Knowledge-Based Systems 23 (2010) 232–238

Contents lists available at ScienceDirect

Knowledge-Based Systems

journal homepage: www.elsevier.com/locate/knosys

Improved trust-aware recommender system using small-worldness of trust networks

Weiwei Yuan [a], Donghai Guan [a], Young-Koo Lee [a,*], Sungyoung Lee [a], Sung Jin Hur [b]

[a] Department of Computer Engineering, Kyung Hee University, Yongin, Republic of Korea
[b] Electronics and Telecommunications Research Institute (ETRI), Republic of Korea

ARTICLE INFO

Article history:
Received 2 July 2009
Received in revised form 23 November 2009
Accepted 31 December 2009
Available online 6 January 2010

Keywords:
Trust
Trust network
Small-world network
Recommender system

ABSTRACT

The trust network is a social network where nodes are inter-linked by their trust relations. It has been widely used in various applications, however, little is known about its structure due to its highly dynamic nature. Based on five trust networks obtained from the real online sites, we contribute to verify that the trust network is the small-world network: the nodes are highly clustered, while the distance between two randomly selected nodes is short. This has considerable implications on using the trust network in the trust-aware applications. We choose the trust-aware recommender system as an example of such applications and demonstrate its advantages by making use of our verified small-world nature of the trust network.

1. Introduction

The trust-aware recommender system (TARS) is the recommender system that 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 behavior within a specific context at a given time. TARS has recently been proposed for use since it is able to solve the well-known data sparseness problem of the collaborative filtering (CF) [1,2]. This is because trust is transitive. It means, if *A* trusts *B* and *B* trusts *C*, *A* trusts C to some extend. So even if there is no direct trust between the active users and the recommenders, the active users can build up some indirect trust relationships with the recommenders via the trust propagations. This contributes to the high rating prediction coverage of TARS. Moreover, the rating prediction accuracy of TARS is no worse than the classical CF [1].

Despite of its high rating prediction accuracy and high rating prediction coverage, the conventional TARS model suffers from the problem that it is not optimized: its computational complexity can be exponentially more expensive by achieving similar rating predication accuracy and rating prediction coverage, and its rating prediction coverage can be significantly worse by achieving similar rating predication accuracy. This is because little is known about the topology of the trust networks used in TARS. The trust network is highly dynamic: a user can join the trust network at anytime by stating its trust on any user of the trust network. This irregular growth leads to the complex structure of the trust network. Since the topology of the trust network is the important information to optimize TARS, this research motives to make clear the structure of the trust network. Furthermore, based on the topology of the trust network, we motive to optimize the conventional TARS model.

The contributions of this paper are mainly in two-fold:

- We conduct experiments to verify the small-world topology of the trust network, which can facilitate its usage in various trust-aware applications. Though the trust network has been assumed to be a small-world network by some existing works [3–5], to the best of our knowledge, no one has verified its small-worldness experimentally or theoretically. By analyzing five trust networks extracted from the real online sites, we contribute to verify that the trust network is the small-world network: on one hand, the nodes of the trust network are highly clustered, which is similar to the regular network; on the other hand, the distance between two randomly selected nodes of the trust network is short, which is similar to the random network.
- We propose a novel TARS model which can effectively overcome the weakness of the conventional TARS model. This is achieved by leveraging our verified small-worldness of trust networks. Experimental results clear show that: our proposed model is superior to the conventional one since it is able to achieve the maximum rating prediction accuracy and the maximum rating prediction coverage with the minimum computational complexity.

* Corresponding author.
E-mail address: yklee@khu.ac.kr (Y.-K. Lee).

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doi:10.1016/j.knosys.2009.12.004

The organization of this paper is as follows: in Section 2, we introduce the most popular TARS model in details and analyze its limitations; in Section 3, we verify the small-worldness of the trust networks; in Section 4, we present a novel TARS model which is based on the small-world topology of the trust network; the last section concludes this paper and points out our future research.

2. Related works

A number of researches [1,6–9] have focused on extending the recommender system with the trust-awareness. Among these works, the TARS model proposed by Massa and Avesani [1,2,10,11] is the most popular one. In addition, their model has already been used in a practical application named Moleskiing.it [12]. Due to its popularity, their TARS model is used as the basis of analysis in this research. The conventional TARS model specifically refers to their model in this research.

