FINAL TECHNICAL REPORT
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CHOOSE YOUR SIDE: PLAYING SELFISH OR SUPPORTIVE

ABSTRACT

This project is about video games. This project specifically includes MOBA games. The idea is about players game styles in this games. Our team thought that the players adopted more aggressive play style in these games. Based on this, we discussed the data of two world popular games. By choosing the relevant criteria, we decided which data could be evidence for us. We conducted research on the selection of the necessary methods and techniques for the use of these data. We decided to make visualizations about the characters in the games. We obtained insights using the game statistics of the players and the machine learning methods we chose for our project. The first of these methods we chose allowed us to divide the players into clusters with k-Means. According to the data we obtained as a result of the Kmeans algorithm, we divided the clusters according to the death and killing rates of the players and divided these clusters into categories as supportive, aggressive, full supportive, full aggressive and noobs. As the second method, we used the Decision Tree. We created a Decision Tree structure based on the averages of the death, kill and assist scores of the characters we knew about the game type before.

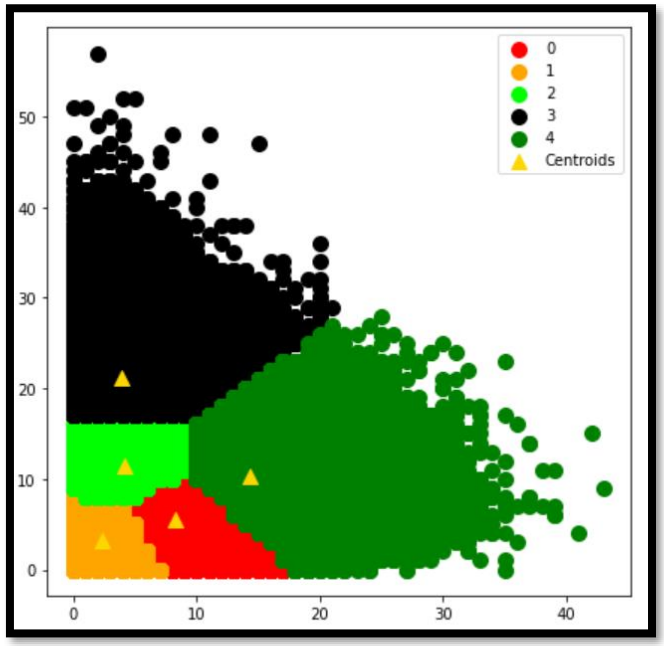

Figure 1: LOL KMeans Output

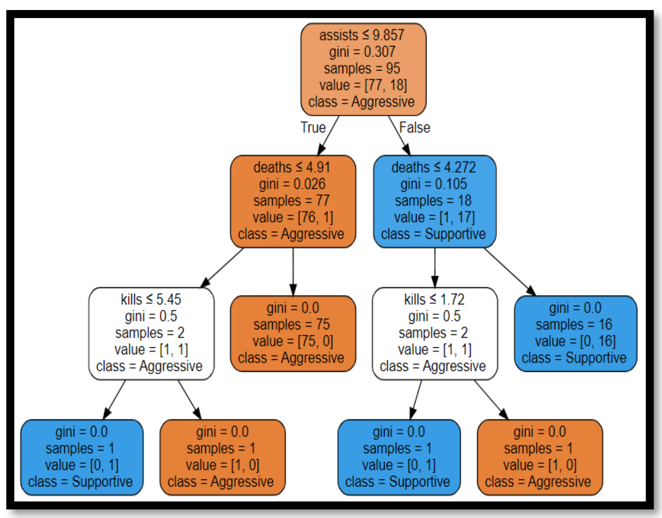

Figure 2: LOL Decision Tree Output

INTRODUCTION

We are working on how the selfish or supportive choices of the players affect the fate of the game. These games are trend in online world. People playing and watching them excitedly. Also players spend remarkable time for these games. But people's selfish game styles can negatively affect the result in MOBA games. We wanted to examine this situation specifically through data. We think that people's real-life characters are reflected in the way they play. Therefore, this research will also help us analyze the characters of the players. For this reason, our topic is very interesting. Also we are interesting with questions like : which type of characters do the players prefer, which characters are commonly chosen?

