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RESEARCH ARTICLE - COMPUTER ENGINEERING AND COMPUTER SCIENCE

Incorporating Social Network and User's Preference in Matrix Factorization for Recommendation

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Abstract

Recommender systems have been comprehensively applied in many industries, such as social Web sites, e-commerce, tourism service and so on, although suffering from the data sparsity and cold start problems. Currently, due to the advantage of online social networking, many social network-based recommendation scenarios have been developed to improve the recommendation accuracy, via exploring hidden social relations between users from the social network. In this article, focusing on addressing these problems, a novel social network and preference-based recommendation method—SRMP, is proposed, which incorporates the social network information and user's preference in matrix factorization for recommendation. In contrast to previous approaches, to improve the recommendation accuracy, SRMP performs recommendation in each independent sub-community, which is derived from the initial social community according to different category tags. The experimental analysis on large real-world datasets demonstrates that the proposed method SRMP outperforms state-of-the-art approaches, especially in recommendation accuracy and solving the cold start problem.

Keywords Matrix factorization · Social network · Preference · Recommender systems

1 Introduction

The ever-growing scale of network greatly increases user's interests on the Internet, meanwhile bringing varieties of social networks, such as Twitter, Yelp and so on. However, the serious problem of how to alleviate the information overload and find the most useful information from vast amounts of data accurately have confused users for a long time [1]. In recent years, recommender systems (RS) have been ubiquitously applied in many industries [2], to provide users with recommendation that they may be interested in. Moreover, RS can help to predict user's personalized preference and habit, such as user's purchasing habit, preferred pop music and so on, via taking into account the past behavior records, assigned ratings and social relations. Currently, the great success of many popular online social Web sites, such as Twitter and Douban, is to design the efficient and effective recommendation engines, which can provide recommendation information to users accurately and timely.

Overall, RS include content-based (CB) RS [3], collaborative filtering (CF) RS [4–7], and hybrid models [8]. In general, CB recommendation systems just simply try to recommend the similar and related items to the given user, without considering other factors. In contrast to CB, CF recommender methods generally consider the historical user-item rating matrix and other available information for rating prediction and provide personalized recommendation for users. Moreover, CF generally includes model-based CF and memory-based CF. In practice, matrix factorization (MF) technique is always employed as the basic tool for CF recommender systems. Obviously, as the mixed integration of CB model and CF model, the hybrid recommender systems can improve the recommendation accuracy significantly, which is also introduced as the basis for other advanced RS and ubiquitously applied in academia and industry areas.

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Previous collaborative filtering (CF) recommendation approaches generally perform recommendation via considering user's historical behavior and utilizing user-item rating matrix for rating prediction, also including user's preference exploring [3,9,10]. In some extent, recommendations provided by these approaches are very effective and accurate, while there are enough numerical ratings assigned by users, for example, probabilistic matrix factorization (PMF) [11] is able to scale linearly with the number of observations and provides accurate recommendation on the Netflix. However, these CF recommendation methods rarely consider the social relations between users, which can make great contributions to the recommendation results.

In recent years, social network-based recommender systems have become increasingly important and widely applied in many industries, taking into account numerical ratings, social relations between users and other available information [12–17]. Social network-based RS can perform well on the dataset, which is extremely sparse and unbalanced; moreover, they can also solve the cold start problem. According to the existing literatures, social network-based methods can indeed improve recommendation accuracy [18,19]. In real world, it is also interpretable that social network-based recommender systems can improve the recommendation accuracy, for example, if Alice and Bob are trust friends, Alice will be much more likely to adopt the recommendation from Bob, which means that the recommendation will be much more credible from trust friends than that from others. This is also the motivation for exploring information in social network between users to improve the recommendation accuracy [20]. On the other hand, exploring user's preference from the historical records can also help to improve the recommendation accuracy [9,17,21]; however, these recommender approaches conduct recommendation only considering some aspects and ignoring other available information.

To tackle these challenges mentioned above, in this article, a hybrid recommendation system—SRMP, is proposed, which combines social network and user's preference together for recommendation. SRMP tries to explore the hidden social information from the social network between users and incorporates user's preference for recommendation. Moreover, the proposed SRMP will divide the original social community into independent sub-communities according to different item category tags and user's past behavior records, that is to say, each inferred sub-community will be associated with one corresponding item category, for example, movies and pop music will belong to different inferred sub-communities. After that, recommendation will be performed in each generated sub-community, respectively. Experimental analysis on public available datasets demonstrate that the proposed model SRMP outperforms other compared algorithms.

The contributions of this article are as follows:

– A general recommendation model SRMP is proposed, which deeply explores the social relationship through user's social network and historical behavior records and then incorporates it and user's preference for recommendation in each generated sub-community, respectively.
– Experimental analysis shows that SRMP can achieve better recommendation accuracy than state-of-the-art methods.
– Through the social network, SRMP outperforms other recommendation approaches in solving the cold start problem.

The remainder of this paper is organized as follows: Sect. 2 will review some related work about recommender systems. Section 3 will introduce the problem definition and preliminaries in this paper. Section 4 will present the proposed recommender model SRMP. The experimental results are presented in Sect. 5. The conclusion and future work are presented in Sect. 6.

2 Related Work

According to the existing literatures, there are many recommender approaches that focus on exploring the social relationship for improving recommendation accuracy [22,23], and matrix factorization (MF) method is widely applied as the basis for these algorithms [18,24,25]. This section will review several social network-based recommendation algorithms, which can perform effectively and efficiently on real-world datasets and provide accurate recommendation for queries.

Probabilistic Matrix Factorization In [4], Koren et al. introduce matrix factorization (MF) for recommendation. In [11], the authors introduce probabilistic matrix factorization (PMF) in recommender systems, which performs well on large dataset. Currently, recommendation systems (RS) generally suppose the users and items are independently and identically distributed, and employ matrix factorization technique as the tool to learn the low-rank feature vectors for users and items [11,26,27]. Actually, this is also the basis for most of the social network-based recommendation algorithms [28,29]. Yang et al. propose to construct a Bayesian network to infer the predicted ratings [27] and develop distributed protocols in online social networks; however, this method just considers the probability distributions of rating similarity between users and ignores the social relations. In [21,30,31], matrix factorization technique is also employed for feature vector learning for recommendation.

Social Network-Based Recommendation Social recommendation methods improve recommendation accuracy from different aspects [18,19,32–34], such as user's trust relations [35]. Forsati et al. design a matrix factorization-based method for recommendation [8], which incorporates both trust and distrust relationships to improve the recommendation accuracy. In addition, positive and negative links between users can be predicted through the existing social network [12, 20]. Social network-based recommendation approaches can enhance the recommendation performance, not only due to the trust relations between users, but also the trust propagation. In [32], Ma et al. propose a social recommendation algorithm, which considers the propagation of tastes in the social network even though the users are not friends. The experimental analysis demonstrates that this method outperforms other methods in recommendation accuracy. Massa et al. replace the similarity finding process with the trust metric [24], which is able to propagate trust relation in the social network and estimate a trust weight. The experiments on a large real dataset show that this method can increase the coverage while not reducing the accuracy. The socialMF has been proposed in [18], which considers the social trust relations and trust propagation in the social network for recommendation. This approach can address the transitivity of trust relations through the social network; furthermore, it can also solve the cold start problem well. On the other hand, circle-based recommendation proposed in [36] assumes that users' social connections are mixed together, and three circle-based algorithms are developed for recommendation, the basic idea of which is that users only concern certain item categories but not all. Moreover, in contrast to other recommendation methods, these circle-based methods perform recommendation in each inferred circle, respectively. In [37], Qian et al. propose a social recommendation algorithm, which fuses personal interest, interpersonal interest similarity and interpersonal influence together. Moreover, this recommender method infers interest circles to explore the hidden information of user's social network, which can improve the recommendation accuracy.

