Exploring Archetypes in Profesional Gaming

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Abstract
In professional gaming, team compositions are crafted carefully to ensure that players are of the highest skill level compatible with each other. However, the process by which players are able to work together, in both professional and non-professional gameplay, leaves room for exploration. In this paper, we use game data sourced directly from League of Legends to analyze similarities between ranked gameplay to gain insight on whether archetypes exist in professional and non-professional gaming.

1 Introduction
League of Legends is a MOBA game that is played competitively worldwide, and is strongest in the East Asian regions. For this paper, we both employ methods to research and compile information about internal game data, as well as attempt to build a representation of player-types within League of Legends.

The task of constructing player archetypes in League of Legends to accurately depict the 150 million players across its 13 different servers is in itself, a problem that requires an extreme amount of data processing to create a large set of data. As such, we will simplify our approach to only analyze the Korean server, simply due to the abundance of data and the country's dominance in e-sports, and construct archetypes for one server as opposed to sampling through all 13 servers.

2 Dataset
2.1 Dataset
The Riot environment is difficult to acquire data off of, and there was no appropriate dataset online that provides in-depth analysis of player gameplay for a large set of players.

To select a set of players and games to analyze, the dataset of professional players chosen were those that participated in the 2019 Spring Professional League (LEC, LCK, CBLoL, LMS, LPL, LCS). The dataset for the non-professional players was chosen through a dataset of high-elo Korean server games, whose players were then extracted and the appropriate data was extracted from each.

To construct an archetype, the standard decided was to average the statistics from *at least 10* games per player, minimizing the possibility of an off-game causing a misrepresentation of the player's abilities. Although there were few datasets that provided partial information of gameplay for sets of players, there was not data to sufficiently average out and analyze a player's abilities. Due to the limitation of dataset completeness, we instead opt to pull the most complete set of game data directly from the Riot API for every game included in the set of players.

In terms of the amount of data pulled, there are 5,000 hand-pulled games from the Korean non-professionals, and a complete set of statistics for every player that participated at one point in time. Therefore, we will attempt to claim that the results from this paper only guarantee to be accurate during the 2019 spring season, at the point in time that the professional player data was pulled.

3 Model Descriptions and Procedures

3.1 K-Means Clustering

To effectively analyze all the games data, we will first cluster players by their game performance, and analyze whether the standard roles exist in each cluster. Instead of employing the standard Elbow method to select the number of clusters, where increasing the clusters could potentially lead to overfitting, we evaluate the standard five declared roles in League of Legends: Top, ADC (Attack Damage Carry), Support, Middle, and Jungle to determine the types of players that fall into each archetype.

3.2 Cluster Analysis

The accuracy of our clustering in relativity to the current game-defined roles can be determined by examining the ratio of players that construct teams in this manner.

The following parameters will be defined as such.

1. The accuracy is defined as the number of players that fall into one of the distinct categories (without another team member included in the same category), over the total number of players on the team.
2. The role error is defined as the number of players that do not fit into the most common role for that category, over the total number of players in the category. The parameter is evaluated on a scale of 1.0 (complete fit) to -1.0 (no fit). We will accept values that are positive, at least half are fit.
    a. For example, assume that Cluster 0 has 5 BOT, 2 TOP. The TOP players will be considered as an error point for the regional stats.

3.2.1 Professional Gameplay

To validate the initial construction of our clusters, we will assume that professional teams are the gold standard of team composition. As such, the clusters constructed from the aggregate of all players in the 2019 spring season will be measured against when considering the results of the non-professional players.

