

Towards Lightweight Cross-domain Sequential Recommendation via External Attention-enhanced Graph Convolution Network

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Abstract. Cross-domain Sequential Recommendation (CSR) is an emerging yet challenging task that depicts the evolution of behavior patterns for overlapped users by modeling their interactions from multiple domains. Existing studies on CSR mainly focus on using composite or in-depth structures that achieve significant improvement in accuracy but bring a huge burden to the model training. Moreover, to learn the user-specific sequence representations, existing works usually adopt the global relevance weighting strategy (e.g., self-attention mechanism), which has quadratic computational complexity. In this work, we introduce a lightweight external attention-enhanced GCN-based framework to solve the above challenges, namely LEA-GCN. Specifically, by only keeping the neighborhood aggregation component and using the Single-Layer Aggregating Protocol (SLAP), our lightweight GCN encoder performs more efficiently to capture the collaborative filtering signals of the items from both domains. To further alleviate the framework structure and aggregate the user-specific sequential pattern, we devise a novel dual-channel External Attention (EA) component, which calculates the correlation among all items via a lightweight linear structure. Extensive experiments are conducted on two real-world datasets, demonstrating that LEA-GCN requires a smaller volume and less training time without affecting the accuracy compared with several state-of-the-art methods.

Keywords: recommendation systems · cross-domain sequential recommendation · attention mechanism · graph neural network · collaborative filtering

1 Introduction

Sequential Recommendation (SR) aims to capture the user’s dynamic behavioral pattern from the interaction sequence that has attracted immense research attention and has wide applications in many domains, such as electronic commerce, online retrieval, and mobile services [17,21,36,1,6]. Though some SR methods

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have achieved great success in many popular tasks, they meet the challenge while characterizing user preferences from the sparse data or cold-start scenarios. Therefore, Cross-domain Sequential Recommendation (CSR) is gaining increasing research attention that mitigates the above problem by leveraging the side information from other domains [37]. The key idea of CSR is to recommend the next-item to the overlapped user whose historical interactions can observe in multiple domains during the same period.

Early Cross-domain Sequential Recommender systems (CSRs) incorporate a Recurrent Neural Network (RNN)-based structure [26,31] to capture the sequential dependencies from the hybrid sequence but fail to model the associations among cross-domain entities. Then, the attention-based methods, e.g., Chen et al. [2] and Li et al. [20], adopt dual-attention structures that attentively transfer the users' sequential preference between domains but have difficulty excavating structural patterns inside the sequential transitions. Recently proposed Graph Convolution Network (GCN)-based methods [37,10,12] for CSR tasks bridge two domains by the Cross-domain Sequential (CDS) graph and transfer the fine-grained domain knowledge by considering structural information. However, the volume and computational complexity of such graph-based methods are enormous, resulting in the low running efficiency of models, which hinders their deployment on generic devices with limited memory (e.g., GPUs).

To realize the memory-efficient lightweight recommender system, recent studies [4,23,28] predominantly focus on compressing the original collaborative filtering matrix to improve the recommendation efficiency. However, the dependency between the origin representations might be disturbed in the process of embedding transformation, and the user's interest migration in a period also can not be sufficiently modeled. Then, to explore the evolution and migration of users' preferences from a lightweight perspective, some researchers [21,27] shift their focus to transformer-based models. Nevertheless, the self-attention mechanism within the Transformer [32] has quadratic complexity that brings a heavy parameter scale. Similar problems also exist in CSRs, even worse, because they need to share information across two domains, which leads to a doubling of the parameter size. Hence, developing the lightweight CSRs is an ongoing trend, but accompanied by two significant challenges: 1) As mentioned earlier, the current CSRs begin to use complex and in-depth models such as graph convolution networks [37,10] to learn the primary preference for users, which brings a lot of burden for model training but contributes little to the node representation learning. 2) The global relevance weighting strategy (e.g., the Transformer-based methods) [12,21,27] may not be the optimal scheme to capture the sequential behavioral pattern, as it has enormous computational complexity and ignore the positional relations of the item from the dual-domain hybrid sequence.

In this work, we propose a novel Lightweight External Attention-enhanced Graph Convolution Network (LEA-GCN) to address the above challenges. Concretely, we first extract the positional information of each item in the original hybrid sequence to better capture the inter-domain behavior evolution of overlapped users. Then, we construct the Cross-domain Sequential (CDS) graph and

model the complicated inner-domain associations among users and items, such as the user-item interactions and the sequential orders of items in each domain. After that, we take two steps to simplify the GCN encoder: 1) By removing the feature transformation matrices and the non-linear activation function (i.e., like the LightGCN [15] does on NGCF [33]), we only keep the simple weighted sum aggregator in GCN to capture the collaborative filtering signals from both domains. 2) Then, we adopt the Single-Layer Aggregating Protocol (SLAP), which reduces the complexity of layer propagation and simultaneously avoids the interference caused by high-order connectivity in the CDS graph. To address the second challenge, we adopt a newly proposed technology, named External Attention (EA), which has attracted extensive research attention in the field of Computer Vision (CV) [7,13]. EA uses two external memory units to optimize the computational complexity of the traditional self-attention mechanism, which surprisingly matches our lightweight purpose. However, the external storage units are independent of the input features, which leads to the deficiency in modeling items' collaborative filtering signal. To avoid that, we devise a dual-channel EA-based sequence encoder to learn the user-specific sequential pattern. It simultaneously calculates the correlation between items and the external memory units by a multi-head structure and the relation score of each item in the sequence via a Multi-Layer Perceptron (MLP). The main contributions of this work can be summarized as follows:

- After pointing out the defects of existing CSR methods in parameter scale and training efficiency, we propose a lightweight GCN-based scheme, namely LEA-GCN, for the memory-efficient cross-domain sequential recommendation.
- We improve the GCN by simplifying the network structure and using the single-layer aggregation protocols. Then, we devise a dual-channel external attention to model the user's sequential preference in a lightweight perspective.
- Extensive experiments on two real-world datasets demonstrate that LEA-GCN performs better and requires fewer parameters than several state-of-the-art baselines.

