Using Stereotypes to Identify Risky Transactions in Internet Auctions

Xin Liu*, Tomasz Kaszuba†, Radoslaw Nielek†, Anwitaman Datta*, Adam Wierzbicki†

*School of Computer Engineering
Nanyang Technological University
Email: liu_xin@pmail.ntu.edu.sg, anwitaman@ntu.edu.sg
†Department of Computer Networks
Polish-Japanese Institute of Information Technology
Email: kaszubat@pjwstk.edu.pl, radek@post.pl, adamw@pjwstk.edu.pl

Abstract—Encountering unknown sellers is very common in online auction sites. In such a scenario, a buyer can not estimate trustworthiness of the unknown seller based on the seller’s past behavior. The buyer is thus exposed to the risk of being cheated. In this paper we describe a stereotypes based mechanism to determine the risk of a potential transaction even if the seller is personally unknown to not only the buyer but also to the rest of the system. Specifically, our approach first identifies discriminating attributes which are capable of distinguishing successful transactions from unsuccessful ones. A buyer can use its own past transactions (with other sellers) to form such stereotypes. Alternatively, the community’s collective knowledge can also be used to build such stereotypes. When posed to a potential transaction with an unknown seller, buyers can estimate trustworthiness (and thus the risk) by combining the corresponding stereotypes. We report experiments over real auction data collected from Allegro, a leading auction site in Eastern Europe. Data driven simulation results show that by setting suitable thresholds our approach can effectively detect (predict) frauds, i.e., has low false positive, with flagging very few successful transactions, that is, it has very low false negative. We also observe from these experiments that local knowledge derived stereotypes are the most accurate, since it is personalized for individual buyers. However, community knowledge derived stereotypes are particularly useful for inexperienced buyers that dominate online auction sites, though there is slight decrease in accuracy. We leverage such analytics to provide a browser (Firefox) based tool to guide buyers during live auctions.

Keywords: online auction, fraud detection, trust, stereotypes

I. INTRODUCTION

Online auction (e.g. eBay1, Taobao2, Allegro3, etc.) constitutes one of the most successful internet business models. Users from all over the world trade goods worth millions of dollars every day using these virtual marketplaces. For an online auction site, one of the most important issues is to ensure high quality of service for the buyers, that is to support buyers by selecting trusted sellers. Unfortunately, rapid commercial success has made auction sites a lucrative medium for committing fraud. The Internet Crime Complaint Center [1] reported that Internet Auction Fraud was by far the most reported offense in 2007, comprising of 35.7% of all complaints. In addition, during the same period, the non-delivery of merchandise and/or payment from non-auction internet transactions represented another 24.9%, pegging the combined total of online sales related fraud complaints at 60.6% of all Internet fraud. So security mechanisms such as trust and reputation management are needed to predict frauds.

However, despite frequent criticisms, only the simplest reputation systems (i.e. aggregated ratings and comments) are used by the most popular internet auctions today because internet auction providers are generally not willing to modify current reputation system infrastructure. As a consequence, an experienced auction buyer is forced to undergo the menial task of reading and judging comments about his potential transaction partners. While human judgement is the best possible way of evaluating this information, the task is time-consuming and error-prone: the sheer number of comments is sometimes an obstacle to making a good decision under uncertainty. On the other hand, the relatively inexperienced buyer becomes an easy target of frauds by being unable to deal with the scattered information.

Many previous solutions [2], [3], [4], [5], [6] endeavor to help inexperienced buyers detect auction frauds by relying on specific sellers’ past behavior. However, such information is not always available or may be insufficient. For instance, the seller newly joins the system or sells items infrequently. However, often the kind of fraudulent behaviors and scams are repeated - by the same sellers, as well as across different sellers [7].

