ICCS261 Term Project Report: Z-LPER - Creating a Composite Metric for Ranking League of Legends Professional Players

Topic: creating a new composite metric that can be used to rank the individual performance of professional League of Legends players.

Problem Statement: The performance of professional League of Legends (LoL) players is most often assessed based on team performance and subjective analyst rankings, often referred to as the "eye test." However, these assessments do not always provide a comprehensive or fair representation of a player's true impact on the game and can be prone to biases. At present, there is a significant lack of objective, statistical ranking systems within the LoL Esports scene, despite the industry being watched by millions. In contrast, nearly every other competitive discipline has established ranking systems to identify the top-performing individuals. The absence of such a system in LoL Esports presents challenges for historical accuracy, performance prediction, and match analysis.

This gap in objective evaluation highlights the need for a statistical metric to rank the individual performance of League of Legends professionals. The goal of this project is to develop Z-LPER, a new composite metric designed to accurately rank professional LoL players. Z-LPER integrates a variety of statistical factors, such as gold per minute (GPM), kills, deaths, assists, and other key metrics identified through testing. By creating this composite metric, the aim is to provide a balanced and objective assessment of a player's contribution to their team's success, which can be used for player rankings, comparisons, and in-depth analysis of individual performance.

Research Design

1. **Aggregation of Data from OraclesElixir**
   I start by collecting player statistics from OraclesElixir (provider of comprehensive statistics per year of LoL Esports) for each year from 2014 to 2024. This gives a comprehensive dataset of performance metrics such as gold earned, kills, deaths, assists, etc. per game played, which will allow for a thorough analysis of player performance over time.

2. **Cleaning the Aggregated Dataset**
   Once the data is aggregated, I cleaned it by removing incomplete or corrupt rows and columns. Any missing or invalid data points are either fixed or discarded, ensuring the dataset is accurate and ready for analysis.

3. **Preparing the Dataset for Testing**
   Since the goal is to create a metric that evaluates individual player performance, I chose to discard any team-oriented statistics such as objectives taken, team gold, etc. Next, I used correlation tests (Pearson correlation) to identify and remove multicollinearity. Highly correlated variables (above 0.8) were removed to prevent redundancy, making the dataset more efficient for analysis.

4. **Hypothesis Test on Player Statistics**
   I conducted a hypothesis test to determine if individual player statistics significantly impact game outcomes. To do this, I trained a Logistic Regression model using all of the statistics in the prepared dataset as input, and the outcome of each game (win or loss) as the target variable. I then plotted a graph displaying the p-values for each feature in the resulting model and extracted every feature below p-value 0.05 to use for my composite metric.

5. **Creating the LPER Formula**
   After identifying the significant statistics, I proceed to calculate their weights by training a Random Forest model using only the significant features as input, with the outcome of each game as the target variable.

   This approach allows me to determine the weights of the selected metrics without normalizing the data, which I avoid due to the varied nature of the features and for ease of calculation. The resulting weighted statistics are then aggregated into the LPER (League of Legends Player Efficiency Rating) formula, which ranks players based on their individual performance and impact on game outcomes.

6. **Separation of Roles**
   Next, I calculated the average LPER for each unique player in the database. One of the initial observations from the LPER scores was that players in certain roles, such as ADC (Attack Damage Carry), were disproportionately favored. ADC players often have higher gold-related metrics due to their in-game role, which was likely what skewed their rankings.

   To address this, I separated players into role-specific tables. By comparing players only within their roles, I ensured that the metric accounted for the unique responsibilities and statistical profiles of each role, whether it be the gold-heavy ADC or the vision-focused Support.

7. **Region Adjustment**
   A second major bias emerged from regional differences. Players from weaker regions, such as North America, were ranked on par with players from highly competitive regions like Korea. This disparity arose because the datasets treated all regions equally, ignoring the differences in competition levels.

   To mitigate this, I adjusted player scores using Riot Games' official regional ELO rankings. These rankings provided a benchmark for the relative strength of each region, allowing me to weigh players' performances based on the competitiveness of their environment.

8. **Z-Score**
   Even with role-based separation and regional adjustments, comparing players across roles required further normalization. This was achieved through Z-Scores, which measure how far a player's performance deviates from the average performance in their role. By standardizing scores within roles, I could compare players from different positions on a level playing field.

