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Published in IET Communications
Received on 16th November 2009
Revised on 11th February 2010
doi: 10.1049/iet-com.2009.0733

ISSN 1751-8628

iTARS: trust-aware recommender system using implicit trust networks

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Abstract: Trust-aware recommender system (TARS) suggests the worthwhile information to the users on the basis of trust. Existing works of TARS suffers from the problem that they need extra user efforts to label the trust statements. The authors propose a novel model named iTARS to improve the existing TARS by using the implicit trust networks: instead of using the effort-consuming explicit trust, the easy available user similarity information is used to generate the implicit trusts for TARS. Further analysis shows that the implicit trust network has the small-world topology, which is independent of its dynamics. The rating prediction mechanism of iTARS is based on the small worldness of the implicit trust network: the authors set the maximum trust propagation distance of iTARS approximately equals the average path length of the trust network's corresponding random network. Experimental results show that with the same computational complexity, iTARS is able to improve the existing TARS works with higher rating prediction accuracy and slightly worse rating prediction coverage.

1 Introduction

As the most widely used technique for the recommender system, the collaborative filtering (CF) predicts ratings by making use of the experiences of their nearest neighbours, in which neighbours refer to the users that have high user similarities with the active users. Despite of its simplicity and effectiveness, CF suffers from the well-known data sparseness problem: the user similarities are only computable against few users, so it is always not easy to find the neighbours for the active users. The trust-aware recommender system (TARS) has therefore been proposed for use since it is able to overcome the data sparseness problem of CF. TARS suggests the worthwhile information to the users on the basis of trust, in which trust is the measure of willingness to believe in a user based on its competence and behaviour within a specific context at a given time. One basic characteristic of trust is its transitivity. It means, if A trusts B and B trusts C, A trusts C to some extent. In case the data are sparse, it is always possible to build up the trust relationships between users via trust propagations. This leads to the superior rating prediction coverage of TARS.

Existing works of TARS [1] focus on using the explicit trust statements. That is, trust should be explicitly pointed out by the users. For example, the model in [2] requires the users to add those whose ratings they have consistently found valuable in their web of trust. The users' trusts on those who are in their web of trust are assigned as 1, and the users' trusts on other users are assigned as 0. The explicit trust statements are used as the inputs of TARS with the ratings on the items to predict the ratings. Although the explicit trust-based TARS has been verified to have high rating prediction coverage and high rating prediction accuracy [1], it has its own limitations: it is sometimes time consuming or expensive to get the explicit trust. This is because the explicit trust needs extra user efforts: users need to specifically point out their personal opinions on the trustees. Therefore in most practical recommender systems, the explicit trust statements are not available.

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We propose to improve the existing TARS by using the implicit trust networks: instead of using the effort-consuming explicit trust in TARS, other cheap and easy available trust sensitive information is used to generate the implicit trusts for TARS. The trust statement is regarded as implicit if it is not explicitly pointed out by the users. To differentiate our TARS model from the conventional models, we name our model as iTARS since it is using the implicit trust statements, whereas we name the conventional TARS models as eTARSs since they are using the explicit trust statements. In our proposed iTARS, we generate the implicit trusts based on the user similarities. By comparing two users' ratings on their co-rated items, it is easy to obtain their similarity, as did in CF. This does not need extra human efforts on labelling the trust statements. The implicit trust is propagated among users and the implicit trust network is therefore constructed for iTARS to achieve high rating prediction performance

The contributions of this paper are three-fold:

- We identify the implicit trust that improves the conventional TARS by releasing extra user efforts on labelling the trust statements.

- We conduct experiments to verify the small-world topology of the implicit trust networks, which can 'facilitate' its usage in iTARS. We show that the nodes of the implicit trust network are highly clustered, whereas the distance between two randomly selected nodes is short. We further verify that the small-world topology of the implicit trust network is independent of its dynamics.

- We propose a novel iTARS model that effectively overcomes the weakness of the conventional TARS. Our model is based on the small worldness of the implicit trust network. Experimental results show that: with the same computational complexity, our model is able to improve the conventional TARS with higher rating prediction accuracy and slightly worse rating prediction coverage.

The rest of the paper is structured as follows: in Section 2, we introduce the most popular eTARS model; in Section 3, we present our proposed iTARS model which improves the conventional eTARS model by making use of the small worldness of the implicit trust network; the last section concludes this paper and points out the future work.

2 Related works

A number of researchers [1, 3–6] have proposed their TARS models. All these models are using the explicate trust statements. Among these models, the model proposed by Massa and Avesani [1, 2, 7, 8] is the most popular one. In addition, their model has already been used in the real applications [1]. Owing to its popularity and practicability, their TARS model is used as the basis of analysis in this research. The eTARS model specifically refers to their model in this research.

The architecture of eTARS is shown in Fig. 1. The inputs are the trust matrix and the rating matrix. The output is the predicted ratings on the items for different users. The trust matrix is the collection of the trust relations between the users of the recommender system. Each element of the trust matrix describes the trust between two users, which is explicitly pointed out by each user. The rating matrix records the users' ratings on the items. Each element of the rating matrix is the rating given by a user on a particular item.

