Social Recommendation with Implicit Social Influence

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ABSTRACT

Social influence is essential to social recommendation. Current influence-based social recommendation focuses on the explicit influence on observed social links. However, in real cases, implicit social influence can also impact users' preference in an unobserved way. In this work, we concern two kinds of implicit influence: Local Implicit Influence of persons on unobserved interpersonal relations, and Global Implicit Influence of items broadcasted to users. We improve the state-of-the-art GNN-based social recommendation methods by modeling two kinds of implicit influences separately. Local implicit influence is involved by predicting unobserved social relationships. Global implicit influence is involved by defining global popularity of each item and personalize the impact of the popularity on each user. In a GCN network, explicit and implicit influence are integrated to learn the social embedding of users and items in social recommendation. Experimental results on Yelp initially demonstrate the effectiveness of proposed model.

CCS CONCEPTS

• **Information systems** → **Recommender systems**.

KEYWORDS

Social recommendation; graph neural network; implicit influence

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1 INTRODUCTION

Social recommendation utilizes the social resources, e.g. interpersonal relations and influence, as extra information to improve the performance of recommendation [4, 8, 19]. Social theory of homogenization supposes that people with social connections will influence each other, leading to similar interests [1, 2, 11]. This theory inspires the research of influence-based social recommendation. In this direction, social recommendation systems use users' social matrix as side information to enhance each user's embedding learning , or to standardize the user's embedding learning by social neighbors [5, 7, 8, 15]. These approaches consider the influence of first-order neighbors of each user, which alleviates the data sparseness problem of collaborative filtering model.

However, in social network, users can be affected not only by first-order neighbors, but also by higher-order neighbors. Recently, influence of high-order neighbors are studied [22, 23]. For example, DiffNet[23] proposes a diffusion network model with hierarchical influence propagation to simulate the high-order recursive social diffusion in social recommendation. DiffNet++[22] improves the DiffNet by connecting user-user social network and user-item interest network according to common users. In this way, higher-order social influence and interest diffusion can be jointly modeled and further improve the performance of recommendation.

Given an observed social network, current social recommendation methods have modeled the high-order explicit influence between users, but ignore the implicit influence. Recent works propose models of implicit influence [12, 25, 27], different from which, We define implicit influence as the influence whose diffusion route is not observed in given social network. Furthermore, we distinguish two kinds of implicit influence: local implicit influence and global implicit influence. Local implicit influence occurs between two people with unobserved social relationship. For example, they have unknown offline relationship instead of observable online connection, or they are friends in a social media not involved in current data. Global implicit influence is broadcasted social influence without depending on interpersonal relationship. For example, the influence of popular items appear in media advertising.

In this paper, we propose DiffNetLG (Diffusion neural Network with Local and Global implicit influence) : a model that unifies the modeling of explicit and implicit social influence for social recommendation. The model combines the social network and interest network. In combined network, local implicit influence is involved by predicting the unobserved social relationship, and global implicit influence is modeled by defining the global popularity of each item. Finally, on combined network, explicit influence and two implicit social influences are jointly modeled with a graph convolution network and achieve improved embedding representations of users and items for social recommendation.

In summary, our major contributions are as follows:

(1) We propose to model implicit social influence in social recommendation. Local and global implicit social influence are defined and modeled respectively without the need for extra information in addition to observed social network.

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(2) Improving state-of-the-art graph convolution network models of social recommendation, we design an unified model connecting social network and interest network, in which implicit and explicit influence are integrated to learn the embedding of users and items.

(3) Extensive experimental results on a real dataset demonstrate the effectiveness of proposed model. There are more than 4% on HR metric and 6% on NDCG metric improvements on the Top-10 recommendation compared to the best-performing baselines.

2 RELATED WORK

Social influence is essential to the research of social recommendation [4, 8, 15, 29]. According to the social impact theory, when information spreads in social networks, users in the network will be affected by their social relations, leading to similar preferences among social neighbors [1, 2, 6, 16]. In early studies, social influence is often represented by social regularization in social recommendation [7, 15]. For example, TrustSVD [5] takes social neighbors' preference as auxiliary feedback on current users, and adds the trust influence of social neighbors on the basis of SVD++[10] model. Similarly, SR[14] learns users' social matrix by introducing factor vectors, SocialMF[7] believes that users' representations are influenced by their friends, and STE[13] combines users' personal interests with that of their friends.

