narrative. Correspondingly, League of Legends' ranking influences concretely the methods of learning and cooperating even outside the game.

In a research conducted by Do Nascimento Jr., Da Costa Melo, Da Costa & Marinho (2017), they individuated 4 levels of performance (Very Low, Moderate, High and Very High) based on the win rate of 110,000 Solo Queue games. Generally speaking, the most relevant features are *deaths*, *killingSprees* and *neutralMinionsKilledEnemyJungle*, while in the Very High performance level additional features can be considered to have more influence. A reason behind this could be that teams and players in the Very High cluster tend to maximize their gold gain, and at the same time, they try to minimize the opponents'. Consequently, the Very low level is exactly the opposite of the Very high cluster. Additional differences between the Low and Moderate levels have also been found, the first one seems to focus more on defense while the second one has a much more aggressive playstyle.

2.5 Literature addition

Previous studies only addressed the issue of evaluating player performance either individually or in a team framework. However, the question whether players perform differently alone compared to when they are included in a team has not been addressed yet. This study will bridge the gap by investigating the difference between the individual and team behavior of League of Legends professional players

3. Method and Experimental Setup

3.1 Dataset description

During this research, multiple datasets were used. The first ones that were retrieved referenced the Spring and Summer Splits of 2019. These were provided through “Oracle’s Elixir”, a website that provides free datasets and statistics about League of Legends’ competitive scene. A second dataset that includes the “Solo Queue” observations was gathered through the usage of a Riot API key. Thanks to a package published by Riot itself on Python 3, called “RiotWatcher”, I was able to collect the data of 20 matches of different professional players, and then converted them into .csv files with almost all the features I would need for my analysis. A full dictionary of the features present in both datasets is available at the following link: https://oracleselixir.com/match-data/match-data-dictionary/. An overview of the datasets used, and their relevant attributes can be found in the following table.

Table 1. Datasets used and relevant information.

Dataset	Last Update Date	Sample Size	Nr. Of Features
2019 Spring	19/05/2019	12,865	98
2019 Summer	15/09/2019	12,613	98
Solo Queue	11/11/2019	1,060	105

In spite of this former data gathering process, I did incur in some troubles while collecting the Solo Queue dataset needed for my analysis. Some of the in-game events, such as “First Blood time” or “First Mid Tower Taken”, were not available in the dataset gathered. As shown in further analysis, these were not crucial features and I discarded them.

3.2 Sample

The first two datasets represented in the abovementioned table were sliced and merged based on the player’s region: in this case, I chose to analyze only North American players, or “LCS” as it’s identified in the datasets. That would provide the first complete dataset, comprised of 98 features and 2.450 observations. The last three datasets were merged, initially, based on the player’s ID, and subsequently merged by their role. The clarification as to why I used such a procedure is explained in Paragraph 3.4.4. The second final dataset counts 123 total features and an average of 212 observations per role. The feature I used as the target during the feature selection process is “Position”. It is a categorical feature that shows to which role the observations refer to. Following, a short description of some features can be found, divided by group of interest.

- *Experience (xpat10, xpdat10):* is an in-game mechanic that allows champions to increase their statistics and abilities upon arriving at a certain amount of points. Experience is not granted passively over time and it can be acquired in several different ways, such as killing an enemy champion or being in the proximity to a minion death. With this feature, we can easily identify the "Lanes" (Top, Mid, Bottom, and Jungle), which are the main paths towards the enemy base. This is due to the fact that experience is shared between champions that participate in the same events; that means that champions that play in shared lanes, canonically just the Bottom one, gain only 62.36% experience.

- *Gold (totalGold, goldat10, gpm):* is an in-game currency that is used to buy items that provide champions with bonus stats and, sometimes, proper abilities. Unlike experience, gold is passively generated and can also be acquired through various means, the most notable is by killing minions and enemy champions. Considering that the main gold income during a match usually comes from the Minions or Monster killed, this feature lets us clearly define the boundaries of the Support role. Since it shared the lane with the ADC, it is not allowed to get the gold by killing the Minions, however, some items increase the passive gold generation. More in general, the amount of gold accumulated thought a match is a solid indicator of the overall player's performance.

- *Monster Kills (monsterKillsOwnJungle, monsterKillsEnemyJungle):* monsters are neutral units that do not fight for either team and are found in the Jungle camps. Generally, killing a monster rewards gold and experience points, but certain specific monsters grant additional rewards, as an individual buff. As this feature only relates to the Jungle lane, it is clear that is a good statistic to determine the Jungler's performance.

- *Minion Kills (minionKills, csat10, csdat10, cspm):* minions are team-aligned units that spawn periodically from the teams' bases and advance along a line toward the opposing team's base. Dealing the killing blow to these units is also known as "last hitting" and it is considered one of the most important basic mechanics; unlike other MOBAs, the gold of the minion kill is given only to the "last hitter". This feature is important to measure the Top, Mid and ADC performances as these are the ones that will try to accumulate as many "last hits" as possible.

3.3 Pre-Processing

The datasets obtained thanks to Oracle's Elixir are already cleaned and organized, and there was no need for further data cleaning processes. The majority of the features that are used for this analysis are numerical, those who are not are coerced into this type for ease of use. After merging the Spring and Summer datasets, a preliminary analysis of the features had to be made. At first, I removed all the features that caused data pollution. These were mostly related to identifying each match. Since I also chose to remove all the observations regarding the Team, two features had their variance reduced to zero: Visible Ward Clear Rate and Invisible Ward Clear Rate. However, that was not an issue on account of the fact that other features can be used in their places. The next step was to check for a correlation between the features. Appendix a shows the correlation table between all the final numerical features.

3.4 Experimental Setup

Nevertheless, I still did not know at this stage which features to remove based on their correlation coefficients since I was not aware of their information potential. Hence, I opted for another approach, commonly referred to as the "Wrapper Method". To use this methodology properly, the starting point would be choosing an adequate Learning Algorithm: in this analysis, the Random Forest is to be considered the most appropriate. The way I proceeded was, however, computationally expensive, even though it yielded the desiderated results. The first step in this course of action was to find a preliminary subset of features: in my case, the unpolluted dataset has 77 features, meaning almost all of them are included. The data was then split into a Training set and Testing set, using a 70/30 ratio, meaning 70% of the observations compose the Training set, and the rest compose the Testing set.

3.4.4 Algorithm

The prediction task performed in the first part of this research is trying to determine to which extent is possible to determine the Position, and which features explain the distinctions between the different Roles. The intention behind this reasoning is that if the algorithm is capable of identifying the different features that distinguish a role from another, then these same features can be explanatory of the role's most important key scores. Since I performed this task using Random Forest, there was no need to change the target feature further, given that in every League of Legends' match there has to be a player for each Position, thus this feature is perfectly balanced.

Random Forest

By definition, the term "Random Forest" indicates a generic expression for aggregating random decision trees, obtained by applying different ensemble methods (Breiman, 2001). By itself, a Decision Tree has a flowchart-like structure, in which each internal tree node represents a question, and the answers are written in the leaves. Decision Trees are built following one simple rule: to find which feature is the most useful in predicting the target feature; if we want to be more specific, we can implement the definition of "Information Gain" (Daumé, 2012). The Information Gain is a metric that measures the quality of a split, and we can calculate that by weighting the entropy of each branch by how many elements it has. Thus, at some point, it will become useless to ask any more questions to further split our sample. The biggest problem with Decision Trees is that they tend to overfit much more often than other algorithms, hence, to resolve this problem we can either limit the depth of the tree (a procedure also called "Pruning") or we can employ the Random Forest. This algorithm is a way of averaging different and complicated Decision Trees, by training them on different parts of the same training set. When choosing the number of trees we want to construct, we have to make a trade-off between performance and computational time (Friedman, Hastie, & Tibshirani, 2001).

The technique used in conjunction with the Wrapper Method, allowed me to run a Random Forest with a starting subset of significant features, looking at the most relevant ones and to which these are most correlated with and then delete the latter. Then I repeated the process until I could find a good balance between the model accuracy and the number of features. The starting subset is comprised of 77 features. The algorithm was capable of predicting perfectly the Support and Jungle role, while the Top and Middle were the ones with the highest error rate. As it is shown in Figure 1, there is a clear distinction between the aforementioned categories.

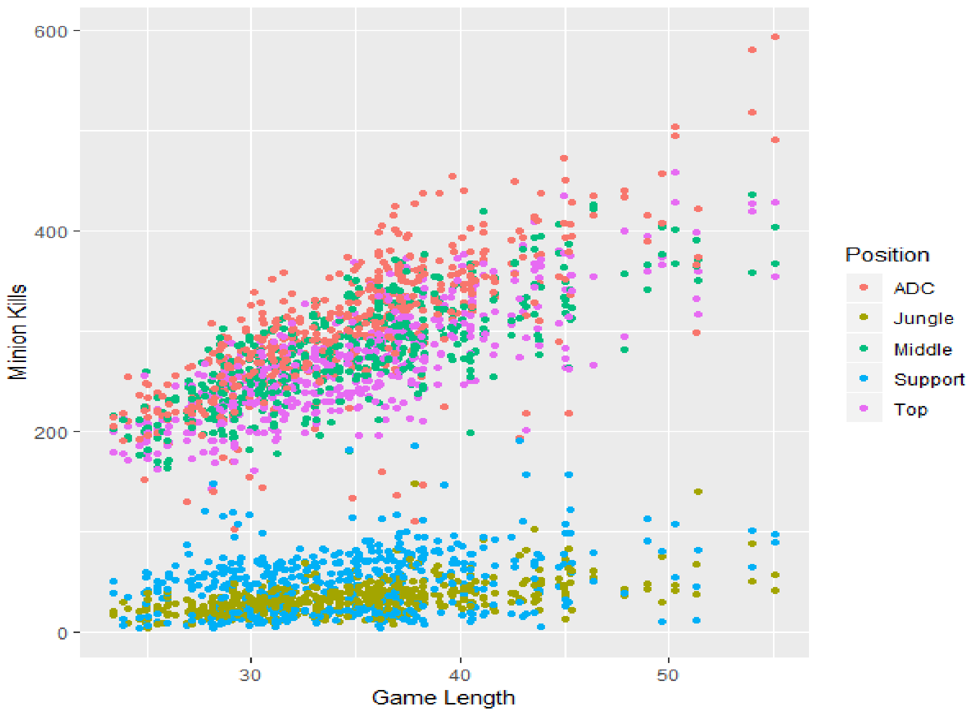


Figure 1. Scatterplot showing the number of Minions killed during various games.

The last model run was on a subset of 39 features. Having reduced the dataset by 59 features with only a 2% loss on accuracy was a suitable result, thus I stopped working on this dataset for the time being and focused my efforts on the Solo Queue one. Given the fact that the same features across the two datasets, Tournament and Solo Queue, would be needed for this analysis, the most uncomplicated approach was to find the corresponding Tournament features in the Solo Queue dataset. However, as I stated in Paragraph 3.1, some of the highlights regarding the occurrences of some in-game events were not immediately available given the API data format. Nevertheless, the exclusion of the features does not compromise the validity of the algorithm, if not for a slight reduction in the overall accuracy. Eventually, this procedure would bring the datasets down to 25 features.

3.5 Evaluation criteria

In view of the fact that the Position feature is balanced for the Tournament dataset, using the accuracy as the performance measure would be appropriate. In a classification task, the Accuracy can be defined as the correctly classified observations divided by the total instances. In addition, to see which classes were the most correctly classified, including the Specificity and Sensitivity metrics was, in fact, useful. According to Metz (1978), Specificity and Sensitivity are nothing more than two different kinds of Accuracy: the former measures the identified cases for the positive class, while the latter accounts for the negative class. Throughout this part of the research, the most correctly identified classes were always Top and Support, while ADC coming a close second.

3.6 Implementation

Gathering the Solo Queue dataset was done using Python 3.0, with the help of the packages *RiotWatcher* (developed by RiotGames) and *pandas*.

The merging, pre-processing and analysis of the datasets was done using RStudio (version 1.1.463). The correlation matrix was obtained using the package *corrplot*, while the other graphs were retrieved using *ggplot2*.

4. Results

This section provides the results of the analysis that was conducted on the relevant features found in the previous Chapter. Each paragraph will show the most important differences between the Tournaments and the Solo Queue games for each Role. Finally, Paragraph 4.6 generalizes addressed the features related to the team objectives. In every paragraph there are different graphs that show the differences between some of the features used to analyze that role; in the Appendix there are additional graphs that display how the different features change between all the roles. For further references, Appendix 1 shows a summary of the statistics used for this analysis.

