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of
Master of Science in Business Analytics

League of Legends Victory Prediction Analysis

By

Calum Palmer



Surrey Business School
Faculty of Arts and Social Sciences
University of Surrey

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Executive Summary

(1000 words; 10% of marks)

Set out on its own immediately after the title page. This often takes the form of a series of summary statements, ordered under similar headings to those used within the Dissertation. These summarise the key information or findings. The Executive summary should be written for an intelligent layman. An example of an Executive summary can be found in SurreyLearn.

Declaration of Originality

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Acronyms

MCTS Monte Carlo Tree Search

MOBA Multiplayer Online Battle Arena

NLP Natural Language Processing

RNN Recurrent Neural Networks

Glossary

baron	A neutral monster that spawns after the 20-minute mark that will give a powerful buff when slain. 4
champion	A unique player-controlled character possessing a distinct set of abilities and attributes. 3, 5
dragon	A neutral monster that spawns every 5 minutes that will give a moderate team-wide buff when slain. 4
gank	When a surprise attack is made upon a player, often made by a jungler or support. 4
jungle	A section of the map where neutral monsters spawn that can be slain for gold, experience and buffs. 3, 4
meta	The most effective strategy for winning. 2
minion	A unit that periodically spawns from the Nexus, advances along a lane towards the enemy Nexus and engages with any enemy they encounter. 3
nexus	A structure that serves as the primary objective of the game. When the enemy Nexus is destroyed, victory is achieved. 4
patch	A version of the game with a set of changes made to the game to update, improve or balance. 5, 6

- rift herald** A neutral monster that spawns between the 8 and 20-minute mark that can be used as a powerful tower sieging tool when slain. 4
- tower** A structure that deals damage to enemies that come into its radius and must be destroyed in order to reach the Nexus. 4
- ward** A deployable unit that grants vision of the surrounding area for a duration, they are typically used to gain valuable information on the enemy. 3, 4

Chapter 1

Introduction

1.1 Context

Esports is a form of competition using video games where participants will compete either individually or in a team for a chance at victory. These competitions attract millions of viewers, with estimates of 532 million spectators by the end of 2022, and this value is expected to grow annually at a value of roughly 8.7% (Newzoo 2022). The rapid growth in Esports has led to the industry becoming professional, with hundreds of players contracted on full-time contracts competing for prize pools of up to \$40 million (Esports Earnings n.d.). According to Newzoo (2022) this viewership will help the industry generate over \$1.38 billion in revenue by the end of 2022. As the Esports industry continues to grow, so does the importance on teams to win and remain relevant in the industry.

In traditional sports, analytics has become an extremely popular field with teams investing heavily in some form of analytics. These analytics can be used from evaluating opposing teams, to individual player forecasting and even used to decide signings or team selection (Sarlis & Tjortjis 2020, Apostolou & Tjortjis 2019). Apostolou & Tjortjis (2019), Sarlis & Tjortjis (2020) shows that these analytics can be applied for each athlete, giving an accurate estimation of key metrics such as goals scored per season or the number

of shots attempted in a given match. This same methodology could be applied to Esports, using these machine learning techniques could highlight specific factors both pre-game and in-game, helping analysts and coaches refine strategies within the game.

The ease of data collection coming from each match has led to a rise in Esports analytics. In-depth analysis of matches, teams and pre-game factors become key techniques for teams to gain this advantage over their competitors, with teams being required by their leagues to have at least one dedicated coach and analyst similar to traditional sports teams (LoLEsports 2022). These coaches and analysts use predictive analytics to maximise their team's likelihood of winning by altering numerous features related to pre-game and in-game strategies, current meta analysis and common patterns of their competition (Kokkinakis et al. 2021). However, this analysis is often completed manually by watching key highlights of matches using the analyst's intuition and using rudimentary analysis of in-game factors.

If matches can be accurately predicted using machine learning techniques, then analysts can provide new opportunities to optimise player strategies and can lead their teams to better outcomes. Applying the same findings found in Gray & Wert-Gray (2012), it can be seen that the overall performance and fan satisfaction with a sports team's performance has a measurable impact on revenue via fan attendance and their media response. Esports fans also appear to increasingly demand skillful performances especially from players that are deemed as '*superstars*', with these players being more likely to attract new viewers, thus increasing the economic gain of the market (Mangeloja 2019, Ward & Harmon 2019). It would then be in the interest of both teams and individual players to maximise their abilities and career longevity using these advanced analytics, so they can fully realise their potential; especially when the volatility of a players job security results in only the top 10% of players having lasting, stable careers (Ward & Harmon 2019).

