IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received April 27, 2019, accepted June 5, 2019, date of publication June 24, 2019, date of current version July 10, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2924443

Exploiting Social Review-Enhanced Convolutional Matrix Factorization for Social Recommendation

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This work was supported in part by the National Natural Science Foundation of China under Grant 61602282, Grant 61772321, and Grant 71301086, in part by the China Postdoctoral Science Foundation under Grant 2016M602181, and in part by the Innovation Foundation of Science and Technology Development Center of Ministry of Education and New H3C Group under Grant 2017A15047.

ABSTRACT To deal with the inherent data sparsity and cold-start problem, many recommender systems try to exploit the textual information for improving prediction accuracy. Due to the significant progress of deep learning techniques, neural network-based content modeling methods have been investigated in recent studies. However, most of these existing methods often assume that users are independent and identically distributed (i.i.d), and the social influence is not considered. However, in the real world, we always turn to our friends for recommendations, and the closer the friendship between the friends, the greater the social impact is. These methods only exploit the reviews from an item perspective and rarely consider the user's reviews to capture the user's interests, but in reality, users often express their preferences by posting different reviews to different items. Based on the above-mentioned observations, we propose a social-enhanced content-aware recommendation method by fusing the social network, item's reviews, and user's reviews in a unified framework. Specifically, to better model the item's reviews, we first introduce the convolutional matrix factorization (ConvMF) as our basic recommendation framework, which utilizes convolutional neural network (CNN) to capture the deeper understanding of the content context. Then, to consider the user's social influence, we integrate the user's social network into ConvMF by a shared user latent factor, which can bridge the user's social interests and user's general preferences in the same latent space. To model the user's reviews, similar to ConvMF, we exploit another CNN to learn a deeper understanding of the user's posted contents. Finally, we conduct experiments on the real-world dataset Yelp to demonstrate the effectiveness of our method. The experimental results indicate that our proposed method can effectively model the social and the review information and outperforms other related methods in terms of root mean squared error (RMSE) and mean absolute error (MAE).

INDEX TERMS Collaborative filtering, convolutional neural network, social network, matrix factorization, social review.

I. INTRODUCTION

With the explosive growth of data generated by users, recommender system as one of the most important information filtering techniques has been widely adopted in many real-world systems (such as Amazon, Facebook and YouTube), where users express their preferences through interacting with different items. However, due to the rapid increase of users and items, users can only interact with a small number of items, and items can only visible to limited users, that is, both users and items often suffer from the data sparsity challenge.

The associate editor coordinating the review of this manuscript and approving it for publication was Gang Li.

To alleviate this problem, many researchers have proposed to utilize textual information such as reviews, abstracts and descriptions to improve Collaborative Filtering (CF) methods [1]–[4]. For example, Wang and Blei [5] proposed the Collaborative Topic Regression (CTR) method to enhance the CF by utilizing the topic model in the scientific article recommendation task. Wang *et al.* [6] further improved CTR by leveraging the deep representation learning technique to tackle the data sparsity problem. But these above methods fail to model the context of the document, which leads to a shallow understanding of the documents. To address this issue, Zhang *et al.* [7] proposed the AutoSVD++ model that integrates the Contractive Auto-encoder to learn the semantic representations from item content information. Kim *et al.* [8] proposed the ConvMF method that integrates CNN into the Matrix Factorization (MF) framework. The CNN model used in ConvMF can capture the contextual information of documents and further improves the rating prediction accuracy. The ConvMF takes advantage of both CNN and MF simultaneously and achieves the state-of-the-art result in content-aware recommendation tasks.

Although the above neural network-based content modeling algorithms have achieved significant improvements compared to traditional methods, most of them often: first, assume users are i.i.d, and the social relationships among users are ignored. But in fact, as we are social animals, we usually turn to our friends for recommendations, and we often make friends with the users that have similar interests with us. Taking the user's social relationship into account is beneficial to the recommender system [9]–[13]. For example, Ma *et al.* [14] assumed that users with social relationships would have similar latent factors. They incorporated social relations as the regularization terms to optimize the MF model and achieved significant improvements. Purushotham *et al.* [15] studied the social influence in a hierarchical Bayesian model by exploiting user's social relations and item's content information to improve recommendations. Liu *et al.* [16] proposed a social recommendation framework named SREPS to learn latent vectors in the social network. In SREPS, the information of rating, consumption and social relationship are modeled jointly based on the essential preference space they introduced. Fan *et al.* [17] proposed a graph neural network framework (GraphRec) for social recommendations, which can model graph data in social recommendations by considering both interactions and opinions in the user-item graph. But these existing social recommendation methods cannot model the context of the content, and only understand the user's opinions on a shallow level.

Second, most of these methods only consider the content information from an item's perspective, and the user's content information is ignored. But in real-world systems, users often express their interests by directly write down their opinions in the posted reviews, which provides a meaningful way to infer the user's preference. Recently, many studies have proved that utilizing review text can improve the rating prediction accuracy of recommender systems, especially when the rating data is sparse [18]–[21]. For example, Ling *et al.* [18] proposed a joint model to model the reviews and ratings simultaneously and improved rating prediction accuracy. But for generating review text, they applied topic modeling, which has certain limitations in extracting textual features. Wang *et al.* [20] proposed a WCN-MF model which can learn a word-driven and context-aware review representation by extending CNN with a DLDA module. However, these models pay more attention to the item's content information rather than the user's, especially the user's review. Modeling the review text of both users and items in a unified social recommendation framework is still largely unexplored.

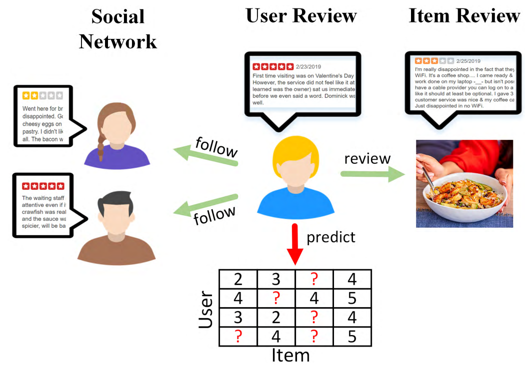


FIGURE 1. **Motivating example for the social-review enhanced recommendation scenario.**

Motivating Example. Suppose there is a social-review based social network, where users can share reviews when they give ratings to the items (i.e., products or services). In addition, users can add friends who may share similar tastes with them. In this kind of recommendation scenario (as shown in Figure 1), when a user proposes to select which item he/she should buy or consume, he/she will first ask his/her friends that have similar opinions with him/her, and then he/she will see the reviews that the item has received. If an item is recommended by one of the user's friends, that is, the users who share similar opinions with he/she, and has received very positive reviews from others, there is a high possibility for the item to be selected by this user.

