PromptDistill: Query-based Selective Token Retention in Intermediate Layers for Efficient Large Language Model Inference

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Abstract

As large language models (LLMs) tackle increasingly complex tasks and longer documents, their inference cost becomes a major bottleneck. To address this, we propose PromptDistill, a novel, training-free method that improves inference efficiency while preserving generation quality. PromptDistill identifies and retains the most informative tokens by leveraging early-layer attention, preserving their hidden states while reducing computation in later layers. Unlike previous methods such as H2O, SnapKV, and GemFilter, which perform compression only after full input processing, or ignore contextual dependencies, PromptDistill dynamically allocates computation to relevant tokens while maintaining global context. Experiments on LLaMA 3.1 8B, Phi 3.5 Mini, Qwen2 7B/14B, Phi 3 128k across LongBench, InfBench, and Needle in a Haystack demonstrate that PromptDistill achieves substantial efficiency gains with minimal quality loss. With a single-stage selection strategy, it outperforms GemFilter, H2O, and SnapKV, achieving an overall 1% to 5% performance improvement with faster inference. Additionally, we explore multi-stage selection, which further improves efficiency while maintaining strong generation performance. These results demonstrate the adaptability of LLM hidden representations and provide valuable insights into optimizing inference for long-context scenarios. Link to codes will be added after anonymous review.

1 Introduction

Large language models (LLMs), such as GPT, LLama, Gemini, Mistral, and Claude (Brown et al., 2020; Grattafiori et al., 2024; Team et al., 2024; Jiang et al., 2023; Anthropic, 2024) have achieved remarkable success across various natural language processing (NLP) tasks, demonstrating strong generalization and reasoning abilities. However, their widespread deployment is often hindered by the high computational and memory costs, particularly during inference with long context. As context lengths continue to grow in modern LLM applications, efficiently handling extended inputs while preserving generation quality has become a critical challenge.

Some approaches, such as MCSD and Mamba (Yang et al., 2024b; Gu and Dao, 2024), attempt to mitigate this issue by compressing internal states into a single vector. While these methods reduce processing complexity from quadratic to linear, they often suffer from performance degradation and scalability challenges, as their designs sacrifice key Transformer advantages. Other methods modify existing architectures to optimize inference efficiency, requiring extensive retraining to adapt model parameters to the new structure (Wang et al., 2024; Gao et al., 2024). Several recent studies further explore training-based compression strategies. CCA-Attention (Chen et al., 2025b) introduces a plug-and-play attention mechanism that dynamically groups and compresses tokens into core representations with minimal fine-tuning. QwenLong-CPRS (Shen et al., 2025) employs instruction-guided, dynamic context optimization with token-critic mechanisms to enhance long-context performance. Although these approaches achieve strong efficiency and accuracy, they depend on additional training or architectural modifications, which limit their direct applicability to existing models.

Methods like H2O and Snap (Zhang et al., 2023; Li et al., 2024b) require no extra training and can be directly applied to existing models for long-context compression. However, they still process all prompt tokens through all model layers once before compression, resulting in significant computational overhead. GemFilter (Shi et al., 2024), which also requires no extra training, mitigates this issue by processing only part of the layers for all prompt tokens before selecting the most important ones. It then re-runs the model using only the selected tokens for full-layer processing. While

this reduces computational cost and GPU memory usage, it also discards all unselected tokens' hidden representations, retaining only token IDs after early-layer processing. This may lead to information loss, disrupt context structures, and ultimately impact performance, especially when the selection process is imperfect or the number of retained tokens is limited.

We propose PromptDistill, a training-free method to address these limitations, achieving high efficiency while maintaining performance. First, we process a few layers for all tokens as in traditional transformers. Then, we select the most important prompt tokens based on the dot product between the query of the last prompt token and the key of each token. This selection criterion is similar to GemFilter, but instead of reprocessing the selected tokens from the first layer, we retain their hidden states after the selection layer and continue processing them through the remaining layers. The selected tokens' hidden states already capture context information from earlier layers' self-attention, allowing us to preserve more comprehensive context and the model's original structure without additional computation.

A potential efficiency issue is that during generation, each new token attends to all prompt tokens in the initial layers, leading to high time and memory costs. To mitigate this, we introduce cache truncation, clearing the keys and values of unselected tokens in the key-value cache for layers before selection. This improves both time and memory efficiency while maintaining performance (as shown in section 2.3 and section 3.3). Our method thus achieves slightly better computational efficiency than GemFilter since we avoid recomputing the selected tokens in the first few layers.

Unlike GemFilter, which can select important tokens only once in a specific layer, PromptDistill allows for multi-stage selection across layers. Early layers struggle to select tokens effectively (Voita et al., 2019), but selecting more tokens in these layers can still enhance efficiency without sacrificing performance. A combination of selecting many tokens in the early layers and fewer in later layers strikes a balance between efficiency and effectiveness.

In our experiments, we apply PromptDistill to LLMs such as LLaMA-3.1, Qwen2(7B), Qwen2.5(14B), Phi3(mini), Phi3(medium), and Phi3.5(Grattafiori et al., 2024; Yang et al., 2024a; Abdin et al., 2024) and evaluate on reliable benchmarks like Longbench, Infbench, and Needle in a Haystack (Bai et al., 2024; Zhang et al., 2024a; Nelson et al., 2024). These extensive experiments clearly show that our method outperforms baseline methods, including full attention, GemFilter, SnapKV, and H2O (Shi et al., 2024; Li et al., 2024b; Zhang et al., 2023). In particular, compared to GemFilter, our method improves time efficiency and achieves better performance.

Additionally, we provide a comprehensive analysis of other aspects of our method, demonstrating how multi-stage selection improves efficiency while preserving performance.

Our contributions are summarized as:

- We propose PromptDistill, a training-free, generic modification for LLMs that significantly boosts efficiency while maintaining comparable performance to full attention. It selects key tokens and retains their hidden states in intermediate layers to create an informative compression of the entire prompt.
- We conduct extensive zero-shot experiments with single-stage selection to evaluate PromptDistill's ability to balance effectiveness and efficiency compared to several well-designed baselines.
- With multi-stage selection, PromptDistill further reduces computational costs without sacrificing performance. The experiments also provide insights into token representativeness across different layers.

2 Method

2.1 Background

To provide a clear background for our approach, PromptDistill, discussed in section 2.2, we first define the relevant preliminaries and introduce the token selection method used in our approach. For a typical LLM, let n represent the input token sequence length, m the attended token sequence length, d the hidden feature dimension, and i the index of a layer. For layer i, the query matrix is $Q^{(i)} \in \mathbb{R}^{n\times d}$, the key matrix is $K^{(i)} \in \mathbb{R}^{m\times d}$, and the value matrix is $V^{(i)} \in \mathbb{R}^{n\times d}$. The standard self-attention operation for each token is:

$$\text{Self-Attn}(Q^{(i)}, K^{(i)}, V^{(i)})$$

$$= \text{Softmax}(\frac{Q^{(i)}K^{(i)\top}}{\sqrt{d}}) \cdot V^{(i)},$$

where $Q^{(i)}K^{(i)\top}$ computes pairwise interactions among tokens, indicating the relative importance of each token within layer i. These pairwise scores are key for identifying salient segments in the input sequence.

Given the input prompt $\mathbf{X} = (x_1, x_2, \ldots, x_n)$ (embedded in $\mathbb{R}^d$ per token) for the LLM, our objective is to efficiently process it and generate high-quality responses. The GemFilter method illustrates that the LLMs can identify important tokens in early layers by attention matrices (Shi et al., 2024). Based on this knowledge, the token selection method plays an important role in enabling our approach, PromptDistill, to achieve its objective.

Specifically, the token selection method identifies the top k important tokens for a given selection layer r using the queries and keys defined above:

$$\text{Select}(Q_n^{(r)}, K^{(r)}, k) = \text{Top}_k \text{Argmax}_j Q_n^{(r)} K_j^{(r)T}$$

2.2 PromptDistill

In section 2.2.1, we introduce the basic design of PromptDistill with single-stage selection, excluding cache truncation. This design has efficiency limitations, which are addressed by the cache truncation process described in section 2.2.2. The combination of both forms our proposed method. We present comprehensive experiments comparing it to multiple baselines, with results in section 3.2. In section 2.2.3, we extend our method to multi-stage selections, with corresponding results in section 3.3.

2.2.1 Basic design

We outline the basic design of PromptDistill in algorithm 2 and algorithm 3 (both included in section D). While algorithm 2 shows the overall process from receiving the prompt to generating the output, algorithm 3 focuses on the core prompt processing and compression.

In algorithm 2, after receiving the embedded prompt, algorithm 3 processes it. We run several layers and collect the key-value cache as usual. After the rth layer, the token selection method in section 2.1 selects the top k tokens. Unlike GemFilter, we retain the hidden states of selected tokens after the rth layer and process the remaining layers for these tokens. This way, even unselected tokens' information is roughly captured in the selected tokens' hidden states due to prior self-attention.

After algorithm 3, the first generated token and previous cache are fed into the normal LLM forward process to generate the remaining tokens. Our approach differs from typical LLMs in that the key-value cache is smaller, as only selected tokens are processed in layers after the rth layer.

2.2.2 Cache truncation

Algorithm 1 LLM-forward-PromptDistill (with cache truncation)

Input: LLM $M_{0:R}$, embedded input prompt X, selection layer r, number of selected tokens k
Cache $\leftarrow$ [ ]
for $i \leftarrow 0 \ldots R$ **do**
  $X, Q_n^{(i)}, K^{(i)}, V^{(i)} \leftarrow M_i(X)$
  Cache$_i \leftarrow K^{(i)}, V^{(i)}$
  if i equals r **then**
    indices $\leftarrow$ Select$(Q_n^{(i)}, K^{(i)}, k)$
    $X \leftarrow X_{\text{indices}}$
    for $j \leftarrow 0 \ldots i$ **do**
      $K^{(j)}, V^{(j)} \leftarrow$Cache$_j$
      $K^{(j)} \leftarrow K^{(j)}_{\text{indices}}$
      $V^{(j)} \leftarrow V^{(j)}_{\text{indices}}$
      Cache$_j \leftarrow K^{(j)}, V^{(j)}$
    end for
  end if
end for
return generate(X), Cache

Although our basic design is significantly more efficient than typical LLMs, which process all tokens across all layers and retain the full key-value cache for generation, it still has efficiency limitations. Specifically, each newly generated token continues to attend to all prompt tokens in the initial layers, leading to unnecessary computational overhead (further discussed in section 2.3). To address this, we introduce a cache truncation mechanism to further reduce computation costs.

