Causality and Correlation Graph Modeling for Effective and Explainable Session-Based Recommendation

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Session-based recommendation, which has witnessed a booming interest recently, focuses on predicting a user’s next interested item(s) based on an anonymous session. Most existing studies adopt complex deep learning techniques (e.g., graph neural networks) for effective session-based recommendation. However, they merely address co-occurrence between items, but fail to distinguish a causality and correlation relationship. Considering the varied interpretations and characteristics of causality and correlation relationships between items, in this study, we propose a novel method denoted as CGSR by jointly modeling causality and correlation relationships between items. In particular, we construct cause, effect, and correlation graphs from sessions by simultaneously considering the false causality problem. We further design a graph neural network-based method for session-based recommendation. To conclude, we strive to explore the relationship between items from specific “causality” (directed) and “correlation” (undirected) perspectives. Extensive experiments on three datasets show that our model outperforms other state-of-the-art methods in terms of recommendation accuracy. Moreover, we further propose an explainable framework on CGSR and demonstrate the explainability of our model via case studies on an Amazon dataset.

CCS Concepts: • Information systems → Recommender systems;

Additional Key Words and Phrases: Session-based recommendation, graph neural network, product relationship

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1 INTRODUCTION

Session-based recommendation (SR) has attracted wide attention in recent years [5]. In contrast to traditional recommendation modeling of users’ static preferences, it processes time-aware user-item interactions to capture the dynamic preferences. Its task is to recommend the next item a user will probably like given an anonymous session. Numerous models have been proposed to
Fig. 1. Two session cases from a real dataset.

improve the performance of SR, ranging from the early Markov chain–based ones [30] to the recent deep learning–based ones, including recurrent neural network (RNN)–based [3, 15], attention mechanism–based [11, 50], and graph neural network (GNN)–based methods [49, 52].

Although some algorithms have obtained encouraging improvements as reported, they still suffer from the following limitations. (1) Most RNN-based and attention-based methods [16, 50] focus on the dependency relationship of items within a session but fail to easily capture item transitions across sessions. (2) The general GNN-based methods [2] alleviate the aforementioned issue by constructing session graph across sessions, but they mainly model the correlation relationship (i.e., co-occurrence) between items. Thus, similar to RNN-based and attention-based methods, they neglect to distinguish directed relationships from undirected relationships well between items.

In this study, we call this directed relationship “causality”, and call the undirected relationship “correlation”. Figure 1 illustrates an example of two sessions from a real dataset. As we can see, there exist two sessions containing interacting items in chronological order. In the first session, the phone leads the user to buy the phone shell, whereas different nail art image plates in the second session indicate the correlation relationship between them. In this case, it is worthwhile to explore different relationships among items in terms of causality and correlation perspectives for more effective session-based recommendation.

In addition, “causality” refers to a direct and asymmetric relationship, which is calculated from a relatively large volume of sessions, and particularly considered for the session-based recommendation scenario. It is not strictly equivalent to that in the traditional sense, such as causal modeling by econometric approaches. Here, the higher the edge weight in causality graph, the higher the probability of this directional relationship between items. Moreover, “causality” relates to both cause and effect where, in a recommendation, the cause item is partly responsible for the effect item, whereas the effect is partly dependent on the cause (cause → effect) [33, 48]. Our model divides it into two parts since we strive to maximize item transition from cause → effect while minimizing that from effect → cause. It should be noted that we consider both “causality” and “correlation” since it is well known that “correlation” does not imply “causality” in recommendation and “correlation” means a kind of more general, undirected relationship, that is, two items are purchased or consumed together.

For example, we can easily observe this kind of directed cause → effect relationship between items in real-world applications. Figure 2 illustrates three examples mined from an Amazon dataset\(^1\) [9]. As can be seen, the number of cases that first buy griddlers (or water bottles/GPS

\(^1\)jmcauley.ucsd.edu/data/amazon/links.html.
Fig. 2. (a) Griddlers and griddler waffle plates; (b) water bottles and cap CAP; (c) GPS navigators and Garmin portable friction mount.

Then, we conduct a more comprehensive analysis to examine how to distinguish the causality and correlation between any two items on a typical session-aware dataset, that is, Diginetica. In Figure 3, $p(a|b)$ (a $\neq$ b) means, in a session, the probability of item a that is interacted given the previously interacted item b. It is particularly calculated as $p(a|b) = \frac{\#(b \rightarrow a)}{\#b \rightarrow *}$, where $\#(b \rightarrow a)$ is the number of item b interacted before item a in the same session, and $\#b \rightarrow *$ is the frequency of item b occurring before all other items. $p(b|a)$ is calculated in the same way. We further rank $p(a|b)$ in ascending order and then divide all the item pairs $(a, b)$ into 10 groups $(\{1, 2, \ldots, 10\})$. Thus, each group has the same number of item pairs, and from group 1 to 10, $p(a|b)$ gets bigger. We deal with $p(b|a)$ similarly. Finally, we can place each item pair $(a, b)$ into a grid in terms of $p(a|b)$ and $p(b|a)$ as shown in Figure 3. For example, 33,758 in grid $(4,1)$ in Figure 3 refers to the number of item pairs that $p(a|b)$ and $p(b|a)$ belong to the corresponding groups 4 and 1, respectively. In this case, if $|p(a|b) - p(b|a)| \geq \epsilon$ (\epsilon is a non-zero value), we consider that the relationship between items a and b is asymmetrical (i.e., sort of directed), and a larger $\epsilon$ indicates a more directed relationship between items a and b. Accordingly, the relationship between item pairs in the bottom right (upper left) of Figure 3 is more asymmetrical, revealing a higher possibility for being in the causal relations. Furthermore, the relationship in the upper right implies a much stronger undirected correlation relationship (i.e., less possible causal relations), since there are quite a lot of item pairs both from item a to item b and item b to item a simultaneously. Both of the directed and undirected relations are quite prevalent (similar patterns can be viewed on Gowalla\textsuperscript{3} and Amazon Home and Kitchen in Figure 4). In this case, we should carefully consider both correlation and causality between items in item modeling for recommendation.

Therefore, considering the difference between the two types of item relationships, we propose a novel method called Causality and Correlation Graph Modeling for Effective and Explainable Session-based Recommendation (CGSR) by particularly taking the causality and correlation relationship between items into consideration. Specifically, other than a correlation graph considering

\textsuperscript{2}competitions.codalab.org/competitions/11161#learn_the_details-data2.
\textsuperscript{3}snap.stanford.edu/data/loc-Gowalla.html.
both first-order and three types of second-order relationships, we construct two graphs to capture causality relationships: a cause graph and an effect graph, which address the false causality by removing the impact of the common cause items given an item pair. Then, we design an end-to-end GNN-based model which takes the three graphs as input, outputs three kinds of item embeddings, and deploys an attention mechanism to obtain corresponding session representations for final recommendations. Experimental results on three real-world datasets validate the superiority of our approach over the state-of-the-art. We further propose an explainable framework based on CGSR for SR, and conduct case studies on an Amazon dataset to showcase that CGSR can also facilitate the explanation task in SR.
The main contributions of this work are four-fold:

- To the best of our knowledge, we are the first to explore causality between items for SR, and propose CGSR to enhance the recommendation and explanation tasks in SR.
- We design an effective mechanism to capture possibly directed causality relationships between items. In particular, we construct an effect graph and a cause graph on sessions which rule out the false causality by eliminating the impact of common cause items for every item pair.
- We design a GNN-based method to combine causality and correlation graphs for effective recommendation. Regarding correlation graphs, we consider both first-order and three types of second-order relationships. Exhaustive experiments on three real datasets verify the superiority of our approach over other baselines, and verify the validity of our designs.
- We contribute to explainable SR by figuring out an explainable framework grounded on CGSR. Case studies on an Amazon dataset demonstrate its usability and feasibility.

2 RELATED WORK

Our work is related to three primary tasks: session-based recommendation, item relation modeling in recommendation, and causal inference in recommendation. In the following subsections, we discuss each part to highlight our contributions over the related studies.

2.1 Session-Based Recommendation

Session-based recommendation (SR) predicts a user’s next item(s) of interest by deploying traditional approaches and deep learning (DL) techniques to process time-aware user-item interactions. Traditional approaches \cite{20,34} apply machine learning (ML) techniques to capture item embedding in the session. For example, FPMC \cite{30} applies matrix factorization (MF) and first-order Markov chains (MCs) to address the sequential relationship among items. SEQ* \cite{14} develops a hidden Markov model for sequence preference, which considers more factors, including two types of dynamic factors and contextual factors. Wu et al. \cite{44} propose a personalized Markov embedding (PME), which embeds songs and users into a Euclidean space, where the distances present the strengths of their relationships. However, they fail to capture the item relationships in relatively longer session sequences. It is worth mentioning that MC-based methods also define the directed relationship between items, which indicates that two items are inclined to be dependent on each other. However, this relationship is not equal to causality. In addition, they possibly ignore the correlation relationship.

