A Generic Network Compression Framework for Sequential Recommender Systems

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ABSTRACT
Sequential recommender systems (SRS) have become the key technology in capturing user’s dynamic interests and generating high-quality recommendations. Current state-of-the-art sequential recommender models are typically based on a sandwich-structured deep neural network, where one or more middle (hidden) layers are placed between the input embedding layer and output softmax layer. In general, these models require a large number of parameters (such as using a large embedding dimension or a deep network architecture) to obtain their optimal performance. Despite the effectiveness, at some point, further increasing model size may be harder for model deployment in resource-constraint devices, resulting in longer responding time and larger memory footprint. To resolve the issues, we propose a compressed sequential recommendation framework, termed as CpRec, where two generic model shrinking techniques are employed. Specifically, we first propose a block-wise adaptive decomposition to approximate the input and softmax matrices by exploiting the fact that items in SRS obey a long-tailed distribution. To reduce the parameters of the middle layers, we introduce three layer-wise parameter sharing schemes. We instantiate CpRec using deep convolutional neural network with dilated kernels given consideration to both recommendation accuracy and efficiency. By the extensive ablation studies, we demonstrate that the proposed CpRec can achieve up to 4–8 times compression rates in real-world SRS datasets. Meanwhile, CpRec is faster during training & inference, and in most cases outperforms its uncompressed counterpart.

1 INTRODUCTION
Sequential (a.k.a. session-based) recommender systems (SRS) have become a research hotspot in the recommendation field. This is because user interaction behaviors in real-life scenarios often exist in a form of chronological sequences. For examples, after purchasing a phone in Amazon, the user is very likely to buy a phone case, earphone, and screen protector in the session; another example comes from TikTok, a popular short-video sharing app where users may watch hundreds of videos in an hour which naturally forms a video playing sequence. In such scenarios, traditional RS based on collaborative filtering [28] or content features [24] fail to model user’s dynamic interests and offer only suboptimal performance. By contrast, sequential recommender models based on recurrent neural networks (RNN) [16] or convolutional neural network (CNN) (often with dilated kernels) [45] have obtained state-of-the-art performance since these models are more powerful in capturing sequential dependencies in the interaction sequence.

In general, modern sequential recommender models based on deep neural networks (DNN) can be split into three major modules: an embedding layer for representing the interaction sequence, a softmax layer for generating the probability distribution of next item, and one or more hidden (either recurrent or convolutional) layers that are sandwiched between them. To increase the capacity of such models, a larger model size with more parameters is a common method in practice. As shown in Figure 1, the prediction accuracy of the sequential recommender model NextItNet [45] can be largely improved by increasing its model size, i.e., using a larger embedding dimension (denoted by $d$) or a deeper network architecture (denoted by $r$). Particularly, NextItNet obtains more than 20% accuracy gains by simply increasing $d$ from 64 to 512, along with about 3 times larger parameters.

Though a large network often brings obvious accuracy improvements, it may also become the major obstacle for model deployment and real-time prediction. Especially for memory-limited devices, such as GPU/TPU or end-user devices, a large sequential model with hundreds of millions or even billions of parameters may easily
hit the memory limitations of available hardware. Another drawback is that both the training and inference speeds will be impacted by employing larger matrices and deeper networks. While model parallelization can be applied for larger networks, the communication overhead still keeps in proportion to the number of parameters in the model. In addition, many published works also evidence that at some point further increasing model size may cause the overfitting problem [44] or unexpected model degradation [21]. Hence, we argue that model compression is essential to achieve compact recommender models that enable real-time responses and better generalization ability.

In fact, the model size problem in the recommender systems domain is much more challenging than other domains, such as computer vision (CV) [8] and natural language processing (NLP) [1, 3, 6]. For example, in CV, the well-known ResNet-101 [47] trained for ImageNet has only 44.5 million parameters [2]. One of the largest NLP model BERT-Large (24 layers, 16 attention heads) has around 340 million trainable parameters [6]. By contrast, in industrial recommender systems, such as Youtube and Amazon, there exist several hundred million items. If we simply assume the number of items as 100 million and set the embedding dimension $d$ to 1024, we can achieve over $2 \times 100$ billion trainable parameters w.r.t. embedding & softmax matrices, which is more than 4000 and 400 times larger than ResNet-101 and BERT-Large, respectively. On the other hand, parameters from the middle layers cannot be ignored in medium-sized or small-scale recommender systems, such as the future in-vehicle recommender systems [25], where memory consumption may be dominant by both middle layers and embedding matrices. Taking NextItNet as an example, the number of parameters in middle layers is $1024 \times 1024 \times 3 \times 32 \approx 100$ million (still much larger than ResNet-101) where 3 and 32 is the kernel size and layers, respectively. Actually, in practice, more convolutional layers may be required for better accuracy if user behavior sequences are longer. Therefore, to reduce the size of sequential recommender models, we need to consider parameter-reduction for both embedding & softmax matrices and middle layers.