2 Related Work

2.1 Sequential Recommendation

As Sequential Recommender Systems (SRs) propose to model the user-item interaction sequence [21], it has been proven effective in capturing the evolution of user behavioral patterns [17]. Existing studies on SR can categorize into traditional methods and deep-learning-based methods. Early traditional SR methods usually incorporate Markov chain assumption to capture high-order sequential patterns [14,5]. With the development of deep neural networks, researchers have applied the RNN-based [30,34], Graph Neural Network (GNN)-based [38,36,6], transformer-based [1,18,3], and self-supervised [29,35] methods to the SR task.

These methods have the powerful capability of representation learning but have difficulty addressing the challenges caused by data sparsity or cold-start.

2.2 Cross-domain Sequential Recommendation

By treating the information from other domains as a supplement, the Cross-domain Sequential Recommendation (CSR) approaches can alleviate the data sparsity and the cold-start problems for SR [25]. In early explorations, π -net [26] and PSJNet [31] are two RNN-based solutions for CSR that parallel share the information between domains and simultaneously learn the sequence representations for both of them. Then, Zheng et al. [37] and Guo et al. [10,12] address CSR from the graph-based perspective, which first builds the CDS graph and attentively learns the user-specific representations in both local and global aspects. Another research direction is attention-based methods, such as Chen et al. [2] and Li et al. [20], which provide cross-domain recommendations by matching the user’s sequential preference with candidate items through a dual-attention learning mechanism. With the increasing depth of the neural networks and the complexity of the model structure, these CSR methods are gradually becoming uncontrollable on the size of parameters or the memory overhead, exceeding the load of most conventional devices.

2.3 Lightweight Recommendation

To simplify the structure of the recommender system yet make it easier to be implemented on various devices, the concept of lightweight recommendation has attracted a lot of attention [28]. In traditional methods, recent studies have focused on lightening the structure of DeepFM [24], DNN [23,22], GCN [28], and transformer [27] to improve the memory efficiency of recommenders. Li et al. [21] are the first ones that introduce a lightweight solution for Sequential Recommendation (SR) via twin-attention networks to simultaneously address the challenges of lightening the parameter and discovering the temporal signals from all interacted items. As CSR usually requires auxiliary structures to bridge multiple domains, they often need more training time and a larger parameter scale, but the relevant lightweight solutions are mostly unexplored.

3 Method

3.1 Preliminary

CSR task tends to recommend the next item for an overlapped user by modeling her/his historical interactions from the hybrid sequences [37]. Suppose that $U = \{U_1, U_2, \dots, U_k, \dots, U_p\}$ is the set of overlapped users whose historical behaviors are available in two domains, where $U_k \in \mathcal{U}$ ($1 \leq k \leq p$) denotes an independent user in \mathcal{U} . Let S_H be the original hybrid sequence of an overlapped user, we further split the S_H into $S_A = \{A_1, A_2, \dots, A_i, \dots, A_m\}$ and

$S_B = \{B_1, B_2, \dots, B_j, \dots, B_n\}$, which denote the interaction sequences in domain A and B respectively, where $A_i \in \mathcal{A}$ ($1 \leq i \leq m$) represents the items in domain A and $B_j \in \mathcal{B}$ ($1 \leq j \leq n$) represents the items in domain B. Then we let $P_A = \{P_{A_1}, P_{A_2}, \dots, P_{A_i}, \dots, P_{A_m}\}$ and $S_B = \{P_{B_1}, P_{B_2}, \dots, P_{B_j}, \dots, P_{B_n}\}$ be the positional information for the sequence S_A and S_B respectively, which accurately record the position of items from the original hybrid sequence S_H .

The probabilities of being recommended for all candidate items in both domains can be denoted as:

$$P(A_{i+1}|S_A, S_B) \sim f_A(S_A, S_B), \quad (1)$$

$$P(B_{j+1}|S_B, S_A) \sim f_B(S_B, S_A), \quad (2)$$

where $P(A_{i+1}|S_A, S_B)$ is the probability of recommending A_{i+1} as the next consumed item in domain A based on S_A and S_B . And $f_A(S_A, S_B)$ denotes the learning function utilized to estimate the probability. And the similar definition for domain B can be denoted as $P(B_{j+1}|S_B, S_A)$ and $f_B(S_B, S_A)$.

3.2 Overview

The key idea of LEA-GCN is to develop a lightweight graph-based solution for CSR without affecting prediction accuracy. In LEA-GCN, we optimize the structure of GCN by adopting the Single-Layer Aggregating Protocol (SLAP) and simplify the sequence encoder by taking advantage of the External Attention (EA) mechanism. As shown in Fig. 3.2, we first record the position orders of all the items in the hybrid sequences to retain the information on users' inter-domain behavioral patterns. Secondly, by selecting items of each domain with the inner-domain sequential orders fixed from the hybrid sequences, we result in the subsequences S_A and S_B for domains A and B, respectively. Then, we follow the same composition rules as DA-GCN [10] to construct the CDS graph by considering the sophisticated associations among users and items (i.e., inter-domain user-item interactive relations and inner-domain item-item order relations). After constructing the CDS graph, we adopt the Light-GCN [15] graph encoder to linearly propagate embedding on the CDS graph and adopt the SLAP to learn the node representations and optimize the parameter scale synchronously. Subsequently, to further capture the sequential patterns from users' interactions in a lower calculation complexity, we devise a dual-channel External Attention (EA)-based sequence encoder. That calculates the correlation between all the items and considers the positional information (i.e., the \mathbf{V}_A and \mathbf{V}_B) extracted from the hybrid sequence. Then, the resulting sequence-level representations can be denoted as \mathbf{H}_{S_A} and \mathbf{H}_{S_B} for both domains. We finally feed the concatenation of \mathbf{H}_{S_A} and \mathbf{H}_{S_B} to the prediction layer.

