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Social Recommendation with Biased Regularization

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Abstract: Although recommendation systems are the most important methods for resolving the ”information overload” problem, majority of them are beset by their inherent flaws. With the recent emergence of online social networks, the increasing social information has offered opportunities to relieve these flaws. In this paper, a new matrix factorization based social recommendation method is proposed, in which social relations and the rating habit are integrated into the objective function via appending additional penalty term and bias term to classic probabilistic matrix factorization model. In order to involve more social information into traditional recommendation system, the proposed method adopt the social similarity rather than interest similarity to measure the closeness degree between users. Experiment shows that our method has got better performances than homologous methods.

Keywords: Social Recommendation, Matrix Factorization, Regularization, Bias Term, Penalty Term

1 Introduction

With the rapid growth of internet, the challenges faced by people have changed from ”information shortage” to ”information overload”, and recommendation system is one of the most crucial techniques for overcoming them. At present, recommendation system has been successfully applied in commercial fields. On account of its broad application prospect and high business value, recommendation system has attracted large amount of researchers from different fields such as machine learning, data mining, information retrieval etc.

Although having been studied and applied widely for a long time, most recommendation systems are persecuted by their inherent flaws: the first is data sparsity problem, [19] shows that most users mark scores only on few items they interested, and the rating density is usually less than 1% in commercial systems, which means that the rating data is so sparse that the system can't capture users' hobbies and interests adequately; and the second is cold-start problem, that's the system can't acquire users' preference and therefore can't provide good recommendatory results when a new user joins an existing system or a newly-built system hasn't collected any rating data; and the third is the traditional system ignores the social relations among users.

In recent years, a large number of online social networks are surging with the wide application of Web 2.0, such as Facebook[1], Sina weibo[2] etc., and are very popular for their instantaneity, interactivity and high efficiency, and the users are increasing rapidly. The social information collected by online social networks offers new opportunities to improve the performance of traditional systems. [15,20]indicates that people in the social network are influenced by each other, and the friends often make similar choices on the same things. There are many cases that social relations have made effects on recommendations in the real life, for example, when planning to buy a new mobile or choose a restaurant, our decisions often are impacted by friends' suggestions or what they have really chosen. Hence rating data could be combined with social relations to improve the performance of traditional systems.

Actually, users' choices are affected not only by social relations but also by the rating habits of users and item, for example, the optimistic user may easily mark

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[2] http://weibo.com

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higher scores while the pessimistic user may do the opposite, and the popular items may easily gain higher scores while the small-crowd items may do the opposite. This paper will comprehensively consider the effect of the social relations and rating habits on traditional systems, and focus on combining these effect into recommendation system so as to make the recommendation procedure in accordance with the realities and improve the performance of traditional system. Based on the observations of recommendation procedure in real life, three assumptions are made as follows:

– Assumption 1: each user and each item has specific characteristic;
– Assumption 2: user's interest is affected by their social relations;
– Assumption 3: more close users' social relations are, more similar their interests are;

The main contribution of this article lies in the following three aspects: firstly, this article proposed a novel recommendation method named as Biased Regularization algorithm(BR algorithm), and this method take social relations and rating habits into count simultaneously; secondly, link prediction, which is used to measure the closeness between users, are applied in our social recommendation system; thirdly, by exploiting two different data from social relations and rating scores, the proposed BR algorithm has promoted the performance of traditional system, and experiments show that the proposed BR algorithm has boosted the accuracy of recommendation than the homologous methods.

This article is organized as below: Section 2 gives related works of social recommendation, problem description is in Section 3, a social recommendation method with biased regularization is proposed in Section 4, experimental results and evaluation are shown in Section 5, and the last Section gives the conclusion and future works.

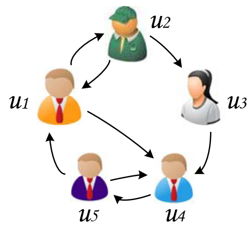
2 Related Works

Most traditional recommendation systems are based on collaborative filtering, and could be categorized into user-based filtering and item-based filtering according to recommendation strategy, also could be categorized into memory-based filtering and model-based filtering. The memory-based collaborative filtering techniques[10] are the most widely used techniques in commercial fields, and their prediction phases are still slow despite they have no training phases; the model-based collaborative filtering build the models in accordance with the recommendation procedure and predict the missing scores according to the trained models. In comparison with memory-based methods, the model-based methods are slow in training phase, but more quick in prediction phase.

