KeepKV: Achieving Periodic Lossless KV Cache Compression for Efficient LLM Inference

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Abstract

Efficient inference of large language models (LLMs) is hindered by an ever-growing key-value (KV) cache, making KV cache compression a critical research direction. Traditional methods selectively evict less important KV cache entries, which leads to information loss and hallucinations. Recently, merging-based strategies have been explored to retain more information by merging KV pairs that would be discarded; however, these existing approaches inevitably introduce inconsistencies in attention distributions before and after merging, causing degraded generation quality. To overcome this challenge, we propose KeepKV, a novel adaptive KV cache merging method designed to preserve performance under strict memory constraints, achieving single-step lossless compression and providing error bounds for multi-step compression. KeepKV introduces the Electoral Votes mechanism that records merging history and adaptively adjusts attention scores. Moreover, it further leverages a novel Zero Inference-Perturbation Merging method, compensating for attention loss resulting from cache merging. Extensive experiments on various benchmarks and LLM architectures demonstrate that KeepKV substantially reduces memory usage while successfully retaining essential context information, achieving over $2\times$ inference throughput improvement and maintaining superior generation quality even with only 10% KV cache budgets.

Code — https://github.com/kkvcache/KeepKV

Extended version — https://arxiv.org/abs/2504.09936

1 Introduction

Transformer-based large language models (LLMs) have demonstrated remarkable capabilities across various applications (Touvron et al. 2023; Jiang et al. 2023; OpenAI et al. 2024; Wan et al. 2024a). To accelerate inference, LLMs commonly employ a key-value (KV) cache mechanism, which stores the KV embeddings of previously processed tokens to avoid redundant computations (Vaswani et al. 2017; Dai et al. 2019). However, as LLMs continue to support increasingly longer context lengths, the size of the KV cache grows rapidly, becoming a major bottleneck for inference (Kwon et al. 2023). For example, in the case of LLaMA-3-70B, a batch size of 128 with an 8K context length requires up to 320GB of KV cache memory (Grattafiori, Dubey et al. 2024). Consequently, compressing the KV cache while preserving generation quality has become a crucial challenge.

Prior works mainly explore two approaches for KV cache compression: eviction-based and merging-based methods, both of which are inherently lossy. Eviction-based approaches selectively retain critical cache entries using heuristics like attention scores and token positions, permanently discarding less critical entries (Xiao et al. 2024b; Zhang et al. 2023; Reid and Zhu 2024; Liu et al. 2024; Li et al. 2024; Yang et al. 2024a) and thus causing context loss and potential hallucinations (Zhang et al. 2024). In contrast, merging-based methods aim to integrate rather than discard KV entries to retain more information. Recent representative studies, such as CaM (Zhang et al. 2024), D2O (Wan et al. 2024b), and KVMerger (Wang et al. 2024), have explored strategies like weighted key-value merging to mitigate context loss. Nevertheless, these methods vary widely in merge candidate selection and merging weight computation, and lack solid theoretical foundations. We observe that existing strategies inevitably induce attention inconsistencies and output perturbation. Specifically, the merged KV pair's attention score is lower than the sum of the original scores prior to merging—a phenomenon we term ”Attention Sag” (illustrated in Figure 1). These issues underline the necessity for an efficient and theoretically grounded KV cache merging strategy.

In this paper, we propose KeepKV, a novel KV cache merging method designed to maintain inference consistency and preserve essential contextual information. To the best of our knowledge, KeepKV is the first approach to achieve single-step lossless compression and to provide theoretical error bounds for multi-step compression. We first conduct a comprehensive theoretical analysis of existing eviction and weighted merging methods, grounded in the attention computation process, to reveal their fundamental limitations.Building on these theoretical insights, we propose a two-stage innovative design in KeepKV:

First, we propose techniques that achieve lossless compression for a single step. Specifically, we introduce the Electoral Votes mechanism, which records merging history, enabling accurate reconstruction of the original KV embeddings from compressed representations. Additionally, we present the Zero Inference-Perturbation Merging (ZIP-Merging) approach, which automatically adjusts weights to compensate

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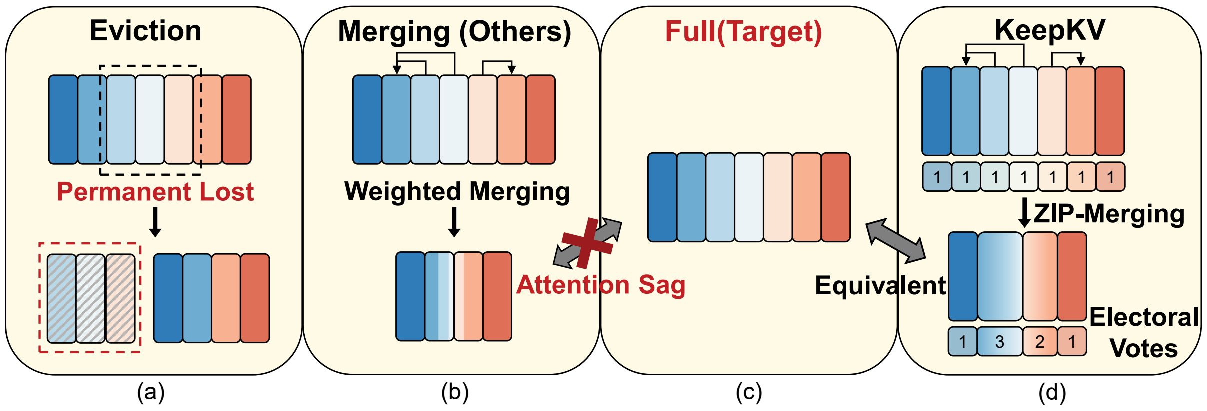


