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Cross-Domain Item Recommendation Based on User Similarity

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Abstract. Cross-domain recommender systems adopt multiple methods to build relations from source domain to target domain in order to alleviate problems of cold start and sparsity, and improve the performance of recommendations. The majority of traditional methods tend to associate users and items, which neglected the strong influence of friend relation on the recommendation. In this paper, we propose a cross-domain item recommendation model called CRUS based on user similarity, which firstly introduces the trust relation among friends into cross-domain recommendation. Despite friends usually tend to have similar interests in some domains, they share differences either. Considering this, we define all the similar users with the target user as Similar Friends. By modifying the transfer matrix in the random walk, friends sharing similar interests are highlighted. Extensive experiments on Yelp data set show CRUS outperforms the baseline methods on MAE and RMSE.

Keywords: cross domain recommendation, trust relation, user similarity, rating prediction, random walk.

1. Introduction

Information overload has become a fairly severe problem on the Internet nowadays [12]. While recommender systems aiming at information overload play an increasingly important role in online services [24] [2] [19]. With the users, services and online data expanding rapidly, recommender systems have become a useful tool to provide suggestions to users [4]. There are many item recommendation, like music recommendation, movie recommendation and book recommendation [16] [6] [26] etc. For recommendation technology, there are some basic methods like social-based recommendation, collaborative filtering, content-based recommendation etc [8]. In recommending system, there are two obvious problems, data sparsity [32] [29] and cold start [5] [33], especially making recommendation for those new users with few records or scores. With more and more social activities and interactions, in recent years, cross-domain recommendation has been proposed based on records on the websites or the social relations, which greatly reduces the problem of sparsity and cold start. Cross-domain recommendation is usually based on the link prediction [3] [18] and the relation between users and items in the social network. While, one important factor, that is trust relation in reality, has been not taken into consideration. Recommendation technology mainly includes content-based recommendation, social network-based recommendation and hybrid recommendation, similarly with cross-domain recommendation.

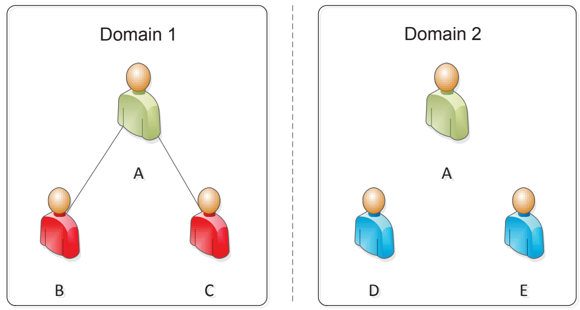

Fig. 1. An example of user network

In this paper, we propose a Cross-domain item Recommendation method based on User Similarity (CRUS), which firstly introduces the friend relation into cross-domain recommendation. It is known to all that there is usually a network consisting of users and their relations as shown in Fig. 1, where red nodes belong to domain 1, blue nodes belong to domain 2 and the target green node belongs to the two domains. For example, in domain 1, user A has two friends B and C, so the item recommendation to user A can be based on the records of user B and C. While user D and E have no relation with user A in domain 2, if recommending the item in domain 2 to user A, what can we do? In this scenario, CRUS shows its superiority. We run the random walk model to get the similar users with the target user. According to the records of similar users, we get the rating list of items and the recommending list. Usually, friends have a tendency to select the similar items and ratings [11], while differences still exist, no except for friends, so we must find out the most similar friends with the target user. Here we define all the similar users with the target user as Similar Friends. Therefore, firstly, we get the relatively similar users by the cosine similarity of rating vector. Then, during the random walking process, we modify the transfer matrix to enhance the walking probability to the similar friends. As the definition, user A' similar friends in Fig. 2 can be divided into three kinds of users, respectively user B, E and G. Users B is the direct similar friend of user A and user E is the indirect similar user who can be reached by his friends of user A. For user G, he can not reach user A. While one in the same is that they have the similar interests. From this way, we can get more relevant data from other domains to recommend items for the new user A in domain2. Therefore, CRUS not only achieves the cross-domain item recommendation, but also solves the problem of sparsity and cold start in recommendation. We take the Directing Friend-based recommendation model (DF) and Random Walk-based recommendation model (RW) for comparison. Experimental results show that CRUS outperforms DF and RW.

