

# A Framework for Trust Modeling in Multiagent Electronic Marketplaces with Buying Advisors to Consider Varying Seller Behavior and the Limiting of Seller Bids

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In this article, we present a framework of use in electronic marketplaces that allows buying agents to model the trustworthiness of selling agents in an effective way, making use of seller ratings provided by other buying agents known as advisors. The trustworthiness of the advisors is also modeled, using an approach that combines both personal and public knowledge and allows the relative weighting to be adjusted over time. Through a series of experiments that simulate e-marketplaces, including ones where sellers may vary their behavior over time, we are able to demonstrate that our proposed framework delivers effective seller recommendations to buyers, resulting in important buyer profit. We also propose limiting seller bids as a method for promoting seller honesty, thus facilitating successful selection of sellers by buyers, and demonstrate the value of this approach through experimental results. Overall, this research is focused on the technological aspects of electronic commerce and specifically on technology that would be used to manage trust.

Categories and Subject Descriptors: I.2.11 [**Distributed Artificial Intelligence**]: Intelligent agents

General Terms: Algorithms

Additional Key Words and Phrases: Multiagent systems, trust modeling, electronic commerce applications, social networks

## ACM Reference Format:

Zhang, J. and Cohen, R. 2013. A framework for trust modeling in multiagent electronic marketplaces with buying advisors to consider varying seller behavior and the limiting of seller bids. *ACM Trans. Intell. Syst. Technol.* 4, 2, Article 24 (March 2013), 22 pages.

DOI = 10.1145/2438653.2438659 <http://doi.acm.org/10.1145/2438653.2438659>

## 1. INTRODUCTION

For the enterprise of electronic commerce, where buyers and sellers meet online in order to form partnerships, the value of representing buyers and sellers with intelligent agents has been explored by several researchers (e.g., Jennings [2001], Tran and Cohen [2004]). Intelligent selling agents can learn about the behavior of the buyers in the marketplace, in order to make effective sales. Perhaps more importantly, intelligent buying agents can model the sellers, in order to help their users to avoid untrustworthy business partners.

Buying agents are tasked with recommending sellers to their users. In order for these recommendations to be effective when the buyers have not had much experience

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© 2013 ACM 2157-6904/2013/03-ART24 \$15.00

DOI 10.1145/2438653.2438659 <http://doi.acm.org/10.1145/2438653.2438659>

in the marketplace, it then becomes beneficial to leverage a social network of buyers who do have knowledge of the sellers under consideration.

Our research is focused on the modeling of trust, including techniques for detecting and coping with malicious agents. In particular, we propose a method for constructing a social network of advisors that focuses on modeling trustworthiness according to both private and public reputation. Only the most trustworthy agents are kept as advisors. Included is an important process of retaining only the most recent ratings provided by an advisor within each specific time window, in order to deflect the behavior of advisors possibly presenting a large number of malicious reports. Advisors may be providing unfairly high ratings to promote the seller (“ballot stuffing” [Dellarocas 2000]) or unfairly low ratings to drive a seller out of the marketplace (“bad-mouthing” [Dellarocas 2000]).

We develop as well a model for determining the trustworthiness of sellers, where the most trustworthy sellers are then recommended to the buyer. This model retains the design of combining private and public reputation modeling and, in contrast with the models of other researchers, leverages time windowing in order to cope with varying agent behavior. The ultimate selection of sellers by a buyer is conducted within a marketplace operated by a central server, where we introduce a technique where the buyer limits the number of seller bids that will be considered. As will be discussed, this becomes an important element to promote honesty amongst sellers.

We are able to demonstrate the robustness of our particular approach through experiments of simulated marketplaces populated by buying and selling agents. Our results show that buyers making use of advisors, modeled according to our proposed methods, gain more profit and that this can be sustained even when sellers vary their behavior; and failing to limit seller bids exposes buyers to more dishonesty. In addition, we are able to show that our proposed method for modeling trustworthiness of advisors has certain advantages over competing approaches that employ the same probabilistic reasoning as our model but that do not consider sufficiently well the combination of public and private trustworthiness and varying agent behavior. As a result, we offer a valuable framework promoting effective recommendations with a social network of buyers, for applications of e-commerce.

## 2. RELATED WORK

A growing number of researchers in artificial intelligence have been studying how to model the trustworthiness of selling agents in multiagent-based electronic marketplaces, in an effort to enable buying agents to make effective recommendations of selling agents to be considered by their users [Ramchurn et al. 2004]. For example, Tran and Cohen [2004] have buying agents use reinforcement learning to determine the trustworthiness of the sellers, after the true value of delivered goods is evaluated and compared to the buying agent’s expected value for the goods. Selling agents can be classified as untrustworthy if their reputation values fall below a certain threshold and buying agents can try to recommend the trustworthy selling agent with the highest expected value for the goods to their users. The work of Debenham and Sierra Debenham and Sierra [2008] builds a map between sellers’ behavior and trust. Sellers’ behavior is obtained from buyers’ direct observation that the enactment of commitments will be in-line with what was promised by the sellers. These approaches both rely only on buyers’ personal experience with sellers. However, a (new) buyer may not have much personal experience with some sellers.

In modeling the trustworthiness of sellers in e-marketplaces, the value of allowing buyers to seek advice from other buyers has been promoted first of all by researchers in economics and sociology. Horner [2002] points out that in order to sustain high-quality equilibrium, the honest sellers have to be rewarded by a widening of the buyer base. To widen the buyer base, it is required that potential buyers should be able to recognize

which sellers are reputable. This in turn requires that buyers have reliable information about a seller's reputation, either through direct evidence of a seller's popularity or indirectly through the advice of acquaintances. Rob and Fishman [2005] describe a model where buyers are allowed to ask advice about sellers from other buyers (advisors). In this setting, they prove that there exists a reputation equilibrium, which indicates that sellers have incentives to produce high-quality products to attract more buyers over time. In addition, Kim [1998] and Calzolari and Spagnolo [2006] show that if buyers limit the number of competitors, those sellers will tend to provide acceptable quality of goods, to enhance their reputation and earn future profit. In all, this research motivates our decision to keep sellers honest through the limiting of seller bids in the marketplace, in our environment where other buyers are acting as advisors.

The use of a social network of advisors to assist buyers in selecting sellers has also been explored by artificial intelligence researchers. One challenge that arises in this environment is coping with possible deceptive or unreliable ratings provided by advisors. The Beta Reputation System (BRS) of Whitby et al. [2005] employs a probability density function to estimate the reputation of a selling agent by propagating ratings provided by multiple advisors. They filter out those ratings that are not in the majority amongst other ones by using the iterated filtering approach. More specifically, feedback provided by each advisor consists of ratings supporting both good reputation and bad reputation of a seller, and is represented by a beta distribution. If the cumulated reputation of the seller falls between the lower and upper boundaries of feedback, this feedback will be considered as fair feedback. However, the iterated filtering approach is only effective when a significant majority of the ratings are fair. TRAVOS, developed by Teacy et al. [2005], proposes that possibly unreliable ratings of sellers provided by advisors will be discounted when the buying agent tries to reason about the trustworthiness of the sellers. However, this model does not work well when sellers vary their behavior widely. The second problem is that this model relies only on a buyer's personal experience with the advisors' advice. It will be problematic when the buyer does not have much experience with selling agents. We are therefore motivated by this collective research to retain the valuable approach of reasoning probabilistically but to develop an improved approach for trust modeling, as part of our effort to develop an effective framework for e-commerce, one that addresses the challenge of varying agent behavior. This challenge has also been discussed in the work of Tran and Cohen [2004] and that of Urbano et al. [2010] that sellers may build up their trust first and lie in the consequent few business transactions.

