Social Networks

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1 Introduction

League of Legends (also known as LoL) is a "Multiplayer Online Battle Arena" (MOBA) game, released on October 27, 2009 by Riot Games. The game has gained a lot of popularity since its release and in July 2012 became the most played computer game in the world. The game has three main maps that the user can play. There are a number of different game modes for some of the maps, but in all of them the purpose of the game is the same and only the amount of players or the objective of the game changes accordingly. Players compete against each other in groups of between 3 to 5 players in games that last an average of 15-30 minutes, depending on the map and game status. In all different game modes, all team members work together to win, by destroying the main team of the rival team, the Nexus. In all game modes, the player controls the character / hero (Champion) chosen by him before the game starts. Each hero has a different set of 4 abilities and one passive ability, plus 2 abilities in which each player can choose from 11 fixed abilities available to everyone.

Figure 1: Gameplay

2 Goal

Teams can be defined by their interactions and their successful performance that rely on the behavior of their team members. In the first article [1], networks will serve as a new approach to understanding how League Of Legend professional players help each other during a competitive game and link their social behavior-mediated computer interactions to their team's performance. And the main purpose of the second article [2] is to classify those players into cluster groups related to their ego game habits, starting from solo to team players.

3 Novelty

Although the advent of research has focused on MMORPG over the past decade, few studies come close to multiple online games from genres or sub-genres and other subspecies like MOBA games. Few games show a greater need for social awareness services than this relatively new genre, as it brings new ways to collaborate and compete on the table, address cultural challenges, and even new social networks that have to deal with inherent behavior in these contexts.

In the first article, the author also compares traditional sports with eSports, and draws conclusions that match the nature of the game.

4 Data

In the first article, a dataset containing all professional matches since the 2014 World Championship is extracted. The data contains basic information about 7,582 matches played by 244 teams. 190,060 kills happened over the recorded matches with 453,386 assists in total (therefore, in average, every kill is helped by slightly over half of the rest of the team).

In the second article all matches played in 2016 by each of 439 players were extracted through the League of Legends API provided by Riot (both articles used the same API). As a result, a total of 228,117 matches were obtained, with a mean of 520 matches per player (SD=424). Therefore, for each player and for each match, the relationship between all team members is registered. Every relationship is counted as many times as it appears. Thus, the weight of the link reflects how many matches two players have played together.

Extra of the information was taken from a RIOT survey is covered part of type of peoples plays the game. This information described the player character.

5 Method

In the first article, the author construct multiple graphs that for each match 2 graphs are created and compare between those graphs for their performance on the game. Linear regression is used to estimate linear relationships between the obtained and performance variables. Random effects considerations are added to linear mixed-effects models to determine whether effective network structures League of Legends are independent of their region, year or season. To ascertain whether increased interaction intensity within a team is associated with higher team performance and increased concentration of interaction affects negative team performance. Linear regression is a machine learning method for finding the parameters of the relationship between an independent variables X and a dependent variable Y, assuming that their relationship is linear, that is, the form Y = aX + b.

In the second article the authors construct one network where nodes are players and edges are weighted how many times they play with each other on the same team. Clustering analysis is implemented by unsupervised machine learning affinity propagation algorithm technique that allow to discover hidden structures in data where the ground truth is unavailable. The goal of this technique is to find a natural grouping in data such that elements in the same cluster are more similar to each other than those from different clusters. This technique force to divide to groups without promise how many, unlike K means algorithm that promise K groups. The package used in this analysis is the standard Python scikit-learn library.

6 Centrality Indicators

First article:

6.1 In and Out Degree

the indegree quantifies the tendency of a player to receive actions while the outdegree does the same with the tendency to make them. It is thus possible to define the outdegree $C_{OD}(i)$ of a node i as the sum of the values of the outgoing edges (assists by this player) and the indegree $C_{ID}(i)$ of a node i as the sum of the weights of the incoming arcs (therefore, the number of assists a player receives in his or her kills).