To address the aforementioned issues, we present two generic model compression methods to lower memory consumption for SRS. First, to reduce parameters in the embedding and softmax matrices mentioned above, we propose block-wise adaptive decomposition to approximate the original large embedding matrices. Specifically, we separate all candidate items into clusters according to their frequencies, and the embedding matrix of each cluster, referred to as block, is decomposed by two low-rank matrices, where the rank value is also determined by the item frequencies in the cluster — a larger rank value is assigned to the blocks with more frequent items, and vice versa. Our idea here is motivated by the well-known finding that the item frequency distribution in recommender systems is generally long-tailed — i.e., only a few items may contain rich information due to their high frequency, while others may only contain limited information. Given this structure, a fixed large embedding dimension for all items is redundant and may lead to suboptimal performance. By the block-wise adaptive decomposition, we are able to assign different dimensions to the block of each cluster. Second, motivated by the cross-layer parameter sharing method of ALBERT [21], we introduce cross-block, adjacent-layer and adjacent-block parameter sharing methods to reduce parameters in the middle layers. Since the two parameter-reduction methods are orthogonal, we can naturally combine them together to achieve a higher compression rate. We name the proposed joint compression framework CpRec.

We summarize our main contributions as follows.

- We propose a block-wise adaptive decomposition method to approximate the original large input/output embedding matrices in SRS. Unlike the standard low-rank decomposition [5], our method enables a better and fine-grained approximation by exploiting the inherent structure of item distribution. To the best of our knowledge, CpRec is the first model compression method in SRS, which directly targets reducing parameter size of the embedding matrices.
- Inspired by the class-based softmax [22] for language model, we design a probability approximation method based on a tree representation in the softmax layer, which replaces the vanilla softmax and notably reduces the training time. Unlike [22], we perform class-based softmax on the decomposed embedding matrix.
- We propose three different layer-wise parameter sharing methods to reduce redundant parameters in the middle layers, which effectively constrains the parameter size as the model grows deeper.
- We obtain a compression ratio of 4–8x on four real-world SRS datasets. Moreover, we demonstrate that CpRec outperforms the uncompressed counterpart in most cases and is faster for both training and generating.

2 RELATED WORK

2.1 Sequential Recommendation

Traditional recommender systems, such as collaborative filtering [28] and content-based recommendations [24, 43], often produce non-optimal performance in dynamic recommendation scenario, where user’s preferences evolve dynamically with his interaction behaviors. This is mainly because these models cannot explicitly capture the sequential patterns from previous user interactions. To solve such issues, much early work of SRS propose using the Markov chain [7] techniques, which estimate the next item by calculating the transition probability of the interaction sequence. Since a Markov chain only conditions on a fixed window — the current state is determined by the former one or several previous states, such methods cannot model relatively long-term and complicated dependencies.

Recently, deep neural networks (DNNs) have brought great improvements for SRS and almost dominate this field. Thus far, three types of DNN models have been explored for SRS. Among them, Recurrent Neural Networks (RNNs) are often a natural choice for modeling sequence data [10]. GRU4Rec [16, 32] is regarded as the seminal work that firstly applied gated recurrent units (GRU) architecture for sequential recommendation tasks. Inspired by them, a variety of RNN variants have been proposed to address the sequential recommendation problems, such as personalized SRS with hierarchical RNN [41], content- & context-based SRS [9, 29], data augmentation-based SRS [32]. While effective, these RNN-based models seriously depend on the hidden state of the entire past, which cannot take full advantage of modern parallel processing resources [45], such as GPU/TPU. By contrast, convolutional neural networks (CNNs) and pure attention-based models do not have such limitations since the entire sequence is already available during
training. In addition, CNN and attention-based sequential models can perform better than RNN recommenders since much more hidden layers can be stacked by the residual block architecture [13]. To be more specific, [45] proposed a CNN-based generative model called NextItnNet, which employs a stack of dilated convoluted layers to increase the receptive field when modeling long-range sequences. Likewise, self-attention based models, such as SASRec [20] and BERT4Rec [31] also obtained competitive results. Compared with NextItnNet, the self-attention mechanism is computationally more expensive since calculating self-attention of all timesteps requires quadratic complexity and memory.

All above mentioned sequential recommender models consist of three major modules: two embedding layers for input & output items and several middle layers sandwiched between them. In this paper, we focus on exploring model compression technology for these sandwich-like recommender models. For the below description, we specify CpRec by using the NextItnNet architecture, although it can be directly applied to a broad range of recommendation models, such as GRU4Rec and SASRec, etc.

2.2 Model Compression

Training larger and deeper neural networks have become a common practice to obtain state-of-the-art results for a variety of tasks. Meanwhile, the performance gain is usually accompanied by the price of slow processing speed and a huge amount of memory, which makes these models difficult to be deployed on devices with limited resources. As such, more and more attention has been paid to model compression methods. In general, compression methods can be divided into four categories.

Low-rank factorization. This method is originally proposed for solving the matrix completion problem, and have been widely used for the recommendation, NLP and CV tasks [5, 26, 46]. The basic idea is to factorize the original large matrix into a product of two low-rank matrices. In terms of model compression, it is mainly used for compressing fully-connected and convolutional layers. For example, [5] argued that there was significant redundancy in the parameterization of deep neural networks. As a result, they used two smaller matrices to represent the weight matrix learned from images to reduce free parameters. [27] proposed using low-rank factorization to reduce parameters in the softmax layer. A more recent work in ALBERT [21] performed standard low-rank approximation to decompose both the input and softmax layers into two smaller matrices. By contrast, our proposed method is distinct from them because we perform embedding low-rank factorization adaptively for different blocks according to their item frequencies.

