

SKVQ: Sliding-window Key and Value Cache Quantization for Large Language Models

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Abstract

Large language models (LLMs) can now handle longer sequences of tokens, enabling complex tasks like book understanding and generating lengthy novels. However, the key-value (KV) cache required for LLMs consumes substantial memory as context length increasing, becoming the bottleneck for deployment. In this paper, we present a strategy called SKVQ, which stands for sliding-window KV cache quantization, to address the issue of extremely low bitwidth KV cache quantization. To achieve this, SKVQ rearranges the channels of the KV cache in order to improve the similarity of channels in quantization groups, and applies clipped dynamic quantization at the group level. Additionally, SKVQ ensures that the most recent window tokens in the KV cache are preserved with high precision. This helps maintain the accuracy of a small but important portion of the KV cache. SKVQ achieves high compression ratios while maintaining accuracy. Our evaluation on LLMs demonstrates that SKVQ surpasses previous quantization approaches, allowing for quantization of the KV cache to 2-bit keys and 1.5-bit values with minimal loss of accuracy. With SKVQ, it is possible to process context lengths of up to 1M on an 80GB memory GPU for a 7b model and up to 7 times faster decoding. Code will be released at <https://github.com/cat538/SKVQ>.

1 Introduction

Recently, large Language Models (LLMs) have achieved great success in the area of artificial intelligence. With the advancement of LLMs, the need to support the longer context has grown. For instance, OpenAI GPT-4 Turbo can handle 128k tokens (Achiam et al., 2023), and Google Gemini 1.5 can process up to 1 million tokens (Team et al., 2023). This expanded token support enables LLMs to tackle more complex tasks like book reading, large image understanding, and video processing, making them more versatile. LLM inference operates in an auto-regressive manner, generating sentences token by token. To reduce the computation overhead, inference system always store the key and value activations in memory and reuse them during subsequent token generation steps. The saved data is known as key and value cache (KV Cache). With the increasing popularity of utilizing LLM for long sequence tasks, the KV cache consumes a significant amount of memory. On the other hand, the large amount of KV cache can also bring a large amount of memory access in the attention mechanism when generating the output tokens. The system will be stuck on the memory access, known as the memory-bound problem in LLM inference (Yuan et al., 2024).

To tackle the problem of large KV cache size in language models, several compression techniques have been proposed. One approach is KV eviction (Zhang et al., 2023), which

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involves removing less important key-value pairs from the cache to free up space. However, this may impact the accuracy of inference. Another method is KV offloading (Sheng et al., 2023), which transfers a portion of the KV cache to slower but larger storage devices like main memory and even secondary storage. However, this may slow down the system due to the low bandwidth of these devices. Scientists have recently been studying the compression of KV cache using quantization. This involves converting floating point KV cache, which initially utilizes a large number of bits, into a format that uses fewer bits. Several novel approaches have been developed to accomplish this, including KVQuant (Hooper et al., 2024), WKVQuant (Yue et al., 2024), and KIVI (Liu et al., 2024). Previous quantization methods have been successful in reducing memory requirements and the number of memory accesses. However, they faced a challenge when using very low-bitwidth quantization because it led to a significant decrease in accuracy, as shown in Figure 1.

In this paper, we observe that there is a significant difference in the distribution of different channels during the quantization process. This has a great impact on quantization accuracy, especially in extremely low-bitwidth scenarios. To alleviate this problem, we propose the clipped dynamic quantization with channel reorder. First, we use a transformation invariant permutation to group similar channels based on their statistical characteristics. Second, we apply clipped dynamic quantization to further mitigate the outlier problem. In this way, we greatly reduce the quantization error within each group, thus improving the accuracy of the quantized model.

Meanwhile, we discover that the protecting the accuracy of these small portion of but more important caches in KV cache quantization is critical. Due to the locality of attention, these recently generated KV caches are highly likely to be attended to with a high probability. We propose a sliding window quantization strategy. This mechanism preserves a small portion of the most recently generated KV cache from being quantized. After generating new tokens, the probability of attending to the old tokens' KV cache decreases significantly, so the accuracy loss caused by quantizing them is minimal. The proposed method is named as sliding-window KV cache quantization (SKVQ). It is efficient and easy to implement in existing inference system, which makes it practical for real-world deployment.

To evaluate the effectiveness of our method, we experiments on models of LLaMA(Touvron et al., 2023) and Mistral(Jiang et al., 2023) family. The experiments show that our methods can quantize the key cache into 2 bits and value cache into 1.5 bits with almost no accuracy drop. Compared with the previous quantization method, our approach can achieve optimal performance under different average bit widths as shown in Figure 1. Our performance analysis shows SKVQ enables 1M context length in a single A100-80GB for a 7b model. As for the inference latency, in the case of batch size 128 and sequence length 200k, the theoretical 7x speedup in decoding phase can be achieved¹.

2 Related Work

There are many multi-billion scale transformer quantization methods designed for LLMs. A main branch of LLM quantization is weight-only quantization, which only involves the quantization of model weights to lower precision. For instance, GPTQ(Frantar et al., 2022) uses second-order approximation to quantize weights, enabling the weight quantization of LLMs into 4-bit. AWQ(Lin et al., 2023) quantizes model weights to 4bits whith an activation-aware manner. SqueezeLLM(Kim et al., 2023) adopts the concept of sensitivity-

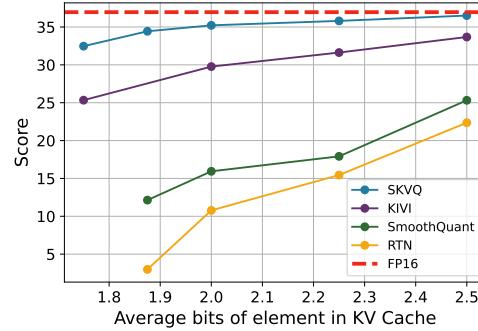


Figure 1: Results on GovReport and MultiFieldQA-zh (Mistral-7b-Instruct-V0.2). We count the storage for meta data including quantization params and reorder index.

