Computing and Informatics, Vol. 33, 2014, 1095–1115

A METHOD OF EVALUATING TRUST AND REPUTATION FOR ONLINE TRANSACTION

Sunhong Kim, Wookju Ha, Jiwan Seo, Sangyong Han*

School of Computer Science and Engineering
Chung-Ang University
Heuk seok-dong, Dongjak-gu
Seoul 156-756, Korea
e-mail: shkim@ec.cse.cau.ac.kr, hansy@cau.ac.kr

Mucheol Kim

A Group of Industry-University Cooperation
Sungkyul University
53, Sungkyuldaehak-ro
Manan-gu, Anyang, Korea
e-mail: mucheol.kim@gmail.com

Abstract. The widespread use of the Internet and evaluater-based technologies has transformed the way business is conducted. Traditional offline businesses have increasingly become online, and there are new kinds of businesses that solely exist online. Unlike offline business environments, interpersonal trust is generally lacking in online business settings. Trading partners might feel insecure about the exchange of products and services over the net as they have limited information about each other's reliability or about the product quality. Considering that enough trust needs to be created to get the online buyer and seller to take actions, trust is a precious asset in online transactions. In order to address the issue of evaluating trust and reputation in online transaction environments, this paper makes use of a social network that graphically represents interpersonal relationships. This paper proposes computational models that systematically evaluate the quantitative level of trust and reputation based on the social network. A method that combines the evaluated trust and reputation levels is also proposed to increase the reliability of online transactions.

* corresponding author

Keywords: Social network, trust, reputation, online transaction, e-commerce, fuzzy logic

Mathematics Subject Classification 2010: 68M10

1 INTRODUCTION

With the widespread use of the Internet, online business has grown dramatically over the past few years. Traditional offline businesses have increasingly become available online, and numerous new business opportunities are introduced in online settings. For instance, online transactions that allow the exchange of products and services entirely electronically can offer the advantages of reduced costs and increased convenience [1]. While technical issues related to online transactions such as security and network availability have improved and reached a more or less "steady stage", sociological aspects such as trust and reputation still require extensive research. In online transaction environments, trust relationships are difficult to establish because there is no physical contact or interaction between people who are involved in such transactions (sellers, buyers and administrators) [4]. Considering that online users often mention the lack of trust as one reason for not transacting online, trust is an important component of successful online transactions. In existing online transaction systems, information such as user's personal information, transactions' histories and previous customers' comments or ratings are given to help online users make decisions related to trust. Most of these systems, however, provide only an intuitive approach to trust and reputation without much understanding of these concepts. The provided information is often incomplete, ambiguous and unreliable. Hence, more systematic approaches to formalize and transform the sociological concept "trustworthiness" into quantitative, computational information are required for reliable online transactions [5].

A social network is a graphical representation of a social structure made of individuals or organizations that are tied (connected) by one or more specific types of interdependencies [10]. The social network views social relationships in terms of network theory via nodes and ties. Nodes are the individual actors within the networks, and ties are the relationships between the actors. Since ties (or patterns of ties) can be interpreted in many different ways, social networks are useful to map various, complex relationships between the members of social systems. Moreover, transforming qualitative, social concepts into quantitative information is relatively simple in social networks that are mathematical structures (i.e., network theory). Thus, social networks have become a popular topic of study, and several applications and technologies that use social networks have emerged in the last few years.

This paper proposes the computational models that systematically evaluate quantitative trust and reputation levels based on the social network, and it proposes a method that combines the evaluated trust and reputation values. The rest of this paper is organized as follows. Section 2 presents related works and background information. Section 3 describes computational methods for evaluating trust and reputation. Section 4 introduces the computational model that evaluates the trustor's trust toward the trustee in the social network. Section 5 describes the computational model that evaluates the collective reputation (public opinion) about the trustee in the social network. Section 6 explains the method that combines the evaluated trust and reputation levels to support reliable online transactions. In Section 7, the experiments conducted to evaluate the accuracy of the proposed models and methods in evaluating trust and reputation are presented. Finally, conclusions and future research directions are given in Section 8.

2 RELATED WORK AND BACKGROUND

2.1 FOAF (Friend Of A Friend)

A social network represents interpersonal relationships in terms of the network theory. Every member (node) has his/her own human connections in the network, either direct or indirect. In the social network depicted in Figure 1, the node titled "Person" has two directly connected nodes and four indirectly connected nodes. The nodes that are not directly connected to the node "Person" can still be linked to it through intermediate nodes (i.e., FOAF applied) [26].