Preference Exploring Obviously, recommendation according to user's interests and preference can indeed improve the performance of RS [9,21,37–39] and many previous researches try to address this issue. In general, user's preference exploring can be learned via statistic and probabilistic inference, according to the historical records. In [37], Qian et al. explore user's interests and preference via the naive statistic of behavior records. In [9], Liu et al. employ the probabilistic topic model–Latent Dirichlet Allocation (LDA) [40] for latent interests exploring. Analogously, Ren et al. regard that textual reviews can reflect user's interests and preference and perform preference exploring via LDA. Experimental analysis over real-world datasets shows that preference exploring can help to improve the recommendation accuracy significantly.

Table 1 Parameters and meanings

Parameter	Meaning
$\mathbb{U} = \{u_1, \ldots, u_N\}$	The set of users
$\mathbb{I} = \{i_1, \ldots, i_M\}$	The set of items
d	Dimension for latent feature vector
R_{ui}	The observed ratings assigned by user u on item i
$\widehat{R}_{ui}$	The predicted ratings
$U \in \mathbb{R}^{d\times N}$	Latent feature vector for users
$V \in \mathbb{R}^{d\times M}$	Latent feature vector for items
$\mathcal{S}$	Original social network
$\mathcal{S}^{c1}, \ldots, \mathcal{S}^{ck}$	Generated sub-communities
$\mathcal{S}_{uv}$	User u's social relationship toward user v
Φ_u	The set of items user u have assigned ratings
$\mathcal{T}_{uv}$	User u trusts user v
$\mathcal{E}_u$	User u's expertise level value
$\mathcal{P}_u$	User u's preference

3 Problem Definition and Preliminaries

Traditional recommendation systems generally employ the basic matrix factorization (MF) approach for recommendation due to its effective and efficient performance. In this section, probabilistic matrix factorization(PMF) will be reviewed as the basis for SRMP.

Let $\mathbb{U} = \{u_1, \ldots, u_N\}$ denote the set of users, $\mathbb{I} = \{i_1, \ldots, i_M\}$ denote the set of items, and rating matrix $\mathbb{R} = \{R_{ui}\}_{N\times M}$ denote the rating values user u has assigned on item i, and R_{ui} are often integers ranging from 1 to 5. Without loss of generality, the numerical rating values can be normalized to [0, 1]. Furthermore, $U \in \mathbb{R}^{d\times N}$ and $V \in \mathbb{R}^{d\times M}$ are introduced to denote the latent low-rank feature vectors for users and items, respectively. After trained in the user-item rating matrix using matrix factorization (MF) technique, the predicted rating $\widehat{R}_{ui}$ for user u over item i can be obtained via: $\widehat{R}_{ui} = U^T V$. The key parameters referred in this article are list in Table 1.

Just like the approaches in [11,26–28,41,42], here, suppose that the users and items are independently and identically distributed, and, place zero mean Gaussian priors on U and V:

$$
\begin{aligned}
p(U|\sigma_U) &= \prod_{u=1}^{N} \mathcal{N}(U_u|0, \sigma_U^2 I),\\
p(V|\sigma_V) &= \prod_{i=1}^{M} \mathcal{N}(V_i|0, \sigma_V^2 I).
\end{aligned}
\tag{1}
$$

Note that here $\mathcal{N}(x|\mu, \sigma^2)$ denotes the Gaussian distribution, with mean μ and variance σ^2 (Here, $\mu = 0$), and indicator function $I_{ui} = 1$ if user u has assigned rating on item i, and $I_{ui} = 0$ otherwise. Accordingly, the conditional distribution over the observed ratings $R \in \mathbb{R}^{N \times M}$ can be computed as follows:

$$\begin{aligned} & p(R_{ui} - U_u^T V_i | 0, \sigma^2) \\ & \quad = P(R|U, V, \sigma^2) \\ & \quad = \prod_{u=1}^{N} \prod_{i=1}^{M} \mathcal{N}(R_{ui} | U_u^T V_i, \sigma^2)]^{I_{ui}} . \end{aligned} \tag{2}$$

Accordingly, through Bayesian inference, the posterior probability of U and V over the latent feature vectors for users and items can be obtained as follows:

$$\begin{aligned} & p(U, V | R, \sigma^2, \sigma_U^2, \sigma_V^2) \\ & \quad = p(R|U, V, \sigma^2) P(U|\sigma_U^2) P(V|\sigma_V^2) \\ & \quad = \prod_{u=1}^{N} \prod_{i=1}^{M} [\mathcal{N}(R_{ui} | U_u^T V_i, \sigma^2)]^{I_{ui}} \\ & \quad \times \prod_{u=1}^{N} \mathcal{N}(U_U | 0, \sigma_U^2 I) \\ & \quad \times \prod_{i=1}^{M} \mathcal{N}(V_i | 0, \sigma_V^2 I). \end{aligned} \tag{3}$$

After that, the latent feature vectors for U and V can be learned through the following objective function $\mathcal{L}$:

$$\begin{aligned} \mathcal{L} = & \frac{1}{2} \sum_{u=1}^{N} \sum_{i=1}^{M} I_{ui} (R_{ui} - g(U_u^T V_i))^2 \\ & + \frac{\lambda_U}{2} \|U\|_F^2 + \frac{\lambda_V}{2} \|V\|_F^2 , \end{aligned} \tag{4}$$

where the logistic function $g(x) = 1/(1 + e^{-x})$, $\lambda_U = \sigma^2/\sigma_U^2, \lambda_V = \sigma^2/\sigma_V^2$, and $\|.\|_F^2$ denotes the Frobenius norm.

After that, local minimum of $\mathcal{L}$ can be obtained by performing stochastic gradient descent (SGD) over U and V. Consequently, the predicted ratings can be calculated through the product of U and V. The corresponding graphical model is presented in Fig. 1.

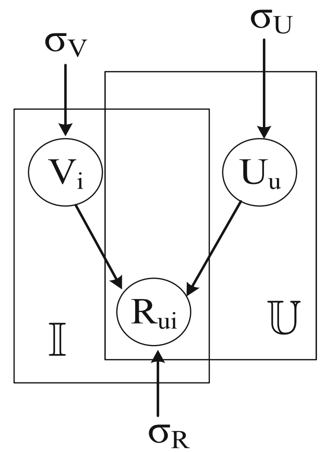


Fig. 1 Graphical illustration of PMF model

4 The Proposed Model

According to existing literatures, probabilistic matrix factorization (PMF) can be easily extended to improve recommendation performance with considering social network between users [33,43]. In this article, the proposed recommendation method SRMP firstly infers sub-communities according to different item category tags from the original social community, and then, incorporates social relations and user's preference for conducting recommendation over each independent sub-community. In this section, the proposed recommendation system SRMP will be presented in detail, including sub-community inference, user's preference exploring, the model training, and the complexity analysis.

4.1 Sub-community Generation

In real world, actually, users always prefer some special items according to their interests, such as classic movies, pop music and so on. On the other hand, they often consult their trust friends for recommendation before making decisions; consequently, their behaviors are often influenced by others' recommendation. Motivated by these, the proposed SRMP will explore user's preference and perform recommendation in each special sub-community, respectively, which is inferred from the original social community.

Sub-communities are inferred according to different item category tags, such as music, movie, book and so on. Suppose the original social network $\mathcal{S}$ as a complete social community; then, it can be divided into several sub-communities $\mathcal{S}^{c1}, \ldots, \mathcal{S}^{ck}$, according to different item categories, the basis of which is that user's interests and preferences in each sub-community are more or less similar to that of others'; consequently, recommendations will be much more accurate in such sub-community with relatively small scale. Let $\mathcal{T}_{uv}$ to denote that user u trusts user v; moreover, $\mathcal{T}_{uv} = 1$ if u trusts v and 0 otherwise. Note that the social network matrix $\mathcal{S}$ is asymmetric, which means that user u trusts v doesn't equal to that user v trusts u. Here, each generated sub-community contains only one corresponding item category, which can decrease the influence from other items during training phase and enhance the recommendation accuracy. Consequently, the social community and sub-community can be defined as follows:

Definition 1 *(Social Community)*. The given original social community $\mathcal{S}$ contains all users, items and social network: $\mathcal{S} = \{\mathcal{S}^{c1}, \ldots, \mathcal{S}^{ck}\}$, where k is the number of item categories.

