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Session-based Recommendation Based on Long-term and Short-term Interest Incorporating Social Information

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Abstract: In session-based recommendation systems, user interests are dynamic and purchasing actions are often influenced by both long-term and short-term interest preferences. However, user interests are not solely influenced by the users themselves but also by other external factors, such as social connections. To address these issues, a method utilizing a Graph Attention Network is proposed, which effectively integrates both the long-term and short-term interests of users and their friends. Experiments on the Douban and Delicious datasets demonstrate that the proposed algorithm outperforms baseline models.

Keywords: Session Recommendation; Short-term and Long-term Interest; Social Relationship; Graph Attention Network.

1. Introduction

With the explosive growth of internet information, users often encounter difficulties in filtering valuable session content, and models struggle to accurately capture user interests due to their constant changes. In an information-overloaded environment, session-based recommendation systems serve as a personalized recommendation approach by analyzing the session operation sequences of anonymous users within a short time frame to predict the next item that may interest them. These systems can not only capture users' short-term interests but also provide effective recommendations when user information is incomplete, making them a current research hotspot.

User interests are dynamic, and session-based recommendation systems need to consider the contributions of both long-term and short-term interests. To obtain a more comprehensive representation of user interests, it is also necessary to incorporate users' social information. For instance, a user looking for comedy movies might be influenced by a friend who likes martial arts movies to watch a martial arts film. Therefore, we propose a method to model the influence of users' own long-term and short-term interests as well as the impact of their social information. The user's action sequence is arranged in time sequence, the conversation graph is constructed, and the long-term and short-term interest information of the user is extracted by graph neural network combined with gating technology, and is set as short-term interest within one week, set it as a long-term interest a week ago to get short-term and long-term interest from users. The graph convolution network is used to capture the long-term and short-term interests of users in social relationships, combining the attention mechanism to form graph attention network to fuse the long-term and short-term interests of users and their friends. Experimental results on 2 datasets show that the proposed model is superior to other baseline methods.

In summary, we make the following contributions:
We consider the long-term and short-term interests of users and the impact of social relations on users' interests.

We propose a model that uses graph neural network to extract short-term and long-term interests of users, and graph attention network to extract the interests of users' social friends.

Experimental results on two real data sets show the effectiveness of the proposed algorithm.

2. Related Work

2.1. Social Recommendation

Social recommendation system provides personalized recommendation service through user's relationship and action in social network. Unlike traditional recommender systems, social recommender systems provide more accurate results by analyzing users' social networks to better understand their interests and preferences. Collaborative filtering based on social networks uses the information of users' friends or followers in social networks to recommend the content that these friends or followers like to users, but it is difficult to deal with large-scale social networks and complex social relationships, and is limited to users' existing social circles. Recommendation based on social influence analysis users' influence and communication ability in social networks, and recommends the content recommended or liked by influential users. However, the calculation and prediction of social influence is complicated and difficult to achieve. The model based on the structure of social networks analysis the structure and connection mode between user nodes in social networks, and deduces the social influence and information transmission path of users, so as to make recommendations, but it is difficult to deal with the dynamic changes of social networks and the complexity of large-scale networks. Traditional methods have their own characteristics and applicable scenarios when using social information for recommendation. However, with the growth of social network data and the complexity of user action, more advanced technologies and algorithms (such as neural network and attention mechanism, etc.) need to be combined to further improve the effect of social recommendation system and user experience. This section will review the development of social recommendation and session recommendation in recent years, which is divided into three parts: social recommendation and session recommendation and session recommendation based on graph structure.

2.2. Session Recommendation

The session recommendation system is a personalized recommendation method that aims to predict the next item of interest to the user based on the sequence of the user's session action in a short period of time. Chen Q, et al propose that it can't only capture the short-term interest of the user, but also achieve effective recommendation in the case of incomplete user information. hang, session recommendation system has become a hot research direction because of its excellent performance in dealing with dynamic user interest and information overload. The traditional method based on matrix decomposition decomposes the user-project interaction matrix into a low-dimensional vector representation of users and projects, so as to capture the long-term preferences of users, but it is difficult to capture the short-term interests and dynamic changes of users. The method based on Markov chain predicts the user's next possible action based on the historical action sequence, but the model relies too much on the historical data and is difficult to handle the rapid change of the user's interest. Recursive neural network-based methods use recurrent neural networks to model a user's conversational action sequentially, capturing the user's short-term interest, but have limited ability to capture long sequence data. These traditional methods have laid the foundation for the study of session recommendation system, but there are some limitations in dealing users' dynamic interest and social influence.

