On Successful Team Formation

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ABSTRACT
Teamwork plays an important role in many areas of today's society. Thus, the question of how to form an effective team is of increasing interest. In this paper we use the team-oriented multiplayer online game Dota 2 to study cooperation within teams and the success of teams. Making use of game log data, we choose a statistical approach to identify factors that increase the chance of a team to win. The factors that we analyze are related to the roles that players can take within the game, the experiences of the players and friendship ties within a team. Our results show that such data can be used to infer social behavior patterns.

Categories and Subject Descriptors
J.4 [**Social and Behavioral Science**]: Sociology; H.5.m [**Information Interfaces and Presentation**]: Miscellaneous

Keywords
Online game, Online community, Team formation, Social ties, Statistical analysis

1. INTRODUCTION
Successful teams and how to build them is a hot topic in a wide range of fields. In every day's work, in professional sports as well as in leisure activities there is a growing interest in how people cooperate and which factors influence team performance in a positive way. Plenty of articles are published that provide tips for managers on how to compose effective teams (e.g., [8]). As research has shown, teamwork also plays an increasing role in the production of high impact science [2].

As more and more human activities are moving to the Web, the Web has become a mirror of modern society. Data is easily available and can be used to study human relations and behavioral patterns. Thus, the Web provides an unprecedented opportunity to observe social interaction on the large scale.

Our aim in this context is to study cooperation within teams and success of teams. To do this, we use the multiplayer online game Dota 2. In this game two teams, consisting of five members each, play against each other, and the task is to defeat the opposed team. To achieve this goal, close cooperation and intelligent interaction between the members of the team are needed – hence, a challenge that is present in many "real world" situations as well. Particularly, we want to find out whether or not the success of a team is influenced by a) the distribution of the roles that are chosen by the players in the game, b) previous experiences of the team members, and c) friendship ties within a team. Furthermore, related to the chosen roles of the players, we investigate which of the two factors has a higher influence on the team's success: either the *individual choices* of the roles by the players or the *combination of the role choices* of the entire team.

Online games have already widely been used to study social interactions. By now research mainly focused on so-called Massively Multiplayer Online Role-Playing Games. Although in these types of games cooperation is possible, each player makes his/her own progress and has individual tasks. Dota 2, in contrast, is a game in which the players are always assigned to a team and thus have common goals and interests. Furthermore, most of the existing studies are qualitative, using surveys and questionnaires to learn about the behavior and the motivations of users. As opposed to this, our analysis is based on log data, i.e., data that is automatically generated to record the events that are happening during a game. Our quantitative approach provides the opportunity to draw a global picture that can lead to new insights and a better understanding on what is needed to make a team successful.

Figure 1: The Map of Dota 2.

The rest of the paper is organized as follows: In section 2 we describe the game in more detail. In section 3 the related work is presented. In section 4 and section 5 descriptive statistics of the data are provided and the preprocessing steps for further analysis are discussed. In section 6 the analysis is presented and the results are shown. Our conclusions and plans for future work are presented in section 7.

2. THE GAME AND ITS COMMUNITY

Dota 2 [19] is a so-called multiplayer online battle arena (MOBA) video game developed by Valve [21]. Each player controls a character called "hero", who participates in a team combat with the objective to demolish the opposing team's fortified stronghold. We are aware that this is a very cruel terminology, but we stick to it since it stems from the game creators.

Players are pitted against each other as two distinct factions of five players each, the *Radiant* and the *Dire*. Their strongholds, called *base towers*, are located at opposing ends of a geographically balanced squared map (see Figure 1). These are connected by three main lanes, which are guarded by defensive towers and weaker computer-controlled units, called *creeps*. Killed heroes revive in the corresponding area of their base after a waiting time proportional to their level and the game time. Through the destruction of enemy forces, heroes may gain both experience and gold. The former accumulates to gain higher levels that enhance the hero's attributes and abilities. The latter is the currency of the game, which is distributed to the team members according to their accomplishments. Gold also accumulates periodically to each hero. It is mainly used to acquire items that substantially complement or alter abilities, as well as to buy an instant revival of the hero.