Definition 2 *(Sub-Community)*. Sub-Communities are derived from the original social community. For any user $u \in \mathcal{S}^c$, if and only if the following conditions hold:

- $\mathcal{C}_{cat}$=1 ;
- $|\mathcal{O}_u| > 0$, and $\mathcal{T}_{uv} = 1$, where $v \in \mathcal{S}^c$;
- $|\Phi_u| \geq 0$,

where $\mathcal{C}_{cat}$ denotes the item category number in $\mathcal{S}^c$; $\mathcal{O}_u$ denotes the set of user u's friends; Φ_u denotes the set of items rated by user u in $\mathcal{S}^c$.

Note that if $|\mathcal{O}_u| > 0$ and $|\Phi_u| = 0$, that means user u is belong to the generated sub-community $\mathcal{S}^c$ but has assigned no rating; however, in this case, user u's personalized preference can be also inferred according to u's social trust relation in $\mathcal{S}^c$. Afterward, recommendation will be performed in each generated sub-community $\mathcal{S}^c$, respectively. Graphical illustration for a toy example of $\mathcal{S}^c$ is presented in Fig. 2.

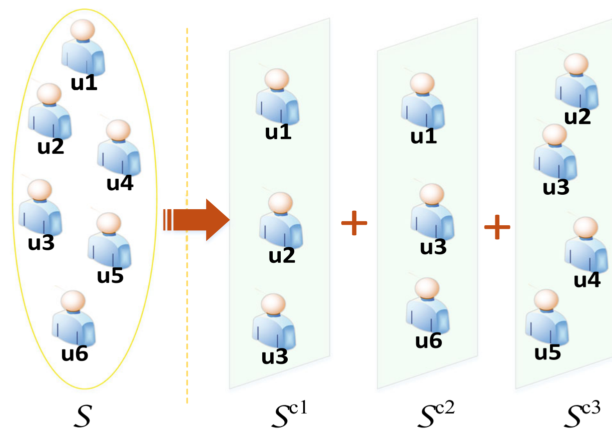
4.2 Social Relationship Value

In last section, the original social community is divided into several sub-communities according to different item categories. Actually, user's individual preference and historical behavior over items are different from each other. In this section, $\mathcal{E}_u$ is introduced to denote the expertise level value for user u in the generated sub-community $\mathcal{S}^c$; moreover, $\mathcal{E}_u$ is composed of two parts: the number of ratings user u assigned on items in the user-item rating matrix, and the number of trust friends in the sub-community $\mathcal{S}^c$. The formula of $\mathcal{E}_u$ is defined as the combination of two parts as follows:

$$\mathcal{E}_u = \varphi_1 \mathcal{E}_{u,R} + \varphi_2 \mathcal{E}_{u,\mathcal{T}}, \tag{5}$$

where $\mathcal{E}_{u,R}$ denotes the part from ratings, and $\mathcal{E}_{u,\mathcal{T}}$ denotes the part from social relations. Large value of $\mathcal{E}_u$ means that u has assigned much more ratings and owns much more trust friends in $\mathcal{S}^c$; consequently, other users in the community will be much more likely to trust u and adopt u's recommendation, and vice versa.

As mentioned before, the trust relationship is asymmetric in social community $\mathcal{S}^c$, that is to say, if user u trusts user v, here, it means that user v is a followee of user u, and $\mathcal{O}_u^-$ is employed to denote the set of u's followees in $\mathcal{S}^c$, such as v; Likewise, $\mathcal{O}_u^+$ is employed to denote the set of u's followers.



(a)

	i_1	i_2	i_3	i_4	i_5	i_6
u_1	4	5	2	5	3	1
u_2	5	?	4	?	5	?
u_3	5	3	?	5	?	1
u_4	2	5	3	5	2	?
u_5	?	4	?	3	?	5
u_6	5	?	2	?	3	1

(b)

Fig. 2 Graphical illustration for a toy example: **a** three generated sub-communities $\mathcal{S}^{c1}, \mathcal{S}^{c2}, \mathcal{S}^{c3}$ from the original social community $\mathcal{S}$. Each sub-community is associated with one item category; **b** the corresponding user-item rating records in community $\mathcal{S}$

Here, the union of $\mathcal{O}_u^+$ and $\mathcal{O}_u^-$ denotes the total trust relations in the generated sub-community $\mathcal{S}^c$, and $\mathcal{O}_u = \mathcal{O}_u^+ \cup \mathcal{O}_u^-$. Afterward, user u's expertise level value can be defined in $\mathcal{S}^c$ via $\mathcal{O}_u^+$ and $\mathcal{O}_u^-$ as follows:

$$\begin{aligned}\mathcal{E}_u &= \varphi_1 \mathcal{E}_{u,R} + \varphi_2 \left(\sum_{\mathcal{O}_u^+} \mathcal{E}_{u,\mathcal{T}} + \sum_{\mathcal{O}_u^-} \mathcal{E}_{u,\mathcal{T}} \right) \\ &= \varphi_1 \sum_{\mathcal{S}^c} |\Phi_u| / M + \varphi_2 \left(\sum_{v \in \mathcal{O}_u^+} |\mathcal{T}_{vu}| + \sum_{v \in \mathcal{O}_u^-} |\mathcal{T}_{uv}| \right) \Big/ N.\end{aligned} \tag{6}$$

The variable $\mathcal{E}_u \in [0, 1]$ indicates user u's expertise level in the generated sub-community $\mathcal{S}^c$. Here, $\mathcal{S}_{uv}^c$ is employed to denote user u's social relationship value toward user v in the community $\mathcal{S}^c$, which is defined as the product of user's trust relations $\mathcal{T}_{uv}$ and expertise level value $\mathcal{E}_v$ as follows:

$$\mathcal{S}_{uv}^c = \begin{cases} \mathcal{T}_{uv}\mathcal{E}_v, & \text{if } \mathcal{T}_{uv} = 1, \\ 0, & \text{otherwise.} \end{cases} \tag{7}$$

The generated interpersonal relationship matrix $\mathcal{S}^c_{uv}$ is also asymmetric obviously; moreover, $\mathcal{S}^c_{uv} \in [0, 1]$. If user u trusts user v, and v's expertise level value $\mathcal{E}_v$ is large, the social relationship value $\mathcal{S}^c_{uv}$ for user u toward user v will be large, and vice versa. Accordingly, the conditional distribution for each user through the social network can be obtained as follows:

$$p(U|\mathcal{S}^c, \sigma_{\mathcal{S}}) = \prod_{u=1}^{N} \mathcal{N}\left(U_u | \sum_{v \in \mathcal{O}_u} \mathcal{S}^c_{uv} U_u, \sigma^2_{\mathcal{S}} I\right). \tag{8}$$

4.3 User's Preference to Sub-community

Due to the inner individual interests and personality, user's preference to different sub-communities vary seriously. For example, Bob prefers music to movies, but Alice prefers movies to music. Here, to draw user's interests and preference distribution, $\mathcal{P}$ is employed to denote user's preference coefficient according to the historical behavior records, and $\mathcal{P}_u$ denotes user u's preference degree toward sub-community $\mathcal{S}^c$:

$$\mathcal{P}_u = \sum_{\mathcal{S}^c} \Phi_u \Big/ \sum_{\mathcal{S}} \Phi_u. \tag{9}$$

