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A Novel Implicit Trust Recommendation Approach for Rating Prediction

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ABSTRACT Rating predictions, as an application that is widely used in recommender systems, have gradually become a valuable way which can help user narrow down their choices quickly and make wise decisions from the vast amount of information. However, most existing collaborative recommendation models suffer from poor accuracy due to data sparsity and cold start problems that recommender systems contain only a few explicit data. To solve this problem, a new implicit trust recommendation approach (ITRA) is proposed to generate item rating prediction by mining and utilizing user implicit information in recommender systems. Specifically, user trust neighbor set that has similar preference and taste with a target user is first obtained by trust expansion strategy via user trust diffusion features in a trust network. Then, the trust ratings mined from user trust neighbors are used to compute trust similarity among users based on user collaborative filtering model. Finally, using the above filtered trust ratings and user trust similarity, the prediction results are generated by a trust weighting method. In addition, the empirical experiments are conducted on three real-world datasets, and the results demonstrate that our rating prediction model has obvious advantages over the state-of-the-art comparison methods in terms of the accuracy of recommendations.

INDEX TERMS Rating prediction, recommender systems, data sparsity, implicit trust, collaborative filtering.

I. INTRODUCTION

Which country is more likely to win the 2022 World Cup in Qatar? How the ESPN (Entertainment and Sports Programming Network) basketball columns push news to Internet users? What features should be considered by e-commerce systems to recommend items based on user needs? All these online services are inseparable from recommendation systems [1]–[3], which have greatly enriched user experience.

In the era of big data, how to push items or products accurately is the focus of academic research. However, information overload has become an increasingly serious Internet problem [4]. Irrelevant and redundant information interferes with the users' choices and impedes them to target the information that they need [5]. An effective way to resolve these problems is the intelligent recommendation, which helps users push news, movies, online goods based on their needs and interests. In addition, online recommendation systems can not only provide personalized services to users, but also build long-term trust relationships with active users.

Now as one of the most classic and focused approaches in recommender systems, Collaborative Filtering models [6] can help users choose the right services and products based on their preferences and habits. They generally adopt neighborhood or decomposition algorithms, and take advantage of user historical rating profile to calculate the similarity among users or items. Then, the preferences of a target user are modeled by using the weighting evaluation model of user near neighbors, and the algorithms predict the final recommendation results. However, a key issue is that these models suffer from data sparsity and cold start problems that users only rate a small number of products [7]–[9], and those rating matrices in recommendation systems are also very sparse. Furthermore, in some cases it is easy for item rating prediction to ignore the implicit transitivity of social users, resulting in poor recommendations. For example, in a social network user u_1 can directly connect to user u_2, and user u_2 can directly connect to user u_3. Nevertheless, since u_1 and u_3 rarely rate the common items, the collaborative filtering

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algorithm believes that the two users are not in contact. Therefore, many similar users and their potential preferences are difficult to find and obtain.

To alleviate these problems and improve rating prediction accuracy, many other prediction models have been proposed, including association rule-based models [10], content-based models [11], and knowledge-based models [12]. However, the above models are only applied from a static perspective to profiling user needs and hard to obtain a high-quality prediction framework for item predictions. In addition, some data analysis methods derived from deep learning are applied to the collaborative recommendation frameworks such as, Bayesian classification [13], Feature augmentation [14], and Matrix filling [15]. However, better recommendation performance cannot be achieved. Furthermore, though some recent trust methods which mainly utilize user explicit trust have been also proposed, the final prediction results are not worth relying on.

In our paper, we present a novel rating prediction approach based on implicit trust, which is regarded as users' opinion toward others in providing available trust ratings and profiling the preferences of target users. The task of the proposed prediction model is to improve the rating accuracy of recommendations and to alleviate sparse data and cold start problems. In detail, the target user's trusted neighbors are first explored and obtained through trust expansion algorithm. Then, a trust weighting approach is designed to compute trust similarity among users based on the filtered item set and Pearson Correlation Coefficient (PCC) [16], [17]. In addition to trusting neighbors' ratings, the ratings of respective items among users are also collected to locate the preferences of the target user and to find similar user communities. Finally, the recommendation items are predicted by integrating user trust similarity into the classic collaborative filtering model. The experiments on several datasets are conducted to demonstrate the performance of the proposed model in terms of rating accuracy, and the results also show that our algorithm has achieved the competitive performance compared with other comparison algorithms. The main contribution of the paper is as follows.

1) A novel trust expansion strategy that generates user's trusted neighbor set to provide more available ratings for the following recommendations. This method aggregates more user neighbors to explore the positive impact on rating prediction.

2) A new implicit trust recommendation algorithm for combining trust similarity and implicit trust value in trust network scenarios. More implicit information is mined and utilized to improve the accuracy of rating predictions and alleviate sparse data problem.

3) Extensive experiments were conducted on the several real-world datasets, and the results also proved that our proposed ITRA method had impressive prediction accuracy.

The remainder of this article is shown as follows. Section 2 introduces the related research on rating prediction systems. Then, our model is described in Section 3, where we also give an illustrative example of the proposed approach. Immediately after, the experiments based on three real-world datasets are performed in Section 4 to verify the accuracy of our rating prediction. Finally, the conclusion and future research on item recommendations are described in Section 5.

