Multi-Behavior Sequential Recommendation With Temporal Graph Transformer

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Abstract—Modeling time-evolving preferences of users with their sequential item interactions, has attracted increasing attention in many online applications. Hence, sequential recommender systems have been developed to learn the dynamic user interests from the historical interactions for suggesting items. However, the interaction pattern encoding functions in most existing sequential recommender systems have focused on single type of user-item interactions. In many real-life online platforms, user-item interactive behaviors are often multi-typed (e.g., click, add-to-favorite, purchase) with complex cross-type behavior inter-dependencies. Learning from informative representations of users and items based on their multi-typed interaction data, is of great importance to accurately characterize the time-evolving user preference. In this work, we tackle the dynamic user-item relation learning with the awareness of multi-behavior interactive patterns. Towards this end, we propose a new Temporal Graph Transformer (TGT) recommendation framework to jointly capture dynamic short-term and long-range user-item interactive patterns, by exploring the evolving correlations across different types of behaviors. The new TGT method endows the sequential recommendation architecture to distill dedicated knowledge for type-specific behavior relational context and the implicit behavior dependencies. Experiments on the real-world datasets indicate that our method TGT consistently outperforms various state-of-the-art recommendation methods. Our model implementation codes are available at https://github.com/akxli/TGT.

Index Terms—Graph neural network, multi-behavior recommendation, sequential recommendation

1 INTRODUCTION

PERSONALIZED recommender systems have become increasingly important to alleviate information overload and satisfy user diverse interests in many online platforms (e.g., E-commerce sites, online movie and music sites) [9], [17], [62]. While many collaborative filtering methods have been proposed to model user-item interactions [12], [59], they focus on the static settings and ignore the dynamic nature of user’s time-evolving preferences [26]. Hence, among various recommendation scenarios, sequential recommender systems are introduced to model dynamic preference of users based on their sequential interaction behaviors [28], [36], [40]. The key idea of sequential recommendation models is to understand the evolution of user’s preference by capturing temporal dependency of user-item interactions, based on the past observed behaviors.

With the advent of deep learning techniques in recent years, a substantial number of approaches have been proposed to solve the sequential recommendation problem, via utilizing different neural network techniques. For example, recurrent neural network-based models propose to encode the sequential information from the interacted item sequence of each user [13], [32]. In addition, convolutional neural networks and attention mechanism also serve as effective solutions for modeling sequential patterns of item-item transitions. e.g., Caser [37] designs convolution-based kernel functions to aggregate information from neighboring time slots. NARM [23] and SASRec [22] develop attentive relation encoder to capture users’ general interests with long-term temporal dependency. Inspired by the effectiveness of graph neural networks, several GNN-based methods (e.g., HyRec [41], MA-GNN [28] and MTD [16]) exploit the user-item graph structure to guide the embedding learning with the incorporation of temporal context of user interactions.

While the aforementioned methods have achieved compelling results, we argue that there is a common deficiency in them: most of current frameworks are designed for single behavior type. In practice, the intention of user-item interactions can change over time depending on different contexts [20], [38]. Let us consider an example from online retailing platforms: users could view products or tag them as favourites if they like, or make final purchase if the products meet their needs [7] (as illustrated in Fig. 1). Hence, user-item interactions are often exhibited with time-dependent and behavior diversity in nature. To recommend the future purchase for a user, it is important and beneficial to
We conduct empirical studies on two real-world Graph Temporal Multi-behavior Pattern Fusion. This work tackles the multi-behavior sequential recommendation problem with heterogeneous relational context, inter-dependent relations, it is challenging to be responsive for the evolution of multi-behavior semantics and the underlying cross-type behavior dependency. In practical applications, users often interact with items in a variety of behaviors which are inherently correlated, due to his/her specialty at different timestamps. Therefore, to build effective multi-behavior sequential recommendation model, it requires the careful design to jointly distill the behavior heterogeneity and underlying type-dependent patterns. In light of these challenges, we propose a multi-behavior sequential recommendation model with Temporal Graph Transformer (short for TGT). In particular, to capture the short-term multi-typed interaction patterns of users, we develop a behavior-aware transformer network to inject the behavior heterogeneous signals into the sequential modeling of item transitions. In this regard, we preserve the expressive multi-behavior characteristics and the changes in interaction semantics. To exploit the long-term multi-behavior dependencies, we propose a temporal graph neural network to infer the latent user representations from their diversified activities on items with arbitrary durations. Instead of parameterizing each type of user-item interactions into separate embedding spaces, our designed multi-channel augmented message passing paradigm allows behavior of different types to maintain not only their specific time-aware semantics, but also the behavior type-specific dependent representations with long-range dynamics. Furthermore, in TGT, we recursively refine the global-level representations over the time-aware user-item interaction graph to capture the dynamic cross-sequence correlations among different users. This has been largely overlooked by most of existing sequential recommender systems [28], [36], [41] for simplifying the model design.

We summarize the contributions of this work as follows:

- This work tackles the multi-behavior sequential recommendation with the exploration of multi-behavior characteristics of users from both the short-term and long-term perspectives. We show that modeling the dynamic cross-type behavior inter-dependency is essential for improving the recommendation quality.
- We propose a general sequential recommendation model TGT to maintain the dedicated representations for different types of user-item interactions over time. In TGT, we adopt the graph neural network along the temporal dimension to capture the dynamism of multi-behavior interaction patterns.
- We conduct empirical studies on two real-world datasets to demonstrate the superiority of our TGT framework when competing with various 18 recommendation baselines. Our evaluation also justifies the effectiveness of components in our TGT model, as well as the interpretability of the learned multi-behavior dependent representations.

The remainder of this paper is organized as follows. Section 2 discusses the related work. In Section 3, we introduce the details of our proposed framework TGT. We report our experimental results that demonstrate the effectiveness of the proposed model in Section 4. Finally, Section 5 concludes our study and discusses the future work.

2 RELATED WORK

In this section, we summarize the relevant research work from the following research lines: i.e., i) sequential recommendation, ii) graph-based recommender systems, iii) recommendation with heterogeneous relational context, iv) multi-behavior/intent recommendation.

2.1 Sequential Recommender Systems

The sequential recommendation is usually formulated as sequence prediction problem with the modeling of item transitional regularities [19], [42], [64]. Some earlier studies are on the basis of Markov Chain to model correlations between different items, such as factorizing personalized Markov Chains (FMPC) [33] and fusing item similarity with Markov Chains (Fossil) [10]. To tackle the challenge of sequential behavior learning, many neural network-based methods have been proposed to capture complex sequential information [6]. In particular, recurrent neural network is utilized as an intuitive way to model temporal dependencies [13]. Attention mechanisms allows the model to identify specific parts of input item sequences and preserve long-term dependencies, e.g., NARM [23] and SASRec [22]. For example, SASRec relies on the self-attention mechanism to identify item relevance from user past behaviors [22]. In addition, SR-GNN [53], MTD [16] and GCGNN [48] convert
the sequential item transitions into graphs and design graph neural networks for item representations. However, these models only consider singular type of sequential behaviors. Given users’ interacted item sequence, how to effectively exploit dynamic multi-behavior knowledge to improve recommendation accuracy, remains a significant challenge.

