

SSD4Rec: A Structured State Space Duality Model for Efficient Sequential Recommendation

Haohao Qu †
 The Hong Kong Polytechnic University
 Hong Kong, China
 haohao.qu@connect.polyu.hk

Wenqi Fan *
 The Hong Kong Polytechnic University
 Hong Kong, China
 wenqifan03@gmail.com

Yifeng Zhang †
 The Hong Kong Polytechnic University
 Hong Kong, China
 yifeng.zhang@connect.polyu.hk

Liangbo Ning
 The Hong Kong Polytechnic University
 Hong Kong, China
 BigLemon1123@gmail.com

Qing Li
 The Hong Kong Polytechnic University
 Hong Kong, China
 qing-prof.li@polyu.edu.hk

ABSTRACT

Sequential recommendation methods are crucial in modern recommender systems for their remarkable capability to understand a user's changing interests based on past interactions. However, a significant challenge faced by current methods (e.g., RNN- or Transformer-based models) is to effectively and efficiently capture users' preferences by modeling long behavior sequences, which impedes their various applications like short video platforms where user interactions are numerous. Recently, an emerging architecture named **Mamba**, built on state space models (SSM) with efficient hardware-aware designs, has showcased the tremendous potential for sequence modeling, presenting a compelling avenue for addressing the challenge effectively. Inspired by this, we propose a novel generic and efficient sequential recommendation backbone, **SSD4Rec**, which explores the seamless adaptation of Mamba for sequential recommendations. Specifically, SSD4Rec marks the variable- and long-length item sequences with sequence registers and processes the item representations with bidirectional Structured State Space Duality (SSD) blocks. This not only allows for hardware-aware matrix multiplication but also empowers outstanding capabilities in variable-length and long-range sequence modeling. Extensive evaluations on four benchmark datasets demonstrate that the proposed model achieves state-of-the-art performance while maintaining near-linear scalability with user sequence length. <https://github.com/ZhangYifeng1995/SSD4Rec>.

CCS CONCEPTS

- Information systems → Recommender systems.

* Corresponding author: Wenqi Fan, Department of Computing, and Department of Management and Marketing, The Hong Kong Polytechnic University.

† The authors contribute equally to this paper.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

Conference'17, July 2017, Washington, DC, USA

© 2024 Association for Computing Machinery.
 ACM ISBN 978-x-xxxx-xxxx-x/YY/MM...\$15.00
<https://doi.org/10.1145/nnnnnnn.nnnnnnn>

KEYWORDS

Sequential Recommendation, Recommender Systems, Mamba, State Space Model (SSM), State Space Duality (SSD), Transformer.

ACM Reference Format:

Haohao Qu †, Yifeng Zhang †, Liangbo Ning, Wenqi Fan *, and Qing Li. 2024. SSD4Rec: A Structured State Space Duality Model for Efficient Sequential Recommendation. In *Proceedings of ACM Conference (Conference'17)*. ACM, New York, NY, USA, 10 pages. <https://doi.org/10.1145/nnnnnnn.nnnnnnn>

1 INTRODUCTION

Recommender systems (RecSys) stand out as a crucial branch in the realm of data mining, offering an essential and powerful solution to alleviate information overload issues and enhance user experiences across a wide array of applications [11, 29, 43]. As a prevalent task in practical applications, sequential recommendation strives to capture users' dynamic preferences and predict the next items that users are likely to interact with based on their historical behaviors, which have been widely used in various domains, such as e-commerce [34, 38], streaming media [15, 31], and news recommendation [39]. Differing from conventional RecSys [8, 9], which generates recommendations solely based on the user-item interaction in a static fashion, the user's preferences are often dynamic, changing with time and influenced by various factors in the context of sequential recommendation tasks. For example, after purchasing an iPad, a user might continue to buy related Apple accessories such as the Apple Pencil.

To capture the sequential dynamic interests from the users' historical interactions, a surge of studies have been proposed to leverage the powerful capabilities of advanced deep learning architectures, including Recurrent Neural Networks (RNNs) [3, 7, 41] and Transformer [21, 35] for sequential recommendations. For example, Donkers et al. [6] propose a novel extension of Recurrent Neural Networks tailored for sequential recommendations. Sun et al. [35] proposes BERT4Rec, which introduces and leverages deep bidirectional self-attention based on Transformer for modeling user behavior sequences. Despite their prevalence and effectiveness in sequential recommendations, there are still some limitations for existing methods based on various deep learning architectures. For example, RNN-based recommender systems process users'

historical sequences step by step, requiring the completion of hidden state calculations from the previous time step before making predictions for the next time step, leading to significant time costs. However, recommendation systems, such as Amazon, often demand real-time recommendations, as excessive delays can diminish user experience and impact company revenue [19, 28]. Another prevalent approach, transformer-based RecSys, due to their utilization of self-attention mechanisms, exhibits a quadratic growth in computational complexity as the input sequence length increases. This implies that such models face challenges in handling users who interact with a large number of items.

Recently, a promising architecture, structured state space models (SSMs) [14, 27, 30], have emerged to efficiently capture complex dependencies in sequential data, becoming a formidable competitor to existing popular deep neural networks. As one of the most successful SSM variants, **Mamba** [4, 13] achieves comparable modeling capabilities to Transformers while maintaining linear scalability with sequence length by introducing a Structured State Space Model and corresponding hardware-computational algorithms. Inspired by the success of Mamba-based models for capturing sequential and contextual information in various domains [30], such as text summarization [1, 32], speech analysis [20, 23], and question-answering systems [17, 24], it is appealing to transfer this success from other domains to sequential recommendations to address the aforementioned limitations of existing sequential RecSys. More specifically, Mamba proposes attention-like matrix multiplication based on the property of Structured State Space Duality (SSD) [4] to allow SSM to compute parallelly, which can decrease the time consumption of recurrent operations in RNNs. Moreover, Mamba introduces a Structured State Space Model that circumvents the need for self-attention mechanisms. With the growth in input length, Mamba maintains linear time complexity, significantly boosting the model’s capabilities in processing long sequence data. Thus, given their advantages, Mamba provides great opportunities to advance sequential recommendations.

However, directly applying Mamba to sequential recommendation remains highly challenging, primarily due to two key hurdles. Due to varying length of users’ historical sequences towards items, most existing sequential modeling methods need *padding* or *truncation* operations for sequences with different lengths in recommender systems, resulting in excessive computational overhead (padding) or the potential loss of critical information that could enhance recommendations (truncation), as illustrated in Figure 2. Thus, the first challenge is how to model the dynamic users’ preference with variable- and lone-length historical interaction sequences. Meanwhile, naive Mamba-based models employ a *left-to-right uni-directional* modeling paradigm, which limits the power of hidden representations for items in historical sequences [35]. Specifically, each item can only encode information from preceding items, making it difficult to capture precise user preferences and achieve optimal performance in sequential recommendations. This is due to the fact that users’ historical interactions might not follow a rigidly ordered sequence in practice. Thus, the second challenge is how to capture context from both preceding items and subsequent items within the users’ interaction history.

To address such challenges, in this paper, a Structured State-Space Duality-empowered recommendation framework (**SSD4Rec**)

is proposed based on the advanced Mamba architecture to capture the dynamics underlying variable- and long-length user interaction sequences effectively and efficiently. A novel strategy is introduced to encode the user’s sequential interactions into a variable-length item sequence without requiring padding and truncation, thereby accommodating an unlimited input window. Meanwhile, a Bidirectional State Space Duality (Bi-SSD) block based on the Mamba architecture is designed to swallow the numerous item representations and predict corresponding user preferences for proper recommendations.