Traditional system suppose users' flavors are independent and identical distributed(i.i.d) and haven't taken the influence of the social relations into account, so they make recommendations only according to historic scores (rating matrix). On one hand, traditional system haven't token full consideration of the effects of social relations on users' interests; on the other hand, online social networks have collected huge users' social relations data and provided convenient research conditions to study the recommendation systems with social relations integrated(namely, social recommendation). Therefore more and more researchers begin to study how to promote the performance of traditional system by making good use of the social relations among users. Actually, the emergence of online social network has greatly expedited the studies of social recommendation.

The social recommendation aims to boost the performance of traditional recommendation systems and overcome some of their shortcomings by exploiting social information. In social network, persons are treated as nodes, social relations between persons are treated as edges, and different social relations (for example, friend relations, trust relations, cooperation relations, and so on) can form different social networks. The initial social recommendations are based on the trust relations and therefore named as trust-based system. The trust-based system assumes that people prefer to accept recommendations they trust. The Jennifer's studies [3] have justified the fact that the trust relations can improve the performance of traditional systems dramatically.

Recently, some more social recommendation methods are put forward. The TidaTrust model [3] searches the shortest paths between users, and predicts rating scores according to the length of the shortest paths, trusties' rating scores and the trust degrees. In order to eliminate the effects of the noise data, the TrustWalker method [6]makes use of random walk to predict the rating scores combining the trust relations and item-base collaborative filtering. The SoRec model [13], a matrix factorization-based method, factorizes the rating matrix and social adjacent matrix simultaneously, while it cannot provide reasonable interpretations in real life. The SocialMF model [7] has blended the trust relations in matrix factorization, and assumes that one's preference is entirely affected by trusties, but this assumption doesn't conform to the realities. Thought the STE model [12]considers that one's rating score is affected partly by oneself and partly by his trusties, it has no regard for the rating habits. Therefore, as a booming research orientation, social recommendation hasn't be well studied. This paper will analyze the influence of social relations, rating hatbits of users and items on social recommendation, and aim to build novel high-performance social recommendation systems based on matrix factorization.



(a) Social Network of Users

	u_1	u_2	u_3	u_4	u_5
u_1	0	1	0	1	0
u_2	1	0	1	0	0
u_3	0	0	0	1	0
u_4	0	0	0	0	1
u_5	1	0	0	1	0

(b) Adjacent Matrix A

	i_1	i_2	i_3	i_4
u_1		5		1
u_2	3	?	3	
u_3	4			2
u_4	2	1		
u_5			1	5

(c) Rating Matrix R

	i_1	i_2	i_3	i_4
u_1	3.2	5	4.1	1
u_2	3	2.1	3	0.3
u_3	4	2.8	1.5	2
u_4	2	1	2.7	3.1
u_5	0.8	3.3	1	5

(d) Prediction Matrix $\hat{R}$

Fig. 1: Description of Social Recommendation Problem

3 Problem Description

Recommendation system contains a set of users $\mathbb{U} = \{u_1, u_2, \cdots, u_M\}$, a set of items $\mathbb{I} = \{i_1, i_2, \cdots, i_N\}$, and rating matrix $R = [R_{u,i}]_{M\times N}$ gathering all the rating scores users marked, where M and N denote the number of users and items respectively. $R_{u,i}$, a entry of R, indicates the score that user u has marked on item i, and its value is typically an integer between 1 and 5. If user u hasn't marked item i, the corresponding $R_{u,i}$ is missing-value as shown in Figure 1(c). Since users usually mark scores only on a fraction of all available items, matrix R is very sparse and vast majority of entries in R is missing-value, and it means that a mass of 'holes' rather than rating scores are distributed on R. The social relations can be represented by adjacent matrix $A = [A_{u,v}]_{M\times M}$, and $A_{u,v}$ indicates whether there exists social relation between user u and user v shown as Figure 1(a) and Figure 1(b), and if the relation exists, then $A_{u,v}$ is 1, otherwise 0.

