Application of game theory techniques for improving trust based recommender systems in social networks

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Abstract—**Recommender system is a solution to the information overload problem in websites that allow users to express their interests about items. Collaborative filtering is one of the most important methods in recommender systems which predicts ratings for active user based on opinions and interests of other users who are similar to the active user. Accuracy of ratings prediction can be considerably improved using trust statements between users in recommender systems. In this paper, a novel method is proposed to determine effectiveness coefficient of the users in trust network of the active user. For this purpose, the Pareto dominance concept is used to identify dominance users of the active user and the trust statements between users are calculated based on this concept. Experimental results on Epinions dataset show that the proposed method improve accuracy of ratings prediction while provide suitable coverage rather than several well-known state-of-the-art methods.**

Keywords-recommender systems; social networks; game theory; Pareto dominance; trust

I. INTRODUCTION

Nowadays, the huge amount of online information makes users to spend more time and energy to find their interested products. However, they cannot get satisfactory results in most cases. Due to the stable and long-lasting social bindings, people are more willing to share their personal opinions with their friends, and typically trust recommendations from their friends more than those from strangers and vendors [1]. Furthermore, the activity of the users can be tracked and recorded on the social networks and e-commerce sites. This makes it easier to analyze the preference of users. Recommender systems provide a mature approach by making use of different sources of information for addressing the information discovery challenge facing online users. Accurate recommendations allow users to locate desirable items quickly, without being overwhelmed by irrelevant information. It is of great interest for vendors to recommend to their potential customers products matching their interests, and hopefully turn them into committed buyers.

Recommender systems technology currently is used in many application domains such as recommendation of photo groups in Flickr [2], the books in Amazon [3], videos in YouTube [4], and results in the Web search [5]. Collaborative filtering (CF) is the most popular recommender system technique which makes recommendation for a particular user according to the items previously rated by similar users. In other words, the aim of the CF is to determine which users are similar to the active user and recommends those items preferred by neighbor users who are similar to him or her. This simple intuition is effective in generating recommendations and has been widely used [6-14].

However, the collaborative filtering also suffers some inherent weaknesses, for instance, cold start problem, data sparsity, scalability and security [6, 9-12, 15-20]. The cold start problem is related to the sparsity of information available in the recommendation algorithm [6, 10-12]. For example in movies or books domain, a typical user will only rate a small number of items. In fact, the process of comparing two users with the goal of computing their similarity involves comparing the ratings they provided to items. In addition, in order to be comparable, it is needed that two users rate at least some items in common. As a result, the recommender system may not be able to make predictions for a user and the accuracy of the recommendations may be poor [1, 6, 9, 13, 15, 18]. Another important and under considered weakness is related to the fact that RS can be easily attacked by creating fake user profiles with the goal of being considered as similar to the target user and influences the recommendations he/she gets [21, 22].

The evidences suggests that, people tend to rely more on recommendations from their friends than on recommendations from similar but anonymous individuals [23]. Therefore, to overcome the mentioned issues, friendship information of the users (also known as trust information) can be incorporated into collaborative filtering as additional information to model user preferences more accurately. The alternative view of CF systems, based on trust, follows the epigram “Tell me who your friends are, and I will tell you who you are". The basic idea of trust based recommender system is to search for trustable users by exploiting trust propagation over the trust network. There have been several trust-based approaches proposed in the literature and the improvements to some extent have been achieved [18, 24, 25].

In this paper, we present a novel method that improves the trust based recommendation system by using the game theory concept. This concept is used to identify those trustable users who correctly represent the interests of the user correctly and who therefore should be considered as candidate neighbors. The proposed method involves a pre-filtering process that reduces the effectiveness factor of the least representative users from those of selected trust users. Moreover, the effectiveness factor of the most promising uses is also increased. In order to show the effectiveness of the proposed method, several experiments have been carried out on Epinions[1] dataset and the

[1]http://www.epinions.com/.

results show significant improvements in all tested quality measures when the proposed method is applied.

The rest of the paper is organized as follows. Section II discusses related work. Section III gives a high level description of the proposed system and Section IV is devoted to the presentation of evaluation metrics and the description of our experimental results. Finally, the last section concludes this paper.