3.3 Lightweight Node Representation Learning

Graph Construction. Inspired by Guo et al. [12], we construct the CDS graph to link two domains by considering two types of associations: 1) user-item interactions between both domains; 2) item-item sequential transitions within both

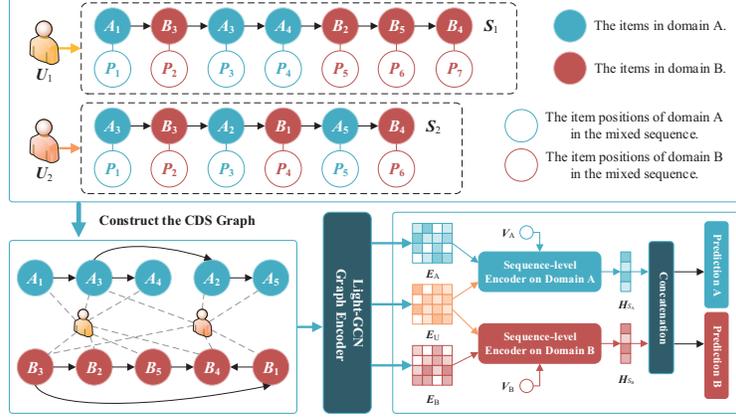


Fig. 1. An overview of our proposed LEA-GCN, where S_1 and S_2 denote the hybrid sequence of two different overlapped users U_1 and U_2 , respectively.

domains, where users and items in each domain are nodes and their associations are edges. However, such a composition method only retains the inner-domain sequential transferring characteristics, but discards the order dependency of items from the original hybrid sequences. To fix the above defects, we additionally record the positional information of items in the hybrid sequence before constructing the CDS graph, so as to use them in the sequence-level representation learning.

Then, the CDS graph $\mathcal{G} \in \mathbb{R}^{(m+p+n) \times (m+p+n)}$ can be described in a matrix-form as:

$$\mathcal{G} = \begin{bmatrix} \mathbf{A} & \mathbf{0} \\ \mathbf{0} & \mathbf{B} \end{bmatrix}; \quad \mathbf{A} = \begin{bmatrix} \mathbf{0} & \mathbf{R}_{AU} \\ \mathbf{R}_{AU}^T & \mathbf{0} \end{bmatrix}; \quad \mathbf{B} = \begin{bmatrix} \mathbf{0} & \mathbf{R}_{BU} \\ \mathbf{R}_{BU}^T & \mathbf{0} \end{bmatrix}, \quad (3)$$

where $\mathbf{A} \in \mathbb{R}^{(m+p) \times (m+p)}$ and $\mathbf{B} \in \mathbb{R}^{(p+n) \times (p+n)}$ respectively denote the compressed Laplace matrices of both domains, $\mathbf{R}_{AU} \in \mathbb{R}^{m \times p}$ and $\mathbf{R}_{BU} \in \mathbb{R}^{p \times n}$ represent the user-item interaction matrix of domain A and B, respectively, $\mathbf{R}_{AU}^T \in \mathbb{R}^{m \times p}$ and $\mathbf{R}_{BU}^T \in \mathbb{R}^{p \times n}$ are the transpose matrices.

Single-Layer Aggregation Protocol (SLAP). It has been proven effective in early proposed state-of-the-art methods NGCF [33] and LightGCN [15], which adopt a Multi-Layer Aggregating Protocol (MLAP) to propagate embeddings from nodes layer by layer. The core idea of the MLAP is to use the high-order connectivity on the user-item bipartite graph to obtain the potential association between them, thereby enhancing the performance of node representation learning. The node representation learning on the l -th layer can be detailed as:

$$\mathbf{E}^{(l)} = H(\mathbf{E}^{(l-1)}, \mathcal{G}), \quad (4)$$

where \mathcal{G} is the user-item bipartite graph and $\mathbf{E}^{(l)}$ denotes the node representations at the l -th layer, $\mathbf{E}^{(l-1)}$ is that of the previous layer. $H(\cdot)$ represents the function for neighbor aggregation.

However, the MLAP may not be suitable for the CDS graph. For example, when learning the item representation of domain A by considering the high-order connectivity of the items in domain B. It will also bring high-order domain-specific structural information from domain B, which might be the noise message for domain A, interfering with the interest expression of overlapped users. Hence, we develop a single-layer propagation rule (a.k.a., the Single-Layer Aggregating Protocol (SLAP)) to consider first-order neighbor aggregation on the CDS graph as:

$$\mathbf{E}_U = \sum_{k \in U} \left(\sum_{i \in S_A} \frac{1}{\sqrt{|N_U|} \sqrt{|N_A|}} e_{i \rightarrow k} + \sum_{j \in S_B} \frac{1}{\sqrt{|N_U|} \sqrt{|N_B|}} e_{j \rightarrow k} \right); \quad (5)$$

$$\mathbf{E}_A = \sum_{i \in S_A} \sum_{k \in U} \frac{1}{\sqrt{|N_U|} \sqrt{|N_A|}} e_{k \rightarrow i}; \quad (6)$$

$$\mathbf{E}_B = \sum_{j \in S_B} \sum_{k \in U} \frac{1}{\sqrt{|N_U|} \sqrt{|N_B|}} e_{k \rightarrow j}; \quad (7)$$

where $e_{i \rightarrow k}$ and $e_{j \rightarrow k}$ denote the passing message from the items to the overlapped user, $e_{k \rightarrow i}$ and $e_{k \rightarrow j}$ respectively denote the message transferred from users to items of domain A and domain B, N_U is the set of overlapped users that interact with item A_i or item B_j , N_A and N_B are the set of items that are interacted by user u . By adopting the SLAP, the knowledge between domains could be transferred with less impact from the domain-specific information and simultaneously reduces the parameter scale.

