Temporal Graph Neural Networks for Social Recommendation

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***Abstract*—In social recommendation, the purchase decision of users is influenced by their basic preference of items, as well as the social influence of peers. Such social connections had been proved to be effective in modeling users' preference of items. However, most models in social recommender literature only considered two types of relations, *i.e., user-item* relation in interaction network and *user-user* relation in social network. The temporal sequential information of items, *i.e., item-item* relation, can also be utilized to infer the preference of users, but had been ignored in almost all of the graph based recommendation models. Two issues of such temporal information had not been well studied in social recommender systems: the temporal strength information, *i.e.,* the real purchase time of an item, and its influence on social relations. To address the above issues, we propose a novel Temporal Enhanced Graph Model for Social Recommendation (TGRec). In TGRec, the purchase time information between items is characterized as a special temporal relation, and the purchase decision of users depends on three factors: (1) a user's basic preference of items, (2) the collaborative influence of peers, (3) the temporal impact of previous items bought by the user. Experimental results on three real-world commerce datasets demonstrate the effectiveness of our model for social recommendation, showing the usefulness of modeling the temporal information in heterogeneous graph.**

***Index Terms*—Social Recommendation, Graph Neural Networks, Temporal Information**

I. Introduction

Recommender systems often leverage social activities among friends for enhancing the activeness and retention of users, and to make better recommendations. Compared to traditional item recommender systems which mainly focus on modeling user-item interactions, social recommendation models [2], [8], [13] also utilize the social relations among users, *i.e.,* user-user relation, for better understanding the behaviors of users and recommending appropriate items. However, in the existing studies, temporal information, like the order information in item sequence, as well as the purchase time interval information, has not attracted enough attention in network structure based social recommendation. The two missing elements about temporal information in the existing models are as follows: (1) **The heterogeneous temporal relations modeling**. Almost all the graph based social recommendation models [2] considered two types of relations, *i.e., user-item* relation in interaction network and *user-user* relation in social network. Few studies have explored temporal sequential relation of items, *i.e., item-item* relation, which contains the purchase time interval information between items, and can also be utilized to infer the dynamic preference of users. Based on this consideration, to learn the temporal information, we construct a temporal graph with three heterogeneous relations: a user's basic preference of items (*i.e.,* user-item relation), the collaborative influence of peers (*i.e.,* user-user relation) and the temporal dependence relation of items (*i.e.,* item-item relation). (2) **The strength of temporal relation modeling**. The temporal strength information refers to the real purchase time of an item. It reveals the consumption period of items, and has been proved crucial for boosting the accuracy of recommender systems [1]. However, in social recommendation literature, few existing work has explored such purchase time information. Besides, the temporal strength between items also reflects the strength of social relation.

Motivated by the above observations, we propose a novel **T**emporal Enhanced **G**raph Model for Social **Rec**ommendation (**TGRec**). We take full advantage of temporal information and its influence on social strength to predict the preference of a user. Particularly, the real purchase time information between items is characterized as a special temporal relation (*i.e.,* item-item relation). And we utilize the real purchase time interval as the temporal strength. We design a **T**emporal **G**raph **N**eural **N**etwork (**TGNN**) to capture the mutual effects among user-item, user-user and item-item relations. And a novel attentive cross-view training strategy is

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utilized to synchronously update the embeddings of users and items in the temporal graph. Compared with previous studies, our model is capable of learning the temporal strength, *i.e.,* the purchase time of an item, and make a way to study the relationships among the user basic preference, social influence from peers, and the temporal purchase information.

Our contributions are as follows:

- We incorporate temporal information in social recommendation, and propose a novel temporal graph neural network, in which the temporal relation and its strength are considered. To the best of our knowledge, such time-aware social influence has been much less explored in social recommender systems.
- For modeling the temporal graph with heterogeneous relations (user-item, user-user, item-item), we propose a novel attentive cross-view training strategy to aggregate the node information in different views.
- Experimental results on three real-world datasets demonstrate the effectiveness of our model for next-item recommendation.