2.2 Graph Neural Network for Recommendation

Motivated by the strength of graph neural network, there exist many recently proposed recommendation methods modeling user-item interaction graph via information propagation between connected user/item nodes [4], [45], [56], [61], [66]. For example, Wang et al. [45] and Ying et al. [60] introduces the graph convolutional network in modeling collaborative effects between users and items. The embedding propagation is conducted over the constructed user-item interaction graph. Later on, He et al. [11] propose to improve training efficiency by removing the feature transformation and nonlinear activation operations with the light graph convolutional framework. With the self-supervised learning techniques, SGL [50] performs data augmentation on user-item interaction graphs to generate additional supervision signals. HCCF [56] enhances the graph-based collaborative filtering with hypergraph-enhanced contrastive learning. In this work, our TGT framework is built upon the dynamic graph neural architecture to capture the high-order connectivity, with the exploration of evolving multi-behavior preference.

2.3 Recommendation With Heterogeneous Relations

Another relevant research line is to consider different types of relationships in recommender systems [15], [21]. First, with the emergence of online social networks, social-aware recommendation models have been proposed to jointly consider user-user and user-item interactions for better user embedding generation [5], [18], [52]. Second, recent studies attempt to incorporate knowledge graph relational information as side features to model item correlations [1], [2], [30]. Third, to further alleviate data sparsity issue, heterogeneous graph learning approaches aims to transfer knowledge from both user and item domains (e.g., social links, item semantic relatedness), with the goal of augmenting the data of user-item pairs [27], [35]. Different from those methods which rely on the side information to construct meta-relations between users and items, this work focuses on exploiting the dynamic characteristics of multi-behavioral interaction data and validates its positive effects in sequential recommendation.

2.4 Multi-Behavior/Intent Recommender Systems

There exist some recommendation methods which aim to learn the collective knowledge from different types of user-item interactions (e.g., clicks, purchases) [7], [20], [49], [57]. For example, Gao et al. [7] define the cascading relationship to account for multiple types of user behaviors. AIR [3] is an attention-based recurrent neural model to capture the intention-aware sequential patterns. In Intention2Basket [43], heterogeneous user intentions are considered to encode the dynamic user preference for next-basket planning. Additionally, RIB [65] proposes to learn the sequential patterns from the perspective of micro behaviors, so as to improve the recommendation performance. In a session-based recommendation scenario, Meng et al. [31] introduces a new recommender system MKM-SR to integrate the item knowledge and different types of user behaviors for capturing item transitional patterns under a multi-task learning framework. MATN [54] is an attention-based recommendation method which fuses behavior-aware patterns to generate weighed summarized representations. Additionally, based on graph neural networks, Jin et al. [20] uses graph convolutional network to model behavior-aware collaborative signals. CML [49] designs a self-supervised learning method for multi-behavior recommendation. However, those models are designed for static recommendation scenarios, and can hardly be adaptive for modeling user-item interactions which are inherently dynamic. To fill this gap, we design a dedicated temporal graph-contextualized transformer network for modeling multi-behavior sequential interactions. Additionally, disentangled representation learning has been leveraged to separate embedding into distinct factors [29], [46], [63]. Nevertheless, most of existing disentangled representation learning works focus the embedding separation with the assumption of implicit factor independence. Different from them, this work exploits the dynamic dependency across different types of behavioral interaction patterns in an explicit manner.

3 METHODOLOGY

In this section, we first introduce the problem formulation and then elaborate our proposed TGT framework. The model flow of our method is illustrated in Fig. 2. We also summarize key notations of our methodology in Table 1.

3.1 Task Formulation

In our recommendation scenario, we let \( U = \{u_1, \ldots, u_m, u_2, \ldots, u_n\} \) denote the set of users and \( V = \{v_1, \ldots, v_m, v_2, \ldots, v_n\} \) denote the set of items. We further define \( B \) (indexed by \( b \)) to represent the types of different interaction behaviors, such as browsing, adding to cart, tagging as favorite and purchasing. We differentiate users’ interactions by associating them with the corresponding behavior types (\( b \in B \)).

**Definition 1.** Multi-behavior Interaction Sequence \( S_i \). Given a user \( u_i \in U \), his/her behavior-aware interaction sequence \( S_i \) is consisted of individual triple \((v_{i_b}, b, t)\), representing the \( k \)th interacted item (ordered by time) under the \( b \)th behavior type at time \( t \), i.e., \( S_i = [(v_{i_1}, t_{i_1}, b_1), \ldots, (v_{i_k}, t_{i_k}, b_k), \ldots, (v_{i_K}, t_{i_K}, b_{K_i})] \), where \( K \) (indexed by \( k \)) is the sequence length \( K = |S_i| \).

In our multi-behavior sequential recommendation problem, we define the behavior type we aim to forecast as target behavior (e.g., purchase in online retailing platforms). Other types of user behaviors (e.g., page view, tag-as-favorite) are considered as context behavior for characterizing the preference of users over the target behavior. This work aims to predict the future item that user \( u_i \) will be interested after the observed interaction sequence \( S_i \), with the exploration of multi-behavior sequential patterns and interaction relation heterogeneity. Formally, our studied problem can be formalized as: Input: the past multi-behavior interacted item
sequence of each user $S_i (u_i \in U)$; Output: a learning function which accurately predicts the interacted item of each user after time $t_{K,i}$.

3.2 Framework Overview

Our proposed TGT is an integrative multi-behavior sequential recommendation framework which consists of several key learning phases (as shown in Fig. 2):

- To capture the behavior-aware sequential dependency across user-item interactions, we design an integrative relational learning framework with a behavior-aware context embedding module and an item-wise sequential dependency encoder. This component is able to model the temporal interaction patterns of users with the preservation of multi-behavior contextual signals.

- The component of multi-behavior pattern aggregation is proposed to capture short-term user preference over behavior-aware sub-interactions. In this module, the time-aware user-item interactive patterns are encoded by the dual-stage behavior-aware message passing paradigm for embedding propagation and refinement.

- Finally, a global context learning component is introduced to endow our TGT with the ability of incorporating the long-term multi-behavior patterns into the preference learning framework. Through the recursive embedding propagation, both the short-term and long-term behavior-specific interaction patterns are preserved in the learned representations of users/items.

