Network Embedding Based Recommendation Method in Social Networks

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ABSTRACT

With the advent of online social networks, the use of information hidden in social networks for recommendation has been extensively studied. Unlike previous work regarded social influence as regularization terms, we take advantage of network embedding techniques and propose an embedding based recommendation method. Specifically, we first pre-train a network embedding model on the users' social network to map each user into a low dimensional space, and then incorporate them into a matrix factorization model, which combines both latent and pre-learned features for recommendation. The experimental results on two real-world datasets indicate that our proposed model is more effective and can reach better performance than other related methods.

CCS CONCEPTS

• **Information systems** → **Data mining**; *Collaborative filtering*;

KEYWORDS

Social Recommendation, Network Embedding, Matrix Factorization

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1 INTRODUCTION

In social networks, users are more likely to seek suggestions from their friends. Social relationships provide an independent source of information about users beyond rating information. Therefore, how to utilize social information to assist recommendation has been widely studied in recent years [2, 3, 5]. For example, Mohsen et al.[2] incorporated the mechanism of trust propagation into Matrix Factorization (MF) to predict the behavior of users. However, most of these existing works mainly regard social influence as regularization terms, and the deeper structural information of social networks has not been fully explored.

Motivated by the success of network embedding techniques, we first pre-train the network embedding model node2vec[1] to learn high-level network representations from social relations, and then incorporate them into the MF based model. By combining the latent and pre-learned network features together, our method not only can make use of the social network information deeply, but also can take advantage of the collaborative filtering model for recommendation. Experimental results on two real-world datasets demonstrate the effectiveness of our proposed approach.

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2 RECOMMENDATION METHOD

In this section, we first introduce the classic latent factor model, and then focus on how to combine the pre-trained network representations into MF to conduct social recommendation.

2.1 Low-rank Matrix Factorization Model

Let $\mathcal{U}$=$\{u_1...u_M\}$ denote the user set, $\mathcal{I}$=$\{i_1...i_N\}$ denote the item set, and $R = [R_{u,i}]_{M\times N}$ denote the user-item rating matrix, where $R_{u,i}$ represents the ratings of user u on item i. A low-rank matrix factorization approach seeks to approximate the rating matrix R by a multiplication of k-rank factors, and its objective function can be arrived as:

$$\min_{U,I} \frac{1}{|D|} \sum_{(u,i)\in D} \mathcal{L}(R_{u,i}, \widehat{R}_{u,i}(U,I)) + \Omega(U,I) \qquad (1)$$

Where D is the observed user-item rating pairs, U and I are the latent feature factors of users and items, with column vectors $U_u \in \mathbb{R}^k$ and $I_i \in \mathbb{R}^k$ representing user-specific and item-specific feature vectors, respectively. $\widehat{R}_{u,i}(U,I) = U_u^T I_i$ is the predicted score for the dyad (u,i), $\mathcal{L}(\cdot,\cdot)$ is the square loss function, and $\Omega(U,I) = \frac{\lambda_U}{2}\|U\|_F^2 + \frac{\lambda_I}{2}\|I\|_F^2$ is the corresponding regularization term.

2.2 Combined with Pre-learned Features

As users in social networks often express their social interest by making different friends, a better understanding of these social networks is potentially helpful for recommendation. Let $\mathcal{G}$ present the social relationships among users, where an edge denotes there is a friend relationship between user u and v. To mine the deep social structure from $\mathcal{G}$, we introduce the network embedding model node2vec[1] to learn the high-level user representations[1], and let $X_u \in \mathbb{R}^d$ represent the learned feature vector of user u, which denotes how well a user is influenced by his friends in graph $\mathcal{G}$. By fusing these pre-trained features with the latent features from collaborative filtering model linearly, we can arrive at our embedding based recommendation method MFn2v:

$$\mathcal{L}(U, I, W) = \min_{U,I,W} \frac{1}{2} \sum_{u=1}^{M} \sum_{i=1}^{N} (R_{u,i} - U_u^T I_i - W_u^T X_u)^2 + \frac{\lambda_U}{2} \|U\|_F^2 + \frac{\lambda_I}{2} \|I\|_F^2 + \frac{\lambda_W}{2} \|W\|_F^2 \qquad (2)$$

where $W_u \in \mathbb{R}^d$ is the weighted vector that indicates how much the pre-trained network features should contribute to user u.

