MARM: Unlocking the Future of Recommendation Systems through Memory Augmentation and Scalable Complexity

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ABSTRACT

Scaling-law has guided the language model designing for past years, to estimate expected model performance with respect to the size of learnable parameters and training samples data-scales, e.g. GPTs. It is worth noting that the scaling laws of NLP cannot be directly applied to recommendation systems due to the following reasons: (1) The amount of training samples and model parameters is typically not the bottleneck for the model. Our recommendation system can generate over 50 billion user samples daily, and such a massive amount of training data can easily allow our model parameters to exceed 200 billion, surpassing many LLMs (about 100B). (2) To ensure the stability and robustness of the recommendation system, it is essential to control computational complexity FLOPs carefully. In training, we need to process a vast number of recommendation samples every day. During online inference, we usually need to respond within milliseconds (LLMs are usually a few seconds). Considering the above differences with LLM, we can draw a conclusion that: for a RecSys model, compared to model parameters, the computational complexity FLOPs is the more expensive factor that requires careful control.

In this paper, we propose our milestone work, **MARM** (Memory Augmented Recommendation Model), which explores a new cache scaling-laws successfully. By caching part of complex module calculation results, Our MARM extends the single-layer attention-based sequences interests modeling module to a multiple-layer setting

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with minor inference complexity FLOPs cost (i.e, module time complexity $\mathcal{O}(n^2*d) \to \mathcal{O}(n*d)$). Equipped with the cache idea, our MARM solution significantly overcomes computational bottlenecks, and could seamlessly empower all user sequences interest extracting modules, and even other models. To support our MARM, we construct a 60TB cache storage center for offline training and online serving. Comprehensive experiment results show that our MARM brings offline 0.43% GAUC improvements and online 2.079% play-time per user gains. Our MARM has been deployed on Kwai short-videos platform, serving tens of millions of users daily.

CCS CONCEPTS

• Information systems \rightarrow Recommender systems.

KEYWORDS

Scaling-Laws; Cache Technique; Low-Resource Large Model;

ACM Reference Format:

1 INTRODUCTION

In recent years, the scaling of model size and data-scale has been a vital point in various fields, e.g., NLP, CV, and RecSys. According to OpenAI Scaling-laws technique report[9], the volume of data and the breadth and depth of models increase, the performance of the models follows a certain power-law improvement. Following the excited Scaling-laws tenet, many Transformer-based large models are proposed and achieve remarkable performance, e.g., ChatGPT for conversation, Qwen-VL[2] for multi-modal understanding, DeepSeek-Coder[7] for code generation, and Kling for Video generation. There are also some efforts to valid Scaling-laws

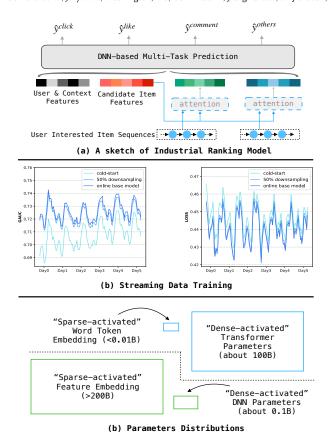


Figure 1: (a) A toy example of ranking model. (b) Performance gap in Streaming Data Training. Warming up from the online base model, a 50% sample downsampling leads to a continuous decline in model performance. On the other hand, there is a significant performance gap between a cold-start model trained from scratch and the online base model, but the gap decreases as the training data increases. (c) Parameter distributions. The parameters of an LLM model (blue) mainly are located in 'dense-activated' transformer-based DNN module, while ranking models (green) have a parameter distribution primarily composed of 'sparse-activated' feature embeddings.

in RecSys area (e.g., Wukong[19], HSTU[18]), but these methods make strong assumptions on features engineering or model architectures, e.g., remove all statics features, replace entire model modules by Transformer. Actually, the common wisdom always formed RecSys ranking model designing as follows: first crafting hundreds elaborated features as model input and then use multitask prediction module to obtain the click/like/comment/others scores for a user and item candidate pair (in Figure 1(a)). Nevertheless, the recent RecSys Scaling-laws studies are greatly changing such learning paradigms, which is difficult to directly deploy them in real online RecSys ranking models. In this paper, we focus on exploring the Scaling-laws under the above wide-used ranking model architecture. Due to differences in ranking model architecture and

usage with pure Transformer-based LLMs, we conclude three elements that the reasons why NLP Scaling-laws do not match to RecSys ranking model:

- For the training samples: different from NLP models having a stable data corpus to train an LLM from scratch, the industrial RecSys model always follows a streaming training paradigm. At Kuaishou, our model is streaming trained over 50 billion user logs daily, here we give three model variants training details, e.g., the 'online base model', 'online base model with 50% training data downsampling', and 'cold-start', where the 'online base model' is trained over years. From Figure 1(b), we can draw conclusions that: (1) training from scratch will hurt performance significantly; (2) although the model parameters is warm-start from a several years well-trained model, down-sampling the real-time training samples will still have performance degradation. Such phenomenons validate the RecSys model is data-hunger for infinite data to capture real-time users' preferences. Therefore, the analysis of training data-scale is unnecessary in industry.
- For the learning parameters: As shown in Figure 1(c), instead of LLM parameters are mainly located in 'dense-activated' Transformer-based DNN module (about 100 Billion) but with a small 'sparse-activated' word token parameters (<0.01B). Ranking models always have contrary parameter distribution that: the major learnable parameters are concentrated on the 'sparseactivated' feature parameters (>200B) while 'dense-activated' DNN parameters space (about 0.1B) is much smaller. Where the 'sparse' means only small part parameters will activate to involve calculating (i.e., we only need to look up few words tokens for a sentence in LLM; we only need to look up one user/item ID for a user-item training sample in RecSys), and the 'dense' means the calculation flow parameters that will fully activate to estimate final results. Indeed, in terms of the amount of learnable parameters, our ranking model (> 200B) far exceeds many LLMs (around 100B), which indicates that learnable parameters are not the bottleneck of ranking models.
- For the inference complexity, FLOPs: Actually, the RecSys model inference complexity FLOPs is much smaller than LLM and has its upper bound. This is because our model needs to process hundreds of millions of requests efficiently, and that's why our dense-activate DNN module is much smaller (about 0.1B). Hereby we could not blindly increase the inference complexity, to ensure our service's stability and robustness of processing each request in milliseconds (LLMs are usually a few seconds).