Large value of $\mathcal{P}_{uc}$ means that user u prefers to sub-community $\mathcal{S}^c$, and vice versa. Place zero mean Gaussian prior over it:

$$p(\mathcal{P}|\sigma_{\mathcal{P}}) = \prod_{u=1}^{N} \mathcal{N}(\mathcal{P}_u|0, \sigma^2_{\mathcal{P}} I). \tag{10}$$

Suppose each user's preference to the sub-communities are independently distributed; therefore, the conditional distribution for $\mathcal{P}$ can be obtained as follows:

$$p(\mathcal{P}|U, V, R) = \prod_{u=1}^{N} \prod_{i=1}^{M} [\mathcal{N}(\mathcal{P}_u U_u, \sigma^2_{\mathcal{P}})]^{I^R_{ui}}. \tag{11}$$

4.4 Model Training

As stated above, with considering the social network $\mathcal{S}^c$ and the preference $\mathcal{P}$, the posterior probability distribution of latent feature vectors for users and items can be obtained through Bayesian inference as follows:

$$\begin{aligned}
& p(U, V|R, \mathcal{S}^c, \mathcal{P}, \sigma^2_R, \sigma^2_{\mathcal{S}}, \sigma^2_{\mathcal{P}}, \sigma^2_U, \sigma^2_V) \\
& \quad \propto p(R|U, V, \sigma^2_R) p(U|\mathcal{S}^c, \sigma^2_{\mathcal{S}}) p(\mathcal{P}|R, U, V) \\
& \quad p(U|\sigma^2_U) p(\mathcal{P}|\sigma^2_{\mathcal{P}}) p(V|\sigma^2_V) \\
& \quad = \prod_{u=1}^{N} \prod_{i=1}^{M} [\mathcal{N}(R_{ui}|g(U_u^T V_i), \sigma^2_R)]^{I^R_{ui}} \\
& \quad \times \prod_{u=1}^{N} \mathcal{N}\left(U_u | \sum_{v \in \mathcal{O}_u} \mathcal{S}^c_{uv} U_u, \sigma^2_{\mathcal{S}} I\right) \\
& \quad \times \prod_{u=1}^{N} \mathcal{N}(U_u|0, \sigma^2_U I) \times \prod_{u=1}^{N} \mathcal{N}(|\mathcal{P}_u U_u, \sigma^2_{\mathcal{P}} I) \\
& \quad \times \prod_{u=1}^{N} \mathcal{N}(\mathcal{P}_u|0, \sigma^2_{\mathcal{P}} I) \times \prod_{v=1}^{M} \mathcal{N}(V_i|0, \sigma^2_V I),
\end{aligned} \tag{12}$$

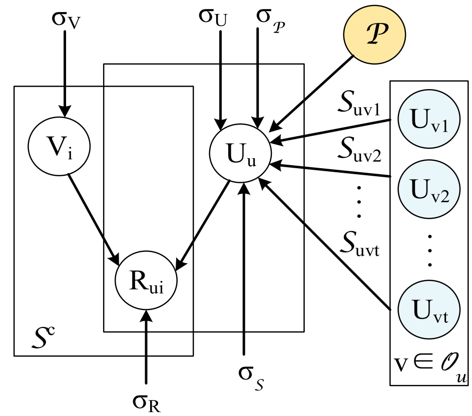


Fig. 3 Graphical illustration of the proposed model SRMP, which performs recommendation in each generated sub-community $\mathcal{S}^c$, with considering both the social relations and user's preference $\mathcal{P}$

In this recommendation model, the social network $\mathcal{S}^c$ and user's preference $\mathcal{P}$ are incorporated into matrix factorization systematically. The corresponding graphical illustration of SRMP is presented in Fig. 3. Consequently, the log-posterior distribution over U and V can be obtained as follows:

$$\begin{aligned}
& ln\, p(U, V|R, \mathcal{S}^c, \mathcal{P}, \sigma^2_R, \sigma^2_{\mathcal{S}}, \sigma^2_{\mathcal{P}}, \sigma^2_U, \sigma^2_V) \\
& = -\frac{1}{2\sigma^2_R} \sum_{u=1}^{N} \sum_{i=1}^{M} I^R_{ui} (R_{ui} - g(U_u^T V_i))^2 \\
& - \frac{1}{2\sigma^2_U} \sum_{u=1}^{N} U_u^T U_u - \frac{1}{2\sigma^2_V} \sum_{i=1}^{M} V_i^T V_i - \frac{1}{2\sigma^2_{\mathcal{P}}} \sum_{u=1}^{N} \mathcal{P}_u^T \mathcal{P}_u \\
& - \frac{1}{2\sigma^2_{\mathcal{S}}} \sum_{u=1}^{N} \left(\left(U_u - \sum_{v \in \mathcal{O}_u} \mathcal{S}^c_{uv} U_v \right)^T \left(U_u - \sum_{v \in \mathcal{O}_u} \mathcal{S}^c_{uv} U_v \right) \right) \\
& - \frac{1}{2\sigma^2_{\mathcal{P}}} \sum_{u=1}^{N} \mathcal{P}_u \left(R_{ui} - \sum_{i \in \Phi_u} U_u^T V_i \right)^T \left(R_{ui} - \sum_{i \in \Phi_u} U_u^T V_i \right) \\
& - \frac{1}{2} ln \sigma^2_R \sum_{u=1}^{N} \sum_{i=1}^{M} I^R_{ui} - \frac{1}{2}(N \times d) ln \sigma^2_U \\
& - \frac{1}{2}(M \times d) ln \sigma^2_V - \frac{1}{2}(N \times d) ln \sigma^2_{\mathcal{S}} \\
& - \frac{1}{2}(N \times d) ln \sigma^2_{\mathcal{P}} + \mathcal{M},
\end{aligned} \tag{13}$$

where $\mathcal{M}$ is constant. Note that the premise of SRMP is that user's interests and preference will remain unchanged over a short period of time. As stated above, the social network matrix $\mathcal{S}^c$ and user's preference $\mathcal{P}$ are incorporated into matrix factorization to learn latent feature vectors for users and items; moreover, SRMP will conduct recommendation in each inferred sub-community $\mathcal{S}^c$. Maximizing the log-posterior distribution in Eq. (13) is equivalent to minimizing the objective function as follows:

$$\begin{aligned}\mathcal{L}(U, V, R, \mathcal{S}^c, \mathcal{P}) &= \frac{1}{2}\sum_{u=1}^{N}\sum_{i=1}^{M} I_{ui}^{R}(R_{ui} - g(U_u^T V_i))^2 \\ &+ \frac{\alpha}{2}\left(\sum_{u=1}^{N} U_u^T U_u + \sum_{i=1}^{M} V_i^T V_i + \sum_{u=1}^{N} \mathcal{P}_u^T \mathcal{P}_u\right) \\ &+ \frac{\beta}{2}\sum_{u=1}^{N}\left(U_u - \sum_{v\in\mathcal{O}_u} \mathcal{S}_{uv}^c U_v\right)^T\left(U_u - \sum_{v\in\mathcal{O}_u} \mathcal{S}_{uv}^c U_v\right) \\ &+ \frac{\gamma}{2}\sum_{u=1}^{N} \mathcal{P}_u\left(R_{ui} - \sum_{i\in\Phi_u} U_u^T V_i\right)^T\left(R_{ui} - \sum_{i\in\Phi_u} U_u^T V_i\right). \end{aligned} \tag{14}$$

To obtain the local minimum of the objective function $\mathcal{L}$ in Eq. (14), here, stochastic gradient descent (SGD) is employed to learn variables U and V for users and items.

$$\begin{aligned} U_u \leftarrow U_u + \eta &\left(\left(\sum_{i=1}^{M} \nabla V_i - \alpha U_u\right.\right. \\ &- \frac{\beta}{2}\sum_{u=1}^{N}\left(U_u - 2\sum_{v\in\mathcal{O}_u} \mathcal{S}_{uv}^c U_v\right) \\ &\left.+ \frac{\gamma}{2}\sum_{u=1}^{N}\sum_{i=1}^{M} \mathcal{P}_u\left(\sum_{i=1}^{M} U_u^T V_i - U_u\right)^T V_i\right), \end{aligned} \tag{15}$$

$$\begin{aligned} V_i \leftarrow V_i + \eta &\left(\sum_{u=1}^{N} \nabla U_u - \alpha V_i\right. \\ &\left.+ 2\gamma \sum_{u=1}^{N}\sum_{i=1}^{M} \mathcal{P}_u U_u (U_u^T V_i - 1)\right), \end{aligned} \tag{16}$$

where η is learning rate, $\nabla = (g(U_u^T V_i) - R_{ui})g'(U_u^T V_i)$. During the training phase, initial values of U_u and V_i are samples from normal noises with zero mean. After the training phase, the predicted rating values $\widehat{R}_{ui}$ can be obtained via the product of U_u and V_i: $\widehat{R}_{ui} = U_u^T V_i$. Algorithm of SRMP is presented in Table 2.

