Your Social Circle Affects Your Interests: Social Influence Enhanced Session-Based Recommendation

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Abstract. Session-based recommendation aims at predicting the next item given a series of historical items a user interacts with in a session. Many works try to make use of social network to achieve a better recommendation performance. However, existing works treat the weights of user edges as the same and thus neglect the differences of social influences among users in a social network, for each user's social circle differs widely. In this work, we try to utilize an explicit way to describe the impact of social influence in recommender system. Specially, we build a heterogeneous graph, which is composed of users and items nodes. We argue that the fewer neighbors users have, the more likely users may be influenced by neighbors, and different neighbors may have various influences on users. Hence weights of user edges are computed to characterize different influences of social circles on users in a recommendation simulation. Moreover, based on the number of followers and PageRank score of each user, we introduce various computing methods for weights of user edges from a comprehensive perspective. Extensive experiments performed on three public datasets demonstrate the effectiveness of our proposed approach.

Keywords: session-based recommendation · social recommendation · social influence.

1 Introduction

In an era of information explosion, the rapid growth of online shopping and services makes it difficult for users to choose what they prefer from innumerable goods and services. As is known to all, different people's interests and preferences are completely different, and in some scenarios, individuals are not very certain about their needs. Driven by the above backgrounds, recommendation system emerges as the times require [4] [25] [38].

Recommendation system is applied to capture users' interests based on their personal information and historical interactions with the items [12] [13]. Further,

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it predicts the next item to users that they may interact with according to user preferences [3] [14] [30].

Session-based recommendation (SR) is first introduced to tackle the case that users' personal information (even the user IDs) can not be acquired [8]. A session is defined as a continuous interaction sequence of items in close proximity [23]. User preferences are usually captured by mining sequential transition patterns in a session [18] [21]. Recurrent Neural Network (RNN) is proposed to model the sequence dependencies to learn users' preferences in [27]. Domain-Aware Graph Convolutional Network (DA-GCN) [5] builds a graph and applies a graph neural network to gain users' interests.

Fortunately, user IDs can be obtained in many cases, but we can still make use of SR to conduct a recommendation [1]. Even given the same session historical items, various people may interact with different items out of their personalized interests. So customized session-based recommendation can be made for users [6] [22] [34].

When user IDs are available, users' social network can be acquired as well. It is obvious that user's interest are easily influenced by their friends [17] [24] [35]. As a result, a better recommendation can be made when considering the preferences of users' friends. Lots of works have made efforts to take advantage of users' social network to get a more accurate recommendation [11] [26] [37]. However, when it comes to SR, brand new methods should be considered due to the abovementioned special features (modeling sequential dependencies for recommendation). In social SR, recent work [2] builds a heterogeneous graph, which consists of social network and all historical user behaviors. It learns social-aware user and item representations, and gets a state-of-the-art (SOTA) performance. Although exiting works take the social influence into account, they set the weights of user-user edges as the same value, and do not detail the differences of social influences among users in social network, instead using a model to capture the impact of social influence on user preferences.

In this situation, we argue that the probabilities of users being affected are different among various users in SR and diverse users may have various influences on their followers. Therefore, we analyze social influence for SR in an explicit manner. Specially, we argue that the fewer people one follows, the more likely he/she may be affected by his/her social circle. Moreover, the more influential users are, the larger impact they will impose on their followers. To verify our thought, we propose a social influence enhanced model, which uses Social-aware Efficient Recommender (SERec) [2] as a backbone. The in-degree and PageRank [19] score for each user node in the social network are primarily computed, which reflect the social influences. Then we take the results as weights among connected user nodes in the graph. Finally, the social network obtains the knowledge of social influences, and we can utilize it to get a more accurate preference for each user.

Our contributions are summarized as follows:

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1. We incorporate influence degree of each user affecting and being affected into the social network to capture a more accurate user preference in an explicit way.

2. We come up with some simple but effective methods to obtain the influence weights of social network to make our approach practical.

3. Extensive experiments are performed to verify the effectiveness of our proposed method.

In the rest of this paper, related work is introduced in Section 2. We detail our method in the following Section 3. Last but not least, we conduct extensive experiments in Section 4 and sum up our work in Section 5.

