User Interests Imbalance Exploration in Social Recommendation: A Fitness Adaptation

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ABSTRACT

Recent years have witnessed an increasing interest in how to incorporate social network information into recommendation algorithms to enhance the user experience. In this paper, we find the phenomenon that users in the contexts of recommendation system and social network do not share the same interest space. Based on this finding, we proposed the social regulatory factor regression model (SRFRM) which could connect different interest spaces in different contexts together in an unified latent factor model. Specifically, different from the traditional social based latent factor models with strong limitation that all sides share the same feature space, the proposed method leverages the regulatory factor number on both sides to meet the fact that users and items or users in different contexts may not share the same interest space. It works by incorporating two linear transformation matrices into the matrix co-factorization framework that matrix factorization of user ratings is regularized by that of social trust network. We study a large subsets of data from epinions.com and douban.com respectively. The experimental results indicate that users in different contexts have different interest spaces and our model achieves a higher performance compared with related state-of-the-art methods.

Categories and Subject Descriptors

H.3.3 [**Information Search and Retrieval**]: Information filtering; H.5.3 [**Information systems**]: Web-based Interaction

General Terms

Algorithms, Experimentation

Keywords

Social Network, Recommender System, Matrix Factorization

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1. INTRODUCTION

The last few years have seen an incredibly fast development of social networks. In particular, a statistic shows that the amount of worldwide social commerce revenue has reached $14 billion in 2013 and is projected to $20 billion by the end of 2014 and $30 billion in 2015[1]. In the mean time, more and more websites and applications start to exploit the recommender system to personalized their products. Recently not only academic world but also industries like Facebook.com noticed the great value of social network which may help to improve the recommender system.

Hence, to improve recommender systems with the auxiliary of social networks information has become a hot research topic. Recently, there are several research works [2, 3, 4, 5, 6] focus on incorporating social trust data into recommender systems.

The main notion underlying existing efforts[3, 4, 7] is the strong assumption that, by joinly modeling user rating behaviors and user trust relations, users have the same interests space in both contexts. That is, the dimensionality of a user interests space in rating context is the same as that in social trust network context. Obviously, due to the different interests in products and social relations, making the dimensionality of user interests equal in different contexts is insufficient because in real-world the interests of users making ratings and motivation of trusting their online 'friends' are based on different concepts and vari-size grained features. We call that *users interests imbalance* problem in social recommendation. Moreover, we study the density characteristics of Epinions[8] and Douban[4], two of popular real-world datasets for social recommendation, as shown in Table 1. However, by tuning the common dimensionality parameter of user feature space and item feature space, many methods based on matrix factorization cannot alleviate the overfitting problem elegantly, especially the data sparsity in rating data and trust relations data vary widely. From this intuition, we further suppose that user interests space in the contexts of recommendation system and social network are different. On the other hand, utilizing inherent characteristics of user interests other than the common consensus of dimen-

Table 1: Density statistics of two datasets

	Epinions	Douban
Ratings	0.01%	0.22%
Social relations	0.02%	0.05%

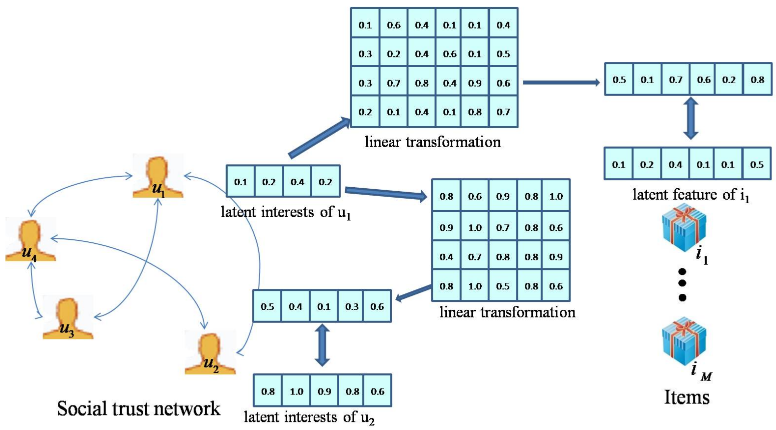


Figure 1: An illustrator on social regulatory factor regression model (SRFRM). The latent interests of users are linearly transformed to fit the latent features of items and the latent interests of trustees.

sionality, which might benefit the construction of more accurate recommendation performance, nevertheless remains unexplored in the literature.

From the motivations above, we intend to model both rating-specific and social-specific feature spaces for user interests in social recommendation. Accordingly, in this paper, we propose a matrix factorization approach based on social trust graph to overcome these problems and exploit the most reasonable factor numbers of users, items, and user trusts feature spaces, which saves human efforts for collecting the auxiliary knowledge. Figure 1 illustrates the key idea of our method. The method is based on probabilistic matrix factorization method to connect user-item rating matrix and social trust network trough a shared user latent feature space, which can also linearly transform the latent interests of an user (denoted as $u1$) to fit the latent features of an item (denoted as $i1$) and the latent interests of his trustee (denoted as $u2$). We then perform gradient descent on the objective function and determine the latent user-specific and item-specific matrices to predict user ratings of different items. This simultaneous implicit and explicit exploration of user interests enables this study to provide the following threefold contributions:

- We explore the user interests imbalance problem that are very common in social recommendation. As far as we know, this is the first work to exploit this problem for social recommendation.
- We propose a social regulatory factor regression model (SRFRM) aiming at exploring the proper dimensionality of user, item and trust relations latent feature spaces to explore the reasonable user interests and alleviate the overfitting problem.
- Experimental results on two real-world dataset indicate that the proposed approach can greatly boost the performance for recommendation and demonstrate the supposal that users should have different interest spaces in the contexts of recommendation system and social network.

