Seller's Credibility in Electronic Markets: A Complex Network based Approach

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ABSTRACT

In the last decade, there has been an explosion of online commercial activity enabled by the World Wide Web. An electronic marketplace (e-market) provides an online method to perform transactions between buyers and sellers, potentially supporting all of the steps in the entire order fulfillment process. Credibility is an important requirement for the success of an e-market. In this work we model and characterize an e-market as a complex network and use the network structure to investigate the sellers' credibility. We propose a new algorithm, based on the structure of the negotiation network, to recommend whether the seller is trustable or not. We use real data from a online marketplace from the biggest Brazilian Internet Service Provider as case study. Besides being a prelimary work, our technique achieves good results in terms of accuracy, predicting correctly the results in more than 80%. It can be used to provide a more effective reputation system for electronic negotiations, which can be very useful as a support decision mechanism for buyers.

Categories and Subject Descriptors

K.4.4 [**Computers and Society**]: Electronic Commerce; E.1 [**Data Structures**]: Graphs and networks

General Terms

Algorithms, Experimentation, Reliability

Keywords

e-markets, e-business, credibility, reputation, trust, complex networks, information credibility evaluation, Web 2.0

1. INTRODUCTION

In the past few years, there has been an explosion of online commercial activity enabled by the World Wide Web (WWW). These online services range from simple product advertising to more complex systems that facilitate electronic product ordering, either directly from one company, or through electronic markets. The relationship between organizations and consumers is increasingly being facilitated through electronic information technology (IT).

An electronic marketplace (e-markrt) is an inter-organizational information system that allows the participating buyers and sellers to exchange information about prices and product offerings [3]. E-markets provide an electronic method to facilitate transactions between buyers and sellers that potentially provides support for all of the steps in the entire order fulfillment process.

In this rich and complex scenario of e-markets, thousands of players trade billions of dollars. We can model this scenario as a complex network, where the players interact with each other buying and selling products, exchanging information and knowledge, establishing different kinds of relationships.

A complex network, whose social networks are an instance [14], is a structure made of nodes, generally individuals or organizations, and edges, which represent relationships between nodes. According to Newman [17, 18], a social network is a set of people or groups of people connected through patterns of social interaction, which can be represented as nodes and links, respectively, in a graph. The study of complex networks is a young and active area of scientific research inspired largely by the empirical study of real-world networks such as computer networks and social networks.

In this research we investigate how complex network metrics and models can help us in understanding some electronic market properties. The main objectives of this research are: modeling and characterizing an electronic market as a complex network; and using the network structure to evaluate seller's credibility and to model trust, proposing a new technique to provide recommendation for buyers. In the context of our research, credibility can be defined as believability [26]. Thus seller's credibility can be associated to how much beliveable is a seller.

Despite this is a preliminary stage of the research, our technique achieves good results in terms of accuracy, predicting correctly the negotiation recommendation in more than 80%. It is important to explain that our strategy is to use this recommendation, which is based on the negotiation network, as a complement to the typical reputation system adopted by the marketplace. Our approach can provide a more complete qualification system for electronic negotiations that can be adopted as a support decision tool for buyers.

The remainder of this paper is organized as follows. Section 2 describes the related work and Section 3 explains the *TodaOferta* marketplace, which we use as case study. Section 4 describes the analysis and characterization of the negotiation network. Section 5 evaluates the reputation system of *TodaOferta*. Section 6 introduces the concept of trust and presents our new approach to qualify the seller's credibility, which can be adopted to recommend sellers to buyers. Finally, Section 7 presents our conclusion.

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2. RELATED WORK

Complex networks have been getting high attention recently. As showed by [19], this can be explained by the availability of a large amount of actual data and also by the existence of several interesting applications in biological, sociological, and information technology systems.

The theory of complex networks seems to offer an appropriate framework for such a large-scale analysis in a representative class of complex systems, with examples ranging from cell biology and epidemiology to the Internet [27, 24, 28, 5]. The research in this area has been motivated by the discovery of universal structural properties in real-world networks and the theoretical understanding of evolutionary laws governing the emergence of these properties [29, 4].

Electronic commerce applications present several properties that can be modeled through complex networks. Previous work has studied how to improve online marketplaces using the knowledge provided by social relationships. In [25], the authors study some aspects of an auction site integrated to a social network. The main goal of this work is to evaluate the impact of social connections on business transactions. The results show a high correlation between the social relationships and the user satisfaction, which is a motivation to the use of social networks to improve marketplaces. [12] identifies how data about social influence can be used by e-commerce web sites to aid the user decision making process. A general view of the impact of the Web 2.0, characterized by, among others, the existence of communities and social relationships, over the electronic markets is given by [30]. Carnes et al. [6] considered how a company can introduce a new product into a market using viral marketing (based on social networks). They found out that it is possible to capture the majority of the market by a relatively small set of right consumers.

