

# HMT: Hierarchical Memory Transformer for Efficient Long Context Language Processing

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## Abstract

Transformer-based large language models (LLM) have been widely used in language processing applications. However, due to the memory constraints of the devices, most of them restrict the context window. Even though recurrent models in previous works can memorize past tokens to enable unlimited context and maintain effectiveness, they have “flat” memory architectures. Such architectures have limitations in selecting and filtering information. Since humans are good at learning and self-adjustment, we believe that imitating brain memory hierarchy is beneficial for model memorization. Thus, we propose the Hierarchical Memory Transformer (HMT)<sup>1</sup>, a novel framework that facilitates a model’s long-context processing ability by imitating human memorization behavior. Leveraging memory-augmented segment-level recurrence, we organize the memory hierarchy by preserving tokens from early input segments, passing memory embeddings along the sequence, and recalling relevant information from history. Evaluating general language modeling, question-answering tasks, and the summarization task, we show that HMT consistently improves the long-context processing ability of existing models. Furthermore, HMT achieves a comparable or superior generation quality to long-context LLMs with  $2 \sim 57 \times$  fewer parameters and  $2.5 \sim 116 \times$  less inference memory, significantly outperforming previous memory-augmented models.

## 1 Introduction

Transformer (Vaswani et al., 2017) has demonstrated its strength in contextual learning and is utilized in various applications in language processing (Dong et al., 2019) and computer vision (Dosovitskiy et al., 2020). For a decoder-only transformer model, each transformer block contains a

self-attention and a feedforward network module. An optimized self-attention layer has a quadratic computational and linear space complexity (Dao et al., 2022) regarding the sequence length since it computes interactions between each token and all previous tokens in the sequence. To maintain the inference speed and satisfy memory requirements, most transformer models enforce maximum sequence length. For example, the Llama 3 model is designed to process 8192 tokens (Dubey et al., 2024) and the Llama 2 can process up to 4096 tokens (Touvron et al., 2023). However, real-world applications involving long documents, such as book summarization (Rae et al., 2019) and lifelong question-answering tasks (Sun et al., 2019; Dai et al., 2022), can have an enormous or even infinite stream of inputs.

Existing research attempts to build long context transformers using sparse attention (Beltagy et al., 2020; Zhang et al., 2021; Kitaev et al., 2020), retrieval-augmented models (Bertsch et al., 2023; Wu et al., 2022), and recurrent sequence models (Peng et al., 2023a; Gu and Dao, 2023; Rae et al., 2019). Still, these models face at least one of two issues: (1) difficulty in adapting to future models due to a change in the core model architecture and (2) low effectiveness for long-range inputs under frequent context switching. In this work, we propose the Hierarchical Memory Transformer (HMT), a novel framework to enable and augment models’ long-context processing ability. HMT transforms models into a memory-augmented recurrent model that imitates the brain’s memory hierarchy and human memorization behavior. It has the following unique features:

**Hierarchical Memorization:** HMT mimics the memory hierarchy of the brain (Burgin, 2011) employing both learned memory tokens and current input tokens. HMT stratifies memory into sensory, short-term, and long-term, with interactions between each other.

<sup>1</sup><https://github.com/OswaldHe/HMT-pytorch>

**Memory Retrieval Mechanism:** HMT imitates memory recall by storing encoded memory embeddings generated from previous iterations and searching based on the relevance to current token segments.

One key advantage of utilizing HMT over other memory-augment models is that HMT is a **model-independent plug-and-play** framework: future decoder-only models can directly serve as the backbone model of HMT to augment their long context processing ability without extra implementation efforts. With joint training and fine-tuning of newly introduced and original parameters of the backbone model, HMT is applicable to a wide range of LLMs, including transformer-based models and state-space models. Our contributions include:

- **HMT consistently improves models’ generation quality with long context for various model architectures.** We demonstrate HMT on both transformer-based architecture and state-space models. Evaluating on WikiText-103, PG-19 (Rae et al., 2019), and PubMedQA (Jin et al., 2019) datasets with multiple contexts concatenated, HMT can improve the effectiveness by up to 25.5% in perplexity and 1.0% higher prediction accuracy over the baseline models.
- **HMT with small backbone models can outperform large models trained on longer context samples, implying a high memory efficiency.** We evaluate HMT with SmoLM (Allal et al., 2024), OPT (Zhang et al., 2022), and OpenLlamaV2 (Geng and Liu, 2023) models on the LongBench (Bai et al., 2023b) benchmark. In sum, HMT can achieve comparable or higher metric results with  $2 \sim 57 \times$  fewer parameters and  $2.5 \sim 116 \times$  lower inference memory requirement than long-context large language models.
- **HMT surpasses previous methods specialized for efficient long-context processing by compressing contexts.** We compare HMT with RMT (Bulatov et al., 2022), LongMem (Wang et al., 2024), Memorizing Transformer (Wu et al., 2022), CCM (Kim et al., 2023), and HOMER (Song et al., 2024), which are recent SoTA of memory-augmented and hierarchical methods. With the same or similar size backbone model, HMT has a better generation quality in both general language modeling and QA tasks. Furthermore, HMT has a lower memory complexity, indicating better scalability as the input length increases.

## 2 Related Works and Problem Formulation

We will first discuss the existing efforts on long-range transformers and recurrent sequence models for infinitely long context language processing. Then, we highlight a problem that is crucial in real-world applications.

### 2.1 Long Context Transformers

Since one of the bottlenecks of transformers is the quadratic computational complexity of self-attention, a natural approach is sparsifying attention computation. A naive sparse attention pattern is the sliding window attention (Kovaleva et al., 2019), where each token attends to neighbors within a local window. However, this neglects long-range interaction between words. Existing works such as Longformer (Beltagy et al., 2020) and Poolingformer (Zhang et al., 2021) extend the sliding window attention by adding global attending tokens and applying pooling to expand the receptive field area. Unlimiformer (Bertsch et al., 2023) adopts the retrieval-augmented generative method by searching the top K most important tokens for the incoming sequence. It then applies attention to just those tokens in the decoders, resulting in pruned computations with minor losses. Nevertheless, the contribution of less relevant tokens may accumulate over time and impact the overall sequence generation. Although these methods extend the attainable context length, they cannot prevent increasing memory consumption as the input length increases. Alternatively, compressing past tokens using a recurrent sequence model can potentially reduce memory consumption by condensing the information into a fixed-size embedding.

### 2.2 Recurrent Sequence Models

Recurrent Neural Networks (RNN) have been extensively explored in sequence processing research, including Long Short-term Memory (Hochreiter and Schmidhuber, 1997) and Gated Recurrent Unit (Chung et al., 2014). They reveal that RNNs perform well in memorizing past information and are hardware-friendly for implementing customized accelerators (Chang et al., 2015). However, RNNs have limited advantages in learning contextual relationships between words compared with self-attention in language processing (Bahdanau et al., 2014). One approach to alleviate this issue is the coarse-grain recurrence, in which the model

splits inputs into segments, performs attention inside each segment, and propagates states (i.e., compressed information as embeddings) between segments. The Compressive Transformer (Rae et al., 2019) further stores and compresses previous states to enhance memorization. The Recurrent Memory Transformer (RMT) (Bulatov et al., 2022) utilizes a memory token to summarize and propagate segment information without modifying the transformer block architecture. Theoretically, they can process unlimited long sequences, but previous information will be diluted after multiple summarizations and generation quality can drop when less relevant information occupies the memory. Recent works (Chevalier et al., 2023; Kim et al., 2023) aim to further optimize RMT to improve generation quality by concatenating the results of summarizations, but this sacrifices the inference memory efficiency.

Another approach augments RNN by involving interactions between the current inputs and the previous states to learn contextual relationships in a similar way as self-attention and accelerate the computation with linear convolution. One of the representatives, RWKV (Peng et al., 2023a), is an RNN model inspired by the attention-free transformer (AFT) (Zhai et al., 2021). It includes a time-mixing module to learn from previous states and a channel-mixing module to learn from the previous output. Mamba (Gu and Dao, 2023) is another recurrent method based on the state-space model that employs gated convolution to accelerate model inference. These models are energy and memory-efficient with fast training speed and are able to achieve high performance in memorization tasks (e.g., associative recall), but have limitations on capturing contextual relationships and filtering irrelevant information. Recent works combine transformers with Mamba (Lieber et al., 2024; Team et al., 2024) to mitigate this issue, but this reintroduces the scaling issue of the transformers.

### 2.3 Problem Formulation: Adaptive Long-context Processing

We intend to develop a model that can handle *infinitely long context* inputs with *context adaptability*: Based on the context/topic of the input stream, the model can adaptively select past relevant information to enhance effectiveness, since irrelevant context can distract the model (Shi et al., 2023).

In real-world applications, restrained by memory bandwidth and capacity, as well as data generation

Table 1: Notation used to illustrate HMT’s architecture in Section 3 and Figure 1.