The remainder of this paper is organized as following: In Section 2, the problem is formally discussed. In Section 3, we introduce our proposed model and demonstrates the parameter learning method. In Section 4, we experimentally evaluate our approach on two real-world datasets. We compare the performance of our approach to three appropriate baselines, and discuss the results of these experiments. In Section 5, we briefly reviews some related works. Finally, in Section 6 we conclude this paper.

2. PROBLEM DEFINITION

Traditional recommender systems consist of three entities: N users in the systems $U = \{u_1, ..., u_N\}$, M items for recommendations $V = \{v_1, ..., v_M\}$ and the user-item ratings matrix R, where R_{ij} denotes the score u_i votes for v_j. The problem discussed in this paper incorporates social network information between users into the CF methods of the traditional recommender system to improve the recommendations. In social recommender systems, prediction for a user is not only judged by oneself, but also influenced by one's friends. The problem we investigates in this paper is how to make predictions by employing social relation data while finding the reasonable latent factor numbers of users and items.

Here, we will introduce several notations and definitions used in this paper and then formally define the problem of fitness adaptation of user interests in social recommendation. The social trust network can be represented as $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where the vertex set $\mathcal{V} = \{v_i\}_{i=1}^N$ represents all the users in a social network and the edge set $\mathcal{E}$ represents the relations between users.

Now we define the matrices that will be used in our approach as follows:

Definition 1. *User-item matrix:* Let R be a $N \times M$ matrix in which each row corresponds to a user and each column an item; and each element records the rating score, i.e., R_{ij} is item j rated by user i.

Definition 2. *Social trust matrix:* Let S be a $N \times N$ matrix of $\mathcal{G}$ in which each row and column both corresponds to a user. The value of element S_{ik} represents the degree that how user i trust user k in social trust network.

Definition 3. *Users and items latent feature matrix:* Let U be an $N \times k_1$ matrix in which each row is a user and each column is a latent factor corresponds to a user's interests; Let V be a $M \times k_2$ matrix in which each row is an item and

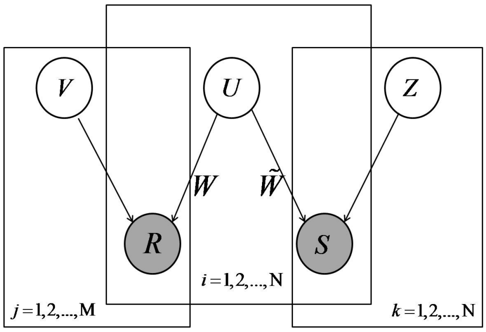


Figure 2: Graphical representation for social regulatory factor regression model (SRFRM). Variance components are omitted for succinctness.

each column is a latent factor representing a feature of this item.

Definition 4. *Trustee latent feature matrix:* Let Z be an $N \times k_3$ matrix factorized out by our approach in which each row corresponds to a user who is trusted by any other user in trust relations network and each column is latent factor, which can also be interpreted as the appeal features of trustees.

Definition 5. *User-item linear transformation matrix:* Let W be a $k_1 \times k_2$ matrix in which each row corresponds to a latent factor in users latent feature matrix U, which linearly map them to fit the latent features of items in matrix V.

Definition 6. *Trustor-trustee linear transformation matrix:* Let $\widetilde{W}$ be a $k_1 \times k_3$ matrix in which each row corresponds to a latent factor in users latent feature matrix U, which linearly map them to fit the appeal features of trustees in matrix Z.

Based on the above matrices definitions, now we formally define the problem of fitness adaptation of user interests in social recommendation.

The problem of fitness adaptation of user interests in social recommendation is defined as: Given the user-item matrix R and social trust matrix S, we aim to learn the appropriate dimensionality of latent feature matrices U,V to best fit the matrices R and S:

$$\mathcal{F}(U, V) \to R, S$$

3. METHOD

For the purpose of clearly reflecting the feature dimensionality imbalance on social trust network side as well as recommender system side, we consider a kind of co-factorization framework, similar to [3, 9]. Social recommendation systems in this group perform a co-factorization in the user-item matrix and the social trust matrix by sharing the same user preference latent factor. That is, observation matrices R and S can be factorized into three latent feature matrices: U, V and Z, where the trustee latent feature matrix Z represents users interests in their friends or the appeal feature matrix of trustees. Since latent factors are to some extent correlated, we incorporate the user-item linear transformation matrix W to make a linear combination of user interests and map that to fit the item features and similarly use the trustor-trustee linear transformation $\widetilde{W}$ to linearly transform that to fit the appeal of trustees. Accordingly, five latent matrices need to be learnt and the objective is

$$\mathcal{F}^*(U, V, Z, W, \widetilde{W}) \to R, S$$

The graphical representation of our approach is illustrated in Figure 2.