Weight quantization. Network quantization uses low-precision float to represent weight values, which is a general compression method for any deep learning model. For instance, [8, 11, 39] quantized weight and then applied k-means clustering to identify shared weights. [36] used 8-bit quantization to convert activation and intermediate layer weights, which easily leads to significant memory compression. Similarly, [40] proposed single-level quantization method for high-bit quantization and multi-level method for low-bit quantization. Due to its generality, network quantization can also be applied to CpRec for further compression.

Parameter pruning and sharing. Parameter pruning improves parameter efficiency by cutting out redundant parameters. For example, [12, 30] pruned unimportant connections iteratively to lower the storage and computation resources required by the model. ALBERT [21] and [4] adopted the cross-layer parameter sharing method. While model sizes were shrunk notably, the performance of their models also significantly decreased. [1] tie the weights of the input embedding layer and output softmax layer to achieve further compression after the low-rank factorization. Inspired by these work, we introduce three different but more effective layer-wise parameter sharing strategies.

Knowledge Distillation (KD). The basic idea of KD-based compression is to transfer knowledge from a large, pretrained teacher model to a student one that is typically smaller. Recently, [35] proposed the first KD-based model for the learning to rank problem in recommendation. They showed that the proposed KD method achieved similar ranking performance but with smaller model size and higher inference efficiency. However, throughout the paper, they only investigated the proposed ranking distillation on two very shallow embedding models. The performance of KD on larger & deeper recommender models keeps completely unknown. In addition, they only obtained 2°2.5x compression rate, which is much smaller than that of CpRec.

To the best of our knowledge, model compression techniques have not been well studied in recommender systems. One reason may be that authors in existing literature tended to apply a very small embedding dimension (e.g., d = 5 for IRGAN on MovieLens [38], d = 10 for Fossil on Foursquare [14], d = 20 & 30 for NMF [17] & LambdaFM [43] on Yelp, d = 50 for NARM on YOOCHOOSE1 [23], d = 50 for RSGAN on LastFM [42]) for research purpose. The other reason is that thus far there seems no existing literature using deep learning models higher than 20 layers for the recommendation task. However, as clearly evidenced in Figure 1, a large NextItnNet with d = 512 and r = 32 indeed performs better on the benchmark dataset.

3 METHODS

In this section, we present two main model compression techniques to improve the parameter efficiency of SRS. In what follows, we describe the proposed CpRec by using the NextItnNet architecture.

3.1 Block-wise Adaptive Decomposition

In recommender systems, a well-known observation is that frequencies of items generally obey a long-tailed distribution, where some “head” (or popular) items have a large number of user interactions, yet only a few interactions are available for the “tail” items. In view of this, we argue that assigning a fixed embedding dimension to all items is sub-optimal and unnecessary. Intuitively, items with higher frequencies may contain more information than the rare ones, and thus should be assigned with more capacity during training. In other words, the embedding dimensions of more frequent (or popular) items are supposed to be larger than those of unpopular items.

An obvious difficulty is that if we set adaptive (i.e., variable-sized) embeddings to items, they cannot be directly trained by the typical sequential recommender model due to inconsistent dimensions of middle layers. To this end, we perform dimension transformation by multiplying a projection matrix. From a reverse perspective, the transformation process is equivalent to a low-rank factorization given that the original large embedding matrix is reconstructed by two smaller matrices.
Accordingly, we can partition the embedding matrix \( E \) since it is unknown which cluster the item belongs to during inference process. To denote its embedding vector /\( v \)/alt, given an item label ID \( j \), we use the following look-up operation. Given an item label ID \( j \), the representation of each item is different from the one by vanilla \( \text{softmax} \) layer, we factorize the block matrix \( E \) into blocks \( R \) and \( S \) as follows: (a) the vanilla input or output embedding matrix; (b) the embedding matrix of (a) is partitioned into several blocks based on item frequencies; (c) performing low-rank decomposition for blocks in the input layer; (d) performing low-rank decomposition for blocks in the output layer.

Figure 2: Illustration of the proposed block-wise embedding decomposition methods: (a) the vanilla input or output embedding matrix; (b) the embedding matrix of (a) is partitioned into several blocks based on item frequencies; (c) performing low-rank decomposition for blocks in the input layer; (d) performing low-rank decomposition for blocks in the output layer.

