Exploiting High-Order Interaction Relations to Explore User Intent (Student Abstract)

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Abstract

This paper studies the problem of exploring the user intent for session-based recommendations. Its challenges come from the uncertainty of user behavior and limited information. However, current endeavors cannot fully explore the mutual interactions among sessions and do not explicitly model the complex high-order relations among items. To circumvent these critical issues, we innovatively propose a HyperGraph Convolutional Contrastive framework (termed HGCC) that consists of two crucial tasks: 1) The session-based recommendation (SBR task) that aims to capture the beyond pair-wise relationships between items and sessions. 2) The self-supervised learning (SSL task) acted as the auxiliary task to boost the former task. By jointly optimizing the two tasks, the performance of the recommendation task achieves decent gains. Experiments on multiple real-world datasets demonstrate the superiority of the proposed approach over the state-of-the-art methods.

Introduction

Recommender systems (RS) are increasingly crucial as they generally provide personalized information in a growing volume of items on offer. However, in many real-world scenes, the user's historical interactions are not always available, e.g., with new or anonymous users. And only their ongoing click actions, namely sessions, are available (Xia et al. 2021). Thus, it is crucial to model limited behavior in short sessions and generate recommendations accordingly. In view of this, a question is raised: ***how to precisely infer the user's intent in short sessions for session-based recommendation (SBR)***? Graph neural networks (GNNs) (Wu et al. 2019; Zheng et al. 2022) have achieved great success in session-based recommendation owing to their powerful capability in modeling relational data, and also have shown prominent performance. While effective, a key limitation of these GNNs-based models is that they only exploit the simple pairwise relations and ignore the ubiquitous high-order relations among sessions (Yu et al. 2021). Consider the example to better illustrate, A apple can be viewed differently, i.e., as an option for fruits in session 1, or as part of the ingredients for fruit cake in session 2. In a sense, the meaning of an item (and what it reveals about user intent) could be inferred from contextual sessions, each containing a set of consecutive items showing up together within a session. Simple graphs cannot depict such set-like relations, e.g., the pairwise linkage between strawberries and apples is not enough to reveal that the user intends to buy various fruits. But such evidence could be inferred by analyzing the triadic relations among strawberries, apples, and pitaya as defined. Consequently, hypergraph is a proper model method to generalize the concept of graphs connecting more than two nodes, providing a natural way to model complex high-order relations among sessions. Additionally, the items sparsity issue is ubiquitous in various practical scenarios since most users only sporadically interact with a minimal number of items. Most graph-based models cannot perform well on short sessions due to the data sparsity phenomenon and skewed interaction distribution.

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Methodology

In this work, we present a HyperGraph Convolutional Contrastive framework, named HGCC, to address the above challenges. The proposed method consists of two critical tasks: one is the main task for the session-based recommendation (SBR), and the other is the self-supervised learning (SSL) task that acted as the auxiliary task to boost the former. The motivation of this work is to effectively capture the high-order relations in items and exploit these relations to explore user intent for improving recommendation performance. We now detail the proposed model as follows.

Hypergraph Convolutional Network for SBR Task The SBR task aims to exploit hypergraph convolutional layers to propagate high-order relations and complete recommendations accordingly. To capture the beyond pairwise relations in SBR, we adopt a hypergraph $\mathcal{G}_h = (\mathcal{V}, \mathcal{E}, \mathbf{W})$ to denote each session as a hyperedge, in which each hyperedge can connect any number of vertices. For a more rigorous description, we define each item $i_{s,m} \in \mathcal{V}$ and each hypergraph as $\epsilon = [i_{s,1}, i_{s,2}, \cdots, i_{s,k}, \cdots, i_{s,m}] \in \mathcal{E}$. After hypergraph construction, we further develop hypergraph layers to capture the item-level complex relations. Referring to the spectral hypergraph convolution proposed in (Feng et al. 2019), we can build the following formulation:

$$\mathbf{X}^{(l+1)} = ((1-\gamma_l)\mathbf{Q}\mathbf{X}^{(l)} + \gamma_l \mathbf{X}^{(0)})\Theta^{(l)}, \mathbf{Q} = \hat{\mathbf{D}}^{-1}\mathbf{H}\mathbf{W}\mathbf{B}^{-1}\mathbf{H}^T \tag{1}$$

where $\mathbf{X}^{(l)}$ represents the l-th layer's item embeddings. $\Theta^{(l)}$ is the learnable filter matrix. Denote that $\hat{\mathbf{D}}^{-1}$ and $\mathbf{B}^{-1}$ play a role of normalization. γ_l is a hyper-parameter, which is a pivotal point in preventing *over-smoothing*. Finally, we conduct the final recommendation generation.