2 Related Works

Since we focus on social session-based recommendation (SR), we first discuss the relative works of SR and then talk about social recommendation.

Session-based Recommendation: Session-based recommendation can be regarded as a sequential modeling task for the reason that a session is composed of a series of user historical interactions with the items. Naturally, RNNs are preferred to model item transition patterns [7] [9]. In [8], Hidasi et al. first give a formal definition of session-based recommendation and come up with a multi-layered Gated Recurrent Unit (GRU) model, which is a variant of RNN to capture sequential dependences in a session. This work is generally treated as a pioneer attempt for SR. Following Hidasi's work, an improved RNN [27] creatively points out a data augmentation technique to improve the performance of RNN. Subsequent works take Convolutional Neural Networks (CNNs) into consideration to model sequential dependencies [28] [29]. A Dilated CNN [36] proposes a stack of holed convolutional layers to learn high-level representation from both short- and long-range item dependencies. Furthermore, attentive mechanism is introduced into recommendation to reduce noise item impact and focus on users' main purposes, i.e. Neural Attentive Recommendation Machine (NARM) [15], and Short-Term Attention/Memory Priority model (STAMP) [16]. Recently, Graph Neural Networks (GNNs) have been widely used in a large number of tasks on account of their superior performances besides session-based recommendation [10] [20] [39]. SR-GNN [33] is a typical GNN work for SR. It builds all session data into graphs, in which items are regarded as nodes and an edge is added if there is a transit between two items. SR-GNN employs a gated neural network to capture complex transitions of items. These methods try to model item dependencies in sessions, but do not take social influence into account.

Social Recommendation: As a widely studied research field, social network has been applied for recommendation in depth [31] [32]. However, when social session-based recommendation is mentioned, there is not yet much work for the reason that SR is a relatively new topic, and previous social recommendation methods are not suitable for SR due to their lack of modeling sequence dependencies. Recently Dynamic Graph Recommendation (DGRec) [26] models

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dynamic user behaviors with a recurrent neural network, and captures context-dependent social influence with a graph-attention neural network. DGRec gets a better recommendation performance, but its inefficiency can not be ignored, because it has to deal with lots of extra sessions to make a recommendation. To solve the efficiency issue that DGRec meets, SERec [2] implements an efficient framework for session-based social recommendation. In detail, SERec precomputes user and item representations from a heterogeneous graph neural network that integrates the knowledge from social network. As a result, it reduces computations during predicting stage. Efficient as it is, SERec just adds users' social network into the interaction graph and sets weights among user nodes as the same value without considering influence differences among various users.

3 Modeling Methods

3.1 Problem Definition

In session-based recommendation, we define $U = \{u_1, u_2 ..., u_N\}$ as the set of users, $I = \{i_1, i_2, ...i_M\}$ as the set of items. Each user $u \in U$ generates a set of sessions, $S^u = \{s_1^u, s_2^u, ...s_T^u\}$. For each session, there are a series of items that a user interacts with sorted by timestamp. For example, $s_1^u = \{i_1^u, i_2^u, ...i_L^u\}$, and L is the length of session s_1^u. All sessions of users constitute users' historical behaviors dataset B. The goal of session-based recommendation is as follows: given a new session of user u, $S = \{i_1^u, i_2^u, ...i_n^u\}$, predict i_{n+1}^u for the user u by recommending top- K items $(1 \leq K \leq M)$ from all items I that might be interesting to the user u.

In addition, in social session-based recommendation, besides users' historical behaviors B, a social network can be utilized to improve recommendation. Let $SN = (U, E)$ denote the social network, where U is the nodes of users, E is the set of edges. There is an edge if a social link exits between two users. For example, an edge (u, v) from u to v means that u is followed by v, in other words, v follows u.

3.2 Social Influence Modeling

Social Session-Based Behaviors Graph Building We first construct a heterogeneous graph from all users' behaviors B and social network SN. Then we apply a GNN (Graph Neural Network) [37] to learn representations of users and items. The user representations can capture user preferences and more accurate social influences. Item representations can learn useful information from user-item interactions and cross-session item transition dependencies.

