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Exploiting social trust via weighted voting strategy for recommendation systems improvement

Hussain J. Oudah
Website Unit, University of Kerbala, Karbala, Iraq; 2Department of Computer Science, College of Computer Science and Information Technology, University of Kerbala, Karbala, Iraq, hussain.j@uokerbala.edu.iq

Mohsin H. Hussein
Website Unit, University of Kerbala, Karbala, Iraq; 2Department of Computer Science, College of Computer Science and Information Technology, University of Kerbala, Karbala, Iraq

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Keywords

Recommendation System; Collaborative Filtering; Social Information; Trust Propagation; Weighted Voting; Explicit and Implicit Feedback

RESEARCH PAPER

Exploiting Social Trust Via Weighted Voting Strategy for Recommendation Systems Improvement

Hussain J. Oudah [a,*], Mohsin H. Hussein [b]

[a] Website Unit, University of Kerbala, Karbala, Iraq
[b] Department of Computer Science, College of Computer Science and Information Technology, University of Kerbala, Karbala, Iraq

Abstract

Recently, social trust information has become a significant additional factor in obtaining high-quality recommendations. It has also helped to alleviate the problems of collaborative filtering. In this paper, we exploit explicit and implicit trust relations and incorporate them to take advantage of more ratings (as they exist) of trusted neighbors to mitigate the sparsity issue. We further apply the idea of weighted voting of the ensemble classifier for the election of the most appropriate trust neighbors' ratings. Additionally, the certainty of these elected rating values was confirmed by calculating their reliability using a modified version of Pearson's Correlation Coefficient. Finally, we applied the K-Nearest Neighbors method with a linear combination of original and trust-elected ratings using a contribution weight to obtain the best prediction value. Extensive experiments were conducted on two real-world datasets to show that our proposed approach outperformed all comparable algorithms in terms of both coverage and accuracy. Specifically, the improvement ratio ranged approximately from 4% as a minimum to 20% on FilmTrust, and to 10% on Epinions as a maximum in terms of F-measure between the inverse of Mean Absolute Error (accuracy) and coverage.

Keywords: Recommendation system, Collaborative filtering, Social information, Trust propagation, Weighted voting, Explicit and implicit feedback

1. Introduction

The term ‘information overload’ arose with the accelerated development of information technology and extended to different commercial and service enterprises in e-commerce and social media, resulting in users having to deal with this increasingly problematic online problem [1]. This means that many items have been supplied to users, leading to the possibility of users not being able to make quick decisions according to their interests and requirements [2]. A recommender system (RS) is an intelligent and successful information filtering system that offers items of interest to users [3], thus helping them to deal with difficulties related to information overload [4,5], and providing a personalized top items list per user.

In general, there are three types of RSs [6]: content-based (CB), collaborative filtering (CF), and hybrid approaches. The CB approach entails recommending items to a user after comparing the content of those items with others that the same user previously liked. On the other hand, CF relies on computing the similarity between users (user-based) or items (item-based), or both to predict the score of an item that may be of interest to a user [7]. In addition to these memory-based methods, there is another method also used in CF called model-based [8]. Lastly, hybrid systems simply combine CB and CF approaches in numerous ways to take advantage of both and reduce their respective shortcomings [7]. CF is considered the most frequently used species in RS studies [9].

Broadly, CF techniques suffer from multiple problems, the most common of which are sparsity

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* Corresponding author.
E-mail address: hussain.j@uokerbala.edu.iq (H.J. Oudah).

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[10] and cold-start [11]. Due to these problems, the accuracy of prediction becomes diminished. Sparsity means that users have rated only a very small number of items relative to all available items in the user-item rating matrix [12]. In RS, there is a case where new users join the system with no history preferences or several items added to the system, which have few or no ratings assigned to them yet. This is what is called the cold-start problem [12]. However, solutions to these problems were proposed in the RS research in an attempt to mitigate them. One of these solutions is to exploit additional information such as users' demographic information [13]. However, this solution is rarely used as most real-world datasets do not provide such information to protect users' privacy [14]. Another solution is to use deep learning algorithms [15] as long as the time required for their implementation and the computational resources are available. A more promising solution is the use of social information such as trust relationships to enrich the sparse nature of the rating matrix [14,16,17]. According to Refs. [18,19], who mentioned the increased progress of RSs embedded on the web, social information plays an integral role in reducing such CF-related problems.

In general, many works have been proposed to improve the accuracy of RSs by reducing their associated problems (i.e., rating sparsity and cold-start). Some of these works [20–24] benefited from trust network information as additional implicit information besides explicit numerical ratings. It can be said that these studies are the motivation behind thinking about proposing the weighted voting technique with the expansion of the trust relations network through the trust propagation attribute.

This work is proposed for improving the prediction accuracy of RSs, as we have suggested the weighted voting technique to be an alternative to the technique known as the weighted average used in most of the previous works [22–24]. The weighted average technique will produce fractional values that may significantly influence the overall prediction error. However, these outcomes will be elected as exists (i.e., non-fractional values) when applying our proposed method, thus eliminating these extra details. In particular, we embody the election idea by assuming that the trusted neighbors are the classifiers, and the rating scales are the classes (labels) to be voted on for inclusion in the profile of the target user by the weighted voting technique as Fig. 1 shows.

One of the challenges of the proposed work is how to implement the weighted voting technique within the scope of RSs. In addition, in order to exploit the trust propagation feature, we need to reach an appropriate depth that helps reduce the problem of rating sparsity, thus taking advantage of the trustworthy neighbors' ratings to enrich the rating matrix.

In this work, we will attempt to answer the following research questions:

1. Can our method (election by weighted voting) give better and more accurate results than the comparable methods?
2. If we try to linearly combine the two prediction results of original ratings and trust-elected ratings using a contribution weight, would that increase the coverage of estimated ratings while improving its accuracy?

