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How to Boost the Performance of Recommender Systems by Social Trust? Studying the Challenges and Proposing a Solution

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ABSTRACT With the increasing number of items in electronic retailers, news websites, etc., finding interesting items concerning the taste of users is becoming more challenging. Recommender Systems (RS) are a well-known solution to this issue. Collaborative filtering (CF) is a widely accepted and popular technique to implement an RS. However, cold-start and data sparsity problems reduce the performance of CF methods. One promising solution for these issues is to use the social trust information. However, how to properly use social trust information is a hot and still open question. In this paper, we propose a similarity measure and a simple link prediction method to address this question and employ them in trust-aware matrix factorization. Especially, our proposed similarity measure is asymmetric to consider the nature of social relationships. Also, to have a more accurate similarity estimation, we have considered both the user's historical ratings and trust relations, and we have determined the weight of each source. Finally, we have used the item-based model and the level of interest a user's trustees have for an item to improve the performance of the proposed method for sparse datasets. We conduct extensive performance evaluations in terms of rate prediction and interesting items found. Experimental results on three real-world datasets demonstrate the effectiveness of the proposed method, especially in terms of Mean Absolute Error.

INDEX TERMS Matrix factorization, recommender system, similarity measure, social trust, trustor clustering.

I. INTRODUCTION

The increasing number of items available in electronic retailers, news and video websites, etc., has made the role of Recommender Systems (RS) critical in today's industry. These systems aim to find and suggest appropriate items, like books to read and products to buy, in a massive number of items concerning each user's taste. So, as it is evident, they can significantly help to increase user satisfaction and loyalty and also result in more income for the company [1]. In the literature, two tasks are defined in the RS domain: 1) rate prediction, and 2) item recommendation. The goal of the rate prediction task is to predict the rate for an un-rated item for an active user, while the goal of the item recommendation task is the separation of favorite items from unfavorite items for an active user.

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Generally, in terms of approach, recommender systems can be classified into three categories: Content-Based (CB), Collaborative Filtering (CF), and hybrid approaches. The idea of CB methods is to learn users' profiles based on items' features (like genre and actors in movie-recommendation) [2], [3]. CF methods are based on the idea that similar users have similar tastes. They apply this idea by predicting the target user's taste on a query item using the captured opinions of similar users. Thus, CF methods rely only on past user behavior (like rating history), and they do not need to create explicit profiles like in CB methods [1]. In other words, CF methods do not require any extra information rather than ratings' history. Finally, in the third approach, hybrid methods, the ideas of both paradigms are applied. Note that CB methods have the major disadvantage that they cannot be applied in the domains where item features are not available. On the other hand, CF methods have been successfully employed in many real-world applications and websites like Amazon, Netflix, Twitter, Facebook, Movielens, Douban, etc. [4], [5].

Despite the attractive characteristics of CF, this family of approaches suffers from two main issues: data sparsity and cold-start users (new users) [6]. Data sparsity refers to the fact that only a small portion of items are rated by each user; thus, most cells of the rating matrix are empty. Cold-start is about the problem that new users only give a few ratings, and so there would be a lack of rating history for new users. Therefore, CF methods will face a hard challenge in modeling the preference of new users. These issues degrade the accuracy of predicting a user's rating for an un-rated item [7].

In recent years, people are paying more and more attention to online social networks. Also, people usually tend to make links with other people who are similar to them (the concept of homophily in social networks). Furthermore, sociological studies have proved that social influence can affect users' decisions [8]. In conclusion, a user's taste can be determined by analyzing the feelings of his or her friends (trustee) [9]. Thus, the social relationship (trust) information seems to have a positive effect on the RS's performance and a promising solution for data sparsity and cold-start issues [10].

Surprisingly, early usage of social trust in RS models, although the idea is very encouraging, did not yield to more accurate models than CF methods, which are merely based on the rating matrix [7]. After that, several researchers analyzed the problem and tried to provide better utilization of social trust in RS models. In [11], Yeung and Iwata explained two important points about using social trust in CF models: 1- Two users may establish a trust relation just because they know each other, while they have different tastes. 2- Two users may have similar preferences in some areas (e.g., technology) while having different tastes in other areas (e.g., sport). In [12], it is explained that due to the low cost of establishing a social relationship, the relationship strengths are not the same; thus, a model with varying relationship strengths can boost the efficiency of trust-based CB methods. Guo *et al.* [7] explained another important point: some trust-based CF methods focus much on the users' trust and pay less attention to the history of users. In addition, the explicit trust relation provided by users could be very limited. Thus, mining implicit trust relation can improve performance of SRS [13], [14]. Based on the points described in these studies and other similar ones, more accurate trust-based CF models have been developed [15]–[21]. However, we believe that properly applying social trust is still an open problem, and trust-based CF methods can still be improved.

In this paper, we contribute to answering this question: How can an RS designer better utilize the trust relation. In summary, the contributions of this paper are as follows:

1- We provide a practical review of recent studies that have applied social trust for the recommendation task and discuss the problems involved in degrading the performance of applying social relations. After that, we try to propose a trust-aware approach that alleviates these problems. Especially, our method takes advantage of a new asymmetric similarity measure that considers both social trust and user's history and determines the weight of each source. The asymmetric characteristic of similarity measure is an essential note for using social trust.
2- To further reach a more accurate prediction, we have applied several effective strategies as a postprocessing step based on social trust and the item-based model.
3- Finally, we have validated the performance of our proposed method on real-world datasets and shown its outperformance against prior methods, especially in terms of MAE measure.

TABLE 1. Mathematical notations.

Notation	Description
U, I	user set and item set
n, m	number of users and items
R	rating matrix
T	social trust matrix
P, Q	user and item feature matrix
R_u	set of ratings expressed by the user u
Z_i	the set of user's ratings on the item i
$r_{u,i}$	the rating made by user u on item i
$\hat{r}_{u,i}$	the prediction rate for user u on item i
$\lvert . \rvert$	the number of elements in the set.
S_R, S_T	The similarity based on rating and social trust
w_{MF}, w_{UB}, w_{IB}	the tradeoff parameters
u^+, u^-	the set of u's out-link and in-link
k	the average of $\lvert R_u \rvert$ by $u \in U$.
$N_U(.)$	the set of similar users
$N_I(.)$	the set of similar items

The rest of this paper organized as follows: Section II discusses related work. Section III describes the proposed method in detail. We report the experimental results and analysis in Section IV. Finally, Section V concludes the paper.