Our major contributions are summarized as follows:

- We seamlessly integrate the Mamba into the recommendation framework and propose a novel Structured State Space Duality-empowered sequential recommendation (**SSD4Rec**), which utilizes the advantages of Mamba to effectively and efficiently capture the dynamic users’ preferences and accurately generate next-item recommendations.
- We propose a novel strategy to encode the users’ historical behavior with varying lengths and a Bidirectional Structured State-Space Duality (Bi-SSD) block to capture contextual information for user behavior sequence modeling, effectively addressing the challenges of adapting Mamba for sequential recommendations.
- We conducted extensive experiments on four commonly used datasets to empirically showcase the efficacy of SSD4Rec, including its superior recommendation performance and its scalability in predicting the preferences of users with variable- and long-length interaction histories. Specifically, SSD4Rec is 154.62% and 66.21% faster than the representative attention-based and SSM-based methods (i.e., SASRec [21] and Mamba4Rec [25]), respectively, when training to extract features on user interactions at the length of 200.

The remainder of this paper is structured as follows. Section 2 introduces the proposed approach, which is evaluated in Section 3. Then, Section 4 summarizes the recent development of sequential recommendation and sequence modeling. Finally, conclusions are drawn in Section 5.

2 THE PROPOSED METHOD

This section will begin by formulating the problem of sequential recommendation. Then, we provide an overview of the proposed SSD4Rec, followed by a detailed explanation of each model component. Finally, we will discuss the model training and inference of the proposed SSD4Rec.

2.1 Notations and Definitions

The primary goal of sequential recommendation is to predict the next interaction within a sequence. Let $\mathcal{U} = \{u_1, u_2, \dots, u_{|\mathcal{U}|}\}$ and $\mathcal{V} = \{v_1, v_2, \dots, v_{|\mathcal{V}|}\}$ be the sets of users and items, respectively. Each user $u_k \in \mathcal{U}$ is characterised by a chronologically ordered sequence $S_k = [v_1^{u_k}, \dots, v_t^{u_k}, \dots, v_{L_k}^{u_k}]$, where $v_t^{u_k} \in \mathcal{V}$ represents the item that u_k has interacted with at time step t , and $L_k > 1$ denotes the interaction sequence length for user u_k , which may vary from user to user. Notably, for typical sequential recommendation methods, the input sequence length will be uniformed into a fixed hyper-parameter L using the special padding token and truncation. Specifically, if $L_k < L$, the sequence is modified to $S_k^L =$

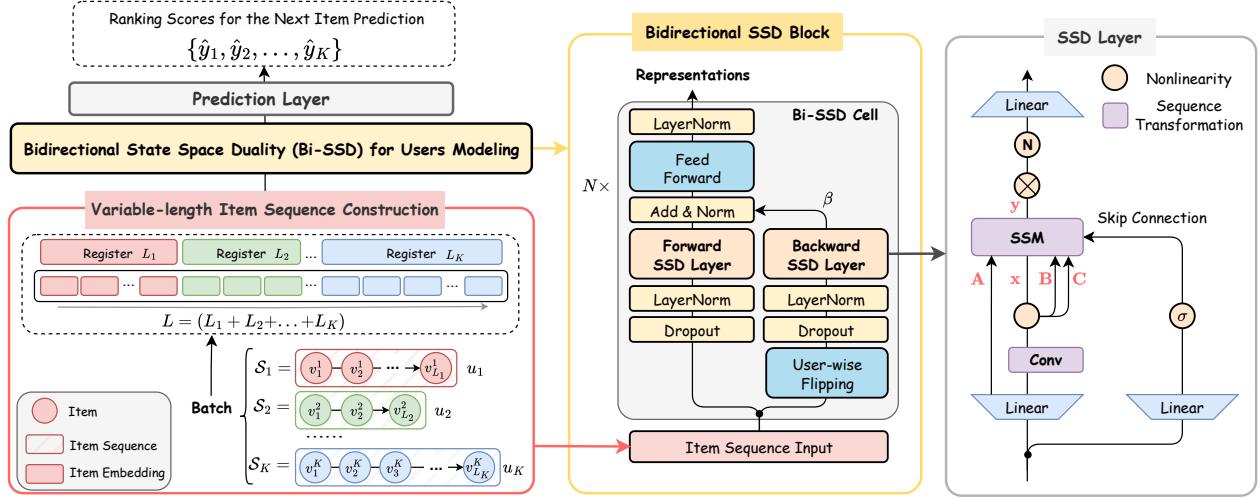


Figure 1: The overall framework of the proposed SSD4Rec for variable- and long-length sequential recommendation, which consists of the input construction with variable-length item sequences in a batch and the bidirectional block constructed with State Space Duality (SSD) layers for efficient and effective sequence modeling.

$[pad, \dots, pad, v_1^{u_k}, \dots, v_{L_k}^{u_k}]$, with the number of padding instances equal to $(L - L_k)$. In contrast, if $L_k > L$, the sequence is truncated into $S_k^L = [v_{(L-k-L)}^{u_k}, \dots, v_{L_k}^{u_k}]$. To represent items efficiently, it is common practice to use an embedding table $Q = \{\mathbf{q}_1, \mathbf{q}_2, \dots, \mathbf{q}_{|\mathcal{V}|}\}$ for the item base \mathcal{V} , where \mathbf{q}_j is a latent dense vector with dimensionality d for item v_j .

In general, a typical sequential recommendation method, denoted as **SeqRec**, analyzes the input sequence to capture user preferences and computes item ranking scores by performing the inner product between the predicted user preference and item embeddings. For user u_k , such a process can be formulated as follows:

$$\hat{\mathbf{p}}_k = \text{SeqRec}(S_k^L), \quad (1)$$

$$r_k = \hat{\mathbf{p}}_k \cdot Q, \quad (2)$$

where $\hat{\mathbf{p}}_k$ denotes the preference representation of user u_k , and r_k is a score distribution of user u_k over all items in the item base Q . This distribution is used to generate a ranked list of items representing the most likely interactions for user u_k at step $L + 1$.

2.2 An Overview of the Proposed SSD4Rec

Mamba models have recently demonstrated significant achievements across diverse domains, owing to their exceptional ability to capture intricate dynamics in long sequence modeling [4, 13]. By introducing advanced Structured State Space Models with hardware-aware expansions, Mamba facilitates attention-like modeling capabilities while maintaining a linear complexity in computing. Motivated by these advancements, this paper proposes to explore Mamba's potential for effective and efficient sequential recommendations. Specifically, unlike the conventional sequential recommendation methods based on RNN or Transformer architecture, the proposed SSD4Rec is designed to handle variable-length item sequences seamlessly without requiring padding or truncation, thereby ensuring that the model receives complete information and retains essential knowledge. As shown in Figure 1, the proposed model consists of two key modules, namely variable-length item

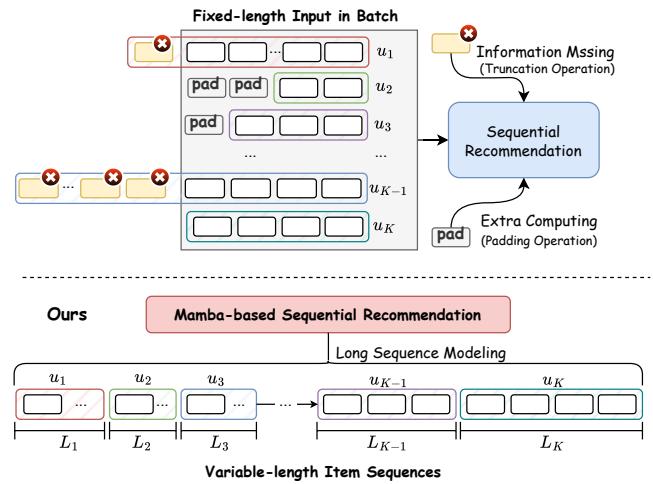


Figure 2: Compared to the typical sequential recommendation input with a fixed sequence length, the proposed input construction strategy achieves the seamless adaptation of Mamba to sequential recommendations, thus avoiding information loss and additional computation.

sequence construction and Bidirectional Structured State Space Duality (Bi-SSD) for user modeling. The first module aims to tackle the core challenge of managing variable-length sequences from diverse users within a certain batch. Meanwhile, the proposed block enables attention-like content-aware interaction modeling while upholding linear complexity in computation. Further elaboration on the proposed method will be provided in the upcoming sections.