The architecture of TARS 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. 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 the conventional TARS model is similar as that of CF. The difference is that CF weights each recommendation based on the active user's similarity with the recommender, while TARS weights each recommendation based on the active user's trust on the recommender:

$$p_{a,i} = \overline{r_a} + \frac{\sum_{u=1}^{k} w_{a,u}(r_{u,i} - \overline{r_u})}{\sum_{u=1}^{k} w_{a,u}}, \quad (1)$$

where $p_{a,i}$ is the predicted rating on the item i for the active user a, $\overline{r_a}$ is the active user's average rating on its rated items, $\overline{r_u}$ is the recommender u's average rating on its rated items, $r_{u,i}$ is the recommender u's recommendation on the item i, and k is the number of recommenders. $w_{a,u}$ is the weight of the recommender u with respect to the active user a, it is calculated as

$$w_{a,u} = \frac{d_{\max} - d_{a,u} + 1}{d_{\max}}, \quad (2)$$

where $d_{\max}$ is the maximum trust propagation distance (MTPD) between users of the recommender system. The value of MTPD is preset by the administrator of TARS. $d_{a,u}$ is the active user a's trust propagation distance to the recommender u. In TARS, the trust propagation distance refers to the number of hops in the shortest trust propagation path from the trustor to the trustee.

As shown in the prediction mechanism of the conventional TARS model, MTPD is the fundamental parameter for the rating prediction. However, existing works of TARS did not propose any mechanism to set MTPD. They just randomly choose some value for this extremely important parameter. For example, in [1], the authors randomly set the value of MTPD as 1, 2, 3 and 4 to conduct different experiments of TARS. They did not verify whether these values are the suitable values. And they did not consider the relationship between the value of MTPD and the scale of TARS. On one hand, if the value of MTPD is set too small, TARS might lose some valuable recommendations. On the other hand, the computational complexity of constructing trust networks for TARS is $O(k^{d_{\max}})$, in which k is the number of trusts stated per user, and $d_{\max}$ is the value of MTPD, so if the value of MTPD is set too big, the computational complexity of TARS increases exponentially. Intuitively, the optimized value of MTPD for TARS should have some relationship with the topology of the trust network. We therefore analyze the characteristics of the trust network and optimize the conventional TARS model based on the topology of the trust network.

3. Finding small-world properties in trust networks

Based on five trust networks extracted from the real online sites, we verify in this section that the trust network is the small-world network.

3.1. Definition of small-world networks

The small-world network is a kind of network between the regular network and the random network. The regular network is highly clustered yet has long distance between two randomly selected nodes. The random network is not clustered yet has short distances between nodes. The small-world network is defined as the network that has [13]: (1) Large clustering coefficient, which is much larger than that of its corresponding random network, and (2) short average path length, which is almost as short as that of its corresponding random network, in which a network's corresponding random network refers to the random network that has the same number of nodes and same number of edges per node as this network. The relationship between the regular network, the random network and the small-world network is summarized in Table 1. We further list the explanations of the notations used in this section in Table 2.

The clustering coefficient C represents the cliquishness of a typical neighborhood [13], i.e., how close the node and its neighbors are to be a complete network. The clustering coefficient of a network is the mean of the clustering coefficient of each node, in which the clustering coefficient of a node is the fraction of the allowable edges and the edges that actually exist between the neighbors of this node [13]:

$$C = \frac{1}{n}\sum_{i=1}^{n} C_i = \frac{1}{n}\sum_{i=1}^{n} \frac{(\text{number of connected neighbor pairs})}{k_i(k_i - 1)}. \quad (3)$$

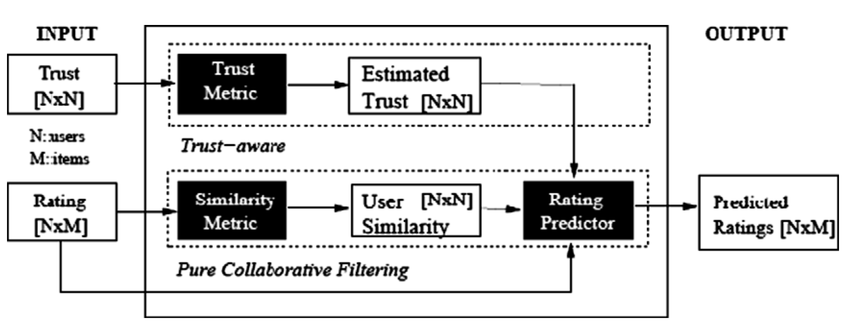

Fig. 1. Trust-aware recommender system architecture [1].

