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A Novel Trust Computation Method Based on User Ratings to Improve the Recommendation

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ABSTRACT

Today, the trust has turned into one of the most beneficial solutions to improve recommender systems, especially in the collaborative filtering methods. However, trust statements suffer from a number of shortcomings, including the trust statements sparsity, users' inability to express explicit trust for other users in most of the existing applications. To overcome these problems, this work presents a method for computing implicit trust based on user ratings, in which four influential factors including Similarity, Confidence, Analogous Opinion, and Distance are utilized to achieve trust. For computing users' similarity, Person Correlation Coefficient measure was applied. Confidence was computed through users' common in rated items. To compute users' analogous opinions, their ratings were evaluated from three aspects of their satisfaction, dissatisfaction, and indifference about the items. Euclidean distance was employed on users ratings for computing the distance. Finally, the factors were combined to reach the implicit trust. Moreover, fuzzy c-means clustering was applied to initially partition similar users for enhancing the performance positively. Finally, two MovieLens datasets of 100K and 1M have been used to evaluate this approach, and results have shown that the approach significantly increases Accuracy, Precision and Recall, compared to some other existing methods.

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1. INTRODUCTION

The active extension of the web society and social networks has dramatically changed the way users search the web and share their interests. In recent years, with the growth and development of e-commerce sites, which have sought to attract customers and sell their products, the choices available to individuals have increased vastly. This has caused users to be confused about finding and selecting their favorites from an immense amount of information and items. Recommendation systems have been developed to help the users of social networks and clients of e-commerce sites find their favorite items (such as books, movies, travelling tours, music and needed things) and providing them with high-quality suggestions. The first recommendation system was introduced by the Tapestry project in 1992 [1]. Today, all e-commerce sites (such as Amazon), regular websites (like MovieLens, Netflix, Yahoo!Music, and YouTube), and Cloud Services are using different types of recommendation systems [2-6].

Recommendation systems generally are divided into three classes, which are Content-based (CB), Collaborative Filtering (CF), and Hybrid Methods. The CF method is one of the most widespread and successful methods of recommendation, which predicts the score of the unknown items -which have not been given any scores by the target user- based on similar users' scores [6]. Collaborative filtering algorithms usually consist of three steps, namely dataset pre-processing, finding nearby neighbors, and recommendation offering or score prediction [7]. The CF method are sub-divided into memory-based and model-based procedures. Generally, memory-based processes employ a similarity criterion to attain a collection of similar users to the target user based on the overall users-items data (which includes the user's scores to items) and ultimately make the recommendation. In contrast, model-based processes

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use machine-learning algorithms in the user-item matrix to find models that are better for prediction. Several examples of model-based systems can be mentioned, including the Bayesian method [8], Dimension Reduction technique [9], Matrix Factorization methods [10], and clustering techniques [11] which improved the performance of CF systems. In addition, researchers have shown that the use of clustering algorithms in the CF method leads to more accurate predictions for items that have been rated less frequently [11, 12]. Despite the popularity of CF-based recommender systems for personalized recommendations, they usually suffer from a variety of issues. Some of these problems include data sparsity, cold start, and also the fact that CF methods are hit simply by copying users biographies and changing predicted rates [13, 14]. Various strategies have been designed to resolve these problems, one of the most important is the trust that has acquired lots of thought in recent years [15]. There are several investigations, which have reported that trust statements increase the quality of the recommendation in CF-based systems [14-27].

Interactions and communications require users to highly trust each other and share the contents in web environments, whereas gaining sufficient insight to build such trust is difficult. In recommender systems, trust defined as believing others to provide reliable and precise information concerning matters, which are relevant to target user's interests and preferences [4]. The original theory of trust is that there is a good and direct relationship between the trust and similarity of the two users that can be used to predict the score of the unknown items [28]. The main task of trust in CF techniques is to fix the problem of choosing neighbors [4], therefore, it has a fundamental role in collaborative filtering systems. Trust can be divided into two explicit and implicit categories. The former is explicitly collected from users, for example, FilmTrust and Epinions are programs where users can clearly identify their trust or distrust in others. In contrast, the implicit trust usually is obtained from users' behaviors, such as how they have rated certain items.