Each player selects one hero out of 96 available in Dota 2. These heroes are unique characters that differ in their initial attributes and special abilities. On the one hand, initial attributes categorize heroes primarily according to their strength, agility and intelligence. On the other hand, special abilities are a set of four unique spells specific to each hero (for example, there are such spells as "Enchant totem", "Greevil's greed", "Nature's guise" and so on). Both attributes and abilities are enhanced with experience accumulated over the course of the game. Through the combination of initial attributes and special abilities different heroes are suited for different strategies (in Dota 2 they say game "roles") and can be played in a variety of ways (e.g. "Pusher", "Carry", "Nuker", etc.). Each player chooses a strategy not only based on the selected hero, but also on the heroes of the other members of the team. Through the choices of these strategies the flexibility of the team is increased and facilitating the formation of more competitive teams.

To get more details about each attribute, ability as well as game role, we recommend to address the official wiki page of Dota 2 [5]. In Table 1 we present three heroes from Dota 2: "Treant Protector", "Phantom Lancer" and "Lina". We also provide the values of their main three attributes ("Strength", "Intelligence" and "Agility") as well as class to which they belong and game roles in which these heroes can be played.

Dota 2 is a team-oriented game in which strategy and team coordination is decisive to achieve a victory. Communication between team members is a vital part of the game, acting as a binding force that makes a team function. Players can communicate through typing, voice chat, pinging the map and writing on the minimap.

Valve has built a social network around Dota 2 utilizing Valve's Steam software [20] in order to provide social and community functionality for the game. Steam accounts save personal files and settings on the online accounts. The players can set up private games with friends or join public games. In private games, teams might, however, be formed not only by humans but also by Artificial Intelligent (AI) bots. In this case other players in the community are locked out and the game is played with computer-controlled heroes, who can also interpret simple commands of human players. Dota 2 has not been publicly released yet. Even if its beta version limits its test early access, it is currently one of the cornerstone games at several electronic sports tournaments, and considered one of the best and highest e-sport games [9, 17, 10].

On the basis of the data from the game we want to investigate team formations and which factors influence the success of the team in the game. We formulate the following hypotheses:

1. team selection of heroes influences the game outcome;
2. overall gaming experience of players influences the game outcome;
3. playing with friends increases the chance to win;
4. individual selection of heroes as well as the combination of selected heroes influence the game outcome.

3. RELATED WORK

Virtual worlds are playing an important role in the study of diverse fields such as sociology [11], psychology [23, 6],

Table 1: Examples of heroes with some of their characteristics.

	 Treant Protector	 Phantom Lancer	 Lina
Class	Strength	Agility	Intelligence
Strength	25	18	18
Agility	15	23	16
Intelligence	17	21	27
Game role	Durable Initiator Lane support Disabler	Carry Escape Pusher	Nuker Disabler Support

economy [13, 16], etc. These studies raise the question of how the mechanisms of human behavior are being translated and developed in an artificial environment.

Gameplay data and player characteristics are drawing the attention of recent studies in the field of social computing and web science [14]. In particular the study of Massively Multiplayer Online Role-Playing Games (MMORPGs) are gathering most of the attention. This is due to their nature that allows players' cooperation and competition on a large scale, as well as interaction assuming the role of a character whose actions can be controlled, in the case of MMORPGs. The social interactions that take place in them are well explored demonstrating the crucial role that they play. Cole et al. [3] examine them through the analysis of online questionnaires that interrogate about social interactions that occur both within and outside MMORPGs. Their results show that these are extremely social games that favor the possibilities of players making life-long friends and partners. Recent studies analyze log data of this kind of games with the aim to build models of human features and behavior, such as activities, interactions and cooperations [18]. Kałuża et al.[11] carried out their research of an MMORPG. They use *World of Warcraft* as a case study that they analyze from a sociological viewpoint. In their study they identify players' communication as as a driver for community engagement. Likewise they relate gamers' intercultural communication to its influence on players' behavior and group organization in such artificial communication environment. Their descriptive research concludes that origin, culture and language are important factors of player attractiveness that have an effect on the creation of national guilds, communication problems and generalization of players' behavior based on the country of origin. Group formation of gamers is also examined in one of the latest studies of Keegan et al. [12] who collected data about characters and accounts from the Sony Online Entertainment's MMORPG *EverQuest II*.