1.2 League of Legends

1.2.1 General Information

League of Legends is a Multiplayer Online Battle Arena (MOBA) game developed by Riot Games released in 2009, it is one of most popular esports games in the world with over 180 million monthly players and a peak of 73.8 million concurrent viewers (Riot Games 2021, McLaughlin 2021). A MOBA is fusion genre of real-time strategy, role-playing and action games in which two sets of teams will compete in a known arena. The objective of each game is to defeat the opposition by destroying the enemy's base. Each player will select and control a unique champion with their own set of distinct abilities, this champion will be selected before the game starts and cannot be changed until the game has ended - this will be covered further in Section 1.2.2. Players can strengthen their champions by gaining experience and gold, this can be done by slaying enemy minions, jungle monsters, enemy structures or enemy champions. This gold can be spent in the shop allowing players to purchase items that enhance the attributes of their champion, as well as various utility items such as wards.

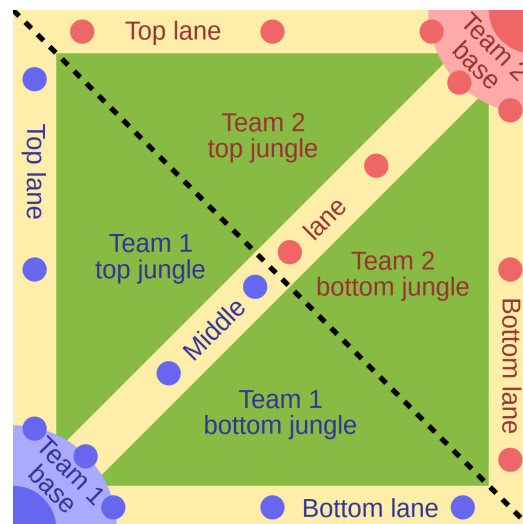


Figure 1.1: Map of League of Legends

A map of League of Legends can be seen in Figure 1.1. There are three lanes, Top, Middle and Bottom, with the jungle filling the space between these lanes. Typically, a player will be assigned to each of these lanes including the jungle, the exception being two players assigned to the bottom lane. The roles are typically labeled as follows:

- Top laner - Starts in the top-lane, often a champion who has larger health and resistance to damage with the ability disrupt enemy players.
- Jungler - Roams in the jungle, they help their laners whenever possible often using surprise attacks on enemy laners commonly referred to as a gank.
- Mid laner - Starts in the mid-lane, often a champion who is a spell-caster that can cause magic damage over a wide area or has high single-target burst damage.
- Attack Damage Carry (ADC) - Starts in the bottom-lane, often a long-ranged champion that requires gold in order to deal massive damage towards the latter stages of the game.
- Support - Also starts in the bottom-lane, often a champion that can provide aid to the ADC throughout the game via protective abilities and utility such as wards.

Each coloured dot represents a tower that must be taken in order to reach the enemy Nexus. A river separates the territories between the Blue (Team 1) and the Red team (Team 2) along the dotted black line seen in Figure 1.1. In this river you can find Baron or Rift herald in top-side and the Dragon in the bottom-side, they are key objectives that will often be contested.

1.2.2 Champion Selection

Champion Selection plays an important part in every game of League of Legends. Certain champions have inherent synergies with one another, meaning they are beneficial to be picked with each other. Likewise, some champions

are considered counter matchups when they are good at stopping another champion. This means that picking a good mixture of champions that are solid synergistically, whilst also ensuring the opponents champions do not counter yours is vital. These ideas are the fundamentals of champion selection, and they are what professional coaches and analysts attempt to solve each week. Factors such as player champion experience, the current game balance patch or a champion's ability to be flexible across different lanes will change champion select from game to game.

As seen in Figure 1.2, the current draft phase works as follows:

- Ban Phase 1 begins with the Blue team, in turn each team bans three champions from the pool.
- Pick Phase 1 begins with a singular pick from the Blue side, followed by two picks from the Red side. Blue side will get two more picks, followed by a singular pick from Red side for three picks each.
- It will then enter Ban Phase 2. Here both teams will ban two more champions in turn, with Red side starting.
- Pick Phase 2 will begin. Here Red side get their fourth champion pick, followed by the final two picks from Blue side and finally Red side pick their final champion.

