Time Interval-Enhanced Graph Neural Network for Shared-Account Cross-Domain Sequential Recommendation

Lei Guo, Jinyu Zhang, Graduate Student Member, IEEE, Li Tang, Tong Chen, Member, IEEE, Lei Zhu, Senior Member, IEEE, and Hongzhi Yin, Senior Member, IEEE

Abstract—Shared-account cross-domain sequential recommendation (SCSR) task aims to recommend the next item via leveraging the mixed user behaviors in multiple domains. It is gaining immense research attention as more and more users tend to sign up on different platforms and share accounts with others to access domain-specific services. Existing works on SCSR mainly rely on mining sequential patterns via recurrent neural network (RNN)-based models, which suffer from the following limitations: 1) RNN-based methods overwhelmingly target discovering sequential dependencies in single-user behaviors and they are not expressive enough to capture the relationships among multiple entities in SCSR; 2) all existing methods bridge two domains via knowledge transfer in the latent space and ignore the explicit cross-domain graph structure; and 3) none existing studies consider the time interval information among items, which is essential in the sequential recommendation for characterizing different items and learning discriminative representations for them. In this work, we propose a new graph-based solution, namely, time interval-enhanced domain-aware graph convolutional network (TiDA-GCN), to address the above challenges. Specifically, we first link users and items in each domain as a graph. Then, we devise a domain-aware graph convolution network to learn user-specific node representations. To fully account for users’ domain-specific preferences on items, two effective attention mechanisms are further developed to selectively guide the message-passing process. Moreover, to further enhance item- and account-level representation learning, we incorporate the time interval into the message passing and design an account-aware self-attention module for learning items’ interactive characteristics. Experiments demonstrate the superiority of our proposed method from various aspects.

Index Terms—Cross-domain recommendation (CR), sequential recommendation (SR), shared-account recommendation, time interval modeling.

I. INTRODUCTION

ROSS-DOMAIN sequential recommendation (CSR) task aims at recommending the next item by leveraging a user’s historical interactions from multiple domains. It is gaining immense research attention as users tend to sign up on different platforms to access domain-specific services, such as video watching and news pushing platforms. Ma et al. [1] proposed a mixed information flow network to simultaneously consider the flow of behavioral information and knowledge across domains. Li et al. [2] devised a dual learning mechanism to transfer information between two related domains in an iterative manner for CSR. However, existing studies mainly focus on making recommendations for single users, and they fail to consider the common fact that people share accounts with others in many real applications. The shared account is a kind of account that is shared by a group of users with similar interests or who have intense social relationships. For example, friends and family members tend to share an account for watching movies (e.g., Netflix) and online shopping (e.g., Amazon).

In this work, we study CSR in an emerging yet challenging scenario, i.e., shared-account CSR (SCSR), where multiple individual users share a single account and their interaction behaviors are recorded in multiple domains [3]. The shared account is different from the user overlapping concept in the cross-domain recommendation (CR) since user overlapping means there are common users between two domains (e.g., the source and target domains), based on which we can align two domains. Previous studies on making recommendations to shared accounts [4] are proposed to capture the user relationships under the same account with latent representations. None of them consider the cross-domain context, and thus, they are inapplicable to SCSR. Compared to CSR, SCSR is a more challenging task because of the following: 1) users’ diverse interests are mixed in an interaction sequence [3], [5], and under such circumstances, directly treating an account as a virtual user may get suboptimal results since this strategy will easily result in the loss of the user-specific information and 2) the existence of shared accounts will amplify the noise in the interaction data and impede uncovering users’ preferences from the data in two domains.

Recently, several methods have been developed for SCSR. Among them, π-Net [3] is the first work for SCSR.

Authorized licensed use limited to the terms of the applicable license agreement with IEEE. Restrictions apply.
It solves a parallel sequential recommendation (SR) problem with a gated recurrent unit (GRU)-based information-sharing network. Another related work is the PSJNet method [6]. It improves π-Net by using a split-join strategy on recurrent neural networks (RNNs). However, these existing works still have the following limitations.

1) Existing methods for SCSR are all RNN-based methods, which overwhelmingly target discovering sequential dependencies and have limited capability for capturing the complex relationships among associated entities (i.e., users and items) in both domains. As a result, this limits the expressiveness of learned user and item representations.

2) All existing methods try to transfer the domain knowledge in the latent space and overlook the explicit structural information (e.g., item–user–item paths) linking two domains. Though traditional cross-domain recommenders [7] that focus on knowledge transfer can partially solve this problem, most of them implicitly share the cross-domain knowledge in the latent space, and the explicit structural information bridging the two domains is not sufficiently explored. Zhao et al. [8] proposed a graph-based CR method. However, their work ignores the important sequential information and relies on explicit user ratings that are not usually available in both domains. Moreover, their method cannot handle the entangled user preferences on shared accounts.

3) None of the existing studies on SCSR considers the time interval information among items. We argue that only regarding interaction histories as ordered sequences, without the time intervals, will result in inaccurate sequence modeling and suboptimal recommendations in SR [9], [10], [11], [12].

Intuitively, different types of items have different frequencies and periodicities when being consumed, and therefore, they should have different influences on the next item. For instance, users tend to consume fast-moving consumer goods in a short period and buy electronic products at long intervals. Such additional knowledge provides strong predictive signals when inferring the next item to be visited.

To address the above limitations in SCSR, in our previous work, we devise a graph-based solution, namely, domain-aware graph convolutional network (DA-GCN), and publish it as a conference paper in IJCAI 2021 [5]. Specifically, to incorporate the complicated interaction relationships (limitation 1), DA-GCN constructs a cross-domain sequence (CDS) graph in advance to link users and items in different domains. To model the structural information across domains (limitation 2), DA-GCN devises a domain-aware message-passing strategy in a graph convolutional network (GCN) to learn user-specific account and item representations from their connected neighbors. However, DA-GCN solely focuses on solving limitations 1 and 2, and it does not address limitation 3. Moreover, as DA-GCN only leverages one representative item as the sequence-level representation, the users’ preferences over other items and their interactive characteristics are both ignored. Though the average-pooling strategy can take all the items into consideration, it treats items equally and cannot learn their different contributions to the sequence.

To further deal with limitation 3 and capture the interactive characteristics that are ignored by DA-GCN, we extend DA-GCN by devising a time interval-enhanced graph neural network, namely, time interval-enhanced DA-GCN (TiDA-GCN). To be more concrete, to model the time interval information between items (limitation 3), we further develop a time interval-aware message-passing strategy, where the sequential orders and the relative time intervals between any two items are both exploited. Afterward, to learn items’ interactive characteristics from the sequence level, we introduce an account-aware self-attention network to aggregate all the items attentively. Consequently, we can model the multifaceted interactions and transfer the fine-grained domain knowledge by considering the time interval-aware structure information. Compared with the conference version, we have rewritten the related work (Section II), the methodologies (Section III), and the experiments (Sections IV–VI).

The main contributions of this work are summarized as follows:

1) We investigate an emerging yet challenging recommendation task, namely SCSR. After pointing out the defects of existing solutions, we bring a new take on the SCSR problem with a time interval-enhanced graph neural network.

2) We develop a time interval message-passing strategy by further considering the time interval information on the basis of DA-GCN to enhance the item representation learning.

3) We devise an account-aware self-attention mechanism to model items’ interactive characteristics in the account representation learning.

4) We conduct extensive experiments on two real-world datasets and demonstrate the superiority of our proposed method compared with several state-of-the-art baselines.

II. RELATED WORK

This section surveys four types of related works: CR, shared-account recommendation, GCN-based recommendation, and time interval-aware SR.

A. Cross-Domain Recommendation

CR that concerns data from multiple domains has proven useful for dealing with cold-start [13], [14], [15] and data sparsity issues [16], [17]. In this work, we limit the number of domains to two, which is a common practice in most CR methods [15], [18], [19], [20]. Existing studies with this limitation can be categorized into shallow methods and deep-learning-based methods.

1) Shallow Methods: In this type, two main ways are developed for addressing CR. One is to aggregate knowledge between two domains. For example, Loni et al. [21] first defined a domain as a type of item and then applies factorization machines to CR by incorporating user interaction patterns that are related to particular types of items. Chen et al. [22] tended to connect different domains by embedding all users and items into the same low-dimensional potential space and learning parameters via normalizing the proximity between them. Man et al. [23] studied CR from an embedding and mapping perspective and captured...
the underlying mapping relationship between the user/item feature vectors in different domains by devising a multilayer perceptron (MLP)-based mapping function. The other focuses on transferring knowledge from the source domain to the target domain. For example, Hu et al. [24] leveraged a tensor-based factorization method to share latent features between different domains. Doan and Sahebi [25] investigated a transition-based cross-domain collaborative filtering method to model both within and between domain transitions of user historical sequential behaviors.

