TruCom: Exploiting Domain-Specific Trust Networks for Multicategory Item Recommendation

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***Abstract*—Recommender systems (RSs) have become important tools for solving the problem of information overload. With the advent and popularity of online social networks, some studies on network-based recommendation have emerged, raising the concern of many researchers. Trust is one kind of important information available in social networks and is often used for performance improvement in social-network-based RSs. However, most trust-aware RSs ignore the fact that people trust different subsets of friends pertaining to different domains, such as music and movies, because people behave differently in diverse domains according to different interests. This paper proposes a novel recommendation method called TruCom. In a multicategory item recommendation domain, TruCom first generates a domain-specific trust network pertaining to each domain and then builds a unified objective function for improving recommendation accuracy by incorporating the hybrid information of direct and indirect trust into a matrix factorization recommendation model. Through relevant benchmark experiments on two real-world data sets, we show that TruCom achieves better performance than other existing recommendation methods, which demonstrates the effectiveness and reliability of TruCom.**

***Index Terms*—Collaborative filtering (CF), item recommendation, matrix factorization (MF), recommender system (RS), trust networks.**

I. Introduction

With the increasing amount of information available, it has become difficult for users to find useful and relevant information. Recommender systems (RSs), which aim to automatically suggest items of potential interest to users in particular domains, such as movies and music, for solving the problem of information overload, have attracted more and more attention [1]–[7]. Generally, there are two classes of recommendation approaches: content-based and collaborative filtering (CF) approaches. Content-based approaches make recommendations based on users' choices made in the past. Traditional CF approaches usually collect and analyze users' rating information to predict uses' interests [8]. CF plays an important role in the domain of recommendation, and CF RSs have been successfully applied in many fields such as movies [9], [10], music [11], e-commerce [12], [13], e-learning [14], [15], and so on.

Recently, with social networks becoming increasingly popular, social-network-based RSs [16]–[23] are being studied by more and more researchers because social networks can provide lots of useful information such as user and item profiles, friend networks, trust networks, etc. The trust of users in social networks is very important and often used to improve recommendation performance and to address some challenges such as data sparsity and cold start [24]. The common concept of trust-based RSs is that users' interests can be influenced by their trusted friends in social networks. However, users behave differently across different domains because of different interests or preferences. This means that users often express different trust relations in different domains. For example, a user u may trust user v in terms of books, but the same user u may not trust user v in terms of movies. Traditional trust-based recommendation methods often use trust information without the consideration of each domain, which is not consistent due to the fact that trust is not applicable in different domains. It is therefore important to develop appropriate methods that utilize trust relations of users for recommendation in different domains.

In this paper, we propose a novel recommendation method called *TruCom* for multicategory item recommendation. *TruCom* first utilizes users' rating information and the original trust network to generate a domain-specific trust network, which is composed of users as well as their direct and indirect relations. Based on the generated domain-specific trust network, we then incorporate the hybrid information of direct and indirect trust relations between users to build a matrix factorization (MF) recommendation model for performance improvement. We conduct some important experiments on two publicly available data sets, and our results demonstrate that *TruCom* achieves better performance than existing recommendation methods in terms of recommendation accuracy.

The major contributions of this paper can be summarized as follows.

1) We propose a recommendation method that generates a domain-specific trust network through domain partition and use of direct and indirect trust relations.
2) We incorporate the use of the hybrid information of direct and indirect trust to build an MF-based recommendation model for performance improvement based on the generated domain-specific trust network.

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3) We conduct experiments using two publicly available data sets Epinions and Ciao, to verify the effectiveness of the proposed recommendation model in terms of recommendation accuracy.

The rest of this paper is organized as follows. Section II describes the problem. Section III introduces the details of our proposed recommendation. Experimental results are presented and analyzed in Section IV. Section V discusses related work. Finally, Section VI concludes this paper.

II. Problem Statement

In RSs, there are a set of users $U = \{u_1, \ldots, u_N\}$ and a set of items $I = \{i_1, \ldots, i_M\}$. The ratings expressed by users on items are represented as a rating matrix $R = [R_{u,i}]_{N\times M}$, where $R_{u,i}$ denotes the rating of user u on item i. $R_{u,i}$ can be any real number, but often, ratings are integers in the range of 1–5.

MF is a typical model-based CF method. MF performs a low-rank MF on the user–item rating matrix based on the assumption that a few latent patterns influence user rating behaviors. Let $P_u \in R^K$ and $Q_i \in R^K$ be the user preference vector for user u and item feature vector for i, respectively, where K is the number of latent vectors. The objective function of the MF method is

$$L(P,Q) = \sum_{u\in U, i\in I} W_{u,i}(R_{u,i} - P_u Q_i) + \lambda\left(\|P\|_F^2 + \|Q\|_F^2\right) \tag{1}$$

where $W_{u,i}$ is an indicator function that is equal to 1 if user u expressed rating on item i and equal to 0 otherwise, $\|\cdot\|_F^2$ denotes the Frobenius norm, and λ is the regularization coefficient. By performing gradient descent in P_u and Q_i, the minimum of the objective function above can be found, and then, P and Q can be obtained. Next, the prediction rating $\hat{R}_{u,i}$ can be computed as follows:

$$\hat{R}_{u,i} = \overline{r} + P_u Q_i \tag{2}$$

where $\overline{r}$ is a (global) offset value.