On the contrary, DL methods \cite{8,45} are capable of dealing with a much longer sequence than traditional models. GRU4Rec \cite{10} first applies an RNN (i.e., a multi-layer gate recurrent unit) to process session data. Later, there are a lot of variants with regard to GRU4Rec. For instance, HRNNs \cite{28} extend it to the hierarchical form which simultaneously considers both short-term and long-term preferences with two GRU constructs, that is, the session-level GRU (GRUses) and the user-level GRU (GRUusr). Donkers et al. \cite{4} model the temporal dynamics of consumption sequences based on the gated RNN and explicitly represent the individual user in a gated architecture. NARM \cite{16} combines GRUs and a vanilla attention mechanism to better extract the main purpose from the current session, which can effectively eliminate noise from unintended behaviors. However, these methods mainly address behavior dependency in a session, but cannot directly capture item relationships across different sessions. In addition, they ignore distinguishing causality relationships from correlation relationships between items.
With the rapid development of GNNs in recent years, we have witnessed their great success in many downstream tasks, for example, node classification and recommender systems. Therefore, some studies have started to deploy GNNs for session-based recommendation and have obtained encouraging results \cite{23, 24, 27}. For example, SR-GNN \cite{43} first combines different sessions into session graphs and then uses a GNN \cite{17} to learn representation of each item and finally obtain session representations through an attention mechanism. Experimental results on Yoochoose and Diginetica verify that it can obtain better performance than both RNN-based models (e.g., GRU4Rec) and attention-based models (e.g., STAMP \cite{19}). Subsequently, quite a few variants of SR-GNN \cite{2, 42, 46} have been proposed. For example, Xu et al. \cite{46} introduce a novel graph contextual self-attention model based on the GNN called GC-SAN, which obtains local graph structured dependencies of separated session sequences and model contextualized non-local representations. LESSR \cite{2} further reduces information loss by proposing an edge-order preserving aggregation layer and a shortcut graph attention layer. Hypergraph networks are also applied in session-based recommendation. For instance, SHARE \cite{38} proposes the hypergraph structure and hypergraph attention networks, which exploit the relationship among items within various contextual windows. However, as have been discussed, all GNN-based methods have not directly considered the directed causality relationship between items, which might lead to incorrect recommendations.

### 2.2 Relation Modeling in Recommendation

Quite a few studies target exploring various relationships between items using side information such as textual and visual information \cite{22, 51}. For example, Sceptre \cite{21} casts the item relations identification problem as a supervised link prediction task, and predicts substitutable and complementary items by learning latent topics from textual information. Zhang et al. \cite{51} propose a neural complementary recommender Encore, which can jointly learn complementary item relationships and user preferences through Bayesian inference. However, these studies aim to design specific models for identifying the well-studied relationship (e.g., substitute and complementary) between items from side information other than interaction data. In contrast, in our study, relying on the sequential interaction data in sessions, we try to identify the directed causality relationship between items for effective recommendation. Our causality relationship is expected to complement the identified item relationship widely discussed in the business area.

### 2.3 Causal Inference in Recommendation

There are also some studies that have explored the causal inference for recommendation \cite{18, 32, 39, 40}. For example, Bonner and Vasile \cite{1} optimize the causal recommendation outcomes via user implicit feedback based on the factorizing matrices, which presents that the objective of causal recommendations is equal to factorizing a matrix of user responses. Wang et al. \cite{41} consider that the core of a recommender system is to address a causal inference question by solving two problems: which items the users decide to interact with and how the users rate them. Qiu et al. \cite{26} propose a deconfounded recommender, which utilizes Poisson factorization to infer confounders in treatment assignments. CauSeR \cite{7} provides a more holistic causal view of item popularity–related biases at two stages: the data generation and training stages. CR-VAR \cite{47} designs a post-hoc causal explanation for the black-box sequential recommendation methods, where the causal explanations are obtained through a perturbation model and a causal rule learning model.

We can see that this line of research is more related to unbiased recommendation and tries to reason about personalized user preference well, which is quite different from our research scenario. In our study, we try to explore the directed causality relationship between items to facilitate session-based recommendation.
3 GRAPH CONSTRUCTION

In this section, we first formally define the research problem and then present how to construct causality and correlation graphs from sessions as well as the edge weights in great detail.

3.1 Problem Statement

In session-based recommendation, let $\mathcal{V} = \{v_1, v_2, \ldots, v_N\}$ denote the set of items ($|\mathcal{V}| = N$). An anonymous session $S$ can be represented by $S = \{v^S_1, v^S_2, \ldots, v^S_l\}$, where its length equals $l$ and $v^S_i \in \mathcal{V}$ means the $i$-th interacted item within $S$. There are $M$ sessions in total. Given session $S$, the goal of session-based recommendation is to predict the next item (i.e., the $l+1$-th) that will be purchased. Therefore, in our CGSR, we strive to first construct graphs (i.e., causality and correlation graphs) from training sessions and then learn effective representation of session $S$. Third, we generate recommendation score $\hat{y}_j$ for each candidate item $v_j \in \mathcal{V}$ and, finally, recommend top $K$ items with the highest recommendation scores.

Next, we will elaborate causality and correlation graph construction in detail.

3.2 Constructing Causality Graphs

While constructing causality graphs from sessions, we aim to maximally identify the truly directed causality relationship while ruling out the false ones (i.e., the noisy information). To fulfill the goal, as shown in Figure 8(a), we first build a session graph from sessions, on the basis of which we then construct an effect graph and a cause graph by removing the impact of noisy information. Note that, in causality graphs, we only consider first-order relationships since we strive to directly extract the most probability causal relations between items given that historical data and high-order ones might involve more noise. Besides, the GNN model is supposed to automatically capture high-order relations.

**Session graph construction.** Without the loss of generality, let $\mathcal{G}^s = (\mathcal{V}^s, \mathcal{E}^s)$ be the correspondingly directed session graph, where $\mathcal{V}^s$ indicates the node set, which is identical to the item set in all sessions, and $\mathcal{E}^s$ denotes the edge set. An edge $E^s_{i,j} \in \mathcal{E}^s$ refers to the fact that in a session, item $v_i$ is first interacted followed by item $v_j$, and $w^s_{i,j}$ is the corresponding occurred frequency to denote the weight of edge $E^s_{i,j}$. For example, in Figure 5, these three sessions in Figure 5(a) can form a directed session graph in Figure 5(b).
Causality graphs construction. To better represent the causality relationship, we construct two graphs on the basis of the session graph: an effect graph ($G^e$) and a cause graph ($G^c$). Specifically, in the effect graph, we want to learn representation of an item where the item is playing the effect role in the directed cause–effect relationship between two items. Consequently, each item representation is expected to integrate the information of the adjacent cause items by information propagation via the GNN. In contrast, the cause graph is to capture the item information where the item is playing the cause role in the directed relationship. We clarify the following two issues. (1) The node and edge sets of the effect graph are initially the same as those of the session graph, mainly because the session graph models the temporally directed relationship between items, basically indicating all the possible causality relationships from sessions. However, as $G^e$ may involve false causality relationships (elaborated later), we will eliminate its impact by justifying the corresponding weight of each edge. (2) The cause graph is quite similar to the effect graph except that the direction of each edge is opposite to that of the effect graph considering that in the cause graph, we want to explore the part of the item information leading to the purchase of other items.

Towards the first issue, we elaborate how to get rid of the impact of false causality relationships. We mainly adopt the idea of bias of confounders in causal inference [12], where confounders denote variables that influence both independent variables and the dependent variable. In causal inference, estimating the effect of an independent variable on the dependent variable without accounting for confounders could result in strongly biased estimates and, thus, invalid causal conclusions. Therefore, we adapt this idea into our scenario. Let us first view an example in session-based recommendation. There are three sessions: $S_1$ ["iPhone", "charging line", "charger", "phone shell"], $S_2$ ["iPhone", "charger", "charging line"], and $S_3$ ["iPhone", "charging line", "phone shell"]. Based on the three sessions (training data), a phone shell will be recommended given session ["charging line", "charger"], which is quite odd since few users will purchase a phone shell having previously bought a charging line and charger. By examining the data, intuitively, we see that "owning an iPhone" is a common cause to also purchase a charging line, charger, and phone shell. In this case, such an odd recommendation is probably induced by the false causality relationship led by the common cause (i.e., "iPhone") in training data. That is, purchasing an "iPhone" leads to the purchase of a "charger" and "phone shell" instead of purchasing a "charger", causing the purchase of a "phone shell".

To overcome this issue, we appropriately calculate the weight of each edge in $G^e$ by taking the common cause of two items into consideration. Specifically, for each item pair $v_i$ and $v_j$, we first identify every common cause $v_k \in I_i^j \cap I_j^i$ ($I^*$ is the node set directed into node $v_i$ in $G^e$). For example, in Figure 5(b), $v_1$ is the common cause to $v_2$ and $v_3$. Second, to identify the true causality strength of $v_i \rightarrow v_j$ in $G^e$, we eliminate the impact of every common cause $v_k$ to calculate the weight of $E_{i,j}^c$, $w_{i,j}^c$:

$$w_{i,j}^c = \frac{w_{i,j}^s - \sum_{v_k \in I^j_i \cap I^i_j} \#\{v_k, v_i, v_j\}}{\#\{v_i, v_j\}},$$

where $\#\{v_k, v_i, v_j\}$ is the number of sequence $[v_k, v_i, v_j]$ and the number of sequence $[v_i, v_j]$ ($v_s \in V$) existing in all sessions (training data), respectively. For example, the weights of edges in Figure 5(c) are computed as $w_{1,2} = (1-0)/2$; $w_{1,3} = (1-0)/2$; $w_{2,3} = (2-1)/2$; $w_{3,2} = (1-1)/2$; $w_{3,5} = (2-0)/3$; and $w_{5,4} = (1-0)/1$. After obtaining the effect graph $G^e$, we reverse its directions of edges to get the cause graph $G^c$.

3.3 Constructing a Correlation Graph

In addition to the directed causality relationship between items, we consider the undirected correlation relationship, whose effectiveness in SR has been validated in previous GNN-based
studies [42, 43]. While constructing the correlation graph, apart from the generally adopted first-order relationship (neighbor in sequence), we additionally consider the second-order relationship (neighbor of neighbor), by following the study of [42]. Note that, in contrast to [42], we distinguish three kinds of second-order relationships (i.e., chain, fork, and collider; see Figure 6) for better exploring the correlation relationship for effective recommendation.