2) **Deep-Learning-Based Methods**: Deep-learning-based methods are well suited to transfer learning, as they can learn high-level abstractions among different domains [8], [20], [26]. For example, Hu et al. [20] investigated the benefit brought by the deep transfer learning method and proposed a collaborative cross-network to enable dual knowledge transfer across domains via introducing cross-connections from one base network to another and vice versa. Zhao et al. [8] constructed a cross-domain preference matrix to model the interactions of different domains as a whole and design a preference propagation network on the basis of GCN. Zhang et al. [15] investigated the dual-target CR task with partially overlapping entities and presented a kernel-induced knowledge transfer-based recommendation method to address this issue. Wang et al. [16] focused on the data sparsity and data imbalance issues in cross-domain recommender systems and proposed a discriminative adversarial network to transfer the latent representations from a source domain to a target domain in an adversarial way. However, the above works are mainly focused on users’ static interactions, and user behaviors’ sequential patterns and the shared-account characteristic are not considered. π-Net [3] and PSJNet [6] are two recently proposed methods for SCSR, but their studies are all based on RNNs, which are neither expressive enough to capture the multiple associations nor can model the structure information that bridges two domains.

There are also a few studies focusing on the multidomain CR scenario [27], [28], [29], whose main purpose is to improve recommendations for all domains simultaneously via capturing the informative domain-specific features from all of them. Compared with the scenarios of two domains, there is a new challenge in the multidomain CR [30], that is, the recommendation performance in some domains may decline as more domains join in (especially sparser domains). This is also termed the negative transfer problem, i.e., the transferred knowledge may negatively affect the recommendation accuracy in the target domain. Though the recommendations in two domains may also face negative transfer issues, this problem in the multidomain CR scenario is amplified since the information/knowledge in each domain should be transferred to other domains more than once. We will extend our problem setting to multiple domains in our future work. Another kind of CR is the single-target multidomain recommendation task [31], [32], which tends to transfer the knowledge of common users among multiple domains to make recommendations for a different domain. However, as they are designed to make a single-target recommendations for one domain, they differ significantly from our SCSR task.

**B. Shared-Account Recommendation**

The task of recommending items for a shared account is to make recommendations by modeling the mixture of user behaviors, which usually performs user identification first and then makes recommendations [33], [34]. For example, Wang et al. [35] are the first to study user identification from a novel perspective, in which they employ user preference and consumption time to indicate a user’s identity. Bajaj and Shekhar [4] focused on decomposing online TV accounts into distinct personas by a similarity-based channel clustering method and then made recommendations to individualize the experience for each persona. Jiang et al. [34] introduced an unsupervised framework to judge users within the same account and then learn the preferences for each of them. In their method, a heterogeneous graph is exploited to learn the relationship between items and the metadata. However, all the above methods are focused on identifying latent users in a single domain, rather than a cross-domain scenario. Wen et al. [36] addressed the shared-account challenge in a session-aware recommendation task, where a multiuser identification module drawing on the attention mechanism to distinguish behaviors of different users is proposed. The recently proposed methods π-Net [3] and PSJNet [6] argue that this task can be treated in an end-to-end manner and can also be improved by simultaneously considering the cross-domain information. In their approaches, each account is assumed to have $H$ latent users, and the account representation is learned by merging all the user-specific representations of latent users within it.

**C. GCN-Based Recommendation**

The development of graph neural networks [37], [38], [39] has attracted a lot of attention to exploring graph-based solutions for recommender systems [40], [41], [42]. For example, Ying et al. [43] developed a data-efficient GCN by combining random walks and graph convolutions to generate embeddings for items. Wang et al. [37] exploited high-order proximity by propagating embeddings on the user–item interaction graph to simultaneously update the representations for all users and items efficiently by implementing the matrix-form rule. He et al. [44] found that two common designs in GCN, i.e., feature transformation and nonlinear activation, contribute little to the collaborative filtering method and proposed a simplified version of GCN to make it more concise and appropriate for the recommendation. To explore GCN for SRs, Wu et al. [45] modeled session sequences as graph-structured data to capture the complex transitions of items, which are difficult to be revealed by previous conventional sequential methods. Qiu et al. [46] addressed the session-based recommendation problem via proposing a novel full graph neural network to model the item dependencies between different sessions. Chang et al. [47] dealt with the challenges that users’ behaviors are often noisy signals and their preferences usually change over time by proposing a graph neural network. To be more specific, they first integrate different types of preferences into clusters and then perform cluster- and query-aware graph convolutional propagation on the constructed graph. However, none of the GCN-based methods can be directly applied to SCSR as they
either fail to capture the critical sequential information [48] or focus on the recommendation problem in a single domain.

D. Time Interval-Aware SR

Time interval as one of the important factors reflecting users’ dynamic preferences has been widely studied in the SR scenario. Based on different research perspectives, existing studies can be categorized into user- and item-oriented modeling methods. User-oriented methods [49], [50] are mainly focused on exploring the time intervals from the user side to study users’ continuous preferences. For example, Chen et al. [49] proposed a self-modulating attention mechanism to model the complex evolution of user preferences over time, which enables eliminating the impact of the items that the user might not be interested in during certain time intervals. Wang et al. [50] combined the temporal factor with a personalized tag recommendation method by adjusting the users’ preference weights according to the time intervals between their past behaviors and the current time. Though the temporal dynamics on the user side are well investigated, the time gaps between items are often ignored and assumed that they are of equal contributions.

To tackle this limitation, recent works have also focused on investigating the importance of time spans between items [51], [52], [53], [54], [55], [56], [57]. For example, Zhu et al. [56] modeled time intervals between users’ actions by equipping long short-term memory networks (LSTM) with specifically designed time gates to better capture both users’ short- and long-term interests, so as to improve the recommendation performance. TGSRec [57] is a recent time interval-aware SR method that explicitly models collaborative signals and time gaps among items via a collaborative attention network, where the time span is represented as a kernel value of the corresponding encoded time embeddings. Chen et al. [51] first segmented the whole timeline into a specified number of equal-length time slices and then constructed a user–item graph for each time slice to learn user and item representation. Li et al. [53] argued that user interaction sequences should be modeled as a sequence with different time intervals and devised a time-aware self-attention mechanism to capture the time intervals. However, both of them only explore the time intervals in SRs within a single domain, and none of them investigate it in SCSR.

E. Differences

The proposed TiDA-GCN method in this article significantly extends and advances the methodology in the conference version (DA-GCN). In particular, our previous work [5] only leverages the structural information to learn account and item representations with a DA-GCN, while this work further incorporates the time interval information by devising an interval-aware message-passing strategy to consider items’ different attractions to users. Furthermore, this work develops an account-aware self-attention network to model items’ interactive characteristics, ignored by DA-GCN, at the sequence level to enhance the account representation learning.

Compared with the time interval modeling methods, our method also has significant differences from them. For example, the TiDA-GCN method is different from [51] since we focus on designing time interval-aware message-passing strategies for representation learning in GCNs, rather than directly learning items’ dynamic representations through RNNs. Another related work to ours is [53], which models time intervals in an interaction sequence as the relation between items. However, this work mainly explores the time intervals for the self-attention mechanism and proposes an extension to self-attention, while ours mainly focus on improving GCNs via devising time interval-aware message-passing strategies. Moreover, all the existed studies only explore the time intervals in SRs within a single domain, and none of them investigate it in SCSR, which is the main task of our work.

III. Methodologies

In this section, we first provide the preliminaries of this work and formulate the SCSR task that we intend to address. Then, we introduce how we leverage the GCN technique to meet the challenges and propose a TiDA-GCN as our solution. For clarity, we also introduce our previous work DA-GCN [5] that learns account and item representations without the time interval and sequence-level information as a comparison.

A. Preliminaries

Suppose that \( U = \{U_1, U_2, \ldots, U_k, \ldots\} \) is the set of shared accounts in both domains, where \( U_i \in U \) (\( 1 \leq k \leq n \)) denotes a single account index in \( U \) (\( n \) is the size of \( U \)). Let us define \( S_A = \{A_1, A_2, \ldots, A_i, \ldots\} \) and \( S_B = \{B_1, B_2, \ldots, B_j, \ldots\} \) as the sequences from a shared account in domains A and B, respectively, where \( A_i \in A \) (\( 1 \leq i \leq p \)) represents a single item index in domain A and \( A \) denotes the whole item set in domain A (\( p \) is the number of items in \( A \)). Analogously, \( B_j \in B \) (\( 1 \leq j \leq q \)) denotes a single item index in domain B and \( B \) is the whole item set in B (\( q \) is the number of items in \( B \)). Given \( S_A \) and \( S_B \), our SCSR task tends to recommend the next item for an account by modeling the behavior sequences from it. We define the recommendation probabilities for all candidate items in domains A and B 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 \( P(A_{i+1}|S_A, S_B) \) denotes the probability of recommending the item \( A_{i+1} \) that will be consumed in domain A, given \( S_A \) and \( S_B \). \( f_A(S_A, S_B) \) represents the learned function that is utilized to estimate \( P(A_{i+1}|S_A, S_B) \). For domain B, we apply similar definitions to \( P(B_{j+1}|S_B, S_A) \) and \( f_B(S_B, S_A) \).

B. Overview of TiDA-GCN

The key idea of TiDA-GCN is to explore the multiple associations among users and items, and the structure-aware domain knowledge via devising a DA-GCN, which not only models users’ interests from source domain A but also transfers the information to target domain B to improve the recommendation performance for B and vice versa. Fig. 1 shows the workflow of our recommendation framework, which consists of five components.
1) The CDS graph is constructed from the mixed behavior sequences to model four types of sophisticated associations among accounts and items, that is, sequential transitions among items in domain A, sequential transitions among items in domain B, account–item interactions in domain A, and account–item interactions in domain B. Note that, for the interactions between sequences, we handle them by constructing a global interaction graph according to items’ sequential transition relationships in each domain, that is, for any two items, as long as they are adjacent in the sequences, we will assume that they have a sequential relationship and connect them in the CDS graph, that is to say, items between sequences are connected because they are adjacent in a sequence; otherwise, they will not be connected.

