Computational Trust and Its Impact over Rational Purchasing Decisions of Internet Users

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Abstract

As web-based online communities are rapidly growing, the agents in the communities need to know their measurable belief of trust for safe and successful interactions. In this paper, we propose a computational model of trust resulting from available feedbacks in online communities. The notion of trust can be defined as an aggregation of consensus given a set of past interactions. The average trust of an agent further represents the center of gravity of the distribution of its trustworthiness and untrustworthiness. Furthermore, we precisely describe the relationships among reputation, trust and average trust through concrete examples showing their computations. We apply our trust model to online social networks in order to show how trust mechanisms are involved in the rational purchasing decision-making of buyers and sellers, and we summarize our simulation results.

Keywords: Reputation, computational model of trust, rational purchasing decisions, online social networks

This paper is the extended version of our paper, which has been selected as a remarkable paper of the ICONI/APIC-IST 2009 Special Issue. We have added aggregation operators and the simulation results showing the relationship between buyer's benefit and seller's cost in online multi-agent settings. This work has been supported by the Catholic University of Korea research fund granted in the program year of 2009.

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1. Introduction

Traditional notion of trust [1] refers to an agent's belief that other agents intend to be honest and positive with the agent, and it can be usually built up through direct interactions in person. As online communities on the Internet are rapidly growing, the agents have been exposed to virtual interactions as well as face-to-face interactions. Agents in online social networks communicate anonymously and have only limited inspections. These features have made it hard for agents to determine whether or not other agents may be positive or benevolent towards them. Thus, it is essential that these agents could have a tangible model of trust for safe and successful interactions, even in the case that they do not have prior and direct interactions. This paper addresses how to assess trust in social networks, particularly applicable to online communities. We build up the computational model of trust as a measurable concept.

Our approach to the computational model of trust starts with the lesson from "Tit for Tat" strategy in game theory for the iterated Prisoner's Dilemma [2], which encourages social cooperation among agents. As a result of mutual behaviors in online multi-agent settings, agents will get more positive feedbacks from other agents if the agents are willing to cooperate with others; otherwise, these agents will receive more negative feedbacks from others. We translate the feedbacks resulting from social activities into the agent's reputation as a quantitative concept. The next steps of our trust model are to apply the aggregation rules to given reputation values to reach a consensus, and to calculate the average trust interpreted as the center of gravity of the distributions of trustworthiness and untrustworthiness. The notion of trust in our framework then represents positive expectations about future behavior of others.

Given our computational model of trust, we also study the impact of trust on online social communities by analyzing the relationships among trust estimates of web-based users, their expected utilities and the size of contracts. Let us consider that web-based users buy and sell goods or services through online social networks. From their own perspectives, these users would try to pursue their own benefits, which will be presented as expected utilities. If the users fail to make a deal, the expected utilities themselves would be meaningless. The users' common goal is to make a contract. Both should enter an agreement that is acceptable to each other, and trust between the both sides is indispensable. Therefore, the estimates of trust to each other should be included to compute the value of the expected utilities. This paper proves that if the mutual trust estimates and the expected utilities of the buyer and the seller get greater, then the amount of trades also could be increased.

This paper is organized as follows. In the following section, we briefly compare our approach to related work. Section 3 is devoted to our trust model that defines reputation, trust and average trust. We precisely describe the relationship among them through a concrete example of their computations. In Section 4, we apply our trust model to online Internet transactions showing how trust affects the rational decision-making of buyers and sellers. In the conclusion, we summarize our work and mention our future research issues.

