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Dynamics of Trust Reciprocation in Multi-Relational Networks*

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***Abstract*—Understanding the dynamics of reciprocation is of great interest in sociology and computational social science. The recent growth of Massively Multi-player Online Games (MMOGs) has provided unprecedented access to large-scale data which enables us to study such complex human behavior in a more systematic manner. In this paper, we consider three different networks in the EverQuest2 game: chat, trade, and trust. The chat network has the highest level of reciprocation (33%) because there are essentially no barriers to it. The trade network has a lower rate of reciprocation (27%) because it has the obvious barrier of requiring goods or money for exchange; morever, there is no clear benefit to returning a trade link except in terms of social connections. The trust network has the lowest reciprocation (14%) because this equates to sharing certain within-game assets such as weapons, and so there is a high barrier for such connections In general, we observe that reciprocation rate is inversely related to the barrier level in these networks. We also note that reciprocation has connections across the heterogeneous networks. Our experiments indicate that players make use of the medium-barrier reciprocations to strengthen a relationship. We hypothesize that lower-barrier interactions are an important component to predicting higher-barrier ones. We verify our hypothesis using predictive models for trust reciprocations with features from trade interactions. Incorporating the number of trades (both before and after the initial trust link) boosts our ability to predict if the trust will be reciprocated up to 11% with respect to the AUC. More generally, we see strong correlations across the different networks and emphasize that network dynamics, such as reciprocation, cannot be studied in isolation on just a single type of connection.**

Keywords-*MMOGs, trust, reciprocation, multi-relational network, prediction*

I. Introduction

The rapid growth in the amount and richness of online interactions, through Massive Multi-player Online Games (MMOGs) such as EverQuest[1], and World of Warcraft[2] are creating social interaction data at an unprecedented scale. These virtual worlds provide a rich environment for studying user interactions and have been used in several recent experimental studies [1], [2], [3], [4]. The ages of the players of these games vary from 13 to 60 and more than 50% of the players are employed full-time[3]. They spend an average of 22 hours per week and 60% of them reported playing 10 hours continuously[3]. In this paper, we use one such MMOG called Sony EverQuest II[1], for analyzing the reciprocation of trust relationship in heterogenous interaction networks, including chat, trade, and trust relationships.

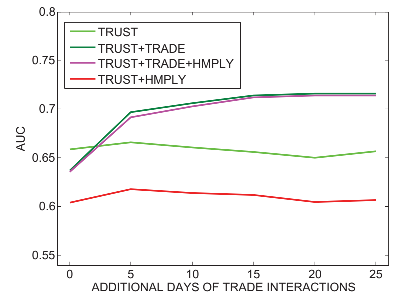


Fig. 1: Figure shows improvement in AUC by adding trade interaction for predicting trust reciprocation.

Dynamics of the reciprocation varies from network to network depending on the level of barrier for reciprocation. The barrier for reciprocating a trust relationship could be lack of resources or high risk involved. Needless to say, these barriers affect the levels of reciprocation significantly in different networks. For instance, in a chat network users have a very low barrier level for trusting each other as there is no commitment from either side to participate in any involved relationship or potential loss. On the other hand, in a trust network players grant access to each other's housing resources. The barrier level in the latter is very high. It is important to understand questions related to reciprocation across different types of interactions. For instance, do people reciprocate differently for trust building activities compared to trust cancellations?

The dynamics of complex network relationships cannot be studied in isolation because low barrier interactions may play a critical role as precursors to high barrier reciprocations. Understanding such dynamics offers several key insights. For instance, our experiments verify that players use low barrier interactions, like trade, before reciprocating trust. We verify our hypothesis by building a predictive model for trust reciprocation; using features from the trade network boosts the AUC by up to 11% as shown in Figure 1.