Table 1
The comparison between the regular network, the random network and the small-world network.

	Regular network	Small-world network	Random network
Clustering coefficient	Large	Large	Small
Average path length	Long	Short	Short

Table 2
Notations used in the small-worldness verification.

Symbol	Explanation
n	Size of the network
k	Average degree of the nodes in the network
k_i	Degree of node i
C_i	Clustering coefficient of node i
C	Clustering coefficient of the network
C^R	Clustering coefficient of the random network
L	Average path length of the network
L^R	Average path length of the random network

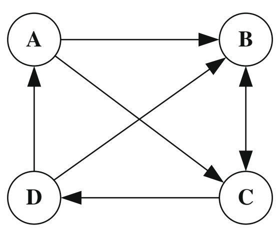

Fig. 2. A network with 4 nodes and 7 edges.

We use the network shown in Fig. 2 as an example to explain the calculation of Eq. (3). Node A has 3 neighbors, i.e., B, C and D, so at most 6 edges can exist between A's neighbors. Four edges actually exist in A's neighborhood: BC, CB, CD and DB. So we get $C_A = 4/6 = 2/3$, and similarly $C_B = 1/2$, $C_C = 1/2$ and $C_D = 2/3$. The clustering coefficient of the network is: $C = (C_A + C_B + C_C + C_D)/4 = 7/12$.

The clustering coefficient of a random network with n nodes and k edges per node is calculated as [13]:

$$C^R = \frac{k}{n}. \tag{4}$$

The average path length L is defined as the number of edges in the shortest path between two nodes, averaged over all pairs of nodes [13]. The average path length of a random network with n nodes and k edges per node is calculated as [13]:

$$L^R = \frac{\ln(n)}{\ln(k)}. \tag{5}$$

3.2. Experimental verifications on the small-worldness of trust networks

We experimentally verify the small-worldness of the trust networks using data extracted from the real applications. The experimental verification methodology is used since it is the most popular way to verify the small-world topology of various networks [13–18].

3.2.1. Experimental setup

Five trust networks are used in this research to verify the small-worldness. They are named as Epinions, Kaitiaki, Squeakfoundation, Robots and Advogato respectively. These networks are extracted from the trust network datasets released at trustlet.org[1].

Table 3
Description of the trust networks used in this research.

	Number of nodes	Number of edges per node
Epinions	49,288	9.88
Kaitiaki	64	2.41
Squeakfoundation	461	5.85
Robots	1646	2.1
Advogato	5412	9.98

Epinions consists of 49,288 users and 487,183 trust statements. The data is extracted from epinions.com[2] from November to December of 2003. Epinions.com is a recommender system that recommends items based on other users' ratings. In addition to the ratings on the items, the users are required to explicitly express their trust on other users. The trustor evaluates its trust on the trustee as 1 if the trustor consistently finds the ratings given by the trustee are valuable, otherwise, the trustor evaluates its trust on the trustee as 0.

Advogato consists of 5412 users and 54,012 trust statements. The data is extracted from advogato.org[3] on June 1, 2009. Advogato.org is an online community site dedicated to free software development. On advogato.com users can certify each other as several levels: Observer, Apprentice, Journeyer or Master [19]. Masters are supposed to be excellent programmers who work full-time on free software, Journeyers contribute significantly, but not necessarily full-time, Apprentices contribute in some way, but are still acquiring the skills needed to make more significant contributions, and observers are users without trust certification. These certifications are regarded as the trust statements of Advogato.

Kaitiaki consists of 64 users and 154 trust statements. The data is extracted from kaitiaki.org[4] on September 1, 2008. The trust statements of Kaitiaki are weighted at four different levels: Kaitiro, Te Hunga Manuhiri, Te Hunga Käinga, Te Komiti Whakahaere. Squeakfoundation consists of 461 users and 2697 trust statements. The data is extracted from squeak.org[5] on November 1, 2008. The trust statements of Squeakfoundation are weighted at three different levels: Apprentice, Journeyer, and Master. Robots consists of 1646 users and 3456 trust statements. The data is extracted from robots.net[6] on March 1, 2009. The trust statements of Robots are weighted at three different levels: Apprentice, Journeyer, and Master. Kaitiaki.org, squeak.org and robots.net are all web community sites which use the same software which powers the Advogato web community site, mod virgule. These three datasets are much smaller than the Advogato dataset.