Figure 1: Illustration of KeepKV vs. Existing Methods. The three middle blocks represent KV subject to eviction/merging. (a) Eviction methods permanently discard them. (b) Merging methods integrates them into retained KV, but the result is not equivalent to the full KV, causing ”Attention Sag.” (c) Full KV serves as the ideal baseline. (d) KeepKV uses Electoral Votes as merging records and applies ZIP-Merging to minimize output disturbance, ensuring consistency and improving performance.

for any losses caused by merging, maintaining attention consistency. These designs theoretically guarantee zero output perturbation at the current iteration despite compression.

Second, we extend KeepKV to multi-step generation by estimating attention scores based on historical patterns. This is motivated by our empirical observation of strong locality in attention scores, also confirmed in prior studies (Dong et al. 2024; Zhang et al. 2024). Crucially, we provide theoretical analyses guaranteeing bounded output perturbation across multiple steps, thereby ensuring consistent inference quality under extended generation. Moreover, we offer a theoretical interpretation for prevalent similarity-based candidate selection methods, incorporating it into our design.

By integrating these innovations, KeepKV further enables periodic lossless KV cache compression by storing a complete KV cache externally and periodically loading compressed representations into memory, thereby maintaining inference consistency and preserving essential contextual information. Through theoretical derivation and extensive experiments, we demonstrate that KeepKV effectively preserves attention stability and output consistency, outperforming state-of-the-art KV cache eviction and merging methods. The contributions of this paper are summarized as follows:

- We propose KeepKV, a novel adaptive KV cache merging approach designed to eliminate output perturbation caused by compression. KeepKV introduces the Electoral Votes mechanism and Zero Inference-Perturbation Merging to keep attention consistency.
- Extensive experiments across various tasks and models show that KeepKV maintains better performance under limited cache, outperforming existing KV cache eviction and merging methods.
- We are the first to theoretically analyze KV merging from the perspective of eliminating output perturbation. We provide guarantees on the perturbation bound of KeepKV and reveal the theoretical basis for merge candidate selection and weight design.

2 Related Work

KV cache has become a major bottleneck for efficient LLMs inference. Post-training optimization serves as a key solution due to its real-time and extensible capabilities.(Shi et al. 2024). Existing methods fall into three categories: **quantization**, **eviction**, and **merging**.

KV Cache Quantization. Quantization methods convert tensor values to lower precision to reduce bit-width. KVQuant (Hooper et al. 2024) applies Per-Channel Quantization for keys and Per-Token Quantization for values. MiKV (Yang et al. 2024b) introduces mixed-precision KV caching, where less critical KV are stored at lower precision. Additionally, GEAR (Kang et al. 2024) leverages low-rank matrix approximation for quantization residuals to minimize quantization loss. Our KeepKVis orthogonal to quantization methods and can be combined for better efficiency.

KV Cache Eviction. Eviction methods only retain more important KV entries. StreamingLLM (Xiao et al. 2024b) and LM-infinite (Han et al. 2024) identifies the importance of the initial k tokens for generation. H2O (Zhang et al. 2023), ScissorsHand (Liu et al. 2024) and RoCo (Reid and Zhu 2024) recognize crucial KV based on attention scores, while SnapKV (Li et al. 2024) utilizes attention within an observation window. Recent works explore improved budget allocation strategies across layers and heads. Pyramid (Cai et al. 2024; Yang et al. 2024a) allocates more cache to lower layers, whereas AdaKV (Feng et al. 2024), HeadKV (Fu et al. 2024), and DuoAttention (Xiao et al. 2024a) focus on inter-head differences. However, eviction causes irreversible information loss, potentially degrading generation quality.

KV Cache Merging. KV cache merging combines less important KV entries instead of discarding them. DMC (Nawrot et al. 2024) learns when and how to merge through training, which limits generalization and introduces extra overhead. CaM (Zhang et al. 2024) adaptively merges evicted value states into others but does not merge the corresponding keys. Recently, D2O (Wan et al. 2024b) selects merge candidates and assigns merging weights based on cosine similarity between key states, while KVMerger (Wang et al. 2024) introduces a clustering-based method to group merge candidates and uses Gaussian Kernel Weights. However, these methods fail to maintain attention consistency before and after merging, leading to output perturbation. We propose a novel merging approach designed to eliminate output perturbation, supported by theoretical analysis and extensive comparisons.