Particularly, as shown in Figure 7, based on the session graph $G_s^s$ that has been constructed, we calculate the weight of each possible edge by considering the first-order and second-order neighbors.

For the first-order relationship, namely, $(v_i, v_j)$ in session graph $G_s^s$, considering that $G_s^s$ is directed whereas correlation graph $G_r$ is undirected, the first-order weight of each edge, $w_r^{i,j}$, is computed as

$$w_r^{i,j} = \frac{2 \times w_s^{i,j}}{\sum_{v_k \in O_i^s} w_s^{i,k} + \sum_{v_k \in I_j^s} w_s^{k,j}} + \frac{2 \times w_s^{j,i}}{\sum_{v_k \in O_j^s} w_s^{j,k} + \sum_{v_k \in I_i^s} w_s^{k,i}},$$

where $O_i^s$ and $I_j^s$ refer to the node (item) set directed out and into item $v_i$ in $G_s^s$, respectively.

For the second-order relationship, we first extract all possible second-order relationships for each item pair $v_i$ and $v_j$ based on $G_s^s$. That is, if $v_k$ is the neighbor of both $v_i$ and $v_j$, we say that there is a second-order correlation between $v_i$ and $v_j$. In particular, with the consideration of the link directions among the corresponding three items, we identify three types of second-order relationships, intuitively denoted as chain, fork, and collider (see Figure 6). We treat the three types separately mainly because they act differently on casting correlation relationships between items [37], which are modeled as different weighting factors in our study (see $\lambda_1, \lambda_2$, and $\lambda_3$ in Equation (3)). Thus, the weight of link $(v_i, v_j)$ in terms of second-order correlation, $w_r^{i,j,2}$, is
computed as
\[
\begin{align*}
    w_{i,j}^{r,2} &= \lambda_1 \frac{\sum_{v_k \in O^i \cap I^i_j} (w_{k,i}^s + w_{k,j}^s)}{\sum_{v_k \in I^i_j} w_{k,i}^s + \sum_{v_k \in I^j} w_{k,j}^s} \\
    &+ \lambda_2 \frac{\sum_{v_k \in I^i_j} (w_{k,i}^s + w_{k,j}^s)}{\sum_{v_k \in I^i_j} w_{k,i}^s + \sum_{v_k \in I^j} w_{k,j}^s} \\
    &+ \lambda_3 \frac{\sum_{v_k \in I^i_j} (w_{k,i}^s + w_{k,j}^s)}{\sum_{v_k \in I^i_j} w_{k,i}^s + \sum_{v_k \in I^j} w_{k,j}^s},
\end{align*}
\]
where \( \lambda_1, \lambda_2, \) and \( \lambda_3 \) are trainable parameters to balance the impact of the three second-order relationship types.

Finally, we get the weight of every edge \( E_{i,j}^r \) in correlation graph \( G^r \), \( w_{i,j}^r \), by adding the first-order and second-order weights, namely, \( w_{i,j}^r = w_{i,j}^{r,1} + w_{i,j}^{r,2} \), as depicted in Equations (2) and (3). Note that compared with \( G^s, G^c \) can obtain new edges by the three types of second-order correlations, for example, \( E_{1,5}^r, E_{2,5}^r, E_{3,4}^r \) in Figure 7(c).

4 THE CGSR MODEL

In this section, we present our proposed CGSR model in detail. Figure 8 outlines the overview of CGSR, which consists of four components: (a) Graph Construction, (b) Item Representation Learner, (c) Session Representation Learner, and (d) Recommendation Score Generator. In particular, we first build three types of graphs (effect graph \( G^e \), cause graph \( G^c \), and correlation graph \( G^r \)) in Graph Construction as introduced in Section 3. Item Representation Learner deploys a weighted graph attention network (WGAT) on each of the three graphs to obtain a representation for each item. That is, for each item \( v_i \), we obtain three types of representations, \( x_i^e, x_i^c \), and \( x_i^r \), given \( G^e, G^c, \) and \( G^r \). Session Representation Learner uses an attention layer to aggregate each type of learned item representation in session sequence \( S \) to obtain session representation \( S^e, S^c, \) and \( S^r \), respectively. We also get session representation \( S^0 \) by averaging the three types of session representation. Recommendation Score Generator strives to calculate the recommendation score, \( \hat{y}_j \) of each candidate item \( v_j \in V \) on the basis of the learned item and session representations. Next, we elaborate the last three components of CGSR.

4.1 Item Representation Learner

Here, we aim to learn item embedding on built graphs \( G^e, G^c, \) and \( G^r \). Considering that the three graphs are either weighted (correlation graph) or simultaneously directed and weighted (cause and effect graphs), we thus adopt a WGAT [25] to obtain item representations. Specifically, we denote \( X^0 \in \mathbb{R}^{|V| \times d_0} \) as the initial embedding matrix of the item set (for item \( v_i \in V \), initial item embedding \( x_i^0 = X^0_{i,:} \in \mathbb{R}^{d_0} \)):

\[
X^0 = \text{nn.Embedding}(N, d_0),
\]

where \text{nn.Embedding()} is a function in PyTorch, which randomly initializes a vector following a normal distribution \( N(0,1) \).

Then, taking cause graph \( G^c \) as an example, in WGAT, a self-attention mechanism is deployed to aggregate information from each node (item) \( v_i \)'s directed-into neighbors. Since in our scenario a session is normally not very long, all first-order neighbors are considered. Thus, the importance between \( v_i \) and its neighbor \( v_j \) (\( v_j \in I^i_2 \), and \( I^i_2 \) is the node set directed into \( v_i \) in \( G^c \)), \( e_{i,j}^c \) (i.e., self-attention coefficient) is computed as

\[
e_{i,j}^c = \sigma \left( W_{c,2}^T \ast \left[ W_{c,1}^0 x_i^0; W_{c,1} x_j^0; w_{j,i}^c \right] \right),
\]

where \( \sigma \) is a non-linear function.
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Fig. 8. The overview of our proposed CGSR model.

where $\sigma(.)$ is the Leaky ReLU function, $W_{c,1} \in \mathbb{R}^{d \times d_0}$ and $W_{c,2} \in \mathbb{R}^{2d+1}$ are trainable parameters, and $w_{j,i}^c$ is the weight of link $v_j \rightarrow v_i$. The softmax function is further adopted to normalize the $e_{ij}^c$:

$$\alpha_{ij}^c = \text{softmax}(e_{ij}^c) = \frac{\exp(e_{ij}^c)}{\sum_{k \in I_i^c} \exp(e_{ik}^c)}.$$ (6)

Third, the information from neighbors is weighted to get item $v_i$’s embedding, $x_i^c \in \mathbb{R}^d$:

$$x_i^c = \sigma \left( \sum_{j \in I_i^c} \alpha_{ij}^c W_{c,3} x_j^0 \right).$$ (7)

where $W_{c,3} \in \mathbb{R}^{d \times d_0}$ is a trainable parameter matrix and $\sigma(.)$ is the Leaky ReLU function.
In the multi-head attention mechanism of WGAT, we average obtained embedding from \( K_m \) heads to output final item embedding:

\[
x^c_i = \frac{1}{K_m} \sum_{k=1}^{K_m} x^c_{i,k},
\]

(8)

where \( x^c_{i,k} \) is \( v_i \)'s representation output by the \( k \)-th head using Equations (5) to (7).

Similarly, we get the embedding of \( v_i \), \( x^e_i \) and \( x^r_i \), from effect graph \( G^e \) and correlation graph \( G^r \), respectively.

### 4.2 Session Representation Learner

In Item Representation Learner, we obtain three embeddings for each item \( v_i \) in terms of three graphs. Specifically, \( x^c_i \) considers information from \( v_i \)'s effect neighbors, whereas \( x^e_i \) and \( x^r_i \) involve information from its cause and correlated neighbors, respectively.

In contrast to previous studies [42] fusing embedding from various sources to generate session representation, in CGSR, Session Representation Learner treats each type of item representation separately. That is, it learns a specific session representation given each type of item embedding for the purpose of obtaining a rather pure session representation for each relationship instead of losing information by aggregating them too early.

Specifically, for instance, in terms of cause graph \( G^c \), to generate the representation of session \( S = \{v^S_1, \ldots, v^S_l\} \), \( S^c \), using an attention mechanism, we first compute the weighted factor \( \alpha^c_k \) depicting the importance of the \( k \)-th item (first item, \( v^S_k \)) to the \( l \)-th item (last item, \( v^S_l \)) in \( S \):

\[
\alpha^c_k = \mathbf{q}^T_e \sigma \left( \mathbf{W}^c_{4} x^c_{i,S} + \mathbf{W}^c_{5} x^c_{k,S} + \mathbf{b}_c \right),
\]

(9)

where \( \mathbf{q}_e \in \mathbb{R}^d \) denotes the weighting vector, \( \mathbf{W}^c_{4}, \mathbf{W}^c_{5} \in \mathbb{R}^{d \times d} \) are the weighting matrices, \( \mathbf{b}_c \in \mathbb{R}^d \) is the bias vector, \( \sigma(.) \) is the sigmoid function, and \( x^c_{i,S} \) and \( x^c_{k,S} \) denote the embedding of the \( l \)-th and \( k \)-th items given the cause graph, respectively. We thus use weighted factors to aggregate all item information for session representation:

\[
S^c_g = \sum_{k=1}^{l} \alpha^c_k x^c_{k,S}.
\]

(10)

Following the previous studies, we also particularly consider the information of the most recent behavior in the session (i.e., \( v^S_l \)), to get the concatenation of \( S^c_g \) and \( x^c_{l,S} \). We further project the concatenation to get the final session representation via

\[
S^c = \mathbf{W}^c_{6} \left[ x^c_{l,S}; S^c_g \right],
\]

(11)

where \( \mathbf{W}^c_{6} \in \mathbb{R}^{d \times 2d} \) is the projecting matrix.

