A Time Interval Aware Approach for Session-Based Social Recommendation

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Abstract. Users on social media like Facebook and Twitter are influenced by their friends. Social recommendation exploits users' social activities for modeling their interests to enhance the activeness and retention of users. Besides, their interests change from time to time. Session-based recommendation divides users' interaction history into sessions and predict users' behaviors with the context information in each session. It's essential but challenging to model the social activities and the dynamic property in an unified model. Besides, most of existing session-based recommendation approaches model users' interaction history as ordered sequence in regardless of real timestamps of those interactions. To solve the above issues together, we design a heterogeneous graph for modeling the complex interactions among users and items and propose a Time Interval aware graph neural network-based Recommendation approach(TiRec) to model both the social activities and the dynamic property of users' interaction with items. Furthermore, to capture users' dynamic preference, we propose a time interval aware and self-attention based aggregator to model users' preference in each session. Experimental results on several real-world datasets demonstrates the effectiveness of our proposed approach over some competitive baselines.

Keywords: Session-based recommendation · Time Interval · Social recommendation

1 Introduction

People interact with items like movies, books and music on social media like Douban by purchasing, rating and leaving comments. And users often share their thoughts and communicate with others, through which users' activities tends to be influenced by their related friends. Besides, users' interests are dynamic and change from time to time. A user may be interested in sports for a period of time and then be attracted to video games. Session-based recommendation divides users' interaction records into sessions and model users' preference in each session separately. As a result, social influence among users are often context-dependent. Like when a user want to buy a camera, she tends to consult for her friends who are photography enthusiast instead of those who are interested at sports.

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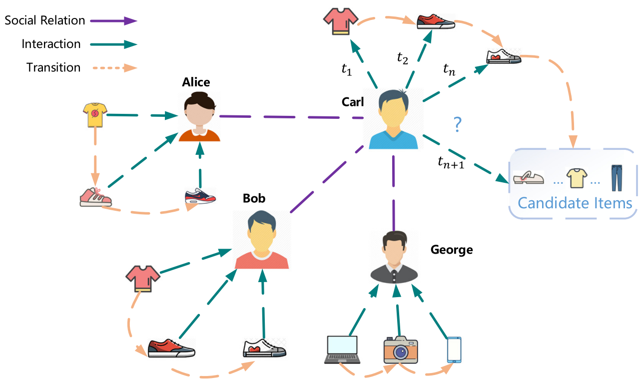

Fig. 1. The illustration of session-based social recommendation.

As the example in Fig. 1, Carl is interested in shoes in the current session while his friend Bob and Alice bought some sporting shoes recently. Then the next purchase decision of Carl may be more influenced by Bob and Alice instead of George, who is an electronic enthusiast instead. It's essential but challenging to model social activities and users' dynamic preference together. However, most of existing work focus on modeling either social activities or users' dynamic preference, instead of them together. To solve those challenges, we propose a graph neural network-based model to model the heterogeneity of users' social activities and interaction activities and the dynamic of users interests.

Our contributions are summarized as follows:

- We propose a Time Interval aware graph neural network-based Recommendation approach(TiRec) to model both the social activities and users' dynamic preference in an unified manner.
- We propose a time interval aware aggregator to model users' preference in each session which utilizes time interval information.
- Experimental results on two real-world datasets demonstrate the effectiveness of our model, showing the usefulness of modeling time interval information in social recommender systems.

The rest of this paper is organized as follows: Some related work is discussed in Sect. 2. We then present the problem definition and introduce our model in Sect. 3. Following it, Sect. 4 presents experiments results and analysis. Finally, Sect. 5 concludes this paper.

2 Related Work

Social Recommendation. Leveraging the social network information provides an effective approach to alleviate data sparsity and improve performance in social recommendation, which has received attention from researchers [2,6,12].