3 Methodology

3.1 Preliminary: Inference with KV Cache

We first introduce the attention computation process with KV cache. For simplicity, we consider a single attention head at one layer. Let the attention module's weight matrices be $W_q, W_k, W_v \in \mathbb{R}^{d\times d}$, where d denotes the hidden dimension. During the prefill stage, given an input prompt tensor $X_L \in \mathbb{R}^{L\times d} = [x_1, x_2, \ldots, x_L]$, where L represents the prompt length, the KV states are computed and stored in the KV cache as follows:

$$\begin{aligned} K_L &= X_L W_k = [k_1, k_2, \ldots, k_L], \\ V_L &= X_L W_v = [v_1, v_2, \ldots, v_L]. \end{aligned} \tag{1}$$

In the decoding phase, KV cache are repeatedly utilized, while the newly computed KV pairs are continuously appended to it. Specifically, given the input at the t-th generation step, $x_t \in \mathbb{R}^d$, the KV cache update and attention computation are performed as follows:

$$\begin{aligned} K_t &= [K_{t-1}, k_t], \quad k_t = x_t W_k \\ V_t &= [V_{t-1}, v_t], \quad v_t = x_t W_v \end{aligned} \tag{2}$$

$$\begin{aligned} A^t &= \text{softmax}\left(\frac{q_t K_t^T}{\sqrt{d}}\right), \quad q_t = x_t W_q \\ s_i^t &= e^{\frac{q_t k_i}{\sqrt{d}}}, \quad o_t = \sum_{i=1}^{t} A_i^t v_i = \frac{\sum_{i=1}^t s_i^t v_i}{\sum_{i=1}^t s_i^t} \end{aligned} \tag{3}$$

KV cache effectively reduces redundant computation, but at the cost of increased memory consumption. Therefore, an important challenge is to compress the KV cache while maintaining model performance.

3.2 Rethinking KV Cache Eviction and Merging

Eviction and merging methods reduce memory usage by decreasing the number of stored KV pairs. The core motivation behind these studies is to minimize the impact of cache compression on the output. A fundamental *subtask* is to ensure that the output (o_t) remains as close as possible before and after compression at the current step. However, our analysis shows that existing methods inevitably introduce output perturbation and can not accomplish this task.

Perturbation in KV Cache Eviction. Eviction methods discard KV pairs deemed unimportant. Suppose we discard the pair (k_e, v_e), and denote the output as o'_t. Based on Equation 3, we obtain:

$$o'_t = \frac{\sum_{i=1, i\neq e}^t s_i^t v_i}{\sum_{i=1, i\neq e}^t s_i^t} = \frac{1}{1 - A_e^t}\left(o_t - A_e^t v_e\right). \tag{4}$$

Remark 1. *Equation 4 reveals that evicting (k_e, v_e) causes o'_t to deviate from o_t, with the deviation primarily determined by A_e^t. This formally explains why eviction methods generally prioritize discarding KV pairs with lower attention scores.*

Although current methods optimize eviction and cache allocation strategies (Yang et al. 2024a; Fu et al. 2024) to minimize output impact, they cannot eliminate the perturbation in Equation 4. Previous studies have indicated that attention is not always sparse, especially in tasks requiring full context, as shown in Figure 2. Moreover, evicted KV may become important later, but irreversible eviction leads to permanent loss.

Attention Sag in KV Cache Merging. Merging methods integrate less important KV into others rather than discarding them. Existing studies typically use weighted merging (Nawrot et al. 2024; Wan et al. 2024b; Wang et al. 2024); formally, merging (k_e, v_e) into (k_c, v_c) is expressed as:

$$k_r = w_e k_e + w_c k_c, \quad v_r = w_e v_e + w_c v_c. \tag{5}$$

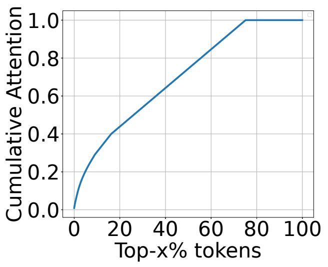
Here, (k_r, v_r) are the merged vectors, with weights w_e, w_c determined by the merging method. In D2O (Wan et al. 2024b), they depend on the cosine similarity between k_e and k_c, while in KVMerger (Wang et al. 2024), they are computed using Gaussian Kernel values. The weights satisfy the normalization condition $w_e + w_c = 1$. However, this widely used convex combination method also introduces output perturbations:

Theorem 2. *Current weighted merging (convex combination) methods reduce the merged KV pair's attention score compared to the sum of the original scores before merging, i.e., ${A'}_r^t < A_e^t + A_c^t$, ultimately leading to $\|o'_t - o_t\| > 0$.*

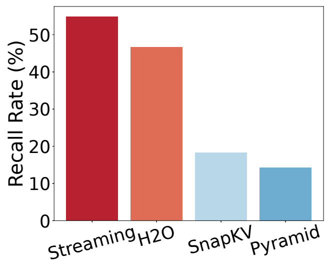
The formal proof is in Appendix. We term this attention inconsistency from merging as **Attention Sag** and Figure 2 (c) illustrates this phenomenon. We provide an intuitive comprehension: existing methods merge multiple vectors into one, treating it equivalently as any other single vector in subsequent attention computations. This erases merging history, making it impossible to distinguish whether a KV pair is original or has absorbed numerous others.