We propose a stereotypes based approach to estimate trustworthiness of a potential transaction where seller is unknown to the buyer, i.e. buyer has no or little historical information of this seller to study. Our approach builds upon some recent advances: (1) a novel computational trust model called StereoTrust [8], which utilizes meta-information based stereotypes to estimate trust of an agent whose past behavior is not available, and (2) a web browser plug-in called ProtoTrust [9] to crawl auction sites and use a library of new and existing algorithms and decision making rules to detect frauds.

The novelty of this work is the use of stereotypes derived from meta-information, instead of specific sellers’ historic information (alternatively, complementing it) leveraging on the
In our approach, buyer estimates trust of the potential transaction, which is conducted by an unknown seller by combining corresponding stereotypes. A stereotype is determined by attributes, which can be taken from the profiles of the sellers. To build stereotypes, the past transactions that a buyer knows are classified into different groups according to the attributes. For instance, the transactions which sell items in the category Mobile Phone are grouped. Two types of past transactions are used: buyer’s individual local knowledge (i.e., this buyer’s past transactions with sellers) and community knowledge (i.e., collection of other buyers’ past transactions with sellers). Then when facing the potential transaction, buyer derives trust of this transaction using stereotypes on multiple such groups to which this transaction belongs. So to detect auction frauds, it is crucial to identify attributes whose values are capable of distinguishing successful transactions from unsuccessful transactions. By studying Allegro dataset, we identify three useful classes of attributes: (1) category of the item sold in the transaction, (2) price of the item and (3) number of items already sold by the seller when the transaction is conducted. We combine these three attributes to form the stereotypes.

The contribution of this paper is threefold. First, we propose a stereotypes based approach for online auction sites to detect the frauds. This approach is particularly designed for the scenario that the seller of the potential transaction is unknown to the buyer. In case that seller’s historical information is available, history based trust and reputation mechanisms can be used. Use of stereotypes is complementary. Please note that the goal of our approach is to identify whether the encountered transaction is good or not, so we do not discuss how to maintain trusts of the known sellers. Second, our approach is generic and complementary. It does not require any modifications of current online auction sites. It is being integrated into a library of trust management tools developed in the Universal Trust project (uTrust) [10] whose aim is to create standard trust management services for distributed, open systems. Third, experiments conducted over a large-scale, real dataset shows that our approach is effective to detect auction frauds while avoiding missing successful transactions.

II. BACKGROUND AND RELATED WORKS

In this section, we first introduce StereoTrust [8] and ProtoTrust [9], which are utilized by this work. Then we survey related solutions for fraud detection in auction sites, as well as the literatures on trust and reputation systems that auction sites typically use to prevent frauds.

A. StereoTrust

StereoTrust [8] is a trust model that estimates trust of a target agent whose past behavior is not available using stereotypes learned from interactions with other agents. This work is inspired by [11], [12], which study the relation between the reputation of a company and its employees: The company’s reputation can be modeled as an aggregate of employees’ reputations and it can suggest a prior estimate for employee’s reputation. In StereoTrust, agents form stereotypes by aggregating information from their interaction partners’ profile pages, or the context of the transaction. Example stereotypes are (“agents selling mobile phones are less honest than others” or “agents living in small towns are more honest”). To build stereotypes, an agent has to group other agents (“agents selling mobile phones” or “agents living in small towns”). These groups do not have to be mutually exclusive. Then, when facing a new agent, the estimator estimates the agent’s trust using stereotypes on groups to which the new agent belongs (“does she sell mobile phones?”, “does she live in a small town?”). Note that our model further creates dichotomies (honest or dishonest) inside such groups to derive trust more accurately. Fig. 1 shows the process of combining multiple stereotypes to derive trust of agent. The weight factor for each group is fraction of trustor’s interactions with members of that group.

