Lookahead Q-Cache: Achieving More Consistent KV Cache Eviction via Pseudo Query

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https://github.com/noforit/Lookahead_Q-Cache

Abstract

Large language models (LLMs) rely on key-value cache (KV cache) to accelerate decoding by reducing redundant computations. However, the KV cache memory usage grows substantially with longer text sequences, posing challenges for efficient deployment. Existing KV cache eviction methods prune tokens using prefilling-stage attention scores, causing inconsistency with actual inference queries, especially under tight memory budgets. In this paper, we propose Lookahead Q-Cache (LAQ), a novel eviction framework that generates low-cost pseudo lookahead queries to better approximate the true decoding-stage queries. By using these lookahead queries as the observation window for importance estimation, LAQ achieves more consistent and accurate KV cache eviction aligned with real inference scenarios. Experimental results on LongBench and Needle-in-a-Haystack benchmarks show that LAQ outperforms existing methods across various budget levels, achieving a $1 \sim 4$ point improvement on LongBench under limited cache budget. Moreover, LAQ is complementary to existing approaches and can be flexibly combined to yield further improvements.

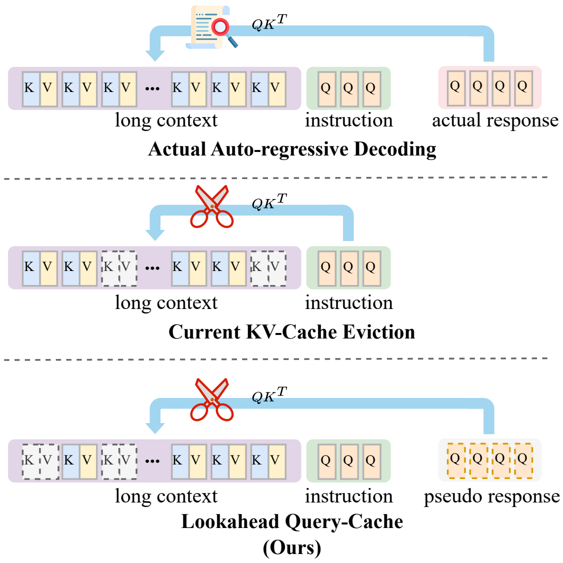

Figure 1: Illustration of the differences between the proposed Lookahead approach and existing methods. Pseudo queries are introduced to probe the importance of cached keys and values.

1 Introduction

Large language models (LLMs) have demonstrated strong capabilities in long-sequence text modeling tasks (Liu et al., 2025a,b) such as code generation (Guo et al., 2024a; Hui et al., 2024), document summarization (Liu et al., 2024c), and mathematical reasoning (Chen et al., 2025). To improve inference efficiency during the decoding stage, LLMs leverage key-value cache (KV-Cache) to reduce redundant computations and accelerate inference. However, increasing text lengths lead to a substantial rise in KV cache memory usage, introducing considerable obstacles (Shi et al., 2024; Li et al., 2024a; Yuan et al., 2024) to efficient model deployment. Recent work (Liu et al., 2024d; Sun et al., 2024) has focused on lightweighting the KV cache in long-context scenarios.

As a straightforward and effective compression method, KV cache eviction has attracted widespread attention (Ge et al., 2024; Liu et al., 2023; Tang et al., 2024) from researchers. The method improves decoding efficiency by performing token-level pruning on the prefilling-stage KV cache. Following the observations of Liu et al. (2023); Zhang et al. (2023), the majority of studies adopt cumulative attention scores as the criterion for token pruning. Compared to direct accumulation, SnapKV (Li et al., 2024b) achieves more accurate KV cache importance estimation by leveraging an observation window. In addition, some studies (Cai et al., 2024; Feng et al., 2024) aim to allocate finer-grained budgets across layers or at-

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Proceedings of the 2025 Conference on Empirical Methods in Natural Language Processing, pages 34158–34174
November 4-9, 2025 ©2025 Association for Computational Linguistics

tention heads to achieve higher compression rates.

Although existing methods have partially alleviated the KV cache overhead in long-context scenarios, several challenges remain to be addressed. One key issue is the **inconsistency between compression and inference**. Under a constrained budget, KV cache eviction seeks to maintain the key-value pairs most likely to be accessed by future queries during decoding. However, as shown in Figure 1, current approaches rely on prefilling-stage queries to approximate those in the decoding stage when selecting key-value pairs for KV cache retention. This inconsistency significantly reduces the accuracy of cache selection under a low budget, thereby degrading the performance of eviction algorithms.

In this paper, we observe that employing the prefix of the generated response as the observation window leads to more consistent KV cache selection. Notably, this phenomenon is insensitive to the quanlity of the generated response: even incorrect answers are often able to recall the key cache entries required for generating the correct one. Motivated by these findings, we propose a KV cache eviction framework, **LookAhead Q-Cache (LAQ)**, which aligns more closely with the actual inference situation. Specifically, unlike prior works that select observation windows from the input text to compute the importance of KV cache, our method generates lookahead queries in a low-cost manner that are more consistent with the actual response queries. Once the lookahead queries are cached, we use them as the observation window for importance estimation, and then proceed with standard KV cache eviction. Experimental results on LongBench and Needle-in-a-Haystack tasks demonstrate that LAQ consistently outperforms existing methods across various budget settings. By leveraging Q-Cache, which better aligns with inference scenarios, the proposed method even outperforms some dynamically budgeted approaches under low-budget settings. Furthermore, experiments show that the proposed method can be integrated with existing methods to yield orthogonal improvements.

The main contributions of this paper are as follows:

- We propose the Lookahead Q-Cache, a novel framework that mitigates the inconsistency issue during both compression and inference phases by leveraging pre-generated low-quality pseudo queries.
- The proposed method offers orthogonal improvements when combined with existing approaches, and its flexible configuration enables broad applicability.
- Experiments across diverse benchmarks indicate that the proposed method significantly outperforms existing strategies, consistently achieving performance improvements of $1 \sim 4$ percentage points on LongBench.

2 Related Works

2.1 KV Cache Eviction

KV Cache eviction aims to prune redundant KV cache entries from the prefill stage at the token level, improving decoding speed and alleviating memory usage without compromising decoding performance. Previous work primarily builds on Liu et al.; Zhang et al.'s (2023; 2023) findings, utilizing the attention mechanism as an inherent evaluation criterion to assess the importance of KV-Cache entries and guide their eviction. However, using global attention scores often lacks specificity. Li et al. (2024b) discover that the suffix of the input window exhibits behavior more consistent with the generation phase. By maintaining a local window to guide KVCache eviction, lower performance degradation is achieved.

Due to conflicts between obtaining attention scores and existing acceleration techniques (such as FlashAttention (Dao et al., 2022; Dao, 2024)), some methods focus on identifying alternative importance evaluation metrics. Devoto et al. (2024) identify a correlation between the norm of the key values and their importance, and propose an L2 norm-based KV cache eviction method that is compatible with existing acceleration frameworks. Building on this, Guo et al. (2024b) also explore the norm of the value vectors and achieve more precise KV Cache eviction by combining the attention mechanism with the L2 norm of Value caches. Despite alleviating performance degradation, existing KV Cache eviction strategies continue to face the inconsistency problem in compressed inference illustrated in Figure 1, thereby constraining the upper bound of eviction performance.

2.2 KV Cache Compression

In addition to direct eviction, some studies (Wan et al., 2024) focus on merging similar KV cache entries to improve efficiency. To preserve as much information from the prefill stage as possible, some methods (Bolya et al., 2023; Zhang et al., 2024) build upon KV cache eviction and further explore token-level cache fusion, leading to improved task performance after eviction. Going further, with appropriate processing and training (Sun et al., 2024; Liu et al., 2024b; Zuhri et al., 2024; Ma et al., 2024), KV cache entries across layers can be merged and compressed to reduce memory consumption, offering additional efficiency gains.

Moreover, dimensionality reduction of the KV cache (Shazeer, 2019) serves as an effective approach to improve efficiency. The most straightforward compression method is to reduce the precision bit-width (He et al., 2024) of the KV Cache. Liu et al. (2024d) propose separate quantization methods based on channels and tokens to address the distinct distribution characteristics of the key and value, achieving nearly lossless 2-bit quantization. Additionally, some methods employ low-rank techniques for compression. GQA (Ainslie et al., 2023) achieves significant compression by sharing keys and values across multiple groups of queries, and has been widely adopted in various applications (Grattafiori et al., 2024). Multi-Head Latent Attention (MLA) (Liu et al., 2024a) of DeepSeek significantly reduces KV cache size through low-rank compression and decoupled RoPE, achieving efficient inference while maintaining model performance.

3 Observations

To investigate the inconsistency between the compression and inference stages, we first evaluate the recall rate of the selected KV cache using fix-length observation windows at different positions. Specifically, the position includes not only the input portion but also the output tokens generated during the inference stage. The recall rate of the selected KV cache is defined as the proportion of indices selected by the observation window that overlap with those selected by all response tokens. The final recall rate $Recall_W$ can be calculated as follows:

$$M_{gold} = \mathrm{ArgSort}(\sum_{i \in R} q_i K^T)[: \mathrm{Budget}] \quad (1)$$

$$M_{pred} = \mathrm{ArgSort}(\sum_{i \in W} q_i K^T)[: \mathrm{Budget}] \quad (2)$$

$$Recall_W = \frac{|M_{pred} \cap M_{gold}|}{|M_{gold}|} \quad (3)$$

As shown in Figure 2, we conduct evaluations on the GovReport dataset (Huang et al., 2021) for the summarization task. By analyzing the figure, we obtain several insightful findings.

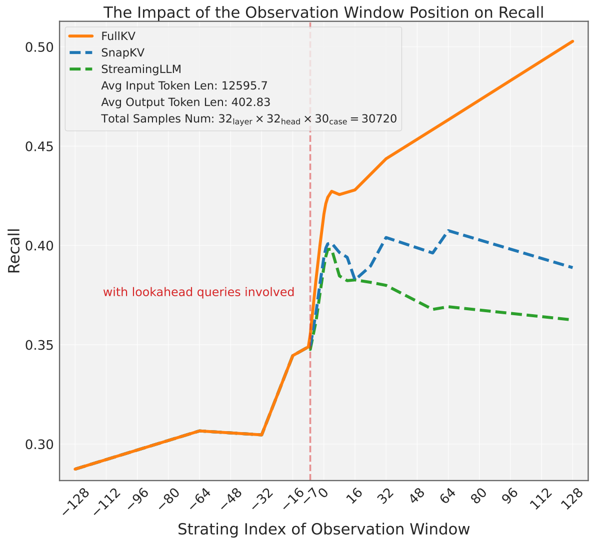


Figure 2: An illustration of the average recall rate with different starting index of the observation window, where 0 indicates the position of the first generated token. The observation window has a fixed length of 8, and the budget is set to 1024.

(1) Response prefix queries significantly boost recall over instruction. Similar to the conclusion of Li et al. (2024b), we find that local windows near the end of the input achieve higher recall rates compared to other input windows. However, once tokens from the output portion appear in the observation window (as indicated by the red vertical line in the figure), the recall rate of the window experiences a sudden increase. Although the recall rate gradually increases as the window shifts forward, just 1-2 tokens from the generation phase are sufficient to bring a substantial improvement. This phenomenon indicates a significant discrepancy between input and output queries and suggests that existing eviction methods still have substantial room for improvement.

