League of Legends - Which Resource In The Summoner's Rift Will Most Likely To Carry You to The Victory?

We build a logit model with more than 96% accuracy to prove that League of Legends is a tower destroying the game.

Dingyi Yu

22 December 2020

Abstract

As one of the most popular video games in the world, League of Legends had nourished a significantly profitable industry. From the original purpose of personal relaxation to those e-sports players who pursue championship in world-wide competitions, the game is welcomed among people in a generation and had created more than a million job opportunities and immeasurable value. Dividing into two groups of five, each group aims to destroy the Nexus of the other group to win the game and thus all players need to gain as much resource as possible to keep the lead position throughout the game. That leads to the key question to be researched in this study: Among all those available resources, what is the most significant attribution that will lead to the final victory of a single game? To make further analysis, a logit model is constructed with 96% accuracy showing that destroying the first inhibitor is the indicator of winning.

Keywords: League of Legends; Logit Model; Ranked Game; e-Sport; World Championship;
Code: Code and data are available at https://github.com/eddieyyy/League-of-Legends (https://github.com/eddieyyy/League-of-Legends)

Introduction

In the past few years, the e-sport community was under an accelerated stage. The e-sport industry, which used to focus on leisure and entertainment, expect to create value of more than 1.8 billion dollar by 2022. Despite many video games thriving in the industry, few games could maintain their leading position in the community like League of Legends (Xia and Zhou 2017). The Season 9 World Championship in 2019, which was the most recent annual world-wide competition of League of Legends (LoL), had attracted more than 100 million audiences globally (Novak 2020).

Launched in 2009, League of Legends is a free Multi-player Online Battle Arena (MOBA) video game developed by Riot Games(Cavadenti and Kaytoue. 2016). The game quickly captured the interests of youth and kept thriving for ten years remaining the top popular video game world-wide. In each single game of League of Legends, ten players are divided into two groups of five. Each player controls a unique champion and the goal is to destroy a construction called "Nexus" of the other group to win a game. During the game, players need to obtain and allocate resources to maximize their uses. Those sources are available in many ways, such as killing the hostile champions from the other group, killing minions, killing dragons and barons to obtain buffs and destroying constructions such as turrets and inhibitors. To win a game, at least five turrets and one inhibitor needed to be destroyed until the team could reach to the hostile Nexus. Other targets, such as the number of kills, money and buffs, are not indispensable but are undoubtedly beneficial indicators(Cavadenti and Kaytoue. 2016).

The diverse mechanism of the game leads to a new occupation, the gaming analysts. Similar to traditional sports team, the e-sport professional teams also require such analysts who could provide useful strategies that help the team to win the game in the competition. Despite the arguments that such formal analysis seems to be unnecessary for most players who just want to play the game for fun, it is still useful for those players to know how to utilize the resources in the most efficient way and increase the probability of win (Novak 2020).

In this study, we had randomly collected data of 5000 games from different levels of players to see what is the most significant resource that contributes to the final win. Aiming to find the attributes that most related to the victory, a logit model is built to predict the binary outcome of the game, win or lose (McFadden 1974). All statistical analyses were conducted using R (R Core Team 2020), with Tidyverse package (Wickham et al. 2019) for the convenience of data processing .

Data

Data Variables

The data used in the analysis consists of following 14 variables:

matchId is a categorical variable indicates each unique match. We will use it only for identification of certain matches, not for analysis.

tier is a categorical variable indicates the match's ranked level which shows the level of the player participated in the match. It has 5 categories including BRONZE, SILVER, GOLD, PLATINUM and DIAMOND in an ascending order.

blue_kill is a numeric variable indicates the total number of kills for blue team, each kill will bring approximately 300 gold to the player.

red_kill is a numeric variable indicates the total number of kills for red team, each kill will bring approximately 300 gold to the player.

blue_gold is a numeric variable indicates the total number of gold earned by all five players from blue team. Gold is the only way for players to buy or update their equipment such as weapons which increases damage or armors which increases the defense. Gold could be earned by killing minions and champions from the enemy team, destroying towers and killing monsters such as Baron. There is also stable increment in a rate of approximately 1.9 gold per second.

red_gold is a numeric variable indicates the total number of gold earned by all five players from red team. Gold is the only way for players to buy or update their equipment such as weapons which increases damage or armors which increases the defense.

blue_firstBlood is a logical variable indicates whether blue team gets the first blood (get the first kill of the game), if the value is False meaning the red team gets the first blood. Note that first blood will bring 500 gold to the player. Golds could be earned by killing minions and champions from the enemy team, destroying towers and killing monsters such as Baron. There is also stable increment in a rate of approximately 1.9 gold per second.

blue_firstTower is a logical variable indicates whether blue team destroy the first tower of the game, if the value is False meaning the red team destroys the first tower. Note that there are eleven towers for each team, and at least five towers need to be destroyed for winning most games (without occurrence of surrender). Destroying the first tower will bring 650 gold to the team (100 gold each player and 150 extra gold for the players who destroyed the first tower).

blue_firstInhibitor is a logical variable indicates whether blue team destroy the first inhibitor of the game, if the value is False meaning the red team destroys the first inhibitor. Note that there are three inhibitors for each team, and at least one inhibitor needs to be destroyed for winning most games (without occurrence of surrender). At least three towers must be destroyed before destroying an inhibitor. Once an inhibitor is destroyed, it would produce super minion which is powerful for destroying structures.

