Large-scale study of social network structure and team performance in a multiplayer online game

Antti Ukkonen
Department of Computer Science
University of Helsinki, Helsinki, Finland
antti.ukkonen@helsinki.fi

Juho Hamari
University of Tampere, Tampere, Finland
juho.hamari@uta.fi

November 1, 2017

Abstract

A question of interest in both theory and practice is if and how familiarity between members of a team, expressed in terms of social network structure, relates to the success of the team in a given task. In this paper we revisit this important question in a novel manner by employing game outcome statistics from Dota 2, a popular team-based multiplayer online game, combined with network data from Steam Community, a social networking service for gamers. We conduct a large-scale analysis of 4168 teams to study how network density, and the minimum and maximum degree of the within-team social network are associated with team performance, and determine how this association is moderated by team skill. We observe that minimum degree is strongly associated with good performance, especially in teams with lower skill. Together with previous results on network density that we corroborate in this paper, our findings suggest that a successful team is not only moderately connected overall, but its members should also individually have not too few nor too many within team connections.

1 Introduction

Teamwork is prevalent in various occupations, such as health care (e.g. surgery teams), transportation (e.g. airline cabin crews), sports/eSports, school work (e.g. ad-hoc study groups), and knowledge work (e.g. R&D teams). In all these fields, a crucial topic of interest is team performance, and how it can be improved. Team performance in general is affected by a number of factors, such as the organisational environment in which the team operates [Thamhain 2004], individual team members cognitive abilities [Devine and Philips 2001] and dispositions and skills [Stewart 2006], as well as interpersonal relations and trust between
team members (De Dreu and Weingart 2003). In this paper we focus on the two latter factors, by revisiting the question of how social network structure within a team affects its performance, and how this is moderated by the overall skill level of the team.

Intuition suggests that when team members are more familiar with each other, they also communicate and collaborate more efficiently, and consequently achieve higher performance. Therefore, a number of previous studies have considered the effects of a teams density, i.e., the fraction of dyadic ties it contains, on performance. These studies have found a positive effect of network density (or simple variants thereof) on performance in a variety of contexts, such as R&D (Baldwin et al. 1997, Reagans and Zuckerman 2001, Huckman et al. 2009), healthcare (Reagans et al. 2005, ElBardissi et al. 2008), education (de Montjoye et al. 2014), as well as sports (Grund 2012). A meta-analysis by Balkundi and Harrison (2006) of 37 studies involving 3098 teams in total supports these findings. But on the other hand, a number of studies have also observed that very high levels of within team connections may also have detrimental effects on performance (Katz and Allen 1982, Berman et al. 2002, Kratzer et al. 2004, Oh et al. 2004, Uzzi and Spiro 2005, Guimera et al. 2005). This phenomenon is usually attributed to the teams being static and developing stagnant working routines that result in inferior performance, or failures to innovate as novel ideas are often introduced by new team members.

Previous literature has thus found support both for a positive effect between density and performance, as well as a nonlinear relationship where further increases in density tend to weaken performance. Of course studies that only test for linear relationships cannot find nonlinear effects even if they exit. Moreover, especially with small networks, density may not be an ideal measure to study within team social dynamics, as we discuss below in Section 1.1 in more detail.

Hence, we take an approach that combines novel, large-scale data with an exploratory yet statistically sound analysis technique that also considers the minimum and maximum degree of a network in addition to its density. In concrete, we collected performance data for 4168 teams from Dota 2 (Valve Corporation 2017, see also Figure 1), one of the most popular online games at the moment, and joined this with network data from Steam, a social networking service for gamers. This methodology allows to control for a number of issues that may affect team performance studies in general. Namely, in the real-world 1) teams vary in size as well as skill, 2) the tasks are often not precisely identical, 3) the contexts may differ and be difficult to control, 4) the tasks or projects vary in length, 5) teams might be formed by different mechanics, and finally, 6) the number of teams available for a study (e.g. from a single organisation) can be fairly low.

We argue that by using data from a multiplayer online game we can very efficiently overcome these limitations to conduct an investigation of team performance in a realistic, large-scale, yet controlled environment, where the teams are carrying out exactly the same task. At the time of writing, Dota 2 is the largest eSports game in the world (Hamari and Sjöblom 2017) with thousands of matches being played daily. In this game two teams of five members each play against each other in matches of (approximately) 30 minutes in length. Moreover, much like sports teams, the teams in Dota 2 need both skilled individuals, as well as good group dynamics to be successful. This makes Dota 2 an ideal platform to study team performance in a context that nicely addresses all six issues mentioned above. In particular, in Dota 2 all teams 1) consist of exactly five members having roughly equal skill, 2) have
one and the same goal, 3) organize and act in exactly the same environment, 4) the length of the activity is the same for all teams, 5) all teams are formed in the same manner, and finally 6) collecting large quantities of data is easy.

In this paper we focus on the social network between team members, called “team network” below. We assume that an edge between two members in the team network signals the presence of pre-existing, voluntary, informal, self-reported interactions between the team members. The network does thus not reflect external structures, such as fixed communication channels, or supervisor-subordinate relationships. For every member of the team, the other members are assumed to be either prior acquaintances or strangers. Our definition of a dyadic tie can be thus understood as being *expressive rather than instrumental* (Lincoln and Miller 1979).