1. DATASETS

In first step, we used datasets about League Of Legends and DOTA. Datasets include LoL and DOTA games, champions, stats, matches statistics. Our datasets available in this link:

https://drive.google.com/drive/folders/1sv2068wcvvtYPBMUKscdCGayWN0Wu5Rm?usp=sharing

We shared all of them via Google Drive so you can easily access all datasets.
We used the loc method for choosing columns in dataset. Then we applied head method for get top values in datas. Then we needed merge different datasets for decide champion’s types as aggressive or supportive. For this reason, we used pandas merge method.

2. METHODOLOGY

We decided to use k-Means clustering method for learn players game styles like aggressive or supportive. Firstly, we get data about players kill, death and assist stats for each match from our datasets. Then we applied k-Means this data and got a distribution. In this distribution, we have different regions. Some them represents the game styles which we interested in. If players have lots of kills and few assists it means their style is aggressive. On the other hand, if players have lots of assists and few kills it means their style is supportive. We used this technique for cluster players kill/assists then decide the game styles.

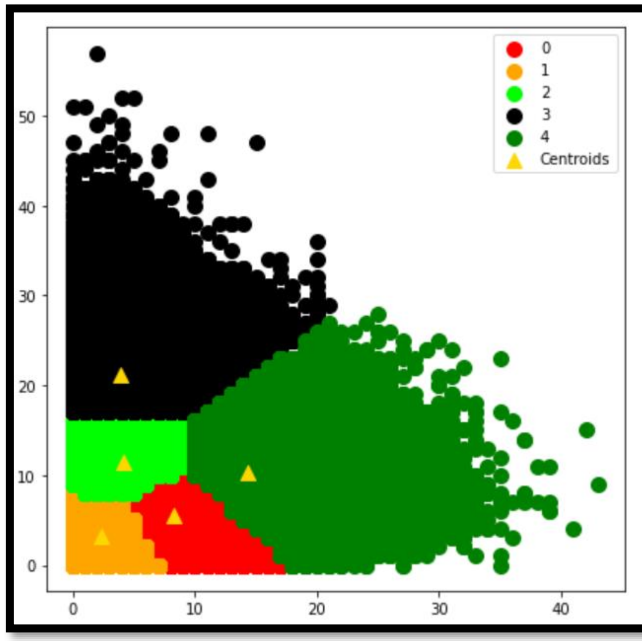

Figure 3: LOL Kmeans Output

In this graph, the Y-axis includes the assist scores of the players, while the X-axis includes the kill scores of the players.

Clusters close to the Y-axis are composed of players with a more supportive playing style, while clusters close to the X-axis are composed of players with a more aggressive playing style.

Players with low kills and assists are in the yellow cluster and we defined them as noobs players. Noob literally represents players with low knowledge and skill level in a game.

Using the K-Means algorithm, we divided about 1 million records into 5 clusters based on kills and assists. The upper left cluster (black cluster) in the clusters reflects the more supportive type of player. The cluster on the right (green cluster) reflects the more aggressive type of player.

1. Cluster 0 (Agressive) -> 233.901 %23 of players
2. Cluster 1 (Noobs) -> 312.281 %31 of players
3. Cluster 2 (Supportive) -> 245.914 %24 of players
4. Cluster 3 (Full Supportive)-> 88.573 %10 of players
5. Cluster 4 (FullAgressive)-> 119.330 %12 of players

- %34 of total players are supportive.
- %35 of total players are agressive.
- %31 of total players are noobs.