II. Related Work

Recommender system approach can be classified into two main categories: content-based approach and collaborative filtering approach [26]. In the content-based approach, the system learns to recommend items based on a description of the item and the user profiles [27, 28]. While, the collaborative filtering (CF) makes user's recommendation based on the preferences of a group of users which are similar to the active user. This approach generally classified into memory-based and model-based approaches [6, 9-14]. The memory-based approach uses the user-item matrix to find similar users and generates a prediction [8, 11, 13, 14, 20, 29-31]. While, the model-based approach first build a user-model in an offline learning phase and then apply the model in online mode to generate the recommendation [1, 10, 12, 18, 25, 32]. It is shown in previous researches that the CF approach has gained considerable results compared to that of the content based approach. The CF approach is known to be sensitive against cold-start and data sparsity problems. The data sparsity refers to the problem of uncompleted data, or sparseness, in the user-item matrix. While the cold-start problem refers to recommended those of items with only few ratings [7, 11, 13, 15, 16].

To better model the user preferences for the new users, additional information is needed. For example friendship, membership and trust information of the users on the online social networks and the e-commerce sites can be taken into consideration in the recommender systems. In comparison with the friendship and the membership information, the trust information of the users has less ambiguity and has a close relationship with the similarity measures. In recent researches, the trust information has been identified as an effective means to utilize the social network information in order to enhance the recommendation accuracy. The trust information can be collected explicitly from the users or can be inferred implicitly from the users' ratings or the user profiles. Up to now, several researches have been proposed in the field of the trust-based recommender systems. For example, Guha et al. developed a framework of trust propagation schemes [33]. The framework assumes that users explicitly state the trust values in the other users. They have also introduced the notion of distrust and the propagation of distrust in their research. Moreover, Golbeck et al. applied the concept of the trust to the social network [34]. They have described that how the trust can be computed and how it can be used in applications. Specifically, they proposed two algorithms for inferring the trust relationships between individuals who are not directly connected in the network. The researchers applied their technique to the TrustMail application, which is an email client that uses the trust algorithms to sort the email messages in the user's inbox. In [35] a model is proposed which used quantitative and qualitative parameters to build the trust relationships between entities based on their common choices. Furthermore, the trust propagation was used to extend the trust relationships beyond the direct neighbors. This type of recommender system was tested on various lengths or "hops" of trust propagation. The experimental results showed a considerable decrement in data sparseness and prediction error.

On the other hand the work proposed by Massa et al. [18] was focused on using the explicit trust as input with the user–item rating matrix to predict the unknown ratings. They have analyzed explicit trust collected in epinions.com and shown that by exploiting the web of trust, it is possible to propagate the trust and infer an additional weight for the other users. Moreover, the new users can also use the trust propagation as well as the users provide at least one trusted friend. Another method is proposed by Bhuiyan et al to develop a trust network from the user tagging information [36]. They could develop the trust network from the tags while still needs descriptions of the items. Their approach did not provide the item descriptions and could not be applied to the recommender systems. Different from trust-based recommendation, the authors of [1] proposed a method to use conditional probability distributions to calculate the similarity between friends in the social networks. Probability distributions carry richer information compared to that of the trust values. Moreover their method also provided the ability of employing Bayesian networks to conduct multiple-hop recommendation in online social networks.

III. Proposed Method

In this section, we propose a novel trust-aware recommender system using the Pareto dominance concept in the social networks. In the trust-aware methods, the ratings of the trusted users are used to predict the unseen items for the active user. The Pareto dominance concept is used to calculate the effectiveness factor of each trusted user in the trust network of the active user. Those of the non-dominated users have higher effect on recommendation results compared to those of the dominated users. In this paper, a novel method is proposed to increase the prediction accuracy and rate coverage measures based on this concept in recommendation systems. The proposed method is described in algorithm 1. This method consists of five phases which will be discussed with some more detail in their corresponding subsections.