In the following subsections, we will elaborate the design motivations and technical details of each learning component in our proposed TGT framework.

3.3 Dynamic Individual Interest Modeling

To capture the time-evolving user interests with the modeling of underlying relation heterogeneity across different types of behaviors, we develop a multi-behavior transformer network to distill short-term behavior dynamics. In particular, we explicitly model user short-term preference by splitting multi-behavior interaction sequence $S_i$ into $R$ fine-grained sub-sequences $S_i^r$ (indexed by $r$). Formally, we define $S_i^r = [(v_i^r, t_i^r, b_i^r), \ldots, (v_i^r, t_i^r, b_i^r)]$. Without loss of generality, the individual interaction instance in the $r$th sub-sequence is denoted as $(v_i^r, t_i^r, b_i^r)$.

3.3.1 Behavior-Aware Context Embedding Layer

We design an embedding layer to jointly inject the multi-behavior contextual and temporal signals into the item representations. Following the mainstream recommendation paradigms [1], [34], we first describe individual item $v$ with id-corresponding embedding $e_v \in \mathbb{R}^d$, where $d$ denotes the latent state dimensionality. Then, user behaviors are differentiated with behavior type embedding $e_b \in \mathbb{R}^d$ corresponding to $b$th type of user-item interaction. Furthermore, to capture the behavior dynamics, we enhance the context embedding layer by introducing a temporal encoding strategy. Motivated by the positional embedding method in Transformer [39], we adopt the sinusoid functions over timestamp information to generate base time embeddings.
where $\tau(\cdot)$ represents the time slot mapping function with temporal periods. The odd and even index of 2 $d$-dimensional vector $\mathbf{t}^t_k$ are represented by 2 $l$ and 2$l + 1$. We further apply $\sqrt{d}$ as the scale factor to alleviate the effect of large embedding values. In addition, we introduce a tunable linear projection over the generated base time embedding $\mathbf{t}^t_k$ to endow our model with learning flexibility of temporal context as $\mathbf{e}^t_k = \mathbf{t}^t_k \cdot \mathbf{W}^t_k$, where $\mathbf{W}^t_k \in \mathbb{R}^{2d \times d}$. After that, we inject the compound contextual signals of multi-behavioral patterns and interaction dynamics with the integration operation as: $\mathbf{E}^t_k = \mathbf{e}^t_k \oplus \mathbf{v}^t_k \oplus \mathbf{e}^t_{r,k}$, where $\mathbf{E}^t_k \in \mathbb{R}^d$ is the learned context-aware item embedding, and $\oplus$ denotes the element-wise addition operation.

### 3.3.2 Item-Wise Sequential Dependency

To capture the dynamism of short-term transitions across different items, our item-wise sequential dependency encoder is built upon the transformer architecture, based on self-attention mechanism under multi-head representation spaces. In specific, the encoded embedding of $k$th interacted item $\mathbf{v}^t_k$ is calculated by the following multi-head dot-product attention for item-wise mutual relation learning:

$$
\mathbf{E}^t_k = \mathbb{H} \left( \sum_{h=1}^{H} \sum_{l=1}^{K} \alpha_{k,l'} \mathbf{V}^h \mathbf{E}^t_{l'} \right) 
\alpha_{k,l'} = \sigma \left( \left( \mathbf{Q}^h \mathbf{E}^t_k \right)^\top \left( \mathbf{K}^h \mathbf{E}^t_{l'} \right) \right) \sqrt{d/H}
$$

where $\mathbf{Q}^h, \mathbf{K}^h, \mathbf{V}^h \in \mathbb{R}^{d \times d}$ denote the $h$th head query, key and value transformations, respectively. With the integration of context embedding layer and item-wise dependency encoder, our TGT not only preserves the cross-item transitional relations, but also captures the multi-behavioral dynamism.

### 3.4 Multi-Behavior Pattern Aggregation

In this section, we perform the multi-behavior pattern aggregation with the modeling of time-aware user-item interactions. Towards this end, a bipartite graph $G_r = \{ u'_i \cup S_{i,r}, E'_r \}$, where $u'_i$ denotes the intermediate user vertex corresponding to the $r$th interaction sub-sequence $S_{i,r}$, $E'_r$ represents the interactions between user $u_i$ and all items included in the sequence $S_{i,r}$. To capture the short-term behavior heterogeneity, we design a behavior-aware message passing scheme to differentiate and aggregate interactive patterns from different behavior types. This is a two-phase message passing paradigm which consists of propagating and refining embeddings from user to item side and vice versa. Given the learned item representations $\mathbf{E}^t_k \in \mathbb{R}^d$ by injecting multi-behavioral temporal context, the message passing from item to user side can be formally represented as follows:

$$
\mathbf{H}^t_k = \text{Aggre}(\mathbf{E}^t_k, b) = \sigma \left( \sum_{h=1}^{K} \phi(b^t_k = b) \cdot \mathbf{E}^t_k \cdot \mathbf{W}_b \right)
$$

where $\mathbf{H}^t_k \in \mathbb{R}^d$ represents the generated embedding of node $u'_i$ under the $b$th behavior type. We utilize $\mathbf{W}_b$ as behavior-aware transformation to enhance the modeling of behavior-specific semantics. $\sigma(\cdot)$ is the ReLU activation function. We define $\phi(\cdot)$ as an indicator function to fit the behavior type-aware embedding propagation, i.e., $\phi(b) = 1$ given $b^t_k = b$.

#### 3.4.1 Multi-Channel Projection

To effectively discriminate multi-typr of interactions during the message passing process, we adopt a multi-channel parameter learning strategy for the calculation of transformation $\mathbf{W}_b \in \mathbb{R}^{d \times d}$, which can be formalized as follows:

$$
\mathbf{W}_b = \sum_{h=1}^{H} \beta_h \cdot \mathbf{W}_h; \quad \beta_h = \sigma (\mathbf{P} \cdot \mathbf{b} + \mathbf{\mu})(h)
$$

where $\mathbf{W} \in \mathbb{R}^{d \times d}$ denotes the $H$ base transformations (indexed by $h$) shared by all behavior types. $\beta_h$ is the learned weight for the $h$th latent channel representation, which is calculated by a fully-connected layer with transformation $\mathbf{P} \in \mathbb{R}^{H \times d}$ and bias $\mathbf{\mu} \in \mathbb{R}^H$.

In our TGT framework, the multi-channel projection layer serve as an important component in the global item-wise dependency modeling with the preservation of behavior heterogeneity. Specifically, our designed multi-channel projection aims to differentiate the multi-relational interactions during the message passing across time. After the behavior embedding projection over multiple base transformations, the behavior-aware semantics are encoded with the developed channel-wise aggregation layer, which endows our TGT method to preserve the inherent behavior semantics of different types of user-item interactions.

