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A reliability-based recommendation method to improve trust-aware recommender systems

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ABSTRACT

Recommender systems (RSs) are programs that apply knowledge discovery techniques to make personalized recommendations for user's information on the web. In online sharing communities or e-commerce sites, trust is an important mechanism to improve relationship among users. Trust-aware recommender systems are techniques to make use of trust statements and user personal data in social networks. The accuracy of ratings prediction in RSs is one of the most important problems. In this paper, a Reliability-based Trust-aware Collaborative Filtering (RTCF) method is proposed to improve the accuracy of the trust-aware recommender systems. In the proposed method first of all, the initial trust network of the active user is constructed by using combination of the similarity values and the trust statements. Then, an initial rate is predicted for an unrated item of the user. In the next step, a novel trust based reliability measure is proposed to evaluate the quality of the predicted rate. Then, a new mechanism is performed to reconstruct the trust network for those of the users with lower reliability value than a predefined threshold. Finally, the final rate of the unrated item is predicted based on the new trust network of the user. In other words, the proposed method provides a dynamic mechanism to construct trust network of the users based on the proposed reliability measure. Therefore, the proposed method leads to improve the reliability and also the accuracy of the predictions. Experimental results performed on two real-world datasets including; Epinions and Flixster, demonstrated that the proposed method achieved higher accuracy and also obtained reasonable user and rate coverage compared to several state-of-the-art recommender system methods.

1. Introduction

With the rapid development of the World Wide Web, the search process for relevant information spends a lot of times. Recently, e-commerce sites, where people can easily share their opinions on various products and services, are becoming increasingly popular (Kim & Phalak, 2012). In the presence of existing thousands of products in these sites, making recommendations for users about their interested items is an important problem. Accurate recommendations enable the users to quickly locate desirable items without being overwhelmed by irrelevant information. Recommender systems are widely used in the e-commerce applications to provide high quality personalized recommendations and also help the users to find those of the interested items among available choices.

Collaborative filtering (CF) is one of the most important and successful approaches in the recommender systems (Javari & Jalili, 2014a; Bojnordi & Moradi, 2013; Adomavicius & Tuzhilin, 2005; Gharibshah & Jalili, 2014; Herlocker, Konstan, Terveen, & Riedl, 2004; Ramezani, Moradi, & Akhlaghian, 2014; Yu, Schwaighofer, Tresp, Xu, & Kriegel, 2004; Su & Khoshgoftaar, 2009). The CF approach is based on the assumption that similar users share similar interests. Therefore, to provide suitable recommendations for an active user, the opinions of the other users with similar tastes are used in this approach. The CF-based methods use those of rate values given by the active user to different products in the system to find its neighbors and also make a list of recommendations on unseen items based on opinions of the neighbors. In other words, these methods generally use a similarity measure to determine the distance between each pair of the users to identify the active user neighbors. The basic idea of the CF-based methods is that two users with similar ratings are more appropriate to make recommendations, and also it is most likely that they will prefer similar items (Javari & Jalili, 2014b; Jeong, Lee, & Cho, 2009a; Kiasat & Moradi, 2012; Kim, Kim, & Cho, 2008; Kim, Kim, & Ryu,

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2009; Balabanovic & Shoham, 1998; Lee, Park, & Park, 2008; Park & Chang, 2009). Therefore, these approaches can be able to use those of the items that are rated by the neighbors as preferred items to the active user.

The CF-based algorithms can be classified into two well-known categories including: memory-based and model-based methods. The memory-based methods use a given similarity measure to act directly on user-item rating matrix which contains the rate values of all users who have expressed their opinions on the collaborative service. The similarity metric is used to compute the distance between a pair of the users or items based on their respective ratings. Moreover, the memory-based methods attempt to find a group of the users with similar interests and use the entire user-item rating matrix to produce a prediction for the active user. On the other hand, the model-based methods employ machine learning algorithms to fit a statistical model, and also estimate rates values for those of unseen items using the generated model (Hofmann, 2004). Several model-based methods have been proposed in the literature including: Bayesian belief nets (Miyahara & Pazzani, 2000; Su & Khoshgoftaar, 2009), dimensionality reduction techniques (Goldberg, Roeder, Gupta, & Perkins, 2001), clustering models (Javari & Jalili, 2014a; Birtolo & Ronca, 2013; Guo, Zhang, & Smith, 2015a; Moradi, Ahmadian, & Akhlaghian, 2015; Kim & Phalak, 2012), matrix factorization methods (Navgaran, Moradi, & Akhlaghian, 2013; Guo, Zhang, & Smith, 2015b; Deng, Huang, & Xu, 2014; Jamali & Ester, 2010; Ocepek, Rugelj, & Bosnić, 2015; Pirasteh, Hwang, & Jung, 2015), latent semantic models (Hofmann, 2004), and Markov decision process-based CF systems (Shani, Heckerman, & Brafman, 2005). A review of the research indicates that the memory-based techniques are more widely used than the model-based techniques (Breese, Heckerman, & Kadie, 1998; Huete, Fernández-Luna, de Campos, & Rueda-Morales, 2012; Resnick, Iacovou, Suchak, Bergstrom, & Riedl, 1994; Soboroff & Nicholas, 2000).

Although CF-based recommender systems are the most commonly used methods to personalized recommendations, these approaches often suffer from several shortcomings. These methods use a similarity metric to calculate the similarity value between a pair of the users based on the given ratings to the items by these users (Herlocker, Konstan, Borchers, & Riedl, 1999a; Herlocker, Konstan, & Riedl, 2002; Ciaccia & Patella, 2011). Although, to make good recommendations it is need to extensive data which contains exclusively the ratings made by the users over most of the items, the e-commerce users typically rate only a few number of the items. Therefore, the CF-based methods have problem to identify similar neighbors. This problem is called data sparsity problem. It should be noted that, based on the existing similarity metrics, the CF-based methods could be able to suggest those of the users that at least rated sufficient number of the items. Therefore, these methods are weak to deal with cold start users who have rated a few number of the items (Lee, Yang, & Park, 2004). Moreover, the CF approach is not able to provide suitable recommendations for the cold start users and also this approach is weak on sparse user-item rating matrixes. Furthermore, recommending the new items that have just been added into the system is also challenging because there are not available sufficient feedbacks on these items. Another problem of the CF approach is malicious attacks on the system (Mahony & Hurley, 2005). The recommender systems can be easily attacked by coping user profiles and shifting the predicted ratings of a particular item in order to influence the recommendations for genuine users (Massa & Avesani, 2007).

Several approaches have been proposed in the literature to overcome the mentioned problems of the CF-based methods. One of the most important approaches to improve the CF shortcomings is incorporating trust statements into the online recommender systems (Golbeck, 2006; O'Donovan and Smyth, 2005; Massa & Avesani, 2007). The main idea behind the trust statements is that there is high correlation between the trust and the user similarity. Therefore, the trust statements can be used as the same way of the similarity values to predict unknown rates in the recommender systems (Rahman & Hailes, 2000). On the other hand, the central roles of a trust network in the CF approach are to resolve the neighbor selection problem. Combining a user's trust network with the user-item rating matrix can resolve the data sparsity problem through the capture of information that is stored outside of each user's local similarity neighborhood (O'Donovan and Smyth, 2005; Jamali & Ester, 2009, 2010; Lathia, Hailes, & Capra, 2008; Bedi & Vashisth, 2014; Massa & Avesani, 2004, 2007; Moradi et al., 2015; Yan, Zheng, Chen, & Wang, 2013; Kim & Phalak, 2012). On the other hand, the trust networks can resist shilling attacks to a certain extent. Thus, using the trust statements in the CF approach can prevent the malicious attacks.

Recently, a measurement has been introduced to show the reliability of a prediction in the recommender systems, where it is shown that the measure has a high correlation with the accuracy of the predicted ratings (Hernando, Bobadilla, Ortega, & Tejedor, 2013). This measure just uses the similarity values between the users and does not consider the trust statements. In this paper, we attempt to propose a novel method to improve the performance of the recommender systems by means of incorporating reliability measures and the trust statements in these systems. The main insufficient of the current reliability measures is their lower performance while dealing with sparse data. To deal with this problem, in this research we consider both similarity and trust statements to calculate a novel reliability measure in the CF approach. Furthermore, a novel mechanism is proposed to reconstruct the trust networks of the users to improve the accuracy of the rating prediction by using the proposed trust based reliability measure. In the proposed reconstruction mechanism, first of all a trust network is generated for each user and then this network is used to predict the initial rate for a given unseen item. Then, the proposed trust based reliability measure is used to evaluate the predicted rate. If the corresponding reliability value is lower than a predefined threshold value, then a new trust network with higher quality than the previous one is constructed based on two positive and negative factors. These factors are used to identify the lower reliable users and remove them from the trust networks. Finally, the final rate of the unseen item is predicted based on the new trust network. In order to evaluate the performance of the proposed method, several experiments were performed on the Epinions and Flixster datasets. The results show that the proposed method could significantly improve the accuracy of the trust-aware recommender systems while preserving a good coverage compared to the well-known state-of-the-art methods.

The remainder of this paper is organized as follows: Trust-aware recommender systems are reviewed in Section 2; Section 3 introduces the proposed approach for trust-aware recommender systems; In Section 4, we validate the effectiveness of the proposed method by experimental evaluation on two real-world datasets; and Section 5 outlines conclusions.

