Social Context-Aware Trust Prediction in Social Networks

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Abstract. Online social networks have been widely used for a large number of activities in recent years. Utilizing social network information to infer or predict trust among people to recommend services from trustworthy providers have drawn growing attention, especially in online environments. Conventional trust inference approaches predict trust between people along paths connecting them in social networks. However, most of the state-of-the-art trust prediction approaches do not consider the contextual information that influences trust and trust evaluation. In this paper, we first analyze the personal properties and interpersonal properties which impact trust transference between contexts. Then, a new trust transference method is proposed to predict the trust in a target context from that in different but relevant contexts. Next, a social context-aware trust prediction model based on matrix factorization is proposed to predict trust in various situations regardless of whether there is a path from a source participant to a target participant. To the best of our knowledge, this is the first context-aware trust prediction model in social networks in the literature. The experimental analysis illustrates that the proposed model can mitigate the sparsity situation in social networks and generate more reasonable trust results than the most recent state-of-the-art context-aware trust inference approach.

Keywords: Social Networks, context, trust prediction, social recommendation.

1 Introduction

In recent years, a growing and large number of users have joined e-commerce, online employment and social network web sites while online social networks have proliferated to be the platforms for a variety of rich activities, such as seeking employees and jobs, and trustworthy recommendations for products and services. In such activities, *trust* (the commitment to a future action based on a belief that it will lead to a good outcome, despite the lack of ability to monitor or control the environment [2]) is one of the most critical factors for the decision making of users. It is context dependent and it is rare for a person to have

X. Franch et al. (Eds.): ICSOC 2014, LNCS 8831, pp. 527–534, 2014.

full trust on another in every facet. For example, the case of full trust in all aspects is less than 1% at popular product review websites of Epinions.com and Ciao.co.uk [12]. In real life, people's trust to another is limited to certain domains.

Trust prediction is the process of estimating a new pair-wise trust relationship between two participants in a context, who are not directly connected by interactions in the context [14]. Recently, some studies suggest to predict trust taking into account some kind of social contextual information. Liu et al. [7] propose a randomized algorithm for searching a sub-network between a source participant and a target one. In this work, contextual factors, such as social intimacy and role impact factor, are taken into account as constraints for searching, rather than simple trust inference or propagation. Wang et al. [12] propose a probabilistic social trust model to infer trust along a path in a social network exploring all available social context information. However, this method only relies on trust paths and ignores participants off the path who might also have an impact on the predicted trust.

In the literature, most trust prediction models suffer from the following drawbacks: (i) The property of trust values has not been studied sufficiently. For example, the similarity of people's trust can be modeled not only from the trust values but also from their distributions [14]. (ii) The diversity of social contexts is not well dealt with. In real life, the connection between two people can be any of friendship, family member, business partnership, or classmate etc. Even the same relationships—say friendship, their interaction frequency and interaction contexts can be largely different [12]. (iii) The ways to incorporate social information require further study as inappropriate introduction of social information may introduce noise and degrade the trust prediction quality. (iv) Differences of contextual information are not handled properly. For example, how to model the relationship of two contexts? To what extent, the trust in context C_i can be transferred to context C_j?

In order to address the above drawbacks, we first present a social context-aware network model taking into account both personal properties (i.e., features extracted from personal preference, habit, expertise and active context revealed in historical data) and interpersonal properties (i.e., features extracted from two participants including social relationship, social intimacy, similarity etc.) of participants. Then, we propose a new approach to compute the trust transferred from interaction contexts to a target context considering both the properties of participants and the features of contexts in which they have interactions. Finally, we modify matrix factorization methods, by introducing indicator functions of both interaction trust and transferred trust, to predict the trust of a participant in others' minds regarding a certain target context.

The main contributions of our work are summarized as follows: (i) we introduce relevant context information into our model; (ii) we propose a context-aware trust transference method that can mitigate the sparsity problem and enhance the trust prediction accuracy; and (iii) we propose a matrix factorization based method that can predict the trust between two participants in a target context regardless of whether there is a path connecting them.

2 Contextual Social Networks

Context is a multi-faceted concept across different research disciplines with various definitions [10]. In this paper, we define *context* as any information available for characterizing the participants and the situations of interactions between them. If participant p_1 has an interaction with participant p_2, the context about p_1 and p_2 in the social society is referred to as the *social context*, among which the *interaction context* refers to any information about the interaction including time, place, type of services etc. If p_2 recommends a service to p_1, then the information about the service is referred to the *target context.*

2.1 Social Context

Social context describes the context about participants. Before it can be used to predict trust of participants, the properties of each aspect must be extracted modeling the characteristics of participants and the relationship between them. Therefore, social contexts can be divided into two groups according to the characteristics of each impact factor: *personal properties* (e.g., role impact factor, reliability and preference) and *interpersonal properties* (e.g., preference similarity, social intimacy and existing trust).