NOTATION	MEANING
$H_n$	HIDDEN EMBEDDINGS OF THE $n^{th}$ SEGMENT
$L$	SEGMENT LENGTH
$H_n[L-k, L)$	LAST $k$ EMBEDDINGS OF $H_n$
$H_n[0, j)$	FIRST $j$ EMBEDDINGS OF $H_n$
BBM ·	BACKBONE MODEL
$P_n$	MEMORIZATION PROMPT EMBEDDING
$H_n^{out}$	HIDDEN EMBEDDING FOR LOGITS GENERATION
$M_n$	MEMORY EMBEDDING OF THE $n^{th}$ SEGMENT
$N$	NUMBER OF CACHED MEMORY EMBEDDINGS
$M_{[n-N+1, n]}$	CACHED MEMORY EMBEDDINGS
$T$	SEGMENT SUMMARIZATION PROMPT EMBEDDING
$S_n$	SUMMARY EMBEDDING OF THE $n^{th}$ SEGMENT

speed, long documents cannot be read as a whole by the computing hardware (Agerri et al., 2015). Furthermore, users who are constantly interacting with the language model can refer to the previous topic or switch to another topic that has high relevance to past information. For effectiveness, most recurrent models need to encode all previous inputs in the states, which can contain irrelevant information and degrade the model’s quality.

## 3 Hierarchical Memory Transformer

The main idea of HMT is to store information hierarchically and search for relevant information throughout the memory hierarchy. Table 1 describes all notations we use to illustrate the HMT architecture in this section.

### 3.1 Overall Workflow

Given a backbone model to enhance, HMT chunks the input into  $L$ -token segments and operates on the hidden embeddings of the token segments ( $\{H_n\}_{n=0}^{\infty}$ ), generated by the token embedding layer of the backbone model. For every segment  $n$ , HMT walks through four steps shown in Figure 1:

- 1) *Representation encoding* by the backbone model, which encodes part of the segment containing the essence of the ongoing topic into a single embedding to represent its context, denoted by  $H_n$ .
- 2) *Memory search*, which utilizes the current context as a query to find relevant information in the memory.
- 3) *Prepending sensory memory*, which augments the segment to capture information in the previous segment and other relevant information.
- 4) *Decoding and summarization*, which processes the augmented segment to get hidden embeddings

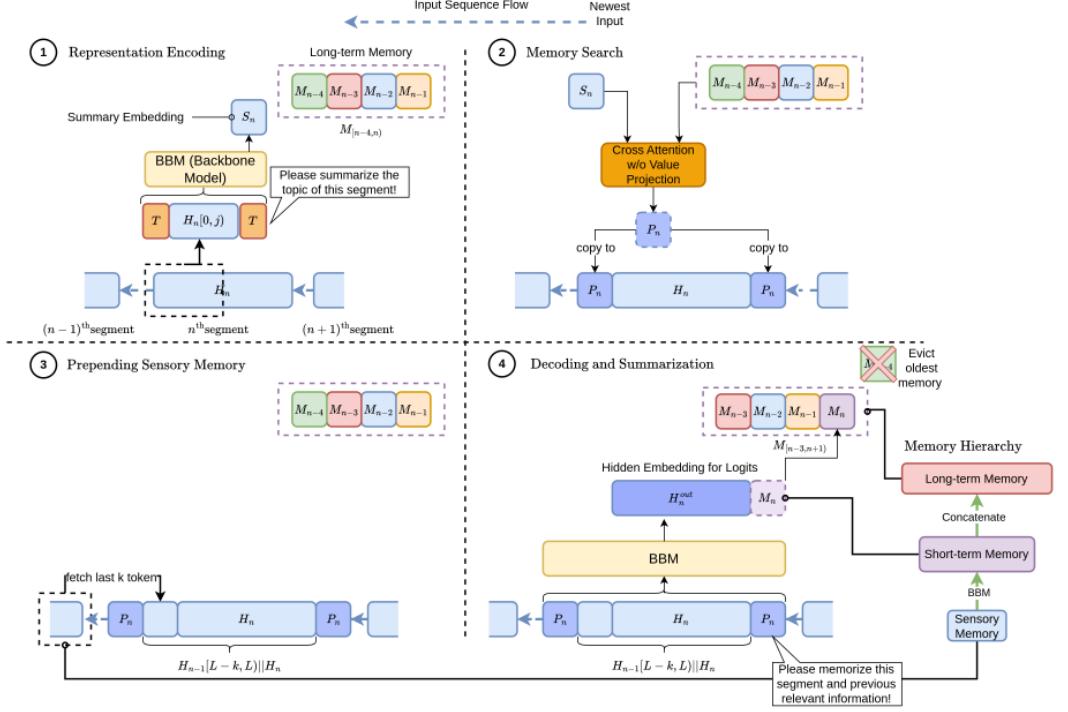


Figure 1: Overall workflow of HMT. For a segment, (1) HMT will first perform **representation encoding**, utilizing the segment summarization prompt embedding ( $T$ ) to summarize part of the segment. (2) The generated segment summary embedding ( $S_n$ ) is used with the cached memory embeddings for **memory search** with cross attention. The output is a memorization prompt embedding ( $P_n$ ) which contains information relevant to the current segment. (3) The memorization prompt embedding and the last  $k$  embeddings from the previous segment will augment the segment. (4) The backbone model (BBM) will process the augmented segment and generate hidden embeddings for logits ( $H^{out}$ ) and the memory embedding ( $M_n$ ), which will be pushed into the long-term memory.

for generating logits and a memory embedding that summarizes the augmented segment.

The first two steps are the *memory retrieval mechanism* discussed in Section 3.2. Steps 3 and 4 are explained in Section 3.3 along with the concept of hierarchical memorization.

### 3.2 Memory Retrieval Mechanism

To handle context switching and prevent the intervention of irrelevant context, HMT performs memory retrieval to extract only relevant information from past knowledge. The memory retrieval mechanism involves three steps: representation extraction, memory search, and memory augmentation.

**Representation Encoding:** Depicted in Step 1 of Figure 1, HMT selects the first  $j$  embeddings from the hidden embeddings of the  $n^{th}$  segment,  $H_n$ , to extract the topic of the segment. The embeddings are augmented with the **segment summarization prompt embedding**  $T$ .  $T$  is a learnable parameter embedding, deployed to prompt the backbone model (BBM) to summarize the segment

by soft prompt tuning (Liu et al., 2023). Instead of extracting from the token embedding of BBM, we make  $T$  learnable to allow a larger prompt embedding space for summarization. The backbone model will then process the augmented embeddings and generate a new embedding at the end of the output as the representation of the segment:

$$S_n = \text{BBM } [T || H_n[0, j) || T][j, j + 1] \quad (1)$$

where  $S_n$  is the summary embedding of the  $n^{th}$  segment only,  $\text{BBM } (\cdot)$  is the backbone model, and “||” is the concatenation operator.  $S_n$  will be used for memory search.

**Memory Search:** Shown in Step 2 of Figure 1,  $S_n$  is utilized as a query to find relevant memory embeddings generated from Step 4 when processing previous segments. We keep a sliding window of  $N$  embeddings ( $M_{[n-N+1, n]}$ ) and then compute:

$$Q_n = S_n W_q, K_n = M_{[n-N+1, n]} W_k \quad (2)$$

$$P_n = \text{softmax } \frac{Q_n K_n^T}{\sqrt{d_h}} M_{[n-N+1, n]} \quad (3)$$

where  $d_h$  is the hidden dimension of the cross attention. The computation is similar to cross-attention without value and output projection. Softmax  $\frac{Q_n K_n^T}{\sqrt{d_h}}$ ) calculates the normalized similarity score and applies it directly to  $M_{[n \dots N+1]n}$  to ensure similar distributions of output value and old memory tokens. We expect that the projection  $W_q$  and  $W_k$  can be trained such that summarizations containing similar contexts have high attention scores after projections.

The output of a memory search is a **memorization prompt embedding**  $P_n$  containing information relevant to the  $n^{th}$  segment. It will be applied to augment the  $n^{th}$  segment. Notice that HMT’s memory is accumulative: the  $n^{th}$  memory embedding contains information of all previous  $n - 1$  segments, with a higher loss of information for older segments. We hope that retrieving memory will strengthen the relevant memory and reduce this loss.

In practice, representation encoding is executed in parallel with the model inference on GPUs since they are independent tasks. Memory search has time complexity  $O(N)$ , and can also run in parallel with the segment inference when  $N$  is small (e.g.,  $N = 300$ ). Thus, the overall runtime overhead of HMT is negligible.

### 3.3 Hierarchical Memorization

Human memory can be categorized into three strata: sensory memory, short-term memory, and long-term memory (Burgin, 2011). Sensory memory refers to very short-term memory generated from sensory information, such as vision and hearing. Short-term and long-term memory are long-lasting memories, differentiated by how long they persist in the brain. HMT is inspired by this memory hierarchy.

**Sensory Memory:** Sensory memory for the  $n^{th}$  segment refers to the last  $k$  token embeddings of  $H_{n-1}$ ,  $H_{n-1}[L-k, L]$ . When inferencing the  $n^{th}$  segment, HMT will augment the corresponding token embeddings  $H_n$  by prepending it with  $H_n[L-k, L]$ , shown in Step 3 of Figure 1.

**Short-term Memory:** HMT will encode the segment into an embedding that serves as a “summarization” of the segment. First, HMT will append and prepend the memorization prompt embedding  $P_n$  to the augmented segment. This guides the backbone model to compress the segment and relevant context into a summarization embedding with

awareness of the relative positions of contexts. As depicted in Step 4 of Figure 1, we train HMT such that

$$H = \text{BBM } P_n || H_{n-1}[L-k, L] || H_n || P_n \quad (4)$$

$$H_n^{out} || M_n = H[k+1, L+k+2] \quad (5)$$

where  $M_n$  is the memory embedding of the  $n^{th}$  segment.  $H_n^{out}$  is a collection of  $L$  hidden embeddings that will be used to generate logits.