2) Account representation learning that leverages a domain-aware message-passing strategy to learn node representations with latent users (suppose that there are $H$ latent users sharing an account), where a domain-aware attention mechanism is developed to capture users’ distinct preferences over different items on both source and target domains (the details can be seen in Section III-C).

3) Item representation learning via exploiting a sequence-aware attention mechanism on the item side to access the varying relevance of linked users/items to the target item. Moreover, as item pairs with different time intervals may have different needs for users, such as fast-moving consumer goods and electronic products, the time intervals among them provide us important signals for item distinction. Hence, we further enhance the representation learning process by incorporating the time interval information into the message aggregation strategy (the details can be seen in Section III-D).

4) Sequence representation learning that aims at investigating the sequential preferences of accounts at the sequence level, where a self-attention mechanism is leveraged (the details can be seen in Section III-F).

5) The model prediction layer conducts item recommendation by a joint training strategy to simultaneously optimize the cross-entropy objective function in both domains (the details can be seen in Section III-G). Note that, we can achieve our preliminary work DA-GCN by disabling the time interval information and using the max-pooling operation for sequence embedding.

C. Account Representation Learning With Latent Users

In reality, as an account is usually shared by multiple users and users under the same account often have different preferences, uniformly treating accounts as virtual users is inappropriate. Intuitively, the users sharing an account should have diversified representations, due to their multifaceted personalities and preferences. Motivated by this observation, we assume $H$ latent users ($U_{1,k}, U_{2,k}, \ldots, U_{h,k}, \ldots, U_{h,k}$) under each account $U_k$ and denote the embedding of the $h$th latent user $U_{k,h}$ as $e_{U_{k,h}} \in \mathbb{R}^d$, which is learned by aggregating the messages passed from items in both source and target domains (this process is shown in Fig. 2). Note that, as in real-world scenarios, we have no further information to distinguish the exact users sharing an account, such as family TV accounts; we subsume that each account has $H$ latent users and leverage $H$ as a hyperparameter by fine-tuning it in different application scenarios.

1) Message Passing: Let $A_i \in \mathcal{N}_{A_i}^{U_{k,h}}$ and $B_j \in \mathcal{N}_{B_j}^{U_{k,h}}$ be the connected items of $U_{k,h}$ in domains A and B, respectively, where $\mathcal{N}_{A_i}^{U_{k,h}}$ denotes the neighbor set of $U_{k,h}$ in domain A and $\mathcal{N}_{B_j}^{U_{k,h}}$ denotes the neighbor set of $U_{k,h}$ in domain B. Then, we define the representation $(m_{U_{k,h} \rightarrow A_i})$ of the passed message from $A_i$ to $U_{k,h}$ in domain A as

$$m_{U_{k,h} \rightarrow A_i} = y_{A_i}^{U_{k,h}} (W_1 e_{A_i} + W_2 (e_{A_i} \circ e_{U_{k,h}}))$$

(3)

where $W_1, W_2 \in \mathbb{R}^{d \times d}$ are the trainable weight matrices and $e_{A_i}, e_{U_{k,h}} \in \mathbb{R}^d$ are the embedding vectors of item $A_i$ and user $U_{k,h}$, respectively. The elementwise product $e_{A_i} \circ e_{U_{k,h}}$ denotes the information interaction between $A_i$ and $U_{k,h}$. $y_{A_i}^{U_{k,h}}$ is a learnable parameter that indicates how much information we pass from $A_i$ to $U_{k,h}$. The learning process of it is introduced in the following.

Similar to domain A, we define the representation $(m_{U_{k,h} \rightarrow B_j})$ of the passed message from item $B_j$ to the target user $U_{k,h}$ in domain B as

$$m_{U_{k,h} \rightarrow B_j} = y_{B_j}^{U_{k,h}} (W_1 e_{B_j} + W_2 (e_{B_j} \circ e_{U_{k,h}}))$$

(4)

Besides, we further add a self-connection to $U_{k,h}$ to keep the information carried by the target user. The passed information
(\textbf{\textit{m}}_{U_{i,k} \rightarrow U_{i,b}}) is defined as

\begin{equation}
\textbf{\textit{m}}_{U_{i,k} \rightarrow U_{i,b}} = \gamma_{U_{i,k}}^{U_{i,b}} (\textbf{\textit{W}}_1 \textbf{\textit{e}}_{U_{i,k}}) \tag{5}
\end{equation}

where \( \gamma_{U_{i,k}}^{U_{i,b}} \) and \( \gamma_{U_{i,b}}^{U_{i,k}} \) are the attentive weights indicating the strength of each passed message, whose values are also computed by the following attention mechanism.

2) Domain-Aware Attention Mechanism: To fully capture the distinct preferences of each latent user over different items on both domains, we devise a domain-aware attention mechanism to measure the importance of item neighbors to the target user. The importance of \( A_i \), \( B_j \) to \( U_{i,b} \) in domain A is defined as

\begin{equation}
\gamma_{A_i}^{U_{i,b}} = f(\textbf{\textit{e}}_{U_{i,b}}, \textbf{\textit{e}}_{A_i}) \tag{6}
\end{equation}

where \( f(\cdot) \) is a pairwise similarity metric. In this work, the cosine similarity function is applied.

Then, we achieve the attentive weight on each item \( A_i \) via the following normalization operation:

\begin{equation}
\gamma_{A_i}^{U_{i,b}} = \exp(s_{A_i}) \left( \sum_{A_i' \in N_{A_i}^{U_{i,b}}} \exp(s_{A_i'}) + \sum_{B_j \in N_{B_j}^{U_{i,b}}} \exp(s_{B_j}) + s_{A_i} \right) \tag{7}
\end{equation}

where \( s_{A_i} \) and \( s_{B_j} \) weight the importance of each item \( B_j \) to \( U_{i,b} \) in domain B and the self-connection within \( U_{i,b} \), respectively (similar to the definition of \( s_{U_{i,b}}^{A_i} \)). By replacing the corresponding user/item embeddings, we can further obtain \( \gamma_{B_j}^{U_{i,b}} \) and \( \gamma_{A_i}^{U_{i,b}} \) in a similar way.

3) Message Aggregation: Thereafter, we can obtain the embedding (\( \textbf{\textit{e}}_{U_{i,b}} \)) of user \( U_{i,b} \) by aggregating all the passed messages in both domains

\begin{equation}
\textbf{\textit{e}}_{U_{i,b}} = \text{LeakyReLU} \left( \textbf{\textit{m}}_{U_{i,k} \rightarrow U_{i,b}} + \sum_{A_i \in N_{A_i}^{U_{i,k}}} \textbf{\textit{m}}_{U_{i,k} \rightarrow A_i} \right.
\end{equation}

\begin{equation}
\left. + \sum_{B_j \in N_{B_j}^{U_{i,b}}} \textbf{\textit{m}}_{U_{i,b} \rightarrow B_j} \right) \tag{8}
\end{equation}

where LeakyReLU is a nonlinear activate function, \( \textbf{\textit{m}}_{U_{i,k} \rightarrow U_{i,b}} \) is the information from herself, and \( \textbf{\textit{m}}_{U_{i,k} \rightarrow A_i} \) and \( \textbf{\textit{m}}_{U_{i,b} \rightarrow B_j} \) are the passed messages from domains A and B, respectively.

To this end, we achieve the account representation by merging the embeddings of all the latent users

\begin{equation}
\textbf{\textit{e}}_{U_k} = \frac{1}{|H|} \sum_{h=1}^{H} \textbf{\textit{e}}_{U_{i,h}} \tag{9}
\end{equation}

where \( \textbf{\textit{e}}_{U_{i,h}} \) is the representation of account \( U_k \).

D. Time Interval-Aware Item Representation Learning

We model an item by aggregating the information from two types of nodes with connections, i.e., the connected users and items within the same domain. Moreover, as the item pairs with different time intervals usually reveal different attractions to users, such as users tend to buy fast-moving consumer goods in a short period and buy electronic products at long intervals, modeling time intervals helps distinguish different items and capture fine-grained preferences.

1) Message Passing: Let \( U_{i,b} \in N_{U_{i,k}}^{A_i} \) and \( A_i - 1 \in N_{A_i}^{A_i} \) denote the connected user and item nodes, respectively, where \( N_{U_{i,k}}^{A_i} \) represents the users connected with \( A_i \) and \( N_{A_i}^{A_i} \) indicates the items connected with \( A_i \) in domain A. Then, we can formulate the passed message (\( \textbf{\textit{m}}_{A_i \rightarrow U_{i,b}} \)) from user \( U_{i,k} \) to \( A_i \) as

\begin{equation}
\textbf{\textit{m}}_{A_i \rightarrow U_{i,b}} = \gamma_{U_{i,k}}^{A_i} (\textbf{\textit{W}}_1 \textbf{\textit{e}}_{U_{i,k}} + \textbf{\textit{W}}_2 (\textbf{\textit{e}}_{U_{i,b}} \odot \textbf{\textit{e}}_{A_i})) \tag{10}
\end{equation}

where \( \textbf{\textit{e}}_{U_{i,k}} \) and \( \textbf{\textit{e}}_{A_i} \) denote the presentations of \( U_{i,k} \) and \( A_i \), respectively, and \( \gamma_{U_{i,k}}^{A_i} \) is a learnable weight that controls how much information we should pass from \( U_{i,k} \) to \( A_i \).