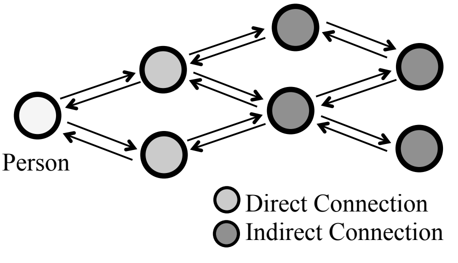


Figure 1. Social network graph

In a social network, there can be more than one path between two nodes. Each of such paths has its own trust score. This section describes the computational methods for evaluating trust and reputation in a social network. This section is composed of two parts

1. the computational model that evaluates the trust score of a single path and
2. the method that combines the trust scores of multiple paths.

2.2 Trust-Based System

Trust and reputation that are established in a natural manner through social contacts and activities play a significant role in business. With the rise of online markets, the roles of such social and psychological factors in online business have attracted considerable research interest. Trust is an essential component of building any relationship between individuals/organizations. Reputation is the opinion (or expectation) of the public toward a person based on his/her actions [6]. Trust and reputation exert their influence on every activity and technology involving interactions between people, and serve as a barometer to estimate the degree of trustworthiness of the potential counterparts [3]. Lately, there has been increasing research on formalizing trust and reputation via computational models.

Marsh proposed a computational model for trust that is applicable to the domain of Distributed Artificial Intelligence (DAI) [2]. In this model, trust is represented as a subjective real number between -1 and $+1$. The model is simple but exhibits problems at the extreme values, and it has trouble dealing with negative trust values. A contribution of this work is its detailed exploration of the possibilities of future work in the issue of formalizing trust as a computational concept.

Zacharia et al. proposed reputation mechanisms that rely on collaborative rating and personalized evaluation of the various ratings assigned to each user in the context of electronic commerce [7]. Their mathematical formulation dynamically evaluates the user's reputation with respect to a certain topic or criterion, instead of storing and using the net rating scores as they are.

Gao et al. proposed a comprehensive multidimensional model, which contains crucial factors having been researched and commonly accepted by precious scholars [28]. They analyzed the intrinsic character and importance of each factor, including the interaction between consumer trust and purchase intention. In addition they show the ranking results of their model on the five famous E-commerce websites.

Kim et al. proposed an identity management-based social trust model in order to mediating information sharing and information protection in online social networks [29]. This model solves the sparsity problem by using relationship model between users, quantified through the chronological records of users. Furthermore, the proposed social trust model has minimized unnecessary information leakages through active identity management.

Resnick et al. analyzed a way to increase the reliability of a system using a feedback rating mechanism in online transactions [1]. In their model, reputation is taken to be a function of the cumulative positive and non-positive ratings of a seller or buyer. In addition, trust by one agent of another is evaluated by an implicit mechanism in which the ratings that an agent receives from others are taken into account. Their algorithm was designed to be applicable to eBay reputation systems.

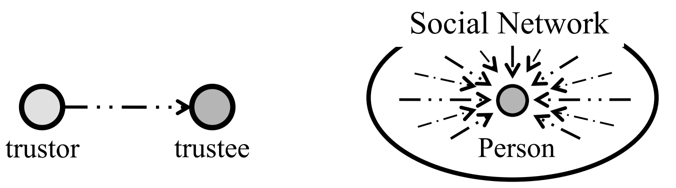
Mui et al. distinguished the difference between trust and reputation, and proposed a mathematical model to calculate agents' trust and reputation on a probabilistic basis [3]. They defined reputation as a quantity relative to the particular embedded social network of the evaluating agent and encounter history, and an agent's reputation score is evaluated based on the accumulated positive feedback from previous transactions. In addition, they provide a mechanism that evaluates trust of the trustor toward the trustee from the reputation data about the trustee.

Golbeck et al. presented an algorithm for aggregating and evaluating reputation and trust ratings on a semantic web-based social network [8, 12]. In their work, trust between two individuals that are not directly connected in the network is evaluated based on locally-calculated trust ratings of intermediate nodes. In addition, they proposed a quantitative model that evaluates reputation by combining the trust scores of the searched paths. The proposed method was applied to the TrustMail system, an email client that looks up the mail sender in the reputation network and provides a trust rating for each email message.

3 COMPUTATIONAL METHODS FOR EVALUATION

3.1 Trust and Reputation

Definining and extracting appropriate trust factors in online environment are important issues. Figure 2 shows a schematic representation of trust and reputation viewed in this paper. As shown in a), trust is a particular degree of the subjective probability an individual has toward another one [30], which affects the decision of whether or not to transact. In Figure 2, b) represents the notion of reputation. Reputation is what is generally said or believed about a person's or thing's character or standing [31]. Like trust, reputation is built through interpersonal interactions, and it can also be evaluated by combining several individually occurred trust ratings.



a) b)

Figure 2. a) Trust and b) reputation

A social network is created to represent the interpersonal or inter-organizational relationships in the online transaction system of interest. Each node in the network represents a user of the online transaction system, and ties represent the contacts between the users. A quantitative score assigned to each tie indicates the level of trust between the users that are connected by that tie. This trust score is directed, i.e., it is the trustor's trust toward the trustee, but not the other way round. An assumption made is that every user in a social network gives a subjective trust score to other users who are directly connected in the network. The given trust score is a rational number between 0 and 10. The trust score 0 is considered as "no connection". The FOAF (Friend of a Friend) theory is adopted to evaluate trust and reputation about strangers [26]. That is, an online transaction user evaluates the trust and reputation information about another user that s/he does not know well by searching paths to that stranger in the network, starting from his/her acquaintances.

