Using Trust in Collaborative Filtering for Recommendations

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***Abstract*—Recommender systems are increasingly being used in e-commerce websites to solve the problem of finding right kind of information. Collaborative filtering is considered as most promising method for recommendation because it recommends items based on common interests of users. Trust Aware Recommender Systems (TARS) is an enhancement of traditional recommendation systems to improve recommendation quality which uses trusted users for recommending an item to an active user. From literature, it is proven that including all trusted users in recommendation process reduces its performance so this research work performs a filtration process on users for reduction of trusted neighborhood of an active user. The main idea of this research work is to keep only those users in trusted neighborhood whose rating behavior is similar to an active user. Subspace clustering method is used for filtration process. The proposed algorithm uses both implicit and explicit trust for trust value calculation. The results demonstrates that the proposed algorithm improves results in terms of Mean Absolute Error and Coverage as compared to other conventional methods.**

Keywords*—*Collaborative filtering, Neighborhood filtration, Implicit trust

I. Introduction

Due to advancement in information technology, getting useful information in less time is becoming difficult for users. Many applications are now using Recommender systems to propose items to the users they might like by finding the user's preferences. These applications includes music, shopping, travelling, restaurants, E-commerce etc. [1].

There are three main methods for designing a recommender systems which includes 1) content based filtering (CBF), collaborative filtering (CF) and hybrid filtering approach. Collaborative filtering is commonly known approach in recommendation systems. In CF, users with common interests are considered by calculating the rating similarity of the users. A user gets the recommendation for an item if a user in its neighborhood has rated that item. Many applications such as Amazon, Netflix and many more, use CF to make browsing easy for their users. As a result, the sale rate of Amazon is increased by 29% [2] and movie rental rate of Netflix is increased by 60% in recent years [3].

Data sparsity and Cold start problem are the two main issues in collaborative filtering approaches. Data sparsity occurs when there are multiple items in dataset and users have only rated few items and many items have an empty or zero rating which means popular items in dataset will also have very less ratings leading to unrealistic results [4]. Cold start problem occurs if we are unable to predict reliable ratings because of the lack of initial ratings for the specific item in the system [5].

Trust Aware Recommender Systems (TARS) is an enhancement of collaborative filtering based recommender systems which is being used to resolve data sparsity problems [52]. TARS develops trust models by getting data of social relationship between users. Trust statements are used like similarity measures to assign weights to neighboring users for recommendation process. Since neighbors are the main source of information in collaborative filtering, the quality of recommendation can be improved by considering only trusted neighbors in recommendation process [6]. Many researchers have worked on this issue to formulate an effective neighborhood of user for improving recommendation accuracy based on different criteria. [6], [43], [45].

In this research work, implicit and explicit trust along with the subspace clustering method [48] is used to consider only effective trusted users in recommendation process. In [48], a subspace clustering method is proposed to find users that provide maximum information about the likes and dislikes of the active user. Subspace clustering is basically an enhancement of the traditional clustering method which finds the groups of similar objects that are embedded in a large dataset [7]. The proposed algorithm contains four steps. First step is trust network construction which uses both implicit and explicit trust to find trusted neighborhood of a target user. Then those trusted neighbors are used in second step to find the initial ratings for unrated items. Third step uses subspace clustering method to reduce the trusted neighborhood of target users to only those trusted neighbors that provide the maximum information about active user. Finally, trust and rating values of trusted neighbors are used to find the ratings for unrated items.

The rest of the paper is organized as follows: Relevant research work is studied in Section 2. Section 3 defines proposed algorithm in detail and section 4 presents an example to solve each step of algorithm. Experimental results on dataset are discussed in section 5 and section 6 concludes the presented research work.

II. Literature Review

Collaborative filtering approaches are being used in research from past few years to improve recommendation accuracy. One approach of CF is memory based collaborative filtering (also called user based collaborative filtering). It predicts items based on similar users to target user [8]. The second method is model based collaborative filtering also called item based collaborative filtering. Here, we calculate the similar items by using the rate values given by users to different items [8].