The forward function of PromptDistill with cache truncation is detailed in algorithm 1. Compared to the basic design, after selecting important tokens and discarding the hidden states of unselected ones, we further prune the key-value cache by keeping only entries corresponding to the selected tokens across all processed layers. This significantly reduces both computation time and GPU memory usage, making our method even more time-efficient than GemFilter.

Crucially, our experiments show that cache truncation does not degrade performance (see section 3.3). Therefore, we adopt PromptDistill with cache truncation as our proposed method.

2.2.3 Multi-stage selection

Unlike GemFilter, which can only select tokens at a single layer, our approach allows multiple selection stages. The key insight behind multi-stage selec-

tion is that LLMs have limited ability to identify and compress important tokens in very early layers. A single selection in a mid-layer with a small number of tokens requires processing all tokens in many layers before selection, leading to high computational and memory costs. Instead, selecting a large number of tokens in early layers and refining the selection in later layers provides a better balance between efficiency and effectiveness.

Algorithm 4 (included in section D) integrates multi-stage selection with cache truncation. Here the selection layer r becomes a list of layers, and k corresponds to the number of selected tokens at each stage. Unlike single-stage selection, where the cache is truncated to match the final selection size, multi-stage selection introduces a user-defined parameter tt, representing the number of truncation steps. This ensures that the final cache size matches $k[tt-1]$.

The model processes layers normally until reaching a selection layer, where it retains only the selected tokens' hidden states. If this is the p-th selection step (p starting from 0) and $p < tt$, truncation is applied to remove unselected tokens from all completed layers. The process repeats until all layers are completed, allowing for flexible cache structuring for further token generation.

To maintain consistency in baseline comparisons, we primarily evaluate the single-stage version of PromptDistill. However, we showcase the effectiveness of multi-stage selection in our analysis.

2.3 Theoretical Analysis

In table 1, we provide a theoretical comparison of computation time and GPU memory usage between our method and various baselines. Variable definitions are provided in the table caption. To ensure consistency, we analyze PromptDistill with single-stage selection and cache truncation. "AllKV" refers to the original LLM using full attention. Baseline values are taken from GemFilter's paper (Shi et al., 2024), with our method's values added for comparison.

Inference efficiency is analyzed in two parts: prompt computation and token generation. For GemFilter, all n tokens are processed for r layers to select k important tokens, which are then used for rerunning the full m layers to generate tokens. They put the part of processing all tokens in r layers in the prompt computation stage and the remaining, including processing the selected prompt, in the generation stage. Following this structure, we also place our computation for the first r layers in the prompt computation stage, while the subsequent processing of selected tokens and token generation falls under the generation stage.

For the time cost, in the first stage, both PromptDistill and GemFilter only need to run r layers for all tokens, while other methods run all layers for all tokens. This gives PromptDistill and GemFilter the same time cost in this stage, both better than other methods. In the second stage, while GemFilter runs selected prompt tokens for $\Theta(mhk^2d)$, PromptDistill only processes the remaining $m-r$ layers for the selected tokens' hidden states, requiring $\Theta((m-r)hk^2d)$. Both methods then generate t tokens with a key-value cache size of k, taking $\Theta(mh(kt+t^2)d)$. Thus, GemFilter's total time cost in the second stage is $\Theta(mhk^2d + mh(kt+t^2)d) = \Theta(mh(k^2+t^2)d)$, while PromptDistill's is $\Theta((m-r)hk^2d + mh(kt+t^2)d) = \Theta(mh(k^2+t^2)d - rhk^2d)$. Since GemFilter is already more efficient than AllKV, SnapKV, and H2O(Shi et al., 2024) as shown in its paper, and PromptDistill further improves generation time efficiency over GemFilter, PromptDistill achieves the best overall time efficiency.

For GPU memory usage, in the first stage, we require only r layers of model weights, which is rw, the same as GemFilter. Since all keys and values must be stored before selecting tokens, memory usage is $2rhnd$, proportional to the number of layers before selection. In the second stage, we retain the full model weights and store up to $k+t$ tokens' keys and values for all layers, the same as GemFilter, SnapKV, and H2O.

Further analysis about theoretical analysis for different settings of PromptDistill (without Cache Truncation, with multi-stage selection) is presented in section E.

3 Experiments

3.1 Experimental Setup

For our main experiments, we use PromptDistill with single-stage selection and cache truncation. Since compression methods primarily improve efficiency for long inputs, we evaluate on three authoritative long-context benchmarks: LongBench, InfBench, and Needle in a Haystack (Bai et al., 2024; Zhang et al., 2024a; Nelson et al., 2024).

For base models, we select Llama 3.1 8B Instruct (supporting 128000 input length), Phi 3.5 Mini Instruct (supporting 128000 input length), Qwen2 7B

Table 1: Complexity Analysis. Here m is the total layer number of LLM, h is the number of attention heads, n is prompt token length, d is the hidden dimension of each head, r is the index of layer for token selection in GemFilter and PromptDistill, k is the number of selected tokens (for GemFilter and PromptDistill) and the cache size for generation (for SnapKV, H2O, GemFilter and PromptDistill), t is the number of generated tokens, w is the GPU memory used for model parameters in each layer, $n \geq max\{d, k, t\}$

	Stage	AllKV	SnapKV and H2O	GemFilter	PromptDistill (proposed)	PromptDistill (no truncation)
Time	Prompt	$\Theta(mhn^2d)$	$\Theta(mhn^2d)$	$\Theta(rhn^2d)$	$\Theta(rhn^2d)$	$\Theta(rhn^2d)$
	Generation	$\Theta(mh(nt+t^2)d)$	$\Theta(mh(kt+t^2)d)$	$\Theta(mh(k^2+t^2)d)$	$\Theta(mh(k^2+t^2)d - rhk^2d)$	$\Theta(mh(k^2+t^2)d + rh(nt-kt-k^2)d)$
GPU	Prompt	$mw + 2mhnd$	$mw + 2hnd + 2mhkd$	$rw + 2hnd$	$rw + 2rhnd$	$rw + 2rhnd$
	Generation	$mw + 2mh(n+t)d$	$mw + 2mh(k+t)d$	$mw + 2mh(k+t)d$	$mw + 2mh(k+t)d$	$mw + 2mh(k+t)d + 2rh(n-k)d$

Instruct (supporting 32768 input length), Qwen2.5 14B Instruct (supporting 32768 input length), Phi 3 medium 128k instruct (supporting 128000 input length), and Phi 3 mini 128k instruct (supporting 128000 input length) (Grattafiori et al., 2024; Abdin et al., 2024; Yang et al., 2024a). Baseline methods include full attention (original model), SnapKV, H2O, and GemFilter (Li et al., 2024b; Zhang et al., 2023; Shi et al., 2024). For both PromptDistill and GemFilter (Shi et al., 2024), a selection layer must be specified. We use layer 13 (out of 32) for Llama 3.1, layer 19 (out of 32) for Phi 3.5, layer 16 (out of 28) for Qwen2, layer 24 (out of 48) for Qwen2.5(14B), layer 23 (out of 40) for Phi 3 medium, and layer 19 (out of 32) for Phi 3 mini. The choices for Llama 3.1 and Phi 3.5 follow GemFilter's settings for consistency, while Qwen2's and Phi3's selection layers are chosen based on GemFilter's performance across layers, which will be further discussed in section 3.3. In section 3.3, we conduct ablation studies and further exploration, testing various PromptDistill settings, including multi-stage selection and cache truncation removal.

3.2 Main Results

3.2.1 Long Bench

We first apply our method, along with all baseline approaches, to three base models on LongBench, a benchmark comprising various long-context tasks well-suited for evaluating compression methods(Bai et al., 2024). To ensure fair comparisons, we follow the experimental settings of (Shi et al., 2024). Under these settings, we evaluate All KV (the full-attention original model), H2O with a KV cache size of 4096, SnapKV, GemFilter, and PromptDistill, using selected tokens or KV cache sizes of 1024, 2048, and 4096. We conduct preliminary tests on the baseline methods and find that our results closely match those reported in the GemFilter paper. Therefore, we directly use their reported results for baselines and integrate our findings into the table.

In table 2, we present all results, highlighting our differences compared to GemFilter. The results show that while PromptDistill is significantly more efficient than full attention, it achieves performance close to full attention in general and even surpasses it when using the Qwen2 model with 4096 selected tokens. Compared to H2O, which is less efficient than our method, PromptDistill demonstrates a clear performance advantage. Similarly, while SnapKV is also less efficient than our method, our results remain comparable overall. Finally, compared to GemFilter, which requires slightly more computation time but is more memory-efficient on GPUs, PromptDistill consistently achieves better results across all cases.

3.2.2 InfBench

For InfBench, a benchmark consisting of long-context tasks with even longer prompts (average data length exceeding 100K tokens), including both synthetic and real-world tasks across diverse domains(Zhang et al., 2024a), we adopt the same method settings as in LongBench, although baseline results for InfBench from GemFilter's report are not available. The results are presented in table 3. Compared to H2O and GemFilter, PromptDistill once again demonstrates a clear performance advantage, as observed in LongBench evaluations. More importantly, this time PromptDistill achieves an obvious performance advantage over SnapKV. The extremely poor performance of the Phi-3.5 model with GemFilter at 4096 selected tokens is explained in section B.