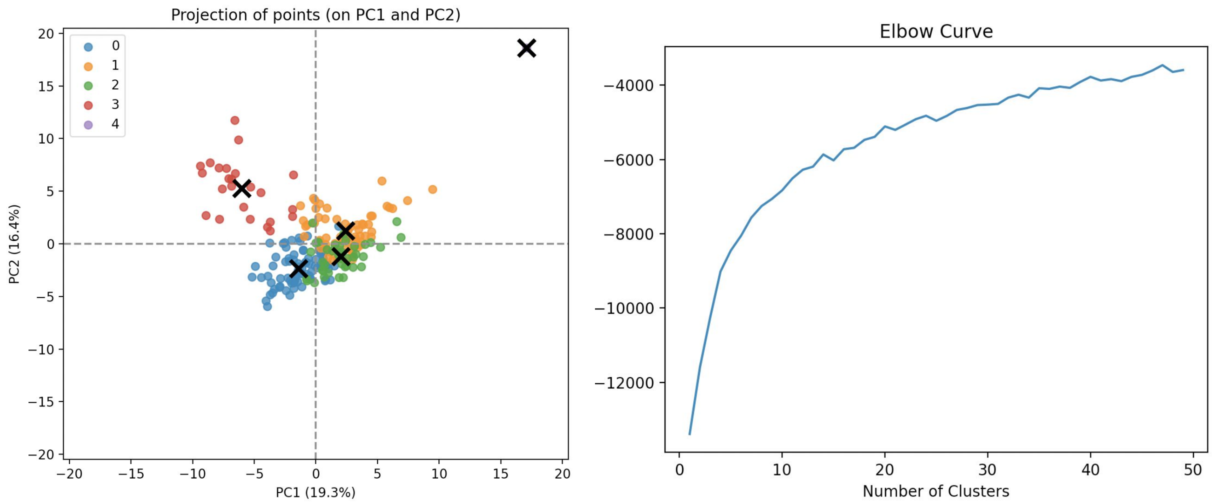


Figure 1: Professional Player Team Clustering

Tournament	Teams Considered	Player Count	Accuracy	Role Error
LEC	Fnatic, SK Gaming, Splyce, Excel Esports, Vitality, Schalke 04, Rogue, Misfits, Origen, G2 Esports	68	0.6444	1.54043
LCK	SK Telecom T1, Jin Air Green Wings, Damwon Gaming, Gen.G, KT Rolster, Hanwha Life Esports, Kingzone DragonX, Griffin, Sandbox Gaming, Afreeca Freecs	85	0.600833	1.243333
CBLoL	Flamengo eSports, KaBuM e-Sports, Vivo Keyd, Uppercut esports, ProGaming Esports, Redemption eSports, INTZ e-Sports, CNB e-Sports Club	59	0.666667	0.970370
LMS	G-Rex,J Team,AHQ e-Sports Club,MAD Team,Alpha Esports,Dragon Gate Team,Hong Kong Attitude,Flash Wolves	67	0.620000	0.496667
LCS	Team Liquid,Cloud9,100 Thieves,Team SoloMid,Counter Logic Gaming,OpTic Gaming,FlyQuest,Golden Guardians,Clutch Gaming,Echo Fox	79	0.580476	1.362222
LPL	Snake Esports,Edward Gaming,Funplus Phoenix,Rogue	134	0.668750	1.093750

	Warriors,Invictus Gaming,Topsports Gaming,JD Gaming,Bilibili Gaming,LGD Gaming,OMG,Suning,Royal Never Give Up,SinoDragon Gaming,Team WE,Victory Five,Vici Gaming			
MSI	Phong Vu Buffalo,Bombers,Fenerbahce Esports,Isurus Gaming,MEGA Esports,DetonatioN FocusMe,Vega Squadron,INTZ e-Sports,Team Liquid,Flash Wolves,G2 Esports,SK Telecom T1,Invictus Gaming	80	0.713333	1.371667

Table 1: Professional Player Teams Aggregates

K-means naturally has variation in its clustering, and as such the role error changes ever so slightly depending on edge-case players who are closely between clusters. As such, while the calculation of difference in one or two role values may change the role error, the majority of roles being played within a cluster remains the same. Thus, the accuracy for the clusters will remain the same, as the teams for professional gameplay are consistent and their roles are set.

3.2.2 Non-Professional Gameplay

That being said, for non-professional players, without further data processing, it is difficult to get a good measure of their team composition. Therefore, we will analyze on a game-by-game basis, redefining the following parameters and establishing the following assumptions.

1. A game that the player with majority losses will not be considered, as winning will be considered as an assumption of a good team composition. An overhead of a good win rate is 50% or higher, and winrates of 20-40% are on the lower end of acceptable. In this case, we will use players that are above the 20% threshold, in assumption with the balancing algorithm within Riot's system.
2. The role error is thus defined as the percentage of wins in which the player's current role matches the most common role for that category, over the total number of players in that category.