Electronic markets are getting more popular each day. One of the most common e-markets application is online auctions, which have extensively been studied lately. Several studies have focused on reputation systems and trust in online auctions. Some of them have analyzed the importance of reputation in auction outputs, mainly in final prices. In [2], the authors investigate the effectiveness of reputation systems and how reputation correlates to auction results. They conclude that reputation plays an important role in trust and leads to higher ending prices. In [13], is analyzed the effect of trust and reputation over the profits obtained by intermediaries in electronic commercial connections. Different trust and distrust propagation schemes in e-commerce negotiations are studied and evaluated in [10]. Resnick et al. [21] show that sellers with high reputation are more capable of selling their products, but the gains in final prices are reduced. Using a controlled experiment, Resnick et al. [22] study more accurately the impact of reputation on the auction outputs. The results show that, in general, bidders pay higher prices to sellers with higher reputation.

There are many algorithms that use only the social network and trust values to compute how much one user should trust another. These have been shown to give relatively accurate results, but are only effective when users are connected in the social network. Collaborative filtering (CF) algorithms, on the other hand, use only profile information when computing recommendations for users [9]. CF algorithms generally compute the overall similarity or correlation between users, and use that as a weight when making recommendations. These algorithms are relatively good at making recommendations for users, and could be applied to compute trust recommendations, but they are only effective when users have a common set of rated items. When the ratings are sparse, it is difficult to compute similarity measures between users.

How profile similarity relates to trust is a relatively unexplored space. Goldbeck et. al [9] explore the relationship between trust and profile similarity. They show through surveys and analysis of data in existing systems that when users express trust, they are capturing many facets of similarity with other users. In a system that has a trust component, users will have made some direct statements about people they trust. These statements form a social network.

There is a large body of work on algorithms for inferring trust in social networks. While designed for peer-to-peer systems rather than social networks, one of the most widely cited trust algorithms is EigenTrust [11] . It considers trust as a function of corrupt versus valid files that a peer provides. A peer maintains information about the trustworthiness of peers with which it has interacted based on the proportion of good files it has received from that peer. For one peer to determine the trustworthiness of another with which it has not interacted, it needs to gather information from the network and infer the trustworthiness. The EigenTrust algorithm calculates trust with a variation on the PageRank algorithm [20, 1], used by Google for rating the relevance of web pages to a search.

Machine learning algorithms, more specifically classification techniques [23], can also be used for recommendation, however it is not the focus of our research. Metrics such as recall, precision and F-score [7] can be applied to evaluate our work in comparison with classification algorithms (e.g., Naive Bayes). We plan to perform this comparison later, since this research is at a preliminary stage.

The main objective of our research is to model and characterize an electronic market as a negotiation network (complex network), using this network structure to assess seller's credibility and to provide trust. This paper is an initial part of the research, where we first perform a characterization of a real marketplace as a complex network. Moreover, we design and evaluate a network-based technique to predict the qualification received by the seller who offers the product. Our proposal is to improve this technique later and adopt the seller recommendation obtained from the analysis of the network as a complement to the information that the buyer can use from the typical reputation system adopted by the marketplace.

3. THE TODAOFERTA MARKETPLACE

This section describes *TodaOferta*[1], which is a new marketplace from the biggest Latin America Internet Service Provider, named Universo OnLine Inc. (UOL) [2]. UOL gathers the largest content in Portuguese language around the world and has about 1.7 million subscribers.

TodaOferta is a website for buying and selling products and services through the web. Table 1 presents a short summary of the *TodaOferta* dataset. It has a significant number of users, offers, and negotiations, which correspond to a dataset sample obtained from *TodaOferta* (UOL). As *TodaOferta* has a high number of registered users that have never bought or sold any item, we consider active users those that have negotiated (bought or sold) at least one item at *TodaOferta*. Due to a confidentiality agreement, most of the quantitative information about this dataset can not be presented.

As we mentioned before, an important aspect related to the application of social network concepts and techniques in the electronic commerce scenario is to enhance reputation systems through the social relationships. The Todaoferta marketplace employs a quite simple reputation mechanism. After each negotiation, buyers and

[1] www.todaoferta.com.br

[2] www.uol.com.br

Coverage (time)	06/04/2007 - 07/31/2008
#categories	32
AVG offers / user	10.1
#negotiations	123,601
Negotiation options	Fixed Price and Auction

Table 1: TodaOferta Dataset Sample - Summary

sellers qualify each other with a rate of value 1 (positive), 0 (neutral), or -1 (negative). User's reputation is defined as the sum of all qualifications received by him/her. To avoid cheating by the creation of fake users to provide several positive feedbacks to a given user, known as sybil attack [15], *TodaOferta* considers only unique feedbacks in the calculation of users' reputation score. Reputation systems are useful to provide trust in electronic commerce application. However, *TodaOferta* offers other information about sellers and buyers that can be as well used to identify trustful and distrustful users (e.g., time since the user is registered, comments left by users who negotiated with him/her).