3.2.3 Needle in a Haystack

We also evaluate the methods on Needle in a Haystack, which tests an LLM's ability to retrieve accurate information from a specific sentence hidden within a large document (Nelson et al., 2024). While GemFilter (Shi et al., 2024) only evaluates selected tokens or KV cache sizes of 1024, we con-

Method	NrQA	qasp	MF-en	hotpqa	2wkqa	musq	gov_rep	qmsum	m_news	trec	triqa	sam	PCount	PRe	Mean
LLama 3.1 8B Instruct															
All KV	32.02	13.04	27.34	16.23	16.05	11.22	34.52	23.41	26.89	73.0	91.64	43.8	7.16	97.73	36.72
H2O-4096	22.94	12.61	26.48	16.63	15.81	10.14	33.51	23.47	26.81	69.0	91.15	43.97	6.66	71.67	33.63
Snap-1024	31.98	11.17	25.33	14.81	15.73	10.69	26.95	22.89	25.86	67.5	91.89	42.85	7.67	98.16	35.25
Gem-1024	20.71	11.0	29.28	19.12	17.01	13.01	30.37	21.75	25.17	63.0	90.7	42.5	7.15	92.22	34.50
PrDist-1024	24.24	11.36	28.01	16.59	14.92	11.7	29.68	22.29	25.77	73.5	91.65	43.61	5.87	95.8	35.36(+0.86)
Snap-2048	31.45	11.94	26.24	15.73	16.03	11.66	29.64	23.24	26.44	69.5	91.48	42.68	7.21	98.03	35.80
Gem-2048	24.36	12.63	25.39	19.58	17.03	14.11	33.15	22.31	26.49	69.5	91.59	42.64	4.61	98.75	35.87
PrDist-2048	28.24	12.86	26.75	17.47	15.88	12.46	32.06	23	26.86	73.5	91.54	43.22	5.62	97.79	36.23(+0.36)
Snap-4096	32.13	13.12	27.38	16.11	16.08	11.6	32.39	23.47	26.76	71.5	91.64	43.46	7.33	97.24	36.44
Gem-4096	25.66	12.95	27.38	17.76	15.6	12.02	34.17	23.25	26.87	70.0	92.36	43.34	5.96	98.0	36.09
PrDist-4096	30.2	13.24	26.91	16.41	16.12	11.6	34.2	23.08	26.86	72.5	91.47	44.17	5.24	97.22	36.37(+0.28)
Phi 3.5 Mini 3.8B Instruct															
All KV	27.51	17.23	35.63	21.7	25.7	11.68	34.14	23.17	24.95	71.5	87.37	13.08	7.17	83.85	34.62
H2O-4096	19.74	16.23	34.17	21.02	23.05	10.49	33.42	21.95	24.95	67.5	86.13	16.71	1.55	47.46	30.31
Snap-1024	24.31	16.03	34.93	20.72	26.02	13.74	28.27	22.03	24.02	67.5	87.71	14.57	6.08	85.6	33.68
Gem-1024	16.57	18.29	35.91	24.22	26.1	9.7	30.29	18.96	23.64	64.5	85.85	23.02	0.2	81.12	32.74
PrDist-1024	23.42	21.79	33.69	23.46	24.07	12.87	30.39	22.07	24.14	68.5	87.51	13.56	3.28	83.58	33.74(+1)
Snap-2048	26.41	16.59	36.99	21.8	26.07	12.57	30.88	22.37	24.51	69.5	87.54	13.13	6.57	83.92	34.20
Gem-2048	19.63	14.84	35.99	21.38	19.72	10.13	32.39	21.24	24.71	65.0	86.49	20.47	2.17	69.5	31.69
PrDist-2048	23.85	17.81	35.98	21.57	24.78	11.13	32.79	22.22	24.7	69.5	87.42	13.5	4.43	82.75	33.75(+2.06)
Snap-4096	27.25	17.42	36.9	21.37	25.42	12.55	32.9	22.6	24.87	70.5	87.45	13.28	6.81	84.04	34.53
Gem-4096	20.95	19.98	35.22	28.82	28.21	13.98	34.2	22.45	25.08	64.5	85.86	18.68	3.43	65.56	33.35
PrDist-4096	24.67	16.5	35.88	20.54	25.58	12.47	34	22.51	24.97	71	87.37	13.57	5.8	82.97	34.13(+0.78)
Qwen2 7B Instruct															
All KV	24.59	44.4	45.25	12.99	12.68	8.9	37.64	24.68	27.32	78.5	88.77	46.57	6	74.5	38.06
H2O-4096	8.98	15.89	16.64	21.38	22.42	8.81	0.02	0.02	0	19	39.8	0	8	56.62	15.54
Snap-1024	24.48	42.66	45.41	12.76	12.33	8.46	28.97	24.23	26.43	71	88.47	45.89	6.67	73.17	36.50
Gem-1024	22.8	38.78	43.34	12.8	14.49	9.81	27.85	21.03	26.04	74.5	88.55	43.21	6.88	46.17	34.02
PrDist-1024	24.35	38.54	43.36	13.33	13.3	9.06	29.25	21.54	26.35	74.5	89.44	44.36	11	71.62	36.43(+2.41)
Snap-2048	24.44	44.69	45.05	13.06	12.16	8.72	32.45	24.35	27.1	76	88.77	46.06	6.67	74.83	37.45
Gem-2048	24.01	43.68	44.27	11.77	13.44	10.03	31.49	22.3	27.14	78.5	88.43	43.58	5.88	55.7	35.73
PrDist-2048	25.65	41.99	44.73	13.07	13.53	8.01	33.11	22.47	27.28	77.5	88.99	46.55	8.67	73.67	37.52(+1.79)
Snap-4096	24.87	44.36	44.14	13.32	12.39	8.67	35.06	24.83	27.3	77.5	88.77	46.45	6.75	75.17	37.83
Gem-4096	25.49	46.62	43.38	12.09	13.09	9.03	33.85	23.28	27.51	79	89.49	44.85	4.92	64.75	36.95
PrDist-4096	25.76	44.99	44.98	12.95	12.92	8.66	35.65	23.56	27.43	77.5	89.07	46.24	7.33	76.04	38.08(+1.13)
Qwen2.5 14B Instruct															
All KV	4.11	10.85	25.58	12.18	13.46	8.8	33.93	21.34	25.27	77.5	90.1	47.54	5.19	89.04	33.21
H2O-4096	4.01	11.3	24.82	10.92	12.85	6.84	32.9	20.1	25.26	76.0	89.25	46.85	5.1	68.08	31.02
Snap-1024	3.97	10.6	23.68	12.82	13.77	9.14	27.81	21.82	24.38	72.5	89.07	46.43	5.78	88.58	32.17
Gem-1024	3.5	7.31	18.91	10.67	12.92	7.05	28.73	16.43	23.16	71.5	85.67	41.72	2.42	70.25	28.59
PrDist-1024	3.39	8.92	21.13	10.68	13.28	7.51	28.3	18.07	23.95	78.0	90.2	47.11	2.82	88.83	31.59(+3)
Snap-2048	3.98	10.84	25.4	12.65	13.95	8.81	30.63	21.55	25.23	74.5	89.94	46.69	5.86	88.21	32.73
Gem-2048	3.92	9.76	21.23	12.01	13.23	7.31	31.2	17.51	24.9	75.5	89.37	42.38	2.06	82.92	30.95
PrDist-2048	3.63	9.85	22.35	11.89	13.57	7.63	31.03	19.07	25.01	79.0	90.38	47.79	3.62	90.04	32.49(+1.54)
Snap-4096	4.08	10.99	25.29	12.29	13.68	9.07	32.24	21.15	25.42	77.0	89.99	47.12	5.65	88.29	33.02
Gem-4096	3.69	10.72	23.03	11.74	13.59	7.65	33.32	18.46	25.36	77.0	90.35	44.37	1.75	90.04	32.22
PrDist-4096	3.65	10.71	24.75	11.92	13.56	8.4	33.07	19.78	25.56	78.0	90.27	47.96	4.42	90.92	33.07(+0.85)
Phi 3 medium 128k instruct															
All KV	19.65	22.83	36.77	26.09	21.87	18.59	35.28	21.01	27.03	74.0	90.28	44.74	7.02	89.33	38.18
H2O-4096	14.36	23.45	36.52	24.03	20.57	13.21	34.83	20.21	26.85	70.5	89.6	43.25	6.37	54.88	34.19
Snap-1024	19.54	18.82	35.08	27.38	22.3	20.04	27.21	22.9	25.66	72.0	90.72	44.98	8.64	88.25	37.39
Gem-1024	15.9	20.08	33.22	20.03	21.73	15.8	31.04	20.45	27.02	62.0	81.94	32.48	2.03	78.83	33.04
PrDist-1024	17.7	22.69	35.79	26.0	22.97	17.91	31.07	21.94	26.24	72.0	90.95	43.75	9.61	88.08	37.62(+4.58)
Snap-2048	20.69	21.33	35.65	28.0	22.23	18.8	30.93	22.06	26.66	73.0	90.45	44.46	9.43	88.58	38.02
Gem-2048	18.61	22.73	34.03	22.76	18.8	17.09	32.81	20.94	26.92	66.5	87.18	40.03	4.2	89.42	35.86
PrDist-2048	19.65	22.28	36.28	27.14	23.34	19.68	33.29	21.64	26.98	73.5	90.62	44.6	8.89	87.17	38.22(+2.36)
Snap-4096	20.61	22.62	36.58	28.03	21.63	18.85	33.47	22.01	27.0	74.0	90.28	45.12	9.43	88.5	38.44
Gem-4096	9.68	14.87	17.05	11.93	8.99	5.31	2.51	6.61	22.19	41.5	47.19	11.04	1.0	0.0	14.28
PrDist-4096	20.93	22.23	35.47	28.15	22.51	18.84	34.24	21.41	27.01	74.0	90.45	45.19	10.4	88.08	38.49
Phi 3 mini 128k instruct															
All KV	11.07	13.07	31.75	17.83	14.67	12.6	34.73	22.73	26.15	67.5	86.71	25.85	4.5	73.79	31.64
H2O-4096	10.15	12.53	30.54	15.77	15.81	9.51	34.07	20.17	26.14	64.0	83.99	19.55	5.27	45.6	28.08
Snap-1024	10.19	11.0	28.14	17.9	13.28	12.58	27.86	21.38	24.62	66.5	86.47	30.93	4.17	71.16	30.44
Gem-1024	9.25	11.05	31.36	15.23	15.33	9.37	31.24	17.21	24.95	62.5	82.85	22.65	2.92	50.25	27.58
PrDist-1024	9.9	14.01	30.49	17.21	15.55	12.41	30.9	21.14	24.9	67.0	86.74	23.67	4.0	68.58	30.46(+2.88)
Snap-2048	11.3	12.55	27.77	17.9	15.1	12.89	30.47	22.14	25.75	67.5	86.76	32.37	4.04	73.16	31.41
Gem-2048	10.75	12.52	30.56	15.45	15.2	11.03	33.19	20.12	25.73	67.0	87.15	21.23	2.75	39.08	27.98
PrDist-2048	10.05	13.43	29.42	17.76	14.86	12.15	33.22	21.44	25.91	69.0	86.84	23.0	4.0	69.33	30.74(+2.76)
Snap-4096	11.06	13.57	29.9	17.82	15.63	13.81	33.05	22.43	25.9	67.5	86.51	30.88	4.62	74.2	31.92
Gem-4096	5.77	6.66	11.58	4.84	3.23	2.59	6.35	4.5	21.75	27.5	13.98	4.03	1.02	1.08	8.21
PrDist-4096	11.25	13.64	29.04	17.81	15.24	12.71	34.7	21.74	26.03	68.0	86.74	23.51	4.5	73.28	31.3

Table 2: Evaluation Results for Longbench (PromptDistill's difference from GemFilter is labeled). All KV denotes the uncompressed model, offering the highest performance but lowest efficiency. Compression methods are designed to approach its performance while exceeding others in efficiency.