II. Preliminaries

A. Problem Statement

Assume we have a set of users and items, denoted by U and I respectively. Given a user $u \in U$, his purchase records I^u is a sequence of items sorted by time, which can be represented as $I^u = \{i^u_{t_1}, i^u_{t_2}, ..., i^u_{t_j}, ..., i^u_{t_n}\}$, where $i^u_{t_j} \in I$ is the item purchased by user u at time t_j. $\Delta t_j = t_{j+1} - t_j$ is the purchase time interval between two purchase transactions. For modeling the social influence, we define the users who will produce social influence of a user u as U_s.

Given the purchase history I^u of a user u and his/her social connected peers U_s, the next-item recommendation aims to predict the next item that u would probably buy at time t_{n+1}:

$$P(i^u_{t_{n+1}}) = \mathcal{F}(i \in I | u, I^u, U_s), \tag{1}$$

where $P(i^u_{t_{n+1}})$ is the probability of item $i \in I$ being purchased by u at the next time t_{n+1}, and $\mathcal{F}$ is the prediction function. With the ranked list of all items, we recommend the top K items with the largest probabilities to the user.

B. Constructing Temporal Graph

To learn the temporal information, we first construct a **T**emporal **Graph** (**TGraph**). As shown in Fig. 1, TGraph contains three different kinds of edges marked with different colors, *i.e.,* undirected user-item, user-user edges and directed item-item edges. The temporal strength (*i.e.,* the purchase time interval) is characterized as value of the directed edge between two items. By doing this, the sequential information of items is characterized as a special temporal relation in TGraph. To utilize the temporal strength information and the powerfulness of Graph Neural Networks (GNN), we propose a novel **T**emporal **G**raph **N**eural **N**etwork (**TGNN**) to learn the representation of users and items.

We propose to map the heterogeneous relations and nodes in different viewpoints, and encode the neighborhood information in the corresponding view. The three views are defined as follows

- User-item view (UI): In this view, a user's purchase is influenced by his basic preference of items, *i.e.,* the user-item relation in TGraph.
- User-user view (UU): a user's purchase is influenced by the collaborative influence of peers, *i.e.,* user-user relation.
- Item-item view (II): a user's purchase is influenced by the temporal impact of previous items, *i.e.,* item-item relation.

III. Our Proposed Model

A. Encoding Information in TGraph.

1) Encoding item neighborhood information: In the view with user-item relations (*i.e.,* UI view), the purchase of a user is inferred by the basic preference of items. We aggregate the item neighbors to generate the representation of users. Considering that a user may have different interests on different items, we adopt an attention mechanism to obtain the representation $\mathbf{v}^{UI}_u$ of a user u

$$\mathbf{v}^{UI}_u = \sigma(\mathbf{W}^{UI} \cdot (\sum_{i \in N^{UI}_u} \alpha_{u,i} \cdot \mathbf{e}_i) + \mathbf{b}^{UI}) \tag{2}$$

where N^{UI}_u is the item neighbors of u in UI view in TGraph, $\mathbf{e}_i$ is the representation of an item i that directly linked to user u, $\alpha_{u,i}$ is the attention weight of item i, σ is the non-linear activation function (*i.e.,* a rectified linear unit), $\mathbf{W}^{UI}$ and $\mathbf{b}^{UI}$ are the transformation matrix and bias of the neural network.

The attention weight $\alpha_{u,i}$ of an item i represents the contribution of the item to infer the preference of user u in UI view. It is computed by considering the similarity a_{ui} with the embedding $\mathbf{e}_u$ of user u. The attentive score $a_{u,i}$ is defined as

$$a_{u,i} = \hat{\sigma}(\mathbf{w}^\top \cdot [\mathbf{e}_u \oplus \mathbf{e}_i] + b) \tag{3}$$

where $\mathbf{w}$ and b are the transformation vector and bias respectively, $\oplus$ is vector concatenation operation, and $\hat{\sigma}$ is the Leaky ReLU activation function.