¹The performance analysis can be found in Appendix C

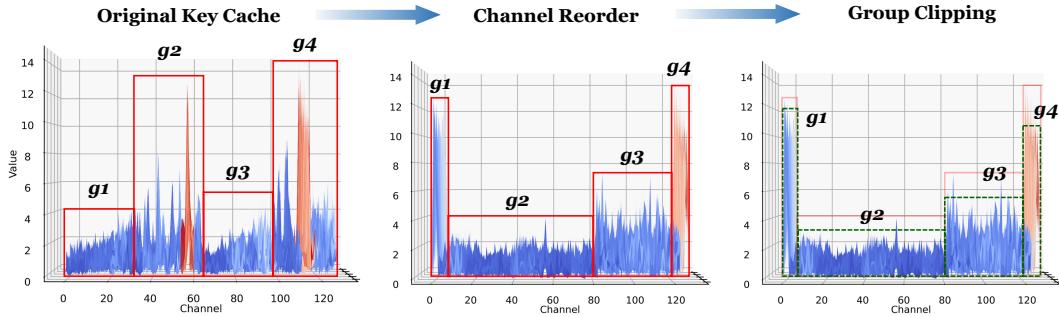


Figure 2: Visualization of the key cache going through channel reorder and group clipping in sequence. The elements in the red/green box will be placed in the same group to share the quantization parameters.

based non-uniform quantization along with Dense-and-Sparse decomposition. This line of work is orthogonal to ours, as they can be combined together.

Another line of work focuses on weight-activation quantization. `llm.int8()`(Dettmers et al., 2022) retain outlier channel to full precision, so that other parts can be better compressed to 8bits. SmoothQuant(Xiao et al., 2022) uses equivalent transformations to balance the quantization complexity for both activation and weight, making the activation easier to quantize. RPTQ(Yuan et al., 2023) reorder the channels to reduce the variance in one quantization cluster, further enhancing the accuracy. ATOM(Zhao et al., 2023) improves quantization performance and reduces inference latency by using finer-grained quantization with an efficient kernel. However, since these works are not specifically designed for KV cache quantization, even applying the best results from such works still results in significant losses in KV cache compression. We compare with these works in the experimental section.

Recently, as natural language tasks require processing longer contexts, researchers have focused on quantizing key-value caches. Several new methods have been developed, such as KVQuant (Hooper et al., 2024), WKVQuant (Yue et al., 2024), and KIVI (Liu et al., 2024). Quantizing the KV cache can significantly reduce both the memory requirements and the number of memory accesses needed. Our experimental results show that the performance of our method on long context tasks performs the best in this type of work.

There are also a series of work dedicated to the design of KV cache eviction strategy (Liu et al., 2023; Ge et al., 2023; Zhang et al., 2023; Xiao et al., 2023). Unlike KV cache quantization, which retains all caches but compresses them to low precision, these methods selectively retain part of the KV cache and discard other caches directly. These methods usually allocate a fixed-size buffer for KV cache . When the generated KV cache exceeds the buffer limit, some tokens considered less important will be evicted from the buffer. These methods are inevitably and irrecoverably discarding KV pairs deemed, in one way or another, less important than others. Our approach is inspired by and can be well integrated with such work.

3 Method

3.1 Clipped Dynamic Quantization with Channel Reorder

Quantization is to transform the high-bitwidth float values into low-bitwidth integer values. The quantization process can be formulated as $\text{clamp}(\lfloor \frac{X-z}{h} \rfloor, 0, 2^N - 1)$, where X is the float values and h is scaling factor and z is zero point. Previous studies have highlighted significant variations in numerical values among activation channels (Xiao et al., 2022; Wei et al., 2022; 2023). As shown in Figure 2, we also observe substantial variations between channels and tokens in the KV cache (high channel variance). Therefore, directly quantizing the KV cache leads to substantial quantization errors. If values in different channels share the scaling factor and zero point, the value from outlier channels skew the quantization range. Especially in the low-bitwidth case, this makes almost all elements except outlier channel

quantize to the same value, and this loss of information leads to significant performance drop. To tackle this issue, we introduce channel transformation based quantization.

To address this problem, some methods have proposed using additional quantization parameters or keeping certain channels in float format to handle outliers (Dettmers et al., 2022). However, we have noticed that the concept of outliers is relative. The channels with the highest values are outliers compared to the medium-sized channels, and the medium-sized channels are outliers compared to the small-sized channels. Other methods propose smoothing the difference between channels by multiplying an extra factor before quantization (Shao et al., 2023; Yue et al., 2024). However, these methods do not take into account the differences in token dimensions. The magnitude of values can vary between different tokens. We have observed that the variation in magnitude of non-outlier channels is relatively high. Specifically, some channels experience magnitude changes of several times or even dozens of times. Smoothing is not effective in addressing this phenomenon, especially in extremely low bitwidth quantization.

Channel Reorder. Inspired by RPTQ(Yuan et al., 2023), we employ a permutation invariant transformation and then apply group clipping to solve the problem of extremely low bitwidth quantization for KV cache . The permutation invariant transformation allows us to change the order of computation without changing a operation’s output. For example, when we execute the matrix multiplication $S = Q \times K^T$, we can rearrange the columns of Q and the rows of K (which represent their channel dimension) in the same order without affecting the result of the computation.

We perform channel reorder on KV cache to make channels with similar data distribution are grouped together for quantization. Values in channels with similar distribution are quantized together. By this way, we can greatly reduce the quantization error of channels with smaller ranges. The same as Yuan et al. (2023), we do the corresponding equivalent permutation for Q and W_o to avoid explicit reorder operation. The calculation of attention module $O = \text{Softmax}(QK^T) \cdot V \cdot W_o$ is transformed as:

$$O = \text{Softmax}(P_k Q \cdot (K^T P_k^T)) \cdot P_v V \cdot W_o P_v^T \quad (1)$$

where $P_k \in \mathbb{R}^{C_{in} \times C_{in}}$ and $P_v \in \mathbb{R}^{C_{in} \times C_{in}}$ are channel reorder matrix of Key and Value respectively². In our algorithm, the index is calculated based on the statistical characteristics of each channel. Specifically, we extract the distribution feature of each channel and then use the KMeans algorithm to cluster channels with similar characteristics into the same group. We also compared channel reordering with mathematical equivalent smoothing, and the results in AppendixD demonstrated the effectiveness of the former.