blue_firstBaron is a logical variable indicates whether blue team kills the first Baron of the game, if the value is False meaning the red team kills the first Baron. Note that killing Baron will add an extra 4-minute buff to allied team, which includes reduced recalling time, strengthening the nearby minions' movement speed, defense, damage and attack range. The Baron buff is extremely helpful for destroying structures as it decreases the time for towers to kill minions. The first Baron appears at 20 minutes of the game,

blue_firstDragon is a logical variable indicates whether blue team kills the first dragon of the game, if the value is False meaning the red team kills the first dragon. Killing the first dragon will bring a permanent buff to the team, which might be the increment of movement speed, health regen, defense or damage, depending on the types of the dragon. The first dragon appears at 5 minutes of the game.

blue_firstRiftHerald is a logical variable indicates whether blue team kills the first Rift Herald of the game, if the value is False meaning the red team gets the first Rift Herald. Killing the first rift herald can summon a rift herald which could cause tremendous damage to the tower. Note that the rift herald appears at 8 minutes of the game and disappears at 19.5 minutes of the game.

gameDuration is a numeric variable indicates the total length of the game in seconds. Note that only games which exceed 15 minutes would be considered since game ending before 15 minutes is abnormal and thus non-representative.

result is a categorical variable shows the winner of the match.

A brief overview of the statistical information for the numerical data is shown below

variable name	Min	Median	Mean	Max
blue_kill	0	0	0	0
red_kill	0	0	0	0
blue_gold	15166	49548	49811	110544
red_gold	16575	49644	49506	110531
gameDuration	902	1605	1621	3641

Data features and strengths

The data is collected through the bronze to diamond ranked-game record from 2020-08-07 to 2020-09-07 in Korean server which is retrieved from (Riot Games 2020c). There are 5000 games in total with 1000 game records in each tier.

The time of the data is relatively closed to today, which is a remarkably strength of the data. Since the version of the game updates frequently and any significant update may change the way of winning the game.

The data is recorded from ranked-game, which is more relevant to common players comparing to analyze data from professional competitions. Moreover, ranked-game data also has an advantage to observe a more generalized trend of winning a game comparing to data from professional competitions as professional teams tend to play in designed ways for certain strategies.

The data also records players of a wide range from bronze to diamond, which makes the result representative to most players. Since players at different levels tend to perform differently in a game, it is better to include data from different levels to make sure that the characteristics of most players can be captured by the model.

Data weaknesses

As mentioned above, the data is from the Korean server only, which makes it hard to be generalized to players from other regions. It had been shown that players in different regions tend to have different playing style, which could affect their competition to certain resources such as Baron and dragons. Besides, the killing number and the duration of a game could also be affected by game style as game in Korean server do not favor team-fighting but focus on destroying constructions such as towers and inhibitors.

Furthermore, due to certain restrictions, the size of the sampled data is relatively small, as we need to perform model validation for training and testing our model. In order to effectively utilize the limited data, the cross-validation will be performed while building the model which potentially increase the cost by doing calculation.
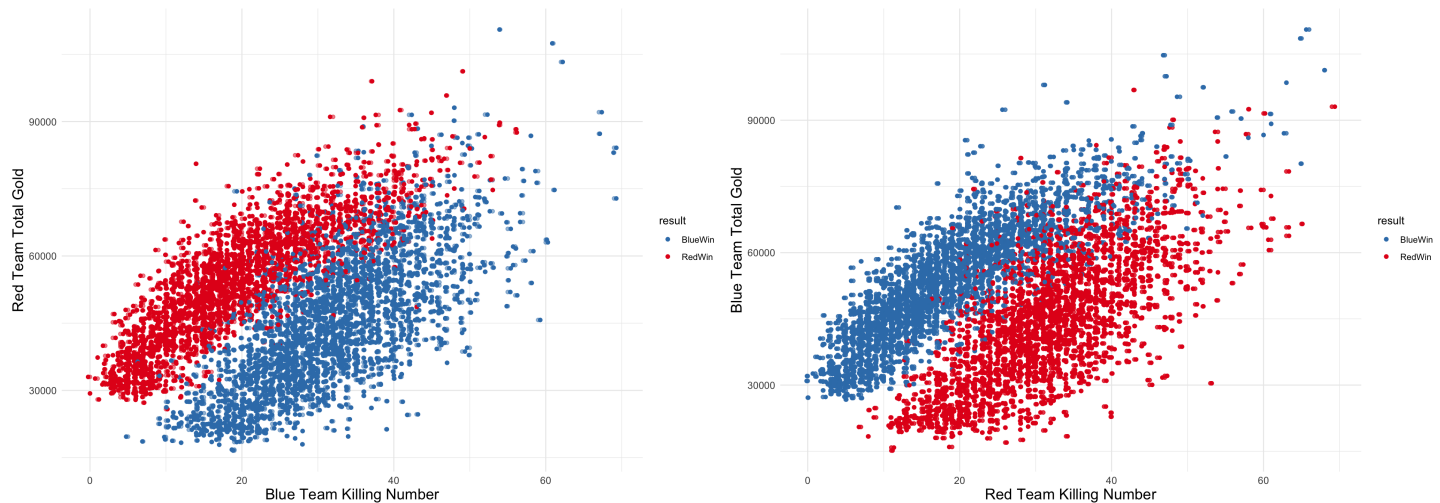
Data Visualization

