Modeling Context Aware Dynamic Trust
Using Hidden Markov Model[*]

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Abstract

Modeling trust in complex dynamic environments is an important yet challenging issue since an intelligent agent may strategically change its behavior to maximize its profits. In this paper, we propose a context aware trust model to predict dynamic trust by using a Hidden Markov Model (HMM) to model an agent's interactions. Although HMMs have already been applied in the past to model an agent's dynamic behavior to greatly improve the traditional static probabilistic trust approaches, most HMM based trust models only focus on outcomes of the past interactions without considering interaction context, which we believe, reflects immensely on the dynamic behavior or intent of an agent. Interaction contextual information is comprehensively studied and integrated into the model to more precisely approximate an agent's dynamic behavior. Evaluation using real auction data and synthetic data demonstrates the efficacy of our approach in comparison with previous state-of-the-art trust mechanisms.

Introduction

In recent years, people have taken a more active role in participating in various large-scale, open and dynamic systems like social networks, Peer-to-Peer (P2P) systems, e-commerce, etc. By intensively interacting with other system participants, user's Internet experience has been significantly enhanced. However, due to the system characteristics like openness, anyone can easily join the systems, it is thus challenging to ensure a reliable interaction environment for honest users. Traditional security solutions like public key infrastructure (PKI) may help but they are not applicable to address uncertainty of the user behavior in the interactions. Trust management has emerged as a popular alternative to reason about uncertainty, thus aiding decision support by indicating the trustworthiness of interaction partners.

A lot of approaches have been proposed to estimate trust based on the target agent's past behavior (Jøsang and Ismail 2002; Regan, Poupart, and Cohen 2006; Teacy et al. 2006; Li and Wang 2010). However, most such approaches assume a relatively static agent behavior, and thus are not able

to capture an agent's dynamic behavior patterns, which is the norm in large-scale open systems. For instance, in an online auction site, a malicious seller may act honestly in selling cheap items to gather sufficient reputation and then cheat in selling an expensive item. Recently, several Hidden Markov Model (HMM) based approaches (Moe, Tavakoli-fard, and Knapskog. 2008; Malik, Akbar, and Bouguettaya 2009; ElSalamouny, Sassone, and Nielsen 2009) have been proposed to handle agents' dynamic behaviors. These approaches model trust as a dynamic variable, changing with time. An agent may switch from one state in the previous interaction to another state in the next interaction. That is, the trustor is able to deduce the trustworthiness state of the target agent based on its past interactions. Since the system state is hidden, HMM is naturally applied to infer the state probability distribution which can be used to estimate outcome of the next interaction with the target agent.

Although HMM is potentially a good tool to model dynamic trust, its accuracy greatly depends on observations probability distribution. Most existing approaches intuitively use the outcomes of the past transactions as the observation sequence. This method is effective when an agent changes its behavior frequently or in specific patterns, but is not well suited to identify relatively infrequent dishonest behavior of an agent who has a good behavior record, or the implicit patterns from the random behaviors. For instance, when most of an agent's past transactions are satisfactory, it is quite challenging to detect its 'sudden' behavior change. In this paper, we first argue that by carefully investigating interaction contextual information, an agent's dynamic behavior can be reflected better. We provide a comprehensive discussion on contextual information of an interaction using online auction site as the demonstration example. Such contextual information is characterized by a set of features. In order to achieve efficient prediction, we apply information theory (entropy based information gain) and multiple discriminant analysis (MDA) to select the most useful features and combine the same to generate a compact and effective feature vector, which is viewed as the observations associated with each interaction. We then propose a HMM based trust model considering such contextual information to capture dynamic behavior of the target agent. Specifically, we assume the outcome of an interaction has x levels (e.g., good, medium, bad). Each outcome

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level corresponds to a trustworthiness state of the target agent. We thus construct the x-state HMM where the observable is the contextual information associated with each interaction. Experimental results show that our approach is more effective in detecting an agent's dynamic behavior than state-of-the-art trust approaches (Zhang and Cohen 2008; Moe, Tavakolifard, and Knapskog. 2008; ElSalamouny, Sassone, and Nielsen 2009).