A. Dominance concept

The concept of dominance has been widely used in designing algorithms which can solve multi-objective optimization problems. We have used Pareto Dominance concept used in multi-objective optimization problems [37] to identify those users who correctly represent the user and who therefore must be considered to be candidate neighbors. In a multi-objective optimization problem, it is said that a solution x' is Pareto-optimal, efficient or non-dominated if no other feasible solution exists which takes a lower value in some objective without causing a simultaneous increase in at least one other one. In this problem we must find the vector $x = (x_1, \dots, x_n)^T \in X$ that optimizes the multi-objective function $f(x) = (f_1(x), \dots, f_m(x))^T$ [8].

It's said that a solution $x' \in X$ is a non-dominated solution if there is no other solution $x \in X$ such that

$f\ i(x) \le f\ i(x')$ for all $i = 1, \ldots, m$ and there is at least one index i such that $f\ i(x) < f\ i(x')$ [8].

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Algorithm: Pseudo-code of proposed method

Input: A directed trust graph G(V, E)
       User-item matrix
Output: Items prediction for active users
Begin algorithm
  Phase 1: Data preprocessing
    Step 1. Dataset preprocessing to extract the different users and items
    Step 2. Storing the users and items information in database
  Phase 2: Trust network construction
   Trust network construction using the trust statements which is explicitly denoted by the user
  Phase 3: Finding dominance trusted users
    Step 1. Identify non-dominance and dominance trusted users by active user u
    Step 2. Calculate trust value for non-dominance and dominance trusted users
  Phase 4: Trust network reconstruction
    Step 1. Trust network reconstruction for active user by trusted users
    Step 2. Assigning trust value to trusted users by calculated trust value in phase 2
  Phase 5: Rating prediction
    Step 1. Aggregating ratings of trusted users
    Step 2. Calculating the rate value for items
End algorithm
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1) Data preprocessing

In this phase, a data preprocessing will be applied on dataset to extract the user ratings on different items and also trust statements of users. The extracted information will be used by next steps of the proposed method.

2) Trust network construction

In order to choose the trusted users, we use the trust statements which is explicitly denoted by the user. Therefore, we made our trust network based on the user's trust information. This network is a weighted directed graph where the users and the trust statements are supposed to be nodes and the weights of this graph edges, respectively. The following equation (i.e. Eq.1) is used to calculate the trust statement for the trust network:

$$t_{u,v} = \left(\frac{d_{max} - d_{u,v} + 1}{d_{max}}\right) \tag{1}$$

where $t_{u,v}$ is the trust value between users u and v in the specified depth, d_{max} is the maximum allowable propagation distance between users in trust network and $d_{u,v}$ shows the trust propagation distance between users u and v. d_{max} can be calculated using the Eq. (2) in which L^R is the average of network paths length and n is the size of network, and k equals the average of the trust network degree [18].

$$d_{max} = \lceil L^R \rceil = \left\lceil \frac{ln(n)}{ln(k)} \right\rceil \tag{2}$$

3) Finding dominance trusted users

In this phase, the trusted users will be found and dominant and non-dominant users will be separated. Assuming $I_u = \{i \in I | r_{u,i} \neq \bullet\}$ be the set of items rated by the user u and $d(r_{u,i}, r_{v,i})$ be the absolute difference between the ratings given by user u and user v to the item i.

$$d(r_{u,i}, r_{v,i}) = \begin{cases} |r_{u,i} - r_{v,i}| & r_{v,i} \neq \bullet \\ \infty & r_{v,i} = \bullet \end{cases} \tag{3}$$

We say that user u dominates user v with respect to the active user a (denoted as $u >_a v$) if condition below is satisfied [8]:

$$u >_a v \iff \forall_i \in I_a : d(r_{a,i}, r_{u,i}) \le d(r_{a,i}, r_{v,i}) \wedge \exists i \in I_a \mid d(r_{a,i}, r_{u,i}) < d(r_{a,i}, r_{v,i}) \tag{4}$$

So, using Eq. (4), dominant users with respect to the active user will be found among trusted users of each active user and the remainder users will be considered as non-dominant users.