In summary, we make the following contributions in this paper.

- To deal with cross-domain item recommendation, we develop CRUS based on a random walk model. CRUS firstly introduces the trust relation among friends into the cross-domain item recommendation, which solves the problem of sparsity and cold start.

- To strengthen the weight of similar friends, we modify the transfer matrix in the random walking process, which can guarantee the validity and precision of the recommendation results.
- Extensive experiments on Yelp data set measure the directing friend-based recommendation model and random walk-based recommendation model for comparison and promising results are presented and analyzed.

The remainder of the paper is structured as follows. Section 2 briefly surveys the related work regarding of item recommendation, cross-domain recommendation, link prediction. We discuss the details of our proposed model in Section 3, which highlights the modification of transfer matrix. In Section 4 we discuss our experimental settings and analyze the results. Finally, Section 5 concludes the paper.

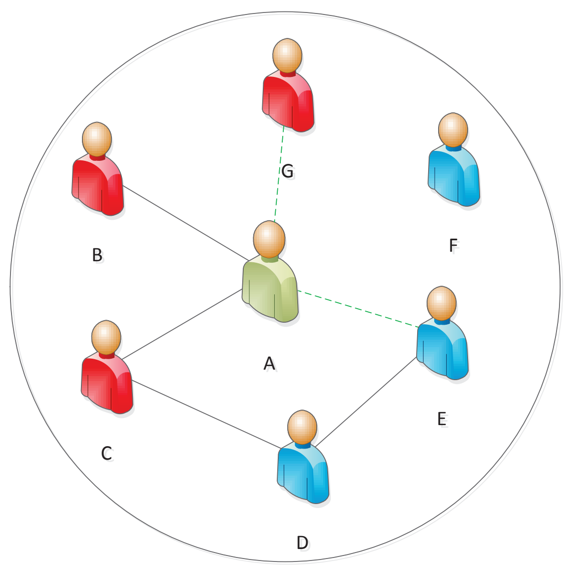

Fig. 2. Example of Similar Friends

2. Related Work

For the item recommendation online, there are often many new users and many users do not have records ever. So the problems of sparsity and cold start have become a big challenge for recommendation. Cross-domain recommendation with the data in other domains has well alleviated the problem of sparsity and cold start. Xu et al. [32] made recommendations on similar users' ratings in the same domain. Yan et al. [33] investigated the cross-platform social relation and behavior information to address the cold start friend recommendation problem. As for the item recommendation, it can be converted into rating prediction problem. For example, Hu et al. [12] present a CDTF model to predict the ratings for better recommendation. Symeonidis et al. [27] also evaluate the performance of proposed method Social-Union by the accuracy of predicting ratings for the products. While, besides rating predictions, Adamopoulos [1] moved their focus to a historic experience to users by avoiding the over-specialization of generated recommendations and providing the users with sets of non-obvious but high quality recommendations.

There are some methods usually used in the cross-domain recommendation, and Collaborative Filtering (CF) method is the basic method. Winoto and Tang [30] reported their efforts on uncovering the association between user preferences on related items across domains. They also tested CF method on their cross-domain data set. Besides, Pham et al. [22] proposed a clustering approach to collaborative filtering recommendation technique and it also outperformed the baseline method. Similarly, Mirbakhsh and Ling [21] proposed a method, which is a clustering-based matrix factorization in single domains into cross domains. Results showed that their method improved the recall to 21%, which was quite significant especially for cold start. Shi et al. [25] proposed a novel tag-induced cross-domain collaborative filtering algorithm that exploited shared tags to link different domains and achieved better performance.

Additionally, with the social network is well researched nowadays, the social-based random walk model is also adopted often in recommending systems. The cross-domain social network is full of complex social relations. Random walk model is usually used to analyze the network structure. Jiang et al. [15] present a novel hybrid random walk model which integrated multiple domains into a star-structured hybrid graph with user graph. Gu et al. [10] investigated the problem of how to mine query intent patterns across a large number of searchable domains. They proposed a novel cross domain random walk algorithm, which was a semi-supervised learning algorithm in a transfer of learning view. Tang et al. [28] analyzed the cross-domain collaboration data and proposed a Cross-domain Topic Learning (CTL) model which alleviated the sparseness issue. Also the collaborator recommendation, Xia et al. [31] present MVCWalker based on social network with three academic factors modifying the random walk.