Khosravifar et al. [2009] propose a model similar to ours, which combines direct interaction ratings and indirect interaction ratings of sellers for a buyer to model the trustworthiness of a seller. The indirect interaction ratings of sellers are provided by trusted other agents of the buyer and referee agents introduced by the seller, called consulting agents. The authors also make use of a forgetting factor to discount the older ratings in order to deal with the seller varying behavior. However, it is not clear how their approach can model the trustworthiness of consulting agents that are not known by the buyer. The public reputation part of our personalized approach compares the advisors' ratings with others' ratings for the same sellers to model the trustworthiness of advisors. In addition, our personalized approach for modeling the trustworthiness of advisors is also able to cope with the problem of sellers' varying behavior, through the use of time windows. The formal trust model of Wang and Singh [2007] focuses on modeling the certainty of trust from evidence reported by multiple buyers. The authors assume that sellers' varying behavior will result in buyers having conflicting reports about sellers. Therefore, when modeling the certainty, their model takes into account not only the number of reports but also the conflict among those reports. The certainty decreases when conflict among reports increases, which is reflected by the aggregation

of reports. However, we argue that the varying behavior of sellers may also cause false consensus. For example, suppose an honest buyer reported a rating of 1 about a honest seller 10 days ago. Now, the seller becomes dishonest, and another dishonest buyer will also report a rating of 1 towards the seller. The formal model of Wang and Singh[2007] may not be able to deal with this kind of scenario.

A new trend of approaches that apply stereotype learning to deal with the experience scarcity problem has been recently emerging [Urbano et al. 2010; Liu et al. 2010]. These approaches make use of data mining and machine learning techniques to classify sellers into the categories of trustworthy or untrustworthy based on some features. However, some of the feature information is often difficult to obtain. Another problem is that once sellers realize that they have been modeled based on certain features, they may act deceptively to vary their feature values.

### 3. OVERVIEW OF MODEL

For the remainder of this article, we discuss the scenario where the buyers and sellers are brought together by a procurement (reverse) auction, where the auctioneer is a buyer and bidders are sellers. There is a central server that runs the auction. In our system, a buyer that wants to purchase a product sends a request to the central server. This request indicates not only the product that the buyer is interested in but also the buyer's evaluation criteria for the product (discussed in more detail in the following section). Sellers interested in selling the product to the buyer will register to participate in the auction.

The buyer will first limit the sellers it will consider for the auction, by modeling their trustworthiness. This is achieved by having each buyer maintain a neighborhood of trusted other buyers, which will be asked to provide ratings of the sellers under consideration. The buyer will then convey to the central server which sellers it is willing to consider, and the pool of possible sellers is thus reduced. Sellers that are allowed to participate in the auction will submit their bids and the buyer will select the winner of the auction as the seller whose product (described in its bid) gives the buyer the largest profit, based on the buyer's evaluation criteria. Once a buyer has selected the winning seller, it pays that seller the amount indicated in the bid. The winning seller is supposed to deliver the product to the buyer. However, it may decide to alter the quality of the product or to not deliver the product at all. The buyer will report the result of conducting business with the seller to the central server, registering a rating for the seller. It is precisely these ratings of the seller that can then be shared with those buyers that consider this buyer as their neighbor.

In summary, the central server runs the auction and maintains information that is shared with sellers and buyers; buyers announce their intention to purchase products, consult with neighbors, choose a winning seller, and report a final rating for the seller.

### 4. FORMALIZATION OF MODEL

To formalize our model, we consider a scenario where a buyer  $B$  wants to buy a product  $p$ . The buyer specifies its evaluation criteria for a set of  $h$  ( $h \geq 1$ ) non-price features  $\{f_1, f_2, \dots, f_h\}$ , as well as a set of weights  $\{\omega_1, \omega_2, \dots, \omega_h\}$  that correspond to each non-price feature. Each weight represents how much its corresponding non-price feature is worth. A higher weight for a non-price feature implies that the buyer cares more about the feature. The buyer also provides information in its evaluation criteria about the conversion from descriptive non-price feature values to numeric values (for example, a 3-year warranty is converted to the numeric value of 10 on a scale of 1 to 10).<sup>1</sup> We

<sup>1</sup>In this article, we focus on non-price features that are still objective, for example, delivery time. Handling subjective features is left for future work.

define the function  $\tau()$  to denote such a conversion. Sellers in the marketplace are able to know the buyer's values of their products, which can be formalized as follows.

$$V_B = \sum_{i=1}^h \omega_i \tau(f_i) \quad (1)$$

To avoid doing business with possibly dishonest sellers, the buyer  $B$  first models the trustworthiness of sellers, using an approach formalized in Section 4.2. A seller is considered trustworthy if its trust value is greater than a threshold  $\gamma$ . It will be considered untrustworthy if the trust value is less than  $\delta$ . The buyer in our mechanism will allow only a limited number of the most trustworthy sellers to join the auction. This can be achieved by using the trust thresholds. If there are no trustworthy sellers, the sellers with trust values between  $\gamma$  and  $\delta$  may also be allowed to join the auction. Similar to Tran and Cohen's model [Tran and Cohen 2004], sellers about which the buyer  $B$  does not have information will also be allowed to join the auction with a small probability. This probability value is set to be 1 originally and decreases over time to a fixed small value.

Sellers  $\{S_1, S_2, \dots, S_m\}$  ( $m \geq 1$ ) allowed to join the auction submit their bids by setting the prices and values for the non-price features of the product  $p$ . After receiving sellers' bids, the buyer  $B$  will then determine the winner of the auction. The winner of the auction is the seller whose bid includes the highest valuation of the product  $p$  that it is willing to offer, which can be formalized as

$$S_{win} = \arg \max_{i=1}^m (V_B - P_{S_i}), \quad (2)$$

where  $P_{S_i}$  is the price of product offered by seller  $S_i$ .

In the sections that follow, we first describe the personalized approach which is used to create the social network of buyers.<sup>2</sup> We then formalize how the buyer  $B$  should model the trustworthiness of sellers by considering the advice provided by its neighbors.

#### 4.1. Social Network of Buyers

Our model allows the central server to maintain for each buyer a fixed number of neighbors from which the buyer can ask advice about sellers' trustworthiness. The central server records the trust value a buyer has of another buyer (an advisor) derived through a personalized approach. Buyers first represent private reputation values, based on what is known about the advisors' ratings for sellers with which the buyer has already had some experience. Next, buyers construct a public model of trustworthiness of advisors based on common, centrally held knowledge of sellers and the ratings provided by advisors, including the trust ratings of sellers totally unknown to the buyer. Then both private and public models can be combined, in order to obtain a value for the trustworthiness of each possible advisor. Next we describe in detail how these calculations are done.

In the personalized approach, the buyer  $B$  may evaluate the private reputation it has of an advisor  $A$  by comparing their ratings for commonly rated sellers  $\{S_1, S_2, \dots, S_l\}$ . For one of the commonly rated sellers  $S_i$  ( $1 \leq i \leq l$  and  $l \geq 1$ ),  $A$  has the rating vector  $\bar{r}_{A,S_i}$  and  $B$  has the rating vector  $\bar{r}_{B,S_i}$ . A rating for  $S_i$  from  $B$  and  $A$  is binary (1 or 0, for example), in which 1 means that the seller delivers the product and the valuation of the product is not less than that described in its bid, and 0 otherwise. In this case, the rating of 1 will be considered as a positive rating, and 0 will be considered as a negative rating. The ratings in  $\bar{r}_{A,S_i}$  and  $\bar{r}_{B,S_i}$  are ordered according to the time when they are

<sup>2</sup>The first version of this model was presented by Zhang and Cohen [2006].

provided. The ratings are then partitioned into different elemental time windows. The length of an elemental time window may be fixed (e.g., one day) or adapted by the frequency of the ratings to the seller  $S_i$ , similar to the way proposed in Dellarocas [2000]. It should also be considerably small so that there is no need to worry about the changes of sellers' behavior within each elemental time window. We define a pair of ratings  $(r_{A,S_i}, r_{B,S_i})$ , such that  $r_{A,S_i}$  is one of the ratings of  $\overline{r_{A,S_i}}$ ,  $r_{B,S_i}$  is one of the ratings of  $\overline{r_{B,S_i}}$ , and  $r_{A,S_i}$  corresponds to  $r_{B,S_i}$ . The two ratings,  $r_{A,S_i}$  and  $r_{B,S_i}$ , are correspondent only if they are in the same elemental time window, the rating  $r_{B,S_i}$  is the most recent rating in its time window, and the rating  $r_{A,S_i}$  is the closest and prior to the rating  $r_{B,S_i}$ .<sup>3</sup> We then count the number of such pairs for  $S_i$ ,  $N_{S_i}$ . The total number of rating pairs for all commonly rated sellers,  $N_{all}$  will be calculated by summing up the number of rating pairs for each commonly rated seller as  $N_{all} = \sum_{i=1}^l N_{S_i}$ .