### 1.1 Density, minimum and maximum degree, skill level

Network science literature is abundant with various statistics to characterise network structure, such as the average shortest-path length or the clustering coefficient (Wasserman and Faust 1994). Also other complex characterisations of the team network such as core-periphery structures (Borgatti and Everett 2000) and structural holes (Burt 2004) have been considered, and are certainly meaningful for team performance, see for instance (Cummings and Cross 2003). However, the above measures are mainly intended to address global properties of a possibly very large network, and are hence less suitable for very small networks, such as the ones studied here. Hence, we have chosen to use two simple and intuitive metrics of the
Figure 2: Two social networks, A and B, both having five nodes and six edges and thus equal density, but very different structure. Note that network A has minimum and maximum degrees of 2 and 4, while for B these numbers are 0 and 3.

team network: density, minimum degree and maximum degree. Not only are these easy to explain and understand, but they are also simple enough for practical management settings when assembling teams.

Density is a standard measure used in almost all previous studies on network structure and team performance, and it captures the overall connectedness of a team. Since all of our networks contain precisely five nodes, we can express density simply as the number of edges in the network, with ten being the maximum.

On the other hand, node degree, i.e., the number of connections a team member has in the team network, is another simple way to quantify network structure. In the context of teams, node degree has been used previously to address questions e.g. about success of enterprise system adoption (Sasidharan et al. 2012), effects of skill on team performance (Devine and Philips 2001), software engineering practices (Zanetti et al. 2013), as well as tie strength (de Montjoye et al. 2014). The minimum and maximum degrees are simply the degrees of the least and most connected team members, respectively.

Minimum and maximum degree are measures complementary to density. To see this, consider the two team networks shown in Figure 2, both having exactly five members, of which team A consists of two triangles that share one node, while team B is structurally a clique of four nodes together with a single isolated node. Both networks have exactly six edges, and hence the same density, but the networks are structurally extremely different. It does not seem at all obvious that these structures would affect team performance in the same manner. On the other hand, the minimum and maximum degrees of the first network are 2 and 4, respectively, while in the second network these numbers are 0 and 3. The minimum and maximum degree thus capture structural properties that are not taken into account when considering only density.$^1$

Furthermore, skill and experience in the activity the team is engaged in have as such a positive effect on team performance (Neuman and Wright 1999, Humphrey et al. 2009). And, as the team members become more skilled, performance may become less affected by network structure (Balkundi and Harrison 2006). This has been considered in previous literature to a lesser extent, possibly partly due to the difficulty in collecting suitable data.

$^1$Note that average degree is in fact equivalent to density up to a constant factor.
A further advantage of using an online game to study team performance is that controlling for the overall skill level of a team is very easy. To provide an enjoyable gaming experience, the Dota 2 platform aims to always pair equally skilled teams against each other. Every team in our data is associated to one of three skill levels that is determined automatically by the game platform based on previous gameplay results of the teams members. (The precise details of this mechanism are proprietary to the game designers.) The outcome of a single match is thus not affected by substantial differences in overall skill level of the two teams. By comparing matches of low skilled teams to matches of teams having high skill, we can study to what extent skill moderates effects that network structure has on performance.

1.2 Research question and basic methodology

In summary, we employ (to the best of our knowledge) the largest (N=4168) real-world data about network structure and team performance to date

a) to replicate results of existing studies about effects of network structure on performance in a novel setting,

b) to study the association between minimum/maximum (within team) degree and performance, and

c) to determine if team skill level moderates the above effects.

We argue that our study has high internal validity, because of the systematic nature of the Dota 2 game. In particular, all teams are of equal size (5 members), and have the same time (≈30 minutes) to accomplish the same objective (reach the game objectives).

Team performance is operationalised by a binary variable indicating if the team won or lost a match, while network structure is captured by the three statistics described above: density, as well as minimum and maximum degree. This study is exploratory in nature. Our basic methodology is to estimate expected winning probabilities for different types of team networks (as characterised by the network statistics) and skill levels, and compare these against probability estimates from a statistical baseline model where associations between network structure and performance have been explicitly removed. This approach allows us to identify types of networks in which structure indeed is associated with a significant decrease or increase in performance. Finally, there are some subtle issues with data collection and preparation that our analysis technique must carefully take into account. These are discussed in more detail below.

2 Materials and methods

One of the contributions of this paper is to demonstrate the use of combining real-world game data with a separate social network for team performance studies. This presents some methodological challenges related to data collection, preparation, and analysis. In short, we retrieved publicly available Dota 2 match statistics from a website about game outcomes (dotabuff.com), and joined these with publicly available contact lists of the players from the Steam social network (steamcommunity.com). Both the match statistics as well as the
contact lists are obtained by downloading publicly accessible web pages from the Internet, and parsing the relevant information from these with an automated script. We first give an overview of Dota 2 and Steam, then describe data collection and preparation, and conclude this section by discussing technical issues that our data presents for analysis, and how we tackle these with a simple but statistically robust analysis technique.

2.1 Dota 2

Dota 2 (Valve Corporation 2017) is a so called MOBA (Multiplayer Online Battle Arena) game produced by Valve Corporation with over 10 million active players at the time of writing. In MOBAs players play in discrete matches involving two teams of a few players. In Dota 2 the two teams are called “Radiant” and “Dire”, and there are exactly five players in both teams. Dota 2 and other MOBA games are commonly played from an isometric perspective on a symmetric map, where every player controls a single character as shown in Figure 1. Both teams occupy a stronghold at opposite corners of the map. The objective is to destroy the opposing team’s main structure(s) as well as other buildings (marked as green and red dots on the map seen in the lower left corner of Figure 1). The first team to reach this objective is the winner.

Before a match begins, the teams are formed in an ad-hoc manner by a mechanism that aims to assign roughly equally skilled players together. Moreover, the matches are balanced in the sense that both teams are approximately of the same skill level. There are three skill levels, called “normal”, “high”, and “very high”. See also A.1. In the matches that we consider the teams are transient. That is, a certain set of five players play together in very few matches, and most teams participate in only a single match.