2. Related Work

Our work builds on efforts by several other researchers who have made the social concept of trust computable in a society of multi-agents. In the field of multi-agent community, there have been several approaches to support a computational model of trust. Marsh [3] introduces a simple, computational model of trust that is a subjective real number ranging from -1 to 1. His model has trouble with handling negative values of trust and their propagation. Mui [4] describes trust in a pseudo-mathematical expression and represent it as posteriors using expected utility notation. The scheme only counts the number of cooperations (or positive events). In a distributed reputation system [5], they use the aging factor, distance factor and new experience to update trust. However, the assumption of these components of trust is not likely to be realistic. As they pointed out, their scheme does not correctly handle negative experiences. Our model of trust represents an aggregation of consensus without any problem of fusion, and it effectively deals with the agent's trustworthiness and untrustworthiness in the range of 0 and 1, respectively, which are based on actual positive and negative feedbacks in social networks.

Other rigorous efforts have also focused on the formulation of measurable belief representing trust. One of them is to use a subjective probability [6][7] that quantifies trust as a social belief. In the subjective logic, an agent's opinion is presented by degrees of belief, disbelief and uncertainty. Handling uncertainty in various trust operations is too intuitive to be clear. Further, the subjective logic provides not a certain value of trust but a probability certainty density function. However, our trust model provides a specific trust value as an average trust by simultaneously considering agent's trustworthiness and untrustworthiness. In another approach, a simple e-Bay feedback system [8] uses a feedback summary, which is computed as arithmetically subtracting the number of negative feedbacks from the number of positive feedbacks. Sabater and Sierra [9] review the research in terms of computational trust and reputation models, from the perspectives of multi-agent system paradigm and e-commerce, based on the classification dimensions of conceptual model, information sources, context dependability, model type, and so on. The contribution of our work is to precisely define the notion of trust as a measurable social belief, to clearly describe the relationship between reputation, trust and average trust, and to apply our trust model to Internet transactions in online social multi-agent settings.

3. The Measurable Belief of Trust

We propose a formal model of reputation resulting from feedbacks in social networks. Our reputation model takes into account direct agent experiences and witness information from third party agents [9]. The notion of trust then can be defined as an aggregation of consensus given a set of reputations. The calculation of average trust further results in a precise trust value as a metric. In this section, we describe the relationship between reputation, trust and average trust through a concrete example of their computations.

3.1 Modeling Reputation

Feedbacks in social networks [8][10] represent reputation associated with the society of multiple agents. The cumulative positive and negative events or feedbacks for an agent, thus, constitute the agent's reputation [4][5]. Reputation can be described by a binary proposition[1] *p*, for example, "A seller deals with only qualified products and delivers them on time." in the

[1] Any reputation in the form of proposition can be expressed according to the contexts as follows: "A buyer has an intention and capability to pay," "The network system could be safe from any intrusions," "A car could be reliable for ten years," and so on.

field of online Internet transactions. Given a binary proposition *p* and an agent-group *i* judging an agent in *p*, the reputation of the agent in *p*, ω_i^p , can be defined as follows:

$$\omega_i^p = \{T_i, U_i\} \tag{1}$$

where

- $T_i = PF_i/N_i$ and $0 \le T_i \le 1$;
- PF_i is the number of positive feedbacks for *p* within an agent-group *i*;
- $U_i = NF_i/N_i$ and $0 \le U_i \le 1$;
- NF_i is the number of negative feedbacks for *p* within an agent-group *i*;
- ZF_i is the number of neutral feedbacks for *p* within an agent-group *i*;
- N_i is the total number of feedbacks for *p* within an agent-group *i* and $N_i = PF_i+NF_i+ZF_i$.

In the definition of reputation, as described in (1), we assume that the feedbacks given by agents within an agent-group evaluating *p* are independent, and further, the opinions supporting *p* can be only loosely related to the possible opinions supporting $\neg p$, since there could be neutral feedbacks from the agent-group. The notion of reputation, thus, is based on independent opinions, and the sum of T_i and U_i is not necessarily being 1. Our model of reputation needs to preprocess a set of feedbacks and to classify them into positive, negative and neutral ones. The reputation in our framework also relies on the agents within any agent-group who honestly rate the others without cheating.

