
Homogeneous Keys, Heterogeneous Values: Exploiting Local KV Cache Asymmetry for Long-Context LLMs

Wanyun Cui^{*,+} and Mingwei Xu^{*}

^{*}Shanghai University of Finance and Economics

⁺MoE Key Laboratory of Interdisciplinary Research of Computation and Economics, Shanghai University of Finance and Economics

^{*}cui.wanyun@sufe.edu.cn, mingweixu@stu.sufe.edu.cn

Abstract

Recent advances in Large Language Models (LLMs) have highlighted the critical importance of extending context length, yet the quadratic complexity of attention mechanisms poses significant challenges for efficient long-context modeling. KV cache compression has emerged as a key approach to address this challenge. Through extensive empirical analysis, we reveal a fundamental yet previously overlooked asymmetry in KV caches: while adjacent keys receive similar attention weights (*local homogeneity*), adjacent values demonstrate distinct *heterogeneous* distributions. This key-value asymmetry reveals a critical limitation in existing compression methods that treat keys and values uniformly. To address the limitation, we propose a training-free compression framework (AsymKV) that combines homogeneity-based key merging with a mathematically proven lossless value compression. Extensive experiments demonstrate that AsymKV consistently outperforms existing long-context methods across various tasks and base models. For example, on LLaMA3.1-8B, AsymKV achieves an average score of 43.95 on LongBench, surpassing SOTA methods like H₂O (38.89) by a large margin. Our code can be found in this link.

1 Introduction

The ability to process long contexts is crucial for Large Language Models (LLMs) [13, 23]. However, processing such long contexts poses significant challenges: pre-trained LLMs face both architectural and computational constraints in handling extended contexts. In particular, as the context length increases, the complexity of attention mechanisms increases quadratically ($O(n^2)$), while storage overhead increases linearly ($O(n)$) [7].

Various approaches have been proposed to address this challenge, with KV cache compression emerging as a promising direction [15]. These methods aim to compress the KV cache while preserving essential information for maintaining model performance. A straightforward strategy is to keep tokens with high historical importance (e.g., attention scores [16, 19, 20, 33]). This approach leverages the observation that attention weights exhibit significant variation across different tokens. Another line of work attempts to identify more general token importance rather than the history information [28, 27, 5]. However, these approaches share a fundamental limitation: they fail to capture certain tokens that are less important in the history but suddenly become critical for subsequent predictions.

To address the information loss caused by directly discarding tokens, cache merging methods have been proposed to merge multiple tokens into fewer representations rather than hard pruning, thereby preserving more information [32, 26, 27]. These merging approaches implicitly assume that certain

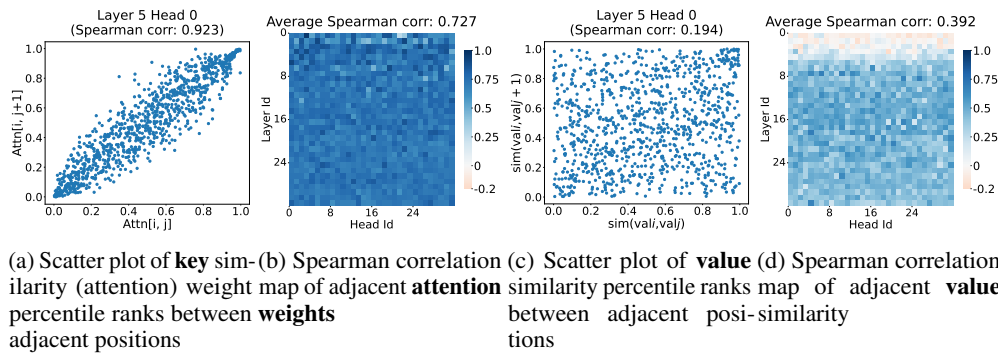


Figure 1: Contrasting distributions of **local homogeneity in attentions (keys) versus local heterogeneity in values**. Statistics are from Llama-2-7b-chat on the ShareGPT dataset. (a-b) demonstrate strong positive correlations between adjacent attention percentile ranks (normalized to $[0,1]$, where 1 indicates highest attention) across all layers and heads, supporting the local homogeneity hypothesis for keys. (c-d) reveal weak or negative correlations between adjacent value similarity percentile ranks, computed from $\text{sim}(\text{val}_i, \text{val}_j)$, indicating distinct heterogeneity in values. The similarity is measured by cosine. This fundamental difference between keys and values suggests the need for separate compression strategies.

redundancies or patterns exist in the KV cache. This raises a new fundamental question: *what specific characteristics of LLMs lead to these redundancies and make cache merging feasible?* We answer this question by identifying the key-value asymmetry in LLM attention mechanisms.

Local Key-Value Asymmetry Through extensive empirical analysis, we reveal a fundamental pattern in attention distributions: the *homogeneity of local keys*. Specifically, we observe that **adjacent tokens consistently receive similar attention weights** - when a query assigns high attention to position j , the neighboring position $(j + 1)$ typically receives comparable attention weight (Fig. 1a). This pattern shows remarkable consistency across all layers and attention heads, with an average Spearman correlation coefficient of 0.727 (Fig. 1b). This consistent local attention pattern, arising from query-key interactions, suggests an underlying *homogeneity of local keys* - adjacent keys must share certain structural properties to produce such stable attention patterns. Such key homogeneity naturally emerges from language structure, where adjacent words form coherent semantic units and contribute collectively to meaning representation.

The observed homogeneity of adjacent keys provides evidence for merging neighboring tokens, offering a principled explanation to recent token merging approaches. Specifically, when multiple adjacent keys exhibit high homogeneity, computing and storing only one key for the merged representation effectively approximate the original attention output, leading to both computational and memory efficiency.

However, our analysis reveals a striking asymmetry: while keys exhibit strong local homogeneity, adjacent values demonstrate markedly distinct *heterogeneous distributions*. As shown in Fig. 1c and Fig. 1d, when switching from keys to value similarities, adjacent value vectors ($\mathbf{v}_i$ and $\mathbf{v}_{i+1}$) often show much lower or even negative correlations in some layers.

This local key-value asymmetry reveals critical limitations in existing methods: cache merging methods [32, 26] apply identical merging strategies to both keys and values, overlooking their fundamentally different distributional characteristics. More studies of this phenomenon will be discussed in § A.

Training-free Asymmetry Modeling Based on the above analysis, the key challenge in cache merging lies in modeling heterogeneous values. Fortunately, through careful examine of attention mechanisms' mathematical structure, we discover an elegant solution to this value heterogeneity. We develop a mathematically proven value representation scheme that guarantees lossless attention computation after merging adjacent keys. Notably, our method remains distribution-agnostic, making it inherently robust to value heterogeneity.

Building on the key-value asymmetry and the property for values, we propose AsymKV, a novel training-free cache merging method for efficient long-context modeling. Our key insight is to shift the information loss from heterogeneous values to homogeneous keys during merging, thereby minimizing overall loss. Extensive experiments demonstrate that our method consistently outperforms existing long-context methods across various tasks and base models. On LLaMA3.1-8B, AsymKV achieves an average score of 43.95 on LongBench, surpassing H₂O [33] (38.89) by a significant margin. These results demonstrate AsymKV’s effectiveness in extending LLMs’ context handling capabilities without additional training.

Our Contributions: The key contributions of this work are threefold. First, we reveal a contrasting, yet previously overlooked asymmetry of local keys and values in LLM attention mechanisms. Second, based on this asymmetric property, we propose a novel training-free compression framework that combines homogeneity-based key merging with a mathematically proven lossless value representation. Third, we demonstrate through extensive experiments that our method consistently outperforms existing long-context methods across various tasks and base models.

2 Related Work

KV Cache Pruning Recent research focuses on compressing the KV cache through selective token retention and importance-based pruning. H₂O [33] introduces the concept of “Heavy Hitters” - tokens that contribute significantly to attention scores - and develops a theoretically-grounded eviction policy. Building on this idea, RoCo [22] improves the robustness of cache compression by considering both temporal attention scores and stability measures. More recent works like SnapKV [16] and Scissorhands [19] leverage the persistence of token importance across generation steps, while [9] demonstrates that L_2 norm-based compression can achieve competitive results with a simpler implementation. However, these compression methods face a fundamental challenge: they rely heavily on token-centric measures (e.g., attention scores or norm values) to determine which tokens to retain, potentially discarding tokens that suddenly become crucial for future predictions.

