An ELO-Based Method to Evaluate Player Performance in League of Legends Esports

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LEAGUE OF LEGENDS

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Contents

1 Abstract

In many "traditional" sports, such as baseball, football, and basketball, data analytics have recently become a integral part of player evaluation and decision-making. Data analytics can easily rank different players or teams in ways other than a simple win-loss record, as wins and losses may not capture the entire story of a team. These rankings can then be used to predict the outcomes of matches or a team's future trajectory. However, in the relatively new field of esports, publicly available analytics remain scarce. Raw match data is readily available, but at the time of writing, the predictive power of this data has largely remained locked away. In this paper, we will provide a basic system for ranking professional players across four major leagues in *League of Legends*, or LoL, one of the world's most popular video games and esports. We will aim to convey these findings in a form that requires little to no knowledge of the mechanics of the video game itself. The system employed will use the in-game statistic of gold difference and will be related to the ELO system, which was first used to rank chess players, but has since been applied to some traditional sports, as well. We will then use these individual player ratings to infer team ratings, predict the outcome of real-life playoff matches, and provide an ELO-informed probability for such a prediction. Finally, we will suggest potential areas for future areas of research, as this is a novel area of interest.

2 Introduction

2.1 Motivation

One of the earliest motivations for this project was the movie *Moneyball*, which covers the Oakland Athletics' journey through the 2002 MLB season as they built a roster comprised of washed-up veterans and flawed outcasts using the philosophies of baseball statistician Bill James, one of the first people to introduce analytics to baseball. The team defied conventional baseball wisdom, much to the dismay of their fans, owners, coaches, and staff, but after a slow start, they set an MLB record for most consecutive games won (20) and made the playoffs while spending a third as much on their payroll as the New York Yankees, their first round opponent [1].

In the movie, conventional baseball experts use vague language and the "eye test" to evaluate players' skills, but these evaluations are not backed by numbers and do not always translate to tangible results. Right now in LoL esports, much of the same is done by the public to describe player performance. Players are described as good or bad at certain aspects of the game based simply on how they look, but players and teams who are labeled good do not always win more games. This begs two questions: are these players actually good, and to what extent does being good at those phases of the game actually help players win? To answer these questions, we must simplify LoL into just a few variables and use those variables to rank player performance.

In North America, some teams spend millions of dollars to import players who look good from other countries, such as South Korea, because those countries typically achieve better results in international competitions. However, they often see these imports underperform their high expectations. This phenomenon has sparked major controversy among North American fans and teams as some people feel as if North American players are being neglected by teams who would rather pay foreign talent than develop native talent, even though there would likely be no difference in results. My original goal was to find hidden value in North American players so that teams could field cheap, native rosters to beat these expensive, imported rosters and compete at a higher level internationally. This goal has since evolved over the course of this project.

2.2 ELO System in Other Contexts

The ELO system for evaluating was invented by Arpad Elo as a means to rate chess players [4]. The system assumes that every player X_i acts as a normal random variable with fixed variance σ^2, typically 400 [5], and expected value of R_i, where R_i is their ELO rating. Players are considered more likely, but not guaranteed, to defeat players of lower rating [4]. Specifically, player i has probability $f(R_i - R_j)$ to defeat player j, where

$$f(x) = \frac{1}{1 + 10^{\frac{-x}{\sigma^2}}}. \tag{1}$$

The ELO ratings of each player is recursively updated each game by

$$R_i^* = R_i + K(S_{ij} - \mu_{ij}), \tag{2}$$

where

$$S_{ij} = \begin{cases} 1 & \text{if player } i \text{ defeats player } j, \\ 0 & \text{if player } j \text{ defeats player } i, \\ 0.5 & \text{if players } i \text{ and } j \text{ make a draw,} \end{cases} \tag{3}$$

$$\mu_{ij} = f(R_i - R_j), \tag{4}$$

and K is a constant called the K-Factor [4]. We call S_{ij} and μ_{ij} the actual and expected results, respectively. Note that

$$S_{ij} + S_{ji} = 1, \tag{5}$$

which is necessary to ensure that ELO is conserved for fixed K. Furthermore, because $f(x)$ has a range of $(0, 1)$, this system guarantees that a player's rating will always increase for a win and always decrease for a loss.