II. RELATED WORK

In this section, we review several related studies. Due to the importance of the similarity measures, this concept is briefly reviewed in Section II-A. Afterward, in Section II-B and II-C, we study neighborhood-based (NB) and model-based approaches as the two main categories of the CF methods. Finally, in section II-D, we briefly introduce the other RS domain approaches which have recently received attention. Since a major part of our study is about model-based CF, our focus in reviewing the related papers is more on model-based approaches, especially those that have used trust relations.

We have summarized the mathematical notations used in this paper in Table 1.

A. SIMILARITY MEASURES

Similarity measures play a vital role in NB models [16], [17], and are frequently used in model-based RS. Most of the traditional similarity measures, such as cosine similarity and Pearson Correlation Coefficient, has several drawbacks. These measures depend on co-rated items; however, as mentioned in section I, most of the rating matrixes are quite sparse. Therefore, co-rated items are extremely rare, and the calculated similarity is not accurate [22]–[24]. Furthermore, these similarity measures compute the user similarity in symmetric mode [22]. Symmetric mode means two users have an equal impact on each other; however, this is not always true. It is worth mentioning that some similarity measures are calculated based on social relationships; in this case, instead of the ''similarity'' term, other terms like link's weight or influence weight can also be used. Also, some measures are a combination of rating similarity and social trust similarity [16] and [25].

B. NEIGHBORHOOD-BASED APPROACHES

NB methods rely on an intuition that an item might be interesting to a user if similar users have preferred it, or if the user has preferred similar items to the un-rated item [24]. The NB models can be classified into two categories: user-based and item-based. In user-based models, rate prediction for an un-rated item of a target user is done by finding similar users (neighborhood) to the target user. In contrast, in item-based models, rate prediction is performed by finding the items similar to the target item. However, searching for similar users/items in the entire rating matrix is quite time-consuming. One solution to this issue is to reduce the search space [26]. Clustering methods have widely been applied to limit the search space in the online phase of the recommendation. Clustering-based CF methods can quickly identify the nearest neighbors of the target users or items by searching in the members of the same cluster, and they do not need to query the whole dataset [27]. As an example of a clustering-based CF model, we can refer to the method proposed by Deng *et al.* [28]. They proposed an improved Kullback–Leibler (KL) divergence measure to calculate item similarity. Next, they tried to form clusters using a K-medoids based clustering algorithm. An interesting advantage of their approach is that all rating information is used to find item similarity; this is while in most neighborhood-based strategies, only co-rated items are used. Note that the efficiency of the NB strategies highly depend on the similarity measure. Also, in some works, social trust information is employed to find better neighbors for a user [29]–[31]. Li et al [14] proposed the ITRA algorithm that uses the trust relation to find the user's neighborhood set. To get a more accurate prediction, they apply a trust expansion strategy on the explicit trust relations to mine more neighbors for each user. Margaris et al [32] proposed an algorithm that finds two neighborhood sets for a target user. The first set of neighbors is formed by means of the social network, while the second set is formed by the rating matrix. Then, based on each neighborhood set, a partial prediction is conducted. The final prediction of RS is a weighted combination of these predictions, where the weights vary for each user.

C. MODEL-BASED APPROACHES

In model-based approaches, machine learning algorithms are applied to build a predictive model based on the users' history, such as user's ratings. Generally, model-based approaches are proven to be more accurate and scalable methods [33]. Also, they are widely employed in the real-world application of RS. Matrix Factorization (MF) models are one of the most popular model-based RS approaches due to their attractive scalability and accuracy [34], [35]. The basic idea of MF is that the user-item rating matrix factorizes into two low-rank matrices for user-feature and item-feature [7]. Elements in user and item vectors express the weights of users or items on latent factors. Therefore, one can explain users' factor vector as the preference vector of users [33].

Let $P_i \in \mathbb{R}^{1\times K}$ and $Q_j \in \mathbb{R}^{1\times K}$ be the user and item vectors for the *i*-th user and *j*-th item, respectively. Also, suppose that K is the number of latent factors. Generally, MF-based RS tries to solve the following objective function [16].

$$\min_{P,Q} \sum\nolimits_{i=1}^{n} \sum\nolimits_{j=1}^{m} H_{ij}\left(R_{ij}-P_iQ_j^T\right)^2 + \alpha\left(\|P\|_F^2 + \|Q\|_F^2\right), \quad (1)$$

where $P = [P_1^T, P_2^T, \ldots, P_n^T]^T \in \mathbb{R}^{n\times K}$ and $Q = [Q_1^T, Q_2^T, \ldots, Q_m^T]^T \in \mathbb{R}^{m\times K}$. Also, n and m are the number of users and items respectively. The term $\alpha\left(\|P\|_F^2 + \|Q\|_F^2\right)$ is used to avoid overfitting. $R, H \in \mathbb{R}^{n\times m}$ are rate and weight matrices, where R_{ij} indicates the rate (preference) of *i*-th user to *j*-th item. Generally, H is a binary matrix where $H_{ij} = 1$ if user i has rated item j, or 0 otherwise. Note that H can be defined in other schemas too [36].

Many MF-based algorithms have been proposed for the recommendation task [35], [37]. Notably, using social trust to improve MF algorithms' performance has attracted much attention in recent years. Ma *et al.* developed several approaches by adding different trust regularization terms to the matrix factorization model [17], [19], [38]. Tang *et al.* proposed the SoDimRec algorithm, a trust-aware MF approach [16]. The idea behind SoDimRec is that users with similar interests are more likely to interact with each other. Then, these interactions set up some groups in online social networks where members in each group have similar interests. To form these groups, an overlapping community detection algorithm is applied to the trust matrix. After groups (clusters) are extracted, SoDimRec tries to predict an un-rated item for an active user by utilizing a novel objection function. One advantage of SoDimRec is that a user can be a member of several groups in which each group probably has a focus on a specific domain of item.

Yuan *et al.* [39] proposed a social recommendation framework, BSSR, where an MF-based algorithm is used to predict the users' taste. The key part of BSSR is buddy and susceptibility mining. The user's ''buddy set'' is a set of user's friends who have a strong influence on him or her. Users in the buddy set can have different impacts on the target user. For a user with a high susceptibility value, the rate prediction is mainly calculated based on the user's buddy set. In contrast, for an unsusceptible user, the rate prediction is calculated mainly based on his or her taste. The importance of users in social networks is also considered in the other researches. For instance, Davoudi and Chatterjee proposed a trust model-based approach that considers user importance and similarity [40].