To support our view, we conduct a series of ablation experiments to investigate the impact of the layer depth. Due to the space limitation, we only report the experimental results of DOUBAN (i.e., a real-world dataset which will be detailed in Section 4.1) on Table 1.

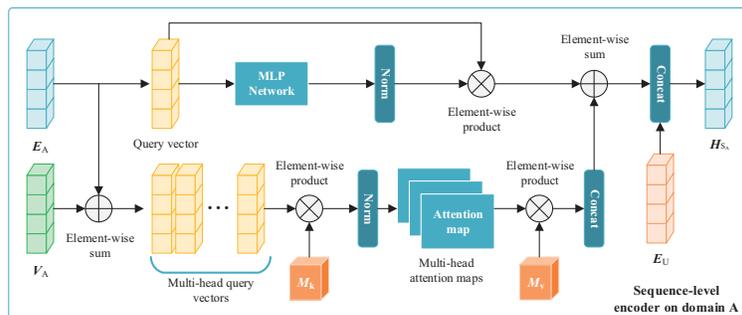
As shown in Table 1, we search the performance of LEA-GCN at different layers compared with two state-of-the-art GCN-based methods (i.e., LightGCN [15] and DA-GCN [10]). To make the LightGCN comparable to other two CSR methods, we simultaneously report its performance on both domains. Then, we have the following observations: 1) Increasing the number of layers can improve the performance of LightGCN, demonstrating the effectiveness of considering the high-order connectivity while propagating embedding on the user-item graph within a single domain. 2) DA-GCN and LEA-GCN with SLAP perform better than them with MLAP, which supports our hypothesis that simply aggregates message from the high-order connectivity on the CDS graph may bring more noise to the node representation learning and proves the significance of adopting SLAP for the CSR task.

Table 1. Performance (%) comparison between LightGCN, DA-GCN and our proposed GCN-based solution at different layers.

Domain		A			B		
Layer Numbers	Method	RC10	MRR10	NDCG10	RC10	MRR10	NDCG10
@ 1 Layer	LightGCN	78.03	75.06	48.24	68.28	52.03	37.52
	DA-GCN	83.55	80.84	51.53	71.91	58.31	40.67
	LEA-GCN	83.83	81.22	52.06	76.14	66.15	45.01
@ 2 Layers	LightGCN	78.33	75.25	48.89	68.19	52.00	37.66
	DA-GCN	83.12	80.55	50.92	71.42	57.45	40.16
	LEA-GCN	83.53	81.08	51.35	74.63	63.67	42.91
@ 3 Layers	LightGCN	78.52	75.35	48.93	68.32	52.11	37.79
	DA-GCN	81.99	80.08	49.35	71.08	57.17	39.85
	LEA-GCN	83.40	81.02	51.05	74.22	63.29	42.11

3.4 External Attention (EA)-based Sequence Encoder

Self-attention uses the combination of self values to refine the input sequence representations, which only considers the relation between items within a sequence but ignores implied relationships between items in different sequences [13]. And the high computational complexity of $O(N^2)$ presents another significant drawback to use self-attention. To accurately measure different items' contributions to the sequence yet with lower computational costs, we replace the self-attention-based algorithms [12,27] by External Attention (EA) mechanism which have achieved great success on the task of image classification, object detection, and semantic segmentation [13].

**Fig. 2.** The workflow of our proposed dual-channel external attention-based sequence encoder (take domain A as an example), where M_k and M_v are two different external memory units.

Different from the self-attention mechanism, External Attention (EA) uses external storage units to reserve the global sharing weights. As shown in Fig. 3.4, We devise a dual-channels composite linear structure to implement the EA (take domain A as an example). Specifically, in the first channel, we attach the positional information \mathbf{V}_A from the hybrid sequence to the item representation \mathbf{E}_A . Then, we calculate the external attention between items and two external memory units (i.e., \mathbf{M}_k and \mathbf{M}_v), which respectively act as the key and value matrices. The score calculations can be formulated as:

$$\mathbf{T}_{S_A}^{(1)} = \text{Norm}[(\mathbf{E}_A + \alpha \mathbf{V}_A) \mathbf{M}_k^T]; \quad (8)$$

$$\mathbf{H}_{S_A}^{(1)} = \mathbf{T}_{S_A}^{(1)} \mathbf{M}_v^T, \quad (9)$$

where α is a hyper-parameter that controls the participation of the positional information, $\mathbf{T}_{S_A}^{(1)}$ is the external attention map, $\mathbf{H}_{S_A}^{(1)}$ represents the final output embedding of sequence S_A from the first channel. For the i -th item A_i in S_A , the calculation can be further detailed as:

$$\mathbf{a}_{i,j}^{(1)} = \text{Norm}[(e_{A_i} \oplus (\alpha \cdot v_{A_i})) m_j^k]; \quad (10)$$

$$\mathbf{H}_{S_A}^{(1)} = \sum_{i=1}^{|S_A|} \mathbf{a}_{i,j}^{(1)} m_i^v, \quad (11)$$

where $\mathbf{a}_{i,j}^{(1)}$ is the pair-wise affinity between i -th items e_{A_i} and the j -th row m_j^k of matrix \mathbf{M}_k . v_{A_i} denotes the positional information of A_i and m_i^v denotes the i -th row of the second memory unit.

