# Social Influence Analysis
# Networks and Teams

Research Stay at Northwestern University
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# Contents

# 1 Introduction

Funded by the Austrian Marshall Plan Foundation [1], I had the opportunity to spend almost 4 months at the Science of Networks in Communities (SONIC) group at Northwestern University. Northwestern University [16] is a private university in Illinois, USA. Its main campus is located in Evanston, a northern suburb of Chicago with approximately 75,000 inhabitants, directly at the shores of Lake Michigan. Northwestern University possesses moreover a side campus in Downtown Chicago. The university was founded in 1851 and comprises 12 schools today. At the moment there are about 17,000 fulltime students enrolled, about half of them in graduate or professional programs. The ratio of students to faculty members is 7:1 [17, 26]. Northwestern University is member of the Association of American Universities (AAU), an exclusive group of 60 US and 2 Canadian universities that aim to foster high quality academic research and education [4]. Various well-accepted university rankings attest Northwestern University academic excellence [26, 25, 6].

The Science of Networks in Communities (SONIC) laboratory at Northwestern University aims at bringing forward theories, methods, and tools to study social and knowledge networks [23]. It has an interdisciplinary focus and its director, Prof. Noshir Contractor, is Professor of Behavioral Sciences and affiliated to three of Northwestern University's Schools – the McCormick School of Engineering, the School of Communication as well as the Kellogg School of Management – and to the Northwestern Institute on Complex Systems (NICO) [15]. The research conducted at the SONIC lab focuses on networks in online communities and virtual teams with the goals to better understand the emergence and functions of such networks. Theoretical and conceptual frameworks are developed to model the formation and maintenance of dynamical networks. Therefore advanced mathematical, statistical and computational techniques are used and combined with theories from social and behavioral sciences. The networks that are studied range from a small scale, where data is collected with help of surveys, to large-scale networks obtained from digital traces. Current research projects, in which SONIC is involved, deal for instance with academic networks, medical communities, networks in the context of public health, environmental and sustainability networks as well as virtual worlds. Also a network recommender system for team formation is developed [23].

During my stay from August 5, 2013 to November 15, 2013 I was working on two projects:

The first one is related to churn behavior and social influence in online communities. In online games as well as many online social sites, the success and attractiveness of a community is strongly determined by the active participation of its members. Analyzing why people leave and predicting churn behavior becomes a critical challenge, especially with the mutual influence among users. The purpose of this study is to explore important factors that influence quitting decisions in games from three dimensions: achievement, commitment, and social network effects. In EverQuest II, a massively multiplayer online role-playing game, we identify different player attributes such as their progress and rewards in game, time committed on different game activities, and team and organization relations and examine their impacts on the likelihood of unsubscribing the game. In particular, we focus on social influence in players' teaming network and characterize the contagious effect of quitting behavior. We use a generalization of Exponential Random Graph Models to study the social influence among users who played together. Our results show that players with higher achievement, such as higher levels, more award items, and more kills, are less likely to quit the game. The commitment on game activities has a mixed effect: players who spend more time on building items are more likely to quit but players who spend more time on trading items are less likely to quit. For social effects, we find that players who have more teammates and join a guild are less likely to quit. However, the likelihood of quitting increases significantly with the number of quitting teammates. This study is described in Section 2 of this report.

The second study is about network and teams. While network approaches are used to study how the assembly of teams impacts their performance, there has been little attention to assess the impact of assembly on the relative performance of two teams in a head to head contest. In this work, we focus specifically on assembly factors that influence performance of short-duration contests in mid-sized teams playing a multiplayer online game, Dota2, where two teams consisting of five players each compete with each other. We determine the attributes and relational factors that help a team to defeat the opponent. Among attributes we consider the players' skills as well as the diversity of their skills and their roles. Relational factors include the friendship relations within a team, previous co-playing experiences of team members as well as the embeddedness of the team, i.e., whether team members belong to a community that often plays together. We use game log data for short matches (under 30 minutes) within Dota2 to empirically test this model. We find that teams with players who have more diverse roles are more likely to win. We also find some evidence that teams consisting of players who have focused on training their fighting skills rather than on non-fighting skills have an advantage. However, when relational factors are included in the model, some skill factors are no longer significant. Instead, friendship ties between team members as well as the embeddedness of the team within the community have a positive impact on the likelihood of a team to win. More details can be found in Section 3.

Both studies will be presented at this year's Sunbelt Conference [9] and will be published afterwards.

# 2 Churn Behavior in Online Communities

## 2.1 Motivation and Background

The success of an online community is typically strongly related to the commitment and the active participation of its members. Thus, besides gaining new users, operators of online platforms also face the challenge to retain actual ones. So the question, why people leave a community becomes crucial and the analysis as well as the prediction of churn behavior gains more and more importance.

The goal of our work is to examine different factors that might lead to quitting decisions. Apart from individual attributes of the users, we examine social network effects. In particular we want to find out whether quitting behavior is contagious and try to quantify the influence of quitting neighbors of a user in an online social network. For this study we focused on a network of co-players in the Massively Multiplayer Online Role Playing Game (MMORPG) EverQuest II [24]. Virtual words and online games are widely used to study human becavior and social interaction. In EverQuest II each player controls a character and leads this character through different adventures. This includes the exploration of various environments in order to complete quests and to kill monsters. An important aspect of the game is the facilitation of players' interactions. To solve different tasks the players can form groups or join guilds.

We focus on the following questions:

1. What are the main factors that increase the likelihood of quitting a MMORPG?
2. What role does social influence play in this context?

In EverQuest II players are more likely to quit in the early stage of the game. Furthermore, solo players are three times more likely to quit than players with partner. Here, we will focus on the latter because we are interested in social effects. Other factors that we are studying are related to achievement of the players and their commitment.

Factors related to achievement include the levels of the characters in the game, the number of rare items that the player has harvested or how much gold the player has acquired. Factors related to commitment are for example the time spent in the game and how many different characters the player controls. Social effects are either social payoff that the player receives by interactions with other players and guild activities or social influence of quitting co-players.

Our hypotheses are:

- **Achievement Hypothesis**
  H1: High level players are less likely to quit EverQuest II than low level players.
- **Commitment Hypothesis**
  H2: Players are less likely to quit EverQuest II if they play more in the game.
- **Relational Payoff Hypothesis**
  H3: Players are less likely to quit if they have more partners.
- **Social Influence Hypothesis**
  H4: Players are more likely to quit if their partners quit EverQuest II .

- **Local Cluster Hypothesis**
  H5: Players are less likely to quit EverQuest II if their partners are closely connected.
- **Community (Attachment) Hypothesis**
  H6: Players are less likely to quit EverQuest II if they are a part of a guild.

Although a lot of research is conducted related to quitting behavior, hardly any model takes social influence into account [10, 18]. Exceptions form the work of Kawale et al. [11] and the work of Phadke et al. [18]. Both apply data mining approaches. In the first paper, also a co-players network of EverQuest II is studied. It is assumed that the probability of a player to quit the game depends on two factors: 1) his or her engagement in the game, 2) social influence from co-players. To each player (i.e., node in the network) an influence vector is assigned. A diffusion model is developed to spread social influence through the network. During the diffusion process, the influence vector is iteratively updated. In the end, it forms the basis to predict churn behavior. In combining engagement and social influence, this model performs significantly better than simpler models.