By normalizing the attentive scores of all interacted items using softmax function, the final attention weight α_i to item i is defined as

$$\alpha_{u,i} = \frac{exp(a_{u,i})}{\sum_{\forall j \in N^{UI}_u} exp(a_{u,j})} \tag{4}$$

2) Encoding the social friends information: In User-User view (*i.e.,* UU view), the purchase item of a user is influenced by the purchases of his/her friends. The purchase of a user u in UU view is composed of two factors: strength of social relationships and purchased items of the social friends. We design a hierarchical attention mechanism to capture the influences from a friend $u_s \in N^{UU}_u$ and the interaction items of u_s in UI view, denoted as

$$\mathbf{v}^{UU}_u = \sigma(\mathbf{W}^{UU} \cdot (\sum_{u_s \in N^{UU}_u} \alpha_{u,u_s} \mathbf{v}^{UI}_{u_s}) + \mathbf{b}^{UU}) \tag{5}$$

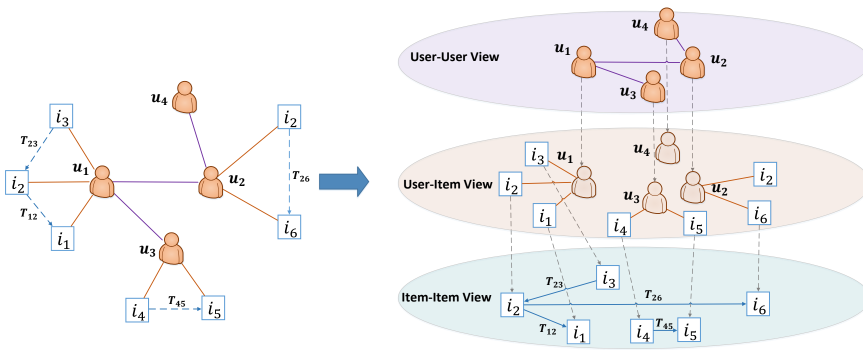


Fig. 1. The illustration of temporal enhanced graph. We map user-user, user-item, item-item relations into three views.

where $N_u^{UU} \subseteq U$ is the user neighbors of u, α_{u,u_s} is the attention weight of u_s, $\mathbf{v}_{u_s}^{UI}$ is representation of u_s in UI view (see Eq. 2), $\mathbf{W}^{UU}$ and $\mathbf{b}^{UU}$ are the transformation matrix and bias in UU view of the neural network.

Similar to the attention weight $\alpha_{u,i}$ of item i in UI view (see Eq. 3 and Eq. 4), the social attention weight α_{u,u_s} is computed by normalizing attentive score a_{u,u_s}. As the behaviors of users in social networks and item purchasing in e-Commerce are different, modeling them with one single unified representation may result in a representation with limited utility. Hence we use a distinct representation $\mathbf{e}_u^s$ of user u in social space. The attention score a_{u,u_s} is defined as

$$a_{u,u_s} = \hat{\sigma}(\mathbf{w}'^{\top} \cdot [\mathbf{e}_u^s \oplus \mathbf{v}_{u_s}^{UI}] + b') \tag{6}$$

where $\mathbf{w}'$ and b' are the transformation vector and bias respectively. Then the attention weight α_{u,u_s} is formulated as the normalized attentive score a_{u,u_s} as in Eq. 4.