In trust-based RSs, there is also a trust network $T = [T_{u,v}]_{N\times N}$ among users. If user u trusts user v, then $T_{u,v}$ denotes the value of this trust, and the value is a real number in the range of 0–1. Zero means no trust, and one means full trust. Trust-based recommendation approaches perform well because of the effects of selection and social influence that have been postulated by sociologists for a long time. Selection means that people tend to relate to people with similar attributes and due to social influence related people in a social network have an impact on each other to become more similar [25]. The high availability of online social network data has provided support to verify these sociological models. For example, Crandall *et al.* [26] experimentally verified that people are similar to their neighbors in a social network for these reasons. By analyzing a network of people having social interactions and a similarity network where users are connected to their most similar users, it was shown that social interaction and similarity graphs have little overlap, sharing fewer than 15% of their edges. It has been confirmed from the results in [26] and other

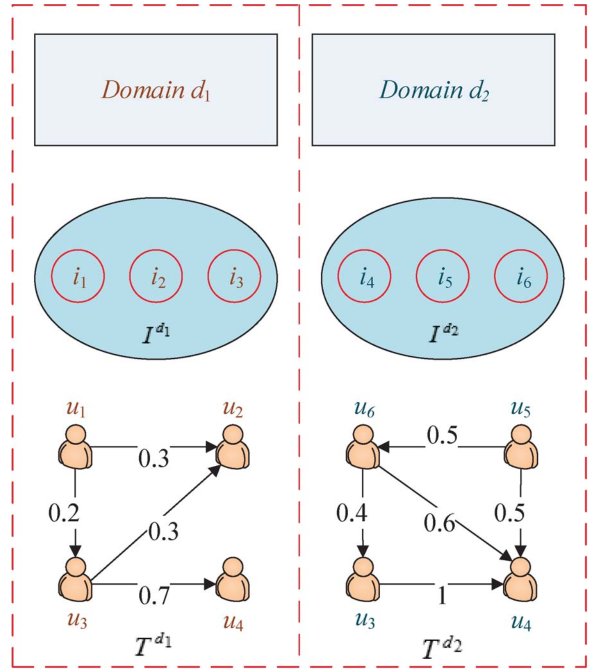

Fig. 1. Relations among users, items, trust networks, and domains.

similar works that a social network provides an independent source of information, which can be exploited to improve the quality of recommendations.

In traditional trust-based RSs, trust networks are used without the consideration of the domains related to users' interests. As enumerated above, these traditional approaches are not consistent with the fact that users often behave differently across different domains because of their different interests or preferences.

In item recommendation, let d denote a domain that represents an interest/preference of users related to a set of items I^d. Let T^d denote a trust matrix pertaining to domain d, which is indeed a trust network. Fig. 1 illustrates the relations among users, items, domains, and trust networks. As shown in Fig. 1, users' interests include domains d_1 and d_2. According to the domains users behave in, the set of items I and the set of users U are grouped into different subsets related to those domains. d_1 involves the user set $U^{d_1} = \{u_1, u_2, u_3, u_4\}$ and the item set $I^{d_1} = \{i_1, i_2, i_3\}$. d_2 involves the user set $U^{d_2} = \{u_3, u_4, u_5, u_6\}$ and the item set $I^{d_2} = \{i_4, i_5, i_6\}$. At the same time, there exist domain-specific trust networks T^{d_1} and T^{d_2}.

With the notations above, our problem can be stated in the following two steps: 1) Given the rating information $\{R, U, I\}$ and the original trust network T, partition the set of items and the set of users according to the domains and build domain-specific trust networks; 2) build the recommendation model based on the domain-specific trust network for good performance.

III. Proposed Solution

Here, we first describe the methodology of our proposed recommendation scheme. Then, we introduce the two important

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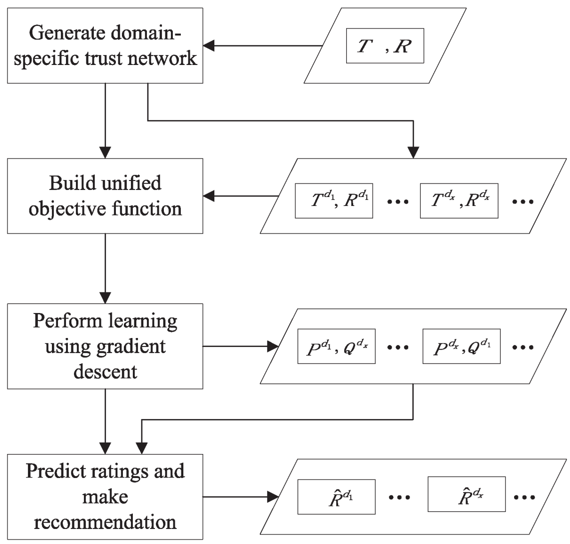

Fig. 2. Recommendation process of the proposed scheme.

steps involved in our scheme: 1) how to generate the specific-domain trust network by utilizing the original trust network and user–item rating information; 2) how to build the unified objective function for recommendation based on the previously generated specific-domain trust network.

A. Recommendation Process

Our proposed recommendation scheme exploits trust relations in different domains to improve recommendation accuracy. As shown in Fig. 2, the four main steps are as follows: 1) generate a domain-specific trust network based on the original trust and rating matrices; 2) after obtaining domain-relevant trust networks, build a unified objective function pertaining to each domain; 3) perform gradient descent to learn users' preference and items' feature matrices for different domains; 4) predict users' ratings on domain-relevant items and make recommendation according to rating ranking.

B. Generating Domain-Specific Trust Network

The generation process of the domain-specific trust network mainly includes two steps: domain partition and domain-specific trust network generation.

1) Domain Partition: As enumerated above, users often behave differently across multiple domains of interest. In most electronic business sites, items are usually grouped into different categories. These categories represent the domains of interest for users to some extent. Therefore, in this paper, we partition different domains according to items' categories. Consequently, each category is considered as the default domain.

