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Impact of network characteristics on performance of a team

– Study of social network characteristics and the differences between their sizes in geographic regions.

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# Abstract

*The problem that is studied in this paper is the impact of the network structure characteristics on the performance of the team. This paper focuses on the in-game behaviours of the people who play League of Legends. It includes similar measurements as the paper written by Mora-Cantalops and Sicilia (2019), but it differs with the regard to the population. The main research question of this paper is whether there is a relation between the network characteristics and the performance of the team. The main hypothesis of the paper is that intensity of the network has a positive impact on the performance of the team. Additional hypotheses are related to the negative impact of the centralisation on the team’s performance and to the differences between the regions in which these teams operate. The relations are derived from the environment of the game, but the aim is to apply this framework onto other areas such as business or other working environments. The paper contains four models (linear models, a multilevel analysis, and a generalised linear model). There are 3830 observations. Each observation represents a team which played a match. In each match there were 2 teams of 5 players and the connections between the players assisting in killing the enemy players create a network. As a final part of this paper, there is a comparison of regions in which the players play in order to see potential differences implied by the geographic location. The results show that intensity has an insignificant negative impact on the performance of the team. The indegree and outdegree centrality exhibit positive impacts with the first being less impactful and significant than the latter. The differences between regions appear to be small in the interactions of the main effect which is intensity.*

# Introduction

Improving the performance of the team is a complicated task and doing that would be rewarding in the efficiency of workers. However, unsuccessful efforts in improving the efficiency of the team can be a problem. Having an inefficient group of workers is an issue for both the employer and employees who do not feel fulfilled if they are not seeing positive results of their work. Then, the employer might want to improve the performance of the group of workers. However, one’s first thought might not be to look at a structure of the network that this group creates. Whereas, the structure might be a solution to the low efficiency of the team.

The performance of the team is often impacted by multiple different factors such as the team composition or decisions made by the members of the team. Neither the size nor the amount of the impactful factors is always known. However, the research was done on the structural characteristics and their impact on the performance of the team. In many articles, quoted in this paper (such as: Mora-Cantallops and Sicilia (2019) or Ngamassi (2013)) it is indicated that the structural characteristics are important in improving the efficiency of the team. Therefore, understanding the connections between the structure of the network of a team could help us improve the performance of the teams or organisations as a whole. Structural characteristics such as density (Mora-Cantallops & Sicilia, 2019; Ngamassi, Maitland, Tapia, & Kvasny, 2013; Grund, 2012; Shan, Walker, & Kogut, 1994), centrality (Ngamassi, Maitland, Tapia, & Kvasny, 2013; Freeman, 1978; Graf, 2011) or centralisation (Mora-Cantallops & Sicilia, 2019; Grund, 2012) have been found to be crucial to the performance of the team.

The aim of this thesis is to check whether particular characteristics of the network have a positive impact on the performance of the team. In this paper, the focus is put on the density and centralisation of the network as the structural characteristics of the network. The density refers to the number of ties which is vital for teams that need to cooperate in order to achieve their goal whereas, centralisation is crucial since it describes the equality of the distribution of connections among the members of a network. However, these network characteristics can have a different impact on the performance if researched in different environments.

The focus of the past research was put on traditional disciplines such as, football or basketball which have been widely researched (Cintia et al., 2015; Fewell, Armbruster, Ingraham, Petersen, & Waters, 2012). The networks which consist of the traditional sport players are universal to research because they allow to inspect the mechanisms that appear in other areas such as eSport or organisational networks.

Firstly, organisational networks have been researched with the use of similar measurement tools as the traditional sports. Structure of the network describes the relations between the nodes. These relations are crucial in the situation when multiple people work together around solving one common problem. Articles such as those written by Graf (2011), Grant and Baden (2004), Shi & Li (2019) or Shan, Walker & Kogut (1994) have researched networks in or between organisations. They have looked at density and centralisation of networks of organisations and the impacts of these characteristics on the performance of those firms. These papers show that having a higher number of connections as a node is generally related to the increase in its performance. They do not present an overall impact on the entire network. However, it is possible to estimate that if an increase of connections increases the performance of a node, it could increase the performance of multiple nodes in one network furtherly positively impacting the performance of a network as a whole.

Recently, the popularity of the eSport has emerged and the idea that network analysis can be also used in the research of eSports has become reasonable. This idea has been confirmed by Cunningham et al. (2018), who in the discussion with co-authors found the similarities in the research of traditional sports and the research of eSport. They stated that the research of traditional sports is relevant for the research on eSport and encouraged researchers to work in this field.

In their paper, Mora-Cantallops and Sicilia (2019) did just that. They combined the research of traditional sports and implemented it into eSports. Mora-Cantallops and Sicilia (2019) have researched the professional players of League of Legends and their behaviours but, in my opinion this sample can be improved in order to show more natural outcome. However, the results they found allowed the readers to grasp an idea of the impact of the characteristics of the network on the performance of the team. The authors have concluded that the density of the network impacts the performance positively. They created directed network in their paper in which one edge comes from an assistant to a killer and it is meant to represent one assist. The rules by which their networks were defined are identical as they are in this paper.

Mora-Cantallops and Sicilia (2019), have also found that the centralisation has a negative influence on the performance. In this situation, centralisation represents the concentration of a resource in one of the nodes in an entire network. Mora-Cantallops and Sicilia (2019) claim that better performance can be achieved when the resources are distributed as equally as possible. What is more, they imply that it is less important who assists, and more important that these assists are shared evenly. Therefore, the high centralisation of assists is more destructive towards the team’s performance than the high centralisation of assistants.

There are several differences between the majority of players and the research population used by Mora-Cantallops and Sicilia (2019). Most of the players are not professional gamers and their performance is worse than of those who earn money by playing the game. There is a significant difference in the mentality of professional players and those who play the game non-professionally. What is more, competitive eSport allows the players to take some actions that can change the results of models that are meant to research the characteristics of the network and their impact on the performance of the team. This difference can be a reason that will alter the results of the research on the performance of the team. These reasons lead me to believe that changing the population can also change the results and make the research more versatile than the one conducted by Mora-Cantallops and Sicilia (2019).

Each region has their unique playstyle which is tightly related to their performance. As it was shown in the paper by Mora-Cantallops and Sicilia (2019), the differences of the impacts of the network characteristics are visible between the said regions. However, these mechanisms do not appear only in the game but also in other areas of research. For example, the differences between European countries with regard to economic performance show a clear distinction of how the same factors have different impacts on the economic growth in European Union (Druzhinin & Prokopyev, 2018). In another area, it was found that children in Brazil exhibit different object control skills between geographic regions. What is more, if the children are exposed similar kinds of activities that are meant to improve their results, they change in a different scope in separate geographic regions (Nobre, Valentini, & Rusidill, 2019). In the topic of traditional sports, regions were also found to differ with regard to the representation of the top 300 players in tennis (Filipcic, Panjan & Reid, 2013). Finally, on the basis of the applicants to medical schools in Mexico, it can be seen that regions differ greatly with regard to the recruitment points of the applicants. What is more, the medical schools differ as well when it comes to dividing them by the geographic regions (Hernández-Gálvez & Roldán-Valadez, 2019).

Lastly, the topic of the diversity within the teams needs to be clarified. The differences between individuals and their approaches to the game are crucial to the performance of the team. Their attitudes or mindsets can be decisive towards the outcome of the game. However, the data set for this paper contains below 20 000 players. Identity of neither of these players is known to the researcher. Therefore, it is impossible to take into account any measurements of diversity between the members of the team. However, the impact of the diversity on the performance of the team is undeniable. Each team is composed of five different individuals and the way they play together is crucial in determining whether they win or lose the match. The players can have a different approach to the game, or a different skill set that makes them cooperate with other teammates better than others. In addition, there are differences between matches played by the same individuals because each of their decisions influences the further progress of the game. What is more, their uniqueness can carry influence from one match to another since some players are better at handling a loss than others therefore, impacting their next games. However, members of the teams which are researched in this paper cannot be controlled for their diversity since they are mostly anonymous. Therefore, diversity adds up to the omitted variable bias.

The data in this paper is focused around 10 individuals. They reappear in half of the matches that are included in the data set. It is possible that they fit better in some teams than in the others and that their playstyle is more efficient in a team that is different. In this situation, there are other factors that can impact the performance of the team which are not related to the structural characteristics. However, it is important to keep in mind that the matchmaking process in the non-professional games is mostly random and that people are not matched with a team that they will necessarily perform better on. This is another factor that cannot be found in the research done by Mora-Cantallops and Sicilia (2019), because they look at professional players who play on a professional stage. There are fewer random factors that impact the professional stage matchmaking. What is more, they look at professional teams in a period of several years. In this time the players were able to change teams and it is impossible to consider this migration and it is anything but random.

The structure of this paper is presented below. Firstly, the literature review explains the interactions in traditional sports which were aimed to be located in the eSports environment. What is more, it shows similarities between the eSport research and other areas such as performance of the employee groups in the organisations. Then, the hypotheses and research question is specified. What is more, it contains explanation of the crucial differences in the population that make it reasonable to look for different outcomes of the same mechanisms. Additionally, it presents the research that shows similarities between eSports and sports or organisations and implies that findings based on eSports can be applicable to other sports or real life. Later on, in the next section, the game is described including the in-game procedures, roles of players and customary rules that appear in the game. The results section contains multiple tables which show impacts of the network structure on the performance of the gaming teams. Lastly, this paper finds the differences between behaviours of professional League of Legends players and the non-professional ones. The findings are not consistent with what Mora-Cantallops and Sicilia (2019) found.

# Literature review

The research of the networks of players bears similarities to the network of the employees of the organisation or the networks of the organisations itself. Aside from density, centrality in the collaboration network was found to have a positive impact on the firm’s innovative performance (Graf, 2011). Additionally, they found that the increase of links between firms leads to the diversification of knowledge bases allowing for development of the firm what could lead to the increase of performance in a longer period of time. This effect was found to be related to the number of indirect collaboration ties that each firm has. Additionally, Shi and Li (2019) in their paper about cooperation between IT firms and research institutes found that the number of connections impacts the performance of the IT firms positively. What is more, relationships in collaboration networks were found to have a positive impact on the innovative output of a firm (Shan, Walker & Kogut, 1994). Ahuja (2000) in their research found that firms by accessing the knowledge bases about developed competencies of other firms, can improve their innovation performance by enhancing their knowledge bases with the received knowledge and technologies. These results can imply that the increase in interactions in a cooperation network can impact the performance positively. The players are not as complicated of an entity as organisations but, they cooperate with each other to achieve a common goal. The collaboration of the players is not identical to the collaboration of the organisations. However, finding an identical structure of the cooperation would force the researchers to look only at the researched game or - at most - games of the same genre.

Aside from military and organisational environments, research was conducted on networks in traditional sports. Interactions between the players can be seen in, for example, passes during the match (Cotta, Mora, Merelo, & Merelo-Molina, 2013). They have found that each team regardless of performance has its own playstyle that makes it unique. What is more, traditional sports allowed for the research of other properties of the network than density. For example, Peña and Touchette (2012) have looked at the weighted and directed networks of passes made during the match. Then they used these passes to determine the centrality of the players. However, Grund (2012) has looked at both centralisation and density and they also found a positive impact of the density on the performance. They defined the number of connections between the players as the measurement of density and, the number of scored goals as the indicator of team’s performance. What is more, the same research has found that centralisation of these passes has a negative impact on the team’s performance. Therefore, if the research regarding density is predominantly unanimous, then the impact of centralisation seems to be defined by other factors. Finally, Cintia et al. (2015) have found the research of the network structure, capable of accurately predicting the rankings of the top teams. If the network analysis in traditional games can be used to predict the outcomes of the played matches, then it could be useful in the prediction in eSports.