II. RELATED WORKS

In current rating prediction approaches, many models are designed to alleviate sparse data and cold start problems to improve the prediction accuracy of recommendations. In particular, the prediction methods based on collaborative filtering are one of the most mature models in recommendation systems. They have been applied in many fields, such as e-commerce websites, video push, information retrieval, social application. Some efficient models have been proposed successively. Deshpande and Karypis [18] take full advantage of rating matrix to profile relationships among various items, and then use their relationships to compute the recommendation set. Liu *et al.* [19] propose a novel user similarity algorithm which not only utilizes the textual information of rating profile, but also the preferences of registered users. In addition, a neighborhood method based on the Matrix Decomposition is proposed by [20]. To improve the recommendation performance, they simplify training pattern of matrix decomposition to regulate the mathematic paradigm with linear biases, and then predict the final item rating. Although the above models can achieve better rating accuracy to some extent, they cannot handle the dynamic datasets well due to static trained models. And since different applications need to deal with data patterns from different systems, the further exploration and research are expected.

Some trust-based research has also been proposed to better locate user preference. Chen *et al.* [21] design a novel rating prediction framework where they can make use of user trust and distrust networks to identify potential users for making accurate predictions. A hybrid recommendation approach based on group and individual trust integrates trust evaluation indicator into the prediction model to solve the cold start caused by the lack of rating information [22]. As a result, individual trust can be enhanced by group trust to refine recommendation framework to improve the recommendation accuracy. Furthermore, Guo *et al.* [23] propose the adaptable and flexible similarity method with the integration of user explicit trust for item recommendations. The basic principle of the proposed model is that user social relationships derived from the trust networks have a positive influence on user preferences.

In addition, the feature of trust diffusion can be applied to recommendation systems, and has been shown to effectively reduce prediction bias and improve the accuracy of rating predictions. The framework integrates social trust relationship and rating confidence indicator into the retrieval of user similarity on a base of node transitivity in user trust networks [17]. The prediction results are generated by computing the ratings of similar neighbors. Yu *et al.* [24] outline a novel prediction framework which utilizes trust propagation and user interest to profile user preferences. The method considers the reputation mechanism to balance other users' influence on the target user, and then profiles user interests according to their rating records. Further, some forward-looking models that incorporate trust are also introduced, such as [25]–[27]. Nevertheless, the trust information mined by the above algorithms can only be explicitly used from user files, and data sparsity in recommendation systems cannot be resolved well. In our paper, we focus on how to better improve the prediction accuracy of collaborative filtering models by mining implicit trust information.

The methods most relevant to our paper are as follows. Deng *et al.* [28] merge social rating prediction technique with Relevant TrustWalker to mine the trust relationships among users, and the prediction results are obtained by a variant random walk algorithm. Although experimental results demonstrate that the recommendation accuracy can be improved to some extent, the coverage rate of model training is still very slow. Differently, [29] proposes a dynamical prediction mechanism based on reliable evaluations to build trust networks of users. The proposed method uses user unrated items initializing user ratings, and then these users with high trust values than recommendation system threshold in a reconstructed trust network are collected as candidate neighbor set to generate rating prediction results. Both models have their own advantages and disadvantages, which gives us some ideas for our research. Furthermore, the Denoising Auto-Encoders can be utilized to design a new deep learning method [30], which learns effective and compact representations from original ratings and trust information to bridge relations among users. The new neutral network model with some hidden layers is proposed to balance the importance of the learned representations. However, this model works poorly in cold recommendation situations where only a small amount of user information is available.

In addition, other research on trust has been proposed by [31]–[36]. Although these algorithms improve the rating prediction accuracy of recommendation systems, they are at the cost of time or low coverage. Therefore, they fail to work well in cold start cases, and data sparsity remains a stubborn challenge [37]. Inspired by the problem, our paper attempts to alleviate this problem by introducing the implicit trust recommendation approach. In the proposed model, a trust expansion method is used to aggregate user trusted neighbors, and then more available trust information hidden behind recommendation systems is mined to improve the accuracy of item rating predictions in the proposed ITRA model.

III. PROPOSED IMPLICT TRUST RECOMMENDATION APPROACH

In the next section, the process of our ITRA approach is described in detail, along with a small example of the proposed approach. For convenience, the commonly used symbols are listed in Table 1.

TABLE 1. Summary of symbols and their meanings.

Notation	Meaning
u, i, r	User, item, and rating respectively
U, I, R	The collections of user, item and rating respectively
$r_{v,i}$	The rating given by the user v on the item i
$\hat{r}_{ui}$	The prediction rating given by the user u on the item i
$IT_{u,v}$	Inferred trust value
TNS_u	Trust neighbor set
CI_u	Candidate item set
CS_u	User candidate set
$Tsim_{u,v}$	Trust similarity between user u and user v
$\psi_{u,v}$	Trust weight
$p_{u,j}$	Predicted rating
ζ_{Ts}	Similarity threshold
ζ	Trust threshold

A. THE PROCESS OF THE PROPOSED APPROACH

The cold recommender systems in online networks are generally considered to be those in which most users have only a few rating records. Therefore, based on the lack of user ratings in those systems, some implicit trust data can be mined to locate user preferences in our article.