In the heterogeneous graph, all the users and items in B and SN make up the graph nodes, and the set of edges consists of four kinds of edges. A user-user edge (u, v) exists if v follows u (in other words, u is followed by v). It is worth noting that we make such a design because in our model a user node representation is learned by the incoming edges and users are more influenced by those they

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follow than those following them. If a user u has ever clicked an item i in any session, there will be two edges, namely (u, i) and (i, u). Lastly, there is an edge (i, j) if item i transmits directly to item j.

Now, we take edge weights into consideration. The weight of user-item (u, i) and item-user (i, u) is the times of user u clicked item i. And the weight of item-item (i, j) is the times of item i transmitted to j.

When considering weights of user-user (u, v), SERec [2] defines all the weights of user-user as an identical number 1. However, we argue that different weights should be designed among users in the social network, for various influences may have on different users in the social network. As a result, we compute every weight between user-user edge to explicitly represent the social influence.

Social Influence Computing After the heterogeneous graph is constructed, we compute the weights among user nodes in the following method inspired by [40].

Given a user node v, the node in-degree d denotes the number of users that v follows. We view all the incoming edges' weights W as the user v's degree of being influenced. In other words, the weight of edge (u, v) is calculated in the following equation:

$$W(u, v) = C/d, \tag{1}$$

where C is a positive constant to control the range of weight.

For example, if a node v follows three users u_1, u_2, u_3, then there are three edges $(u_1, v), (u_2, v), (u_3, v)$. So the in-degree of v is 3, and the weights of the three edges are all set to $W = C/3$.

We further make a research on the ability of users to influence their followers. We apply PageRank [19] to calculate the importance of a user in the social network, which is a way of measuring the importance of website pages. Intuitively, the larger of the importance value users get, the more influence users may have on their followers. In detail, the influence of node u is computed as follows:

$$F_u = (1 - A)/N + A * (F_{v_1}/out(v_1) + F_{v_2}/out(v_2) + ... + F_{v_n}/out(v_n)), \tag{2}$$

where $out(v_i)$ denotes the out-degree of node v_i. $v_1...v_n$ is the followers of user u, A is a coefficient, N is the number of user nodes.

For example, if a node u is followed by three users v_1, v_2, v_3, then there are three edges $(u, v_1), (u, v_2), (u, v_3)$. Then weights of the three edges are all set to be F_u.

3.3 Model Architecture and Training

In this section, we briefly illustrate how to capture user preferences by modeling user sequential patterns. Our model selects SERec as a backbone, and utilizes a Graph Neural Network (GNN) [37] and gated GNN [33] to capture user preferences. As is demonstrated in Figure 1, our model is composed of two modules: heterogeneous graph embedding module and user dynamic preference embedding module.

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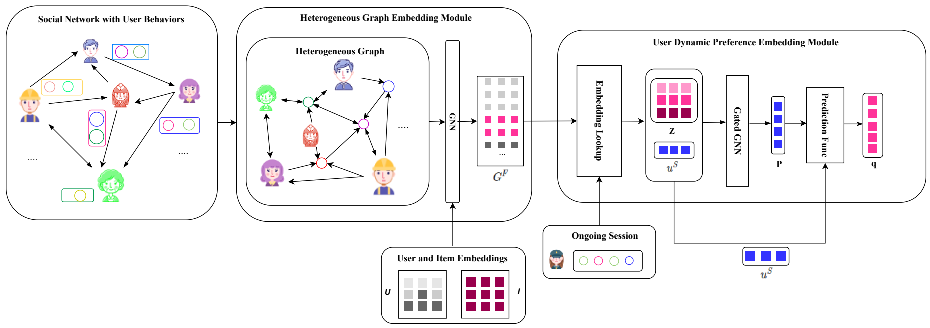

Fig. 1. An overview of model architecture. Heterogeneous graph embedding module is applied to learn representations of users and items. User dynamic preference embedding module applies a gated GNN to obtain a user preference embedding in the ongoing session.

