IMGD 2905 Project 4: *League of Legends* Analytics

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Using the data from the Riot Games API and various Python scripts, 100 competitive *League of Legends* matches played by the summoner "Winter" are analyzed below in Sections 1 and 2. Section 3 analyzes data gathered from seven participants, including myself, of the "Puck Hunt" study, which tested how lag in games impacts the user via a simple challenge where players had to move a mouse to click on a random target (which sometimes moved) as fast as they could while being subjected to various levels of lag.

Section 1. Professional Summoner

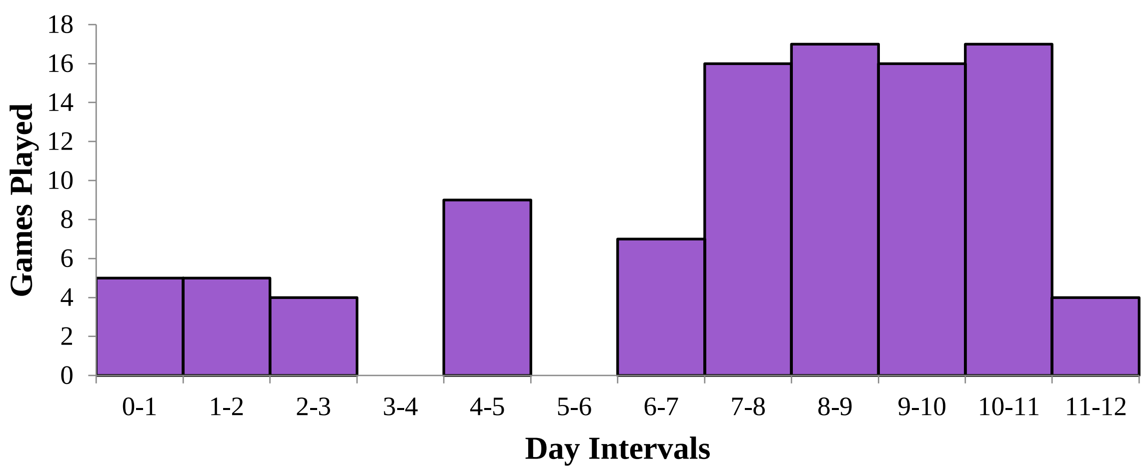

Figure 1 – Histogram of Number of Games Played per Day.

Figure 1 shows the distribution of the 100 games over the course of several days as a histogram. The bin sizes on the x-axis represent the number of days passed since the first game Winter played, while the number of games Winter played during each day interval are on the y-axis. For example, the 7-8 bin shows the number of games that Winter played after the 7th day mark but before the 8th day mark. None of the game start times fell exactly on a day mark. The number of games played per day is not consistent over the twelve-day period, with only 23 games played during the first six days compared to the 77 played in the latter six days. In fact, during days three and five, no games were played at all. The maximum number of games that Winter played on a single day is 17, on days eight and ten.

While the trends in this data could simply be the result of Winter's personal schedule at the time the games were played, in a larger context it may suggest something about a *League of Legends* player's state of flow. In general, game flow is used to describe how immersed a player may be in a game, though the quality of immersion can vary from game to game. To hypothetically extrapolate from the data in Figure 1, a *League of Legends* player may become mechanically immersed for a few days at a time (like during days seven to ten, for example) if they are winning a lot or are just starting to master a new champion. While the data presented in Figure 1 is not sufficient to make such an assumption, more analysis on the number of games that *League of Legends* players play over time could be used to test this hypothesis.