Similarly, we can learn the session representation on effect and correlation graphs, \( S^e \) and \( S^r \), respectively. We also generate a session representation (\( S^p \), referred to as preference-related session representation) by fusing the three types of session representation using mean operator, and further project it into a new latent space:

\[
S^p = \mathbf{W}_7 \ast \text{mean}(S^c, S^e, S^r),
\]

(12)

where \( \mathbf{W}_7 \in \mathbb{R}^{d \times d} \) is the projecting matrix and \( \text{mean}(*) \) function outputs the corresponding average value.

In summary, Session Representation Learner outputs four session representations of session \( S \), that is, \( S^c \), \( S^e \), \( S^r \), and \( S^p \).
4.3 Recommendation Score Generator

Given the learned session representations of session $S$, for each candidate item $v_j$, Recommendation Score Generator will output its recommendation score. Particularly, the final score is three-fold: (1) causality score; (2) correlation score; and (3) preference score.

**Causality score** strives to maximize item transition from cause $\rightarrow$ effect while simultaneously minimizing that from effect $\rightarrow$ cause. Accordingly, the causality score of item $v_j$, $Score_{ca}^j$, is calculated as

$$Score_{ca}^j = Score_c^j - Score_e^j = (S^c)^T x_j^c - \gamma_1 (S^e)^T x_j^e,$$

where $\gamma_1$ is a trainable parameter to balance the two components.

**Correlation score** and **preference score** of $v_j$, $Score_r^j$, and $Score_p^j$, are defined as

$$Score_r^j = (S^r)^T x_j^r; \quad Score_p^j = (S^p)^T x_j^p,$$

where $x_j^p = \text{mean}(x_j^c, x_j^e, x_j^r)$.

Finally, we compute the overall score of candidate item $v_j$ ($Score_j$):

$$Score_j = Score_p^j + \gamma_2 Score_{ca}^j + \gamma_3 Score_r^j,$$

where $\gamma_2$ and $\gamma_3$ are trainable parameters. The softmax function is further deployed to obtain the final recommendation score $\hat{y}_j$:

$$\hat{y}_j = \text{softmax}(Score_j) = \frac{\exp(Score_j)}{\sum_{v_k \in V} \exp(Score_k)}.$$

We adopt cross-entropy loss to train the CGSR model:

$$L = - \sum_{j=1}^{N} y_j \log(\hat{y}_j) + (1 - y_j) \log(1 - \hat{y}_j),$$

where $y_j$ is the ground truth of item $v_j$ (1 or 0; 1 indicates that $v_j$ is the next interacted item and 0 means that $v_j$ is not).

5 EMPIRICAL EVALUATIONS

In this section, we conduct extensive experiments on three datasets to validate the effectiveness of our proposed CGSR, with the goal of answering four specific research questions (RQs):

- **RQ1**: How does CGSR perform compared with other state-of-the-art approaches?
- **RQ2**: How do different components of CGSR (e.g., causality graphs) contribute to the recommendation performance?
- **RQ3**: How do different hyper-parameters affect the performance of CGSR?
- **RQ4**: How does CGSR facilitate the explanation task of session-based recommendation?

5.1 Experimental Setup

5.1.1 Datasets. We choose three real-world datasets, Diginetica, Gowalla, and Amazon home and kitchen, which (especially the first two) are commonly used in session-based recommendation, to evaluate the performance of different approaches. **Diginetica** is from CIKM cup 2016 and consists of typical transactions data. Following [2, 16, 19, 25, 29, 43], we filter out items with less than 5 interactions and sessions with length smaller than 2. We use around 80% as the train data, around 10% as the validation data, and the sessions occurring in the last week as the test set (around 10%). **Gowalla** is a check-in dataset for point-of-interest (POI) recommendation. Following [2, 6, 36], we keep the top 30,000 most popular items, and treat a user’s check-ins within a day as a session. In addition, we filter out sessions with length smaller than 2 or larger than 20. **Amazon** contains...
Table 1. Statistics of the Three Datasets

| Dataset    | Diginetica | Gowalla | Amazon  |
|------------|------------|---------|---------|
| # transactions | 982,961    | 1,122,788 | 335,639 |
| # items     | 43,097     | 29,510  | 38,689  |
| # sessions  | 780,328    | 830,893 | 246,661 |
| average length | 5.12       | 3.85    | 3.77    |
| # train sessions | 647,370    | 592,481 | 174,201 |
| # validation sessions | 72,100     | 83,080  | 24,660  |
| # test sessions  | 60,858     | 155,332 | 47,800  |

product reviews and metadata from Amazon in the home and kitchen category. We consider a user’s interactions occurring in a day as a session and filter out items with less than 5 interactions and sessions with length smaller than 2. For the Gowalla and Amazon datasets, we sort sessions with increasing timestamps and take 70% of sessions as the train set, 10% as the validation set, and the remaining 20% as the test set. The statistics of the three datasets are summarized in Table 1.

5.1.2 Baseline Models. We compare our CGSR with three traditional methods (POP, ItemKNN, and FPMC), two recurrent neural network (RNN)-based methods (GRU4Rec and NARM), one attention-based method (BERT4Rec), and three state-of-the-art (SOTA) graph neural network (GNN)-based methods (SR-GNN, FGNN, and LESSR) for session-based recommendation.

- **POP** recommends the most popular items in the training set.
- **ItemKNN** [31] recommends items having the highest similarity with the last item of the session.
- **FPMC** [30] combines matrix factorization with the first-order MCs.
- **GRU4Rec** [10] stacks GRUs to process session data and tailors a ranking loss function to train the model.
- **NARM** [16] is a strong and solid RNN-based approach for SR, which utilizes vanilla attention to model the relationship of the last item with other items in a session to capture the main purpose.
- **BERT4Rec** [35] is a deep bidirectional sequential model with a Cloze objective loss.
- **SR-GNN** [43] uses a gated graph convolutional layer to obtain item embedding on a session graph, and applies a self-attention mechanism to last item embedding to obtain session representation.
- **FGNN** [25] designs a novel model to collaboratively incorporate sequence order and latent order in the session graph.
- **LESSR** [2] proposes a lossless encoding scheme and an edge-order preserving aggregation layer based on GRU, and designs a shortcut graph attention layer to effectively capture long-range dependencies among items.

We summarize the different variants of our CGSR model in Table 2.

5.1.3 Evaluation Metrics. We adopt three widely used ranking-based metrics, HR@K, MRR@K, and NDCG@K to evaluate the recommendation accuracy, where a higher value indicates better performance, and K is set to 5, 10, and 20, respectively. HR@K (Hit Ratio) denotes...
Table 2. Descriptions of the CGSR Variants

| CGSR variants | Description |
|---------------|-------------|
| CGSR-ca       | Remove both cause graph $G_c$ and effect graph $G_e$ |
| CGSR-r        | Ignore correlation graph $G_r$ |
| CGSR-p        | Do not consider the session representation $S_p$ |
| CGSR_mean     | Only consider $Score_p$ in Equation (15) |
| CGSR-W        | Edge weights in cause and effect graph are set to 1 |
| cause_random  | Do not rule out the impact of common cause |
| effect_random | Make the cause graph into a random graph |
| CGSR-chain    | Remove the “chain” relationship |
| CGSR-fork     | Ignore “fork” type |
| CGSR-collider | Do not consider second-order neighbors of collider type |
| CGSR-ca_sec   | Consider the second-order relationship in cause and effect graphs |

Table 3. Hyper-parameter Setups of Baselines

| Method     | Datasets          | Hyper-parameter setups                                                                 |
|------------|-------------------|----------------------------------------------------------------------------------------|
| GRU4Rec    | Diginetica, Gowalla, Amazon | GRU size=100, Batch size=32, Lr=0.2                                                     |
| NARM       | Diginetica, Gowalla, Amazon | Embedding size=50, Batch size=512, Lr=0.001                                             |
| BERT4Rec   | Diginetica, Amazon  | Embedding size=128, Batch size=512, Lr=0.001                                             |
|            | Gowalla            | Embedding size=64, Batch size=512, Lr=0.001                                             |
| SR-GNN     | Diginetica, Gowalla, Amazon | Embedding size=100, Batch size=100, Lr=0.001, $L_2$ penalty=1e-5                      |
|            |                   | Embedding size=170, Batch size=100, Lr=0.001, $L_2$ penalty=1e-5                      |
| FGNN       | Diginetica, Gowalla, Amazon | Embedding size=100, Batch size=100, Lr=0.001, $L_2$ penalty=1e-5                      |
|            |                   | Embedding size=150, Batch size=100, Lr=0.001, $L_2$ penalty=1e-5                      |
| LESSR      | Diginetica, Gowalla, Amazon | Embedding size=32, Batch size=512, Lr=0.001, $L_2$ penalty=1e-4                  |
|            |                   | Embedding size=64, Batch size=512, Lr=0.001, $L_2$ penalty=1e-4                  |
|            |                   | Embedding size=128, Batch size=512, Lr=0.001, $L_2$ penalty=1e-4                  |

In the original papers, NARM, SR-GNN, FGNN, and LESSR have used Diginetica; LESSR has processed Gowalla datasets. Thus, for these scenarios, we directly implemented the corresponding settings.