TCRec is another MF based approach that uses trust relation [15]. The main idea behind TCRec is that trustors who follow the same trustee have similar features and taste. To apply the idea, they first perform a clustering algorithm, where for each trustee, a cluster is formed by adding all trustors of the trustee. Next, by proposing a loss function (Eq. 2), it tries to converge the feature matrices P, Q, and S to minimize the distance between the feature vector of users in the same clusters.

$$\min_{P,Q,S} \sum_{i=1}^{n}\sum_{j=1}^{m} H_{ij}\left(R_{ij} - P_i Q_j^T\right)^2 + \beta \sum_{i=1}^{n}\sum_{k\in i^+} W_{ik}.\, \|p_i - s_k\|_2^2 + \lambda_p \|P\|_F^2 + \lambda_q \|Q\|_F^2 + \lambda_s \|S\|_F^2 + \lambda_b \left(\|b_i\|_2^2 + \left\|b_j\right\|_2^2\right) \tag{2}$$

where $\|.\|_F^2$ denotes the Frobenius norm and b_i and b_j represent users and items bias. The matrix S is composed of each cluster's group features, and s_k represents the average of the latent features of all trustors in cluster k. In other words, all users who trust user k, form a cluster, and s_k represents the average of users' latent features. Finally, the matrix W in Eq (2) is the weight matrix that shows the level of the influence that trustors get from their trustees. The strength of influence in TCRec is only determined by social trust, and the rating matrix is not considered. In Fig. (1), there are three clusters C_4, C_5 and C_6 that are formed around users u_4, u_5 and u_6. The members of cluster C_4 are u_1, u_2, and u_7 that trust u_4. Also, u_2 participate in both C_4 and C_5 since it trusts both u_4, and u_5.

Duan *et al.* proposed a method to find expert users and utilize these users in a trust-aware matrix factorization [41]. Based on the definition expressed in [41], an expert user is a user with two characteristics: (1) They have a positive attitude on ratings (based on the number of rated items which rated above a threshold). (2) They are more likely to have more in-links.

D. OTHER APPROACHES

Besides the approaches studied in subsections A-C, other different approaches have recently gotten attention. One of these approaches is proposing recommender systems based on Knowledge Graphs (KGs). KG-based recommender systems try to improve their performance by leveraging external knowledge as auxiliary information [42]–[44]. A KG is a heterogeneous directed graph where nodes represent items or item attributes, and edges represent relations between these nodes [42]. One recent work in using KGs was proposed by Sun *et al.*, where they proposed a multi-modal knowledge graph that considers a variety of data types [44]. KGs could be represented by heterogeneous information networks

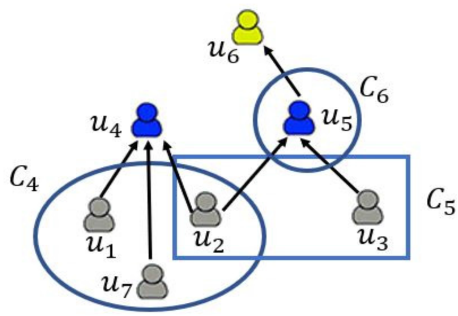

FIGURE 1. Forming clusters for each trustee.

(HIN) [45]. A HIN can model complex information; therefore, HIN-based RS has gotten more attention recently [46] of which most are random walk-based methods [47]–[49].

E. NOTES FOR AN RS DESIGNER

In this section, we list notes that could help an RS designer to utilize the trust relation better:

1) Two users with a trust relation may have different tastes [11].
2) Two users may have similar preferences in some areas while having different tastes in other areas [11].
3) It is better to consider a variety of relationship strengths and not to assume that each relation has the same strength [12].
4) There should be a balance in paying attention to the users' trust information and their history [7].
5) Mining implicit trust relations can improve the performance of RS [13], [14].
6) Asymmetric similarity measure is more compliant with the nature of trust relationships.

More details on each note have been presented in sections I and II.

III. PROPOSED METHOD

In this section, we describe the structure of our proposed method. In brief, the first step in our method is link prediction for cold-start users that do not have any out-link. Since there is not much information available for these users (in terms of both rating history and trust relation), mining their taste is too difficult. Therefore, using link prediction for these users would help the RS a lot. Then by a new similarity measure (Eq. 7), the level of influence that trustors get from their trustees is determined (matrix W). After that, a trust-aware MF-based RS is applied. Finally, for datasets with a high degree of sparsity, we apply a further step of postprocessing.

The proposed W can be used in most of the trust-aware MF approaches. However, in our method, we have used the objective function of TCRec (Eq.2) as the MF-based algorithm, mainly due to the simplicity and efficiency of this method. Fig. 2 represents an overview of our proposed method, where $\acute{T}$ shows the trust matrix after link prediction.

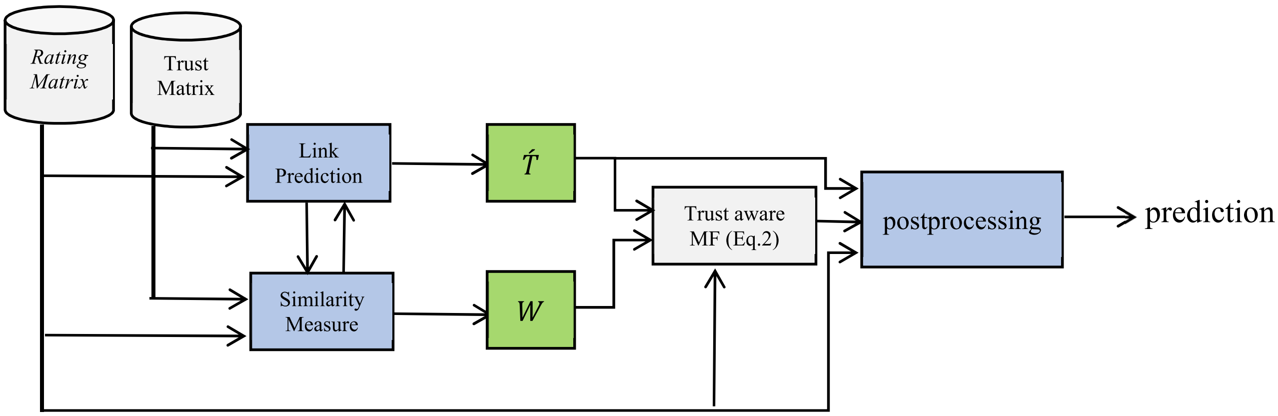

FIGURE 2. An overview of our proposed method.