More specifically, we first sort all items based on their frequencies \( S = \{x_1, x_2, \ldots, x_K\} \), where \( x_1 \) and \( x_K \) are the most popular and unpopular items, respectively. Denote the number of clusters as \( n \). We partition the item set \( S \) into \( n \) clusters: \( S = S_1 \cup S_2 \cup \cdots \cup S_n \), where \( S_1 = \{x_1, x_2, \ldots, x_{k_1}\} \), \( S_2 = \{x_{k_1+1}, \ldots, x_{k_1+k_2}\} \), \( \ldots, S_n = \{x_{k_1+n-1}, \ldots, x_K\} \), where \( S_1 \cap S_2 = \emptyset, \alpha \neq \beta \), and the number of items of each cluster is \( k_1, k_2, \ldots, k_n \). In all clusters, the parameters of input layer \( P \) is saved to the root node, and other blocks are saved to the leaf nodes in the second layer. For each cluster, each item is represented by one distinct class; whereas for other clusters, we assign two nodes to each item: a root node using its cluster position as its parent class and a leaf node representing the specific position in this cluster. By doing so, the items in the same cluster share the same parent class. To be more specific, we use the similar clustering configuration of block-wise embedding in the input layer. A major difference here is that the first block matrix is extended to \( \tilde{P}_1 \in R^{K \times (n-1)} \) in the output layer, where \( n - 1 \) represents the number of parents that the leaf nodes belong to. The label set of the first cluster is extended to \( S'_1 = \{1, 2, \ldots, k_1 + n - 1\} \), where \( k_1 + 1 \) to \( k_1 + n - 1 \) correspond to the parent class labels of the clusters 2 to \( n \). The other block matrices in the output layer are \( P_j = \tilde{W}_j \tilde{P}_j \), where \( j = 2, \ldots, n \). Compared with the vanilla softmax layer, we reduce the number of parameters of the output layer from \( O(K \times d) \) to \( O((k_1 + n - 1) \times d + \sum_{i=2}^{n} (k_i + d) \times d_i) \). In the rest of this section, we describe how to formulate the objective function during training and how to perform generating during inference in detail.

During training, to predict the next item given a context vector \( h \in R^d \) (i.e., the final hidden vector of a sequential recommender model), we need to first determine the search space based on the label of next item, e.g., \( x \). If \( x \) belongs to the first cluster, we only compute its logits in this cluster. If \( x \) belongs to the other clusters, we compute the logit in both its parent class and the current cluster. The logit \( \hat{y} \) is given as

\[
\hat{y} = \sum_{i=1}^{n} \log \left( \frac{e^{\tilde{W}_j \tilde{P}_j x}}{\sum_{i'=1}^{n} e^{\tilde{W}_{i'} \tilde{P}_{i'} x}} \right)
\]
where we stipulate that each item $x$ belonging to the leaf node have a parent class label $c(x)$ in the first cluster. Correspondingly, the training process includes two steps. In the first step, the logits of the first cluster are computed, which takes $O(k_1 + n - 1)$ time. In the second stage, if the item label $x$ belongs to one of the leaf class, we compute the logits of that leaf cluster, which takes $O(k_j)$ time. By doing so, we reduce the training time from $O(K)$ using vanilla softmax to between $O(k_1 + n - 1)$ and $O(k_1 + k_j + n - 1)$ using the block-wise embedding.

Let $\hat{p}$ be the normalized value of $\hat{y}$ by the softmax function. The loss function $f$ with respect to $\hat{p}$ and ground-truth label vector $y$ is given:

$$f(y, \hat{p}) = \begin{cases} 
\frac{1}{y_i} \log \hat{p}_i & \text{if } x \in S_1 \\
\frac{1}{y_i} \log \hat{p}_i - \sum_{i=1}^{k_j} y_i \log \hat{p}_i & \text{if } x \in S_j \text{ and } j \neq 1
\end{cases}$$

$$f(y, \hat{p}) = \begin{cases} 
\frac{1}{y_i} \log \hat{p}_i & \text{if } x \in S_1 \\
\frac{1}{y_i} \log \hat{p}_i - \sum_{i=1}^{k_j} y_i \log \hat{p}_i & \text{if } x \in S_j \text{ and } j \neq 1
\end{cases}$$

Different from the training phase, it is unknown which cluster the item belongs to during inference. Yet, we are able to calculate the probability distributions of items in all clusters according to the condition distribution, given as follows:

$$p(x) = \begin{cases} 
p(x|c(h, S_1)) & \text{if } x \in S_1 \\
p(x|c(x), h) p(c(x)|h, S_1) & \text{if } x \in S_j \text{ and } j \neq 1
\end{cases}$$

where $p(x|c(h, S_1))$, $p(c(x)|h, S_1)$ and $p(x|c(x), h)$ can all be calculated by Eq. 2. Finally, we are able to recommend the top-N items based on $p(x)$. In practice, it is usually not necessary to compute the softmax probabilities for all items during the inference phase. We can perform an early-stop search to speed up the generating process. Specifically, if the top-N probability scores are in the first cluster, we do not need to compute scores in the other clusters (i.e., $p(x|c(x), h)$) since $p(x|c(x), h) p(c(x)|h, S_1)$ (where $p(c(x)|h, S_1) < 1$) is always smaller than the top-N scores of the first cluster.

### 3.2 Layer-wise parameter sharing

User behavior sequence can be very long in many real-world recommender systems, such as short video and news recommendation. To model long-range interaction sequence, a common approach is to build a deeper network architecture. As explained in the introduction section, parameter size in middle layers may dominate the overall memory consumption, especially for small-scale applications in mobile or end-user devices. Hence, the proposed compression method in this section is mainly concentrated on sequential recommender models which have a number of middle layers and every two of them are connected by a residual block (one the most popular ResNet [13] structure), such as NextItNet.

To lower parameter consumption in middle layers, ALBERT [21] proposed the cross-layer parameter sharing approach. While a large number of redundant parameters are reduced, the expressivity of neural network models is also restricted to some extent. In fact, we notice that the performance significantly decreased in both the original paper and our recommendation task by using the cross-layer sharing scheme. To further evidence this observation, we propose an advanced version, namely the cross-block parameter sharing as shown in Figure 3b, where all higher layers reuse parameters of the first residual block (i.e., the two bottom layers).