KV Cache Merging Another line of works have explored merging similar KV cache positions to reduce memory footprint during inference. CaM [32] proposes an adaptive merging strategy guided by attention scores, while D₂O [26] introduces a two-level discriminative approach considering both layer-wise patterns and token similarities. KVMerger [?] adaptively constructs the KV cache by analyzing the intrinsic structure of attention modules. However, a fundamental limitation of these approaches is their uniform treatment of keys and values during merging despite their distinct distributional characteristics. As discovered in the introduction, this oversight is particularly problematic given the inherent heterogeneity of value vectors, which, unlike keys, often exhibit significant variations even between adjacent positions.

Context Segmentation and Sliding One popular variant of KV cache compression leverages context segmentation and sliding. These approaches stem from *StreamingLLM* [28], which discovered that initial tokens and recent tokens are more important than other middle tokens in the attention. Therefore, it only keeps such tokens. *LongCache* [18] expands *StreamingLLM* by keep critic middle tokens. These tokens are identified via the historical attention weights. *SirLLM* [31] uses token entropy to identify and keeps critic middle tokens. These segmentation-based methods require minimal KV cache operations, making them computationally efficient. However, these compression strategies essentially involve directly discarding tokens with lower weights, which results in significant information loss when these tokens suddenly become critical for future predictions.

3 Proposed Method

Building on the key-value asymmetry, we propose AsymKV. Our main idea is to shift the information loss from heterogeneous values to homogeneous keys during merging, thereby minimizing the loss. We show the key intuition and framework of AsymKV in Figure 2. (Left) Previous approaches that apply identical merging strategies to both keys and values suffer from significant information loss, especially considering the heterogeneous nature of values. In contrast, we leverage the asymmetry between keys and values in the attention mechanism. Our method compresses keys with minimal information loss (§ 3.1) due to their local homogeneity nature, while preserving the distinct characteristics of heterogeneous values through cardinality-aware normalization (§ 3.2).

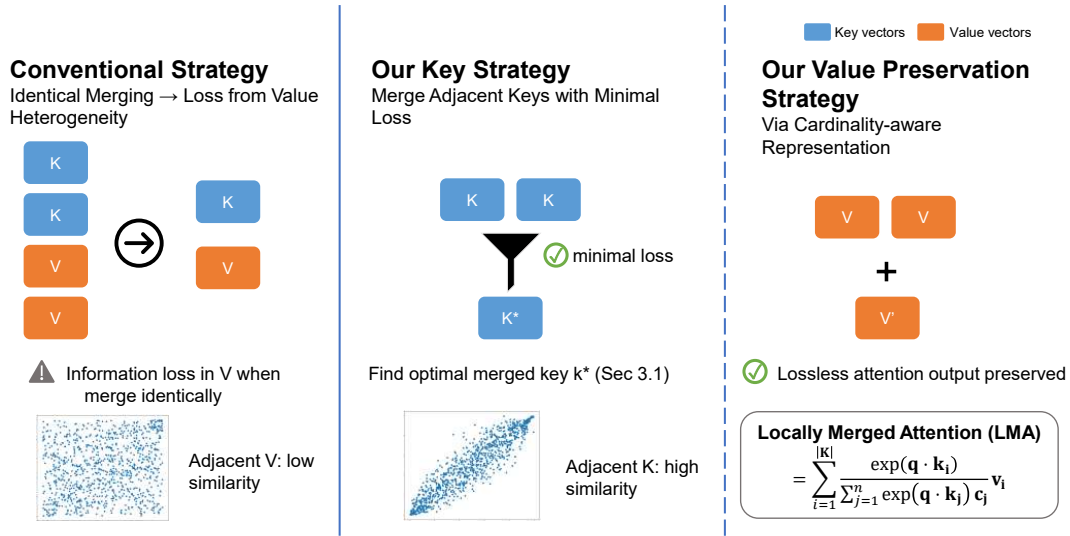


Figure 2: Illustration of our AsymKV mechanism. Left: Conventional approaches that uniformly merge both keys and values lead to information loss. Middle: We merge adjacent homogeneous keys for minimal loss. Right: We preserve their heterogeneous values through cardinality-aware normalization.

3.1 Homogeneous Key Merging

Our primary goal of adjacent token compression is to convert the original n tokens in the KV cache into $n - 1$ by merging a pair of adjacent positions $m, m + 1$.

First, consider the key merging. Based on our observation of adjacent key homogeneity, we can merge adjacent keys without significantly affecting model performance. Given key vectors $\mathbf{K} = [\mathbf{k}_1, \mathbf{k}_2, \dots, \mathbf{k}_n]$ from the KV cache and a pair of adjacent positions $m, m + 1$ to be merged, let $\mathcal{L}(\mathbf{K})$ denote the language modeling loss. After compressing $\mathbf{k}_m, \mathbf{k}_{m+1}$ into one embedding $\mathbf{k}$, we denote the new loss as:

$$\mathcal{L}([\mathbf{K}_{<m}, \mathbf{k}, \mathbf{K}_{>m+1}]) \quad (1)$$

where $\mathbf{K}_{<i}$ denotes the sequence $[\mathbf{k}_1, \dots, \mathbf{k}_{i-1}]$, and $\mathbf{K}_{>i}$ denotes $[\mathbf{k}_{i+1}, \dots, \mathbf{k}_n]$. Our objective of optimal key compression is to find $\mathbf{k}$ that minimizes the information loss.

Due to the dimensional mismatch between the original $\mathbf{K}$ and $[\mathbf{K}_{<m}, \mathbf{k}, \mathbf{K}_{>m+1}]$ in Eq. (1) ($n \times d \rightarrow (n - 1) \times d$), our cache merging takes two steps: **1.** Find a pair of identical embeddings ($\mathbf{k}^*, \mathbf{k}^*$) to replace $(\mathbf{k}_m, \mathbf{k}_{m+1})$ while preserving dimensionality, which is mathematically tractable. **2.** Leverage attention properties to merge the two tokens.

We first find optimal embeddings $\mathbf{k}$ that minimize $\mathcal{L}([\mathbf{K}_{<m}, \mathbf{k}, \mathbf{K}_{>m+1}])$ while keeping the dimensionality. For simplification, we denote it as $\mathcal{L}(\mathbf{k}, \mathbf{k})$, and the optimal $\mathbf{k}$ as $\mathbf{k}^*$: $\mathbf{k}^* = \arg \min_{\mathbf{k}} \mathcal{L}(\mathbf{k}, \mathbf{k})$.

We approach this optimization problem using a Newton-like method. By applying a second-order Taylor expansion of $\mathcal{L}(\mathbf{x}, \mathbf{y})$ around $(\mathbf{k}_m, \mathbf{k}_{m+1})$:

$$\mathcal{L}(\mathbf{x}, \mathbf{y}) \approx \mathcal{L}(\mathbf{k}_m, \mathbf{k}_{m+1}) + \nabla \mathcal{L}(\mathbf{k}_m, \mathbf{k}_{m+1})^\top \begin{bmatrix} \mathbf{x} - \mathbf{k}_m \\ \mathbf{y} - \mathbf{k}_{m+1} \end{bmatrix} + \frac{1}{2} \begin{bmatrix} \mathbf{x} - \mathbf{k}_m \\ \mathbf{y} - \mathbf{k}_{m+1} \end{bmatrix}^\top \mathbf{H} \begin{bmatrix} \mathbf{x} - \mathbf{k}_m \\ \mathbf{y} - \mathbf{k}_{m+1} \end{bmatrix} \quad (2)$$

where $\mathbf{H}$ is the Hessian matrix at $(\mathbf{k}_m, \mathbf{k}_{m+1})$. We denote the Hessian matrix $\mathbf{H}$ as:

$$\mathbf{H} = \begin{bmatrix} \mathbf{H}^{11} & \mathbf{H}^{12} \\ \mathbf{H}^{21} & \mathbf{H}^{22} \end{bmatrix} \quad (3)$$