A. Related Work

The notion of reciprocation is well studied in sociology; and, as defined by Gouldner [5], it is the norm of reciprocation that people should help those who help them. Leider et al. [6] use reciprocation as a means to study human behavior in social altruism in terms of favors and gifting. They conclude, by several online field experiments, that there is a 52% increase in directed altruism towards friends compared to random strangers. This number further increases by another 24% when it leads to further prospects of receiving return favors or gifts. Hansen [7] reveals that social location and kinship improves reciprocation of interaction in social networks for child care. In another recent work [8], the Twitter reply network is analyzed to understand reciprocation in relation to user happiness.

In terms of graph models, Zlatic and Stefancic [9] develop a growing model for Wikipedia using three key parameters:

* full version: http://arxiv.org/abs/1303.6385
[1] https://www.everquest2.com/
[2] http://us.battle.net/wow/en/
[3] http://www.nickyee.com/daedalus/gateway_demographics.html

reciprocal edges, degree, and size of modeled network. Durak et al. [10] propose a null model for directed graphs that combines the reciprocal and the one-way edges to generate directed graphs that match the in-, out-, and reciprocal-degree distributions. Ahmad et al. [11] use theories of social exchange as a basis for building a generative model GTPA for modeling temporally evolving directed networks.

There are other recent works, such as Gralaschelli and Loffredo [12] that use statistical measures to conclude that the reciprocation of a network is never at random and it is either reciprocal or anti-reciprocal. Similarly, Zamora-Lopez et al. [13] propose a method to compute the expected reciprocation of the network as a function of in- and out-degree distributions. Reciprocation in weighted directed networks, especially in large scale mobile communication networks, is discussed in [14], [15]. Szell et al. [16] show that negative interactions have a lower reciprocation compared to the positive interactions. Reciprocation has also been used for link prediction [17], [18], [19].

II. MMOG Data Sets

In this section, we describe the networks used in our experiments.

A. Trust Network

In EQ II, players form teams in order to complete the game tasks. As the players are limited by the number of items they can carry at a time, players buy houses as a temporary storage to retain their armory and other accessories. Through the trust network, players share their house access with other players. For this reason, we also refer to this network as the trust network. We have 9 months of data from Jan-01-2006 to Sep-11-2006 with 63684 nodes and 140514 edges. Each node in the network is a player character in the game, and each edge is a permission level granted by the character to another character. Each edge has a time stamp when the access was granted. The trust levels are described as follows.

- *Trustee*: Player can store, touch, move, add, and remove things, and has almost same access as the owner.
- *Friend*: Player can store, touch, and move things.
- *Visitor*: Player can enter the house and view things.
- *None*: Player can see the house externally but cannot enter it.

B. Trade Network

In the EQ II trade network, players exchange goods for coins or goods. In this activity, a trade link is established between the seller (initiator) and the buyer (acceptor) in the trade network. We analyzed such a trade network containing 295,055 nodes and 11,913,994 edges over a period of 9 months from Jan-01-2006 and Sep-11-2006.

C. Chat Network

The chat network is a communication medium where players exchange instant messages. The number of nodes in this network is 349,654, and the number of edges is 86,948,748, spanning over a period of one month from Jul-29-2006 to Sep-10-2006.

D. Network Profiles

We present the degree distribution of these networks in Figure 2. The distributions were constructed using snapshots of different networks over the entire observation period. The distributions seem to follow the power law with exponent of the power law ranging from 1 to 3. The exponent was calculated using the slope of a least squares fit in the log-log plot.

TABLE I: Statistics of reciprocation in trade, chat and trust networks.

Network Type (period)	All Forward Edges	First Reciprocation	Total Reciprocation
Chat (1 month)	1840492	441039 (23.9%)	599548 (32.6%)
Trade (9 months)	520861	74137 (14.23%)	136809 (26.3%)
Trust (9 months)	62674	8452 (13.5%)	8083 (14.0%)

III. Reciprocation in Different Networks

The reciprocation of a network is the ratio of forward edges (say from player a to b) that have a corresponding backward edge (from player b to a), i.e., the ratio of mutual interactions.