The task of social recommendation is: if user u hasn't marked a score on item i, which means $R_{u,i}$ is missing-value, it needs to predict the value of $R_{u,i}$ (denoted as $\hat{R}_{u,i}$) in terms of the existing rating scores in R and social relations in adjacent matrix A, and it is shown as Figure 1(d).

4 Social Recommendation with Biased Regularization

4.1 Matrix Factorization for Recommendation System

As effective and high efficient methods, matrix factorization based methods factorize the user-item matrix R into user-profile matrix U and item-profile matrix V firstly, and then predicts the entries with missing values in R [16]by using formula $R \approx U^T V$. The vectors in U represent users' preferences, and the vectors in V represent items' characteristics. Latent semantic model [4]consider that users' preference and items' characteristics is determined by only minor factors. Therefore if supposing that D is number of factors and meets the condition $D \ll \min(M,N)$, $U_{M\times D}$ can be used to represent user profile matrix, and the ith row vector of U (denoted as U_i) represents the preference of user i; and similarly $V_{N\times D}$ can be used to represent item profile matrix, and V_j denotes the characteristic of item j.

The problem of matrix factorization can be transferred into an optimization problem, and its objective function is: $\mathscr{L}_2 = \frac{1}{2}\left\|R - U^T V\right\|_F$. U and V can be calculated by searching the local minimum value of $\mathscr{L}_2$, in which $\|\cdot\|_F$ denotes Frobenius Norm. As most entries in R are missing values, the function above can be rewritten as:

$$\arg\min_{U,V} \mathscr{L}_2(R,U,V) = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{i,j}(R_{i,j} - U_i{}^T V_j)^2$$

where I is an indicator matrix, and if $R_{i,j}$ isn't missing value, $I_{i,j}$ is 1, otherwise 0. To avoid over-fitting problem, the regularization items $\frac{\lambda_1}{2}\|U\|_F$ and $\frac{\lambda_2}{2}\|V\|_F$ are added to function above , and it's shown as formula1:

$$\arg\min_{U,V} \mathscr{L}_2(R,U,V) = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{i,j}(R_{i,j} - U_i{}^T V_j)^2 + \frac{\lambda_1}{2}\|U\|_F + \frac{\lambda_2}{2}\|V\|_F \quad (1)$$

where λ_1 and λ_2 are regular coefficients. Ruslan et al [17] have given probabilistic explication of low-rank matrix factorization through probabilistic graph model.

4.2 Integrating Social Relations into Matrix Factorization

In social network, user's preference may be influenced by his friends easily. If profile vector U_u and U_f represent preferences of user u and user f, then their preference difference can be represented as $\left\|U_u - U_f\right\|_F$; If $\mathbb{OF}(u)$ denotes all the friends that user u is familiar with(that is the successive nodes of node u), also $\mathbb{IF}(u)$ denotes all the persons who are familiar with user u, and preference difference of u and all his friends can be represented as $\sum_{f\in\mathbb{OF}(u)} \left\|U_u - U_f\right\|_F$. In accordance with the previous assumptions in this paper, more closer social relations are, more greatly they effect on preference. Suppose that function $S(u,f)$ is used to measure social similarity of user u and f, and the weighted preference difference of user u and all his friends can be represented as $\sum_{f\in\mathbb{OF}(u)} S(u,f)\left\|U_u - U_f\right\|_F$. In order to integrate all social relations into matrix factorization, the gross preference differences of all the users are added into Formula 1 with taking them as penalty term, and it is shown as Formula 2:

$$\begin{aligned}\arg\min_{U,V} \mathscr{L}_2(R,U,V) = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{i,j}(R_{i,j} - U_i^T V_j)^2 \\ + \frac{\beta}{2}\sum_{u=1}^{m}\sum_{f\in\mathbb{OF}(u)} S(u,f)\left\|U_u - U_f\right\|_F \\ + \frac{\lambda_1}{2}\|U\|_F + \frac{\lambda_2}{2}\|V\|_F \end{aligned} \tag{2}$$

in which β is regularization coefficient. Formula 2, named as SR2 in [14], can be resolved by searching for local minimum value through gradient descent method.