The rest of this paper is organized as follows: Section 2 discusses the related works. In Section 3, we provide a comprehensive study on trust contextual information using online auction site as the demonstration example. In Section 4, we propose a HMM based trust model. We first introduce the basic notations and background of HMM in Section 4.1 and then discuss the theory of our HMM based trust model in Section 4.2. Section 4.3 elaborates how to integrate contextual information into the model. Evaluation using real auction dataset and synthetic dataset is conducted to quantify the performance of the proposed approach in Section 5. Section 6 summarizes this work and discusses future work.

Related Work

Modeling dynamic trustworthiness of an agent is important yet challenging (Castelfranchi 2011). Some early efforts on this issue is to extend the popular Beta (or Dirichlet) based trust models by adopting the "forgetting factor" (Jøsang and Ismail 2002; Buchegger and Boudec 2004; Teacy et al. 2006). Briefly, these approaches pay more attention to the recent encounters than the old ones. This, to some extent, reflects an agent's recent behavior variation. In advance of "forgetting factor", Zhang et al. (Zhang and Cohen 2008) took into account an agent's dynamic behavior by introducing the concept of time window. The ratings of the target agent are partitioned into different elemental time windows. In each time window, the trustor counts the numbers of successful and unsuccessful transactions. The trustworthiness of the target agent is firstly calculated by aggregating numbers of successful and unsuccessful transactions in each time window (also taking into account forgetting rate) and then is adjusted according to reputations of the indirect experience providers.

Recently, several works applied HMM to model dynamic trust. In (Moe, Tavakolifard, and Knapskog. 2008), a trust model for multi-agent systems is developed to help the agent make optimal trust decisions over time in a dynamic environment. The target agents's behavior is predicted according to the HMM trust estimation module following the Q-learning greedy policy. ElSalamouny et al. (ElSalamouny, Sassone, and Nielsen 2009) modeled the real dynamic behavior of an agent by HMMs. They further justified the consistency of the model by measuring the difference between real and estimated predictive probability distributions using relative entropy. The work (Moe, Helvik, and Knapskog 2009) conducted a comparison study between HMM based trust approaches and Beta based trust approaches (with forgetting factor). The results show that HMM based approach performs better in detecting agent's behavior changes thus is more realistic for dynamic environments. The works (Moe, Helvik, and Knapskog 2008)

and (Malik, Akbar, and Bouguettaya 2009) demonstrate how HMM based trust approaches are applied to distinct application scenarios: routing protocol design in mobile and ad-hoc networks (MANET), and web service providers selection. However, these works do not make full use of the contextual information, which may also reflect the dynamic behavior of an agent.

Different from HMM based approaches, Liu et al. (Liu and Datta 2011) proposed to model an agent's dynamic behavior by learning its past behavior patterns. Specifically, the authors first identified features which are capable of describing context of an interaction. These features are then used to calculate similarity between context of the two interactions. Trustworthiness of the potential transaction is estimated based on outcome of the specific past transaction which has the most similar context. The main limitation of this work is that it greatly relies on the sequence of the past transactions. Our approach also makes use of the contextual information of the interactions (but in a different way), which will be discussed in the next sections.

Interaction Contextual Information

From the perspective of behavior science and psychology (Coons and Leibowitz 2010), we believe that an agent's behavior change in the interactions is correlated with and can be inferred (to certain extent) by the associated interaction contextual information. For instance, in an online auction site like eBay, a seller may vary his behavior consciously or unwittingly in selling different items (e.g., he may be very careful in selling very expensive items while be imprudent when trading individual cheap items). Next, using online auction site as the demonstration example, we provide a comprehensive study on the interaction contextual information, which will be used in our HMM based trust model.

