Joint Modeling of Local and Global Behavior Dynamics for Session-based Recommendation*

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Abstract. Session-based recommendation is critical in modern recommender systems, which aims to predict the next interested item given anonymous behavior sequences of users. While prior works have made efforts to addressing the session-based recommendation problem, two significant limitations exist: i) They ignore the fact that items may be correlated with other across different session units; ii) existing solutions are also limited in their assumption of rigidly ordered pattern over intra-session item transition, which may not be true in practice. To address these above limitations, we propose a Local-Global Session-based Recommendation framework–LGSR which generalizes the modeling of behavior dynamics from two perspectives: we first design a cross-session item dependency encoder to learn the inter-session item relation structures from a global perspective. Additionally, a dual-stage attentive aggregation module is developed to capture local item transition dynamics, without the restriction of rigid sequential process for jointly modeling user's current interest and intra-session purpose. With the exploration of both complex intra- and inter-session interest transitional regularities, our LGSR model enables the representation learning of user behavior dynamics via jointly mapping local and global signals into the same latent space. The experimental results on two real-world datasets demonstrate the superiority of the proposed LGSR framework over state-of-the-art methods.

1 Introduction

To alleviate the information explosion and identify the items for users with their personalized interests, modeling user's preferences over items based on their historical interactions has become increasing popular in recent real-world recommender systems, such as e-commerce platforms [15, 14], online movie sites [2] and location-based services [37]. Under the realistic circumstances that specific user information is not always available (due to privacy issues), conventional recommendation strategies (*e.g.*, collaborate filtering-based methods [11, 36]) can hardly generate promised results. In such cases, session-based recommendation has become a key task with the aim of predicting the next item and making recommendations based on anonymous behavior sequences (*i.e.*, clicked items) from a short-term period [12, 20, 23, 35].

To model sequential dynamics of user behaviors, many session-based recommendation methods have been developed to capture various sequential transition regularities of user behavioral data. In particular, recurrent neural networks (*e.g.*, GRU) have been utilized to model non-linear sequential correlations between past and future user behavior [12]. To extract user's main purpose in the current session, attention mechanisms serve as key techniques to be integrated with recurrent framework as a hybrid encoder for modeling users' sequential preferences [23, 20]. In addition, another line of session-based recommendation model leverages the graph neural networks to capture complex transition relations between items for modeling structured session data [35].

Despite the effectiveness of the aforementioned approaches, we argue that two key limitations exist in these methods. *First*, they only focus on the item transitional relations within a single session, which makes them insufficient to distill cross-session collaborative signals from the users' collective behaviors. In real-world session-based recommendations, any pair of user's interested items could potentially be related across different session units [32]. For example, item v_1 and v_2 is clicked in chronological order ($v_1 \rightarrow v_2$) in session A. In another session B, item v_3 is browsed right after v_2 ($v_2 \rightarrow v_3$). While there is no explicit intra-session sequential transitions between item v_1 and v_3, they are no longer independent with each other, and implicit relationship between v_1 and v_3 should be considered to accurately capture user's dynamic interests. Hence, the complex item sequential transition regularities are often exhibited with high-order relation structure from not only the intra-session dependencies (local transitional information) but also the inter-session correlations (global transitional information) [34]. The failure of jointly modeling local and global item transitional signals leads to suboptimal recommendation results.

Second, another deficiency of existing session-based recommendation models lies in the rigid order assumption of item transitional relationships. However, user's dynamic preferences are affected by many complex unobservable factors [4] and may not follow a rigid order assumption in practical recommendation scenarios [26, 30]. The utilization of current recurrent framework and its extensions

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(*e.g.*, attentive recurrent network) assume that a rigidly temporally ordered pattern for item sequences, *i.e.*, user's preference is propagated in a sequential manner. This assumption limits the representation ability of existing deep recommendation techniques, and it is likely that the learned dynamic users' behavioral patterns are inaccurate. Therefore, it would be really valuable if a session-based recommendation model could recognize such behavior dynamics without the rigid order assumption of item transition regularities.

With the consideration of existing session-based recommendation methods, we believe that it is of critical importance to develop a approach that enables the joint modeling of local and global user behavior dynamics in an explicit and end-to-end manner. Towards this end, we propose a framework, Local-Global Session-based Recommendation (LGSR), to jointly perform global item relation structure learning and local dynamic item transition modeling for accurate session-based recommendations. Specifically, LGSR is equipped with two designs to correspondingly address the challenges in local-global behavior dynamics modeling: i) cross-session item dependency encoder, which aims to learn item contextual representations with the preservation of implicit correlations between items across different sessions. ii) hierarchical attentive aggregation module, which is a dual-stage attention network with the cooperation of the self-attention mechanism and another attentive aggregation layer, in order to capture both user's current preference and session-specific purpose. Our LGSR is conceptually advantageous to existing methods in that both the local (intra-session item transitions) and global (inter-session item dependencies) item high-order relations are factored into the recommendation model.

The contributions of this work are summarized as follows:

- We provide a principled way to exploit both local and global behavior dynamics of users in the session-based recommendation.
- We propose a new framework LGSR, which simultaneously performs global item relation structure learning by maximizing the likelihood of preserving cross-session item correlations, and local dynamic item transition modeling via a hierarchically structured attentive aggregation module.
- We perform extensive experiments on two real-world datasets for session-based recommendation to validate the rationality by joint learning of local-global item transition relationships. Experimental results demonstrate the effectiveness and interpretability of our developed LGSR framework.

