

An Improved Familiarity Measurement for Formalization of Trust in E-commerce Based Multiagent Systems

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Abstract

Familiarity between agents is often considered to be an important factor in determining the level of trust. In electronic marketplaces, trust is modeled, for instance, in order to allow buying agents to make effective selection of selling agents. In previous research, familiarity between two agents has been simply assumed to be the similarity between them, which is fixed for the two agents. We propose an improved familiarity measurement based on the exploration of factors that affect a human's feelings of familiarity and the mapping from those factors to the properties of agent societies. We examine the trust model in the context of a multiagent system within an e-commerce framework. We also carry out experiments to compare the stability of the system using the trust model with the improved familiarity measurement and that with the fixed familiarity values. Experimental results show that the stability of the system is increased by 33.47% through the improved familiarity measurement.

keywords: Trust, Familiarity, Multiagent Systems, E-commerce

1 Introduction

In the financial field, trust has always been a focus because greater trust is strongly related to better economic outcomes. Trust has often been bundled with familiarity to become a popular topic in the fields of psychology, sociology, and computer science. The correlation between familiarity and trust has been explored and proven by many researchers from different perspectives. Through an experimental investigation involving an investment game and an ultimatum game, Barr [2] demonstrated that people in resettled villages trust each other less than people in non-resettled villages due to the lack of familiarity. Other researchers have explored the relationship between trust, familiarity and

investment. It has been shown that individuals often prefer familiar investments, and fear change and the unfamiliar [4]. This phenomenon shows the effects of familiarity on financial decisions through trust. Huberman [12] summarized many research findings: Kilka and Weber discovered that business students are more optimistic about their home countries' stocks than other countries'; Coval and Moskowitz found that U.S. investment managers prefer local companies. After having listed many instances of investment in the familiar, he analyzed the geographic distribution of the shareholders of a Regional Bell Operating Company (RBOC) and related the amount of individuals' investment in the RBOCs to the typical U.S. household's net worth and stock holdings to offer the explanation of the home country bias: people simply prefer to invest in the familiar.

As the enterprise of electronic commerce becomes increasingly popular, one challenge that arises is to ensure that organizations participating in e-commerce have sufficient trust in order to bring their businesses on-line. The first step of undertaking the challenge is to study how trust can influence Internet users' decisions and how their trust on the organizations can be built. Towards this purpose, Gefen [10] studied familiarity and trust in the context of e-commerce based on survey data from 217 potential users of Amazon.com, an e-commerce site on the Internet. The results show that although trust and familiarity are different, trust is significantly affected by familiarity. Gefen also emphasized the importance of familiarity because it is a building block and a precondition of trust. Minsky [14] distinguished two kinds of trust, familiarity-based trust and regularity-based trust. Familiarity-based trust is the trust based on personal familiarity, whereas regularity-based trust is based on the recognition that the trusted party belongs to a class or a community. Although the focus of Minsky's work was regularity-based trust in e-commerce, he also concluded that familiarity-based trust and regularity-based trust are complementary and regularity-based trust often relies on

certain familiarity-based trust.

In order to assist both individual users and business organizations in conducting both B2B and B2C e-commerce, researchers in artificial intelligence have been designing intelligent agents to perform the tasks of buying or selling, on behalf of their human clients. While these agents assist in offloading the processing required by people in order to find the best business partnerships, it then becomes critical for these agents to make effective decisions. A new trust model was proposed to effectively formalize agents' trust in multiagent e-commerce systems (see Carter and Ghorbani [6]). The concept of trust was viewed as a combination of self-esteem, reputation, and familiarity. Trust was formalized through a concept graph map, which also indicates that the two major factors, reputation and self-esteem, are determined by roles based on the underlying values. Carter and Ghorbani proposed that the formalization of familiarity can contribute to the formalization of trust. However, familiarity was simply assumed to be the similarity of the underlying value-systems of the two individuals. On the other hand, Luhmann [13] defined familiarity as a complex understanding, which is often based on previous interactions, experiences, and learning of others.

In this paper, we explore a variety of human factors that affect the feeling of familiarity based on analysis done by many researchers in the fields of psychology and sociology. These factors are prior experience, repeated exposure, the level of processing, and the forgetting rate [18]. We build a hierarchy of all the factors, and map them to the properties of agent societies. We then propose a way of measuring the familiarity value between two agents and continuously updating the value based on those factors. Next we extend the formalization of trust through the improved familiarity measurement.

