



SPARE: Shortest Path Global Item Relations for Efficient Session-based Recommendation

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ABSTRACT

Session-based recommendation aims to predict the next item based on a set of anonymous sessions. Capturing user intent from a short interaction sequence imposes a variety of challenges since no user profiles are available and interaction data is naturally sparse. Recent approaches relying on graph neural networks (GNNs) for session-based recommendation use global item relations to explore collaborative information from different sessions. These methods capture the topological structure of the graph and rely on multi-hop information aggregation in GNNs to exchange information along edges. Consequently, graph-based models suffer from noisy item relations in the training data and introduce high complexity for large item catalogs. We propose to explicitly model the multi-hop information aggregation mechanism over multiple layers via shortest-path edges based on knowledge from the sequential recommendation domain. Our approach does not require multiple layers to exchange information and ignores unreliable item-item relations. Furthermore, to address inherent data sparsity, we are the first to apply supervised contrastive learning by mining data-driven positive and hard negative item samples from the training data. Extensive experiments on three different datasets show that the proposed approach outperforms almost all of the state-of-the-art methods.

CCS CONCEPTS

• Information systems → Recommender systems.

KEYWORDS

Recommender Systems, Session-based Recommendation, Graph Neural Network, Supervised Contrastive Learning

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1 INTRODUCTION

Recommender systems are an important tool for users to obtain useful information. They are widely adopted in various areas like e-commerce or online streaming services and implicitly boost business revenue by improving user experience. However, most conventional recommender systems rely on the availability of user profiles and long-term interaction histories and therefore, are not suitable for scenarios in which this data is not available (for instance, anonymous sessions). Tackling this task, session-based recommendation (SBR) aims at predicting the next most likely item based solely on an anonymous session [22].

Early works in this field considered Markov Chains and recurrent neural networks (RNNs) to model the temporal dependencies of items in the session sequence [9, 23]. Based on the similarity of sessions, nearest-neighbor methods were also deployed for session-based recommendation [5, 11, 17]. Other approaches incorporated convolutional neural networks [27, 41] and attention mechanisms [15, 16]. Recent studies have deployed graph neural networks (GNNs) to model sessions via graphs and have been shown to be state-of-the-art [30, 33, 36]. However, the success of current GNN models relies on using complex multi-layer graphs or several graphs to augment different aspects of data. While these ideas can be useful in complementing collaborative information, they can also introduce irrelevant information that adversely affects recommendation performance as well as being inefficient and computationally expensive. However, generating different views of a graph via augmentation with different edge drop-out rates, for instance, does not adversely affect the performance of contrastive learning-based recommendation models, and in fact, even a large drop-out rate on edges (e.g., 0.9) is beneficial [39]. This finding would result in the loss of a huge amount of raw structural information and therefore, should only have a negative impact. Considering this, in this paper, we investigate the more general question: Do contrastive learning-based recommendation models indeed require complex graphs?

Taking into account the above-discussed limitations of noisy and computationally expensive input graphs, in this paper, we propose **Shortest-Path Relations (SPARE)** to enrich a global item graph with informative connections. With SPARE, we introduce a graph-building strategy that relies on a shortest-path search to drop irrelevant item connections in the graph. This procedure can be considered as edge sparsification in the graph and is correlated with the long-standing concept of finding frequent item sets with high support [1]. As a further important benefit, adding shortest-path shortcut connections explicitly models item-item importance and imitates the n-hop neighbor information aggregation of standard GNNs with multiple layers for efficient item representation

learning. We illustrate this concept in Figure 1, where we present template sessions of an e-commerce grocery retailer. In this example, we have dough, salami, tomato, and cheese—ingredients in a pizza recipe—in our frequently occurring sessions (sessions 2 and 4). There are also people who purchase less-common ingredients such as pineapple amongst pizza ingredients (sessions 1 and 5). Additionally, in some sessions, customers may buy unrelated items, such as shampoo or chocolate (sessions 3 and 6). The purchase of shampoo or chocolate seems like an irrelevant outlier for a customer who is looking for ingredients for a pizza recipe. However, pineapple should be considered as an interesting pattern for the customers who buy pizza ingredients, even in the case that tomato is in the basket (no co-purchase). Through the high support of pineapple \rightarrow dough and dough \rightarrow tomato relations, a shortest-path search in a global item graph finds a direct connection (shortcut connection) between pineapple and tomato. Furthermore, since item relations containing shampoo or chocolate have low support, shortest-path search disregards them as irrelevant, given a proper threshold value, resulting in a sparse global item graph. However, graph edge sparsification comes with the risk of increasing data sparsity and popularity bias. To counteract the sparsity of data and reinforcement of the popular item sets, for the first time, we apply Supervised Contrastive Learning (SCL) [13] by mining positive and negative item samples in a data-driven manner. With SCL, we not only tackle the sparsity of data but also improve the model’s performance by refining the encoder and item representations through the self-supervised learning objective.

We summarize our main technical contributions as follows:

- We propose a novel global item graph-building strategy (SPARE) based on shortest paths to introduce item shortcut connections and graph edge sparsification.
- We integrate a supervised contrastive learning task based on data-driven hard negative samples to tackle data sparsity and the inherent popularity bias to enhance recommendation performance.
- Extensive experiments show that our proposed model provides higher efficiency while significantly outperforming state-of-the-art competitors.
- To ensure reproducibility, we published the code of our experiments and analysis at GitHub¹.

¹<https://github.com/dbis-uibk/SPARE>

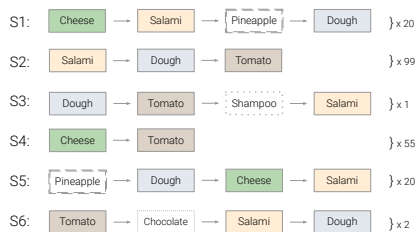


Figure 1: A toy example of an e-commerce grocery retailer scenario. Numbers indicate the frequency of each session.

2 RELATED WORK

Sequential recommendation leverages user data and long-term interactions, whereas session-based recommendation is limited to anonymous sessions only. In this section, we review both tasks and present related research.

2.1 Sequential Recommendation

The initial phase of sequential recommendation focuses on discovering short-term item representations and interaction patterns. Markov decision processes are used in early works to model the interaction sequences. In FPMC [23], first-order Markov chains capture sequential patterns while matrix factorization models long-term user preferences. Also, convolutional neural networks (CNNs) have been found to be useful, where items are seen as images and short-term sequential patterns are learned via convolutional filters [26]. Xu et al. [37] combine CNNs with long-short-term memory to extract additional complex long-term dependencies. In HGN [18], a feature and instance gating mechanism is used to capture long- and short-term user interests. Other studies apply the attention mechanism to obtain and fuse different levels of interaction information [25, 40].