Heterogeneous Graph Embedding Module We apply GNN (graph neural network) to model user and item embedding, which has fused social influence. Supposing GNN is comprised of F layers, let $G^f[x]$ denote the representation of node x at layer f, where x may be a user or an item. The new node representation $G^f[x]$ is computed as follows:

$$G^f[x] = ReLU(W_1^f(G^{f-1}[x]||\hat{G}^f[x]) + b_1^f), \tag{3}$$

where $G^{f-1}[x]$ is the old node representation. $\hat{G}^f[x]$ is the aggregated information from node x's neighbors $N(x)$, and y belongs to $N(x)$ if there is an edge (y, x) pointing to x. W_1^f and b_1^f are learnable parameters.

The aggregation information from node x's neighbors is calculated by the equation below:

$$\hat{G}^f[x] = \sum_{y \in N(x)} Attention(y, x) * (W_2^f G^{f-1}[y] + b_2^f), \tag{4}$$

where W_2^f and b_2^f are learnable parameters. *Attention* function is detailed in [2].

User Dynamic Preference Embedding Module Given an ongoing session S of user x, a graph $G = (V, E)$ is constructed in the same way mentioned in Section 3.2, where V denotes items in S, E denotes item transitions, and the weight of an edge is the times of item transitions. Since we build a heterogeneous graph on all historical sessions of users and social network, global user and item representations are obtained. Then for the ongoing session S, we first retrieve the relative user and item representations to initialize node representations Z. We utilize a gated GNN [33] to model the session-specialized item representation:

$$g_i = v_i \odot tanh(W_c(\hat{N}[z_i]||z_i) + b_c) + (1 - v_i) \odot W_z z_i, \tag{5}$$

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$$v_i = sigmod(W_i(\hat{N}[z_i]||z_i) + b_i), \tag{6}$$

where z_i is the node vector of an item in session S, $\hat{N}[z_i]$ is the aggregated information from z_i's neighboring nodes, g_i represents the vector of node i for specialized session S. W_c, b_c, W_z, W_i and b_i are learnable parameters. Based on g_i, we get a user preference embedding in the ongoing session S:

$$P = \sum_{1 \leq i \leq |S|} b_i * g_i, \tag{7}$$

$$b_i = softmax(r^T sigmod(W_v g_i + W_{last} g_{last} + W_u u^S)), \tag{8}$$

where g_{last} is the embedding of the last item in session S to capture user's recent interest, u^S is the user embedding to capture user u's general preference. r, W_v, W_{last} and W_u are learnable parameters.

Finally, we generate the score q for every item in I via multiplying its embedding e_i by user preference embedding in the ongoing session S:

$$q = softmax(P^T e_i). \tag{9}$$

We apply a cross-entropy of the prediction and the ground truth as the loss function in the following form:

$$L = -\sum_{m=1}^{M} q_m log(\hat{q}) + (1 - q_m) log(1 - \hat{q}), \tag{10}$$

where $\hat{q}$ denotes the one-hot encoding vector of the ground truth item.

4 Experiments

4.1 Experimental Setup

Datasets Following the existing classic social recommendation works [2] [26], we evaluate our proposed method on three public real-world benchmark datasets:

(1)**Foursquare**: The Foursquare[1] dataset is a publicly online available dataset which consists of users' check-in records on different venues in a period of time. Records are regarded as the same session if the check-in time interval is shorter than a day, and records are viewed as different sessions if interval is longer than a day.

(2)**Gowalla**: Gowalla[2] is another check-in data, and the socail network is based on location social network website. Sessions are extracted by the same way as Foursquare.

[1] `https://sites.google.com/site/yangdingqi/home/foursquare-dataset`
[2] `https://snap.stanford.edu/data/loc-gowalla.html`

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Table 1. Datasets Statistics.

Datasets	all users	all items	all clicks	social links	all sessions
Foursquare	39,302	45,595	3,627,093	304,030	888,798
Gowalla	33,661	41,229	1,218,599	283,778	258,732
Delicious	1313	5793	266,190	9130	60,397

(3)**Delicious**: Delicious[3] is an online bookmarking system. We consider a sequence of tags a user has marked to a book as a session (marking time is recorded).

We split each dataset into training/validation/test sets, following the settings in [2]. And we conduct our experiments on augmented datasets. To be specific, for a session $S = (v_1, v_2, v_3, ..., v_n)$, we generate a series of interaction sequences and labels $([v_1], v_2), ([v_1, v_2], v_3), ..., ([v_1, v_2, ..., v_{n-1}], v_n)$, where $[v_1, v_2, ..., v_{n-1}]$ is user's historical sequence, v_n is the next-clicked item, namely the label.

