Memorize Step by Step: Efficient Long-Context Prefilling with Incremental Memory and Decremental Chunk

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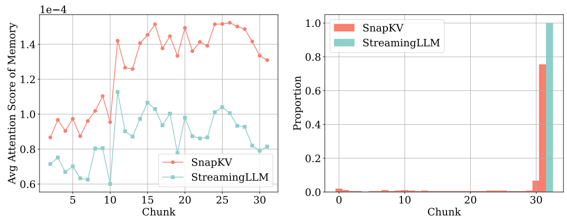
Abstract

The evolution of Large Language Models (LLMs) has led to significant advancements, with models like Claude and Gemini capable of processing contexts up to 1 million tokens. However, efficiently handling long sequences remains challenging, particularly during the prefilling stage when input lengths exceed GPU memory capacity. Traditional methods often segment sequence into chunks and compress them iteratively with fixed-size memory. However, our empirical analysis shows that the fixed-size memory results in wasted computational and GPU memory resources. Therefore, we introduces Incremental Memory (IM), a method that starts with a small memory size and gradually increases it, optimizing computational efficiency. Additionally, we propose Decremental Chunk based on Incremental Memory (IMDC), which reduces chunk size while increasing memory size, ensuring stable and lower GPU memory usage. Our experiments demonstrate that IMDC is consistently faster (1.45x) and reduces GPU memory consumption by 23.3% compared to fixed-size memory, achieving comparable performance on the LongBench Benchmark.

1 Introduction

The evolution of Large Language Models (LLMs) has reached new frontiers, with models like Claude (Anthropic, 2024) and Gemini (Reid et al., 2024) capable of processing contexts spanning up to a 1 million tokens. However, the efficiency of processing long sequences with LLM still faces significant challenges.

The inference of LLM can be divided into two parts: Prefilling and Decoding. LLM inference for long documents faces significant challenges in both stages. In the prefill stage, the model needs to read long sequences and endure the quadratic complexity of attention calculations with respect



(a) Memory Attention (b) Memory Distribution

Figure 1: (a): The average attention scores of memory at each step. (b): The distribution of memory content across chunks, where we count the number of key-value pairs in memory originating from each chunk. For both Figure (a) and (b), we used KV Cache pruner (SnapKV (Li et al., 2024) and StreamingLLM (Xiao et al., 2023)) to compress memory and chunk.

to the sequence length. During the decoding stage, decoding each token requires accessing the substantial Key-Value (KV) Cache generated in the prefill stage. Most efforts to optimize the efficiency of LLM for long sequence focus on the decoding stage, particularly on compressing the KV Cache (Xiao et al., 2023; Zhang et al., 2023; Liu et al., 2024c; Hooper et al., 2024; Liu et al., 2024a; Sun et al., 2024). However, when the input length during the prefilling stage exceeds the maximum length supported by GPU memory capacity, even prefilling cannot proceed. Existing works (Bulatov et al., 2023a,b; Ge et al., 2023b; Liu et al., 2020; Munkhdalai et al., 2024) tackle this problem by dividing the sequence into chunks with the same size and iteratively compress these chunks with a fixed-size buffer as memory.

In this work, we made an empirical investigation on the chunked prefilling with compressed KV-Cache, which we refer to simply as memory. Our anlysis on the memory displayed in Figure 1 reveals that: 1) the attention scores of memory starts at a relatively low value and gradually increases throughout the prefill process (Figure 1a.), which suggests that early-stage memory has minimal in-

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fluence on the next-step computation; 2) once the prefill phase concludes, the memory distribution is primarily concentrated at the end of the sequence (Figure 1b), implying that most of the early-stage memory is not retained by the end of the prefill.

Overall, our findings suggest that the early-stage memory in the prefill phase is less impactful compared to the later-stage memory. It is unnecessary to maintain a large memory size at the early stage of prefilling. This implies that approaches (Bulatov et al., 2023a,b; Ge et al., 2023b; Munkhdalai et al., 2024) that maintaining a fixed-size buffer to compress long sequences may result in wasted computational and memory resources.

To avoid computational waste during the early stage of prefilling, we propose **Incremental Memory** (IM), which starts with a small memory size and gradually increases it until the end of the prefilling phase. During this growth phase, the memory size of IM remains smaller than the maximum length, resulting in greater efficiency compared to the commonly used fixed-size memory.

While analyzing memory distribution across different layers[1], we observed that higher layers exhibit a more uniform memory distribution compared to lower layers. Consequently, we propose an adaptive memory growth strategy to set memory sizes for each layer based on the proportion of memory retained after compression, with layers retaining more memory being allocated larger memory sizes.

Although IM is faster than fixed-size memory, it does not significantly reduce peak GPU memory usage, as the memory size of IM is the same as that of fixed-size memory at the end of the prefilling phase. Therefore, we propose **Decremental Chunk** based on **Incremental Memory** (IMDC), which starts with a large chunk size that decreases as memory size increases. When the memory size is small, the chunk size is large, and vice versa. The incremental memory and decremental chunk strategies complement each other, maintaining stable GPU memory usage that is lower than fixed-size memory, which is illustrated in Figure 2.

Our experiments show that IMDC is consistently faster (1.45x) than fixed-size memory and consumes less GPU memory (23.3% reduction) during the prefill stage, yielding comparable results on LongBench Benchmark (Bai et al., 2023).

Contributions Our main contributions include:

[1]The results are shown in Figure 6.

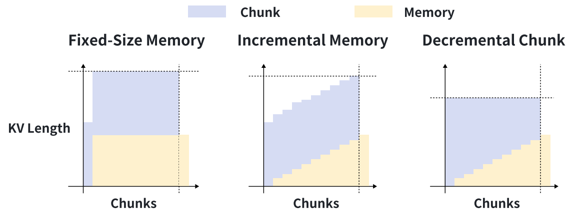


Figure 2: The illustration of Fixed-Size Memory, Incremental Memory (IM) and Incremental Memory with Decremental Chunk (IMDC).