Also in [18] a diffusion model is proposed. Here, churn behavior of customers in the telecommunication domain is analyzed. A mobile call graph is constructed and based on different features, a tie strength measure between pairs of users is introduced. This measure forms the basis for the developed influence propagation model. When the diffussion process ends, each node has accumulated a certain amount of influence. This distribution of influence is then used as predictor variable for churn behavior in classical machine learning algorithms. Other predictor variables that are included are either related to telecommunication patterns of the user or to network measures such as number of quitting neighbors. The algorithm that performs best in this context is “ensemble decision tree classification”. The results show that churn behavior is predicted with higher accuracy if the accumulated influence is taken into account.

## 2.2 Methodological Approach

When looking at literature it turns out that in many studies, where social network analysis is applied, this is mainly done in a descriptive way. For example, often the numbers of nodes, edges and triangles are indicated, network measures such as density and clustering are reported, the nodes are ranked according to different centrality measures, and community detection algorithms uncover densely connected subgroups of the network. On the other hand, statistical inference in the context of network data is rarely done or worse, wrongly applied. The reason is that standard statistical techniques for hypotheses or significance testing are often not appropriate when studying networks because these methods presume that the observations are independent. This, for sure, is not true for network data, which is per definition relational [14]. Other approaches use data mining techniques to make predictions for network processes. Also here often the dependent character of the data is not taken into account adequately. For example, a network cannot be divided into a training and a testing set in the same way as if the data were independent; or due to network effects, interdependencies between attributes of nodes might occur. Thus, more sophisticated approaches are needed to enable statistical inference also in the context of networks. Exponential Random Graph Models (ERGMs) help to overcome these problems.

### 2.2.1 Exponential Random Graph Models (ERGMs)

ERGMs are statistical models that allow inference of link forming processes of networks. The main idea is to assign a probability to a given network. This probability is derived by comparing the propensity of the structure of the network to the propensity that would occur only by chance. This can be mathematically expressed by the formula:

$$\Pr(\mathbf{X} = x) = \frac{1}{\kappa(\theta)} e^{\theta^T z(x)} = \frac{1}{\kappa(\theta)} e^{\theta_1 z_1(x) + \theta_2 z_2(x) + \cdots + \theta_p z_p(x)}. \tag{1}$$

Here, $\Pr(\mathbf{X} = x)$ indicates the probability of the network under consideration, $\theta = (\theta_1, \ldots, \theta_n)$ is a vector containing the parameters of the model and $z(x) = (z_1(x), \ldots, z_n(x))$ indicates a vector of network statistics (i.e., counts of configurations in the graph such as number of edges, number of triangles, centrality indices, etc.), and $\kappa(\theta)$ is a normalizing factor [12, 22].

To make the idea intuitively comprehensible, the concept is sometimes compared to a multiple regression model in the sense that the resulting probability is the weighted sum of the variables $z_i(x)$, $i = 1, \ldots, n$ with weights $\theta_i$, $i = 1, \ldots, n$ .

An extension to Equation 1 allows to integrate effects related to nodes' attributes and their interaction with the edges of the network:

$$\Pr(\mathbf{X} = x | \, \mathbf{Y} = y) = \frac{1}{\kappa(\theta)} e^{\theta^T z(x) + \theta_a^T z_a(x,y)} \tag{2}$$

Here, the additional term $\theta_a^T z_a(x, y)$ is the inner product of the vector $\theta_a$, which contains the parameters of the interactions of network ties $x$ and attributes $y$, and the vector $z_a(x, y)$, which contains the corresponding statistics. Such models are called *social selection models* [12]. With the help of these models it can, for instance, be tested whether there is a higher likelihood of a tie between two nodes that have the same attribute (e.g., "female") than between two arbitrary nodes.

Thus, also exogenous factors, i.e., attributes of the nodes, can be included into the model, and so hypotheses can be tested about the formation of network ties that are related to various link forming mechanisms. Thus, different sociological theories can be taken into account within one model. Furthermore, the results might lead to insights on different levels of analysis, i.e., on the individual level, on the group level (e.g., pairs, triadic configurations, etc.) on the global level. This makes ERGMs a powerful methodology to study empirical networks and allow for a multitheoretical, multilevel approach [14].

### 2.2.2 Social Influence Models

In our study we use a generalization of ERGMs that allow to take also social influence into account. These models were proposed by Robins et al. [21]. Here, the dependent variable is the attribute of interest (e.g., whether or not a node exhibits a certain behavior). Network ties on the other hand are considered as independent, as opposed to the ERGMs in Section 2.2.1. There the structure of the observed network is seen as dependent variable.

So, let $Y = (Y_i)_{i=1,\ldots,n}$ be a binary vector that represents the attribute of interest. By $y = (y_i)_{i=1,\ldots,n}$ we denote a realization of this vector where $y_i = 1$ if the attribute is present at node $i$ and $y_i = 0$ otherwise. A binary matrix contains information on the network edges, where $x_{ij} = 1$

if the edge exists, and $x_{ij} = 0$ otherwise. Also other predictor attributes $W$, which are denoted by $w = (w_i)$, might be included in the model. Then the probability for a vector of attributes conditional on an observed network is given by

$$\Pr(Y = y | X = x) = \frac{1}{\kappa(\theta_I)} e^{\sum_I \theta_I z_I(y,x,w)}, \tag{3}$$

where $\theta_I$ and $z_I$ are the vectors containing parameters and statistics of configurations of the network including interactions of the dependent attribute $y$, network ties $x$ and other independent variables $w$. Since network ties are seen here as independent variables, network based social influence effects may be inferred if the presence or absence of the attribute of interest of node $i$ is associated with the attributes of other nodes that have ties (i.e., social relations) to node $i$. [12].

We see, these models aim at explaining a distribution of an attribute (that represents for example a certain behavior) across a network with fixed structure. The main idea is that the attribute of one node might depend on the attributes of others. So, the model also allows insights into diffusion processes.

If we transform Equation 3 to conditional log-odds, we can write it as:

$$\log \frac{\Pr(Y_i = 1 | y_{-1}, x, w)}{\Pr(Y_i = 0 | y_{-1}, x, w)} = \theta_1 + \sum \theta_p z_p(x) + \sum \theta_I z_I(x,y) + \sum \theta_C z_C(w) + \sum \theta_{IC} z_{IC}(x,w). \tag{4}$$

The larger this ratio the higher the probability of the attribute being present at node $i$ as compared to the attribute being absent at that node conditioned on $y_{-1}$ (i.e., the attribute of interest at all other nodes $j \neq i$), $x$ (i.e., the ties of the network) and $w$ (i.e., the other predictor variables). The parameter $\theta_1$ denotes an intercept term. The parameters $\theta_P$ aim at predicting $Y_i$ from the structural position of node $i$ ("P" stands for "position") and the variables $z_P$ are related to the corresponding network configurations. The parameters $\theta_I$ aim at predicting attribute $Y_i$ of node $i$ from the presence of the same attributes of other nodes $j$ who are linked to node $i$ ("I" stands for "influence"). The statistics $z_I$ represent network configurations that involve both node $i$ and $j$. The parameters $\theta_C$ aims at predicting $Y_i$ from other predictor variables of the same node $i$ ("C" stands for "covariate") and $\theta_{IC}$ aims at predicting $Y_i$ from other predictor variables of nodes $j$ that are connected to node $i$. The terms $z_C$ respectively $z_{IC}$ indicate the corresponding network configurations [12].