The stereotypes are based entirely on the local perspective and local information of the trustor, and, therefore, are naturally suited for large-scale systems; personalized for each trustor; and less susceptible to false or unsuitable information from third parties. However, when some of third parties’ opinions about an agent are available, an enhancement (d-StereoTrust), which creates a “good” and a “bad” sub groups inside each stereotype is proposed. The trustor assigns each one of her previous interaction partners to one of these sub groups based on the her personal experience with the partner (e.g., the ratio of failed interactions). Then, the estimator uses the aggregated third parties’ opinions about the unknown agent to determine how similar is the agent to the “good” and “bad” sub groups. Third parties’ opinions are a small subset of information used by traditional mechanisms (such as feedback aggregation [3] or Eigentrust-type algorithms [13]).

In this paper, StereoTrust is modified a bit: we group past transactions instead of agents; the similarity between potential transaction and the two sub groups is measured by attributes instead of by requesting third parties’ information.
B. ProtoTrust

In the work ProtoTrust [9], several algorithms are developed to detect Internet auction frauds. These algorithms perform three tasks: (i) they support the decision of the buyers based on various trust management algorithms, (ii) they increase the amount of information available from the auction site by considering implicit non-positive feedbacks and (iii) they perform a classification of auction comments to support the buyers in understanding them. ProtoTrust is implemented as an extension of Firefox web browser. Integration with web browser has several advantages such as availability (system independent), easy installation and access to information directly from the auction sites. ProtoTrust consists of three major modules: the thread management module, the presentation module and the Trust Management (TM) module. Figure 2 shows the ProtoTrust architecture in details.

![Fig. 2. ProtoTrust architecture](image)

After initializing the extension, the buyer can add her preferences to tune the system. Preferences can be changed at any time even after computation. Extension is activated by specifying context and the target seller (i.e. visiting the item page). Thread management initiates all objects and synchronizes all crawling and presentation threads with the web browser’s main thread. The TM module is the most crucial element in ProtoTrust. It accesses the network and uses local storage (if available) to search for information that will be used to support the buyer. The information found by Web crawler is stored locally for future use. After a fixed amount of time or when sufficient data is collected, ProtoTrust uses the uTrust library [10] to perform the desired trust management algorithms. When the computation is complete, ProtoTrust presents the results to the user. The presentation module, which is based on user preferences can suggest the buyer to enter or leave the potential transaction.

C. Related Solutions

Chua et al. [7] identified various internet auction frauds. Many attempts have been made to help people detect the fraudsters in online auction sites. For instance, many internet articles [14], [15] give suggestions on how to prevent being cheated and online auction sites also provide guidance to the buyers especially the beginners. However, most of these attempts are “common sense” and heuristic. They require a considerable amount of time and effort in investigating potential sellers before transacting with them.

Reputation systems [16] are widely used by current online auction sites to help buyers detect frauds: After one transaction, buyer rates the sellers as positive (1), neutral (0) or negative (-1). Reputation of the seller is simply the aggregation of these ratings. Such approach can be fooled by the malicious sellers easily. Resnick et al. [17] demonstrated the problems of low feedback rates and reporting biases. Several works are proposed to solve these problems: (1) Some approaches rely on centralized entities. Ba et al. [18] provided a Trusted Third Party mechanism to issue certificates to both sellers and buyers. This mechanism can induce cooperative behavior if both buyers and sellers obtain the verifications from the Trusted Third Party. Dellarocas [19] proposed to charge a listing fee contingent on a seller’s announced quality and reward the seller based on his announced quality and the rating given to that seller by the winning bidder for that listing. (2) Some approaches focus on evaluating the feedbacks provided by other buyers. The beta reputation system proposed by Jøsang et al. [3] estimates reputation of selling agents using a probabilistic model (i.e. based on the beta probability density function). This model is able to estimate the reputation of a seller by propagating feedbacks provided by multiple advisors. TRAVOS [5] is a trust and reputation model for agent-based virtual organizations. It addresses inaccurate reputation feedbacks by accomplishing two tasks. The first one is to estimate the accuracy of the current feedback provided by the advisor about the seller, based on the buyer’s past experience with the advisor’s previous feedbacks. The second task is to adjust reputation advice according to its accuracy to reduce the effect of inaccurate advice. The works [4], [6] developed incentive mechanisms of rewards and punishments to induce both sellers and buyers to report honestly.