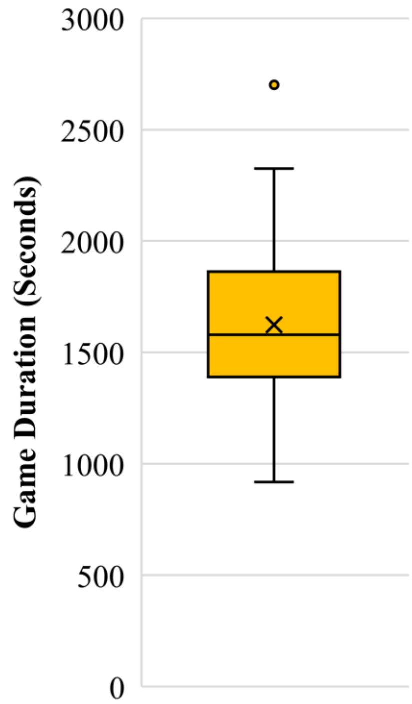

Figure 2 – Box-and-Whisker Chart of Game Durations.

Figure 2 shows the variation of game duration, in seconds, across the 100 games in the form of a box-and-whisker chart. The minimum and maximum durations are indicated by the lower and upper whisker ends, values of 919 and 2325 seconds, respectively. The first quartile, 1389.5 seconds, is at the lower end of the box while the third quartile, 1862 seconds, is the upper end of the box. The median of 1579.5 seconds is indicated by the line inside the box, and the mean of 1623.48 seconds is indicated by the "X." There is only one formal outlier, 2701 seconds, indicated by the circle marker above the box and whiskers.

Between the outlier and the fact that there is more spread between the median and 75th percentile than the median and the 25th percentile, it makes sense that the average game duration would be greater than the median game duration. This variation in game duration may be a good indication that different strategies are being employed from game to game (e.g. rushing the Nexus may result in a shorter game) and that no single approach is dominant.

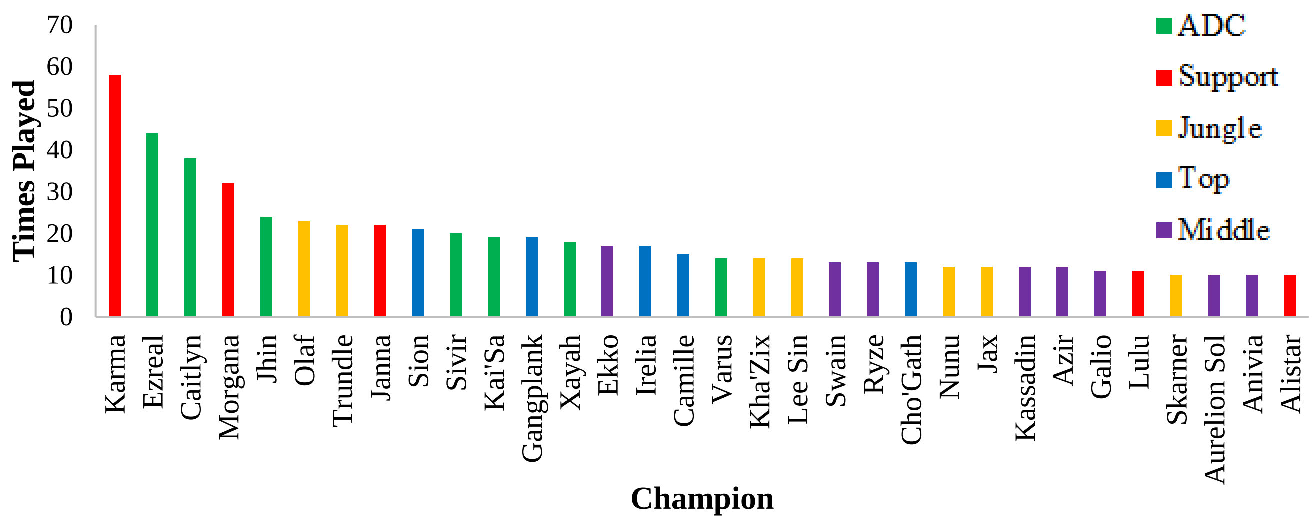

Figure 3 – Bar Chart of Champions Played.