Thus, regarding structural effects, this model takes into account how much the probability of the attribute being observed depends on

- The structural position of a node ($\theta_P$);
- The presence or absence of the attribute of interest in the local neighborhood of a node ($\theta_I$);
- The interactions with covariate attributes of other nodes ($\theta_{IC}$).

If there are no structural effects, then $\theta_P = \theta_I = \theta_{IC} = 0$ and we get a standard logistic regression model with $\theta_1$ and $\theta_C$ as parameters. In that sense the social influence model can be seen as a generalization of standard logistic regression. However, when structural effects occur, the model behaves differently. Then the same variable $Y_i$ is not only a dependent variable but also occurs on "the other side of the equation" as an independent variable (when predicting the attribute of other nodes $j$). This is the reason why those models are also called auto-logistic models. These dependencies cannot be addressed by standard logistic regression [12].

## 2.3 Data and Analysis

For our analysis of churn behavior, we used a data sample of one game server of EverQuest II [24]. This sample included statistics about players on that server for the month March to August in 2006. From this, we constructed a co-playing network in the following way: We considered two players as co-players if they were solving some task together, e.g., killing a monster. Thus, a node in the network represented a player and we added an edge between a pair of them if they were co-players in the observation period. Furthermore, we added a weight to an edge that represented the number of times those players had played together. This graph comprised 8438 nodes and 37620 edges.

In a next step we removed all edges from that graph with a weight equal to one. Those players were only playing once together, which indicates a very weak relation. We considered those relations as not relevant for a player's decision to leave the game. After deleting those edges, we obtained a graph with 8438 nodes and 32483 edges. Descriptive statistics for this graph can be found in Table 1.

| | |
|---|---|
| Number of Nodes | 8438 |
| Number of Edges | 32483 |
| Avg. Degree | 7.7 |
| Avg. Path Length | 4.36 |
| Graph Diameter | 12 |
| Graph Density | 0.001 |
| Connected Components | 436 |
| Size of Largest Component | 7638 |
| Number of Isolates | 123 |
| Avg. Local Clust. Coef. | 0.131 |
| Number of Triangles | 8355 |

Table 1: Descriptive Statistics Co-Playing Graph

We considered a player as a quitter (i.e., we set the quitting attribute to 1) if the player either

- Cancelled his or her account (i.e., canceled credit card based subscription) during the observation period or
- Was inactive for at least one month.

About 35% of the players quitted the game during that period. As described in Section 2.1, we took factors related to achievement, commitment and relations into consideration to predict whether a player does quit the game. Descriptive statistics of those factors can be found in Table 2. Furthermore, most of the players are in a guild (about 77%).

For the analysis we developed logistic regression models on the one hand and social influence models as described in 2.2.2 on the other hand.

Software tools that we used were R with various packages and IPNet. R is a software environment as well as a programming language for statistical computing [3]. It is free and available for all

| **Attributes** | **Min.** | **1st Qu.** | **Median** | **Mean** | **3rd Qu.** | **Max.** |
|---|---|---|---|---|---|---|
| Level | 1.00 | 29.00 | 50.00 | 46.41 | 67.00 | 70.00 |
| Guild Size | 0.00 | 2.00 | 25.00 | 37.15 | 61.00 | 192.00 |
| Number of Characters | 1.00 | 4.00 | 5.00 | 5.25 | 6.00 | 20.00 |
| Number of Character Classes | 1.00 | 3.00 | 5.00 | 4.92 | 6.00 | 16.00 |
| Number of Servers | 1.00 | 1.00 | 1.00 | 1.49 | 2.00 | 7.00 |
| Gold | 0.00 | 45.01 | 294.8 | 1496 | 1104 | 228000 |
| Total Time Played (Days) | 0.01 | 11.30 | 40.91 | 64.73 | 97.24 | 486.80 |
| Time Trading (Days) | 0.00 | 0.04 | 0.41 | 2.38 | 2.19 | 124.20 |
| Time Vendor (Days) | 0.00 | 0.00 | 0.08 | 5.73 | 2.76 | 393.40 |
| Time Adventure (Days) | 0.00 | 8.28 | 28.62 | 44.33 | 66.43 | 355.70 |
| Rare Items Main Character | 0.00 | 5.00 | 25.00 | 58.79 | 70.00 | 2216.00 |
| Rare Items All Characters | 0.00 | 10.00 | 44.00 | 91.69 | 116.00 | 2384.00 |
| PvP Kills | 0.00 | 0.00 | 0.00 | 31.17 | 0.00 | 4321.00 |
| Number Quitting Neighbors | 0.00 | 0.00 | 1.00 | 1.30 | 2.00 | 28.00 |
| Degree | 0.00 | 2.00 | 5.00 | 8.24 | 11.00 | 158.00 |
| Weighted Degree | 0.00 | 112.00 | 424.00 | 986.60 | 1221.00 | 18090.00 |
| Local Clust. Coef. | 0.00 | 0.00 | 0.01 | 0.13 | 0.15 | 1.00 |

Table 2: Describtive Statistics of Attributes

platforms. The logistic regression model was developed within R. There exist, moreover a high number of packages for specific applications. These packages can usually be easily integrated within the R environment. To construct and analyze the co-playing network, for instance, the R package igraph [7] was used.

#### 2.3.1 IPNet

The program IPNet is a version of PNet for social influence models [13]. PNet is a program that allows fitting Exponential Random Graph Models (ERGMs) to network data. It can be used for ERGMs parameter estimation, for the simulation of distributions of networks with specific parameters as well as for Goodness of Fit tests of specific models with particular parameters [27].

IPNet facilitates the analysis of social influence models as described in Section 2.2.2. The conditional probability of the attribute of interest can be tested by specifying parameters that represent certain configurations. As described in Equation 4, these configurations can be related to network position effects (parameter $\theta_P$), to network attribute effects (parameter $\theta_I$) or to covariate effects (parameters $\theta_C$ and $\theta_{IC}$).

