Sequence-Graph Duality: Unifying User Modeling with Self-Attention for Sequential Recommendation

Zeren Shui
University of Minnesota
shuix007@umn.edu

Ge Liu
AWS AI
gliua@amazon.com

Anoop Deoras
AWS AI
adeoras@amazon.com

George Karypis
AWS AI
gkarypis@amazon.com

Abstract

User modeling is of great importance in personalization services. Many existing methods treat users as interaction sequences to capture users' evolving interests. Another line of research models each user as a user graph in which the users' interactions are modeled as nodes. Nodes (interactions) in user graphs are connected via edges that reflect certain relations such as item similarity. The graph-based user modeling can flexibly store item relationships. In this work, we introduce a novel user representation, Heterogeneous User Graph (HUG), which unifies sequence- and graph-based user modeling to take advantage of both methods. A HUG is associated with two types of edges: *sequential edges* that preserve the order of interactions and *collaborative edges* that connect collaboratively similar items (i.e., items interacted by similar sets of users). To learn latent user representations for recommendation tasks, we propose a multi-head attention-based architecture called Heterogeneous User Graph Transformer (HUGT). HUGT is developed on the basis of SASRec and can concurrently capture the sequential pattern and graph topology encoded in HUGs. We conduct experiments on four real-world datasets from three different application domains. Experimental results show that (1) jointly modeling users as sequences and graphs with HUG provides better recommendation performance over sequence-only and graph-only user modeling; (2) HUGT is effective in learning user latent representations from HUGs; (3) HUGT outperforms the baselines by up to 10% on datasets with long sequences and aligns with the state-of-the-art performance on datasets with short sequences.

1 Introduction

As internet services grow fast, users are facing a vast amount of information and products in their daily life. Recommender systems play a critical role in filtering information and presenting relevant content that matches users' interests. Due to the dynamic nature and complexity of users' interests, learning patterns in users' interaction history and encoding them into the users' latent representations for recommendation have been a prevalent research topic.

There has been a surge of methods that model users by their sequences of item interactions and apply sequential models such as RNNs [9] and Transformers [22] to learn user representations [17, 8, 13, 20, 3]. These methods demonstrated that encoding item transition patterns in users' latent representations helps capture users' evolving interests and improves recommendation accuracy. Another line of research advocates modeling users as user graphs in which the users' interacted items are modeled as nodes, and certain item-item relations are modeled as edges [27, 1, 25]. The item

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relations are usually similarity or item co-occurrence patterns extracted from user-item interaction matrices or item meta-data. Graph neural networks (GNNs) [15, 5] have been a popular choice for encoding topology from such graphs into latent user representations. Most of the existing literature on recommender systems focuses on sequence-only or graph-only user modeling. It is underexplored whether a joint sequence-graph user modeling provides better recommendation performance than a standalone-modality user modeling.

In this work, we propose a method to link the two worlds by jointly modeling users as sequences and graphs to encode both sequential patterns and graph topology. A HUG is a graph of user-interacted items, in which nodes are connected by two types of edges: *sequential edges* that preserve the sequential ordering of interactions (e.g., chronological precedence) and *collaborative edges* that characterize item-item collaborative similarity, i.e., a measure of similarity in regards users' preference on the items. On the basis of SASRec [13], we design a transformer model to concurrently fuse and encode the sequential patterns and the graph topology into latent user representations for recommendation. We call our method Heterogeneous User Graph Transformers (HUGT).

We summarize our contributions as the following: First, we propose HUG, an effective data structure that jointly encapsulates sequential patterns and collaborative graph topology for user modeling. Secondly, we design HUGT to efficiently learn user representations from their HUGs. We propose two variants of HUGT: HUGT-SE which learns graph structure with spatial encoding, and HUGT-MP which computes a sparse attention matrix to simulate message passing in GNNs. Finally, we conduct comprehensive experiments on four real-world datasets from three different domains. We empirically demonstrate that jointly modeling users as sequences and graphs via HUGs outperforms standalone sequence modeling or graph modeling of the users, HUGT is effective in concurrently fusing and encoding the sequence and graph aspects of HUG, and HUGT achieves state-of-the-art performance in sequential recommendation on the four baseline datasets.

