CAOTE: OPTIMIZING KV CACHE MEMORY THROUGH ATTENTION OUTPUT ERROR-BASED TOKEN EVICTION

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ABSTRACT

Long-context support in large language models (LLMs) amplifies memory and compute bottlenecks during inference, especially in resource-constrained environments. A major contributor is the key–value (KV) cache, which grows linearly with sequence length and can exceed model size. Token eviction—removing less important tokens from the cache—is a widely adopted post-training strategy, but existing methods rely solely on attention scores, ignoring the contribution of value vectors to the attention output. We introduce **CAOTE**, a closed-form criterion that minimizes the change in attention output caused by eviction. CAOTE integrates attention weights and value vectors to compute an exact eviction error per token, and can serve as a meta-policy atop existing heuristics such as H2O, TOVA, and SNAPKV. Across LLaMA-3 and Qwen-2.5 models, CAOTE consistently improves accuracy on LONGBENCH, reduces perplexity gaps, and boosts Needle-in-Haystack recall by up to **60%** at tight budgets (2k–4k tokens). Theoretical analysis shows CAOTE adds negligible overhead ($< 0.1\%$ of prefill FLOPs for 4k–32k contexts), and an efficient variant (FastCAOTE) achieves similar gains with further compute savings. By bounding KV memory while preserving task quality, CAOTE offers a practical, drop-in solution for long-context LLM serving.

1 INTRODUCTION

Large Language Models (LLMs) power applications such as retrieval-augmented generation (RAG), long-form document understanding (Liao et al., 2024), summarization Zhang et al. (2024a), and multi-turn dialogue Thoppilan et al. (2022). These workloads often require processing tens of thousands of tokens, giving rise to long-context inference. A key systems challenge in this setting is the memory and latency overhead of the key–value (KV) cache. While KV caching accelerates autoregressive decoding by reusing past states Pope et al. (2023), its size grows linearly with sequence length and can exceed the model footprint Zhang et al. (2024c). This creates severe bottlenecks for serving stacks, especially under fixed GPU memory budgets or edge deployments. Existing solutions fall into two categories: (i) training-based approaches Zhang et al. (2023); Xiao et al. (2024b), and (ii) post-training eviction policies that dynamically prune tokens to respect memory constraints. The latter is widely adopted in production because it requires no retraining.

Current eviction methods—such as H2O Zhang et al. (2024c), TOVA Oren et al. (2024), and SnapKV Li et al. (2024)—rank tokens by attention scores. However, attention scores capture only query–key alignment, ignoring the contribution of value vectors to the attention output. Since the attention output directly influences hidden states and logits, this omission can lead to suboptimal eviction decisions.

Method	Keys	Values	Min eviction error
H2O	✓	✗	✗
TOVA	✓	✗	✗
CAKE	✓	✗	✗
SnapKV	✓	✗	✗
X+CAOTE	✓	✓	✓

Table 1: Overview of recent token eviction methods compared to CAOTE based on components used during eviction.

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We introduce **CAOTE**, a closed-form criterion that minimizes the change in attention output caused by eviction. CAOTE integrates attention weights and value vectors to compute an exact eviction error per token and can serve as a meta-policy atop existing heuristics. We also propose FastCAOTE, an efficient approximation with negligible compute overhead. Table 1 summarizes recent token eviction methods. Unlike prior approaches that rely solely on keys and attention scores, CAOTE integrates value vectors and directly minimizes attention-output error in closed form.

CAOTE is designed for deployment: it is model-agnostic, parallelizable across heads, and add minimal latency overhead. Both CAOTE and its efficient variant, FastCAOTE, introduce negligible compute overhead during prefill and generation. For typical sequence lengths (4k–32k), CAOTE adds less than 0.1% of prefill FLOPs, while FastCAOTE further reduces cost by replacing the attention-output term with a mean-value approximation, achieving similar accuracy with minimal latency impact. When combined with H2O, TOVA, or SnapKV, CAOTE improves accuracy on LONGBENCH, reduces perplexity gaps, and boosts Needle-in-Haystack recall by up to **60%** at tight budgets—all while bounding KV memory growth.