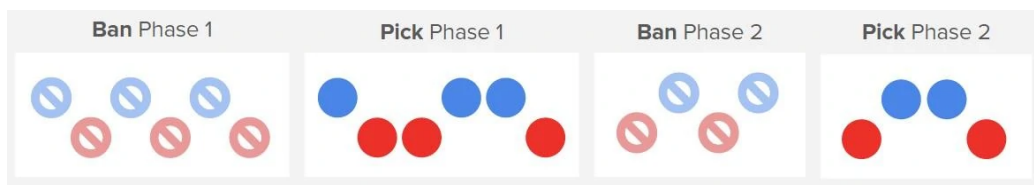


Figure 1.2: A depiction of the Champion Selection phase

This champion selection structure leads to clear opportunities for teams to ban out champions that are deemed too strong in Ban Phase 1. Blue side getting the first pick gives them a chance to pick any champion that is deemed too strong that still remains after Ban Phase 1. Whilst Red side

getting the last pick gives a defined opportunity to pick a counter match-up to any given lane. These factors can give one side the edge based on the Patch, leading to varying strength levels of Blue side vs Red side and can make side selection important.

1.3 Structure, Aims, and Objectives

The following section explores an overview of this dissertation:

The next chapter, Chapter 2, discusses the role of...

Chapter 3 follows the techniques and tools used for predicting the effect of pre-game choices on the outcome of the match. Beginning with...

Chapter 4 then proceeds with a discussion of the work carried out and presents the outputs of the model created. An evaluation of...

Finally, chapter 5 will conclude the dissertation giving an overall summary of the work completed, as well as any further opportunities for research.

Having pre-established the landscape of Esports and its relationship with analytics, it is clear that refinement in the way that this industry uses its highly available data is needed. Many academics have predicted the outcomes of matches in Esports titles such as Silva et al. (2018). However, performing these studies, few academics addressed the implications of the champion select phase on the overall outcome on a given League of Legends match. Often it is put into the model as a singular feature defined as champion or ban, without giving much implication on how an individual champion effects a game more than another. In contrast to other studies, this study uses a much larger, updated dataset and will concentrate much more on the overall effects of the pre-game choices that a team will make inside champion select. This includes the effects of each individual champion on the likelihood of winning a match. Therefore, the research question that will be addressed is as follows:

Can the outcome of a League of Legends match be predicted?

This research will provide an overview of the changing ways in which video games are being consumed, both in the emergence of esports and of the betting activities associated therewith. Subsequently, this article outlines the hypothesised relationships between demographic characteristics, media consumption practices and esports betting practices before describing the research model employed in this study. After outlining the methods, measures, participants and procedures this article presents, the results of the study in reference to demographic characteristics and measures of consumption. The findings are discussed alongside their theoretical and practical implications, potential avenues of future research, and the limitations of this work.

This research will thus contribute to the growing body of literature related to the convergence of gambling and (video) gaming. Specifically, this study investigates the interrelations between the motivations for consuming esports, consumption of digital media products associated with esports and participation in esports betting. As such, this work will provide evidence whether esports betting replicates relationships present in traditional sports betting, or if this emergent activity is accompanied by novel relationships.

Chapter 2

Literature Review

This section aims to review previous literature of prediction models in the esports industry that was explored during in Chapter 1. These literatures will help create a better working understanding of how to properly model, extract and gain knowledge from the datasets. It will cover papers from traditional sports where prediction models are widespread and lesser researched esports models, to research on the betting industry with its new relation to esports.

2.1 Predictive Analytics in Traditional Sports

In the mid to late 2000s the use of prediction modelling exploded academically, being applied to a multitude of fields from biology and medicine to political sciences or sports. This academic surge of interest caused thousands of studies all using various forms of predictive modelling. Not only did this evolve many practises across these fields, but it also helped develop the techniques of predictive modelling today. This is section we will explore literature related to how predictive analytics are used in sports, and how insights can be gained from this type of modelling. Sarlis & Tjortjis (2020) studied the impact of how various performance evaluation metrics can be used to identify dominant attributes that will help predict candidates for the Most Valuable Player (MVP) award, as well as Defender of the Year. They concluded that using their Propagation Neural Networks with 8 years of training data, that

their model was able to accurately predict the MVP of the season with 100% accuracy, and could also predict the Defender of the Year. Similar studies have been performed with football such as Pantzalis & Tjortjis (2020), where they analysed 4 top football leagues in Europe and predicted the final standings with up to 70% accuracy. Scelles et al. (2021) shows us that transferring this level of analysis from a traditional sports team to an esports team is highly supported, with claims that ‘esports... could provide some insights about the future development of sport’. This suggests that prediction modelling is likely to work when used to predict both player performances, whilst potentially being able to predict standing of esports leagues globally.

