Exploring Global Information for Session-based Recommendation

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Session-based recommendation (SBR) is a challenging task, which aims at recommending items based on anonymous behavior sequences. Almost all existing SBR studies model user preferences only based on the current session while neglecting the global item-transition information from the other sessions. Specifically, we first propose a basic GNN-based session recommendation model on SBR problem by solely using session-level item-transition information on session graph. Then, we also proposes a novel approach, called Session-based Recommendation with Global Information (SRGI), which infers the user preferences of the current session via fully exploiting global item-transitions over all sessions from two different perspectives: (i) Fusion-based Model (SRGI-FM), which recursively incorporates the neighbor embeddings of each node on global graph into the learning process of session-level item representation; and (b) Constrained-based model SRGI-CM, which treats the global-level item-transition information as a constraint to ensure the learnt item embeddings are consistent with the graph structure. Extensive experiments conduct on three popular benchmark datasets demonstrates that both (SRGI-FM) and (SRGI-CM) outperform the state-of-the-art methods consistently.

CCS Concepts: • Information systems → Recommender systems.

Additional Key Words and Phrases: Recommendation system, Session-based recommendation, Graph neural network

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1 INTRODUCTION

Recommendation systems play critical roles on various on-line platforms, due to their success in addressing information overload problem by recommending useful content to users. Conventional recommendation approaches (e.g., collaborative filtering [4, 6, 13]) usually rely on the availability of user profiles and long-term historical interactions, and may perform poorly in many recent real-world scenarios, e.g., on-line shopping platform like Amazon\(^1\), and mobile stream media like YouTube\(^2\) and Tiktok\(^3\), when such information is unavailable (e.g., unlogged-in user) or limited available (e.g., short-term historical interaction). Besides, users’ recent preference is neglected in conventional methods, which is important [24] when predicting the next actions of users. For example, users have a higher probability to click Bluetooth earphone or wireless charger after buying a phone. Consequently, session-based recommendation is proposed to predict the next interested item based on a given anonymous behavior sequence in chronological order, which has attracted extensive attention recently.

Most of early studies on session-based recommendation fall into two categories, i.e., similarity-based [17] and chain-based [18]. The former heavily relies on the co-occurrence information of items in the current session while neglecting the sequential behavior patterns. The later infers all possible sequences of user choices over all items, which may suffer from intractable computation problem for real-world applications where the number of items is large. Recently, with the development of deep learning techniques, many neural networks based approaches are proposed for the task, which make use of pairwise item-transition information to model the user preference of a given session [3, 7, 9, 26, 28, 30]. These approaches have achieved encouraging results, but they still face the following issues. First, some of them infer the anonymous user’s preference by sequentially extracting the session’s pairwise item-transition information in chronological order using recurrent neural networks (RNN) (e.g., GRU4REC [3], NARM [9]) and memory networks (e.g., STAMP [11]). However, a session may contain multiple user choices and even noise, and thus they may be insufficient in generating all correct dependencies, which suffer from the inability of modeling the complicated inherent order of item-transition patterns in embedding. Second, the others are based on graph neural networks [10, 33, 34] with self-attention mechanisms such as SR-GNN [33]. They learn the representation of the entire session by calculating the relative importance based on the session’s pairwise item-transition between each item and the last one, and the performance heavily rely on the relevance of the last item to the user preference of the current session.

Furthermore, almost all the previous studies model user preference only based on the current session while ignoring the useful item-transition patterns from other sessions. To the best of our knowledge, CSRM [28] is the only work incorporating collaborative information from the latest \(m\) sessions to enrich the representation of the current session in end-to-end manner. CSRM treats sessions as the minimum granularity and measure similarities between the current and the latest \(m\) sessions to extract collaborative information. However, it may unfortunately encode both relevant and irrelevant information of the other sessions into the current session embeddings, which may even deteriorate the performance [30]. We illustrate this with an example in Figure 1. Without loss

\(^1\)https://www.amazon.com/
\(^2\)https://www.youtube.com/
\(^3\)https://www.tiktok.com/
of generality, suppose the current session is “Session 2”, and the session-based recommendation aims to recommend the relevant accessories related to “Iphone”. From Figure 3, we observe that: (i) Utilizing the item-transition of the other sessions might help model the user preference of the current session. For example, we can find relevant pairwise item-transition information for Session 2 from “Session 1” and “Session 3”, e.g., a new pairwise item-transition “[Iphone, Phone Case]”; and (ii) Directly utilizing the item-transition information of the entire other session may introduce noise when part of the item-transition information encoded in such session is not relevant to the current session. For instance, CSRM [28] may also consider to utilize “Session 3” to help modeling the user preference of “Session 2” if “Session 3” is one of the latest \( m \) sessions, and it will introduce the irrelevant items (i.e., “clothes” and “trousers”) when learning “Session 2”’s embedding as it treats “Session 3” as a whole without distinguishing relevant item-transition from irrelevant item-transition, which is challenging.

To this end, we propose a novel approach to exploit the item-transitions over all sessions from two perspectives for better inferring the user preference of the current session for session-based recommendation, which is named Session-based Recommendation with Global Information (SRGI). In SRGI, we propose to learn two levels of item feature from session graph and global graph, respectively: (i) Session graph, which is to learn the session-level item feature by modeling pairwise item-transitions within the current session; and (ii) Global graph, which is to learn the global-level item feature by modeling pairwise item-transitions over sessions (including the current session).

SRGI first employs a basic GNNs model (B-GNN) on the session graph to learn session-level item embedding within the current session, then the learnt item representations is aggregated by a soft attention mechanism with reversed position information, which can be seen as the preference of current user. Based on the constructed global graph, we present two versions of SRGI that incorporates the global transition information into SBR: (i) Fusion-based Model (SRGI-FM), which directly incorporates the neighbors’ features of each node on the global graph through a session-aware attention mechanism, where the neighbors’ features can be seen as external knowledge to enrich the features of current session; and (ii) Constraint-based Model (SRGI-CM), which preserves the global proximity to ensure the learnt item embeddings are consistent with the global graph structure, via skip-gram and negative sampling on random path.

The main contributions of this work are summarized as follows:
• We propose a basic GNN-based session recommendation model, which is capable of learning the item representations through a mean pooling based graph neural networks layer to explicitly extracting item features derived from three kinds of relations on session-level graph;

• We propose a novel unified framework (named SRGI) to fully and effectively explore the pairwise item-transition information from two levels of graph models, i.e., session graph and global graph from two different aspects, i.e., Fusion-based Model that circularly incorporates the global neighbor information into the item embedding learning process for enhancing the session-level item representations, and Constraint-based Model treats the global-level item-transition information as a constraint to ensure the learnt item embeddings are consistent with the global graph structure;

• We conduct extensive experiments on three real-world datasets, which demonstrate the efficacy of SRGI-FM and SRGI-CM over state-of-the-art baselines.

2 RELATED WORK

Many research efforts have been conducted on session-based recommendation, which will be reviewed in this section.

Markov Chain-based SBR. Several traditional methods can be employed for SBR although they are not originally designed for SBR. For example, markov Chain-based methods map the current session into a Markov chain, and then infer a user’s next action based on the previous one. Rendle et al. [16] propose FPMC to capture both sequential patterns and long-term user preference by a hybrid method based on the combination of matrix factorization and first-order Markov chain for recommendation. It can be adapted for SBR by ignoring the user latent representation as it is not available for anonymous SBR. However, MC-based methods usually focus on modeling sequential transition of two adjacent items. In contrast, our proposed model converts the sequentially item-transitions into graph-structure data for capturing the inherent order of item-transition patterns for SBR.