Based on the analysis of the above three aspects, compared to LLM, we can observe that our ranking model has its **advantages** and *disadvantage* are: (1) 'unlimited' streaming data, (2) massive parameter storage, (3) relatively low-FLOPs DNN module. In other words, for ranking model, the data and storage resources are cheap relatively, but inference computing resources are cautiously expensive. Motivates by such point, we consider that can we use the model the strengths in data and storage bootstrapping its weakness in computing. In other words, can we cache part of complex module calculation results to degenerate its time complexity?

To answer the question, we propose our milestone work, MARM (Memory Augmented Recommendation Model), which achieves a

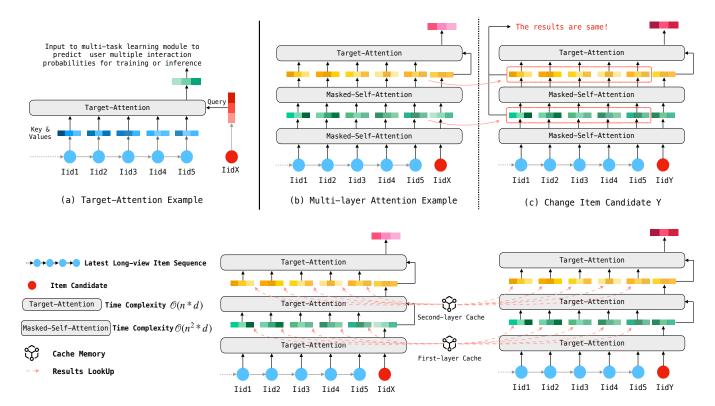


Figure 2: Motivation of MARM, using caching idea to reduce higher-FLOPs self-attention to lower-FLOPs target-attention.

new RecSys scaling-laws between the cache size and model performance. At MARM, we extend one of the most important user interests extraction modules in industry ranking model, which aims to calculate users historical item importance with the candidate item, as shown at the bottom of Figure 1(a). To the best of our knowledge, in implementing this module, many outstanding methods (e.g., DIN[23], SIM[11], SDIM[3], TWIN[4]) are utilized a single-layer target-attention mechanism, as shown in Figure 2(a). Intuitively, such module could be further enhanced by stacking multi-layer self-attention before the final target-attention, as shown in Figure 2(b). Unfortunately, the self-attention mechanism time complexity $\mathcal{O}(n^2 * d)$ is much higher than target-attention mechanism time complexity $\mathcal{O}(n * d)$ (*n* denotes the sequence length, d denotes representation dimension), which is more sensitive on longer sequences (e.g., n>1000) and will result in a large increasing in FLOPs. In online-serving, our ranking model needs to predict 50~8000 user/item-candidate pairs at same time to find the best dozens items for a user, causing the naive multi-layer attention mechanism will produce a lot of repeated calculations, which will bring heavy pressure for our system (in Figure 2(c)).

If we cache the frequently used masked self attention module results, the complex masked self attention layer can be replaced by the simple target attention layer to efficiently predict different item candidates well, as shown in Figure 2(d). In this way, our MARM extends the single-layer attention-based sequences interests modeling module to a multiple-layer setting with minor inference complexity

FLOPs cost. Specifically, our MARM solution significantly overcomes computational bottlenecks, and could seamlessly empower all user sequences interest extracting modules. Moreover, based on the MARM cache results, we find it can contribute to other models, such as retrieval and cascading models. In our experiments, we fully explore the scaling-laws between cache size and model performance, seeking a perfect balance in terms of cached attention depth, sequence length and embedding dimension.

The main contributions of this work are:

- We give detailed reasons why the scaling-laws of NLP do not match the ranking scenario, and we are the first work to explore new scaling-laws under the wide-used ranking model architecture from a fresh cache-performance perspective.
- We devise a simple-yet-efficient approach, MARM, which utilizes
 the strengths of ranking model in data and storage to degenerate complex masked-self-attention time complexity that we
 successfully extend the single-layer attention-based sequences
 interests modeling module to a multiple-layer setting with minor
 inference complexity FLOPs cost.
- We show our MARM is highly adaptable and scalable, seamlessly
 integrating into existing high-performance transformer-based
 models, and facilitating a smooth transition towards GPT-style
 models. Besides, extensive experiments and comparative ablation
 studies were conducted offline&online (average improves 0.43%
 GAUC offline & 2.079% play-time per user online).

2 METHODOLOGY

In this section, we do not explain the total details of our ranking model's architectures or losses, its sketch illustration is shown in Figure 1(a). Specifically, for better understanding, we dive into the MARM module and explain how it works only. We first introduce the base MARM workflow, then the MARM with SIM extensions, and finally show MARM how to improve other models. Further, we also discuss the cache scaling-law and management strategies, seeking a balance between model complexity and performance.

