

Social Contextual Recommendation

Meng Jiang^{†§}, Peng Cui^{†§}, Rui Liu[§], Qiang Yang[¶], Fei Wang[‡]
Wenwu Zhu^{†§}, Shiqiang Yang^{†§}

[†]Beijing Key Laboratory of Networked Multimedia

[§]Department of Computer Science and Technology, Tsinghua University, Beijing, China

[‡]Healthcare Transformation Group, IBM T J Watson Research Center, USA

[¶]Department of Computer Science and Engineering, Hong Kong University of Science and Technology
jm06@mails.tsinghua.edu.cn, cuip@tsinghua.edu.cn, lr09@mails.tsinghua.edu.cn

feiwang03@gmail.com, qyang@cse.ust.hk, wwzhu@tsinghua.edu.cn, yangshq@tsinghua.edu.cn

ABSTRACT

Exponential growth of information generated by online social networks demands effective recommender systems to give useful results. Traditional techniques become unqualified because they ignore social relation data; existing social recommendation approaches consider social network structure, but social context has not been fully considered. It is significant and challenging to fuse social contextual factors which are derived from users' motivation of social behaviors into social recommendation. In this paper, we investigate social recommendation on the basis of psychology and sociology studies, which exhibit two important factors: individual preference and interpersonal influence. We first present the particular importance of these two factors in online item adoption and recommendation. Then we propose a novel probabilistic matrix factorization method to fuse them in latent spaces. We conduct experiments on both Facebook style bidirectional and Twitter style unidirectional social network datasets in China. The empirical result and analysis on these two large datasets demonstrate that our method significantly outperform the existing approaches.

Categories and Subject Descriptors

H.3.3 [Information Search and Retrieval]: Information Filtering; J.4 [Computer Applications]: Social and Behavioral Sciences

General Terms

Algorithms, Experimentation

Keywords

Social Recommendation, Individual Preference, Interpersonal Influence, Matrix Factorization

1. INTRODUCTION

Users on social networks generate large volume of information and urge recommender systems to provide useful results. Traditional techniques typically based on collaborative filtering become unqualified in solving the social recommendation problem because they ignore social relation or interaction data. Recently, Ma et al. [20, 21] propose a framework of social recommender systems that utilize the social relation data, from which friendships and trust relationships are exploited to regularize the latent user space, but social contextual information has not been fully considered. It is significant and challenging to discover social contextual factors from contextual information and fuse them into social recommendation.

Figure 1 shows the entire social contextual information which can be derived from links on social networks. Users intend to judge received items from its content and sender. For example in Twitter, when a user receives a tweet that is posted by one of his friends (the sender), he usually reads its content to see whether the item is interesting. We can get this knowledge from item content and user-item interaction information. He also cares about who the sender is and whether the sender is a close friend or authoritative. If more than one of friends send him the same tweet, he may read it more attentively. This knowledge can be learnt from social relation and user-user interaction information. Both of these aspects are important for the user to decide whether to adopt (e.g. retweet, comment) the item. The above can be summarized as two contextual factors: (1) individual preference and (2) interpersonal influence.

Besides the experiential assumptions, psychology and sociology studies have proved that individual preference and interpersonal influence affect users' decisions on information adoption. In Bond's work[5], it is indicated that individuals are to some extent influenced by others' behaviors, rather than making decisions independently (i.e. purely preference driven). In [25], web-based experiments are designed for music adoption prediction in an artificial music market. This work demonstrates that the introduction of interpersonal influence into the preference driven decision process (as is the case in real social networks) makes user behaviors more complex and thus increases the unpredictability of the item adoption. Therefore, only when individual preference and interpersonal influence are properly incorporated into recommendation, the unpredictability can be reduced and the recommendation performance can be improved accordingly.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. To copy otherwise, to republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee.

CIKM'12, October 29–November 2, 2012, Maui, HI, USA.
Copyright 2012 ACM 978-1-4503-1156-4/12/10 ...\$15.00.

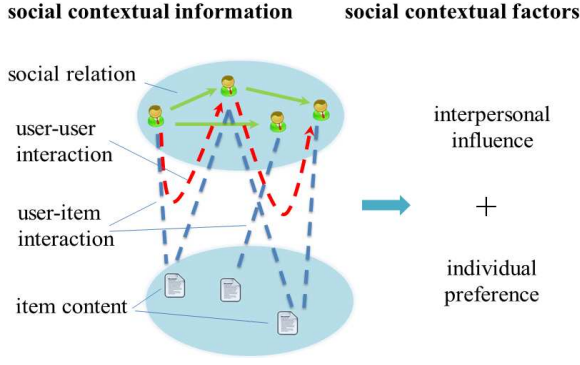


Figure 1: From Social Contextual Information to Social Contextual Factors

To address this problem, we propose a social contextual recommendation framework (as shown in Figure 2) based on a probabilistic matrix factorization method to incorporate individual preference and interpersonal influence to improve the accuracy of social recommendation. More specifically, we factorize the user-item interaction matrix into two intermediated latent matrices: user-item influence matrix and user-item preference matrix, which are generated from three objective latent matrices: user latent feature matrix, item latent feature matrix, and user-user influence matrix. Moreover, as we can partially observe individual preference and interpersonal influence based on historical user-item and user-user interaction data, we further utilize the observed contextual factors to compute the three objective latent matrices.

We’ve conducted experiments on two real social network datasets. One is collected from Renren (www.renren.com), a Facebook style website in China; and the other is collected from Tencent Weibo (t.qq.com), a Twitter style website in China. The two datasets represent two typical social network datasets, one for bidirectional social relations, and the other for unidirectional social relations. We show that social contextual factors can greatly boost the performance of recommender systems on social network data, and our method greatly outperforms the previous algorithms by a large margin. We attribute this result to the incorporation of complete social contextual factors from both individual and interpersonal sides, and experiments verify this conclusion.

This paper is organized as follows. Related work is introduced in section 2. We introduce the effectiveness of two contextual factors with studies on social datasets in section 3. Our social contextual model is formulated in section 4 and experimental results are reported in section 5. Conclusion comes in section 6.

2. RELATED WORKS

In this section, we review several major approaches to recommendation methods. Collaborative filtering and content-based filtering have been widely used to help users find out the most valuable information. With the emerge of social networks, researchers design trust-based [22, 23, 11] and influence-based [16, 17, 10, 7] methods to take use of the power coming from user relationships for recommendation. Matrix factorization methods have been proposed for social

recommendation due to their efficiency to dealing with large datasets. Although there are some mixture models of these methods, it is valuable to understand social recommendation from users’ motivation of item adoption.

Collaborative filtering methods have broad applications, which are divided into two categories, i.e. memory-based and model-based. In the memory based methods, item-based approaches [26, 14] calculate the similarity between all users based on their ratings of items. Si et al. [27] combine collaborative filtering and content-based filtering [1] which selects items based on the correlation between the contents of items and preferences of users. The model-based methods learn a model based on patterns recognized in the ratings of users using Bayesian networks and other clustering techniques [6, 8, 19]. Collaborative filtering only requires the information about user interactions, but it is not able to make full use of the graph-based social relations and rich social knowledge including user profiles and detailed item descriptions.