2. Trust-aware recommender systems

Online social networks are growing across the web and joining more users to these systems leads to increasing distribution of through social network services (Oufi, Kim, & Saddik, 2012; Jiang, Wanga, & Wub, 2014). Social networks increasingly provide users with the ability to engage in social interaction with other users, such as online friending, making social comments, social tags, and etc. These networks allow different users to build trust relationships similar to those in the real world, thus trust relationship is a key issue in the online social networks (Paul, Pan, & Jain, 2011). In other words, social interactions among the users are constructed based on the trust statements that are established from user's subjective perspective (Abdessalem, Cautis, & Souhli, 2010). Considering the real world situation in which one's decision to purchase is more likely to be influenced by suggestions from friends than by website advertising, a user's social network may be an important source if it exists in a recommender system. Thus, trust based recommender systems offer opportunities for making recommendations by utilizing users' trust statements especially for systems whose rating data is too sparse to conduct collaborative filtering.

Several studies have been shown that including social factors or trust statements in the recommender systems leads to increase the quality of the recommendations (Lika, Kolomvatsos, & Hadjiefthymiades, 2014; Gago, Agudo, & Lopez, 2014; Liu & Yuan, 2010; Martinez-Cruza, Porcela, Bernabé-Moreno, & Herrera-Viedma, 2015; Jamali & Ester, 2009, 2010; Jiang et al., 2014; Moradi et al., 2015). Trust-aware methods can be classified into implicit and explicit methods. The explicit methods use pre-established social links among the users in the system as the trust statements. These methods analyze pre-existing relationships in a web of trust for an active user (Guo, Zhang, & Smith, 2015a; Bedi & Vashisth, 2014; Yan et al., 2013). On the other hand, the implicit methods make inferences on the trust statements among the users on the basis of the item ratings (Guo et al., 2015b; Li & Kao, 2009). In these methods, a trust network between two users is built on the basis of how each user rates the items in the system. In Massa and Avesani (2004), an undefined trust value was roughly predicted based on an assumption that users closer in the trust network to the source user have higher trust value. In Golbeck (2006), a systematic algorithm called "TidalTrust" was proposed to address the trust-based rating prediction problem. In O'Donovan and Smyth (2005), two types of trusts called profile-level and item-level are defined in order to decrease recommendation error. The profile level denotes the percentage of correct predictions from the view of general profile while the item-level indicates the percentage of correct predictions from the view of specific items. Moreover, in Shimon et al. (2007), personal social trees were constructed for active users and then computed the distances from active users to others, which can be seen as a reflection of trust, are considered as the final predicted weights.

In Hwang and Chen (2007), the authors analyzed the local and global trust matrixes in a recommender system and their results show that both local and global trust-awareness lead to increase in both recommendation coverage and accuracy. Jamali and Ester (2009) proposed a method called "TrustWalker" which combines trust information of the selected neighbors with an item-based technique by considering the ratings of the target item and similar items are considered. Furthermore, in Liu and Lee (2010), the authors reported that more accurate predictions are possible by incorporating the trust statements into the traditional CF algorithms. They proposed a specific approach which taken into account the number of messages exchanged among the users in the system and did not directly used the trust statements. Due to need for reliable tools for online web services and social networks, trust and reputation concepts get much attention. Furthermore, most of the recommender system based researches focused on both of the explicit trust statements and reputation concepts to make suitable recommendations (Liu & Lee, 2010; Shambour & Lu, 2015). The explicit information of the other users is used to calculate the trust value between each pair of the users. Moreover, in these systems the feedback of the users who are asked about their opinions is used to compute the reputation of the items (Ingoo, Kyong, & Tae, 2003). On the other hand, in the implicit based systems the reputation of the items is calculated by studying how the users work with these items (Jeong, Lee, & Cho, 2009b). Recently, in Guo, Zhang, and Thalmann (2014), a novel method called "Merge" is proposed to overcome the data sparsity and cold start problems in the recommender systems. In this method, ratings of a user's trusted neighbors are merged to complete the preferences of the user and to find other users with similar preferences as the user's neighbors.

Furthermore, trust is also adopted in model-based approaches. For example, in Yang, Guo, and Liu (2013) a Bayesian-inference-based recommendation method is proposed for online social networks. In this method, the similarity value between each pair of the users is measured by using a set of conditional probabilities derived from their mutual ratings. Moreover, the authors of Azadjalal, Moradi, and Abdollahpouri (2014) applied game theory techniques to improve accuracy and coverage of the recommender systems. Their method uses Pareto dominance concept to identify those of the users which are dominated by the active user. In Javari and Jalili (2014a), a probabilistic framework is introduced for sign prediction in social networks with positive and negative links. Recently, in Moradi et al. (2015) a model-based collaborative filtering method is proposed by applying a specific graph clustering algorithm and also considering trust statements. In this method, the graph clustering algorithm is performed to obtain the appropriate users/items clusters. The identified clusters are used as a set of neighbors to recommend unseen items to the current active user.

Moreover, several matrix factorization based recommender systems have been proposed as model based methods in the literature (Navgaran et al., 2013; Bojnordi & Moradi, 2013; Liu, Wu, & Liu, 2013; Jamali & Ester, 2010; Pirasteh et al., 2015; Deng et al., 2014; Ocepek et al., 2015). The basic idea of these methods is to use the matrix factorization methods for improving the accuracy of the recommender systems. Bojnordi and Moradi (2013) applied a matrix factorization method as a preprocessing step to predict unknown rates in the user-item matrix. In Navgaran et al. (2013), an evolutionary based matrix factorization method has been proposed for improving accuracy of the recommender systems. In Ocepek et al. (2015), a matrix factorization based framework is proposed for the imputation of missing values into the ratings matrix. The authors of Pirasteh et al. (2015) applied a matrix factorization method to the user similarity matrix in order to discover the similarities between the users who have rated different items. Moreover, several methods applied the matrix factorization algorithms on trust statements. For example, in Ma, Yang, Lyu, and King (2008) a latent factor model called "SoRec" is proposed which is based on probabilistic matrix factorization. Moreover, in Jamali and Ester (2010), a matrix factorization based method is proposed to enhance trust based recommendation method in the social networks. For this purpose, a trust propagation mechanism is incorporated in the matrix factorization based method which leads to improve the accuracy of the predicted ratings. Recently, in Deng et al. (2014), a social network based recommendation method called "Relevant Trust Walker" is proposed to improve trust based recommender systems. In this method, first of all a matrix factorization method is used to assess the trust values between the users in social network. Finally, the recommendation results of the system are obtained by using an extended random walk algorithm.

All the mentioned approaches simply applied the trust statements directly to predict unknown rate values without considering the quality of the predicted rates. While, it has been shown that inaccurate or incomplete trust networks may further decrease the performance of the trust-aware recommender systems (Srivatsa & Hicks, 2012). Therefore, it is important to infer and refine the trust statements for better recommendation performance. Therefore, in this paper we focus on a better trust network which is most suitable for recommender systems. Thus, the proposed method has some contributions in compare to the mentioned existing methods. First of all, in the proposed method a novel reliability measure is proposed to evaluate the quality of the predicted ratings. The proposed reliability measure is based on the similarity values and the trust statements between the users. Then, a new reconstruction method is proposed to reconstruct the trust network of the users by using the reliability measure. In other words, the trust network is reconstructed for those of the users which their reliability values are lower than a predefined threshold. Moreover, unlike previous methods, the proposed method uses a dynamic trust network to predict unrated items of the active user based on the proposed reliability measure and trust network reconstruction mechanism.

3. Proposed method

One of the most important challenges in the recommender systems is the accuracy of the predicted ratings in these systems. A method which predicts the rates of unseen items accurately makes better recommendations for the users of the recommender systems. In this paper, we aimed at providing a novel method to improve prediction accuracy of the trust-aware recommender systems based on a novel reliability measure. The overview of the proposed method called Reliability-based Trust-aware Collaborative Filtering (in short RTCF) is shown in Fig. 1. The proposed method consist of six steps including: (1) Trust network construction, (2) Initial rate prediction, (3) Calculating reliability measure, (4) Trust network reconstruction, (5) Final rate prediction, and (6) Top-N recommendations. Additional details of the RTCF steps are discussed in their corresponding subsections.

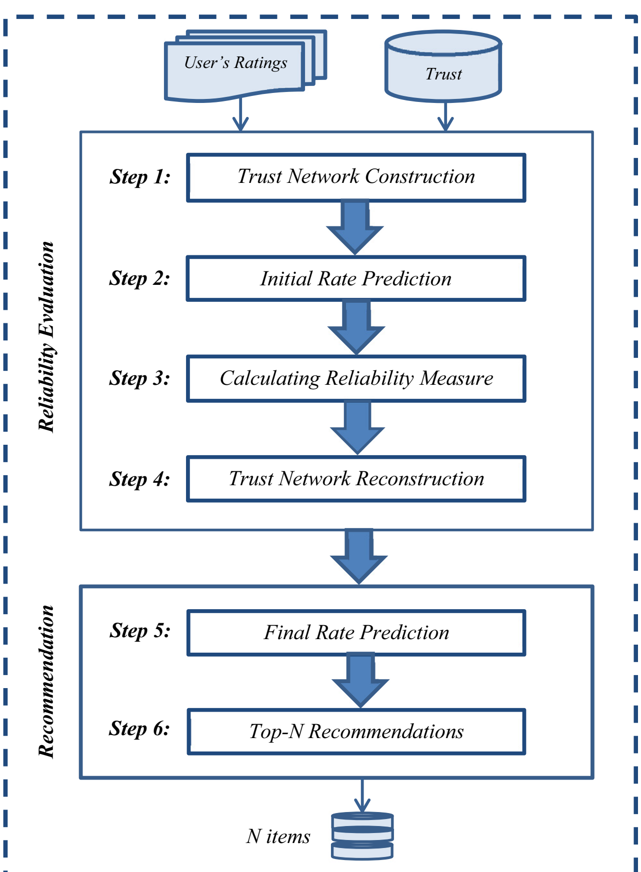

Fig. 1. Overview of the proposed method.