A. PROPOSED LINK PREDICTION METHOD

Using the trust matrix is a critical part of social-based RS algorithms, like TCRec, to achieve higher performance. However, most trust-aware RS methods cannot appropriately use the trust matrix for a user if the user does not have any relation. For example, TCRec cannot put users with zero out-link in any cluster to tune their preference vector. If these users have rated a lot of items, it is possible to mine their taste by their past activity. However, if they did not rate enough items (e.g., new users), their past information is not sufficient to mine their taste.

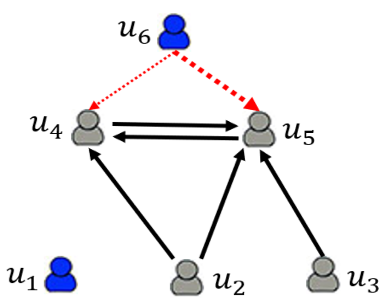

FIGURE 3. Link prediction for cold start users.

Algorithm 1 Link Prediction Based on the Expertise of Users

for i in I :
  $expert_i = \max_{(u \epsilon Z_i)} |u^-|$
for u in U :
  if $\left(\left(\left|u^+\right| == 0\right)$ *and* $(u$ *is cold start user*$)\right)$:
    for i in R_u :
      add $expert_i$ *to expert_set*
  calculate similarity of u with each member in expert_set using Eq.(7)
  expert ← *find most similar member in expert_set with u*
  create virtual link from u to expert

To alleviate this problem, we have proposed a simple and fast link prediction algorithm based on finding expert trustees. In our method, we first find an expert user on each item. The expert user on item i is the user who has the maximum number of in-links (followers) among the users who have rated item i. Note that in this context, more in-links means more expertise level of a user. Then, for each cold-start user with zero out-link, we establish a link from this user to the expert user with the most similarity calculated by our proposed similarity measure (Eq. 7). The pseudocode of the link prediction method is depicted in Algorithm 1. To illustrate the process through an example, consider that in Fig. (3), user u_1 and u_6 do not have any out-link, and u_6 has rated a few items while u_1 has rated many items. Therefore, by the past activity of u_1, its preference could be mined. However, we cannot mine u_6's preference by its history, and link prediction is necessary. Also, suppose that user u_4 and u_5 have been identified as expert users for items rated by u_6 and similarity measure shows that u_6 is more similar to u_5. So, an out-link from u_6 to u_5 is created.

B. PROPOSED SIMILARITY MEASURE

The similarity measure plays a vital role in the RS algorithm. The conventional similarity measures that only use the rating matrix fail for users who have rated a few items. On the other hand, similarity measures based on the trust matrix also fail for users with no relation. Besides, as mentioned in section I, focusing much on the users' trust and paying less attention to the history of users may degrade the performance of CF methods [7]. Thus, to reach an acceptable similarity estimation and solve this problem, it is best to use a weighted combination of rating and trust similarity. Also, the similarity measure should be asymmetric to be more compliant with the nature of trust relationships. For example, an expert user may have a strong effect on a novice user, while vice versa is not correct. Another important point about similarity measure, suggested in [12], is that it is better to consider the relationship strengths (e.g., not to use a simple binary value). To address these issues, an asymmetric similarity measure that takes advantage of both the rating matrix and the trusts matrix is proposed. The proposed similarity measure calculates the similarity between users more accurately than other measures that only consider one source of information (rating or trust matrix).

Suppose that there is a link from user u to user v (user u trusts user v, so that u gets influence from v). Eq. (3) indicates the strength of the link from u to v in terms of social trust (S_T). Note that, a higher number of trustors for a trustee shows that more users trust the trustee, and so, the trustee's opinion is important for its trustors (for more details on the impact of the number of trustors, readers could refer to [15] and [41]).

$$S_T\left(u,v\right)=\frac{\left|v^{-}\right|}{\left|u^{+}\right|+\left|v^{-}\right|} \tag{3}$$

If v has a few in-links and u has many out-links (trustees), then S_T is close to zero. If u has a few out-links, and v has many in-links, S_T is close to one. Also, Eq (4) calculates the similarity based on ratings:

$$S_R(u,v)=\frac{|R_u\cap R_v|}{|R_u|} \tag{4}$$

With an increasing number of items rated by both u and v, mining their taste and calculating the similarity based on ratings, get more reliable. However, if at least one of them has not rated enough items, calculating the similarity based on ratings would not be accurate. Therefore, we first check the number of rated items by u and v and then calculate the similarity by integrating a weighted combination of the similarity obtained by the trust and the similarity obtained by the rating matrix.

$$m_r=\min\left(|R_v|,|R_u|\right) \tag{5}$$

$$w=\frac{1}{1+e^{(k-m_r)}} \tag{6}$$

$$sim(u,v)=(w\times S_R)+((1-w)\times S_T) \tag{7}$$

m_r is the minimum number of rated items by u and v. By increasing m_r, the weight (w) of S_R in similarity calculation will increase (Eq. 6). To clarify, suppose that the average of $|R_u|$ for $u\epsilon U$ is 12, $k = 12$. The weight of S_R based on the value of m_r is depicted in Fig. (4). Note that $m_r = 0$ means that there isn't any history available for at least one of the users. Thus, the calculation of similarity based on the rating matrix is not possible (the similarity measure is zero). In summary, as historical ratings for both users increase, calculation of similarity based on the rating matrix gets more accurate, and so, gets a higher weight in the proposed similarity measure; otherwise, the similarity based on trust would get a higher weight.

C. POSTPROCESSING

To have a better prediction in sparse datasets, we can apply some simple tuning mechanisms by using the available data. This phase of the proposed method can be considered as a postprocessing phase. We can use the following auxiliary mechanisms to get an accurate prediction for un-rated items:

1- If a user has some trustees that have rated the target item, we can use this data to make a more accurate prediction, taking advantage of the idea of a user-based model. It should be noted that as the neighborhood for a user is formed based on its social trust, this phase can be done quickly.

