TRPC: An Ensembled Online Prediction Mechanism for Trusted Recommender System

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Abstract: - The most recent invasions in social networks make it inevitable to develop a network with high dependence and confidence to users. Even though recommender systems of today use advanced parallelism in web development, achieving trustworthiness in such a system has been a challenging task for several years. To overcome the existing sparsity, scalability and dynamism in new item/user issues, we propose a framework TRust Propagation and Clustering (TRPC), to build a trust network using the social distance between every pair of users and similarity measure of clustered users based on the users' tastes and preference. Our proposed technique to predict the ratings of items by users involves three major steps which comprise both implicit and explicit social relationship and propagation mechanism. The second step involves clustering the trusted users and third step predicts the products/subjects between them based on the alike criteria. The proposed rating prediction promises a better eminent recommendation for all buyers and online users who gain access to the community. To validate the effectiveness of our work, we experimented with two real world datasets Epinions and Movie Lens.

Key-Words: - Trust propagation, Trusted path, Clustering, Social networks, Recommendation systems, Similarity metrics

1 Introduction

Online Social Networks (OSN) such as Facebook, Twitter, Myspace has attracted millions of users and offer features to share their interest both in business and with personal contacts. They have become an inevitable factor in the day to day life and about two billion users are connected and consuming the user generated content [1]. This has accelerated the interest of research over this field. The main aim of the users of OSNs is to create profiles and utilize the features and applications provided by OSN. Moreover extracting information from large amounts of data, for visualizations and prediction is a recent ongoing research problem [2]. Also, users are restricted from information access which makes social network services lose their original benefit. The huge content creation and increased user interaction raise the question of trust [3]. There is an increasing need to analyze the notion of trust in online sharing communities. The system which stores and uses the information to form trusting and affects the user behavior is referred to as trust based system [4].One of the approaches to measure the trust of unknown target user is trust propagation [5]. The major drawback which affects the previous trust prediction models are (1) organization of the huge amount of data (2) dynamic changes in user behavior. Thus inferring trust from a large scale trusted graph has been a current research problem.

1.1 Trust on Social Web

The definition of trust in a social web is given by Golbeck [6] " Trust in a person is a commitment to an action based on a belief that the future actions of that person will lead to good outcome". In several multinational organizations, social networking plays a vital part in examining and analyzing the customers as well as the feedback services provided by them. It acts as a decision making tool for business professionals and high authorities. Therefore trust is one of the factors to be measured among the direct and indirect users. There are two types of trust, referral trust and functional trust [7]. Referral trust is used to recommend a target while functional trust tells the ability of the target. Another type of trust, indirect trust [8] in which trustor puts on a trustee through recommenders is known as recommendation trust. This trust is different from the above mentioned two types of trust. Most existing works on trust evaluation are not effective for large scale networks because they are based on several short trusted paths. Thus in large scale networks, finding optimal and reliable path is a challenging issue.

Previous research works also deal with several trust metrics which leads to improvements over similarity-based recommendation techniques, and user-assigned trust ratings grabbed a number of sophisticated types of similarity techniques. Our method incorporates trust metrics into clustering techniques that employs the similarity measurements for trust prediction which leads to statistical benefits. The rest of the paper is organized as follows. Section 2 briefs the existing methods for trust estimation and prediction of ratings. Section 3 defines our proposed method of ensemble trust propagation and clustering. Section 4 details the experimental evaluation of our approach. Finally, Section 5 provides the future research of our work.

2 Related Work

In online social networking, the notion of trust is important for proper operation [9]. Identifying trusted people to protect private information of the user or protecting the network is crucial for a variety of applications. Hence there arises a need for an effective trust inference mechanism to resolve issues in social networking applications.

Trust algorithms can be categorized into two types: a global approach and a local approach [10]. A local approach computes the trust based on individual user's perspective whereas the global approach calculates trust value regardless of individual perspective. There are pros and cons on both trust metrics which are briefed in [11]. A number of recent researches have shown that trust includes multiple trust factors [12]. Wang and Wu [8] also described Flow trust metric model to evaluate the trusted graph with network flows supporting multi dimensional trust. Zuo et al., [13] presented a framework to evaluate the trust based on trusted chain sets. An algorithm to identify the set through exhaustive enumeration was discussed. Marmol and Perez [14] introduced the components of a complete trust and reputation models. They are rated, scoring, rewarding, punishing or gathering behavioral information. Guha et al., [15] proposed an algorithm that combines distrust with a trust which lower the error rate. But the distrust value is not always specified in online social networks.