2.2 Steam and the Steam Community social network

Steam (www.steam.com) is an online service for gamers provided by Valve Corporation. It is both a retail marketplace for game developers, as well as a social networking service (similar to e.g. Facebook or Twitter) for players. Steam is the largest digital distribution platform for PC games with 1,800 titles for sale and 35 million active users (Valve Corporation 2017). In practice almost everyone who actively plays games on a PC is bound to use Steam at least to purchase games.

To use Steam, a player must create a digital identity called a Steam profile. Similar to other social networking sites, the players can connect with each other by adding the profiles of other Steam users to their list of friends. This social network can be accessed at steamcommunity.com. The network is symmetric, and a connection is formed only when both players choose to accept this. Importantly, players are never automatically connected on the Steam platform. The semantics of a connection in the network varies. Players may connect because they know each other in the real-world, but many connections are between players who have only met online.
2.3 Data collection

Steam has a built-in data collection mechanism that is based on an opt-in system for collecting game statistics from all players who have agreed to share their data. In case of Dota 2, the statistics provide information about the outcome, player identities, and various other game related parameters for every match. For matches where at least one of the players had decided to upload his information, basic statistics about the match appear at various websites. One such website is dotabuff.com. We wrote a simple computer program that periodically polls the dotabuff.com website, and downloads detailed statistics of every public Dota 2 match that appears on the site. This data was joined with public contact lists of the Steam social network for those players for which profile information was available. Data was collected from November 13, 2014 until January 5, 2015. (Also see A.3.) This raw data contains statistics for 93158 public Dota 2 matches. While this sounds like a large number, most of the matches must be discarded due to part of the data missing, as we discuss next.

2.4 Data preparation

For further analysis we only keep matches that used “normal matchmaking” to build the teams, and are based on the “all pick” game mode (see Appendix Section A.2). These are the most common types of matches, and our data contains 76174 of them (81.8% of the raw data). Matches of this type commonly last for approximately 30 minutes.

We then constructed the team networks for both teams. If two team members appear on each others contact lists in Steam, we inserted the corresponding edge into the team network. (Note that the two networks are always disjoint. We only consider within-team connections, even if between-team links might exist.) This can only be done when both team members have opted-in to the data collection process, otherwise their Steam identifiers are not available in the match statistics obtained from dotabuff.com. As it is impossible to match anonymous players to their Steam profiles at steamcommunity.com, the team network remains incomplete if some players have not revealed their profiles.

To construct the complete team network, we can therefore only consider matches where the Steam profile identifier of all five players in at least one of the teams is known. See Table 1 for a breakdown of the matches in terms of the number of non-anonymous players for both Radiant and Dire. Only matches from the bottom row and the rightmost column in Table 1 can thus be used (shown in bold, 3822 matches in total, 4.1% of the raw data).

From these matches we derive three datasets, Radiant, Dire and Both, for the remaining analysis. The dataset Radiant (2186 teams) consists of those team networks where where all five Radiant team members are non-anonymous. The dataset Dire (1972 teams) is constructed in the same manner using Dire teams. The third dataset Both (4168 teams) is simply the combination of Radiant and Dire. Most of the analysis concerns the dataset Both, but by considering the Radiant and Dire teams also separately, we can conveniently compare two subpopulations where possible associations between network structure and performance should remain the same. Indeed, there is no prior reason to assume any differences between Radiant and Dire in this sense. For every team in every dataset we of course also know if the team won the match in which it played.
Table 1: Breakdown of the number of observed matches in terms of the numbers of known player identities in both teams.

|       | Radiant | 0   | 1   | 2   | 3   | 4 | 5 |
|-------|---------|-----|-----|-----|-----|---|---|
| Dire  |         |     |     |     |     |   |   |
| 0     | 20557   | 7218| 2879| 1183| 444 | 142|   |
| 1     | 7286    | 4951| 2847| 1511| 718 | 232|   |
| 2     | 2980    | 3030| 2380| 1702| 931 | 308|   |
| 3     | 1249    | 1641| 1773| 1601| 1075| 439|   |
| 4     | 504     | 762 | 1059| 1124| 947 | 505|   |
| 5     | 117     | 253 | 372 | 514 | 594 | 346|   |

2.5 Network statistics and winning probability

We continue with basic definitions of our operationalisations of network structure and team performance. The density $e$ of a team network is the number of edges it contains. We group the edge density $e$ to six buckets that consist of $0$, $1 - 2$, $3 - 4$, $\ldots$, $9 - 10$ edges. The degree of a player is the number of neighbours the player has in the team network. With teams of five members, the degree ranges from zero (0) to four (4). The minimum and maximum degrees of a team, denoted $d_{\text{min}}$ and $d_{\text{max}}$, are the degrees of its least and most connected members. In practice each dataset can be viewed as having four variables that are $e$, $d_{\text{min}}$, $d_{\text{max}}$, and a binary variable $w$ that indicates if the team won the match.

Our objective is to study how different values of $e$, $d_{\text{min}}$, and $d_{\text{max}}$ are associated with team performance. In the subsequent analysis we thus consider the winning probability $\Pr(w)$ of a team, conditioned on some value of either $e$, $d_{\text{min}}$, or $d_{\text{max}}$. We write $\Pr(w \mid x = i)$, where $x$ is either $e$, $d_{\text{min}}$, or $d_{\text{max}}$ to denote the winning probability in the condition $x = i$. For example, $\Pr(w \mid d_{\text{min}} = 3)$ denotes the winning probability of a team in the condition where the least connected player has exactly three within-team connections. Every condition corresponds thus to some specific type of network structure.