As interactions among users and items can be naturally modeled as a graph, Graph Neural Network(GNN) based approaches have attracted much attention recently [2,11,12]. GNN-based approach socialGCN [12] captures how users' preferences are influenced by the social diffusion process in social networks. GraphRec [2] is for rating prediction in a social recommendation setting, which aggregates information from users and items' connected neighbors. Wu et al. [11] designs a layer-wise influence propagation structure to model how users preferences evolve as the social influence propagates recursively. Our Model is also based on graph neural network, which models social influence and users' dynamic interests together.

Session-Based Recommendation. Capturing the purchase appetites of users and their evolution over time has attracted researchers' attention in recent years, which utilizes sequential information among items to capture users' dynamic interests [1,5,10]. GNN based model are also proposed for session-based recommendation [8,13]. DGRec [8] is the first work to work on session-based social recommendation. They propose a dynamic graph attention network which models the social influence and the sequential pattern of users' actions together. However, the real time interval information is neglected when predicting users' interests, as only the order information in the action sequences is utilized.

3 Model

In this section, we will introduce the problem definition and the details of our model, which is mainly composed of two modules modeling users' dynamic interests and social influence.

3.1 Problem Definition

Definition 1. *(Session-based Social Recommendation) Assume that we have a set of users and items, denoted by U and I respectively. $G_{social} = (U, E_{UU})$ is the social network, where E_{UU} is the social links between users. Given a new session $S^u_{T+1} = \{i^u_{T+1,t_1}, i^u_{T+1,t_2}, ..., i^u_{T+1,t_n}\}$ of user u, the goal of session-based social recommendation is to recommend a set of items from I that u is likely to be interested in at the next timestamp t_{n+1} by exploiting her dynamic interests (i.e., from previous sessions) and social influence received from her social links $N(u)$.*

3.2 Dynamic Interests Aggregator

Dynamic interests aggregator aims to learn user u's latent factor, denoted by $h_S(u)$, from his latest session $S_T(u)$(Our model can be easily generalized to more sessions). The challenge here is to incorporate the real time interval information and sequential information together. To address this challenge, we adopt a self-attention based aggregator, inspired by [4]. The input is user u's latest session

$S_T(u) = \{i^u_{T,t_1}, i^u_{T,t_2}, ..., i^u_{T,t_n}\}$. The sequence is truncated or padded according to a threshold as the max sequence length. As mentioned above, each user-item interaction is associated with a timestamp t_i. So each session $S_T(u)$ is also associated with a timestamp sequence $t = (t_1, t_2, ..., t_n)$. The output of dynamic interest aggregator is $H = (h_1, h_2, ..., h_n)$ in which h_i is the hidden representation of first i elements.

As two sessions may have a same item sequence but with different time intervals among items, we take not only order information between two items i^u_{T,t_j} and i^u_{T,t_k} but also the time interval $\delta_{jk} = |t_k - t_j|$ of two interactions into consideration. δ_{jk} is clipped into a proper range, since a too large time interval or too small time interval tends to be meaningless. δ_{jk} is taken as an index to get a relative temporal encoding $r(\delta_{jk}) \in R^d$. Following [4], we adopt a fixed set of sinusoid functions as basis, with a learnable linear project function $f_{Linear}(\cdot)$ to obtain δ_{jk}:

$$Base(\delta_{jk}, 2i) = sin(\delta_{jk}/10000^{2i/d}) \tag{1}$$

$$Base(\delta_{jk}, 2i+1) = cos(\delta_{jk}/10000^{2i/d}) \tag{2}$$

$$r(\delta_{jk}) = f_{Linear}(Base(\delta_{jk})) \tag{3}$$

With the relative temporal encoding, a weighted sum of the linearly transformed representations of first i elements in the sequence, the position encoding and the relative temporal encoding, denoted by $\hat{h_i}$, is computed as:

$$\hat{h_i} = \sum_{j=1}^{n} \alpha_{ij}(W^V e_i + r(\delta_{ij}) + p_j) \tag{4}$$

where e_i is the embedding of the i-th element, W^V is the linear transformation matrix, $r(\delta_{ij})$ is the relative temporal encoding and p_j is the position encoding. The position encoding is also computed with sinusoid function like the relative temporal encoding following [9].