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Two main problems in collaborative filtering approaches are Data sparsity and Cold start problem. Many techniques have been introduced to solve data sparsity issue. A possible method is to remove the unrepresentative items and users to solve sparsity problem [9]. But these kind of methods decrease the performance of system. Another approach is to apply matrix completion methods to fill the rating matrix with implicit ratings of user or with default values [10]. Another method is to find out the accurate users to use in rate prediction by using different methods such as pattern mining [11], similarity measures [29], resource allocation [13] and social networks [14].

The cold start user problem is a major issue in collaborative filtering. It occurs because when a new user enter into system, he do not have any rate history so nothing will be recommended to him. This problem may occur even after the new user has made some ratings but those are not enough for collaborative filtering based recommender system to make recommendations so that the new user will feel that system is not offering the expected services and may leave the system [15]. Many methods have been presented in literature to resolve cold start user problem. The studies can be divided into three main groups which are 1) Using additional sources of data, 2) use hybrid methods to enhance prediction process and 3) select most prominent analogous users [16], [24], [18], [28], [19], [20].

Many techniques from literature comes under these three groups. Vozalis et al. [21] proposed an enhanced version of K-nearest neighbor algorithm by including demographic vector of user to the user profile to calculate similarity. Zhang et al. proposed a technique to use social tags to make recommendation for users [22]. Son et al. [25] proposed a filtering method that uses fuzzy geographically clustering [26], [27] called as MIPFGWC-CS which solves problem of similarity between missing ratings and items and selected demographic attributes.

From recent research we can conclude that use of social factors e.g. trust statement can help to overcome the major drawbacks of recommender systems and can improve the recommendation results [29], [30]. Trust is a property that is related to people in real world and also to the social media users [31], [32]. There are many methods presented in literature that uses trust statements in recommendation process. These approaches are classified into two categories in which one is explicit trust and other is implicit trust.

Explicit trust methods asks the user to rate other users in the system and a trust network is created based upon that rating. There are many approaches in previous research that uses explicit trust method. In [33], a method named as TidalTrust is proposed that uses trusted users to make recommendations. Guha et al. [34] proposed a trust propagation framework which is based upon assumption that trust values are explicitly stated by users. They also presented concept of distrust and its propagation. In [52], a trust propagation technique is introduced that is used for calculation of trust weight which we can use at the place of similarity weight. This method also uses explicit trust statements. In [35], a practical application of explicit trust is presented which applies the method on a website where user can express his views about condition of snow on various ski routes. Other users can view the opinion and are also able to show their trust on the opinion.

Implicit trust statements are calculated from other information like user's profile, rating values and user's social interactions. Implicit approach develops the trust relationships between users using their common ratings on different items in system [37]. In [38], TARS (Trust Aware Recommendation System) is developed that uses the idea of dynamic trust within the users of system. A Trust Walker method is proposed in [39], which performs walk along the whole system and asks users about the ratings of their direct and indirect friends on target item. Another approach uses the concept of conditional probability for finding the level of similarity of friends on social network [40]. In [41], a method is proposed that uses quantitative as well as qualitative values for building trust statements between users on basis of their interrelated choices. A research method uses implicit trust statements to improve recommendation accuracy for cold start problems [42]. In [52], results shows that adding data from social networks in collaborative filtering have significant impact on recommendation results.

As in collaborative filtering method, main source of information are neighbors of a user because recommendation is mainly dependent upon the neighbors and we can improve quality of recommendation if we use trusted neighbors in recommendation process [6]. Many researchers have worked on this issue to formulate an effective neighborhood of user for improving recommendation accuracy. Guo et al. presented a merging technique that firstly combines the rate values of trusted users to find similar users in the system. Then to check the rating quality, confidence is calculated using ratio of positive and negative ratings. The confidence value is used in recalculating the similar users and the final recommendation is based upon the opinion of the finally selected users. The method is dependent upon explicit trust method so it is applied upon Epinions, FilmTrust and Fixter datasets [43]. Moradi et al. proposed a new measure to calculate reliability which is used for reconstructing the trust network to remove useless users from the network [44]. In [45], pareto dominance is used to find the most effective users from the confident users to use in recommendation process. Hence, this approach merges both the confidence and pareto dominance concept to improve the recommendation process.

