Improving Prediction Accuracy in Trust–aware Recommender Systems

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Abstract

Trust–aware recommender systems are intelligent technology applications that make use of trust information and user personal data in social networks to provide personalized recommendations. Earlier research in trust-aware systems have shown that the ability of trust-based systems to make accurate predictions coupled with their robustness from shilling attacks make them a better alternative than traditional recommender systems. In this paper we propose an approach for improving accuracy of predictions in trust-aware recommender systems. In our approach, we first reconstruct the trust network. Trust network is reconstructed by removing trust links between users having correlation coefficient below a specified threshold value. For prediction calculation we compare three different approaches based on trust and correlation. We show through experiments on real life Epinions data set that our proposed approach of reconstructing the trust network gives substantially better prediction accuracy than the original approach of using all trust statements in the network.

1. Introduction

Recommender systems are technology based systems that provide personalized recommendations to users. In these systems, opinions and actions of other users with similar tastes are used to generate recommendations. Recommender systems primarily use ratings data given by a user to different items present in the system to make personalized recommendations. Recommender systems are a ubiquitous feature in most ecommerce sites such as Amazon.com, Ebay.com, Netflix.com, Last.fm etc. Recommendation systems popularity is not only because of their ability to provide personalization features but also due to their impact in higher sales and profits. In [2], it has been shown empirically on Amazon.com dataset that recommender systems indeed improved sales. However, with increasing popularity of recommender systems in ecommerce sites they have become susceptible to attacks by malicious users who try to influence the systems by inserting biased data into the system [10]. Recent research on trust aware recommender systems [4, 6, 7, 8] has shown that they are more robust against shilling attacks and are more capable of generating recommendations for new users in the system. Trust aware systems also have been shown to produce recommendations which are better than or as accurate as collaborative filtering based recommender systems. Trust aware systems are able to make more accurate recommendation compared to traditional systems as they use the concept of trust propagation over a trust network. Because of these advantages over traditional systems, trust aware recommender systems are generating much research interest.

Social networking based websites are one of the most successful web based applications. While both recommender systems and social networks can exist independently, the quantity and quality of personal and social data captured about users in social networks make them an ideal platform where recommender systems can be used to create socially intelligent systems. Furthermore, research in the area of application of recommender systems in social networks has shown that users prefer recommendations from friends and systems they trust [13], as compared to getting predictions from strangers. Availability of trust data in social networks makes them ideal for the application of trust-aware recommender systems in them. Researchers have already started focusing on application of trust-based recommender systems in social networks. In [4], it has been shown how trust based recommender system outperform traditional recommendation approach on data from Filmtrust.com a website that integrates social networking features into recommender systems. Similarly in [6] superiority of trust-based systems has been experimentally shown on data from Epinions.com.

Earlier approaches for prediction in trust aware system make predictions in trust-aware systems utilizing all the trust statements present in the data. The reason explained for the superiority of trust based recommendation over traditional recommendation approach has been attributed to the

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fact that there is high correlation between trust and user similarity. In [1], it has been shown that user develop social connections with people that have similar tastes. In [14] they have empirically shown correlation between trust and similarity in an online community Allconsuming.net. Existing approaches in trust-aware systems assume that a trust statement passed between two users imply that similarity between both users will be high. We believe that every trust statement passed by a user A on user B does not signify that correlation between A and B will also be high. User may pass trust statements on another user on the basis of perceived notion that his preferences matches with the other user, while similarity calculated based on ratings may show that they are different. We believe that presence of trust statements between users with low similarity impacts prediction quality adversely. In this paper we propose an approach where we reconstruct the trust network by removing those statements between users where similarity between the users fall below a set threshold correlation. We also examine different weightage schemes to generate prediction. Existing approaches only use trust as weightage. Through experimental evaluation on Epinions data set [3] we show that our proposed strategy of using reconstructed trust network for generating predictions shows substantial improvement in accuracy over existing trust-aware recommender systems.

This paper is organized as follows. In section 2 we provide a brief summary of trust-aware recommender systems. In section 3 we describe our proposed recommendation approach. In section 4 we describe the experimental evaluation process and report the results obtained in section 5. We conclude the paper in section 6.