#### 3.4.2 Aggregation Over Cross-Type Relations

After encoding the type-specific behavior semantics, the next step is to feed the behavior-aware embeddings into an aggregation layer to uncover the implicit relations across different types of behavioral patterns. Different from static attentive relation aggregation schemes [47], [58], we fit our learning scenario with the dynamic user preference, by proposing an adaptive attention network to distinguish influence of different behavior types in predicting the target one, with the awareness of time-evolving multi-behavioral interaction patterns.
\[
H' = \sum_{b=1}^{B} \gamma_b \cdot H'_b \\
\gamma_b = \sigma_1( (H'_b)^T \cdot \sigma_2 \left( \sum_{b=1}^{B} H'_b W_A + \mu_A \right) )
\]

where \(W_A \in \mathbb{R}^{d \times d}\), \(\mu_A \in \mathbb{R}^d\) are the transformation and bias for our aggregation layer, respectively. \(\sigma_1(\cdot)\) denotes the softmax function, and \(\sigma_2(\cdot)\) denotes the ReLU function. \(\gamma_b\) is the learned attentive weight for the \(b\)th behavior type, calculated using the summation of all behavioral embeddings as query. As a result, we explicitly preserve the time-aware multi-behavior contextual information in the user representation \(H'\).

To model time-aware user’s influence over different items, we perform the message passing from user to item side through the aforementioned embedding propagation and aggregation schemes:

\[
\bar{E}_j^h = \sigma \left( \sum_{i,j \in \mathcal{I}} \phi(i,j) \cdot H' \cdot W_b \right); \quad \bar{E}_j = \sum_{b=1}^{B} \gamma_b \cdot \bar{E}_{j,b}
\]

where \(W_b\) is calculated by the multi-channel projection scheme with different transformation mappings (Eq 4), and \(\gamma_b\) is returned from our attentive aggregation mechanism. It is worth noting that \(\bar{E}_j^h, \bar{E}_j \in \mathbb{R}^d\) are cross-time embeddings of item \(v_j\) (without super-script \(r\)), which could capture changes in item semantics over time.

### 3.5 Global Relational Context Learning

Since user’s preference is inherently dynamic and evolve over time, our TGT further proposes to inject the long-term dynamics into the global-level graph relation encoder, which captures the dynamic multi-behavior patterns from both the long-term and short-term perspectives. We define a global user graph to contain all users \((u_i \in U)\) and their intermediate sub-sequence nodes \((u'_i \in U_t)\), i.e., \(G = \{ U, U_t, E \}\), where \(E\) represents the connections between each user \(u_i\) and his/her intermediate sub-sequence nodes \(u'_i\), i.e., an edge connects \(u_i\) and \(u'_i\) \((1 \leq r \leq R)\). In this component, the global user embedding \(\Gamma_i \in \mathbb{R}^d\) is generated by performing graph-structured information aggregation, over short-term user preference embeddings \((H')\) across different interaction sub-sequences.

#### 3.5.1 Global-Level User Representation

To learn global-level user representations, we incorporate the temporal context into the message passing procedure of attentional graph neural architecture, to allow the short-term preference encoded with different timestamps to interact with each other in a differentiable manner:

\[
\Gamma_i = \Phi(H') = \sigma \left( \sum_{t=1}^{T} \eta_t \cdot \bar{H}' \right) \\
\eta_t = \Gamma_t^r \cdot H' \quad \bar{H}' = \Gamma' + t'
\]

where \(\eta_t\) is the learned attentive weights for pairwise relationship between \(u_i\) and \(u'_i\). \(\Phi(\cdot)\) denotes the global information aggregation function with the \(\sigma(\cdot)\) activation function. \(t' \in \mathbb{R}^d\) is our temporal embedding encoded from our context embedding layer. The sub-sequence representation \(H'\) will be updated with the injection of temporal localized information as: \(H' = \Gamma_i + t'\), where \(\Gamma_i \in \mathbb{R}^d\) is the user embedding which is either initialized or smoothed by the neighboring nodes. By doing so, TGT maintains the user preference embeddings from different time periods as a unified feature embedding for global user representation, with the modeling of temporal dependency and evolution of user interaction patterns.

### 3.6 High-Order Relation Aggregation

As discussed above, TGT performs two-phase information aggregation for encoding information of i) short-term multi-behavior interactions between user and item; ii) long-range dynamic structural dependency of user interest across time durations. Generally, our TGT architecture takes the relational structure of \(G\) and \(G\) as computation graphs for embedding propagation, during which the local relational features from neighborhood will be aggregated to obtain a contextual representation. Such message passing paradigm can be generalized with the incorporation of high-order connectivity as follows (suppose \(l\) denotes the \((l)\)th GNN layer in the graph-based information propagation architecture):

\[
\bar{H}_r^{(l)} = \sum_{b=1}^{B} \gamma_b \cdot \left( \sigma \left( \sum_{k=1}^{K} \phi(b'_k = b) \cdot \bar{E}_k^{(l)} \cdot W_b \right) \right) \\
\Gamma_i^{(l+1)} = \sigma \left( \sum_{l=1}^{L} \eta_l \cdot \bar{H}_r^{(l)} \right), \quad \bar{H}_r^{(l+1)} = \Gamma_i^{(l)} + t' \\
\bar{E}_j^{(l)} = \sum_{b=1}^{B} \gamma_b \cdot \sigma \left( \sum_{i,j \in \mathcal{I}} \phi(i,j) \cdot \bar{H}_r^{(l+1)} \cdot W_b \right)
\]

where \(\bar{E}_j^{(l)}, \Gamma_i^{(l)}\) are initialized id-corresponding item and user embeddings, respectively. We endow TGT with the ability of capturing high-order collaborative effects across different users/items, by extending our developed graph relation encoder from one layer to multiple layers (i.e., \(L\)). We finally generate user \((\Gamma_i \in \mathbb{R}^d)\), item \((\bar{E}_j \in \mathbb{R}^d)\) and intermediate sub-sequence node \((\bar{H}_r \in \mathbb{R}^d)\) embeddings across \(L\) graph layers with the element-wise summation:

\[
\Gamma_i = \sum_{l=1}^{L} \Gamma_i^{(l)}, \quad \bar{H}_r = \sum_{l=0}^{L} \bar{H}_r^{(l)}, \quad \bar{E}_j = \sum_{l=0}^{L} \bar{E}_j^{(l)}
\]

### 3.7 Model Prediction and Optimization

Following the same settings in sequential recommender systems [41], to reflect the dynamic characteristics of user preference, we leverage the time-aware user representation \(H'\) to make forecasting on future user-item interactions. The probability of future interaction between user \(u_i\) and item \(v_j\) is estimated by \(P_{r,ij} = z(\bar{H}_r^{-1} \circ \bar{E}_j)\), where \(z \in \mathbb{R}^d\) is a parametric vector. \(\bar{H}_r^{-1}\) represents the embedding of the last interacted item of user \(u_i\) in the \(r\)th interaction sub-sequence. \(\circ\) denotes the element-wise multiplication operation. Next, we will describe our defined optimized objective and perform the time complexity analysis for our TGT framework.