3.2 A Computational Model for Inferring the Path Trust Score

As described above, there can be multiple paths between two nodes in a social network. The evaluated trust score of a certain path searched in a social network is called the "path trust score". Since a set of nodes comprising a path is different in each path, the evaluated path trust score varies according to the path.

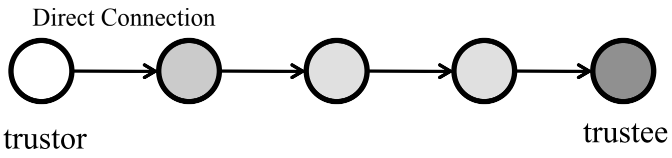


Figure 3. A path between two nodes of interest

Figure 3 shows a path between two nodes of interest (from the trustor to the trustee) searched in the social network. The following symbols are defined to evaluate the trust score of the searched path:

- T_d – trust score in a direct connection
- T_i – trust score in an indirect connection
- T_r – evaluated trust score (path trust score).

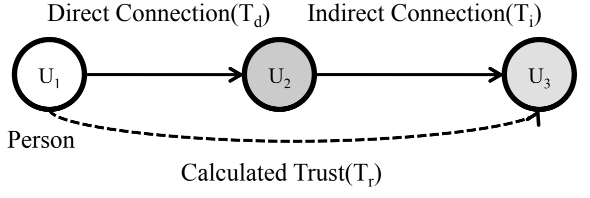


Figure 4. Schematic diagram of single path trust computation

In Figure 4, the path has three nodes on it. U_1's trust score toward U_2 connected directly in the network is a trust score in a direct connection, whereas the trust score of U_2 toward U_3 is considered as a trust score in an indirect connection. The trust score evaluated based on T_d and T_i is called a path trust score. T_r is evaluated using the Equation (1):

$$T_r = \frac{T_i * (T_d + (V_{max} - T_i))}{V_{max}}. \tag{1}$$

As trust is represented as a rational number between 0 and 10, the maximum possible trust score denoted as V_{max} is 10.0. In the proposed trust evaluation model, the significance of "direct" trust (T_d) and that of "indirect" trust (T_i) are not taken equally. Intuitively, it is reasonable that T_d rated directly by the trustor should play a more significant role in trust computation than T_i derived indirectly. Thus, a weighting scheme that adds T_d's complement (i.e., $V_{max} - T_d$) to T_i is used to adjust the significance level between T_d and T_i. For example, if the trust score of U_1 toward U_2 (T_d) is 9, it is presumed that the distrust level of U_1 toward U_2 is symmetrically 1 (i.e., T_d's complement is 1). This distrust level toward U_2 becomes a weight value assigned to T_i that is a trust score given by U_2. The path trust score T_r is evaluated by multiplying T_d with T_i weighted by T_d's complement, and then dividing the multiplication result by V_{max}.

This trust computation process is applied recursively for the consecutive nodes on a single path in the network until all the intermediate nodes between the trustor and the trustee are covered. That is, an evaluated path trust score T_r evaluated using Equation (1) becomes a new T_d for the adjacent node in the next cycle of computation. Table 1 shows the pseudo code of the proposed trust evaluation method.

```
func CalculatePathTrust(User, nextUser) {
  if  nextUser.next != TargetUser  then
    directTrust = User.trust
    indirectTrust = nextUser.trust
    User.trust = directTrust*
      (indirectTrust+(MaximumValue−directTrust))/MaximumValue
    nextUser = nextUser.next
    CalculatePathTrust(User, nextUser)
  else
    output User.trust
}
```

Table 1. Pseudo code of the evaluating the path trust score

As described in this section, the trust score of each path between a trustor and a trustee in a social network can be evaluated using the proposed trust evaluation model for a single path.