The rest of the paper is organized as follows. Section 2 reviews the related work of rating prediction approaches. After that, our proposed method will be detailed in section 3, including the

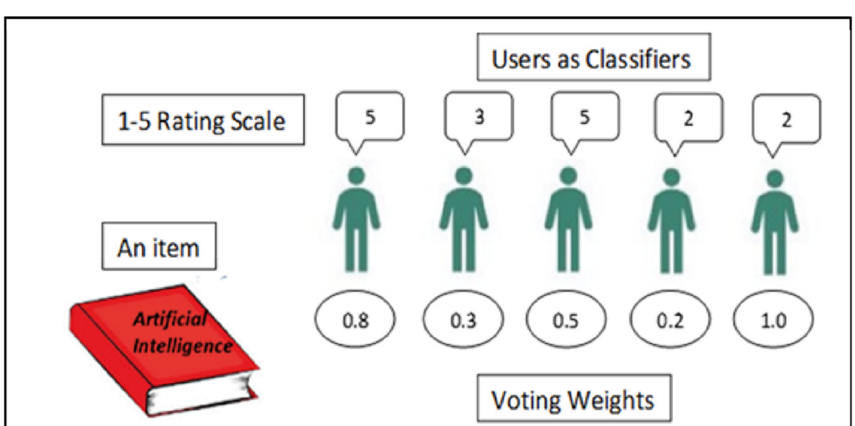

Fig. 1. The weighted voting technique.

description of notations and the structure scheme. Then, section 4 presents and discusses the experimental results on two real-world datasets to verify the accuracy of our rating prediction approach. Finally, the conclusion and future work are presented in section 5.

2. Related work

Most existing work on rating prediction algorithms has centered on solving the aforementioned sparsity and cold-start problems by using some available auxiliary information such as the scarce demographic or abundant social information. Thus, much trust-based research has been proposed in the literature to better recognize user preferences [20]. The authors in Ref. [21] have suggested an item recommendation model with the idea that the trusted network be utilized to show the users' social relations which have a significant influence on their tastes. The model enters the user's direct (explicit) trust with an adjustable similarity method to make a recommendation. However, the flaw in their work was that they did not take advantage of indirect implicit trust.

Additionally, it has been confirmed that the trust propagation feature can be productively applied to decrease prediction deviation, thus enhancing the prediction results. According to this, the social trust relationships and confidence evaluation of ratings have been used to return the most similar trusted neighbors, depending on the transitive property of the node (user) in the social trust graph. Then the results of the prediction can be computed through the merged ratings of trusted neighbors [22]. Moreover, the EIMerge approach was proposed in Ref. [23] to exploit explicit and implicit trust in order to reduce sparsity and cold-start by merging the ratings of the trusted neighbors after filtering them using the Pearson's Correlation Coefficient (PCC) as a trust similarity metric. As a result, a new user profile is formed to compute prediction via the classic CF approach. A similar approach (ITRA) is presented in Ref. [24] where the authors also utilize the implicit trust information of a trust relations network to enhance prediction accuracy. The first step is to aggregate the trust neighbors for every user in a set of users employing the trust expansion algorithm and then compute the trust similarity between the target user and every other user based on the collected candidate items and applying PCC. In the last step, a trust weighting approach is applied to boost the trust weight of the candidate users, which will contribute to the final prediction phase.

The last three approaches have given us the procedure to implement our idea. And since each of these methods has its advantages and disadvantages, in our approach we have benefited from the former and avoided the latter.

In this work, we conduct an election method with inspiration from the ensemble classifiers [25], in particular, the type of weighted voting. Moreover, we show the strength of mixing the original ratings and trust-elected ratings in terms of a rating prediction evaluation by involving a contribution weight in a linear combination process. Additionally, we take advantage of indirect implicit trust after computing it, reaching the three-step depth as the best choice to set beneficial information. PCC has also been used as the trust similarity metric [26] and the classic CF as the prediction function through the implementation of the K-Nearest Neighbors (KNN) algorithm by selecting the top K trusted neighbors [18].

3. Methodology

In this section, we explain our method in detail. It is worth noting that we follow the procedure used in Refs. [22,23], but by applying our weighted voting (election) method rather than the weighted average method for electing (i.e., merging) ratings. The basic idea is leveraging from the top K trusted neighbors of the social trust network by electing their ratings for an active user to boost his preference profile.

In particular, three methods shaped our methodology. The first method is the original rating prediction which includes preprocessing the rating matrix and then applying the CF prediction formula after calculating the rating similarity among users. The second method is called the trust-elected rating prediction, which includes multiple steps beginning with data preprocessing and ending with determining the reliability of the elected rating. Next, the values of trust rating similarity are incorporated to compute the prediction. This is further described in the following subsections. Lastly, there is a linear combination process using the results of the above two methods and a contribution weight to obtain the final rating prediction. Fig. 2 illustrates the general scheme.

3.1. Data preprocessing

After building the user-item rating matrix *R* from the rating file in the dataset, each null value *NAN* is converted to zero to avoid any subsequent failure in the calculations. It is worth mentioning that we

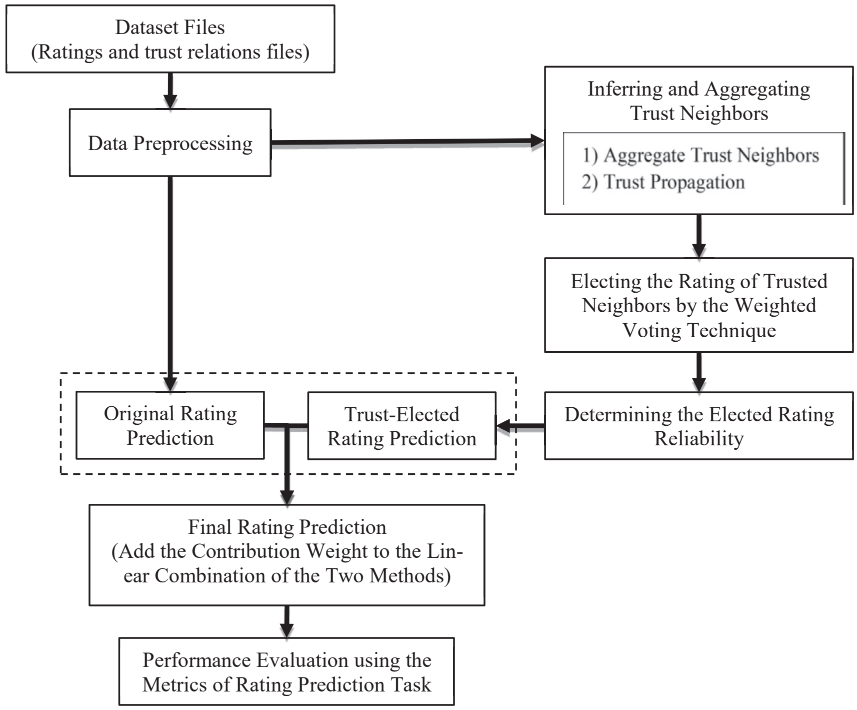

Fig. 2. Steps of the proposed method.

sampled a subset from the Epinions dataset by randomly selecting 1923 users who recorded 27,013 ratings on 4221 items. This was done because it was impossible to represent the rating matrix from the original numbers of users and items due to memory limitations on our local machine.