2. Trust-aware Recommender Systems

Algorithmic approaches used in recommender systems [5] can be classified into two major categories, namely content based and collaborative filtering based. In content based recommendations, content data like a set of keywords that describe items contents are used to make recommendations. In collaborative filtering, a user is recommended items that people with similar tastes and preferences liked in the past. This technique mainly relies on explicit ratings given by the user and is the most successful and widely used technique. There are two primary approaches which are used to build collaborative filtering (CF) memory based recommender systems, user-based CF [5] and item-based CF [12].

Trust aware recommender systems also use rating data for making predictions but in addition to rating data they also utilize trust data. Initial research [11] on trust-aware recommender systems used trust values derived from ratings, subsequent research on trust-ware recommender systems [4,6,7] used explicitly made trust statements. This paper also uses trust data based on explicitly stated trust statements between users. Trust data are trust statements made by a user about another. In the Epinions data set used for evaluation, trust statement given by a user A to another user B represents a explicit score provided by user A expressing how much value user A attaches to the ratings and reviews given to different items by user B. Trust statements are weighted, subjective, context dependent and asymmetric[6]. For making predictions to an active user, trust-aware systems use the ratings made on different items by users trusted by the active user. While in collaborative filtering, ratings made by users similar to the active user are used for making predictions. One of the major weaknesses of collaborative filtering system is their inability to calculate similarity between two users when numbers of co-rated items by both the users are few. Trust based systems overcome this drawback by using the concept of trust propagation [6]. Using the concept of trust propagation the system predicts the trust value between two users even if it has not been explicitly stated. The predicted trust value is dependent on the trust metric used. Trust metric can be global or local. Much research work is been done in the area of trust metrics [9].

Prediction generation in trust-aware systems depend on the trust weightage between the active user and other users connected to it, the propagation distance k and the ratings given by the trusted users to the item for which prediction is to be made. Users connected directly to the active user are said to be connected to the active user at trust propagation distance k=1or in other words users are present in web of trust level 1 for the active user. Users who are directly connected to trusted users of the active user at k=1 form the set of trusted users at trust propagation level 2 for the active user. As users at propagation distance k=2 are not directly connected to the active user, their trust value with the active user is calculated using a trust metric. Final prediction for an item is made using the following formula

$$r_{ui}=\frac{\sum_{v\in N} T_{uv} r_{vi}}{\sum_{v\in N} T_{uv}} \quad (1)$$

Here r_{ui} denotes the rating given to item i by user u., predicted rating for item i is the average of the rating given to i by those users who are connected to u within propagation distance k weighted by their trust value with user u. T_{uv} is the trust value between user u and those users who have rated i and are present in the network N i.e. users connected to u within trust propagation distance k.

3. Our Recommendation Approach

In a trust network, a trust statement passed by user A on user B indicates that user A considers user B ratings of different items as agreeable or similar to his own likeness for the same set of items. Considering the earlier statement as true, we can safely conclude that similarity between user A and user B will be high if user A has made a positive trust statement on user B. Similarity is calculated using the Pearson correlation coefficient r. If two users have given similar ratings to the same set of items, r will be equal to +1 and in case of exactly opposite ratings r will be -1. Therefore, in a scenario where user A has passed a positive trust statement on user B ,correlation coefficient between user A and user B can be expected to be greater than 0.5.

To test whether the assumption that a positive trust statement between two users implies high correlation between the two users holds true, we analyzed the Epinions data set [3]. Analysis of the data presented in figure 1 shows a different picture. For a trust statement passed between two users, the user who has made the trust statement is the source user and the user on which the trust statement has been made is known as the target user. We observe that for majority of trust statements made, correlation between the source user and target user can be calculated only for a small fraction. Out of 487183 trust statements made, for only 12.84 % of the trust statements correlation can be calculated between the source user and target user. Furthermore, from the 12.84% trust statements only in 52% of the cases, source user and target user have at least 4 co-rated items. Also, out of 487183 trust statements, only 2.91% have a similarity value of greater than 0.5 and at least 4 co-rated items between source user and target user. This observation that majority of the trust statements passed between users cannot be seen as a reflection of similarity between the two users leads us to believe that the existing approach of generating predictions for a user in a trust-aware recommender systems cannot be the most accurate technique.

Current recommendation approach considers all trust statements made within the network to generate predictions. This approach is based on the assumption that a trust statement between two users signals high correlation between the two users. In our proposed approach we reconstruct the trust network by removing all trust statements that fall below a threshold correlation value. Recommendations are generated utilizing the reconstructed network. Thus, our proposed approach can be divided into two major steps: Reconstruction of the trust network and rating prediction. We explain below in detail the two steps.