The cumulative positive feedbacks in social networks result from cooperativeness, i.e., trusty interactions, and they establish agent trustworthiness in *p* while the possible number of negative feedbacks from society affects agent untrustworthiness. Thus, the trustworthiness of an agent represents the positive expectations of third party agents about its future behaviors. The trustworthiness and untrustworthiness together constitute a reputation function as a quantitative concept. The reputation of an agent varies with the time and size of society, and reputation clearly influences the agent's trust. Given a set of reputations, which are collected at different times and from various interactions made by other agent-groups, trust as a representative reputation will be derived.

3.2 Calculating Trust Using Aggregation Rules

We define trust as a consensus from an aggregation of reputations. The trust[2] ω^p for an agent in a proposition *p* is defined as

$$\omega^p = \omega_i^p \otimes \omega_j^p = \{T, U\} \tag{2}$$

where

- ω_i^p and ω_j^p represent reputations accumulated from an agent-group *i* and an agent-group *j*, respectively;
- *T* is the trustworthiness of the agent in a proposition *p* and $0 \le T \le 1$;

[2] For the sake of simplicity, we explain our trust model in a much simpler case of two agent-groups *i* and *j*. Our model of trust can be simply extended in more complicated settings involving multiple agent-groups without loss of generality.

- U is the untrustworthiness of the agent in a proposition p and $0 \leq U \leq 1$.

Trust, as described in (2), consists of trustworthiness and untrustworthiness. These two components are determined by a set of reputations, as previously defined in (1). We propose a set of aggregation rules to formulate the agent's trust from reputations expressed in degrees of trustworthiness and untrustworthiness that may or may not have the mathematical properties of probabilities [11]. Given reputations of ω_i^p and ω_j^p , the aggregation operators, $\otimes = \{\Psi_1, ..., \Psi_n\}$, in this paper, are as follows:

- Minimum (Ψ_1): $T = \min(T_i, T_j)$, $U = \min(U_i, U_j)$;
- Maximum (Ψ_2): $T = \max(T_i, T_j)$, $U = \max(U_i, U_j)$;
- MinT and MaxU (Ψ_3): $T = \min(T_i, T_j)$, $U = \max(U_i, U_j)$;
- MaxT and MinU (Ψ_4): $T = \max(T_i, T_j)$, $U = \min(U_i, U_j)$;
- Mean (Ψ_5): $T = (T_i + T_j)/2$, $U = (U_i + U_j)/2$;
- Product (Ψ_6): $T = T_i T_j$, $U = U_i U_j$;
- Dempster-Shafer theory [12][13][14] (Ψ_7):

$$T = \frac{T_i T_j}{1 - (T_i U_j + T_j U_i)}, \quad U = \frac{U_i U_j}{1 - (T_i U_j + T_j U_i)}.$$

The trust representing the degrees of belief on agent's truthfulness can be obtained by applying aggregation rules to a set of reputations. The goal of aggregation is to combine reputations when each of them estimates the probability of trustworthiness and untrustworthiness for an agent, and another goal is to produce a single probability distribution that summarizes the various reputations.

The possible sets of trustworthiness (T) and untrustworthiness (U) value include taking minimum, maximum, minimum for T and maximum for U, and maximum for T and minimum for U. The above four aggregation rules are applied to all the sets of reputations, and provide a single value for T and U, respectively. The mean aggregation operator simply extends a statistic summary and provides an average of T_k's and U_k's coming from different agent-groups. The product rule summarizes the probabilities that coincide with T and U, respectively, given a set of reputations. In this case, neither of T and U should be zero, since the product operator suffers from the limitation that if one operand is zero, the entire product will be zero. To avoid the zero results of trust values using the product operator, in general, they assume that these zeros could be replaced with very small positive number being close to zero. Dempster's rule[3] for combining degrees of belief produces a new belief distribution that represents the consensus of the original opinions [14]. Using Dempster's rule, the resulting values of T and U indicate the degrees of agreement on trustworthiness and untrustworthiness of original reputations, respectively; however, they completely exclude the degrees of

[3] In this paper, a set of original reputations embedded in social networks are assumed to be consistent in measuring them. This assumption avoids the counterintuitive results obtained using Dempter's rule in the presence of significantly conflicting evidence, which was originally pointed out by Lotfi Zadeh [15].

disagreement or conflict. The advantage of using the Dempster's rule in the context of trust is that no priors and conditionals are needed.