In order to fully utilize the advantage of stacking layers and meanwhile improve parameter efficiency, we propose another two layer-wise parameter sharing methods: adjacent-layer and adjacent-block parameter sharing. Specifically, the adjacent-layer parameter sharing denotes that the two individual layers in each residual block share the same set of parameters, as shown in Figure 3c. The adjacent-block parameter sharing denotes that parameters are shared between each adjacent residual block, as shown in Figure 3d. Our parameter sharing strategies are considered to bring two major benefits: (1) as a way of regularization, they stabilize the training process and improves model’s generalization; (2) they can significantly reduce the number of parameters without degrading performance like the cross-layer parameter sharing. Particularly, we find that the recommendation quality is always slightly better than the base model by the adjacent-block parameter sharing.

### 3.3 General Architecture of CpRec

By instantiating CpRec using the NextItNet architecture, we show the overall neural network architecture in Figure 4.

#### 3.3.1 Input layer

Given a user-item interaction sequence $\{x_1, x_2, ..., x_t\}$, the recommender model retrieves the embeddings of the first $t$ items $\{x_1, x_2, ..., x_t\}$ via look-up table based on the block-wise embedding. After the dimensional projection, we can stack these item embeddings into a new matrix (as shown in the left part of Figure 4, where $t = 5$), which serves as inputs for the middle layers.

#### 3.3.2 Middle layers

As shown in the middle part of Figure 4, we use the dilated convolutional layers [45] for CpRec, where every two layers are wrapped by a residual block structure. CpRec obtains an exponential growth in the size of the receptive field by doubling the dilation for every layer, e.g., $\{1, 2, 4, 8\}$. In addition, it is a common approach to repeat this structure several times to further enhance model expressiveness and improve accuracy, e.g.,

![Image of the cross-layer/block parameter sharing and our proposed adjacent-layer/block parameter sharing.](image-url)
Table 1: Statistic of the evaluated datasets. "M" is short for million, "t" is the length of interaction sequences. For ColdRec, the left and right values devided by '/' denote the source and target dataset, respectively.

| Dataset    | #items | #actions | #sequences | t   |
|------------|--------|----------|------------|-----|
| Weishi     | 65998  | 10M      | 1048575    | 10  |
| ML20       | 53869  | 27.7M    | 1491478    | 20  |
| TikTok     | 513879 | 38.2M    | 1018155    | 50  |
| ML100      | 53879  | 27.7M    | 457350     | 100 |
| ColdRec    | 191014 | 82.5M/3.8M | 1649095/3798114 | 50/1-3 |

\{1, 2, 4, 8, \ldots, 1, 2, 4, 8\}. Then, we can apply the proposed layer-wise parameter sharing scheme on these middle layers to improve their parameter efficiency.

### 3.3.3 Softmax layer
The softmax layer adopts the block-wise embedding decomposition with a tree structure so as to represent blocks of each cluster. As described before, for both the training and inference phases, CpRec can achieve significant speed-up by such a structure. Following NextItNet, given each input sequence \{x_1, x_2, \ldots, x_t\}, CpRec estimates the probability distribution of the output sequence representing \{x_2, x_3, \ldots, x_{t+1}\}, where \(x_{t+1}\) is the next item expected.

## 4 EXPERIMENTAL SETUP
This section introduces our experimental setup including datasets, baseline models, our implementation details and evaluation metrics.

### 4.1 Datasets
- **Movielens\(^2\):** This is a popular benchmark dataset widely used for both traditional recommendation and sequential recommendation [20, 31, 33, 34] tasks. The original dataset contains about 280,000 users, 58,000 videos and 27 million user-item interactions with timesteps. To alleviate the impact of cold users and items, we perform the basic pre-processing by filtering out interactions with less than 5 users and users with less than 10 items. Then, we define the maximum length of the interaction sequence as \(t\), and split sequences that exceed the maximum length into multiple sub-sequences. Sequences shorter than \(t\) will be padded with zero in the beginning of the sequence to reach \(t\), following [45]. In this paper, we set \(t\) to 20 and 100 as short- and long-range sequences respectively, namely, ML20 and ML100.
- **TikTok\(^3\):** This dataset is released in ICME 2019 short video understanding challenge. It targets at predicting the next preferred videos for a user according to the historical watching behaviors. The original dataset is very large since it contains a large number of cold users and items. We follow the same procedure as in Movielens to remove cold users and items. The dataset after basic pre-processing better fits our GPU memory and helps speed up our experiments.
- **Weishi\(^4\):** Weishi is a private short-video recommendation dataset collected by Tencent (China). It containing more than 60,000 videos and we set \(t\) to 10.
- **ColdRec:** This dataset is used to investigate the transfer learning task based on user interaction sequence. It contains a source dataset and a target dataset. The source dataset contains a userID and his interaction sequence in the QQ Brower\(^5\) recommender system, whereas the target dataset includes the same users and with less than 3 interactions in another recommender system — Tencent Kandian\(^6\). ColdRec is used as a cold-user based recommendation task by performing transfer learning on the sequential recommender model (i.e., NextItNet).