2.1 Recommender systems and its Challenges

Recommendation systems are applications which assist the users to opt for the relevant information available online. The recommendation approaches are broadly classified into two categories, content based filtering and collaborative filtering (CF) [16,17]. Content based filtering technique recommend an item based on the features of the content preferred by the user. In the latter approach, preferences of the similar users are considered to predict the ratings of an item for the target user. The collaborative filtering technique can be implemented using memory based and model based approaches [18, 19]. Both the approaches have pros and cons. The scalability problem in memory based approach has been overcome in model based approach with the compromise of recommendation accuracy. A hybrid recommendation method has been proposed to improve both the memory based and model based approaches. The user profile is the main source of information for a recommendation system. But the publicly available profiles are not clearly available.

Generally most recommendation systems allow their users to maintain a trusted set of users. The recommendation provided by those users can be utilized to improve the accuracy of such systems [20]. The existing approaches like Mole Trust [21], Tidal Trust [22] modified the collaborative filtering approach to incorporate the trust values of the users. For the successful recommendations of the recommender system, the issues such as sparsity, dynamic nature of user interest and trust and different rating scales must be considered. Trust based ant recommender system (TARS) [23] provides qualitative recommendations with low accuracy due to the fewer feedback on recommended items. Trust based recommendation system proposed by Moghaddam et al. [24] considered feedback but the common interest between the users is ignored. O'Donovan and Smith's [25, 26] error based trust models provides valuable recommendation but doesn't take into account social distance and different rating scales. In our work, to overcome the sparsity and scalability problem, a simple method for inferring trust using the social relationship and propagation mechanism was proposed. Also clustering of users will lead to a reduction of dissimilarity between users. The integration of trust and clustering mechanisms with similarity based recommendation system will generate ratings predictions with high precision and accuracy.

3 Methodology

3.1 Framework of the System

Our proposed mechanism TRPC comprises of three major steps to predict the items for recommendation (1) To identify the trusted set of users by generating a trusted network (2) Clustering the users together to reduce the dissimilarity and sparseness of data (3) to measure the similarity between the users. Finally the above measures for the rating prediction will lead to a better outcome of recommendation. Fig.1 shows our framework for modeling the trusted and accurate recommender system.

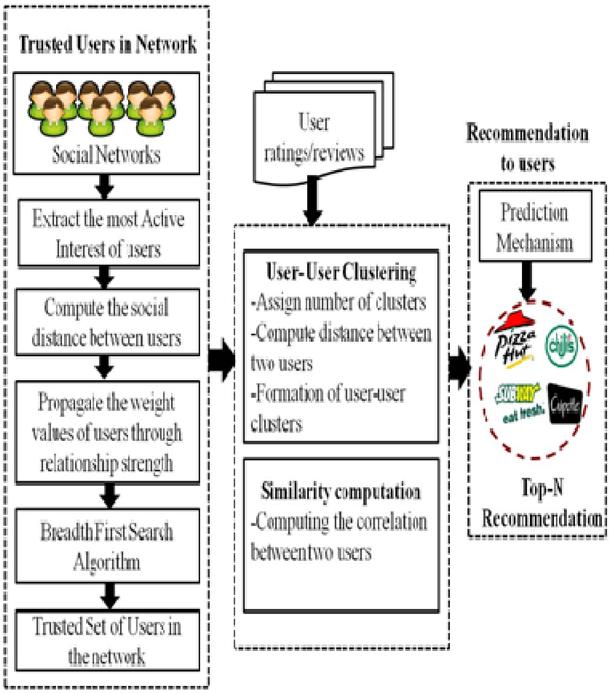

Fig. 1. Overall Architecture of our Approach

3.2 Building a Trust Network

To build a trust network, the first step is to identify the friends with some common characteristics. An online social network is usually represented as a graph structure. Let $G = (V, E)$ be a directed acyclic graph, representing the social network, where V is the set of nodes which corresponds to users and E is the set of edges that represents the relationship between the users. Let the trustor node be $T \in V$. For a given trustor node T, let $G_t = (V_t, E_t)$ be a subgraph of G where $V_t \subset V$, represents the reachable node from given trustor node T and $E_t \subset E$ is the set of edges that connects any two nodes in V_t. The algorithm to identify the trusted set of users is depicted as in Fig.2.