3.3 Method: KeepKV

Electoral Votes and ZIP-Merging Electoral Votes. To address Attention Sag, we propose the Electoral Votes mechanism, which records the number of merges p_i (initialized to 1) each KV pair undergoes. A natural analogy is the Electoral College system, where electors hold votes proportional to their state's population rather than a uniform share. The attention score of each KV is then scaled by its votes to approximate the original multiple KV's influence before merging. For example, if a KV pair (k_r, v_r) has a vote count of $p_r = 3$, it is equivalent to three identical and independent instances of (k_r, v_r) participating in the attention computation. Formally, the outputs before (o_t) and after merging (o'_t) are defined as follows:



(a)



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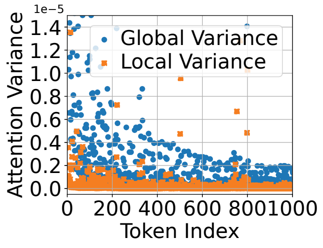

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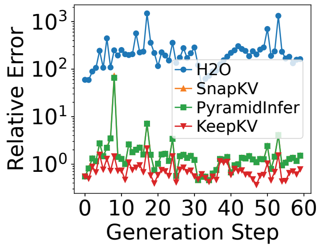


(d)

Figure 2: (a) Cumulative distribution of attention scores. Retaining the top-k tokens does not always preserve the majority of scores. (b) Proportion of to-be-evicted prompt tokens appearing in the top-20% attention scores during generation (compression rate = 20%). (c) Each token's variance of its attention scores at each generation step (blue dots) is greater than the average variance within a sliding window (orange dots).(d) Relative errors for prediction of KeepKV and existing methods.

$$\begin{aligned} o_t &= \frac{\sum_{i=1}^{t} p_i s_i^t v_i}{\sum_{i=1}^{t} p_i s_i^t}, \\ o'_t &= \frac{\sum_{i=1, i\neq e,c}^{t} p_i s_i^t v_i + p_r s_r^t v_r}{\sum_{i=1, i\neq e,c}^{t} p_i s_i^t + p_r s_r^t}, \\ p_r &= p_e + p_c. \end{aligned} \tag{6}$$

Zero Inference-Perturbation Merging (ZIP-Merging). The Electoral Votes mechanism enables the elimination of output perturbations. We define the merging equations and theorem as follows:

$$\begin{aligned} k_r &= \frac{(w_e k_e + w_c k_c)\ln \frac{w_e + w_c}{p_e + p_c}}{w_e \ln s_e^t + w_c \ln s_c^t}, \\ v_r &= \frac{w_e v_e + w_c v_c}{w_e + w_c}, \\ w_e &= p_e s_e^t, \quad w_c = p_c s_c^t. \end{aligned} \tag{7}$$

Theorem 3. *The merging method in Equation 7 is perturbation-free, that is,* $\|o'_t - o_t\| = 0$

Remark 4. *The proof is in Appendix. Intuitively, our method ensures attention consistency by preserving historical information via Electoral Votes and applying proper scaling (ZIP-Merging) to* (k_r, v_r) *instead of a convex combination.*

This theorem confirms that our novel merging approach can eliminate output perturbations and complete the subtask introduced at the beginning of this section. However, its applicability remains limited to the current iteration, and extending it to multi-step generation requires additional design.

Extending to Multi-Step Generation EMA Attention Scores. For ZIP-Merging to be effective in real-world multi-step generation, a solid comprehension of attention score dynamics is essential. Fortunately, empirical observations show that attention scores exhibit strong locality (Figure 2 (d)), meaning a token's attention scores evolve smoothly across adjacent steps, which is also validated by prior studies (Yang et al. 2024a; Zhang et al. 2024; Dong et al. 2024). From this, we employ the Exponential Moving Average (EMA) (Hunter 1986; Busbridge et al. 2023) with bias correction, a widely used technique in time-series analysis, formulated as follows:

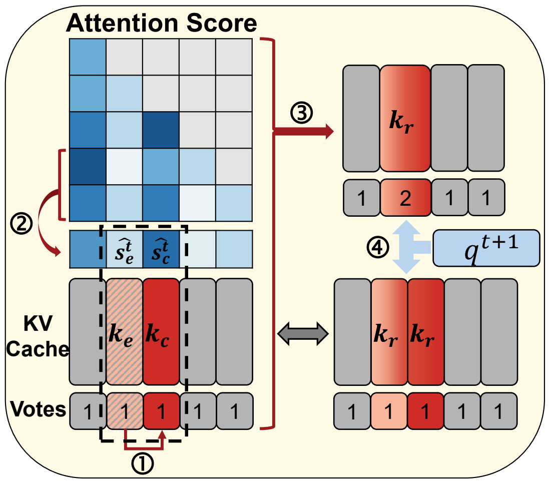
$$\hat{s^t} = \frac{1}{1-\alpha^t} S^t, \; S^t = \begin{cases} \sum\limits_{k=t-w}^{t} (1-\alpha)\alpha^{t-k} s^k, t = L \\ \alpha S^{t-1} + (1-\alpha) s^t, t > L \end{cases} \tag{8}$$