The characteristics of our explored trust networks are summarized in Table 3. All users involved in these trust networks act as the trustors, the trustees or both.

3.2.2. Experimental results

Experiments are held on the above trust networks to verify their small-worldness.

Firstly, we verify that trust networks have large clustering coefficients. Using Eqs. (3) and (4), we get the clustering coefficients of our explored five trust networks and their corresponding random networks, which are summarized in Table 4. Comparing the

1 http://www.trustlet.org/wiki/Datasets.
2 http://www.epinions.com/.
3 http://www.advogato.org/.
4 http://www.kaitiaki.co.nz/.
5 http://www.squeak.org/Foundation/.
6 http://robots.net/.

Table 4
The clustering coefficients of the trust networks and their corresponding random networks.

	n	k	C	C^R
Epinions	49,288	9.88	0.22	2×10^{-4}
Kaitiaki	64	2.41	0.24	3.77×10^{-2}
Squeakfoundation	461	5.85	0.44	1.27×10^{-2}
Robots	1646	2.1	0.22	1.28×10^{-3}
Advogato	5412	9.98	0.23	1.84×10^{-3}

Table 5
The average path lengths of the trust networks and their corresponding random networks.

	n	k	L	L^R
Epinions	49,288	9.88	3.96	4.71
Kaitiaki	64	2.41	2.16	4.73
Squeakfoundation	461	5.85	2.85	3.47
Robots	1646	2.1	3.94	9.98
Advogato	5412	9.98	3.80	3.74

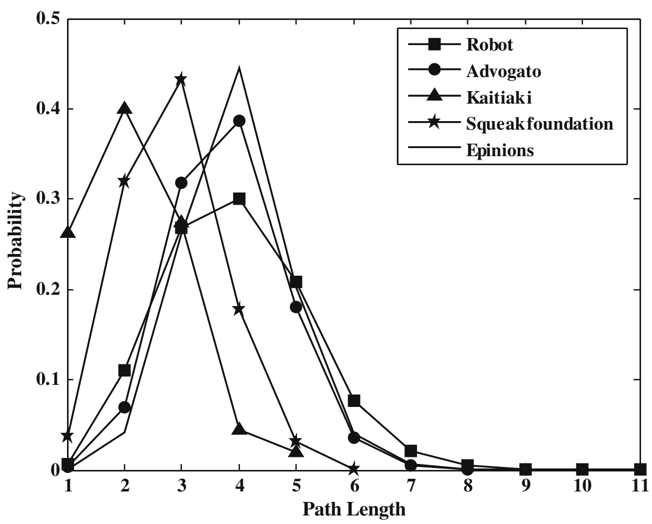

Fig. 3. The distribution of the trust networks' path lengths.

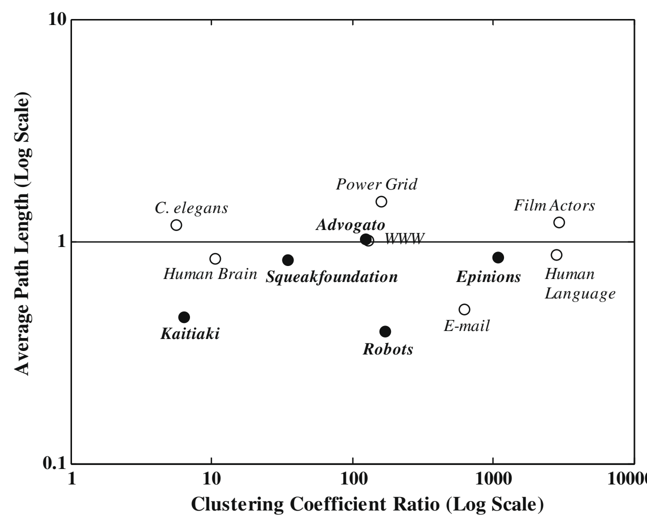

Fig. 4. The small-world characteristics of the trust networks and some well-known small-world networks.

clustering coefficients of the trust networks with those of their corresponding randomly networks, it is obvious that the trust networks have much larger (higher order of magnitude) clustering coefficients than their corresponding random networks. This satisfies the first condition of the small-world network's definition.