The private reputation of the advisor is estimated by examining rating pairs for all commonly rated sellers. We define a rating pair  $(r_{A,S_i}, r_{B,S_i})$  as a positive pair if  $r_{A,S_i}$  is the same value as  $r_{B,S_i}$ . Otherwise, the pair is a negative pair. Suppose there are  $N_f$  number of positive pairs. The number of negative pairs will be  $N_{all} - N_f$ . The private reputation of the advisor  $A$  is estimated as the probability that  $A$  will provide reliable ratings to  $B$ . Because there is only incomplete information about the advisor, the best way of estimating the probability is to use the expected value of the probability. The expected value of a continuous random variable is dependent on a probability density function, which is used to model the probability that a variable will have a certain value. Because of its flexibility and the fact that it is the conjugate prior for distributions of binary events, the beta family of probability density functions is commonly used to represent probability distributions of binary events (see, e.g., the generalized trust models BRS [Jøsang and Ismail 2002] and TRAVOS [Teacy et al. 2005]). Therefore, the private reputation of  $A$  can be calculated as

$$\alpha = N_f + 1, \quad \beta = N_{all} - N_f + 1,$$

$$R_{pri}(A) = E(Pr(A)) = \frac{\alpha}{\alpha + \beta}, \quad (3)$$

where  $Pr(A)$  is the probability that  $A$  will provide fair ratings to  $B$ , and  $E(Pr(A))$  is the expected value of the probability. We consider an advisor's rating to be a fair rating if it is the same as the buyer's rating.<sup>4</sup>

When there are not enough rating pairs,  $A$ 's public reputation will also be considered.<sup>5</sup> The public reputation of  $A$  is estimated based on its ratings and other ratings for the sellers rated by  $A$ . Each time  $A$  provides a rating for a seller  $r_{A,S}$ , the rating will be judged centrally to determine whether it is consistent with the majority of the other ratings for that seller provided by other buyers. We define a rating for a seller as a fair rating if it is consistent with that majority of ratings for the seller.<sup>6</sup> We consider only the ratings that are within the same time window as  $r_{A,S}$ , and we only consider the most

<sup>3</sup>We consider ratings provided by  $B$  after those by  $A$  in the same time window, in order to incorporate into  $B$ 's rating anything learned from  $A$  during that time window, before taking an action. According to the solution proposed by Zacharia et al. [1999], by keeping only the most recent ratings, we can avoid the issue of advisors' "flooding" the system.

<sup>4</sup>As explained, the advisor's rating is examined in the same time window and is submitted prior to the buyer's experience. The buyer's experience is used to judge the fairness of the rating.

<sup>5</sup>This is determined by Eqs. (5) and (6) for calculating the weight of private reputation, which will be explained later in this section. When the weight is less than 1, there are not enough rating pairs and public reputation will also be considered.

<sup>6</sup>Determining consistency with the majority of ratings can be achieved in a variety of ways, for instance, averaging all the ratings and seeing if that is close to the advisor's rating.

recent rating from each advisor within any time window. In so doing, as sellers change their behavior and become more or less trustworthy to each advisor, the majority of ratings will be able to change.

Suppose that the advisor  $A$  provides  $N_{all}^A$  ratings in total. If there are  $N_f^A$  fair ratings, the number of unfair ratings provided by  $A$  will be  $N_{all}^A - N_f^A$ . In a similar way as estimating the private reputation, the public reputation of the advisor  $A$  is estimated as the probability that  $A$  will provide fair ratings. It can be calculated as follows.

$$\alpha' = N_f^A + 1, \quad \beta' = N_{all}^A - N_f^A + 1,$$

$$R_{pub}(A) = \frac{\alpha'}{\alpha' + \beta'} \quad (4)$$

This also indicates that the more the percentage of fair ratings advisor  $A$  provides, the more reputable it will be.

To estimate the trustworthiness of advisor  $A$ , we combine the private reputation and public reputation values together. The private reputation and public reputation values are assigned different weights. The weights are determined by the reliability of the estimated private reputation value.

We first determine the minimum number of rating pairs needed for  $B$  to be confident about the private reputation value it has of  $A$ . The Chernoff Bound theorem [Mui et al. 2002] provides a bound for the probability that the estimation error of private reputation exceeds a threshold, given the number of rating pairs. Accordingly, the minimum number of pairs can be determined by an acceptable level of error and a confidence measurement as

$$N_{min} = -\frac{1}{2\varepsilon^2} \ln \frac{1-\eta}{2}, \quad (5)$$

where  $\varepsilon \in (0, 1)$  is the maximal level of error that can be accepted by  $B$ , and  $\eta \in (0, 1)$  is the level of confidence buyer  $B$  would like to attain. If the total number of all rating pairs is larger than or equal to  $N_{min}$ , buyer  $B$  will be confident about the private reputation value estimated based on its ratings and the advisor  $A$ 's ratings for all commonly rated sellers. Otherwise, there are not enough rating pairs, the buyer will not be confident about the private reputation value, and it will then also consider public reputation. The reliability of the private reputation value can be measured as follows.

$$w = \begin{cases} \frac{N_{all}}{N_{min}} & \text{if } N_{all} < N_{min} \\ 1 & \text{otherwise} \end{cases} \quad (6)$$

The trust value of  $A$  will be calculated by combining the weighted private reputation and public reputation values as follows.

$$Tr(A) = wR_{pri}(A) + (1-w)R_{pub}(A) \quad (7)$$

It is obvious that the buyer will consider less the public reputation value when the private reputation value is more reliable. Note that when  $w = 1$ , the buyer relies only on private reputation.

For a new buyer, the central server randomly assigns to it some other buyers as candidates for its neighbors. The new buyer then randomly selects some candidates as its neighbors. The neighbor list will be updated periodically. Each time, the most trustworthy candidates will be selected as neighbors.<sup>7</sup> The candidate list is also updated

<sup>7</sup>This may be determined by a threshold set by the buyer or by alternatively constantly maintaining a fixed-sized neighborhood.

periodically. Each time, a small portion of buyers is chosen randomly as candidates from all buyers with high public reputation values.

#### 4.2. Modeling Trustworthiness of Sellers

We now propose an algorithm for the buyer to model the trustworthiness of the sellers, making use of ratings from advisors and our personalized approach for modeling the trustworthiness of those advisors. This algorithm is in the same spirit as the personalized approach. The private reputation of the sellers is first modeled by the buyer based on its own ratings for the sellers. If the buying agent does not want to rely fully on its personal experience with the sellers, it will ask for its neighbors' ratings of the selling agents. It then can derive a public reputation of the sellers based on the ratings provided by the advisors.