4.3 Integrating Rating Habits into Matrix Factorization

Users and Items usually have stable rating habits due to users' personalities and items' characteristics, and users' rating habits are constant regardless of different items, also it is the same to items' rating habits. Here users' rating habits are represented by $BU = [bu_1, bu_2, \ldots, bu_M]$ where bu_i denotes the rating habit of user i, and items' rating habits are represented by $BI = [bi_1, bi_2, \ldots, bi_N]$ where bi_j denotes the rating habit of item j. Inspired by the Integrated Models proposed by Koren et al [5,1], authors believe that rating score $R_{i,j}$ is not only determined by profile U_i and V_j, but also by rating habits bu_i and bi_j, which can be formalized as $R_{i,j} \approx U_i^T V_j + bu_i + bi_j$. Taking BU and BI as bias terms and integrating them into Formula 2, a novel matrix factorization model considering rating habits can be represented as Formula 3:

$$\begin{aligned}&\arg\min_{U,V,BU,BI} \mathscr{L}_2(R,U,V,BU,BI) \\ &= \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{i,j}(R_{i,j} - U_i^T V_j - bu_i - bi_j)^2 \\ &+ \frac{\beta}{2}\sum_{u=1}^{m}\sum_{f\in\mathbb{OF}(u)} S(u,f)\left\|U_u - U_f\right\|_F \\ &+ \frac{\lambda_1}{2}\|U\|_F + \frac{\lambda_2}{2}\|V\|_F + \frac{\lambda_3}{2}\|BU\|_F + \frac{\lambda_4}{2}\|BI\|_F \end{aligned} \tag{3}$$

which can be resolved through gradient descent as Formula 2. So partial derivative U, BU, BI and V of $\mathscr{L}_2$ can be deduced as below:

$$\begin{aligned}\frac{\partial \mathscr{L}_2}{\partial U_i} &= \sum_{j\in\{j|R_{i,j}>0\}} (U_i^T V_j + bu_i + bi_j - R_{i,j})V_j + \lambda_1 U_i \\ &+ \beta \sum_{f_1\in\mathbb{OF}(i)} S(i,f_1)(U_i - U_{f_1}) \\ &+ \beta \sum_{f_2\in\mathbb{IF}(i)} S(i,f_2)(U_i - U_{f_2}), \end{aligned} \tag{4}$$

$$\frac{\partial \mathscr{L}_2}{\partial bu_i} = \sum_{i\in\{i|R_{i,j}>0\}} (U_i^T V_j + bu_i + bi_j - R_{i,j}) + \lambda_3 bu_i \tag{5}$$

$$\frac{\partial \mathscr{L}_2}{\partial bi_j} = \sum_{i\in\{i|R_{i,j}>0\}} (U_i^T V_j + bu_i + bi_j - R_{i,j}) + \lambda_4 bi_j \tag{6}$$

$$\frac{\partial \mathscr{L}_2}{\partial V_j} = \sum_{i\in\{i|R_{i,j}>0\}} (U_i^T V_j + bu_i + bi_j - R_{i,j})U_i + \lambda_2 V_j. \tag{7}$$

4.4 Description of Biased Regularization Algorithm(BR algorithm)

According to the above discussions, a novel social recommendation algorithm, which is named as BR algorithm, is proposed here. The BR algorithm has involved rating scores, social relations and rating habits simultaneously. The procedure of BR algorithm contains three stages in sequence:(i)initialization stage, (ii)iteratively solving problem stage and (iii)prediction stage. The whole procedure is described as Algorithm 1:

From Algorithm 1, U, V, BU and BI are initialized by standard normal distribution, and then these variables are updated repeatedly by gradient descent, and finally the prediction matrix $\hat{R}$ is calculated. Social relations are injected into Algorithm 1 via Formula 4, 5, 6, 7 where similarity function $S(\cdot,\cdot)$ is used to measure the social similarity between users. Two extra arguments, learning rate *rate* and maximum time of iteration *maxIter*, are introduced in the algorithm to control the speed and time of training respectively.