To maximize the use of a small number of available rating profiles, our model can utilize the trust feature in social networks that can be propagated among different users. In a user trust network, any two social users can be linked through the six-degree segmentation model [38], [39] and thus the trust value is inversely proportional to their distance in our work. In our proposed model, the trust network is a relationship network among users, which can be constructed offline according to the meta-attributes in the dataset including basic meta (users, items, ratings), user context (users, links) and other contexts (labels etc.). In a trust network, the nodes represent the users, and the edges represent the links among users. Thus, a user trust network can be formed through reachable links among users. The inferred trust value $IT_{u,v}$ is defined and represented as follows.

$$IT_{u,v} = \frac{1}{sd_{u,v}} \tag{1}$$

$sd_{u,v}$ is the shortest distance between users u and v in a trust network, which can be calculated and obtained offline by Breadth First Search algorithm [40]. Hence, the meaning of distance in a trust network is the shortest length of the reachable path between any two users. To reduce consumption and noise, our paper defines the distance $sd_{u,v} \leq 3$ achieving better predictions and recommendations. Conversely, if the distance $sd_{u,v}$ is greater than 3, the available information that can be mined does not increase significantly. And as the distance increases, the accuracy of recommendations is likely to decrease. Therefore, the shortest distance in our article is

Algorithm 1 Trust Expansion Strategy

Inputs: User set U and Trust relationships graph G;
Output: Trust neighbor set TNS_u;
1. **Initialize** TNS_u;
2. **for** active user u in U
3. traverseBreadthFirst(u, G)
4. **if** v_i has a directional path from u and $sd_{u,v} \leq 3$ in G // G is obtained offline
5. addUser(v_i, TNS_u)
6. **end if**
7. **end for**
8. **Return** TNS_u

set to less than or equal to 3. The same strategy can be referred to in [4] and [41].

Then, in our proposed prediction model, the target user's trust neighbor set is defined as follows.

$$TNS_u = \{v | IT_{u,v} > \delta, v \in U\} \tag{2}$$

δ denotes a trust threshold, U is the user collection in trust networks.

Since the trust distance is no more than 3, our model considers all trusted neighbors to be available on the basis of actual grid computing. Moreover, each user u trusts itself, and its TNS_u contains itself. In addition, in our proposed model, implicit trust is focused on and utilized to obtain user trust neighbor sets and infer the target user preferences, and then the known explicit ratings in recommender systems are combined into the proposed approach to better generate recommendation results. Furthermore, our method infers implicit trust values among users based on their social networks and trust diffusion features, while no explicit trust values are directly utilized to improve the accuracy of rating predictions.

In many cases, the previous models employ original users to compute the similarity among users in recommendation systems [42], [43]. However, accurate recommendations cannot be achieved due to data sparsity. To improve the accuracy of rating predictions, the trusted neighbors of the target user are first gathered by trust expansion strategy (TES) which can mine user implicit trust in user trust networks to better model user preference. The detailed steps of TES algorithm is shown as follows.

In Line 1, since the active user u trusts itself, TNS_u is initialized by user u. The next two lines of our model traverse all users in trust networks to find the trustworthy users for the active user u. Line 4 will judge if v_i is on the reachable path and the distance is less than 3. In line 5, the filtered trusting users are added in TNS_u. Finally, the TNS_u is output.

After obtaining the trusted neighbors, some available items can be identified as the candidate item set to compute user similarity. Thus, the candidate items are defined as follows.

$$CI_u = \{ci \in I | \exists v \in TNS_u : r_{v,ci} \in R\} \tag{3}$$

where $r_{v,ci}$ denotes the rating given by user v on the item ci, taking a certain integer in recommendation systems, such as an integer from 1 to 5. Given the Equation (3), the candidate item set is the set rated by at least one trusted neighbor. Therefore, based on the collected items, the trust similarity among users is computed by the PCC model. Since trust similarity is defined as symmetric and calculated by using the ratings of trusted neighbors, PPC can be used to calculate the trust similarity.

$$Tsim_{u,v} = \frac{\sum_{i \in CI_{u,v}} (r_{u,i} - \bar{r}_u)(r_{v,i} - \bar{r}_v)}{\sqrt{\sum_{i \in CI_{u,v}} (r_{u,i} - \bar{r}_u)^2} \cdot \sqrt{\sum_{i \in CI_{u,v}} (r_{v,i} - \bar{r}_v)^2}} \tag{4}$$

In the formula above, $\bar{r}_u$ and $\bar{r}_v$ are the average ratings for users u and v. $r_{u,i}$ and $r_{v,i}$ denote the ratings for users u and v on item i. $CI_{u,v} = CI_u \cap CI_v$ is the set of items rated by users u and v after TES, and $Tsim_{u,v} = [-1, 1]$ is the trust similarity between users u and v. In addition, if user u does not rate item i, then $r_{u,i} = 0$ is used to calculate the trust similarity in our article. It is important to note that the trust similarity $Tsim_{u,u}$ is 1 due to the trusted user $u \in TNS_u$ in our profile. Furthermore, $Tsim_{u,v} > 0$ indicates the trust relationship between users u and v, $Tsim_{u,v} < 0$ indicates the distrusted relationship and $Tsim_{u,v} = 0$ implies no relationship. In the proposed approach, since the negative similarity among users may be meaningless, our model only considers the active trusted users, that is $Tsim_{u,v} > 0$.

