HqeKV: Towards Hybrid Quantization and Eviction for KV Cache in Long-Context LLM Inference

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Abstract

The autoregressive inference in large language models requires repeated computation across transformer layers. While caching intermediate key-value (KV) pairs eliminates redundancy, it introduces severe memory overhead, particularly in long-context settings. Most existing cache compression methods operate solely on either quantization or eviction, based on importance estimation of cached data. However, they are limited by coarse compression choices and inaccurate importance assessment, leading to suboptimal inference quality. To address this, we propose HqeKV, a hybrid compression framework built on both quantization and eviction, offering finer-grained compression options that adapt smoothly to the varying importance of cached KV pairs. An integrated optimizer automatically selects the best compression action for each cached element, maximizing quality while insulating end-users from tedious low-level tuning details. We further design a joint K–V importance metric to provide more accurate importance assessment results so that the optimizer can make smarter decisions. Additionally, HqeKV supports flexible conversion policies across multiple quantization precision levels, to further reduce quality degradation. Extensive experiments show that HqeKV improves output quality under the same memory constraints, outperforming state-of-the-art alternatives. Code is available at https://github.com/skywclouds/HqeKV.

1 Introduction

Large Language Models (LLMs) are gaining increasing popularity due to their remarkable performance across a wide range of tasks. LLMs work through Inference-as-a-Service (IaaS) where the prompt from an end-user is processed autoregressively through stacked transformer layers to generate output tokens. Each newly generated output is appended to the input sequence and then processed together, resulting in substantial redundant computations for the repeated input. Caching intermediate key-value (KV) pairs of previously processed tokens can effectively mitigate this inefficiency, but introduces a significant memory bottleneck. The size of KV Cache grows linearly with sequence length and can exceed the model's own memory footprint, especially for long-context IaaS.

Many recent efforts have been devoted to compressing KV Cache, which primarily fall into two categories, i.e., quantization and eviction. Quantization methods reduce numerical precision, typically converting FP16 values to a single low-precision format (Su et al., 2025) or, at most, two mixed low-precision formats (Li et al., 2025). However, their coarse quantization granularity and the uniform converting strategy cannot adapt to the varying information density present in different cached pairs, forcing a difficult trade-off between inference quality and memory savings. Eviction methods, on the other hand, discard KV pairs deemed less important (Qin et al., 2025), avoiding (de)quantization runtime penalty and enabling faster inference, but often incur noticeable quality degradation. Crucially, both lines of compression works rely on distinguishing the importance of cached data. Current metrics, however, either consider only the key (K) vectors while ignoring the value (V) vectors, or take V into account but in an unreasonable manner, leading to imprecise assessments that further exacerbate the conversion loss. Some works integrate quantization and eviction (Feng et al., 2025; Sharma et al., 2025). However, these approaches typically operate at a coarse compression granularity, prioritizing system throughput over generation quality, and largely amount to engineering-level integration of quantization and eviction mechanisms without deeper algorithmic co-optimization.

Motivated by these limitations, we propose

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HqeKV, a hybrid framework that combines quantization and eviction for efficient KV Cache compression. Cached KV pairs are sorted by importance in ascending order. The top-tier pairs are quantized to high precision or even not compressed, the middle tier to medium or low precision, and the bottom tier is evicted. To better accommodate varying importance levels, we particularly expand the candidate precision levels to three, after balancing bit utilization and runtime latency. Furthermore, a built-in optimizer automatically determines the optimal boundaries among FP16, three quantization precisions and eviction, based on available memory capacity, thereby maximizing inference quality.

The increased number of compression options amplifies the challenge of accurate importance assessment, which is fundamental to optimizing action boundaries. This problem is exacerbated by the standard cumulative attention weight metric, which relies solely on K vectors and excludes V vectors since the information of the latter is not readily available in advance. To address this gap, we first observe a positive correlation between inference quality degradation and the range of V vectors. Leveraging this observation and adhering to the principles of attention computation, we propose a new joint K-V metric to accurately assess the importance of cached pairs.

We further find that within our fine-grained quantization scheme, the optimal conversion strategies differ by bit-width. The uniform conversion works best for high bit-widths/precision, while the normalized conversion is superior for low bit-widths/precision. HqeKV accordingly applies the tailored strategy for each precision level, thereby enhancing inference quality.

Our contributions are summarized as below.

- Proposing a hybrid compression framework HqeKV that combines quantization and eviction where cached pairs are processed using one of five compression actions——FP16 (full precision), three fine-grained quantization precisions or eviction. By adaptively optimizing the action boundaries and selecting tailored conversion strategies for different precisions, HqeKV maximizes inference quality within given memory limits.
- Proposing a novel importance metric that jointly incorporates both key (K) and value (V) tensors, based on the observed positive correlation between quality degradation and the range of V vectors. This refined metric improves the distinction among cached pairs, leading to superior boundary decisions and enhanced inference quality.
- Extensive experiments on the widely used LongBench suite and multiple LLMs show that HqeKV significantly outperforms the state-of-the-art, improving quality from 40.53 to 49.98 under the same memory limit.

2 Preliminary

2.1 Transformer Architecture

Most of the state-of-art LLMs currently are built by stacking multiple decoder-only Transformer layers. Each Transformer layer maps its input vector x to an output vector of the same dimension.

The core of a single Transformer layer is the Multi-Head Self-Attention (MHSA) mechanism. Given input vector x, MHSA firstly generate Q, K, V as query, key, and value for every head. Then, the self-attention for every head is computed by:

$$O = \text{Softmax}\left(\frac{QK^\top}{\sqrt{d_h}}\right)V, \tag{1}$$

where the Softmax$(QK^\top/\sqrt{d_h})$ is called attention weights.

2.2 LLM Inference and KV Cache

LLM inference consists of two phases, including prefilling and decoding. In prefilling, text is encoded into tokens and then processed through transformer layers to produce the first output token x_0. In decoding, the model iteratively appends new tokens to the prefix and re-inputs it, causing redundant calculations of K, V and self-attention. To optimize this, KV Cache stores previous Keys and Values matrices. When generating x_{t+2}, only the newly produced vector x_{t+1} is projected into key and value spaces k_{t+1}, v_{t+1}. These projections are then concatenated with the cached matrices $K = [K|k_{t+1}], V = [V|v_{t+1}]$. This incremental reuse technique is called KV Cache mechanism.

2.3 Quantization Strategies

Quantization is a kind of methods mapping numbers from high precision to low precision. This paper employs uniform and normalized quantization. The following first introduces the uniform quantization. Let the vector to be quantized be $\Xi \in \mathbb{R}^{1\times D}$,

then the quantization and de-quantization output is shown as follows:

$$\Xi_q = \frac{\Xi - z}{s}, \quad \Xi_{dq} = \Xi_q \cdot s + z,$$

where $z = \min(\Xi)$ is the offset, and $s = \frac{\max(\Xi)-\min(\Xi)}{2^b-1}$ is the scaling factor, and b is the quantization precision. This process can be regarded as placing each number at the center of a set of equal-length intervals.

Second, we introduce the normalized quantization. The first step in normalized quantization is shown as follows:

$$\Xi' = \frac{\Xi - m}{s},$$

where m and s is the mean value and standard deviation of ξ. Then, let $C = [c_0, \cdots, c_{2^b-1}]$ to be the $\frac{1}{2^b}, \cdots, \frac{2^b-1}{2^b}$ quantile of the standard normal distribution. The quantization output of numbers in vector Ξ is shown as follows:

$$\Xi_{iq} = \min_{0<j<2^b-1} \int_{\min(c_j, \Xi'_i)}^{\max(c_j, \Xi'_i)} \varphi(u)\mathrm{d}u,$$

where $\varphi(t)$ is the standard normal density function. And the de-quantization output is shown as follows:

$$\Xi_{dq} = C[\Xi_q] \cdot s + m.$$

This process can be regarded as placing each number at its nearest quantile of the standard normal distribution.

