Interactive Visualization of Team Compositions Using Association Rules in League of Legends

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Introduction

League of Legends (LoL) is a popular multiplayer online battle arena (MOBA) game created in 2009 played by millions everyday. The goal of the game is to destroy the opponent's team base. Two teams of five players each select a champion they want to play and enter the arena. The champions come from a shared pool of about 150 and all bring unique skills and roles to the game. Team composition is extremely important in order to win but most amateur (or general audience) players aim their focus on the fighting aspect of the game (as that is generally the more exciting part). We are going to create a tool to help the general audience with selecting a strong team of champions.

Problem Definition

Research currently leans into the black box problem where the general audience is rather detached from the non-trivial sophisticated solutions, which will be discussed in length throughout the survey section. We can see the limitations of the literature in its accessibility to the general audience and see the popularity of online analytics providers. However, these online analytics providers tend to favor basic descriptive statistics and answer individual based questions relating to the users' operational skills. There is a dearth of solutions that are both accessible and sophisticated in regards to character selection and team composition that primarily focuses on team synergy for the general audience; our goal is to fill this gap.

Survey

In terms of the character selection phase of the game, there are many sophisticated recommendation systems for what characters are most likely to be picked in professional matches using sequential data for both LoL (Hong et al., 2020) and another popular MOBA game Defense of the Ancients 2 (DoTA 2) (Summerville et al., 2021). Hanke and Chaimowicz (2021, 44-46) present a methodology close to our project where the researchers use two sets of association rules for characters in the same team and for characters in the opposing team iteratively to select an optimum team composition where the neural network would finally predict the outcome based on the selections made. Semenov et al. (2017, 26) presents a systematic review by comparing multiple sophisticated models while including interaction terms between characters during character selections that ultimately augmented the performance of their models in terms of predicting game outcomes. Using a Genetic Algorithm, others have developed an approach to automatically generate sets of characters which conform to certain macro-level in-game strategies, although it ignores win probability and has poor player interactivity (Costa et al., 2019). Others have implemented recommendation systems by analyzing the user's history and suggesting similar characters while purposely ignoring statistical win rates (Do et al., 2020).

Pobiedina et al (2013, 62). presents a framework of factors on team formation of a team-oriented online video game associated with win rates. Different attributes of world-class teams in a team-oriented online video game are studied as they relate to the success of the team, with the conclusion that tactical awareness of the team collectively plays a bigger role than operational skill of individual team members

(Xia et al., 2017). It has also been shown that specific teammates can influence the short-term and long-term performance of other players, emphasizing the team element of MOBAs (Sapienza et al., 2019). Feature selection associated with win rates and specific game metrics are discovered using Single and Multi-Layered Neural Networks, and subsequently fed into a Deep Neural Network to predict game outcomes (No et al., 2021). Berner et al. (2019, 43-45) developed ground breaking artificial intelligence systems that played DoTA 2 where similar feature variables were used in the reward function to train the AI systems' actions to maximize win probabilities. We see a rudimentary implementation of Berner et al. by Lohokare et al. where the reward functions are based on spatial distances between the AI system and objectives instead of game metric centered feature variables (2020, 323).

Hong et al. and Summerville et al. focus solely on the pick and ban phase for professional games. The recommendation system by Hanke and Chaimowicz forces users to select specific characters while Do et al. and Afonso et al. completely ignores team compositions and win rates. Semenov et al. attempts to solve the accessibility problem by providing their dataset to the public. Kim, Keegan et al., Pobiedina et al., Sapienza et al., and Xia et al. reinforce our belief that a team-based analysis is more impactful than an individual-based analysis, but Pobiedina et al. and Sapienza et al. only suggest analysis of player-to-player influence whereas Xia et al. only evaluates professional matches. Kim, Keegan et al. demonstrates that, in addition to team decisions for character selection, accounting for character preferences of individual players is important for influencing win probability. No et al. leans into the same problem where the general audience can not interact with or understand the non trivial process. Brener et al. attempts to solve this lack of human interaction by offering the AI systems as a practice tool for humans while Lohokare et al. is still in the developing stages of launching their systems.