- Our analysis on memory reveals that, the early-stage memory in the prefilling is less impactful than the later-stage memory.
- Based on this finding, we propose the Incremental Memory and Decremental Chunk (IMDC) approach, which dynamically increases memory size while decreasing chunk size.
- Our experiments demonstrate that IMDC is 1.45 times faster than the commonly used fixed-size memory and consumes 23.3% less GPU memory during the prefill stage, without sacrificing performance on long-context benchmarks.

2 Related Works

The long-context efficiency of LLM has been widely studied, which can be classified into two categories: prefilling and decoding.

Prefilling The prefilling of LLM encounters quadratic complexity in attention calculations with respect to sequence length. Numerous research efforts have sought to reduce this quadratic complexity through methods such as low-rank approximation (Wang et al., 2020; Peng et al., 2021; Choromanski et al., 2020) and sparsification (Child et al., 2019; Vyas et al., 2020; Kitaev et al., 2020). Tay et al. (2023) provided a comprehensive review of these approaches. These methods modify the computation mode of attention, often resulting in a trade-off with model performance. In contrast, flash attention (Dao et al., 2022) identified that the efficiency bottleneck lies primarily in input/output (I/O) operations rather than computational processes. By implementing CUDA operations, they significantly accelerated attention calculations without altering the fundamental computation of attention. RMT (Bulatov et al., 2023a) proposed an iterative compression scheme for long texts, maintaining and dynamically updating a

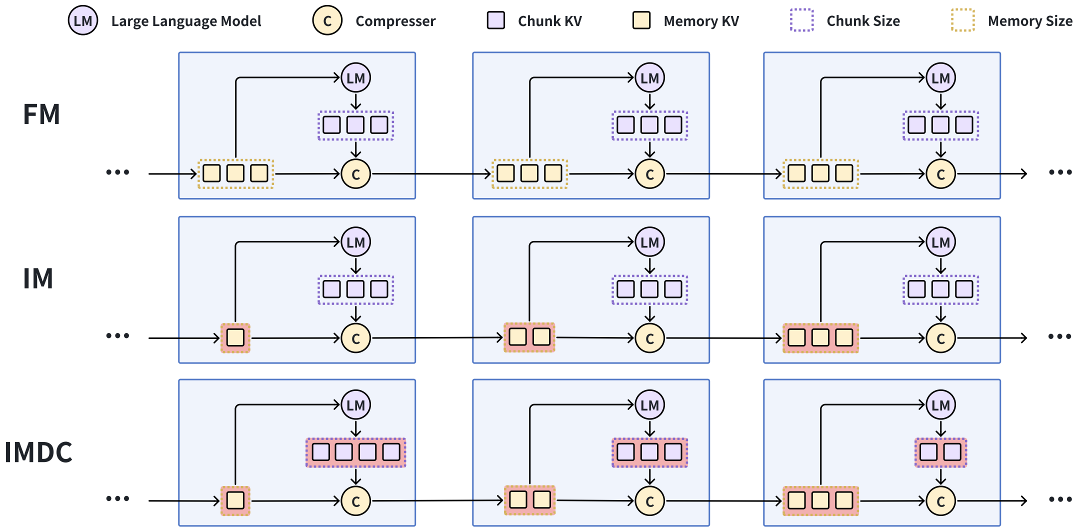


Figure 3: The illustration of iterative compression with Fixed-Size Memory (FM), Incremental Memory (IM) and Decremental Chunk based on Incremental Memory (IMDC). The iterative compression involves multiple steps of compression on the KV cache of memory and chunk.

fixed-size memory, which is followed by (Bulatov et al., 2023b; Ge et al., 2023b; Liu et al., 2020; Munkhdalai et al., 2024). AutoCompressors (Liu et al., 2020) also introduced incremental memory, but different from our method, they increase memory size to enhance the model performance, which results in significant overhead. [2]

Decoding Most efforts to optimize the efficiency of long-context decoding have focused on KV Cache compression. Research in this area can be categorized into KV Cache Pruning (Zhang et al., 2023; Xiao et al., 2023; Liu et al., 2023), low-rank approximation (Shazeer, 2019; Ainslie et al., 2023; Shao et al., 2024), quantization (Liu et al., 2024c; Hooper et al., 2024; Liu et al., 2024b), and layer sharing (Liu et al., 2024a; Sun et al., 2024; Brandon et al., 2024). Key works in KV Cache pruning include H2O (Zhang et al., 2023) and StreamingLLM (Xiao et al., 2023). H2O selects important KVs based on cumulative attention scores, while StreamingLLM retains only the KVs closest to the end of the sequence. Subsequent works (Oren et al., 2024; Ge et al., 2023a; Dong et al., 2024; Ren and Zhu, 2024; Li et al., 2024) proposed several improvements to H2O, all of which determine KV importance based on attention scores. Notable approaches for low-rank approximation include multi-query attention (Shazeer, 2019) and grouped query attention (Ainslie et al., 2023), where different queries share the same KVs. Layer sharing methods (Liu et al., 2024a) identify redundancy among the KV Caches of different layers, retaining only the KVs of certain layers. Quantization compression (Liu et al., 2024c) reduces KV Cache precision from fp16 to int8 through various quantization methods (Dettmers et al., 2022).

Our research adopted the iterative compression method from RMT. However, unlike RMT (Bulatov et al., 2023a), which compresses sequences into Soft Tokens, we used StreamingLLM and SnapKV to compress KV Cache, because they do not require training and can maintain a constant memory size during the iteration.

3 Method

3.1 Iterative Compression

When the input sequence length during the prefill stage exceeds the maximum length supported by the GPU memory limit, the sequence is segmented into multiple chunks and compressed iteratively, as illustrated in Figure 3. In each iteration, the LLM reads the memory as the KV cache for attention. After the attention computation, the newly generated KV cache is sent to the compressor, which updates the memory.