(2) Queries from low-quality responses remain effective. Although output queries are effective, they are not accessible during the actual inference stage. To address this, we further evaluate the recall rate of observation windows composed of queries from low-quality responses generated under common KV-Cache eviction strategies. As shown by the dashed lines in Figure 2, the recall rate is lower than that achieved with the full KV cache, yet a noticeable jump in recall can still be observed with these low-quality queries. This suggests that the

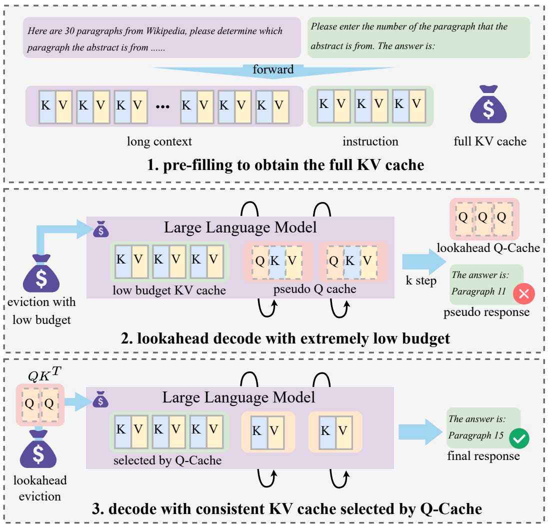


Figure 3: Main workflow of the proposed Lookahead Q-Cache. Queries from incorrect answers can still retrieve KV cache entries aligned with the actual outputs.

selection of KV cache may not be highly sensitive to response correctness. Actually, cache patterns attended by incorrect responses remain more consistent with those of correct responses than traditional input-based selections.

Based on the above insights, if we can obtain the query corresponding to the response prefix as a observation window, the consistency between the compression and inference stages can be improved, leading to substantial gains for existing KV-Cache eviction strategies. Notably, although the golden query is not accessible during inference, some pseudo queries obtained through eviction strategies can still achieve strong performance. These pieces of evidence motivate the design of a two-stage KV-Cache eviction algorithm, which enables more precise cache eviction by leveraging pseudo response-prefix windows with more consistent distributions.

4 Lookahead Q-Cache

4.1 Overall Workflow

Given the outcomes in Section 3, the proposed LookAhead Q-Cache (LAQ) aims to cache queries from some low-quality responses in advance as the observation window to achieve KV-Cache eviction more consistent with the inference stage. Our main workflow, as illustrated in Figure 3, consists of three stages: the prefilling stage, the lookahead stage (Section 4.2), and the eviction-based decoding stage (Section 4.3).

4.2 Lookahead Query Construction

After obtaining the KV cache during the pre-filling stage, we first employ certain KV cache selection strategies to construct lookahead queries. To balance efficiency, we adopt KV cache eviction methods (such as StreamingLLM (Xiao et al., 2024) and snapKV (Li et al., 2024b)) with a low budget to generate a specified number of response tokens at a lower cost. Considering that the primary bottleneck for model generation in long-text scenarios lies in the pre-filling stage, a few additional decoding steps introduce minimal impact on the overall latency. We further analyze the latency introduced by the Lookahead Q-Cache in Section 6.3.

Unlike standard generation, the lookahead generation process requires retaining the Query hidden states as a Q-Cache for use in subsequent observation windows. However, since we decode only up to 8 steps ahead, the additional memory overhead introduced by the Q-Cache is negligible in the context of long sequences.

4.3 KV-Cache Re-eviction

Given the previously obtained Q-Cache Q, we use it as an observation window to perform a second-round eviction of the KV-Cache. The retained KV-Cache indices under budget B can be formulated as:

$$M_{ahead} = \text{ArgSort}(\sum_{q_i \in Q} q_i K^T)[: B] \quad (4)$$

After obtaining the KV cache ranking under the lookahead observation window, we can perform cache re-eviction based on the given budget, followed by standard autoregressive decoding for generation. Specifically, the pseudo Query cache can be combined with the queries from the local window obtained during the prefilling stage to form a unified observation window for generation:

$$M_{ahead} = \text{ArgSort}(\sum_{q_i \in W \cup Q} q_i K^T)[: B] \quad (5)$$

where W represents the local context window, similar to that employed in SnapKV (Li et al., 2024b). We denote this integrated method as LAQ++.

5 Experiments

5.1 Setup

Evaluation benchmarks and model setup. Following prior works (Li et al., 2024b; Cai et al.,

Table 1: Performance comparison of different methods across various LLMs on LongBench.

	LLMs	Single-Document QA			Multi-Document QA			Summarization			Few-shot Learning			Synthetic		Code		Avg.
		NrtvQA	Qasper	MF-en	HotpotQA	2WikiMQA	Musique	GovReport	QMSum	MultiNews	TREC	TriviaQA	SAMSum	PCount	PRe	Lcc	RB-P	
Mistral-7B-v0.2-Instruct	Full KV	26.90	33.14	49.26	42.77	27.35	18.77	32.95	24.21	27.13	71.00	86.23	42.72	2.75	86.98	57.12	54.51	42.74
	KV Cache Size = 128																	
	H2O	21.62	21.34	38.61	30.46	20.38	12.20	20.59	22.51	22.03	39.00	82.33	40.64	3.06	**80.56**	51.17	48.46	34.69
	SnapKV	19.71	21.13	42.75	36.45	22.36	15.76	19.05	21.81	21.36	47.50	84.15	40.29	2.41	68.26	52.26	48.75	35.25
	PyramidKV	21.98	22.78	43.78	32.30	22.31	15.81	20.41	21.82	21.23	66.00	83.51	39.83	2.99	65.81	51.61	46.42	36.16
	LAQ	24.94	**27.77**	45.43	40.35	25.25	17.91	**22.06**	22.68	**22.50**	69.50	**86.36**	41.16	1.49	76.85	53.31	**51.02**	39.29
	LAQ++	**25.62**	27.21	**46.16**	**40.60**	**25.93**	**18.44**	21.60	**23.07**	22.42	**70.00**	86.18	**42.03**	**3.51**	74.81	**54.68**	50.92	**39.57**
	KV Cache Size = 256																	
	H2O	21.42	23.04	42.60	30.75	22.42	13.82	22.35	22.54	23.12	40.50	83.78	40.73	3.51	85.85	53.18	49.95	36.22
	SnapKV	22.44	24.07	48.01	38.66	22.66	15.59	21.83	23.23	22.94	61.50	85.45	41.32	3.13	85.79	55.11	51.73	38.97
	PyramidKV	21.69	25.18	47.61	38.77	26.12	15.23	22.52	22.52	22.59	68.00	84.27	42.10	3.43	76.60	53.08	48.40	38.63
	LAQ	24.68	**29.25**	48.00	40.56	26.01	18.24	**24.04**	22.96	**23.80**	70.00	85.81	42.52	2.01	82.34	54.96	**53.00**	40.51
	LAQ++	**25.23**	29.16	**49.24**	**41.70**	**26.85**	**18.62**	23.73	**23.69**	23.38	**70.50**	**86.24**	**42.54**	**3.36**	**86.11**	**55.59**	52.49	**41.15**
	KV Cache Size = 512																	
	H2O	21.72	25.54	44.72	32.39	23.16	14.75	23.61	23.03	24.58	42.00	85.22	41.61	**3.42**	86.45	54.82	51.11	37.38
	SnapKV	24.14	28.11	48.78	39.49	25.09	17.40	23.67	23.18	24.60	67.00	85.88	41.39	2.78	**86.56**	56.61	53.47	40.51
	PyramidKV	22.99	28.74	48.45	39.73	25.74	16.58	24.48	23.40	24.52	70.00	85.99	42.40	3.32	81.63	55.93	52.38	40.39
	LAQ	24.65	**31.21**	49.15	39.90	**27.18**	18.38	25.55	23.91	24.87	**71.00**	86.33	42.14	1.87	86.41	**56.84**	53.08	41.40
	LAQ++	**25.49**	30.92	**49.72**	**41.50**	26.84	**19.20**	**25.67**	**24.04**	**25.31**	**71.00**	**86.43**	**43.14**	2.90	85.27	56.80	**53.54**	**41.70**
Llama3.1-8B-Instruct	Full KV	31.85	15.55	28.17	29.93	22.98	18.20	34.39	23.79	27.12	72.50	92.14	43.66	8.37	97.59	65.05	54.78	41.63
	KV Cache Size = 128																	
	H2O	25.06	7.09	18.58	17.86	19.88	9.14	22.28	22.68	21.55	40.00	90.89	40.78	8.30	92.96	59.15	49.36	34.10
	SnapKV	24.65	7.29	22.01	19.11	18.85	11.07	20.48	21.62	20.16	47.50	90.24	40.47	**10.75**	92.51	59.99	49.08	34.74
	PyramidKV	24.79	8.29	20.72	14.86	13.84	8.90	22.41	22.76	21.53	62.00	90.35	39.23	9.27	93.51	58.77	46.46	34.86
	LAQ	27.80	**10.66**	24.86	20.64	20.04	15.40	**24.18**	23.09	**22.88**	**72.00**	91.55	**43.43**	9.04	**95.85**	61.12	50.33	38.30
	LAQ++	**28.65**	10.65	**26.04**	**24.23**	**21.56**	**15.67**	23.50	**23.74**	22.75	**72.00**	**91.95**	42.19	8.37	94.81	**62.18**	**50.95**	**38.70**
	KV Cache Size = 256																	
	H2O	26.01	8.42	19.69	17.28	18.21	9.91	23.64	22.89	23.20	41.50	91.29	41.60	8.00	94.31	60.79	50.31	34.82
	SnapKV	28.05	9.83	22.71	21.48	19.36	10.96	22.86	22.75	22.98	58.00	92.28	40.87	8.10	95.30	63.64	51.35	36.91
	PyramidKV	26.40	10.08	22.46	15.20	16.38	8.60	23.86	22.93	23.17	69.00	90.99	40.60	**8.42**	93.74	60.59	48.11	36.28
	LAQ	28.86	12.40	26.44	21.80	20.91	15.77	**25.83**	23.30	**24.26**	**72.50**	**93.08**	42.57	7.53	**95.80**	63.51	51.09	39.10
	LAQ++	**30.25**	**12.43**	**26.63**	**25.77**	**22.83**	**18.45**	25.07	**23.67**	23.75	72.00	91.97	**43.17**	6.93	94.59	**64.07**	**53.38**	**39.69**
	KV Cache Size = 512																	
	H2O	25.44	8.35	20.97	20.08	19.23	9.51	24.44	23.50	24.35	44.00	92.10	41.16	7.43	96.41	62.73	51.77	35.72
	SnapKV	30.34	10.75	23.54	24.65	21.55	12.98	24.82	23.15	24.61	68.00	**92.33**	42.16	7.83	96.86	64.74	**53.60**	38.87
	PyramidKV	28.38	11.59	25.02	20.06	18.80	10.64	25.73	24.03	25.01	70.00	92.22	41.73	**8.47**	96.42	63.44	51.02	38.29
	LAQ	**30.89**	**14.04**	25.86	26.00	23.19	17.73	**27.07**	24.01	**25.29**	**72.50**	92.25	**43.13**	6.96	**96.97**	64.87	52.58	40.21
	LAQ++	29.64	13.22	**26.79**	**27.58**	**23.49**	**18.63**	26.94	**24.04**	25.21	**72.50**	92.25	42.83	8.43	96.25	**65.00**	53.37	**40.39**

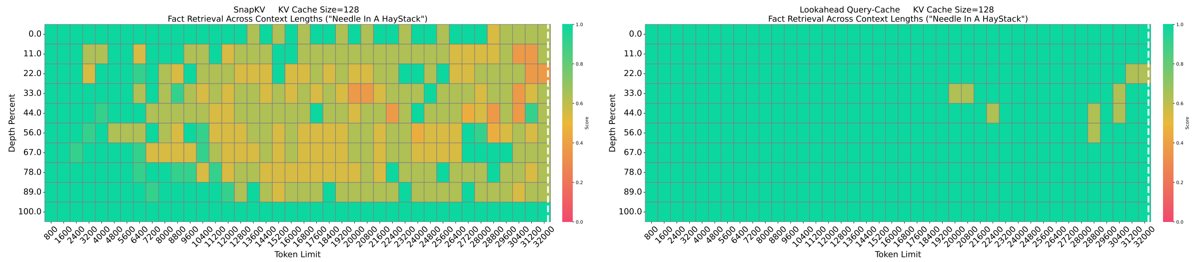
2024), we evaluate the proposed method using the LongBench benchmark (Bai et al., 2023) and the Needle-in-a-Haystack test (Kamradt, 2023). For LongBench, we adopt three KV cache budget settings: 128, 256, and 512. To comprehensively evaluate the generalization ability of the proposed method, we conduct experiments on Mistral-7B-v0.2-Instruct (Jiang et al., 2023), Llama3.1-8B-Instruct (Grattafiori et al., 2024), and Qwen2.5-7B-Instruct (Yang et al., 2025). Due to space limitations, additional experimental results are presented in Appendix D.