4.5 User Similarity

User similarity is an important factor effecting the performance of recommendation system, and is traditionally measured on rating matrix R. The similarity measured on R, which is used to collect the users' interests, is named as interest similarity in this paper, such

Algorithm 1: Description of BR Algorithm

Input : rating matrix $R_{M\times N}$, social regularization parmater β ,learning rate *rate* and maximum number of iterator *maxIter*
Output: predicting rating matrix $\hat{R}_{M\times N}$

begin
  initialization
  $U_{M\times D} \leftarrow \mathscr{N}ormal(0,1)$;
  $V_{N\times D} \leftarrow \mathscr{N}ormal(0,1)$;
  $BU_{M\times 1} \leftarrow \mathscr{N}ormal(0,1)$;
  $BI_{N\times 1} \leftarrow \mathscr{N}ormal(0,1)$;
  solving U,BU,BI and V by gradient descent
  for $epoch = 1$ **to** *maxIter* **do**
    foreach (i,j) **in** $\{(i,j)|R_{i,j} > 0\}$ **do**
      calculate $\frac{\partial \mathscr{L}_2}{\partial U_i}$ by Formula 4;
      calculate $\frac{\partial \mathscr{L}_2}{\partial bu_i}$ by Formula 5;
      calculate $\frac{\partial \mathscr{L}_2}{\partial bu_j}$ by Formula 6;
      calculate $\frac{\partial \mathscr{L}_2}{\partial V_j}$ by Formula 7;
      $U_i \leftarrow U_i - rate * \frac{\partial \mathscr{L}_2}{\partial U_i}$;
      $bu_i \leftarrow bu_i - rate * \frac{\partial \mathscr{L}_2}{\partial bu_i}$;
      $bi_j \leftarrow bi_j - rate * \frac{\partial \mathscr{L}_2}{\partial bi_j}$;
      $V_j \leftarrow V_j - rate * \frac{\partial \mathscr{L}_2}{\partial V_j}$;
  prediction
  $\hat{R} = UV^T + BU \cdot 1^T + BI \cdot 1^T$

as Vector Space Similarity(VSS)[18], Pearson Correlation Coefficient(PCC)[2], etc., and the similarity measured on A, which is used to collect the users' social relations, is correspondingly named as social similarity. From Formula 3, it is seen that indicator matrix I can be regarded as the implicit feedback of user's ratings. In order to balance between rating data and social relations data, it is need to inject more social relations into the algorithm, and similarity function $S(\cdot,\cdot)$ can serve as the "entrance" just right. As shown in subsection 4.2 and 4.3, user similarity can be blended in the BR algorithm via similarity function $S(\cdot,\cdot)$.

Problem of measuring social similarity is essentially the problem of link prediction [11], which is the problem of predicting the presence or absence of edges between nodes of a graph, and has important practical applications, such as predicting interactions between pairs of proteins and recommending friends in social networks. In order to compare the effects on BR algorithm between social similarity and interest similarity, we introduces two link prediction algorithms, Katz algorithm [9], SimRank algorithm [8], as the metric of social similarity to evaluate the proposed algorithm.

Katz similarity is based on the ensemble of all paths, which directly sums over the collection of paths and is exponentially damped by length to give the shorter paths more weights, and Katz similarity function $S_{Katz}(\cdot,\cdot)$ can be defined as:

$$S_{Katz}(u,v) = \left[(I-\varepsilon A)^{-1} - I\right]_{u,v}$$

where, u,v is user's identity, matrix A represents social relations, I is identity matrix, and ε is a free parameter slightly less than the maximum eigenvalue of A.

SimRank similarity is defined in a self-consistent way, according to the assumption that two nodes are similar if they are connected to similar nodes, and SimRank similarity function $S_{SimRank}(\cdot,\cdot)$ can be defined as:

$$S_{SimRank}(u,v) = C \cdot \frac{\sum_{w\in\Gamma(u)} \sum_{w'\in\Gamma(v)} S_{SimRank}(w,w')}{k_u \cdot k_v}$$

where $S_{SimRank}(x,x) = 1, C \in [0,1]$ is the decay factor, $\Gamma(x)$ is the neighbors of x in social network and k_x is the degree of x.

5 Experimental Results and Evaluation

5.1 Datasets

Experiments in this paper are based on real Flixster dataset[3] and Douban dataset[4]. Flixster[5]is a social network site about movies which let users' share their marked scores on movies, discuss new ones, and recognize persons who have similar interests. The Flixster dataset is collected by Jamali, which contains 1 million users, 8.2 millions rates, 4.9 million movies and 26.7 million bidirectional friend relations. The rating scores are discrete value arrange in $[0.5,5]$, and can be divided into 10 levels.