2.3 Variable-length Item Sequence Construction

The typical sequential recommendation methods (e.g., RNN-based and Transformer-based) perform padding or truncation operations to have fixed-length historical sequences of users' behaviors for

the input of sequential architectures within a mini batch [2, 21]. However, such fixed-length inputs suffer from intrinsic limitations, such as missing information and additional computational burdens for existing deep learning sequential recommendation methods, as depicted in Figure 2. These limitations can lead to sub-optimal performance in capturing users' preferences for various modern web applications, such as e-commerce and social media platforms, where user interactions are significantly diverse. To address the problem, we introduce a novel strategy to encode user interactions of varying lengths within a mini-batch. More specifically, within a batch, the proposed strategy combines item sequences of varying lengths into an extended integrated sequence and subsequently introduces *segment registers* to facilitate user-aware interaction understanding. Similar to the positional embeddings utilized in visual tasks for location-aware modeling, these registers delineate different segments of the integrated sequence originating from particular users. By doing so, a standardized batch input can be built, encapsulating different item sequences from diverse users without the need for padding or truncation.

Formally, given K users in the b -th batch $\mathcal{U}_b = \{u_1, \dots, u_k, \dots, u_K\}$ of varying interaction lengths, they can be characterized by their item sequences $\{\mathcal{S}_1, \mathcal{S}_k, \dots, \mathcal{S}_K\}$, correspondingly. In our case, the embeddings of these item sequences are concatenated into an extended integrated sequence, as expressed in

$$\mathcal{E}_b = [\underbrace{\mathcal{E}_{u_1}, \dots, \mathcal{E}_{u_k}, \dots, \mathcal{E}_{u_K}}_{b\text{-th batch with size } K}], \quad (3)$$

where $\mathcal{E}_{u_k} \in \mathbb{R}^{L_k \times D}$ denotes the sequence of item embeddings $\{\mathbf{q}_1^{u_k}, \dots, \mathbf{q}_{L_k}^{u_k}\}$ for user u_k with the sequence length of L_k , and $\mathcal{E}_b \in \mathbb{R}^{1 \times (\sum L) \times D}$ represents the integrated embedding sequence in the b -th batch. To delineate separate interactions, we incorporate segment registers based on user identifiers (IDs) with the integrated batch input. The registers can be written by

$$\mathcal{R}_b = \{[u_1, \dots, u_1]^{L_1}, \dots, [u_k, \dots, u_k]^{L_k}, \dots, [u_K, \dots, u_K]^{L_K}\}, \quad (4)$$

where $[u_k, \dots, u_k]^{L_k}$ denotes the ID-based register of length L_k for user u_k . It is important to note that these registers do not possess a corresponding embedding; rather, they are employed to indicate the sequence computation to the SSD-based sequential recommendation. As a result, the integrated sequence and its registers are combined and utilized as the model input X in the b -th batch:

$$X = (\mathcal{E}_b, \mathcal{R}_b). \quad (5)$$

In adopting this strategy, we transform the problem of batch processing sequences of varying lengths into a long sequence modeling task and leverage the capabilities of Mamba to address this issue effectively. This strategy contributes to constructing a variable-length input for each batch without requiring padding or truncation, guaranteeing that the model receives comprehensive information from all user interactions.

2.4 Bidirectional State Space Duality (Bi-SSD) for User Modeling

With the substantial length of the constructed input $X = (\mathcal{E}_b, \mathcal{R}_b)$ and the diverse user information it contains, the primary challenge

arises in the computation process. In this context, RNN-based methods face challenges in training efficiency due to their lack of parallel computing capabilities, resulting in underutilization of the computational power offered by GPUs. Moreover, as the sequence length expands, the complexity of Transformer-based methods escalates in quadratic time, leading to a notable increase in computing expenses. Thus, instead of processing all items in a recurrent format or calculating their attention scores, we propose to utilize a promising sequence modeling architecture, i.e., structured state-space models (SSMs), especially Mamba [4, 13], to handle the lengthy input sequence for the sequential recommendation. Specifically, inspired by the most advanced mamba framework based on state space duality (SSD) layers [4], our proposed SSD4Rec is capable of executing block-based matrix multiplications on the extended input sequence X , allowing segments associated with different users to be computed concurrently. Furthermore, due to the complexities and variability of real-world behaviors, users' historical interactions might not adhere to a strictly ordered sequence in practice [35]. However, naive Mamba methods adhere to a left-to-right unidirectional modeling approach, constraining its modeling capabilities in such scenarios. To this end, we propose to integrate reverse information from user interaction histories to construct a bidirectional block, enhancing Mamba's capacity for comprehensive recommendations. In order to elucidate further, we will explain how SSD4Rec processes the integrated input sequence leveraging the structured state-space duality property and detail the construction of the bidirectional block in the subsequent subsections.

2.4.1 Structured State Space Duality. To enable classical state space models the capabilities of content-aware modeling and efficient computation, Mamba [4, 13] introduces a selection mechanism to make state matrices become functions of model input and proposes hardware-aware algorithms based on the property of Structured State-Space Duality. In general, a standardized SSM with structured state space duality processes an input $\mathbf{x} \in \mathbb{R}^{K \times L \times D}$ and its corresponding state matrices $\mathbf{A} \in \mathbb{R}^{K \times L \times D \times N}$, $\mathbf{B} \in \mathbb{R}^{K \times L \times N}$, and $\mathbf{C} \in \mathbb{R}^{K \times L \times N}$ to generate an output sequence $\mathbf{y} \in \mathbb{R}^{K \times L \times D}$, where K , L , D , and N represent the batch size, sequence length, input dimension, and hidden dimension. This process can be expressed by

$$\mathbf{y} = \text{SSM}(\mathbf{A}, \mathbf{B}, \mathbf{C})(\mathbf{x}) = \mathbf{Mx}, \quad (6)$$

$$\text{s.t. } \mathbf{M} = \begin{bmatrix} (\mathbf{C}^0)^T \mathbf{A}^{0:0} \mathbf{B}^0 & & & \\ (\mathbf{C}^1)^T \mathbf{A}^{1:0} \mathbf{B}^0 & (\mathbf{C}^1)^T \mathbf{A}^{1:1} \mathbf{B}^1 & & \\ \cdots & \cdots & \cdots & \\ (\mathbf{C}^j)^T \mathbf{A}^{j:0} \mathbf{B}^0 & (\mathbf{C}^j)^T \mathbf{A}^{j:1} \mathbf{B}^1 & \cdots & (\mathbf{C}^j)^T \mathbf{A}^{j:i} \mathbf{B}^i \end{bmatrix}, \quad (7)$$

where $\mathbf{M}^{ji} = (\mathbf{C}^j)^T \mathbf{A}^{j:i} \mathbf{B}^i$ represents the mapping of the i -th token in the input sequence \mathbf{x} to the j -th token in the output \mathbf{y} ; $(\mathbf{A}^i, \mathbf{B}^i, \mathbf{C}^i)$ denote the state matrices for the i -th token, derived through linear projection from the corresponding token embedding; and $\mathbf{A}^{j:i}$ is the product of the state matrix \mathbf{A} from j to i . Given such a formulation, the structured state-space model allows for block-based matrix multiplication, thus achieving attention-like content-aware modeling and subquadratic-time computation.