Besides regularization, social influence of neighbors can also be represented in social embedding of users and items, especially using graph neural networks. For example, GCN[9] based methods [20, 21, 26, 28] are proved to be more effective than regularization. Among these methods, earlier studies focus on modeling influence of first-order neighbors, e.g., GraphRec[3]. Recent works explore higher-order influence, e.g., PinSage[26] learns nodes embedding by combining random walk and graph convolution, NGCF[21] determines the association between message propagation and the central node, and DiffNet[23] simulates user preferences based on user social relationships and historical behavior.

Besides explicit influence, different implicit influence is also studied.[12] introduces implicit influence in social regularization. SoInp[25] models the implicit influence from the perspective of information propagation which is inferred from ratings on the same items. [27] captures the implicit users through meta-path based embedding in heterogeneous network.

Although GNN-based social recommendation has well modeled the explicit social influence, the implicit influence on unobserved social links is still an open problem. In this work, we improve the state-of-the-art GNN-based social recommendation by modeling implicit social influence from both local and global perspectives.

3 METHODOLOGY

3.1 Problem Statement and overall framework

In social recommendation, we have users set $U(|U| = M)$ and items set $V(|V| = N)$. The social network of users is defined as a directed graph $G_S =< U, S >$, where $S \in \mathbb{R}^{M\times M}$ is a matrix representing social relations between users. The user interest network is defined as an undirected bipartite graph $G_I =< U \cup V, R >$, where $R \in \mathbb{R}^{M\times N}$ is a matrix representing users' real-valued preferences to items. In addition, each user a is associated with a real-valued attribute vector, denoted as x_a in an user attribute matrix $X \in \mathbb{R}^{d_1\times M}$. Each item i is also associated with an attribute vector y_i in item attribute matrix $Y \in \mathbb{R}^{d_2\times N}$. The task of social recommendation in this work is to predict users' unknown real-valued preferences to items in $R \in \mathbb{R}^{M\times N}$ according to given G_S, G_I, X and Y.

We propose DiffNetLG model as shown in Fig.1. DiffNetLG has three parts: the fusion layer, the social and interest influence diffusion layers and the rating predicting layer. By taking inputs, the fusion layer fuses features and free embeddings of users and items. In the social and interest influence diffusion layers, we use GCN to jointly model explicit and implicit influence. Explicit influence is modeled by observed links in social and interest networks. For implicit influence, we model local implicit influence by predicting unobserved user-user social links which are added as observed links for the next iteration in GCN learning, we model global implicit influence by calculating the popularity of each item on all users and combine it with items' explicit influence on users. Finally, with trained embedding of users of items, the rating predicting layer predicts the preference score of each unobserved user-item pair.

3.2 Explicit Influence Modeling

In DiffNetLG, observed links in social and interest network are modeled with the edges in a graph convolution network. The explicit influence diffusion on observed links are modeled with iterative representation learning of user and item embedding in the graph.

In initial step of learning, for each user a, a free embedding vector p_a and the relevant feature vector x_a are fused. The fused vector u_a^0 is taken as the initial vector of a. Similarly, for each item i, the free embedding vector q_i and the relevant feature vector y_i are fused to be the initial vector v_i^0. By inputting initial potential vectors of users and items, hierarchical convolution modeling is recursively performed for the dynamic propagation of users' and items' potential preferences in the network. We learn the embedding of each review word and get the feature vector of each user/item by averaging learned word vectors of the user/item. This iteration step starts at $k = 0$ and ends when the recursion reaches a predefined depth K. In our model, for best effect, we set $K = 2$.

For each item i, given its k-th layer embedding v_i^k, its update embedding for the $(k+1)$-th layer can be modeled as:

$$\tilde{v}_i^{k+1} = \sum_{a\in R_i} \eta_{ia}^{k+1} u_a^k \tag{1}$$

where u_a^k is the k-th layer embedding vector of user a, η_{ia}^{k+1} represents the aggregated weights where R_i is the set of users have rated item i. We use an average pooling that performs a mean operation of all interacted users' latent embedding at the k-th layer.

For each user a, u_a^k represents his/her k-th potential embedding. The $(k+1)$-th update embedding of users are influenced by two aspects: social network influence and interest network influence. Let $\tilde{p}_a^{k+1}$ represents the explicit influence of neighbor users on the $(k+1)$-th layer, $\tilde{q}_{a-E}^{k+1}$ represents the explicit influence of neighbor items on the $(k+1)$-th layer. Explicit influences are modeled as:

$$\tilde{p}_a^{k+1} = \sum_{b\in S_a} \alpha_{ab}^{k+1} u_b^k \quad , \quad \tilde{q}_{a-E}^{k+1} = \sum_{i\in R_a} \beta_{ai}^{k+1} v_i^k \tag{2}$$