Deep-learning based SBR. In recent years, neural network-based methods that are capable of modeling sequential data have been utilized for SBR. Hidasi et al. [3] propose the first work called GRU4REC to apply the RNN networks for SBR, which adopts a multi-layer Gated Recurrent Unit (GRU) to model item interaction sequences. Then, Tan et al. [21] extend the method [3] by introducing data augmentation. Li et al. [9] propose NARM that incorporates attention mechanism into stack GRU encoder to capture the more representative item-transition information for SBR. Liu et al. [11] propose an attention-based short-term memory networks (named STAMP) to captures the user’s current interest without using RNN. Both NARM and STAMP emphasize the importance of the last click by using attention mechanism. Inspired by Transformer [22], SASRec [7] stacks multiple layers to capture the relevance between items. ISLF [19] takes into account the user’s interest shift, and employs variational auto-encoder (VAE) [14] and RNN to capture the user’s sequential behavior characteristics for SBR. MCPRN [30] proposes to model the multi-purpose of a given session by using a mixture-channel model for SBR. However, similar to MC-based methods, RNN-based methods focus on modeling the sequential transitions of adjacent items [29] to infer user preference via the chronology of the given sequence, and thus cannot model the complex item-transition patterns (e.g., non-adjacent item transitions).

Recently, several proposals employ GNN-based model on graph built from the current session to learn item embeddings for SBR. Wu et al. [33] propose a gated GNN [10] based model (named SR-GNN) to learn item embeddings on the session graph, and then obtain a representative session embedding by integrating each learnt item embedding with attentions, which is calculated according
to the relevance of each item to the last one. Following the success of SR-GNN, some variants are also proposed for SBR, such as GC-SAN [34]. Qiu et al. [15] propose FGNN to learn each item representation by aggregating its neighbors’ embeddings with multi-head attention, and generate the final session representation by repeatedly combining each learnt embeddings with the relevance of each time to the session. However, all these approaches only model the item-transition information on the current session. In contrast, our proposed model learns the item-transition information over all sessions to enhance the learning from the current session.

Collaborative Filtering-based SBR. Although deep learning based methods have achieved remarkable performance, collaborative filtering (CF) based methods can still provide competitive results. Item-KNN [17] can be extended for SBR by recommending items that are most similar to the last item of the current session. KNN-RNN [5] makes use of GRU4REC [3] and the co-occurrence-based KNN model to extract the sequential patterns for SBR. Recently, Wang et al. [28] propose an end-to-end neural model named CSRM, which achieves state-of-the-art performance. It first utilizes NARM over item-transitions to encode each session, then enriches the representation of the current session by exploring the latest $m$ neighborhood sessions, and finally utilizes a fusion gating mechanism to learn to combine different sources of features. However, it may suffer from noise when integrating other sessions’ embeddings for the current one. In contrast, our proposed method considers the collaborative information in item-level: we use the item embeddings in other sessions to enrich the item embeddings of the current session, and then integrate them into session representation for SBR.

3 PRELIMINARIES

In this section, we first present the problem statement, and then introduce two types of graph, i.e., session graph and global graph, based on different levels of pair-wise item transitions over sessions for learning item representations, in which we highlight the modeling of global-level item transition information as it is the basis of global graph construction. For clarity, frequently used notations are summarized in Table 1.

3.1 Problem Statement

Let $V = \{v_1, v_2, ..., v_m\}$ be all of items, and each session $S$ be denoted by $S = \{v^S_1, v^S_2, ..., v^S_l\}$, consisting of a sequence of interactions (i.e., items clicked by a user) in chronological order, where $v^S_i$ denotes an item clicked at time-step $i$ within session $S$, and the length of $S$ is $l$.

Given a session $S$, the problem of session-based recommendation aims to recommend the top-$N$ items $(1 \leq N \leq |V|)$ from $V$ that are most likely to be clicked by the user in the next timestamp.

3.2 Graph Models: Session Graph and Global Graph

In this subsection, we present two different graph models to capture different levels of item transition information over all available sessions for item representation learning.

3.2.1 Session Graph Model. Session-based graph aims to learn the session-level item embedding by modeling sequential patterns over pair-wise adjacent items in the current session. Inspired by [33], each session sequence is converted into a session graph for learning GNN-based item embeddings of the current session. More concretely, for each session $S = \{v^S_i\}_{i=1}^l$, the corresponding session graph is defined as a 2-tuple $G_S = (V_S, E_S)$, where $V_S \subseteq V$ and $E_S = \{e^S_{ij}\}$ are denoted the clicked item set and the edge set in $S$ respectively, and $e^S_{ij} = (v^S_i, v^S_j)$ indicates the adjacent edge of node $v^S_i$ and $v^S_j$ in $S$, which is called session-level item-transition pattern.
Table 1. Notations and Definitions.

| Notation | Definition |
|----------|------------|
| **Input** | Anonymous session, $S = \{v_1^1, v_2^1, ..., v_l^1 \}$ |
| **Graph** | Session graph and global graph $G_s, G_g$ Nodes in session graph and global graph $V_s, V_g$ Edges in session graph and global graph $E_s, E_g$ Number of co-occurrences of item $i$ and item $j$ $w_{ij}$ Neighbor set of node $v$ in global graph $N_\varepsilon(v)$ Neighbor set of node $v$ in session graph $N^S_v$ |
| **Attention Weight** | Attention weight between item $v_i$ and item $v_j$ in global graph $\pi(v_i, v_j)$ Attention weight between item $v_i$ and item $v_j$ in session graph $\alpha_{ij}$ Contribution weight of the item $v_i$ to current session representation $\beta_i$ |
| **Latent Variable** | Features of the neighbors of the item $v_i$ obtained from global graph $h_{N_\varepsilon v_i}$ Features of the item $v_i$ obtained from global graph $h^G_{v_i}$ Features of the item $v_i$ obtained from session graph $h^S_{v_i}$ Average of item representations of the current session $s$ Final representation of the item $v_i$ $h^*_v$ Final representation of the current session $S$ |
| **Output** | Output probabilities of each item $\hat{y}$ |

3.2.2 Global Graph Model. Similar to conventional recurrent neural network (e.g., RNN [9]) based approaches, session graph can efficiently capture sequential *intra*-relations (i.e., the graph-structured patterns within a session) to learn session-level item embeddings. However, it neglects the complicated *inter*-relations of items over sessions, e.g., the item-transition information from other sessions, which is called *global*-level item transition information.

**Global-level Item Transition Modeling.** Here, we take into account global-level item transitions for global-level item representation learning, via integrating all pairwise item transitions over sessions. As such, we propose a novel global graph model for learning global-level item embeddings, which breaks down sequence independence assumption with linking all pairs of items based on pairwise transitions over all sessions (including the current one). Next, we firstly introduce a new definition (i.e., $\varepsilon$-neighbor set) for modeling global-level item transition, and then give the definition of global graph.

**Definition 1. $\varepsilon$-Neighbor Set ($N_\varepsilon(v)$).** For any item $v^p_i$ in session $S_p$, the $\varepsilon$-neighbor set of $v^p_i$ indicates a set of items, each element of which is defined as follows,

$$N_\varepsilon(v^p_i) = \{ v^q_j \mid v^p_i = v^p_i \in S_p \cap S_q; v^q_j \in S_q; j \in [i' - \varepsilon, i' + \varepsilon]; S_p \neq S_q \},$$

where $i'$ is the order of item $v^p_i$ in session $S_q$, $\varepsilon$ is a hyperparameter to control the scope of modeling item-transition between $v^p_i$ and the items in $S_q$. Note that, parameter $\varepsilon$ favors the modeling of short-range item transitions over sessions, since it is helpless (even noise, e.g., irrelevant dependence) for capturing the *global*-level item transition information if beyond the scope ($\varepsilon$).
According to Definition 1, for each item \( v_i \in V \), global-level item transition is defined as \( \{(v_i, v_j)|v_i, v_j \in V; v_j \in \mathcal{N}_\varepsilon(v_i)\} \). Notably, we do not distinguish the direction of global-level item transition information for efficiency.

