Lightweight Self-Attentive Sequential Recommendation

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ABSTRACT

Modern deep neural networks (DNNs) have greatly facilitated the development of sequential recommender systems by achieving state-of-the-art recommendation performance on various sequential recommendation tasks. Given a sequence of interacted items, existing DNN-based sequential recommenders commonly embed each item into a unique vector to support subsequent computations of the user interest. However, due to the potentially large number of items, the over-parameterised item embedding matrix of a sequential recommender has become a memory bottleneck for efficient deployment in resource-constrained environments, e.g., smartphones and other edge devices. Furthermore, we observe that the widely-used multi-head self-attention, though being effective in modelling sequential dependencies among items, heavily relies on redundant attention units to fully capture both global and local item-item transition patterns within a sequence.

In this paper, we introduce a novel lightweight self-attentive network (LSAN) for sequential recommendation. To aggressively compress the original embedding matrix, LSAN leverages the notion of compositional embeddings, where each item embedding is composed by merging a group of selected base embedding vectors derived from substantially smaller embedding matrices. Meanwhile, to account for the intrinsic dynamics of each item, we further propose a temporal context-aware embedding compression scheme. Besides, we develop an innovative twin-attention network that alleviates the redundancy of the traditional multi-head self-attention while retaining full capacity for capturing long- and short-term (i.e., global and local) item dependencies. Comprehensive experiments demonstrate that LSAN significantly advances the accuracy and memory efficiency of existing sequential recommenders.

1 INTRODUCTION

Modelling sequential user behaviours has received great attention in contemporary applications, such as e-commerce, online services, and smart transport [49]. Among these applications, sequential recommender systems (SRs) have become a prominent solution to information overload on the web. The main goal of SRs is to make a proactive recommendation on the next item a user may be interested in by mining the user’s recent preferences from the sequence of her/his interacted items.

Early SRs incorporate Markov chain-based models [7, 10, 33] to capture high-order sequential patterns based on Markov chain (MC), which essentially factorises a user-specific item-item transition tensor by considering first-order Markov chain. However, these methods primarily learn the transition patterns based on the most recent item interactions, neglecting long-term (i.e., global) user preferences. With the revolution of deep neural networks (DNNs), various deep methods have been proposed for the sequential recommendation [21, 28–31], especially recurrent neural network-based [3, 4, 6, 22, 53] sequential recommenders. Notably, the majority of state-of-the-art SRs are latent factor models, where each item is mapped into a unique vector representation (a.k.a. embedding), and the item embedding is then used to calculate the sequential preferences of the target user.

With the fast pace of digitisation and hardware revolution, there has been a recent surge of moving data analytics from cloud servers to edge devices [35] to ensure timeliness and privacy. As sequential recommendation involves frequent updates on a user’s behaviour records, developing lightweight SRs appears to be an ongoing trend, because such on-device computation capability can prevent potential latency caused by communications with the cloud and effectively retains users’ personal data on their own devices. Due to the sheer volume of different items (e.g., Alibaba’s billion-scale item set [41]), the item embeddings in latent SRs are the main source of memory consumption [42] rather than other parameters like weights and biases of DNNs. In this regard, recent studies on lightweight recommenders [5, 23, 24, 34] are predominantly focused on compressing the originally large item embedding matrix to improve the memory efficiency of recommenders. Their core idea of such compression is compositional embeddings, where a recommender consists of a small number (substantially smaller than the number of all items) of base embeddings, such that an item can be represented as a distinct combination of selected base embeddings. However, most compositional embedding-based recommenders are designed for static recommendation settings, where the recommendation...
results for each user are purely conditioned on the static user-item affinity instead of her/his interest dynamics.

As a common practice, the aforementioned lightweight recommenders usually combine compositional embeddings with off-the-shelf deep recommendation modules (e.g., the DLRS in [34] and the DeepFM in [25]). Though a similar solution can be sought for lightweight SRSs by straightforwardly feeding compositional item embeddings into sequential DNNs (e.g., recurrent neural networks), an over-parameterised network structure will in fact defeat the purpose of a memory-efficient model. Also, the excessive computations may impede the timeliness of a model’s on-device inference. Hence, in addition to a lightly parameterised item embedding scheme, a lightweight SRS should also be able to thoroughly discover the temporal signals from all interacted items with a carefully designed, compact, yet effective sequence mining paradigm.

To this end, we propose lightweight self-attentive network (LSAN), a novel solution to memory-efficient sequential recommendation that simultaneously addresses those two key challenges. Specifically, LSAN aggressively replaces the item embedding matrix with $N$ base embedding matrices, each of which contains substantially fewer embedding vectors (i.e., base embeddings) than the total amount of items, i.e., $N \ll |V|$ for item set $V$. Then, compositional item embeddings are generated by fusing $N$ base embeddings respectively selected from each base embedding matrix. To ensure the uniqueness of each composed item embedding, we design a context-aware temporal compositional embedding scheme, where base embeddings are located via a quotient-remainder operation. Unlike traditional compositional item embeddings that stay fixed regardless of any temporal information in a sequence, we propose to dynamically alter the generated item embedding according to sequence-specific contexts by attentively merging the base embeddings for each item. The rationale is that in a sequence, every item’s relevance is sensitive to factors like seasonal changes and adjacent items [20, 43], hence we let LSAN account for such information when generating compositional item embeddings.

In LSAN, we resort to self-attention for modelling the temporal patterns among the interacted items. However, though the self-attention [17, 27, 55] is widely acknowledged as a light-ly-parameterised and effective approach for capturing sequential information in SRSs compared with the popular alternative – RNNs, our observation is that recommenders using self-attention can still incur parameter redundancy. For sequential recommendation tasks, the attention module should be able to capture both long- and short-term (i.e., global and local) preferences of a user. Unfortunately, recent studies [44, 46] point out that self-attention tends to over- emphasise local relationships between adjacent items, making it difficult to learn the correlations between items that are far from each other in a sequence. Hence, existing recommenders commonly employ multi-head self-attention, so as to enhance the modelling capacity and acquire sufficient global information. Such redundancy can be tolerated and may benefit the recommendation accuracy when the computing resource allows, but it fails to meet the highly constrained deployment environment in the context of memory-efficient SRSs. In light of this, we introduce a novel twin-attention paradigm in LSAN, where the global and local preference signals are separately captured via two specialised modules instead of a group of general attention units. As such, coupled with the dynamic compositional item embedding scheme, LSAN effectively learns local and global user preference signals for accurate sequential recommendation without the need for an excessively complex and large model.

With the proposed LSAN, our main contributions to lightweight sequential recommendation are three-fold:

- We devise a dynamic context-aware compositional embedding scheme, which largely decreases the memory footprint of item embedding matrix – the major consumer of memory space of SRSs – and ensures the uniqueness and dynamics of generated item embeddings at the same time.
- We propose a novel twin-attention sequential framework, which specialises the learning of long- and short-term user preference signals via a dedicated self-attention and convolution operation, respectively. This facilitates explicit modeling of both global and local patterns while avoiding the redundancy of multi-head self-attention modules.
- Extensive experiments are conducted on three benchmark datasets. The results demonstrate the advantageous effectiveness and memory efficiency of LSAN against state-of-the-art baseline methods.

