Social Network Analysis of High-Level Players in Multiplayer Online Battle Arena Game

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Abstract. Recently, the MOBA (Multiplayer Online Battle Arena) game has become one of the most popular video game genres. It is also known as the DotA (Defense of the Ancients)-like game. As an online-based matching game, it could be important to analyze players' social structure. In LOL (League of Legends), the most popular MOBA game, players form a team and fight against enemy together. In the games, they build communities like other conventional social network service (SNS). In this paper, we analyze the social network of LOL constructed from the team/players data extracted by official API (Application Programming Interface). Especially, the ranks of players are considered in the analysis. The experimental results show the important features of social structure of LOL useful for the applications of player modeling and match making.

Keywords: Social network · Online game · Multiplayer Online Battle Arena

1 Introduction

Recently, the MOBA (Multiplayer Online Battle Arena) game such as LOL (League of Legends) has become one of the most popular video game genres. They are an online matching game with simplified RTS (Real-Time Strategy) game environments. In the game, several players are grouped into two teams and compete each other as a team. It looks like RTS games but each player has control of only one powerful character (champion). Instead, other parts of the game are handled by AI (Artificial Intelligence) and human players focus on their character. It's interesting that the game has social network of players similar to conventional SNS (Social Network Service) such as Twitter, and Facebook. In the SNS, each user connects to others with friend relationship. In this work, we investigate the social network of LoL in order to find useful knowledge. LoL has become very popular and provides API (Application Programming Interface) to access team/players data.

There are some works on social network or community analysis of online games. Lim and Harrell propose novel approach for player preference modeling based on social network data [1]. They use social network data in *Steam* to predict player customization in their profile of *Team fortress 2*. Bialas *et al.* survey the relationship

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adfa, p. 1, 2011.

between culture and game playing style in *Battlefield 3* [2]. They use game statistics in *Battlefield 3* to measure the competitiveness, cooperation, and tactics of each player and compare them based on the nationality of players.

In this paper, we analyze the LOL social network. To the best of our knowledge, it is the first time to apply social network analysis to the MOBA game genre. We implement data crawlers using official API to collect user data. In the LOL, there are leagues based on ranks and player's performance. It is one of the important features in match making. Hence, we analyze the players' league in the same team. It can help to understand the way users create the teams.

2 Data Collection

The data for LOL includes the information about summoner, ranks, leagues, teams, games, and statistics of games. LOL provides an easy access to in-game data and we build data crawler based on the API. Like web crawlers, it starts from some seed players. It send queries with player's ids to collect the player's detailed information and corresponding teams. In fact, each player can create several teams and it is similar to friendship in conventional social networks. In the network analysis, two players in the same team are friend. The crawler continuously extracts the friends of the player and send queries with the friend's id.

We use top 100 ranked players' ids as the seed players. Because it is easy to get high ranked players' name from the game community site. On the other hand, collecting low ranked (common) players' ids is relatively hard. Therefore, we concentrate our effort on the collection of high ranked players' data. Since they are royal to the game, we expect they can show important social structure of this game.

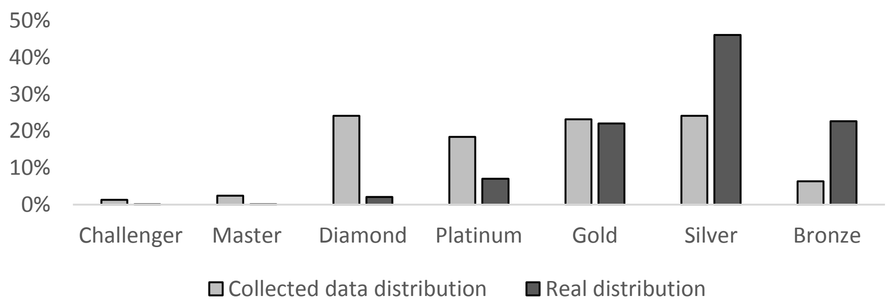

Fig. 1. Distribution of player league

We collect about 23,000 players' data for two weeks (August 2014) in Korea server. Fig. 1 shows the distribution of players based on their ranks. In LOL, there are seven layers of players and they call it a league. The *Challenger* is the highest league and the *Bronze* is the lowest. Also, there are unranked players but we ignore them in this study. It shows that the crawlers collect data mainly from the high and middle ranked players (Challengers, Master, Diamond, and Platinum). Because the crawler starts from the top best players, it takes much time to get enough low-ranked players. Also, the official API has several constraints to speed up the data crawling (currently, only 10 times in 10 seconds).