2 Methodology

We first present the problem formulation and the model overview. Then, we explain key modules of LGSR in details.

2.1 Problem Formulation

The goal of the session-based recommendation is to predict the item that the user will interested in (*e.g.*, click) at the next time step based on their historical behavior sequences. Generally, it recommends k items that users may be interested in from the item candidate set $V = \{v_1, v_2, ..., v_n\}$, where n is the number of items. This problem is formalized as follows: Given a temporally-ordered item sequence $\boldsymbol{s} = [v_{s,1}, v_{s,2}, ..., v_{s,t}]$, where $v_{s,i} \in V$ denotes the i-th item clicked by the user in the session s, and t denotes the length of $\boldsymbol{s}$, the session-based recommendation aims to output a list $Y = [y_1, y_2, ..., y_n]$ based on the session s, where y_i denotes the probability of item v_i will be clicked by user. The recommendation result is a set of items with top-k probability values in Y.

2.2 Framework Overview

Our developed LGSR framework consists of two major modules: cross-session item dependency encoder and hierarchically structured attentive aggregation module. The architecture of LGSR is shown in Figure 1. We first devise a cross-session item dependency encoder to model the global item relation structures. This module aims to learn global context-aware item representations based on the cross-session item graph, by maximizing the likelihood of preserving item correlations across session units. Furthermore, we propose a dual-stage attention network to capture user's dynamic preferences and session-specific main purpose. In the architecture of LGSR, these two modules cooperate with each other by sharing a embedding layer.

2.3 Cross-Session Item Dependency Encoder

We formulate a directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ with items as nodes from all historical sessions $\boldsymbol{S} = \{\boldsymbol{s}_1, \boldsymbol{s}_2, ..., \boldsymbol{s}_m\}$, where m is the number of historical sessions. Each session can be regarded as a path which starts from the first item and ends at the last item in $\mathcal{G}$. The global context of item relations in graph $\mathcal{G}$ helps us to learn inter-session item transitions. As shown in Figure 1, we can see that before clicking v_4, the click on item v_1, v_3 appear in different sessions, which indicates that European distance among the continuous feature representation of v_4 and v_1, v_3 should be relatively small. Previous session-based recommendation systems only focus on the item relations in a single session but ignore the complex item inter-dependencies in different sessions. In order to obtain the low-dimensional vector representation of the items in graph $\mathcal{G}$ and maintain the homogeneity of items, we utilize a cross-session item dependency encoder to generate item embedding. The output is the vector representation of the items on the graph, i.e., $\boldsymbol{V} = \{\boldsymbol{v}_1, \boldsymbol{v}_2, ..., \boldsymbol{v}_n\}$, where $\boldsymbol{v}_i \in \mathbb{R}^d$, d is the dimensionality of latent item representations.

In order to distinguish the importance of the different adjacent items, we assign the weight of each edge according to the number of the occurrence in all sessions. After constructing graph $\mathcal{G}$, the item's corpus is generated by truncating random walk on the graph, and then we train a skip-gram model on the corpus. The random walk traverses all items and generates the context of each item. To fully exploit the contextual signals of item relationships on the graph, we generating the context, it will sample a node from the neighborhood of the current node according to the weight of edge until the length equals to L with the number of walks as T (both parameters are studied in Section 3). After conducting the random walk process, we obtain a plurality of item sequences, as well as the corpus of items $\boldsymbol{C} = \left\{\boldsymbol{c}_1, \boldsymbol{c}_2, ..., \boldsymbol{c}_{(T\times n)}\right\}$. Then, the skip-gram model [27], which maximizes the co-occurrence probability of two words that appear simultaneously in a window, is utilized to model the item co-occurrence on the corpus $\boldsymbol{C}$:

$$\text{maxmize} \prod_{v_i \in \boldsymbol{c} \wedge \boldsymbol{c} \in \boldsymbol{C}} \prod_{v_c \in \boldsymbol{c}_w(v_i)} \mathrm{P}(v_c|v_i) \tag{1}$$

where $\boldsymbol{c}_w(v_i)$ denotes the context items of item v_i in sequence $\boldsymbol{c}$ in a window size N_w. The conditional probability $\mathrm{P}(v_c|v_i)$, which denotes how likely v_c is observed in the contexts of v_i, is computed by the inner product kernel with softmax for output:

$$\mathrm{P}(v_c|v_i) = \frac{\exp(\boldsymbol{v}_i^T \boldsymbol{\theta}_c)}{\sum_{k=1}^{|V|} \exp(\boldsymbol{v}_i^T \boldsymbol{\theta}_k)} \tag{2}$$

