Title
The Measurement and Evaluation of Professional League of Legends Teams for Optimal Strategy

Author
Wong, Victor

Publication Date
2019

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA

Los Angeles

The Measurement and Evaluation of Professional League of Legends Teams for Optimal Strategy

A thesis submitted in partial satisfaction

of the requirements for the degree

Masters of Applied Statistics

by

Victor Richard Wong

2019

2019

ABSTRACT OF THE THESIS

The Measurement and Evaluation
of Professional League of Legends Teams
for Optimal Strategy

by

Victor Richard Wong
Masters of Applied Statistics
University of California, Los Angeles, 2019
Professor Frederic R Paik Shoenburg, Co-chair
Professor Robert L. Gould, Co-chair

With ever improving streaming technologies and accessibility to video games, it comes as no surprise that competitive gaming or eSports have blown up in recent time. League of Legends, former gaming startup Riot Games' sole intellectual property, has the title most popular eSport in the world with a thriving competitive scene and international competition that rivals traditional sports leagues such as the MLB, the NBA and the NFL [Staff, 2013]. With the high stakes involved in the burgeoning eSports industry, it is imperative that these organizations develop methods that can differentiate players based on their skill through their in-game performance metrics and determine potential acquisitions. Additionally, we want to leverage the data within Riot Games' databases on how the general playerbase approaches the game to determine what how in game performance metrics change as player skill increases. The end goal of this analysis is to create a method to gauge team performance and assess weak links in strategy.

The thesis of Victor Richard Wong is approved.

Guido Fra Montufar Curatas

Robert L. Gould, Committee Co-chair

Frederic R Paik Shoenburg, Committee Co-chair

University of California, Los Angeles

2019

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

Introduction

Within ten years, League of Legends has developed a rich competitive infrastructure that spans across China, North America, Western Europe, Korea and many other regions. Each region has its own franchised league that broadcasts professional matches on a weekly basis similar to how the NFL runs weekly Football games in North America. Each league consists of 10 teams, each owned by a gaming organization with lucrative sponsors such as Geico, State Farm, Logitech, and many others. Each professional match brings hundreds of thousands of viewers. In addition to these weekly games each season, these leagues end their respective competitive splits by sending their best teams to a world championship to crown the best region and team in the world. The final match of the world championship draws around 100 million viewers online and has filled venues such as the Staple Center [Tassi, 2013]. As eSports organizations move to acquire and trade players for millions of dollars, there arises a need within the industry to utilize a data driven approach to evaluate the performance of these teams to drive improvement, and stay on top of emerging strategies within the game.

CHAPTER 2

Background

2.1 The Game

League of Legends is a competitive, team-based strategy game team akin to games such as chess and basketball that pits two teams of 5 players against each other. The goal of the game is for one team to destroy the other team's base. To accomplish the destruction of the base, each team has to overcome a series of turrets that defend the pathway into the base and combat players on the opposing team. Additionally, each team contests each other for resources found in the arena.

Figure 2.1: The Arena known canonically as 'Summoner's Rift'

The two resources players are contesting are gold and experience. Players are granted both resources by destroying creatures in the nearby jungles and taking down enemy players. In addition to these smaller creatures, the jungle also contains Dragons, large neutral creatures that require teamwork in order to capture. Upon capture, a team-wide statistical bonus is awarded to the capturing team.

Gold and experience are then converted into statistical augmentations for each players' avatar, meaning player avatars with more gold and experience will be inherently stronger than a player avatar with less gold and experience. This advantage is akin to a basketball player becoming taller and faster upon scoring a basket.

Figure 2.2: The Dragon, a neutral objective that is hotly contested by both teams

Figure 2.3: Side by side image of an area covered by Fog of War, and revealed by a ward

Another important feature of League of Legends that differentiates it from other traditional sports and games is the prescence of a 'Fog of War,' a virtual fog that covers a majority of the map that can only be uncovered by a player being in the area, or through the use of a temporary object called a ward that can reveal an area in the fog of war for a set amount of time. Each player is only allowed to have at most 3 active wards at a time, and the ability to clear wards is limited as players need to give up their ability to place wards in order to clear them. Maintaining vision through the Fog of War is an important skill that is highly valued at the highest level of play, as the Fog of War can be used to mask the movements of either team. The advantages accrued by teams in game have been used in statistical models to predict the outcome of matches.

2.2 Logistic Win Predictor

The effects of gold and dragons have very clear impacts felt by players at all levels. So much so that it can be seen with a quick glimpse into the results of competitive matches. Below we see the histograms of gold held by players at various game states, where result = 0 denotes a loss and result = 1 denotes a win; a player will have around 12,000 gold on average. We see in Figure 2.4 that games resulting in wins multiple dragons are slain, and the distribution of gold starts to skew leftwards as players acquire more gold. In the case where no dragons are slain in lost matches, the distribution of player gold amounts is centered around 10,000 gold.

In both won and lost matches where where teams have secured 2 to 4 dragons, we see the distribution shift its center around 15,000 gold. Additionally, there are very few instances of teams losing with 3 dragons and above. Another caveat to note is that dragons become available for capture at 5 minutes into the game and spawn every 6 minutes after capture. With each game averaging around 30 to 40 minutes in length, the number of total dragons captured in a game seldom reaches 6.

With the very clear impact of acquiring dragons and gold in mind, there have been models developed by the community to gauge their impact. Below we have a logistic regression model for Y, the outcome of a match, based on a specific game state at 15 minutes into a game[Sevenhuysen, 2015].

$$P(Y=1) = \frac{1}{1+e^{-(\beta_0+\beta_g x_g+\beta_c x_c+\beta_i x_i+\beta_m x_m \beta_o x_o+\beta_{ms}+x_{ms})}}$$

Where...

$$Y = \{0,1\} \text{ ; (0 = Loss, 1 = Win)}$$

$$\beta_0 = 0.2890224 \text{ ; Constant}$$

$$\beta_g = 0.0006172 \text{ ; } x_g = \text{Gold Difference Between Teams}$$

$$\beta_c = 0.3793107 \text{ ; } x_c = \text{Cloud Dragon Difference}$$

$$\beta_i = 0.4428261 \text{ ; } x_i = \text{Infernal Dragon Difference}$$

$$\beta_o = 0.1553903 \text{ ; } x_o = \text{Ocean Dragon Difference}$$

$$\beta_m = 0.2281888 \text{ ; } x_m = \text{Mountain Dragon Difference}$$

$$\beta_{ms} = \text{-}0.5611279 \text{ ; } x_{ms} = \{0,1\} \text{ ; Map Side (0 = Blue Team, 1 = Red Team)}$$

Utilizing this model , we can derive a rating called Early Game Rating (EGR) which describes a team's ability to manipulate a game state into a positive scenario at the 15 minute mark; EGR is the average projected win rate at 15 minutes, expressed as a number (ie projected win rate at 15 minutes of 65% is expressed as an EGR of 65) [Sevenhuysen, 2015].

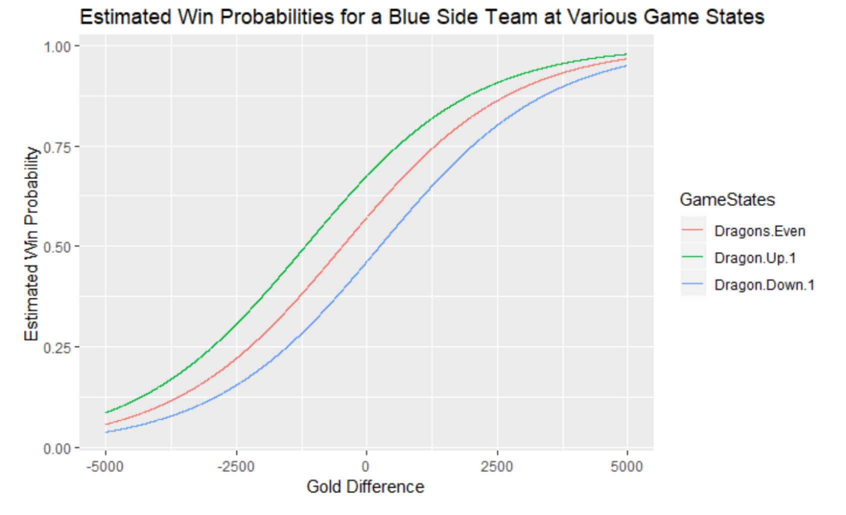


Figure 2.4: At a 1 dragon deficit and even gold, a team has a projected 46% chance to win the match; whereas a team with a 1 dragon lead and even gold has a 67% chance to win the match

When we delve into the results of the most recent World Championship, it becomes clear that the best teams in the world tend to have a high EGR, which is indicative of their ability to create a positive game state. In the next section, we will be looking into the general population versus the professional level of League of Legends to trace how player statistics change as they get to higher ranks. With this in mind, it is also important to look into how players of various skill brackets are performing, and gain insight on how they can impact the game state.