3.1. Trust network construction

A trust network for the active user can be constructed based on combination of the trust statements and the Pearson correlation coefficient measure as final similarity values (Herlocker, Konstan, Borchers, & Riedl, 1999b). This network is a weighted directed graph where the neighbors of the active user are nodes of the graph and the adjusted similarity values between two nodes forms the weights of their associated edge. The following equation is used to calculate the trust statements between a pair of the users a and u:

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

where, $T_{a,u}$ is the trust statement between the users a and u, d_{max} is the maximum allowable propagation distance between the users, and $d_{a,u}$ shows the trust propagation distance between the users a and u (Massa & Avesani, 2004). The value of d_{max} approximately equals to the average path length between the users in the trust network (Yuan, Guan, Lee, & Lee, 2010). The trust propagation distance refers to the number of hops in the shortest trust propagation path from the trustor to the trustee.

$$d_{max} = L^R = \frac{\ln(n)}{\ln(k)} \tag{2}$$

where, L^R is the average path length of the network, n represents the size of the trust network, and k denotes average degree of the trust network.

Finally, the adjusted weight between the users a and u which is denoted by $w_{a,u}$ is calculated as follows:

$$w_{a,u} = \begin{cases} \frac{2 \times sim(a,u) \times T_{a,u}}{sim(a,u) + T_{a,u}} & \text{if } sim(a,u) + T_{a,u} \neq 0 \\ & \text{and } sim(a,u) \times T_{a,u} \neq 0 \\ T_{a,u} & \text{else if } sim(a,u) = 0 \text{ and } T_{a,u} \neq 0 \\ sim(a,u) & \text{elseif } sim(a,u) \neq 0 \text{ and } T_{a,u} = 0 \\ 0 & \text{else} \end{cases} \tag{3}$$

where, $sim(a,u)$ is a similarity value between the users a and u that is calculated by means of the Pearson correlation coefficient function as follows:

$$sim(a,u) = \frac{\sum_{i \in A_{a,u}} (r_i(a) - \bar{r}(a))(r_i(u) - \bar{r}(u))}{\sqrt{\sum_{i \in A_{a,u}} (r_i(a) - \bar{r}(a))^2} \sqrt{\sum_{i \in A_{a,u}} (r_i(u) - \bar{r}(u))^2}} \tag{4}$$

where, $r_i(u)$ is the rate of the item i given by the user u, $\bar{r}(u)$ is the average of the rates given by the user u, and $A_{a,u}$ is the set of items which are rated by both of the users a and u.

After calculating the similarity weights between the active user and the other users, then top K nearest neighbors of the active user are selected according to their similarity weights (see Eq. (3)). Then, the trust network of the active user is constructed based on the selected neighbors.

3.2. Initial rate prediction

The trust network can be used to predict the initial rates of the unseen items for the active user (see Eq. (3)). The initial rate of the item i for the active user a is predicted using the following equation:

$$P_{a,i} = \overline{r_a} + \frac{\sum_{u \in K_{a,i}} w_{a,u} (r_{u,i} - \overline{r_u})}{\sum_{u \in K_{a,i}} w_{a,u}} \tag{5}$$

where, $\overline{r_a}$ refers to the average of ratings for the user a, $K_{a,i}$ is a set of neighbors for the user a who have rated the item i, and $w_{a,u}$ represents the similarity weight between the users a and u.

3.3. Calculating reliability measure

Reliability measure is used to evaluate the quality of the predicted rate. In Hernando et al. (2013), a reliability measure is proposed based on the positive and negative factors. This reliability measure only uses the user-item rating matrix to calculate the quality of the predicted rate, thus it cannot be applicable for trust based recommender systems. To this end, in this paper a novel reliability measure is proposed that considered the trust statements in its computations. The proposed reliability measure is used in the *Trust network reconstruction* step in order to improve the accuracy of the recommendations by providing a feedback on the quality of the predicted rates. The proposed reliability measure is calculated as follows:

$$R_{a,i} = \left(f_s(S_{a,i}) \cdot f_v(V_{a,i})^{f_s(S_{a,i})}\right)^{\frac{1}{1+f_s(S_{a,i})}} \tag{6}$$

where, $f_S(S_{a,i})$ and $f_V(V_{a,i})$ are the positive and negative factors of the reliability measure, respectively. Moreover, the positive factor is calculated by Eq. (7):

$$f_s(S_{a,i}) = 1 - \frac{\overline{S}}{\overline{S} + S_{a,i}} \tag{7}$$

where, $S_{a,i} = \sum_{u \in K_{a,i}} w_{a,u}$, is the value of positive factor to calculate the proposed reliability measure, $w_{a,u}$ is calculated by Eq. (3), $K_{a,i}$ is a set of neighbors for the user a who have rated the item i and $\overline{S}$ is the median of the values of $S_{a,i}$ in the specific recommender system. Furthermore, the negative factor is calculated as follows:

$$f_V(V_{a,i}) = \left(\frac{max - min - V_{a,i}}{max - min}\right)^{\gamma} \tag{8}$$

where,

$$\gamma = \frac{\ln 0.5}{\ln \frac{max - min - \overline{V}}{max - min}} \tag{9}$$

and $V_{a,i}$ is the value of negative factor to calculate the proposed reliability measure which is calculated using Eq. (10), $\overline{V}$ is the median of the values of $V_{a,i}$ in the specific recommender system, *max* and *min* are the maximum and minimum values of ratings for items in the specific recommender system, respectively.

$$V_{a,i} = \frac{\sum_{u \in K_{a,i}} w_{a,u} \cdot (r_{u,i} - \bar{r}_u - P_{a,i} + \bar{r}_a)^2}{\sum_{u \in K_{a,i}} w_{a,u}} \tag{10}$$

3.4. Trust network reconstruction

In this step, the proposed trust based reliability measure is used to evaluate the quality of the predicted rates. If the reliability value $R_{a,i}$ for the active user a and the item i is less than a threshold value (θ), the trust network for the active user will be reconstructed by the proposed trust network reconstruction mechanism. In other words, this step attempts to form a new trust network with higher quality than the initial one for the active user. This step is necessary in order to improve the accuracy of the predictions. To reconstruct the trust network, it is need to remove some of the useless users from the trust network. For this purpose, we use $w_{a,u}$ and $V(u)$ values as the positive and negative factors to identify those of inappropriate users in the trust network. The negative factor for the user u is calculated as follows:

$$V(\mathrm{u}) = \frac{w_{a,u} \cdot (r_{u,i} - \bar{r}_u - P_{a,i} + \bar{r}_a)^2}{4(max - min)^2} \tag{11}$$

where, $r_{u,i}$ denotes the rate of the user u for the item i, $P_{a,i}$ is the initial predicted rate of the item i for the active user and $\bar{r}_u$ and $\bar{r}_a$ denote the average rates for the user u and the active user, respectively. Moreover, max and min show the maximum and minimum values of ratings for items in the specific recommender system, respectively.

In the proposed trust network reconstruction mechanism, two threshold values α and β are used to identify those of the useless users. In other words, the user u will be removed from the trust network of the active user a if $w_{a,u}$ ($V(u)$) is lower (higher) than the threshold $\alpha(\beta)$.

3.5. Recommendation

The recommendation phase consists of two steps including *Final rate prediction* and *Top-N recommendations*. In the *Final rate prediction* step, final rate of the unseen item for the active user is calculated based on the new constructed trust network. To this end, Eq. (5) is used to predict the rate of the item i for the active user. The neighbors of the active user are identified by using the reconstructed trust network. Furthermore, in the *Top-N recommendations* step, the algorithm predicts the rates of the unseen items and then selects the top-N items as recommendation list to suggest to the active user.

3.6. An illustrated example

In this section, an example is presented to describe the steps of the proposed method to predict an unrated item for a given user. For this purpose, we used a user-item rating matrix with five users and five items, where each user rated a few number of the items. The rate values in this example are in the range of 1 (min) and 5 (max). Moreover, a user-user trust matrix is also provided to show the trust statements between the users. In this matrix the value of 1 indicates the trust relation between two users. The user-item rating matrix and user-user trust matrix are shown in Table 1. The purpose of this example is to apply the proposed method to predict the rate of item i_3 (highlighted by the question mark) for active user u_1.

The aim of first step of the proposed method is to construct trust network of the active user (i.e. u_1) by applying Eqs. 1–4. For simplicity, in this example we set $d_{max} = 1$ for Eq. (1) and $K = 2$ to select top K nearest neighbors of the active user. Therefore, the final weights between the active user and the other users are calculated using Eq. (3), where $w_{1,2}$, $w_{1,3}$, $w_{1,4}$, and $w_{1,5}$ are equal to 1.0, −1.0, −1.0, and 0.48, respectively. Based on these weights and considering the value of K, users u_2 and u_5 are identified as nearest neighbors of the active user. Then, in the second step, the rates of the nearest neighbors users (i.e. u_2 and u_5) are used to predict initial rate of the item i_3 for the active user by using Eq. (5). In this case, the initial rate of the item i_3 for the active user u_1 is equal to 4.15 (i.e. $P_{1,3} = 4.15$) which obtained using Eq. (5).

In the third step, the proposed reliability measure is calculated by using Eq. (6) to evaluate the quality of the predicted rate. In this case, the reliability value of the predicted rate (i.e. $R_{1,3}$) is 0.45 (i.e. $R_{1,3} = 0.45$). For simplicity, we set $\overline{S} = 2$ and $\overline{V} = 1$ in the Eqs. (7) and (9), respectively. Suppose that the threshold value for the reliability measure is equal to 0.7 (i.e. $\theta = 0.7$). It can be seen that the calculated reliability measure (i.e. $R_{1,3} = 0.45$) is less than the predefined threshold value (i.e. $R_{1,3} < \theta$). Therefore, in this situation the proposed trust network reconstruction mechanism is applied in order to remove useless users from the trust network of the

Table 1
The example dataset consisting of both rating and trust information.