#### 3.7.1 Optimization Objective

During the training phase, the parameter inference process is optimized by leveraging historical user-item interactions for label data augmentation [22], [36]. In this case, the
prediction score for \( u_i \) and \( v_j \) during the time interval of sub-sequence \( S_i \) is calculated as: \( \Pr_{S_i} = z^T (H'_i \circ E_j) \). We formally define our objective function with the marginal pairwise loss as follows:

\[
    \mathcal{L} = \sum_{i=1}^{N} \sum_{r=1}^{R_i} \sum_{c=1}^{C} \max(0, 1 - \Pr_{i,p} + \Pr_{i,n_c}) + \lambda \cdot \|\Theta\|_p^2 \quad (10)
\]

where \( N \) represents the number of users and \( R_i \) denotes the number of interaction sub-sequences for user \( u_i \). \( p_r \) and \( n_c \) refer to \( C \) positive and the negative samples (indexed by \( c \)), respectively. We further apply the weight-decay is the weight-decay regularization term \( \lambda \cdot \|\Theta\|_p^2 \) for alleviating overfitting phenomenon.

**Algorithm 1. Model Inference of TGT Framework**

```
Input: user-item interaction sequences \( S_i \), sub-user size \( |S'_i| \), graph iterations \( L \), target behavior \( B \), sample number \( C \), maximum epoch number \( E \), regularisation weight \( \lambda \), learning rate \( \rho \)
Output: trained parameters in \( \Theta \)
1. Initialize all parameters in \( \Theta \)
2. Divide \( S_i \) into sub-sequences \( S'_i \) of size \( |S'_i| \)
3. for \( e = 1 \) to \( E \) do
   4. Generate behavior-aware context embeddings \( E'_k \)
   5. Capture item-wise sequential dependency to yield \( E'_k \)
   6. for \( l = 1 \) to \( L \) do
      7. Compute sub-users’ behavior embeddings \( H'_l \)
      8. Conduct cross-type aggregation to get \( H' \)
      9. Aggregate for the global user embedding \( \Gamma_i \)
     10. Refine the sub-users embedding \( H' \) using \( \Gamma_i \)
     11. Update the item embeddings \( \bar{E}_j \) using \( \bar{H} \)
   12. end
13. Integrate the cross-order graph embeddings \( \Gamma_i, H', \bar{E}_j \)
14. Draw a mini-batch \( U \) from all users, each with \( C \) positive-negative samples
15. \( \mathcal{L} = \lambda \cdot \|\Theta\|_p^2 \)
16. for each \( u_i \) \in \( U \) do
   17. Compute predictions \( \Pr_{i,p}, \Pr_{i,n} \)
   18. \( \mathcal{L}_+ = \sum_{i=1}^{C} \max(0, 1 - \Pr_{i,p} + \Pr_{i,n}) \)
   19. end
20. for each parameter \( \theta \) \in \( \Theta \) do
   21. \( \theta = \theta - \rho \cdot \partial \mathcal{L} / \partial \theta \)
22. end
23. end
24. return all parameters \( \Theta \)
```

We summarize the learning process of our TGT in Alg 1. In particular, the model optimization involves several key steps: (i) We first generate behavior-aware context embeddings \( E'_k \). Then, we feed it into the item-wise sequential dependency encoder to obtain \( E'_k \) corresponding to the \( k \)th behavior type and \( r \)th interaction sub-sequence. (ii) Through the recursive message passing procedure, we learn the sub-sequence behavior representation \( H'_l \) of users and inject the cross-type behavior relations into the refined embedding \( H' \). (iii) The aggregated global user embedding \( \Gamma_i \) preserves his/her long-term multi-behavior patterns. The sub-user and item embeddings are updated accordingly. (iv) Layer-specific embeddings are combined to generate cross-layer representations \( \Gamma_i, H', \bar{E}_j \).

### 3.7.2 Model Complexity Analysis

In this subsection, we analyze the time complexity of our TGT model. In particular, in the encoding process of item-wise sequential dependency, the computational cost for pairwise item relation learning and embedding projection are \( O(|S'| \times |S'| \times d) \) and \( O(|S'| \times d^2) \), respectively. Different from directly performing sequential learning over the entire item sequence \( S_i \), our method significantly reduces the computational cost for self-attention operations. Additionally, during the message passing and aggregation in the graph neural architecture, TGT costs \( O(L \times |S'| \times d + (M + |E|/|S'|_r) \times L \times d^2) \) for encoding the short-term multi-behavioral patterns, and \( O(|E|/|S| \times L \times d) \) for learning global relation context, where \( L \) is the depth of our graph neural network. Considering the small value of \( L \), this complexity term has very small influence on the overall model cost. Under the same experimental settings (e.g., sequence length and latent state dimensionality), TGT could achieve comparable complexity to the most recently developed baselines: HyRec [41] and GCGNN [48].

### 4 Evaluation

In this section, we perform experiments to validate the effectiveness of our proposed TGT recommendation framework by investigating the research questions as follows:

- **RQ1**: How does our proposed TGT method perform compared with state-of-the-art recommendation methods?
- **RQ2**: How do the different components (e.g., behavior-aware transformer network and global relational context learning) of TGT contribute to the model performance?
- **RQ3**: How do the integration of different types of behavioral patterns affect the prediction of target behavior?
- **RQ4**: How do the configurations of model hyper-parameters affect the recommendation performance?
- **RQ5**: Can the proposed TGT framework show model interpretability, through the effective modeling of sequential multi-behaviour patterns?

### 4.1 Experiment Settings

In this section, we first describe the details of our experimented datasets and introduce the evaluation metrics. Then, we present the baseline methods from a variety of research lines for performance comparison, as well as the parameter settings of our developed TGT framework.

#### 4.1.1 Data Description

In our evaluation, experiments are performed on two public datasets (see Table 2) collected from real-world online platforms. Both datasets contain different types of user behaviors in e-commerce services. **Taobao-Data**: This data records four types of user-item interactions collected from the Taobao online retail system-one of the world’s e-commerce marketplace. Particularly, multi-typed behaviors include page view, add-to-cart, tag-as-favorite and purchase. **IJCAI-Contest Data**: This data is released by IJCAI competition to record users’ online activities from online business-to-consumer e-commerce site, also involving four types of behaviors: clicking,
adding-to-cart, tagging with favor and purchasing. The temporarily-ordered multi-typed interaction logs are used to generated multi-behavior sequence $S_i$ for each user ($u_i \in U$). Because of the importance of customer purchase activities in practical e-commerce platforms [17], [51], we consider the purchases of users as the target behaviors and other types of user behaviors are regarded as the context behaviors for representation enhancement.