The trust model is examined within the context of a multiagent system operating in an e-commerce environment. In particular, we explore how a buyer can use this familiarity-based model of trust in order to make effective selection of selling agents with which to do business. We analyze the stability of the system. In our case, this is the ranking of selling agents performed by all buying agents reflecting their level of trust in those selling agents. A high stability implies that sellers will not change much in their ranking within the system. We carry out experiments to compare the stability of the system that uses the trust model with the improved familiarity measurement and that with the fixed familiarity value. Experimental results show that the stability of the system is increased by 33.47% through the application of the improved familiarity measurement. The higher stability is also explained by two phenomena: when buying agents rank selling agents, these sellers in the system can find their position in the trustworthiness ranking more quickly; and they will more likely retain correctly the ap-

propriate rankings. We will discuss the usefulness of system stability in Section 6.

The rest of the paper is organized as follows. Section 2 briefly explains the trust model. Section 3 describes in detail all the major factors affecting familiarity. The way of measuring and updating familiarity is proposed in Section 4. Section 5 discusses the simulation of the e-commerce based multiagent system that is used to objectively examine the trust model. Experimental results are presented and discussed in Section 6. Finally, the conclusions of the present study and future work are presented in Section 7.

2 The Trust Model

Carter and Ghorbani [6] have established a new model of trust formalization for agent societies with the primary goal of clarifying the concept of trust. This work is carried out based upon their previous research of formalizing reputation within the confines of an information sharing multiagent society [5]. The new model proposes that trust is a combination of self-esteem, reputation, and familiarity within a multiagent system context. The set of dependencies amongst those concepts are further discussed through the concept graph illustrated in Figure 1. The concept graph denotes that trust can be defined as being dependent on an agent's reputation. Reputation, in turn, is dependent on the roles that are used to define it, such as an assistant, a service provider, and a citizen. Roles act as a manifestation of values. Trust can also be defined as being indirectly dependent on values through self-esteem. Self-esteem acts as an assessment of the trustworthiness of an agent in its own trusting mechanism. Finally, as with people, trust between two agents is also dependent on familiarity between them.

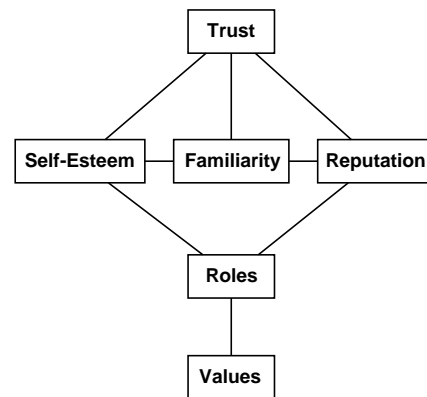


Figure 1. Concept Graph of Trust [6]

The concepts discussed above are linked to the idea of fulfillment. The model proposes that an agent's trust is ascribed based on the degree of role fulfillment assessed in accordance with the goals and ideals of other agents. In this

sense, it is similar to the Socio-Cognitive model of trust proposed by Castelfranchi and Falcone [7]. For example, they claim that in order for an agent a_i to trust another agent a_j , a_i must have some goal, and must believe that a_j is willing to do what a_i needs and is capable of doing so.

Different roles have been chosen based on the agent type. In a multiagent e-commerce system, an agent can be seen as an assistant, a service provider (seller), or a citizen (buyer). The values of responsibility, honesty, and independence are embedded directly within the role of an assistant. These values imply the following desirable qualities of any assistant: dependability, reliability, honesty, self-reliance, and self-sufficiency. Separately, an assistant agent can be an assistant to its owner (the user) or another agent. If an agent is an assistant to another agent, the values of ambition and helpfulness are useful to take into account in addition to those of any assistant. An agent that is seen as an assistant to an owner must value obedience on top of the other qualities of an assistant. A service provider must value capability and intellect. A citizen must value honesty, obedience, capability, and intellect in order to facilitate trust. These values enable a non-trivial update of trust. This is similar in spirit to the cognitive attribution process proposed by Falcone and Castelfranchi [9]. They claim that update of the trust agent a_i has of agent a_j from a_i 's direct experience with a_j should be based on not only the amount of a_j 's success and failure, but also other cognitive attributes, for instance, a_i 's reliance on a_j .