2.2 Predictive Analytics in Esports

2.2.1 Match Outcome Prediction

The work of predictive modelling in esports only started in the mid 2010s, with one of the original papers by Lin (2016) exploring match outcomes in League of Legends. This work focused on the relationship between the potential feature-sets that a game such as League of Legends can create, and how they impact the predicted match outcome both pre-game and in-game. The data was collected using the Riot API from matches with average ranked players, with the in-game data being extracted from the statistics published at the end of a match. It becomes apparent that the data used in this initial study appears to be highly correlated with the match result, and this is reflected by the 95% success rate on prediction using in-game data.

Two studies built upon the previous research just two years later. Silva et al. (2018) introduces the use of Recurrent Neural Networks (RNN) to predict esports matches through time intervals between the 0 and 25 minute mark, and uses data from matches between 2015 to early 2018. They concluded that these RNNs were capable of obtaining prediction accuracy of between 63.91% to 83.54%, depending on the time interval in-game. Their

study presented evidence of the predictability of each match and its positive correlation with the in-game timer, showing that the accuracy of prediction becomes stronger as matches progress, reflecting the snowballing nature of the game itself. However, it should be noted that the study ignores the presentation of each feature’s weighting and thus does not provide any insight into what features are most influential in these victories.

Gaina & Nordmoen (2018) built upon the study from Lin (2016), analysing the features that predict match outcomes at the 10-minute interval. Moreover, the correlation between the impact of early performance on the match result for each individual player in all 5 roles was found to be ‘a medium correlation’, with ‘a weaker one’ when overall team performance is compared. Other scholars such as Ani et al. (2019) have presented findings that suggest that prediction model accuracy can reach performance levels of 99.75%, with a combination of pre-game and in-game predictors using the Random Forest algorithm. An interesting note about Ani et al. (2019) is whilst using Adaboost, Gradient Boosting and Extreme Gradient Boosting they were only able to achieve an accuracy of 57.22% to 65.67% using only pre-game features which is drastically lower than the Random Forest algorithm. In the literature, both the Random Forest algorithm and Gradient Boosted Trees are commonly used machine-learning strategies that are used inside prediction models. These methods are both decision tree based in which a target variable is predicted based on a number of decision rules inferred from the feature-set, with the main downside is potential overfitting of the data (scikit-learn n.d.). This level of accuracy from pre-game features is more in line with other studies and will be discussed further in Section 2.2.2.

Lee et al. (2020) also produced a match outcome prediction model, using data from the Riot API of high level players from the ranked ladder. Similar to their predecessors of Silva et al. (2018), they tested their dataset across game time intervals, as well as the importance of each feature in the dataset. They achieved a prediction accuracy of between 62.25% and 96.08%, which is an improvement over the RNN used in previous studies. Gold difference

and the number of Towers taken appear to consistently be the two most important features across most studies referenced, with gold difference having a relative feature importance calculated up to 43.08% at the 10-minute mark and turrets having up to a 22% importance (Lee et al. 2020, Ani et al. 2019, Gaina & Nordmoen 2018). Another interesting study comes from Novak et al. (2020), here they apply a coach-centred approach to modelling performances seen at the 2018 League of Legends World Championship. Three coaches rated the proposed feature set using a correlation scale of 1 to 10, with median ratings for features equal or over 6 being retained for modelling. After multicollinearity checks, only 14 predicting features remained and the strongest fixed effect was ‘Tower Percentage’, closely followed by ‘Inhibitors Taken’ and allowed the model to achieve prediction accuracy of 95.8% - which remains consistent with previous studies.