User-item rating matrix						User-user trust matrix					
	i_1	i_2	i_3	i_4	i_5		u_1	u_2	u_3	u_4	u_5
u_1	–	2	?	5	–	u_1	–	1	–	–	1
u_2	–	2	3	4	–	u_2	–	–	1	–	–
u_3	5	–	–	1	3	u_3	–	1	–	1	1
u_4	4	5	2	1	–	u_4	1	–	1	–	–
u_5	–	1	5	2	4	u_5	1	–	1	–	1

active user. Suppose that in the trust network reconstruction step, the threshold values of the positive and negative factors are set to $\alpha = 0.6$ and $\beta = 0.5$, respectively. The positive and negative factors of each neighbor user can be computed using Eqs. (3) and (11), respectively. According to Eq. (11), the negative factor of users u_2 and u_5 are 0.02 and 0.005, respectively (i.e. $V(u_2) = 0.02$ and $V(u_5) = 0.005$). Furthermore, the positive factor of users u_2 and u_5 are 1.0 and 0.48 (i.e.$w_{1,2} = 1$ and $w_{1,5} = 0.48$), respectively. Since the positive factor of the user u_5 is less than the threshold value α (i.e. $w_{1,5} < \alpha$), this user is removed from the trust network of the active user. Finally, the final rate of the item i_3 for the active user is predicted based on the new reconstructed trust network. In this case, the user u_2 is the only trusted neighbor of the active user u_1. Therefore, the final rate is calculated by applying Eq. (5), where in this case, the final predicted rate of item i_3 is equal to 3.5 (i.e. $P_{1,3} = 3.5$).

4. Experiments

In order to evaluate the performance of the proposed method, several experiments were performed. In particular, the proposed method was compared to the pure Collaborative Filtering (CF), the basic model of TARS (Massa & Avesani, 2007), the Trust-aware Collaborative Filtering (TCF), the Relevant Trust Walker (RTW) (Deng et al., 2014), the Bayesian Inference Based Recommendation (BIBR) (Yang et al., 2013), and the Merge (Guo et al., 2014) methods. In the CF algorithm, the Pearson correlation coefficient similarity metric is used to calculate the similarity value between a pair of the users by using Eq. (4). On the other hand, in the TCF algorithm a combination of the similarity values and the trust statements is used to calculate the similarity weights in the trust network according to Eq. (3). The detailed descriptions of the datasets, experimental settings, evaluation measures, and experimental results are mentioned in their corresponding subsections.

4.1. Datasets

In this paper, two real-world datasets including Epinions[1] and Flixster[2] are used in the experiments. The users of the Epinions website will be able to review items and also assign them numeric ratings in the range 1 (min) to 5 (max). Moreover, these users can also express their trust statements with the other users. The values of the trust statements in this dataset are 0 or 1. The extracted dataset from the Epinions website consists of 49,290 users who rated at least once among 139,738 different items. On the other hand, the Flixster dataset is also a social movie site in which the users can make friendship relations and share their rates on the movies. The ratings of the items in the Flixster dataset are scaled from 0.5 (min) to 4.0 (max) with step 0.5. The original dataset is very large and for simplicity, we sampled a subset by randomly choosing 30,000 users with their corresponding rates on the items and the trust statements. The trust statements in the Flixster dataset are scaled from 1 to 10 but they are not available in the existing dataset, thus, we used friend relationships between the users as the trust statements.

4.2. Experimental settings

In the experiments, the datasets were split into different views based on user-related or item-related properties. To perform precise comparisons, six different views are extracted from the datasets. These views including (1) *Cold start users*: those of the users who have rated less than five items; (2) *Heavy raters*: the users who provided more than 10 ratings; (3) *Opinionated users*: the users who rated more than four items and their corresponding standard deviation of the rates is greater than 1.5; (4) *Black sheep users*: the users who provided more than four ratings and the difference between their ratings on a specific item and the average rating of that item is greater than one; (5) *Niche items*: the items receiving less than five ratings; and (6) *Controversial items*: the items which the standard deviation of their corresponding rates is greater than 1.5.

4.3. Evaluation measures

Generally, the leave-one-out method is used to compare two recommendation systems (Massa & Avesani, 2007). In this method, in each step one rating is taken out from the dataset and then this value is compared with the predicted rate obtained by the recommendation method. Such process is iterated through the entire dataset. In this paper, the leave-one-out method is also used in the experiments to compare the proposed method with the other methods. The experimental results are analyzed according to the performance in terms of accuracy and coverage measures. The evaluation measures include Mean Absolute Error (MAE), Mean Absolute User Error (MAUE), Rate Coverage (RC), and User Coverage (UC).

A predicted rating is compared with the real rating and the difference in absolute value is the prediction error. The process is repeated for all the ratings and an average of all the errors is computed as the MAE measure. The MAE measure for the user u is calculated as follows:

$$\mathrm{MAE_u} = \frac{\sum_{i=1}^{N} |r_{u,i} - p_{u,i}|}{N} \tag{12}$$

where, $r_{u,i}$ and $p_{u,i}$ are real and predicated ratings of the item i for the user u, respectively. Also, N is the total number of ratings that are predicated by the recommendation method.

To calculate the MAUE measure, first the MAE measure is computed for each single user independently and then the MAUE measure is defined as average of all the MAEs. The MAUE measure is calculated by Eq. (13) as follows:

$$\mathrm{MAUE} = \frac{\sum_{u \in U} MAE_u}{N_u} \tag{13}$$

where, U is the set of all users, N_u is the number of users in U, and MAE_u denotes the MAE measure for the user u.

The other important measures to evaluate recommender systems are the RC and UC measures. The RC measure simply refers to the fraction of ratings for which, after being hidden, the RS algorithm is able to produce a predicted rate. On the other hand, the UC measure defined as the portion of the users for which the RS algorithm is able to predict at least one rating.

[1] http://www.trustlet.org/datasets/downloaded_epinions.
[2] http://www.cs.sfu.ca/~sja25/personal/datasets/.

4.4. Results of the experiments

In the experiments, the proposed method is compared to the pure CF, the basic model of TARS (Massa & Avesani, 2007), the TCF, the RTW (Deng et al., 2014), the BIBR (Yang et al., 2013), and the Merge (Guo et al., 2014) algorithms. In the TARS algorithm, the trust statements are propagated in the trust network with the length d_{max} (see Eq. (1)) where only trusted neighbors are used to predict ratings of the unseen items for the active user. Moreover, the maximum path length for the trust propagation is calculated by Eq. (2).

In all experiments, certain parameters need to be defined in accordance with the compared algorithms. The threshold value θ is used for the proposed reliability measure $R_{a,i}$ that is equal to 0.7. In the *Trust network reconstruction* step, the threshold values α and β for the $w_{a,u}$ and $V(u)$ are set to $\alpha = 0.6$ and $\beta = 0.5$, respectively. Moreover, in the proposed method, the number of nearest neighbors K is set to $K = 200$ and $K = 100$ for the Epinions and Flixster datasets, respectively.

Table 2 compares the proposed method (i.e. RTCF) with the CF, TARS, TCF, RTW, BIBR, and Merge methods in terms of the MAE and RC measures on the Epinions dataset. The reported results show that the RTCF method obtained the lowest MAE results for all six different views of the dataset. For example, the proposed method obtained the MAE value 0.695 for the *Cold start* users while in the same case the CF, TARS, TCF, RTW, BIBR, and Merge methods obtained 1.024, 0.827, 0.774, 0.832, 0.854, and 0.856 MAE values, respectively. Moreover, the results also show that the proposed method obtained the higher rate coverage (i.e. RC) compared to the other methods except for the TCF and RTW methods based on all data view. For example, while the experiments were performed on the *All data*, the proposed method achieved the RC value of 80.19 while the TCF and RTW methods obtained 83.84 and 97.15 RC values, respectively. This is due to the fact that in the RTCF method the users with lower reliability values are removed from the trust network which leads to reduce the rate coverage measure compared to the TCF and RTW methods.

Moreover, several experiments were performed to compare the MAUE and UC measures of the proposed method with the others. Table 3 shows the corresponding results on the Epinions dataset. It can be seen from the reported results that the proposed method outperformed all of the other methods under the MAUE measure for all of the six different views of the dataset. For example, the results show that the RTCF method obtained 0.683 MAUE value for the view of the *Heavy raters* users while this value is obtained 0.915, 0.827, 0.718, 0.783, 0.768, and 0.859 for the CF, TARS, TCF, RTW, BIBR, and Merge methods, respectively. Moreover, the results also reveal that the RTCF algorithm has lower performance rather than the TCF and RTW algorithms on the UC measures for the *All data* view. Consequently from the Tables 2 and 3 results, it can be concluded that the RC and UC measures of the RTCF algorithm are very close to the results of the TCF algorithm, while these results also show that the RTCF algorithm obtained the higher accuracy compared to the other methods.

Furthermore, the experiments were repeated on the Flixster dataset and the results are reported in Tables 4 and 5. Table 4

Table 2
MAE and RC results over the Epinions dataset.

