Proceedings of the 5th WSEAS International Conference on Applied Computer Science, Hangzhou, China, April 16-18, 2006 (pp925-930)

A Novel Probabilistic Trust Evaluation Algorithm

MUHAMMAD HANIF DURAD[1], YUANDA CAO[2]
[1, 2] Department of Computer Science and Engineering
Beijing Institute of Technology, Beijing
Beijing, P.R. China
[1]n

Abstract: Trust and reputation are being used by commercial reputation or rating systems for online trading communities over Internet. Evaluation of trust for an unknown agent in web environment is a challenging job. In this paper we propose a novel probabilistic trust evaluation algorithm (NPTEA) for computing recommendation trust by modifying parallelization algorithm [1] suggested for Bayesian social networks. In order to solve the problem a definition of trust scaling factor (TSF) has been proposed. We compare the performance of our algorithm with BBK [2] under same environment and show how it can reduce the impact of malicious agents.

Key-Words: Trust, Trust Scaling Factor, Direct Trust, Indirect Trust, Reputation

1 Introduction

Internet services are increasingly being used among strangers for electronic commerce. The trust between individuals is the key components for their success. Trust management is now ready to cope with these new security challenges. The e-transactions are conducted in P2P environment where there is no central authority to mediate these exchanges. Due to lack of sufficient knowledge in such open network collaborations, trust evaluation for an unknown agent is a very difficult job. In this paper we propose a systematic and novel method for trust evaluation.

The usual approach to evaluate trust is based on referral networks [3]. An agent-based referral network is a multi-agent system (MAS) whose member agents give referrals to one another (and are able to follow referrals received from other agents). Trust is regarded as subjective almost by all researchers; therefore how to measure trust becomes an important question. In this paper we assume the trust as a subjective quantity at its evaluation time so as to capture the notion of social control, a new term trust scaling factor (TSF) coined by us, has been suggested.

The rest of this paper is structured as follows; in section 2 related works is discussed and in section 3 we discuss trust characteristics, relationships and our trust evaluation rules. In section 4 modified algorithms for parallelizing referral network is discussed. In section 5 we discuss our experiments and results. Finally in section 6, we conclude the paper. Note that hereafter, the usage of terms agent, node and entity will be synonymous.

2 RELATED WORK

One of the foremost research works which gives a formal analysis of trust was given by Marsh [4]. He attempted to integrate aspects of trust borrowed from sociology and psychology. These foundations made the model complex and difficult to adapt to today's electronic communities. The resulting model only considers an entity's own experiences and doesn't involve any social mechanisms.

In the trust model given by Beth, Borcherding and Klein (BBK) [2], trust can be calculated by prior interactions. They divided trust into direct trust and recommendation trust, both of which can be calculated by the number of positive and negative experiences. They also gave a simple method to combine trust values.

Rahman and Hailes [5] proposed an approach for trust in virtual communities. The main problem is that every entity must keep rather complex data structures that represent a kind of global knowledge about the whole network. Usually maintaining and updating these data structures are laborious and time-consuming.

Yu and Singh [3] develop an approach for distributed reputation management where a reputation of an agent is computed based on testimonies of the witnesses using the Dempster-Shafer theory of evidence. They show how this model can be used to detect agents that are non-cooperative or agents that abuse their reputation by slowly decreasing their level of cooperativeness. Since the witnesses are found through referrals, their approach captures social trust.

Guha et al [6], proposed an algorithm of trust propagation based on weighted average method. They assumed trust values in propagation had specific weights. Those weights were determined using statistic disciplines. They also got large amount of data from Epinions.com to examine their trust propagation model. While in combination of recommendations trust, the weights are hard to determine. Generally they need to be given by experts or obtained using statistical methods. Therefore it highly depends on experts' experiences and requires rather accurate record of experiences. But in real application, such experiences are difficult to get and not accurate as expected. These problems limit the application of weighted average method in trust propagation.

In summary, current trust models have some drawbacks in their application.

1. While calculating trust for an unknown agent, most models are unable to capture the notion of 'social networks' and subjective nature of trust; we have embedded it through TSF.
2. Weighting averages as mentioned in [6] are difficult to implement while calculating for unknown entities trust as stated earlier and need much expertise.
3. Finding disjoint paths in trust graph sometimes becomes impossible as suggested in [7], however if we insist on disjoint paths, we have to ignore the opinion of a part of community, which results in inaccurate trust values.
4. As trust values are known in community, the malicious entities can easily manipulate the values; the confidentiality of our TSF parameter makes it difficult for them to predict trust guesses.
5. Some trust and reputation models are rather complex in construction and hard to implement.

