Team efficiency and network structure: The case of professional League of Legends

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Abstract

Teams can be defined by their interactions and successful performance rests on their members' behaviour. Although this topic has been studied both in sports and management, research on computer mediated team interactions, communication, cooperative work and efficiency in online competitive environments is scarce. In this article, networks will be used as a novel approach to understand how League of Legends professional players assist each other during a competitive match and to link their computer mediated behaviour and social interactions to their team's performance. Starting from a dataset consisting of 453.386 kill assists, the network structure and efficiency is assessed over 7.582 matches in total. After controlling for potential mixed-effects, such as the quality of the involved teams or their geography, this study reinforces previous research showing that team efficiency in the League of Legends professional scene is positively affected by the intensity of their interaction while centralization of resources is detrimental. Networks with high intensity and low inner centralization are, therefore, related to a higher performance as a team not only in traditional sports but also in computer mediated contexts.

Keywords: Network structure, Team performance, Cooperative work, Efficiency, Centralization

1. Introduction

What makes teams effective? This is a topic that has been relevant for researchers since organizations started to grow in size and people. One of the earliest examples is the work conducted at the Hawthorne Works of Western Electric in the 1920s (Roethlisberger and Dickson, 1964; Whitehead, 1938), a time when the determination of optimum working conditions was "left largely to dogma and tradition, guess, or quasi-philosophical argument"

(Mayo, 2004, p.69). While the former were looking to increase workers' productivity, Mayo (2004) already proved that group structures were shaped by interpersonal relations and placed the organization of teamwork (sustained cooperation) among the three persistent problems of management for large-scale industries.

Despite the early start and the increased use of teams in organizations (Guzzo and Dickson, 1996), there was a gap in research until recently, as Cummings and Cross (2003, p.167) noted: "there has been relatively little social network research on the structural properties of natural work groups and their consequences for performance." It wasn't until the twenty-first century, with the emergence of network science (Barabási, 2016), when researchers started to link structural network properties of groups (such as density or centrality) to performance (Balkundi and Harrison, 2006; Borgatti and Foster, 2003). Team performance has been since related to the interactions within the team, between actors, focusing on the "pair" or dyad instead of the individual, which was the relevant object of study for previous works that highlighted individual abilities or leadership over relationships (Sanna and Parks, 1997; Kozlowski and Bell, 2003).

Understanding the structure and dynamics of interpersonal relationships has been, thus, an important challenge for the social sciences. Even the most complex systems emerge from dyadic interactions (Barabasi et al., 2004). This is also true for team sports, a social network where performance results from the interaction among the players. How to perform is a relevant issue not only for the players in the team, but also for all the external ecosystem, from the coach to the management and sponsors. Therefore, it is a relevant question to understand whether (and how) network structures build within teams relate to performance.

Interpersonal coordination tendencies emerge from the couplings of players as social system agents (Passos et al., 2008, 2009). With a limited number of actors in each team, interactions happen in a closed and well-defined environment. These scenarios are, thus, characterized by close interaction between their members (Passos et al., 2011); such strong relationships diffuse ideas and innovations over the network and influence behaviour (Kadushin, 2012). As a result, it can be argued that teams develop patterns of play over time and that, in turn, those patterns impact on the team's success when competing with other teams (and, therefore, with different patterns). In the end, team sports games depend on avoiding the opponent's strengths while taking advantage of the opponent's weaknesses, so social network analysis methods become useful to study them. In the same way as a team of experts is not necessarily an expert team (Bourbousson et al., 2010), a team of talented individual players is not necessarily a good team if they don't synchronize and communicate appropriately (Passos et al., 2011; McGarry, 2005; Duarte et al., 2012; Clemente et al., 2015a,b,c).

Team sports have their electronic-mediated counterpart: eSports. Although competitive video gaming is not new (it could be traced back to the arcades), ”it is with the rise of network gaming that e-sports found its strength” (Taylor, 2012, p.9). Moreover, arcade gaming was mainly individual; widespread team competitive video gaming is much more recent. For this article's purpose, one can think of eSports as ”a form of sports where the primary aspects of the sport are facilitated by electronic systems; the input of players and teams as well as the output of the eSports system are mediated by human-computer interfaces” (Hamari and Sjöblom, 2017). This equation to traditional sports has its critics, though. Despite eSports's increasing recognition and audience, there is still debate over whether to consider it as a sport (Jonasson and Thiborg, 2010). Most of the criticism revolves around physicality, arguing that sport is athletic at its core (Guttmann, 1978; Suits et al., 2007). This is debatable, however, not only because professional gaming also requires high precision in physical skills, motor coordination and agility (Jenny et al., 2017; Taylor, 2012) but also because eSport is a manifestation of sportification, broadening the restrictive traditional sport definition (Cunningham et al., 2017).

What is clear, however, is that online competitive gaming is quickly becoming one of the largest collective human activities globally (Castronova, 2006) and eSports are nothing else than its organized consequences. Player communities, first, and the industry, later, noticed the social and economic potential of competitive playing. Audience followed (Hamari and Sjöblom, 2017) and, soon, organized video game competitions started receiving recognition as entertainment (Funk et al., 2017). Competitive gaming has rapidly institutionalized; national and international governing bodies (Seo, 2013; Kow and Young, 2013) and organizations have been established, such as the ESL (Electronic Sports League) or the LVP (”Liga de Videojuegos Profesional”) in Spain. Even the developers saw an opportunity in eSports to promote their products: Riot Games, League of Legends developer, organizes and manages its own international tournaments and events. Carrillo Vera (2015) claims that the impact achieved by eSports such as League of Legends calls for academic and scientific analysis from a range of disciplines. This consideration is echoed by Mora-Cantallops and Sicilia (2018a), who identify not only a research opportunity behind MOBA (Multiplayer Online Battle Arena) games as a whole but also at professional competition level, which remains largely under-explored.

Drawing from both worlds, this article will combine the innovative social network methods used in traditional team sports with the emerging entertainment product that eSports are, aiming to investigate whether network structure and performance interact in a similar way as it does in traditional sports (Grund, 2012). A dataset consisting of all official and recorded League of Legends matches is obtained from the Riot Developers API[1]. The resulting extraction contains 7.582 matches that range from 2014 to 2018, with 244 teams divided among 15 different regions (or leagues). Data extracted from online competitive games such as League of Legends can help understanding team performance and success looking at the structure of their connections during competitive play. One of the strengths of the current analysis is precisely found in data extraction, as in online gaming environments it is unobtrusively recorded by game servers (Kwak et al., 2015), virtually reducing reporting bias to zero.