Similarly, the passed message from item \( A_i - 1 \) to \( A_i \) can be defined as

\begin{equation}
\textbf{\textit{m}}_{A_i - 1 \rightarrow A_i} = \gamma_{A_i - 1}^{A_i} (W_1 \textbf{\textit{e}}_{A_i - 1} + \textbf{\textit{W}}_2 (\textbf{\textit{e}}_{A_i - 1} \odot \textbf{\textit{e}}_{A_i})) \tag{11}
\end{equation}

where \( \gamma_{A_i - 1}^{A_i} \) weights the information passed from \( A_i - 1 \) to \( A_i \).

Then, we define the retained message of \( A_i \) similarly

\begin{equation}
\textbf{\textit{m}}_{A_i \rightarrow A_{i-1}} = \gamma_{A_i}^{A_{i-1}} (\textbf{\textit{W}}_1 \textbf{\textit{e}}_{A_i}) \tag{12}
\end{equation}

where \( \gamma_{A_i}^{A_{i-1}} \) is also a learnable weight (we will introduce \( \gamma_{A_i}^{A_{i-1}} \), \( \gamma_{A_i}^{A_i} \), and \( \gamma_{A_i}^{A_{i+1}} \) shortly).

However, the above message-passing strategy for items [i.e., (11)] ignores the fact that users usually consume different items with different time intervals. For example, users may repeatedly purchase daily consumer products quickly and purchase electronic products in a long time interval. We can also have similar observations in video streaming services, that is, users may watch news programs every day, but only one movie a week. Intuitively, the time interval between items not only determines users’ needs but also is an important signal for us to distinguish and identify items.
To further enhance the item representation learning, we incorporate the time interval information into the message-passing process and devise a time interval-aware item representation learning method. Let $t_{A_{i-1}}$ be the representation of the time interval $\delta_{i-1} = [t_i - t_{i-1}]$ between items $A_i$ and $A_{i-1}$, where $t_i$ is the timestamp of $A_i$. The time intervals between any two adjacent items in the behavior sequence are represented as learnable embeddings, which are initialized by the Xavier method [58] and optimized by the Adam algorithm [59]. Moreover, all the time interval values (i.e., $\delta_{i-1}$) are further clipped into a proper range since a too large or too small time interval tends to be meaningless.

Then, the passed message from items can be reformulated by adding the time interval with a weighted sum

$$m_{A_i \leftarrow A_{i-1}} = \gamma_{A_{i-1}}^{A_i} (W_1(\alpha e_{A_{i-1}} + (1 - \alpha)t_{A_{i-1}})$$

$$+ W_2(e_{A_{i-1}} \odot e_{A_i}))$$

where $\alpha$ is a hyperparameter that controls to what extent we should pay attention to the time interval information. To this end, we have passed three kinds of information to the target item, i.e., the message from $A_{i-1}$, the interacted information between $A_i$ and $A_{i-1}$, and the representation of the corresponding time interval (the message defined in (11) is the strategy utilized in DA-GCN).

### 2) Sequence-Aware Attention Mechanism

To distinguish the importance of the linked users and items, we develop another attention mechanism to measure their sequential dependencies to the target item, which can be defined as follows:

$$s_{A_{i-1}}^{A_i} = f(e_{A_{i-1}}, e_{A_i})$$
$$s_{U_{i,b}}^{A_i} = f(e_{U_{i,b}}, e_{A_i})$$
$$s_{A_i}^{A_i} = f(e_{A_i}, e_{A_i})$$

where $s_{A_{i-1}}^{A_i}$ and $s_{U_{i,b}}^{A_i}$ denote the importance of item $A_{i-1}$ to $A_i$ and the importance of user $U_{i,b}$ to item $A_i$, respectively, and $s_{A_i}^{A_i}$ is the importance of the self-connection to $A_i$. Then, we can retrieve $\gamma_{A_{i-1}}^{A_i}$ by the following operation: $s_{A_{i-1}}^{A_i}$ as:

$$\gamma_{A_{i-1}}^{A_i} = \exp(s_{A_{i-1}}^{A_i}) \left(\sum_{A_{i-1} \in A_{i-1}} \exp(s_{A_{i-1}}^{A_i}) + \sum_{U_{i,b} \in U_{i,b}} \exp(s_{U_{i,b}}^{A_i}) + s_{A_i}^{A_i}\right)$$

Similarly, we can obtain $\gamma_{U_{i,b}}^{A_i}$ and $\gamma_{A_i}^{A_i}$ in the same way.

### 3) Message Aggregation

Then, the representation of the target item $A_i$ is updated by aggregating all the messages from its connected users and items within the same domain

$$e_{A_i} = \text{LeakyReLU} \left( m_{A_i \leftarrow A_{i-1}} + \sum_{A_{i-1} \in A_{i-1}} m_{A_i \leftarrow A_{i-1}} \right)$$

For clarity, we rename $e_{A_i}$ as $g_{A_i}^{A_i}$ to represent the embedding of item $A_i$ with respect to the $h$th latent user. Then, the account-level representation ($g_{A_i}$) of item $A_i$ can be formulated as

$$g_{A_i} = \frac{1}{H} \sum_{h=1}^{H} g_{A_i}^{h}$$

where an average operation is applied to all the latent representations.

### E. Matrix-Form Propagation Rule

To efficiently learn the representations for all users and items in both domains, we further formulate the propagation rule in a layerwise matrix form (from layer $l - 1$ to $l$) and define it as

$$E_l = \sigma((\alpha(L_l + I))E_{l-1} + (1 - \alpha)\mathcal{L}_T^{T_{l-1}}W_1$$

$$+ \mathcal{L}_E^{E_{l-1}} \odot E_{l-1}W_2)$$

where $E_l \in \mathbb{R}^{(p+n+q)d}$ denotes the representations for all the users and items in domains A and B, $T_l \in \mathbb{R}^{(p+n+q)d}$ denotes all the time intervals in both domains, and $I$ is an identity matrix. $\mathcal{L}_l \in \mathbb{R}^{(p+n+q)x(p+n+q)}$ is the Laplacian matrix of the CDS graph and $\mathcal{L}_E \in \mathbb{R}^{(p+n+q)x(p+n+q)}$ is the time interval Laplacian matrix based on $\mathcal{L}_l$. Their definitions are formulated as

$$\mathcal{L}_l = \begin{bmatrix} Y_{A_iA_i} & Y_{A_iU_i} & 0 \\ Y_{U_iA_i} & 0 & Y_{U_iB_j} \\ 0 & Y_{B_jU_i} & Y_{B_jB_j} \end{bmatrix}$$

$$\mathcal{L}_E = \begin{bmatrix} T_{A_iA_i} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & T_{B_jB_j} \end{bmatrix}$$

where $Y_{A_iA_i} \in \mathbb{R}^{p \times p}$ and $Y_{A_iU_i} \in \mathbb{R}^{p \times n}$ are the attention matrices that weigh the importance of the connected items and users to the target item in domain A, respectively; $Y_{U_iA_i} \in \mathbb{R}^{p \times p}$ represents the weights of the connected items to users in domain A; and $T_{A_iA_i} \in \mathbb{R}^{p \times p}$ represents the time interval weight matrix between any given item $A_{i-1}$ and $A_i$. Similarly, in domain B, we let $Y_{B_jU_i} \in \mathbb{R}^{q \times n}$ and $Y_{B_jB_j} \in \mathbb{R}^{q \times q}$ be the weight matrices from users and items to the target item, respectively. $Y_{U_iB_j} \in \mathbb{R}^{p \times q}$ denotes the weights from any given item to the target user and $T_{B_jB_j} \in \mathbb{R}^{q \times q}$ represents the time interval weights between any two items in domain B.

Note that, we can achieve the propagation rule of the DA-GCN method by setting $\alpha = 1$, that is, disabling the time interval information in item representation learning.

### F. Sequence Representation Learning

After node representation learning, we can get the sequence-level embedding for $S_A$ (or $S_B$) by directly applying the max-pooling operation (as DA-GCN does) to the item representations within it ($g_{A_1}, g_{A_2}, \ldots, g_{A_n}, \ldots$) ([or ($g_{B_1}, g_{B_2}, \ldots, g_{B_n}, \ldots$)]). However, as the above method only leverages one representative item as the sequence-level representation, users’ preferences over other items and their interactive characteristics are both ignored. Moreover, though the average-pooling strategy can take all the items into consideration, it treats items equally and cannot learn their
different contributions to the sequence. In light of this, we first model the interactive features by introducing an account-aware self-attention network and then devise a vanilla attention network to attentively aggregate the items within it (as shown in Fig. 3). What is more, as users’ sequential preferences are often reflected by their recent interactive behaviors, we leverage the last item ($A_t = A_{t-2}$ and $B_t = B_{t-2}$) within the sequence as the supervision signal to guide the sequence representation learning, that is, an attention network is developed to estimate the attention weights of items within the given sequence (we take domain A as an example).