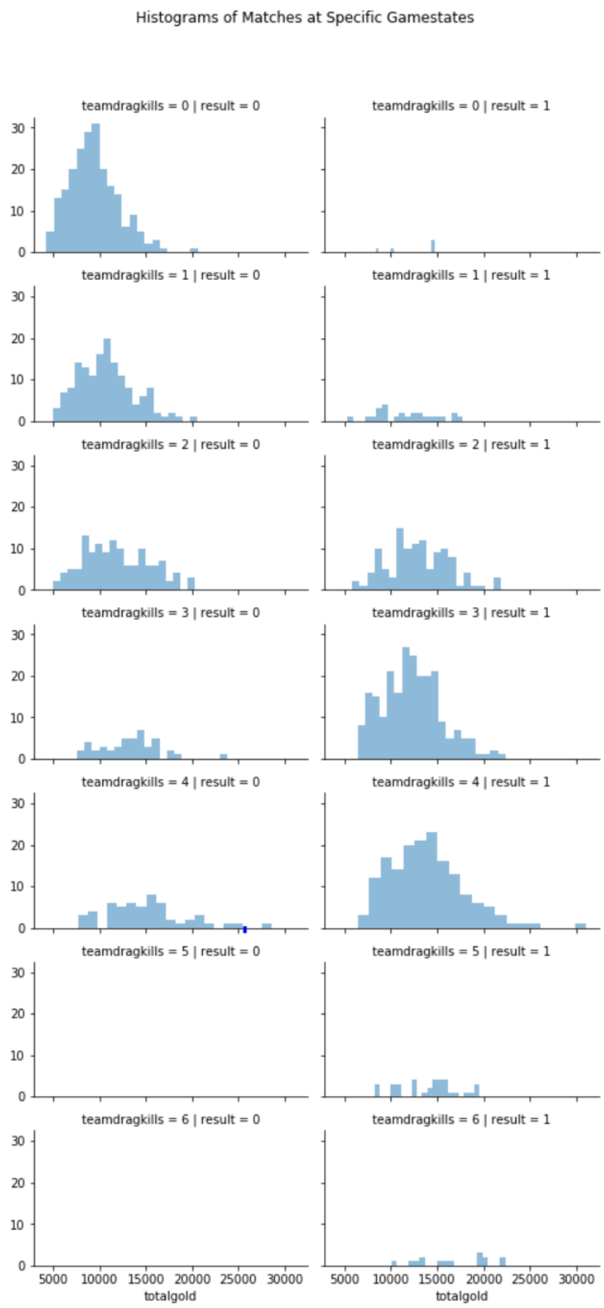


Figure 2.5: Between 2 and 4 Dragon captures wins become very likely so long as teams can generate sufficient gold. Past 4 dragons, victory is almost guaranteed.

CHAPTER 3

The Data: Differences Between the General Population and Professional Level

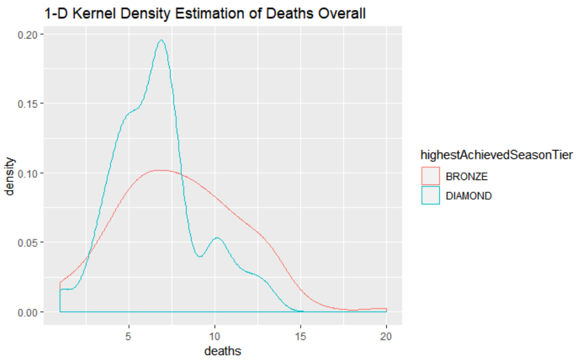
With the wide accessibility of League of Legends, a large amount of match data is available to examine. Unfortunately, the statistics on Dragon and Turret Captures are unavailable in the general population data, but there are statistics to look at when it comes to their combat statistics, map control and resource consumption. For the general population we will be comparing Bronze (50th Percentile w.r.t. skill) level players versus Diamond (98th Percentile w.r.t. skill) level players.

For the professional teams, we will be examining data from the results of professional matches from the Summer Seasons and World Championships of 2018 and 2019. In both years we can explore how each team approaches the game, and attempt to trace how China was able of winning two consecutive World Championship titles.

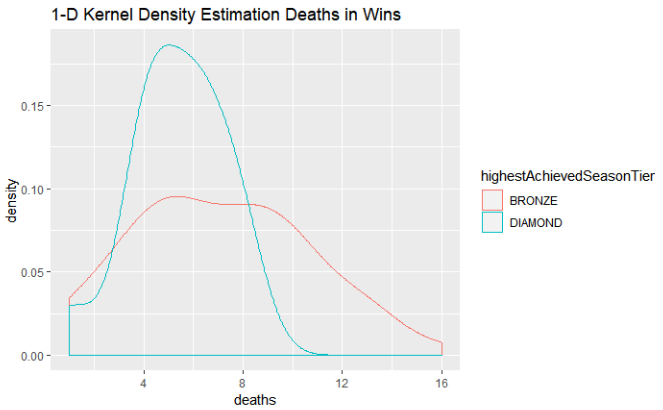
3.1 General Population

It doesn't come as a surprised that Diamond level players have a tendency to die much less on average when compared to their Bronze counterparts, as shown in Figures 3.1a, 3.1b, and 3.1c. Conversely, Diamond level games tend to have much lower kill counts as well, implying much lower risk play patterns. Even in losing matches, Diamond players are dying much less on average than their Bronze counterparts, and aren't dying that much more when compared to won matches. Figures 3.1d, 3.1e, and 3.1f, showcase the converse of the death numbers; Bronze level matches tend to have higher kill counts, and Diamond level matches tend to have much lower kill counts. Figure 3.1e shows that Bronze players have similar kill numbers to Diamond players in won matches, but figure 3.1f shows that Diamond players aren't securing as many kills as Bronze players in losing matches. Figure 3.1f also indicates that Bronze players tend to have a higher variance in their kill numbers in losing matches than Diamond players. The differences in the distribution of kills in deaths indicates a couple fundamental differences in the way Bronze level players and Diamond level players approach the game; Diamond level players will prioritize safety over eliminating their opponents, whereas Bronze players tend to go for kills without minimizing their risk of dying. Additionally, the low number of kills on average in lost games for Diamond players indicates that Diamond-level players have a tendency to protect their leads when winning, and don't open opportunities to their losing opponents to come back into the game by allowing the losing team to score kills. As players increase in skill, the number of total deaths and kills tends to decrease as better players won't open themselves to being killed as easily. Additionally, when looking at warding statistics, Diamond players take a much more active role in using the wards to control the map and denying vision in the Fog of War from their opponents.