The process of iterating through chunks is similar to a recurrent neural network, while the computation within each chunk operates in parallel, akin to a transformer. [3]

[2]We demonstrate the superiority of our method compared to AutoCompressors empirically in Appendix B.4.

[3]The intriguing intersection between KV Cache Pruning

3.2 Incremental Memory

Based on the finding from Figure 1 that it is unnecessary to keep a large memory size at the early stage of prefilling, we propose Incremental Memory (IM), which increases memory size during the iteration of compression. We explore various incremental functions to increase memory size: Linear Function (Section 3.2), Adaptive Function (Section 3.2), and other increasing functions detailed in Appendix A.1.

Linear Function Suppose the number of chunks is n, the memory size increase from m_0 to $m_{\max}$ linearly:

$$m_i = \frac{(m_{\max} - m_0)i}{n-1} + m_0, \tag{1}$$

where n denotes the number of chunks. The middle section of Figure 3 illustrates the linear increase of memory size.

Adaptive Function By visualizing the memory distribution across layers in Figure 6, we observed significant differences in memory usage between high and low layers. Consequently, we propose Adaptive Function to allocate appropriate memory sizes for different layers. We record the memory retention ratio (the proportion of memory retained after the compression) of various layers. Suppose the memory of the j-th layer at the i-th step is $\mathbb{M}_i^j$, the memory retention ratio corresponding to that is defined as:

$$p_i^j = \frac{|\mathbb{M}_{i-1}^j \cap \mathbb{M}_i^j|}{|\mathbb{M}_i^j|}. \tag{2}$$

Intuitively, the more memory retained from the compression, the larger the memory size should be, and vice versa. Therefore, we can determine the memory size of each layer based on its memory retention ratio. We take the linear function as the basis, and scale it with the normalized memory retention ratio. Suppose that the number of layers is N, the memory size of the linear incremental memory of the j-th layer at the i-th step is b_i^j, then the memory size for adaptive incremental memory is:

$$m_i^j = \begin{cases} b_0^j & \text{if } i = 0 \\ \frac{p_j}{\sum p_j} N b_i^j & \text{if } i > 0 \end{cases} \tag{3}$$

and recurrent neural networks is also discussed in Oren et al. (2024).

3.3 Time Complexity Analysis

The acceleration of IM over fixed-size Memory is determined by two factors: 1) the relative sizes of the memory size and chunk size; 2) the proportion of the total computation time occupied by the attention calculation. Assuming the maximum memory size is $m_{\max}$, the memory size at the i step is m_i, the chunk size is c, the number of chunks is n , then the acceleration of IM over fixed-size Memory is given by:

$$r(\frac{m_{\max} + c}{\hat{m} + c} - 1) + 1, \tag{4}$$

where $\hat{m} = \frac{\sum_{i=0}^{n-2} m_i}{n-1}$. Therefore, when $m_{\max} \gg c$ and r is close to 1, incremental memory achieves an ideal acceleration ratio: $\frac{m_{\max}}{\hat{m}}$.

IM reduces the time complexity of the attention calculation from $O(ms + s^2)$ to $O(f(m, s) + s^2)$, where f depends on the specific incremental function. For example, if f is a power function, the time complexity is $O(ms)$.

3.4 Decremental Chunk

Although incremental memory (IM) is faster than fixed-size memory, it does not significantly reduce peak GPU memory usage. To address this issue, we propose **Decremental Chunk** based on **Incremental Memory** (IMDC). IMDC begins with a large chunk size and decreases it as the memory size increases.

Regardless of changes in memory size and chunk size, IMDC maintains a constant average chunk size:

$$\frac{\sum_{i=0}^{n-1} c_i}{n} = c, \tag{5}$$

where c_i represents the chunk size at the i-th step, n is the number of chunks, and c denotes the average chunk size. Since the memory is not involved in the attention computation at the first step, the chunk size of IMDC at the first step is set to the average chunk size ($c_0 = c$).

At the i-th step, the attention key-value (KV) is the concatenation of the chunk at the i-th step and the memory at the $i-1$-th step. Therefore, the length of the attention KV at the i-th step is $c_i + m_{i-1}$. We set the chunk size to ensure that the attention KV length remains constant:

$$c_i + m_{i-1} = \frac{\sum_{i=1}^{n-1}(c + m_{i-1})}{n-1} \quad (i > 0), \tag{6}$$

where m_{i-1} is the memory size at the $i-1$-th step, and $\frac{\sum_{i=1}^{n-1}(c+m_{i-1})}{n-1}$ is the average length of the attention KV across all steps except the first step. Therefore, the chunk size of IMDC at the i-th step is:

$$c_i = \begin{cases} c & \text{if } i = 0 \\ c + \hat{m} - m_{i-1} & \text{if } i > 0 \end{cases} \tag{7}$$

where $\hat{m} = \frac{\sum_{i=0}^{n-2} m_i}{n-1}$.

IMDC is illustrated on the bottom section of Figure 2, where the memory size increases while the chunk size decreases. When the memory size is small, the chunk size is large, and vice versa. The incremental memory and decremental chunk strategies complement each other, maintaining stable GPU memory usage. The attention KV length of IMDC remains constant at $c + \hat{m}$ (except for step 0), whereas for fixed-size memory it is $c + m_{\max}$. Since the memory size is incremental, we have $m_{\max} > \hat{m}$. Therefore, IMDC consumes less GPU memory than fixed-size memory.

4 Experiments

4.1 Experiment Settings

Iterative Compression We divided the sequence into non-overlapping windows and encode position embedding for memory and chunk at each iteration independently instead of reusing the position embedding from the previous steps. Incremental Memory employs the linear increase, with the initial memory size defined as $\frac{m_{\max}}{n}$, where $m_{\max}$ is the maximum memory size and n is the number of chunks. Unless otherwise specified, the configurations of Incremental Memory adhere to this setup.