Inspired by the Transformer [32], we improve the capacity of EA by adopting a multi-head manner [13] to better capture different relations between items as:

$$\mathbf{Z}_h^{(1)} = \text{ExternalAttention}(\mathbf{E}_A, \mathbf{V}_A, \mathbf{M}_k, \mathbf{M}_v); \quad (12)$$

$$\mathbf{H}_{S_A}^{(1)} = \text{Concat}(\mathbf{Z}_h^{(1)}, \dots, \mathbf{Z}_\beta^{(1)}) \mathbf{W}_1, \quad (13)$$

where \mathbf{W}_1 is the linear transformation matrix to align the dimensions of input and output, \mathbf{Z}_h is the h -th head, and β controls the number of heads. In experiments, we search β in [1, 2, 4, 8, 16] and report the experimental results in Section 4.5.

Although external attention can well solve the problem of computational complexity, its final output representation is generated by \mathbf{M}_v . As the external memory units are independent of the input features (i.e., the \mathbf{E}_A), it will lead to the deficiency in modeling items' collaborative filtering signals. To address above questions, in the second channel, an MLP network with a smooth normalization layer (Inspired by Guo et al. [12]) is used to extract the collaborative filtering signals of \mathbf{E}_A . We measure the correlation between e_i and e_j as:

$$\mathbf{a}_{i,j}^{(2)} = \text{Norm}(f(e_{A_i}, e_{A_j})) = \text{Norm}(\mathbf{W}_3^T \text{ReLU}(\mathbf{W}_2[e_{A_i} \oplus e_{A_j}] + \mathbf{b})), \quad (14)$$

where $f(\cdot)$ is a score function implemented by an MLP network, \mathbf{W}_2 and \mathbf{W}_3 are two weight matrices, and \mathbf{b} is the bias vector. Then we can get the sequence representation $\mathbf{H}_{S_A}^{(2)}$ from the second channel:

$$\mathbf{H}_{S_A}^{(2)} = \sum_{i=1}^{|S_A|} \mathbf{a}_{i,j}^{(2)} e_{A_i}. \quad (15)$$

Hence, the resulting user-specific sequence-level representation \mathbf{H}_{S_A} for domain A can be denoted as:

$$\mathbf{H}_{S_A} = \text{Concat}((\mathbf{H}_{S_A}^{(1)} + \mathbf{H}_{S_A}^{(2)}), \mathbf{E}_U). \quad (16)$$

3.5 Prediction Layers

After the sequence representation learning, LEA-GCN gets the sequence embedding \mathbf{H}_{S_A} and \mathbf{H}_{S_B} for domain A and B, respectively. Then, for leveraging the information in both domains, we feed the concatenation of them to the prediction layer:

$$P(A_{i+1}|S_A, S_B) = \text{softmax}(\mathbf{W}_A \cdot [\mathbf{H}_{S_A}, \mathbf{H}_{S_B}]^T + \mathbf{b}_A); \quad (17)$$

$$P(B_{j+1}|S_B, S_A) = \text{softmax}(\mathbf{W}_B \cdot [\mathbf{H}_{S_B}, \mathbf{H}_{S_A}]^T + \mathbf{b}_B), \quad (18)$$

where \mathbf{W}_A and \mathbf{W}_B are the weight matrix of all items in domain A and B, respectively; \mathbf{b}_A and \mathbf{b}_B are the bias term for both domains. Then, to avoid the seesaw phenomena in π -net [26] and DA-GCN [10], we adopt the cross-entropy loss and optimize them independently on both domains:

$$\mathcal{L}_A = -\frac{1}{|\mathcal{S}|} \sum_{S_A, S_B \in \mathcal{S}} \sum_{A_i \in S_A} \log P(A_{i+1}|S_A, S_B), \quad (19)$$

$$\mathcal{L}_B = -\frac{1}{|\mathcal{S}|} \sum_{S_B, S_A \in \mathcal{S}} \sum_{B_j \in S_B} \log P(B_{j+1}|S_B, S_A), \quad (20)$$

where \mathcal{S} denotes the training sequences in both domains.

4 Experiment

We conduct extensive experiments on two real-world datasets to validate the effectiveness of LEA-GCN. In this section, we aim to answer the following Research Questions (RQ):

- RQ1:** Does LEA-GCN work on lightening the model’s weights? How is the training efficiency of the LEA-GCN?
- RQ2:** How does the LEA-GCN perform compared with other state-of-the-art baselines? Does our lightweight strategy lead to the deterioration of recommendation performance?
- RQ3:** Is it helpful to consider the items’ positional relationship in the hybrid input sequences? Does it work by using external attention to learn sequence representation for both domains?
- RQ4:** How do the hyper-parameters affect the performance of LEA-GCN?

4.1 Experimental setup

Datasets and Evaluation Protocols. We evaluate LEA-GCN on two real-world datasets (i.e., DOUBAN [39] and AMAZON [8]). DOUBAN contains historical interactions of overlapped users on domain A and domain B (i.e., douban movies and douban books), which are collected from the well-known Chinese social media platform Douban¹ [39]. AMAZON is a product review dataset collected by Fu et al. [8]. It contains overlapped users’ review behaviors on two different amazon² platforms, i.e., amazon-book (domain A) and amazon-movie (domain B). As shown in Table 2, We randomly choose 80% of all the hybrid sequences of both datasets as the training sets, and the rest 20% as the testing sets. Moreover, for the pretreatments on both datasets, we filter out the cold users with less than ten historical interactions and those cold items which only noticed less than five times [17].

For evaluation, we first treat the last two observed items in each hybrid sequence as the ground truth items for both domains. Secondly, we employ three frequently used metrics (i.e., RC@10, MRR@10, and NDCG@10) [10,11] to evaluate each instance on the testing sets and report their average values.