Contributions.

- We formulate token eviction as minimizing attention-output error and derive a closed-form score that integrates keys and values.
- We show how CAOTE acts as a drop-in policy for existing serving stacks with negligible overhead.
- We empirically demonstrate accuracy and efficiency gains across LLaMA-3 and Qwen-2.5 on long-context benchmarks.
- We provide theoretical overhead analysis and an efficient variant (FastCAOTE) for resource-constrained environments.

2 BACKGROUND

KV caching and token eviction. KV caching accelerates autoregressive decoding by reusing past key–value states, but its memory footprint grows linearly with sequence length and can exceed device constraints. Token eviction mitigates this growth by removing less important tokens, reducing both memory usage and attention computation. In serving environments, combining eviction with *block-wise prefill* yields significant improvements in time-to-first-token (TTFT) for long prompts Holmes et al. (2024); Agrawal et al. (2023). Prior work has explored a variety of post-training eviction policies for decoder-only transformers Xiao et al. (2024b); Oren et al. (2024); Zhang et al. (2024c).

Self-attention preliminaries. We focus exclusively on the self-attention computation that consumes and produces the KV cache, omitting feedforward, normalization, and residual layers for clarity. Let $X^l = [x_1^l, \ldots, x_t^l] \in \mathbb{R}^{t\times d}$ be hidden states at layer l. The attention output is

$$X^l_{\text{attn}} = \underbrace{\text{Softmax}\big(Q^l (K^l)^\top\big)}_{A^l \in \mathbb{R}^{t\times t}} V^l, \tag{1}$$

where $Q^l, K^l, V^l \in \mathbb{R}^{t\times d}$ are Query, Key, and Value respectively. $A^l \in \mathbb{R}^{t\times t}$ is the **attention matrix**. Since token eviction directly modifies the keys and values retained in the cache, we analyze only this attention sublayer.

Block-wise prefill and generation. Rather than processing all t prompt tokens at once, block-wise prefill ingests m tokens at a time. For a new block $t{+}1{:}t{+}m$,

$$X^l_{\text{attn},\, t+1:t+m} = \underbrace{\text{Softmax}\Big(Q^l_{t+1:t+m}\,[K^l_{:t},\, \mathbf{K^l_{t+1:t+m}}]^\top\Big)}_{A^l \in \mathbb{R}^{m\times(t+m)}} [V^l_{:t},\, \mathbf{V^l_{t+1:t+m}}], \tag{2}$$

where bold quantities correspond to newly added tokens. Autoregressive generation is a special case with $m = 1$:

$$X^l_{\text{attn},\, t+1} = \underbrace{\text{Softmax}\Big(Q^l_{t+1}\,[K^l_{:t},\, \mathbf{K^l_{t+1}}]^\top\Big)}_{A^l \in \mathbb{R}^{1\times(t+1)}} [V^l_{:t},\, \mathbf{V^l_{t+1}}]. \tag{3}$$

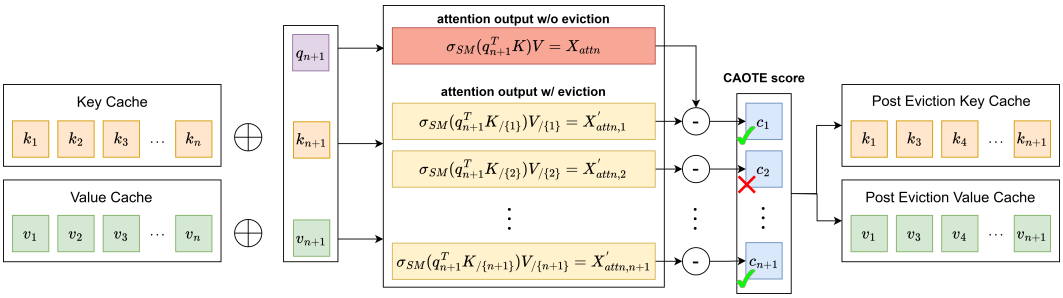


Figure 1: General flow of cache eviction when CAOTE is integrated with existing cache eviction methods. We compute the impact of removal of each token to the attention output, this is same as eviction error (or CAOTE score: $c_1, c_2, \ldots c_{n+1}$). The token with the least impact is removed. Note that σ_{SM} is Softmax operation.