Input - Social graph which represents users and the relationship between the users

Step 1: Determine the categories exists in the social network

Step 2: Compute the common categories between every pair of users

Step 3: Compute the social relationship between the users, sd_{ij}

Step 4: while $(sd_{ij} > 1)$

(i) Compute the weight value of trustor

(ii) Propagate the weight value to trustee

Step 5: Establish the trust measure of the users using sd_{ij}

Step 6: Apply the Breadth first search algorithm to find the shortest path in the network

Output – Trusted network with the set of trustworthy users

Fig. 2. Proposed Trust Propagation Algorithm

3.2.1 Estimation of Social Strength

As a first step, to build a network, represent the relationship that exists between the users in the network. There are various types of relationships such as friend of, colleague, family relations that connect the users in the network as shown in Fig. 3. The trust between the users in implicit environment is a challenging issue to be solved. The trustworthy people can be found by searching the user who is doing the same related thing.

This can be calculated based on active interest of two users. We proceed our work with the following steps. Suppose there are N categories in the social network community $c_1, c_2, c_3 \ldots c_N$. The interested categories of user (i) are denoted by a vector X_i.

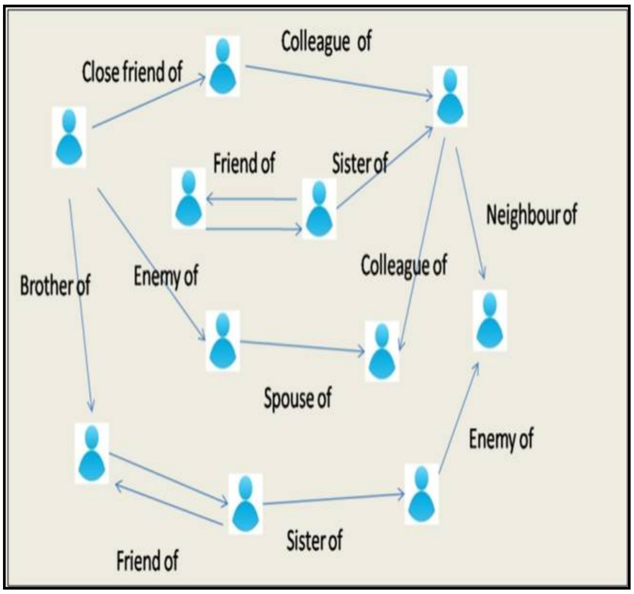

Fig. 3. Relationship between users in the social networks

The interested categories of neighbors (N_{i1}, N_{i2}, N_{i3}, ... N_{ij}) of user i is denoted by vectors X_{i1},X_{i2},….X_{ij}.

The social relationship between a user and his neighbors can be computed using the Eqn. (1)

$$sd_{ij} = |X_{ij}| - |X_i \cap X_{ij}| \quad (1)$$

such that sd_{ij}> 1.This implies that both the users have involved in many common categories but the user j interested categories is higher than the common ones which depicts the interest level of unknown strangers in the network.

3.2.2 Propagation of Trust values

To identify the set of trusted users, first a weight value is assigned to trustor user. This value depends on the directly connected neighbors of the trustor. The weight value of a trustor is calculated as given in Eqn. (2

$$W_t = c * |out(t)| \quad (2)$$

where c represents the constant value used to limit the number of trusted users within a certain level and $out(t)$ is the neighbors who have direct contact with the trustor. The value of c is set between zero and a value preferred by the user. After assigning the initial weight to the trustor, it is diffused via the path from the trustor to its neighbors. Propagating the trust from the initial node depends upon the social distance between the user and its neighbors and the distance between the two nodes. The trust weight of any node can be computed as follows Eqn. (3)

$$W_v = max_{u \in I_{t(v)}}((\propto . d) * sd_{uv} * W_u) \quad (3)$$

$I_{t(v)} \subset V_t$ is the set of in-neighbors of node v that can be reachable from the source node u. d represents the distance between u and v and the factor $\propto$ gradually reduce the weight based on distance. W_u is the weight value of node u. sd_{uv} is the social distance between the users u and v.

In our proposed framework, the optimized trust value is calculated by considering bot the topology of the social network and the social relationship between the users. Thus the trust measurement can be computed as in Eqn. (4)

$$T_v = \gamma * W_v \quad (4)$$

where T_v is the trust value of the user v with respect to the trustor, W_v is the weight of the node based on social distance. γ is the adjusting parameter. The subjective network is converted into a dedicated structure after finding weights of all the nodes in the network paths. The trusted set of users can be determined by applying Breadth first search algorithm.