3) Encoding temporal information: The temporal strength vector $\mathbf{v}_{T_{jk}}$ refers to the real purchase interval between two purchases of item i_{t_j} and i_{t_k}. It is encoded as the distance between the representation of two items with different timestamp. $\mathbf{v}_{T_{jk}}$ is defined as

$$\mathbf{v}_{T_{jk}} = f(\mathbf{e}_{i_{t_k}} - \mathbf{e}_{i_{t_j}}) \tag{7}$$

where $\mathbf{e}_{i_{t_j}}$ and $\mathbf{e}_{i_{t_k}}$ is the item representation of item i_{t_j} and i_{t_k} respectively, with timestamp $t_k \geqslant t_j$, f is the non-linear function, and we adopt Multi-layer Perception (MLP).

So far, we use different views to represent the heterogeneous relations in an unified graph. In the following, we will introduce our proposed cross-view learning strategy in TGraph.

B. Cross-View Learning Strategy

To overcome the semantic gaps in three heterogeneous relation spaces, we design independent loss function in each view, and then combine them together.

1) Learning user-item interactions: We obtain the representation of users by combining information from both item neighborhood and social friends information, the cross-view user representation $\mathbf{h}_u$ is defined as

$$\mathbf{h}_u = \beta_1 \cdot \mathbf{v}_u^{UI} + \beta_2 \cdot \mathbf{v}_u^{UU} \tag{8}$$

where β_1 and β_2 are the attention weights of user and item respectively, and is computed by the same way as in Eq. 3 and Eq. 4.

The item representation with temporal information is defined by

$$\mathbf{h}_i^{II} = \beta_1^{II} \cdot \mathbf{e}_{i_t} + \beta_2^{II} \cdot \mathbf{e}_{i_{t-1}} \tag{9}$$

where β_1^{II} and β_2^{II} are the attention weights of items in II view.

We define the probability p_i (*i.e.,* $P(i_{t_{n+1}}^u | I^u, U_s)$) of an item i being purchased in the next transaction in UI and UU view by

$$p_i^{UI} = f_{UU}(\mathbf{h}_u^{UI}, \mathbf{h}_i^{II}) \tag{10}$$

$$p_i^{UU} = f_{UI}(\mathbf{h}_u^{UU}, \mathbf{h}_i^{II}) \tag{11}$$

where $\mathbf{h}_u^{UI}$ and $\mathbf{h}_u^{UU}$ are the cross-view representations of user u, and they are computed by Eq. 8 with different parameter $\beta_1^{(.)}$ and $\beta_2^{(.)}$. f_{UI} and f_{UU} are two non-linear score functions, and we adopt MLP in our experiments.

2) Learning temporal strength information: The temporal strength is learned in item-item view, we feed the vector $\mathbf{v}_T$ encoded in Eq. 7 in a softmax function to get the predicted probability of time interval by

$$p_T = \frac{\exp(\mathbf{v}_T)}{\sum_{T'=1}^{max(T)} \exp(\mathbf{v}_{T'})}, \tag{12}$$

where $max(T)$ is the maximum purchase interval and we select the time interval with maximum probability as the predicted interval.

C. The Loss Function for Optimization.

Given the purchase history $I_{t_n} = \{i_{t_1}, i_{t_2}, ..., i_{t_j}, ..., i_{t_n}\}$ of a user u, our model is optimized by the next-item accuracy with consideration of the purchase time information. The loss function is defined as

$$\mathcal{L} = \lambda_1 L_{UI} + \lambda_2 L_{UU} + \lambda_3 L_{II} \tag{13}$$

where L_{UI}, L_{UU} and L_{II} are the loss function, and $\lambda_{(.)}$ is the learning weight in UI, UU and II view respectively.

TABLE I
STATISTICS OF THE DATASETS.

Datasets	Ciao	Epinion	Douban
# Users	3,787	8,727	32,094
# Items	16,121	10,009	13,078
# User-Item interactions	35,310	41,933	10,077,494
# Social Links	9,215	21,406	45,107
# User-item Density	0.0578%	0.0480%	2.4000%
# User-user Density	0.0642%	0.0281%	0.0043%

TABLE II
PROPERTIES OF METHODS. S: SOCIAL INFORMATION? G: GRAPH NEURAL NETWORK MODEL? SEQ: SEQUENTIAL INFORMATION? T: TEMPORAL STRENGTH INFORMATION?