3 Method

3.1 Overview of HqeKV

We present HqeKV, a novel KV Cache compression method and the general framework is illustrated in figure 1. In the prefilling phase, the Q, K and V are generated and then in compression phase, a novel importance metric jointly incorporates attention weights and value token ranges guides the allocation of K and V into five precision based on the optimal ratio with specific compression strategy. In the decoding phase, the KV Cache is periodically re-quantized after every T generated tokens.

The remainder of this section is organized as follows. In Section 3.2, we introduce the proposed joint importance metric for KV Cache compression, which incorporates both attention scores and the range of value tokens. Section 3.3 presents a search algorithm designed to determine the optimal allocation ratio across different precision levels. In Section 3.4, we detail the precision-specific compression strategies employed for KV Cache. Finally, Section 3.5 describes the operational mechanism of HqeKV in the decoding phase.

3.2 Joint Importance Metric with Range

Most existing KV Cache compression methods rely on cumulative attention weights to evaluate importance, often overlooking the intrinsic properties of the KV Cache. VATP (Guo et al., 2024) employ the 1-norm of Value but fails to provide a sufficient theoretical explanation for this motivation.In this section, we derive the relationship between conversion loss and data range, providing support for designing a more reasonable KV Cache importance metric.

The quantization process can be regarded as mapping each value to its nearest quantization center. Assuming the data to be quantized is independently and identically distributed as $p(\xi)$, the quantization bit-width b, and denoting the interval that is closest to quantization center c_i in possibility as I_i, the expected conversion loss for any value can be expressed as follows:

$$\begin{aligned} &\underset{\xi\sim p(\xi)}{E}(\mathcal{L}_{\mathrm{n}}(\xi)|\xi \in [\min(\Xi), \max(\Xi)]) \\ &= \frac{\sum_{i=0}^{2^b-1} \int_{\xi \in I_i \bigcap [\min(\Xi), \max(\Xi)]} (\xi - c_i)^2 p(\xi)\mathrm{d}\xi}{\int_{\min(\Xi)}^{\max(\Xi)} p(\xi)\mathrm{d}\xi}. \end{aligned} \tag{2}$$

Equation (2) can be interpreted as drawing a sample ξ from the probability distribution $p(\xi)$, and ξ may fall into any quantization interval. We compute the expected squared distance between ξ and the quantization center within each interval and then sum them up. Owing to the generic formulation, the expression holds for both uniform and normalized quantization—the sole distinction resides in the partitioning policy and the placement of the representative codewords.

From Equation (2), it follows that the quantization error of a vector is determined by its extremal values. Consequently, defining the range of a vector Ξ as $R_\Xi = \max(\Xi) - \min(\Xi)$, the range emerges as a direct indicator of the incurred conversion loss.

To validate the viewpoint, We visualize the Equation (2) and by means of numerical integration. We assume that $p(\xi)$ is the standard normal density

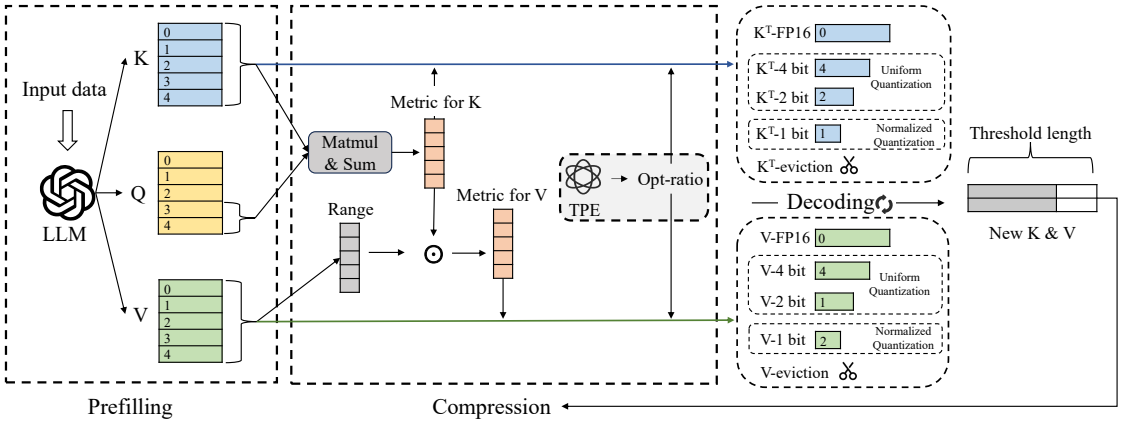
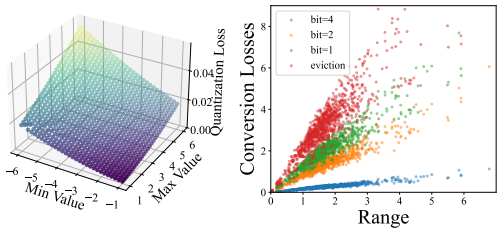


Figure 1: The inference framework of HqeKV in a single Transformer layer.

function, b is 4 and quantization strategy is uniform quantization in Equation (2). We also randomly select 1,000 tokens from the V Cache of Llama-3.1-8B-Instruct, corresponding to the first question in the Qasper dataset of LongBench (Bai et al., 2024) and quantize them to 4, 2 bit-widths under uniform quantization, 1 bit-width under normalized quantization and eviction, evaluating the range and conversion losses as shown in Figure 2.



(a) Numerical integration of Equation (2)

(b) Conversion losses of tokens with range

Figure 2: Numerical integration of Equation (2) under 4 bit-width uniform quantization and the conversion losses of tokens from KV Cache in LongBench with range.

Bit-width	4-bit	2-bit	1-bit	eviction
PCCs (V Cache)	0.96	0.96	0.95	0.91
PCCs (random vectors)	0.88	0.88	0.84	0.73

Table 1: Pearson correlation coefficients (PCCs) of conversion losses and range at 4, 2 and 1 bit-widths and eviction.

From Figure 2 we can obtain that there is a positive correlation between conversion losses and the range of data. We also calculate the Pearson correlation coefficients (PCCs) between the conversion losses and (1) the ranges of randomly selected tokens, and (2) the ranges of 1000 randomly generated 32-dimensional vectors sampled from a normal distribution, as shown in Table 1. And a positive correlation between conversion losses and the range is indicated by the results.

In summary, the range serves as a viable metric for quantifying the conversion losses. Accordingly, we quantify K's importance through cumulative attention weights. Meanwhile, the importance of V is assessed through the product of the cumulative attention weights and the range of each token within V since in Equation (1) there is a multiplication between attention weights and V.

3.3 Optimizer for Precision-Ratio Allocation

The allocation of precision ratio in the scenario of mixed-precision compression is a highly critical issue. The existing approaches typically involve either manual allocation of the ratio of each precision or the establishment of certain thresholds to determine the precision to which a token should be quantized. However, these strategies are clearly not the optimal approach. In contrast, our work adopt an offline search method to determine the ratio of each precision.

Let the average bit-width of compressed KV Cache to be B_{avg} and the ratios of 4, 2, 1 bit-widths and eviction to be $\delta_1, \delta_2, \delta_3, \delta_4$. Then the allocation of ratios for different precision can be expressed by Equation (3).

$$\begin{cases} 4\delta_1 + 2\delta_2 + \delta_3 = B_{\text{avg}} \\ \delta_1 + \delta_2 + \delta_3 + \delta_4 = 1 \end{cases} \quad \text{s.t. } B_{\text{avg}} > 0,\ 0 \le \delta_1, \cdots \delta_4 \le 1. \tag{3}$$

To solve the infinite solutions of Equation (3),

we set δ_3, δ_4 as free variables and represent δ_1, δ_2 in terms of them. We use the Tree-structured Parzen Estimator (TPE) (Bergstra et al., 2011) to efficiently search for the values of δ_3 and δ_4. Specifically, we set the number of iterations to 200. Due to the quantization dimensions of K and V are different, we partition the KV Cache into chunks with size G. Within each chunk, we apply the per-channel quantization to K and the per-token quantization to V. To determine the importance of each chunk, we utilize the average importance of the tokens within the same chunk as a representative measure. We denote the cross-entropy of the model's prefilling output in certain quantization ratio and the full-precision prefilling output on the calibration dataset as $\mathcal{L}_c$. The detail of the calibration dataset is shown in Appendix A.2.