Views	Measures	Methods						
		CF	TARS	TCF	RTW	BIBR	Merge	RTCF
All data	MAE	0.832	0.784	0.697	0.776	0.753	0.794	0.612
	RC (%)	49.46	74.37	83.84	97.15	76.39	77.26	80.19
Cold users	MAE	1.024	0.827	0.774	0.832	0.854	0.856	0.695
	RC (%)	3.22	41.52	45.48	77.38	43.52	47.28	42.57
Heavy users	MAE	0.824	0.817	0.714	0.754	0.764	0.834	0.657
	RC (%)	52.59	71.24	84.45	98.15	74.46	89.36	83.76
Opin. users	MAE	1.153	1.132	0.952	1.078	1.268	1.023	0.897
	RC (%)	49.35	71.43	74.72	98.69	72.18	75.62	73.76
Black sheep	MAE	1.284	1.264	0.982	1.154	1.251	1.087	0.873
	RC (%)	51.83	75.82	80.27	96.37	78.83	77.63	79.64
Contr. items	MAE	1.432	1.543	1.178	1.069	1.367	1.216	0.953
	RC (%)	41.76	81.37	85.68	95.89	83.29	86.34	84.43
Niche items	MAE	0.813	0.812	0.705	0.768	0.725	0.765	0.632
	RC (%)	13.26	21.28	28.64	69.83	29.46	32.68	27.36

Table 3
MAUE and UC results over the Epinions dataset.

Views	Measures	Methods						
		CF	TARS	TCF	RTW	BIBR	Merge	RTCF
All data	MAUE	0.916	0.824	0.713	0.798	0.796	0.854	0.625
	UC (%)	39.76	69.53	80.37	94.15	72.68	73.16	78.63
Cold users	MAUE	1.124	0.815	0.792	0.847	0.857	0.845	0.738
	UC (%)	2.37	45.26	50.36	85.36	49.35	52.78	48.87
Heavy users	MAUE	0.915	0.827	0.718	0.783	0.768	0.859	0.683
	UC (%)	83.47	91.48	95.42	99.87	95.24	96.38	94.76
Opin. users	MAUE	1.263	1.103	0.913	1.098	1.278	0.998	0.873
	UC (%)	60.35	79.56	84.48	98.85	83.78	82.37	84.34
Black sheep	MAUE	1.284	1.257	1.164	1.106	1.197	1.149	0.973
	UC (%)	64.17	79.66	82.36	97.31	81.12	83.29	81.98
Contr. items	MAUE	1.437	1.586	1.274	1.132	1.289	1.284	1.013
	UC (%)	15.49	30.27	35.68	51.48	34.85	42.35	35.24
Niche items	MAUE	0.796	0.801	0.724	0.745	0.746	0.763	0.656
	UC (%)	10.27	34.79	40.56	76.39	42.37	48.32	38.86

Table 4
The MAE and RC results over the Flixster dataset.

Views	Measures	Methods						
		CF	TARS	TCF	RTW	BIBR	Merge	RTCF
All data	MAE	0.968	0.887	0.824	0.853	0.847	0.895	0.714
	RC (%)	65.87	88.83	94.23	98.59	90.25	92.34	91.17
Cold users	MAE	1.224	0.945	0.916	0.978	0.983	0.976	0.786
	RC (%)	3.78	76.73	81.42	93.18	79.34	79.16	79.73
Heavy users	MAE	0.935	0.867	0.816	0.795	0.817	0.872	0.694
	RC (%)	82.34	89.59	93.57	99.24	91.12	91.45	92.28
Opin. users	MAE	1.521	1.454	1.384	1.387	1.487	1.357	1.019
	RC (%)	71.69	89.78	94.84	98.87	91.48	92.68	93.89
Black sheep	MAE	1.386	1.256	1.028	1.123	1.224	1.186	0.994
	RC (%)	74.87	89.36	91.68	97.54	92.37	92.35	91.57
Contr. items	MAE	1.876	1.893	1.368	1.468	1.654	1.542	1.127
	RC (%)	27.68	74.73	87.93	96.22	78.39	84.38	86.28
Niche items	MAE	1.186	1.124	1.027	1.073	1.087	1.069	0.985
	RC (%)	10.65	39.47	66.74	82.36	47.89	52.36	64.23

Table 5
The MAUE and UC results over the Flixster dataset.

Views	Measures	Methods						
		CF	TARS	TCF	RTW	BIBR	Merge	RTCF
All data	MAUE	0.994	0.913	0.847	0.865	0.875	0.942	0.726
	UC (%)	62.92	85.54	89.65	93.62	89.36	89.13	86.27
Cold users	MAUE	1.325	0.967	0.946	0.984	1.024	1.036	0.817
	UC (%)	3.02	69.28	76.57	86.39	73.45	72.54	73.38
Heavy users	MAUE	1.025	0.912	0.863	0.837	0.873	0.936	0.747
	UC (%)	89.27	92.34	94.25	99.85	93.78	95.27	94.08
Opin. users	MAUE	1.346	1.289	1.182	1.126	1.302	1.234	0.989
	UC (%)	86.47	92.97	94.74	99.34	93.68	95.73	93.97
Black sheep	MAUE	1.248	1.127	0.934	1.062	1.086	1.037	0.878
	UC (%)	76.84	91.64	92.34	98.56	94.13	93.29	91.87
Contr. items	MAUE	1.745	1.826	1.275	1.391	1.529	1.426	1.048
	UC (%)	23.52	69.46	83.28	92.85	74.42	75.17	82.48
Niche items	MAUE	1.024	0.996	0.964	0.943	0.924	0.925	0.863
	UC (%)	10.73	41.52	69.08	85.67	52.73	53.28	66.72

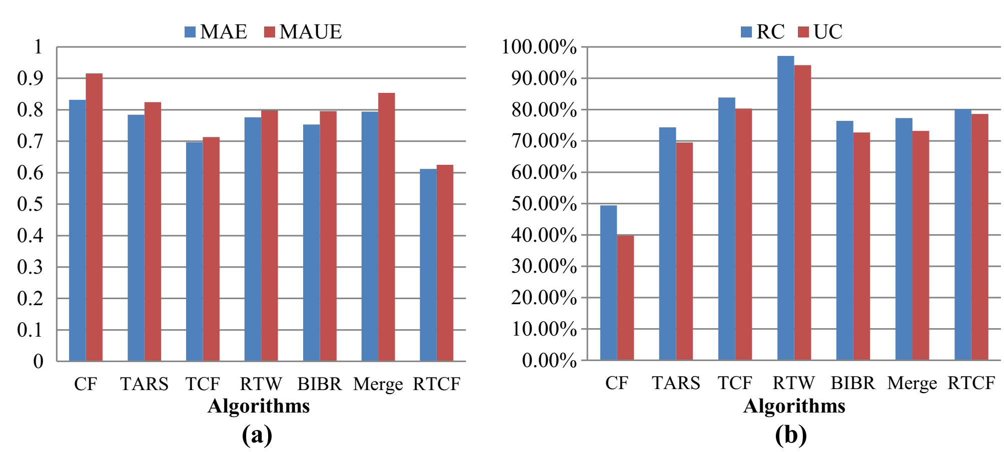

Fig. 2. (a) MAE and MAUE, and (b) RC and UC, results on the Epinions dataset for the *All data* view point.

shows the MAE and RC results while Table 5 reports the results of the MAUE and UC measures on the Flixster dataset. These tables reported the similar results compared to that of the Epinions dataset. From the Tables 4 and 5 results, it can be concluded that the proposed method outperformed the other methods in terms of the MAE and MAUE measures. On the other hand, the results indicated that the RTCF method obtained the lower values in terms of the RC and UC measures than some of the other methods. This is because of the fact that those of the users with low reliability measures are removed in the *Trust network reconstruction* step and thus this work effects on the coverage measure of the RTCF method.

Moreover, Figs. 2 and 3, graphically compare the proposed method with the CF, TARS, TCF, RTW, BIBR, and Merge methods on the Epinions and Flixster datasets, respectively. Fig. 2 (a) compares the accuracy of the proposed method in terms of the MAE and MAUE measures while Fig. 2 (b) reports the comparison results under the RC and UC measures for the Epinions dataset. From the

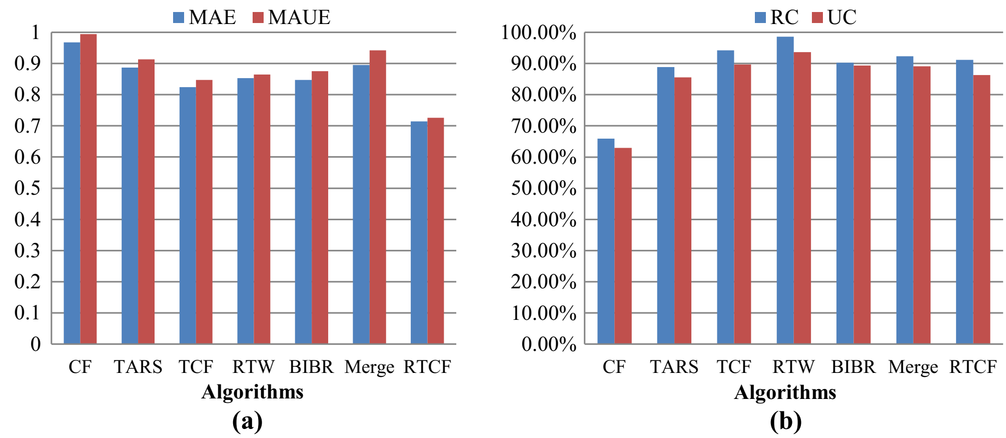

Fig. 3. (a) MAE and MAUE, and (b) RC and UC, results on the Flixster dataset for the *All data* view point.