After a review of literature on network analysis in both traditional sports and eSports, details about the subject game (League of Legends) will be expanded in order to understand the specific terms that will appear the hypothesis that follow. In measures, both performance variables and social network indicators will be presented, followed by the methods section, where the analytical strategy and modelling is described. Results will precede an extended discussion about the ensuing model. The conclusion will, at last, summarize the article's main findings and contributions.

[1]Application programming interface, https://developer.riotgames.com/

2. Background

2.1. Related work

Research combining social network analysis (SNA) with team sports is not uncommon, with prominent and popular sports such as football and basketball in the lead in number of studies (Cintia et al., 2015b; Fewell et al., 2012). In general, networks are considered a valid tool to study team sports as complex social systems and to capture pattern-forming dynamics (Passos et al., 2011). In football (soccer), for example, one article analysed the 2006 FIFA World Cup final and obtained results that suggested ”common and unique network dynamics of two competitive networks, compared with the large-scale networks that have previously been investigated in numerous works” (Yamamoto and Yokoyama, 2011). The European Cup 2008 was also subject of research (Duch et al., 2010), associating the most valuable players in the tournament with the network centralities within their teams. Cotta et al. (2013) analysed the network of passes among the players of the Spanish team during the last FIFA World Cup 2010 to study its performance and playing style. Among other conclusions, they found that the team's style was ”determinant in the game's outcome” and that, even in worse performing games, the team's ”imprint globally remains”, hinting at the small-world property exhibited by the passing network. The same World Cup was used by researchers to run a full description of football teams according to network theory. Using passing data made available by FIFA during the 2010 World Cup, a weighted and directed network in which nodes correspond to players and arrows to passes was built for each team, and then used to identify play patterns and determine central players (Peña and Touchette, 2012).

Using 380 games from the 2008-2009 season of the Spanish Men's Professional League and UEFA Champions League matches, Lago-Peñas et al. (2010, 2011) studied predictors of successful game play using game statistics. Number of assists were found to be positively related to performance. After analysing 283.259 passes between professional English Premier League players (2006/07 and 2007/08 seasons), a relationship between high interaction (number of passes) and performance (in goals scored) was established (Grund, 2012). Moreover, centralization was found to be a negative contributor. Other studies have looked at roles and position: defense-attack transitions were studied in the Portuguese Football League (Malta and Travassos, 2014), while ”passing effectiveness” was measured and related to performance using positional variables in the work by Rein et al. (2017).

More recently, and using both the FIFA World Cup 2014 and the Italian Serie A data, another study established a relationship between network indicators and performance of a team that could be able to predict match outcomes (Cintia et al., 2015b). In 2015, passing behaviour of 1446 games from all four major european leagues was modelled and classified using K-Nearest Neighbour machine learning techniques, being able to predict final season ranking of the top teams with relatively good agreement (Cintia et al., 2015a).

In basketball, teams are composed by five players instead of football's eleven. A study on under-18 French players (Bourbousson et al., 2010) suggested that the limited opportunities to coordinate during the match and the strong team interdependence lead to local adjustments; this meant that most of the time, players were only concerned about their interactions with a single another player, thus coordinating locally within the network. Another study looked at a high-level professional setting (the NBA) and found a centralized star pattern where most passes were between the Point Guard and other players (Fewell et al., 2012) and demonstrated the utility of network approaches in quantifying team strategy and hypothesis testing.

2.2. eSports

Research on eSports has surged over the last few years (Carrillo Vera et al., 2018). Most research, however, is based on the economic ecosystem. Its industrial and management layer was studied by Funk et al. (2017). The audience of eSports and spectator's motivations have also drawn interest in research (Lee et al., 2011; Hamari and Sjöblom, 2017). Last but not least, eSports also raise legal concerns (Holden et al., 2017), as ”esports afford a glimpse to the future of creative competition, business innovation, and the related legal, policy, and litigation implications emerging alongside this new (sporting or otherwise competitive) activity.” In their conceptual discussion, Cunningham et al. (2017) saw ”a number of opportunities for research in the governance, marketing, and management of eSport” calling for further research and considering eSports relevant to sport studies.

On the other hand, and although research on eSports is gaining popularity, studies that link networks and electronic sports are scarce. It is partially expected: early eSports related titles were single player games such as Starcraft, Starcraft II or 1 vs 1 fighting games. Therefore, it is not until the advent and rise of popularity of team FPS (First Person Shooters, such as Counter Strike) and, primarily, MOBA games, when social network analysis starts to become of interest in competitive play. Still, these player networks remain largely unexplored (Pirker et al., 2018; Mora-Cantallops and Sicilia, 2018a). Competitive networks are formed in competitive team-based play and, when combined with additional information, allow for correlation of network measures with player performance or behaviour.

Most works on eSports look at MOBA games, with the most popular being League of Legends, DOTA[2] and DOTA 2. Batsford (2014) work investigated tactics and aimed to calculate an optimal jungling route so the player could get the most experience and gold possible. Rioult et al. (2014) executed an exercise of prediction using team-based topological measures, highlighting its potential for a strategic analysis of team play. Work by Drachen et al. (2014) pointed in the same direction but added spatio-temporal behaviours and skill level to the mix. Schubert et al. (2016) also worked in the definition of ”encounters”, spatio-temporally defined components that allow performance analysis. Yang et al. (2014) modelled combat using graphs and metrics to predict success; while it is not social network analysis in the strict sense, it uses similar principles to look at combat events. A few other studies have looked at successful teams but using only attributes from the game or relationships outside the game (e.g. real-world friendships or matches together) (Yang et al., 2014; Pobiedina et al., 2013; Losup et al., 2014). This is also the case of Marchenko and Suschevskiy (2018), who used mixed methods (including SNA) to analize the structure of the transfer market of players among DOTA 2 teams.

Player-centric networks in League of Legends were explored by Mora-Cantallops and Sicilia (2018b), but the analysed networks look at friendships and social behaviour instead of team-play and efficiency. Similar networks have also been established in some modes or instanced battlegrounds in other MMOG (Massive Multiplayer Online Games) (Miller and Crowcroft, 2009). First-Person Shooters, on the other hand, are also underexplored. Bednárek et al. (2018) combined data from different sources in Counter-Strike: Global Offensive to evaluate player performance. Moon et al. (2006) used social network measures to examine how the players of the game America’s Army changed their performance, play

[2]Defense of the Ancients

styles and social positions after one year of game play experience, while Pirker et al. (2018) analyzed player networks in Destiny, but widely popular games such as CounterStrike or Call of Duty are seldom found in social network research.