2) Trust Network Generation: Domain partition means that the original item set will be partitioned into multiple item subsets according to their domains/categories. In addition, the original user set will also be partitioned into multiple relevant user subsets through a process of grouping users into a relevant set pertaining to a particular domain if the user has rated some

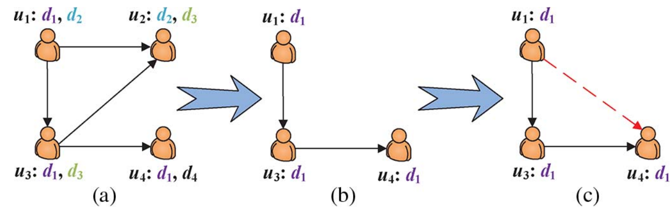

Fig. 3. Trust propagation. (a) Original trust network. (b) Trust network on domain d_1 (only direct trust relations). (c) Trust network on domain d_1 (both direct and indirect trust relations).

items of that domain. Each generated item set and relevant user set will be used to the generate domain-specific trust network.

A trust network is a weighted and directed graph in which nodes are users and edges are the trust relations between the users. Let the graph $G^d = \langle U^d, E^d, W^d \rangle$ be the trust network pertaining to domain d, where U^d, E^d, and W^d, respectively, denote the user set, the trust relation set between the users, and the set of the relations' weight values pertaining to domain d. The matrix representation of the trust network is $T^d = [T^d_{u,v}]_{N^d \times N^d}$, where $T^d_{u,v}$, respectively, denotes the trust relation between users u and v, and N^d denotes the number of the users pertaining to domain d.

In graph theory, the relations between nodes include direct and indirect neighborhood associations. Similarly, there are two relations in the domain-specific trust network: direct trust relation and indirect trust relation. Let TD^d and TI^d be the direct trust relation matrix and the indirect trust relation matrix, respectively. Direct trust relations pertaining to each domain are easily extracted from the original trust network by removing users who are not in the user set pertaining to the domain, as shown in Fig. 3. The weight value of each trust is computed as

$$TD^d_{u,v} = T_{u,v} \times \frac{N^d_u}{\left|\bigcup_{x \in U^d} I^d_x\right|} \tag{3}$$

where N^d_u is the number of items u has rated, and $T_{u,v}$ is the weight value of the trust between users u and v. $|\bigcup_{x \in U^d} I^d_x|$ is the number of items on which users belonging to U^d have expressed rates.

Indirect trust relations are obtained through the process of trust propagation in a path of social network, as shown in Fig. 3. When two users are connected through other users located in a path, we can use a propagation model to calculate trust between them. For example, in Fig. 3, there is no direct trust relation between users u_1 and u_4; however, they are connected through user u_3. We compute the trust values along paths u_1, u_3, and u_4 as follows:

$$T_{u_1,u_4} = T_{u_1,u_3} \times T_{u_3,u_4}. \tag{4}$$

In general, for a path $\text{path}_{u,w}$ from u to w, trust is computed as follows:

$$T(\text{path}_{u,w}) = \prod_{(v_k,v_l) \in (\text{path}_{u,w})} T_{v_k,v_l}. \tag{5}$$

The path with a cycle is not used to compute the trust value pertaining to that path. In addition, we limit the maximum

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length of a valid path to 6 because of the famous theory of six-degree separation. The trust value for all paths from u to w is computed as follows:

$$TI_{u,w} = \sum_{\text{all path}_{u,w}} T(\text{path}_{u,w}) \tag{6}$$

where $TI_{u,w}$ is the indirect trust value between users u and w, and $0 \leq T_{u,w} \leq 1$.

C. Building Unified Objective Function

As mentioned in the previous section, MF is a fundamental model-based CF method for recommendation. For each domain, we obtain a separate user feature vector P^d and item feature vector Q^d. The objective function of the MF method pertaining to each domain is denoted as

$$L_1^d(P^d, Q^d) = \sum_{u \in U^d, i \in I^d} W_{u,i}^d \left(R_{u,i}^d - P_u^d Q_i^d\right)^2 + \lambda \left(\|P^d\|_F^2 + \|Q^d\|_F^2\right) \tag{7}$$

where we only use ratings $R_{u,i}^d$ pertaining to domain d. $W_{u,i}^d$ is an indicator function that is equal to 1 if user u expressed a rating on item i of domain d and equal to 0 otherwise. $\|.\|_F^2$ denotes the Frobenius norm, and λ is the regularization coefficient.

Trust is often used for recommendation because of the theory that a user's taste is similar to and/or influenced by his trusted friends in social networks. Users can be influenced by their trustworthy friends and are more likely to accept recommendations made by their trusted friends than recommendations from strangers. Studies also confirm that people tend to rely on recommendations from their friends and other people they trust more than those provided by RSs in terms of quality and usefulness, although the recommendations given by the RSs have a high novelty factor [27].

The theory of trust-based recommendation stipulates that the tastes of users existent in unidirectional and bidirectional trust relations have to be similar. The similarity between a user and his/her direct neighbor means they have similar interests to some extent. Meanwhile, the similarity between a user and his/her indirect neighbor also signifies similar interests. Thus, we integrate the direct and indirect trust relation information by minimizing the following objective function:

$$L_2^d(P^d) = \sum_{u \in U^d} \left\| P_u^d - \sum_{v \in DN_u^d} TD_{u,v}^d P_v^d - \sum_{v' \in IN_u^d} TI_{u,v'}^d P_{v'}^d \right\|^2 \tag{8}$$

where $TD_{u,v}^d$ denotes the degree of direct trust relation between user u and its direct neighbor v, and DN_u^d is the set of the direct neighbor users of u in the social network pertaining to domain d. $TI_{u,v'}^d$ denotes the degree of indirect trust relation between user u and its indirect neighbor v', and IN_u^d is the set of the indirect neighbor users of u in the social network pertaining to domain d. Each v' can be obtained based on the process of trust propagation.