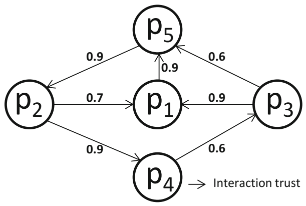
Role Impact Factor: Role impact factor (denoted as $RIF_{p_1}^{c_i}$) has a significant influence on the trust between participants in a society [7]. It illustrates the impact of a participant's social position and expertise on his/her trustworthiness when making recommendations based on that the recommendation from a person who has expertise in a domain is more credible than others with less knowledge. There are various ways to calculate the role impact factor in different domains. For example, the social position between email users is discoverd by mining the subjects and contents of emails in Enron Corporation[1] [4].

Recommendation Reliability: In a certain context, the reliability of recommendations ($RLB_{p_1}^{c_i}$) measures the rate of a participant's recommendations accepted by recommendees [3]. On the dataset MovieLens[2], the leave-one-out approach is used in [3] to calculate the deviation between the predicted rating and the actual ratings as the reliability of a participant.

Preference: Preference ($PS_{p_1,p_2}^{c_i}$) is an individual's attitude or affinity towards a set of objects in a decision making process [6]. This property may differ greatly between different contexts in real life. The similarity of two participants' preferences can impact the trust between them to some extent [12]. Here, $PS_{p_1,p_2}^{c_i} = PS_{p_2,p_1}^{c_i}$. It can be calculated from the rating values given by users using models such as PCC and VSS [8].

Social Intimacy: Social intimacy ($SI_{p_1,p_2}^{c_i}$) refers to the frequency of connections between participants in a social network. The degree of social intimacy can impact trust as people tend to trust these with more intimate social relationships [1]. Here, $SI_{p_1,p_2}^{c_i}$ is not equivalent to $SI_{p_2,p_1}^{c_i}$. Models like PageRank [11], are able to calculate the social intimacy degree values.

[1] `http://www.cs.cmu.edu/~enron/`
[2] `http://movielens.sumn.edu/`



(a) Social network graph

	p_1	p_2	p_3	p_4	p_5
p_1					**0.9**
p_2	**0.7**			**0.9**	
p_3	**0.9**				**0.6**
p_4			**0.6**		
p_5		**0.9**			

(b) Trust matrix

Fig. 1. The social network in a context

2.2 Social Context Similarity

Interaction context is the information about the situation when the interaction happens between participants p_1 and p_2. For example, suppose that p_2 has recommended mobile phones to p_1 many times in the past. As a result, p_1 trusts p_2 with the value $T^{c_i}_{p_1,p_2} = 0.8$ in the context of mobile phones. Now p_2 recommends p_1 a laptop. As there is no historical recommendation in the context of laptops, and there does exist similarity between the contexts of mobile phones and laptops, we need to calculate the context similarity in order to determine how much p_1 can trust p_2 in the target context of recommending laptops. Let $CS^{c_i,c_j} \in [0,1]$ denote the similarity between two contexts c_i and c_j. Only when c_i and c_j are exactly the same context, $CS^{c_i,c_j} = 1$. And $CS^{c_i,c_j} = 0$ indicates that the information in context c_i is not relevant to c_j at all and cannot impact participants' trust in context c_j. Here, $CS^{c_i,c_j} = CS^{c_j,c_i}$. We adopt the classification of contexts introduced in [12] with a number of existing methods to compute similarity [13,12], such as Linear discriminant analysis and context hierarchy based similarity calculation. In addition, the interaction context c_j is relevant to the interaction context c_i if $CS^{c_i,c_j} > \mu$ (μ is a threshold, e.g., 0.7), denoted as $c_i \sim c_j$. Otherwise, if c_j is irrelevant to c_i, denoted as $c_i \nsim c_j$.

2.3 Contextual Presentation of Trust

In order to apply our prediction model on the trust information in different contexts, we present a contextual trust matrix to represent the contextual information and social properties. Fig. 1(a) shows a social network graph in a context c_i, in which the arrows between nodes mean the existing trust resulting from past interactions. In context c_i, we construct a $N_p \times N_p$ matrix R, where N_p is the number of participants. In this 2-D matrix, if we put the trust value between participants at each context, the structure can be shown as in Fig. 1(b).

The contextual social network graph is shown in Fig. 2(a) with the trust links in all contexts, where the superscript c_i, $i = 1...5$ indicates the context in which the trust exists. Taking all contexts into consideration, the matrix R turns into a $N_p \times N_p \times N_c$ matrix as shown in Fig. 2(b), where, N_c is the number of contexts.