4.1 Support

The first set of features that has to be analyzed for the Support role is composed by *wards*, *wardKills* and *visionWardBuys*. That is because the Support has the role to assist the ADC in the first phase of the game, and later to help the entire team. In order to do so, being aware of the enemy team positioning is fundamental. As stated in the previous chapter, wards are usually bought by Supports. Taking into account the number of wards placed (*wards*) in Tournaments and in Solo Queue game, all the metrics regarding the wards placed in Tournaments are doubled compared to those of the Solo Queue games: the mean number of wards bought in Tournaments is 49.50 and only 24.50 in Solo Queue. A similar trend is also shown, more specifically, for the vision wards that are bought (but not necessarily placed) since, even if with considerably smaller number, all the tournaments metrics are still higher in comparison. However, that is not the case for the number of wards killed (*wardKills*). Even with the decreased number of wards placed in the Solo Queue , the difference with the Tournament games is not significant compared to the wards placed or bought.

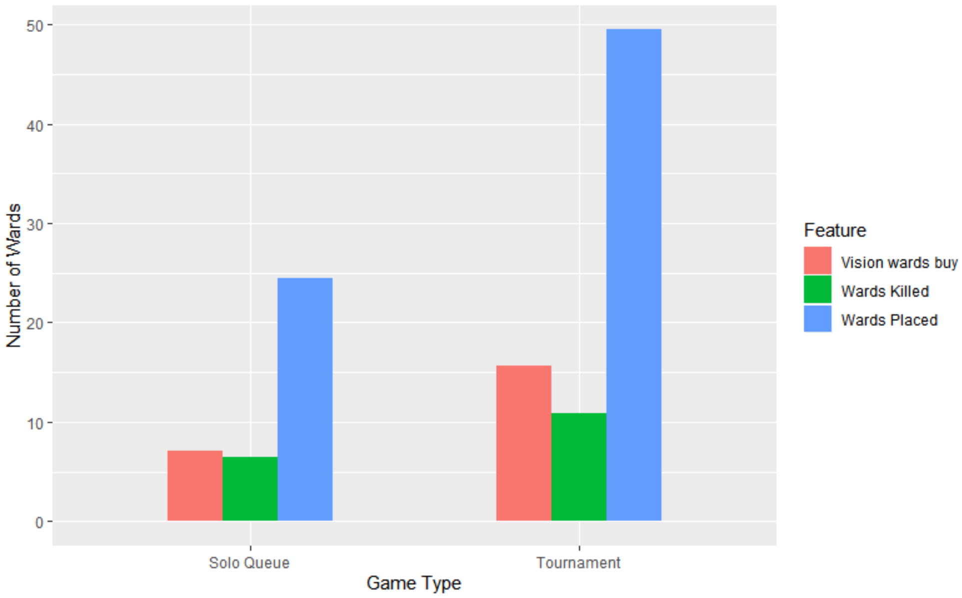


Figure 2 shows the differences of the Wards' features between Solo Queue and Tournaments for the Support role

Gold, Experience, Monster Kills and Minion kills all show the same behavior; there is not much difference between the means and medians, even though the Solo Queue dataset shows much more extreme values, both positives and negatives, and generally a higher standard deviation. Since these are not features that define the performance of a Support player, the results shown are as expected. The metrics regarding the KDA (kill, death, assist ratio) and the Total Damage Dealt to enemy champions (*dmgtochamps*) are higher in the Solo Queue dataset. The one feature among these that matters for the Support role is the number of Assists; while on the Tournament dataset the average is only 7.22, the Solo Queue average increases to 11.23.

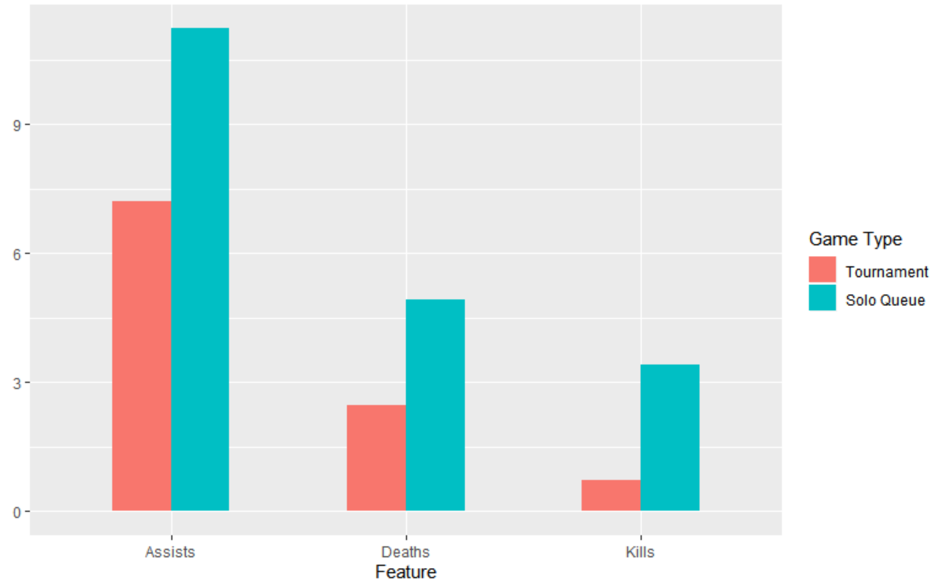


Figure 3 shows the KDA difference between Solo Queue and Tournaments for the Support role

4.2 ADC

What characterizes the ADC role the most is the number of Minions Kills and the Damage Dealt, so I started by analyzing these features. The most evident difference between the Tournament dataset and the Solo Queue dataset is that the *minionKills* metrics are higher in the first one, with an average of 301 minions killed in Tournaments and only 183 in Solo Queue. However, this does not apply when analyzing the creeper score at 10 minutes (*csat10*) and the difference in creeper score (*csdat10*). Even though there are some small differences, the last two features seem much more similar between Tournaments and Solo Queue. In this case, it can be informative to analyze the mean creeper score per minute, since on average, Solo Queue games are shorter than Tournament ones. For the ADC role, the average creeper score per minute (or *cspm*) in Tournaments is 8.85, while it is 6.67 for the Solo Queue.

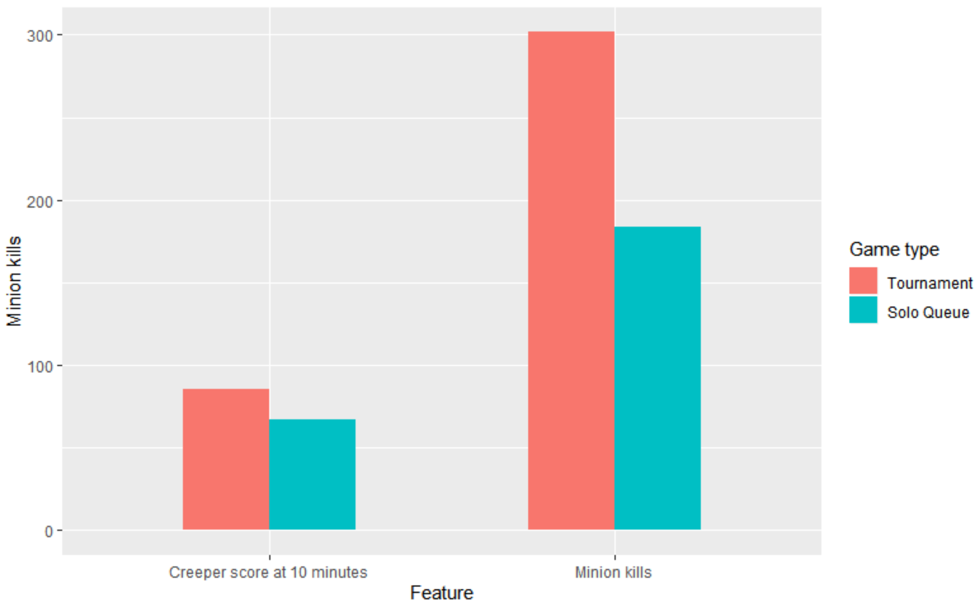


Figure 4 shows the differences in Minions' features between Solo Queue and Tournaments for the ADC role

Despite the shorter game length for the Solo Queue games, the mean damage dealt to champions (*dmgtochamps*) is higher; if the mean damage dealt per minute is taken into consideration, there is a difference of 166.49 points between the Tournament and Solo Queue dataset. ADC players tend to prioritize kills in Solo Queue games, impacting the average gold gain (*totalGold*). However, the gold earned per minute (or *gpm*) is higher in the Solo Queue dataset. On the topic of Experience, it seems like the ADC players in Solo Queues gain more experience, especially during the laning phase. Wards and Jungle Monster have normally low values for both the Tournament and Solo Queue datasets.

4.3 Mid

To analyze the Mid position I used the same criteria I used for the ADC position. Starting from the *minionKills*, there is still a substantial difference between the Tournaments and Solo Queue, the mean value calculated for the first dataset is 277.76 and for the second one 168.47. However, the maximum number of minions killed in one game do not differ too much, being only 6 higher in the Tournament dataset. Subsequently, the metrics related to the creeper score at 10 minutes (*csat10*) and the difference in creeper score (*csdat10*) are higher for the Tournaments. Unlike the ADC role, the difference between Tournaments and Solo Queue in creeper score per minute is lower, being only 1.70.

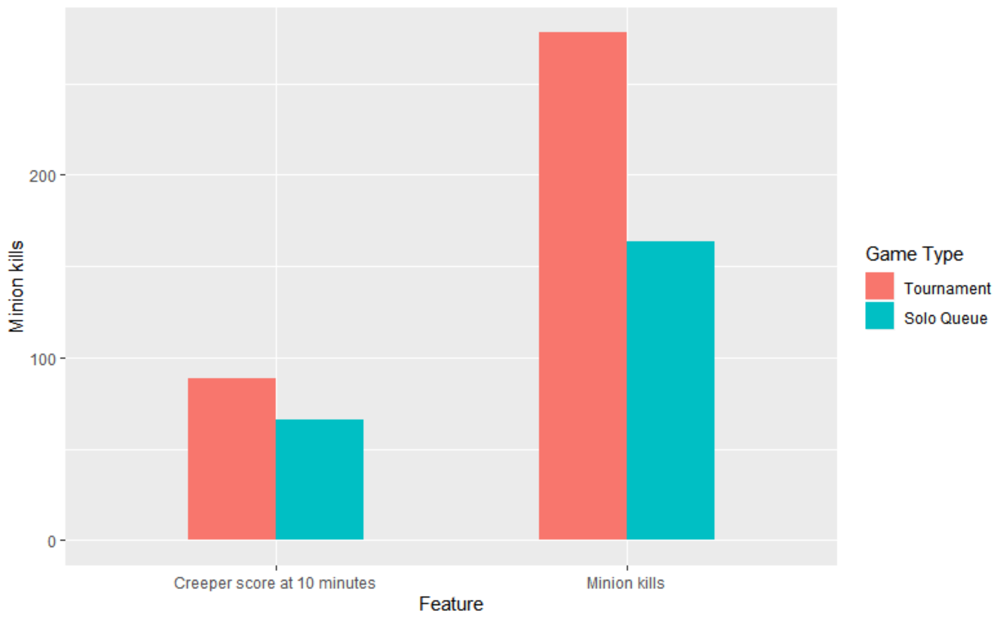


Figure 5 shows the differences in Minions' features between Solo Queue and Tournaments for the Middle role

When looking at the total damage dealt to champions (*dmgtochamps*), the mean values are similar. The only significant difference is in the maximum value of this observation, since it is higher in the Tournament dataset. This can be related to the number of deaths scored in Solo Queue since its mean value is more than doubled compared to the Tournament dataset. The median and mean value for the kill/death ratio is 1-1, meaning that the average Mid player has almost the same number of deaths and kills in Solo Queue. The total gold (*totalGold*) and gold gained at 10 minutes (*goldat10*) share the same differences between the Tournament and Solo Queue datasets; their mean values is slightly lower for the Solo Queue. However, the *gpm* is higher for the Solo Queue game. The statistics regarding the wards placed or killed follow the usual pattern, being lower in the Solo Queue dataset. The same thing happens to the Jungle Monster observations, but that is expected since the Mid role is not supposed to kill those minions.