The K-Factor determines the magnitude that ratings change. If it is too large, ratings may oscillate too much and they will be too biased toward recent results, but if it is too small, ratings may not update fast enough and they will be too biased toward results further in the past [5]. In chess, players are given a higher K-Factor for their first few games to quickly gain a rough estimate of their strength. It is lowered after a certain number of games and further lowered for players above a certain rating [4].

Because chess does not have a scoring system, the ELO system must be modified to account for margin of victory. There are two ways we can do this. Let X_i and X_j be the scores of the respective players. The first way involves introducing a multiplier,

$$\Delta_{ij} = \frac{((X_i - X_j) + 3)^{0.8}}{7.5 + 0.006(R_i - R_j)}, \tag{6}$$

and multiplying that by the $S_{ij} - \mu_{ij}$ in Equation 2, giving us

$$R_i^* = R_i + K\Delta_{ij}(S_{ij} - \mu_{ij}) \tag{7}$$

This is the method employed by popular sports analytics website FiveThirtyEight for their NBA ELOs [8]. The second way requires modifying the function used to update ELO. We let

$$g(x) = f(x) - 0.5, \tag{8}$$

so that the function passes through the origin, and modify Equation 2 to become

$$R_i^* = R_i + Kg((X_i - X_j) - (R_i - R_j)). \tag{9}$$

We will notice that this new equation is very ELO-like because we apply a sigmoid function to an actual margin of victory, $X_i - X_j$, minus an expected margin of victory, $R_i - R_j$. Our function $g(x)$ is positive when $x > 0$ and negative when $x < 0$, so this ensures that rating will increase when a player plays better than expected and decrease when a player plays worse than expected. This is the method used by Marveldoss to assign ELO ratings to NBA players [5].

2.3 League of Legends, a Brief Synopsis

This section should provide the needed background information for a reader who does not play *League of Legends* to understand the rest of this paper. We will avoid discussions of in-game strategies and mechanics as much as possible, as they are largely irrelevant to building an ELO system. Every game consists of two teams of five players each, and these players each play a different role: Top, Jungle, Mid, Bot, and Support. The game can be heavily simplified to a resource collection game where each player's character, called a champion, tries to earn gold through various methods such as killing in-game monsters, destroying turrets, and killing the champions on the other team. While the game does not end until a structure, called the Nexus, in each team's base is destroyed, the team with more gold generally wins. This is because gold can be used to buy items that make champions stronger, thereby making it easier for them to kill the enemy and harder for the enemy to kill them. The gold is not split evenly amongst teammates: the Top, Mid, and Bot players generally earn about the same amount of gold, while the Jungle earns a little less than them, and the Support earns the least. However, the Jungle and Support players do other things that can help the team win the game, so for our purposes we will assume that each player on the team contributes equally to the game. This will later allow us to initialize all players to the same ELO, regardless of position.

3 Methods

3.1 Data Collection

Data was collected from the 2019 Spring Split[1] through the 2023 Spring Split for the League of Legends Championship Series (LCS, North America), League of Legends EMEA Championship (LEC, Europe), and League of Legends Champions Korea (LCK, South Korea) and from the 2021 Summer Split through the 2023 Spring Split for the League of Legends Pro League (LPL, China).[2] These four leagues are considered the world's highest levels of LoL esports. All data was collected on June 9, 2023 from a website called Oracle's Elixir, which has downloadable match data in CSV format, updated daily [7].

After collecting the data, some simple data processing was performed. Each match consists of 10 player rows and 2 team rows, as there are 2 teams of 5 players each, so the team rows were removed. Additionally, we added columns for the corresponding opponent's data from each player, calculated the gold difference for each row by subtracting the player's gold with their opponent's gold, and we removed most columns that did not contain gold or identifying information. Finally, all gold data was normalized to gold per 30 minutes. This is because in LoL, the game length is not fixed, and 30 minutes is slightly shorter than the average game

[1]A split is the same as a season, consisting of regular season and playoffs.