3.3 A Method of Combining Multiple Path Trust Scores

This section proposes a method that combines the trust scores of multiple paths between two nodes of interest (i.e., a trustor and a trustee). The trust scores to be combined can be either trust scores given explicitly by the trustor (i.e., they are attached to the path in the direction of the connection between the trustor and the trustee) or evaluated trust scores evaluated using the trust evaluation method for a single path. As a set of nodes engaged in a certain path is different, the trust scores of multiple paths to be combined are different from one to the other. Instead of evenly aggregating all the trust scores, the combining method proposed in this section employs a weighting scheme that puts more weight on a path having its trust score close to the average trust score of the multiple paths concerned. The purpose of this weighting scheme is to prevent the resulting combined trust value from being directly influenced by a few extreme trust scores:

- T_r – combined trust score
- T_i – trust score associated with i^{th} path
- W_i – weight assigned to i^{th} path

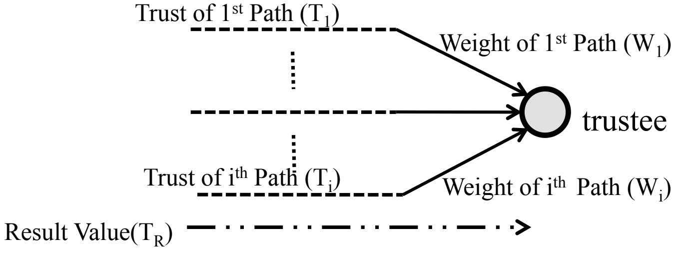


Figure 5. Schematic diagram of combining trust values of multiple paths

As shown in Figure 5, there is more than one path to be combined to evaluate the trustee's trust score T_R. T_i represents the trust score of i^{th} path, and W_i is the weight given to i^{th} path. Equations (2)–(4) are used to calculate the combined trust score T_R.

$$w_i = (V_{\max} - |\text{avg}(T_n) - T_i|)^2 \tag{2}$$

$$W_i = \frac{w_i}{\sum (w_i)} \tag{3}$$

$$T_r = \sum (T_i * W_i) \tag{4}$$

The trust score of an individual path that is close to the average trust score of all the searched paths is given a greater weight. This weighting scheme reduces the influence of a few extreme trust scores, and thus, allows more reliable trust evaluation. The sum of all the weights assigned to the paths should be 1.0. Table 2 shows the pseudo code of the proposed combining method.

4 COMPUTATIONAL MODEL FOR INFERRING TRUST

Based on FOAF implying the ability to access information through the "grape vine" of network members [26], the proposed trust evaluation model can evaluate the trust score of any member in the network by searching the paths to that member.

As shown in Figure 6, there are several paths connecting the trustor to the trustee. The trust score of each single path can be evaluated using the method described in Section 3.1, and the evaluated path trust scores are combined using the

```
func CombineTrust(set of TrustToSink) {
  for each Trust T_i {
    T_i.wi = Square(MaximumValue -
                AbsoluteValue(Average(set of T_i) - T_i))
  }

  for each Trust T_i {
    T_i.Wi = T_i.wi / Average(T_i.w_i)
  }

  for each Trust T_i {
    CombinedTrustValue += T_i.TrustValue * T_i.W_i
  }

  output CombinedTrustValue
}
```

Table 2. Pseudo code of the combining method

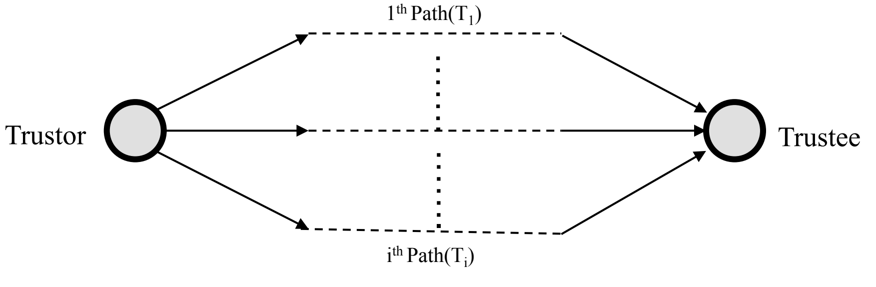


Figure 6. Trust evaluation model

combining method presented in Section 3.2. In this way, a subjectively perceived level of trust toward the trustee is systematically transformed into quantitative information (trust scores). Table 3 shows the pseudo code of the proposed trust evaluation model.

```
func InferringTrust(Source, TargetUser) {
  for each Path Source to TargetUser P_i {
    P_i.Trust = CalculatePathTrust(Source, P_i.NextUser)
  }

  output CombineTrust(set of P_i.Trust)
}
```

Table 3. Pseudo code of the combining method

5 COMPUTATIONAL MODEL FOR INFERRING REPUTATION

For successful online transactions, one should be able to assess the trustworthiness of trading partners. Trust and reputation are typical factors related to trustworthiness. This section addresses the factor "reputation" and proposes a formal model that evaluates reputation in a social network.

Every member in a social network has its own reputation in that particular domain. Reputation refers to a judgment of trustworthiness toward a certain network member, made collaboratively by other members in the same network. Reputation is an objective and collective concept that gathers more than one member's personal trust. This section proposes a computational model that evaluates a trustee's reputation by combining the trust scores of other members toward the trustee.