Self-attention and Transformer-based architectures are widely used for sequential recommendation models. SASRec [12] applies the self-attention mechanism to identify relevant interactions from the user’s history. Others use custom Transformer models to provide more personalized recommendation [3, 32]. In FDSA [44], heterogeneous features of items are integrated via feature sequences, and self-attention is applied to jointly model item and feature transition patterns. S³-Rec [46] utilizes self-supervised learning to enhance the item representations via pre-training methods.

Hsu and Li [10] extract a local subgraph from a user-item pair and apply self-attention to encode long-term and short-term temporal patterns. MA-GNN [19] captures the item contextual information within a short-term period with a graph neural network and utilizes a shared memory network to model long-range dependencies. Zhang et al. [45] extract augmented sequences representations from an item transition graph for a contrastive learning objective.

2.2 Session-based Recommendation

In session-based recommendation, user profiles and long-term interaction histories are no longer available. Consequently, the goal is to effectively model informative session representations. Early works adopted recurrent neural networks (RNNs) to model the sequentiality of item interactions. GRU4Rec [9] uses gated recurrent units (GRUs) to encode interaction sequences. This approach is extended in NARM [15] with an attention mechanism that additionally captures the main intent of a session. To capture the general interest based on the long-term interaction history and the current interest from the most recent clicks, STAMP [16] introduces a short-term attention/memory priority model.

Based on the knowledge contained in other sessions, a different line of research extracts collaborative information for improved session representations. SKNN [11] finds sessions containing the same elements as the current session and relies on selecting items from the most similar session. Its successor VSKNN [17] extends this approach by taking the position and frequency of items into

account. Another nearest-neighbor approach named STAN [5] additionally incorporates factors like recency and different item position weighting strategies. In CSR [29], neighborhood sessions are used to extract collaborative information in a hybrid framework with two parallel memory modules.

Most recent works in session-based recommendation are based on GNNs. As the first to introduce the concept of representing sessions as graphs, SR-GNN [33] models each session as a directed, unweighted graph and applies a gating mechanism to generate session representations. This work is extended by a self-attention mechanism in GCSAN [36] to effectively capture long-range dependencies. Incorporating collaborative knowledge into GNN-based methods leads to a new line of research. GCE-GNN [30] learns item embeddings on a session level as well as on a global level and uses a soft-attention mechanism to fuse the learned item representations. Xia et al. [34] introduce a dual-channel hypergraph to capture beyond-pairwise relations and apply self-supervised learning to maximize the mutual information between both session representations. MGIR [7] shows that global incompatible items are informative and aggregate positive and negative relations for the final session representation.

Chen and Wong [2] tackle the long-range dependency (over-smoothing) problem of session graphs by introducing a lossless encoding scheme and a shortcut graph attention layer. Yang et al. with SPAGAT [38] are the first to introduce the concept of shortest-path attention in GNNs by applying a complex path feature aggregation strategy and is therefore not feasible for recommender systems.

With this work, we are the first to exploit shortest-path search to introduce shortcut connections in a global item graph which significantly increases the computational efficiency of the model. Also, compared to other self-supervised learning methods tackling the data sparsity in SBR, our approach is the first to mine supervised positive and hard negative item samples for the computation of the contrastive loss.

3 PRELIMINARIES

In this section, we first introduce the problem statement and important notations for session-based recommendation. Subsequently, we present the construction of the global item base graph which is based on the sequential appearances of item interactions in the session data.

3.1 Problem Statement and Notations

Let $\mathcal{I} = \{i_1, i_2, i_3, \dots, i_N\}$ be the item universe, where N is the number of items. Each session consists of sequential, temporally ordered interactions with items and is denoted by $s = [i_1^s, i_2^s, i_3^s, \dots, i_l^s]$, where l is the length of session s and i_j^s represents the j^{th} item interacted with within this session. Item representations are learned by encoding all items $i \in \mathcal{I}$ into the same embedding space. Using d dimensions for the embedding, the item representation set is denoted as $\mathbf{X} \in \mathbb{R}^{N \times d}$ and is randomly initialized with a uniform distribution. Given a session s , the task of session-based recommendation is to predict the next item i_{l+1}^s of the interaction sequence.

3.2 Global Item Base Graph

To capture all item relations in the sessions, a global item graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ is constructed. This weighted directed graph is defined by $\mathcal{V} = \mathcal{I}$ being the item catalog set and $\mathcal{E} = \{\varepsilon_{ij}\}$ the set of all sequential relations between items. There exists an edge ε_{ij} from node v_i to node v_j if item i_i is being directly followed by item i_j in a session. Each edge ε_{ij} is assigned a weight w_{ij} defined by the frequency of consecutive appearances of both items across all sessions. This global item base graph is by nature sparse since items are usually connected to a very small subset of other items based on the context of a session.

4 PROPOSED METHOD

In this section, we present the proposed **Shortest-Path Relations (SPARE)** global item graph and the proposed supervised contrastive learning approach for efficient session-based recommendation based on the SPARE graph. Figure 2 presents an overview of the components in SPARE. First, the global base item graph is enriched by shortest-path connections in the graph construction phase. The resulting graph is input to the recommendation component. Particularly, to our graph convolutional layer leading to learned session representations enhanced by the supervised contrastive learning task for SBR. Each component will be described in detail in the following.

4.1 Sparse and Shortest-Path Aware Item Graph

Most graph-based models in SBR using global item graphs rely on \mathcal{G} as their workhorse which by design tends to be noisy and only contains sequential relations of items. Most existing models based on GNNs for SBR cannot capture long-range dependencies (items that are multiple hops apart), since they are limited by the receptive field of each node per layer (1-hop neighbors). Stacking multiple GNN layers enables them to capture multi-hop relations, but introduces the problem of over-smoothing (node representations converge to the same value) if the number of layers is larger than three [2, 14]. However, in real-world datasets, it is very common that sessions contain more than three item interactions; yet, items separated over longer distances hold valuable information (cf. also the dataset statistics presented in Table 1). To solve this issue, we introduce the concept of finding shortest paths in the global item graph to insert suitable shortcut connections between items and circumvent the problem of over-smoothing.