Clipped Dynamic Quantization. Dynamic per-token quantization is widely used method for quantizing the activations in LLMs (Xiao et al., 2022). Different with static quantization that use the static h and z , dynamic quantization will compute new h and z using the maximum value and minimum value for each token: $h = \frac{\max(\mathbf{X}) - \min(\mathbf{X})}{2^N - 1}$, $z = \frac{\min(\mathbf{X})}{h}$.

Previous work about weight quantization (Lin et al., 2023; Shao et al., 2023) has shown that introducing clipping when quantizing weights can improve the quantization performance. According to the second picture in Figure 2, even though we have grouped similar channels together, there are inevitably some outliers within a quantization group. In order to reduce the impact of these outliers on other values in the same group, we propose the clipped dynamic quantization, which can be formulated as:

$$f(\alpha, \mathbf{X}) = \text{clamp}(\lfloor \frac{\mathbf{X} - z}{h} \rfloor, 0, 2^N - 1), \text{ where } h = \frac{\alpha(\max(\mathbf{X}) - \min(\mathbf{X}))}{2^N - 1}, z = \frac{\alpha \min(\mathbf{X})}{h}. \quad (2)$$

We introduce a clipping scale $\alpha \in (0, 1]$ for each group to compute h and z . In order to get the best clipping scale, for each transformer block we try to minimize the MSE of the output of the attention module before and after quantization, i.e., the optimization objective:

$$\alpha^* = \arg \min_{\alpha} \mathcal{L}(\alpha), \quad \mathcal{L}(\alpha) = \text{MSE}(O^q, O) \quad (3)$$

²We fuse the channel reorder index into the projection weight matrix of attention module. We describe the fusion in the AppendixA.

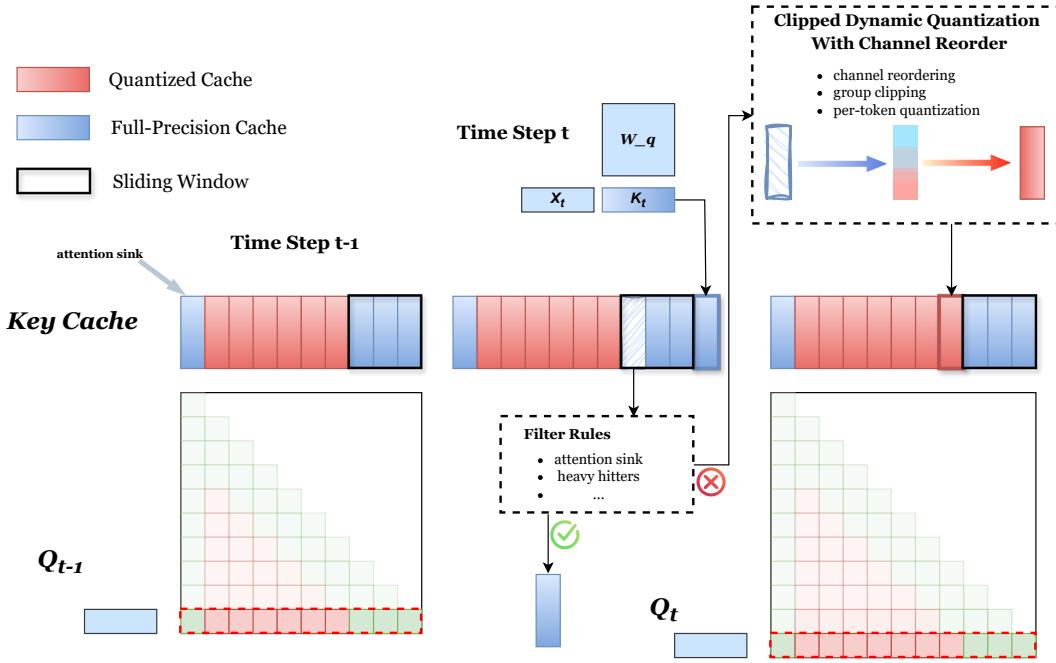


Figure 3: Overview of sliding window quantization Strategy. In each time step, we ensure the latest w KV cache is full precision. For a token cache that slides out of the window, we make a decision based on the filter rules and choose whether to retain it to high precision.

where O^q is the output of attention module after quantizing KV cache. Unlike weight-only quantization, the KV cache is generated at runtime, it is costly to solve this optimization for each inference. Therefore, we approximate it by offline calibration. By performing optimization on a calibration dataset in advance, we get the approximate $\hat{\alpha}^*$ for each group. We share the same $\hat{\alpha}^*$ across different tokens. Using the approximate $\hat{\alpha}^*$, we can also improve the quantization performance without introducing significant inference cost.

Using channel reorder and clipped dynamic quantization, the elements falling within the same group can more fully utilize the numerical range of the quantized data type, thus reducing the quantization error. Because all the parameter P_k , P_v , α is determined offline and the reorder operation can be fused into linear layers, it is efficient to implement the clipped dynamic quantization with channel reorder on existing inference frameworks.

3.2 Sliding Window Quantization Strategy

Although clipped dynamic quantization with channel reorder can improve the quantization performance to a large extent, extremely low-bitwidth KV cache quantization still suffers serious performance degradation, especially when the sequence length become longer. This is because the quantization errors accumulate along the sequence dimension. Because the auto-regressive manner of the LLM, the decoding of a new token depends on the previous KV generated. We realize that this not only a challenge but also a chance, the auto-regressive manner can be fully exploited to develop more flexible quantization strategies.