Intuited by the above observations, to further improve the recommendation performance, we propose a Social Review-enhanced Convolutional Matrix Factorization (SRCMF) method to conduct the rating prediction task by utilizing the user's reviews, social network and item's reviews in a unified framework. Specifically, to model the item's reviews in a more in-depth manner, we introduce the ConvMF method as our basic recommender, which exploits the CNN to model the context of item's reviews and then incorporates the learned representations into the MF framework. To consider the social influence to the recommender, we then incorporate the social network into ConvMF by a shared user latent factor to bridge two different latent feature spaces. To model user's reviews, we further incorporate another similar CNN into ConvMF and reach our final SRCMF. In experiments, we evaluate our proposed method in the real-world dataset Yelp, and the experimental results demonstrate the efficiency and the effectiveness of SRCMF.

The main contributions of this work can be summarized as follows:

- We propose the SRCMF to conduct rating prediction by considering the item's reviews, social network and user's reviews in a unified framework simultaneously.
- To exploit the user's social influence, we propose a social-enhanced ConvMF method by a shared user latent factor to bridge the latent feature space in the social network matrix and the user-item interaction matrix.

- To investigate the user's reviews, we exploit another similar CNN in ConvMF to model the context of the content.
- We conduct experiments on the real-world dataset Yelp to demonstrate the effectiveness of our proposed method.

The remainder of this paper is organized as follows. Section IV gives a short review and discussion of the related work. Section II describes our proposed method in details. Section III presents the experimental setup and results analysis to demonstrate the effectiveness of our method. Section V concludes our work.

II. RECOMMENDATION FRAMEWORK

In this section, we first depict the recommendation task in this work, and then describe how we incorporate social network and social review text into a unified framework to further improve the recommendation performance.

A. TASK DEFINITION

Suppose there is an online social review website, where each item can receive ratings and comments from related users, and each user can make friends with others that have similar interests with them. Let $\mathcal{U} = \{u_1, u_2, \ldots, u_m\}$ and $\mathcal{V} = \{v_1, v_2, \ldots, v_n\}$ be user set and item set, respectively. Let $R = (r_{ij})_{m\times n}$ be the rating matrix from m users to n items with each entry $r_{ij} \in [1, 5]$ indicating how much user i likes item j. Let $\mathcal{G} = (\mathcal{U}, \mathcal{E})$ be the social network of m users with $S = (s_{il})_{m\times m}$ denoting its adjacency matrix, and $\mathcal{E}$ denoting the user's social relationships. Let X and Y denote the set of review texts for items and users respectively. The task of social review based recommendation is then defined as how to make accurate rating predictions in R for all the $\mathcal{U}$ and $\mathcal{V}$ by exploring the document of reviews (X,Y) and user's social network $\mathcal{G}$.

TABLE 1. Symbols used in this work.

Symbols	Definitions and descriptions
$\mathcal{U}, \mathcal{V}$	the user set and item set
$\mathcal{G}$	the user social network
m, n	the number of users and items
R	the user-item rating matrix
S	the adjacent matrix of user's social network
X_j, Y_i	the word vector of item j and user i
U, V	the latent feature factor of users, items
Z	the latent feature factor of social factors
W^1, W^2	the weights in item and user CNN
$\sigma_R^2, \sigma_V^2, \sigma_U^2, \sigma_S^2, \sigma_Z^2$	the Gaussian variance of R, V, U, S, Z
$\sigma_{W^1}^2, \sigma_{W^2}^2$	the Gaussian variance of W^1, W^2
I	the diagonal matrix
$\lambda_U, \lambda_V, \lambda_Z, \lambda_S$	the regularization parameter of U, V, Z, S
$\lambda_{W^1}, \lambda_{W^2}$	the regularization parameter of W^1, W^2
$cnn\left(W^1, X_j\right)$	the item vector learned from CNN model
$cnn\left(W^2, Y_i\right)$	the user vector learned from CNN model

The mathematical notations used in this paper are summarized in Table 1. Note that notations in capital letter like R indicate a matrix, lowercase letter with subscript like r_{ij} indicate a certain element in a matrix, capital letter with subscript like U_i indicate a column/row vector.

B. THE CONVMF METHOD

To capture the contextual information of documents in a deeper level and further enhance the rating prediction accuracy, Kim *et al.* [8] proposed a novel document context-aware recommendation method ConvMF by integrating CNN into a MF [22] framework, which can model the document's context of item and user's collaborative behaviors simultaneously. Figure 2 shows the graphical model of ConvMF.

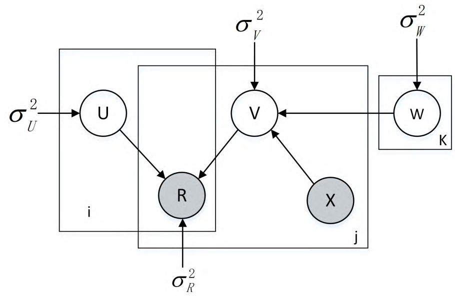


FIGURE 2. Graphical model of ConvMF.

Suppose the observed rating matrix from m users to n items is represented by $R = (r_{ij})_{m\times n}$. The goal of ConvMF is to learn latent feature factors of users and items ($U \in \mathbb{R}^{k\times m}$ and $V \in \mathbb{R}^{k\times n}$) whose product ($U^T V$) can reconstruct the rating matrix R. The conditional distribution over observed ratings is given by:

$$p\left(R|U, V, \sigma_R^2\right) = \prod_i^m \prod_j^n N\left(r_{ij}|U_i^T V_j, \sigma_R^2\right)^{I_{ij}} \tag{1}$$

where $N(x|\mu, \sigma_R^2)$ is the probability density function of the Gaussian normal distribution with mean μ and variance σ_R^2. I_{ij} is an indicator function that is 1 if user i rated item j and 0 otherwise.