We believe that our suggested scheme is simple to implement and more robust against malicious attacks as to be proved later.

3 Trust Characteristics, Relationships and our Evaluation Rules

3.1 Trust Characteristics

Fortunately there is consensus upon the general characteristics of trust; we just state these for the sake of completeness.

1. May be one-to-one, one-to-many, many-to-many, and many-to-one.
2. Trust relationships are not transitive. However they may be conditionally transitive.
3. While evaluating trust for any agent we can only combine trust values from the same context.
4. We assume trust as 'subjective expectation' rather than 'subjective probability' to emphasize the point that trust is a summary quantity that an entity has toward another, based on a number of former encounters between them like [8]
5. Usage of reputation and trust is synonymous in this paper

3.2 Trust relationships

Rahman and Hailes [5] have proposed that the trust concept can be divided into direct and recommender trust. There is some confusion in literature regarding definition of indirect trust. We believe indirect and recommender trust is same thing. Direct trust means that the trustee can directly cooperate with the trustor. With indirect trust, the trustee is not supposed to cooperate directly himself but should forward the cooperation request to a good expert.

The trust relationships can be represented by a directed graph. The nodes of the graph represent agents. There are two types of edges in this graph. The first type is a 'direct edge'; the direct edge A ⟶ B means 'to evaluate the trust value for B, A directly interacts with B and there are no intermediate agents'. The value of direct trust which is genuine trust value has been defined as target's agent intrinsic success probability [9]. The second type of edge is a 'recommendation edge'; the recommendation edge A- -► B represents 'A trusts B or it recommends other nodes to trust B or it further recommends'. Associated with each recommendation and direct edge is a value in the range [0, 1], known as trust value.

3.3 Trust Evaluation Rules

3.3.1 Trust Discounting

As the trust value is determined by direct interactions, trust discounting in propagation expresses as the decrease of trust value derived from [10]. Suppose the source agent 'i has trust value p in an intermediate agent k', and agent 'k recommends a trust value q to target agent j'. Then the 'i trusts the target j by a value pq'. This is shown in figure 1 below.

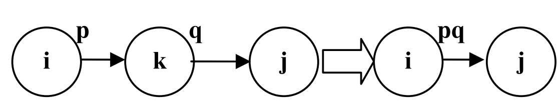

Fig.1 Trust Discounting Rule

The above rule can be extended to unlimited number of intermediaries as possible. It is very common in our practical life if Alice trusts Bob and Bob recommends to trust Carol. Then the Alice's trust in Carol might decrease.

3.3.2 Trust Enhancing

However, if we get two or more recommendations from different disjoint paths, then the trust enhancing in propagation, expresses the increase in the trust value derived from [10]. Suppose the source agent 'i' has got recommendation trust 'p' about an agent 'j' through one path and 'q' through another disjoint path. Then the 'i trusts the target j by a value 1-(1-p) (1-q)' as given in figure 2.

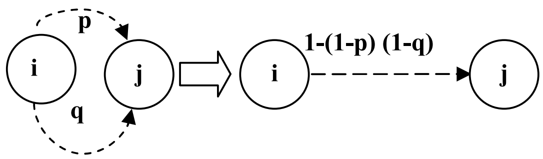

Fig.2 Trust Enhancing Rule

Again it is very logical if Alice tells Tom that Bob is trustworthy and Carol also tells him that Bob is trustworthy. Then the Tom's trust in Bob must be increased.

3.3.3 Trust Scaling

As stated earlier sometimes it is impossible to find disjoint path between to agents while evaluating trust as suggested in [7], consider the following diagram.

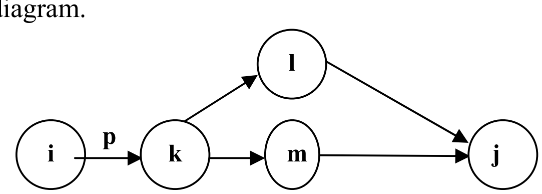

Fig.3 Trust Scaling Rule

Suppose if agent 'i' is evaluating trust for agent 'j', and if we follow [7], then we must choose either agent 'l' or agent 'm'. Now if we choose agent 'm' this is just like ignoring the opinion of agent 'l' about 'j' in community, which is logically incorrect. To solve this problem we introduce a trust scaling factor (TSF=α<1). While evaluating trust for 'j' according to [1], we convert the above network into parallel network as shown below in figure 4 by making two copies of agent k. In this case agent 'k' is making two recommendations, we believe, its opinion 'p' must be must be scaled down to get more realistic value of trust for agent 'j'. A simple thumb rule could be as to give 50 % weightage to k's opinion, so α=1/2 in this case. While calculating the trust, the two paths 'iklj' and 'ikmj' would be treated as disjoint as explained in figure 4.