Building upon this insight, we further take advantage of the state space duality property for our variable- and long-length user

interaction sequence. Unlike the standard formulation mentioned above, we propose to perform the block-based matrix multiplications concurrently for each user sequence in the integrated input \mathcal{X} . Thanks to the use of segment registers, the model can retrieve corresponding structured matrix \mathbf{M} and item sequence $\mathcal{E} \in \mathbb{R}^{1 \times (\sum L) \times D}$ for computation. Formally, given an input $\mathcal{X} = (\mathcal{E}_b, \mathcal{R}_b)$ involving K users in the b -th batch, the parallel SSD-based computation process can be formulated as

$$\mathcal{F} = \text{SSM}(\mathbf{A}, \mathbf{B}, \mathbf{C})(\mathcal{X}) = (\mathbf{M}_1 \mathcal{E}_{u_1}, \dots, \mathbf{M}_K \mathcal{E}_{u_K}), \quad (8)$$

$$\text{s.t. } \mathbf{M}_k^{ji} = (\mathbf{C}_k^j)^\top \mathbf{A}_k^j \dots \mathbf{A}_k^{i+1} \mathbf{B}_k^i, \quad (9)$$

where \mathcal{F} is the intermediate output of an SSD layer, which will be passed as the input sequence to the next SSD layer. \mathbf{M}_k and \mathcal{E}_{u_k} represent the structured matrix and item sequence for user u_k . By adopting this approach, SSD4Rec implements batch processing of user interaction sequences with varying lengths.

2.4.2 Block Design. By leveraging the state space duality (SSD) layer as the foundational component, we construct a network architecture tailored to address the sequential recommendation task, as illustrated in Figure 1. First, in addition to the standard sequential information concerning user behaviors, we propose integrating reverse insights from the interaction history by constructing a bidirectional architecture on top of the unidirectional SSD layer. In which, we introduce a weighted indicator β , to regulate the message integration between the forward and backward sequence modeling, expressed as

$$\mathcal{F}' = \mathcal{F}_{\text{forward}} + \beta * \mathcal{F}_{\text{backward}}, \quad (10)$$

where β is a hyper-parameter to balance the contribution of backward sequence modeling. Empirically, β should be set within the range of 0.1 to 0.3. This bidirectional design encourages the model to learn to reason in a reverse manner, potentially capturing more valuable patterns within the interaction histories. Notably, to conserve computational resources and GPU memory usage, we can utilize a shared SSD layer for the forward and backward modeling processes. Second, the utilization of SSD layers enables our model to facilitate hardware-aware computation, i.e., block-based matrix multiplication [4], thereby achieving attention-like content-aware modeling while preserving efficient learning. Moreover, by stacking multiple bidirectional SSD cells, the proposed model can achieve a deeper network structure with an increased number of learnable parameters. Layer-wise normalization and embedding dropout are further utilized between the stacked cells to improve the model's robustness and stabilize the learning process. Finally, the proposed block predicts the representations of user preferences in a specific batch, which are used to calculate the ranking score distributions for Top-K sequential recommendations. Specifically, given the integrated input $\mathcal{X} = \{\mathcal{E}_b, \mathcal{R}_b\}$ associated with K users in the b -th batch, the proposed Bi-SSD layer outputs the representations of their user preferences $\mathcal{P}_b = \{\hat{\mathbf{p}}_1, \dots, \hat{\mathbf{p}}_k, \dots, \hat{\mathbf{p}}_K\}$, correspondingly. The process can be formulated as

$$\mathcal{P}_b = \text{Bi-SSD}(\mathcal{E}_b, \mathcal{R}_b), \quad (11)$$

where $\hat{\mathbf{p}}_k \in \mathbb{R}^D$ denotes the predicted representation for user u_k .

2.4.3 Prediction Layer. Finally, in the prediction layer, SSD4Rec using the predicted representations to generate the final output prediction scores. In a specific batch b with K users, the prediction process can be written by

$$\hat{\mathcal{Y}}_b = \text{Softmax}(\mathcal{P}_b * Q), \quad (12)$$

where $\hat{\mathcal{Y}}_b = \{\hat{\mathbf{y}}_{u_1}, \dots, \hat{\mathbf{y}}_{u_K}\} \in \mathbb{R}^{1 \times K \times |\mathcal{V}|}$ represents the predicted probability distributions over the next item in the item set \mathcal{V} , and Q denotes the corresponding embeddings for items in \mathcal{V} .

2.5 Learning Objective

To learn the parameters of the proposed method SSD4Rec for sequential recommendation, we use a representative objective function, Cross-Entropy (CE) loss, between the predicted probability distributions and the classification labels of corresponding positive items for optimizing the model. Mathematically, in a batch with K users, the loss function can be expressed as

$$\mathcal{L} = - \sum_{k=1}^K \sum_{d=1}^D g_{u_k, d} \log(\hat{y}_{u_k, d}), \quad (13)$$

where $g_{u_k, d}$ and $\hat{y}_{u_k, d}$ denote the d -th dimensions of the groundtruth distribution and predicted distribution for the user u_k , respectively. Given the loss, we can update our model iteratively in a mini-batch manner.

2.6 Time Complexity Analysis

In general, the typical attention mechanisms require $L^2 N$ total floating-point operations (FLOPs) [4], where L is the length of sequence input and N is the dimensional size of hidden representations. It can be observed that the computational overhead can quadratically increase with the input size. The utilized SSD block involves LN^2 total FLOPs, scaling linearly with the sequence length L . As shown in Table 1, this feature in SSD enables the proposed model to attain reduced computational complexity in various recommendation scenarios characterized by prolonged user interactions, such as news recommendations and social media platforms, where the sequence length L significantly exceeds the dimensional size N of hidden representations, i.e., $L \gg N$. Furthermore, the SSD layer empowers our model to execute Transformer-like matrix multiplications, enhancing efficiency compared to a straightforward selective SSM layer that utilizes the Parallel Associative Scan [13].

Table 1: Comparison of computational complexity between representative sequential recommendation methods, where "M.M." refers to Matrix "Multiplication".

	SASRec [21]	Mamba4Rec [25]	SSD4Rec
Architecture	Attention	SSM	SSD
Training FLOPs	$L^2 N$	LN^2	LN^2
Memory	L^2	LN^2	LN
M.M.	✓		✓

Table 2: Basic statistics of benchmark datasets.