Recently, several matrix factorization methods [18, 13, 14] have been proposed for collaborative filtering. The matrix approximations all focus on representing the user-item rating matrix with low-dimensional latent vectors [24, 15, 12]. Recognizing that influence is a subtle force that governs the dynamics of social networks [16, 17], influence-based recommendation [10] involves interpersonal influence brought by senders and receivers into social recommendation cases. Trust-based approaches [22, 23, 11] exploit the trust network among users and make recommendations based on the ratings of users who are directly or indirectly trusted. SoRec [20] is proposed as a probabilistic factor analysis framework which fuses the users’ tastes and their trusted friends’ favors together. Yang et al. [30] propose that information contained in user-service interactions can help predict friendship propagations and vice versa. They use data from both user-item interactions and user-user relations. Aiming at improving recommender systems by incorporating users’ social network information in both friend network and trust network, Ma et al. [21] propose a matrix factorization framework with social regularization. But this work only constrains user feature vectors from interpersonal side but ignores users’ individual side, which makes the framework lack of complete contextual information to further improve the recommendation accuracy. However, it is still an open issue about what factors motivate user adoption on recommended items and how can they be effectively integrated to further improve the accuracy of social recommendation.

From psychological and sociological views, Bandura [2] gives a social cognitive theory of mass communication and argues that communication systems operate through two pathways. In the direct pathway, they promote changes by informing, enabling, motivating, and guiding participants to get what they prefer. In the socially mediated pathway, media influences participants to social networks and communities that provide natural incentives and personalized guidance. More previously, Benjamin [3] shows the similar opinion that factors such as cognition, feeling, taste, interest and interpersonal relationship develop the structure of social behaviors and interactions. On the social web, these two factors exactly represent individual preference and interpersonal influence, which motivate us to propose a social contextual recommendation framework to incorporate them by analyzing both user motivation and application mecha-

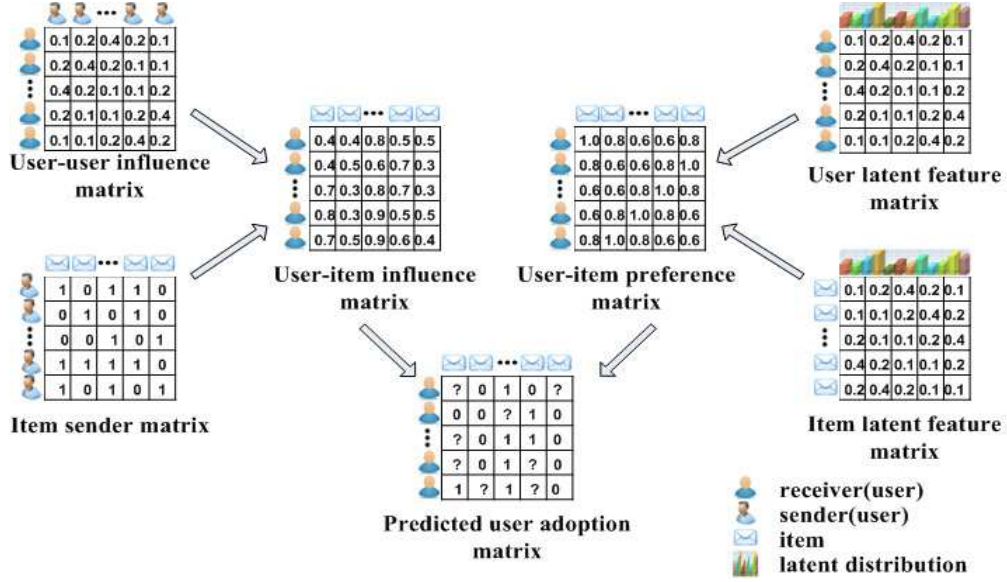


Figure 2: An illustrative on social contextual recommendation framework. Receiver is the user who receives the item (e.g., post, retweet, etc.) and sender is the receiver’s friend or followed user who generated the item.

nism to recommender systems for social networks. In our paper, we incorporate both individual preference and interpersonal influence in a principled manner.

3. SOCIAL CONTEXTUAL FACTORS

In this section, we will demonstrate the existence and significance of social contextual factors (including individual preference and interpersonal influence) for social recommendation on real large datasets.

Given an item, the behavior of user adoption depends on individual preference to understand whether the user likes it or not, and interpersonal influence to tell whether the user has tight relationships with the item senders (e.g. the followed users who generate or retweet the tweet in Twitter) or not. Based on historical data, we apply LDA [4] on the web post (e.g. tweet) content and extract topic-level distributions of items. From user behavior history, we summarize how much user u likes item a with a naïve preference measurement as

$$P_u(a) = T_a \cdot \left(\frac{1}{|A(u, a)|} \sum_{a' \in A(u, a)} T_{a'} \right) \quad (1)$$

where $A(u, a)$ is the set of items adopted by user u excluding a , and T_a is the topic distribution of item a .

To describe interpersonal influence from user-user interactions on social web, we calculate the percentage of recommended items adopted by u from the item a :

$$I_u(a) = \frac{1}{|V(u, a)|} \sum_{v \in V(u, a)} \frac{|\mathcal{S}(u, v) \cap \mathcal{A}(u)|}{|\mathcal{S}(u, v)|} \quad (2)$$

where $V(u, a)$ is the set of senders who send item a to user u , $\mathcal{S}(u, v)$ is the set of items sent from v to u , and $\mathcal{A}(u)$ is the set of items that u adopts.

We classify the items into adopted and refused ones according to user behaviors, and plot the pairs (u, a) as points

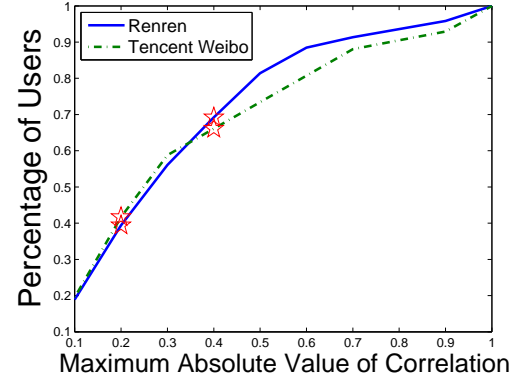


Figure 4: Percentage of Users vs. Correlation Between Preference and Influence

w.r.t. individual preference $P_u(a)$ and interpersonal influence $I_u(a)$ in Figure 3, which shows that users intend to adopt items with better preference scores and from higher influential friends or followers in both Facebook and Twitter style networks.