**Long-term Memory:** Each generated memory embedding will be cached as the long-term memory. The cached embeddings will be utilized as the input of the *memory retrieval mechanism* to generate the memorization token embedding  $P_n$  for each segment as illustrated in the previous sections.

## 4 Experiment

We benchmark HMT with a variety of backbone models including SmollM 135M (Allal et al., 2024), OPT 350M, OPT 2.7B (Zhang et al., 2022), OpenLlamaV2 3B (Geng and Liu, 2023), RWKV 3B (Peng et al., 2023a), and Llama 2 7B (Touvron et al., 2023), under the same memory constraint (i.e. same maximum context window). Moreover, we test several models targeting long contexts (Mamba 370M (Gu and Dao, 2023), Yi-6B-200K (Young et al., 2024), and Mistral 7B (Jiang et al., 2023)) to demonstrate the benefit HMT has on generation quality and memory consumption. We evaluate HMT with state-space models (RWKV and Mamba) as backbones since we believe that models which can already process infinitely long inputs would benefit even further from HMT. All models mentioned are trained and assessed on **4 MD MI210 GPUs**, which can handle models up to 7B parameters. We further test HMT on 4 NVIDIA A100-80GB GPUs for the Qwen 2.5 14B model (Bai et al., 2023a) to justify its scalability to larger models and gain a consistent effectiveness boost. To tune the extra parameters introduced by HMT, we use the RedPajamaV2 (Computer, 2023) dataset to pre-train each model. Notice that HMT introduced new model hyperparameters on top of the backbone model ( $L$ ,  $j$ ,  $N$ , and  $k$ ). A common configuration is  $L = 1024$ ,  $j = 512$ ,  $N = 300$ , and  $k = 32$ , and we adjust these values for each model to achieve the best performance. To compare with previous works (RMT, LongMem, Memorizing Transformer, CCM), we apply the same backbone models if the method is applicable to any

model, or find a backbone model with a similar size if the method requires special architecture.

For the long-context benchmark, we select subsets (NarrativeQA, Qasper, and MultiFieldQA-en for single document QA; HotpotQA, 2WikiMQA, and MuSiQue for multi-document QA; GovReport, QMSum, and Multi-News for summarization; TriviaQA for few-shot learning) from a widely acknowledged benchmark, LongBench (Bai et al., 2023b), and measure them against models reported in the LongBench leaderboard. However, the maximum average document length of test sets in LongBench is shorter than 20k words, which is not very long for modern long-context models. To better understand HMT’s long-context processing ability under various context scenarios, we further study HMT on crafted and controllable dataset samples. For crafted datasets, we derive from existing datasets to form long inputs. For general language tasks, models are tested for next token generation tasks with Wikitext-103 (Merity et al., 2016) (2-3k words per sample) and PG-19 (Rae et al., 2019) datasets (69k words per sample on average). Samples will be concatenated or split into chunks to form longer samples and investigate the relationships between input length and the effectiveness of the model. For question-answering tasks, we chose PubMedQA (Jin et al., 2019), which is a biomedical question-answering dataset with corresponding contexts. We artifact the dataset to assess HMT with multi-context inputs, described in Appendix I.

## 5 Results and Key Observations

In this section, we illustrate the main result of HMT. More ablation studies are in Appendix E and G.

### 5.1 Impacts on Backbone Models

By introducing an additional  $0.5\% \sim 1.3\%$  ( $1.77M \sim 33.5M$ ) of parameters, HMT can enhance models with a variety of architectures to improve generation quality when processing long context inputs. We demonstrate this feature with general language modeling and question-answering tasks.

**HMT consistently improves the backbone models in general language modeling tasks when processing long inputs.** Figures 2 and 3 compare the perplexity of OPT 2.7B, RWKV 3B, and OpenLlamaV2 3B models with and without HMT on the Wikitext-103 and PG-19 datasets. Over input spanning from  $2k \sim 100k$  tokens, HMT consistently raises the generation quality of all these models.

Table 2: Scalability of HMT. Average PPL is computed by taking the average PPL for samples in each sequence length in the experiment.

MODEL	Avg Test PPL (WIKITEXT) (↓)
OPT 350M	15.11
HMT + OPT 350M	14.28 (-5.8%)
OPT 2.7B	12.12
HMT + OPT 2.7B	8.61 (-28.9%)
RWKV 430M	19.33
HMT + RWKV 430M	16.10 (-16.6%)
RWKV 3B	13.30
HMT + RWKV 3B	9.93 (-25.3%)

Moreover, Table 2 presents how improvements are achieved by HMT scales with the model size for same-family models. To further strengthen our argument that HMT can benefit larger models, we evaluate HMT with Qwen 2.5 14B utilizing 4 A100-80GB GPUs for training. As depicted in Figure 4, HMT can still increase the effectiveness of the backbone model on PG-19.

Notice that the improvement is not necessarily contributed solely by the additional parameters. Having more parameters does not always lead to higher performance. For example, HMT boosts OPT 2.7B to realize a lower perplexity than OpenLlama 3B with 20.7% fewer parameters, while OPT 2.7B performs worse without HMT. Section 5.2 describes more examples of HMT achieving superior generation quality with smaller models.

**HMT enhances long-answer contextual reasoning and short-answer prediction ability in question-answering tasks.** One of the use cases of HMT is handling question-answering tasks that involve multiple contexts. Thus, we select the PubMedQA dataset and derive long-context QA samples with controllable context counts to evaluate the effectiveness of HMT. Two metrics are employed: for long answers, we compute the PPL to assess the contextual reasoning of HMT; for short answers, we measure the response accuracy. As seen in Figures 5 and 6, for samples with 2 to 10 contexts, HMT increases the effectiveness in PPL by 9.48% for long answers. For short answer tasks, HMT is 1.0% more accurate than the backbone model and exhibits significant advantages when samples have more contexts. In sum, HMT increases both the correctness and reasoning ability of models in long-context QA tasks.

### 5.2 Comparison to Long Context Models

Combined with small and short-context models, HMT can be more effective than large models



Figure 2: Test Perplexity of HMT, RMT, and three baseline models (OPT 2.7B, RWKV 3B, OpenLlamaV2 3B) with the WikiText-103 dataset. HMT outperforms RMT by 13.0% for OPT and 10.8% for OpenLlamaV2. For RWKV, HMT can even boost the effectiveness by 16.5%, while RMT worsens the effectiveness.

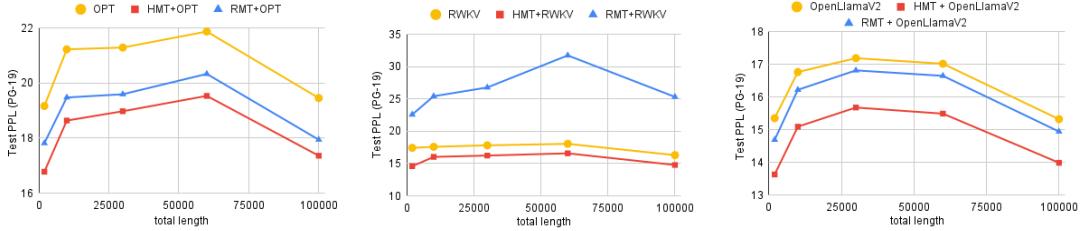


Figure 3: Test Perplexity of HMT, RMT, and three baseline models (OPT 2.7B, RWKV 3B, OpenLlamaV2 3B), evaluated over the PG-19 dataset. HMT outperforms RMT by 3.98% for OPT and 6.85% for OpenLlamaV2. For RWKV, HMT can improve the effectiveness by 9.96%.



Figure 4: Test Perplexity of HMT, RMT, and baseline model for Qwen 2.5 14B on PG-19 dataset. HMT boosts the effectiveness of the baseline model by 10.0%, while RMT worsens its effectiveness.

trained on long-context inputs. Table 3 displays metric results of HMT-augmented models on subsets of LongBench (Bai et al., 2023b) and compares them with large models specialized for long contexts. The subsets contain various generation tasks, including single/multi-document QA, summarization, and few-shot learning. With a significantly lower inference memory requirement, HMT applied to small models can attain comparable or better metrics compared to large models, indicating a significant resource advantage. Specifically, we observe that HMT with small models performs well in generating short responses for long and multi-context inputs, thanks to its context-filtering ability. However, it exhibits comparable or weaker performance in generating long responses, as small models have shorter token generation limits com-

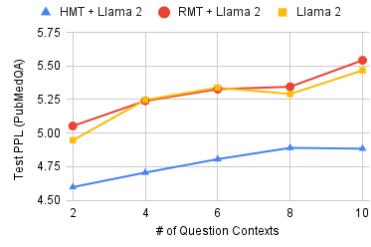


Figure 5: Long answer quality of RMT and HMT applied on Llama-2 7B, evaluated over PubMedQA dataset. HMT is 8.98% more effective than RMT.

pared to large models.

