Player Roles in Competitive League of Legends
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League of legends is a very complicated game with many aspects of the game to consider to determine the skill level of a player. Most analysts, players and spectators believe that league of legends usually needs more than the surface level of stats that are presented on the broadcast such as KDA (kill + assists/ deaths) because it is a team game and many aspects of the game cannot be measured (roamings, flanks, communication,etc). There is also an ongoing debate about players not being restricted to one role because players can and should be able to exercise flexibility. My goal is to explore both these ideas to see if there is any validity to these community sentiments. \

A website named Oracle's Elixir (well known in LOL analyst community) has a compiled list of all 6400+ games played in 2020, broken up by individual players and team stats that can be measured with certain ease: https://oracleselixir.com/tools/downloads. Since that is too large of a subset, I have decided to focus on only Worlds 2020 matches played on patch 10.19 because those are the matches with most importance. I have also decided to ignore team data and focus only on the roles and individual players. I have computed some rows in the dataset using other columns such as KDA, kill+assist/team kills(KA), deaths/team deaths(Dtotal), etc. I have used a variety of different stats, different for each figure.

Figure 1 tries to tackle my first question about simple stats versus a more comprehensive score. Ranking support players in league of legends using regular metrics is very difficult because their roles are less defined (they don't collect gold, they don't kill monsters/objectives, they usually don't do damage). K/DA is usually not reflective of skill level, so I created my own scoring assessment taking into account 11 other stats important to assessing supports such as KA, Total, visionscore, gold per minute, xp diff, first blood assisting, dmg per minute, dmg mitigation, warding, etc. My scoring system actually generally reflected my ranking of best to worst supports in different tiers(S to C), with Mikyx, CoreJJ or Beryl at the top and most of the play-in supports at the bottom. There are 22 supports playing at worlds (114 games * 2 = 228 support games), the legend based on my tiered rankings and the graphs depicts that supports with high KDA had incredible games with the scoring metric (right most on the graph or purple/blue dots) but it especially highlights the players that had great games with a lower KDA and differentiates them from the worse players at worlds (left side upper half, blue/purple dots). It also affirms that certain support with a bad KDA really did have bad games (left side lower half, red/orange dots). Overall, the consistency of the higher tier supports was impressive, none having a score less than 40-50, despite a lower KDA like other supports. By simply including a few more metrics, the better players were more appreciated. Clearly only going off KDA is not the way to judge the support role.

Figure 2 tries to show how a lot of the positions in league of legends are similar and how some are also different. I have always been curious if it is actually possible to differentiate between mid, top and bot roles because they all do most of the damage, spend the game killing minions, collecting and spending gold. So, I decided to do a 2 component PCA on all the position based stats such as damage and gold share (discluded all of the stats that would show large differences in player performance such as gold diff or xp diff) to determine the positions (top, jng, mid, bot, sup) based on the position stats features. First I used a standard scaler fit_transform on my position stats features. Next, I did a PCA with 2 components fit_transform on the standard scaler results, then I graphed my results. The results were as I expected, mid, bot and top were not distinguishable because of the role similarities and lack of distinguishing differences in the stats. It also highlighted that support is the most different from the carry oriented roles (mid, bot, top). Jungle is in the middle because the role has the capacity to carry but rarely is the case and they also spend the most time in the jungle killing monsters and not minions.

Figure 3 is showing the class weights after running a logistic regression pipeline. Before running it through the logistic regression, I did a train_test_split on the data. The pipeline included both a polynomial feature (to the second power) and a standard scaler. This improves the overall score by about 8% (around 80%). I used 4 different features that best indicated role differences, (cs, monster kills, damage to champs, damage mitigated). After this occured, I found the coefficient scores and filtered them to the most relevant scores (>0.5 or < -0.5), then I graphed the coefficient scores for the 5 classes and the recall score for logistic regression. This figure shows that monster kills were especially key to determining the class of an entry in almost all cases, mainly being the determining factor for either being jungle or not the jungle role (since monsters are found in the jungle). Total cs was also another feature that was weighted heavily, especially the lack of cs determining support role and presence of cs indicating a carry role (top, mid, bot). Damage mitigation was also helpful in differentiating the top position from bot and mid, probably since top laners usually play tanks or bruiser champs that frontline damage for mid and bot players. The recall score shows that there was a 100% score for jungle, 95% for support and 90% for top lane. This means that the data was able to identify these roles clearly from the data given. However, mid had an extremely low score of 35% and bot of 70%. This can be concluded because mid and bot can both carry and support in special circumstances, which could lead to the mix ups in the model.

Fig 1: My Scoring vs KDA

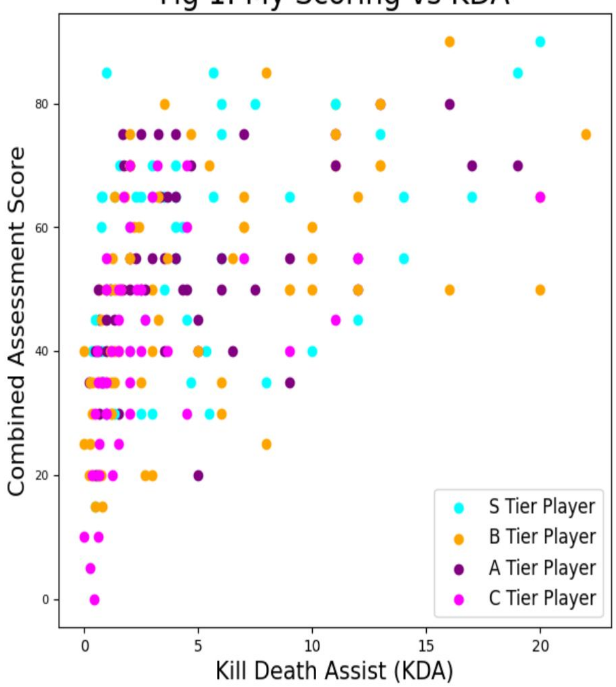

Fig 2: 2 component PCA

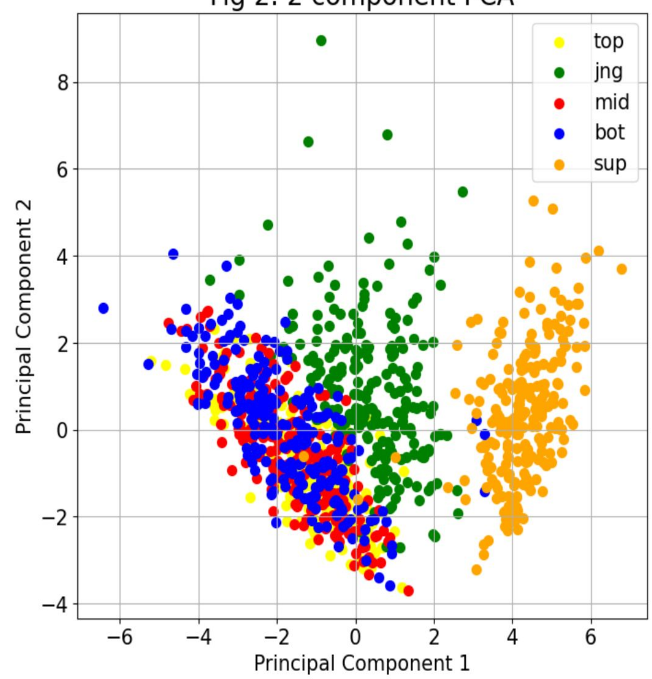

Fig 3: Class Weights