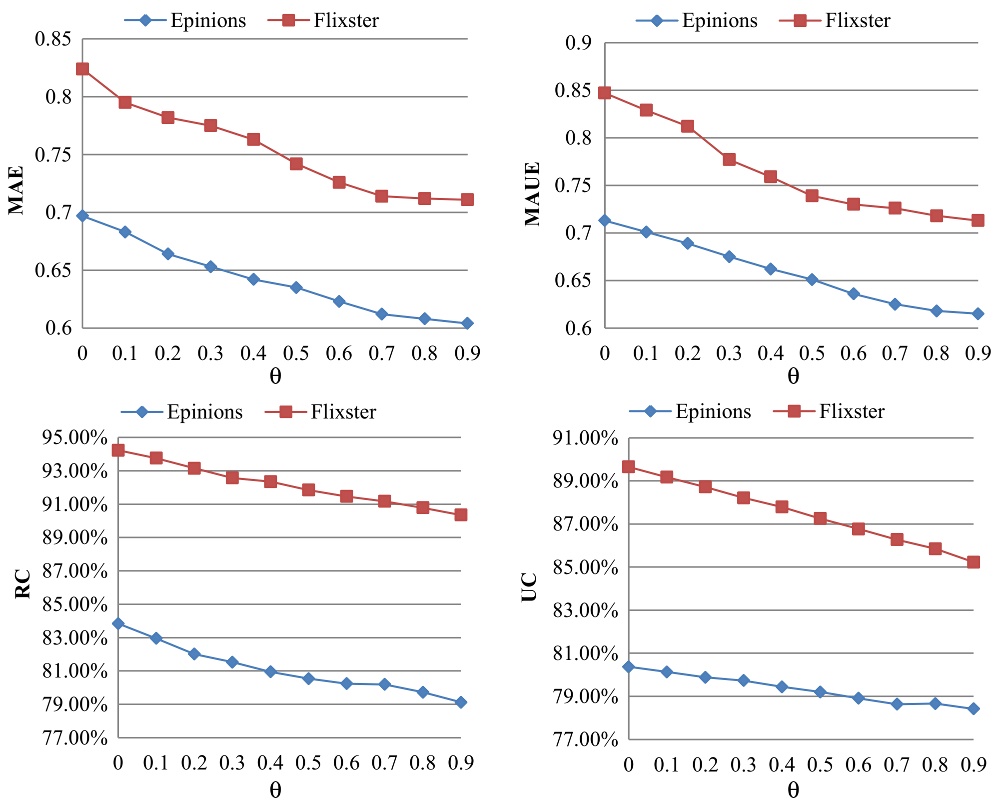

Fig. 4. The effect of parameter θ on the system performance.

results, it can be seen that the RTCF method provides better results in terms of the MAE and MAUE measures and the proposed method shows significant improvement from the accuracy point of view. On the other hand, the results also indicated that the performance of the proposed method on the RC and UC measures are very close to the TCF method. Moreover, Fig. 3 reports the similar results for the Flixster dataset. It should be noted that, there is a trade of between the coverage and accuracy of the predictions in the recommender systems, thus, while the accuracy of the method is improved, the coverage of the items will be decreased. This is due to the fact that while we try to improve the coverage of the method, it means that more items of the users should be considered by the algorithm, thus, the accuracy will be reduced. Furthermore, the reported results from Tables 2–5 and Figs. 2 and 3 show that the accuracy of the proposed method is higher than the other methods, while the user and item coverage of the proposed method is better than those of the CF, and TARS methods and comparable to the other methods.

The parameter θ is an important parameter which is used as the threshold value of the proposed reliability measure. Based on this parameter if the reliability value $R_{a,i}$ (i.e. Eq. (6)) for the active user a and a given item i is less than θ, the trust network for the active user will be reconstructed. In this paper, several experiments were performed to test the effect of different values of the parameter θ on the performance of the proposed method for the Epinions and Flixster datasets. Fig. 4 reports the results of different θ values on the proposed method over MAE, MAUE, RC, and UC measures. It can be seen from the results that the MAE and MAUE measures

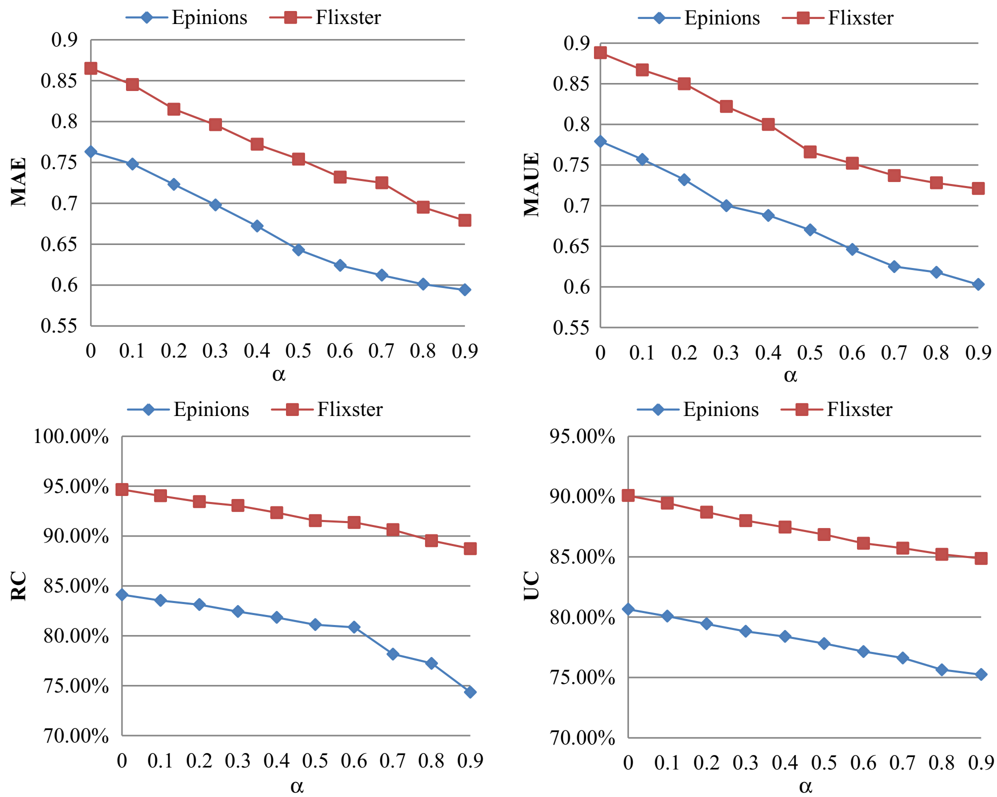

Fig. 5. The effect of parameter α on the system performance.

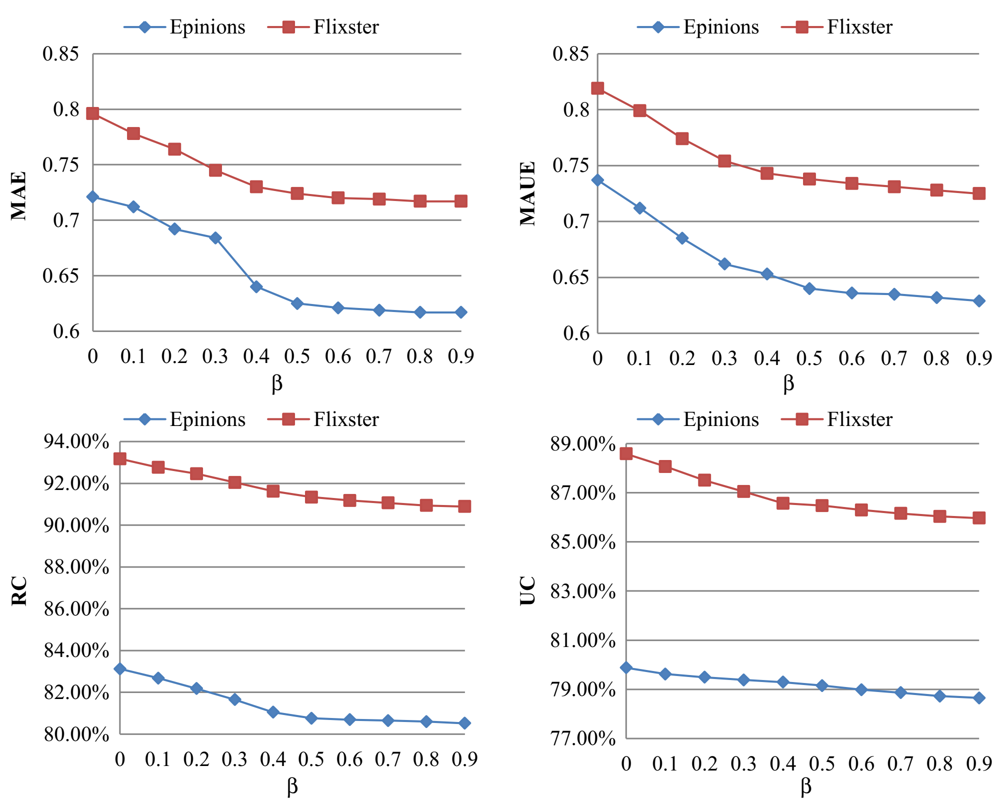

Fig. 6. The effect of parameter β on the system performance.

depend on the θ value and based on these results the proposed method performs better while the value of θ is increased. Furthermore, the results also show that when the value of θ increases, the value of the RC and UC measures will be reduced. Thus, it can be concluded that the lower value of θ leads to reduce the accuracy of the system and improves the coverage measure. On