2.1 MARM Workflow

This section describes MARM workflow under the latest exposure item sequence, to build a multi-layer decoder-only Transformer architecture to capture user interests with respect to a certain target item. Actually, our MARM mainly consists of four parts:

- (1) A sequence generator to produce items exposed to user.
- (2) An external cache memory storage to look up or save results.
- (3) Multi-layer target-attention module to calculate results.
- (4) Sending the intermediate results to cache store.
- 2.1.1 Sequence Generator. Given arbitrary user ID UidX, we assume that our sequence generator could produce his/her latest exposure item sequence in chronological order as:

$$[\operatorname{Iid1}, \dots, \operatorname{Iidn}] = \operatorname{ExposureSeqGen}(\operatorname{UidX}, n). \tag{1}$$

where *n* denotes sequence length, the [Iid1,...,Iidn] is the behavior sequence for user UidX. Of course, since our sequence has clear user feedback, we can also choose to use items that meet certain conditions. For example, we might only use items that have a long-view label.

- 2.1.2 Cache Memory Storage Look-Up. As shown in Figure 2, given UidX's sequence [Iid1,..., Iidn] and item candidate IidY, there are two type representations is need to support our MARM: the learnable ID-based embedding and un-learnable cached results.
- (1) **Learnable embedding**: In RecSys, ID-based embedding is a part of model sparse-activated feature that can look up directly:

$$\label{eq:lidY} IidY = SparseFeatureLookUp(IidY), \\ [Iid1, ..., Iidn] = SparseFeatureLookUp([Iid1, ..., Iidn]). \end{aligned} \tag{2}$$

where $\mathbf{IidY} \in \mathbb{R}^F$, F is a hyper-parameter to control the feature dimension. The $[\mathbf{Iid1}, \dots, \mathbf{Iidn}]$ is the the bottom target-attention input in Figure 2(a). It is worth noting that viewed items could fulfill some other attributes, such as author ID, tags, and user interaction labels. In this paper, for simplicity, we will only retain the item ID to represent them.

(2) **Un-Learnable Cached results**: Considering that we have cached *L*-layer intermediate results in an external key-value memory storage, here we need to look up those results precisely. Therefore, we devise a hash strategy to generate 'key' to reflect the meaning: cached value of user-item pair at layer *i*. for example, given user UidX, and item sequence [Iid1,...] and layer depth *i*, we could generate the hash key list as:

$$[Iid1^{i}_{UidX},...] = UserItemDepthHash(UidX, [Iid1,...], i).$$
 (3)

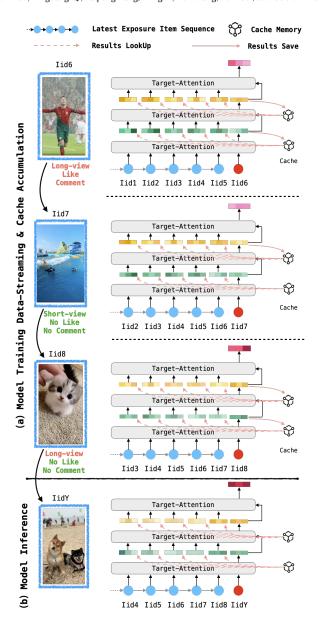


Figure 3: MARM workflow

where the $\mathtt{Iid1}^i_{\mathtt{UidX}} \in \mathbb{Z}$ denotes the Hash-key to access the correct unique cache result. Based on them, we have:

$$[\operatorname{Iid1}_{\operatorname{UidX}}^{i}, \dots] = \operatorname{MARMCacheLookUp}([\operatorname{Iid1}_{\operatorname{UidX}}^{i}, \dots]) \tag{4}$$

where $\mathbf{Iid1}^i_{\mathsf{UidX}} \in \mathbb{R}^d$, and d is attention module dimension. As a result, combining all layers' cache results we have:

$$\begin{bmatrix} \mathbf{Iid1}_{\mathtt{UidX}}^1 & \mathbf{Iid2}_{\mathtt{UidX}}^1 & \mathbf{Iid3}_{\mathtt{UidX}}^1 & \cdots & \mathbf{Iidn}_{\mathtt{UidX}}^1 \\ \mathbf{Iid1}_{\mathtt{UidX}}^2 & \mathbf{Iid2}_{\mathtt{UidX}}^2 & \mathbf{Iid3}_{\mathtt{UidX}}^2 & \cdots & \mathbf{Iidn}_{\mathtt{UidX}}^2 \\ \vdots & \vdots & \vdots & \vdots \\ \mathbf{Iid1}_{\mathtt{UidX}}^L & \mathbf{Iid2}_{\mathtt{UidX}}^L & \mathbf{Iid3}_{\mathtt{UidX}}^L & \cdots & \mathbf{Iidn}_{\mathtt{UidX}}^L \\ \end{bmatrix}$$

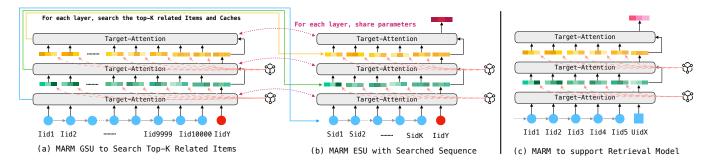


Figure 4: Using the MARM framework to handle long sequences with SIM GSU/ESU; Example to support Retrieval Model.