2 Related Works

2.1 Sequence-based User Modeling

Sequential signal is important in user modeling and can improve recommendation performance. Traditional sequential recommendation models [18, 6, 21] usually rely on factorization methods (e.g., Factorized Item Similarity Models [12]) to capture users' general tastes and Markov Chains (MCs) to learn the sequential signal. This class of methods holds the Markov assumption that the next action is dependent on the previous few interactions and cannot capture complex and long sequential patterns. Moreover, the performance of these methods is limited by the capacity of the factorization models.

In the past decade, researchers developed RNN-based approaches to model users' interaction trajectories. Hidasi et al. [8] proposed GRU4Rec that leverages a variant of RNNs, gated recurrent units (GRU), to capture sequential patterns in sessions. Ma et al. [17] successfully built real-world commercial recommender systems based on hierarchical RNNs. The authors of [29] combined RNNs with CNNs to capture long- and short-term sequential patterns, respectively. Despite the success stories, RNN-based recommendation models suffer from data efficiency (they require a lot of training data to perform well) and data sparsity issues.

2.2 Graph-based User Modeling

Graph-based user modeling is a rising direction that models users as graphs in which their interacted items are nodes. Nodes in these graphs are usually connected via edges that indicate transition/similarity relations [27, 1, 25]. Methods that fall into this class usually use graph neural networks (GNNs) to encode the graph-structured information into item embeddings and use a learnable function to readout user embeddings for recommendation. Although this class of methods can effectively capture graph topology, they usually overlook sequential patterns which are important for recommendation accuracy.

2.3 Transformer and Self-Attention Mechanism

Self-attention mechanism and the Transformer architecture have demonstrated their superior ability for sequence modeling and have become the default methodology in natural language processing

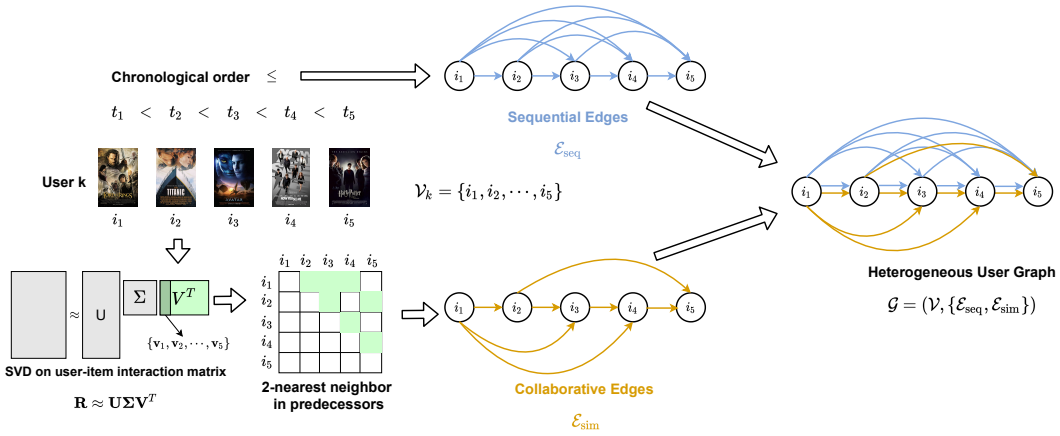

Figure 1: Construction of a heterogeneous user graph from a user's interaction sequence.

tasks [22, 4]. In the recommendation community, the self-attention mechanism is widely adopted for sequential user modeling [13, 20, 26, 11, 16]. He et al [7] propose to augment BERT4Rec by enforcing items in sequences to attend to sequentially close items to reinforce the influence of local items. Chen et al [2] propose to learn a sparse mask over the attention matrix to reduce the influence of noisy items. In our work, we propose a formulation that allows a more flexible design of inductive bias in self-attention-based recommendation models.

Recently, transformers have been applied to and have shown great potential in graph learning. In [24], the authors show that the self-attention mechanism is a special form of graph convolutions. The authors of [30] generalize the definition of self-attention by directed graphs. Ying et al. [28] successfully apply transformers on graph prediction tasks and outperform major GNN variants by augmenting transformers with graph structural knowledge. Hu et al. [10] applied transformers to learn from heterogeneous web-scale large graphs. These works motivate us to use Transformer as the backbone to concurrently learn sequential patterns and collaborative graph topology from HUGs.