Although competitive video games are gaining attention and collaborative relationships within online teams impact team's success (Wax et al., 2017), it is worth noting that no relevant research has been found that focus on professional players and competitions and/or interactions within such competitive games.

2.3. League of Legends

League of Legends is a multiplayer online battle arena game that follows a freemium model, but where in-game transactions do little to impact a player's performance or ability. In essence, MOBA games are a subgenre of real-time strategy games in which two teams, typically consisting of five players each, compete against each other with each player controlling a single character. Contrary to real-time strategy games, there is no unit or building construction in a MOBA game, so much of the strategy revolves around individual character development and cooperative team play in combat (Yang et al., 2014).

Each team in League of Legends is composed by five human players and each player takes a role in the team (Donaldson, 2015). Role definitions have evolved from season to season, but stabilized at five main roles. Three players control the lanes (Top, Mid and Bottom) while Support provides utility to the team (spending most of the game paired with Bottom) and Jungle makes use of the resources in-between lanes (see Figure 1). League of Legends is a team game; all five roles are relevant for the team's success and cooperation is critical.

Most of the strategy in the game revolves around one single element: gold, which can be obtained from multiple sources. Creeps or minions are non playable characters that appear periodically and symetrically in waves for each team. Last-hitting an opponent minion (therefore, killing it) grants gold to the killer. The number of last-hit minions is called the creep score (CS); maximizing CS requires intense focus, timing, and input mastery and is the most basic (and difficult) local objective. Killing other players is another important source of gold, but, unlike minions, not only the last hitting player gets gold. All teammates that contribute to the kill by doing some damage get an "assist" and a smaller amount of gold. When a player is killed, it re-spawns in a variable amount of time: the later in the game,

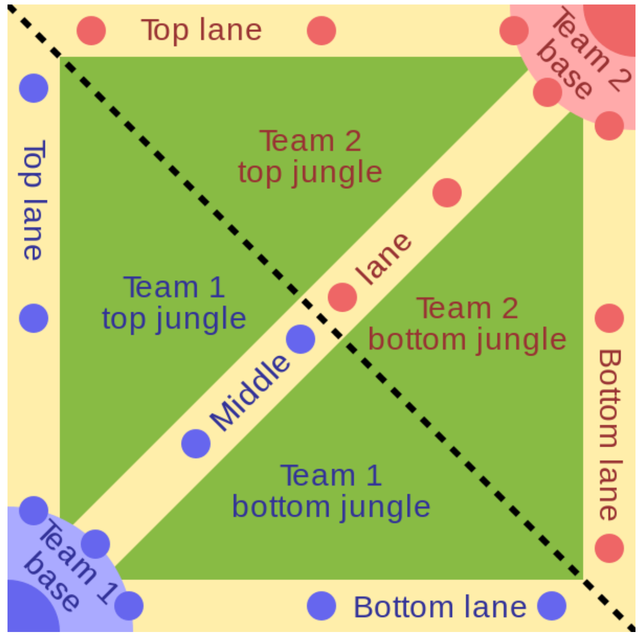

Figure 1: Typical MOBA map (with labelled lanes) for illustrative purposes. Original PNG version by Raizin, SVG rework by Sameboat. (file:Map of MOBA.png (CC 3.0), CC BY-SA 3.0, https://commons.wikimedia.org/w/index.php?curid=29443207)

the longest it takes. For individual players, KDA (Kill-Death-Assist) ratio is often used as a performance indicator, adding kills and assists and dividing by deaths. Other sources of gold include neutral objectives and turrets. But, why do players need gold? They need it to buy and upgrade their items, which empower their avatars. Better itemization is key to success, as it is to get your items before the opponent does (leading to unbalanced periods in favour of the leading team called "power spikes").

A typical League of Legends can be divided in five main phases (Ferrari, 2013), summarized as follows:

1. Draft phase: where players pick the champions they will play. During this phase, bans are issued (champions that will be removed from selection) and each team asymmetrically chooses its composition.
2. Opening phase: a brief 75 seconds phase where players appear in the Summoner's Rift (the playing field) and position themselves while minions appear. Some skirmishes between players might happen, but they are usually non-fatal, as power is still low.
3. Laning phase: in this phase, teams separate across lanes as per their roles. Each lane

has one champion guarding the first turret from the opposing champions and minions except the bottom one, which has a support player whose objective is often not to farm gold but to facilitate kills to his partner and to provide vision. The fifth player, the jungler, attack the neutral monster camps inside their jungles, establishing a route for maximizing their gold farming and providing optional support for lanes. This support often comes in form of ”ganks”, that basically consist of attempts to assist the lane player in killing his or her opponent. While in lane, the primary objective is to accumulate creep score.

4. Teamfight phase: laning phase ends when turrets start to fall, lanes become longer and the leading team has more time to move around the map without losing efficiency. This movement is aimed at securing vision over the map and control over the bigger objectives (dragons and Baron Nashor), neutral powerful monsters that, when killed, provide further utility to the team to get closer to the opponent’s nexus, the final objective. During these phase, fights become team-based, so coordination is crucial.

5. Endgame phase: the final objective of teamfights is to kill as many opponents as possible; as re-spawn times get longer towards the end of the game, a good teamfight near the end guarantees numeric superiority that is often the main driver to end the game. The game ends when one team gains access to the opponent’s base and destroys its nexus.

Phases are way more complex and intricate, but for this article’s purpose it will serve as an introduction to the game. League of Legends is also regularly patched. Every two weeks, the game is updated with changes to items, champions and abilities. Details about what changes are published in detail in their website[3]. Riot implements changes to the game either to balance items or champions that have become dominant or to encourage the use of forgotten champions. Patches are also used to introduce new champions to the game and aesthetic modifications. Most of the metagame revolves around these patches and how players adapt to them (Donaldson, 2015).

It is also relevant to note how League of Legends developer Riot Games provides players

[3]https://na.leagueoflegends.com/en/news/game-updates/patch

with free access to the API, a set of tools that can be used to extract player and game data for further research. In this study, the API will be used to retrieve historical professional match data.

When League of Legends was released in October 2009, its client was deficient in competitive options and lacking for viewers of competitive games (Li, 2017). In the first months, player base stabilized over twenty thousand players, but in the following years it would rise to millions of unique players until it became the most played game in the World[4]. As of 2018, the main professional leagues over the World are the NALCS (North America), the EULCS (Europe), the LCK (Korea), the LCL (China) and the LMS (Taiwan). All leagues have two splits (spring and summer) and the best over the year can access the World Championships, the most prestigious League of Legends competition. Matches are often played in Riot's studios over the world (Berlin for Europe, Los Angeles for North America) or in multi-purpose stadiums for play-offs and international events. These are always streamed via online platforms such as Twitch and YouTube, where they are viewed by millions of watchers all over the World[5].