Locality. Many previous works have shown that attention module has very strong locality(Kovaleva et al., 2019; Beltagy et al., 2020; Ge et al., 2023). That means at each time step, the attention module pays more attention to the recently generated tokens. We indicate that *compared to the large amount of but less important content in the previous KV cache , protecting the accuracy of these small portion of but more important caches in KV cache quantization is critical.*

Motivated by this, we proposed a sliding window quantization strategy, which retain the latest KV cache of a window w tokens to high precision. The workflow is shown in Figure 3. 1) In prefill phase, for each transformer block, after the KV cache is generated, we first compute attention with full precision KV cache , then quantize the KV cache with the last

window_size token cache pairs reserved as full-precision. 2) In decode phase, we only process the token which slides out of the window at each time step. This approach ensures the KV cache of each transformer block generated in the prefill phase are lossless. It also enhance the generated content quality by utlizing the locality of attention module in the decode phase.

Important KV Cache Filter. Except the recent generated tokens, there are some tokens that are sensitive to quantization. We also explored other method to identify important tokens that their KV cache should be kept in high precision. Inspired by (Xiao et al., 2023), the first few tokens of prompt are also very important for the whole generation process, so we add attention sink to the filter rules, i.e., the first few tokens are reserved to high precision. We observed it is effective to keep a small number of sink tokens high precision. Since the positions of sink tokens are fixed, it is easy to implement and we enable it in our experiments. Some cache eviction method monitor for each token its cumulative sum of attention score, then treat these scores as token frequency and only keep the most frequent tokens in the KV cache (Liu et al., 2023; Zhang et al., 2023), which are called heavy hitters. A straightforward idea is to keep heavy hitters to high precision. However, we did not enable it in our experiments for two reasons: 1) The improvement on prediction accuracy by keeping heavy hitters high precision is not significant. 2) If FlashAttention(Dao, 2023) is used, we can't directly obtain the attention score. It is unfriendly to implement in existing inference framework. We believe that there are better methods available to identify important KV caches. Therefore, we have kept this as an interface (filter rules in Figure 3) in our implementation, allowing for the addition of new filters in future research.

By retaining small portion of tokens to high precision, we obtain a substantial performance gain in the long context task, while at the same time incurring almost no additional overhead. We will show the impact of window size on quantization performance in Section 4.3.

4 Experiments

In this section, we introduce the detailed experimental settings and evaluate the effectiveness of the proposed SKVQ.

4.1 Settings

Models. We select a wide range of models with different architectures and different size to demonstrate the generalizability of our approach: Llama2-13b(Touvron et al., 2023), and models fine-tuned based on Llama2: Llama2-7b-chat, Llama2-13b-chat, Llama2-7b-80k(Fu et al., 2024), Vicuna-v1.5-7b-16k(Chiang et al., 2023), LongChat-v1.5-32k(Li et al., 2023). We also evaluate models of Mistral family which are recently very popular: Mistral-7b-v0.1(Jiang et al., 2023), Mistral-7b-instruct-v0.2. Among these models, models of Llama family adopt multi-head attention, mistral-7b-instruct-v0.2 uses multi-query attention, and mistral-7b-v0.1 uses multi-query attention and sliding-window attention.

Tasks. We evaluate SKVQ mainly on long sequence tasks, as this is the scenario for which KV cache quantization is most suitable. We use LongBench(Bai et al., 2023) to evaluate on various datasets. Specifically, MultiFieldQA-zh (F1 score) is a Single-Document QA task; 2WikiMultihopQA is a Multi-Document QA task; GovReport (ROUGE score) is a Summarization task; TREC (classification score) is a Few-shot Learning task; and LCC (similarity score) and RepoBench-P (similarity score) is Code Completion task. We also tested SKVQ on Needle-in-a-Haystack (Kamradt, 2023), which is a popular test-bed for whether models can actually utilize long context length. It requires the model to recite the information in a given sentence, which is placed anywhere in a long document. Finally, to provide a clearer picture of the effects of the SKVQ components and to compare with previous methods, we also measure the perplexity on wikitext2 (Merity et al., 2016) in Section 4.3.

Quantization. Both channel reorder and clipped dynamic quantization requires offline calibration. For calibration dataset, we select 256 pieces of data with length 4096 from the training set of wikitext2-v1, the calibration takes about a few minutes which is quite

Model	Method	LCC	RepoBench-P	PR-en	TREC	2wikimqa	GovReport	MQA-zh	Average
Llama-2-7B-chat	FP16	52.33	44.05	10.25	63	32.09	27.29	11.39	38.50
	RTN	15.44	8.76	0.79	4.00	0.30	1.93	0.07	6.76
	SmoothQuant	35.31	32.18	0.79	28.75	7.45	11.83	1.68	21.92
	RPTQ	22.37	19.08	5	47.5	15.57	20.07	3.24	19.50
	KIVI	49.32	43.71	4.50	63	24.07	24.73	10.24	35.91
	SKVQ	50.69	45.4	5.5	63	28.5	27.07	10.7	37.50
Llama-2-13B-chat	FP16	50.54	52.1	15.25	68.5	13.21	27.52	7.23	38.83
	RTN	20.89	18.62	0.33	0	0.52	1.68	0.16	10.15
	SmoothQuant	32.17	33.86	2.65	48	3.53	12.47	0.47	23.22
	RPTQ	49.18	47.63	5.25	63.5	10.92	23.83	4.54	35.01
	KIVI	48.6	48.81	13.5	68	14.32	25.7	7.01	37.21
	SKVQ	49.53	49.76	12.25	67.5	14.03	26.68	6.63	37.53
Mistral-7B	FP16	68.06	60.46	17.71	68	10.87	20.09	17.1	45.51
	RTN	27.98	26.18	3.34	13	1.11	2.49	0.45	15.58
	SmoothQuant	40.63	35.14	3.40	30.5	6.03	5	4.12	23.85
	RPTQ	55.29	47.12	5.11	59.5	9.71	7.81	12.36	35.05
	KIVI	65.16	58.33	12.43	65	11.03	13.22	13.87	42.43
	SKVQ	67.81	60.54	13.21	67	10.91	17.72	15.9	43.47
Mistral-7B-Instruct	FP16	55.07	48.96	60	70	22.63	31.18	42.74	48.66
	RTN	32.36	33.23	0.67	1	2.25	10.03	2.3	18.02
	SmoothQuant	43.84	38.63	4.79	39.5	10.34	23.61	8.33	29.27
	RPTQ	46.85	44.07	27.67	64.5	16.99	28	24.68	38.91
	KIVI	53.13	48.6	47.5	69	20.68	29.37	33.88	45.48
	SKVQ	54.86	49.05	56.42	70	20.94	30.82	42.4	46.23