There exist many efficient algorithms to find the shortest paths between two nodes in a given graph. In this work, we rely on the widely used Dijkstra algorithm using Fibonacci Heaps [4] due to its low computational cost. We transform each edge weight to its inverse weight by subtracting its weight from the maximal weight of all edges to get the corresponding cost c_{ij} to get from node v_i to node v_j . Then, for each node in the global item graph \mathcal{G} , the shortest path to every other node is computed based on the minimal cost of the sum of edge costs in the path. The receptive field of each node and the sparsity of the graph is controlled via the μ limit parameter. Choosing μ to be in an acceptable range serves as a threshold value to filter out relations not being sufficiently supported in the graph, tackling the problem of noisy sequences introduced in the training data which can mislead the model as

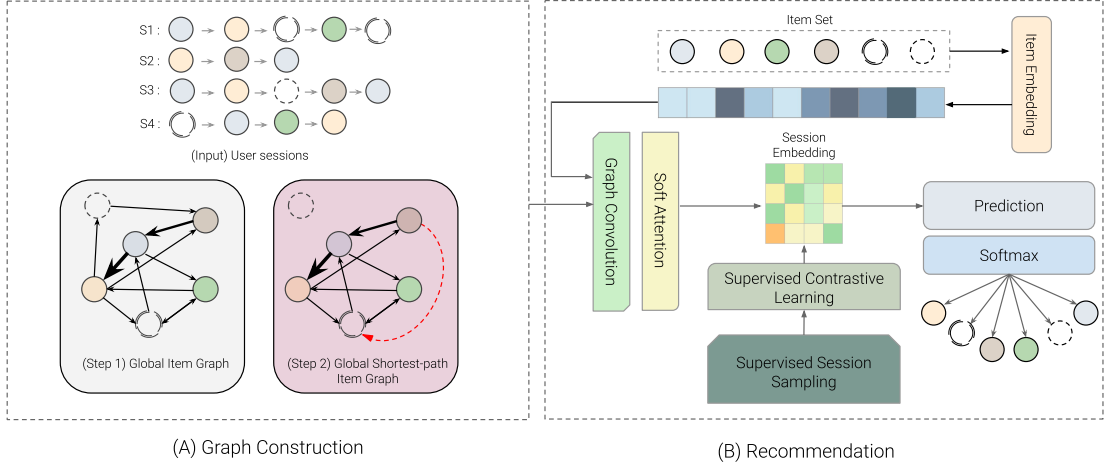


Figure 2: An overview of the global item graph construction and the pipeline of the proposed SPARE model.

shown in [7]. The edge costs \hat{c}_{ij} found through the shortest-path search and the final edge weights \hat{w}_{ij} in the resulting graph $\hat{\mathcal{G}}$ are defined as:

$$\delta_{ij} = \sum_{i=1}^{n-1} c_{i,i+1} \quad (1)$$

$$\hat{c}_{ij} = \begin{cases} \delta_{ij}, & \text{if } \delta_{ij} \leq \mu \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

$$\hat{w}_{ij} = \max(\hat{\mathbf{C}}) - \hat{c}_{ij}, \quad (3)$$

where the sum of individual edge costs δ_{ij} is minimized by path $P = \{v_i, v_{i+1}, \dots, v_j\}$ with length n over all possible nodes and $\hat{\mathbf{C}} \in \mathbb{R}^{N \times N}$ is the final cost matrix where each entry \hat{c}_{ij} corresponds to the minimum cost going from node v_i to node v_j . Additionally, with this approach, we are able to include non-direct relations from the original graph \mathcal{G} as shortcut connections with an adapted weight based on the hop distance. We hypothesize that these weighted shortcut connections imitate the n -hop neighbor information aggregation of standard GNNs with multiple layers, explicitly modeling item-item importance.

Compared to [2] which introduces a local, unweighted graph representation per session and therefore, also includes misleading item connections, our approach is able to filter out noisy item-item relations globally and models the importance of items effectively via corresponding edge weights.

4.2 Path-based Session Graph Encoder

The proposed shortest-path-aware global item graph now contains reliable pairwise item transitions from all sessions. We use a simple graph convolution to encode connections in the graph:

$$\mathbf{H} = \hat{\mathbf{D}}^{-\frac{1}{2}} \hat{\mathbf{A}} \mathbf{X} \hat{\mathbf{D}}^{-\frac{1}{2}}, \quad (4)$$

with $\hat{\mathbf{A}} = \mathbf{A} + \mathbf{I}$, where \mathbf{A} denotes the adjacency matrix $\mathbf{A} \in \mathbb{R}^{N \times N}$, \mathbf{I} the identity matrix and $\mathbf{X} \in \mathbb{R}^{N \times d}$ are the initial item embeddings. We symmetrically normalize the adjacency matrix $\hat{\mathbf{A}}$ by its degree matrix $\hat{\mathbf{D}}$. As shown in [31, 34], applying a non-linear activation

function is not essential for recommender systems and is therefore neglected in this convolutional operation.

In contrast to previous approaches [7, 30], our model does not make use of an attention mechanism to learn the importance of different neighbors but directly adopts the edge weights to quantify the importance of neighboring nodes. We argue that this non-parametric data-driven design more efficiently makes use of the shortest-path adjacency matrix, where each item-item connection already has a corresponding weight, reflecting the importance based on sequences in the data. Since our global item graph also contains shortcut connections to nodes that are multiple hops away, our approach only requires a single convolutional layer (in contrast to other methods that require multiple layers to increase the size of the receptive field per node). We investigate the impact of this design on efficiency in Section 5.6.

After performing the graph convolutional operation we obtain the global item graph representations for each item in a session s , e. g., $\mathbf{H}_s = [\mathbf{h}_{v_1^s}, \mathbf{h}_{v_2^s}, \dots, \mathbf{h}_{v_l^s}]$.

Following [7, 30, 34], we model the sequentiality in sessions via reversed position embeddings. Due to the fact that sessions are of different lengths, reversed position embeddings are able to capture the item importance based on the position in the session more effectively. The learnable position embedding matrix $\mathbf{P} = [p_1, p_2, p_3, \dots, p_l]$, where l is the length of the current session and p_i represents the embedding vector for position i , is integrated into the item representation via concatenation and non-linear transformation:

$$\mathbf{h}'_i = \tanh\left(\mathbf{W}_1 \left[\mathbf{h}_{v_i^s} \parallel p_{l-i+1}\right] + \mathbf{b}_1\right), \quad (5)$$

where $\mathbf{W}_1 \in \mathbb{R}^{d \times 2d}$ and $\mathbf{b}_1 \in \mathbb{R}^d$ are learnable parameters.