2- An item-feature vector is obtained after performing matrix factorization algorithm (see Q in Eq.2). By using this matrix, one can calculate the similarity between two items quickly. The aim of this rule is taking advantage of the idea of an item-based model.

All of these considerations are included in Eq. (14), where $\hat{r}_{MF}$, $\hat{r}_{UB(u,i)}$ and $\hat{r}_{IB(u,i)}$ are the MF-based (the proposed trust-aware MF in section III-B), user-based and item-based prediction, respectively. Also, w_{MF}, w_{UB}, and w_{IB} show the weight of contribution of these predictions to the final rate prediction. These weights are determined by Eq (9-11). The final prediction is mainly based on MF-based prediction; however, if an active user has several trustees with similar tastes who rate item i, we can expect the user-based prediction to be likely accurate. In addition, if an active user ratings several items similar to i, the prediction of the item-based model is likely accurate. In special cases in which we expect both the item and user-based models to perform accurately, the final prediction can be made based on the user and the item-based prediction alone. However, in most cases, due to the small neighborhood set of the user or the item (or both), it is better to use these predictions as a tuning factor for the MF-based prediction.

$$sim\left(i,j\right)=\frac{Q\left(i\right).Q(j)}{\|Q\left(i\right)\|\,\|Q(j)\|} \tag{8}$$

$$w_{UB}=\min(0.5,\frac{|v\in N_U(u)\cap Z_i|}{5}) \tag{9}$$

$$w_{IB}=\min(0.5,\frac{|N_I(i)\cap R_u|}{5}) \tag{10}$$

$$w_{MF}=1-(w_{UB}+w_{IB}) \tag{11}$$

$$\hat{r}_{UB(u,i)}=\bar{u}+\frac{\sum_{(v\in N_U(u)\cap Z_i)} sim\left(u,v\right).(r_{vi}-\bar{v})}{\sum_{(v\in N_U(u)\cap Z_i)} sim\left(u,v\right)} \tag{12}$$

$$\hat{r}_{IB(u,i)}=\bar{i}+\frac{\sum_{j\in N_I(i)} sim\left(i,j\right).\left(r_{uj}-\bar{j}\right)}{\sum_{j\in N_I(i)} sim\left(i,j\right)} \tag{13}$$

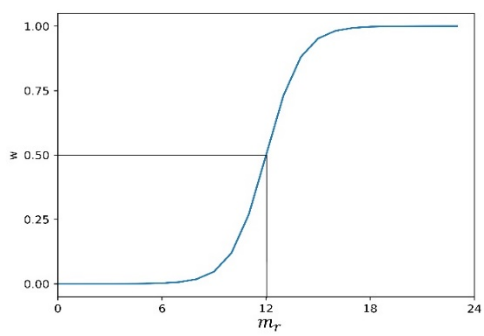

FIGURE 4. Weight of S_R in the similarity measure.

$$\hat{r}_{u,i} = (w_{MF} \times \hat{r}_{MF}) + (w_{UB} \times \hat{r}_{UB(u,i)}) + (w_{IB} \times \hat{r}_{IB(u,i)}) \quad (14)$$

Eq. (8) uses the cosine similarity to calculate the similarity between items i and j. In Eq. (8), Q(i) and Q(j) are feature vectors for items i and j and ‖.‖ is the 2-norm. In Eq. (9), $N_U(u)$ is the set of similar users to u, and $|v \in N_U(u) \cap Z_i|$ specifies the number of users in $N_U(u)$ who rate item i. In Eq. (10), $|N_I(i) \cap R_u|$ indicates the number of rated items similar to i by the active user. In Eq. (12), $sim(.)$ is the similarity between users (Eq. 7), and in Eq. (13), $sim(.)$ is the similarity between items (Eq. 8). Note that both w_{IB} and w_{UB} are in the range $[0 \sim 0.5]$; therefore w_{MF} is in the range $[0 \sim 1]$. Here for simplicity and reducing the number of parameters that need to be tuned, no free parameters are considered in w_{UB}, w_{IB}, and w_{MF}.

IV. EXPERIMENTAL STUDY

In this section, we conduct several experiments to investigate the performance of our approach in comparison with other RS algorithms.

A. DATASET

We conduct our experiments on three real-world datasets frequently used in the trust-based RS literature. Epinions and Ciao[1] are product review websites. In these two websites, users are allowed to specify scores from 1 to 5 to rate items (higher score shows more interest), and they can also establish relations with each other. In FilmTrust,[2] the items are movies, and the ratings are in the range of 0.5 to 4 with a step size 0.5. Statistics of these datasets are reported in Table 2.

B. EXPERIMENTAL SETTINGS

In our experiments, different amounts of training data {60%, 70%, and 80%} are studied. The training sets are selected randomly from the dataset, and the rest is used for testing. Experiments for each size are repeated five times, and the average performance is reported. To evaluate the performance of the proposed method in terms of rate prediction accuracy, two popular metrics, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), are used. Also, we have used F-measure to evaluate in terms of classifying items into interesting and not interesting for each user. Note that a threshold is required for classifying items into interesting and not interesting categories regarding the user's taste. In different studies, different values of the threshold are used in the evaluation. For example, for the rating scaled from $[1 \sim 5]$, Li *et al.* [50] considered 3 as the value of the threshold, while Wang *et al.* [51] considered 5 as their threshold. In this paper, we have considered 4 as the threshold in Ciao and Epinions dataset and 3 in the FilmTrust dataset (where the maximum rating is 4). Note that a higher value for F-measure means better performance; while, a lower value for MAE and RMSE shows higher accuracy. The main goal of our study is to rate prediction, and thus, our focus is mainly on MAE and RMSE.

[1] https://www.cse.msu.edu/~tangjili/trust.html
[2] https://guoguibing.github.io/librec/datasets.html

TABLE 2. Dataset description.