4.5 Complexity Analysis

The training phase of SRMP will take most of the computation cost; therefore, the complexity analysis will focus on the training phase. Supposing that the average numbers of trust friends and ratings for each user are $\overline{s}$ and $\overline{r}$, respectively, the proposed recommendation system SRMP incorporates the social network $\mathcal{S}$ in matrix factorization for recommendation, moreover considering user's preference $\mathcal{P}$ in the social community; consequently, the computational complexity of SRMP is $O(N\overline{r}d + N\overline{s}d)$, which indicates that this recommender algorithm can scale linearly with the number of users.

Table 2 Algorithm of SRMP

Algorithm of SRMP
Input: R_{ui}, social network $\mathcal{S}$;
Output: U, V;
initialize latent vector U_u and V_i
Sub-community generation;
Preference exploring over each sub-community;
While(t<iteration account):
Update U(t) according to Eq. (15);
Update V(t) according to Eq. (16);
Return U(t), V(t);
Compute the predicted ratings via: $\widehat{R}_{ui} = U_u^T V_i$.

5 Experimental Analysis

In this section, we perform a series of experiments to evaluate the proposed recommendation approach SRMP on Epinions, Yelp and Douban Movie datasets, respectively, and compare it with other five existing recommendation approaches. Furthermore, we will discuss the impacts of dimension, epoch, social network and user's preference on the recommendation results, and the top-K performance of SRMP. At last, we will investigate the performance of SRMP on cold start users.

5.1 Datasets

Epinions[1] dataset [34] consists of 571, 235 numerical ratings assigned by 71, 002 users over 104, 356 items with 451 categories, such as cars, movies, book, software and so on. The total number of issued trust statements is 508, 960. In this article, top-8 item categories are selected for experiments, the statistic of which is presented in Table 3.

The Yelp and Douban Movie datasets used in experiments are public available online[2] [19]. Yelp is one of the most popular consumer review website and helps users find great local businesses like dentists, hair stylists and mechanics. In addition to reviews, Yelp users can also find events, assign ratings

[1] http://alchemy.cs.washington.edu/data/epinions/.

[2] https://smiles.xjtu.edu.cn/index.html.

Table 3 Statistic of Epinions dataset

Item category	Users	Items	Ratings	Avg. ratings	Density
Videos & DVDs (V&D)	17,312	10,065	94,261	3.964	5.41E−04
Books (Bo)	11,296	21662	47,889	3.618	1.96E−04
Music (Mu)	10,188	14,905	43,079	3.869	2.84E−04
Video games (VG)	9124	2389	29,661	3.904	1.36E−03
Toys (To)	6373	3344	26,789	4.013	1.26E−03
Software (So)	8290	1624	19,400	3.835	1.44E−03
Destinations (De)	7438	1475	19,395	3.934	1.77E−03
Cars (Ca)	10,847	3108	17,604	3.682	5.22E−04

Table 4 Statistic of Yelp dataset

Item category	Users	Items	Ratings	Avg. ratings	Density
Active life (AL)	5327	7459	24395	4.021	6.11E−04
Beauty & spas (B&S)	5466	8495	21345	3.937	4.60E−04
Home services (HS)	2500	3213	5180	3.707	6.45E−04
Hotel & travel (H&T)	4712	5883	21658	3.824	7.81E−04
Night life (NL)	4000	21,337	99,878	3.594	1.17E−03
Pets (Pe)	1624	1672	3093	3.975	1.14E−03
Restaurants (Re)	2000	32,725	91,946	3.677	1.41E−03
Shopping (Sh)	3000	16,154	33,352	3.819	6.88E−04

Table 5 Statistic of Douban Movie dataset

Item category	Users	Items	Ratings	Avg. ratings	Density
Douban Movie (DM)	2965	39695	912479	3.762	7.75E-03

and communicate with other Yelpers directly, consequently, Yelp creates a local online social community.

The Yelp dataset contains 10,555 users, who have assigned ratings on a total of 1,783,922 items, including 26 big categories from November 2012 to January 2013. Top 8 most popular item categories are selected for experiments, including Active Life, Beauty and Spas, Hotels and Travel, Home Services, Hotels and Travel, Night Life, Pets, Restaurants and Shopping. The statistic distribution for each category is presented in Table 4. Each item category is combined with an independent, corresponding social community, and experiments are performed in each community respectively.

Douban Movie provides users with the latest movie information. Users can assign ratings and reviews to the movies they have watched, and share it with their friends. The version of Douban Movie used in experiments consists of more than 912,479 ratings assigned by 2965 users on 39,695 movies, the detail of which is presented in Table 5. Douban Movie is considered as an independent social community. Figures 4 and 5 are long tail distribution of user popularity and item popularity over Douban Movie, respectively.

Tables 3, 4 and 5 show that these three datasets are rather sparse, and the average rating values assigned by users are around 4.

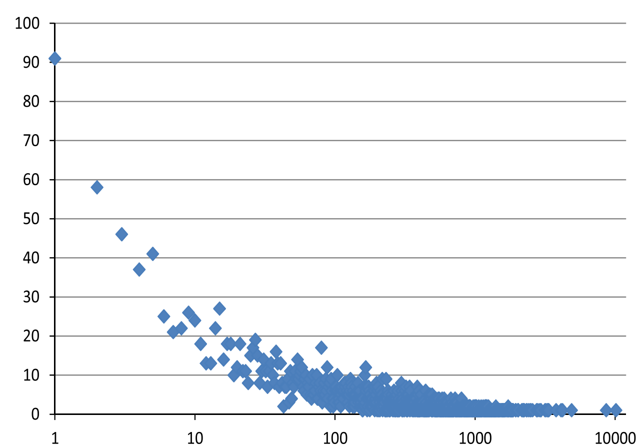


Fig. 4 Long tail distribution of user popularity on Douban Movie

5.2 Metrics

Mean absolute error (MAE), root mean squared error (RMSE) and top-K are employed for measuring the prediction accuracy of the proposed approach. MAE is a useful metric while evaluating prediction accuracy in offline tests, which is defined as:

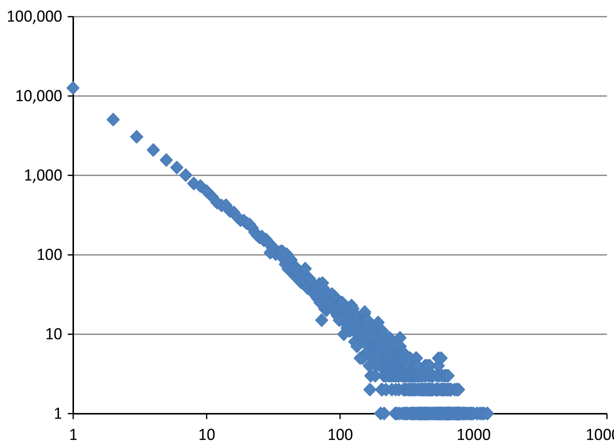


Fig. 5 Long tail distribution of item popularity on Douban Movie

$$\mathrm{MAE} = \frac{\sum_{u,i \in \mathcal{O}_{\text{test}}} \left| \widehat{R}_{ui} - R_{ui} \right|}{|\mathcal{O}_{\text{test}}|}, \tag{17}$$

where $\mathcal{O}_{\text{test}}$ denotes the set of ratings to be predicted, R_{ui} denotes the observed ratings, and $\widehat{R}_{ui}$ denotes the predicted ratings. The RMSE metric is defined as:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{u,i \in \mathcal{O}_{\text{test}}} (\widehat{R}_{ui} - R_{ui})^2}{|\mathcal{O}_{\text{test}}|}}. \tag{18}$$

Top-K can evaluate the precision of the recommendation results, and top-K is defined as the average hit-rate [44]:

$$\mathrm{top} - K = \frac{\#\mathrm{hits}}{K \cdot |\mathbb{U}_{\text{test}}|}, \tag{19}$$

where #hits denotes the total number of successful recommendation items.

