Enhancing Trustworthiness Evaluation in Internetware with Similarity and Non-negative Constraints

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ABSTRACT
Internetware is envisioned as a new software paradigm where software developers usually need to interact with unknown partners as well as the software entities developed by them. To reduce uncertainty and boost collaborations in such setting, it is important to provide trustworthiness evaluation mechanisms so that trustworthy partners/entities can be easily found. In this work, we propose a novel trustworthiness evaluation mechanism by enhancing existing mechanisms with similarity and non-negative constraints. To be specific, we first extend an existing multi-aspect trust inference model by incorporating the non-negative constraint. One of the advantages of such constraint is its strong interpretability. Second, we incorporate similarity into two neighborhood models borrowed from recommender systems. When computing similarity, we make use of the intermediate results from the first step. Finally, these models are combined under a machine learning framework. To show the effectiveness of our method, we conduct experiments on a real data-set. The results show that: both our non-negativity extension and similarity computation improve the evaluation accuracy of the original methods, and the combined method outperforms several state-of-the-art methods.

Categories and Subject Descriptors
H.4.2 [**Information Systems Applications**]: Types of Systems-*Decision support*; H.2.8 [**Database Management**]: Database applications—*Data mining*

General Terms
Algorithms, Experimentation.

Keywords
Trustworthiness evaluation, multi-aspect, similarity, non-negativity, Internetware.

1. INTRODUCTION
Internetware is a new software paradigm where software and systems are developed and deployed over the Internet [1, 2]. Due to the open nature of Internet, software developers in Internetware usually need to interact with unknown partners as well as the software entities developed by them [3, 4]. To reduce uncertainty and boost collaborations in such open environment, it is necessary to evaluate the trustworthiness of the unknown partners. To tackle this problem, trustworthiness evaluation mechanisms or trust inference models are proposed [5, 6].

The main focus of trustworthiness evaluation mechanisms is to infer the trustworthiness of unknown partners based on the opinions from friends, friends of friends, etc. As a result, most existing trustworthiness evaluation mechanisms are built based on trust propagation, i.e., trust is propagated along friends [7]. Recently, in addition to trust propagation, the multi-aspect property of trust is explored to improve the accuracy of trustworthiness evaluation [8]. The idea behind the multi-aspect method is to extract the preferences and capabilities of users from existing trust ratings, and these preferences and capabilities can then be used to infer unknown trust ratings. However, one disadvantage of this method is its low interpretability, i.e., the preferences and capabilities can be any arbitrary values. In addition to trust propagation and multi-aspect, similarity is known to be highly related to trust [9, 10]; however, similarity was largely ignored by existing trustworthiness evaluation mechanisms.

In this work, we propose a novel trustworthiness evaluation mechanism by enhancing existing mechanisms with similarity and non-negative constraints. To be specific, we first extend an existing multi-aspect trust inference model (MaTrI) [8] by incorporating the non-negative constraint. In fact, MaTrI employs the so-called probabilistic matrix factorization (PMF) [11] to extract the preferences and capabilities of users, while we adopt the non-negative matrix factorization (NMF) [12]. To fit in our problem setting, we tailor the original NMF to operate on the observed trustor-trustee ratings only. The main reason of such extension is due to the strong interpretability of NMF. Namely, NMF requires that the preferences and capabilities are non-negative, with 0 means the lowest preference/capability.

Next, we consider similarity as a source for trustworthiness evaluation by incorporating similarity into two neighborhood models borrowed from recommender systems [13]. The basic assumption of neighborhood models is based on the fact that similar trustors tend to trust the same trustee, and similar trustees tend to be trusted by the same trustor. In our method, we also extend the neighborhood models by using the results of the tailored NMF. That is, before computing similarity, we make use of the intermediate results (preferences and capabilities) from NMF to fill in the missing trust ratings. By doing so, we may have more information about the trustors/trustees so that the similarity can be computed more accurately.

Finally, the multi-aspect model and the neighborhood models are combined under a machine learning framework. To show the effectiveness of our method, we conduct experiments on a real

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data-set. The results show that: 1) our tailored NMF method is better than the PMF method and the original NMF method in our trustworthiness evaluation problem, 2) our extended neighborhood models where similarity is computed based on the intermediate results of NMF improve the evaluation accuracy of the neighborhood methods, and 3) the combined method outperforms several state-of-the-art methods.

The rest of the paper is organized as follows. Section 2 reviews related work. Section 3 describes our trustworthiness evaluation mechanism, including the NMF method and the two neighborhood methods. Section 4 presents experimental evaluations. Section 5 concludes the paper.