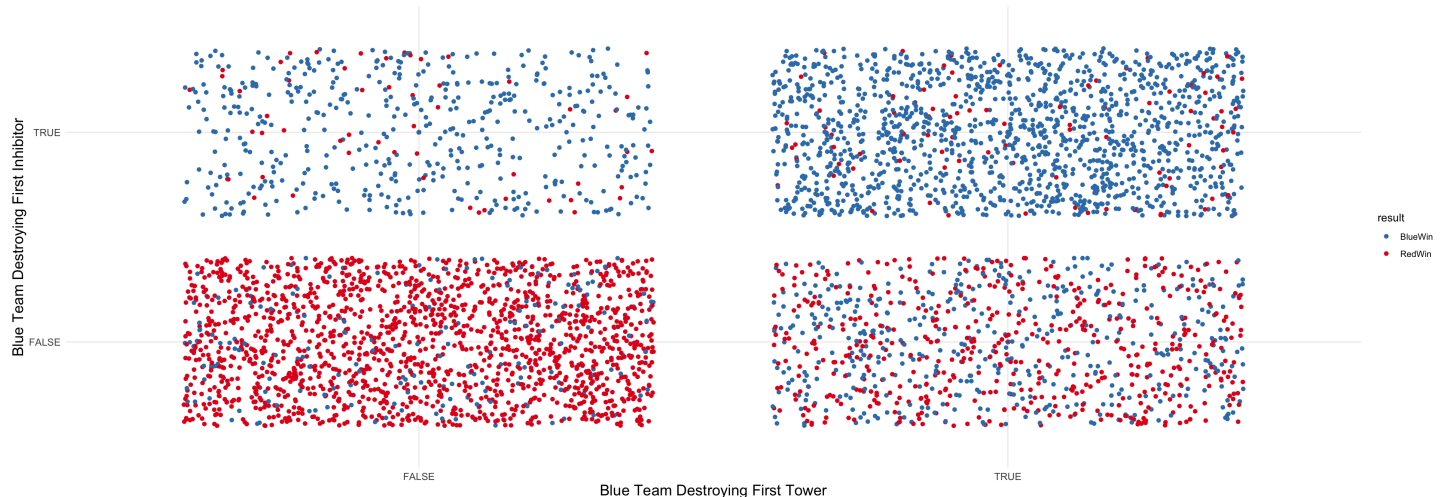Figure 1: Winning team tend to earn more gold and get more killings compared to the losing game..

Figure 2: Destroying first inhibitor is a remarkable indicator for winning a game, while first tower occupation is not that significant.

By observing Figure 2, which combines the first tower and the first inhibitor occupation together as they are both structural resources of the game, we could see that first inhibitor is a remarkable indicator for winning a game, especially when the team also destroys the first tower of the game (Figures in top-right and bottom-left corners). As of the team which does not destroy the first inhibitor but destroys the first tower, one interesting phenomenon is that the it is harder for red teams to win in this case comparing to blue teams (Figures in top-left and bottom-right corners).
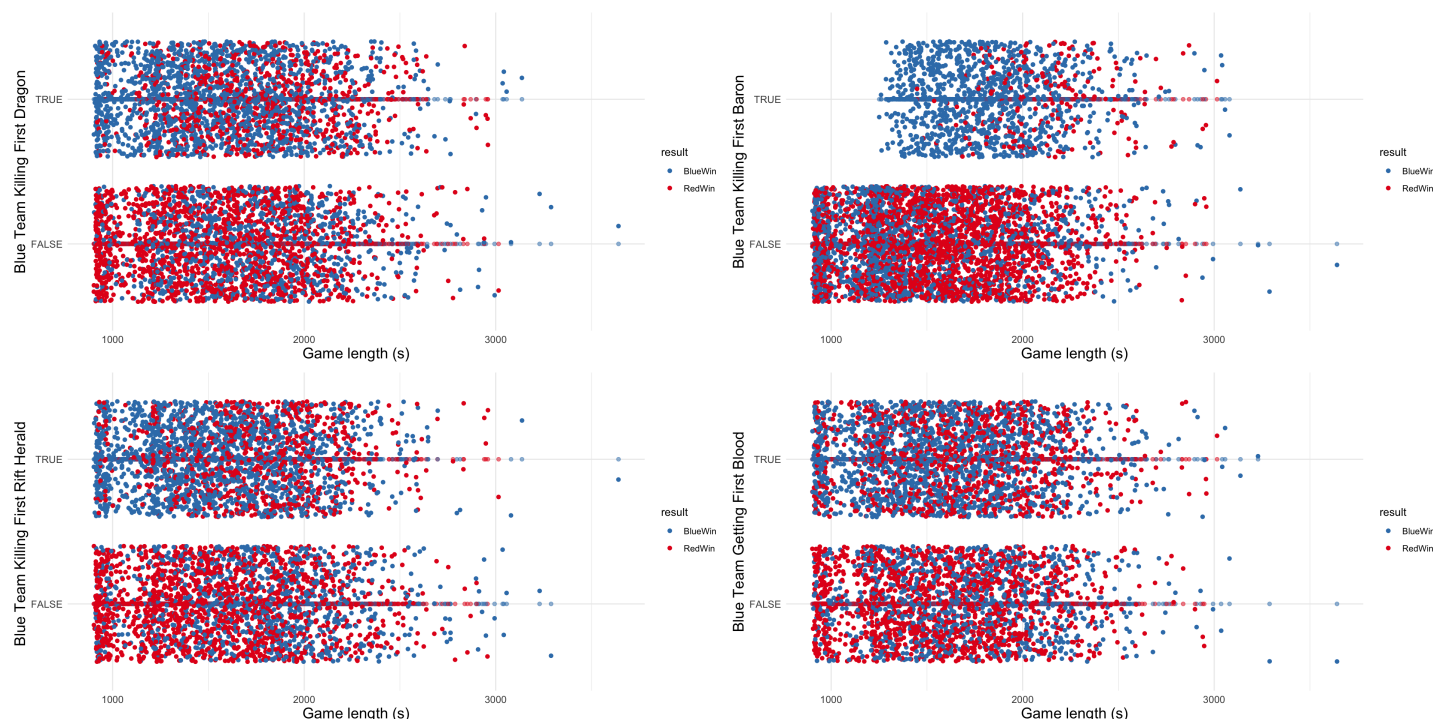