Selected baselines. To highlight the effectiveness of our proposed method, we select three commonly used and strong KV-Cache eviction strategies as baselines: **(1) H2O** (Zhang et al., 2023) evaluates and evicts existing KV cache entries based on cumulative attention scores. **(2) SnapKV** (Li et al., 2024b) utilizes a local observation window to achieve more accurate importance estimation and employs average pooling to retain a more coherent KV Cache. **(3) PyramidKV** (Cai et al., 2024) leverages the characteristics of attention distribution across layers by allocating different budgets to the KV cache at shallow and deep layers, thereby achieving lower performance degradation under low-budget settings.

Method config. In the main experiments, we employ LAQ and LAQ++ as the proposed methods for comparison. Specifically, for LAQ, we adopt a configuration of 8 forward Q-Caches, while for LAQ++, the setup consists of 8 local observation windows in addition to 8 forward Q-Caches. Additionally, we employ SnapKV as the lookahead method, ensuring consistency in budget and experimental settings. We further discuss the impact of hyperparameter choices in LAQ on performance in Sections 6.1 and 6.2.

5.2 Results on LongBench.

Overall. As shown in Table 1, we evaluate the performance of various methods across multiple models on the LongBench benchmark. Overall, the proposed methods achieve a significant improvement of 1$\sim$4 percentage points over existing KV cache eviction strategies across different models and budget settings. By leveraging a pre-fetched lookahead Q-Cache, LAQ is able to make cache selection decisions that are more aligned with those in the actual inference stage. Furthermore, by integrating local observation windows, LAQ++ achieves an orthogonal improvement.



(a) Mistral SnapKV (Score=76.2) (b) Mistral LAQ++ (Score=99.2)

Figure 4: The results of SnapKV and LAQ++ on the needle-in-a-haystack test under a budget setting of 128.

Table 2: The score on Needle-in-a-Haystack task under different KV cache budgets.

Budget	**Method**				
	FullKV	H2O	SnapKV	PyraKV	LAQ++
Mistral-7B-v0.2-Instruct					
64	100	43.2	60.7	84.3	**99.3**
96	100	54.1	71.5	88.2	**99.6**
128	100	59.2	76.2	88.1	**99.2**
Llama3.1-8B-Instruct					
64	100	35.4	68.4	80.7	**99.8**
96	100	42.1	72.0	85.9	**100**
128	100	46.1	73.1	89.9	**100**
Qwen2.5-7B-Instruct					
64	100	46.7	72.8	69.3	**85.1**
96	100	50.2	75.0	84.8	**89.5**
128	100	53.0	76.6	89.7	**92.9**

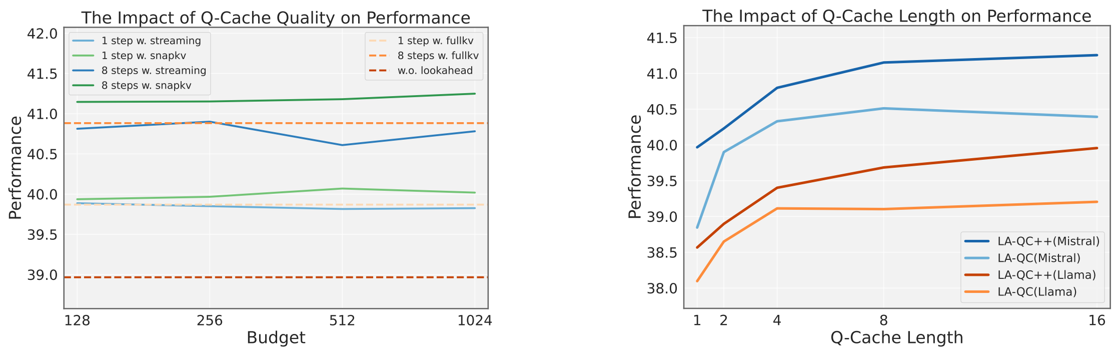
Results across diverse output length settings. Moreover, beyond the overall performance gains, LAQ also demonstrates consistently promising improvements across tasks with varying output lengths. The construction of an 8-step lookahead Query cache enables LAQ to achieve a justified advantage on tasks characterized by shorter output lengths. Nonetheless, it is observed that the proposed method maintains strong performance on summarization tasks where the output length exceeds 300 tokens. This clearly demonstrates that the proposed method can partially mitigate the discrepancy of queries between the compression and inference stages. It achieves this by incorporating pseudo-queries within the observation window. As a result, the method attains performance improvements that are independent of output length.

Performance under varying budgets. In addition to varying models, we also conduct experiments under diverse KV cache budget settings. Compared to baseline methods, we find that LAQ achieves more pronounced improvements under low budget settings. Such low-budget scenarios typically impose greater demands on the recall accuracy of the KV cache within the observation window. This result further highlights the significant gap between queries in the input and output windows, and demonstrates that incorporating a limited number of lookahead queries can effectively mitigate this issue. Furthermore, to ensure a fair comparison, the proposed method employs a fixed budget and has already outperformed the dynamic-budget PyramidKV approach in low-budget scenarios. It is conceivable that combining both approaches could yield greater improvements by enabling more fine-grained budget allocation.

5.3 Results on Needle-in-a-Haystac Test.

Overall setting. In addition to various tasks on LongBench, we also evaluate the proposed method on the Needle-in-a-Haystack test. This test is designed to evaluate ability of LLMs to retrieve specific keys within ultra-long contexts. Since FullKV already achieves strong performance with a 32K context length, in KV cache eviction scenarios, we typically conduct evaluations after evicting a given budget from the KV cache.

Main results. As shown in Table 2, we conduct experiments on various models and budgets under a 32K context length. With a complete KV cache available, the model demonstrates strong capability in successfully completing the retrieval task. However, after evicting a certain portion of the KV cache, all methods experience some degree of performance degradation. The retrieval experiment results exhibit less variability and are more intuitive compared to task performance metrics. Although PyramidKV achieves significant advantages among baseline methods through dynamic budgeting, LAQ++ attains near-lossless performance by leveraging a more consistent Q-Cache mechanism. As discussed above, our proposed method can also be further enhanced by integrating dynamic budget-



(a) The impact of Q-Cache quality on performance.

(b) The impact of Q-Cache length on performance.

Figure 5: Ablation analysis of Q-Cache with respect to quality and length.

ing. A more intuitive example is shown in Figure 4, where compared to SnapKV, LAQ++ can recall nearly all "needles" from a 32K context using only a 128 budget. Further experimental results can be found in Appendix E.

6 Analysis

6.1 The Impact of Q-Cache Quality

As observed in Section 3, queries from low-quality responses still achieve a high recall rate of target KV cache entries compared to those derived from the input. In this subsection, we quantitatively analyze the impact of Q-Cache quality on model performance. Specifically, we employ Lookahead with different budgets and eviction strategies to obtain Q-Cache of varying quality, and we also use the queries obtained under the Full-KV setting as an upper-bound reference. For the configuration of the LAQ method, we conduct experiments on LongBench using two different settings: 1-step and 8-step Lookahead.

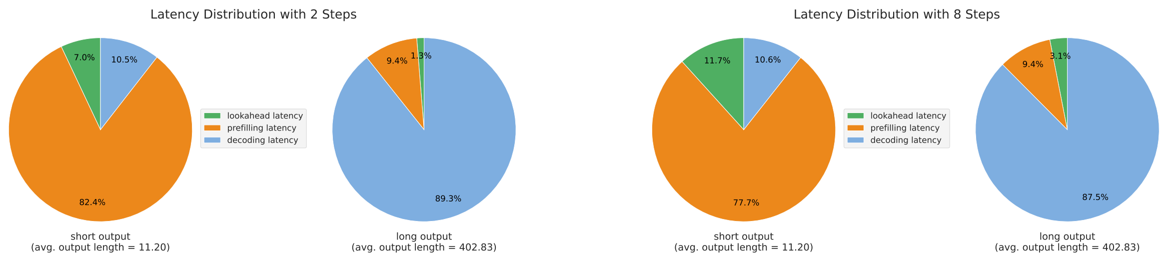
The relationship between overall performance and Q-Cache quality is shown in Figure 5(a). The x-axis represents the budget used in the Lookahead stage for each eviction strategy, while the y-axis indicates the final performance on LongBench based on the KV cache entries selected by the Q-Cache. As shown in the table, reducing the budget has a limited impact on the performance of the proposed method. In addition, under the same number of steps, the performance differences among different eviction strategies are also minimal. Notably, under the 8-step LAQ setting, the Q-Cache generated by the full KV-Cache exhibits worse task performance than that produced by SnapKV with a lower budget. These results further demonstrate the robustness of the proposed method to the quality of the Q-Cache, as responses generated with lower budgets can still effectively mitigate inconsistencies between the compression and inference stages. Compared to the quality of the Q-Cache, the length has a more significant impact on the results.

6.2 The Impact of Q-Cache Length

As described above, compared to the budget, the number of lookahead steps exerts a greater influence on the results. Therefore, we further investigate the impact of different LAQ configurations combined with varying numbers of Lookahead steps on the experimental results. As shown in Figure 5(b), the final task performance increases with the length of the Q-Cache across all settings. This is consistent with the recall trend observed in Figure 2. Moreover, as the performance of low-budget eviction methods gradually degrades during long-sequence generation, the overall effectiveness of subsequent LAQ also tends to converge. Considering the additional latency introduced by lookahead stage, a balanced configuration must be chosen to trade off between performance and efficiency. In the main experiments, we set the step number hyperparameter to 8.

6.3 Latency Analysis

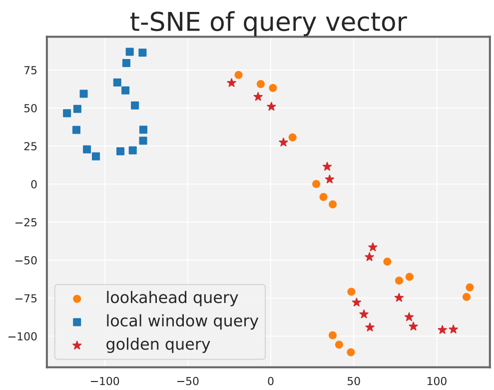
Despite achieving significant performance improvements, the proposed method still incurs additional latency for lookahead operations. To balance task performance and efficiency, we conduct a stage-wise latency analysis of the proposed LAQ (LookAhead Q-Cache) framework. As shown in Figure 6, we evaluate the latency distributions under both 2-step and 8-step configurations. We evaluate on two LongBench scenarios corresponding to short-output (avg. length 11.20 tokens) and long-output (avg. length 402.83 tokens) contexts. The addi-



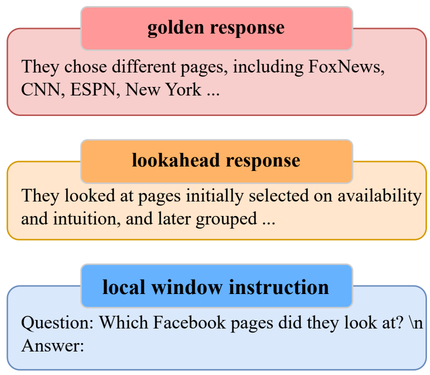
(a) Lookahead Q-Cache with 2-step lookahead.

(b) Lookahead Q-Cache with 8-step lookahead.

Figure 6: Latency breakdown under long- and short-output scenarios for 2-step and 8-step decoding, with green segments indicating the additional latency introduced by the proposed method.



(a) Visualization of query distribution after dimensionality reduction by t-SEN algorithm.



(b) Text comparison of the local window instruction, lookahead response, and golden response.

Figure 7: Case study of lookahead phase.

tional latency introduced by the proposed method is indicated by the green segments.