In recommender systems, the majority of trust researches have focused on explicit trust statement provided by the users because it is more precise and reliable than implicit trust. However, explicit trust also has some limitations. For example, it requires the users' effort to represent their statements of trust in others, so not all users necessarily provide explicit trust statements [28]. Moreover, some websites and applications do not have the ability to obtain the users' explicit trust in others, such as Movie Lens, which is why some studies have proposed methods to compute implicit trust instead [26, 29].

Hence, this research aims at improving the quality of the CF approach by proposing a new method to compute the implicit trust between users. Four key factors that can be effective on computing a reliable implicit trust have been examined, which are the level of users' similarity, the confidence between them, their analogous opinions on items, and the distance between their ratings. All these factors used for determining users' trust statement are based on the same feature of users rating to items, but in different views. In the proposed approach, the similarity between users is estimated based on Pearson's correlation coefficient criterion, which is one of the most popular similarity criteria in the CF [27]. In addition, the confidence level, which is one of the important factors in dealing with trust, has been computed on the basis of the common items that the users have rated. To determine the extent analogous opinions of users, the level of three aspects of their satisfaction, dissatisfaction and indifference base on items that they have rated, were examined. Moreover, due to the case that the proposed technique is based on users' rating, the distance between the ratings has been used to overcome some deficiencies and increase the accuracy. All these four factors will present in Section 3 with more details. Furthermore, this study uses fuzzy c-means clustering for grouping users who are closer together, as an initial state of trust computation to better improve the performance. This article has organized in the following order:

In Section 2, previous researches are reviewed. In Section 3, the proposed method of computing implicit trust is explained. The general approach of the recommendation technique is described in Section 4 and the evaluation outcomes are demonstrated in Section 5. Finally, a conclusion is supplied in Section 6.

2. RELATED WORKS

Trust-based recommender systems are mainly a combination of a trust model and a method of collaborative filtering in order to take a hybrid approach to improve the performance of CF methods [18, 26]. As stated in the introduction section, there are two main methods of recommendation based on trust, depending on the type of trust information, which could be explicit or implicit.

Many successful methods for computing explicit trust have been proposed in literature, some of which are reviewed in this paper. SocialMF is a well-known system that combines the propagation trust mechanism with the Matrix Factorization model, significantly improving the accuracy of prediction [30]. MERGE is a method that combines the level of similarity and trust to solve the problems of data sparsity and cold start [4]. A distrust-based recommendation algorithm has been introduced that uses the distrust information to debug and filter trusted users on the web, showing that the appropriate use of this knowledge could enhance the efficiency of trust-based systems [29]. The TRecSo method assigns two opposite positions to users as the trustor and trustee due to the structure of the network information, using trust information to optimize the top-K ranking prediction accuracy in the recommendation process [30]. In another study, an approach was proposed based on the combination of the trust and distrust of users. In this method, the combination of the two K-nearest neighbor and matrix factorization techniques was used to maximize the profits of preferences and trust. The experimental results showed that distrust information could be useful in predicting the rating, and the designed combination approach could effectively improve the recommendation performance [21]. In another work, the researchers introduced a clustering method based on trust and distrust to improve the performance of CF systems. They also used an SVD-based clustering algorithm to specify trust and distrust [23]. A clustering approach was proposed by Guo et al. based on trust and similarity, aimed at overcoming the low accuracy and coveraging the traditional clustering methods [10]. The users in each cluster have the highest similarity and trust in each other. Guo et al. [25] proposed an approach to recommend items based on the users' implicit feedback by combining three models of similarity and social trust. They also introduced a matrix factorization method to retrieve user preferences from rated and unrated items, so that both user-user and item-item similarities were considered [25].

All of the mentioned approaches have merely used explicit trust statements and combined them with other methods to improve performance of recommendation. Although they have some achievements, as mentioned in the introduction section, explicit trust has some limitations. First, the users should create their own trust network (which is very time consuming and costly), and second, trust statements are sparse (i.e. there are no trust statements for some users in the trust network). To overcome these problems, many methods have been developed to obtain implicit trust between users, some of which are briefly described as follows.