Another important characteristic of *TodaOferta* is that a user profile holds both information about buying and selling. Other marketplaces distinguish buyer and seller profiles, which reduces the amount of information associated to users.

4. CHARACTERIZING THE NEGOTIATION NETWORK

This section presents the characterization of the negotiation network of the electronic marketplace. From *TodaOferta* dataset we select 123,601 fixed-price negotiations to be evaluated in this research, building our negotiation network.

We can represent a complex network as a graph. In this way, the electronic marketplace can be represented by a graph, where the relationship function between the players denotes its structure. A directed graph or digraph G is an ordered pair $G = (V, A)$ where V is a set of vertices or nodes, and A is a set of ordered pairs of vertices, called directed edges, arcs, or arrows. An edge $e = (x, y)$ is considered to be directed from x to y; y is called the head and x is called the tail of the edge.

Using this representation, in the negotiation network each user (that can act as a buyer or a seller) is a vertex and each negotiation between a buyer and a seller is an edge. We have 93,651 users (who can act as a buyer or a seller) and 99,045 unique negotiations (edges).

Figure 1 presents a snapshot of the network of the top 100 buyers and top 100 sellers and their negotiations. To make easier the visualization we put users who negotiate more (top 10 buyers and sellers) in the middle of the graph. As can be observed, there are top 10 buyers that negotiate with top 10 seller (e.g., 2543 with 2698 and 2), however in general the most frequent behavior is the negotiation with other users that are not in the top 10 group (and we also confirm this analyzing this top negotiators and the complete network).

We perform a general characterization of the network to measure some important factors about it. The degree of a vertex in an undirected graph is the number of edges of it. The negotiation network of *TodaOferta* has a minimum degree of 1 and a maximum degree of 4,542. The arithmetic mean is 2.116513 with a high standard deviation of 21.071475. The degree centralization is the variation in the degrees of vertices divided by the maximum degree variation that is possible in a network of the same size. The degree centralization of this network is 4,540.2 (or 0.04848 normalized).

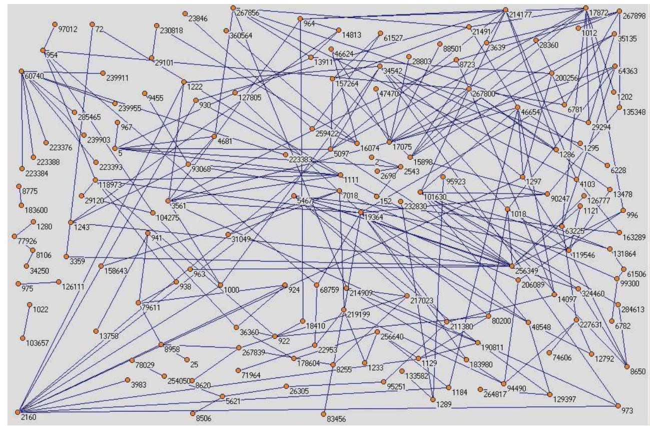

Figure 1: Negotiation Network - Top 100 negotiators

Figure 2 shows the degree distribution of the negotiation network. This distribution follows a power-law ($f(x) = a * x^b$) with $a = 17.53$ and $b = -1.041$ and a R-square of 0.9978.

This degree analysis indicates that there are few users who negotiate many times, while the most part of users negotiate only once. This is confirmed by the analysis of degree distribution, which indicates it is a heavy-tail.

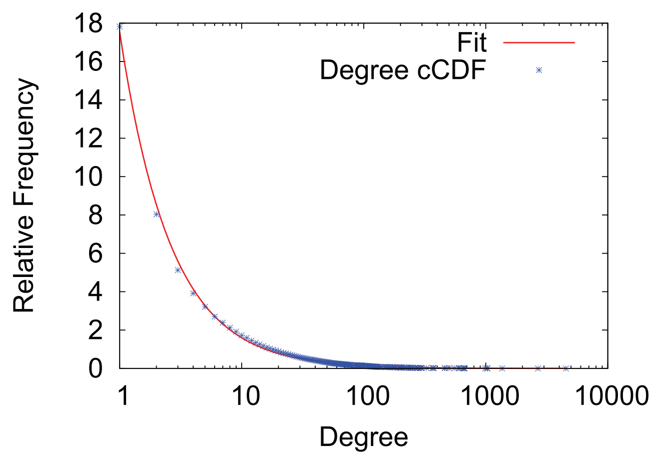

Figure 2: Negotiation Network - Degree Distribution

A component of an undirected graph is a set of nodes such that for any pair of nodes u and v in the set there is a path from u to v.