The above surveyed approaches indeed help reduce frauds in online auction sites, however, they have their limitations. Some of these approaches need modifications of current online auction sites or rely on third parties, which is unlikely to happen overnight, while some of them depend on other buyers’ feedbacks about the seller, which are not always available (i.e. seller has no historical information) and may be unreliable.

Different from existing works, our approach does not need to modify current auction sites and uses a different kind of information, stereotypes to derive trust. This makes our approach able to evaluate a potential transaction conducted by the seller who is unknown to the buyer, even to the whole community.

III. STEREOTYPING TRANSACTIONS

In this section, we present our approach for detecting fraud in online auction sites. The key idea is to use stereotypes to derive trust of a potential transaction. Specifically, given a set of attributes of the transactions, stereotypes are formed by grouping past transactions that the buyer knows. When facing a potential transaction, the stereotypes matching attributes of
this transaction are aggregated to derive its expected trustworthiness. We begin by identifying attributes of transactions for stereotype creation in the next sub section.

A. Identifying Attributes

By studying Allegro dataset, we identify four attributes of the transactions:

- \(A_1\): Category of the item.
- \(A_2\): Price of the item.
- \(A_3\): System age of the seller when the transaction occurs.
- \(A_4\): Number of items already sold by the seller when the transaction occurs.

Next we justify the identified attributes using Allegro data. In order to evaluate discrimination power of each attribute, we compute the ratio \(\delta\) between average value of this attribute for successful transactions and unsuccessful transactions. We only consider the attributes with \(\delta\) (or \(1/\delta\)) at least 2 for next steps of our approach. Table I summarizes the ratio \(\delta\) (or \(1/\delta\)) for all the attributes. We do not show results of the attribute category \(A_1\) because its value can not be computed. Note that the unit for \(A_3\) is hour. According to value of \(\delta\) (or \(1/\delta\)), we choose attribute \(A_2\) and \(A_4\) for stereotypes creation. It has been reported in the literatures [20], [21] that some dishonest sellers may sell some cheap items in a certain category to gain reputation and then cheat in an auction with high price in another category. So we also consider attribute \(A_1\) when forming the stereotypes.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Avg.(successful)</th>
<th>Avg.(unsuccessful)</th>
<th>(\delta) (or (1/\delta))</th>
<th>result</th>
</tr>
</thead>
<tbody>
<tr>
<td>(A_2)</td>
<td>52.59</td>
<td>120.80</td>
<td>2.30</td>
<td>considered</td>
</tr>
<tr>
<td>(A_3)</td>
<td>14713.32</td>
<td>13019.53</td>
<td>1.13</td>
<td>not considered</td>
</tr>
<tr>
<td>(A_4)</td>
<td>358.21</td>
<td>150.00</td>
<td>2.39</td>
<td>considered</td>
</tr>
</tbody>
</table>

B. Creating Stereotypes Using Identified Attributes

After identifying attributes, we now discuss how to use such attributes and past transactions to create stereotypes. We begin with the attribute category. Buyer first collects the past transactions. Then according to category of the item traded in the transaction, these past transactions are classified into different groups \(\{G_{c_1}, G_{c_2}, G_{c_3}, \ldots\}\), where \(c_i\) indicates category \(C_i\). For group \(G_{c_i}\), we denote the numbers of successful and unsuccessful transactions by \(N^s_i\) and \(N^u_i\) respectively. Buyer’s stereotypes on group \(G_{c_i}\) is calculated as \(\frac{N^s_i}{N^s_i+N^u_i}\). So when next time this buyer encounters a potential transaction which sells item in category \(C_i\), he/she can estimate trust of this transaction based on its stereotype on group \(G_{c_i}\).