In a study, two trust levels called Item-Level and Profile-Level were introduced to reduce the recommendation error. The trust of Item-Level and Profile-Level respectively are derived from the percentage of correct predictions with respect to specific items and created profiles. Ultimately, both trust types are merged and the total amount of trust is identified for each individual on the network [31]. Hwang and Chen [32] utilized the users' prediction accuracy based on the other users' ratings to estimate the implicit trust between the users. In 2009, a fuzzy model was introduced to calculate trust. The model considers users' satisfaction and dissatisfaction, reputation of the users and a model to compute the reputation. Finally, it was shown that the combination of both of them increases the performance of CF systems [33]. Also, other fuzzy-based trust models were introduced to improve performance of recommendations in literature [19, 33]. In another study, a novel approach was presented that used the number of exchanged messages between users to obtain implicit trust [17]. iTars is an implicit trust-based recommender system that uses users' similarities to compute trust [28]. The ACO algorithm was used to compute trust in a method referred to as TARS. Based on the calculation of the time address, TARS uses the biometric metaphor of the ant colonies to choose the best neighborhoods [34]. A group of researchers expanded the TARS system to provide a new approach that takes all the distinctive features of trust, such as asymmetry, portability, dynamism, and dependence on the field into account [35]. In an approach, researchers computed trust and distrust based on users' previous scores and statements of the explicit trust from the two personal and impersonal aspects, respectively [20]. Dong et al. [36] presented a method to compute trust, in which the similarity between user ratings and their interests in each item has been combined to create a trust matrix among them. In another paper, a method that used a new confidence criterion was proposed to obtain implicit trust statements. The concepts of Pareto and confidence were also used to identify prominent users whose comments were used in the recommendation process [22]. In another study, the researchers obtained a degree of trust based on the precision of the recommendations to point users by each user as well as the portability of trust between the users. Ultimately, they combined trust with similarity to compute the trust weight [24]. In another paper, the linear combination of the two factors of similarity and centrality was used to compute trust [27]. Gohari et al. introduced a system called CBR, which examined the concept of confidence in the trust level of the user on others and items from both local and global perspectives. This system uses four different confidence models to provide high-quality recommendations to users [26].

3. PROPOSED METHOD

The aim of the proposed approach is to find users who are definitely trusted by the target user in order to improve the prediction accuracy in the collaborative filter recommendation system. In this section, the proposed method for calculating the implicit trust is described. Trust depends on several factors, but those that are taken into consideration in this study include the degree of similarity between users, the extent to which the opinions of users about items are analogous,

TABLE 1. Abbreviations used in formulas

Notations	Description
$r_{u,i}$	The rate user u has given Item I i
$\overline{r_u}$	The average rate of user u
$I_{u,v}$	The common items between two users u and v
I_v	All the items that user v has rated
I_u^S	Items that have received a rate of 4 and above 4 from user u
I_u^D	The number of all items that have received a rate less than 3 from user u
I_u^I	The number of items that have received a rate between 3 and 4 from user u
$\tilde{T}_u$	The set of users that are trusted by user u

the confidence of users, and the distance between the scores of the items that have been rated by the users. Each of these factors is calculated based on the user-rating matrix. Another point about the trust that should be noted is that trust between two users is not symmetrical in real world, i.e. the trust amount of person *u* in a person *v* is different from the trust amount of *v* in *u*. In this approach, we have defined a method for trust computation based on these factors, which is derived from Equation (1).

$$Trust_{u,v} = Simlarity_{u,v} * Confidence_{u,v} * SimilarOpinion_{u,v} * RateDistance_{u,v} \quad (1)$$

The way to calculate each of the similarity, confidence, opinion similarity, and rate distance factors is discussed and described in Sections 3.1 to 3.4. The abbreviations used in the formulas are also introduced in Table 1.

3. 1. Similarity One of the important factors in computing trust based on the user-rating matrix is the similarity. The more similar two users are, the more the trust between them. Several different methods have been introduced to estimate users' similarity in recommendation systems, like the Cosine similarity, Jaccard similarity, Pearson correlation coefficient similarity [37]. Among the similarity measures, Pearson's similarity approach is one of the most successful and widely used methods for calculating user similarities in CF systems, which has been introduced by Sir Carl Pearson [37]. In this study, Pearson's similarity is used to calculate trust, as below:

$$Simlarity_{u,v} = \frac{\left(\sum_{i\epsilon I_{u,v}}(r_{u,i}-\overline{r_u})(r_{v,i}-\overline{r_v})\right)}{\left(\sqrt{\sum_{i\epsilon I_{u,v}}(r_{u,i}-\overline{r_u})^2}\sqrt{\sum_{i\epsilon I_{u,v}}(r_{v,i}-\overline{r_v})^2}\right)} \quad (2)$$

This similarity measure calculates the correlation between two interval or relative variables, and its value is within [-1, 1]. If the earned amount is positive, it indicates that both variables' variations have occurred in a direction alike, i.e. by raising the amount of a variable, another variable also rises. In contrast, both variables change in opposite directions if the amount obtained is negative, i.e. by increasing a variable value, another variable value decreases. There is no correlation between both variables if the earned amount is zero, and if the amount is +1 and -1, the correlation is absolutely conformity and unconformity, respectively [38]. Note that in this approach, negative values of similarity are considered zero.