Cooperation and competition in online games is examined from a different aspect by Yuan et al.[24] by conducting a quantitative study and analyzing game logs. Their results show that the selection based on in-game score level of partners to cooperate with is important for the players, while choosing the opponents is slightly biased.

The categorization MOBA (Multiplayer Online Battle Arena games), also known as Dota-like games, often refers to games with two teams of players competing against each other and controlling a single character in the battlefield. Although this genre emphasizes a more cooperative team-play, the literature about it is very scarce. A very recent paper analyzes the relationship between real life leadership styles (authoritarian, democratic or laissez-faire) and game roles of two MOBA games, Dota 2 and *Heroes of Newerth* [15]. The method used was a close-ended questionnaire to examine daily life and gameplay behaviors.

Dota 2 as a game differs from MMORPGs since this is first of all a team game and only afterwards a game with elements of traditional MMORPGs, and the team perspective is the main focus of our analysis. We are not aware of any recent work using game log data to analyze the behavior and interaction of MOBA players, and with this study we aim to cover the gap.

4. THE GAME AND ITS DATA

The data set used in this study has been retrieved in XML from Steam and Dota 2 utilizing their Web APIs [22, 4] and later migrated to PostgreSQL. The Dota 2 data was made public by the community of Dota 2 players. It contains the match history and the details of the matches played in the year 2011.

Using the Steam API we incorporate additional information of those players that appear in the match history of the Dota 2 data. This information is extracted from the players' profiles in the Steam platform. Such profiles contain user information such as name, country, sign up date, last log off date, etc. The list of friends is also extracted, as well as their type of relationship and starting friendship date. The visibility of this data is, however, dependent on the confidentiality of the user profile, which can public or private.

The entire database contains information on 885,228 matches. Since we focus on team aspects, we need details about both the matches and the players involved, such as start time and duration of the match, its outcome (i.e., which team wins), the number of human players (there are also teams that include AI bots – see Section 2), the difficulty or "skill" of the match, account ids of the players, the heroes they choose, the performance of those heroes in the match (i.e., how often they are defeated, how many others they damage, how much gold they acquire and so on). For the majority of the matches in the database not all this information is provided, so we filter them out. Also we keep only the matches that contain two teams with five players in each team and all players have public profiles.

The resulting data set comprises 87,204 matches, which are played by 138,101 individuals. Since there are ten players per match, each player participates on average in 6.3 matches. 18.7% of the players (25,812) take part in more than 10 matches; and the highest number of matches that is played by one person is 94. On average a match lasts 45 minutes; and 50% of the matches take between 37 and 45.7 minutes. Each of the 138,101 individuals spends on average 284.1 minutes resp. 4.7 hours playing the game.

There are four different difficulty levels of matches. In the dataset variable "skill" indicates the difficulty of the match: 0 - low, 1 - normal, 2 - high, 3 - very high. Unfortunately, in the filtered dataset we have only two matches of the very high difficulty (see Table 2).

Table 2: Amount of matches of different difficulty levels.

Skill	*Low*	*Normal*	*High*	*Very high*
Amount	40216	37481	9505	2

In the dataset under consideration, approximately half of the players (52% resp. 71,869) provide information on their country; 232 distinct countries are indicated. This information will be used in our future studies. In addition, in our dataset each player has on average 34.6 friends. The maximum number of friends a player has is 302; and around 1770 players don't gave any friends at all.

Within the 87,204 matches only 66 distinct heroes out of 96 are chosen by the players. The overall distribution of the heroes' frequency is quite balanced, the most popular hero is chosen in 3.6% of all cases; and 75.8% of the heroes (50 out of the 66) are chosen in more than 1% of the cases.

5. THE GAME AND ITS PLAYERS

As we mention in Section 2, each player has to select one hero at the beginning of the game. This selection influences the role (or equivalently, the strategy) which the player will follow during the game. Since we are interested in the influence of role distribution on the success of the team, we perceive hero selection as an indicator of role distribution inside the team and consider it as an important factor for the team success. However, there arises a difficulty: there are 5 players in each team, and to study role distribution would mean studying all possible combinations of 5 heroes out of 66. That results in 677,040; thus, this approach is not feasible.