The negotiation network of our case study has 4,814 components, which shows that there are many isolated negotiations among pairs of users. The biggest component, called giant strong component, has 78,481 users (equivalent to 83.8% of the active users. There are 2,978 isolated negotiations between two buyer/seller from the network.

One important property of a complex network is the cluster coefficient, which measures how tightly the linked nodes are clustered together. The cluster coefficient (CC) is a measure of the extent to which the neighbors of a node are linked to each other:

$$CC = \frac{1}{n} \sum_{i=1}^{n} \frac{C_i}{N_i(N_i - 1)/2} \quad (1)$$

where n is the number of nodes in the network, C_i is the number of connections between neighbors of node i and N_i is the number of neighbors of node i.

The normalized cluster coefficient for the negotiation network is zero, indicating that the users who negotiates with a node do not negotiate with each other. This can be explained by the fact that a user must act as a buyer and a seller and share an adjacent negotiator with at least one of her/his adjacent negotiators to produce a non-zero clustering coefficient.

Another traditional metric of a network is the path length, which denotes the number of links necessary to connect any pair of vertices in the graph. The average distance among reachable pairs of vertices of the negotiation network is 6.77855 and the diameter (the path length of the most distant vertices) is 25. Figure 3 shows the shortest path length distribution of the negotiation network. The most frequent path length sizes are 6 and 8. The average path length is close to the famous "six degree of separation" [16], also referred to as the "Human Web". It refers to the idea that, if a person is one step away from each person they know and two steps away from each person who is known by one of the people they know, then everyone is no more than six "steps" away from each person in the world.

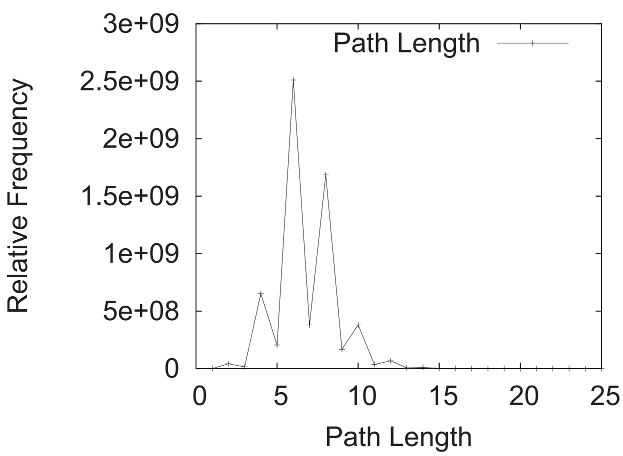

Figure 3: Negotiation Network - Path Length Distribution

The network density is the number of connections in a simple network expressed as a proportion of the maximum number of connections. A complete network is a network of maximum density. The negotiation network has a very low density, only 0.000023, showing there are few negotiations between different pairs of users, considering the universe of possible interactions between sellers and buyers.

We can summarize from this characterization that the negotiation network has a very low average degree with a high standard deviation, providing a quite perfect power-law distribution of degrees. There are many different negotiation networks (4,814 components) and the main one, represented by the giant component, is composed by 83.8% of negotiators from *TodaOferta* marketplace. The average path length of this network is 27% of the geodesic distance. The network density is very low, showing a very sparse structure. Moreover, there is not any relation between the user's adjacent vertices.

From this general characterization we can understand some preliminary aspects about this negotiation network structure. These aspects are the basis to identify how we can create a new reputation model for an electronic marketplace, enhancing the existing reputation systems with new attributes based on the complex network background.

5. CREDIBILITY IN TODAOFERTA

In order to characterize trust in *TodaOferta*, we perform some important analysis about user's reputation and the effect of reputation score in terms of new feedbacks, price premium and success premium. This section describes this analysis, which is the basis to understand the main characteristics of the *TodaOferta*'s reputation system and to propose a recommendation mechanism.

Figure 4 presents the distribution of reputation in log-log scale. As can be seen, there are few users with high reputation scores and many ones with small scores. This distribution function has characteristics of a power-law distribution.