Suppose that  $B$  has the rating vector  $\overline{r_{B,S}}$ , which contains all the ratings provided by  $B$  for the seller  $S$ . The ratings in  $\overline{r_{B,S}}$  are ordered from the most recent to the oldest according to the time when they are submitted. The ratings are then partitioned into different elemental time windows  $\{T_1, T_2, \dots, T_n\}$ . We then count the number of positive ratings  $N_{pos,i}^B$  and the number of negative ratings  $N_{neg,i}^B$  in each time window  $T_i$ . The private reputation of the seller  $S$  can be estimated through the beta family of probability density functions as

$$R_{pri}(S) = \frac{\sum_{i=1}^n N_{pos,i}^B \lambda^{i-1} + 1}{\sum_{i=1}^n (N_{pos,i}^B + N_{neg,i}^B) \lambda^{i-1} + 2}, \quad (8)$$

where  $\lambda$  ( $0 \leq \lambda \leq 1$ ) is a forgetting rate. The forgetting rate is also introduced in Jøsang and Ismail [2002] to deal with possible changes of the seller's behavior over time because old ratings will be given less weight than more recent ones. Note that when  $\lambda = 1$  there is no forgetting (i.e., the weight of every rating provided by buyer  $B$  will be 1). Note as well that when  $\lambda > 0$ , the higher the value of  $\lambda$ , the greater the weight placed on the old ratings provided by  $B$ . When  $\lambda = 0$  only the ratings that are within the current time window  $T_1$  will be considered.

Buyer  $B$  may also consider ratings provided by its neighbors: a list of the most trustworthy other buyers to this buyer. The buyer sends a request to the central server to ask for all the ratings provided by its neighbors  $\{A_1, A_2, \dots, A_k\}$  ( $k \geq 1$ ) for seller  $S$ . We also partition these ratings into different elemental time windows. Suppose that the neighbor  $A_j$  ( $1 \leq j \leq k$ ) provided  $N_{pos,i}^{A_j}$  positive ratings and  $N_{neg,i}^{A_j}$  negative ratings within the time window  $T_i$ . These ratings will be discounted based on the trustworthiness of the neighbor, so that the ratings from less trustworthy neighbors will carry less weight than ratings from more trustworthy ones.

Jøsang [2001] provides a mapping from beliefs defined by the Dempster-Shafer theory to the beta function as

$$\begin{cases} b = \frac{N_{pos,i}^{A_j}}{N_{pos,i}^{A_j} + N_{neg,i}^{A_j} + 2} \\ d = \frac{N_{neg,i}^{A_j}}{N_{pos,i}^{A_j} + N_{neg,i}^{A_j} + 2} \\ u = \frac{2}{N_{pos,i}^{A_j} + N_{neg,i}^{A_j} + 2} \end{cases}, \quad (9)$$

where  $b$ ,  $d$ , and  $u$  represent belief, disbelief, and uncertainty parameters, respectively. In our case,  $b$  represents the probability that the proposition that the seller is trustworthy is true, and  $d$  represents the probability that the proposition is false. Note that  $b + d + u = 1$  and  $b, d, u \in [0, 1]$ . As also pointed out by Jøsang and Ismail [2002] and



Yu and Singh [2003], beliefs and disbeliefs can be directly discounted by the trustworthiness of the neighbor as follows.

$$\begin{cases} b' = Tr(A_j)b \\ d' = Tr(A_j)d \end{cases} \quad (10)$$

From Eqs. (9) and (10) we then can derive a discounting function for the amount of ratings provided by the neighbor  $A_j$  as

$$\begin{cases} D_{pos,i}^{A_j} = \frac{2Tr(A_j)N_{pos,i}^{A_j}}{(1-Tr(A_j))(N_{pos,i}^{A_j} + N_{neg,i}^{A_j}) + 2} \\ D_{neg,i}^{A_j} = \frac{2Tr(A_j)N_{neg,i}^{A_j}}{(1-Tr(A_j))(N_{pos,i}^{A_j} + N_{neg,i}^{A_j}) + 2} \end{cases}, \quad (11)$$

where  $Tr(A_j)$  is the trustworthiness of the neighbor  $A_j$ .

In the same way as estimating the private reputation, the public reputation of the seller  $S$  can be calculated as

$$R_{pub}(S) = \frac{\left[ \sum_{j=1}^k \sum_{i=1}^n D_{pos,i}^{A_j} \lambda^{i-1} \right] + 1}{\left[ \sum_{j=1}^k \sum_{i=1}^n (D_{pos,i}^{A_j} + D_{neg,i}^{A_j}) \lambda^{i-1} \right] + 2}. \quad (12)$$

The ratings provided by the advisors will be also discounted by the forgetting factor  $\lambda$ .

The trustworthiness of the seller  $S$  is estimated by combining the weighted private and public reputation values as follows.

$$Tr(S) = w' R_{pri}(S) + (1 - w') R_{pub}(S) \quad (13)$$

The weight  $w'$  is determined by the reliability of the estimated private reputation value as

$$w' = \begin{cases} \frac{N_{all}^B}{N_{min}^B} & \text{if } N_{all}^B < N_{min}^B \\ 1 & \text{otherwise} \end{cases} \quad (14)$$

where  $N_{all}^B$  is the total number of ratings provided by  $B$  for the seller.  $N_{min}^B$  represents the minimum number of ratings needed for the buyer  $B$  to be confident about the private reputation value it has of  $S$ , which can be determined based on Eq. (5).

## 5. EXAMPLES

We first provide an example to demonstrate how a buyer  $B$  models the trustworthiness of advisors, to retain the most trustworthy ones as its neighbors. We then demonstrate how the buyer  $B$  models trustworthiness of sellers by considering ratings of sellers provided by its neighbors, and how it selects the winning seller to do business with.

### 5.1. Buyer's Neighbor List

In this example, we assume that each buyer can have at most one neighbor. Consider the case where there are three other buyers (advisors)  $A_x$ ,  $A_y$ , and  $A_z$ . Each of them has rated the five sellers ( $S_1$ ,  $S_2$ ,  $S_3$ ,  $S_4$ , and  $S_5$ ). Table I lists the ratings provided by each advisor  $A_j$  ( $j \in \{x, y, z\}$ ) for the five sellers. The symbol “ $T$ ” represents a sequence of time windows, in which  $T_1$  is the most recent time window. To simplify the demonstration, we assume that each advisor provides only one rating within each time window.

Table I. Ratings of Sellers Provided by Advisors

$A_j$	$A_x$					$A_y$					$A_z$				
	$T_1$	$T_2$	$T_3$	$T_4$	$T_5$	$T_1$	$T_2$	$T_3$	$T_4$	$T_5$	$T_1$	$T_2$	$T_3$	$T_4$	$T_5$
$S_1$	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0
$S_2$	1	1	1	1	1	0	1	0	1	1	0	0	0	0	0
$S_3$	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0
$S_4$	1	1	1	1	1	1	0	0	1	0	0	0	0	0	0
$S_5$	1	1	1	1	1	1	1	0	0	1	0	0	0	0	0

Table II. Ratings Provided by the Buyer  $B$ 

$T$	$T_1$	$T_2$	$T_3$	$T_4$	$T_5$
$S_1$	1	1	1	1	1
$S_2$	1	1	1	1	-
$S_3$	1	1	1	-	-
$S_4$	1	1	-	-	-
$S_5$	1	-	-	-	-

Table III. Private and Public Reputation of Advisors

$A_j$	$A_x$	$A_y$	$A_z$
$N_f$	15	8	0
$\alpha$	16	9	1
$\beta$	1	8	16
$R_{pri}(A_j)$	0.94	0.53	0.06
$N_f^{A_j}$	25	12	0
$\alpha'$	26	13	1
$\beta'$	1	14	26
$R_{pub}(A_j)$	0.96	0.48	0.04

As can be seen from Table II, the buyer  $B$  has also provided some ratings for the five sellers. The buyer  $B$  might have not provided a rating for some sellers within some time windows. We assume that the ratings provided by  $B$  are after those provided by  $A_x$ ,  $A_y$ , and  $A_z$  if they are within the same time window.