In order to demonstrate that individual preference and interpersonal influence are not only effective but also complementary social contextual factors, we calculate their correlations in social recommendation cases. We use P and I for each user to denote preference and influence of his adopted items. The Pearson correlation is defined as

$$\rho_{P,I} = \frac{\text{cov}(P, I)}{\sigma_P \sigma_I} = \frac{E[(P - \mu_P)(I - \mu_I)]}{\sigma_P \sigma_I} \quad (3)$$

The correlation is 1 or -1 in the case of perfect positive or negative linear relationship, and zero if preference and influence are uncorrelated. In Figure 4, the absolute correlation values of more than 40% users are less than 0.2 and the

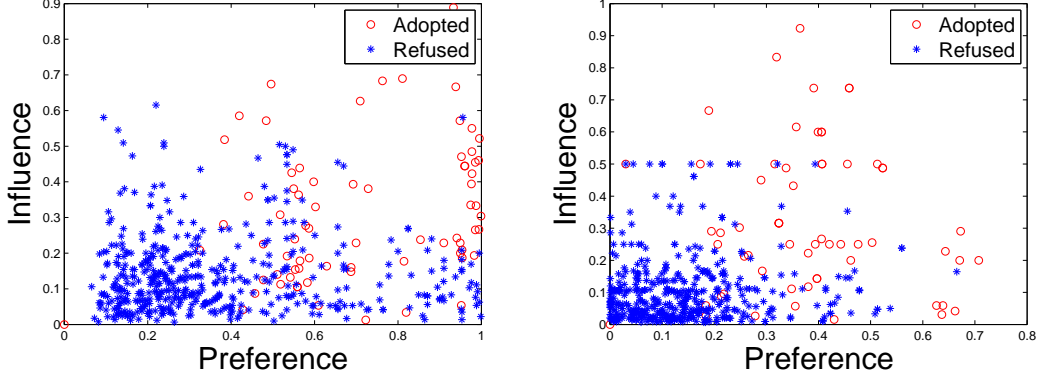


Figure 3: Comparison of Individual Preference and Interpersonal Influence on Adopted and Refused Items: (a) Renren Dataset (b) Tencent Weibo Dataset

values of around 70% are less than 0.4. Thus we conclude that individual preference and interpersonal influence can be applied as two complementary social contextual factors in recommendation.

4. SOCIAL CONTEXTUAL MODEL

In this section, we will introduce details of our social contextual recommendation model. First, we formally define the problem of social recommendation. Suppose that we have M users with the i -th user denoted as u_i , and N items with the j -th item denoted as p_j .

We denote the information adoption matrix as $\mathbf{R} \in \{0, 1\}^{M \times N}$, with its (i, j) -th entry

$$R_{ij} = \begin{cases} 1 & \text{if } u_i \text{ adopted } p_j \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

Then the social recommendation problem is converted to predicting the unobserved entries in the information adoption matrix \mathbf{R} based on the observed entries and other factors.

In our model, we suppose that whether a user adopts an item on social networks is determined by three aspects: (1) what's the item (e.g. descriptive contents)? (2) what items does the user like? and (3) who are the senders?

Let $\mathbf{U} \in \mathbb{R}^{k \times M}$ be the latent user feature matrix, $\mathbf{V} \in \mathbb{R}^{k \times N}$ be the latent item feature matrix. $\mathbf{S} \in \mathbb{R}^{M \times M}$ is the interpersonal influence matrix, with each entry S_{ij} representing the degree of influence user u_i has on user u_j . It should be noted that $S_{ij} > 0$ if and only if u_i is the friend of u_j in social network services such as Facebook and Renren, or is followed by u_j in microbloggings such as Twitter and Tencent Weibo. $\mathbf{G} \in \mathbb{R}^{N \times M}$ is the item sender matrix, with entry $G_{ij} = 1$ meaning that u_j sends the item p_i and vice versa. With these denotations and the assumption that users can only receive items from their friends as social networks usually do ($G_{ii} = 0$), the social recommendation problem is to find out $\mathbf{U}, \mathbf{V}, \mathbf{S}$ so that $((\mathbf{S}\mathbf{G}^\top) \odot (\mathbf{U}^\top \mathbf{V}))$ can well approximate the observed entries in \mathbf{R} without overfitting, where \odot is the Hadamard Product.

In our case, we know the contents of items, user behaviors over the items, and the interactions between users. From these historical data, we can derive the item content representation, individual preference, and interpersonal influence.

We compute the user-user preference similarity matrix $\mathbf{W} \in \mathbb{R}^{M \times M}$, item-item content similarity matrix $\mathbf{C} \in \mathbb{R}^{N \times N}$, and user-user interaction matrix $\mathbf{F} \in \mathbb{R}^{M \times M}$ as

$$W_{i,j} = \frac{\sum_{a \in \mathcal{A}(u_i)} P_{u_i}(a)}{|\mathcal{A}(u_i)|} \cdot \frac{\sum_{a' \in \mathcal{A}(u_j)} P_{u_j}(a')}{|\mathcal{A}(u_j)|} \quad (5)$$

$$C_{i,j} = T_{a_i} \cdot T_{a_j} \quad (6)$$

$$F_{i,j} = |\mathcal{S}(u_i, u_j) \cap \mathcal{A}(u_i)| \quad (7)$$

Though the accuracy of similarity matrices \mathbf{W} and \mathbf{C} depends on LDA performing on previous data, it is fair towards competing methods in experiments to share these matrices.

With the hypothesis that the similarities in observed spaces are consistent with the latent spaces, we regularize the three latent spaces by observed matrices (social contextual factors) in that: (1) the users that are similar in hidden user space have similar preferences (derived from preference similarity matrix); (2) the items that are similar in hidden item space have similar descriptive contents (derived from content similarity matrix); (3) high interpersonal influence in the hidden influence space generates frequent interpersonal interactions; (4) the product of user hidden space and item hidden space corresponds to the users' individual preference on the items; (5) the product of interpersonal influence and individual preference is proportional to the probability of item adoptions.

As the model performance is evaluated by root mean square error (RMSE) on the test set, we adopt a probabilistic linear model with Gaussian observation noise as in [24]. Here we define the conditional distribution over the observed entries in \mathbf{R} as:

$$P(\mathbf{R}|\mathbf{S}, \mathbf{U}, \mathbf{V}, \sigma_R^2) = \prod_{i=1}^M \prod_{j=1}^N \mathcal{N}(\mathbf{R}_{ij} | \mathbf{S}_i \mathbf{G}_j^\top \odot \mathbf{U}_i^\top \mathbf{V}_j, \sigma_R^2) \quad (8)$$

By incorporating the social contextual factors, we define

the posterior distribution as

$$\begin{aligned}
& P(\mathbf{S}, \mathbf{U}, \mathbf{V} | \mathbf{R}, \mathbf{G}, \mathbf{W}, \mathbf{C}, \mathbf{F}, \Omega) \\
&= \frac{P(\mathbf{R}, \mathbf{W}, \mathbf{C}, \mathbf{F}, \mathbf{G} | \mathbf{S}, \mathbf{U}, \mathbf{V}, \Omega) P(\mathbf{S}, \mathbf{U}, \mathbf{V} | \Omega)}{P(\mathbf{R}, \mathbf{G}, \mathbf{W}, \mathbf{C}, \mathbf{F}, \Omega)} \\
&\propto P(\mathbf{R} | \mathbf{S}, \mathbf{U}, \mathbf{V}, \Omega) P(\mathbf{W} | \mathbf{U}, \Omega) P(\mathbf{C} | \mathbf{V}, \Omega) P(\mathbf{F} | \mathbf{S}, \Omega) \\
&P(\mathbf{S} | \Omega) P(\mathbf{U} | \Omega) P(\mathbf{V} | \Omega) \\
&= \prod_{i,j} \mathcal{N}(R_{ij} | \mathbf{S}_i \mathbf{G}_j^\top \odot \mathbf{U}_i^\top \mathbf{V}_j, \sigma_R^2) \prod_{p,q} \mathcal{N}(W_{pq} | \mathbf{U}_p^\top \mathbf{U}_q, \sigma_W^2) \\
&\prod_{m,n} \mathcal{N}(C_{mn} | \mathbf{V}_m^\top \mathbf{V}_n, \sigma_C^2) \prod_{s,t} \mathcal{N}(F_{st} | S_{st}, \sigma_F^2) \\
&\prod_x \mathcal{N}(\mathbf{S}_x | 0, \sigma_S^2) \prod_y \mathcal{N}(\mathbf{U}_y | 0, \sigma_U^2) \prod_z \mathcal{N}(\mathbf{V}_z | 0, \sigma_V^2)
\end{aligned} \tag{9}$$