$C_{OD}(i) = \sum_{j=1}^{N} W_{ij}$
$C_{ID}(i) = \sum_{j=1}^{N} W_{ji}$

consider W_{ij} as the number of assists from player i to j during a match and N as the number of nodes. Assist ratio AR will then be defined as the ratio between number of assists A and kills K in the network, so the interaction opportunities will be controlled.

6.2 Weight centralization

A network is decentralized when centralities are balanced across the actors in the network. We want to find a group closeness index that is purely node based - sum of the differences between the largest node centrality score and the scores of all other nodes in the network divided by the maximum possible sum of differences. As in the node case, a player network would then be less centralized when all tie values are similar and more centralized otherwise, reaching the minimum at equal weights.

$C_W = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N}(W^{max} - W_{ij})}{(N^2 - N - 1)A}$

where W_{max} is the maximum observed weight across the network.

6.3 Node centralization

Degree centralization is the simplest definition of centrality when looking at the players only, in the sense that the nodes with most ties are the ones that could be considered most active.

$C_I = \frac{\sum_{i=1}^{N}(C_{ID}^{max} - C_{ID}(i))}{(N-1)A}$
$C_O = \frac{\sum_{i=1}^{N}(C_{OD}^{max} - C_{OD}(i))}{(N-1)A}$

Second article:

6.4 Degree

The degree of a node, denoted by d(n_i), is the number of edges that are incident with it. Equivalently, it's the number of nodes that are adjacent to it. alters with a small degree will indicate players that played with few other of the ego's alters, while a high degree will show the opposite. The degree measures how related to the ego's social circles: the higher the degree, the closer to the core of the ego's playing community that alter is.

$\bar{d} = \frac{\sum_{i=1}^{N} d(n_i)}{N} = \frac{2E}{N}$

6.5 Node density

Every processed match can add up to four different players to the ego network (the fifth player is always the ego). Therefore, by construction, the maximum possible number of nodes N_{max} equals four times the number of matches (m) the player joined.

$NodeDensity = \frac{N}{N_{max}} = \frac{N}{4m}$

6.6 Betweenness centrality

In the player-centric network, as it's highly possible that the ego reaches new players through his or her frequent colleagues or friends. Betweenness centralization (C_B) for a node $n_k \in$ G can be defined as the number of shortest paths between n_i and n_j that pass through n_k ($\sigma(n_i, n_j|n_k)$) divided by the total number of shortest paths between n_i and n_j (σ (n_i,n_j)).

$C_B(n_k) = \sum_{n_i,n_j \in G} \frac{\sigma(n_i,nj|n_k)}{\sigma(n_i,nj)}$

6.7 Components and largest connected

Let N be the total number of nodes in G and N' the number of nodes in the largest connected component. It's then possible to calculate the largest component proportion as N' divided by N. While the number of components might give an indicator of the different groups of play that the ego has, this proportion will provide an indication of how large is his or her main playing group.

6.8 Modularity

As we learned in the class, a key feature of social networks is high transitivity, meaning that if n_i is connected to n_j and n_j is connected to n_k, there is a high chance of having a connection between n_i and n_k too. This property leads to the formation of clusters called communities. The quality of this division is often measured by the modularity of the partition, a scalar value between -1 and 1 that measures the density of links inside the obtained communities as compared to the links between them.

$a_s = \sum_t e_{st}$

$Q = \sum_s (e_{ss} - a_s^2)$

e_{st} is the fraction of edges in the network that connect nodes in group s to those in group t.

7 Results and Finding

In the first article two main hypotheses have been formulated: first, that the level of interaction or intensity (assists), when controlled by the interaction opportunities (kills), leads to improved team performance. Second, that centralizing efforts in a few players result in worse performance than distributing these efforts over the team.

Multilevel regression results for gold per minute.