## 2 PROBLEM FORMULATION

Let $V, U$ be the sets of items and users, respectively. We use $S_u = \{v_1, v_2, ..., v_T\}$ to denote a sequence of $T$ chronologically ordered items that user $u \in U$ has interacted with. Each item $v_t \in S_u$ is assigned an order index $i = 1, 2, ..., T$ which reflects the position of an item in the sequence. To locate $v_t$ among the set of $|V|$ items, we define a function index($v_t$) that maps $v_t$ to a unique and fixed global index $1, 2, ..., |V|$. Then, given a sequence of interactions $S_u$, our goal is to compute a ranking list consisting of top $K$ items that $u$ is most likely to visit at the next time step $T + 1$.

## 3 METHODOLOGY

In this section, we introduce our proposed memory-efficient sequential recommender, namely LSAN. LSAN consists of two main components: (1) a dynamic context-aware compositional embedding layer that enables a lightweight yet highly expressive item embedding paradigm; and (2) a twin-attention network that effectively learns global and local user preferences without the need for redundant multi-head self-attention modules. In what follows, we present the design of LSAN in detail.

### 3.1 Dynamic Context-aware Compositional Embedding

Recall that in a typical latent factor-based recommender system, each item $v_t$ is associated with a unique $D$-dimensional embedding vector, which corresponds to the $v_t$-th row in an embedding table $E \in \mathbb{R}^{|V| \times D}$. The memory complexity of maintaining such an embedding table is $O(|V|D)$, where the memory cost will become impractical for edge devices when $V$ is large-scale. To reduce the size of $E$ for better memory efficiency, we replace $E$ with a set of $N$ base embedding tables denoted as $\{E_1, E_2, ..., E_N\}$, where $E_n \in \mathbb{R}^{m_n \times D}$ for $n = 1, 2, ..., N$. Here, $m_n$ indicates the number of base embeddings in the $n$-th base embedding table $E_n$. For each item, its compositional embedding is produced by first selecting one
base embedding vector from each $E_n$ and then attentively fusing all selected base embeddings into a single vector. It can be concluded that there are $\Pi_{n=1}^N m_n$ different combinations of base embeddings. Thus, we only need to make $\Pi_{n=1}^N m_n \geq |\mathcal{V}|$ to ensure the uniqueness of constructed embeddings for each item. To guarantee that each item receives a distinct combination of base embeddings, we resort to the quotient-remainder trick [34] that does not introduce any additional learnable parameters. Particularly, taking the first base embedding table $E_1$ as an example, the corresponding base embedding index $q_i$ (i.e., the row index in $E_1$) for item $v_i \in \mathcal{S}_u$ can be computed by a remainder function over the base embedding table size $m_1$:

$$q_i = \text{index}(v_i) \mod m_1.$$  

Then, the first base embedding $\vec{e}_i$ for $v_i$ can be retrieved by a look-up operation on $E_1$ w.r.t. row index $q_i$. Mathematically, let $f_i \in \mathbb{R}^{|\mathcal{V}|}$ be the one-hot encoding of $v_i$, then a hash matrix $R_1 \in \mathbb{R}^{m_1 \times |\mathcal{V}|}$ for $E_1$ can be computed element-wise via:

$$R_{1,i,j}^1 = \begin{cases} 1 & \text{if } j \mod m_1 = \text{index}(v_i) \\ 0 & \text{otherwise} \end{cases}.$$  

Therefore, the look-up operation of $v_i$’s first base embedding $\vec{e}_i^1$ can be mathematically formulated as:

$$\vec{e}_i^1 = \vec{E}_1 \cdot R_1^1 f_i.$$  

Analogously, for $n = 2, 3, \ldots, N$, $v_i$’s hash matrix $R_n$ for the $n$-th base embedding table can be generalised as:

$$R_{n,i,j}^n = \begin{cases} 1 & \text{if } j \mod m_n = \text{index}(v_i) \mod \Pi_{n=1}^{n-1} m_n \\ 0 & \text{otherwise} \end{cases},$$  

where the index in the $n$-th base embedding table for item $v_i$ is determined by the resulting quotient from the prior base embedding tables, i.e., $\text{index}(v_i) \mod \Pi_{n=1}^{n-1} m_n$. Then, we obtain the base embedding $\vec{e}_i^n$ from $R^n$ via:

$$\vec{e}_i^n = \vec{E}_n R^n f_i.$$  

Through the quotient-remainder trick, we now have acquired a set of base embeddings $\{\vec{e}_i^1, \vec{e}_i^2, \ldots, \vec{e}_i^N\}$ for item $v_i$. Intuitively, a unified item embedding can be easily formed by an ensemble operation, such as element-wise addition/multiplication. However, such constructed embeddings are fixed, and are insufficient in capturing the intrinsic dynamics of an item’s properties. As pointed out by [20, 43], learning context-aware temporal item embeddings is beneficial for mining a user’s preferences from her/his interaction sequences. In order to bring such temporal contexts into the generated compositional item embeddings, we propose to attentively assign different weights to the selected base embeddings conditioned on the context around the target item. Specifically, for each item $v_i \in \mathcal{S}_u (i = 1, 2, \ldots, T)$, we have a context $c_i$ representing this item’s situation within the sequence. The construction of $c_i$ can be highly flexible, where in our work, based on the side information shared by all of our experimental datasets (see Section 4), we define $r_i = (c_{i-1}, c_i, \text{time}(i))$ as a triplet of the categories of the previous and current items and the discrete time slot (i.e., every hour of a day). We denote $R = \{r_1, r_2, \ldots, r_T\}$ be the set of unique context tuples. Each tuple $r \in R$ is assigned with a one-hot vector. Then, we can map the one-hot encoding vector $r_i$ into a dense context embedding $c_i \in \mathbb{R}^D$. Note that a padding label for the category information is adopted when $t = 1$. Under a given context $r_i$, we can calculate an attention weight for each base embedding:

$$\alpha_n = \frac{\exp(r_i^T \text{SiLU}(W_a \vec{e}_i^n)))}{\sum_{n=1}^{N} \exp(r_i^T \text{SiLU}(W_a \vec{e}_i^n)))},$$  

Figure 1: An overview of the proposed LSAN model.
where SiLU($x$) = $x \cdot \text{sigmoid}(x)$ is an activation function that is an alternative to ReLU providing non-linearity to the model with faster convergence speed [9]. The attention weight is then used to compute the compositional embedding $h_i$ for item $v_i$:

$$h_i = \sum_{n=1}^{N} \alpha_n \tilde{e}_i^n. \quad (7)$$

Finally, to facilitate side information modelling, we inject the context embedding of the item $i$ (i.e., $r_i$) into the above computed compositional embedding $h_i$ via a non-linear operation:

$$\tilde{h}_i = \text{MLP}([h_i; r_i]), \quad (8)$$

where $[:; ]$ is the concatenation operation and $\text{MLP}(:) : 2D \to D$ denotes a multi-layer perceptron. For a sequence of $T$ interacted items, we can obtain an embedding matrix $H = [h_1; h_2; \ldots; h_T] \in \mathbb{R}^{T \times D}$ by sequentially stacking all compositional item embeddings.