- About the target agent
  The contextual information about the target agent includes the features collected from its profile in the system. For instance, in online auction site, such features include the seller's system age, does he provide a detailed contact information, number of items already sold, reputation value (e.g., fraction of successful transactions), average delivery time, in which categories he is active and so on. Besides its profile in the system, the context may also consist of the agent's natural property including, for instance, the seller's age, gender, location (city/country), etc.

- About the provided services/products
  The second class of contextual information is the features about the services (items in online auction site) provided by the target agent. Such features include the item price, average item price in the same category, comments, number of the same items in stock, number of comments on these items, number of different buyers that already placed bid on it, average age in the system of buyers that already placed bid, etc.

- About the social relationships
  The last class of contextual information relates to the social relationships between the target agent and

other agents. Examples of such relationships include family/colleague/friend/acquaintance ties, community/organization structure, trust networks (Jøsang, Hayward, and Pope 2006) and so on. For instance, the target agent's behavior may be inferred based on trustor's experience with other similar agents (e.g., via stereotypes (Liu et al. 2009)).

We next present how to integrate the identified features into the proposed HMM based trust model.

HMM Based Trust Model

The Basics

Consider a scenario where an agent a_x, a service requestor encounters a potential service provider a_y. A transaction happens when a_x accepts a_y's service. To indicate quality of a service, a_x may rate the transaction, where the rating is a discrete quantitative variable in a certain range, denoted by $\mathcal{L} = \{L_1, L_2, ..., L_l\}$. For instance, the rating could be in the range of [1, 2, 3, 4, 5], where 1 to 5 represents lowest quality, low quality, medium, high quality and highest quality respectively. θ_{a_x,a_y} denotes the transaction between a_x and a_y. We assume that a_x maintains a list of past transactions[1] with a_y: $\Theta_{a_x,a_y} = \{\theta^1_{a_x,a_y}, \theta^2_{a_x,a_y}, ...\}$.

As described in the introduction, we use HMMs to model and approximate the dynamic behavior of an agent. A HMM is a probabilistic model in which the observation sequence is a probabilistic function of a finite set of hidden states. Briefly, a (discrete) Hidden Markov Model (HMM) is defined as a tuple $\lambda = (Q, V, \pi, A, B)$:

- $Q = \{q_0, q_1, ..., q_{N-1}\}$ is the set of distinct states of the Markov process, where N is the number of the states.

- $V = \{v_0, v_1, ..., v_{M-1}\}$ is the set of M observation symbols.

- π is the initial state distribution.

- A is the state transition probabilities (matrix): $Q \times Q \rightarrow [0, 1]$, with $A_{i,j} = P(q_j$ at time $t + 1 | q_i$ at time $t)$ and $\sum_{q_j \in Q} A_{i,j} = 1$.

- B is the observation probability matrix: $Q \times V \rightarrow [0, 1]$, with $B_{j,k} = P(v_k$ at time $t | q_j$ at time $t)$ and $\sum_{v_k \in V} B_{j,k} = 1$.

Consider a state sequence of length s: $X_s = (x_0, x_1, ..., x_{s-1})$, with the corresponding observations $Y_s = (y_0, y_2, ..., y_{s-1})$. π_0 is the initial probability stating in state x_0. Then the probability distribution of the state sequence X given a HMM λ is obtained:

$$P(X_s|Y_s, \lambda) = \pi_0 B_{x_0,y_0} A_{x_0,x_1} B_{x_1,y_1} ... A_{x_{s-2},x_{s-1}} \quad (1)$$
$$B_{x_{s-1},y_{s-1}}.$$

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[1] In case a_x does not have sufficient past experience with a_y, it may resort to other agents who have interacted with a_y. The issues of addressing false feedback have been thoroughly studied (Teacy et al. 2006; Zhang and Cohen 2008) thus is beyond the scope of this work.