Category based stereotype works under the assumption that dishonest sellers cheat buyers in certain categories while acting honestly in other different categories so that buyers finally have clearly different stereotypes on these categories. However, in real world online auction sites, different dishonest sellers may cheat in quite different categories so there is no clear differences among the categories, thus category based stereotype can not accurately predict the potential transaction.

To make our stereotype based approach work well, we take into account other attributes which are identified in section III-A. The main idea is to group past transactions on a finer level. For a category based group \(G_{c_i}\), the transactions in this group are further divided into two disjoint sub groups: a successful sub group \(G^s_{c_i}\) and an unsuccessful sub group \(G^u_{c_i}\). The buyer assigns a transaction in the group to either sub group according to outcome of this transaction (i.e. if a transaction is successful, it is added to the successful sub group, otherwise, it is added to the unsuccessful sub group). Buyer’s stereotypes on successful and unsuccessful sub groups are 1 and 0 respectively.

Each transaction in the sub group has two attributes: price of the item (attribute \(A_2\)) and number of items already sold by the seller when the transaction occurs (attribute \(A_4\)). So each transaction is represented as a point in a two dimension space, described by its values of attributes \(A_2\) and \(A_4\). Fig. 3 depicts the sub groups of group \(G_{c_i}\) in a two dimension space. White points represent successful transactions and black points represent unsuccessful transactions. So when the buyer encounters a potential transaction, he/she first classifies this transaction into corresponding category formed group and then tries to connect it to successful sub group and unsuccessful sub group based on its values of attributes \(A_2\) and \(A_4\). Before presenting how to derive trust of the potential transaction using the corresponding stereotypes in Sec. III-D, we first introduce two kinds of knowledge to form the groups/stereotypes in the next sub section.

C. Local Stereotypes versus Community Stereotypes

To build stereotypes, the past transactions that the buyer knows are classified into different groups. Generally, buyers’ local knowledge reflects buyers’ personalized perspective on the system, thus is the most accurate information to create stereotypes (we call them local stereotypes). However, in online auction sites, most of the buyers are inexperienced (local knowledge is insufficient). To create stereotypes, inexperienced buyer may use other buyers’ past transactions (i.e. community knowledge). We rely on our previous work ProtoTrust.

\(\text{We assume trust/stereotype value in this work is in } [0,1], \text{ where 1 represents trustworthy and 0 represents untrustworthy}\)
[9] to crawl the auction sites to obtain other buyers’ local knowledge. When ProtoTrust plug-in is activated, its crawler works as daemon to collect community knowledge. Crawler gathers information automatically by crawling parts of the auction site (buyers’ comments, transaction archives, buyers or users’ profiles). Community knowledge is rather unalterable so this computation can be performed occasionally. The process of gathering community knowledge is stopped after a fixed amount of time or when certain amount of data is obtained. We call the stereotypes created using community knowledge community stereotypes. Community stereotypes may not be as accurate as buyers’ local stereotypes, however, they provide the whole community’s perspective on the system, which may reveal some information that is unknown to the individual buyers, and are particularly useful for the inexperienced buyers who do not have sufficient local knowledge.

D. Estimating Trust of Transaction Using Stereotypes

After creating stereotypes, we present how to estimate trust of a potential transaction using these stereotypes. We denote the potential transaction by \( T(A^2_i, A^4_i) \), where \( A^2_i \) and \( A^4_i \) represent values of attributes \( A^2 \) and \( A^4 \); and \( t \) indicates these values are for this transaction \( T \). Similarly, the past transactions (local knowledge or community knowledge) are denoted by \( T = \{ T_1(A^2_1, A^4_1), T_2(A^2_2, A^4_2), T_3(A^2_3, A^4_3), \ldots \} \). When encountering \( T(A^2_i, A^4_i) \), we assume that the groups are already formed: \( G = \{ G_{c_1}, G_{c_2}, G_{c_3}, \ldots \} \). For group \( G_{c_i} \), its member transactions are divided into two sub groups: successful sub group \( G_{c_i}^s \) and unsuccessful sub group \( G_{c_i}^u \).