### 3.2 Modelling Long- and Short-term User Preferences with Twin-Attention

Self-attention has been a predominant approach in recent SRSs owing to its simplicity and capability of learning sequential dependencies among items. As discussed in Section 1, existing self-attentive sequential recommenders mostly deploy multiple attention heads in parallel to capture both global and local user preference signals from the sequence, resulting in unnecessary redundancy in both the network structure and parameter size. To alleviate such problem, we propose a twin-attention neural network to better capture the sequential information while maintaining the lightweight nature of LSAN. As depicted in Figure 1, it has two branches: a self-attention branch and a convolution branch specialised for global and local preference modelling, respectively.

#### 3.2.1 Convolution Branch for Local Patterns

Different from the self-attention branch which attends to all items in a sequence, convolution operations have shown success in extracting local features for image recognition and text classification. Their strong capacity in extracting regional features makes them an ideal component for capturing the short-term preferences among items that co-occur in a short time period. As such, with the matrix $H \in \mathbb{R}^{T \times D}$ carrying all $T$ item embeddings in the sequence, we perform 1D convolution over the embedding matrix. Assuming the sliding window size is $L$ and the output size is $D$, the standard convolution operation needs $L^2$ trainable parameters. To decrease the parameter size, we resort to a lightweight version of convolution [45]. In particular, a depth-wise convolution operation is introduced, which applies a shared kernel of size $L$ for each channel (i.e., each item embedding dimension). This reduces the number of required parameters from $O(LD^2)$ to $O(LD)$. Mathematically, the $d$-th element $(d = 1, 2, \ldots, D)$ of $i$-th embedding in the resulted output matrix $H_{\text{conv}} \in \mathbb{R}^{T \times D}$ can be formulated as:

$$H_{\text{conv}}^{i \cdot d} = \sum_{j=1}^{L} W_j^{i \cdot d} H_{(i+j-\lceil \frac{L}{2} \rceil),d} \quad d = 1, \ldots, D, \quad (9)$$

where $W_j^{i \cdot d} \in \mathbb{R}^L$ is the kernel, and $\lceil \cdot \rceil$ denotes the ceiling operation. It is worth noting that, each row in the resulted matrix $H_{\text{conv}}^{i}$ encodes $i$-th item’s interaction with items closely surrounding it within the $L$-sized sliding window, hence is a representation of all the local dependencies within the item sequence.

#### 3.2.2 Self-attention Branch for Global Patterns

The rationale of coupling self-attention with convolution is that, by having a convolution branch dedicated to extracting local sequential patterns, the self-attention branch can now better specialise in learning global patterns, thus reducing the need for using an excessive amount of self-attention units for optimal performance. As for self-attention, it has become one of the most prevalent means in various natural language processing (NLP) and sequential tasks as it can effectively capture relationships among items regardless of their distances (i.e., multi-hop). However, the plain self-attention fails to preserve the inherent orders of items in the sequence, impeding its efficacy for sequential recommendation tasks [17]. In this sense, we make the self-attention branch order-aware. Firstly, we define $T$ learnable position embeddings $p_1, p_2, \ldots, p_T \in \mathbb{R}^D$, which are stacked into a matrix $P \in \mathbb{R}^{T \times D}$. Then, we fuse the positional information into the original item embeddings:

$$\tilde{H} = H + P, \quad (10)$$

where each item is essentially paired with its corresponding positional context in the sequence. After that, a scaled dot-product self-attention is applied to compute item representations $H_{\text{atten}} \in \mathbb{R}^{T \times D}$ by mining the long-range dependencies:

$$\hat{H} = \text{softmax} \left( \frac{QK^T}{\sqrt{D}} \right) V, \quad (11)$$

where $Q = W_q \tilde{H}$, $K = W_k \tilde{H}$ and $V = W_v \tilde{H}$ are transformed item representations that are projected into query, key and value spaces, respectively.

#### 3.2.3 Enhancing Expressiveness with Parallelism

Similar to pure self-attention-based methods, one can employ more than one attention heads for both branches in the twin-attention. For simplicity, we assume the convolution and self-attention modules each have $H$ heads in parallel. Then, the final output of the twin-attention can be obtained by concatenating $2H$ learned representation matrices followed by:

$$H_{\text{twin}} = [H_{\text{conv}}^1; \ldots; H_{\text{conv}}^H; H_{\text{atten}}^1; \ldots; H_{\text{atten}}^H], \quad (12)$$

where $H_{\text{twin}} \in \mathbb{R}^{T \times 2HD}$ is the final output. Note that in LSAN, it is not strictly necessary to set $H > 1$ as the design of twin-attention can already facilitate comprehensively learning both global and local user preferences. One benefit of such parallelism over the traditional multi-head attention is that, with the same total amount of $2H$ attention heads, twin-attention consumes fewer parameters (i.e., $O(H(LD + 3D^2))$ in twin attention versus $O(6HD^2)$ in self-attention, $L \ll D$) and is able to yield stronger performance, as will be illustrated in Section 4.

### 3.3 Prediction Layer

#### 3.3.1 Point-wise Feed-forward Network

To further enhance the representation capacity of LSAN, we incorporate non-linearity into the output of the twin-attention. Specifically, we employ a point-wise feed-forward network (FFN) as follows:

$$\tilde{H} = \text{GeLU}(H_{\text{twin}}W_p^{(1)} + b_p^{(1)})W_p^{(2)} + b_p^{(2)}, \quad (13)$$
where $W_p(1) \in \mathbb{R}^{2HD \times 2HD}, W_p(2) \in \mathbb{R}^{2HD \times D}$ are weight matrices, $b_p(1) \in \mathbb{R}^{2HD \times 1}, b_p(2) \in \mathbb{R}^{D \times 1}$ are bias vectors, and $\tilde{H}_{win} \in \mathbb{R}^{T \times D}$ is the output of the point-wise FFN. Meanwhile, GeLU($\cdot$) denotes the Gaussian error linear unit [8, 12] that we use for non-linearity.

### 3.3.2 Generating Rankings.

With the final representation $\tilde{H}_{win}$ that encodes both the user’s long- and short-term interests, we generate the rankings for all items to facilitate top-$K$ recommendation. This is achieved by estimating the likelihood of having user $u$ interact with each item, which is formulated as learning a $|V|$-dimensional probability distribution $\hat{y}_i$:

$$\hat{y} = \text{softmax}(W_o \tilde{H}_{win} + b_o),$$

where $W_o \in \mathbb{R}^{|V| \times D}$ and $b_o \in \mathbb{R}^{|V|}$ are the learnable weight matrix and bias vector, respectively. By sorting each $y_i$ according to its corresponding probability score $\hat{y}_i \in \hat{y}$ in a descending order, we will be able to truncate $K$ items from the top of the list as our recommendation results.