Another approach would be to classify heroes and then to study the combinations of classes. There are two possible classifications of heroes: the first one considers the main three attributes of heroes (namely, "Strength", "Agility" and "Intelligence"); and the second one is based upon the game roles (for example, "Carry", "Pusher", "Supporter" and so on; there are more than 8 game roles) in which heroes can be played. However, both classifications have shortcomings: the first approach does not consider all the variability of hero attributes (there are in total 17 basic attributes), and in the second approach each hero can be played in more than one of the defined game roles (see, for example, Table 1).

Thus, we introduce a new approach to consider the influence of hero selection on the team success. We use the data about initial attributes of heroes; and for the sake of clarity and better interpretation, we apply a dimension reduction algorithm to receive one single score for each hero. We use logistic regression for this purpose. We take the data about played heroes in a match and its outcome (872,040 data points for 10 players in 87,204 matches) and train the logistic regression model on 70% of observations of our dataset, and then apply the calculated coefficients to the rest.

Logistic regression has been chosen since it can be perceived as a linear transformation of initial attributes with regard of their influence on the match outcome. The coefficients of the trained model indicate that not only strength, agility and intelligence of the heroes are decisive, but also other attributes are very important (especially, movement speed, ranges of day sight and night sight). Thus, for each hero out of 66 we obtain a unique *hero score*.

Another factor which we assume to influence the team success is the experience of players. As for the gaming experience of players, we consider not only information about the amount of previously played and won matches, played time, but also information about performance in previous matches. After the match finishes each player receives statistics about his/her performance which includes 13 different measures such as #kills, #deaths, spent gold, final level and so on. So, in total we get again (like for hero selection) 17 different attributes related to the gaming experience of each player. Following the same reasoning as for hero selection, we use logistic regression on the same dataset (but instead of using attributes of selected heroes by players we use attributes of their experience) to calculate an *experience score* for each player in a specific match.

To have the same base for both scores, we transformed them to be in the interval $[0, 1000]$. Figure 2 shows the results of Spearman correlation test and scatter plots between *hero score*, *experience score* and *win* on the dataset which we use to calculate the scores. Variable *win* is binary and indicates whether player was in the team which won (value 1) or in the

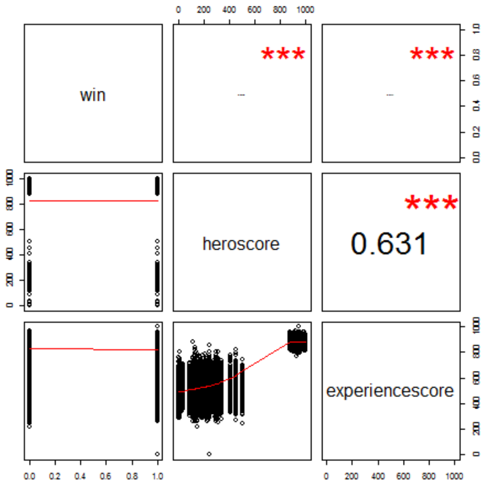

Figure 2: Correlation between *hero score*, *experience score* and *win*.

team which lost (value 0). As we see, there is a significant high correlation coefficient (63%) between *experience score* and *hero score*. This observation can be explained by the fact that the higher gaming experience of the player, the better he/she is at choosing heroes. However, the correlation with variable *win* is, though significant, but very low. It turns out and we will show in the following section that the team composition is an important factor for the match outcome.

6. ANALYSIS AND RESULTS

In this section we show how different factors influence the team success in a virtual environment, using the preprocessed data as described in Sections 5 and 4. We use statistical methods from R [1] to test our hypotheses about the influence of role distribution, experience and social ties on the team success.

To test the difference of scores for teams we perform paired t-test or Mann-Whitney-Wilcoxon test which depends whether the provided samples are normally distributed or not. We apply χ^2-test to test the dependence of the team success on the number of friends in the team.

To make sure that the factors under consideration are important for matches of different difficulty levels (factor *skill*), we perform two way ANOVA.

Since we also want to verify that the selection of hero by each player is important, we also use log-linear analysis with likelihood ratio test (an adjustment of ANOVA).