Based on the trust similarity that has been obtained, user candidate set is represented as CS_u, which has similar preferences with a target user u in recommendation systems.

$$CS_u = \{v | Tsim_{u,v} > \delta_{Ts}, v \in U\} \tag{5}$$

where δ_{Ts} is the similarity threshold predefined by recommender systems. The users are selected in the candidate set CS_u, whose $Tsim_{u,v}$ is greater than the similarity threshold.

The previous prediction methods only utilize original ratings for user similarity calculation, and our model uses the trust similarity of user entity acquired by mining implicit trust in the systems for recommendations. However, the systems may still have some trusted users with low similarity. Hence, to improve rating prediction accuracy, a trust weighting model is designed by considering the inferred trust value and user trust similarity.

$$\psi_{u,v} = \alpha Tsim_{u,v} + (1 - \alpha) IT_{u,v} \tag{6}$$

In the above formula, the trust weighting $\psi_{u,v}$ consists of two variable factors: the trust similarity $Tsim_{u,v}$ and inferred trust value $IT_{u,v}$. The trust parameter $\alpha \in [0, 1]$ manifests the extent to which the combination depends on trust similarity and inferred trust value. The principle behind Equation (6) is that recommender systems may tend to accept all available information that can generate better recommendations.

Finally, all the ratings of candidate users are used to calculate the predicted rating for target items that are not rated by user entity. The prediction equation for recommendations is

Algorithm 2 ITRA Algorithm

Inputs: TNS_u; Item set I; Rating set R
Output: Predicted list
1. **for** each user v in TNS_u // *The initial stage*
2. getting and updating the candidate items of user uCI_u
3. **end for**
4. **for** all ratings R of user u and user v
5. **if** $(r \in R \cap r! = \varphi)$// *The intermediate stage*
6. calculateTrustSim($CI_{u,v}, \bar{r}_u, \bar{r}_v$); //$Tsim_{u,v}$ *is acquired*
obtaining the trust weighting $\psi_{u,v}$ according to Formulas (5) and (6);
7. **end if**
8. **end for**
9. generating rating prediction $p_{u,j}$ //*The prediction stage*
10. **Output**Predicted list.

defined as below.

$$p_{u,j} = \bar{r}_u + \frac{\sum_{v \in CS_u} \psi_{u,v} \cdot (r_{v,j} - \bar{r}_v)}{\sum_{v \in CS_u} |\psi_{u,v}|} \tag{7}$$

In the equation, $p_{u,j}$ represents the predicted rating on item j. The trust weighting ensures that users with greater trust similarity values have more positive impact on the rating predictions. Finally, the algorithm description of the proposed model based on implicit trust prediction model is shown as follows.

Lines 1-3 acquire and update the candidate items CI_u which gathers the available items rated by trusted neighbors. Then, lines 4-8 calculate the trust similarity among users and the trust weighting value under the condition that rating matrix is not empty. In the end, in lines 9 and 10, our algorithm generates and gives the rating prediction list.

B. SMALL EXAMPLES OF PROPOSED METHOD

In this subsection, our paper gives an example to verify the ITRA model via predicting the results for a given item entity. Assuming that there exists seven user entities and six item entities in a recommendation system, each user entity can give a positive integer to rate item entities. The specific entity ratings are shown in Table 2.

Moreover, there is a user trust network in a recommendation system in which the target user u_1 has some social relationships with other user nodes as shown in Fig. 1. In addition, in this network, users are defined as nodes and the trust links among users are seen as direct edges. In other words, the user entity u_1 trusting u_2 is not the same as user entity u_2 trusting u_1.

The process of making recommendations is as follows. First of all, the trusting neighbors of the target user u_1 are explored by the TES algorithm. Based on Table 2 and Equation (1), the shortest distances and inferred trust values are computed as follows $sd_{u_1,u_k} = 0, 1, 1, 2, 3, 4, \varphi$; $IT_{u_1,u_k} = 1.0, 1.0, 1.0, 0.5, 0.33, 0.25, \varphi$. k is 1,2,3,4,5,6,7. In addition, since the target user trusts itself, the IT_{u_1,u_1}

TABLE 2. User-item rating matrix.

	i_1	i_2	i_3	i_4	i_5	i_6
u_1	1	4		?		
u_2	3			4		
u_3		5	3		1	
u_4	1		5		3	
u_5	2	4		3		
u_6					1	2
u_7	1					

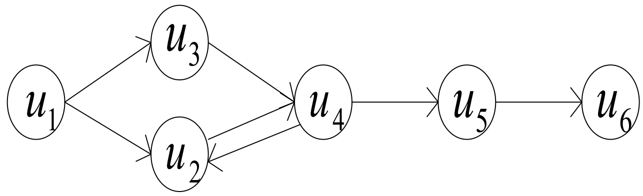

FIGURE 1. The trust network of active user.

value is 1.0. Moreover, φ is expressed as two users have no reachable paths. Although the inferred trust value of user entity u_6 can be computed, it cannot be seen as the trusted neighbor of the target user entity due to the constraint $sd \leq 3$. Thus, the target user' neighbors $TNS_u = \{u_1, u_2, u_3, u_4, u_5\}$ is filtered out and gathered as trusting neighbors. For quick validation and simplified calculations, we set $\alpha = 0$ in Formula (6), and the inferred trust value is fully utilized to calculate user weight. Finally, based on the prediction Equation (7), the rating for item i_4 is output as$p_{u,j} = 2.5 + \frac{1.0\times(4-3.5)+0.33\times(3-3)}{1.0+0.33} = 2.88$, and the recommendation list is generated.