Feature	Ciao	Epinions	FilmTrust
#Users	7265	21111	1400
#Items	11211	14030	1423
#Ratings	149131	434162	34742
Density	0.183%	0.147%	1.744%
# Trustor	6683	14640	487
# Trustees	7185	15038	555
# Trusts	110744	331005	1542

The following is the definition of MAE, RMSE, Precision, Recall, and F-measure. Where $r_{u,i}$ and $\hat{r}_{u,i}$ show the rating score and prediction rating score of u on item i. Also, L indicates the number of rating scores in the test set. TP (true positive) shows the number of interesting items for users in the test set, in which the RS algorithms could truly classify the items as interesting. FN (false negative) and FP (false positive) show the number of items that RS algorithms wrongly classified as not interesting and interesting (for FP), respectively.

$$\mathrm{MAE} = \frac{1}{\mathrm{L}} \sum_{\mathrm{u,i}} |\mathrm{r_{u,i}} - \hat{\mathrm{r}}_{\mathrm{u,i}}| \quad (15)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{L}} \sum_{\mathrm{u,i}} (\mathrm{r_{u,i}} - \hat{\mathrm{r}}_{\mathrm{u,i}})^2} \quad (16)$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \quad (17)$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \quad (18)$$

$$\text{F-measure} = \frac{2 \times \mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \quad (19)$$

We have adopted six existing RS methods for performance comparison: (1) SVD++ [1] which is an RS method merely based on ratings and chosen for its better performance comparing to well-known MF-based algorithms like PMF (Probabilistic Matrix Factorization) [52], (2) SoReg [19] which is a well-known trust-based MF, (3) TCRec [15], (4) ITRA [14], (5) $\mathrm{UIT_{hybrid}}$ [53], and (6) ETBRec [41] which are four state-of-the-art trust-aware recommender methods. To set the optimal parameters in the benchmarking algorithms, we have carried out experiments to find the optimal values for each dataset separately. Also, the optimal values of the parameters used in each method are either determined by our experiments or were set as the values suggested by previous studies. The parameters for FilmTrust, Epinions, and Ciao respectively are: (1) SVD++ $\lambda = 0.1; 0.35; 0.1$. (2) SoReg: $\lambda_u = \lambda_v = 0.1$ (3) TCRec and the proposed method: $\lambda_u = \lambda_v = \lambda_s = 0.1$ for all datasets. (4) ITRA: $\alpha = 0.5$ for all datasets. (5) $\mathrm{UIT_{hybrid}}$: $K = 30, \alpha = \beta = \gamma = 1/3$. (6) ETBRec: $n = 20, \alpha = 0.7, \lambda_u = \lambda_v = 0.1$ *and* $\lambda_b = 0.01$. The number of latent features for SVD++, TCRec, ETBRec and the proposed method is 10; this value is very popular in the literature and caused good performance in most cases. However, for SoReg, the suitable number of latent features is 30,20 and 20 for FilmTrust, Epinions, and Ciao respectively. It should be noted that the rate prediction in ITRA is made by summation of two different values. The first one is the mean of ratings made by the active user, and the second value is from the active user's trust neighbor set. If the active user has no trust relations, then the set of neighbors for the active user is empty. Therefore, the final prediction is equal to the mean of ratings done by active users.

An important note which we would like to highlight is that in the calculation of the RMSE measure, the square of errors is considered. Therefore, large errors are weighted higher in RMSE compared with MAE. Thus, generally, if large errors do not affect F-measure, it seems that MAE can better reflect RS's accuracy in the rate prediction task.

We conducted a set of experiments to show the effectiveness and performance of our proposed method regarding cold-start users and all users. Also, for each set of experiments, different sizes of training data are considered to study the effect of available training data on the performance of our proposed method.

C. EVALUATING THE PERFORMANCE FOR ALL USERS

According to the results in Tables (3-5), for all datasets and all training sizes, the proposed method has performed best in terms of MAE measures and, in some cases (6 out of 9), has performed best in terms of RMSE measures. Koren [1], and [35] demonstrated that small improvements in MAE or RMSE could have a significant impact on the quality of the top-few recommendations [16] and is not a trivial task.

For the Epinions dataset (Table 3), the proposed method has performed best in terms of MAE and RMSE in all training sizes. The superiority of the proposed method compared with other approaches is completely clear in the Epinions dataset.

In terms of F-measure metrics (Fig. 5), the proposed method performed better than TCRec and ITRA in all training sizes in the Epinions dataset. In summary, the proposed method is more accurate than all other benchmarking algorithms in the Epinions dataset.

For the Ciao dataset (Table 4 and Fig. 5), the proposed method has performed best in all training sizes in terms of the MAE measure, and the superiority is significant. In terms of RMSE, TCRec has performed best. However, this superiority is not as significant as the superiority of the proposed method considering the MAE. By a close look at Fig. 5, it is clear that the in comparison with TCRec, the proposed method performs better in all training sizes in terms of F-measure. Also, the proposed method's superiority over the TCRec in terms of MAE is more significant than the TCRec's superiority in terms of RMSE. For example, in training size {60%}, the difference between the RMSE of the proposed method and that of TCRec is 0.0008 while the difference in their MAE is 0.0115 which is much more significant.

Finally, for the FilmTrust dataset (Table 5 and Fig. 5), the proposed method performs better than TCRec in terms of both MAE and RMSE. In training size {80%} the SVD++ performs better in comparison with the proposed method in terms of RMSE; however, in training sizes {60% and 70%} the proposed method performs better in terms of RMSE. In addition, for all training sizes, the proposed method outperformed the SVD++ in terms of the MAE measure.

To verify the statistical significance of the experiment, a paired t-test has been performed on the experimental results. Similar to the manner used in [15], if the output of the t-test is less than 0.01, we consider the result is statistically significant. The output of the t-test is reported in Table 9. In the table, '+' means statistical significance,

TABLE 3. Performance of the proposed method and comparison methods in terms of RMSE and MAE in the case of all users for the Epinions dataset.

Methods	Epinions 60%		Epinions 70%		Epinions 80%	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
SVD++	0.8217	1.0511	0.8175	1.046	0.8157	1.0419
SoReg	0.8210	1.0684	0.8143	1.0625	0.8060	1.0504
ITRA	0.9202	1.2012	0.9141	1.1894	0.9045	1.1784
UIT_{hybrid}	0.8902	1.1750	0.8860	1.1761	0.8824	1.1738
TCRec	0.8028	1.0422	0.7979	1.0372	0.7924	1.0336
ETBRec	0.8075	1.0507	0.8025	1.0454	0.8028	1.0428
Proposed	**0.7942**	**1.0418**	**0.7909**	**1.032**	**0.7881**	**1.0298**

TABLE 4. Performance of the proposed method and comparison methods in terms of RMSE and MAE in the case of all users for the Ciao dataset.