**Global Graph.** Global graph aims to capture the global-level item transition information, which will be used to learn item embeddings over all sessions. Specifically, the global graph is built based on \( \varepsilon \)-neighbor sets of items in all sessions. Without loss of generality, global graph is defined as follows, let \( \mathcal{G}_g = (V_g, E_g) \) be the global graph, where \( V_g \) denotes the graph node set that contains all items in \( V \), and \( E_g = \{e^g_{ij}|(v_i, v_j); v_i \in V, v_j \in \mathcal{N}_\varepsilon(v_i)\} \) indicates the set of edges, each corresponding to two pairwise items from all the sessions. Figure 2b shows an example of building the global graph with \( \varepsilon = 2 \). To distinguish the importance of \( v_i \)’s neighbors (\( \mathcal{N}_\varepsilon(v_i) \)), we treat the co-occurrence over sessions of node \( v_i \) and its neighbor node \( v_j \in \mathcal{N}_\varepsilon(v_i) \) as the weights of the corresponding edge.

**Remark.** (i) For efficiency, we do not dynamically update the topological structure of global graph, and only remain the top-\( N \) edges with the highest weights for each node \( v_i \) on graph \( \mathcal{G}_g \); (ii) The definition of the neighbors (i.e., \( \mathcal{N}_\varepsilon(v) \)) of item \( v \) on graph \( \mathcal{G}_g \) is same as \( \mathcal{N}_\varepsilon(v) \); (iii) \( \mathcal{G}_g \) is an undirected weighted graph as \( \varepsilon \)-neighbor set is undirected; and (iv) Each item in \( V \) is encoded into an unified embedding space at time-step \( t \), i.e., \( h^t_i \in \mathbb{R}^d \) (\( d \) indicates the dimension of item embedding), which is feed with an initialization embedding \( h^0_i \in \mathbb{R}^{|V|} \), here we use one-hot based embedding and it is transformed into \( d \)-dimensional latent vector space by using a trainable matrix \( W_D \in \mathbb{R}^{d \times |V|} \).
4 THE PROPOSED METHOD

To leverage the different levels (e.g., local-level and global-level) information for session-based recommendation task, we first propose a basic GNN-based recommendation framework (i.e., B-GNN, as shown in Fig. 3a) in Section 4.1. Based on the B-GNN framework, we also propose a novel approach (named Session-based Recommendation with Global-level Information, SRGI) with two different variants in Section 4.2 and Section 4.3, which is capable of leveraging the global item-transition information from two different aspects: (a) SRGI-FM (ref. Fig. 3b), it incorporates the global item-transitions information into the learning process of session-level item representation; and (b) SRGI-CM (ref. Fig. 3c), it treats the global-level item-transition information as a constraint to ensure the learnt item embeddings are consistent with the graph structure, which is called global proximity and will be elaborated later on. Next, we will illustrate each part in detail.

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Fig. 3. An overview of the proposed framework. In (a) we show the basic ranking module which first utilizes graph neural networks to exploiting the item transitions in session graph, then the learned item features are combined by attention mechanism. In (b) the neighbors of item in global graph are incorporated into current session by a session-level attention mechanism. In (c) the global transition information are introduced by preserving the global proximity in the embedding space.

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We do not distinguish $N_c(v)$ and $N_g(v)$ when the context is clear and discriminative.
4.1 Basic GNN-based Framework (B-GNN)

In this section, we first propose a basic GNN-based model (called B-GNN, as shown in Fig. 3a) based on graph convolution network [8, 27] (GCN), which solely utilizes three different types (i.e., in, out and in-out, as shown in Fig. 2a) of session-level item transition information for session-based recommendation. Specifically, B-GNN consists of three sub-components, i.e., session-level item representation learning layer, session representation learning layer and prediction, and we will be detailed in the following sub-sections, respectively.

4.1.1 Session-level Item Representation Learning Layer. To learn the session-level item representation, we focus on how to enrich the representation of each item with the help of its 1-hop neighbors, via exploring the pairwise item-transitions within the current session.

**Information Propagation**: For each node \( v_i \) of session \( S \), we consider three different types of relations between \( v_i \) and its neighbors \( N_{v_i} \), i.e., in-coming neighbor, out-coming neighbor and in-out coming neighbor which are denoted by \( N_{v_i}^{s,\text{in}} \), \( N_{v_i}^{s,\text{out}} \) and \( N_{v_i}^{s,\text{in-out}} \) respectively. To calculate the importance of different neighbors, we treat such two kinds of neighbors differently during the propagation of information, which are calculated based on mean pooling, namely,

\[
\begin{align*}
    h_{N_{v_i}^{s,\text{in}}} & = \text{MeanPooling}(h_{v_j} | v_j \in N_{v_i}^{s,\text{in}}) \\
    h_{N_{v_i}^{s,\text{out}}} & = \text{MeanPooling}(h_{v_j} | v_j \in N_{v_i}^{s,\text{out}}) \\
    h_{N_{v_i}^{s,\text{in-out}}} & = \text{MeanPooling}(h_{v_j} | v_j \in N_{v_i}^{s,\text{in-out}})
\end{align*}
\]

(1)

Then, the neighbor representation \( h_{N_{v_i}^s} \) of node \( v_i \) is obtained based on the concatenation of \( h_{N_{v_i}^{s,\text{in}}} \), \( h_{N_{v_i}^{s,\text{out}}} \) and \( h_{N_{v_i}^{s,\text{in-out}}} \), namely,

\[
h_{N_{v_i}^s} = [h_{N_{v_i}^{s,\text{in}}} || h_{N_{v_i}^{s,\text{out}}} || h_{N_{v_i}^{s,\text{in-out}}}],
\]

(2)

where || denotes concatenation operation. In particular, different from SR-GNN [33] and FGNN [15] that use gate GNNs or weight-based GAT for information propagation, here we utilize mean pooling in our propagation layer to significantly reduces the amount of training parameters for avoiding over-fitting and making the training process stable.

**Information Aggregation**: The session-level item representation is generated by aggregating the embeddings of item \( v_i \) and its neighbors \( h_{N_{v_i}^s} \), which is computed via a fully connected layer,

\[
h_{v_i}^s = \tanh(W_S h_{v_i} + W_N h_{N_{v_i}^s} + b_S),
\]

(3)

where \( W_S \in \mathbb{R}^{d \times d}, W_N \in \mathbb{R}^{d \times 2d} \) and \( b_S \in \mathbb{R}^d \) are trainable parameters. The new representations \( h_{v_i}^s \) of each item is aggregated by the features of item itself and its neighbors in the current session.

4.1.2 Session Representation Learning Layer. Based on the learnt item representations, we now present how to obtain the session representations. Different from previous work [11, 33, 34] which mainly focus on the last item, in this paper we propose a more comprehensive strategy to learn the contribution of each part of the session for prediction.

In our method, a session representation is constructed based on all the items involved in the session. Note that the contribution of different items to the next prediction is not equal. Intuitively, the items clicked later in the session are more representative of the user’s current preferences, which shows their greater importance for the recommendation. Moreover, it is important to find the main purpose of the user and filter noise in current session [9]. Hence we incorporate reversed position information and session information to make a better prediction.
After feeding a session sequence into graph neural networks, we can obtain the representation of the items involved in the session, i.e., \( \mathbf{H} = [\mathbf{h}_v^1, \mathbf{h}_v^2, \ldots, \mathbf{h}_v^l] \). We also use a learnable position embedding matrix \( \mathbf{P} = [\mathbf{p}_1, \mathbf{p}_2, \ldots, \mathbf{p}_l] \), where \( \mathbf{p}_i \in \mathbb{R}^d \) is a position vector for specific position \( i \) and \( l \) is the length of the current session sequence. The position information is integrated through concatenation and non-linear transformation:

\[
\mathbf{z}_i = \tanh \left( \mathbf{W}_z \left[ \mathbf{h}_v^i \parallel \mathbf{p}_{l-i+1} \right] + \mathbf{b}_z \right),
\]

where parameters \( \mathbf{W}_z \in \mathbb{R}^{d \times 2d} \) and \( \mathbf{b}_z \in \mathbb{R}^d \) are trainable parameters. Here we choose the reversed position embedding because the length of the session sequence is not fixed. Comparing to forward position information, the distance of the current item from the predicted item contains more effective information, e.g., in the session \( \{v_2 \rightarrow v_3 \rightarrow ?\} \), \( v_3 \) is the second in the sequence and shows great influence to prediction, however in the session \( \{v_2 \rightarrow v_3 \rightarrow v_5 \rightarrow v_6 \rightarrow v_8 \rightarrow ?\} \), the importance of \( v_3 \) would be relatively small. Therefore the reversed position information can more accurately suggest the importance of each item.