Table 2. Statistics of the datasets, where A and B represent different domains for both datasets.

Dataset	DOUBAN		AMAZON	
Domain	A	B	A	B
Items	14,636	2,940	126,526	61,362
Interactions	607,523	360,798	1,678,006	978,226
Users	6,582		9,204	
Sequences (Train)	42,062		90,574	
Sequences (Test)	10,431		14,463	

Baselines. To validate the performance of LEA-GCN, we compared our proposed method with the following baselines: 1) Traditional recommendations: NCF [16], NGCF [33], and LightGCN [15]. We adapt the traditional methods with sequential inputs and report their experimental results in each domain. 2) Sequential recommendations: GRU4REC [17] and HRNN [30]. We report their performance in each domain. 3) Cross-domain Sequential recommendations: π -Net [26], PSJNet [31], DA-GCN [10], and TiDA-GCN [12].

¹ <http://www.douban.com/>

² <http://jmcauley.ucsd.edu/data/amazon/>

Implementation Details. We implement LEA-GCN³ by TensorFlow and accelerate the model training by NVIDIA Tesla K80M GPU. For parameters, we employ Xavier [9] for initialization and optimize them by Adam [19]. To train the model, we set the batch-size as 256, the dropout ratio as 0.1, and the learning rate as 0.002 for domain A and 0.004 for domain B, respectively. For LEA-GCN, we set the embedding size as 16 and the regularization ratio as $1e-7$. The hyper-parameter α is searched in [0-1] with a step size of 0.1 to adjust the participation of the positional information and the number of attention head β is explored within [1, 2, 4, 8, 16] to reach the best performance for LEA-GCN. We detail the experimental results for α and β in 4.4. Moreover, we uniformly set the embedding-size to 16 for all the reference baselines to make their results comparable. As for other hyper-parameters, we refer to the best settings of their papers and fine-tune them on both datasets.

4.2 Parameter Scale & Training Efficiency (RQ1)

In this section, we first conduct a series of experiments by changing the ratio of input data in [0.2 - 1.0] on DOUBAN and AMAZON to measure the time consumption of the model training. Second, we analyze the performance of LEA-GCN in lightweight modeling ability by measuring the scale of its parameters compared with two most competitive baselines (i.e., PSJNet and TiDA-GCN). Then we have the following observations: 1) From Fig. 3 (a) and (b), we notice that LEA-GCN costs lower training time than TiDA-GCN and PSJNet, which demonstrates that LEA-GCN has a better training efficiency and is scalable to the large-scale datasets. 2) From Fig. 3 (c) and (d), we observe that LEA-GCN and LEA-All need far fewer parameters than PSJNet and TiDA-GCN, providing a positive answer to RQ1. Note that, the LEA-All is a variant method that only keeps the GCN encoder in LEA-GCN.

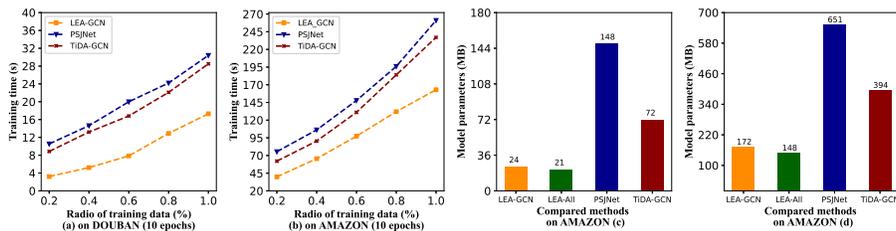


Fig. 3. Time consumption and the parameter scale of LEA-GCN compared with PSJNet and TiDA-GCN.

³ <https://github.com/JinyuZ1996/LEA-GCN>

4.3 Performance on Recommendation Accuracy (RQ2)

Table 3 shows the experimental results of LEA-GCN compared with other state-of-the-art methods on both datasets. The observations are summarized as follows: 1) LEA-GCN achieves the best performance on both domains of AMAZON and outperforms other state-of-the-art baselines in most evaluation metrics on DOUBAN, demonstrating that our lightweight strategy in LEA-GCN has little impact on the prediction accuracy, even improves the model’s performance. 2) The CSR solutions outperform other state-of-the-art methods (i.e., traditional recommenders and sequential recommenders), demonstrating the significance of simultaneously modeling users’ sequential preference and cross-domain characteristics. 3) LEA-GCN outperforms all the CSR baselines, indicating the effectiveness of modeling user-specific preference from the CDS graph by a lightweight structure, and displays the superiority of external attention in capturing users’ sequential patterns.

Table 3. Experiment results (%) of compared methods on DOUBAN and AMAZON. Note that, the bold value denotes the best result in terms of the corresponding metric. Significant improvements are marked with[†] (paired samples t-test, $p < .05$).

Dataset	DOUBAN						AMAZON					
Domain	A			B			A			B		
Metric (@10)	RC	MRR	NDCG	RC	MRR	NDCG	RC	MRR	NDCG	RC	MRR	NDCG
NCF	69.75	58.05	40.26	35.24	23.29	18.28	15.59	11.30	6.12	17.38	13.20	5.29
NGCF	79.21	77.82	49.12	67.37	54.41	37.26	21.52	18.74	12.08	26.55	25.37	17.45
LightGCN	78.52	75.35	48.93	68.32	52.11	37.79	21.67	17.41	10.13	26.49	24.23	15.09
GRU4REC	80.13	75.41	47.81	66.66	54.10	38.03	21.51	17.11	9.66	24.51	22.13	12.94
HRNN	81.25	77.90	48.88	68.32	54.99	38.93	21.92	17.30	9.87	25.10	22.48	13.44
π -net	83.22	80.71	51.22	69.54	55.72	39.18	24.33	20.52	11.80	27.66	25.03	16.20
PSJNet	83.54	80.96	51.72	71.59	58.36	40.71	25.03	21.09	13.54	31.24	28.35	18.93
DA-GCN	83.55	80.84	51.53	71.91	58.31	40.67	24.62	20.91	13.18	31.12	28.21	18.85
TIDA-GCN	83.68	81.27	52.02	72.56	60.27	41.38	25.05	21.23	14.68	32.84	29.65	19.12
LEA-GCN	83.83[†]	81.22	52.06	76.14[†]	66.15[†]	45.01[†]	25.47[†]	21.57[†]	14.93[†]	33.97[†]	30.65[†]	20.46[†]