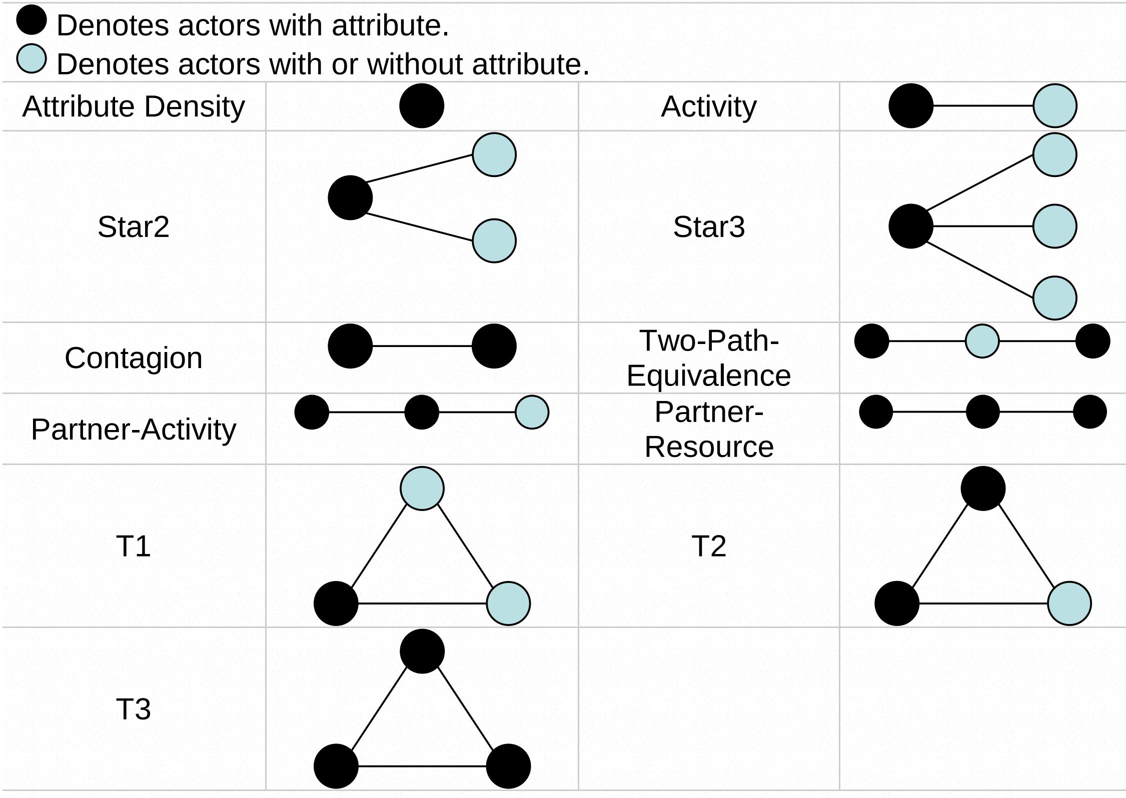


Figure 1: Network position effects and network-attribute effects (from PNet User Manual [27])

In Figure 1 network configurations related to position effects and attribute effects, which can be selected in IPNet, are presented. Nodes that have the attribute of interest are depicted black. In our case, black nodes would be quitting players. The parameters *Attribute Density*, *Activity*, *Star2*, *Star3* and *T1* belong to network position effects. Here, the assumption is that a node can also be influenced only by interactions with others regardless of the attribute statuses of those other nodes. *Density* just captures how many nodes in total exhibit the behavior. The parameter *Activity* examines if a node with links to other nodes is more likely to exhibit the behavior. Related to this, *Star2* and *Star3* allow for taking into account a non-linear association between the behavior of interest and the number of edges. The triangle parameter *T1* tests whether the behavior is related to network closure [12].

The parameters *Contagion*, *Two-Path-Equivalence*, *Partner-Activity*, *Partner-Resource*, *T2* and *T3* in Figure 1 are related to network-attribute effects. If the probability of a node to exhibit a certain behavior is associated with the presence of this behavior for the neighbors of this node then the *Contagion* parameter will be high and positive. *Two-Path-Equivalence* suggests that two nodes are more likely to show the behavior if they are structurally equivalent, i.e., if they are linked to the same nodes. *Partner-Activity* wants to express that a node is more likely to exhibit the behavior if it has a social active neighbor with this behavior. The parameter *Partner-Resource* claims that a behavior is more likely if a neighbor with that behavior also has neighbors with that behavior. The triangle *T2* also expresses a form of structural equivalence. Here there is a link between the nodes that are structurally equivalent. The triangle *T3* can be interpreted as contagion in groups [12].

In Figure 2 covariate effects are illustrated. Here, it is distinguished whether the other attribute is binary, continuous or categorical. The parameters $oOb$ and $oOc$ are related to the parameter $\theta_C$ in Equation 4. As explained previously, if no network effects are present, the dependent variable is only predicted by other attributes of the same node as in standard logistic regression. On the other hand, $o\_Ob$ and $o\_Oc$ identify attributes of neighbors that might influence the behavior. Finally, the parameters for categorical attributes $oO\_Osame$ and $oO\_Odiff$ try to capture whether belonging to the same (resp. a different) category as (resp. than) the neighbor has an influence on the adoption of the behavior. [12]

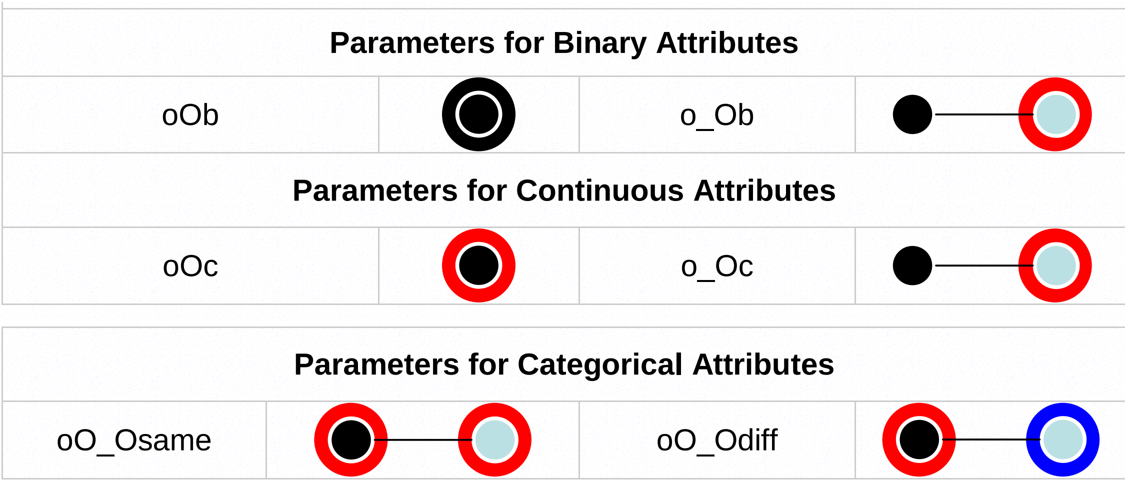


Figure 2: Covariate effects (from PNet User Manual [27])

As already mentioned, in our setting the behavior of interest is quitting behavior and we want to find out whether it is contagious in the co-playing network. Thus, the *Contagion* parameter is of special interest. Furthermore, we assume that network position effects take place, i.e., that players who have interactions with others are less likely to leave. Our hypotheses also address covariate effects but mainly related to the parameter $\theta_C$ rather than $\theta_{IC}$.