The unified objective function for *TruCom* is defined as

$$L^d(P^d, Q^d) = L_1^d(P^d, Q^d) + \alpha L_2^d(P^d) \tag{9}$$

where α is a nonnegative parameter that is used to trade off the two objective functions. The minimum of the objective function can be found by performing gradient descent in P_u^d and Q_i^d, i.e.,

$$\frac{\partial L^d}{\partial P_u^d} = \sum_{u \in U^d, i \in I^d} W_{u,i}^d \left(P_u^d Q_i^d - R_{u,i}^d\right) Q_i^d + \lambda P_u^d + \alpha \left(P_u^d - \sum_{v \in U} TD_{u,v}^d P_v^d - \sum_{v' \in U} TI_{u,v'}^d P_{v'}^d\right) \tag{10}$$

$$\frac{\partial L^d}{\partial Q_i^d} = \sum_{u \in U^d, i \in I^d} W_{u,i}^d \left(P_u^d Q_i^d - R_{u,i}^d\right) P_u^d + \lambda Q_i^d \tag{11}$$

$$P_u^d = P_u^d - \text{learing\_rate} \times \frac{\partial L^d}{\partial P_u^d} \tag{12}$$

$$Q_i^d = Q_i^d - \text{learing\_rate} \times \frac{\partial L^d}{\partial Q_i^d} \tag{13}$$

where $W_{u,i}^d$ is the indicator function that is equal to 1 if u expressed a rate score on i in domain d and equal to 0 otherwise. The initial values of P_u^d and Q_i^d are sampled from the normal distribution with zero mean. In each iteration, P_u^d and Q_i^d are updated based on the latent variables from the previous iteration. Once P_u^d and Q_i^d are learned for each domain d, this model can be used to predict ratings for user–item pairs.

IV. Experiments

Here, we present our experimental evaluations using Epinions and Ciao data sets [28]. We report our experimental results and compare them with other existing methods.

A. Data Sets

Epinions and Ciao are well-known consumer opinion websites where users can make reviews on familiar items such as cars, movies, books, and music and further assign these items numeric ratings in the range from 1 (min) to 5 (max). In addition, users also express their trust to other users and add users to their trust networks if they find their reviews consistently interesting and helpful. In the Epinions and Ciao data sets, trust values between users are binary.

We used the versions of the Epinions and Ciao data set published by Tang *et al.* [28]. The Epinions data set consists of ratings from 22 163 users who rated a total of 296 155 different items from 27 categories. The total number of ratings is 909 143. On the other hand, Ciao is a smaller data set and consists of ratings from 7375 users who rated a total of 105 042 different items from 28 categories. The total number of ratings is 281 909. We removed the users without ratings or trust relations. After preprocessing the two data sets, the distributions of users and items in the top-5 categories of the two data sets are presented in Tables I and II.

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TABLE I
EPINIONS: TOP-5 CATEGORY STATISTICS

Item Category	User Count	Item Count	Rating Count	Trust Relation Count	Rating Sparsity	Trust Relation Sparsity
Movies	10900	25036	129708	56952	0.999525	0.999521
Books	7937	46579	75989	40834	0.999794	0.999352
Music	6365	28246	62230	25340	0.999654	0.999375
Hotels and Travel	7795	12529	41243	36389	0.999578	0.999401
Kids and Family	6037	19679	61586	25814	0.999482	0.999292

TABLE II
CIAO: TOP-5 CATEGORY STATISTICS

Item Category	User Count	Item Count	Rating Count	Trust Relation Count	Rating Sparsity	Trust Relation Sparsity
DVDs	4196	11220	38974	11964	0.999172	0.999320
Books	3155	12516	21596	9849	0.999453	0.999011
Beauty	3176	9311	23601	10109	0.999202	0.998998
Travel	3569	12111	21532	11659	0.999502	0.999085
Ciao Cafe	4317	2882	29931	16013	0.997594	0.999141

B. Experimental Setup

We perform fivefold cross validation in our experiments. In each fold, we use 80% of data as the training set and the remaining 20% as the test set. The evaluation metrics in our experiments are root mean square error (RMSE) and mean absolute error (MAE), as these are some of the most popular accuracy measures in the literature of RSs. Lower values of RMSE and MAE signify better performance. RMSE is defined as

$$\text{RMSE} = \sqrt{\frac{\sum_{R_{u,i} \in R_{\text{test}}} (R_{u,i} - \hat{R}_{u,i})^2}{|R_{\text{test}}|}} \tag{14}$$

and MAE is defined as

$$\text{MAE} = \frac{\sum_{R_{u,i} \in R_{\text{test}}} |R_{u,i} - \hat{R}_{u,i}|}{|R_{\text{test}}|} \tag{15}$$

where $|R_{\text{test}}|$ denotes the number of ratings in the test set. $R_{u,i}$ and $\hat{R}_{u,i}$, respectively, denote the real and prediction values of ratings in R_{test}.

In our experiments, we compare the recommendation results of the following methods to demonstrate the effectiveness of our proposed *TruCom* method.

1) *BaseMF*: This is the baseline MF method proposed in [29], which does not involve the use of trust information in each specific domain/category.
2) *SocialMF*: This is a trust-based recommendation method proposed in [30]. It uses all trust information in an original social network to improve the recommendation accuracy.
3) *CircleCon*: This is a trust-based recommendation method proposed in [31]. It uses the direct trust relations to build a trust network pertaining to each domain.