The session information is obtained by computing the average of item representations of the session,

\[
\mathbf{s}' = \frac{1}{l} \sum_{i=1}^l \mathbf{h}_v^i.
\]

Next, we learn the corresponding weights through a soft-attention mechanism:

\[
\beta_i = \mathbf{q}^\top \sigma \left( \mathbf{W}_4 \mathbf{z}_i + \mathbf{W}_5 \mathbf{s}' + \mathbf{b}_4 \right),
\]

where \( \mathbf{W}_4, \mathbf{W}_5 \in \mathbb{R}^{d \times d} \) and \( \mathbf{q}, \mathbf{b}_4 \in \mathbb{R}^d \) are learnable parameters.

Finally, the session representation can be obtained by linearly combining the item representations:

\[
\mathbf{S} = \sum_{i=1}^l \beta_i \mathbf{h}_v^i.
\]

The session representation \( \mathbf{S} \) is constructed by all the items involved in the current session, where the contribution of each item is determined not only by the information in the session graph, but also by the chronological order in the sequence.

4.1.3 Objective Function. Based on the obtained session representations \( \mathbf{S} \), the final recommendation probability for each candidate item based on their initial embeddings as well as current session representation. Here, \( \ell_2 \)-norm is employed to normalize session representation and item representations (i.e., \( \hat{\mathbf{S}} = \frac{\mathbf{S}}{||\mathbf{S}||_2} \) and \( \hat{\mathbf{h}}_v = \frac{\mathbf{h}_v}{||\mathbf{h}_v||_2} \)) for avoiding popular bias [1]. Then, we use inner-product and apply softmax function to obtain the output \( \hat{\mathbf{y}} \):

\[
\hat{\mathbf{y}}_i = \text{Softmax} \left( \lambda \hat{\mathbf{S}}^\top \hat{\mathbf{h}}_{v_i} \right),
\]

where \( \lambda \) is a scale coefficient for better convergence [1, 25] and \( \hat{\mathbf{y}}_i \in \hat{\mathbf{y}} \) denotes the probability of item \( v_i \) appearing as the next-click in the current session.

The loss function is defined as the cross-entropy of the prediction results \( \hat{\mathbf{y}} \):

\[
\mathcal{L}_S = - \sum_{i=1}^m \mathbf{y}_i \log(\hat{\mathbf{y}}_i) + (1 - \mathbf{y}_i) \log(1 - \hat{\mathbf{y}}_i),
\]

where \( \mathbf{y} \) denotes the one-hot encoding vector of the ground truth item.

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4.2 Fusion-based Model

In this section, we propose a novel fusion-based model under the B-GNN framework, i.e., a variant of our proposed model SRGI (e.g., SRGI-FM, as shown in Fig. 3c), the principle of which is to learn the representations of items within the current session by leveraging the different levels (i.e., session-level and global-level) of item-transitions. Next, we will detail how to leverage the global-level item-transitions derived from other sessions to enhance the session-level item representation of B-GNN, which is built based on the architecture of graph convolution network [8, 27], and here we first describe a single layer consisting of two components: fusion-based information propagation and information aggregation, and then show how to generalize it to multiple layers.

Fusion-based Information Propagation: An item may be involved in multiple sessions, from which we can obtain useful item-transition information to effectively help current predictions. To obtain the first-order (i.e., 1-hop neighbors) neighbor’s features of item $v$, one straightforward solution is to use mean pooling method [2]. However, not all of items in $v$’s $ε$-neighbor set are relevant to the user preference of the current session, and thus we consider to utilize a session-aware attention to distinguish the importance of items in $N_ε(v)$. Therefore, each item in $N_ε(v)$ is linearly combined according to the session-aware attention score,

$$h_{N_εvi} = \sum_{v_j \in N_εvi} \pi(v_i, v_j)h_{vj},$$

(10)

where $\pi(v_i, v_j)$ estimates the importance weight of different neighbors. Intuitively, the closer an item is to the preference of the current session, the more important this item is to the recommendation. Therefore, we implement $\pi(v_i, v_j)$ based on the principle of graph attention network [23]:

$$\pi(v_i, v_j) = q_1^T \text{LeakyRelu}(W_1 [(s \odot h_{vj}) || w_{ij}]).$$

(11)

where || indicates concatenation operation; $w_{ij} \in \mathbb{R}^1$ is the weight of edge $(v_i, v_j)$ in global graph; $W_1 \in \mathbb{R}^{d+1 \times d+1}$ and $q_1 \in \mathbb{R}^{d+1}$ are trainable parameters. Note that here we choose LeakyRelu as activation function, $\odot$ indicates element-wise product. In particular, $s$ can be viewed as the features of current session, which is estimated by calculating the average of item representations of the current session, namely,

$$s = \frac{1}{|S|} \sum_{v_i \in S} h_{v_i}.$$  

(12)

Differentiate from mean pooling, in our model the propagation of information depends on the affinity between $S$ and $v_j$, which means neighbors that match the preference of current session will be more favourable, and we then normalize the coefficients across all neighbors connected with $v_i$ by adopting the softmax function:

$$\pi(v_i, v_j) = \frac{\exp \left( \pi(v_i, v_j) \right)}{\sum_{v_k \in N_εvi} \exp \left( \pi(v_i, v_k) \right)}.$$  

(13)

As such, Eq. (13) is capable of assigning high attention scores to the important global-level 1-hop neighbors of items in the current session.

Information Aggregation: The final step is to aggregate the item representation $h_v$ and its neighborhood representation $h_{N_εv}$, we implement aggregator function agg as follows,

$$h_v^g = \text{relu}(W_2 [h_v || h_{N_εv}]),$$

(14)

where we choose relu as the activation function and $W_2 \in \mathbb{R}^{d \times 2d}$ is transformation weight.
Through a single aggregator layer, the representation of an item is dependent on itself and its immediate neighbors. We could explore the high-order connectivity information through extending aggregator from one layer to multiple layers, which allows more information related to the current session to be incorporated into the current representation. We formulate the representation of an item in the $k$-th steps as:

$$h_v^{(k)} = \text{agg}(h_v^{(k-1)}, h_{N_v}^{(k-1)}),$$  

(15)

$h_v^{(k-1)}$ is representation of item $v$ which is generated from previous information propagation steps, $h_v^{(0)}$ is set as $h_v$ at the initial propagation iteration. In this way, the $k$-order representation of an item is a mixture of its initial representations and its neighbors up to $k$ hops away. This enables more effective messages to be incorporated into the representation of the current session.

After obtaining the representation of the $h_v^{(k)}$, the new representation of each item can be obtained by element-wise sum,

$$h'_v = h_v^{(k)} + h_v^i.$$  

(16)

Consequently, we obtain the new representation for each item of the current session, which integrate both session-level and global-level item-transition information and thus the recommendation prediction can be implemented based on Eq. (4)-(9) via using the new item embedding $h'_v$.

### 4.3 Constrained-based Model

Recall that the strategy of building the global graph is based on the co-occurrence of pairwise items over sessions, namely, pairwise items with high frequency co-occurrences are remained while filtering the ones with low-frequency co-occurrences. To this end, in this section we propose another variant of our proposed model SRGi (i.e., SRGi-CM, as shown in Fig. 3c), which is different from SRGi-FM that aims to integrate different levels of item-transitions for learning item representation, the principle of SRGi-CM is to ensure the learnt item embeddings are consistent with global-level item-transition information, which is called global proximity that can be modeled from two different aspects: (i) Closely-connected pairwise items (i.e., an item and its global neighbors) often have high relevancy (e.g., milk and bread) due to high frequency item-transitions over sessions, and thus should be assigned to the proximal vectors in the learnt embedding space; and (ii) Loosely-connected pairwise items (i.e., without global links to each other) often have low relevancy due to low frequency item-transitions over sessions, and thus should enforce that the representations of such disparate items are distinctive.