### 4.1.2 Evaluation Metrics

In our experiments, we evaluate the recommendation performance of all compared approaches using two widely adopted metrics: NDCG@N and Recall@N, so as to measure the accuracy of top-N recommended item for different users. Note that the better recommendation performance is reflected by higher NDCG@N and Recall@N scores. Here, NDCG score reflects the position-aware recommendation accuracy which assigns high weights for higher ranked item hits. We utilize the leave-one-out evaluation [22], [36] for generating the training and testing data instances based on the temporal information of user behavior data. Specifically, the last interacted item of each evaluated user is considered as the test instance for making recommendation.

### 4.1.3 Methods for Comparison

To comprehensively evaluate the performance, we compare our TGT with state-of-the-art recommendation techniques which can be grouped into different model types:

- **Conventional Matrix Factorization Model**: We first consider the representative matrix factorization method—Bayesian personalized ranking as the baseline.
  - **BPR** [34]. It enhances the matrix factorization model with pairwise loss for learning personalized rankings.
  - **Neural Collaborative Filtering Methods**: The conventional collaborative filtering methods have been enhanced by deep learning techniques for nonlinear deep feature extraction.
    - **NCF** [12]. This approach replaces the dot-product operation in matrix factorization with multi-layer perceptrons to model the non-linearity in user-item interactions.
    - **DeepFM** [8]. This wide-and-deep model augments classic factorization machine with deep neural networks, to consider both low- and high-order feature interactions.

- **RNN-based Sequential Recommendation Method**: Recurrent neural network has been utilized in sequential recommendation model for dynamic behavior modeling.
  - **GRURec** [13]. This method adopts the gated recurrent unit to model sequential behaviors of users, based on the gating mechanism to control the information flow.

**Convolution-based for Sequential Recommendation**: We consider the sequential recommendation method using convolutional filters to encode local temporal patterns.

- **Caser** [37]. It utilizes the convolution neural network to perform information aggregation across temporally-order items in both horizontal and vertical way.

**Attention/Transformer-based Neural Network for Sequential Recommender Systems**: Inspired by the effectiveness of attention mechanism in relational learning, there exist many attentional recommendation frameworks for modeling user dynamic preference in sequential recommendation.

- **NARM** [23]. It jointly learns the sequential patterns of user interactions as well as the session-specific general interest with the integration of recurrent network and attention mechanism.
- **SASRec** [22]. In SASRec, self-attention is employed to encode the sequential patterns of user interaction, without the recurrent operations over input sequences. The embedding transformation is performed with query and key dimensions.
- **Bert4Rec** [36]. It is a transformer-based sequential recommender system with bidirectional self-attention architecture and cloze objective to incorporate sequential signals.

**Knowledge-aware Sequential Recommendation**: We also include the sequential recommendation baseline with the consideration of knowledge-aware item relationships.

- **Chorus** [40]. This method accounts for both temporal context and item correlations in the sequential recommendation model. For this method, the TransE is adopted as the translation function to obtain entity representations.

**Sequential/Session-based Recommendation Models with Graph-based Neural Networks**: Another important research line of time-aware recommender systems lies in the utilization of graph neural networks for behavior dependence learning.

- **HyRec** [41]. It predicts the next interacted item of users by utilizing the hypergraph neural network to model the short-term item relations. Then, a fusion layer is introduced to aggregate dynamic item semantics.
- **MAGNN** [28]. It captures both the short- and long-term user preference with memory-augmented graph neural network. The generated short- and long-term pattern embeddings are aggregated through an interest fusion layer.
- **MGNN** [44]. It is a relation-aware graph neural network-based architecture which utilizes the gating mechanism for representation fusion, with the consideration of multi-relational user sequence.
- **SR-GNN** [53]. It designs a gated graph neural network to generate session-level item representations with transition regularities. The constructed graph data contains different session sequences in session-based recommendation.
- **GCCNN** [48]. This approach performs the information aggregation over the constructed session graphs by considering pairwise item-transition information.

**Heterogeneous Graph Neural Model**: Additionally, we consider another type of baseline by utilizing the heterogeneous...
graph neural network to capture the behavior heterogeneity during the information propagation procedure.

- **HGT** [14]: It is a state-of-the-art heterogeneous graph learning model which integrates the transformer with the graph-based message passing scheme. We utilize its heterogeneous graph relation encoder to model different types of user-item interactions.
  
  **Multi-Behavior Recommendation Frameworks**: Several recent studies attempt to capture multi-behavioral context for recommendation by encoding behavior dependency based on various techniques.

- **NMTR** [7]: It integrates the neural collaborative filtering and multi-task learning paradigm to model the behavior-wise dependency of users with predefined correlations.

- **MATN** [54]: This recommendation method designs memory-based neural units to enhance the attention mechanism, to capture the behavior patterns of users. It only encodes the local connectivity patterns between users and items and cannot capture the high-order dependence.

- **MBGCN** [20]: It is a state-of-the-art graph-based recommendation model which alleviates the data sparsity issue with the modeling of multi-typed user behavior data. In this model, the graph convolution operations are conducted to perform message passing.

### 4.1.4 Parameter Settings

We implement our TGT using TensorFlow and adopt Adam for model optimization. During the training phase, the model inference process is conducted with the learning rate of $10^{-3}$ (configured with 0.96 decay rate). The batch size is selected from the range $[32, 128, 256, 512]$ with the best setting of 256 for Taobao dataset and 512 for IJCAI dataset. The weight-decay regularization term is configured with $\lambda$ selected from $[0.05, 0.01, 0.005, 0.001, 0.0005]$. The default settings for hidden state dimensionality is 16. The length of user’s sub-sequence is chosen from the range $[2, 4, 6, 8, 10]$ with the best setting of 6 for Taobao dataset and 10 for IJCAI dataset.

### 4.2 Performance Comparison (RQ1)

We present the performance comparison results of our TGT and baselines in Table 3 in terms of $(HR@1, HR@5, NDCG@10)$ and $(HR@1, HR@5, NDCG@10)$. As we can see, TGT consistently outperforms all compared methods by a large margin under all metrics. We attribute such improvements to the multi-behavior dependency modeling of TGT: i) through uncovering multi-behavior user intentions, TGT can better characterize the user-item relations; ii) benefiting from our designed temporal graph neural transformer architecture, both short- and long-term behavior-type dependent interests of users are effectively preserved in our learned user and item representations.