IV. EXPERIMENT

In this section, our experiments were performed to evaluate the performance of our ITRA model with the three real-world datasets. Then, two commonly used evaluation indicators were adopted to compare the recommendation results of the proposed method with those of other advanced models.

A. DATASET DESCRIPTION

In this subsection, three real-world datasets are utilized for our experimental training, namely FilmTrust, Douban and Epinions. These datasets are derived from large-scale recommendation systems, and we mainly focus on the trust relationships among users.

Douban is a social rating website (books, movies and music) that integrates expression, taste and communication systems, dedicated to finding interesting things in our lives. We can be free to post and search for relevant comments in the website. The public Douban dataset[1] was crawled by LibRec team in the recommendation tool library [44], and contained 16,830,839 ratings to 58,541 items by 129,490 users.

FilmTrust is a trust-based film rating community, where users can rate a newly released movie or learn about the upcoming movies. The FilmTrust dataset is obtained by crawling the site during the first half of 2016, containing 35,497 ratings to 2,071 items by 1508 users.

Epinion is a social networking site where users can express their opinions on video, products, music, services. The Epinions dataset[2] collected by Richardson and Domingos [45] is composed of 75,888 users, 29,000 items and 681,213 ratings.

B. COMPARISON METHODS

In evaluating the performance of our ITRA approach, we compare the recommendation results with five state-of-the-art algorithms, such as the classic user-based collaborative filtering method (UCF), the trust-aware recommendation model (TAR), social trust recommendation based on probability matrix factorization (STPMF), a novel fuzzy-based trust model (FTM) and the deep learning model (DLM).

(1) The recommendation described in UCF [46] calculates user similarity by utilizing relation ratings, and selects Top-N neighbors whose user similarity are greater than the threshold in recommender systems. Then, the UCF approach makes predictions by expanding candidate users that contains more potential users based on the ratings of user neighbors for recommendations.

(2) The basic principle of the TAR method [47] is that user trust networks are reconstructed to rank item ratings. Firstly, the model proposes a trust matrix concept through analyzing user trust networks, and mines the preferences of a target user based on matrix decomposition. Then, the predicted ratings are generated for recommendation systems.

(3) The STPMF method [48] combines social trust and collaborative matrix factorization to predict user missing ratings and make predictions. The model supposes user decisions on adopting items are affected by their tastes and the favors of trusted friends.

(4) The FTM recommendation [49] presents a novel fuzzy-based trust model, where the behavioral uncertainty of user nodes in mobile ad hoc networks is handled to evaluate and predict the trust value of each user for recommendations.

(5) The deep learning model [50] is an advanced model based on neural networks that learns user or item low-dimensional vectors by embedding semantic information. Furthermore, a feed-forward neural network is utilized to represent the interactions between users and items.

In our experiment, the comparative experiments are repeatedly conducted and verified in the same environment conditions, and the parameters of our ITRA algorithm and other competitor methods are set to optimal values through cross-validation. For example, for the deep learning model (DLM), the proposed learning method has a learning parameter of 0.0005, the bath-size of 64, and the number of cells in the FC layers of 100, as shown in the experiment setting [50].

[1]https://www.librec.net/datasets.html.

[2]http://alchemy.cs.washington.edu/data/epinions/.

C. EVALUATION METRICS

To evaluate the prediction accuracy of the proposed model, the leave-one-out validation approach was leveraged on the three datasets until all test ratings were utilized and covered [51]–[54]. Then, we estimated the experimental performance by exploiting the two most commonly used evaluation indicators: RMSE and MAE. The accumulated errors between the predicated and the ground truth value are recorded during the experiments. The MAE evaluation indicator is described as below.

$$MAE = \frac{\sum_{u}\sum_{i}|p_{u,i} - r_{u,i}|}{\xi} \tag{8}$$

Mean Absolute Error (MAE) measures to what extent the predicted ratings are close to the ground truth. ξ is the number of participating ratings in the testing process. As can be seen from the equation, a smaller MAE value indicates better rating prediction accuracy. The metric reflects the accuracy of item recommendations.

On the other hand, the MAE is not always accurate in the rating predictions, and another more precise metric Root Mean Square Error (RMSE) is further exploited to assess the recommendation results. The RMSE between the true and the predicted ratings is defined as follows.

$$RMSE = \sqrt{\frac{\sum_{u}\sum_{i}(p_{u,i} - r_{u,i})^2}{\xi}} \tag{9}$$

Compared to MAE, RMSE can reduce large errors in different proportion, but they can reflect item rating accuracy. Obviously, the higher MAE and RMSE values reveal the low performance of recommender systems. Hence, in our experiments, RMSE and MAE can be used to verify the prediction accuracy.

In addition, Rating Coverage (RC) is defined to assess the coverage of the recommendation list. $|R_p|$ and $|R_T|$ represent the number of predictable and all ratings.

$$RC = \frac{|R_p|}{|R_T|} \tag{10}$$

D. RESULTS AND DISCUSSIONS

In this section, we compare the proposed ITRA model with the five advanced approaches, including UCF, TAR, FTM, DLM and STPMF. Specifically, we run these approaches on three datasets to verify the accuracy of the ITRA model. The comparative experiments are conducted on 32 bit Windows 10 professional, Intel(R) Core(TM) i5-4590U CPU @3.3GHz, 4.00G of RAM. The detailed prediction results and analysis are shown below.