To preserve global proximity on global graph $G_g$, we adopt the skip-grams with negative sampling on random walk-based paths in the global graph to optimize the learning process of item representation. Specifically, for each node $v_i$ on global graph, the set of closely-connected nodes (i.e., positive set) of $v_i$ is obtained by fixed-length random walks, namely, we treat $v_i$ as the initial node of a path, and then circularly select one of its neighborhoods to be the next one until the path length reaches a certain value (e.g., a pre-defined threshold $\omega$), and thus we use $\Theta^{+}_{v_i} = \{\mathbf{g}_i, \cdots, \mathbf{g}_{\omega}\}$ to indicate the fixed-length random walk sampled based on node $v_i$ ($v_i \in V_g$), where $\mathbf{g}_k$ refers to the $i$-th sampled nodes in path $\Theta^{+}_{v_i}$. In particular, we equally treat the neighbors of node $v_i$, and thus the transition probability from each node $v_i$ to its neighbor node $\mathbf{g}_j$ on a random path is computed by,

$$\Pr\left(\mathbf{g}_k \rightarrow \mathbf{g}_j \mid \mathbf{g}_k = v_i \in V_g; \mathbf{g}_k, \mathbf{g}_j \in \Theta^{+}_{v_i}; |k - j| \leq \omega\right) = \frac{1}{|N_i(v_j)|},$$  

(17)

where $|N_i(v_j)|$ is the number of neighborhoods of $v_i$ on global graph $G_g$. It is worth noting that all of nodes on $G_g$ should be used as the initial node for path sampling, which ensures that the generated walk paths contain all nodes ($v_i \in V_g$). On the other hand, for loosely-connected nodes
(i.e., negative set), we adopt negative sampling to generate a set of negative items (i.e., $\Theta_{u_i}^-$), which includes the items without a link to node $u_i$, i.e., $\Theta_{u_i}^- = \{\mu^i_j\}_{(V_g - \Theta_{u_i})^+}$, and thus each element $\mu^i_j$ is randomly sampled from $(V_g - \Theta_{u_i}^+).$ Finally, we formulate the following loss function based on global proximity, which is called proximity loss function ($L_P$) and defined based on the overall negative log-likelihood, namely,

$$L_P = -\sum_{v_i \in V_g} \sum_{v_j \in \Theta_{v_i}^-} \log \left( \sigma(h_{v_i}^T h_{v_j}) \right) - E_{\mu^i_j \sim P_n(\Theta_{u_i}^-)} \log \left( \sigma(-h_{v_i}^T h_{\mu^i_j}) \right), \tag{18}$$

where $h_{v_i}, h_{v_j}$ and $h_{\mu^i_j}$ denote the item embeddings of node $v_i$, global neighbor $v_j$ and negative item $\mu^i_j$, respectively; and $P_n$ is the negative sampling distribution.

Therefore, the final loss function of SRGI-CM is defined based on prediction loss (rf. Eq. (9)) and proximity loss (rf. Eq. (18)) for learning session-level item embeddings by preserving global proximity,

$$L_G = L_S + \lambda L_P, \tag{19}$$

where $\lambda$ is a trade-off parameter to control the impact of global proximity. Similar to SRGI-FM, the final prediction results are generated via using Eq. (4)-(9) and the new item embedding $h_{v_i}$ that is learnt based on Eq. (19).

5 EXPERIMENTS

We have conducted extensive experiments to evaluate the accuracy of the proposed method by answering the following four key research questions:

- **RQ1**: Does two versions of SRGI outperform state-of-the-art SBR baselines in real world datasets?
- **RQ2**: Does global graph information improve the performance of SRGI? What is the impact of different hyper-parameter on learning global item transitions?
- **RQ3**: How does the mean pooling-based GNNs perform compared with other session-level item representation learning methods?
- **RQ4**: Does reversed position aware session encoder show effective for session-based recommendation?

5.1 Datesets and Preprocessing

To fully evaluate the effectiveness of our proposed method, we employ three real-world datasets in the experiment.

*Diginetica*\(^5\) is from CIKM Cup 2016, which consisting of typical transaction data for five month from e-commerce website. Following [33], we set the sessions of last week (latest data) as the test data, and the remaining historical data for training.

*Tmall*\(^6\) comes from IJCAI-15 competition, which contains anonymized user’s shopping logs on Tmall online shopping platform. Since the amount of items of Tmall is extremely large, we use the portions $1/64$ of the sessions for train and test. Follow [12], the sessions of last data is set as the test data, and the remaining historical data for training.

*Nowplaying*\(^7\) comes from music-related tweets [35], which describes the music listening behavior of users. We set the sessions of last two months as the test data, and the remaining historical data for training.

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\(^5\)https://competitions.codalab.org/competitions/11161
\(^6\)https://tianchi.aliyun.com/dataset/dataDetail?dataId=42
\(^7\)https://dbis-nowplaying.ubk.ac.at/#nowplaying

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Table 2. Statistics of the used datasets.

| Dataset   | Diginetica | Tmall    | Nowplaying |
|-----------|------------|----------|------------|
| # click   | 982,961    | 398,795  | 1,147,166  |
| # train   | 719,470    | 304,577  | 898,416    |
| # test    | 60,858     | 36,799   | 103,827    |
| # items   | 43,097     | 36,098   | 60,623     |
| avg. len. | 5.12       | 6.94     | 7.91       |

Following [33, 34], we conduct preprocessing step over the three datasets. More specifically, sessions of length 1 and items appearing less than 5 times were filtered across all the three datasets. For Tmall and Nowplaying, sessions longer than 50 were also filtered [28]. Furthermore, for a session \( S = [s_1, s_2, ..., s_n] \), we generate sequences and corresponding labels by a sequence splitting preprocessing, i.e., \( ([s_1], s_2), ([s_1, s_2], s_3), ..., ([s_1, s_2, ..., s_{n-1}], s_n) \) for both training and testing across all the three datasets. The statistics of datasets, after preprocessing, are summarized in Table 2.

5.2 Evaluation Metrics

We adopt two widely used ranking based metrics: \( P@N \) and \( MRR@N \) by following previous work[11, 33].

\( P@N \) (Precision)[33]: The P@N score is typically used as a measure of accuracy. It represents the proportion of correctly recommended items in top \( N \) recommended item list, which is defined as:

\[
P@N = \frac{n_{hit}}{n_{test}},
\]

where \( n_{test} \) denotes the number of test data and \( n_{hit} \) denotes the number of the target items appearing in the top \( N \) recommended items.

\( MRR@N \) (Mean Reciprocal Rank)[11]: The MRR@N score is the average of reciprocal rank of the correctly-recommended items. The reciprocal rank is set to zero if the rank exceeds \( N \),

\[
MRR@N = \frac{1}{n_{test}} \sum \frac{1}{\text{Rank}(v_{target})}.
\]

MRR is a normalized score in the range of \([0, 1]\), and a larger MRR value means that correct recommendations are in the top of the ranking list.

Here, we choose \( N = 20 \) for both \( P@N \) and \( MRR@N \), as recommendation systems should focus on top ranked items.

5.3 Baseline Algorithms

We compare our method with classic methods as well as state-of-the-art models. The following baseline models are evaluated.

\( \text{POP} \): It recommends top-\( N \) frequent items of the training set.

\( \text{Item-KNN} \)[17]: It recommends items based on the similarity between items of the current session and items of other ones.

\( \text{GRU4Rec} \)\footnote{https://github.com/hidasib/GRU4Rec} [3]: It is RNN-based model that uses Gated Recurrent Unit (GRU) to model user sequences.
NARM\textsuperscript{9} [9]: It improves over GRU4Rec \textsuperscript{3} by incorporating attention mechanism into hierarchical RNN for SBR.