Among the possible outputs of trust, we denote trust as the consensus output using a specific aggregator, which is defined as

$$\hat{\Psi}(t,u) = \Psi(\Psi_1(t,u),\ldots,\Psi_n(t,u)) \tag{3}$$

where

- Ψ is a function determining a specific aggregation rule;
- $\hat{\Psi}(t,u)$ is the aggregation rule selected with the inputs of $t \in T_k$ and $u \in U_k$.

Example 1. Let ω_1^p = {0.80, 0.10}, ω_2^p = {0.70, 0.20}. This is interpreted that there are two agent-groups evaluating p and, in each group, the resulting number of positive feedbacks is much greater than that of negative feedbacks, respectively. Given reputations, aggregation rules can be applied to get trust, as defined in (2), denoting a consensus out of agent-groups' opinions. The possible outputs of trust using the aggregation rules are summarized in **Table 1**.

Table 1. The example computation of trust using seven aggregation rules

Aggregation rules	ω_1^p = {0.80, 0.10}, ω_2^p = {0.70, 0.20}
	Trust ω^p
Minimum (Ψ_1)	{0.70, 0.10}
Maximum (Ψ_2)	{0.80, 0.20}
MinT and MaxU (Ψ_3)	{0.70, 0.20}
MaxT and MinU (Ψ_4)	{0.80, 0.10}
Mean (Ψ_5)	{0.75, 0.15}
Product (Ψ_6)	{0.56, 0.02}
Dempster-Shafer theory (Ψ_7)	{0.73, 0.03}

For example, when we use Ψ_7 as an aggregation rule, the trust according to reputations is calculated as follows:

$$T = \frac{(0.8)(0.7)}{1-[(0.8)(0.2)+(0.7)(0.1)]} = 0.73;$$

$$U = \frac{(0.1)(0.2)}{1-[(0.8)(0.2)+(0.7)(0.1)]} = 0.03.$$

Among the possible outputs of trust, trust can be denoted as ω^p = {0.70, 0.10}, when $\hat{\Psi}(t,u) = \Psi_1$. When minimum, maximum, MinT and MaxU, MaxT and MinU, and mean aggregators are used, the resulting distribution of trust similarly reflects the distributions of reputation. In cases of product and Dempster-Shafer theory, however, the T's (0.56 and 0.73) of the trusts are much bigger than their U values (0.02 and 0.03), compared with the original distributions of the reputation. The resulting T value in Ψ_7 is interpreted that there is a 0.73

chance that the agent in p has the trustworthiness, while the resulting U value indicates that there is only a 0.03 chance that the agent is negatively estimated. Thus, as we mentioned above, normalizing the original values of trustworthiness and untrustworthiness, which is corresponding to the denominator in the above equation, makes the opinions associated with conflict being away from the trust as a consensus.

To show how the aggregation rules could be adapted to various distributions of reputation, we consider additional set of reputations. The possible outputs of trust with two different set of reputations are displayed in the second and third columns of **Table 2**, respectively. The example in the second column shows the case that the number of positive feedbacks is much less than that of negative feedbacks and the third column is an example that the numbers of both feedbacks are identical. Note that the resulting distributions of trustworthiness and untrustworthiness, as displayed in **Table 2**, mirror their distributions in the original set of reputations.