Secondly, we verify that trust networks have short average path lengths. For large networks, measuring all-pair distances is computational expensive, so an accepted procedure is to measure it over a random sample of nodes [20]. The average path lengths for the larger networks (Epinions and Advogato) in Table 3 are measured on a random sample of 5%. The average path lengths for the smaller networks (Kaitiaki, Squeakfoundation and Robots) in Table 3 are measured on all pairs of nodes. The distributions of the five trust networks' average path lengths are given in Fig. 3. It shows that the trust networks have very small number of direct trusts, i.e., where the path length equals to 1. By propagating trust, users can build up their trust relationships with others within several hops. Another important observation is that very small number of the trust propagations has long distance, e.g. the probabilities that the path lengths are longer than 8 hops (if any) are less than 1%. The path lengths of most trust propagations are from 2 hops to 6 hops. In more details: (1) the maximum path length of Epinions is 11 hops, and its average path length is 3.96 hops; (2) the maximum path length of Kaitiaki is 5 hops, and its average path length is 2.16 hops; (3) the maximum path length of Squeakfoundation is 6 hops, and its average path length is 2.85 hops; (4) the maximum path length of Robots is 11 hops, and its average path length is 3.94 hops; (5) the maximum path length of Advogato is 9 hops, and its average path length is 3.8 hops.

Using Eq. (5), we get the average path lengths of our explored five trust networks' corresponding random networks, which are summarized in Table 5. Comparing the average path lengths of the trust networks with those of their corresponding random networks, it is obvious that the trust networks have similar (the same order of magnitude) average path lengths as their corresponding random networks. This satisfies the second condition of the small-world network's definition.

We further compare the trust networks with some well-known small-world networks documented in the literature: the World Wide Web [14], the human language network [16], the e-mail network [15], the human brain network [17,18], the film actors network [13], the power grid network [13], and the *C. elegans* network [13]. The comparison on the small-world characteristics of these networks is presented in Fig. 4, in which the axes represent the ratios of the selected networks and their corresponding random networks. Note that most small-world networks are concentrated around where the average path length ratio equals to 1. This means that the selected networks have similar average path lengths as their corresponding random networks. In addition, most clustering coefficient ratios of the networks are greater than 10. This means that the selected networks have much larger clustering coefficients than their corresponding random networks. The comparison clearly show that the trust networks have the same properties as other well-known small-world networks: they are highly clustered yet have small average path lengths. We therefore draw the conclusion that the trust network is the small-world network.

4. Improving TARS using small-worldness of trust networks

Using our verified small-world topology of the trust networks, we propose a novel TARS model which optimizes the conventional model by suggesting the values of MTPD. Our proposed method is straightforward and requires little computational efforts.

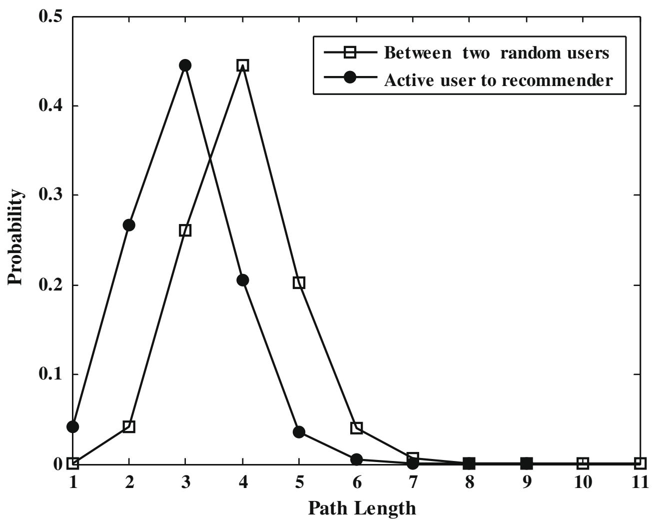

Fig. 5. The distributions of the trust propagation distances between different users of TARS.

4.1. Our proposed TARS model

For different sized TARS, it is hard to directly point out the value of MTPD between two randomly selected users. However, since the trust network of TARS is the small-world network, it is easy to get the approximate average trust propagation distance between two randomly selected users of the trust network: it is similar to the average path length of the trust network's corresponding random network. We only need to know the size and the average degrees of the trust network. Since the value of MTPD is unknown and the average path length of the trust network is the only available information about the distance between two users, it is interesting to explore whether there is some relationship between these two values. For this purpose, we compare the trust propagation distances from the active users to the recommenders with that between two randomly select users.