III. Proposed Algorithm

There are four basic steps in proposed algorithm. Figure 1 shows the diagrammatic representation of the flow.

A. *Trust Network Construction*

In trust aware recommender systems, the usage of trusted friends is an important element in prediction process. However, in most systems there are a number of users that do not have any trust statement which makes rating predication a difficult process. The proposed algorithm uses both implicit trust derived from ratings and explicit trust derived from trust statements for rating predication.

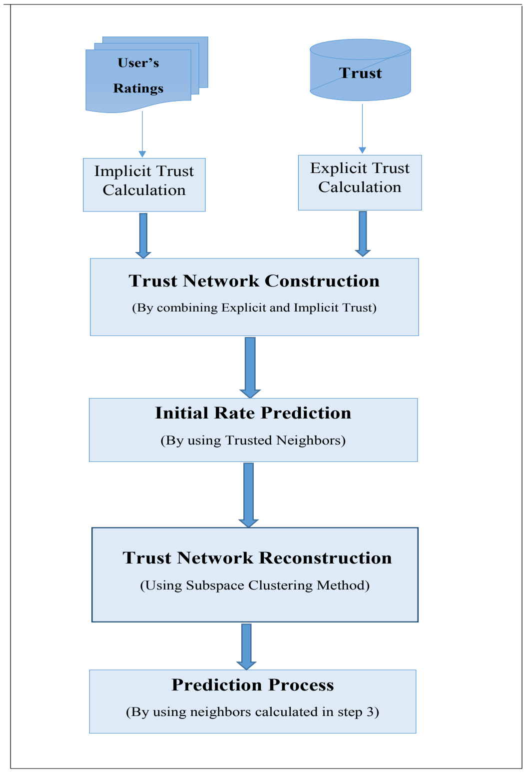

Fig. 1. Overview of Proposed Method

To compute the explicit trust, algorithm uses RTCF [44] as the trust metric. RTCF [44] uses trust network as weighted directed graph where the neighbors of the active user are nodes of the graph. The formula for trust value calculation using graph is as follows:

$$t1_{u,v} = \frac{d_{max} - d_{u,v} + 1}{d_{max}} \tag{1}$$

In this equation, d_{max} is the maximum propagation distance between the users. It is taken as number of hops in the shortest trust propagation path from the trustor to the trustee. d_{max} is set in range $[1, 3]$ in this research work. $d_{u,v}$ is the distance between users u and v which can also be calculated using the graph.

In literature, trust aware recommender system rely only on explicit trust for trust value calculation. But the limitation of explicit trust values is that these values are biased depending upon the personal relationships of the users. In proposed algorithm, implicit trust value is also considered that is computed using Cosine similarity measure for calculation of trust between users u and v. In Cosine based similarity, users are considered as vectors and following formula is used for similarity value calculation between user u and v:

$$t2_{u,v} = \frac{r_u \cdot r_v}{\|r_u\| \cdot \|r_v\|} \tag{2}$$

After the calculation of both explicit and implicit trust values, the algorithm takes the average of both values to find an initial trust value of user u on user v. Final equation for finding initial trust value is as follows:

$$t_{u,v} = \frac{t1_{u,v} + t2_{u,v}}{2} \tag{3}$$

In Equation 3, if $t_{u,v}$ is greater than a specified threshold value θ_t, then user v is considered as a trusted neighbor of user u and it will be used in initial rate prediction process.

B. *Initial Rating Predication*

Next step is the calculation of initial ratings for unrated items. Since, one of the main problem in RS is data sparsity as user-item rating matrix is usually highly sparse. It makes rating prediction a difficult process, even if we utilize trusted neighbors. To handle this issue, the algorithm first calculates the initial ratings for unrated items. Following formula is used for calculation of initial rating:

$$r_{u,i} = \frac{\sum_{v \in T_u} (t_{u,v})(r_{v,i})}{\sum_{v \in T_u} (t_{u,v})} \tag{4}$$

In Equation 4, T_u depicts the trusted neighbors of user u. $r_{u,i}$ is the calculated rating of user u on item i and $t_{u,v}$ is the trust value of target user u on its trusted neighbor v which is calculated in previous step. After calculation of estimated ratings, it will be imputed in the user item rating matrix to fill the empty places.