Table 1 summarizes the statistics of evaluated datasets after basic pre-processing in this work.

### 4.2 Baseline model
We compare CpRec with two typical sequential recommender models, namely GRU4Rec [16] & Caser [34] and one state-of-the-art model NextItNet. It needs to be noted that we use train GRU4Rec autoregressively, which has a similar effect as the data augmentation method in [32]. Particularly, we perform extensive ablation studies by comparing with NextItNet since they have similar neural network architecture. All models are trained by using the cross-entropy loss [45].

\(^2\)https://grouplens.org/datasets/movielens/
\(^3\)https://www.tiktok.com/en/
\(^4\)https://weishi.qq.com
\(^5\)https://browser.qq.com
\(^6\)https://sdi.3g.qq.com/v/20191102006111550
We train all models using Tensorflow and Adam optimizer with a learning rate $1 \times 10^{-3}$ on GPU (Tesla P100). For all shared hyper-parameters, CpRec uses exactly the same as NextItNet for comparison. Regularization and dropout are not applied following the official implementation of NextItNet\footnote{Specifically, on Weishi, we use a batch size (denoted by $b$) of 128 and dilation factors (denoted by $l$) \{1, 2, 2, 4, 1, 2, 2, 4\} (8 layers or 4 residual blocks). On ML20 and ML100, we set $b$ to 128, and $l$ to 2 $\times$ \{1, 2, 4, 8\} (layers) and 8 $\times$ \{1, 2, 4, 8\} (32 layers), respectively. On TikTok, we set $b$ to 32 and $l$ to 4 $\times$ \{1, 2, 4, 8\} (16 layers). The number of layers $l$ and $r$ are empirically set according to the sequence length and the grid-search results. Roughly speaking, CpRec and NextItNet require more layers when the interaction sequence is relatively longer. The embedding size $d$ on all above datasets is set to 512. For GRU4Rec and Caser, we use the same embedding and hidden dimensions. Other specific hyper-parameters are tuned according to the grid-search results on the testing set. For the transfer learning task on ColdRec, we set $b$ to 64 and 512 on the pre-trained and fine-tuned models, respectively. $l$ and $d$ are set to 4 $\times$ \{1, 2, 4, 8\} and 256, respectively. The hyper-parameter settings on ColdRec strictly follow \cite{44}. For CpRec, the model-specific hyper-parameters are the cluster number $n$, partition rules, and the embedding size of each created block. Empirically, $n$ is very easy to be tuned. For example, If we set $n$ to 2, then we can partition $S$ into two clusters and guarantee that $k_1 : (K - k_1) \approx 2 : 8$ due to the 20/80 principle \cite{31} of the long-tailed distribution. This usually performs well and one can also tune the ratio of $k_1 : (K - k_1)$ greedily for a further better result. If we set $n$ to 3, we first partition it into two clusters and then partition the second cluster and guarantee that $k_2 : (K - k_1 - k_2) \approx 2 : 8$. Following this way, one can obtain the maximum compression ratio by fine tuning $n$. In this paper, we set $n$ to 5 on TikTok and 3 for the remaining datasets for evaluation purpose. The embedding size of each block can be set in the form of a geometric progression, such as \{512, 256, 128\}. Our code will be released upon acceptance.}

### 4.3 Implementation details

We train all models using Tensorflow and Adam optimizer with a learning rate $1 \times 10^{-3}$ on GPU (Tesla P100). For all shared hyper-parameters, CpRec uses exactly the same as NextItNet for comparison. Regularization and dropout are not applied following the official implementation of NextItNet\footnote{While we observe that CpRec and NextItNet may perform further better by carefully tuning the regularization in our later work, all conclusions made in this paper hold fully consistent with their regularization variants.}. Specifically, on Weishi, we use a batch size (denoted by $b$) of 128 and dilation factors (denoted by $l$) \{1, 2, 2, 4, 1, 2, 2, 4\} (8 layers or 4 residual blocks). On ML20 and ML100, we set $b$ to 128, and $l$ to 2 $\times$ \{1, 2, 4, 8\} (layers) and 8 $\times$ \{1, 2, 4, 8\} (32 layers), respectively. On TikTok, we set $b$ to 32 and $l$ to 4 $\times$ \{1, 2, 4, 8\} (16 layers). The number of layers $l$ and $r$ are empirically set according to the sequence length and the grid-search results. Roughly speaking, CpRec and NextItNet require more layers when the interaction sequence is relatively longer. The embedding size $d$ on all above datasets is set to 512. For GRU4Rec and Caser, we use the same embedding and hidden dimensions. Other specific hyper-parameters are tuned according to the grid-search results on the testing set. For the transfer learning task on ColdRec, we set $b$ to 64 and 512 on the pre-trained and fine-tuned models, respectively. $l$ and $d$ are set to 4 $\times$ \{1, 2, 4, 8\} and 256, respectively. The hyper-parameter settings on ColdRec strictly follow \cite{44}. For CpRec, the model-specific hyper-parameters are the cluster number $n$, partition rules, and the embedding size of each created block. Empirically, $n$ is very easy to be tuned. For example, If we set $n$ to 2, then we can partition $S$ into two clusters and guarantee that $k_1 : (K - k_1) \approx 2 : 8$ due to the 20/80 principle \cite{31} of the long-tailed distribution. This usually performs well and one can also tune the ratio of $k_1 : (K - k_1)$ greedily for a further better result. If we set $n$ to 3, we first partition it into two clusters and then partition the second cluster and guarantee that $k_2 : (K - k_1 - k_2) \approx 2 : 8$. Following this way, one can obtain the maximum compression ratio by fine tuning $n$. In this paper, we set $n$ to 5 on TikTok and 3 for the remaining datasets for evaluation purpose. The embedding size of each block can be set in the form of a geometric progression, such as \{512, 256, 128\}. Our code will be released upon acceptance.
Table 3: Performance comparison w.r.t. how to apply the block-wise embedding decomposition. NextItNet that uses block-wise decomposition in the input layer, output layer and both are referred to Bi-NextItNet, Bo-NextItNet and Bio-NextItNet, respectively. B1-NextItNet employs the standard low-rank decomposition (i.e., with only 1 block) in the input and softmax layer inspired by [21]. Note that for clarity only the parameters in the input and output matrices (i.e., CpRec without the middle layers) are reported in the Params Column. TT is short for training time (unit: min). The inference speedup is simply omitted due to similar results as in Table 2.