4.4 Jungle

The Jungle position is the most peculiar role in every MOBA. This is because it does not have a proper lane but it spends the first time of the game clearing "Jungle Camps". Jungle Camps are defined spots in the map where the players can find Neutral Monsters, as explained in the Introduction Chapter, and these may also confer the players different buffs. Thus, to analyze the Jungle position, the starting point would be the number of Neutral Monsters killed, both in the allied and enemy jungle (*monsterKillsOwnJungle*, *MonsterKillsEnemyJungle*). Starting with the Neutral Monsters killed in the allied jungle, the mean for this feature is higher for the Tournament dataset, being 91.40; however, the average differences of this feature between the Solo Queue and Tournament dataset has a similar behavior as the ones related with the Creeper

Score for other roles. Having said that, there is no substantial difference in the metrics for the Neutral monsters killed in the enemy jungle; even the difference in means is only 0,36.

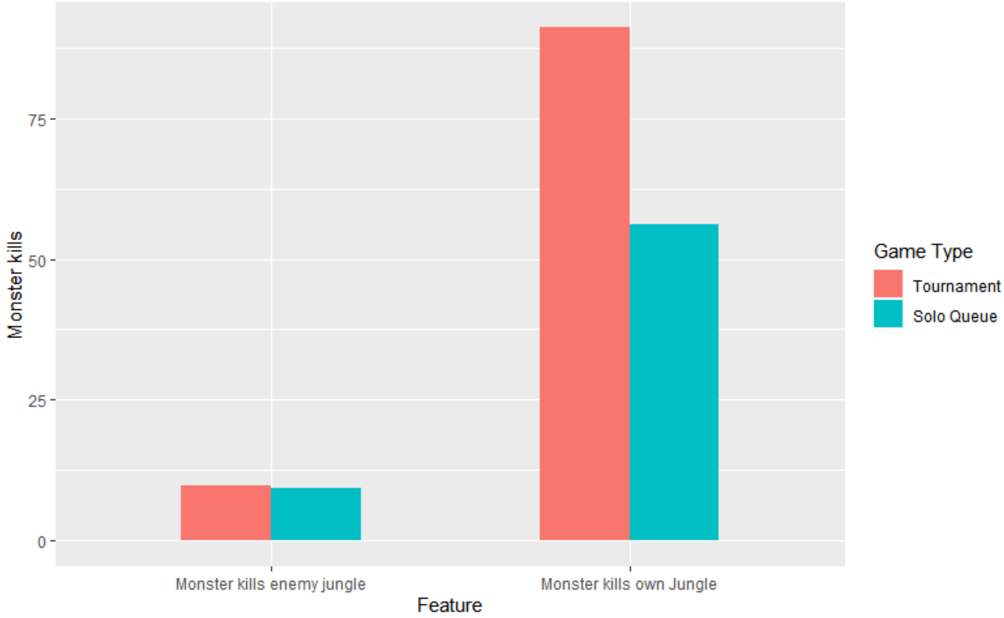


Figure 6 shows the differences in Neutral Monsters' features between Solo Queue and Tournaments for the Jungle role

The next set of features I inquired about are the Wards. The number of wards placed (*wards*) and wards killed (*wardsKilled*) is sensibly higher in the Tournament dataset, but it is generally higher for the Jungle position than for the ADC, Mid and Top roles.

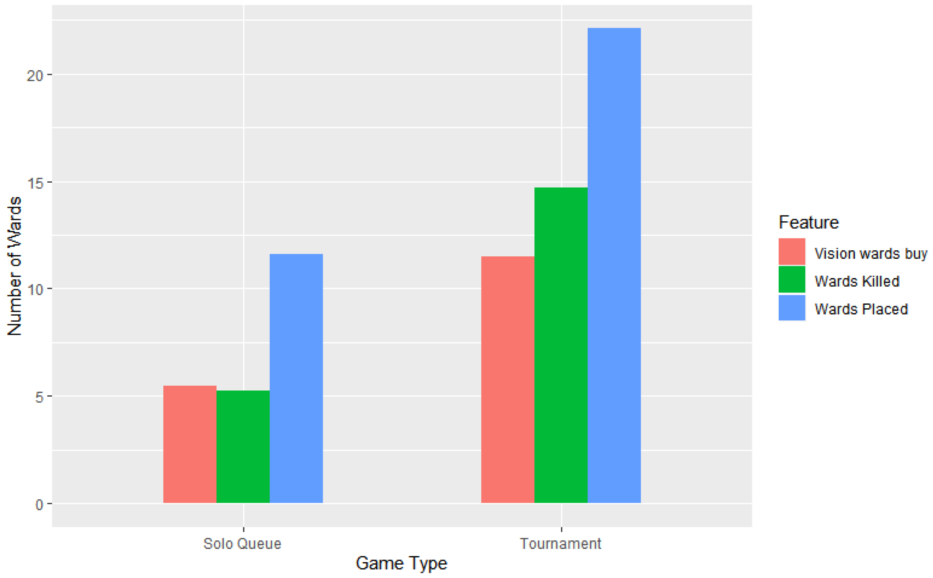


Figure 7 shows the differences in Wards' features between Solo Queue and Tournaments for the Jungle role

The KDA ratio, Gold earned and the Experience gain do not show many relevant differences between the Solo Queue and the Tournament dataset.

4.5 Top

The Top position has many similarities with the ADC and Mid roles. Therefore, I focused the analysis on the same features I mainly used for the other two roles. To start, the average of minions killed (*minionsKills*) is lower in the Solo Queue than in the Tournament dataset; however, the mean difference in creeper score per minute is lower than in the other two aforementioned roles, being only 0.88. The maximum number of minions killed is significantly different between the two datasets, 458 compared to 326, while for the Mid role, the difference was negligible. The metrics related to the creeper score at 10 minutes (*csat10*) also show a similar trend, being overall higher in the Tournament dataset.

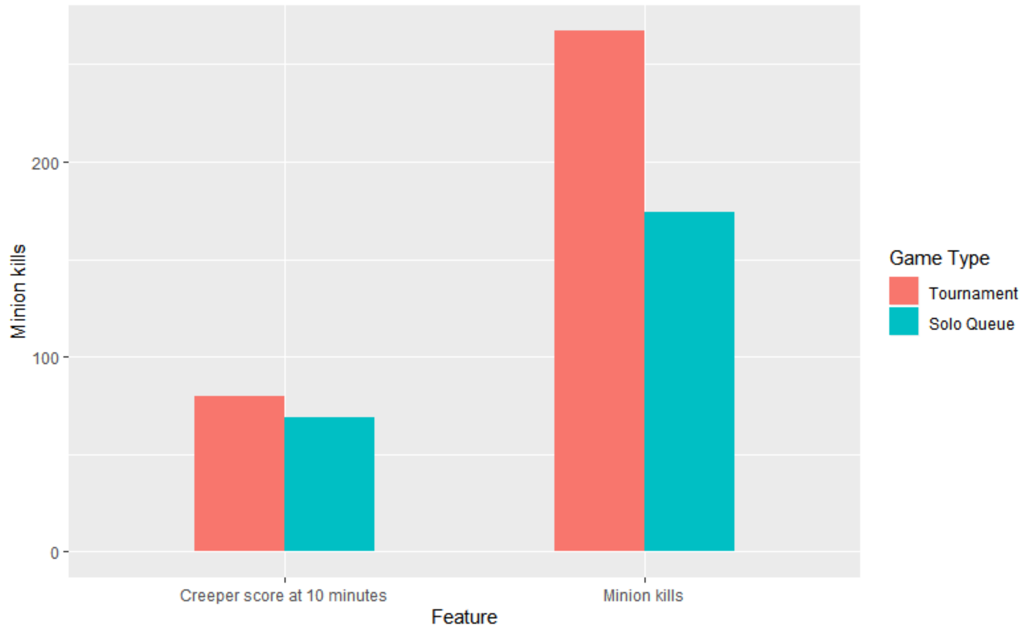


Figure 8 shows the differences in Minions' features between Solo Queue and Tournaments for the Top role

As shown in the previous paragraphs, the damage dealt to champions (*dmgtochamps*) tends to be higher in the Solo Queue dataset, despite the lower game duration. While looking at the KDA ratio, the Top role prioritizes Assists over Kills, but generally there are not conspicuous differences between Solo Queue and Tournaments games. The total gold earned (*totalGold*) shows a significant difference between the Solo Queue and Tournament dataset, the difference in means of this feature is more than 2,500 gold in favor of the Tournament data; however, the average gold earned per minute is higher in the Solo Queue: 426.19 gold per minute against 385.4 gold per minute. The statistics regarding the Wards and the Neutral Monsters killed do not vary a lot between the two datasets, neither does the Experience gained.

4.6 Team Objectives

To analyze the team behavior of the professional players, I had to focus on different sets of features, which can be divided into First Blood, Drakes, Baron and Towers. All of these are considered "team objectives" because they usually involve effort and cooperation of multiple team members. Starting with the First Blood (*fb*, which shows if the player scored the first kill of the game since it is worth more gold than a regular kill) the corresponding statistics reveal that the Jungler role is the one more involved in accomplishing this objective. There are no significant differences between the Solo Queue and Tournament dataset for this feature.

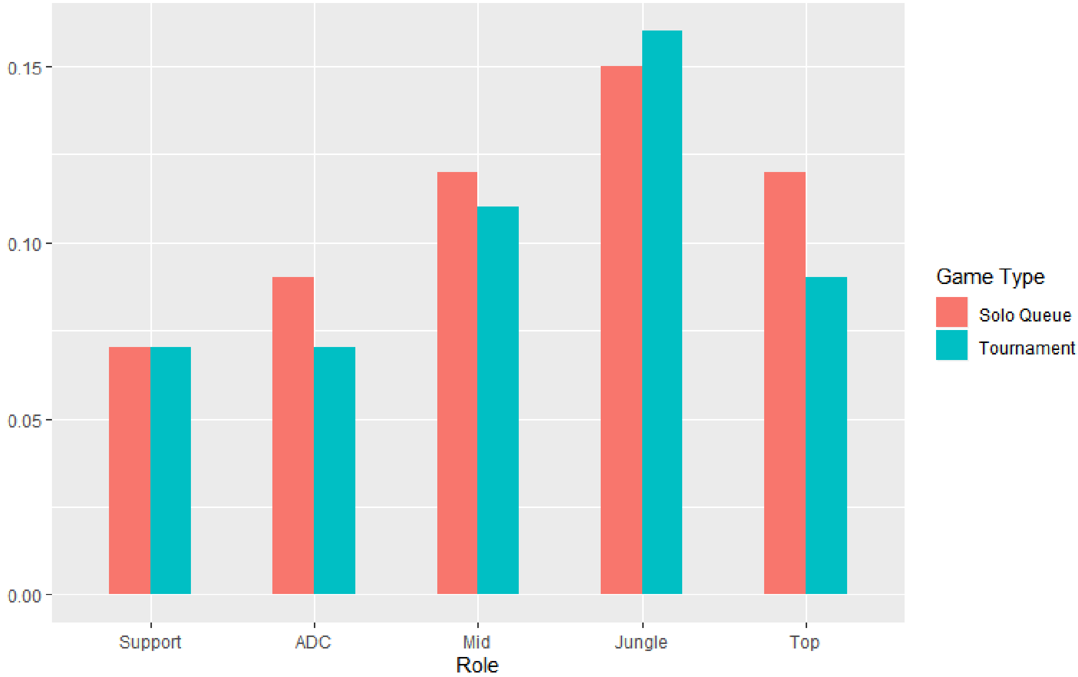


Figure 9 shows the First Blood difference between Solo Queue and Tournaments across all roles

For the Drake features, there is a notable difference both between the roles and between the two datasets. In the Tournament games, only the Jungler is focused on killing the first Drake (*fd*), while in Solo Queue, this involves the whole team. The number of Drakes killed (*teamDragKills*) is inferior in the Solo Queue dataset, with an average of 1.56 Drakes per game across all roles, while the average for the Tournament dataset is 2.28.