Similar to Probabilistic Matrix Factorization (PMF), a zero-mean spherical Gaussian prior is placed on user latent factor U:

$$p\left(U|\sigma_U^2\right) = \prod_i^m N\left(U_i|0, \sigma_U^2 I\right) \tag{2}$$

For the item latent factor V, its conditional distribution over item latent model is given by:

$$p\left(V|W, X, \sigma_V^2\right) = \prod_j^n N\left(V_j|cnn\left(W, X_j\right), \sigma_V^2 I\right) \tag{3}$$

where W is the internal weights from the CNN, and X_j is the document representation of item j. For each weight W_k in W, the zero-mean spherical Gaussian prior is placed:

$$p(W|\sigma_W^2) = \prod_k N(W_k|0, \sigma_W^2) \tag{4}$$

Here, $cnn(W, X_j)$ is the vector of item representation learned from the CNN model.[1] As we can see from Eq.(3), it is used as the mean of Gaussian distribution which plays an important role as a bridge between CNN and PMF that helps to fully analyze both description documents and ratings.

Since CNN can effectively capture local features of documents and better represent the document information, the ConvMF applies CNN to learn the item latent factor for a more accurate recommendation. Although ConvMF can well model both the content context and the rating behaviors, it ignores the user's content context and assumes that users are i.i.d, which might be beneficial for the social review based system.

C. THE SCMF METHOD

To utilize user social relationship in the social review site, we propose a social enhanced ConvMF method SCMF to model the content context of item's reviews and the user's social relationships simultaneously, which utilizes a shared user latent factor to connect the latent feature space of ConvMF and social network. Figure 3 shows the architecture of SCMF.

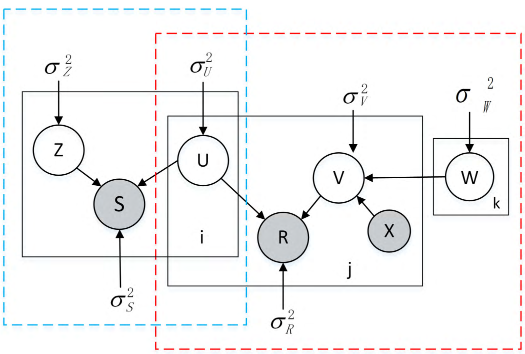


FIGURE 3. Graphical model of SCMF: social network part is in left (dashed-blue); ConvMF part is in right (dashed-red).

Let $S = (s_{il})_{m\times m}$ denote the adjacency matrix of social network $\mathcal{G}$, with each entry s_{il} denoting whether user i has social connection with user l, that is 1 if i is a friend of l and 0 otherwise. We factorize S to learn a high-level representation of user's social influence. Let $U \in \mathbb{R}^{k\times m}$ and $Z \in \mathbb{R}^{k\times m}$ be the latent user and social factor feature matrices, with column vectors U_i and Z_l representing user-specific and social-specific latent vectors respectively. We define the conditional distribution over the observed social network relationships as:

$$P(S|U, Z, \sigma_S^2) = \prod_i^m \prod_l^m N\left(s_{il}|U_i^T Z_l, \sigma_S^2\right)^{I_{il}^S} \tag{5}$$

where I_{il}^S is an indicator function. For the social latent factor Z and user latent factor U, we place the zero-mean spherical Gaussian prior on them:

$$p(Z|\sigma_Z^2) = \prod_l^m N(Z_l|0, \sigma_Z^2 I) \tag{6}$$

$$p(U|\sigma_U^2) = \prod_i^m N(U_i|0, \sigma_U^2 I) \tag{7}$$

Then, through the Bayesian inference, we have

$$p\left(U, Z|S, \sigma_S^2, \sigma_U^2, \sigma_Z^2\right) \propto p\left(S|U, Z, \sigma_S^2\right) p\left(U|\sigma_U^2\right) p\left(Z|\sigma_Z^2\right) \tag{8}$$

To integrate the social network into the ConvMF model, as we have shown in Figure 3, we share the user latent factor U in these two methods. By doing this, the user's interests will be not only affected by the content context and ratings but also their social relationships. After combining CNN with social matrix factorization, the joint probability distribution of SCMF can be written as:

$$\begin{aligned} p&\left(U, V, Z, W|R, S, X, \sigma_R^2, \sigma_S^2, \sigma_U^2, \sigma_V^2, \sigma_Z^2, \sigma_W^2\right)\\ &\propto p\left(R|U, V, \sigma_R^2\right) p\left(S|U, Z, \sigma_S^2\right) p\left(U|\sigma_U^2\right)\\ &\times p\left(V|W, X, \sigma_V^2\right) p\left(Z|\sigma_Z^2\right) p\left(W|\sigma_W^2\right) \end{aligned} \tag{9}$$

To optimize the variables $U, V,\ Z$ and internal weights of CNN, we use the maximum posterior (MAP) estimation as the learning method. By taking negative logarithm on Equation (9), the objective function of SCMF is reformulated as:

$$\begin{aligned} &\mathcal{L}(U, V, Z, W)\\ &= \frac{1}{2}\sum_i^m \sum_j^n I_{ij}\left(r_{ij} - U_i^T V_j\right)^2\\ &+ \frac{\lambda_S}{2}\sum_i^m \sum_l^m I_{il}^S\left(s_{il} - U_i^T Z_l\right)^2 + \frac{\lambda_U}{2}\sum_i^m \|U_i\|^2\\ &+ \frac{\lambda_V}{2}\sum_j^n \|V_j - cnn\left(W, X_j\right)\|^2 + \frac{\lambda_Z}{2}\sum_l^m \|Z_l\|^2\\ &+ \frac{\lambda_W}{2}\sum_k^{|W_k|} \|W_k\|^2 \end{aligned} \tag{10}$$

where $\lambda_U = \sigma_R^2/\sigma_U^2$, $\lambda_V = \sigma_R^2/\sigma_V^2$, $\lambda_Z = \sigma_R^2/\sigma_Z^2$, $\lambda_S = \sigma_R^2/\sigma_S^2$ and $\lambda_W = \sigma_R^2/\sigma_W^2$ are the regularization parameters.

D. THE SRCMF METHOD

In SCMF, the user's social relationship and item review texts are modeled jointly in the PMF framework [22]. But it only considers the reviews from an item perspective, and the user's review content is unexploited, which might be useful to modeling the user's interest representation. With that in mind, we further incorporate another CNN to SCMF to investigate the effectiveness of user's review context and achieve our final recommendation model Social Review-enhanced Convolutional Matrix Factorization (SRCMF). Figure 4 shows

[1] Details of the CNN network can be seen in [8].