KV Cache Compression We tried two pruning algorithms: SnaKV (Li et al., 2024) and StreamingLLM (Xiao et al., 2023). SnaKV filters important key-value pairs based on attention scores, while StreamingLLM selects the most recent key-value pairs without relying on attention scores.

Models We compared our methods with Fixed-Size Memory, abbreviated as FM. Our methods are labeled as IM (Incremental Memory) and IMDC (Incremental Memory with Decremental Chunk). Our experiments were conducted on LLaMA-2-7B (Touvron et al., 2023), Tiny-LLaMA (Zhang et al., 2024) (1.1B), and InternLM2 (Cai et al., 2024) (7B). We used Dynamic NTK (bloc97, 2023) to extend the context length of LLama2-7b and Tiny-LLama. We used flash attention (Dao et al., 2022) to accelerate the attention calculation. However, SnapKV requires attention scores hence is not compatible with flash attention.

GPU	Method	Save Logits	Max length
RTX 3090	Full Attention	Yes	8192
	Iterative Compression	Yes	65536
	Iterative Compression	No	infinity
A800	Full Attention	Yes	65536
	Iterative Compression	Yes	262144
	Iterative Compression	No	infinity

Table 1: The maximum input length supported by Full Attention and Interative Compression on A100 and RTX 3090 was evaluated. "Save Logits" refers to whether the model's output logits should be saved. We use IM for iterative compression which utilizes the StreamingLLM Pruner, both the chunk size and memory size of which are set to 1024.

Evaluation We used Collie (Lv et al., 2023) to implement our methods and evaluate our methods on LongBench (Bai et al., 2023) with OpenCompass (Contributors, 2023). Our Perplexity evaluation used the data collected by Liu et al. (2020), which are sampled from the Github and Arxiv subsets of Redpajama (Computer, 2023).

4.2 Why We Need Iterative Compression

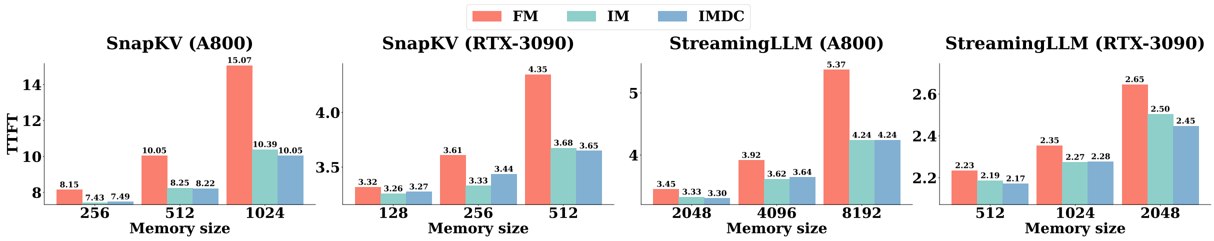
To verify the advantages of iterative compression over Full Attention, we compared the maximum sequence length that iterative compression and Full Attention support at the prefilling stage. We use IMDC for iterative compression and set both the memory size and chunk size to 1024. We use the StreamingLLM pruner as the compressor.

The results are shown in the Table 1. Whether on the A800 or 3090, the maximum sequence length supported by iterative compression is far greater than that supported by Full Attention (4 times greater). If we do not save model's logits, iterative compression can support infinite sequence lengths. This characteristic is particularly important for deploying LLMs on devices with limited GPU memory, such as mobile phones.

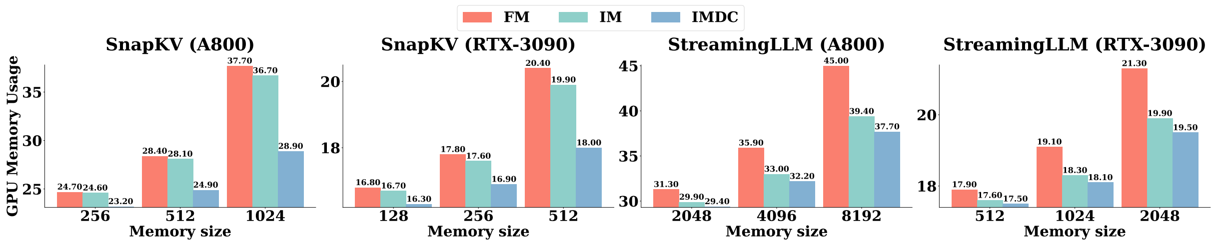
4.3 Efficiency Improvement

We evaluated the efficiency of our methods (IM and IMDC) on both NVIDIA A800 and NVIDIA RTX 3090 GPUs. [4] The results are shown in Figure 4.

[4]Detailed experimental settings are shown in Appendix B.1.



(a) TTFT Comparison (Seconds). TTFT (Time To First Token) refers to the time cost associated with the model encoding the input sequence.



(b) GPU Memory Usage Comparison (GB).

Figure 4: TTFT and GPU Memory Usage of LLama2-7B with Fixed-Size Memory (FM) vs. that with our methods including Incremental Memory (IM) and Incremental Memory with Decremetnal Chunk (IMDC). We use different memory sizes for SnapKV and Streaming LLM, because SnapKV requires attention scores which does not support flash attention.

Time Efficiency We compared the time efficiency of our method versus FM in terms of the time to first token (TTFT), the results of which are shown in Figure 4a. We found that our IM and IMDC consistently demonstrates greater efficiency than FM, regardless of the pruners used and the devices employed. Furthermore, the efficiency gap between them widens as the memory size increases. It is because that the larger memory size has a larger impact on the computation time.