Moreover, applying HMT to long-context models can further improve their effectiveness and reduce inference memory consumption. For example, the AMD MI210 GPU cannot handle inferencing 30k token inputs with the Yi-6B-200K model due to memory constraints. Applying a sliding window strategy with a 5.2K-token window (Yi-6B-SW-5.2K), the model consumes 44.8 GB VRAM. On the contrary, HMT + Yi-6B-200K requires only 33.9 GB VRAM to process 30k tokens with a small segment length (512 tokens), with a 2% effectiveness improvement. Table 4 presents the effectiveness of long-range models on WikiText-103 compared with several HMT-augmented models, including Mamba and Mistral models.

<sup>2</sup>Although this model is trained with 200K-token samples, it cannot be run on MI210 due to memory constraints.

Table 3: Metric results of HMT-augmented small models and large models trained on longer contexts. Models with HMT can process infinitely long context, but only keep a fixed length of KV cache (the value in the parenthesis). We evaluate on subsets of LongBench, including QMSum (QMS), MuSiQue (MSQ), Qasper (QASP), NarrativeQA (NQA), MultiFieldQA-en (MFQA-en), GovReport (GR), TriviaQA (TQA), HotpotQA (HQA), 2WikiMQA (2WMQA), and MultiNews (MN). Mem Req indicates the minimum inference memory required (to store parameters and KV cache). Actual inference may require a larger VRAM.

MODEL	CONTEXT WINDOW	QMS	MSQ	QASP	NQA	MFQA-EN	GR	TQA	HQA	2WMQA	MN	MEM REQ (GB ↓)
GPT-3.5 TURBO	16384	23.4	26.9	<b>43.3</b>	23.6	52.3	29.5	91.4	51.6	37.7	26.7	46.7
LLAMA 2 7B CHAT	4096	20.8	9.4	19.2	18.7	36.8	27.3	77.8	25.4	32.8	25.8	15.1
LONGCHAT V1.5 7B	32768	22.7	9.7	27.7	16.9	41.4	30.8	82.3	31.5	20.6	26.4	22.6
XGEN 7B	8192	20.5	10.3	18.1	18.0	37.7	27.3	77.8	29.7	21.1	26.2	16.2
INTERNLM 7B	8192	15.9	9.0	16.7	12.1	23.4	9.7	77.8	28.7	21.1	22.8	16.2
CHATGLM2 6B	32768	<b>24.0</b>	21.9	31.5	21.1	46.2	32.4	78.7	45.1	34.0	26.5	19.5
VICUNA V1.5 7B	16384	22.8	9.8	26.1	19.4	38.5	27.9	86.2	25.3	20.8	27.2	18.3
CHATGLM3 6B	32768	23.9	40.4	<b>43.3</b>	<b>26.0</b>	51.7	<b>36.8</b>	87.1	<b>54.4</b>	<b>44.9</b>	<b>27.9</b>	19.5
HMT + OPT 350M	∞ (1024)	22.2	32.3	17.2	<b>62.7</b>	13.8	87.2	25.3	29.2	10.5	0.75	
HMT + OPENLLAMAV2 3B	∞ (512)	21.4	<b>42.3</b>	35.7	21.6	58.1	15.8	<b>93.0</b>	29.9	27.7	11.0	6.1
HMT + SMOLLM 135M	∞ (1024)	19.4	14.1	30.2	19.6	48.1	15.7	81.3	27.6	23.3	9.5	<b>0.4</b>
BENCHMARK AVERAGE LEN	(WORDS)	10614	11214	3619	18409	4559	8734	8209	9151	4887	2113	

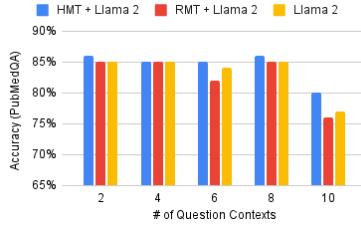


Figure 6: Short response accuracy of RMT and HMT applied on Llama-2 7B, evaluated over PubMedQA dataset. HMT is 1.8% more accurate than RMT.

Table 4: Quality of long context models and HMT with various backbone models. The input size is 30k tokens and the dataset is Wikitext-103.

MODEL	MAX CONTEXT	TEST PPL (WIKITEXT)
RWKV 3B	∞	13.13
MAMBA 370M	∞	87.08
YI-6B-200K	200K	OOM <sup>2</sup>
YI-6B-SW-5.2K	200K	6.89
MISTRAL-7B	32K	5.47
HMT + OPT 350M	∞ (1024)	13.67
HMT + OPENLLAMAV2 3B	∞ (512)	7.04
HMT + RWKV 3B	∞ (256)	10.94
HMT + MAMBA 370M	∞ (256)	16.71
HMT + YI-6B-200K	∞ (512)	6.75
HMT + MISTRAL-7B	∞ (512)	5.12

### 5.3 Comparison to Memory-augmented and Hierarchical Methods

One popular memory-augmented model is the recurrent memory transformer (Bulatov et al., 2022) (RMT). Our assessment indicates that HMT is generally better at both language modeling and question-answering tasks than RMT, illustrated in Figures 2, 3, 5, and 6. The improvement gap is especially significant for recurrent models such as RWKV. HMT can further increase the effectiveness of RWKV while RMT will degrade the performance for both datasets, as demonstrated in

Figure 3. Since RWKV has already compressed past tokens and passed hidden states along the sequence, applying RMT to RWKV re-weights past information compressed in states periodically. This was originally done by the time-mixing module of RWKV. Therefore, the advantage of memory augmentation is limited. Due to the gradient vanishing issue, the model is harder to train with RMT, leading to inferior performance. However, we believe that the memory retrieval mechanism in HMT helps RWKV to select previous hidden states with the most relevance, boosting its effectiveness. Another advantage of HMT over RMT is its scalability with large models: while RMT applied to Qwen 2.5 14B results in reduced effectiveness compared to direct inference with the backbone model, HMT continues to enhance effectiveness, as illustrated in Figure 4.

Furthermore, compared with other memory-augmented models, HMT is not only easy to use but also has higher generation quality. Table 5 picks three memory-augmented methods (Memorizing Transformer (Wu et al., 2022), LongMem (Wang et al., 2024), and CCM-concat (Kim et al., 2023)) and compares them with HMT with the same or similar-sized backbone models. We choose the datasets used by the original works for fair comparisons. Memorizing transformer and LongMem require modifying the core architecture of the base model. Future models cannot easily adopt such modifications. Overall, HMT outperforms these methods. We also list the inference memory overhead complexity for each model, where  $L$  is the total context length,  $l_i$  is the inference segment length,  $l_m$  is the memory size ( $L > l_m > l_i$ ), and  $t$  is the number of memory embeddings con-

Table 5: Comparison between HMT with previous memory-augmented methods (Memorizing Transformer, LongMem, and CCM-concat).

MODEL	TEST PPL (WIKITEXT, 30K TOKEN)	MEM OVERHEAD
MEMTRM	31.51	$O(L)$
HMT + OPT 350M	<b>13.67</b>	$O(l_i)$
MODEL	TEST PPL (ARXIV, VARIABLE)	MEM OVERHEAD
LONGMEM	10.08	$O(l_m)$
HMT + QWEN1.5-0.5B	<b>9.02</b>	$O(l_i)$
MODEL	TEST PPL (PG-19, 60K TOKEN)	MEM OVERHEAD
CCM-CONCAT	7.41	$O(t + l_i)$
HMT + LLAMA 2 7B	<b>7.40</b>	$O(l_i)$

catenated for CCM-concat. HMT has the lowest memory complexity over all previous methods.

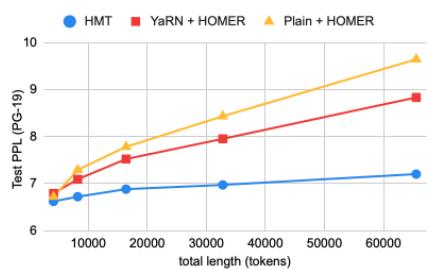


Figure 7: Comparison between HMT and HOMER without context extension and with YaRN, all applying on Llama 2 7B. On average, HMT is 9.9% more effective than HOMER with YaRN on PG-19.

Lastly, we compare HMT with HOMER (Song et al., 2024), a method that hierarchically compresses inputs to reduce their length for inference. In terms of memory complexity, HOMER requires  $O(\log L)$  memory to store the reduction tree, leading to increased peak memory utilization as input length grows. In contrast, HMT maintains a constant peak memory complexity regardless of input length. Regarding effectiveness, HMT achieves 9.9% lower perplexity on PG-19 compared to HOMER with YaRN (Peng et al., 2023b) for context extension. As shown in Figure 7, the benefits of HMT become more substantial as input length increases, highlighting its superior scalability with longer inputs.

## 6 Conclusion

We present HMT, a framework to augment models’ long-range language processing ability with context switching. Inspired by the brain’s memory hierarchy, HMT imitates human memorization behavior by deploying hierarchical memory and the memory retrieval mechanism. HMT consistently improves the generation quality of the backbone models. Compared with other long-context LLMs

and memory-augmented models, HMT achieves higher generation quality with lower memory requirements. Our model provides LLM accessibility to resource-constrained applications and represents a step forward to lifelong language tasks.