3. Research questions

The analysis that follows from this point draws its core structure from previous research by Grund (2012), applying and contrasting his proposed model on professional soccer to, mutatis mutandis, professional League of Legends. Therefore, wherever possible, notation will be assimilated to facilitate comparison of the presented work to traditional sports.

3.1. Density-performance hypothesis

Most literature relates network density (and, therefore, intense interactions between members) as a positive related factor for team performance, labelled as the "density-performance hypothesis" (Balkundi and Harrison, 2006). When team members strongly relate with many other team members, interdependence increases (Sparrowe et al., 2001), raising the need for

[4] https://newzoo.com/insights/rankings/top-20-core-pc-games/. Accessed March 22, 2018.

[5] https://newzoo.com/insights/articles/esports-franchises-70-watch-only-one-game-and-42-dont-play/. Accessed March 22, 2018.

cooperation and coordination of efforts (Molm, 1994). Dense networks encourage information sharing, trust and dependence (Littlepage et al., 1997). The density of team network is, thus, a relative index that measures the overall affection between teammates (Clemente et al., 2016). In line with this idea, it is hypothesized that:

Hypothesis 1. Increased interaction intensity within the team is associated with a higher team performance and efficiency.

3.2. Centralization-performance hypothesis

The distribution of network positions is measured by its centralization, a parameter that can be assessed using different criteria (Sparrowe et al., 2001; Cummings and Cross, 2003). In any case, centralization is a measure of distribution; lower centralization implies equality in relationships over the team while a higher number means that a few players are more central (or popular) than the rest. Decentralized structures should foster coordination and cooperation (Sparrowe et al., 2001; Molm, 1994) as they are less dependent on specific actors. When a single player becomes critical for a team, there is a high chance that the opponent will set up tactics to block that player's performance; in highly centralized structures this can bring the team down. Therefore, the second hypothesis is:

Hypothesis 2. Increased centralization (higher individualization) of interaction affects team performance negatively.

3.3. Mixed-effects hypothesis

League of Legends has been professionally played in Riot competitions since 2013, although available data starts in 2014. The game has changed a lot over the years, patch after patch, and one could even argue that "the League of Legends being played at this moment by millions of players is not the same League of Legends that existed just 2 months ago" (Donaldson, 2015). The way the game is played changes over time, with different champions being used and new characters introduced. On top, it is a globally played game; each region could show different structures. However, team efficiency in League of Legends will be assumed as independent of these mixed-effects, as it is hypothesized:

Hypothesis 3. Efficient network structures in League of Legends are independent of their region, year or season.

4. Measures

As developed in section 2, eSports are just starting to be subject of exploration for researchers and most studies are focused in its consideration as sport and its organization (Cunningham et al., 2017; Funk et al., 2017; Jenny et al., 2017). It is not surprising, thus, to notice that network structure in competitive eSports video games (such as League of Legends) has hardly been explored. For this article, a dataset containing all professional matches since the 2014 World Championship (held in September 2014) is extracted. The data contains basic information about 7.582 matches played by 244 teams. Although, in average, 62 repeated observations of each team are included, the historical teams (that frequently win championships and participate in Worlds) play more games during the year. The most successful teams in League of Legends history, Korea's SKT and Samsung Galaxy have 403 and 322 repeated observations, while TSM (the most successful North American team) has 318. The dataset also contains information about the arguably most relevant repeated events over a game: kills. Kills happen when a player destroys an opponent and are displayed in similar way as goals in soccer. Scoring more kills than the opponent is not necessary to win the game (destroying the nexus is) but it is often used as a general indicator of performance by players, analysts and coaches alike, as kills result in gold. A kill can be executed by one player alone (a solo kill) or with help from other teammates (every helping partner gets an assist). 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). A total of 15.164 directed networks are derived from these assists, with the strength of the ties indicating the total number of assists between two players.

4.1. Performance variable

In League of Legends, as in many team sports, the performance of a team determines the outcome of its matches and the standings at the end of the season. While number of points or wins could be used as variable performance, it is very limited as a variable. Grund (2012) based his approach on goals scored, which is reasonable but biases results towards offensive performance of the team. There is no counterpart to goals in League of Legends (as no ball or goal is involved). There is, however, an arguably more objective measure of performance:

total gold obtained by the team. During a match, players need to be efficient in CS (taking as much gold as possible from minions) while gaining advantages via kills, turrets and neutral objectives. Balancing resources is crucial to get the most gold possible to be converted in items that translate to in-game advantage for the player and for the team. Devoting too many players to kill other players is a loss in CS; devoting none is a loss in openings to build advantages that can snowball the team as a whole. As matches have variable length, gold can be divided by time, obtaining the team's gold efficiency (gold per minute), "much used in the competitive panorama to analyze players's performance [...] as it does not depend on direct confrontation" (Bertran and Chamarro, 2016).

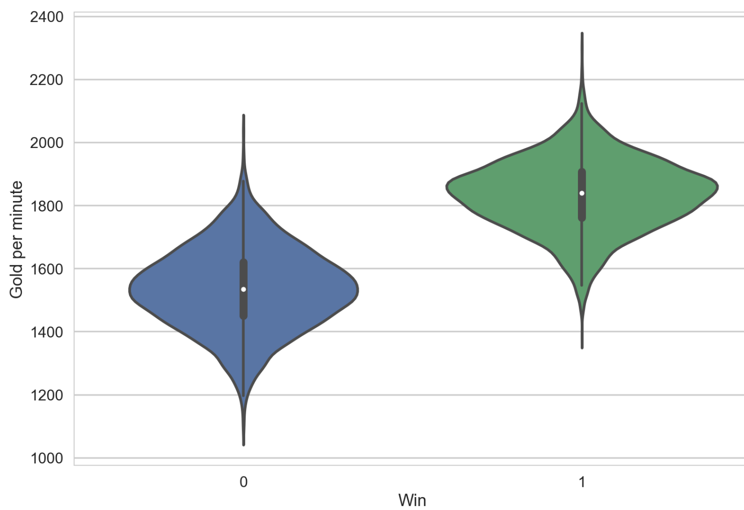

Figure 2: Violin plot of gold per minute. Gold per minute is significantly higher in wins.