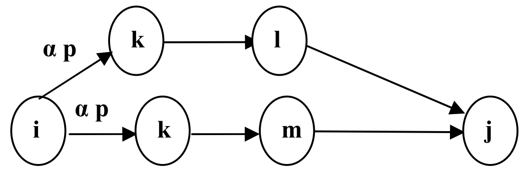

Fig. 4 Explaining the Trust Scaling Factor

This again is true in practice, for example if Bob learns about trustworthiness of Carol and Tom from Alice in some context, then he will not give equal importance to multiple statements from Alice. This is the first modification suggested by us for parallelization algorithm [1].

4 Parallelizing Referral Network

The trust relationships among the agents, forms a trust network with arbitrary network architecture. A typical diagram of trust network between source agents 'i' and target agent 'j' is shown in figure 5.

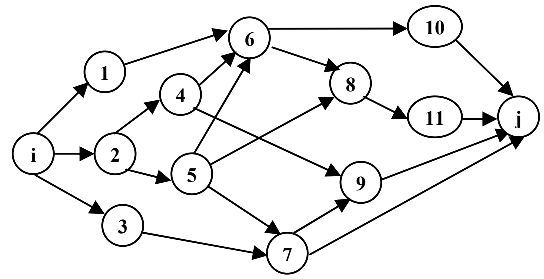

Fig.5 A Generalized Referral Network

There are multiple recommendation paths between source agent 'i' and target agent 'j'. Mui studied this issue and proposed a graph transformation algorithm in [1]. He defined indegree and outdegree of each agent (intermediate agent) and treat each transformation path as one recommendation path of trust network as. As shown in figure 5, using parallelization algorithm proposed by Mui, three recommendation paths with agent 10 as the terminal recommender are produced. It will exaggerate the contribution of direct experiments from agent 10 and other terminal intermediaries. It is logically incorrect as we are not using Bayesian network assumptions. So we suggest another improvement to Mui's parallelizing algorithm and avoid the recalculation of direct experiments in trust evaluation process by terminal intermediate agents. We state here modified algorithm as shown in text box on next page.

Modified Transformation Algorithm:

- Decide the indegree in_i and the outdegree out_i of every intermediate agent i ;
- For any link in network (excluding target agent), remove those links with trust reliability $t_{ij} < \theta$ $(i \neq j)$;
- If all intermediate agents have $in = out = 1$, the graph must be parallel network. Procedure ends;
- For every agent between source agent and the terminal intermediate agent which has direct interaction with target agent, if agent i has $in > 1$ or $out > 1$, form as many as $in_i \times out_i$ parallel paths through a copy of agent i . The referral network between source agent and terminal intermediate agent must be a parallel network.

There 'θ' denotes a threshold to decide the minimum reliability of useful trust relationship in network. It is application dependent and is a function of both the size of network and the amount of error the investigator can tolerate [1].

In the trust network like in figure 5, suppose $t_{6,8} < \theta$ and $t_{5,7} < \theta$, then it can be transformed into following network shown in Figure 6.

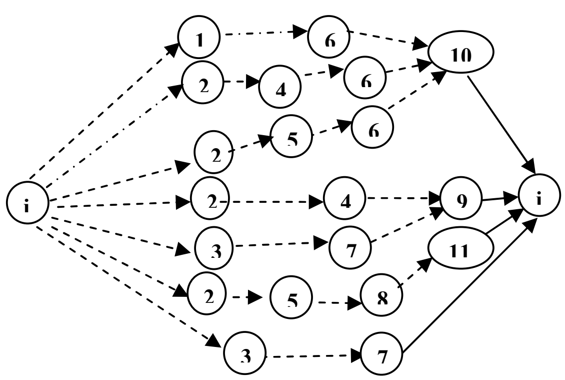

Fig.6 Parallelized Referral Network

Once a generalized network is reduced into a parallel network, the steps in previous sections can be followed for calculating the credibility of target agent.

