Social Network Indices as Performance Predictors in a Virtual Organization

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Abstract—Measuring an individual’s potential to accomplish a goal has key implications in organizational studies, behavioral analysis, business and management among other areas. This relative potential, which is dependent on a myriad of factors, e.g., experience, resource management, cooperation, etc. could shape the individual’s performance, motivation, leadership, and likely success. The increasing prevalence of virtual organizations provides unique challenges and opportunities to study complex research questions via convenient data collection. In this NSF-funded research, we introduce a multi-factor dynamic model to estimate the potential of an individual to accomplish a goal in a virtual organization. We analyze data from a Massive Multi-player Online Role-Playing Game (MMORPG), Travian, collected in a controlled environment for over 3.5 months. The data contains activities of 7,406 players, including, players’ profiles, daily snapshots of individual and alliance attributes, amount of gold, military strength, trades and cooperation, diplomacy status as well as a 2.3 million-message graph. We model player’s potential to survive as a multi-factor function derived from the data attributes, including SNA-based network measures from the message graph. The model predicts a player’s potential to win the game or to achieve a specified goal. The target is to identify the influence of network behavior for the player, and how network statistics for each player influence the accuracy of the prediction.

Keywords: Social networks; virtual organizations; MMORPG; performance; predictive modeling

I. INTRODUCTION

The virtualization of economic and societal processes can be observed at an ever-increasing pace [1][9]. From an organizational perspective, this development is mainly driven by three major trends [1]: First, the changing nature of the organizational environment. Second, the innovation of information and communication technologies (ICT). Third, the dynamics of work and society in general [11][15]. It follows that formerly self-contained and hierarchically integrated structures are becoming more open, permeable and transparent by incorporating innovative forms of virtual work arrangements [8][11][15]. Virtual teams are becoming the rule rather than the exception, as work processes, which were traditionally conducted through physical mechanisms, are increasingly being conducted electronically [3][9][10]. Furthermore, geographic dispersion is no longer a prerequisite for virtuality since colocated team members may also choose to employ virtual means for coordinating their actions [7][10].

Measuring an individual’s potential to accomplish a goal has key implications in organizational studies, behavioral analysis, business and management among other areas. This relative potential, which is dependent on a myriad of factors, e.g., experience, resource management, cooperation, etc. could shape the individual’s performance, motivation, leadership, and likely success. The increasing prevalence of virtual organizations provides unique challenges and opportunities to study complex research questions via convenient data collection. Measuring an individual’s potential to accomplish a goal has key implications in organizational studies, behavioral analysis, business and management among other areas. This relative potential, which is dependent on a myriad of factors, e.g., experience, resource management, cooperation, etc. could shape the individual’s performance, motivation, leadership, and likely success. The increasing prevalence of virtual organizations provides unique challenges and opportunities to study complex research questions via convenient data collection.
Interaction patterns within such virtual organizations as well as online games may be analyzed via Social Network Analysis (SNA). This approach has emerged as a set of methods geared towards an analysis of social structures and investigation of their relational aspects [14][13]. SNA studies social relations among a set of actors assuming a varying degree of importance of relationships among interacting units. Growing interest and increased use of SNA has formed a consensus about the central principles underlying the network perspective. In addition to the use of relational concepts, we note the following as being important: (a) actors and their actions are viewed as interdependent rather than independent autonomous units; (b) relational ties (linkages) between actors are channels for transfer or flow of resources (either material or non material); (c) network models focusing on individuals and view network structural environments as providing opportunities or constraints on individual actions, and (d) network models conceptualize structure (social, economic, cultural, political) as lasting patterns among actors. The granularity at which SNA methods analyze the network is not the individuals; rather it is the collection of individuals (dyads, triads, etc.) and the linkages independent among them.

The goal of this investigation is to model players' potential to survive as a multi-factor function derived from the data attributes, including Social Network Analysis (SNA)-based centrality measures from the game’s message network. This research uses regression analysis to create models for the prediction. We intend the model to predict a player’s/team’s potential to win the game or to achieve a specified goal. The research intends to show that an individual's potential can formally be established as a measure to estimate an individual's centrality in the network and assess a team's probability to successfully achieve goals. The research uses 2.3 million in-game messages to create a social network for the players. The target is to identify the influence of network behavior for the player, and how network statistics for each player influence the accuracy of the prediction.