3.2. Inferring and aggregating trusted neighbors

The trust matrix is almost like the rating matrix in terms of sparsity since it is highly sparse as illustrated in Table 1. Thus, we need to infer and aggregate more implicit trust relations among users so as to define their trusted neighbors. To achieve this, two phases of this step are listed as follows:

a) Inferring trust relations with PCC

Inspired by Papagiles et al. [27], who used the very common PCC as a similarity measure to identify implicitly trusted neighbors for an active user, the PCC calculation formula is as follows:

$$\mathrm{rsim}_{u,v} = \frac{\sum_{i\in I_{u,v}}(r_{u,i}-\bar{r}_u)(r_{v,i}-\bar{r}_v)}{\sqrt{\sum_{i\in I_{u,v}}(r_{u,i}-\bar{r}_u)^2}\sqrt{\sum_{i\in I_{u,v}}(r_{v,i}-\bar{r}_v)^2}} \tag{1}$$

where $rsim_{u,v}$ is the original similarity value between user u and user v, and $r_{u,i}$, $r_{v,i}$ are the actual rating of u and v on an item i. $\bar{r}_u$, $\bar{r}_v$ are the average of ratings belonging to u and v respectively, and $I_{u,v}$ are the co-rated items of both u and v. In order to provide the asymmetric property of the inferred trust relations, we calculated the value of common items set related to the target user. We then combined it with the result of Equation (1) to obtain the average value between them as shown in the following two equations:

$$\mathrm{CIS}_{u,v} = \frac{|I_u \cap I_v|}{|I_u|} \tag{2}$$

$$\mathrm{Rsim}_{u,v} = \frac{(\mathrm{rsim}_{u,v} + \mathrm{CIS}_{u,v})}{2} \tag{3}$$

Table 1. Datasets information.

Datasets	#Users	#Items	#Ratings	#Trust	Rating Sparsity	Trust Sparsity	Average Rating
FilmTrust	1508	2071	35497	1853	98.86%	99.58%	23.53
Epinions	49 K	139 K	664 K	487 K	99.98%	99.97%	16.55
Sampled Epinions	1923	4221	27013	250888	99.66%	99.60%	14.04

where $CIS_{u,v}$ is the set of common items between user u and user v, and I_u, I_v are the set of items that are rated by both users respectively. $Rsim_{u,v}$ is the overall similarity value between the two respective users. According to Ref. [28], the rating similarity threshold was determined ($\theta_{Rsim} = 0.707$) to infer the trust relations between trust network users. Therefore, this value is used as the trust value; otherwise, it will be zero as shown in Equation (4). Moreover, the minimum number of co-rated items between two users should be greater than another threshold which is set as ($\theta_{I_{u,v}} = 2$) depending on [28]. The formula of the inferred (implicit) trust value is as follows:

$$T_{INF_{u,v}} = \begin{cases} Rsim_{u,v}, \text{if } Rsim_{u,v} > \theta_{Rsim} \text{ and } |I_{u,v}| > \theta_{I_{u,v}} \\ 0, \text{otherwise} \end{cases} \tag{4}$$

where $T_{INF_{u,v}}$ is the inferred (implicit) trust degree of user u in user v, and $|I_{u,v}|$ is the number of the co-rated items of both u and v. $\theta_{Rsim}, \theta_{I_{u,v}}$ are the rating similarity threshold and the rating number threshold respectively.

b) Trust propagation

In this phase, the aim is to find the indirectly trusted neighbors by diffusing trust in the network of trust, depending on the transitive property of the trust theory. This results in additional valuable information that can be utilized to improve the recommendation. However, going deeper to propagate inside the trust relations network is not likely to provide significant information. According to our experiment, the best gain is in adopting 3-step propagation to avoid meaningless exploration and useless consumption, especially when dealing with a large-scale dataset (e.g., Epinions) as shown in Equation (5). The indirect (implicit) trust relation can be inferred between any two users in the trust relations network. The implicit trust value is inversely proportional to their shortest distance. This can be calculated using the breadth-first search algorithm. The propagated (implicit) trust degree ($T_{Prop_{u,v}}$) is computed as follows [29]:

$$T_{Prop_{u,v}} = \frac{1}{sd_{u,v}}, |sd_{u,v}| \le 3 \tag{5}$$

where $sd_{u,v}$ is the shortest distance between u and v, and $T_{Prop_{u,v}} \in [0, 1]$. From now on, we use the symbol $T_{u,v}$ to denote each occurrence of the explicit trust given in the dataset and both implied trusts that we called the inferred ($T_{INF_{u,v}}$) and the propagated ($T_{Prop_{u,v}}$) obtained from Equations (4) and (5). In fact, any user trusted by another with a trust value ($T_{u,v}$) more than a pre-defined threshold ($\theta_{T_{u,v}} = 1/4$) is regarded as a trusted neighbor.

$$TN_u = \{v \mid T_{u,v} > \theta_{T_{u,v}}, v \in U\} \tag{6}$$

The trusted neighbors of user u in the network of users U are TN_u, with $\theta_{T_{u,v}}$ referring to the trust threshold which is set based on the 3-step trust propagation process.