Figure 3: First Baron is a good indicator for winning a game, whereas first dragon, first Rift Herald and first blood do not show significant difference for the final outcome.

By observing Figure 3, which shows analysis to the trend that how occupation of first dragon, Baron, Rift Herald and first blood might attribute to the final outcome of the game. Obviously, all those four factors contribute to increase the probability of the final victory. However, among those factors, we could observe that killing the first Baron contributes the most to the final victory, as overturns seldom, if ever, happen when a team kills the first Baron, as it will maximize the superiority by providing the team with enormous power to destroy structures such as inhibitors, which is more essential to the final win.

One thing to notice is that as Baron appears in the game only after 20 minutes, therefore the points in Baron graph indicating Blue team kills the first Baron occurs only after approximately 1200 seconds. For game ends before 20 minutes, Baron is an invalid indicator for making predictions.
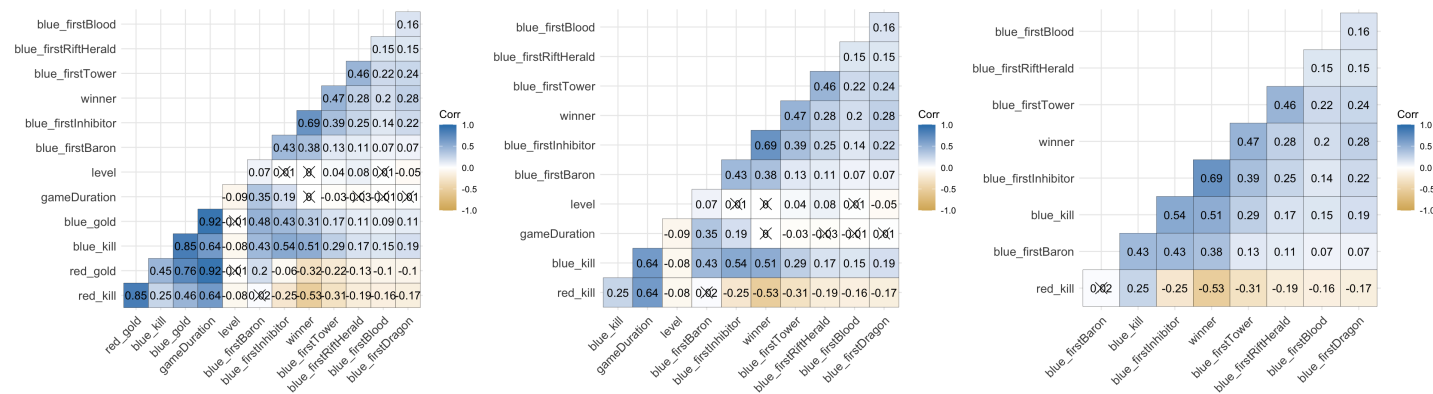

Figure 4: Correlation matrices of all variables

Figure 4 shows the process of filtering variables using correlation matrices. According to the first matrix, where we include all variables (except for the matchId because it makes no sense on predicting the result), we could see that certain variables are high-related, for example, gold versus gameDuration and gold versus kills, which are respectively high as 0.92 and 0.86. Such correlation is reasonable as the amount of gold earned will definitely increase as the game lasts longer or players take more killings (each killing is worth 300 gold in general). Such high correlation between variables might cause the issue of multi-collinearity, which might make it difficult to measure individual influence of certain predictors on the response variable and make the fitted model unstable (McFadden 1974).

To reduce the potential multi-collinearity issue, we further remove the gold variable as it is commonly known that the winner side always end with more gold as it is the essential measurement of taking the lead. The second correlation matrix shows the result without the gold, and we would like to focus on the correlation between winner(our response) and other variables. Based on the value presented by the matrix, we could see that level(which is originally tier in raw data) and gameDuration had rare almost no correlation explaining the final outcome of a game, so we further eliminate the two variables.

The third correlation matrix is ideally constructed, as no correlations between any explanatory variables could exceed 0.5, which helps us avoid the potential multi-collinearity issue. Moreover, we could see that inhibitor and kill are most correlated to final outcome of the game as they have higher correlation to winner comparing to other variables.

Model

As the final outcome of winning a game is a binary result (1 stands for blue team winning the game and 0 stands for red team winning the game), logit model is commonly used to predict such information. We start by building a full model including all variables (except for the matchId because it makes no sense on predicting the result) and see how the model performs.