Douban[6] is one of greatest online social networks in China, which provides marking scores, comments and recommendation services on movies, music and books and so forth. Users can create friendships just like Flixster with each other through such ways like Email, and they can mark scores on items with the values range from 1 to 5. Douban dataset is collected by Chinese University of Hong Kong by crawlers, which contains 129 thousand users, 59 thousand movies, 1.68 million rates and 1.69 million bidirectional friend relations. The statistic data is shown in Table 1 and 2:

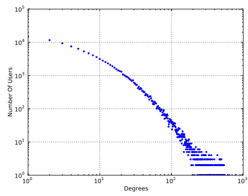
5.2 Evaluation method

Although the performance of recommendation system can be valued in many ways, this paper take the accuracy as the criterion, and Mean Absolute Error (*MAE*) and Root Mean Square Error (*RMSE*) are used to evaluate the accuracy

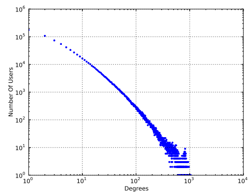
[3] http://www.cs.ubc.ca/~jamalim/datasets/
[4] https://www.cse.cuhk.edu.hk/irwin.king/pb/data/home
[5] http://www.flixster.com
[6] http://www.douban.com.cn

Table 1: Statistics of Flixster and Douban datasets

Statistics	Flixster	Douban
Users	1M	129.5K
Social Relations	26.7M	1.69M
Ratings	8.2M	1.68M
Items	49K	58.5K



(a) Degrees on Douban



(b) Degrees on Flixster

Fig. 2: Degree Distribution of Datasets

of the prediction. Rating scores R is divided into training set $R_{Learning}$ and $R_{testing}$ according to a certain proportion, $R_{Learning}$ is used to train and predict and $R_{testing}$ is used to performance evaluation. Then MAE can be defined as

$$MAE = \frac{1}{|R_{testing}|} \sum_{u,i} |R_{u,i} - \hat{R}_{u,i}|$$

, here $R_{u,i}$ represents historic rating scores of user u on item i, $\hat{R}_{u,i}$ presents predictive scores of user u on item i, $|R_{testing}|$ represents the number of testing rating scores. $RMSE$ can be defined as

$$RMSE = \sqrt{\frac{1}{|R_{testing}|} \sum_{u,i} (R_{u,i} - \hat{R}_{u,i})^2}$$

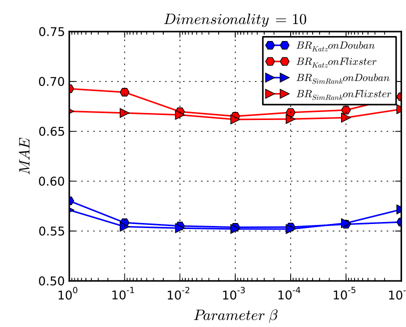
It can be seen from above definitions that the lowerMAE and $RMSE$ are, higher the precision is, also better the performance is.

5.3 Results and Analysis

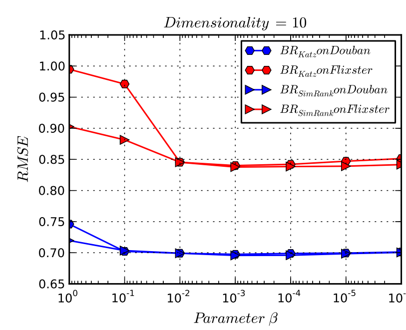
In order to evaluate BR algorithm, authors compare the proposed method with other three homologous methods on two experimental datasets:

–Collaborative Filtering (CF)[10]: most popular memory-based method at present;
–Probability Matrix Factorization (PMF)[17]: canonical user-item matrix factorization method with no considering social relations in users;
–Social Regularization method (SR2)[14]: it combines social relations and interest similarity, such as VSS similarity and PCC similarity, into matrix factorization, but doesn't consider the rating habits;