STAMP\textsuperscript{10} [11]: It employs attention layers to replace all RNN encoders in previous work by fully relying on the self-attention of the last item in the current session to capture the user’s short-term interest.

SR-GNN\textsuperscript{11} [33]: It employs a gated GNN layer to obtain item embeddings, followed by a self-attention of the last item as STAMP\textsuperscript{11} does to compute the session level embeddings for session-based recommendation.

CSRM\textsuperscript{12} [28]: It utilizes the memory networks \textsuperscript{32} to investigate the latest $m$ sessions for better predicting the intent of the current session.

NISER \textsuperscript{1}: It utilizes l2 normalized item representation as input and leverages cosine similarity to compute the similarity between items and current session representation.

GCE-GNN \textsuperscript{31}: A state-of-the-art GNN-based model which directly aggregates global information into current session and utilizes attention mechanism to obtain the session representation.

5.4 Parameter Setup

Following previous methods \textsuperscript{9}\textsuperscript{9} [9]\textsuperscript{11}\textsuperscript{33}, the dimension of the latent vectors is fixed to 100, and the size for mini-batch is set to 100 for all models. We keep the hyper-parameters of each model consistent for a fair comparison. For CSRM, we set the memory size to 100 which is consistent with the batch size. For NISER, we set the scale factor $\sigma = 16$ and dropout ratio = 0.1. For our model, all parameters are initialized using a Gaussian distribution with a mean of 0 and a standard deviation of 0.1. We use the Adam optimizer with the initial learning rate 0.001, which will decay by 0.1 after every 3 epoch. The L2 penalty is set to $10^{-5}$ and the scale coefficient $\lambda$ is set to 12.

Moreover, we set the maximum distance of adjacent items $\epsilon$ and the number of neighbors to 3 and 12, respectively. In AggGESE we use dropout \textsuperscript{20} to avoid overfitting, the dropout ratio is set to 0.5 and the graph depth is searched in \{1, 2\}. In EmbGESE, the graph depth (i.e., walk length $\omega$) is set to 2, the number of negative samples is set to 20 and the trade-off parameter $\lambda_P$ is searched in \{10, 50, 100\}. All the parameters are searched on a validation set which is a random 10\% subset of the training set.

5.5 Overall Comparison (RQ1)

Table 3 reports the experimental results of the state-of-the-art baselines and our proposed model on three real-world datasets, in which the best result of each column is highlighted in boldface. It can be observed that SRGI-FM and SRGI-CM achieve better performance than state-of-the-art baselines across all three datasets in terms of the two metrics, which ascertains the effectiveness of our proposed method.

Among the traditional methods, POP’s performance is the worst, as it only recommends top-N frequent items. Comparing with POP, Item-KNN shows its effectiveness on three datasets. Note it only applies the similarity between items and does not consider the chronological order of the items in a session, and thus it cannot capture the sequential transitions between items.

Compared with traditional methods, neural network based methods usually have better performance for session-based recommendation. In spite of preforming worse than Item-KNN on

\textsuperscript{9}https://github.com/lijingsdu/sessionRec_NARM
\textsuperscript{10}https://github.com/uestcnlp/STAMP
\textsuperscript{11}https://github.com/CRIPAC-DIG/SR-GNN
\textsuperscript{12}https://github.com/wmeirui/CSRM_SIGIR2019
Table 3. The performance of evaluated methods on three datasets.

| Method   | Diginetica | Tmall       | Nowplaying |
|----------|------------|-------------|------------|
|          | P@20       | MRR@20      | P@20       | MRR@20      | P@20       | MRR@20      |
| POP      | 1.18       | 0.28        | 1.95       | 0.75        | 1.77       | 0.58        |
| Item-KNN | 35.75      | 11.57       | 10.40      | 3.86        | 14.76      | 4.68        |
| GRU4Rec  | 30.79      | 8.22        | 10.49      | 4.88        | 9.82       | 5.47        |
| NARM     | 48.32      | 16.00       | 38.10      | 19.97       | 17.66      | 6.11        |
| STAMP    | 46.62      | 15.13       | 26.63      | 15.05       | 16.96      | 7.06        |
| CSRM     | 48.49      | 17.13       | 39.80      | 20.68       | 18.45      | 6.87        |
| SR-GNN   | 51.26      | 17.78       | 39.10      | 19.96       | 18.85      | 7.98        |
| NISER    | 53.39      | 18.72       | 43.00      | 22.21       | 22.47      | 9.13        |
| GCE-GNN  | 54.22      | 19.04       | 44.71      | 22.79       | 23.63      | 9.14        |
| B-GNN    | 53.93      | 19.05       | 45.13      | 22.85       | 23.42      | 9.17        |
| SRGI-FM  | 54.35      | 19.14       | 46.32      | 23.44       | 24.18      | 9.48        |
| SRGI-CM  | **54.71**  | **19.32**   | **47.40**  | **24.13**   | **24.25**  | **9.32**    |

Diginetica, GRU4Rec, as the first RNN based method for SBR, still demonstrates the capability of RNN in modeling sequences. However, RNN is designed for sequence modeling, and session based recommendation problems are not merely a sequence modeling task because the user’s preference may change within the session.

The subsequent methods, NARM and STAMP outperform GRU4REC significantly. NARM combines RNN and attention mechanism, which uses the last hidden state of RNN as the main preference of user, this result indicates that directly using RNN to encode the session sequence may not be sufficient for SBR as RNN only models one way item-transition between adjacent items in a session. We also observe that STAMP, a complete attention-based method, achieves better performance than NARM on Tmall, which incorporates a self-attention over the last item of a session to model the short-term interest, this result demonstrates the effectiveness of assigning different attention weights on different items for session encoding. Compared with RNN, attention mechanism appears to be a better option, although STAMP neglects the chronological order of items in a session.

CSRM performs better than NARM and STAMP over three datasets. It shows the effectiveness of using item transitions from other sessions, and also shows the shortcomings of the memory networks used by CSRM that have limited slots, additionally CSRM treats other sessions as a whole one without distinguishing the relevant item-transitions from the irrelevant ones encoded in other sessions.

Among all the baseline methods, the GNN-based methods perform better on the Diginetica and Nowplaying datasets. By modeling every session sequence as a subgraph and applying GNN to encode items, SR-GNN and NISER demonstrate the effectiveness of applying GNN in session-based recommendation. This indicates that the graph modeling would be more suitable than the sequence modeling, RNN, or a set modeling, the attention modeling for SBR.

Our approach SRGI-FM and SRGI-CM outperforms SR-GNN, NISER and GCE-GNN on all the three datasets. Specifically, SRGI-CM outperforms the NISER by 2.8% on Diginetica, 9.6% on Tmall and 5.2% on Nowplaying on average. Different from SR-GNN and NISER, our approach integrates information from global context, i.e., other session, and local context, i.e., the current session, and also incorporates relative position information, leading to consistent better performance.
5.6 Impact of Global Feature Encoder (RQ2)

In this section, we aim to study the effect of global transition information and the impact of different graph parameters (i.e., graph depth, the number of neighbors and trade-off parameter $\lambda_P$) by conducting experiments over three datasets.

5.6.1 Effect of global transition information. From Table 3, we can observe that both SRGI-FM and SRGI-CM achieve better performance than B-GNN, which shows that global transition information can provide useful information for the learning of current session. Comparing with two version of SRGI, SRGI-CM performs better than SRGI-FM in most instances. It is because SRGI-FM directly incorporate global information into current session, which easily introduces extra noise into the current session. Although we leverage session aware attention mechanism to reduce the influence of noise, it still affects the performance of the model. In comparison, SRGI-CM is less affected by noise information as it does not need to fuse global information directly into the current session representation. SRGI-FM mainly focus on the items in current session when predicting the next item and utilize skip-gram to preserve global proximity. The global proximity forces the closely connected items more similar in the embedding space while the loosely connected item more distinctive, which benefits the item representation learning and the prediction of the current session.