II. LITERATURE REVIEW

Researching the dynamics of virtual teams creates considerable difficulties. Whereas field studies of virtual teams are typically small in scale and often lack quantitative or objective data (e.g., [5][10]), laboratory studies, though allowing for large scale, rigorous quantitative data collecting, involve relatively short-lived simulations with rather small groups in which the participants have little psychological investment (e.g., [6]). In this study, we employed an alternative setting of an online game in which people interact in a realistic manner over an extended period of time in a virtual world. As described in an article in Science [2], scholars in the social sciences are beginning to discover the potential of such virtual worlds as research context. Although laboratory simulations allow for similar sorts of data collection, this context has advantages over such an approach because online games tend to be highly engaging and psychologically meaningful to participants. Often the relationship between players is compared to the relationship between co-workers in their real job and the activities in such games are increasingly similar to the work performed in business corporations [16][17][10]. Recent studies indicate that Massive Multi-player Online Games (MMOGs) could function as online labs for leadership studies providing a glimpse of what team leadership might look like in the future [12].

III. RESEARCH DESIGN AND DATA SET

In this section, we describe the research design, a MMORPG-based virtual organization environment – Travian, and the data collected from the MMORPG. The data for this study was derived from a popular browser-based massive multi-player online role-playing game (MMORPG), called Travian, a gaming company based in Munich (see Fig. 1), in a controlled environment for over three and a half month period. The game itself is a real-time strategy game (RTS). Playing with up to 20,000 users on one server with scarce resources, actors soon find themselves in a social dilemma [4], which is typical for organizations, project teams and economies where parties need to both coordinate and compete with one another. In the race to dominate, actors form teams or “alliances” of up
to 60 members under a leader or a leadership team. Teams are equipped with a shared forum, a chat room and an in-game messaging system. Like in virtual teams at work, teamwork and negotiation skills play a crucial role in this context. Given these characteristics of Travian, the virtual teams in Travian afford an excellent opportunity to study various facets of virtual organizations. In this National Science Foundation (NSF)-funded research, we introduce a multi-factor dynamic model to estimate the potential of an individual to accomplish a goal in a virtual organization.

A. Data Set

Major considerations in our approach were the large volume of 479 attributes in 30 tables for 7,406 players, for 105 days and the peculiarities, especially the lingo contained in the in-game message. We selected 85 attributes describing players’ daily performance from the 30 tables containing game data and loaded them into a data mart that provides an overall snapshot of players at each time instance. The attribute selection was guided by literature review, our understanding of the game attributes, and advice from players familiar with the game. A multi-factor analysis was performed later (Section: Research Methodology) to further reduce the feature space. Given the longitudinal nature of our hypothesis, the data was prepared for time series analysis.

The message data holds particular importance, as it helps in constructing the underlying social network between the players to study the hypothesis. The immediate challenge was the size of the data. The message data contained over 2.3 million messages, which include broadcast messages, i.e., messages sent to all players by the game moderators (“Multi Hunter Messages”) containing texts with up to 32,767 characters. The broadcast messages were not considered in our analysis as the volume could introduce bias in the results. The analysis of this data is aimed at characterizing the communication pattern/behavior of players and player groups and to identify the relationships between this social behavior and player performance in terms of winning the game. In order to efficiently analyze this large dataset, we created a social network describing the communication structure. The nodes of the graph represent players while the directed edges originate from the sender and terminate at the recipient. We recorded the frequency of messages exchanged between any two nodes using the edge weights; the outdegree weight quantifying the number of messages sent by the node and the indegree weight quantifying the number of received messages.

In order to analyze the changes in the communication patterns over the entire period of the game, we constructed social networks for each time instance and compared them via network statistics. The following nine network statistics were considered – indegree, weighted indegree, outdegree, weighted outdegree, degree, weighted degree, closeness centrality, clustering coefficient, and eccentricity. We included clustering coefficient, closeness centrality and eccentricity so as to analyze the effect of “close relationships between players” on the players’ potential for winning in the Travian game in particular and success in a more general (non-game specific) sense. We binned the data into 7-day intervals, which based on our manual observation was sufficient for a robust analysis without overlooking any micro events.

IV. RESEARCH METHODOLOGY

A. Player States

The dataset collected on each of the 105 days of the game reflect players’ states at the time of collection. To meet our goal of analyzing a player’s potential of success we modeled these states as Winner, Finalist, Survivor, and Non-Survivor. Players can only exist in one state at any time instance and the transition from one state to the other is based on daily performance. The definition of each state in our analysis can be described as follow:

- Winner (W): Player (among a group) who completes building the Wonder of the World (WoW) or supports it with resources or troops during the last two weeks.
- Finalist (F): Player (among a group) who has started building WoW or supports it with resources or troops during the last two weeks.
- Survivor (S): Player who is still in the game but is neither a finalist nor a winner.
- Non-Survivor (NS): Player who is no longer in the game.