To compute the estimate of $\Pr(w \mid d_{\text{min}} = 3)$ in a given dataset, we consider all teams with $d_{\text{min}} = 3$ and compute the fraction of teams that won. Likewise for other conditions. These estimates are compared against the baseline probability of winning, denoted $\Pr(w)$ and defined simply as the fraction of winning teams in the entire data. In short, our estimate of $\Pr(w \mid x = i)$ should be “substantially smaller or larger” than $\Pr(w)$ for the estimate to be indicative of an association between networks belonging to condition $x = i$ and performance. Details of this procedure are described next.

2.6 Resampling procedure

In the absence of prior assumptions on team performance and confounding factors, a team should have a fifty-fifty chance of winning. Meaning, without any condition on network structure we should observe a baseline probability of $\Pr(w) = 0.5$ for a team to win, because in every match there are two teams, and one of these always wins (there are no ties). However, our baseline estimate of the winning probability is in practice distorted by two factors.

First, a known property of Dota 2 is that in matches of approximately 30 minutes in
length, the team playing Radiant has a slightly higher chance of winning\footnote{In the player community this is usually attributed to some subtle game design details (e.g. orientation of the game map) that may provide a tiny advantage to Radiant.}. As there are more Radiant teams in Both, this alone will lead to a biased estimate of $\Pr(w)$. Second, our data preparation procedure may introduce another bias. As discussed above, we can only use teams where the identity of all five players is known, but we cannot rule out that these teams perform better in expectation than teams where some players have kept their identities hidden. For instance, perhaps players who have not opted-in to the data collection mechanism are less experienced than those who have. Several teams in our data are from matches where the network of only that particular team was fully observed, and the opposing team had some anonymous members. This may cause $\Pr(w)$ to further deviate from 0.5.

To remove the effects of these (and possibly other unknown but similar) biases, we use a bootstrap procedure\cite{EfronTibshirani1994} where we resample the data with replacement so that $\Pr(w) = 0.5$ in the resulting sample. This is done simply by sampling an equal amount of winning and losing teams, and by making sure that the total number of teams in resampled data is equal to the size of the original data. (As usual with bootstrap sampling, this means that some teams can appear multiple times in the same sample.) This is repeated 10000 times to obtain 95% bootstrap confidence intervals for the estimates of the conditional probabilities $\Pr(w \mid x = i)$ defined above. We use the median of the bootstrap samples as the final estimate of $\Pr(w \mid x = i)$.

But considering these alone is not sufficient to establish an association between different conditions and team performance. In particular, as we partition the teams according to, for example $d_{\text{min}}$, we obtain a slightly different probability estimate for every value of $d_{\text{min}}$, even if there was no connection between $d_{\text{min}}$ and winning whatsoever. The probability estimates will always to some extent deviate from the baseline probability of 0.5 due to statistical variation. Some conditions specified by $d_{\text{min}}$ will always seem to indicate a decrease or an increase in winning probability. To draw robust conclusions about the effects of network structure on performance, the probabilities should be substantially higher or lower than 0.5. But when is a deviation large enough to be statistically significant?

We establish this by simulating the situation where there explicitly is no connection between network structure and team performance. That is, we conduct another type of resampling on our data, where the association between the independent variable ($e$, $d_{\text{min}}$, or $d_{\text{max}}$) and match outcome $w$ is explicitly removed. We do this by permuting the $w$ variable within a dataset uniformly at random across all teams before estimating the winning probabilities. This simple permutation procedure is again repeated 10000 times to obtain 95\% baseline confidence intervals for the estimates of $\Pr(w \mid x = i)$ under the baseline where there is no association between the winning probability and network structure.

The justification for this is that if there is no association between some network statistic and winning the match, then all permutations of $w$ are exchangeable. That is, in a sense the 10000 randomly chosen permutations of $w$, as well as the original observed one, are equally likely to be “true”. This implies that the winning probabilities estimated from the observed values of $w$ should be similar to the ones estimated from the 10000 permuted values of $w$. If, however, this is not the case, meaning that the estimates from observed values are different than the estimates from permuted values, (e.g. consistently larger or smaller), we
Table 2: Number of players broken down in terms of the number of matches in which they appear.

| number of matches | RADI | DIRE | BOTH |
|------------------|------|------|------|
| 1                | 10561| 9591 | 19573|
| 2                | 199  | 133  | 591  |
| 3                | 7    | 1    | 27   |
| 4                | 0    | 0    | 1    |

have support for a hypothesis in which there is an association between the networks statistic and winning.

Indeed, if the bootstrap estimate of \( \Pr(w \mid x = i) \) from the original non-permuted data is outside of the baseline confidence interval defined above, we have support for the hypothesis that network structure as specified by the condition \( x = i \) has an effect on team performance. The resampling procedure, as well as all other analysis, was implemented in R ([R Core Team 2017](#)). See Section A.4 for further technical details.

3 Results

3.1 Descriptive statistics

Skill level: The teams are divided into three tiers in terms of player skill, called “Normal Skill” (1069 teams), “High Skill” (1151 teams), and “Very High Skill” (1948 teams). (There were 166 matches for which the skill specification is unavailable due to missing data. We made the simplifying assumption that teams in these matches are of “Normal Skill”.)

Number of players: The numbers of unique players in Radiant, Dire and Both are 10767, 9725, and 20192, respectively. Table 2 shows the numbers of players in each dataset broken down in terms of the number of matches they appear in. We find that only a handful of players appear in more than two matches. This means that any variation we observe in performance is not caused by some particular players who differ from the others, e.g. have exceptional skill or behave maliciously.

Match duration: The median match duration is 32 minutes with the 5th and 95th percentile at 30 and 35 minutes, respectively.