Dataset	ML-1M	Beauty	Games	KuaiRand
#Users	6,040	22,363	24,303	23,951
#Items	3,416	12,101	10,673	7,111
#Interactions	999,611	198,502	231,780	1,134,420
Avg.Length	165.5	8.9	9.5	47.4
Max.Length	2,314	389	880	809
Sparsity	95.15%	99.92%	99.91%	99.33%

3 EXPERIMENT

3.1 Experimental Settings

3.1.1 Datasets. To showcase the efficiency and effectiveness of our proposed approach, we perform extensive experiments across four benchmark datasets: Amazon-Beauty (referred to as **Beauty**), Amazon-Video-Games (referred to as **Games**), **LastFM**, and MovieLens 1M (abbreviated as **ML1M**). The initial two datasets, sourced from the Amazon e-commerce platform¹, encapsulate a wide array of user engagements with Beauty and Video Games products. Moreover, the ML1M² dataset comprises a compilation of movie ratings provided by users on the MovieLens platform. Finally, the KuaiRand dataset³, retrieved from the recommendation logs of the video-sharing mobile application Kuaishou, includes millions of interactions involving randomly exposed items. The statistics for these four datasets are outlined in Table 2. We follow the leave-one-out policy [21] for training-validation-testing partition.

3.1.2 Baselines. To demonstrate the superiority of the proposed method, four representative sequential recommendation methods and a recently developed Mamba-based method are used as baselines, namely **Caser** [36]: a typical convolution-based sequential recommender; **GRU4Rec** [18]: a RNN-based method constructed by Gated Recurrent Units; **BERT4Rec** [35]: a sequential recommender system based on bidirectional Transformers trained using the BERT-style cloze task; **SASRec** [21]: a representative approach for sequential recommendation leveraging self-attention mechanisms; and **Mamba4Rec** [25]: a pioneering model constructed by SSMs.

3.1.3 Evaluation Metrics. To assess the recommendation results' quality, we employ three commonly utilized evaluation metrics: the top- K Hit Ratio (HR@ K), top- K Normalized Discounted Cumulative Gain (NDCG@ K), and top- K Mean Reciprocal Rank (MRR@ K) [8, 10]. Higher scores signify superior recommendation performance. The average metrics for all users in the test set are provided in the performance comparison. Furthermore, we specify the values of K as 10 and 20, with 10 serving as the default for ablation experiments.

3.1.4 Hyper-parameter Settings. Our evaluation is implemented based on PyTorch⁴ and RecBole⁵. First, to initialize the proposed Mamba-based block, we designate the model dimension as 256 and the SSM state expansion factor as 64. Second, the weighted indicator for backward SSD computation β is searched from 0.1 to 0.9 in 0.2 increments. Moreover, the search space for the learning

¹<https://nijianmo.github.io/amazon/>

²<https://grouplens.org/datasets/movielens/1m/>

³<https://kuaierand.com/>

⁴<https://pytorch.org/>

⁵<https://github.com/RUCAIBox/RecBole>

rate includes values of {0.0001, 0.001, 0.01, 0.1}, while for the batch size, we consider {64, 256, 512, 1024, 2048}. Fourth, the number of Bi-SSD cells is searched from 1 to 3. To accommodate the baselines, we set fixed sequence lengths of 200 for ML1M and 50 for other datasets. Furthermore, for a fair comparison, we ensure consistency in the key hyperparameters across models while setting the other default hyperparameters for baseline methods as suggested in their respective papers. Finally, we employ the Adam [22] optimizer in a mini-batch manner.

3.2 Recommendation Performance Comparison

We first compare the recommendation performance between the proposed model and all baselines over the four benchmark datasets. Table 3 and Table 4 showcase the overall evaluation results. From the two tables, we can make the following observations.

- Our proposed SSD4Rec consistently outperforms all the baselines across all datasets regarding NDCG@10&20 and MRR@10&20. On average, SSD4Rec significantly exceeds the strongest baselines by 6.17% on NDCG@10 and 7.73% on MRR@10 in the KuaiRand dataset. Such improvement demonstrates the effectiveness of our proposed method and the great potential of exploring the Structured State Space Duality property in sequential recommendations.
- While inferior to the proposed model, Mamba4Rec, in most cases, outperforms the conventional deep learning methods, namely the CNN-based model Caser, RNN-based model GRU4Rec, and Attention-based models BERT4Rec and SASRec. This highlights the efficacy of Mamba in capturing user behavior dynamics for recommendation purposes.
- Additionally, it is evident that the benefits of the mamba-based models diminish in the datasets characterized by shorter average sequences, i.e., Beauty and Games. Conversely, their performance excels in datasets like ML1M and KuaiRand, where the average sequence lengths extend to 165.5 and 47.4, respectively. This disparity in performance can be attributed to Mamba's exceptional capacity to capture long-range dependencies.

3.3 Efficiency Analysis

In this subsection, we analyze the training and inference efficiency of SSD4Rec compared with two representative sequential recommendation methods, i.e., SASRec and Mamba4Rec. The evaluation results on the ML1M dataset are presented in Table 5. We can see that the two Mamba-based models, i.e., Mamba4Rec and SSD4Rec are much more efficient compared to the Attention-based SASRec model when $N < L = 200$, which in line with the discussion in Section 2.6, i.e., Mamba enjoys linear scaling in sequence length. When presented with inputs of substantial dimensions, such as $N = 256$, Mamba4Rec exhibits lower efficiency compared to SASRec, even when $L = 400 > N$, showcasing the constraints of Mamba-1 in managing high-dimensional inputs [4]. In contrast, SSD4Rec achieves superior computational efficiency to SASRec and Mamba4Rec in all the cases. This superior performance can be attributed to the utilization of the novel SSD layer and the advancing hardware-aware computation algorithm (i.e., the block-based matrix multiplication). To be specific, when given a lengthy interaction list, i.e., $N = 32$ and $L = 200$, the proposed model is

Table 3: Sequential recommendation performance on the ML1M and Beauty datasets, where NG@K refs to NDCG@K, and the best and second-best results are bold and underlined, respectively.

Method	ML1M						Beauty					
	NG@10	NG@20	MRR@10	MRR@20	HR@10	HR@20	NG@10	NG@20	MRR@10	MRR@20	HR@10	HR@20
Caser	0.1714	0.1948	0.1354	0.1418	0.2892	0.382	0.0294	0.0355	0.0222	0.0239	0.0531	0.0774
GRU4Rec	0.1655	0.1906	0.1276	0.1344	0.2901	0.3897	0.0307	0.0386	0.0221	0.0242	0.0593	0.0907
BERT4Rec	0.1846	0.2082	0.1441	0.1506	0.3171	0.4103	0.0219	0.0279	0.0159	0.0175	0.0419	0.0656
SASRec	0.1718	0.1963	0.1320	0.1386	0.3023	0.4000	0.0395	0.0480	0.0261	0.0284	0.0829	0.1168
Mamba4Rec	<u>0.1847</u>	<u>0.2094</u>	<u>0.1456</u>	<u>0.1523</u>	0.3124	<u>0.4103</u>	<u>0.0442</u>	<u>0.0501</u>	<u>0.0361</u>	<u>0.0376</u>	0.0709	0.0942
SSD4Rec	0.1889	0.2145	0.1495	0.1565	0.3152	0.4194	0.0452	0.0520	0.0363	0.0382	<u>0.0745</u>	<u>0.1015</u>

Table 4: Sequential recommendation performance on the Games and KuaiRand datasets, where NG@K refs to NDCG@K, and the best and second-best results are bold and underlined, respectively.