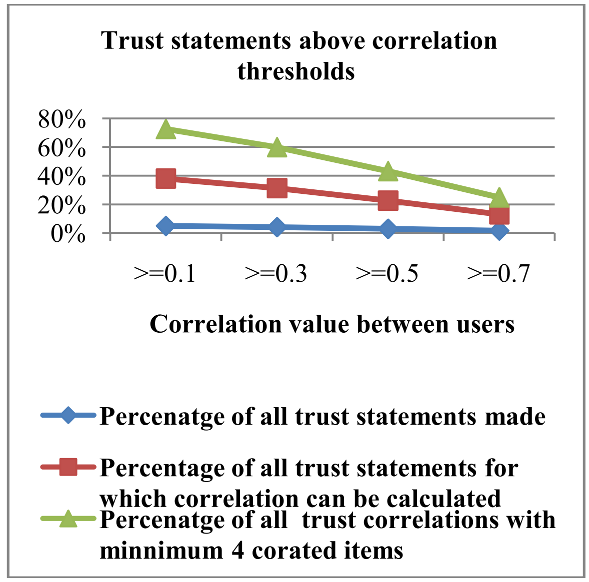

Figure 1: % trust statements having correlation value between users above a set threshold

3.1 Reconstruction of the Trust Network

The first stage of our approach is the most critical stage as it strengthens the trust network ability towards making accurate predictions by removing trust statements that fall below a threshold correlation value. For example, figure 2 shows a trust network consisting of 6 users.

In figure 2, nodes A, B, C, D, E, and F represents users, arrow connecting two users signifies that a trust statement has been passed between the two users. Correlation value between two nodes is shown by the symbol C(x), where x is the correlation value. C(0.60) on the arrow directed from user A to user B implies that correlation value between user A and user B is 0.60. Let the threshold correlation value be set at 0.5, i.e. those trust statements between two users that have correlation value less than 0.5 are removed from the original network. Figure 3 shows the reconstructed network. It can be seen that trust links (A,C) and (C,F) are no longer present in the reconstructed trust network as Corr(A,C) and Corr(C,F) fall below the threshold value 0.5.

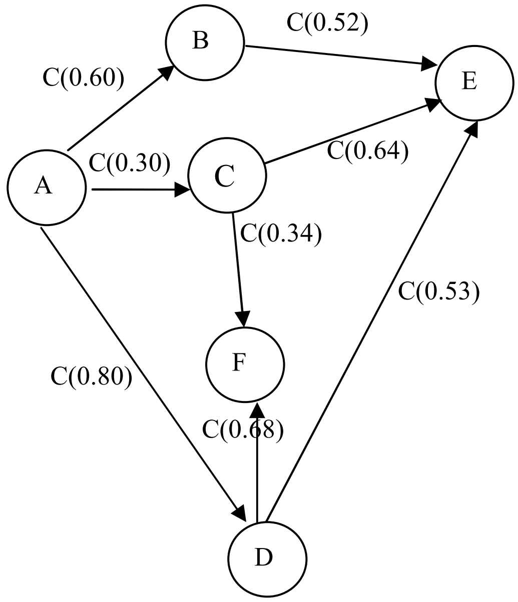

Figure 2: Original trust network

Reconstruction of the trust network is dependent on the important parameter threshold correlation value. Selection of threshold value affects both quality of predictions made and also the coverage i.e. number of items for which predictions can be made for an user. A high threshold value may lead to more accurate predictions but coverage will diminish as an increase in correlation threshold value will lead to fewer trust connections in the reconstructed network. Similarly, a low threshold value will decrease accuracy but will result in better coverage.