5.3 Benchmark Methods

To evaluate the performance of SRMP, five recommender models are introduced for comparison:

BaseMF This method supposes that users and items are independently distributed, and utilizes the basic matrix factorization method called singular value decomposition (SVD) for recommendation [6].

PMF This approach is proposed in [11], which utilizes probabilistic matrix factorization model for recommendation. PMF just considers the user-item rating matrix for rating prediction, without the social relationship between users.

SocialMF This method is proposed in [18], which considers the social relations between users and incorporates the mechanism of trust propagation into the model for recommendation.

MFC This recommendation method is proposed in [33], which incorporates overlapping community-based regularization term into matrix factorization for recommendation.

SRM While SRMP just considers user's social network for recommendation, the method is named SRM. SRM is similar to the method CircleCon in [36], which also consider the social network for recommendation.

SRMP The proposed SRMP not only incorporates the social network between users into matrix factorization, but also considers user's preference; moreover, to improve the performance, SRMP performs recommendation in each inferred sub-community.

5.4 Performance Analysis

In this section, to evaluate the effectiveness and practicability of the proposed recommender method SRMP, experiments are performed over Epinions, Yelp and Douban Movie, and compare the performance with other algorithms. All experiments are conducted on PC with 3.33 GHz CPU and 32 G RAM. Moreover, 80% of each data will be used as training set and the remaining 20% data as the test set.

5.4.1 Performance on Epinions and Yelp

In Epinions and Yelp dataset, each sub-community is derived from the initial dataset and associated with a corresponding item category. To evaluate performance of SRMP, experiments are conducted in initial social community and each inferred sub-community, respectively, and then compare the experimental results. In experiments, the parameter $\beta = 3$ for Epinions, and $\beta = 4$ for Yelp, $\gamma = 15$ for Epinions, $\gamma = 20$ for Yelp, and the dimension of latent feature vectors for users and items is set to $d = 10$ [18].

Figures 6 and 7 show the experimental results on Epinions and Yelp datasets using the proposed recommendation method SRMP and other five approaches. The former 8 experimental results are obtained from each sub-community, and the last one is through experiments with all item categories of the dataset. The experimental results indicate that:

– While training in each sub-community, the proposed algorithm SRMP achieves much smaller RMSE and MAE values compared with BaseMF, PMF, SocialMF, MFC and SRM, which demonstrates that SRMP can indeed improve recommendation accuracy, due to not only considering social network and user's preference, but also performing recommendation in sub-community.
– In Yelp and Epinions datasets, the average RMSE and MAE values obtained through experiments performed in the sub-communities are a little smaller than that through experiments with all item categories, which demonstrates that recommendation conducted in the generated sub-

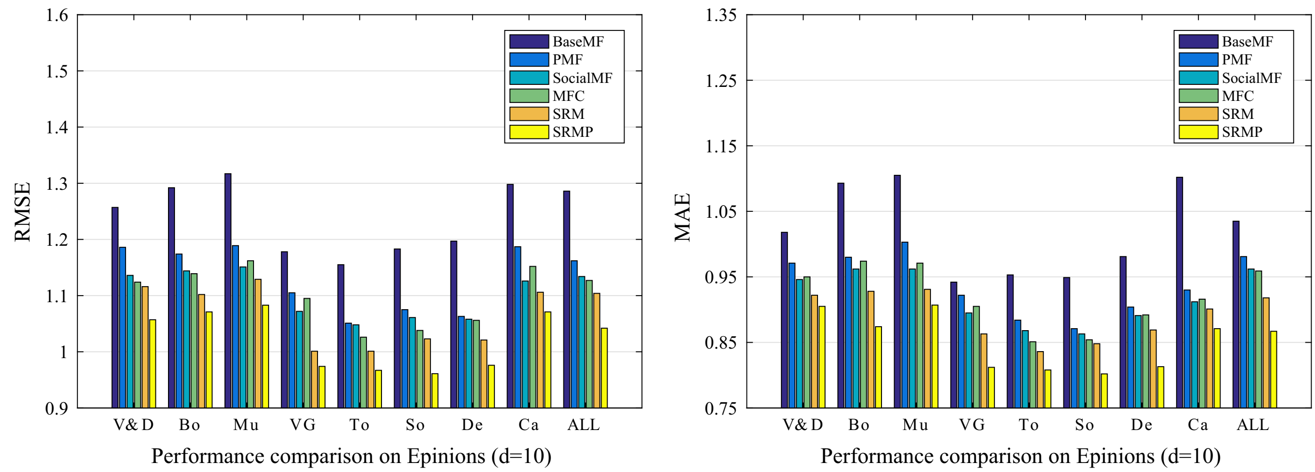


Fig. 6 Performance analysis of RSME and MAE on Epinions dataset. The former 8 results are obtained through experiments performed in each corresponding sub-community, which is derived from the initial social community. The term ALL means that the recommendation results through experiments with all item categories ($d = 10$)

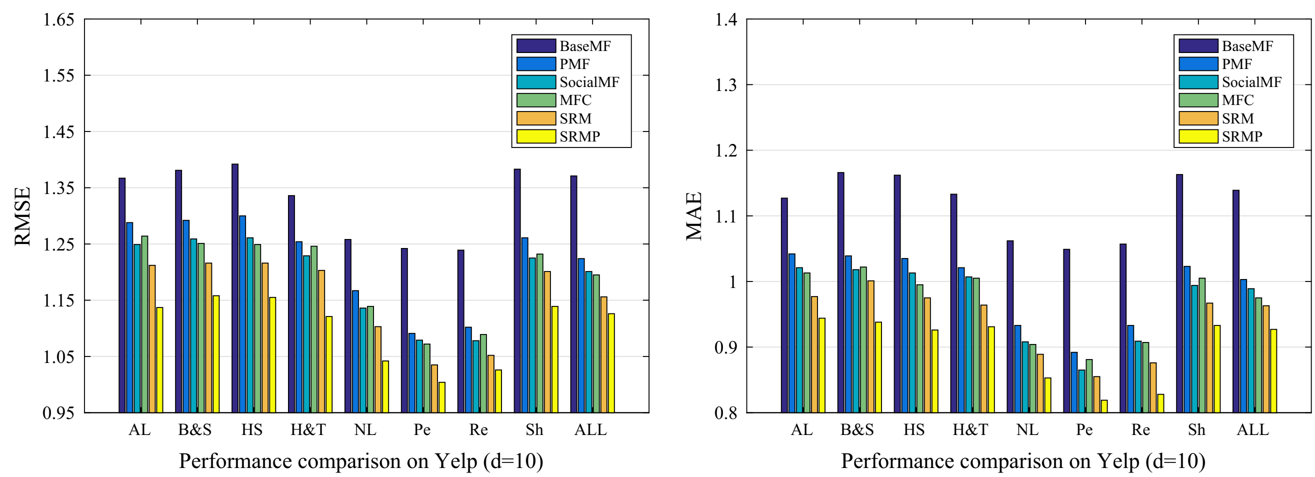


Fig. 7 Performance analysis of RSME and MAE on Yelp dataset. The former 8 results are obtained through experiments performed in each corresponding sub-community, which is derived from the initial social community. The term ALL means that the recommendation results through experiments with all item categories ($d = 10$)

community can improve prediction accuracy, although the RMSE and MAE values obtained over Mu, Ca, HS and Sh are slightly larger than that through experiments with all item categories.