The network analysis of the eSports has not been as popular as it has in the traditional sports. However, its popularity has increased recently (Vera, Terrón, & García, 2018). Prediction of the performance of the team has been done in eSports by Yang et al. (2014) as it was done in traditional sports by Cintia et al. (2015).

Mora-Cantallops and Sicilia (2019) believe that networks of players that are formed in the competitive environment allow to measure the relations between behaviours of the players and the performance of the team. They have investigated the networks of professional players particularly, the matches that take place in the League of Legends professional leagues. The authors used a data set that contains all the professional games that were played since the League of Legends World Championship in 2014. Their research brings about results that go hand in hand with the research of the traditional sports. First of all, the number of interactions is a positive coefficient for team’s performance. Then, it was found that the centralisation of the interactions has a negative impact on team’s performance. It is important to note that the authors have divided the centralisation index into two separate indices. One of them shows the indegree centralisation which is the concentration of kills and the outdegree centralisation which is the concentration of assists. Both of these indices were found to have a negative impact on the performance of the team. Their performance measurement is gold per minute and the intensity is measured by dividing the number of assists by the number of kills. Their results show that highly dense networks perform better. This means that teams, in which there are many assists, manage to gather higher amounts of gold per minute. However, the unequal distribution of both kills and assists has a negative impact on the team’s performance. Both findings are intuitive because team games are created in a way that rewards players who cooperate. What is more, the concentration of resources in one player leads to the rest of the players being deprived of resources and makes them not as helpful as they could be, had the resources been distributed more evenly. However, it is vital to remember that the environment researched by the authors is different from organisational, military, or traditional sports environment.

The differences between geographic regions are not solely focused on the physical distance. They can be related to factors such as affluence, culture, and many others. Therefore, investigating these factors is crucial for this research. Mora-Cantallops and Sicilia (2019) have looked at different regions out of which, each has a different playstyle, and they found that the impacts of structural network characteristics differ between the regions (Mora-Cantallops & Sicilia, 2019). Similar findings outside eSport were included by Druzhinin and Prokopyev (2018) in their paper on the regional economy of the Baltic countries. Their findings have divided the member states into two groups of countries which have joined the EU before 2004 and those which joined later than 2004 or never joined at all. The impact of the investments shows that these countries differ in the usage of the resources which they were given. This paper shows a clear difference in utilisation of those resources between countries which are not as distant from each other as the regions researched in this paper (Druzhinin & Prokopyev, 2018). Further, research of the physical education related skills in Brazil shows that the skills of the children do not develop at the same pace in all the geographic regions. Additionally, it shows differences in affluence of these regions which are highly probable to be related to the main effect (Nobre, Valentini, & Rusidill, 2019). A clear distinction between geographical regions was also found in Mexico included in the paper by Hernández-Gálvez and Roldán-Valadez (2019). They have researched medical schools and their applicants. Their main finding was related to the level of the academic performance of medical schools. They have found a significant difference in the academic performances of the said schools when divided by geographic regions. What is more, an average level of applicants differs between the geographic regions as well. Finally, the research on the tournament structures and the success of the tennis players divided by geographic regions shows a significant difference between the said regions. The authors have used the top 300 ranking as a measurement of performance. Their results clearly show that regions of the world such as North America or Central America are underrepresented in the top 300 in comparison to Europe. What is more, the average winning of the players are not as unequal as the geographical representation. The authors have found that despite having a smaller number of players, North America is drastically closer to Europe in the tournament winnings than any other region (Filipcic, Panjan & Reid, 2013). These findings show that geographic regions differ in the efficiency while aiming to win the tennis tournaments.

# Hypotheses

The aim of this thesis is similar to the research that has been conducted by Mora-Cantallops and Sicilia (2019). They looked at the impact of the intensity, centralisation, and the differences between mixed effects such as the regions, years, or opponents. The population that they chose to research is specific because the professional players are a minority in the gaming world. The authors have calculated intensity as a ratio of kills and assists. The same calculation was done in this paper in order to make sure that their measurements are as close to the ones in this research. This should allow for closer calculations of differences between populations instead of differences between measurements. Centralisation in this paper is understood as the equality of the distribution of resources. The higher the centralisation the more unequal the distribution of resources in a network is. Therefore, networks with low centralisation are characterised by equally distributed resources (Mora-Cantallops & Sicilia, 2019).

However, these findings can also be searched for in the non-professional games and there are major differences between the games played on a professional scene and in the non-professional ones. First of all, in the professional leagues players are aware of who they are going to play against. They can prepare to counter the efforts of the opposing team by gathering knowledge about their playstyle or their champion pool (Taylor, 2012). However, in non-professional play this tool is unavailable. People are matched with other players who - according to the matchmaking algorithm - are on a similar skill level. They may use tools to gather the information about their opponents, but it can be done only after the picking phase (Donaldson, 2015). What is more, the professional players are always able to communicate with each other during the professional league match in order to coordinate their efforts. In the paper written by Maznevski and Chudoba (2000), it was proven that the communication between the teammates significantly impacts the team’s performance (DeSanctis & Monge, 1999; Hertel, Geister, & Konradt, 2005). What is more, the effective communication between the teammates results in a smaller number of errors and a higher quality of decisions in achieving the goal (Larson, Christensen, Franz, & Abbott, 1998). However, the people who play online are restricted to communicate via text chat which is less efficient than verbal communication since it requires more time to write a message, and it does not allow you to play simultaneously. The non-professional players can use the voice chat only if they have grouped up with the players before the match. League of Legends does not contain a tool that allows the entire team to communicate verbally. There are possibilities to use the verbal communication applications such as Discord or Teamspeak, but they are rarely used by the randomly matched players (Donaldson, 2015). Furthermore, coordination of the team is highly prised both in sports and military (Mukherjee, 2016) and it is impossible to deny that the professional teams which have time to prepare are as coordinated as the teams which do not know who they play with or who they play against. In connection to papers about information exchange, such as those written by, Balkundi and Harrison (2006) or about interpersonal ties such as Rulke and Galaskiewicz (2000), it is clear that their findings make the environment of this paper different from the environment in Mora-Cantallops and Sicilia (2019). Finally, the most important difference that distinguishes professional players from non-professional players and which is applicable to organisational environments is practice. Professional players tend to practice around 10 hours per day by playing the game or reviewing the replays from their matches. This cannot be said about neither the non-professional players nor the employees of an organisation. Professional players tend to do their job twice a week for less than an hour – depending on the structure of the tournament. In the remaining time, they practice. However, non-professional players have a ratio of practice to actual gaming which is probably inverted in comparison to the one of professional players. A similar statement can refer to employees of an organisation who most of the time perform their duties and when they are not working, they, most likely, do not practice for their job.

As mentioned in the introduction, professional teams in each of the regions have a unique playstyle. For example, Korean players are known to play more carefully as they fight less and focus on taking objectives instead of killing their opponents and they only fight when they have to. Whereas, Chinese players fight with the other team for the sake of fighting and they need no objective to fight over (theScore esports staff, 2016). The way these playstyles match against each other is normally seen during international tournaments. However, in this paper it is impossible to have teams from Oceania compete against teams from Korea because they play on separate servers and they cannot be matched against each other. This matching was shown in the paper of Mora-Cantallops and Sicilia (2019) because they included international tournaments in their data set. Finally, the literature review presents differences between the geographic regions. They were already presented in the paper by Mora-Cantallops and Sicilia (2019) and these factors are expected to reappear in this paper as well.

Therefore, the hypotheses are as follows:

* H1: The increase of intensity within the team’s network structure is associated with a higher performance.
* H2: The increase of both indegree and outdegree centralisation within the team negatively influences the performance of the team.
* H3: The findings of performance and intensity are consistent between regions.

Therefore, the research questions are similar to the ones in the paper written by Mora-Cantallops and Sicilia (2019).

* Does the increase of the intensity within the team’s structure improve the team’s performance?
* Does the increase in indegree and outdegree centralisation of the connections have a negative impact on the team’s performance?
* Are performance and the impact of intensity similar between the regions?

The results that can be found in this research could be useful not only in the analysis of the eSport teams but also in the analysis of the traditional sports teams and organisational network research. For example, papers written by Jenny, Douglas Manning, Keiper and Olrich (2016) or Pareja-Blanco et al. (2016) have concluded that eSports share characteristics of the traditional sports. What is more, digital games and sports share similarities with regard to impact on viewers or participants, shares of the market or promoting each other (Crawford & Gosling, 2009). E.g., Coates & Parshakov (2016) claim that eSports can be used to test the implications of particular economic theories, such as the tournament theory. They have found eSports to bear similarities that allow them to relate the eSport research to social science. What is more, eSports can be useful in testing and proving evidence of effects that impact the performance of firms (Parshakov, Coates & Zavertiaeva, 2018). Finally, in sport economy literature, eSport is considered a specific sport and researchers have started paying additional attention to it (Parshakov & Zavertiaeva, 2018). This research can prove useful because it takes into account a different population than Mora-Cantallops and Sicilia (2019). As their research can be related to social science, so can this paper. It looks at similar measurement variables, but the research population is more natural and contains crucial differences that can make the outcomes of this paper applicable to particular firms and situations. Having firms which force randomly assigned people to do repetitive tasks and once they are done, match them randomly with other people is uncommon. However, having groups of people who do not communicate before and after doing the task or deciding to use non-verbal means of communication is more common. Furthermore, it is possible that in firms, groups of employees face a problem that they did not have time to prepare against. It is crucial to note that these differences are not meant to represent an organisation or a traditional sport identically. It does not happen often that an organisation gathers a group of random people and orders them to achieve a common goal. These differences are merely meant to represent a less organised and less professional environments with any kind of characteristics. It could mean that these groups of employees are culturally different, they worked in different areas before or they do not like each other which is going to obstruct their coordination and performance. There are multiple factors that can disorganise or deprofessionalise an environment. Therefore, it is possible that the research population of this paper will allow for finding results that apply to particular kinds of firms or working groups.

Finally, the omitted variable bias is present in this research because, there are multiple aspects of the game that cannot be taken into account. Firstly, diversity of the teammates is almost entirely unmeasured since the players are anonymous. However, the sampling method has advantages that subjectively cover this disadvantage since thanks to this approach most of the observations are randomly chosen by the in-game matching algorithm. Secondly, there is a matter of unobserved factors because, the researched units are people and what is happening around them is impossible for the model to take into account. They can have a bad or a good game or even a better or a worse day. They can step away from their computer because they are distracted by something and lead to a loss because they were unable to react to an action taken by the opposing team. On the other hand, the granularity of these factors would lead to a transformation of this paper from the research of network characteristics into a research of the individual characteristics and their impact on the performance of the team. Finally, the composition of the team is pivotal to its performance and it is also unknown for the models in this research. However, this research not related to the team composition but to the characteristics of the network that is created by interactions.