We use the Epinions dataset for the experiments of TARS. This dataset is chosen since the inputs of TARS are the trust data and the rating data, while other datasets shown in Section 3.2.1 only have the trust data, and only the Epinions dataset has these data simultaneously. The Epinions trust network, which is given in Section 3.2.1, acts as the trust data of the TARS inputs. The ratings given by the users of Epinions on various items act as the rating data. The rating data is given in the "epinions dataset".[7] It consists of 20,157 users' ratings on 139,633 items. Each user averagely rated 32.94 items, and each item got around 4.76 ratings. Note that not all users in the trust network are involved in the rating matrix since some users do not give any ratings on the items. E.g. only around 40% users of Epinions are involved in rating matrix. The values of ratings in the rating matrix are integers from 1 to 5, in which 1 means the user likes the item least, and 5 means the user likes the item most. The ratings are predicted on each user's predicted items, in which all other users' ratings on this item are regarded as the recommendations.

The comparison of the trust propagation distances between different users of TARS is given in Fig. 5. It shows that a user tends to has shorter trust propagation distance with the recommender than with a randomly selected user, and the maximum trust propagation distance from the active user to the recommender is shorter than that between two randomly selected users. Therefore, the average path length of the trust network is a value between the active users' average trust propagation distances to the recommenders and the active users' maximum trust propagation distances to the recommenders. In addition, due to small-worldness of the trust network, the active users' maximum trust propagation distances to the recommenders are short – within limited number of hops. So the maximum trust propagation distance from the active user to the recommender can not be significantly greater than the average path length of the trust network.

Table 6
Our proposed rating prediction algorithm.

Algorithm: Our proposed rating prediction algorithm
Input: T (trust matrix), R (rating matrix)
Parameter: a (active user), i (item), $d_{\max}$ (the maximum trust propagation distance), n (size of the trust network), k (average degrees of the trust network)
Output: $p_{a,i}$ (a's predicted rating on i)
Phase 1: MTPD calculation
Phase 2: Recommender searching
Phase 3: Recommender weighting
Phase 4: Rating calculation

Inspired by the above observations, we heuristically choose the average path length of the trust network as the value of MTPD for TARS. We therefore propose our TARS model by improving the conventional one based on the small-worldness of the trust networks. The rating prediction algorithm of our proposed TARS model is shown in Table 6.

Our proposed TARS model consists of four phases:

The first phase is the MTPD calculation. In this phase, we use the average path length of the trust network used in TARS as the value of MTPD. Due to small-worldness of the trust network, this value approximately equals to the average path length of this trust network's corresponding random network:

$$d_{\max} = \lceil L \rceil \approx \lceil L^R \rceil = \left\lceil \frac{\ln(n)}{\ln(k)} \right\rceil, \tag{6}$$

where $\lceil \cdot \rceil$ represents the ceiling of selected value, e.g. $\lceil L \rceil$ is the ceiling of the average path length of the trust network. The value of L^R is calculated by Eq. (5). For the simulation data used in this research, we get $d_{\max} = \lceil L \rceil \approx \lceil L^R \rceil = \lceil 4.71 \rceil = 5$ for TARS.

The second phase is the recommender searching. In this phase, TARS searches all valid recommenders based on our selected MTPD. A recommender is valid if (1) there is at least one trust propagation path from the active user to the recommender in the trust network, and (2) the trust propagation distance from the active user to the recommender is no longer than $\lceil L \rceil$.

The third phase is the recommender weighting. In this phase, the valid recommenders are weighted based on the relationship between the active users' trust propagation distances to the recommenders and our selected MTPD. We use the similar weighting mechanism as the conventional TARS model, as shown in Eq. (2). The difference is that our model explicitly points out the value of MTPD, which is calculated by Eq. (6). The weighting mechanism of our model is

$$w_{a,u} = \frac{\lceil L \rceil - d_{a,u} + 1}{\lceil L \rceil} \approx \frac{\lceil L^R \rceil - d_{a,u} + 1}{\lceil L^R \rceil}. \tag{7}$$

The last phase is the rating calculation. In this phase, we predict the ratings by aggregating the recommendations given by the valid recommenders. Each recommendation is weighted with respect to the weight of the recommender, which is calculated by Eq. (7). The aggregation mechanism used in our model is the same as the conventional TARS model, which is also the one used in CF, as shown in Eq. (1).

[7] http://www.trustlet.org/wiki/Downloaded_Epinions_dataset.