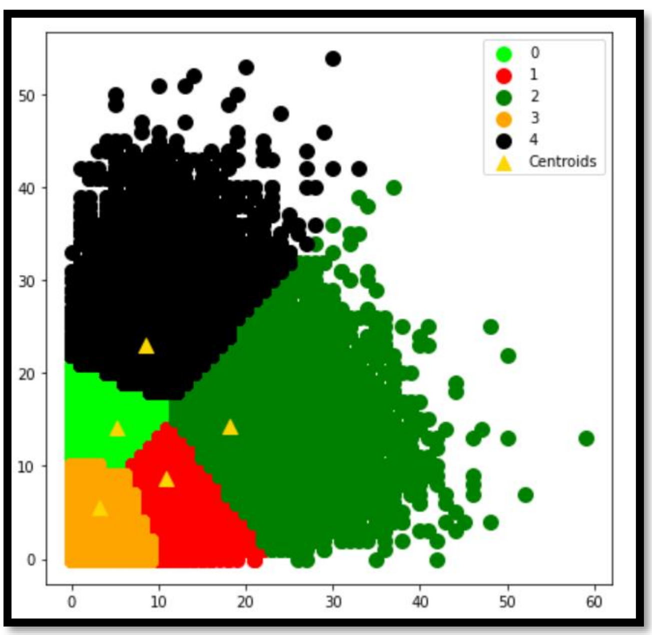

Figure 4: DOTA Kmeans Output

Same K-Means algortihm for DOTA 2 datasets which has 500.000 records.

1. Cluster 0 (Supportive) -> 142.853 -> %28 of players
2. Cluster 1 (Agressive) -> 91.034 -> %18 of players
3. Cluster 2 (Full Agressive) -> 53.280 -> %10 of players
4. Cluster 3 (Noobs) -> 148.700 -> %30 of players
5. Cluster 4 (Full Supportive) -> 64.133 -> %14 of players

- %42 of total players are supportive.
- %28 of total players are agressive.
- %30 of total players are noobs.

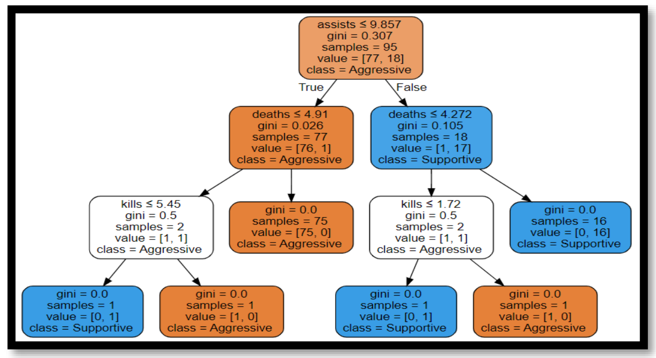

Figure 5: LOL Decision Tree Ouput

For the game in LOL and DOTA 2, we designed our decision trees along with the average death, assist and kill data of the characters. Then it was concluded whether the in-game characters were played in an aggressive or supportive manner, and a success rate of about 93% was achieved.