3.3 Trusted K-means Clustering

K-means clustering algorithm takes a set of users in the network and groups them in a way that tries to reduce the time and efficient use in some criteria. This algorithm includes k-clusters which find a set of users which minimizes the distance from any point to its closest point between two users in the network and hence trivialize the variance within each group. Existing clustering algorithms have a good estimation value when applied to users in a symmetric measure as well as in asymmetric measures. In our system, the trust value between two unknown users is derived based on relationship strength and users are clustered based on the trust value and applied to the measure of similarity, with high trust prediction indicates the better recommendation. The algorithm which defines the clustering and similarity approach is depicted as in Fig.4.

1.Split the dataset into training and testing set
2.Set the number of clusters k and trusted set of users T_S

3. Randomly select k number of users to assign the initial clusters
7. for all $u \in T_s$
8. for cluster $c = 1$ *to* k
9. Calculate squared euclidean distance $\sum_{j=1}^{k} \sum_{x \in c_i} d^2(x, m_j)$
10. end for
11. end for
12. for all $u \in T_s$
13. find the cluster with closest centroid and assign to the new cluster
14. end for
15. for each cluster $c = 1$ *to* k
16. Calculate the similarity sim (u,v) between two users by Correlation Coefficient
17. end for
18. Calculate the predicted rating *p(u)* for the item *i* by combining the trust and similarity

Fig. 4. Trust Prediction Algorithm

3.4 Different Similarity Relationships

User-based CF is also called nearest-neighbor based Collaborative Filtering. It first finds the target users nearest-neighbors, and then combines the preferences of neighbors to produce a prediction or top-N recommendation for the target users. Similarity computing which measures the similarity between two users is the most important part of user-based CF. Choosing a proper similarity method can obviously improve the performance of user-based CF. The three basic similarity methods are as follows:

In Cosine similarity, two users are regarded as two vectors in the n-dimensional item space. The similarity between them is measured by computing the cosine of the angle between these two vectors. Formally, similarity between users i and j is given by,

$$sim(i,j) = \frac{i.j}{\|i\|\|j\|} = \sum_{c \in items} \frac{R_{ic} R_{jc}}{\sqrt{\sum_{c \in items} \left(R_{ic}^{2} * R_{jc}^{2} \right)}} \tag{5}$$

where, i and j represent the n-dimensional vectors that users i and j rated on the items, R_{ic} and R_{jc} denote the ratings user i and j on the item c.

The basic cosine measure has one important drawback that the differences in rating scale between different users are not taken into account. The adjusted cosine similarity offsets this drawback by subtracting the corresponding user average rating from co-rated pair. Formally, the adjusted cosine similarity between user i and user j is given by,

$$sim(i,j) = \frac{\sum_{c \in I_{i,j}} \left(R_{i,c} - \overline{R_i} \right)\left(R_{jc} - \overline{R_j} \right)}{\sqrt{\sum_{c \in items} \left(R_{ic} - \overline{R_j} \right)^2 * \left(R_{jc} - \overline{R_j} \right)^2}} \tag{6}$$

where $I_{i,j}$ represents the items that user i and j co-rated, $\overline{R_i}$, $\overline{R_j}$ denote the average rating of user i and j.

In Pearson Correlation Coefficient, similarity between users i and j is measured by computing the Pearson correlation. To make the correlation computation accurate we isolate the co-rated cases. The correlation similarity is given by,

$$sim(i,j) = \frac{\sum_{c \in I_{i,j}} \left(R_{i,c} - \overline{R_i} \right)\left(R_{jc} - \overline{R_j} \right)}{\sqrt{\sum_{c \in I_{ij}} \left(R_{ic} - \overline{R_i} \right)^2 * \left(R_{jc} - \overline{R_j} \right)^2}} \tag{7}$$

Since Pearson Correlation coefficient includes the negative correlation, we have chosen Pearson Correlation coefficient instead of cosine similarity and adjusted cosine similarity. Hence, we compute a prediction of the target user rating to an item from a combination of the selected neighbours' ratings. The prediction formula is as follows:

$$p_{u,i} = \overline{R} + \frac{\sum_{v \in N_u} \left(\sigma * T(v) + (1-\sigma) sim(u,v) \cdot (R_{iv} - \overline{R_v}) \right)}{\sum_{v \in N_u} \left| \sigma \cdot T(v) + (1-\sigma) \cdot sim(u,v) \right|} \tag{8}$$

According to Eqn.(8), inferring neighborhood similarity is very important to generate recommendations because a user can be considered as neighbor only if it is possible to compute the similarity between two users. Our approach mixed the trust values obtained from direct and indirect related users and similarity of their tastes and preferences for each user.