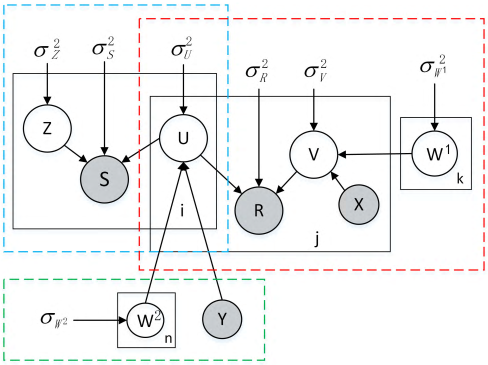


FIGURE 4. Graphical model of SRCMF: social network part is in left (dashed-blue); ConvMF part is in right (dashed-red); CNN part for user reviews is in bottom (dashed-green).

the architecture of SRCMF. In SRCMF, the conditional distribution over user latent factor is modified as:

$$p(U|W^2, Y, \sigma_U^2) = \prod_i^m N\left(U_i|cnn\left(W^2, Y_i\right), \sigma_U^2 I\right) \quad (11)$$

where Y_i represents the review text of user i, W^2 is internal weights in user CNN module. Then, the joint probability distribution in Equation (9) can be rewritten as:

$$\begin{aligned} p\Big(&U, V, Z, W^1, W^2|R, S, X, Y, \sigma_R^2, \sigma_S^2, \sigma_U^2, \\ &\qquad\qquad \sigma_V^2, \sigma_Z^2, \sigma_{W^1}^2, \sigma_{W^2}^2\Big) \\ &\propto p\left(R|U, V, \sigma_R^2\right) p\left(S|U, Z, \sigma_S^2\right) p\left(U|W^2, Y, \sigma_U^2\right) \\ &\times p\left(V|W^1, X, \sigma_V^2\right) p\left(Z|\sigma_Z^2\right) p\left(W^1|\sigma_{W^1}^2\right) \\ &\times p\left(W^2|\sigma_{W^2}^2\right) \end{aligned} \quad (12)$$

By taking negative logarithm on Equation (12), we can arrive at the objective function of SRCMF:

$$\begin{aligned} \mathcal{L}\left(U, V, Z, W^1, W^2\right) &= \sum_i^m \sum_j^n \frac{I_{ij}}{2}\left(r_{ij} - U_i^T V_j\right)^2 \\ &+ \frac{\lambda_S}{2} \sum_i^m \sum_l^m I_{il}^S \left(s_{il} - U_i^T Z_l\right)^2 + \frac{\lambda_Z}{2} \sum_l^m \|Z_l\|^2 \\ &+ \frac{\lambda_V}{2} \sum_j^n \left\|V_j - cnn\left(W^1, X_j\right)\right\|^2 + \frac{\lambda_{W^1}}{2} \sum_k^{|W_k^1|} \left\|W_k^1\right\|^2 \\ &+ \frac{\lambda_U}{2} \sum_i^m \left\|U_i - cnn\left(W^2, Y_i\right)\right\|^2 + \frac{\lambda_{W^2}}{2} \sum_k^{|W_k^2|} \left\|W_k^2\right\|^2 \end{aligned} \quad (13)$$

where Y_i and X_j represent the review text of user i and item j respectively, W^2 and W^1 are the internal weights in user and item CNN modules respectively. $\lambda_{W^2} = \sigma_R^2/\sigma_{W^2}^2$ and $\lambda_{W^1} = \sigma_R^2/\sigma_{W^1}^2$ are the regularization parameters.

Similar to ConvMF, we adopt the coordinate descent as the optimization algorithm which iteratively optimizes a latent variable while fixing the remaining variables. For example, when temporarily assuming Z, V and W^1, W^2 to be constant, the loss function $\mathcal{L}$ (denoted in Equation (13)) becomes a quadratic function with respect to U. Then, the analytical optimal solution of U can be computed in a closed form. The analytical optimal solution of U_i, V_j, Z_l are achieved as follows:

$$\begin{aligned} U_i \leftarrow &\left(VI_iV^T + \lambda_S Z I_i^S Z^T + \lambda_U I_K\right)^{-1} \\ &\times \left(VR_i + \lambda_U cnn\left(W^2, Y_i\right) + \lambda_S Z S_i\right) \end{aligned} \quad (14)$$

$$V_j \leftarrow \left(UI_jU^T + \lambda_V I_K\right)^{-1} \left(UR_j + \lambda_V cnn\left(W^1, X_j\right)\right) \quad (15)$$

$$Z_l \leftarrow \left(\lambda_S U I_l^S U^T + \lambda_Z I_K\right)^{-1} (\lambda_S U S_l) \quad (16)$$

where I_i and I_i^S are diagonal matrices, R_i is a vector with $(r_{ij})_{j=1}^n$ for user i and S_l is a vector with $(s_{il})_{l=1}^m$ for user i. For each item j, I_j and R_j are similarly defined.

Because W^1, W^2 is closely related to the features in CNN architecture, they cannot be optimized by an analytic solution. Nonetheless, as $\mathcal{L}$ can be interpreted as a squared error function when U, V, Z are temporarily constant, the back-propagation algorithm can be utilized to solve the following objective function:

$$\begin{aligned} \varepsilon\left(W^1\right) = &\frac{\lambda_V}{2} \sum_j^n \left\|V_j - cnn\left(W^1, X_j\right)\right\|^2 \\ &+ \frac{\lambda_{W^1}}{2} \sum_k^{|W_k^1|} \left\|W_k^1\right\|^2 + constant \end{aligned} \quad (17)$$

$$\begin{aligned} \varepsilon\left(W^2\right) = &\frac{\lambda_U}{2} \sum_i^m \left\|U_i - cnn\left(W^2, Y_i\right)\right\|^2 \\ &+ \frac{\lambda_{W^2}}{2} \sum_k^{|W_k^2|} \left\|W_k^2\right\|^2 + constant \end{aligned} \quad (18)$$

The learning algorithm of SRCMF can be seen in Algorithm 1.

E. TIME COMPLEXITY ANALYSIS

The time complexity of training SRCMF is mainly caused by computing the loss function (as shown in Equation (13)) and the updating of the model parameters (U, V, Z, W^1 and W^2). The computational complexity of computing the loss function (denoted by Equation (13)) is $O\left(n_R k + n_S k\right) + O\left(CNN\right)$, where n_R and n_S are the numbers of observed ratings and relations in matrices R and S respectively. $O(CNN)$ is the complexity of training a CNN in ConvMF. The computational complexity of updating the latent factors U, V and Z is $O(k^3 m + k^3 n + k^3 m)$, where m and n are the numbers of users and items respectively. k is the dimension of the latent factors. The computational complexity of updating W^1 and W^2 in the CNN component is $O(n_c \cdot p \cdot l \cdot n + n_c \cdot p \cdot l \cdot m)$, where n_c is the number of filters, p is the size of embedding dimension for each word, l is the length of the document. Both these two complexities are linear with respect to the size of dataset.