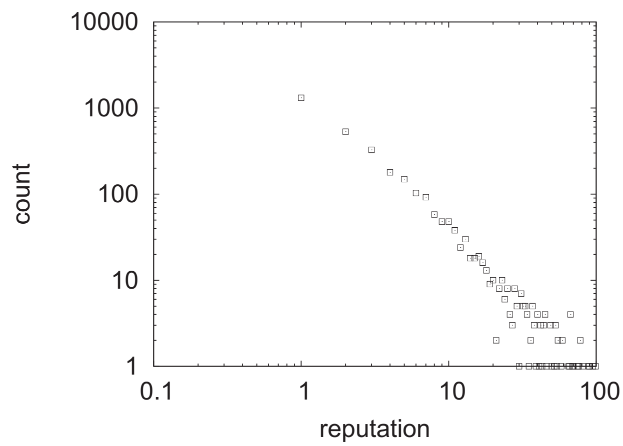

Figure 4: Distribution of Reputation (log x log)

Figure 5 presents the distribution of the number of offers in log-log scale. This figure shows that there are few users with high amount of offers and several ones with small offers. Moreover, this distribution function also has characteristics of a power-law distribution.

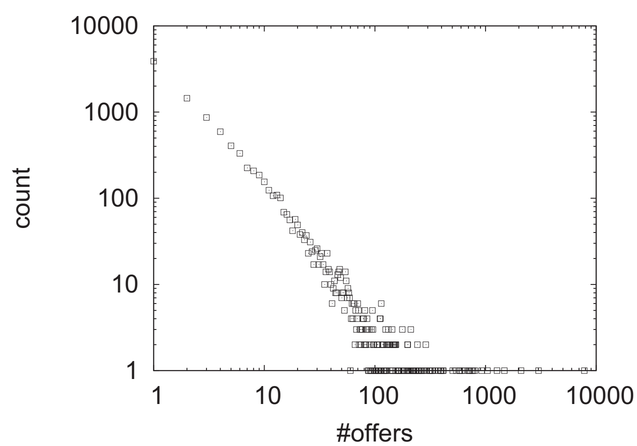

Figure 5: Distribution of the number of offers (log x log)

Figure 6 shows the probability of receiving a positive feedback for different reputation scores. Analyzing the figure, we can see that users with higher reputation scores tend to receive more positive feedbacks in their negotiations. This suggests that the reputation mechanism is coherent with its objective. We can see some intervals of values where variations occur, which can be explained by the absence of many points for analysis.

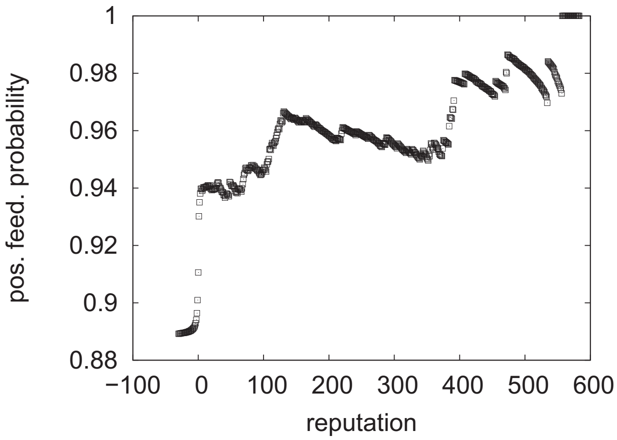

Figure 6: Probability of Positive Feedback x User's Reputation

We can see four typical steps in the graph. The first one from negative reputation scores to zero. The second step, from 0 to 100 (90 to 95% of probability to receive a positive feedback). The third one from score 100 to 400, which corresponds to an average probability of 96% of receiving positive feedback (94 to 96% of probability to receive a positive feedback). And the last step for scores higher than 400, which corresponds to an average probability of 98% of receiving positive feedback.

Figure 7 shows the average price premium (variation in terms of price in comparison to its average value) for different reputation scores. This measure represents the idea of how the reputation score impacts the difference in terms of price relatively to the average price value. It is calculated considering the sellers who have a reputation score lower or equal than each score value (x axis). This analysis shows that users with negative scores or small ones (less than 5) sell items cheaper than the average value from 2 to 7%. Users who present scores from 50 to 150 achieve an average sale's price higher than the average. However, surprisingly, high reputation sellers (higher than 150) do not achieve significant price premiuns, what we believe can be explained by the fact that these sellers try to gain more in sales volume.

Figure 8 shows the average success premium (variation in terms of success rate in comparison to its average value) for different reputation scores. As can be seen, users who have higher reputation scores also present higher chance to achieve success in their negotiation (or analogously, a small probability of failure). This average variation of success is small, only 2.5%.

This previous analysis of reputation in *TodaOferta* allows us to confirm that the reputation mechanism makes sense, despite it is simple and demand more complementary techniques to provide credibility and trust with more confidence to users.