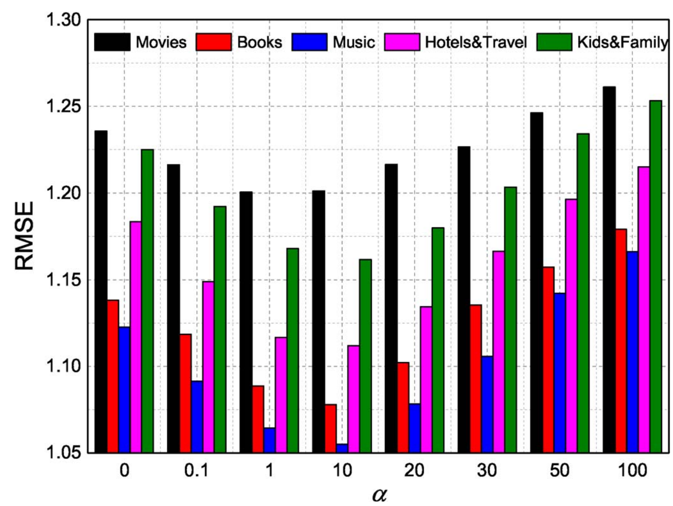

Fig. 4. *TruCom*: Impact of α on RMSE in Epinions.

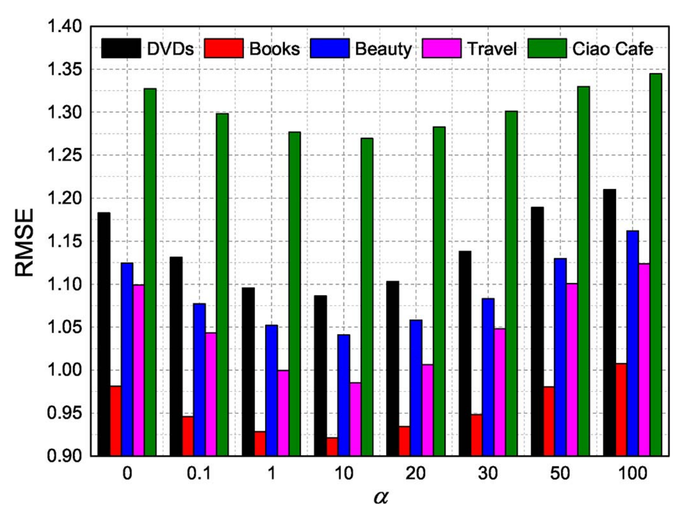

Fig. 5. *TruCom*: Impact of α on RMSE in Ciao.

C. Impact of Parameter

In *TruCom*, parameter α controls the influence of the hybrid trust relations on recommendation results. Larger values of α in the objective function of (9) indicate more impact of the hybrid trust information on the behavior of users. Very small values of α make our scheme close to the baseline MF method.

Figs. 4 and 5 compare the RMSE of our model for different ranges of values for α in both data sets. As shown in Figs. 4

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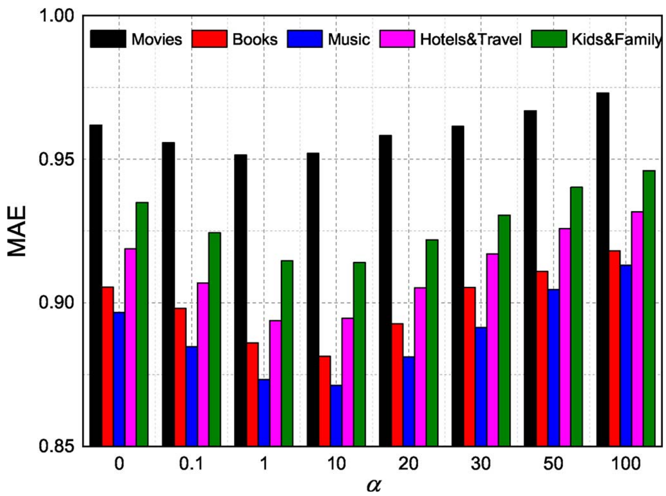

Fig. 6. *TruCom*: Impact of α on MAE in Epinions.

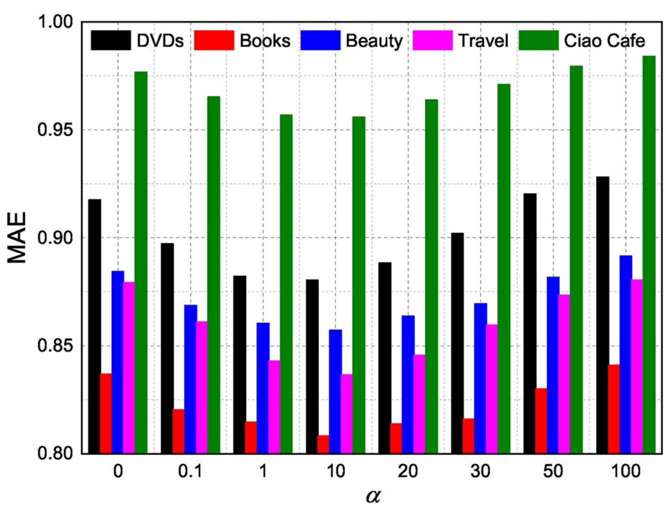

Fig. 7. *TruCom*: Impact of α on MAE in Ciao.

and 5, *TruCom* has its best results on Epinions and Ciao when $\alpha = 10$. Similarly, Figs. 6 and 7 compare the MAE of our model for different ranges of values for α in both data sets. As shown in Figs. 6 and 7, *TruCom* has its best results on Epinions and Ciao when $\alpha = 10$. In addition, a larger or smaller value of α makes the prediction accuracy worse to some extent. These results demonstrate that trust information should be incorporated into traditional recommendation approaches in a proper way.