By dividing the data into 85% for model-training and 15% for model-testing, we use model validation by seeing the accuracy in the form of confusion matrix to evaluate the model performance.

variable name	coefficient	p-value
(Intercept)	-0.0851	0.9247
tierDIAMOND	0.7582	0.1719
tierGOLD	0.4248	0.3901
tierPLATINUM	0.1702	0.7411
tierSILVER	0.3170	0.4797
blue_kill	0.0390	0.2097
red_kill	-0.0261	0.3832
blue_gold	0.0008	$1.6529 * 10^{-29}$
red_gold	-0.0009	$6.1245 * 10^{-35}$
blue_firstBloodTRUE	-0.4430	0.1346
blue_firstTowerTRUE	-1.0374	0.0013
blue_firstInhibitorTRUE	2.0510	$4.7741 * 10^{-10}$
blue_firstBaronTRUE	-1.1690	$4.9835 * 10^{-4}$
blue_firstDragonTRUE	0.2926	0.3177
blue_firstRiftHeraldTRUE	-0.0963	0.7558
gameDuration	0.0031	0.1155

Table 1: The full model summary and statistics P-value

The full model, as shown above in Table 1, could be expressed in the following way:

$$Pr(result) \in \{1, 0\} =$$

$$logit^{-1}(\alpha_0 + \beta_{1[i]}(tier_i) + \beta_2(blue\_firstBlood) + \beta_3(blue\_firstTower) + \beta_4(blue\_firstInhibitor) + \beta_5(blue\_firstDragon)$$
$$+\beta_6(blue\_firstBaron) + \beta_7(blue\_firstRiftHerald) + \beta_8(gameDuration) + \beta_9(blue\_gold) + \beta_{10}(blue\_kill)$$
$$+\beta_{11}(red\_gold) + \beta_{12}(red\_kill) + \epsilon_i)$$

$$\epsilon_i \sim N(0, \sigma_e^2)$$

Using the usual 5% threshold significant level to measure the p-value of variables, we mark certain variables as significant. Significant variables include gold, tower, inhibitor and Baron. The gold's correlation to the final outcome is clear as demonstrated above, and we could see destroying structures is more essential compared to resources from killing and other jungle resources. The Baron appears to be significant could also be explained by its powerful buff for destroying structures.

However, certain coefficients of the predictors in the model tend to be anti-intuitive. For example, teams with the first Baron and first tower are predicted be less possible to win with negative coefficients, which is very likely caused by multi-collinearity issue. To further test the performance of the model, we use confusion matrix to see the accuracy.

Confusion Matrix and Statistics

```
      Reference
Prediction   0    1
        0 336    9
        1    4  375


Accuracy : 0.9820
95% CI : (0.9695, 0.9904)
```

The confusion matrix shows that the accuracy of the prediction using the model is approximately 98%, which is extremely high. Of the 724 testing data, only 13 predictions get wrong. Despite the high accuracy, more improvement could be done through eliminating the multi-collinearity issue for a more reasonable predictors' interpretation of the model. We then build a reduced model by removing gold, gameDuration and tier variables.

variable name	coefficient	p-value
(Intercept)	-0.2125	0.464648
blue_kill	0.3262	$2.000 * 10^{-16}$
red_kill	-0.3605	$2.000 * 10^{-16}$
blue_firstBloodTRUE	-0.3253	0.0687
blue_firstTowerTRUE	0.3325	0.0809
blue_firstInhibitorTRUE	2.3429	$2.000 * 10^{-16}$
blue_firstBaronTRUE	0.7241	0.0003
blue_firstDragonTRUE	0.3817	0.0293
blue_firstRiftHeraldTRUE	0.0109	0.9530

Table 2: The reduced model summary and statistics P-value

The reduced model, as shown in Table 2 above, could be expressed in the following way:

$Pr(result) \in \{1, 0\} =$

$logit^{-1}(\alpha_0 + +\beta_1(blue\_firstBlood) + \beta_2(blue\_firstTower) + \beta_3(blue\_firstInhibitor) + \beta_4(blue\_firstDragon) + \beta_5(blue\_firstBaron) + \beta_6(blue\_firstRiftHerald) + \beta_7(blue\_kill) + \beta_8(red\_kill) + \epsilon_i)$

$\epsilon_i \sim N(0, \sigma_e^2)$

Using the usual 5% threshold significant level to measure the p-value of variables, we mark certain variables as significant. Significant variables include kills, dragon, inhibitor and Baron. Similar explanation could be made as above, except for the fact that significance of gold variable transfers to the significance of the kills variable. Another note-worthy change is that the significance of the first tower decreases in the reduced model, as the P-value indicating it is no more significant in explaining the final outcome. In comparison, the significance of first dragon increases as its P-value reduces to less than 0.05 in the reduced model.

The most remarkable improvement of the reduced model is to revise those unreasonable coefficients of the model, as one could see that acquiring first Baron and tower becomes positively related to the probability of final victory. Among the significant variables, we could see that the destroying the first inhibitor contribute the most to the final victory with an approximate weight of 2.34.

```
      Reference
Prediction   0    1
        0 338   11
        1   18  357


Accuracy : 0.9599
95% CI : (0.943, 0.973)
```

Surprisingly, the confusion matrix shows an accuracy of approximately 96% for the reduced model, which is a bit lower than the full model. Of the 724 testing data, 29 predictions get wrong. However, since 96% accuracy is still much higher than expected, we could change our training and sampling data for fitting the model to check the performance of the reduced model, which will be left for future work.

For now, I would take the reduced model for further analysis, as it presents a more reasonable coefficient and even if lower but still high accuracy

Results

As the model comparison and interpretation shown above, the reduced model is selected for analyzing the final outcome of the game. The model includes variables of killing, first tower, first inhibitor, first blood, first dragon, first Baron and first Rift Herald as predictors.