[2]There were issues with the LPL data from before 2021 Summer, rendering it unusable. Chinese match data has historically been difficult to access because it is kept by a different company than the other regions.

length. However, this is an appropriate normalization because in most traditional sports, statistics are normalized to the full length of a game without overtime, which is slightly shorter than average length because of the possibility of overtime.

3.2 Using Gold as a Scoring System

It is commonly known within the LoL community that in a match, the team with more gold, a common in-game resource, usually wins the game. While this is not always true, we will aim to show that this technicality is negligible, and more importantly, that teams that consistently earn more gold than their opponents win more often. To do this, we will show that gold obeys the Pythagorean Expectation, a formula derived by Bill James:

$$W\% = \frac{PF^n}{PF^n + PA^n}, \tag{10}$$

where PF is Points For and PA is Points Against [3]. It should be noted that this formula is very accurate in baseball, basketball, and football [6]. We compiled all competition data involving 47 teams from the LCS, LEC, LCK, and LPL in the year 2022, including international competitions which may involve teams not from these regions. Using the exponent $n = 9.05$, we achieved a Root Mean Squared Error of 3.285% and R^2 value of 0.941 when comparing a team's predicted Pythagorean Winrate and a team's actual winning percentage. This means that we can treat equate gold to points in LoL, as expected, despite there being no inherent scoring system. This will prove to be extremely useful and will make our job quite easy, as players in LoL each generate their own gold and the team's gold total is simply the sum of the gold earned by each player. Compare this to a sport like football, where nearly every point can be attributed to multiple players (for example, both a quarterback and a receiver get credit for scoring a passing touchdown). An important consequence of this is that a team's ELO is equal to the average of its players' ELOs. We will discuss why we use the average, and not the sum, in a later section.

3.3 Traditional ELO system

For our traditional ELO system, we equate 500 gold with 1 point in our calculation of Δ_{ij} in Equation 6. In other words, we divide the gold by 500 due to the fact that a lot of gold is generated per game. We also say if the gold difference between two opponents is no more than 500 gold, the result is a draw.[3] In this system, it is possible for a player to gain a win

[3]The choice of this 500 gold cut-off is somewhat arbitrary, but it is because players can only buy the weakest in-game items with 500 gold, making them only marginally stronger than their opponents with this difference. Furthermore, this is a negligible amount of gold at 30 minutes into a game, as most non-Support players will have accumulated 10000 gold by this time.

despite their team losing, and vice versa. To update ELOs, we first initialize all players to 1000 ELO and recursively apply Equation 7 to each match.

3.4 Modified ELO system

For our modified ELO system, we will use an approach very similar to the one used in Marveldoss' article [5]. We say that 1000 ELO corresponds to the average gold for each position n using the equation

$$1000 = \eta_n g_n \tag{11}$$

We then calculate

$$X_i = \eta_n g_i, \tag{12}$$

where g_i is the gold generated by player i, for each match. To update ELOs, we first initialize all players to 1000 ELO and recursively apply Equation 9 to each match.

3.5 Predicting Playoff Results

One of the common goals in sports analytics is the ability to predict the outcomes of matches, particularly in the playoffs, when stakes are higher and the possibility of a championship is on the line. This can be especially useful for the average fan in the newly popularized field of sports betting. To do this for a given split, we will update the ELOs of all matches leading up to and including the regular season, but not including the actual playoffs. On top of that, to avoid bias in the system, we will regress each player back to the mean of 1000 after each split using the formula

$$R_i^* = 1000k + R_i(1 - k), \tag{13}$$

where $k = 0.1$ when the new year begins and $k = 0.05$ when a new split begins in the same year. These numbers should be kept small because teams do not play that many matches each season. Then, we will add the ELOs of the five players for each team to get the team's ELO. For each projected matchup, the team with higher ELO will be projected to win. We can also use Equation 1 to calculate the probability of victory in a single match, which we will call P_1, and adjust for Best-of-3 and Best-of-5 series using the following equations:

$$P_3 = P_1^2 + \binom{2}{1} P_1^2(1 - P_1) \tag{14}$$

and

$$P_5 = P_1^3 + \binom{3}{1} P_1^3(1 - P_1) + \binom{4}{2} P_1^3(1 - P_1)^2. \tag{15}$$