The rating prediction mechanism of eTARS is given in Table 1. It consists of three phases:

The first phase is the recommender searching. In this phase, eTARS searches all valid recommenders based on the active user's trust propagation distances to the recommenders. A recommender is valid if (i) there is at least one path from the active user to the recommender in the trust network, and (ii) the trust propagation distance

Table 1 Rating prediction mechanism of eTARS

input: $\boldsymbol{T}$ (explicit trust matrix), $\boldsymbol{R}$ (rating matrix)
parameter: a (active user), i (item)
output: $p_{a,i}$ (a's predicted rating on i)
phase 1: Recommender searching
phase 2: Recommender weighting
phase 3: Rating calculation

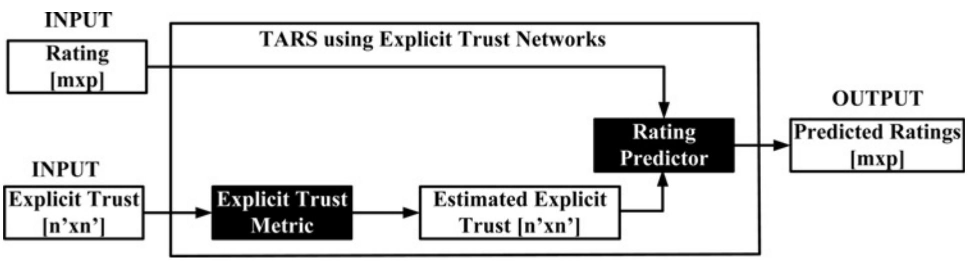

Figure 1 *Architecture of the conventional eTARS model*

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doi: 10.1049/iet-com.2009.0733

from the active user to the recommender is no longer than the maximum trust propagation distance (MTPD).

The second phase is the recommender weighting. In this phase, each valid recommender is weighted based on the relationship between the active user's trust propagation distance to recommenders and MTPD

$$w_{a,u} = \frac{d_{\max} - d_{a,u} + 1}{d_{\max}} \tag{1}$$

in which $w_{a,u}$ is the weight of the recommender u with respect to the active user a, $d_{\max}$ is MTPD and $d_{a,u}$ is the trust propagation distance from a to u. In this paper, the trustor's trust propagation distance to the trustee refers to the number of hops in the shortest path from the trustor to the trustee.

The third phase is the rating calculation. In this phase, eTARS predicts the rating by aggregating the recommendations given by the valid recommenders, in which each recommendation is weighted with respect to the weight of the recommender

$$p_{a,i} = \bar{r}_a + \frac{\sum_{u=1}^{k} w_{a,u}(r_{u,i} - \bar{r}_u)}{\sum_{u=1}^{k} w_{a,u}} \tag{2}$$

in which $p_{a,i}$ is the predicted rating on the item i for the active user a, $\bar{r}_a$ is the active user's average rating on the rated items, $\bar{r}_u$ is the recommender's average rating on the rated items, $r_{u,i}$ is the recommender u's recommendation on the item i and k is the number of valid recommenders.

3 Our proposed TARS model using implicit trust networks

In eTARS, the explicit trust statements are used to weight the recommendations for the rating predictions. However, it is not easy to obtain these explicit trust statements in the practical recommender systems since these information require extra human efforts. We propose a novel TARS model which improves the conventional eTARS model by predicting the ratings without the explicit trust statements. Our model, which is named iTARS, uses the easy available trust sensitive information, that is, the information that needs little or no extra user efforts, to generate the implicit trust network for TARS. Specifically, we use the user similarities to generate the implicit trust between the users. The recommendations are weighted based on the active users' implicit trusts on the recommenders to generate the predicted ratings.

The architecture of our proposed iTARS model is given in Fig. 2. Unlike the architecture of eTARS, as shown in Fig. 1, the input of iTARS is only the ratings given by users on the items. The users do not need to express their trust opinions on others. The output is the predicted ratings that the users would assign to the items. The black boxes in Fig. 2 represent various modules and the white boxes represent the matrices. Our architecture has three modules: the similarity metric module, the implicit trust metric module and the rating predictor module. The similarity metric module is used to evaluate the user similarities between all users of the rating matrix. The implicit trust metric module is used to generate the implicit trust and build the implicit trust network based on the user similarities. The rating predictor module is used to predict the ratings based on the recommendations and the active users' implicit trust on the recommenders. The details of these modules and the performances of our iTARS model are illustrated in the following subsections.

3.1 Building implicit trust networks for iTARS

Our proposed iTARS model predicts ratings based on the implicit trust network. The implicit trust network is built based on the implicit trust between users, which is generated by the user similarities in this research.

We first describe the environment of iTARS. It is composed by:

1. A set U of m distinct users: $U = \{u_1, u_2, u_3, \ldots, u_m\}$: In this research, the term 'user' not only refers to the human being user of the online communities, but also refers to other possible peer that is willing to share resources with others, for example, nodes of the P2P network and the software agents of the intelligent web.

2. A set I of p distinct items: $I = \{i_1, i_2, i_3, \ldots, i_p\}$.

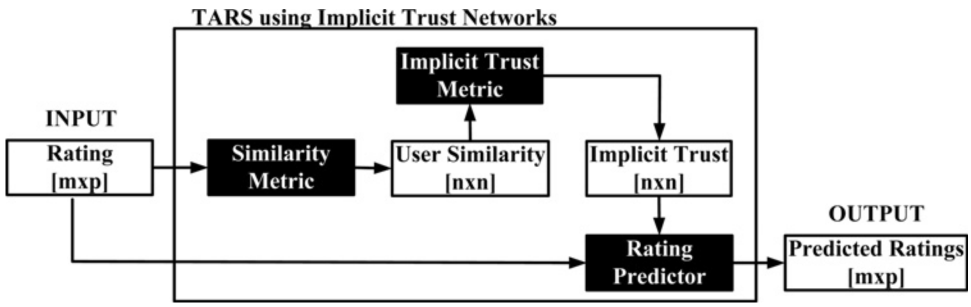

Figure 2 *Architecture of our proposed iTARS model*

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