Table 1: Evaluation of different KV cache quantization methods on LongBench. Group-size(average) 128, key-cache 2bit, value-cache 2bit, window-size 128. We abbreviated PassageRetrieval as PR and MultiFieldQA as MQA. We highlight the result of our method.

lightweight. We perform asymmetric quantization in all experiments. We have explored the FP8(E4M3) datatype to store scale and zero-point. Our experiment results in Table 3 show that FP8 will bring almost no performance degradation, but significantly reduces overhead at extremely low bit-width and fine grained groups.

4.2 Main Results and Analysis

LongBench Results. The performance of SKVQ in the LongBench datasets is summarised in Table 1. We compare our method with Smoothquant(Xiao et al., 2022), RPTQ(Yuan et al., 2023) KIVI(Liu et al., 2024) and per-token RTN(Round To Nearest). Smoothquant and RPTQ are LLM weight-activation quantization schemes. We use them to quantize KV cache without involving model weights and other activation. KIVI(Liu et al., 2024) is a recent 2-bit asymmetric quantization scheme specially designed for KV cache . We set the group size of all the methods to 128. SKVQ utilizes reordering which leads to unequal sizes for each group. In order to ensure the fairness of the comparison, we control the number of groups in SKVQ to ensure the average group size is 128. The window size in SKVQ is set to 128 and the residual length in KIVI is set to 128. α in Smoothquant is set to 1.0 to make the smooth transformation completely inclined to KV cache . Table 1 suggests that SKVQ is an effective method for KV cache compression that outperforms previous quantization approaches across various hard long context generation tasks. We also evaluate Vicuna-v1.5-7b-16k and LongChat-v1.5-7b-32k, the results is in AppendixE.

For all models tested, the accuracy drop of SKVQ is less than 5%. Towards extremely low-bitwidth KV cache quantization, we further quantize the key cache into 2 bits and value cache into 1.5 bits with group size 64. The result in Figure 4 shows that SKVQ can compress key cache into 2 bits and value cache into 1.5 bits with almost no accuracy drop. It is worth noting that the experimental results are under the setting of group size 128. SKVQ can also benefit from a finer-grained group, and achieve almost lossless compression, which is shown in Section 4.3.

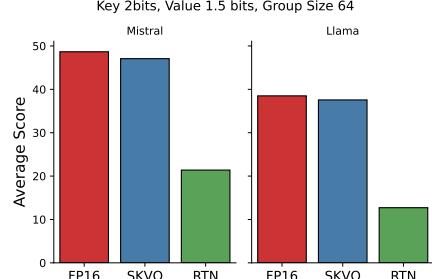


Figure 4: Average score on LongBench of SKVQ for Llama2-7b-chat and Mistral-7b-Instruct-V0.2.

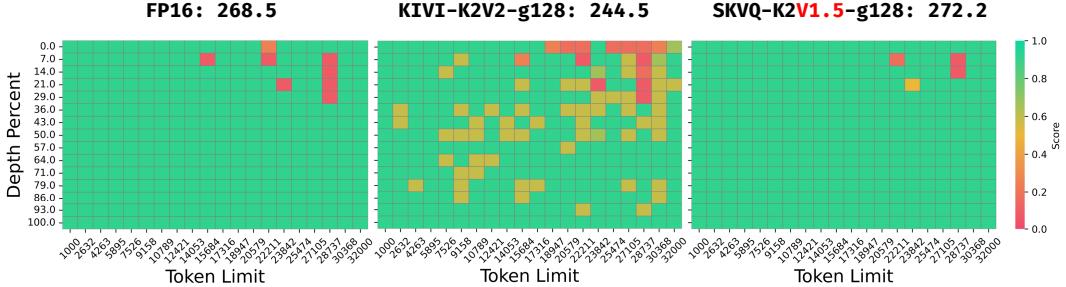


Figure 5: Comparison of SKVQ with KIVI on needle in haystack test. SKVQ achieved higher scores while using lower bitwidth.

Method	4bit		3bit		2bit	
	PPL↓	avg-bits↓	PPL↓	avg-bits↓	PPL↓	avg-bits↓
RTN-sym	4.66	4.25	4.98	3.25	26.83	2.25
KVQuant	4.59	4.32-4.35	4.64	3.32-3.35	4.92	2.32-2.35
Ours	4.60	4.25	4.63	3.25	4.87	2.25

Table 2: Ablation Study: Comparison of our channel reorder based clipped dynamic quantization approach with KVQuant(best setting) and symmetric RTN per-token quantization in different quantization setting. For RTN-sym and our method, we set group-size to 64. Perplexity is Llama-2-13b test on Wikitext-2 with sequence length 4096.

Needle in Haystack Results. For needle in haystack test, we used Llama2-7b-80k(Fu et al., 2024) model for our experiments. We set the context to grow from 1k to 32k for a total of 20 intervals, and for each context length, we insert the needle into 15 different positions of the context. We compare SKVQ with KIVI under the setting of group size 128. For SKVQ, we set the window size to 128 and reserve 5 attention-sinks, i.e., when the first 5 token cache pairs slide out of the sliding window, they are retained to full precision instead of quantized to 2 bits. The residual length in KIVI is set to 128. We follow the method in (Fu et al., 2024) to calculate the recall, and finally average the scores of all test cases as the overall score. As shown in Figure 5, in key cache 2bits, value cache 2bits, group size 128 setting, KIVI got 244.5, while our SKVQ achieved 272.2 even with 2 bits key cache and 1.5 bits value cache in group size 128.