D. Comparison Against Existing Methods

Tables III and IV summarize the performance comparisons of the above recommendation methods on Epinions and Ciao data sets regarding RMSE and MAE, respectively. From the experimental results, it can be observed that *SocialMF* performs better than *BaseMF* in terms of RMSE and MAE. This is because the use of trust information helps improve the recommendation performance by forcing trusted users to be more similar. We can also see that *CircleCon* and *TruCom* perform better than *BaseMF* in terms of RMSE and MAE because of the same utilization of trust information. This further proved the necessity and effectiveness of incorporating trust information into RS for performance improvement.

TABLE III
EPINIONS: PERFORMANCE COMPARISONS

Item Category	BaseMF	SocialMF	CircleCon	TruCom	Metric
Movies	1.2356	1.2151	1.1988	**1.1860**	RMSE
	0.9618	0.9560	0.9509	**0.9456**	MAE
Books	1.1382	1.1149	1.0846	**1.0405**	RMSE
	0.9054	0.8969	0.8844	**0.8635**	MAE
Music	1.2256	1.0876	1.0606	**1.0214**	RMSE
	0.8967	0.8832	0.8716	**0.8543**	MAE
Hotels&Travel	1.1835	1.1444	1.1133	**1.0806**	RMSE
	0.9188	0.9050	0.8923	**0.8769**	MAE
Kids&Family	1.2251	1.1883	1.1653	**1.1370**	RMSE
	0.9349	0.9221	0.9139	**0.9011**	MAE
Average	1.1901	1.1619	1.1385	**1.1108**	RMSE
	0.9304	0.9208	0.9119	**0.8992**	MAE

TABLE IV
CIAO: PERFORMANCE COMPARISONS

Item Category	BaseMF	SocialMF	CircleCon	TruCom	Metric
DVDs	1.1828	1.1434	1.1182	**1.0860**	RMSE
	0.9176	0.9019	0.8934	**0.8804**	MAE
Books	0.9810	0.9523	0.9385	**0.9214**	RMSE
	0.8369	0.8217	0.8158	**0.8083**	MAE
Beauty	1.1246	1.0878	1.0681	**1.0410**	RMSE
	0.8843	0.8705	0.8655	**0.8573**	MAE
Travel	1.0991	1.0572	1.0236	**0.9850**	RMSE
	0.8793	0.8636	0.8512	**0.8366**	MAE
Ciao Cafe	1.3273	1.3036	1.2875	**1.2695**	RMSE
	0.9766	0.9686	0.9628	**0.9559**	MAE
Average	1.1644	1.1306	1.1091	**1.0827**	RMSE
	0.9071	0.8936	0.8861	**0.8760**	MAE

In addition, it can be shown from Tables III and IV that *CircleCon* and *TruCom* are better than *BaseMF* and *SocialMF* in terms of RMSE and MAE. The two methods benefit from the use of different trust information pertaining to different domains. Meanwhile, it can be observed from the tables that the proposed method *TruCom* is better than *CircleCon* in terms of RMSE and MAE. This observation reveals that the use of the hybrid information of direct and indirect trust can help further improve prediction accuracy by determining more similar users because the direct and indirect trust information express similarities between users' interests to some extent.

Direct and indirect trust information can be combined for recommendation using (16)–(18) to integrate the two trust relations. Unlike the usage of trust information in *TruCom*, direct trust and indirect trust are incorporated into an MF recommendation model by weighing the trust information, respectively. Here, we call this method *TruCom2*. Using the Epinions and Ciao data sets, we compared the performance of *TruCom2* to *CircleCon* in terms of RMSE and MAE on Epinions and Ciao. The results achieved are shown in Figs. 8–11. We can verify from Figs. 8–11 that *TruCom2*, which incorporates hybrid trust information, is worse than *CircleCon* in terms of both RMSE and MAE. This demonstrates that the use of hybrid trust information may produce a negative effect on recommendation performance. It might be due to the fact that the direct and the indirect trust are relative but cannot be combined in a proper recommendation way. How to combine different trust

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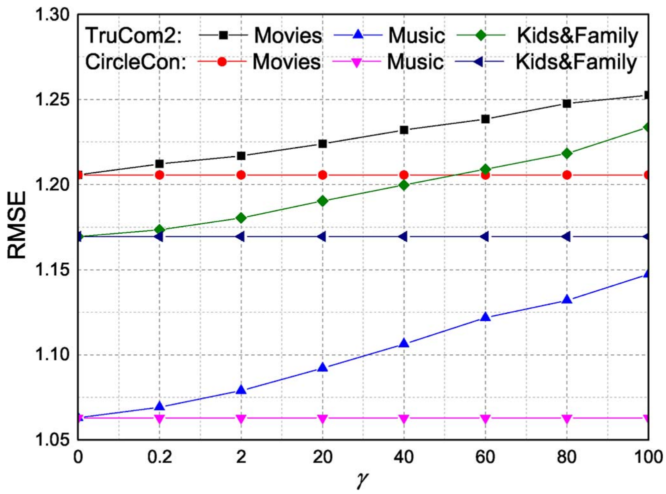

Fig. 8. Performance comparison of *CircleCon* and *TruCom2* in terms of RMSE in Epinions.