For prompts that exceed memory limits (**memory is hard constrained by a budget** of b tokens), processing a block of m tokens and then evicting within a budget b ensures that the active cache never exceeds b tokens per layer, yielding attention matrices of size $A^l \in \mathbb{R}^{m\times(b+m)}$.

Training-free eviction policies. Most eviction strategies operate directly on the attention matrix. A scoring operator $f_{\text{score}}(A^l) \in \mathbb{R}^{b+m}$ assigns each token a retention score, and the top-b tokens are kept. For example, *H2O* uses row-sums $f_{\text{score},j} = \sum_{i=1}^{m} A^l_{i,j}$ Zhang et al. (2024c), and *TOVA* uses only the latest query's attention $f_{\text{score},j} = A^l_{m,j}$ Oren et al. (2024). Other approaches include query-aware sparsity (*Quest* Tang et al. (2024)), adaptive deletion (*CAKE* Qin et al. (2025)), cache merging (*CaM* Zhang et al. (2024b)), and sliding-window/token-sink mechanisms (*StreamingLLM* Xiao et al. (2023)). While effective, these heuristics primarily rely on *attention scores* and ignore the contribution of value vectors—even though the attention output that drives hidden states is a weighted combination of values.

Value-aware eviction via CAOTE. *CAOTE* addresses this limitation by measuring the change in the attention output that would result from evicting a token. This yields a value-aware retention score that better reflects a token's true influence under fixed memory budgets. We formalize this criterion and its efficient computation in the next sections.

3 Method

3.1 Problem Setup and Notation

We analyze eviction at the level of a single self-attention head. At layer ℓ and head h, the current query attends over the $b+1$ available value vectors. Let

$$A^{\ell,h} = [\alpha_1, \ldots, \alpha_{b+1}] \in \mathbb{R}^{1\times(b+1)}, \qquad V^{\ell,h} = [v_1, \ldots, v_{b+1}] \in \mathbb{R}^{d_{\text{head}}\times(b+1)}.$$

The attention output is the weighted sum

$$X^{\ell,h}_{\text{attn}} = \sum_{j=1}^{b+1} \alpha_j v_j, \qquad \sum_{j=1}^{b+1} \alpha_j = 1.$$

Since the cache must return to budget b, one token must be removed. The goal is to choose the token whose removal minimally perturbs the attention output (see Fig. 1). Formally,

$$j^\star = \underset{j\in\{1,\ldots,b+1\}}{\operatorname{argmin}} \left\| X^{\ell,h}_{\text{attn}} - \tilde{X}^{\ell,h}_{\text{attn},j} \right\|_2,$$

where $\tilde{X}^{\ell,h}_{\text{attn},j}$ denotes the renormalized attention output after evicting token j.

We now introduce CAOTE, a closed-form score that computes this eviction impact efficiently.

3.2 CAOTE: CLOSED-FORM EVICTION ERROR

Let α_j be the pre-eviction attention weight of token j and $X_{\text{attn}} = \sum_i \alpha_i v_i$. After evicting j, the remaining weights renormalize to $\alpha'_i = \alpha_i/(1-\alpha_j)$ for $i \neq j$. The post-eviction attention output is (removing dependence on layer (l), head (h) for simplicity)

$$\tilde{X}_{\text{attn},j} \;=\; \frac{1}{1-\alpha_j}\Big(X_{\text{attn}} - \alpha_j v_j\Big). \tag{4}$$

The *eviction error* equals

$$e_{\text{eviction},j} \triangleq \big\|X_{\text{attn}} - \tilde{X}_{\text{attn},j}\big\|_2 \tag{5}$$