Session embeddings are computed by aggregating the item representations contained in the session. To further refine the session embeddings, a soft attention mechanism is usually applied in graph-based SBR models to prioritize different items in the session [30, 34]. By using this technique, attention weights are obtained as follows:

$$\alpha_i = \mathbf{q}^\top \sigma(\mathbf{W}_2 \mathbf{h}'_i + \mathbf{W}_3 \mathbf{h}_s + \mathbf{b}_2), \quad (6)$$

where $\mathbf{W}_2, \mathbf{W}_3 \in \mathbb{R}^{d \times d}$ and $\mathbf{q}, \mathbf{b}_2 \in \mathbb{R}^d$ are trainable parameters. The average of the session's item representations is denoted by \mathbf{h}_s . The final session representation is obtained via linear combination:

$$\mathbf{z} = \sum_{i=1}^l \alpha_i \mathbf{h}_{\sigma_i^s} \quad (7)$$

4.3 Supervised Contrastive Learning

Previous works employing self-supervised learning for SBR [34, 35] use different views of a single session as ground truth (positive) supervision signals and views from other sessions in the mini-batch as negative. In this scenario, InfoNCE [28] has proven to be a successful learning objective [34, 35]. In our approach, we explicitly mine data-driven positive and hard negative item samples from all training sessions. The selection of hard negative item samples is crucial to truly contribute to the gradient of the optimization.

For mining data-driven item samples we define positive sessions as sessions in the training data with the same target item as the input session. Based on the assumption that in session-based scenarios the last-clicked item in a session is most important to the target item, the last items in each of the positive sessions and the target item of the input session are seen as positive item samples. To ensure the same amount of positive samples per session in a batch, k positive sessions are randomly sampled from all available positive sessions per input session s resulting in $c_k^{s^+}$.

To find hard negative items, all sessions containing one or more items from the input session, excluding sessions with the same target item, are sampled. These negative candidate sessions are refined by borrowing a metric from the NLP domain: To our best knowledge, we are the first to use the BLEU score [20] for session similarity computation. In contrast to nearest-neighbor methods for SBR which rely mainly on set-based similarity measures [11, 17], the BLEU score is easily applicable in sequential scenarios. It relies on a modified precision score p_n for n -grams up to length N which we adopt to the setting of SBR: We count the number of matching n -grams of items between reference sessions (input and positive) and each of the negative session candidates. Then the candidate counts are summed up and normalized. With this modification, repeated item appearances are penalized, allowing for more informative negative session candidates.

BLEU essentially computes the geometric average of the n -grams precision and additionally adds a brevity penalty (BP):

$$BP = \begin{cases} 1 & \text{if } l_n > l_p \\ e^{(1-l_p/l_n)} & \text{if } l_n \leq l_p, \end{cases} \quad (8)$$

where l_n is the session length (number of interacted items) of the negative candidate and l_p is the session length of the input or the positive sample session closer to l_n . The BP favors sessions with the exact same length as the reference sessions and prevents too short/long sessions from being selected as a hard negative session sample. Given this brevity penalty BP, the BLEU score is computed as follows:

$$BLEU = BP \cdot \exp \left(\sum_{n=1}^N w_n \log \rho_n \right), \quad (9)$$

where w_n are positive, uniform weights (e. g., $1/N$) to compute the geometric mean of different n -gram sizes and ρ_n are the n -grams

precision scores. We use the top- k sessions with the highest BLEU score (denoted as S_{BLEU}^-) as hard negative sessions and use their last-clicked items and target items as negative item samples $c_k^{s^-}$:

$$c_k^{s^-} = \text{top-}k(S_{BLEU}^-). \quad (10)$$

Following InfoNCE [28, 34] to maximize the agreement between the representations of the last-clicked items and the target items in combination with the session context, the learning objective is defined as follows:

$$\mathcal{L}_{SCL} = -\log \frac{\sum_{i \in c_k^{s^+}} \psi(\mathbf{h}_s^{last}, \mathbf{z}_s, \mathbf{h}^i)}{\sum_{i \in c_k^{s^+}} \psi(\mathbf{h}_s^{last}, \mathbf{z}_s, \mathbf{h}^i) + \sum_{j \in c_k^{s^-}} \psi(\mathbf{h}_s^{last}, \mathbf{z}_s, \mathbf{h}^j)}, \quad (11)$$

where \mathbf{h}_s^{last} is the graph representation of the last-clicked item of the given input session s and $\psi(x_1, x_2, x_3)$ is defined as $\exp(f_D(x_1 + x_2, x_2 + x_3))$ with temperature parameter τ to control the effect of discrimination. The discriminator function $f_D(\cdot)$ takes two vectors as input and scores the agreement between them. In our case, we implemented the cosine operation as discriminator. This contrastive learning approach refines the representations of the last-clicked items and the target item so that the model is able to distinguish between positive sessions and similar, but different target item sessions more effectively. Since this self-supervised loss incorporates target information from the training data to contrast positive and negative samples, this learning approach can be regarded as supervised contrastive learning.

4.4 Prediction and Model Optimization

Based on the learned item and session representations, the final score for each candidate item $v_i \in \mathcal{V}$ to be recommended for a session is computed by the dot product of the session representation and the global item graph representations. We use a weighted normalization [6, 42] which has been shown to improve the training process stability and sensitivity to hyper-parameters:

$$\hat{\mathbf{z}} = w_z L_2 Norm(\mathbf{z}), \hat{\mathbf{h}}_i = L_2 Norm(\mathbf{h}_i) \quad (12)$$

$$y_i = \hat{\mathbf{z}}^T \hat{\mathbf{h}}_i, \quad (13)$$

where w_z is the normalized weight, \mathbf{z} corresponds to the final session representation and \mathbf{h}_i is the computed global item graph embedding of item i . $L_2 Norm$ denotes the L_2 normalization function.

The final prediction probabilities \hat{y}_i are computed by applying the softmax function to the score of each candidate item:

$$\hat{y}_i = \frac{\exp(y_i)}{\sum_{v_j \in \mathcal{V}} \exp(y_j)}. \quad (14)$$

As a loss function to be minimized, the cross-entropy of the prediction results \hat{y} is used:

$$\mathcal{L}_{CE}(y, \hat{y}) = - \sum_i^{|V|} (y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)) + \lambda \|\Theta\|_2^2, \quad (15)$$

where y denotes the one-hot encoding vector of the ground truth item. Additionally, λ is a hyper-parameter to control the L_2 regularization, given Θ as the model parameters.