3 Heterogeneous User Graph

We introduce heterogeneous user graph (HUG), a data structure that stores both sequence patterns and graph topology for user modeling. A HUG $\mathcal{G} = (\mathcal{V}, \{\mathcal{E}_{\text{seq}}, \mathcal{E}_{\text{sim}}\})$ is constructed from an user's interaction sequence. We define the nodes $\mathcal{V}$ in the HUG as the interacted items in the sequence. With the heterogeneity of HUGs, there could be various types of edges to encode different transition patterns. In this paper, we construct two types of edges, sequential edges $\mathcal{E}_{\text{seq}}$ and collaborative edges $\mathcal{E}_{\text{sim}}$, to capture sequential signal and collaborative similarity, respectively.

Sequential Edges. The sequential edges are to store the chronological order of each pair of items. For $i, j \in \mathcal{V}$, $(i, j) \in \mathcal{E}_{\text{seq}}$ if $t_i < t_j$ where t_i denotes the position of i in the sequence.

Collaborative Edges. Collaborative edges encode collaborative similarity, a measure of similarity in regard to the users' preference patterns on the items. In order to measure collaborative similarities among items, we conduct a truncated singular value decomposition (SVD) on the user-item interaction matrix $\mathbf{R} \in \{0, 1\}^{|\mathcal{U}| \times |\mathcal{I}|}$ to obtain a set of low-dimensional item embeddings $\mathbf{V} \in \mathcal{R}^{d \times |\mathcal{I}|}$. We compute the cosine similarity between the embedding of each item in the HUG ($i \in \mathcal{V}$) with its predecessors $\{j | j \in \mathcal{V}, t_j \leq t_i\}$. Each item is connected to its k-nearest predecessors.

We show the overall construction process in Figure 1. Note that the collaborative edge can be easily generalized to capture other types of item-item relations as well.

4 Heterogeneous User Graph Transformer

In this section, we present heterogeneous user graph transformer (HUGT) that learns from HUGs to concurrently encode sequential signal and graph topology into latent user representations.

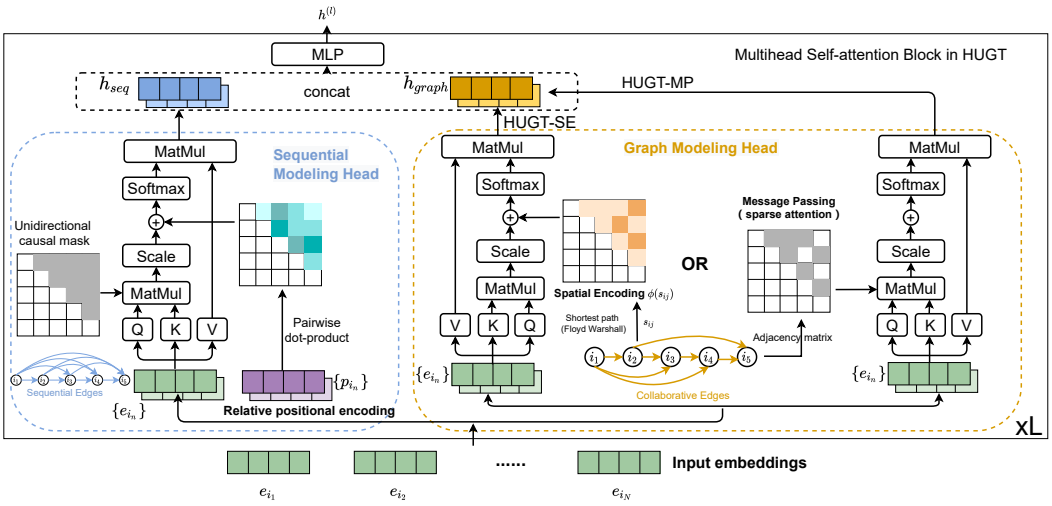

Figure 2: Computation flow of Heterogeneous User Graph Transformer (HUGT). The attention heads of the transformer are split into two groups. One group learns sequential patterns from the sequential edges while the other group learns graph topology from the collaborative edges.

4.1 Generalized Self-Attention Mechanism

In the standard self-attention, the item at each position aggregates weighted information from all items in the sequence to selectively build the context. Generalized self-attention (GSA) mechanism generalizes the standard self-attention by allowing each item to attend to any subset of the positions in the sequence and enlarges the design space of self-attention.