3.3. Electing the rating of trusted neighbors

The ratings of trusted neighbors are elected as a single value on some items j that an active user u did not rate. These $j \in I'_u$ are rated at least by one trusted neighbor (i.e., I'_u are the items that are not rated by a target user). Therefore, the voting weight of a trusted neighbor that represents the relationship degree with the active user must be accumulated to achieve the election process. In addition to the rating similarity ($rsim_{u,v}$) and trust value ($T_{u,v}$), which are calculated in Equations (1), (4) and (5), the factor of social confidence is required to obtain the voting weight, as suggested in Ref. [30]. It represents the indicator of the users' trustworthiness in relation to each other. It is calculated as the ratio of common users similar to the target user, as in the following equation:

$$SC_{u,v} = \begin{cases} \dfrac{|TN_u \cap TN_v|}{|TN_u|}, \text{if } |TN_u| > 0 \\ 0, \qquad \text{otherwise} \end{cases} \tag{7}$$

where $SC_{u,v}$ is the social confidence between the two users u, v and its range is in $[0, 1]$. Hence, a linear combination of the three factors with parameters α, β, and Y needs to obtain the voting weight $vw_{u,v}$ between an active user u and every trusted neighbor v, as follows:

$$vw_{u,v} = \alpha \,.\, T_{u,v} + \beta \,.rsim_{u,v} + Y \,.\, SC_{u,v} \tag{8}$$

where α, β, and Y represent how much each factor contributes to the linear combination. These constants are tuned according to our experiments. Their values (α, β, Y) are set to 0.5, 0.3, 0.2 on FilmTrust and 0.7, 0.2, 0.1 on Epinions respectively. It is important to involve all three factors ($rsim_{u,v}$, $T_{u,v}$, $SC_{u,v}$) instead of just only trust value to have a significant influence on prediction results and to avoid tie votes. Moreover, it is worth mentioning that only the positive rating similarity $rsim_{u,v} > 0$ was considered in the formula above.

After saving the voting weight between every active user and his/her trusted neighbors for every rating r in the rating scale, the single elected value can be selected as the rating r that is associated with the maximum voting weight:

$$\tilde{r}_{u,j} = r_{\underset{j}{\arg\max} \sum_{v}^{TN_u} vw_{u,v}^{j}} \tag{9}$$

where $\tilde{r}_{u,j}$ is the elected rating of an active user u on an item $j \in I_u'$, and $vw_{u,v}^{j}$ is the voting weight on the item j of every trusted neighbor v that belongs to TN_u.

3.4. Determining the elected rating reliability

For the purpose of approbating the elected ratings, the rating reliability must be computed to ensure the certainty of these ratings. This is computed according to Ref. [31], where it can be defined as the system certainty in the elected rating. Basically, two factors are necessary to obtain the rating reliability. First is the maximum voting weight that is involved in choosing the elected rating. Second is all voting weight values associated with each rating value in the rating scale. The notion of reliability is that the less reliable an elected value is, the more liable it is to be inaccurate. According to Ref. [31], the reliable value $RL_{u,j}$ of the elected rating $\tilde{r}_{u,j}$ of the active user's unknown items $j \in I_u'$ can be computed as follows:

$$RL_{u,j} = \frac{\max\left(vw_{u,v}^{j}\right)}{\sum_{r\ \in scale} vw_{u,v}^{j}}, \forall v \in TN_u \tag{10}$$

where $RL_{u,j}$ is the rating reliability of the elected rating $\tilde{r}_{u,j}$ on an item $j \in I_u'$. It is in the interval $[0,1]$. Further, *scale* is the rating range, which is $[1-5]$ in Epinions and $[0.5-4]$ in FilmTrust. Regarding the actual ratings, their reliability will be the highest $RL_{u,i} = 1$ for all items $i \in I_u$.

3.5. Linear combination of two prediction methods

By the end of the election process, every item $i \in I$ will be associated with two values, actual $r_{u,i}$ or elected $\tilde{r}_{u,i}$ rating and identical reliability $RL_{u,j}$. Thus, a new preference profile is provided for every user $u \in U$. Depending on this new profile, the user-based CF algorithm can be applied for prediction ratings. Therefore, two steps are conducted next. Firstly, the trust similarity among users is calculated in terms of the reliable Pearson Correlation Coefficient (RPCC) which is the same version of PCC in addition to incorporating the rating reliability value so as to reduce the impact of less reliable elected ratings. The RPCC formula is:

$$Tsim_{u,v} = \frac{\sum_{i \in I_{u,v}} RL_{u,i}\left(\tilde{r}_{u,i} - \bar{r}_u\right)\left(r_{v,i} - \bar{r}_v\right)}{\sqrt{\sum_{i \in I_{u,v}} RL_{u,i}^2\left(\tilde{r}_{u,i} - \bar{r}_u\right)^2}\sqrt{\sum_{i \in I_{u,v}}\left(r_{v,i} - \bar{r}_v\right)^2}} \tag{11}$$

where $Tsim_{u,v} \in [-1,1]$ denotes the trust similarity between u and v. It is important to note that $Tsim_{u,u} = 1$ due to the user u being part of his trusted neighbors TN_u. A trust similarity threshold ($\theta_{Tsim_{u,v}} = 0$) can be set to filter in only the positive relations among users. The filtered users are then added to the group of nearest neighbors NN_u.

$$NN_u = \left\{v \mid Tsim_{u,v} > \theta_{Tsim_{u,v}}, v \in U\right\} \tag{12}$$