The beginning of the experiments, we studied how the trust parameter α defined in Equation (6) influenced the accuracy of our model. We computed the trends of the RMSE and MAE that were accompanied by trust parameter α from 0 to 1 with step 0.1. The experimental results are shown in Fig. 2 and Fig. 3.

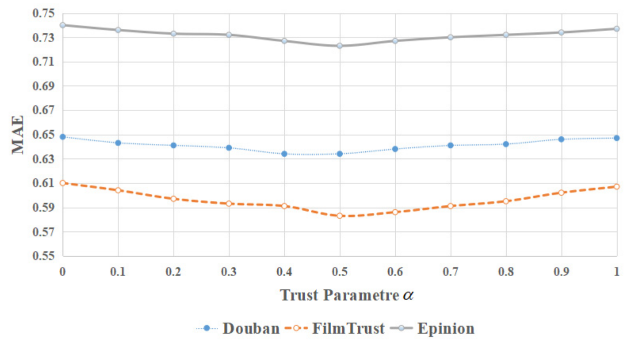

FIGURE 2. **Recommendation performance of three datasets on trust parameter α (MAE).**

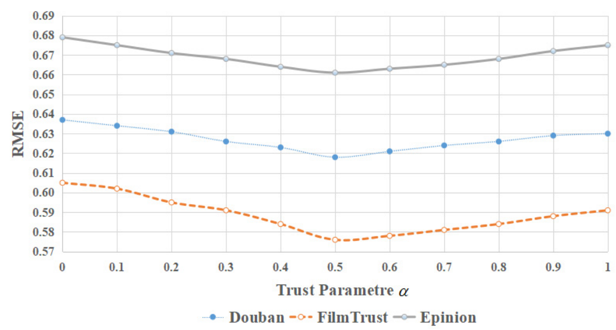

FIGURE 3. **Recommendation performance of three datasets on trust parameter α (RMSE).**

In Fig. 2 and Fig. 3, while the trust parameter α gradually increases, the prediction accuracy of our ITRA model is getting better and better. In particular, the best result is achieved, when the trust parameter α is equal to 0.5. That may be because more trusting neighbors are involved in the prediction process by mining implicit trust in recommendation systems. Then, with further experiments, the MAE and RMSE values increase dramatically, and the prediction accuracy of these algorithms are getting worse and worse. In addition, when the trust parameter α is 0, the trust weighting completely depends on the inferred trust value. When the trust parameter α is 1, the trust weighting $\psi_{u,v}$ depends entirely on user trust similarity. Here, the performance of our ITRA model is slightly better than the case where the trust parameter is 0. Therefore, the trust parameter can be set to 0.5 such that the accuracy of rating prediction is at its best for the next experiments.

To have a better understanding of the prediction accuracy, our article conducts comparative experiments to compare the prediction accuracy of our ITRA model with those of other advanced algorithms on three datasets. In addition, to compare the experimental accuracy, the target user's nearest neighbors (NN) can be set from small to large: 5, 15, 25, 35, 45, 55, 65, 75, 85 and 95. The prediction results are shown as follows.

Fig. 4 and Fig. 5 show the prediction accuracy of six models on the Douban dataset. We can see that with the increasing of nearest neighbors, the prediction accuracy of all algorithms gradually increases. When the number of NN is around 25, the performance of the proposed ITRA is the best. This is because many trusted neighbors are obtained by mining more ratings and implicit trust information. Then, the prediction accuracy decreases slightly with some useless ratings being utilized. Moreover, it can also be seen from the above figures, our ITRA model achieves better accuracy compared with other algorithms, and the UCF model performs the worst.

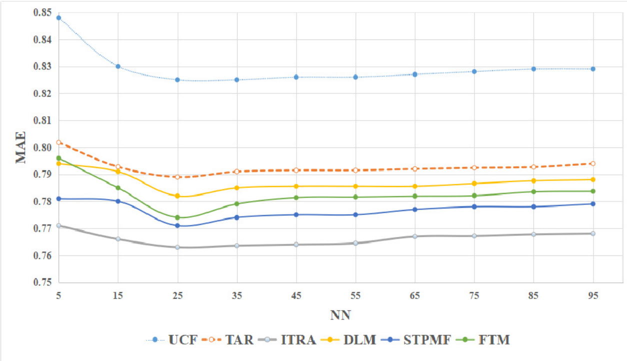

FIGURE 4. **Recommendation performance of six methods on Douban (MAE).**

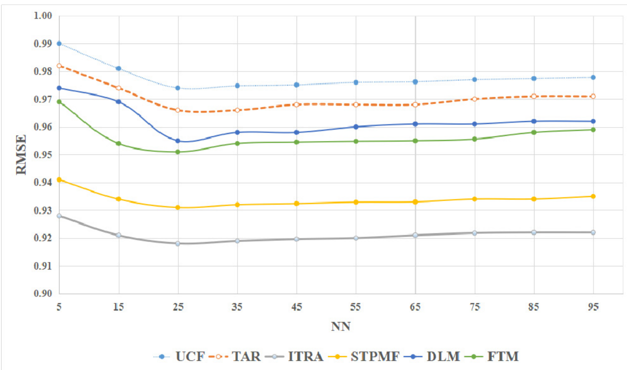

FIGURE 5. **Recommendation performance of six methods on Douban (RMSE).**

Fig. 6 and Fig. 7 adopt the FilmTrust dataset to display the comparison performance of all models. The similar trends of the experimental performance verify that the ITRA model is the best of all models in terms of the MAE and RMSE metrics. In addition, compared with our ITRA method, the accuracy of UCF is significantly poor, and the DLM and STPMF have slightly lower accuracy for rating predictions. Therefore, the proposed approach in our paper has higher prediction accuracy.