4.4 Ablation Study (RQ3)

In this section, we conduct a series of ablation studies on DOUBAN and AMAZON to explore the impact of different components on LEA-GCN. Due to space limitations, we only report the results on DOUBAN. As shown in Table 4, the LEA-Pos is a variant that disables the participation of the positional information from the hybrid sequence. LEA-EA is another variant model that removes the external attention-based sequence encoder. LEA-All is a variant that disables both the positional information and the EA. The observations of Table 4 are summarized as follows: 1) LEA-GCN outperforms LEA-All and LEA-Pos, demonstrating the importance of the positional information of items from the

Table 4. The experimental results (%) of ablation studies on the DOUBAN dataset.

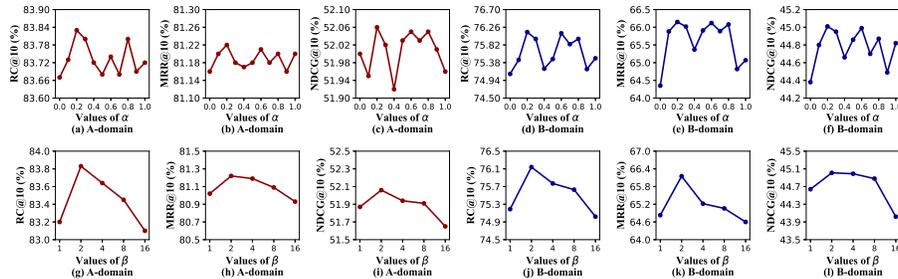
Domain	A			B			
	Metric (@10)	RC	MRR	NDCG	RC	MRR	NDCG
LEA-Pos		83.67	81.16	52.00	75.10	64.35	44.38
LEA-EA		82.62	79.14	50.43	72.82	61.92	42.41
LEA-All		82.12	78.10	49.64	71.28	59.43	41.28
LEA-GCN	83.83	81.22	52.06	76.14	66.15	45.01	

original hybrid sequence for learning overlapped users’ sequential characteristics. 2) LEA-GCN performs better than LEA-EA, demonstrating the contribution of the external attention component for sequence-level representation learning.

4.5 Hyper-parameters Analysis (RQ4)

The hyper-parameter α controls the participation of the positional information attached to the item representations for both domains. Fig. 4 (a) to (f) show the performance of LEA-GCN with different $\alpha \in [0 - 1]$. The experimental results prove the significance of leveraging the positional information from the original hybrid sequences. However, it is not advisable to regard it as equally important as the sequence representation.

The hyper-parameter β controls the head number of the multi-head external attention component. The experimental results in Fig. 4 (g) to (l) demonstrate that only with an appropriate number of heads, does the EA mechanism benefits the sequence representation learning process.

**Fig. 4.** Impact of hyper-parameters α and β on DOUBAN.

5 Conclusions

In this work, we propose a lightweight GCN-based solution for CSR, which simultaneously simplifies the structure of GCNs and optimizes the calculation

complexity of the sequence encoder. Specifically, we only keep the neighborhood aggregation to reduce the parameter scale of the GCN encoder and propose the Single-Layer Aggregating Protocol (SLAP) to propagate embedding on the CDS graph. Then, we devise a dual-channel External Attention (EA)-based sequence encoder to calculate the correlation among all items via a lighter linear structure. The experimental results on two real-world datasets demonstrate the superiority of our lightweight solution.

References

1. Ai, Z., Wang, S., Jia, S., Guo, S.: Core interests focused self-attention for sequential recommendation. In: DASFAA. pp. 306–314 (2022)
2. Chen, C., Guo, J., Song, B.: Dual attention transfer in session-based recommendation with multi-dimensional integration. In: SIGIR. pp. 869–878 (2021)
3. Chen, H., Lin, Y., Pan, M., Wang, L., Yeh, C.M., Li, X., Zheng, Y., Wang, F., Yang, H.: Denoising self-attentive sequential recommendation. In: RecSys. pp. 92–101 (2022)
4. Chen, T., Yin, H., Zheng, Y., Huang, Z., Wang, Y., Wang, M.: Learning elastic embeddings for customizing on-device recommenders. In: KDD. pp. 138–147 (2021)
5. Cheng, C., Yang, H., Lyu, M.R., King, I.: Where you like to go next: Successive point-of-interest recommendation. In: IJCAI. pp. 2605–2611 (2013)
6. Dong, X., Jin, B., Zhuo, W., Li, B., Xue, T.: Sirius: Sequential recommendation with feature augmented graph neural networks. In: DASFAA. pp. 315–320 (2021)
7. Fang, J., Yang, C., Shi, Y., Wang, N., Zhao, Y.: External attention based transunet and label expansion strategy for crack detection. TITS pp. 19054–19063 (2022)
8. Fu, W., Peng, Z., Wang, S., Xu, Y., Li, J.: Deeply fusing reviews and contents for cold start users in cross-domain recommendation systems. In: AAAI. pp. 94–101 (2019)
9. Glorot, X., Bengio, Y.: Understanding the difficulty of training deep feedforward neural networks. In: AISTATS. pp. 249–256. JMLR (2010)
10. Guo, L., Tang, L., Chen, T., Zhu, L., Nguyen, Q.V.H., Yin, H.: DA-GCN: A domain-aware attentive graph convolution network for shared-account cross-domain sequential recommendation. In: IJCAI. pp. 2483–2489 (2021)
11. Guo, L., Zhang, J., Chen, T., Wang, X., Yin, H.: Reinforcement learning-enhanced shared-account cross-domain sequential recommendation. TKDE (2022)
12. Guo, L., Zhang, J., Tang, L., Chen, T., Zhu, L., Yin, H.: Time interval-enhanced graph neural network for shared-account cross-domain sequential recommendation. TNNLS (2022)
13. Guo, M.H., Liu, Z.N., Mu, T.J., Hu, S.M.: Beyond self-attention: External attention using two linear layers for visual tasks. TPAMI (2022)
14. He, R., Kang, W., McAuley, J.J.: Translation-based recommendation. In: RecSys. pp. 161–169 (2017)
15. He, X., Deng, K., Wang, X., Li, Y., Zhang, Y., Wang, M.: Lightgcn: Simplifying and powering graph convolution network for recommendation. In: SIGIR. pp. 639–648 (2020)
16. He, X., Liao, L., Zhang, H., Nie, L., Hu, X., Chua, T.S.: Neural collaborative filtering. In: WWW. pp. 173–182 (2017)
17. Hidasi, B., Karatzoglou, A., Baltrunas, L., Tikk, D.: Session-based recommendations with recurrent neural networks. In: ICLR (2016)