where Ω denotes that zero-mean spherical Gaussian priors [28] are placed on latent feature vectors and observed matrices. Then

$$\begin{aligned}
& \ln P(\mathbf{S}, \mathbf{U}, \mathbf{V} | \mathbf{R}, \mathbf{G}, \mathbf{M}, \mathbf{C}, \mathbf{F}, \Omega) \\
&\propto -\frac{1}{2\sigma_R^2} \sum_{i,j} (R_{ij} - \mathbf{S}_i \mathbf{G}_j^\top \odot \mathbf{U}_i^\top \mathbf{V}_j)^2 \\
&- \frac{1}{2\sigma_W^2} \sum_{p,q} (W_{pq} - \mathbf{U}_p^\top \mathbf{U}_q)^2 \\
&- \frac{1}{2\sigma_C^2} \sum_{m,n} (C_{pq} - \mathbf{V}_p^\top \mathbf{V}_q)^2 - \frac{1}{2\sigma_F^2} \sum_{s,t} (F_{st} - S_{st})^2 \\
&- \frac{1}{2\sigma_S^2} \sum_x \mathbf{S}_x^\top \mathbf{S}_x - \frac{1}{2\sigma_U^2} \sum_y \mathbf{U}_y^\top \mathbf{U}_y - \frac{1}{2\sigma_V^2} \sum_z \mathbf{V}_z^\top \mathbf{V}_z
\end{aligned} \tag{10}$$

Maximizing the posterior distribution is equivalent to minimizing the sum-of-squared errors function with hybrid quadratic regularization terms:

$$\begin{aligned}
\mathcal{J} = & \|\mathbf{R} - \mathbf{S} \mathbf{G}^\top \odot \mathbf{U}^\top \mathbf{V}\|_F^2 + \alpha \|\mathbf{W} - \mathbf{U}^\top \mathbf{U}\|_F^2 \\
& + \beta \|\mathbf{C} - \mathbf{V}^\top \mathbf{V}\|_F^2 + \gamma \|\mathbf{S} - \mathbf{F}\|_F^2 \\
& + \delta \|\mathbf{S}\|_F^2 + \eta \|\mathbf{U}\|_F^2 + \lambda \|\mathbf{V}\|_F^2
\end{aligned} \tag{11}$$

where $\alpha = \frac{\sigma_R^2}{\sigma_W^2}, \beta = \frac{\sigma_R^2}{\sigma_C^2}, \gamma = \frac{\sigma_R^2}{\sigma_F^2}, \delta = \frac{\sigma_R^2}{\sigma_S^2}, \eta = \frac{\sigma_R^2}{\sigma_U^2}, \lambda = \frac{\sigma_R^2}{\sigma_V^2}$, and $\|\cdot\|_F$ is the Frobenius norm.

We can adopt a block coordinate descent scheme to solve the problem. That is, starting from some random initialization on $\mathbf{S}, \mathbf{U}, \mathbf{V}$, we solve each of them alternatively with the other two matrices fixed and proceed step by step until convergence. As the objective is obviously lower bounded by 0 and the alternating gradient search procedure will reduce it monotonically, the algorithm is guaranteed to be convergent. In this paper, we use the gradient search method to solve the problem. Specifically, the gradients of the objective with

respect to the variables are

$$\begin{aligned}
\frac{\partial \mathcal{J}}{\partial \mathbf{S}} = & 2 \left(-\mathbf{R}(\mathbf{G} \odot \mathbf{V}^\top \mathbf{U}) + (\mathbf{S} \mathbf{G}^\top \odot \mathbf{U}^\top \mathbf{V}) \mathbf{G} \right. \\
& \left. + \gamma(\mathbf{S} - \mathbf{F}) + \delta \mathbf{S} \right)
\end{aligned} \tag{12}$$

$$\begin{aligned}
\frac{\partial \mathcal{J}}{\partial \mathbf{U}} = & 2 \left(-\mathbf{V} \mathbf{R}^\top + \mathbf{V}(\mathbf{G} \mathbf{S}^\top \odot \mathbf{V}^\top \mathbf{U}) - 2\alpha \mathbf{U} \mathbf{W} \right. \\
& \left. + 2\alpha \mathbf{U} \mathbf{U}^\top \mathbf{U} + \eta \mathbf{U} \right)
\end{aligned} \tag{13}$$

$$\begin{aligned}
\frac{\partial \mathcal{J}}{\partial \mathbf{V}} = & 2 \left(-\mathbf{U} \mathbf{R} + \mathbf{U}(\mathbf{G} \mathbf{S}^\top \odot \mathbf{U}^\top \mathbf{V}) - 2\beta \mathbf{V} \mathbf{C} \right. \\
& \left. + 2\beta \mathbf{V} \mathbf{V}^\top \mathbf{V} + \lambda \mathbf{V} \right)
\end{aligned} \tag{14}$$

Thus, we apply the following gradient based approach on our social contextual model in Algorithm 1. \mathcal{J} decreases the fastest in the direction of gradients during each iteration and the sequence $(\mathcal{J}^{(t)})$ converges to the desired minimum.

Algorithm 1 Social Contextual Model Gradient Algorithm

Require: $0 < \alpha_S^{(t)}, \alpha_U^{(t)}, \alpha_V^{(t)} < 1$, $t = 0$. Initialization $\mathcal{J}^{(0)} = \mathcal{J}(\mathbf{S}^{(0)}, \mathbf{U}^{(0)}, \mathbf{V}^{(0)})$.

Ensure: $\mathcal{J}^{(0)} \geq 0$, $\mathcal{J}^{(t+1)} < \mathcal{J}^{(t)}$

for $t = 1, 2, \dots$ **do**

 Calculate $\frac{\partial \mathcal{J}}{\partial \mathbf{S}}^{(t-1)}, \frac{\partial \mathcal{J}}{\partial \mathbf{U}}^{(t-1)}, \frac{\partial \mathcal{J}}{\partial \mathbf{V}}^{(t-1)}$

$\mathbf{S}^{(t)} = \mathbf{S}^{(t-1)} - \alpha_S^{(t-1)} \cdot \frac{\partial \mathcal{J}}{\partial \mathbf{S}}^{(t-1)}$

$\mathbf{U}^{(t)} = \mathbf{U}^{(t-1)} - \alpha_U^{(t-1)} \cdot \frac{\partial \mathcal{J}}{\partial \mathbf{U}}^{(t-1)}$

$\mathbf{V}^{(t)} = \mathbf{V}^{(t-1)} - \alpha_V^{(t-1)} \cdot \frac{\partial \mathcal{J}}{\partial \mathbf{V}}^{(t-1)}$

$\mathcal{J}^{(t)} \leftarrow \mathcal{J}(\mathbf{S}^{(t)}, \mathbf{U}^{(t)}, \mathbf{V}^{(t)})$

end for

Our model can be applied in the real system to deal with incrementally increasing data. It has been proved both storage and computational efficient by solving the smoothly evolved factorized matrices in [29].