Algorithm 1 MARM Training and cache accumulation procedure.

```
Input: n denotes sequence length, L denotes depth of MARM, d denotes dimension
Output: Updated MARM Cache Storage.
 1: while (UidX, IidY, ) from data-streaming do
          #####SEQUENCE GENERATION#####
          [Iid1, ..., Iidn] = ExposureSeqGen(UidX, n)
           #####PREPARE MARM INPUT#####
          IidY = ModelSparseFeatureLookUp(IidY)
           [Iid1, ..., Iidn] = ModelSparseFeatureLookUp([Iid1, ..., Iidn])
 8:
               [\mathtt{Iid1}^i_{\mathtt{UidX}}, \ldots, \mathtt{Iidn}^i_{\mathtt{UidX}}] = \mathtt{UserItemDepthHash}(\mathtt{UidX}, [\mathtt{Iid1}, \ldots], i)
               \big[ \mathbf{Iid1}_{\mathtt{UidX}}^{i}, \ldots, \mathbf{Iidn}_{\mathtt{UidX}}^{i} \big] = \mathtt{MARMCacheLookUp}\big( \big[ \mathtt{Iid1}_{\mathtt{UidX}}^{i}, \ldots \big] \big)
 9:
10:
11:
           #####MARM FORWARD#####
          IidY^1_{\texttt{UidX}} = \texttt{Target-Attention}(IidY, [Iid1, \dots, Iidn])
12:
          for i from 1 \rightarrow L do
13:
              \mathbf{IidY}_{\mathtt{UidX}}^{i+1} = \mathtt{Target-Attention}^i(\mathbf{IidY}_{\mathtt{UidX}}^i, [\mathbf{Iid1}_{\mathtt{UidX}}^i, \ldots, \mathbf{Iidn}_{\mathtt{UidX}}^i])
14:
15:
          #####SAVE RESULTS TO CACHE MEMORY####
16:
          \big[ \mathtt{IidY}^1_{\mathtt{UidX}}, \dots, \mathtt{IidY}^L_{\mathtt{UidX}} \big] = \mathtt{UserItemDepthHash}(\mathtt{UidX}, \mathtt{IidY}, [1, \dots, L])
17:
18:
          \texttt{MARMCacheSave}([\texttt{IidY}^1_{\texttt{UidX}},\ldots,\texttt{IidY}^L_{\texttt{UidX}}],[\texttt{IidY}^1_{\texttt{UidX}},\ldots,\texttt{IidY}^L_{\texttt{UidX}}])
19: end while
```

2.1.3 Multi-Layer Target-Attention. Up to now, we have obtained the learnable target-attention ID embedding and subsequent unlearnable target-attention cached results. According to the learnable embedding, we first calculate them with respect to a certain target item information IidY through target attention mechanism:

$$IidY^{1}_{IiidX} = Target-Attention(IidY, [Iid1, ...]),$$
 (5)

Next, we feed the results $\mathbf{IidY}^1_{\mathsf{UidX}} \in \mathbb{R}^d$ to calculate with unlearnable cached results to simulate the high-FLOPS masked-self-attention $(\mathcal{O}(n^2*d))$ by the low-FLOPS target-attention $(\mathcal{O}(n*d))$:

$$\begin{split} & \mathbf{IidY}_{\mathsf{UidX}}^2 = & \mathsf{Target-Attention}^1(\mathbf{IidY}_{\mathsf{UidX}}^1, [\mathbf{Iid1}_{\mathsf{UidX}}^1, \dots]), \\ & \mathbf{IidY}_{\mathsf{UidX}}^3 = & \mathsf{Target-Attention}^2(\mathbf{IidY}_{\mathsf{UidX}}^2, [\mathbf{Iid1}_{\mathsf{UidX}}^2, \dots]), \\ & \qquad \qquad \dots \\ & \mathbf{IidY}_{\mathsf{UidX}}^{L+1} = & \mathsf{Target-Attention}^L(\mathbf{IidY}_{\mathsf{UidX}}^L, [\mathbf{Iid1}_{\mathsf{UidX}}^L, \dots]), \end{split}$$

where the $\operatorname{IidY}^{L+1}_{\operatorname{UidX}} \in \mathbb{R}^d$ denotes the final sequences interests modeling output belongs to (UidX, IidY) pair, which will feed to latter multi-task learning module to fit a real label.

2.1.4 Sending results to Cache Memory. The above sections have introduced our MARM calculating process, next we will explain how to save such intermediate results to the cache store. In a similar way, we first generate the 'hash key' to indicate the result meaning,

```
e.g., the (UidX, IidY) result at different layers [1, ..., L]:
```

$$[\operatorname{IidY}^1_{\operatorname{UidX}}, \dots, \operatorname{IidY}^L_{\operatorname{UidX}}] = \operatorname{UserItemDepthHash}(\operatorname{UidX}, \operatorname{IidY}, [1, \dots, L]). \quad (7)$$

Afterwards, we can send the values with their keys in order:

$$\texttt{MARMCacheSave}([\texttt{IidY}^1_{\texttt{UidX}},\ldots,\texttt{IidY}^L_{\texttt{UidX}}],[\texttt{IidY}^1_{\texttt{UidX}},\ldots,\texttt{IidY}^L_{\texttt{UidX}}]) \ \ (8)$$

In streaming training, as we continuously save the real-time computation results, our MARM cache will gradually accumulate the computation results of each layer of the model for all of the user's historical behaviors. Through the natural accumulation of cache, our MARM successfully applies decoder-only Transformer architecture with minor inference complexity FLOPs cost. The pseudo-code of our MARM is shown in Algorithm 1, and Figure 3 also provides a user-watching example in streaming setting.

2.2 MARM with SIM

In Section 2.1, we have discussed a naive MARM setting, modeling the users' interests under the latest watched items sequence. However, since the sequence length n in Eq.(1) is limited (about 100), thus the earlier stored results will no longer be used once out of range, resulting in a waste of storage resources. This section further extends MARM with Search-based interests model (SIM)[11], to maximize Cached results effectiveness.