5.6.2 Impact of the graph depth. We next conduct experiments on three datasets to evaluate the impact of the graph depth on two version of SRGI. In SRGI-FM, the number of neighbors of each item increases exponentially as the graph depth increases, therefore we only evaluate the impact of 1-hop and 2-hop neighbors for SRGI-FM. In contrast, in SRGI-CM the number of neighbors is obtained by the product of the number of paths and the walk length, which means changing
the walk length will only lead the number of sampled neighbors to grow linearly, therefore we evaluate the performance of SRGI-CM with the graph depth from 1-hop to 4-hop. Figure 4 shows the performance of two versions of SRGI with different graph depth. It can be observed that both SRGI-CM and SRGI-FM outperform the B-GNN with graph depth from 1-hop to 4-hop over three datasets. Specifically, SRGI-FM with 2-hop performs better than SRGI with 1-hop in most situation, which indicates that high-level exploring might obtain more effective information from global graph. Besides, the performance of SRGI-CM is better than SRGI-FM on Diginetica and Tmall, which demonstrates the effectiveness of global proximity for session-based recommendation. Further, we observe the performance of SRGI-CM drops when graph depth is set to 4 on Nowplaying in terms of two metrics, which shows that higher-level exploring might also introduce more noise. The results in Figure 4 demonstrates that the neighbors in global graph contain useful global transitions information for current session.

5.6.3 Impact of the number of neighborhoods on global graph. As Figure 1 shows, there will be irrelevant items in a session when user clicked items. As we collect the $\epsilon$-Neighbor set of each item to obtain the global item transitions information, the inclusion of noise was unavoidable. In the proposed method, we only keep top-$N$ edges with the highest weights (i.e., frequency) to reduce the influence of noise. When the number of neighbors $N$ increases, more useful global transitions information can be captured, and at the same time more noise will be introduced. Here, we conduct experiment over three datasets to evaluate the impact of $N$ on the performance of our proposed method. From Figure 5, we can observe that with the number of neighbors increase from 4 to 12, the performance of SRGI-CM in terms of MRR@20 becomes better over three datasets. It is because SRGI-CM can capture more effective global transitions information from the neighbors of each item, which benefits the prediction of current session. However, SRGI-CM with more neighbors does not perform well on Nowplaying, which is affect by the increasing noise in the neighbors.

5.6.4 Impact of the trade-off parameter $\lambda_P$ in global graph. Trade-off parameter $\lambda_P$ is an important scalar, which controls the influence of global proximity. Higher $\lambda_P$ means that SRGI-CM pays more attention to the global-level item transitions. Therefore, we conduct experiments to study the impact of $\lambda_P$ on the performance of SRGI-CM over three datasets. From Table 4 we observe that with the $\lambda_P$ increases, the performance of SRGI-CM improves in terms of P@20 over three datasets, which shows the effective of global information to the current session. However, the performance of SRGI-CM drops in terms of MRR@20 on Nowplaying when $\lambda_P$ increases, which is suffer from the noise in the global graph.
Table 4. The performance of SRGI-CM with different $\lambda_P$.

| Dataset    | Measures    | Diginetica | Tmall  | Nowplaying |
|------------|-------------|------------|--------|------------|
| $\lambda_P = 10$ | P@20 | 54.38 | 9.31 | 19.36 | 47.12 | 23.74 | 24.25 |
|            | MRR@20      | 19.31      | 23.74  | 9.32      | 23.76 |
| $\lambda_P = 50$ | P@20 | 54.55 | 9.33 | 19.36 | 47.12 | 23.96 | 24.25 |
|            | MRR@20      | 19.36      | 23.96  | 9.32      | 24.08 |
| $\lambda_P = 100$ | P@20 | 54.71 | 9.33 | 19.32 | 47.32 | 24.13 | 25.19 |
|            | MRR@20      | 19.32      | 24.13  | 8.98      | 25.39 |
| $\lambda_P = 150$ | P@20 | 54.84 | 9.33 | 19.33 | 47.50 | 24.19 | 25.39 |
|            | MRR@20      | 19.33      | 24.19  | 8.81      | 25.44 |
| $\lambda_P = 200$ | P@20 | 54.85 | 9.32 | 19.32 | 47.13 | 24.26 | 25.44 |
|            | MRR@20      | 19.32      | 24.26  | 8.79      | 25.44 |

Table 5. The performance of contrast models.

| Dataset    | Measures    | Diginetica | Tmall  | Nowplaying |
|------------|-------------|------------|--------|------------|
|            | P@20       | MRR@20     | P@20   | MRR@20     |
| B-GNN-GGNN |            | 53.89      | 18.81  | 44.57      | 22.71 |
|            |            | 23.76      | 8.37   |            |      |
| B-GNN-GAT  |            | 53.61      | 18.85  | 45.08      | 22.00 |
|            |            | 22.81      | 8.49   |            |      |
| B-GNN      |            | 53.93      | 19.05  | 45.13      | 22.85 |
|            |            | 23.42      | 9.17   |            |      |

Table 6. The performance of contrast models.

| Dataset    | Measures    | Diginetica | Tmall  | Nowplaying |
|------------|-------------|------------|--------|------------|
|            | P@20       | MRR@20     | P@20   | MRR@20     |
| B-GNN-WP   |            | 53.08      | 18.54  | 45.62      | 22.57 |
|            |            | 22.43      | 8.57   |            |      |
| B-GNN-FP   |            | 53.64      | 18.76  | 44.84      | 22.75 |
|            |            | 23.21      | 8.87   |            |      |
| B-GNN      |            | 53.93      | 19.05  | 45.13      | 22.85 |
|            |            | 23.42      | 9.17   |            |      |

5.7 Comparison with Different Session-level item representation learning methods. (RQ3)

In this work, we use mean pooling-based GNNs to convey information from item’s neighbors to item itself in the session graph. Specifically, We consider three different kinds of relations of each item and utilize fully connected layer to obtain the new representation of each item. As the representation learning of items is significant for session based recommendation, we conduct experiments to compare our proposed B-GNN with a series of contrast models:

- B-GNN-GGNN: B-GNN with gated GNNs replacing the mean pooling-based GNNs.
- B-GNN-GAT: B-GNN with GAT replacing the mean pooling-based GNNs.

Table 5 shows the performance of B-GNN and different contrast models. We can observe that the proposed B-GNN outperforms B-GNN-GGNN and B-GNN-GAT on Diginetica and Tmall. Gated GNNs introduce gated recurrent units into GNNs and GAT leverages attention mechanism into graph, which enhance the ability of graph neural network to extract features. However, more parameters and nonlinear layers will make the network more prone to overfitting and these models do not consider three relations in the session graph. Our GNNs layer utilize mean pooling layer to reduce the parameters and capture three kinds of relations in the session graph. The results in Table 5 demonstrate the effectiveness of our proposed GNNs layer.

5.8 Comparison with Different Session Encoder. (RQ4)

To efficiently learn the importance of each item in the session sequence, we propose reversed-position aware session encoder. It incorporates the reversed position information with session information, which is used to drive our model to learn the contribution of each item in the current
session. SASRec [7] injects forward position vector into the model to improve performance, however, we argue that reversed position vector contains more useful information than forward position vector. To verify this and evaluate the effectiveness of using the position vector in a reverse order, which is proposed in our method, we design a series of contrast models:

- B-GNN-WP: B-GNN without using position information when aggregating the item features.
- B-GNN-FP: B-GNN with forward position vector replacing the reversed position vector.

Table 6 shows the performance of different contrast models. We can observe that B-GNN-WP’s performance is not satisfactory, as the model is unable to capture the chronological information in the sessions without position vector. B-GNN-FP perform better than B-GNN-WP on Diginetica and Nowplaying, which demonstrates the importance of position information. However, the length of the session is not fixed, which makes the improvement limited.