3. 2. Confidence The confidence indicates the reliability between two users based on items that are given a score by both users [39]. Although similarity plays an important role in determining the trust level between users, it also has deficiencies that confidence can solve. Also, reliability and trustworthiness are two sides of the same coin, and a user's reliability in the eyes of others plays a key role in making him or her trustworthy as well [40]. For example, the more confidence user *u* has in the user *v*, the greater their trust in the user *v*. The confidence in the proposed approach is calculated according to Equation (3).

$$Confidence_{u,v} = \frac{I_{u,v}}{I_v} \quad (3)$$

In Equation (3), the confidence level is different between the two users, which means that the confidence of user *u* in user *v* varies with the confidence of user *v* in the user *u*. This helps to calculate the asymmetric trust in the proposed approach; in fact, the asymmetric confidence calculation makes the trust of users asymmetric as well.

3. 3. Analogous Opinions One of the other important factors in assessing trust is the analogous opinions of users on items. In this research, the degree of analogy is calculated based on the matrix score and the three aspects of satisfaction, dissatisfaction and indifference toward items. The equation of analogous opinions is defined as:

$$SimilarOpinion_{u,v} = \frac{Satisfied_{u,v}+DisSatisfied_{u,v}+Indifference_{u,v}}{3} \quad (4)$$

It is noteworthy that the degree of opinion similarity is in [0,1], and the degree of the three aspects lies within [0,0.5]. Each of the aspects, which has been used to compute the opinion similarity, is defined in the following:

Satisfaction. The satisfaction aspect measures the likeness of users' interest in items, in a way that if the minimum and maximum points are 1 and 5 in the system, the users have an interest in the item if it has been given a score of 4 or above. In this approach, the satisfaction degree of two users is computed on the basis of the ratio of their common satisfaction with the items to the sum of total items that the two users have been satisfied with, according to Equation (5).

$$Satisfied_{u,v} = \frac{|I_u^S \cap I_v^S|}{|I_u^S \cup I_v^S|} \tag{5}$$

Dissatisfaction. The dissatisfaction aspect shows the level of users' similarity considering their lack of interest in items. Users are not interested in an item if they rate it less than 3. The degree of user dissatisfaction is calculated on the basis of the ratio of their common discontent in items to the sum of the total items that the two users have been dissatisfied with, according to Equation (6).

$$DisSatisfied_{u,v} = \frac{|I_u^D \cap I_v^D|}{|I_u^D \cup I_v^D|} \tag{6}$$

Indifference. The indifference aspect indicates items that the users are neither satisfied nor dissatisfied with. In fact, users have had no particular interest in these items and regarded them as neither good and nor bad. In this approach, users are indifferent to items that have scored between 3 and 4, which is computed by Equation (7).

$$Indifference_{u,v} = \frac{|I_u^I \cap I_v^I|}{|I_u^I \cup I_v^I|} \tag{7}$$

3. 4. Rate Distance Another important factor that has been considered in this study is the distance between the users' rates for their common items. Furthermore, one of the deficiencies of Pearson's similarity criterion is that it does not take the distances between the user ratings into consideration. Therefore, by considering this parameter, we have somehow eliminated this similarity defect and increased the trust quality of the proposed approach. Additionally, the rate distances have a similar and direct effect on the degree of analogous opinions and confidence between users. In this approach, the rate distances between users are calculated based on the Euclidean distance and are scaled to [0,1]. Equation (8) shows how to compute the rates distances.

$$RateDistance_{u,v} = \frac{1}{1+\left(\sqrt{\sum_{i \epsilon I_{u,v}} (r_{u,i} - r_{v,i})^2}\right)} \tag{8}$$