III. EXPERIMENTS

In this section, we conduct several experiments on the real-world dataset Yelp to evaluate the performance of SRCMF.

Algorithm 1 The Learning Algorithm of SRCMF

Input:

User-item rating matrix R; user social network matrix S; user review text; item review text; hyper-parameters λ_U, λ_V, λ_S, λ_Z; threshold ϵ;

Output:

Latent vectors U, V, Z; item CNN weights W^1, user CNN weights W^2;

Generate item word latent matrix X;
Generate user word latent matrix Y;
Initialize U, V, Z, W^1, W^2;
while $\frac{|Loss - PrevLoss|}{PrevLoss} < \epsilon$ **do**
  for each user i **do**
    Get $cnn\left(W^2, Y_i\right)$ from user cnn model;
    Update U_i according to Eq.(14);
  end for
  for each item j **do**
    Get $cnn\left(W^1, X_j\right)$ from item cnn model;
    Update V_j according to Eq.(15);
  end for
  for each user l in S **do**
    Update Z_l according to Eq.(16);
  end for
  Update W^1 according to Eq.(17);
  Update W^2 according to Eq.(18);
  Compute $Loss$ according to Eq.(13);
end while
return U, V, Z, W^1, W^2;

The extensive experimental results help us to answer the following three questions:

- RQ1: Does our proposed approach perform better compared to other state-of-the-art recommendation methods?
- RQ2: Is the social network useful for improving the prediction accuracy?
- RQ3: How do the item's reviews impact the effectiveness of ConvMF, SCMF and SRCMF?
- RQ4: Do the user's reviews contribute to the performance of SRCMF?
- RQ5: Can our model converge quickly compared to the ConvMF?

In the following, we will first describe the experimental settings, including dataset, evaluation metrics and implementation details. Then, we will show the experimental results comparing to the baselines. Finally, we will analyze the impact of related parameters to answer the above three questions.

A. EXPERIMENTAL SETTINGS

1) DATASET

To demonstrate the effectiveness of SRCMF, we use the real-world dataset Yelp[2] as our data source, which is a subset of their users, reviews, and businesses across 11 metropolitan areas in four countries. We use this dataset for businesses recommendation. Considering the dataset is too large, we first divide the Yelp data into several sub-datasets according to the areas that the businesses are located in, and then select two preventative areas, that is, North Carolina (NC) and Wisconsin (WI), to conduct experiments. To alleviate data sparsity, we further filter out users that have less than 3 ratings and businesses that do not have any reviews. The statistics of these two sub-datasets are shown in Table 2.

TABLE 2. The statistics of NC and WI in Yelp.

Dataset	# users	# businesses	# ratings	# relations
NC	22,737	12,502	225,580	111,394
WI	8,386	4,593	80,643	34,099

2) EVALUATION METRICS

In order to quantitatively evaluate the performance of our approach, we randomly select 80% of the resulted datasets as the training set, 10% of the data as the validation set, and the remaining as the test set, where each user and item appears at least once in the training set. All selection processes are conduced independently 5 times.

We adopt two popular metrics RMSE and MAE to evaluate our proposed method [23]. The training objective is to minimize the value of RMSE and MAE between the predicted ratings and true ratings. RMSE is defined as:

$$RMSE = \sqrt{\frac{\sum_{i,j}^{m,n}\left(r_{ij} - \hat{r}_{ij}\right)^2}{T}} \tag{19}$$

MAE is defined as:

$$MAE = \frac{\sum_{i,j}^{m,n}\left|r_{ij} - \hat{r}_{ij}\right|}{T} \tag{20}$$

where r_{ij} is the observed rating value of user i to item j, $\hat{r}_{ij}$ is the corresponding prediction, and T is the number of tested samples.

3) IMPLEMENTATION DETAILS

We implement our method using Python and Keras library with NVidia Tesla K80 GPU. Here are some implementation details:

(1) *Parameter Settings*: For both of these two datasets, the dimension of the latent factors U, V and Z is set as 50. The regularization parameters are set as $\lambda_U = 10$, $\lambda_V = \lambda_Z = 100$, $\lambda_S = 300$ for SCMF and $\lambda_U = \lambda_V = 100$, $\lambda_Z = 0.01$, $\lambda_S = 10$ for SRCMF. For ConvMF, we set λ_U and λ_V as 1, 100 respectively.

(2) *Data Preprocessing*: When preprocessing review texts, similar to [24] and [8], we follow the following steps: 1) remove stop words, 2) remove words whose document frequency is higher than 0.5, 2) calculate the tf-idf score [25] for each word, 3) select top 8,000 distinct words as the

[2]https://www.yelp.com/dataset

vocabulary, 4) set maximum length of text to 300 for each item and user.

(3) *CNN Training*: For the sake of fairness, we use the same settings to train CNN as in ConvMF: 1) we initialize the word vectors by a pre-trained word embedding model (word2vec) with dimension 200. 2) In the convolutional layer, we use various window sizes (3, 4 and 5) to consider various length of surrounding words, and use 100 shared weights per window size. 3) We use max-pooling in pooling layer. 4) To prevent CNN from over-fitting, the dropout rate is set as 0.2.

B. COMPARISON RESULTS (RQ1)

In order to evaluate the performance of our SRCMF method, we compare SRCMF with the following baseline methods:

- PMF [22]: This is a popular matrix factorization method that only uses rating scores for recommendations.
- Social Recommendation (SoRec) [14]: This is a social recommendation method that fuses social network and PMF in a unified framework.
- Social Matrix Factorization (SocialMF) [26]: This is another social recommendation method that explores social propagation to enhance traditional recommendations.
- Social Collaborative Filtering by Trust (TrustMF) [27]: This method conducts social recommendation by distinguishing the relationship between the truster and trustee.
- Trust-based Matrix Factorization (TrustSVD) [28]: This is the state-of-the-art trust-based recommender that incorporates both the explicit and implicit influence of ratings and trust information.
- Deep Cooperative Neural Networks (DeepCoNN) [19]: This is a state-of-the-art method that utilizes reviews for recommendation. This approach consists of two parallel neural networks to model users and items by jointly using review text.
- ConvMF [8]: This is the recent document context-aware recommendation method, which investigates the document context by integrating the CNN into the matrix factorization method.
- SCMF-user: This is a variant of SRCMF, which removes the item's review and social network components, and only utilizes user's reviews for recommendations. This is to verify the importance of the user's review component.
- SCMF: This is another variant version of SRCMF, which considers user's social interest and item's reviews for content context-aware recommendation, but the user's review is unexploited.