Method	passkey	N_str	kv_retr	Lb_sum_en	Lb_ch_en	Lb_qa_en	Lb_qa_chn	Ld_qa_en	mathf	coderun	codedebug	Mean
LLama 3.1 8B Instruct												
All KV	81.36	81.36	66.6	18.86	67.25	14.85	12.35	15.0	33.14	1.0	1.27	35.73
H2O-4096	6.78	6.1	2.0	18.86	47.16	8.79	10.32	7.0	34.0	0.0	18.53	14.5
Snap-1024	81.36	71.36	0.4	15.45	67.69	11.72	11.89	12.0	34.0	1.0	1.27	28.01
Gem-1024	81.36	81.36	1.8	15.66	36.68	12.08	13.11	14.0	34.29	0.0	19.29	28.15
PrDist-1024	81.36	78.98	2.0	16.02	65.5	12.04	12.39	9.5	32.57	1.25	1.27	28.44(+0.29)
Snap-2048	81.36	77.12	1.2	16.78	67.69	13.41	11.86	10.5	34.0	1.0	1.02	28.72
Gem-2048	81.36	81.36	4.4	17.02	43.23	11.77	12.91	17.5	31.71	0.0	19.04	29.12
PrDist-2048	81.36	79.49	4.0	16.94	66.38	14.28	12.2	13.0	32.57	1.25	1.02	29.32(+0.2)
Snap-4096	81.36	78.98	3.6	16.44	67.69	14.12	12.21	15.5	34.0	0.75	1.02	29.61
Gem-4096	81.36	81.36	13.0	18.05	44.54	11.81	13.93	11.5	35.14	0.0	14.97	29.61
PrDist-4096	81.36	80.34	9.2	18.26	66.81	14.71	12.48	14.5	32.86	0.25	0.76	30.14(+0.53)
Phi 3.5 Mini 3.8B Instruct												
All KV	40.68	40.68	26.8	17.68	48.03	9.1	12.88	10.0	24.57	1.0	19.29	22.79
H2O-4096	6.78	6.78	0.4	16.71	35.37	6.84	9.78	6.5	29.14	0.75	5.58	11.33
Snap-1024	62.54	15.25	0.2	13.87	56.33	8.62	12.71	11.5	14.29	0.0	17.51	19.35
Gem-1024	40.68	40.68	0.6	13.53	45.41	7.01	11.48	7.0	15.14	1.5	10.41	17.59
PrDist-1024	40.68	40.68	1.0	15.18	46.72	7.92	12.88	11.5	22.29	1.0	17.01	19.71(+2.12)
Snap-2048	40.51	15.93	0.2	15.18	44.54	8.19	12.95	12.5	26.86	1.25	20.05	18.01
Gem-2048	40.68	40.51	2.0	14.42	45.85	7.33	11.69	7.5	19.43	2.0	16.75	18.92
PrDist-2048	40.68	40.68	2.0	16.0	45.85	8.13	12.53	9.0	23.71	2.0	18.02	19.87(+0.95)
Snap-4096	40.68	17.29	1.4	15.83	44.54	8.33	13.2	12.0	26.29	1.75	20.05	18.31
Gem-4096	0.0	0.0	0.0	1.53	27.51	5.17	1.38	0.5	1.71	0.0	0.0	3.44
PrDist-4096	40.68	40.68	6.0	16.17	46.72	8.25	12.7	10.0	24.57	1.75	18.02	20.5
Qwen2 7B Instruct												
All KV	27.12	27.12	13.8	16.42	54.59	6.23	10.0	7.0	28.57	0.0	26.14	19.73
H2O-4096	0.85	3.05	0.0	0.0	47.6	1.41	2.11	1.0	24.29	0.0	0.0	7.3
Snap-1024	24.75	5.25	0.4	13.92	55.02	5.91	9.93	8.0	29.14	0.0	26.9	16.29
Gem-1024	27.12	27.12	0.2	13.43	43.67	8.17	18.22	12.0	10.0	0.0	28.43	17.12
PrDist-1024	27.12	27.12	0.2	13.72	54.59	5.66	9.67	11.5	27.14	0.0	28.93	18.7(+1.58)
Snap-2048	25.25	6.78	0.6	14.51	55.02	6.11	9.93	8.5	28.29	0.25	26.65	16.54
Gem-2048	27.12	27.12	0.2	14.45	44.54	9.17	18.01	14.0	10.86	0.0	28.17	17.6
PrDist-2048	27.12	27.12	0.2	15.01	55.9	5.97	9.61	12.0	28.29	0.0	28.43	19.06(+1.46)
Snap-4096	26.44	9.66	1.2	15.18	55.02	6.21	9.91	9.0	29.14	0.25	26.9	17.17
Gem-4096	27.12	27.12	0.8	15.4	44.54	7.56	12.81	16.0	12.0	0.0	28.68	17.46
PrDist-4096	27.12	27.12	0.6	15.74	56.33	6.09	9.59	11.0	28.29	0.0	28.68	19.14(+1.68)
Qwen2.5 14B Instruct												
All KV	27.12	27.12	18.2	17.65	60.7	7.01	8.5	18.5	34.57	0.0	38.07	23.4
H2O-4096	6.78	6.78	0.8	16.78	53.28	4.86	7.29	12.0	31.43	0.0	32.23	15.66
Snap-1024	27.12	21.36	0.8	16.24	60.7	6.79	9.02	13.5	35.43	0.0	38.83	20.89
Gem-1024	27.12	27.12	0.0	15.32	40.17	4.1	7.51	16.0	13.71	0.0	25.38	16.04
PrDist-1024	27.12	27.12	0.0	15.93	58.95	5.38	7.86	13.0	33.71	0.0	35.28	20.4(+4.36)
Snap-2048	27.12	22.71	4.2	16.39	60.26	6.9	8.38	14.5	36.0	0.0	38.83	21.39
Gem-2048	27.12	27.12	0.0	16.13	44.1	4.59	8.08	17.0	11.71	0.0	25.89	16.52
PrDist-2048	27.12	27.12	0.2	16.76	58.95	5.88	8.45	16.0	34.86	0.0	35.79	21.01(+4.49)
Snap-4096	27.12	24.75	9.6	16.85	59.83	6.96	8.68	17.5	36.57	0.0	38.83	22.43
Gem-4096	27.12	27.12	0.2	16.57	47.16	5.15	8.61	21.0	10.57	0.25	26.65	17.31
PrDist-4096	27.12	27.12	0.2	17.49	60.26	6.15	8.26	18.0	35.71	0.0	36.04	21.49(+4.18)
Phi 3 medium 128k instruct												
All KV	40.68	40.51	8.6	15.78	62.01	8.25	15.93	6.5	4.86	1.0	29.7	21.26
H2O-4096	6.78	6.61	0.4	15.9	46.29	6.69	12.63	6.5	31.14	1.0	27.66	14.69
Snap-1024	40.68	20.0	0.2	12.55	55.46	7.83	14.36	5.5	5.14	1.0	29.44	17.47
Gem-1024	40.68	40.68	1.0	15.6	48.03	6.88	14.12	11.0	11.14	0.0	28.17	19.75
PrDist-1024	40.68	40.68	1.0	13.91	62.45	8.22	15.52	8.5	0.0	1.5	29.95	20.22(+0.47)
Snap-2048	40.68	24.07	0.2	13.81	58.95	8.16	14.8	8.0	5.14	1.0	29.7	18.59
Gem-2048	40.68	40.68	2.8	15.43	48.03	6.7	13.93	7.5	15.71	0.0	29.44	20.08
PrDist-2048	40.68	40.68	1.8	14.76	63.76	8.26	15.56	8.5	0.29	1.5	29.95	20.52(+0.44)
Snap-4096	40.68	29.32	0.4	14.1	59.83	8.4	14.93	10.5	5.43	0.5	30.46	19.5
Gem-4096	0.34	0.0	0.0	0.28	6.11	2.86	2.94	0.0	7.43	0.0	0.25	1.84
PrDist-4096	40.68	40.68	3.0	14.17	63.32	8.67	16.0	9.5	1.43	1.0	29.7	20.74
Phi 3 mini 128k instruct												
All KV	40.68	40.51	26.4	15.67	55.02	8.71	11.78	7.0	26.86	1.25	21.32	23.2
H2O-4096	6.78	6.44	1.0	15.23	44.98	6.63	9.25	10.0	30.0	0.25	12.18	12.98
Snap-1024	40.51	13.9	0.2	12.24	55.02	8.11	10.93	7.0	28.57	1.25	21.07	18.07
Gem-1024	40.68	40.68	2.0	13.49	42.79	6.79	12.88	6.0	16.86	1.75	25.38	19.03
PrDist-1024	40.68	40.51	2.2	13.98	55.46	8.76	11.62	8.5	24.86	1.0	17.01	20.42(+1.39)
Snap-2048	40.51	14.75	0.6	13.4	55.02	9.15	11.01	7.0	26.29	1.5	21.07	18.21
Gem-2048	40.68	40.51	4.8	13.97	43.23	7.25	12.29	5.0	21.43	1.75	24.62	19.59
PrDist-2048	40.68	40.51	5.2	14.66	54.15	8.01	12.03	11.0	26.57	1.5	20.3	21.33(+1.74)
Snap-4096	40.51	15.93	1.6	14.05	55.02	9.12	11.77	8.5	27.43	1.25	22.08	18.84
Gem-4096	0.0	0.0	0.0	2.97	33.19	3.53	1.46	0.0	1.71	0.0	0.0	3.9
PrDist-4096	40.68	40.51	12.2	14.42	54.15	8.19	12.7	9.5	25.14	1.25	21.57	21.85

Table 3: Evaluation Results for Infbench (PromptDistill's difference from GemFilter is labeled). All KV denotes the uncompressed model, offering the highest performance but lowest efficiency. Compression methods are designed to approach its performance while exceeding others in efficiency.

Table 4: Evaluation Results for Needle in a Haystack. Instruct versions of the models are used.