For the final loss, we combine the recommendation task with the supervised contrastive learning task, where the total loss is given

as:

$$\mathcal{L} = \mathcal{L}_{CE} + \beta \mathcal{L}_{SCL}, \quad (16)$$

where β is a hyper-parameter to control the magnitude of the contrastive learning. This loss is then jointly optimized during training. The whole training procedure of the proposed SPARE model is summarized in Algorithm 1.

Algorithm 1: Training procedure of SPARE.

Input : Training sessions S , item embeddings X

Output : Recommendation list per session

```

1 Construct global item graph  $\mathcal{G}$ ;
2 Compute shortest-path global item graph  $\hat{\mathcal{G}}$  given threshold
  parameter  $\mu$ ;
3 foreach epoch do
4   foreach batch do
5     Learn global item graph representations through
      Eq. (4);
6     foreach session  $s$  do
7       Compute session representation following
          Eq. (5) to Eq. (7);
8       Obtain positive and negative item samples via
          Eq. (8) to Eq. (10);
9       Compute supervised contrastive learning loss
          with Eq. (11);
10    end
11    Jointly optimize the supervised and self-supervised
      objectives in Eq. (16);
12  end
13 end

```

5 EXPERIMENTS AND RESULTS

In this section, we provide the setup and results of extensive experiments to evaluate our proposed SPARE model, where we compare SPARE to various state-of-the-art models in SBR. Given our overall goal of investigating the impact of the proposed graph edge modifications and supervised contrastive learning approach and investigating whether contrastive learning-based approaches indeed require complex graph structures, we establish the following research questions:

- **RQ1:** How does SPARE perform compared to other state-of-the-art SBR methods on different datasets?
- **RQ2:** How do different components in SPARE contribute to the performance?
- **RQ3:** How sensitive is SPARE to different settings of hyper-parameters (e. g., μ , w_z , k)?
- **RQ4:** How does SPARE perform under different similarity measures for computing the contrastive samples?
- **RQ5:** What is the impact of SPARE in terms of efficiency compared to other graph-based models?

5.1 Experimental Setup

5.1.1 Datasets and Preprocessing. To evaluate the performance of our approach, we conduct experiments on three representative and

widely used datasets from the e-commerce and music domains. The *Tmall*² dataset was published as part of the IJCAI-15 competition and contains user logs of an online shopping platform. *RetailRocket*³ is a dataset on user browsing activities within six months and was released by an e-commerce company as part of a Kaggle contest. Lastly, the *Last.fm*⁴ dataset includes music listening histories in which items are artists of the listened songs.

Table 1: Dataset statistics: Number of sessions, items and average session length.

Dataset	# Train	# Test	# Items	Avg. Length
Tmall	351,268	25,898	40,728	6.69
RetailRocket	433,643	15,132	36,968	5.43
Last.fm	2,837,330	672,833	38,615	11.78

We follow the preprocessing steps used in [30, 33] for the three datasets. To be more specific, sessions with length 1 and items appearing less than 5 times are filtered out across all datasets. The most recent data (e. g., last week) is set as test data and the remaining data serves as training data. Additionally, we augment a session $S = [i_1, i_2, \dots, i_n]$ with a sequence splitting method which leads to multiple labeled sequences $([i_1], i_2), ([i_1, i_2], i_3), \dots, ([i_1, i_2, \dots, i_{n-1}], i_n)$, where the last item in each set is the corresponding label (or target item) of the sequence. Table 1 provides an overview of the datasets after preprocessing.

5.1.2 Evaluation Metrics. Following previous works [30, 34, 43], we adopt $P@k$ (Precision) and $MRR@k$ (Mean Reciprocal Rank) to evaluate the quality of the recommendation results. For each metric, k is set to 20.

5.1.3 Baseline Methods. We compare SPARE with the following representative baseline and state-of-the-art methods for session-based recommendation:

- **Item-KNN** [24]: recommends items based on the similarity between items of the current session and the items of other user sessions.
- **FPMC** [23]: captures sequential effects and user preferences with matrix factorization and first-order Markov chains. To make it applicable for session-based recommendation, user latent representations are not used when computing recommendation scores.
- **GRU4Rec** [9]: a RNN-based method that applies Gated Recurrent Unit (GRU) in combination with a ranking-based loss function to model user interaction sequences.
- **NARM** [15]: extends GRU4Rec with an attention mechanism to capture the user’s main purpose efficiently.
- **STAMP** [16]: replaces all RNN encoders in previous works by attention layers and relies on the self-attention mechanism of the last item to capture short-term interests.
- **SR-GNN** [33]: employs a gated GCN layer to obtain item embeddings. Similarly to STAMP, self-attention of the last item is used to compute the session embeddings.

²<https://tianchi.aliyun.com/dataset/dataDetail?dataId=42>

³<https://www.kaggle.com/retailrocket/e-commerce-dataset>

⁴<http://ocelma.net/MusicRecommendationDataset/lastfm-1K.html>

- **FGNN** [21]: converts sessions into directed graphs and uses a graph attention layer to learn item representations.
- **GCE-GNN** [30]: constructs a session-level and a global co-occurrence graph to capture local and global information of items.
- **S^2 -DHCN** [35]: captures beyond pairwise-relations with hypergraph modeling. It additionally integrates self-supervised learning into the training of the GNN.
- **COTREC** [34]: employs a self-supervised co-training approach. GCN encoders produce two views of a session on an item and session level for the contrastive learning task.
- **MGIR** [7]: models incompatible relations in a graph in addition to sequential and global co-occurrence.

5.1.4 Implementation Details. Along the lines of previous works [7, 30, 34, 35], the embedding size is set to 100 and the parameters are initialized with a Gaussian distribution. For optimization, we use Adam with a learning rate of 0.001 and a batch size of 100. The L_2 regularization is set to 10^{-5} for all three datasets. Additionally, we apply a learning rate decay strategy, where the learning rate is decreased by a factor of 10 every 3 epochs. The maximum session length is set to 50 for all three datasets. The weighted normalization hyper-parameter w_z , the weight of the self-supervised loss β , and the number of samples k are searched in the ranges of $\{10, 11, 12, \dots, 20\}$, $\{0.001, 0.005, \dots, 0.5\}$ and $\{1, 2, 4, 8, 16, 32\}$, respectively. Since we use the same evaluation setup and datasets as the baseline methods, we adopt their best parameter setup and directly report their results if available. Our implementation is based on PyTorch 1.10.2 and Python 3.8.12. All experiments are performed on a workstation with an AMD Ryzen 2950X, a GeForce RTX 2070, and 256 GB main memory. We publish the code and the pre-processed datasets on GitHub⁵.