We define **CAOTE** score as c_j, which is given by:

$$c_j \;\triangleq\; \frac{\alpha_j}{1-\alpha_j}\,\big\|v_j - X_{\text{attn}}\big\|_2 \tag{6}$$

We show in Appendix A that CAOTE score and eviction error are equivalent for a token j: $e_{\text{eviction},j} = c_j$

Intuitively, it evicts the token whose value vector is *closest* to the current attention output, tempered by its normalized mass $\alpha_j/(1-\alpha_j)$. Note that the CAOTE score can be computed in parallel for each token.

Impact of Attention Perturbation on Downstream Performance. Since next-token logits are derived from the residual stream that includes X_{attn}, minimizing $\|X_{\text{attn}} - \tilde{X}_{\text{attn},j}\|$ helps keep logits stable. This stability ensures CAOTE optimizes for better downstream task performance by reducing perturbations in the prediction layer (see formal derivation in Appendix C.2).

Multi-token eviction formulation. For evicting $m > 1$ tokens jointly during block-wise prefill, interdependencies arise because each removal changes the renormalization of attention weights. While a closed-form expression exists for all $\binom{b+1}{m}$ combinations, enumerating these is computationally infeasible. In practice, we use greedy CAOTE, selecting the top-m tokens by c_j. Appendix B provides the theoretical formulation and discusses trade-offs, though we do not report experimental results for this extension.

Next, we extend CAOTE to act as a meta-policy over existing heuristic scores.

3.3 USING CAOTE AS A META-POLICY OVER EXISTING SCORES

Many post-training methods provide *scores* $H = [h_1, \ldots, h_{b+1}]$ that rank tokens but do not sum to one (e.g., H2O accumulators). These scores are often heuristic and lack probabilistic interpretation, making direct comparison difficult. CAOTE acts as a *meta-policy* by converting any such scores to a probability simplex and then applying (6). Let $h_j^{\text{norm}} = h_j / \sum_i h_i$; define

$$c_j \;=\; \frac{h_j^{\text{norm}}}{1-h_j^{\text{norm}}}\,\big\|\underbrace{\sum_i h_i^{\text{norm}} v_i}_{X_{\text{attn}}^{(\text{H})}} - v_j\big\|_2^2. \tag{7}$$

Special cases: (i) TOVA already yields weights that sum to one (plug in directly), (ii) H2O needs the simple normalization above (see Appendix C.1).

3.4 FASTCAOTE: A LOW-OVERHEAD APPROXIMATION

To further reduce compute, we approximate X_{attn} by the mean value vector: $\bar{v} = \frac{1}{b+1}\sum_i v_i$. The **FastCAOTE** score is

$$c_j^{\text{fast}} \;=\; \frac{\alpha_j}{1-\alpha_j}\,\big\|\bar{v} - v_j\big\|_2. \tag{8}$$

Empirically, c_j and c_j^{fast} exhibit high rank correlation across layers (see Appendix Table 7 for layer-wise Spearman coefficients), while c_j^{fast} avoids forming X_{attn} explicitly.

Lastly, CAOTE introduces negligible additional computation beyond standard attention. Details on FLOPs and latency overhead are provided in Section 4.1 (Results).

4 EXPERIMENTS

In this section, we demonstrate the efficacy of CAOTE for boosting performance on state-of-the-art token eviction methods on a wide range of downstream benchmarks on recent frontier models: `Llama3` and `Qwen2.5`.