In Fig. 1(b) and Fig. 2(b), only the trust vales are shown in the matrix for illustration purposes. Actually, each element in the matrix is a social property vector containing all the relative properties discussed in detail in this section.

(a) Social network graph

(b) Contextual trust matrix

Fig. 2. Contextual social network

3 Contextual Trust Prediction

The process to predict the trust between participants p_x and p_y in the target context of c_j can be divided into two situations based on available information. They are discussed in the following subsections.

3.1 Trust Transference between Contexts

The trust in relevant interaction contexts can be transferred to the target context. The result is called *transferred trust*. This process is *trust transference*.

As introduced in Section 2, the personal properties and interpersonal properties can impact how much of the trust in interaction contexts can be transferred to that in a target context, which is termed as *trust transference degree*. Thus the transference degree of trust to p_y in p_x's mind from interaction context c_i to target context c_j can be calculated from the following equation:

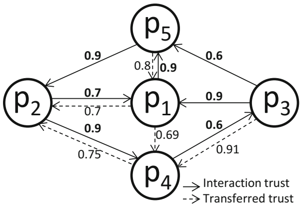
$$\alpha^{c_i,c_j}_{p_x,p_y} = \omega_1 \cdot PS^{c_i}_{p_x,p_y} + \omega_2 \cdot SI^{c_i}_{p_x,p_y} + \omega_3 \cdot CS^{c_i,c_j} \qquad (1)$$

This equation assumes that participant p_x trusts participant p_y with the trust value $T^{c_i}_{p_x,p_y}$ after interactions in context c_i in the past. It calculates the transference degree from the trust in interaction context c_i to the trust in target context c_j, when participant p_y makes recommendations to participant p_x. Here, $\{\omega_i\}, i = 1...5$ are the weights of the properties that impact the trust of p_y in the mind of p_x, and $\sum_i \omega_i = 1$. Therefore, the trust value to p_y in the mind of p_x regarding the context c_i, $T^{c_i}_{p_x,p_y}$, can be transferred to the one in the target context c_j by $\alpha^{c_i,c_j}_{p_x,p_y} \cdot T^{c_i}_{p_x,p_y}$.

However, in the target context c_j, even if participant p_x has no interaction with participant p_y, p_x can trust p_y to some extent primarily due to p_y's social effect and his/her ability to give an appropriate recommendation, which can be depicted by the role impact factor and recommendation reliability. We use the term *"basic trust"* [9] to refer to this kind of trust, which can be formulated as:

$$BT^{c_j}_{p_x,p_y} = \delta_1 \cdot RIF^{c_j}_{p_y} + \delta_2 \cdot RLB^{c_j}_{p_y} \qquad (2)$$

where, $\delta_1 + \delta_2 = 1$. Finally, based on the trust in all the interaction contexts C and the basic trust in the target context c_j, the transferred trust representing



(a) Social network graph

	p_1	p_2	p_3	p_4	p_5
p_1		0.7		0.69	**0.9**
p_2	**0.7**			**0.9**	
p_3	**0.9**			0.91	**0.6**
p_4		0.75	**0.6**		
p_5	0.8	**0.9**			

(b) Contextual trust matrix

Fig. 3. Contextual social network with transferred trust

how much participant p_x can trust p_y in the target context c_j can be formulated as follows:

$$\tilde{T}^{c_j}_{p_x,p_y} = \beta_1 \max_{c_i \in C}\{\alpha^{c_i,c_j}_{p_x,p_y} \cdot T^{c_i}_{p_x,p_y}\} + \beta_2 BT^{c_j}_{p_x,p_y} \tag{3}$$

where, $\beta_1 + \beta_2 = 1$; $\max\limits_{c_i \in C}\{\cdot\}$ means the maximum trust value among all the trust values transferred from relevant contexts without basic trust. These coefficients can be calculated using leave-one-out approach [3] in the historical data.

3.2 Trust Prediction Using Matrix Factorization

A more complicated situation is to predict trust between a source participant and a target participant when they have no interaction trust between each other in both the target context and relevant contexts, but they do have interactions with other participants respectively. In such a situation, even if all the trust in all the interaction contexts has been transferred to the target context using the method introduced in Subsection 3.1, the trust we want to predict in the target context is still absent. For instance, we want to predict the trust between p_2 and p_3 in Fig. 3.