5.2 Overall Performance (RQ1)

To demonstrate the recommendation performance of our proposed method, we compare SPARE with several other state-of-the-art and baseline SBR methods. The overall performance on the three datasets is shown in Table 2. From this table, we can draw distinct conclusions which we will elaborate in the following.

Conventional methods like FPMC are outperformed by RNN-based methods (e. g., GRU4Rec, NARM, STAMP), which indicates the importance of modeling the sequential information of sessions. NARM and STAMP additionally incorporate an attention mechanism to learn item importance and show a large performance improvement compared to GRU4Rec. Since GRU4Rec only considers sequential behavior, it is not able to capture shifts in user preference.

Graph-based models easily outperform the aforementioned RNN-based methods and display the advantages of using graphs to model sessions. GCE-GNN and MGIR include inter- and intra-session information and are able to achieve a substantial performance boost compared to SR-GNN, demonstrating the importance of capturing different levels of information. S^2 -DHCN and COTREC both have a two-branch architecture to make use of a contrastive learning framework and are easily competitive. Specifically, COTREC shows

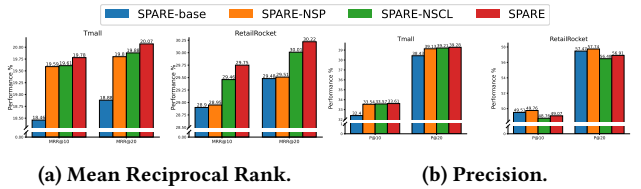


Figure 3: Ablation study of components in SPARE.

superior performance to most of the graph-based models indicating the advantage of using self-supervised learning.

Our proposed method SPARE significantly surpasses all current state-of-the-art baseline methods on the three datasets on all provided metrics. Particularly, our model improves the performance significantly by 7.88% on Precision@20 and 11.25% on MRR@20 for the *Tmall* dataset, showing the importance of dropping unreliable relations from e-commerce data. Additionally, we observe that COTREC and MGIR have competitive performance on the *RetailRocket* and *Last.fm* datasets in terms of MRR. However, both of these methods introduce a complex architecture and have a higher running time compared to SPARE, limiting their practical applicability. We provide more details about the efficiency and running time of all current state-of-the-art models in Section 5.6.

5.3 Ablation Study (RQ2)

To investigate the impact of each component in our approach, including the shortest-path aware item graph (Section 4.1) and the supervised contrastive learning (Section 4.3), we present different variants of SPARE in this section: **SPARE-base**, **SPARE-NSP**, and **SPARE-NSCL**. In **SPARE-base** we omit the shortest-path search as well as the supervised contrastive learning. For **SPARE-NSP** only the shortest-path search on the global item graph is removed and in **SPARE-NSCL** only the supervised contrastive learning component is discarded. These models will be evaluated against the full SPARE model on the *Tmall* and the *RetailRocket* dataset. Due to space restrictions, we omit evaluation on the *Last.fm* dataset. As previous studies [34, 35] already have shown that the reversed position embeddings and the soft-attention mechanism are important components; therefore, we discard these variants for our study.

In Figure 3a and Figure 3b we display the performances of all models in terms of precision and MRR, both with cutoffs set to 10 and 20. It can be observed that each of our introduced components consistently contributes to the performance of the model. On the *Tmall* dataset both, the shortest-path search and the supervised contrastive learning, are able to improve the performance significantly if applied separately. Still, the integration of both components leads to the best-performing models on all metrics, showing that supervised contrastive learning complements the sparse, shortest-path graph representation learning. The evaluation on the *RetailRocket* dataset shows a slightly different result. Surprisingly SPARE-base is able to outperform SPARE in terms of precision by a slight margin but heavily lacks in MRR performance. We ascribe this to the edge sparsification due to the shortest-path search which removes noisy items and increases the ranking of important ones, which has a positive impact on the MRR score.

⁵<https://github.com/dbis-uibk/SPARE>

Table 2: Model performance on all three datasets for baselines, state-of-the-art models (SotA), and our proposed SPARE approach. All improvements of SPARE compared to the second best performing model are significant (paired t -test, $p < .01$). The best results are in boldface and the second-best results are underlined.

Method	Tmall				RetailRocket				Last.fm				
	P		MRR		P		MRR		P		MRR		
	@10	@20	@10	@20	@10	@20	@10	@20	@10	@20	@10	@20	
Baselines	Item-KNN	6.65	9.15	3.11	3.31	22.48	24.00	10.43	10.70	9.77	14.84	4.48	4.85
	FPMC	13.10	16.06	7.12	7.32	25.99	32.37	13.38	13.82	11.67	17.68	4.58	4.99
	GRU4Rec	9.47	10.93	5.78	5.89	38.35	44.01	23.27	23.67	12.86	17.90	5.29	5.39
	NARM	19.17	23.30	10.42	10.70	42.07	50.22	24.88	24.59	15.03	21.83	6.71	7.59
	STAMP	22.63	26.47	13.12	13.36	42.95	50.96	24.61	25.17	15.65	22.01	7.50	7.98
	SR-GNN	23.41	27.57	13.45	13.72	43.21	50.32	26.07	26.57	16.90	22.33	7.85	8.23
	FGNN	20.67	25.24	10.07	10.39	41.78	50.20	24.59	25.89	15.90	22.20	7.28	8.02
SotA	GCE-GNN	28.01	33.42	15.08	15.42	47.90	55.59	28.04	28.58	<u>18.28</u>	24.39	8.32	8.63
	S ² -DHCN	26.22	31.42	14.60	15.05	46.15	53.66	26.85	27.30	15.37	22.06	6.95	7.57
	COTREC	30.62	36.35	<u>17.65</u>	<u>18.04</u>	48.61	56.17	<u>29.46</u>	<u>29.97</u>	16.89	23.34	7.81	8.24
	MGIR	<u>30.65</u>	<u>36.41</u>	17.06	17.42	<u>48.87</u>	<u>56.62</u>	29.35	29.84	17.99	<u>24.72</u>	<u>8.37</u>	<u>8.82</u>
	SPARE	33.61	39.28	19.78	20.07	49.07	56.91	29.75	30.22	19.66	27.00	8.41	8.91
Improv. (%)	9.66	7.88	12.07	11.25	0.41	0.51	0.98	0.83	7.55	9.22	0.48	0.91	
p -value	$1e^{-9}$	$7e^{-11}$	$7e^{-10}$	$1e^{-10}$	$9e^{-3}$	$2e^{-3}$	$6e^{-3}$	$6e^{-3}$	$4e^{-10}$	$4e^{-10}$	$3e^{-3}$	$2e^{-4}$	