In order to formalize trust, the measurement of each role's degree of role fulfillment has been established [6]. This work extends the previous model of Carter and Ghorbani [5], which did not model familiarity. However, in this work, the familiarity between two agents is roughly the similarity between them based on the argument that familiarity is a result of similarity in the underlying value-systems of the two individuals. Similarity of two agents is measured as the Hamming distance of their value hierarchies, each of which is a vector of value importance. As an example, the vector $H = \{4, 3, 2, 1\}$ represents the importance of four predefined values. It indicates that the value corresponding to the fourth element is the most important while the element in the first position is the least important. The vector of value importance is fixed for each agent. Therefore, the similarity value of two agents is also fixed for them.

As stated in [13], familiarity should be a complex understanding, often based on previous interactions, experiences, and learning of others. To formalize familiarity and extend the formalization of trust, we further study familiarity based on our exploration of factors that affect human familiarity. We also map those factors to the properties of agent societies.

3 Factors Affecting Familiarity

Some factors to include in our model of familiarity are motivated by research on familiarity in the fields of psychology and sociology [17, 16, 15]. Yonelinas [17] reviewed 30 years of studies of two types of memories: recollection and familiarity. He examined the models and methods that have been developed to measure recollection and familiarity. The focus of his work was to review how differently each factor can affect recollection and familiarity. He concluded that there are some factors affecting familiarity, such as forgetting rate and level of processing. Whittlesea [16] carried out experiments based on human's memory of four-letter words. Although experimental results show that feelings of familiarity can be aroused in the absence of prior experience, he did point out that prior experience can produce feelings of familiarity. Experiments on recognizing people's faces were carried out by Moreland and Zajonc [15] to explore the relationship between familiarity, similarity and attraction. In this work, they defined familiarity in terms of actual frequency of exposing objects, which implies that repeated exposure can increase familiarity. In summary, the major factors affecting human's feelings of familiarity are prior experience, repeated exposure, level of processing, and forgetting rate. Exploration of each factor is further described separately as follows:

- **Prior Experience:** Prior experience produces feelings of familiarity [16]. The source of prior experience is not necessarily the object itself, but the meaning of it or an object which semantically relates to the current object. As also stated in [17], familiarity relies on memory of prior experience. For example, it arises when processing of an object is attributed to prior experience with the object or similar objects.
- **Repeated Exposure:** The methods used for experiments in [15] imply that repeated exposure will increase the feeling of familiarity. The repeated exposure in their experiments is represented as the frequency with which the same photograph of a person's face is shown.
- **Level of Processing:** The amount of familiarity that can be gained from processing is associated with the level of the processing [17]. Deep processing (processing the meaning) leads to greater increase in familiarity than shallow processing (processing the perceptual aspects). For example, the process of a word's meaning can increase familiarity more than that of judging whether the word is in upper or lower case.
- **Forgetting Rate:** Both immediate delays and long-term delays decrease familiarity [17]. As an example, the results of experiments on item recognition conducted

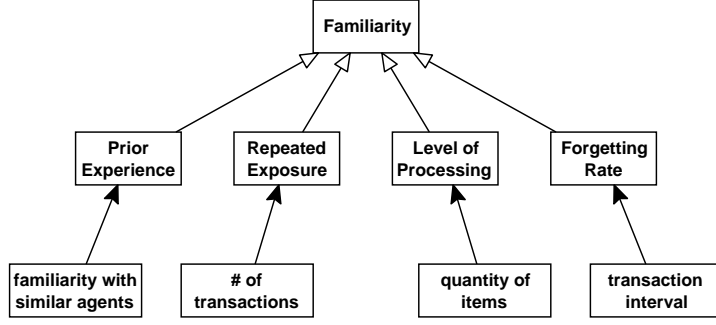


Figure 2. Mapping Human Factors to Properties of Agent Societies

by Hockley in [11] show that across 32 intervening items in a continuous recognition test, familiarity for single items decreases significantly.

3.1 Factors Hierarchy

As explored above, familiarity is affected by four major factors: prior experience, repeated exposure, level of processing, and forgetting rate. A mapping from those factors to properties of agent societies is shown in Figure 2.

For two agents in the agent society that have not encountered each other, one agent’s prior experience with another agent is based on its familiarity with other that are similar to the latter. Repeated exposure is represented by how many transactions have been established between the two agents. The feeling of familiarity will be increased after each transaction established by two agents. The more times agents interact with each other and establish transactions, the more familiar they will be with each other. Level of processing is determined by the quantity of items bought in each transaction. A greater number of items involved in the transaction implies a deeper level of processing, which will lead to a greater increase in familiarity. The forgetting rate is calculated based on the interval between the last transaction and the current transaction, and the character of the agent society. The longer the interval between the transactions of agents, the greater the decrease in the feeling of familiarity.