| Data   | Model     | MRR@5    | HR@5    | TT   | Params |
|--------|-----------|----------|---------|------|--------|
| Weishi | NextItNet | 0.1053   | 0.1721  | 27   | 68M    |
|        | B1-NextItNet | 0.0959   | 0.1582  | 18   | 17M    |
|        | Bi-NextItNet | 0.1059   | 0.1724  | 25   | 38M    |
|        | Bo-NextItNet | 0.106   | 0.1729  | 14   | 38M    |
|        | Bio-NextItNet | 0.1068  | 0.1734  | 12   | 8M     |
| ML20   | NextItNet | 0.1057   | 0.1755  | 104  | 55M    |
|        | B1-NextItNet | 0.0958   | 0.1603  | 79   | 14M    |
|        | Bi-NextItNet | 0.1058   | 0.1761  | 102  | 34M    |
|        | Bo-NextItNet | 0.1063  | 0.1766  | 66   | 34M    |
|        | Bio-NextItNet | 0.1064  | 0.1766  | 64   | 12M    |
| TikTok | NextItNet | 0.012    | 0.0242  | 300  | 527M   |
|        | B1-NextItNet | 0.0109   | 0.0226  | 162  | 132M   |
|        | Bi-NextItNet | 0.0117   | 0.0239  | 278  | 296M   |
|        | Bo-NextItNet | 0.0122  | 0.0249  | 78   | 296M   |
|        | Bio-NextItNet | 0.0123  | 0.0250  | 64   | 66M    |
| ML100  | NextItNet | 0.109    | 0.1781  | 489  | 55M    |
|        | B1-NextItNet | 0.0917   | 0.1619  | 439  | 14M    |
|        | Bi-NextItNet | 0.1092   | 0.1791  | 487  | 34M    |
|        | Bo-NextItNet | 0.109   | 0.178  | 402  | 34M    |
|        | Bio-NextItNet | 0.1109  | 0.1818  | 400  | 12M    |

4.4 Evaluation Metrics

In order to evaluate the recommendation accuracy of CpRec, we randomly split all datasets into training (80%) and testing (20%) sets. Following previous works [15, 16, 18], we use the popular top-N metrics, including MRR@N (Mean Reciprocal Rank), HR@N (Hit Ratio) and NDCG@N (Normalized Discounted Cumulative Gain), where N is set to 5 and 20. To evaluate the parameter efficiency, we report the total number of parameters (without special mention) of each model by Params. To reflect the training efficiency, we report the training time for each model until convergence, denoted by Training Time (min). The inference speedup compared to the baseline is also reported. Similarly to [20, 45], we only evaluate the prediction accuracy of the last item in each interaction sequence in testing set.

5 EXPERIMENTAL RESULTS

The key contribution of CpRec is to improve the memory efficiency for sequential recommender models based on deep neural networks. In this section, we answer the following research questions:

1. RQ1: Does CpRec significantly reduce the model size of a typical sequential neural network, i.e., NextItNet in this paper? If so, does it perform comparably to NextItNet in terms of recommendation accuracy? Are there other advantages that CpRec has over NextItNet?

2. RQ2: What impacts (effectiveness & efficiency) does the adaptive decomposition have on CpRec? Particularly, is the adaptive decomposition helpful compared with decomposing a standard matrix? How about the layer-wise parameter sharing methods?

3. RQ3: Is CpRec a generic framework? or does it work well for other sequential recommender models, such as GRU4Rec?

4. RQ4: Since sequential recommender models can also be applied for the pretraining and finetuning based transfer learning task [44], does CpRec work as well as the non-compressed model for such a task.

5.1 Quantitative Evaluation (RQ1)

We present the results of CpRec and the baseline models on the four sequential recommendation datasets in Table 2. First, we find that NextItNet performs better than GRU4Rec and Caser with notable improvements in the recommendation accuracy across all datasets. Our observation here is consistent with that in [33, 37, 45].