# Description of the game

This section describes the rules of League of Legends which is a MOBA (Multiplayer Online Battle Arena). This means that in the game there are two teams which consist of 5 players who compete against each other while one person is responsible for controlling one character in the game. The general rule of this game is that the stronger you or your teammates are, the easier the game should be for your team. The players coordinate their efforts in order to destroy a building that is located in the base of the opposing team. The building whose destruction concludes the game is called nexus (red arrow in Fig.1) and a road that leads to it is guarded by three towers (orange arrows) that you need to destroy if you want to get close to the nexus. Inhibitors (yellow arrows) give gold to the team that destroys them and then they trigger the destroyer’s nexus to create one additional stronger minion.[[1]](#footnote-1)

There are multiple possible approaches to the game out of which many require having the team cooperate with other players. E.g., one person will have a lower chance of winning against two people at once. Therefore, players who work together have a higher chance of winning than those who work alone.

**Figure 1.**

The map of the location where the match of League of Legends takes place.



Source: https://agegaming.wordpress.com/2015/05/29/ages-league-of-legends-season-5-basics-guide-part-3-summoners-rift/

The purchases of items that make one’s character stronger can be made with the in-game currency which is gold. Gold, as a benefit, is distributed to individuals for killing the members of the opposing team, destroying their structures, and killing minions. Minions are non-player characters which spawn next to the nexus and then march towards the enemy nexus through one of the lanes. The main individual incentive in this situation is present in the distribution of gold. Gold is also given directly to the people who assist in the killing of the enemy player. Therefore, if there is a duel, a winner gets 300 gold. However, if there are three people in a fight and two of them are on the same team, then the one who kills the enemy receives 300 gold and the one who helped them kill the enemy receives 150 gold while the loser gets nothing and dies only to respawn sometime later. This is highly correlated to why the intensity is expected to have a positive impact on the performance. It means that the more people participate in the takedown of the enemy, the more money they get as a team. However, the reward for assists is not consistent because the increase of the number of players who assist decreases the size of the reward. If three people assist, they will not receive 150 gold each as mentioned above. They will receive a smaller amount of gold. In addition, the more times a player dies, the less money they are worth. Therefore, rewards for assists do not contribute to the overall gold as much as kills or other sources.

The conflict of the interests within the team is a common occurrence. Investing resources into particular roles is more efficient when it comes to killing the enemies. However, some players are overconfident in their skills and are unable to kill the enemies as effectively as other players would be. Therefore, players might disagree over who to invest the resources in. Another conflict of interests can happen when a person is indifferent about winning the game and wants to sabotage their teammates by depriving them of resources. Finally, the occurrence of the conflict of interests depends on one’s understanding of the game and their idea on how to play the game in order to win. Therefore, it is common for players to disagree over what is the most efficient course of action. There is also a chance of free riding one’s way to a victory. If one player is mechanically skilled and receives enough resources, they can lead their team to victory. On the other hand, there is also a chance of one person causing the entire team to lose. In the researched game, coordination is essential even in the pettiest aspects of the match. Deciding who to invest the resources in, is in principle what the researched networks consist of. Therefore, the networks are created by players and they, in most of the situations, decide where the connection will start and where it will end. Obviously, not everything in any game has to go according to a plan. Therefore, it is impossible to say that the players create the networks the way they want to. However, they coordinate their efforts in order to ensure that the distribution of kills and assists is as profitable to them as it can.

Individual costs of players are mostly based on lost opportunities. For example, in situations in which one could claim a bounty for a kill but, decides to leave it for another player. Additionally, players can sacrifice themselves for others who are worth more gold to the enemy team or they can die while luring the enemy team into a trap. Individual benefits stem from situations in which players decided to donate the resources into other players who they deem to be a crucial factor in winning a match. This mechanism is seen on the bottom lane where support does not take the resources from the other player in order to allocate as much gold as possible in this one player. Judging by the negative influence of the centralisation that was found in the paper of Mora-Cantallops and Sicilia (2019), allocating team’s resources in one individual is not the most efficient solution. The authors have looked at the stage games and the mechanism behind this factor has not been explained but, it could be caused by the fact that one player is easier to be killed than two players. E.g., if the enemy team knows who the biggest threat is, they can coordinate their efforts to eliminate this person. Whereas, it is more difficult to achieve when there are two considerable threats located on opposite sides of the map.

The game also contains a ranking system which is vital for this research. After a match, all players have their score affected. If they win, they receive so called League Points. However, if they are defeated, they lose these points. The ranking in which these points position the players consists of multiple divisions. The lowest is Iron and the next divisions skill wise increasingly are Bronze, Silver, Gold, Platinum, Diamond, Master, Grandmaster and Challenger. In order to climb higher than Platinum division, a player needs to perform well and play many games. That is why, partially the three top divisions (Master, Grandmaster and Challenger) are occupied by professional players or streamers who make their living out of playing League of Legends. These divisions accumulate roughly 1% of all the players[[2]](#footnote-2).

# Data

The data is gathered from Riot’s (the company which has created League of Legends) API. Their API contains tables with all the events in the match that a chosen person has played. This includes buying items, destroying the building, or killing an enemy. Every kill has additional variables with the IDs of the teammates who assisted in killing the enemy. This allows to see how many kills a person has gathered and which teammates have assisted. This information leads to the creation of the researched networks. The data in this paper was designed around the best players in the regions on 8th of December 2020. The best players are determined by the ranking system explained above. Websites as op.gg offer a look into the highest divisions and the people who are on the top of these divisions. Therefore, the matches that were played by these players were downloaded from the history of the games of these particular players. Their teammates and enemies are matched randomly, and they will most likely not be professional players which allows for obtainment of an altered environment. Therefore, the data is constructed around two players who were considered the best in regions such as South Korea, North America, Europe, Brazil, and Oceania. The database is almost entirely anonymised except for the in-game names of the players who were used as sources in order to make sure that the remaining players who appear in both friendly and opponent team, are considered to have a similar skill in the game. Therefore, the sampling is done by taking the ten players and looking at last 200 of their matches. Focusing on the best players allows for making sure that the mechanical abilities of the players do not differ as much as they do in lower divisions.

Mechanical abilities, in the context of gaming mean the players ability to react to an action that happens in the game. This includes the reaction time or the efficiency of the reaction. These are the abilities that are incorporated into micro behaviours in the game such as using a particular ability at a certain time in order to counter the action of the opponent. One can have a winning strategy and still lose because of not reacting fast enough or buying wrong items. The risk of this event to happen was minimalised by focusing on the highest ranked players. In the higher divisions mechanical abilities do not matter as much as the strategy and the composition of the team.

This sampling technique is not flawless because it does not allow for the complete randomisation of the networks. Nevertheless, out of 19 150 players who appear in the complete data set, 1915 are not randomly chosen. These players are considered the best in their respective regions which prevents having different outcomes in the models solely because the players are not as mechanically capable as the professional players in the paper written by Mora-Cantallops and Sicilia (2019). They have a data base of professional players who play against other professional players. Therefore, it is safe to assume that they are the best since they compete in tournaments and leagues. What is more, they are paid to play the game and they practice constantly.

The final sample size is 3830. 200 matches of each player are downloaded. Pre-emptive conclusions of the game happen often therefore, the sample size is not 4000. Matches that were excluded from the data did not have enough assists or kills to allow for the creation of the network. In one match there are 2 teams. Hence, 400 observations stemming from each player. This leads to a certain level of interdependency, because two teams play against each other and they impact each other’s performance. However, this allows for a considerate balance of performance since half of the teams lost and the other half won. Therefore, the team that won will skew the average performance of the team up and, the other team from the same match will drag the average performance down.

In eSports, there is a concept of behaviour that is called “trolling”. This is any kind of deliberately destructive behaviour that is aimed at making the team of the “troll” lose. This behaviour is a common occurrence in the lower divisions of the ranking ladder in League of Legends. It is not entirely unheard of in the highest divisions, but it is definitely seen more rarely which is one of the reasons why the researched population is positioned in the higher divisions. Occurrence of “trolling” might be one of the reasons why many matches were concluded before enough kills could be taken.

# Network

The network was created from an edge list that included one observation as a single connection between the members of one team. It is directed and weighted. One connection is a situation in which one player assisted another player in killing an opponent. Therefore, one connection is a single assist. The maximum number of assists in one kill is four, because the size limit of the network is 5 and one player cannot assist themself. That is why, there are more connections than amounts of kills. It is possible to note kills without assists, but these situations are not a connection in the edge list however, they are included in the kill count. Edges in the network are directed from the person who assists in the kill to the person who kills. Therefore, the indegree centralisation refers to the concentration of kills and the outdegree centralisation refers to the concentration of assists. The measurements of centralisation range from 0 to 1 e.g., 0 indegree centralisation appears when all the kills in the team are distributed evenly among the players. Whereas, outdegree centralisation equal to 1 can be seen when all the assists in the team are concentrated in one of the players with the rest of the team having no assists. Mora-Cantallops and Sicilia (2019) have based their centralisation calculations on the following equations. Outdegree centralisation (COD) is calculated by the following equation:

Whereas, the indegree centralisation (CID) is calculated as follows:

*i* and *j* represent the ID’s of the nodes. Whereas, *N* stands for the number of the nodes that appear in the network. Finally, *wij* indicates the number of connections between *i* and *j*. Since, the networks are always small because the maximum number of nodes is 5, the centralisation degree is standardised so, divided by the maximum centralisation of a node.

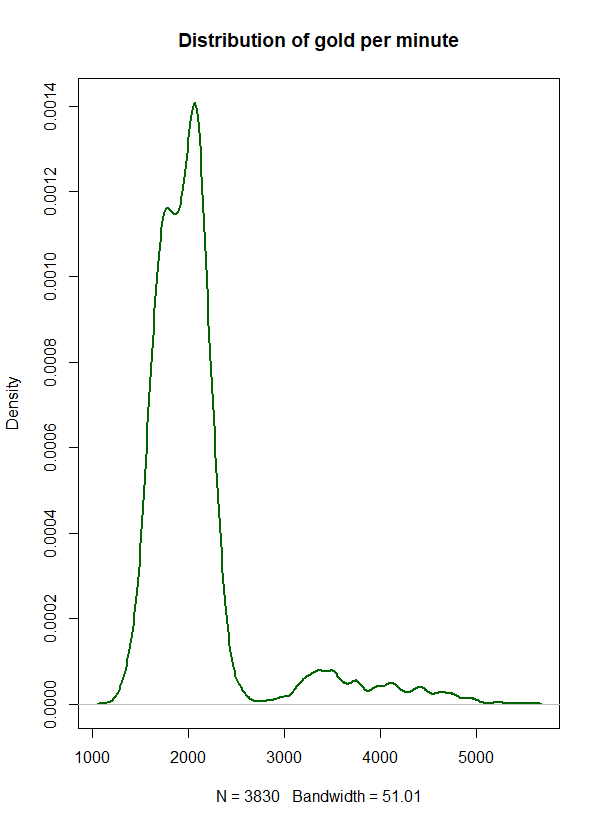
Corelation of the number of kills and the number of assists was adjusted by dividing these measures by the duration of the match. Additionally, this measurement was adjusted as the intensity measurement. Intensity is meant to show the number of edges that are present in the network and divide them by the number of kills.

These measures were chosen in order to represent the ones that were used in Mora-Cantallops and Sicilia (2019). The variables that are included in the models are defined as follows:

* Gold per minute – amount of gold gathered by the entire team by the end of the match, divided by the duration of the match in minutes. This is the performance variable.
* Kills – the number of kills that the particular team amassed.
* Kills per minute – the number of kills that the particular team amassed, divided by the duration of the match in minutes.
* Assists – the number of times one member of the team assisted another. This variable also represents the number of connections in a network.
* Assists per minute - the number of times one member of the team assisted another, divided by the duration of the match in minutes.
* Indegree centralisation – standardised concentration of kills in one member of the team rather than distributing kills evenly between the remaining members of the team.
* Outdegree centralisation – standardised concentration of assists in one member of the team rather than distributing assists evenly between the remaining members of the team.
* Intensity – ratio of the number of assists and the number of kills.