4 The Improved Familiarity Measurement

Having explored the factors affecting agents’ familiarity and mapped the factors to the properties of agent societies, we propose an improved familiarity measurement. The improved familiarity measurement consists of two stages. Before an agent a_i establishes the first transaction with another agent a_j , its prior experience with a_j is based on its initial familiarity value with a_j . The initial familiarity value a_i has with a_j is determined based on its familiarity with other agents that are similar to a_j . In the second stage, the famil-

ilarity value between these two agents will then be updated before each transaction. It will be decreased or increased based on three factors, including repeated exposure, level of processing, and forgetting rate.

4.1 Initializing the Familiarity Value

For an agent society A with n agents, $A = \{a_1, a_2, \dots, a_n\}$, let $F(a_i, a_j)$ and $S(a_i, a_j)$ represent the familiarity and similarity between agents a_i and a_j , respectively. Similarity between two agents is determined by the Hamming distance of their value hierarchies. If agent a_i has not encountered a_j before, its initial familiarity value with a_j can be determined by how much a_i is familiar with other agents that are similar to a_j . We believe that the agents that are more similar to a_j can affect a_i ’s feeling of familiarity with a_j more heavily. Thereby, we use a weighted average function to compute the initial familiarity value as follows:

$$F_0(a_i, a_j) = \frac{\sum_{k=1}^n F(a_i, a_k) S(a_j, a_k)^2}{\sqrt{\sum_{k=1}^n S(a_j, a_k)^2}} \quad (1)$$

where $k \neq i \neq j$, $F \in [0, 1]$, and $S \in [0, 1]$.

We believe that the familiarity value increases with the increase of experience following the trend of a logic function such as the one shown in Equation 2. The value of familiarity can be calculated from the experience that the agent a_i has with the agent a_j as follows:

$$F_c(a_i, a_j) = \frac{2}{1 + e^{-\lambda E_c(a_i, a_j)}} - 1, \quad (2)$$

where $F_c(a_i, a_j)$ and $E_c(a_i, a_j)$ represent the familiarity value and the experience value that the agent a_i has from the perspective of the agent a_j before the current, c , transaction, respectively. λ ($\lambda \in (0, 1]$) is a steepness rate to represent how fast familiarity will increase with the increase of experience. We used $\lambda = 1$ in our experiments.

The prior experience the agent a_i has with the agent a_j is associated with its initial familiarity value with a_j . According to Equation 2, the prior experience E_0 can be calculated as follows:

$$E_0(a_i, a_j) = -\frac{1}{\lambda} \ln\left(\frac{2}{F_0(a_i, a_j) + 1} - 1\right). \quad (3)$$

Equation 2 will be also used when updating familiarity from experience.

4.2 Updating the Familiarity Value

An agent's familiarity with another agent can be calculated from the agent's experience through the reverse of Equation 2. We first update the agent's prior experience. Since the familiarity value is affected by the previous level of processing and the forgetting rate, a simple formula for updating the agent's experience is as follows:

$$E_c(a_i, a_j) = E_p(a_i, a_j) + L_p(a_i, a_j) - G_p(a_i, a_j), \quad (4)$$

where $E_p(a_i, a_j)$ and $E_c(a_i, a_j)$ represent the experience values that agent a_i had with agent a_j before the previous and the current transactions, respectively. $L_p(a_i, a_j)$ is the level of processing of agents a_i and a_j during the previous transaction, and $G_p(a_i, a_j)$ represents the forgetting value between the previous and the transactions. The prior experience value of agent a_i , $E_0(a_i, a_j)$, can be determined by Equations 1 and 3.

Bahrack [1] observed students' learning of Spanish with different levels of training. He used a variety of criteria to score students' learning, such as number of Spanish courses taken. The scores increase exponentially with the increase in the level of training, which implies that the learning curve should be similar to an exponential curve. Learning is also affected by the previous experience that the agent has with a_j . Thus, the previous level of processing of the agents a_i and a_j can be calculated by:

$$L_p(a_i, a_j) = E_p(a_i, a_j)(1 - e^{-Q_p/l}), \quad (5)$$

where Q_p represents the quantity of the items in the previous transaction and l represents the learning coefficient. The value of l differs for different agent societies.