Second, CpRec with our proposed layer-wise parameter sharing methods (i.e., CpRec-Cb, CpRec-Al & CpRec-Ab) yields competitive results with NextItNet on all evaluation metrics. Particularly, CpRec-Ab performs consistently better than NextItNet — e.g., on TikTok CpRec-Ab obtains 7.5% improvements in terms of MRR@5. Moreover, CpRec has obvious advantages over NextItNet in terms of both parameter efficiency and training/inference time. Specifically, CpRec achieves a large compression ratio compared with
5.2 Ablation Study (RQ2)

In order to evaluate the impacts of different components on CpRec, we report the ablation test from two aspects: (1) the impact of block-wise adaptive decomposition on the input layer, the output layer, and both. (2) the impact of layer-wise parameter sharing strategies.

5.2.1 Block-wise adaptive decomposition. Table 3 shows the results of block-wise embedding decomposition with 3 different settings as mentioned above. The experimental results clearly demonstrate that Bi- & Bo-based NextItNet achieve similar improvements on parameter efficiency, compressing models to 57% ~ 74% of the original size. By combining Bi- & Bo-, we obtain Bio-NextItNet, which gives the best compression ratio as well as the highest top-N results and fastest training speed. In addition, we observe that B1-NextItNet performs much worse than NextItNet with around 5~8% accuracy loss. By contrast, Bio-NextItNet performs better than NextItNet & B1-NextItNet although Bio-NextItNet is more compact than B1-NextItNet. These results suggest that the proposed adaptive decomposition is more effective than the standard decomposition. We also note that the standard decomposition works relatively well in NLP [21]. This is probably because the word-word matrix in NLP is much denser than the user-item matrix in SRS [46]. As a result, the basic compression method may work well for the NLP tasks.

5.2.2 Layer-wise parameter sharing. Unlike the block-wise embedding decomposition, layer-wise parameter sharing approaches focus on reducing parameters of the middle layers, and thus are only useful for deep neural network based recommender models. Table 4 presents experimental results for the four layer-wise parameter sharing strategies. Clearly, the results indicate that the proposed adjacent-block strategy (i.e., Ab-NextItNet) always yields the best recommendation accuracy, and even outperforms the standard NextItNet. In addition, it reduces the parameters to half of the original size. Among these approaches, the cross-layer strategy (i.e., Cl-NextItNet) gains the best parameter efficiency, but significantly hurts the model accuracy. By contrast, the cross-block strategy (i.e., Cb-NextItNet) seems also a worth trade-off given its slightly inferior accuracy but a good compression rate. So it may depend on the practical scenario when determining which of the three proposed approaches to use.

5.3 Adaptability Experiment (RQ3)

In order to verify the adaptability of CpRec on other sequential recommender models, we specify CpRec with GRU4Rec and report results in Table 5. Similar behaviors have been observed by other datasets, which however are omitted for saving space. Note that since we observe that using more hidden layers does not improve the accuracy of GRU4Rec, we only investigate the block-wise adaptive decomposition for it. Similar to the above experiments, we prefix the model name with Bi-, Bo- and Bio-. As expected, Bio-GRU4Rec obtains the best accuracy, compression rate and training speed. The results can well evidence the applicability and generality of our CpRec.

5.4 Transfer Learning Experiment (RQ4)

Deep learning based sequential recommender models can not only recommending items from where they come from, but also work as a knowledge transfer learning tool to improve recommendation quality in other systems. In other words, we first use CpRec as a pretrained model and fully train it using the source dataset of ColdRec. Then, we simply add a new softmax layer on the final hidden layer of CpRec, and fine-tune all parameters on the target dataset by using the pretrained weights as a warm start. Our transfer learning framework strictly follows a recent work in [44]. We report the results in Table 6.
Table 6: CpRec vs. NextItNet on the transfer learning task. Note that our evaluation strictly follows [44]. MRR@5 & HR@5 are the finetuned accuracy, whereas Params and training time are evaluated on the pretrained model, which is computationally more expensive than the finetuned model.

| Model       | MRR@5 | HR@5 | Params | Training Time (min) |
|-------------|-------|------|--------|---------------------|
| NextItNet   | 0.2012| 0.3496| 102M   | 578                 |
| CpRec-Ch    | 0.2035| 0.354 | 31.5M  | 118                 |
| CpRec-Al    | 0.2022| 0.3507| 32.7M  | 118                 |
| CpRec-Ab    | 0.2025| 0.3517| 32.7M  | 118                 |

As shown, CpRec obtains more than 3 times compression rate on ColdRec, but consistently outperforms NextItNet with all proposed layer-wise parameter sharing methods. The HR@5 result of NextItNet reported here is exactly the same as that in the original paper (i.e., FineAll in Table 2 in [44]). In addition, the pretraining time of CpRec is also several times faster than NextItNet, similar to the next item recommendation task.

6 CONCLUSIONS

In this paper, we have proposed CpRec, a flexible & generic neural network compression framework for learning compact sequential recommender models. CpRec significantly reduces parameter size in both the input and softmax layer by leveraging the inherent long-tailed item distribution. Moreover, CpRec performs further compression by a series of layer-wise parameter sharing methods. Through extensive experiments on real-world datasets, we show that CpRec generates recommendations with higher speed, lower memory and often better accuracy. An important conclusion made from these results is that the commonly used recommender models are not compact at all. Hence, we expect CpRec to be valuable for existing SRS based on deep neural networks.

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