C. *Trust Network Reconstruction*

This step uses subspace clustering method [48] to find most effective trusted users in recommendation process. Subspace clustering method [48] converts the rating matrix into three different subspaces i-e interested item list, Not Interested Item list (NIU) and Uninterested item list. Since the creation of three subspaces increases the complexity of the algorithm, [48] converts the rating matrix into three binary matrices of interested, NIU and uninterested items. For interesting item subspace, the items rated greater than or equal to 4 by the target user are taken as 1 and remaining are given the value zero. For NIU item binary matrix, it replaces every rating which is equal to 3 or 3.5 as 1 and all others are considered as zero. For Uninterested item binary matrix, ratings equal to 0.5, 1, 1.5, 2 and 2.5 are set to 1 and all others are considered as zero.

After creating the binary matrices for each subspace, these matrices are converted into lists of items. These lists only contain the item number for which the corresponding matrix has value of 1. The, final subspaces of items is calculated by comparing the item sub spaces of the target user with its trusted neighbors. The algorithm selects only those trusted users whose item subspace is similar to the item subspace of the target user. For this, the algorithm discovers the trusted users whose interested, NIU and uninterested items are analogous to the target user. These neighbors will be used in final recommendation process.

D. *Prediction Process*

The final step of algorithm is prediction process where ratings for unrated items are predicted using final trusted neighborhood of users. Equation 5 is used to calculate the final rating values of unrated item of target user. The rating is based upon the neighbor users calculated after applying the subspace clustering.

$$P_{u,i} = \frac{\sum_{v \in F_u} (T_{u,v})(r_{v,i})}{\sum_{v \in F_u} (T_{u,v})} \tag{5}$$

Here F_u means Final trust value which is calculated using equation 3. It calculates the trust value of only those trusted neighbors which are discovered using step 3.

IV. An Illustrative Example

This section provides an example to describe the working of each step of proposed algorithm. Let us consider, a user-item matrix shown in Table I which contains 8 users and 9 items. A value from 0.5 to 5 is given as a rating of a user on any item and zero shows that user has not rated that item. Table II shows user-user trust matrix which contains 8 users and their trust relationship with every other user in the network.

TABLE I. User Item Rating Matrix

	i1	i2	i3	i4	i5	i6	i7	i8	i9
u1	2	0	0	1	4	2.5	0	1	0
u2	0	4	0	1.5	0	0	1	5	4
u3	1.5	0	0	0	4.5	0	5	0	0
u4	0	3.5	3	0	0	1	0	2	3
u5	0	0	2.5	0	3.5	0	0	0	4.5
u6	0	1	1.5	0	0	0	2	0	0
u7	2	0	0	3	0	0	0	1	5
u8	4	3	0	1	0	1.5	0	0	3.5

TABLE II. User User Trust Matrix

	u1	u2	u3	u4	u5	u6	u7	u8
u1	1	1	1	0	0	0	0	0
u2	0	1	1	1	0	0	0	1
u3	0	0	1	0	1	0	0	0
u4	1	0	0	1	0	1	0	1
u5	0	0	0	0	1	1	1	0
u6	0	0	0	1	0	1	1	1
u7	0	0	0	1	0	1	1	0
u8	0	0	0	1	0	0	0	1

In this example, rating value given by user $u3$ on item $i2$ is predicted by using the algorithm described above. Firstly, the algorithm finds an initial trust value of user $u3$ on other users in the network by constructing the trust network of user $u3$. Figure 2 represents the trust network of user $u3$.