For the $i$th item in $S_{A}$ ($A_{i}$), we compute its relevance to $A_{j}$ by

$$a_{i,j} = f(z_{A_i}, z_{A_j})$$

where $z_{A_i}$ is the representation of $A_i$ with learned interactive features and $f(\cdot)$ is a score function that measures the correlation between $z_{A_i}$ and $z_{A_j}$. Inspired by [61], we parameterize $f(\cdot)$ by an MLP network

$$f(z_{A_i}, z_{A_j}) = W_2^T ReLU(W_1[z_{A_i} \odot z_{A_j}] + b)$$

where $W_1$ and $b$ are weight matrix and bias vector, respectively, to map the input into a hidden layer and $W_2$ is a weight vector that projects the output of the first layer into an attention weight.

Then, we can get the sequence representation with the following attention network:

$$h_{S_{A}} = \sum_{i=1}^{|S_{A}|} a_{i,j} z_{A_i}$$

$$a_{i,j} = \frac{\exp(f(z_{A_i}, z_{A_j}))}{\sum_{i=1}^{|S_{A}|} \exp(f(z_{A_i}, z_{A_i}))}$$

where $h_{S_{A}}$ denotes the final representation of sequence $S_{A}$, which is learned by attentively aggregating the items within it. $\beta \in [0, 1]$ is the smoothing exponent [61] that aims at suppressing the value of the denominator to avoid overly punishing the attention weights for active users (i.e., sequences that have relatively more items). In experiments, we set $\beta = 0.5$.

**G. Prediction Layer**

After the sequence representation layer, we can get the sequence embedding $h_{S_{A}}$ (or $h_{S_{B}}$) for $S_{A}$ (or $S_{B}$). Then,
to leverage the information in both domains, we feed the concatenation of \( h_{S_A} \) and \( h_{S_B} \) to the prediction layer

\[
P(A_{i+1}|S_A, S_B) = \text{softmax}(W_A \cdot (h_{S_A}, h_{S_B})^T + b_A) \\
P(B_{j+1}|S_B, S_A) = \text{softmax}(W_B \cdot (h_{S_B}, h_{S_A})^T + b_B)
\]

where \( W_A \) and \( W_B \) are the embedding matrices of all the items in domains A and B, respectively; and \( b_A \) and \( b_B \) are the bias terms. Then, we leverage the cross entropy as our loss function to train TiDA-GCN in both domains

\[
L_A(\theta) = -\frac{1}{|S|} \sum_{S_A, S_B \in S} \sum_{A \in S_A} \log P(A_{i+1}|S_A, S_B) \quad (30)
\]

\[
L_B(\theta) = -\frac{1}{|S|} \sum_{S_A, S_B \in S} \sum_{B \in S_B} \log P(B_{j+1}|S_A, S_B) \quad (31)
\]

where \( S \) represents the training sequences in domains A and B and \( \theta \) denotes the model parameters of TiDA-GCN. To enhance the CR, a joint training scheme is applied to both domains

\[
L(\theta) = L_A(\theta) + L_B(\theta) \quad (32)
\]

All the parameters in TiDA-GCN are learned via the gradient backpropagation algorithm in an end-to-end training manner.

### IV. EXPERIMENTAL SETUP

This section first introduces the research questions to be answered in experiments and then describes the datasets, evaluation protocols, and baselines utilized in our work.

#### A. Research Questions

We intend to answer the following research questions.

**RQ1** How does our devised TiDA-GCN method perform compared with other state-of-the-art methods?

**RQ2** What is the performance of TiDA-GCN on different domains? Can we benefit from the cross-domain information?

**RQ3** Is it helpful to leverage the sequence and time interval information in learning node representations? How do the key components of TiDA-GCN, i.e., attention mechanism, time interval modeling, and sequence modeling, contribute to the recommendation performance?

**RQ4** How do the hyperparameters (i.e., \( H \) and \( \alpha \)) affect the performance of our solution?

**RQ5** How is the training efficiency of our TiDA-GCN method?

#### B. Datasets

We evaluate our TiDA-GCN method on two real-world datasets that are released for the SCSR task, i.e., HVIDEO [3] and HAMAZON [6].

HVIDEO is collected from a smart TV platform that involves the watching logs of family accounts on two domains, i.e., the education domain (E-domain) and video domain (V-domain), from October 2016 to June 2017. The E-domain refers to the educational videos for students at all stages and instructional videos on daily life. The V-domain refers to the videos from the video-on-demand platform on movies, cartoons, TV series, and so on. As family accounts are usually shared by family members and their watching logs are the mixed behaviors of a family, this dataset is suitable for the SCSR task. To reduce the impact of noisy data, we further filter out the accounts with less than ten watching records and those logs with less than 300 s of watching time. As a result, our final data keep 13 714 family accounts and 134 349 watching sequences.

HAMAZON is another benchmark dataset for SCSR, which contains the user review records on two Amazon domains, i.e., movie domain (M-domain) and book domain (B-domain), from May 1996 to July 2014. The M-domain specifies the watching and reviewing logs from Amazon users to movies. The B-domain refers to the reading and rating behaviors of Amazon users on books. As the original Amazon data are not released for SCSR, the domain and account information cannot directly meet our requirement. Therefore, we follow the strategy in [6] and preprocess the Amazon data by the following steps: 1) as in our settings, users can simultaneously interact with items from different domains; we only retain the users who have interactions in both domains and 2) to simulate the shared-account characteristic, we first split the schedule into six intervals (i.e., 1996–2000, 2001–2003, 2004–2006, 2007–2009, 2010–2012, and 2013–2015). Then, in each interval, we randomly merge 2–4 users and their interaction records as one shared account. After that, we split each sequence within one year into small fragments and further filter out all the sequences with less than five items in M-domain and two items in B-domain to achieve our final data. The resulting data contain 13 724 accounts and 143 885 sequences. The statistics of HVIDEO and HAMAZON are reported in Table I.

| Datasets     | HVIDEO | HAMAZON |
|--------------|--------|---------|
| Items        | E-domain | M-domain |
| #Items       | 8,367   | 67,161  |
| #Interactions| 2,129,500 | 2,196,574 |
| Avg. sequence length | 15.85   | 15.27   |
| #Accounts    | 13,714  | 13,724  |
| #Sequences   | 134,349 | 143,885 |
| #Train-sequences | 114,197 | 122,303 |
| #Test-sequences | 20,152  | 21,582  |

Note that, due to missing the time interval information in our previously prepossessed data [5], they cannot be directly applied to our solutions. Hence, we regenerate both datasets from their original form and re-conduct all the experiments accordingly.

#### C. Evaluation Protocols

In the experiments, we randomly select 85% of all the sequences as the training data and the remaining as the test set for both HVIDEO and HAMAZON. For evaluation, we treat the last item in each sequence for each domain as the ground truth and intend to evaluate the ability of our model
in predicting the next item given one account’s historical behavior sequence.

We explore the effectiveness of our proposed models by reporting the top-$N$ recommendation results measured by two commonly used metrics, Recall@$N$ and MRR@$N$ [62], [63] (we set $N \in \{5, 20\}$ in the experiments).

1) Recall@$N$ measures how many desired items of the test data can be covered among the top-$N$ recommended items. Note that recall does not consider the actual rank of the item and it can work well in practical scenarios where the absolute item order does not matter.

2) MRR@$N$ (mean reciprocal rank) computes the average of the reciprocal ranks of the desired items, and the reciprocal rank above $N$ is set to zero. Compared with recall, MRR considers the rank order of the item, and it is an important measurement for the recommendation scenarios where the item ranking order matters.

D. Baseline Methods

We evaluate TiDA-GCN by comparing it with the following baselines in six categories: traditional recommendation, shared-account recommendation, CR, SR, time interval-aware SR, and SCSR.

1) Traditional Recommendation Methods: For comparison, we adapt them to the SR task and report their results in each domain.

1) Item-KNN [64]: This is a simple yet frequently used baseline that recommends items according to the item-to-item similarity, defined as the cosine similarity of two items measured by the sequences in which they appear.

2) BPR-MF [62]: This is a matrix factorization method that is commonly used as a ranking-based baseline. We apply it to SR by representing sequences with the average latent factors of items appearing in them.

3) NCF [65]: This is a collaborative filtering method implemented by a neural network. We exploit it for SR by treating users as sequences and learning their representations via an average-pooling layer over the latent factors of items within them.

4) LightGCN [44]: This method models the sequences and collaborative filtering mechanism by a GCN, where an item representation is learned by aggregating the information from its neighbors.

2) Shared-Account Recommendation Methods: These kinds of methods are devised for making recommendations for shared accounts [66], [67], [68]. However, most of them need extra information unavailable in our dataset, such as explicit ratings and item descriptions, for user identification. Hence, we select the following method that needs similar input to ours as comparisons.

1) VUI-KNN [35]: This method supposes different users within a shared account should get used to consuming services during different periods. Then, it decomposes users in a composite account by dividing consuming logs into periods, which are further viewed as virtual users. The users in an account are identified by the combinations of virtual users.

2) CR Methods: The following conditions hold.