As shown in the violin plot in figure 2, gold per minute is significantly higher in wins than in losses, relating gold efficiency to team success. A Mann-Whitney-Wilcoxon Test determines that both groups are statistically different with $p << 0.001$. Gold per minute will be, therefore, used as performance indicator for the proposed model.

4.2. Network structure and centralization

Teams in League of Legends are not only clearly defined and composed by five players each, but their interactions are also clearly identified within the extracted data. While only one player gets the kill, he or she can be assisted by zero to four teammates. But, to assist another player, communication and coordination needs to be in place: only those players that damage the killed opponent get rewarded with an assist and a gold amount. It is important to note that, to get an assist, the teammate needs to deal damage; other helpful interactions such as healing the killer or stunning the enemy are not considered, as neither the League of Legends API records them nor provide any gold to the team.

Thus, the assist relationship, in general, indicates two things:

- Coordination and collaboration between players.
- Proximity between players[6].

Assists, therefore, give an idea the interactions that happen within a team during the game and are, most likely, the most relevant dyadic indicator available in the game's obtained data. For each team in each match a network graph is built. For each kill, all assists are represented as directed edges from the "assistant" to the "killer". An example of the resulting network is represented in Figure 3, extracting the assist information from TSM's win over C9 in the North American LCS (January 24, 2015)[7].

	Dyrus	Santorin	Bjergsen	WildTurtle	Lustboy
Dyrus	-	0	5	3	0
Santorin	1	-	7	5	0
Bjergsen	2	1	-	5	0
WildTurtle	2	1	7	-	0
Lustboy	2	1	7	5	-

Table 1: Assist network of TSM in Figure 3 represented as an adjacency matrix.

The "assist network" is also represented as an adjacency matrix in Table 1. A few things should be noted. There are no substitutions over a match, so all five starting players end the game. There are players that might not get an assist or a kill over a whole game. There

[6] Although some champions (e.g. Gangplank) can assist from far away due to their global abilities, they still require the player to focus on the killer position. Therefore, although not physically close with the champion, the assisting player is still personally close as both player screens look at the same zone in the map.

[7] Available at https://goo.gl/ZnE3Bx.

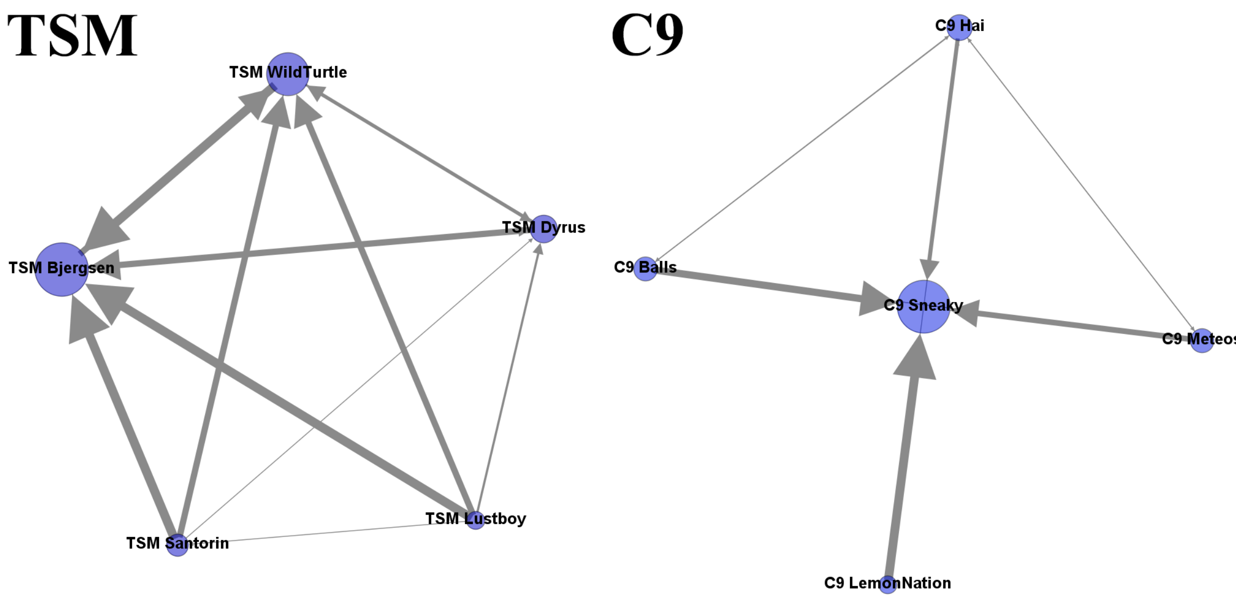

Figure 3: Network patterns of TSM against C9; January 24, 2015.

are even teams that might not get a kill over a game, although it is rare (in the dataset, it's reduced to 0.7% of the games). And there are some players getting much more attention than others. Again, in Figure 3, C9's Sneaky is assisted by all members of his team in his kills, while the others either get a small number of kills or no kills at all. TSM, on the other hand, has two significant players during that same match, Bjergsen and Wildturtle. Often, this "centric" players are the damage dealers, so it is expected to see higher in-degrees in "carries" and higher out-degrees in "supports".

4.2.1. Network intensity

The density of a graph is defined as the proportion of possible lines (or edges) that are present in the graph (Wasserman and Faust, 1994). In small graphs that are weighted and almost complete (such as the ones generated from the League of Legends dataset, density is less useful as a measure. Taking into account that edges are weighted, however, the intensity of the interaction between nodes can be assessed using the nodal indegree and outdegree. In a directed graph, adjacency depends on the direction of the arc; 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).

$$C_{OD}(i) = \sum_{j=1}^{N} w_{ij} \tag{1}$$

$$C_{ID}(i) = \sum_{j=1}^{N} w_{ji} \tag{2}$$

Equations 1 and 2 consider w_{ij} as the number of assists from player i to j during a match and N as the number of nodes (which, in this analysis, will always be 5). These equations, however, depend on the number of kills; the more kills a team gets in a match, the higher degrees will become. It makes sense, thus, to standardize this measures to measure the global interaction dividing the total degree by the number of kills K. 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.