One basic problem that a HMM can solve is to find the optimal state sequence for the underlying Markov process given the past states/observations: $P(x_s|X_s, Y_s, \lambda)$. With this important property, we are able to predict the target agent's trustworthiness (i.e., outcome of the next interaction) based on the past interactions and observations (i.e., the corresponding feature vectors).

HMM Based Approach

Based on the properties of HMM, from the perspective of the trustor a_x, the target agent a_y's dynamic trustworthiness can be modeled by a finite-state HMM. Such a model is then used to estimate the predictive probability distribution of a_y's next state. Since we assume that outcome of a transaction is a discrete quantitative variable in a certain range $\mathcal{L}$, the l-state HMM constructed by a_x for modeling dynamic behavior of a_y is denoted by $\lambda^l_{x,y} = (\mathcal{L}, \mathcal{F}_{x,y}, \pi^{x,y}, A^{x,y}, B^{x,y})$.

Now we handle the problem of estimating outcome of the next transaction with a_y given sequence of outcomes of the past transactions and the associated observed features. Here the state of a_y at discrete time point t corresponds to the rating of outcome $L_i \in \mathcal{L}$ of the transaction $\theta^t_{a_x,a_y}$ happened at time t. Let $H_m = s_0 s_1 s_2 ... s_{m-1}$ (where $\forall_{i=0,1,...,m-1} s_i \in \mathcal{L}$) be a random variable representing any sequence of outcomes of transactions between a_x and a_y where s_0 is the outcome of the oldest transaction and s_{m-1} is the outcome of the most recent one. We then denote the next transaction by s_m (and hence $H_{m+1} = H_m \bigcap s_m$). The corresponding observed features associated with each transaction is denoted by $F_m = f_0 f_1 f_2 ... f_{m-1}$, and $F_{m+1} = F_m \bigcap f_m$ (where $\forall_{i=0,1,...,m} f_i \in \mathcal{F}$). The estimated probability distribution of outcome of the next transaction given the HMM $\lambda^l_{x,y}$ is thus obtained:

$$P(s_m = L_j | F_{m+1}, \lambda^l_{x,y}) = \frac{P(s_m = L_j, F_{m+1}, \lambda^l_{x,y})}{P(F_{m+1}, \lambda^l_{x,y})}. \quad (2)$$

Since

$$P(s_m = L_j, F_{m+1} | \lambda^l_{x,y}) = \frac{P(s_m = L_j, F_{m+1}, \lambda^l_{x,y})}{P(\lambda^l_{x,y})}. \quad (3)$$

$$P(F_{m+1} | \lambda^l_{x,y}) = \frac{P(F_{m+1}, \lambda^l_{x,y})}{P(\lambda^l_{x,y})}. \quad (4)$$

We have

$$P(s_m = L_j | F_{m+1}, \lambda^l_{x,y}) = \frac{P(s_m = L_j, F_{m+1} | \lambda^l_{x,y})}{P(F_{m+1} | \lambda^l_{x,y})}. \quad (5)$$

$P(s_m = L_j, F_{m+1} | \lambda^l_{x,y})$ can be interpreted as the joint probability that the sequence $f_0 f_1 ... f_m$ is observed and the state s_m of a_y when the next transaction happens is $L_j \in \mathcal{L}$; and $P(F_{m+1} | \lambda^l_{x,y})$ is the probability of the observation sequence F_{m+1}, given the model.

By summing up all possible state sequences we have

$$P(F_{m+1}|\lambda_{x,y}^l) = \sum_{\forall H_{m+1}} P(F_{m+1}, H_{m+1}|\lambda_{x,y}^l)$$

$$= \sum_{\forall H_{m+1}} P(F_{m+1}|H_{m+1}, \lambda_{x,y}^l) P(H_{m+1}|\lambda_{x,y}^l)$$

$$= \sum_{\forall H_{m+1}} \pi_{s_0}^{x,y} B_{s_0,f_0}^{x,y} A_{s_0,s_1}^{x,y} B_{s_1,f_1}^{x,y} \cdots A_{s_{m-1},s_m}^{x,y}$$