2.3. Session recommendation based on graph structure

The session recommender system based on graph structure captures the complex relationship between users and projects and its dynamic changes by constructing and analyzing graph data structure . The graph structure can naturally represent the interaction between users and items, the social relationship between users and the association between items, which provides rich contextual information and structured representation for recommendation systems. In recent years, Graph Neural Networks have been widely used in session recommendation because they can effectively process Graph-structured data and capture high-order relationships and dependencies. The user-project bipartite graph is constructed by graph-based collaborative filtering, and the similarity between user nodes and project nodes is calculated to make recommendation. Based on graph attention network, the information is aggregated in graph structure by using attention mechanism, and the influence of recommendation, but the model complexity is high, training time is longer. GSSN model can effectively improve the recommendation accuracy by combining users' interests and social information, and using graph attention network.

3. Problem Definition

To model user action sequences as session graphs, we divide them chronologically, defining ten minutes as a session. In this model, let U represent the set of users, I represent the set of items, t represent time, and S represent sessions. Each user has a different number of sessions, and the action sequence for each session is represented as $S^u = \{i_1, i_2, ..., i_k\}$. The time series is represented as $T^u = \{t_1, t_2, ..., t_k\}$. The goal of the recommendation is to predict the next item that a user will be interested in.

4. GSSN Model

The model is divided into four modules: Session Building Module, long-term and short-term interest extraction module, social information fusion module, prediction module. First, the session building module: the user's action sequence is arranged chronologically and model as a session diagram. Long-term and short-term interest extraction module: after the conversation graph is obtained, the graph neural network technology is used to extract and spread the user's interest, and divide the long-term and short-term interest according to the time sequence, and set it as short-term interest within one week, one week for the long-term interest, you can get the long-term and short-term interests of users themselves. Social Information Fusion Module: the user's social information is built as a social network graph, and the long-term and short-term interests of the user's friends are extracted according to the graph attention network. Prediction module: will be the end-user interest probability forecast, predict the next user will click on the item. The model is shown in Fig. 1.

4.1. Session Graph Building Module

Firstly, each session sequence is connected and the item is built as a digraph $G = (V, E)$, where each node is a unique item, V represents the node set in the digraph, E represents the edge of the digraph to represent the sequential relationship of items, the edges in the diagram are $e = (v_{s,i}, v_{s,i+1})$, indicating that the user clicked and then clicked, and indicating the relationship between the project and the session. Each item is embedded into a unified embedding space, and the session node $s_k \in S$ is embedded into the unified embedding space. Figure G can establish connections between items that appear in all sessions, enriching the user's representation of interest and providing more direction for recommendations.

4.2. Long and Short-Term Interest Extraction Module

The purpose of interest extraction module is to extract the long-term and short-term interests of users. GNN is used to explore the complex conversation influence at the project level and divide the short-term interests into long-term interests. The embedding layer of graph neural network includes the embedding of items and information propagation, which embeds the items in the cross-session graph into a unified embedding space $V \in R^{d \times d}$, where d is the vector dimension. GRU gating loop unit is used to capture and characterize global time dependence in short-term sequence data. GRU is a good variant for processing short-term interest sequence vectors, it can solve the long dependence problem in RNN network more effectively. Short-term interest sequences are defined as $h = \{h_{v_1^u}, h_{v_2^u}, ..., h_{v_t^u}\}$,GRU containing update and reset gates to control the flow and forgetting of information. GRU can be expressed as:

$$z_t^u = \sigma\left(W_z^1 h_{v_t^u} + W_z^2 h_{t-1}^u + b_z\right) \quad (1)$$

$$r_t^u = \sigma\left(W_r^1 h_{v_t^u} + W_r^2 h_{t-1}^u + b_r\right) \quad (2)$$

$$\tilde{h}_t^u = \tanh\left(W_h^1 h_{v_t^u} + W_h^2 h_{t-1}^u + b_h\right) \quad (3)$$

$$h_t^u = \left(1 - z_t^u\right) \odot h_{t-1}^u + z_t^u \odot \tilde{h}_t^u \quad (4)$$