Among the predictors, we could see that the most significant indicator that could be used to forecast the final victory is destroying the first inhibitor. It is reasonable as destroying the first inhibitor would cause the spawning of superior minions, which will cause much trouble to the other team. Moreover, having the first Baron is also a good sign for winning a game, as it will indirectly increase the probability of destroying more structures including inhibitors by providing allied minions powerfully buff while attacking structures.

As of killing, despite the fact that killing more enemies also contributes to the final victory of the game, it is not wise to spend much time on team fighting as destroying structures is more effective for winning a game. Even though one single killing could increase the probability to win by approximately 0.33 unit which seems to be an attractive choice, involving into a fight is in fact a risky choice as a death could also lead to the increment of winning chance of the enemy team (Maymin 2020). Moreover, the first blood attribution is inversely related to the possibility of winning a game, as its coefficient remains negative in both models. Though the attribution is not considered to be significant, its p-value is very closed to the threshold of 5% which make it worth consideration. One possible interpretation is that the reward of first kill is not significant enough, whereas it might lead to an illusion to the team that they are holding a safe lead and make wrong decisions (Cavadenti and Kaytoue. 2016).

variable name	weight
blue_kill	0.3262
red_kill	−0.3605
blue_firstInhibitorTRUE	2.3429
blue_firstBaronTRUE	0.7241
blue_firstDragonTRUE	0.3817

Table 3: Significant predictors and corresponding weight contributing to the final victory
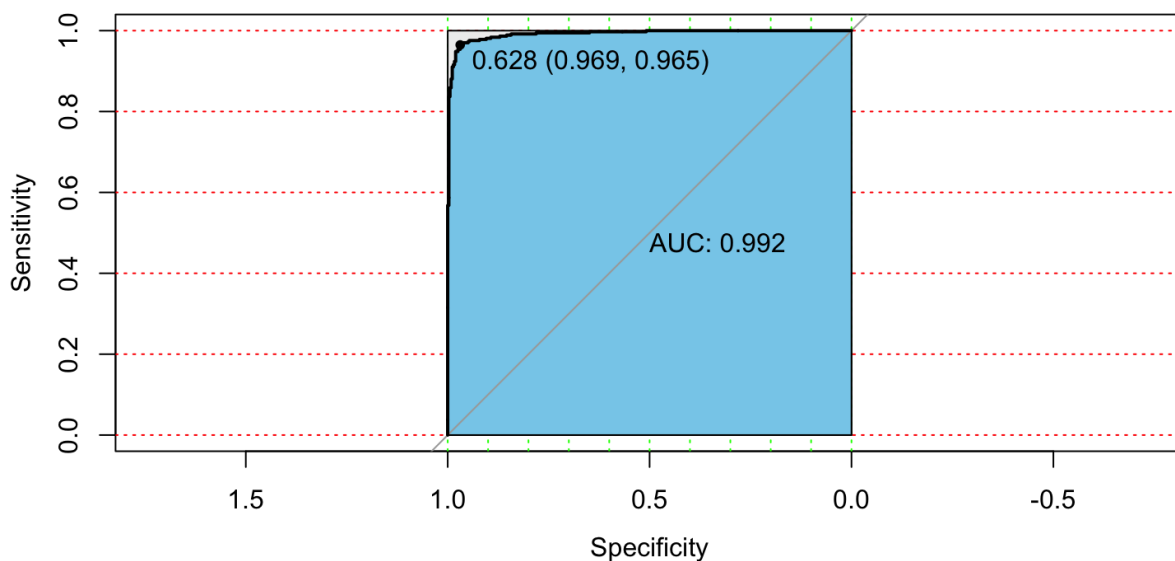

Figure 5: ROC Curve of the reduced-model, with an accuracy of 99.2%

We then want to use Receiver Operating Characteristic (ROC) Curve to see the accuracy of the model agian by using package (Robin et al. 2011). Note that the area under the curve, represented by the gray square, have a sum of 1. The blue area stands for the accuracy that our predicted voting preference matches the real response. In the curve, the accuracy is measured to be 72% (Figure 5) (Narkhede 2019).

In conclusion, according to the model, the team must play smartly and utilize the resources as efficiently as possible to destroy structures and pay extra attention on the first Baron to win a game. When it comes to make decisions on resource exchange with the enemy team, taking or defending structures should be in a top priority.

Discussion

The logit model considered certain variables in a normal ranked game and demonstrates a rank of significance of relevant variables. As shown in aforementioned discussions, the essence of the game is to destroy structures as the occupation of first inhibitor and tower could be seen as a remarkable sign of winning the game. However, it is not fair to ignore the importance of the team fight, most structure destruction could be done only after winning a team fight (Maymin 2020). Furthermore, the resources coming from the structure are limited, as towers do not revive once being destroyed.

The total gold and killings, as is shown in the analysis, is highly related to the final outcome of a game. The two variables is in fact self-related as killing itself means more gold, and team with more gold is more likely to win a team fight or perform solo-kill which leads to the potential increase of killing number (Cavadenti and Kaytoue. 2016). Besides, for the team winning a team-fight, the gold increase is usually far more than the gold earned from killing, but always associated with incoming gold from destroying structures, killing monsters and more farming time. In the study, to avoid multi-collinearity, the total gold variable is removed since the model aims to focus on the specific attribution that could be actively chosen by players rather than a general trend. However, gold could not be fully taken over by killings as the reasons explained before. For certain champions, such as Twisted Fate, their gold is naturally higher than other champions with other conditions keep the same as its part of their abilities (Riot Games 2020a).