$$B_{s_m,f_m}^{x,y}. \tag{6}$$

However, such a computation is very expensive, thus is infeasible in practice. In order to find $P(F_{m+1}|\lambda_{x,y}^l)$ (and hence $P(s_m = L_j|F_{m+1}, \lambda_{x,y}^l)$), we apply the forward algorithm (Rabiner 1989). For $t = 0, 1, ..., m$ and $k = 0, 1, ..., l$-1, we define

$$\alpha_t(k) = P(F_{t+1}, s_t = L_k|\lambda_{x,y}^l). \tag{7}$$

This is the joint probability of the observation subsequence (from the first observation to the tth one), and the corresponding state s_t is L_k. The $\alpha_t(k)$ is derived recursively:

Step 1: Let $\alpha_0(k) = \pi_k^{x,y} B_{k,0}^{x,y}$, for $k = 0, 1, ..., l$-1.

Step 2: For $t = 0, 1, ..., m$ and $k = 0, 1, ..., l$-1, we derive

$$\alpha_t(k) = [\sum_{q=0}^{l-1} \alpha_{t-1}(q) A_{q,k}^{x,y}] B_{k,t}^{x,y}. \tag{8}$$

Step 3: From definition of $\alpha_t(k)$ (Eq. 7), it is straightforward that $P(F_{m+1}|\lambda_{x,y}^l)$ can be obtained by

$$P(F_{m+1}|\lambda_{x,y}^l) = \sum_{k=0}^{l-1} P(F_{m+1}, s_m = L_k|\lambda_{x,y}^l)$$

$$= \sum_{k=0}^{l-1} \alpha_m(k). \tag{9}$$

Finally, according to Eq. 5 and 9 we have the probability distribution of the outcome of the next transaction with a_y:

$$P(s_m = L_j|F_{m+1}, \lambda_{x,y}^l) = \frac{\alpha_m(j)}{\sum_{k=0}^{l-1} \alpha_m(k)}. \tag{10}$$

where $\sum_{j=0}^{l-1} P(s_m = L_j|F_{m+1}, \lambda_{x,y}^l) = 1$.
We can then obtain the most likely outcome by:

$$s_m = \arg\max_{L_j \in \mathcal{L}} [P(s_m = L_j|F_{m+1}, \lambda_{x,y}^l)]. \tag{11}$$

To conduct the computation above, we need to learn the state transition matrix $A^{x,y}$ and the observation probability matrix $B^{x,y}$. $A^{x,y}$ can be easily derived based on the outcomes of the previous transactions. Different from traditional HMM based approaches which treat transaction outcome as the observation, our approach uses transaction contextual information associated with each transaction as the observations. We next detail how to integrate such contextual information into our HMM based trust model.

Processing Contextual Information

According to the discussion on trust contextual information (see interaction contextual information section), we select a set of features $\Omega = \{\omega_1, \omega_2, ...\}$ to describe/characterize each transaction[2]. These features are expected to have the potential to distinguish different levels ($\in \mathcal{L}$) of the transaction outcome. To do such a feature selection, we use entropy based information gain (MacKay 2003). Given the past transactions $\Theta_{a_x,a_y} = \{\theta_{a_x,a_y}^1, \theta_{a_x,a_y}^2, ...\}$ between a_x and a_y, we denote the fraction of transactions with outcome L_j by p_j. Then the entropy of all past transactions Θ_{a_x,a_y} is:

$$Entropy(\Theta_{a_x,a_y}) = -\sum_{j=0}^{l-1} p_j \log_2 p_j. \tag{12}$$

Entropy is used to characterize (im)purity of a collection of examples. For each feature $\omega_r \in \Omega$, we assume it has a set of values (e.g., discrete variable) or intervals (e.g., continuous variable), which is denoted by $\Upsilon(\omega_r)$. For each $\upsilon \in \Upsilon(\omega_r)$, we denote the set of past transactions that are associated with υ for feature ω_r by $\Theta_{a_x,a_y}^\upsilon$. The information gain of feature ω_r is thus calculated by:

$$IGain(\Theta_{a_x,a_y}, \omega_r) = Entropy(\Theta_{a_x,a_y}) -$$

$$\sum_{\upsilon \in \Upsilon(\omega_r)} \frac{|\Theta_{a_x,a_y}^\upsilon|}{|\Theta_{a_x,a_y}|} Entropy(\Theta_{a_x,a_y}^\upsilon). \tag{13}$$