Additionally, we design a regularization term $\mathcal{L}_{reg} = \alpha x_3 + \beta x_4$. We aim to reduce the ratios of low precision through the incorporation of this regularization term. So the final loss function is defined as $\mathcal{L} = \mathcal{L}_c + \mathcal{L}_{reg}$.

The ratio that minimizes $\mathcal{L}$ is considered as the optimal ratio. And we retain the most important 2 chunks in full precision to further improve the model performance under quantization. The process of the search is shown in Appendix A.3.

3.4 Precision-Specific Quantization Strategies

Existing KV Cache mixed-precision quantization methods uniformly apply a single quantization strategy across all precision levels, overlooking the fact that distinct strategies are better suited to different bit-widths. To substantiate this claim, we extract the KV Cache of Llama-3.1-8B-Instruct from the first question on Qasper dataset in LongBench (Bai et al., 2024), randomly selecting 128 channels for K and 128 tokens for V and quantizing them to 4, 2 and 1 bit-widths under uniform and normalized quantization. We avoid 8 bit-width since its 256 states exceed the 128-dimensional attention heads in current LLMs, causing unnecessary overhead. The conversion losses are shown in Table 2.

Strategies	K			V		
	4-bit	2-bit	1-bit	4-bit	2-bit	1-bit
Uniform	**5.28**	25.59	92.06	**0.29**	1.44	4.67
Normalized	9.28	23.29	**37.44**	0.62	1.47	**2.05**

Table 2: Conversion losses for the K and V cache across different bit-widths and quantization strategies. The quantization group size is set to 32.

Table 2 reveals that, for both K and V, normalized quantization produces larger conversion losses than uniform quantization at 4-bit. A reversal occurs only in the 1-bit regime, where normalized quantization exhibits a decisive advantage over its uniform counterpart.

Since NQKV (Cai et al., 2025) confirm that the data in KV Cache follows a normal distribution, we randomly sampled 128 vectors $\in \mathbb{R}^{128}$ from the standard normal distribution and quantize them to 4, 2 and 1 bit-widths. The conversion losses are shown in Table 3.

We can obtain the same phenomenon from Table 2 and Table 3. In summary, we decide to perform uniform quantization for 4 and 2 bit-width and normalized quantization for 1 bit-width. For quantization dimension, we adopt per-channel and per-token quantization to K and V.

Strategies	4-bit	2-bit	1-bit
Uniform	**0.87**	4.38	15.46
Normalized	1.47	4.07	**6.77**

Table 3: Conversion losses for random vectors from standard normal distribution across different bit-widths and quantization strategies. The quantization group size is set to 32.

To reduce the computational overhead, we only select m most recent tokens to calculate the cumulative attention weights. The detailed algorithm is shown in Appendix A.4.

3.5 Strategy in Decoding Phase

In the decoding phase, we re-quantize all KV Cache after every T generated tokens. If the precision of a token is lower than that in the previous quantization, we further quantize it. Otherwise, it is retained unchanged. This strategy is motivated by the observation that only a minimal fraction of the KV Cache transitions to higher precision. Further details are provided in Appendix A.5.

4 Experiments

4.1 Experimental Setup

We conduct our experiments on Llama-3.1-8B-Instruct (Grattafiori et al., 2024) and Qwen3-8B (Yang et al., 2025), which are widely used open-source models with a maximum context length of 128k.

We evaluate the model on LongBench (Bai et al., 2024) and AIME-2025 (Balunović et al., 2025).

LongBench is a pioneering bilingual, multi-task benchmark for long context understanding which comprises 21 datasets across 6 task categories in both English and Chinese, including single-doc QA, multi-doc QA, summarization, few-shot learning, synthetic tasks, and code completion. AIME-2025 comprises 30 problems from the 2025 American Invitational Mathematics Examination which is particularly challenging as it demands multi-step logical deduction and genuine problem-solving abilities.

We benchmark baselines against five state-of-the-art methods, including single-precision quantization methods KIVI (Liu et al., 2024) and OTT (Su et al., 2025), mixed-precision quantization methods ZipCache (He et al., 2024), KVTuner (Li et al., 2025) and eviction method CAKE (Qin et al., 2025). We set the average compression bit-width for HqeKV to 2, 3.2 and 3.25 corresponding to the compression bit-width of quantization baselines. And we set the eviction ratio of CAKE to the same level as 3.2 bit-width quantization. The detailed hyper-parameters setup is shown in appendix A.6.

Finally, all experiments are conducted on a NVIDIA RTX A6000 GPU (48GB) device.

4.2 Evaluation on Inference Quality

The brief evaluation results of HqeKV with all baselines on the LongBench dataset are shown in Table 4 and the detailed results with quantization baselines are shown in Appendix A.7.1. Moreover, the comparison of HqeKV and eviction method CAKE is shown in Appendix A.7.2.

As shown in Table 4, HqeKV demonstrates superior performance compared to all baselines. Notably, HqeKV achieves 123.69% improvement over CAKE on Multi-Document QA and 120.99% improvement on Single-Document QA. HqeKV not only achieves the highest average score, but also sets a new state-of-the-art in 81.25% of the individual tasks. Even in some tasks that do not exceed baselines, there is only a slight gap. Remarkably, in several scenarios HqeKV delivers superior accuracy while operating under a 14.29% stricter KV Cache memory budget. Specifically, ZipCache and KVTuner may encounter out-of-memory (OOM) issues and CUDA ERROR. It should be particularly noted that the "Avg" scores for ZipCache-2.8, ZipCache-3.2 and HqeKV-3.2 near ZipCache in Table 4 are calculated from non-OOM columns. And the "Avg" scores for KVTuner-3.25 and HqeKV-3.25 near KVTuner in Table 4 are calculated from the non-ERROR columns. The scores from the non-OOM and non-ERROR columns are marked with "*".

We also conduct a comparative evaluation of HqeKV-2 and KIVI-2 on the AIME-2025 using the Qwen3-8B model. The AIME-2025 In our experiments, HqeKV-2 achieves an accuracy of 0.20, while KIVI-2 attains 0.17, demonstrating the effectiveness of our proposed method on this rigorous mathematical reasoning task.

4.3 Evaluation on Inference Scalability

We evaluate the inference Scalability by examining memory usage and throughput. Specifically, we first investigate the maximum batch size achievable by different methods across varying context lengths. Additionally, we analyze the memory usage of different methods with varying batch sizes, focusing on a context length of 4096 tokens. The number of generated new tokens in both evaluations above is set to 32, and the results are illustrated in Figure 3.

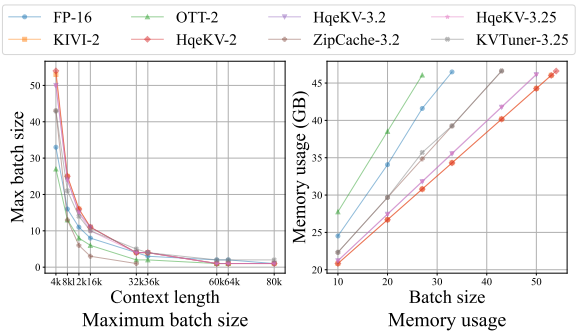


Figure 3: Maximum batch size and memory usage of different methods.