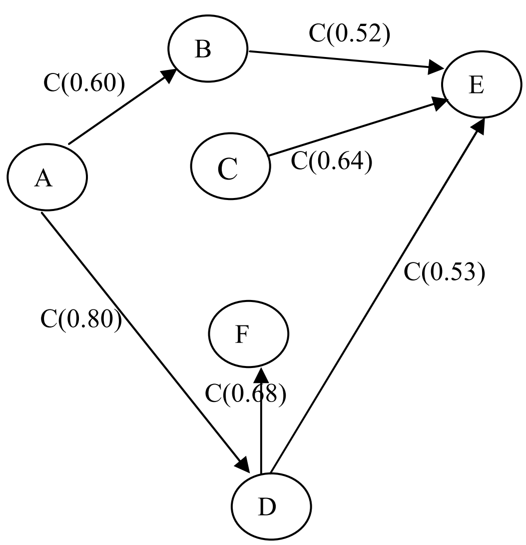

Figure 3: Reconstructed trust network

3.2 Rating Prediction

This section explains the process of predicting the rating of an unseen item for an active user in the trust network. As explained earlier in section 2, there are two stages involved in predicting the rating that an active user U_a will give to an item I_t unseen by him in a trust-aware recommender system within trust propagation level *k*. First, those users who have rated the item I_t and are connected to the active user U_a in the trust network within trust propagation level *k* are selected. In the second step, prediction is calculated by taking the weighted sum of the rating given to I_t by the set of users selected in the first step. Weightage used is the trust value between the selected users and the user U_a. While in the original process prediction was generated by using trust as weightage over the whole trust network or trust-net, in our approach we use the reconstructed network. For weightage we have used three strategies namely trust, correlation multiplied with trust which we call correl_trust and top-n correl_trust values only. The example below illustrates the process.

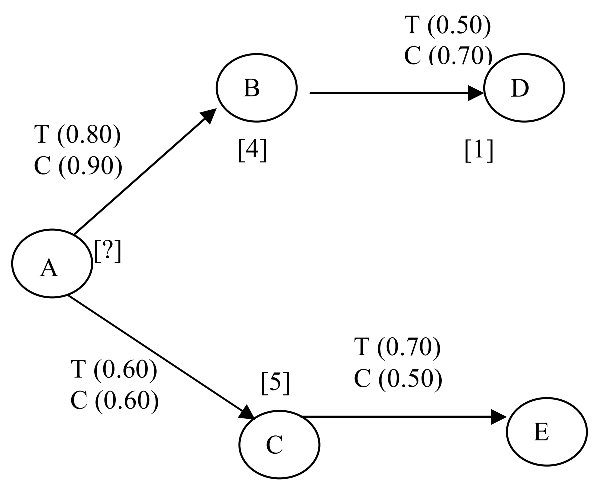

Figure 4: Reconstructed trust network for user A

Let us consider a user A, for whom we will predict the rating he will give to an item I_t, using the three strategies. Figure 4 shows the reconstructed network for user A. Reconstructed network shown is for trust propagation level 2.

User B and C are connected to user A at web of trust level 1. B and C have rated the test item I_t as 4 and 5 respectively as shown in square brackets in figure 4. At web of trust level 2, A is connected to user D and E .While user D has rated item I_t as 1, user E has not rated I_t. As during calculating prediction for

I_t only users who rated item I_t are considered, even though user E is present in A trust network it does not affect the predicted rating of item I_t by user A. Values of trust and correlation between users are depicted on the arrows connecting them. T(0.80) on the arrow directed from user A to user B implies a trust statement of value 0.8 has been passed on user B by user A where trust value of 1 signifies the highest amount of trust. Similarly, C (0.90) implies that correlation between user A and user B is 0.90.

Assuming that trust is propagated linearly i.e. trust propagation value at web of trust level 2 is 0.5, we show below the predicted rating that user A will give to item I_t according to our approach.

Trust: On using trust as weightage the predicted rating will be $\frac{0.80 \text{ x } 4+0.60 \text{ x } 5+(0.5 \text{ x } 0.5) \text{ x } 1}{0.80 + 0.60+(0.5 \text{ x } 0.5)} = 3.9$.

Correl_trust: On using correlation multiplied with trust as weightage the predicted rating will be calculated as follows

$\frac{0.80 \text{ x}0.90\text{x } 4+0.60\text{x}0.60 \text{ x } 5+(0.5 \text{ x } 0.5)\text{x}0.70\text{x } 1}{0.80\text{x}0.90 + 0.60\text{x}0.60+(0.5 \text{ x } 0.5)\text{x}0.70} = 3.87$.

Top-n Correl_trust: On using top-n correl_trust values only as weightage (in this example n=2), the predicted rating will be calculated as follows,

$\frac{0.80 \text{ x}0.90\text{x } 4+0.60\text{x}0.60 \text{ x } 5}{0.80\text{x}0.90 + 0.60\text{x}0.60} = 4.33$.

4. Experimental Evaluation

We performed the experimental evaluation of our approach on the publicly available Epinions data set [3]. This is the most widely used recommender system dataset which has trust data. It consists of 50,000 users and 140,000 items. Total number of ratings is 660,000 and number of trust statements made is 490,000.Trust value is always one. Majority of users [53%] in dataset have rated less than 5 items. A detailed analysis of the data set can be found at [6, 8].