The information gain of a feature measures expected reduction in entropy by considering this feature. Clearly, the higher the information gain, the lower the corresponding entropy becomes and thus the better the classification of past transactions is achieved. Then we may select the top-K features that have the highest information gain[3].

After selecting the features, we apply multiple discriminant analysis (MDA) (McLachlan 2004) to combine the features to generate a smaller but more effective feature set. The aim of the MDA is to find a transformation Φ that can maximize the inter class variance and minimize the intra class variance[4]. The original feature set Ω is then transformed as

$$\Omega' = \Phi^T \Omega. \tag{14}$$

In this way, each transaction between a_x and a_y $\theta_{a_x,a_y}^i \in \Theta_{a_x,a_y}$ is described/characterized by the transformed feature set, denoted by $\Omega'_{a_x,a_y,i}$. Such a transformed feature set is actually the observation in our HMM based trust model.

Finally, the observation probability matrix $B^{x,y}$ is derived based on the outcomes of the past transactions and the associated transformed feature sets. Note that in case the feature values are continuous, we resort to the methods (e.g., C4.5 (Quinlan 1993)) used in decision tree to handle the continuous feature.

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[2] Feature selection is application dependent. We will show what features are selected using online auction site as the example in the next section.

[3] Alternative way may choose features by setting a information gain threshold.

[4] Each class represents a set of transactions with a certain level of outcome $Ł_j \in \mathcal{L}$

Evaluation

Experimental Methodology

We use real dataset collected from an Internet auction site Allegro (http://allegro.pl/) as well as synthetic data to evaluate performance of our HMM based trust model. The Allegro dataset contains 10,000 sellers, 10,000 buyers, more than 200,000 transactions and over 1.7million comments. In order to fully understand how a seller changes its behavior in the transactions, we select a set of (150) sellers which have sufficient historical information (i.e., over 100 past transactions).

We assume binary outcome of a transaction, i.e., a transaction is considered to be successful if its feedback is positive, otherwise, it is considered to be unsuccessful. So we construct a 2-state HMM. The features we select to characterize the context of each transaction include: (1) category of the item, (2) difference between item price and average price over the items in the same category, (3) number of items already sold by the seller at the time the transaction happened and (4) reputation (i.e., fraction of successful transactions) when the transaction happened. Note that we do not use the first feature directly in the computation, but use it to collect the relevant transactions to construct the model.

Real Allegro data provides a realistic environment, however, behavior patterns of the sellers in real data are predetermined (i.e., fixed), and for which we do not have ground truth. In order to comprehensively evaluate performance of our approach under different circumstances, and also to more flexibly control agents' behavior, we generate synthetic data derived from real data. Specifically, we generate a synthetic seller with 100 past transactions. All transactions with their outcomes and features are taken from real Allegro dataset (i.e., a good/bad synthetic transaction is generated from a randomly selected good/bad real transaction). We simulate three types of dynamic behavior following the configurations of (Keung 2011) and (Moe, Helvik, and Knapskog 2009): (1) the agent behaves honestly in several transactions and then cheats in the next transaction; (2) the agent changes its behavior half way (from honesty to dishonesty); (3) the agent changes its behavior randomly (but still acting honestly with a higher probability, say 70%).

We compare our approach with traditional HMM based trust models (i.e., without contextual information)[5]. The metrics we use to evaluate performance of the approaches include:

- *false positive rate*
  The transaction is unsuccessful but the algorithm predicted that it would be successful.