4. RECOMMENDATION METHODOLOGY

In this section, the system steps are elaborated. The block diagram of the recommendation strategy can be observed in Figure 1. In the initial step, the database is partitioned into a five-fold subset, as done in [11], and 80% of the data is taken as training and another 20% as the test. Then, the training data is clustered based on the user-item matrix, which includes users rating to items. Clustering methods are able to increase the performance of CF systems, considering the problem of data sparsity [11]. Many successful clustering methods have been introduced in literature, K-means, SOM, and Fuzzy C-means (FCM) are among some of the most well-known ones. In a study, these three clustering methods were compared on the same dataset used in this study, and the results have shown that the FCM clustering algorithm

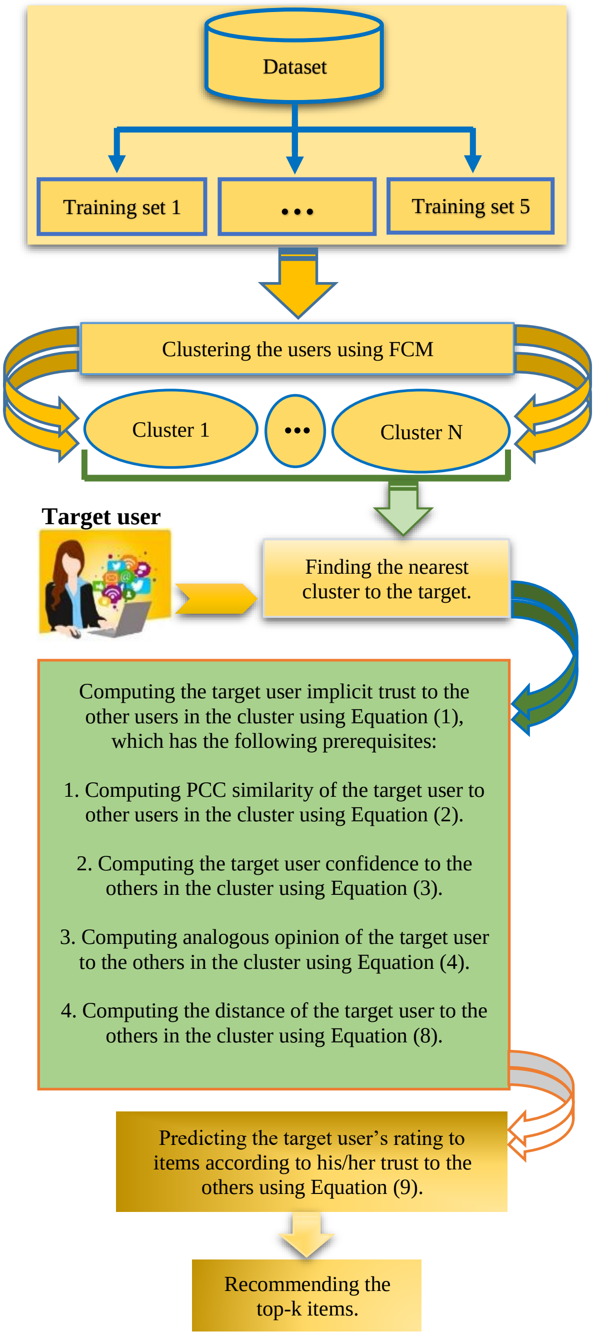

Figure 1. The block diagram of the recommendation strategy

improved the performance of CF systems better than the other two methods [11]. Therefore, the proposed approach uses the FCM clustering algorithm to improve its performance. FCM is a clustering method that provides each user with a different membership value. Finally, the maximum value of the defuzzification technique is used to determine the membership. After training the data clustering procedure, the target users are evaluted through the test data and they are appointed to a cluster, which is most resembling with them, by using Euclidean Distance measure. In the next step, those users that new users trust them are distinguished among the closest clusters of each user by using the proposed method of trust computation in this research, i.e. Equation (1). Afterwards, the target users' rating is predicted on the basis of their trustees by the following formula:

$$PredictRate_{\,u,i} = \bar{r_u} + \frac{\sum_{v\epsilon \bar{T}_u} Trust_{u,v}(r_{v,i}-\bar{r_v})}{\sum_{v\epsilon \bar{T}_u} Trust_{u,v}} \qquad (9)$$

After predicting the target users' rating for each item, k-top items are recommended to them.

5. EXPERIMENTAL EVALUATION

5. 1. Dataset In this paper, two databases of MovieLens[1] have been used to evaluate the proposed approach, including MovieLens 100K and 1M. These databases have been reaped by GroupLens[2] research group, known as the major database to evaluate recommender systems. The 100K database holds 943 users, 1682 movies and 100,000 ratings on a scale of 1 (inferior movies) to 5 (masterpieces). On the other hands, the 1M database holds 6040 users, 3952 movies and 1,000,209 ratings on a scale of 1 to 5.