After the previous transaction, agent a_i started forgetting. The forgetting value is, of course, based on the experience that the agent a_i has with the agent a_j up to the moment when the transaction is completed. Thus, the forgetting value of agent a_i and agent a_j can be calculated as follows:

$$G_p(a_i, a_j) = E_p(a_i, a_j)(2 - e^{-Q_p/l})r_p, \quad (6)$$

where r_p is the forgetting rate for the previous transaction. As discovered by Ebbinghaus in 1885 [8], forgetting has an exponential nature. Thus, the forgetting rate can be roughly described by the following formula:

$$r_p = 1 - e^{-\Delta t_p/m}, \quad (7)$$

where m represents the memory coefficient. Although it slightly changes for different agents, m differs largely for different agent societies with different characteristics. Δt_p represents the time difference between the current transaction and the previous transaction of agents a_i and a_j .

Finally, the current experience that agent a_i has with agent a_j is updated as follows:

$$E_c(a_i, a_j) = E_p(a_i, a_j)(2 - e^{-Q_p/l})e^{-\Delta t_p/m} \quad (8)$$

4.3 An Example

Let's consider an example involving five agents $\{a_0, a_1, a_2, a_3, a_4\}$. Agent a_0 has not met agent a_1 before, but it has previously encountered the three other agents. We assume that the familiarity values that agent a_0 has with a_2 , a_3 and a_4 , and the similarity values between agent a_1 and the three agents are as follows:

$$F(a_0, a_2) = 0.7, \quad S(a_1, a_2) = 0.2;$$

$$F(a_0, a_3) = 0.4, \quad S(a_1, a_3) = 0.3;$$

$$F(a_0, a_4) = 0.2, \quad S(a_1, a_4) = 0.4;$$

The initial familiarity a_0 has with a_1 can be calculated by Equation 1 as follows:

$$F_0(a_0, a_1) = \frac{0.7 \times 0.2^2 + 0.4 \times 0.3^2 + 0.2 \times 0.4^2}{\sqrt{0.2^2 + 0.3^2 + 0.4^2}} = 0.18$$

In this example, λ is assumed to be 1. From the initial familiarity value, we can calculate prior experience a_0 has with a_1 using Equation 3 as follows:

$$E_0(a_0, a_1) = -\ln\left(\frac{2}{0.18 + 1} - 1\right) = 0.36$$

We assume that agent a_0 conducts a transaction with agent a_1 . In this transaction, they exchanged 3 items. We assume that the time interval between the first transaction and the second transaction is 10 days. We also assume that agent a_0 has the learning coefficient of 10 ($l = 10$) and the memory coefficient of 100 ($m = 100$). We can update the experience agent a_0 has with a_1 using Equation 8:

$$E_1(a_0, a_1) = 0.36 \times (2 - e^{-\frac{3}{10}})e^{-\frac{10}{100}} = 0.41$$

Finally, the current familiarity value a_0 has with a_1 can be calculated from Equation 2 as follows:

$$F_1(a_i, a_j) = \frac{2}{1 + e^{-0.41}} - 1 = 0.2$$

which indicates that the familiarity value has been increased up to the moment of the second transaction.

5 The E-commerce Based Multiagent System

The trust model with the improved familiarity measurement is now examined within the context of an e-commerce framework. The e-commerce based multiagent system (shown in Figure 3) is composed of buying (B) agents and selling (S) agents that wish to conduct business, and a market manager (denoted by a pentagon) and a mystery shopper (denoted with a cross symbol) agents.

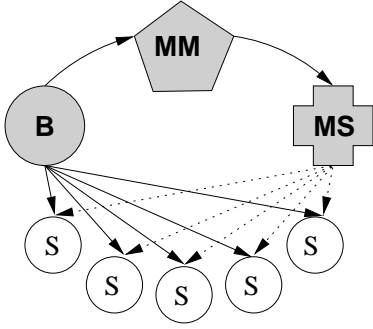


Figure 3. The E-commerce Based Multiagent System [6]

Selling agents set prices according to supply and demand functions and quote prices to customers. The selling agents know each other's true selling prices, but are not restricted to quoting the true prices. Each seller is assigned a reputation by a buyer based on the buyer's perception of the fulfillment of the values outlined in Section 2.