Recently, 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 [20]. Jamali and Ester [13] proposed model combining the trust-based and collaborative filtering approach for recommendation. Liu et al. [17] proposed a aulticategory item recommending system based on trust network. Their works proved that, taking the trust relation between friends into account can improve the recommendation. Because the trust relation impact us a lot to make decisions in real life. Considering those factors, we introduces the trust relation among friends into cross-domain recommendation and proposed CRUS, a random walk based model.

Table 1. Notations

Symbol	Description
$u, v, \ldots$	Users in the network
$R_{u,i}$	Rating of user u on item i
R_u	Rating vector of user u
PR	Importance vector of each user
PR_u^t	Importance value of user u after iterating t times
$\mathbf{S}$	Transfer matrix
$\mathbf{S}_{u,v}$	Probability of user u transferring to user v
$CosSim(u, v)$	Similarity between user u and v
Q	Initial vector of PR
t	Iteration times
α	Damping Coefficient

3. Design of CRUS

In this section, we describe the details of CRUS. Firstly, we give an overview of CRUS. Then, we introduce the details from three parts. Notations used in CRUS are listed in Table 1.

3.1. Overview of CRUS

In item recommendation systems, there are usually two entities, user and items. There are friend relations or trust relations among users. In this work, we model the network based on these entities and relations. The nodes of the network are users and the edges are those relations. CRUS is inspired by the truth that friends usually have similar interests with them, so when they want to get an item, they are easily to accept the recommendations from their friends. Because other users may also have the similar interest with the target user besides the direct friends. In this work, we assume the interests of user do not change with time, because this is not the key point for this work. So we define the similar users as similar friends of the target user. Considering the trust relation between friends, CRUS is based on the relation of friends to predict the ratings. We use the random walk model to ge-t the similar users, where every user have the same weight in the network. But it is not reasonable or precise considering their different ratings based on interests. So we enhance the weight of similar friends in the random walking process by modifying the transfer matrix. In the following part, we introduce CRUS from three parts: random walk, modifying transfer matrix and rating prediction. Fig. 3 shows the structure of CRUS. First, we model the friend network by random walk with the nodes of users and edges of relations. Then, we get the similarity of users by running random walk, during which we modify the transfer matrix to obtain the similar users. And then we predict the ratings by the most similar friends. Finally, we get the recommendation list.

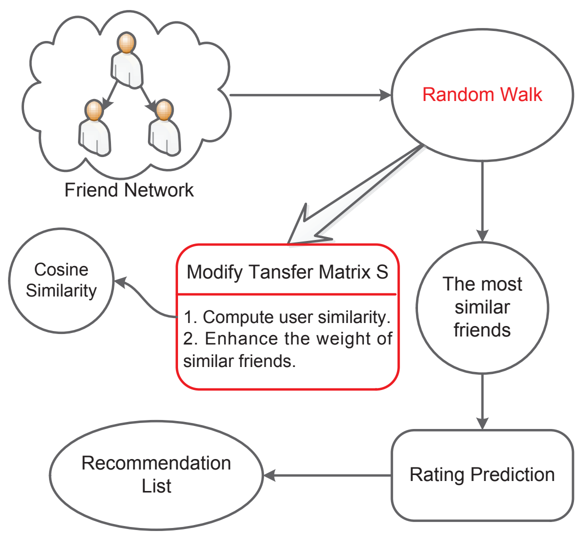

Fig. 3. Structure of CRUS

3.2. Random Walk

We use the ratings of friends to get the rating prediction of target user. How to find out the similar friends with the target user? Here we use the random walk model [13] as shown in Algorithm 3.2, which can compute the importance of each user to the target user. The input of random walk is the network composed of users and relations. Output is the value representing user importance to the target user, which can also show the similarity between users. With respect to each node in the whole graph, the personalized random walk process is defined as Equation 1, which shows the iteration process of random walking.

$$PR^{t+1} = \alpha \mathbf{S} \cdot PR^{t} + (1-\alpha)Q. \tag{1}$$

where PR^t is the rank score vector at step t that shows the importance of each user to the target user. $\mathbf{S}$ is the transfer matrix, which determines the transferring probability from a user to next user. α is the damping coefficient that can determine the transfer probability to the next nodes or the prior nodes. Q is the initial vector, where each node represents $\frac{1}{N}$.