5. 2. Evaluation Metrics In this study, we have used accuracy, precision and recall to evaluate the proposed scheme [41, 42]. The formulae for computing each of the criteria are given in Equations (10), (11) and (12).

$$Accuracy = \frac{\sum True\ Positive + \sum True\ Negative}{\sum Total\ Population} \qquad (9)$$

$$Precision = \frac{\sum True\ Positive}{\sum Test\ Outcome\ Positive} \qquad (10)$$

$$Recall = \frac{\sum True\ Positive}{\sum Realy\ Positive} \qquad (11)$$

Accuracy indicates a ratio of correct instances among entire instances that the system was successful in predicting. Precision is a ratio of the instances that correctly predicted as positive cases from all positive prediction instances, and Recall is a ratio of the correct positive predicted among truly positive specimens [11, 41]. The three mentioned parameters are estimated the confusion matrix as manifested in Figure 2.

5. 3. Results The proposed approach, namely Implicit Trust Computation Method (ITCM), has been compared with the approach proposed by Koohi and Kiani, 2016 (which has suggested the combination of Pearson's method and fuzzy clustering algorithm for CF systems), and the HRAT method which is a hybrid recommendation algorithm based on implicit trust [24]. It has been shown that the proposed implicit trust is superior to the Pearson and HRAT methods in improving the CF systems performance.

The evaluation was done with four different numbers of the cluster to show the ITCM increases the performance more than the methods in various cluster numbers.

Table 2 shows the results of the comparison and evaluation of ITCM with the Pearson similarity method with different numbers of clusters on the MovieLens datasets of 100K and 1M. The results show the better performance of the CF system based on the ITCM than the Pearson method at different numbers of clusters.

In 100K dataset, the highest values for accuracy and precision are respectively 84.15, 74.24 for ITCM and 81.18, 63.26% for the Pearson method with 3 fuzzy clusters; also, the highest recall value for ITCM and the Pearson method are 36.41 and 16.43% with 7 and 9 cluster numbers, respectively. In 1M dataset, the highest values for accuracy and precision are respectively 80.06, 71.98% for ITCM and 74.75, 54.32% for the Pearson method with 5 fuzzy clusters; also, the highest recall value for ITCM and the Pearson method are 20.86 and 6.73% with 9 fuzzy clusters.

The results of the evaluation of ITCM and HRAT are given in Table 3, which shows that ITCM has a better performance than HRAT at different numbers of clusters. In 100K dataset, the ITCM highest values for

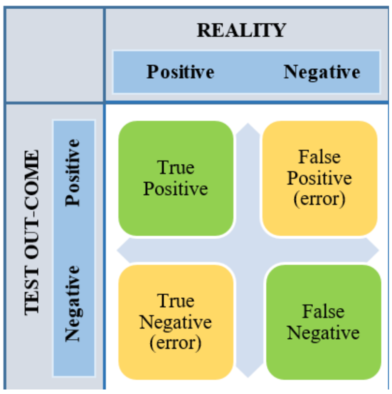

Figure 2. The confusion matrix

[1] http://grouplens.org/datasets/movielens/
[2] https://grouplens.org/

accuracy and precision are respectively 84.15 and 74.24% with 3 fuzzy clusters; in contrast, the HRAT highest values for accuracy and precision are respectively 82.16 and 68.96% with 3 and 5 fuzzy clusters; also, the highest recall value for ITCM and HRAT methods are 36.41% and 25.02% with cluster numbers of 7 and 5, respectively. In 1M dataset, the highest values for accuracy and precision are respectively 80.06, 71.98 for ITCM and 76.98, 57.64% for HRAT with 5 fuzzy clusters. Also, the highest recall value for ITCM and HRAT are 20.86% and 7.69% with cluster numbers of 9 and 3, respectively. In addition, the maximum and minimum values of accuracy, precision, and recall on each dataset of 100K and 1M respectively are shown in Tables 4 and 5.

In Figure 3, a comparison of the average results of the three methods is given, showing that performance of the ITCM method, interms of accuracy, precision and recall have increased by 3.18, 12.93 and 20.21% compared to the Pearson method, and 2.04, 5.81 and 11.87% compared to the HRAT method.