These probabilities form the basis of why we choose to use average instead of sum when calculating a team's ELO. If we used the sum, the difference in team ELOs would become very large, hundreds of points possibly, which could yield P_1 values that are above 90% for some Best-of-1 matches, leading to higher P_3 and P_5 values. Some probabilities would even exceed 99%. From a sports perspective, it is very unrealistic to predict the outcome of a match with such high certainty, and from personal experience, upsets occur in LoL much more frequently than these percentages indicate. Using the average would make the difference in ELOs smaller and keep most percentages below a reasonable 70%.

4 Results

4.1 Some General Observations

The algorithm which we outlined enforces that the players have an average ELO of 1000. However, significantly more players are rated lower than 1000 than above. For example, using the traditional system in the LCS,[4] 116 players have rating less than or equal to 1000, while only 64 have rating above 1000. That number increases to 129 less than or equal to 1010, with only 51 with rating above 1010. Why is this? Picture a graph of all League of Legends players in the world, as in Figure 1. This graph would probably look somewhat like a bell curve, with only the players on the far right side of the graph being good enough to play professionally. Since at the highest levels of play, the number of players decreases as the skill level increases, it would make sense that there are fewer players above average than there are players below average. This is a concept that has already been recognized in traditional sports. In baseball, the Wins Above Replacement statistic was created because it is much easier to find players who are below average than players who are average or above average, which ultimately led to the definition of a "replacement-level" player [2].

4.2 Playoff Predictions

To truly test the efficacy of the model, we attempted to predict the outcome of the playoffs for each season from 2019 to Spring 2023. A March Madness-style scoring system was implemented, meaning that 1 point was awarded for predicting the correct winner of each match, regardless of whether the opponent was predicted correctly. We tested different K-factors from 10 to 35 at intervals of 5. The best perfomance was observed with $K = 20$ for the traditional system and $K = 15$ for the modified system.[5] Out of the 239 playoff series and 32 playoff tournaments played between 2019 and Spring 2023, the traditional system was

[4] Complete results, along with a list of player ELOs, can be found in the Appendix.
[5] Once again, complete results can be found in the Appendix.

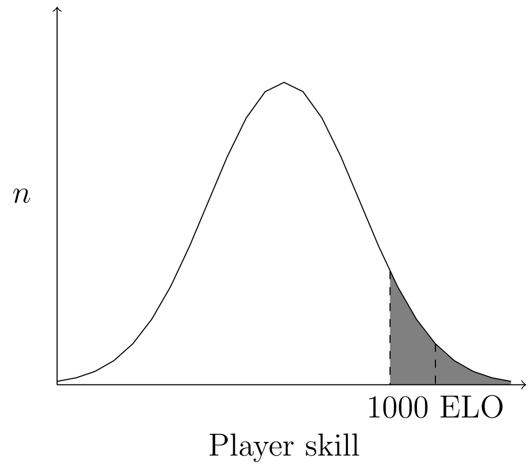

Figure 1: A visualization of the number of LoL players versus their skill level, not to scale. The gray shaded area represents the players who play professionally.

able to correctly predict 134 correct winners (56.07%) and 18 correct champions (56.25%), while the modified system was able to correctly predict 133 correct winners (55.65%) and 18 correct champions.