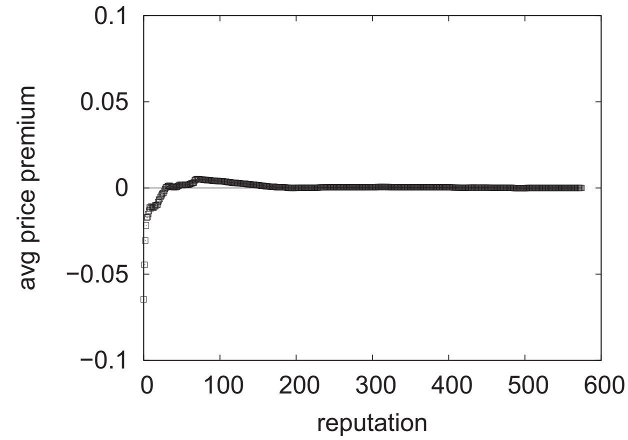

Figure 7: Price Premium x Reputation

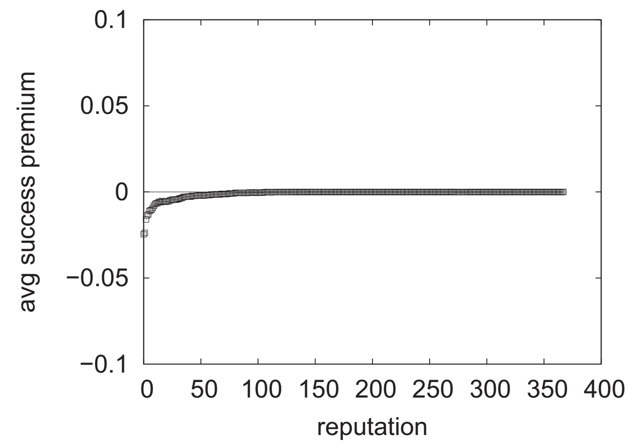

Figure 8: Success Premium x Reputation

6. TRUST IN NEGOTIATION NETWORKS

This section presents our research about trust in negotiation networks. This concept is very important in e-business, since it is a requirement in order to provide credibility, therefore we decided to study it and propose new strategies to deal with trust in e-business, using the structure of complex networks. More specifically, we investigate it in the real negotiation network of our case study, as described in Section 4.

We divide this section in three parts: first, we present some important concepts about trust. Then we describe our new approach to recommend sellers based on the seller's credibility and the negotiation network structure. Finally, the results of applying our algorithm are showed in Subsection 6.3.

6.1 Trust

Social notions of trust have become a topic of interest in computer science. Trust can be defined as some criteria that can be used to support the decision about with whom we should share and accept information, from whom we should trade in e-markets, and what consideration to give to information from people when aggregating or filtering data.

To effectively use trust in e-markets, it is important to understand what users mean when they say that they trust someone and how much they trust them. The sociological literature has extensively studied reasons for trust. However, when using web-based social networks, most of the information that Sociology considers important is not available (e.g. we do not know the history between people, the user's own background and how likely they are to trust in general, the business/friend relationship between users, etc.). Thus, we must address trust only from the available information.

In the case of trust in web-based social networks, the information we have available is the social network and the profiles of users [8]. Those profiles include personal information and frequently include the users' opinions and ratings of items. This information can be used to explain the magnitude of trust between people or to compute recommendations about how much one user should trust another.

In this work we propose a new algorithm for predicting trust based on the concept of affinity, that is, an inherent similarity between users in our negotiation network. Section 6.2 explains this algorithm and the results are presented in Section 6.3.

6.2 Algorithm

In the last sections, we modeled the social interactions between sellers and buyers as a social network, which we called negotiation network. We also characterized the negotiation network and important characteristics of a reputation system using data from a real Brazilian e-commerce application, the *TodaOferta* marketplace. In this section, we study how to exploit the negotiation network for recommendation of trustful sellers.

Most of the reputation systems applied by real e-commerce sites (like *TodaOferta*) measure the sellers' reputation by an absolute score. However, the characteristics of the buyers may affect the way they score a seller after a negotiation. It is important to provide a more personalized recommendation for buyers, considering these buyers' differences, in order to improve the quality of the existing reputation systems.