Let $\mathbf{H} = [\mathbf{h}_1, \mathbf{h}_2, \cdots, \mathbf{h}_n] \in \mathcal{R}^{d \times n}$ be the latent representation of a sequence $\mathcal{S}$ from the previous layer, where n and d denotes the length of the sequence and the dimension, respectively. GSA computes the representation of an item i as

$$\text{GSA}(\mathbf{h}_i) = \sum_{j \in \mathcal{N}(i)} \frac{\exp(\pi_{ij})}{\sum_{j' \in \mathcal{N}(i)} \exp(\pi_{ij'})} \mathbf{v}_j \tag{1}$$

$$\mathbf{q} = \mathbf{W}_q \mathbf{h}, \quad \mathbf{k} = \mathbf{W}_k \mathbf{h}, \quad \mathbf{v} = \mathbf{W}_v \mathbf{h}, \text{ and } \pi_{ij} = \mathbf{q}_i^T \mathbf{k}_j / \sqrt{d},$$

where $\mathbf{W}_q$, $\mathbf{W}_k$, and $\mathbf{W}_v$ are learnable parameters that map the input embedding to query, key, and value domain, respectively. $\mathcal{N}(i)$ denotes the set of items that item i attends to. When $\mathcal{N}(i) = \mathcal{S}$, the GSA fully recovers the standard self-attention. In unidirectional attention with causal masking (i.e., each item can only attend to its precedents) used in SASRec [13], $\mathcal{N}(i) = \{j | t_j < t_i\}$.

4.2 User Modeling with Multi-head Self-Attention

Embedding Layer. We use a learnable embedding table $\mathbf{E} \in \mathcal{R}^{d \times |\mathcal{I}|}$ to convert discrete item ids $[i_1, i_2, \cdots, i_n]$ to a matrix representation, $\mathbf{X} = [\mathbf{e}_{i_1}, \mathbf{e}_{i_2}, \cdots, \mathbf{e}_{i_n}] \in \mathcal{R}^{d \times n}$ where d is the dimensionality of the embeddings and n is the maximum sequence length that the model can take. The latent representation is fed into a stack of self-attention blocks to generate user embeddings.

Self-Attention Block. A self-attention block (SAB) consists of a generalized self-attention (GSA) layer that is introduced in Section 4.1 and a feed-forward layer (MLP) that adds non-linearity and considers interactions between latent dimensions, i.e.,

$$\text{MLP}(\mathbf{h}_i) = \mathbf{W}_2 \text{ReLU}(\mathbf{W}_1 \mathbf{h}_i + \mathbf{b}_1) + \mathbf{b}_2, \tag{2}$$

A SAB takes the output from the previous SAB as input, and passes the result to the next block, i.e.,

$$\mathbf{h}_i^{(l+1)} = \text{SAB}(\mathbf{h}_i^{(l)}) = \text{MLP}(\text{GSA}(\mathbf{h}_i^{(l)})), \tag{3}$$

where $\mathbf{h}_i^{(l)}$ denotes the output of the l-th SAB block, and $\mathbf{h}_i^{(0)} = \mathbf{e}_i$ is the output of the initial embedding layer. Following [13], we use layer normalization to accelerate training and residual

connections to preserve low-level information. We stack L SABs and use the output embedding at the last position of the last SAB as the final user representation for recommendation, i.e., $\mathbf{h}_u = \mathbf{h}_n^{(L)}$.

4.3 Sequential Modeling with Relative Positional Encoding

In contrast to RNNs that rely on recurrent operations to capture sequential signals, Transformers use positional encoding to break the order equivariance. We use an embedding table $\mathbf{P} \in \mathcal{R}^{d \times n}$ to map the positions to continuous representations $[\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_n]$. The positional embedding table could be either learnable or pre-computed by a set of sinusoid functions. In this paper we follow [13] and use learnable positional embeddings.

There are two major ways to incorporate the positional embeddings into self-attention, adding them to the input item features at the corresponding positions (absolute positional encoding) [22] and adding a relative score computed by the two embeddings of the corresponding positions to the attention score computed in Equation 1 (relative positional encoding) [19], i.e.,

$$\pi_{ij} = \frac{\mathbf{q}_i^T \mathbf{k}_j}{\sqrt{d}} + \psi(\mathbf{p}_{t_i}, \mathbf{p}_{t_j}),$$

where $\psi(\cdot, \cdot)$ is a learnable function. Empirically, we found that relative positional encoding outperforms absolute positional embedding in sequential recommendation tasks.