Formally, SIM proposes a two-stage cascading modeling paradigm: (1) introduce a coarsen General Search Unit (GSU) to retrospect user life-long history (e.g. >10000) for target item, and then search the top-K most related item sequences; (2) employ fine-grained Exact Search Unit (ESU) to compress the searched sequence information to obtain precise user interests with respect to target item. In past years, SIM has been the vital engine for ranking model iteration, and the recent effort is TWIN, which utilizes the shared GSU and ESU modules for two-stage unbiased modeling. Inspired by the TWIN, we also considering applying a synchronous GSU module to **search the top-K related cache results for each layer** (as shown in Figure 4(a)). Given the latest long-term sequence [Iid1,..., Iid10000] of user UidX, the MARM GSU aims to generate the multi-layer searched input sequences, for example:

$$[\operatorname{Sid1}^{i}, \dots, \operatorname{SidK}^{i}] = \operatorname{MARMGSU}(\operatorname{IidY}, [\operatorname{Iid1}, \dots, \operatorname{Iid10000}], K, i), \tag{9}$$

where the MARMGSU shared same Target-Attention parameters with our ranking model ESU, and the [Sid1,...,SidK] is the top-K

highest attention weights items sequence regarding to item candidate IidY. Combining all layers' searched keys, we can formulate:

$$\begin{bmatrix} \operatorname{Sid1} & \operatorname{Sid2} & \operatorname{Sid3} & \dots & \operatorname{SidK} \\ \operatorname{Sid1}^1 & \operatorname{Sid2}^1 & \operatorname{Sid3}^1 & \dots & \operatorname{SidK}^1 \\ \operatorname{Sid1}^2 & \operatorname{Sid2}^2 & \operatorname{Sid3}^2 & \dots & \operatorname{SidK}^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \operatorname{Sid1}^L & \operatorname{Sid2}^L & \operatorname{Sid3}^L & \dots & \operatorname{SidK}^L \end{bmatrix}$$

where the different layer searched sequence maybe different e.g., $Sid1^i \neq Sid1^{i+1}$. Afterwards, we can look up their corresponding cached results to support our MARM module in Figure 4(b).

2.3 MARM to Support Other Models

Actually, the industrial RecSys always introduces several models to filter items candidates layer by layer:

- Retrieval model: without item candidate, only utilizing user's latest interaction items to find a **thousands** items group from the full billion item pool.
- Cascading model: a small ranking model, utilizing extremely
 efficient modules to select top **hundreds** item candidates from
 the retrieval model generated thousands of items candidates.
- Ranking model: in a broad sense, it is the most complex model, to find the best dozens items from hundreds of candidates.

Generally, these models are trained using different strategies and are isolated from each other. Therefore, here is an interesting assumption: can such our ranking model MARM cache storage contribute to other Retrieval/Cascading models? Unsurprisingly, we found our MARM results could support them seamlessly:

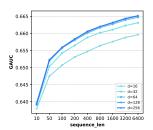
- For Retrieval model, since there is no candidate set of items, we use user's latest 200 watched items to look up the cache results from MARM, and then apply the user ID feature to replace item candidates to conduct target-attention as shown in Figure 4(c).
- For Cascading model, we implement a same multi-layer targetattention process as our Ranking model in Eq.(6). It is important to note that in the cascading model, we do not perform re-accumulation of the MARM cache; instead, we directly use the already accumulated MARM cache. This approach saves resources while also enhancing the consistency between cascading and ranking models. However, due to limited computational power, we also only used latest short-term sequences of users, rather than GSU searched cache results for each item candidate.

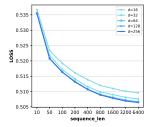
3 CACHE SCALING-LAWS

In this section, we will explore a new Scaling-Laws to unlock the future of RecSys, the MARM's Cache Scaling-Laws.

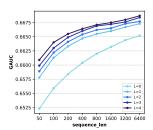
3.1 Evaluation Setting

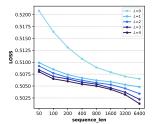
3.1.1 Datasets. To evaluate the effectiveness of our MARM, we conduct detailed experiments at Kuaishou's international business (Kwai). To be specific, this short-video scenario includes approximately 30 million users and 62 million short videos, with each user reading an average of 133 short videos per day. We collect past 6 months logs of this scenario, and then conduct the common multi-task learning with naive MARM setting (without SIM) in streaming training manner.



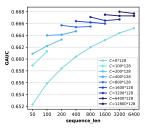


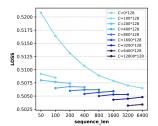
(a) Model performance of dimension d and length n scaling up while keeping L=0





(b) Model performance of depth L and length n scaling up while keeping d=128





(c) Model performance of cache size C scaling up

Figure 5: Model performance of MARM scaling up.

3.1.2 Metrics. For brevity, we present the GAUC and training loss of the **long-view prediction task only** to reflect the model's performance. Indeed, GAUC has been validated on Kuaishou as a metric most closely related to online effectiveness, which employs a weighted average of the AUC for each user, where the weights are determined by the number of samples for that user:

$$GAUC = \sum_{u} w_{u}AUC_{u} \quad \text{where } w_{u} = \frac{\log s_{u}}{\text{total_logs}}, \tag{10}$$

We show the average GAUC and training loss of the last day.

3.2 Discussion of Cache Scaling Laws

Before going on, we first present an important concept, the **cache size** C = L * n * d, where L is the attention layer depth of MARM, n is the length of the item sequence, and d is the representation dimension. It is worth noting that the computational complexity and storage size of the cache size are both linearly proportional, which ensures that the increase in FLOPs is offset by the efficiencies gained from the cache techniques.

3.2.1 Scaling up the dimension d and sequence length n. Generally speaking, the influence of the representation dimension d on

Table 1: Offline comparison with SOTAs. Each module is added individually to the baseline model. The best and runner-up results are highlighted in bold/underlined.