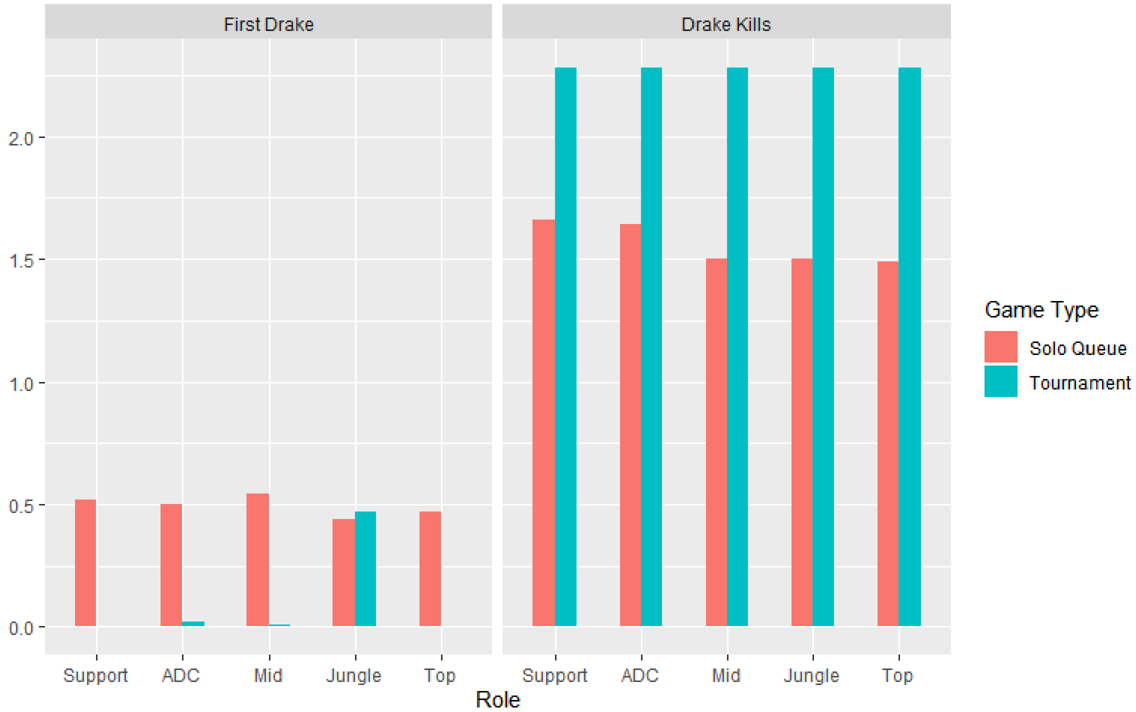


Figure 10 shows the Drake kills difference between Solo Queue and Tournaments across all roles

The metrics for the Baron features do not differ significantly from each role, and are slightly lower in the Solo Queue than in the Tournament dataset. Overall, these two features (*fbaron* and *teamBaronKills*) are not able to tell much about the differences in team behavior. The last set of features refer to the Towers destroyed; there is a small difference in the metrics about the First Tower destroyed (*ft*), but the Top lane has the highest average above all roles. The Number of Towers Destroyed, on the other hand, is similar between all roles, but the average is higher in the Tournament dataset.

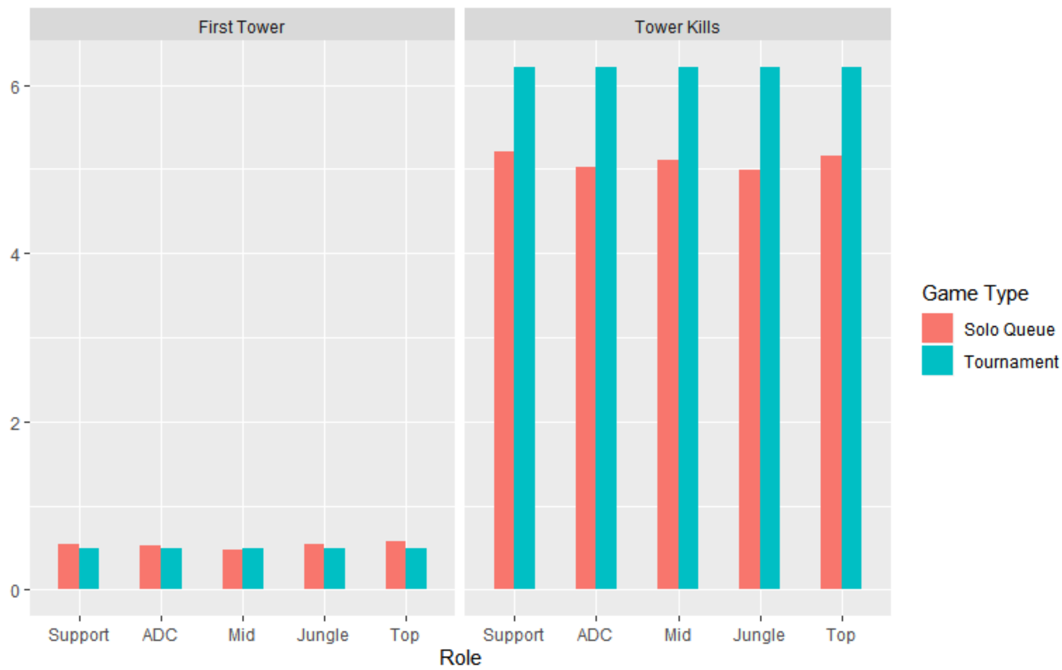


Figure 11 shows the Tower kills difference between Solo Queue and Tournaments across all roles

4.7 Summary

The table below summarizes the results found, for each group of features, explaining what are the differences between a Solo Queue and a Tournament game. In the following chapter I will discuss the reasons behind these dissimilarities.

Table 2 shows a summary of the differences between the Solo Queue and Tournament

KDA and Damage Dealt	The ADC, Mid and Top role have the minimum difference in Damage Dealt to enemy Champion between Solo Queue and Tournaments. All the KDA metrics are higher for the Solo Queue
Wards	The Ward features show the most significant differences for the Support and Jungle roles, especially for the average number of Wards placed.
Minion	The Creeper Score per minute is higher in the Tournament games for the ADC, Mid and Top roles. During Tournaments, these players focus more on killing minions rather than killing the opponent.
Neutral Monster	This group of features is relevant for the Jungle role only. The *neutralMosterKillsOwnJungle* feature is higher for the Tournament games, while *neutralMonsterKillsEnemyJungler* does not show a significant difference.
Gold	The Gold per minute has a higher value for all the roles in Solo Queue. Even with a lower cspm, the players still focus on earning as much gold as possible.
Experience	The Solo Queue Jungle player earns more experience than the Tournament one. The Mid and Top roles, on the contrary, earn more experience in Tournament games. The ADC and Support role do not show a significant difference.

5. Discussion and Conclusion

This section provides a discussion of the analyses conducted and the results found. In the first part, the research questions formulated in the Introduction Chapter will be answered. Then, the contribution of this study within the existing research will be discussed, along with the limitations of this analysis and the recommendations for future research.

5.1 Answers to research questions

This research dealt with the following problem statement:

> *To what extent are there differences in professional players performances between solo queue and tournaments?*

In order to find an answer to this problem statement three research questions were formulated, which will be discussed below.

Research question 1: Is it possible to create a reliable metric to calculate player performance in League of Legends?

According to various studies on Team-based Online games, the most used metric to calculate player performance is the Kill/Death/Assist ratio, or sometimes only the Kill/Death ratio. However, even if this set of features is surely significant, it oversimplifies the calculation of player performance in MOBA games, since their gameplay is far more extended and complicated than other online games. The analysis performed in this research confirms that different features are needed to calculate player performance in League of Legends and that those features vary depending on the player's role. As shown in a study by Ong et al. (2015), it is possible to identify different gameplay clusters using a reasonable amount of features. The five clusters they distinghuished are the following: Ranged physical attacker, Ambusher, Team support, Magic attacker and Miscellaneous. Even if they add that these clusters' behaviours do not always correspond to the official roles expected gameplay, I still find their results useful for my analysis. As stated in the Experimental Setup Chapter, if it is possible to identify the different in-game roles, then the most of the relevant features used to predict the roles are representative of their expected performance. This has been proved accurate for the most part, during this research, since some features are indicative of a positive player performance independently of the role chosen.

Consequently, I have found three major gameplay clusters during my analysis: Carry, Support and

Jungler. For the first cluster, it is possible to aggregate three roles, since they all have similar individual metrics. The ADC, Mid and Top role all show high priority on getting the most Minion and Champion kills, thus score the highest on the Gold and Damage dealt to champions features. The second cluster includes only the Support role, and has high values for the Wards and Assist features for the most part; however, it is important to note the fact that the Minion features need to be as low as possible most of the time. That is because since the Support shares the lane with the ADC, only the latter can take priority on the Minion kills. So, having a high number of Minion kills would have a negative impact on the Support player performance. This also applies to the last cluster, which overlaps the Jungle role; in this case, however, the Jungler has another set of features to deal with: Monster kills. Also, looking at the Wards metrics, the Jungler role has the second highest values, meaning that they also have a heavier weight for this role than for the Carry cluster. Lastly, I have found that Team Objectives such as Drakes, Baron and First Blood appear more frequently when analyzing the Jungle role. The remaining features, Experience and KDA ratio, can be generalized to all the aforementioned clusters since they indicate a good performance independently of the chosen "play style" or gameplay. Team Objectives are also features that concur in positive team performance and, unlike for the Jungle role, they may not always be achievable by an individual player, therefore they are much more subjective to the influence of teamwork and communication between players.

In conclusion, it is possible to create a metric to represent player performance, but it has to be done for each role separately and, in general, will differ for different types of gameplay.

Research question 2: Which features explain the differences in performance in Solo Queue and during Tournaments?

When analyzing which features can determine the differences in performance between Solo Queue and Tournament game, the results will differ for the different roles. Retaining the cluster division I made in the previous paragraph, the main set of features for the Carry cluster that show a difference in the two datasets are Minions, Gold Earned and Damage Dealt to champions. For the Minion and Gold features, both the absolute value at the 10-minute mark, and the average score per minute are used. The general trend for the three roles in this cluster is to have a higher creeper score per minute and a higher number of minions killed at 10 minutes. However, this does not apply when analyzing the Gold per minute, Gold at 10 minutes and Damage dealt to champion. All of them have higher metrics in Solo Queue than in the Tournaments. For the Support cluster, the main set of features to analyze are the Wards, since it is the only one that shows relevant differences between the two datasets. While the average number of Wards Killed does not change much, the main gaps between the Tournament and Solo Queue games are found within the Wards placed and bought, as it is shown in the previous Chapter. In addition, the average number of Minions killed is lower for the Solo Queue dataset, and while by itself this might seem odd, it indicates that Support players seem to be more projected into the expected role behaviour for these features. The last cluster that needs to be discussed is the Jungler. As for the Support role, for the Jungler the metrics for the Wards features are higher in the Tournament dataset, even the number of Wards Killed is significantly different. However, the main set of features for the Jungler is the Neutral Monster killed. In this case, the analysis conducted does not show a difference in the average number of Neutral Monsters killed in the enemy jungle between the Tournament and Solo Queue game; however, the average number of Neutral monsters killed in the allied jungle is higher in the Tournament dataset. Lastly, the Damage Dealt to enemy champions is significantly higher for the Solo Queue games.

In conclusion, different features demonstrate the differences in performance between the Solo Queue and Tournament games, and they vary for each role. For the Carry cluster, some of them are related to the Gold Gain, which in return increases the capability of the player to deal more damage to the enemies. For the Support role, the most important features are related to the Wards. And eventually, for the Jungle role, the main focus is on the number of Neutral Monsters killed and secondly the number of Wards placed and cleared.

Research question 3: To what extent can we indicate the differences between Solo Queue and Tournaments?

During the analysis conducted during this research, the main differences between Solo Queue and Tournaments were not difficult to understand. Generally speaking, in-game behaviour differs consistently between the two types of games analyzed. Starting by looking at the mean Game Duration, the Solo Queue metrics are lower, indicating that, on average, Solo Queue players' focus will be more on the early phases of the game rather than at the later phases. This does explain the lower number of Turrets destroyed, since the minimum necessary to win the game (unless the enemy team agrees to surrender) is 6 Turrets, and the Solo Queue average is closer to this number. A plausible explanation can imply that players focus on winning one lane while leaving the others alone, especially if they are losing. This is shown by the lower Experience gain in Solo Queue, for all the roles, and the lower average number of Neutral Monsters killed for the Jungle role. The lower amount of experience signifies higher mobility around the map since it is difficult for a player to earn experience if he/she is not killing Monsters or Minions. On the other hand, leaving the lane to help another player securing a kill or an objective is a much more risky play, but also can be more rewarding. In addition, other features that depend on the Game Duration as Drakes, Baron, Neutral Monsters and Minions will necessarily be lower in the Solo Queue, since they all have fixed spawning times and are not infinite. However, as it was mentioned in the previous paragraph, some of these features, if calculated per minute, result higher in the Solo Queue dataset rather than in the Tournaments. In this case, the results show that the Gold earned and Damage Dealt per minute is higher in Solo Queue, while the Creeper Score per Minute is lower. That happens because the Solo Queue players' behaviour is much more aggressive than in

Tournaments, as it is shown by the higher number of Kills and Deaths. As a consequence, the gold earned with the increased number of Kills balances the gold loss in Minion kills.