Method	LLa3	Ph3.5	Q2 7B	Q2.5 14B	Ph3 Med	Ph3 Mi
All KV	85.2	91.7	91.2	90.4	91.7	91.7
Snap-1024	64.0	91.7	90.5	90.6	90.2	91.7
Gem-1024	81.8	91.7	69.7	68.7	91.7	91.7
PrDist-1024	82.6	91.7	71.6	73.3	91.7	91.7
Snap-2048	71.7	91.7	90.8	90.3	91.7	91.7
Gem-2048	84.7	91.7	81.8	79.7	91.7	91.7
PrDist-2048	84.3	91.7	82.2	83.8	91.7	91.7
Snap-4096	77.1	91.7	91.0	90.4	91.7	91.7
Gem-4096	83.3	5.1	89.3	86.9	7.9	7.4
PrDist-4096	84.6	91.7	90.2	88.5	91.7	91.7

Table 5: Top-5 multi-stage selection performance on LongBench (LLama 3.1 8B Instruct), with k and r denoting the token numbers and stages for selection, respectively (space-separated for multiple stages). Here, Δ_1 is the difference in mean score from PromptDistill-13-1024, and Δ_2 from GemFilter-13-1024.

k	r	Mean Score	Δ_1	Δ_2
1024	13	35.36	0	0.86
8192 1024	8 13	35.39	0.03	0.89
16384 8192 1024	7 8 13	35.42	0.06	0.92
16384 8192 1024	5 8 13	35.53	0.17	1.03
16384 8192 1024	3 8 13	35.42	0.06	0.92
16384 8192 1024	1 8 13	35.32	-0.04	0.82

duct a more comprehensive evaluation using settings similar to those in LongBench and InfBench.

Since our results differ from those in GemFilter's report—likely due to differences in hardware, Python, or CUDA versions—we do not use their results as baselines for fair comparison.

For maximum input length, we set 120K for LLaMA 3.1 8B Instruct (following GemFilter's work (Shi et al., 2024)), 86K for Phi-3.5 Mini 3.8B Instruct (due to GPU memory limitations for the full attention method), and 32.2K for Qwen2 7B Instruct (due to its input length limit). The results are presented in table 4, with additional detailed figures in section H. For Phi-3.5, all method settings yield the same results except GemFilter-4096, which encounters the same issue discussed in section 3.2.2 and in section B. Overall, PromptDistill outperforms GemFilter in most cases and surpasses SnapKV in half of the evaluations.

3.3 Analysis

We empirically determine the selection layer for Qwen2 7B Instruct, Qwen2.5 14B Instruct, Phi 3 medium 128k instruct, and Phi 3 mini 128k instruct in our main evaluations by assessing GemFilter across different layers on LongBench. We select the layer where GemFilter performs well while ensuring it is as early as possible for efficiency. This approach ensures a fair comparison, as choosing a layer where GemFilter performs well highlights its selection ability. We show further details of this selection process for Qwen2 7B Instruct as an example in section G. We present detailed analysis and empirical results in section C, showing that Cache Truncation significantly increases efficiency while maintaining performance.

3.3.1 Multi-stage Selection Analysis

For multi-stage PromptDistill, different configurations can be explored. Using LongBench for evaluation, we start from a baseline that selects 1024 tokens at layer 13, with the KV cache truncated to 1024 tokens in all trials. Well-performing settings are summarized in section F (table 6), and the best ones are shown in table 5.

We first add a selection layer before layer 13 that keeps 2048 tokens. Since early-layer selection of 2048 tokens degrades performance, we focus on layers selecting 4096 tokens. Layer 10 performs best, leading us to test 8192 tokens, first on top of 1024@L13, then 4096@L10+1024@L13. This yields four strong configurations (rows 3–6 in table 6). Further adding 16384-token layers gives the remaining results.

Both tables highlight clear contrasts with GemFilter and single-stage PromptDistill. Some multi-stage settings match single-stage performance, while others slightly reduce accuracy but gain higher efficiency, still surpassing GemFilter. Combined with the theoretical analysis in section 2.3, these results confirm that multi-stage selection can substantially close the memory–efficiency gap between PromptDistill and GemFilter, offering much faster inference while preserving performance advantages.

4 Conclusion

PromptDistill is a novel, training-free method that improves large language model inference efficiency by retaining only the most informative hidden states from intermediate layers while preserving essential context. Unlike prior methods such as GemFilter, SnapKV, and H2O, it achieves a better balance between speed, memory, and output quality. Moreover, multi-stage selection further enhances efficiency with minimal performance loss. Extensive experiments across diverse LLMs and benchmarks demonstrate that PromptDistill is both effective and generalizable for long-context tasks.

Limitations

While PromptDistill demonstrates clear improvements in inference efficiency and maintains strong generation quality, several limitations remain. First, the method relies on attention scores from early or intermediate layers to select important tokens. This assumes that early attention signals are sufficient for identifying informative tokens, which may not always hold, especially for tasks requiring nuanced understanding at later layers. Although multi-stage selection partially addresses this, optimal configurations remain empirically determined and model-specific, requiring additional tuning.

Second, PromptDistill incurs additional memory overhead due to its design choice to preserve contextual richness. Specifically, in order to compute informative hidden states for the selected tokens, it must first process and store hidden states of all tokens up to the selection layer. This ensures that selected tokens embed sufficient context information, but also leads to increased memory usage compared to methods like GemFilter, which discard the intermediate states of unselected tokens early on. While PromptDistill reduces recomputation, this storage strategy may limit scalability, particularly for very long contexts or resource-constrained deployments. Future methods may better balance memory usage and context preservation by selectively compressing or approximating the influence of discarded tokens.

Lastly, our current evaluation is conducted on long-context benchmarks such as LongBench, InfBench, and Needle-in-a-Haystack, which are primarily focused on extractive or reading comprehension tasks. While these benchmarks are valuable, they only capture a narrow slice of the challenges faced by LLMs in real-world usage. In practice, models often need to solve more diverse and open-ended problems—such as multi-step reasoning, decision-making, or synthesis of unstructured information—where the ability to efficiently locate, integrate, and reason over relevant content is crucial. Developing broader, task-oriented benchmarks that reflect these realistic and complex settings would allow for a more comprehensive evaluation of long-context methods like PromptDistill.

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A Related Work

A.1 Acceleration of Long-Context LLM Inference

As large language models (LLMs) are increasingly applied to long-context tasks, the computational and memory overhead during inference has become a critical bottleneck. FastGen (Ge et al., 2023) adaptively selects one of five KV cache compression methods based on attention head profiling, reducing generation overhead. StreamingLLM (Xiao et al., 2023) mitigates the "attention sink" issue by introducing placeholder tokens and a local attention mechanism. MInference (Jiang et al., 2024) leverages sparse computation patterns like A-shape, Vertical-Slash, and Block-Sparse to reduce latency in the prefilling stage. ThinK (Xu et al., 2025b) prunes redundant attention channels by observing imbalances in the key cache's channel dimension. SnapKV (Li et al., 2024b) clusters KV positions to focus on key prompt features. Mistral (Jiang et al., 2023) employs a sliding window strategy for efficient long-text inference, while KIVI (Liu et al., 2024b) applies 2-bit KV cache quantization to reduce memory and computation costs. LongGen (Ge et al., 2024) combines sparse attention patterns with lightweight training strategies, while RefreshKV (Xu et al., 2025a) dynamically switches between full-context and partial token attention to improve efficiency. However, our work builds upon these strategies by focusing on identifying informative prompt tokens in intermediate layers. This approach enables efficient token selection without additional training, achieving minimal performance degradation. Furthermore, by leveraging this structure during tuning, we demonstrate improved adaptability of the model under extreme compression scenarios.

A.2 Prompt Selection for Computation Reduction

Minimizing the number of prompt tokens processed during computation is a straightforward yet powerful method for enhancing efficiency. QLLM (Li et al., 2024a) partitions text into blocks and selects relevant ones using query tokens. H2O (Zhang et al., 2023) retains only influential tokens, while Scissorhands (Liu et al., 2023a) discards less relevant tokens based on the "importance persistence hypothesis." Retrieval-augmented speculative Decoding (Chen et al., 2025a) incorporates a retrieval-augmented generation (RAG) strategy,

where a draft LLM generates content based on a simplified context. RetrievalAttention (Liu et al., 2024a) indexes and searches KV cache vectors to selectively retain only information relevant to the current generation. RECOMP (Xu et al., 2023) integrates extraction and summarization techniques to preprocess the original context before feeding it as a prompt, effectively condensing the information. Deja Vu (Liu et al., 2023b) trains a lightweight algorithm to predict context sparsity at each layer, providing guidance for token selection in subsequent steps. Selective Context (Li et al., 2023) leverages self-information calculations to prune redundant lexical units directly. Meanwhile, Selective Attention (Zhang et al., 2024b) introduces targeted modulation within the self-attention mechanism, allowing the model to adjust its attention distribution dynamically based on context importance. ATTRIEVAL (Zhang et al., 2025) employs attention mechanisms to better capture implicit facts, ensuring minimal information loss while reducing token counts. Unlike these approaches, which mainly reduce input context tokens, our method targets effective token selection across intermediate layers, achieving greater resource efficiency while maintaining strong performance in constrained environments.

B Case of extreme performance for GemFilter

We observe that in InfBench and Needle in a Haystack, the Phi-3.5 model with GemFilter performs exceptionally poorly when the selected token count is 4096. After further investigation, we find that on our machines, Phi-3.5 fails to generate meaningful responses when the input length is exactly 4096, whereas inputs of 4000 or 4100 tokens still yield high-quality outputs. This issue may stem from factors such as the specific hardware used, CUDA version differences, or the fine-tuning process of the Phi-3.5 model. Since GemFilter selects important tokens and reruns them, the 4096-token prompt length disrupts its performance.

C Cache Truncation Analysis

Here, we present fig. 1, a bar chart comparing PromptDistill with and without cache truncation on LongBench using Llama 3.1 8B Instruct (selection layer 13, selected token counts 1024, 2048, 4096). The results clearly show that performance does not decrease and even improves in these cases.

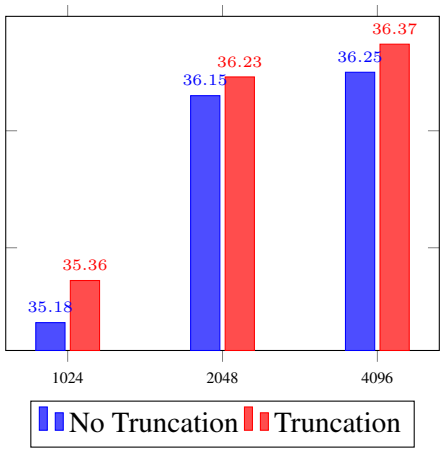


Figure 1: The effect of cache truncation.

Since PromptDistill with cache truncation is significantly more efficient than the basic design without truncation (discussed in section 2.3) while maintaining performance, we confidently adopt cache truncation for both higher efficiency and stable performance.