TABLE 3. Overall average result on six method.

Method	Douban		FilmTrust		Epinions	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
UCF	0.8293	0.9779	0.9500	1.1279	0.7657	0.8822
TAR	0.7929	0.9704	0.9314	1.1076	0.7572	0.8626
DLM	0.7871	0.9620	0.9290	1.1006	0.7419	0.8550
FTM	0.7828	0.9565	0.9447	1.1230	0.7527	0.8657
STPMF	0.7768	0.9339	0.9143	1.0811	0.7353	0.8362
ITRA	**0.7662**	**0.9212**	**0.9050**	**1.0756**	**0.7181**	**0.8200**

TABLE 4. Overall improvement of ITRA on five comparative methods.

Method	Douban		FilmTrust		Epinions	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
UCF	8.23%	6.16%	4.97%	4.86%	6.63%	7.59%
TAR	3.48%	5.34%	2.92%	2.98%	5.44%	5.20%
DLM	2.73%	4.43%	2.65%	2.32%	3.31%	4.27%
FTM	2.17%	3.83%	4.39%	4.41%	4.82%	5.57%
STPMF	1.39%	1.38%	1.03%	0.60%	2.40%	1.98%

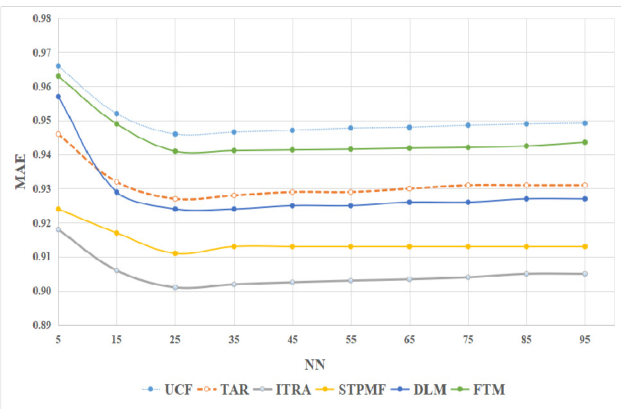

FIGURE 6. Recommendation performance of six methods on FilmTrust (MAE).

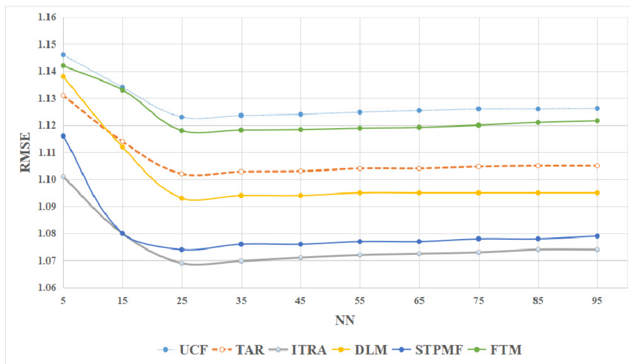

FIGURE 7. Recommendation performance of six methods on FilmTrust (RMSE).

TABLE 5. Accuracy results of six methods on Epinions under cold start condition.

	UCF	TAR	DLM	FTM	STPMF	ITRA
MAE	1.0021	0.9542	0.9408	0.9398	0.9311	**0.9297**
RMSE	1.3124	1.1128	1.1024	1.0845	0.9987	**0.9849**

Fig. 8 and Fig. 9 show the comparative results of all methods on the Epinion dataset in terms of the RMSE and MAE. As can be seen from Fig. 8 and Fig. 9, we can still find that the prediction performance of six models is relatively stable, and the ITRA and STMF perform better than other methods with the increasing of nearest neighbors. When the NN is around 25, the prediction accuracy of ratings for all models reaches the best. This is because at the beginning of the algorithms, the accuracy of rating prediction increases quickly as more and more user trusted neighbors are mined for recommendations. When the NN reaches 25, the number of available trusted neighbors mined is relatively stable, and the performance of the algorithms also tends to be stable. Furthermore, as the NN further increases, the accuracy of rating prediction decreases slightly due to the influence of some noises. Therefore, the analysis based on the

TABLE 6. Rating coverage results for all methods.