Baseline chances of winning: In all of our over 93k matches we find that Radiant wins with probability 0.584, and Dire with 0.416. This is in accordance with other studies, in which Radiant has been reported to have a higher winning probability. In the Radiant, Dire and Both datasets the probabilities of Radiant to win are 0.623, 0.556, and 0.59, respectively. Notice that by definition in every match in Radiant, the Radiant team members are all non-anonymous, and their winning probability is 0.623 > 0.584 (exact binomial test \( p = 0.00017, 95\% \ CI= [0.603, 0.644] \)), and in Dire all Dire team members are known and Radiant wins with probability 0.556 < 0.584 (exact binomial test \( p = 0.012, 95\% \ CI= [0.534, 0.578] \)). This suggests that teams where all players can be identified have a slightly higher chance of winning than teams with anonymous players. Note that in the analysis below performance is estimated for teams with five non-anonymous members only.
Network structure: For teams of five players, the team network has 34 different possible configurations\(^3\) i.e., ways to assign connections between the players. Figure 3 shows 32 team configurations (out of the possible 34) as well as their occurrence frequencies observed in Both. Note that two of the possible configurations do not exist in the data at all. In general the commonly occurring configurations tend to consist of a clique plus some isolated nodes. Also the completely disconnected team with five isolated nodes is one of the more commonly occurring structures. Networks that are more “random” are also less frequent in our data. We want to point out that network density is not correlated with occurrence frequency. The frequent and infrequent configurations contain both dense and sparse structures. In the top-7 configurations (representing 3023 teams, or 72.5% of all teams in Both) there are no networks with open triangles, i.e., sets of three nodes that contain two edges only, while all of the infrequent configurations have several open triangles. This is an expected outcome, as social networks such as the one used here tend to exhibit triadic closure (Granovetter 1973), meaning that “two of my friends are most likely also friends with each other”.

3.2 Network structure and performance

We proceed to describe our basic findings on network structure and team performance. The moderating role of team skill is discussed later in Section 3.3. Figure 4 consists of nine panels, each showing condition-specific estimates of the winning probability (black plus signs) together with a bootstrap confidence interval (in red), as well as the “null hypothesis” confidence intervals (in blue) that indicate the range of probable values of the estimate when there is no association between network structure and performance. The topmost row shows

\(^3\)More formally, there are 34 isomorphism classes of undirected graphs that have five vertices each. Two graphs, \(G_1\) and \(G_2\), are isomorphic if we can rename the vertices of \(G_1\) so that the resulting network is identical to \(G_2\) without making any modifications to the edges.
Figure 4: Estimates of winning probability and the associated confidence intervals (red) in three datasets (columns) for three different network statistics (rows). The blue intervals show ranges of probable values of the estimate under a model where the association between network structure and winning has been explicitly removed.
density, the middle row shows minimum degree, and the bottom row shows maximum degree. Each column shows a different dataset.

We are especially interested in cases where the probability estimate (black plus sign) is outside (or very close to either end) of the baseline CI (blue lines). Moreover, when comparing the estimates for two conditions (of the same network statistic), the bootstrap confidence intervals (in red) should overlap as little as possible if the claim is that one of the conditions is associated with better performance than the other. In general, we refrain from using e.g. p-values or other “black-box” statistics, and rely on simple visual inspection of confidence intervals instead. This is because we are mainly interested in finding cases where any increases or decreases in winning probability would translate to a concrete practical advantage. That is, small deviations are less interesting even if they might be significant in terms of our baseline model.

We observe a number of cases in Fig. 4 where the probability estimate of some condition is low or high in relation to what is expected given the baseline model:

1. \( \text{Pr}(w \mid e = 5 - 6) \) is **low** in Radiant,
2. \( \text{Pr}(w \mid d_{\text{min}} = 2) \) is **very high** in Radiant,
3. \( \text{Pr}(w \mid e = 7 - 8) \) is **high** in Dire,
4. \( \text{Pr}(w \mid e = 9 - 10) \) is **low** in Both,
5. \( \text{Pr}(w \mid e = 7 - 8) \) is **very high** in Both,
6. \( \text{Pr}(w \mid d_{\text{min}} = 1) \) is **outside baseline CI** in Both,
7. \( \text{Pr}(w \mid d_{\text{min}} = 2) \) is **very high** in Both, and
8. \( \text{Pr}(w \mid d_{\text{min}} = 4) \) is **low** in Both.

As we have no reason to assume that network structure and winning probability would have different associations in Radiant and Dire, we can use them as controls for each other. (I.e., this is a simple way of simulating a replication of the same experiment within the same study.) Beginning with item 1 above that suggests the condition \( e = 5 - 6 \) to have a low winning probability in Radiant, we find no similar effect in Dire, where \( \text{Pr}(w \mid e = 5 - 6) \) is in fact rather elevated. However, for items 2 and 3 we find that the other dataset indicates a qualitatively similar effect, albeit less strong. In the combined dataset Both we observe five interesting cases (items 4–8), two of which (items 5 and 7) were also observed in either of the subsets and corroborated by the other. Observations in items 4, 6, 8 above, however, are not suggested by either Radiant or Dire alone, and only become visible in the combined data. Here we note that the magnitude of their effects, i.e., the absolute decrease or increase in winning probability is rather small (less than 0.05 in all three cases), even if residing outside the baseline CI as is the case for item 6. Notably, the maximum degree indicates no significant effects whatsoever. Also, Radiant and Dire behave inconsistently for \( d_{\text{max}} \) suggesting that there indeed is no connection between this statistic and team performance.

Taken together, our main findings from Fig. 4 are the following:
Figure 5: Estimates of winning probability for different skill levels in dataset Both. We find that network structure is associated with performance for moderately skilled ("Normal" and "Normal + High") teams, but for teams having "Very High" skill such effects are not present.

1. When considering **density**, we find that there is a substantial difference (as indicated by the bootstrap CIs shown in red) in winning probability between $e = 7 - 8$ and $e = 9 - 10$, as well as between $e = 0$ and $e = 7 - 8$. Performance is thus decreased when the team network is very sparse or a complete clique, and best performance is found for a moderately connected network.