In Figure 4, a comparison of the average results of the three methods on 1M dataset is given, showing that performance of the ITCM method, interms of accuracy, precision and recall have increased by 5.83, 17.24 and

TABLE 2. ITCM method vs. Pearson method

Cluster No.	Dataset	Method	Accuracy	Precision	Recall
3	100K	Pearson	81.18%	63.26%	15.9%
		ITCM	**84.15%**	**74.21**%	35.88%
	1M	Pearson	73.92%	53.87%	5.62%
		ITCM	79.34%	71.12%	19.78%
5	100K	Pearson	80.92%	62.1%	15.52%
		ITCM	83.98%	74.02%	35.92%
	1M	Pearson	74.75%	54.32%	5.2%
		ITCM	**80.06%**	**71.98%**	19.47%
7	100K	Pearson	80.55%	60.06%	16.04%
		ITCM	83.69%	73.8%	**36.37**%
	1M	Pearson	73.14%	53.96%	5.12%
		ITCM	79.13%	70.51%	20.26%
9	100K	Pearson	80.21%	58.91%	16.43%
		ITCM	83.73%	73.95%	36.19%
	1M	Pearson	72.12%	52.61%	6.73%
		ITCM	78.72%	70.14%	**20.86%**
Average	100K	Pearson	80.715%	61.217%	15.972%
		ITCM	83.887%	73.995%	36.06%
	1M	Pearson	73.482%	53.69%	5.667%
		ITCM	79.312%	70.93%	20.092%

TABLE 3. ITCM method vs. HRAT method

Cluster No.	Dataset	Method	Accuracy	Precision	Recall
3	100K	HRAT	82.16%	67.34%	23.41%
		ITCM	**84.15%**	**74.21**%	35.88%
	1M	HRAT	75.7%	55.62%	7.69%
		ITCM	79.34%	71.12%	19.78%
5	100K	HRAT	81.34%	68.96%	25.02%
		ITCM	83.98%	74.02%	35.92%
	1M	HRAT	76.98%	57.64%	6.42%
		ITCM	**80.06%**	**71.98%**	19.47%
7	100K	HRAT	81.82%	68.33%	24.44%
		ITCM	83.69%	73.8%	**36.37**%
	1M	HRAT	76.32%	57.24%	6.98%
		ITCM	79.13%	70.51%	20.26%
9	100K	HRAT	82.07%	68.12%	23.89%
		ITCM	83.73%	73.95%	36.19%
	1M	HRAT	75.24%	56.93%	7.21%
		ITCM	78.72%	70.14%	**20.86%**
Average	100K	HRAT	81.847%	68.18%	24.19%
		ITCM	83.887%	73.995%	36.06%
	1M	HRAT	76.06%	56.857%	7.075%
		ITCM	79.312%	70.93%	20.092%

TABLE 4. Maximum and minimum value of results for ITCM, Pearson, and HRAT methods on the 100K dataset

Measure	Method	Maximum		Minimum	
		Value (%)	Cluster No.	Value (%)	Cluster No.
Accuracy	Pearson	81.18	3	80.21	9
	HRAT	82.16	3	81.34	5
	ITCM	**84.15**	3	**83.69**	7
Precision	Pearson	63.26	3	58.91	9
	HRAT	68.96	5	67.34	3
	ITCM	**74.21**	3	**73.8**	7
Recall	Pearson	16.43	9	15.52	5
	HRAT	25.02	5	23.41	3
	ITCM	**36.37**	7	**35.88**	3

TABLE 4. Maximum and minimum value of results for ITCM, Pearson, and HRAT methods on the 1M dataset

Measure	Method	Maximum		Minimum	
		Value (%)	Cluster No.	Value (%)	Cluster No.
Accuracy	Pearson	74.75	5	72.12	9
	HRAT	76.98	5	75.24	9
	ITCM	**80.06**	5	**78.72**	9
Precision	Pearson	54.32	5	52.61	9
	HRAT	57.64	5	55.62	3
	ITCM	**71.98**	5	**70.14**	9
Recall	Pearson	6.73	9	5.12	7
	HRAT	7.69	3	6.42	5
	ITCM	**20.86**	9	**19.47**	5