Each submatrix $\mathbf{H}^{ab}$ is a $d \times d$ matrix. To minimize $\mathcal{L}(\mathbf{k}, \mathbf{k})$, we set $\mathbf{x} = \mathbf{k}$, $\mathbf{y} = \mathbf{k}$ and substitute into our quadratic approximation:

$$\mathcal{L}(\mathbf{k}, \mathbf{k}) \approx \mathcal{L}(\mathbf{k}_m, \mathbf{k}_{m+1}) + \nabla \mathcal{L}(\mathbf{k}_m, \mathbf{k}_{m+1})^\top \begin{pmatrix} \mathbf{k} - \mathbf{k}_m \\ \mathbf{k} - \mathbf{k}_{m+1} \end{pmatrix} + \frac{1}{2} \begin{pmatrix} \mathbf{k} - \mathbf{k}_m \\ \mathbf{k} - \mathbf{k}_{m+1} \end{pmatrix}^\top \mathbf{H} \begin{pmatrix} \mathbf{k} - \mathbf{k}_m \\ \mathbf{k} - \mathbf{k}_{m+1} \end{pmatrix} \quad (4)$$

Following the Newton method, we find the critical point by setting the gradient of this quadratic approximation to zero. This yields the optimal solution (details in Appendix C):

$$\mathbf{k}^* = (\mathbf{H}^{11} + 2\mathbf{H}^{12} + \mathbf{H}^{22})^{-1} [\mathbf{H}^{11}\mathbf{k}_m + \mathbf{H}^{12}(\mathbf{k}_m + \mathbf{k}_{m+1}) + \mathbf{H}^{22}\mathbf{k}_{m+1} - (\mathbf{g}_m + \mathbf{g}_{m+1})] \quad (5)$$

where $\mathbf{g}_m = \nabla_{\mathbf{k}_m} \mathcal{L}$ and $\mathbf{g}_{m+1} = \nabla_{\mathbf{k}_{m+1}} \mathcal{L}$.

To efficiently compute the Hessian matrix $\mathbf{H}$, we use the Fisher information matrix as an approximation, which is a common technique in second-order optimization methods. Following the approach in neural network pruning [12], we assume that the interactions between parameters are negligible and approximate the Fisher information matrix as a diagonal matrix. The diagonal elements can be efficiently computed using their gradients:

$$\mathbf{H}_{ii} = F_{ii} = \nabla \mathcal{L}(\mathbf{k}_m, \mathbf{k}_{m+1})_i^2 \quad (6)$$

In our empirical analysis, we discover that the magnitude of gradient terms $\mathbf{g}_m$ and $\mathbf{g}_{m+1}$ can exceed that of $\mathbf{H}$ by six orders of magnitude in Eq. (5). This is a known issue in Newton-like methods when the function is far from its minimum or when the curvature is very small. To stabilize the optimization and maintain $\mathbf{k}^*$ as a valid key, we adopt a modified Newton approach by dropping the gradient terms from Eq. (5), effectively using only the curvature information to guide our solution.

Compression Position Selection To minimize information loss during merging, we select positions $m, m+1$ with the lowest sum of attention scores, where positions receiving minimal attention have the least impact on the model's attention mechanism.

3.2 Cardinality Normalization for Lossless Value Merging

After replacing adjacent keys with identical embeddings, two challenges remain: (1) how to reduce input tokens $(\mathbf{k}^*, \mathbf{k}^*) \rightarrow \mathbf{k}^*$ to improve computing efficiency; (2) how to merge their corresponding values. We elaborate how to extend the attention mechanism to address both challenges while maintaining output equivalence.

In the original attention mechanism, the output for query $\mathbf{q}$ is:

$$\text{Attention}(\mathbf{q}, \mathbf{K}, \mathbf{V}) = \sum_{i=1}^{|\mathbf{K}|} \frac{\exp(\mathbf{q} \cdot \mathbf{k}_i)}{\sum_{j=1}^{|\mathbf{K}|} \exp(\mathbf{q} \cdot \mathbf{k}_j)} \mathbf{v}_i \quad (7)$$

After key compression where $\mathbf{k}_m = \mathbf{k}_{m+1} = \mathbf{k}^*$ in § 3.1, we have:

$$\text{Attention}(\mathbf{q}, \mathbf{K}, \mathbf{V}) = \sum_{i \in [1, n] \setminus \{m, m+1\}} \frac{\exp(\mathbf{q} \cdot \mathbf{k}_i)}{\sum_{j=1}^{|\mathbf{K}|} \exp(\mathbf{q} \cdot \mathbf{k}_j)} \mathbf{v}_i + \underbrace{\frac{\exp(\mathbf{q} \cdot \mathbf{k}^*)}{\sum_{j=1}^n \exp(\mathbf{q} \cdot \mathbf{k}_j)} (\mathbf{v}_m + \mathbf{v}_{m+1})}_{\text{attention to one merged KV pair (key}=\mathbf{k}^*, \text{value}=\mathbf{v}_m + \mathbf{v}_{m+1})} \quad (8)$$

Examining Eq. (8), we observe a key insight: after converting both $\mathbf{k}_m, \mathbf{k}_{m+1}$ to $\mathbf{k}^*$, the attention output for two original tokens m and $m+1$ is mathematically equivalent to the attention output for a single compressed token with key $\mathbf{k}^*$ and value $(\mathbf{v}_m + \mathbf{v}_{m+1})$.

(Locally Merged Attention) The insight above naturally suggests an alternated attention mechanism for merged tokens, which we denote as Locally Merged Attention (LMA):

$$\text{LMA}(\mathbf{q}, \mathbf{K}, \mathbf{V}, \mathbf{C}) = \sum_{i=1}^{|\mathbf{K}|} \frac{\exp(\mathbf{q} \cdot \mathbf{k}_i)}{\sum_{j=1}^n \exp(\mathbf{q} \cdot \mathbf{k}_j) \mathbf{c}_j} \mathbf{v}_i \quad (9)$$

where c_i indicates the number of original tokens represented by the i -th compressed token. The cardinality vector $\mathbf{c}$ is designed to maintain the denominator in Eq. (8), ensuring mathematical equivalence between the original and compressed attention mechanisms. Initially, $c_i = 1$ for all tokens. After merging positions m and $m + 1$, we update $\mathbf{C}$ as $[\mathbf{C}_{<m}, \mathbf{c}_m + \mathbf{c}_{m+1}, \mathbf{C}_{>m+1}]$, ensuring the denominator in our attention calculation remains equivalent to the original uncompressed attention.

(Equivalence) Using LMA, the following equivalence holds:

$$\text{Attention}(\mathbf{q}, \mathbf{K}, \mathbf{V}) = \text{LMA}(\mathbf{q}, \mathbf{K}', \mathbf{V}', \mathbf{C}) \quad (10)$$

where $\mathbf{K}, \mathbf{V}$ are KV caches for n tokens while $\mathbf{K}', \mathbf{V}'$ are for $n - 1$ tokens:

$$\begin{aligned} \mathbf{K}' &= [\mathbf{K}_{<m}, \mathbf{k}^*, \mathbf{K}_{>m+1}] \\ \mathbf{V}' &= [\mathbf{V}_{<m}, \mathbf{v}_m + \mathbf{v}_{m+1}, \mathbf{V}_{>m+1}] \end{aligned} \quad (11)$$

This equivalence reveals an elegant characteristic of attention mechanisms: they permit lossless compression of values through simple vector addition. The only cost is to store $\mathbf{C}$ with n integers. This property is particularly powerful as it enables preservation of attention outputs while reducing sequence length, effectively solving the quadratic complexity challenge of long-sequence processing.

3.3 Efficient Implementations for Long-Text Generation

3.3.1 Time-Efficiency by Chunk-wise Parallel Compression

We propose a chunk-based parallel compression method for efficient long-text generation. The process predicts the next token using HLA in place of the original attention, without requiring any model fine-tuning. More specifically, when the context length reaches `max_length`, after every `chunk_size` new tokens, we compress `max_length + chunk` tokens into `max_length` tokens in parallel by: **1.** Identifying chunk pairs of adjacent tokens with lowest attention scores. **2.** Computing optimal compression according to Eq. (5). **3.** Merging keys, values and cardinalities.