**Figure 2**

Distribution of gold per minute.



*Note*. This figure shows a distribution of gold per minute which is later on used as the dependent variable.

*N* = 3830

The plot on the side shows the distribution of the dependent variable which is gold per minute. The line does not resemble a perfect normal distribution. There is a part of results on the right side of the main part. However, most of the results are clustered together in a shape that is not distant from a normal distribution indicating shape.

**Table 1**

*Descriptive statistics of the networks.*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variable | Mean | Standard deviation | Min | Max | Observations |
| Gold per minute | 2085 | 597.303 | 1190 | 5531 | 3830 |
| Kills per minute | 1.118 | 0.649 | 0.084 | 5.801 | 3830 |
| Assists per minute | 0.862 | 1.176 | 0.004 | 9.710 | 3830 |
| Intensity | 0.771 | 0.773 | 0.015 | 2.927 | 3830 |
| Indegree centralisation | 0.214 | 0.094 | 0.000 | 0.600 | 3830 |
| Outdegree centralisation | 0.252 | 0.111 | 0.000 | 0.750 | 3830 |

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1.

*Note.* This table shows the descriptive characteristics of the networks used in the paper.

*N* = 3830

***Figure 3***

*Violin plot of the gold distribution.*

Chart

Description automatically generated

The figure on the left presents a violin plot of gold distribution. The object on the left shows the gold of the team that loses and the object on the right presents the team that wins. It can be seen that the mean gold is higher for the team that wins which is an intuitive result.

*Note*. This figure shows a distribution of gold in the shape of a violin plot.

*N* = 3830

# Method

The paper contains two separate types of statistical models. A linear model is a simple tool but in calculations of continuous variables such as gold per minute, intensity, and centralisation it can prove useful. Secondly, the multilevel regression model is used in order to account for the mixed effects in the calculation. In this paper the mixed effects are set on the regions to take into consideration the factors that impact the results exclusively in this one region. What is more, the regions are measured multiple times over a longer period. In this situation, due to the inclusion of mixed effects and the measurement over time, the multilevel regression appears to be a suitable tool. Both kinds of the models include gold per minute as the dependent variable. Then, independent variables are kills per minute, intensity (assists per kill), indegree centralisation and outdegree centralisation. What is more, the multilevel regression model includes regions as mixed effect. Additional models are included in order to measure the impacts of particular variables which are excluded in those models. One of the models is a generalised linear model of the binomial family which is aimed to be predicting the impact of the network characteristics on the probability of winning since winning a match is the ultimate performance measurement. Then, additional model excludes intensity which is expected to be highly correlated with the gold per minute in order to measure solely the network characteristics. Finally, the last model contains a different dependent variable which is kills per minute. This is done in order to inspect entirely different measurement variable and the extent to which the network characteristics have an impact. As in a standard social science paper, the confidence interval was decided to be set as 0.05.

# Results

Not all of the assumptions of the linear model were fully met. Firstly, linearity is visible in the plot of dependent and the independent variable. However, Durbin-Watson test shows that there is autocorrelation between the residuals. What is more, autocorrelation can be seen in the plot of residuals and time. Then, homoscedasticity assumption is not met as well. Residuals and fitted plot shows an increase of spread of residuals with the increase of fitted values. Transforming either dependent or independent variables in the model has not brought results that would satisfy this condition. Lastly, normality assumption has been met. Normal Q-Q plot shows a roughly normal distribution of residuals. What is more, the mean of residuals is close to 0.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Variable | Linear model | | | Multilevel regression | | |
| Estimate | SE | p-value | Estimate | SE | p-value |
| Gold per minute | 1064.023 | 15.927 | <2e-16 \*\*\* | 1065.606 | 22.056 | < 2e-16 \*\*\* |
| Kills per minute | 866.144 | 5.771 | <2e-16 \*\*\* | 865.336 | 5.753 | < 2e-16 \*\*\* |
| Intensity | -17.182 | 7.955 | 0.031 \* | 5.262 | 4.915 | 0.284 |
| Indegree centralisation | 81.760 | 44.778 | 0.068 . | 75.733 | 44.452 | 0.089 . |
| Outdegree centralisation | 124.293 | 37.476 | 0.001 \*\* | 126.531 | 37.173 | 0.000 \*\*\* |
| Intensity Brazil | 13.851 | 10.385 | 0.182 | - | - | - |
| Intensity Europe | 17.657 | 10.193 | 0.083 . | - | - | - |
| Intensity Oceania | 35.813 | 10.000 | 0.001 \*\*\* | - | - | - |
| Intensity Korea | 43.480 | 9.625 | 6.45e-06 \*\*\* | - | - | - |
| Random effects | | | | | | |
| Region | - | | | Variance | SD | |
| 1180 | 34.36 | |
| Observation | 3830 | | | 3830 | | |

**Table 2**

*Regression using gold per minute as the dependent variable.*

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1.

*Note*. This table shows the results of the statistical model with gold per minute as a dependent variable.

*N* = 3830, R2 = 0.870

This linear model has a R2 of 0.8702, which implies that dependent variable is relatively well explained by the dependent variables. The third table shows that an increase in kills per minute leads to an increase of the team’s performance. Both have a low p-value which indicates that these coefficients are significant. What is more, intensity also has a positive impact on the gold per minute. However, the p-value and standard error are high, indicating that this coefficient needs to be carefully analysed. Then, indegree centralisation shows a positive influence on the performance of the team but, once again p-value is high. Lastly, outdegree centralisation is an impactful coefficient that alongside with its increase, improves the team’s performance as well.

The introduction of the regions as random intercepts does not severely impact the measurements of the ones seen in the linear model. The most notable change in the size of the coefficient appears in the intensity and indegree centralisation coefficients. The p-value of the first increases together with the size of the coefficient. This implies that this impact might not be suitable for binding analysis. Furthermore, the p-value of the latter increases as well. However, the size of the coefficient itself decreases significantly. Overall, kills per minute and, centralisation have a positive impact on the performance of the team. Finally, the random intercept, which is a region in the multilevel regression analysis, shows that there are differences between the average performance of the regions.

**Table 3**

Generalised linear model predicting wins.

|  |  |  |  |
| --- | --- | --- | --- |
| Variables | Estimate | SE | p-value |
| Win | 1.393 | 0.124 | < 2e-16 \*\*\* |
| Intensity | -0.372 | 0.077 | 1.52e-06 \*\*\* |
| Indegree centralisation | -0.307 | 0.440 | 0.485 |
| Outdegree centralisation | -4.361 | 0.381 | < 2e-16 \*\*\* |
| Intensity Brazil | 0.158 | 0.101 | 0.116 |
| Intensity Europe | -0.032 | 0.099 | 0.749 |
| Intensity Korea | 0.098 | 0.094 | 0.293 |
| Intensity Oceania | 0.094 | 0.097 | 0.331 |

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1.

*Note*. This table shows the results of the generalised linear model with win dummy set as the dependent variable.

*N* = 3830, R2 = 0.071

The model described above is a generalised linear model of binomial family with winning as a dependent variable. However, Nagelkerke’s R squared showed a poor fit of data to this model regardless of included variables. The model shows that an increase in all of the included network characteristics decreases a chance of winning. The most impactful of them being concentration of assists (outdegree centralisation) and the least influential concentration of kills (indegree centralisation). What is more, indegree centralisation had a high p-value making this coefficient unable to be bindingly analysed. The intensity was included as an interaction with the North American region. It implies that an increase in the intensity has a negative impact on the chance of winning both in North America and Europe. However, in the remaining regions the coefficient of intensity is not as detrimental to the chance of winning. According to the results, Brazil is the region whose chance of winning is the least negatively impacted by the increase in intensity. However, all the interactions have a high p-value which makes it impossible to draw binding conclusions out of these results.

|  |  |  |  |
| --- | --- | --- | --- |
| Variables | Estimate | SE | p-value |
| Gold per minute | 2565.192 | 32.544 | < 2e-16 \*\*\* |
| Intensity | -65.882 | 20.869 | 0.002 \*\* |
| Indegree centralisation | -284.663 | 117.393 | 0.015 \* |
| Outdegree centralisation | -1440.679 | 94.511 | < 2e-16 \*\*\* |
| Intensity Brazil | 9.833 | 27.266 | 0.718 |
| Intensity Europe | -126.183 | 26.644 | 2.26e-06 \*\*\* |
| Intensity Korea | 106.288 | 25.248 | 2.62e-05 \*\*\* |
| Intensity Oceania | -33.244 | 26.228 | 0.205 |

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

**Table 4**

Linear model on the performance of the team.

*Note*. This table shows the results of the linear model with gold per minute as the dependent variable.

*N* = 3830, R2 = 0.105

Additionally, there is a linear model which was used to look solely on the characteristics of the network and their impact on the performance of the team. It excluded kills per minute since it is highly correlated with both intensity and gold per minute. However, the model showed a poor fit to the data and it was visible in the R2 which equalled 0.105. It implied that concentration of assists (outdegree centralisation) was the most influential coefficient to the performance of the team. It showed that increase of the concentration of assists, significantly decreases the gold per minute. Aside from this coefficient, the remaining variables were found to have a smaller but, still negative impact on the dependent variable. Concentration of kills as well as intensity were negative coefficients that implied that their increase would decrease the performance of the team. Finally, intensity was an interaction with the North American region once again. According to these results, Europe and Oceania exhibit a more negative impact of the intensity on the gold per minute. The same type of influence can be seen in Brazil but, it is slightly more positive than the reference coefficient of North America. Finally, Korea appears to be the sole region whose intensity coefficient has a positive impact on the gold per minute. However, coefficients for Brazil and Oceania are insignificant since their p-values exceed the set confidence interval.

|  |  |  |  |
| --- | --- | --- | --- |
| Variables | Estimate | SE | p-value |
| Kills per minute | 1.733 | 0.035 | < 2e-16 \*\*\* |
| Intensity | -0.056 | 0.022 | 0.012 \* |
| Indegree centralisation | -0.423 | 0.125 | 0.001 \*\*\* |
| Outdegree centralisation | -1.807 | 0.101 | < 2e-16 \*\*\* |
| Intensity Brazil | -0.005 | 0.029 | 0.873 |
| Intensity Europe | -0.166 | 0.028 | 5.71e-09 \*\*\* |
| Intensity Korea | 0.073 | 0.027 | 0.007 \*\* |
| Intensity Oceania | -0.080 | 0.028 | 0.004 \*\* |

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

**Table 5**

*Linear model on the performance of a team with a different measurement.*

*Note*. This table shows the results of the linear model with kills per minute as the dependent variable.

*N* = 3830, R2 = 0.136

Lastly, the additional linear model which includes a different variable as an indicator of performance was run. In this situation, performance is measured by kills per minute in comparison to the gold per minute in the remaining models. R2 equalled to 0.136 which signals an unsatisfactory fit of the data to the model. However, the majority of variables is significant except for the interaction of intensity and the region of Brazil. The reference intensity coefficient represents North America, and it shows a negative impact on performance. In combination with the factors of regions, performance suffers with the increase of intensity. The only exception is Korea, which together with the main effect maintains a positive influence on the performance. The remaining regions (being Europe and Oceania) clearly show a more impactful negative influence on the performance of a team. The most detrimental effect appears to take place in the European region. Brazil shows a slightly more negative impact of intensity on performance however, the p-value is high which does not allow to draw binding conclusions. Finally, both indices of centralisation have a negative impact on performance as well. Indegree centralisation is less impactful in comparison to outdegree. However, both measurements of concentration clearly indicate that their increase is significantly detrimental to the performance of a team.