2. When considering **minimum degree**, we find that low values ($d_{\text{min}} = 1$ and $d_{\text{min}} = 2$) are associated with substantially better performance than higher minimum degrees ($d_{\text{min}} \geq 3$). However, networks with isolated nodes ($d_{\text{min}} = 0$) do not show increased performance. This suggests that not only should the team network as a whole be "moderately connected" (as suggested by results on density), but each individual should also be "moderately connected" within the team.

3. We find no statistical support for **maximum degree** being associated with performance.
3.3 Team skill as a moderating variable

It is conceivable that in highly skilled teams, factors such as previous familiarity with other members, is not strongly associated with performance. Our data seems to support this hypothesis. Figure 5 shows again nine panels similar to the ones in Fig. 4. This time we only consider the dataset Both, and have broken down the teams in terms of the skill level they were assigned to by the game platform. Fig. 5 shows “Normal” skill teams in the leftmost column, and “Very High” skill teams in the rightmost column. The middle column shows a combination of “Normal” and “High” skill.

For teams with “Normal” skill, we can observe that the estimate of winning probability is outside the baseline CI for the conditions

1. $e = 9 - 10$ (below baseline),

2. $e = 7 - 8$ (slightly above baseline),

3. $d_{\text{min}} = 2$ (substantially above baseline), and

4. $d_{\text{max}} = 3$ (slightly above baseline).

These findings are compatible with those found above from Figure 4 for all of Both, but the effects are considerably stronger. Most importantly, we find that $\Pr(w | d_{\text{min}} = 2)$ is clearly above 0.65, suggesting a substantial increase in absolute magnitude of winning probability (an increase over 0.15 over the baseline of 0.5) for teams having moderately connected members. Also the pairwise differences between $d_{\text{min}} = 2$ and the other conditions are significant as indicated by the non-overlapping bootstrap CIs (shown in red). Interestingly, we observe a significant increase also for $d_{\text{max}} = 3$ albeit the effect is rather small in terms of magnitude (approx increase of 0.05 over baseline of 0.5). This is further support for our finding that in addition to the team being moderately connected as a whole, every member should also be moderately connected at the individual level. Note that there are only 1151 “Normal” skill teams. When “Normal” and “High” skill are considered together (resulting in approximately twice as many teams as in “Normal”, middle column of Fig. 5), we obtain essentially the same findings, with minor differences in what conditions are substantially outside the baseline CIs.

Finally, when we only consider the “Very High” skill teams, the picture is considerably different. With a single exception, all estimates of the winning probability for different conditions on density, as well as minimum and maximum degree, are clearly within the baseline confidence intervals. The only difference is the estimate for $\Pr(w | d_{\text{min}} = 1)$, where we observe an almost significant and in absolute magnitude rather small increase in comparison to the baseline. However, unlike with “Normal” skilled teams (including “High” skill), we find no support for a robust association between performance and network structure for the “Very High” skill teams.

4 Discussion

Social network structure has been highlighted as an important factor of team performance. Previous literature, rather comprehensively summarised in Balkundi and Harrison 2006,
has provided evidence for network density being positively associated with team performance. Some studies, such as work by (Oh et al. 2004) for example, have also argued that ever increasing density can be detrimental to performance. In this work we replicate these existing results using novel, large-scale data from an online game.

Importantly, we observe that moderate density is associated with increased performance, while complete cliques have substantially decreased performance. As an important novel contribution we consider team skill as a moderating variable, and show that for teams having very high skill there is essentially no association between network structure and performance, something also suggested by Balkundi and Harrison (2006), while for teams of moderate skill such effects are present.

Another novelty of our approach is the use of node degrees as a characterisation of network structure. When team skill is not considered, we do not in general find any strong associations between the maximum degree of a network and team performance, but we do find that networks where the minimum degree $d_{\text{min}}$ is equal to 2 tend to exhibit substantially increased performance. For teams of normal skill, we in addition to the above result also observe a small but significant increase for performance when the maximum degree $d_{\text{max}}$ is equal to 3. While the precise values of $d_{\text{min}} = 2$ and $d_{\text{max}} = 3$ are most likely specific to our networks having exactly five members, these results suggests that teams where every member is “moderately connected” (in relation to the size of the team) exhibit better performance. Previous literature on team density suggest that as a whole, a team should be moderately connected within itself, and our findings augment this with the observation that the same holds for individual members of the team, especially if the team is less skilled.

We hypothesise that our findings can be partly explained by global properties of social networks. As can be seen from Figure 3, networks with $d_{\text{min}} = 2$ (marked by the red squares) tend to violate the triadic closure property (Granovetter 1973). Such networks are more likely to have members from a number of different communities. In this case some members act as “bridges” by belonging to at least two of these communities, and are hence directly connected to members from both. This type of network structure may introduce diversity into the teams that is beneficial for overall performance.

Numerous studies have argued that networks with the so called “small-world” property facilitate information diffusion within the network, and thereby increase the performance of the entire system irrespective of the underlying process (Watts and Strogatz 1998, Kleinberg 2000, Latora and Marchiori 2001, Cowan and Jonard 2004, Bassett and Bullmore 2006). These studies, however, have focused on system-level phenomena in large networks, which may not directly carry over to smaller groups, such as teams. Previous work on creative teams, in particular musical production teams and scientific collaborations, has suggested a connection between the structure of the global social network of the team members and success of the musical (Uzzi and Spiro 2005), as well as the diversity of scientific teams in terms of incumbent members and newcomers and team performance (Guimera et al. 2005). These studies have also found that teams that have both familiar, as well as non-familiar members tend to perform better. In this study we obtain similar results by looking at the teams individually, and only by considering the within team social networks. Moreover, very recently similar results have also been reported for larger teams (14 members on average) in another multiplayer online game (Benefield et al. 2016).
4.1 Limitations

Our data is limited to small ad-hoc teams that are assembled on the fly to perform a relatively short, well-defined task. However, we believe this is an important context for studying this problem, as for example knowledge work is increasingly carried out by independent freelancers in transient, information systems mediated teams.