3.1 Social Regulatory Factor Regression Model

We propose a social regulatory factor regression model (SRFRM) based on probabilistic matrix factorization. In our model, zero-mean spherical Gaussian priors[10, 11] are imposed on latent feature matrices U, V and Z, postulated as

$$P(U|\sigma_U^2) = \mathcal{N}(U|0, \sigma_U^2\mathbf{I})$$

$$P(V|\sigma_V^2) = \mathcal{N}(V|0, \sigma_V^2\mathbf{I})$$

$$P(Z|\sigma_Z^2) = \mathcal{N}(Z|0, \sigma_Z^2\mathbf{I})$$

In order to solve easily, we incorporate two linear transformation matrices W and $\widetilde{W}$ with Gaussian priors to map the interest features of users U to fit the profile features of items V and the appeal features of trustees Z given by

$$P(W|\sigma_W^2) = \mathcal{N}(W|0, \sigma_W^2\mathbf{I})$$

$$P(\widetilde{W}|\sigma_{\widetilde{W}}^2) = \mathcal{N}(\widetilde{W}|0, \sigma_{\widetilde{W}}^2\mathbf{I})$$

Without loss of generality, we map the rating score r from the 5-star rating system to the interval $[0, 1]$ by using the function $f(r) = (r - 1)/4$. Moreover, instead of using a simple linear-Gaussian model, which may lead predictions outside the range of valid rating values and users trust degree values, we use the logistic function $\rho(x) = 1/(1 + exp(-x))$ to bounds the range:

$$P(R|U, W, V, \sigma_R^2) = \prod_{i=1}^{N}\prod_{j=1}^{M}\left[\mathcal{N}(R_{ij}|\rho(U_i^T W^T V_j), \sigma_R^2)\right]^{H_{ij}^R} \quad (1)$$

Moreover, $S \in \mathcal{R}^{N\times N}$ is a similarity matrix. Let δ_{ik} denotes the relation indicator variable between user i and user k. It should be noted that $\delta_{ik} = 1$ if and only if u_i is the friend of u_k in social networks such as Facebook, or is followed by u_k in microblogging services such as Twitter. However, in social trust network, the indicator variable δ_{ik} can't accurately describe the relations between users since it ignores the graph structure information of social network and contains noise. The confidence of trust value S_{ik} should be decreased if user i trusts lots of users and increased if user k is the trustee of lots of users to reduce this noise in the social trust network, which is defined as

$$S_{ik} = \sqrt{\frac{d^-(v_k)}{d^+(v_i) + d^-(v_k)}} \cdot \delta_{ik} \quad (2)$$

where $d^+(v_i)$ represents the outdegree of node v_i and $d^-(v_k)$ indicates the indegree of node v_k [3].

We adopt a probabilistic model with Gaussian observation noise to fit the user-item rating matrix and the user-user trust relation matrix. The conditional distribution over the observed entries in **R** and **S** are defined as

$$P(R,S|U,V,Z,W,\widetilde{W},\sigma_R^2)=\prod_{i=1}^{N}\prod_{j=1}^{M}\left[\mathcal{N}(R_{ij}|\rho(U_iW^TV_j),\sigma_R^2)\right]^{H_{ij}^R}$$
$$\prod_{i=1}^{N}\prod_{k=1}^{N}\left[\mathcal{N}(S_{ik}|\rho(U_i\widetilde{W}^TZ_k),\sigma_S^2)\right]^{H_{ik}^S} \tag{3}$$

The log of the posterior distribution is given by

$$\begin{aligned}&lnP(U,V,Z,W,\widetilde{W}|R,S,\Omega)\\&\propto -\frac{1}{2\sigma_R^2}\sum_{i,j}H_{ij}^R\circ(R_{ij}-\rho(U_i^TW^TV_j))^2-\frac{1}{2\sigma_U^2}\sum_x U_x^TU_x\\&-\frac{1}{2\sigma_S^2}\sum_{i,k}H_{ik}^S\circ(S_{ik}-\rho(U_i^T\widetilde{W}^TZ_k))^2-\frac{1}{2\sigma_V^2}\sum_y V_y^TV_y\\&-\frac{1}{2\sigma_Z^2}\sum_t Z_t^TZ_t-\frac{1}{2\sigma_W^2}\sum_p W_p^TW_p-\frac{1}{2\sigma_{\widetilde{W}}^2}\sum_q \widetilde{W}_q^T\widetilde{W}_q\end{aligned} \tag{4}$$