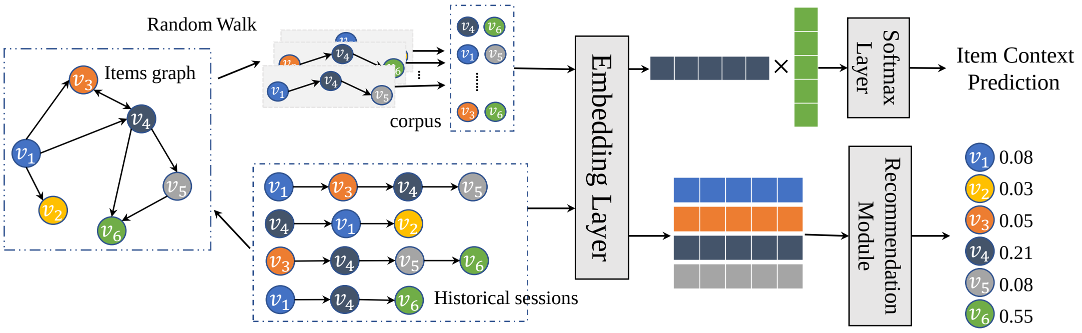


Figure 1. The Architecture of the Proposed LGSR Framework.

The corresponded loss function in our cross-session dependency encoder is defined as follows:

$$\mathcal{L}_g = \sum_{v_i \in \boldsymbol{c} \wedge \boldsymbol{c} \in C} \sum_{v_c \in C_w(v_i)} \log \frac{\exp(\boldsymbol{v}_i^T \boldsymbol{\theta}_c)}{\sum_{k=1}^{|V|} \exp(\boldsymbol{v}_i^T \boldsymbol{\theta}_k)} \tag{3}$$

where $\boldsymbol{v}_i$ is the vector representation of v_i, $\boldsymbol{\theta}_c \in \mathbb{R}^d$ denotes the role of v_c as a context. Nevertheless, minimizing $\mathcal{L}_g$ is non-trivial because the denominator term in (3) is very time-consuming. Negative sampling is an effective strategy to optimize the training complexity. The idea of negative sampling is to approximate the costly denominator term in (3) with some sampled negative instance. NCELoss [10] applies a binary classifier to discriminate the target item and the sampled negative items. The conditional probability $P(v_c|v_i)$ is computed by (4):

$$P(v_c|v_i) = \begin{cases} \sigma(\boldsymbol{v}_i^T \boldsymbol{\theta}_c) & if\ v_c \in C(v_i) \\ 1 - \sigma(\boldsymbol{v}_i^T \boldsymbol{\theta}_c) & if\ v_c \in N_s(v_i) \end{cases} \tag{4}$$

Hence, the updated loss function is shown as below:

$$\mathcal{L}_g = -\sum_{v_i \in \boldsymbol{c} \wedge \boldsymbol{c} \in \boldsymbol{C}} \sum_{v_c \in \boldsymbol{c}_w(v_i)} \log \sigma(\boldsymbol{v}_i^T \boldsymbol{\theta}_c) + \sum_{v_c' \in N_s(v_i)} \log \sigma(-\boldsymbol{v}_i^T \boldsymbol{\theta}_c') \tag{5}$$

where the $N_s(v_i)$ denotes the set of negative samples for current item v_i. σ is the sigmoid function $1/(1+e^{-x})$.

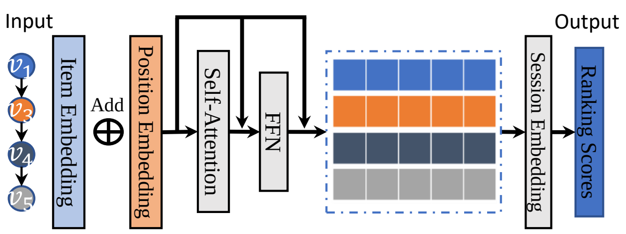


Figure 2. The Hierarchical Structured Attentive Aggregation Module.

2.4 Hierarchical Attentive Aggregation Module

This aggregation network serves as the recommendation module in our LGSR framework, by taking a single session $\boldsymbol{s} = [v_{s,1}, v_{s,2}, ..., v_{s,t}]$ as input and outputting the relevance probability for all items. As shown in Figure 2, This module is equipped with two attention networks: (1) self-attention network: models the complex structures in sessions and captures the complicated transition between items, and (2) session aggregation network: capture the long-term preference and current interest of users.

2.4.1 *Self-Attention Network*

We map the items in $\boldsymbol{s}$ into a unified vector space via the item embedding layer which shared with the cross-session dependency encoder module and get $\boldsymbol{V}_s = [\boldsymbol{v}_{s,1}, \boldsymbol{v}_{s,2}, ..., \boldsymbol{v}_{s,t}]$. Since the self-attention model is not aware of the item positions in the session, we add a position embedding $\boldsymbol{P} \in \mathbb{R}^{t \times d}$ into the item embedding, and got $\boldsymbol{E}_s = [\boldsymbol{e}_{s,1}, \boldsymbol{e}_{s,2}, ..., \boldsymbol{e}_{s,t}]$, where $\boldsymbol{e}_{s,i} = \boldsymbol{v}_{s,i} + \boldsymbol{p}_i$. Motivated by [16], we utilize a learnable position embedding rather than a fixed position-aware vectors. Self-attention mechanism is a special case of the dot-product attention which calculates a weighted sum of all values($\boldsymbol{V}$), where the weight relates to queries($\boldsymbol{Q}$) and keys($\boldsymbol{K}$) and defined as:

$$\text{Attention}(\boldsymbol{Q}, \boldsymbol{K}, \boldsymbol{V}) = \text{softmax}(\frac{\boldsymbol{Q}\boldsymbol{K}^T}{\sqrt{d_k}})\boldsymbol{V} \tag{6}$$

where d_k is the dimension of $\boldsymbol{K}$, and $\sqrt{d_k}$ denotes a scale factor to avoid overly large values of the inner product. When $\boldsymbol{Q}$, $\boldsymbol{K}$, $\boldsymbol{V}$ are the same, the dot-product attention becomes so-called self-attention. In our case, they all equal to $\boldsymbol{E}_s$. The self-attention (SA) is defined as:

$$\boldsymbol{S}_s = \text{SA}(\boldsymbol{E}_s) = \text{Attention}(\boldsymbol{E}_s \boldsymbol{W}_q, \boldsymbol{E}_s \boldsymbol{W}_k, \boldsymbol{E}_s \boldsymbol{W}_v) \tag{7}$$

where $\boldsymbol{W}_q, \boldsymbol{W}_k$, and $\boldsymbol{W}_v \in \mathbb{R}^{d \times d}$ are the learnable parameters. Since self-attention is a linear operation, it is necessary to add a feed-forward network to endow the model with nonlinearity. In this work, a two-layer feedforward network is applied to $\boldsymbol{S}_s$:

$$\boldsymbol{F}_s = \text{FFN}(\boldsymbol{S}_s) = \text{ReLU}(\boldsymbol{S}_s \boldsymbol{W}^{(1)} + \boldsymbol{b}^{(1)})\boldsymbol{W}^{(2)} + \boldsymbol{b}^{(2)} \tag{8}$$

where $\text{ReLU}(x) = \max(0, x)$ is the activation function which aims to add nonlinearities to the model. $\boldsymbol{W}^{(1)}, \boldsymbol{W}^{(2)} \in \mathbb{R}^{d \times d}$ and $\boldsymbol{b}^{(1)}, \boldsymbol{b}^{(2)} \in \mathbb{R}^d$ are the learnable parameters.

In the self-attention layer, when calculating the attentive weight of the i-th item, it should only consider the first $(i-1)$-th items due to the nature of sequences. So, we forbid all links between $\boldsymbol{Q}_i$ and $\boldsymbol{K}_j$ for all index which j is larger than i. Additionally, the multi-head attention, which jointly attend to information from different representation subspaces at different positions, can enhance the expression ability of self-attention. However, in our case, the experiment result shows that it isn't as effective as expected. The main reason may be the value of d is quite small in our case and it is no need to project them into the multiple learning subspace.

2.4.2 *Session Aggregation Layer.*

After self-attention, we obtain $\boldsymbol{F}_s = [\boldsymbol{f}_{s,1}, ..., \boldsymbol{f}_{s,t}]$. Each $\boldsymbol{f}_{s,i}$ adaptively extracts information from previous items. We apply another attention layer to generate session embedding by aggregating the learned sequential signals. The representation of current session composed of two parts: long-term preference and the current interest. We define the current interest $\boldsymbol{s}_c$ as $\boldsymbol{f}_{s,t}$, and employ attention mechanisms on $\boldsymbol{F}_s$ to capture the long-term preference:

$$\alpha_i = \mathrm{softmax}_i(\boldsymbol{q}^T \sigma(\boldsymbol{W}_1 \boldsymbol{f}_{s,t} + \boldsymbol{W}_2 \boldsymbol{f}_{s,i})) \tag{9}$$

where $\boldsymbol{q}, \boldsymbol{c} \in \mathbb{R}^d$, and $\boldsymbol{W}_1, \boldsymbol{W}_2 \in \mathbb{R}^{d \times d}$. The long-term preference $\boldsymbol{s}_l = \sum_{i=1}^{t} \alpha_i \boldsymbol{f}_{s,i}$, where the $\mathrm{softamx}$ function makes sure that the sum of all weights equals to 1. The final session embedding $\boldsymbol{s}_f = \boldsymbol{W}_3[\boldsymbol{s}_c; \boldsymbol{s}_l]$ where $\boldsymbol{W}_3 \in \mathbb{R}^{d \times 2d}$ is the linear transformation of the concatenation of $\boldsymbol{s}_c$ and $\boldsymbol{s}_l$. Next, the scores of each candidate item $z_i = \boldsymbol{s}_f^T \boldsymbol{v}_i$, the inner product of the item embedding $\boldsymbol{v}_i$ and session embedding $\boldsymbol{s}_f$. The probability of all candidate items to be next clicked by the user in the current sessions is calculated by $\mathrm{softmax}$ function.

$$\tilde{\boldsymbol{y}} = \mathrm{softmax}(\boldsymbol{z}) \tag{10}$$

The loss function of the recommendation module with hierarchical attentive aggregation network is defined based on the cross-entropy:

$$\mathcal{L}_{rec} = -\sum_{i}^{N} \boldsymbol{y}_i \log(\tilde{\boldsymbol{y}}_i) + (\boldsymbol{1} - \boldsymbol{y}_i)\log(\boldsymbol{1} - \tilde{\boldsymbol{y}}_i) \tag{11}$$

where $\boldsymbol{y}_i$ denotes the label of i-th instance, which is the one-hot encoding vector of the ground truth.