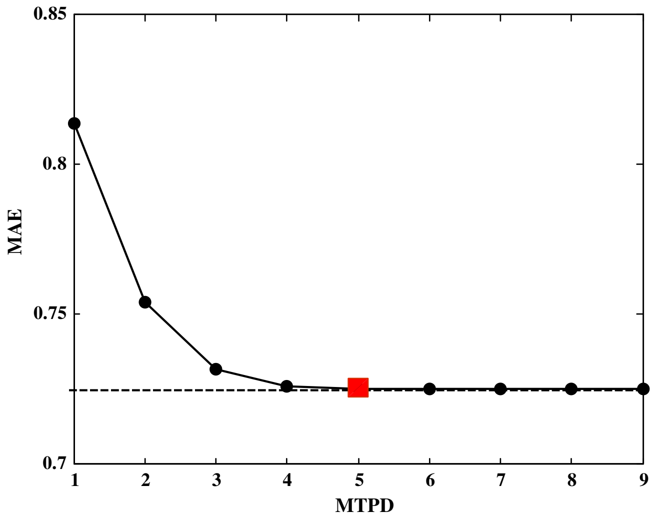

Fig. 6. The MAE of TARS: the MAE of the conventional TARS model can be any of the nine dots, while the rectangular dot represents the MAE of our proposed model.

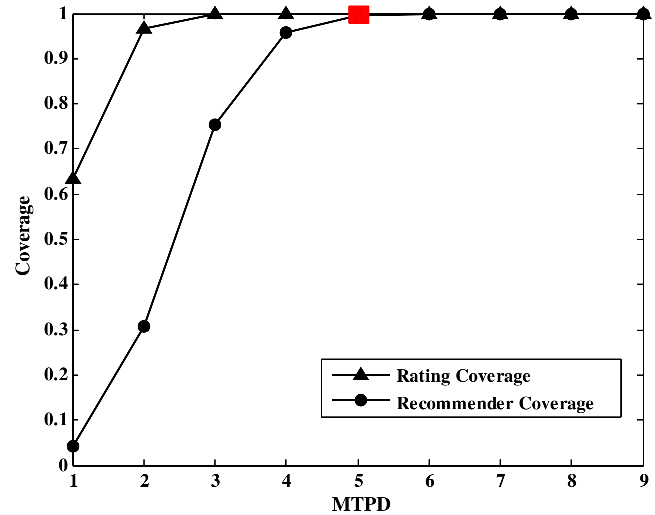

Fig. 7. The rating coverage and the recommender coverage of TARS: the coverages of the conventional TARS model can be any of the nine dots, while the rectangular dots represent the coverages of our proposed model.

4.2. Experimental results

We examine the performance of our proposed TARS model in three aspects to verify its effectiveness. These three aspects include the rating prediction accuracy, the rating prediction coverage and the computational complexity. The data used for simulations are those shown in Section 4.1.

The rating prediction accuracy is measured by the error of the predicted ratings of TARS. Specifically, we calculate the mean absolute error (MAE) since it is very appropriate and useful for evaluating prediction accuracy in offline tests [1]. To calculate MAE, the predicted rating is compared with the real rating and the difference (in absolute value) is the prediction error, this error is then averaged over all predictions to obtain the overall MAE. By predicting the rating on each rated item of our explored experimental data, we report the MAE of TARS with different values of MTPD in Fig. 6. Since the conventional TARS model did not mention how to choose the value of MTPD, its MAE can be any of the nine dots shown in Fig. 6. The rectangular dot shown in Fig. 6 represents the MAE of our proposed model, in which $\lceil L \rceil$ is selected as the value of MTPD. The experimental results show that: (1) If MTPD is set to be smaller than our suggested value, the rating prediction accuracy of TARS is getting worse. (2) If MTPD is set to be greater than our suggested value, the rating prediction accuracy of TARS dose not significantly change.