Methods	Ciao 60%		Ciao 70%		Ciao 80%	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
SVD++	0.7848	1.0574	0.7774	1.0493	0.7763	1.0484
SoReg	0.7865	1.0398	0.7662	1.0162	0.7550	1.0032
ITRA	0.7805	1.0631	0.7742	1.0451	0.7689	1.0318
UIT_{hybrid}	0.7913	1.0719	0.7871	1.0572	0.7865	1.0716
TCRec	0.7372	**0.9783**	0.7316	0.9712	0.7286	**0.9699**
ETBRec	0.7408	0.9838	0.736	0.9782	0.7349	0.9797
Proposed	**0.7257**	0.9791	**0.7184**	**0.9657**	**0.7191**	0.9702

TABLE 5. Performance of the proposed method and comparison methods in terms of RMSE and MAE in the case of all users for the FilmTrust dataset.

Methods	FilmTrust 60%		FilmTrust 70%		FilmTrust 80%	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
SVD++	0.6091	0.7979	0.5984	0.7814	0.594	**0.7748**
SoReg	0.6545	0.8493	0.6408	0.8332	0.6295	0.8201
ITRA	0.6258	0.819	0.6281	0.8191	0.6292	0.8218
UIT_{hybrid}	0.6498	0.8533	0.6532	0.8517	0.6626	0.8684
TCRec	0.6094	0.7916	0.6012	0.7784	0.6008	0.7797
ETBRec	0.6152	0.7951	0.6106	0.7868	0.615	0.7932
Proposed	**0.5989**	**0.7879**	**0.5934**	**0.7735**	**0.589**	0.7758

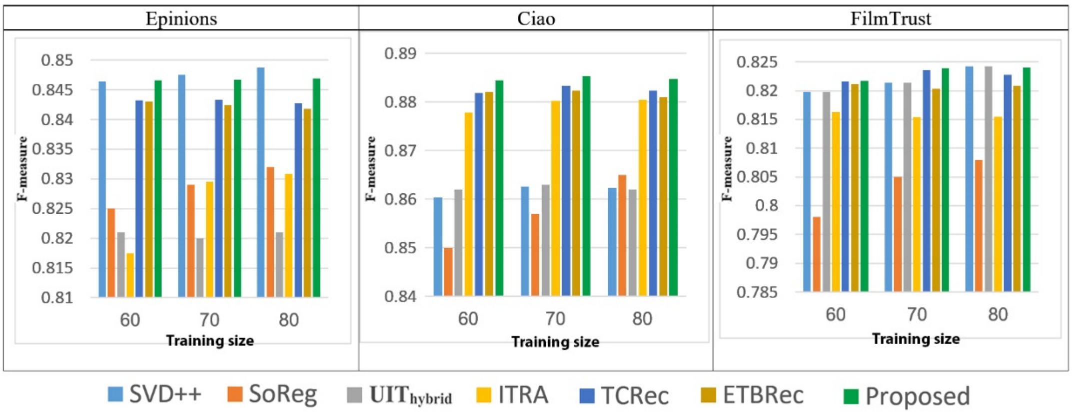

FIGURE 5. F-measure of the proposed method and comparison methods (all users).

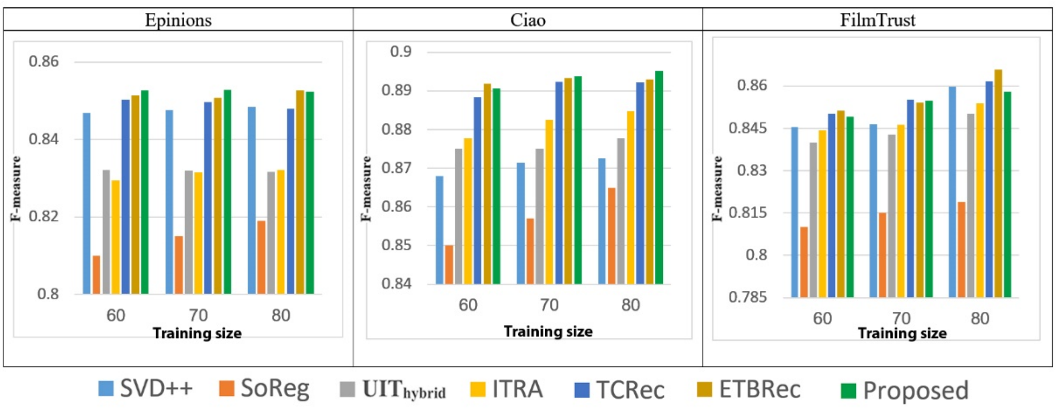

FIGURE 6. F-measure of the proposed method and comparison methods (cold start users).

TABLE 6. Performance of the proposed method and comparison methods in terms of RMSE and MAE in the case of cold-start users for the Epinions dataset.

Methods	Epinions 60%		Epinions 70%		Epinions 80%	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
SVD++	0.8551	1.0987	0.85	1.0926	0.8547	1.0962
SoReg	0.8849	1.1435	0.8751	1.1315	0.8721	1.1294
ITRA	0.9687	1.2803	0.9591	1.264	0.9540	1.2553
UIT_{hybrid}	0.9155	1.2009	0.9137	1.2048	0.9158	1.2108
TCRec	0.8359	1.0817	0.8317	1.0769	0.8337	1.0843
ETBRec	0.8400	1.0948	0.8352	1.0876	0.8413	1.0945
Proposed	**0.8247**	**1.0809**	**0.8235**	**1.0703**	**0.8248**	**1.0781**

and '-' means no statistical significance. As one can see, in most cases, the t-test output is significant. In the cases the t-test is not significant, the proposed method still has a good performance.

D. EVALUATING THE PERFORMANCE FOR COLD-START USERS

In this sub-section, we study the performance of the proposed method for cold-start users. The cold-start users are users who

TABLE 7. Performance of the proposed method and comparison methods in terms of RMSE and MAE in the case of cold-start users for the Ciao dataset.