	UCF	TAR	DLM	FTM	STPMF	ITRA
Douban	81.25%	71.08%	72.16%	74.35%	77.17%	**83.54%**
FilmTrust	67.25%	59.68%	62.18%	64.39%	66.57%	**69.24%**
Epinion	82.74%	69.88%	77.65%	78.65%	79.84%	**86.98%**

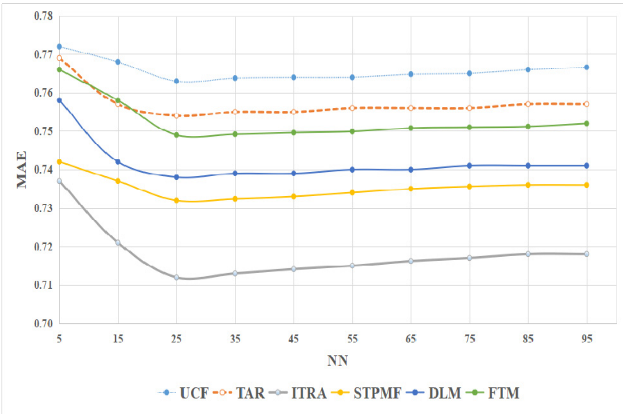

FIGURE 8. Recommendation performance of six methods on Epinions (MAE).

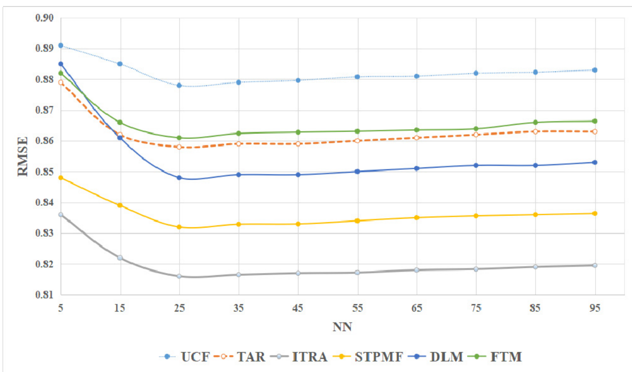

FIGURE 9. Recommendation performance of six methods on Epinions (RMSE).

Fig. 8 and Fig. 9 demonstrates that the proposed method still has the best accuracy in all models.

To further investigate the overall performance of the proposed ITRA approach, this paper calculated the average MAEs and RMSEs to compare the accuracy of item rating prediction. The results shown in Table 3 demonstrate that the proposed model performs better than other advanced methods. In addition, Table 4 displayed the percentage improvement of our method over the other approaches. The experimental results showed that the ITRA delivered the greatest improvement over User-based collaborative filtering recommendation (UCF) by around 10%. Compared with the deep learning and matrix factorization recommendations, the proposed method also attained an improvement of 2-4%.

A conclusion can be summarized from the experimental results in Tables 3 and 4 that our approach consistently performs better than other comparison models, and significantly improves the accuracy of item rating prediction.

To observe the performance of the proposed algorithm under cold start conditions, the comparative experiments were conducted on the Epinions dataset when the data sparsity is 0.02%. The specific results are shown in Table 5, and the comparative analysis is summarized as follows.

The results in Table 5 demonstrate that compared to other comparison methods, our proposed algorithm still shows the best performance in terms of rating predictions even under cold start condition. In addition, other datasets have similar accuracy results.

Furthermore, it is observed that rating coverage of ITRA method is significantly improved compared with other comparison methods from Table 6. This is because more implicit trust information and trusted neighbors are identified and used in the rating calculation process. Naturally, rating coverage of the classical UCF method is very close to that of the proposed ITRA model because there are not many parameters involved in the calculation.

In a word, the above results demonstrated that compared to prediction accuracy of other algorithms, the prediction results obtained through our ITRA were more accurate on three datasets, especially when user nearest neighbors is around 25. The previous models cannot generate good predictable items, especially in data sparsity situations. Therefore, this shows that implicit trust is significant to improve the accuracy of rating prediction services.

V. CONCLUSION AND FUTURE WORK

In our article, by mining user implicit trust, a new ITRA model was proposed to improve the accuracy of rating predictions. Specifically, we utilized the TES algorithm to mine the trusted neighbors of the target user and reduce possible noise. Secondly, according to the trust ratings from TNS, trust similarity among users was calculated to model user preference. Finally, the trust weighting approach was proposed to generate predictions by using inferred trust value and trust similarity. Moreover, we compared the ITRA model with other advanced approaches, namely, UCF, TAR, FTM, DLM and STPMF. In addition, compared to the prediction accuracy of previous synthetic algorithms applied in recommendation systems [45], [47], [55], the proposed model in our article is much more suitable for recommendations in terms of accuracy. That is to say, by mining user implicit trust, more efficient rating predictions can be achieved. In particular, the focus of our work is how to exploit the user social network and trust diffusion features to mine the implicit trust hidden behind the rating data to expand the scale of available rating information used for item rating predictions, which is very different from the previous approaches, and this is also the major contribution of our work. In summary, the experimental results demonstrate that the ITRA method can achieve better accuracy in rating prediction and alleviate cold start problems.

However, the trust relationships of users in the trust network are considered to be invariant, which does not deal well with the dynamic needs of users in recommendation systems in some cases. In addition, the proposed method may not work well in cross-domain scenarios. Therefore, the application of user trust features to dynamic and cross-domain scenarios is the focus of our future research.

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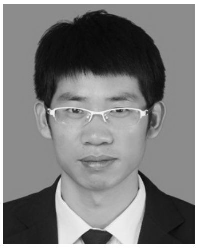

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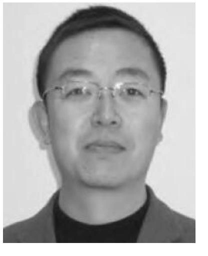

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