Increasing Stability of Value-Centric Trust Model through Improved Familiarity Measurement

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Abstract. The relationship between trust and familiarity has been clarified through a value-centric trust model. Formalization of familiarity contributes to formalization of trust through the trust model. However, familiarity was assumed to be the similarity of values (fixed for two agents), and stability of the trust model was relatively low. To increase the stability, we propose an improved familiarity measurement based on the exploration of factors that affect human familiarity, and the mapping from those factors to the properties of agent societies.
The trust model is examined within the context of a multiagent system (MAS) based on an e-commerce framework. Experiments are also carried out to compare the stability of the trust model with the improved familiarity measurement and with the fixed familiarity value. It is observed that the stability is increased by 33.47% through the improved familiarity measurement.

Introduction

In the financial field, trust has always been a focus because greater trust is strongly related to better economic outcomes. Trust has always 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 proved by many researchers from different perspectives. Through an experimental investigation involving an investment game and an ultimatum game, Barr [1] demonstrated that people in resettled villages trust each other less than people in non-resettled villages due to lack of familiarity. Many other researchers explored the relationship between trust, familiarity and investment. Individuals prefer familiar investments, and fear change and the unfamiliar [2]. This phenomenon shows the effects of familiarity on financial decisions through trust. Huberman [3] 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.

The relationship between trust and familiarity has been further clarified through the value-centric trust model proposed by Carter and Ghorbani [4, 5]. Many definitions of trust have been also summarized from different perspectives, and properties of trust have also been explored. The concept of trust has been clarified by the new model of trust: trust is a combination of self-esteem, reputation, and familiarity. Trust has also been formalized through a concept graph map, which also indicates that the two major ingredients, reputation and self-esteem, are determined by roles based on underlying values, the foundation of trust. As also pointed out, trust is multidimensional in that it can be facilitated through familiarity. Therefore, formalization of familiarity can contribute to the formalization of trust. However, familiarity was assumed to be the similarity of values based on the argument that familiarity between two agents is a result of similarity in the underlying value-systems of the two individuals. The familiarity value is then determined by the Hamming distance of agent value hierarchies and is fixed for given two agents. In consequence, stability of the trust model is relatively low, which implies that the ranks of trustworthiness of a given agent do not remain close. However, people in nature prefer relatively stable societies.

To increase stability of the trust model, we propose an improved familiarity measurement by exploring a variety of human factors that affect the feeling of familiarity based on analysis done by many researchers' work in the fields of psychology and sociology. These factors are prior experience, repeated exposure, level of processing, study duration, and forgetting rate [6]. By building the hierarchy of all the factors, we map them to the properties of agent societies. A way of measuring familiarity value and continuously updating its value based on those factors will be proposed as well.

The rest of the paper is organized as follows. Section 1 briefly explains the value-centric trust model. Section 2 describes in detail all the five major factors affecting familiarity. The way of measuring and updating familiarity is proposed in Section 3. Section 4 discusses a validation model and a simulation that is used to objectively test the stability of the trust model. Experimental results are presented and discussed in Section 5. Finally, the conclusions of the present study are presented in Section 6.

1 Value-Centric Trust Model

Carter and Ghorbani have established a new model of trust for agent societies with a primary goal of clarification of 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 [7]. The new model proposes that trust is a combination of self-esteem, reputation, and familiarity within a MAS context. The set of dependencies amongst those concepts are further discussed through a concept graph. 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. Roles act as a manifestation of values. Trust is already defined as being directly dependent on values through reputation; it is believed that trust can be directly dependent on values as well. 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.

The concepts discussed above are linked to the idea of fulfillment. The model proposes that an agent's trust is based on fulfillment of roles, goals, and ideals of other agents. Different roles have been chosen based on the agent type. An agent can be seen as an assistant, a service provider, or a citizen. 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, honest, self-reliant, and self-sufficient. 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 have 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.

In order to formalize trust, the measurement of each role's degree of role fulfillment has been established [7, 4, 5]. Within the context of Carter and Ghorbani's previous work [7], trust was exercised based solely on reputation. But it failed to address important aspects of familiarity between two agents. Later, they have taken into account the familiarity when formalizing the trust [4, 5]. However, in their work, the familiarity was roughly the similarity of values based on the argument that familiarity between two agents is a result of similarity in the underlying value-systems of the two individuals. It is fixed for any two agents because of the fixed values of these two agents. In consequence, stability of the trust model is relatively low, which implies that agents will change much in their rankings.

To increase the stability, we propose an improved familiarity measurement based on the exploration of factors that affect human familiarity, and the mapping from those factors to the properties of agent societies.