## 2.4 Results

First we applied logistic regression to gain first insights and preliminary results. However, as discussed in Section 2.2.1, standard logistic regression cannot account for network effect as there should not be interdependencies between the observations. So, we sub-sampled the data in a way that no pair of nodes in this sub-sample was linked to each other. Thus, we removed the dependency between two observations. The results of the analysis can be seen in Table 3. The correlations between the factors can be found in Table 4.

| Hypotheses | Measures | Attributes | Attributes + Relations |
|---|---|---|---|
| **H1: Achievement** | Level | -0.01(.00) *** | -0.01(.00) ** |
| **H1: Achievement** | Gold | 0.12(.08) . | -0.00(.00) . |
| **H1: Achievement** | Rare Items All Character | -0.01(.00) *** | -0.01(.00) *** |
| **H1: Achievement** | PvP Kills | 0.00(.00) ** | 0.00(.01) ** |
| **H2: Commitment** | Number of Characters | -0.06(.02) ** | -0.04(.01) * |
| **H2: Commitment** | Number of Servers | 0.05(.05) | 0.00(.05) |
| **H2: Commitment** | Time Trading (Days) | 0.02(.01) ** | 0.10(.01) * |
| **H2: Commitment** | Time Vendor (Days) | -0.01(.00) ** | -0.01(.00) ** |
| **H3: Relational Payoff** | Degree | | -0.08(.10) *** |
| **H3: Relational Payoff** | Weighted Degree | | 0.00(.00) *** |
| **H4: Social Influence** | Number Quitting Neighbors | | 0.16(.05) ** |
| **H5: Local Cluster** | Local Clust. Coef. | | -0.21(.12) |
| **H6: Community** | In Guild | -0.27(.10) ** | -0.22 (.10) * |
| **H6: Community** | Guild Size | -0.00(.00) | 0.00(.00) |
| | $R^2$ | 0.18 | 0.21 |

Table 3: Results (***p<.001, **p<.01, *p <.05, .p<.1)

We see that most of the hypotheses cannot be rejected. The model indicates that achievements of player, his or her commitment and being within a community decrease the likelihood significantly that this player will quit. Also social interactions tie the player to the game. However, it seems to be less important whether partners of players interact themselves since H5 is not supported by the result. Including relational information into the model increases the amount of variance that is explained by the model.

We fitted similar models for several sub-samples and the results were highly consistent.

Then we started to develop models with IPNet. Although the findings of the logistic regression could be confirmed, we encountered various problems:

- We only could use very small sub-samples because IPNet is very slow.
- Due to this low velocity we only were able to include very few predictor variables into the model.
- The simulation process is not stable.

## 2.5 Discussion

In this study we used the massively multiplayer online role-playing game (MMORPG) EverQuest II to identify different attributes that increase the likelihood of a player to quit the game. Those factors are related to achievements of the players within the game including the level the character could reach or awards in the game such as rare items. If a player has already spent a lot of time playing he or she is less likely to leave. Furthermore, we could show that community aspects play

| | Level | InGuild | GuildSize | #Char. | #Serv. | Gold | Trading |
|---|---|---|---|---|---|---|---|
| Level | 1.00 | 0.40 | 0.30 | 0.30 | 0.03 | 0.24 | 0.21 |
| In Guild | 0.40 | 1.00 | 0.52 | 0.19 | -0.01 | 0.08 | 0.10 |
| Guild Size | 0.30 | 0.52 | 1.00 | 0.08 | -0.00 | 0.07 | 0.03 |
| #Characters | 0.30 | 0.19 | 0.08 | 1.00 | 0.30 | 0.12 | 0.19 |
| #Servers | 0.03 | -0.01 | -0.00 | 0.30 | 1.00 | -0.02 | -0.03 |
| Gold | 0.24 | 0.08 | 0.07 | 0.12 | -0.02 | 1.00 | 0.30 |
| Time Trading | 0.21 | 0.10 | 0.03 | 0.19 | -0.03 | 0.30 | 1.00 |
| Time Vendor | -0.02 | 0.00 | -0.03 | 0.06 | -0.03 | 0.24 | 0.16 |
| Rare Items | 0.37 | 0.18 | 0.09 | 0.31 | -0.01 | 0.35 | 0.31 |
| PvP Kills | 0.14 | 0.03 | 0.01 | 0.12 | 0.15 | 0.07 | 0.05 |
| Degree | 0.33 | 0.25 | 0.20 | 0.21 | -0.03 | 0.07 | 0.04 |
| Quit. Neighb. | 0.19 | 0.12 | 0.11 | 0.17 | -0.00 | 0.03 | 0.04 |
| Local Clust. | 0.13 | 0.11 | 0.03 | 0.03 | -0.04 | 0.06 | 0.05 |
| Weighted Degree | 0.27 | 0.12 | 0.07 | 0.16 | -0.08 | 0.12 | 0.10 |

| | Vendor | RareIt. | Kills | Degr. | QuitNeighb. | LocalClust. | WeightDegr. |
|---|---|---|---|---|---|---|---|
| Level | -0.02 | 0.37 | 0.14 | 0.33 | 0.19 | 0.13 | 0.27 |
| In Guild | 0.00 | 0.18 | 0.03 | 0.25 | 0.12 | 0.11 | 0.12 |
| Guild Size | -0.03 | 0.09 | 0.01 | 0.20 | 0.11 | 0.03 | 0.07 |
| #Characters | 0.06 | 0.31 | 0.12 | 0.21 | 0.17 | 0.03 | 0.16 |
| #Servers | -0.03 | -0.01 | 0.15 | -0.03 | -0.00 | -0.04 | -0.08 |
| Gold | 0.24 | 0.35 | 0.07 | 0.07 | 0.03 | 0.06 | 0.12 |
| Time Trading | 0.16 | 0.31 | 0.05 | 0.04 | 0.04 | 0.05 | 0.10 |
| Time Vendor | 1.00 | 0.13 | 0.02 | -0.01 | -0.01 | 0.07 | 0.07 |
| Rare Items | 0.13 | 1.00 | 0.17 | 0.22 | 0.12 | 0.05 | 0.21 |
| PvP Kills | 0.02 | 0.17 | 1.00 | 0.02 | 0.03 | 0.01 | -0.05 |
| Degree | -0.01 | 0.22 | 0.02 | 1.00 | 0.66 | 0.05 | 0.22 |
| Quit. Neighb. | -0.01 | 0.12 | 0.03 | 0.66 | 1.00 | 0.02 | 0.16 |
| Local Clust. | 0.07 | 0.05 | 0.01 | 0.05 | 0.02 | 1.00 | 0.16 |
| Weighted Degree | 0.07 | 0.21 | -0.05 | 0.22 | 0.16 | 0.16 | 1.00 |

Table 4: Correlation Table Churn Analysis

an important role keep the game attractive. Players who participate in a guild are less likely to quit. Also structural effects have an impact in this context, when including them into the model we can improve the prediction accuracy.

Our results also indicate that social influence can have a negative effect; quitting behavior can become contagious. This is confirmed by different logistic regression models as well as by our preliminary results with IPNet. However, the logistic regression models are not ideal because they cannot adequately address social relations. This is the reason why we are working on improving our preliminary models with IPNet. With this type of social influence models we could draw a more comprehensive picture as relational aspects can be better taken into account. At the moment IPNet is available as Java-based stand-alone tool and it is quite slow. That's why we are in contact with the developers of IPNet from MelNet [13] to find a way to speed-up the fitting and testing of models for larger networks and/or models that contain more parameters. It seems that IPNet has not been used on a larger scale so far, we did not find any publications that deploy it. By now, other packages that can be used to develop ERGMs such as the R package statnet [8] do not provide the possibility to fit social influence models as described in Section 2.2.2.

# 3 Team Competitions and Networks

## 3.1 Motivation and Background

While network approaches have widely been used to study how the assembly of teams impacts their performance, there has been little attention to study the impact of assembly on the relative performance of two teams in a head to head contest. Only related to sports games, some studies can be found (see for example[5]).