We further summarize several observations as follow:

- (1) Our TGT method consistently outperforms baseline methods BPR, NCF, DeepFM in all cases on different datasets, which validates the superiority of our...
proposed multi-behavior sequential recommender. Most of sequential recommendation methods achieve better performance than BPR, NCF and DeepFM. This observation suggests the benefits of modeling behavior dynamics with sequential interaction patterns for predicting user preference. Furthermore, the performance superiority of multi-behavior recommender systems as compared to NCF and DeepFM justifies the importance of incorporating multi-behavior dependencies into the modeling of complex and diverse user preferences.

- (2) Bert4Rec method achieves better performance than other attention-based approaches (i.e., NARM, SASRec) and convolution-based sequential recommender system (i.e., Caser), which indicates the effectiveness of transformer in encoding sequential patterns. However, the performance improvement of our method over Bert4Rec shows that TGT significantly boosts the recommendation performance by embracing sequential multi-behavior modeling for recommendation.

- (3) The performance gap between TGT and GNN-based recommender systems with the modeling of temporal information (i.e., HyRec, MAGNN, SR-GNN, GCNNN), clarifying the importance of encoding behavior heterogeneity during the message passing paradigms. In particular, our TGT is equipped with dynamic multi-behavior modeling under a graph-based global relation aggregation, which shows the superior performance in encoding users’ diverse preference.

- (4) For a comprehensive performance comparison settings, we also compare TGT with two recently developed time-aware recommendation (MAGNN) and network embedding (HGT) methods with heterogeneous graph neural networks. As relation-aware graph neural models, these models are generally superior to other GNN-based methods by considering the interaction heterogeneity. However, they fail to capture dynamic cross-type behavior dependencies from both short- and long-term perspectives, which limits their capability in effectively transferring knowledge among different types of user behaviors.

- (5) As Table 3 shows, TGT effectively improves the recommendation performance when competing with state-of-the-art multi-behavior recommendation models (i.e., NMTR, MBGCN and MATN). We can observe the relative improvement ratio (measured by NDCG@10) between our TGT and MBGCN is 22.5% and 12.1% on Taobao and IJCAI-Contest dataset, respectively. Such performance improvement further verifies the rationality of our designed temporal graph neural architecture, which enables TGT to accurately capture the dynamic multi-behavior patterns. In most existing multi-behavior recommender systems, the time-evolving cross-type behavior dependencies are ignored, which degrades the performance.

4.3 Model Ablation Study (RQ2)

To verify the effects of the designed different components in our model, we perform a detailed model ablation study of TGT on the IJCAI-Contest dataset. Specifically, we design different variants to make comparison with our TGT recommendation framework:

- w/o CE (Context Embedding): The time- and behavior-aware context are ignored during the sequential dependency encoding. Only item and positional embeddings are fed into the sequential dependency encoding component.
- w/o SD (Sequential Dependency): We do not involve the multi-behavior transformer for capturing short-term preference, and directly apply the temporal graph neural network to model the behavior heterogeneity.
- w/o MCP (Multi-Channel Projection): This variant simplifies the designed multi-behavior message passing paradigm without the multi-channel projection layer to preserve distinct behavior semantics.
- w/o LBD (Long-Term Behavior Dynamics): This model does not take the long-term multi-behavior dynamics into consideration. It ignores the global relation learning with behavior type-aware message passing component.
- w/o CTA (Cross-Type Behavior Aggregation): This model variant does not explore the cross-type behavioral relations with our attentive aggregation layer. Instead, we directly concatenate the propagated type-specific behavior embeddings to generate the user representation.

We show the ablation results in Table 4 and discuss the findings and summarization from different aspects as below:

(1) Effect of Behavior-Aware Context Embedding. Compared to w/o CE variant, TGT achieves better results. We owe it to the injection of multi-behavioral context into the modeling of item-wise sequential dependency, which allows the model to preserve short-term multi-behavioral semantics.

(2) Effect of Item-Wise Short-Term Dependency Modeling. Our multi-behavior transformer framework enhances the value transformer with the incorporation of behavior-

| Setting | Top-5 Metrics | Top-10 Metrics |
|---------|----------------|----------------|
| w/o CE  | 0.392 1.8% 0.290 1.0% 0.515 0.7% 0.321 2.8% |
| w/o SD  | 0.367 8.7% 0.265 10.5% 0.499 3.9% 0.306 7.7% |
| w/o MCP | 0.346 15.4% 0.240 22.3% 0.490 5.8% 0.306 7.9% |
| w/o LBD | 0.387 3.1% 0.283 3.5% 0.511 1.7% 0.319 3.6% |
| w/o CTA | 0.392 1.7% 0.287 2.0% 0.510 1.8% 0.323 2.2% |
| FBA     | 0.379 5.3% 0.274 6.9% 0.511 1.6% 0.320 3.1% |

**TABLE 4:** Ablation Study on IJCAI Contest Dataset
aware context into the modeling process of item-wise sequential dependencies. By comparing the performance of TGT with w/o SD, it is clear that with the multi-behavior transformer network, TGT achieves better performance by exploring short-term item-transition information under multi-behavior context. The designed multi-behavior transformer enables the item sequence encoder with the awareness of multi-behavior contextual signals between users and items, so as to capture the heterogeneous item-wise multi-relational dependencies.

(3) Effect of Multi-Channel Projection. We can observe that TGT is superior to w/o LBD. This demonstrates that the multi-channel projection layer is beneficial to enhance the encoding of behavior semantics during the multi-behavior pattern aggregation.

(4) Effect of Long-Term Multi-Behavior Pattern Aggregation. The performance gap between TGT and w/o LBD indicates the importance of capturing user’s long-term preference through discriminating different types of interactions. To characterize multi-behavior sequential patterns, we design the graph-structured embedding propagation to learn global-level user/item representations.

(5) Effect of Cross-Type Behavior Dependency Learning. With the designed attention-based aggregation network, the recommendation performance of our TGT is improved over the variant w/o CTA (performing simplified embedding concatenation). In the variant w/o CTA, our graph learning framework will give same weights to the propagated type-specific behavior representations, which may weaken the multi-behavior collaborative effect modeling. This suggests that the implicit relations across different types of interaction behaviors cannot be equally weighted. In addition, we design a new method variant FBA which fuses the multi-behavior patterns with the behavior-specific interaction frequency information. From the results, we can observe that our TGT consistently outperforms the FBA variant with different top-N item positions (e.g., top-5, top-10, top-20). This further justifies the effectiveness of the learnable weight mechanism for cross-type behavior dependency modeling.