Since the merge operation is performed only once every `chunk_size` tokens (e.g., 512 tokens), its computational overhead is minimal relative to the overall inference process. The compression step requires only a single backward pass to compute the Hessian matrices for all candidate compression positions, followed by parallel execution of the optimal compression operations. This design ensures that AsymKV maintains inference efficiency. More experimental results are shown in § 4.5.

3.3.2 Memory-Efficiency by Selective Gradient Computation

Our method requires gradient computation (Eq. (5)) which might raise concerns about increased memory usage. However, AsymKV still maintains memory efficiency compared to other approaches. Unlike typical backpropagation that computes gradients for all parameters, we only compute gradients for **key embeddings within the current chunk, not for all model parameters**.

To elaborate further from a quantitative perspective, this selective gradient computation yields a gradient tensor of size approximately $c \times d$, where c denotes the chunk size and d is the dimension per token. In contrast, a standard forward pass (and its associated gradient computation) requires storing the full model parameters (with size $O(p)$, where p is the total number of parameters) along with the KV cache states, sized at $2 \times l \times d$ (where l represents the maximum sequence length). Thus, the additional memory overhead from our selective gradients is on the order of $O(cd)$, which is significantly smaller than the baseline's $O(2ld + p)$ when $c \ll l$ (a typical scenario in chunked processing). This avoids unnecessary gradient computations across the entire sequence, ensuring that both memory and computational overhead are greatly reduced. Detailed memory statistics are provided in § 4.5.

4 Experiments

4.1 Experimental Setup

Baselines We compare AsymKV against several categories of approaches: *KV cache compression*: H₂O [33], *KV cache merge*: CaM [32], *prompt compression*: LLMingua-2.0 [21], *context segmentation*: StreamingLLM [28] and LongCache [18].

Table 1: Performance on LongBench. AsymKV outperforms its baselines on most settings.

	Single-Doc	Multi-Doc	Sum	Few-shot	Synthetic	Code	Avg.
Llama2-7B-chat							
Full Context	25.80	21.47	24.62	62.86	4.96	48.90	32.00
StreamingLLM	19.29	21.05	23.15	60.85	1.81	48.58	29.61
LongCache	19.73	20.06	23.19	61.26	2.24	49.05	29.71
H ₂ O	19.92	25.64	23.85	61.37	4.27	50.28	31.34
LLMLingua-2	21.47	23.29	23.53	33.23	6.17	35.12	24.20
CaM	19.53	20.64	22.67	61.81	4.18	48.53	30.15
AsymKV	24.63	24.15	24.22	62.11	10.18	52.16	33.12
Llama3.1-8B-Instruct							
Full Context	43.73	44.49	29.12	69.36	53.56	52.94	60.21
StreamingLLM	28.15	27.19	25.15	63.17	16.33	54.02	35.73
LongCache	28.98	27.84	25.35	64.73	19.68	53.60	36.70
H ₂ O	33.30	34.43	26.60	66.23	14.75	55.56	38.89
LLMLingua-2	32.02	32.24	24.99	27.87	17.67	52.63	30.75
CaM	32.14	32.63	24.91	63.09	16.77	54.03	37.49
AsymKV	39.42	38.93	27.30	65.66	39.39	55.24	43.95
Mistral-7B-Instruct-v0.3							
Full Context	38.74	38.29	29.04	70.70	51.00	55.06	46.40
StreamingLLM	24.80	22.14	25.18	66.49	15.14	53.51	34.57
LongCache	26.05	22.31	25.44	66.21	14.93	53.43	34.80
H ₂ O	29.66	28.22	26.32	67.78	14.83	53.95	37.09
LLMLingua-2	28.12	28.62	25.75	45.85	16.00	48.81	32.17
CaM	26.15	29.06	26.81	66.16	20.96	53.76	37.12
AsymKV	33.71	32.81	27.04	67.21	34.56	54.93	41.33
Qwen2-7B-Instruct							
Full Context	37.07	41.77	28.27	68.61	36.25	50.67	43.81
StreamingLLM	27.73	28.14	24.32	66.85	7.50	49.55	34.70
LongCache	27.98	28.98	24.80	66.38	9.00	48.34	34.94
H ₂ O	29.91	28.49	25.21	68.08	12.25	53.63	36.68
LLMLingua-2	30.04	31.71	24.63	46.32	6.50	50.09	31.96
CaM	29.14	28.59	25.87	66.33	9.25	48.88	35.38
AsymKV	33.72	34.46	26.24	69.88	14.25	49.33	38.76

Base Models To demonstrate the generality of AsymKV, we evaluate across diverse model architectures: Llama2-7B-chat [24], Llama3.1-8B-Instruct [10], Mistral-7B-Instruct-v0.3 [11], and Qwen2-7B-Instruct [29].

Implementation Details Unless otherwise specified, we set the compression context `max_length` to 2048 tokens and `chunk_size` to 512. All baselines use the same settings for fair comparison. For H₂O, we set recent budget to 2048 and heavy budget to 512. Following attention sink [28], we always preserve the initial 32 tokens. All experiments are conducted on NVIDIA A100 80GB.

4.2 Long Context Performance Evaluation

We evaluate AsymKV’s effectiveness on LongBench [2], a comprehensive benchmark for long-context understanding. LongBench contains 16 English tasks from a wide range of categories.

Results As shown in Table 1, AsymKV consistently outperforms existing long-context methods across different models and tasks. On LLaMA3.1-8B, AsymKV achieves a 43.95 average score, surpassing H₂O (38.89) and other baselines by a significant margin. The improvement is particularly pronounced in challenging tasks like Synthetic reasoning, where AsymKV scores 39.39 compared to H₂O’s 14.75. For all base models, AsymKV maintains its advantage with average scores, showing substantial improvements over baselines.

Table 2: Performance on LongBenchV2.

Model	Overall	Easy	Hard	Short	Medium	Long
Full Context	30.02	30.73	29.58	35.00	27.91	25.93
StreamingLLM	27.04	27.60	26.69	32.78	23.26	25.00
LongCache	28.43	28.13	28.62	32.78	25.58	26.85
H ₂ O	28.23	28.12	28.29	31.67	26.98	25.00
CaM	28.23	28.64	27.97	31.67	26.98	25.00
AsymKV	30.02	30.23	29.90	32.78	27.44	28.85

Table 3: Performance on early topic retrieval.

Model	Qwen2-7B	Llama3.1-8B	Mistral-7B
Full Context	47.33	80.00	42.67
StreamingLLM	0.00	0.00	0.00
LongCache	0.00	0.00	8.67
CaM	12.67	24.67	15.33
H ₂ O	21.33	63.33	38.67
LLMLingua2	0.00	0.00	0.00
AsymKV	36.00	75.33	40.67

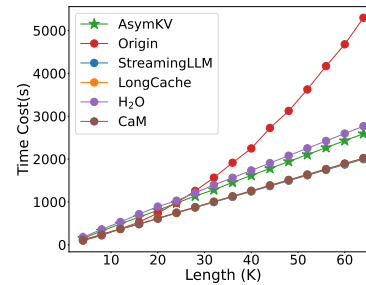


Figure 3: Inference efficiency.

Precise Information Retrieval In Single-Doc and Multi-Doc QA tasks, which require precise information retention, AsymKV consistently outperforms other methods by significant margins (5-10 points). This suggests that our homogeneity-based compression effectively preserves key information needed for accurate question answering.

Extreme Long-Context Compression We evaluate AsymKV on LongBenchV2 [3], a benchmark with contexts ranging from 8,000 to 2 million tokens across six task categories (multi-document QA, code comprehension, temporal reasoning, mathematical derivation, cross-lingual understanding, and hierarchical information synthesis). Using Llama3.1-8B-Instruct with `cache_size=8192`, Table 2 shows that AsymKV matches full-context methods in short contexts while significantly outperforming baselines in medium to long contexts (up to millions of tokens), demonstrating its effectiveness in extreme long-context scenarios.