2.5 Model Optimization

By integrating the introduce two key modules, we define our joint loss function as follows:

$$\mathcal{L} = \mathcal{L}_{rec} + \lambda_1 \mathcal{L}_g + \lambda_2 \|\boldsymbol{\Theta}\|_2^2 \tag{12}$$

λ_1 balances the loss from two tasks. $\boldsymbol{\Theta}$ is the parameter set of LGSR, and the last term of (12) is the regularization term. λ_2 is another balancing parameter for preventing over-fitting. Since the input of the recommendation module and the cross-session dependency encoder are different, so we employ mini-batch Adam [18] to optimize $\mathcal{L}_{rec}$ and $\mathcal{L}_g$ alternatively. It is challenging to use λ_1 to adjust the weight of two losses in alternatively optimizing. Inspired by [32], we use an additional parameter g, which denotes the training frequency of $\mathcal{L}_g$ optimization in each epoch, to balance two losses.

3 Evaluation

We perform experiments on two real-world datasets to comprehensively evaluate our proposed *LGSR* method. In particular, we aim to answer the following research questions:

- **RQ1**: How does *LGSR* perform as compared to state-of-the-art session-based recommendation methods?
- **RQ2**: How is the performance of *LGSR*'s variants with different designed modules in the joint framework?
- **RQ3**: How do different hyperparameter settings affect the recommendation performance of *LGSR*?
- **RQ4**: How is the interpretation of our *LGSR* framework in capturing dynamic correlation weights between items?

Table 1. Statistics of Experimented Datasets

Datasets	Yoochoose-1/64	Yoochoose-1/4	Diginetica
#.train	369859	5917745	719470
#.test	55898	55898	60858
#.item	17376	30444	43097
Average Length	6.16	5.71	5.13

3.1 Experimental Settings

3.1.1 Data Description

To validate the effectiveness of *LGSR*, we utilize two real-world datasets from Diginetica[8] and Yoochoose[9]. We summarize the statistical information of experimented datasets in Table 1 and present data details as follows:

- **Diginetica Data**. This dataset contains the click records of users over different items from an e-commerce service spanning the time period of six months. For fair comparison, we follow the same data preprocessing strategy as [20] and filter out the sessions which include only one item (*i.e.*, with the session length of 1). We also remove items whose frequency of appearance is less than 5. There are 43097 items and 204771 sessions remaining in the Diginetica dataset after preprocessing.
- **Yoochoose Data**. This data records users' clicked item logs from another online retailing site. By performing the same preprocessing steps as the Diginetica data, 37483 items and 798150 sessions are included in the final Yoochoose data.

In our experiments, we split the data into training and test set in chronological order. Considering different data scales of Diginetica and Yoochoose, we follow the same experimental settings in [20, 35], and construct the test set of Diginetica and Yoochoose data by selecting sessions from the last week and last day, respectively. To be consistent with the settings in [20, 23], we report the evaluation results on the recent fractions with $\frac{1}{64}$ and $\frac{1}{4}$ of temporally ordered session from the generated training sequences. We also present the average session length of Diginetica and Yoochoos in Table 1.

3.1.2 Methods for Comparison

In our experiments, *LGSR* is evaluated against the following various state-of-the-art baselines: (i) popularity-based recommendation strategy (*i.e.*, POP and S-POP); (ii) K-nearest neighbor modeling algorithm (*i.e.*, item-KNN); (iii) recurrent recommendation technique (*i.e.*, GRU4Rec); (iv) session-based recommendation with graph neural network (*i.e.*, SR-GNN); (v) attentive recommendation models (*i.e.*, NARM and STAMP).

- **POP**: It makes recommendations based on the popularity of items. For all sessions, POP recommends the most frequent items from the historical clicked item logs.
- **S-POP**: It is another popularity-based recommendation strategy by recommending most popular items in the current session.
- **item-KNN** [5]: This baseline leverages the K-Nearest Neighbors algorithm and uses the cosine similarity to estimate the correlations between items.
- **GRU4Rec** [12]: This session-based recommendation approach utilizes the recurrent neural network (*i.e.*, GRU) to encoder sequential transitional regularities of user preferences.

[8] http://cikm2016.cs.iupui.edu/cikm-cup
[9] http://2015.recsyschallenge.com/challenge.html

Table 2. Performance Comparison on Yoochoose-1/64, Yoochoose-1/4 and Diginetica.

Algorithm	Yoochoose-1/64		Yoochoose-1/4		Diginetica	
	P@20(%)	MRR@20(%)	P@20(%)	MRR@20(%)	P@20(%)	MRR@20(%)
POP	6.71	1.65	1.33	0.30	0.89	0.20
S-POP	30.44	18.35	27.08	17.75	21.06	13.68
Item-KNN	51.60	21.81	52.31	21.70	35.75	11.57
GRU4Rec	60.64	22.89	59.53	22.60	29.45	8.33
NARM	68.32	28.63	69.73	29.23	49.70	16.17
STAMP	68.74	29.67	70.44	30.00	45.64	14.32
SR-GNN	70.57	30.94	71.36	**31.89**	50.73	17.59
LGSR	**71.97**	**31.29**	**72.23**	31.39	**53.77**	**18.88**

- **SR-GNN** [35]: This method incorporates graph neural networks to model transitions between items of session sequences, and capture users' current interests within the session.
- **NARM** [20]: It is an integrative recommendation model with the attention mechanism and recurrent neural network based on an encoder-decoder learning architecture.
- **STAMP** [23]: This method utilizes the multi-layer perceptron network and attention mechanism to extract users' preferences from the long-term session contextual signals.