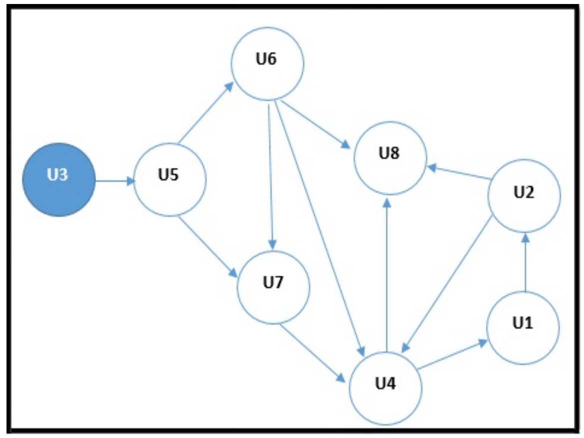

Fig. 2. Trust Network of u3

Next the trust value of $u3$ with every user is calculated using equation 3. dmax is set to 3 in this case. The calculation of trust value of $u3$ on $u1$ is shown in following equation:

$$t1_{u3,u1} = \frac{3 - 4 + 1}{3}$$

$$t1_{u3,u1} = 0$$

$$t2_{u3,u1} = 0.4082$$

$$t_{u3,u1} = \frac{0 + 0.4082}{2}$$

$$t_{u3,u1} = 0.2041$$

Similarly, trust values of $u3$ on $u1$, $u2$, $u4$, $u5$, $u6$, $u7$ and $u8$ are 0.20, 0.01, 0.16, 0.70, 0.33, 0.33 and 0.16 respectively. As the threshold values of $t_{u,v}$ is 0, any value below the threshold is eliminated so for this example, all users are part of trusted neighborhood of $u3$ and are used for initial rate prediction.

Second step is calculation of initial rating for the unrated item using equation 4. Rating given by user $u3$ on item $i2$ is calculated as follows:

$$r_{u3,i2} = \frac{0{+}4{\times}0.01{+}0{+}(3.5{\times}0.16){+}0{+}(1{\times}0.33){+}0{+}(3{\times}0.16)}{0.0{+}0.01{+}0.0{+}0.16{+}0.0{+}0.33{+}0.0{+}0.16}$$

$$r_{u3,i2} = 2.15$$

Similarly, the initial rating matrix for all users is shown in Table III.

TABLE III. INITIAL USER ITEM RATING MATRIX

	i1	i2	i3	i4	i5	i6	i7	i8	i9
u1	2	3.39	2.57	1	4	2.5	2.79	1	3.85
u2	2.44	4	2.43	1.5	4.1	1.62	1	5	4
u3	1.5	2.15	2.29	1.94	4.5	1.72	5	1.29	4.31
u4	2.62	3.5	3	1.56	4	1	2.24	2	3
u5	2.55	2.22	2.5	2.08	3.5	1.43	2.59	1.32	4.5
u6	2.95	1	1.5	1.84	3.75	1.41	2	1.67	3.94
u7	2	2.61	2.27	3	3.9	1.46	2.14	1	5
u8	4	3	2.04	1	0.1	1.5	1.98	1.52	3.5

After the calculation of initial rate, the algorithm reconstructs the trust network using subspace clustering method. The algorithm clusters the items of $u3$ in 3 subspaces Interesting, NIU and Uninteresting items as follows:

$$InterestingItemList = [5, 7]$$

$$NIUItemList = []$$

$$UninterestingItemList = 1$$

Table IV shows item lists of each user in the network.

TABLE IV. ITEM LISTS OF ALL USERS

	Interesting Items	NIU Items	Uninteresting Items
u1	5	6	[1,4,8]
u2	[2,8,9]	[]	[4,7]
u3	[5,7]	[]	1
u4	[]	[3,9,2]	[8,6]
u5	[9]	[5,3]	[]
u6	[]	[]	[7,3,2]
u7	9	4	[1,8]
u8	1	[9,2]	[4,6]

Next the item lists are compared with Interesting, NIU and Uninteresting Lists of trusted neighbors of $u3$ that are $u1$, $u2$, $u4$, $u5$, $u6$, $u7$ and $u8$ and those users are considered in prediction process whose Interesting, NIU and Uninteresting Item Lists are most similar to the item Lists of $u3$.