Note that after the prefill stage, we compute EMA scores using a recent window of length w rather than the entire sequence to obtain a more accurate estimation (Li et al. 2024; Yang et al. 2024a). We find that this method outperforms mainstream approaches, such as cumulative attention and sliding window averaging, in predicting attention scores.Building on this, replacing all score s_i^t in Equation 7 with our EMA scores $\hat{s_i^t}$ from Equation 8 successfully achieves the extension to multi-step generation. Consequently, the future output perturbation becomes estimable and controllable. We present the following theorem and lemma(proof in Appendix):

Theorem 5. *For the* t'*-th step, let* $\left|1 - \frac{\hat{s_i^{t'}}}{s_i^{t'}}\right| \leq \epsilon, \epsilon < 1$, *the output perturbation satisfies* $\Theta_{t'} < \frac{2\epsilon(1+\epsilon)\gamma}{(1-\epsilon)^2}$, *provided that* $\|v_i - v_j\| \leq \gamma, \forall i \in [t'], j \in \{e, c\}$.

Lemma 6. *As the prediction error* ϵ *decreases and the merged candidates become increasingly similar, the output perturbation reduces to zero. That is, when either* $\epsilon = 0$ *or* $(k_e, v_e) = (k_c, v_c)$, *we have:* $\Theta_{t'} = 0$.

Similarity-driven merging. Lemma 6 shows that output perturbation decreases as prediction error ϵ reduces, and closer merging objects result in lower perturbation. Clearly, if the merged KV pairs are identical, retaining one pair and setting its Electoral Votes to 2 introduces no error in subsequent computations. This provides a theoretical justification for prior merging strategies favoring high-similarity KV pairs (Wan et al. 2024b; Wang et al. 2024). Following this, we merge each evicted KV pair with the retained one having the highest cosine similarity of keys, using a predefined threshold T to determine whether merging should occur, avoiding the overhead of dynamic adjustments like D2O (Wan et al.