Tasks We study the impact of CAOTE on different token eviction methods by evaluating on LongBench Bai et al. (2024), covering single QA, multiple QA, single/multi-document summarization, synthetic, and code generation tasks. We measure long-context perplexity on the Booksum dataset Kryściński et al. (2021), and lastly, measure recall accuracy on Needle In A Haystack task Liu et al. (2024); Kamradt (2023). Details on context and generation lengths are in Appendix F.1

Baselines We compare the performance of CAOTE to various token eviction methods including: H2O Zhang et al. (2024c), TOVA Oren et al. (2024), and SNAPKV Li et al. (2024), on `Llama3` models: `Llama 3.2-3B-Instruct` and `Llama 3.1-8B-Instruct` Dubey et al. (2024), and `Qwen2.5` models: `Qwen 2.5-3B-Instruct` and `Qwen 2.5-7B-Instruct` Yang et al. (2024) for all subsequent experiments. "Additionally, we compare our cache management approach with StreamingLLM (also known as Sink) Xiao et al. (2023) in Appendix F.

Budgets We evaluated all methods with various KV cache budget sizes of 2048, 4096, 6144, and 8192, denoted by 2k, 4k, 6k, and 8k, respectively.

Prompt consumption *Unlike other token eviction methods that assume to prefill prompt at once followed by KV cache eviction, we propose to consume tokens in block-wise manner* as described in Section 2 with the block-size of 128, i.e., at each inference of LLM during the prefill phase, there are 128 new tokens incoming and being added to the cache, and 128 tokens from the cache are evicted once the total number of tokens reaches the cache budget limit.

We begin with LongBench results, followed by perplexity evaluations, and conclude with precision-focused Needle benchmarks and compute overhead analysis.

LongBench We present the accuracy of `Llama 3.1-8B-Instruct`, `Llama 3.2-3B-Instruct` and, `Qwen 2.5-3B-Instruct`, `Qwen 2.5-7B-Instruct` using baseline eviction methods with budget of 2k, 4k, both with and without CAOTE in Table 2 and Table 3. We observe that the best average performance is given by SNAPKV-FastCAOTE for the `Llama3` models, while for `Qwen2.5` models SNAPKV-CAOTE performs the best. **H2O shows $> 30\%$ improvement with CAOTE**, while TOVA, SNAPKV also show overall improvements, making their average accuracy closer to dense accuracy. Moreover, we obserive that for **QA tasks (Qasper, MF-en, Musique, 2WikiMQA), H2O-FastCAOTE performs best**. We have bolded the best accuracy eviction method for 2k budget in Table 2. Additional results for the 6k, 8k budget are shown in Table 10, Table 11 for `Llama3` and `Qwen2.5` respectively, in Appendix F.2, which follow a trend similar to the 2k, 4k budgets. Table 10 also has (Xiao et al., 2024b)

Perplexity We use the Booksum dataset Kryściński et al. (2021) to measure generation perplexity of different eviction methods for various budgets. In Table 4, we show perplexity gap between a model using a given eviction strategy and that of the model without token eviction with cache budgets of 2k, 4k and 6k. We observe that when CAOTE is applied to existing eviction methods, the perplexity either improves or surpasses the perplexity of the baseline model. TOVA-FastCAOTE, SNAPKV-CAOTE, and SNAPKV-FastCAOTE perform best for 6k, 4k, 2k budgets, respectively, for `Llama 3.1-8B-Instruct`; for `Llama 3.2-3B-Instruct`, TOVA-FastCAOTE performs best with 2k and 4k budgets and SNAPKV-FastCAOTE beats other methods using 6k and 8k. Perplexity results for `Qwen2.5` models are shown in Table 12 in Appendix F.3.

Needle In A HayStack We run extensive experiments on Needle-In-A-Haystack benchmark Liu et al. (2024); Kamradt (2023) and show quantitative results in Table 5 and visualizations for 6k budget for `Llama3.1-8B-Instruct` in Figure 2. We observe in Table 5 that H2O-FastCAOTE performs best for all budgets with `Llama3.2-3B-Instruct`. H2O-CAOTE performs best for `Llama3.1-8B-Instruct` with budget = $\{$2k, 6k$\}$ and H2O-FastCAOTE per-

Table 2: **LongBench results for Llama 3.1-8B and Llama 3.2-3B-Instruct.** Higher number is better. We highlight the best performing methods within a given budget with **bold**.