$$InterestingUsers = 1$$

$$NIUUsers = []$$

$$UninterestingUsers = 1, 7$$

In the example, user $u3$ is left with only $u1$ and $u7$ as effective trusted users, which will be used for prediction process. Final trust value of $u3$ on $u1$ and $u7$ are calculated using equation 3 which are 0.20 and 0.33 respectively. Then, Final rating of u3 on i2 is calculated using Equation 5 which is shown as follows:

$$P_{u3,i2} = \frac{(0.20 \times 3.39) + (0.33 \times 2.61)}{0.20 + 0.33}$$

$$P_{u3,i2} = 2.90$$

Similarly we can find rating value for every unrated item in user-item rating matrix using the above procedure. (Shown in Table V)

TABLE V. FINAL USER ITEM RATING MATRIX

	i1	i2	i3	i4	i5	i6	i7	i8	i9
u1	2	3.14	2.44	1	4	2.5	2.59	1	3.89
u2	2.82	4	2.16	1.5	4.1	1.72	1	5	4
u3	1.5	2.90	2.38	2.24	4.5	1.85	5	1	4.5
u4	2.7	3.5	3	1.65	4	1	2.32	2	3
u5	2.22	2.93	2.5	2.47	3.5	1.29	2.18	1.36	4.5
u6	2.44	1	1.5	1.5	4.10	1.62	2	5	4
u7	2	3.22	2.68	3	3.97	1.49	2.43	1	5
u8	4	3	2.99	1	4	1.5	2.23	2.02	3.5

V. EXPERIMENTAL RESULTS

In this section, different experiments are performed for evaluation of proposed algorithm in terms of accuracy and coverage.

A. *Dataset Description*

FilmTrust dataset is used in this research study for experimentation. FilmTrust is trust aware social website on which users share their interests about movies by rating them and also share their reviews. As the proposed algorithm need both rating and trust information for its implementation, FilmTrust is most suitable dataset for this research work. There are 1508 users and 2071 items (movies) in the dataset. Rating matrix contains 35,497 ratings. Ratings are accepted from 0.5 up to 4.0 with a step size of 0.5. There exists 1853 trust relationships between 609 users of the dataset. Data sparsity is one of most common problems in recommender systems [4]. FimTrust dataset also has this problem. Statistics shows that there are 58.16% of the users who do not have any trust relationships [45].

B. *Evaluation Measures*

There are prediction accuracy matrices which are used to measure the prediction error [50]. Mean Absolute Error (MAE) is most commonly used measure that has been used in many research works [52], [51]. It calculates the average absolute deviation between the actual rating and the predicted rating using following formula:

$$MAE = \frac{\sum_{u \in U} \sum_{i \in I} |r_{u,i} - p_{u,i}|}{N} \quad (6)$$

In equation 6, U and I represents users and items sets, $r_{u,i}$ represents actual rating and $p_{u,i}$ represents the rating predicted by the proposed algorithm where N is the number of ratings.

Most of times, the recommendation algorithms do not focus on coverage and just improve the recommendation accuracy. Coverage means how much data from a dataset is used in recommendation process. Rating and User coverage are also used in this research work to assess the coverage of proposed algorithm. The rating and user coverage of recommendation algorithm can be calculated using Equation 7 and Equation 8.

$$RC = \frac{N_r}{N_c} \quad (7)$$

Rating coverage (RC) depicts percentage of hidden ratings for which the algorithm is able to predict a rate value. In Equation 7, RC is rating coverage, N_r means number of predictable ratings and N_c means total number of ratings in the dataset.

$$UC = \frac{N_i}{N_t} \quad (8)$$

User Coverage means the number of users in system for which the proposed method has predicted at least one rating. In Equation 8, UC is user coverage, N_i means the number of users in system for which the proposed method has predicted at least one rating and N_t shows total number of users in the dataset.