It is noteworthy that we have selected the top-K method to determine the neighborhood, which is optimal at K = 25, as selected in the ITRA model [24]. Secondly, the prediction of unrated items can be computed by collecting all the ratings of u nearest neighbors NN_u on the target item j and multiplying it by their trust similarity with the active user. The similarity weight assures more influence for the most like-minded neighbors to the active user. The CF prediction formula is as follows:

$$\bar{r}_{u,j} = \bar{r}_u + \frac{\sum_{v \in NN_u} Tsim_{u,v}\left(r_{v,j} - \bar{r}_v\right)}{\sum_{v \in NN_u}\left|Tsim_{u,v}\right|} \tag{13}$$

where $\bar{r}_{u,j}$ refers to the predicted value of the unrated item j obtained from the trust similarity. In order to answer the second research question, we include an examination of the impact of mixing original ratings and trust-elected ones on the CF prediction outcome. Therefore, in addition to the above method based on trust similarity, we present a method that depends only on the original rating similarity. This is calculated using Equation (1) and repeating Equations (12) and (13) by replacing trust similarity $Tsim_{u,v}$ with the original rating similarity $rsim_{u,v}$ to obtain the prediction result $\bar{\bar{r}}_{u,j}$ from them. Then, we linearly combine the results of the two methods by incorporating a contribution weight CW ranging from 0 to 1 and observing the results to set the appropriate weight that gives the best possible prediction and coverage, as follows:

$$\hat{r}_{u,j}=\begin{cases}\bar{r}_{u,j}.(1-CW)+\bar{\bar{r}}_{u,j}.CW, \text{if} \bar{r}_{u,j}>0 \text{and} \bar{\bar{r}}_{u,j}>0\\ \bar{\bar{r}}_{u,j}, \text{if} \bar{r}_{u,j}=0 \text{and} \bar{\bar{r}}_{u,j}>0\\ \bar{r}_{u,j}, \text{if} \bar{\bar{r}}_{u,j}=0 \text{and} \bar{r}_{u,j}>0\\ 0, \text{otherwise}\end{cases} \quad (14)$$

where $\hat{r}_{u,j}$ refers to the final predicted value of the unrated item j after involving the two prediction results $\bar{r}_{u,j}$ and $\bar{\bar{r}}_{u,j}$. These are the predicted values obtained from the trust and original rating similarities respectively. We note from the above equation that if one of the two outcomes is greater than zero, it is taken in full without adding the contribution weight to it. However, when they are not available (both are zero), the last result will be zero.

4. Experimental evaluation

We conducted our experiments to verify the outcomes of the proposed approach on two real-world datasets, namely FilmTrust and Epinions. Four popular metrics (MAE, RMSE, Rating Coverage and F-measure) were used to evaluate the results of the proposed approach against the other compared methods. Our aim was to discover how the linear combination of the two prediction methods with their contribution weight can improve prediction accuracy and coverage in addition to the position of our proposed approach compared with its counterparts.

Two datasets (FilmTrust and Epinions) were obtained for the experiment and for evaluation purposes. In addition to the rating information contained in these datasets, explicit trust relations were found as additional information. The statistics of these datasets are summarized in Table 1. It is worth mentioning that our experiments were conducted on a 64-bit OS Windows 10 Pro, Intel® Core™ i3-3120M CPU 2.50 GHz, 4.00 GB of RAM (3.82 GB useable) computer. This is why, due to RAM limitations, we randomly sampled from the large-scale Epinions dataset.

In order to evaluate the prediction accuracy of our approach, three methods (Merge, EIMerge, and ITRA) were selected that utilized the "merge" mechanism of rating in their implementation and applied to the same datasets (FilmTrust and Epinions). These methods are compared with our proposed approach.

4.1. Evaluation metrics

For the purpose of assessing the performance of our proposed approach, the major metrics were derived from the comparable models for a fair comparison with them. Two commonly used measures, namely MAE and RMSE, are used to accumulate the errors between the estimated and actual ratings for all testing data. The third important metric, called RC, is used to compute the prediction coverage proportion. The fourth was introduced because both coverage and accuracy (the inverse of error) are two essential metrics to measure the overall productivity of a model. These can be represented together through an aggregate measure. According to Ref. [22], F1 is a measure that takes into account both coverage and accuracy to assess the overall performance in a balanced manner. It is calculated as follows:

$$F1=\frac{2\ .\ iMAE\ .\ RC}{iMAE+RC} \quad (15)$$

where *iMAE* is defined as the inverse *MAE* as formulated in Ref. [22], which is the accuracy of prediction normalized by the maximum and minimum numbers in the rating scale. Accuracy is better when the *iMAE* values are higher.

$$iMAE=1-\frac{MAE}{r_{max}-r_{min}} \quad (16)$$

4.2. Results and discussions

In this section, we performed extensive experiments to show the efficiency of our approach in comparison to similar approaches in answering the research questions with which every experiment began. The analysis process and detailed findings are presented below.

A. Final prediction result based on contribution weight (*CW*)

The main step for the final rating prediction is to calculate the results of the two methods. These depended on the nearest neighbors NN_u with their trust and original rating similarity values ($Tsim_{u,v}$ and $rsim_{u,v}$). The values mentioned are both obtained from Equations (11) and (1) respectively. Their results, however, are separately computed with Equation (13) to obtain $\bar{r}_{u,j}$ and $\bar{\bar{r}}_{u,j}$). This process is done by using an important parameter (viz., contribution weight) in their linear combination (refer to Equation (14)). Our idea involves an examination of the impact of mixing the original and trust-elected ratings on the final prediction outcome. According to this notion, we vary the contribution weight values from 0 to 1 in increments of 0.1, as shown in Fig. 3.

Through our experiments, it was concluded that the optimal value of the contribution weight is 0.9 and 1 on FilmTrust and Epinions respectively. This means the larger this weight, the more accurate the results and vice versa. In this situation, the final prediction outcome $\hat{r}_{u,j}$ will be dependent to a large extent on the result of the original rating method $\bar{\bar{r}}_{u,j}$ (refer to Equation (14)). Yet, if this is not available, the result of the trust-elected rating method $\bar{r}_{u,j}$ is taken.

The final prediction results follow the same pattern when applied to both datasets. In terms of all measures, the best result is obtained when the contribution weight value is high (viz., 0.9 or 1), as the F1 values shown in Fig. 3.

The high weight values, see the first part of Equation (14), indicate that the original (pure) ratings have a significant role in calculating the final prediction value $\hat{r}_{u,j}$. The matter is logical given that they were placed explicitly and spontaneously by the user (i.e., they were not implicitly inferred). This clarifies the high accuracy of pure rating in the combination process as it has contributed the largest share (viz., 0.9 of the value). Trust-elected ratings, nonetheless, play an influential role in supporting the original ratings, albeit with a small ratio contribution within the combination process. Still, they are very important to increase the coverage and accuracy of the prediction.