4. Experimental Analysis

4.1 Dataset Description

In this section, the experimental analyses on different metrics are compared with the existing prediction algorithms. In our evaluation, we consider two online community sites Epinions and Movie Lens datasets. However, these two datasets differ in their size and distribution of ratings of users, they are large real life datasets which is used specifically for evaluation of our recommendation approach. Epinions dataset contains both the item rating matrix and trust matrix of users which is highly useful for our comparison. High Learning capability of similarity between neighbourhood users is achieved through denser ratings. Movie Lens dataset is denser compared to Epinions datasets. Hence these two datasets allows a better study of the performance and behaviour of the different techniques.

4.1.1 Epinions Dataset

The Epinions dataset is a publicly existing online social community site where users can easily rate and review the products and express their opinions on the products and their services from sports and music to food and restaurants. The Web of Trust formed by the user interaction can be used for the classification process. In this dataset users can directly review their rating on a particular product in which they are concerned. Users' rate these articles on a scale of 1 to 5 ranging from not helpful to most helpful based on their interest and behaviour. The dataset has 1,560,144 reviews and 12,668,319 ratings for reviews. Among all provider reviews, only 48% of the reviews received at least one rating. On average, the reviews which are evaluated by at least one user have 18 ratings. The total number of users who participated in writing reviews was 326,983 and they provided an average of 4.77 reviews. Within that total, 92% of writers provided fewer than 5 reviews, and less than 1% of writers provide more than 100 reviews.

4.1.2 MovieLens Dataset

This data set contains 10000054 ratings and 95580 tags applied to 10681 movies by 71567 users of the online movie recommender service Movie Lens. Users were selected at random for inclusion. All users selected had rated at least 20 movies. Each user is represented by an ID, and no other information is provided. The data are contained in three files, movies.dat, ratings.dat and tags.dat. Also included are scripts for generating subsets of the data to support five-fold cross-validation of ratings predictions.

4.2 Performance Metrics

In the datasets evaluation, 10% of the data were randomly used as test set and the remaining were used as the training set. The more items from the test set are recommended, proves the better performance of our recommendation algorithm. For predicting such items, the traditional evaluation metrics are Precision and Recall. Hence we measure the accuracy of our approach using metrics: MAE, Precision, Recall and F Score.

MAE is defined as the average absolute difference between predicted rating and the true rating value of each user.

$$MAE = {}^{1}/_{n} \sum_{i=1}^{n} \left| r_{pi} - r_{ti} \right| \quad (9)$$

Where r_{pi} is the predicted rating of items for users and r_{ti} is the actual rating of items.

Precision is the ratio of the number of relevant records retrieved to the total number of irrelevant and relevant records retrieved. Precision value is calculated as,

$$Precision = {}^{tp}/_{tp + fp} \quad (10)$$

Recall is the ratio of the number of relevant records retrieved to the total number of relevant records in the database. Recall value is denoted by,

$$Recall = {}^{tp}/_{tp + fn} \quad (11)$$

FScore is the measure that combines both precision and recall by the mean of precision and recall. It is denoted by

$$Fscore = {}^{2 * Precision * Recall}/_{(Precision + Recall)} \quad (12)$$

4.3 Performance Comparison and Analysis

4.3.1 Analysis of Trusted Graph

With the increased explosion of social network usage in day to day activities, trust is vital and important in the OSN analysis since it affects the decision making process. Especially in e-Business and e-Commerce sites, the opinion of every user should be trustworthy and valuable to provide confidence to unknown new users in the community. So we evaluated our procedural algorithm in both implicit and explicit trust relations to accurately forecast the items preferred by users. In our both datasets, Epinions and Movie Lens, we sort the users with regard to their ordering of Subject IDs. Then we normalize these two datasets by eliminating the duplicate IDs present. Then we continue our observation by categorizing the User IDs into 6 domains. This creates a smaller subset of the entire graph network for easier evaluation. For every domain we determined the social distance between every pair of users in the graph which is evolved from the common topic assigned. Hence the performance of the trusted set of users is obtained by varying the standard values of parametric constant *c*. The obtained results are compared by varying the discrete values of *d* ranging from 1 to 5. Fig 5 shows the precision, recall and F-Score metric for $\alpha = 0.5$ with constant $c = 5$ and 10 respectively.