Figure 3 shows the breakdown of all champions played more than ten times by any summoner across the 100 games. Each champion is listed on the x-axis in order of most to least played, while the y-axis shows the number of times a given champion was played. Additionally, each champion is colored by the role that they are most often played as (according to *Champion.gg*): green for ADC, red for Support, yellow for Jungle, blue for Top, and purple for Middle. Of the 32 champions that appeared more than ten times, Karma was played the most, appearing 58 times.

Regarding the roles played, ADC and Support champions appear to be the most popular, with the top five champions falling into either of those two categories. However, the distribution of roles is pretty consistent, with five Support, seven ADC, seven Jungle, five Top, and eight Middle champions being represented.

Section 2. Gold

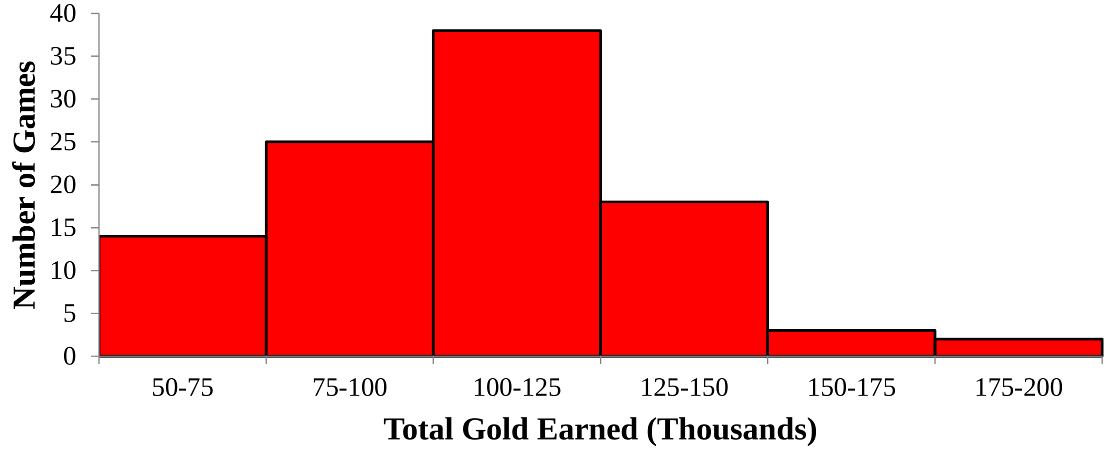

Figure 4 – Histogram of Total Gold Earned per Game.

Figure 4 shows a histogram with the frequencies of total gold earned (in thousands) in a single game by all players. The x-axis represents how much gold was earned in bin sizes of 25,000 gold, starting at 50,000 since there were no games where less than 50,000 gold was earned. The y-axis represents the number of games where that amount of gold was earned. For example, there are 25 games in the 75-100 bin, so for a quarter of all the games analyzed, the total amount of gold earned by all ten summoners in a given match was between 75,000 and 100,000.

The most common range was 100,000 to 125,000 gold, with 38 games falling into that bin. There were only 5 games total where more than 150,000 gold was earned, and no game ever broke the 200,000-gold threshold.

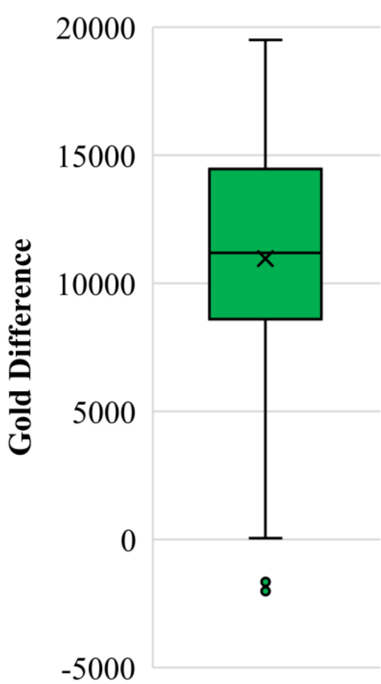

Figure 5 – Box-and-Whisker Chart of Gold Difference.