5. EXPERIMENTS

5.1 Datasets Description

We collect data from Renren, a typical social networking service that enables users to put on their profiles and add friends. One of the most popular actions on Renren is sharing blogs, photos and external video links (denoted as items in the paper). After an item is shared by a user, the item will be sent to the user's friends and appear in his friends' pages in real time. We crawled relationships and shared items of nearly 1 million users from February 2007 to December 2009. The statistics of Renren dataset are summarized in Table 1.

Meanwhile, we crawled data from Tencent Weibo, which allows users to follow any other user and receive messages from those followed users. Like Twitter, it also empowers users to spread information by forwarding the messages. We crawled tweets, retweets and user lists during January 2011 from more than 100 thousand users. The statistics of Tencent Weibo dataset are summarized in Table 2.

In Figure 5, we show the characteristics of Renren and Tencent Weibo datasets by plotting curve (a) the number of users with respect to the number of shared or forwarded posts (calculated by $\sum_i G_{ij}$ for user u_j) and curve (b) the

Table 1: Statistics of Renren Dataset

Value	Description
939,363	user number
1,625,689	sharing item number
5,829,368	sharing behavior number

Table 2: Statistics of Tencent Weibo Dataset

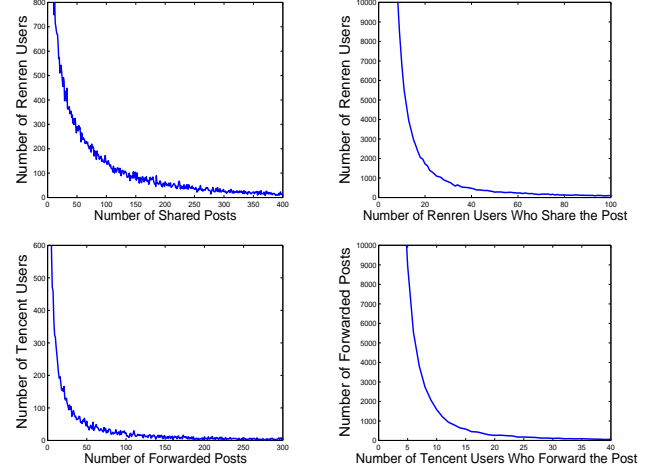
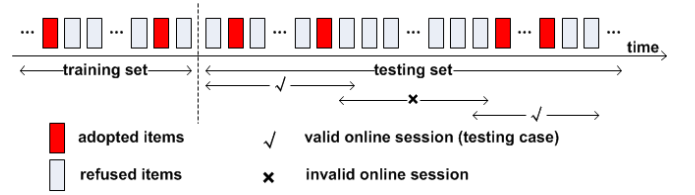
Value	Description
163,661	user number
529,615	tweet number
1,566,609	forward number

number of posts with respect to the number of users who share or forward them (calculated by $\sum_j G_{ij}$ for post p_i). We can see that all the four figures follow power law distributions, which reflect that user behaviors are always very sparse on social networks. Calculated with user number, item number and adoption number, the density of Renren dataset is 0.59%, and the density of Tencent Weibo dataset is 0.09%. The sparsity problem is very serious in our case.

5.2 Experimental Settings

We design our experiments based on two user tasks [9]: (1) annotation in context (2) find good items. The first task requires the recommender to generate predictions for the items that the user is reading. The second task requires a more direct focus on actual recommendation and provides users with a ranked list of recommended items, along with predictions for how much the users would like them.

Different from those static held-out experiments on datasets without time information, the recommendation on social items, e.g. tweets, should be evaluated in a temporal setting. For example, given an item and a user, the interpersonal influence that the user receives at t_1 on the item may be different from that the user receives at a later time t_2 , if new friends (or followers) share (or retweet) the item during the time $t_2 - t_1$. Moreover, as we do not have any information about when the user is online, we can not decide which items the user actually reads. Thus, here we use online sessions to represent the time when the user is online, and we suppose the user will read all the items received from his relationships during the online session time. Given a user, we randomly select a number of online session candidates with the session width being 15 items. And we select the candidates that include at least 2 adopted items as valid online sessions. Then based on the valid online sessions, we design the temporal social recommendation experiments as shown in Figure 6. We arbitrarily select a time to divide the dataset into the training and testing parts. Our model learns interpersonal influence matrix and latent features of users and items from the training set. Meanwhile, we generate valid online sessions from the testing set as testing cases. Then we conduct all baseline algorithms and our method on these test cases. Although the estimation of online session cannot be guaranteed to be perfect, the experiment settings are fair for all the comparative algorithms and the proposed one. Thus, it is adequate to demonstrate the advantages and characteristics of the methods.

**Figure 5: Characteristics of Renren (a)(b) and Tencent Weibo (c)(d) Datasets****Figure 6: An Illustration on Experiment Settings**

5.3 Comparative Algorithms

We implement the following baselines for comparison with our social contextual model (Context MF).

- Content-based [1]: This method recommends similar items with ones that the receiver has shared or forwarded before. It only uses adopted items' content.
- Item CF [26]: The standard item-based collaborative filtering assumes that users like what their close friends or followers like. It only uses user-item interaction information.
- FeedbackTrust [23]: This method improves the basic trust-based recommendation algorithm [22] with users feedback. It is accurate to compute users' correlations in trust network, but only interactions between users.
- Influence-based [10]: This method estimates influence as social utility based on a gradient ascent algorithm. It uses information of user interactions through items, but fails to discover individual correlations between users and items.
- SoRec [20]: This method jointly analyzes social network data and user-item data by extracting a common latent factor from the shared mode, using *Probabilistic Matrix Factorization*. It does not take into account influence from user interactions.
- SoReg [21]: This method designs a matrix factorization objective function with *Social Regularization* to constraint social recommendation. It considers tastes

of all the friends when estimates the user latent features, but both user and item features should be regularized with respect to individual preference on items.

Meanwhile, we implement different configurations of our model to demonstrate the effectiveness of our proposed algorithm.