D More Algorithms

Three of the algorithms (algorithm 2, algorithm 3, algorithm 4) described in section 2.2 are presented here.

Algorithm 2 PromptDistill

Input: LLM M, embedded input prompt X, selection layer(s) r, number(s) of selected tokens k, max generated token length T, (optional) truncation times tt
for single-stage selection, r, k will be integers

for multi-stage selection, r, k will be lists of integers with the same length
Generation ← [ ]
new_token, Cache ← LLM-forward-PromptDistill(M, X, r, k, (optional)tt)
Generation$_0$ ← new_token
for $t \leftarrow 1 ... T-1$ **do**
  new_token, Cache ← LLM-forward(M, new_token, Cache)
  Generation$_t$ ← new_token
end for
return Generation

E More Theoretical Analysis

The efficiency of the basic design without cache truncation is also shown in table 1 for comparison.

Algorithm 3 LLM-forward-PromptDistill (single-stage selection, without cache truncation)

Input: LLM $M_{0:R}$, embedded input prompt X, selection layer r, number of selected tokens k
M has $R+1$ layers in total
X has token length = n
Cache ← [ ]
for $i \leftarrow 0...R$ **do**
  $X, Q_n^{(i)}, K^{(i)}, V^{(i)} \leftarrow M_i(X)$
  $\text{Cache}_i \leftarrow K^{(i)}, V^{(i)}$
  if i equals r **then**
    indices ← Select($Q_n^{(i)}, K^{(i)}, k$)
    $X \leftarrow X_{\text{indices}}$
  end if
end for
return generate(X), Cache

Algorithm 4 LLM-forward-PromptDistill (multi-stage selection, with cache truncation)

Input: LLM $M_{0:R}$, embedded input prompt X, selection layers r, numbers of selected tokens k, truncation times tt
r, k are lists with indices $0 : m-1$
n always refer to the end index of X
Cache ← [ ]
for $i \leftarrow 0...R$ **do**
  $X, Q_n^{(i)}, K^{(i)}, V^{(i)} \leftarrow M_i(X)$
  $\text{Cache}_i \leftarrow K^{(i)}, V^{(i)}$
  if i equals r_p for any p **then**
    indices ← Select($Q_n^{(i)}, K^{(i)}, k_p$)
    $X \leftarrow X_{\text{indices}}$
    if $p < tt$ **then**
      for $j \leftarrow 0...i$ **do**
        $K^{(j)}, V^{(j)} \leftarrow \text{Cache}_j$
        $K^{(j)} \leftarrow K^{(j)}_{\text{indices}}$
        $V^{(j)} \leftarrow V^{(j)}_{\text{indices}}$
        $\text{Cache}_j \leftarrow K^{(j)}, V^{(j)}$
      end for
    end if
  end if
end for
return generate(X), Cache

In stage one, the time cost is the same as our proposed method since cache truncation occurs after selection. In stage two, while the basic design also requires $\Theta((m-r)hk^2d)$ for processing selected tokens, it differs in key-value cache handling. Since all prompt tokens' keys and values are kept in the first r layers, the generation step takes $\Theta(rh((n+t)t)d + (m-r)h((k+t)t)d) = \Theta(rh(nt+t^2)d + (m-r)h(kt+t^2)d) = \Theta(rh((n-k)t)d + mh(kt+t^2)d)$. The total time cost then becomes $\Theta((m-r)hk^2d + rh((n-k)t)d + mh(kt+t^2)d) = \Theta(mh(k^2+t^2)d + rh((n-k)t)d - rhk^2d) = \Theta(mh(k^2+t^2)d + rh(nt-kt-k^2)d)$. For GPU memory in stage two, since the cache in the first r layers is not truncated, memory usage is $mw + 2rh(n+t)d + 2(m-r)h(k+t)d = mw + 2mh(k+t)d + 2rh(n-k)d$. This confirms that cache truncation is essential for efficiency.

For multi-stage selection, different configurations are possible. As an example, consider selecting k' tokens at layer r' and then k tokens at layer r with $r > r', k' > k$, finally truncating the cache to k tokens. The time cost in stage one is $\Theta(r'hn^2d + (r-r')hk'^2d)$. Since a first truncation occurs after the initial selection, GPU memory usage in stage one is $max\{r'w + 2r'hnd, rw + 2rhk'd\}$. After stage one, the cache size is the same as in single-stage selection, so stage two has identical time and memory costs. This shows that multi-stage selection can significantly improve efficiency with well-chosen selection layers and token counts.

F Multi-stage selection performance

Here in table 6, we present the complete table of Multi-stage Selection performance.

G Layer choice experiments

For the Qwen2-7B Instruct model, which consists of 28 layers, we need to select a layer where GemFilter performs well - demonstrating a strong ability to identify important tokens — while also ensuring efficiency by avoiding layers that are too late in the sequence. As shown in fig. 2, GemFilter achieves a sudden performance boost at layer 16, reaching a score of 34.02, significantly higher than neighboring layers. Although higher scores are observed at layer 21 (35.15) and layer 23 (34.87), these layers are too late in the model, leading to reduced efficiency. Since layer 16 achieves a performance close to the best-performing layers while maintaining better efficiency, we select it as the

Table 6: Multi-stage selection performance on LongBench (LLama 3.1 8B Instruct)

Selection token nums	Selection stages	Mean Score	Delta from PromptDistill-13-1024	Delta from GemFilter-13-1024
1024	13	35.36	0	0.86
4096 1024	10 13	35.00	-0.36	0.5
8192 1024	8 13	35.39	0.03	0.89
8192 1024	5 13	34.78	-0.58	0.28
8192 1024	4 13	34.67	-0.69	0.17
8192 4096 1024	8 10 13	35.03	-0.33	0.53
16384 8192 1024	7 8 13	35.42	0.06	0.92
16384 8192 1024	6 8 13	35.38	0.02	0.88
16384 8192 1024	5 8 13	35.53	0.17	1.03
16384 8192 1024	4 8 13	35.32	-0.04	0.82
16384 8192 1024	3 8 13	35.42	0.06	0.92
16384 8192 1024	2 8 13	35.29	-0.07	0.79
16384 8192 1024	1 8 13	35.32	0.04	0.82
16384 8192 1024	0 8 13	35.30	-0.06	0.8
16384 8192 1024	1 5 13	34.94	-0.42	0.44
16384 8192 1024	0 5 13	34.81	-0.55	0.31
16384 8192 1024	3 4 13	34.81	-0.55	0.31
16384 8192 1024	2 4 13	34.67	-0.69	0.17
16384 8192 1024	1 4 13	34.64	-0.72	0.14
16384 8192 1024	0 4 13	34.57	-0.79	0.07
16384 8192 4096 1024	5 8 10 13	35.00	-0.36	0.5
16384 8192 4096 1024	4 8 10 13	34.95	-0.41	0.45
16384 8192 4096 1024	3 8 10 13	34.92	-0.44	0.42
16384 8192 4096 1024	2 8 10 13	34.85	-0.51	0.35
16384 8192 4096 1024	1 8 10 13	34.90	-0.46	0.4
16384 8192 4096 1024	0 8 10 13	34.80	-0.56	0.3

final selection layer.

H Figures for Needle in a Haystack

Here, we present figures illustrating the detailed Needle in a Haystack performance, corresponding to the scores shown in table 4. Each graph corresponds to a base model with a specific compression method setting. The grids in the graphs display scores for different context sizes, depth percentages (needle locations within the context).

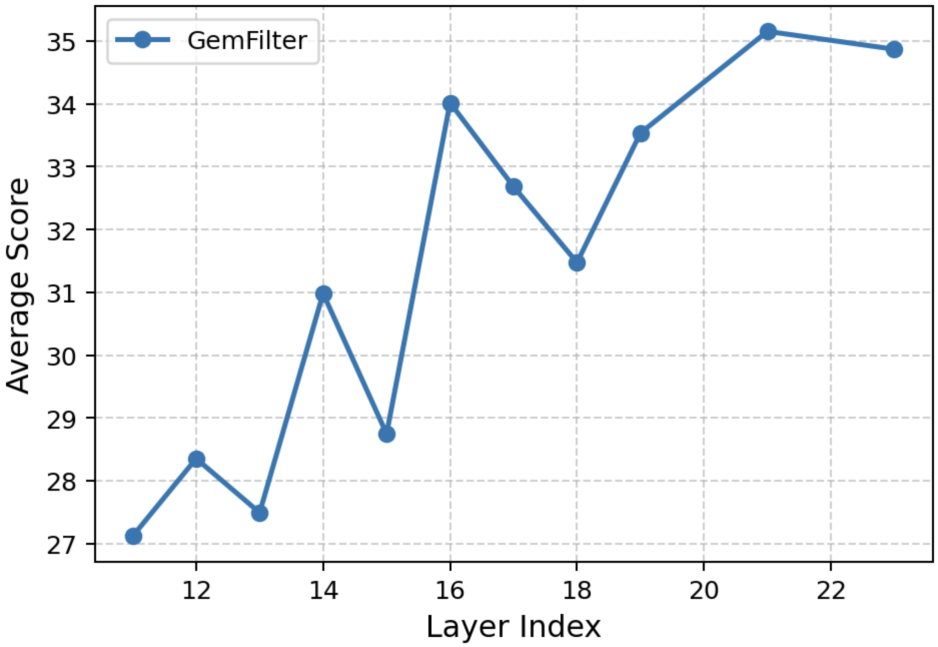
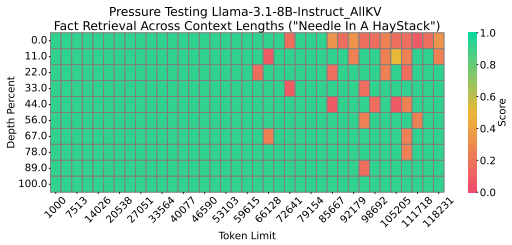
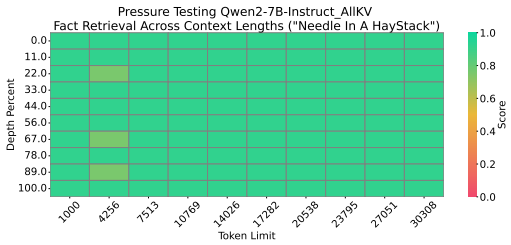


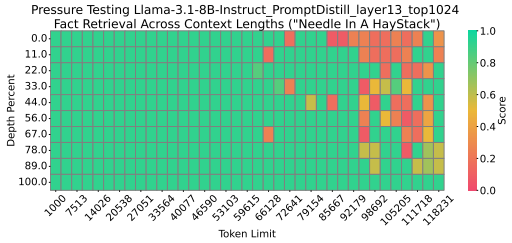
Figure 2: Performance of GemFilter + Qwen2 7B Instruct on LongBench with different selection layers.