As depicted in Figure 3, HqeKV enables the largest batch size in most cases and reduces memory usage by 29.6%, 8.3% and 8.6% on average compared to OTT, ZipCache and KVTuner. The reason is that their compression strategies introduce substantial storage overhead, degrading overall memory efficiency. OTT computes the 1-norm for every token, incurring substantial memory overhead. ZipCache samples 10% token for cumulative attention weights, leading to higher memory usage. KVTuner sacrifices efficiency by storing quantized values without bit-packing, leaving significant unused memory. In contrast, HqeKV adopts a memory-efficient design and incorporates a customized Triton kernel that densely packs quantized values, thereby minimizing the memory footprint.

Methods	Single-Document QA	Multi-Document QA	Summarization	Few-shot Learning	Synthetic Task	Code Completion	Avg
Llama-3.1-8B-Instruct							
FP16	47.7	40.45	26.19	63.26	66.81	56.59	49.76
KIVI-2	46.84	39.79	25.9	63.04	65.38	55.22	48.96
OTT-2	47.02	40.04	25.95	62.92	64	57.99	49.43
HqeKV-2	46.53	**40.12**	25.82	**63.07**	**66.4**	**58.17**	**49.71**
ZipCache-3.2	52.13*	39.82	22.73*	68.66*	66.73	61.32*	50.98*
HqeKV-2.8	54.03*	40.17	22.86*	68.15*	67.14	60.77*	51.26*
HqeKV-3.2	**54.2***	**40.93**	**22.88***	67.76*	**67.3**	61.25*	**51.49***
CAKE-3.2	21.44	17.28	22.96	61.19	58.89	57.6	40.3
HqeKV-3.2	**47.38**	**40.93**	**25.81**	**62.45**	**67.3**	**57.83**	**49.91**
KVTuner-3.25	46.78	43.06*	25.78	62.58	66.98	60.91*	49.94*
HqeKV-3.25	**47.06**	**44.55***	**26.08**	**62.86**	66.17	**61.91***	**50.33***
CAKE-3.25	24.64	18.57	22.8	60.41	60.5	58.59	40.53
HqeKV-3.25	**47.06**	**41.54**	**26.08**	**62.86**	**66.17**	58.02	**49.98**
Qwen3-8B							
FP16	47.14	40.52	23.9	63.12	66.5	66.11	51.24
KIVI-2	46.05	40.85	23.82	63.71	63.89	63.62	50.36
OTT-2	46.25	41.35	23.89	63.09	65	64.7	50.75
HqeKV-2	**46.44**	**41.68**	**24**	63.55	**66.64**	**65.83**	**51.37**
ZipCache-3.2	53.55*	40.15	20.38*	62.53	66.5	66.93*	51.22*
HqeKV-2.8	**54.94***	**41.03**	**20.95***	62.12	**67.42**	**68.72***	**51.98***
HqeKV-3.2	54.77*	40.62	20.82*	**63.05**	67.17	67.88*	51.89*
CAKE-3.2	47.06	40.71	22.01	62.13	66.33	64.17	50.45
HqeKV-3.2	46.86	40.62	**23.94**	**63.05**	**67.17**	**66.15**	**51.29**

Table 4: Inference scores of Llama-3.1-8B-Instruct and Qwen3-8B on LongBench.

We compare the Time to first token (TTFT) of HqeKV with that of quantization baselines on the Wikitext-2 (Merity et al., 2016) dataset with a context length of 161 tokens and 338 newly generated tokens on Llama-3.1-8B. The results are illustrated in Table 5.

Methods	HqeKV-2	KIVI-2
TTFT(s)	10.64	9.35
Methods	HqeKV-3.2	ZipCache-3.2
TTFT(s)	11.18	20.13
Methods	HqeKV-3.25	KVTuner-3.25
TTFT(s)	11	9.27

Table 5: Time to first token (TTFT) of HqeKV with that of quantization baselines on Wikitext-2 dataset.

Table 5 shows that HqeKV indeed has a gap compared to some of the baselines. But the additional time required is at most 2 seconds on average. We believe this cost is acceptable.

We analyze the throughput efficiency by comparing the time per output token (TPOT) of HqeKV with that of quantization baselines on the Wikitext-2 dataset. Specifically, the comparison is conducted under two different settings, including one with a context length of 161 tokens and 338 newly generated tokens, and the other with a context length of 4096 tokens and 128 newly generated tokens. The results are illustrated in Figure 4.

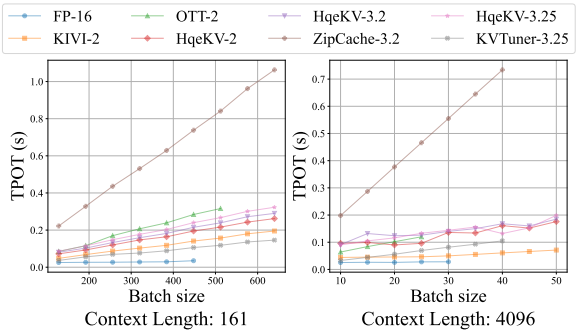


Figure 4: Time per output token (TPOT) of HqeKV with that of quantization baselines on Wikitext-2 dataset across varying context lengths.

The superior efficiency of HqeKV over OTT and ZipCache stems from that HqeKV introduces a specialized CUDA kernel that integrates the dequantization and vector-matrix multiplication processes. Although HqeKV exhibits higher TPOT than KIVI and KVTuner, this overhead remains within an acceptable range.

To evaluate the runtime overhead of periodic re-quantization during inference, we measured the execution time under the following settings: context length of 4096 tokens, batch size of 10, and generation length of 128 tokens. The re-quantization times for three consecutive periods were 0.52 s,

0.36 s, and 0.33 s, respectively. These measurements confirm that the computational cost of periodic quantization is negligible compared to overall inference latency.

4.4 Overall Performance Analysis

To intuitively compare the methods across multiple dimensions and thereby judge their overall performance, we plot a radar chart to provide a multi-dimensional comparison of the HqeKV, KIVI, OTT and ZipCache based on the obtained experimental results, as shown in Figure 5.

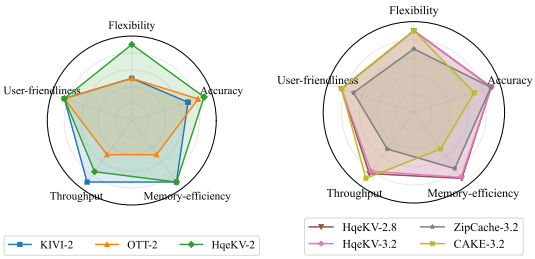


Figure 5: Multi-dimensional performance comparison of HqeKV and other methods.

The accuracy score in Figure 5 corresponds to the average score in LongBench with Llama-3.1-8B-Instruct. The memory-efficiency score is evaluated under context length of 4096 where batch-size is 20, and the throughput score is evaluated under context length of 161 where batch-size is 448. All three metrics are linearly rescaled so that higher values always indicate superior performance. For flexibility score, KIVI and OTT are restricted to a single precision, exhibiting the lowest flexibility. ZipCache allows the compression bit-width between 2 and 4, but the narrow span confines its flexibility to a moderate level. In contrast, both HqeKV and CAKE support a more wide compression ratios spectrum, endowing them with the highest flexibility. For user-friendliness score, ZipCache obliges the user to manually derive and balance precision ratios, rendering it the least user-friendly. Other methods accept a single global compression ratio as direct input. Consequently, their user-friendliness is regarded as uniformly high.

Figure 5 reveals that that HqeKV surpasses other methods since its largest area.

4.5 Ablation Study

To systematically evaluate how each proposed innovations contributes, we conducted an ablation study of Llama-3.1-8B-Instruct on LongBench for evaluation. The brief results are shown in Table 6 and, the descriptions of "Method" column in Table 6 are provided in Appendix A.9.2, and the detailed results are given in Appendix A.9.3.