1) NCF-MLP++ [3]: This is an improved NCF method [65] that shares the collaborative filtering in different domains.

2) Conet [20]: This is a CR method based on a cross-stitch network, where the domain sharing mechanism is modeled by a neural collaborative filtering model.

4) SR Methods: As these methods are mainly proposed for the SR on a single domain, we report their results on each domain.

1) GRU4REC [62]: This is an RNN-based SR method, which employs a GRU component and a ranking-based loss function to learn users’ sequential patterns.

2) HGRU4REC [69]: This method further improves GRU4REC by incorporating a hierarchical RNN structure, where the sequential relations among sessions and user identities are simultaneously considered.

3) NAIS [61]: This is an item-based CF method that explores a nonlinear attention network to learn item similarities. The neural attention design enables NAIS to distinguish the importance of items in users’ historical sequential behaviors.

5) Time Interval-Aware SR Methods: The following conditions hold.

1) Time-LSTM [56]: This is a time interval-aware recommendation method that models time gaps between users’ actions with time gates in a new LSTM variant.

2) TGSRec [57]: This is another time interval-aware SR method that explicitly models collaborative signals and time gaps among items via a collaborative attention network, where the time span is represented as a kernel value of the corresponding encoded time embeddings.

6) SCSR Methods: The following conditions hold.

1) π-Net [3]: This is a state-of-the-art method proposed for SCSR, which explores a parallel RNN and a gating mechanism to transfer the shared information across domains. For the shared-account characteristic, a shared account filter unit (SFU) is applied to learn user-specific representations.

2) PSJNet [6]: This is another recently developed method for SCSR, which improves π-Net via splitting the mixed representations to get role-specific representations and joining them to get cross-domain representations. Note that, due to the limitation of our GPU memory, we fail to get the expected results on the HAMAZON dataset. To complete the training process on HAMAZON, we only select 80,000 sequences to optimize PSJNet.

3) DA-GCN [5]: This is a preliminary version of our work, which achieves the state-of-the-art performance in our previous experiments. However, this method does not consider the time interval information between items, which is incapable of distinguishing the timeliness of sequential correlations between them. Moreover, DA-GCN fails to consider the importance of different items and their interactive characteristics, hindering us from learning more accurate representations.

E. Implementation Details

We implement our proposal based on the Tensorflow platform and accelerate the training processes using a Quadro RTX 6000 GPU. For model optimization, we use the Xavier method [58] to randomly initialize all the parameters and take Adam [59] as our optimization algorithm. For the hyperparameters of the optimizer, we set the learning rate as
TABLE II

| Methods        | HVIDEO          |         | HAMAZON          |         |
|----------------|-----------------|---------|------------------|---------|
|                | E-domain (%)    | V-domain (%) | M-domain (%)    | B-domain (%) |
|                | MRR  @5 @20    | Recall  @5 @20 | MRR  @5 @20    | Recall  @5 @20 |
| Item-KNN       | 3.52           | 4.20     | 3.73           | 9.41     |
| BPR-MF         | 2.82           | 3.33     | 2.52           | 5.56     |
| NCF            | 5.77           | 7.85     | 11.25          | 20.12    |
| LightGCN       | 11.55          | 13.56    | 20.70          | 39.92    |

|                  | HVIDEO          |         | HAMAZON          |         |
|------------------|-----------------|---------|------------------|---------|
| UVI-KNN          | 3.21            | 4.08    | 3.44            | 6.92     |
| NCF-MLP++        | 6.55            | 8.82    | 11.37           | 21.92    |
| Conet            | 7.88            | 9.52    | 13.30           | 25.52    |
| GRU4REC          | 13.33           | 15.48   | 22.47           | 44.18    |
| HGRU4REC         | 13.76           | 16.14   | 22.55           | 47.98    |
| NAIS             | 11.45           | 13.24   | 19.80           | 40.17    |

| Time-LSTM       | 11.19           | 13.27   | 20.71           | 41.45    |
| TGSRec          | 13.95           | 15.73   | 19.91           | 41.80    |
| π-Net           | 15.36           | 17.52   | 25.13           | 47.08    |
| PSJNet          | 15.37           | 17.56   | 24.80           | 46.68    |
| DA-GCN          | 35.63           | 37.27   | 51.35           | 66.93    |
| TiDA-GCN        | 38.66\(^a\)    | 40.23\(^a\) | 54.11\(^b\)  | 68.98\(^b\) |

|                  |                |         |                  |         |
|                  |                |         |                  |         |
| Bold value       | represents     | the     | best result       | of the  |
|                  | the compared  | compared| the            | baseline |
|                  | methods in    | methods  | corresponding    | results |
|                  | terms of      | terms   | metric.           | (DA-GCN) are marked with \(^{\dagger}\) (t-test, p < .05). |

0.001 and the batch size as 256. The dropout ratio is set as 0.1 at the model training stage on both datasets. For the model hyperparameters, we set the embedding size of both users and items as 16. For the number of users sharing an account (H), we search its value within \(\{1, 2, 3, 4, 5\}\). For the importance of the time interval information (α), we search its value in \([0, 1]\) with a step size of 0.1.

For the hyperparameters in baselines, we refer them to the settings in their publications and fine-tune them on different datasets. For example, the following conditions hold.

1) For Item-KNN, we set the neighbor size per item as 20.
2) For BPR-MF, we set the embedding size of both users and items as 16.
3) For NCF, NCF-MLP++, and NAIS, we enhance the training data by augmenting four negative samples per positive.
4) For VUI-KNN, we follow its strategy by cutting a day into six pieces to simulate the shared-account characteristic.
5) For LightGCN, we set its layer number as 4 and the embedding size of its hidden unit as 16.
6) For Conet, we set the class size and the input size both as 2 to make it comparable with ours.
7) For π-Net and PSJNet, we set the number of latent users sharing an account both as 4 to reach their best performance.
8) For TGSRec, we set the dimension of node and time interval representations both as 16 and the number of heads as 2.
9) For Time-LSTM, we set the number of its hidden units as 128.

Note that, for a fair comparison, we do not follow the evaluation methods in NCF, NCF-MLP++, and NAIS, which only test their ability in ranking 100 randomly sampled negatives per positive; instead, we treat all the items as the candidate set to ensure the stability of the methods. Moreover, we conduct the one sample paired \(t\)-tests to verify the significance of our improvement over the baseline results (\(p < .05\)).

V. EXPERIMENTAL RESULTS (RQ1 AND RQ2)

The comparison results with baselines on HVIDEO and HAMAZON are presented in Table II, from which we have the following observations.

1) TiDA-GCN and DA-GCN outperform other baselines on both datasets, demonstrating the effectiveness of our proposals in solving the SCSR task, that is, the capability of our models in capturing the shared-account characteristics, structural cross-domain knowledge, time interval information, and users’ sequential behaviors.
2) TiDA-GCN and DA-GCN achieve the best performance on both domains, indicating the benefits of considering the cross-domain information and the capabilities of our solutions in transferring the domain knowledge.

3) TiDA-GCN outperforms DA-GCN, denoting the importance of considering the time interval information and modeling the sequence representations from a multiaspect view. TiDA-GCN and DA-GCN perform better than RNN-based methods (i.e., GRU4REC, HGRU4REC).
TABLE III

ABLATION STUDIES ON HVIDEO AND HAMAZON

| Variants | HVIDEO | HAMAZON |
|----------|--------|---------|
|          | MRR    | Recall  | MRR    | Recall  | MRR    | Recall  | MRR    | Recall |
|          | @5     | @20     | @5     | @20     | @5     | @20     | @5     | @20    | @5     | @20     |
| GCN-S    | 35.52  | 37.24   | 51.07  | 66.41   | 59.48  | 60.22   | 75.28  | 82.12  | 19.22  | 19.24   | 20.78   | 21.22  | 21.03  | 21.05   | 23.43  | 23.59  |
| GCN-A    | 35.14  | 36.91   | 50.81  | 65.99   | 59.13  | 60.00   | 74.99  | 81.58  | 18.57  | 19.05   | 18.99   | 19.73  | 19.91  | 20.05   | 21.34  | 23.0   |
| GCN-AS   | 34.94  | 36.80   | 50.74  | 65.55   | 59.07  | 59.90   | 74.77  | 81.23  | 18.42  | 18.63   | 20.71   | 21.50  | 19.22  | 19.49   | 22.01  | 22.80  |
| TGCN-Ti  | 36.38  | 38.05   | 51.61  | 67.71   | 60.55  | 61.39   | 75.87  | 83.30  | 20.38  | 20.66   | 23.09   | 23.83  | 21.09  | 21.13   | 23.86  | 24.22  |
| TGCN-M   | 35.38  | 37.34   | 50.81  | 66.61   | 59.57  | 60.36   | 74.97  | 82.36  | 18.77  | 19.03   | 21.54   | 22.90  | 20.13  | 20.42   | 22.87  | 23.48  |
| DA-GCN   | 35.63  | 37.27   | 51.35  | 66.93   | 59.78  | 60.55   | 75.39  | 82.37  | 20.09  | 20.19   | 22.93   | 23.90  | 21.35  | 21.39   | 23.93  | 24.25  |
| TiDA-GCN | 35.66  | 40.23   | 54.11  | 68.98   | 63.58  | 65.37   | 76.37  | 83.58  | 20.91  | 21.23   | 23.55   | 24.33  | 21.85  | 22.21   | 24.69  | 24.82  |

HGRU4REC, π-Net, and PSJNet), showing the advantage of leveraging the GCN technique to model the multiple relationships among users and items. Furthermore, TiDA-GCN and DA-GCN have a better performance than π-Net and PSJNet, again demonstrating the importance of the cross-domain and time interval information, and the advantage of our proposals in modeling the cross-domain characteristic.