- **Influence MF:** This method uses only one kind of social contextual factors (interpersonal influence) in our social recommendation model. The adjusted function to minimize is

$$\mathcal{J} = \|\mathbf{R} - \mathbf{S}\mathbf{G}^\top\|_F^2 + \gamma\|\mathbf{S} - \mathbf{F}\|_F^2 + \delta\|\mathbf{S}\|_F^2 \quad (15)$$

- **Preference MF:** This method only uses individual preference for the matrix factorization model. The degenerated function is

$$\mathcal{J} = \|\mathbf{R} - \mathbf{U}^\top \mathbf{V}\|_F^2 + \alpha\|\mathbf{W} - \mathbf{U}^\top \mathbf{U}\|_F^2 + \beta\|\mathbf{C} - \mathbf{V}^\top \mathbf{V}\|_F^2 + \eta\|\mathbf{U}\|_F^2 + \lambda\|\mathbf{V}\|_F^2 \quad (16)$$

5.4 Evaluation Measures

Error Metrics: To measure the prediction quality of our proposed approach in comparison with other collaborative filtering and matrix factorization algorithms, we use two popular metrics, the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE). The metrics MAE is defined as

$$MAE = \frac{1}{|\mathcal{R}|} \sum_{R_{ij} \in \mathcal{R}} |\mathbf{R}_{ij} - \mathbf{S}_i \mathbf{G}_j^\top \odot \mathbf{U}_i^\top \mathbf{V}_j| \quad (17)$$

where R_{ij} denotes the information adoption value (0 or 1) given to j -th item by user u_i . The metrics RMSE is defined as

$$RMSE = \sqrt{\frac{1}{|\mathcal{R}|} \sum_{R_{ij} \in \mathcal{R}} (\mathbf{R}_{ij} - \mathbf{S}_i \mathbf{G}_j^\top \odot \mathbf{U}_i^\top \mathbf{V}_j)^2} \quad (18)$$

Therefore, a smaller MAE or RMSE value means a better performance.

Precision on Top K Recommendation: Precision is defined as the ratio of adopted items to number of items recommended. Precision represents the probability that a recommended item is adopted. Recommendation algorithms are often evaluated by Precision@K [26], which is more important w.r.t. precision, because the recommendation space is limited and only the top k recommended items make sense in real recommendation applications. Here we range K value from 2 to 10.

Ranking Coefficients: Compared to the absolute value prediction accuracy, the predicted order accuracy is more important in real recommendation scenarios. Here we use two ranking-based evaluation methods to evaluate the performance: Kendall's ranking coefficient $\hat{\tau}$ and Spearman's $\hat{\rho}$. They start by defining the following intuitive statistics: the number of ranking order switches, which means how many of the pairs in the test data are ordered incorrectly by the model.

$$T = \sum_{i < j} 1(s_i > s_j) \quad (19)$$

The weighted sum of order switches, which weighs the incorrect ordered pairs by the ranking difference:

$$R = \sum_{i < j} (j - i) \cdot 1(s_i > s_j). \quad (20)$$

These two measures are transformed linearly into the range $[-1, 1]$, where 1 corresponds to perfect model performance ($T, R = 0$) and -1 corresponds to making all possible errors, thus attaining perfect reverse ranking. Thus after we re-scale T and R , we have the non-parametric correlation prevalent data analysis tools:

$$\hat{\tau} = 1 - \frac{4T}{n(n-1)} \quad (21)$$

$$\hat{\rho} = 1 - \frac{12R}{n(n-1)(n+1)} \quad (22)$$

T-test: An algorithm that gives higher probabilities on adopted items than refused items will better help the recommender systems. In order to demonstrate the distinguish ability, for each method, a group of T-tests are conducted to compare numerical gaps between good recommendations and bad ones. When T is higher, the classification is more accurate on whether user adoption will happen or not.

5.5 Parameter Settings

Here we focus on parameter settings. We investigate the performance when the parameters change, and implement algorithms of our model and all baselines with these parameters.

Tradeoff Parameters: The tradeoff parameters $\alpha, \beta, \gamma, \delta, \eta$ and λ in our model play the role of adjusting the strengths of different terms in the objective function Equation (11). To balance the components in this function, these parameters are proportional to $\frac{1}{\|\mathbf{W} - \mathbf{U}^\top \mathbf{U}\|_F^2}, \frac{1}{\|\mathbf{C} - \mathbf{V}^\top \mathbf{V}\|_F^2}, \frac{1}{\|\mathbf{S} - \mathbf{F}\|_F^2}, \frac{1}{\|\mathbf{S}\|_F^2}$ and $\frac{1}{\|\mathbf{V}\|_F^2}$. Taking the scales of $\mathbf{S}, \mathbf{U}, \mathbf{V}, \mathbf{F}, \mathbf{W}$ and \mathbf{C} into account (Table 1 and 2), we scan orders of magnitude and try different combinations of parameters as shown in Table 3. We use the second row for Renren dataset and the third row for Tencent Weibo dataset. Although they are not the perfect ones, the following experiments demonstrate they are adequate. We tune parameters following the same way as *Context MF* for *Preference MF* and *Influence MF*. We also find the best configurations while applying original versions of competing methods on our real datasets to make sure comparisons are fair.

Number of Hidden Features: We train \mathbf{U}, \mathbf{V} to find the proper number of hidden features k for users and items. If k is too small, the recommender system cannot make a distinction between any users or items. If k is too large, users and items will be too unique for the system to calculate their similarities and the complexity will considerably increase.

Thus, we conduct experiments with k ranging from 3 to 80 on both Renren and Tencent Weibo datasets. The results are shown in Figure 7, from which we can find that with the hidden feature number k increasing, RMSE reduces gradually. It shows obviously that when $k > 60$ on both datasets, RMSE decreases rather slow. Considering the recommendation effect and time efficiency, we choose $k = 60$ as the latent space dimension in our experiments.

Number of Iterations: In Figure 8, we can observe that both RMSE and the objective function value \mathcal{J} decrease

Table 3: Tradeoff Parameters on Renren (a) and Tencent Weibo (b) Datasets (60 Hidden Features and 60 Iterations)

α, η	β	γ, δ	λ	MAE	RMSE
Renren Dataset					
10^{-4}	10^{-7}	10^{-6}	10^{-5}	0.2452	0.3139
10^{-3}	10^{-6}	10^{-5}	10^{-4}	0.2416	0.3086
10^{-2}	10^{-5}	10^{-4}	10^{-3}	0.2431	0.3115
10^{-1}	10^{-4}	10^{-3}	10^{-2}	0.2676	0.3392
Tencent Weibo Dataset					
10^{-3}	10^{-6}	10^{-5}	10^{-4}	0.1613	0.2529
10^{-2}	10^{-5}	10^{-4}	10^{-3}	0.1539	0.2432
10^{-1}	10^{-4}	10^{-3}	10^{-2}	0.1514	0.2348
1	10^{-3}	10^{-2}	10^{-1}	0.1795	0.2767

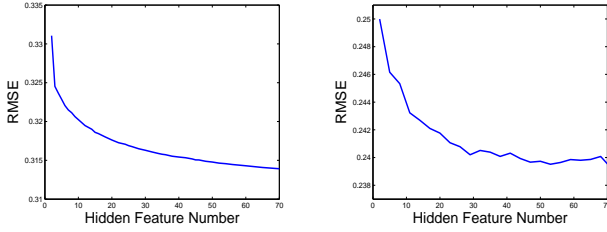


Figure 7: RMSE vs. Hidden Feature Number on Renren (a) and Tencent Weibo (b) Datasets (60 Iterations)

gradually with the number of iterations increasing. It shows that, by incorporating effective regularizers, our method successfully avoids the overfitting problem which often occurs in gradient algorithms. On both datasets, it is better to run 60 iterations in order to reach a converged result with an acceptable time cost.

5.6 Recommendation Performance

We evaluate each algorithm with the accuracy measured as MAE, RMSE and ranking coefficients. As shown in Table 4, our social contextual model, which recommends items based on matrix factorization algorithm with social contextual factors, provides reasonably accurate recommendations that are much better than baselines. On Renren and Tencent Weibo datasets, we decrease the prediction error by 19.1% and 12.8% on MAE, by 24.2% and 20.7% on RMSE over *SoReg*, a state-of-the-art algorithm with social regularization.