Method	Games						KuaiRand					
	NG@10	NG@20	MRR@10	MRR@20	HR@10	HR@20	NG@10	NG@20	MRR@10	MRR@20	HR@10	HR@20
Caser	0.0460	0.0587	0.0330	0.0364	0.0891	0.1396	0.0545	0.0692	0.0414	0.0453	0.0982	0.1571
GRU4Rec	0.0520	0.0654	0.0373	0.0409	0.1011	0.1543	0.0563	0.0722	0.0426	0.0470	0.1017	0.1653
BERT4Rec	0.0372	0.0482	0.0263	0.0293	0.0735	0.1170	0.0534	0.0683	0.0404	0.0444	0.0968	0.1563
SASRec	0.0531	0.0689	0.0330	0.0373	0.1189	0.1817	<u>0.0567</u>	<u>0.0733</u>	0.0426	<u>0.0471</u>	<u>0.1040</u>	0.1705
Mamba4Rec	<u>0.0605</u>	<u>0.0738</u>	<u>0.0461</u>	<u>0.0497</u>	0.1081	0.1610	0.0558	0.0710	<u>0.0427</u>	0.0468	0.0994	0.1601
SSD4Rec	0.0610	0.0740	0.0461	0.0497	<u>0.1102</u>	<u>0.1617</u>	0.0602	0.0759	0.0460	0.0503	0.1076	<u>0.1704</u>

Table 5: Comparison of the computational efficiency on the ML1M dataset, which involves measuring the training time per epoch and the inference time for all test users in seconds (s).

L=200	N	SASRec*	Mamba4Rec	SSD4Rec	Imp.*	N=256	L	SASRec*	Mamba4Rec	SSD4Rec	Imp.*
Training (s)	32	106.18	44.98	22.90	363.67%	Training (s)	50	42.79	119.87	29.37	45.69%
	64	112.43	82.16	24.69	355.37%		100	69.50	173.78	47.73	45.61%
	128	125.24	156.45	35.86	249.25%		200	161.91	326.87	74.13	118.41%
	256	161.91	326.87	74.13	118.41%		400	450.64	687.46	101.51	343.94%
Inference (s)	32	0.158	0.061	0.039	305.13%	Inference (s)	50	0.057	0.217	0.057	0.00%
	64	0.178	0.114	0.046	286.96%		100	0.111	0.272	0.089	24.72%
	128	0.199	0.218	0.062	220.97%		200	0.27	0.484	0.129	109.30%
	256	0.27	0.484	0.129	109.30%		400	0.75	1.152	0.167	349.10%

3.6× and 3× faster than the Attention-based method SASRec in the training and inference phases, respectively. This substantial acceleration underscores a notable enhancement in computational efficiency. Moreover, even when configured with high-dimensional input sequences, i.e., $N = 256 > L = 200$, our model experiences a speedup of exceeding 100% in comparison to SASRec for both the training and inference tasks, underscoring the significance of the hardware-aware computation algorithm employed by SSD.

Table 6: Ablation studies conducted by eliminating the effects of each key component, where NG@10 refs to NDCG@10.

Component	ML1M		KuaiRand	
	NG@10	MRR@10	NG@10	MRR@10
Full	0.1889	0.1495	0.0602	0.0460
w/o Bidirection	0.1869	0.1474	0.0593	0.0454
w/o Register	0.1871	0.1466	0.0545	0.0421
w/o Varlen	0.1852	0.1456	0.0565	0.0434
w PE	0.1736	0.1353	0.0566	0.0431
1 Layer	0.1872	0.1483	0.0579	0.0441
3 Layers	0.1933	0.1529	0.0597	0.0455

3.4 Ablation Study

In order to assess the effectiveness of the proposed key components, we conducted ablation experiments on the ML1M and KuaiRand datasets, where the influence of each component was eliminated separately as follows:

- w/o Bidirection: Deactivate the backward SSD layers to eliminate backward information of user interactions.
- w/o Register: Remove the user-aware segment registers from the model input. By doing so, the model will consider the integrated sequence containing diverse interactions from different users as a successive item list.
- w/o Varlen: Deploy a fixed window on the model input through padding and truncation. In contrast to the proposed variable-length input, there is a tendency to lose information from the long-tail user interaction histories.
- w PE: Incorporate learnable position embeddings into the item embedding sequences.

From the ablation results in Table 6, we can see that each component in our approach contributes to the overall performance since eliminating any of them would result in performance degradation. Moreover, the results demonstrate that the integration of learnable positional embeddings does not improve the performance, due to

the recurrent nature of the Mamba block. Finally, stacking Mamba layers yields performance improvements on the ML1M dataset with larger, long-sequence user interactions, but it would lead to a linear increase in the model size. Considering the increased complexity resulting from the stacked layers, we have designated the 2-layer SSD4Rec as our default model for performance evaluations.

3.5 Hyper-parameter Analysis

In SSD4Rec, we introduce two critical hyper-parameters, namely the weighted indicator of backward processing β and the max length of item sequences L . Their value sensitivities are evaluated in this section to facilitate the future application of our proposed model.

3.5.1 Effect of Backward Indicator β . This hyper-parameter determines the degree to which backward information can propagate through the SSD layer. Figure 4 shows the corresponding performance change of SSD4Rec on NDCG@10. We can find that introducing a small ratio of backward knowledge brings performance improvements. In most cases, the recommendation performance of our proposed method improves when $\beta < 0.3$. The experimental results also reveal that the recommendation performance degrades when the masking ratio $\beta \geq 0.5$, suggesting excessive backward information should be avoided.

3.5.2 Effect of Max Sequence Length L . To evaluate whether extending sequence lengths benefits our proposed method, we explore hyperparameter values L within the range of 25, 50, 100, 200 for SSD4Rec on the ML1M and KuaiRand datasets. As illustrated in Figure 4, our model demonstrates progressively improved performance for sequential recommendations on both datasets as the maximum sequence length increases. Notably, by leveraging all user interaction histories and extracting valuable information through the sophisticated selection mechanism introduced by Mamba, our approach excels in scenarios with variable-length inputs. These results underscore the exceptional performance of SSD4Rec in long-tail sequential recommendation tasks.

4 RELATED WORK

4.1 Sequential Recommendation

In general, existing sequential recommendation studies can be divided into two categories [12]:

1) **Traditional methods** employ conventional data mining techniques to obtain the users' preferences from their historical interactions [5, 16, 26, 37, 44]. For example, as a typical Markov chains-based method, TransRec He et al. [16] introduces a novel unified method to model third-order interactions in large-scale sequential prediction tasks by embedding items into a transition space and leveraging translation vectors to capture complex user-item and item-item relationships. Twardowski [37] propose a matrix factorization-based sequential RecSys to capture user behavior dependencies without explicit user identification, utilizing user activity within single sessions as sequences of events to provide recommendations.

2) **Deep learning-based methods** leverage the powerful representation capabilities of deep neural networks to model the users' preferences based on the user-item interaction history. For example, Tang and Wang [36] propose a Convolutional Sequence Embedding

Recommendation Model for top-N sequential recommendation by embedding users' interaction sequence into an "image" into the time and latent space and using convolutional filters to capture the sequential patterns. Zhang et al. [42] utilize the self-attention mechanisms to estimate the weights for each item within the users' historical behavior to model the users' preferences for next-item recommendation. Chen et al. [3] systematically investigates the impact of temporal information in sequential recommendations by uncovering and incorporating two fundamental temporal patterns of user behaviors, 'absolute time patterns' and 'relative time patterns', into the memory-augmented neural networks to model user dynamic preferences effectively.

4.2 Structured State Space Models (Mamba)

Due to Mamba's powerful sequential modeling capabilities and computational efficiency, numerous studies have applied it across various domains in real-life applications [30]. For instance, Lieber et al. [24] proposes a cutting-edge large language model called Jamba that combines Transformer and Mamba layers in a hybrid mixture-of-experts architecture, resulting in a high-performance, memory-efficient model capable of handling long-context sequences effectively. Ruan and Xiang [33] introduce Vision Mamba UNet (VM-UNet), a novel U-shape architecture model for medical image segmentation that leverages State Space Models (SSMs) to address the limitations of CNNs and Transformers by incorporating a Visual State Space (VSS) block to capture extensive contextual information for medical image segmentation. Xing et al. [40] a pioneering 3D medical image Segmentation Mamba model that leverages the efficiency of State Space Models (SSM) to effectively capture long-range dependencies within whole-volume features at various scales, outperforming Transformer-based methods in whole-volume feature modeling even with high-resolution volume features and achieving superior processing speed and efficacy in medical image segmentation tasks. For more details on existing works, please refer to a comprehensive survey of mamba [30].