4.3 The Challenges in Predicting Double Elimination Brackets

These results are decent, but they do not capture the full story. Unlike March Madness, the playoff formats in these leagues change frequently, usually by increasing the number of matches for the purpose of viewer engagement. Therefore, we can split the different tournaments into by number of matches, as shown in Figures 2 and 3. Both systems perform significantly better when there are fewer matches in the bracket. The reason for this trend is that many tournaments are double elimination, which can lead to all kinds of problems when predicting.

4.3.1 Multiple Paths to the Final

First of all, there are many possible paths to the final instead of one, so getting one winner wrong can instantly make it impossible to get other winners further down the road right. One of the most unusual instances occurred in the LEC 2020 Spring Split,[6] when first seed

[6]For more details on any split's playoff, search for "[League] [Year] [Split] playoffs" on Google. It would take up too much space to include everything in the Appendix.

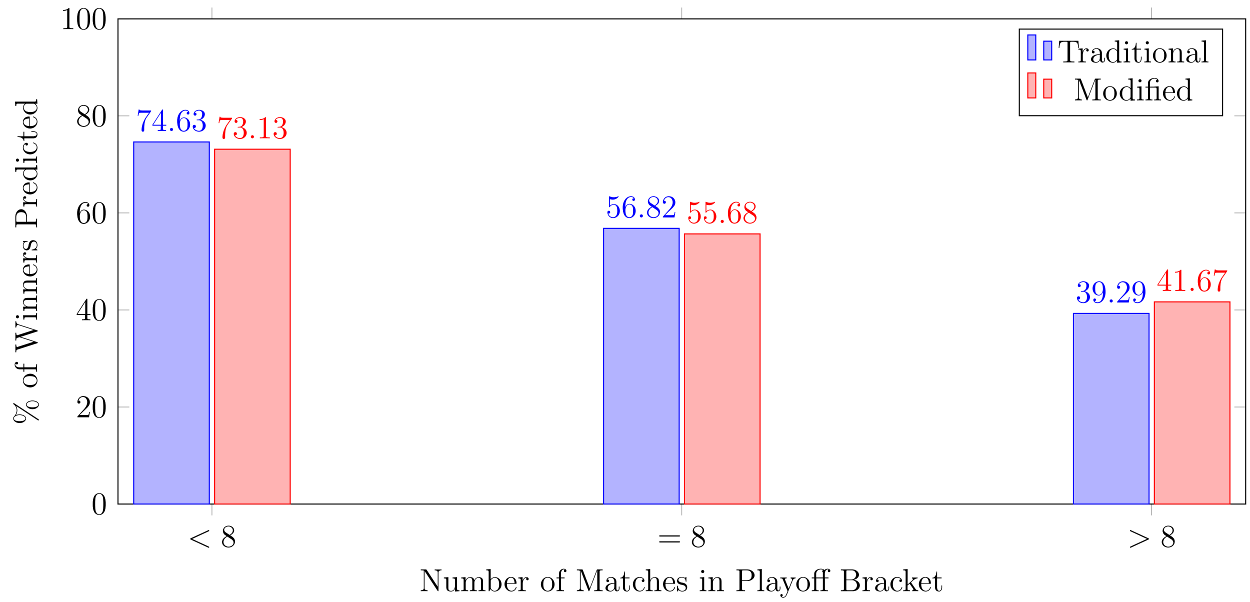

Figure 2: Number of correct winners predicted in a playoff bracket, split by number of total matches in the bracket. $n = 67$ for < 8, $n = 88$ for $= 8$, and $n = 84$ for > 8.