	$\mathrm{AUC}(mean\pm std)$	$\mathrm{GAUC}(mean \pm std)$
Baseline	0.8233 ± 0.0001	0.7093 ± 0.00005
DIN	0.8235 ± 0.00019	0.7010 ± 0.00012
SIM Soft	0.8241 ± 0.00004	0.7109 ± 0.00007
TWIN	0.8249 ± 0.00005	0.7142 ± 0.00009
TWIN V2	$\underline{0.8251 \pm 0.00023}$	0.7147 ± 0.00007
MARM(L=1)	0.8256 ± 0.00008	0.7157 ± 0.00006
MARM(L=2)	0.8262 ± 0.0004	0.7169 ± 0.00012
MARM(L=4)	0.8270 ± 0.0003	0.7183 ± 0.00008
Improvement	0.19%	0.36%

modeling effectiveness is related to the features used and the complexity of the dataset. To prevent a combinatorial explosion, we performed a grid search on the representation dimension d and sequence length n without our MARM module (i.e., L=0, equivalent to DIN, with one layer of target attention). As shown in Figure 5(a), we can see that once the d reaches 128, further increases have a minimal impact on performance. Therefore, in the following, we fix the dimension d=128 to conduct more comprehensive analyses.

3.2.2 Scaling up the depth L and sequence length n. As shown in Figure 5(b), we can see a significant positive correlation to increase MARM depth L and sequence length n. Additionally, it is observed that when the length of the user's behavior sequence increases, even reaching 6400, increasing the MARM depth L still could lead to a notable improvement in model performance, which validates caching the intermediate results is a potential way to unlock new direction to build better RecSys.

3.2.3 Scaling up the cache size \mathcal{C} . Based on the above studies, we further analyzed the relationship between the model's performance with the cache size C. Specifically, we draw several lines to represent same Cache size and FLOPs variants but with different settings, e.g., 400^*128 has three variants 4^*100^*128 , 2^*200^*128 , and 1^*400^*128 . As shown in Figure 5(c), there is a noticeable power-law improvement trend in model performance when the cache size is increased. An interesting phenomenon is that when the cache size is small, increasing the sequence length n yields significantly better results than increasing the depth L, e.g., 200^*128 . However, once the cache size reaches a certain level, the effects of increasing sequence length and MARM depth become comparable, which leads to an excited observation that models with same enough Cache size will show similar performance, e.g., 6400^*128 .

3.3 Real-World Experiments

This section focuses on answering the following research questions:

- **RQ1**: How does MARM perform compared to other sequence modeling algorithms?
- RQ2: How does MARM bring improvements to the industry ensemble model?
- RQ3: How does the SIM idea work as expected in MARM?
- RQ4: What are the costs associated with MARM?

Table 2: Ensemble comparison with SOTAs. If each module brings a significant gain in confidence, it will be added one by one. Taking TWIN V2 as an example, it includes the Baseline, DIN, SIM Soft, TWIN, and TWIN V2.

	$\mathrm{AUC}(mean\pm std)$	GAUC (mean \pm std	
Baseline	0.8233 ± 0.0001	0.7093 ± 0.00005	
DIN	0.8235 ± 0.00019	0.7010 ± 0.00012	
+SIM Soft	0.8251 ± 0.00004	0.7111 ± 0.00008	
+TWIN	0.8260 ± 0.00005	0.7156 ± 0.00006	
+TWIN V2	0.8268 ± 0.00023	0.7167 ± 0.00011	
+HSTU*	0.8268 ± 0.00017	0.7168 ± 0.00021	
+MARM(L=1)	0.8270 ± 0.00023	0.7180 ± 0.00020	
+MARM(L=2)	0.8272 ± 0.00019	0.7191 ± 0.00021	
+MARM(L=4)	0.8286 ± 0.00013	0.7210 ± 0.00011	
Improvement	0.22%	0.43%	

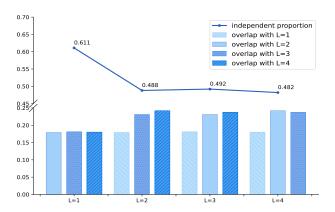


Figure 6: GSU Top-k overlapped rate between different layers.

- **RQ5**: How does MARM contribute to the online gains?
- 3.3.1 Compared Approaches Details. Generally speaking, MARM can be seen as a user sequence modeling module, therefore we select the following strong methods to verify MARM ability:
- Baseline: A model using the multi-task MoE structure with user features, video features, and statistical features, where the user sequence information is the result of sum pooling of the user's short-term historical behavior.
- DIN[23]: The most commonly used algorithm for modeling user short-term historical behavior, utilizing a target attention mechanism. The user history length we are using here is 50.
- SIM Soft[11]: A two-stage modeling approach with GSU-ESU, where GSU uses pre-trained multi-modal embeddings of videos to calculate the inner product and select the top-k most relevant videos from the user's history. The user history length we are using here is 15000.
- TWIN[4]: A two-stage modeling approach under the SIM architecture, aligning the computation methods of GSU and ESU to enhance consistency between the two stages. The user history length we are using is 15,000.
- TWIN V2[13]: This approach uses hierarchical clustering to reduce the scale of ultra-long user historical lengths, followed by

Stages	Watch Time Metrics		Interaction Metrics				
	Average Watch Time	Watch Time	Video View	Like	Comment	Forward	Follow
Retrieval	+0.489%	+0.456%	+0.463%	+0.167%	+0.675%	-0.550%	+0.288%
Cascading	+0.276%	+0.260%	+0.086%	+0.100%	-0.017%	+0.495%	+0.870%
Ranking	+1.314%	+1.370%	+0.103%	+0.605%	-0.669%	-0.114%	-0.227%

Table 3: Online A/B testing results of Short-Video services at Kwai.

modeling using the TWIN method. The user history length we are using is 100,000.

- HSTU*[18]: This method employs an HSTU-style multi-layer self-masked attention mechanism to model user history (time complexity $\mathcal{O}(n^2*d)$). Due to computational limitations, each historical item only uses a few features: item ID, author ID, tag, and user feedback, with a history length of 2000 and an attention depth of 4.
- MARM: Using the MARM with SIM approach, the first layer reuses the existing TWIN module, we then stack MARM modules, with each MARM module storing a length of 6000 and a maximum attention depth *L* of 4¹.