Regularization Effect of AsymKV. AsymKV often outperforms the full-context model across various tasks, suggesting that it acts as a form of regularization in long-context settings. Due to the inherent limitations of LLMs in handling extended contexts, full KV caches tend to accumulate redundant tokens with low attention scores, diluting focus on relevant information. By selectively merging these low-attention tokens, AsymKV effectively suppresses contextual noise, leading to more focused and efficient inference. A similar regularization phenomenon has also been observed in related KV-cache optimization methods [33].

4.3 Comprehensive Information Retention

KV cache compression methods face multiple challenges in information retention: they must preserve not only early context details but also maintain the ability to capture document-level semantic structure and sequential relationships. To evaluate models' comprehensive information retention capabilities, we conduct experiments using TopicRet [14] from L-Eval [1]. This benchmark is particularly challenging as it requires models to answer questions about *the second or third topic in multi-topic documents*, testing their ability to retain early context information.

The results in Table 3 reveal several key findings. First, context segmentation methods (StreamingLLM, LongCache) and prompt compression approaches (LLMLingua2) completely fail at this task, scoring zero or near-zero across all models. This dramatic performance drop confirms our hypothesis that discarding or imprecisely compressing early tokens severely impairs models' ability to access historical information. Although methods like CaM and H₂O show some capability in retaining early information, their performance significantly lags behind full-context processing. In contrast, AsymKV demonstrates remarkable effectiveness in preserving early context information, achieving scores close to full-context processing (75.33 vs 80.00 on LLaMA3.1-8B).

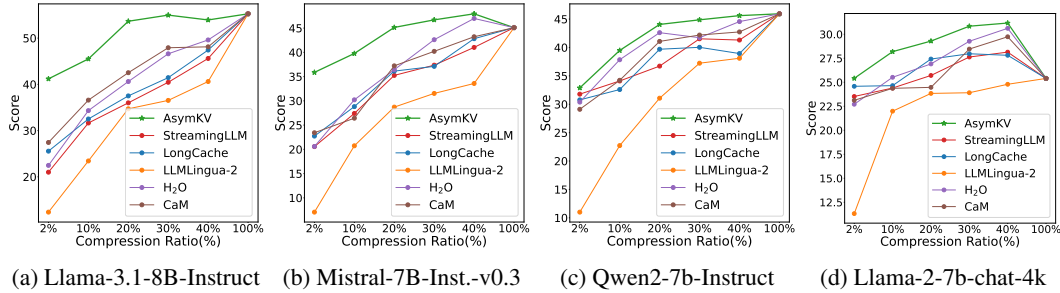


Figure 4: Effect of different compression ratios.

Table 4: Peak GPU Memory (MB)

Method	L.2-7B	L.2-13B
StreamingLLM	19,592	39,911
LongCache	24,968	49,236
H ₂ O	22,479	47,310
CaM	22,548	47,476
AsymKV	24,923	48,671

Figure 5: Ablation study on different merge strategies.

Key Merge Strategy	Value Merge Strategy	
	Same as Key	Asymmetric
Mean Merge	18.93	21.86
Weighted by Cardinality	20.90	23.91
Weighted by Attention	14.99	23.83
Optimal k* (Eq. (5))	21.21	24.43

4.4 Compression Rate Analysis

To systematically evaluate AsymKV’s context compression capabilities, we analyze its performance across different compression rates on the long-context HotpotQA [30] task from LongBench. Here, the compression rate is defined as the ratio between the compressed and original token counts.

As shown in Fig. 4, AsymKV demonstrates superior compression capabilities across all compression rates. Most notably, with only 20% of the original context length, AsymKV achieves performance comparable to full-context processing, significantly outperforming all baseline methods. This robust performance highlights AsymKV’s effectiveness in preserving crucial contextual information even under aggressive compression.

4.5 Inference Efficiency

We evaluated the computational efficiency of different approaches during text generation. To do this, we had the models generate text using greedy sampling on Mistral-7B-Instruct-v0.3 and measured the time required to generate different numbers of tokens.

Inference Speed Fig. 3 reveals that among the evaluated methods, context segmentation approaches (StreamingLLM and LongCache) achieve the highest computational efficiency due to their minimal KV cache operations. However, this efficiency comes at the cost of performance. AsymKV strikes a better balance, achieving the highest efficiency among compression-based methods.

Memory Consumption We measure peak GPU memory usage on LLaMA3.1-8B-Instruct with a cache size of 2048 and chunk size of 128. As shown in Table 4, AsymKV’s memory consumption is comparable to other baselines. This validates that both generation and compression costs are practical and scalable.

4.6 Ablations on Merge Strategies

We conduct an ablation study to compare different strategies for merging keys and values during compression. For key merging, we compare four approaches: simple mean pooling, cardinality-weighted averaging, attention score-weighted averaging, and our optimal strategy derived from Eq. (5). For each key merge strategy, we experiment with two value merge strategies: either using the identical strategy as keys, or using our proposed asymmetric cardinality-normalized method.

Results in Table 5 are scores on the multi-hop QA task MuSiQue [25] from LongBench. The results demonstrate two key findings. First, our theoretically-derived optimal key merge strategy consistently

outperforms other approaches. This empirically validates the foundation of our optimal merging strategy presented in § 3.1. Second, the results show that using distinct strategies for keys and values is beneficial.

5 Conclusion

In this paper, through extensive empirical analysis, we reveal a fundamental yet previously overlooked pattern: local KV cache Asymmetry. This property motivates our key technical innovation—a training-free merging framework that combines homogeneity-based key merging with mathematically proven lossless value representation. We present AsymKV, a novel approach to address the computational challenges of long-context modeling in LLMs. Our comprehensive experiments demonstrate that AsymKV outperforms existing long-context methods across various tasks and base models.

Limitations. Further applications of AsymKV need to consider compatibility with methods like FlashAttention and vLLM. We view this as an engineering problem and are actively working to address it.

Acknowledgments and Disclosure of Funding This paper was supported by the Shanghai Natural Science Foundation (25ZR1402137).

References

- [1] Chenxin An, Shansan Gong, Ming Zhong, Xingjian Zhao, Mukai Li, Jun Zhang, Lingpeng Kong, and Xipeng Qiu. L-eval: Instituting standardized evaluation for long context language models. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 14388–14411, Bangkok, Thailand, August 2024. Association for Computational Linguistics.
- [2] Yushi Bai, Xin Lv, Jiajie Zhang, Hongchang Lyu, Jiankai Tang, Zhidian Huang, Zhengxiao Du, Xiao Liu, Aohan Zeng, Lei Hou, Yuxiao Dong, Jie Tang, and Juanzi Li. LongBench: A bilingual, multitask benchmark for long context understanding. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 3119–3137, Bangkok, Thailand, August 2024. Association for Computational Linguistics.
- [3] Yushi Bai, Shangqing Tu, Jiajie Zhang, Hao Peng, Xiaozhi Wang, Xin Lv, Shulin Cao, Jiazheng Xu, Lei Hou, Yuxiao Dong, Jie Tang, and Juanzi Li. Longbench v2: Towards deeper understanding and reasoning on realistic long-context multitasks. *arXiv preprint arXiv:2412.15204*, 2024.
- [4] Zefan Cai, Yichi Zhang, Bofei Gao, Yuliang Liu, Yucheng Li, Tianyu Liu, Keming Lu, Wayne Xiong, Yue Dong, Junjie Hu, and Wen Xiao. Pyramidkv: Dynamic kv cache compression based on pyramidal information funneling, 2025.
- [5] Guoxuan Chen, Han Shi, Jiawei Li, Yihang Gao, Xiaozhe Ren, Yimeng Chen, Xin Jiang, Zhenguo Li, Weiyang Liu, and Chao Huang. Sepllm: Accelerate large language models by compressing one segment into one separator. *arXiv preprint arXiv:2412.12094*, 2024.
- [6] Wei-Lin Chiang, Zhuohan Li, Zi Lin, Ying Sheng, Zhanghao Wu, Hao Zhang, Lianmin Zheng, Siyuan Zhuang, Yonghao Zhuang, Joseph E. Gonzalez, Ion Stoica, and Eric P. Xing. Vicuna: An open-source chatbot impressing gpt-4 with 90%* chatgpt quality, March 2023.
- [7] Tri Dao, Dan Fu, Stefano Ermon, Atri Rudra, and Christopher Ré. Flashattention: Fast and memory-efficient exact attention with io-awareness. *Advances in Neural Information Processing Systems*, 35:16344–16359, 2022.
- [8] Pradeep Dasigi, Kyle Lo, Iz Beltagy, Arman Cohan, Noah A Smith, and Matt Gardner. A dataset of information-seeking questions and answers anchored in research papers. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 4599–4610, 2021.
- [9] Alessio Devoto, Yu Zhao, Simone Scardapane, and Pasquale Minervini. A simple and effective l_2 norm-based strategy for KV cache compression. In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen, editors, *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 18476–18499, Miami, Florida, USA, November 2024. Association for Computational Linguistics.
- [10] Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, et al. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*, 2024.
- [11] Albert Q. Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, L  lio Renard Lavaud, Marie-Anne Lachaux, Pierre Stock, Teven Le Scao, Thibaut Lavril, Thomas Wang, Timoth  e Lacroix, and William El Sayed. Mistral 7b, 2023.
- [12] Yann LeCun, John Denker, and Sara Solla. Optimal brain damage. *Advances in neural information processing systems*, 2, 1989.