In conclusion, it appears that the main difference between Solo Queue and tournaments is the behaviour players have during the lane phase (until 10 minutes approximately) and their winning conditions. In Solo Queue, games tend to be shorter and more focused on getting the minimum amount of Turrets to kill the enemy Nexus, while in Tournament, the focus is shifted on more than one lane. That is also because there are champions that are referred to as “Solo Queue picks” since they have more “snowball” potential, meaning that they are more able to carry the game without the help of other teammates, while not having strong synergies with other Champions. The Solo Queue behaviour is indeed more individualistic and player-centred than the Tournament one, and it is closer to the “high risk - high reward” mindset.

5.2 Contribution

This research provides some insights into the factors of League of Legends’ player performance. Existing literature uses a variety of conceptual frameworks to describe the performance in video games, but they do not approach this issue from a statistical viewpoint. Thus, by introducing another point of view to player performance analysis, a contribution is made to the existing research area. In addition, this research also provides insights which may improve the scouting mechanism for professional players starting from their Solo Queue games.

5.3 Limitations and further research

The first problem encountered during the studies presented above was during the data gathering process, since some features were not immediately available within the Riot API; however, since those features were considered of low significance for the analyses conducted, they were discarded. An additional limitation regarding the features was related to the Creeper, Experience and Gold difference at 10 minutes, for the Tournament dataset. This happened because the first dataset is perfectly balanced so that it has equal numbers of observations from one team and the opposing one. This leads to the difference in those metrics being 0, therefore not significant for some parts of this research. The last limitation is the size of the dataset gathered. Since the limit for the Riot API key was relatively low, I was able to request only 20 observations per player. That total expected number of observations was further reduced from the fact that not all the players have a traceable League of Legends account in North America’s server.

Further implementations can be made by both adding observations and expanding the research questions. For the first part, the same kind of analyses can be conducted in different regions and then the different kinds of behaviours can be pointed out. This research only focuses on the North America region, which is considered having a rather low performance compared to the rest of the other major regions. Therefore, the gap between the Solo Queue and Tournament games may be different on other servers, or it can even be defined by other features.

The dataset can also be used to find answers to new research questions, to further explain the difference between Solo Queue and Tournament. One of the possible analyses may research the different Champions or Items that are picked, since it is well known by Team Coaches and experienced players that the Champion pick phase is much more structured in Tournaments, where professional players usually play a small selection of Champions and follow a more strict selection on itemization.

References

Badatala, A., Leddo, J., Islam, A., Patel, K. & Surapaneni, P. (2017). The effects of playing cooperative and competitive video games on teamwork and team performance. *International Journal of Humanities and Social Science Research, 2. 24-28*. Available at: https://www.researchgate.net/profile/John_Leddo/publication/311792939_The_effects_of_playing_cooperative_and_competitive_video_games_on_teamwork_and_team_performance/links/585ab27308aeffd7c4fe9443/The-effects-of-playing-cooperative-and-competitive-video-games-on-teamwork-and-team-performance.pdf

Breiman, L. (2001). Random Forests. *Machine Learning. 45(1), 5–32*. Available at: https://doi.org/10.1023/A:1010933404324

Daumé III, H. (2012). Decision Trees. *A course in Machine Learning, Chapter 1, 8-18*. Available at: http://ciml.info/dl/v0_99/ciml-v0_99-ch01.pdf

Do Nascimento Jr., F. F., Da Costa Melo, A. S., Da Costa, I. B. & Marinho, L. B. (2017). Profiling Successful Team Behaviors in League of Legends. *Brazillian Symposium on Multimedia and the Web, 23.* Available at: https://www.researchgate.net/publication/320389574_Profiling_Successful_Team_Behaviors_in_League_of_Legends

Ewoldsen, D.R., Eno, C.A., Okdie, B.M., Velez, J.A., Guadagno, R.E. & DeCoster, J. (2012) Effect of playing violent videogames cooperatively or competitively on subsequent cooperative behavior. *Cyberpsychology, Behavior, and Social Networking*. Available at: https://doi.org/10.1089/cyber.2011.0308

Friedman, J., Hastie, T., & Tibshirani, R. (2001). *The elements of statistical learning, 1(10).* New York: Springer series in statistics.

Jagad, L. Ms., "Online Gaming and Teamwork." Thesis, Georgia State University, 2011. Available at: https://scholarworks.gsu.edu/communication_theses/83

Ji Kim, Y., Engel, D., Williams Woolley, A., Yu-Ting Lin, J., McArthur, N. & Malone, T. H. (2017). What Makes a Strong Team? Using Collective Intelligence to Predict Team Performance in League of Legends. *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing, 2316-2329.* Available at: http://mitsloan.mit.edu/shared/ods/documents/?DocumentID=2710

Kou, Y. & Gui, X. (2014). Playing with Strangers: Understanding Temporary Teams in League of Legends. *Proceedings of the first ACM SIGCHI annual symposium on Computer-human interaction in play, 161-169.* Available at: https://dl.acm.org/doi/10.1145/2658537.2658538

Kou, Y., Gui, X. & Kow, Y. M. (2016). Ranking Practices and Distinction in League of Legends. *Proceedings of the 2016 Annual Symposium on Computer-Human Interaction in Play (CHI PLAY '16), 4–9*. Available at: https://doi.org/10.1145/2967934.2968078

Metz, C.E. (1978). Basic principles of ROC analysis. *Seminars in Nuclear Medicine, 8 (4): 283–98.* Available at: https://doi.org/10.1016/S0001-2998(78)80014-2

Pobiedina, N., Neidhardt, J., Calatrava Moreno, M. d. C., Grad-Gyenge, L. & Werthner, H. (2013). On Successful Team Formation: Statistical Analysis of a Multiplayer Online Game, *2013 IEEE 15th Conference on Business Informatics*, *55-62*. Available at: https://ieeexplore.ieee.org/abstract/document/6642858

Salas, E., Burke, C.S. & Cannon-Bowers, J.A. (2000), Teamwork: emerging principles. *International Journal of Management Reviews*, *2*, *339-356*. Available at: https://doi.org/10.1111/1468-2370.00046

Salas, E., Cooke, N. J., & Rosen, M. A. (2008). On Teams, Teamwork, and Team Performance: Discoveries and Developments. *Human Factors*, *50*(3), *540–547*. Available at: https://doi.org/10.1518/001872008X288457

Sapienza, A., Zeng, Y., Bessi, A., Lerman, K. & Ferrara, E. (2018). Individual performance in team-based online games. *Royal Society Open Science,5(6).* Available at: http://dx.doi.org/10.1098/rsos.180329

Shim, K. J., Sharan, R. & Srivastava, J. (2010). Player performance prediction in massively multiplayer online role-playing games (MMORPGs). *Advances in Knowledge Discovery and Data Mining: 14th Pacific-Asia Conference, PAKDD 2010, Hyderabad, India, June 21-24: Proceedings. 6119, 71-80*. Available at: https://ink.library.smu.edu.sg/sis_research/1490

Shim, K. J., Hsu, K. W., Damania, S., DeLong, C. & Srivastava, J. (2011). An Exploratory Study of Player and Team Performance in Multiplayer First-Person-Shooter Games. *2011 IEEE International Conference on Privacy, Security, Risk, and Trust, and IEEE International Conference on Social Computing, 617-620*. Available at: https://www.researchgate.net/profile/Jaideep_Srivastava2/publication/220875980_An_Exploratory_Study_of_Player_and_Team_Performance_in_Multiplayer_First-Person-Shooter_Games/links/55c9bfc808aebc967df93624/An-Exploratory-Study-of-Player-and-Team-Performance-in-Multiplayer-First-Person-Shooter-Games.pdf

Wang, T. (2018). Predictive Analysis on eSports Games – A Case Study on League of Legends (LoL) eSports Tournaments. Available at: https://cdr.lib.unc.edu/concern/masters_papers/8s45qd54c

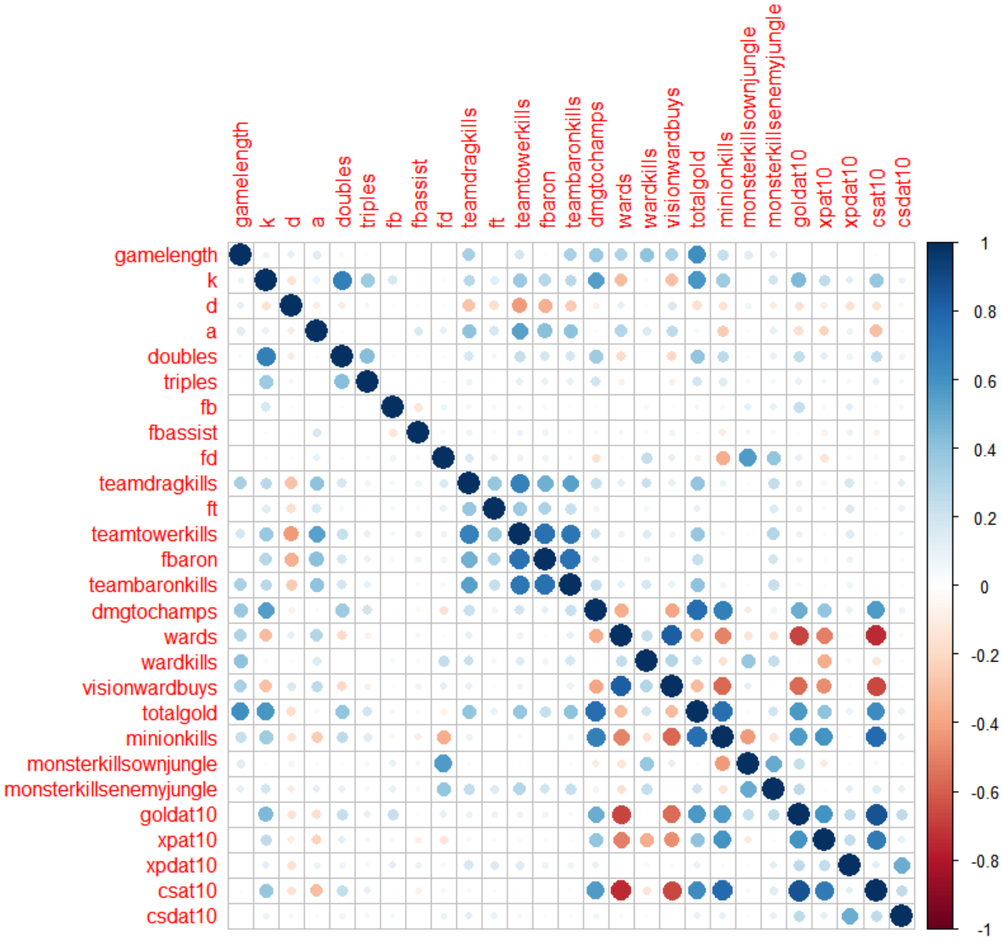
Rank Distribution. (n.d.). Available at: https://www.leagueofgraphs.com/it/rankings/rank-distribution

Novak, A. R., Bennett, K. J. M., Pluss, M. A., & Fransen, J. (2019a). Performance analysis in esports: part 1 - the validity and reliability of match statistics and notational analysis in League of Legends. *SportRxiv*. Available at: https://osf.io/preprints/sportrxiv/sm3nj/