2 Factors Affecting Familiarity

Human psychological factors affecting familiarity have to be found in order to measure familiarity within virtual and agent societies. As discovered by many researchers, the major factors include prior experience, repeated exposure, level of processing, study duration, and forgetting rate. A mapping from the human factors to the properties of agent societies will be clarified as well.

2.1 Exploration of Factors

A review of 30 years of research is given for the purpose of distinguishing recollection and familiarity [8]. Although aging does not significantly affect familiarity because familiarity is different from recollection, some factors discovered in the review are empirical findings, such as study duration, forgetting rates, level of processing and so on. Perceptual matching is one factor mentioned in [8]. Changing the modalities of an object leads to decrease in familiarity. However, the relationship between familiarity and implicit memory is also mentioned in [8]. A lot of research shows that familiarity is functionally dissociable from performance on perceptual implicit memory tasks. Therefore, we do not take changes made to agents into account. Whittlesea [9] suggested that feelings of familiarity can be aroused even without prior experience if the perceptual processing of the stimulus is fluent. However, we are not interested in the fluency of the processing of the stimulus as long as we believe that the understanding or learning of services provided by agents is not fluent. On the other hand, Whittlesea did point out that prior experience of a stimulus can produce the feeling of familiarity. Two experiments were carried out in [10] to explore the relationship between familiarity and similarity. Note that the factors of properties of different objects that will affect familiarity are not included because only different levels of familiarity with the (roughly) same object is analyzed in our work. However, familiarity with similar agents does affect familiarity with the current agent. This characteristic will be used to calculate the prior experience with an agent. Exploration of each factor is further described separately as follows.

Prior experience produces feelings of familiarity. 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. According to [10], similarity has an effect on the feeling of familiarity as well. Prior experience is based on familiarity with similar agents, of course, and will have an effect on the feeling of familiarity.

The experiments carried out in [10] show that *repeated exposure* will affect the feeling of familiarity. The feeling of familiarity will increase 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 associated with how much familiarity can be gained [8]. Deep processing (processing the meaning) leads to greater increase in familiarity than shallow processing (processing the perceptual aspects). Deep processing and shallow processing produce different feelings of familiarity. In our work, we treat the difference as the number of widgets that have been involved in the current transaction.

An increase in *study duration* leads to corresponding increases in familiarity [8]. In our work, study duration is not taken into account because the transaction time is not a main concern in the e-commerce framework for the purpose of formalizing trust.

Both immediate delays and long-term delays decrease familiarity. *Forgetting rate* is determined by the interval between two times of consecutive transactions between two agents. The longer the interval between the transactions, the greater the decrease in the feeling of familiarity.

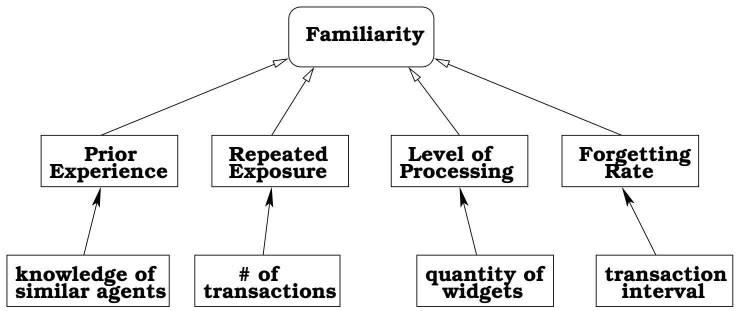

Fig. 1. Human Factors ⇒ Properties of Agent Societies

2.2 Factors Hierarchy

As explored above, familiarity is affected by five major factors: prior experience, repeated exposure, level of processing, study duration, and forgetting rate. A mapping from those factors to properties of agent societies is shown in Fig. 1.

Prior experience is determined by knowledge of similar agents in the agent society. Repeated exposure is represented by how many transactions are established between the two agents. Level of processing is determined by the quantity of widgets in each transaction. Forgetting rate is calculated by the interval between the last transaction and the current transaction, and the character of the agent society. Note that study duration is not included in the hierarchy because the transaction time is not relatively important in agent societies.

3 Measuring Familiarity

Before an agent establishes the first transaction with another agent, its familiarity value will be initialized based on its prior experience with similar agents. The familiarity value between these two agents will be updated before each transaction. It will be decreased or increased based on three factors, including repeated exposure, level of processing, and forgetting rate.