4.4 Graph Modeling

Message Passing. Graph neural networks that rely on message passing along graph edges have shown their ability to encode graph topology into latent node/graph embeddings. Note that, Equation 1 could be viewed as a message passing operation on a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}_{\text{sim}})$ by setting $i \in \mathcal{V}$ and $\mathcal{N}(i) = \{j | (i, j) \in \mathcal{E}_{\text{sim}}\}$. In fact, Equation 1 is a special implementation of graph attention networks (GAT). We skip the details of GAT and refer the readers to [23] for more information.

In this paper, we directly apply GSA on the collaborative edges in HUGs as one way to encode graph structural information. With such formulation, each node adaptively aggregates information from its graph neighbors and updates its representation. The stacked SABs allow nodes to accumulate information that is several hops away and encode graph topology into their latent representations.

Graph Spatial Encoding. The standard self-attention allows each item to attend to all items in the sequence. This brings the advantage of a global receptive field, but also raises the challenge of encoding graph structural information into item representations. We tackle this challenge by pre-extracting graph-related properties and learning to incorporate the properties into the computation of self-attention.

In this paper, we first compute the length of the shortest-path $s_{ij} \in \mathcal{Z}^+$ between each pair of nodes $i, j \in \mathcal{V}$ via collaborative edges to measure the spatial distance between the two nodes. We encode this information via a learnable mapping $\phi : \mathcal{Z}^+ \mapsto \mathcal{R}$ that converts the distance to a real scalar $\phi(s_{ij})$ and directly adds this value to the attention base, i.e., $\pi_{ij} = \mathbf{q}_i^T \mathbf{k}_j / \sqrt{d} + \phi(s_{ij})$. We clip the shortest-path length to an upper bound S, i.e., a length larger than S will be set to S. The clipping enables the model to generalize to unseen lengths during training, controls the model size, and provides encoding for disconnected item pairs.

4.5 Information Fusion with Multi-head Attention

Recall that in Equation 1, the input matrix $\mathbf{H}$ to each layer is mapped to a key $\mathbf{K}$, query $\mathbf{Q}$, and value $\mathbf{V}$ domain for the computation of self-attention. In a multi-head self-attention mechanism, $\mathbf{H}$ is mapped by multiple sets of projection matrices to several key-query-value spaces (each space corresponds to one attention head) to compute self-attention in parallel. The resulting representation from all attention heads is concatenated and projected to be the final representation, i.e.,

$$\mathbf{h} = \mathbf{W}_o \text{Concat}\left(\mathbf{h}^1, \mathbf{h}^2, \cdots, \mathbf{h}^m\right), \tag{4}$$

where m is the number of heads, $\mathbf{W}_o \in \mathcal{R}^{d \times (d \times m)}$ is a projection matrix, $\mathbf{h}^i$ is the output of the i-th attention head.

The multi-head formulation allows each item to aggregate information from different attention paths in one attention block. This provides flexibility to cope with the heterogeneity of HUGs. In each attention block, We separate the attention heads into two groups, the sequential modeling heads which learn from the sequential edges, and the graph modeling heads which learn from the collaborative edges. The two groups of attention heads adopt different mechanisms to capture the two sources of information. By stacking such multi-head attention blocks, we can effectively fuse and encode information from the two types of edges into user representations.

4.6 Prediction and Model Training

With the learned user representation at position t, i.e. $\mathbf{h}_u^t$, the final prediction $\hat{y}_{ui}^t$ of an item i is computed by

$$\hat{y}_{ui}^t = \mathbf{w}_i^T \mathbf{h}_u^t + b_i, \tag{5}$$

where $\mathbf{w}_i$ and b_i are decoder weight and bias for item i. We notice that the model generalizes better by sharing weights of the input embedding table with the item decoder.

We train the model by optimizing the cross-entropy loss

$$\mathcal{L} = -\sum_{u \in \mathcal{B}} \sum_{1 \le t \le n} \log \left(\frac{\exp\left(\hat{y}_{ui}^t\right)}{\sum_{j \in \mathcal{C}_u^t} \exp\left(\hat{y}_{uj}^t\right)} \right), \tag{6}$$

where $\mathcal{B}$ is a batch of users and $\mathcal{C}_u^t$ is a set of candidate items for user u at t. n is the maximum length of the sequence.