To conduct our evaluation, we randomly selected 50 distinct user-item combinations to test our approach. First, we randomly selected a set of 50 users from the set of those users that have a minimum of 10 trust statements and have correlation of value greater or equal to 0.5 with at least 4 users. .Only correlation values between users which have more than 3 co-rated items were considered. For each of the 50 random test users we have selected, we choose an item randomly from the set of items the user has rated to be our test item for which rating will be predicted. The reason for having the condition was to select test users from whom many predictions can be made. Selecting a user with very few trust statements will result in very few item predictions that can possibly be predicted for him. Similarly, reconstructed network cannot be constructed by selecting test users which have measurable correlation values with very few users.

Our approach was implemented as explained in section 3. We compare our approach to the original approach of calculating prediction over the actual trust network using trust weightage as explained in section 2. We call this approach as OT. We call our three approaches for generating predictions by using trust, correl_trust and top-n correl_trust as weightage over the reconstructed trust network as RT, RC, and RN respectively. For RN approach i.e. using top-*n* trust multiplied by correlations values as weightage, value of *n* used in the experiments is 5.

To calculate similarity among users we use the Pearson-r correlation coefficient. Let the set of items rated by both users u and v be denoted by *I*, then similarity coefficient ($Sim_{u,v}$) between them is calculated as

$$Sim_{u,v} = \frac{\sum_{i\in I}(r_{u,i} - \overline{r_u})(r_{v,i} - \overline{r_v})}{\sqrt{\sum_{i\in I}(r_{u,i} - \overline{r_u})^2}\sqrt{\sum_{i\in I}(r_{v,i} - \overline{r_v})^2}} \quad (2)$$

Here $r_{u,i}$ denotes the rating of user *u* for item *i*, and $\overline{r_u}$ is the average rating given by user *u* calculated over all items rated by *u*. Similarly, $r_{v,i}$ denotes the rating of user v for item *i*, and $\overline{r_v}$ is the average rating given by user *v* calculated over all items rated by *v*. As trust statement values in the dataset were all 1, we use a linear decay approach for propagating trust [6]. The formula used for the trust metric is $(d - n + 1)/d$, where d is the maximum propagation distance and *n* the distance of the target user from the source user. For the purpose of measuring the effectiveness of a strategy we choose the widely used metric mean absolute error (MAE) [5]. MAE is the difference between the actual rating and predicted rating. For a particular approach, the MAE for each test user-item at a trust propagation distance is calculated by averaging the MAE of each of the 50 user- item combination present in the group. For each approach, we measured the MAE at trust propagation distance of 1, 2, 3, and 4 respectively. For each approach, experiments were conducted for reconstructed network threshold value of 0.1, 0.3, 0.5 and 0.7 respectively.

5. Results and Discussion

Figures 5, 6, 7, and 8 show the graphs for MAE values within trust propagation distance 1, 2, 3 and 4 respectively. Figures 9, 10, 11, and 12 show how MAE values change with increase in propagation distance for different correlation values. Results clearly show RN approach that is the approach of selecting top-n trust multiplied by correlation values performs substantially better than other approaches.

It can be seen that as trust propagation distance increases MAE values increase. In figures 9, 10, and 11, approach RT, OT, and RC have higher difference between MAE values at propagation distance 1 and 2 as compared to approach RN. In figure 6, 7, and 8 also it can be observed that for approach RN, MAE values remain nearly same at different correlation threshold values. A valid explanation for this could be that most of the top 5 correl_trust values for a user occur within propagation distance 1 or 2. In case of approach RC it can be seen that it shows a different sequence of values in figure 12 i.e. MAE values for correlation >=0.7 as compared to figure 9, 10, and 11. At correlation>=0.7 the probability of having very few trust statements in the reconstructed network increases that could be the reason why approach RC values shows a departure from it's normal sequence of values in figure 12. While strategy RN performs better than the original approach of predicting rating i.e. OT by a large margin, other two approaches RT and RC perform better or equally as compared to OT for all values of correlation and trust propagation distance. From our experiments we say for best recommendations we should use trust propagation level 1 users for generating predictions. And the best value for correlation threshold i.e. the parameter for reconstructing the trust network is 0.5.