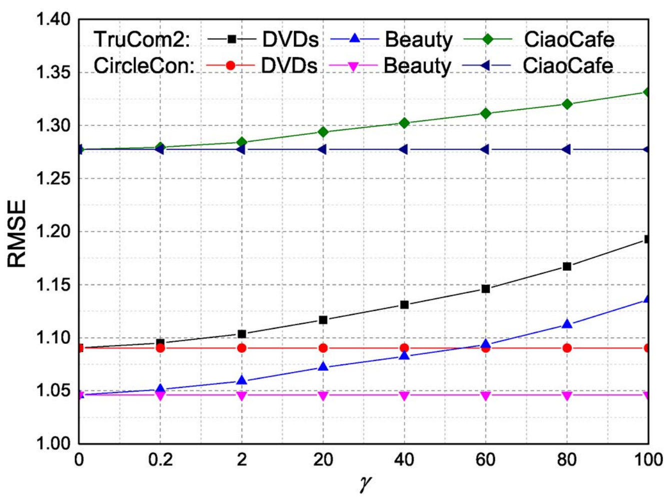

Fig. 9. Performance comparison of *CircleCon* and *TruCom2* in terms of RMSE in Ciao.

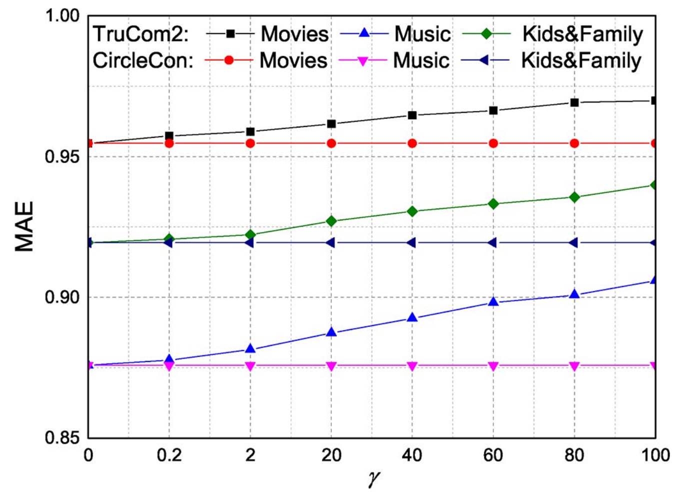

Fig. 10. Performance comparison of *CircleCon* and *TruCom2* in terms of RMSE in Epinions.

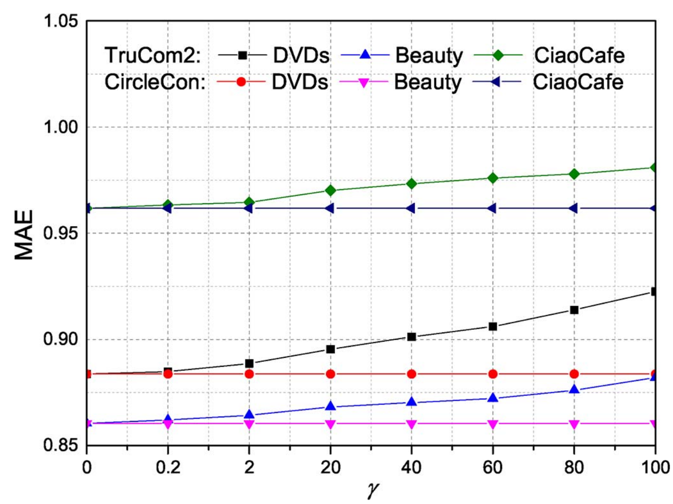

Fig. 11. Performance comparison of *CircleCon* and *TruCom2* in terms of RMSE in Ciao.

information for the improvement of the recommendation performance will be an important future research direction, i.e.,

$$L_3^d(P^d) = \sum_{u \in U^d} \left\| P_u^d - \sum_{v \in DN_u^d} TD_{u,v}^d P_v^d \right\|^2 \qquad (16)$$

$$L_4^d(P^d) = \sum_{u \in U^d} \left\| P_u^d - \sum_{v' \in IN_u^d} TI_{u,v'}^d P_{v'}^d \right\|^2 \qquad (17)$$

$$L^d(P^d, Q^d) = L_1^d(P^d, Q^d) + \beta L_3^d(P^d) + \gamma L_4^d(P^d). \qquad (18)$$

V. Related Work

Trust is a property that is associated with the relations between people in the real world as well as users in social media. Therefore, trust plays a crucial role across many domains and forms an important feature of our everyday lives. The challenges of the existing RSs include cold start [32]–[35], data sparsity [3], [32], [36], [37], and attacks [38]–[40]. It has been shown that the use of trust information can help mitigate some of the challenges. Here, we review some related work on trust-aware recommendation methods.

Trust-aware RS is one kind of social-network-based RS, which emerges from social networks that involve information about the relations between users. Trust-aware RSs utilize trust information to make more personalized recommendations, and users receive recommendations from those who are in their trust networks (web of trust). By utilizing extra information to construct a user–user similarity matrix and incorporating similarity, traditional RSs mainly benefit from three aspects: improving the quality of the recommendation, improving accuracy or coverage, and addressing some of the challenges in traditional RSs.

In a trust-aware RS, trust information can be used in one of the following approaches along with traditional RSs: 1) trust-aware memory-based CF approaches, which use memory-based

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CF techniques as their basic methods; and 2) trust-aware model-based CF approaches, which use model-based CF techniques as their basic methods.

A. Trust-Aware Memory-Based CF Approaches

Trust-aware memory-based CF approaches incorporate trust information to depress recommendations from distrusted users and boost recommendations from trusted users. These recommendation approaches use trust information to either filter distrusted users using (19) or weigh the recommendation results made by all users using (20), i.e.,

$$\hat{R}_{u,i} = \overline{R}_u + \frac{\sum_{T_{u,v} > T_{\text{threshold}}} (R_{v,i} - \overline{R}_v) \times S_{u,v}}{\sum_{T_{u,v} > T_{\text{threshold}}} S_{u,v}} \quad (19)$$

$$\hat{R}_{u,i} = \overline{R}_u + \frac{\sum (R_{v,i} - \overline{R}_v) \times T_{u,v}}{\sum T_{u,v}}. \quad (20)$$

Trust-aware memory-based CF approaches focus on computing the trust value for incorporating trust information. TidalTrust [41] performs a modified breadth first search in the trust network to compute trust values based on the following two observations: 1) Shorter propagation paths produce more accurate trust estimates, and 2) paths with higher trust values create better results. TidalTrust first searches all paths from the source user to raters and finds all raters with the shortest distance. Then, it computes the trust value through the aggregation process of their ratings weighted by the trust between the user and the raters.