All tests are performed with 95% confidence level. Additionally, whenever possible all the assumptions of the corresponding test are verified (for example, normality, equal variances, homogeneity of variances, independece).

6.1 Hero Selection

One of the first hypotheses which we want to test is that the role distribution (i.e., selecting a specific hero) is important for the team success. In Section 5 we show how to obtain *hero score* using a supervised dimension reduction method. We calculate the *team hero score* for each team in a specific match as the average of *hero score* for the heroes selected by team members. Remember that in Section 5 we show that this score is the indicator of role distribution inside the team. We normalize the *team hero score* across all matches and teams. Afterwards, we form two samples: the first contains scores for the winning team (win-team) and the second has scores of the loosing team (loss-team). Both samples still follow normal distribution.

To show that hero selection influences the team success, we need to test whether the mean difference of *team hero score* is equal to zero. In case it is not zero, that would mean that *team hero score* is different for win-team and loss-team, and thus, hero selection is an important success factor. We formulate the corresponding null-hypothesis.

H_0: win-team and loss-team have the same means of *team hero score*.
H_1: members of win-team make better selection of heroes which results in a higher *team hero score* compared to loss-team.

We perform a paired t-test to test the null-hypothesis. However, F-test shows that we cannot claim that both samples have equal variances with 95% confidence level. That is why we perform a paired Welch's t-test for these two samples. Our test is paired since both samples are aligned according to the matches.

We reject the null hypothesis with p-value$= 1.802e - 06$ which is significantly lower than the significance level and accept the alternative hypothesis. This means that a win-team has on average a higher *team hero score* than a loss-team. This observation leads to the conclusion that *team hero score* influences the team success.

Since there are matches of different difficulty levels, we perform a two-factor analysis to identify whether *team hero score* is influential in matches of all difficulty levels. Remember that factor "skill" (see Table 2) indicates the difficulty level: there are three difficulty levels from 0 (low) to 2 (high). We perform ANOVA test with *team hero score* being the dependent variable and the two independent factors *win* and *skill*.

The results of ANOVA confirm our previous ones of significant dependence of the *team hero score* on the team success (loss or win). Figure 3 demonstrates the results of ANOVA by using Tukey multiple comparison. The full comparison chart includes 15 levels, but for the sake of interpretation we include only 3 levels which are relevant to our study. We explain the meaning of labels on y-axis by the first row. Label $0:0-1:0$ means that the difference of *team hero score* for teams $0:0$ (teams which lost in matches of low difficulty level) and teams $1:0$ (teams which won in matches of low difficulty level) is compared. So, the first number in the level encoding shows the value of factor *win* and the second number corresponds to the value of *skill* factor.

According to Figure 3, there is a significant difference in the

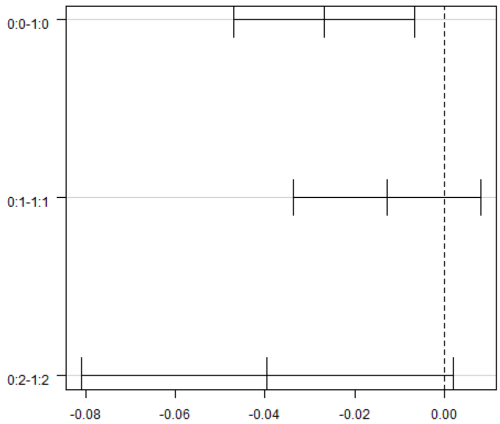

Figure 3: Means of *team hero score* with regard to team success (win 1 and loss 0) and difficulty levels (low 0, normal 1 and high 2).

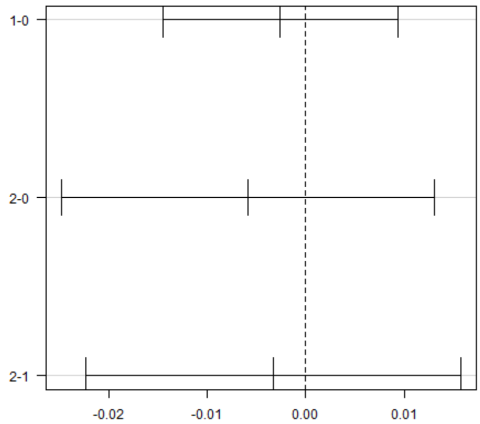

Figure 4: Means of *team hero score* across matches of different difficulty levels (low 0, normal 1 and high 2).

means of *team hero score* only for matches of the lowest skill ($skill = 0$): a win-team has a higher score than a loss-team. As for the difficulty levels 1 (normal) and 2 (high), we also see that *team hero score* is higher for the win-team, but this difference in scores is not statistically significant.