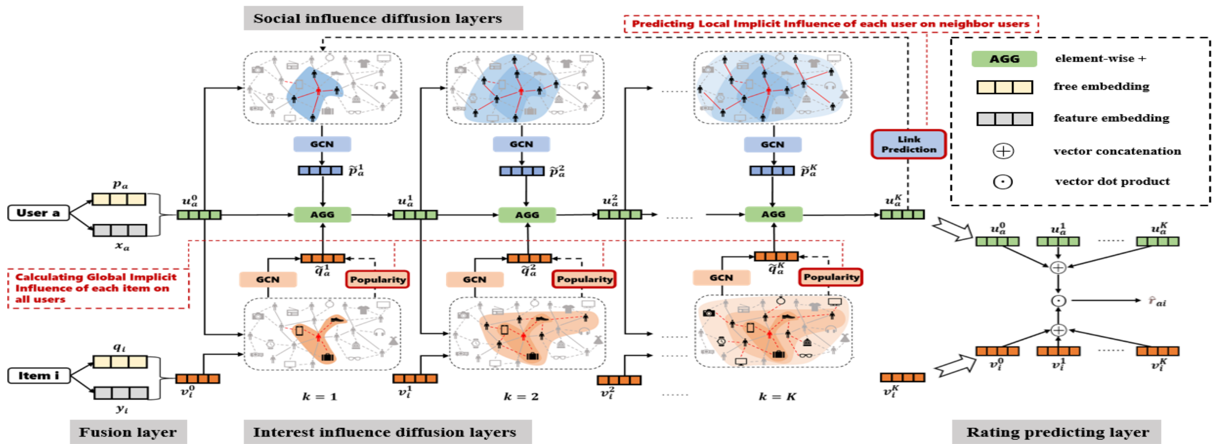

Figure 1: The overall structure of DiffNetLG. The fusion layer integrates the free embedding and feature embedding of users and items. Inputted integrated embedding, social influence (blue) and interest influence (orange) diffusion layers update the embedding through GCN training. With trained embedding, rating predicting layer predicts unobserved user-item pairs.

where α_{ab}^{k+1} represents the influence weight of user b on user a at the $(k+1)$-th layer in social network, β_{ai}^{k+1} represents the influence weight of item i on user a at the $(k+1)$-th layer in interest network. S_a and R_a is the users set and items set that rated and followed by user a, respectively. Like η_{ia}^{k+1}, α_{ab}^{k+1} and β_{ai}^{k+1} use an average pooling to aggregate the influence of users and items on a.

3.3 Implicit Influence Modeling

In this work, local and global implicit influence are separately modeled and integrated into the embedding learning of users and items.

3.3.1 Local Implicit Influence. Local implicit influence occurs on unobserved interpersonal links. To involve implicit influence in DiffNetLG, we adopt the techniques of link prediction to predict unobserved interpersonal links. It is noted that, in a network, the performance of nodes embedding learning and that of link prediction are closely depending on each other. Therefore, in our GCN learning, the predicted interpersonal links on K-th layer are added to next training process as observed links, so that the learning of nodes embedding and link prediction can benefit each other.

In our algorithm, the probability of unobserved links are measured by the similarity between the embedding vectors of a pair of user nodes. Specifically, we measure the similarity between the embedding vectors into the proximity of two vectors in Euclidean space. For example, the probability of existing an unobserved link between two unconnected users u_i and u_j in social network is:

$$P(u_i^K, u_j^K) = \frac{1}{1 + exp(-(u_i^K)^T u_j^K)} \tag{3}$$

where, $u_i^K, u_j^K \in \mathbb{R}^D$ is the (K-th) embedding vector of node u_i and u_j, and D is the dimension of the vectors. We set a threshold (0.9) of calculated probability to identify unobserved links.

3.3.2 Global Implicit Influence. Global implicit influence is assumed as broadcasted influence of each item to all users. In this work, global implicit influence of each item is calculated as a popularity value, which is updated in each iteration of GCN learning and concatenated with item embedding. The popularity pop_i of an item i is quantified by a smoothed ratio of linked users of i to the linked users of all items: $pop_i = (|R_i| + 1)/(\sum_{j \in V} |R_j| + |V|)$, where R_i is the set of the users linked to i and V is the set of all items.