C. *Experimental Settings*

For experimentation, Dataset is partitioned in two sections which are training and testing datasets. 80% dataset is selected as training dataset and the other 20% dataset is the testing data. In proposed method, there are two parameters whose values are adjusted according to the dataset. The parameters are d_{max} and θ_t. d_{max} is the maximum propagation distance. It means the minimum number of hops needed to reach from trustor to trustee in the trust graph. Different recommendation methods uses different propagation distance. However, the maximum propagation distance is $d_{max} = 3$ which means hop 3. Another adjustable parameter is θ_t which is used to define initial trusted neighbors of a user. This value is set to 0 for this research work. So if in equation 3, the value of θ_t is greater than 0 then the user v is considered as the trusted neighbor of user u.

D. *Results*

A set of experiments are performed to evaluate the performance of proposed algorithm. Firstly, the Mean absolute error (MAE) is used to compare the performance of the proposed algorithm with other conventional algorithms namely, TCF [49], Merge method [43], RTCF method [44], HUIT [37] and MoleTrust [52]. Table VI shows comparison of MAE of proposed methods with above mentioned methods on FilmTrust dataset. The proposed method gives better results in terms of MAE as compared to other methods.

TABLE VI. COMPARISON OF MAE OF MOLETRUST ALGORITHM, TCF ALGORITHM, MERGE METHOD, RTCF METHOD AND HUIT ALGORITHM WITH PROPOSED ALGORITHM ON FILMTRUST DATASET

Method	MAE
MoleTrust [52]	0.771
TCF [49]	0.719
HUIT [37]	0.702
RTCF [44]	0.641
Merge [43]	0.708
Proposed Method	0.633

TABLE VII. COMPARISON OF RC OF MOLETRUST ALGORITHM, TCF ALGORITHM, MERGE METHOD, RTCF METHOD AND HUIT ALGORITHM WITH PROPOSED ALGORITHM ON FILMTRUST DATASET

Method	RC
MoleTrust [52]	95.19%
TCF [49]	30.38%
HUIT [37]	95.06%
RTCF [44]	92.35%
Merge [43]	91.36%
Proposed Method	94.21%

Table VII presents the Rating Coverage of the proposed algorithm along with other recommendation methods. In these experiments value of d_{max} is set to 3.

E. *Sensitivity Analysis of Parameters*

The algorithm presented in this research work has two parameters (d_{max} and θ_t) that can affect the performance of the algorithm. The impact of various values of these parameters is examined in this section.

d_{max} is maximum propagation distance. For finding out the most accurate value for d_{max}, different experiments are conducted with value of d_{max} =1, d_{max}=2 and d_{max}=3. Experiments proves that maximum propagation distance at hop3 gives best results in term of MAE which shows that including friends of friends in recommendation process improves prediction accuracy.

The second important parameter is θ_t which is used in Trust Network Construction step of algorithm for calculation of initial trusted neighbors. According to algorithm, if the value $t_{u,v}$ is greater than a specified threshold value than user v is considered as an initial trusted neighbor of user u. This threshold is set to 0 for experiments in this research work which means if value of $t_{u,v}$ is less than or equal to 0 then v will not be in trust network of user u. Figure 3,4 and Figure 5 presents the result of proposed algorithm for various values of θ_t with reference to MAE, RC and UC.

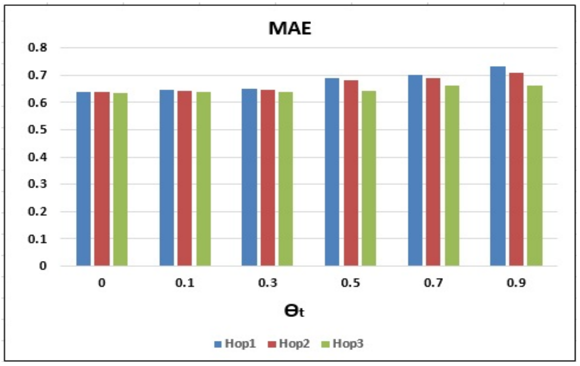

Fig. 3. Comparison of different values of θ_t at hop1, hop2 and hop3 with reference to MAE