Going a step further, we look at the dependency of *team hero score* and *skill* of match. We do this to obtain further insights how well a team selects heroes based on the difficulty level of the match. We state the following null-hypothesis and its alternative.

H_0: *team hero score* is the same across matches of different difficulty levels.
H_1: the higher the skill of the match, the better teams select heroes.

The results of ANOVA test show that we do not reject the the null-hypothesis. In Figure 4 we present again the Tukey multiple comparison chart. The label $1 - 0$ on y-axis means that we compare the means of *team hero score* for matches of difficulty level 1 and 0. The results imply that the selection of heroes is balanced across all difficulty levels of matches.

This analysis concludes that *team hero score* is an important factor for the team success irrelevant of the difficulty level of match. It provides support for our first hypothesis.

6.2 Individual Hero Selection vs Team Hero Selection

We want to check what is more influential for the match outcome: very good selection of heroes by individual players or very good combination of heroes selected by team. For this purpose we extract *hero score* for each player in the team and sort them in the increasing order. We obtain 5 samples for win-team and loss-team separately: each sample corresponds to *hero score* of players in the ranking order either from win-team or loss-team. We normalize the scores in all samples using the mean and standard deviation calculated previously. The correlation analysis shows that *team hero score* (which we studied previously) correlates significantly with the individual scores having the highest correlation coefficient with the second ranked *hero score* in the team.

Then, we perform paired Mann-Whitney-Wilcoxon-tests for samples of *hero score* of the same rank from win-team and loss-team, in total we do 5 tests. All 5 tests conclude that there is a significant mean difference in *hero scores* for win-team and loss-team, and win-team has a higher score.

To consider also interaction between *hero scores* of different ranks we perform log-linear analysis, that is we use logit model to fit our data and for this model we perform ANOVA with likelihood ratio test. By interaction we mean all possible combinations of *hero scores* for 5 players in the team. In total there are 26 combinations: 10 pairwise, 10 three-wise, 5 four-wise and 1 total combinations. In Table 3 we present the results of ANOVA with likelihood ratio test where each term corresponds either to *hero score* of a specific rank (from p1 being the weakest to p5 being the strongest) or a specific combination of *hero score* for players (from p1:p2 till p1:p2:p3:p4:p5).

From Table 3 we see that the most influential *hero score* is the one for the strongest hero selected in the team which we call team leader (term “p5”). However, further analysis of deviance uncovers that the weakest (term “p1”) and the fourth strongest (term “p4”) heroes matter as well as different combinations of heroes in the team (for example, terms “p2:p4”, “p1:p2”, “p1:p2:p3:p4”). Thus, we may conclude that the team success depends significantly on the team leader as well as successful combination of heroes in the team. This conclusion provides support for our fourth hypothesis that individual selection of heroes as well as their combination is important for the team success.

Table 3: ANOVA results using likelihood ratio test.

Term	*Deviance*	*p-value*
p1	18.09	$2.096e-05$ ***
p2	0.35	0.552
p3	1.56	0.210
p4	21.57	$3.410e-06$ ***
p5	267.25	$4.504e-60$ ***
p1:p2	104.54	$1.533e-24$ ***
p1:p3	7.74	0.005 **
p2:p3	0.005	0.941
p1:p4	52.93	$3.443e-13$ ***
p2:p4	161.59	$5.059e-37$ ***
p3:p4	101.58	$6.841e-24$ ***
p1:p5	70.25	$5.212e-17$ ***
p2:p5	65.50	$5.808e-16$ ***
p3:p5	56.17	$6.618e-14$ ***
p4:p5	51.51	$7.115e-13$ ***
p1:p2:p3	41.87	$9.726e-11$ ***
p1:p2:p4	4.84	0.027 *
p1:p3:p4	2.90	0.0884 .
p2:p3:p4	66.17	$4.126e-16$ ***
p1:p2:p5	1.46	0.225
p1:p3:p5	0.42	0.512
p2:p3:p5	0.14	0.702
p1:p4:p5	3.50	0.0612 .
p2:p4:p5	11.92	0.0005 ***
p3:p4:p5	2.40	0.121
p1:p2:p3:p4	21.70	$3.181e-06$ ***
p1:p2:p3:p5	0.0007	0.978
p1:p2:p4:p5	0.64	0.421
p1:p3:p4:p5	1.83	0.175
p2:p3:p4:p5	1.18	0.276
p1:p2:p3:p4:p5	0.15	0.694