– While training with all item categories, SRMP can also achieve better performance than other methods in terms of RMSE and MAE.

Figure 6 shows that BaseMF obtains a little larger RMSE and MAE values than other methods, since it performs prediction via just considering the numerical ratings. PMF doesn't consider user social network, as a result, it gets a little larger RMSE and MAE values than SocialMF, MFC and SRM, all of which consider the social network while learning latent feature vectors for users and items. Obviously, the proposed SRMP achieves the best performance compared with other five methods. Over sub-community So, the best values for RMSE and MAE for SRMP are 0.961 and 0.802, respectively, the improvement of which is more than 6% compared to other methods. On the other hand, the RMSE and MAE values on V&D, Bo, Mu and Ca are relatively a little larger than that on other four sub-communities, since the former are much more sparse.

In Fig. 7, for each sub-community of Yelp dataset, the results are similar to that of Epinions. The obtained best values for RMSE and MAE are 1.004 and 0.819, respectively, for SRMP over Pe, the improvement of which is more than 5% in contrast to other methods. The RMSE and MAE values

Table 6 Performance comparison on Douban Movie in RMSE and MAE ($d = 10$). The results for SRM and SRMP are in bold

Dataset	BaseMF		PMF		SocialMF		MFC		**SRM**		**SRMP**	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
Douban Movie	1.174 14.31%	0.967 14.78%	1.128 10.81%	0.905 8.95%	1.107 9.12%	0.896 8.03%	1.092 7.87%	0.876 5.93%	**1.072**	**0.854**	**1.006**	**0.824**

on AL, B&S, HS, H&T and Sh are a little larger than that on NL, Pe and Re, due to the different data sparsity. Moreover, The RMSE and MAE values on Epinions are relatively a little smaller than that on Yelp, since Epinions contains much more users, movie categories and ratings assigned by users; consequently, the recommendation results over it will be much more accurate. Both of Figs. 6 and 7 can demonstrate the advantage of SRMP while performing recommendation.

5.4.2 Performance on Douban Movie

Douban Movie is considered as an independent social community while performing recommendation. Parameter $\beta = 4, \gamma = 20$. The performance comparison of SRMP with other five recommendation methods is presented in Table 6, which shows that the proposed SRMP obtains the best prediction results: RMSE = 1.006, MAE = 0.824.

From the experimental analysis on these three datasets, we can conclude that SRMP can improve prediction accuracy by at least 5% than the compared methods, and even by more than 10% in contrast to BaseMF, which demonstrates that the proposed method SRMP can indeed improve the recommendation accuracy, via considering the social network and user's preference in each independent social community.

5.5 Discussion

5.5.1 Dimension and Epoch

To investigate the impacts of the dimension d and training epochs on the prediction results, experiments are performed on V&D, Mu, B&S, NL and DM using SRMP, respectively. Figure 8 indicates that the RMSE and MAE values decrease drastically while the value of dimension is below 10; however, while the value of dimension is bigger than 10, the RMSE and MAE values fluctuate very little; on the other hand, the time consumption increases exponentially. Curves for RMSE and MAE on these three datasets share the similar trend, respectively. Obviously, $d = 10$ can be chosen as the optimal value.

In Fig. 9, curves for RMSE and MAE share the similar trends on these datasets. The optimal value for epoch is around 20. While the value of epoch increases bigger than 20, the prediction accuracy begins to decrease slowly, which results in overfitting.

5.5.2 Social Network and Preference

Parameters β and γ denote the influence of social network and user's preference on the prediction results, respectively. In this section, in order to find the optimal values for β and γ on Epinions, Yelp and Douban Movie, experiments are conducted on VG, Ca, HS, Sh and DM datasets in detail, using the proposed SRMP. Parameter β indicates the influence of user's social relationship while learning latent feature vectors for users and items, and parameter γ denotes user's personal preference to the social community. Small values denote the slight influence; however, large values will result in overfitting and inaccurate prediction.

In Fig. 10, the sub-communities VG and Ca are derived from Epinions, and red curves for the social network influence in terms of RMSE and MAE over VG and Ca share the similar trend: The optimal value for parameter β is around 3; meanwhile, the social network influence on HS and Sh share the similar trends, which are denoted by blue curves: The optimal value for parameter β on Yelp is around 4; analogously, the optimal value for parameter β on Douban Movie is around 4. Figure 11 indicates that the optimal values for γ are around 20 over Epinions, and 30 over Yelp and Douban Movie. If parameter γ is set to 0, the model is called SRM; If $\beta = 0$ and $\gamma = 0$, this model just equals to PMF; if parameters β and γ are bigger than the optimal values, it will cause overfitting. On the other hand, the experimental analysis demonstrates that the similar inner-structure of social relations exists in the different social communities, which is also the motivation for the proposed recommendation method SRMP.

5.5.3 top-K Performance

With the obtained optimal value for each parameter, in this section, top-K performance of SRMP is investigated over Douban Movie. Here, values chosen for K are {5, 10, 20, 30}. Figure 12 shows that the proposed method SRMP can achieve much more accurate recommendation results than other methods, which demonstrates the advantage of SRMP.

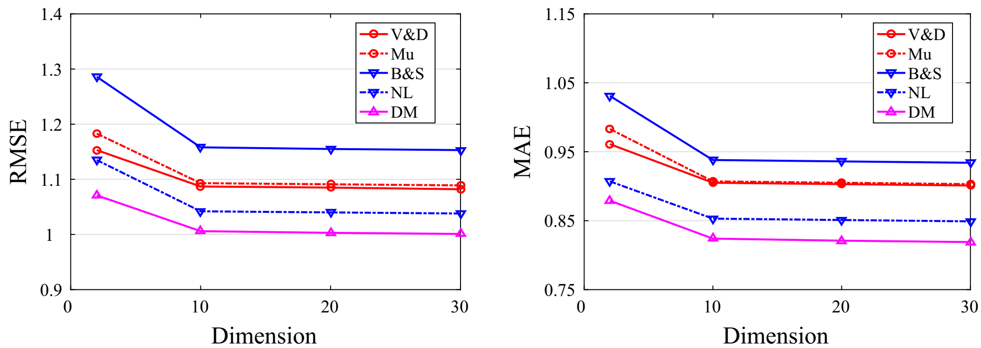


Fig. 8 Performance analysis of dimension over Epinions, Yelp and Douban Movie for SRMP. Left panel: the impact of dimension in terms of RMSE; right panel: the impact of dimension in terms of MAE. Curves of RMSE and MAE on sub-communities V&D, Mu, B&S, NL and DM share the similar trends. The optimal value for dimension is around 10

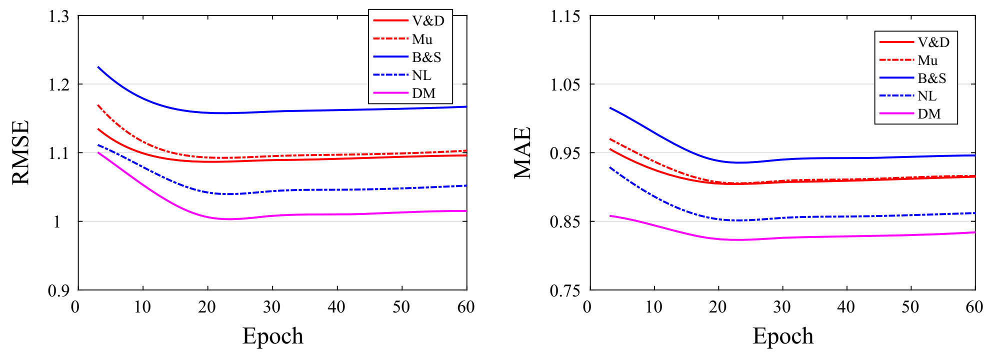


Fig. 9 Performance analysis of epoch over Epinions, Yelp and Douban Movie for SRMP. Left panel: the impact of epoch in terms of RMSE; right panel: the impact of epoch in terms of MAE. Curves on V&D, Mu, B&S, NL and DM show the optimal value for epoch is around 20