This paper designed experiment A and B, with A used to compare the performances of BR algorithm and other methods, and B used to research the effect of argument β to BR algorithm. Experiment A is divided into two groups, the first one takes 90% and 80% of Flixster dataset as training set, and the rest are used as testing set separately; the second one takes 80% and 60% of Douban dataset as training set, and the rest are used as testing set separately, and then values of MAE and $MRSE$ in each method are computed. In order to get stable results, each group of experiments will be repeated five times and the average of five results is used as final one. Owing to Flixster dataset is sparser than Douban dataset, training sets of Flixster dataset account for higher proportion. In experiments, regularization arguments λ_1, λ_2, λ_3, λ_4 and β are valued as 10^{-3}, dimensionality D uses experimental value 10. Due to collaborative filtering is not the method based on matrix factorization, the above-mentioned argument are not used. Experiments have justified that social similarities, Katz similarity and SimRank similarity, bring out better performance than interest similarity, also SimRank similarity outperform Katz similarity. Comparison of each experiment is listed as Table 2.



(a) Impact of β on MAE



(b) Impact of β on RMSE

Fig. 3: Impacts of parameter β on BR algorithm

In experiment A, λ_1, λ_2, λ_3 and λ_4 are trival regularization coefficients and their values are set as

Table 2: Performance comparation of different methods($Dimensionality = 10$)

Dataset	Training	Metric	CF	PMF	SR2_VSS	SR2_PCC	BR_Katz	BR_SimRank
Flixster	90%	MAE	0.7130	0.6951	0.6758	0.6756	**0.6651**	**0.6619**
		RMSE	0.9142	0.8782	0.8529	0.8517	**0.8401**	**0.8377**
	80%	MAE	0.7166	0.6980	0.6769	0.6762	**0.6682**	**0.6660**
		RMSE	0.9269	0.8822	0.8607	0.8574	**0.8427**	**0.8408**
Douban	80%	MAE	0.5767	0.5693	0.5548	0.5543	**0.5538**	**0.5521**
		RMSE	0.7235	0.7200	0.6992	0.6988	**0.6975**	**0.6957**
	60%	MAE	0.5783	0.5737	0.5598	0.5593	**0.5563**	**0.5549**
		RMSE	0.7360	0.7290	0.7046	0.7042	**0.7024**	**0.7011**

empirical values in [14] , while β is important and used to control what degree the social relations effect on recommendation system. In experiment B, β is adjusted in a large range to observe the trends of MAE and $MRSE$, other arguments are same as those in experiment A. The results of Experiment B are shown in Figure 3(a) and 3(b). Figure 3(a) illustrates the effect of argument β on MAE, if β is less than 10^{-4} or more than 10^{-3}, MAE will increase (performance of system will decrease) regardless of Katz similarity or SimRank similarity; in a similar way, it can be seen from Figure 3(b) that if β is less than 10^{-4} or more than 10^{-2}, $MRSE$ will increase. Therefore it's proper that β is set to 10^{-3}. And it also shows that considering the influence of social relations on recommendation procedure 'temperately' will improve performance of traditional recommendation system further.

6 Disscusioin

In this paper, we take more care of injecting social relations into recommendation system and comparing the difference between interest similarity and social similarity, so one of our future works is to introduce more efficient link prediction methods to tune the performance of our method. We might as well consider to add items-side "social relations" or the corresponding regularization term to Formula 3, so that the method can involve both users-side and items-side social relations and balance them by coefficient of regularization. A simple and practical method to construct the items-side social relations is K Nearest Neighbor with item similarity being measured by Vector Space Similarity [18], Pearson Correlation Coefficient[2], etc.,

7 Conclusion

In this article a novel matrix factorization based social recommendation method is put forward, and this method adopts social similarity rather than interest similarity to measures the closeness between users. Further more, users' similarities are measured by link prediction methods, and eventually social similarities of users and rating habits are integrated into the low-rank matrix factorization of rating matrix. Also this method constructs the objective function of matrix factorization via regularization technology, and takes preference difference of users as penalty term and user's rating habit as bias term. The objective function is resolved by the gradient descent method, and the solutions, namely low-level profile matrixes and the habit vectors, are then used to make rating prediction. Experiments have shown that in large-scale sparse rating data circumstance, the proposed BR algorithm has better performance than other homogenous methods.

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