Here we focus on the multiplayer online game Dota 2. In this game two teams consisting of five players each compete with each other with the goal to destroy the opposing team's stronghold. Those teams are called *Radiant* and *Dire*. In the game, each player controls a hero with different abilities and attributes. Those heroes evolve during match, acquire experience and gold and can revive. On average, a match takes about 40 minutes. Each match starts from the scratch, players cannot transfer experience scores or gold that has not been spent to another match. The map in Figure 3 gives an overview of the virtual setting of the game.

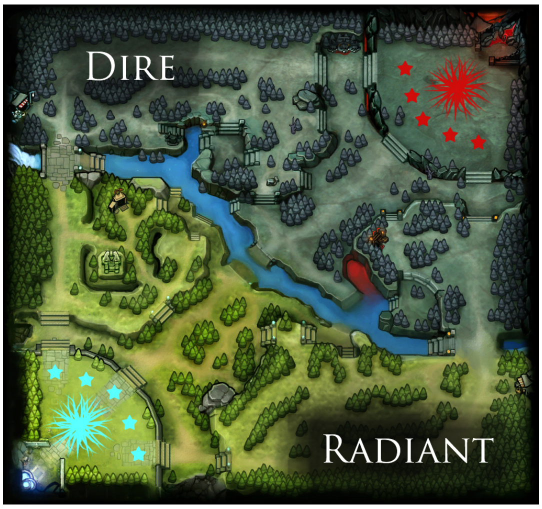


Figure 3: Map of Dota 2 (from [20])

In our analysis, we study the relative performance of those teams with the objective to determine attributes that help a team to quickly defeat the opponent. Attributes that we consider include the skills of the players in a team, the composition of a team, friendship relations within a team, previous co-playing experiences of team members as well as structural relations between teams, i.e., membership interlock. Although the setting can be compared to some sports games such as soccer there are certain differences; e.g., Dota 2 matches are not limited in their length. In previous work with colleagues from the Vienna University of Technology, we studied factors that have a positive impact on a team's likelihood to win in Dota 2. There we did not investigate the relative performance in a match [20, 19].

We focus on the following questions:

- How to win quickly (in short matches) (what is not captured by the match-making algorithm)?
- What roles do skills, strategies, relations, and teams play in Dota 2 matches?

When staring a match, a team gets automatically assigned to another team. In order to make a match balanced usually two teams are assigned that are alike. However, it is not known how this algorithm works and it will turn out that the outcome of a match is very hard to predict.

## 3.2 Methodological Approach

We used machine learning techniques to classify win and loss situation from the perspective of one team. The best results were achieved by applying binary logistic regression:

- Dependent variable: This binary variable captures whether team Radiant beats team Dire; in the first case it was set to one.
- Independent variables: To account for relative performance, we included the differences ($\Delta$) of the attributes, i.e., attribute of team Radiant minus the same attribute of team Dire, in the model. We could show that the so constructed variables are suitable predictors.

## 3.3 Data and Analysis

We developed our model based on the following data sample:

- First we selected a week of December 2011.
- From that week we chose all matches that had a short duration (under 30 minutes) and the lowest difficulty level.
- In our sample, we have 4,703 players and 499 matches.

For details about the data, please refer to [20, 19].

To capture team collaboration we constructed various measures. Those measures are related to

1. In-game statistics of a player in previous matches

   (a) a. Kills / deaths / denies / assist;
   (see [2]for the exact meaning of those terms in the context of this game)
   For each player in a team we computed the average of his or her number of kills in previous matches. We used the number of kills in a match as a baseline: For previous deaths of a player in a game, his or her denies and assists we did the same after standardizing these measures for each match by the corresponding number of kills. This we did to make these performance measures better comparable. To a team we assigned the average of the players' statistics.

   (b) b. Gold
   For each player we calculated the average gold that he or she acquired in previous matches.

   To a team we assigned the average of the team-members' statistics.

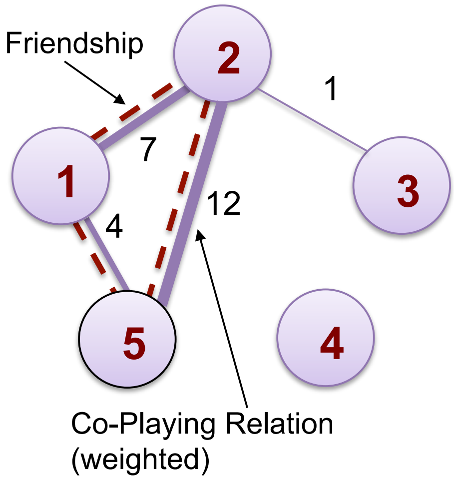


Figure 4: Relations Within a Team

2. Hero types classification of hero types into three categories:
   a. Fighter; b. Mage; c. Ranger or Scout
   In Dota 2, a player can chose out of a high number of different characters; in the data sample 66 distinct heroes occur. These heroes are characterized by basic numbers such as cast duration, sight range, etc. Furthermore, they can evolve in the course of the match with different growth rates and foci. Thus, to account for the diversity within a time is a challenging task. However, based on those basic characteristics (movement speed, etc.) we found a meaningful subdivision in three different types: fighters are characters that are strong but slow, mage have high interlligence scores and characters of the third category are fast.
   We used Blau's diversity index to capture the composition of a team. This index is calculated by $1 - \sum p_i^2$. Here, $p_i$, $i = 1, \ldots, 3$ is the fraction of heroes in a team in each of the three categories.

3. Friendship ties
   On the platform where the game is embedded, also social network functions are provided. Here, player can become friends. For each time we constructed the friendship network at the time of the match. This is illustrated in Figure 4. For these networks we calculated several network measures.

4. Co-playing relations
   Similar to the friendship network we constructed a network for each team where we connected two players by an edge if they had been members of the same team before. Furthermore we assigned a weight to each edge that expressed the number of times those two players had played together before (again, see 4). Also here we calculated standard network measures.

5. Team interlock
   To capture team overlap we constructed a weighted hypergraph: Here, each node represents a team (hyperedge) in a match. Two teams are connected by an edge if a player is member in both teams and the weight of the edge represents the number of players that participate in both teams. This concept is depicted in 5.