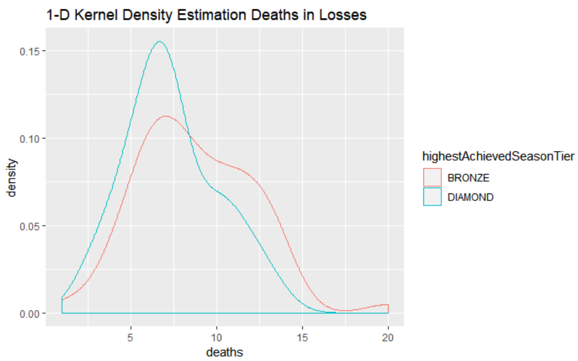
Figures 3.2a, 3.2c and 3.2e showcase wider variance in warding patterns in Diamond players and lower variance in warding patterns for Bronze players. We see that Bronze players on average are placing roughly the same amount of wards as Diamond players, but the Diamond players tend to have a wider range in the number of wards they are putting onto the map. Additionally, the density curves for the Diamond players show a second peak to the right, which reflects the efforts of the players in the support role in placing wards on the map, and the area under the curve for indicates that more players are making efforts to establish vision control in both winning and losing matches. The second peak in figure 3.2e might also be explained by the losing team attempting to regain vision control as their territory and vision is annexed by the winning team. Figures 3.2b, 3.2d, and 3.2f show the density of the number of wards cleared by each player, and the shapes of the density curves in these figures indicate a sharp difference in how Bronze and Diamond approach vision as Diamond players are clearly more proactive in clearing wards as Bronze players average around 1 ward cleared in a game, while Diamond players clear 5 or more on average. As a converse to figure 3.2c, figure 3.2d shows that in winning matches, Diamond players are clearing out a lot of



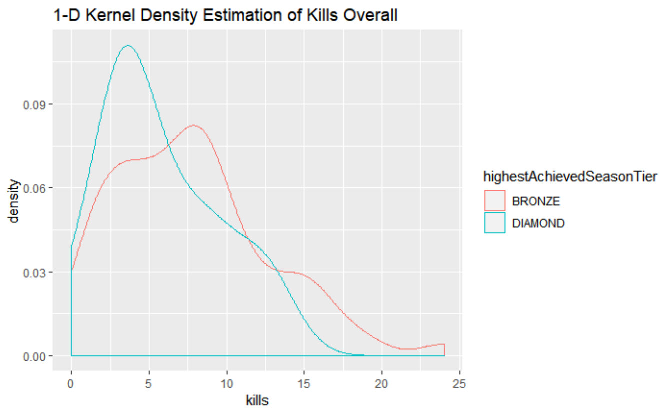
(a) 3.1a



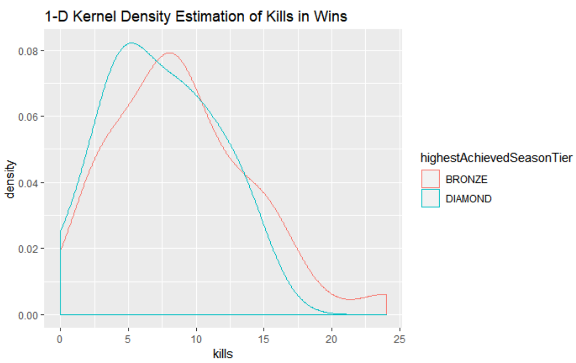
(b) 3.1b



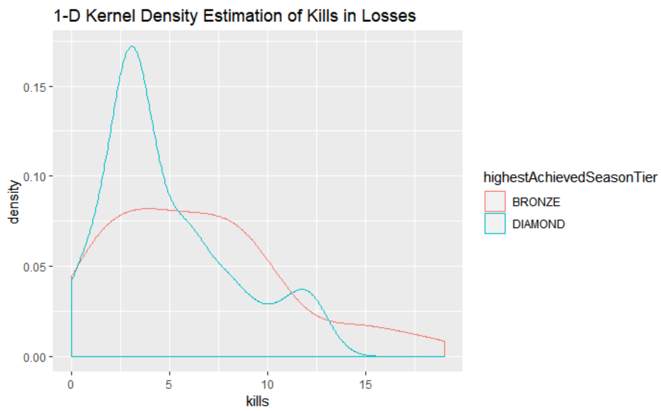
(c) 3.1c



(d) 3.1d



(e) 3.1e

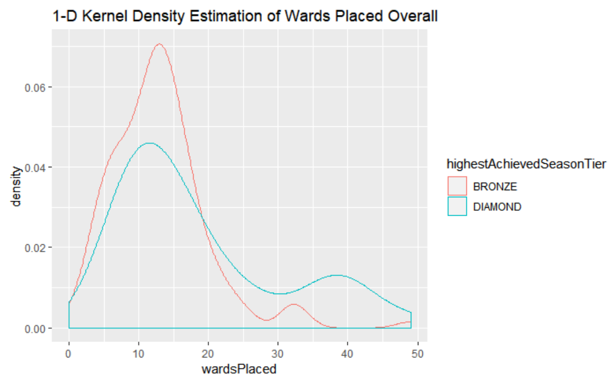


(f) 3.1f

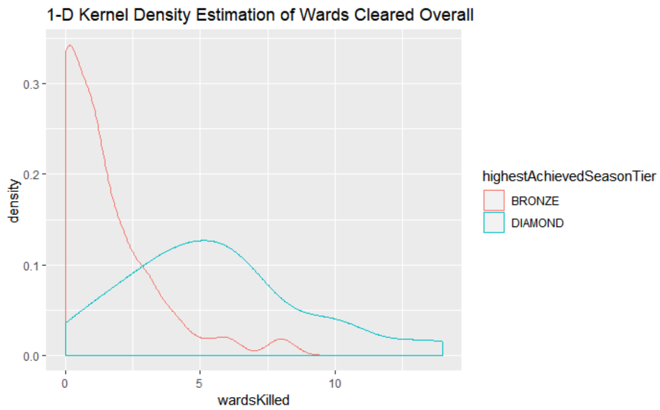
Figure 3.1: 1 Dimensional Kernel Density Estimation of Deaths and Kills

the ward placed by the losing team, which restricts the information given to the losing team, which consequently reduces the number of safe moves the losing team can make.

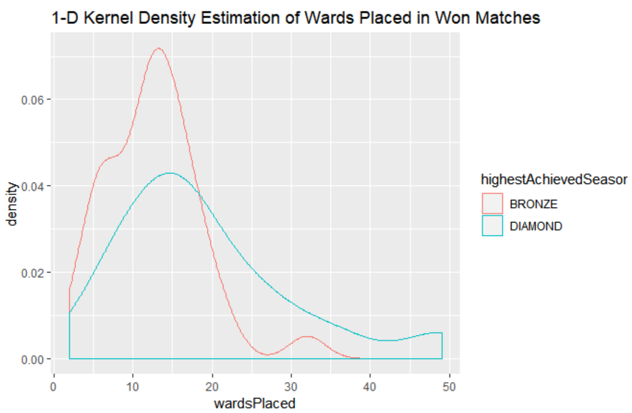
Figure 3.3 showcases a 2 dimensional kernel density estimation of total deaths and wards placed by each player in Diamond and Bronze level games. The densities indicate that Bronze level players have a tendency to die a lot with very few wards placed, whereas Diamond level players have a low variance in the times they die, and have much more wards placed on the map. Fundamentally, this lines up with a lot of common intuition that is used when assessing the skill level of players, as the higher levels of play tend to focus more on controlling territory as opposed to scoring kills on other players. This territory-focused game play is reflected in the highest levels of play as the neutral objectives and vision is utilized in order to make moves on the map. As Bronze players tend to lack awareness of the map state and prioritize scoring kills and skirmishing rather than securing territory; while the Diamond players are constantly factoring vision into their decision making and actively attempting to acquire it. In conclusion, the main difference that can be discerned between Diamond and Bronze is the Diamond player's concern with the game from a macro perspective, that emphasizes controlling territory and information through the placing and clearing of wards as well as the low number of kills and deaths they accrue. This conclusion confirms the conventional intuition regarding the macro approach Diamond players take to the game, but also dispels the notion that Diamond players are constantly trying to out duel each other and score kills. Even though Diamond players are incredibly skilled at piloting their champions, the fact that they are playing against equally skilled opponents prevents them from reliably scoring kills, which leads to the development of strategies beyond scoring kills.