Massa and Avesani [42] proposed a new trust metric called MoleTrust, which is similar to TidalTrust except that MoleTrust needs a predefined trust threshold to determine which users to consider in the rating aggregation process. MoleTrust consists of two main steps: 1) transform the original trust network into a directed acyclic graph by removing trust cycles beforehand and 2) compute trust values based on the obtained directed acyclic graph by performing a simple graph random walk.

Jamali and Ester [43] proposed a recommendation model called TrustWalker, which combines trust-based and item-based recommendation. TrustWalker consists of two major components: 1) random walk in the trust network for visiting a user's direct and indirect friends and 2) probabilistic item rating selection on each visited node for avoiding going too deep in the network without close users having rated the target item. TrustWalker queries a user's direct and indirect friends' ratings for the target item as well as similar items by performing a random walk in online social networks.

B. Trust-Aware Model-Based CF Approaches

MF techniques are widely used as recommendation methods in model-based CF. The common rationale behind the trust-aware model-based MF approaches [30], [44]–[49] is that users' preferences are similar to or influenced by their trusted users.

Ma *et al.* [48] proposed an ensemble method that involved the basic idea that users and their trust networks should have similar ratings on items, and a missing rating for a given user is predicted as a linear combination of ratings from the user and his/her trust network. This method models a rating expressed by user u on item i using

$$\hat{R}_{u,i} = P_u Q_i + \alpha \sum_v T_{u,v} P_v Q_i. \quad (21)$$

Finally, this method incorporates trust information for recommendation by minimizing the following objective function:

$$L(P,Q) = \sum_{u,i} W_{u,i} \left(R_{u,i} - P_u Q_i - \alpha \sum_v T_{u,v} P_v Q_i \right)^2. \quad (22)$$

Tang *et al.* [45], [46] assume that user u shares the same user preference vector P_u in the rating space (rating information) and the trust relation space. They perform a cofactorization procedure in the user–item matrix and the user–user trust relation matrix by sharing the same user preference latent factor. Menon *et al.* [45], [47] reconstructed the trust matrix T to perform trust relation prediction. The representative method SoRec [46] learns the user preference matrix P from both rating information and trust information by minimizing the following objective function for the improvement of recommendation quality:

$$\begin{aligned} L(P,Q,Z) = &\sum_{u,i} W_{u,i} (R_{u,i} - P_u Q_i)^2 \\ &+ \alpha \sum_u \sum_z (T_{u,v} - P_u Z_k)^2 \\ &+ \lambda \left(\|P\|_F^2 + \|Q\|_F^2 + \|Z\|_F^2 \right). \end{aligned} \quad (23)$$

Jamali *et al.* [30], [49] assume that a user's preferences should be similar to that of her trust network. For a given user u, these methods force a user's preference to be closer to that of users in u's trust network. SocialMF [30] forces the preferences of a user to be closer to the average preference of the user's trust network and then builds the following objective function:

$$L(P,Q) = \sum_{u,i} W_{u,i} (R_{u,i} - P_u Q_i)^2 + \alpha \sum_u \left(P_u - \sum_v T_{u,v} P_v \right)^2. \quad (24)$$

The methods above incorporate trust information to build a recommendation model for performance improvement but ignore the previously described problem that users behave differently across different domains, such as movies and music, because of different interests or preferences. Yang *et al.* [31] proposed a method called CircleCon, which is similar to our work. CircleCon uses SocilMF [30] as a base method and focuses on inferring category-specific social trust circles from available rating information combined with social network information where social trust relations across all categories are mixed together. Through experiments on publicly available data, it was demonstrated that CircleCon can better utilize users' social trust information to achieve a more accurate recommendation than the traditional MF approaches that do not

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use any social trust information and the existing social trust-based recommendation approaches that use mixed social trust information across all categories. Unlike CircleCon [31], we propose to build a domain-specific trust network for efficient recommendation by exploiting the hybrid information of direct and indirect trust relations.

VI. Conclusion

Most existing trust-based recommendation methods ignore the fact that people often trust different subsets of friends pertaining to different domains, such as music and movies, because people often behave in different domains according to their different interests or preferences. In this paper, we have proposed a novel recommendation method called *TruCom* for multicategory item recommendation. *TruCom* first generates a domain-specific trust network pertaining to each domain and then builds a unified objective function for improving recommendation accuracy by incorporating the hybrid information of direct and indirect trust into an MF recommendation model, based on the theory that the tastes of users between whom there are the expressions of direct and indirect trust are similar. We conducted experiments on two publicly available data sets, and the results show that the proposed method performs better than other existing recommendation methods in terms of recommendation accuracy.

TruCom does not involve distrust information. The use of distrust information may potentially improve recommendation performance because distrust relations between two users signify the dissimilarity of their tastes to some extent. As a future work, we will consider incorporating distrust information and build distrust networks for recommendation. In addition, temporal information is an important factor in RSs. Both rating information and trust relations vary over time. This means users' interests or preferences also vary over time. Therefore, another future work is to predict the changes in users' ratings and trust relations and to study the impact of the changes in trust-aware RSs.

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