A. Barriers of Reciprocation

Barriers of reciprocation can be broadly grouped into risk and utility. The risk factors include loosing an asset, in-game points, or in-game time; and the utility include, immediate gains in terms of points and assets and long term future prospects. Each network has specific characteristics that lead to low, medium or high barriers for reciprocation. Accordingly, the *trust network* has the *highest* level of barrier. In the case of trade network, the barrier of reciprocation fall in to *medium* barrier category. The *chat network* falls into the *low barrier* group.

B. Multiple reciprocations

There can be several overlapping forward and backward arcs between each pair of players. For the purpose of measuring the reciprocation and response time, we first partition the timeline into several partitions. We consider the start time of first forward edge and the corresponding end time of the first response as the first partition. Similarly, the second forward arc and its response marks the end of the second partition and so on. For the remainder of this paper, unless specified, we always refer to the overall reciprocation rate. In Table I we show multiple reciprocation rate for three different networks.

C. Reciprocation in Trust,Chat and Trade Networks

In this section, we study the reciprocation behavior in trust, chat and trade as independent homogenous networks. Then, in the next section, we analyze the interactions of chat and trade relationships in affecting the reciprocation of the trust network. The chat and trade networks have simple edge types with no attributes except time stamps. For the trust network, the Trust level corresponds to being a Trustee. We collapse the lower trust levels, (Friend, Visitor, and None), to a single Not-Trust level.

We summarize the total reciprocation for each network type in Table I. In the trust network, being a high barrier relationship, only 14.0% of the forward trust (8803 one-way) links receive a trust response (reciprocation) back and their response time distribution is shown in Figure 3a. As the chat network is a low barrier activity, it has the highest amount of reciprocation with 32.6% of forward edges reciprocated. The low barrier in this network is due to the instant nature of the communication and minimal risk involved in making a chat reciprocation. On contrary, in the medium barrier trade activities the reciprocation rate is 26.3%, lower than chat but more than the trust network. The reasons why a player may not

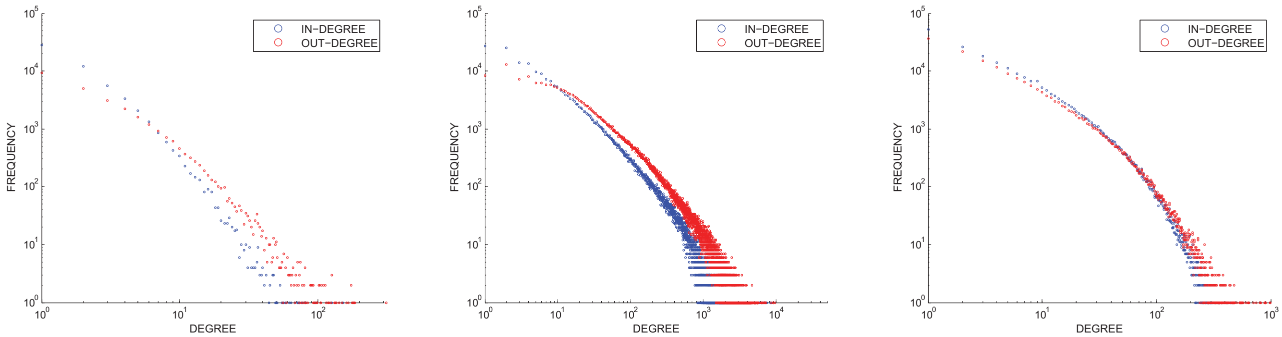
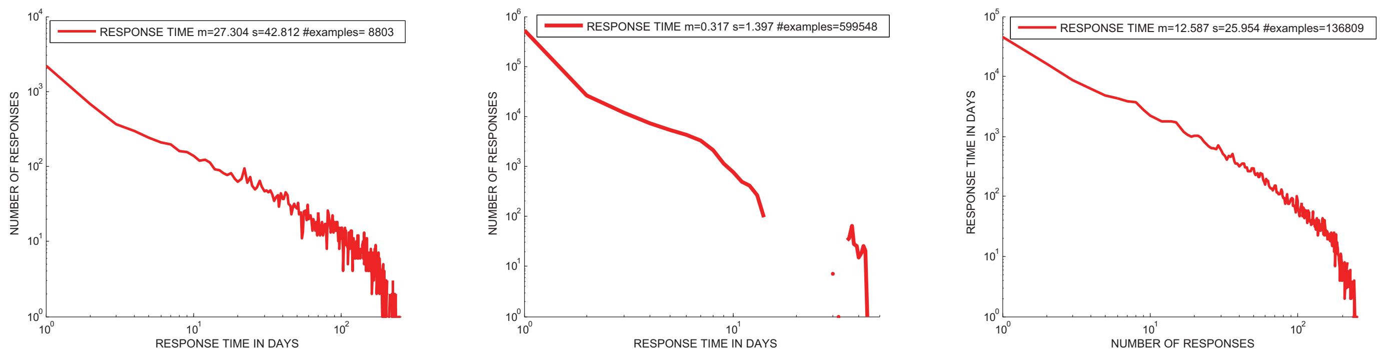