Among them: $z_t^u \in R^{d \times d}$ and $r_t^u \in R^{d \times d}$ expressed as reset door and update door, respectively, W_z、 W_r、 W_h for reset door, update door and output door can be trained parameters.

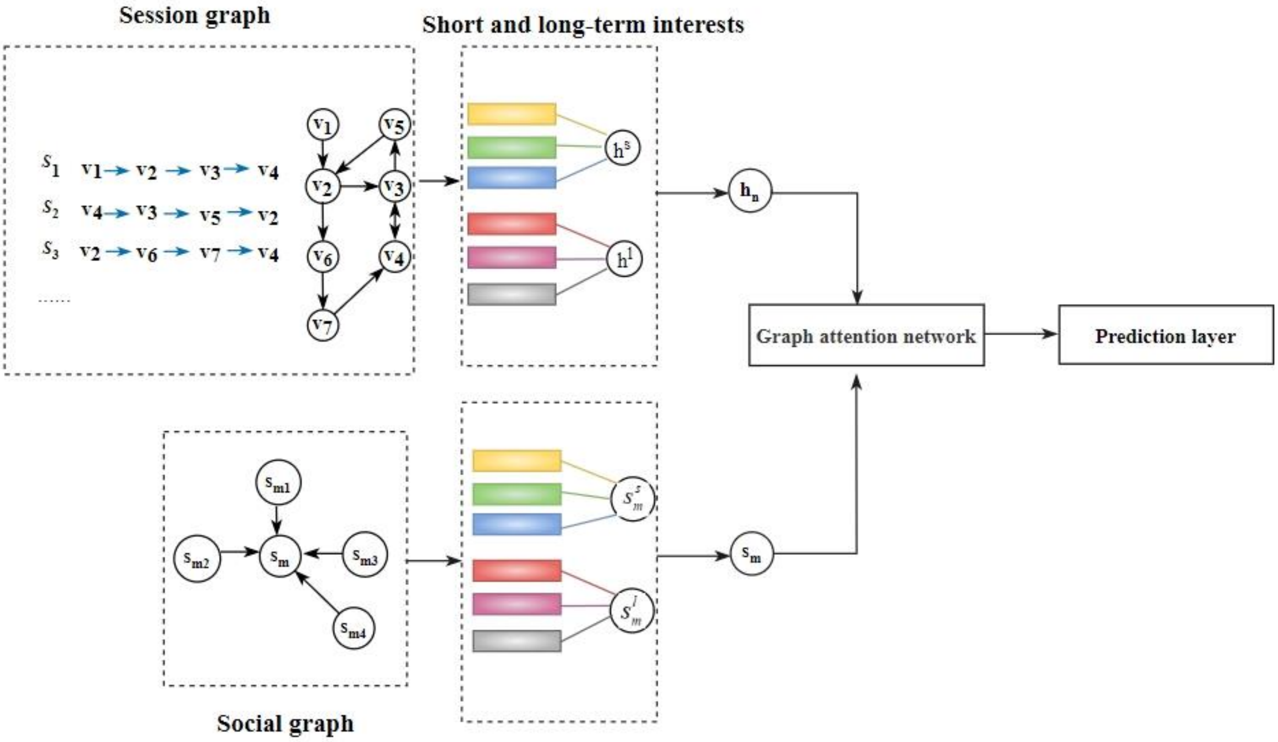

Fig. 1 GSSN model

4.3. Social Information Fusion Module

4.3.1. Social Graph

Users' interests are determined not only by their own short- and long-term interests, but also by their social connections. For example, if a user wants to buy a book, the brain may recommend different types of books based on what the user liked in the past as well as what they like now. If a user's friend likes another type of book, it may also have an effect on the user's purchase intention. This module applies the graph attention network to combine the representation of the target user and the representation of the friends, and the resulting user representation combines the interests of the users and their friends. For the target user, a weighted directed graph is constructed, where the nodes correspond to the target user and their friends. For each user, build subgraph containing only the user and their friends, as shown in Fig. 2.