It should be noted that *Preference MF* and *Influence MF* achieve better performance than *SoRec*, which demonstrates the effectiveness of introducing either individual preference or interpersonal influence. The large improvement margin achieved by *Context MF* over both *Preference MF* and *Influence MF* demonstrates the importance of incorporating complete contextual information from both individual and interpersonal sides for social recommendation. Moreover, the fact that our proposed *Context MF* performs better than *SoReg* proves the effectiveness of incorporating the two social contextual factors from users' motivations on item adoption, instead of adding average-based or individual-based regularization to user latent vectors [21].

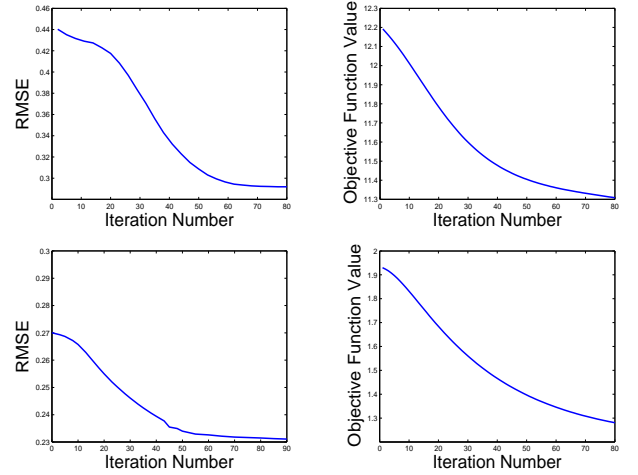


Figure 8: RMSE and Objective Function Value \mathcal{J} vs. Iteration Number on Renren (a)(b) and Tencent Weibo (c)(d) Datasets (60 Hidden Features)

Table 4: Recommendation Performance on Two Datasets (Renren and Tencent Weibo)

Method	MAE	RMSE	$\hat{\tau}$	$\hat{\rho}$
Renren Dataset				
Content-based [1]	0.3842	0.4769	0.5409	0.5404
Item CF [26]	0.3601	0.4513	0.5896	0.5988
FeedbackTrust [23]	0.3764	0.4684	0.5433	0.5469
Influence-based [10]	0.3859	0.4686	0.5394	0.5446
SoRec [20]	0.3276	0.4127	0.6168	0.6204
SoReg [21]	0.2985	0.3537	0.7086	0.7140
Influence MF	0.3102	0.3771	0.6861	0.7006
Preference MF	0.3032	0.3762	0.6937	0.7036
Context MF	0.2416	0.3086	0.7782	0.7896
Tencent Weibo Dataset				
Content-based [1]	0.2576	0.3643	0.7728	0.7777
Item CF [26]	0.2375	0.3372	0.7867	0.8049
FeedbackTrust [23]	0.2830	0.3887	0.7094	0.7115
Influence-based [10]	0.2651	0.3813	0.7163	0.7275
SoRec [20]	0.2256	0.3325	0.7973	0.8064
SoReg [21]	0.1997	0.2962	0.8390	0.8423
Influence MF	0.2183	0.3206	0.8179	0.8258
Preference MF	0.2111	0.3088	0.8384	0.8453
Context MF	0.1514	0.2348	0.8570	0.8685

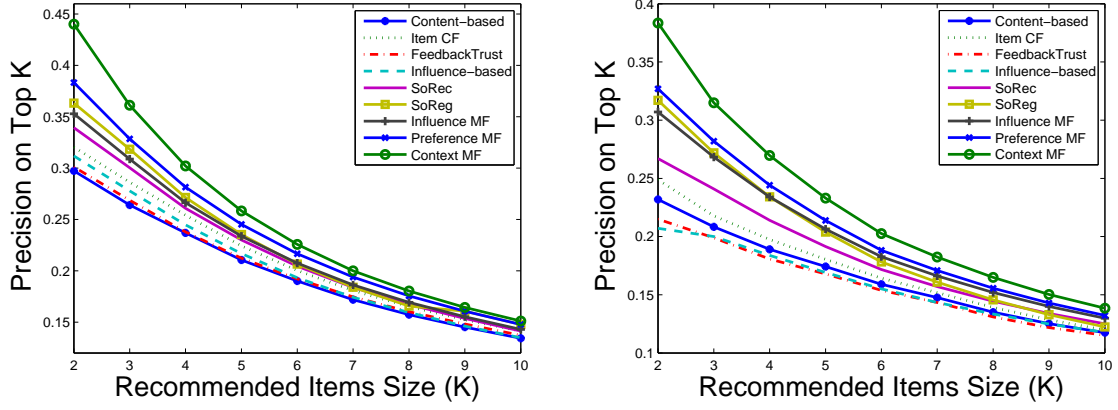


Figure 9: Top K Precision Curve on Renren (a) and Tencent Weibo (b) Datasets

We draw the precision curve on top K recommendation-s in Figure 9. The performance increases regularly as we decreases the size of recommended items. Compared with baselines, our top 5 precision increases by 21.7% and top 10 precision increases by 10.8% on Renren dataset. The top 5 precision increases by 12.3% and top 10 precision increases by 6.85% on Tencent Weibo dataset. The advantage of our method is much more obvious when K is small. As the user adoption behavior is very sparse, it is difficult to distinguish excellent methods when K is rather large. That's why all the baseline algorithms tend to converge as K becomes larger.

To compare the distinguish-ability of our method with baselines, we report average and variance of prediction and T-test results in Table 5. Our model gives the highest T (1.78 and 1.26 times of the best baseline on Renren and Tencent Weibo datasets), which shows the social contextual model has better distinguish-ability compared with baselines.

We conduct 100 parameter-fixed experiments to test the stability of our model with different random starts. As shown in Table 6, the low variances of MAE and RMSE (less than 0.001) show that our algorithm not only performs well on both social networking and microblogging datasets, but also runs without big fluctuation.

6. CONCLUSIONS

We conducted extensive experiments on two large real-world social network datasets, and showed that social contextual information can greatly boost the performance of recommendation on these social network data. In particular, we have gained increases of 24.2% and 20.7% in prediction accuracy and 21.7% and 12.3% in recommendation Precision@K upon previous approaches on these social networks, respectively. Also, the proposed algorithm is general and can be easily adapted according to different real-world recommendation scenarios.