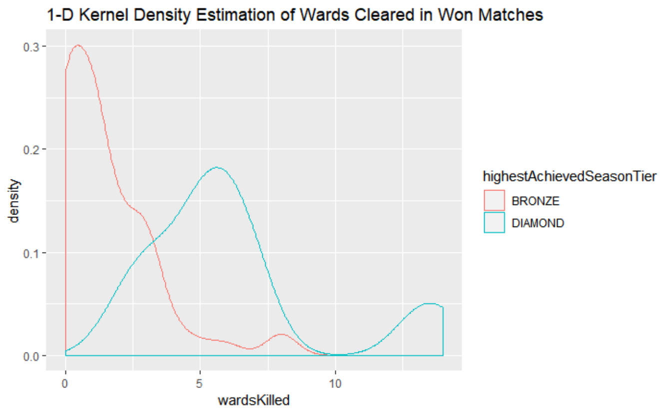
(a) 3.2a



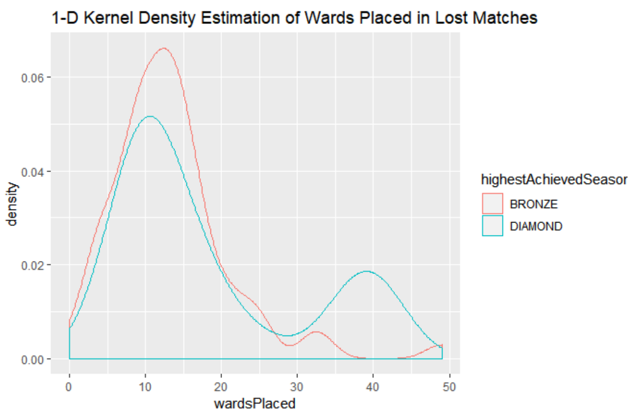
(b) 3.2b



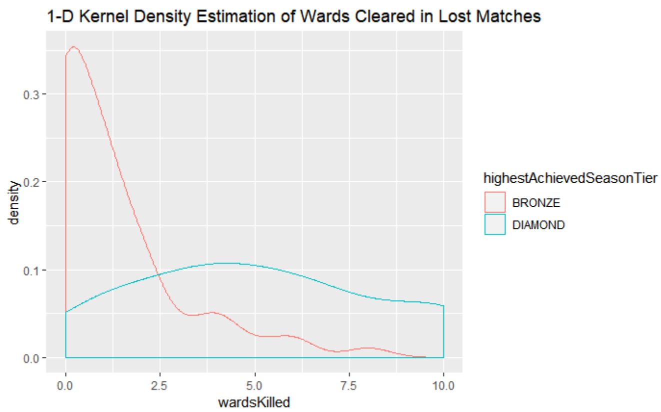
(c) 3.2c



(d) 3.2d



(e) 3.2e



(f) 3.2f

Figure 3.2: 1 Dimensional Kernel Density Estimation of Vision Control

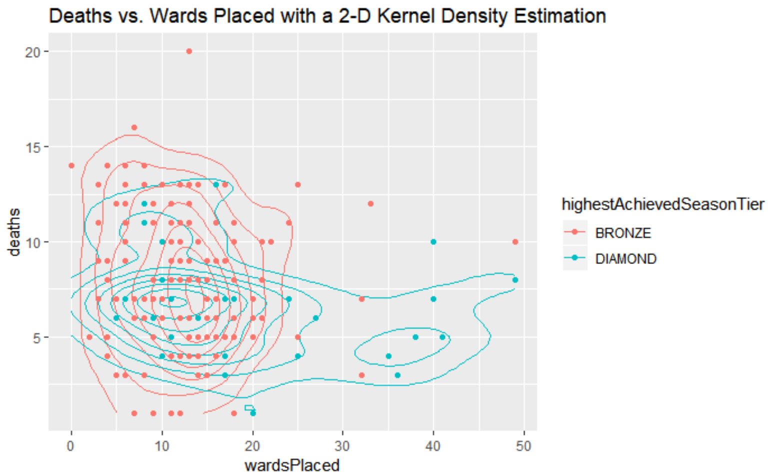
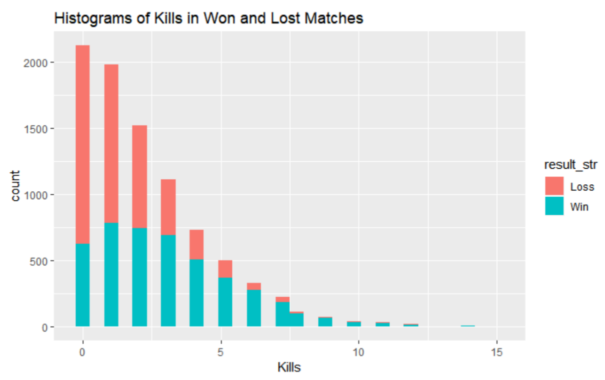


Figure 3.3: 2D Kernel Density Estimation on Deaths vs Wards

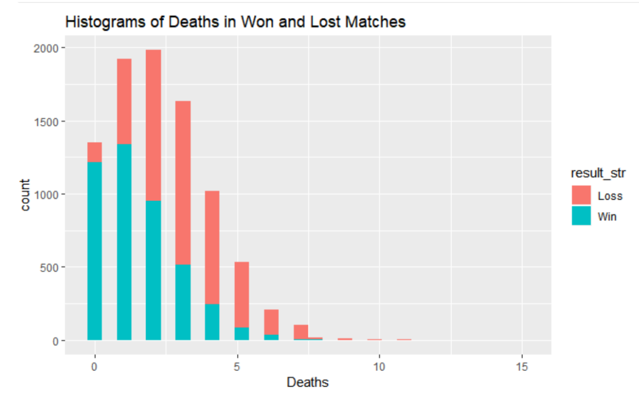
3.2 Professional Players and Teams

The histograms for kills and deaths for players participating professional matches are similar to the density curves in the Diamond level games with low average kills and deaths. When comparing the densities between lost matches and winning matches, there are only slight differences; players in winning matches have 1 or 2 more kills with a couple less deaths on average, and vice versa for losing matches. The minute differences in the kill and death scores for players in these matches imply that there is very little room for error as a single death can be very punishing, and that opportunities to score eliminations aren't readily available without a forced error or major mistake by the opposing team.
When looking at the use of wards, there is very little difference in warding between winning and losing matches, and on average the number of wards placed and cleared are much higher than the number of placed and cleared wards in non-professional matches. This observation lines up with the traditional intuition that due to the nature of communication at the highest levels, teams will be prioritizing the acquisition of vision and the denial of vision from the opposing team.
With the difference in combat statistics and vision statistics being so small, it appears that in professional games the combat and vision statistics among players aren't as sufficient in describing their impact on the outcome of a match. On the other hand, the difference between winning and losing games become more apparent when considering the objectives captured by each team.

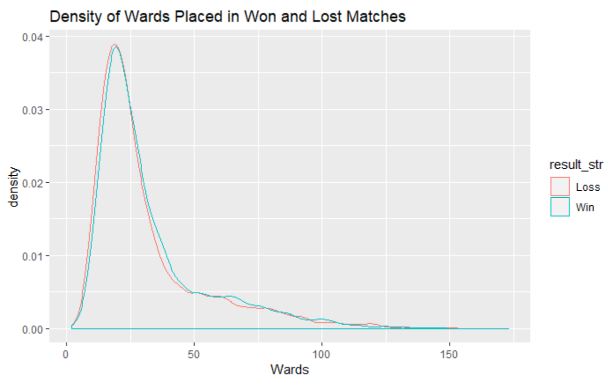
Figure 3.5 is a grid of histograms of team tower kills conditioned on the result of the match and if the team captured the first tower (ft). ft = 0 corresponds to matches where a team didn't get the first turret, and ft = 1 corresponds to matches where a team killed the first turret. In winning matches, there is a left skew in the number of turrets taken in winning matches if a team is the first to capture a turret. 64% of won matches were earned by teams that secured the first turret, whereas 30% of lost matches were earned by teams that secured the first turret. This implies that securing the first turret is correlated with capturing more turrets.



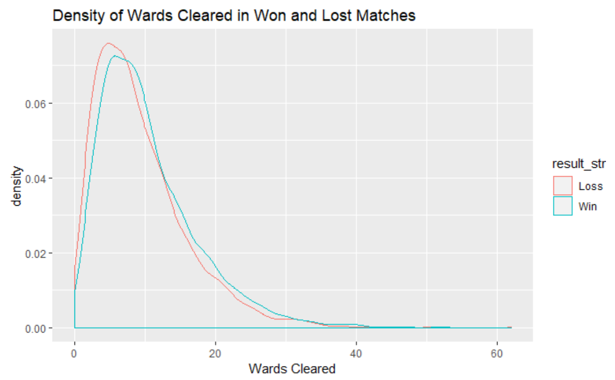
(a) 3.4a



(b) 3.4b



(c) 3.4c



(d) 3.4d

Figure 3.4: 1 Dimensional Kernel Density Estimation of Vision Control

Figure 3.6 showcases a grid of histograms for team dragon captures based on the result of matches and whether or not the teams were able of securing the first dragon (fd). As with ft, fd = 1 corresponds to a successful first dragon capture, and fd = 0 corresponds to a failed first dragon capture.

Figure 3.7 shows that between 1 and 4 dragon captures and above five turret captures leads into a winning match, and once 3 dragons are successfully captured, the number of losing matches drops off sharply. The graph suggests that around 2 and 3 dragon captures and above 6 dragon captures is when the game state becomes favorable.