Enhancing SBR with SSL Task Compared with other recommendation paradigms, SBR suffers more accessible from the problem of data sparsity due to the short-term interactions. Furthermore, although hypergraph modeling achieves significant performance, we consider that the inherent data sparsity issue might limit the benefits of hypergraph modeling, resulting in suboptimal recommendation performance. Inspired by the successful practices of SSL on graphs, which holds vast potential to tackle the data sparsity issue, we innovatively integrate SSL into the hypergraph network to enhance the recommendation performance. To this end, we innovatively propose a Hyperedge-to-Node Signal Strategy (HNSS) to integrate and model the enriched neighborhood. Concretely, HNSS constructs hyperedge-level and node-level contrastive objectives based on extended structural neighbors to enhance the supervised signal. For the hypergraph convolution, which has a two-stage performing *nodes-hyperedges-nodes* feature transformation. We can obtain hyperedges features in stage 1, while getting hypernode features in stage 2. In this way, we treat initial hyperedge (or hypernode) representations and their corresponding neighbors' representations as positive pairs for contrastive learning. Finally, we unify the SBR and SSL task into a joint learning framework and combine them to get the total loss function. It should be noted that, we jointly optimize the two throughout the training.

Experiments

To investigate the effectiveness of our model, we evaluate the performance of HGCC and compare it with the state-of-the-art methods, including **SR-GNN** (Wu et al. 2019),**FGNN** (Qiu et al. 2019), **GCE-GNN** (Wang et al. 2020), S^2**-DHCN** (Xia et al. 2021). We report the empirical results on three benchmark datasets: *Tmall*, *Nowplaying*, *Diginetica*, and all detailed information about datasets refer to (Wu et al. 2019). To keep the same setting as previous baselines, we adopt the widely used ranking based metric: P@K by following previous works (Wang et al. 2020; Qiu et al. 2019). Specifically, we mainly choose to use top-20 items to evaluate our models for session-based recommendation.

The preliminary results are shown in Table 1. Intuitively, we have the following observations: **1)** Overall, we can see that our proposed model consistently shows strong performance across all datasets, which ascertains our proposed method's effectiveness. Especially on the Tmall dataset, we note that existing baselines have already obtained high enough performance; Our approach still pushes that boundary forward. **2)** We notice that our method achieves more competitive results compared with graph-based baselines. Particularly, considering that S^2-DHCN and our method both have hypergraph architecture, we think that the improvements mainly derive from the different contrastive learning. We construct hyperedge-level and node-level contrastive objectives to focus on more fine-grained supervised signals. **3)** Compared with another strong baseline GCE-GNN, HGCC is competitive in performance and efficiency, showing the effectiveness of hypergraphs.

Methods	**Tmall**	**Nowplaying**	**Diginetica**
SR-GNN	27.57	18.87	50.73
FGNN	25.24	18.78	50.58
GCE-GNN	33.42	22.37	54.22
S^2-DHCN	31.42	23.51	53.66
Ours	**35.59**	**24.13**	**54.57**

Table 1: Performance comparisons of HGCC with the state-of-the-art methods (%)

Conclusions

In this paper, we present a hypergraph Contrastive Learning framework (HGCC) by modeling session-based data as a hypergraph for better inferring the user preference of the current session. Moreover, to further enhance the network, we innovatively integrate self-supervised into the network's training. Experiments demonstrate the superiority of the proposed model over the current advanced methods. Meanwhile, the research of hypergraph modeling for SBR remains in its infancy, and its application in graphs has potential development, which is worthy of further exploration.

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