In case of inability to calculate one of the two methods' predictions ($\bar{r}_{u,j}$, $\bar{\bar{r}}_{u,j}$) owing to the sparse nature of the rating and trust relations matrices, the available prediction value is taken as shown in the second and third parts of Equation (14). This is another reason why to rely significantly on the original ratings when there are no trust-elected ones or to depend entirely on the latter to compensate for the absence of the former. This leads to an increase in the coverage and accuracy of the final prediction, which reflects positively on the overall performance.

Indeed, mixing the prediction result of original and trust-elected ratings by linearly combining them using the optimal value of contribution weight could increase the coverage and accuracy of the final estimated value $\hat{r}_{u,j}$. This superiority is attributed to how we formulate Equation (14), which takes the available results of the two methods to calculate the final prediction values. Figs. 4 and 5 illustrate the rating coverage ratios of our approach versus the comparison methods on both datasets.

According to Figs. 4 and 5, we note the dominance of our proposed approach in covering predictions compared to the other methods mentioned in the next section. A confirmation of the foregoing clear statement on the importance of the predictions elected by trust in raising this pivotal coverage metric and the overall F-measure as shown in Table 2.

In the end, through this section, the second research question is answered. It is related to confirming the support of the trust-elected ratings to the original ones. Thus, the rating coverage of

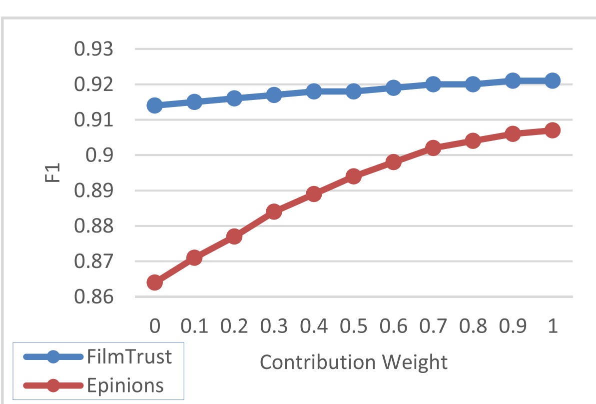

Fig. 3. The contribution weight experiment.

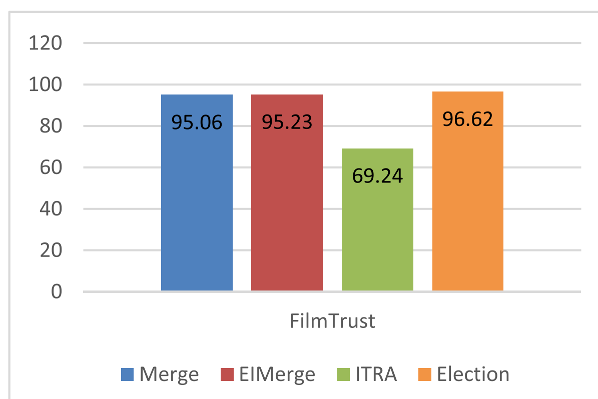

Fig. 4. The rating coverage ratios on FilmTrust.

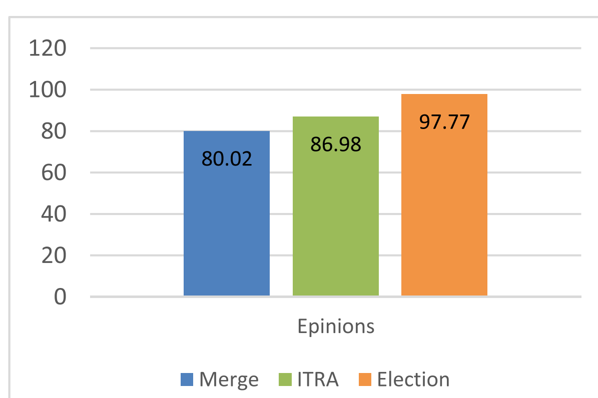

Fig. 5. The rating coverage ratios on epinions.

Table 2. The predictive results on FilmTrust and Epinions datasets.

Datasets	Metrics	Methods			
		Merge [22]	EIMerge [23]	ITRA [24]	Election
FilmTrust	MAE	0.708	0.6819	0.9050	**0.4191**
	RMSE	N/A	N/A	1.0756	**0.5916**
	RC (%)	95.06	95.23	69.24	**96.62**
	F1	0.8674	0.8726	0.7160	**0.9212**
Epinions	MAE	0.820	N/A	0.7181	**0.6181**
	RMSE	N/A	N/A	**0.8200**	0.8362
	RC (%)	80.02	N/A	86.98	**97.77**
	F1	0.7976	N/A	0.8444	**0.9068**

predictions is improved in addition to maintaining their accuracy at a high level.

B. Comparison with other methods

For all the previously mentioned comparable methods, we recorded the available results on two datasets (FilmTrust and Epinions) as found in their respective papers [22–24] and as illustrated in Table 2.

In this section, we will illustrate our findings using the weighted voting technique on both datasets used. We return to section 3.3, which explains Equation (8) that calculates the most crucial factor in this technique, namely, the voting weight $vw_{u,v}$. In order to describe the effect of this weight on the results of our proposed approach in the two datasets as shown in the last column of Table 2, we consider the proportions of parameters (α, β, Y), which participated in the voting weight calculation.

With a deep look at Equation (8), we notice that the α value associated with the value of the trust relation increased from 0.5 in FilmTrust to 0.7 in Epinions. This indicates that the trust network density of users in Epinions is larger than that in FilmTrust. It positively led to a rise in the prediction coverage of the second group in Table 2 (see the RC metric). Conversely, the β value associated with the value of the original rating decreased from 0.3 in FilmTrust to 0.2 in Epinions. Looking at Table 1, we see that the average rating in FilmTrust is greater than the sampled Epinions. This indicates that the rating density of the original matrix in the former dataset is greater than that in the latter. It results in an increase in the prediction accuracy of the first group in Table 2 (see MAE and RMSE metrics).

The diversity of the parameters' values (α, β), which assisted in calculating the voting weight to be compatible with the characteristics of each dataset, showed a clear advance in our proposed approach represented by the F1 values (see Table 2) obtained from the accuracy and coverage metrics (refer to Equation (15)).