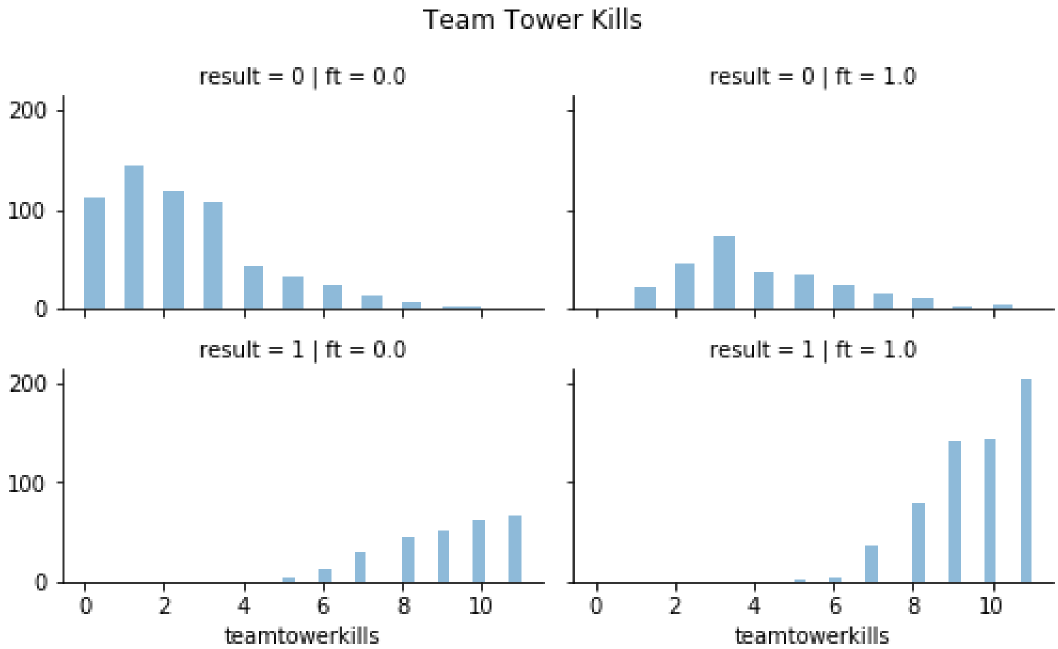


Figure 3.5: Histograms of Team Turret Kills conditioned on Match Result and First Turret Taken

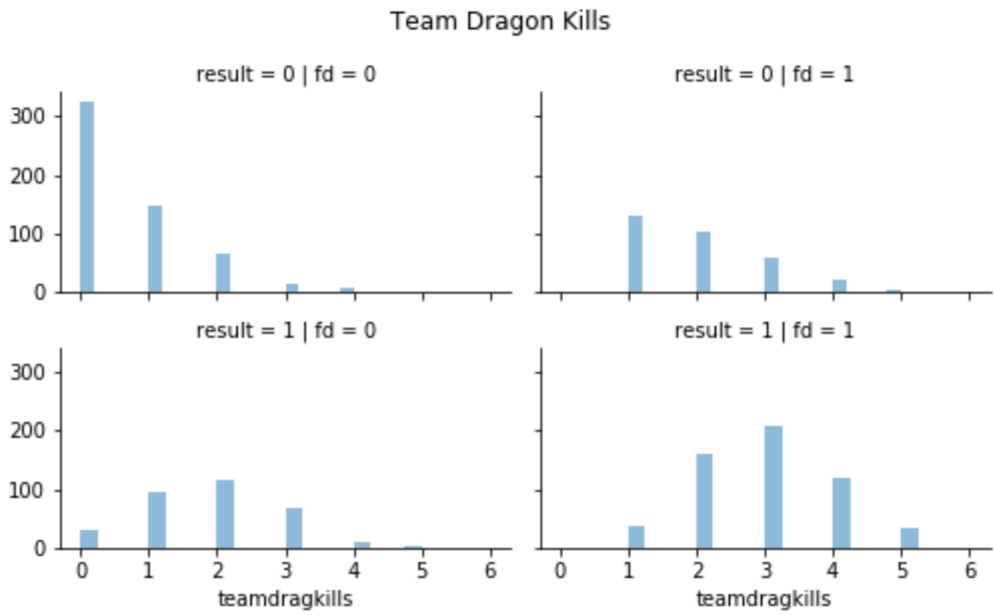


Figure 3.6: Histograms of Team Dragon Kills conditioned on Match Result and First Dragon

In conclusion, the combat and vision statistics don't tell the entire story on how a win

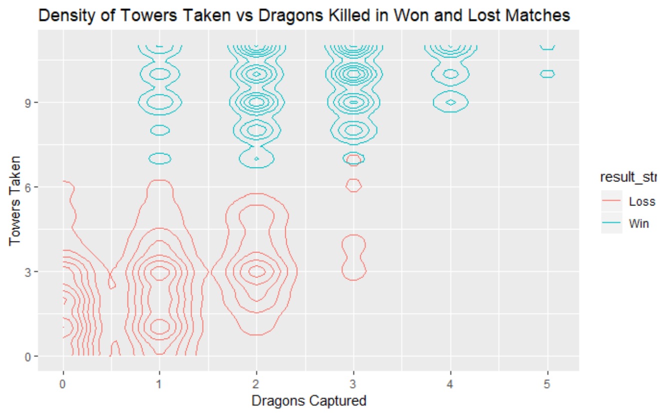


Figure 3.7: Conditional Joint Probability Density of Towers taken and Dragons Killed Given a Win or Loss

is achieved. When looking at the graphs of dragons and turrets claimed, it becomes apparent that these objectives are more indicative of the game state. As such, a regression model on the count of Dragons killed could give insight as to what steps a team needs to take in order to gain control of the dragons and subsequently gain advantages to win the match.

CHAPTER 4

Poisson Regression of Dragon Captures

Although the EGR model from 2.2 provides valuable predictive information on how well a team controls the game state 15 minutes into a match, it doesn't provide much insight into how teams are creating a favorable game state. The issue is in 2 of its predictor variables: Gold Differential at 15 Minutes and Map Side. The issue with these variables is that they don't provide much value in terms of formulating a winning strategy as map side is determined at the beginning of a match through a coin flip, and Gold Differential boils down to players out-dueling or matching their respective counterparts on the opposing team or 'playing better.' However, the third predictor, Dragon Captures, warrants additional exploration as it is a team effort in order to acquire, and the game doesn't have a hard coded method of securing Dragons unlike Gold. By building a predictive model for the number of Dragon captures within a given match, we can derive what factors are important in securing the Dragons and translate those factors into a strategy.

To build a predictive model for predicting the number of dragons within a given match, we can utilize a Poisson Regression model as the mean and the variance of the dragon captures in the professional matches are equal at 1.8. We will be fitting the model on using data from the matches played in the 2018 World Championship, and testing the model on the 2019 World Championship data. Utilizing a Poisson regression on the number of dragons a team has captured, we find that Kills, First Dragon, time of first dragon taken, and team turret kills have a positive effect on the occurrence of total dragon captures. Utilizing the Robust Standard Errors for each predictor variable, we see that Monster Kills, Kills, Deaths, First Dragon time have the lowest standard error rates for the model. [Cameron and Trivedi, 2009] These predictor variables were ultimately chosen as they were all found to be statistically significant with p-values well below 0.05, meaning the null hypothesis can be rejected with these variables. Total deaths and the time of the first dragon capture have a negative effect on the incident rate of dragon captures, which lines up with traditional intuition regarding the game as later first dragons means less opportunities for total captures as the game continues. When examining the variance inflation factors (VIF), we find that Monster Kills and Team Tower Kills have VIF values close to and over 5. Standardizing the variables failed to lower the VIF values, indicating that Monster Kills and Team Tower Kills exhibit collinearity. The Residuals versus Fitted plot in figure 4.1a suggests that there are no outliers in the data, and the 6 parallel curves are in line with the expected cases of one through 6 Dragon captures [Cameron and Trivedi, 1998]. The QQ plot is normal in shape, which means the assumption of independence of the predictor variables holds.