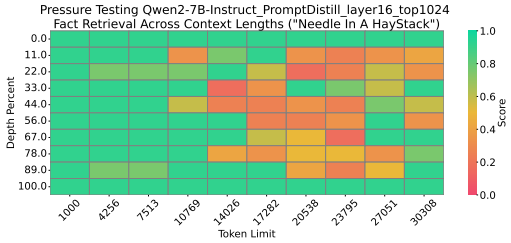
(a) LLama 3.1 8B Instruct + All KV: Score = 85.2



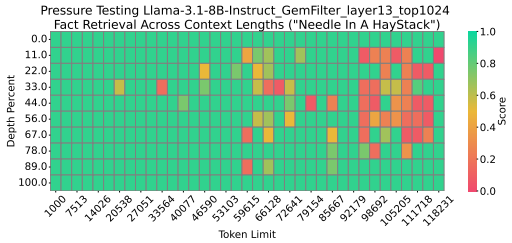
(b) Qwen2 7B Instruct + All KV: Score = 91.2



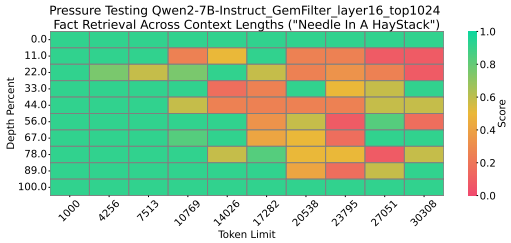
(c) LLama 3.1 8B Instruct + PromptDistill-1024: Score = 82.6



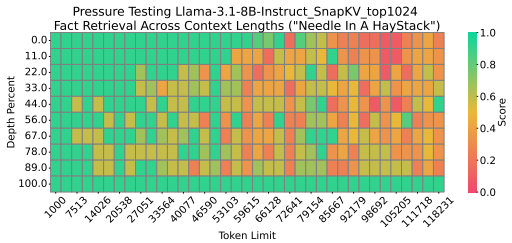
(d) Qwen2 7B Instruct + PromptDistill-1024: Score = 71.6



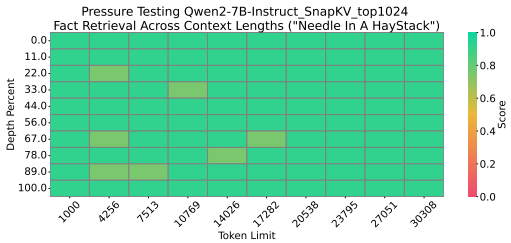
(e) LLama 3.1 8B Instruct + GemFilter-1024: Score = 81.8



(f) Qwen2 7B Instruct + GemFilter-1024: Score = 69.7

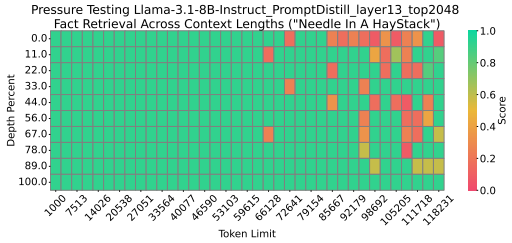


(g) LLama 3.1 8B Instruct + SnapKV-1024: Score = 64.0

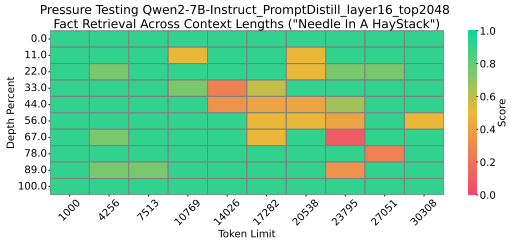


(h) Qwen2 7B Instruct + SnapKV-1024: Score = 90.5

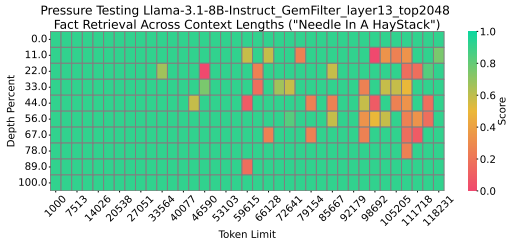
Figure 3: Evaluation Results for Needle in a Haystack: LLaMA 3.1 8B Instruct's and Qwen2 7B Instruct's scores in all test cases with model settings AllKV, PromptDistill-1024, GemFilter-1024, SnapKV-1024. (The x-axis represents the length of the input tokens, while the y-axis shows the position depth percentage of the 'needle' information)



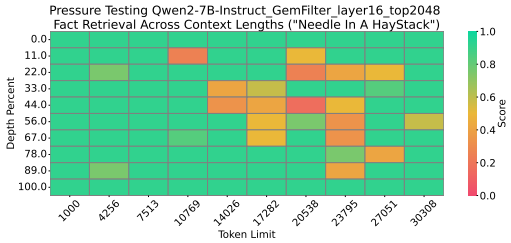
(a) LLama 3.1 8B Instruct + PromptDistill-2048: Score = 84.3



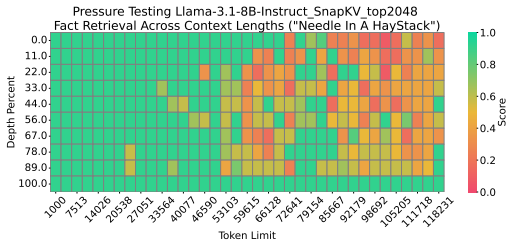
(b) Qwen2 7B Instruct + PromptDistill-2048: Score = 82.2



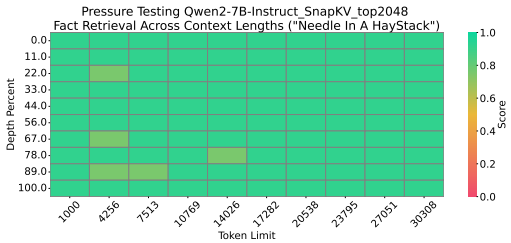
(c) LLama 3.1 8B Instruct + GemFilter-2048: Score = 84.7



(d) Qwen2 7B Instruct + GemFilter-2048: Score = 81.8

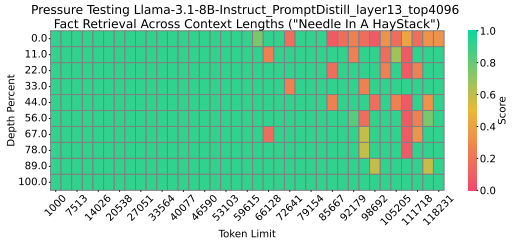


(e) LLama 3.1 8B Instruct + SnapKV-2048: Score = 71.7

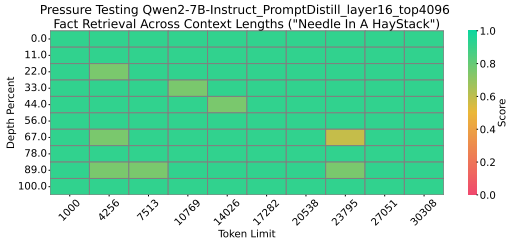


(f) Qwen2 7B Instruct + SnapKV-2048: Score = 90.8

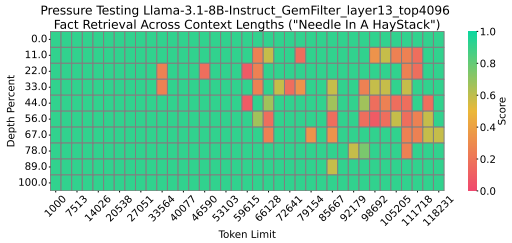
Figure 4: Evaluation Results for Needle in a Haystack: LLaMA 3.1 8B Instruct's and Qwen2 7B Instruct's scores in all test cases with model settings PromptDistill-2048, GemFilter-2048, SnapKV-2048. (The x-axis represents the length of the input tokens, while the y-axis shows the position depth percentage of the 'needle' information)



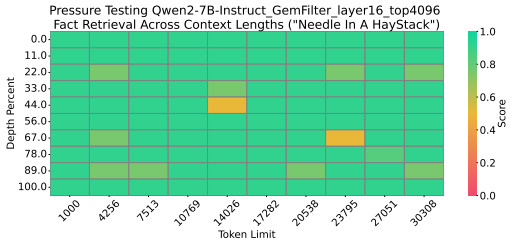
(a) LLama 3.1 8B Instruct + PromptDistill-4096: Score = 84.6



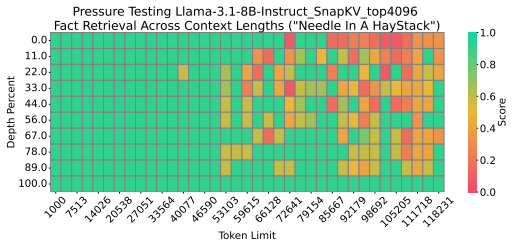
(b) Qwen2 7B Instruct + PromptDistill-4096: Score = 90.2



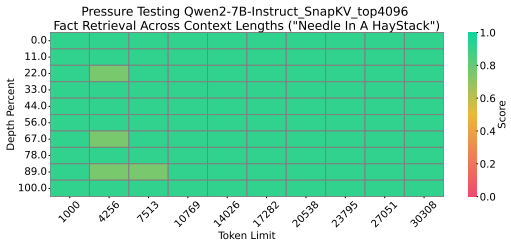
(c) LLama 3.1 8B Instruct + GemFilter-4096: Score = 83.3



(d) Qwen2 7B Instruct + GemFilter-4096: Score = 89.3

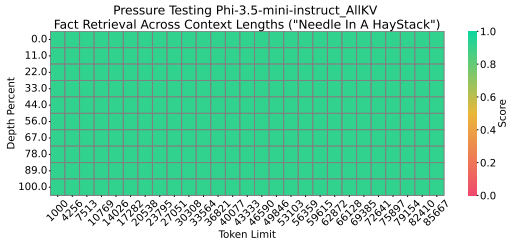


(e) LLama 3.1 8B Instruct + SnapKV-4096: Score = 77.1

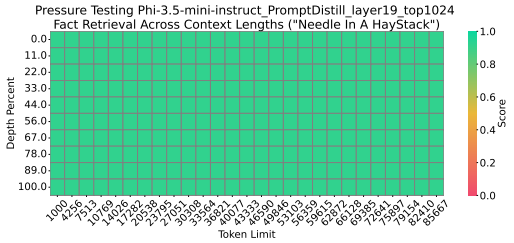


(f) Qwen2 7B Instruct + SnapKV-4096: Score = 91.0

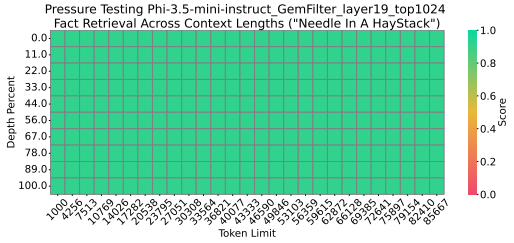
Figure 5: Evaluation Results for Needle in a Haystack: LLaMA 3.1 8B Instruct's and Qwen2 7B Instruct's scores in all test cases with model settings PromptDistill-4096, GemFilter-4096, SnapKV-4096. (The x-axis represents the length of the input tokens, while the y-axis shows the position depth percentage of the 'needle' information)