Based on the above approaches, we conducted two types of experiments with respect to the conventions of academics and industry:

- Individual experiment: This way only contains the baseline model and the corresponding method modification.
- Ensemble experiment: After a modification is verified to be effective, such method will be fused with latter modifications.
- 3.3.2 Individual Experiment Performance Comparisons (RQ1). In this section, we introduce different sequence modeling modules into the baseline model, and the experimental results are shown in Table 1. MARM achieves the best performance compared to all the baselines. It is worth noting that although MARM does not use a user history length in the range of 100,000 like TWINV2, but only 6000, its performance still significantly outperforms TWINV2. Thanks to MARM's ability to scale linearly in depth, we can expand the attention depth, not just the sequence length of the users. Furthermore, we can observe that with the increase in attention depth, MARM still shows significant improvement.
- 3.3.3 Ensemble Experiment Offline Performance (RQ2). This section aims to verify the following question: could MARM module provide further improvements to a model that already incorporates various long-term and short-term user behavior modeling? Therefore, we conducted another set of ensemble experiments and the results are shown in Table 2. Specifically, we sequentially added the DIN, SIM Soft, TWIN, TWIN V2, and MARM modules to the baseline, observing the improvements brought by each new module. From this Table, after adding a series of long-term and short-term modeling modules, adding a simplified HSTU-style module did not lead to significant improvements, possibly because the features we used, attention depth, or historical length did not reach a certain scale. Besides, another reason might be that our MARM could save more interaction sample knowledge. While a pure item sequence

has only fewer tens of attributes, the MARM's cached results are always thousand-dimension compressed target item query information, which achieves potential sample communication within MARM. In addition, directly adding an HSTU-style module significantly increased the computational burden on our model. In our scenario, when we add MARM to a system that includes several long-term and short-term sequence modeling models, there is still a significant improvement in accuracy. MARM is a very practical module that can be added to most recommendation models at a very controllable cost.

3.3.4 GSU searched Top-K Overlapped Rate of MARM (RQ3). This section aims to understand how the attention depth of MARM can lead to sustained improvements. In the framework of MARM with SIM, each layer of the MARM Block models the GSU and ESU phases in a manner similar to TWIN. The GSU returns the top-k user histories that are most relevant to the target item. As shown in Figure 6, we analyzed the overlap of the histories returned by the GSU of the four-layer MARM Block and found that the proportion of independence for each layer is relatively high, exceeding 50%. Moreover, the direct overlap between any two layers is less than 20%. This indicates that each layer of MARM focuses on different historical content, forming a high-level expression of interests.

3.3.5 MARM Cost Discussion (RQ4). Improving the attention depth in the user sequence modeling module of recommendation models is a very challenging task. HSTU follows a first sample-aggregation then learning paradigm to alleviate calculation pressure, its overall computational complexity for a user with a lifelong historical behavior is about $O(L*n^2*d*(\frac{N}{r}))$, where N denote the total interaction amount of a user, and r << n is the aggregation level of user samples, meaning that every r user samples are aggregated together for training. In practice, a larger aggregation r typically reduces the modeling complexity but can lead to delays in user feedback entering the model training, and easily results in a decline in online metrics, creating a trade-off between cost and effectiveness.

Compared to the above HSTU applies a high-FLOPs masked-self-attention, our MARM is a more low-resource solution, which does not need to aggregate training samples for user modeling. For the overall learning process of a user, the computational complexity of the MARM is about O(L*n*d*N)). As a replacement, MARM does require additional storage, which we previously referred to as cache size \mathcal{C} . In our scenario, with an attention depth L=4 and a sequence length n=6000, the storage used by MARM is 60TB. The combined storage and increased computational overhead is approximately 1/8 that of a direct multi-layer self-attention approach.

¹Actually, the MARM framework can be stacked based on any existing user sequence modeling module, and of course, we acknowledge that the foundational module will significantly impact the final results.

3.3.6 Online Results (RQ5). To quantify the contribution of the MARM model to Kuaishou's international business (Kwai), we implemented it across the Retrieval, Cascading, and Ranking stages, validating its effectiveness through our online A/B testing system. The model's performance was assessed based on key metrics, including core playtime metrics and interaction metrics such as average watch time per use and the number of likes. Table 3 presents the online results of MARM across various recommendation stages.

Notably, during the fine ranking stage, MARM achieved a significant increase in average user watch time of +1.314% and a watch time gain of +1.370%, highlighting its crucial role in enhancing user watch time. In the Retrieval stage, MARM also demonstrated remarkable gains, with average user watch time and total watch time increasing by +0.489% and +0.456%, respectively. While there were some negative impacts on Comment/Forward/Follow, significant gains were achieved in user interactions through Like, thereby the online results still within a reasonable range of substitution. Furthermore, in the Cascading ranking stage, MARM resulted in a notable increase in average user watch time of +0.276%, with overall interactions remaining largely positive. Overall, our online results demonstrate that our MARM not only could extend Ranking stage, but also enable both the Cascading and Retrieval stages to effectively leverage its computational capabilities.