## 7 Limitations and Ongoing Works

- Currently, HMT will save  $N$  memory embeddings for memory search, which is a cross-attention layer. When  $N$  is small (e.g.,  $N = 300$ ), which is already sufficient for 100k token samples, the overhead is negligible. However, when  $N$  grows and the memory embeddings are stored in different physical memory hierarchies, the overhead can be significant. An intelligent memory prefetching mechanism can potentially alleviate the latency overhead, which we leave as future work.

- Due to the large computational graph of models when training with BPTT, tuning the extra parameters introduced by HMT can be memory-consuming, impeding experiments on larger-scale models. A more efficient way to extend BPTT depth without memory overhead is a future research direction.

- Although HMT employs only one level of long-term memory, one may use multiple levels of long-term memory to improve information access efficiency. Similar techniques have been used for multilevel optimization in VLSI physical design (Cong and Shinnerl, 2013; Chan et al., 2005).

## 8 Ethical Statements

The capability of memorizing information by HMT offers convenience to people’s daily lives, while also raising concerns about privacy leakage through conversation with language model agents. Nevertheless, with further efforts to deploy it on edge devices without network connections, this issue can be resolved.

## Acknowledgement

This research is partially supported by the PRISM (000705769) center under the JUMP 2.0 program by DARPA/SRC and NSF SEED funding. It is also supported by CDSC industrial partners (<https://cdsc.ucla.edu/partners>) and the AMD HACC Program.

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## Other Related Works

The memory-augmented long-context transformer has been an active research topic in recent years. LongMem (Wang et al., 2024) chunks the long-document input into segments and caches the attention keys and values for each segment. During the inference of a segment, LongMem will select relevant key-value embedding pairs by computing the attention score between token embeddings and the cached key embeddings and fuse the top k embeddings. Memorizing Transformer (Wu et al., 2022) also caches the key-value embedding pairs similar to LongMem, but utilizes a kNN search to retrieve information similar to Unlimiformer. RET-LLM (Modarressi et al., 2023) employs prompt engineering to store the informative context in a database and search keywords when the context involves questions. Memory<sup>3</sup> (Yang et al., 2024) compresses segments of tokens into “explicit” memory blocks and stores them directly into a memory bank for retrieval. While these works can precisely retrieve contexts, they are not scalable due to the **increasing memory consumption** of storing long contexts without compression. Segment-level recurrent models, such as EMMA (Moro et al., 2023), Memformer (Wu et al., 2020), and Transformer-XL (Dai et al., 2019), attempt to compress memory throughout the recurrence to reduce memory consumption. EMMA composes long-term memory from multiple short-term memory by linear combination and concatenates long and short-term memory to augment the segments. Transformer-XL propagates the compressed memory states derived from the attention of current layers to the previous layers for every iteration. Memformer augments the attention with the stored memory embeddings per time step and retrieves information using the cross-attention layer of the encoder-decoder model. However, Memformer employs a forgetting network to remove irrelevant context similar to LSTM, which can potentially delete useful contexts for unseen inputs. On the other hand, HMT condenses contexts into embeddings and retrieves information precisely without requiring a forgetting network to remove information permanently. Also, some of these works, including Memorizing Transformer, Memformer, TransformerXL, and Unlimiformer, need to fundamentally change the model architecture or inject new adapters based on different base model architecture. It makes deployment and extension to future LLMs very expensive. HMT avoids this issue by having a model-independent plug-and-play framework.

## B Comparison to LongMem

Unlike HMT, LongMem (Wang et al., 2024) operates on the key and value caches of each layer of the model and requires caching long caches to capture distant context. To compare with LongMem, we pick the Qwen1.5-0.5B (Bai et al., 2023a) model as the backbone model and train HMT by 700 steps with 4 segments over 100 samples of the ArXiv subset of the Pile dataset (Gao et al., 2020). The subset has 15.4K tokens on average and 60K tokens on maximum per sample, as (Wang et al., 2024) described. Due to the large storage consumption of the training subset of the Pile dataset, we only extract the ArXiv subset in the validation and test split. HMT is trained on the validation set and tested on the test set. Table 6 illustrates that HMT + Qwen1.5-0.5B realizes lower PPL, with a smaller parameter size and in-memory length (number of memory embeddings, which is the number of key and value embeddings cached for LongMem). This indicates that HMT is memory efficient.

Table 6: Effectiveness of LongMem (Wang et al., 2024) and HMT + Qwen1.5-0.5B models over ArXiv subset of the Pile dataset. With HMT, the Qwen1.5-0.5B model can obtain better effectiveness with fewer parameters and shorter memory, after 700 steps of update. The result for LongMem comes from the original paper. Subscription is the standard deviation.

MODEL	# PARAMS	SEGMENT LENGTH	IN-MEMORY LENGTH	TEST PPL (ARXIV)
LONGMEM	558M	1K	65K	10.08
HMT + QWEN1.5-0.5B	463M	1K	300	9.02 <sub>±0.04</sub>

Table 7: Training and fine-tuning configurations for the backbone models (OPT 350M, Mamba 370M, OPT 2.7B, RWKV 3B, OpenLlamaV2 3B, Llama 2 7B, Yi-6B-200K, and Mistral 7B) and the modified model after applying RMT and HMT. S1 and S2 denote the first stage and the second stage of multi-stage training for HMT. 4 AMD MI210 GPUs cannot train larger models. The given learning rate is the starting learning rate and will decay by a factor of 0.9 for OPT, OpenLlamaV2, and RWKV models and 0.7 for the remaining models for every 100 steps. The batch size is 2.

MODEL	INPUT LENGTH	SEGMENT LENGTH	LEARNING RATE	TRAINING STEPS	EXTRA PARAM
OPT 350M / SMOLLM 135M	2048	1024	1E-5	700	1.77M (0.5% - 1.3%)
	+RMT	1024	1E-5	700	
	+HMT (S1)	1024	1E-5	200	
	+HMT (S2)	1024	1E-5	500	
OPT 2.7B / OPENLLAMA V2 3B	2048	512	1E-5	700	13.1M (0.5%)
	+RMT	512	1E-5	700	
	+HMT (S1)	512	1E-5	200	
	+HMT (S2)	512	1E-5	500	
RWKV 3B	1280	256	1E-5	700	13.1M (0.5%)
	+RMT	256	1E-4	700	
	+HMT (S1)	256	1E-5	200	
	+HMT (S2)	256	1E-5	500	
LLAMA 2 7B	2048	256	1E-4	700	33.5M (0.5%)
	+RMT	256	1E-4	700	
	+HMT (S1)	256	1E-4	200	
	+HMT (S2)	256	1E-4	500	
MAMBA 370M	1536	256	1E-4	700	4.1M (1.1%)
	+HMT (S1)	256	1E-4	200	
	+HMT (S2)	256	1E-4	500	
YI-6B-200K / MISTRAL 7B	2048	-	2E-4	700	33.5M (0.5%)
	+HMT (S1)	512	2E-4	200	
	+HMT (S2)	512	2E-4	500	

## C Comparison to Unlimiformer

There are two major differences between a previous retrieval-augmented model, Unlimiformer ([Bertsch et al., 2023](#)), and HMT in terms of the memory retrieval mechanism:

- Unlimiformer retrieves the information with kNN search over the collection of encoded token segments, while HMT uses cross-attention. We believe there are several advantages of employing cross-attention: (1) Attending Top K’s most similar token segments still introduces information loss. Regarding the self-attention layer, the aggregation of tokens with less similar encodings may positively contribute to the quality of the final output. On the other hand, cross-attention fuses all cached hidden embeddings, weighted by the relative similarity, which captures the whole context. (2) The output of the cross-attention is a single embedding, which has lower computational overhead compared to attending k extra tokens.
- Each cached memory embedding encodes the current token segment and the previous memory embedding in HMT. Therefore, HMT can capture the whole context even with a limited number of cached embeddings. Memory recall is mainly used to rescale the importance of past information. On the other hand, the Unlimiformer needs to store all encodings, which is memory-consuming.

In terms of usage, Unlimiformer targets encoder-decoder models and injects retrieval modules into the backbone model. Although the authors recently added support for decoder-only models for token generation, only the Llama model architectures ([Touvron et al., 2023](#)) can be applied and the training/evaluation procedure is not specified. This is one of the biggest challenges for Unlimiformer to adapt to future LLMs for validation and generation. On the contrary, HMT focuses on decoder-only models. Since HMT does not inject new modules in the backbone model, it is effortless to adapt to future LLMs.

## D HMT, RMT, and Baseline Training Details and Hyperparameters

Table 7 are the training configurations of the backbone models and HMT/RMT.