3.1 Initializing Familiarity Value

Prior experience is determined by how much experience the agent has with similar agents. For an agent society A with n agents, $A = \{a_1, a_2, ..., a_n\}$, 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. The initial familiarity value that the agent a_i has with the agent a_j can be calculated through the formula as follows:

$$F_0(a_i, a_j) = \max_{k=1}^{n} F(a_j, a_k) S(a_i, a_k) \quad (k \neq i \neq j, F \in [0,1], S \in [0,1]) \tag{1}$$

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

$$F_c(a_i, a_j) = \frac{2}{1 + e^{-K_c(a_i, a_j)}} - 1, \tag{2}$$

where $F_c(a_i, a_j)$ and $K_c(a_i, a_j)$ represent the familiarity value and the knowledge value that the agent a_i has from the perspective of the agent a_j before the current, c, transaction, respectively. Therefore, the prior knowledge K_0 can be calculated as follows:

$$K_0(a_i, a_j) = -\ln\left(\frac{2}{F_0(a_i, a_j) + 1} - 1\right). \tag{3}$$

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

3.2 Updating Familiarity from Knowledge

Since the familiarity value is affected by the previous level of processing and the forgetting rate, and it is determined by the agent's knowledge, a simple formula for updating the agent's knowledge is as follows:

$$K_c(a_i, a_j) = K_p(a_i, a_j) + L_p(a_i, a_j) - R_p(a_i, a_j), \tag{4}$$

where $K_p(a_i, a_j)$ and $K_c(a_i, a_j)$ represent the knowledge values that agent a_i had about agent a_j before and after the previous transaction, respectively. $L_p(a_i, a_j)$ is the level of processing of agents a_i and a_j during the previous transaction, and $R_p(a_i, a_j)$ represents the forgetting value since the previous transaction. The initial knowledge value of agent a_i, $K_0(a_i, a_j)$, can be determined by Equations 1 and 3.

According to Bahrick's work [11], the learning curve is similar to an exponential curve. It is affected by the pre-knowledge that the agent has. Thus, the previous level of processing of the agents a_i and a_j is calculated by:

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

where Q_p represents the quantity of widgets 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 knowledge that the agent a_i has about 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:

$$R_p(a_i, a_j) = K_p(a_i, a_j)(2 - e^{-Q_p/l})r_p, \tag{6}$$

where r_p is the forgetting rate for the previous transaction. As discovered by Hermann Ebbinghaus in 1885 [12], forgetting has an exponential nature. Thus, the forgetting rate can be roughly described by the following formula:

$$r_p = 1 - e^{-\triangle t_p/m}, \tag{7}$$

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

Finally, the current knowledge that agent a_i has about agent a_j is calculated as follows:

$$K_c(a_i, a_j) = K_p(a_i, a_j)(2 - e^{-Q_p/l})e^{-\triangle t_p/m} \tag{8}$$

4 Validation Model

The value-centric trust model with the improved familiarity measurement is examined and its stability is evaluated within the context of an e-commerce framework. In the validation model, the e-commerce based multiagent system (shown in Fig. 2) is composed of buying (B) agents and selling (S) agents that wish to conduct business, and market manager (denoted by the pentagon) and mystery shopper (denoted as the cross symbol) agents.

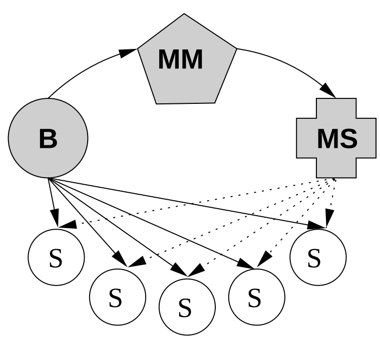

Fig. 2. The E-commerce based Multiagent System

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 1.

Buying agents in the agent society form the majority of the MAS. They are responsible for fulfilling requests by end-users. End-users supply the quantity of widgets 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 is currently highest on the stack of desirable sellers. The rating of desirability for each seller s from the perspective of buyer b is decided by shopping factor δ_s^b as follows:

$$\delta_s^b = \frac{T_s^b}{d(s,b)} \tag{9}$$

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

Here, T_s^b denotes the trustworthiness of the selling agent s from the perspective of buying agent b based on the proposed model of trust. $d(s,b)$ denotes the physical distance between seller s and buyer b. T_s^b is calculated as follows:

$$T_s^b = w_1 F_s^b + w_2 R_s, \tag{11}$$

where F_s^b represents the familiarity of the buying agent b with the selling agent s, R_s denotes the reputation of seller s based on the trust model, and w_1 and w_2 are weights of familiarity value and reputation value, respectively.

The buying agent engages in a transaction with the selling agent and receives a price quote for the widget along with the quotes of fellow competitors. The agent considers the information it has received. Based on a generated suspicion value, an agent decides whether or not to trust the information provided by the current seller. If the agent is suspicious of the information, the agent returns 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. Hopefully, 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.