These results demonstrate that it is practical to quantize the key-value cache into extremely low-bitwidth for these tasks. More result on needle in haystack test can be found in Appendix B.

4.3 Ablation Study

In this section, we decompose each part of SKVQ separately in detail and study the effect from each technique and different parameter settings.

Breakdown of different components of SKVQ. We study the accuracy gain or loss of different quantization techniques used in SKVQ. We first use RTN and adopt per-token quantization with group size 32. We then apply other quantization techniques used in SKVQ, i.e. sliding window, clipping, channel reorder, attention sink and FP8. We present the LongBench average score in Table 3. Attention sink size is set to 5, i.e. the first 5 token cache pairs are retained to full-precision. We see that sliding-window and channel reorder can significantly enhance the accuracy. FP8(E4M3) stands for using FP8 datatype to store the per-group quantization parameters, i.e. scale and

Method	Avg Score↑
FP16	48.66
RTN	35.55
+ Window-128	45.73 (10.18↑)
+ Group Clipping	46.44 (0.71↑)
+ Channel Reorder	47.99 (1.55↑)
+ Attention Sink	48.14 (0.15↑)
+ FP8(E4M3)	48.04 (0.1↓)

Table 3: Ablation Study: The performance gain or loss by applying each technique in SKVQ based on RTN method. Quantization setting: kv 2bits with group size 32.

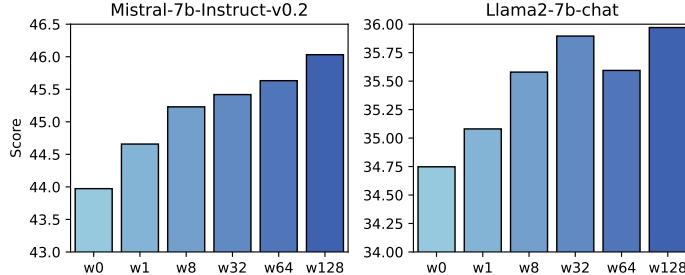


Figure 6: Ablation Study: Average score of Mistral-7b-Instruct-v0.2 on LongBench under different window sizes. Quantization setting: KV cache 2bits with group size 128

zero-point. In our study, Using FP8 will results in a relative minor accuracy decreasing compared with FP16. However, at extremely low-bitwidth and fine-grained group size, using FP8 to store the quantization parameter significantly reduce storage overhead. For example, KV 2bits with group size 32, if we use FP16 to store quantization parameters, the average bits of element in KV cache is $2 + 16 * 2/32 = 3$, but if we use FP8, then average bits is $2 + 8 * 2/32 = 2.5$, which is 50% smaller.

The effect of clipped dynamic quantization with channel reorder. To further demonstrate the effect of our quantization approach without sliding window, we perform evaluation by measuring Llama-2-13b perplexity on wikitext2. The result in Table 2 shows that by only applying channel reorder based clipped dynamic quantization, we have outperformed KVQuant (Hooper et al., 2024). We set group size to 64 and use FP8 to store quantization parameter so that the average bits is equal to asymmetric approach adopt in ATOM and FlexGen. We also reserve the first 5 tokens to FP16 as attention sink. It worth noting that we are comparing the best score of KVQuant i.e. nuq with 1% outliers are retained to full-precision, which results in higher storage overhead than SKVQ.

The effect of window size. To further investigate the effect of sliding window on the final results, we set up different sizes of windows and tested them on LongBench, and the average scores are shown in the Figure 6. The result shows that the average score increases as the window size increases. In general, different sub-tasks can all benefit more or less from the sliding window strategy, and the extra overhead brought by a window with size of about 128 is negligible in long context scenarios, so we use a window of size 128 in the main experiments.

The effect of group Size. We vary group size from 128 to 32 to test SKVQ on LongBench, the average score on LongBench is as shown in Table 4. It shows that SKVQ can always benefit from finer-grained group. While finer-grained group brings better accuracy, it increases the computation overhead for quantization/dequantization and storage overhead for quantization parameters, which is noted as average bits. Since the performance of SKVQ on various tasks does not drop significantly when the group size is set to 128, we employ 128 group size in the main experiments.

Group size	Avg Score↑	Avg Bits
128	35.365	2.125
64	35.805	2.25
32	36.51	2.5

Table 4: Ablation Study: Average scores of Mistral-7b-Instruct-v0.2 on GovReport and MultiFieldQA-zh dataset for different group sizes. Quantization setting: KV cache 2bits, window size 128.

5 Conclusion

In this paper, we achieve accurate ultra-low precision KV cache quantization. By channel reordering, we group similar channels together, and apply group clipping to further mitigate the outlier problem. We propose a sliding window quantization strategy with filter rules, which greatly improves the performance of the KV cache quantization method on long context tasks by reserving a small portion of the cache to full precision. By combining theses two approaches, we successfully quantize the KV cache to Key 2bits value 1.5 bits

without significant precision loss. We believe this work will further advance the design of mixed-precision quantization strategies for KV cache . In the future, we will further optimize the filter rules and the kernel implementation.

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A Detailed Implementations

We describe our algorithm as shown in algorithm1. The subroutine get_permutation_matrix and get_group_clipping is described in sec3.1. It's worth noting that the prologue only needs to be executed once before deploying, and we do not pay for it during the inference phase.