The baselines are assessed using the sliding window attention for context-constrained models to control the memory consumption for a fair comparison. Due to the limited VRAM of GPUs, we shrink the

segment length for the larger backbone model. Also, increasing memory token size does not improve the effectiveness as (Bulatov et al., 2022) suggested. Thus, both RMT and HMT apply memory tokens with a length of 1. For RMT, we utilize the maximum BPTT unroll depth with the best effectiveness that the GPUs can handle. HMT is trained with the multi-stage training technique illustrated in Section F. The first stage (S1) is trained with 2 segments, and the second stage (S2) is trained with the maximum BPTT unroll depth that the GPUs can manage. The size of long-term memory is 300 (i.e.,  $N = 300$ ) for OPT, SmoLLM, OpenLlama, Yi, and Mistral models and 400 ( $N = 400$ ) for the rest of the models to capture sufficient contexts and we summarize half of the segment for representation extraction (i.e.,  $j = L/2$ ). We observed that the benefit of increasing  $N$  is diminishing and stops at 300 for 100k token inputs, described in Appendix E. We select the learning rate for HMT, RMT, and the baseline to optimize the effectiveness. Furthermore, HMT preserves 32 tokens ( $k = 32$ ) from the previous segment as the sensory memory. All models are trained with 700 steps, which is sufficient to converge the training loss. For models with HMT, we first pretrain the model with RedPajamaV2 (Computer, 2023) with 700 steps, then finetune the model for the downstream tasks with 700 steps. For LongBench, the evaluation metrics are the same as the original work and we use the Huggingface evaluate package to compute Rouge-L and F1 score. For parameter-efficient training, LoRA (Hu et al., 2021) with rank 8 is applied to models with high training memory consumption (Llama 2 7B, Mamba 370M, Yi-6B-200K, and Mistral 7B). For the rest of the models, we finetune all parameters in the backbone model. All experiments are done with 3 random seeds and we take the average metrics.

## E ablation Study

We conduct ablation studies regarding the memory retrieval mechanism to demonstrate that (1) memory retrieval is beneficial, (2) partial summarization of a segment in memory retrieval can speed up inference while maintaining similar effectiveness, and (3) caching more memory embedding can raise the effectiveness of HMT.

**Impact of memory retrieval mechanism.** Figure 8 displays the advantages of having a memory retrieval mechanism in HMT for long context input with context switching. For any tested input length, the effectiveness of HMT with memory retrieval outperforms that without memory retrieval. Furthermore, when the memory retrieval mechanism is deployed, the effectiveness improves for the OPT 350M backbone model or tends to improve for the OPT 2.7B backbone model as the input sequence length grows, demonstrating better scalability of HMT.

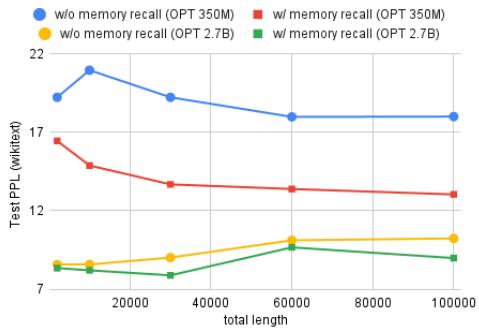


Figure 8: Effectiveness of HMT with and without the memory retrieval mechanism for OPT 350M and 2.7B as the backbone models. The inputs are extracted from the Wikitext-103 dataset with up to 100k tokens.

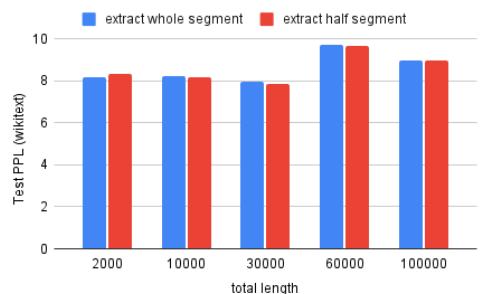


Figure 9: Effectiveness of HMT with OPT 2.7B when performing representation extraction on the whole segment for half of the segment. The impact is negligible, justifying that summarizing half of the segment is a valid method for inference acceleration.

**Impact of summarizing partial segment in memory retrieval.** To overlap or reduce the inference time of the previous segment with the representation extraction of the next segment, it is necessary to prefetch only the first  $l$  tokens in the segment for summarization. In the experiment, we select half of the segment for representation extraction. We examine the model that extracts the whole segment and

compare the effectiveness, depicted by Figure 9. The impact is negligible. We hypothesize that the start of a segment contains enough information about the overall topic for memory retrieval, which is intuitive as humans can capture the concepts by browsing keywords or segments instead of reading the whole paragraphs.

**Impact of limited cached memory embeddings.** Due to memory constraints, we only cache the most recent 300 memory embeddings for memory retrieval. Figure 10 depicts the relationship between the number of cached memory embeddings and the effectiveness of HMT with Llama 2 7B over the Wikitext-103 dataset with 100k-token samples. We observed that increasing the window of cached memory benefits the effectiveness, but the improvement becomes marginal. We hypothesize that HMT is more likely to recall recent memory embeddings in the Wikitext-103 dataset. Figure 11 plots the frequency distribution of the distance between the current segment and the segment corresponding to the memory embedding with the highest softmax score in the memory retrieval mechanism. 6.5% of the segments retrieve memory tokens within 2 segments. This signals the importance of local context. However, the long-context memory retrieval still exists. A possible explanation is that entries in Wikipedia may refer to other entries through hyperlinks and related context, and HMT discovers this long-context relationship and recalls the relevant information.

In our experiments, we store the most recent 300 memory embeddings to balance the trade-off between retrieval effectiveness and computational efficiency. Theoretically, storing  $\lceil M/L \rceil$  embeddings is sufficient to handle up to  $M$  token inputs, ensuring robust performance. For longer inputs, high-quality processing is still achievable if recent contextual information is more relevant to the prompt.

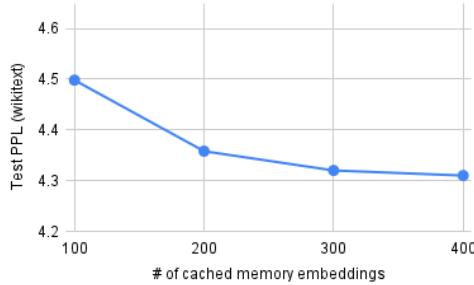


Figure 10: Relationship between number of cached memory embeddings and the effectiveness of HMT + Llama 2 7B. Each sample has 100k tokens from the Wikitext-103 dataset. As HMT stores more memory embeddings, the effectiveness is marginally better.

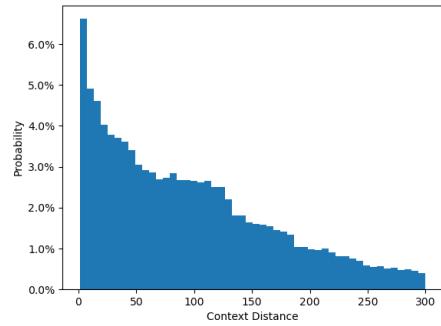


Figure 11: Histogram of context distance between the current segment and the segment corresponding to the memory embedding with the highest softmax score in the memory retrieval mechanism. The dataset evaluated is the Wikitext-103.

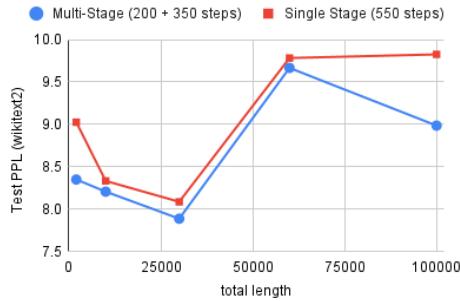


Figure 12: Training HMT + OPT 2.7B with the memory retrieval mechanism in two steps results in a better performance than using the mechanism to train HMT directly. Total training time is 902 s for multi-stage training and 1680 s for single-stage training on 4 AMD MI210 GPUs.

## F Multi-stage Training

Since HMT introduces parameters for memory retrieval, we need to train new parameters and fine-tune the parameters of the backbone model cooperatively. Training HMT involves multiple segments of tokens to learn how to encode input tokens and retrieve information properly. Therefore, we split training HMT into two stages. In the first stage, The model is trained without the memory retrieval mechanism employing BPTT with 2 segments unrolled. BPTT saves the model checkpoint locally. Then, the memory retrieval mechanism loads and extends the train model in the second stage. At this point, BPTT trains the modified model by unrolling the maximum number of segments that the GPUs can handle to maximize the effectiveness, which is 15 in our experiment. Since the architecture of HMT is complex, breaking up training into two stages is beneficial for local optimization and improves long context inference performance compared with single-stage training. Figure 12 exhibits the performance difference between the multi-stage and single-stage training of the OPT 2.7B model with HMT for long-context inputs. Since Stage 1 involves a shorter training sequence length and a simpler recurrent architecture than Stage 2, training with Stage 1 is faster per iteration (1.15 s/iteration) than Stage 2 (3.36 s/iteration). Within the same number of training steps, multi-stage training obtains better effectiveness and lower total training time than single-stage training.

## G HMT Memory Retrieval Behavior

One insight of using memory retrieval in HMT is handling frequent context switching to previously discussed topics or new topics. To evaluate this property, we employ PubMedQA and artifact the dataset with multiple contexts, mentioned in Section 5.1. In this section, we will discuss other dataset manipulations on PG-19 to investigate the memory retrieval behavior of HMT further.

One way to manually introduce context switching is by interleaving the samples. For every 2 samples in the PG-19 dataset, we alternatively concatenate a segment of 256 tokens in each sample together to create a new sample. Therefore, a context switch will be invoked every 256 tokens. We fine-tuned and benchmarked HMT with Llama 2 7B over the artifact dataset. As a result, HMT can enhance the effectiveness of the baseline Llama 2 model, while RMT will worsen it, as shown in Figure 13. We record the context distance of memory retrieval for 30k-token input, illustrated in Figure 14, and notice a periodical recall distribution, indicating that HMT can capture the context-switching pattern.