While our approach of reconstructing the network performs substantially better than the original approach it does have its limitations. One of the limitations is that it can only generate predictions for those users who have at least passed a few trust statements and have rated a few items. Unless a user has rated a few items it is not possible to calculate correlations of that user with other users in the network. Correlations play a major role in our approach as they form the basis on which the trust network is reconstructed. Another limitation is that coverage of our approach i.e. number of items for which ratings can be predicted is less than the coverage of the original approach.

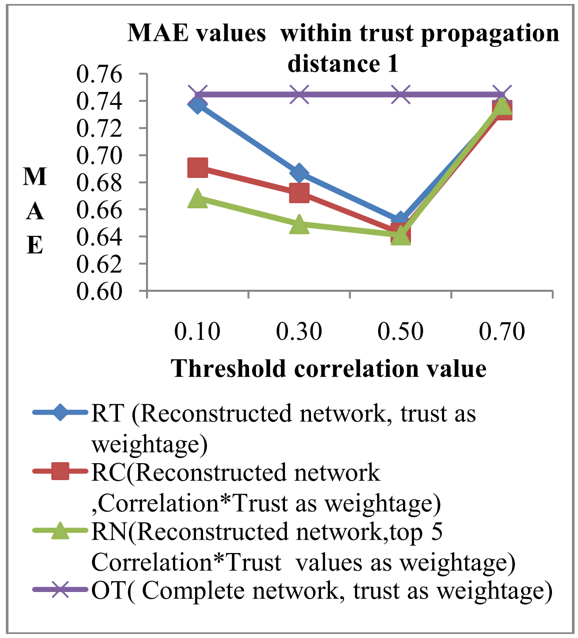

Figure 5: MAE values within trust propagation distance 1 calculated over different correlation threshold values.

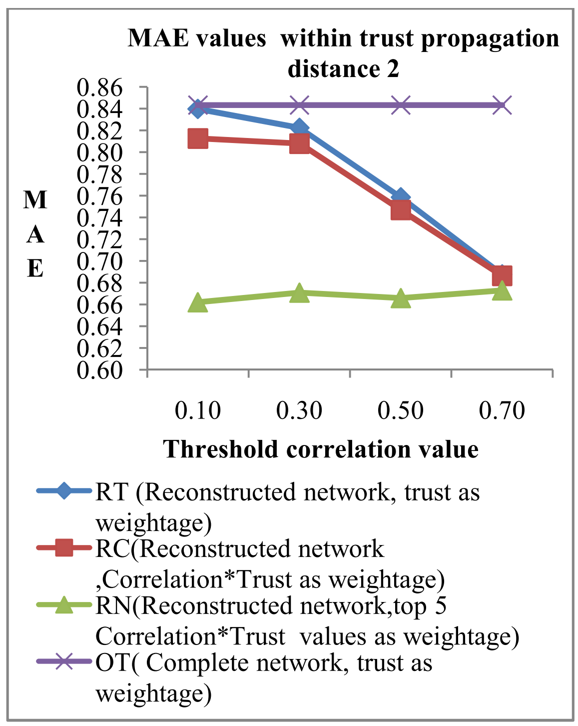

Figure 6: MAE values within trust propagation distance 2 calculated over different correlation threshold values.

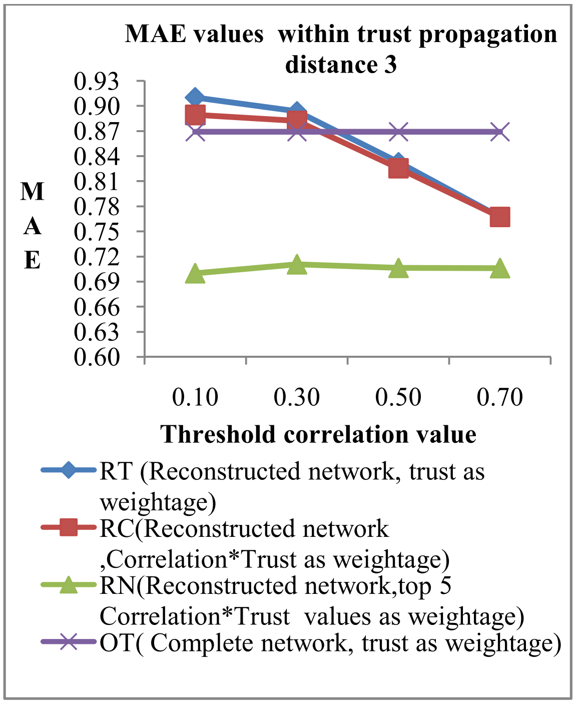

Figure 7: MAE values within trust propagation distance 3 calculated over different correlation threshold values.