Table 2. The possible outputs of trust with two different set of reputations

Aggregation rules	ω_1^p ={0.20, 0.80}, ω_2^p ={0.30, 0.70}	ω_1^p ={0.30, 0.30}, ω_2^p ={0.50, 0.50}
	Trust ω^p	Trust ω^p
Ψ_1	{0.20, 0.70}	{0.30, 0.30}
Ψ_2	{0.30, 0.80}	{0.50, 0.50}
Ψ_3	{0.20, 0.80}	{0.30, 0.50}
Ψ_4	{0.30, 0.70}	{0.50, 0.30}
Ψ_5	{0.25, 0.75}	{0.40, 0.40}
Ψ_6	{0.06, 0.56}	{0.15, 0.15}
Ψ_7	{0.10, 0.90}	{0.21, 0.21}

Since the available feedbacks from multiple agent-groups in social networks are classified into positive, negative and neutral ones, the positive and negative feedbacks among them are adopted for the components of our trust model. However, these two values contradicting each other are still not enough to represent trust itself as degrees of belief on agent's truthfulness. From a pragmatic perspective, trust is required to be a precise value as a metric.

3.3 Average Trust

We define average trust as the center of gravity of the distribution of beliefs, i.e., the degrees of trustworthiness and untrustworthiness of an agent. The average trust $\hat{\omega}^p$ is given as

$$\hat{\omega}^p = \frac{T}{T+U} \tag{4}$$

taking into account both trustworthiness and untrustworthiness of an agent. The average trust, thus, represents the overall beliefs on agent's truthfulness or cooperativeness, and it translates the agent's trust into a specific value where $0 \le \hat{\omega}^p \le 1$. In the notion of average trust, the higher the average trust level of the agent, the higher the expectation that the agent will be truthful or cooperative in future interactions. The calculation of average trust using equation (4) gives social insight into the agent's trust.

Example 2. Given a set of reputations in the three agent-groups above, the average trusts are shown in **Table 3**.

Table 3. The average trust values in three example sets of reputations

Aggregation rules	$\omega_1^p = \{0.80, 0.10\}$, $\omega_2^p = \{0.70, 0.20\}$	$\omega_1^p = \{0.20, 0.80\}$, $\omega_2^p = \{0.30, 0.70\}$	$\omega_1^p = \{0.30, 0.30\}$, $\omega_2^p = \{0.50, 0.50\}$
	average trust $\hat{\omega}^p$		
Ψ_1	0.88	0.22	0.50
Ψ_2	0.80	0.27	0.50
Ψ_3	0.78	0.20	0.38
Ψ_4	0.89	0.30	0.63
Ψ_5	0.83	0.25	0.50
Ψ_6	0.97	0.10	0.50
Ψ_7	0.96	0.10	0.50

This example illustrates that the average trust provides a metric for the agent's overall truthfulness, which consists of trustworthiness and untrustworthiness. The simple aggregation rules, i.e., minimum, maximum, MinT and MaxU, MaxT and MinU, mean, and product, give a pretty representative trust value considering both trustworthiness and untrustworthiness, even though it is not clear which one is good for a particular setting. This may be the reason that these simple but surprisingly well applicable rules keep on being popular in any contexts [11]. The product rule and Dempster-Shafer theory highly rate the agent's average trust than the other simple rules. We attribute this sharp contrast between trustworthiness (refer to 0.97 and 0.96 in **Table 3**) and untrustworthiness (0.10 and 0.10 in **Table 3**) to their purely conjunctive operation with completely ignoring the degrees of disagreement or conflict.

4. Applying the Trust Model to Online Internet Transactions

We apply our trust mechanisms to online Internet transactions. Given the actual feedbacks of agent-groups in online multi-agent settings, we can convert the feedbacks into the agent's reputation, denote its trust as an aggregation of reputations, and we compute the average trust for a measurable belief on the agent's truthfulness. In this section, we pursue how the trust mechanisms are involved in the rational decision-making of buyers and sellers.

Suppose that there are sellers and buyers in online Internet settings. Let R be the contract price, s the quantitative size of the contract, $V(s)$ the buyer's benefit (or value) function, which reflects his/her satisfaction acquired by purchasing a number of commodities, and $C(s)$ be the seller's cost function, which indicates the cost to produce the amount of commodities.