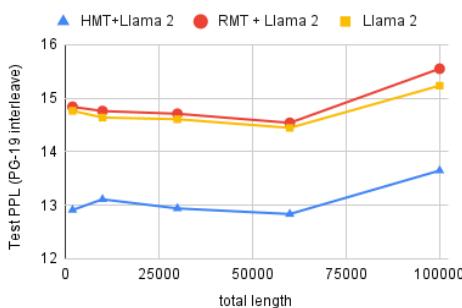


Figure 13: Effectiveness of HMT and RMT with Llama 2 7B evaluated over PG-19 with interleaving samples. HMT is 12.02% better than RMT in terms of PPL for 2k to 100k-token samples.

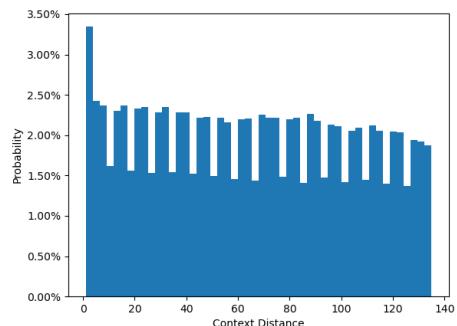


Figure 14: Histogram of context distance between the current segment and the segment corresponding to the memory embedding with the highest softmax score in the memory retrieval mechanism. The dataset evaluated is the PG-19 with interleaving samples.

To demonstrate that HMT’s behavior is aligned with the context-switching pattern, we further manipulate the PG-19 dataset by inserting 256 “\$” tokens for every 256 tokens to dilate each sample. Intuitively, the segment containing “\$” should be considered as irrelevant information and recalled infrequently. Figure 15 shows the memory retrieval pattern of HMT with Llama 2 7B over the diluted PG-19 dataset.

We observe that HMT not only exhibits a periodical recall pattern but also successfully captures the position of irrelevant segments and avoids recalling them.

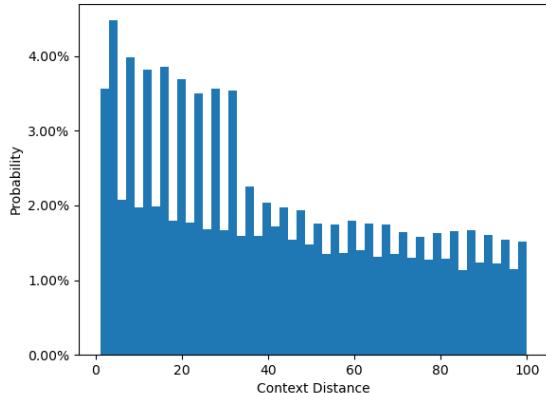


Figure 15: Histogram of context distance between the current segment and the segment corresponding to the memory embedding with the highest softmax score in the memory retrieval mechanism. The dataset evaluated is the dilated PG-19 dataset. Each sample is 25.6k tokens.

## H Relationships Between Effectiveness and Size of Sensory Memory

During the experiment, we observed a general trend in the relationships between the effectiveness of HMT-augmented models and the size of sensory memory: the effectiveness will be first enhanced and then degraded as more and more embeddings are preserved for sensory memory. For instance, Table 8 illustrates the change of effectiveness of HMT + Llama 2 7B evaluated on Wikitext-103 with different sensory memory sizes. The PPL drops to the minimum when having 32 embeddings for the sensory memory.

Table 8: Effectiveness of HMT + Llama 2 7B evaluated on Wikitext-103 with 100k-token samples, with various sensory memory sizes. The segment size is 256 tokens. The effectiveness improves and then degrades with an increasing number of embeddings that are preserved for sensory memory.

# OF EMBEDDINGS FOR SENSORY MEMORY	TEST PPL (WIKITEXT)
8	4.54
16	4.25
32	4.19
64	4.31
128	4.57

## I Dataset Construction for PubMedQ

The original PubMedQA dataset does not have training, validation, and test dataset splits. In the experiments, we choose the pqa\_artificial subset and partition the training, validation, and test split, where the training split is the first 75% of samples, the validation split is the next 15% of samples, and the test split is the remaining 10% samples.

We artifact the long-context dataset from PubMedQA as the following: (1) select  $M$  question-context-answer tuples from the dataset. Let this set of tuples be  $\{ (C_0, Q_0, A_0), (C_1, Q_1, A_1), \dots, (C_T, Q_T, A_T) \}$ , where  $C_n$  are contexts,  $Q_n$  are questions,  $A_n$  are answers for  $0 \leq n \leq M$ . Answers can be either long answers with detailed reasoning or short answers (either “yes”, “no”, or “maybe”). (2) Concatenate all the contexts from each tuple to form a long context and append the questions and answers for each tuple. This will create  $M$  sequences:  $C_0 C_1 \dots C_T Q_0 A_0, C_0 C_1 \dots C_T Q_1 A_1, \dots, C_0 C_1 \dots C_T Q_T A_T$ .

By controlling the value of  $M$ , we can determine the fraction of useful information in the context for each question and better understand the filtering and selection ability of HMT and the baseline model.

## J Gradient Stability in HMT and RMT

Both HMT and RMT are trained using backward propagation through time (BPTT) (Mozer, 2013), a technique utilized to train the RNN model by unrolling recurrent forward passes of the model to optimize long-sequence learning. One issue with RMT training with BPTT is the gradient explosion and vanishing problem. With a higher BPTT unroll depth, the effectiveness of RMT will first increase and then decrease, with a slow reduction or even an increase in training loss. As seen in Figure 16, we use the Wikitext-103 dataset with various BPTT unroll depths to access the effectiveness of RMT with the OPT 2.7B backbone model. For both 2k and 10k token inputs, we observe a rising PPL when unrolling more than 5 segments during training.

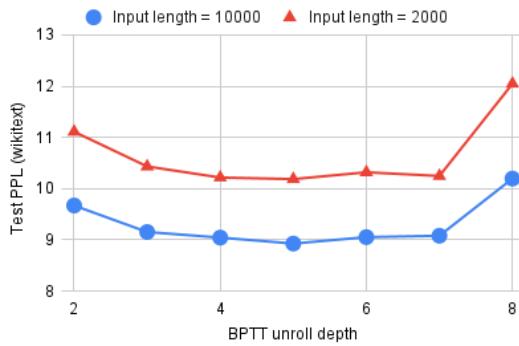


Figure 16: Effectiveness of training RMT with BPTT with different unroll depths for 2K tokens and 10K tokens input from the Wikitext-103 dataset. The backbone model is OPT 2.7B, with 256 tokens per segment during inference.

Table 9: Relationship between the BPTT unroll depth and the test PPL of Wikitext-103 for OPT 2.7B with HMT. The experiment is evaluated on samples with 10k tokens. HMT preserved 32 tokens from the previous segment as the sensory memory and saved 300 memory embeddings for the memory retrieval. The segment size is 256 tokens.

BPTT UNROLL DEPTH	TEST PPL (WIKITEXT)
2	9.36
5	9.15
15	8.20

Unlike RMT, HMT does not suffer from gradient vanishing or explosion as BPTT unroll depth increases due to the memory retrieval mechanism. Table 9 reveals that HMT can improve its effectiveness continuously as the BPTT unroll depth increases during training. Therefore, HMT will be more effective when the BPTT unroll depth increases. A detailed gradient stability analysis is presented in Appendix J. Furthermore, we applied several techniques to optimize the GPU memory consumption to increase the maximum trainable BPTT unroll depth compared with RMT, described in Appendix K.

In this section, we will formulate a mathematical description for the gradient stability of HMT when training with BPTT. BPTT with RMT behaves similarly to RNN which suffers from a vanishing or exploding gradient when there is a long chain of the gradient graph after unrolling (Pascanu et al., 2013). Specifically, for a generic RNN model with the following form:

$$H_t = \dots H_{t-1} + \mathbf{B}x_t)$$

where  $H_t$  is the hidden state at time  $t$ ,  $x_t$  is the input at time  $t$ , and  $\dots$  and  $\mathbf{B}$  are parameters, the gradient will explode if  $\|\mathbf{A}^T\| > 1$  and vice versa. A similar phenomenon occurs when training segment-level