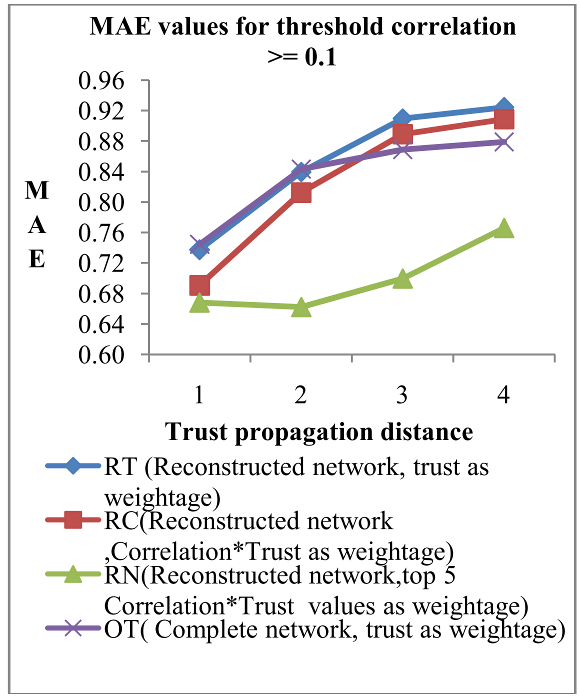

Figure 9: MAE values at correlation threshold value >= 0.1 calculated over different trust propagation distances.

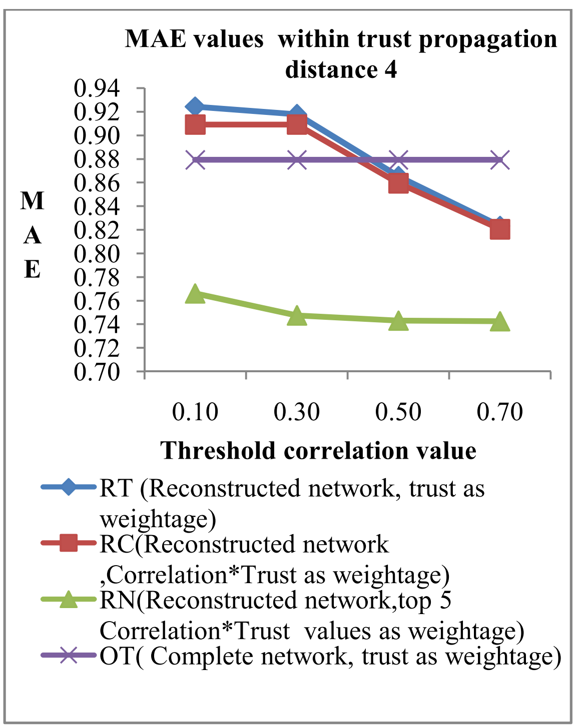

Figure 8: MAE values within trust propagation distance 4 calculated over different correlation threshold values.

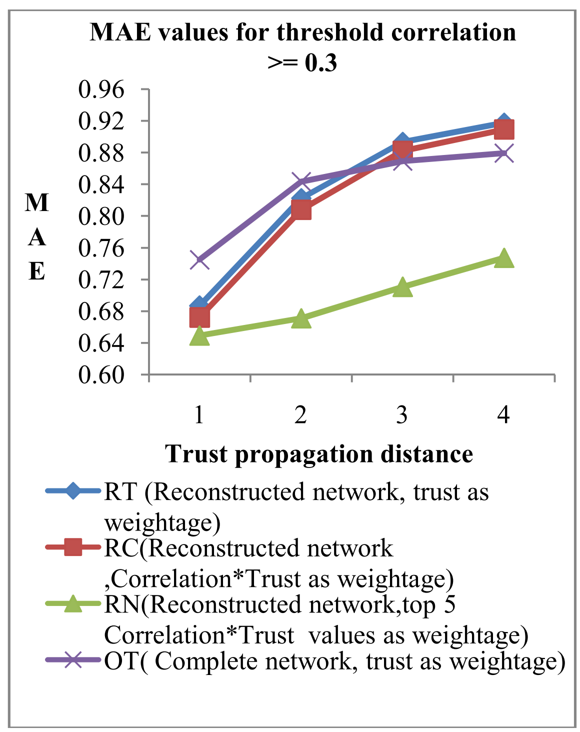

Figure 10: MAE values at correlation threshold value >= 0.3 calculated over different trust propagation distances.