4.3.2 Performance of Clustering and Similarity

Here, we analysed the various similarity functions by comparing the recommendation output of our approach. These evaluated prediction results depend mainly on the similarity function used. Jeong. et.al analyzed the major similarity functions such as cosine, adjusted cosine and correlation similarity factors and proved that correaltion provides much exact results for exixting memory based approach. We consider Movielens and Epinions dataset and evaluated the MAE and Precision metric using three similarity functions as in Table 1 and 2 for varying number of clusters from 5 to 25. Fig .6 and Fig.7 shows that the Pearson correlation coefficient similarity measure is found to have minimum error value than the other two similarity measures. Likewise, precision also founds to be improved when correlation measure is adopted.

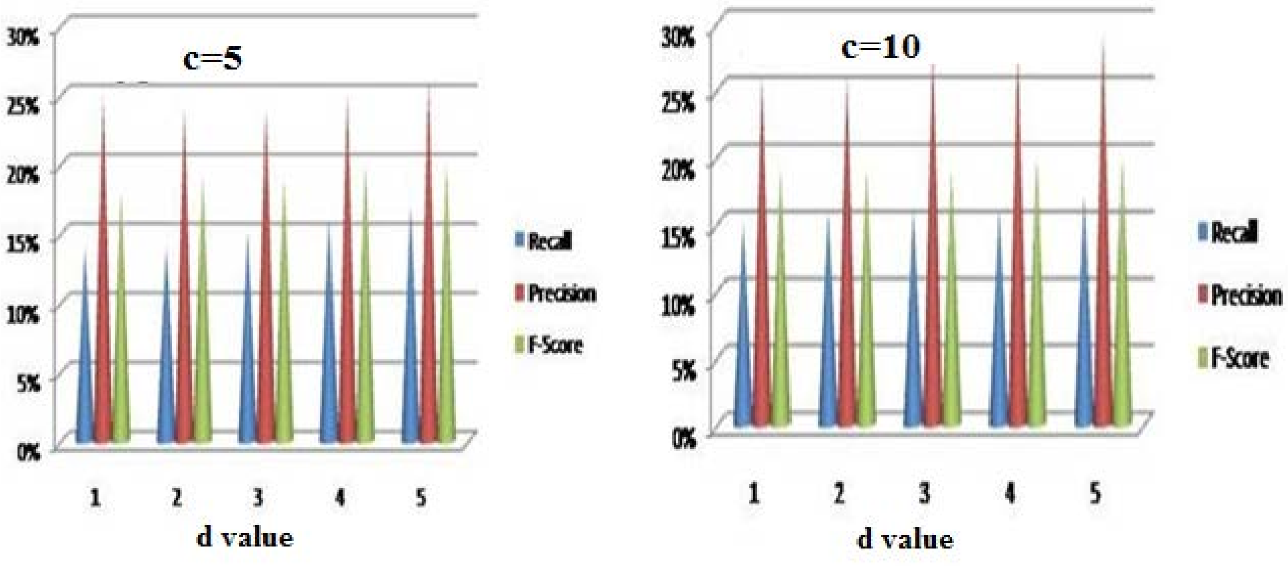

Fig. 5. Comparing Recall, Precision and F-Score value of different d values

Table 1. Performance metrics of Similarity statistics for Movie Lens dataset

Number of Clusters	MAE			Precision		
	Cosine similarity	Adjusted Cosine similarity	Pearson Correlation similarity	Cosine similarity	Adjusted Cosine similarity	Pearson Correlation similarity
5	0.8632	0.8559	0.8514	0.7627	0.7773	0.7985
10	0.9234	0.9179	0.9064	0.8132	0.8233	0.8278
15	0.9576	0.9568	0.9454	0.8516	0.8658	0.8893
20	1.0788	1.0747	1.0489	0.8983	0.8989	0.9095
25	1.1647	1.1575	1.0982	0.9059	0.9098	0.9149