In the A800 experiments, IMDC achieved up to approximately 1.45x (SnapKV) and 1.26x (StreamingLLM) speedup over FM. In the RTX 3090 experiments, the speedup of IM was 1.2x (SnapKV) and 1.08x (StreamingLLM). Increasing the memory size would make the speedup more significant.

The acceleration of our methods on SnapKV is more significant than that on StreamingLLM. This is because that SnapKV cannot use flash attention, leading to a higher proportion of time spent on attention calculation. Currently, the majority of pruning methods also requires attention scores (Zhang et al., 2023; Oren et al., 2024; Liu et al., 2023; Ren and Zhu, 2024). Our methods can also achieve significant speedup for these approaches. These empirical results align with our theoretical analysis in Section 3.3 that the acceleration of incremental memory is influenced by two factors—the memory size and the proportion of time spent on attention calculation relative to total computation time.

GPU Memory Efficiency We evaluated the peak memory usage during model prefilling. The results, presented in Figure 4b, indicate that both IM and IMDC consume less GPU memory compared to FM. As the memory size increases, our methods save even more memory compared to the FM.

In experiments conducted on the A800, the IMDC reduced GPU memory usage by up to 23.3% for SnapKV and 16.2% for StreamingLLM compared to FM. Similarly, on the RTX 3090, the reductions were 11% for SnapKV and 8% for StreamingLLM.

IM also conserves GPU memory usage because the chunk at the i-th step is concatenated with the memory produced at the $i-1$-th step for attention. Assuming the iteration involves n chunks (0, 1, ..., $n-1$), the peak GPU memory is determined by the memory size at the $(n-2)$-th step rather than the last step. However, the GPU memory reduction achieved by IM is not as significant as that achieved by IMDC, especially in the SnapkV experiment, where the number of chunks is large.

4.4 Perplexity Comparison

We compared the perplexity (PPL) of LLama2-7b when using different types of memory: FM, IM and IMDC. The test data for perplexity is sampled from

Model	Pruner	Memory	Single-Doc QA	Multi-Doc QA	Summarization	Few-shot Learning	Synthetic	Code	Avg
LLaMA2-7b	Full-Attn	NA	16.4	7.89	11.61	50.58	3.68	63.34	28.15
	SnapKV	FM	15.63	**8.78**	11.83	48.17	3.50	**63.57**	27.85
		IM	15.53	8.75	11.74	**48.70**	4.41	63.51	**27.99**
		IMDC	**15.64**	8.47	**11.95**	46.78	**4.58**	63.32	27.65
	StreamingLLM	FM	12.89	7.90	**10.96**	**45.86**	3.40	**61.65**	**26.32**
		IM	**13.22**	7.92	10.90	44.47	3.86	61.44	26.14
		IMDC	12.95	**8.19**	10.78	44.88	**3.90**	61.23	26.15
InternLM2-7b	Full-Attn	NA	40.93	34.79	22.78	57.78	33.23	59.44	42.56
	SnapKV	FM	**23.50**	21.39	**17.88**	46.60	6.92	**59.87**	31.64
		IM	22.36	21.54	17.41	45.90	6.05	59.62	31.13
		IMDC	23.38	**22.38**	17.66	**48.67**	**8.45**	59.66	**32.24**
	StreamingLLM	FM	**23.14**	**21.49**	**16.79**	46.34	4.88	59.31	31.00
		IM	22.42	21.00	16.22	47.07	5.21	**59.95**	30.99
		IMDC	23.06	20.89	16.61	**47.31**	**5.73**	59.88	**31.25**
Tiny-LLaMA	Full-Attn	NA	2.77	0.99	5.76	2.12	0.59	18.06	5.78
	SnapKV	FM	16.06	9.43	16.91	**33.60**	2.95	50.27	23.50
		IM	16.22	9.41	15.74	31.09	2.85	**50.75**	22.98
		IMDC	**17.59**	**9.94**	**17.25**	33.16	**3.27**	49.58	**23.69**
	StreamingLLM	FM	16.31	10.07	16.77	31.46	2.96	51.92	23.60
		IM	16.32	9.85	17.07	30.37	**3.33**	51.81	23.45
		IMDC	**16.99**	**10.27**	**17.38**	**31.52**	2.41	**52.11**	**23.81**

Table 2: The performance comparison on LongBench. Full-attn: Full Attention; FM: Fixed-Size Memory; IM: Incremental Memory (ours); IMDC: Incremental Memory with Decremental Chunk (ours). For all models, both the chunk size and memory size are set to 1024.

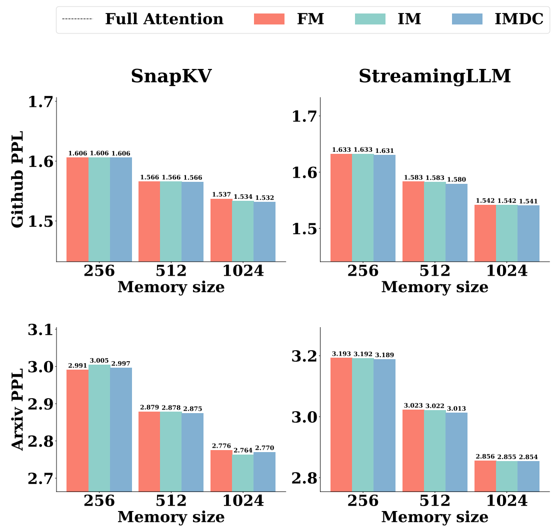


Figure 5: Perplexity of LLama2-7B with Fixed-Size Memory (FM) versus that with our methods (Incremental Memory (IM) and Incremental Memory with Decremental Chunk (IMDC)).

Redpajama and encompasses two domains (GitHub and ArXiv). The sequence length and chunk size configurations adhere to the A800 settings specified in Appendix B.1.