*Sign. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

6.3 Experience of Players

In Section 5 we obtain an *experience score* by using a supervised dimension reduction method. As in Section 6.1, we calculate a *team experience score* for each team in a specific match as an average of *experience scores* of team members. We then normalize *team experience score* across all matches and teams. Again we form two samples: the first contains scores for the team which won (win-team) and the second has scores of the team which lost (loss-team). Both samples still follow normal distribution (null hypothesis of normality test accepted).

In order to show the dependence of team success on *experience score*, we formulate the following null-hypothesis and its alternative.

H_0: win-team and loss-team have the same *team experience score*.
H_1: members of win-team have higher *team experience score* compared to loss-team.

Like in the case of *hero score*, we perform a paired Welch's t-test for the two samples with *team experience score*. The results of the test lead us to the rejection of the null hypothesis with p-value=0.007, and we accept the alternative hypothesis. This means that a win-team has on average a higher *team experience score* than a loss-team, i.e. experience matters.

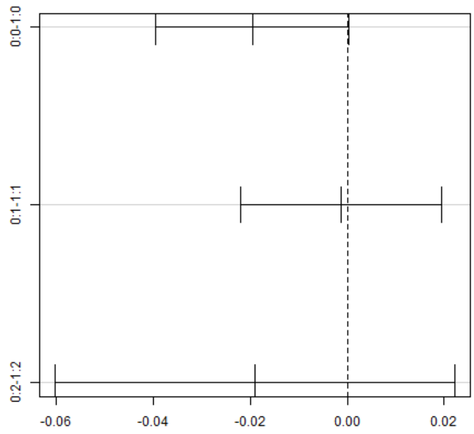

Figure 5: Means of *team experience score* with regard to team success (win 1 and loss 0) and difficulty levels (low 0, normal 1 and high 2).

Again, to obtain more insights we relate experience to the difficulty of the match (factor "skill"). We perform ANOVA test with *team experience score* being the dependent variable and the two independent factors *win* (value 0 means that team lost and value 1 means that team won) and *skill*.

Figure 5 visualizes the results of ANOVA with Tukey multiple comparison plot. The full comparison chart includes 15 levels, but for the sake of interpretation we include only 3 levels which are relevant to our study. The meaning of labels on y-axis is the same as in Section 6.1. As we see, win-team has a higher *team experience score* than loss-team, but this difference is not statistically significant. We need more data and insights to investigate this fact.

To verify the dependence of *team experience score* on the difficulty level of the match we again perform ANOVA test with score as a dependent variable and skill as independent factor. We state the null-hypothesis as follows.

H_0: *team experience score* is the same across matches of different skills.
H_1: the higher the skill of the match, the higher *team experience score* is.

Figure 6 shows Tukey multiple comparison plot for ANOVA test, and according to the results of ANOVA test and this figure we reject the null-hypothesis: teams in matches of high difficulty level have considerably higher *team experience score* than those of low and normal difficulties. Though, the mean difference between difficulties "low" and "normal" cannot be claimed significant. Obviously, the more experience a player is, the more difficult matches he/she participates in.