Maximizing this log-posterior with fixed hyperparameters (i.e., observation noise variance and prior variances) is e-quivalent to minimizing the following sum-of-squared-errors objective functions with quadratic regularization terms given by

$$\begin{aligned}\mathcal{L}=&\frac{1}{2}||H^R\circ(R-\rho(U^TW^TV))||_F^2+\frac{\lambda_U}{2}||U||_F^2+\frac{\lambda_V}{2}||V||_F^2\\&+\frac{\alpha}{2}||H^S\circ(S-\rho(U^T\widetilde{W}^TZ))||_F^2+\frac{\lambda_Z}{2}||Z||_F^2\\&+\frac{\lambda_W}{2}||W||_F^2+\frac{\lambda_{\widetilde{W}}}{2}||\widetilde{W}||_F^2\end{aligned} \tag{5}$$

where $\lambda_U=\frac{\sigma_R^2}{\sigma_U^2}$, $\lambda_V=\frac{\sigma_R^2}{\sigma_V^2}$, $\lambda_Z=\frac{\sigma_R^2}{\sigma_Z^2}$, $\lambda_W=\frac{\sigma_R^2}{\sigma_W^2}$, $\lambda_{\widetilde{W}}=\frac{\sigma_R^2}{\sigma_{\widetilde{W}}^2}$, $\alpha=\frac{\sigma_R^2}{\sigma_S^2}$, $||\cdot||_F$ denotes the Frobenius norm and $\circ$ represents the Hadamard element-wise product. H^R and H^S are indicator matrices. $H_{ij}^R=1$ if and only if $R_{ij}>0$ and $H_{ij}^R=0$ when $R_{ij}=0$. Similarly, $H_{ik}^S=1$ when $S_{ik}>0$ and $H_{ik}^S=0$ otherwise.

3.2 Model Learning

We extended a block coordinate descent scheme to minimize the objective function (5). That is, starting from some random values assignment for initialization on U,V,Z,W and $\widetilde{W}$, we solve each of them with others fixed and proceed step by step until convergence. Thus, the gradients of the objective with respect to the variables are as follows

$$\begin{aligned}\frac{\partial\mathcal{L}}{\partial U}=&H^R\circ\rho\prime(U^TW^TV_j)(\rho(U^TW^TV)-R)W^TV\\&+\alpha H^S\circ\rho\prime(U^T\widetilde{W}^TZ_k)(\rho(U^T\widetilde{W}^TZ)-S)\widetilde{W}^TZ\\&+\lambda_uU\end{aligned} \tag{6}$$

$$\frac{\partial\mathcal{L}}{\partial V}=H^R\circ\rho\prime(U^TW^TV)(\rho(U^TW^TV)-R)U^TW^T+\lambda_vV \tag{7}$$

$$\begin{aligned}\frac{\partial\mathcal{L}}{\partial Z}=&\alpha H^S\circ\rho\prime(U^T\widetilde{W}^TZ))(\rho(U^T\widetilde{W}^TZ))-S)U^T\widetilde{W}^T\\&+\lambda_ZZ\end{aligned} \tag{8}$$

$$\frac{\partial\mathcal{L}}{\partial W}=H^R\circ\rho\prime(U^TW^TV)(\rho(U^TW^TV)-R)VU^T+\lambda_WW \tag{9}$$

$$\frac{\partial\mathcal{L}}{\partial\widetilde{W}}=\alpha H^S\circ\rho\prime(U^T\widetilde{W}^TZ)(\rho(U^T\widetilde{W}^TZ)-S)ZU^T+\lambda_{\widetilde{W}}\widetilde{W} \tag{10}$$

Specifically, the gradient descent based approach is applied on our social regulatory factor regression model illustrated in Algorithm 1. The loss function $\mathcal{L}$ decreases fastest in the direction of the negative gradients and the result sequence ($\mathcal{L}^{(t)}$) of each epoch can head towards and finally converge to the desired minimum efficiently.

Algorithm 1 SRFRM Gradient Based Algorithm

Require: $0<\epsilon_U^{(t)},\epsilon_V^{(t)},\epsilon_Z^{(t)},\epsilon_W^{(t)},\epsilon_{\widetilde{W}}^{(t)}<1$, $t=0$.
  Initialization $\mathcal{L}^{(0)}=\mathcal{L}(U^{(0)},V^{(0)},Z^{(0)},W^{(0)},\widetilde{W}^{(0)})$
Ensure: $\mathcal{L}^{(0)}\geq 0$, $\mathcal{L}^{(t+1)}<\mathcal{L}^{(t)}$
  for $t=1,2,...$ **do**
    Calculate $\frac{\partial\mathcal{L}}{\partial U}^{(t-1)}$, $\frac{\partial\mathcal{L}}{\partial V}^{(t-1)}$, $\frac{\partial\mathcal{L}}{\partial Z}^{(t-1)}$, $\frac{\partial\mathcal{L}}{\partial W}^{(t-1)}$, $\frac{\partial\mathcal{L}}{\partial\widetilde{W}}^{(t-1)}$
    $U^{(t)}=U^{(t-1)}-\epsilon_U^{(t-1)}\cdot\frac{\partial\mathcal{L}}{\partial U}^{(t-1)}$
    $V^{(t)}=V^{(t-1)}-\epsilon_V^{(t-1)}\cdot\frac{\partial\mathcal{L}}{\partial V}^{(t-1)}$
    $Z^{(t)}=Z^{(t-1)}-\epsilon_Z^{(t-1)}\cdot\frac{\partial\mathcal{L}}{\partial Z}^{(t-1)}$
    $W^{(t)}=W^{(t-1)}-\epsilon_W^{(t-1)}\cdot\frac{\partial\mathcal{L}}{\partial W}^{(t-1)}$
    $\widetilde{W}^{(t)}=\widetilde{W}^{(t-1)}-\epsilon_{\widetilde{W}}^{(t-1)}\cdot\frac{\partial\mathcal{L}}{\partial\widetilde{W}}^{(t-1)}$
    $\mathcal{L}^{(t)}\leftarrow\mathcal{L}(U^{(t)},V^{(t)},Z^{(t)},W^{(t)},\widetilde{W}^{(t)})$
  end for

4. EXPERIMENTS

In this section, we conduct several experiments to compare the recommendation qualities of our approaches with other state-of-the-art collaborative filtering and trust-based methods. Our experiments are intended to address the following questions:

1. How does our approach compare with other related collaborative filtering and trust-based recommendation methods for item recommendation?
2. How does the trade-off parameter affect the the performance of prediction?
3. How does the performance vary as the dimensionality of user, item and trustee feature spaces change?