We compare the ratings provided by  $A_x$ ,  $A_y$ , and  $A_z$  in Table I and ratings provided by  $B$  in Table II. The buyer  $B$  has the same number of rating pairs with each advisor ( $N_{all} = 15$ ). However,  $B$  has different numbers of  $N_f$  positive rating pairs with  $A_x$ ,  $A_y$ , and  $A_z$ , which are listed in Table III. Accordingly, as can be seen from Table III, the private reputation values of  $A_x$ ,  $A_y$ , and  $A_z$  are different, in which the private reputation value of  $A_x$  is the highest and that of  $A_z$  is the lowest. The result indicates that the advisor  $A_x$  is most likely to provide fair ratings, whereas  $A_z$  will most likely provide unfair ratings (e.g., will lie).

According to Table I, the total number of ratings provided by each advisor is the same ( $N_{all}^{A_j} = 25$ ). We also count the number of fair ratings each advisor provides. A rating here is considered as a fair rating when it is consistent with the majority of ratings for the seller within a same time window. Consider the case where all of the five sellers are trustworthy and the majority of ratings are fair. In this case, a rating of 1 provided by an advisor will be considered as a fair rating, whereas a rating of 0 will be considered as an unfair rating. From the advisors' ratings listed in Table I, we can see that ratings provided by the advisor  $A_x$  are all fair, the advisor  $A_z$  always gives unfair ratings, and some of the ratings provided by the advisor  $A_y$  are unfair. Table III lists the number of

Table IV. Buyers' Evaluation Criteria for  $p$ 

Features	Delivery Time (day)			Warranty (year)		
Weights	0.4			0.6		
Descriptive	7	3	1	1	2	3
Numeric	3	5	10	3	5	10

Table V. Ratings of Sellers Provided by  $A_x$ 

$T$	$T_1$	$T_2$	$T_3$	$T_4$	$T_5$
$S_6$	0	0	0	1	1
$S_7$	-	-	-	-	-
$S_8$	1	1	1	1	1
$S_9$	1	1	1	1	0

fair ratings provided by each advisor and the corresponding public reputation value of it. From Table III, it is clear that advisor  $A_x$  is most likely to provide fair ratings, and advisor  $A_z$  most likely will not.

To combine private reputation and public reputation, the weight  $w$  should be determined. The value of  $w$  depends on the values of  $\varepsilon$  and  $\eta$ , and the number of rating pairs  $N_{all}$ , which is the same for every advisor in our example. Suppose we set  $\varepsilon = 0.2$  and  $\eta = 0.8$ . According to Eq. (6), the weight  $w$  will be 0.52. The trust values of  $A_x$ ,  $A_y$ , and  $A_z$  will be 0.95, 0.506, and 0.05, respectively.  $A_x$  is the most trustworthy. The buyer  $B$  will choose  $A_x$  as its neighbor.

## 5.2. Buyer Choosing Winning Seller

Suppose that the buyer  $B$  wants to buy a product  $p$ . It sends the request to the central server. In its request, the buyer specifies the two non-price features of the product  $p$ , the weight for each non-price feature, and the information about the conversion from descriptive non-price feature values to numeric values, as presented in Table IV. To prevent it from doing business with possibly dishonest sellers, the buyer  $B$  models trustworthiness of sellers and selects trustworthy ones to do business with. Suppose that the four sellers  $S_6$ ,  $S_7$ ,  $S_8$ , and  $S_9$  are all willing to sell the buyer the product  $p$ . We also suppose that the buyer  $B$  previously has not done business with any one of them. Therefore the buyer  $B$  has no ratings for these sellers. The private reputation of  $S_6$ ,  $S_7$ ,  $S_8$ , and  $S_9$  can be calculated according to Eq. (8) as  $R_{pri}(S_6|S_7|S_8|S_9) = \frac{0+1}{(0+0)+2} = 0.5$ .

The buyer  $B$  then considers ratings of sellers provided by its neighbor  $A_x$ . The ratings of the sellers provided by the advisor  $A_x$  are listed in Table V. Note that these ratings of the sellers are not used for estimating the public reputation of  $A_x$  because there is no central information about the trustworthiness of the sellers. Also note that  $A_x$  does not have ratings for the seller  $S_7$  because  $A_x$  has not done business with  $S_7$ .

The amount of positive or negative ratings provided by  $A_x$  within each time window will be discounted by using Eq. (11). The discounted amount of positive and negative ratings of sellers is listed in Table VI. For example, the discounted amount of positive ratings of seller  $S_6$  in time window  $T_4$  is calculated to be 0.93.

In this example, we set  $\lambda$  to be 0.9, which means that the buyer  $B$  does not have much forgetting. According to Eq. (12), the public reputation of the sellers can be calculated as  $R_{pub}(S_6) = \frac{\sum_{i=4}^5 0.93 * 0.9^{i-1} + 1}{\sum_{i=1}^5 0.93 * 0.9^{i-1} + 2} = 0.39$ ,  $R_{pub}(S_7) = 0.5$ ,  $R_{pub}(S_8) = 0.83$ , and  $R_{pub}(S_9) = 0.72$ .

Because the buyer  $B$  has not done business with any of the sellers before, the weights of the private reputation of the sellers are all 0. The trustworthiness of the sellers can be calculated by using Eq. (13) as  $Tr(S_6) = 0 * 0.5 + (1 - 0) * 0.39 = 0.39$ ,  $Tr(S_7) = 0.5$ ,  $Tr(S_8) = 0.83$ , and  $Tr(S_9) = 0.72$ . We set the threshold  $\gamma$  to be 0.7. In this case, only

Table VI. Discounted Amount of Ratings of Sellers

$T$	$T_1$	$T_2$	$T_3$	$T_4$	$T_5$
$D_{pos,i}^{Ax}(S_6)$	0	0	0	0.93	0.93
$D_{neg,i}^{Ax}(S_6)$	0.93	0.93	0.93	0	0
$D_{pos,i}^{Ax}(S_7)$	0	0	0	0	0
$D_{neg,i}^{Ax}(S_7)$	0	0	0	0	0
$D_{pos,i}^{Ax}(S_8)$	0.93	0.93	0.93	0.93	0.93
$D_{neg,i}^{Ax}(S_8)$	0	0	0	0	0
$D_{pos,i}^{Ax}(S_9)$	0.93	0.93	0.93	0.93	0
$D_{neg,i}^{Ax}(S_9)$	0	0	0	0	0.93

the sellers  $S_8$  and  $S_9$  will be considered as trustworthy sellers by the buyer  $B$ , and are allowed to submit their bids.

The bid submitted by the seller  $S_8$  specifies that  $S_8$  will deliver the product with a 3-year warranty in three days and the price of the product  $P_{S_8}$  is 4. The bid submitted by the seller  $S_9$  specifies that  $S_9$  will deliver the product with a 2-year warranty in three days and the price of the product  $P_{S_9}$  is also 4. The values of the product  $p$  in their bids are calculated as  $V(p, S_8) = V_B - P_{S_8} = 0.4 * 5 + 0.6 * 10 - 4 = 4$  and  $V(p, S_9) = 1$ . The value of the product in the bid of  $S_9$  is lower than that of  $S_8$ . Seller  $S_8$  will be selected as the winner. Buyer  $B$  pays  $S_8$  the price of 4. Later on, seller  $S_8$  delivers the product. Suppose that the seller delivers the product with a 3-year warranty in three days; we say that the seller is trustworthy in this transaction. Buyer  $B$  will submit a rating of 1 to the central server.