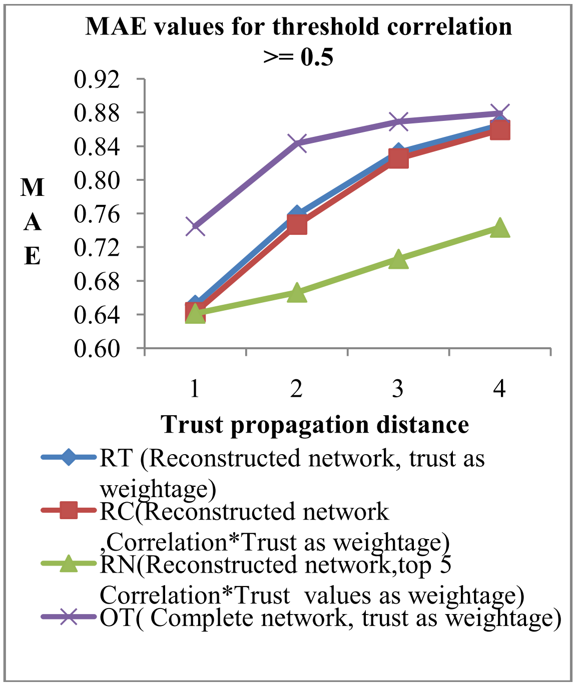

Figure 11: MAE values at correlation threshold value >= 0.5 calculated over different trust propagation distances.

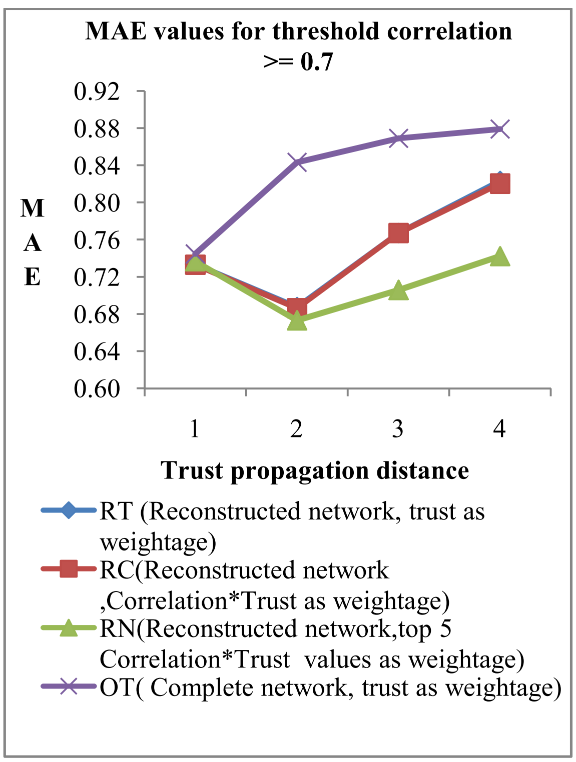

Figure 12: MAE values at correlation threshold value >= 0.7 calculated over different trust propagation distances.

6. Conclusion

In this paper we have proposed an approach for improving prediction accuracy in trust-aware recommender systems. Our approach reconstructs the trust network by removing trust links between users that have correlation value between them fall below a specified threshold value. Trust, correlation multiplied with trust and top-*n* correlation multiplied with trust are three weightage schemes for rating predictions that we have proposed and compared in this paper. We show through experiments on Epinions data set, best results are obtained when correlation threshold value is 0.5 and top-5 correlation multiplied with trust values is used as weightage for prediction generation. Our approach consistently performs better than the original approach for different levels of trust propagation and threshold correlation values.

One limitation of our approach is that it has been tested on only one dataset i.e. Epinions dataset. In future we would like to test the effectiveness of our approach on trust datasets that exhibit characteristics different from Epinions dataset. Two important research questions that we would like to examine are: a) Study the improvement in recommendation accuracy when our approach is applied to a dataset where there is high correlation between trust and similarity b) Study the effect on recommendation accuracy when trust statement value varies between 0 and 1, in Epinions dataset all the trust statements have their value as 1. Designing a strategy for reconstructing the trust network that does not impact coverage as much our proposed approach does, can be another aspect that can be explored in future.

7. Acknowledgements

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