5 Experiments and Result

A test-bed has been constructed to examine practicability and reliability of our trust evaluation model. The test-bed models real application, like e-commerce environment. We calculate the recommendation trust values and discuss the results as:

5.1 Computing Recommendation Trust

We take figure 6 as the example of trust network in our experiment. Each intermediate agent establishes a stable trust relationship with its neighbors after a series of interactions. The trust values obey uniform distribution in [0.7, .9]. We transform the trust network to parallel network using modified transformation algorithm proposed in section 4 and calculate recommendation trust using the rules explained in section 3. We compare it with simple graph parallelization algorithm suggested by Mui [1] and our suggested algorithm NPTEA. We vary target agent's intrinsic success probability (T) from 0.1 to 1.0 (i.e. 10% to 100%) and calculate recommendation trust (RT) values as shown in figure 7.

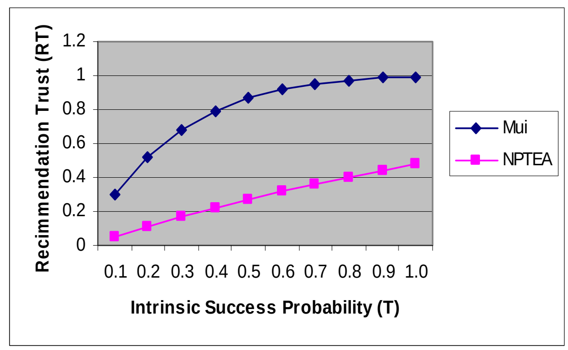

Fig.7 Plot of T versus RT for Mui's and NPTEA

The experiment demonstrates that our NPTEA give more realistic values as compared to Mui's simple algorithm. If we use Mui's method in our case, the values we obtain are not rational. For example consider the first point in the graph when T=0.1 (i.e. 10%), the RT=.0.05 (i.e. 5 %) as calculated by NPTEA and RT=0.30 (i.e. 30%) by Mui's method. This is just like saying that if three persons tell us about Alice is 10% reliable, but we believe she is 30% reliable, where as the persons giving us statement about her, may not be 100% trustworthy whereas NPTEA value is around 5% which is very reasonable. This is a logical notion and captures the subjective nature of trust. Hence, we believe our algorithm can be used safely to compute recommendation trust in a social network.

5.2 Transforming Trust Network

We simulate the transformation algorithms in this paper as proposed by Mui. The intrinsic success probability of the target agent is 0.55 (averaged from 0.1 to 1). We change the number of terminal intermediate (NTI) agents from 1 to 5. We apply the following transformations to figure 5 as listed in the following table

Table:1 Listing Transformations

NTI	Transformation Description
5	Add 8→j
4	No change
3	Remove 7 →j
2	Remove7 →j, 9→ j and Add 9→11
1	Remove 10 →j, add 10 →11

We plot calculated recommendation trust (RT) against the number of intermediate terminal (NTI) agents as shown in Figure 8.

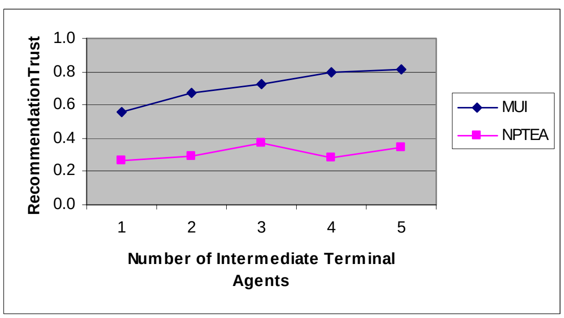

Fig.8 Plot of NTI versus RT for Mui's and NPTEA values at fixed value of T at 0.5

Again the same reasoning applies to this graph like figure 7. However when NTI=3, we remove 7 →j, in this case 3's trust in 7 has α=1, so no scaling factor is applied for 3→ 7 i.e. 3 is giving only single recommendation for 7, RT for our NPTEA is higher then NTI=4, which is very rational, where as in Mui's method it has no significant impact because of multiple contributions from same agent as explained earlier.

5.3 Comparison to BBK [2]

Here we borrow the diagram from [11], where the author explains the effect of misbehaving agent on BBK [2], as shown in figure 9.

The values shown along each directed edge represent intrinsic success probability trust of one agent in another. First we convert figure 9(a) into parallel referral network using our modified transformation algorithm. Then we calculate Recommendation Trust (RT) for BBK and NPTEA using α=1/2 for agent 5 since it is making two recommendations whose values are as under:

$$RT=\begin{cases}0.6491 \text{ for BBK}\\ 0.4184 \text{ for NPTEA}\end{cases}$$

We believe the above value suggested by BBK may be reasonable but our computed value is more realistic and safe in this case.