4.1 Datasets Description

Two real-world datasets for social recommendation are used in our study: Epinions[1] and Douban[2] datasets. Epinions.com is a consumer opinion site where users can review items (e.g., movies, books and cars) and also assign them numeric ratings ranging from 1 to 5.We choose Epinions as our experiment data because its site users can delimit their Web of Trust. Douban is a well-known Chinese online community providing user rating, review, and recommendation services for movies, music and books. Also, it supplies Facebook-like social network services for users to find their friends they actually know in reality through searching for emails and nick names.

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

Table 2: Statistics of User-Item Matrix

	Statistics	User	Item
Epinions	Avg. Num. of Ratings	37.08	3.34
Douban	Avg. Num. of Ratings	125.26	83.59

Table 3: Statistics of Trust Network of Epinions

Statistics	Trust per User	Be Trusted per User
Max. Num.	1385	1703
Avg. Num	27.66	27.66

Epinions dataset used in this experiment consists of 10,000 unique users randomly selected from the dataset in[8]. The users totally rated 139,738 different items at least once. The density of the user-item rating matrix is less than 0.0334%, as well as 294,956 issued trust statements with density of 0.2903%. As shown in Table 2, the average number of ratings per user is 37.08 and per item received is 3.34. The trust network of Epinions is an unidirectional graph. Statistics in Table 3 show that the maximum number of trust per user is 1385 and be trusted is 1703, both are averaged 27.66.

Douban dataset employed in our experiment consists of 20,000 unique users randomly selected from the dataset in[4]. The users totally rated 58,541 unique movie items. The density of the user-item rating matrix used in our experiment is about 0.4179%. The average number of ratings is 125.26 rated by a user and 83.59 received by a movie. As to the social trust network, the total number of trust links between users is 45,880 with density 0.0115%. It is a bidiagraph that the maximum number of trust links per user is 147, and 2.29 on average, as reported in Table 4.

4.2 Experimental Settings

We use different training data settings (70%, 80% and 90%) to evaluate the performance of all considered rivals as well as our approach. Training data 70%, for example, means we randomly select 70% of the ratings from user-item rating matrix as the training data to predict the marked off 30% of ratings. The random selection was performed five times independently. The parameters in our model are meaningful and necessary but not difficult to set. We tune the parameters of our *SRFRM* and all baseline algorithms to reach their best performance. In all the experiments conducted in this paper, the value of λ_U, λ_V, λ_Z, λ_W and $\lambda_{\widetilde{W}}$ are set to a trivial value 0.01. In Table 1 and 2, dimensionality of *PMF* and *SoRec* are set to 30 and *SoReg* set to 10. The trade-off parameter α of our approach is set to 1 on Epinions dataset and 10 on Douban dataset. In order to get the best performance of our method, we use grid search to find the appropriate latent factor number of our approach. We will give very detailed analysis of the impacts of these parameters in Section 4.4 and 4.5.

Comparison Methods. In order to demonstrate the improvement of our approach, we implement the following baselines as comparison rivals with our model.

- **PMF:** This method[11] makes recommendation only uses the user-item rating data.
- **SoRec:** This method[3] jointly analyzes user-item rating data and users' social trust data by extracting a common shared latent factor, using *Probabilistic Matrix Factorization.*
- **SoReg:** This method[4] is based on matrix factorization with social regularization to constraint user features in social recommendation. It also takes the similarity of interests of presenting users with the ones they trust into consideration.

Table 4: Statistics of Trust Network of Douban

Statistics	Trust per User
Max. Num.	147
Avg. Num	2.29

Prediction Error. To assess the performance of our proposed approach in comparison with its considered rivals, we use as our evaluation metrics the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE), which reads Eq. 11 and Eq. 12 respectively

$$MAE = \frac{1}{N}\sum_{i,j}|R_{i,j} - \hat{R}_{i,j}| \tag{11}$$

and

$$RMSE = \sqrt{\frac{1}{N}\sum_{i,j}(R_{i,j} - \hat{R}_{i,j})^2} \tag{12}$$

where $R_{i,j}$ denotes user i gave to item j, $\hat{R}_{i,j}$ denotes the rating user i gave to item j as predicted by our approach, and N denotes the number of tested ratings.

4.3 Recommendation Performance

We judge recommendation performance of the mentioned models and algorithms in performance on user behavior prediction.We list recommendation performance of different methods on the selected data sets in Table 5 and 6 respectively. Our approach show incredibly improvement compared with the rivals on Epinions and Douban datasets. From the results, we can observe our approach consistently outperforms the considered rivals on these two datasets in all settings. The MAE and RMSE values generated by all the approaches on Epinions dataset are higher than those on Douban dataset.