2. Related Work

The main insight of the vast majority of existing trustworthiness evaluation mechanisms is trust propagation. The first way to use trust propagation is to aggregate the trust ratings from the witnesses who have direct interactions with the trustee. Here, the major issue is how to decide the credibility of the ratings. For example, PeerTrust system for peer-to-peer e-commerce environment proposes a reputation-based measure and a similarity-based measure to decide the credibility [14].

The second way to use trust propagation is to find a set of connected paths or a connected component from the trustor to the trustee [7]. Trust then flows from the trustor to the trustee over these paths or components. For example, PowerTrust uses a flow-based trust calculation approach, with special consideration of the power-law distribution of feedback [15].

Recently, in addition to trust propagation, the multi-aspect property of trust is explored to improve the accuracy of trustworthiness evaluation [8]. The idea behind the multi-aspect method is to extract the preferences and capabilities of users from existing trust ratings, and these preferences and capabilities can then be used to infer unknown trust ratings. However, one disadvantage of this method is its low interpretability, i.e., the preferences and capabilities can be any arbitrary values. In this work, we extend this model by incorporating the non-negative constraint on the preferences and capabilities.

Trust and similarity are also two related concepts that have been widely studied [9, 10, 16, 17]. On one hand, there is empirical evidence showing that trust and similarity are positively correlated [16]. Further, trust not only correlates with overall similarity, but also correlates to more fine-grained similarities (e.g., the largest opinion difference) [9]. On the other hand, similarity can be used to weight opinions from recommenders (i.e., witnesses who have direct interactions with the trustee) [14, 17]. In this work, we borrow the two neighborhood models from recommender systems to make use of similarity. That is, not only we can compute the similarity between trustor and witnesses (which is very similar to the trust propagation idea), but also we can compute the similarity between the trustee and the users that the trustor has interacted before. In the latter case, we assume that the trustor tend to rate similarly on similar trustees. To the best of our knowledge, this idea has not been explored by existing work.

3. The Proposed Trustworthiness Evaluation Mechanism

In this section, we present the proposed trustworthiness evaluation mechanism. After we introduce the notations, we will extend the multi-aspect model and the neighborhood models, and finally combine them together.

3.1 Notations

The symbols used through the paper are defined in Table 1.

Table 1: Symbols

Symbol	Definition and Description
$\mathbf{R}$	The partially observed trust matrix, size is $n \times n$
$\mathbf{P}$	The characterized trustor matrix, size is $n \times r$
$\mathbf{Q}$	The characterized trustee matrix, size is $n \times r$
$\mathbf{R}'$	The transpose of matrix $\mathbf{R}$
$\mathbf{R}(i,j)$	The element at the i^{th} row and the j^{th} column of matrix $\mathbf{R}$
$\bar{\mathbf{R}}$	The trust matrix after we fill in the missing values
sr(i,j)	The similarity of the i^{th} row and the j^{th} row in matrix $\bar{\mathbf{R}}$
sc(i,j)	The similarity of the i^{th} column and the j^{th} column in matrix $\bar{\mathbf{R}}$
$\mathbf{R}(i,:)$	The i^{th} row of matrix $\mathbf{R}$
n	The number of users
r	The number of factors
N(v)	The set of index of existing elements in $\mathbf{R}(:,v)$
M(u)	The set of index of existing elements in R$(u,:)$
X(u,v)	The trustor score of user u to user v
Y(u,v)	The trustee score of user u to user v
$\bar{\mathbf{R}}(u,v)$	The score of user u to user v by NMF
$\hat{\mathbf{R}}$	The finally estimated trust matrix
$\mathbf{\Omega}$	The set of observed elements in matrix $\mathbf{R}$

As we can see from the table, we use bold letter $\mathbf{R}$ to indicate the observed trust matrix, where $\mathbf{R}(i,j)$ is defined as the trustworthiness score from trustor user i to user j. Usually, this $\mathbf{R}$ matrix is very sparse, and the goal of trustworthiness evaluation is to infer the missing values in $\mathbf{R}$ based on the observed ratings.

3.2 Incorporating Non-negative Constraint

In our previous work [8], we tackle the trustworthiness evaluation problem from the multi-aspect property by formulating the problem as follows:

$$\min_{\mathbf{P},\mathbf{Q}} \sum_{i,j\in\mathbf{\Omega}} (\mathbf{R}(i,j) - \mathbf{P}(i,:)\mathbf{Q}(j,:)')^2 + \lambda\|\mathbf{P}\|^2 + \lambda\|\mathbf{Q}\|^2 \quad (1)$$