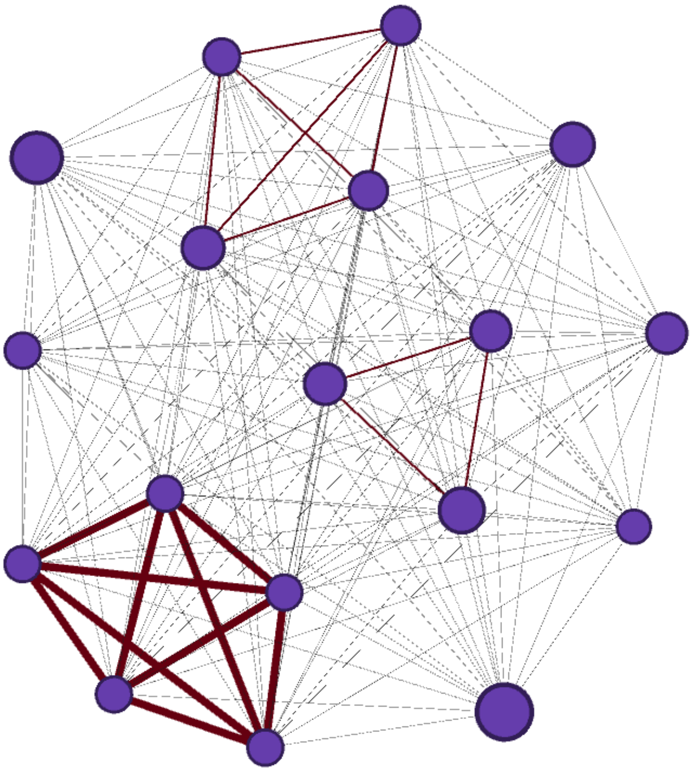

Figure 5: Relations Within a Team

Related to these measures we had the following hypotheses:

- **In-game statistics**
  - H1a Teams with higher average players' skills are more likely to win quickly.
  - H1b Teams with players focusing on non-fighting activities are less likely to win quickly.
- **Hero types classification**
  - H2 Teams with a higher diversity of players' skills and roles are more likely to win quickly.
- **Friendship ties**
  - H3 Teams with more friendship ties among the players are more likely to win quickly.
- **Co-playing relations**
  - H4 Teams with players who share more previous co-playing experiences are more likely to win quickly.
- **Team interlock**
  - H5 Teams that have a higher embeddedness are more likely to win quickly.

In Table 5 descriptive statistics of the attributes in our model is listed: both the figures for the teams and the relative measures ($\Delta$). In Table 6 the frequency distributions of the Blau's index of team compositions is given. When looking at the relative measures we discretize the Blau's index and just take into account if team Radiant has a higher resp. lower diversity index than team Dire or if they have the same diversity index (see Table 7). Finally, in Table 8 descriptive statistics of the relations are given, again both for each team and relative measures.

| **Attributes** | **Min.** | **1st Qu.** | **Median** | **Mean** | **3rd Qu.** | **Max.** |
|---|---|---|---|---|---|---|
| Kills | 0.00 | 14.00 | 26.00 | 29.22 | 38.30 | 137.40 |
| $\Delta$ Kills | -93.0 | -11.77 | -0.50 | -1.38 | 10.04 | 88.33 |
| Deaths/Kills | 0.00 | 1.23 | 1.65 | 1.83 | 2.16 | 13.00 |
| $\Delta$ Deaths/Kills | -10.90 | -0.59 | 0.02 | 0.05 | 0.72 | 11.80 |
| Denies/Kills | 0.00 | 0.43 | 0.82 | 0.94 | 1.27 | 8.00 |
| $\Delta$ Denies/Kills | -8.00 | -0.44 | 0.05 | 0.00 | 0.46 | 5.40 |
| Assists/Kills | 0.00 | 1.80 | 2.24 | 2.37 | 2.81 | 13.00 |
| $\Delta$ Assists/Kills | -7.80 | -0.61 | 0.04 | 0.06 | 0.72 | 12.49 |
| Gold | 0.00 | 3578 | 6505 | 7436 | 9829 | 38451 |
| $\Delta$ Gold | -24149.8 | -3116.4 | -221.8 | -175.4 | 2832.6 | 26148.7 |

Table 5: Descriptive Statistics of Attributes

| **Team Composition BI** | **0** | **0.32** | **0.48** | **0.56** | **0.64** |
|---|---|---|---|---|---|
| **Frequency** | 4 | 47 | 156 | 274 | 517 |

Table 6: Frequency Distribution of Blau's Index (BI)

| **Relative Team Composition BI** | **BI Team R $>$ BI Team D** | **BI Team R $=$ BI Team D** | **BI Team R $<$ BI Team D** |
|---|---|---|---|
| **Frequency** | 177 | 175 | 147 |

Table 7: Frequency Distribution of Relative Blau's Index (BI)

| Relations | Min. | 1st Qu. | Median | Mean | 3rd Qu. | Max. |
|---|---|---|---|---|---|---|
| Friendship Density | 0.00 | 14.00 | 26.00 | 29.22 | 38.30 | 137.40 |
| Δ Friendship Density | -93.0 | -11.77 | -0.50 | -1.38 | 10.04 | 88.33 |
| Co-Playing Avg. Weighted Degree | 0.00 | 1.23 | 1.65 | 1.83 | 2.16 | 13.00 |
| Δ Co-Playing Avg. Weighted Degree | -10.90 | -0.59 | 0.02 | 0.05 | 0.72 | 11.80 |
| Co-Playing Avg. Weig. Degr. (var) | 0.00 | 0.43 | 0.82 | 0.94 | 1.27 | 8.00 |
| Δ Co-Playing Avg. Weig. Degr. (var) | -8.00 | -0.44 | 0.05 | 0.00 | 0.46 | 5.40 |
| Team Clustering Coefficient | 0.00 | 1.80 | 2.24 | 2.37 | 2.81 | 13.00 |
| Δ Team Clustering Coefficient | -7.80 | -0.61 | 0.04 | 0.06 | 0.72 | 12.49 |
| Team Weighted Degree | 0.00 | 3578 | 6505 | 7436 | 9829 | 38451 |
| Δ Team Weighted Degree | -24149.8 | -3116.4 | -221.8 | -175.4 | 2832.6 | 26148.7 |

Table 8: Descriptive Statistics of Relations

Both the computing of the various measures and the analysis was entirely done within the R [3] environment.

## 3.4 Results

The results are listed in Table 9. We compare two models, one containing only attributes (i.e., In-game statistics and Hero types classification) and one containing both attributes and relations. The correlation table can be found in Figure 6.

We find that teams with players who have more diverse roles are more likely to win quickly. We also find some evidence that teams consisting of players who have focused on training their fighting skills rather than on non-fighting skills have an advantage. Furthermore, teams perform better if they are more diverse. However, when relational factors are included in the model, some skill factors are no longer significant. Instead, friendship ties between team members as well as the embeddedness of the team within the community have a positive impact on the likelihood of a team to win.

| Hypotheses | Measures | Attributes | Attributes + Relations |
|---|---|---|---|
| | Δ Kills | 0.02(.01) ** | 0.04(.01) *** |
| **H1a: Skills (protect)** | Δ Deaths/Kills | -0.15(.01) . | -0.11(.08) |
| **H1a: Skills (denies)** | Δ Denies/Kills | 0.23(.10) * | 0.21(.10) * |
| **H1a: Skills (assist)** | Δ Assists/Kills | 0.12(.08) | 0.10(.09) |
| **H1b: Non-Fighting** | Δ Gold | -0.0001(.00) . | -0.00003(.00) |
| **H2: Role diversity** | Δ Team Composition | 0.25(.12) * | 0.24(.12) * |
| **H3: Friendship** | Δ Density | | 0.92(.50) . |
| **H4: Co-Playing** | Δ Avg. Weighted Degree | | 0.02(.05) |
| | Δ Avg. Weig. Degr. (var) | | -0.01(.01) . |
| **H5: Embeddedness** | Δ Clust. Coefficient | | 0.81(.38) * |
| | Δ Weighted Degree | | -0.03(0.02) . |
| | $R^2$ | 0.062 | 0.123 |