The weighted coefficient α_{ij} is computed with a softmax function on similarity on e_{ij}, which is computed with a similarity function as:

$$e_{ij} = \frac{W^Q e_i (W^K e_j + r(\delta_{ij}) + p_j)^T}{\sqrt{d}} \tag{5}$$

where W^Q and W^K are linear transformation matrix for query and key in self-attention mechanism. And the final output is obtained performing a feed-forward network $g(\cdot)$ on $\hat{h_i}$ as $h_i = g(\hat{h_i})$.

So far, we have obtained the representation of session $S_T(u)$ which is the short-term preference of user u. And user u's long-term preference is represented with a base embedding e_u. The final representation $h_I(u)$ of the dynamic interest aggregator is compute with a non-linear transform on the long-term interest representation e_u and short-term interest as h_n:

$$h_I(u) = ReLU(W^I[e_u; h_n]) \tag{6}$$

where $ReLU(x) = max(0, x)$ is a non-linear activation function and W_I is the transformation matrix.

3.3 Social Influence Aggregator

We observe that users receive influence from her friends when making a decision. To model such social relation, we adopt an attention-based aggregator. The output of the social influence aggregator $h_S^{(L)}(u)$ is computed as:

$$\tilde{h_S^{(L)}}(u) = \sum_{\forall j \in N(u) \cup u} \alpha_{ij} h_S^{(L-1)}(u) \tag{7}$$

where α_{ij} is the weight coefficient, computed as follows:

$$\alpha_{ij} = \frac{exp(h_S^{(L-1)}(i) \cdot h_S^{(L-1)}(j)^T)}{\sum_{k=1}^{k=n} exp(h_S^{(L-1)}(i) \cdot h_S^{(L-1)}(k)^T)} \tag{8}$$

The final output $h_S^{(L)}(u)$ of the aggregator is computed as $h_S^{(L)}(u) = ReLU(W \cdot \tilde{h_S^{(L)}}(u))$. Through stacking more layers of the social influence aggregator, target user u can receive influence from higher-order neighbors. $h_S^{(0)}(u) = h_I(u)$. The final output of social influence aggregator is $h_S^{(L)}(u)$.

3.4 Recommendation

The final interest representation $h(u)$ of user u is computed by combining both the short-term preference and social influence as:

$$h(u) = ReLU(W[h_I(u); h_S^{(L)}(u)] \tag{9}$$

Then the probability user u will interact with item i is computed with:

$$p(i|S_{T+1}(u), \{S_T(i), \forall k \in N(i)\}) = \frac{exp(e_i \cdot h(u)^T)}{\sum_{k=1}^{k=|I|} exp(e_k \cdot h(u)^T)} \tag{10}$$

where e_k is the item embedding for item k and $|I|$ is the number of items. Items with highest probability will be taken as candidate items.

3.5 Loss

The whole model is trained through maximizing the below loss as follows:

$$\mathcal{L} = \sum_{\forall u \in U} \sum_{t=2}^{t=T} \sum_{n=1}^{N_{u,t-1}} log(p(i_{t,n+1}^u | \{i_{T+1,t_1}^u, i_{T+1,t_2}^u, ..., i_{T+1,t_n}^u\}, \{S_T(i), \forall k \in N(i)\})) \tag{11}$$

That is, for each observed item $i_{t,n+1}^u$ in all sessions, we maximize its likelihood with previously observed items $\{i_{T+1,t_1}^u, i_{T+1,t_2}^u, ..., i_{T+1,t_n}^u\}$ in its current session and social influences $\{S_T(i), \forall k \in N(i)\}$ received from peers.

4 Experiments

In the following part, we will first introduce our experimental settings, including datasets, baselines, and evaluation metrics. Then we analyze the experimental results.

4.1 Experimental Settings

Datasets. We experiment with some representative real-world datasets in social recommendation: Delicious[1], Douban Movie[2] and Epinions[3], which contain both the users' interaction records and social relations, such as trust and following. Table 1 summarizes the statistics of the datasets.

Table 1. Statistics of the datasets.