- [13] Mosh Levy, Alon Jacoby, and Yoav Goldberg. Same task, more tokens: the impact of input length on the reasoning performance of large language models. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 15339–15353, Bangkok, Thailand, August 2024. Association for Computational Linguistics.
- [14] Dacheng Li, Rulin Shao, Anze Xie, Ying Sheng, Lianmin Zheng, Joseph Gonzalez, Ion Stoica, Xuezhe Ma, and Hao Zhang. How long can context length of open-source llms truly promise? In *NeurIPS 2023 Workshop on Instruction Tuning and Instruction Following*, 2023.
- [15] Haoyang Li, Yiming Li, Anxin Tian, Tianhao Tang, Zhanchao Xu, Xuejia Chen, Nicole Hu, Wei Dong, Qing Li, and Lei Chen. A survey on large language model acceleration based on kv cache management. *arXiv preprint arXiv:2412.19442*, 2024.
- [16] Yuhong Li, Yingbing Huang, Bowen Yang, Bharat Venkitesh, Acyr Locatelli, Hanchen Ye, Tianle Cai, Patrick Lewis, and Deming Chen. Snapkv: Llm knows what you are looking for before generation. In A. Globerson, L. Mackey, D. Belgrave, A. Fan, U. Paquet, J. Tomczak, and C. Zhang, editors, *Advances in Neural Information Processing Systems*, volume 37, pages 22947–22970. Curran Associates, Inc., 2024.
- [17] Yuhong Li, Yingbing Huang, Bowen Yang, Bharat Venkitesh, Acyr Locatelli, Hanchen Ye, Tianle Cai, Patrick Lewis, and Deming Chen. Snapkv: Llm knows what you are looking for before generation. In *Proceedings of the 38th International Conference on Neural Information Processing Systems*, NIPS '24, Red Hook, NY, USA, 2025. Curran Associates Inc.
- [18] Xiaoran Liu, Qipeng Guo, Yuerong Song, Zhigeng Liu, Kai Lv, Hang Yan, Linlin Li, Qun Liu, and Xipeng Qiu. Farewell to length extrapolation, a training-free infinite context with finite attention scope. *arXiv preprint arXiv:2407.15176*, 2024.
- [19] Zichang Liu, Aditya Desai, Fangshuo Liao, Weitao Wang, Victor Xie, Zhaozhuo Xu, Anastasios Kyrillidis, and Anshumali Shrivastava. Scissorhands: Exploiting the persistence of importance hypothesis for llm kv cache compression at test time. *Advances in Neural Information Processing Systems*, 36, 2024.
- [20] Matanel Oren, Michael Hassid, Nir Yarden, Yossi Adi, and Roy Schwartz. Transformers are multi-state RNNs. In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen, editors, *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 18724–18741, Miami, Florida, USA, November 2024. Association for Computational Linguistics.
- [21] Zhuoshi Pan, Qianhui Wu, Huiqiang Jiang, Menglin Xia, Xufang Luo, Jue Zhang, Qingwei Lin, Victor Ruhle, Yuqing Yang, Chin-Yew Lin, H. Vicky Zhao, Lili Qiu, and Dongmei Zhang. LLMLingua-2: Data distillation for efficient and faithful task-agnostic prompt compression. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Findings of the Association for Computational Linguistics ACL 2024*, pages 963–981, Bangkok, Thailand and virtual meeting, August 2024. Association for Computational Linguistics.
- [22] Siyu Ren and Kenny Q Zhu. On the efficacy of eviction policy for key-value constrained generative language model inference. *arXiv preprint arXiv:2402.06262*, 2024.
- [23] Kimi Team. Kimi k1.5: Scaling reinforcement learning with llms. 2025.
- [24] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023.
- [25] Harsh Trivedi, Niranjan Balasubramanian, Tushar Khot, and Ashish Sabharwal. Musique: Multihop questions via single-hop question composition. *Transactions of the Association for Computational Linguistics*, 10:539–554, 2022.
- [26] Zhongwei Wan, Xinjian Wu, Yu Zhang, Yi Xin, Chaofan Tao, Zhihong Zhu, Xin Wang, Siqi Luo, Jing Xiong, Longyue Wang, and Mi Zhang. D2o: Dynamic discriminative operations for efficient long-context inference of large language models. In *The Thirteenth International Conference on Learning Representations*, 2025.

- [27] Zheng Wang, Boxiao Jin, Zhongzhi Yu, and Minjia Zhang. Model tells you where to merge: Adaptive kv cache merging for llms on long-context tasks, 2024.
- [28] Guangxuan Xiao, Yuandong Tian, Beidi Chen, Song Han, and Mike Lewis. Efficient streaming language models with attention sinks. *ICLR*, 2024.
- [29] An Yang, Baosong Yang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Zhou, Chengpeng Li, Chengyuan Li, Dayiheng Liu, Fei Huang, Guanting Dong, Haoran Wei, Huan Lin, Jialong Tang, Jialin Wang, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Ma, Jianxin Yang, Jin Xu, Jingren Zhou, Jinze Bai, Jinzheng He, Junyang Lin, Kai Dang, Keming Lu, Keqin Chen, Kexin Yang, Mei Li, Mingfeng Xue, Na Ni, Pei Zhang, Peng Wang, Ru Peng, Rui Men, Ruize Gao, Runji Lin, Shijie Wang, Shuai Bai, Sinan Tan, Tianhang Zhu, Tianhao Li, Tianyu Liu, Wenbin Ge, Xiaodong Deng, Xiaohuan Zhou, Xingzhang Ren, Xinyu Zhang, Xipin Wei, Xuancheng Ren, Xuejing Liu, Yang Fan, Yang Yao, Yichang Zhang, Yu Wan, Yunfei Chu, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, Zhifang Guo, and Zhihao Fan. Qwen2 technical report, 2024.
- [30] Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William Cohen, Ruslan Salakhutdinov, and Christopher D Manning. Hotpotqa: A dataset for diverse, explainable multi-hop question answering. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 2369–2380, 2018.
- [31] Yao Yao, Zuchao Li, and Hai Zhao. SirLLM: Streaming infinite retentive LLM. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 2611–2624, Bangkok, Thailand, August 2024. Association for Computational Linguistics.
- [32] Yuxin Zhang, Yuxuan Du, Gen Luo, Yunshan Zhong, Zhenyu Zhang, Shiwei Liu, and Rongrong Ji. Cam: Cache merging for memory-efficient llms inference. In *Forty-first International Conference on Machine Learning*, 2024.
- [33] Zhenyu Zhang, Ying Sheng, Tianyi Zhou, Tianlong Chen, Lianmin Zheng, Ruisi Cai, Zhao Song, Yuandong Tian, Christopher Ré, Clark Barrett, et al. H2o: Heavy-hitter oracle for efficient generative inference of large language models. *Advances in Neural Information Processing Systems*, 36:34661–34710, 2023.