5.1.4 Hyper-parameter Setups. Regarding each method, we empirically adopt the optimal hyper-parameter settings according to validation sessions on each dataset. For the proposed CGSR, we apply one layer WGA-T in Item Representation Learner, and use Adam optimizer with the initial learning rate (Lr) 0.001 on Diginetica and Gowalla and initial Lr 0.003 on Amazon. The representation size of each $d_0$ and $d$ are 110 on Diginetica, 60 on Gowalla, and 150 on Amazon. All parameters are initialized using Gaussian distribution with a mean of 0 and a standard deviation of 0.1. The L2 penalty is set to $1e-6$ on Gowalla and $5e-6$ on Diginetica and Amazon. Moreover, the batch size is 20 on Diginetica, 40 on Gowalla, and 100 on Amazon. For baselines, we adopt the optimal settings mentioned in either the original papers for these datasets or the original codes. The settings of baselines are shown in Table 3. Note that for CGSR and the best baseline, for fair comparison, we run each experiment six times, report the average as the final result in Table 4, and conduct pair-wise t-test to validate the significance of the performance difference.

the hit ratio, that is, the coverage rate of targeted predictions; **MRR@K** (Mean Reciprocal Rank) indicates the ranking accuracy based on the ranking position of the recommended items (hits), and a larger value means that the ground-truth items are ranked in the top of the ranked recommendation lists. **NDCG@K** (Normalized Discounted Cumulative Gain) also rewards each hit based on its position in the ranked recommendation list.

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Table 4. Performance of All Methods on Three Datasets in Terms of $K = 5, 10, 20$

| Datasets | Metrics | Traditional | RNN-based | attention-based | GNN-based | Improv. |
|----------|---------|-------------|-----------|----------------|-----------|---------|
|           |         | POP ItemKNNFPMC Gru4Rec NARM BERT4Rec SR-GNN FGNLESSR CGSR |           |               |          |         |
| Gowalla   | HR@5    | 0.0040 0.1447 0.1416 | 0.1576 0.2557 0.2672 | 0.2673 0.2640 0.2729 0.3230 | 18.36%*** |         |
|           | HR@10   | 0.0064 0.2130 0.1769 | 0.2233 0.3647 0.3823 | 0.3774 0.3792 0.3852 0.4399 | 14.20%*** |         |
|           | HR@20   | 0.0970 0.2897 0.2573 | 0.3004 0.4889 0.5087 | 0.5076 0.5113 0.5147 0.5567 | 16.16%*** |         |
|           | MRR@5   | 0.0019 0.0807 0.0614 | 0.0894 0.1419 0.1513 | 0.1519 0.1457 0.1561 0.1823 | 16.78%*** |         |
| Diginetica| MRR@10  | 0.0022 0.0897 0.0663 | 0.0981 0.1581 0.1665 | 0.1665 0.1610 0.1708 0.1979 | 15.87%*** |         |
|           | MRR@20  | 0.0024 0.0965 0.0707 | 0.1034 0.1647 0.1752 | 0.1755 0.1702 0.1799 0.2041 | 13.62%*** |         |
|           | NDCG@5  | 0.0024 0.0965 0.0625 | 0.1063 0.1658 0.1799 | 0.1804 0.1749 0.1845 0.2172 | 17.47%*** |         |
|           | NDCG@10 | 0.0032 0.1185 0.0718 | 0.1274 0.2024 0.2170 | 0.2159 0.2121 0.2212 0.2549 | 15.24%*** |         |
|           | NDCG@20 | 0.0040 0.1379 0.0788 | 0.1469 0.2315 0.2489 | 0.2488 0.2455 0.2538 0.2858 | 12.61%*** |         |
| Gowalla   | HR@5    | 0.0183 0.2614 0.1869 | 0.2874 0.3506 0.3547 | 0.3557 0.3471 0.3577 0.3802 | 6.29%*** |         |
|           | HR@10   | 0.0277 0.3248 0.2287 | 0.3558 0.4272 0.4341 | 0.4359 0.4281 0.4340 0.4612 | 5.80%*** |         |
|           | HR@20   | 0.0500 0.3891 0.2834 | 0.4326 0.4989 0.5127 | 0.5149 0.5080 0.5104 0.5389 | 4.66%*** |         |
|           | MRR@5   | 0.0090 0.1718 0.0976 | 0.1863 0.2209 0.2381 | 0.2383 0.2212 0.2403 0.2477 | 3.08%*** |         |
| Amazon    | HR@5    | 0.0046 0.0433 0.0372 | 0.0418 0.0446 0.0456 | 0.0550 0.0464 0.0570 0.0607 | 4.49%*** |         |
|           | HR@10   | 0.0087 0.0515 0.0497 | 0.0513 0.0571 0.0552 | 0.0684 0.0618 0.0691 0.0709 | 2.60%*** |         |
|           | HR@20   | 0.0160 0.0591 0.0589 | 0.0649 0.0718 0.0661 | 0.0816 0.0781 0.0813 0.0835 | 2.33%*** |         |
|           | MRR@5   | 0.0021 0.0288 0.0256 | 0.0283 0.0300 0.0329 | 0.0377 0.0304 0.0369 0.0410 | 11.13%*** |         |
|           | MRR@10  | 0.0026 0.0299 0.0281 | 0.0297 0.0317 0.0341 | 0.0394 0.0325 0.0412 0.0457 | 10.92%*** |         |
|           | MRR@20  | 0.0031 0.0304 0.0288 | 0.0303 0.0327 0.0349 | 0.0403 0.0336 0.0420 0.0466 | 10.95%*** |         |
|           | NDCG@5  | 0.0027 0.0325 0.0295 | 0.0312 0.0336 0.0361 | 0.0420 0.0344 0.0439 0.0478 | 8.88%*** |         |
|           | NDCG@10 | 0.0040 0.0351 0.0313 | 0.0339 0.0377 0.0391 | 0.0463 0.0394 0.0478 0.0519 | 5.85%*** |         |
|           | NDCG@20 | 0.0059 0.0370 0.0346 | 0.0369 0.0414 0.0419 | 0.0496 0.0435 0.0507 0.0546 | 2.77%*** |         |

The best performance is boldfaced, and the runner-up is underlined. We compute the improvements that CGSR achieves relative to the best baseline. Statistical significance of pairwise differences of CGSR vs. the best baseline is determined by a paired t-test (* for p-value ≤ 0.05, ** for p-value ≤ 0.01, and *** for p-value ≤ 0.001).

5.2 Experimental Results

Here, we present results to answer the first three RQs (1–3).

5.2.1 Effectiveness of CGSR over Baseline Methods (RQ1). To demonstrate the overall performance of CGSR, we compare it with SOTA baseline methods. The comparative results on the three datasets are present in Table 4, where we have some interesting observations: (1) The DL-based methods (both RNN-based and GNN-based) generally perform better than traditional methods, demonstrating the capability of DL techniques on processing session data for effective recommendation. Particularly, among the traditional methods, ItemKNN, which is grounded on the similarity between items within a session, performs much better than POP, and slightly better than first-order MC-based FPMC. (2) Across the DL-based methods, GNN-based methods generally outperform RNN-based methods, which validates the effectiveness of GNN models and graph data structures for SR. For the two RNN-based methods, NARM performs better than Gru4Rec, and its performance is comparable to other GNN-based methods. (3) The performance of CGSR is significantly better than SOTA GNN-based methods, validating its effectiveness in distinguishing causality relationships between items from correlation relationships. Among all the GNN-based baselines, LESSR performs the best as it captures both local and long-range dependencies among items.

From Table 4, we also observe that the improvements of CGSR on Diginetica and Amazon are both larger than those on Gowalla. This can be partially explained by Figures 3 and 4, which show that a stronger causality relationship between items is more prevalent on Diginetica (Amazon)
### Table 5. Impact of Causality and Correlation

| Datasets   | Metrics | CGSR-ca | CGSR-r | CGSR-p | CGSR_mean | CGSR |
|------------|---------|---------|--------|--------|-----------|------|
| Diginetica | HR@5    | 0.2950  | 0.2663 | 0.3171 | 0.2641    | 0.3230|
|            | HR@10   | 0.4054  | 0.3811 | 0.4349 | 0.3787    | 0.4399|
|            | HR@20   | 0.5173  | 0.5117 | 0.5544 | 0.5103    | 0.5567|
|            | MRR@5   | 0.1644  | 0.1408 | 0.1771 | 0.1386    | 0.1823|
|            | MRR@10  | 0.1784  | 0.1561 | 0.1940 | 0.1507    | 0.1979|
|            | MRR@20  | 0.1873  | 0.1687 | 0.2002 | 0.1651    | 0.2044|
|            | NDCG@5  | 0.2321  | 0.2115 | 0.2492 | 0.2105    | 0.2549|
|            | NDCG@10 | 0.2612  | 0.2427 | 0.2794 | 0.2408    | 0.2858|
|            | NDCG@20 |         |        |        |           |      |
| Gowalla    | HR@5    | 0.3718  | 0.3601 | 0.3798 | 0.3561    | 0.3802|
|            | HR@10   | 0.4516  | 0.4388 | 0.4601 | 0.4332    | 0.4612|
|            | HR@20   | 0.5272  | 0.5183 | 0.5386 | 0.5041    | 0.5389|
|            | MRR@5   | 0.2399  | 0.2338 | 0.2467 | 0.2304    | 0.2477|
|            | MRR@10  | 0.2451  | 0.2444 | 0.2575 | 0.2397    | 0.2585|
|            | MRR@20  | 0.2532  | 0.2499 | 0.2629 | 0.2456    | 0.2640|
|            | NDCG@5  | 0.2708  | 0.2653 | 0.2802 | 0.2614    | 0.2808|
|            | NDCG@10 | 0.2954  | 0.2908 | 0.3063 | 0.2873    | 0.3070|
|            | NDCG@20 | 0.3143  | 0.3109 | 0.3258 | 0.3054    | 0.3267|
| Amazon     | HR@5    | 0.0560  | 0.0523 | 0.0547 | 0.0515    | 0.0607|
|            | HR@10   | 0.0687  | 0.0641 | 0.0675 | 0.0627    | 0.0709|
|            | HR@20   | 0.0815  | 0.0773 | 0.0801 | 0.0758    | 0.0835|
|            | MRR@5   | 0.0373  | 0.0365 | 0.0390 | 0.0352    | 0.0440|
|            | MRR@10  | 0.0408  | 0.0389 | 0.0416 | 0.0371    | 0.0457|
|            | MRR@20  | 0.0433  | 0.0416 | 0.0434 | 0.0410    | 0.0466|
|            | NDCG@5  | 0.0427  | 0.0401 | 0.0429 | 0.0390    | 0.0478|
|            | NDCG@10 | 0.0475  | 0.0446 | 0.0473 | 0.0433    | 0.0519|
|            | NDCG@20 | 0.0505  | 0.0473 | 0.0504 | 0.0460    | 0.0546|

than that on Gowalla. In addition, Gowalla relates to location-based social networking, where users share their locations by check-ins. In this case, the directed relationship between check-ins might not be so significant compared with that on typical transaction datasets such as Diginetica and Amazon.