To measure trustworthiness of the potential transaction, buyer first calculates distances between \( T(A^2_i, A^4_i) \) and the two sub groups for each group (i.e. distances between potential transaction and centroids of the two sub groups). The centroids of the two sub groups \((\text{Avg}_{G_{c_i}}^2, \text{Avg}_{G_{c_i}}^4)\) and \((\text{Avg}_{G_{c_i}}^2, \text{Avg}_{G_{c_i}}^4)\) are calculated\(^3\) as the average values of attributes \( A^2 \) and \( A^4 \). Then the distances are calculated as:

\[
D^s_i = \sqrt{(\text{Avg}_{G_{c_i}}^2 - A^2_i)^2 + (\text{Avg}_{G_{c_i}}^4 - A^4_i)^2}
\]

\[
D^u_i = \sqrt{(\text{Avg}_{G_{c_i}}^2 - A^2_i)^2 + (\text{Avg}_{G_{c_i}}^4 - A^4_i)^2}
\]

Fig. 3 shows distances between potential transaction \( T \) and the two sub groups in group \( G_{c_i} \). The stars in the two sub groups represent centroids of these two sub groups. The distances demonstrate how close is the potential transaction and the two sub groups. That is, if \( D^s_i < D^u_i \), potential transaction is closer to successful sub group, which means it is more likely to be successful. Otherwise, this transaction is more likely to be unsuccessful. The distances can be used to measure weights of buyer’s stereotypes on the two sub groups:

\[
w^s_i = \frac{1}{D^s_i + 1/D^u_i}
\]

\[
w^u_i = \frac{1}{D^u_i + 1/D^s_i}
\]

\(^3\)When calculating the average values, in order to avoid abnormal values, it is necessary to normalize the values to a certain range, e.g. \([0,1]\).

Buyer’s stereotypes on successful and unsuccessful sub groups are 1 and 0 respectively. For the potential transaction \( T(A^2_i, A^4_i) \), buyer’s stereotype on group \( G_{c_i} \) is computed as the weighted sum of its stereotypes on the two sub groups, where weights are measured by the distances\(^6\):

\[
S_i = w^s_i * 1 + w^u_i * 0
\]

After calculating buyer’s stereotypes on each group, we need to estimate weights of these groups to combine the corresponding stereotypes to derive trust of the potential transaction. We define importance factor \( \lambda \) to indicate the importance of each category/group. Two attributes may influence importance of a category: the number of items sold and prices of the items in this category. If the amount of items sold in a category is large, it means this category is very popular for the buyers thus it deserves more importance. And if the prices of the items in a category are very high, it means buyers suffer high risks when buying these items thus this category also deserves more importance. So the importance factor \( \lambda_i \) for group \( G_{c_i} \) is calculated as:

\[
\lambda_i = \frac{N_i}{\sum_k \lambda_k}
\]

Where \( N_i \) is the amount of items sold in this category and \( p_j \) is the price of the \( j \)th item. Using important factors, we calculate weight of each group \( G_{c_i} \):

\[
W_i = \frac{\lambda_i}{\sum_k \lambda_k}
\]

Where \( k \) indicates index of each group. After calculating stereotypes on the groups and their weights, we combine these stereotypes to derive trust of the potential transaction:

\[
T_R = \sum_k W_k * S_k
\]

Fig. 4 depicts the whole process of combining all stereotypes.

\(^6\)Other kinds of weights may also be applied. For instance, if \( D^s_i < D^u_i \), we simply set the stereotype on the group as 1 (i.e. the potential transaction clearly belongs to successful sub group).
IV. Evaluation

In this section, we conduct experiments over Allegro dataset to evaluate performance of our proposed stereotypes based approach. We first discuss methodology in Sec. IV-A and then present results in Sec. IV-B.