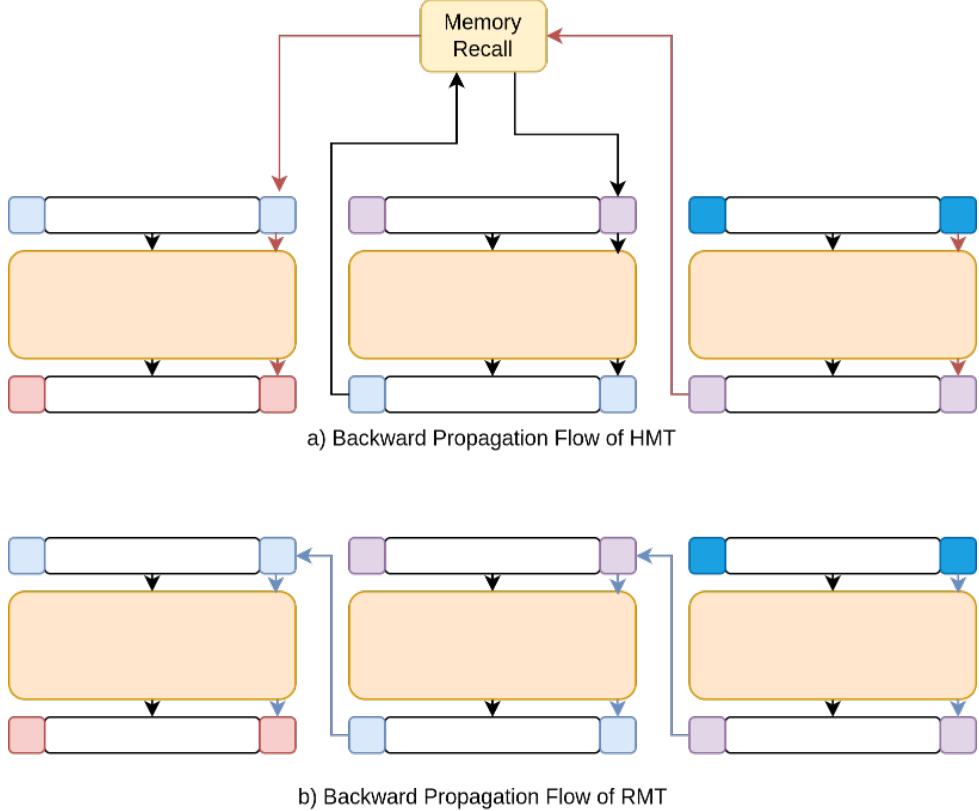


Figure 17: Backward propagation flows of HMT and RMT. The gradient of the first memorization prompt embedding (the red block on the right of the first segment) has multiple branches through the memory retrieval unit. Where the HMT gradient does not require propagation through each segment, the RMT gradient does.

recurrent models such as RMT. Here we provide a scratch calculation on the gradient of loss with respect to the memory token at the starting time, which is one of the parameters in both RMT and HMT, after  $t$  steps for RMT. Let  $y'_{t+1} = H(x_t, m_t)$  be the logits and  $m_{t+1} = F(x_t, m_t)$  be the generated memory embedding at time  $t$ , where  $x_t$  is the input,  $m_t$  is the memory token. The loss of inference is

$$L_{t+1} = \mathcal{L}(y'_{t+1}, y_{t+1}) \quad (6)$$

Therefore, the gradient can be calculated by the chain rule as

$$\begin{aligned} \frac{\partial L_{t+1}}{\partial m_0} &= \frac{\partial L_{t+1}}{\partial y'_{t+1}} \times \frac{\partial y'_{t+1}}{\partial m_0} \\ &= \frac{\partial L_{t+1}}{\partial y'_{t+1}} \times \frac{\partial H}{\partial m_t}(x_t) \times \frac{\partial m_t}{\partial m_0} \\ &= \frac{\partial L_{t+1}}{\partial y'_{t+1}} \times \frac{\partial H}{\partial m_t}(x_t) \times \prod_{i=0}^{t-1} \frac{\partial F}{\partial m_i}(x_i) \end{aligned} \quad (7)$$

Whether the gradient will explode or vanish depends on the input distribution and the function  $F_t$ . If  $\forall x_t, \frac{\partial F}{\partial m_t}(x_t) > 0$ , then the gradient will explode. Otherwise if  $\forall x_t, \frac{\partial F}{\partial m_t}(x_t) < 0$ , the gradient vanishes. Consequently, training RMT with a very high BPTT unroll depth can be inefficient. For HMT, with the assistance of the memory retrieval mechanism, the gradient is not prone to explosion or vanishing. Intuitively, the backward propagation of HMT for the memorization prompt embedding contains multiple short sub-branches to prevent gradient vanishing and the memory retrieval mechanism can modulate the propagation chain to avoid gradient explosion (Figure 17). Let  $G_t(z_t, m_t, m_{t-1}, \dots, m_1) = m'_t$  be the memory search function where  $z_t$  is the representation extraction of segment at time  $t$ . Let  $s$  be the

summarization token for representation extraction. The gradient for HMT is

$$\begin{aligned}
\frac{\partial L_{t+1}}{\partial m_0} &= \frac{\partial L_{t+1}}{\partial y'_{t+1}} \times \frac{\partial y'_{t+1}}{\partial m_0} \\
&= \frac{\partial L_{t+1}}{\partial y'_{t+1}} \times \frac{\partial H}{\partial m'_t} (x_t) \times \frac{\partial G_t}{\partial m_0} \\
&= \frac{\partial L_{t+1}}{\partial y'_{t+1}} \times \frac{\partial H}{\partial m'_t} (x_t) \times \prod_{k=1}^t \frac{\partial G_t}{\partial m_k} (z_k, m_t, \dots, m_{k-1}, m_{k+1}, \dots, m_1) \times \frac{\partial F}{\partial m_0}) \\
&= \frac{\partial L_{t+1}}{\partial y'_{t+1}} \times \frac{\partial H}{\partial m'_t} (x_t) \times \prod_{k=1}^t \frac{\partial G_t}{\partial m_k} (z_k, m_t, \dots, m_{k-1}, m_{k+1}, \dots, m_1) \times \frac{\partial F}{\partial m'_k} \times \frac{\partial G_{t-1}}{\partial m_0}) \\
&= \dots
\end{aligned} \tag{8}$$

The root cause of the gradient explosion or vanishing comes from the long chain of gradient products in the formulation. For HMT, there are multiple short branches of the multiplication chain after expanding the expression. The longest chain over all components in the gradient is

$$\frac{\partial L_{t+1}}{\partial y'_{t+1}} \times \frac{\partial H}{\partial m'_t} (x_t) \times \prod_{k=1}^{t-1} \frac{\partial F}{\partial m'_k} \times \frac{\partial G_k}{\partial m_k}) \times \frac{\partial F}{\partial m_0} \tag{9}$$

For gradient vanishing, since  $\frac{\partial L_{t+1}}{\partial m_0}$  still has components with a shorter chain, the gradient will not disappear even when  $\left\| \frac{\partial F}{\partial m'_k} \times \frac{\partial G_k}{\partial m_k} \right\| < 1$ . For gradient explosion, empirically,  $\frac{\partial G_k}{\partial m_k}$  are different for each  $k$  by the property of cross attention and can modulate the term  $\frac{\partial F}{\partial m_k}$  to distribute near 1. Thus, HMT is less prone to gradient explosion.

A similar proof can be deduced for the segment-level summarization token embedding of HMT for representation extraction.

## K Distributed Training with Memory Consumption Optimization

Although (Bulatov et al., 2022) proves that unrolling more segments can improve the model effectiveness, they limit the number of segments unrolled to 4 with 2 NVIDIA A100 80GB GPUs since the maximum BPTT unroll depth is bounded by the GPU VRAM limit. There are three sources of VRAM consumption: model parameters, intermediate data (input segments, long-term memory, raw outputs of each segment, etc.), and optimization data (gradient and optimizer states). Although the computations of later segments do not require the intermediate data from the previous segment, the original BPTT will keep them on GPU by default. To reduce memory consumption, we customize the program to offload and load intermediate data for each input segment between the CPU and GPUs and distribute optimizer states and gradients throughout multiple GPUs running Zero Redundancy Optimizer (ZeRO) (Rajbhandari et al., 2020) Stage 2 in DeepSpeed (Rasley et al., 2020). These allow the model to unroll up to 15 segments with HMT. To train larger models, we employ LoRA (Hu et al., 2021) with rank 8. This allows us to fit 7B models to 4 MI210 GPUs.

## L License and Links of Datasets and Models

Datasets:

- Wikitext (Texts from Wikipedia): CC BY-SA 4.0, <https://huggingface.co/datasets/Salesforce/wikitext>
- PG-19 (Books from Project Gutenberg): Apache License V2.0, <https://huggingface.co/datasets/emozilla/pg19>
- PubMedQA (Biomedical QA dataset): MIT License, <https://huggingface.co/datasets/qiaojin/PubMedQA>

- RedPajamaV2 (Pretraining data corpus): Apache License V2.0, <https://huggingface.co/datasets/togethercomputer/RedPajama-Data-V2>
- LongBench (Long context evaluation dataset): Licenses are mentioned in the original work (Bai et al., 2023b), <https://huggingface.co/datasets/THUDM/LongBench>

Models:

- OPT models: MIT License, <https://huggingface.co/facebook/opt-350m>
- Llama models: Llama 2 Custom License, <https://huggingface.co/meta-llama/Llama-2-7b-hf>
- OpenLlamaV2: Apache License V2.0, [https://huggingface.co/openlm-research/open\\_llama\\_3b\\_v2](https://huggingface.co/openlm-research/open_llama_3b_v2)
- RWKV: Apache License V2.0, <https://huggingface.co/RWKV/rwkv-4-3b-pile>
- Mamba: Apache License V2.0, <https://huggingface.co/state-spaces/mamba-370m-hf>
- Mistral: Apache License V2.0, <https://huggingface.co/mistralai/Mistral-7B-v0.3>
- Yi: Yi-License, <https://huggingface.co/01-ai/Yi-6B-200K>
- Qwen: Tongyi Qianwen License, <https://huggingface.co/Qwen/Qwen1.5-0.5B>, <https://huggingface.co/Qwen/Qwen2.5-14B>
- SmoLLM: Apache License V2.0, <https://huggingface.co/HuggingFaceTB/SmoLLM-135M>

All datasets and models are publicly available and free to use.