2.2.2 Champion Selection Prediction

As described earlier in Section 1.2.2, champion selection is a key part of any MOBA game and has the ability to give your team an inherent advantage in-game before the game even begins. Previous works have explored the ideas of character recommendation systems with two key methodologies in mind - models based upon historical win rates of each character and an association rule model based on common selection frequencies. Chen et al. (2018) proposed a Monte Carlo Tree Search (MCTS) recommendation model in another popular MOBA game - DOTA 2, that suggests characters to add to the team in the draft phase that will maximise the team’s victory probability. The draft phase is approximated to a combinatorial, sequential, zero-sum game with perfect information and deterministic rewards. Therefore, an optimal pick at each stage will be the highest predicted win-rate character at a given stage, when both teams behave optimally in the process. Due to the large branching factor of the draft process, the decision-making scales exponentially larger as the draft process progresses and the computational power required does too. The MCTS is a tree search algorithm that is commonly used to solve deterministic games such as Chess, Tic Tac Toe and Go (Duck-

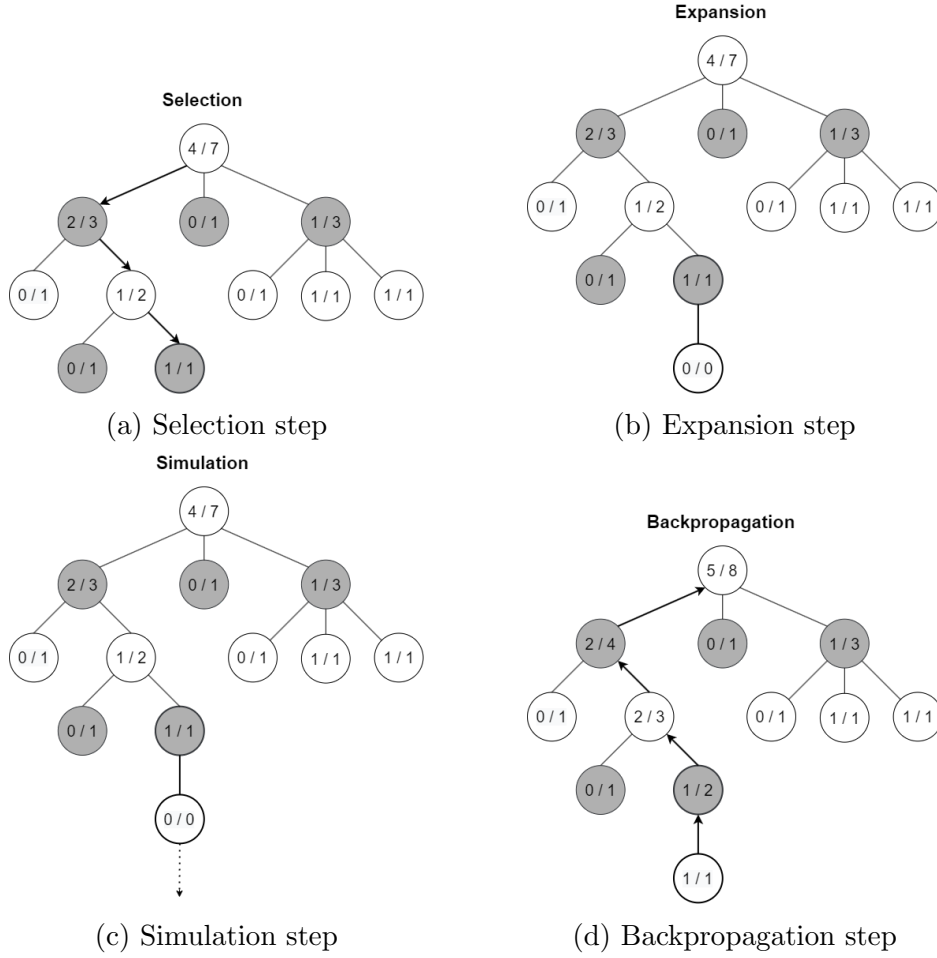


Figure 2.1: A graph showing the steps of a Monte-Carlo Tree Search

ett 2016). As seen in Figure 2.1, this algorithm explores the choice tree from root to leaf, selecting child nodes that represent the best winning outcomes.

If the leaf node does not terminate the game, it will create the next step with more child nodes throughout the tree, and if this simulated child node gives optimistic result probabilities it will update and back-propagate up the tree towards the root. At its core, the MCTS chooses the optimal move from the current state of a game's tree with the help of reinforcement learning. Using this system, Chen et al. (2018) were able to achieve a win-rate of up to 88.0% versus a standard association rule draft recommendation system used in studies such as Hanke & Chaimowicz (2017).