NeurIPS Paper Checklist

1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

Answer: [\[Yes\]](#)

Justification: The abstract and introduction clearly state:

- Discovery of KV cache asymmetry (key homogeneity vs. value heterogeneity).
- Proposal of AsymKV, a training-free compression framework combining key merging and lossless value representation.
- Experimental validation showing SOTA performance (e.g., 43.95 vs. 38.89 for H₂O on LongBench).

Guidelines:

- The answer NA means that the abstract and introduction do not include the claims made in the paper.
- The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
- The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
- It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [\[Yes\]](#)

Justification: Please see § 5. We discussed the potential engineering adaption problem.

Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. Theory assumptions and proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [Yes]

Justification: The paper includes detailed mathematical derivations for its key compression (Eq. 5) and lossless value compression (Eq. 8) methods. Assumptions, such as the use of the Fisher information matrix as an approximation for the Hessian, are explicitly stated. Complete proofs are provided in the main text and appendices, supported by references to established techniques like Taylor expansion.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. Experimental result reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [Yes]

Justification: The experimental setup is thoroughly described, including the models, datasets, and hyperparameters. As AsymKV is a training-free approach, the compression strategy is clearly outlined, providing sufficient detail for others to replicate the results.

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general, releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
 - (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
 - (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
 - (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).

- (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: Will be added in the supplemental material.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so “No” is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. Experimental setting/details

Question: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [Yes]

Justification: Since AsymKV is training-free, no training details are required. Meanwhile, the paper provides comprehensive inference settings, including compression rates, chunk sizes, and model configurations. Key hyperparameters, such as max_length and chunk size, are explicitly listed, ensuring clarity.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

7. Experiment statistical significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [Yes]

Justification: The paper does not include traditional error bars due to the computational expense of long-context experiments, which allowed for only one run per configuration. However, the statistical significance of results is established through comprehensive evaluations across multiple models (Llama-3.1-8B, Mistral-7B, Qwen2-7B, Llama-2-7B) and various settings. This extensive cross-model validation demonstrates the consistent performance advantages of AsymKV across different settings, providing strong evidence for the robustness of the reported results.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).
- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. Experiments compute resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [Yes]

Justification: The paper specifies that experiments were run on NVIDIA A100 80GB GPUs and includes details on memory usage in 4.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. Code of ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics <https://neurips.cc/public/EthicsGuidelines>?

Answer: [Yes]

Justification: The research focuses on improving LLM efficiency and does not involve human subjects, sensitive data, or applications with potential harm. It fully aligns with the ethical standards outlined in the NeurIPS Code of Ethics.

Guidelines:

- The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. **Broader impacts**

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [No]

Justification: This paper is a foundational research and does not directly point to any potential negative social impacts.

Guidelines:

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.
- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. **Safeguards**

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer:[NA]

Justification: No new high-risk assets released.

Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. **Licenses for existing assets**

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [Yes]

Justification: the paper credits the original sources of datasets and models, mentioning applicable licenses and adhering to their terms of use.

Guidelines:

- The answer NA means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, paperswithcode.com/datasets has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. New assets

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [Yes]

Justification: We release the implementation code of our proposed method to support reproducibility.

- **Asset Type:** Source code (implementation of the proposed method *AsymKV*).
- **Intended Use:** Research and reproducibility. Enables replication and extension of the reported results.
- **License:** Apache License 2.0
- **Repository:** <https://github.com/the-scale-lab/AsymKV>
- **Documentation:** Usage instructions, environment setup, and experimental commands are provided in the repository README.md.
- **Ethical Considerations:** No human or personal data are involved. All external datasets and models comply with their original licenses.

Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. Crowdsourcing and research with human subjects

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [NA]

Justification: No human subjects involved.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. Institutional review board (IRB) approvals or equivalent for research with human subjects

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [NA]

Justification: No human subjects are involved in this research, rendering IRB approvals unnecessary.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

16. Declaration of LLM usage

Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

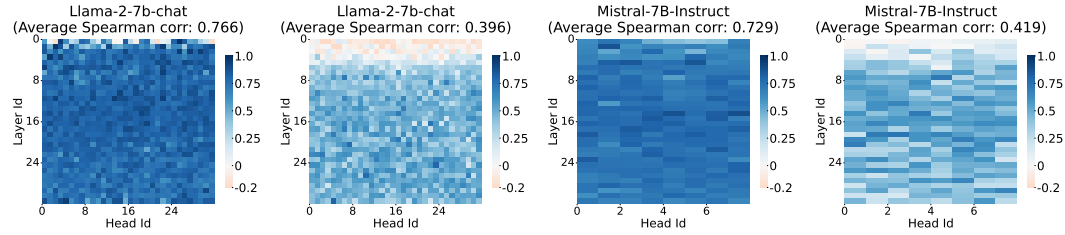
Answer: [Yes]

Justification: The paper clearly states that LLMs serve as the base models for evaluating AsymKV. Their usage is standard and well-documented, requiring no further declaration beyond what is provided.

Guidelines:

- The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
- Please refer to our LLM policy (<https://neurips.cc/Conferences/2025/LLM>) for what should or should not be described.

A Analysis: Key-Value Asymmetry in Attentions



(a) Key similarity correlation heatmap on QASPER (b) Value similarity correlation heatmap on QASPER (c) Key similarity correlation heatmap (d) Value similarity correlation heatmap

Figure 6: Contrasting distributions of local key distributions versus local value distributions across different datasets and model architectures. Heatmaps show Spearman correlation coefficients between adjacent tokens across layers (y-axis) and attention heads (x-axis). The consistent strong positive correlations for local keys (a,c) and weak/negative correlations for local values (b,d) suggesting these are universal properties of LLM KV caches.

Initial experiments with Llama2-7b-chat on ShareGPT [6] data (Fig. 1) revealed a striking asymmetry between local key and value distributions. To obtain a more direct observation, we analyze the Spearman correlation coefficient of $\text{sim}(\text{key}_i, \text{key}_j)$ and $\text{sim}(\text{val}_i, \text{val}_j)$ for different i, j . To validate the universality of these patterns, we conducted a comprehensive analysis across diverse settings: (1) different data distributions, including academic papers (QASPER [8]) and multi-domain questions (MultiFieldQA(en) [2]) and (2) various model architectures, specifically Mistral-7B-Instruct-v0.3 and Qwen2-7B-Instruct [29]). The results for QASPER and Mistral-7B-Instruct-v0.3 are shown in Fig. 6, with additional results for MultiFieldQA and Qwen2-7B-Instruct presented in Appendix B.

Key Homogeneity: Adjacent keys exhibit consistently strong positive correlations across all layers and attention heads (average correlation coefficient > 0.7), indicating robust encoding of local semantic relationships in key representations.

Value Heterogeneity: In stark contrast, adjacent values show significantly lower (average correlation coefficient < 0.4) or even negative correlations, suggesting that value vectors encode distinct and complementary aspects of token information. This heterogeneity appears essential for maintaining the model’s representational capacity.

B Distribution of Local Keys and Values in More Models and Datasets

To validate that our observations about the asymmetric properties of keys and values are general across different models and datasets, we conduct additional experiments on the Multifieldqa(en) dataset and the Qwen2-7B-Instruct model. The results are shown in Figure 7.

As shown in Figure 7, the key similarity heatmaps (Figure 7a, 7c) consistently exhibit strong diagonal block patterns, indicating high local homogeneity. In contrast, the value similarity heatmaps (Figure 7b, 7d) show heterogeneous distributions. These results confirm that the asymmetric properties we observed are inherent characteristics of transformer attention mechanisms rather than artifacts of specific models or datasets.