After training the Poisson Regression model on the 2018 regular season's games, the model is then tested on the match results of the 2019 regular season, which is made up of about 1700 matches. Figure 4.2a shows a plot of the expected number of dragons captured versus the time in which the first dragon was captured, while Figure 4.2b shows a plot of the actual dragon captures versus the time of the first dragon capture. The red line denotes

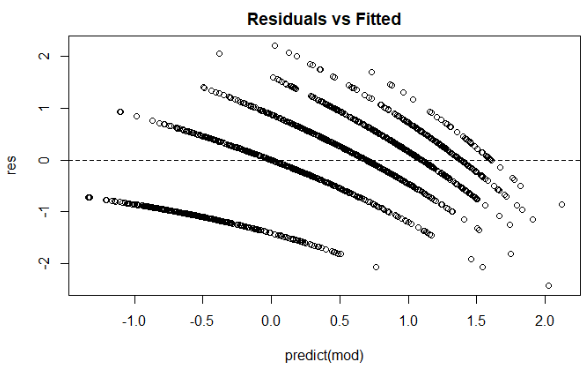
	Estimate	Robust SE	Pr(>|z|)	VIF
(Intercept)	-1.145 (β_0)	0.0816	0.00	NA
Kills (x_k)	0.01363 (β_k)	0.0025	0.00	2.84
Deaths (x_d)	-0.01058 (β_d)	0.0026	0.00	2.48
First Dragon (x_{fd})	0.6685 (β_{fd})	0.0284	0.00	NA
First Dragon Time (x_{fdt})	-0.04206 (β_{fdt})	0.0032	0.00	1.18
First to Three Towers (x_{ftt})	0.1836 (β_{ftt})	0.0311	0.00	2.07
Monster Kills (x_{mk})	0.003 (β_{mk})	0.0004	0.00	4.61
Team Tower Kills (x_{ftk})	0.05103 (β_{ftk})	0.0062	0.00	6.7

Table 4.1: Poisson Regression Output from R (Null Deviance: 2165; Residual Deviance: 945)

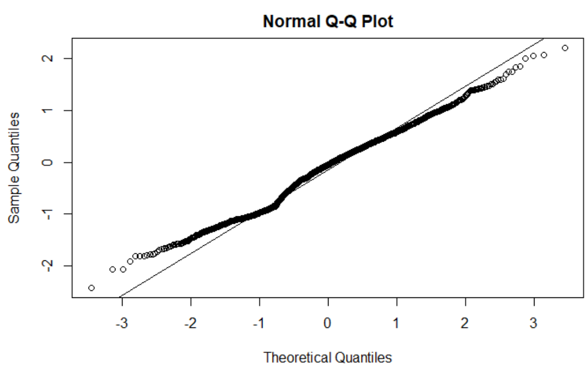
matches in which a team failed to secure the first dragon, while the blue denotes matches in which a team was able to secure the first dragon. Figure 4.4a and 4.4b show the actual and predicted Dragons captured versus the time of the first Dragon capture. As demonstrated by the EGR model of section 2.2, teams with more dragons at 15 minutes tend to win more; however, the Poisson model shows that the time in which the first dragon is captured can also have an impact on the outcome of the match as more winning matches occur when teams are able to secure the first Dragon before 15 minutes. Even though the positive effect Dragon captures have on the outcome of a match is known, the Poisson model demonstrates that the timing in which a Dragon is taken can facilitate more captures, which in turn has a positive correlation with winning match.

These predictor variables, first dragon and first dragon capture time, were chosen for the visualization as they both were shown to have the highest impact on the response variable based on the magnitude of their coefficients. The model was able to trace the general trend of the actual data, but has issues in predicting the matches in which teams are unable of securing any dragons whatsoever. With the coefficients taken from the Poisson GLM of Table 4.1, the following regression model can be derived, where Y_d is the count of the dragons captured.

$$Y_d = exp(\beta_k x_k + \beta_d x_d + \beta_{fd} x_{fd} + \beta_{fdt} x_{fdt} + \beta_{ftt} x_{ftt})$$

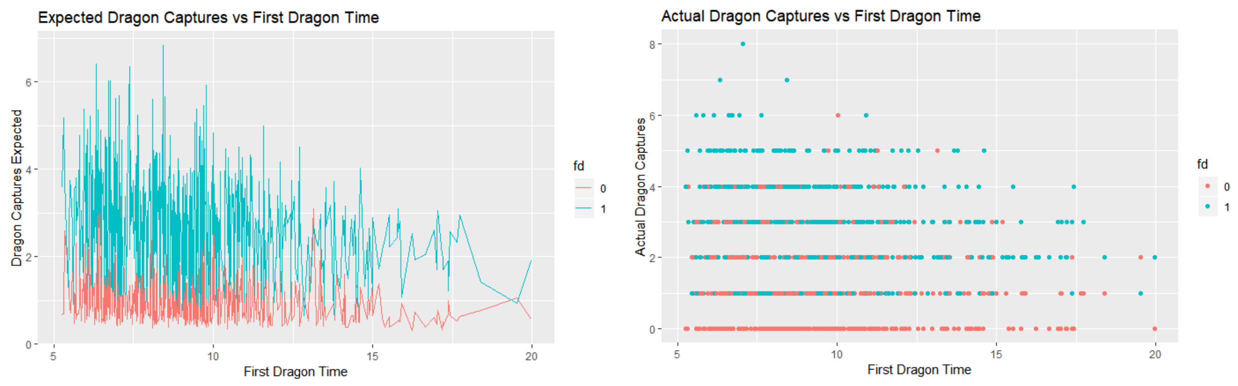


(a) Residuals vs Fitted



(b) QQPlot

Figure 4.1: Residuals vs Fitted and QQ Plot

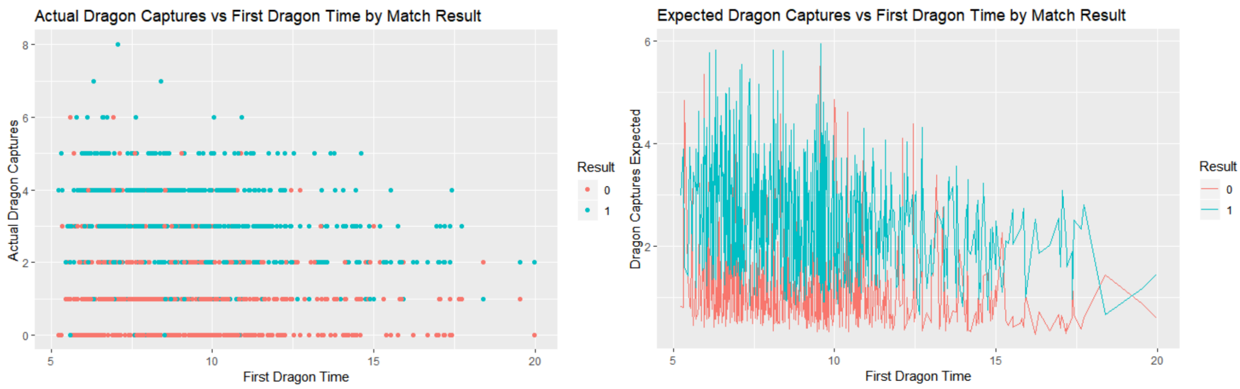


(a) 4.2a

(b) 4.2b

Figure 4.2: Actual and Expected Dragon Captures vs First Dragon Time

(a) Points and curves are separated by whether or not the first Dragon was taken, 0 indicates the first dragon wasn't acquired, wheras 1 indicates a team was successful in securing the first Dragon



(a) 4.4a

(b) 4.4b

Figure 4.4: Actual and Expected Dragon Captures vs First Dragon Time

(a) Points and curves are separated by match result, 0 indicates a loss and 1 indicates a win

The results of this regression analysis, and previous analyses imply that professional League of Legends matches revolve around the capture of dragons early in a match as the power they provide gives a sharp edge to the capturing team. Based on the regression model, the ideal strategy for securing the dragons will involve scoring Kills, minimizing Deaths, killing Monsters in the jungle, destroying Towers and securing the dragon as early as possible. One caveat in this strategy is the emphasis on tempo, being the team that is the first to accomplish specific actions such as securing the Dragon and destroying 3 Towers and doing so as early as possible in the game. The importance of time can be seen in the coefficient of the First Dragon Time, which is roughly 4 times greather than the coefficient for Deaths and 3 times greater than the coefficient for Kills.