4.2.2. Weight centralization

Although one of the primary uses of graph theory in social network analysis is to identify the most important or popular nodes in a social network, there is little consensus on how to measure this prominence and many authors have attempted to quantify this notion (Wasserman and Faust, 1994). A network is decentralized when centralities are balanced across the actors in the network. For a more detailed discussion see (Freeman, 1978; Everett and Borgatti, 2003; Borgatti et al., 2013). Freeman (1978) proposed a group closeness index that is purely node based. His strategy is based on the standardized actor closeness centralities and can be computed in two steps: first, one obtains the sum of the differences between the largest node centrality score and the scores of all other nodes in the network and, second, the result is divided by the maximum possible sum of differences (Wasserman and Faust, 1994). Although this measure is purely node-based, an edge-based counterpart can be defined. Using edge weights, "one would then measure network centralization not by examining the distribution of node characteristics but rather by investigating the distribution of tie characteristics" (Grund, 2012). 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. Formally, C_w will be defined as:

$$C_w = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} (w^{max} - w_{ij})}{(N^2 - N - 1)A} \tag{3}$$

where w^{max} is the maximum observed weight across the network. Denominator in equation 3 reflects the centralization when all assists happen in a single directed dyad, thus standardizing the result.

4.2.3. Node centralization

Degree centralization is, perhaps, the simplest definition of centrality when looking at the actors only (Wasserman and Faust, 1994), in the sense that the nodes with most ties are the ones that could be considered most active. In small weighted networks such as the League of Legends teams, degree is less useful as almost all players are connected to the rest of teammates. Following Freeman's closeness index principle (Freeman, 1978) and taking indegrees and outdegrees into account, node centralization (or dispersion) can be defined as follows:

$$C_I = \frac{\sum_{i=1}^{N} (C_{ID}^{max} - C_{ID}(i))}{(N-1)A} \tag{4}$$

$$C_O = \frac{\sum_{i=1}^{N} (C_{OD}^{max} - C_{OD}(i))}{(N-1)A} \tag{5}$$

where both C^{max} are the largest observed indegrees and outdegrees, respectively. Indegree centralization C_I will therefore reach its maximum when all assists are received by a single player and C_O will do the same when all assists are done by a single player. Both equations are, again, standardized dividing by the maximum node centralization.

4.3. Descriptive statistics

After computing all networks and their related variables, their descriptive statistics are presented in Table 2 and Figure 4. On average, League of Legends professional teams execute 12.53 kills and 29.90 assists per match (so, a ratio of 2.33 assists per kill). Once normalized by match duration, averages are 0.35 kills per minute and 0.82 assists per minute (same

	Mean	Std dev	Min	Max	Obs
(1) A/min: assists per minute	0.82	0.50	0	3.57	15164
(2) K/min: kills per minute	0.35	0.20	0	1.87	15164
Network intensity					
(3) AR: assist ratio	2.33	0.59	0.00	4.00	15164
Network centralization					
(4) C_w: weight centralization	0.13	0.10	0.00	1.00	15164
(5) C_I: indegre centralization	0.35	0.20	0.00	1.00	15164
(6) C_O: outdegree centralization	0.14	0.10	0.00	1.00	15164
Team performance					
(7) Gold per minute	1684.70	192.30	1083.70	2310.03	15164

Table 2: Descriptive statistics

ratio). Network centralization is lower in weight and outdegree than in indegree; apparently, networks are more focused in helping a few select players (or carries). Notice that the standardized scores range from 0 to 1, meaning that although most cases are in the middle, both extremes exist in the datased (so, there are networks with no indegree centralization but there are also networks that are fully focused in a single player). Finally, teams accrue 1684.70 units of gold per minute in average.

In his study, Grund (2012) derived a single dimension for network centralization, as it made sense for soccer. In League of Legends, however, some players have roles that become more prone to assisting (Support, Jungle) or to receive assists (Top, Middle, Bottom/ADC). It is, therefore, interesting to keep indegree and outdegree centralization as separated variables, so the impact of both tendencies can be properly assessed.

5. Method

Before fitting a model, dimensionality will be reduced using the variable inflation factor (VIF) (James et al., 2013), which measures the ratio of variance in a model with multiple terms divided by the variance of a model with one term alone. It quantifies the severity of multicollinearity in an ordinary least squares regression analysis. In each step in Table 3, the variable with the highest VIF is removed until no variables have a VIF over 5, which is the commonly accepted cut parameter (James et al., 2013). After the selection, only Kills,

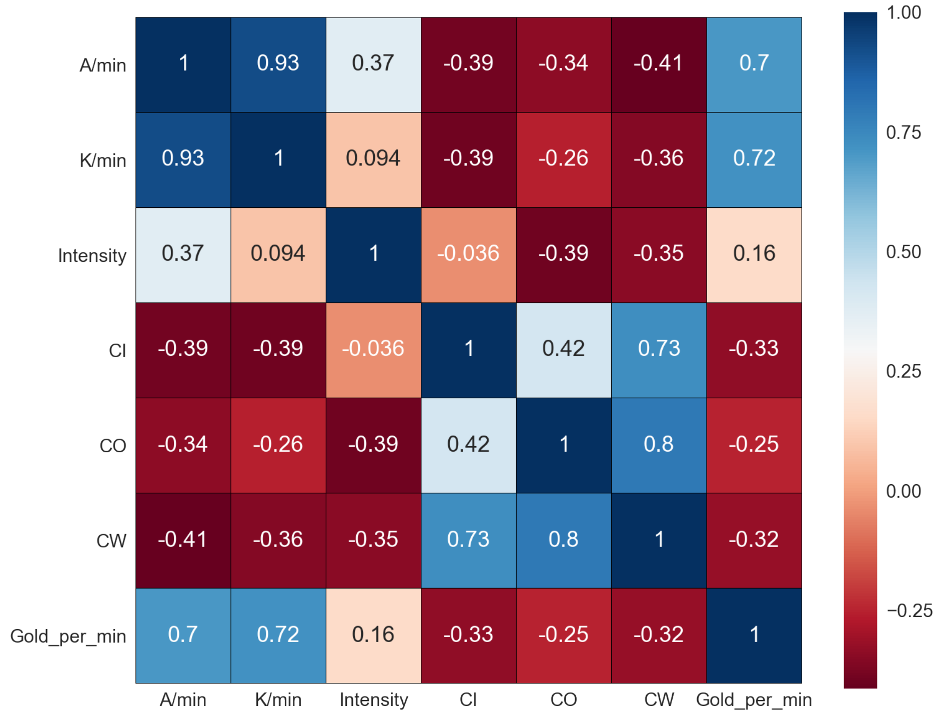

Figure 4: Correlation matrix of variables.

Intensity (Assist Ratio) and both indegree and outdegree centralization remain.

	(1)	(2)	(3)
A/min	18.04	Drop	Drop
K/min	15.59	1.20	1.20
Intensity	2.97	1.30	1.21
C_W	6.50	6.37	Drop
C_I	3.08	2.97	1.39
C_O	3.37	3.36	1.48

Table 3: VIF iterative selection.