Suppose a single random walker that starts from the node u. The walker iteratively transmits to its neighborhood with the probability $\alpha \mathbf{S}_{u,v}$, which is proportional to their link importance. At each step, it has the probability of $(1-\alpha)\mathbf{S}_{u,v}$ to return to node u.

3.3. Transfer Matrix

Despite direct friends usually have the similar interests with us, not all the time. Maybe they have the same interest in one domain, but not absolutely same in another domain.

Algorithm 1 Pseudo-code of Random Walk

S $\leftarrow$ TransferMatrix()
$PR^0, Q \leftarrow InitVector()$
for $t \leftarrow 1$ to $MaxIteration$ **do**
    $diff \leftarrow 0$
    for $u \leftarrow 1$ to $len(Q)$ **do**
        $PR_u^t = \alpha \sum_{v=1}^{len(Q)} (S_{u,v} \cdot PR_v^{t-1}) + (1-\alpha)Q$
        $diff \leftarrow diff + (PR_u^t - PR_u^{t-1})$
    end for
    if $diff < MinDelta$ **then**
        break
    end if
end for
$FriendsList \leftarrow TopN(PR)$
return $FriendsList$

Similarly, users who are not the direct friends may have the similar interests, those may be our friends of friends and we can reach them through several steps of random walking. All these similar users are defined as similar friends in this paper. Considering friends have great influence on the decision making of the target user, we highlight the weight of friends by modifying the transferring probabilities.

So, first we need to find out the similar friends. Here we compute the similarity between users, then find out the relatively similar friends. We use Cosine Similarity method to compute the user similarity by evaluating their rating similarity. Cosine similarity is defined as Equation 2:

$$CosSim(\overrightarrow{u}, \overrightarrow{v}) = \frac{\overrightarrow{u} \cdot \overrightarrow{v}}{\mid \overrightarrow{u} \mid * \mid \overrightarrow{v} \mid}. \tag{2}$$

where $\overrightarrow{u}$ and $\overrightarrow{v}$ are the rating vectors of user u and user v. By computing the cosine similarity of rating vectors, we can know the similarity between users. In this work, we regard the cosine similarity of users as the weight of the link in random walk. Thus, $\mathbf{S}_{u,v} = CosSim(\overrightarrow{u}, \overrightarrow{v})$

However, some users do not have the ratings in the same domain, so their similarity is 0. While in reality, that does not mean they have nothing similar with each other, maybe in other domains they share similar interests. Thus, after lots of experiments, we set the initial similarity to 0.01 if it is 0. If not, we add the 0.01 to the original similarity. From this way, we can guarantee those who share similar interests in other domains will not be removed.

Table 2. An example of rating prediction

User	a	b	c	d	e
PR	0.4	0.25	0.15	0.12	0.08
Rating	3	1	5	4	0

3.4. Rating Prediction

For item recommendation, the essence is rating prediction [21]. CRUS gets the rating prediction by ratings of friends. The computing method is shown in Equation 3.

$$R_{u,i} = \frac{\sum_{v \in V}(PR_v * R_{v,i})}{\sum_{v \in V} PR_v}. \tag{3}$$

R represents the rating. This computing method is based on CF, which is greatly used in recommendation. Collaborative filtering method usually divides into user-based CF and item-based CF. In this part, we use the user-based CF to compute the rating of target user. Following we give an example of predicting the rating. The PR values and ratings of user a, b, c, d and e are shown in Table 2. Users a, b, c, d and e are the similar friends of user u after random walking. Their PR values and the ratings for the item i are shown as below.