As evidenced by the results, both 2-step and 8-step configurations achieve significant performance improvements while contributing only $2 \sim 10\%$ to the total latency. In short-output scenarios, the prefilling phase dominates the latency budget, making the overhead of additional steps negligible. For long-output scenarios, the substantial number of decoding steps renders the overhead of processing a few extra tokens marginal, typically accounting for less than 5% of the total runtime.

6.4 Case Study

To further investigate how the proposed method improves the final KV cache eviction performance through the use of the pseudo Q-Cache, we conduct a case analysis of the queries and responses generated during the lookahead stage. As shown in Figure 7, we select a specific case to illustrate the response content and the distribution among the corresponding Q-Cache.

In Figure 7(b), we present the local context window, along with the low-quality response generated in advance and the gold response generated using the full KV cache. The three responses differ semantically in their textual content. Due to the constraints with low budget KV cache, the lookahead response fails to provide a sufficiently accurate answer. However, as shown in Figure 7(a), dimensionality reduction reveals a striking consistency between the Query representations of the two responses across the three text segments. This also validates our observation above that the gap between the input and output queries is greater than that between the incorrect outputs and the correct outputs. Our proposed method leverages this feature by employing a pre-generated Q-Cache to achieve more consistent KV cache eviction.

7 Conclusion

In this paper, we investigate the inconsistency between the Query entries of input and output. Based on our observational findings, we propose the Lookahead Q-Cache, which performs KV cache eviction by using pre-generated pseudo responses as the observation window. Experiments across multiple backbones demonstrate that the proposed method significantly outperforms existing KV cache eviction techniques, achieving improvements of 1 to 4 points on LongBench.

Limitations

Although the additional computational cost introduced by our method is minimal, there remains room for further optimization, particularly with respect to latency. Given the potential overlap between pseudo and golden responses, one promising direction is to integrate the Lookahead Q-Cache mechanism with acceleration techniques such as speculative decoding. This combination could reduce unnecessary computations and improve real-time performance. Building on this idea, our future work will focus on designing a more efficient KV Cache strategy that unifies these complementary approaches, aiming to achieve consistent improvements in both task performance and inference efficiency.

Acknowledge

We gratefully acknowledge the support of the National Natural Science Foundation of China (NSFC) via grant 62236004, 62206078, 62441603 and 62476073.

References

Joshua Ainslie, James Lee-Thorp, Michiel de Jong, Yury Zemlyanskiy, Federico Lebron, and Sumit Sanghai. 2023. GQA: Training generalized multi-query transformer models from multi-head checkpoints. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 4895–4901, Singapore. Association for Computational Linguistics.

Yushi Bai, Xin Lv, Jiajie Zhang, Hongchang Lyu, Jiankai Tang, Zhidian Huang, Zhengxiao Du, Xiao Liu, Aohan Zeng, Lei Hou, and 1 others. 2023. Longbench: A bilingual, multitask benchmark for long context understanding. *ArXiv preprint*, abs/2308.14508.

Daniel Bolya, Cheng-Yang Fu, Xiaoliang Dai, Peizhao Zhang, Christoph Feichtenhofer, and Judy Hoffman. 2023. Token merging: Your vit but faster. In *The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023*. OpenReview.net.

Zefan Cai, Yichi Zhang, Bofei Gao, Yuliang Liu, Tianyu Liu, Keming Lu, Wayne Xiong, Yue Dong, Baobao Chang, Junjie Hu, and 1 others. 2024. Pyramidkv: Dynamic kv cache compression based on pyramidal information funneling. *ArXiv preprint*, abs/2406.02069.

Qiguang Chen, Libo Qin, Jinhao Liu, Dengyun Peng, Jiannan Guan, Peng Wang, Mengkang Hu, Yuhang Zhou, Te Gao, and Wanxiang Che. 2025. Towards reasoning era: A survey of long chain-of-thought for reasoning large language models. *ArXiv preprint*, abs/2503.09567.

Tri Dao. 2024. Flashattention-2: Faster attention with better parallelism and work partitioning. In *The Twelfth International Conference on Learning Representations, ICLR 2024, Vienna, Austria, May 7-11, 2024*. OpenReview.net.

Tri Dao, Daniel Y. Fu, Stefano Ermon, Atri Rudra, and Christopher Ré. 2022. Flashattention: Fast and memory-efficient exact attention with io-awareness. In *Advances in Neural Information Processing Systems 35: Annual Conference on Neural Information Processing Systems 2022, NeurIPS 2022, New Orleans, LA, USA, November 28 - December 9, 2022*.

Alessio Devoto, Yu Zhao, Simone Scardapane, and Pasquale Minervini. 2024. A simple and effective l_2 norm-based strategy for kv cache compression. *ArXiv preprint*, abs/2406.11430.

Yuan Feng, Junlin Lv, Yukun Cao, Xike Xie, and S Kevin Zhou. 2024. Ada-kv: Optimizing kv cache eviction by adaptive budget allocation for efficient llm inference. *ArXiv preprint*, abs/2407.11550.

Suyu Ge, Yunan Zhang, Liyuan Liu, Minjia Zhang, Jiawei Han, and Jianfeng Gao. 2024. Model tells you what to discard: Adaptive KV cache compression for llms. In *The Twelfth International Conference on Learning Representations, ICLR 2024, Vienna, Austria, May 7-11, 2024*. OpenReview.net.

Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Alex Vaughan, and 1 others. 2024. The llama 3 herd of models. *ArXiv preprint*, abs/2407.21783.

Daya Guo, Qihao Zhu, Dejian Yang, Zhenda Xie, Kai Dong, Wentao Zhang, Guanting Chen, Xiao Bi, Yu Wu, YK Li, and 1 others. 2024a. Deepseek-coder: When the large language model meets programming–the rise of code intelligence. *ArXiv preprint*, abs/2401.14196.

Zhiyu Guo, Hidetaka Kamigaito, and Taro Watanabe. 2024b. Attention score is not all you need for token importance indicator in kv cache reduction: Value also matters. *ArXiv preprint*, abs/2406.12335.

Yefei He, Luoming Zhang, Weijia Wu, Jing Liu, Hong Zhou, and Bohan Zhuang. 2024. Zipcache: Accurate and efficient KV cache quantization with salient token identification. In *Advances in Neural Information Processing Systems 38: Annual Conference on Neural Information Processing Systems 2024, NeurIPS 2024, Vancouver, BC, Canada, December 10 - 15, 2024*.

Luyang Huang, Shuyang Cao, Nikolaus Parulian, Heng Ji, and Lu Wang. 2021. Efficient attentions for long document summarization. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1419–1436, Online. Association for Computational Linguistics.

Binyuan Hui, Jian Yang, Zeyu Cui, Jiaxi Yang, Dayiheng Liu, Lei Zhang, Tianyu Liu, Jiajun Zhang, Bowen Yu, Keming Lu, and 1 others. 2024. Qwen2. 5-coder technical report. *ArXiv preprint*, abs/2409.12186.

Albert Q. Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, Lélio Renard Lavaud, Marie-Anne Lachaux, Pierre Stock, Teven Le Scao, Thibaut Lavril, Thomas Wang, Timothée Lacroix, and William El Sayed. 2023. Mistral 7b.

G Kamradt. 2023. Needle in a haystack–pressure testing llms.

Haoyang Li, Yiming Li, Anxin Tian, Tianhao Tang, Zhanchao Xu, Xuejia Chen, Nicole Hu, Wei Dong, Qing Li, and Lei Chen. 2024a. A survey on large language model acceleration based on kv cache management. *ArXiv preprint*, abs/2412.19442.

Yuhong Li, Yingbing Huang, Bowen Yang, Bharat Venkitesh, Acyr Locatelli, Hanchen Ye, Tianle Cai, Patrick Lewis, and Deming Chen. 2024b. Snapkv: LLM knows what you are looking for before generation. In *Advances in Neural Information Processing Systems 38: Annual Conference on Neural Information Processing Systems 2024, NeurIPS 2024, Vancouver, BC, Canada, December 10 - 15, 2024*.

Aixin Liu, Bei Feng, Bing Xue, Bingxuan Wang, Bochao Wu, Chengda Lu, Chenggang Zhao, Chengqi Deng, Chenyu Zhang, Chong Ruan, and 1 others. 2024a. Deepseek-v3 technical report. *ArXiv preprint*, abs/2412.19437.

Akide Liu, Jing Liu, Zizheng Pan, Yefei He, Reza Haffari, and Bohan Zhuang. 2024b. Minicache: KV cache compression in depth dimension for large language models. In *Advances in Neural Information Processing Systems 38: Annual Conference on Neural Information Processing Systems 2024, NeurIPS 2024, Vancouver, BC, Canada, December 10 - 15, 2024*.

Jiaheng Liu, Dawei Zhu, Zhiqi Bai, Yancheng He, Huanxuan Liao, Haoran Que, Zekun Wang, Chenchen Zhang, Ge Zhang, Jiebin Zhang, and 1 others. 2025a. A comprehensive survey on long context language modeling. *ArXiv preprint*, abs/2503.17407.

Ran Liu, Ming Liu, Min Yu, He Zhang, Jianguo Jiang, Gang Li, and Weiqing Huang. 2024c. Sumsurvey: An abstractive dataset of scientific survey papers for long document summarization. In *Findings of the Association for Computational Linguistics ACL 2024*, pages 9632–9651.

Yijun Liu, Jinzheng Yu, Yang Xu, Zhongyang Li, and Qingfu Zhu. 2025b. A survey on transformer context extension: Approaches and evaluation. *ArXiv preprint*, abs/2503.13299.

Zichang Liu, Aditya Desai, Fangshuo Liao, Weitao Wang, Victor Xie, Zhaozhuo Xu, Anastasios Kyrillidis, and Anshumali Shrivastava. 2023. Scissorhands: Exploiting the persistence of importance hypothesis for LLM KV cache compression at test time. In *Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 - 16, 2023*.

Zirui Liu, Jiayi Yuan, Hongye Jin, Shaochen Zhong, Zhaozhuo Xu, Vladimir Braverman, Beidi Chen, and Xia Hu. 2024d. KIVI: A tuning-free asymmetric 2bit quantization for KV cache. In *Forty-first International Conference on Machine Learning, ICML 2024, Vienna, Austria, July 21-27, 2024*. OpenReview.net.

Da Ma, Lu Chen, Situo Zhang, Yuxun Miao, Su Zhu, Zhi Chen, Hongshen Xu, Hanqi Li, Shuai Fan, Lei Pan, and 1 others. 2024. Compressing kv cache for long-context llm inference with inter-layer attention similarity. *ArXiv preprint*, abs/2412.02252.

Noam Shazeer. 2019. Fast transformer decoding: One write-head is all you need. *ArXiv preprint*, abs/1911.02150.

Luohe Shi, Hongyi Zhang, Yao Yao, Zuchao Li, and Hai Zhao. 2024. Keep the cost down: A review on methods to optimize llm's kv-cache consumption. *ArXiv preprint*, abs/2407.18003.

Yutao Sun, Li Dong, Yi Zhu, Shaohan Huang, Wenhui Wang, Shuming Ma, Quanlu Zhang, Jianyong Wang, and Furu Wei. 2024. You only cache once: Decoder-decoder architectures for language models. In *Advances in Neural Information Processing Systems 38: Annual Conference on Neural Information Processing Systems 2024, NeurIPS 2024, Vancouver, BC, Canada, December 10 - 15, 2024*.

Jiaming Tang, Yilong Zhao, Kan Zhu, Guangxuan Xiao, Baris Kasikci, and Song Han. 2024. QUEST: query-aware sparsity for efficient long-context LLM inference. In *Forty-first International Conference on Machine Learning, ICML 2024, Vienna, Austria, July 21-27, 2024*. OpenReview.net.

Zhongwei Wan, Xinjian Wu, Yu Zhang, Yi Xin, Chaofan Tao, Zhihong Zhu, Xin Wang, Siqi Luo, Jing Xiong, and Mi Zhang. 2024. D2o: Dynamic discriminative operations for efficient generative inference of large language models. *ArXiv preprint*, abs/2406.13035.