	BPR	SBPR	SocialMF	SocialRec	GraphRec	DGRec	TGRec
S	×	√	√	√	√	√	√
G	×	×	×	×	√	√	√
Seq	×	×	×	×	×	√	√
T	×	×	×	×	×	×	√

Given the a user u and item i at timestamp t, the final predicted result are $\hat{y}^{UI}$, $\hat{y}^{UU}$ and $\hat{T}$. The loss functions are defined as

$$\begin{aligned} L_{UI} &= -\sum_{(u,i,k)\in Y} \ln \delta(\hat{y}_{ui}^{UI} - \hat{y}_{uk}^{UI}) \\ L_{UU} &= -\sum_{(u,i,k)\in Y} \ln \delta(\hat{y}_{ui}^{UU} - \hat{y}_{uk}^{UU}) \end{aligned} \tag{14}$$

where $(u, i, k) \in Y$ is the training pair in training set Y, item i is the positive sample that user u had purchased, while k is the negative sample, and δ is the sigmoid function.

As for the time interval prediction, given the real purchase time interval T, we utilize mean square error as objective function, defined as

$$L_{II} = \sum_{(i_t, i_{t-1})\in Y} (T - \hat{T})^2. \tag{15}$$

IV. EXPERIMENTS

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

A. Experimental Settings

1) Datasets: We experiment with three representative real-world datasets in social recommendation: Ciao[1], Epinion[2] and Douban Movie[3]. All the datasets contain both the user-item interaction information, and the user-user social relations, such as trust and following. Table I summarizes the statistics of the datasets.

2) Baseline Methods: We compare our model with the state-of-the-art methods from different types of recommendation approaches, Table II summarizes the properties of different methods.

- BPR [11]. It optimizes the MF model with a pairwise ranking loss. The social information is ignored in this method.
- SBPR [19]: It's a social Bayesian ranking model that considers social relationships in the learning process.
- SocialMF [5]: It considers the influence from users' friends into the matrix factorization model for rating prediction.

[1]https://www.librec.net/datasets.html
[2]https://cseweb.ucsd.edu/ jmcauley/datasets.html#social/_data
[3]https://www.dropbox.com/s/u2ejjezjk08lz1o/Douban.tar.gz?dl=0

- SocialReg [10]: It's a social-based model that regularizes and weighs friends' latent factors with social network information.
- GraphRec [2]: This is a graph neural network based social recommendation model, which models users and items in social and item domains for better representation learning.
- DGRec [12]: It is a session-based social recommender system, which models user's dynamic interest using recurrent neural network.
- TGRec: our proposed TGRec combines the influence from social relation, user basic interaction of items and the temporal item relevance into consideration for social recommendation.
- TGRec-T: This variant ignores the transition relation among items in item-item view, which only uses the user-user view and user-item view.
- TGRec-S: The social network information of TGRec is removed. This variant only uses the user-item view and item-item view.

3) Evaluation Metrics: We adopt two widely used ranking-based metrics Hit Ratio@k and NDCG@k to evaluate the performance of a ranked list. Since it is time-consuming to rank all items for every user during evaluation, we followed the common strategy that randomly samples 100 items that had not been interacted by the user, ranking the test item among the 100 items for evaluation.

4) Parameter Settings: For the hyper parameters of each method, we test different settings on validation data to obtain the best results. For the embedding size d, we test the values of $[32, 64, 128, 256]$. 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. We stop training if the evaluation metrics on validation set decreased for 10 successive epochs.

B. Main Results

We present the results of Hit@k and NDCG@k, (*i.e.,* K=5 and K=10) on the next-item recommendation task in Table III, we have the following observations:

(1) The models with social information, *i.e.,* SBPR, SocialMF, SocialReg, GraphRec, DGRec and our TGRec significantly outperform BPR. This demonstrates that the social network information is helpful in predicting the preference of users.