Algorithm 1 KeepKV Merging at t-th Step

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 1: Input: Attention scores $s^t$, EMA scores $S^{t-1}$, KV cache
 2: Let $K_e$ denote the to-be-evicted cache
 3: Let $K_c$ denote the retained cache
 4: $U = \text{cosineSimilarity}(K_e, K_c)$
 5: For each $k_e \in K_e$, select $k_c = \text{Argmax}_{k_c \in K_c}(U^e),\ U_{e,c} > T$
 6: $\hat{s}^t = \text{updateEMA}(S^{t-1}, s^t)$                        ▷ Eq. (8)
 7: Merge:
 8:     $k_r = \frac{\ln((p_e \hat{s}_e^t + p_c \hat{s}_c^t)/(p_e + p_c))}{p_e \hat{s}_e^t \ln \hat{s}_e^t + p_c \hat{s}_c^t \ln \hat{s}_c^t}(p_e \hat{s}_e^t k_e + p_c \hat{s}_c^t k_c)$
 9:     $v_r = \frac{1}{p_e \hat{s}_e^t + p_c \hat{s}_c^t}(p_e \hat{s}_e^t v_e + p_c \hat{s}_c^t v_c)$
10:     $p_r = p_e + p_c$
11: Discard $(k_e, v_e), (k_c, v_c)$ and insert $(k_r, v_r)$ into KV cache
12: Output: Updated KV cache
```

Figure 3: Illustrative example of KeepKV. (0) (k_e, v_e) is selected for eviction by specific compression method. (1) The retained KV with the highest cosine similarity, (k_c, v_c), is selected. (2) EMA attention scores are updated. (3) ZIP-Merging is performed. (4) Consequently, with the Electoral Votes, the compressed KV can preserve the influence of the original KV in attention computations.

2024b). Furthermore, we observe that, during the prefill stage, reversing the conventional order—by first merging based on key similarity and then applying the eviction strategy, instead of merging after eviction as commonly done—can improve generation quality.

We present the workflow of KeepKV in Figure 3. Notably, KeepKV imposes no specific constraints on cache allocation or token selection. It can directly integrate with common token selection methods by designating the merging pairs based on their eviction and retention sets, and it is also compatible with various cache allocation strategies. Thus, KeepKV demonstrates strong adaptability and can be combined with mainstream cache compression methods, significantly enhancing both compression capability and generation quality.

4 Experiment

4.1 Experiment Settings

Tasks We evaluate KeepKV on datasets with standard and extended context lengths, covering question-answering, summarization, and synthetic tasks. Specifically, for question-answering, we utilize MathQA (Amini et al. 2019), OpenBookQA (Mihaylov et al. 2018) and other tasks from the lm-eval-harness framework (Gao et al. 2024). For summarization, we employ the XSUM(Narayan, Cohen, and Lapata 2018) and CNN/DailyMail(Nallapati et al. 2016) tasks provided by the HELM framework. To assess performance on long-context tasks, we adopt LongBench(Bai et al. 2024), which effectively examines the algorithm's compression capabilities across diverse subtasks, including single-document QA, multi-document QA and synthetic tasks.

Models and baselines. Our evaluation is based on several representative LLMs, including Llama-2 (Touvron et al. 2023), Llama-3 (Grattafiori, Dubey et al. 2024), and Mistral (Jiang et al. 2023). We compare our method against multiple baseline approaches: representative cache eviction methods such as Streaming (Xiao et al. 2024b), H2O (Zhang et al. 2023) and PyramidInfer (Yang et al. 2024a), and prominent cache merging methods including CaM (Zhang et al. 2024) and D2O (Wan et al. 2024b). More detailed comparison results are provided in the Appendix.

Implementation. In our main experiments, we set the merging threshold T to 0.8. For token selection and cache allocation, we follow the strategy recommended by PyramidInfer (Yang et al. 2024a), which allocates fixed cache budgets, making it simple and efficient. And it is sufficient to demonstrate the advantages of our algorithm. In contrast, D2O (Wan et al. 2024b) applies dynamic allocation based on extra computation after prefill phase for each sequence. We conduct most experiments on NVIDIA A100 80GB GPUs.

4.2 Accuracy on KV Cache Compression Ratios