# Discussion

The models that appeared in this paper partially resonate with the findings in the papers that looked at non-gaming environments. However, it is impossible to state that the results of the models replicate the findings of the models run in non-gaming environments. Intensity overall shows a negative impact on the performance. However, the main model, which is shown in Table 2, presents a positive influence of both indegree and outdegree centralisation on the performance of a team. These results do not go hand in hand with the findings Mora-Cantallops and Sicilia (2019). Firstly, the first hypothesis was rejected because intensity was found to have a negative impact on the performance. This coefficient is consistent throughout all the models with the exception of multilevel regression analysis, where the coefficient is insignificant. Furthermore, the second hypothesis about the impact of the concentration of kills or assists having a negative impact on the performance of the team was rejected. This result is not consistent throughout the models. All of the tables except for the Table 2, show a negative impact of centralisation on the performance of the team. These findings resemble the results of the original paper most. The hypotheses about a negative impact of the centralisation in the paper written by Mora-Cantallops and Sicilia (2019) was supported because they found a negative impact of both indegree and outdegree centralisation on the performance of the teams. This difference could have occurred due to multiple reasons. One of those reasons might be the difference in the sample which is the main discrepancy between these two papers. As written in the research question, people who are included in the population for this research are not playing on the stage. They do not know who they will go against or who they will have in their team. This does not allow for elaborate planning. Additionally, the communication is restricted therefore, decreasing the efficiency of the team in dealing with the problems they encounter. Overall, these differences have probably occurred due to the lesser extent, to which the environment is organised. However, other reasons can cause differences in the measurement of the multilevel regression analysis, since Mora-Cantallops and Sicilia (2019) have included three additional factors that they later used to measure the changes in the coefficients. However, in this paper there is only one possibility to measure that which is by including the regions as the random intercept. On the other hand, a person who is well acquainted with the rules of the game, knows that there are more variables that impact the performance of the team which cannot be considered. They can only manifest themselves more visibly in the environments which are not as controlled as the environment in which the professional players play on the stage as a part of the season of a league. Finally, the introduction of regions as random intercepts shows a small change in the outcomes of the model. What is more, the interactions between regions and intensity constantly show that the regions differ not only with regard to the performance, but also with regard to the impact of intensity. Therefore, supporting the third hypothesis and showing that the impact of network structure characteristics and performance differ between regions.

The differences between the results in this paper and the paper written by Mora-Cantallops and Sicilia (2019) can be interpreted with regard to the working environment. The impact of the centralisation can be positive in the working environment when it resembles the non-professional League of Legends. That would imply a smaller number of preparations for the task or a restricted verbal communication at work. Possibly, environments in which workers cooperate with each other equally would be less efficient than the ones which resemble ego networks. Since the intensity coefficients were negative in the majority of the models, it is reasonable to assume that a less organised environments do not benefit from dense networks as much as more organised environments do. In general, the differences between the professional play and the non-professional play, as specified in the literature review, can be also seen in the working environment. It is possible that the same differences, in the impacts of intensity and centralisation, would be noted in a research of two separate working environments. One of them resembling the population that was included in the paper written by Mora-Cantallops and Sicilia (2019) and the other research similar to the population which was included in this paper. This calls for additional investigation that would put emphasis on these particular differences.

# Conclusion

The video games are becoming a more popular activity that people choose to do in their spare time and the amount of data they create by simply playing the game is overwhelming. However, this allows the researchers to analyse the behaviours and mechanisms that rule the gaming world with a high accuracy. Furthermore, these finding can be translated onto other areas of human life such as working environments, military, or marketing. This paper highlights a group of points that are worth noting. First of all, League of Legends creates an opportunity to research the behaviours of people and then use this framework to look for possible similarities in other areas of research. Secondly, the density is positively affecting the performance of the team regardless of the region. The same impact can be caused by the indegree centralisation of the network and the outdegree centralisation as well. The indegree centralisation was found to have a positive influence on the performance of the team. What is more, outdegree centralisation is a positive factor that increases the performance. It shows an even bigger impact on the performance. Additionally, the regions do not differ between each other when it comes to the sizes of the impacts of density, indegree centralisation and outdegree centralisation of the network on the performance of the team. However, the characters are repeatedly positive therefore, the findings are consistent between the regions. This kind of research allows the players and teams to improve their performance in the game. What is more, it can be useful for managers or coaches who are responsible for planning the composition of their team. However, due to the differences in the findings between this paper and the one written by Mora-Cantallops and Sicilia (2019), it is reasonable to call for further research on the impact of the structure of the network on the performance of the team in order to make sure that the teams can improve from learning about these findings.

# Appendix

Pseudo code:  
1. Creating vectors with names of csv files that contain the IDs of the matches in order to load them.

2. Loading the csv files with the IDs of killers, assistants, total gold of the team, duration of the match in seconds, ID of the team and a dummy indicating whether the killer with this ID won.

3. Calculating the amounts of kills for every ID of the killer.

4. Summing up kills in order to know the final performance of the team.

5. Calculating variables such as kills per minute, assists per kill, gold per min etc.

6. Reshaping the data sets so that they can be turned into edge lists.

7. Calculating the characteristics of the structure of the team network.

8. Running the statistical models.

Code:

library(lme4)

library(lmerTest)

library(igraph)

library(fmsb)

library(ggplot2)

setwd("C:/Users/Mateusz/Documents/Studia/Thesis/Gaming competition")

europe1<-list()

europe2<-list()

korea1<-list()

korea2<-list()

brazil1<-list()

brazil2<-list()

oceania1<-list()

oceania2<-list()

america1<-list()

america2<-list()

for(i in 1:193){

korea1[[i]]<-read.csv(file=paste0("C:/Users/Mateusz/Documents/Studia/Thesis/Gaming competition/kr/1/",i,".csv"))

}

for(i in 1:195){

brazil1[[i]]<-read.csv(file=paste0("C:/Users/Mateusz/Documents/Studia/Thesis/Gaming competition/br/1/",i,".csv"))

}

for(i in 1:198){

america2[[i]]<-read.csv(file=paste0("C:/Users/Mateusz/Documents/Studia/Thesis/Gaming competition/na/2/",i,".csv"))

}

for(i in 1:197){

brazil2[[i]]<-read.csv(file=paste0("C:/Users/Mateusz/Documents/Studia/Thesis/Gaming competition/br/2/",i,".csv"))

oceania1[[i]]<-read.csv(file=paste0("C:/Users/Mateusz/Documents/Studia/Thesis/Gaming competition/oc/1/",i,".csv"))

}

for(i in setdiff(1:190,152)){

europe2[[i]]<-read.csv(file=paste0("C:/Users/Mateusz/Documents/Studia/Thesis/Gaming competition/eun1/2/",i,".csv"))

}

for(i in setdiff(1:197,c(145,152))){

oceania2[[i]]<-read.csv(file=paste0("C:/Users/Mateusz/Documents/Studia/Thesis/Gaming competition/oc/2/",i,".csv"))

}

for(i in setdiff(1:195,139)){

korea2[[i]]<-read.csv(file=paste0("C:/Users/Mateusz/Documents/Studia/Thesis/Gaming competition/kr/2/",i,".csv"))

}

for(i in setdiff(1:198,126)){

europe1[[i]]<-read.csv(file=paste0("C:/Users/Mateusz/Documents/Studia/Thesis/Gaming competition/eun1/1/",i,".csv"))

}

for(i in setdiff(1:197,c(52,126))){

america1[[i]]<-read.csv(file=paste0("C:/Users/Mateusz/Documents/Studia/Thesis/Gaming competition/na/1/",i,".csv"))

}

europe<-c(europe1,europe2)

europe[[126]]<-NULL

europe[[349]]<-NULL

europe[[292]]<-NULL

europe[[4]]<-NULL

europe[[77]]<-NULL

europe[[224]]<-NULL

europe[[275]]<-NULL

europe[[373]]<-NULL

europe[[107]]<-NULL

korea<-c(korea1,korea2)

korea[[332]]<-NULL

korea[[131]]<-NULL

korea[[293]]<-NULL

brazil<-c(brazil1,brazil2)

brazil[[43]]<-NULL

brazil[[159]]<-NULL

brazil[[184]]<-NULL

brazil[[201]]<-NULL

brazil[[254]]<-NULL

brazil[[264]]<-NULL

brazil[[119]]<-NULL

brazil[[22]]<-NULL

brazil[[95]]<-NULL

brazil[[108]]<-NULL

brazil[[119]]<-NULL

oceania<-c(oceania1,oceania2)

oceania[[342]]<-NULL

oceania[[348]]<-NULL

oceania[[35]]<-NULL

oceania[[121]]<-NULL

oceania[[124]]<-NULL

oceania[[364]]<-NULL

america<-c(america1,america2)

america[[52]]<-NULL

america[[125]]<-NULL

america[[13]]<-NULL

america[[93]]<-NULL

america[[132]]<-NULL

america[[271]]<-NULL

america[[132]]<-NULL

america[[38]]<-NULL

america[[268]]<-NULL

america[[310]]<-NULL

america[[337]]<-NULL

america[[382]]<-NULL

america[[324]]<-NULL

idk1 <- list()

idk2 <- list()

idk3 <- list()

idk4 <- list()

idk5 <- list()

idk6 <- list()

idk7 <- list()

idk8 <- list()

idk9 <- list()

idk10 <- list()

ide1 <- list()

ide2 <- list()

ide3 <- list()

ide4 <- list()

ide5 <- list()

ide6 <- list()

ide7 <- list()

ide8 <- list()

ide9 <- list()

ide10 <- list()

ido1 <- list()

ido2 <- list()

ido3 <- list()

ido4 <- list()

ido5 <- list()

ido6 <- list()

ido7 <- list()

ido8 <- list()

ido9 <- list()

ido10 <- list()

idb1 <- list()

idb2 <- list()

idb3 <- list()

idb4 <- list()

idb5 <- list()

idb6 <- list()

idb7 <- list()

idb8 <- list()

idb9 <- list()

idb10 <- list()

ida1 <- list()

ida2 <- list()

ida3 <- list()

ida4 <- list()

ida5 <- list()

ida6 <- list()

ida7 <- list()

ida8 <- list()

ida9 <- list()

ida10 <- list()

for (j in 1:385){ #Calculating the ammounts of kills for every ID

idk1[[j]] <- length(which(korea[[j]]$PLAYERID=="1"))

idk2[[j]] <- length(which(korea[[j]]$PLAYERID=="2"))

idk3[[j]] <- length(which(korea[[j]]$PLAYERID=="3"))

idk4[[j]] <- length(which(korea[[j]]$PLAYERID=="4"))

idk5[[j]] <- length(which(korea[[j]]$PLAYERID=="5"))

idk6[[j]] <- length(which(korea[[j]]$PLAYERID=="6"))

idk7[[j]] <- length(which(korea[[j]]$PLAYERID=="7"))

idk8[[j]] <- length(which(korea[[j]]$PLAYERID=="8"))

idk9[[j]] <- length(which(korea[[j]]$PLAYERID=="9"))

idk10[[j]] <- length(which(korea[[j]]$PLAYERID=="10"))