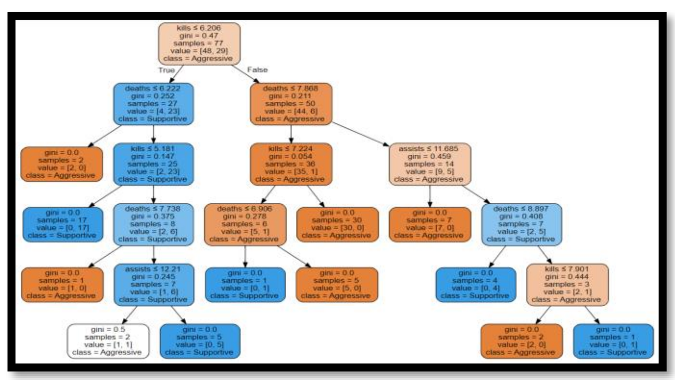

Figure 6: DOTA Decision Tree Output

3. EXPERIMENTS AND RESULTS

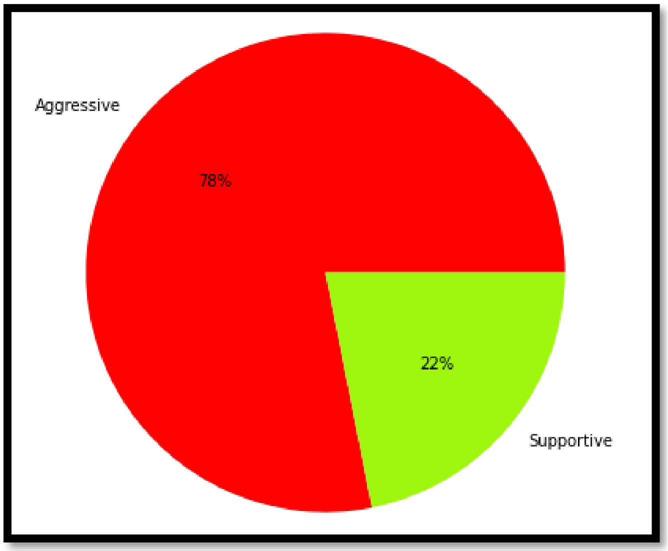

Figure 8: LOL Most Selected Characters

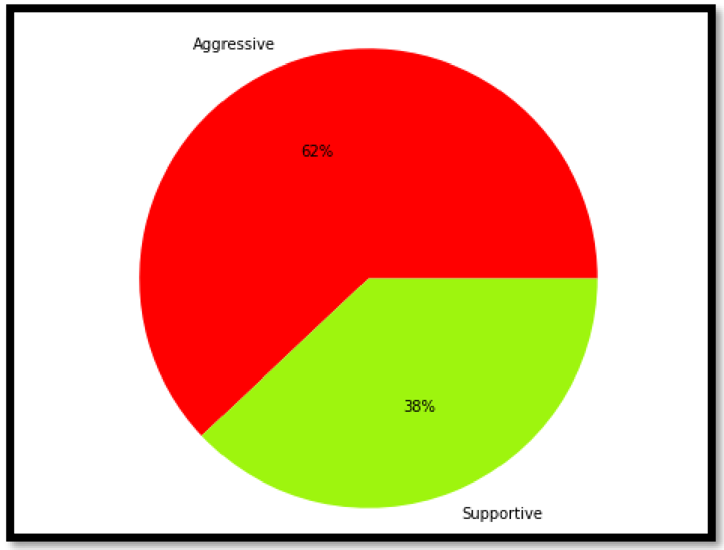

Figure 7: DOTA Most Selected Characters

In the graphic in Figure 7, we have compared which type of character the players in the LOL game mainly choose. In order to make this ratio, we used 3 different datasets and merged these datasets with each other. While our first dataset contains the ids and names of the characters, our second dataset contains the data of all players who played in 180 thousand matches. Since there are 10 players in a match, there were a total of 1.8 million character selections. In our last dataset, the playing styles of the characters are specified. By combining these 3 datasets, we reached the supportive or aggressive ratios of the selected characters in total and visualized it in a pie chart.

In the graphic in Figure 8, we have compared which type of character the players in the DOTA game mainly choose. There were a total of 0.5 million character selections.

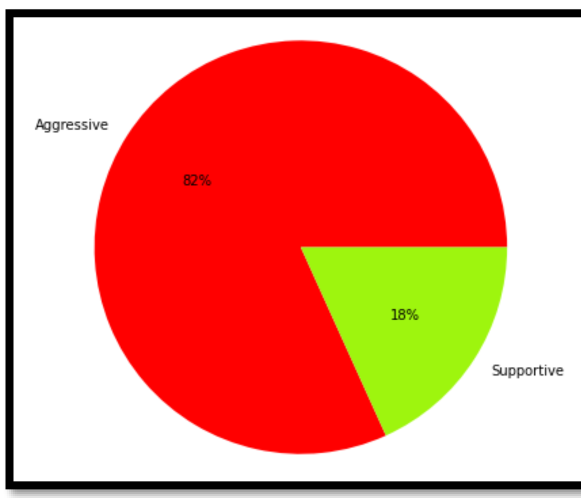

Figure 9: LOL Most Banned Characters

In Figure 9, we have grouped the most banned characters in the LOL game according to their playing style. We performed this grouping using the "groupby" function with the same technique as in the previous charts.