Each of the player states described above serve as the target variables in the stepwise multivariate linear regression model described next.

B. Data Analysis

For the analysis, the data was divided into three sets – training, validation, and test datasets, with each set having the same proportion of target variables (i.e. Winner, Finalist, Survivor and Non-Survivor). Fifty percent of the dataset was used for training the model, while the remaining was divided in equal proportions and used for validation and testing. The validation data was used to select the best among the models generated by the training data and the test data set was used to measure the performance or accuracy of the chosen model.

Stepwise multivariate linear regression was used to predict the final state of a player from different time instances during the game. It was also used to measure – (i) the correlation of the 85 direct game attributes to the given states, (ii) the correlation of the 9 network statistics to the given states, and (iii) the correlation between the 85 direct game attributes and the 9 network statistics. The main aim of the analysis is to determine if the network statistics improve the accuracy of the prediction. Furthermore, we aim to identify the most significant network statistics for the aforementioned prediction.
To aid our analysis, each nominal variable was transformed into multiple variables each representing a value in the nominal field containing a Boolean expression. The nominal target variable was also binarized accordingly. In order to show any non-linear characteristics of the regression model, the numeric variables were binned. The model was trained using players’ states on the last day of the game (i.e. the final state was used as a target for each day analysis).

F-statistics and stepwise algorithm were used for variable selection. At each step, the variable with the highest correlation coefficient is added and any variable in the model with less than five percent probability of affecting the model is removed. This procedure is repeated until there are no variables with F-statistics lower than five percent. The threshold is subject to user’s choice, which governs model’s stability – the lower the threshold, the higher the stability. The validation data is used to determine the step and hence the model with the highest prediction accuracy. The distribution of the target states in the test data is considered during the player classification. For example, if the test data contains 5%, 25%, 20% and 50% of winners, finalists, survivors and non-survivors respectively, the top 5% of players with the highest score are classified as winners, the following 25% as finalists, etc.

For comparison, the above analysis was performed for two different sets of input variables, signifying the model variations with network statistics and without network statistics, i.e., – (i) a combination of the 85 direct game variables and the 9 social network variables and (ii) the 85 direct game variables. These analyses will provide a basis for quantifying the model performance in presence/absence of network behavior and identifying the most significant variables for assessing a player’s potential for success.

V. RESULTS AND DISCUSSIONS

In order to effectively assess the role of network behavior on an individual’s performance abilities, we compare two different versions of the stepwise multivariate regression model. The first version or the baseline model (M1) is trained on the 85 direct game variables. The second version combines the 85 direct game variables with the 9 social network based variables (M2). Please recall that the social network based variables are computed using the in-game messages exchanged between the players. The baseline model consist of variables that reflect the amount of players’ resources, trade activities, population development/growth, etc., whereas the network model couples the aforementioned variables with the players’ network behavior, such as communication, centrality, ability to form cohesive clusters, etc.

First, we present the factor analysis used to select optimal number of features to train the model. As explained in data analysis above, F-statistics and stepwise algorithm were used for variable selection. These results are illustrated in Fig. 2 and Fig. 3. The overlaid curve depicts the prediction accuracy of the regression model on the validation data. It can be observed that approximately 40
variables are selected using this strategy for the baseline model. Please note that Fig. 2 is truncated beyond the selected variables due to space restrictions. A similar strategy is used to select network-based features as depicted in Fig. 3.

Next, we compare the two models, M1 (baseline) and M2 (direct game attributes + network-based attributes). The comparison is achieved by dividing the classification accuracy of the M2 model by the accuracy of the M1 model. For instance, if the accuracy of the M2 model is 0.66 and the accuracy of the M1 model is 0.6, then the performance gain is computed as 110%. The performance gain of the M2 model over the M1 model is computed for all the weeks starting from week #2 to week #17 for the four target variables (W, F, S, NS). The longitudinal analysis is illustrated in Fig. 4. A few observations that can be made include:

1. For ‘survivor’ and ‘finalist’ target states, M2 outperforms M1 during the initial phase of the game (week #2 through #4). This could possibly imply that as the ‘survivor’ and ‘finalist’ players are warming up to the game, they are much more focused on exploring teaming options, as compared to ‘winner’ and ‘non-survivor’ players.

2. During the middle of the game (week #6 through #11), ‘winner’ players exhibit exceptionally predictable network behavior. In other words, ‘winner’ players could be much more accurately predicted during the middle of the game, if network-based statistics are used (M2 model).