Many scholars have argued that longitudinal analysis is necessary to disentangle the relationship between network structure and performance (Sparrowe et al., 2001; Katz et al., 2004; Grund, 2012). Until recently, such repeated observations were difficult to obtain, but in the case of League of Legends this data is available. Although mixed-effects models "provide a powerful and flexible tool for the analysis of grouped and longitudinal data", in this study a simpler linear regression is going to be first used to evaluate the linear relationships between the obtained variables and performance. Afterwards, random effects considerations will be added to a linear mixed-effects model to test hypothesis 3 and to verify hypothesis 1 and 2.

5.1. Linear regression

Linear regression is a conceptually simple yet very powerful statistical technique. The essence of regression is to use sample data to estimate parameter values and their standard errors. To do so, hundreds of models exist, but the simplest of them is the linear model (Crawley, 2015). Linear regression for n variables can be modelled following the equation:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n + \varepsilon \tag{6}$$

where each β represents one of the model's parameters that are estimated, y is the response variable and each x is a different explanatory or predictor variable.

5.2. Multi-level regression

The key feature of longitudinal data is that the same individuals (or teams, in this case) are measured repeatedly over time. Using this data uncritically in a linear regression only could hide pseudoreplication effects (Crawley, 2015). This possible correlation between observation needs to be taken into account. One alternative is cross-sectional study, as used in Grund (2012). As a linear model has been considered previously, linear mixed effects are going to be computed. Mixed effects models take this name from their duality, as they consider explanatory variables as a mixture of fixed effects (which influence only the mean of the response variable) and random effects (which impact the variance of the response variable only). In short, "mixed effects models allow intercepts or slopes of regression to vary across groups" (Grund, 2012). Each random effect represents an additional source of variance beyond one grouping factor; this basically means that there are variables that are able to describe a data sample that is a subset of the full data. Linear mixed-effects models are an important class of statistical models that are used directly in many fields of applications. The parameters in these models are typically estimated by maximum likelihood (Bates and DebRoy, 2004). While traditional analysis can still be useful, mixed models provide additional flexibility, taking into account the inner clusters variation. Multiple works have analysed both the advantages and disadvantages of this approach (Locker et al., 2007; Baayen et al., 2008; Barr et al., 2013). In the mixed-effects models (Bates et al., 2015), the error ε is split into a residual error term and as many components as random effects are considered. This components are assumed to have a population mean of zero and a certain variance, and are assumed to be normally distributed. Consider a simplification of the League of Legends dataset: the response variable y_{mi} is the gold per minute that can be expected from team i in a particular match m. Then, if K_{mi} is the number of kills of that team in that particular match, I_{mi}, C_{Imi} and C_{Omi} its network structural scores, and ζ_{1i} the random effect of the team considered, the model would then be:

$$y_{mi} = \beta_0 + \beta_1 K_{mi} + \beta_2 I_{mi} + \beta_3 C_{Imi} + \beta_4 C_{Omi} + \zeta_{1i} + \varepsilon_{mi} \tag{7}$$

where ε_{mi} is the residual error term and $\zeta_{1i} \approx N(0, \psi_1)$. This model can be extended for as many variables as required, but writing them in place of equation 7 would complicate the notation of the expression unnecessarily. For this study, three crossed random effects are going to be considered (team, opponent and region) with an additional nested effect (year and season, as season is hierarchically related to year).

6. Results

Teams are characterized by their interactions and this study investigates whether these interactions, represented by the trace they leave in the network structure that arises among players of the same team in League of Legends, impact team performance and efficiency. Two main hypothesis 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.

Table 4 shows the linear regression and multiple multilevel regression results. As the regression is linear, coefficients can be directly translated to performance: a variation of one unit in the independent variable translates to that increase or decrease in the predicted variable. The p-values are included in parenthesis. A total of five models are presented, ordered by increasing complexity.

	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		15164	15164	15164	15164	15164
Log likelihood		-	-93944.6	-93220.2	-93180.5	-91460.3

p-values in parentheses

$^{**}p << 0.001$ $^{*}p < 0.05$

Table 4: Multilevel regression results for gold per minute.

The first column, "Linear", presents the results using a linear regression model without random effects ($R^2 = 0.53$). Kills per minute is significant in all models, which was expected, as kills provide direct gold for the team. Regarding network structure, a clear effect related to intensity (or assist ratio) is found, implying that increases in the assist ratio are indeed beneficial for the team performance. Increases in indegree centralization are detrimental for the team, as predicted and as exposed in previous literature. Thus, spending all resources in a few team members is less fruitful overall than sharing them. Outdegree centralization, on the other hand, shows the same inclination but is not statistically significant in the mixed models. Therefore, although it becomes clear that increased centralization is a negative factor, a higher concentration of killers seems to be worse than a higher concentration of assistants. Columns (1) to (4) introduce random effects sequentially (see Table 4), controlling for unobserved team, opponent, region and temporal effects. The overall magnitude of the predicted effects shows little change as more random effects are added to the model and significance is similar. For all models, it can be established that hypothesis 3 holds true (efficient teams are independent of their region or season) and that this study replicates earlier findings in traditional sports and brings them to the newer world of eSports.

7. Discussion

The obtained model explains, at least partially, how the structure of a team network might influence team performance, findings that can be not only useful for strategical decision making for competition but also for non-gaming contexts. The network approach has made identification of certain patterns possible, suggesting that the interaction among players is crucial to understand the team's effectiveness and eventual success.

Previous work had looked at network structure in traditional sports already and found two main relationships. First, that the overall level of interaction within a network was related to a stronger performance while, second, team centralization was detrimental for the team. In spite of League of Legends' large audience and player base, this represents the first attempt to model team network structure in Riot's video game, confirming the conclusions of previous research and filling the gap between traditional sports and eSports which, at least regarding team performance, seem to exhibit similar properties.

Network intensity (so, the ratio of interactions among team members) is a predictor of performance and efficiency, while centralization is a negative influence. It should be noted, however, that although indegree centralization has been shown as having a clear detrimental effect, outdegree centralization seems to be much less influential or not statistically relevant at all. In order to obtain better results as a team it is thus suggested to distribute resources as evenly as possible. In the case of League of Legends, however, from whom this resources come from is less relevant; it is more important to share the assists than to balance who is assisting. This finding justifies the presence of helper or support player roles in the team, as having net "givers" in the network seems to be less of an issue if they distribute what they give across the team. These findings are stable over all regions and years studied.