With the resulting $\mathbf{P}$ and $\mathbf{Q}$, the estimated trustworthiness score from trustor u to trust v can be then represented as:

$$\bar{\mathbf{R}}(u,v) = \mathbf{P}(u,:)\mathbf{Q}(v,:)' \quad (2)$$

One disadvantage of the previous method is its low interpretability. To improve the interpretability, a natural solution is to add non-negative constraints to the elements of $\mathbf{P}$ and $\mathbf{Q}$. In [18], the non-negative matrix factorization (NMF) method is proposed to deal with the matrix factorization problem with non-negative constraints. In NMF, all elements of matrix $\mathbf{P}$ and $\mathbf{Q}$ got by this method are non-negative.

$$\begin{cases} \mathbf{P}(i,j) \leftarrow \mathbf{P}(i,j)\dfrac{(\mathbf{RQ})(i,j)}{(\mathbf{PQ}'\mathbf{Q})(i,j)+\lambda} \\ \mathbf{Q}'(i,j) \leftarrow \mathbf{Q}'(i,j)\dfrac{(\mathbf{P}'\mathbf{R})(i,j)}{(\mathbf{P}'\mathbf{PQ}')(i,j)+\lambda} \end{cases} \quad (3)$$

According the work of [19], NMF update the **P** and **Q** matrices according to the above rule Eq. (3).

One problem about using NMF in our problem is that NMF operates on all the elements in matrix **R**. However, our **R** matrix is very sparse. Therefore, we need to deal with the sparseness problem carefully so that the exact formulation in Eq. (1) can be solved. For example, for those unknown values in **R**, we cannot simply treat them as 0 (which means no trust), as they are actually missing. As a result, we adapt the update rule only on the observed ratings as the following formula:

$$\begin{cases} \mathbf{P}_1(i,j) = \mathbf{P}_0(i,j)\dfrac{\mathbf{R}\big(i,\mathrm{M}(i)\big)\mathbf{Q}(\mathrm{M}(i),j)}{\mathbf{P}_0(i,:)\mathbf{Q}(\mathrm{M}(i),:)'\mathbf{Q}(\mathrm{M}(i),j)+\lambda} \\ \mathbf{Q}_1'(i,j) = \mathbf{Q}_0'(i,j)\dfrac{\mathbf{P}'\big(i,\mathrm{N}(j)\big)\mathbf{R}(\mathrm{N}(j),j)}{\mathbf{P}'\big(i,\mathrm{N}(j)\big)\mathbf{P}(\mathrm{N}(j),:)\mathbf{Q}_0'(:,j)+\lambda} \end{cases} \tag{4}$$

After finite steps of update operation, the cost value defined in Eq. (1) will converge. At that moment, the trustor matrix **P** and trustee matrix **Q** can be used to estimate trustworthiness score for unknown user pairs as shown in Eq. (2).

3.3 Extending Neighborhood models with Similarity computation

In the trustworthiness evaluation problem, the similarity also exists. We can use this property to improve the result of trustworthiness evaluation. In this paper, we use the cosine function of two vectors as the similarity. As there are many unknown values in matrix **R**, making the similarity computation inaccurate. We use the intermediate result from the NMF method, i.e., matrix $\overline{\mathbf{R}}$ to compute users' similarities.

In this paper, borrowing the idea of neighborhood models from recommender system, we define the following two similarity measures: *trustor similarity* and *trustee similarity*.

The *trustor similarity* represents the similarity of trustors. It is based on the observation that similar trustors often have similar evaluations on certain trustee. We use sr(*i*,*j*) to indicate the similarity of the i^{th} trustor and the j^{th} trustor based on $\overline{\mathbf{R}}$.

The *trustee similarity* represents the similarity of trustees. It is based on the observation that similar trustees are often trusted by same trustor and the trustor may have similar evaluations on them. We use sc(*i*,*j*) to indicate the similarity of the i^{th} trustee and the j^{th} trustee based on matrix $\overline{\mathbf{R}}$.

The computational formulae of sr(*i*,*j*) and sc(*i*,*j*) are shown as follows:

$$\begin{cases} \mathrm{sr}(i,j) = \mathrm{cosine}(\overline{\mathbf{R}}(i,:),\overline{\mathbf{R}}(j,:)) \\ \mathrm{sc}(i,j) = \mathrm{cosine}(\overline{\mathbf{R}}(:,i),\overline{\mathbf{R}}(:,j)) \end{cases} \tag{5}$$

Based on the above defined similarity, we define the following two estimated trustworthiness score corresponding to the two similarity measures: *trustor score* X(*u*,*v*) and *trustee score* Y(*u*,*v*). They are obtained by combing all the scores of others to user *v* or from user *u* to others.

$$\begin{cases} \mathrm{X}(u,v) = \dfrac{\sum_{i\in\mathrm{N}(v)}\mathrm{sr}(u,i)\,\mathbf{R}(i,v)}{\sum_{i\in\mathrm{N}(v)}\mathrm{sr}(u,i)} \\ \mathrm{Y}(u,v) = \dfrac{\sum_{j\in\mathrm{M}(u)}\mathrm{sc}(j,v)\,\mathbf{R}(u,j)}{\sum_{j\in\mathrm{M}(u)}\mathrm{sc}(j,v)} \end{cases} \tag{6}$$