The team networks were built with “friend” lists from the Steam social network. These are analogous to friendships in e.g. Facebook, meaning that we can assume two connected team members to know each other at least to some degree, but the depth or longevity of their relationship remains unknown.

Also, we observe and construct the team networks only after a match has been played. This is because we can retrieve the contact lists only once information about the match becomes public. Due to technical reasons this happens only a couple of hours after the match has taken place. Our data does not reveal if two players were disconnected during the match, but became connected in a period of a few hours after the match, or were connected during the match, but became disconnected later. However, there are no obvious reasons to assume that this would introduce a systematic bias to our observations, even if it may occasionally happen in our data.

Finally, the observation about performance decreasing for very high density networks may be an artefact of the way Dota 2, or similar online games in general are played. For densely connected teams the real source of enjoyment for players may simply be time spent with friends, and winning the match is secondary. However, it can also be argued that the converse is true: a group of friends might play together often, and hence employ finely tuned strategies and communicate more efficiently that teams composed of strangers.

4.2 Conclusion and future work

While network density (or, equivalently, average degree) is a natural way to operationalise the overall cohesion or familiarity within a team, the degree of a node captures a different phenomenon. It focuses on an individual, and expresses the within-team connectivity from the perspective of a single team member. Our results suggest that taking this point of view may provide additional insights to why certain network structures seem beneficial for team performance. For example, future studies may ask if individuals who encounter both familiar as well as unfamiliar people in their teams experience a stronger need to perform well to give a good impression of their skills to the others? And is this effect reduced when there are only familiar members?

A Appendix

A.1 Additional details about Dota 2 matchmaking

For every match, players can either search for a match by themselves or with 1–4 Steam friends as a team (up to total of 5 players). The “normal matchmaking” algorithm first finds players or other partially filled teams with equal skill level to make a full team of 5 players. Then the matchmaking algorithm finds another team of equal total skill level and pits these
two teams against each other. The teams move into a shared lobby, where they start picking
their characters before the actual match begins. The games matchmaking algorithm pairs
teams who have equal skill level with the expected winning likelihood of 50% based on players
so called matchmaking rating. Therefore, the skill level of individual players is to a large
degree controlled for. As there are thousands of simultaneous Dota 2 players, the likelihood
for not finding equally skilled players and teams is very unlikely.

A.2 Additional details about Dota 2 game modes
We focus on games played with the default game mode “All pick”. This sets the least
amount of settings on the game, as well as teams’ character selection. Specialised rules
could introduce opaque complexities into how the game is played. In the “All pick”-mode
there are no restrictions as to what characters the players can choose.

A.3 Additional details about data scraping
Dotabuff.com shows identity information only for players who have opted in to share their
data. The identity of all 10 players who participated in a match is known only in a fraction of
all observed matches, however. Some players are anonymous because they have chosen to opt-
out of the data collection process. Of every non-anonymous player, the script we use for data
scraping finds the identifier of their Steam profile on the page downloaded from dotabuff.com,
and then proceeds to download their list of contacts from steamcommunity.com using this
identifier. The Steam identifier is a unique, essentially random number that is assigned to
every user account in the Steam system. We use the Steam profile identifier as the primary
key to identify each player.

A.4 Implementation details of the resampling procedure
The combined bootstrap/permutation method that we use is implemented as shown below:

1. Let $D$ denote the data we are resampling, let $n$ denote the size of $D$.
2. For $N = 10000$ times, do:
   (a) Draw $n/2$ rows with replacement from those teams in $D$ that won ($w = 1$).
   (b) Draw $n/2$ rows with replacement from those teams in $D$ that lost ($w = 0$).
   (c) Combine the two samples drawn above to form a new dataset $D'$.
   (d) Use $D'$ to compute $\Pr(w \mid e = i)$ and $\Pr(w \mid d_{\text{min}} = j)$ for all $i$ and $j$. These
       estimates are used to construct the bootstrap distribution of the observed winning
       probabilities. (I.e., the red lines in figures 4 and 5.)
   (e) Create a new dataset $\tilde{D}'$ that is a copy of $D'$, but where the $w$ variable has been
       permuted uniformly at random across all observations. That is, we explicitly
       make sure that the connection between either $e$ or $d_{\text{min}}$ and $w$ is broken.
(f) Use $D'$ to compute $\Pr(w \mid e = i)$ and $\Pr(w \mid d_{\text{min}} = j)$ for all $i$ and $j$. These estimates are used to construct the baseline confidence intervals of the winning probabilities. (I.e., the blue lines in figures 4 and 5.)

This procedure results thus in two distributions: one over the non-permuted bootstrap samples, and another over the bootstrap samples where the $w$ variable was subsequently permuted.

References

Baldwin, T. T., Bedell, M. D., and Johnson, J. L. (1997). The social fabric of a team-based MBA program: Network effects on student satisfaction and performance. *Academy of Management Journal*, 40(6):1369–1397.

Balkundi, P. and Harrison, D. A. (2006). Ties, leaders, and time in teams: Strong inference about network structure’s effects on team performance. *Academy of Management Journal*, 49(1):49–68.

Bassett, D. S. and Bullmore, E. (2006). Small-world brain networks. *The Neuroscientist*, 12(6):512–523.

Benefield, G. A., Shen, C., and Leavitt, A. (2016). Virtual team networks: How group social capital affects team success in a massively multiplayer online game. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing, CSCW*, pages 677–688.