4.7 Complexity Analysis

Let $\mathcal{G}$ be an user HUG with n nodes. The time and space complexity of a m-head HUGT is the same as the standard Transformer, i.e., $\mathcal{O}(mn^2)$. In the pre-processing steps, we apply a truncated SVD on a sparse user-item interaction matrix which costs $\mathcal{O}((|\mathcal{U}| + |\mathcal{I}|)d^2 + Td)$ where T is the cost of a sparse matrix-vector multiplication and d is the dimension. When applying HUGT-SE, pre-computing the shortest path between each pair of nodes costs $\mathcal{O}(n^3)$. Since these steps only need to be applied once and could be computed in parallel, they are not efficiency barriers to our method.

5 Experiments

In this section, we carefully design experiments to investigate three research questions in regard of the HUG modeling of users and the HUGT:

- **RQ1**: How does HUGT perform in sequential recommendation compared to the state-of-the-art methods?
- **RQ2**: Is jointly modeling users as graphs and sequences better than a standalone sequence/graph user model?
- **RQ3**: Is a concurrent sequence-graph model better than modeling a user as a graph first and then a sequence?

5.1 Experimental Setup

5.1.1 Datasets

We experiment with four benchmark datasets, **ML1M**, **Netflix**, **Steam**, **Taobao**, that fall into three different application domains, movie recommendation, game recommendation, and E-commerce. The datasets are different in regard to their size, shape, density, and sequence length. The detailed statistics of the datasets are shown in Table 1. For all the datasets, we convert the ratings/reviews/interactions to implicit feedback (i.e., existing entries are assumed positive while missing entries are treated as negative signals).

Table 1: Statistics of the datasets

Dataset	# Users	# Items	# Interactions	Density	Avg. Len.
ML1M	6040	3398	997923	4.86%	165.11
Netflix	376076	17673	31324749	0.47%	83.29
Steam	1198725	13055	6419630	0.04%	5.36
Taobao	40023	205495	3933299	0.05%	98.28

Table 2: Performance comparison of the two HUGT variants, Message Passing (MP) and Spatial Encoding (SE), against baselines on the four datasets. In each row, we highlight the best performance in boldface.

	ML1M		Netflix		Steam		Taobao	
Metric	HR@10	N@10	HR@10	N@10	HR@10	N@10	HR@10	N@10
Pop	0.0117	0.0054	0.0197	0.0112	0.1029	0.0565	0.0024	0.0012
Fossil	0.0778	0.0314	0.0639	0.0258	0.2253	0.095	0.0027	0.001
GRU4Rec	0.2112	0.1164	0.2684	0.1615	0.1459	0.0811	0.1559	0.0942
SR-GNN	0.1516	0.0819	0.2253	0.1302	0.1059	0.0562	0.0921	0.0573
SASRec	0.1432	0.0599	0.2154	0.1143	0.2715	0.1985	0.1046	0.064
FISSA	0.0911	0.0387	0.1405	0.0711	0.1665	0.0899	-	-
BERT4Rec	0.153	0.0764	0.2462	0.1431	0.2979	0.2504	0.1342	0.0805
SASRec-Ours	0.2052	0.1039	0.3267	0.2028	0.3027	0.2581	0.1612	0.095
HUGT-MP	**0.2233**	**0.1218**	0.3286	0.2043	**0.3028**	**0.2585**	**0.1734**	0.1032
HUGT-SP	0.2225	0.1191	**0.3333**	**0.2085**	0.3022	0.2573	0.172	**0.1048**
Improv.	5.73%	4.64%	2.02%	2.81%	0.03%	0.15%	7.57%	10.32%

5.1.2 Baselines and Implementation Details

We compare the performance of HUGT with state-of-the-art sequential recommendation baselines that fall into the categories of factorization-based methods (**Fossil** [6]), RNN-based methods (**GRU4Rec** [8]), GNN-based methods (**SR-GNN** [27]), and Self-Attention-based methods (**FISSA** [16], **BERT4Rec** [20], and **SASRec** [13]).