The comparison results are shown in Table 3, from which we have the following observations:

(1) PMF is the weakest baseline in all datasets, since it is a basic method that only uses rating matrix for recommendations.

(2) Among these classic social recommendation methods (SoRec, SocialMF, TrustMF, TrustSVD), TrustSVD achieves the best performance on both of these two datasets, which indicates that trust and ratings are complementary to each other, and both crucial for more accurate recommendations. Compared to TrustSVD, our SCMF improved about 2% on these two datasets, and SRCMF improved about 4.5%, 3.2% on WI and NC respectively, which demonstrates the effectiveness of our social-review based recommendation strategy. The difference between SCMF and traditional social recommendation methods is that SCMF considers item's reviews to model the content context of items, which has also been demonstrated in ConvMF, and can help SCMF achieve a better performance that making recommendations with only social relations. From the result of SRCMF which incorporates user review based on SCMF, we can conclude that considering the social interests and content context simultaneously can perform better than single social network information, and the CNN-based document modeling method can model the content context effectively.

TABLE 3. Comparison results on WI and NC state. The △(%) denotes the significant improvements of SRCMF, which is given by t-test with $p < 0.01$.

Model	WI		NC	
	RMSE/△(%)	MAE/△(%)	RMSE/△(%)	MAE/△(%)
PMF	1.288/15.7%	1.039/18%	1.352/15.5%	1.098/18.8%
SoRec	1.179/7.9%	0.936/9%	1.220/6.4%	0.965/7.7%
SocialMF	1.173/7.4%	0.928/8.2%	1.259/9.3%	0.967/7.8%
TrustMF	1.194/9%	0.940/9.9%	1.234/7.7%	0.971/8%
TrustSVD	1.137/4.5%	0.902/5.5%	1.180/3.2%	0.933/4.5%
DeepCoNN	1.108/2.0%	0.876/2.7%	1.150/0.7%	0.897/0.7%
ConvMF	1.165/6.8%	0.899/5.2%	1.205/5.2%	0.922/3.4%
SCMF	1.114/2.5%	0.863/1.3%	1.162/1.7%	0.910/2.1%
SCMF-user	1.133/4.1%	0.890/4.3%	1.188/3.9%	0.933/4.5%
SRCMF	**1.086/-**	**0.852/-**	**1.142/-**	**0.891/-**

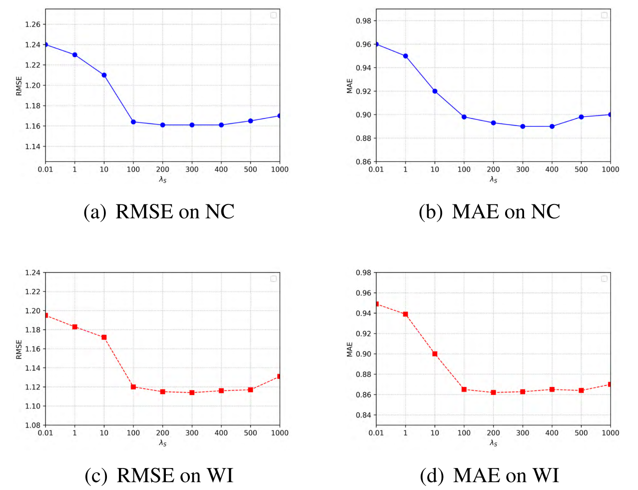
(3) As proved in [8], the ConvMF achieves significant improvement over PMF, which indicates that the item document context information helps construct the item latent model. Our SCMF outperforms ConvMF at least 3.5% on these two datasets, which demonstrates the importance of social influence in modeling user's preferences. As for SRCMF, it gained 2.5% and 1.7% in term of RMSE over SCMF on WI and NC respectively, which demonstrates that the user's reviews are helpful to learn more accurate user representation and can further improve the recommendation performance. Moreover, compared to DeepCoNN [19], SRCMF can also achieve a better result, which, again, demonstrates the effectiveness of our SRCMF in the rating prediction task.

(4) The gap between SCMF-user and ConvMF validates the importance of the user's views, and the feasibility of modeling the user's content context by using the CNN module. More discussions about the importance of user's views are shown in the next subsection.

C. PARAMETER ANALYSIS

1) IMPACT OF SOCIAL INFLUENCE (RQ2)

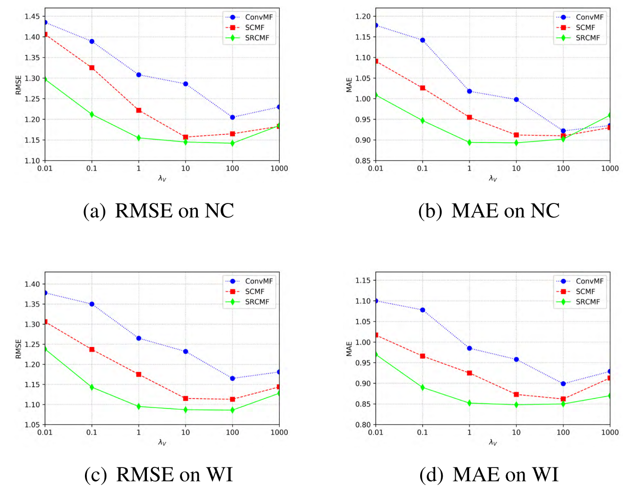
To study the influence of user's social network, we compare SCMF with ConvMF, which is a variant of SRCMF and considers the social relations and rating matrix for recommendation. In SCMF, the parameter λ_S represents how much social information is utilized in our model. It plays a role to



(a) RMSE on NC (b) MAE on NC

(c) RMSE on WI (d) MAE on WI

FIGURE 5. Impact of parameter λ_S in SCMF on two datasets.



(a) RMSE on NC (b) MAE on NC

(c) RMSE on WI (d) MAE on WI

FIGURE 6. Impact of parameter λ_V in ConvMF and SRCMF on two datasets.

balance the information from ConvMF and the user's social network. If $\lambda_S = 0$, SCMF will only utilize the rating matrix and content context to model the user's interests. If $\lambda_S = \infty$, SCMF will only utilize the social network information to make recommendations.