#### 5.2.2 Effectiveness of Causality Graphs vs. Correlation Graphs (RQ2)

CGSR considers both causality and correlation graphs. To explore the effectiveness of each type of relationship, we compare CGSR with four variants: (1) CGSR-ca removes both cause graph $G^c$ and effect graph $G^e$; (2) CGSR-r ignores correlation graph $G^r$; (3) CGSR-p does not consider the session representation $S^p$; and (4) CGSR_mean only considers $Score^p$ in Equation (15). The performance of CGSR and the four variants are shown in Table 5.

As shown in Table 5, CGSR performs superior to the four variants across all metrics, validating the effectiveness of the four designs, particularly distinguishing directed causality relationships from undirected correlation relationships between items. In addition, CGSR-ca performs better than CGSR-r, implying that only considering correlation graphs is better than only considering causality relationships. This might be due to the fact that undirected correlation graphs might already cover causality relationships but not vice versa.
We also explore the effectiveness of weights designs in cause and effect graphs (i.e., impact of causality weights). CGSR defines weights of causality-related graphs, as discussed in Section 3. To validate the effectiveness, we compare CGSR with two alternatives: (1) CGSR-W, where edge weights in cause and effect graphs are set to 1; and (2) CGSR-CC, which does not rule out the impact of common causes. As can be seen in Table 6, CGSR performs better than the two variants, verifying the effectiveness of our design and the necessity of removing common causes in identifying causality relationships.

To further validate the impact of cause and effect graphs, we make the cause graph and effect graph into a random graph (cause_random and effect_random), respectively. The results are shown in Figure 9, where we can see that cause_random and effect_random perform consistently worse than CGSR, also implying the effectiveness of building cause and effect graphs.

### Table 6. Performance of Different Causality Weights

| Datasets | Metrics | CGSR-W | CGSR-CC | CGSR |
|----------|---------|--------|---------|------|
| Diginetica | HR@5 | 0.3192 | 0.3168 | 0.3230 |
| | HR@10 | 0.4351 | 0.4332 | 0.4399 |
| | HR@20 | 0.5515 | 0.4982 | 0.5567 |
| | MRR@5 | 0.1773 | 0.1782 | 0.1823 |
| | MRR@10 | 0.1917 | 0.1925 | 0.1979 |
| | MRR@20 | 0.2003 | 0.2007 | 0.2044 |
| | NDCG@5 | 0.2101 | 0.2113 | 0.2172 |
| | NDCG@10 | 0.2506 | 0.2524 | 0.2549 |
| | NDCG@20 | 0.2786 | 0.2794 | 0.2858 |
| Gowalla | HR@5 | 0.3797 | 0.3795 | 0.3802 |
| | HR@10 | 0.4601 | 0.4607 | 0.4612 |
| | HR@20 | 0.5375 | 0.5379 | 0.5389 |
| | MRR@5 | 0.2471 | 0.2470 | 0.2477 |
| | MRR@10 | 0.2581 | 0.2580 | 0.2585 |
| | MRR@20 | 0.2635 | 0.2634 | 0.2640 |
| | NDCG@5 | 0.2807 | 0.2801 | 0.2808 |
| | NDCG@10 | 0.3068 | 0.3064 | 0.3070 |
| | NDCG@20 | 0.3264 | 0.3263 | 0.3267 |

5.2.3 Ablation Study (RQ2). Besides causality graphs, we have some other innovative designs in CGSR: (1) three types of second-order relationships in building correlation graphs; (2) first-order relationships in building cause and effect graphs; and (3) adopting one layer WGAT in Item Representation Learner.

Regarding the first issue, to explore the effectiveness of the second-order relationship, we compare our model with three variants: (1) CGSR-chain removes the “chain” relationship; (2) CGSR-fork ignores “fork” type; and (3) CGSR-collider does not consider second-order neighbors of collider type. Table 7 summarizes the comparative results and shows that all three types contribute to performance improvement, but fork relation is less significant than the other two. This is consistent with directed graphical model principles, which indicate that $v_i$ and $v_j$ in Figure 6 are inclined to be independent from each other given a known $v_k$ in fork pattern [13].

Regarding the second issue, we compare CGSR with the variant CGSR-ca_sec, which considers the second-order relationship in cause and effect graphs. The results of CGSR and the variant are shown in Table 8. From Table 8, CGSR performs superior to the variant across all metrics, partially validating the effectiveness of only considering first-order relationships in our study.
Regarding the third issue, other models such as gated graph neural networks (GGNNs) [17] are also suitable for directed and weighted graphs. To verify the validity of one-layer WGAT for CGSR, we consider model variants by varying the number of GGNN layers and WGAT layers. The comparative results regarding these variants are summarized in Table 9, which shows that WGAT-related variants perform better than GGNN-related variants, and one-layer WGAT consistently performs better across all scenarios, demonstrating the effectiveness of our design in Item Representation Learner.

5.2.4 Sensitivity of Hyper-parameters (RQ3). We investigate the impact of embedding size $d$ and batch size on CGSR models by deploying a grid search in the range of $\{40, 50, 60, 70, 80, 90, 100, 110, 120\}$ and $\{20, 40, 60, 80, 100\}$ for $d$ and batch size, respectively. Figure 10 shows the experiment results. Generally speaking, our method is comparatively insensitive to the two hyper-parameters. In addition, while varying the hyper-parameters, the performance on Diginetica fluctuates more obviously, which is consistent with our previous analysis that causality patterns are more prevalent on Diginetica than on Gowalla.

To further verify the convergence of our model, we present how the loss of our model varies over epochs during the training process on the three datasets. Figure 11 contains the experiment results, which show that the model consistently converges.

5.3 Case Study on Explanation Task (RQ4)
Since CGSR has distinguished causality from the correlation relationship between items, it is expected to facilitate the explanation task in SR in a fine-grained fashion. In this case, we design
Table 7. Impact of Second-Order Relationships in Correlation Graphs

| Datasets | Metrics | CGSR-chain | CGSR-fork | CGSR-collider | CGSR |
|----------|---------|------------|-----------|---------------|------|
| Diginetica | HR@5 | 0.3149 | 0.3153 | 0.3129 | 0.3230 |
|         | HR@10 | 0.4323 | 0.4339 | 0.4318 | 0.4399 |
|         | HR@20 | 0.5507 | 0.5519 | 0.5497 | 0.5567 |
|         | MRR@5 | 0.1783 | 0.1789 | 0.1775 | 0.1823 |
|         | MRR@10 | 0.1900 | 0.1907 | 0.1894 | 0.1979 |
|         | MRR@20 | 0.1984 | 0.1992 | 0.1978 | 0.2044 |
|         | NDCG@5 | 0.2092 | 0.2097 | 0.2081 | 0.2172 |
|         | NDCG@10 | 0.2472 | 0.2480 | 0.2465 | 0.2549 |
|         | NDCG@20 | 0.2777 | 0.2788 | 0.2769 | 0.2858 |
| Gowalla | HR@5 | 0.3754 | 0.3780 | 0.3759 | 0.3802 |
|         | HR@10 | 0.4552 | 0.4596 | 0.4560 | 0.4612 |
|         | HR@20 | 0.5327 | 0.5372 | 0.5335 | 0.5389 |
|         | MRR@5 | 0.2457 | 0.2459 | 0.2450 | 0.2477 |
|         | MRR@10 | 0.2564 | 0.2569 | 0.2557 | 0.2585 |
|         | MRR@20 | 0.2617 | 0.2623 | 0.2611 | 0.2640 |
|         | NDCG@5 | 0.2781 | 0.2788 | 0.2776 | 0.2808 |
|         | NDCG@10 | 0.3039 | 0.3053 | 0.3036 | 0.3070 |
|         | NDCG@20 | 0.3235 | 0.3249 | 0.3232 | 0.3267 |