The statistics of datasets are summarized in Table 1.

Evaluation Metrics We evaluate all models with three widely used ranking-based metrics:

(1)**REC@K**: It measures the recall of the top-K ranked items in the recommendation list over all the testing instances. In our experiments, only one item is set as the label, so REC@K is used to measure whether the label item is contained in the top-K ranked items according to the scores.

(2)**MRR@K**: It measures the mean reciprocal rank of the predictive position of the true target item on the top-K ranked items in the recommendation list. The target item is expected to rank ahead in terms of ranking scores.

(3)**NDCG@K**: NDCG is a standard ranking metric. In the context of session-based recommendation, it also measures the position of target item in the recommendation list.

K is set to 10 and 20 in our experiments.

Comparison Methods SERec [2] and DGRec [26] are regarded as two typical works related to social session-based recommendation, and SERec as the SOTA social SR model has proved it enjoys a more effective performance than DGRec [2]. Consequently, we only compare our method with SERec. Moreover, our work is realized on the basis of graph structure by taking social influence explicitly into consideration, we also want to verify if it is effective compared with the existing none-social SR methods like SR-GNN [33], which applies a gated graph convolutional layer to learn item transitions. Last but not least, as mentioned above in Section 3.2, we put forward two ways (in-degree and PageRank) on how to compute the social influences, and we test the two different types and combination of both on SERec and SR-GNN to prove our proposed method.

[3] `https://grouplens.org/datasets/hetrec-2011/`

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Implementation Details Following the backbone method, we set the model hyper-parameters as mentioned in [2]. Generally, user and item IDs are made an embedding into low dimensional latent spaces with the same dimensionality 128. Adam optimizer was used to train the models and the batch size for mini-batch is 128. The above models' performance are reported under their optimal hyper-parameter settings [2]. Specially, we find that our model gets an optimal performance when C is set to 100 and A to 0.85, so we report our model performance under this optimal settings. To compute PageRank scores of user nodes, we first initialize PageRank score of each user node to $1/N$ (N is the number of user nodes in the social network), then update all user nodes' PageRank scores using Equation (2) for five times iteratively. Since we filter out user nodes without followers or followees, each user node can obtain a PageRank score in the social network.

4.2 Experimental Evaluations

Weights Calculating for Social Network We first compute $W(u, v)$ and F_v for each user in the social network using Equations (1) and (2), and set the weights of user-user edges in the following three ways to verify our proposed method:

(1)Using $W(u, v)$ only as the weight for edge (u, v) to demonstrate our idea that the fewer people that users follow, the more influence their social circles may have on their interests;

(2)Using F_u only as the weight of edge (u, v) to prove that the more influential that users are (the PageRank scores are high), the more impact they may have on their followers' behaviors;

(3)Using the sum of $W(u, v)$ and F_u as the weight of edge (u, v) to test the relation between the above two weight computing ways.

Results Analysis As is mentioned above, the explicit social influence is evaluated in three manners, and experiments are implemented based on SERec and SR-GNN to check if our method can achieve a high performance. The experimental results of overall performance are reported in Table 2, Table 3 and Table 4. The optimal and suboptimal results of each column are highlightd in boldface and underline for SERec and SSR-GNN respectively. We denote SSR-GNN for social-aware SR-GNN and denote model with the three weight computing ways by adding a postfix 'W, F, C ' respectively. And 'R, M, N' is short for 'REC, MRR, NDCG'. The following observations can be drawn from the results.

First of all, let us focus on the performance of our method on the SOTA model SERec. In general, our proposed method outperforms SERec. It is proved that the model can learn more accurate user preferences by explicitly adding social influence as the weights of user-user edges. Furthermore, considering users' influence to their followers has a similar improvement on the model with thinking about the degree of users being influenced. To be more specific, SERecW may win a little bit than SERecF. However, to our surprise, simply summing up

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Table 2. Performance on Foursquare.