The results shown in Figure 5 indicate that there is no significant difference in perplexity between IM/IMDC and FM for either SnapKV or StreamingLLM. When the memory size is 1024, IM/IMDC even performs slightly better than FM. We hypothesize that IM/IMDC selects KV pairs more concentrated towards the end of the sequence, which is beneficial for lowering PPL.

Additionally, we observe that SnapKV achieves significantly lower perplexity than StreamingLLM under identical conditions. This indicates that efficiency improvements on SnapKV are more critical. Our experiments in Section 4.3 demonstrate that IM and IMDC achieve more substantial acceleration and memory reduction on SnapKV.

4.5 Benchmark Comparison

We compared the performance of our methods including IM and IMDC versus FM on LongBench. As shown in Table 2, the performance differences between IM and FM are minimal (<=0.5) under any settings. In most experiments, the performance differences between IM and FM are within 0.15. On InternLM2 and Tiny-LLaMA, IMDC is even better than FM. This may be because the uneven Chunk Size is more closed to the full attention. An extreme case is that a sequence of length n is divided into two chunks with length $n-1$ and 1.

We also found that the average score of Full Attention on Tiny-LLaMA is only 5.78, even with the Dynamic NTK. It is because that the maximum sequence length that Tiny-LLaMA supports is limited to 2048 tokens. In contrast, the average scores

Method	Memory Size	Single-Doc QA	Time (seconds)
Iterative Compression	1024	22.36	3181.7
	2048	27.34	3187.2
	4096	34.88	3693.2
	8192	39.16	3802.9
Full Attention	NA	40.93	12101.4

Table 3: The performance and inference time of Full Attention Versus Iterative Compression with different memory sizes evaluated on a subset of LongBench (Single-Document QA). We use IM for iterative compression and LLama2-7b for the test model.

Model	**Method**	**Seq len**	**Loss**	**TTFT**	**GPU Memory**
LLama2-7B	Full Attention	128k	-	-	OOM
	FM	1M	2.00	505	36
	IM	1M	2.08	351	35
	IMDC	1M	2.11	**328**	**27**
LLama2-13B	Full Attention	64k	-	-	OOM
	FM	1M	1.83	711	59
	IM	1M	1.85	517	59
	IMDC	1M	1.87	**506**	**46**

Table 4: The performance of Full Attention and iterative compression (FM, IM, and IMDC) evaluated with 1M tokens sampled from Github subsets of Redpajama (Computer, 2023). The iterative compression used Streaming-LLM Pruner for KV-Cache Compression. Time to First Token (TTFT) and GPU memory usage were measured in seconds and gigabytes (GB), respectively.

of all iterative compression methods (FM, IM and IMDC) exceed 20, indicating the superiority of iterative compression over full attention.

In Table 2, the performance of InternLM2-7B with full attention is much better than iterative compression (FM/IM/IMDC), particularly in QA tasks. We hypothesize that the small memory size is the main cause of this discrepancy. Consequently, we conducted a comparative study of iterative compression and Full Attention with an increased Memory Size.

The results are shown in Table 3, where we can observe that increasing memory size is beneficial to narrow the gap between iterative compression and full attention. If the memory size is set to 8192, the performance of iterative compression on Single-Document QA is comparable with that of full attention, while requiring only 31% inference time.

4.6 Scaling to 1M tokens

In Section 4.2, we validated that iterative compression can handle sequences of infinite length without encountering out-of-memory issues. However, it remains unclear whether iterative compression experiences extrapolation issues during infinite-length prefilling. To address this, we evaluated the performance of LLama2-7B and LLama2-13B using one million tokens on the A800. The results are presented in Table 4.

The results show that iterative compression (FM/IM/IMDC) does not exhibit extrapolation issues, despite the original model supporting an input length of only 4096. This is because relative positions, rather than absolute positions, are encoded for memory and chunks. In iterative compression, the maximum position is the sum of the memory size and chunk size, which is smaller than 4096. As a result, iterative compression avoids extrapolation issues regardless of input length. Furthermore, IM/IMDC achieve perplexity (PPL) comparable to FM while significantly reducing both prefilling time (TTFT) and GPU memory usage

Pruner	Incremental Function	Single-Doc QA	TTFT Time
SnapKV	LINEAR	22.35	5.11
	SQRT	**23.35**	5.83
	SQUARE	21.90	**4.49**
	SQUARE-SQRT	**23.24**	5.15
	ADAPTIVE	**23.20**	5.13
Streaming LLM	LINEAR	**22.41**	2.34
	SQRT	22.27	2.42
	SQUARE	22.08	2.27
	SQUARE-SQRT	21.97	2.35
	ADAPTIVE	**22.36**	2.36

Table 5: Performance comparison of different incremental functions. **LINEAR**: linear growth; **SQRT**: fast initial growth that slows down, in the form of $x^{1/2}$; **SQUARE**: slow initial growth that speeds up, in the form of x^2; **SQUARE-SQRT**: growth in the form of SQUARE in low layers and SQRT in high layers; **ADAPTIVE**: set the memory size based on the memory retention ratio in each layer. [5]

4.7 Optimal Incremental Strategy

In this experiment, we explored different functions to increase memory size and compared their impact on the performance and efficiency of the InternLM2-7b. We used InternLM2-7b for evaluation because the performance gap between IM/IMDC and FM on InternLM2-7b is more significant than that on LLama-7b. The results are shown in Table 5. The outcomes for SnapKV matched our expectations. The SQRT function achieved the best performance, significantly outperforming

[5]The specific formulas for the SQRT and SQUARE functions are described in Appendix A.1, and the implementation details of the ADAPTIVE function are presented in Section 3.2. We set both Chunk Size and Memory Size to 1024.