Table 8. Impact of First-Order Relationships in Cause and Effect Graphs

| Datasets | Metrics | CGSR-ca_sec | CGSR |
|----------|---------|-------------|------|
| Diginetica | HR@5 | 0.3132 | 0.3230 |
|         | HR@10 | 0.4320 | 0.4399 |
|         | HR@20 | 0.5504 | 0.5567 |
|         | MRR@5 | 0.1778 | 0.1823 |
|         | MRR@10 | 0.1897 | 0.1979 |
|         | MRR@20 | 0.1979 | 0.2044 |
|         | NDCG@5 | 0.2085 | 0.2172 |
|         | NDCG@10 | 0.2469 | 0.2549 |
|         | NDCG@20 | 0.2770 | 0.2858 |
| Gowalla | HR@5 | 0.3624 | 0.3802 |
|         | HR@10 | 0.4448 | 0.4612 |
|         | HR@20 | 0.5254 | 0.5389 |
|         | MRR@5 | 0.2273 | 0.2477 |
|         | MRR@10 | 0.2384 | 0.2585 |
|         | MRR@20 | 0.2440 | 0.2640 |
|         | NDCG@5 | 0.2610 | 0.2808 |
|         | NDCG@10 | 0.2878 | 0.3070 |
|         | NDCG@20 | 0.3081 | 0.3267 |

an explainable framework on CGSR to clarify why a specific item \( v_j \in \mathcal{V} \) is recommended given session \( S \) on both session and item levels by generating a set of explanation scores. Specifically, in the explainable framework, on the session level, three scores leading to the final recommendation score of \( v_j \) (i.e., \( Score_{ca}^{\text{ca}}, Score_{r}^{\text{r}}, Score_{p}^{\text{p}} \)) are output by Recommendation Score Generator in CGSR.
Table 9. Performance with Different GNN Layers

| Datasets | Metrics | 3*GGNN | 2*GGNN | GGNN | 3*WGAT | 2*WGAT | WGAT+GGNN | WGAT |
|----------|---------|--------|--------|------|--------|--------|-----------|------|
| Diginetica | HR@5 | 0.2751 | 0.2762 | 0.2761 | 0.2807 | 0.2913 | 0.3064 | 0.3230 |
|          | HR@10 | 0.3907 | 0.3918 | 0.3914 | 0.4011 | 0.4123 | 0.4241 | 0.4399 |
|          | HR@20 | 0.5153 | 0.5161 | 0.5155 | 0.5279 | 0.5389 | 0.5439 | 0.5567 |
|          | MRR@5 | 0.1576 | 0.1588 | 0.1580 | 0.1566 | 0.1587 | 0.1687 | 0.1823 |
|          | MRR@10 | 0.1706 | 0.1721 | 0.1720 | 0.1728 | 0.1756 | 0.1846 | 0.1979 |
|          | MRR@20 | 0.1806 | 0.1819 | 0.1809 | 0.1813 | 0.1813 | 0.1912 | 0.2044 |
|          | NDCG@5 | 0.1857 | 0.1863 | 0.1857 | 0.1866 | 0.1908 | 0.2017 | 0.2172 |
|          | NDCG@10 | 0.2248 | 0.2250 | 0.2247 | 0.2257 | 0.2307 | 0.2406 | 0.2549 |
|          | NDCG@20 | 0.2550 | 0.2551 | 0.2548 | 0.2571 | 0.2615 | 0.2710 | 0.2858 |
| Gowalla  | HR@5 | 0.3570 | 0.3652 | 0.3471 | 0.3489 | 0.3613 | 0.3730 | 0.3802 |
|          | HR@10 | 0.4370 | 0.4438 | 0.4270 | 0.4276 | 0.4425 | 0.4547 | 0.4612 |
|          | HR@20 | 0.5167 | 0.5219 | 0.5081 | 0.5056 | 0.5213 | 0.5349 | 0.5389 |
|          | MRR@5 | 0.2322 | 0.2392 | 0.2270 | 0.2209 | 0.2311 | 0.2432 | 0.2477 |
|          | MRR@10 | 0.2429 | 0.2497 | 0.2377 | 0.2315 | 0.2420 | 0.2541 | 0.2585 |
|          | MRR@20 | 0.2484 | 0.2551 | 0.2434 | 0.2369 | 0.2474 | 0.2597 | 0.2640 |
|          | NDCG@5 | 0.2633 | 0.2706 | 0.2569 | 0.2529 | 0.2635 | 0.2756 | 0.2808 |
|          | NDCG@10 | 0.2892 | 0.2860 | 0.2828 | 0.2783 | 0.2899 | 0.3020 | 0.3070 |
|          | NDCG@20 | 0.3093 | 0.3158 | 0.3043 | 0.2981 | 0.3098 | 0.3223 | 0.3267 |

Fig. 10. Model performance of different embedding sizes and batch sizes ($K = 20$).

On the item level, we calculate the score (importance) of each item $v_i^S$ in $S$ to $v_j$ under each relationship type (i.e., $Score_{ij}^{ca}$ for causality relationship and $Score_{ij}^{r}$ for correlation relationship):

$$Score_{ij}^{ca} = (W_c \cdot [x_i^s; x_j^S])^T x_j^S - \gamma_1 (W_e \cdot [x_i^s; x_j^S])^T x_j^S$$

$$Score_{ij}^{r} = (W_r \cdot [x_i^S; x_j^S])^T x_j^S$$

Consequently, with the framework, given a recommended item $v_j$ and session $S$, we can not only understand the impact of $S$ under each type of relationship on $v_j$ from the session level but can also recognize the importance of each item in $S$ as either cause item or correlation item to $v_j$ from the item level.
Fig. 11. The convergence of our model.

Fig. 12. Two sessions $\{\text{Cake Lifter, Cooling Rack, Griddler, Griddler Waffle Plates}\}$ and $\{\text{Mini-Prep Plus Food Processor, Oven with Dual Handles, Slow Cooker, Griddler}\}$, and the corresponding explanation scores on both the session level and item level.

In our experiment, to showcase the effectiveness of our explainable framework, we instantiate it on the Amazon dataset. We choose an Amazon dataset because item information on Amazon is publicly available whereas on the other two datasets it is anonymously encoded. Figure 12 depicts two cases on Amazon, which relate to two randomly chosen sessions: $S_1 \{\text{Cake Lifter, Cooling Rack, Griddler, Griddler Waffle Plates (recommended item)}\}$ and $S_2 \{\text{Mini-Prep Plus Food Processor, Oven...}$.}
with Dual Handles, Slow Cooker, Griddler (recommended item). The histogram on the left side presents the explainable scores on the session level, whereas the histogram on the right side shows those on the item level.

As shown in Figure 12, for $S_1$, causality score $\text{Score}^{ca}$ is higher than correlation score $\text{Score}^{r}$, implying that on the session level, Cake Lifter, Griddler and Cooling Rack in $S_1$ are more like cause items leading to buy Griddler Waffle Plates. On the item level, under the causality relationship, the score of Griddler is higher than the other two items, which means that Griddler is the main reason motivating the user to also purchase the Griddler Waffle Plates. Towards $S_2$, the correlation score is higher than the causality score. For each item in $S_2$, the corresponding correlation score with Griddler is also higher than the causality score. This is consistent with the reality that Griddler has a correlation relationship rather than a causality relationship with Mini-Prep Plus Food Processor, Oven with Dual Handles, and Slow Cooker. From the two case studies, we can see that our explainable framework can provide valuable and reasonable explanations towards recommendations in SR.

6 CONCLUSIONS

The directed causality relationship between items, which has been ignored by previous studies, is quite important for effective session-based recommendation (SR). In this article, we proposed a novel method denoted as CGSR to explicitly consider the causality and correlation relationships in SR. Specifically, on the basis of sessions, we constructed a cause graph, an effect graph, and a correlation graph considering both first-order and three types of second-order relationships, which are fed into a GNN and attention mechanism–based model to obtain four types of session representations for recommendation. By doing this, we can capture both causality and correlation relationships between items and maximize item transition from cause to effect while simultaneously minimizing that from effect to cause. Extensive experimental results on three real-world datasets first revealed the superiority of our model over the state-of-the-art, validating the effectiveness of distinguishing causality and correlation relationships. Second, exhaustive ablation studies verified the effectiveness of every component in CGSR. Third, we also investigated the sensitivity of hyper-parameters and demonstrated the convergence of our model. We further designed an explainable framework on CGSR to improve the explainability of SR. Case studies on an Amazon dataset showcased that our framework can facilitate the explanation task in session-based recommendation.

For future work, we will continue to explore the causality and correlation relationships among items and even mine other relationship types for further improving recommendation accuracy. We also aim to reveal the underlying factors leading to these directed item relationships by using popular causal inference techniques. Moreover, we strive to design other studies to provide the corresponding explainability.

REFERENCES

[1] Stephen Bonner and Flavian Vasile. 2018. Causal embeddings for recommendation. In Proceedings of the 12th ACM Conference on Recommender Systems. 104–112.
[2] Tianwen Chen and Raymond Chi-Wing Wong. 2020. Handling information loss of graph neural networks for session-based recommendation. In Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. 1172–1180.
[3] Michal Dobrovolny, Ali Selamat, and Ondrej Krejcar. 2021. Session based recommendations using recurrent neural networks-long short-term memory. In Proceedings of the 13th Asian Conference on Intelligent Information and Database Systems. Springer, 53–65.
[4] Tim Donkers, Benedikt Loepp, and Jürgen Ziegler. 2017. Sequential user-based recurrent neural network recommendations. In Proceedings of the 11th ACM Conference on Recommender Systems. 152–160.
[5] Hui Fang, Danning Zhang, Yiheng Shu, and Guibing Guo. 2020. Deep learning for sequential recommendation: Algorithms, influential factors, and evaluations. ACM Transactions on Information Systems 39, 1 (2020), 1–42.
[6] Lei Guo, Hongzhi Yin, Qinyong Wang, Tong Chen, Alexander Zhou, and Nguyen Quoc Viet Hung. 2019. Streaming session-based recommendation. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. 1569–1577.