Table 2. Performance metrics of Similarity statistics for Epinions dataset

Number of Clusters	MAE			Precision		
	Cosine similarity	Adjusted Cosine similarity	Pearson Correlation similarity	Cosine similarity	Adjusted Cosine similarity	Pearson Correlation similarity
5	0.8532	0.8859	0.8314	0.7727	0.8073	0.8285
10	0.9134	0.9279	0.9196	0.8232	0.8483	0.8578
15	0.9786	0.9768	0.9454	0.8616	0.8758	0.8893
20	1.3388	1.2947	1.1589	0.8984	0.9012	0.9075
25	1.4547	1.4275	1.1586	0.9149	0.9105	0.9198

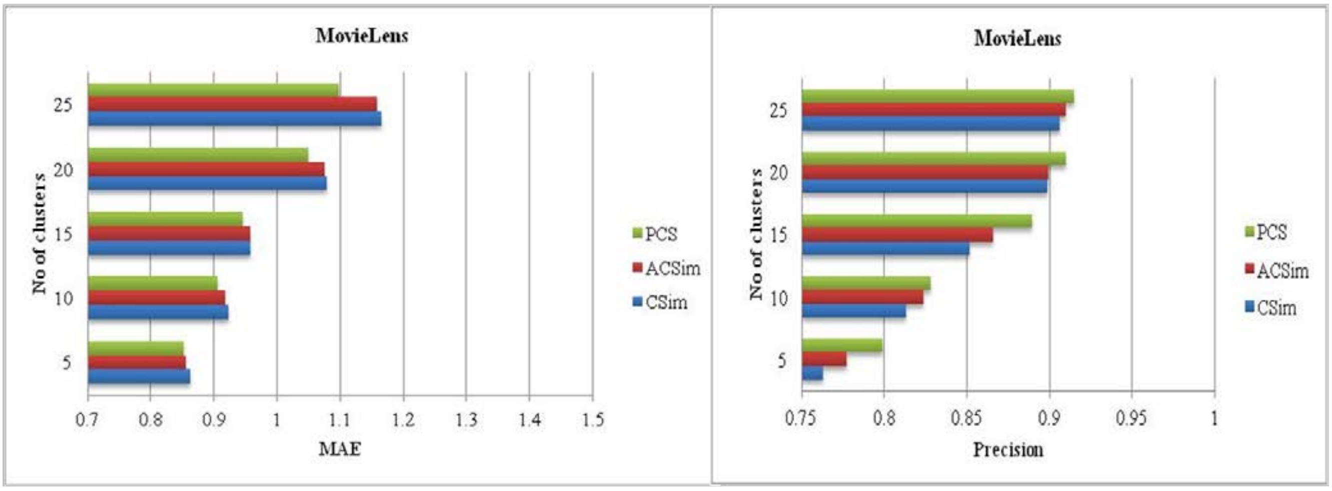

Fig. 6. Performance comparison of two performance metrics MAE and Precision for Cosine, adjusted cosine similarity and Pearson correlation coefficient for Movie Lens dataset