Given the average trust of the buyer $\hat{\omega}^M$, the expected utility of the buyer is given by[4]

$$EU_M(s) = \hat{\omega}^M V(s) - R. \tag{5}$$

Given the average trust of the seller $\hat{\omega}^N$, and also, the expected utility of the seller is defined as

[4] Our notation follows [16].

$$EU_N(s) = \hat{\omega}^N R - C(s). \tag{6}$$

In equations (5) and (6), the average trust is interpreted as the overall beliefs in the buyer's and seller's truthfulness or cooperativeness, respectively. When the average trusts of the seller and buyer get higher further, their expected utilities also increase. The Nash equilibrium [16][17] in online transactions then provides a solution concept when the buyer and seller have no incentives in case of choosing other alternatives. The Nash bargaining solution is

$$\arg\ \max_R (\hat{\omega}^M V(s) - R)(\hat{\omega}^N R - C(s)) \tag{7}$$

so that the buyer and seller are beneficial to each other if they agree on their bargaining behavior. Note that equation (7) has a unique Nash equilibrium since an R can be determined given the average trusts of the buyer and seller, *V(s)* and *C(s)*, respectively.

To derive R given the Nash bargaining solution, as defined in (7), let us take the first derivative of equation (7) as follows:

$$\begin{aligned}
&\frac{d}{dR}(\hat{\omega}^M V(s) - R)(\hat{\omega}^N R - C(s)) = 0; \\
&\frac{d}{dR}(-\hat{\omega}^N R^2 + (\hat{\omega}^M \hat{\omega}^N V(S) + C(s))R - \hat{\omega}^M V(S)C(S)) = 0; \\
&\therefore R = \frac{\hat{\omega}^M \hat{\omega}^N V(s) + C(s)}{2\hat{\omega}^N}.
\end{aligned} \tag{8}$$

Thus, the contract price, R, that the buyer and seller agree on can be determined in a Nash equilibrium. Substituting the above into (5) and rearranging terms, we get

$$\begin{aligned}
EU_M(s) &= \hat{\omega}^M V(s) - R \\
&= \hat{\omega}^M V(s) - \left(\frac{\hat{\omega}^M \hat{\omega}^N V(s) + C(s)}{2\hat{\omega}^N}\right) \\
&= \left(\frac{\hat{\omega}^M \hat{\omega}^N V(s) - C(s)}{2\hat{\omega}^N}\right)
\end{aligned} \tag{9}$$

In a similar way, the expected utility of the seller is

$$\begin{aligned}
EU_N(s) &= \hat{\omega}^N R - C(s) \\
&= \hat{\omega}^N \left(\frac{\hat{\omega}^M \hat{\omega}^N V(s) + C(s)}{2\hat{\omega}^N}\right) - C(s) \\
&= \left(\frac{\hat{\omega}^M \hat{\omega}^N V(s) - C(s)}{2}\right)
\end{aligned} \tag{10}$$

Substituting (9) and (10) into the formula of (7), given the fact that the numerators of (9) and (10), i.e., $(\hat{\omega}^M \hat{\omega}^N V(s) - C(s))$, are identical, we observe that both buyer and seller make their maximum gains, when the numerator is maximized.

Example 3. Suppose that the buyer's benefit function *V(s)* is *48ln(2s)* and that the seller's cost function *C(s)* is s^2*-2s+3*, as usual.[5] When $\hat{\omega}^M = \hat{\omega}^N = 0.8$, the quantitative size of the contract *s* can be determined by

$$\frac{d}{ds}\left(\hat{\omega}^M \hat{\omega}^N V(s) - C(s)\right) = 0;$$
$$\frac{d}{ds}\left(0.8 \times 0.8 \times 48 \ln(2s) - (s^2 - 2s + 3)\right) = \left(-2s + 2 + 0.8 \times 0.8 \times 48 \times \frac{1}{s}\right) = 0;$$
$$\therefore s = 4.45.$$

That is, both buyer and seller maximize their expected utilities and, once the buyer's benefit function and the seller's cost function are decided, the quantitative size of the contract is computed as above. Thus, *s* = 4.45. The expected utilities of the buyer and the seller also can be calculated, and, in this case, we get $EU_M(s)$ = 33.28 and $EU_N(s)$ = 26.63 from equations (9) and (10). Consider now that the seller's average trust is low, say, $\hat{\omega}^N = 0.2$. Then, *s* = 2.52, and their expected utilities are $EU_M(s)$ = 20.28 and $EU_N(s)$ = 4.06.