3. Towards the end of the game (week #12 through #17), network-based statistics do not help improve the model performance significantly. The significance values are reported in parentheses for each target variable in the legend in Fig. 4. This could also imply that during the final stages of the game, the performance of players considers all types of attributes almost equally and does not prefer any particular type of attribute.

4. M2 significantly outperforms M1 for ‘finalist’ players for the entire game duration. This could possibly mean that throughout the game, the players that tend to be finalists exhibit predictable social network behavior.

Due to the lack of space we could not present the analysis of a third model variation (M3), where only network-based statistics were considered. M3 and M1 resulted in comparable prediction accuracy, which implies that social network information derived from in-game message is equally (if not more) important as compared to other direct game variables such as, the amount of players’ resources, trade activities, population development/ growth, etc. Such social network indices based predictors can be much more conveniently generalized to various different settings and to real-world scenarios.

To gain further insights into the comparative analysis presented above and dig deeper into the role of network behavior on an individual’s performance, we conducted a drill-down study. Here, we analyze the correlation between the four player target states and various network-based statistics. Due to space restrictions, we present the correlation analysis between target states and the clustering coefficient. The results are illustrated in Fig. 5. It can be observed from Fig. 5 that targets ‘finalist’ and ‘winner’ are positively correlated with the clustering coefficient values, which implies that both these type of players have cohesive team structure. On the contrary, ‘survivor’ and ‘non-survivor’ players do not have cohesive team structures. In other words, players within teams consisting of ‘winner’ and ‘survivor’ players tend to communicate with everyone, indicating a strong team-effort.

![Figure 5. Correlation between players’ state targets and clustering coefficient.](image)

Several interesting observations could be made from Fig. 5, such as:

1. The increasing correlation between clustering coefficient and ‘finalist’, as the game progresses, could indicate the need for intensive communication and coordination efforts among the alliance members to defend and thwart attacks by competing alliances.

2. The decreasing correlation between clustering coefficient and survivor target, as the game progresses, could indicate that the players have either given up on their efforts to win or they are isolate nodes - fallouts from alliances.

3. The widening gap between the correlation trend of ‘finalist’ and ‘survivor’ players are of particular interest, as both the targets sustain in the game till the end, but the former exhibit greater performance abilities as compared to the latter. Such an analysis could have far-reaching implications in virtual organizations, where performance is evaluated beyond passive participation in a project, albeit unsuccessful.

The different degree and weighted degree based network statistics have all very similar correlation structure except indegree and weighted indegree have higher correlation for ‘winner’ and ‘finalist’ than the other degree variables. This
implies that for a successful player it is much more important to receive messages than sending them. This is also intuitive, as being volatile doesn't necessarily mean that the individual is influential.

VI. LIMITATIONS AND CHALLENGES

The volume and computation intensity of the network statistics required parallel processing in a high performance computing environment for timely completion. The average computation time for computing the 7 days social networks statistics on a regular dual core processor computer was 8 hours; hence a total of 6 days for the entire 18 weeks network statistics. However, running all computations in parallel on a grid computer, it was completed in less than 12 hours. Analysis of the message content such as semantics and keywords may provide additional predictive indicator for the network statistics. This, however, was not included in the present study due to the challenges in analyzing the context of the unusually short messages, and the peculiar in-game lingo.

VII. CONCLUSIONS AND FUTURE DIRECTIONS

In this research, we show that an individual's potential can formally be established as a measure by estimating an individual’s network behavior and assess a team’s probability to successfully achieve the predefined goals. Although, the network statistics generally improve the prediction model, the volatility of the winner state (Fig. 4) suggests more in-depth research before only the network statistics can be reliably used for modeling a player’s success potential. A possible reason for the observed volatility may be the relatively small proportion of winners in the dataset. The longitudinal analysis highlighted specific network behaviors for different target player states that warrant further exploration. The network statistics indicates that the amount of social capital (measured by incoming and outgoing messages) acquired by a player in the first 9 weeks (first half) of the game is crucial for success. Within this period, the average correlation of indegree, outdegree and closeness centrality correlation are 1.80, 0.14 and 0.11, respectively.

At the moment, we only record misclassifications for each state. In the future, a cost-sensitive classification would allow us to measure the quality more precisely because it is less desirable from a model to classify a “winner” as a “non-survivor” as opposed to classifying as a “finalist”. Alliance-based analysis providing insights to the characteristics of groups relative to individuals can have wide applications beyond virtual organizations. Given that we have information on alliances within the game, conducting a similar analysis for alliances is natural.

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REFERENCES