}

for(j in 1:379){

ide1[[j]] <- length(which(europe[[j]]$PLAYERID=="1"))

ide2[[j]] <- length(which(europe[[j]]$PLAYERID=="2"))

ide3[[j]] <- length(which(europe[[j]]$PLAYERID=="3"))

ide4[[j]] <- length(which(europe[[j]]$PLAYERID=="4"))

ide5[[j]] <- length(which(europe[[j]]$PLAYERID=="5"))

ide6[[j]] <- length(which(europe[[j]]$PLAYERID=="6"))

ide7[[j]] <- length(which(europe[[j]]$PLAYERID=="7"))

ide8[[j]] <- length(which(europe[[j]]$PLAYERID=="8"))

ide9[[j]] <- length(which(europe[[j]]$PLAYERID=="9"))

ide10[[j]] <- length(which(europe[[j]]$PLAYERID=="10"))

}

for(j in 1:388){

ido1[[j]] <- length(which(oceania[[j]]$PLAYERID=="1"))

ido2[[j]] <- length(which(oceania[[j]]$PLAYERID=="2"))

ido3[[j]] <- length(which(oceania[[j]]$PLAYERID=="3"))

ido4[[j]] <- length(which(oceania[[j]]$PLAYERID=="4"))

ido5[[j]] <- length(which(oceania[[j]]$PLAYERID=="5"))

ido6[[j]] <- length(which(oceania[[j]]$PLAYERID=="6"))

ido7[[j]] <- length(which(oceania[[j]]$PLAYERID=="7"))

ido8[[j]] <- length(which(oceania[[j]]$PLAYERID=="8"))

ido9[[j]] <- length(which(oceania[[j]]$PLAYERID=="9"))

ido10[[j]] <- length(which(oceania[[j]]$PLAYERID=="10"))

}

for(j in 1:381){

idb1[[j]] <- length(which(brazil[[j]]$PLAYERID=="1"))

idb2[[j]] <- length(which(brazil[[j]]$PLAYERID=="2"))

idb3[[j]] <- length(which(brazil[[j]]$PLAYERID=="3"))

idb4[[j]] <- length(which(brazil[[j]]$PLAYERID=="4"))

idb5[[j]] <- length(which(brazil[[j]]$PLAYERID=="5"))

idb6[[j]] <- length(which(brazil[[j]]$PLAYERID=="6"))

idb7[[j]] <- length(which(brazil[[j]]$PLAYERID=="7"))

idb8[[j]] <- length(which(brazil[[j]]$PLAYERID=="8"))

idb9[[j]] <- length(which(brazil[[j]]$PLAYERID=="9"))

idb10[[j]] <- length(which(brazil[[j]]$PLAYERID=="10"))

}

for (j in 1:382){

ida1[[j]] <- length(which(america[[j]]$PLAYERID=="1"))

ida2[[j]] <- length(which(america[[j]]$PLAYERID=="2"))

ida3[[j]] <- length(which(america[[j]]$PLAYERID=="3"))

ida4[[j]] <- length(which(america[[j]]$PLAYERID=="4"))

ida5[[j]] <- length(which(america[[j]]$PLAYERID=="5"))

ida6[[j]] <- length(which(america[[j]]$PLAYERID=="6"))

ida7[[j]] <- length(which(america[[j]]$PLAYERID=="7"))

ida8[[j]] <- length(which(america[[j]]$PLAYERID=="8"))

ida9[[j]] <- length(which(america[[j]]$PLAYERID=="9"))

ida10[[j]] <- length(which(america[[j]]$PLAYERID=="10"))

}

edt <- cbind(unlist(ide1),unlist(ide2),unlist(ide3),unlist(ide4),unlist(ide5),unlist(ide6),unlist(ide7),unlist(ide8),unlist(ide9),unlist(ide10))

edt <- as.data.frame(edt)

adt <- cbind(unlist(ida1),unlist(ida2),unlist(ida3),unlist(ida4),unlist(ida5),unlist(ida6),unlist(ida7),unlist(ida8),unlist(ida9),unlist(ida10))

adt <- as.data.frame(adt)

kdt <- cbind(unlist(idk1),unlist(idk2),unlist(idk3),unlist(idk4),unlist(idk5),unlist(idk6),unlist(idk7),unlist(idk8),unlist(idk9),unlist(idk10))

kdt <- as.data.frame(kdt)

bdt <- cbind(unlist(idb1),unlist(idb2),unlist(idb3),unlist(idb4),unlist(idb5),unlist(idb6),unlist(idb7),unlist(idb8),unlist(idb9),unlist(idb10))

bdt <- as.data.frame(bdt)

odt <- cbind(unlist(ido1),unlist(ido2),unlist(ido3),unlist(ido4),unlist(ido5),unlist(ido6),unlist(ido7),unlist(ido8),unlist(ido9),unlist(ido10))

odt <- as.data.frame(odt)

edt[,11] <- rowSums(edt[,1:5],na.rm = T)

adt[,11] <- rowSums(adt[,1:5],na.rm = T)

kdt[,11] <- rowSums(kdt[,1:5],na.rm = T)

bdt[,11] <- rowSums(bdt[,1:5],na.rm = T)

odt[,11] <- rowSums(odt[,1:5],na.rm = T)

edt[,12] <- rowSums(edt[,6:10],na.rm = T)

adt[,12] <- rowSums(adt[,6:10],na.rm = T)

kdt[,12] <- rowSums(kdt[,6:10],na.rm = T)

bdt[,12] <- rowSums(bdt[,6:10],na.rm = T)

odt[,12] <- rowSums(odt[,6:10],na.rm = T)

for(i in 1:379){

edt[i,13]<-europe[[i]][1,8]/60

europe[[i]][,10]<-paste0(europe[[i]][,7],europe[[i]][,9])

if(europe[[i]][1,10]==1000){

edt[i,14]<-0}

if(europe[[i]][1,10]==2001){

edt[i,14]<-0}

if(europe[[i]][1,10]==2000){

edt[i,14]<-1}

if(europe[[i]][1,10]==1001){

edt[i,14]<-1}

if(europe[[i]][1,10]==1000){

edt[i,15]<-1}

if(europe[[i]][1,10]==2001){

edt[i,15]<-1}

if(europe[[i]][1,10]==2000){

edt[i,15]<-0}

if(europe[[i]][1,10]==1001){

edt[i,15]<-0}

edt[i,16]<-unique(europe[[i]][which(europe[[i]][,7]==100),][,6])#T1 gold

edt[i,17]<-unique(europe[[i]][which(europe[[i]][,7]==200),][,6])#T2 gold

edt[i,18]<-edt[i,11]/as.numeric(edt[i,13])#T1 kill per minute

edt[i,19]<-edt[i,12]/as.numeric(edt[i,13])#T2 kill per minute

edt[i,20]<-edt[i,16]/as.numeric(edt[i,13])#T1 gold per minute

edt[i,21]<-edt[i,17]/as.numeric(edt[i,13])#T2 gold per minute

edt[i,22]<-length(which(europe[[i]][c(1:nrow(europe[[i]])),c(1:4)]<6))#T1 assists

edt[i,23]<-edt[i,22]/as.numeric(edt[i,11])#T1 assists per kill

edt[i,24]<-edt[i,22]/as.numeric(edt[i,13])#T1 assists per minute

edt[i,25]<-length(which(europe[[i]][c(1:nrow(europe[[i]])),c(1:4)]>5))#T2 assists

edt[i,26]<-edt[i,24]/as.numeric(edt[i,11])#T2 assists per kill

edt[i,27]<-edt[i,24]/as.numeric(edt[i,13])#T2 assists per minute

}

for(i in 1:385){

kdt[i,13]<-korea[[i]][1,8]/60

korea[[i]][,10]<-paste0(korea[[i]][,7],korea[[i]][,9])

if(korea[[i]][1,10]==1000){

kdt[i,14]<-0}

if(korea[[i]][1,10]==2001){

kdt[i,14]<-0}

if(korea[[i]][1,10]==2000){

kdt[i,14]<-1}

if(korea[[i]][1,10]==1001){

kdt[i,14]<-1}

if(korea[[i]][1,10]==1000){

kdt[i,15]<-1}

if(korea[[i]][1,10]==2001){

kdt[i,15]<-1}

if(korea[[i]][1,10]==2000){

kdt[i,15]<-0}

if(korea[[i]][1,10]==1001){

kdt[i,15]<-0}

kdt[i,16]<-unique(korea[[i]][which(korea[[i]][,7]==100),][,6])

kdt[i,17]<-unique(korea[[i]][which(korea[[i]][,7]==200),][,6])

kdt[i,18]<-kdt[i,11]/as.numeric(kdt[i,13])

kdt[i,19]<-kdt[i,12]/as.numeric(kdt[i,13])

kdt[i,20]<-kdt[i,16]/as.numeric(kdt[i,13])

kdt[i,21]<-kdt[i,17]/as.numeric(kdt[i,13])

kdt[i,22]<-length(which(korea[[i]][c(1:nrow(korea[[i]])),c(1:4)]<6))#T1 assists

kdt[i,23]<-kdt[i,22]/as.numeric(kdt[i,11])#T1 assists per kill

kdt[i,24]<-kdt[i,22]/as.numeric(kdt[i,13])#T1 assists per minute

kdt[i,25]<-length(which(korea[[i]][c(1:nrow(korea[[i]])),c(1:4)]>5))#T2 assists

kdt[i,26]<-kdt[i,24]/as.numeric(kdt[i,11])#T2 assists per kill

kdt[i,27]<-kdt[i,24]/as.numeric(kdt[i,13])#T2 assists per minute

}

for(i in 1:381){

bdt[i,13]<-brazil[[i]][1,8]/60

brazil[[i]][,10]<-paste0(brazil[[i]][,7],brazil[[i]][,9])

if(brazil[[i]][1,10]==1000){

bdt[i,14]<-0}

if(brazil[[i]][1,10]==2001){

bdt[i,14]<-0}

if(brazil[[i]][1,10]==2000){

bdt[i,14]<-1}

if(brazil[[i]][1,10]==1001){

bdt[i,14]<-1}

if(brazil[[i]][1,10]==1000){

bdt[i,15]<-1}

if(brazil[[i]][1,10]==2001){

bdt[i,15]<-1}

if(brazil[[i]][1,10]==2000){

bdt[i,15]<-0}

if(brazil[[i]][1,10]==1001){

bdt[i,15]<-0}

bdt[i,16]<-unique(brazil[[i]][which(brazil[[i]][,7]==100),][,6])

bdt[i,17]<-unique(brazil[[i]][which(brazil[[i]][,7]==200),][,6])

bdt[i,18]<-bdt[i,11]/as.numeric(bdt[i,13])

bdt[i,19]<-bdt[i,12]/as.numeric(bdt[i,13])

bdt[i,20]<-bdt[i,16]/as.numeric(bdt[i,13])

bdt[i,21]<-bdt[i,17]/as.numeric(bdt[i,13])

bdt[i,22]<-length(which(brazil[[i]][c(1:nrow(brazil[[i]])),c(1:4)]<6))#T1 assists

bdt[i,23]<-bdt[i,22]/as.numeric(bdt[i,11])#T1 assists per kill

bdt[i,24]<-bdt[i,22]/as.numeric(bdt[i,13])#T1 assists per minute

bdt[i,25]<-length(which(brazil[[i]][c(1:nrow(brazil[[i]])),c(1:4)]>5))#T2 assists