A. Methodology

The dataset used in this paper was provided by Allegro, a leading auction site in Eastern Europe. At the beginning of the fourth quarter in 2006, 10,000 sellers and 10,000 buyers have been randomly selected; their profiles and received comments have been stored. During the next 6 months all transactions conducted by the selected users were monitored and recorded. For every partner who appeared in transaction and was not in the primary database, all historical information about the received feedback has been collected, but with respect to new auctions only the originally selected users have been monitored. In the first quarter in 2007 the database contained more than 200,000 transactions and over 1.7 million comments (1,712,886 positive feedbacks, 9,437 neutral feedbacks and 5,722 negative feedbacks). In the experiments, a transaction is considered successful if its feedback is positive, otherwise, it is considered unsuccessful.

In the experiments, each transaction is described by three attributes, which are identified in Sec. III-A: category of the item, Price of the item and number of items already sold by the seller when the transaction occurs. To evaluate performance of our approach that uses individual buyer’s local knowledge to create stereotypes, we randomly select 100 buyers with sufficient local knowledge (i.e. at least 15 historical transactions). Then we randomly select 1000 transactions (50% are successful and 50% are unsuccessful). Each buyer evaluates 10 transactions to decide whether or not to enter the transactions. To evaluate our approach that uses community knowledge, we select 10000 buyers at random to form the knowledge pool (community knowledge). Then we evaluate the 1000 randomly selected transactions (50% are successful and 50% are unsuccessful) using community knowledge to create the stereotypes. We estimate accuracy of prediction by comparing the decisions made by our approach with the ground truth (real outcomes of these transactions).

B. Results

1) False Positive versus False Negative: Fig. 5 demonstrates false positive and false negative caused by our approach that uses buyer’s local knowledge and community knowledge to create stereotypes respectively. As discussed before, the derived trust value of the potential transactions is in the range of [0,1]. To help buyer make the binary decision, we set the threshold that is also in the range of [0,1]. We vary the threshold from 0 to 1 with 0.02 as the increment to observe the changes of percentages of false positive and false negative. From Fig. 5(a) and 5(b), we can see no matter what kind of knowledge is used, the percentages of the falseness vary with the varying threshold. When threshold increases, percentage of false positive declines and percentage of false negative ascends. This is because when threshold is high, the probability that an unsuccessful transaction is predicted as a successful one is low but the probability that a successful transaction is predicted as an unsuccessful one is high (i.e. the transactions whose trust values are not quite high are considered unsuccessful). Since percentages of false positive and false negative changes with thresholds conversely, it is difficult to set a threshold to keep percentages of the two kinds of falseness lowest simultaneously. In the next sub section, we show results of combining false positive and false negative to demonstrate performance of our approach.

2) Overall Falseness: We define the overall falseness to combine false positive and false negative by taking into account harmfulness factor $\theta$ (see Eq. 9). Fig. 6 shows the overall falseness of our approach that uses buyer’s local knowledge and community knowledge to create stereotypes respectively. We vary harmfulness factor $\theta$ from 0.6 to 0.9 with 0.1 as increment. From Fig. 6(a) and Fig. 6(b), we observe that the general trend of percentage of overall falseness is: it declines with the increasing threshold and stops at a certain point, then...
it starts ascending. So the lowest point is the optimal result that our approach is able to achieve and the corresponding threshold is the design parameter we are looking for. From the two figures, we also observe that no matter which kind of knowledge is used, when \( \theta \) is bigger, the corresponding percentage of overall falseness is lower. This is because percentage of false negative is higher than that of false positive (i.e. try to keep false positive as few as possible). So when \((1 - \theta)\) becomes smaller, \((1 - \theta) \ast FN \) (see Eq. 9) makes the percentage of overall falseness lower despite the fact that \( \theta \ast FP \) becomes bigger.