From the tables, we observe that on these two datasets, *SoRec* achieve better performance than *PMF* which demonstrates incorporating social network information can benefit recommender systems. Besides, *SoReg*, a state-of-the-art algorithm with social regularization, is better than *SoRec* because it utilizes all the social connections of each user. Moreover, our method averagely decrease the prediction error by 15.64% and 27.20% on MAE, by 20.71% and 25.23% on RMSE over *SoReg*, which proves the significant effectiveness of the fitness adaptation of user interests in social recommendation instead of making equal all dimensionality in different contexts.

4.4 Trade-off Parameter Analysis

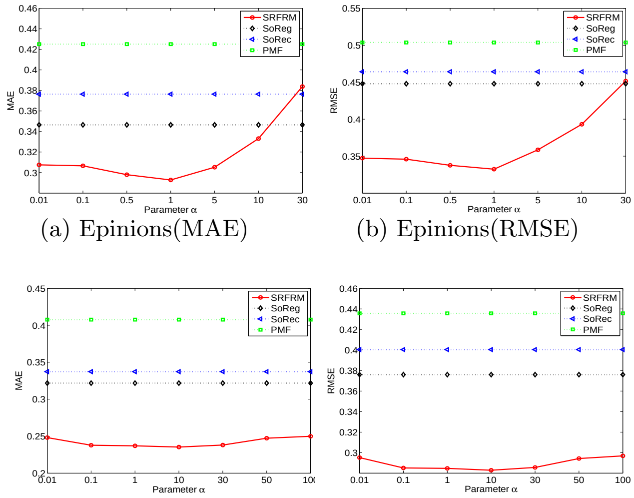
In our model, the trade-off parameter α plays a significant role that balances the information from the user-item rating matrix and the social trust network. In one extreme case, setting a very small value of α ignores the contribution of social trust relations and only model user interests by the

Table 5: Recommendation Performance Comparisons on Epinions data set

Training	Metrics	PMF	SoRec	SoReg	SRFRM
90%	MAE	0.4031	0.3586	0.3313	**0.2741**
	RMSE	0.4818	0.4451	0.4310	**0.3492**
80%	MAE	0.4107	0.3661	0.3361	**0.2860**
	RMSE	0.4896	0.4533	0.4370	**0.3578**
70%	MAE	0.4251	0.3764	0.3465	**0.2952**
	RMSE	0.5038	0.4642	0.4480	**0.3365**

Table 6: Recommendation Performance Comparisons on Douban data set

Training	Metrics	PMF	SoRec	SoReg	SRFRM
90%	MAE	0.4041	0.3365	0.3195	**0.2319**
	RMSE	0.4320	0.3997	0.3717	**0.2761**
80%	MAE	0.4053	0.3367	0.3205	**0.2330**
	RMSE	0.4332	0.3999	0.3719	**0.2781**
70%	MAE	0.4077	0.3373	0.3218	**0.2353**
	RMSE	0.4357	0.4004	0.3760	**0.2829**



(a) Epinions(MAE) (b) Epinions(RMSE)

(c) Douban(MAE) (d) Douban(RMSE)

Figure 3: Impact of Parameter α

user-item matrix. On the other hand, setting a large value will enhance the contribution of social trust relations and vise versa.

Figure 3 show how the changes of parameter α affects recommendation performance on MAE and RMSE. Here, we use 70% as training data and the other 30% as testing data. We observe that the value of α impacts the recommendation results significantly, which demonstrates that fusing the user-item rating matrix with the user social network greatly improves the recommendation accuracy. As α increases, the prediction accuracy also increases at first, but when α surpasses a certain threshold, the prediction accuracy decrease with further increase of the value of α. This phenomenon coincides with the intuition that purely using the user-item matrix or purely using the social trust matrix cannot generate better performance than fusing these two resources together.

In this experiment, we obtain the best performance of our approach when parameter α is set to 1 on Epinions dataset and is set to 10 on Douban dataset. These show the differences of sparsity disparity of social trust relations on these two datasets, which means if the social trust matrix is much sparser than the user-item matrix, the trade-off parameter α should be set larger to strengthen social trust contribution. We observe from the figures that the parameter α impacts the recommendation results significantly on Epinions dataset. On the contrary, recommendation performances is insensitive to α on Douban dataset. It is probably because the social links is far less than the ratings on Douban dataset while more on Epinions dataset. In addition, under the fine tunning dimensionality, our method can always get much better performances with different α settings. This is not difficult to understand since the impacts of social trust relations is much smaller than recommender systems (as discussed in Section 4.5) and finding a reasonable dimensionality of user interests is especially important to recommendation results.