		Single Doc. QA			Multi Doc. QA			Summarization			Fewshot Learning			Synthetic		Code		
		Narrative QA	Qasper	MF-en	HotpotQA	2WikiMQA	Musique	GovReport	QMSum	MultiNews	TREC	TriviaQA	SAMSum	PCount	PR-en	Lcc	RB-P	Avg.
	Llama 3.1-8B	30.05	47.00	56.12	57.33	47.81	32.25	34.86	25.32	27.02	73.00	91.61	43.37	8.33	99.50	61.66	51.94	49.20
2k	H2O	1.74	21.15	25.33	26.11	24.15	8.78	2.17	2.70	16.78	44.00	29.36	7.62	2.25	5.88	40.15	12.14	16.89
	+ CAOTE	14.32	38.34	45.97	37.77	**42.51**	22.06	29.57	15.11	**27.02**	62.00	63.60	27.34	2.00	15.50	56.99	32.87	33.31
	+ FastCAOTE	15.15	**41.27**	**46.6**	39.91	40.02	**24.55**	**30.05**	16.19	26.95	63	62.39	26.86	3.08	17.5	56.87	34.75	34.07
	TOVA	22.57	37.26	39.43	45.74	34.48	14.77	28.87	21.17	26.95	62.50	90.73	42.74	0.00	18.00	**62.68**	52.48	37.52
	+ CAOTE	21.92	37.47	38.28	45.88	35.2	15	29.02	21.21	27	62.5	91.34	43.22	1.5	23	**62.60**	**54.13**	38.08
	+ FastCAOTE	21.94	38.22	38.22	**46.72**	36.93	14.31	29.06	21.72	26.98	63	**91.65**	**43.53**	1.5	22	62.44	52.88	38.19
	SnapKV	21.81	37.22	37.19	46.10	35.42	16.53	29.83	21.05	26.77	61.00	88.84	42.56	**4.03**	51.50	62.37	51.45	39.60
	+ CAOTE	21.75	37.49	36.86	44.62	37.26	16.82	**30.30**	21.67	26.88	64	90.65	42.8	2.09	53.00	62.5	52.09	40.05
	+ FastCAOTE	**23.26**	38.54	39.16	43.2	38.27	17.54	**30.28**	**21.97**	26.76	**65.5**	90.91	42.71	2.84	**56.00**	62.36	52.4	**40.73**
4k	H2O	4.07	**36.16**	36.00	33.52	32.87	17.78	6.66	5.95	24.09	55.00	47.65	17.41	4.00	24.50	54.85	21.43	26.37
	+ CAOTE	20.28	46.08	**51.45**	47.38	**46.05**	**30.89**	**33.39**	20.8	26.93	**69.00**	80.12	38.27	4.31	32	59.22	40.51	40.42
	+ FastCAOTE	24.4	44.32	48.11	48.19	43.69	21.12	31.55	22.36	26.98	65.00	91.18	43.11	2	46.5	61.62	53.35	42.09
	TOVA	22.68	44.55	47.87	46.76	44.54	20.56	30.95	22.13	26.96	61.50	90.56	43.27	3.00	43.50	**61.62**	**53.40**	41.49
	+ CAOTE	**24.68**	43.88	48.07	49.64	44.91	22.57	31.25	22.25	26.98	63.00	91.29	43.29	2.5	46.5	**61.60**	**53.45**	42.24
	+ FastCAOTE	24.4	44.32	48.11	48.19	43.69	21.12	31.55	22.36	26.98	65	91.18	43.11	2	46.5	**61.62**	53.35	42.09
	SnapKV	**24.79**	44.22	47.30	48.49	**46.73**	20.55	32.19	22.68	26.95	67.50	90.98	43.14	**5.17**	89.50	61.44	51.20	45.18
	+ CAOTE	24.41	43.16	47.77	**50.87**	44.11	21.04	32.51	**22.98**	26.93	**69.00**	**91.31**	43.18	3.33	92.00	61.04	51.74	45.34