For Fossil [1] and FISSA [2], we use the implementation associated with the original paper. For GRU4Rec, we use the implementation from [17], and we use a PyTorch implementation of BERT4Rec[3]. We implement SASRec using PyTorch an we find that our implementation greatly outperforms the original SASRec implementation. In our experiments, we select the hidden dimensions from $\{50, 300\}$. For Markov chain(MC)-based methods, we consider the MC order from $\{1, 2, 3, 4, 5\}$. For attention-related methods such as SASRec and BERT4Rec, we choose the number of attention heads from $\{1, 2, 3, 4\}$. For batch size and optimization related hyper-parameters, we follow the instructions from the original paper if provided. Otherwise, we set the batch size to 128 and optimize the model using the Adam [14] optimizer with a learning rate of 0.001.

The maximum length for each dataset is set to be able to cover the average sequence lengths of the dataset. We choose 200 for ML1M, 100 for Netflix and Taobao, and 50 for Steam. For constructing collaborative edges in HUG, we consider the k value from $\{5, 10, 20, 30, 50, 70\}$ for ML1M, Netflix, and Taobao. For the Steam dataset, we only consider $\{2, 3\}$ since its average sequence length is 5. When computing the ranking objective in Equation 6, we use all the items as candidate items for ML1M, Netflix, and Steam. Since the Taobao dataset has a large number of items, we compute the loss on a randomly selected $0.5\sqrt{|\mathcal{I}|}$ candidate items to reduce GPU memory consumption. We use the Adam algorithm to optimize the parameters of HUGT with a learning rate of 0.001. We set the batch size for ML1M, Netflix, and Steam to 128, and Taobao to 32. In our experiments, we set the number of attention heads to be 4 and consider different combinations of sequence heads and graph heads.

[1] https://drive.google.com/file/d/0B9Ck8jw-TZUEeEhSWXU2WWloc0k/view?usp=sharing

[2] http://csse.szu.edu.cn/staff/panwk/publications/Code-FISSA.zip

[3] https://github.com/jaywonchung/BERT4Rec-VAE-Pytorch

5.2 Experimental Settings

We use the first 90% of the interactions of each user as the training set and the last 10% of the interactions for evaluation purposes. We follow an auto-regressive manner in evaluating the recommendation models, i.e., we compute a user's state/representation from her current interaction sequence, make a prediction (a ranked list of items) for the next interaction, evaluate the recommendation list with the ground truth item, append the ground truth item to the tail of her sequence, and update the user's state/representation for next prediction. We validate on 30% of the users for model selection and early stopping and report test performance on the remaining 70% of the users.

We train HUGT and all the baselines on the training set and evaluate their performance on the validation set after each training epoch. We stop training if the validation score does not decrease in ten epochs or the number of training epochs reaches 100. We report the test performance of the checkpoint that performs the best on the validation set.

5.2.1 Evaluation Metrics

In this paper, we use HR@k and NDCG@k to evaluate the performance of the models. HR@k and NDCG@k compute the proportion of cases when the ground truth item is in the top-k prediction list. HR equally weighs the hit items while NDCG weighs the hit items decreasingly by their corresponding rank in the top-k list.

5.3 Recommendation Performance (RQ1)

We compare recommendation performance of the proposed HUGT with the state-of-the-art sequential recommendation methods on the four benchmark datasets. The overall performance is shown in Table 2. We observe that our proposed HUGT significantly outperforms all the baselines on ML1M, Netflix, and Taobao while its performance on Steam is similar to SASRec. This provides evidence that the collaborative graph topology is helpful for user modeling and our HUGT can effectively capture this signal to improve recommendation performance. Note that, the ML1M, Netflix, and Taobao datasets have an average sequence length of 165, 83, and 98, respectively, while the average length of Steam is 5. This shows that our proposed method works well in settings where the interaction sequences are long. When the sequences are generally short, our method performs on par with SASRec.

Table 3: Necessity of concurrent modeling of sequences and graphs. G-S denotes the model architecture that asynchronously encodes graph topology and then sequential signal. S-G denotes the architecture that reverses the above order. Concur is the default HUGT that learns sequential signal and graph topology concurrently.

Dataset	Model	G-S	S-G	Concur
ML1M	HR@10	0.2179	0.2136	**0.2206**
	NDCG@10	0.1184	0.1158	**0.1196**
Netflix	HR@10	0.3217	0.3219	**0.3286**
	NDCG@10	0.1991	0.1991	**0.2043**
Steam	HR@10	0.3020	0.3023	0.3020
	NDCG@10	0.2578	0.2580	0.2582
Taobao	HR@10	0.1679	0.1503	**0.1734**
	NDCG@10	0.1007	0.0904	**0.1032**

We observe that the two graph learning schemes, message passing (MP) and spatial encoding (SE), show advantages in different datasets. This demonstrates that some datasets could benefit from the global receptive field of the SE method while others may enjoy the local structure of the MP scheme.