5 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 trust model within the proposed simulation. The stability of the model is considered with respect to trustworthiness ranking. The simulation and analysis are based on the trust model introduced in this work using the values and formulas discussed in [4, 5]. The values held by the agents are those already outlined in Section 1. 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 trust model with two kinds of familiarity measurements is presented as well. For later use, two notions are defined as follows:

- **TMIFM**: the trust model with improved familiarity measurement.
- **TMFFV**: the trust model with fixed familiarity value.

Within this work, stability is connected to the idea of ranking. Each selling agent maintains a certain reputation within the MAS. These agents can be ranked in ascending order of social reputation. The social reputation can be acquired by averaging the reputation of each seller by each buyer. 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. The stability refers to the degree of change of rankings of sellers. A high stability implies that agents will not change much in their shift in 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:

$$\overline{v} = \frac{\sum_{i=1}^{m} v_i}{m}, \tag{12}$$

where $\overline{v}$ 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 $\overline{v}$ reflects higher stability.

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%

The comparative stability of TMIFM and TMFFV is presented in Table 2 and Fig. 3. 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.

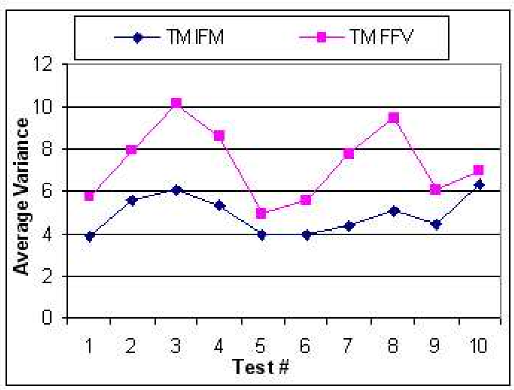

Fig. 3. Stability of TMIFM and TMFFV

The result can be further illustrated by analyzing the change of rank of any given agent as shown in Fig. 4. From this figure, it is obvious that the variance of the rank produced by TMIFM is lower than that produced by TMFFV. Therefore, TMIFM is more stable than TMFFV.

Experimental results show that 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 trust models, TMIFM and TMFFV. One phenomenon is that agents are pushed faster to the right spot that they

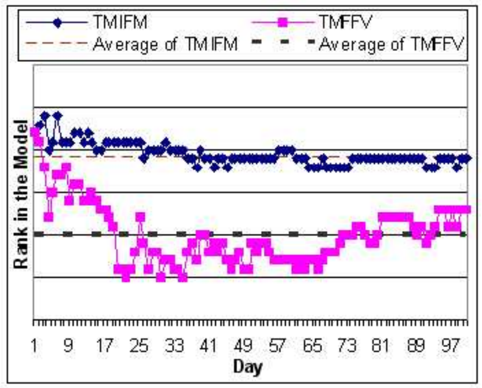

Fig. 4. Change of Rank of Any Given Agent

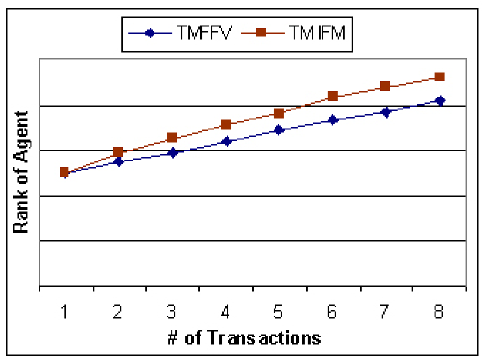

Fig. 5. Comparison of Changing Speed of Rank

should be on in TMIFM than in TMFFV, which can be seen from Fig. 4. The agent in TMIFM nearly reaches the average line earlier (approximately on day 15) than in TMFFV (approximately on day 40). This happens because the improved familiarity measurement increases the speed of pushing the agent to the right spot. Fig. 5 illustrates how the rank of an agent changes with the change in the number of transactions. From this figure, it is obvious that ranks of agents in TMIFM increase/decrease more rapidly than they do in TMFFV. Another phenomenon is that once agents have been given a spot, they remain close to that spot. This phenomenon can also be seen in Fig. 4. 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 on their right spots in TMIFM.

6 Conclusions

We proposed the improved familiarity measurement by exploring the factors mainly affecting familiarity. The five factors include prior experience, repeated exposure, level of processing, study duration, and forgetting rate. Those human factors were mapped to the properties of agent societies. We then devised a convenient way to measure and update familiarity value. The improved familiarity measurement has been integrated into the value-centric model. The trust model with the improved familiarity measurement has been examined within the context of the e-commerce framework. Experiments were carried out to compare the stability of the trust model with the improved familiarity measurement and with the fixed familiarity value. Experimental results show that the stability has been increased by 33.47% through the improved familiarity measurement.

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