4) Trust network reconstruction

In this phase, the trust factor value for each trusted user depending on the user type indicated in previous phase will be calculated while constructing the trust network using expression below:

$$trust(u, v) = \begin{cases} t_{u,v} \quad , & if\ v \in UND_u \\ t_{u,v} \times w_{u,v}, & if\ v \in UD_u \end{cases} \tag{5}$$

where $trust(u, v)$ is the trust between users u and v. Also, the weight between the users u and v, which is a combination of similarity and confidence denoted by $w_{u,v}$ is calculated using Eq. (6).

$$w_{u,v} = \begin{cases} \dfrac{2 \times s_{u,v} \times c(v|u)}{s_{u,v} + c(v|u)}, & if\ s_{u,v} \neq 0\ and\ c(v|u) \neq 0 \\ k \times c(v|u) \quad , & if\ s_{u,v} = 0\ and\ c(v|u) \neq 0 \\ 0 \quad , & if\ s_{u,v} = 0\ and\ c(v|u) = 0 \end{cases} \tag{6}$$

where, indicates the similarity value which is calculated using Pearson correlation coefficient similarity measure [38] which is shown in the Eq. (7).

$$s_{u,v} = \frac{\sum_{i \in I_{u,v}} (r_{u,i} - \bar{r}_u).(r_{v,i} - \bar{r}_v)}{\sqrt{\sum_{i \in I_{u,v}} (r_{u,i} - \bar{r}_u)^2 \ .\ \sum_{i \in I_{u,v}} (r_{v,i} - \bar{r}_v)^2}}, v \in UD_u \tag{7}$$

where $s_{u,v}$ denotes the similarity between two users u and v, and $I_{u,v} = I_u \cap I_v$ is the set of items rated by both users u and v, $r_{u,i}$ and $r_{v,i}$ are the ratings of u , v to the item i, also r_u and r_v are the average rating of user u and v respectively.

The confidence between users u and v is shown as $c(v|u)$ which determines the amount of interest user u should have in user v and vice versa. Amount of confidence user u should have on user v is given as:

$$c(v|u) = \frac{I_u \cap I_v}{I_u}, \qquad v \in UD_u \tag{8}$$

Combining $s_{u,v}$ with $c(v|u)$ reduces the sparseness in user similarity matrix, since the sparse user–item rating matrix results in sparseness in user similarity matrix, therefore $w_{u,v} = k \times c(v|u)$ when $s_{u,v} = 0$ but $c(v|u) \neq 0$ reduces the sparseness problem [39].

5) Rating Prediction

After calculating the trust factor value for each trusted user, the rate of the item i for the active user u which is denoted by $p_{u,i}$ is predicted using Eq. (9) [18].

$$p_{u,i} = \bar{r}_u + \frac{\sum_{v \in C_{u,i}} trust_{u,v} . (r_{v,i} - \bar{r}_v)}{\sum_{v \in C_{u,i}} trust_{u,v}} \tag{9}$$

where $\bar{r}_u$ is the average of ratings for user u, $C_{u,i}$ is a set of neighbors for trusted user $u$who have rated the item i and $trust_{u,v}$ denotes the trust factor between the users u and v.

IV. Performance Evaluation

In this section, the performance of the game theory-based recommendation is evaluated using Epinions dataset. Epinions dataset contains both item rating information and trust network topology information, which allows us to compare the performance of game theory-based recommendation with that of trust-aware recommendation.

A. Epinions Dataset

Epinions dataset is a consumer opinion site in which users can review and rate items, such as movies, books, software, etc. The dataset consists of 49,290 users, 664,824 reviews/ratings, and 139,738 rated items and the ratings are in range of 1 to 5. Users also indicate their trust to a set of users whose reviews/ratings are found to be valuable. There are 487,181 issued trusts in total. In trust-aware recommender systems, a user receives recommendation only if it is connected with other users by means of the trust relationship [18].

B. Experimental settings

Several views are formed for the purpose of detailed comparison[18]:

- **All Data**, represents the whole dataset users.
- **Heavy raters** who have rated more than 10 items.
- **Opinionated users**, who have rated more than 4 items and whose standard deviation of ratings is greater than 1.5.
- **Black sheep users**, who have rated more than 4 items and for which the average distance of their rating on item i with respect to mean rating of item i is greater than 1.
- **Cold start users**, who have rated from 1 to 4 items.
- **Controversial items**, which have received ratings whose standard deviation is higher than 1.5.
- **Niche items**, which have received less than 5 ratings.