9. **Z-LPER**
   To make the final scores more interpretable, I scaled the Z-Scores by multiplying them by 1000 and rounding to integers. This resulted in Z-LPER (Z-Score League of Legends Player Efficiency Rating), which preserves more than enough precision while offering a more intuitive scale reminiscent of ELO for ranking players. The final step involved merging the role-based tables into a unified ranking sorted by Z-LPER.

10. **Evaluation**
    The final stage of this process was dedicated to evaluating the Z-LPER rankings for their accuracy and fairness. This step was particularly critical, as it provided an opportunity to validate whether the metric achieved its goal of objectively ranking players based on their individual contributions.

    To begin, I conducted qualitative analyses by comparing the Z-LPER rankings with existing expert opinions and widely accepted rankings in the League of Legends professional scene. This comparison involved reviewing insights from analysts, commentators, and historical records of player performance in international tournaments. The goal was not to perfectly replicate these subjective rankings but rather to ensure that Z-LPER aligned with observable performance trends while introducing a more data-driven perspective.

Results and Discussion:
The findings of this research provide several important insights:

1. **Alignment with Expert Consensus:**
   When comparing the Z-LPER rankings to expert opinions from analysts and professional casters, the results aligned closely with the average consensus. This indicates that Z-LPER has significant potential for application in League of Legends Esports analysis, offering a data-driven complement to traditional subjective rankings.

2. **Low Correlation with Player Accomplishments:**
   A low correlation was observed between Z-LPER rankings and player accomplishments, such as trophies won or MVP statuses. This suggests that individual metrics alone cannot fully encapsulate a player's greatness or contributions to their team's success.

3. **Faker's Ranking as a Case Study:**
   The ranking of Faker, widely regarded as the greatest player of all time, illustrates this limitation. Despite his unparalleled achievements—5 Worlds titles, 10 LCK titles, and an MSI trophy—he ranks only 28th in Z-LPER. This highlights how intangible qualities like leadership, adaptability, and clutch performance are not captured by individual metrics alone, a challenge also seen in other sports.

4. **Regional Bias Towards LCK Players:**
   The rankings are heavily skewed toward players from the LCK (the strongest region by Riot ELO), reflecting the region's dominance in international competition. However, standout players from weaker regions, such as Caps from the LEC, appear to be underrated. This raises questions about whether the metric is overly biased toward stronger regions or if analyst sentiment may overrate players from less competitive regions for inclusion purposes or personal biases.

5. **Recent Players Outperforming Historical Players:**
   The rankings suggest a preference for more recent players over those whose careers peaked in earlier eras. This observation raises a critical question: Is the game becoming progressively more optimized, leading to better statistics for newer players, or does Z-LPER inadequately adjust for differences in play styles across eras? This debate underscores the evolving nature of competitive gaming and the challenges of cross-era comparisons.

6. **Raising Key Questions:**
   These findings bring forward larger discussions about the balance between subjective and objective evaluation methods in esports, the influence of regional strength on player metrics, and the challenges in evaluating players across different time periods. By highlighting these issues, Z-LPER not only provides a fresh analytical tool but also serves as a starting point for deeper conversations within the community.

Discussion/Limitations:
There are numerous limitations with this research including, but not limited to:

1. **Exclusion of LPL Data:**
   A significant limitation is the absence of data from the LPL (the second strongest region by Riot ELO). This omission excludes many top-tier players who would have provided critical data points for training the model and refining the Z-LPER metric. The lack of LPL representation limits the universality and accuracy of the rankings, particularly when comparing players from regions with incomplete data.

2. **Lack of Prior Research:**
   To my knowledge, no similar statistical analysis of League of Legends players has been conducted prior to this research. This absence of prior work means there are no established benchmarks or comparable studies to validate or contrast the findings. Consequently, qualitative methods, such as analyst rankings and expert opinions, were relied upon for validation, which may introduce subjectivity into the evaluation process.

3. **Emphasis on Individual Metrics:**
   Z-LPER's focus on individual statistics means it cannot account for intangible qualities like leadership, synergy, or adaptability, which are often critical to a player's success. This limitation was particularly evident in the lower rankings of players like Faker, who excel in areas not captured by quantitative metrics.

Conclusion
Z-LPER provides a data-driven approach to ranking professional League of Legends players, aligning well with expert opinions while highlighting challenges like regional biases and limited data. Despite its constraints, it offers a strong foundation for future refinement to creating a valuable tool for deeper analysis in League of Legends Esports.