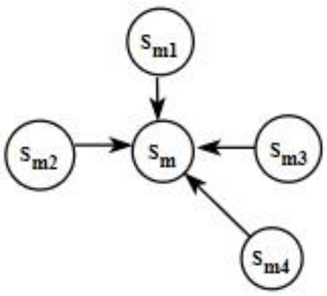

Fig. 2 Social graph

4.3.2. Expression of Interest in Social Relationships

This module is also divided into short-term and long-term interests to predict, and different from the above, the graph convolution network to extract the interest of the above social graph, solved the problem of interest dynamic change, the long-term interest is extracted by embedding, and the vector is embedded into the space to get the change of friends' interest at different scales. For the current user's short-term session action $S_{v_t^u}$, the friend's short-term interest is reflected in the session before the $t+1$ session. The action of each friend m is model by the RNN, and the short-term preference s_m^s of friend m is represented by the final output of the RNN, after long-term and short-term interest, S_m is obtained by splicing:

$$s_m^s = f\left(i_{t,N_{m,t}}^m, r_{N_{m,t-1}}\right), s_m^l = W_u\left[m,:\right] \quad (6)$$

$$s_t^m = \left\{i_{t,1}^m, i_{t,2}^m, \ldots, i_{t,N_{m,t}}^m\right\} \quad (7)$$

$$s_m = RELU\left(W_1\left[s_m^s, s_m^l\right]\right) \quad (8)$$

4.3.3. Graph Attention Networks

Based on the node features defined in the previous section, this paper proposes a novel graph attention network to simulate context-dependent social influence. In order to distinguish the influence of each friend, this paper uses the attention mechanism to calculate the weight score and guide the influence spread. The user representation and friend representation are integrated together to obtain the final user interest representation and the final graph representation vector.

$$\alpha_{um}^{(l)} = \frac{\exp\left(f\left(h_u^{(l)}, h_m^{(l)} \right) \right)}{\sum j \in N(u) \exp\left(f\left(h_u^{(l)}, h_j^{(l)} \right) \right)} \quad (9)$$

$$\tilde{h}_u^{(l)} = \sum_{k \in N(u)} \alpha_{um}^{(l)} h_m^{(l)} \quad (10)$$

4.4. Prediction Module

Since the user's interests depend on recent action and social influence, the user ultimately says that by combining them using a fully connected layer:

$$\tilde{h}_n = W_2 \left[h_n : h_u^M \right] \quad (11)$$

$$y = \frac{\exp\left(\hat{h}_n^t z_y \right)}{\sum_{j=1}^{|I|} \exp\left(\hat{h}_n^t z_j \right)} \quad (12)$$

5. Experiment

5.1. Data Set

In this experiment, Douban, Delicious, are used to evaluate the effectiveness of the model and the accuracy of the algorithm. Douban is a movie review site, and the data set contains two pieces of information: the user's interactions with the project and social relationships between users. Delicious is an online bookmarking system. The data set contains two pieces of information: the user's interaction with the project and the social relationship between the user. Each session is a sequence of tags that the user assigns to the bookmark. The statistics for the two data sets are shown in Table 1.

Table 1. The statistics for the two data sets

	Douban	Delicious
Users	32,314	1,650
Items	14,109	4,282
Events	3,493,821	296,705
Social relations	331,315	15,328
Average session length	4.38	3.30

5.2. Evaluation Indicators

Hit@K and NDCG@K are widely used ranking-based measures to evaluate all models for accuracy in their predictions. Hit@K is a measure of the zero per cent rate, and table zero shows the percentage of items tested. NDCG@K is a comprehensive measure of the accuracy of recommendations and the ranking of items on the recommendation ranking list. It is a comprehensive measure of recommendation accuracy with a K = 20.