[7] Priyanka Gupta, Ankit Sharma, Pankaj Malhotra, Lovekesh Vig, and Gautam Shroff. 2021. CauSeR: Causal session-based recommendations for handling popularity bias. In Proceedings of the 30th ACM International Conference on Information & Knowledge Management. 3048–3052.

[8] Tajuddeen Rabiu Gwadabe and Ying Liu. 2022. Improving graph neural network for session-based recommendation system via non-sequential interactions. Neurocomputing 468 (2022), 111–122.

[9] Ruining He and Julian McAuley. 2016. Ups and downs: Modeling the visual evolution of fashion trends with one-class collaborative filtering. In Proceedings of the 25th International Conference on World Wide Web. 507–517.

[10] Balázs Hidasi, Alexandros Karatzoglou, Linas Baltrunas, and Domonkos Tikk. 2016. Session-based recommendations with recurrent neural networks. In Proceedings of the 4th International Conference on Learning Representations.

[11] Wang-Cheng Kang and Julian McAuley. 2018. Self-attentive sequential recommendation. In IEEE International Conference on Data Mining. IEEE. 197–206.

[12] Katherine Keith, David Jensen, and Brendan O’Connor. 2020. Text and causal inference: A review of using text to remove confounding from causal estimates. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics.

[13] Daphne Koller and Nir Friedman. 2009. Probabilistic Graphical Models: Principles and Techniques. MIT Press.

[14] Duc-Trong Le, Yuan Fang, and Hady W. Lauw. 2016. Modeling sequential preferences with dynamic user and context factors. In Proceedings of the Joint European Conference on Machine Learning and Knowledge Discovery in Databases. Springer, 145–161.

[15] Youfang Leng and Li Yu. 2021. Hierarchical context-aware recurrent network for session-based recommendation. IEEE Access 9 (2021), 51618–51630.

[16] Jing Li, Pengjie Ren, Zhumin Chen, Zhaochun Ren, Tao Lian, and Jun Ma. 2017. Neural attentive session-based recommendation. In Proceedings of the 26th ACM International Conference on Conference on Information and Knowledge Management. 1419–1428.

[17] Yuja Li, Daniel Tarlow, Marc Brockschmidt, and Richard Zemel. 2015. Gated graph sequence neural networks. In Proceedings of the 3rd International Conference on Learning Representations.

[18] Dawen Liang, Laurent Charlin, and David M. Blei. 2016. Causal inference for recommendation. In Causation: Foundation to Application, Workshop at UAI. AUAI.

[19] 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 and Data Mining. 1831–1839.

[20] Xin Liu, Yong Liu, Karl Aberer, and Chunyan Miao. 2013. Personalized point-of-interest recommendation by mining users’ preference transition. In Proceedings of the 22nd ACM International Conference on Information and Knowledge Management. 733–738.

[21] Julian McAuley, Rahul Pandey, and Jure Leskovec. 2015. Inferring networks of substitutable and complementary products. In Proceedings of the 21st ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. 785–794.

[22] Julian McAuley, Christopher Targett, Qinfeng Shi, and Anton Van Den Hengel. 2015. Image-based recommendations on styles and substitutes. In Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval. 43–52.

[23] Zhiqiang Pan, Fei Cai, Wanyu Chen, Honghui Chen, and Maarten de Rijke. 2020. Star graph neural networks for session-based recommendation. In Proceedings of the 29th ACM International Conference on Information and Knowledge Management. 1195–1204.

[24] Ruishing Qiu, Zi Huang, Jingjing Li, and Hongzhi Yin. 2020. Exploiting cross-session information for session-based recommendation with graph neural networks. ACM Transactions on Information Systems 38, 3 (2020), 1–23.

[25] Ruishing Qiu, Jingjing Li, Zi Huang, and Hongzhi Yin. 2019. Rethinking the item order in session-based recommendation with graph neural networks. In Proceedings of the 28th ACM International Conference on Information and Knowledge Management. 579–588.

[26] Ruishing Qiu, Sen Wang, Zhi Chen, Hongzhi Yin, and Zi Huang. 2021. CausalRec: Causal inference for visual debiasing in visually-aware recommendation. In Proceedings of the 29th ACM International Conference on Multimedia. 3844–3852.

[27] Ruishing Qiu, Hongzhi Yin, Zi Huang, and Tong Chen. 2020. GAG: Global attributed graph neural network for streaming session-based recommendation. In Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval. 669–678.

[28] Massimo Quadrana, Alexandros Karatzoglou, Balázs Hidasi, and Paolo Cremonesi. 2017. Personalizing session-based recommendations with hierarchical recurrent neural networks. In Proceedings of the 11th ACM Conference on Recommender Systems. 130–137.
[30] 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.

[31] Badrul Sarwar, George Karypis, Joseph Konstan, and John Riedl. 2001. Item-based collaborative filtering recommendation algorithms. In Proceedings of the 10th International Conference on World Wide Web. 285–295.

[32] Tobias Schnabel, Adith Swaminathan, Ashudeep Singh, Navin Chandak, and Thorsten Joachims. 2016. Recommendations as treatments: Debiasing learning and evaluation. In Proceedings of the 33rd International Conference on Machine Learning. PMLR, 1670–1679.

[33] Bernhard Schölkopf. 2019. Causality for machine learning. arXiv preprint arXiv:1911.10500 (2019).

[34] Guy Shani, David Heckerman, Ronen I. Brafman, and Craig Boutilier. 2005. An MDP-based recommender system. Journal of Machine Learning Research 6, 9 (2005).

[35] Fei Sun, Jun Liu, Jian Wu, Changhua Pei, Xiao Lin, Wenwu Ou, and Peng Jiang. 2019. BERT4Rec: Sequential recommendation with bidirectional encoder representations from transformer. In Proceedings of the 28th ACM International Conference on Information and Knowledge Management. 1441–1450.

[36] Jiaxi Tang and Ke Wang. 2018. Personalized top-n sequential recommendation via convolutional sequence embedding. In Proceedings of the 11th ACM International Conference on Web Search and Data Mining. 565–573.

[37] Ben Taskar, Ming-Fai Wong, Pieter Abbeel, and Daphne Koller. 2003. Link prediction in relational data. Advances in Neural Information Processing Systems 16 (2003), 659–666.

[38] Jianling Wang, Kaize Ding, Ziwei Zhu, and James Caverlee. 2021. Session-based recommendation with hypergraph attention networks. In Proceedings of the 2021 SIAM International Conference on Data Mining (SDM). SIAM, 82–90.

[39] Xiaojie Wang, Rui Zhang, Yu Sun, and Jianzhong Qi. 2019. Doubly robust joint learning for recommendation on data missing not at random. In Proceedings of the 36th International Conference on Machine Learning. PMLR, 6638–6647.

[40] Yixin Wang, Dawen Liang, Laurent Charlin, and David M. Blei. 2018. The deconfounded recommender: A causal inference approach to recommendation. arXiv preprint arXiv:1808.06581 (2018).

[41] Yixin Wang, Dawen Liang, Laurent Charlin, and David M. Blei. 2020. Causal inference for recommender systems. In Proceedings of the 14th ACM Conference on Recommender Systems. 426–431.

[42] 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.

[43] Shu Wu, Yuyuan Tang, Yanqiao Zhu, Liang Wang, Xing Xie, and Tieniu Tan. 2019. Session-based recommendation with graph neural networks. In Proceedings of the 33rd AAAI Conference on Artificial Intelligence, Vol. 33. 346–353.

[44] Xiang Wu, Qi Liu, Enhong Chen, Liang He, Jingsong Lv, Can Cao, and Guoping Hu. 2013. Personalized next-song recommendation in online Karaoke. In Proceedings of the 7th ACM Conference on Recommender Systems. 137–140.

[45] Xin Xia, Hongzhi Yin, Junliang Yu, Yingxia Shao, and Lizhen Cui. 2021. Self-supervised graph co-training for session-based recommendation. In Proceedings of the 30th ACM International Conference on Information and Knowledge Management. 2180–2190.

[46] Chengfeng Xu, Pengpeng Zhao, Yanchi Liu, Victor S. Sheng, Jiajie Xu, Fuizhen Zhuang, Junhua Fang, and Xiaofang Zhou. 2019. Graph contextualized self-attention network for session-based recommendation. In Proceedings of the 28th International Joint Conference on Artificial Intelligence, Vol. 19. 3940–3946.

[47] Shuyuan Xu, Yunqi Li, Shuchang Liu, Zuoqiu Fu, Yingqiang Ge, Xu Chen, and Yongfeng Zhang. 2021. Learning causal explanations for recommendation. In Proceedings of the 1st International Workshop on Causality in Search and Recommendation.

[48] Liuyi Yao, Zhixuan Chu, Sheng Li, Yaliang Li, Jing Gao, and Aidong Zhang. 2020. A survey on causal inference. arXiv preprint arXiv:2002.02770 (2020).

[49] Bo Yu, Ruoqian Zhang, Wei Chen, and Junhua Fang. 2021. Graph neural network based model for multi-behavior session-based recommendation. GeoInformatica (2021), 1–19.

[50] Xiangde Zhang, Yuan Zhou, Jiaping Wang, and Xiaojun Lu. 2021. Personal interest attention graph neural networks for session-based recommendation. Entropy 23, 11 (2021), 1500.

[51] Yin Zhang, Haokai Lu, Wei Niu, and James Caverlee. 2018. Quality-aware neural complementary item recommendation. In Proceedings of the 12th ACM Conference on Recommender Systems. 77–85.

[52] Huachi Zhou, Qiaoyu Tan, Xiao Huang, Kaixiong Zhou, and Xiaoling Wang. 2021. Temporal augmented graph neural networks for session-based recommendations. In Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval. 1798–1802.

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