Algorithm 1: SKVQ Algorithm

SKVQ Parameter: window size W , group size G , filter rules $F \leftarrow \{f_1, f_2, \dots\}$,
processed KV cache length $processed \leftarrow 0$

Attention Module Parameter: $W_q, W_k, W_o \in \mathbb{R}^{d \times d}$

Prologue:

```

 $P_k, P_v, group\_indices \leftarrow get\_permutation\_matrix(calibration\_set)$ 
 $clipping \leftarrow get\_group\_clipping(calibration\_set, P, group\_indices)$ 
 $W_k \leftarrow P_k \cdot W_k$ 
 $W_v \leftarrow P_v \cdot W_v$ 

```

end

Input: $X \in \mathbb{R}^{l \times d}$, $K_{cache}, V_{cache} \in \mathbb{R}^{h \times d}$, where h is context length(prefill phase $h = 0$),
 l is current input length(prefill phase $l = \text{len}(prompt)$, decode phase $l = 1$)

Algorithm algo(Attention module with SKVQ algorithm):

```

 $Q = X \cdot W_q, K = X \cdot W_k, V = X \cdot W_v$ 
 $K_{cache} \leftarrow dequant(K_{cache})$ 
 $V_{cache} \leftarrow dequant(V_{cache})$ 
 $K_{cache} \leftarrow concat(K_{cache}, K)$ 
 $V_{cache} \leftarrow concat(V_{cache}, V)$ 
 $S \leftarrow Q \cdot reorder(K_{cache})^T$ 
 $O \leftarrow S \cdot reorder(V_{cache}) \cdot W_o$ 
 $ctx\_len \leftarrow \text{len}(V_{cache})$ 
 $indices \leftarrow [processed : ctx\_len - W]$ 
if  $indices \neq \emptyset$  then
     $kmask \leftarrow [processed : ctx\_len - W; False]$ 
     $vmask \leftarrow [processed : ctx\_len - W; False]$ 
    for  $filter$  in  $F$  do
         $kmask \leftarrow filter(K_{cache}[indices]) \wedge kmask$ 
         $vmask \leftarrow filter(V_{cache}[indices]) \wedge vmask$ 
    end
     $K_{cache}[indices] \leftarrow clipping\_quant(K_{cache}[indices], kmask)$ 
     $V_{cache}[indices] \leftarrow clipping\_quant(V_{cache}[indices], vmask)$ 
     $processed += \text{len}(indices)$ 
end
return  $O$ 
end
function  $clipping\_quant(X, mask)$ :
     $groups \leftarrow split\_groups(X, group\_indices)$ 
     $quant\_cache \leftarrow \emptyset$ 
    for  $group$  in  $groups$  do
         $group\_min, group\_max \leftarrow minmax(group)$ 
         $group\_min \leftarrow clipping[group] \times group\_min$ 
         $group\_max \leftarrow clipping[group] \times group\_max$ 
         $quant\_group \leftarrow group\_quant(group\_min, group\_max, group)$ 
         $quant\_group[mask] \leftarrow group[indices]$ 
         $quant\_cache \leftarrow concat(quant\_cache, quant\_group)$ 
    end
    return  $quant\_cache$ 
end

```

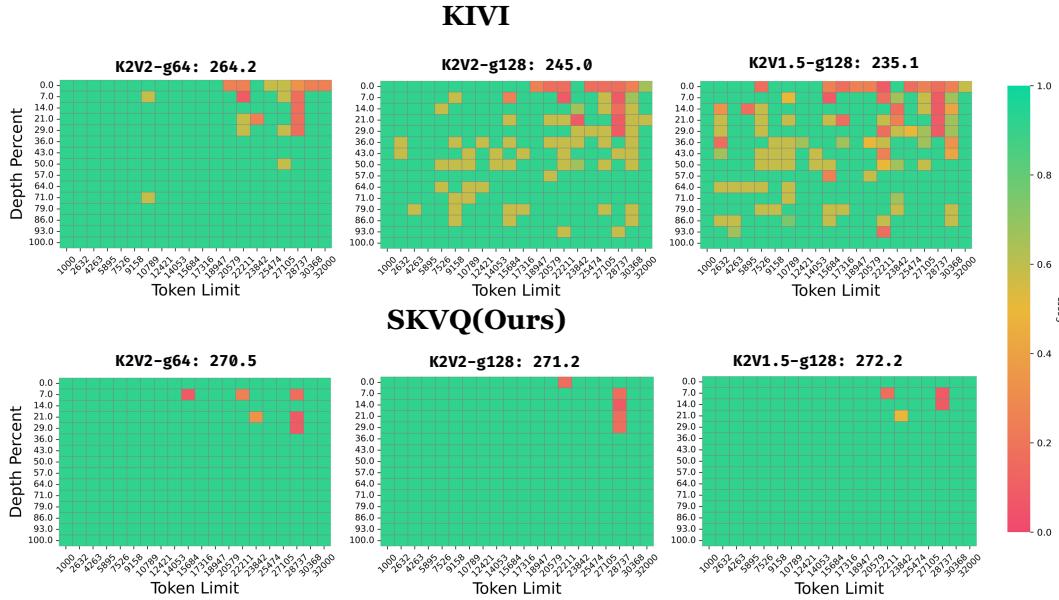


Figure 7: Comparison of SKVQ with KIVI on 32k context length needle in haystack test. The baseline score is 268.5. We vary the group size from 64 to 128, and vary the quantization bits from (key 2bits, value 2bits) to (key 2bits, value 1.5bits).

B More Experimental Results of Needle in Haystack

The results in Figure7 show SKVQ is clearly better than KIVI, especially in K2V1.5-g128, SKVQ achieve the same level with FP16, while KIVI suffers significant accuracy loss. These results shows the robustness of our approach.

C Memory and Latency Analysis

In order to further illustrate the benefits of quantizing KV cache to extremely low-bitwidth, we use LLM-Viewer(Yuan et al., 2024) to analyze the benefits in terms of memory consumption and inference latency. The result is shown in table5. When batch size and sequence length are relatively large, KV cache dominates almost all the memory consumption, and load KV cache becomes the performance bottleneck of the entire inference system. By quantizing KV cache with SKVQ, we can significantly reduce both latency and memory consumption. The analysis result shows SKVQ enables 1M context length in a single A100-80GB. As for the inference latency, we show the results of decoding phase, which domain the inference time in long context tasks. In the case of batch size 128 and sequence length 200k, the theoretical 7x speedup can be achieved.