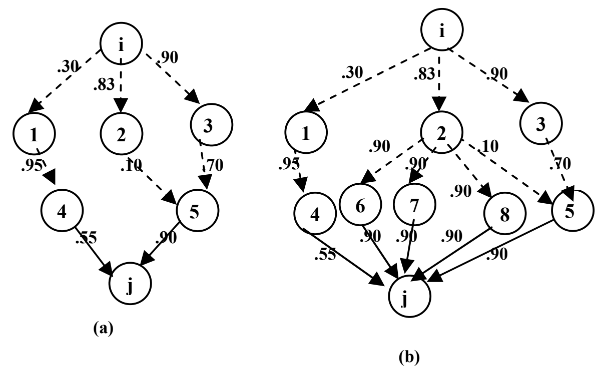

Fig. 9 Effect of misbehaving agent on BBK

Again we apply BBK and NPTEA both to figure 9(b). Here the agent 2 is misbehaving has created additional artificial paths from i to j through other agents 6, 7, 8 that 2 'invented' for altering the trust values. In this case α=1/3 for new links of agent 2 and α=1/2 for 5 as before. We calculate the values of RT as below:

$$RT=\begin{cases}1 \text{ for BBK}\\ 0.7312 \text{ for NPTEA}\end{cases}$$

Here BBK completely fails and our algorithm is still stable. It has restricted the malicious agent to affect the trust referral network. Hence it can be concluded that our algorithm is more attack resistant than BBK. Further more in figure 10 we show how BBK fails as its RT values shoot to 1(i.e. 100%) , where as our algorithm is very stable as proved in figure 10 by comparison.

Note that we have analyzed variations in T for agent 6, 7 and 8 where the remaining network is stable.

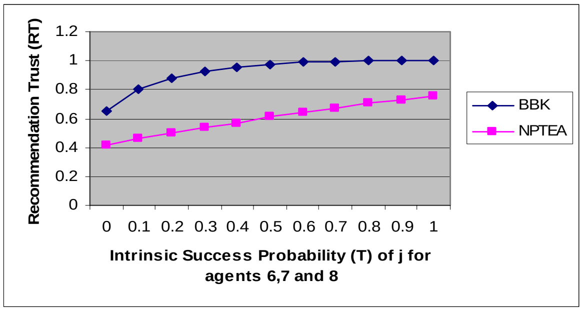

Fig. 10 Plot of T versus RT for BBK and NPTEA

6. Summary

Over the last few years, a number of e-commerce related sites have made a trust network one of their cornerstones. Evaluation of trust is a fundamental problem that needs to be addressed in context of such systems. In this paper, we focus on the evaluation and scaling of recommendation trust to capture the social nature of trust in referral networks and propose a systematic and novel method to solve this problem.

We have analyzed current trust evaluation methods, including the models based on weighted average model and BBK [2]. Furthermore, we propose a definition of trust scaling factor. We also propose an improved parallelization transformation algorithm for trust networks. We build a testbed to examine our model and the result shows our novel model can get very reliable recommendation trust even in the presence of malicious agents.

References:

[1] Mui L. Computational models of trust and reputation: agents, evolutionary games, and social networks. Ph.D Thesis, MIT, Massachusetts. 2003.

[2] T. Beth, M. Borcherding, B. Klein. Valuation of trust in open networks. In Proceedings of the European Symposium on Research in Security (ESORICS). Brighton: Springer-Verglag , 1994, 59-63

[3] Yu B, Munindar P. An evidential model of distributed reputation management AAMAS02. July 15-19, 2002.

[4] S. Marsh. Formalizing Trust as a Computational Concept. Ph.D. dissertation, University of Stirling, Department of Computer Science and Mathematics, 1994

[5] Abdul-Rahman and S. Hailes. Supporting trust in virtual communities. In Proceedings of Hawaii International Conference on Systems Science 33, 2000.

[6] Guha R, Kumar R, Raghavan P. Propagation of trust and distrust. WWW2004 May 17-22, 2004

[7] Lee S, Sherwood R, Bhattacharjee B. Cooperative Peer Groups in NICE. IEEE Infocom, April, 2003.

[8] L. Mui, M. Mohtashemi, A. Halberstadt. A Computational Model of Trust and Reputation. In Proceedings of the 35th Hawaii International Conference on System Sciences (HICSS'02), 2002

[9] Xu F, et. al. Design of a Trust Valuation Model in Software Service Coordination. Journal of Software. 2003, 14(06), p1043-1051

[10]R. Levien and A. Aiken. Attack-resistant trust metrics for public key certification In 7th USENIX Security Symposium, pages 229–242, 1998

[11]Reiter M.K., Stubblebine S.G. Toward acceptable metrics of authentication. In: Proceedings of the 1997 IEEE Symposium on Research in Security and Privacy.