5.3. Parameter Set

The experimental environment is Python, the Optimizer uses Adam to optimize the objective function, the batch size is set to 200, the embedding Dimension D is set to 50, the maximum sequence length N is set to 50, and the learning rate is set to 0.01, the output dimension is set to 100, the activation function is softmax, and the regularization item is set to L2. For contrast methods, use the default parameter settings in addition to the embedded dimension.

5.4. Baseline Model

To validate the performance of the model algorithm, the GSSN model is compared with the following baseline models:

Item-KNN: transformed from the KNN model, it captures items that are similar to what the user liked in the past.

BPR-MF: an application of matrix decomposition techniques to train prediction using ranking as the goal.

Deep-SoR: a deep neural network-based social recommendation model that uses deep neural networks to capture social relationships and integrate them into probabilistic matrix decomposition models for scoring predictions.

SR-GNN: a method in which a gated GNN network is used to capture the complex transformation of an item, and then to extract and integrate the long-term and current preferences of users to better predict their next preference item.

GCE-GNN: a GNN-based model that uses global and session-level diagrams to capture project transitions in all sessions to better infer user preferences.

Graph-Rec: a graph attention network-based social recommendation model that uses graph attention networks to capture interaction information in user-project diagrams.

DGREC: A method that uses RNN to obtain dynamic user interest, and makes recommendation based on social information.

MNNS: is a recommendation that uses session model to capture users' interests for a global graph and to identify the influence of friends in conjunction with social relationships.

Table 2. The experimental results of GSSN model compared with baseline models

Baseline model	Douban		Delicious	
	Hit@20	NDCG@20	Hit@20	NDCG@20
Item-KNN	14.31	16.35	27.29	22.41
BPR-MF	1.63	11.10	27.75	22.93
DeepSoR	1.83	10.59	29.48	23.91
SR-GNN	16.43	18.54	34.45	25.81
Graph-Rec	16.84	11.78	37.54	22.91
GCE-GNN	17.34	16.59	37.82	26.45
DGREC	18.61	19.50	40.66	29.44
MNNS	18.75	19.91	41.03	28.87
GSSN	18.95	20.12	41.45	29.60

5.5. Results Analysis

Table 2 shows the experimental results of GSSN model compared with other baseline models. The experimental results show that GSSN model is better than other baseline models. Through the comparison of the experiments, the following conclusions are obtained:

Some traditional model methods, such as Item-KNN and BPR-MF, have the worst experimental results, because the matrix decomposition-based methods tend to recommend the items clicked previously, and do not take into account the current items, resulting in poor experimental results. DeepSoR fuses social information into matrix decomposition model through neural network. Compared with traditional matrix decomposition model, it improves the experiment effect. The SR-GNN model is based on the graph neural network to extract the long-term and short-term interest information of users. GCE-GNN adopts the information transformation of global graph and session graph and uses graph neural network to obtain high-order information to capture user's interest. GRAPHREC uses graph-based attention network, which combines graph-based neural network and attention mechanism to capture user interaction information. DGREC uses graph attention network to combine user's interest information and social information to get better experimental results. MNNS used cross-sectional short-and long-term sequence information combined with social information to get the best results at baseline. However, the GSSN model proposed in this paper is superior to the above baseline methods, and the experimental results on two real data sets have been improved, it shows that user's interest is not only determined by their own long-term and short-term interests, but also influenced by external social information, the experimental results and algorithm precision are improved.

6. Conclusion

In this paper, a short-term and long-term conversation recommendation model GSSN is proposed, which integrates social information. Firstly, the model constructs the conversation graph by the conversation sequence, links the user with the item, and obtains the long-term and short-term interest of the user through the neural network model, divide short-and long-term interests into chronological order. The long-term and short-term interests of users' friends are combined into graph attention network through graph convolution network and attention mechanism. The graph attention network successfully combined the interests of the two, generating interest vectors that helped to improve recommendations. Experiments on two real data sets, Douban and Delicious performed best compared to other baseline models, the validity and accuracy of the algorithm are verified.

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