As shown in Fig. 3(b), the trust matrix R is a $N_p \times N_p$ matrix representing the trust from trusters (recommendees) to trustees (recommenders). The matrix factorization model maps trust values to a joint latent factor space of dimensionality l so that each trust value r_{ij} in matrix R is the inner product of truster vector $u_i \in \mathbb{R}^l$ (the relationship between truster i and the l latent factors) and trustee vector $v_j \in \mathbb{R}^l$ (the relationship between trustee j and the l latent factors).

$$r_{ij} \approx u_i^T v_j \tag{4}$$

Accordingly, the truster-trustee trust matrix R is modeled as the inner product of a truster-specific matrix $U = \{u_i\}$ and a trustee-specific matrix $V = \{v_j\}$.

$$R \approx U^T V \tag{5}$$

The factorization process is approximated by minimizing the following equation:

$$\min_{U,V} \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} (I_{ij} + \eta \tilde{I}_{ij})(r_{ij} - u_i^T v_j)^2 + \frac{\lambda_1}{2}||U||^2 + \frac{\lambda_2}{2}||V||^2, \tag{6}$$

where $||.||_F^2$ represents the Frobenius norm; I_{ij} is an indicator function of interaction trust. $I_{ij} = 1$ *iff* participant p_i (truster) trusts participant p_j (trustee) in the target context originally, $i \neq j$. Otherwise, $I_{ij} = 0$. In addition, $\tilde{I}_{ij}$ is another indicator function of transferred trust. $\tilde{I}_{ij} = 1$ *iff* participant p_i (truster) has trust calculated by Eq. (3) to participant p_j (trustee), $i \neq j$. Otherwise, $\tilde{I}_{ij} = 0$. $\eta \in [0, 1]$ is a coefficient controlling the weight of transferred trust. Once the learning process of the method is achieved by Eq. (6), the trust we want to predict can be calculated by Eq. (4).

4 Experiments

We evaluate the effectiveness of our model in typical scenarios including the basic cases of social networks in real world and compare our model with the state-of-the-art approach social context-aware trust inference (SocialTrust) [12], as well as the prevalent multiplication strategy (MUL) [5]. Due to space limitations, only the comparison of trust inference between contexts is presented here.

In real life, a typical situation needing trust prediction is that a recommender and a recommendee do not have any interactions in the target context c_j. However, they have many interactions in the past in other relevant contexts $C_h = \{c_i\}$, $i = 1, ...n$ and $i \neq j$. Without any loss of generality, the trust values between two participants are generated using a random function in Matlab. We adopt the coefficients from SocialTrust giving the same weight for each coefficient, where applicable, and set $\omega_1 = \omega_2 = \omega_3 = 0.333$, $\delta_1 = \delta_2 = 0.5$, $\beta_1 = \beta_2 = 0.5$, $CS^{c_1,c_2} = 0.8$, $CS^{c_1,c_3} = 0.1$. The context information we used in this case study can be found in Table 1. In this situation, the trust values to p_2

Table 1. Contextual tust to p_2 in p_1's mind

ID	Context	Context Relation	T_{p_1,p_2}	PS_{p_1,p_2}	SI_{p_1,p_2}	RIF_{p_1}	RIF_{p_2}	RLB_{p_1}	RLB_{p_2}
c_1	Teaching VC	$c_1 \sim c_2$ & $c_1 \nsim c_3$	?	0	0	0	0.8	0	0.9
c_2	Teaching Java	$c_2 \sim c_1$ & $c_2 \nsim c_3$	0.7	1	1	0.5	0.8	0.5	0.9
c_3	Car repair	$c_3 \nsim c_1$ & $c_3 \nsim c_2$	0.8	1	1	0.5	0.8	0.5	0.9

in p_1's mind calculated by Eq. (3) and SocialTrust are 0.57 and 0.74 respectively. MUL does not apply in this case, as it does not deal with trust between contexts.

SocialTrust neglects the concept of basic trust while taking the role impact factor of p_1 in the target context c_1 into account. In real life, this value should be 0 consistently, because when a participant seeks suggestions from others, he/she usually has no experience in the target context. Otherwise, he/she has his/her own trust in the target context already and may not need recommendations. Therefore, our result is the most reasonable one in this scenario. It fits the case in real life that, a VC teacher is usually also good at teaching Java, as teaching Java and teaching VC are similar contexts.

5 Conclusions

As trust prediction is a dynamic and context sensitive process. In this paper, we have first analyzed the properties that can impact trust transference between different but relevant contexts. Based on these impact properties, we have proposed a new trust transference method to transfer trust from interaction contexts to a target context considering personal properties and interpersonal properties. Then, a social context-aware trust prediction model has been proposed to predict trust from a source participant to a target participant. The proposed approach analyzes and incorporates the characteristics of participants' trust values, and predicts the missing trust in the target context using modified matrix factorization. The conducted experiments show that our proposed model transfers trust between contexts in a reasonable way and is able to predict trust between source and target participants.

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