3) Our GCN-based methods (TiDA-GCN and DA-GCN) achieve a better performance than the SR methods (i.e., GRU4REC, HGRU4RE, NAIS, Time-LSTM, and TGSRec), indicating the importance of the cross-domain knowledge in making recommendations for users with mixed behaviors. The gap between TiDA-GCN and traditional recommendation methods (e.g., BPR-MF, NCF, and Light-GCN) shows the importance of the shared-account and cross-domain characteristics, and the effectiveness of our solutions.

4) The improvement of our proposed methods (i.e., TiDA-GCN and DA-GCN) over the methods that do not consider the shared-account information (e.g., NAIS, Conet, and Light-GCN), denoting the benefit of modeling an account from a multiuser view. From Table II, we also notice that only modeling the shared-account characteristic (e.g., VUI-KNN) while ignoring the sequential patterns of user behaviors cannot get better results than considering them simultaneously.

VI. EXPERIMENTAL ANALYSIS

In this section, we first conduct ablation studies to analyze the importance of different model components. Then, we investigate the impact of hyperparameters and the training efficiency of our solutions.

A. Ablation Studies (RQ3)

To explore the importance of different components in TiDA-GCN and DA-GCN, we conduct ablation studies on both datasets while keeping all the hyperparameters fixed. We compare our solutions with the following variants of them.

1) GCN-S: This is a variant of DA-GCN that disables the sequential information when constructing the CDS graph, that is, ignoring the sequential relationships among the items in both domains.

2) GCN-A: This is another variant of DA-GCN that does not exploit the attention mechanisms when aggregating the passed messages.

3) GCN-AS: This variant of DA-GCN removes both components (i.e., the attention mechanisms and the sequential information) from it. This is to demonstrate the benefits brought by considering the sequential information and attention mechanism for SCSR.

4) TGCN-Ti: This is a variant of TiDA-GCN that disables the time interval information when learning user and item representations. We conduct this experiment to investigate the importance of the time interval information in the graph neural network.

5) TGCN-M: This method removes the sequence learning component from TiDA-GCN and only utilizes a simple max-pooling operation to learn the account representations from the sequences (as DA-GCN does). Note that, DA-GCN can also be viewed as a variant of TiDA-GCN that removes both the time interval and sequence learning module from it.

The experimental results are shown in Table III, from which we have the following observations.

1) DA-GCN outperforms GCN-S and GCN-AS on both datasets, demonstrating the importance of modeling the sequential relationships among items and the effectiveness of our GCN-based solution.

2) DA-GCN achieves a better result than GCN-A and GCN-AS, showing the importance of the attention mechanism in aggregating the passed messages, that is, treating each neighbor differently can result in better node representations than weighting them equally. The gap between DA-GCN and GCN-AS again demonstrates the importance of the sequential information and the attention mechanism.

3) TiDA-GCN performs better than TGCN-Ti, denoting the significance of incorporating the time interval information into the node representation learning process. From this result, we can indicate that the time intervals among items provide us evidence to distinguish different types of item pairs, which leads to a better recommendation result.

4) TiDA-GCN has a better performance than TGCN-M, demonstrating the importance of our sequence learning module, that is, learning items’ interactive characteristics and treating them differently can benefit the sequence-level account representation. The improvement
Fig. 4. Impact of the hyperparameters $H$ and $\alpha$ to TiDA-GCN on HVIDEO. (a)–(d) and (i)–(l) E-domain. (e)–(h) and (m)–(p) V-domain.

of TiDA-GCN over DA-GCN shows the benefits brought by our time interval and sequence modeling components.

B. Impact of Hyperparameters (RQ4)

In this section, we further investigate the impact of hyperparameters to DA-GCN and TiDA-GCN on HVIDEO (similar trends are obtained on HAMAZON) and report the experimental results in Figs. 4 and 5.

1) Impact of Hyperparameter $H$: $H$ is introduced as a hyperparameter in both DA-GCN and TiDA-GCN to denote the number of latent users sharing an account. Considering the common size of shared accounts in reality, we search its value within $\{1, 2, \ldots, 5\}$. The experimental results are shown in Figs. 4 and 5, from which we find that both DA-GCN and TiDA-GCN perform worst when setting $H = 1$ and perform best when $H = 2$. Moreover, we also observe that both of them are getting worse with further increasing the value of $H$. This result demonstrates that viewing an account as a virtual user cannot get a better result than modeling it as $H$ latent users, which is more conducive to discovering the interests of different users from mixed behaviors.

2) Impact of Hyperparameter $\alpha$: To further explore the impact of considering time interval in generating the node representations, we introduce the hyperparameter $1 - \alpha$ within $[0, 1]$ to denote its contribution to TiDA-GCN. When setting $1 - \alpha = 0$, meaning that we will disable the time interval formation in the graph convolution process and vice versa. From the experimental results presented in Fig. 4, we can observe that the time interval information impacts TiDA-GCN significantly, and it reaches its best result when $\alpha = 0.8$ on most metrics. From the results, we also find that just disabling or relying too much on the time interval information cannot get better performance than combining it with the node information probably.

C. Training Efficiency and Scalability (RQ5)

To explore the training efficiency and scalability of DA-GCN and TiDA-GCN, we further investigate their time cost of model training with different dataset proportions (i.e., $\{0.2, 0.4, 0.6, 0.8, 1.0\}$). The comparison results with other state-of-the-art recommendation methods for SCSR are reported in Fig. 6. From these results, we can find that the following conditions hold.

1) Our DA-GCN and TiDA-GCN methods need less training time than other baselines on both datasets, demonstrating the higher training efficiency of our models in dealing with mixed user behaviors. The reason that training TiDA-GCN needs to pay more time than DA-GCN is mainly because TiDA-GCN further considers the time interval and interactive characteristics of items in the representation learning process.

2) From the results, we also observe that with the dataset ratio gradually increasing from 0.2 to 1.0, the time costs for training DA-GCN and TiDA-GCN grow almost linearly, which demonstrates the scalability of our model to large-scale data and provides us positive evidence to answer RQ5.

VII. CONCLUSION AND FUTURE WORK

In this work, we propose TiDA-GCN for SCSR to learn user and item representations from their interactions, as well
as the explicit structural information. To model the multiple associations among users and items, we first link them in a CDS graph. To model the structure information of the transferred knowledge, we then develop a domain-aware GCN to learn user-specific node representations, where two attention mechanisms are devised to weight the local neighbors of the target. To enhance the item and account representation learning, a time interval-aware message-passing strategy and an interactive characteristic modeling component are further devised. The experimental results on two real-world datasets show the superiority of our graph-based solution.

One of the limitations of TiDA-GCN is that it limits the number of domains to two, which may not match the real-world application scenarios. As one of our further works, we will extend TiDA-GCN to a more practical multidomain scenario and deal with the more serious negative transfer issue within it since the information/knowledge in each domain should be transferred to other domains more than once.