We propose the use of the patterns associated to the history of buyer's negotiations to access a personalized recommendation system. These patterns can be identified through the buyers' social interactions in the negotiation network. More specifically, the patterns of interest are paths composed by agreeing qualifications between the seller and the buyer, which we call agreeing paths. In these paths, buyers who negotiate with the same seller give the same qualification to her/him. Figure 9 shows a simple graph to illustrate the concept of agreeing path. Each vertex is an user and there is an arc from ui to uj if the user ui bought a product from uj. We label the arcs with the score given by ui to uj, which can be positive (+), negative (-) or neutral (0). The arcs are used to identify the role played by the user (buyer or seller), but paths are found in the corresponding undirected graph. The path ((u0,u1), (u1,u2), (u2,u3)) is an agreeing path between u0 and u1. However, the path ((u0,u7), (u7,u5),(u5,u6)) does not constitute an agreeing path, since the buyers u0 and u5 did not give the same qualification to the seller u7. The agreeing path between u0 and u6 is ((u0,u1), (u1,u2), (u2,u4), (u4,u5), (u5,u6)).

Based on the concept of agreeing path, we may predict the qualification given by a buyer to a seller. An agreeing path contains agreements about the qualification given to sellers. If two buyers agree with each other about a seller, assuming that the seller's behavior is constant along the time, there is an evidence that these buyers are similar. We consider this similarity as a transitive property. A buyer b0 is similar to b1 if they agree about a seller s0, and b1 and b2 are similar if they agree about a seller s1. Therefore, if b0 is similar to b1 and b1 is similar to b2, b0 is similar to b2.

By the identification of agreeing paths between a seller s0 and a buyer b0, we determine buyers who are similar to b0 and have negotiated to s0. The feedback given by similar buyers may provide important knowledge about how the buyer s0 would qualify the seller after the negotiation. A positive qualification indicates that the negotiation provides buyer's satisfaction, a negative one represents the opposite, and neutral feedback is indifferent. If a similar buyer has given a positive feedback to s0, there is an evidence that b0 will also give a positive feedback to s0. However, it is possible the existence of several agreeing paths between a seller and a buyer or even the non-existence of agreeing path between them. The first case can be treated by taking the shortest path. The intuition behind the shortest agreeing path is that it has few sellers, and so on, it is less dependent of the transitive property, what we believe may lead to more accurate predictions. The second case is more challenging, it can occur if buyer and seller are in different components of the network, if one of them is negotiating for the first time, or if none of the paths between them are agreeing. We decided not to deal with this problem in this study. Nevertheless, in case of non-existence of an agreeing path between the seller and the buyer, the traditional absolute score based reputation system can be applied.

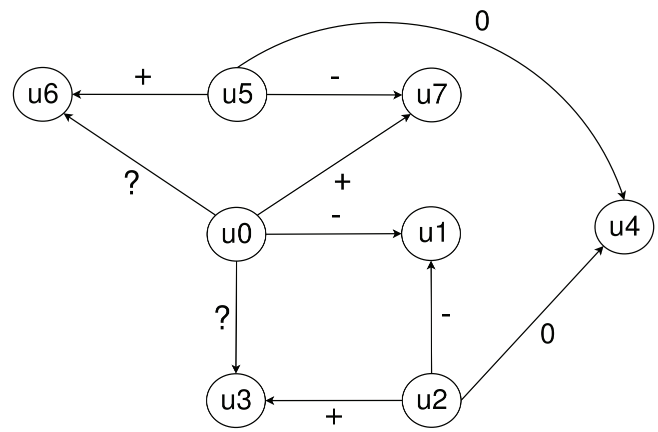

Figure 9: Negotiation network - Example

We can exemplify the application of the proposed recommendation system using the example of network of Figure 9. Suppose that the arcs labeled as '?' represent those negotiations to have the resultant buyer's feedback predicted and the other arcs are previous qualifications given by buyers. In this case, our strategy predicts the feedback from u0 to u3 as positive, as the nearest buyer similar to u0 (u2) has given a positive feedback to u3. In the same manner, the feedback from u0 to u6 is predicted as positive.

The proposed recommendation technique is implemented by Algorithm 1. This algorithm receives as inputs: the negotiation network (NW), a buyer (B), and a seller (S). The search for the shortest agreeing path between B and S is implemented by the function **FindShortestAgreeingPath**. The possible outputs are: (1) The qualification given to S by the nearest buyer similar to B ($SellerQualification$), (2) the non-existence of a path between B and S in the network ($NoPath$), and (3) the non-existence of any previous negotiation involving S or B ($NewNode$).

In the next section, we present the results obtained by our algorithm using the real dataset from the *TodaOferta* marketplace.