4.5 Dimensionality Analysis

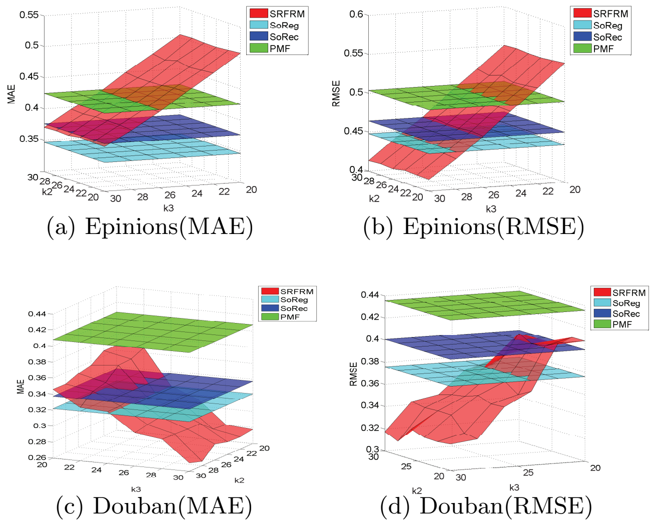
In this section, we discuss the influences of $k1$, $k2$ and $k3$. As previously described, $k1$ is the dimensionality of users latent features representing the number of interest factors of users, $k2$ is the dimensionality of item latent features describing the number of the profile factors of the items, and $k3$ is the dimensionality of trustees latent features expressing the number of the appeal factors of trustees. If these dimensionality are too small, the recommender system cannot make a distinction between any users or items. If they are too large, users and items will be too unique for the system to calculate their similarities and the complexity will considerably increase. Therefore, we conduct experiments with two of them ranging from 20 to 30 and the remaining one is fixed at 20 on both Epinions and Douban datasets. We use 70% as training data and the other 30% as testing data. In Figure 4, 5 and 6, dimensionality of baseline methods are setting to 30 and we show their best performances. Following, we will discuss their influences on three fronts.

Dimensionality impacts of the profile features of the items and the appeal features of trustees:

Figure 4 show performances of all methods with $k2$ and $k3$ changes while $k1$ set to 20. From the figures we can observe that on both datasets when $k1$ is fixed as a relatively low dimensionality, MAE and RMSE change little according to $k2$, while reduce gradually with the increasing of $k3$. This phenomenon illustrates that under this circumstances dimensionality of trustee appeal is to some extent has a little impact on recommender system side. It is expected that in Figure 4 (a), our approach cannot achieve a relatively good performance, because on the dataset with tiny sparse disparity between both sides like Epinions, users have fine-grained interests and dimensionality of user interests should be larger.

Dimensionality impacts of the interest features of users and the appeal features of trustees:

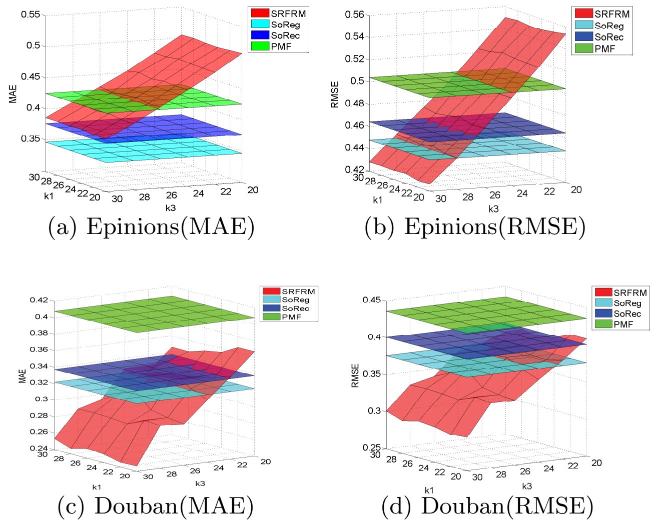
The performances of all methods are shown in Figure 5, where $k1$ and $k3$ changes while $k2$ is fixed at 20. From the figures we can observe that on both datasets when $k2$ is fixed at a low dimensionality, MAE and RMSE change little with the variantion of $k1$ at any constant value of $k3$, while



(a) Epinions(MAE) (b) Epinions(RMSE)

(c) Douban(MAE) (d) Douban(RMSE)

Figure 4: Performance variation with dimensionality of the interest features of users fixed at 20, while dimensionality of the profile features of items and the appeal features of trustees range from 20 to 30



(a) Epinions(MAE) (b) Epinions(RMSE)

(c) Douban(MAE) (d) Douban(RMSE)

Figure 5: Performance variation with dimensionality of the profile features of items fixed at 20, while dimensionality of the interest features of users and the appeal features of trustees range from 20 to 30

reduce gradually in the opposite case. However, in Figure 5 (a), performance of our approach are so weak that cannot be better than its comparison rivals *SoRec* and *SoReg* even when $k1$ is large, which illustrates the significant impacts of the dimensionality of the profile features of the items.

Dimensionality impacts of the interest features of users and the profile features of the items:

The variation trend of MAE and RMSE of all methods with $k3$ fixed at a relatively small value 20 are shown Figure 6. We can find that the accuracy of our approach improve fast as $k1$ and $k2$ are simultaneously increasing and are easy to get a commendable performances when $k1$ and $k2$ are set to large values, which reflects that user interests are more related to item profiles than social trust relations. And because of the larger variation of performances on Douban dataset which has far more ratings than social trust links, we can conclude that users have more extensive interests in movies than their trusts of online friends.