- *false negative rate*
 The transaction is successful but the algorithm predicted that it would be risky.

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[5]Since the work (Moe, Helvik, and Knapskog 2009) has proven that HMM based approaches are more effective than the 'forgetting factor' based approaches, we thus only compare our approach with existing HMM based trust models

Results

We first compare our model with traditional HMM based trust model (e.g., (ElSalamouny, Sassone, and Nielsen 2009)) using Allegro dataset. We study how false positive rate and false negative rate evolve with different volumes of HMM training data. That is, for each (of 150) selected target seller, we use first $x\%$ of the previous transactions to build a HMM (initially $x = 50$) by which we predict the outcome of the next transaction. From Fig. 1 we observe that for both approaches, false positive rate and false negative rate decrease with the increasing fraction of transactions for HMM construction. This is mainly because with more training data, HMM is able to more accurately estimate probability distribution over all possible dynamic behavior patterns, and hence provide more precise prediction on the outcome of the next transaction. We also observe that our trust model incurs lower rate for both false positive and false negative than traditional HMM based trust model. This validates that by considering transaction contextual information (i.e., the selected features) which correlates with the seller's behavior or intent, the trustor can identify certain implicit behavior patterns that may be difficult to be detected by simply investigating outcomes of the previous transactions.
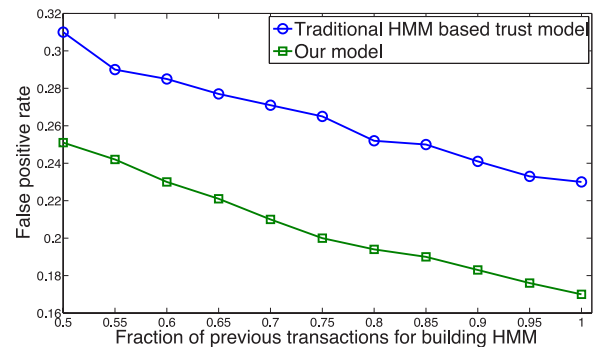

(a) False positive.
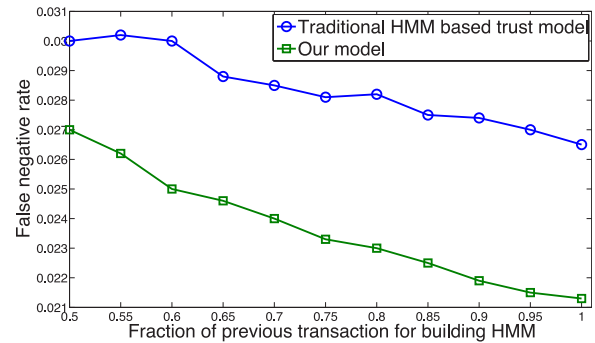
(b) False negative.

Figure 1: Experiments using Allegro dataset.

We then conduct a comparison study of the HMM based trust models under three types of simulated dynamic behaviors. Fig. 2(a) demonstrates performance of the approaches when the target agent behaves honestly in several transactions (e.g., random value from 8 to 12) and then cheats in