4.4 Effects of Context Behaviors (RQ3)
This section evaluates the influence of type-specific behavior data in the recommendation performance for users’ target behaviors. For IJCAI-Contest data, we define “-pv,” “-fav,” “-cart” to represent our multi-behavior sequential recommendation framework by removing the individual behavior type of “page view,” “tag-as-favorite,” “add-to-cart” behavior, respectively. In our ablation study, another variant “+buy” is designed to only contain the target type of user behaviors for making recommendation. TGT denotes the full version of our method to incorporate all types of user behaviors.

The results (measured by HR@10 and NDCG@10) are shown in Fig. 3. We can see that TGT consistently achieves the best performance in all cases, which verifies the significance of context behavior diversity for modeling sequential interaction patterns. We can observe that the page view and browse behaviors contribute more for purchase prediction, which shows consistent trend across two different datasets. Furthermore, we can notice that leaving behavior relation heterogeneity untapped (i.e., variant “+buy”) will degrade the recommendation performance. Overall, the effect studies of context behavior integration reveal that the characteristics of multi-behavior data offer useful insights for modeling user sequences.

We conduct experiments to evaluate the model performance by varying the percentages of removing user auxiliary behaviors. In particular, the percentage of 0% indicates that we removing all behavior data under a specific type (e.g., page view or tag-as-favorite or add-to-cart); the percentage of 50% indicates that we only keep 50% of a specific type of user behaviors in the effect studies of context behaviors. From the new results shown in Fig. 3, we can observe that incorporating more context behavior data into the multi-behavior pattern modeling is helpful in improving the performance.

4.5 Study on Model Hyperparameters (RQ4)
To explore the effects of modeling dynamic multi-behavior patterns, we study how three key hyperparameters (i.e., number of projection channels $H$, the depth of graph model $L$) affect the performance of our TGT framework. We show the empirical study results in Fig. 4 and draw the following conclusions:

4.5.1 Impact of Projection Channels
In the component for encoding multi-behavior patterns, we design a multi-channel parameter learning scheme for embedding transformation. From the evaluation results shown in Fig. 4, we can observe that the best recommendation performance can be achieved with the configuration of two projection channels. When we further increase the number of channels ≥ 4, the performance becomes worse due to the overfitting problem.

4.5.2 Impact of Interaction Sub-Sequence Length
In our TGT, the interaction sub-sequence $S_i$ serve as the sequence unit for short-term multi-behavior pattern modeling. From the results shown in Fig. 4, we observe that the influence of encoded sequence length may vary by datasets.

Fig. 3. Impact study of behavioral relation integration.
In particular, the performance on IJCAI-Contest data is not very sensitive to the sequence length. The reason is that the short-term item-transitions could also be captured through the high-order information propagation paradigm over the constructed large-scale graph. When the sub-sequence is short, the model cannot achieve better performance, because the involved interaction behaviors are sparse.

4.5.3 Impact of Graph Model Layers

In our proposed TGT framework, the number of graph neural network layers is searched in the range of \{1,2,3\}. We can observe that increasing the number of embedding propagation layers to 2 (TGT-2) could substantially improve the performance over TGT-1 (with the relation learning over one-hop connections). Such performance gain can be attributed to the exploration of high-order multi-behavior patterns as well as the underlying cross-sequence relations. When we stack more propagation layers for information propagation, the performance of TGT-3 begins to deteriorate. The reason of such observation lies in the over-smoothing issue with more message passing layers, which is consistent with the findings in recent graph neural networks [24], [25].

4.6 Case Study of TGT (RQ5)

In this section, we conduct case studies on Taobao dataset to offer an intuitive impression of our model explainability from the perspectives of both short-term and long-term multi-behavior pattern modeling in our sequential recommender system. The results are shown in Fig. 5. We show the case study details as follows:

- We sample several users and their sub-sequences as concrete examples. For example, we can observe that the purchase behavior of user \( u_3 \) on item \( i_{578} \) shows dependence on his/her recent activities (in the 23th sub-sequence \( S_{23} \)) with the learned different relevance scores, such as the view behavior on item \( i_{585} \), add-to-cart behavior on item \( i_{566} \), and purchase behavior on item \( i_{561} \). Hence, the behavior-aware item correlations learned by our TGT model can show the explicit relevance scores among different types of short-term behaviors pertinent to the user’s target behavior.

- We present the learned item-wise dependencies encoded by our method across different user sub-sequences. From the sampled user cases, we can observe that the purchase behavior of user \( u_0 \) on item \( i_{39} \) is correlated with his/her view activity on item \( i_{41} \) and item \( i_{41} \). The dependencies between view behaviors on item \( i_{41} \) and item \( i_{41} \) across sub-sequences \( S_{10} \) and \( S_{20} \) can also be captured with the explicit weights by our global relational context learning in TGT. Therefore, the dynamic long-term behavior-aware relationships between items can be preserved through our global message passing scheme.

4.7 Model Efficiency Test

We conduct experiments to measure the training time of our proposed TGT method and several representative baselines on both Taobao and IJCAI datasets. We report the results in Table 5. Evaluations are conducted on the machine with the configuration of NVIDIA TITAN RTX GPU, Xeon W-2133 CPU. We can observe that our method TGT can achieve comparable model efficiency when competing with state-of-the-art recommendation techniques based on graph neural networks in terms of model training time. This indicates the scalability of our TGT in handling large-scale datasets.

| Model       | Taobao | IJCAI | Model       | Taobao | IJCAI |
|-------------|--------|-------|-------------|--------|-------|
| MATN        | 13.6   | 39.7  | GCGNN       | 35.5   | 80.9  |
| HGT         | 22.7   | 41.4  | MAGNN       | 32.4   | 86.7  |
| MBGCN       | 23.8   | 56.3  | DeepFM      | 40.5   | 105.8 |
| MGNN        | 34.8   | 72.0  | TGT         | 32.0   | 83.1  |
5 Conclusion

In this paper, we propose a novel learning framework (TGT) for sequential recommendation by decomposing interactions with behavior heterogeneity. The goal of TGT is to aggregate dynamic relation contextual signals from different types of user behaviors and generate contextualized representations for making predictions on target behaviors. Extensive experiment results demonstrate the superiority of TGT as compared to state-of-the-art baselines, and verify the rationality of incorporating multi-behavioral patterns in performing sequential modeling of user-item interactions. Moreover, our evaluation also provides ablation study and efficiency study to further show the model effectiveness.

In this work, we enhance the sequential recommender system with the consideration of multi-typed user-item interactions for user preference learning. There exist several promising research directions for future investigation. For example, future work could involve the investigation of external user and item features (e.g., user profile and location, item multi-modal features) to improve the recommendation performance for online user behavior modeling scenarios. In addition, how to effectively alleviate the bias factors which confounds the user preference learning for recommender systems, is also desirable to explore in future work.

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