Buying agents in the agent society form the majority of the population of the multiagent system. They are responsible for fulfilling requests by end-users. End-users supply the quantity of items and the expectation of how much each will cost. Buying agents use both factors to construct measurements of expectation and cost-efficiency fulfillment. After the potential sellers are established, a buying agent must visit the selling agent that currently has highest rank on the list of desirable sellers. The expectation is that once a buyer has increased its familiarity with this desirable seller, the seller will remain highly ranked in the society. The rating of desirability for each seller s from the perspective of buyer b is decided by a shopping factor $\delta(b, s)$ as follows:

$$\delta(b, s) = \frac{T(b, s)}{d(b, s)} \quad (9)$$

$$d(b, s) = |x_b - x_s| + |y_b - y_s| \quad (10)$$

Here, $T(b, s)$ denotes the trustworthiness of the selling agent s from the perspective of buying agent b based on the trust model. $d(b, s)$ denotes the physical distance be-

tween seller s and buyer b . Carter and Ghorbani [6] calculate $T(b, s)$ as follows:

$$T(b, s) = w_1 F(b, s) + w_2 R_p(b, s) + w_3 R_s \quad (11)$$

where w_1 , w_2 and w_3 are weights of familiarity, personal reputation and social reputation values, respectively, and they sum to one. $F(b, s)$ represents the familiarity of the buying agent b with the selling agent s . We use the improved familiarity measurement to calculate $F(b, s)$. $R_p(b, s)$ denotes the personal reputation buyer b has of seller s . It is evaluated based on buyer b 's direct observations of the seller's degree of role fulfillment. R_s represents the seller's social reputation. It can be acquired by averaging the trust value each buyer has of the seller.

The buying agent engages in a transaction with the selling agent and receives a price quote for the item along with the quotes of fellow competitors. The agent considers the information it has received. Based on a suspicion value, an agent decides whether or not to trust the information provided by the current seller. The suspicion value is measured based on the seller's reputation variance [3]. If the seller's reputation is reduced to a significant degree, the agent will become suspicious of the information provided by the seller. The agent will then return to the request state and engages the next seller on the stack. Otherwise, the agent trusts the currently available information and does not need to visit any more sellers.

The market manager agent is responsible for overseeing the market and enforcing rules to curb macroeconomic behavior of the system. Buying agents that generate an unacceptably large suspicion, report their findings to the market manager agent. When the market manager's profile of a given seller generates enough internal suspicion about the seller, an undetectable mystery shopper is released into the environment to approach the seller. The seller is unable to recognize a mystery shopper. In the case of deceit, the mystery shopper will be lied to and the market manager's suspicions will be confirmed. In such a case, the market manager then reduces the social reputation of the selling agent by decreasing the value fulfillment of honesty. Such reductions take the form of interactions rather than speculations within a buying agent, as the buying agent can always trust the market manager.

6 Analysis of Stability

In the previous section, the design of the proposed simulation was presented. This section is devoted to the analysis of the stability of the simulated multiagent system that uses the trust model to model trust. The stability of the system is considered with respect to trustworthiness rankings. The simulation and analysis are based on the trust model introduced in this work using the values and formulas discussed

in [6]. The values held by the agents are those already outlined in Section 2. Both the two kinds of familiarity measurements, improved familiarity measurement and fixed familiarity value calculated by the similarity of two agents, are implemented and embedded in the trust model of the simulation. A comparison of the stability of the system with two kinds of familiarity measurements is presented as well. For later reference, two notions are defined as follows:

- **TMIFM**: the system using the trust model with the improved familiarity measurement to model trust.
- **TMFFV**: the system using the trust model with fixed familiarity values to model trust.

Within this work, stability is connected to the idea of ranking. Each selling agent maintains a certain social reputation within the system. These agents can be ranked in ascending order of social reputation. A sample result of ranking is given in Table 1.

Table 1. Sample Result of Ranking

| Day | Seller 1 | Seller 2 | ... | Seller m |
|-----|----------|----------|-----|----------|
| 1 | 1 | 5 | | 4 |
| 2 | 2 | 3 | | 4 |
| 3 | 1 | 6 | | 3 |
| ... | | | | |
| n | 3 | 5 | | 4 |

The ranking of sellers may shift on a daily basis as presented in Table 1. Stability refers to the degree of change in sellers ranking. A high stability implies that agents will not change much in their rankings. Due to the random nature of the simulation, descriptive statistics must be used to measure the stability in order to eliminate as much randomness as possible in the data. Stability is measured through an examination of the average variance of the selling agents' ranks on a daily basis, as calculated by the formula as follows:

$$\bar{v} = \frac{\sum_{i=1}^n v_i}{n}, \quad (12)$$

where \bar{v} represents the average variance of the selling agents' ranks and v_i represents the variance of ranking of agent i on a daily basis. Lower values of \bar{v} reflect higher stability.