### 3.4 Learning Objective

With the estimated probability vector $\hat{y}$, we then employ cross-entropy loss function to quantify the error of predicting the next item for LSAN:

$$\mathcal{L} = \frac{1}{S} \sum_{s=1}^{S} \log(\hat{y}_s) + \lambda \|\Psi\|_2^2,$$

where $s \leq S$ is the index of training samples, $y_s$ is the one-hot vector representing the ground truth of the next item, and $\Psi$ is the set of all trainable parameters under the $L2$ regularisation term with coefficient $\lambda$.

## 4 EXPERIMENTS

In this section, we evaluate the recommendation effectiveness and memory efficiency of our LSAN model for sequential recommendation. Specifically, we first analyze the performance of LSAN by comparing it with state-of-the-art sequential recommenders from both accuracy and model size perspectives. After that, we further investigate the impact of the key components and hyperparameters in LSAN.

### 4.1 Experimental Settings

#### 4.1.1 Dataset.

We conduct experiments on four commonly-used benchmark datasets. The statistical details of all datasets after pre-processing are reported in Table 1, including the number of users, items, interactions, categories, average interactions per user (Avg. Int./User) and average interactions per item (Avg. Int./Item). All the experimental datasets are highly sparse. We briefly introduce their properties below:

- **Beauty, Sports and Toys**\(^1\): These three datasets are provided by [11], which are collected from Amazon and contain product reviews and abundant metadata.
- **Yelp**\(^2\): The dataset contains user check-in data provided by Yelp, where businesses are viewed as items. The data we use for our experiments span across 2019.

For each dataset, we group interactions by user IDs, and then generate one chronological item sequence for each user. The inactive users and unpopular items with less than 5 interactions are discarded.

### 4.2 Evaluation Metrics

We adopt the leave-one-out evaluation approach, i.e., for each user interaction sequence, we use the last item as the test instance, the second last item as a validation sample, and the remaining items for training. We choose Hit Ratio at Rank $K$ (HR@$K$) and Normalised Discounted Cumulative Gain at Rank $K$ (nDCG@$K$) on top-$K$ ranked items, which are widely used in recommender systems [3, 17] for top-$K$ performance and overall ranking performance evaluation. We report the performance results on HR@{$5, 10, 20$} and nDCG@{$5, 10, 20$}, respectively. As suggested by [19], to eliminate potential biases, we rank each ground truth item along with the whole item set (i.e., $V$) to compute all metrics, and report the average scores over all users.

### 4.3 Baseline Methods

We compare LSAN with the most representative, state-of-the-art sequential recommendation methods below:

- **FPMC** [33]: It is a combination of matrix factorisation with Markov chain, which can simultaneously capture sequential information and long-term user preferences.
- **GRU4Rec** [13]: It is an RNN-based sequential recommender with session-wise mini-batch training strategy. The model is optimised by a pair-wise ranking loss.
- **Caser** [39]: This is a CNN-based method that models high-order Markov-chain probability by performing convolutional operations on the item embedding matrix.
- **SASRec** [17]: It is a next-item sequential recommendation method based on the Transformer architecture, which employs multi-head self-attention mechanism to explore implicit user interactions.
- **BERT4Rec** [37]: It is an improvement of SASRec, which contains an additional Cloze objective and bidirectional self-attention structure.

### 4.4 Implementation Details

LSAN is implemented using PyTorch with Nvidia GTX 2080 Ti. In LSAN, we set the dimension size $D$ to 128, CNN kernel size $L$ to 5, the number of attention heads $H$ to 2 for each branch, and the

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\(^1\)http://jmcauley.ucsd.edu/data/amazon/links.html

\(^2\)https://www.yelp.com/dataset
number of stacked twin-attention layers to 1 on all datasets. All the trainable parameters in our model are optimised using Adam optimiser [18] with the batch size of 256, learning rate of 0.001 and L2 regularisation strength \( \lambda \) of 1e − 5. For a fair comparison on accuracy and model size, we apply the same dimension size \( D \) for all methods’ embeddings. Note that in LSAN, altering either \( N \) or \( m_2 \) can lead to different compression rates on the original embedding table. Hence, we fix \( N = 2 \) and vary \( m_1 \) (\( m_2 = \frac{|V|}{m_1} \)) for the ease of hyper-parameter tuning. In Section 4.5, we will first test LSAN’s performance with \( m_1 = 2 \), while we will further discuss how LSAN performs when we compress the model size more aggressively with a larger \( m_1 \) in Section 4.6.

### 4.5 Overall Performance Comparison

We summarise the results of all models on four benchmark datasets in Table 2. From the table, we can draw the following observations:

Among all sequential baseline methods, FPMC receives the worst results over all evaluation metrics. This is mainly because FPMC only exploits first-order dependencies where the higher-order relationships among items are neglected. In comparison, Caser utilises convolutional kernels to extract k-hop adjacent item dependencies, thus, obtaining better performance results than FPMC. However, since the sliding window size of Caser could only cover a small number of items, which lacks the ability on handling sparse datasets with long sequences, e.g., Yelp. As a result, it can be observed that the RNN-based method, GRU4Rec, has better performance than Caser on those datasets. SASRec and BERT4Rec are state-of-the-art self-attentive approaches, which have clear margins with the other baseline methods. This shows the superiority of the self-attention architecture in sequential behaviour modelling. It is worth noting that BERT4Rec does not outperform SASRec under our evaluation settings (i.e., full test sample set), which is different from their original paper. We think this maybe because there may exist improper biases in the naïve negative sampled test sets according to their original implementation details.

We present the performance results and relative improvements over the best baseline of two versions of our proposed LSAN in Table 2, i.e., LSAN\(_{\text{full.emb}}\) and LSAN. The only difference between them is that LSAN is our proposed model, while LSAN\(_{\text{full.emb}}\) is trained using a full-sized embedding table. From the results, using either full-sized embedding table or our proposed dynamic context-aware compositional embedding can surpass the best baseline method SASRec with significant margins on most evaluation metrics. This proves the effectiveness of our twin-attention structured model on handling long-term and short-term user preferences. Moreover, though a large number of parameters are reduced via our compositional embeddings, LSAN performs even much better than LSAN\(_{\text{full.emb}}\) on all datasets. We believe that by incorporating seasonal and categorical factors (i.e., temporal dynamics) within the model can largely enhance the expressiveness of LSAN with fewer trainable parameters.

In addition, an obvious model size reduction can be observed from both LSAN and LSAN\(_{\text{full.emb}}\). We provide a more detailed discussion on memory usage in the following section.

#### 4.6 Impact of Embedding Compression Rate

In this section, we study how the compression rate affects the model performance. Intuitively, the model will have worse performance when the compression rate \( m_1 \) increases. We compare the model size and next-item recommendation performance of LSAN at different compression rates with the best baseline method, SASRec. From the results shown in Table 3, we can observe that when \( m_1 = 2 \), our LSAN model surpasses SASRec over most metrics with only around 60% of parameters in SASRec on all datasets. When \( m_1 \) increases to 3 (i.e., around 45% of SASRec parameters), LSAN still produce comparable recommendation results on Beauty, Toys and Yelp datasets, which further approves the outstanding memory efficiency and recommendation effectiveness of our model. However, when \( m_1 \) goes up greater than 3, we can see a clear performance drop. It is understandable that when the model contains a very small number of parameters, the model is under-parameterised resulting in the failure of capturing meaningful information from items.