Datasets	Delicious	Douban	Epinions
# Users	1,650	32,094	8,727
# Items	4,282	13,078	10,009
# User-Item interactions	296,705	10,077,494	41,933
# Social Links	15,328	45,107	21,406
# User-item Density	4.1994%	2.4000%	0.0480%
# User-user Density	5.6301%	0.0043%	0.0281%

Baseline Methods. In our experiment, we take Hit Ratio@k and NDCG@k as evaluation metrics. We report the average value on all testing sessions. Baseline methods are listed below:

– BPR [7]. It optimizes the MF model with a pairwise ranking loss.
– SBPR [14]: It's a social Bayesian ranking model that considers social relationships, which is improved on BPR.
– SocialReg [6]: It's a social-based model that regularizes and weighs friends' latent factors with social network information.
– GraphRec [2]: It is a graph neural network based social recommendation model. It models users in social and item domains separately.
– RNN-Session [3]: It's a recurrent neural network-based model for session-based recommendation.
– DGRec [8]: It is a graph neural network-based model which models users' dynamic interests and social influence.
– TiRec: Our proposed TiRec combines the influence from social relation, temporal information into consideration.

[1] https://grouplens.org/datasets/hetrec-2011/.
[2] https://www.dropbox.com/s/u2ejjezjk08lz1o/Douban.tar.gz?dl=0.
[3] https://cseweb.ucsd.edu/~jmcauley/datasets.html#social_data.

Parameter Settings. We test different settings on validation data to obtain the best hyperparameters. For the embedding size d, we fix the embedding size of users and items as 100. We sample 10 or 15 friends for each user to accelerate computing. The batch size and learning rate are searched in $[32, 64, 128, 256, 512]$ and $[0.001, 0.005, 0.01, 0.05, 0.1]$, respectively. We user Adam for optimization due to its effectiveness. To avoid overfitting, we set the dropout rate as 0.2. We stop training if the evaluation metrics on validation set decreased for 10 successive epochs.

Table 2. Performance on the next-item recommendation task.

Datasets	Delicious		Douban		Epinions	
Models	Hits@20	NDCG@20	Hits@20	NDCG@20	Hits@20	NDCG@20
BPR	0.2765	0.2287	0.0159	0.1112	0.1174	0.0592
SBPR	0.2954	0.2393	0.0168	0.1062	0.1253	0.0623
SocialReg	0.2699	0.2283	0.0177	0.1123	0.1093	0.0543
RNN-Session	0.3453	0.2593	0.1639	0.1802	0.1289	0.0774
GraphRec	0.2745	0.2287	0.0168	0.1187	0.1183	0.0599
DGRec	0.4071	0.2935	0.1867	0.1958	0.1332	0.0898
TiRec	**0.4157**	**0.3128**	**0.1988**	**0.2123**	**0.1384**	**0.0923**

4.2 Main Results

For the session-based social recommendation task, we present the results of Hit@k and NDCG@k, (*i.e.* $K = 20$) in Table 2. We have the following observations:

(1) The models utilizes social information outperforms those don't. The improvement is more significant on the Delicious dataset than other two datasets, which has a larger density. This demonstrates that the social network information is helpful in predicting the preference of users.
(2) The models capture users' dynamic preference, including RNN-Session, DGRec and TiRec, performs better than other methods. This implies the effectiveness of capturing users' dynamic interests.
(3) Our TiRec performs better compared with all the baseline methods, which captures users' social influence and temporal information in interaction sequences with two kinds of aggregators. TiRec performs better than DGRec as TiR ec utilizes the time interval information while DGRec doesn't.

5 Conclusions

In this work, we explore combined effects of social relations and sequential information in social recommender systems and propose a graph neural network-based model. Our model models dynamic interests of users with an aggregator based on self-attention, which utilizes both sequential information between items and real time intervals. To capture social influence, we leverage an attention-based aggregator. Experimental results on several real-world datasets have demonstrated the effectiveness of our proposed model. For future work, it's also possible to incorporate rich attribute information (*i.e.* category, price) and textual description of items to provide better prediction performance.

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