According to the rating prediction method, the rating of user u for item i can be computed as: $R_u = \frac{0.4*3+0.25*1+0.15*5+0.12*4+0.08*0}{0.4+0.25+0.15+0.12+0.08} = 2.68$.

Table 3. 8 domains in Yelp

ID	1	2	3	4	5	6	7	8
Content	active	beautysvc	homeservices	hotelstravel	nightlife	pets	restaurants	shopping

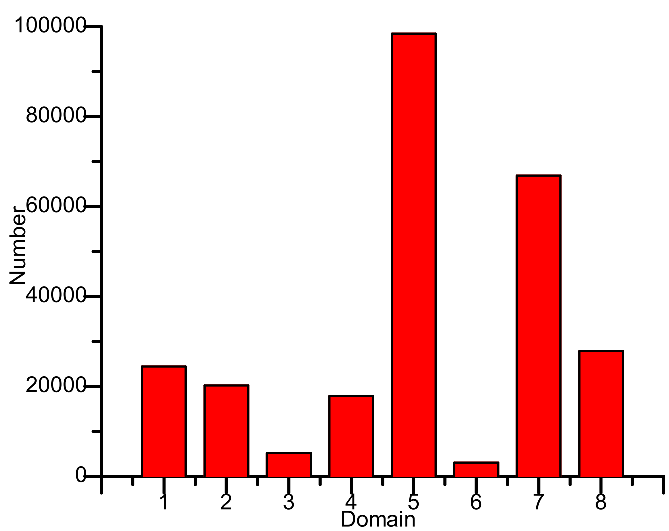

Fig. 4. Number of Ratings

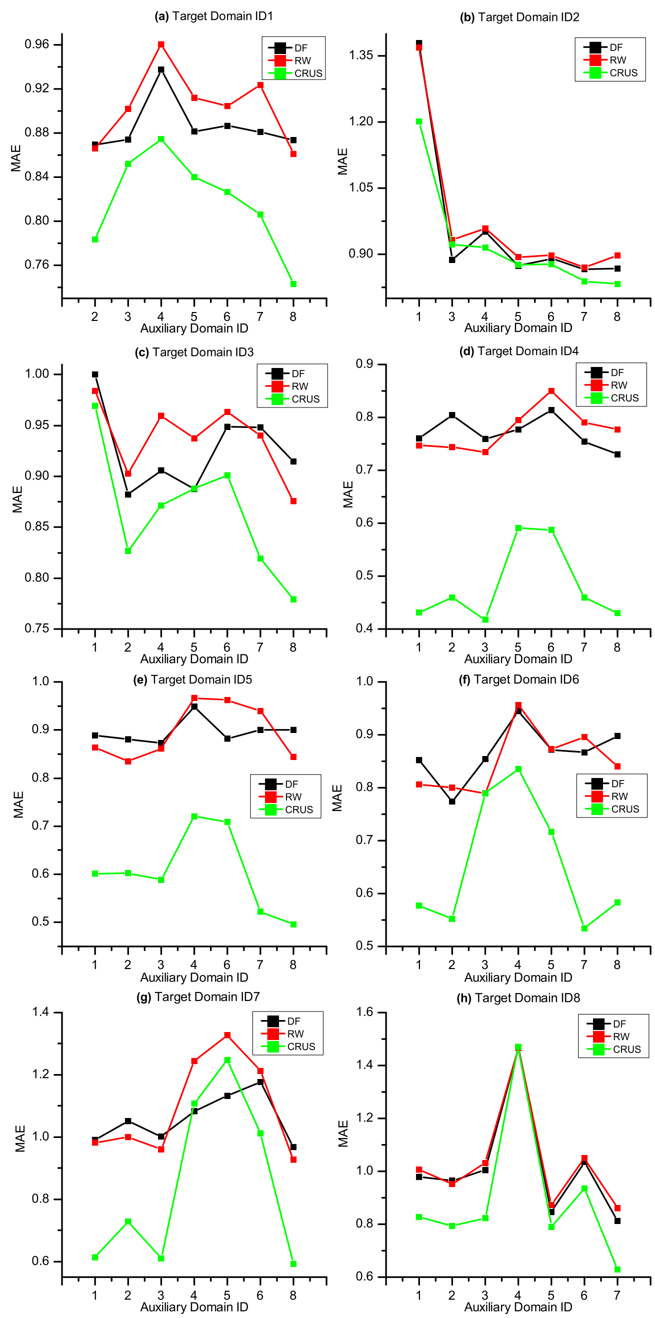

Fig. 5. Performance on MAE of CRUS, DF and RW model

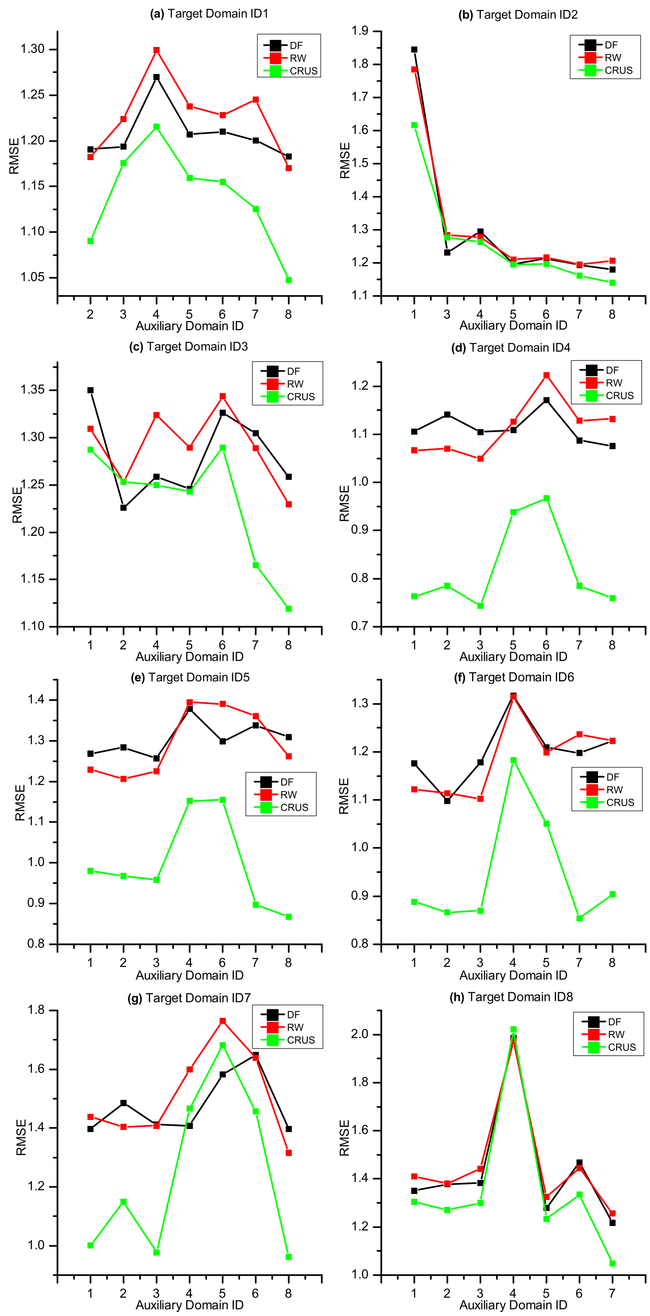

Fig. 6. Performance on RMSE of CRUS, DF and RW model

4. Experiments and Evaluation

We conducted extensive experiments using the data set from Yelp [11]. In this section, we describe the processing of data set, the evaluation metrics we employed and the experimental results, as well as the analyses. To improve the performance of cross-domain recommendation, we introduce friend relation and highlight the relation of similar friends by modifying the transfer matrix in the random walk. Through plenty of experiments on adjusting the parameters, we get the optimal α as 0.85 and iteration times t as 6. Additionally, we carried out experiments on DF and RW models as the comparison methods with CRUS in terms of two error metrics Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). CRUS is based on friend relation and random walk. Similarly, DF [7] is widely used only based on friend relation to give recommendations. RW [31] is the random walk model that is usually used in social-network based recommendations.

All experiments were performed on a 64-bit Linux-based operation system, Ubuntu 12.04 with a 4-duo and 3.2-GHz Intel CPU, 4-G Bytes memory. All the programs were implemented with MATLAB.