3.1.3 Parameter Settings and Reproductivity

We implement our *LGSR* with TensorFlow. The regulation penalty is set as $\lambda_2 = 10^{-6}$. During the learning process, we perform the parameter inference using the Adam optimizer with the batch size and learning rate as 512 and 10^{-3}, respectively. We set the training frequency $\mathcal{L}_g$ in each epoch as 2. The path length L and the walks per node T are set to 50 and 13, respectively. We further set the window size N_w to 8 and the number of the negative samples N_s to 512. In addition, we apply the dropout layers with the dropout rate as 30% to alleviate the overfitting issue during the training phase. To make our results fully reproducible, all the relevant source codes have been made public at `https://github.com/chenjh1988/LGSR.git`.

3.1.4 Evaluation Metrics

We use the following metrics that are widely used in the session-based recommendation [20, 23] to evaluate all compared methods.

P@20 (Precision): it represents the proportion of correctly recommended items in the top-20 items among all test instances.

MRR@20 (Mean Reciprocal Rank): it takes average on the reciprocal ranks of users' desired items. We set the reciprocal rank as 0 when the desired item is not among the top-20 recommended items. This metric measures the position of the top relevant recommendation results.

Note that larger P@20 and MRR@20 values indicates better recommendation performance.

3.2 Performance Comparison (RQ1)

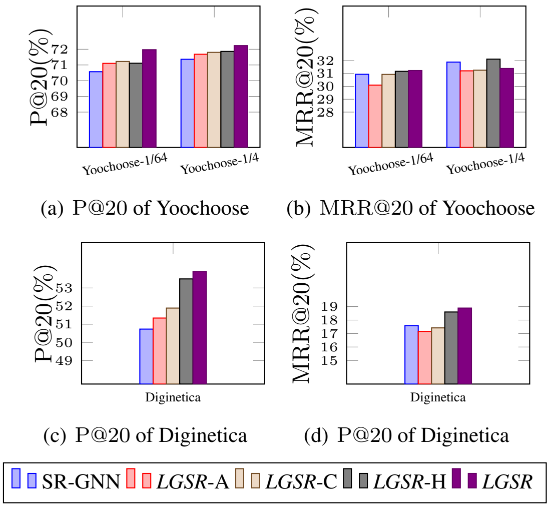
We present the evaluation results of all compared methods on all datasets in Table 2 and summarize the following key observations:

- In general, we can observe that *LGSR* consistently yields the best performance in terms of precision and mean reciprocal rank in most evaluation cases. In the occasional cases that *LGSR* misses the best performance, it still generates very competitive results. We attribute the performance improvement to the reason that the proposed *LGSR* jointly considers local and global item interdependencies, which can help to model intra- and inter-session transitional regularities of user's dynamic preference simultaneously for more accurate recommendation results.
- Compared to attention-based recommendation models (*i.e.*, NARM and STAMP) and RNN-based approach (*i.e.*, GRU4Rec), the performance gap between *LGSR* and them might be attributed to the utilization of self-attention mechanism–automatically specifying the attentive weights of correlated items without the rigid order assumption of sequential item transition relationships. Another advantage of the proposed method over these baselines lies in its proper consideration cross-session item relations, which enables the generation of better item representations.
- The performance of *LGSR* is followed by SR-GNN which leverages graph neural network to learn the item relations within the individual session. This further demonstrates the rationality of relaxing the assumption of rigid temporally-ordered item correlations. However, SR-GNN ignores the inter-session item relation structures, which could easily lead to suboptimal recommendation results. Furthermore, the large performance gap between the deep neural network methods and frequency-based approaches (*i.e.*, POP, S-POP and item-KNN) indicates the limitation of these approaches–only replying on the stationary item frequency statistics can hardly capture dynamic user preferences in real-world recommendation scenarios.

3.3 Model Ablation Study of *LGSR* (RQ2)

We also perform ablation experiments over the key components of *LGSR* so as to have a better understanding of their impacts, *i.e.*, cross-session item dependency encoder and hierarchical attentive aggregation module. We design the following model variants corresponds to different perspectives.

- **Efficacy of cross-session item dependency encoder**. *LGSR*-C: In order to investigate the impact of incorporating the implicit item relations across different session units, we design this model variant (*i.e.*, without the dependency encoder between sessions) to capture dynamic user preferences via pure attention networks to model item transitional relationships.
- **Effectiveness of attentive aggregation layer**. *LGSR*-A: another variant of *LGSR* which makes recommendations only by performing the self-attentive operation over the time-ordered item sequences. We regard the learned latent representations from the last



(a) P@20 of Yoochoose (b) MRR@20 of Yoochoose

(c) P@20 of Diginetica (d) P@20 of Diginetica

Figure 3. Performance of *LGSR*'s Model Variants.

time step of the self-attention mechanism, i.e., $\boldsymbol{f}_{s,t}$ as the representation of the user's interest in current session, and generate the ranking score based on it.