Table 6 shows that removing any one of the four innovations degrades performance, while adding any one improves it, confirming that all HqeKV innovations are effective.

Method	Brief Description	Avg
HqeKV-3.2	-	**49.91**
w/o I	w/o metric with range	49.78
w/o II	uniform quantization	41
w/o III	randomly non-opt ratio	49.8
w/o eviction	w/o eviction	49.47
III on w/o II	opt ratio on uni-quant	49.87
only I	metric with range	30.38
only II	specific quant strategies	49.81
only III	opt ratio allocation	46.34
w/o I, II & III	only quant-eviction	29.91

Table 6: Scores on LongBench in ablation study.

We also explored the performance of the model by the hyper-parameters α and β. We conduct an evaluation on HotpotQA from LongBench with the Llama-3.1-8B-Instruct model. Under the configuration ($\alpha = 2$, $\beta = 4$), the model achieves the highest score of 56.75, outperforming the alternatives: 54.76 ($\alpha = 2$, $\beta = 2$), 55.15 ($\alpha = 4$, $\beta = 2$), and 55.49 ($\alpha = 4$, $\beta = 4$). These results indicate that $\alpha = 2$ and $\beta = 4$ are the optimal hyper-parameters among the considered configurations.

4.6 Analysis of the Optimizer for Precision-Ratio Allocation

The optimizer performs an offline search for precision-ratio allocation. We analyze the time consumption and the the impact of iterations.

Our analysis of this offline search shows that it incurs moderate computational overhead. Specifically, the offline search procedure for the 3.2-bit configuration completed in 7 minutes and 46 seconds. We consider this one-time pre-processing cost acceptable given the substantial inference efficiency gains achieved.

To determine an appropriate iteration count for the offline search, we conducted a comparative experiment between 200 and 300 iterations under the 3.2-bit quantization setting. For 200 iterations, the corresponding values for 4-bit width, 2-bit width,

1-bit width, and eviction were 0.64, 0.31, 0.04, and 0.02, respectively. For 300 iterations, the corresponding values were 0.65, 0.28, 0.06, and 0.02, respectively. All reported values are rounded to two decimal places. As demonstrated by these results, the performance difference between 200 and 300 iterations is marginal.

5 Related work

5.1 KV Cache Eviction

Researchers have proposed multiple methods to reduce the memory usage of KV Cache by eviction. H2O (Zhang et al., 2023) utilizes cumulative attention weights to determine which tokens should be retained or evicted. Scissorhands (Liu et al., 2023) retains tokens with a relatively high cumulative attention score over a period of time in the past. VATP (Guo et al., 2024) employ the 1-norm of Value to assess the importance of KV Cache. SnapKV (Li et al., 2024) retains tokens with high cumulative attention weights in each head and several recently tokens. StreamingLLM (Xiao et al., 2024) retains only the initial few tokens and the most recent few tokens. PyramidKV (Cai et al., 2024) adopts a pyramid-style allocation to different layers, allocating a larger budget to the early layers and a smaller budget to the final layers. CAKE (Qin et al., 2025) quantifies the saliency of each layer by jointly considering both spatial and temporal characteristics and allocates memory to each layer. MorphKV (Ghadia et al., 2025) evicts the token with the lowest importance. ThinK (Xu et al., 2025) retains the top-ranked channels selected by the query-dependent Frobenius norm.

5.2 KV Cache Quantization

KV Cache Quantization is an effective strategy to reduce memory use of KV Cache. Atom (Zhao et al., 2024) adopts uniform group quantization on KV Cache. KIVI (Liu et al., 2024) applies per-channel and per-token uniform group quantization on Key Cache and Value Cache. KVQuant (Hooper et al., 2024) uses the K-means clustering weighted by the fisher information matrix and quantizes Key Cache before RoPE, storing outliers separately in full precision. SKVQ (Duanmu et al., 2024) clusters channels of similar orders of magnitude together and quantizes KV Cache per-token. QJL (Zandieh et al., 2025) performs the JL Transform to the Key Cache and quantizes it to 1 bit. OTT (Su et al., 2025) stores outliers token separately and quantizes others like (Liu et al., 2024). SpinQuant (Liu et al., 2025) employs learnable Hadamard transformations to reduce outliers in the KV Cache. MiKV (Yang et al., 2024) quantizes tokens with less importance in low precision and proposes a per-channel balancer to reduce outliers. ZipCache (He et al., 2024) uses channel-separable tokenwise quantization to reduce the impact of outliers. QAQ (Cheng et al., 2025) determines quantization precision based on token-level standard deviation. Oaken (Kim et al., 2025) quantizes numbers near and far from zero to low precision and others to high precision. PQCache (Zhang et al., 2025) uses product quantization to compress KV Cache. KVTuner (Li et al., 2025) leverages Pareto frontier theory to assign layer-specific quantization levels. Cocktail (Tao et al., 2025) adopts the methods in RAG to evaluate the importance of KV Cache and quantizes them to different precision.

5.3 KV Cache Quantization-Eviction

Several methods integrate quantization and eviction for KV cache compression. EVICPRESS (Feng et al., 2025) proposes a unified utility function that quantifies the effects of quality degradation and access latency associated with lossy compression or eviction. Based on this utility metric, the method determines which KV caches undergo quantization or eviction. MiniKV (Sharma et al., 2025) presents an engineering-level integration of existing KV cache quantization and eviction techniques. it employs PyramidKV to allocate memory budget across layers, adopting existing quantization and eviction methods to compress the KV Cache.

6 Conclusion

In this paper, we propose HqeKV, a novel KV Cache compression method that integrates mixed-precision quantization and eviction. We provide both theoretical and empirical evidence demonstrating a positive correlation between conversion losses and range. We propose a joint KV Cache importance metric that combines cumulative attention weights and token range of V. HqeKV features fine-grained compression precision levels combining 4, 2, 1 bit-widths and eviction with specific quantization strategies. Moreover, HqeKV employs a search algorithm to determine the optimal precision ratio allocation. Extensive experiments show that HqeKV outperforms other state-of-the-art KV Cache compression methods.

Limitations

Despite its strong empirical performance, HqeKV is not without limitations. The offline search for optimal precision ratios, while optimized using TPE, remains agnostic to user-level or task-level heterogeneity, precluding true personalization. While normalized quantization mitigates accuracy loss at 1-bit precision, significant conversion loss still occurs at such extreme compression levels, highlighting the trade-off between bit-width and accuracy. The fixed re-quantization interval during decoding, though empirically set, introduces a sensitivity that could affect both latency and quality, especially in longer-context scenarios. Furthermore, its behavior under multi-modal architectures requires further research.

Ethics Statement

This work aims to reduce the memory usage of Large Language Models (LLMs), thereby reducing the energy required for deployment. Therefore, our approach aligns with the goals of Green AI and sustainable computing.

However, we acknowledge that if the underlying backbone models are not properly aligned, compressing their KV Cache may inadvertently lead to the generation of harmful or biased content. Since HqeKV is a training-free method that does not modify the model weights, the safety properties and biases of the generated text remain inherent to the pre-trained backbones. We advocate for the responsible deployment of HqeKV, accompanied by robust safety guardrails and content filtering mechanisms.

Disclosure on AI Assistance. We utilized AI-based tools (e.g., ChatGPT) solely for grammatical polishing, rephrasing, and improving textual fluency. All scientific claims, experimental designs, and empirical results presented in this paper are the original work of the authors and have been manually verified.

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A Appendix

A.1 Relationship Between Quantization–Eviction and Structural Compression

This section clarifies the relationship between the proposed quantization–eviction strategy and structural compression approaches.

Quantization and eviction reduce memory by making the KV Cache smaller or sparser, whereas structural compression reduces memory by transform the KV Cache to a more compact form. The former preserves the original high-dimensional structure, while the latter fundamentally projects the cache into a lower-dimensional subspace. After the structured compression, the data can be further subjected to quantization operations. However, after quantization, the data cannot be structurally compressed. For eviction, structured compression can be carried out after the eviction.