TABLE III
PERFORMANCE COMPARISON OF DIFFERENT METHODS ON THE NEXT-ITEM RECOMMENDATION TASK.

Datasets	Ciao				Epinions				Douban			
Models	Hit@5	Hit@10	NDCG@5	NDCG@10	Hit@5	Hit@10	NDCG@5	NDCG@10	Hit@5	Hit@10	NDCG@5	NDCG@10
BPR	0.2466	0.3821	0.1640	0.2134	0.0645	0.1174	0.0423	0.0592	0.3166	0.4971	0.2040	0.2622
SBPR	0.3493	0.4670	0.2454	0.2817	0.1138	0.1847	0.0790	0.1048	0.3210	0.4844	0.2039	0.2567
SocialMF	0.3741	0.5086	0.2645	0.3053	0.1432	0.1906	0.1011	0.1095	0.3409	0.5023	0.2201	0.2723
SocialReg	0.3631	0.5008	0.2546	0.3073	0.1423	0.2033	0.0991	0.1170	0.3398	0.5056	0.2186	0.2722
GraphRec	0.3394	0.5196	0.2139	0.2762	0.1338	0.1935	0.0902	0.1088	0.3178	0.4989	0.2047	0.2715
DGRec	0.3976	0.5235	0.2910	0.3360	0.1700	0.2087	0.1023	0.1235	0.3695	0.5384	0.2395	0.2687
TGRec	**0.4137**	**0.5365**	**0.2998**	**0.3452**	**0.1785**	**0.2189**	**0.1195**	**0.1399**	**0.3765**	**0.5507**	**0.2453**	**0.2793**
TGRec-T	0.3953	0.5155	0.2935	0.3277	0.1683	0.1885	0.1327	0.1359	0.3585	0.5177	0.2375	0.2608
TGRec-S	0.3768	0.5180	0.2555	0.3125	0.1365	0.1856	0.0997	0.1205	0.3275	0.5043	0.2235	0.2724
Gain[%]	**4.04**	**2.48**	**3.02**	**2.74**	**5.00**	**4.89**	**16.8**	**13.1**	**1.89**	**2.28**	**2.08**	**3.64**

(2) The GraphRec performs worse than other baseline methods except for BPR. In our experimental settings, we do not utilize the user opinion (*i.e.,* rating) information, which may limit the power of the model.

(3) DGRec outperforms other social based methods like SBPR, SocialMF and SocialReg. DGRec captures users' social influence as well as the dynamic sequential information of items. It indicates the helpfulness of incorporating the sequential information of items.

(4) Our TGRec performs the best compared with all the baseline methods. TGRec captures users' social influence and interaction information with hierarchical attention mechanism, and utilizes the temporal interval information between items in the purchase sequence.

(5) TGRec-T and TGRec-S perform worse than TGRec, which indicates that both social information and temporal strength information are useful in predicting the purchase of next item for a user. TGRec-S performs worse than TGRec-T, which demonstrate that the social information is more important in user behavior modeling.

(6) The evaluation results on DGRec and our TGRec, show a larger improvement on Douban dataset than on the other two datasets with less interaction density. This indicates that by incorporating the temporal strength information among items, our TGRec has a higher capability to handle the data sparsity problem.

C. Experimental Analysis

In this part, we take a deeper look at the social influence in recommendation.

1) The effectiveness of social attention mechanism: We present the effectiveness of social attention, *i.e.,* user-user attention for the space limitation. The basic hypothesize is that, for the item preference of a user, the larger attention weight comes from social relation (*i.e.,* influence from his/her friends), the more likely they purchase the similar products.

To verify this, we randomly select five users and five friends of each user from Douban dataset. We compare the attention weight of a user's social friends and the similarity of there purchasing. The similarity of the purchasing of a user u and his/her friend u_s is computed by the proportion of common items (*i.e.,* both the user and his/her friends had purchased).