Berman, S. L., Down, J., and Hill, C. W. (2002). Tacit knowledge as a source of competitive advantage in the national basketball association. *Academy of Management Journal*, 45(1):13–31.

Borgatti, S. P. and Everett, M. G. (2000). Models of core/periphery structures. *Social networks*, 21(4):375–395.

Burt, R. S. (2004). Structural holes and good ideas 1. *American journal of sociology*, 110(2):349–399.

Cowan, R. and Jonard, N. (2004). Network structure and the diffusion of knowledge. *Journal of Economic Dynamics and Control*, 28(8):1557–1575.

Cummings, J. N. and Cross, R. (2003). Structural properties of work groups and their consequences for performance. *Social networks*, 25(3):197–210.

De Dreu, C. K. and Weingart, L. R. (2003). Task versus relationship conflict, team performance, and team member satisfaction: a meta-analysis. *Journal of Applied Psychology*, 88(4).
de Montjoye, Y.-A., Stopczynski, A., Shmueli, E., Pentland, A., and Lehmann, S. (2014). The strength of the strongest ties in collaborative problem solving. *Scientific reports, 4*:5277.

Devine, D. J. and Philips, J. L. (2001). Do smarter teams do better a meta-analysis of cognitive ability and team performance. *Small Group Research, 32*(5):507–532.

Efron, B. and Tibshirani, R. J. (1994). *An introduction to the bootstrap*. CRC press.

ElBardissi, A. W., Wiegmann, D. A., Henrickson, S., Wadhera, R., and Sundt, T. M. (2008). Identifying methods to improve heart surgery: an operative approach and strategy for implementation on an organizational level. *European Journal of Cardio-Thoracic Surgery, 34*(5):1027–1033.

Granovetter, M. S. (1973). The strength of weak ties. *American journal of sociology, 78*(6):1360–1380.

Grund, T. U. (2012). Network structure and team performance: The case of english premier league soccer teams. *Social Networks, 34*(4):682–690.

Guimera, R., Uzzi, B., Spiro, J., and Amaral, L. A. N. (2005). Team assembly mechanisms determine collaboration network structure and team performance. *Science, 308*(5722):697–702.

Hamari, J. and Sjöblom, M. (2017). What is esports and why do people watch it? *Internet Research, 27*(2).

Huckman, R. S., Staats, B. R., and Upton, D. M. (2009). Team familiarity, role experience, and performance: Evidence from indian software services. *Management science, 55*(1):85–100.

Humphrey, S. E., Morgeson, F. P., and Mannor, M. J. (2009). Developing a theory of the strategic core of teams: a role composition model of team performance. *Journal of Applied Psychology, 94*(1):48.

Katz, R. and Allen, T. J. (1982). Investigating the not invented here (nih) syndrome: A look at the performance, tenure, and communication patterns of 50 r & d project groups. *R&D Management, 12*(1):7–20.

Kleinberg, J. M. (2000). Navigation in a small world. *Nature, 406*(6798):845–845.

Kratzer, J., Leenders, O. T. A., and Van Engelen, J. M. (2004). Stimulating the potential: Creative performance and communication in innovation teams. *Creativity and Innovation Management, 13*(1):63–71.

Latora, V. and Marchiori, M. (2001). Efficient behavior of small-world networks. *Physical Review Letters, 87*(19):198701.

Lincoln, J. R. and Miller, J. (1979). Work and friendship ties in organizations: A comparative analysis of relation networks. *Administrative Science Quarterly, 24*:181–199.
Neuman, G. A. and Wright, J. (1999). Team effectiveness: beyond skills and cognitive ability. *Journal of applied psychology, 84*(3):376.

Oh, H., Chung, M.-H., and Labianca, G. (2004). Group social capital and group effectiveness: The role of informal socializing ties. *Academy of Management Journal, 47*(6):860–875.

R Core Team (2017). *R: A Language and Environment for Statistical Computing.* R Foundation for Statistical Computing, Vienna, Austria. http://www.R-project.org/.

Reagans, R., Argote, L., and Brooks, D. (2005). Individual experience and experience working together: Predicting learning rates from knowing who knows what and knowing how to work together. *Management science, 51*(6):869–881.

Reagans, R. and Zuckerman, E. W. (2001). Networks, diversity, and productivity: The social capital of corporate r&d teams. *Organization Science, 12*(4):502–517.

Sasidharan, S., Santhanam, R., Brass, D. J., and Sambamurthy, V. (2012). The effects of social network structure on enterprise systems success: A longitudinal multilevel analysis. *Information Systems Research, 23*(3-part-1):658–678.

Stewart, G. L. (2006). A meta-analytic review of relationships between team design features and team performance. *Journal of management, 32*(1):29–55.

Thamhain, H. J. (2004). Linkages of project environment to performance: lessons for team leadership. *International Journal of Project Management, 22*(7):533–544.

Uzzi, B. and Spiro, J. (2005). Collaboration and creativity: The small world problem. *American Journal of Sociology, 111*(2):447–504.

Valve Corporation (2017). Welcome to valve. http://www.valvesoftware.com/company.

Valve Corporation (29017). Dota 2. http://blog.dota2.com.

Wasserman, S. and Faust, K. (1994). *Social network analysis: Methods and applications,* volume 8. Cambridge university press.

Watts, D. J. and Strogatz, S. H. (1998). Collective dynamics of small-world networks. *Nature, 393*(6684):440–442.

Zanetti, M. S., Scholtes, I., Tessone, C. J., and Schweitzer, F. (2013). Categorizing bugs with social networks: a case study on four open source software communities. In *ICSE’13: Proceedings of the 2013 International Conference on Software Engineering*, pages 1032–1041.