4 CONCLUSION

We propose the Memory Augmented Recommendation Model (MARM), a multi-layer recommendation model that utilizes Memory Cache to accelerate inference. In recommendation scenarios, computational complexity is a significant performance constraint. We use caching to store partial computation results of complex models, reducing the complexity of single modeling from $\mathcal{O}(n^2 * d) \to \mathcal{O}(n * d)$. Based on the MARM framework, we can extend sequence modeling from single-layer target attention to multi-layer with linear resource consumption, significantly breaking through the computational bottleneck of recommendation models and enabling modeling of users' life-long histories. We explored the scaling law within the MARM framework, confirming a proportional relationship between cache size and recommendation performance. Furthermore, our MARM method can seamlessly integrate with existing recommendation models, including fine ranking, coarse ranking, and recall. Through the MARM series of methods, we achieved 2.079% increase in average app viewing time per user in Kuaishou's overseas operations, demonstrating the effectiveness and practicality of the MARM model. To the best of our knowledge, MARM is the first recommendation model to achieve multi-dimensional scaling in the field of life-long sequence modeling.

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5 APPENDIX

5.1 Related Work

5.1.1 KV Cache Techniques. The KV Cache strategy is based on the observation that the computational complexity of the attention mechanism in Transformers[14] is proportional to the square of the sequence length. By caching the computed K-V pairs, it is possible to avoid redundant calculations and improve the inference speed of large language models. However, the KV Cache strategy faces limitations in terms of storage space when dealing with extremely long sequences. A series of works have thoroughly explored the sparsification of KV Cache. StreamingLLM[15] noted the distribution characteristics of attention weights, which tend to concentrate at the beginning and end of historical sequences, and proposed a sliding window-based KV Cache. H2O[21] recognized the sparse nature of the KV Cache, where a small number of tokens (Heavy Hitters, H2) provide the majority of the weights. Consequently, it proposed a KV Cache eviction strategy (a greedy algorithm) to remove infrequently used or less important cache values, thereby dynamically maintaining a balance between the most recent tokens and H2 tokens. SubGen[17] capitalized on the significant clustering tendency of key embeddings in the attention module to design a caching method with sub-linear complexity. LESS[6] accumulates the information discarded by the sparse strategy into a constantsized low-level cache by learning the residual between the original attention output and the attention output with the sparse strategy, allowing the attention computation to still access previously ignored information.

In addition, there is a series of works focusing on KV Cache sharing techniques. For example, MQA[12] and GQA[1] propose multiquery attention and group query attention, respectively, which group tokens to share KV Cache values. FlashInfer[16] introduces the Recursive Attention method, which uses multi-query attention to compute the shared portion of the document K-V values. Hydragen[8] achieves efficient prefix attention computation through cross-sequence batch queries, thereby decomposing the attention computation sequence into shared prefixes and unique suffixes.

5.1.2 Life-long User Behavior Sequence Modeling. Long-term user behavior modeling is an essential aspect of click-through rate prediction, as it allows for a more nuanced understanding of user preferences over time. Early modeling methods such as DIN[23] and DIEN[22] incorporate attention mechanisms to model users' historical behaviors. Subsequently, MIMN[10] focused on utilizing memory networks to retain user interests over time, enhancing its ability to model user sequences to a level of 1000. Other approaches, such as "User Behavior Clustering and Sampling" (UBCS[20]), aim to simplify the modeling process by sampling sub-sequences from the entire user behavior history, making it more efficient to work with long sequences of user interactions.

Recently, two-stage user interest modeling has been widely applied in the industry. For example, SIM[11] employs a two-stage search architecture to capture user interests. It first retrieves relevant long-term behaviors associated with the target item, followed by modeling short-term interests using the most recent interactions.

resulting in notable enhancements in both scalability and effectiveness when modeling large-scale sequential behavior data for CTR prediction. Building on this foundation, locality-sensitive hashing is used to efficiently retrieve relevant behaviors. For instance, ETA[5] and SDIM[3] investigated locality-sensitive hashing and Hamming distance to effectively retrieve pertinent behaviors.

To further enhance the accuracy of user interest recall and adapt to large-scale data, TWIN[4] and TWIN-V2[13] have implemented a series of innovative measures. TWIN significantly improves retrieval accuracy by employing a consistent target behavior relevance metric across two phases. Additionally, it extends the maximum length of lifelong behavior from approximately 10^3 to 10^4 – 10^5 through the optimization of the target attention mechanism. Building on this foundation, TWIN-V2 further introduces a divide-and-conquer compression strategy and hierarchical clustering techniques, which enhance the accuracy and diversity of recommendations, demonstrating excellent performance in practical applications. These methods effectively address the challenges posed by dynamic user interest changes and data sparsity.

5.2 Cache Strategy Discussion

This section analyzes the differences between our MARM cache technique and NLP KV cache technique. Actually, the NLP KV cache technique is typically applied in the **inference stage** of autoregressive LLM to reduce the time complexity of generating the next token. Nevertheless, our MARM cache technique is used **in both the training stage and the inference stage**. Due to the fundamentally different scenario, we have the following insightful and crucial innovations:

- Cache Generation: Different from NLP KV cache technique
 which generates cache results while predicting the next token in
 model inference process, our MARM generates the cache results
 in training process, which aims to save the positive user-item
 behavior pattern information. In our MARM inference, which is
 shared with training produced cache results, focusing on utilizing
 the saved cache results for better prediction.
- Cache Life-Cycle: In particular, the NLP KV Cache for current sentence generation only needs temporary life-cycle storage in GPU memory. Consequently, once the sentence is generated completely, its corresponding cached data is no longer necessary and cache results will be deleted. Unlike language sentences that have endpoints, in streaming recommendation systems, useritem behaviors are generated sequentially, and our users do not have an 'endpoint' to finish. Thus our MARM Cache should have a long-term life-cycle to store user interests, to ensure that our model can access those cached results at any time to provide high-quality recommendation accuracy.
- Cache Scope: In NLP KV Cache, it focuses on caching all tokens' transformed Key-results and Value-results, waiting for the newcoming Query to aggregate them. In our MARM, we do not cache the transformed Key-results and Value-results, but cache the final calculated Query outputs, which could reduce the overall storage requirement, conserving resources efficiently.