Recently, Shen et al. (2022) initiated studies into the champion recommendation using a mix of Natural Language Processing (NLP) techniques and Bidirectional long-short term memory models. They found that their proposed recommendation mechanisms were effective in both the coverage of champions and user satisfaction. Whilst this paper reiterated the fact that the champion selection phase can be predicted, it gives a unique perspective of adding a level of subjectivity to model by using user feedback and offers a wider-coverage of champions who are deemed less popular picks. But this lack of objective measure gives it no quantifiable metric onto which this study can extract valuable information from.

2.3 Esports Betting

As esports has grown, so has the ability of bookmakers to capitalise on a new developing market and create revenue. According to Absolute Reports (2022), the global esports betting market has been estimated to be worth up to \$10 Billion in 2021, and is forecasted to double by the year 2028 with a compound annual growth rate of 13.1%. A new focus of esports has grown throughout traditional bookmakers, with an increasingly larger number of esports titles to bet on and some bookmakers even sponsoring some events (Byrne 2019). With the large variety of titles comes the challenge of creating odds that are representative of the outcomes that will occur. There are numerous studies showing how gambling markets in most traditional sports can change how a given team is evaluated, often with regard to sentiment bias (Feddersen et al. 2018, Na et al. 2019). This means that odds-makers must create predictive models that can accurately replicate the true likelihood of match outcome in order to ensure money is continually being made. According to the efficient-market hypothesis, sport bets should be subject to all available information that may be publicly available and this information will be reflected in the odds themselves (Even & Noble 1992). The betting market is therefore thought of as a fair and efficient market in which match outcomes can be accurately predicted.

Betting within esports has taken on many forms. Money line bets and proposition bets are the most common types of bets. Money line bets are bets that are placed on the outcome of a specific match, with payouts based on the odds that are created by the odds-makers using their internal prediction models. Proposition bets are bets made based on whether a specific event will take place within the game itself while the match is ongoing. A common proposition bet is whether a team would achieve the first kill of the game - commonly referred to as First Blood. All these types of bets require highly calculated odds ensuring the bookmakers will make money. With esports betting being in its early form, there are no regulatory structures put in place to effectively to keep match integrity in place similar to those found within most sports (Dos Reis 2017). This lack of match integrity causes potential match-fixing scandals which threatens the competitive integrity of both the league and the gambling market, as well as ruining games for spectators alike. Whilst studies such as Abarbanel & Johnson (2019) claim that esports spectators aren't deeply concerned about potential match-fixing, with most spectators being willing to forgive infractions that have occurred previously. Cases of match-fixing have already been investigated, with a Chinese player- 'Bo' being suspended after being coerced into match-fixing in the Chinese academy leagues, subsequently causing a league-wide large-scale investigation (Dot Esports 2021). This caused a call for harsher punishments and stricter measures to ensure infractions like these would become highly disincentivised, however no regulatory structures apart from the league's punishment systems currently exist.

2.4 Summary

This chapter provided an overview of key literature in predictive analytics and its relation to both sports and esports, as well as an . Starting with a background on predictive analytics in sports and the various uses scholars have modelled with. This was followed with studies showing how these

predictive analytics can be applied to various esports titles. The various methodologies that have been used previously were explained such as the Monte-Carlo Tree Search and the Random Forest classifier. The betting industry was then explored, showing its relation to the world of esports and how they use prediction modelling for their business. With the information gained throughout this literature review, the following research hypotheses have been created:

Hypothesis 1: League of Legends matches are snowballing in nature, therefore prediction accuracy will increase as in-game time increases.

Hypothesis 2: League of Legends prediction models will naturally suffer from some level of multicollinearity.

Hypothesis 3: A decision tree algorithm will likely be the optimal machine learning technique for prediction.

Hypothesis 4: Esports betting indicates that highly accurate prediction models for match outcomes are feasible outside of academia and provide value to a business.

Chapter 3

Methodology

In this chapter, the methodology that is used to research the topic is presented. This study attempts to produce a predictive analytics model that uses a machine learning approach that can predict the match outcomes of a League of Legends match. Firstly, an explanation of the pre-processing data-pipeline - how the data was collected, a description of the dataset, and how the data is prepared and cleansed for modelling. The subsequent section then follows the dataset through the prediction methodology, and ends with how the predictive capability of the model is tested and assessed.