Figure 5 shows the impact of λ_S on RMSE and MAE when fixing $\lambda_U = 10$, $\lambda_V = 100$ which make best performance in SCMF. We can observe that social network information affects the recommendation results of SCMF significantly. When the value of λ_S increases, the prediction error decreases at first. But when λ_S surpasses a certain threshold (300 and 500), the increase of λ_S leading to the increase of the prediction error. The SCMF achieves the best performance when λ_S is around 300. This result also demonstrates that we cannot get better results with only social network or ConvMF than fusing them. In a word, Figure 5 shows the significant impact of social network on the performance of recommendation.

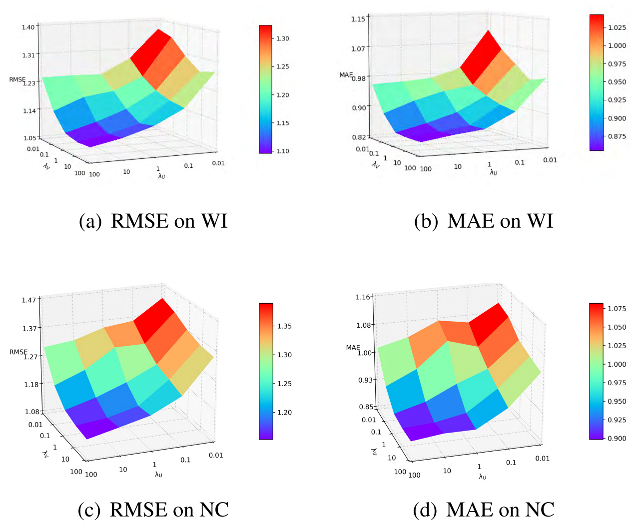
2) IMPACT OF ITEM'S REVIEW (RQ3)

Item's review is a common information utilized for generating item latent model in SCMF, SRCMF and ConvMF (the baseline). The parameter λ_V controls how much information these models are dependent on the item's reviews. We analyze the impact of λ_V by fixing the other parameters that can make these three models work best. More specifically, for ConvMF, we set $\lambda_U = 1$. For SCMF, we set $\lambda_U = 10$, $\lambda_S = 300$. For SRCMF, we set $\lambda_U = 100$, $\lambda_S = 10$.

The experimental results are shown in Figure 6. From Figure 6, we can see that the prediction errors change significantly with varying the value of λ_V for three models. In all these three models, the predictions errors experience a process of first decreasing (recommendation performance increasing) and then increasing (recommendation performance decreasing). This result provides us evidence that the item's document context is useful to learn the item latent factor. The SCMF, SCMF, ConvMF achieve their best performance when λ_V is equal to 10, 100, 100 respectively. The values of λ_V are different indicating that the contribution of item's reviews in these three models are different. Since we incorporate extra information in SRCMF and SCMF, SRCMF and SCMF perform better than ConvMF, and SRCMF always gets the lowest prediction error in all datasets.

3) IMPACT OF USER'S REVIEW (RQ4)

In SRCMF, we integrate another CNN component for generating user's reviews features. Thus the representation of user's latent factor can be modeled by rating matrix, social network as well as user's review texts. To find out the influence of user's review on SRCMF, we investigate the impact of two parameters (λ_U and λ_V) on the performance of SRCMF by fixing social parameters $\lambda_S = 10$, $\lambda_Z = 0.01$.



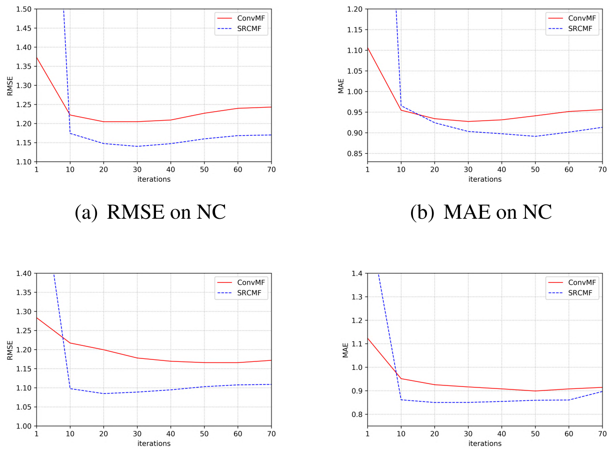
(a) RMSE on WI (b) MAE on WI

(c) RMSE on NC (d) MAE on NC

FIGURE 7. Impact of parameters λ_U and λ_V in SRCMF on two datasets.

Figure 7 shows the changing trend of RMSE and MAE with different combinations of λ_U and λ_V on the WI and NC datasets. From the results we can observe that SRCMF achieves the best performance when λ_U and λ_V are set as

100, 10 on WI and 100, 100 on NC respectively. Compared to SCMF which gets its lowest error when λ_U and λ_V are (10, 100) on both datasets, the optimal configuration of λ_U and λ_V differs a lot in SRCMF. We can find that the value of λ_U in SRCMF increases to make better results compared to SCMF, which indicates the contribution of user's reviews. Figure 7 shows different errors resulted from various values of λ_U and λ_V in SRCMF. In other words, λ_U and λ_V can balance the importance of user's review texts and item's review texts. In general, we can conclude that it is feasible and effective to use another CNN in SRCMF for modeling user's interest.



(a) RMSE on NC (b) MAE on NC

(c) RMSE on WI (d) MAE on WI

FIGURE 8. Training error of ConvMF and SRCMF during each iteration.

D. CONVERGENCE ANALYSIS (RQ5)

To evaluate the efficiency of our algorithm, we report the convergence rate of ConvMF and SRCMF. Figure 8 shows the prediction errors of ConvMF and SRCMF during each interaction. In experiments, we set the max interaction to 200 and adopt an early stopping when achieving the expected validation errors. From Figure 8, we can observe that SRCMF has similar convergence rate with ConvMF after we incorporate the social and user's review content. In some cases, it even converges faster than ConvMF. For example, in Figure 8(c), the SRCMF converges after 20 iterations, while ConvMF takes around 60 iterations to reach convergence. This result directly answers the question that our method can efficiently model the social and the content context while achieving a better recommendation result.

IV. RELATED WORK

Traditional recommendation methods only utilize user-item interactions to model the user's preferences. However, with the increasing number of users and items in real-world systems, the data sparsity has become one of the biggest challenges hindering the development of recommendation systems. To solve this problem, many researchers have tried to exploit auxiliary information (such as item contents and user social networks) to enhance the recommender system and have achieved significant improvements. In this section, we will briefly review some related work about content-aware recommendations and social recommendations. Additionally, to address the ability of CNN in extracting content features, we also introduce some CNN-based content modeling methods.