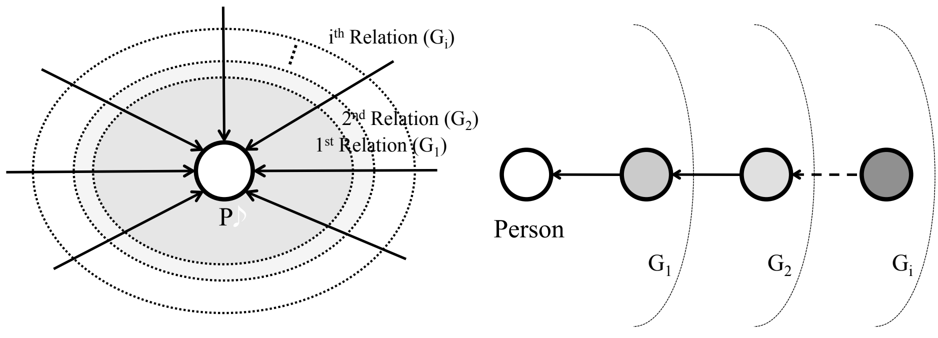


Figure 7. Reputation evaluation model

As shown in Figure 7, the node of interest "Person" has a group of members who are directly connected to (the primary group denoted as G_1). Next, the node has a group of members who are indirectly connected via one intermediate node. This group is called the secondary group and is denoted as G_2. Similarly, the node continues to have the next group of adjacent nodes that are linked through an increased number of intermediate nodes each time. Those groups are collectively denoted as G_i. Other members in the same network (both directly and indirectly connected) have subjective trust scores toward the node Person, so the Person's reputation can be evaluated by combining those individual trust scores.

In the proposed reputation evaluation model, the trust scores of other members in the network toward the member of interest, Person, are evaluated first. For the nodes in G_1, the directly given trust scores are used as they are. To get the trust scores of the members belonging to the groups other than G_1 (i.e., indirectly connected nodes), the trust evaluation model presented in Section 4 is used. The computed trust scores of multiple members are then combined to derive a collective reputation score about the node Person. As described below, the proposed reputation evaluation model uses a variable that limits the range of the connection to be considered in the reputation evaluation:

- l – variable for the connection range limitation.

The value of the variable l is used to limit the range of the connection to be considered in reputation evaluation. With this value, the nodes that are too distant to be significant are excluded, and those closely linked to the node of interest are concerned. According to the given value of l, only the nodes belonging to the groups within the boundary of this value (i.e., from G_1 to G_l) are taken into account in evaluating reputation, thereby reducing the computational load. Table 4 presents the pseudo code of the proposed reputation evaluation model.

```
func InferringReputation(TargetUser) {
for each User U_i adjacent to source within l {
U_i.TrustToTargetUser = InferringTrust(U_i , TargetUser)
}

output CombineTrust(set of U_i.Trust)
}
```

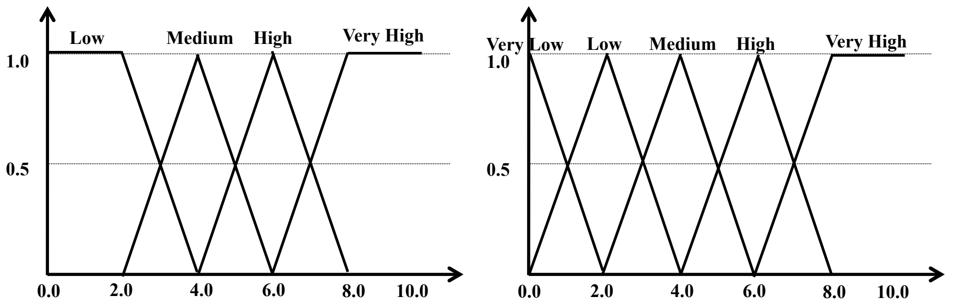
Table 4. Pseudo code of the reputation evaluation model

6 A METHOD OF COMBINING TRUST AND REPUTATION FOR RELIABLE ONLINE TRANSACTIONS

In conventional marketplaces, the trustworthiness of trading partners is estimated over trust evidences such as direct experiences from former encounters, witness information and information about past transactions. However, such information sources are not available or are very limited in an online setting where there are no direct, physical contacts. The computational models based on social networks described in Sections 4 and 5 can be used to systematically evaluate trust and reputation in such online settings.

This section presents the method that combines the evaluated trust and reputation for reliable online transactions. As described earlier, trust is a subjective judgment of trustworthiness between two trading partners, and reputation is a collective assessment of someone's trustworthiness made by multiple members in the network. According to the characteristics of the trades in online transactions, sometimes the subjective attributes associated with trust might be more important, and there might be other cases in which the objective attributes associated with reputation play a more significant role. There can also be some cases where both subjective and objective attributes should be evenly considered. To address this point, this paper makes use of the fuzzy logic [24, 25] and constructs a computational model that combines trust and reputation. In this model, two trustworthiness factors "trust" and "reputation" become fuzzy descriptors.