In Figure 4, we benchmark KeepKV on lm-eval-harness and HELM frameworks, comparing the fully cached KV version against multiple KV cache compression methods, including our proposed KeepKV. The x-axis represents the compression ratio, defined as the ratio between the compressed KV cache budget and the prompt length L. The results demonstrate that KeepKV consistently outperforms all other compression methods across various compression ratios. Particularly at extremely low compression rates, KeepKV achieves significantly better performance, highlighting its superior compression capability to retain maximal information within highly constrained memory budgets while effectively minimizing output perturbations introduced by compression.

4.3 Accuracy on Long-context Tasks

We evaluate KeepKV on the LongBench across Llama and Mistral model families,including Llama-2-7B, Llama-2-13B, Llama-3-8B and Mistral-7B, as shown in Table 3. The evaluation tasks include Single-Document QA, Multi-Document

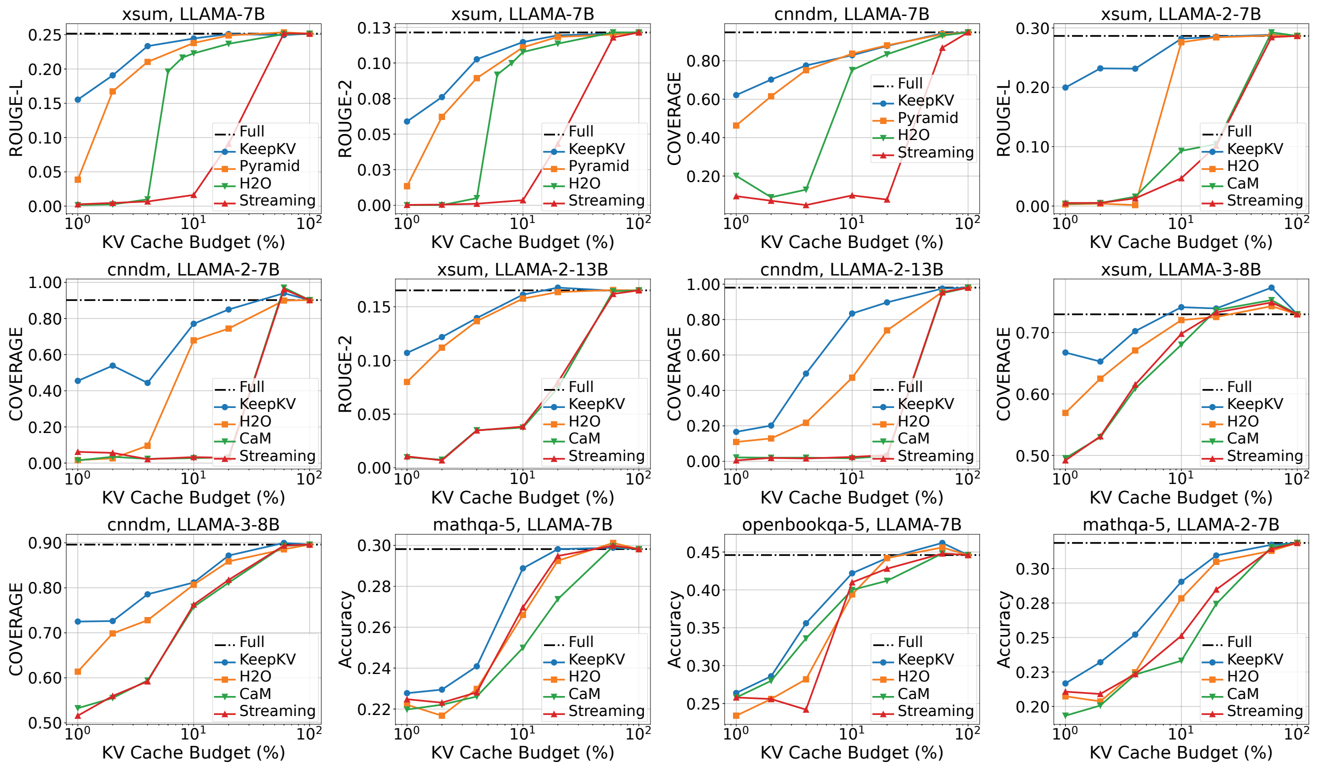


Figure 4: Performance of KeepKV and other methods for LLama backbones on HELM and LM-Eval evaluations.

Methods	Batch Size	Throughput (tokens/s)
Full cache	2	116.54
H2O	8	317.33
D2O	8	214.8
KeepKV	8	255.99

Table 1: Throughput comparison of KeepKV and other methods (4k context, 20% compression ratio).

Prompt / Decoding Len	Latency (s/token)	GFLOPs	GPU Mem (GB)
2048/128	0.034	14.8	14.3

Table 2: KeepKV's computational overhead (cache size = 400).

QA, Summarization, Synthetic, and Code. The results indicate that KeepKV achieves performance closer to the full-cache baseline on most tasks, maintaining high generation quality despite limited cache availability. Notably, KeepKV significantly outperforms eviction-based methods, such as Local Window, StreamingLLM (Xiao et al. 2024b), and H2O (Zhang et al. 2023). Furthermore, KeepKV also surpasses existing KV-cache merging methods, like CaM(Zhang et al. 2024) and D2O(Wan et al. 2024b), underscoring the effectiveness of our carefully designed merging strategy in enhancing output accuracy. More results can be found in the appendix.

4.4 Throughput Analysis

Our experiments demonstrate that KeepKV significantly enhances the inference throughput of the model by efficiently compressing the KV Cache, as illustrated in Table 1. We conducted experiments on the Llama-2-7B model using an A100-80G GPU, with tasks derived from the LongBench evaluation framework. The experimental results indicate that various compression techniques improve throughput by reducing cache size and increasing batch size. Compared to the original full-cache method, KeepKV achieved over 2$\times$ increase in throughput. It is noteworthy that, due to the additional computations, the throughput per request of merging methods is typically lower than that of classical eviction methods, such as H2O (Zhang et al. 2023). Nonetheless, KeepKV achieves higher throughput than the state-of-the-art (SOTA) merging-based algorithm, D2O (Wan et al. 2024b). This advantage arises because D2O computes attention distribution variance for real-time cache allocation. Table 2 summarizes the latency, GFLOPs, and peak GPU memory during decoding of KeepKV measured on an RTX 4090.

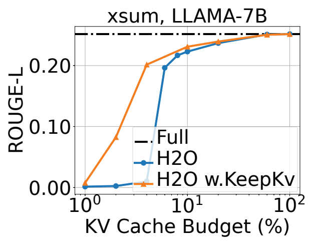
4.5 Ablation Study

To evaluate the generalizability of KeepKV, we conducted ablation experiments combining KeepKV with existing state-of-the-art eviction methods. Since KeepKV does not impose specific requirements on cache allocation or eviction/preservation strategies, it can be directly integrated with commonly used eviction/preservation policies. This only requires setting the merged parties as the eviction and preservation sets deter-

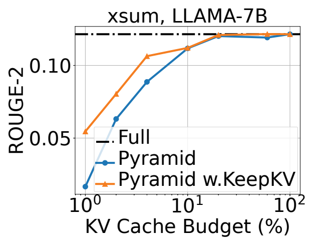
Methods	Single-Doc QA			Multi-Doc QA			Summarization			Synthetic		Code	
	NrtvQA	Qasper	MF-en	HotpotQA	2WikiMQA	Musique	TREC	TriviaQA	SAMSum	PCount	PRe	Lcc	RB-P
						Llama-2-7B							
Full Model	15.8	9.39	22.09	8.56	10.85	4.3	65.0	89.64	34.16	1.0	8.29	66.77	60.1
Local Window	2.22	9.29	1.83	5.14	7.18	1.02	17.5	4.07	3.17	1.5	2.58	16.31	15.35
StreamingLLM	11.81	5.18	19.26	7.07	10.48	3.71	55.5	87.31	31.84	1.5	4.29	63.79	56.07