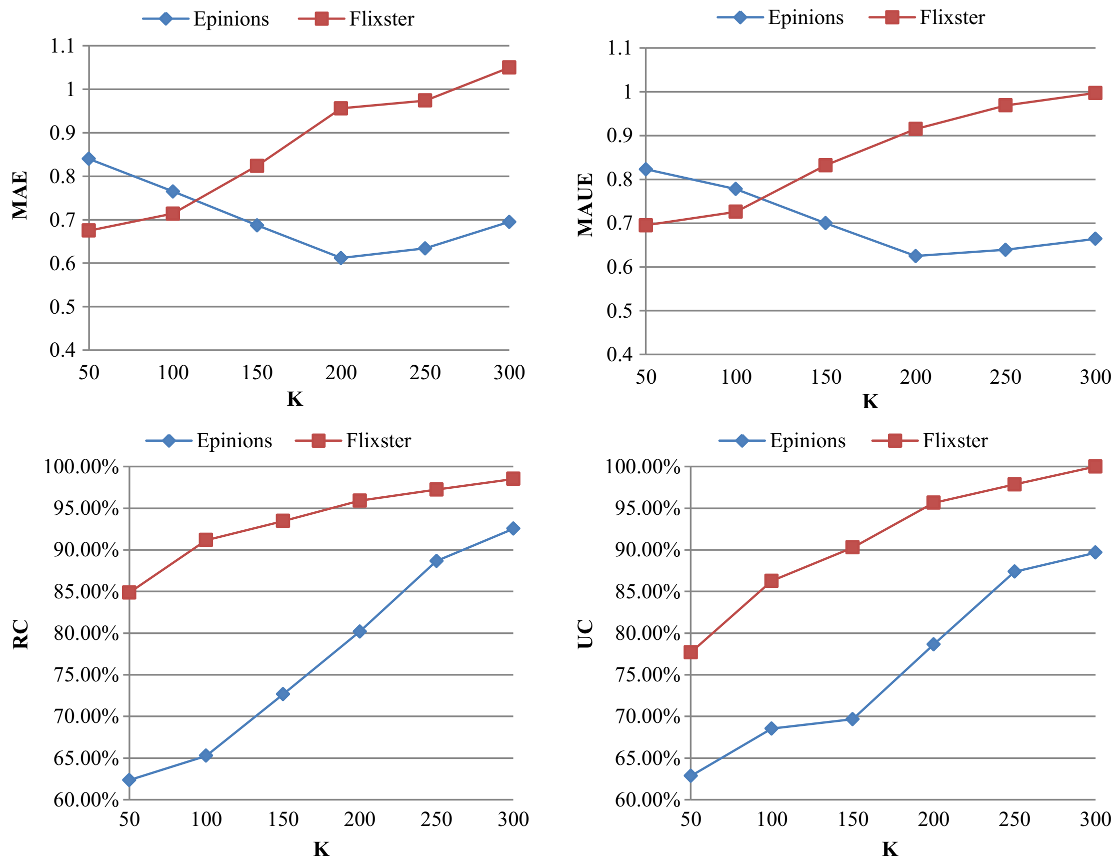

Fig. 7. The effect of parameter K on the system performance.

the other hand, the higher value of θ results in improving the accuracy of the system and reducing the coverage measure. Therefore, we should select a value for θ as a good trade-off between the accuracy and coverage measures. Thus, we use $\theta = 0.7$ in our experiments to get best performance in the accuracy and coverage measures for both of the datasets. Moreover, this value for parameter θ is used in all of the experiments to compare the proposed method with those of the other methods.

Furthermore, the parameters α and β are the threshold values which are used in the *Trust network reconstruction* step. These threshold values are used to remove those of the useless users from the trust network of the active user. The performed experiments also test the effect of different values of α and β parameters on the mentioned measures for the Epinions and Flixster datasets. Figs. 5 and 6 show the effect of the different values of α and β thresholds respectively on the performance of the proposed method. From the results, it can be concluded that the different values of these thresholds lead to different performances of the proposed method in terms of the MAE and MAUE measures. On the other hand, the results show that the coverage measures (i.e. UC and RC) will be decreased when the values of α and β thresholds are increased. Base on the sensitivity analysis of the parameters, in the experiments the values of α and β parameters are set to $\alpha = 0.6$ and $\beta = 0.5$ in order to balance between the accuracy and coverage measures.

Moreover, the parameter K is another important parameter which defines the number of nearest neighbors for the active user. The performed experiments also test the effect of different values of K (i.e. $K = 50$, 100, 150, 200, 250, and 300) on the mentioned measures for the Epinions and Flixster datasets. Fig. 7 reports the MAE, MAUE, RC and UC results based on different values of the parameter K for both of the mentioned datasets. The results show that the RC and UC measures increase as long as the number of the nearest neighbors grows. On the other hand, when the number of nearest neighbors is more than a significant value, the MAE and MAUE measures decrease. The significant value is depend on the used dataset and thus we have used $K = 100$ and $K = 200$ in the experiments as a good trade-off between the prediction quality and rating coverage in the Flixster and Epinions datasets, respectively.

5. Conclusions

Recommender systems are responsible for providing the users with a series of personalized suggestions for certain types of the items. Trust is a concept that recently takes much attention and has been considered in online social networks. In this paper, a novel method is proposed to improve the accuracy of the trust-aware recommender systems. In the proposed method, a novel reliability measure is proposed which is based on the combination of the similarity values and the trust statements. In addition, a novel mechanism is also proposed to reconstruct trust network of the users based on the proposed reliability measure. In other words, the quality of predicted rates is evaluated using the proposed reliability measure and then, the trust network reconstruction mechanism is used to improve the performance of the predicted rates. The proposed method uses a different trust network to predict each unknown rate value of the active user. In other words, unlike previous methods, based on the proposed reliability measure and trust network reconstruction mechanism, the proposed method uses a specific trust network to predict the rate value of an unrated item of the active user. The obtained results from the performed experiments show that the proposed method achieved higher accuracy compared to those of the state-of-the-art methods while preserving a good coverage.

Although the performance of the proposed method on the accuracy measures is very significant, its performance on the coverage measures is reduced due to use of the trust network reconstruction mechanism. This is because of the fact that those of the users with lower performance are removed from the trust network of the active user in the proposed trust network reconstruction mechanism. For this reason, a trust network reconstruction mechanism with higher performance can be proposed to improve the coverage measures. In addition, different factors such as distrust statements can be considered to propose new reliability measures. On the other hand, further improvements of the reliability measures and also the trust network reconstruction mechanisms result in improve the performance of the other types of recommender systems such as context-aware recommender systems.

References

Abdessalem, T., Cautis, B., & Souhli, A. (2010). Trust Management in Social Networks. In: Télécom ParisTech, LTCI. Paris, France.

Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE Transactions on Knowledge and Data Engineering, 17*, 734–749.

Azadjalal, M. M., Moradi, P., & Abdollahpouri, A. (2014). Application of game theory techniques for improving trust based recommender systems in social networks. In *4th international eConference on computer and knowledge engineering (ICCKE), 2014* (pp. 261–266). IEEE.

Balabanovic, M., & Shoham, Y. (1998). Content-based, collaborative recommendation. *Communication of the ACM, 40*, 66–72.

Bedi, P., & Vashisth, P. (2014). Empowering recommender systems using trust and argumentation. *Information Sciences, 279*, 569–586.

Birtolo, C., & Ronca, D. (2013). Advances in clustering collaborative filtering by means of fuzzy C-means and trust. *Expert Systems with Applications, 40*, 6997–7009.

Bojnordi, E., & Moradi, P. (2013). A novel collaborative filtering model based on combination of correlation method with matrix completion technique. *Iranian Journal of Science and Technology, Transaction of Electrical Engineering, 37*, 93–100.

Breese, J. S., Heckerman, D., & Kadie, C. (1998). Empirical analysis of predictive algorithms for collaborative filtering. In *Proceedings of the fourteenth conference on uncertainty in artificial intelligence* (pp. 43–52). Madison, Wisconsin: Morgan Kaufmann Publishers Inc..

Ciaccia, P., & Patella, M. (2011). Metric information filtering. *Information Sciences, 36*, 708–720.

Deng, S., Huang, L., & Xu, G. (2014). Social network-based service recommendation with trust enhancement. *Expert Systems with Applications, 41*, 8075–8084.

Gago, C. F., Agudo, I., & Lopez, J. (2014). Building trust from context similarity measures. *Computer Standards & Interfaces, 36*, 792–800.

Gharibshah, J., & Jalili, M. (2014). Connectedness of users–items networks and recommender systems. *Applied Mathematics and Computation, 243*, 578–584.

Golbeck, J. (2006). Generating predictive movie recommendations from trust in social networks. In: *4th international conference on trust management*. Pisa, Italy.

Goldberg, K., Roeder, T., Gupta, D., & Perkins, C. (2001). Eigen-taste: A constant time collaborative filtering algorithm. *Information Retrieval, 4*, 133–151.

Guo, G., Zhang, J., & Smith, N.Y. (2015b). TrustSVD: Collaborative filtering with both the explicit and implicit influence of user trust and of item ratings. In: *Association for the advancement of artificial intelligence (AAAI)*.

Guo, G., Zhang, J., & Smith, N. Y. (2015a). Leveraging multiviews of trust and similarity to enhance clustering-based recommender systems. *Knowledge-Based Systems, 74*, 14–27.

Guo, G., Zhang, J., & Thalmann, D. (2014). Merging trust in collaborative filtering to alleviate data sparsity and cold start. *Knowledge-Based Systems, 57*, 57–68.

Herlocker, J.L., Konstan, J.A., Borchers, A.L., Riedl, J.T. (1999). An algorithmic framework for performing collaborative filtering. In: *Proceedings of the 22nd annual international ACM SIGIR conference*.

Herlocker, J.L., Konstan, J.A., Borchers, A., Riedl, J.T. (1999). An algorithmic framework for performing collaborative filtering. SIGIR, 230–237.

Herlocker, J. L., Konstan, J. A., & Riedl, J. T. (2002). An empirical analysis of design choices in neighborhood-based collaborative filtering algorithms. *Information Retrieval, 5*, 287–310.

Herlocker, J. L., Konstan, J. A., Terveen, L. G., & Riedl, J. T. (2004). Evaluating collaborative filtering recommender systems. *ACM Transactions on Information Systems, 22*, 5–53.

Hernando, A., Bobadilla, J., Ortega, F., & Tejedor, J. (2013). Incorporating reliability measurements into the predictions of a recommender system. *Information Sciences, 218*, 1–16.

Hofmann, T. (2004). Latent semantic models for collaborative filtering. *ACM Transactions on Information Systems, 22*, 89–115.