The elite jungle monsters, including dragons, Barons and Rift Heralds, are also marked as important competitive resources as they provide extremely helpful buffs that are essential for winning the game. Such significance is also reflected in our model. Recalling from Table 3, occupying the first Baron is a significant attribution for winning the game, only after destroying the first Inhibitor. That indirectly emphasized the importance of structure destroying in this game, as Baron buff essentially increase the probability of destroying towers by empower minions rather than empower champions directly. In other words, killing a Baron and have the buff has nothing to do with winning a team-fight, but increase the probability of taking towers down avoid involving into a fighting (due to the fire range increment of the minions). In the earlier version of the game, when killing Baron simply provide a team with significant amount of gold and buffs increasing attack damage and health regen, team without Baron buffs always took strategies by clearing the minions and avoided fighting until the end of the buffs. As a result, when one team was in a great lead, taking Baron buff would not help them end the game quickly. That concern led to the reform of Baron buff, which was designed to empower the minions and thus make it hard to clear the lane. Therefore, when a game proceeds to be after 20 minutes, to keep the wards in the Baron region is a significant task for each of the ten players, especially for support player (who is in general responsible for putting wards). Take the Season 8 World Championship as an example, a number of teams surpassed successfully by stealing the Baron due to the lack of wards of the other team in Baron area (Novak 2020). Also, Baron area is one of the riskiest area that a 5v5 team fight will happen, which is always the most significant team fight throughout the game which we sometimes called it "winning hand" (Cavadenti and Kaytoue. 2016). Here we leave a motivation for further analysis on the value of Baron buff in future study.

When it comes to dragons, which is also included in Table 3 as a significant attribution winning the game, we could see that the model marks the value of killing the first dragon only a bit more than a kill. Unlike Baron buff which is temporal but powerful, dragon buff is powerful only if a team could keep killing following dragons and obtain the cumulative permanent buff. Therefore, it is not comprehensive to focus only on the first dragon buff, as killing the first dragon does not necessarily contributes to the occupation of following dragons. As is reflected in a number of professional matches, for teams with a comparatively less powerful champions in early game, they usually give up the first dragon or taking other resources for exchange. For following dragons, however, it is less possible for them to give up (Novak 2020). Moreover, as the types of dragons in a game is random, and certain champions might prefer certain types of dragons which might lead to the high rate of taking the first dragon. In comparison, Rift Herald does not play significant role in the model for predicting the final outcome. Rift Herald is used for a one-time huge damage to a tower, and thus has a high correlation with the rate of taking first tower (0.46) as shown in Figure 4. However, since first tower is not included in the significant list (will be discussed later), the attribution of first Rift Herald is thus not remarkable. Furthermore, according to Novak, during the professional competitions, Rift Herald is usually the second choice of resource exchange for teams who lost the first dragon. In other words, teams occupying the first Rift Herald usually lost the first dragon. Among the 4822 observations (after data cleaning), only approximately 27% of the games have a team with both the first Rift Herald and the first Dragon.

The most remarkable signal for winning a game, as shown in the model, is taking the first inhibitor. Taking the first inhibitor means the big pressure coming from the superior minions, which makes it hard for the enemy team to clear the lane. Moreover, spending too much time on clearing the lane will lead to lack of attention on other important factors, such as warding the Baron, especially when the lost inhibitor is on the bottom lane (farthest from the Baron area). Though the variable itself is biased as taking the first inhibitor is equivalent to a safe lead in a game, it does reflect a basic concept of winning this game, which is to destroy structures, as the spawning of superior minions must be handled or otherwise they will destroy towers naturally. In 83.4% of the sample used in this study, team taking the first inhibitor won the game. However, such rate decreases to 73.7% when it comes to the first tower.

Small World vs Large World (McElreath 2020)

For the small world of our self-contained model, the accuracy score of our forecasting model is more than 96%, which is high enough to proof the fitness of the model to the small world. From the data, we also found that inhibitor and Baron have obvious pattern of effect on final outcome of the game. Therefore, for our logit model's small world, it is better to use reduced model to generate the results as the interpretation of coefficient is more reasonable.

For the large world of broader context, there are factors that have not been considered and imagined in the small world. For example, the small world only focuses on fitting the model based on the sampled data, however, the situation of the games that are not covered in the small world while exist in the large world, has never been imagined. Also, in the large world with more realistic context, the effect of other demographic factors such as different player skills and different champion selections are not in the small world's consideration, as well. Overall, in a broad-context large world, it is not as fitted as it was in the small world. And the issues noticeable here are just the things that we could improve in the future.

Weaknesses and next steps

Despite the model performs well on predicting the results of the game, limitations exist in this study as always.

The model does not consider the players' skill, as the variable is hard to quantify. Different players master different champions and the one they play might not always be the one they are good at. Various reasons could cause the situation, such as the champion is banned or the player want to practice other champions. Even all players are assumed to play champions they master, skill difference still exists even in the same tier level. The skill difference might lead to the hit rate of attacks, farming efficiency (last hit the minion to earn gold) and decision making.

Moreover, the model fails to include the number of minions killed by a team, which is believed as the most important source of gold earning in a game(Maymin 2020). However, as the missing attribution is highly related to the total gold earned by a team, the lack of such information could somewhat be compensated. Despite attempt to avoid much multi-collinearity by removing correlated variables, the issue still exists as it is hard to select independent variables in a game. For example, the first inhibitor and first tower variables are unavoidably correlated. Certain problems should be handled by representing variables in a more reasonable way, such as using the total tower destroyed instead of the first tower to decrease the effect of Rift Herald.