Trust = {Low, Medium, High, Very High}
Reputation = {Very Low, Low, Medium, High, Very High}



a) b)

Figure 8. Fuzzy graph: a) trust, b) reputation

Figure 8 shows the fuzzy graphs regarding trust and reputation. Such fuzzy graphs can be flexibly constructed according to the members and the types of online transactions applied. In the fuzzy set graphs, the fuzzy descriptor Trust has four membership values – low, medium, high and very high. The fuzzy descriptor Reputation has five membership values – very low, low, medium, high and very high. The trust and reputation scores produced using the proposed evaluation models are mapped to those fuzzy membership values, and the most relevant one (i.e., having the highest mapping value) is selected.

Table 5 shows a fuzzy rule base which defines the fuzzy sets and membership values shown in Figure 9. There are 20 cases with regard to two fuzzy descriptors, 4-scale Trust and 5-scale Reputation, and the result value of each case is listed. The combined result value taking into account both trust and reputation can be derived from the table.

In addition, a fuzzy graph as shown in Figure 9 is created to evaluate a quantitative level of trustworthiness by simultaneously considering trust and reputation. In the graph, there are seven membership values – very low, low, rather low, medium, rather high, high and very high. The result value is determined by combining the ratios of two fuzzy descriptors Trust and Reputation. In this way, the trustworthiness of an online user can be quantitatively evaluated.

7 EXPERIMENTAL RESULT

The accuracy of the proposed evaluation models for trust and reputation are evaluated through experimental simulations. As mentioned earlier, every member in

	Trust	Reputation	Result
1	Low	vLow	vLow
2	Low	Low	Low
3	Low	Med	rLow
4	Low	High	Med
5	Low	vHigh	rHigh
6	Med	vLow	Low
7	Med	Low	rLow
8	Med	Med	Med
9	Med	High	rHigh
10	Med	vHigh	High
11	High	vLow	rLow
12	High	Low	Med
13	High	Med	rHigh
14	High	High	High
15	High	vHigh	vHigh
16	vHigh	vLow	rLow
17	vHigh	Low	Med
18	vHigh	Med	rHigh
19	vHigh	High	High
20	vHigh	vHigh	vHigh

Table 5. Fuzzy rule base (vLow = very low, rLow = rather low, rHigh = rather high, vHigh = very high)

a social network has a trust rating toward other directly connected members (a rational number between 0 and 10.0), and this trust score is directed (i.e., the trustor's trust level toward the trustee, not vice versa).

7.1 Experiment 1

Trust is the trustor's subjective judgment of trustworthiness toward the trustee, so its accuracy is evaluated by solely considering the relationships between the trustor and the trustee. A social network is created to evaluate the proposed trust evaluation model, and several attributes are given to each member in the social network. In the created social network, each member has 20 directly connected nodes on average, and the trust scores given to those directly connected nodes are determined by assessing the similarity of the attributes attached to the two nodes. Based on the given trust scores of directly connected nodes, the proposed trust evaluation model evaluates the trust score of a trustor toward a trustee. The accuracy of the proposed model is then evaluated by comparing the evaluated trust score with the trust score directly given to the trustee earlier based on the similarity of the associated attributes. The experimental settings are as follows:

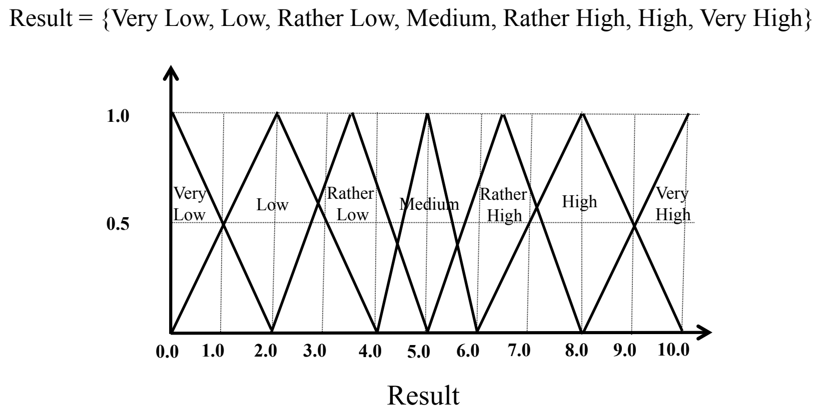


Figure 9. Result graph

- the number of members in the network: 500
- the average number of directly connected members: 20
- the number of simulations (experiment repetitions): 1 000.

The proposed trust evaluation model is compared to TidalTrust, conventional trust evaluation model [12]. TidalTrust, a trust network inference algorithm, is used as the basis for generating predictive ratings personalized for each user. The accuracy of the recommended ratings is shown to outperform both a simple average rating and the ratings produced by a common recommender system algorithm.