Fig. 2: Degree distributions of trust (left), trade (right-top) and chat networks (right-bottom).



(a) Trust (b) Chat (c) Trade

Fig. 3: The response time distribution for the three networks.

reciprocate in this network, could be lack of either resources or a need for doing so. Further, we wish to analyze the response time distributions of these networks to understand some key questions, such as, does all reciprocations occur within a certain number of days or are they spread uniformly over a longer period of time?

Figure 3a shows the response time distribution for the trust relationship. We find that the response time distribution follows a power law, with a mean response time of 27 days. For the Chat activity, the response time distribution is shown in figure 3b. The distribution roughly follows a power law. There is an outlier region around 45 days. We investigated this region and found that these are first time users who are not familiar with the system. We note that such users are extremely rare in the dataset (less than 0.01%). The figure also shows that most of the users in the low barrier, chat network reciprocate within the same day or at most the next day. This is evident since the mean first response time in the chat network is less than one day (0.317). In the chat network there is a sharp truncation [20] after 7 days, as the significance of a message beyond a week becomes completely irrelevant to the context of the game.

For the trade network, we show the response time distribution in Figure 3c; the distribution has a heavy tail and seems to follow a power law. The slope of this distribution is not as steep as that of the chat network, implying the trade reciprocation is not as quick as in chat. As the barrier for reciprocation in the trade network is more than chat, the average response time in trade is 43X slower at around 13 days.

IV. Reciprocation in Heterogeneous Networks

We will now overlay the trust, chat, and trade networks to analyze the interactions among heterogeneous edges. As

TABLE II: The reciprocation counts for first interaction (first forward request and first reply) in a heterogeneous MMOG network for a period of one month.

Forward Type	First Forward Edges	Chat Reciprocation	Trade Reciprocation	Trust Reciprocation
Chat	1645623	435758	1187	105
Trade	74428	7953	11402	335
Trust	10502	907	1016	722

the chat data is available only for a month, we restrict the other data sets also to this one month period. The focus of this section is to answer questions, such as: How many times does a trust granting from player a to b result in a trust reciprocation from b to a? Does a player b prefer to reciprocate with trade or some other low barrier interaction such as chat before granting a high barrier relationship such as trust to player a. The first interaction, as noted earlier in Figure 3b, captures all the characteristics of the additional interactions, hence we consider only the first interaction for this experiment. For each forward edge type, we count the number of first reciprocation between pairs of players in the consolidated network. In the case of tie reciprocations across multiple edge types, we include all the tied edges while counting. We have summarized the reciprocations for each forward interaction type in Table II.

As we see from Table II, the players who perform chat predominantly make a reciprocation using the chat link (26.48%). The same observation is made for the trade activity, which is also a low barrier activity (but higher than chat). Here also we find that trade responses are the predominant type of responses for a trade relationship. However,this is not the same in the case of a trust forward edge type since trust is a high barrier relationship and a more time consuming activity. So people are very careful before reciprocating for such relationships and reciprocations are first initialized through low barrier activities before reciprocating with a high barrier relationship, such as trust. The reciprocations for trust forward edge is predominantly through chat (8.63%) or trade (9.67%).