18. Kang, W., McAuley, J.J.: Self-attentive sequential recommendation. In: ICDM. pp. 197–206 (2018)
19. Kingma, D.P., Ba, J.: Adam: A method for stochastic optimization. In: ICLR (2015)
20. Li, P., Jiang, Z., Que, M., Hu, Y., Tuzhilin, A.: Dual attentive sequential learning for cross-domain click-through rate prediction. In: KDD. pp. 3172–3180 (2021)
21. Li, Y., Chen, T., Zhang, P., Yin, H.: Lightweight self-attentive sequential recommendation. In: CIKM. pp. 967–977 (2021)
22. Lian, D., Wang, H., Liu, Z., Lian, J., Chen, E., Xie, X.: Lightrec: A memory and search-efficient recommender system. In: WWW. pp. 695–705 (2020)
23. Liu, H., Zhao, X., Wang, C., Liu, X., Tang, J.: Automated embedding size search in deep recommender systems. In: SIGIR. pp. 2307–2316 (2020)
24. Liu, S., Gao, C., Chen, Y., Jin, D., Li, Y.: Learnable embedding sizes for recommender systems. In: ICLR (2021)
25. Ma, M., Ren, P., Chen, Z., Ren, Z., Zhao, L., Liu, P., Ma, J., de Rijke, M.: Mixed information flow for cross-domain sequential recommendations. TKDD pp. 64:1–64:32 (2022)
26. Ma, M., Ren, P., Lin, Y., Chen, Z., Ma, J., Rijke, M.d.: π -net: A parallel information-sharing network for shared-account cross-domain sequential recommendations. In: SIGIR. pp. 685–694 (2019)
27. Mei, M.J., Zuber, C., Khazaeni, Y.: A lightweight transformer for next-item product recommendation. In: RecSys. pp. 546–549 (2022)
28. Miao, H., Li, A., Yang, B.: Meta-path enhanced lightweight graph neural network for social recommendation. In: DASFAA. pp. 134–149 (2022)
29. Qiu, R., Huang, Z., Yin, H., Wang, Z.: Contrastive learning for representation degeneration problem in sequential recommendation. In: WSDM. pp. 813–823 (2022)
30. Quadrana, M., Karatzoglou, A., Hidasi, B., Cremonesi, P.: Personalizing session-based recommendations with hierarchical recurrent neural networks. In: RecSys. pp. 130–137 (2017)
31. Sun, W., Ma, M., Ren, P., Lin, Y., Chen, Z., Ren, Z., Ma, J., De Rijke, M.: Parallel split-join networks for shared account cross-domain sequential recommendations. TKDE (2021)
32. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, L., Polosukhin, I.: Attention is all you need. In: NIPS. pp. 5998–6008 (2017)
33. Wang, X., He, X., Wang, M., Feng, F., Chua, T.: Neural graph collaborative filtering. In: SIGIR. pp. 165–174 (2019)
34. Wu, C., Ahmed, A., Beutel, A., Smola, A.J., Jing, H.: Recurrent recommender networks. In: WSDM. pp. 495–503 (2017)
35. Xie, X., Sun, F., Liu, Z., Wu, S., Gao, J., Zhang, J., Ding, B., Cui, B.: Contrastive learning for sequential recommendation. In: ICDE. pp. 1259–1273 (2022)
36. Zang, Y., Liu, Y., Chen, W., Li, B., Li, A., Yue, L., Ma, W.: GISDCN: A graph-based interpolation sequential recommender with deformable convolutional network. In: DASFAA. pp. 289–297 (2022)
37. Zheng, X., Su, J., Liu, W., Chen, C.: DDGHM: dual dynamic graph with hybrid metric training for cross-domain sequential recommendation. In: MM. pp. 471–481 (2022)
38. Zheng, Y., Liu, S., Li, Z., Wu, S.: DGTN: dual-channel graph transition network for session-based recommendation. In: ICDM. pp. 236–242 (2020)
39. Zhuang, F., Zhou, Y., Ying, H., Zhang, F., Ao, X., Xie, X., He, Q., Xiong, H.: Sequential recommendation via cross-domain novelty seeking trait mining. JCST pp. 305–319 (2020)