REFERENCES

[1] M. Ma et al., “Mixed information flow for cross-domain sequential recommendations,” ACM Trans. Knowl. Discovery Data, vol. 16, no. 4, pp. 64:1–64:32, 2022.
[2] P. Li, Z. Jiang, M. Que, Y. Hu, and A. Tuzhilin, “Dual attentive sequential learning for cross-domain click-through rate prediction,” in Proc. SIGKDD, Aug. 2021, pp. 3172–3180.
[3] M. Ma, P. Ren, Y. Lin, Z. Chen, J. Ma, and M. D. Rijke, “r-Net: A parallel information-sharing network for shared-account cross-domain sequential recommendations,” in Proc. SIGIR, Jul. 2019, pp. 685–694.
[4] P. Bajaj and S. Shekhar, “Experience individualization on online TV platforms through persona-based account decomposition,” in Proc. MM, Oct. 2016, pp. 252–256.
[5] L. Guo, L. Tang, T. Chen, L. Zhu, Q. V. H. Nguyen, and H. Yin, “DA-GCN: A domain-aware attentive graph convolution network for shared-account cross-domain sequential recommendation,” in Proc. IJCAI, Aug. 2021, pp. 2483–2489.
[6] W. Sun et al., “Parallel split-join networks for shared account cross-domain sequential recommendations,” IEEE Trans. Knowl. Data Eng., early access, Dec. 13, 2021, doi: 10.1109/TKDE.2021.3130927.
[7] F.-Z. Zhang et al., “Sequential recommendation via cross-domain novelty seeking trait mining,” J. Comput. Sci. Technol., vol. 35, pp. 305–319, Mar. 2020.
[8] C. Zhao, C. Li, and C. Fu, “Cross-domain recommendation via preference propagation GraphNet,” in Proc. CIKM, Nov. 2019, pp. 2165–2168.
[9] T. Bai et al., “CTRRec: A long-short demands evolution model for continuous-time recommendation,” in Proc. SIGIR, Jul. 2019, pp. 675–684.
[10] C. Wang, M. Zhang, W. Ma, Y. Liu, and S. Ma, “Make it a chorus: Knowledge-and time-aware item modeling for sequential recommendation,” in Proc. SIGIR, 2020, pp. 109–118.
[11] N. T. Tam, M. Weidlich, D. C. Thang, H. Yin, and N. Q. V. Hung, “Retaining data from streams of social platforms with minimal regret,” in Proc. IJCAI, Aug. 2017, pp. 2850–2856.
[12] Q. Zhang, L. Cao, C. Shi, and Z. Niu, “Neural time-aware sequential recommendation by jointly modeling preference dynamics and explicit feature couplings,” IEEE Trans. Neural Netw. Learn. Syst., early access, Apr. 14, 2021, doi: 10.1109/TNNLS.2020.3060058.
[13] F. Abel, E. Herder, G.-J. Houben, N. Henze, and D. Krause, “Cross-system user modeling and personalization on the social web,” User Model. User-Adapted Interact., vol. 23, no. 2, pp. 169–209, 2013.
[14] Y. Lu, Y. Fang, and C. Shi, “Meta-learning on heterogeneous information networks for cold-start recommendation,” in Proc. SIGKDD, Aug. 2020, pp. 1563–1573.
[15] Q. Zhang, J. Lu, D. Wu, and G. Zhang, “A cross-domain recommender system with kernel-induced knowledge transfer for overlapping entities,” IEEE Trans. Neural Netw. Learn. Syst., vol. 30, no. 7, pp. 1998–2012, Jul. 2019.
[16] C. Wang, M. Niepert, and H. Li, “RecSys-DAN: Discriminative adversarial networks for cross-domain recommender systems,” IEEE Trans. Neural Netw. Learn. Syst., vol. 31, no. 8, pp. 2731–2740, Aug. 2020.
[17] C. Gao et al., “Cross-domain recommendation without sharing user-relevant data,” in Proc. WWW, 2019, pp. 491–502.
[18] W. Liu, J. Su, C. Chen, and X. Zheng, “Leveraging distribution alignment via stein path for cross-domain cold-start recommendation,” in Proc. NeurIPS, 2021, pp. 1923–1924.
[19] F. Zhu, Y. Wang, C. Chen, G. Liu, and X. Zheng, “A graphical and attentional framework for dual-target cross-domain recommendation,” in Proc. IJCAI, Jul. 2020, pp. 3001–3008.
[20] G. Hu, Y. Zhang, and Q. Yang, “CoNet: Collaborative cross networks for cross-domain recommendation,” in Proc. CIKM, Oct. 2018, pp. 667–676.
[21] B. Loni, Y. Shi, M. Larson, and A. Hanjalic, “Cross-domain collaborative filtering with factorization machines,” in Proc. ECIR, 2014, pp. 656–661.
[22] L. Chen, J. Zheng, M. Gao, A. Zhou, W. Zeng, and H. Chen, “TLRec: Transfer learning for cross-domain recommendation,” in Proc. ICKB, 2017, pp. 167–172.
[23] T. Man, H. Shen, X. Jin, and X. Cheng, “Cross-domain recommendation: An embedding and mapping approach,” in Proc. IJCAI, Aug. 2017, pp. 2464–2470.
[24] L. Hu, J. Cao, G. Xu, L. Cao, Z. Gu, and C. Zhu, “Personalized recommendation via cross-domain triadic factorization,” in Proc. WWW 2013, pp. 595–606.
[25] T.-N. Doan and S. Sahebi, “TransCrossCF: Transition-based cross-domain collaborative filtering,” in Proc. CIMLA, Dec. 2020, pp. 320–327.
[26] M. Liu, J. Li, G. Li, and P. Pan, “Cross domain recommendation via bi-directional graph collaborative filtering networks,” in Proc. CIKM, Oct. 2020, pp. 885–894.
[27] C. Zhao, C. Li, R. Xiao, H. Deng, and A. Sun, “CATN: Cross-domain recommendation for cold-start users via aspect transfer network,” in Proc. SIGIR, Jul. 2020, pp. 229–238.
[28] S. Qin, C. Wei, Y. Zhang, and Q. Zhang, “Herograph: A heterogeneous graph framework for multi-target cross-domain recommendation,” in Proc. RecSys, 2020, pp. 1–7.
[29] Y. Zhang et al., “Learning personalized itemset mapping for cross-domain recommendation,” in Proc. IJCAI, Jul. 2020, pp. 2561–2567.
[30] F. Zhu, Y. Wang, C. Chen, J. Zhou, L. Li, and G. Liu, “Cross-domain recommendation: Challenges, progress, and prospects,” in Proc. IJCAI, Aug. 2021, pp. 4721–4728.
[31] Y. Bi, L. Song, M. Yao, Z. Wu, J. Wang, and J. Xiao, “DCDIR: A deep cross-domain recommendation system for cold start users in insurance domain,” in Proc. SIGIR, Jul. 2020, pp. 1661–1664.
[32] W. Fu, Z. Peng, S. Wang, Y. Xu, and J. Li, “Deeply fusing reviews and contents for cold start users in cross-domain recommendation systems,” in Proc. AAAI, 2019, pp. 94–101.
[33] Y. Zhao, J. Cao, and Y. Zhang, “Passenger prediction in shared accounts for flight service recommendation,” in Proc. APSCC, 2016, pp. 159–172.
[34] J.-Y. Jiang, C.-T. Li, Y. Chen, and W. Wang, “Identifying users behind shared accounts in online streaming services,” in Proc. SIGIR, Jun. 2018, pp. 65–74.
[35] Z. Wang, Y. Yang, L. He, and J. Gu, “User identification within a shared account: Improving IP-TV recommender performance,” in Proc. ADIS, 2014, pp. 219–233.
[36] X. Wen, Z. Peng, S. Huang, S. Wang, and P. S. Yu, “MISS: A multi-user identification network for shared-account session-aware recommendation,” in Proc. DASFAA, 2021, pp. 228–243.
[37] X. Wang, X. He, M. Wang, F. Feng, and T.-S. Chua, “Neural graph collaborative filtering,” in Proc. SIGIR, Jul. 2019, pp. 165–174.
[38] Y. Wang, H. Yin, H. Chen, T. Wo, J. Xu, and K. Zheng, “Origin-destination matrix prediction via graph convolution: A new perspective of passenger demand modeling,” in Proc. SIGKDD, Jul. 2019, pp. 1227–1235.
[39] Z. Yu et al., “Semisupervised classification with novel graph construction for high-dimensional data,” IEEE Trans. Neural Netw. Learn. Syst., vol. 33, no. 1, pp. 75–88, Jan. 2022.
[40] X. Wang, X. He, M. Wang, F. Feng, and T.-S. Chua, “Neural graph collaborative filtering,” in Proc. SIGIR, Jul. 2019, pp. 165–174.
[41] Y. Wang, H. Yin, H. Chen, T. Wo, J. Xu, and K. Zheng, “Origin-destination matrix prediction via graph convolution: A new perspective of passenger demand modeling,” in Proc. SIGKDD, Jul. 2019, pp. 1227–1235.
Lei Guo received the Ph.D. degree in computer science from Shandong University, Jinan, China, in 2015.

He is currently an Associate Professor and a Master's Supervisor with Shandong Normal University, Jinan. His research interests include information retrieval, social networks, and recommender systems.

Dr. Guo is also the Director of the Shandong Artificial Intelligence Society and a member of the Social Media Processing Committee of the Chinese Information Society.

Jinyu Zhang (Graduate Student Member, IEEE) is currently pursuing the master's degree in computer science with the School of Information Science and Engineering, Shandong Normal University, Jinan, China.

His research interests include sequential recommendation and cross-domain recommendation.

Li Tang received the master's degree in management science and engineering from Shandong Normal University, Jinan, China, in 2022.

Her research interests include cross-domain recommendation and social media mining.

Tong Chen (Member, IEEE) received the Ph.D. degree in computer science from The University of Queensland, St Lucia, QLD, Australia, in 2020.

He is currently a Lecturer with the Data Science Research Group, School of Information Technology and Electrical Engineering, The University of Queensland. His research interests include data mining, recommender systems, user behavior modeling, and predictive analytics.

Lei Zhu (Senior Member, IEEE) received the B.S. degree from the Wuhan University of Technology, Wuhan, China, in 2009, and the Ph.D. degree from the Huazhong University of Science and Technology, Wuhan, in 2015.

He was a Research Fellow with The University of Queensland, St Lucia, QLD, Australia, from 2016 to 2017, and Singapore Management University, Singapore, from 2015 to 2016. He is currently a Full Professor with the School of Information Science and Engineering, Shandong Normal University, Jinan, China. His research interests are in the area of large-scale multimedia content analysis and retrieval.

Hongzhi Yin (Senior Member, IEEE) received the Ph.D. degree in computer science from Peking University, Beijing, China, in 2014.

He is currently an Associate Professor and a Future Fellow with The University of Queensland, St Lucia, QLD, Australia. His research interests include recommendation systems, user profiling, topic models, deep learning, social media mining, and location-based services.

Dr. Yin received the Australian Research Council Future Fellowship and the Discovery Early-Career Researcher Award in 2016 and 2021, respectively.