	Average accuracy
Our model	97.2 %
TidalTrust	93.4 %

Table 6. Trust evaluation model experiment

As shown in Table 6, the accuracy of the proposed model increases by 3.8 % compared to TidalTrust. In TidalTrust, evaluation accuracy decreases as the length of the connection path between two nodes increases. On the other hand, the proposed model maintains the accuracy irrespective of the path length. It is notable that the reputation evaluation model proposed in this paper evaluates reputation by combining the trust scores evaluated using the proposed trust evaluation model, so the accuracy of the trust evaluation model shown in this experiment also demonstrates the accuracy of the proposed reputation evaluation model to some degree.

7.2 Experiment 2

In the second experiment, the accuracies of the proposed trust evaluation model, reputation evaluation model and the method of combining the evaluated trust scores are examined. Each member in the social network receives a presumed exact trust score (called "standard value"). The standard value serves as a barometer against which the trust score evaluated using the proposed trust evaluation model is compared, in order to assess the accuracy of the proposed model. As in Experiment 1, each node in the network gives a subjective trust score to the directly connected node. The difference here is that the given trust score is relative to the standard value S_V and the assigned rating accuracy R_A. The trust scores given to the directly connected nodes are used in evaluating trust and reputation using the proposed evaluation models and combining methods. The evaluated trust and reputation scores are compared to the standard values, so as to evaluate the accuracy of the proposed evaluation models and combining method:

- S_V – standard value
- R_A – rating accuracy.

500 members (nodes) are created in the network. The standard value for each member is given to form a normal distribution with the average 5.0 (i.e., the given standard values of 500 nodes cluster around trust score 5.0). Once the standard value S_V is assigned to every member in the network, a trust rating score (a rational number between 0 and 10.0) is given to the directly connected node based on R_A and the node's S_V. For example, if R_A is 100 %, then the given trust score toward a directly connected node is the same as S_V of that node. As R_A decreases by 10 %, the difference between the trust score given to the directly connected node and its S_V increases by 1.0 (± 0.5). As shown below, the accuracy of the evaluated trust and reputation scores is evaluated by varying R_A:

- avg(S_V) – 5.0
- R_A range – $0 \sim 100.0$ (%)
- the number of network members: 500
- the average number of directly connected members: 20
- the number of simulations (experiment repetitions): 1 000.

Figure 10 shows the comparison of the evaluated trust and reputation scores to the standard values as the simulations are repeated by increasing R_A. When R_A is low, the accuracy of the evaluated trust and reputation is relatively low; but their accuracy improves as R_A increases. This result indicates that R_A directly set by users considerably influences the accuracies of the proposed evaluation models. In evaluating the trust score of a single path, the evaluated trust score varies according to the path chosen, and thus, the resulting accuracy graph does not increase consistently.

Table 7 shows the average difference (or average error) between S_V and the trust and reputation scores evaluated using the proposed evaluation models as the simulations continue by increasing R_A. As R_A increases, the difference between S_V and the evaluated trust and reputation decreases. In other words, as R_A

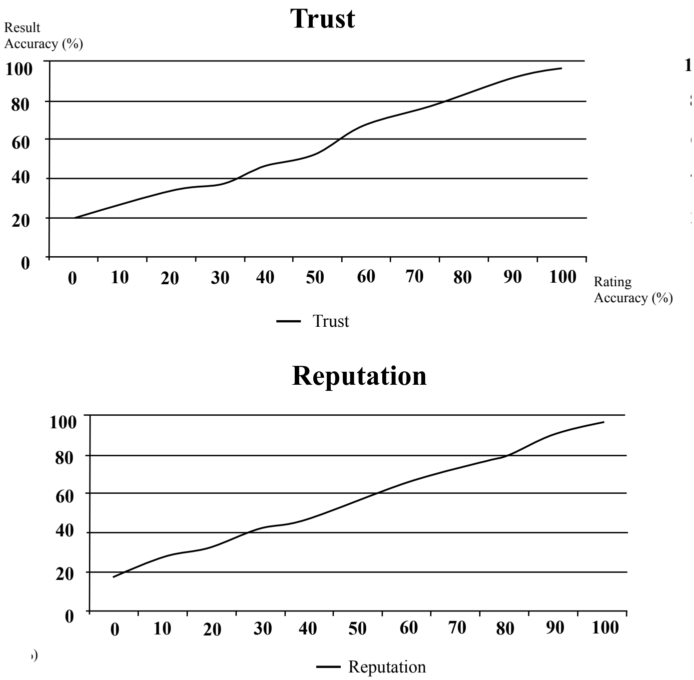


Figure 10. Accuracy of the evaluated trust and reputation

R_A	Average Error: Trust	Average Error: Reputation
80 %	81.142 % (0.9429)	79.746 % (1.0127)
85 %	85.694 % (0.7153)	85.164 % (0.7418)
90 %	90.542 % (0.4729)	90.918 % (0.4541)
95 %	92.832 % (0.3584)	93.290 % (0.3355)
100 %	96.198 % (0.1901)	96.410 % (0.1795)

Table 7. Average accuracy by R_A (average error)

increases, the evaluation accuracy of the proposed models increases and becomes nearly identical to R_A. When R_A is 100 %, the accuracy of the proposed trust evaluation model is 96 %, and the accuracy of the proposed reputation evaluation model is 97 %.