Model	Foursquare					
	R@10	**M@10**	**N@10**	**R@20**	**M@20**	**N@20**
SERec	61.67	34.11	40.69	70.07	34.71	42.84
SERecF	63.15	36.83	43.11	70.86	37.37	45.11
SERecC	63.21	36.82	43.12	70.89	37.37	45.11
SERecW	**63.34**	**36.91**	**43.27**	**70.94**	**37.44**	**45.20**
SSRGNN	60.94	33.62	40.15	69.28	34.21	42.29
SSRGNNF	61.02	33.56	40.13	69.53	34.16	42.29
SSRGNNC	61.04	33.55	40.12	**69.65**	34.15	42.31
SSRGNNW	**61.21**	**33.83**	**40.39**	69.60	**34.42**	**42.52**

Table 3. Performance on Gowalla.

Model	Gowalla					
	R@10	**M@10**	**N@10**	**R@20**	**M@20**	**N@20**
SERec	45.88	25.26	30.06	53.48	25.78	31.93
SERecF	46.76	**26.54**	31.34	53.85	**27.05**	33.17
SERecC	46.75	26.14	31.00	**54.07**	26.65	32.85
SERecW	**46.87**	26.53	**31.49**	53.92	27.03	**33.27**
SSRGNN	45.32	24.81	29.68	52.94	25.33	31.59
SSRGNNF	**45.50**	24.85	29.74	**53.01**	25.37	31.62
SSRGNNC	45.45	**25.01**	**29.88**	52.87	**25.53**	**31.76**
SSRGNNW	45.29	24.76	29.65	52.79	25.28	31.53

the first two social influence computing results as the weights does not gain a best performance. One possible reason may be that the two weights computing methods represent different views of social influence, and can not be added on the same dimension.

Secondly, when it comes to SSR-GNN, after applying our proposed method to original SSR-GNN, it can make a progress on recommendation results. Other conclusions are nearly the same as SERec, except that SSR-GNNC achieves the best results on some metrics. This further illustrates the uncertainty of summing up the two different weights for their various practical significance.

We have to mention that among the three datasets, our method performs better on Foursquare and gowalla, but is not stable on Delicious. Through deep research, we find that the data characters may lead to such a result. Let us review the statistics of the three datasets in Table 1, Foursquare and Gowalla have rich social links, which can help models learn user preferences by considering the social influence in a more explicit way. On the contrary, Delicious has far less social links than the other two, so models learn little extra information from social network by adding social influence among users, even performs worse possibly due to large data variance. All in all, our proposed method can gain a significant performance promotion on large amounts of datasets, but may meet unstableness on less amounts of datasets.

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Table 4. Performance on Delicious.

Model	Delicious					
	R@10	**M@10**	**N@10**	**R@20**	**M@20**	**N@20**
SERec	**40.22**	21.22	25.70	**49.50**	21.87	28.05
SERecF	39.79	**21.39**	**25.80**	49.33	**22.05**	**28.19**
SERecC	40.12	21.11	**25.80**	48.96	21.75	28.15
SERecW	40.15	21.31	25.64	49.18	21.98	28.09
SSRGNN	39.73	**21.55**	**25.85**	48.78	**22.18**	**28.13**
SSRGNNF	39.92	21.53	25.83	49.23	22.10	28.06
SSRGNNC	**40.09**	21.48	25.83	**49.62**	22.11	**28.13**
SSRGNNW	39.77	21.35	25.68	49.33	22.01	28.10

5 Conclusion

In this paper, we propose an explicit view to discuss how users' social network influences their behaviors. Based on the sense that the smaller one person's social circle is, the more influence his/her social network may have on his/her interests, and the more influential users are, the more likely that they may affect their followers. To verify our idea, we build a heterogeneous social graph, and explicitly compute the influences as weights in social network graph according to in-degrees and PageRank scores of user nodes. Finally, extensive experiments are conducted on three public datasets. It is demonstrated that modeling social influences in an explicit way can outperform the SOTA model on large datasets while get a degradation on a small dataset. In the future, we will explore the influence of social network formation to session-based recommendation. We consider how a user's social network is formed. For example, they share the same topic. This kind of social network may lead to a more stable influence on users' interest, we would study such influence to session-based recommendation.

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