5 CONCLUSION

While existing deep learning-based sequential recommendation methods achieve promising prediction performance, they fail to effectively and efficiently capture user preferences with long-tail interactions. To tackle these challenges, we propose a novel framework, named SSD4Rec, based on Mamba architecture for sequential recommendation. To be specific, the proposed SSD4Rec consists of two key modules, i.e., a novel strategy for batch processing of variable-length item sequences and a Bi-SSD block for efficient user behavior sequence modeling. Specifically, using the bidirectional structure enables a comprehensive information understanding, and the SSD layer equips the model with attention-like learning capabilities and superior computational efficiency. Through comprehensive experiments on four distinct datasets, we revealed that our model could achieve state-of-the-art sequential recommendation performance while also exhibiting the capacity to achieve fast training and inference.

REFERENCES

- [1] Florian Le Bronnec, Song Duong, Mathieu Ravaut, Alexandre Allauzen, Nancy F Chen, Vincent Guigue, Alberto Lumbrieras, Laure Soulier, and Patrick

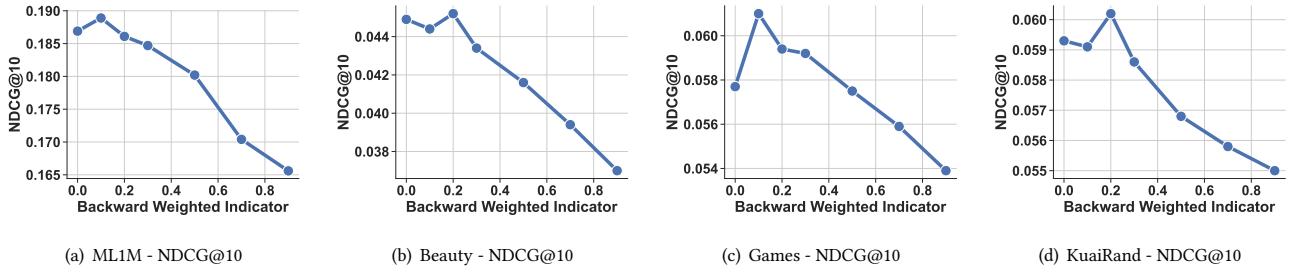


Figure 3: The effect of backward weighted indicator β under NDCG@10.

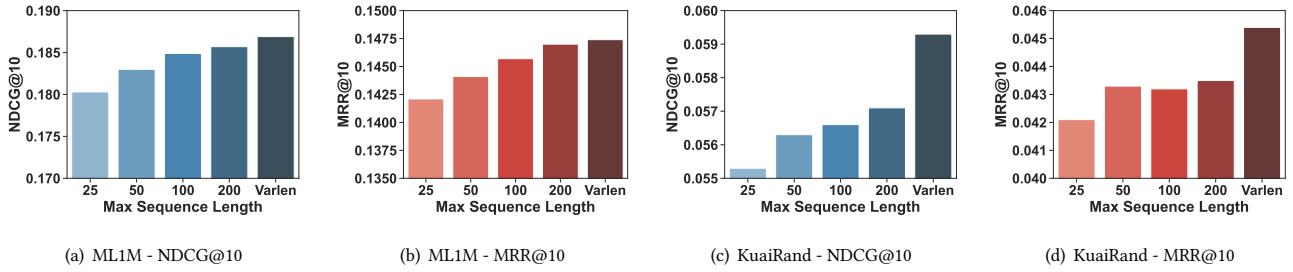


Figure 4: The effect of max sequence length L on the ML1M and KuaiRand datasets.

- Gallinari. 2024. LOCOST: State-Space Models for Long Document Abstractive Summarization. *arXiv preprint arXiv:2401.17919* (2024).
- [2] Jianxin Chang, Chen Gao, Yu Zheng, Yiqun Hui, Yanan Niu, Yang Song, Depeng Jin, and Yong Li. 2021. Sequential recommendation with graph neural networks. In *Proceedings of the 44th international ACM SIGIR conference on research and development in information retrieval*. 378–387.
- [3] Xu Chen, Hongteng Xu, Yongfeng Zhang, Jiaxi Tang, Yixin 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*. 108–116.
- [4] Tri Dao and Albert Gu. 2024. Transformers are SSMs: Generalized Models and Efficient Algorithms Through Structured State Space Duality. In *International Conference on Machine Learning (ICML)*.
- [5] James Davidson, Benjamin Liebold, Junning Liu, Palash Nandy, Taylor Van Vleet, Ullas Gargi, Sujoy Gupta, Yu He, Mike Lambert, Blake Livingston, et al. 2010. The YouTube video recommendation system. In *Proceedings of the fourth ACM conference on Recommender systems*. 293–296.
- [6] Tim Donkers, Benedikt Loeppe, and Jürgen Ziegler. 2017. Sequential user-based recurrent neural network recommendations. In *Proceedings of the eleventh ACM conference on recommender systems*. 152–160.
- [7] Jiasheng Duan, Peng-Fei Zhang, Ruihong Qiu, and Zi Huang. 2023. Long short-term enhanced memory for sequential recommendation. *World Wide Web* 26, 2 (2023), 561–583.
- [8] Wenqi Fan, Xiaorui Liu, Wei Jin, Xiangyu Zhao, Jiliang Tang, and Qing Li. 2022. Graph trend filtering networks for recommendation. In *Proceedings of the 45th international ACM SIGIR conference on research and development in information retrieval*. 112–121.
- [9] Wenqi Fan, Yao Ma, Qing Li, Yuan He, Eric Zhao, Jiliang Tang, and Dawei Yin. 2019. Graph neural networks for social recommendation. In *The world wide web conference*. 417–426.
- [10] Wenqi Fan, Yao Ma, Qing Li, Jianping Wang, Guoyong Cai, Jiliang Tang, and Dawei Yin. 2020. A graph neural network framework for social recommendations. *IEEE Transactions on Knowledge and Data Engineering* 34, 5 (2020), 2033–2047.
- [11] Wenqi Fan, Xiangyu Zhao, Lin Wang, Xiao Chen, Jingtong Gao, Qidong Liu, and Shijie Wang. 2023. Trustworthy Recommender Systems: Foundations and Frontiers. In *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*. 5796–5797.
- [12] Hui Fang, Danning Zhang, Yiheng Shu, and Guibing Guo. 2020. Deep learning for sequential recommendation: Algorithms, influential factors, and evaluations. *ACM Transactions on Information Systems (TOIS)* 39, 1 (2020), 1–42.
- [13] Albert Gu and Tri Dao. 2023. Mamba: Linear-time sequence modeling with selective state spaces. *arXiv preprint arXiv:2312.00752* (2023).
- [14] Albert Gu, Karan Goel, and Christopher Ré. 2021. Efficiently modeling long sequences with structured state spaces. *arXiv preprint arXiv:2111.00396* (2021).
- [15] Lei Guo, Hongzhi Yin, Qinyong Wang, Tong Chen, Alexander Zhou, and Nguyen Quoc Viet Hung. 2019. Streaming session-based recommendation. In *Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining*. 1569–1577.
- [16] Ruining He, Wang-Cheng Kang, and Julian McAuley. 2017. Translation-based recommendation. In *Proceedings of the eleventh ACM conference on recommender systems*. 161–169.
- [17] Wei He, Kai Han, Yehui Tang, Chengcheng Wang, Yujie Yang, Tianyu Guo, and Yunhe Wang. 2024. Densemamba: State space models with dense hidden connection for efficient large language models. *arXiv preprint arXiv:2403.00818* (2024).
- [18] Balázs Hidasi, Alexandros Karatzoglou, Linas Baltrunas, and Domonkos Tikk. 2015. Session-based recommendations with recurrent neural networks. *arXiv preprint arXiv:1511.06939* (2015).
- [19] Xianjiang Huang, Bin Cui, Wenyu Zhang, Jie Jiang, and Ying Xu. 2015. Tencentrec: Real-time stream recommendation in practice. In *Proceedings of the 2015 ACM SIGMOD international conference on management of data*. 227–238.
- [20] Xilin Jiang, Cong Han, and Nima Mesgarani. 2024. Dual-path mamba: Short and long-term bidirectional selective structured state space models for speech separation. *arXiv preprint arXiv:2403.18257* (2024).
- [21] Wang-Cheng Kang and Julian McAuley. 2018. Self-attentive sequential recommendation. In *2018 IEEE international conference on data mining (ICDM)*. IEEE, 197–206.
- [22] D.P. Kingma. 2014. Adam: a method for stochastic optimization. *arXiv preprint arXiv:1412.6980* (2014).
- [23] Kai Li and Guo Chen. 2024. Spmamba: State-space model is all you need in speech separation. *arXiv preprint arXiv:2404.02063* (2024).
- [24] Opher Lieber, Barak Lenz, Hofit Bata, Gal Cohen, Jhonathan Osin, Itay Dalmedigos, Erez Safafi, Shaked Meiron, Yonatan Belinkov, Shai Shalev-Shwartz, et al. 2024. Jamba: A hybrid transformer-mamba language model. *arXiv preprint arXiv:2403.19887* (2024).
- [25] Chengkai Liu, Jianghao Lin, Jianling Wang, Hanzhou Liu, and James Caverlee. 2024. Mamba4rec: Towards efficient sequential recommendation with selective state space models. *arXiv preprint arXiv:2403.03900* (2024).
- [26] Langming Liu, Liu Cai, Chi Zhang, Xiangyu Zhao, Jingtong Gao, Wanyu Wang, Yifei Lv, Wenqi Fan, Yiqi Wang, Ming He, et al. 2023. Linrec: Linear attention mechanism for long-term sequential recommender systems. In *Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 289–299.
- [27] Chris Lu, Yannick Schroecker, Albert Gu, Emilio Parisotto, Jakob Foerster, Satinder Singh, and Feryal Behbahani. 2024. Structured state space models for in-context reinforcement learning. *Advances in Neural Information Processing Systems* 36 (2024).