Figure 5 shows the variation of the difference of gold earned by the winning team and the gold earned by the losing team for each of the 100 games, calculated by subtracting the losing team's earnings from the winning team's earnings. On average, the winning team earned about 11,000 more gold, and the mean and median are almost equal at 10,951 and 11,184 gold respectively. The greatest difference between gold earnings was 19,498, while the smallest was 46. However, there were two cases where the losing team actually ended up earning more than the winning team, indicated by the two outliers at -1664 and -2029. The first and third quartiles are at 8,589.25 and 14,456 gold respectively.

While winning a *League of Legends* match usually means that you will have earned more gold than your losing counterparts, the amount can certainly vary depending on how each player performed and what strategies were taken. For example, a player who is consistently getting the last hit on an enemy champion kill is probably going to earn more than their teammate who is just farming minions the entire game.

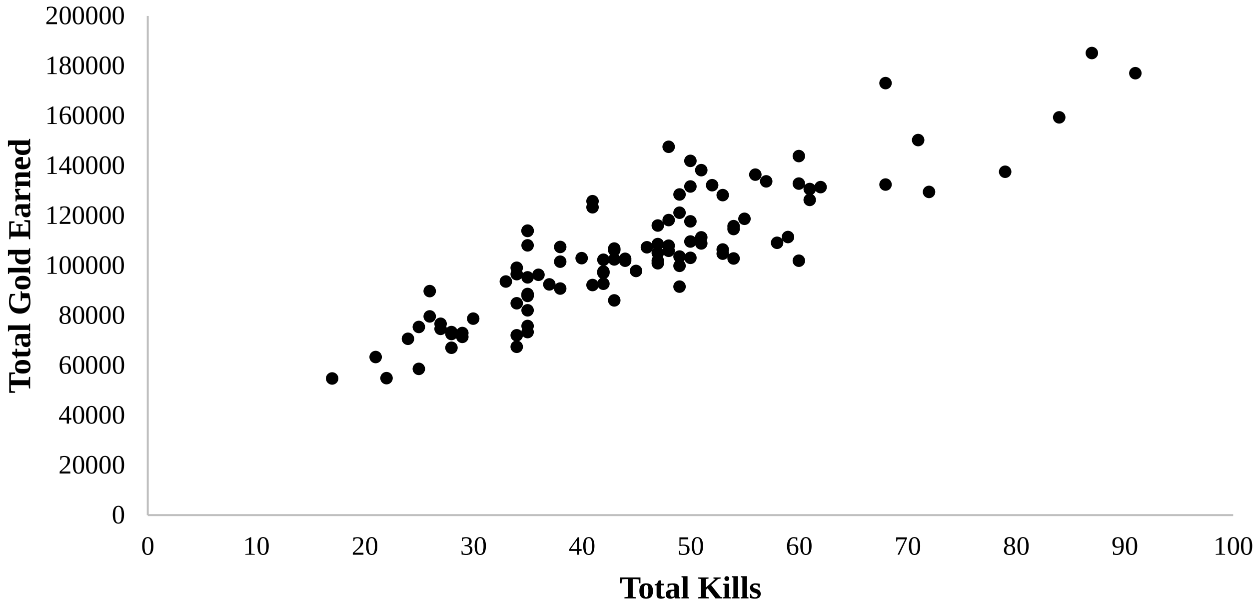

Figure 6 – Scatter Plot of Total Gold Earned vs. Total Kills.

Figure 6 shows a scatter plot the total gold earned by all summoners in a game compared to the total number of kills during that game (for both teams). Each point represents one game, with its x-coordinate representing total kills and its y-coordinate representing the total gold earned. There is a direct positive correlation, and generally more gold is being earned the more kills there are.