In order to personalize the global implicit influence of item i to each user, cosine similarity between the embedding of i and each user is calculated after influence iteration of each layer. Therefore, the global implicit influence weight of item i to user a on $(k+1)$-th layer is: $\tau_{ai}^{k+1} = pop_i \times cos(u_a^k, v_i^k)$. Then the implicit influence of items on a on $(k+1)$-th layer can be formalized as:

$$\tilde{q}_{a-I}^{k+1} = \sum_{i \in N} \tau_{ai}^{k+1} v_i^k \tag{4}$$

For each user, the explicit influence in Eq.(2) and the global implicit influence in Eq.(4) are combined with a trade-off parameter $\hat{\lambda}$, and the aggregated influence of user a's neighbor items on $(k+1)$-th layer can finally be modeled as:

$$\tilde{q}_a^{k+1} = \hat{\lambda} \tilde{q}_{a-E}^{k+1} + (1 - \hat{\lambda}) \tilde{q}_{a-I}^{k+1} \tag{5}$$

3.4 Fusion Approach and Model Training

In GCN training, given the k-th layer embedding v_i^k of an item i, the update embedding v_i^{k+1} of the $(k+1)$-th layer is: $v_i^{k+1} = \tilde{v}_i^{k+1} + v_i^k$, where $\tilde{v}_i^{k+1}$ aggregates neighbor users' embedding by Eq.(1).

Given k-th layer embedding u_a^k of an user a, the update embedding u_a^{k+1} of the $(k+1)$-th layer is influenced by both social and interest network: $u_a^{k+1} = u_a^k + \tilde{p}_a^{k+1} + \tilde{q}_a^{k+1}$, where $\tilde{p}_a^{k+1}$ aggregates influence of a's neighbor users' by Eq.(2). $\tilde{q}_a^{k+1}$ aggregates influence of items on a by Eq.(5).

After the iterative diffusion process with K times, we obtain the embedding set of u and i with u_a^k and v_i^k for k = [0, 1, 2..., K]. Then, for each user a, the final embedding is denoted as: u_a^f =

$[u_a^0||u_a^1||...||u_a^K]$ that concatenates each layer's embedding. Similarly, each item i's final embedding is: $v_i^f = [v_i^0||v_i^1||...||v_i^K]$. After that, the predicted rating is modeled as the inner product between the final user and item embeddings: $\hat{r}_{ai} = (u_a^f)^T v_i^f$.

With learned embedding of users and items, a pair-wise ranking based loss function is used to optimize social recommendation:

$$\min_{\Theta} \mathcal{L}(R, \hat{R}) = \sum_{(a,i)\in R^+ \cup (a,j)\in R^-} - \ln \sigma(\hat{r}_{ai} - \hat{r}_{aj}) + \lambda||\Theta||^2 \quad (6)$$

where R^+ is the set of positive samples (observed user-item pairs), and R^- is the set of negative samples (unobserved user-item pairs that randomly sampled from R). σ(x) is sigmoid function, $\Theta = [\Theta_1, \Theta_2]$. with $\Theta_1 = [P, Q]$, and the parameter set in the fusion layer, i.e, $\Theta_2 = [F, [W^k]_{k=0}^{K-1}]$, λ is a regularization parameter that controls the complexity of user and item free embedding matrices. All the parameters in the above loss function are differentiable.

4 EXPERIMENTS

Dataset. We conducted experiments on widely used *Yelp*[1] dataset, where users make friends and review restaurants. We randomly select 10%, 10% and 80% of the data for testing, validation and training, respectively. The count of users, items, links and ratings is 17K, 38K, 143K, 204K, respectively. The link density is 0.048%.

Baselines. We compared our model with three sets of baselines, including classical CF models (BPR[18], FM[17]) without social information, social recommendation models (SocialMF[7], TrustSVD[4], ContextMF[8], CNSR[24]) modeling first-order social influence and the state-of-the-art GNN-based social recommendation models (GraphRec[3], PinSage[26], NGCF[21], DiffNet[23], DiffNet++[22]) modeling high-order social influence.

For our proposed model, besides the main DiffNetLG model involving both local and global influence, we also investigate the performance of two variants named DiffNetL and DiffNetG, which only involves local and global implicit, respectively.

Evaluation Metrics. Recommending Top-N items for each user, we used two popular ranking based metrics: Hit Ratio (HR) and Normalized Discounted Cumulative Gain (NDCG). HR measures the percentage of hit items in Top-N list and NDCG puts more emphasis on top ranked items. We ranked all the items to calculate the values of metrics and randomly selected 1,000 unrated items that a user has not interacted with as negative samples of this user. We mixed these pseudo negative samples and corresponding positive samples (in the test set) to select Top-N candidate items. We repeated this procedure 10 times and report the average ranking results.