#### 4.7 Ablation Study

Comparing with the existing self-attentive methods, LSAN mainly contains two novel components: dynamic context-aware compositional embeddings and twin-attention layers. To verify the effectiveness of each component, we conduct ablation studies on all benchmark datasets. Table 4 shows the performance of our default model and its two degraded variants (\( D = 128 \)). We give a brief description and detailed analysis of each variant in the following:

Specifically, we compare LSAN with the following degraded variants:

- **LSAN\(_{\text{w/odynamic}}\):** This variant removes the dynamic compositional embedding component. The embedding part becomes exactly the same as the QR embedding introduced in [34]. More concretely, we create this variant by modifying Eq. (7) to \( h_i = \sum_{n=1}^{N} \mathbf{e}_n \). We can see a significant performance drop on most datasets when the temporal information is removed from the composited embeddings. This suggests that respecting temporal dynamics is of great importance in user preference modelling.

- **LSAN\(_{\text{plain.attn}}\):** This variant replaces the twin-attention layers with self-attention layers. There is a clear performance drop on three datasets when only self-attention is applied. This reveals that the self-attention does not have sufficient capability to uncover both long-term and short-term user preferences with limited attention heads.

#### 4.8 Hyper-parameter Analysis

We further examine the impact of four various hyper-parameters, including dimension size \( D \), partition size \( m \), number of attention heads \( H \), and number of stacked twin-attention layers. For each test, we vary the value of one hyper-parameter, while keep the others be the optimal settings. The results are demonstrated in Figure 2.

**4.8.1 Impact of Dimension Size.** The dimension of The value of dimension size is examined from 16 to 256. We can observe that a small dimension size (i.e., 16) cannot preserve sufficient latent information of items for user sequential behaviour modelling. The model performance increases steadily when the dimension size...
Table 2: Comparison on sequential recommendation accuracy and model sizes. In each row, the best and second best results are highlighted in boldface and underlined, respectively. The parameter size of each model is obtained when $D = 128$.

| Datasets | Metrics | FPMC | GRU4Rec | Caser | SASRec | BERT4Rec | LSAN $\text{full.emb}$ | Improv. | LSAN | Improv. |
|----------|---------|------|---------|-------|--------|-----------|------------------------|--------|------|--------|
| Beauty   | HR@5   | 0.0149 | 0.0164 | 0.0205 | 0.0419 | 0.0312 | 0.0432 | 3.10% | 0.0492 | 17.42% |
|          | HR@10  | 0.0273 | 0.0283 | 0.0347 | 0.0650 | 0.0468 | 0.067 | 3.08% | 0.0785 | 20.77% |
|          | HR@20  | 0.0438 | 0.0479 | 0.0556 | 0.0872 | 0.0737 | 0.0992 | 13.76% | 0.1201 | 37.73% |
|          | nDCG@5 | 0.0096 | 0.0099 | 0.0131 | 0.0263 | 0.0223 | 0.0276 | 4.94% | 0.0316 | 20.15% |
|          | nDCG@10| 0.0133 | 0.0137 | 0.0176 | 0.0337 | 0.0272 | 0.0352 | 4.45% | 0.041 | 21.66% |
|          | nDCG@20| 0.0173 | 0.0187 | 0.0229 | 0.0372 | 0.0340 | 0.0433 | 16.4% | 0.0515 | 38.44% |
|          | #Parameters | 8.26M | 4.06M | 8.42M | 1.75M | 4.29M | 1.71M | - | 1.11M | - |
| Toys     | HR@5   | 0.0099 | 0.0097 | 0.0166 | 0.0450 | 0.0136 | 0.045 | 0.0% | 0.0437 | -2.89% |
|          | HR@10  | 0.0175 | 0.0176 | 0.0270 | 0.0690 | 0.0195 | 0.0676 | 4.00% | 0.0711 | 9.38% |
|          | HR@20  | 0.0273 | 0.0301 | 0.0420 | 0.0925 | 0.0333 | 0.097 | 4.86% | 0.1181 | 27.68% |
|          | nDCG@5 | 0.0064 | 0.0059 | 0.0107 | 0.0300 | 0.0077 | 0.0305 | 1.67% | 0.0283 | -5.67% |
|          | nDCG@10| 0.0088 | 0.0084 | 0.0141 | 0.0370 | 0.0096 | 0.0378 | 2.16% | 0.037 | 0.00% |
|          | nDCG@20| 0.0112 | 0.0116 | 0.0179 | 0.0456 | 0.0130 | 0.0452 | 3.67% | 0.0488 | 11.93% |
|          | #Parameters | 7.77M | 4.01M | 7.9M | 1.73M | 4.24M | 1.68M | - | 1.28M | - |
| Sports   | HR@5   | 0.0088 | 0.0129 | 0.0116 | 0.0201 | 0.0139 | 0.0229 | 13.93% | 0.0314 | 56.22% |
|          | HR@10  | 0.0160 | 0.0204 | 0.0194 | 0.0314 | 0.0207 | 0.0366 | 16.56% | 0.0481 | 53.18% |
|          | HR@20  | 0.0259 | 0.0333 | 0.0314 | 0.0486 | 0.0438 | 0.0578 | 18.93% | 0.0759 | 56.17% |
|          | nDCG@5 | 0.0055 | 0.0086 | 0.0072 | 0.0129 | 0.0085 | 0.0146 | 13.18% | 0.0211 | 63.57% |
|          | nDCG@10| 0.0077 | 0.0110 | 0.0097 | 0.0164 | 0.0106 | 0.0191 | 16.46% | 0.0264 | 60.98% |
|          | nDCG@20| 0.0100 | 0.0142 | 0.0126 | 0.0208 | 0.0162 | 0.0244 | 17.31% | 0.0334 | 60.58% |
|          | #Parameters | 12.76M | 5.83M | 12.93M | 2.55M | 6.05M | 2.51M | - | 1.73M | - |
| Yelp     | HR@5   | 0.0116 | 0.0152 | 0.0151 | 0.0210 | 0.0184 | 0.0251 | 19.52% | 0.0385 | 83.33% |
|          | HR@10  | 0.0211 | 0.0263 | 0.0253 | 0.0356 | 0.0259 | 0.0451 | 26.69% | 0.0682 | 91.57% |
|          | HR@20  | 0.0352 | 0.0439 | 0.0422 | 0.0575 | 0.0430 | 0.0744 | 29.39% | 0.1148 | 99.65% |
|          | nDCG@5 | 0.0074 | 0.0099 | 0.0096 | 0.0126 | 0.0114 | 0.0157 | 24.6% | 0.0205 | 62.7% |
|          | nDCG@10| 0.0103 | 0.0134 | 0.0129 | 0.0176 | 0.0138 | 0.0225 | 25.57% | 0.0301 | 71.02% |
|          | nDCG@20| 0.0137 | 0.0178 | 0.0171 | 0.0230 | 0.0181 | 0.0294 | 27.83% | 0.0417 | 81.3% |
|          | #Parameters | 10.20M | 5.32M | 10.37M | 2.32M | 5.61M | 2.27M | - | 1.53M | - |

Figure 2: Effect of dimensionality, number of attention heads, number of twin-attention layers (nDCG@20).