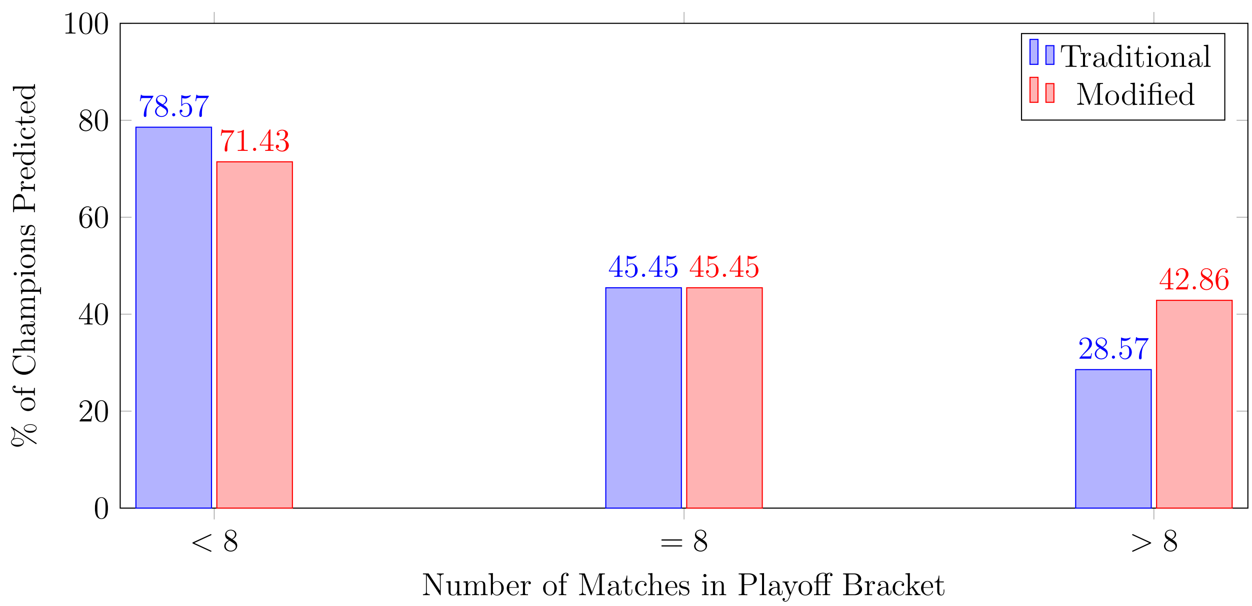

Figure 3: Number of champions predicted correctly, split by number of total matches in the bracket. $n = 14$ for < 8, $n = 11$ for $= 8$, and $n = 7$ for > 8.

G2 Esports lost in the first round but eventually won the championship. Because they had the highest ELO of all the teams in the playoff, they were predicted to win in the first round and the championship. However, the LEC's playoff contains a "gauntlet" format for its Loser's Bracket, where the lower seeded loser from Winner's Bracket Round 1 would enter the Loser's Bracket in Round 2, while the higher seeded loser would meet the winner of Round 2 in Round 3. In real life, G2 Esports lost to Mad Lions and Origen lost to Fnatic in Winner's Bracket Round 1. Then, Origen won their match in Loser's Bracket Round 2 before losing to G2 Esports in Loser's Bracket Round 3. However, the prediction system predicted fourth-seeded Mad Lions to lose in Round 1, sending them to Round 2. It correctly predicted third-seeded Origen to lose in Round 1, but incorrectly sent them to Round 3. It then predicted Mad Lions to win Round 2 and Origen to win Round 3, which were both marked incorrect: Mad Lions did not play in Round 2 in real life and Origen was predicted to beat the weaker Mad Lions team in Round 3. Had the system placed Origen and G2 Esports in the correct spots in the Loser's Bracket, it would have predicted the correct winner in both Round 2 and Round 3. This created a situation where both models predicted the correct champion but only 2 out of 8 correct winners.

4.3.2 Number of Matches

Another problem is that there are many more matches played than there would be if the tournaments were single elimination. For example, the 8-team playoff format currently used by the LCS during the Summer Split includes 12 matches, with each match being a Best-of-5 series. Compare this to the 7 Best-of-1 matches that occur when there are 8 teams remaining in March Madness (the Elite Eight). This makes upsets much more likely, and it also means that a team's ELO could change significantly from the start of playoffs until the end. Because of this, using the team's ELO at the end of the regular season becomes increasingly inaccurate as they play more matches. For example, in the LCS 2020 Summer Split, TSM was the fourth-highest rated team at the start of playoffs and lost 3-0 in the first round. They then won five straight Best-of-5 series to win the championship, playing a total of 25 games in playoffs, even though the regular season is only 18 games.[7] As a result, TSM's ELO increased from 1034 to 1071 in the traditional system and 1022 to 1046 in the modified system. This leap would have put them as the third-highest rated team, and only 5 points lower than the second-highest rated team in both systems. While this would not have been enough to predict their championship outright, it would have been enough to