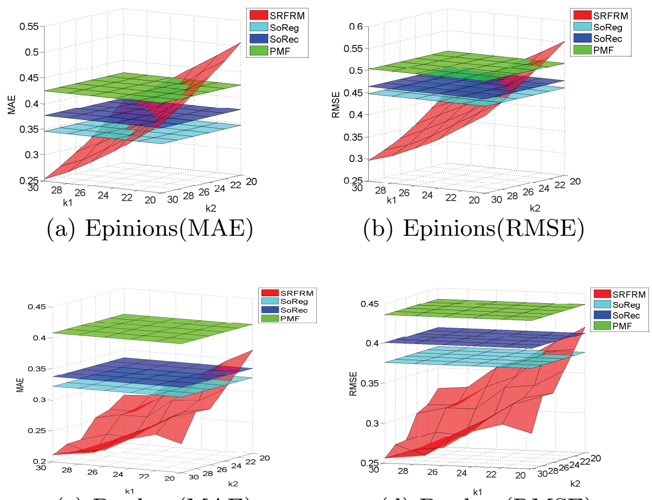
In general, comparing performance variation surfaces on these two datasets in all of the figures, we can find that the surfaces are less smooth and more gradient on Douban dataset than on Epinions dataset. It demonstrates that our approach is sensitive to dimensionality fluctuation on the dataset with large sparsity disparity between item side and social side. Also, it may be caused by that Douban dataset contains much more noise than Epinions used in our experiment. Moreover, it is easy to find from the figures that dimensionality of the profile features of items gives more impacts on recommendation performances rather than dimensionality of the interest features and that of the appeal features of trustees. The above explicit phenomenon reveal the fact that users have more extensive and fine-grained interests in rating behaviors in recommender systems than social trust networks on both dataset. That is, users should have different interests in different contexts.

5. RELATED WORKS

The recommender systems have already received quite a bit of attention, which mainly employ the techniques on collaborative filtering. Recently, several collaborative filtering methods based on matrix factorization [12, 13, 14, 15, 16] are proposed. Matrix factorization techniques has a nice probabilistic interpretation of Gaussian noise and is very flexible to allow us to include prior knowledge. These efforts [17, 18, 11] make the assumption that only a very small number of latent factors affect the user preferences in the user-item rating matrix, and a user's preference vector could be represented by a linear combination of these latent factors.

All of the above collaborative filtering approaches ignore the social trust relations between users, which is inconsistent with reality. Therefore, with the popularity of online social networks, many social trust-based recommendation approaches have been proposed to address this problem.

Trust-based methods [19, 20, 21, 22] exploiting the users trust network are proposed for improving recommendation accuracy. Massa et al. [23] propose a trust-aware collaborative filtering method for recommender systems. In this work, the collaborative filtering process is informed by the reputation of users which is computed by propagating trust. Bedi et al. in [24] propose a trust-based recommender system for the Semantic Web; this system runs on a server with the knowledge distributed over the network in the form of ontologies, and uses the Web of trust to generate the recommendations. However, in the above mentioned methods the relationship between the trust network and the user-item matrix have not been studied systematically. *SoRec* [3] is proposed as a probabilistic matrix factorization framework which jointly model users' tastes and their trustors' tastes in the social trust network. Due to the lack of physical explaination, this method does not reveal the underlying relations among the users. In [25], the authors interpret one user's final rating decision as the balance between this us-



(a) Epinions(MAE) (b) Epinions(RMSE)

(c) Douban(MAE) (d) Douban(RMSE)

Figure 6: Performance variation with dimensionality of the appeal features of trustees fixed at 20, while dimensionality of the interest features of users and the profile features of items range from 20 to 30

er's own taste and his/her trusted users' favors. Finally, an ensemble probabilistic matrix factorization method is presented to carefully consider tastes among users. Ma et al. [4] also propose a trust-based matrix factorization framework with social regularization, which assumes that users' tastes are similar to their friends.

There are also some works focus on the similarity measurement between users to make a good use of social trust network information. Yu et al. [26] start from feature similarity between trustor and trustee and propose a more practical similarity function distinct from the former efforts. In [27], this paper propose a method based on graph Laplacian to regularize the user-specific latent space and compare several relationship functions among the different users. In [9], homophily effect for trust prediction is exploited based on social correlation theories, where the user preferences of two socially connected users are correlated via a correlation matrix.

Nevertheless, dimensionality of the user interest features in social recommendation cases are still not well studied. In this paper, we take the problem of users interests imbalance in recommender systems side and in social trust networks side into consideration, which is the major difference between our work and the formers.

6. CONCLUSION

In this paper, we study the problem of user interests imbalance in social recommendation. We first expound the latent feature dimensionality imbalance of user interests between social trust relations and recommender systems. Then a model based on probabilistic matrix factorization, *SRFRM*, is proposed to utilize social trust relations to improve collaborative prediction performance. *SRFRM* can adjust the appropriate latent dimensions of user interests and estimate the most appropriate feature dimensionality of items. Experiments on two real-world datasets show that *SRFRM* effectively improves performance of the accuracy of item recommendation. The experimental results also validate the conjecture of different user interest spaces in recommender system context and social trust network context.

In future, we intend to apply nonlinear kernel methods and Bayesian nonparametrics to select the latent factor numbers automatically.

7. ACKNOWLEDGMENTS

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