Further, the data limitation is obvious, as is discussed in the data session. The data is from the Korean server and thus the result is hard to be generalize to all players as the playing style in different. According to the statistics from World Championship, teams from China region loves team fight whereas teams from Korea focus on lane manipulation and destroying towers (Maymin 2020). Also, the sample size is not big enough to eliminate the negative effects caused by possible noises. After processing the data, only 4822 observations left for analysis which is divided to 5 tiers. Since we perform the model validation and divide 15% of the data for testing, only around 4000 observations is used for building the model.

What's more, the champion selection is not considered while doing the analysis, which cannot be ignored when analyzing the game outcome. There are more than 150 champions that could be selected in a game, and due to the different abilities each champion uniquely has, different strategies could be used for winning a game. For example, ADC players (Attack Damage Carry) will lead the late game whereas assassin champions tend to be powerful in the early game. Since the model tends to focus on the resources from early game, such as first blood and first tower, it inevitably favors the teams which are more potentially lead the earlier game. Besides, there are "combos" for certain champions, which would increase the possibility of winning. For example, if one team selects Yasuo, with or without teammates having airborne ability will significantly affect the winning probability, as the ultimate ability of Yasuo requires the enemy to be airborne (Riot Games 2020b).

Finally, the data processing method has room for improvement. In this study, as the raw data does not have missing value, we only filtered out games ended before 15 minutes to remove outliers caused by disconnected players. However, certain techniques could be used to handle those cases as we do not have enough data.

Next Steps

• Collect sampled data with closer date for the future analysis: Since the update of the game is frequently, and strategies also changes along with the version. Getting a match data closer to today will make the model and results more reflective.

• Larger sample size: With only 4000 observations for model training and around 800 observations for accuracy testing, the high accuracy of the model only has theoretical stringency. For further analysis, more samples could be selected and more testing cases should be generalized. One may consider including more records from different servers and even from the professional matches to enlarge the sample size. With a larger sample size, the data for all factors, will be more adequate to find out more accurate results.

• Include more predictors in the model. As discussed above, many factors could contribute to the final outcome of a game. Also I am interested in adding more unstable variables such as hitting rate and players' skills and frequently played champions to make the model more complex but could capture more extreme situations.

• Try different kinds of statistics model and make comparison. We did not perform such comparison since the model is good enough for making prediction indicated by its high accuracy. However, it is always better for exploring more possibilities. Moreover, it is also interesting to explore the effect of certain attribution in depth. Instead of analyzing the general model, we could possibly focus on the effect of certain attribution such as Barons and Dragons.

References

Cavadenti, V. Codocedo, O., and M. Kaytoue. 2016. "What Did I Do Wrong in My Moba Game? Mining Patterns Discriminating Deviant Behaviours." *Data Science and Advanced Analytics (DSAA), 2016 IEEE International Conference on. IEEE* 662 (71).

Maymin, Philip Z. 2020. "Smart Kills and Worthless Deaths: ESports Analytics for League of Legends." *Journal of Quantitative Analysis in Sports* 12 (2): 809–17. https://doi.org/https://doi.org/10.1515/jqas-2019-0096 (https://doi.org/https://doi.org/10.1515/jqas-2019-0096%20).

McElreath, Richard. 2020. "Small Worlds and Large Worlds." In *Statistical Rethinking a Bayesian Course with Examples in R and Stan*. CRC Press, Taylor & Francis Group.

McFadden, D. L. 1974. "Conditional Logit Analysis of Qualitative Choice Behavior." In *In Frontiers in Econometrics*.

Narkhede, Sarang. 2019. "Understanding Auc - Roc Curve." *Medium*. Towards Data Science. https://towardsdatascience.com/understanding-auc-roc-curve-68b2303cc9c5 (https://towardsdatascience.com/understanding-auc-roc-curve-68b2303cc9c5).

Novak, Bennett, A. R. 2020. "Performance Analysis in Esports: Modelling Performance at the 2018 League of Legends World Championship." *International Journal of Sports Science & Coaching* 15 (3): 809–17.

R Core Team. 2020. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/ (https://www.R-project.org/).

Riot Games, Inc. 2020a. "The Card Master, Twistedd Fate." https://na.leagueoflegends.com/en-us/champions/twisted-fate/ (https://na.leagueoflegends.com/en-us/champions/twisted-fate/).

———. 2020b. "The Card Master, Twistedd Fate." https://na.leagueoflegends.com/en-us/champions/yasuo/ (https://na.leagueoflegends.com/en-us/champions/yasuo/).

———. 2020c. "Riot Api." https://developer.riotgames.com/ (https://developer.riotgames.com/).

Robin, Xavier, Natacha Turck, Alexandre Hainard, Natalia Tiberti, Frédérique Lisacek, Jean-Charles Sanchez, and Markus Müller. 2011. "PROC: An Open-Source Package for R and S+ to Analyze and Compare Roc Curves." *BMC Bioinformatics* 12: 77.

Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D'Agostino McGowan, Romain François, Garrett Grolemund, et al. 2019. "Welcome to the tidyverse." *Journal of Open Source Software* 4 (43): 1686. https://doi.org/10.21105/joss.01686 (https://doi.org/10.21105/joss.01686).

Xia, H. Wang, B., and R. Zhou. 2017. "What Contributes to Success in Moba Games? An Empirical Study of Defense of the Ancients 2?" *Games and Culture* 14 (5): 498–522.