We now analyze the dependency between trust relationship against trade and chat interactions. The aim of this experiment is to quantify how chat and trade, low barrier relationships, influence reciprocation in a high barrier relationship.

For any two nodes a and b in the trust network, we start our analysis from the time when a forward TRUST edge from a to b is established. For such a forward edge there can either be a TRUST reply to complete the TRUST relationship or no TRUST reply (incomplete TRUST relationship). The TRUST relationship is determined as incomplete if there is no trust response from b to a within the average trust response time which is 4.6 days in this case. In other words, we truncate the response time for the incomplete reciprocations by the mean response time (4.6 days) and use only the period before this mean response time for further analysis. There can also be several other responses (low barrier interactions) from b to a before b replies with a TRUST link. Understanding these other relationships, such as chat and trade, before a TRUST reply is formed from b to a is crucial to decipher the nature of socialization required for a healthy mutual trust relationship.

As a result of this experiment, we find that complete and incomplete TRUST differ from each other in terms of chat and trade responses. We observe that the responses are exactly in an opposite order in the two rows. For the complete TRUST we observe that there were 743 forwards edges that were responded back with TRUST. However, before the TRUST is completed between a and b, we see that there are 408 trade responses from b to a. These trade responses account for nearly 63% of the total responses. We have only 243 chat responses from b to a, which is comparatively smaller than the trade responses. Surprisingly, the amount of low barrier responses for the incomplete TRUST gets completely reversed. There are 9145 forward TRUST edges which do not get a TRUST reply back and remain one sided. For these TRUST requests from a to b, we find that the chat responses from b to a are now 6962 (approximately 75% of the total responses) while the trade responses are significantly lower (as low as 25%).

This experiment confirms that a TRUST relationship between a and b is more likely to complete if there are more trade responses than chat responses from b. This interesting result can be used to infer the future TRUST relationships based on some low barrier relationships such as chat and trade.

V. Predicting trust reciprocation

In this section we evaluate how well can we predict a high barrier relationship, such as a trust, using information about the medium barrier activities between the nodes. The empirical analysis in the previous section showed that the success (completion) of high barrier trust relationship depends on some medium barrier relationship like trade. We use this as our motivation to quantify how well the medium barrier relationship can help to predict high barrier relationship completion. However, we use the entire 9 months of data in order to make any conclusions for the trust reciprocation prediction. The chat relationship has to be excluded from this experiment because of its limited availability for a single month. But we add several other features to make the experiment more interesting.

TABLE III: Table comparing reciprocation prediction accuracy using different feature sets.

Classifier	CWA	AUC	Average Precision	Average Recall	F-measure
only trust	0.515	0.659	0.800	0.863	0.806
trust+trade(K=0)	0.526	0.637	0.825	0.866	0.816
trust+homophily	0.519	0.604	0.788	0.849	0.808
trust+trade(K=0)+homophily	0.527	0.636	0.826	0.866	0.817
trust+trade(K=20)	0.588	0.714	0.871	0.885	0.851

For the trust network data for 9 months, there are a total of 61006 trust requests (forwards edges). The trust links that are reciprocated is 8252 whereas 52574 forwards edges remained incomplete. For the forward requests, we ignored the requests that started in the last (9th) month because it is hard to determine whether the requests were completed. Thus the number of trust requests are slightly less than those mentioned in earlier sections. So the completed trust link (reciprocated) forms one class and the incomplete trust links (unreciprocated) forms the second class. The following features will be used to build the prediction model.