3.1 Data Pre-processing

3.1.1 Data Overview

The data used in this project is based upon the match data collected from all the League of Legends esports leagues found globally in 2021. Oracle's Elixir is a website that collects all the esports match data provided by Riot Games; the publisher of League of Legends, and aggregates them into datasets that are freely downloadable and offered to coaches, analysts and fans alike (Oracle's Elixir n.d.). These datasets are updated daily, and go back until 2014. When the dataset is downloaded, it is given in a .csv format that can be opened Microsoft Excel to get an easier perspective of the data. Once opened, it can be seen that it is a huge dataset contained within one spreadsheet with

149,496 rows and 123 columns, and will have to be prepared in order to be ready for modelling. The rows contain data from a unique player within a given match, this starts off with the Blue side Top Lane player and continues serially until the Red side Support player is reached, it will then contain a row for each team’s collective data. This means there are 12 rows for each unique match before reaching data for the next match, this can be seen in Table 3.1.

Table 3.1: An excerpt from the dataset.

Participant	Side	Position	TeamName
1	Blue	top	DWG KIA
2	Blue	jng	DWG KIA
3	Blue	mid	DWG KIA
4	Blue	bot	DWG KIA
5	Blue	sup	DWG KIA
6	Red	top	Nongshim RedForce
7	Red	jng	Nongshim RedForce
8	Red	mid	Nongshim RedForce
9	Red	bot	Nongshim RedForce
10	Red	sup	Nongshim RedForce
100	Blue	team	DWG KIA
200	Red	team	Nongshim RedForce

The target variable is the intended prediction variable, and is found at the eighteenth column named ‘Result’. It is a binary value and simply denotes whether a team wins or loses using 1 and 0 respectively. Preceding this column are the match descriptor variables, here lies the unique match id, the league in which the game is played, the date, the game number for best of 5 series, and other information such as match length and those found in Table 3.1. One of the key columns that will be used is the ‘datacompleteness’ variable, this contains 4 options of ‘complete’, ‘found’, ‘partial’ and ‘reparse’, and describes the state of the data in a given row. Following these 18 match descriptor variables, are the 105 in-game statistic variables that have been recorded. The values in these columns will be the key predictors in our match-outcome prediction model, however the usefulness of each variable

will be decided later in Section 3.1.2. These predictors range from simple statistics such as the total number of kills or deaths in a given match, to more advanced statistics such as GSPD - The average gold spent difference between teams. Many of these statistics also come in the form such as ‘goldat10’ and ‘goldat15’, which is simply the amount of gold obtained by the 10 and 15-minute mark in-game respectively. These time-based statistics will be important in factoring how much the match outcome varies by the in-game time. Another note about the data, is the fact that it tracks the opponent statistics for all of these statistics inside each row, so this should allow the use of data from only one side whilst maintaining all the statistics from both teams.

3.1.2 Data Preparation

Data Prep work

3.2 Data Modelling

Chapter 4

Results

3000 words

You should present your data in an appropriate form, which may include tables, graphs or in the case of qualitative data, verbatim quotes. Select the format that best suits your data, and do not present your data in more than one form. Ensure that the text around your presented data pulls out the key findings, rather than repeats what is already given. A table/figure should never be presented without supporting text. Tables and figures should be clearly and consistently labelled either above or below, and the reader should be able to understand the table/figure from the title without referring to the text for explanations. Units of measurement, the year to which the data refer, geographical area covered, and sources should be clearly stated. The labels in the text and in the lists should correspond exactly.

4.1 J

4.2 K

4.3 L

Chapter 5

Conclusion

1500 words

It can be hard to know which section to discuss your results – this or the preceding one – and you may decide to combine these two sections into one or more chapters based on theme, depending on your topic and your supervisor’s views. However, what is vital is that your Dissertation contains sufficient analytical discussion in addition to the more descriptive ‘scene setting’ material of the literature review sections, and presentation of results. It is here that you will compare and contrast your findings with those already reported in the literature.

Here you need to answer the “So what?” question. What significance do your research findings have? For whom? Why? and How? In this chapter you link the research problem with literature review and findings, stating what you can conclude based on the work conducted. Based on your conclusions you should comment on managerial implications, the limitations of the research, suggest further work and better ways to resolve the problem.

5.1 M

5.2 N

5.3 O

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Appendix A

Python Code

Code goes here

Appendix B

Data Description

Data description table

Appendix C

Feature Correlations

Correlations

Appendix D

Idk

Put other stuff here