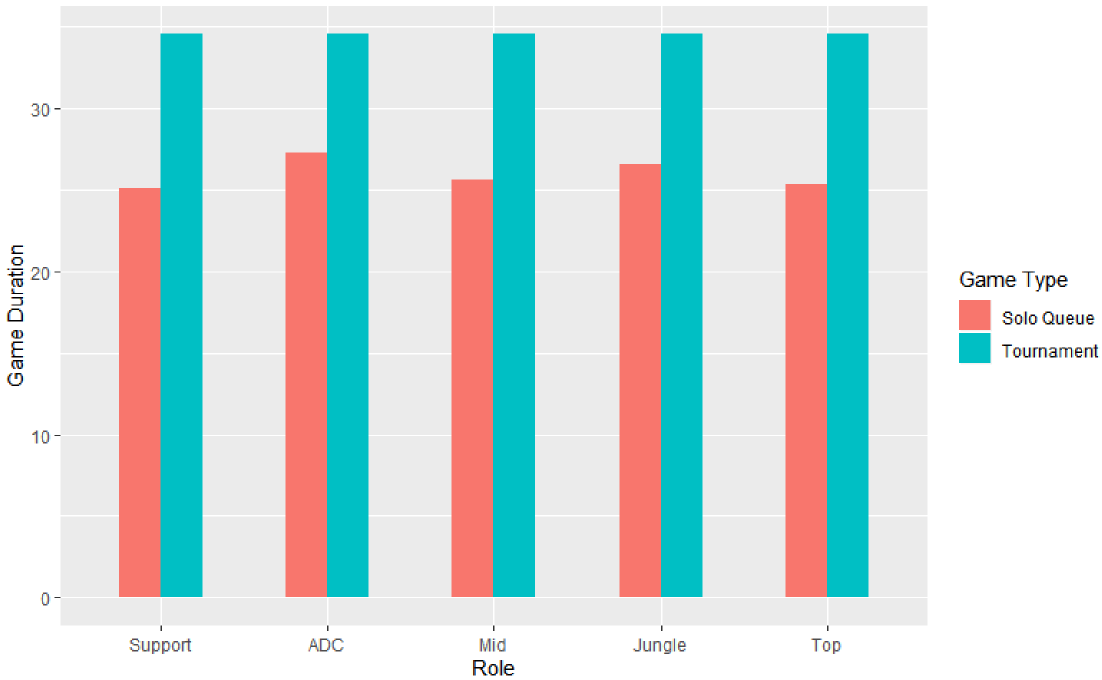
Novak, A. R., Bennett, K. J. M., Pluss, M. A., & Fransen, J. (2019b). Performance analysis in esports: part 2 – modelling performance at the 2018 League of Legends World Championship. *SportRxiv*. Available at: https://www.researchgate.net/publication/336567262_Performance_analysis_in_esports_part_2_-_modelling_performance_at_the_2018_League_of_Legends_World_Championship

Qiu, L., Tay, W. W. & Wu, J. (2009). The impact of virtual teamwork on real-world collaboration. *Proceedings of the International Conference on Advances in Computer Entertainment Technology (ACE '09)*, 44–51. Avalilable at: https://doi.org/10.1145/1690388.1690396

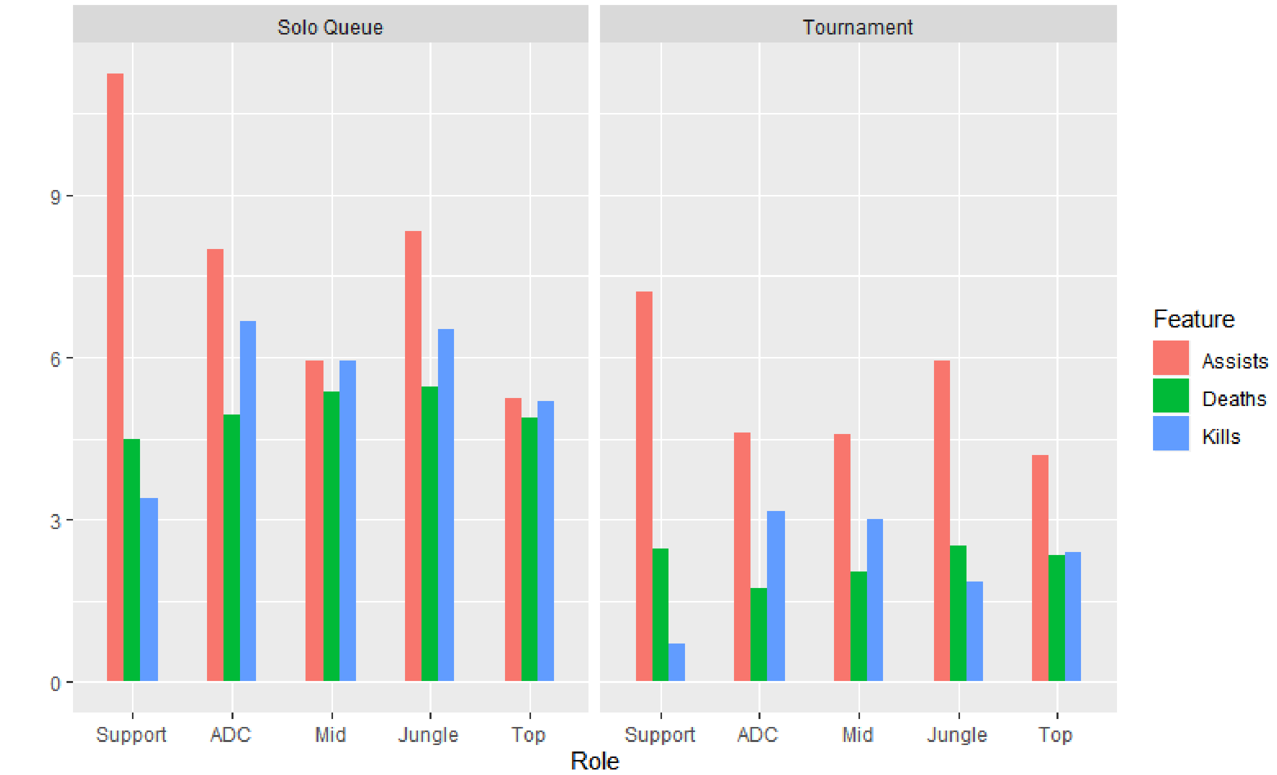
Appendix



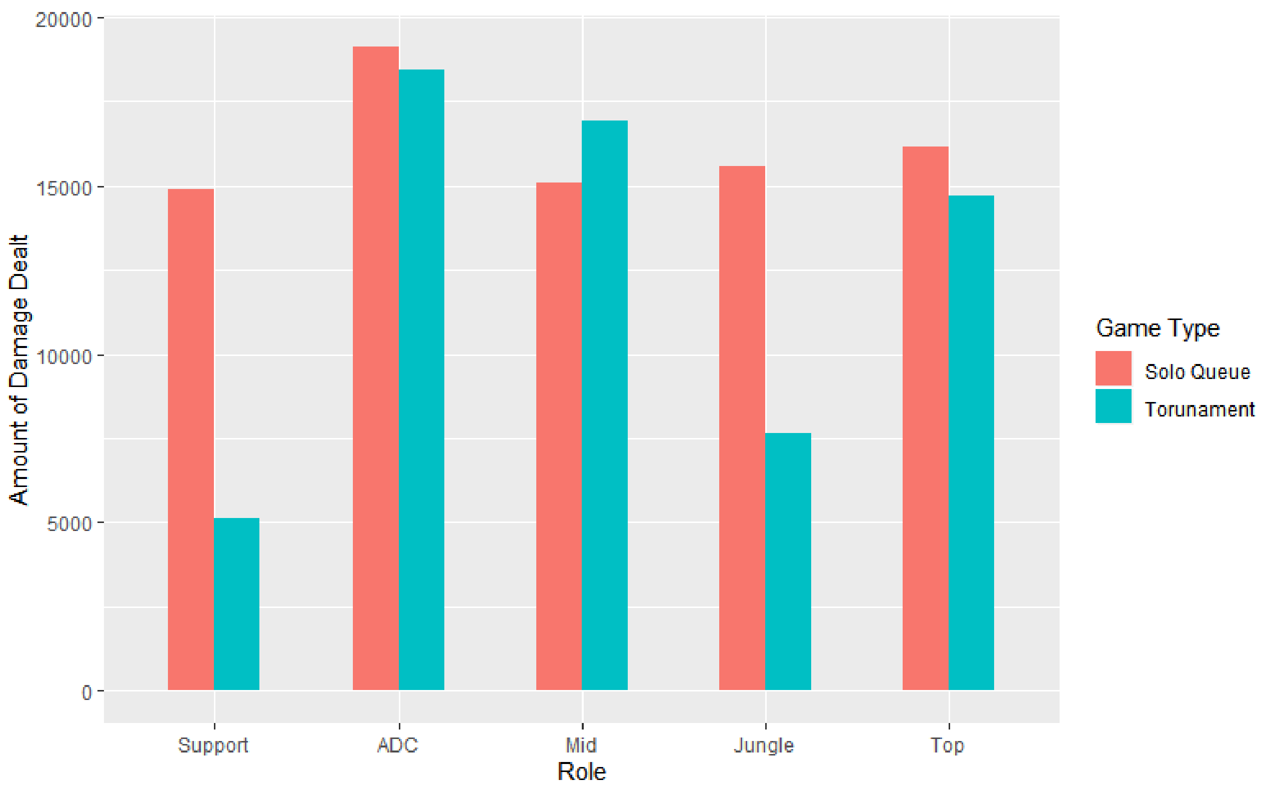
Appendix a. Correlation Matrix between the final features



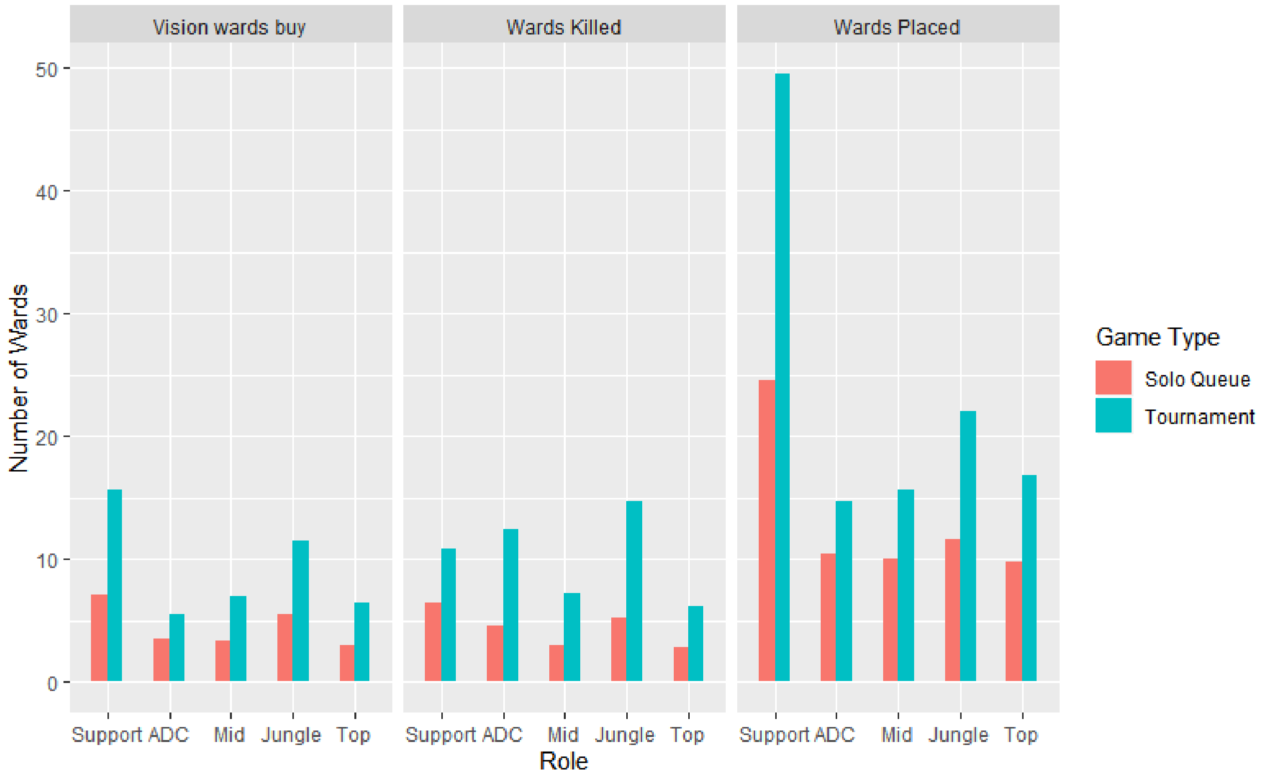
Appendix b. Average Game Duration per Role and Game Type