	Trust	Reputation
Our model	96.198 %	96.410 %
J. Golbeck's model	91.286 %	92.572 %

Table 8. Comparison with other evaluation model (R_A: 100 %)

Table 8 shows the comparison of the proposed models for evaluating trust and reputation to conventional evaluation methods, trust and the reputation evaluation model proposed by Golbeck, when R_A is 100 % [8]. That is, the trust and reputation scores evaluated using the evaluation model proposed in this paper and those evaluated using conventional methods are compared with S_V. It is expected that the evaluated scores should be equivalent to S_V because R_A is 100 %. The results in Table 4 show that the error ratio of the proposed trust and reputation evaluation models to conventional models is 0.4, so the proposed models can yield more accurate trust and reputation evaluation than the conventional methods.

8 CONCLUSION

This paper has presented the computational models that evaluate trust and reputation from a social network representing human relationships. Trust and reputation are an antecedent to a successful online transaction, so the proposed evaluation models for trust and reputation can contribute to promoting online transactions that offer many advantages in terms of cost and convenience. This paper has analyzed how trust and reputation are acquired and how they are used in traditional offline environments, and this paper proposed formal models to systematically evaluate trust and reputation in online transaction environments. In addition, this paper has proposed a method that flexibly combines the evaluated trust and reputation according to the characteristics of the transactions. The proposed evaluation models can serve as a framework that transforms the sociological concept "trustworthiness" into quantitative information applicable in online systems. The proposed models contribute also to increasing the overall reliability of a social network by offering an accurate way to gauge network members' trust and reputation levels.

One of the practical limitations of this work is that it requires explicit trust ratings to evaluate trust and reputation. The trust scores given by a user are based on the user's subjective judgment, so the accuracy of the given trust scores varies depending on which user is in charge of the ratings. The proposed evaluation models for trust and reputation are demonstrated in terms of the accuracy of the evaluation process, but they do not currently address the subjective probability regarding trust. To improve this problem, generalizing and refining the valid range of explicit trust ratings will be studied in our future works.

Acknowledgements

This research was supported by the Chung-Ang University Research Scholarship Grants in 2012 and the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (No. 2014018334).

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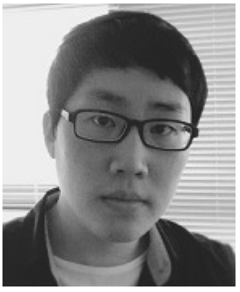
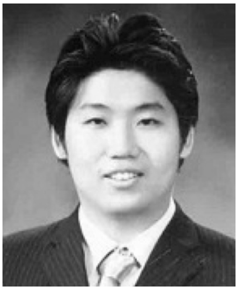


Sunghong Kim received his B. Sc. degree in computer science and engineering from Chung-Ang University, South Korea, in 2008. Having got a B. Sc. degree, he took a master course in E-Commerce Application Laboratory, School of Computer Science and Engineering, Chung-Ang University. His research interests include trust and reputation model, decision making, and fuzzy theory.



Mucheol Kim is an Assistant Professor in a group of Industry University Cooperation at Sungkyul University in Korea. He was a Senior Researcher in Korea Institute of Science and Technology Information (KISTI), Daejeon, Korea. He received the B. Sc., M. Sc. and Ph. D. degrees from the School of Computer Science and Engineering at Chung-Ang University, Seoul, Korea in 2005, 2007 and 2012, respectively.

Wookju Ha received his Bachelor of Science in computer science and engineering from Chung-Ang University, South Korea, in 2012. Having got a Bachelor of Science degree, he took a master course in E-Commerce Application Laboratory, School of Computer Science and Engineering, Chung-Ang University. His research interests include trust and reputation model, and knowledge ecosystem.

Jiwan Seo received his Bachelor of Science in 2010 and Master degrees in computer science and engineering, Chung-Ang University in 2012; he is Ph. D. candidate in E-Commerce and Internet Application Laboratory, School of Computer Science and Engineering, Chung-Ang University. His research interests include online social networks, trust and reputation model, and big data analysis.

Sangyoung Han is a Professor of the School of Computer Science and Engineering, ChungAng University, Korea. He received Bachelor of Engineering from College of Engineering, Seoul National University in 1975, and the Ph. D. degree in 1984. Between 1984 and 1995, he worked at Poughkeepsie Lab. and Watson Research Center in IBM, USA. His research interests include web technologies, web services, semantic web, information retrieval and multimedia.