Methods	Ciao 60%		Ciao 70%		Ciao 80%	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
SVD++	0.7849	1.0647	0.7775	1.0566	0.7707	1.0515
SoReg	0.9143	1.1579	0.9124	1.1618	0.8852	1.1358
ITRA	0.8183	1.126	0.8075	1.1146	0.8030	1.1052
UIT_{hybrid}	0.7989	1.0802	0.7957	1.0801	0.7915	1.0787
TCRec	0.7477	**0.9945**	0.7397	0.9825	0.7328	**0.9813**
ETBRec	0.7454	0.9985	0.7395	0.9888	0.7419	0.9953
Proposed	**0.735**	0.9952	**0.7254**	**0.9821**	**0.7241**	0.9825

TABLE 8. Performance of the proposed method and comparison methods in terms of RMSE and MAE in the case of cold-start users for the FilmTrust dataset.

Methods	FilmTrust 60%		FilmTrust 70%		FilmTrust 80%	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
SVD++	0.6089	0.8031	0.5988	0.7872	**0.5793**	0.7702
SoReg	0.6696	0.8773	0.6466	0.8474	0.6387	0.8365
ITRA	0.6370	0.8493	0.6314	0.8444	0.6244	0.8366
UIT_{hybrid}	0.6380	0.8448	0.6247	0.8218	0.6200	0.8226
TCRec	0.6153	**0.7948**	0.6047	**0.7738**	0.5953	0.7685
ETBRec	0.6297	0.8073	0.6174	0.7906	0.6079	0.7847
Proposed	**0.6032**	0.7962	**0.5931**	0.7753	0.5823	**0.7606**

TABLE 9. The paired t-test results.

Dataset	Methods	Metric	Training size 60%		Training size 70%		Training size 80%	
			All user	Cold start	All user	Cold start	All user	Cold start
Epinions	SVD++	MAE	+	+	+	+	+	+
		RMSE	+	+	+	+	+	+
	SoReg	MAE	+	+	+	+	+	+
		RMSE	+	+	+	+	+	+
	ITRA	MAE	+	+	+	+	+	+
		RMSE	+	+	+	+	+	+
	UIT_{hybrid}	MAE	+	+	+	+	+	+
		RMSE	+	+	+	+	+	+
	TCRec	MAE	+	+	+	+	+	+
		RMSE	-	-	+	-	-	+
	ETBRec	MAE	+	+	+	+	+	+
		RMSE	+	+	+	+	+	+
Ciao	SVD++	MAE	+	+	+	+	+	+
		RMSE	+	+	+	+	+	+
	SoReg	MAE	+	+	+	+	+	+
		RMSE	+	+	+	+	+	+
	ITRA	MAE	+	+	+	+	+	+
		RMSE	+	+	+	+	+	+
	UIT_{hybrid}	MAE	+	+	+	+	+	+
		RMSE	+	+	+	+	+	+
	TCRec	MAE	+	+	+	+	+	+
		RMSE	-	-	+	-	-	-
	ETBRec	MAE	+	+	+	+	+	+
		RMSE	-	-	+	+	+	+
FilmTrust	SVD++	MAE	+	+	+	+	+	-
		RMSE	+	+	+	+	-	+
	SoReg	MAE	+	+	+	+	+	+
		RMSE	+	+	+	+	+	+
	ITRA	MAE	+	+	+	+	+	+
		RMSE	+	+	+	+	+	+
	UIT_{hybrid}	MAE	+	+	+	+	+	+
		RMSE	+	+	+	+	+	+
	TCRec	MAE	+	+	+	+	+	+
		RMSE	-	-	-	-	-	+
	ETBRec	MAE	+	+	+	+	+	+
		RMSE	+	+	+	+	+	+

have rated at most ten items in the training dataset. Note that only cold-start users are considered in the experiments of this section.

For the Epinions dataset, the proposed method has performed best in terms of MAE and RMSE in all training sizes (Table 6), exactly like the result of the ''all users'' case.

For the Ciao dataset (Table 7 and Fig. 6), although TCRec performs better than the proposed method in terms of RMSE for training sizes {60% and 80%}, in terms of MAE, the proposed method performs better than all other compared methods in all training sizes. The superiority of the proposed method in terms of MAE is much more significant than the superiority of TCRec in terms of RMSE. For example, in training size 60%, the values of MAE for the proposed method and TCRec are 0.735 and 0.7477, respectively, and thus, the proposed method has achieved 0.0127 lower value in terms of MAE. This is while TCRec's outperformance is about 0.0007 in terms of RMSE. In addition, in terms of F-measure, the proposed method has performed better than the other approaches in all training sizes.

Finally, for the FilmTrust dataset (Table 8 and Fig. 6), in terms of MAE, the proposed method performed better than all other compared methods in most cases. In terms of F-measure, the TCRec performs better in comparison with the proposed method, where this advantage in training sizes {60% and 70%} is small. Note that the number of ratings in the test set for cold-start users case in the FilmTrust with training size {80%} is small (in fact, FilmTrust has considerably fewer ratings than Epinions and Ciao). Therefore, to study the special case of the cold-start users in the FilmTrust, it is better to pay more attention to the experimental results with training size {60%} or {70%}.

In summary, in most cases (17 out of 18), the proposed method has performed best in terms of MAE in all datasets, and for both the cold-start and all users cases. Besides, in terms of other performance measures, in most cases, the proposed method works better than the other approaches; however, for those cases that the proposed method is not the best, it shows an acceptable performance. In other words, the proposed method works well for both new users and the users with a rich history. The other observation from experimental results is that the approaches that consider expert users (the proposed method and ETBRec) work well in predicting unseen items, especially for cold-start users.

V. CONCLUSION AND FUTURE WORK

In this paper, we studied how an RS designer can use social trust as a complementary source to improve the performance of an MF-based RS algorithm. As discussed, the simple use of social trust cannot improve the performance of CF algorithms, and how to best use social trust is still an open question. To answer this question, we proposed an asymmetric similarity measure to better comply with the asymmetric nature of social relationships. Also, the similarity measure considers both ratings and trust matrices, which lead to higher performance. In addition, a simple link prediction algorithm is proposed in order to utilize social trust better. Finally, we used the user and item-based model to improve the performance of the proposed method in a postprocessing step. The result of all these considerations is that, in most cases, the proposed method outperformed the state-of-the-art trust-aware MF methods in terms of MAE measure. It also works well in datasets with different levels of sparsity. For future work, an interesting research direction would be to investigate in which particular circumstances, the prediction may degrade. Another research direction could be to use a more complex but accurate combination of information or RSs schemes in the postprocessing phase.

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