- [28] Yifei Ma, Balakrishnan Narayanaswamy, Haibin Lin, and Hao Ding. 2020. Temporal-contextual recommendation in real-time. In *Proceedings of the 26th ACM SIGKDD international conference on knowledge discovery & data mining*. 2291–2299.
- [29] Haohao Qu, Wenqi Fan, Zihuai Zhao, and Qing Li. 2024. TokenRec: Learning to Tokenize ID for LLM-based Generative Recommendation. *arXiv preprint arXiv:2406.10450* (2024).
- [30] Haohao Qu, Liangbo Ning, Rui An, Wenqi Fan, Tyler Derr, Xin Xu, and Qing Li. 2024. A Survey of Mamba. *arXiv preprint arXiv:2408.01129* (2024).
- [31] Jérémie Rappaz, Julian McAuley, and Karl Aberer. 2021. Recommendation on live-streaming platforms: Dynamic availability and repeat consumption. In *Proceedings of the 15th ACM Conference on Recommender Systems*. 390–399.
- [32] Liliang Ren, Yang Liu, Yadong Lu, Yelong Shen, Chen Liang, and Weizhu Chen. 2024. Samba: Simple Hybrid State Space Models for Efficient Unlimited Context Language Modeling. *arXiv preprint arXiv:2406.07522* (2024).
- [33] Jiacheng Ruan and Suncheng Xiang. 2024. Vm-unet: Vision mamba unet for medical image segmentation. *arXiv preprint arXiv:2402.02491* (2024).
- [34] Uriel Singer, Haggai Roitman, Yotam Eshel, Alexander Nus, Ido Guy, Or Levi, Idan Hasson, and Eliyahu Kiperwasser. 2022. Sequential modeling with multiple attributes for watchlist recommendation in e-commerce. In *Proceedings of the Fifteenth ACM international conference on web search and data mining*. 937–946.
- [35] Fei Sun, Jun Liu, Jian Wu, Changhua Pei, Xiao Lin, Wenwu Ou, and Peng Jiang. 2019. BERT4Rec: Sequential recommendation with bidirectional encoder representations from transformer. In *Proceedings of the 28th ACM international conference on information and knowledge management*. 1441–1450.
- [36] Jiaxi Tang and Ke Wang. 2018. Personalized top-n sequential recommendation via convolutional sequence embedding. In *Proceedings of the eleventh ACM international conference on web search and data mining*. 565–573.
- [37] Bartłomiej Twardowski. 2016. Modelling contextual information in session-aware recommender systems with neural networks. In *Proceedings of the 10th ACM Conference on Recommender Systems*. 273–276.
- [38] Jianling Wang, Raphael Louca, Diane Hu, Caitlin Cellier, James Caverlee, and Liangtie Hong. 2020. Time to Shop for Valentine’s Day: Shopping Occasions and Sequential Recommendation in E-commerce. In *Proceedings of the 13th International Conference on Web Search and Data Mining*. 645–653.
- [39] Chuhan Wu, Fangzhao Wu, Tao Qi, Chenliang Li, and Yongfeng Huang. 2022. Is news recommendation a sequential recommendation task?. In *Proceedings of the 45th international ACM SIGIR conference on research and development in information retrieval*. 2382–2386.
- [40] Zhaohu Xing, Tian Ye, Yijun Yang, Guang Liu, and Lei Zhu. 2024. Segmamba: Long-range sequential modeling mamba for 3d medical image segmentation. *arXiv preprint arXiv:2401.13560* (2024).
- [41] Wenwen Ye, Shuaiqiang Wang, Xu Chen, Xuepeng Wang, Zheng Qin, and Dawei Yin. 2020. Time matters: Sequential recommendation with complex temporal information. In *Proceedings of the 43rd international ACM SIGIR conference on research and development in information retrieval*. 1459–1468.
- [42] Shuai Zhang, Yi Tay, Lina Yao, Aixin Sun, and Jake An. 2019. Next item recommendation with self-attentive metric learning. In *Thirty-third AAAI conference on artificial intelligence*, Vol. 9.
- [43] Zihuai Zhao, Wenqi Fan, Jiatong Li, Yunqing Liu, Xiaowei Mei, Yiqi Wang, Zhen Wen, Fei Wang, Xiangyu Zhao, Jiliang Tang, et al. 2024. Recommender systems in the era of large language models (llms). *IEEE Transactions on Knowledge and Data Engineering* (2024).
- [44] Kun Zhou, Hui Yu, Wayne Xin Zhao, and Ji-Rong Wen. 2022. Filter-enhanced MLP is all you need for sequential recommendation. In *Proceedings of the ACM web conference 2022*. 2388–2399.