According to Table 2, the ITRA model was the worst on FilmTrust in terms of all metrics. Similarly, the Merge method had the worst performance on Epinions based on only MAE and RC (because the RMSE metric was not included in their evaluation). This explains why the two methods did not benefit from the step of aggregating trust relations (refer to section 3.2 (a)) before the trust propagation step, which would expand the pool of users who might be candidates to contribute their ratings to the "merge" process within the rating matrix. Differently, the trust aggregation step is utilized by our approach and the EIMerge method, which obviously shows their superiority in both data sets (see Table 2).

The EIMerge method was tested only on FilmTrust and achieved better accuracy (MAE) relative to the other comparison methods. Yet, it is still behind our approach as the second best, although it exploits the trust aggregation step. The superiority of our approach is due to reaching the 3-step propagation of trust relations. On the other hand, they were propagated by 1-step or 2-step within the EIMerge. Moreover, the most prominent reason is to alternate the weighted average technique with the election by weighted voting. This would get rid of the redundant details of error between the computed prediction and the actual one.

According to Figs. 4 and 5, the rating coverage of our approach is better than the comparison methods on both datasets. Uniquely, we leveraged any prediction available in both the original and trust-elected ratings (refer to Equation (14)), which justifies this coverage vantage by affirming the positive support of the trust-elected ratings to the original ones.

Our approach and ITRA were the only two approaches that considered the RMSE in their experiments. Thus, depending on this metric, the performance was competitive between them on both datasets. Specifically, our approach outperforms on FilmTrust. In contrast, ITRA had a slightly better RMSE value on Epinions compared to our approach. This slight regression of our approach is due to two things. The first is that we relied on a sample Epinions dataset, which may have affected the distribution of the original ratings. The second, which is a more convincing one, is that our approach achieved a coverage rate much higher than that achieved by the ITRA model. Subsequently, our approach is totally better in terms of the F1 measure (see Table 3). It is worth noting that for the purpose of comparison, we calculated the value of the F1 measure for the ITRA model as it is not available in their research.

According to the results shown in Table 2, our approach has outstanding prediction outcomes in

Table 3. The improvements of our approach compared to the other methods in F1 measure.

Datasets	Metric	Comparison Methods		
		Merge	EIMerge	ITRA
FilmTrust	F1 (%)	5.38	4.86	20.51
Epinions	F1 (%)	10.92	N/A	6.24

both datasets except for the RMSE metric on Epinions, which is already justified above. Nevertheless, our approach consistently outperforms the ITRA model in both datasets. In particular, our MAE value was better since we used the weighted voting technique as an alternative to the weighted average. Another reason is the formulation of Equation (14) that utilized any prediction available in both the original and trust-elected ratings. Thus, our RC value was excellent. As a result, the F1 value of our approach is highly improved compared to the ITRA model.

For a better look at the overall improvement that our approach achieves, we further calculate the improvement ratios that our approach makes compared to the comparison methods in terms of the F1 measure, as illustrated in Table 3. The improvement values on each dataset were obtained by subtracting the F1 values of our approach from the F1 values of other methods. The more positive the difference between our approach and the other methods, the more improvements we made.

Eventually, in this section, the first research question is answered. It is related to the ability of our proposed method (the election by weighted voting) to give a better result as displayed in Table 3. Such results justify the preference for using the weighted voting technique over the weighted average one.

5. Conclusions

In this work, we took advantage of several successful functions used in the latest CF methods and implemented the election by weighted voting. In particular, the process of eliciting implicit trust by adopting trust propagation has considerably helped to reduce the sparsity problem. Indeed, our method, which elects ratings to enrich users' preference profiles, greatly assists in decreasing the noise of the weighted average technique used mostly in CF methods. Additionally, we calculate the reliability of elected values with RPCC, which contributes to more balanced results. Finally, we found that mixing the methods of original and trust-elected ratings contributes positively to extending the prediction coverage and increases its accuracy due to how we formulated Equation (14), which takes the available results of the two methods to calculate the final prediction.

Extensive experiments were conducted on two real-world datasets, which showed that our proposed approach outperformed all comparable algorithms in terms of coverage and accuracy. As a future direction, we intend to develop our approach by exploiting the other properties of trust theory, namely dynamic trust and context dependence. These aspects might provide the system with more trustworthy neighbors, thus improving the prediction accuracy of RSs.

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References

[1] C. Zhang, M. Yang, J. Lv, W. Yang, An improved hybrid collaborative filtering algorithm based on tags and time factor, Big Data Min. Anal. 1 (2018) 128−136, https://doi.org/10.26599/BDMA.2018.9020012.

[2] S. Forouzandeh, M. Rostami, K. Berahmand, Presentation A trust walker for rating prediction in recommender system with biased random walk: effects of H-index centrality, similarity in items and friends, Eng. Appl. Artif. Intell. 104 (2021) 104325, https://doi.org/10.1016/j.engappai.2021.104325.

[3] S.M. Ali, G.K. Nayak, R.K. Lenka, R.K. Barik, Movie recommendation system using genome tags and content-based filtering, in: M. Kolhe, M. Trivedi, S. Tiwari, V. Singh, eds., Lecture Notes in Networks and Systems, Springer, Singapore. 2018, pp. 85−94.

[4] L. Jiang, L. Liu, J. Yao, L. Shi, A hybrid recommendation model in social media based on deep emotion analysis and multi-source view fusion, J. Cloud Comput. 9 (2020) 1−16, https://doi.org/10.1186/s13677-020-00199-2.

[5] W. Shafqat, Y.C. Byun, A hybrid GAN-based approach to solve imbalanced data problem in recommendation systems, IEEE Access 10 (2022) 11036−11047, https://doi.org/10.1109/ACCESS.2022.3141776.

[6] A. Pal, P. Parhi, M. Aggarwal, An improved content based collaborative filtering algorithm for movie recommendations, in: 2017 Tenth Int. Conf. Contemp. Comput. (IC3), IEEE. 2017, pp. 1−3, https://doi.org/10.1109/IC3.2017.8284357.

[7] T. Widiyaningtyas, I. Hidayah, T.B. Adji, User profile correlation-based similarity (UPCSim) algorithm in movie recommendation system, J. Big Data 8 (2021) 1−21, https://doi.org/10.1186/s40537-021-00425-x.