- **Efficacy of hierarchical attentive aggregation module**. *LGSR*-H: This model variant replace the hierarchical attentive aggregation module with the SR-GNN baseline as the recommendation module for making final recommendations.

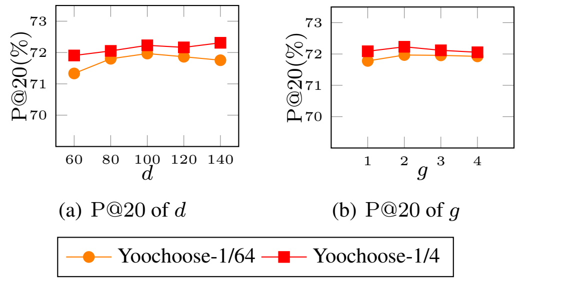
Figure 3 presents the evaluation results of model architecture ablation study of *LGSR*. We also show the result of SR-GNN baseline for convenient comparison. We can notice that the full version of our developed framework *LGSR* achieves the best performance in most cases and analyze the effects of key modules respectively as below:

- We observe that the joint learning model *LGSR* outperforms the variant *LGSR*-C. This observation suggests the effectiveness of our designed cross-session item dependency encoder in capturing item influences across different sessions.
- The performance gain between *LGSR* and *LGSR*-A indicates that the attentive aggregation layer in our hierarchical attentive aggregation component can further help to model the complex transition regularities of time-varying user's preferences.
- Overall, *LGSR* achieves better recommendation performance than *LGSR*-H in most evaluation cases, which justifies the efficacy of our hierarchical attentive aggregation module in encoding the session-specific item correlations. While the graph neural network based recommendation module (SR-GNN) also relaxes the sequential item transition hypothesis, it is difficult to capture the arbitrary item dependencies with a generated graph structure.

3.4 Hyperparameter Study of *LGSR* (RQ3)

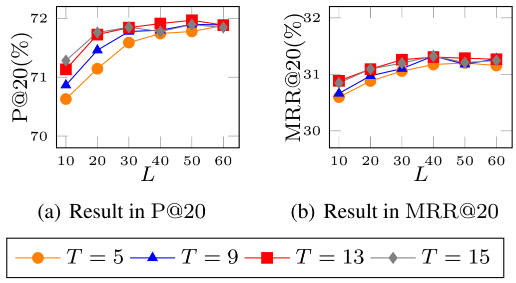
We now study how the different hyperparameter settings affects the recommendation performance. The key parameters involve the hidden state dimensionality d, training frequency g, walks per item T, path length L and the number of negative samples N_w. Except for the parameter being tested, we set other parameters at the default values we described before.

Impact of hidden state dimensionality d. We vary the value of d from 60 to 140 to study how the dimension of item embedding effects the model performance. The results on both Yoochoose-1/64 and Yoochoose-1/4 in terms of P@20 are shown in Figure 4. We can



(a) P@20 of d (b) P@20 of g

Figure 4. Impact study of hidden state dimensionality d and training frequency g on Yoochoose-1/64 and Yoochoose-1/4 dataset.



(a) Result in P@20 (b) Result in MRR@20

Figure 5. Impact of L and T on Yoochoose-1/64

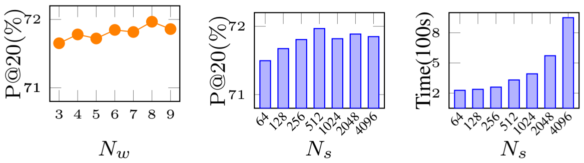
observe that the larger hidden state dimensionality brings better representation learning capability for item relations at the earlier stage, and the performance tends to saturate as d reaches 100. In our experiments, d is set to 100.

Impact of training frequency g. We investigate the influence of the training frequency of $\mathcal{L}_g$ by varying g from 1 to 4. Figure 4 indicates that a higher g value will mislead the objective function of *LGSR* and take more training time, while a small g can make full use of the global information of item dependencies. Hence, we set $g = 2$ to obtain better performance.

Impact of walks T **and path length** L **per item**. The truncated random walk generates T walks with length of L for each item. We vary L and T to investigate their effect in our cross-session item dependency encoder of *LGSR*. From Figure 5, we can observe the similar trend of these two parameters, *i.e.*, the performance first increases and then remains stable. The larger value of L and T indicates that the cross-session item correlations are more fully excavated. However, when L and T is large, the model may overstate the role of global relation signals while reducing the importance of intra-session item transitions.

Impact of window size N_w. The window size N_w of the skip-gram determines the number of co-occurrence item pairs to be considered in our cross-session dependency encoder, *i.e.*, the larger the window size is, the more items pairs will be optimized in training process. We vary N_w from 3 to 9 and show the evaluation results in Figure 6. We can notice that the larger window size first improves the model performance but hurts the recommendation accuracy later.