A. CONTENT-AWARE RECOMMENDATION

To alleviate the data sparsity in traditional recommendation methods, many researchers have exploited content information (such as reviews, synopses and abstracts) to improve the recommendation accuracy [29]–[32]. For example, McAuley and Leskovec [33] proposed a hidden factor topic method to combine rating data with topics in review content for product recommendation, and achieved better results than using rating data alone. Similarly to [33], Ling *et al.* [18] exploited information in both ratings and review content in a unified framework. In order to get more powerful feature expressions of content information, Wang *et al.* [6] integrated Stacked Denoising Autoencoder (SDAE) into PMF and proposed a hierarchical Bayesian model Collaborative Deep Learning (CDL). The item content is integrated into CF in this framework, which alleviates the problem of data sparsity.

However, these existing approaches do not consider the contextual information of documents (such as surrounding words and word orders), which results in a shallow understanding of the document content. To overcome this problem, Kim *et al.* [8] employed a CNN to generate a more accurate representation of documents, and then incorporated them into MF framework and proposed a document context-aware recommendation method ConvMF. By taking advantage of CNN and MF, ConvMF can model the item documents and ratings simultaneously. Inspired by the successful use of CNNs, Seo *et al.* [34] introduced a CNN architecture to perform the hashtag recommendation and achieved better results than other methods. Lee *et al.* [4] proposed a deep hybrid model using deep neural network for quotes recommendation. In their work, the CNN is applied to learn significant local semantics from tweets. Tuan and Phuong [35] leveraged CNNs to learn feature representations form item content information to enhance the accuracy of session based recommendation. Shen *et al.* [36] designed an e-learning resource recommendation method, and utilized CNN to extract item features from text information of learning resources to enhance the accuracy of recommendations. However, these above existing methods only consider the contents from an item view and the methods that consider the user's content information and social influence in a unified framework are mostly unexploited.

B. CNN-BASED CONTENT MODELING METHOD

CNN as one of the state-of-the-art deep neural networks for image recognition and classification [37]–[39] has been demonstrated in many computer vision systems. Recently, many researchers found that CNN can also work well in many natural language processing tasks [40]–[42]. For example, Kim [24] utilized CNN for training the word vectors for sentence-level classification tasks and the results show that a simple CNN with one convolution layer can perform remarkably better than other traditional methods. He *et al.* [43] proposed a CNN based method to compute sentence similarity, which can extract deep feature representations from sentences via convolutional networks. Reference [40] introduced a dynamic CNN model for the semantic modeling of sentences. The network can extract valuable information of the sentence while retaining word order information. Yin and Schütze [44] proposed an architecture with two CNN modules for paraphrase identification. The experimental results of this method show better performance than previous neural network work. Wang *et al.* [41] used semantic clustering and CNN for short text categorization, where the CNN is used to fully exploit the contextual information of short texts to improve the representations. Ruder *et al.* [45] made use of CNN for sentiment analysis and proved its effectiveness in modeling sentence tasks. These above methods demonstrate the capability of CNNs in extracting document features, which provide us an effective way to mine the semantic clues in content documents. In Section II, we will introduce how we utilize CNN to improve the representation of both users and items.

C. SOCIAL RECOMMENDATION

The social recommendation aims to alleviate the data sparsity by leveraging the social influence between users [46], [47]. Recently, numerous social recommender systems have been proposed to improve the recommendations bys incorporating social network information into traditional collaborative filtering approaches [48]–[52]. For example, Ma *et al.* [14] proposed the SoRec algorithm by fusing a user-item rating matrix with the user's social network based on probabilistic matrix factorization framework. Their experimental results show that the social network information can better enhance the traditional collaborative filtering algorithms. To consider trust propagation between users, Jamali and Ester [26] assumed the user's latent features are dependent on the latent features of their direct neighbors and proposed the SocialMF method to incorporate social information into the MF. Different from [26], Liu and Liu [27] adopted the MF technique to map users into low-dimensional feature space in terms of their trust relationship, aiming to reflect users' mutual influence on their own opinions more reasonably. Guo *et al.* [28] incorporated not only the explicit but also the implicit influence of both ratings and trust into the recommendation model to alleviate the data sparsity problem.

However, the above methods only take social relationships into account to model user's preference and the content information is ignored. To leverage the content information to improve the recommendation performance further, researchers started to find ways to merge these data. For example, Chen *et al.* [53] proposed a context-aware hierarchical Bayesian method by combining diverse types of information including ratings, context, item content and social relationships. Considering the complementary of two different data sources, Hu *et al.* [54] connected the latent factors from social relations and topics from item reviews in a joint model, where the user-item ratings, social network and item reviews are modeled simultaneously. But these methods still have limitations in extracting content features, and user's content information is not considered.

Differences: Our work is different from these existing methods in two aspects. First, compared with the content-based recommendation methods (such as CTR [5], CDL [6], ConvMF [8]), we not only consider the content context of item's reviews, but also the user's content context and social influence, which is more realistic than existing methods. Second, compared with existing social recommendation methods, we incorporate content context from both user's and item's reviews via two additional CNN networks, which not only improve the recommended performance but also make our model more interpretive. We will introduce our recommendation model in detail in the next section.

V. CONCLUSION AND FUTURE WORK

In this work, we investigate the social recommendation problem under the social-review based scenario and propose a social review-enhanced recommender SRCMF to deal with the encountered challenges. Specifically, we first propose SCMF by sharing the user latent factor between social network and ConvMF to consider the social influence and item reviews simultaneously. Then, to learn a better user representation, we propose SRCMF to fully explore the context of user's reviews. The SRCMF models user's social network and review contents of both users and items in a joint matrix factorization model and facilitates them to enforce with each other. By conducting extensive experiments on the Yelp dataset, we find SRCMF outperforms other related methods in terms of RMSE and MAE, and the effectiveness of the social influence and user's review content.

In SRCMF, we mainly focus on the network and content features, and other context features are ignored, which may be also crucial to recommender system. In the future, we will consider how to leverage more context features to further improve the recommendation as our work.

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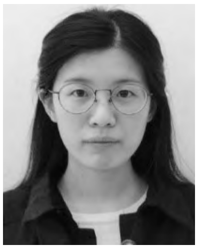

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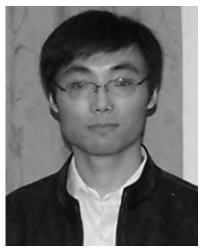

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