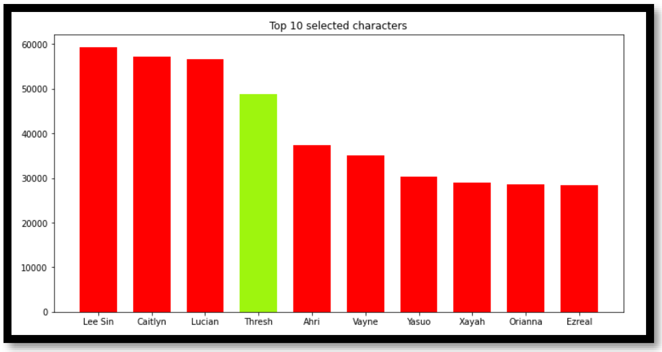

Figure 10: LOL Top 10 Selected Characters

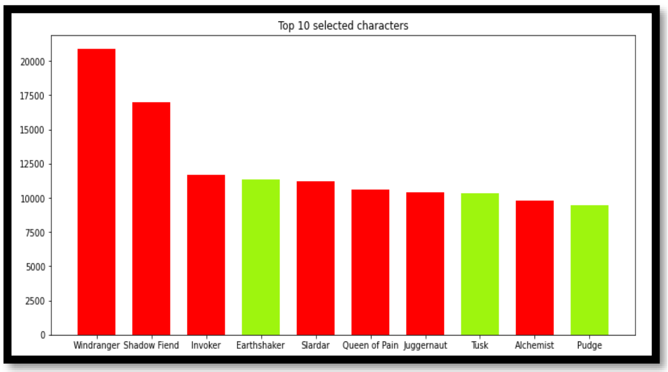

Figure 11: DOTA Top 10 Selected Characters

As can be seen, an average of 8 of the 10 most selected characters in LOL and DOTA games are aggressive characters. In both games, we showed the 10 most selected characters along with how much they were chosen on the bar chart and observed this result.

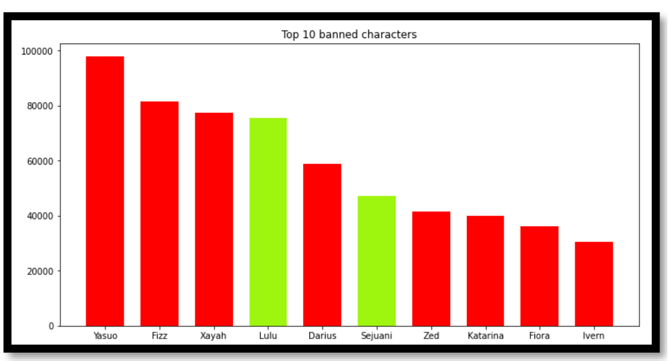

Figure 12: LOL Top 10 Banned Characters

As can be seen here, it is seen that 8 of the 10 most banned characters in LOL are aggressive characters.

4. CONCLUSIONS

According to the data we visualized, we examined whether the players played aggressively or supportively. In the graphics, it is seen that the players choose the characters with more aggressive play style. Although the players choose aggressive characters, 82% of the players in the opposing team do not want the aggressive character to come against them and therefore they are banned.

As we predicted before, LOL and DOTA players like aggressive characters more and play more.

According to the results we got in the K Means algorithm, approximately 33% of the players in the two games are "Noob" players. When we cluster the players according to the number of kills and assists, although the players choose aggressive characters, the rates of playing in an aggressive and supportive style are approximately equal.

5. REFERENCES

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