Guangxuan Xiao, Yuandong Tian, Beidi Chen, Song Han, and Mike Lewis. 2024. Efficient streaming language models with attention sinks. In *The Twelfth International Conference on Learning Representations, ICLR 2024, Vienna, Austria, May 7-11, 2024*. OpenReview.net.

An Yang, Bowen Yu, Chengyuan Li, Dayiheng Liu, Fei Huang, Haoyan Huang, Jiandong Jiang, Jianhong Tu, Jianwei Zhang, Jingren Zhou, and 1 others. 2025. Qwen2. 5-1m technical report. *ArXiv preprint*, abs/2501.15383.

Jiayi Yuan, Hongyi Liu, Shaochen Zhong, Yu-Neng Chuang, Songchen Li, Guanchu Wang, Duy Le, Hongye Jin, Vipin Chaudhary, Zhaozhuo Xu, and 1 others. 2024. Kv cache compression, but what must we give in return? a comprehensive benchmark of long context capable approaches. *ArXiv preprint*, abs/2407.01527.

Yuxin Zhang, Yuxuan Du, Gen Luo, Yunshan Zhong, Zhenyu Zhang, Shiwei Liu, and Rongrong Ji. 2024. Cam: Cache merging for memory-efficient llms inference. In *Forty-first International Conference on Machine Learning, ICML 2024, Vienna, Austria, July 21-27, 2024*. OpenReview.net.

Zhenyu Zhang, Ying Sheng, Tianyi Zhou, Tianlong Chen, Lianmin Zheng, Ruisi Cai, Zhao Song, Yuandong Tian, Christopher Ré, Clark W. Barrett, Zhangyang Wang, and Beidi Chen. 2023. H2O: heavy-hitter oracle for efficient generative inference of large language models. In *Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 - 16, 2023*.

Zayd Muhammad Kawakibi Zuhri, Muhammad Farid Adilazuarda, Ayu Purwarianti, and Alham Fikri Aji. 2024. Mlkv: Multi-layer key-value heads for memory efficient transformer decoding. *ArXiv preprint*, abs/2406.09297.

A Detailed Latency Comparison

To provide a more intuitive comparison of our method with other baselines, such as SnapKV, we conducted additional latency analysis experiments. These experiments were performed on a single A100-80GB GPU. We calculated the average wall-clock time (in seconds) for each method at different stages, with a fixed output length of 256 tokens and varying input lengths.

As shown in the Table 3, the additional Stage 2 in our method incurs a minimal time overhead, typically less than 5%. This minor increase in latency is a small trade-off for the significant performance enhancements in the eviction algorithm, particularly under low-budget conditions (see Table 1 in the main text and Tables 6 and 7 in the appendix). This demonstrates the practical value of our approach.

Table 3: Average wall-clock time (in seconds) for different methods. The output length is fixed at 256 tokens.

Method	Pre-filling	Stage 2	Decoding
INPUT 16K			
Full KV	1.46615	-	12.38489
StreamingLLM	1.49165	-	8.79209
H2O	1.47285	-	8.62985
SnapKV	1.48718	-	8.64949
LAQ++ (2)	1.46968	0.12636	8.75256
LAQ++ (8)	1.46952	0.31302	8.61714
INPUT 32K			
Full KV	3.58076	-	18.63942
StreamingLLM	3.65054	-	8.73857
H2O	3.58777	-	8.75228
SnapKV	3.61811	-	8.61096
LAQ++ (2)	3.59406	0.22643	8.83214
LAQ++ (8)	3.59088	0.41255	8.64124

B Analysis of Forward Templates

To investigate the impact of different forward templates, we conducted experiments using templates such as "The answer is" and "I have found the answer!". These templates were designed to provide a fixed semantic guide without requiring additional decode computation. The goal was to determine if the performance gains observed in our method, LAQ++, were due to semantic guidance rather than the query vector information derived from lookahead. The Table 4 shows the experimental results on the LongBench benchmark with a 512 KV-Cache budget for two different base models: Mistral-7B-v2.0-Instruct and Llama3.1-8B-Instruct. Unfortunately, our findings indicate

Table 4: LongBench scores for different forward templates with a 512 KV-Cache budget.

Base Model	Method	Score
Mistral	Full KV	42.74
	Streaming	31.63
	H2O	37.38
	SnapKV	40.51
	"The answer is"	38.20
	"I have found the answer!"	37.79
	LAQ++	**41.70**
Llama	Full KV	41.63
	Streaming	34.61
	H2O	35.72
	SnapKV	38.87
	"The answer is"	36.86
	"I have found the answer!"	36.59
	LAQ++	**40.39**

that these simple, fixed templates do not yield substantial performance improvements compared to other baselines. The scores for "The answer is" and "I have found the answer!" are significantly lower than those of our LAQ++ method and even SnapKV. This suggests that the performance gains

Table 5: RULER Task Performance on Llama 3.1-8B-Instruct

Method	Budget	Avg.
FullKV	32K	89.28
StreamingLLM	128	12.19
H2O	128	14.40
SnapKV	128	36.87
LAQ++	128	**51.57**
StreamingLLM	256	13.31
H2O	256	25.25
SnapKV	256	51.58
LAQ++	256	**62.81**
StreamingLLM	512	14.83
H2O	512	36.44
SnapKV	512	60.89
LAQ++	512	**69.83**

from LAQ++ are likely not due to simple semantic guidance provided by the text, but rather from the pseudo vector information that is more effectively aligned with the output distribution. Consequently, constructing the Q-Cache through a lookahead mechanism remains a crucial and necessary component of our approach.

C RULER Task Evaluation

Beyond the standard LongBench and "needle in a haystack" benchmarks, we have included a more challenging evaluation using the RULER task to assess the long-context capabilities of our model. The experimental setup is consistent with the methodology described in Section 5.1. The following Table 5 presents the experimental results for the Llama 3.1-8B-Instruct model:

As demonstrated by the results, the RULER task reveals a more significant performance differentiation among the various methods, particularly with a low KV-Cache budget. The proposed method, LAQ++, shows a nearly 10-point improvement over SnapKV when evaluated on this task.

D Full Evaluation on LongBench

We present additional experimental results, including those for Qwen2.5-7B-Instruct. The evaluation is conducted with a context length of 32K for Mistral and Qwen, 8K for Llama3, and 100K for Llama3.1.

E Evaluation on Needle-in-a-Haystack

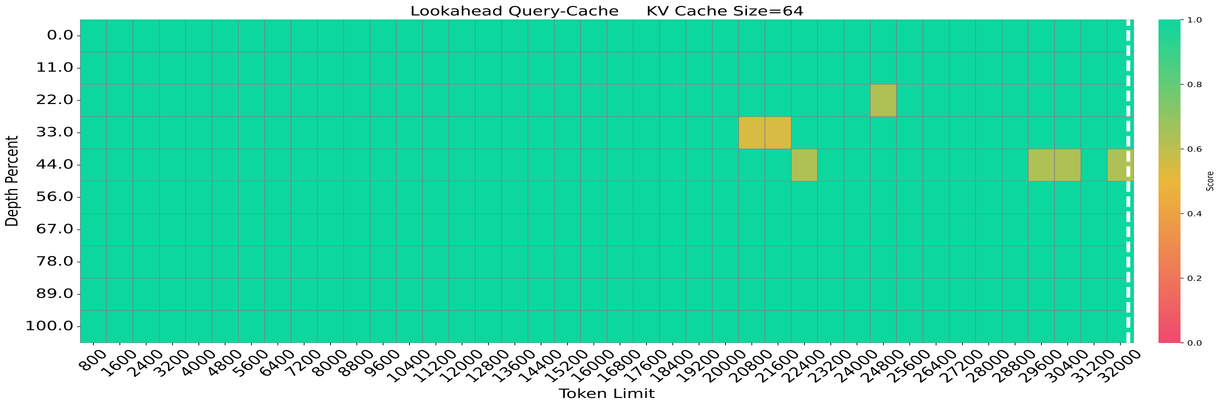
Due to space limitations, we present the complete results of the needle-in-a-haystack tests in the appendix. The evaluation covers models from the Mistral, Qwen, and LLaMA families, along with a range of representative KV cache eviction methods.

Table 6: Performance comparison of different methods across various LLMs on LongBench. The brackets in LAQ denote the Q-Cache length.