## 6. EXPERIMENTAL RESULTS

We have introduced a particular framework for buyers to model the trustworthiness of sellers, making use of ratings provided by advisors. In this section, we demonstrate the value of this approach experimentally, showing that: (i) buyers that make use of advisors in order to model sellers, using our framework, gain greater profit than those acting without advice (demonstrated in environments with varying amounts of lying by advisors), (ii) buyers using our proposed approach to model advisors obtain better profit than those using competing approaches for the modeling, (iii) honest buyers are effectively assigned to neighborhoods, providing a useful social network, (iv) our approach for modeling advisors is robust even when sellers vary their behavior, (v) buyers modeling sellers using our proposed approach that includes advisor ratings obtain better profit than competing approaches. These results confirm the intrinsic value of our proposed methods for trust modeling. We then move on to consider whether seller honesty can be promoted in the marketplace as a result of our framework. Here, we present results that show: (i) seller honesty is promoted by the buyers using advisors to model sellers (ii) the limiting of seller bids within the framework in particular contributes to seller honesty.

We simulate a marketplace operating with our framework for a period of 60 days. The marketplace involves 90 buyers. These buyers are grouped into three groups. They have different numbers of requests. Every 10 of the buyers in each group has a different number (20, 40, and 60) of requests. This is to simulate that some buyers may be more active and others may be less active in the marketplace. In our experiments, we assume that there is only one product in each request and each buyer has a maximum of one request each day. For the purpose of simplicity, we also assume that the products requested by buyers have the same non-price features, where the cost for sellers to produce the products is set to be 8 price units and the buyers' valuation of the products is 15 price units. The buyer's valuation of the products is set higher than the cost for sellers to produce the products in order to be realistic. After they finish business

with sellers, buyers rate sellers. Some buyers will provide unfair ratings. Each group of buyers provides different percentages (0%, 20%, and 40%) of unfair ratings, to simulate buyers with different dishonesty levels. We also simulate the scenario where buyers may freely join or leave the marketplace. We allow 2 buyers from each group to leave the marketplace at the end of each day. Accordingly, we also allow 6 buyers to join the marketplace at the end of each day. These buyers will also provide different percentages (0%, 20%, and 40%) of unfair ratings, to keep the number of buyers in each group the same. Initially, we randomly assign 5 buyers to each buyer as its neighbors.

There are also 18 sellers in total in the marketplace. Each 6 sellers acts dishonestly in different percentages (0%, 25%, and 75%) of their business with buyers, to simulate sellers with different dishonesty levels. We assume that all sellers have the same cost for producing the products because all products have the same non-price features.

We also set other parameters in the experiments. We set the threshold  $\gamma$  to be 0.7 and  $\delta$  to be 0.3. Therefore, a seller is considered trustworthy if its trust value is greater than 0.7 and untrustworthy if it is below 0.3.<sup>8</sup> We also set the value of  $\epsilon$  to be 0.3 and  $\eta$  to be 0.8 for calculating the minimum number of buyer ratings in Eq. (5).<sup>9</sup> The forgetting factor  $\lambda$  is set to be 0.7 in our experiments, to discount buyers' old experience quite a bit so that the impact of sellers' changing behavior can be kept small.

### 6.1. Value of Our Modeling Methods

We carry out experiments to show that buyers will gain more profit by using our personalized approach to model the trustworthiness of others. We have two different settings for this experiment. In the first setting, the first group of buyers does not provide any unfair ratings, but the second and third groups provide 20% and 40% of unfair ratings respectively. In the second setting, the first group of buyers still does not lie. The second and third groups lie more. They provide 50% and 100% of unfair ratings respectively. In both of the settings, one half of the buyers in the first group model other buyers and select the most trustworthy ones as their neighbors from which they can ask advice about sellers. Another half of the buyers do not model the trustworthiness of other buyers. They randomly select some other buyers as their neighbors.

We compare the total profit<sup>10</sup> gained by these two types of buyers in the two settings. Results<sup>11</sup> are shown in Figure 1. From this figure, we can see that buyers modeling the trustworthiness of other buyers and selecting the most trustworthy ones as their neighbors will be able to gain more total profit. It is also clear that the buyers that do not model the trustworthiness of other buyers will gain much less profit when the other buyers provide a lot of unfair ratings. Therefore, it is better off for buyers to model the trustworthiness of other buyers and select the most trustworthy ones as their neighbors from which they ask advice about sellers.

We also compare the total profit gained by buyers using our personalized approach to model the trustworthiness of other buyers with that gained by the buyers using only

<sup>8</sup>This serves to model a liberal treatment, where sellers are not rejected unless they become quite unreasonable, but where sellers need to perform quite well in order to be labelled as trustworthy. In this way, many sellers that are not considered trustworthy or untrustworthy yet will still have a chance to be selected to join the auctions and to build up their trust. Buyers will also have the chance to experience more sellers with somewhat questionable trustworthiness, in order to progressively learn that they are not trustworthy.

<sup>9</sup>The reasonably large  $\epsilon$  and small  $\eta$  produce a small value for the minimum number of buyer ratings, which means that buyers will rely more on their personal experience with advisors because direct experience is the more reliable source of information for modeling the trustworthiness of the advisors.

<sup>10</sup>A buyer's profit from a good is determined by the value of the good they receive from the seller, minus the price they are charged for the good (according to Eq. (1)). When a buyer selects sellers that are trustworthy, the goods that are received should bring greater value to the buyer and hence greater profit.

<sup>11</sup>All experimental results in Section 6 are averaged over 500 rounds of the simulation.

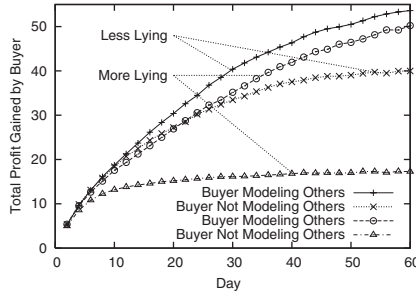


Fig. 1. Profit gained by buyers modeling vs. not modeling other buyers.

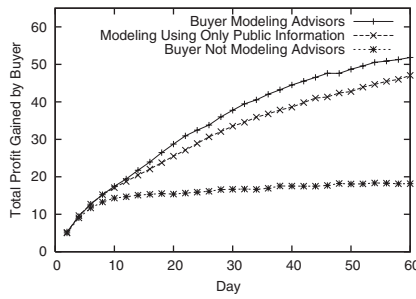


Fig. 2. Profit gained by buyers modeling other buyers using combination vs. only public information.

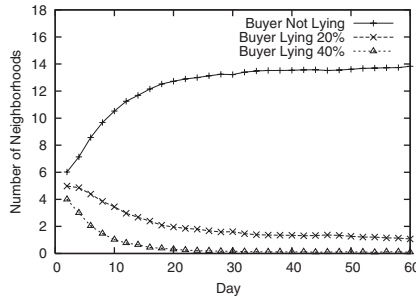


Fig. 3. Reputation of different buyers.

public reputation to represent the trustworthiness of other buyers. Results shown in Figure 2 indicate that buyers using our personalized approach by taking into account both private and public reputation values will be able to gain more total profit, showing the importance of using both private and public reputation components for modeling the trustworthiness of advisors.

Here, we also present experimental results to show that buyers that are honest will be able to become neighbors of many other buyers, using our personalized approach for modeling the trustworthiness of buyers. We first measure the reputation of buyers that provide different percentages of unfair ratings. In our experiments, a buyer's reputation is represented by the number of other buyers considering this buyer as their neighbor. The results are shown in Figure 3. From this figure, we can see that the buyers providing the smaller percentages of unfair ratings will have larger reputation values. These results indicate that our personalized approach is able to effectively

Table VII. Seller Varying Behavior

Buyer	Not Lying		Lying 20%		Lying 40%	
	m	std	m	std	m	std
1	5.8	0.06	5.04	0.02	4.13	0.05
10	12.5	0.09	2.22	0.06	0.31	0.04
20	13.9	0.21	1.03	0.18	0.07	0.04
30	14.1	0.38	0.88	0.35	0.05	0.03
40	14.1	0.40	0.82	0.37	0.05	0.04
50	14.1	0.28	0.81	0.25	0.05	0.04
60	14.2	0.28	0.74	0.25	0.04	0.04

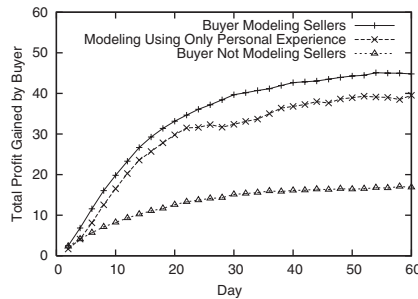


Fig. 4. Profit gained by different buyers.

keep honest buyers in the neighborhood of other buyers, that is, that our approach for modeling the trustworthiness of advisors is functioning as it should.