We apply stochastic gradient descent method to find a local minimum of Eq. 2, and update the latent factors U, I and W by the following gradients:

$$\frac{\partial \mathcal{L}(U, I, W)}{\partial U_u} = \sum_{i=1}^{N} (U_u^T I_i + W_u^T X_u - R_{u,i}) I_i + \lambda_U U_u$$

$$\frac{\partial \mathcal{L}(U, I, W)}{\partial I_i} = \sum_{u=1}^{M} (U_u^T I_i + W_u^T X_u - R_{u,i}) U_u + \lambda_I I_i$$

$$\frac{\partial \mathcal{L}(U, I, W)}{\partial W_u} = \sum_{i=1}^{N} (U_u^T I_i + W_u^T X_u - R_{u,i}) X_u + \lambda_W W_u$$

3 EVALUATION

3.1 Experimental Setup and Comparisons

We utilize two real-world datasets (Ciao and Epinions) to evaluate our recommendation method, and for Ciao[5] the latent factor dimension k is set as 15 and the regularization parameters are set as $\lambda_U = \lambda_I = 0.6$ and $\lambda_W = 0.001$. For Epinions[5], the parameters are set as: k =15, $\lambda_U = \lambda_I = 0.6$, $\lambda_W = 0.005$.

For both of these two datasets, 80% of randomly selected ratings are used for training, and RMSE and MAE[5] are utilized as the evaluation metrics. In this work, we compare our method with three related approaches: MF, LFL[4] and SocialMF[2].

Table 1: The Performance Comparison on Ciao and Epinion

Dataset	Metrics	MF	LFL	SocialMF	MFn2v
Ciao	MAE	0.782	0.760	0.755	0.746
	RMSE	1.006	1.002	0.990	0.974
Epinions	MAE	0.846	0.842	0.830	0.823
	RMSE	1.086	1.070	1.062	1.058

[1]The parameter settings of our pre-trained node2vec model are: d = 10; l = 80; r = 10; k = 10; p = 1; q = 0.5.

The experimental results are shown in Table 1, from which we can find: As MF only uses the rating information for recommendation, it does worse than other methods. The state-of-the-art social recommendation method SocialMF achieves a better performance than both MF and LFL, which demonstrates the social relationship is helpful to model users' preference. From this result, we can also find that our proposed method MFn2v can perform better than SocialMF, and reach the best performance in experiments, which indicates that fusing the pre-trained embedding with latent factors is helpful, and can effectively model both the users' personal and social interests.

3.2 Convergence Analysis

To explore the efficiency of our model, we further conduct experiments to compare the convergence of our MFn2v method with MF method on Ciao. To make them comparable, same learning rates are adopted. Fig.1 shows the comparison results, from which we can observe both these two methods converge very fast (converge within 80 iterations). The convergence rate of MFn2v is not slowed down by incorporating the social network representations, on the contrary it can make a better performance than MF method (Similar results can also be reached on the Epinions data).

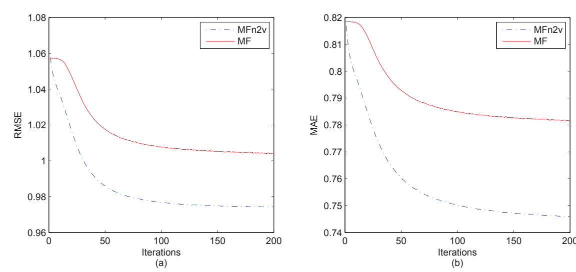

Figure 1: Convergence analysis on the Ciao data (a) RMSE (b) MAE.

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