[7]This is absolutely unheard of in the four major sports in the United States. In baseball, the most playoff games a team can play is 22, compared to a 162-game regular season. In football, the most playoff games a team can play is 4, compared to a 17-game regular season. In both basketball and hockey, the most playoff games a team can play is 28, compared to an 82-game regular season. This does not count the NBA Play-In Tournament, which could add 1 or 2 games, depending on results.

correctly predict the winner of the final, when they played against FlyQuest, who were the third-highest rated team at the start of playoffs.

4.3.3 Possibility of Rematches

The biggest problem, which can be seen as a combination of the first two problems, is that teams may sometimes play twice in the same double elimination tournament, which we call a "rematch." If the result In the time period of interest, there were 18 of these rematches. The team that lost the first series got their revenge in the second series 9 times, with a win-loss record of 38-31 in individual games. Only 1 of these series wins occurred in the LPL, compared to 5 losses, which means that in the LCS, LEC, and LCK, teams were 8-4, 29-16 in individual games, in rematches. The cause of this trend is likely due to the fact that teams must play more matches in the lower bracket, so they gain more experience with the meta, which stands for Most Effective Tactics Available. Because LoL is an online video game available to the general public, it is updated frequently. Usually, these updates can change which champions or items are considered strong. They may sometimes fundamentally change how the game works. A team that understands the meta better would theoretically possess an advantage over a team that does not, even if their ELOs do not reflect such an advantage. The LPL probably does not obey this trend because teams in that league are much more stylistic in nature, meaning that they each develop their own unique strategies of playing the game based on the strengths of their players, with less attention to the meta. Naturally, some strategies counter other strategies, making it harder for a team to get its revenge in a rematch against a team that counters them.

4.4 Ideal K-Factor

Another goal we had was to find the best-performing K-Factor for our updating algorithm. The algorithm was performed repeatedly, changing K by intervals of 0.5, on the LCS, LEC, LCK, and LPL data and the Mean Squared Error (MSE) was calculated by

$$MSE = \sum (S_{ij} - \mu_{ij})^2 \tag{16}$$

for the traditional system or

$$MSE = \sum ((X_i - X_j) - (R_i - R_j))^2 \tag{17}$$

for the modified system. The K-Factor that minimized the MSE for each league was selected, and the results are displayed in Figure 4. The LCS and LPL had slightly lower K-Factors, while the LEC and LCK had slightly higher K-Factors, but it is unclear why this occurred.

League	Traditional	Modified
LCS	24.5	21.5
LEC	34	29.5
LCK	36	28
LPL	23	24

Figure 4: A table showing the best K-factor for each league and system.

However, it should be noted that the optimal K-Factors for the playoff predictions were lower than all of the K-Factors in Figure 4. Moreover, these K-Factors are higher than those used in chess [4]. Recall that lower K-Factors place more emphasis on results further in the past, while higher ones place more emphasis on more recent results. This could indicate that there is some truth to the belief commonly held in most sports that experience is key to winning in the playoffs, but also that there is a lot of variation in results between splits, so ELOs must be updated more quickly to account for that in the regular season.

5 Future Areas of Research

5.1 More Predictions

Because this is a novel area of research, there is much more that can be investigated. The first, which can be done with the existing ELO system, is the prediction of individual matches. Because the playoff predictions were successful when there were fewer matches, it is likely that these predictions will also be accurate. As described in Section 3.5, we can find also find the probability that a team will win a match, whether it is a single game or a playoff series. Using these probabilities, we can simulate the regular season or the playoffs by iterating through the match schedule thousands of times and assigning each team a probability of winning the championship. This would be much more powerful than the current conclusion, which only assigns one predicted winner, which is always the team with the highest ELO rating. However, in order to do this with a high level of confidence, we must also improve the ELO system itself.