[8] A.M. Ahmed Al-Sabaawi, H. Karacan, Y.E. Yenice, Exploiting implicit social relationships via dimension reduction to improve recommendation system performance, PLoS One 15 (2020) 1−18, https://doi.org/10.1371/journal.pone.0231457.

[9] A.M.A. Al-Sabaawi, H. Karacan, Y.E. Yenice, A novel overlapping method to alleviate the cold-start problem in recommendation systems, Int. J. Softw. Eng. Knowl. Eng. 31 (2021) 1277−1297, https://doi.org/10.1142/S0218194021500418.

[10] H. Koohi, K. Kiani, A new method to find neighbor users that improves the performance of collaborative filtering, Expert Syst. Appl. 83 (2017) 30−39, https://doi.org/10.1016/j.eswa.2017.04.027.

[11] M. Hasan, F. Roy, An item−item collaborative filtering recommender system using trust and genre to address the cold-start problem, big data cogn, Comput 3 (2019) 1−15, https://doi.org/10.3390/bdcc3030039.
[12] M.H. Hussein, A.A. Alsakaa, H.A. Marhoon, Adopting explicit and implicit social relations by SVD++ for recommendation system improvement, Telkom. Telecommun. Comput. Electron. Contr. 19 (2021) 471−478, https://doi.org/10.12928/TELKOMNIKA.v19i2.18149.
[13] Q. Shambour, J. Lu, An effective recommender system by unifying user and item trust information for B2B applications, J. Comput. Syst. Sci. 81 (2015) 1110−1126, https://doi.org/10.1016/j.jcss.2014.12.029.
[14] M.H. Hussein, W.S. Bhaya, H.N. Nawaf, Exploiting Social Influence for Recommendation System Improvement, Doctoral dissertation, University of Babylon. 2017.
[15] Y. Wu, H. Cao, G. Yang, T. Lu, S. Wan, Digital twin of intelligent small surface defect detection with cyber-manufacturing systems, ACM Trans. Internet Technol. (2022), https://doi.org/10.1145/3571734 in press.
[16] A.M.A. Al-Sabaawi, H. Karacan, Y.E. Yenice, SVD++ and clustering approaches to alleviating the cold-start problem for recommendation systems, Int. J. Innov. Comput. Inf. Control. 17 (2021) 383−396, https://doi.org/10.24507/ijicic.17.02.383.
[17] M.H. Hussein, W.S. Bhaya, H.N. Nawaf, Exploiting the shared neighborhood to improve the quality of social community detection, in: 2017 Annu. Conf. New Trends Inf. Commun. Technol. Appl. (NTICT),, IEEE. 2017, pp. 52−56, https://doi.org/10.1109/NTICT.2017.7976121.
[18] J. Bobadilla, F. Ortega, A. Hernando, A. Gutiérrez, Recommender Systems Survey, Knowledge-Based Syst. 46, 2013, pp. 109−132, https://doi.org/10.1016/j.knosys.2013.03.012.
[19] J. Shokeen, C. Rana, A trust and semantic based approach for social recommendation, J. Ambient Intell. Humaniz. Comput. 12 (2021) 10289−10303, https://doi.org/10.1007/s12652-020-02806-1.
[20] F. Roy, M. Hasan, Comparative analysis of different trust metrics of user-user trust-based recommender system, Comp. Sci. 23 (2022) 337−375, https://doi.org/10.7494/csci.2022.23.3.4227.
[21] G. Guo, J. Zhang, F. Zhu, X. Wang, Factored similarity models with social trust for top-N item recommendation, Knowl. Base Syst. 122 (2017) 17−25, https://doi.org/10.1016/j.knosys.2017.01.027.
[22] G. Guo, J. Zhang, D. Thalmann, Merging trust in collaborative filtering to alleviate data sparsity and cold start, Knowl. Base Syst. 57 (2014) 57−68, https://doi.org/10.1016/j.knosys.2013.12.007.
[23] H. Zhao, Y. Zhang, Y. Xiao, A new collaborative filtering algorithm with combination of explicit trust and implicit trust, in: 2018 13th Int. Conf. Comput. Sci. Educ. (ICCSE), IEEE. 2018, pp. 1−5, https://doi.org/10.1109/ICCSE.2018.8468763.
[24] Y. Li, J. Liu, J. Ren, Y. Chang, A novel implicit trust recommendation approach for rating prediction, IEEE Access 8 (2020) 98305−98315, https://doi.org/10.1109/ACCESS.2020.2997040.
[25] Z.H. Zhou, Ensemble Methods: Foundations and Algorithms, first ed., Chapman and Hall/CRC, New York. 2012.
[26] Y. Mu, X. Liu, L. Wang, A Pearson's correlation coefficient based decision tree and its parallel implementation, Inf. Sci. 435 (2018) 40−58, https://doi.org/10.1016/j.ins.2017.12.059.
[27] M. Papagelis, D. Plexousakis, T. Kutsuras, Alleviating the sparsity problem of collaborative filtering using trust inferences, in: P. Herrmann, V. Issarny, S. Shiu, eds., Lecture Notes in Computer Science, Springer, Berlin, Heidelberg. 2005, pp. 224−239.
[28] A.E. Castro Sotos, S. Vanhoof, W. van den Noortgate, P. Onghena, The transitivity misconception of Pearson's correlation coefficient, Stat. Educ. Res. J. 8 (2009) 33−55, https://doi.org/10.52041/serj.v8i2.394.
[29] B. Pal, M. Jenamani, Trust inference using implicit influence and projected user network for item recommendation, J. Intell. Inf. Syst. 52 (2019) 425−450, https://doi.org/10.1007/s10844-018-0537-0.
[30] R. Barzegar Nozari, H. Koohi, Novel implicit-trust-network-based recommendation methodology, Expert Syst. Appl. 186 (2021) 115709, https://doi.org/10.1016/j.eswa.2021.115709.
[31] P. Valdiviezo Diaz, F. Ortega, E. Cobos, R. Lara Cabrera, A collaborative filtering approach based on naïve bayes classifier, IEEE Access 7 (2019) 108581−108592, https://doi.org/10.1109/ACCESS.2019.2933048.