D Comparison Between Smooth and Reorder

To improve the accuracy of per-token quantization, we utilize the reorder to cluster similar channels together. There are also other methods to improve the accuracy, one of them is smoothing, which is adopted in (Xiao et al., 2022; Shao et al., 2023; Yue et al., 2024). This approach smooth the difference between channels by multiplying an extra factor before quantization. We explore and compare smoothing with reordering, the experimental results are shown in table6. SKVQ-smooth represents our sliding window strategy together with smoothing and SKVQ-reorder represents the approach we described in 3.1. The results demonstrate that reordering can effectively improve the per-token quantization performance while the smoothing cannot. This is mainly because smoothing does not take into account the differences in token dimensions.

Batch Size	Seq Length	Latency(ms) / Memory(GB)	FP16	KV4	KV2
1	32k	Inference Time	10.6	7.5	7
		Memory Access	21.6	15.3	14.3
		Memory Consumption	29.7	17.2	15.1
	128k	Inference Time	23.1	10.8	8.7
		Memory Access	47.2	22	17.8
		Memory Consumption	80.1	29.7	21.4
	200k	Inference Time	32.5	13.3	10
		Memory Access	66.3	27	20.5
		Memory Consumption	118	39.2	26.1
64	32k	Inference Time	274.1	76.6	43.7
		Memory Access	559	156	89.1
		Memory Consumption	1100	282	147
	128k	Inference Time	1100	286.4	154.8
		Memory Access	2200	584	316
		Memory Consumption	4300	1100	551
	200k	Inference Time	1700	443	238.1
		Memory Access	3400	905	485
		Memory Consumption	6700	1700	853
128	32k	Inference Time	541.8	146.8	81
		Memory Access	1100	299	165
		Memory Consumption	2200	550	282
	128k	Inference Time	2100	566.4	303.1
		Memory Access	4400	1200	618
		Memory Consumption	8600	2200	1100
	200k	Inference Time	3300	881.1	469.7
		Memory Access	6800	1800	958
		Memory Consumption	13400	3400	1700

Table 5: LLaMA-7B memory and latency analysis with roof line model. The hardware platform is A100 80G, we assume flash-attention is used.

Model	Method	LCC	RepoBench-P	PR-en	TREC	2wikimqa	GovReport	MQA-zh	Average
LLaMA-2-7B-chat	FP16	52.33	44.05	10.25	63	32.09	27.29	11.39	38.50
	SKVQ-reorder	50.69	45.4	5.5	63	28.5	27.07	10.7	37.50
	SKVQ-smooth	48.93	40.12	4.75	62.5	26.75	23.19	7.93	34.77
LLaMA-2-13B-chat	FP16	50.54	52.1	15.25	68.5	13.21	27.52	7.23	38.83
	SKVQ-reorder	49.53	49.76	12.25	67.5	14.03	26.68	6.63	37.53
	SKVQ-smooth	47.78	47.28	7.5	67	11.61	24.07	5.55	35.34
Mistral-7B	FP16	68.06	60.46	17.71	68	10.87	20.09	17.1	45.51
	SKVQ-reorder	67.81	60.54	13.21	67	10.91	17.72	15.9	43.47
	SKVQ-smooth	64.18	57.95	9.49	63.5	10.11	13.99	12.77	41.52
Mistral-7B-Instruct	FP16	55.07	48.96	60	70	22.63	31.18	42.74	48.66
	SKVQ-reorder	54.86	49.05	56.42	70	20.94	30.82	42.4	46.23
	SKVQ-smooth	49.83	45.74	40.42	66	17.11	28.32	30.32	42.11

Table 6: Comparison of different methods(i.e. smooth v.s. reorder) on LongBench. Group-size(average) is set as 128, key-cache 2bit, value-cache 2bit, window-size 128. We abbreviated PassageRetrieval as PR and MultiFieldQA as MQA.

Model	Method	LCC	RepoBench-P	PR-en	TREC	2wikimqa	GovReport	MQA-zh	Average
Vicuna-v1.5-7b-16k	FP16	51.38	46.18	4.5	69	21.3	27.79	43.74	41.02
	RTN	13.22	17.78	1.2	0	0.59	2.39	0.61	8.23
	SmoothQuant	40	29.27	1.94	18.25	8.33	14.86	7.19	22.37
	RPTQ	40.64	41.4	3.75	59.5	15.92	23.16	19.41	32.68
	KIVI	49.32	43.35	5.56	68	23.3	24.47	38.86	39.19
	SKVQ	50.98	44.07	6	69	22.04	26.55	40.82	40.20
LongChat-v1.5-7b-32k	FP16	54.89	59.05	30.5	66.5	24.58	30.89	35.33	47.27
	RTN	5.11	3.73	1.5	0	0.42	0.51	0.08	2.461
	SmoothQuant	36.21	31.91	2.45	36.5	13.94	17.21	6.59	24.70
	RPTQ	40.4	43.2	8	61	17.31	24.79	20.01	34.01
	KIVI	49.86	54.77	20.5	66	23.79	28.75	31.58	43.22
	SKVQ	55.01	57.24	22	67	22.4	30.03	31.68	45.37

Table 7: Evaluation results of Vicuna and LongChat on LongBench. Group-size(average) 128, key-cache 2bit, value-cache 2bit, window-size 128. We abbreviated PassageRetrieval as PR and MultiFieldQA as MQA. We highlight the result of our method.

E More Results of LongBench Evaluation

We also evaluated LongChat-v1.5-7b-32k and Vicuna-v1.5-7b-16k, which are two famous long-context models fine-tuned based on Llama2-7b. The results in Table7 demonstrate that our SKVQ outperformed previous methods, which highlight the generalizability of our approach.