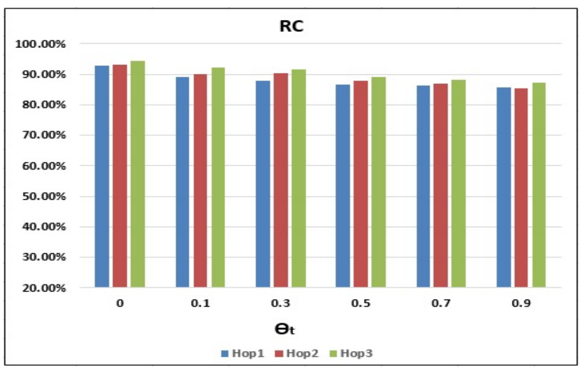

Fig. 4. Comparison of different values of θ_t at hop1, hop2 and hop3 with reference to RC

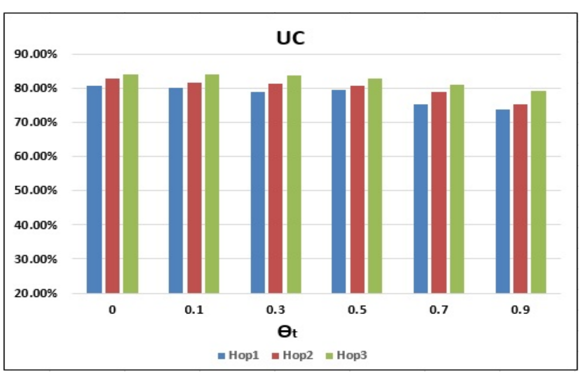

Fig. 5. Comparison of different values of θ_t at hop1, hop2 and hop3 with reference to UC

Table VIII,IX and Table X presents the result of comparison of best value of θ_t with $\theta_t = 0.9$ (Highest value) in FilmTrust dataset with reference to MAE, RC and UC.

TABLE VIII. MAE OF PROPOSED ALGORITHM, COMPARING THE BEST OBTAINED θ_t WITH $\theta_t = 0.9$ (HIGHEST VALUE) IN FILMTRUST DATASET AT HOP1, HOP2 AND HOP3

Propagation Distance	MAE at $\theta_t = 0$	MAE at $\theta_t = 0.9$
Hop1	0.639	0.73
Hop2	0.637	0.71
Hop3	0.633	0.662

TABLE IX. RC OF PROPOSED ALGORITHM, COMPARING THE BEST OBTAINED θ_t WITH $\theta_t = 0.9$ (HIGHEST VALUE) IN FILMTRUST DATASET AT HOP1, HOP2 AND HOP3

Propagation Distance	RC at $\theta_t = 0$	RC at $\theta_t = 0.9$
Hop1	92.88%	85.68%
Hop2	93.12%	85.31%
Hop3	94.21%	87.12%

TABLE X. UC OF PROPOSED ALGORITHM, COMPARING THE BEST OBTAINED θ_t WITH $\theta_t = 0.9$ (HIGHEST VALUE) IN FILMTRUST DATASET AT HOP1, HOP2 AND HOP3

Propagation Distance	UC at $\theta_t = 0$	UC at $\theta_t = 0.9$
Hop1	80.78%	73.68%
Hop2	82.91%	75.31%
Hop3	84.00%	79.12%

VI. CONCLUSION

Collaborative filtering is considered as most promising method for recommendation because it helps the users to find items of their interest. TARS is an enhancement of traditional recommendation systems to improve recommendation quality. In TARS, trusted users are used for recommending an item to an active user. The reduction in number of trusted neighbors that are to be used in recommendation process is an important step for producing quality recommendations. To solve this issue, the proposed algorithm uses sub-space clustering method which clusters the users based on their rating values. There are four basic steps in proposed algorithm. First steps is to create a trust network of users, Second step calculated initial trust and rating values for unrated items based on trusted neighbors, Third step uses subspace clustering method to reduce the number of trusted neighbors of users to only useful users which are later used in step 4 for calculation of final predicted rating for unrated items. For evaluation, the proposed algorithm is compared with other conventional techniques using FilmTrust dataset. Different quantitative analysis measures such as MAE, RC and UC are used to verify the accuracy of the proposed algorithm. The results of proposed algorithm clearly demonstrates the enhanced performance of the proposed algorithm as compared to other techniques.

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