Results. Recommendation results are shown in Table 1 and Table 2 with various embedding size D and Top-N values, respectively. In the results, BPR and FM only use observed user-item rating matrix and mostly suffers from data sparsity. SocialMF, TrustSVD, ContextMF and CNSR mitigate this problem by using first-order neighbor users as auxiliary information. GraphRec achieves further improvement by combining interest neighbors. Beyond first-order influence, GCN-based PinSage, NGCF and Diffnet show advantage of modeling higher-order user-item graph or social structure. Latest DiffNet++ integrates the higher-order user-item graph and social structure and achieves the state-of-the-art performance.

[1]http://www.yelp.com/

Models	HR			NDCG		
	D=16	D=32	D=64	D=16	D=32	D=64
BPR[18]	0.2435	0.2616	0.2632	0.1468	0.1573	0.1554
FM[17]	0.2768	0.2835	0.2825	0.1698	0.1720	0.1717
SocialMF[7]	0.2571	0.2709	0.2785	0.1655	0.1695	0.1677
TrustSVD[4]	0.2826	0.2854	0.2939	0.1683	0.1710	0.1749
ContextMF[8]	0.2985	0.3011	0.3043	0.1758	0.1808	0.1818
CNSR[24]	0.2702	0.2817	0.2904	0.1723	0.1745	0.1746
GraphRec[3]	0.2873	0.2910	0.2912	0.1663	0.1677	0.1812
PinSage[26]	0.2944	0.2966	0.3049	0.1753	0.1786	0.1855
NGCF[21]	0.3050	0.3068	0.3042	0.1826	0.1844	0.1828
DiffNet[23]	0.3293	0.3437	0.3461	0.1982	0.2095	0.2118
DiffNet++[22]	0.3406	0.3552	0.3694	0.2070	0.2158	0.2263
DiffNetL (ours)	0.3372	0.3478	0.3629	0.2067	0.2165	0.2283
DiffNetG (ours)	0.3383	0.3565	0.3705	0.2082	0.2205	0.2324
DiffNetLG (ours)	**0.3427**	**0.3593**	**0.3711**	**0.2114**	**0.2218**	**0.2333**

Table 1: Overall comparison of HR@10 and NDCG@10 with different dimension size D.

Models	HR			NDCG		
	N=5	N=10	N=15	N=5	N=10	N=15
BPR[18]	0.1695	0.2632	0.3252	0.1231	0.1554	0.1758
FM[17]	0.1855	0.2825	0.3440	0.1341	0.1717	0.1876
SocialMF[7]	0.1739	0.2785	0.3365	0.1324	0.1677	0.1841
TrustSVD[4]	0.1882	0.2939	0.3688	0.1368	0.1749	0.1981
ContextMF[8]	0.2045	0.3043	0.3832	0.1484	0.1818	0.2081
CNSR[24]	0.1877	0.2904	0.3458	0.1389	0.1746	0.1912
GraphRec[3]	0.1915	0.2912	0.3623	0.1279	0.1812	0.1956
PinSage[26]	0.2105	0.3049	0.3863	0.1539	0.1855	0.2137
NGCF[21]	0.1992	0.3042	0.3753	0.1450	0.1828	0.2041
DiffNet[23]	0.2276	0.3461	0.4217	0.1679	0.2118	0.2307
DiffNet++[22]	0.2503	0.3694	**0.4493**	0.1841	0.2263	0.2497
DiffNetL (ours)	0.2536	0.3629	0.4426	0.1888	0.2283	0.2522
DiffNetG (ours)	0.2568	0.3705	0.4459	0.1937	0.2324	0.2578
DiffNetLG (ours)	**0.2599**	**0.3711**	0.4473	**0.1941**	**0.2333**	**0.2586**

Table 2: Overall comparison of HR@N and NDCG@N with different Top-N values (D=64).

Introducing implicit influence into Diffnet, our models exceed all baselines in most cases, which verifies the general advantage of modeling implicit influence. Furthermore, DiffNetLG with both local and global implicit influence exceeds DiffNetL and DiffNetG involving only one implicit influence, which demonstrates the necessary of modeling both implicit influence. In addition, compared with Diffnet++ using attention mechanism, DiffNetLG has higher convergence speed and less time cost.

5 CONCLUSIONS

For social recommendation, we propose to model two kinds of implicit influence on users' preference, besides explicit social influence. The local implicit influence is modeled by predicting unobserved links and global implicit influence is modeled by personalized popularity of items. Explicit and implicit influence are recursively updated through an unified GCN network and achieve optimized social embedding of users and items. In initial experimental results on Yelp, the proposed model exceeds the state-of-the-art baselines.

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