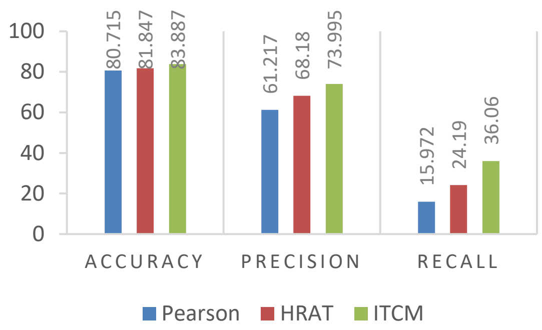

Figure 3. The comparison of the average results of the three methods on 100K dataset

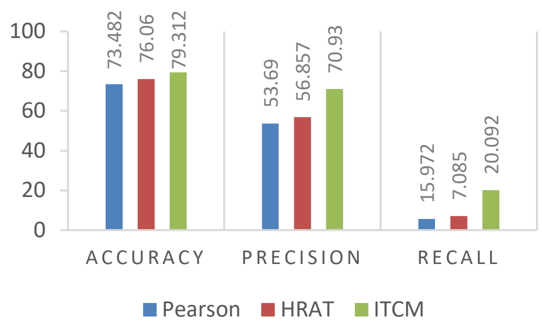

Figure 4. The comparison of the average results of the three methods on 1M dataset

14.42% compared to the Pearson method, and 3.25, 14.07 and 13.01% compared to the HRAT method.

Finally, all of the comparisons show that the ITCM approach significantly improves the efficiency of CF systems compared to the HRAT and Pearson methods.

6. CONCLUSION

The goal of CF-based recommender systems is attaining users' interests based on similar users' opinions. Therefore, to increase the accuracy of recommendations, finding similar users is an important challenge. Trust is one of the most primary elements in the social relationships between individuals in the real world and it is believed that a more trusted person has a greater influence on the choices of other people. Thus, this study has used the concept of trust to solve the existing problems in trust-based approaches and provides a method for calculating the implicit trust based on the user rating matrix to identify trusted users (who have similar interests) and improves the performance of CF systems. The results and evaluations show that the proposed approach improves the performance of CF systems, thus using the trust method to find neighbor users and predict the item ratings is superior to the other methods. Therefore, it can be helpful for e-commerce websites to recommend products that are close to what customers are interested in. As future works, the researchers are going to extend ITCM by considering other factors and features effecting on social trust such as users' demographic transmission.

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A Novel Trust Computation Method Based on User Ratings to Improve the Recommendation

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چکیده

امروزه اعتماد به یکی از راه حل‌های مفید برای بهبود سیستم‌های توصیه‌گر به ویژه روش فیلتر همکاری تبدیل شده است. با این حال، اظهارات اعتماد دارای کاستی‌هایی چون پراکندگی اظهارات اعتماد، عدم وجود امکان بیان اظهارات اعتماد برای کاربران در اکثر برنامه‌های کاربردی موجود و غیره، می‌باشد. از این رو، این پژوهش روشی برای محاسبه اعتماد به صورت ضمنی برای غلبه بر این مشکلات ارائه داده است. روش پیشنهادی بر پایه امتیازهای کاربران می‌باشد، که از چهار عامل مهم شامل تشابه، عقاید مشابه کاربران، قابلیت اطمینان و فاصله برای برآورد اعتماد بهره می‌برد. برای محاسبه تشابه کاربران، معیار ضریب همبستگی پیرسون مورد استفاده قرار گرفت. قابلیت اطمینان از طریق اشتراک‌های کاربران در آیتم های امتیاز داده شده محاسبه شد. برای محاسبه عقاید مشابه کاربران، اینکه آنها چه امتیازی به آیتم‌ها داده اند در سه جنبه رضایتمندی شان، نارضایتمندی و ممتنع بودن شان در مورد آیتم‌ها مورد بررسی قرار گرفت. همچنین، فاصله اقلیدوسی برای محاسبه فاصله امتیازهای کاربران استفاده شد. مزید بر این، روش خوشه‌بندی فازی سی‌مینز به منظور خوشه‌بندی ابتدایی کاربران مشابه نیز به کار گرفته شد تا عملکرد را افزایش دهد. در پایان برای ارزیابی رویکرد پیشنهادی از دو مجموعه داده‌ای MovieLens شامل دیتابیس 100K و دیتابیس 1M استفاده شده است و نتایج نشان داده‌اند که رویکرد این پژوهش مقدار صحت، دقت و فراخوانی سیستم را به میزان قابل توجهی افزایش می دهد.

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