6.3 Results

This section evaluates our algorithm using the actual dataset from *TodaOferta*. In order to do it, we perform the following steps:

1. Construct the initial negotiation network: we use three months of data, consisting of 11,700 negotiations;

Algorithm 1 Algorithm for Recommending Sellers

```
function GetRecommendation(NW, B, S)
    if FindUserInNetwork(NW, B, S) then
        if FindShortesAgreeingPath(NW, B, S) then
            SellerQualification ← EdgeValue
            return(SellerQualification, Distance)
        else
            return(NoPath)
    else
        AddNodeToNetwork(NW, Node)
        return(NewNode)
```

2. Get each negotiation from the dataset;

3. Apply the algorithm to the each negotiation chosen in the last step;

4. Set the value returned by the algorithm: the qualification, when a *Match* occurs or *NoPath* (there is not a path between the buyer and the seller in the network) or *NewNode* (the buyer who is going to negotiate has not been in the network yet);

5. Compare the qualification predicted by the algorithm with the real qualification obtained by the seller;

6. Analyze the results.

These previous steps show the dynamic nature of our network, which changes its structure at each negotiation.

Table 2 shows the results of applying our algorithm in order to predict the qualification of sellers. The *Accuracy* is defined as the number of hits in the predicting of the seller qualification by the total number of tries, which represents the hit ratio.

Hit	Miss	Hit Ratio (Accuracy)
4,215	995	80.90%

Table 2: Results

The results show that our algorithm achieved a good accuracy, predicting correctly the seller recommendation in more than 80%.

In spite of this, the use of the proposed algorithm is limited to the information presented in the network structure, that is, the buyers and sellers relations. It is important to explain that our idea is to adopt the seller recommendation as a complement to the static information that the buyer can evaluate from the typical reputation system adopted by the marketplace. In the experiment we evaluate 22,622 negotiations, using the initial network that consists of 11,700 negotiations. There were 13.69% of new users (*NewNode* - users that do not exist in the network at the moment where the algorithm performs) and 63.27% of pairs buyer-seller for which there were not any path in the network connecting them (*NoPath*). These limitations tend to be minimized as the network grows.

Table 3 presents more details about the results, refining them according to each feedback (qualification) type: positive, negative and neutral.

The results show that the precision is higher for positive feedback (85.48%) than for negative (63.93%) and neutral (66.40%) feedbacks. These results are good, considering that this is our first approach to provide trust using complex network modeling. Moreover, the objective is to use this technique in conjunction with the traditional reputation system, therefore the accuracy of the recommendation tends to rise. We are also planning to consider the distance of the agreeing path to provide more confidence to the predicting approach.

Feedback	#Instances	Hit	Miss	Accuracy
Positive	4,002	3,421	581	85.48%
Negative	330	211	119	63.93%
Neutral	878	583	295	66.40%

Table 3: Results (refining)

7. CONCLUSION

Complex networks offer a powerful modeling for interactions, especially social relationships, which can be applied to a variety of domains. Based on the commercial relationships created in electronic marketplaces, our goal is to provide mechanisms to improve the trust in e-business.

Electronic markets constitute an important research scenario due to their popularity and revenues over the last years. The amount of users, products, and services involved in online negotiations nowadays are huge and growing. Therefore, understanding how electronic commerce applications work and how they can be improved are important and challenging research topics.

We study the problem of designing new reputation systems using social network modeling. We proposed a negotiation network, where each user is represented by a node and links are negotiations between users. These interactions can be studied in order to identify trustful sellers and buyers, enhancing the existing reputation systems.

In this research, we first perform some characterization of an electronic market, showing how complex network metrics and models can help us to understand some electronic market properties. Then we use the network structure, formed by the negotiation network, to propose a technique to model trust and provide recommendation for buyers. We investigate the idea of enhancing reputation systems through social network modeling. It is important to emphasize that it is a preliminary stage of our research in credibility in electronic markets, where we perform basic characterizations to understand the scenario and the typical reputation system.

The results show that our algorithm achieves a good accuracy, predicting correctly the negotiation recommendation (seller qualification) in more than 80%. It is a nice result considering that this is the first version of our algorithm and there are many improvements to develop for it. The proposed technique has limitations, since our algorithm is based only on the complex network structure, demanding information about each user and its relation to the other ones.

It is important to emphasize that our proposal is to adopt the seller recommendation as a complement to the static information that the buyer can use from the typical reputation system adopted by the marketplace. Therefore, we are going to use this proposed approach together with the traditional reputation mechanism in order to provide a more complete qualification system that can be adopted by buyers to support their decisions.

As ongoing work we are going to develop new versions of our algorithm in order to improve it and also test it with the complete dataset. We have already identified aspects that can be used to optimize its precision and also insert new features to it. We plan to evaluate the impact of the different *Agreeing Path* sizes in the accuracy of the prediction, to use more confident metrics to evaluate the algorithms (such as recall, precision and F-score - typical classification techniques measures), and to use static information from reputation to complement the proposed technique. Moreover, we also consider important to compare the results obtained by the research with other approaches that are used to prediction, such as classification techniques.

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