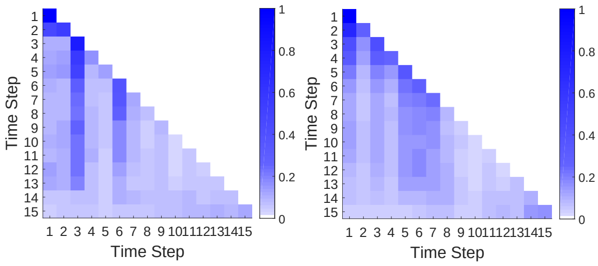
Impact of the number of negative samples N_s. An appropriate sampling strategy and size can accelerate the training phase while maintaining satisfactory results. Hence, another key hyperparameter in our *LGSR* is the number of the negative samples N_s. We evaluate the performance and time cost of different sample sizes. As N_s increases, the performance enhances and the more computationaly training time is required. However, when N_s further increases (*i.e.*,



(a) P@20 of N_w (b) P@20 of N_s (c) Time cost of N_s

Figure 6. Impact of N_w and N_s on Yoochoose-1/64

$\leq$ 512), the performance becomes relatively stable while the time cost still increases. Therefore, we set $N_s = 512$ by considering the trade-off between model accuracy and computational cost.



(a) weights of case 1 (b) weights of case 2

Figure 7. Visualization of self-attention weights in two modeled sessions. The depth of the color corresponds to the importance scores of items.

3.5 Model Interpretation Study (RQ4)

Apart from the superior forecasting performance, another key advantage of *LGSR* is its ability in interpreting the importance weights of item correlations. To demonstrate this, we perform case studies to show the interpretability of our model by visualizing the attention weights obtained from *LGSR*. Particularly, we visualize both the self-attention weights in sequential modeling and the attention weights in long-term preference capturing of extracted samples on Yoochoose-1/64 data, to illustrate the explainability of attention mechanism intuitively. Figure 7 shows two heatmaps of self-attention weights of two samples sessions with 15 items. There are few previous items related to current item (deeper color) in most cases. This may owe to the interest transfer of users. As showed in Figure 8, we present some attention weights when calculating the long-term preference of the user in the current session. Overall, a few consecutive items are related to the next click in current session and the most important items often appear in the end of the session. Hence, we could observe that *LGSR* enables the dynamic modeling of correlations between the target item and other relevant items.

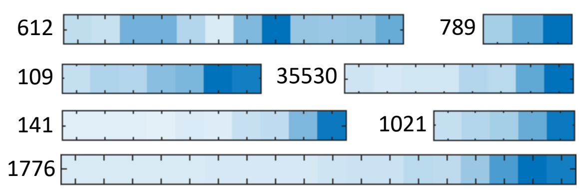


Figure 8. Visualization of the attention weights in capturing users' long-term preference. The depth of the color corresponds to the importance scores of items. The numbers indicate case indexes.

4 Related Work

4.1 Session-based Recommendation

Conventional recommendation techniques. The primary purpose of the session-based recommendation is to make predictions on users' interests based on anonymous user's behavior sequences (*e.g.*, clicked item sequences) [13, 9]. Without the availability of user's profile information results in the failure of traditional collaborative filtering approaches [19]. There exists conventional frequency-based methods are developed to study the session-based recommendation problem, such as neighborhood search-based methods [29] and Markov chain-based methods [28]. However, the aforementioned conventional recommendation techniques are difficult to be adapted to capture the time-evolving user's preferences and are expected to perform poorly when the user's online behavior is highly dynamic.

Recurrent recommendation methods. Recurrent neural networks (RNNs), which is specifically designed for sequence modeling (*e.g.*, machine translation [3] and image caption [25]), have received a great amount of attention due to their capability in modeling nonlinear sequential correlations [24, 6]. In session-based recommendation scenarios, RNN-based methods have been proposed to explore sequential patterns of user behavior [12]. However, RNN-based method is designed for modeling item sequential transitions from single view, which goes against the hierarchical item inter-dependencies and may not fit the true distributions of user behavior data.

Attention-based learning models. Based on the architecture of recurrent neural networks, attention-based neural models have been successfully used in session-based recommendation tasks [20, 23]. For example, NARM [20] regarded the last hidden state as user behavior representation, and weighted combined all hidden states as the main purpose of the user in the current session. While attention mechanism has addressed the limitation of RNN without the fixed length internal representation [17, 31], these methods aimed to assign weights to intra-session item relations. Different from those models, our LGSR framework jointly learns intra- and inter-session item dependencies in a fully automatics manner.

4.2 Multi-Task Learning

Multi-task learning has been applied to enhance performance of many learning tasks [1], such as sequence modeling [21, 22] and multi-modal behavior modeling [7]. Recent work has demonstrated the effectiveness of multi-task learning in recommendations. For example, PACE [38] and BiNE [8] enhance personalized recommendation by user-item bipartite graph node embedding. KGAT [33] employs the graph attention network to perform representation learning on the knowledge graph and simultaneously makes recommendation. Motivated by the insights from these work, we design a multi-task learning framework LGSR for the session-based recommendation, by simultaneously performs global item relation structure learning and local dynamic item transition modeling.

5 Conclusion

In this work, we explore both the local and global user behavior dynamics for session-based recommendations. We devise a new framework LGSR, which explicitly models the intra- and inter-session item transition signals. At its core is the integration of cross-session dependency encoder and a dual-stage attentive aggregation network, which learns effective item representations–preserving the item relation heterogeneity. Extensive experiments on two real-world datasets demonstrate the rationality and effectiveness of LGSR.

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