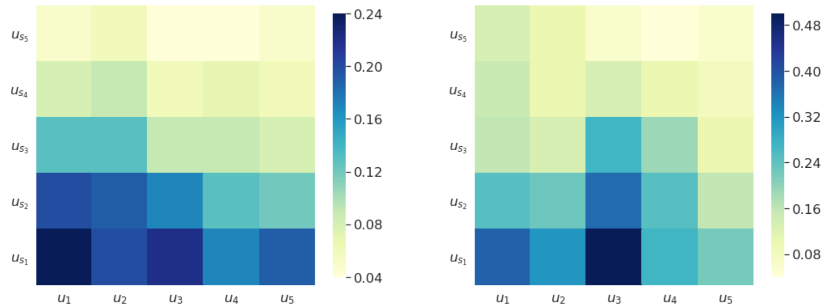
As shown in Fig. 2, we present the heat map figures of the attention weights α_{u_s} (see in Eq. 5) between a user u and his friend u_s in Fig. 2(a), and the similarity of user purchasing in Fig. 2(b). We can see that the results on two figures are highly consistent in most of cases, that is to say, when the user and his/her friend have purchased a lot of common items in purchase history, our model is able to learn the high social influence attention weights of such social relations.

V. RELATED WORK

We summarize the related literature of social recommendation, graph based recommendation and temporal based recommendation.

Social recommendation. Leveraging the social network information provides an effective approach to alleviate data sparsity and improve performance in the social recommendation [10]. Many proposed social recommendation models are based on Gaussian or Poisson matrix factorization [3], [10], which incorporate social network information into traditional matrix factorization approaches. However, they ignore temporal information of interactions among users and items which can help provide precise and better performance. DGRec [12] is a session-based social recommender system, which models the user's dynamic interest and context-dependent social influence. Our proposed model takes both temporal information and influences received by users from their neighbors' specific behaviors into consideration.

Graph based recommendation. Recent years have witnessed great developments in deep neural networks applied on graph data [4], [14], which are also known as Graph Neural Networks. As interactions among users and items can be naturally modeled as a graph, there are many methods in recommender systems based on graph neural networks [2], [15], [18]. Pinsage [18] generates items embeddings from both graph structure and item features with random walk and graph CNNs which is suitable for large-scale web recommender systems. Some GNN-based model are proposed for social recommendation [2], [17]. socialGCN [17] captures how users' preferences are influenced by the social diffusion process in social networks with the strengths of GCNs.



(a) Attention weights

(b) Similarities

Fig. 2. Heatmaps of Social attention weights and Similarities.

Temporal based Recommendation. Detecting the purchase appetites of users and their evolution over time has attracted researchers' attention in recent years. Temporal-based methods utilize sequential information among items to model users' interests [7], [9]. LSTNet [7] combines CNN and RNN into a mixture model to extract short-term local dependency patterns and discover long-term patterns for different time series treads. To better capture users' preference for session-based recommendation, attention mechanism has been utilized in [9] to capture users' main interests which assign different weights on items in the current session.

VI. Conclusion

In this work, we combine the effects of modeling the purchase time and social relations in recommender systems, and propose a novel temporal enhanced graph model for social recommendation. Our model characterizes the real purchase time information between items as a special temporal relation in our constructed temporal graph. Experimental results demonstrate the effectiveness of our proposed temporal enhanced graph model in social recommendation.

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References

[1] Ting Bai, Lixin Zou, Wayne Xin Zhao, Pan Du, Weidong Liu, Jian-Yun Nie, and Ji-Rong Wen. CTrec: A long-short demands evolution model for continuous-time recommendation. In *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 675–684. ACM, 2019.