Proposed Method

Our project attempts to present a team oriented approach to League of Legends analytics while providing an approachable, interactive, non-trivial, flexible, and simple solution that conforms to the target audience (Bowman et. al, 2012). Users will be able to interact with the graphs and visualize pools of characters with high win rates that the user can flexibly choose from instead of being forced to select specific characters. D3 will be used for graph visualizations, thus users will view/interact from a web browser.

Our objective is to create a visual analytics tool for the MOBA game League of Legends. Our project will be an exercise in data mining with data collected from the Riot LoL API and using pairwise association rule learning (Agrawal et al., 1993) as the base algorithm to find the conditional probabilities associated with item sets (character selections per team). Data collection and association rule learning will be performed using Python. Since association rule learning lacks data visualization, we will leverage the characters and their respective association rules by extending them as nodes and edges and applying graph theory methods to evaluate a global network of popular and high functioning (high win rate) characters while also determining high functioning communities (team compositions).

The first graph will be a global network where directed, weighted edges are confidences from pairwise association rules and node-edge pairs are pruned using support, confidence, and lift thresholds (Kim et al.). The second graph will be an interactive network where users can find communities for a specific character. Undirected, weighted edges will be created using pairwise occurrences of characters and node-edge pairs are pruned using occurrence thresholds (Raeder and Chawla, 2010). Community detection will be used to visualize team compositions associated with the user selected character. We will augment both graphs using aggregated pairwise win rates in conjunction with the pairwise metrics between characters since both aforementioned methodologies lack in determining high value item combinations. Another layer of differentiation between Kim et al. and the team's first graph is that we will also prune the node-edge pairs using lift thresholds since lift is a measure of dependence.

For the first graph, users will be able to see a large force-directed graph and intuitively understand the relationship between characters as seen in the leftmost graph in the below figure:

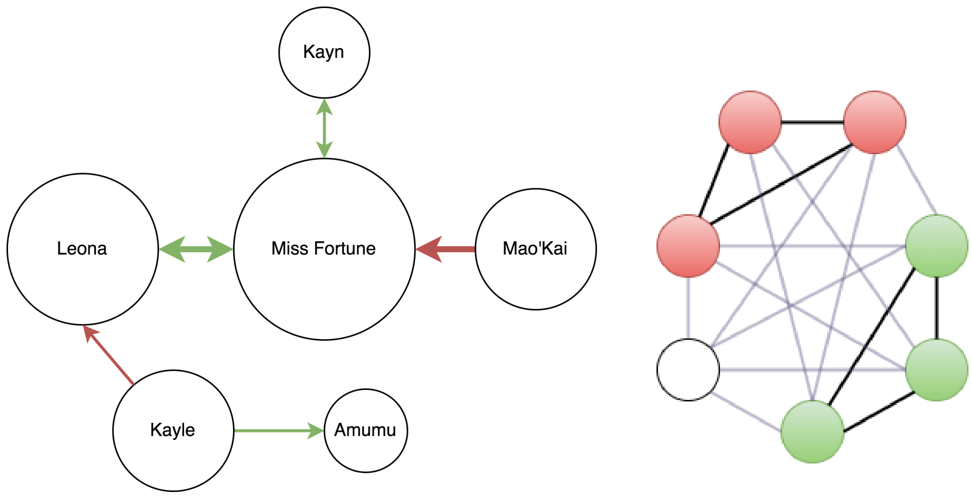

Figure 1. Example force-directed graph with weighted edges, varying node/edge size, and edge directionality on the left. Example force-directed graph with isolated communities on the right.

The first graph can be understood as followed:

1. The larger a node is, the more popular the character is;
2. The larger the edges are, the more popular the pair is;
3. Directionality of edge indicates dependence; in other words, if a team member has chosen Kayle, the user knows that Leona or Amumu are frequently chosen also;
4. If the edges are green, the pairs of characters have a high win rate whereas red edges indicate less than optimum win rates; and finally,
5. Hovering over edges will display a tooltip indicating the win rate for that pair.