The coverage of TARS is measured by both the rating coverage and the recommender coverage. The rating coverage is the portion of items that TARS is able to predict, i.e., the portion of items that the active user can get at least one recommendation. However, this quantity is not always informative about the quality of TARS. TARS is sometimes good on the rating coverage, but only involve small portion of recommenders. This is because an item usually has a number of recommendations, so a good rating coverage does not necessarily imply a good coverage on the recommenders. Since it facilities the rating prediction by involving as many recommendations as possible in TARS, we introduce the term recommender coverage. The recommender coverage is the portion of recommenders that could be involved in TARS. By using different values of MTPD, the rating coverage and the recommender coverage of our explored experimental data are given in Fig. 7. Since the conventional TARS model did not mention how to choose the value of MTPD, its rating coverage and the recommender coverage can be any of the nine dots shown in the lines of Fig. 7. The rectangular dots shown in Fig. 7 represent the rating coverage and the recommender coverage of our proposed model, in which $\lceil L \rceil$ is selected as the value of MTPD. The experimental results show that: (1) If MTPD is set to be smaller than our suggested value, both the rating coverage and the recommender coverage of TARS decrease, in which the recommender coverage decreases significantly. (2) If MTPD is set to be greater than our suggested value, the rating coverage and the recommender coverage of TARS do not significantly change. This is because the rating coverage and the recommender coverage of TARS are both very high, more than 99%, by using our suggested value of MTPD.

The computational complexity of constructing the trust network for TARS is $O(k^{d_{\max}})$, as mentioned in Section 2. Therefore, if MTPD (represented by $d_{\max}$) is set to be smaller than our suggested value, the computational complexity of constructing trust networks for TARS is exponentially less expensive. On the other hand, if MTPD is set to be greater than our suggested value, the computational complexity of constructing trust networks for TARS is exponentially more expensive.

To sum up, though setting MTPD smaller than our suggested value is computational less expensive, the rating prediction accuracy and the rating prediction coverage of TARS are worse; while setting MTPD greater than our suggested value leads to similar rating prediction accuracy and similar rating prediction coverage of TARS, but it is computational exponentially more expensive. We therefore draw the conclusion that $\lceil L \rceil$ is a good estimation of MTPD which provides the maximum rating prediction coverage and the maximum rating prediction accuracy with the minimum computational complexity. This verifies the effectiveness of our proposed model.

5. Conclusions and future work

Analyzing five trust networks obtained from the real online sites, we verify that the trust network is the small-world network. This means that it is able to build up the trust relationship between two randomly selected users of the trust network within limited number of hops, and the average path length of the trust network is similar to that of the random network that has the same number of users and same number of edges per user as the trust network. This verified small-world nature of the trust network can facilitate its usage in various applications. In this paper, we use TARS as an example of the applications, and show how the small-worldness of the trust network contributes to the applications. Specifically, we propose a novel TARS model by using $\lceil L \rceil$ as MTPD for TARS. The simulation results show that: by involving recommenders that are within $\lceil L \rceil$ hops away from the active user, it is possible to achieve high rating coverage and recommender coverage; while it is computational exponentially less expensive than using a greater value of MTPD. On the other hand, by using $\lceil L \rceil$ as MTPD, the error of the predicted ratings is less than the error of using a smaller value of MTPD. These simulation results verify the effectiveness of our proposed methodology of TARS.

Our future work focuses on several aspects. Firstly, we will improve the existing TARS models with the implicit trust network. Existing works of TARS focus on using the explicit trust, while it is sometimes time consuming or expensive to get the explicit trust. Explicit trust refers to the trust that should be explicitly pointed out by the users. These explicit trust statements are then used as the inputs of TARS with the recommendations to predict the ratings. Though the explicit trust based TARS models have high rating prediction coverage and high rating prediction accuracy, the explicit trust statements are not always available. Therefore, we will try to use other cheap and easy available trust sensitive information to generate the implicit trust statements for TARS. Secondly, we will focus on how to filter out the unfair recommendations for TARS. TARS suggests information to the active users based on the recommendations given by various recommenders. However, there may exist some self-interested recommenders who give unfair recommendations to maximize their own gains (perhaps at the cost of others). So it is essential to avoid or reduce the influence of the unfair positive or negative recommendations from the self-interested recommenders. For this purpose, we intend to introduce the users' distrust statements into our TARS model. By analyzing the recommendations given by each user's distrusted recommenders and the relationship between the trust statements and the distrust statements, the reliable recommendations will be chosen for the rating aggregations of our proposed TARS model.

Acknowledgements

The authors would like to thank the anonymous reviewers and the editors of the journal for their valuable comments. This research was supported by the MKE (Ministry of Knowledge Economy), Korea, under the ITRC (Information Technology Research Center) support program supervised by the IITA (Institute of Information Technology Advancement) (IITA-2009-(C1090-0902-0002)). Also, this work was supported by the IT R&D program of MKE/KEIT. [2009-S-033-01, Development of SaaS Platform for S/W Service of Small and Medium sized Enterprises].

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