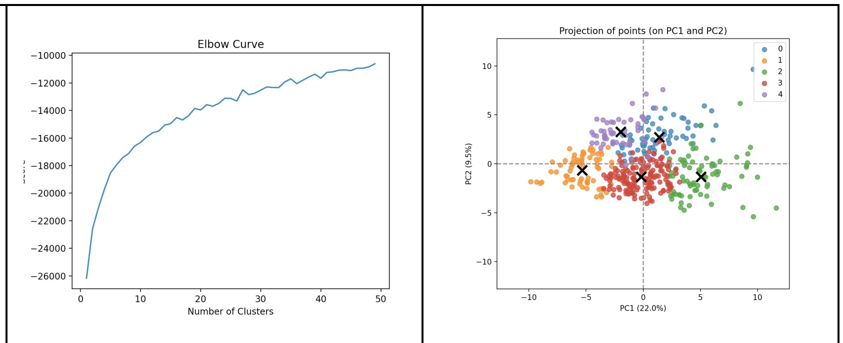
Cluster Characteristics	Player Count	Role Error
0	136	0.613971
1	268	0.336431
2	221	0.497738
3	26	0.615385
4	143	0.79021

Table 2: Average Korean Player Performance

The above table is computed through averaging the values of 4 k-means runs, as randomization causes the clusters to be very slightly different each time. The tolerance, or the amount that the centroids may shift per re-iteration, is set to 0.001, the standard tolerance defined in documentation for k-means[1].

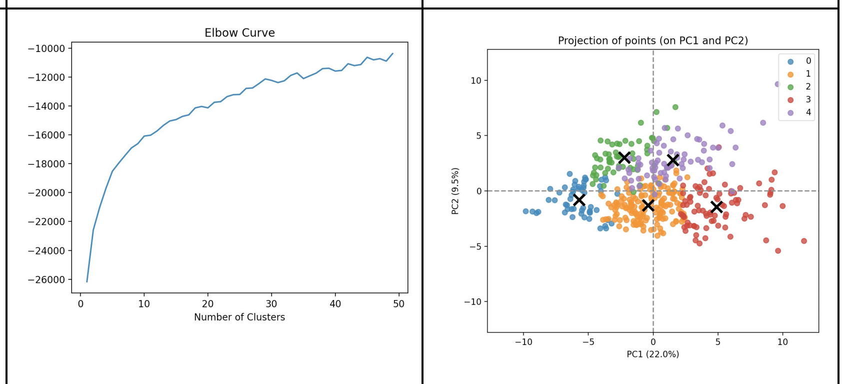
Cluster	Player Count	Role Error
0	146	0.791096
1	49	0.646259
2	209	0.509569
3	271	0.357934
4	120	0.612500

ARE = (0.791096 + 0.646259 + 0.509569 + 0.357934 + 0.612500) / 5 = **0.5834716**



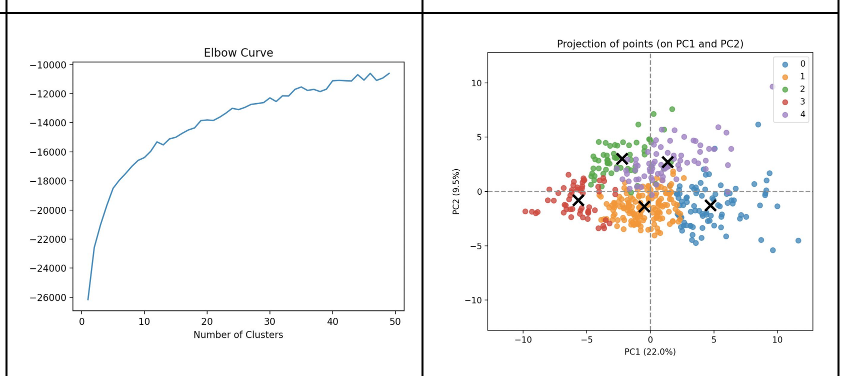
Cluster	Player Count	Role Error
0	26	0.615385
1	276	0.340580
2	136	0.613971
3	213	0.511737
4	144	0.791667