H_2O	16.54	7.57	20.61	7.68	9.28	4.09	**64.0**	87.98	33.62	1.34	9.14	65.34	58.49
CaM	11.79	5.1	19.12	7.26	**10.48**	3.64	56.0	87.31	31.85	1.5	4.29	63.66	55.98
D_2O	16.04	6.54	19.48	8.14	10.12	4.62	63.5	88.39	**34.1**	1.39	7.54	65.8	**59.44**
Ours	**17.32**	**7.48**	**22.2**	**8.51**	9.72	**4.65**	60.5	**88.87**	33.2	**2.23**	**8.45**	**65.9**	56.36
						Llama-2-13B							
Full Model	12.64	8.61	19.82	9.1	10.98	5.8	69.5	87.04	41.89	2.0	6.03	67.08	57.53
Local	4.95	5.11	3.82	7.05	9.87	3.42	19.0	7.83	2.63	1.17	6.51	16.7	14.65
StreamingLLM	5.04	5.75	12.24	9.4	10.47	4.71	57.0	82.48	37.21	1.5	5.04	61.47	50.84
H2O	**13.83**	6.41	15.52	9.04	9.55	5.53	66.0	86.08	40.2	**2.88**	7.37	64.52	55.46
CaM	5.16	5.95	12.31	9.19	10.52	4.66	57.0	82.48	37.28	2.5	5.25	61.75	50.71
D2O	12.76	6.53	14.87	8.59	10.34	5.75	66.5	**86.52**	40.52	2.0	6.99	**65.23**	55.84
Ours	12.09	**6.89**	**17.81**	**9.49**	**10.54**	**5.79**	**66.8**	82.72	**41.35**	1.75	**7.55**	64.81	**56.29**
						Llama-3-8B							
Full Model	14.34	13.68	21.7	9.42	10.75	6.99	72	90.7	45.13	3.74	6.72	70.54	66.04
Local	2.14	6.69	5.17	6.16	5.0	2.42	34.25	30.5	10.66	2.36	2.0	28.91	24.52
StreamingLLM	10.43	7.84	13.85	9.18	10.44	5.47	61.0	90.37	44.35	2.6	10.5	68.49	63.94
H2O	**13.73**	10.02	17.2	9.31	10.62	6.42	63.3	90.44	45.02	3.29	7.56	68.95	63.84
CaM	10.43	7.83	13.89	9.11	10.37	5.47	61.0	90.37	44.31	3.16	10.5	68.59	64.04
D2O	13.5	8.86	17.21	9.16	10.52	6.35	**65.5**	**90.52**	44.64	3.44	5.8	68.49	64.84
Ours	12.76	**10.63**	**18.57**	**9.37**	**10.72**	**6.53**	64.5	90.33	**45.2**	**3.54**	**7.16**	**69.05**	**65.68**
						Mistral-7B							
Full Model	22.92	39.74	51.46	43.28	39.46	25.59	74.0	88.64	46.97	4.0	63.5	61.42	58.72
Local	16.89	16.92	21.11	23.33	22.49	10.23	58.5	81.29	36.3	2.1	**7.71**	41.1	47.88
StreamingLLM	16.76	17.28	21.41	24.16	22.54	10.72	60.3	82.21	37.43	2.14	7.67	51.19	47.94
H2O	18.06	16.75	22.28	24.77	21.68	8.86	61.0	83.03	30.34	2.15	5.76	56.5	49.88
CaM	16.46	17.26	21.4	25.66	22.54	**10.72**	59.17	82.21	37.33	2.14	7.67	51.01	47.89
D2O	**18.58**	15.92	21.71	26.41	21.68	9.07	61.5	83.12	39.5	2.18	7.3	57.51	50.59
Ours	18.16	**17.95**	**22.93**	**26.56**	**23.18**	9.42	**62**	**83.47**	**39.7**	**2.19**	7.26	**58.9**	**50.71**

Table 3: Performance evaluation of KeepKV on various models in LongBench benchmarks (20% compression ratio).

mined by their respective algorithms; it can also be applied with various cache allocation strategies, simply by modifying the cache configurations between layers and attention heads. As shown in Figure 5, we combined KeepKV with existing mainstream eviction methods, H2O(Zhang et al. 2023) and PyramidInfer(Yang et al. 2024a), using the HELM evaluation framework. The results demonstrate that, with KeepKV incorporated, the methods outperform the original ones across all compression ratios. This proves that our algorithm is highly scalable and versatile, capable of being integrated with various eviction schemes to enhance their compression efficiency and generation quality.



(a) Combining with H2O.



(b) Combining with Pyramid.

Figure 5: Accuracy experiments combining KeepKV with existing eviction methods.

5 Conclusion

In this paper, we conduct a comprehensive analysis of the impact of KV cache compression on attention computation and propose KeepKV, which introduces the Electoral Votes mechanism and Zero Inference-Perturbation Merging to adaptively and dynamically merge the KV cache while minimizing output disturbance. KeepKV effectively preserves more information within limited memory, significantly mitigating the adverse effects of KV cache compression on generation quality. Our experiments demonstrate that KeepKV achieves performance closest to that of the full cache across various compression ratios. It also excels in both standard and long-context tasks. We believe KeepKV provides a novel perspective and a powerful tool for advancing KV cache compression methods, laying the foundation for efficient LLM inference.

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