5.2 Improving the ELO System

5.2.1 Dynamic K-Factor

Right now, the ELO system is very primitive. The K-Factor is held constant for every player in order to enforce a fixed average rating of 1000. However, this is not what is done for chess.

New chess players have very high K-factors in order to quickly gain a rough estimate of their skill level. This K-factor drops after they play a certain number of games and drops even further if they surpass a certain rating [4]. This idea should be mimicked for our LoL ELOs. In the case of the LCS, each team plays exactly 18 games per split,[8] which is simply not enough to accurately rate a new player by the end of their first split, unless their K-Factor is raised for their first games. That being said, by having different players use different K-Factors, we would not be able to maintain a fixed average rating. However, by applying Equation 13 after each split and year, we can ensure the mean approaches 1000 over time.

5.2.2 In-Game Factors

The system, in its current state, omits many features in LoL. There is only one parameter used to calculate ELO: gold. But this ignores the most important part of the game, the champions that each player controls in the game. Based on the role that they fulfill, some champions naturally demand more gold than others, because they rely on their more heavily on buying items to become useful. There are over 150 of these champions that players can choose from, and it may be possible to assign a gold modifier of some sort to different champions based on how dependent on gold they are. For example, if a champion that wants a lot of gold was matched against a champion that does not need as much gold, the expected result would be that the former has more gold than the latter. But that does not necessarily mean the latter should lose ELO rating, because both players are doing their jobs to help their teams win. Another important aspect of the game that is currently overlooked are various objectives that do not inherently grant gold, the most notable being vision. Vision is a critical component of the game because teams can use it to gain significant advantages in information, which can be easily converted to gold through other actions. Granting vision is one of the primary goals of the Support position, and they sacrifice gold in order to accomplish this goal. This is the main reason why earlier, we assumed that each position contributes equally: Support players give up their own gold so that their efforts can earn the whole team more gold. There are in-game vision statistics collected, which many analysts cite to evaluate Support gameplay, so it could be possible to incorporate these statistics into our calculations.

5.2.3 Esports Factors

As with any professional sport, the business of the sport can often influence performance. In LoL Esports, players frequently change teams and regions, much more frequently than

[8]This number is not fixed in the LEC (as of 2023), LCK, or LPL. Teams that finish in the bottom 2 places of a split only play 9 games per split in the LEC. The LCK and LPL play Best-of-3 series during the regular season, instead of Best-of-1 matches, with 18 and 16 respectively.

in traditional sports. When switching teams, a player must reintegrate themselves into their new environment and learn new strategies to win. Accordingly, their ELO should be adjusted slightly, perhaps another regression to the mean, and their K-Factor should be increased in order to see how the new team affects the player's performance. Moreover, a 1000 rating in the LCS is certainly not equal to a 1000 in the LEC, LCK, or LPL, because these other regions typically outperform the LCS at international competitions. It would be useful to quantify the difference between the regions in terms of ELO points, so we can manually adjust a player's rating when they transfer from one region to another. This would especially be important in the LCS, which imports many players from other regions. This would also enable us to perform similar predictions at international competitions and even simulate the World Championship.

5.3 Synergy Between Players to Build a Team

LoL is a team game, and the assumption that the five roles act independently from each other is simply untrue. The current system was unable to predict the disappointments described in Section 2.1, which most of the applicable teams attributed to poor teamwork and high pressure. This is because these teams would generally play very well in the regular season, when the stakes are not as high. Our algorithm deliberately removes the concept of teamwork, so a new one must be made to account for it. Creation of such an algorithm would be a great accomplishment for the LoL Esports and could be instrumental in helping the LCS develop native teams that can compete with the best teams around the world.

6 References

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7 Appendix

All code and CSV files can be found HERE.

Also see sections 4.1 and 4.2