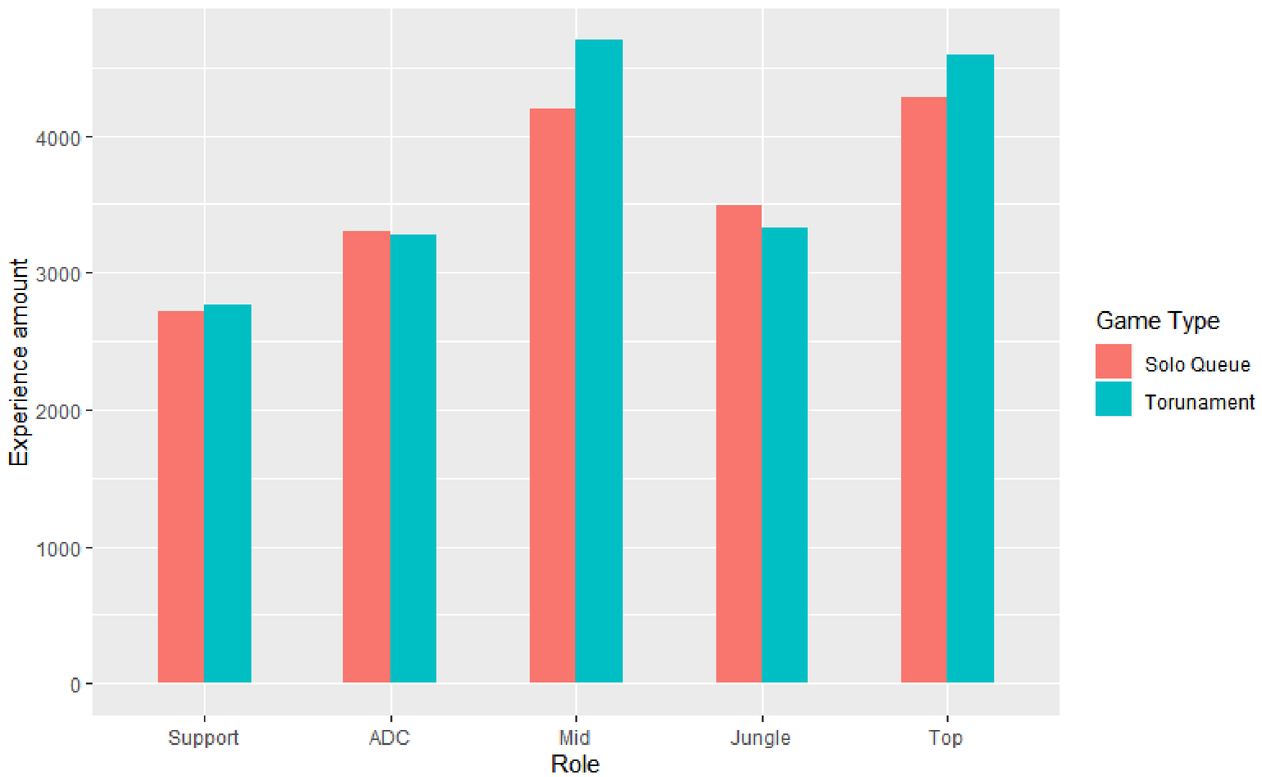
Appendix c. Average KDA for each role and Game Type



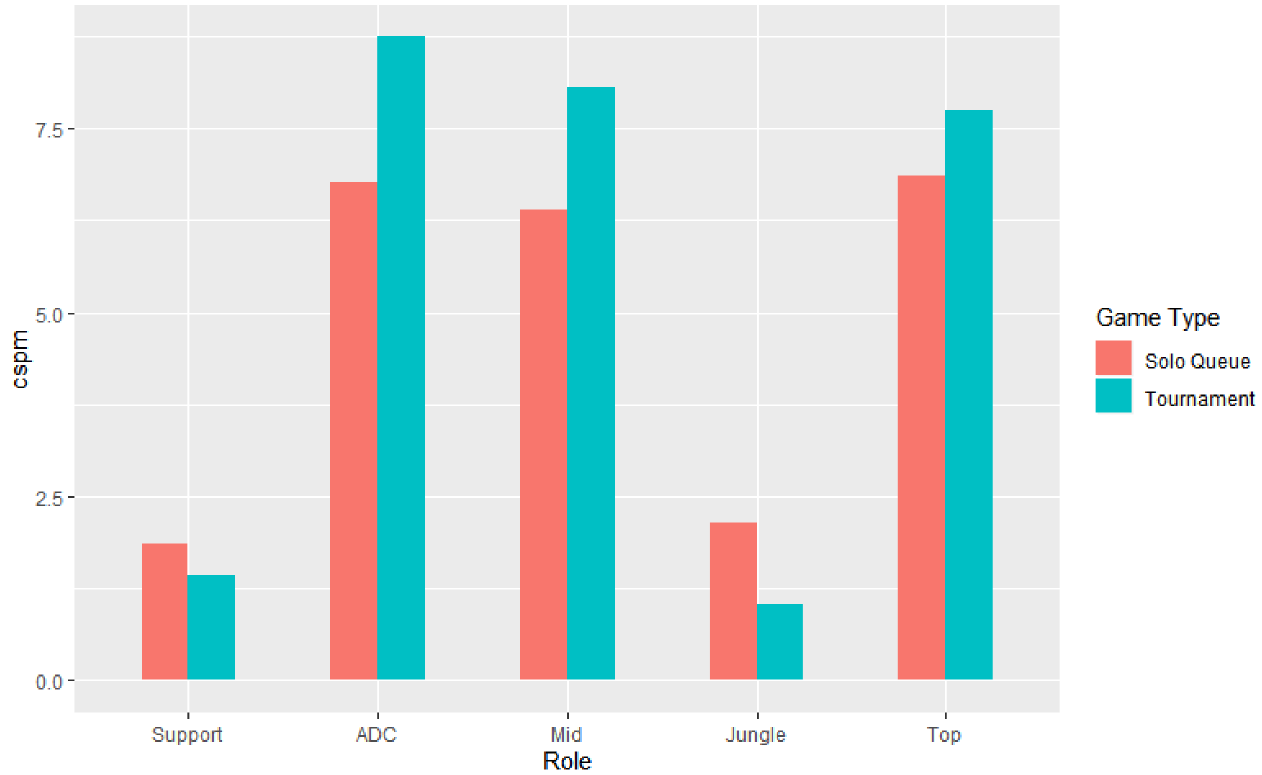
Appendix d. Average Damage Dealt to Champion by role and Game Type



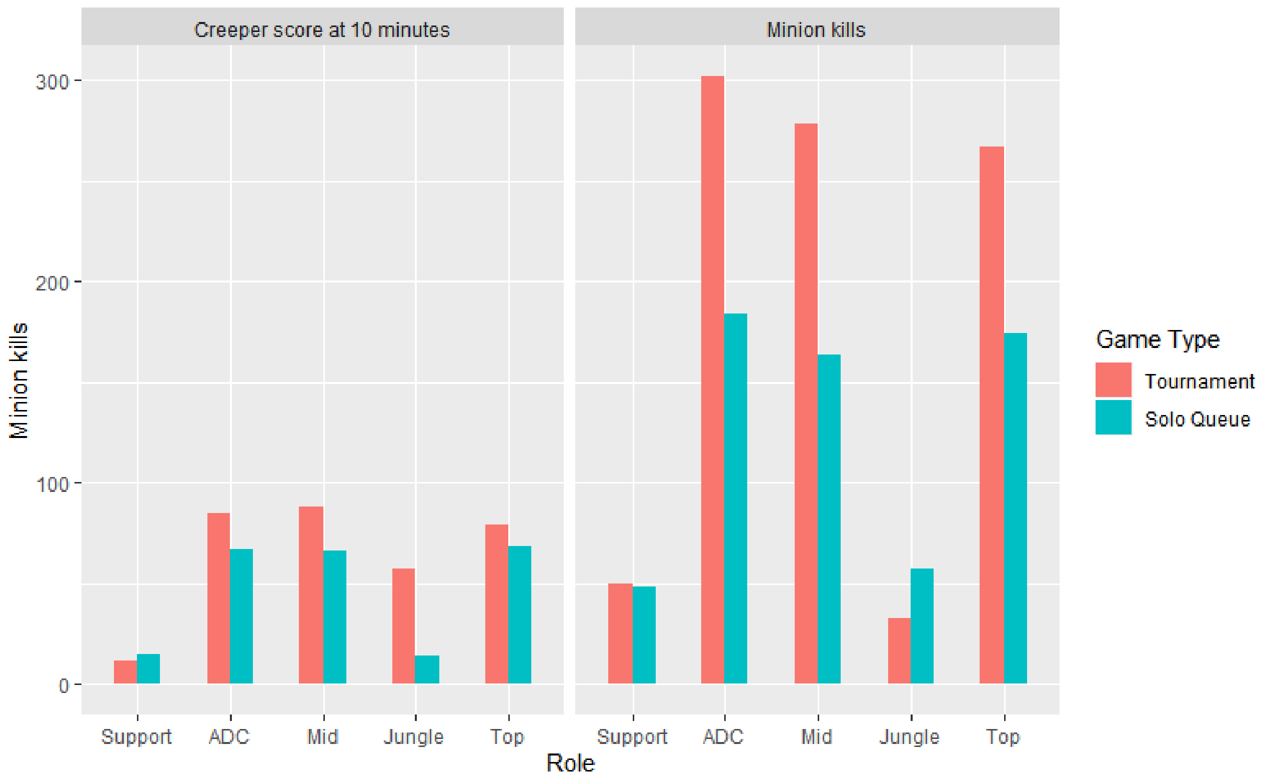
Appendix e. Average Ward features by Role and Game Type



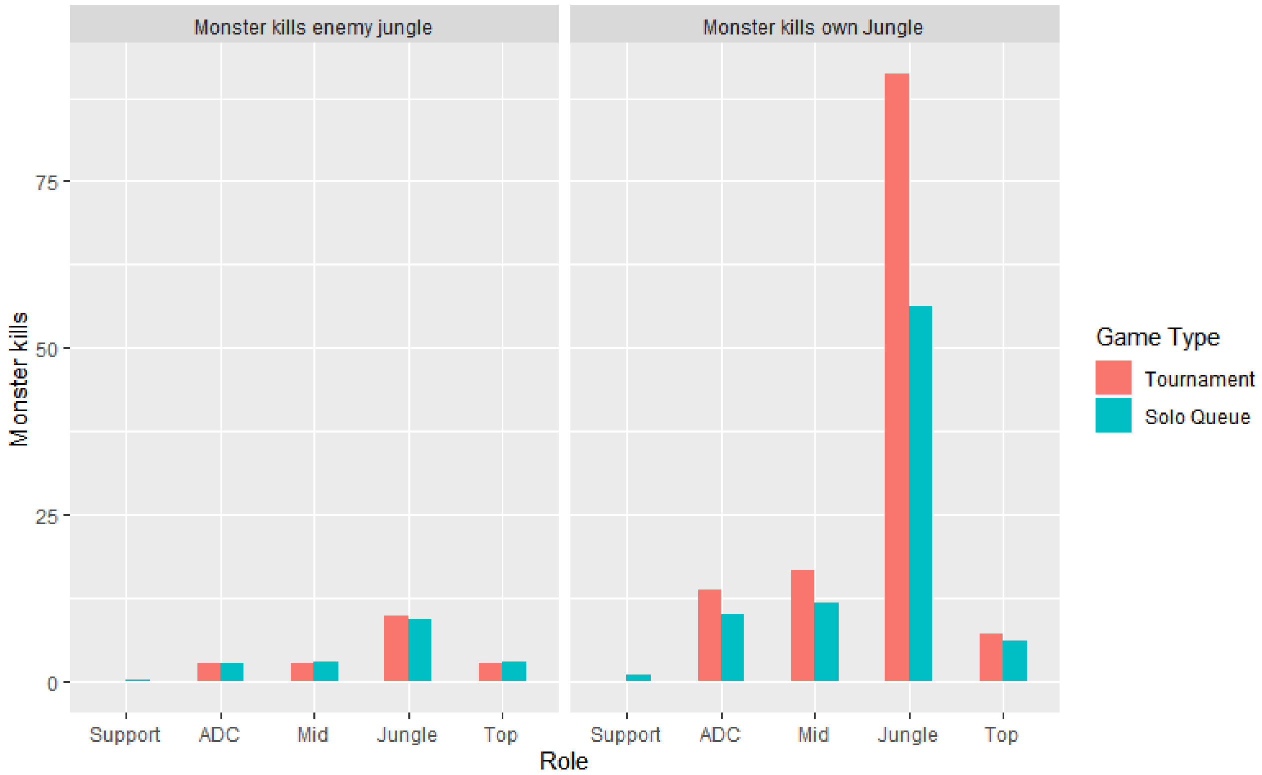
Appendix f. Average Experience Gain by Role and Game Type