A.2 Detailed Information of Calibration Dataset in Precision-Ratio Allocation

The dataset we used as the calibration dataset is wikitext-2 (Merity et al., 2016), a dataset comprising approximately 2 million tokens extracted from verified Good and Featured articles on Wikipedia. We concatenated a 16k-tokens data sequence from the wikitext-2 dataset in the default order of the data. Additionally, wikitext-2 and LongBench are two separate datasets, and the data of the two does not overlap with each other.

A.3 Algorithm of Optimal Precision Ratio Allocation Search

The search process is shown in Algorithm 1.

Algorithm 1 Optimal Precision Ratio Search

Input: The average compression bit-width $B_{\text{avg}} \in (0, 4)$

Output: Optimal ratio list R_{opt}

initialize minimum loss $L \leftarrow \text{Inf}$
initialize Optimal ratio list $R_{\text{opt}} \leftarrow \{\}$
initialize input S from calibration dataset
$F \leftarrow \text{LLM}(S)$ ▷ Output in full precision
for $iteration = 0$ **to** 200 **step** 1 **do**
  $x_3, x_4 \leftarrow \text{TPE\_Sample}(0, 1)$
  $x_1 \leftarrow B_{\text{avg}} - 2 + x_3 + 2x_4$
  $x_2 \leftarrow 4 - B_{\text{avg}} - 3x_3 - 4x_4$
  $R \leftarrow \{x_1, x_2, x_3, x_4\}$
  if $x_1 < 0$ or $x_2 < 0$ **then**
    $L_{\text{temp}} \leftarrow \text{Inf}$
  else
    $L_{\text{temp}} \leftarrow \mathcal{L}(F, \text{LLM}(S, R)) + \mathcal{L}_{\text{reg}}$
  end if
  if $L_{\text{temp}} < L$ **then**
    $L \leftarrow L_{\text{temp}}, R_{\text{opt}} \leftarrow R$
  end if
  $\text{TPE\_Update}(L_{temp}, x_3, x_4)$
end for
return R_{opt}

A.4 Algorithms of KV Cache Compression

The compression algorithms of HqeKV in prefilling and decoding phase are shown in Algorithm 2 and 3. In the decoding phase, Algorithm 3 will be continuously executed until the inference is completed.

A.5 Transitions from Lower to Higher Precision

We conduct a detailed statistical analysis of the transitions in the KV Cache from lower precision to higher precision during the second compression phase. This analysis is performed while running the first question from the DuReader dataset in LongBench, using a mixed-quantization ratio of 0.05 for 4 bit-width, 0.9 for 2 bit-width, and 0.05 for 1 bit-width, on the Llama-3.1-8B-Instruct model. The results are shown in Table 7.

K or V	$1 \rightarrow$ 2-bit	$2 \rightarrow$ 4-bit	$4 \rightarrow$ FP16	Sum
K Cache	1.18%	2.16%	0	3.33%
V Cache	1.3%	2.09%	0	3.39%

Table 7: Transitions of KV Cache from lower precision to higher precision in decoding phase.

As shown in Table 7, only a minimal fraction of the KV Cache transitions from lower precision to higher precision. These low transition rates suggest that the occurrence of higher precision transitions can be effectively disregarded.

Algorithm 2 KV Cache Compression in Prefilling Phase

Input: $Q \in \mathbb{R}^{b\times h_Q\times s\times d}$, $K, V \in \mathbb{R}^{b\times h_{KV}\times s\times d}$, quantization group size G, number of recent tokens calculating cumulative attention weights m, Optimal ratio list R_{opt}

Output: Compressed KV Cache K', V', residual full precision KV Cache $K_{\text{full}}, V_{\text{full}}$,recent attention weights window $A \in \mathbb{R}^{m\times d}$, range of V $Range$

initialize $Q_{\text{r}} \in \mathbb{R}^{b\times h_Q\times m\times d}$ from Q.
initialize compression length $C \leftarrow \lfloor \frac{s}{G} \rfloor \times G$
initialize $K_{\text{c}} \in \mathbb{R}^{b\times h_{KV}\times C\times d}$ from K.
initialize $V_{\text{c}} \in \mathbb{R}^{b\times h_{KV}\times C\times d}$ from V.
initialize $K_{\text{full}} \in \mathbb{R}^{b\times h_{KV}\times (s-C)\times d}$ from K.
initialize $V_{\text{full}} \in \mathbb{R}^{b\times h_{KV}\times (s-C)\times d}$ from V.
initialize $Range \leftarrow \text{range}(V_{\text{c}})$.
$A \leftarrow \text{softmax}\left(\frac{Q_{\text{r}}K_{\text{c}}^T}{\sqrt{d}}\right)$
$A \leftarrow \text{sum}(A, \text{dim} = (0, 1))$
$Range \leftarrow \text{sum}(Range, \text{dim} = (0, 1))$
$\text{metric}_K \leftarrow \text{reshape}(A, (m, \lfloor \frac{s}{G} \rfloor, G))$
$Range \leftarrow \text{reshape}(Range, (\lfloor \frac{s}{G} \rfloor, G))$
$\text{metric}_K \leftarrow \text{average}(\text{metric}_K, \text{dim} = 2)$
$Range \leftarrow \text{average}(Range, \text{dim} = 2)$
$\text{metric}_K \leftarrow \text{cumulative}(\text{metric}_K, \text{dim} = 0)$
$\text{metric}_V \leftarrow \text{metric}_K \odot Range$
$K' \leftarrow \text{compress}(K_{\text{c}}, \text{metric}_K, R_{\text{opt}})$
$V' \leftarrow \text{compress}(V_{\text{c}}, \text{metric}_V, R_{\text{opt}})$
return $K', V', K_{\text{full}}, V_{\text{full}}, A, Range$

A.6 Detailed Hyper-Parameters Setup

For KIVI (Liu et al., 2024), we configure quantization group-size to 32 and residual length to 128. For OTT (Su et al., 2025), we set number of outlier tokens to 5, size of outlier pool to 32 and residual length to 96. For ZipCache (He et al., 2024), we set the saliency ratio to 0.6 and streaming gap to 128. For CAKE (Qin et al., 2025), we set window size to 32 and $\tau_1 = 1.6$, $\tau_2 = 0.4$. For KVTuner (Li et al., 2025), we employ per-channel and per-token quantization for K and V, with a quantization group-size of 32, residual length of 128, and an average bit-width of 3.25. For our method, we set the re-quantization gap T and quantization group-size G to 32. In addition, we set the number of tokens calculating cumulative attention weights m to 20 and hyperparameter α to 2 and β to 4.