While calculating *experience score* we take into consideration only experience of players individually. A more sophisticated approach is required to calculate overall team experience, taking into account experience of pairwise combina-

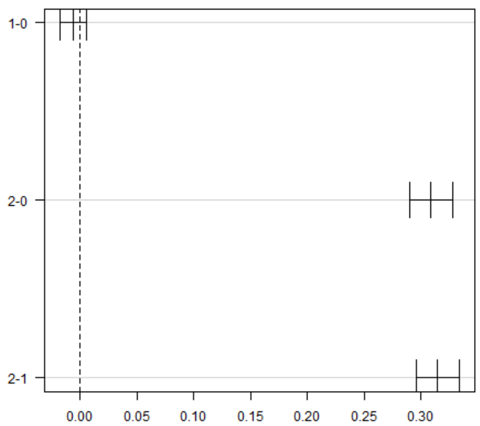

Figure 6: Means of experience score across matches of different difficulty levels (low 0, normal 1 and high 2).

tions of team members as well as of the whole team. This approach may lead to further insights of the dependence of team success on the experience of team members.

To conclude, we show that *team experience score* is a significant indicator of team success, especially in the matches of low difficulty. This conclusion supports our third hypothesis that experience matters.

6.4 Social Ties

Since Valve gives an opportunity to retrieve community information from Steam account of players, we ongoing investigate how the social perspective influences the outcome of the game.

For each player in the team we calculate how many friends are playing together with him/her in the team. This is a number from 0 to 4. Then we select the maximum number of friends for the 5 players in this team, and call it *max # friends*. We do admit that a more sophisticated calculation (like calculating maximum clique in the friendship network of the team members) might be more appropriate, but we leave it for the future work.

Table 4 illustrates that the winrate increases if more friends play in the team. We perform χ^2-test to check whether this dependence is significant or not. The test accepts the alternative hypothesis: two variables are dependent with $p-value < 2.2e-16$ and $\chi^2 = 189.0624$. Though χ^2-test shows that team success depends on the number of friends in the team, it cannot answer the question how exactly the number of friends influences on the team success.

Thus, we again form two samples with *max #friends* for win-team on one hand and for loss-team on the other hand. We want to check the following null-hypothesis.

H_0: *max #friends* for win-team and loss-team are equal.
H_1: win-team has higher amount of friends playing together

Table 4: Winrate depending on the maximum amount of friends playing in the match

max #friends	*#matches*	*#wins*	*winrate*
0	43609	21140	48.48%
1	69764	34397	49.30%
2	40010	20391	50.96%
3	14342	7589	52.91%
4	6683	3687	55.17%

than loss-team.

Since *max #friends* is not normally distributed, we perform a paired Mann-Whitney-Wilcoxon test to show that the mean amount of friends for win-team is significantly higher than for the loss-team. We reject the null-hypothesis with p-value$< 2.2e-16$. This means that if a higher amount of friends play together in the team, this leads to the higher chance of winning the match. Thus, we conclude that it is very important to strengthen social ties inside the team. Further investigation is required to test the dependence of the strength of social ties and team success.

The stated above results provide evidence for our third hypothesis that friends have a higher probability to win.

7. CONCLUSIONS AND FUTURE WORK

We use the data from the online game Dota 2 and its community to treat the questions of success factors for teams. We provide evidence for the following accepted hypotheses:

1. a better role distribution in a team increases the chance to win a game;
2. teams with more experienced players have a higher chance to win;
3. playing with friends increases the chance to win;
4. the selection of a proper leader as well as a good matching of heroes inside a team positively influence the success.

In a next step we plan to study the compositions of the teams in more detail. In the presented work we only take into account the individual experience of the players. In the future we want to investigate how often subgroups of the team members as well as the team as a whole have already played together before. We will use our data to construct a co-playing network. Network analysis techniques can then lead to deeper insights into both the *local* structure (i.e., clusters of individuals that often play within a team) and the *global* structure (i.e., number and size of connected components, density,...).

Whereas the above described network is implicit in the sense that it refers to the co-playing relationships within teams, the obtained data models also the explicit friendship network of players. In this case network analysis can also be applied to show how friendship networks impact the outcome of games. Thus, we might also be able to answer the question whether players of the game become friends because they play together or rather they convince already existing friends to join the game.

Our results show that the data on online gaming and gaming communities can be used to infer social behavior patterns. But we would also like to stress that the biggest part of work does not go into the statistical analysis but rather into the preparation of data for this analysis. Needed is knowledge from computer science, statistical methods and social science, underlining the insight that Web Science is an interdisciplinary endeavor.

8. ACKNOWLEDGEMENTS

We are thankful to the team of Dotabuff [7] for sharing their dataset.

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