The comparative stability of TMIFM and TMFFV is presented in Table 2 and Figure 4. On average, the average variance of TMIFM is 33.47% lower than that of TMFFV, which means that the former is more stable than the latter. Note that the average values in Table 2 are calculated after setting aside the highest and lowest values.

The result can be further illustrated by analyzing the change of rank of any given agent as shown in Figures 5

Table 2. Comparison of Stability of TMIFM and TMFFV

| Test # | TMIFM | TMFFV | Percentage Difference |
|---------|-------|-------|-----------------------|
| 1 | 3.92 | 5.77 | 32.06% |
| 2 | 5.61 | 7.91 | 29.08% |
| 3 | 6.11 | 10.12 | 39.62% |
| 4 | 5.36 | 8.62 | 37.82% |
| 5 | 4.00 | 4.96 | 19.35% |
| 6 | 3.94 | 5.61 | 29.77% |
| 7 | 4.39 | 7.75 | 43.35% |
| 8 | 5.11 | 9.51 | 46.27% |
| 9 | 4.47 | 6.10 | 26.72% |
| 10 | 6.35 | 7.00 | 9.29% |
| Average | 4.73 | 7.11 | 33.47% |

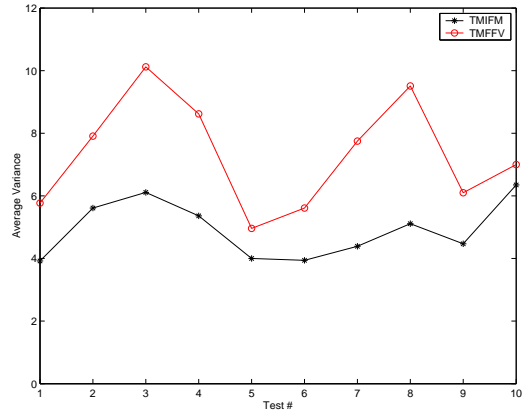


Figure 4. Comparison of Stability of TMIFM and TMFFV

and 6. From the two figures, it is obvious that the variance of the rank in TMIFM is lower than that in TMFFV. Therefore, TMIFM is more stable than TMFFV.

Experimental results show that the system that uses the trust model with the improved familiarity measurement has higher stability. The reason for this can be explained by analyzing two phenomena in both of the two systems, TMIFM and TMFFV. One phenomenon is that agents are pushed faster to their correct position in trustworthiness in TMIFM compared with TMFFV, which can be seen in Figures 5 and 6. The agent in TMIFM nearly reaches the average line earlier (approximately on day 25) than in TMFFV (approximately on day 40). This happens because the improved familiarity measurement increases the speed of pushing the agent to its preferred position. Figure 7 illustrates how the rank of an agent changes with the change in the number of transactions. From this figure, it is obvious that ranks