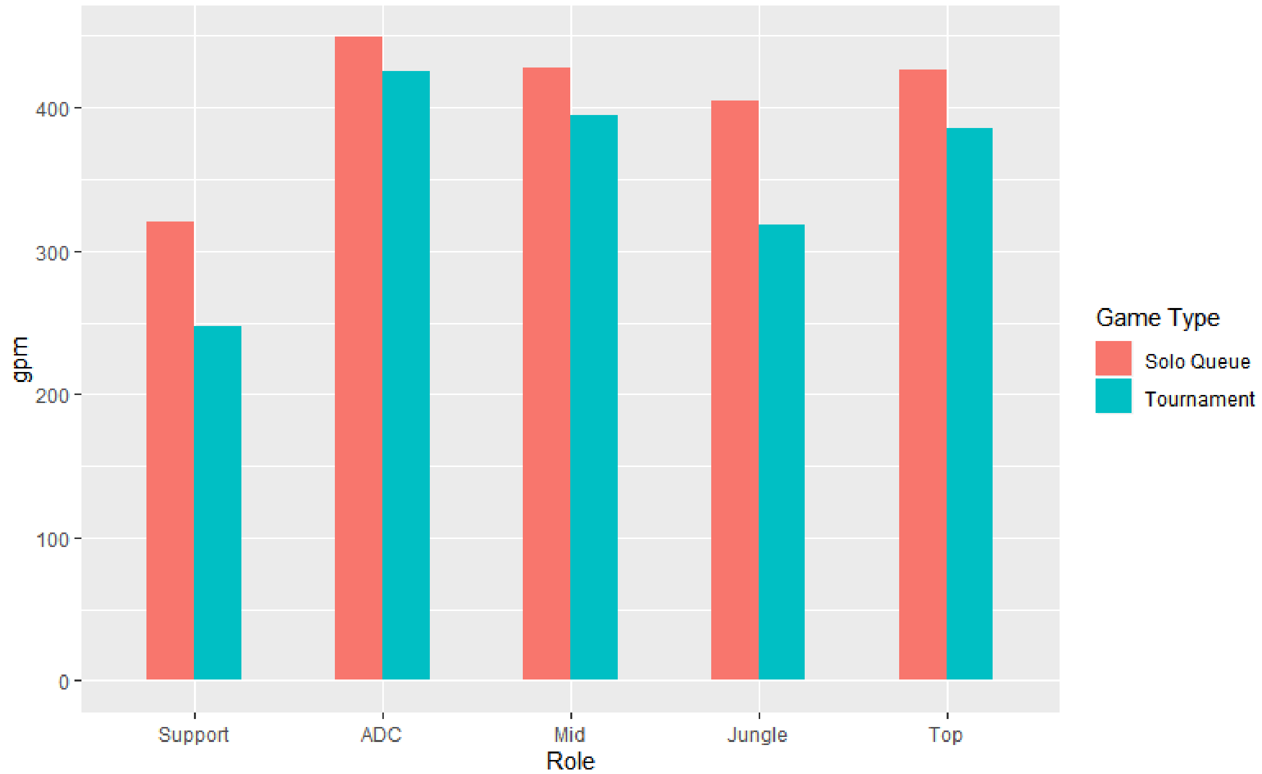
Appendix g. Average Creeper Score per minute by Role and Game Type



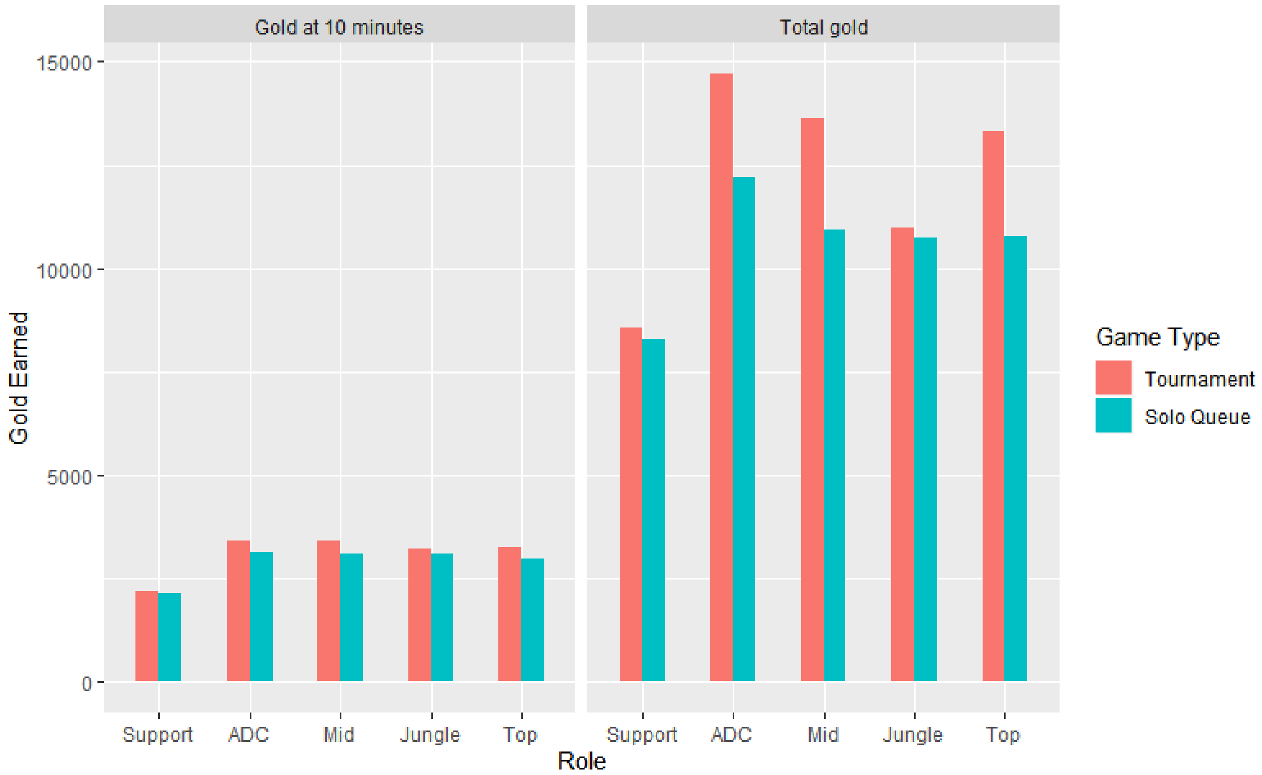
Appendix h. Average Minion kills by Role and Game Type



Appendix i. Average Neutral Monster kills by Role and Game Type



Appendix j. Average Gold per Minute by Role and Game Type



Appendix k. Average Gold features per Role and Game Type

Appendix l. Tables with the mean and standard deviation calculated for each Role. Complete versions can be found at the following link: https://imgur.com/a/Zm4PCGq

KDA ratio and Damage to enemy champions

	Support		ADC		Mid	
	T	SQ	T	SQ	T	SQ
Kill	0.71 (0.92)	3.41 (2.86)	3.16 (2.48)	6.68 (4.35)	3.00 (2.35)	5.94 (3.90)
Death	2.47 (1.71)	4.94 (2.68)	1.75 (1.43)	4.93 (2.86)	2.05 (1.58)	5.38 (3.24)
Assist	7.22 (4.44)	11.23 (6.90)	4.60 (3.14)	7.99 (4.80)	4.58 (3.08)	5.95 (4.04)
Damage to Champions	5095.80 (2976.07)	10105.80 (6733.67)	18450.93 (9267.68)	19096.20 (11017.12)	16918.86 (7934.58)	17647.44 (9533.06)

	Jungle		Top	
	T	SQ	T	SQ
Kill	1.86 (1.72)	6.52 (4.21)	2.40 (1.92)	5.12 (3.85)
Death	2.53 (1.71)	5.46 (3.13)	2.34 (1.62)	4.89 (2.90)
Assist	5.95 (3.73)	8.33 (5.10)	4.19 (3.16)	5.25 (4.15)
Damage to Champions	7631.13 (3924.24)	15588.23 (8818.81)	14676.33 (6637.62)	16130.88 (9316.39)

Ward features

	Support		ADC		Mid		Jungle		Top	
	T	SQ	T	SQ	T	SQ	T	SQ	T	SQ
Wards	49.46 (14.70)	24.51 (14.46)	14.68 (5.13)	10.45 (6.96)	15.68 (4.71)	10.01 (5.05)	22.09 (13.41)	11.62 (7.93)	16.79 (5.29)	9.74 (3.98)
Ward Kills	10.85 (5.23)	6.40 (5.33)	12.38 (6.25)	11.50 (4.54)	7.26 (4.43)	2.93 (2.51)	14.69 (6.30)	5.25 (4.25)	6.21 (3.90)	2.82 (2.87)
Vision Wards Buys	15.63 (5.13)	7.10 (4.59)	5.57 (2.33)	5.00 (3.48)	6.99 (3.00)	3.35 (2.35)	11.15 (3.63)	5.50 (3.11)	6.50 (2.94)	2.95 (1.90)

Minion and Neutral monster features

	Support		ADC		Mid		Jungle		Top	
	T	SQ	T	SQ	T	SQ	T	SQ	T	SQ
Minion Kills	49.70 (30.6)	47.87 (46.51)	301.56 (68.26)	183.65 (72.16)	277.79 (50.76)	163.64 (64.64)	33.06 (16.28)	56.87 (61.16)	267.20 (53.25)	174.04 (63.32)
cspm	1.44	1.85	8.74	6.74	8.05	6.39	1.02	2.14	7.74	6.87
Minion kills at 10 minutes	11.98 (11.11)	15.19 (19.9)	85.16 (15.40)	67.06 (23.07)	88.34 (9.13)	65.89 (24.13)	57.43 (7.32)	14.26 (22.09)	79.40 (10.30)	68.57 (20.80)
Minion kills difference at 10 minutes	0 (16.60)	1.23 (9.85)	0 (20.16)	3.30 (8.79)	0 (10.95)	4.48 (14.95)	0 (10.73)	0.26 (6.64)	0 (14.97)	7.63 (14.18)
Monster kills own Jungle	0.02 (0.26)	1.06 (5.72)	13.76 (10.08)	10.24 (14.36)	16.72 (10.11)	11.78 (20.12)	91.40 (19.31)	56.16 (36.17)	7.14 (7.44)	6.34 (11.36)
Monster Kills enemy Jungle	0.06 (0.47)	0.42 (2.03)	2.81 (4.27)	2.77 (4.47)	2.84 (3.88)	2.96 (4.83)	9.84 (8.35)	9.38 (9.66)	2.72 (4.77)	2.92 (4.80)

Gold features

	Support		ADC		Mid	
	T	SQ	T	SQ	T	SQ
Total Gold	8548.24 (1937.34)	8286.41 (2863.20)	14697.65 (3303.92)	12223.11 (4228.38)	13638.54 (2805.84)	10930.99 (3693.34)
gpm	247.63	319.86	425.77	448.88	395.03	427.49
Gold at 10 minutes	2193.77 (280.64)	2160.73 (665.98)	3434.74 (322.90)	3144.98 (729.18)	3427.81 (260.11)	3115.72 (649.44)

	Jungle		Top	
	T	SQ	T	SQ
Total Gold	10965.56 (2155.41)	10750.93 (3593.46)	13304.09 (2881.62)	10799.53 (3834.84)
gpm	317.66	404.62	385.40	426.19
Gold at 10 minutes	3230.70 (301.85)	3096.07 (838.20)	3272.31 (309.23)	3002.23 (774.17)

Experience features

	Support		ADC		Mid	
	T	SQ	T	SQ	T	SQ
Experience at 10 minutes	2761.08 (258.89)	2710.82 (656.60)	3275.14 (251.65)	3305.71 (541.41)	4694.18 (284.26)	4201.37 (751.25)
Experience difference at 10 minutes	0 (307.32)	33.93 (410.02)	0 (350.60)	102.93 (441.77)	0 (383.58)	56.89 (654.43)

	Jungle		Top	
	T	SQ	T	SQ
Experience at 10 minutes	3328.89 (349.04)	3487.85 (864.67)	4586.62 (312.35)	4279.40 (944.41)
Experience difference at 10 minutes	0 (493.34)	23.40 (578.65)	0 (426.20)	223.28 (583.98)