3.4 Combing with logistic method

As both NMF method and similarity can be used to estimate the trustworthiness score for a pair of user *u* and *v*. Using Eq. (2) and Eq. (6), we can get three trustworthiness scores for user *u* to user *v*, i.e., $\overline{\mathbf{R}}(u,v)$, X(*u*,*v*), Y(*u*,*v*). We consider to use machine learning method to combine these three values together. In this paper, the logistic regression is chosen to combine the values computed by those methods as follows:

$$\widehat{\mathbf{R}}(\mathrm{u},\mathrm{v}) = \frac{1}{1+e^{-\overline{\mathbf{R}}(u,v)w_1-\mathrm{X}(u,v)w_2-\mathrm{Y}(u,v)w_3-w_0}} \tag{7}$$

In Eq. (7), w_i are the coefficient of logistic regression that should be learnt through training set.

4. EXPERIMENTS

In this section, we evaluate the proposed method on a real data-set. All the experiments are designed to show that 1) our proposed extensions can truly improve the accuracy of trustworthiness evaluation, and 2) our proposed method is more accurate than several state-of-the-art methods.

4.1 Dataset Description

The data-set we use in this work is selected from advogato[1], which is an online community and social networking site dedicated to free software development. The data-set we use is a snapshot on June 23, 2011, which contains 5428 nodes and 51,493 edges.

4.2 Experimental Results

4.2.1 Comparison between NMF and PMF

We first compare the results of the non-negative matrix factorization and the original probabilistic matrix factorization to show the usefulness of the non-negative constraints. Besides, we also compare the results got by original NMF method and our tailored NMF method to show the superiority of our tailored NMF method and the necessity of upgrading the original NMF method in our problem setting.

Table 2 Comparison between NMF and PMF

	RMSE	MAE
PMF	0.256	0.194
Original NMF	0.635	0.586
Tailored NMF	0.171	0.115

The result is shown in Table 2. From the table, we can see that our tailored NMF method has a significant improvement in both RMSE and MAE compared with PMF. For example, the tailored NMF method improves the PMF method by 33.2% in RMSE and 40.7% in MAE. Our tailored NMF method also improves a lot in both RMSE and MAE compared with the original NMF method. From the result, we can draw the conclusion that non-negative matrix factorization can be a useful tool in trustworthiness evaluation problem.

4.2.2 Comparison of Similarity Computation

In this part, we carry out experiments to evaluate the usefulness of using different methods to compute similarities between users. In order to confirm the effect of the proposed similarity computation method, we compare *trustor score* and *trustee score* got by using **R** and $\overline{\mathbf{R}}$.

[1] http://www.trustlet.org/wiki/Advogato_dataset.

Table 3 Comparison of Similarity Computation

RMSE/MAE	*trustor score*	*trustee score*
Using **R**	0.235/0.147	0.217/0.154
Using $\overline{\mathbf{R}}$	0.220/0.144	0.211/0.158

The result is shown in Table 3. From the table, we can see that filling missing values in original matrix **R** for similarity computation helps to improve trustworthiness evaluation. For example, after filling missing values, the performance of *trustor score* improves 6.4% in RMSE, and the performance of *trustee score* also improves 2.8% in RMSE.

4.2.3 Comparisons with Existing Methods

In this part, we compare our method with some other methods. These methods include the low rank approximation algorithm [20] (referred to as HCD), the CertProp [21] method, and the basic multi-aspect trustworthiness evaluation model [8] with probabilistic matrix factorization (referred to as MaBasic).

Table 4 Comparisons with existing methods

	RMSE	MAE
HCD	0.269	0.219
CertProp	0.269	0.155
MaBasic	0.256	0.194
Our method	0.165	0.111

The result is shown in Table 4. From the table, we can find that our method has the best performance compared with other methods. For example, our method improves 38.7% in RMSE and 31.0% in MAE when compared with CertProp. Also, our method improves the MaBasic method and the HCD method. For example, compared with MaBasic, our method improves 35.5% in RMSE and 42.8% in MAE.

5. CONCLUSION

In this paper, we have proposed a trustworthiness evaluation mechanism by incorporating non-negative constraints and similarity with existing mechanisms. First, we extend the existing multi-aspect trustworthiness evaluation model with tailored non-negative matrix factorization. Then, we borrow the neighborhood models form recommender systems and extend them with NMF based similarity computation. Finally, we combine the extended models together by logistic regression. Experiment results on the real data-set show that our method can significantly improve the accuracy of trustworthiness evaluation when compared with other state-of-the-art methods.

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