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Our objective is to create a visual analytics tool for players of the popular multiplayer online battle arena (MOBA) game League of Legends (LoL). Our project will be an exercise in data mining using pairwise association rule learning (Agrawal et al., 1993) as the base algorithm to find the conditional probabilities associated with item (character) selections. 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 undirected, weighted edges are supports from pairwise association rules and node-edge pairs are pruned using support threshold and respective confidence levels (Kim et al., 2012). The second graph will be an interactive network where users can find communities of a specific character by creating undirected, weighted edges using pairwise occurrences of characters, node-edge pairs are pruned using occurrence thresholds, and community detection (Raeder and Chawla, 2010) to visualize team compositions associated with the user selected character. We will augment both graphs using aggregated pairwise win rates in conjunction to the pairwise metrics between characters since both methodologies lack in determining high value item combinations.

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).

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Research currently leans into the black box problem where the general audience is rather detached from the non-trivial sophisticated solutions. 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. 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.

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. Moreover, other accessible, sophisticated visualization tools further attempt to maximize users' operational skills irrespective of team composition (Afonso et al., 2019). 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.

According to Twitchtracker.com, there were an estimated 149,143 average viewers for the month of September on the popular streaming platform Twitch.tv. According to Activeplayer.io, there were an estimated 123,954,700 average players in the last 30 days. There are currently 5,386,372 subscribers to the League of Legends community on the popular social media platform Reddit.

If successful, we can possibly change the paradigm on advanced analytics within the general scene. We plan on raising awareness of our project on multiple social media platforms, such as Reddit and Twitter. We can release surveys on the aforementioned platform to gauge player responses.

Risks include the rate limitations with Riot's API, deploying complicated graphs using D3 and Javascript, and improper data processing using Python. Payoffs include providing an accessible analytics tool to the general audience that complements the current paradigm of analytics that focuses on operational skill by adding a team dimension focused element. Furthermore, the project will cost $0.00.

During Oct 18 - 31, data collection using Riot's LoL API and data processing will be performed. During Nov 1 - 14, data will be analyzed using Agrawal's algorithm and Python to create proper data to be used by graphs while also writing the progress report. Nov 7 - 22 will be focused on deploying the graphs with user functionality using D3 . Nov 23 - Dec 3 will be focused on procuring the final report and poster presentation. All team members will contribute equally to the data collection, data processing, and data visualization phases and to the rough drafts of the final and progress reports. Final drafts of the progress and final reports will be done by the team contact.

Midterm exams to check for success include: sufficient knowledge of Riot API's documentation, at least 500,000 rows of clean data, and creating proper graph data. Final exam metrics include intelligible graphs and user functionalities, such as character selection, edge value filtering, community isolation, etc.

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