bdt[i,26]<-bdt[i,24]/as.numeric(bdt[i,11])#T2 assists per kill

bdt[i,27]<-bdt[i,24]/as.numeric(bdt[i,13])#T2 assists per minute

}

for(i in 1:388){

odt[i,13]<-oceania[[i]][1,8]/60

oceania[[i]][,10]<-paste0(oceania[[i]][,7],oceania[[i]][,9])

if(oceania[[i]][1,10]==1000){

odt[i,14]<-0}

if(oceania[[i]][1,10]==2001){

odt[i,14]<-0}

if(oceania[[i]][1,10]==2000){

odt[i,14]<-1}

if(oceania[[i]][1,10]==1001){

odt[i,14]<-1}

if(oceania[[i]][1,10]==1000){

odt[i,15]<-1}

if(oceania[[i]][1,10]==2001){

odt[i,15]<-1}

if(oceania[[i]][1,10]==2000){

odt[i,15]<-0}

if(oceania[[i]][1,10]==1001){

odt[i,15]<-0}

odt[i,16]<-unique(oceania[[i]][which(oceania[[i]][,7]==100),][,6])

odt[i,17]<-unique(oceania[[i]][which(oceania[[i]][,7]==200),][,6])

odt[i,18]<-odt[i,11]/as.numeric(odt[i,13])

odt[i,19]<-odt[i,12]/as.numeric(odt[i,13])

odt[i,20]<-odt[i,16]/as.numeric(odt[i,13])

odt[i,21]<-odt[i,17]/as.numeric(odt[i,13])

odt[i,22]<-length(which(oceania[[i]][c(1:nrow(oceania[[i]])),c(1:4)]<6))#T1 assists

odt[i,23]<-odt[i,22]/as.numeric(odt[i,11])#T1 assists per kill

odt[i,24]<-odt[i,22]/as.numeric(odt[i,13])#T1 assists per minute

odt[i,25]<-length(which(oceania[[i]][c(1:nrow(oceania[[i]])),c(1:4)]>5))#T2 assists

odt[i,26]<-odt[i,24]/as.numeric(odt[i,11])#T2 assists per kill

odt[i,27]<-odt[i,24]/as.numeric(odt[i,13])#T2 assists per minute

}

for(i in 1:382){

adt[i,13]<-america[[i]][1,8]/60

america[[i]][,10]<-paste0(america[[i]][,7],america[[i]][,9])

if(america[[i]][1,10]==1000){

adt[i,14]<-0}

if(america[[i]][1,10]==2001){

adt[i,14]<-0}

if(america[[i]][1,10]==2000){

adt[i,14]<-1}

if(america[[i]][1,10]==1001){

adt[i,14]<-1}

if(america[[i]][1,10]==1000){

adt[i,15]<-1}

if(america[[i]][1,10]==2001){

adt[i,15]<-1}

if(america[[i]][1,10]==2000){

adt[i,15]<-0}

if(america[[i]][1,10]==1001){

adt[i,15]<-0}

adt[i,16]<-unique(america[[i]][which(america[[i]][,7]==100),][,6])

adt[i,17]<-unique(america[[i]][which(america[[i]][,7]==200),][,6])

adt[i,18]<-adt[i,11]/as.numeric(adt[i,13])

adt[i,19]<-adt[i,12]/as.numeric(adt[i,13])

adt[i,20]<-adt[i,16]/as.numeric(adt[i,13])

adt[i,21]<-adt[i,17]/as.numeric(adt[i,13])

adt[i,22]<-length(which(america[[i]][c(1:nrow(america[[i]])),c(1:4)]<6))#T1 assists

adt[i,23]<-adt[i,22]/as.numeric(adt[i,11])#T1 assists per kill

adt[i,24]<-adt[i,22]/as.numeric(adt[i,13])#T1 assists per minute

adt[i,25]<-length(which(america[[i]][c(1:nrow(america[[i]])),c(1:4)]>5))#T2 assists

adt[i,26]<-adt[i,24]/as.numeric(adt[i,11])#T2 assists per kill

adt[i,27]<-adt[i,24]/as.numeric(adt[i,13])#T2 assists per minute

}

unicol<-c("ID1","ID2","ID3","ID4","ID5","ID6","ID7","ID8","ID9","ID10","T1Kills","T2Kills","Time","T1Win","T2Win","T1Gold","T2Gold","T1Killspermin","T2Killspermin",

"T1Goldpermin","T2Goldpermin","T1Assists","T1Assistsperkill","T1Assistspermin","T2Assists","T2Assistsperkill","T2Assistspermin")

colnames(edt)<-unicol

colnames(kdt)<-unicol

colnames(bdt)<-unicol

colnames(odt)<-unicol

colnames(adt)<-unicol

feeu<-list()

fekr<-list()

febr<-list()

feoc<-list()

feam<-list()

eeu <- list()

ekr <- list()

eam <- list()

ebr <- list()

eoc <- list()

eeu1 <- list()

eeu2 <- list()

ekr1 <- list()

ekr2 <- list()

ebr1 <- list()

ebr2 <- list()

eoc1 <- list()

eoc2 <- list()

eam1 <- list()

eam2 <- list()

weeu1<-list()

weeu2 <- list()

wekr1 <- list()

wekr2 <- list()

webr1 <- list()

webr2 <- list()

weoc1 <- list()

weoc2 <- list()

weam1 <- list()

weam2 <- list()

coneu1<-list()

coneu2<-list()

conkr1<-list()

conkr2<-list()

conbr1<-list()

conbr2<-list()

conoc1<-list()

conoc2<-list()

conam1<-list()

conam2<-list()

geu<-list()

gkr<-list()

gbr<-list()

goc<-list()

gam<-list()

geu1<-list()

geu2<-list()

gkr1<-list()

gkr2<-list()

gbr1<-list()

gbr2<-list()

goc1<-list()

goc2<-list()

gam1<-list()

gam2<-list()

for (i in 1:379){ #Modifying the data sets so that they can be turned into edge lists

feeu[[i]] <- europe[[i]][,c(1:5)]

eeu[[i]] <- reshape2::melt(feeu[[i]], id.vars = "PLAYERID")

eeu[[i]] <- eeu[[i]][!is.na(eeu[[i]][, 3]), c(1, 3)]

eeu[[i]] <- as.matrix(eeu[[i]])

eeu1[[i]] <- eeu[[i]][eeu[[i]][,1]<6,]

eeu2[[i]] <- eeu[[i]][eeu[[i]][,1]>5,]

weeu1[[i]]<-as.data.frame(paste(eeu1[[i]][,1],eeu1[[i]][,2], sep=""))

weeu2[[i]]<-as.data.frame(paste(eeu2[[i]][,1],eeu2[[i]][,2], sep=""))

coneu1[[i]]<-nrow(weeu1[[i]])

coneu2[[i]]<-nrow(weeu2[[i]])

geu[[i]] <- graph\_from\_edgelist(eeu[[i]])

geu1[[i]] <- graph\_from\_edgelist(eeu1[[i]])

geu2[[i]] <- graph\_from\_edgelist(eeu2[[i]])

}

for(i in 1:381){

febr[[i]] <- brazil[[i]][,c(1:5)]

ebr[[i]] <- reshape2::melt(febr[[i]], id.vars = "PLAYERID")

ebr[[i]] <- ebr[[i]][!is.na(ebr[[i]][, 3]), c(1, 3)]

ebr[[i]] <- as.matrix(ebr[[i]])

ebr1[[i]] <- ebr[[i]][ebr[[i]][,1]<6,]

ebr2[[i]] <- ebr[[i]][ebr[[i]][,1]>5,]

webr1[[i]]<-as.data.frame(paste(ebr1[[i]][,1],ebr1[[i]][,2], sep=""))

webr2[[i]]<-as.data.frame(paste(ebr2[[i]][,1],ebr2[[i]][,2], sep=""))

conbr1[[i]]<-nrow(webr1[[i]])

conbr2[[i]]<-nrow(webr2[[i]])

gbr[[i]] <- graph\_from\_edgelist(ebr[[i]])

gbr1[[i]] <- graph\_from\_edgelist(ebr1[[i]])

gbr2[[i]] <- graph\_from\_edgelist(ebr2[[i]])

}

for(i in 1:385){

fekr[[i]]<-korea[[i]][,c(1:5)]

ekr[[i]] <- reshape2::melt(fekr[[i]], id.vars = "PLAYERID")

ekr[[i]] <- ekr[[i]][!is.na(ekr[[i]][, 3]), c(1, 3)]

ekr[[i]] <- as.matrix(ekr[[i]])

ekr1[[i]] <- ekr[[i]][ekr[[i]][,1]<6,]

ekr2[[i]] <- ekr[[i]][ekr[[i]][,1]>5,]

wekr1[[i]]<-as.data.frame(paste(ekr1[[i]][,1],ekr1[[i]][,2], sep=""))

wekr2[[i]]<-as.data.frame(paste(ekr2[[i]][,1],ekr2[[i]][,2], sep=""))

conkr1[[i]]<-nrow(wekr1[[i]])

conkr2[[i]]<-nrow(wekr2[[i]])

gkr[[i]] <- graph\_from\_edgelist(ekr[[i]])

gkr1[[i]] <- graph\_from\_edgelist(ekr1[[i]])

gkr2[[i]] <- graph\_from\_edgelist(ekr2[[i]])

}

for(i in 1:388){

feoc[[i]]<-oceania[[i]][,c(1:5)]

eoc[[i]] <- reshape2::melt(feoc[[i]], id.vars = "PLAYERID")

eoc[[i]] <- eoc[[i]][!is.na(eoc[[i]][, 3]), c(1, 3)]

eoc[[i]] <- as.matrix(eoc[[i]])

eoc1[[i]] <- eoc[[i]][eoc[[i]][,1]<6,]

eoc2[[i]] <- eoc[[i]][eoc[[i]][,1]>5,]

weoc1[[i]]<-as.data.frame(paste(eoc1[[i]][,1],eoc1[[i]][,2], sep=""))

weoc2[[i]]<-as.data.frame(paste(eoc2[[i]][,1],eoc2[[i]][,2], sep=""))

conoc1[[i]]<-nrow(weoc1[[i]])

conoc2[[i]]<-nrow(weoc2[[i]])

goc[[i]] <- graph\_from\_edgelist(eoc[[i]])

goc1[[i]] <- graph\_from\_edgelist(eoc1[[i]])

goc2[[i]] <- graph\_from\_edgelist(eoc2[[i]])

}

for (i in 1:382){

feam[[i]] <- america[[i]][,c(1:5)]

eam[[i]] <- reshape2::melt(feam[[i]], id.vars = "PLAYERID")

eam[[i]] <- eam[[i]][!is.na(eam[[i]][, 3]), c(1, 3)]

eam[[i]] <- as.matrix(eam[[i]])

eam1[[i]] <- eam[[i]][eam[[i]][,1]<6,]

eam2[[i]] <- eam[[i]][eam[[i]][,1]>5,]

weam1[[i]]<-as.data.frame(paste(eam1[[i]][,1],eam1[[i]][,2], sep=""))

weam2[[i]]<-as.data.frame(paste(eam2[[i]][,1],eam2[[i]][,2], sep=""))

conam1[[i]]<-nrow(weam1[[i]])

conam2[[i]]<-nrow(weam2[[i]])

gam[[i]] <- graph\_from\_edgelist(eam[[i]])

gam1[[i]] <- graph\_from\_edgelist(eam1[[i]])

gam2[[i]] <- graph\_from\_edgelist(eam2[[i]])