4.1. Data Set

We got the Yelp data set [9,23] from SMILES LAB from Xian Jiaotong University. SMILES LAB filtered out the privacy information of users based on the original data set from Yelp Inc. Yelp is a real online social network[1], which provides a homepage for each local commercial entity. Yelp is also a commercial and rating website built in 2004 by Jeremy Stoppelman and Russel Simmons and most of users in Yelp come from New York. Yelp provides users search for restaurants, shopping, nightlife, hotels, auto services, financial services, etc, where users can give their ratings for the entities or products. About 33 million of people visit Yelp every month for its various of products.

In addition, the social network features of Yelp attract many more users. All the users have their own homepage containing some basic information and they can make their own voices or reviews. In particular, Yelp allows users to invite their friends to join Yelp and make new friends already at Yelp. The difference is that the friendship is mutual. When a user a adds another user b as a friend, a will be automatically added as a friend of b.

In this data set, all the private information are removed or hidden by other numbers and each user is distinguished by the id. There are totally 8 domains of records as Table 3. After analyzing the data in Yelp, we get the number of ratings in each domain as shown in Fig. 4 and the friend relation on the website.

4.2. Metrics

We choose two popular error metrics MAE and RMSE [14] to evaluate CRUS, DF and RW. As the performance of CRUS is shown by the precision of rating prediction, so we evaluate the effectiveness of rating prediction. The metric MAE and RMSE are defined as:

$$MAE = \frac{\sum_{u,i \in T} \mid R_{u,i} - \widehat{R}_{u,i} \mid}{\mid T \mid}. \tag{4}$$

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

$$RMSE = \sqrt{\frac{\sum_{u,i \in T}(R_{u,i} - \widehat{R}_{u,i})^2}{\mid T \mid}}. \tag{5}$$

where $R_{u,i}$ means the real rating of user u on item i and $\widehat{R}_{u,i}$ means the predicting rating of user u on item i. T means the user and item set. According to the two metrics, we can see the prediction quality. The more lower of MAE and RMSE, the better performance of recommendation.

4.3. Results and Analysis

After modifying the transfer matrix and implementing the random walk model, we conducted lots of experiments on CRUS, DF and RW. Data set is divided into training set and test set according to different domains respectively. So there are totally 8 experimental results aiming at different domain.

Fig. 5 shows the performance of CRUS, DF and RW model on MAE. In the case of the first experiment, as shown in the a subfigure of Fig. 5, the target is domain 1. We set the domains 2 to 8 as auxiliary domain. CRUS shows a lower MAE value when forecasting the score. It means that, CRUS performs better than DF and RW in this scene. When we set the target domain as others, CRUS can also performs better than DF and RW, especially the d and e experiments. In addition, CRUS shows better at setting auxiliary domain as others. Anyway, on the whole, CRUS outperforms other two comparison methods on MAE.

Similarly, Fig. 6 shows the performance of CRUS, DF and RW model on RMSE. We also conducted 8 experiments to evaluate the performance on RMSE. Conforming to the theoretical, they have the similar tendency with MAE. We can see from Fig. 6, CRUS is lower than DF and RW almost in all the 8 experiments, especially for domain 1, 4, 5, 6. CRUS performs better in most cases. It can further prove that, CRUS can do well at cross-domain item recommendation and it performs better than DF and RW.

5. Conclusion

In this paper, we mainly focused on cross-domain item recommendation based on user similarity. To this end, we proposed a model based on random walk model called CRUS, which introduces the friend and trust relation into cross-domain item recommendation. We modified the transfer matrix in the random walking process to strengthen the friend relation. Finally, extensive experiments on Yelp data set were conducted to measure the direct friend-based recommendation model and random walk-based recommendation model for comparison. The results of these experiments show that, CRUS performs better on MAE and RMSE when comparing the other two methods, which alleviates the problem of cold start and sparsity to some extent. As a future work, more solutions on modifying the transfer matrix will be implemented and evaluated. Besides, considering the interests of users can be changed according to the time, our future work is to measure the impact of the variation of users with the time on recommendation result.

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