To demonstrate how important each minute past the time the Dragon spawns we can examine a typical situation at 6 minutes into the game. As shown in Figures 3.4a and 3.4b, most professional players are scoring between 0 and 5 Kills and dying between 0 and 5 times at 30 minutes into the game. At 6 minutes into a game a team is usually sitting on 1 Kill and 0 Deaths. Utilizing the coefficients for Kills, Deaths, and First Dragon Time and ignoring the other factors, we get the situation below. Overall there is a negative effect on the dragon count that outpaces the effect of kills and almost negates the positive effects of acquiring the first dragon. This is apparent in Figures 4.2a and 4.2b as the total dragon captures caps out at 3 once the time of the first dragon capture reaches 15 minutes and beyond.

$$\beta_k(1) + \beta_d(0) + \beta_{fdt}(1) = -0.02843$$

Although the EGR model from section 2.2 in has about a 78% accuracy when it comes to predicting win rate based on the game state at 15 minutes, EGR doesn't provide much in terms of building a strategy as it only considers the resources a team was able to acquire over their opponents [Sevenhuysen, 2015]. That being said, the Poisson Model helps give insight into how teams are going about acquiring Dragons as the pathway to capturing the Dragons isn't as straight forward as accruing other resources. The Poisson model adds to the EGR model by showing what teams can do in order to capture Dragons and secure a positive game state. Utilizing findings from this model, we can begin to take a critical look at the strategies employed by the top teams in the world.

CHAPTER 5

Case Studies

Up until the year of 2018, the League of Legends World Championship was primarily dominated by South Korea, who had won 5 consecutive titles, while Western regions could not produce a team that could get out of the initial stages of the tournament. In 2018 a Chinese team, Invictus Gaming, had successfully won the tournament by beating a European team, Fnatic in the final series of the tournament. In 2019, the final match of the tournament ended up being between a Chinese and a European team again, with China emerging the victor for the second year in a row. With the aforementioned logistic and Poisson regression models developed, a thorough breakdown of how the best teams in the world achieve their wins can be performed.

5.1 Dominance of China

Table 5.1 shows the top 5 teams from the 2018 World Championship with the predictors used in the aforementioned Poisson Regression model, and the Logistic Regression model. From an initial glance, the first place team, Invictus Gaming, tops the chart in almost all metrics, except first dragon captures, but they've been able to secure 77% of dragons accross all the matches they've played. Even though they weren't securing the first dragon in 44% of their matches, they were still able of securing large gold leads at 15 minutes and making of their deficit in dragons. Additionally their large kill numbers reflect the ability of their players to generate advantages on their respective corners of the map.

Figure 5.1a shows that over all the matches played by Invictus gaming, their kill numbers aren't too different from their fellow finalist, Fnatic, but Invictus Gaming ends up dying much

Team	Win	Loss	Kill	Death	EGR	GD.15	F3T%	FD%	DRG%
Invictus Gaming	14	4	287	170	62.00	1,205	83%	56%	77%
Fnatic	12	5	238	193	56.20	605	53%	47%	54%
Cloud9	7	6	157	166	48.00	-251	54%	62%	54%
G2 Esports	7	8	164	168	47.20	-145	53%	47%	42%
KT Rolster	7	4	119	98	61.00	601	64%	64%	39%

Table 5.1: Top 5 Teams of the 2018 World Championship

(a) EGR: Early Game Rating

(b) GD.15: Gold Difference at 15 Minutes

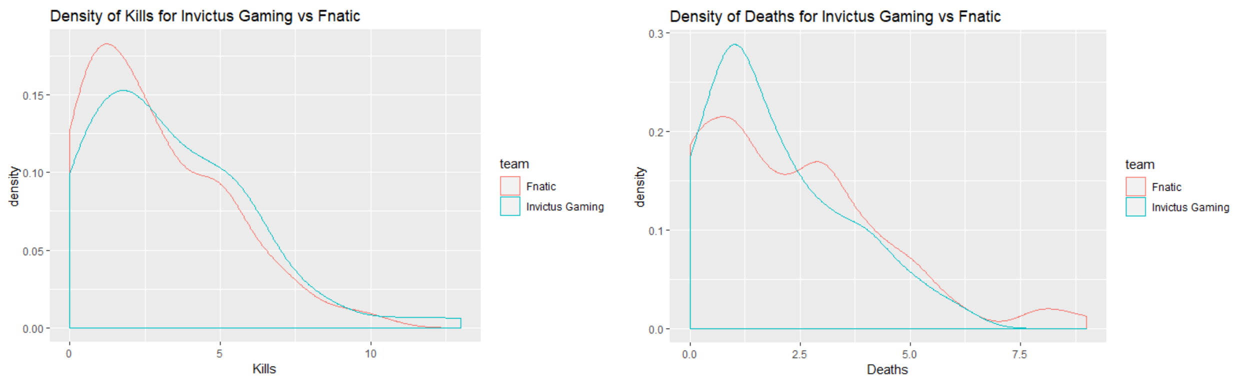
(c) F3T%: Percentage of games where first 3 turrets were secured

(d) FD%: Percentage of games where first dragon was secured

(e) DRG%: Percentage of total dragons secured

less overall. As far as warding goes, Invictus Gaming has a slight edge in the number of wards cleared as shown in figure 5.2a, but there is no appreciable difference in the number of wards placed as shown in figure 5.2b. The edge Invictus gaming had in this tournament was their ability to deny information to their opponents by clearing wards, and dying less, which prevents them from losing out on objectives such as the dragon, not necessarily scoring more kills every game.

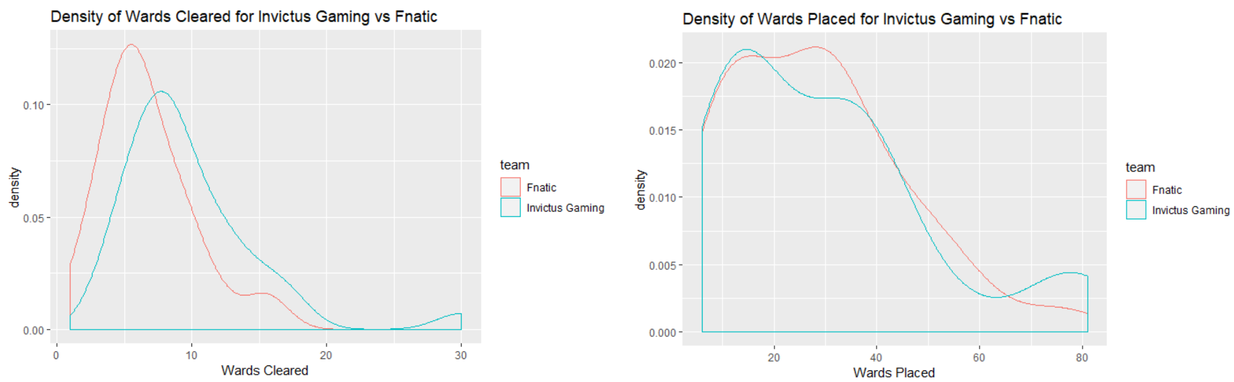
In the 2019 World Championship, the final match for first place was down to a European and a Chinese team, with the Chinese team, Funplus Phoenix, emerging as the victor. Much like their predecesor, Funplus Phoenix had the highest number of kills in the entire tournament, and a very high EGR, indicating their ability to secure dragons and gold at the 15 minute mark. Their ability to secure the first three turrets, but the first dragon frequency and percentage of dragons secured were higher than what Invictis Gaming had achieved in the previous world championship. Additionally, the European team, G2 Esports, managed finish in second place despite not achieving a positive game state through securing dragons and generating gold leads.



(a) 5.1a

(b) 5.1b

Figure 5.1: Kills and Deaths of IG vs Fnatic



(a) 5.2a

(b) 5.2b

Figure 5.2: Actual and Expected Dragon Captures vs First Dragon Time

5.2 The Rise of Europe

Table 5.4 shows that the Poisson model was able of predicting the average number of Dragons captured by Fun Plus Phoenix in the final match, but misses the mark when predicting the Dragons captured by G2 Esports in the final series of the 2019 World Championship. Throughout the tournament G2 Esports had only secured 47% of the dragons in their matches and wasn't consistently generating a sizable gold lead during the early stages of the game, which runs contrary to what the previous EGR and Poisson model suggests as the winning strategy.