Our attention network with reversed position vector performs better than the B-GNN-FP over three datasets, it is because reversed position vector can help the model learn the relative position information between the current item and the target item. The results demonstrate the effectiveness of reversed position vector and superiority of our session encoder.

6 CONCLUSION

This paper studies the problem of session-based recommendation, which is a challenging task as the user identities and historical interactions are often unavailable due to privacy and data protection concern. It presents two different ways to leverage the high-order global information for session-based recommendation via GNN: (i) SRGI-FM, which recursively incorporates the neighbors’ feature of each node on global graph via session-aware attention mechanism; and (ii) SRGI-CM, which treats session-based recommendation as a multi-task learning problem and utilizes skip-gram and negative sampling on random paths for preserving global proximity to learn item representations. Furthermore, it also incorporates the reversed position embedding to empower the proposed model to better learn the contribution of each item. Comprehensive experiments demonstrate that the proposed method significantly outperforms state-of-the-art baselines over three benchmark datasets consistently, indicating it can be effectively used to solve real-world session-based recommendation problems.

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REFERENCES

[1] Priyanka Gupta, Diksha Garg, Pankaj Malhotra, Lovekesh Vig, and Gautam Shroff. 2019. NISER: Normalized Item and Session Representations with Graph Neural Networks. arXiv preprint arXiv:1909.04276 (2019).
[2] Will Hamilton, Zhitao Ying, and Jure Leskovec. 2017. Inductive representation learning on large graphs. In NIPS. 1024–1034.
[3] Balázs Hidasi, Alexandros Karatzoglou, Linas Baltrunas, and Domonkos Tikk. 2016. Session-based recommendations with recurrent neural networks. In ICLR.
[4] Cheng-Kang Hsieh, Longqi Yang, Yin Cui, Tsung-Yi Lin, Serge Belongie, and Deborah Estrin. 2017. Collaborative metric learning. In Proceedings of the 26th international conference on world wide web. 193–201.
[5] Dietmar Jannach and Malte Ludewig. 2017. When recurrent neural networks meet the neighborhood for session-based recommendation. In Proceedings of the Eleventh ACM Conference on Recommender Systems. 306–310.
[6] Santosh Kabbur, Xia Ning, and George Karypis. 2013. Fism: factored item similarity models for top-n recommender systems. In Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining. 659–667.
[7] Wang-Cheng Kang and Julian McAuley. 2018. Self-attentive sequential recommendation. In ICDM. 197–206.
[8] Thomas N Kipf and Max Welling. 2017. Semi-supervised classification with graph convolutional networks. In ICLR.
[9] Jing Li, Pengjie Ren, Zhumin Chen, Zhaocun Ren, Tao Lian, and Jun Ma. 2017. Neural attentive session-based recommendation. In CIKM. 1419–1428.
[10] Yujia Li, Daniel Tarlow, Marc Brockschmidt, and Richard Zemel. 2016. Gated graph sequence neural networks. In ICLR.
[11] Qiao Liu, Yifu Zeng, Refuoe Mokhosi, and Haibin Zhang. 2018. 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, 1831–1839.
[12] Malte Ludewig and Dietmar Jannach. 2018. Evaluation of session-based recommendation algorithms. User Modeling and User-Adapted Interaction 28, 4–5 (2018), 331–390.
[13] Andriy Mnih and Ruslan Salakhutdinov. 2008. Probabilistic matrix factorization. In Advances in neural information processing systems. 1257–1264.
[14] Yunchen Pu, Zhe Gan, Ricardo Henao, Xin Yuan, Chunyuan Li, Andrew Stevens, and Lawrence Carin. 2016. Variational autoencoder for deep learning of images, labels and captions. In Advances in neural information processing systems. 2352–2360.
[15] Ruihong Qiu, Jingjing Li, Zi Huang, and Hongzhi Yin. 2019. Rethinking the Item Order in Session-based Recommendation with Graph Neural Networks. In CIKM. 579–588.
[16] Steffen Rendle, Christoph Freudenthaler, and Lars Schmidt-Thieme. 2010. Factorizing personalized markov chains for next-basket recommendation. In Proceedings of the 19th international conference on World wide web. 811–820.
[17] Badrul Sarwar, George Karypis, Joseph Konstan, and John Riedl. 2001. Item-based collaborative filtering recommendation algorithms. In Proceedings of the 1st conference on Recommendations at the World Wide Web. 285–295.
[18] Guy Shani, David Heckerman, and Ronen I Brafman. 2005. An MDP-based recommender system. JMLR, 1265–1295.
[19] Jing Song, Hong Shen, Zijing Ou, Junyi Zhang, Teng Xiao, and Shangsong Liang. 2019. ISLF: Interest Shift and Latent Factors Combination Model for Session-based Recommendation. In IJCAI. 5765–5771.
[20] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. 2014. Dropout: a simple way to prevent neural networks from overfitting. JMLR (2014), 1929–1958.
[21] Yong Kiam Tan, Xinxing Xu, and Yong Liu. 2016. Improved recurrent neural networks for session-based recommendations. In Proceedings of the 1st Workshop on Deep Learning for Recommender Systems. 17–22.
[22] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In NIPS. 5998–6008.
[23] Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio. 2018. Graph attention networks. In ICLR.
[24] Chenyang Wang, Min Zhang, Weizhi Ma, Yiqun Liu, and Shaoping Ma. 2020. Make it a chorus: knowledge-and time-aware item modeling for sequential recommendation. In Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval. 109–118.
[25] Feng Wang, Xiang Xiang, Jian Cheng, and Alan Loddon Yuille. 2017. Normface: L2 hypersphere embedding for face verification. In Proceedings of the 25th ACM international conference on Multimedia. 1041–1049.
[26] Huizhao Wang, Guanfeng Liu, An Liu, Zhixu Li, and Kai Zheng. 2019. DMRAN-A Hierarchical Fine-Grained Attention-Based Network for Recommendation. In IJCAI. 3698–3704.
[27] Hongwei Wang, Miao Zhao, Xing Xie, Wenjie Li, and Minyi Guo. 2019. Knowledge graph convolutional networks for recommender systems. In The world wide web conference. 3307–3313.
[28] Meirui Wang, Pengjie Ren, Lei Mei, Zhumin Chen, Jun Ma, and Maarten de Rijke. 2019. A Collaborative Session-based Recommendation Approach with Parallel Memory Modules. In SIGIR.
[29] Shoujin Wang, Liang Hu, Yan Wang, Longbing Cao, Quan Z. Sheng, and Mehmet Orgun. 2019. Sequential Recommender Systems: Challenges, Progress and Prospects. In IJCAI. 6332–6338.
[30] Shoujin Wang, Liang Hu, Yan Wang, Quan Z. Sheng, Mehmet Orgun, and Longbing Cao. 2019. Modeling Multi-Purpose Sessions for Next-Item Recommendations via Mixture-Channel Purpose Routing Networks. In IJCAI. 3771–3777.
[31] Ziyang Wang, Wei Wei, Gao Cong, Xiao-Li Li, Xian-Ling Mao, and Minghui Qiu. 2020. Global Context Enhanced Graph Neural Networks for Session-based Recommendation. In Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval. 169–178.
[32] Jason Weston, Sumit Chopra, and Antoine Bordes. 2014. Memory networks. arXiv preprint arXiv:1410.3916 (2014).
[33] Shu Wu, Yuyuan Tang, Yangjiao Zhu, Liang Wang, Xing Xie, and Tieniu Tan. 2019. Session-based recommendation with graph neural networks. In AAAI. 346–353.
[34] Chengfeng Xu, Pengpeng Zhao, Yanchi Liu, Victor S. Sheng, Jiajie Xu, Fuohen Zhuang, Junhua Fang, and Xiaofang Zhou. 2019. Graph Contextualized Self-Attention Network for Session-based Recommendation. In IJCAI. 3940–3946.
[35] Eva Zangerle, Martin Pichl, Wolfgang Gassler, and Günther Specht. 2014. #nowplaying Music Dataset: Extracting Listening Behavior from Twitter. In ISMM. 21–26.