We carry out another experiment to demonstrate how our personalized approach is able to cope with the situation where sellers may change their behavior. In this experiment, we have four types of sellers. The first type of sellers lies (i.e., fails to deliver the good as promised) uniformly in their business. The second type of sellers also lies uniformly but more often. The third type of sellers acts honestly first and dishonestly later on. The last type of sellers acts dishonestly first and then honestly. We run simulations separately 500 times for each type of sellers and average the results. We then calculate the mean and standard deviation of reputation values for different buyers (i.e., buyers not lying, buyers providing 20% or 40% of unfair ratings). Results are listed in Table VII. The standard deviation is considerably smaller than the mean values, which indicates that buyers' reputation modeled using our personalized approach is not affected by the changes of sellers' behavior. Therefore, we can conclude that our personalized approach is robust to the changes of sellers' behavior.

We also carry out an experiment to show the value of our approach for modeling the trustworthiness of sellers. In this experiment, one-third of the buyers models the trustworthiness of sellers based on their personal experience with the sellers and advice about the sellers provided by their neighbors. Another third of the buyers uses only personal experience to model the trustworthiness of sellers. These buyers allow only a number of the most trustworthy sellers to join their auctions. The rest of the buyers do not model sellers. They allow randomly selected sellers to submit a bid.

We compare the total profit gained by these three types of buyers. Results are shown in Figure 4. From this figure, we can see that buyers modeling the trustworthiness of sellers and limiting their participation will be able to gain more total profit. It is also clear that buyers modeling sellers by taking into account as well the advice provided by other buyers will be able to gain more profit. In summary, it is better off for buyers

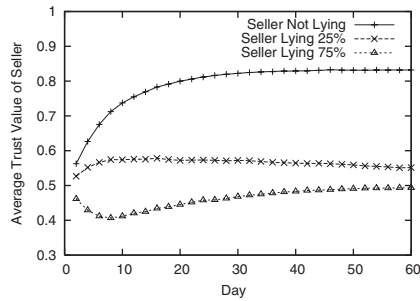


Fig. 5. Average trust of different sellers.

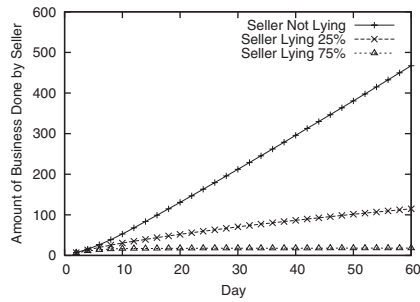


Fig. 6. Amount of business done by different sellers.

to selectively choose sellers to participate in their auctions and to take into account the advice provided by other buyers when buyers lack personal experience with sellers.

## 6.2. Promoting Seller Honesty

In this section, we carry out experiments to demonstrate that sellers in the marketplace are promoted to be honest when our proposed approaches are in use. We compare the average trust values of different sellers. The average trust value of a seller is calculated as the sum of the trust value each buyer has of the seller divided by the total number of buyers in the marketplace (90 in our experiments). As shown in Figure 5, results indicate that sellers being dishonest more often (i.e., lying and failing to deliver the good as promised) will have smaller average trust values. From this figure, we can see that the average trust values of the sellers being dishonest in 25% and 75% of their business are nearly 0.5 after 30 days. This is because they do not have much chance to do business with buyers and will not have many ratings. A seller without any ratings will have a default trust value of 0.5. This also explains why the average trust values of the sellers being dishonest in 25%, and 75% of their business increase and decrease respectively at the beginning and then become closer to 0.5.

We compare the amount of business that different sellers have done with buyers. From the results shown in Figure 6, we can see that sellers being honest more often will be able to gain more opportunities for business with buyers. We also compare total profit gained by different sellers. Results are shown in Figure 7. From this figure, we can see that sellers being honest more often will gain more profit. Therefore, it is better off for sellers to be honest. Our framework promotes seller honesty.



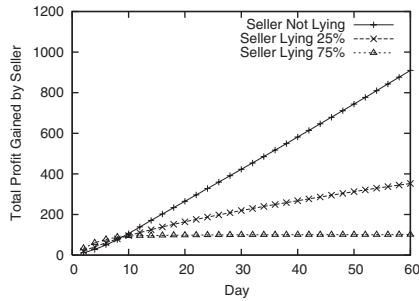


Fig. 7. Total profit gained by different sellers.

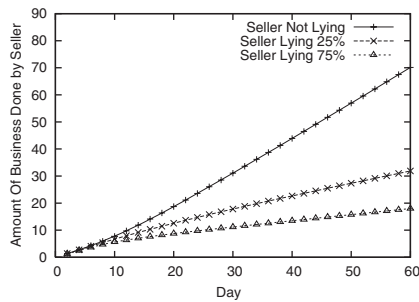


Fig. 8. Amount of business done by sellers.

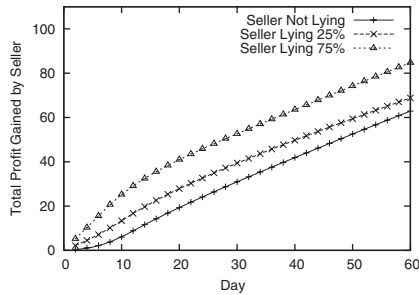


Fig. 9. Total profit gained by sellers when not limiting seller bids.

### 6.3. Limiting Number of Bidders

We carry out experiments to show the importance of limiting seller bids. In these experiments, we have 90 sellers. Similarly, each 30 sellers acts dishonestly in different percentages (0%, 25%, and 75%) of their business with buyers. In the first experiment, we allow 30 sellers to join each buyer's auctions. Figure 8 shows the amount of business done by different sellers. Sellers being honest more often are still able to gain more opportunities to do business with buyers. We also compare total profit gained by different sellers in this setting. However, from the results shown in Figure 9, we can see that sellers being dishonest more often will gain more total profit. In this case, many sellers are allowed to join each buyer's auctions and the competition among the sellers is high. The sellers have to lower their prices of products in order to win the auctions. Sellers being honest can only gain very little profit from each business with buyers; therefore, dishonesty will be promoted.

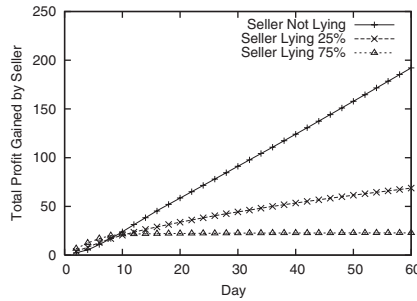


Fig. 10. Total profit gained by sellers when limiting seller bids.

In the second experiment, we limit the number of bidders allowed in each of the buyers' auctions to be 6. As shown in Figure 10, sellers being honest more often will be able to gain more total profit. By limiting the number of bidders in buyers' auctions, the competition among sellers is reduced. The prices of the sellers' products thus get increased and the winning (honest) sellers will be able to gain more profit from each business. Therefore, limiting the number of allowed bidders will promote seller honesty.

#### 6.4. Additional Experimentation: Comparative Evaluation

We also conduct experiments to demonstrate that our approach for modeling advisors provides improvements over the models of BRS [Whitby et al. 2005] and TRAVOS [Teacy et al. 2005] (see Section 2). These three approaches are all based on the beta density function. We set the lower and upper boundaries for BRS to be 0.1 and 0.99 respectively, as recommended in Whitby et al. [2005]. The parameters used by the TRAVOS model are chosen to produce the best results in our experiments. In our experiments, a buyer is considered to be honest if its trust value is greater than 0.5; otherwise, it is dishonest.