5.4 Impact of Hyper-Parameters (RQ3)

Furthermore, we investigate the impact of the three key hyper-parameters β (weight of the self-supervised loss), w_z (weighted L_2 normalization), and k (number of samples in SCL). The weight parameter β controls the magnitude of the self-supervised learning task and achieves the best performance if set to 0.2 and 0.15 for *Tmall* and *RetailRocket* as shown in Figure 4a. Additionally, we explore the influence of w_z , where setting it to 1 is equivalent to employing cosine similarity and delivers the poorest results. As w_z increases we observe a gradual improvement on both datasets until it over saturates which can be seen in Figure 4b. This demonstrates the importance of this scaling factor to stabilize the training, since target items with higher L_2 Norm are more prone to be predicted. In Figure 4c different settings for k corresponding to the number of positive and negative samples used in the supervised contrastive loss are displayed. It can be observed that on the *Tmall* dataset, a smaller number is sufficient, whereas the *RetailRocket* dataset benefits from a higher number of samples.

Furthermore, we investigate the impact of the hyper-parameter μ (cost limit for shortest paths) on the sparsity of the global item graph and the model performance. The sparsity value per cost limit (or rather, the increase of sparsity) is defined as follows:

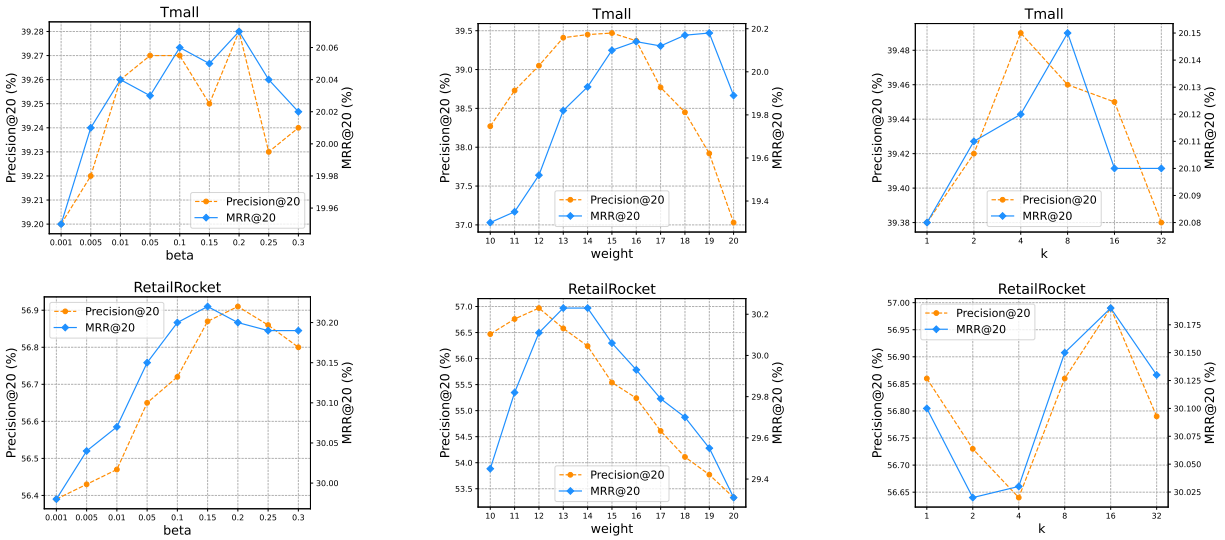
$$\text{Sparsity} = 1 - \frac{\# \text{ edges}}{\# \text{ original edges}}, \quad (17)$$

which defines the ratio of increase or decrease of sparsity compared to the original global item graph and allows us to directly investigate the relationship between higher sparsity (more reduced noise) and prediction performance. In Figure 5 the sparsity and the MRR@20 score per dataset are displayed. Higher sparsity of the global item graph and therefore possibly dropping unreliable relations for *Tmall* and *RetailRocket* has a considerable impact on the performance as shown in Figure 5. It is worth noting, that for *Tmall*

and *RetailRocket* the maximum edge cost in the original global item graph is 197 and 331 correspondingly. For *Last.fm*, we observe a different behavior: Instead of filtering out non-frequent relations by setting μ below the maximum edge cost, we reach better performance by using a limit that is the same as the maximum edge cost (1526) and therefore introducing a slightly denser global item graph through the addition of shortest-path shortcut connections. We ascribe this to the inherent characteristics of music datasets compared to other domains to be more prone to the popularity bias of songs and benefit more from dense user data for personalized recommendations [8]. Also, this shows the data-driven versatility of our proposed method, being able to adapt to different data sparsity conditions. This special behavior of SPARE on Last.fm is analyzed in more detail in Section 5.6, where we show that this dataset our approach also benefits from a higher number of layers in the GNN.

5.5 Impact of Supervised Contrastive Learning (RQ4)

In Section 4.3 we introduced BLEU as a measure for session similarity. To justify this design choice of measure and display the impact of the supervised contrastive learning component in our model we compare different session similarity measures. Nearest-neighbor-based methods usually rely on session similarity measures to filter out relevant sessions for the computation of potential next-item candidates [5, 11, 17]. Following their intuition of defining sessions as a set of items we include the following set-based similarity measures: Cosine-similarity (for sets) and Jaccard-index. Additionally, we also include the Damerau-Levenshtein distance, which is usually used to measure the edit distance between two sequences, in the comparison. As shown in Table 4 most of the different session similarity measures are able to improve the performance of the base model without supervised contrastive learning. Interestingly,



(a) Weight parameter β for self-supervised loss. (b) Weight parameter w_z of L_2 normalization. (c) Number of samples parameter k for computing the contrastive loss.

Figure 4: Impact of hyper-parameters in SPARE.