ARE = (0.615385+ 0.340580+ 0.613971+ 0.511737+ 0.791667) / 5 = **0.574668**



Cluster	Player Count	Role Error
0	230	0.478261
1	253	0.355731
2	136	0.613971
3	28	0.750000
4	148	0.790541

ARE = (0.478261+ 0.355731+ 0.613971+ 0.750000+ 0.790541) / 5 = **0.5977008**



Cluster	Player Count	Role Error
0	148	0.790541
1	253	0.355731
2	136	0.613971
3	230	0.478261
4	28	0.750000

ARE = (0.790541+ 0.355731+ 0.613971+ 0.478261+ 0.750000) / 5 = **0.5977008**

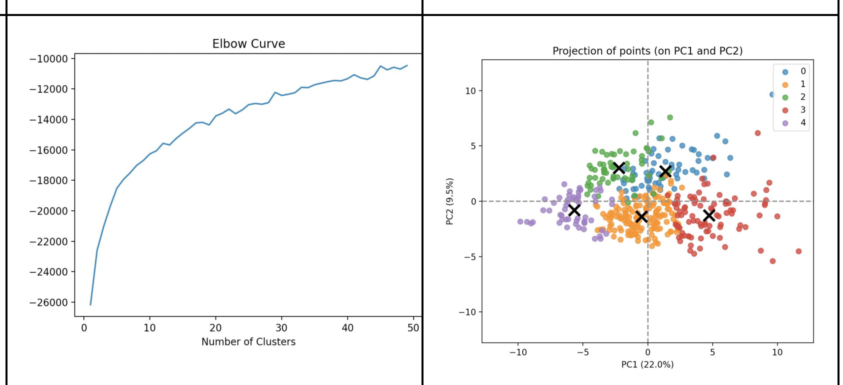


Figure 4: 4 Iterations of K-Means for Non-Professional Players

4 Results

The accuracy and role error of each of the clusters is represented in the above tables.

In terms of pro-player performance, the clusters were much less defined, with the last cluster being insignificant. As exhibited by the non-professional players performance, the division between centroids and variation among players was much greater than those of the professionals. This variation can both be attributed to the raw greater amount of non-professionals sampled, but also due to the variation in skill of the players sampled.

The professional clusters tended to all converge towards a tightly compacted sector, in which does not exist in the non-professional clusters. For a highly skilled non-professional, the reason that separates them from being a professional is likely due to a gap in their skill. The strong association between professional clusters likely demonstrates the extent to which professionals have reached a skill bar that leaves little room for error, unlike those of their non-professional counterparts.

The role error for each professional player cluster was much lower than that of non-professional player performance, likely due to less ambiguity between players in terms of their roles, as well as each having a distinct playstyle during tournament games as opposed to standard ranked games. For professional players, the average role error of 1.154 was much closer to a perfect score, defined as 1.0, meaning that all players strongly associated with a certain archetype cluster. In contrast, the non-professional player sample averaged 0.588, meaning that approximately a quarter of players in a cluster were playing roles that their performance did not match up against.

$$\textit{average role error (ARE)} = 1/n * \sum_{i=0}^{n} \textit{role error}$$

$ARE_{professional} = (1.54043+1.24333+0.970370+0.496667+1.362222+1.093750+1.371667) / 7$
$ARE_{non\text{-}professional} = (0.5977008+0.5977008+0.574668+0.5834716) / 4 = 0.5883853$

5 Conclusion

With the above results, it is clear that there are a set of archetypes that exist for the general League population, but players are more similar and less archetypes for higher skill levels. This is exhibited in the difference in cluster strength, as well as the accuracy of classifying players into certain roles within clusters.

Further research could explore the possibility of classifying different play styles within the clusters themselves, and using those playstyles to emulate professional players. That being said, the playstyle of non-professionals will be much less coherent than those of professionals, who are trained to work well together. Other methods could instead go the route of using a kNN, which would allow for a better recommendation system, which could apply to players looking to construct teams that emulate a certain game experience. By matching players whose playstyles are more naturally compatible, this approach could help lower the amount of toxicity between players in-game, resulting in an overall more positive experience playing the game for all players.

6 References

[1] Sklearn.cluster.KMeans. (n.d.). Retrieved December 20, 2020, from https://scikit-learn.org/stable/modules/generated/sklearn.cluster.KMeans.html