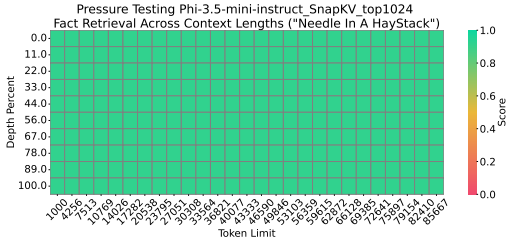
(a) Phi 3.5 Mini 3.8B Instruct + All KV: Score = 91.7



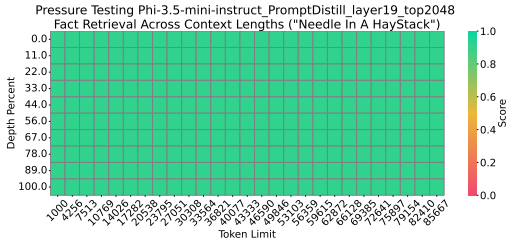
(b) Phi 3.5 Mini 3.8B Instruct + PromptDistill-1024: Score = 91.7



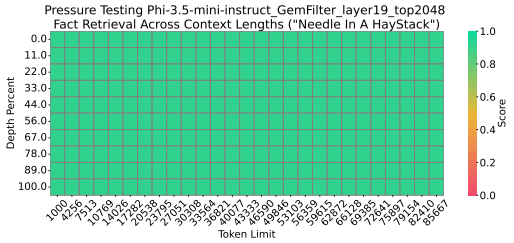
(c) Phi 3.5 Mini 3.8B Instruct + GemFilter-1024: Score = 91.7



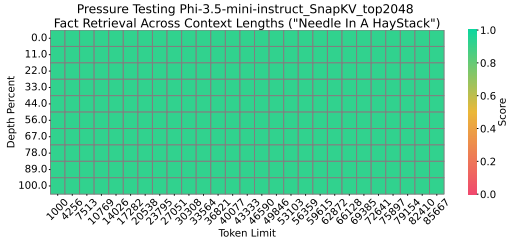
(d) Phi 3.5 Mini 3.8B Instruct + SnapKV-1024: Score = 91.7



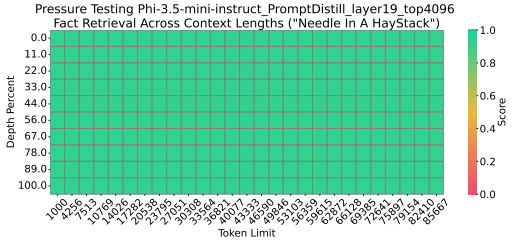
(e) Phi 3.5 Mini 3.8B Instruct + PromptDistill-2048: Score = 91.7



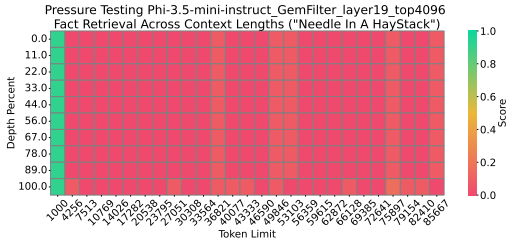
(f) Phi 3.5 Mini 3.8B Instruct + GemFilter-2048: Score = 91.7



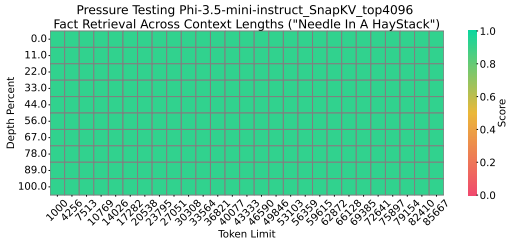
(g) Phi 3.5 Mini 3.8B Instruct + SnapKV-2048: Score = 91.7



(h) Phi 3.5 Mini 3.8B Instruct + PromptDistill-4096: Score = 91.7

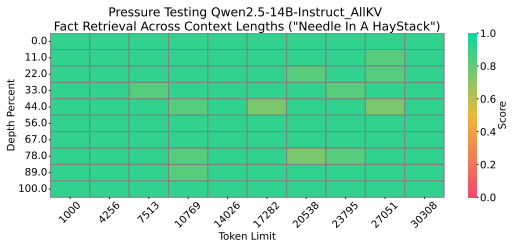


(i) Phi 3.5 Mini 3.8B Instruct + GemFilter-4096: Score = 5.1

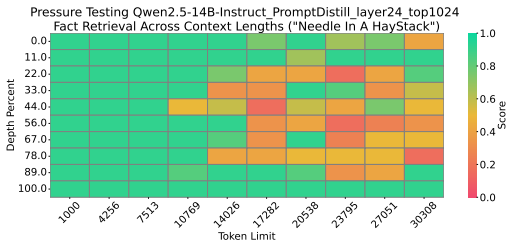


(j) Phi 3.5 Mini 3.8B Instruct + SnapKV-4096: Score = 91.7

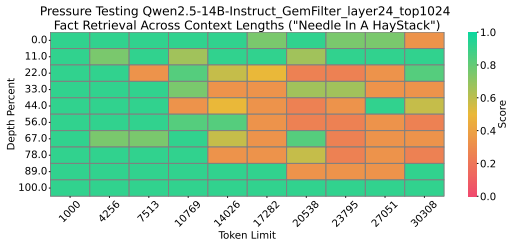
Figure 6: Evaluation Results for Needle in a Haystack: Phi 3.5 Mini 3.8B Instruct's scores in all test cases with all model settings. (The x-axis represents the length of the input tokens, while the y-axis shows the position depth percentage of the 'needle' information)



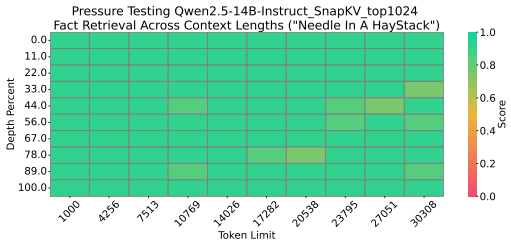
(a) Qwen2.5 14B Instruct + All KV: Score = 90.4



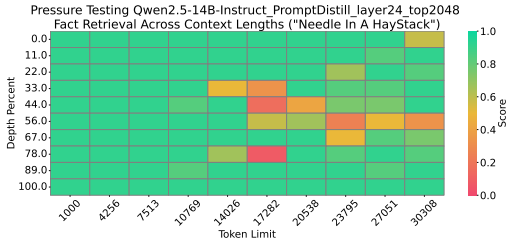
(b) Qwen2.5 14B Instruct + PromptDistill-1024: Score = 73.3



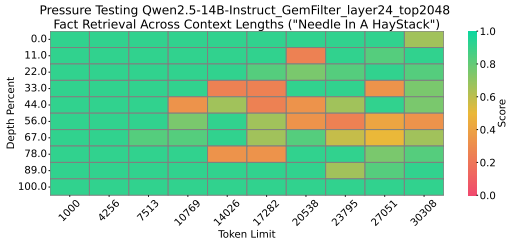
(c) Qwen2.5 14B Instruct + GemFilter-1024: Score = 68.7



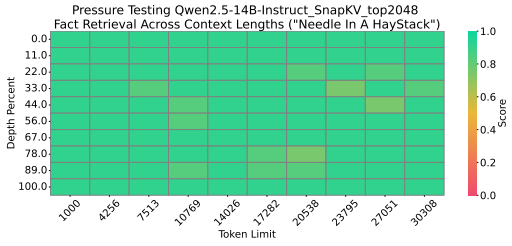
(d) Qwen2.5 14B Instruct + SnapKV-1024: Score = 90.6



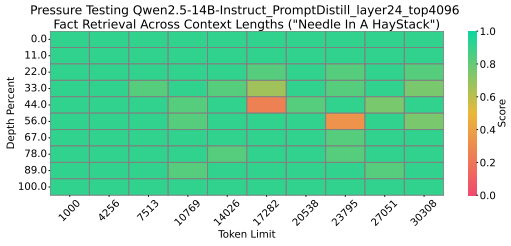
(e) Qwen2.5 14B Instruct + PromptDistill-2048: Score = 83.8



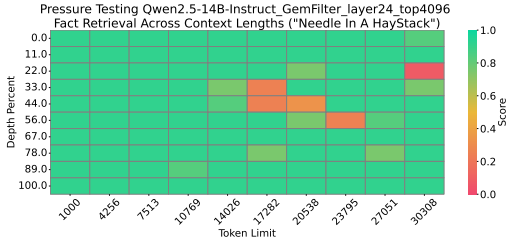
(f) Qwen2.5 14B Instruct + GemFilter-2048: Score = 79.7



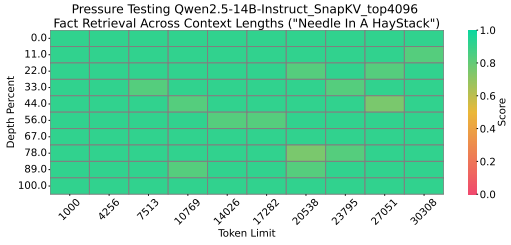
(g) Qwen2.5 14B Instruct + SnapKV-2048: Score = 90.3



(h) Qwen2.5 14B Instruct + PromptDistill-4096: Score = 88.5



(i) Qwen2.5 14B Instruct + GemFilter-4096: Score = 86.9



(j) Qwen2.5 14B Instruct + SnapKV-4096: Score = 90.4

Figure 7: Evaluation Results for Needle in a Haystack: Qwen2.5 14B Instruct's scores in all test cases with all model settings. (The x-axis represents the length of the input tokens, while the y-axis shows the position depth percentage of the 'needle' information)