Algorithm 3 KV Cache Compression in Decoding Phase

Input: $Q \in \mathbb{R}^{b\times h_Q\times 1\times d}$, $K, V \in \mathbb{R}^{b\times h_{KV}\times 1\times d}$, Compressed KV Cache K', V', residual full precision KV Cache $K_{\text{full}}, V_{\text{full}}$,recent attention weights window $A \in \mathbb{R}^{m\times d}$, range of V $Range$, quantization group size G, requanztization gap T, Optimal ratio list R_{opt}

Output: Compressed KV Cache K', V', residual full precision KV Cache $K_{\text{full}}, V_{\text{full}}$,recent attention weights window $A \in \mathbb{R}^{m\times d}$

initialize $Range_{\text{new}} \in \mathbb{R}^{b\times h_{KV}\times 1} \leftarrow \text{range}(V)$.
$A_{\text{new}} \leftarrow \text{softmax}\left(\frac{QK^T}{\sqrt{d}}\right)$
$A_{\text{new}} \leftarrow \text{sum}(A, \text{dim} = (0, 1))$
$A \leftarrow \text{update}(A, A_{\text{new}})$
$Range_{\text{new}} \leftarrow \text{sum}(Range_{\text{new}}, \text{dim} = (0, 1))$
$Range \leftarrow \text{update}(Range, Range_{\text{new}})$
$K_{\text{full}} \leftarrow \text{Concat}(K_{\text{full}}, K)$
$V_{\text{full}} \leftarrow \text{Concat}(V_{\text{full}}, V)$
$FullLength = \text{shape}(K_{\text{full}}, \text{dim} = 2)$
if $FullLength == T$ **then**
    $\text{metric}_K \leftarrow \text{reshape}(A, (m, \lfloor \frac{s}{G} \rfloor, G))$
    $Range \leftarrow \text{reshape}(Range, (\lfloor \frac{s}{G} \rfloor, G))$
    $\text{metric}_K \leftarrow \text{average}(\text{metric}_K, \text{dim} = 2)$
    $Range \leftarrow \text{average}(Range, \text{dim} = 2)$
    $\text{metric}_K \leftarrow \text{cumulative}(\text{metric}_K, \text{dim} = 0)$
    $\text{metric}_V \leftarrow \text{metric}_K \odot Range$
    $K' \leftarrow \text{compress}(K', K_{\text{full}}, \text{metric}_K, R_{\text{opt}})$
    $V' \leftarrow \text{compress}(V', V_{\text{full}}, \text{metric}_V, R_{\text{opt}})$
    $K_{\text{full}} \leftarrow \text{Null}$
    $V_{\text{full}} \leftarrow \text{Null}$
end if
return $K', V', K_{\text{full}}, V_{\text{full}}, A$

A.7 Additional Experiment Results

A.7.1 Detailed Evaluation Results on LongBench

The detailed evaluation results on LongBench (Bai et al., 2024) with quantization baselines are shown in Table 11. It should be particularly noted that the "Avg" scores for ZipCache-2.8, ZipCache-3.2 and HqeKV-3.2 in Table 11 are calculated from non-OOM columns. In addition, the "Avg" scores for KVTuner-3.25 and HqeKV-3.25 in Table 11 are

calculated from the columns that do not experience CUDA error in KVTuner. The scores from the non-OOM and non-ERROR columns are marked with "*".

A.7.2 Comparison with Eviction Methods

The evaluation results of HqeKV with CAKE (Qin et al., 2025) are shown in Table 12.

A.7.3 Comparison with KVTuner on Qwen3-8B

Since the code for the quantization configuration search part of KVTuner is not open source, we can only use the quantization configurations it has released for our experiments. Unfortunately, KVTuner has not made its quantization configuration for the Qwen3-8B model open source. We randomly set up a quantization configuration with a 3.278 average bit-width for the experiment and selected several datasets from LongBench. The results are shown in the Table 8.

Methods	NQA	Qasper	MFQA-en	MFQA-zh	HPQA	2WMHQA	MSQ	Avg
KVTuner-3.278	24.37	45.34	53.26	62.82	60.39	41.75	34.23	45.75
HqeKV-3.2	24.94	47.79	54.2	62.18	59.19	41.94	34.37	**46.08**

Table 8: Comparison with KVTuner on LongBench based on Qwen3-8B.

A.7.4 Additional Memory Usage Comparison with KVTuner

Since KVTuner transforms all quantized data into 8 bits, we also make HqeKV adopt the conversion strategy of KVTuner. Under a context length of 4096 and a batch size of 10, the memory usage of HqeKV was 22.66 GB, while that of KVTuner was 22.33 GB. Although HqeKV is a hybrid method that introduces additional intermediate variables relative to KVTuner, its comparable memory footprint implies that HqeKV achieves good memory savings.

A.8 Detailed Compression Ratios

A.9 Detailed Ablation Study

A.9.1 Ablation Study of Range-Only

The ablation comparing the range-only is shown in the Table 10. The results in the table indicate that the range should not be regarded as the sole metric for determining importance; it must be combined with the attention weights.

Methods	4-bit	2-bit	1-bit	eviction
Llama-3.1-8B-Instruct				
HqeKV-2	0.0315	0.922	0.0299	0.0165
HqeKV-2.8	0.416	0.568	0.0012	0.0153
HqeKV-3.2	0.637	0.307	0.037	0.0186
HqeKV-3.25	0.679	0.225	0.0847	0.0116
Qwen3-8B				
HqeKV-2	0.164	0.672	0.0006	0.164
HqeKV-2.8	0.659	0.081	0.001	0.259
HqeKV-3.2	0.778	0.0431	0.0009	0.178

Table 9: Detailed compression ratios.

Methods	NQA	Qasper	MFQA-en	MFQA-zh	HPQA	2WMHQA	MSQ	Avg
HqeKV-3.2	28.62	45.43	55.13	62.27	56.75	42.59	30.9	**45.62**
range-only	20.28	22.62	34.26	20.06	24.04	17.94	9.11	20.7

Table 10: Ablation study results comparing the range-only.

A.9.2 Detailed Ablation Study Methods Descriptions

Detailed descriptions of ablation study are shown in Table 13.

A.9.3 Detailed Ablation Study Results

Detailed results of ablation study are shown in Table 14.

Methods	Single-Document QA				Multi-Document QA				Summarization			
	NQA	Qasper	MFQA-en	MFQA-zh	HPQA	2WMHQA	MSQ	DR	GR	QMSum	MN	VCSUM
Llama-3.1-8B-Instruct												
FP16	29.12	45.26	55.18	63.11	53.83	46.51	29.62	31.84	34.81	25.44	27.16	17.35
KIVI-2	28.19	45.2	52.86	62.61	53.78	43.82	29.51	32.03	34.95	24.87	26.79	16.98
OTT-2	28.77	44.41	53.47	63.04	52.51	44.44	31.63	31.57	35.1	24.41	27.14	17.16
HqeKV-2	**28.86**	43.1	**53.98**	62.05	53.77	**45.4**	29.77	31.53	35	24.67	**26.81**	16.8
ZipCache-3.2	OOM	42.59	53.92	60.34	54.4	45.19	30.61	29.1	OOM	24.19	26.68	17.31
HqeKV-2.8	28.51	**46.54**	54.13	61.44	53.02	**44.04**	29.46	**34.17**	34.84	24.55	26.75	17.27
HqeKV-3.2	**28.62**	45.43	**55.13**	**62.27**	**56.75**	42.59	**30.9**	33.49	**34.59**	**25.11**	**26.85**	16.68
KVTuner-3.25	29.61	43.75	53.41	61.96	56.87	44.19	28.11	ERROR	34.51	24.72	26.64	17.25
HqeKV-3.25	**30.73**	**44.07**	**54.39**	60.89	55.97	**45.95**	**31.73**	**32.51**	**34.91**	**25.02**	**26.73**	**17.66**
Qwen3-8B												
FP16	26.16	47.17	54.37	62.67	59.37	42.43	33.11	27.16	33.17	23.91	24.68	13.84
KIVI-2	22.79	46.51	54.06	62.86	60.05	42.04	33.48	27.23	32.82	23.99	24.56	13.91
OTT-2	24.58	46.8	53.96	61.57	60.07	44.47	33.83	27.03	32.99	23.78	24.8	13.97
HqeKV-2	24.54	46.75	53.5	62.75	**61.76**	44.36	33.12	**27.5**	**33.28**	23.8	24.78	**14.13**
ZipCache-3.2	OOM	46.71	51.21	62.14	58.83	43.37	33.53	24.86	OOM	22.93	24.19	14.02
HqeKV-2.8	24.77	47.69	54.17	**62.78**	61.53	41.67	33.07	**27.88**	33.15	24.19	**24.66**	14
HqeKV-3.2	**24.94**	**47.79**	**54.2**	62.18	**59.19**	41.94	**34.37**	26.98	**33.29**	**24.23**	24.4	13.84