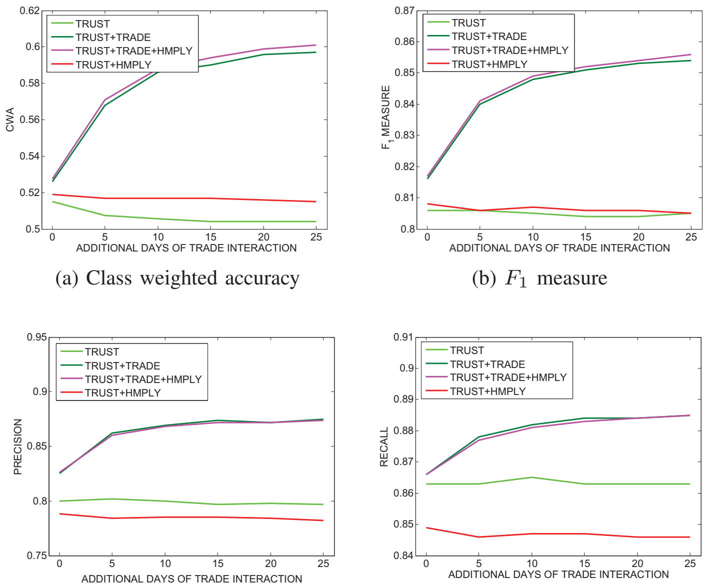
Features from high barrier relationship (trust): These features characterize the position of players (nodes) in the trust network. For the reciprocation links (A, B) we consider two structural features. The first structural feature describes the connectivity of A to other nodes in a trust network. The second structural feature is the connectivity of B with other nodes in the trust network. For convenience, we refer these features as "trust" features.

Features from medium barrier relationship (trade): This feature set consists of features from three sub-categories namely, structural, past-behavioral and future-behavioral. For a link (A, B) the structural feature corresponds to the degree of A and degree of B in the trade network. The past-behavioral features for a link (A, B) correspond to the count of the trade interaction of the type A to B and B to A before the trust request from A to B started. This feature takes into account the trade behavior between A and B before any trust interaction started between them. The future-behavioral features takes into account the behavior of trade interaction between A and B once the trust request is sent from A to B. Here we use a time window K (in days) starting from the time when trust request was initiated from A to B. We count the number of trade interactions in this time window K.

Features from player demography (homophily): In this feature set we take into account the two types of homophilies. The first type of homophily is gender homophily. The gender homophily between A and B is 1 if A and B has the same gender, and 0 otherwise. The second demographic feature is the experience homophily between A and B. It is computed as $X(A, B) = X(A) - X(B)$, where, $X(A)$ is the experience level of A.

As mentioned earlier, the aim of this experiment is to quantitatively compare the impact of using different features (described above). We used these feature sets to build binary classifier (random forest decision tree) to predict whether a trust reciprocation with happen or not.

Table III compares the trust reciprocation accuracy for various feature sets. The addition of trade features boosts the performance of the predictive model over the case when no



(a) Class weighted accuracy

(b) F_1 measure

(c) Precision

(d) Recall

Fig. 4: Comparing class weighted accuracy, F_1 measure, precision, and recall for trust reciprocation prediction.

trade features are used.

We extend this experiment to include the variation of future time window size (K) for all features and monitor its impact in term of accuracy of the prediction model. Figure 4 shows the results of this experiment. As mentioned earlier, we study the impact of varying the time windows size (from 0 to 25 days) for all the features. As shown in Figures 4 and 1, using trade as an additional feature in the prediction model outperforms the model which uses only trust or trust and homophily only. We also find that addition of homophily features do not have a significant impact in predicting reciprocation in trust network. This is an interesting finding for trust reciprocation prediction because it is a general notion that homophily is significant in predicting trust links [21]. A possible explanation of this observation is that the reciprocation phenomenon is significantly different from a normal trust formation phenomenon. As we know, in reciprocation there is already a one sided relationship established and a reciprocation might depend on entirely other dynamics such as trade interactions.

VI. Conclusion

We have studied various social factors affecting reciprocation in three different interaction networks from Sony EverQuest II MMOG. We, using response time analysis, show that people are slow in building mutual high trust relationships compared to low barrier ones. We extend our analysis from single-type networks to heterogeneous networks, where we confirm that high degree of medium barrier activities is crucial for reciprocation in high barrier relationships.

Acknowledgments

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