C Solving for the Optimal Key Vector

Continue from (4):

Gradient Term Expansion:

$$\nabla \mathcal{L}(\mathbf{k}_m, \mathbf{k}_{m+1})^\top \begin{bmatrix} \mathbf{k} - \mathbf{k}_m \\ \mathbf{k} - \mathbf{k}_{m+1} \end{bmatrix} = \mathbf{g}_m^\top (\mathbf{k} - \mathbf{k}_m) + \mathbf{g}_{m+1}^\top (\mathbf{k} - \mathbf{k}_{m+1}) \quad (12)$$

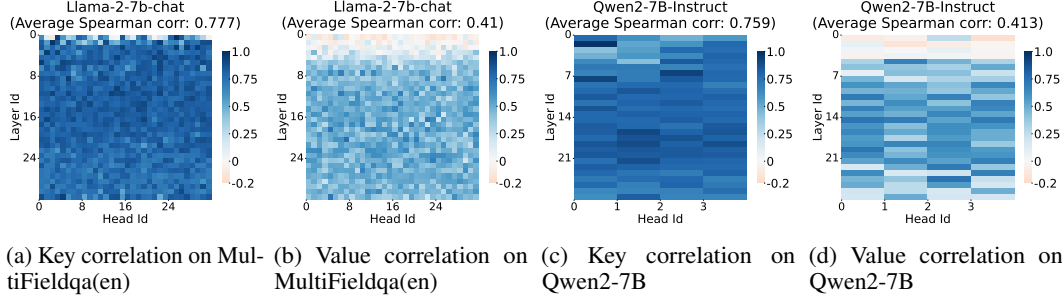


Figure 7: Similarity heatmaps of local keys and values across different models and datasets (LLaMA2-7B-chat on MultiFieldqa(en) and Qwen2-7B-Instruct on ShareGPT). The diagonal blocks in key heatmaps (a, c) indicate strong local homogeneity, while the more scattered patterns in value heatmaps (b, d) demonstrate heterogeneity.

Quadratic Term Expansion:

$$\begin{aligned} \frac{1}{2} \begin{bmatrix} \mathbf{k} - \mathbf{k}_m \\ \mathbf{k} - \mathbf{k}_{m+1} \end{bmatrix}^\top \mathbf{H} \begin{bmatrix} \mathbf{k} - \mathbf{k}_m \\ \mathbf{k} - \mathbf{k}_{m+1} \end{bmatrix} &= \frac{1}{2} (\mathbf{k} - \mathbf{k}_m)^\top \mathbf{H}^{11} (\mathbf{k} - \mathbf{k}_m) + (\mathbf{k} - \mathbf{k}_m)^\top \mathbf{H}^{12} (\mathbf{k} - \mathbf{k}_{m+1}) \\ &\quad + \frac{1}{2} (\mathbf{k} - \mathbf{k}_{m+1})^\top \mathbf{H}^{22} (\mathbf{k} - \mathbf{k}_{m+1}) \end{aligned} \quad (13)$$

Constructing the Total Objective Function

Adding the above terms, the objective function with respect to $\mathbf{k}$ is:

$$\begin{aligned} \mathcal{L}(\mathbf{k}) &\approx \mathcal{L}(\mathbf{k}_m, \mathbf{k}_{m+1}) + \mathbf{g}_m^\top (\mathbf{k} - \mathbf{k}_m) + \mathbf{g}_{m+1}^\top (\mathbf{k} - \mathbf{k}_{m+1}) + \frac{1}{2} (\mathbf{k} - \mathbf{k}_m)^\top \mathbf{H}^{11} (\mathbf{k} - \mathbf{k}_m) \\ &\quad + (\mathbf{k} - \mathbf{k}_m)^\top \mathbf{H}^{12} (\mathbf{k} - \mathbf{k}_{m+1}) + \frac{1}{2} (\mathbf{k} - \mathbf{k}_{m+1})^\top \mathbf{H}^{22} (\mathbf{k} - \mathbf{k}_{m+1}) \end{aligned} \quad (14)$$

Taking the Derivative of $\mathcal{L}(\mathbf{k})$ with Respect to $\mathbf{k}$ and Setting to Zero

Taking the derivative:

$$\frac{\partial \mathcal{L}}{\partial \mathbf{k}} = \mathbf{g}_m + \mathbf{g}_{m+1} + \mathbf{H}^{11} (\mathbf{k} - \mathbf{k}_m) + \mathbf{H}^{12} (\mathbf{k} - \mathbf{k}_{m+1}) + \mathbf{H}^{12\top} (\mathbf{k} - \mathbf{k}_m) + \mathbf{H}^{22} (\mathbf{k} - \mathbf{k}_{m+1}) \quad (15)$$

Since the Hessian matrix is symmetric, i.e., $\mathbf{H}^{12} = \mathbf{H}^{21}$, we have:

$$\frac{\partial \mathcal{L}}{\partial \mathbf{k}} = \mathbf{g}_m + \mathbf{g}_{m+1} + (\mathbf{H}^{11} + 2\mathbf{H}^{12} + \mathbf{H}^{22}) \mathbf{k} - (\mathbf{H}^{11} \mathbf{k}_m + \mathbf{H}^{12} (\mathbf{k}_m + \mathbf{k}_{m+1}) + \mathbf{H}^{22} \mathbf{k}_{m+1}) \quad (16)$$

Setting the derivative to zero yields the optimal condition:

$$(\mathbf{H}^{11} + 2\mathbf{H}^{12} + \mathbf{H}^{22}) \mathbf{k}^* = \mathbf{H}^{11} \mathbf{k}_m + \mathbf{H}^{12} (\mathbf{k}_m + \mathbf{k}_{m+1}) + \mathbf{H}^{22} \mathbf{k}_{m+1} - (\mathbf{g}_m + \mathbf{g}_{m+1}) \quad (17)$$

Solving for the Optimal Key Vector $\mathbf{k}^*$

The optimal key vector $\mathbf{k}^*$ is obtained as:

$$\mathbf{k}^* = (\mathbf{H}^{11} + 2\mathbf{H}^{12} + \mathbf{H}^{22})^{-1} (\mathbf{H}^{11} \mathbf{k}_m + \mathbf{H}^{12} (\mathbf{k}_m + \mathbf{k}_{m+1}) + \mathbf{H}^{22} \mathbf{k}_{m+1} - (\mathbf{g}_m + \mathbf{g}_{m+1})) \quad (18)$$

D Comparison of AsymKV with Other New Baselines

We also conducted additional comparisons with SnapKV [17], PyramidKV [4], TOVA [20], D2O [26] and L_2-Norm [9]. These experiments were performed on the LongBench dataset based on the Llama3-8b-Instruct with compression context max_length=2048.

As show in Table 5 AsymKV still demonstrates performance improvements compared to these baselines.

Table 5: Comparison of AsymKV with other new baselines on LongBench.

	Single-Doc	Multi-Doc	Sum	Few-shot	Synthetic	Code	Avg.
Llama3-8B-Instruct							
Full Context	32.19	34.59	24.96	68.48	36.96	54.41	41.46
StreamingLLM	27.90	25.92	24.49	65.09	13.87	55.02	35.50
LongCache	28.26	25.64	24.69	65.75	15.50	54.65	35.83
H ₂ O	30.65	32.77	24.61	61.83	37.08	54.87	39.59
LLMLingua-2	26.50	30.80	24.10	39.30	22.50	32.20	29.47
CaM	30.49	31.48	24.85	63.83	37.02	55.46	39.81
TOVA	31.82	27.94	24.57	64.34	19.29	54.06	37.04
L2	30.18	27.41	24.70	63.29	37.34	51.78	38.43
D2O	30.81	32.87	24.64	67.42	36.67	56.49	40.85
SnapKV	32.17	34.20	25.28	68.57	37.21	53.30	41.36
PyramidKV	31.79	34.02	25.44	68.57	37.24	54.97	41.49
AsymKV	34.45	33.64	26.17	67.94	38.66	56.61	42.32

E Licenses for Existing Assets

We list the assets used in this paper and their licenses below:

- [24],llama2
- [10],llama3
- [11],Apache 2.0 License
- [29],Apache 2.0 License
- [2],MIT License
- [14],Apache 2.0 License
- [30],CC BY-SA 4.0
- [3],MIT License
- [1],GNU General Public License v3.0
- [6],llama2
- [28],MIT License