C. Evaluation metrics

The performance of all mentioned methods is evaluated in terms of both accuracy and coverage. The errors between the predicated ratings and the ground truth are accumulated. The evaluation measures are described as follows:

$$MAE = \frac{\sum_u \sum_i |r_{u,i} - p_{u,i}|}{N} \tag{10}$$

MAE denotes the Mean Average Error in which N is the number of ratings. So, the smaller the MAE value is, the closer a prediction is to the ground truth. The mean absolute user error (MAUE) measure also is used in the experiments [5]. In order to calculate MAUE, first the MAE is computed for each user independently and then MAUE is defined as average of all the MAEs as follows:

$$MAUE = \frac{\sum_{u \epsilon U} MAE_u}{N_u} \tag{11}$$

where, U denotes the set of all users, N_u is the number of users in U and MAE_u is the mean absolute error for user u.

Ratings Coverage (RC) measure the degree to which the ratings can be predicted and covered relative to the whole ratings. This measure is shown in Eq. (12).

$$RC = \frac{N_r}{N_c} \tag{12}$$

where N_r and N_c denote the number of predictable and all the ratings, respectively.

User Coverage (UC) measure also is used, which is defined as the part of users for which the RS is able to predict at least one rating. This measure is shown in Eq. (13).

$$UC = \frac{N_i}{N_t} \tag{13}$$

where, N_i denotes the total number of users which the RS is able to predict at least one rating for them and N_t is the total number of users.

D. Results of the experiments

In this section, we conduct a series of experiments on Epinions dataset to demonstrate the effectiveness of our method relative to others. We compare the performance of the proposed method with a number of trust-aware methods as well as a conventional user-based CF method.

- **CF** computes user similarity using the Pearson correlation coefficient measure denoted in Eq. (7), selects the users whose similarity is above 0.
- **MoleTrust** algorithm [18] in which trust is propagated in the trust network of users with the length 3. trusted users are used to predict item ratings
- **TrustAll** algorithm [18] in which all users are considered as trusted users.

In our method, parameter k in confidence factor was set to 0.2 while calculating $w_{u,v}$ when $s_{u,v}$ is equal to 0. In all mentioned algorithms and also the proposed method Eq. (9) is used to generate item predictions. The experimental results based on coverage and accuracy are shown in Table I and Table II, respectively.

Table I. THE EXPERIMENTAL RESULTS FOR MAE AND RC MEASURES

MAE / RC				
Views	Algorithms			
	CF	*MoleTrust*	*TrustAll*	*Our Model*
All data	0.892 50.84%	0.797 72.14%	0.714 **88.13%**	**0.673** 72.12%
Cold users	1.102 3.28%	0.754 41.17%	0.765 **91.82%**	**0.639** 41.16%
Heavy raters	0.851 57.43%	0.796 75.93%	0.794 **87.49%**	**0.699** 75.93%
Opin. users	1.223 49.74%	1.176 71.16%	1.203 **92.73%**	**0.940** 71.14%
Black sheep	1.353 52.67%	1.202 70.94%	1.211 **96.95%**	**0.959** 70.92%
Contr. items	1.534 44.61%	1.602 81.52%	1.626 **99.81%**	**0.981** 81.50%
Niche items	0.812 13.06%	0.810 20.75%	0.853 **55.33%**	**0.671** 20.75%

Table II. THE EXPERIMENTAL RESULTS FOR MAUE AND UC MEASURES

MAUE / UC				
Views	Algorithms			
	CF	*MoleTrust*	*TrustAll*	*Our Model*
All data	0.964 40.36%	0.794 63.28%	0.786 **97.86%**	**0.706** 63.25%
Cold users	1.178 2.94%	0.721 43.42%	0.762 **94.94%**	**0.647** 43.40%
Heavy raters	0.907 86.02%	0.817 84.29%	0.795 **100%**	**0.714** 84.29%
Opin. users	1.361 61.25%	1.202 74.07%	1.187 **100%**	**0.986** 74.05%
Black sheep	1.385 65.21%	1.237 71.30%	1.243 **100%**	**0.996** 71.29%
Contr. items	1.527 14.89%	1.554 30.28%	1.563 **37.12%**	**1.012** 30.27%
Niche items	0.843 11.24%	0.823 34.61%	0.858 **51.98%**	**0.674** 34.61%