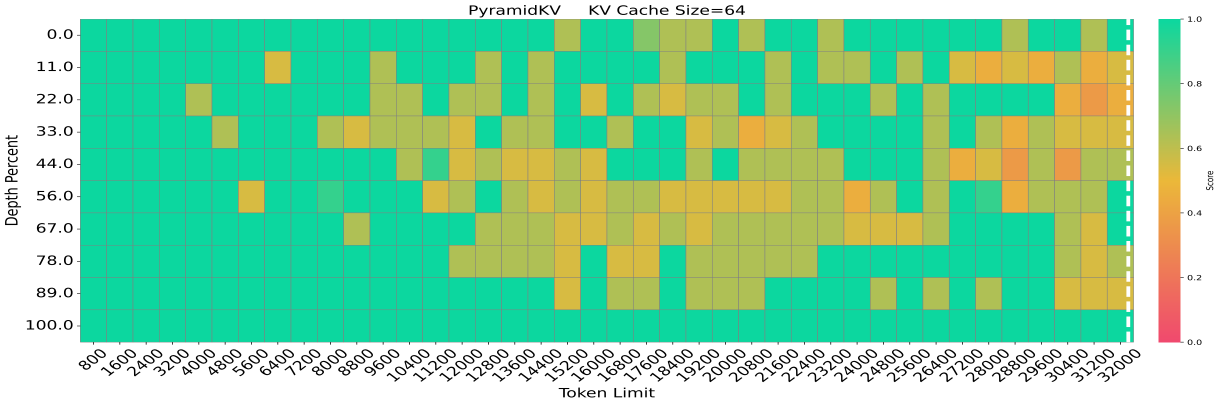
	LLMs	Single-Document QA			Multi-Document QA			Summarization			Few-shot Learning			Synthetic		Code		
		NrtvQA	Qasper	MF-en	HotpotQA	2WikiMQA	Musique	GovReport	QMSum	MultiNews	TREC	TriviaQA	SAMSum	PCount	PRe	Lcc	RB-P	Avg.
Mistral-7B-v0.2-Instruct	Full KV	26.90	33.14	49.26	42.77	27.35	18.77	32.95	24.21	27.13	71.00	86.23	42.72	2.75	86.98	57.12	54.51	42.74
	KV Cache Size = 128																	
	StreamingLLM	17.12	13.43	27.31	29.54	21.91	11.94	15.61	19.18	17.72	44.00	79.92	37.37	3.50	23.77	51.44	45.95	28.73
	H2O	21.62	21.34	38.61	30.46	20.38	12.20	20.59	22.51	22.03	39.00	82.33	40.64	3.06	**80.56**	51.17	48.46	34.69
	SnapKV	19.71	21.13	42.75	36.45	22.36	15.76	19.05	21.81	21.36	47.50	84.15	40.29	2.41	68.26	52.26	48.75	35.25
	PyramidKV	21.98	22.78	43.78	32.30	22.31	15.81	20.41	21.82	21.23	66.00	83.51	39.83	2.99	65.81	51.61	46.42	36.16
	LAQ(2)	24.12	24.60	43.96	**40.84**	25.94	17.37	21.51	21.82	**22.81**	**70.50**	86.22	40.27	2.69	66.00	51.78	47.44	37.99
	LAQ(8)	24.94	**27.77**	45.43	40.35	25.25	17.91	**22.06**	22.68	22.50	69.50	86.36	41.16	1.49	76.85	53.31	**51.02**	39.29
	LAQ(2)++	24.40	25.32	46.06	39.37	**26.11**	17.05	21.05	22.56	21.80	**70.50**	**86.39**	41.19	3.33	66.46	52.33	49.03	38.31
	LAQ(8)++	**25.62**	27.21	**46.16**	40.60	25.93	**18.44**	21.60	**23.07**	22.42	**70.00**	86.18	**42.03**	**3.51**	74.81	**54.68**	50.92	**39.57**
	KV Cache Size = 256																	
	StreamingLLM	19.22	15.08	28.01	30.40	22.02	11.21	18.09	19.59	20.09	51.00	80.71	39.89	2.96	18.40	54.30	47.38	29.90
	H2O	21.42	23.04	42.60	30.75	22.42	13.82	22.35	22.54	23.12	40.50	83.78	40.73	3.51	85.85	53.18	49.95	36.22
	SnapKV	22.44	24.07	48.01	38.66	22.66	15.59	21.83	23.23	22.94	61.50	85.45	41.32	3.13	85.79	55.11	51.73	38.97
	PyramidKV	21.69	25.18	47.61	38.77	26.12	15.23	22.52	22.52	22.59	68.00	84.27	42.10	3.43	76.60	53.08	48.40	38.63
	LAQ(2)	25.50	26.54	46.12	40.57	26.46	17.84	23.29	22.47	**23.84**	**70.50**	86.03	41.98	**3.63**	79.75	53.91	49.97	39.90
	LAQ(8)	24.68	**29.25**	48.00	40.56	26.01	18.24	**24.04**	22.96	23.80	70.00	85.81	42.52	2.01	82.34	54.96	**53.00**	40.51
	LAQ(2)++	**25.52**	26.90	47.71	41.12	**27.17**	**18.93**	23.02	23.24	23.25	**70.50**	**86.41**	41.83	3.38	79.25	54.59	50.86	40.23
	LAQ(8)++	25.23	29.16	**49.24**	**41.70**	26.85	18.62	23.73	**23.69**	23.38	**70.50**	86.24	**42.54**	3.36	**86.11**	**55.59**	52.49	**41.15**
	KV Cache Size = 512																	
	StreamingLLM	20.91	16.47	30.56	29.62	22.16	11.02	21.51	20.10	23.03	61.50	81.86	41.66	2.84	18.57	55.27	49.07	31.63
	H2O	21.72	25.54	44.72	32.39	23.16	14.75	23.61	23.03	24.58	42.00	85.22	41.61	**3.42**	86.45	54.82	51.11	37.38
	SnapKV	24.14	28.11	48.78	39.49	25.09	17.40	23.67	23.18	24.60	67.00	85.88	41.39	2.78	**86.56**	56.61	53.47	40.51
	PyramidKV	22.99	28.74	48.45	39.73	25.74	16.58	24.48	23.40	24.52	70.00	85.99	42.40	3.32	81.63	55.93	52.38	40.39
	LAQ(2)	25.32	28.71	47.79	40.87	26.60	18.48	25.18	23.51	24.96	**71.00**	86.30	42.91	2.50	83.90	55.05	51.30	40.90
	LAQ(8)	24.65	**31.21**	49.15	39.90	**27.18**	18.38	25.55	23.91	24.87	**71.00**	86.33	42.14	1.87	86.41	**56.84**	53.08	41.40
	LAQ(2)++	**26.24**	29.51	48.32	40.67	27.11	18.98	25.05	23.48	24.72	**71.00**	86.29	42.95	2.91	83.28	55.75	52.51	41.17
	LAQ(8)++	25.49	30.92	**49.72**	**41.50**	26.84	**19.20**	**25.67**	**24.04**	**25.31**	**71.00**	**86.43**	**43.14**	2.90	85.27	56.80	**53.54**	**41.70**
Llama3.1-8B-Instruct	Full KV	31.85	15.55	28.17	29.93	22.98	18.20	34.39	23.79	27.12	72.50	92.14	43.66	8.37	97.59	65.05	54.78	41.63
	KV Cache Size = 128																	
	StreamingLLM	16.46	5.11	14.05	14.52	14.61	7.08	17.16	20.00	18.10	40.50	87.93	38.31	**11.50**	95.47	58.39	47.52	31.67
	H2O	25.06	7.09	18.58	17.86	19.88	9.14	22.28	22.68	21.55	40.00	90.89	40.78	8.30	92.96	59.15	49.36	34.10
	SnapKV	24.65	7.29	22.01	19.11	18.85	11.07	20.48	21.62	20.16	47.50	90.24	40.47	10.75	92.51	59.99	49.08	34.74
	PyramidKV	24.79	8.29	20.72	14.86	13.84	8.90	22.41	22.76	21.53	62.00	90.35	39.23	9.27	93.51	58.77	46.46	34.86
	LAQ(2)	24.74	**11.12**	22.02	20.02	20.53	13.87	23.72	22.74	22.79	**72.50**	91.59	41.51	8.25	95.45	60.09	47.06	37.38
	LAQ(8)	27.80	10.66	24.86	20.64	20.04	15.40	**24.18**	23.09	**22.88**	**72.00**	91.55	**43.43**	9.04	**95.85**	61.12	50.33	38.30
	LAQ(2)++	**28.68**	10.51	24.92	20.53	20.32	14.50	22.88	23.16	22.45	**72.50**	91.65	41.59	8.21	91.96	61.72	49.30	37.81
	LAQ(8)++	28.65	10.65	**26.04**	**24.23**	**21.56**	**15.67**	23.50	**23.74**	22.75	**72.00**	**91.95**	42.19	8.37	94.81	**62.18**	**50.95**	**38.70**
	KV Cache Size = 256																	
	StreamingLLM	18.76	5.47	13.88	13.81	14.32	6.73	19.94	20.19	20.85	44.50	89.01	40.51	**11.33**	92.42	61.87	49.33	32.68
	H2O	26.01	8.42	19.69	17.28	18.21	9.91	23.64	22.89	23.20	41.50	91.29	41.60	8.00	94.31	60.79	50.31	34.82
	SnapKV	28.05	9.83	22.71	21.48	19.36	10.96	22.86	22.75	22.98	58.00	92.28	40.87	8.10	95.30	63.64	51.35	36.91
	PyramidKV	26.40	10.08	22.46	15.20	16.38	8.60	23.86	22.93	23.17	69.00	90.99	40.60	8.42	93.74	60.59	48.11	36.28
	LAQ(2)	28.23	11.51	24.66	21.57	22.81	15.15	24.81	23.18	23.83	**72.50**	92.25	43.13	8.52	94.30	62.01	49.93	38.65
	LAQ(8)	28.86	12.40	26.44	21.80	20.91	15.77	**25.83**	23.30	**24.26**	**72.50**	**93.08**	42.57	7.53	**95.80**	63.51	51.09	39.10
	LAQ(2)++	**30.49**	11.95	25.79	22.99	21.36	15.35	24.40	23.38	23.53	**72.50**	91.97	42.45	7.50	94.49	63.65	50.55	38.90
	LAQ(8)++	30.25	**12.43**	**26.63**	**25.77**	**22.83**	**18.45**	25.07	**23.67**	23.75	72.00	91.97	**43.17**	6.93	94.59	**64.07**	**53.38**	**39.69**
	KV Cache Size = 512																	
	StreamingLLM	20.86	6.62	14.97	14.74	13.87	6.79	22.78	20.84	23.93	57.00	89.57	41.10	**11.75**	93.73	63.37	51.79	34.61
	H2O	25.44	8.35	20.97	20.08	19.23	9.51	24.44	23.50	24.35	44.00	92.10	41.16	7.43	96.41	62.73	51.77	35.72
	SnapKV	30.34	10.75	23.54	24.65	21.55	12.98	24.82	23.15	24.61	68.00	**92.33**	42.16	7.83	96.86	64.74	**53.60**	38.87
	PyramidKV	28.38	11.59	25.02	20.06	18.80	10.64	25.73	24.03	25.01	70.00	92.22	41.73	8.47	96.42	63.44	51.02	38.29
	LAQ(2)	30.65	12.95	26.69	25.29	22.31	16.57	26.51	22.99	25.27	**72.50**	92.25	42.88	8.11	96.66	64.09	51.56	39.83
	LAQ(8)	**30.89**	**14.04**	25.86	26.00	23.19	17.73	**27.07**	24.01	**25.29**	**72.50**	92.25	**43.13**	6.96	**96.97**	64.87	52.58	40.21
	LAQ(2)++	30.85	12.95	26.03	27.31	21.66	17.73	26.40	23.51	24.83	**72.50**	91.97	43.01	7.90	96.79	64.17	52.84	40.03
	LAQ(8)++	29.64	13.22	**26.79**	**27.58**	**23.49**	**18.63**	26.94	**24.04**	25.21	**72.50**	92.25	42.83	8.43	96.25	**65.00**	53.37	**40.39**

Table 7: Performance comparison of different methods across various LLMs on LongBench. The brackets in LAQ denote the Q-Cache length.