Methods	Few-shot Learning				Synthetic Task			Code Completion		Avg
	TREC	TriviaQA	SAMSum	LSHT	PC	PR-en	PR-zh	LCC	RB-P	
Llama-3.1-8B-Instruct										
FP16	73	90.9	43.62	45.5	7.59	99.5	93.35	59.8	53.38	49.76
KIVI-2	73.5	90.92	43.22	44.5	7.09	99	90.06	58.96	51.47	48.96
OTT-2	73.5	89.09	44.1	45	4.43	99.5	88.09	60.95	55.03	49.43
HqeKV-2	72.5	**91.17**	44.1	44.5	7.67	**100**	**91.53**	**61.94**	54.39	**49.71**
ZipCache-3.2	71.5	91.45	43.02	OOM	5.94	99.5	94.74	61.32	OOM	50.98*
HqeKV-2.8	70	90.42	44.04	45.5	7.34	99.5	94.58	60.77	**54.83**	51.26*
HqeKV-3.2	70	89.12	**44.16**	**46.5**	**8.67**	99.5	93.72	61.25	54.4	**51.49***
KVTuner-3.25	73	88.27	42.31	46.75	4.77	99.5	96.67	60.91	ERROR	49.94*
HqeKV-3.25	71.5	**89.18**	**44.01**	46.75	5.55	99.5	93.47	**61.91**	**54.12**	**50.33***
Qwen3-8B										
FP16	73	89.32	44.4	45.75	1	100	98.5	67.52	64.69	51.24
KIVI-2	73.5	89.64	44.71	47	2.5	98	91.17	65.75	61.48	50.36
OTT-2	72	89.66	44.68	46	4.33	99.5	94.17	67.23	62.17	50.75
HqeKV-2	72	**90.36**	**44.85**	47	2.42	**100**	**97.5**	**68.53**	**63.12**	**51.37**
ZipCache-3.2	70	89.85	44.25	46	1	100	98.5	66.93	OOM	51.22*
HqeKV-2.8	69	88.72	**44.77**	46	**3.75**	100	98.5	**68.72**	63.73	**51.98***
HqeKV-3.2	**72.5**	89.07	44.63	46	3	100	98.5	67.88	**64.41**	51.89*

Table 11: Inference scores of Llama-3.1-8B-Instruct and Qwen3-8B on LongBench.

Methods	NQA	Qasper	MFQA-en	MFQA-zh	HPQA	2WMHQA	MSQ	DR	GR	QMSum	MN	VCSUM	TREC	TriviaQA	SAMSum	LSHT	PC	PR-en	PR-zh	LCC	RB-P	Avg
Llama-3.1-8B-Instruct																						
CAKE-3.2	28.65	12.97	26.04	19.24	19.13	14.44	11.01	24.54	29.91	22.26	24.41	15.24	68.5	89.78	40.98	45.5	5.17	96.16	75.34	61.09	54.11	40.03
HqeKV-3.2	28.62	45.43	55.13	62.27	56.75	42.59	30.9	33.49	34.59	25.11	26.85	16.68	70	89.12	44.16	46.5	8.67	99.5	93.72	61.25	54.4	**49.91**
CAKE-3.25	28.65	12.94	26.69	19.53	18.7	17.09	12.68	25.81	29.52	22.3	24.06	15.31	64.5	91.72	40.9	44.5	7.51	95.04	78.96	61.67	55.5	40.53
HqeKV-3.25	30.73	44.07	54.39	60.89	55.97	45.95	31.73	32.51	34.91	25.02	26.73	17.66	71.5	89.18	44.01	46.75	5.55	99.5	93.47	61.91	54.12	**49.98**
Qwen3-8B																						
CAKE-3.2	26.97	46.69	53.87	62.42	60.22	42.53	35.07	25.01	30.69	23.8	20.71	12.83	71	89.23	42.27	46	1	100	98	66.4	63.02	50.45
HqeKV-3.2	24.94	47.79	54.2	62.18	59.19	41.94	34.37	26.98	33.29	24.23	24.4	13.84	72.5	89.07	44.63	46	3	100	98.5	67.88	64.41	**51.29**

Table 12: Comparison with CAKE on LongBench based on Llama-3.1-8B-Instruct and Qwen3-8B.

Method	Description
w/o I	opt ratio and specific quantization strategy and metric with range, w/o metric with range
w/o II	uniform quantization to 4, 2 and 1 bit-widths base on the opt-ratio from specific quantization strategy and metric with range
w/o III	randomly selected non-opt ratio allocation on specific quantization strategy and metric with range
w/o eviction	opt ratio on 4, 2 and 1 bit-width quantization, specific quantization strategy and metric with range
III on w/o II	opt ratio on uniform quantization to 4, 2 and 1 bit-widths base on the opt-ratio from specific quantization strategy and metric with range
only I	randomly selected non-opt ratio allocation on uniform quantization to 4, 2 and 1 bit-widths and metric with range
only II	randomly selected non-opt ratio allocation on specific quantization strategies, w/o metric with range
only III	opt ratio allocation on 4, 2 and 1 bit-width uniform quantization and eviction, w/o metric with range
w/o I, II & III	randomly selected non-opt ratio allocation, w/o specific quantization strategies and w/o metric with range

Table 13: Detailed description of methods in ablation study.

Methods	NQA	Qasper	MFQA-en	MFQA-zh	HPQA	2WMHQA	MSQ	DR	GR	QMSum	MN	VCSUM	TREC	TriviaQA	SAMSum	LSHT	PC	PR-en	PR-zh	LCC	RB-P	Avg
HqeKV-3.2 bit	28.62	45.43	55.13	62.27	56.75	42.59	30.9	33.49	34.59	25.11	26.85	16.68	70	89.12	44.16	46.5	8.67	99.5	93.72	61.25	54.4	49.91
w/o innovation I	28.81	44.2	53.97	61.76	51.57	43.15	31.19	33.23	34.81	24.29	26.82	17.18	71	86.04	44.23	47.5	4.97	99.5	94.49	62.5	56.31	49.78
w/o innovation II	24.37	27.56	42.35	48.73	48.75	36	24.92	12.83	18.74	17.73	18.04	10.99	53.5	90.53	39.06	30	4.72	99.5	94.86	51.07	45.37	41
w/o innovation III	29.11	43.83	53.25	60.41	55.71	44.64	29.8	31.42	34.8	25.29	26.5	16.62	72.5	90.39	43.94	46	6.78	99.5	93.81	61.69	55.05	49.8
w/o eviction	29.62	44.63	55.17	59.68	54.39	44.42	28.24	31.75	34.33	24.93	26.3	16.66	68	90.85	43.99	45.5	9.08	99.5	91.87	60.07	55.87	49.47
innovation III on w/o II	27.98	46.26	52.91	62.22	52.82	45.1	29.8	31.87	34.5	24.73	26.53	16.91	73.5	89.79	43.94	45.5	6.22	99.5	93.46	62.12	55.5	49.87
innovation I	16.99	17.47	24.37	27.41	35.97	18.38	13.42	9.02	18.49	14.37	15.52	10.39	45.5	86.33	26.2	23.5	7.56	98.29	37.08	37.02	35.5	30.38
innovation II	29.26	43.97	53.37	60.08	56.62	44.02	28.52	32.27	34.73	25.23	27.09	17.29	73	91.49	43.87	45	5.67	99.5	93.14	62.21	54.72	49.81
innovation III	27.91	40.25	49.96	55.67	53.11	44.51	29.21	21.03	22.06	20.97	21.41	11.6	64	87.45	43.37	41.5	6.44	99.5	95.62	58.33	52.69	46.34
w/o innovation I, II & III	16.33	16.38	23.37	27.02	32.73	20.88	14.79	8.59	18.64	14.42	14.95	10.22	41.75	84.29	25.88	26.75	5.67	99	34.3	37.34	34.73	29.91

Table 14: Ablation study results on LongBench of Llama-3.1-8B-Instruct.