As shown in Table I and Table II, the proposed method provided less MAE and MAUE in comparison with the other methods. So, the proposed method has increased the accuracy while providing suitable coverage for the users and the items. Also, as shown in results, TrustAll algorithm has better UC and RC than the proposed method and the other ones, but it's sensitive to the attack because of setting all trust values to 1, while our method only uses the trusted users to predict the items, So the attack issue has been solved in our method as well as the MoleTrust algorithm. Also, the proposed method has improved the accuracy in compression with MoleTrust algorithm and also maintain its advantages which are overcoming the attack issue and rating cold users.

Figure I, shows the results using MAE and MAUE measures for all methods in which the better accuracy of the proposed method can be seen. Also Figure II, depicts the results using RC and UC measure visually in which the coverage for items and users based on proposed method can be seen respectively.

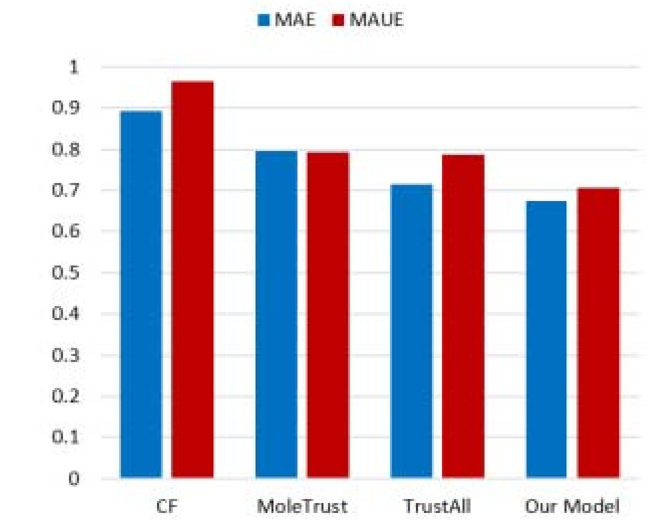

Figure I. MAE and MAUE measures on all data. The x axis represents the methods and the y axis denotes the error rates.

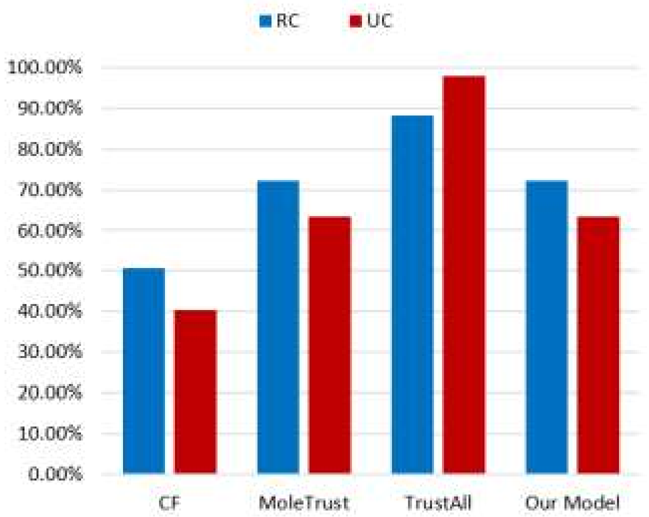

Figure II. Rate coverage (RC) and User coverage (UC) measures on all data. The x axis represents the methods and the y axis denotes the coverage rates.

V. CONCLUSION

Collaborative filtering approach is a robust technology for users to find their interested information. Trust is a concept that recently takes much attention and has been recently identified as an effective means to utilize social network to improve the recommendation quality. In this paper, a novel method is proposed to improve the trust-aware recommender systems by using the game theory concept. For this purpose, the Pareto dominance concept is used to identify trust value between trusted users and active user. The proposed method adopts a five-phase approach in order to provide predictions for each user. In other word, our goal was to reach the coverage of the Moletrust algorithm as well as increasing the accuracy. The experimental result show that in most cases the proposed method outperforms the trust-aware recommenders systems and is comparable with these methods in term of coverage.

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