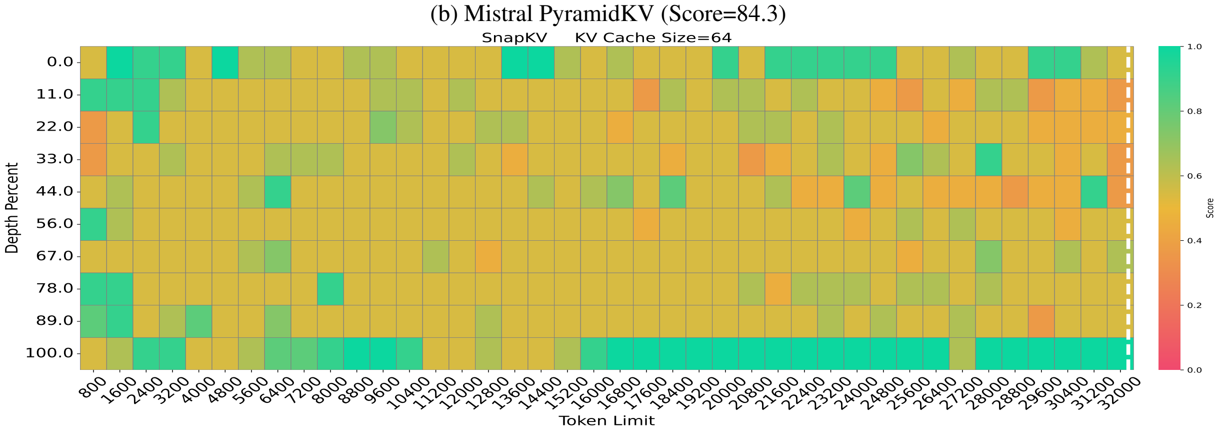
	LLMs	Single-Document QA			Multi-Document QA			Summarization			Few-shot Learning			Synthetic		Code		Avg.
		NrtvQA	Qasper	MF-en	HotpotQA	2WikiMQA	Musique	GovReport	QMSum	MultiNews	TREC	TriviaQA	SAMSum	PCount	PRe	Lcc	RB-P	
Qwen2.5-7B-Instruct	Full KV	17.07	43.76	52.61	57.70	47.13	29.85	32.00	23.61	23.95	39.50	87.65	40.08	8.50	100.00	6.62	9.79	38.74
	KV Cache Size = 128																	
	StreamingLLM	11.77	23.65	26.44	40.90	37.09	16.42	16.12	18.03	14.69	12.00	76.26	35.50	**8.50**	24.50	**10.26**	**13.44**	24.10
	H2O	16.61	29.58	37.25	51.04	42.14	20.82	20.33	**22.05**	18.07	18.50	80.85	**39.04**	**8.50**	**98.00**	6.29	9.77	32.43
	SnapKV	16.23	32.72	45.14	52.95	44.10	24.16	19.27	20.81	17.27	21.50	85.83	37.75	**8.50**	95.00	7.26	11.28	33.74
	PyramidKV	15.40	30.67	44.89	51.54	41.22	25.62	19.51	19.71	16.69	25.75	84.22	34.08	**8.50**	96.00	5.29	6.32	32.84
	LAQ(2)	15.32	35.05	46.87	54.16	42.66	25.82	21.52	20.90	18.48	33.50	87.52	37.58	**8.50**	97.00	4.90	7.25	34.81
	LAQ(8)	17.98	39.17	48.85	56.76	44.96	**28.96**	**22.39**	20.66	**18.77**	35.00	87.78	37.75	**8.50**	**98.00**	5.82	9.35	36.29
	LAQ(2)++	**18.21**	36.81	48.80	55.97	44.96	28.91	21.24	21.22	18.09	33.00	**87.96**	36.52	**8.50**	96.00	5.35	7.58	35.57
	LAQ(8)++	18.14	**39.40**	**50.26**	**56.83**	**46.07**	28.12	21.74	21.80	18.65	**35.50**	87.56	37.06	**8.50**	**98.00**	6.13	9.96	**36.48**
	KV Cache Size = 256																	
	StreamingLLM	11.50	24.44	26.81	41.85	37.25	17.39	18.90	18.12	17.11	17.50	80.66	37.47	**9.00**	24.50	**8.42**	**13.54**	25.28
	H2O	16.05	32.25	43.63	52.73	43.40	23.98	22.66	22.30	19.60	19.50	83.55	39.24	8.50	**99.50**	6.71	9.29	33.93
	SnapKV	16.25	36.47	50.35	55.44	44.37	26.62	21.96	21.76	19.35	31.00	86.89	38.47	8.50	98.00	6.52	9.98	35.75
	PyramidKV	16.81	34.46	47.17	54.72	42.74	25.86	21.45	20.39	17.61	33.75	85.76	36.93	8.50	98.50	5.15	7.21	34.81
	LAQ(2)	16.31	39.64	47.04	57.01	44.78	27.35	23.86	21.59	19.69	36.00	87.81	38.98	8.50	98.50	5.35	7.51	36.25
	LAQ(8)	**17.62**	**41.16**	50.84	57.16	**46.48**	**29.37**	**24.23**	22.17	**20.30**	38.50	**88.10**	**39.12**	8.50	99.00	6.14	9.83	**37.41**
	LAQ(2)++	16.79	38.96	49.78	57.13	45.59	27.95	23.27	21.33	19.92	**39.00**	87.51	37.82	8.50	98.50	5.40	8.07	36.60
	LAQ(8)++	16.76	41.04	**51.23**	**57.50**	45.94	28.28	24.09	**22.36**	20.24	38.00	87.61	38.54	8.50	98.50	6.93	9.84	37.21
	KV Cache Size = 512																	
	StreamingLLM	12.56	27.00	29.75	42.48	36.44	16.15	22.30	18.68	20.01	24.00	83.99	38.09	**8.50**	24.00	**8.36**	**12.54**	26.55
	H2O	16.77	35.32	45.82	52.30	44.39	24.29	24.20	22.29	21.45	21.00	86.29	39.16	**8.50**	**100.00**	6.82	9.09	34.86
	SnapKV	17.63	40.73	50.71	55.63	45.18	27.85	24.41	22.84	21.16	38.50	**88.12**	39.21	**8.50**	99.50	7.09	10.16	37.33
	PyramidKV	17.49	37.81	50.45	56.36	44.64	27.46	23.00	20.97	19.60	35.25	87.62	37.82	**8.50**	99.00	5.62	7.94	36.22
	LAQ(2)	16.46	41.86	49.68	57.64	46.46	27.79	25.71	21.72	21.58	38.50	87.55	**40.02**	**8.50**	**100.00**	5.45	8.42	37.33
	LAQ(8)	17.26	42.64	**51.73**	57.56	46.59	29.12	**26.57**	22.67	21.86	**39.00**	87.65	39.40	**8.50**	**100.00**	6.52	9.91	**37.94**
	LAQ(2)++	**17.92**	41.84	50.99	**57.76**	46.74	28.72	25.30	22.05	21.63	38.75	87.65	39.13	**8.50**	99.50	5.56	8.25	37.52
	LAQ(8)++	17.31	**43.32**	51.17	57.61	**46.81**	**29.29**	25.98	**22.97**	**21.96**	**39.00**	87.65	39.01	**8.50**	99.50	6.75	10.11	37.93
Llama3-8B-Instruct	Full KV	25.56	32.27	39.71	43.56	35.09	21.18	28.71	23.26	26.64	73.50	90.48	42.33	4.80	69.25	59.29	54.05	41.86
	KV Cache Size = 128																	
	StreamingLLM	18.13	8.54	21.21	32.86	26.27	15.41	16.71	20.46	18.06	45.00	74.58	36.32	5.75	68.50	56.12	53.06	32.31
	H2O	22.12	13.19	29.53	37.42	32.71	18.25	20.49	22.03	21.11	38.50	87.75	39.14	5.83	**69.50**	57.01	54.74	35.58
	SnapKV	20.96	13.63	30.75	36.65	29.24	19.12	19.07	21.67	20.19	45.00	87.82	38.01	5.13	69.35	57.51	55.31	35.59
	PyramidKV	21.40	16.92	31.62	38.45	28.72	18.59	19.96	**22.49**	20.96	66.50	89.35	38.43	**5.92**	69.00	57.86	51.80	37.37
	LAQ(1)++	**25.01**	16.34	33.73	**42.92**	35.00	19.54	20.23	22.32	21.73	73.50	90.25	39.18	5.18	**69.50**	59.05	54.61	39.26
	LAQ(8)++	24.75	**18.87**	**34.84**	41.13	**36.50**	**20.13**	**21.32**	22.20	**22.32**	**74.00**	**90.37**	**40.38**	5.39	**69.50**	**60.94**	**57.64**	**40.02**
	KV Cache Size = 256																	
	StreamingLLM	17.98	11.10	20.58	33.68	26.16	16.03	19.24	20.46	20.80	52.50	80.18	39.31	**5.83**	68.37	58.56	54.46	34.08
	H2O	23.82	16.61	31.66	38.64	31.72	20.05	21.28	22.22	22.19	39.00	89.22	39.52	5.57	69.50	58.01	54.28	36.46
	SnapKV	24.35	18.32	33.83	42.23	32.89	20.73	20.74	22.05	22.54	62.00	90.14	39.51	5.75	**70.00**	59.76	56.66	38.84
	PyramidKV	23.99	20.51	36.06	42.47	31.34	20.28	21.37	**22.69**	22.79	71.00	**90.48**	39.86	5.83	69.25	58.64	54.06	39.41
	LAQ(1)++	24.57	21.01	35.80	43.52	35.23	20.62	21.61	22.20	23.18	73.50	90.44	40.32	5.50	69.70	59.46	56.62	40.21
	LAQ(8)++	**24.51**	**22.56**	**37.15**	**44.31**	**36.79**	**21.60**	**22.61**	22.30	**23.47**	**73.50**	90.37	**41.46**	5.64	69.70	**62.04**	**58.00**	**41.00**
	KV Cache Size = 512																	
	StreamingLLM	20.70	12.16	22.06	35.93	26.75	15.79	21.00	20.62	23.73	62.00	83.36	39.98	5.35	67.97	60.32	55.13	35.80
	H2O	23.52	17.89	33.52	41.71	33.56	19.27	22.17	22.64	23.83	41.00	90.46	40.20	5.87	69.50	58.14	56.01	37.46
	SnapKV	24.85	23.49	36.53	42.96	34.93	20.28	22.40	22.66	23.80	70.50	90.52	40.39	5.81	**70.00**	60.45	56.17	40.36
	PyramidKV	24.83	23.32	35.19	43.29	31.87	20.55	23.41	**22.80**	24.29	71.50	90.61	40.81	**5.91**	69.50	59.60	54.71	40.14
	LAQ(1)++	24.96	25.91	37.07	43.19	**37.09**	21.49	23.10	22.61	24.26	**73.50**	**90.64**	41.61	5.43	69.70	60.89	57.83	41.21
	LAQ(8)++	**25.53**	**27.59**	**37.99**	**43.82**	36.52	**21.55**	**23.58**	22.64	**24.63**	**73.50**	**90.64**	**42.34**	5.13	69.70	**62.77**	**58.45**	**41.65**



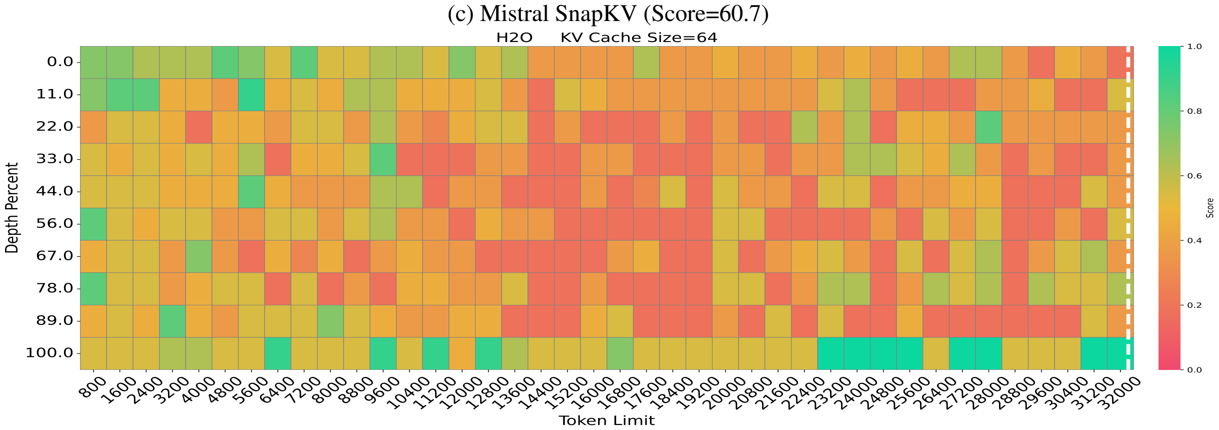
(a) Mistral LAQ++ (Score=99.3)



(b) Mistral PyramidKV (Score=84.3)

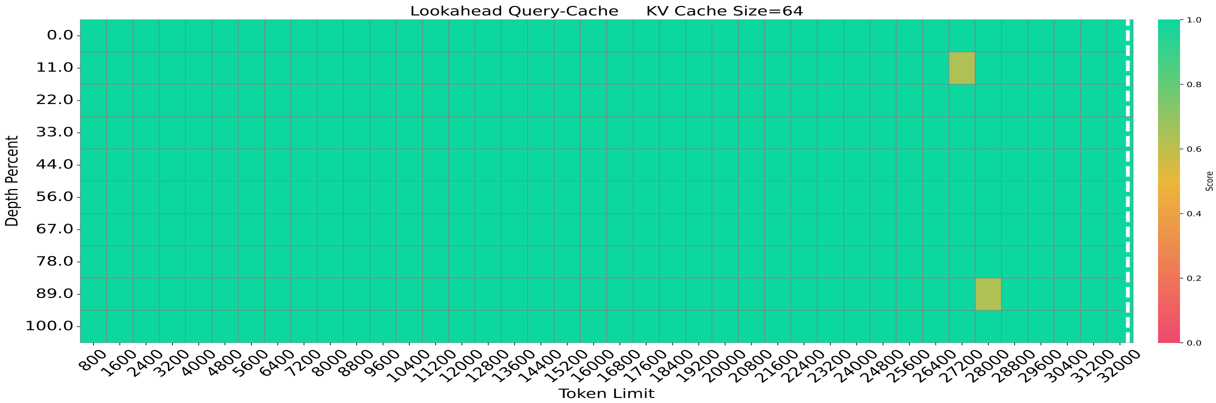


(c) Mistral SnapKV (Score=60.7)