For the second graph, users will be able to see a large force-directed graph with community detection enabled. The graph validation process includes popularity of team compositions and associated win rates. The user will be able to understand that these teams are not only popular but powerful as well.

For both graphs, the user will be able to not only understand which compositions have higher associated win rates, but also be able to have an assortment of characters that the user can choose from depending on their preferences. Thus, we can conclude with a list of innovations to summarize our approach:

1. Provide an intuitive, interactive, and flexible solution for LoL character selection;
2. Incorporate/emphasize dynamics of character synergy in the selection phase by
    a. Augmenting Kim et al. network analysis of itemsets by including directed edges via confidences and pruning said edges using lift measures and aggregate pairwise win rates, and
    b. Augmenting Raeder and Chawla's methodology by including pairwise win rates to determine high value compositions.

Experiments/Evaluation (In Construction)

As of writing the progress report (10/30/2021), we are currently on schedule in terms of data collection, and slightly ahead of schedule in terms of data processing according to the following:

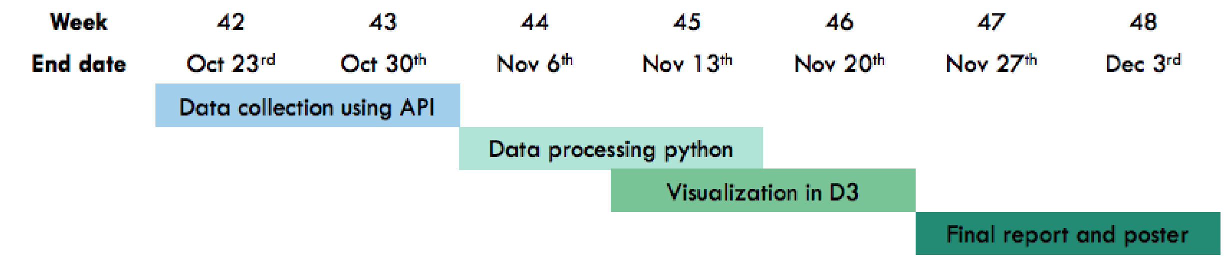

Figure 2. Gantt chart of project milestones.

There are currently 1,834,906 rows of clean data ready for analyzing.

	Top	Jungle	Middle	Bot	Support	Win
0	Darius	Viego	Katarina	Kaisa	Thresh	1
1	Diana	Kindred	Yone	Ashe	Yuumi	0
2	Jayce	Olaf	Sylas	Samira	Yuumi	1
3	Volibear	Warwick	Khazix	Zed	Yasuo	1
4	Fiora	Kayn	Yasuo	Kaisa	Brand	0
5	Jayce	Warwick	Qiyana	Xayah	Rakan	0
6	Nasus	Viego	Diana	Samira	Seraphine	1
7	Irelia	Zed	Lissandra	Aphelios	Morgana	1
8	Malphite	Graves	Lux	Jhin	Soraka	1
9	LeeSin	Warwick	Veigar	Tristana	Pyke	0

Figure 3. Excerpt of cleaned data in proper format.

As stated in prior deliverables, all stakeholders have contributed equally to the project activities thus far, including the data collection part. Due to the rate limit of the Riot LoL API, each member was assigned a geographic region of the LoL servers and laboriously extracted 100,000+ rows of data from said region. Two milestones have been reached; all members have demonstrated sufficient knowledge of the Riot LoL API, and more than 500,000 rows of data have been collected. The next milestones are to have processed graph data (due Nov 13th) and their visualization in D3 (due Nov 20th).

The first graph will be worked on by Jos, Cheukming and Johnnie. Christopher, Hanbit and Hyeongsun will take care of the second graph. We do not have a detailed distribution of tasks for the other parts of the project, but our experience so far is that everybody is fully invested and wants to contribute. This is supported by us being ahead of schedule at the moment. We will distribute tasks more formally if we fall behind schedule. The remaining tasks include: Calculating pairwise win rates, creating graph data, pruning graph data according to graph specific metrics, and data visualization using D3.

All codes, data, and findings have been posted on the team's private GitHub repository. Access will be granted for CSE6242 course staff upon request.

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