Pruner	Compression Rate	Context\Depth	Percentage									
			0%	10%	20%	30%	40%	50%	60%	70%	80%	90%
Full Attention	-	8k	1	1	1	1	1	1	1	1	1	1
		16k	1	1	1	1	1	1	1	1	1	1
		24k	1	1	1	1	1	1	1	1	1	1
		32k	1	1	1	1	1	1	1	1	1	1
FM (SnapKV)	25%	8k	1.0	0.6	0.8	0.8	1	1	1	1	1	1
	12.5%	16k	1.0	0.4	0	0.2	0	0.8	0.8	1	1	1
	6.25%	24k	1.0	0	0	0	0.2	0.2	0.2	1	1	1
	3.125%	32k	1.0	0	0	0	0	0	0	0.2	0.6	1
IM (SnapKV)	25%	8k	0	0	0	0.6	1	1	1	1	1	1
	12.5%	16k	0	0	0	0.6	0.8	1	1	1	1	1
	6.25%	24k	0	0	0	0	1	1	1	1	1	1
	3.125%	32k	0	0	0	0.2	1	1	1	1	1	1

Table 6: The performance of full-attention, IM and IMDC on the needle-in-a-haystack test.

the LINEAR function, but it was also the slowest among the five functions. This is reasonable because the memory size of the SQRT function is larger than that of the other functions. Both SQUARE-SQRT and ADAPTIVE are designed to set the appropriate memory size for different layers. They exhibited the same performance as the SQRT function and the same efficiency as the LINEAR function. The SQUARE function was the most efficient among the five functions, but its performance was the worst.

4.8 Needle-in-a-Haystack Test

We conducted a needle-in-a-haystack test based on the pass-key retrieval task (Mohtashami and Jaggi, 2023). The LLama3-7B model fine-tuned on long context served as the base model.[6] To compress the KV Cache, we employed SnapKV (Li et al., 2024) with a chunk size of 1024 and a memory size of 2048. The results are presented in Table 6. A depth of 0% indicates the passkey is placed at the beginning of the sequences, whereas a depth of 90% denotes the passkey is placed at the end of the sequences.

Our findings indicate that Full Attention can successfully complete the 32k length needle-in-a-haystack test. Although FM and IMDC do not perform as well as Full Attention, they can handle most deep retrievals when the context length is within 16k, which compresses the KV Cache to 1/8 of its original size.

We observed that IM, in comparison to FM, has difficulty retrieving information from the beginning of sequences. This is expected, as the memory size of IM during the early stage of prefill is relatively small. However, when the sequence length exceeds 24k, IM outperforms FM. This is because maintaining a smaller memory size during the initial prefill stage can reduce noise within the memory when useful information is not located at the beginning of the sequence.

We believe that with the larger memory size, KV Cache pruning has the potential to effectively handle needle-in-a-haystack retrieval tasks. Currently the maximum memory size can only be set to 2048, since SnapKV relies on attention scores, which is not compatible with flash attention.

5 Conclusion

In this paper, we addressed the inefficiencies in long-context prefilling of LLM by introducing two novel techniques: Incremental Memory and Decremental Chunk. Incremental Memory optimizes memory usage by dynamically increasing the memory size during prefilling, avoiding unnecessary computational overhead. Decremental Chunk complements this approach by dynamically adjusting the chunk size, maintaining stable and lower GPU memory usage. Experiments show that the combination of these methods significantly improves efficiency, with less prefilling times and GPU memory consumption compared to traditional fixed-size memory approaches.

[6] https://huggingface.co/winglian/Llama-3-8b-64k-PoSE

Limitations

1. In our experiments, we tested the performance and efficiency of our methods using sequences with length of 32k tokens. However, iterative compression can support inputs of unlimited length. We have not yet validated the effectiveness of our method on longer sequences, such as those with one million tokens.
2. We have evaluated our methods on LLama2-7b, InternLM2-7b, and Tiny-LLama. However, due to limitations in computational resources, we have not tested our model on the larger models, such as LLama2-70b. Nevertheless, we believe our method is more suitable for larger models because the memory bottleneck is more pronounced in these cases.

Ethics Statement

This paper honors the EMNLP Code of Ethics. The dataset used in the paper does not contain any private information. The code will be are open-sourced under the MIT license.

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A Supplementary Method Details

A.1 Alternative Incremental Functions

We present several alternatives to the linear function for increasing memory size, namely the SQRT and the SQUARE:

$$m_i^{\text{square}} = \frac{(m_{\max} - m_0)i^2}{(n-1)^2} + m_0 \tag{8}$$

$$m_i^{\text{sqrt}} = \frac{(m_{\max} - m_0)\sqrt{i}}{\sqrt{n-1}} + m_0 \tag{9}$$

The growth rate of the SQRT is initially slow but accelerates over time, whereas the SQUARE function exhibits the opposite behavior. The memory size of the SQUARE function is smaller than that of the LINEAR, which in turn is smaller than that of the SQRT function.

Based on the memory distribution visualization in Section B.2, we observed that the memory distribution in the higher layers of LLaMA2-7b is more uniform compared to the lower layers. Therefore, we propose a new increase function, SQUARE-SQRT, which combines the SQUARE and SQRT function: using SQUARE function for the lower layers, and SQRT function for the higher layers.

The integral of the sum of SQUARE and SQRT function ($m_i^{\text{high}} + m_i^{\text{low}}$) over the interval $[0, n-1]$ equals $n(m_{\max} + m_0)/2$, which is the same as that of linear function. Therefore, theoretically, the computational cost of SQUARE-SQRT is equivalent to that of LINEAR.

B Supplementary Experiments

B.1 Experiment Setting of Chunk size and Sequence Length

Since the GPU memory of A800 is much larger than that of RTX 3090, we set a larger sequence length and chunk size for the experiment on A800. Furthermore, SnapKV does not support flash attention, hence the chunk size and sequence of which is larger than that of StreamingLLM. We report the detail setting in Table 7. Both the experiments of Efficiency Comparison (4.3) and PPL Comparison (4.4) follow this setting.