	Hypothesis	Linear	(1)	(2)	(3)	(4)
Fixed part						
Kills/min	–	658.69^{**} (0.000)	665.80^{**} (0.000)	661.58^{**} (0.000)	663.84^{**} (0.000)	687.87^{**} (0.000)
Intensity (AR)	> 0	27.82^{**} (0.000)	27.38^{**} (0.000)	26.00^{**} (0.000)	25.63^{**} (0.000)	24.44^{**} (0.000)
Indegree centralization	< 0	-49.02^{**} (0.000)	-43.90^{**} (0.000)	-43.69^{**} (0.000)	-43.88^{**} (0.000)	-45.39^{**} (0.000)
Outdegree centralization	< 0	-27.40^{*} (0.031)	−21.48 (0.057)	−20.60 (0.052)	−20.09 (0.058)	−15.77 (0.099)
Random part						
$\sqrt{\psi_1}$ (Team)		–	97.67	82.62	83.60	48.06
$\sqrt{\psi_2}$ (Opponent)		–	–	68.07	66.15	31.60
$\sqrt{\psi_3}$ (Region)		–	–	–	30.71	17.05
$\sqrt{\psi_4}$ (Year/Season)		–	–	–	–	123.61/9.09
Team effects		No	Yes	Yes	Yes	Yes
Opponent effects		No	No	Yes	Yes	Yes
Region effects		No	No	No	Yes	Yes
Year/Season effects		No	No	No	No	Yes
Observations		15,164	15,164	15,164	15,164	15,164
Log likelihood		–	−93,944.6	−93,220.2	−93,180.5	−91,460.3

p-Values in parentheses.
* $p < 0.05$.
** $p \ll 0.001$.

Figure 2: Multilevel regression results for gold per minute

In the second article the resulting networks were analysed and eight structural indicators were computed for each of them. In order to infer the underlying hidden structure, machine learning techniques were used, applying an affinity propagation algorithm. After a few iterations and removal of individual variables, the best clustering was achieved with three indicators: modularity, number of components (standardized) and the proportion of nodes covered by the largest emerging component found in the network. Together, they establish four degrees or categories that describe how social the ego (or the player) is in his or her gaming habits.

Indicators extracted from sample player-centric networks.

	Matches	Nodes	Modularity	Standardized Number of Components	Largest Component Proportion
C1	693	1335	0.323	0.059	0.878
C2	668	1606	0.598	0.178	0.690
C3	699	2069	0.775	0.383	0.423
C4	699	2641	0.992	0.816	0.058

Figure 3: Indicators extracted from sample player-centric networks

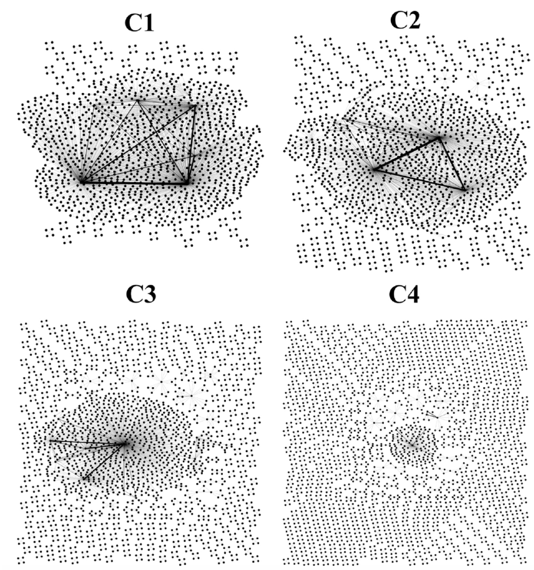

Figure 4: Graphical representation of sample player-centric networks

from the obtained information can then be used for player segmentation, both to improve player experience (by adapting the game to their structural social needs) and to improve the game (adapting its matchmaking system).

8 Improvements

We can check if rank depends on more than pure results (e.g. playing with honour, being a good teammate, helping others). there are many more events that could be considered and extracted, such as other helpful interactions (healing, stunning, slowing). We can add character sorting to figure out what combination of characters to use. We can use the survey that used in the second article and using the graphs method in the first article and then we will extract more information about them.

References

[1] Team efficiency and network structure: The case of professional League of Legends. Marçal Mora-Cantallops, Miguel-Ángel Sicilia. University of Alcalá, Alcalá de Henares, Madrid, Spain.

[2] Player-centric networks in League of Legends. Marçal Mora-Cantallops, Miguel-Ángel Sicilia. University of Alcalá, Alcalá de Henares, Madrid, Spain.