[2] Wenqi Fan, Yao Ma, Qing Li, Yuan He, Eric Zhao, Jiliang Tang, and Dawei Yin. Graph neural networks for social recommendation. In *The World Wide Web Conference*, pages 417–426. ACM, 2019.

[3] Guibing Guo, Jie Zhang, and Neil Yorke-Smith. Trustsvd: collaborative filtering with both the explicit and implicit influence of user trust and of item ratings. In *Twenty-Ninth AAAI Conference on Artificial Intelligence*, 2015.

[4] Will Hamilton, Zhitao Ying, and Jure Leskovec. Inductive representation learning on large graphs. In *Advances in Neural Information Processing Systems*, pages 1024–1034, 2017.

[5] Mohsen Jamali and Martin Ester. A matrix factorization technique with trust propagation for recommendation in social networks. In *Proceedings of the fourth ACM conference on Recommender systems*, pages 135–142. ACM, 2010.

[6] Thomas N Kipf and Max Welling. Semi-supervised classification with graph convolutional networks. *arXiv preprint arXiv:1609.02907*, 2016.

[7] Guokun Lai, Wei-Cheng Chang, Yiming Yang, and Hanxiao Liu. Modeling long-and short-term temporal patterns with deep neural networks. In *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval*, pages 95–104. ACM, 2018.

[8] Tzu-Heng Lin, Chen Gao, and Yong Li. Recommender systems with characterized social regularization. In *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*, pages 1767–1770. ACM, 2018.

[9] Qiao Liu, Yifu Zeng, Refuoe Mokhosi, and Haibin Zhang. Stamp: short-term attention/memory priority model for session-based recommendation. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 1831–1839. ACM, 2018.

[10] Hao Ma, Dengyong Zhou, Chao Liu, Michael R Lyu, and Irwin King. Recommender systems with social regularization. In *Proceedings of the fourth ACM international conference on Web search and data mining*, pages 287–296. ACM, 2011.

[11] Steffen Rendle, Christoph Freudenthaler, Zeno Gantner, and Lars Schmidt-Thieme. Bpr: Bayesian personalized ranking from implicit feedback. In *Proceedings of the twenty-fifth conference on uncertainty in artificial intelligence*, pages 452–461. AUAI Press, 2009.

[12] Weiping Song, Zhiping Xiao, Yifan Wang, Laurent Charlin, Ming Zhang, and Jian Tang. Session-based social recommendation via dynamic graph attention networks. In *Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining*, pages 555–563. ACM, 2019.

[13] Jiliang Tang, Xia Hu, and Huan Liu. Social recommendation: a review. *Social Network Analysis and Mining*, 3(4):1113–1133, 2013.

[14] Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio. Graph attention networks. *arXiv preprint arXiv:1710.10903*, 2017.

[15] Xiang Wang, Xiangnan He, Meng Wang, Fuli Feng, and Tat-Seng Chua. Neural graph collaborative filtering. In *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR 2019, Paris, France, July 21-25, 2019.*, pages 165–174, 2019.

[16] Chao-Yuan Wu, Amr Ahmed, Alex Beutel, Alexander J Smola, and How Jing. Recurrent recommender networks. In *Proceedings of the tenth ACM international conference on web search and data mining*, pages 495–503. ACM, 2017.

[17] Le Wu, Peijie Sun, Richang Hong, Yanjie Fu, Xiting Wang, and Meng Wang. Socialgcn: An efficient graph convolutional network based model for social recommendation. *arXiv preprint arXiv:1811.02815*, 2018.

[18] Rex Ying, Ruining He, Kaifeng Chen, Pong Eksombatchai, William L Hamilton, and Jure Leskovec. Graph convolutional neural networks for web-scale recommender systems. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 974–983. ACM, 2018.

[19] Tong Zhao, Julian McAuley, and Irwin King. Leveraging social connections to improve personalized ranking for collaborative filtering. In *Proceedings of the 23rd ACM international conference on conference on information and knowledge management*, pages 261–270. ACM, 2014.