We measure the overall amount of trades, the expected utilities of the seller and the buyer, and the contract price given the quantitative size of the contract, while their trust estimates are scaled from 0 to 1 with the interval of 0.01. The simulation results are depicted in **Fig. 1**, **Fig. 2**, **Fig. 3** and **Fig. 4**.

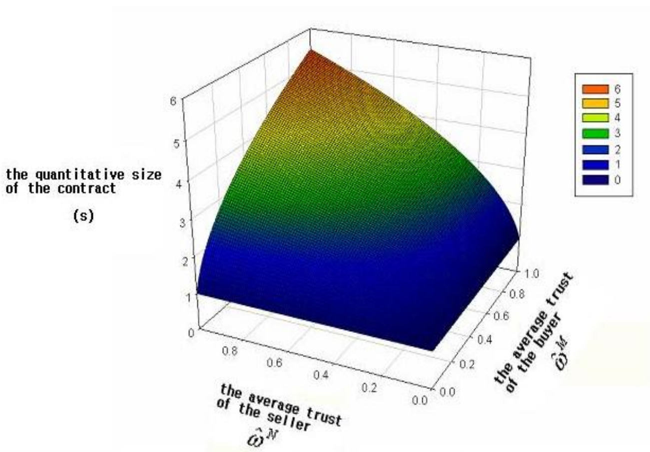

Fig. 1. The overall quantitative size of contract (s) given the buyer's and seller's average trust values.

[5] We assume that the buyer's benefit does not necessarily increase in proportion to the quantitative size of commodities while the seller's cost proportionally increases to produce a certain amount of commodities.

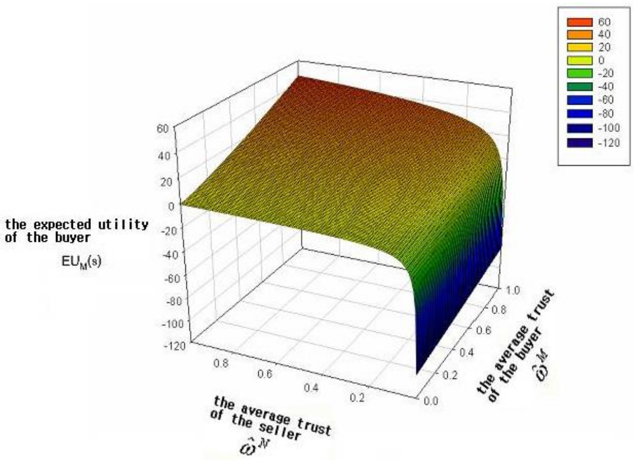

Fig. 2. The expected utilities of the buyer (M) given the buyer's and seller's average trust values.

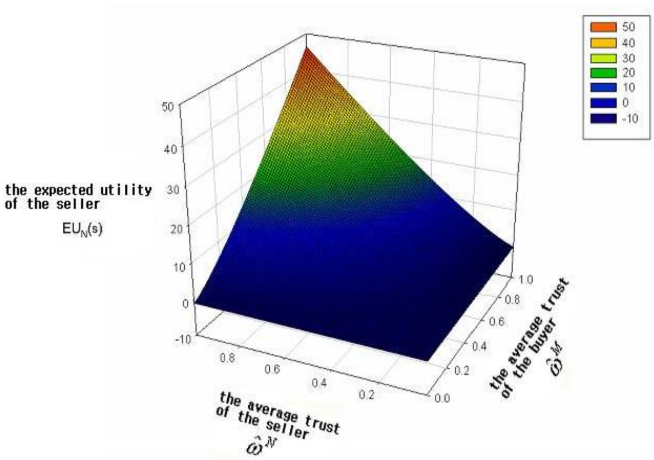

Fig. 3. The expected utilities of the seller (N) given the buyer's and seller's average trust values.