3) Local Stereotypes Versus Community Stereotypes: Now we compare performance of local stereotypes and community stereotypes. Fig. 7 shows percentage of overall falseness caused by our approach that uses local stereotypes and community stereotypes respectively. We set the harmfulness \( \rho \) as 0.8 and 0.9 respectively. From the figure we observe that under the same \( \theta \), local stereotypes based approach outperforms community stereotypes based approach. When \( \rho = 0.8 \), the lowest percentage of overall falseness for local stereotypes based approach is 0.029 and that for community stereotypes based approach is 0.0626. When \( \rho = 0.9 \), the lowest percentage of overall falseness for local stereotypes based approach is 0.027 and that for community stereotypes based approach is 0.038. This is because local stereotypes are derived using individual buyer’s local knowledge, which is the most accurate information source for that buyer while community stereotypes take into account other buyers’ opinions which may be different from this buyer’s opinion. However, we notice that even if local stereotypes are more accurate than community stereotypes, the difference is not very big. Moreover, community stereotypes are particularly useful for the inexperienced buyers, which almost dominate the online auction sites. So we believe community stereotypes are also useful and can be seen as a kind of complementary knowledge. Table II summaries percentage of overall falseness and the corresponding thresholds for local knowledge based approach and community knowledge based approach with different \( \theta \) values.

V. CONCLUSION

We consider the problem of predicting trust of a potential transaction where the seller is unknown to the buyer in online auction sites. Traditional approaches to this problem derive seller’s trust essentially by studying the direct observations; or by combining trust of third parties to the seller with the buyer’s trust of these third parties; or simply by aggregating third parties’ feedbacks about the sellers. In contrast, Our proposed approach uses different kind of information: that of semantic similarity of the potential transaction to other past transactions that the buyer knows. This is analogous to spam email filtering, however, the approach itself is novel. In our approach, a buyer builds stereotypes that aggregate and summarize the past experience according to certain attributes. Facing a potential transaction with an unknown agent, the buyer builds its trust by cumulating the experience from the stereotypes to which the potential transaction conforms.

Two kinds of knowledge can be used to form the stereotypes: individual buyer’s local knowledge or community knowledge, which is a collection of many buyers’ local knowledge. Community knowledge is obtained by crawling part of the auction sites using our previous work ProtoTrust. Generally, local knowledge is the most accurate information source for the buyer to use, thus the created stereotypes are the most accurate. However, in current online auction sites, most of buyers are inexperienced. In this case, community knowledge can be used to derive the stereotypes. Although community stereotypes may not be as accurate as local stereotypes, they provide a complementary knowledge to evaluate...
the transaction. Furthermore, community knowledge may contain some information that is unknown to the buyer but may be useful for future transaction prediction. For instance, when a buyer wants to buy items in a totally new category, he/she may resort to community knowledge to predict the trust of this transaction.

We conducted experiments over a large-scale real auction dataset to evaluate performance of our approach. Two criterion are used: percentages of false positive and false negative. Generally, false positive is more harmful to the buyer than false negative. However, false negative should not be ignored. So to effectively evaluate our approach, we use the criteria percentage of overall falseness, which is calculated as the weighted sum of percentages of false positive and false negative. More weight is given to false positive. Simulation results show that local stereotypes based approach outperforms community stereotypes based approach, but the advantage is not quite obvious. We also find out the thresholds that achieve the lowest percentage of overall falseness. That are 0.6 for local stereotypes based approach and 0.84/0.86 for community stereotypes based approach. These values can make suggestions to the system designers on parameter configuration. The proposed approach has been integrated into ProtoTrust (version 2) as a Firefox extension to guide buyers during the live auctions. The extension will be released soon.

In current approach, when a buyer has sufficient local knowledge, it does not take into account community knowledge, which however may be useful for future prediction. We hope to extend current approach by combining local knowledge and community knowledge. The second research direction is to apply our stereotypes based approach to some other applications because even though this approach is designed particularly for online auction, its idea of using stereotypes to derive trust is generic. For instance, it may be applied for email spam filtering, or it may be used to recommend related information on Web 2.0 sites (e.g. YouTube, Digg, etc.).

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