B.2 Visualization of Memory Map

We conducted a statistical analysis of the memory distribution across chunks by recording the chunk ID of each key-value pair in the memory.[7] For this analysis, we utilized fixed-size memory instead of incremental memory. The results illustrated in Figure 1 indicate that the majority of the memory is concentrated in the last few chunks, irrespective of the models or pruners used.

Device	Pruner	Chunk Size	Sequence Length
A800	SnapKV	1024	32k
	StreamingLLM	8192	32k
RTX 3090	SnapKV	512	8k
	StreamingLLM	2048	8k

Table 7: Setting of Chunk Sizes and Sequence Lengths for Different Devices and Pruners

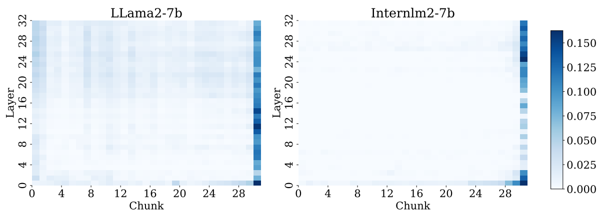

Figure 6: The memory distribution across different chunks in various layers for LLaMA2-7b and Internlm2-7b. The horizontal axis represents the Chunk ID, while the vertical axis represents the Layer ID. The intensity of the color reflects the proportion of memory distribution, with brighter colors indicating a higher proportion of memory within a given chunk. We have excluded the last column, as the majority of memory key-value pairs are concentrated in the final chunk.

We further investigated memory distribution across different layers for both LLaMA2-7b and InternLM2-7b. The results are shown in Figure 6. We found significant variation in memory distribution across different layers of LLaMA2-7b, with higher layers exhibiting a more uniform distribution than lower layers. Conversely, for InternLM2-7b, the differences in memory distribution across layers are minimal.[8]

B.3 Incremental Long-Term Memory

The test data was sampled from the Github and Arxiv subsets of RedPajama, with each sample containing 32k tokens. During the iteration, the memory is continuously updating. We visualized the memory retention ratio defined in Equation 2 in Figure 7.

[7] The data for this evaluation is the same as that used for the PPL Comparison in Section 4.4.

[8] We propose adaptive Incremental Memory in Section 3.2 inspired by this observation.

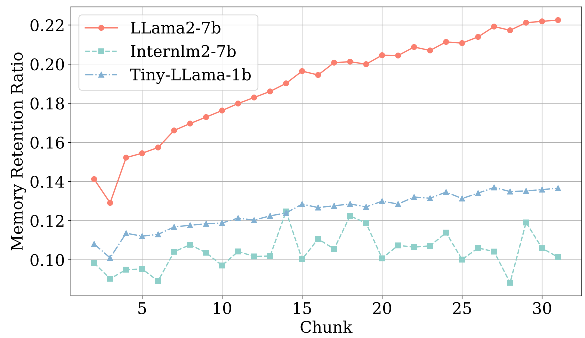

Figure 7: The variation of the Memory Retention Ratio during the iteration. The Memory Retention Ratio is defined as the proportion of memory retained after compression, see Equation 2. The higher Memory Retention Ratio indicates the less memory being forgotten after compression. The pruner used is SnapKV.

We observed that the memory retention ratio for LLaMA2-7b and Tiny-LLaMA increases linearly with iterations, whereas the memory retention rate for Internlm2-7b exhibits fluctuations. The increasing memory retention ratio suggests that as the model undergoes more iterations, it tends to retain more long-term memory.

B.4 Incremental Fixed Memory Versus Incremental Dynamic Incremental

AutoCompressors (Liu et al., 2020) also dynamically increases the memory size while iterating over chunks. Although their memory size grows incrementally, they do not compress the existing memory; instead, they append the compressed chunks to the existing memory. In other words, their memory consists entirely of long-term memory that is neither updated nor forgotten. Conversely, our method updates the memory content through compression at each step.

Which kind of incremental memory is better? We compared the performance of them by evaluating the perplexity of LLaMA2-7b. The experimental setup is consistent with that in Section subsection 4.4, and the results are shown in Figure Figure 8. We refer to AutoCompressors (Liu et al., 2020) as Incremental Fixed Memory, and our method as Incremental Dynamci Memory.

According to Figure 8, the perplexity of Dynamic Incremental Memory is significantly lower than that of Fixed Incremental Memory in almost all configurations, which demonstrates the superiority of our method and suggests that memory needs to be updated, i.e., long-term memory alone

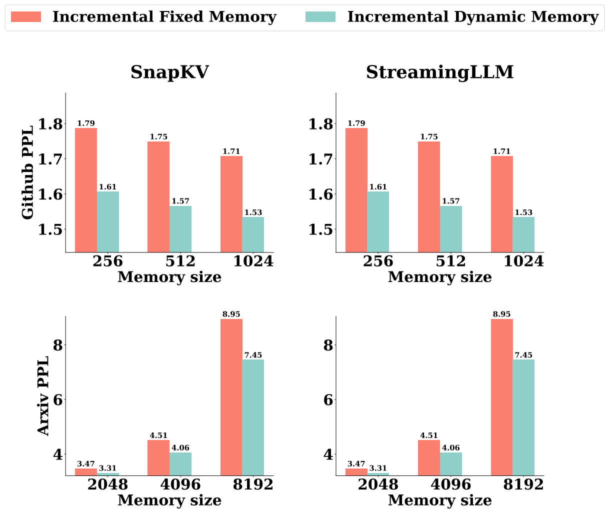

Figure 8: Incremental Fixed Memory (Liu et al., 2020) versus Incremental Dynamic Memory (ours). The data for evaluation is the same as that used in PPL Comparison (Section 4.4). Both approaches increase memory size linearly during iterative compression. For both methods, the chunk size and the maximum memory size are set to 1024.

is insufficient.