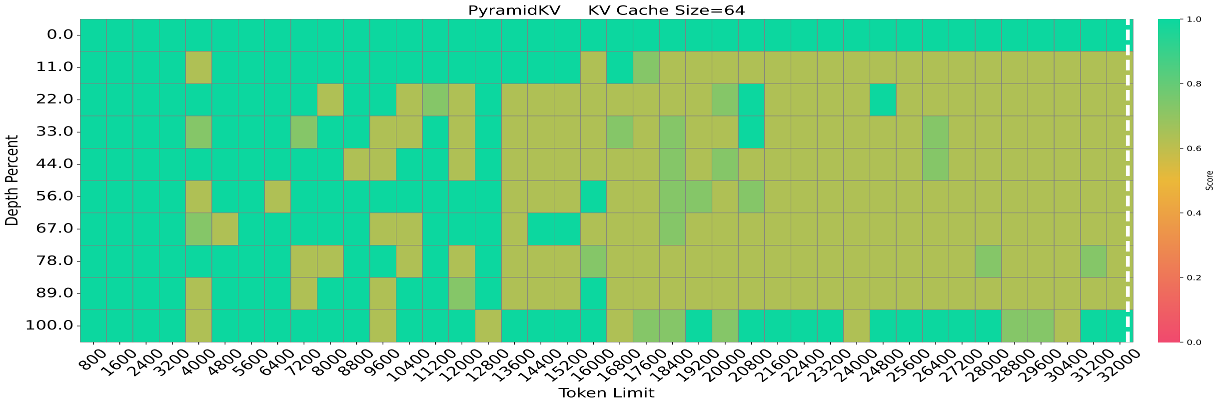


(d) Mistral H2O (Score=43.2)

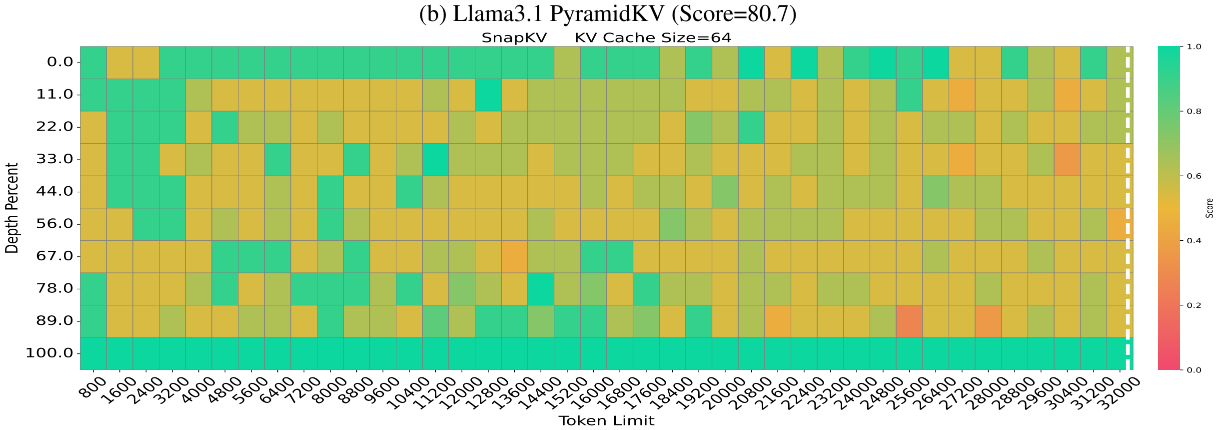
Figure 8: The results of different methods of Mistral-7B-v0.2-Instruct on the needle-in-a-haystack with 32k context size under a budget setting of 64.



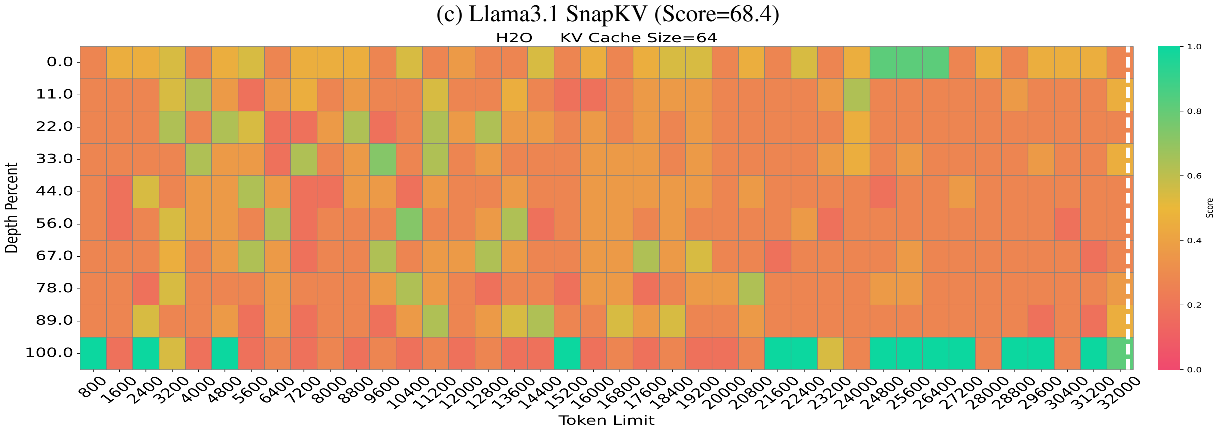
(a) Llama3.1 LAQ++ (Score=99.8)



(b) Llama3.1 PyramidKV (Score=80.7)

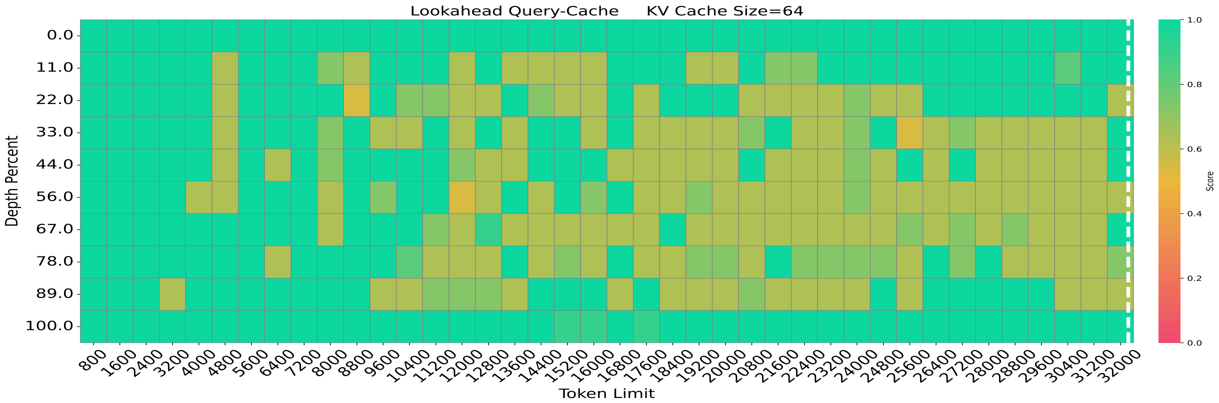


(c) Llama3.1 SnapKV (Score=68.4)

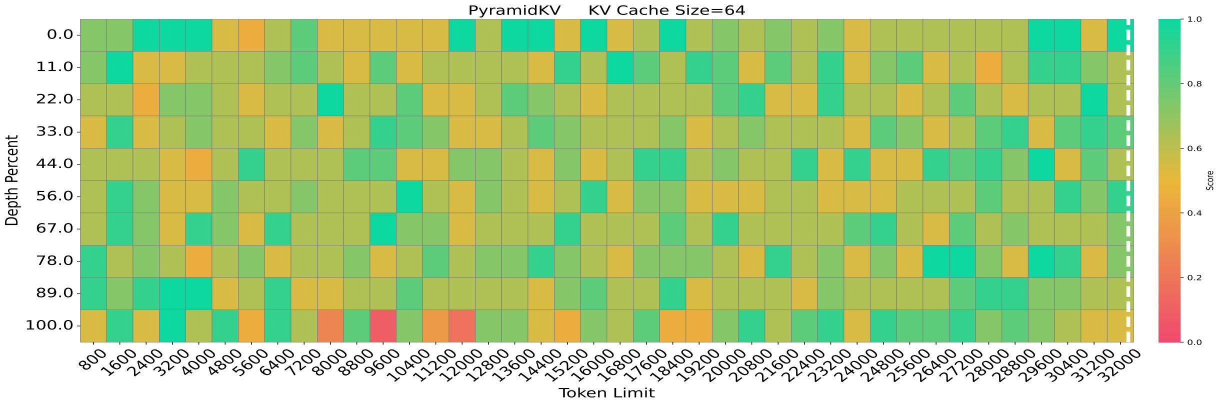


(d) Llama3.1 H2O (Score=35.4)

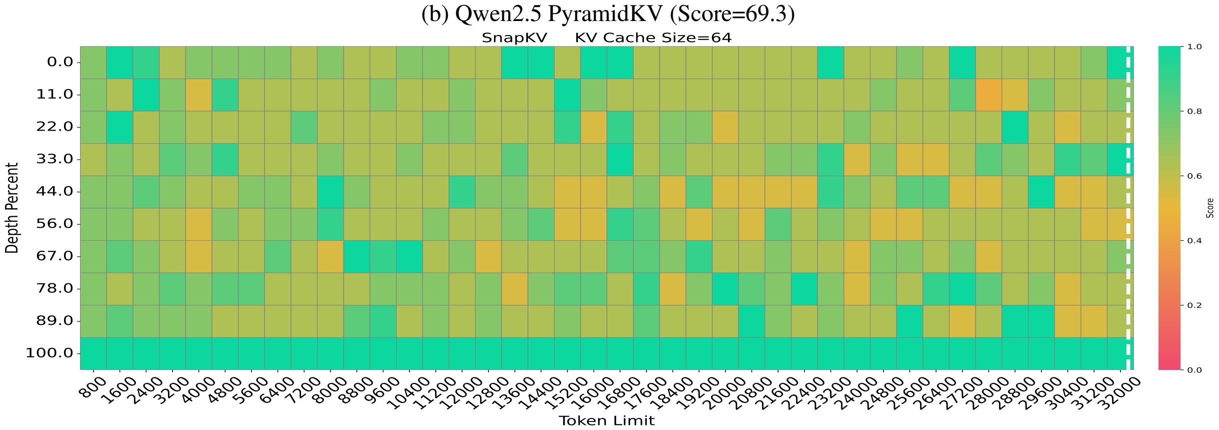
Figure 9: The results of different methods of Llama3.1-8B-Instruct on the needle-in-a-haystack with 32k context size under a budget setting of 64.



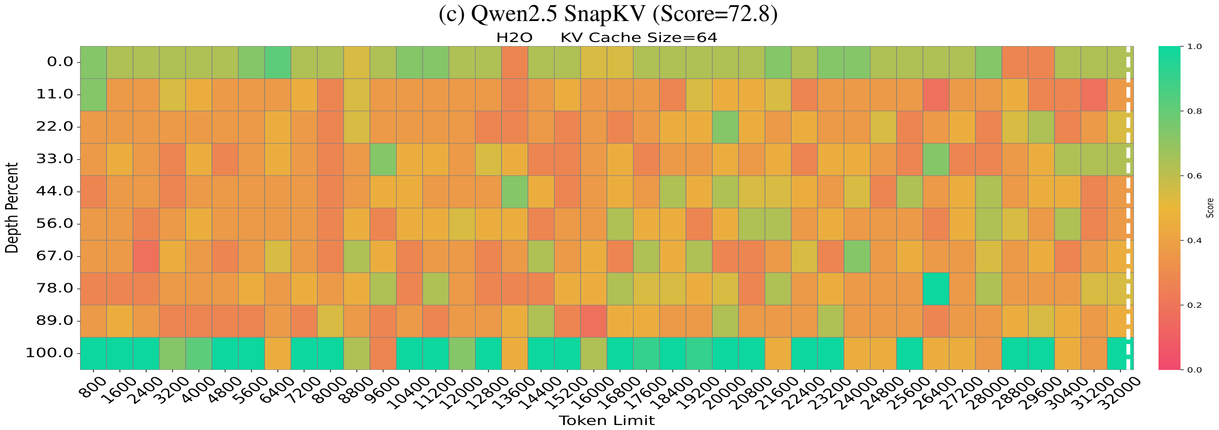
(a) Qwen2.5 LAQ++ (Score=85.1)



(b) Qwen2.5 PyramidKV (Score=69.3)



(c) Qwen2.5 SnapKV (Score=72.8)



(d) Qwen2.5 H2O (Score=46.7)

Figure 10: The results of different methods of Qwen2.5-7B-Instruct on the needle-in-a-haystack with 32k context size under a budget setting of 64.