3 Social Network Analysis

Fig. 2 shows the social network structure of players' in higher league (Challenger, Master, Diamond, and Platinum). At the center of network, there are approximately 6,000 nodes (players) and 12,000 edges (friend relation). The average number of friends is 2.139 ± 3.644 for Challenger, 2.839 ± 4.097 for Master, 3.103 ± 4.092 for Diamond, and 2.891 ± 3.778 for Platinum. In the most of league, each player has average two or three friends. There are trends that the number of friends of higher ranked players (Challenger and Master) is slightly lower than medium ranked players (*Diamond* and *Platinum*).

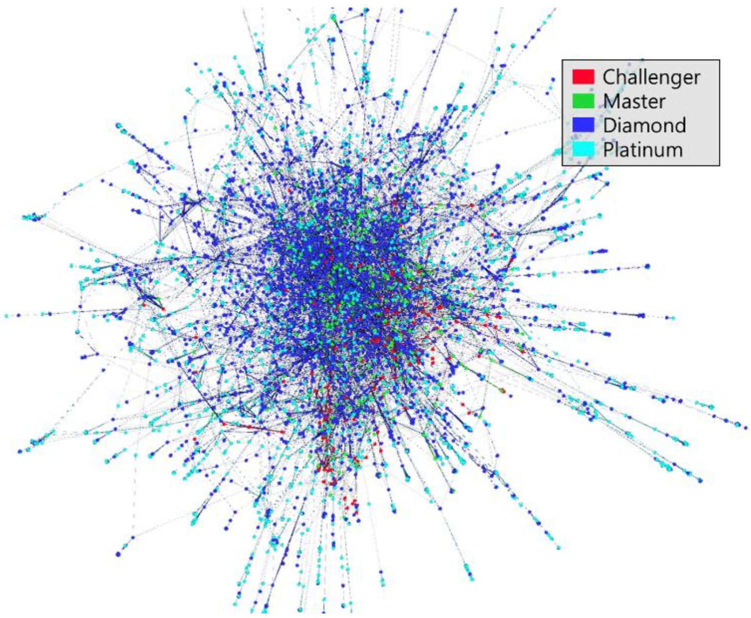

Fig. 2. Social network visualization

Usually, we can guess that each player makes teams with others from the same or similar leagues because it is the most natural strategy to form a team. However, sometimes players could create a team with the players from different leagues. We can interpret that it is the special situation, for example, they are friends in real world although they're not at the same levels. Table 1 shows how many players make a team with different leagues. Each league in row is the team owner's league and horizontal is the team participant (the friend of the team owner). This table shows the result similar to the number of friends analysis. Players in *Diamond* and *Platinum* make many teams and players in *Challenger* and *Master* make fewer teams. Also, it seems to be that *Diamond* and *Platinum* players make teams with the same league players, but sometimes *Challenger* and *Master* players make teams with lower league (*Diamond*) players. Probably, this happens because the number of players are limited in *Challenger* and *Master*.

Table 1. Distribution of friends in different league

	Challenger	Master	Diamond	Platinum
Challenger	19.2 %	3.4 %	9.5 %	1.5 %
Master	1.4 %	25.2 %	14.2 %	2.2 %
Diamond	0.6 %	1.5 %	41.3 %	4.2 %
Platinum	0.2 %	0.3 %	5.7 %	36.3 %

4 Conclusion

In this paper, we perform basic analysis of LOL (*League of Legends*) social networks structure. The LOL is the one of the most favorite MOBA games. We focus on how players make a team. Each player can make several teams. Usually, we can guess that each player makes a team with others with similar performance. In order to investigate LOL players' social structure, we collect data using our crawler. It uses LOL official API and collects data of players' in higher league (*Challenger*, *Master*, *Diamond* and *Platinum*) in Korea server for two weeks. We investigate the number and types of friends for each ranks. The results show that each player creates teams with players in the same league and their average number of friends are about 2~3. Also, there are difference between high ranked players (*Challenger* and *Master*) and low ranked players (*Diamond* and *Platinum*). Usually, high ranked players make small number of teams compared to the low ranked players.

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