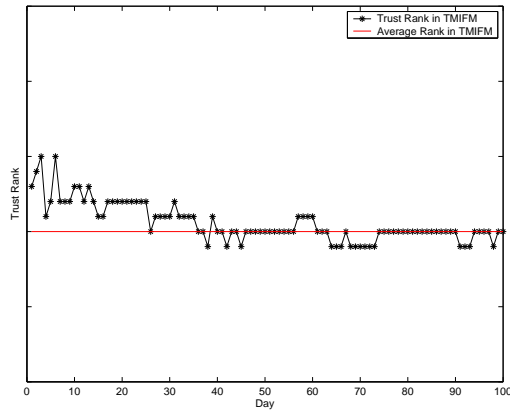


Figure 5. Change of Rank of Any Given Agent in TMIFM

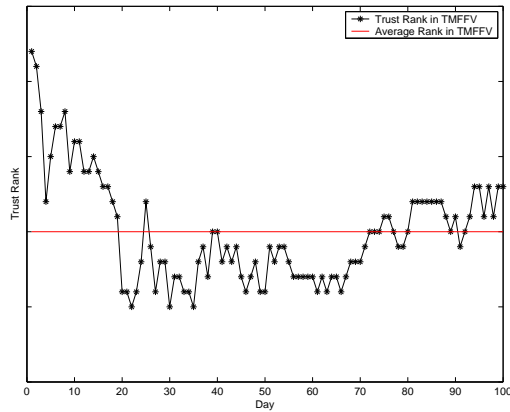


Figure 6. Change of Rank of Any Given Agent in TMFFV

of agents in TMIFM increase/decrease more rapidly than they do in TMFFV. Another phenomenon is that once agents have been given a position, they remain close to that position. This phenomenon can also be seen in Figures 5 and 6. From day 25 on, the rank of the agent in TMIFM stays close to the average line, whereas the rank of the agent in TMFFV keeps changing. This phenomenon is also explainable. The selling agents with higher/lower rank have more/less possibility of being selected to establish transactions with buying agents in both TMIFM and TMFFV. As pointed out, the ranks of agents in TMIFM increase/decrease more rapidly than in TMFFV. Consequently, the selling agents with higher rank and the ones with lower rank are pushed further in TMIFM than in TMFFV. Therefore, both the selling agents with higher rank and those with lower rank will more likely stay in their preferred positions in TMIFM.

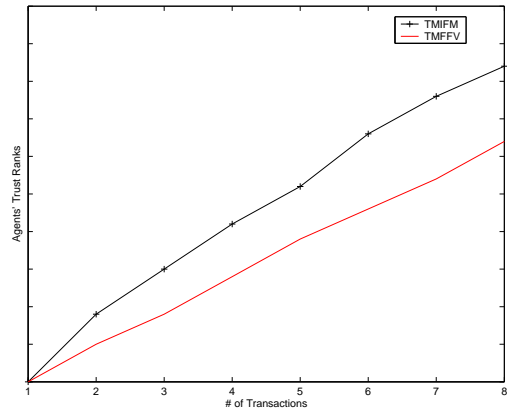


Figure 7. Comparison of Changing Speed of Agents' Trust Rankings

The e-commerce based multiagent system using the trust model with the improved familiarity measurement has higher stability. Buying agents in this system first of all select the most trustworthy selling agents to do business with. The familiarity buyers have with these desirable sellers will also be increased according to our familiarity measurement, which will increase their trustworthiness. At the same time, the untrustworthy selling agents will have less chance to be selected by buyers. The familiarity buyers have with these undesirable agents will also decrease because of forgetting, which will decrease their trustworthiness. As a result, the gap between trustworthy and untrustworthy selling agents will be enlarged. In brief, the multiagent system that uses the trust model with the improved familiarity measurement remains stable and keeps the most trustworthy selling agents on the top of the ranking list. Therefore, it is able to assist buyers in selecting the most trustworthy selling agents to do business with.

7 Conclusions and Future Work

We proposed the improved familiarity measurement by exploring the factors mainly affecting familiarity. The four factors included in our model are prior experience, repeated exposure, level of processing, and forgetting rate. Those human factors were mapped to the properties of agent societies. Note that these factors are motivated by psychological research and as such should provide a good basis for satisfying human users employing agents who model familiarity in this way. We then devised a convenient way to measure and update familiarity value. The improved familiarity measurement has been integrated into a new trust model. The trust model with the improved familiarity measurement has been examined within the context of the e-commerce frame-

work. Different experiments were carried out to compare the stability of the system that uses the trust model with the improved familiarity measurement and that exploited the fixed familiarity value. Experimental results show that the stability has been increased by 33.47% through the improved familiarity measurement.

In multiagent e-commerce systems, selling agents may attempt to raise prices in order to maximize profits. In future work, we will examine how the trust model with the improved familiarity measurement can effectively cope with such dishonest behavior. The effectiveness of the model can be measured by how much the acceleration of inflation can be prevented. The inflation rate can be determined by net aggregate demand and net aggregate supply.

Furthermore, scalability of a trust model is also crucial. We will conduct experiments to analyze the scalability of the trust model with the improved familiarity measurement over changes in the agent population. We will examine how changes in the agent population will affect stability of the system that uses the trust model. We are encouraged by results presented in [6] that prove the model of Carter and Ghorbani to be scalable over changes in agent population. Our model is an extension of this one, with an improved familiarity measurement. In addition, we know that the improved familiarity measurement is linear in the sense that it updates agents' familiarity values before each transaction. Therefore, our model should also scale well.

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