4.8.2 Impact of Attention Head Number. The results in the second graph in Figure 2 show that more attention heads contribute better to the model performance. It is worth noting that the actual number of our twin-attention heads are doubled. Thus, LSAN model reaches best performance on most datasets, when it is equipped with 2 self-attention heads and 2 convolution heads.
Table 3: A comparison of performance results and number of model parameters using different embedding compression rate $m_1$ on four datasets.

| Datasets | Metrics  | SASRec | LSAN(2x) | LSAN(3x) | LSAN(4x) | LSAN(5x) |
|----------|----------|--------|----------|----------|----------|----------|
| Beauty   | HR@20    | 0.0872 | 0.1201   | 0.0981   | 0.043    | 0.0456   |
|          | nDCG@20  | 0.0372 | 0.0515   | 0.0385   | 0.0158   | 0.0178   |
|          | #Parameters | 1.75M | 1.11M    | 0.71M    | 0.58M    | 0.5M    |
|          | Relative Size | 100.00% | 63.43%   | 40.57%   | 33.14%   | 28.57%   |
| Toys     | HR@20    | 0.0925 | 0.1181   | 0.0887   | 0.0618   | 0.0539   |
|          | nDCG@20  | 0.0436 | 0.0488   | 0.0341   | 0.0232   | 0.0211   |
|          | #Parameters | 1.73M | 1.28M    | 0.88M    | 0.75M    | 0.68M    |
|          | Relative Size | 100.00% | 73.99%   | 50.87%   | 43.35%   | 39.31%   |
| Sports   | HR@20    | 0.0486 | 0.0759   | 0.0551   | 0.0370   | 0.0311   |
|          | nDCG@20  | 0.0208 | 0.0334   | 0.0249   | 0.0159   | 0.0125   |
|          | #Parameters | 2.55M | 1.73M    | 1.34M    | 1.14M    | 1.03M    |
|          | Relative Size | 100.00% | 67.84%   | 52.55%   | 44.71%   | 40.39%   |
| Yelp     | HR@20    | 0.0575 | 0.1148   | 0.1087   | 0.0472   | 0.0436   |
|          | nDCG@20  | 0.023 | 0.0417   | 0.0434   | 0.0187   | 0.0161   |
|          | #Parameters | 2.32M | 1.53M    | 1.03M    | 0.85M    | 0.74M    |
|          | Relative Size | 100.00% | 65.95%   | 44.40%   | 36.64%   | 31.90%   |

Table 4: Ablation study of different variants on four datasets.

| Datasets | Metrics  | LSAN_{w/o.dyn} | LSAN_{plain.attn} | LSAN |
|----------|----------|-----------------|-------------------|------|
| Beauty   | HR@20    | 0.977           | 0.108             | 0.120 |
|          | nDCG@20  | 0.038           | 0.045             | 0.051 |
| Toys     | HR@20    | 0.094           | 0.063             | 0.118 |
|          | nDCG@20  | 0.033           | 0.021             | 0.049 |
| Sports   | HR@20    | 0.076           | 0.066             | 0.076 |
|          | nDCG@20  | 0.033           | 0.030             | 0.033 |
| Yelp     | HR@20    | 0.104           | 0.011             | 0.115 |
|          | nDCG@20  | 0.038           | 0.046             | 0.042 |

4.8.3 Impact of Twin-attention Layer Number. LSAN receives the best performance with 1-layer architecture. Different from SASRec and BERT4Rec, which usually require 2 or 3 layers to fully capture various-order item dependencies. With the help of our proposed twin-attention structure, our model is capable of capturing various sequential information with only one layer. We also observe that the model performance drops obviously when more twin-attention layers are stacked on all dataset. This may be because of the over-fitting problem when LSAN is launched on extremely sparse datasets.

4.9 Attention Weight Visualisation

Recall that in Section 1, we argue that self-attention-based models put too much emphasise on local patterns, which is the motivation of our design on twin-attention architecture. To more intuitively demonstrate how twin-attention performs effective user behaviour modelling, we examine three randomly selected user interaction sequence samples and calculate the averaged attention weights on the last 10 items from each sample over all attention heads. The heat maps of the normalised attention weights from LASN and SASRec are illustrated in Figure 3. From the figure, it can be easily distinguished that the attention module in LSAN focus on item global patterns (i.e., no diagonal pattern shown in the figure), thus leaving local pattern modelling to the convolution branch in our twin attention. In comparison, the heat maps of SASRec show a clear concentration on local patterns, which fails to model global patterns effectively.

5 RELATED WORK

5.1 Sequential Recommendation

Early work on sequential recommendation is mainly based on Markov chains. Rendle et al. [33] propose FPMC that combines the power of matrix factorisation and Markov-chain to learn an item-to-item transition probability matrix, which is then used to make next item prediction based on the user’s latest interaction. After that, several models built upon high-order Markov chains are introduced [10, 11]. The advances in recurrent neural networks (RNNs) have brought significant performance boost in sequential recommendation. Hidasi et al. [13] propose a sequential recommender based on RNNs, which employs gated recurrent units (GRUs) to extract the high-order sequential information from the user’s interaction...
history. Subsequent RNN-based approaches leverage attention networks [38], memory networks [14, 15], copy mechanism [32], or reinforcement learning scheme [47], to improve the effectiveness of sequential user interest modelling. Another line of work [39] treats a sequence of item embeddings as a feature map of an image, and performs convolution operation upon embeddings to capture local dependencies among items.

Owing to the promising capability in sequential data modelling, attention mechanism has become popular and widely studied in various domains, such as text classification [48] and machine translation [1]. However, these approaches treat attention mechanism as an additional module upon the RNN backbone, resulting in higher computational cost. To solve this issue, a new attention architecture, transformer, is proposed in [8, 40]. Its main building block is multi-head self-attention, which allows faster parallel computation and achieves state-of-the-art performance in a wide range of sequence modelling tasks. In light of self-attention, Kang et al. [17] propose a self-attentive framework named SASRec, which adopts a multi-head self-attention layer to capture the user’s sequential behaviours and achieves state-of-the-art performance on various sequential datasets. Later on, Sun et al. [57] encode sequence data in bidirectional manner by introducing BERT4Rec together with a masked training scheme. However, all aforementioned sequential recommendation methods suffer from high memory cost in two aspects, which are infeasible for on-device applications. First, the large item embedding table brings high memory complexity. Second, as discussed in [46], the multi-head self-attention architecture tends to pay more attention on local dependencies, resulting in weak global preference modelling. In contrast, our proposed LSAN largely reduces the memory cost from the embedding table by a dynamic compositional embedding scheme. Besides, LSAN effectively learns global and local dependencies by a novel twin-attention, where the heavy redundancy in traditional self-attentive recommenders are resolved by two specialised branches for long- and short-range pattern mining.