While this may suggest that champion kills are an efficient way to earn gold, there are likely some underlying factors that could be affecting the data. Games with more kills probably have a longer duration, giving players more time to obtain gold from other sources as well. A more in-depth analysis might compare gold earned to total kills only for games that are of the same duration to better see if champion kills are the most effective way to earn gold.

Section 3. Puck Hunt

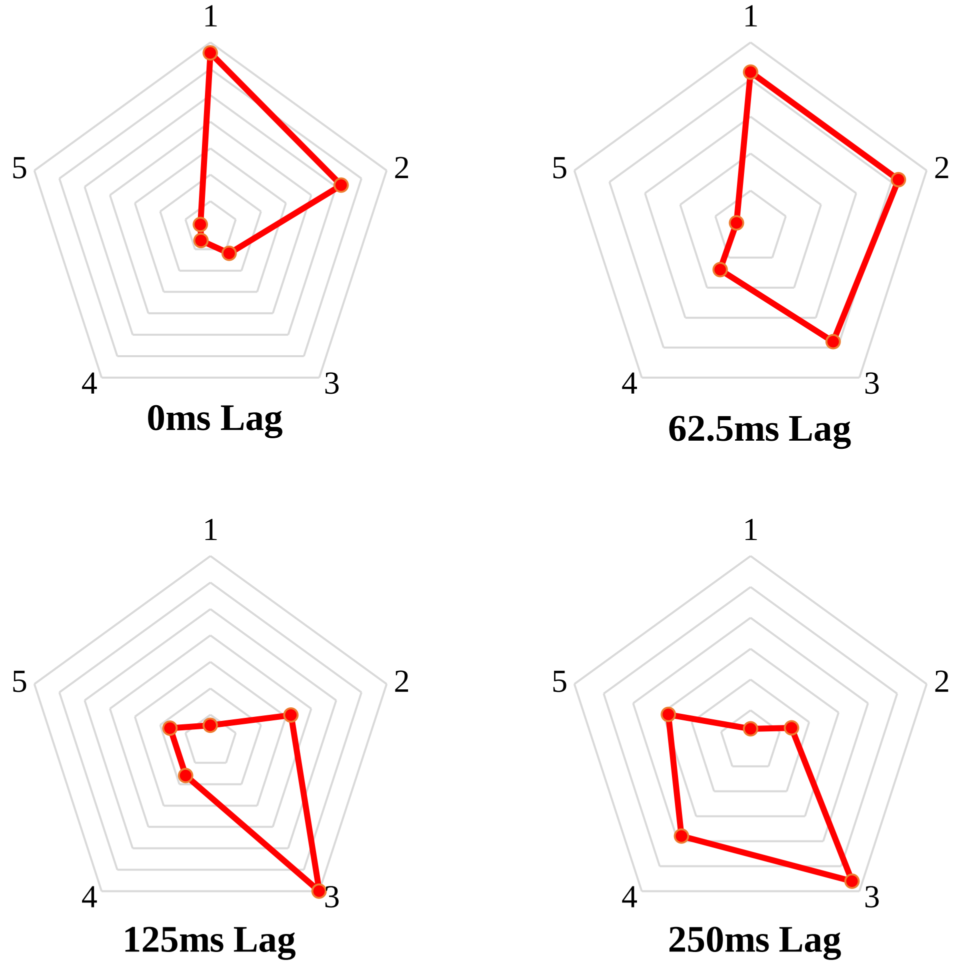

Figure 7 – Radar Charts of Lag Ratings.

Figure 7 shows four radar charts depicting the breakdown of lag ratings on a scale of one to five (i.e. "How much lag did you experience?"), represented on the vertices of each radar chart, that users gave to Puck Hunt rounds with each of the four possible lag times: 0, 62.5, 125, or 250 milliseconds. The data set used had data on seven Puck Hunt testers, each of whom rated ten rounds at each level of lag (forty rated rounds total), so each individual radar chart depicts the distribution of seventy ratings. Fittingly, 5 was the least common rating for both 0ms and 62.5ms of lag, with only two people reporting a 5 for those levels. For 125ms and 250ms of lag, 1 was the least common answer, with only three and two people respectively reporting a 1 for those levels.