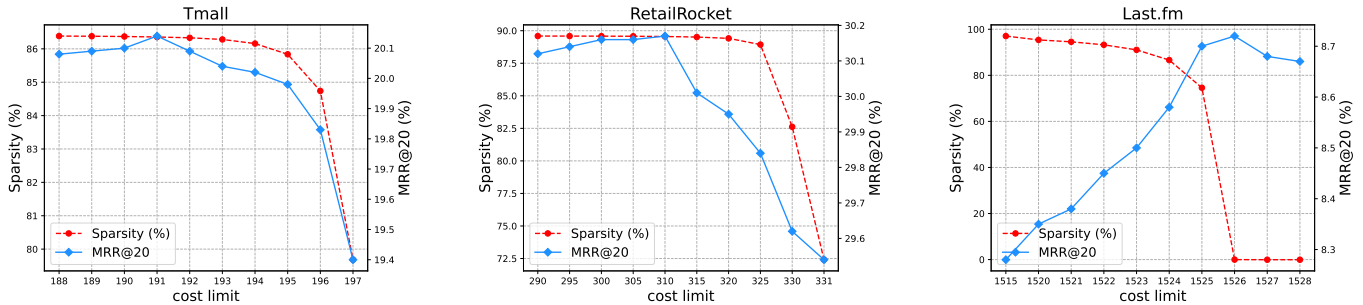


Figure 5: Different cost limits μ for shortest-path search affect sparsity of the original global item graph and have an impact on the corresponding MRR@20 performance. Sparsity is defined as the fraction (given in %) of additional pruned edges compared to the number of edges in the original item graph.

the set-based measures perform better than the more sequence-oriented Damerau-Levenshtein distance. Nevertheless, BLEU with its n-gram overlap-dependent measurement outperforms all other session similarity measures and shows the importance of considering the sequential features of sessions. In addition, the positive impact on both performance metrics through supervised contrastive learning can be seen. On the *RetailRocket* dataset the incorporation of the supervised contrastive learning loss leads to an increase in performance of 0.76% in Precision@20 and 0.69% in MRR@20.

5.6 Impact of Number of Layers and Running Times (RQ5)

Here we discuss the assumption that SPARE through its shortest-path shortcut connections inherently introduces a large receptive

Table 3: Comparison of different distance measures for session similarity computation.

Similarity	Tmall		RetailRocket	
	P@20	MRR@20	P@20	MRR@20
SPARE-NSCL	39.21	19.88	56.48	30.01
Cosine	39.12	19.96	56.69	30.05
Jaccard	<u>39.23</u>	<u>20.02</u>	<u>56.79</u>	<u>30.09</u>
Levenshtein	39.08	19.95	56.74	30.03
BLEU	39.28	20.07	56.91	30.22

field per node. Consequently, SPARE does not have to rely on multiple layers to aggregate node information from neighbors multiple

hops away. To confirm this intuition we compare SPARE-NSCL (our model without the supervised contrastive learning component) and COTREC (the model showing the second-best overall performance) with a different number of layer settings, since they use a similar graph convolutional operation. To combine learned node embeddings over multiple layers, we follow the strategy of COTREC, where item embeddings are averaged over L layers to get the final embeddings:

$$X^{(L)} = \frac{1}{L+1} \sum_{l=0}^L X^l. \quad (18)$$

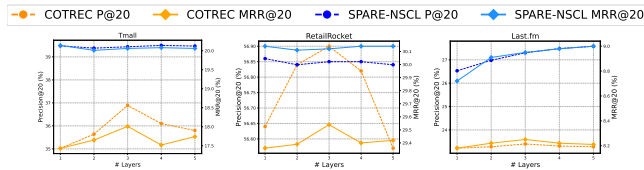


Figure 6: Comparison of Precision@20 and MRR@20 of COTREC [34] versus SPARE-NSCL dependent on different number of layers.

Figure 6 exhibits the results of the experiments on all three datasets. We can observe that COTREC heavily relies on learning the item representations in the graph by using information from n -hop neighbors and constantly reaches its best performance in the 3-layer setting, but clearly over-smooths with a higher number of layers. In contrast, our proposed method SPARE has stable performance across all settings of layers, indicating that multi-hop connections are effectively captured by shortest-path shortcut connections. Especially, on the *Last.fm* dataset our model is able to constantly improve its performance with a higher number of layers and is not affected by the over-smoothing issue.

Our model introduces a simple, yet effective architecture and mostly has to rely on only a single GNN layer (except for *Last.fm*) to compute the global item embeddings. To demonstrate the practicability of our approach, we compare the running times as a proxy for efficiency with the state-of-the-art graph-based methods for SBR (based on Table 2) on all three datasets. Similar to previous approaches [7] we define the graph construction as external pre-processing step and do not include this step in the running time. Although the positive and negative session sampling is a CPU-bound operation and can easily be parallelized, we include them in the measurement for a fair comparison. The running times per model are averaged over 5 epochs.

As shown in Table 4 our approach has the fastest running time on the *Tmall* as well as the *RetailRocket* dataset. To be more specific, SPARE is able to reach a speed-up factor of 1.84 \times compared to the fastest graph-based method (GCE-GNN) on *RetailRocket*. If compared to the second-best performing model in terms of P@20 and MRR@20 on *Last.fm* (MGIR), as shown in Table 2, SPARE is faster by 1.56 \times in training. This clearly indicates that our approach learns global item representations more efficiently than every other state-of-the-art graph-based method.

Table 4: Comparison of training running times per epoch per graph-based SotA method (in seconds).

Method	Tmall	RetailRocket	Last.fm
GCE-GNN	116	1,154	832
S ² -DHCN	664	1,313	14,453
COTREC	1,170	1,233	5,220
MGIR	448	1,344	2,408
SPARE	105	624	1,540

6 CONCLUSION

Session-based recommendation inherits many challenges including sparse session data, anonymous users, and current preference shifts. In this paper, we propose a novel session-based recommendation model which relies on a shortest-path search to filter out unreliable relations and to introduce shortcut connections to items multiple hops away for a dense graph representation. Moreover, we present a novel supervised contrastive learning method based on data-driven positive and negative item samples for SBR. To find hard negative samples we propose to use the BLEU metric to find similar sessions to the reference sessions. An extensive experimental evaluation comparing with different state-of-the-art models shows the effectiveness of our approach and its superiority over other baseline models.

In future work, we plan to use the denoised global item graphs to extract explainable recommendations. Furthermore, we aim to investigate the impact of supervised contrastive learning in combination with weighted L_2 normalization on improving popularity bias. Potentially, these techniques can be applied to a various number of other methods in an extension-like fashion.

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