the next transaction. Similar to the results using real Allegro data, for both approaches, false positive rate and false negative rate decrease as training data (for HMM) volume increases. It is obvious that our model is more accurate than traditional HMM based trust model. This is mainly because most of the past transactions are successful, predicting outcome of the next transaction simply based on outcomes of the previous transactions is likely to 'miss' a potentially risky transaction.
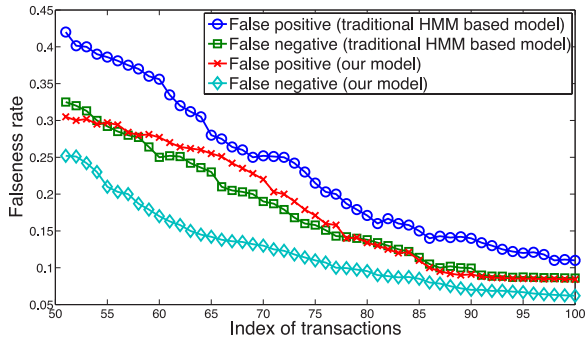
(a) Dynamic behavior pattern (1).
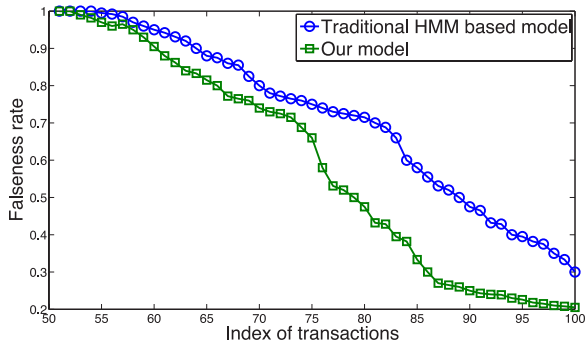
(b) Dynamic behavior pattern (2).
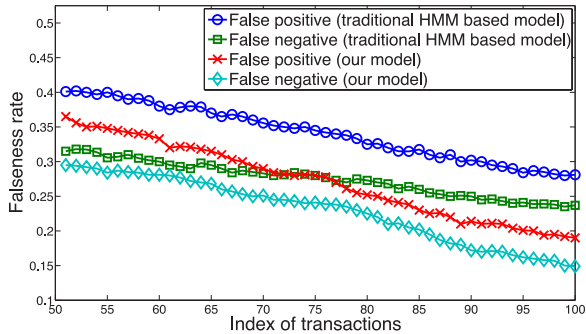
(c) Dynamic behavior pattern (3).

Figure 2: Synthetic dataset.

When the second type of behavior pattern (i.e., seller acts honestly for the first half transactions and acts dishonestly for the rest ones) is applied, we observe that neither approaches can detect dishonest behavior for the first several transactions[6] (see Fig. 2(b)). However, our approach can quickly learn the context of the transaction thus is able to identify the unsuccessful transactions earlier than traditional HMM based trust model.

From Fig. 2(c) we observe that when the target agent behaves randomly (i.e., behavior patter 3), our model still outperforms traditional HMM based approach. The reason for this is that although traditional HMM based approach is capable of detecting explicit behavior patterns, it is difficult for this approach to identify implicit patterns from the random behaviors. In contrast, our trust model improves traditional approach by considering transaction contextual information that correlates with the agent's behavior. Another interesting phenomenon is that different from the other results (see Fig. 2(a) and 2(b)) where more training data (i.e., past transactions) evidently lowers the falseness rates, in this scenario, the improved accuracy resulting from larger volume of training data is limited. This is because even if more past transactions are used to build a HMM, it is not easy to detect implicit patterns from the random behaviors thus restricting the improvement on the prediction accuracy (for both approaches).

Conclusion

This paper presented a HMM based context aware trust model. The dynamic behavior of an agent is approximated by a finite state HMM. Different from traditional HMM based trust approaches that rely on a sequence of outcomes of the past interactions with the target agent to estimate probability distribution over the outcome of the next interaction, our approach investigates and utilizes the interaction contextual information (as the observation) to build a HMM. Information theory (i.e., information gain) and machine learning technique (i.e., multiple discriminant analysis) are applied to select and process the contextual information to achieve accurate prediction. This strategy can help in revealing the behavior patterns which cannot be identified by simply statistically studying the outcomes of the previous interactions. Real auction dataset and synthetic data based evaluation demonstrates that our approach is more effective in detecting various dynamic behavior patterns than traditional HMM based approaches that do not consider contextual information.

In the future, we aim to apply the proposed trust model to various multi-agent systems to validate its practicability. Specifically, analyzing the complexity and studying the optimization issues according to different application scenarios would be the next research focuses.

Acknowledgement

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[6]Note that since we only predict the second half transactions so only false positive rate is shown.

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