As one would expect, the rating levels tend to increase as the lag time does. For 0ms of lag, ratings of 1 and 2 were by far the most common. With 62.5ms of lag, the number of 1s, 2s, and 3s was just about equal. Ratings of 3 dominated the 125ms lag level, with exactly half of the seventy ratings being a 3. While 3s were still the most common at 250ms, 4s and 5s followed closely behind as one would imagine for the highest level of lag (which was also double the previous level) in the study.

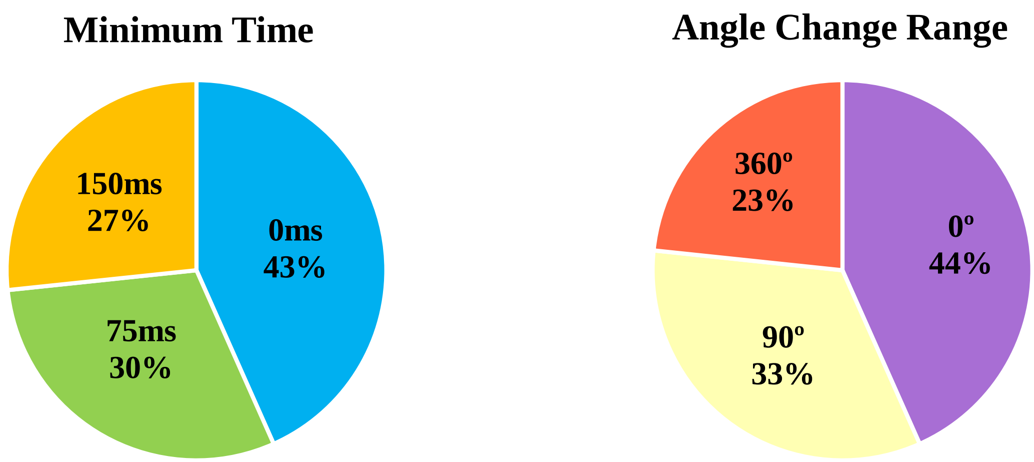

Figure 8 – Pie Charts of Minimum Time and Angle Change Range for Select Rounds.

Figure 8 depicts two pie charts detailing the minimum time between target movements (in milliseconds) and the range that the target's angle could change (in degrees) for all "Puck Hunt" rounds with a lag time of less than 250ms that received either a 4 or 5 rating from the user, in order to see if the users' ratings may have been influenced by the target's movement patterns.

For the minimum time pie chart on the right, the three possible values for minimum movement time of the target were 0ms, 75ms, and 150ms. Ideally the first level, 0ms, would make the target the most difficult to accurately click on given that the target is moving faster at that level. To support this, 43% of all the rounds that fit the aforementioned criteria had a target with the 0ms minimum movement speed, 30% at 75ms, and 27% at 150ms. Since 0ms is supposedly the hardest, and 75ms would likely still be more difficult than 150ms, it is very possible that some users gave the analyzed rounds higher ratings because of the minimum movement time of the target rather than the lag.

On the left is the pie chart for the possible ranges that the target's angle could have changed by while moving. The three possible values for that were 0º (i.e. the angle would not change at all), 90º, and 360º (i.e. the angle could change by any possible value). A target whose angle did not change during its movement would likely be easier to predict and therefore accurately click on, whereas an unpredictable target with an angle change range of 360º would be more difficult to click. However, the angle change range chart in Figure 8 does not necessarily support this hypothesis. Of the rounds analyzed, 44% of the targets had a range of 0º, 33% had 90º, and only 23% had 360º. While this is not to say that the 360º rounds were not more challenging, how the user rated the lag experience was probably not influenced by the target's angle change range.