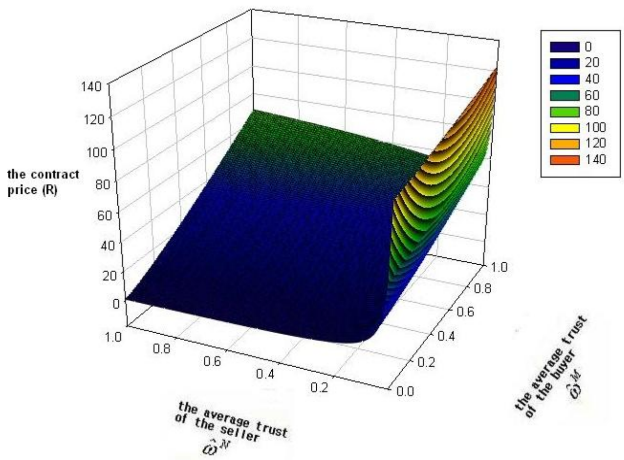

Fig. 4. The contract price (R) given the buyer's and seller's average trust values.

As calculated in Example 3, **Fig. 1**, **Fig. 2** and **Fig. 3** show the fact that both the overall quantitative size of contracts and the expected utilities of the buyer and seller are larger, when the average trust values of the agents are higher. As known in (9), the expected utility of the buyer sharply goes up, even if the average trust value of the seller is very small, i.e., about 0.2 (refer to **Fig. 2**). On the contrary, the expected utilities of the seller gradually respond to the change of both trust estimates, as is shown in **Fig. 3**. This is because both trust estimates only affect the buyer's benefit function in the numerator of (10). **Fig. 4** shows the contract price, as computed in (8), given a specific quantitative size of contract and specific average trust values of the buyer and seller. Due to the denominator of (8), when the average trust of the seller is close to 0, say, 0.01, the contract price is very high in **Fig. 4**.

5. Conclusion

The model of trust in social networks has been continuously studied for achieving safe and successful interactions. Our work contributes to achieving a computational model of trust as an aggregation of consensus associated with multiple agent-groups. We formulated reputation based on available feedbacks driven by social interactions, calculated trust among a set of reputations using aggregation rules, and represented average trust as a metric for the agent's truthfulness or cooperativeness. We have shown how our trust model can be calculated in a detailed example.

To show how the trust mechanisms are involved in the rational purchasing decision-making of interactive agents, our trust model has been applied to simulated online social networks. We have summarized our simulation results, which show the relationships among the mutual trust estimates of web-based users, their expected utilities and the amount of trades. When web-based users agree on their bargaining behavior, their trust estimates, their expected utilities and the amount of trades are maximized. We believe the computational trust model and its mechanism on online communities should be applicable to real online societies of multi-agent environments.

As part of our ongoing work, we are planning to provide a guideline as to which aggregation operator could be optimally selected given a social network. A tapestry of experiments will be executed on our test-bed, and the best aggregation operator at a specific scenario will be recommended through our experiments. In parallel, we are applying our trust model to online Internet e-markets. To this end, we are designing and developing a practical test-bed to evaluate various models of trust including our framework. Given the actual feedbacks of customers in online multi-agent settings, we will convert the feedbacks into the agent's reputation, denote its trust as a numerical aggregation of reputations, and pursue how trust affects the rational decision-making of buyers and sellers. We will benchmark the amount of interactions between the buyers and the sellers when they have higher trust values and/or lower trust values. The experiments that we are performing will also measure the global profits in a set of agent-groups employed with different trust values.

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