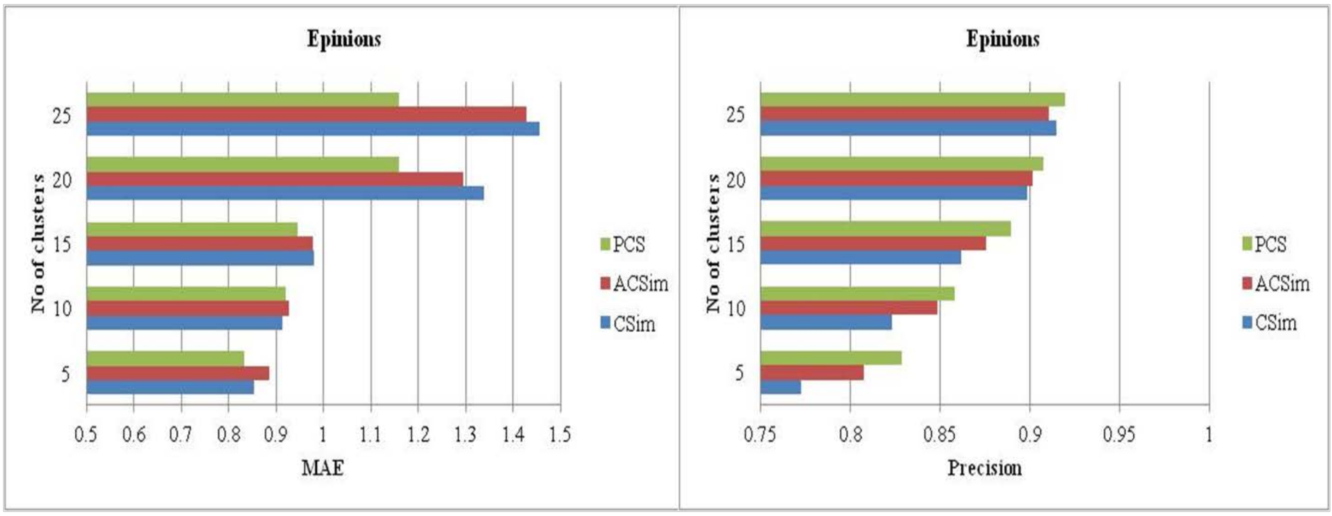

Fig .7. Performance comparison of two performance metrics MAE and Precision for Cosine, adjusted cosine similarity and Pearson correlation coefficient for Epinions dataset.

Table 3. Different algorithms and their performance evaluation for MovieLens Dataset

Algorithm	Mean Absolute Error	Precision
IPTrust	0.8765	0.8479
TARS	0.8586	0.8639
Trust CF	0.7128	0.8987

Table 4. Different algorithms and their performance evaluation for Epinions Dataset

Algorithm	Mean Absolute Error	Precision
IPTrust	0.8765	0.7679
TARS	0.8386	0.7739
Trust CF	0.7278	0.8587

Comparison with other methods - Our algorithm Trust CF is compared with existing IPTrust and TARS algorithms for Movie Lens and Epinions dataset as shown in Table 3. and Table 4. Our algorithm outperforms well in terms of Mean Absolute Error and Precision Metric because it ensembles the Trust propagation and Clustering based prediction technique.

The recommendations provided by such a system is valuable by dynamically including the user similarity and preferences. In Fig .8 we have graphically showed that our algorithm improves approximately as large as 10 percent compared to existing baseline algorithms.

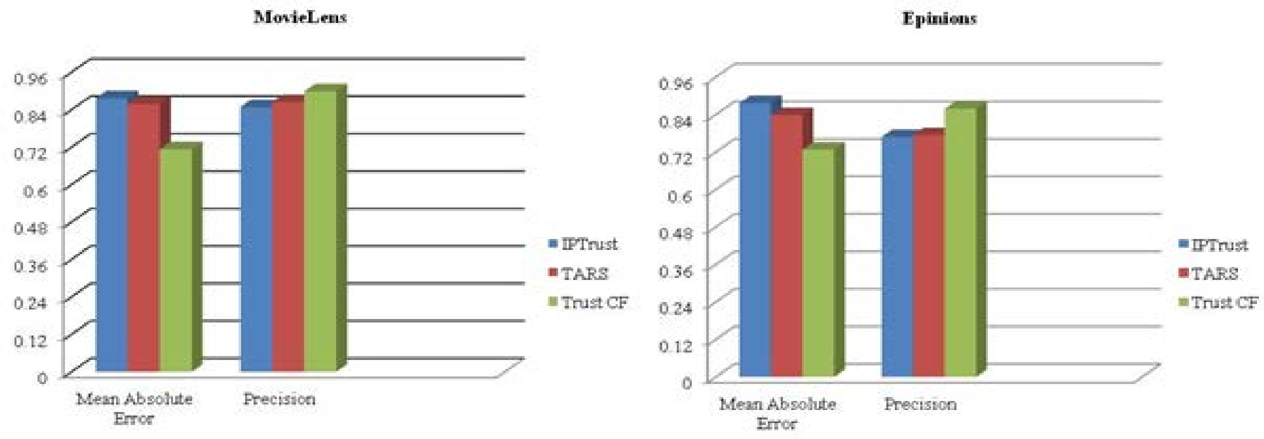

Fig. 8. Different algorithms and their performance evaluation for both datasets

5. Conclusion

In this paper, we propose the improved prediction mechanism to discover the set of trusted users based on social relationship between the users. The propagation mechanism is used to diffuse the weight values to the nodes in the network. Then using the algorithm, we determined the ordered set of users. The clustering based approach helps to reduce the dissimilarity between the users. The prediction of ratings by combining trust evaluation through propagation and clustering based similarity evaluation will lead to useful recommendations for new users within the network. The experimental evaluation with the real dataset shows the effectiveness of our approach. It offers better improvement in recommendation quality by solving sparsity, scalability and dynamism of new users/items problems. In the future, considering the explicit relationship such as family members, colleagues etc., to discover the trusted users and exploring all kinds of social networks are our main work.

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