This study is not without limitations. The first question would be whether this results can be, as claimed, extrapolated to other sorts of teams, sports or not. Previous work has emphatized the advantages of investigating sports as configurational dynamics are more visible (Elias and Dunning, 1966). If that's the case for traditional sports, it's arguably even more advantageous for eSports, as the measurement process is also benefited by how information is automatically recorded and extracted, minimizing reporting bias.

Roles or tactical setups have not been directly taken into account, although they might present a significant impact. As exposed in section 2, League of Legends teams are composed by five players with five different and separated roles. Some of these roles are itemized and prepared to deal damage to the opponents (so, focusing on kills) while other roles, mostly Jungle and Support, are itemized to help the damage dealers in their attempts. There is, therefore, asymmetry between players and this can be noticed in the obtained networks. Moreover, the difference in signification for indegree and outdegree highlights this role-based bias within any team. Tactics are more complex to take into account but might also play their part; when teams decide their composition during the draft phase, they do so with a tactic in mind. More often than not, this tactic implies protecting one powerful champion or exploiting an opponent weakness by focusing on its weaker lane. This might result in different network configurations that could explain part of the unexplained variance of the final model.

This study only considers the network as it is built at the end of the game, so time is not taken into account. This could be further studied, as a team might perform differently in different game phases (for example, a weak early game and a strong late game) also depending on their compositions and strategy. One could perhaps observe teams that fail if they don't survive the early phases of the game but always succeed otherwise. Temporal network structure could also reflect this evolution, although the analysis would become more complex (as game phases are not clearly bounded).

Although the obtained model is purely quantitative data based, it could benefit of qualitative complementary research. The results could be used to conduct focus group studies or semi-structured interviews with professional players and coaches to provide additional context and to understand whether other measures, formal or informal, are currently being used by teams (and managers) to assess their own performance.

Last but not least, this study has been based only in in-game networks. Further research is needed to assess the relevancy of the rest of the networks that may exist around professional players and their attributes. Do players perform differently when playing against previous teammates? Do common language speakers or players from the same nationality assist each other more often than other players? What's the role of experience? There are a lot of questions that don't yet have an answer; studying them might potentially bring increased understanding of what teams (and performance) are about.

8. Conclusions

Quantification of human behaviour and social dynamics has been a long-lasting challenge for social sciences. The main reasons are the complexity of long-range interactions and the comparably poor availability and quality of the studied data (Szell and Thurner, 2010; Lazer et al., 2009; Watts, 2007). Multiplayer online games such as League of Legends or the MOBA genre in general can contribute to bridge this gap while bringing new insights, as digitization reworks the very meaning of social relations (Latour, 2007). Online competitive gaming environments allow for a wide range of actions that are both related to social interaction and recorded, often unobtrusively, by the game servers (Kwak et al., 2015). This data becomes easily available when the developers or data providers allow researchers or players to access it, either via APIs or datasets, providing an unprecedented opportunity to observe social interaction on the large scale (Pobiedina et al., 2013). Taking into account how online gaming is quickly becoming one of the largest collective human activities globally, such games provide both sufficient participation numbers and careful control of experimental conditions, unlike any other social science research technology (Castronova, 2006). As video games evolve and multiplayer online games popularity grows, video game and player culture also grow, but they do so supported by the relationships that arise from their social activity (both online and offline) (Adamus, 2012). Connection is not only a constitutive fact of social life, but also the pillar where online gaming stands. Players influence each other by means of competition or collaboration and, sometimes, become involved in longer and meaningful relationships, as in the studied teams. Data extracted from online competitive games such as League of Legends can help understanding the structure of player's connections and networks during online play.

The obtained dataset and the computed model confirmed that small networks and social network analysis techniques might be useful for understanding the relationship between team's network structural features and their performance. While far from establishing causal relationships, a statistically relevant influence has been found. Further research to take into account many more variables is needed. The main findings, implications and contributions are stated following these lines:

- eSports such as League of Legends present an unprecedented opportunity to study and understand team dynamics from a data based point of view.
- Computer science methods and modelling can be useful to analyse large amounts of data retrieved from the game's servers.
- Team efficiency (and, therefore, performance) is positively affected by the intensity of interaction in League of Legends as it is in traditional sports.
- Indegree centralization is detrimental for the team performance in League of Legends. Distributing resources and efforts lead, in general, to a more efficient gold per minute ratio.
- Contrary to other sports, however, outdegree centralization seems to be less significant for the team performance. This discrepancy calls for further research.
- Team performance seems to be unaffected by regional leagues and temporal circumstances, at least in professional League of Legends competition.

Such information could be specially valuable to eSports managers, teams and organizations. Adding SNA techniques to optimize their gameplay, understanding the kind of players (from a SNA perspective) they need to fill a position or building strategies to maximize their networked performance could bring an additional layer of knowledge to their training and improve teams' efficiency. Platform creators or designers, on the other hand, could be interested in designing games where a strong collaboration is key to success (in order to better engage players and to build communities); measuring the level of collaboration required to succeed using the proposed techniques could help balancing and adjusting the game to their intended design.

9. Limitations and Future Work

Many opportunities for further research arise. In this study, high indegree centrality was related to ”carry” players; these are the players who receive the most attention within the team. This, in network language, is called a preferential attachment. Identifying them, especially in small networks, can be a ”very useful way to accurately identify key ’decision makers’ during important phases of competitive performance” (Passos et al., 2011). In League of Legends terminology, this would help to identify not only the carries but also the ”shot callers” (or decision makers in a team).

Another interesting question that appears is to look at franchise players in League of Legends teams. Riot’s competitions draw a lot from franchise-based competitions such as the NBA; it is natural, therefore, to notice how some players are related to a particular teams while the rest seem to rotate and change teams frequently. How do teams re-organise around these changes? Are preferential attachments somehow hierarchical around the franchise or popular players? Do (hierarchically) flat teams perform better or worse than teams with a stronger reference? Particularly successful teams such as SKT, TSM or G2 could also be looked in detail. Why does SKT win both in their league (LCK) and the Worlds Championships while dominating North American and European teams struggle in the World Championships? Do they have different network configurations?

The extracted data was not without limitations, so it could be extended in further studies. In order to build team networks, only kills and assists were taken into account. Although they represent the most direct and clear form of interaction (as players need to coordinate and cooperate to obtain them), there are many more events that could be considered and extracted, such as other helpful interactions (healing, stunning, slowing) and spatio-temporal variables (Drachen et al., 2014); not all these variables are recorded by the game servers, however, which would need a much more resource consuming posterior video analysis. Although data is easily available for some online games, it is highly restricted by the developers API to what the developer wants to share publicly. Future collaboration between the industry (companies) and the research community is, therefore, requested.

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