5.2 Lightweight Deep Learning Models

DNN-based methods have demonstrated strong capability in various recommendation tasks. However, with the rapid development of edge devices, there has been an increasing demand on adopting DNN-based models on mobile phones and even smaller edge devices for stability and reliability. In this line of research, the methodologies can be roughly categorised into four types: pruning, quantisation, knowledge distillation, and compositional embedding. Network pruning approaches manage to reduce the overfitting parameters by discarding unnecessary ones from the neural model. Zhou et al. [54] introduce a group-sparse regularisation upon CNN kernel to produce a compact version without losing accuracy. However, most pruning methods require more iterations to reach convergence leading to extreme time cost. The second line of work aim to create one or more codebooks for a group of similar item representations. Jégou et al. [16] propose to decompose the item representation space into multiple subspaces, and then a codebook of each subspace can be obtained by clustering items in each subspace. The recent work, LightRec [23], develops a recurrent composite embedding encoder to learn diversified codebooks in a recursive manner. However, the learning of codebooks is independent of learning the item representations. Thus, the model cannot be trained end-to-end. Recently, knowledge distillation has gained popularity due to its high adaptivity to various complex models. This line of work primarily trains a large complex teacher network at the first place, and subsequently utilises soft labels obtained from the teacher model to train a lightweight student model. Wang et al. [42] devise a tensor-train decomposed lightweight RNN model, and train the model using a well-tuned state-of-the-art teacher model via knowledge distillation for next POI recommendation. With the observation that the embedding matrices in recommender systems are the major source of memory consumption, some recent studies resort to embedding compression. A number of studies [2, 26, 36, 50–52] introduce the idea of converting a continuous-valued embedding vector to a discrete code, where each bit refers to the learned index of a base embedding table. However, this still requires the model to store extra discrete code for each item. To solve the limitation, Shi et al. [34] propose a quotient-remainder indexing technique, which is able to obtain a unique set of base embeddings without allocating extra embedding space. Nevertheless, all the above-mentioned embedding compression work is designed for static recommendation scenario, which neglects the dynamics of user interests in sequential recommendation. To address this issue, we design a context-aware temporal compositional embedding scheme that incorporates temporal information by attentively merging base embeddings for each item. As such, our proposed LSAN is capable of preserving the temporal dynamics and optimising memory efficiency simultaneously.

6 CONCLUSION

In this paper, we introduce a lightweight twin-attention sequential recommender named LSAN, where two parallel branches are respectively specialised for short-term and long-term user preference modelling. To overcome the common bottleneck of large memory cost in existing DNN-based sequential recommender, we introduce temporal context-aware compositional embedding scheme, which largely reduces the memory cost and preserves intrinsic temporal dynamics of sequential data. Extensive experiments conducted on four real-world datasets clearly demonstrate the effectiveness and efficiency of our proposed model.

ACKNOWLEDGMENTS

This work is partially supported by the Australian Research Council under the streams of Discovery Project (No. DP190101985), Future Fellowship (No. FT210100624), Centre of Excellence (No. CE200100025), and Industry Transformation Training Centre (No. IC200100022).

REFERENCES

[1] Dmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural Machine Translation by Jointly Learning to Align and Translate. In 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings, Yoshua Bengio and Yann LeCun (Eds.).

[2] Ting Chen, Martin Renqiang Min, and Yizhou Sun. 2018. Learning K-way D-dimensional Discrete Codes for Compact Embedding Representations. In Proceedings of the 35th International Conference on Machine Learning, ICML 2018, Stockholmsmässan, Stockholm, Sweden, July 10-15, 2018 (Proceedings of Machine Learning Research, Vol. 80). PMLR, 853–862.
[3] Tong Chen, Hongzhi Yin, Hongxu Chen, Rui Yan, Quoc Viet Hung Nguyen, and Xue Li. 2019. AIR: Attentional Intention-Aware Recommender Systems. In 35th IEEE International Conference on Data Engineering, ICDE 2019, Macao, China, April 11-15, 2019. IEEE, 304–315. https://doi.org/10.1109/ICDE.2019.00035

[4] Tong Chen, Hongzhi Yin, Quoc Viet Hung Nguyen, Wen-Chih Peng, Xue Li, and Xiaofang Zhou. 2020. Sequence-Aware Factorization Machines for Temporal Predictive Analytics. In 36th IEEE International Conference on Data Engineering, ICDE 2020, Dallas, TX, USA, April 20-24, 2020. IEEE, 1405–1416.

[5] Tong Chen, Hongzhi Yin, Yuja Zheng, Zi Huo, Yang Wang, and Meng Wang. 2021. Learning Elastic Embeddings for Customizing On-Device Recommenders. In KDD '21: The 27th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, Virtual Event, Singapore, August 14-18, 2021. ACM, 138–147.

[6] Xu Chen, Hongteng Xu, Yongfeng Zhang, Jiashu Tang, Yuxin Cao, Zheng Qin, and Hongyuan Zha. 2018. Sequential Recommendation with User Memory Networks. In Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining, WSDM 2018, Marina Del Rey, CA, USA, February 5-9, 2018. ACM, 108–116. https://doi.org/10.1145/3159652.3159668

[7] Chen Cheng, Haqin Yang, Michael R. Lyu, and Irwin King. 2013. Where You Like to Go Next: Successive Point-of-Interest Recommendation. In Proceedings of the 23rd International Joint Conference on Artificial Intelligence, Beijing, China, August 3-9, 2013. IJCAI’13, 2605–2611.

[8] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers). Association for Computational Linguistics, 4171–4186.

[9] Stefan Eilertw, Eiji Uchibe, and Kenji Doya. 2018. Sigmoid-weighted linear units for neural network function approximation in reinforcement learning. Neural Networks 107 (2018), 3–11.

[10] Ruining He, Wang-Cheng Kang, and Julian J. McAuley. 2017. Translation-based Recommendation. In Proceedings of the Eleventh ACM Conference on Recommender Systems, RecSys 2017, Como, Italy, August 27-31, 2017, Paolo Cremonesi, Francesco Ricci, Shlomo Berkovsky, and Alexander Tuzhilin (Eds.). ACM, 161–169.

[11] Ruining He and Julian J. McAuley. 2016. Fusion Similarity Models with Markov Chains for Sparse Sequential Recommendation. In ACM 16th International Conference on Data Mining, ICDM 2016, December 12-15, 2016, Barcelona, Spain. IEEE Computer Society, 191–200.

[12] Dan Hendrycks and Kevin Gimpel. 2016. Bridging Nonlinearities and Stochastic Regularizers with Gaussian Error Linear Units. CoRR abs/1606.08415 (2016).

[13] Balázs Hidasi, Alexandros Karatzoglou, Linas Baltrunas, and Domenics Tikk. 2016. Session-based Recommendations with Recurrent Neural Networks. In 4th International Conference on Learning Representations, ICML 2016, San Juan, Puerto Rico, May 2-4, 2016, Conference Track Proceedings.