Table 9: Results (***p<.001, **p<.01, *p <.05, .p<.1)

| | Δ Kills | Δ Deaths/ Kills | Δ Denies/Kills | Δ Assists/Kills | Δ Gold | Δ Team Composition | Δ Density (Friendship) | Δ Avg. Weighted Degr. (Co-Playing) | Δ Avg. Weig. Degr. (var) (Co-Playing) | Δ Clust. Coefficient (Team) | Δ Weighted Degree (Team) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Δ Kills** | 1.00 | | | | | | | | | | |
| **Δ Deaths/ Kills** | -0.13 | 1.00 | | | | | | | | | |
| **Δ Denies/Kills** | -0.03 | 0.16 | 1.00 | | | | | | | | |
| **Δ Assists/Kills** | -0.09 | 0.65 | 0.28 | 1.00 | | | | | | | |
| **Δ Gold** | **0.86** | -0.05 | 0.03 | 0.02 | 1.00 | | | | | | |
| **Δ Team Composition** | 0.05 | 0.04 | 0.01 | 0.03 | 0.03 | 1.00 | | | | | |
| **Δ Density** | 0.03 | -0.06 | 0.06 | 0.04 | 0.02 | 0.03 | 1.00 | | | | |
| **Δ Avg. Weig. Degree** | 0.50 | -0.04 | -0.04 | 0.00 | 0.44 | -0.04 | 0.32 | 1.00 | | | |
| **Δ Avg. Weig. Degr. (var)** | 0.51 | -0.05 | -0.03 | -0.02 | 0.47 | -0.02 | 0.18 | **0.77** | 1.00 | | |
| **Δ Clust. Coefficient** | 0.25 | 0.06 | 0.10 | 0.09 | 0.23 | -0.01 | 0.31 | 0.34 | 0.23 | 1.00 | |
| **Δ Weighted Degree** | **0.85** | 0.01 | 0.01 | 0.01 | **0.82** | 0.03 | -0.01 | 0.54 | 0.53 | 0.11 | 1.00 |

Figure 6: Correlation Table Dota 2 Analysis

## 3.5 Discussion

In this study we try predict the outcome of a team-vs-team online game by taking into account factors related to previous performances of the players, diversity of selected characters and relations. Although we could find several factors that have a significant impact, those factors only account for around 12% of the variance. This shows how hard it is to predict which team is going to win. Here, we focused on shorter matches. When looking at matches of longer duration the situation becomes worse, the outcome becomes more and more random. The model was only developed on a small data set but since the log contains all matches of the year 2011, the sample can easily be extended to test the stability of the model. Although the co-playing measures are conceptually related to the team interlock measures they did not have significant impact. This requires further investigations.

# References


[1] Austrian Marshall Plan Foundation. http://www.marshallplan.at, January 2014.

[2] Dota 2 Wiki. http://dota2.gamepedia.com/Dota_2_Wiki, January 2014.

[3] The R project for statistical computing. http://www.r-project.org/, January 2014.

[4] Association of American Universities. Member institutions and years of admission. http://www.aau.edu/about/default.aspx?id=5476, December 2013.

[5] Duch, J., Waitzman, J. S., and Amaral, L. A. N. Quantifying the performance of individual players in a team activity. *PloS one 5*, 6 (2010), e10937.

[6] Forbes. America's top colleges. http://www.forbes.com/top-colleges/list/, December 2013.

[7] Gabor Csardi and and Tamas Nepusz. The igraph library for complex network research. http://igraph.sourceforge.net, January 2014.

[8] Handcock, M. S., Hunter, D. R., Butts, C. T., Goodreau, S. M., and Morris, M. *statnet: Software tools for the Statistical Modeling of Network Data*. Seattle, WA, 2003.

[9] INSNA - International Network for Social Network Analysis. Sunbelt XXXIV. http://www.sunbelt2014.org, January 2014.

[10] Karnstedt, M., Rowe, M., Chan, J., Alani, H., and Hayes, C. The effect of user features on churn in social networks. *Proceedings of the ACM WebSci 11* (2011), 14–17.

[11] Kawale, J., Pal, A., and Srivastava, J. Churn prediction in mmorpgs: A social influence based approach. In *Computational Science and Engineering, 2009. CSE'09. International Conference on* (2009), vol. 4, IEEE, pp. 423–428.

[12] Lusher, D., Koskinen, J., and Robins, G. *Exponential Random Graph Models for Social Networks: Theory, Methods, and Applications*. Cambridge University Press, 2012.

[13] MelNet Social network analysis and theory. PNet – a program for the simulation and estimation of exponential random graph models (ERGMs) for social networks. http://sna.unimelb.edu.au/PNet, January 2014.

[14] Monge, P. R., and Contractor, N. S. *Theories of communication networks*. Oxford University Press New York, 2003.

[15] NICO. Northwestern institute on complex systems. http://www.nico.northwestern.edu, December 2013.

[16] Northwestern University. Main page. http://www.northwestern.edu, December 2013.

[17] Northwestern University. Northwestern facts. http://www.northwestern.edu/about/facts/index.html, December 2013.

[18] Phadke, C., Uzunalioglu, H., Mendiratta, V. B., Kushnir, D., and Doran, D. Prediction of subscriber churn using social network analysis. *Bell Labs Technical Journal 17*, 4 (2013), 63–75.

[19] Pobiedina, N., Neidhardt, J., Calatrava Moreno, M. d. C., Grad-Gyenge, L., and Werthner, H. On successful team formation: Statistical analysis of a multiplayer online game. In *Proceedings of The 15th IEEE Conference on Business Informatics (CBI)* (2013), IEEE, pp. 55–62. Vortrag: The 15th IEEE Conference on Business Informatics (CBI), Vienna; 2013-07-15 – 2013-07-18.

[20] Pobiedina, N., Neidhardt, J., Calatrava Moreno, M. d. C., and Werthner, H. Ranking factors of team success. In *WWW 2013 Companion* (2013), Companion Publication of the IW3C2 WWW 2013 Conference, pp. 1185–1193. Vortrag: Workshop on Web Intelligence & Communities at the World Wide Web (WWW) Conference 2013, Rio de Janeiro, Brazil; 2013-05-13 – 2013-05-17.

[21] Robins, G., Pattison, P., and Elliott, P. Network models for social influence processes. *Psychometrika 66*, 2 (2001), 161–189.

[22] Shumate, M., and Palazzolo, E. T. Exponential random graph (p*) models as a method for social network analysis in communication research. *Communication Methods and Measures 4*, 4 (2010), 341–371.

[23] SONIC. Advancing the science of networks in communities. `http://sonic.northwestern.edu`, December 2013.

[24] Sony Online Entertainment. Everquest ii. `https://www.everquest2.com`, January 2014.

[25] THE World University Rankings. Rankings 2013-2014. `http://www.timeshighereducation.co.uk/world-university-rankings/2013-14/world-ranking`, December 2013.

[26] US News, college rankings and reviews. Northwestern university. `http://colleges.usnews.rankingsandreviews.com/best-colleges/northwestern-university-1739`, December 2013.

[27] Wang, P., Robins, G., and Pattison, P. Pnet: Program for the estimation and simulation of p* exponential random graph models, user manual. *Department of Psychology, University of Melbourne* (2006).