5.4 HUG vs. Standalone User Modeling (RQ2)

In this section, we design experiments to investigate the necessity of the unified sequence-graph user representation and the graph learning scheme. For each dataset, we train five HUGT-MP models that each has four attention heads. The five HUGT-MP models have a number of sequential heads ranging from zero to four while the rest of the heads are graph heads. We show the recommendation performance of the models in Figure 3. We observe a performance drop on all the datasets when we set the number of sequence heads to zero. This shows the importance of sequence patterns in user modeling. On the three datasets with long sequences (ML1M, Netflix, Taobao), we observe a performance drop when we set the number of graph heads to zero. This demonstrates that the

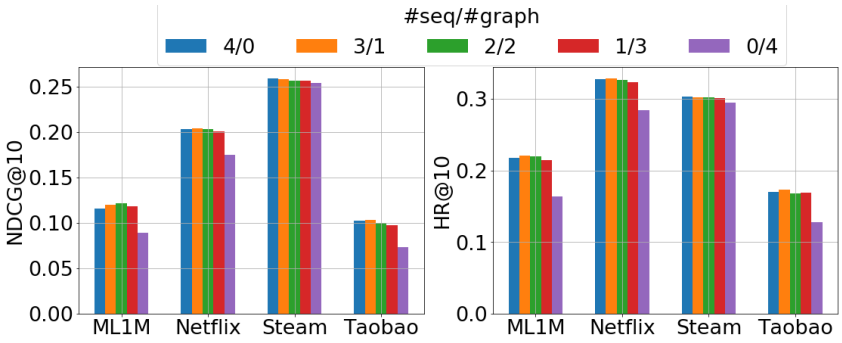

Figure 3: Recommendation performance with different combinations of sequential heads and graph heads on ML1M.

collaborative graph topology is important in a long sequence setting and the graph learning schemes that we proposed are effective in capturing this information. On the Steam dataset that has short sequence lengths, the recommendation performance is not influenced by cutting the graph heads. This suggests that the transition patterns in short sequence settings are not very sophisticated and could be very well captured by a naive sequential model.

5.5 Importance of Concurrent Modeling (RQ3)

In a HUGT block, to incorporate the heterogeneity of HUG, we split multiple attention heads to sequence heads and graph heads to concurrently encode sequential patterns and graph topology. In this section, we conduct experiments to answer the question that whether this formulation is better than its asynchronous alternatives. We design two architectures that process the sequence heads and the graph heads sequentially. One that applies an HUGT with only graph heads on the HUG to encode only graph topology into the item embeddings then applies an HUGT with only sequence heads on the HUG whose initial node embeddings are the output of the previous graph-only HUGT to mix graph topology and sequential patterns. The second architecture is similar but applies a sequence-only HUGT first and then a graph-only HUGT. The recommendation performance of the default HUGT and the two alternative architectures are shown in Table 3. We observe that on the three datasets with long sequences (ML1M, Netflix, Taobao), concurrent modeling of sequences and graphs outperforms the asynchronous alternatives. This demonstrates the effectiveness of the heterogeneous graph modeling of users and the proposed Transformers. On the Steam dataset, there is no significant performance difference between the three architectures.

6 Conclusion

We introduce a novel heterogeneous user graph (HUG) that jointly models users as sequences and graphs to encode item transition patterns and complex item relations. To leverage the item transition patterns and graph topology stored in HUGs for recommendation tasks, we develop heterogeneous user graph transformer (HUGT) that extends the standard self-attention for concurrent sequence learning and graph learning. Experimental results show that the unified sequence-graph user modeling is better than either sequence-only modeling or graph-only modeling and HUGT achieves state-of-the-art performance on all benchmarks.

HUG and HUGT provide a flexible framework for future research to incorporate complex item relations into user modeling. A valuable direction to explore is the choice of graphs for user modeling. We demonstrated that the collaborative similarity graph could provide extra context information for user modeling. There remain a lot of choices such as item temporal graph, or item feature similarity graph. We leave them as future works.

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