Huete, J. F., Fernández-Luna, J. M., de Campos, L. M., & Rueda-Morales, M. A. (2012). Using past-prediction accuracy in recommender systems. *Information Sciences, 199*, 78–92.

Hwang, C. S., & Chen, Y. P. (2007). Using trust in collaborative filtering recommendation. *New Trends in Applied Artificial Intelligence* (Vol. 4570, pp. 1052–1060). Berlin Heidelberg: Springer.

Ingoo, H., Kyong, J. O., & Tae, H. R. (2003). The collaborative filtering recommendation based on SOM cluster-indexing CBR. *Expert Systems with Applications, 25*, 413–423.

Jamali, M., Ester, M. (2010). A matrix factorization technique with trust propagation for recommendation in social networks. In: *ACM conference on recommender systems*.

Jamali, M., & Ester, M. (2009). TrustWalker: A random walk model for combining trust-based and item-based recommendation. In *15th ACM SIGKDD international conference on Knowledge discovery and data mining* (pp. 397–406). New York, NY, USA: ACM.

Javari, A., & Jalili, M. (2014a). Cluster-based collaborative filtering for sign prediction in social networks with positive and negative links. *ACM Transactions on Intelligent Systems and Technology, 5*.

Javari, A., & Jalili, M. (2014b). A probabilistic model to resolve diversity–accuracy challenge of recommendation systems. *Knowledge and Information Systems*, 1–19.

Jeong, B., Lee, J., & Cho, H. (2009a). An iterative semi-explicit rating method for building collaborative recommender systems. *Expert Systems with Applications, 36*, 6181–6186.

Jeong, B., Lee, J., & Cho, H. (2009b). User credit-based collaborative filtering. *Expert Systems with Applications*, 7309–7312.

Jiang, W., Wanga, G., & Wub, J. (2014). Generating trusted graphs for trust evaluation in online social networks. *Future Generation Computer Systems, 31*, 48–58.

Kiasat, F., & Moradi, P. (2012). A new similarity measure for improving recommender systems based on fuzzy clustering and genetic algorithm. In: *The international conference on contemporary issues in computer and information sciences (CICIS 2012)*. Zanjan, Iran.

Kim, J. K., Kim, H. K., & Cho, Y. H. (2008). A user-oriented contents recommendation system in peer-to-peer architecture. *Expert Systems with Applications, 34*, 300–312.

Kim, H. K., Kim, J. K., & Ryu, Y. U. (2009). Personalized recommendation over a customer network for ubiquitous shopping. *IEEE Transactions on Services Computing, 2*, 140–151.

Kim, Y. A., & Phalak, R. (2012). A trust prediction framework in rating-based experience sharing social networks without a web of trust. *Information Sciences, 191*, 128–145.

Lathia, N., Hailes, S., & Capra, L. (2008). Trust-based collaborative filtering. In *Proceedings of trust management II* (pp. 119–134). US: Springer.

Lee, T. Q., Park, Y., & Park, Y. T. (2008). A time-based approach to effective recommender systems using implicit feedback. *Expert Systems with Applications, 34*, 3055–3062.

Lee, S., Yang, J., & Park, S. Y. (2004). Discovery of hidden similarity on collaborative filtering to overcome sparsity problem. In *Proceedings of discovery science* (pp. 396–402). Berlin, Germany: Heidelberg: Springer-Verlag.

Li, Y. M., & Kao, C. P. (2009). TREPPS: A trust-based recommender system for peer production services. *Expert Systems with Applications, 36*, 3263–3277.

Lika, B., Kolomvatsos, K., & Hadjiefthymiades, S. (2014). Facing the cold start problem in recommender systems. *Expert Systems with Applications, 41*, 2065–2073.

Liu, F., & Lee, H. (2010). Use of social network information to enhance collaborative filtering performance. *Expert Systems with Applications, 37*, 4772–4778.

Liu, J., Wu, C., & Liu, W. (2013). Bayesian probabilistic matrix factorization with social relations and item contents for recommendation. *Decision Support Systems, 55*, 838–850.

Liu, B., & Yuan, Z. (2010). Incorporating social networks and user opinions for collaborative recommendation: Local trust network based method. In *Proceedings of the workshop on context-aware movie recommendation* (pp. 53–56). New York, USA: ACM.

Ma, H., Yang, H., Lyu, M. R., & King, I. (2008). SoRec: Social recommendation using probabilistic matrix factorization. In *Proceedings of the 17th ACM conference on information and knowledge management* (pp. 931–940). Napa Valley, California, USA: ACM.

Mahony, M. P. O., & Hurley, N. J. (2005). Recommender systems: Attack types and strategies. *Artificial Intelligence*.

Martinez-Cruza, C., Porcela, C., Bernabé-Moreno, J., & Herrera-Viedma, E. (2015). A model to represent users trust in recommender systems using ontologies and fuzzy linguistic modeling. *Information Sciences, 311*, 102–118.

Massa, P., & Avesani, P. (2004). Trust-aware collaborative filtering for recommender systems. In: *Federated int. conf on the move to meaningful internet*.

Massa, P., & Avesani, P. (2007). Trust-aware recommender systems. In: *2007 ACM conference on recommender systems*. Minneapolis, Minnesota, USA.

Miyahara, K., & Pazzani, M. J. (2000). Collaborative filtering with the simple Bayesian classifier. In *Proceedings of the 6th pacific rim international conference on artificial intelligence* (pp. 679–689). Berlin, Germany: Heidelberg: Springer-Verlag.

Moradi, P., Ahmadian, S., & Akhlaghian, F. (2015). An effective trust-based recommendation method using a novel graph clustering algorithm. *Physica A: Statistical Mechanics and its Applications*. http://dx.doi.org/10.1016/j.physa.2015.05.008.

Navgaran, D.Z., Moradi, P., Akhlaghian, F. (2013). Evolutionary based matrix factorization method for collaborative filtering systems. In: *21st Iranian conference on electrical engineering (ICEE)* (pp. 1–5).

Ocepek, U., Rugelj, J., & Bosnić, Z. (2015). Improving matrix factorization recommendations for examples in cold start. *Expert Systems with Applications, 42*, 6784–6794.

O'Donovan, J., Smyth, B. (2005). Trust in recommender systems. In: *Proceedings of the 10th international conference on intelligent user interfaces* (IUI) (pp. 167–174).

Oufi, S. A., Kim, H. N., & Saddik, A. E. (2012). A group trust metric for identifying people of trust in online social networks. *Expert Systems with Applications, 39*, 13173–13181.

Park, Y. J., & Chang, K. N. (2009). Individual and group behavior-based customer prole model for personalized product recommendation. *Expert Systems with Applications, 36*, 1932–1939.

Paul, S., Pan, J., & Jain, R. (2011). Architectures for the future networks and the next generation internet: A survey. *Computer Communications, 34*, 2–42.

Pirasteh, P., Hwang, D., & Jung, J. (2015). Exploiting matrix factorization to asymmetric user similarities in recommendation systems. *Knowledge-Based Systems, 83*, 51–57.

Rahman, A.A., & Hailes, S. (2000). Supporting trust in virtual communities. In: *33th Hawaii international conference on system sciences*. Hawaii, USA.

Ramezani, M., Moradi, P., & Akhlaghian, F. (2014). A pattern mining approach to enhance the accuracy of collaborative filtering in sparse data domains. *Physica A: Statistical Mechanics and its Applications, 408*, 72–84.

Resnick, P., Iacovou, N., Suchak, M., Bergstrom, P., & Riedl, J. (1994). GroupLens: An open architecture for collaborative filtering of netnews. In *Proceedings of the 1994 ACM conference on computer supported cooperative work* (pp. 175–186). Chapel Hill, North Carolina, USA: ACM.

Shambour, Q., & Lu, J. (2015). An effective recommender system by unifying user and item trust information for B2B applications. *Journal of Computer and System Sciences*.

Shani, G., Heckerman, D., & Brafman, R. I. (2005). An MDP-based recommender system. *Journal of Machine Learning Research, 6*, 1265–1295.

Shimon, D. B., Tsikinovsky, A., Rokach, L., Meisles, A., Shani, G., & Naamani, L. (2007). Recommender system from personal social networks. *Advances in Intelligent Web Mastering* (Vol. 43, pp. 47–55). Berlin Heidelberg: Springer.

Soboroff, I., & Nicholas, C. (2000). Collaborative filtering and the generalized vector space model (poster session). In *Proceedings of the 23rd annual international ACM SIGIR conference on research and development in information retrieval* (pp. 351–353). Athens, Greece: ACM.

Srivatsa, M., & Hicks, M. (2012). Deanonymizing mobility traces: Using social network as a side-channel. In *Proceedings of the 2012 ACM conference on computer and communications security* (pp. 628–637). Raleigh, North Carolina, USA: ACM.

Su, X. Y., & Khoshgoftaar, T. M. (2009). A survey of collaborative filtering techniques. *Advances in Artificial Intelligence, 4*, 1–19.

Yan, S., Zheng, X., Chen, D., & Wang, Y. (2013). Exploiting two-faceted web of trust for enhanced-quality recommendations. *Expert Systems with Applications, 40*, 7080–7095.

Yang, X., Guo, Y., & Liu, Y. (2013). Bayesian-inference-based recommendation in online social networks. *IEEE Transactions on Parallel and Distributed Systems, 24*, 642–651.

Yu, K., Schwaighofer, A., Tresp, V., Xu, X., & Kriegel, H. (2004). Probabilistic memory-based collaborative filtering. *IEEE Transactions on Knowledge and Data Engineering, 16*, 56–69.

Yuan, W., Guan, D., Lee, Y. K., & Lee, S. (2010). The small-world trust network. *Applied Intelligence, 35*, 399–410.