[14] Jin Huang, Zhaoshun Ren, Wayne Xin Zhao, Gaole He, Ji-Rong Wen, and Daxiang Dong. 2019. Taxonomy-Aware Multi-Hop Reasoning Networks for Sequential Recommendation. In Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining, WSDM 2019, Melbourne, VIC, Australia, February 11-15, 2019. ACM, 573–581.

[15] Jin Huang, Wayne Xin Zhao, Hongjuan Dou, Ji-Rong Wen, and Edward Y. Chang. 2019. Improving Temporal Recommendations with Knowledge-Enhanced Memory Networks. In The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval, SIGIR 2018, Ann Arbor, MI, USA, July 08-12, 2018. ACM, 505–514.

[16] Hervé Jégou, Matthijs Douze, and Cordelia Schmid. 2011. Product Quantization for Nearest Neighbor Search. IEEE Trans. Pattern Anal. Mach. Intell. (2011).

[17] Wang-Cheng Kang and Julian J. McAuley. 2016. Self-Attentive Sequential Recommendation. In IEEE International Conference on Data Mining, ICDM 2018, Singapore, November 17-20, 2018. IEEE Computer Society, 197–206.

[18] Diederik P. Kingma and Jimmy Ba. 2015. Adam: A Method for Stochastic Optimization. In ICLR.

[19] Walid Khreich and Steffen Rendle. 2020. On Sampled Metrics for Item Recommendation. In KDD.

[20] Srijan Kumar, Xikun Zhang, and Jure Leskovec. 2019. Predicting Dynamic Embedding Trajectory in Temporal Interaction Networks. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, KDD 2019, Anchorage, AK, USA, August 4-8, 2019. ACM, 1269–1278.

[21] Yang Li, Tong Chen, Yadun Luo, Hongzhi Yin, and Zi Huo. 2021. Discovering Collaborative Signals for Next POI Recommendation with Iterative Seq2Graph Augmentation. In Proceedings of the Thirtieth ACM International Conference on Artificial Intelligence, IJCAI 2021, Virtual Event / Montreal, Canada, 19-27 August 2021, Zhi-Hua Zhou (Ed.). ijcai.org, 1491–1497.

[22] Yang Li, Yadun Luo, Zheng Zhang, Shazia W. Sadad, and Peng Cui. 2019. Context-Aware Attention and Data Augmentation. In Proceedings of the Thirtieth ACM International Joint Conference on Artificial Intelligence, IJCAI 2021, Virtual Event / Montreal, Canada, 19-27 August 2021, Zhi-Hua Zhou (Ed.). ijcai.org, 1491–1497.

[23] Defu Lian, Haoyu Wang, Zheng Lue, Jianxun Lian, Enhong Chen, and Xing Xie. 2020. LightRec: A Memory and Search-Efficient Recommender System. In WWW.
in alibaba. In SIGKDD. 839–848.

[42] Qinyong Wang, Hongzhi Yin, Tong Chen, Zi Huang, Hao Wang, Yanfang Zhao, and Nguyen Quoc Viet Hung. 2020. Next Point-of-Interest Recommendation on Resource-Constrained Mobile Devices. In WWW ’20: The Web Conference 2020, Taipei, Taiwan, April 20-24, 2020. ACM / IW3C2, 906–916.

[43] Chao-Yuan Wu, Amir Ahmed, Alex Beutel, Alexander J. Smola, and How Jing. 2017. Recurrent Recommender Networks. In Proceedings of the Tenth ACM International Conference on Web Search and Data Mining, WSDM 2017, Cambridge, United Kingdom, February 6-10, 2017. ACM, 495–503.

[44] Felix Wu, Angela Fan, Alexei Baevski, Yann Dauphin, and Michael Auli. 2019. Pay Less Attention with Lightweight and Dynamic Convolutions. In ICLR.

[45] Felix Wu, Angela Fan, Alexei Baevski, Yann N. Dauphin, and Michael Auli. 2019. Pay Less Attention with Lightweight and Dynamic Convolutions. In 7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019. OpenReview.net.

[46] Zhanghao Wu, Zhijian Liu, Ji Lin, Yujun Lin, and Song Han. 2020. Lite Transformer with Long-Short Range Attention. In 8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020. OpenReview.net.

[47] Xin Xin, Alexandros Karatzoglou, Ioannis Arapakis, and Joemon M. Jose. 2020. Self-Supervised Reinforcement Learning for Recommender Systems. In Proceedings of the 43rd International ACM SIGIR conference on research and development in Information Retrieval, SIGIR 2020, Virtual Event, China, July 25-30, 2020. ACM, 931–940.

[48] Zichao Yang, Diyi Yang, Chris Dyer, Xiaodong He, Alexander J. Smola, and Edward H. Hovy. 2016. Hierarchical Attention Networks for Document Classification. In NAACL. The Association for Computational Linguistics, 1480–1489.

[49] Hongzhi Yin and Bin Cui. 2016. Spatio-Temporal Recommendation in Social Media. Springer.

[50] Peng-Fei Zhang, Yang Li, Zi Huang, and Xin-Shun Xu. 2021. Aggregation-based Graph Convolutional Hashing for Unsupervised Cross-modal Retrieval. IEEE Transactions on Multimedia (2021), 1–1.

[51] Yan Zhang, Hongzhi Yin, Zi Huang, Xingzhong Du, Guowu Yang, and Defu Lian. 2018. Discrete Deep Learning for Fast Content-Aware Recommendation. In Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining, WSDM 2018, Marina Del Rey, CA, USA, February 5-9, 2018. ACM, 717–726.

[52] Zheng Zhang, Guo-Sen Xie, Yang Li, Sheng Li, and Zi Huang. 2019. SADIH: Semantic-Aware Discrete Hashing. In The Thirty-Third AAAI Conference on Artificial Intelligence, AAAI 2019, The Thirty-First Innovative Applications of Artificial Intelligence Conference, IAAI 2019, The Ninth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2019, Honolulu, Hawaii, USA, January 27 - February 1, 2019. AAAI Press, 5853–5860.

[53] Lin Zheng, Naicheng Guo, Weihao Chen, Jin Yu, and Dazhi Jiang. 2020. Sentiment-guided Sequential Recommendation. In Proceedings of the 43rd International ACM SIGIR conference on research and development in Information Retrieval, SIGIR 2020, Virtual Event, China, July 25-30, 2020. ACM, 1957–1960.

[54] Hao Zhou, Jose M. Alvarez, and Fatih Porikli. 2016. Less Is More: Towards Compact CNNs. In Computer Vision - ECCV 2016 - 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part IV (Lecture Notes in Computer Science, Vol. 9908). Springer, 662–677.

[55] Kun Zhou, Hui Wang, Wayne Xin Zhao, Yutao Zou, Sirui Wang, Fuzheng Zhang, Zhongyuan Wang, and Ji-Rong Wen. 2020. S3-Rec: Self-Supervised Learning for Sequential Recommendation with Mutual Information Maximization. In CIKM ’20: The 29th ACM International Conference on Information and Knowledge Management, Virtual Event, Ireland, October 19-23, 2020. ACM, 1893–1902.