We measure the performance of these approaches based on their ability of detecting dishonest advisors. An effective approach should be able to correctly detect dishonest advisors. This performance can be measured by the False Positive Rate (FPR) and False Negative Rate (FNR). A false positive represents that a honest advisor is incorrectly detected as a dishonest advisor. A false negative represents that an advisor is misclassified as honest but actually is dishonest. The lower values of FPR and FNR imply better performance. Here, we use Matthew's Correlation Coefficient (MCC) [Matthews 1975] to measure the approaches' performance on detecting dishonest advisors. MCC is a convenient measure because it gives a single metric for the quality of binary classifications, and is computed as  $MCC = (t_p \cdot t_n - f_p \cdot f_n) / \sqrt{(t_p + f_p)(t_p + f_n)(t_n + f_p)(t_n + f_n)}$  where  $f_p$  = false positives,  $t_p$  = true positives,  $f_n$  = false negatives,  $t_n$  = true negatives. An MCC value is between  $-1$  and  $+1$ . A coefficient of  $+1$  represents a perfect detection,  $0$  an average random detection, and  $-1$  the worst possible detection.

In this experiment, we vary the percentage of dishonest buyers (from 20% to 80%) in the marketplace environment. We then measure the average MCC values for TRAVOS, BRS, and our personalized approach for the period of 60 days. Results are shown in Figure 11. From this figure, we can see that the personalized approach produces the highest MCC values for different percentages of dishonest buyers. TRAVOS performs better than BRS. The performance of these approaches will generally decrease when more buyers are dishonest. Note that the performance of BRS is close to random classification when 50% of buyers are dishonest and becomes much worse when the majority of buyers are dishonest. This result confirms our argument in Section 2.

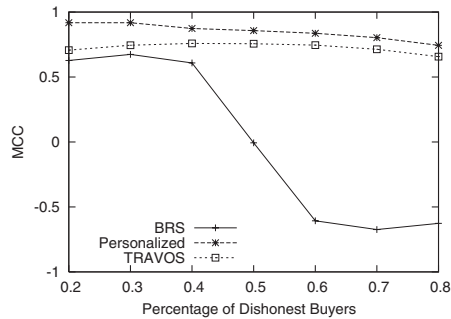


Fig. 11. Comparing the three approaches in detecting dishonest buyers.

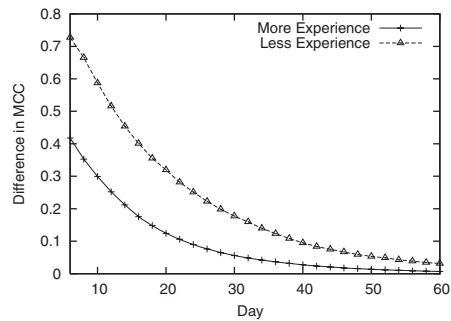


Fig. 12. Personalized vs. TRAVOS.

In another experiment, we directly compare the performance of the personalized approach with that of TRAVOS in the scenario where buyers do not have much experience with sellers. In the experimental setting, 30% of buyers are dishonest. Half of all buyers have more requests for products and another half have fewer requests. Buyers having more requests will have more experience with sellers. We measure how much the personalized approach outperforms TRAVOS in detecting dishonest buyers. Results are shown in Figure 12. In both cases when buyers have more or less experience with sellers, the personalized approach outperforms TRAVOS. From the figure, we can see that the difference is larger when buyers do not have much experience with sellers. The performance difference will decrease day after day because buyers will have more and more experience with sellers. This suggests that an approach of modeling the trustworthiness of advisors should rely on public knowledge of advisors' advice as well when buyers do not have much experience with sellers.

## 7. CONCLUSIONS AND FUTURE WORK

In this article, we propose a model for buyers to effectively select business partners among the most trustworthy sellers in the marketplace, an approach that emphasizes the value of limiting the number of seller bids. In our model, buyers use a personalized approach to effectively model the trustworthiness of other buyers. We use this approach to create a social network of buyers. Each buyer in the society retains a neighborhood of the most trustworthy buyers, as advisors. Buyers then model the trustworthiness of sellers by also considering ratings provided by their neighbors. We carry out experiments under a simulated electronic marketplace environment. Results show that buyers that use our proposed approaches for modeling others will be able to gain more profit and that with our modeling of sellers in place, it is more profitable for sellers

to be honest. As such, we offer a framework for buyers to leverage trust modeling in electronic marketplaces in order to make effective business decisions in electronic marketplaces. Moreover, we are able to demonstrate the robustness of our proposed approach in environments where sellers may be dynamically varying their behavior. We also have some indication of the value of our particular methods for modeling advisors, in comparison with competing approaches.

In future work, we will need to further study the properties of our social network, for example, the proper size of each neighbor list reflecting the population of buying and selling agents in the marketplace and how actively buying agents rate selling agents. Larger neighborhood size will increase the computation of maintaining and updating buying agents' neighbor lists, and may decrease the accuracy for predicting selling agents' trustworthiness from feedback provided by neighbors. Smaller neighborhood size may increase the accuracy, but will have higher chance the neighbors have insufficient experience [Herlocker et al. 2002]. We are currently exploring how best to set the size of a social network through experimental methods involving an initial limiting to reduce inaccuracy, followed by a replacement of advisors that lack sufficient expertise [Gorner and Cohen 2010].

In the current work, the decision of a winning seller is based only on the bids submitted by sellers once the sellers are allowed to join the auction because they are considered as trustworthy by the buyer. Adding information about sellers' trustworthiness into winner selection for the auctions may introduce some challenges. For example, when sellers submit bids, they may do so trying to incorporate reasoning about the trustworthiness of their competitors (as well as their view of their own trustworthiness). The work of Hazard and Singh [2010] provides some hints about how to discount buyer utility based on sellers' trustworthiness. In future work, we will investigate how their approach may provide the possibility of taking into account sellers' trustworthiness when selecting the winning seller in the auction.

Another avenue for future work is to make adjustments to the current model, to broaden its applicability. For example, we could move beyond binary ratings for sellers to accept ratings in different ranges representing how much more or less the valuation of the product that is delivered compares with that described in the seller's bid. Accordingly, the Dirichlet family of probability density functions [Gelman et al. 2004] would be used to represent probability distributions of ratings.

A more dramatic path to explore in the future would be to allow for less predictable behavior from sellers, in order to detect and cope with possible dishonesty. Currently, we determine the likelihood of dishonest behavior probabilistically, based on past experiences. When agents exhibit very inconsistent behavior, researchers such as Regan et al. [2006] suggest some value in modeling the evaluation functions being used by agents as a step forward. This is a possible avenue for our future research.

In addition, if sellers were to be more selectively dishonest, providing disadvantages for only some specific agents in the marketplace, this may pose some challenges, in the sense that the dishonest reputation of these sellers would not build up among a significant portion of the population, to discourage future buyers. This may require instead a more selective social network of those buyers who are in fact similarly affected, in order to stigmatize the dishonest behavior. An initial step forward for future research would be to populate our simulations with sellers exhibiting a form of dishonesty that is more targeted and selective in order to determine where these sellers would escape detection, leading to some novel directions for the actual trust modeling that is performed.

Coping with unfair ratings from advisors in e-marketplaces by a modeling of their trustworthiness has some similarity with the challenge of addressing shilling attacks in recommender systems. The research of Lam and Riedl [2004] suggests that the general

algorithms used by attackers (i.e., the kind of attacks) may be useful to model and that the areas being attacked (e.g., low use items) may influence the possible damage that can be inflicted. For future work, it would be useful to explore these proposals further, to integrate with our approach.

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Received July 2010; revised March 2011; accepted March 2011