7. ACKNOWLEDGMENTS

This work is supported by the Natural Science Foundation of China (No.60933013, No.61003097), 973 Program (No.2011CB302206), National Significant Science and Technology Projects of China (No.2011ZX01042-001-002) and

Table 5: T Statistics on Two Datasets (Renren and Tencent Weibo)

Method	Adopted	Refused	T-test
Renren Dataset			
Content-based [1]	0.7019(0.046)	0.6653(0.052)	1.055
Item CF [26]	0.3596(0.001)	0.2679(0.001)	1.342
FeedbackTrust [23]	0.3632(0.082)	0.343(0.080)	1.060
Influence-based [10]	0.6413(0.004)	0.5898(0.004)	1.087
SoRec [20]	0.4733(0.010)	0.3465(0.003)	1.366
SoReg [21]	0.5234(0.012)	0.3356(0.007)	1.560
Influence MF	0.3505(0.015)	0.2131(0.006)	1.645
Preference MF	0.1324(0.028)	0.0555(0.015)	2.384
Context MF	0.4556(0.095)	0.1074(0.019)	4.244
Tencent Weibo Dataset			
Content-based	0.4173(0.048)	0.2764(0.029)	1.509
Item CF	0.6374(0.004)	0.2436(0.001)	2.617
FeedbackTrust	0.7920(0.019)	0.6096(0.009)	1.299
Influence-based	0.8004(0.019)	0.3918(0.007)	2.043
SoRec	0.4949(0.004)	0.0580(0.004)	8.532
SoReg	0.5523(0.003)	0.0602(0.006)	9.1744
Influence MF	0.5222(0.012)	0.0620(0.005)	8.423
Preference MF	0.5758(0.015)	0.0517(0.001)	11.13
Context MF	0.8115(0.020)	0.0580(0.001)	13.99

Table 6: Stability of Performance on Renren and Tencent Weibo Datasets (60 Hidden Features and 60 Iterations)

Renren Dataset					
	MAE	RMSE	$\hat{\tau}$	$\hat{\rho}$	T
\bar{x}	0.2416	0.3086	0.7783	0.7897	4.2437
σ	0.0001	0.0001	0.0006	0.0006	0.5545
Tencent Dataset					
	MAE	RMSE	$\hat{\tau}$	$\hat{\rho}$	T
\bar{x}	0.1514	0.2348	0.8571	0.8686	13.989
σ	0.0001	0.0002	0.0002	0.0001	1.8962

8. REFERENCES

- [1] M. Balabanovic and Y. Shoham. Fab: content-based, collaborative recommendation. *Communications of the ACM*, 40:66–72, March 1997.
- [2] A. Bandura. Social cognitive theory of mass communication. *Media Psychology*, 2001.
- [3] L. S. Benjamin. Structural analysis of social behavior. *Psychological Review*, 1974.
- [4] D. M. Blei, A. Y. Ng, and M. I. Jordan. Latent dirichlet allocation. *Journal of Machine Learning Research*, 3:993–1022, March 2003.
- [5] R. Bond and P. B. Smith. Culture and conformity: a meta-analysis of studies using asch’s (1952b, 1956) line judgment task. *Psychological Bulletin*, 119:111–137, January 1996.
- [6] Y. Chen and J. Canny. Recommending ephemeral items at web scale. In *Proceedings of the 34th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR)*, pages 1013–1022, 2011.
- [7] P. Cui, F. Wang, S. Liu, M. Ou, S. Yang, and L. Sun. Who should share what? item-level social influence prediction for users and posts ranking. In *Proceedings of the 34th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR)*, pages 185–194, 2011.
- [8] M. Harvey, M. J. Carman, I. Ruthven, and F. Crestani. Bayesian latent variable models for collaborative item rating prediction. In *Proceedings of CIKM*, pages 699–708, 2011.
- [9] J. L. Herlocker, J. A. Konstan, L. G. Terveen, and J. T. Riedl. Evaluating collaborative filtering recommender systems. *ACM Transactions on Information Systems (TOIS)*, 22:5–53, January 2004.
- [10] J. Huang, X. Cheng, J. Guo, H. Shen, and K. Yang. Social recommendation with interpersonal influence. In *Proceedings of the 19th European Conference on Artificial Intelligence (ECAI)*, pages 601–606, 2010.
- [11] M. Jamali and M. Ester. Trustwalker: a random walk model for combining trust-based and item-based recommendation. In *Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD)*, pages 397–406, 2009.
- [12] D. Kong, C. Ding, and H. Huang. Robust nonnegative matrix factorization using l21-norm. In *Proceedings of CIKM*, pages 673–682, 2011.
- [13] Y. Koren. Factorization meets the neighborhood: a multifaceted collaborative filtering model. In *Proceeding of the 14th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD)*, pages 426–434, 2008.
- [14] Y. Koren. Collaborative filtering with temporal dynamics. In *Proceeding of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD)*, 2009.
- [15] Y. Koren, R. Bell, and C. Volinsky. Matrix factorization techniques for recommender systems. *Computer*, 42:30–37, 2009.
- [16] J. Leskovec, A. Singh, and J. Kleinberg. Patterns of influence in a recommendation network. *Lecture Notes in Computer Science*, 3918:380–389, 2006.
- [17] L. Liu, J. Tang, J. Han, M. Jiang, and S. Yang. Mining topic-level influence in heterogeneous networks. In *Proceedings of CIKM*, pages 199–208, 2010.
- [18] N. N. Liu, M. Zhao, and Q. Yang. Probabilistic latent preference analysis for collaborative filtering. In *Proceedings of CIKM*, pages 759–766, 2009.
- [19] Q. Liu, E. Chen, H. Xiong, C. Ding, and J. Chen. Enhancing collaborative filtering by user interest expansion via personalized ranking. *IEEE Transactions on Systems, Man, and Cybernetics - Part B (TSMCB)*, 42(1):218–233, February 2012.
- [20] H. Ma, H. Yang, M. R. Lyu, and I. King. Sorec: Social recommendation using probabilistic matrix factorization. In *Proceedings of CIKM*, pages 931–940, 2008.
- [21] H. Ma, D. Zhou, C. Liu, M. R. Lyu, and I. King. Recommender system with social regularization. In *Proceedings of the 4th ACM International Conference on Web Search and Data Mining (WSDM)*, pages 287–296, 2011.
- [22] P. Massa and P. Avesani. Trust-aware recommender systems. In *Proceedings of the 2007 ACM Conference on Recommender Systems (RecSys)*, 2007.
- [23] S. Moghaddam, M. Jamali, M. Ester, and J. Habibi. Feedbacktrust: using feedback effects in trust-based recommendation systems. In *Proceedings of the 3rd ACM Conference on Recommender Systems (RecSys)*, pages 269–272, 2009.
- [24] R. Salakhutdinov and A. Mnih. Probabilistic matrix factorization. *Neural Information Processing Systems (NIPS)*, 2007.
- [25] M. J. Salganik. Experimental study of inequality and unpredictability in an artificial cultural market. *Science*, 311:854–856, 2006.
- [26] B. Sarwar, G. Karypis, J. Konstan, and J. Reidl. Item-based collaborative filtering recommendation algorithms. In *Proceedings of the 10th International Conference on World Wide Web (WWW)*, pages 285–295, 2001.
- [27] L. Si and R. Jin. Unified filtering by combining collaborative filtering and content-based filtering via mixture model and exponential model. In *Proceedings of CIKM*, pages 156–157, 2004.
- [28] M. E. Tipping and C. M. Bishop. Probabilistic principal component analysis. *Journal of the Royal Statistical Society, Series B*, 61:611–622, 1999.
- [29] F. Wang, H. Tong, and C.-Y. Lin. Towards evolutionary nonnegative matrix factorization. In *Proceedings of the 25th AAAI Conference on Artificial Intelligence (AAAI)*, pages 501–506, 2011.
- [30] S.-H. Yang, B. Long, A. Smola, N. Sadagopan, Z. Zheng, and H. Zha. Like like alike: joint friendship and interest propagation in social networks. In *Proceedings of the 20th International Conference on World Wide Web (WWW)*, 2011.