}

t1con<-setdiff(c(12:54),c(16:20,22,26:30,33,36:40,44,46:50,55))

t2con<-setdiff(c(67:98,106:109,610,710,810,910),c(70:75,77,80:85,88,90:95,99))

for(h in 1:379){#EU1

for(i in 1:coneu1[[h]]){

for(j in t1con){

if(weeu1[[h]][i,1]==j){

weeu1[[h]][i,2]<-length(which(weeu1[[h]]==j))/nrow(weeu1[[h]])

}

}

}

}

for(h in 1:379){#EU2

for(i in 1:coneu2[[h]]){

for(j in t2con){

if(weeu2[[h]][i,1]==j){

weeu2[[h]][i,2]<-length(which(weeu2[[h]]==j))/nrow(weeu2[[h]])

}

}

}

}

for(h in 1:385){#KR1

for(i in 1:conkr1[[h]]){

for(j in t1con){

if(wekr1[[h]][i,1]==j){

wekr1[[h]][i,2]<-length(which(wekr1[[h]]==j))/nrow(wekr1[[h]])

}

}

}

}

for(h in 1:385){#KR2

for(i in 1:conkr2[[h]]){

for(j in t2con){

if(wekr2[[h]][i,1]==j){

wekr2[[h]][i,2]<-length(which(wekr2[[h]]==j))/nrow(wekr2[[h]])

}

}

}

}

for(h in 1:381){#BR1

for(i in 1:conbr1[[h]]){

for(j in t1con){

if(webr1[[h]][i,1]==j){

webr1[[h]][i,2]<-length(which(webr1[[h]]==j))/nrow(webr1[[h]])

}

}

}

}

for(h in 1:381){#BR2

for(i in 1:conbr2[[h]]){

for(j in t2con){

if(webr2[[h]][i,1]==j){

webr2[[h]][i,2]<-length(which(webr2[[h]]==j))/nrow(webr2[[h]])

}

}

}

}

for(h in 1:388){#OC1

for(i in 1:conoc1[[h]]){

for(j in t1con){

if(weoc1[[h]][i,1]==j){

weoc1[[h]][i,2]<-length(which(weoc1[[h]]==j))/nrow(weoc1[[h]])

}

}

}

}

for(h in 1:388){#OC2

for(i in 1:conoc2[[h]]){

for(j in t2con){

if(weoc2[[h]][i,1]==j){

weoc2[[h]][i,2]<-length(which(weoc2[[h]]==j))/nrow(weoc2[[h]])

}

}

}

}

for(h in 1:382){#NA1

for(i in 1:conam1[[h]]){

for(j in t1con){

if(weam1[[h]][i,1]==j){

weam1[[h]][i,2]<-length(which(weam1[[h]]==j))/nrow(weam1[[h]])

}

}

}

}

for(h in 1:382){#NA2

for(i in 1:conam2[[h]]){

for(j in t2con){

if(weam2[[h]][i,1]==j){

weam2[[h]][i,2]<-length(which(weam2[[h]]==j))/nrow(weam2[[h]])

}

}

}

}

edt1 <- edt[,c(1:5,11,13,14,16,18,20,22,23,24)]

edt2 <- edt[,c(6:10,12,13,15,17,19,21,25,26,27)]

adt1 <- adt[,c(1:5,11,13,14,16,18,20,22,23,24)]

adt2 <- adt[,c(6:10,12,13,15,17,19,21,25,26,27)]

kdt1 <- kdt[,c(1:5,11,13,14,16,18,20,22,23,24)]

kdt2 <- kdt[,c(6:10,12,13,15,17,19,21,25,26,27)]

bdt1 <- bdt[,c(1:5,11,13,14,16,18,20,22,23,24)]

bdt2 <- bdt[,c(6:10,12,13,15,17,19,21,25,26,27)]

odt1 <- odt[,c(1:5,11,13,14,16,18,20,22,23,24)]

odt2 <- odt[,c(6:10,12,13,15,17,19,21,25,26,27)]

edt1[,15]<-rep("Europe",379)

edt2[,15]<-rep("Europe",379)

adt1[,15]<-rep("America",382)

adt2[,15]<-rep("America",382)

kdt1[,15]<-rep("Korea",385)

kdt2[,15]<-rep("Korea",385)

bdt1[,15]<-rep("Brazil",381)

bdt2[,15]<-rep("Brazil",381)

odt1[,15]<-rep("Oceania",388)

odt2[,15]<-rep("Oceania",388)

for(i in 1:379){

geu1[[i]]<-set.edge.attribute(graph = geu1[[i]],name = "weight",value = weeu1[[i]][,2])

geu2[[i]]<-set.edge.attribute(graph = geu2[[i]],name = "weight",value = weeu2[[i]][,2])

geu1[[i]]<-simplify(geu1[[i]],remove.multiple = T)

geu2[[i]]<-simplify(geu2[[i]],remove.multiple = T)

edt1[i,16]<-centr\_degree(geu1[[i]], mode = "in",normalized = T)[[2]]

edt2[i,16]<-centr\_degree(geu2[[i]], mode = "in",normalized = T)[[2]]

edt1[i,17]<-centr\_degree(geu1[[i]], mode = "out",normalized = T)[[2]]

edt2[i,17]<-centr\_degree(geu2[[i]], mode = "out",normalized = T)[[2]]

}

for(i in 1:385){

gkr1[[i]]<-set.edge.attribute(graph = gkr1[[i]],name = "weight",value = wekr1[[i]][,2])

gkr2[[i]]<-set.edge.attribute(graph = gkr2[[i]],name = "weight",value = wekr2[[i]][,2])

gkr1[[i]]<-simplify(gkr1[[i]],remove.multiple = T)

gkr2[[i]]<-simplify(gkr2[[i]],remove.multiple = T)

kdt1[i,16]<-centr\_degree(gkr1[[i]], mode = "in",normalized = T)[[2]]

kdt2[i,16]<-centr\_degree(gkr2[[i]], mode = "in",normalized = T)[[2]]

kdt1[i,17]<-centr\_degree(gkr1[[i]], mode = "out",normalized = T)[[2]]

kdt2[i,17]<-centr\_degree(gkr2[[i]], mode = "out",normalized = T)[[2]]

}

for(i in 1:381){

gbr1[[i]]<-set.edge.attribute(graph = gbr1[[i]],name = "weight",value = webr1[[i]][,2])

gbr2[[i]]<-set.edge.attribute(graph = gbr2[[i]],name = "weight",value = webr2[[i]][,2])

gbr1[[i]]<-simplify(gbr1[[i]],remove.multiple = T)

gbr2[[i]]<-simplify(gbr2[[i]],remove.multiple = T)

bdt1[i,16]<-centr\_degree(gbr1[[i]], mode = "in",normalized = T)[[2]]

bdt2[i,16]<-centr\_degree(gbr2[[i]], mode = "in",normalized = T)[[2]]

bdt1[i,17]<-centr\_degree(gbr1[[i]], mode = "out",normalized = T)[[2]]

bdt2[i,17]<-centr\_degree(gbr2[[i]], mode = "out",normalized = T)[[2]]

}

for(i in 1:388){

goc1[[i]]<-set.edge.attribute(graph = goc1[[i]],name = "weight",value = weoc1[[i]][,2])

goc2[[i]]<-set.edge.attribute(graph = goc2[[i]],name = "weight",value = weoc2[[i]][,2])

goc1[[i]]<-simplify(goc1[[i]],remove.multiple = T)

goc2[[i]]<-simplify(goc2[[i]],remove.multiple = T)

odt1[i,16]<-centr\_degree(goc1[[i]], mode = "in",normalized = T)[[2]]

odt2[i,16]<-centr\_degree(goc2[[i]], mode = "in",normalized = T)[[2]]

odt1[i,17]<-centr\_degree(goc1[[i]], mode = "out",normalized = T)[[2]]

odt2[i,17]<-centr\_degree(goc2[[i]], mode = "out",normalized = T)[[2]]

}

for(i in 1:382){

gam1[[i]]<-set.edge.attribute(graph = gam1[[i]],name = "weight",value = weam1[[i]][,2])

gam2[[i]]<-set.edge.attribute(graph = gam2[[i]],name = "weight",value = weam2[[i]][,2])

gam1[[i]]<-simplify(gam1[[i]],remove.multiple = T)

gam2[[i]]<-simplify(gam2[[i]],remove.multiple = T)

adt1[i,16]<-centr\_degree(gam1[[i]], mode = "in",normalized = T)[[2]]

adt2[i,16]<-centr\_degree(gam2[[i]], mode = "in",normalized = T)[[2]]

adt1[i,17]<-centr\_degree(gam1[[i]], mode = "out",normalized = T)[[2]]

adt2[i,17]<-centr\_degree(gam2[[i]], mode = "out",normalized = T)[[2]]

}

unicol <- c("ID1","ID2","ID3","ID4","ID5","Kills","Time","Win","Gold","Killspermin","Goldpermin","Assists","Intensity","Assistspermin","Region","IndegCent","OutdegCent")

colnames(edt1)<-unicol

colnames(edt2)<-unicol

colnames(adt1)<-unicol

colnames(adt2)<-unicol

colnames(kdt1)<-unicol

colnames(kdt2)<-unicol

colnames(bdt1)<-unicol

colnames(bdt2)<-unicol

colnames(odt1)<-unicol

colnames(odt2)<-unicol

unidt <- rbind(edt1,edt2,adt1,adt2,kdt1,kdt2,bdt1,bdt2,odt1,odt2)

summary(unidt$Assistspermin)

summary(unidt$Killspermin)

summary(unidt$Intensity)

summary(unidt$IndegCent)

summary(unidt$OutdegCent)

summary(unidt$Goldpermin)

NagelkerkeR2(glm(Win~Intensity+OutdegCent+IndegCent+Intensity:Region, unidt, family="binomial"))

boxplot(Goldpermin~Win,data=unidt, main="Gold per min vs Win",

xlab="Win", ylab="Gold")

ggplot(unidt, aes(Win==1,Gold)) + geom\_violin(fill="dark green") + labs(x="Win", y="Gold", title="Violin plots of gold distribution") + stat\_summary(fun.data=mean\_sdl, geom="pointrange", color="black")

plot(density(unidt$Goldpermin), main = "Distribution of gold per minute", lwd=2, col="dark green")

summary(glm(Win~Intensity+OutdegCent+IndegCent+Intensity:Region, unidt, family="binomial"))

summary(lm(Goldpermin~Intensity+IndegCent+OutdegCent+Intensity:Region, unidt))

linear<-summary(lm(Goldpermin~Killspermin+Intensity+IndegCent+OutdegCent, unidt))

lineari<-summary(lm(Goldpermin~Killspermin+Intensity+IndegCent+OutdegCent+Intensity:Region, unidt))

mixed<-summary(lmer(Goldpermin~Killspermin+Intensity+IndegCent+OutdegCent+(1|Region),unidt))

lineark<-summary(lm(Killspermin~Intensity+IndegCent+OutdegCent+Intensity:Region, unidt))

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1. More information on how the game is played can be found on this website: <https://na.leagueoflegends.com/en-us/how-to-play/> (last access: 25.03.2020). [↑](#footnote-ref-1)
2. <https://www.leagueofgraphs.com/rankings/rank-distribution> (last access: 11.12.2020). [↑](#footnote-ref-2)