G2 Esports had a very unexpected run during the 2019 World Championship, making

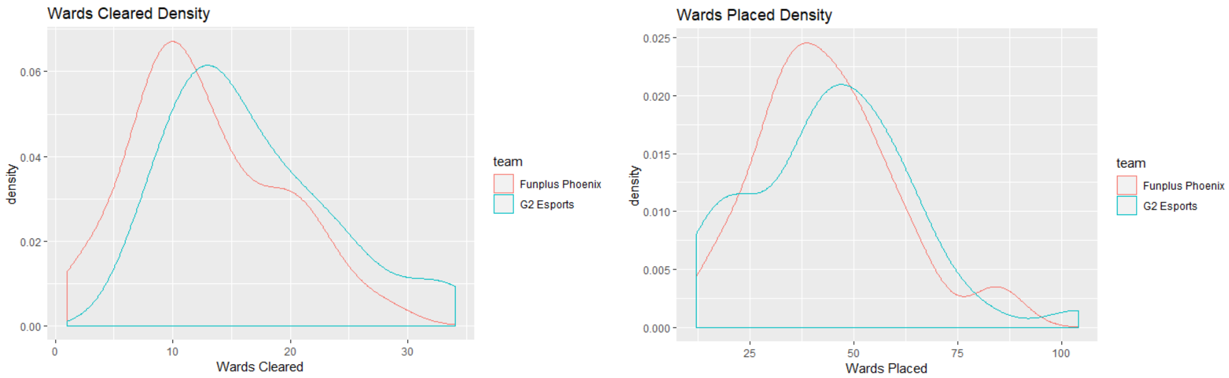
Team	Win	Loss	Kill	Death	EGR	GD.15	F3T%	FD%	DRG%
Funplus Phoenix	14	4	335	199	70.90	1,763	67%	72%	70%
G2 Esports	11	7	242	259	49.80	64	61%	44%	47%
SK Telecom T1	9	5	217	172	57.80	948	64%	64%	67%
Invictus Gaming	8	6	209	227	45.60	-55	43%	21%	42%
Griffin	7	4	171	105	62.50	1,189	64%	82%	68%

Table 5.3: Top 5 Teams of the 2019 World Championship

Team	Average Dragon Captures	Predicted Dragon Captures
Fun Plus Phoenix	2.67	2.60
G2 Esports	2.00	1.28

Table 5.4: Average versus Predicted Dragon Captures in FPX and G2 Final Matches

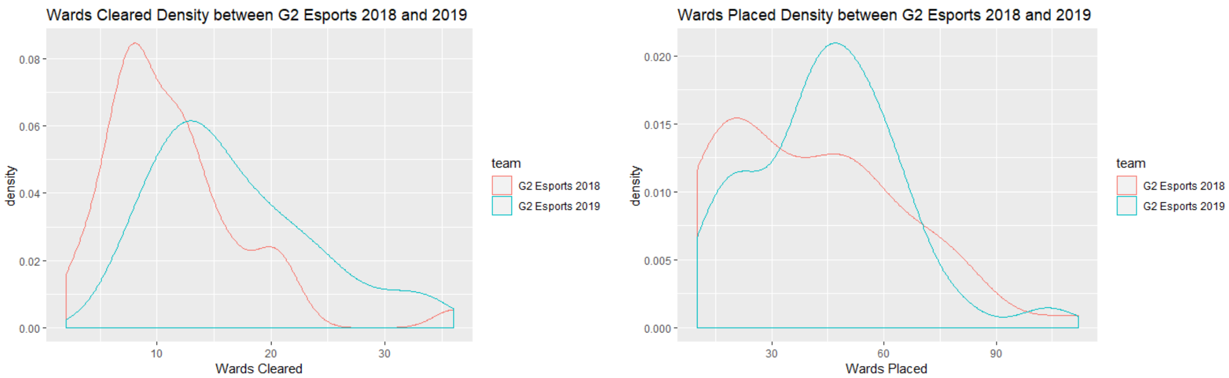
it to second place when in the previous year they were knocked out in the quarterfinals. Contrary to what the regression models had predicted, G2 Esports defied expectations and managed to make a deep run despite not generating a positive game state or securing a majority of the dragons, their ability to secure the first 3 turrets is still competitive with the other top 5 teams in the tournament. Based on the metrics shown, G2 Esports should not have made it to second place, which implies that G2 Esports utilized a different strategy that wasn't reliant on leveraging a positive game state at 15 minutes in order to achieve their wins. Even though the warding statistics haven't been shown to be statistically significant in the regression models, G2 Esports' strategy hinged on how they manipulated the information available on the map. We can compare the warding statistics between G2 Esports and the first place team, Funplus Phoenix. Despite the overall dominance that Funplus Phoenix had demonstrated in their run through the tournament, they were still placing less wards than G2 Esports on average, and G2 Esports had been clearing more wards on average than Fun Plus Phoenix as shown in Figures 5.2a and 5.2b. Even though a Welch's t-test doesn't reveal a statistically significant difference between the ward output of G2 Esports and other teams, the fact of the matter is that G2 Esports' play style centers around denying the enemy information on their players' positions by clearing the wards, and making moves on the map through the fog. Often times, G2 Esports is willing to give up early advantages such as the Dragon in order to gain control of their opponent's territory and securing single eliminations that translate into capturing turrets. The important thing to note is that G2 Esports compensating for their lack of a statistical advantages by denying their opponents critical information through their emphasis on clearing wards and positioning their players to make moves through the fog of war.



(a) Wards Cleared for G2 vs FPX

(b) Wards Placed for G2 vs FPX

Figure 5.3: 1 Dimensional Kernel Density Estimation of Vision Control



(a) Wards Cleared by G2 in 2018 vs 2019

(b) Wards Placed by G2 in 2018 vs 2019

Figure 5.4: 1 Dimensional Kernel Density Estimation of Vision Control for G2 in 2018 vs 2019

CHAPTER 6

Conclusion

With a new competitive season of League of Legends on the horizon it is important to evaluate the strategies employed by the top teams in the world to build a tactical base for the coming year and to improve the overall understanding of the game as a whole. The key strategy to note in the current state of competitive League of Legends is the focus on controlling the game state within the first 15 minutes of a match. As evidenced by the EGR and Poisson, the best strategy for winning a majority of League of Legends professional matches lies in acquiring dragons early in the game, generating gold, and leveraging that gold lead to control the opponent's territory. This pathway to victory has been demonstrated by the Chinese teams, who have consistently built advantages early in the game, minimized their deaths, and transitioned their pressure into wins.

However, as G2 Esports has shown with their deep run through the 2019 World Championship, small changes in a team's strategy can be all a team needs in order to find success in competition. In Figures 5.4a and 5.4b we see a change in the warding patterns of G2 Esports; G2 Esports simply increased the number of wards they placed on the map and simultaneously increased the number of wards they were clearing from the map. The increase in wards placed and wards cleared, has allowed G2 Esports to gain control of the information on the map that is available to them and their opponents, and they have shown that they are able of using the Fog of War to catch their opponents off guard despite the advantages their opponents may have accrued early on in the game. Even though the increase in wards placed and wards cleared show isn't statistically significant, this change was definitely a factor in allowing G2 Esports to make the jump from 4th place to 2nd place in just a year. Although the EGR and Poisson models support the efficacy of the Chinese teams' approach to winning games, G2 Esports has shown that the utilization of the Fog of War is another skill that can be refined into a world class strategy.

REFERENCES

[Cameron and Trivedi, 1998] Cameron, A. C. and Trivedi, P. K. (1998). *Regression Analysis of Count Data*. Stata Press, Cambridge Press, NY.

[Cameron and Trivedi, 2009] Cameron, A. C. and Trivedi, P. K. (2009). *Microeconometrics Using Stata*. Stata Press, College Station, TX.

[Sevenhuysen, 2015] Sevenhuysen, T. (2015). Early game rating, win prediciton. http://oracleselixir.com/2015/10/egr-and-mlr-new-team-ratings. Accessed on 2019-11-11.

[Staff, 2013] Staff, S. (2013). League of legends gets more viewers than super bowl. https://www.cnbc.com/2019/04/14/league-of-legends-gets-more-viewers-than-super-bowlwhats-coming-next.html. Accessed on 2019-11-11.

[Tassi, 2013] Tassi, P. (2013). League of legends finals sells out las staples center in an hour. https://www.forbes.com/sites/insertcoin/2013/08/24/league-of-legends-finals-sells-out-las-staples-center-in-an-hour. Accessed on 2019-11-11.