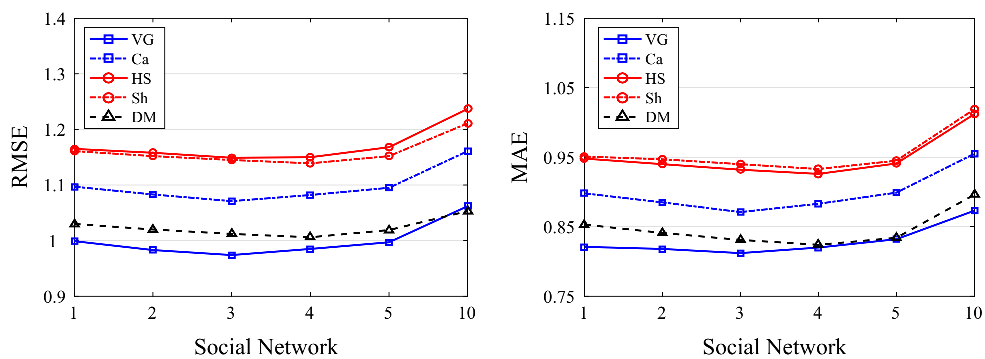


Fig. 10 Left panel: social network influence in terms of RMSE for SRMP; right panel: social network influence in terms of MAE for SRMP. Blue curves are for sub-communities VG and Ca of Epinions; Red curves are for sub-communities HS and Sh of Yelp; Black curve is for Douban Movie

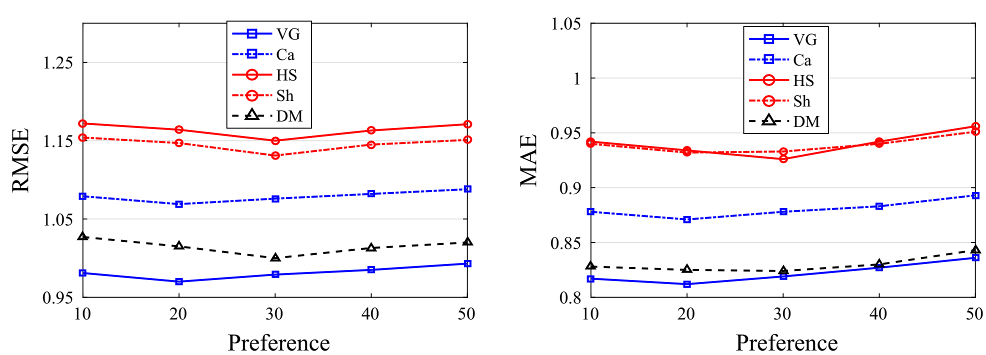


Fig. 11 Left panel: impact of user's preference in terms of RMSE for SRMP; right panel: impact of user's preference in terms of MAE for SRMP. Blue curves are for sub-communities VG and Ca of Epinions; red curves are for sub-communities HS and Sh of Yelp; black curve is for Douban Movie

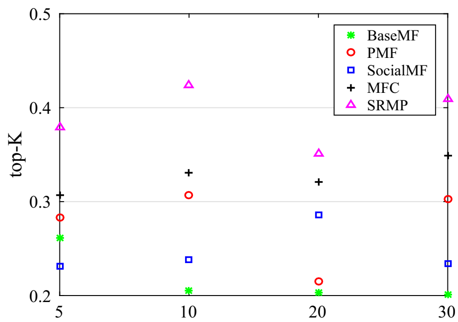


Fig. 12 Top-K performance comparison over Douban Movie, in terms of average hit-rate

5.6 Performance on Cold Start Problem

In this section, the performance of the proposed recommender model SRMP in solving the cold start problem will be evaluated. Due to cold start, users have assigned no ratings on any item; accordingly, the latent feature vectors $\hat{U}_u$ for cold start users can be generated according to the social network $\mathcal{S}$ in SRMP.

$$\hat{U}_u = \frac{\sum_{v \in \mathcal{O}_u} \mathcal{S}_{uv} U_v}{\sum_{v \in \mathcal{O}_u} \mathcal{S}_{uv}} \tag{20}$$

Douban Movie will be taken for example, and the users who have assigned less than 3 ratings will be considered as cold start users [18]. Figure 13 shows that SRMP outperforms BaseMF, PMF, SocialMF, MFC and SRM on Douban Movie in terms of RMSE and MAE, which demonstrates that SRMP can address the cold start problem well through the social network while there are not enough behavior records and numerical ratings.

6 Conclusion and Future Work

Recommender systems (RS) play crucial role in many industries, such as social networks, commercial Web sites and so on, which can provide useful online information effectively and bring great benefits to users. According to the existing literatures, exploring the social relations and preference for users can indeed help to improve the recommendation accuracy significantly and address the cold start problem; therefore, it deserves much more efforts to research it.

In this article, a hybrid social network-based recommendation approach—SRMP, is proposed, the incentive of which is to incorporate the social network and user's preference in matrix factorization for accurate prediction. SRMP will infer independent sub-communities from the original social community according to different item category tags, and then conduct recommendation in each sub-community, respectively, considering user's social relations and preference; consequently, the prediction ratings can be obtained via the product of the learned feature vectors for users and items.

A series of experiments are performed over Epinions, Yelp and Douban Movie datasets, and the experimental analysis shows that SRMP achieves much better recommendation results than other approaches, which can demonstrate that SRMP can better utilize the social network and user-item rating matrix to learn the low-rank feature vectors for users and items. Furthermore, the impacts of dimension, epoch, social network and user's preference on the recommendation results are investigated, respectively, and the optimal value is obtained for each parameter. Moreover, top-K performance analysis demonstrates the advantage of SRMP overall. In addition, to evaluate the performance of SRMP on cold start users, experiments are conducted on Douban Movie, and the results certificate that SRMP outperforms other compared approaches while solving cold start problem.

A major problem for SRMP is that it is hard to measure the variance of the social network. As future work, deep learning methods will be introduced to deep explore the variance of social relations for SRMP, to achieve better recommendation performance.

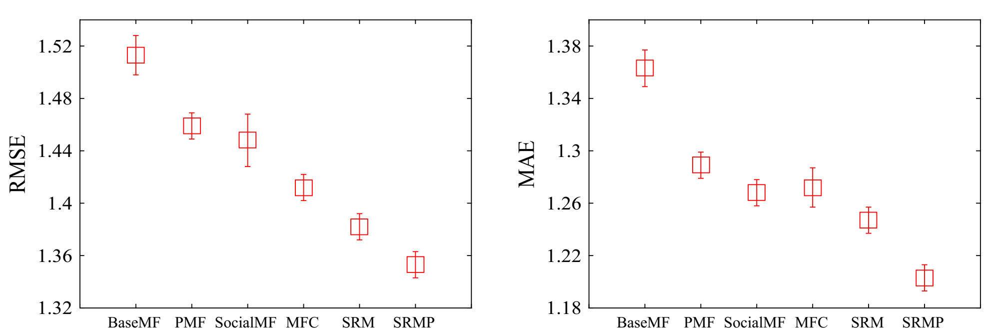


Fig. 13 Performance comparison for cold start users in terms of RMSE and MAE over Douban Movie ($d = 10$). Obviously, SRMP outperforms other compared methods in solving cold start problem

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