	+ FastCAOTE	24.12	44.59	47.39	50.82	44.07	22.38	32.33	**22.92**	**27.01**	**69.00**	**91.31**	**43.53**	4.58	**94.50**	61.31	52.11	**45.75**
	Llama 3.2-3B	23.76	40.23	50.09	50.69	42.29	26.84	33.09	24.30	25.21	72.50	90.11	42.58	3.00	96.50	56.22	56.52	45.87
2k	H2O	1.63	19.96	20.20	18.02	19.56	2.88	0.78	1.55	15.97	41.00	21.97	9.83	0.50	0.50	39.71	13.91	14.25
	+ CAOTE	6.38	**34.36**	**40.6**	32.52	31.08	12.69	27.36	15.04	24.6	59	52.83	26.78	3.7	7.56	51.09	36.33	28.87
	+ FastCAOTE	7.27	34.23	39.74	32.22	30.08	12.63	**27.86**	15.48	25.15	60.5	53.09	26.94	2.17	8.12	51.2	35.06	28.86
	TOVA	17.14	30.14	32.44	35.96	30.05	13.08	26.15	19.70	25.04	56.50	87.81	40.48	2.50	11.50	55.51	52.36	33.52
	+ CAOTE	17.75	30.45	32.19	37.53	29.35	13.33	26.92	19.93	25.18	60.50	88.08	**41.65**	1.00	12.5	54.92	53.22	34.03
	+ FastCAOTE	17.93	30.52	33.1	37.01	30.7	**13.88**	26.39	20.28	24.96	60.50	**88.95**	41.27	2.00	12.5	55.65	53.56	34.33
	SnapKV	17.38	31.37	31.48	37.77	30.05	11.54	27.03	19.93	24.97	59.00	88.13	40.48	3.50	32.50	56.32	55.91	35.46
	+CAOTE	**19.11**	33.12	31.09	38.68	**32.09**	12.31	27.48	**20.38**	**25.20**	64.00	87.7	40.78	2.5	35	**57.03**	56.21	36.42
	+FastCAOTE	18.96	32.97	33.61	**39.00**	31.36	12.35	27.48	20.15	**25.24**	**65.00**	87.2	40.70	**4.5**	**36.5**	56.06	**57.12**	**36.76**
4k	H2O	2.92	31.94	33.23	24.49	28.08	7.55	5.44	6.30	22.77	53.00	38.85	20.33	1.50	7.50	51.23	22.94	22.38
	+CAOTE	12.87	**40.79**	47.56	40.28	**39.07**	16.61	30.82	19.65	25.12	65.5	69.29	34.16	2.35	17	55.32	45.12	35.09
	+FastCAOTE	11.85	40.41	**47.93**	40.81	38.93	17.36	**31.22**	19.67	25.1	65	71.25	34.89	3.5	15	55.5	44.3	35.17
	TOVA	**20.52**	39.53	42.47	44.12	38.42	18.22	29.36	21.36	24.96	63.50	88.98	41.50	3.00	23.50	**55.72**	56.66	38.24
	+CAOTE	19.59	39.79	42.03	45.25	37.07	**19.3**	29.39	21.57	24.92	63	**89.14**	41.77	3.00	29.5	55.68	56.19	38.57
	+FastCAOTE	19.77	39.23	43.13	45.28	37.04	18.82	29.25	21.94	24.96	63	88.64	**41.92**	**3.5**	29	55.68	56.41	38.6
	SnapKV	19.85	39.22	39.86	**46.70**	37.98	16.64	29.79	21.21	25.01	65.50	89.35	40.95	2.50	62.50	**55.74**	**56.88**	40.60
	+CAOTE	20.1	39.74	41.01	45.64	38.26	18.64	30.07	21.53	24.98	**67.5**	89.08	41.78	3.00	67	**55.73**	**56.71**	41.30
	+FastCAOTE	19.68	39.24	41.03	44.52	**39.09**	18.62	30.15	**21.72**	**24.97**	67	88.86	41.24	3.00	**71**	55.67	56.64	**41.40**

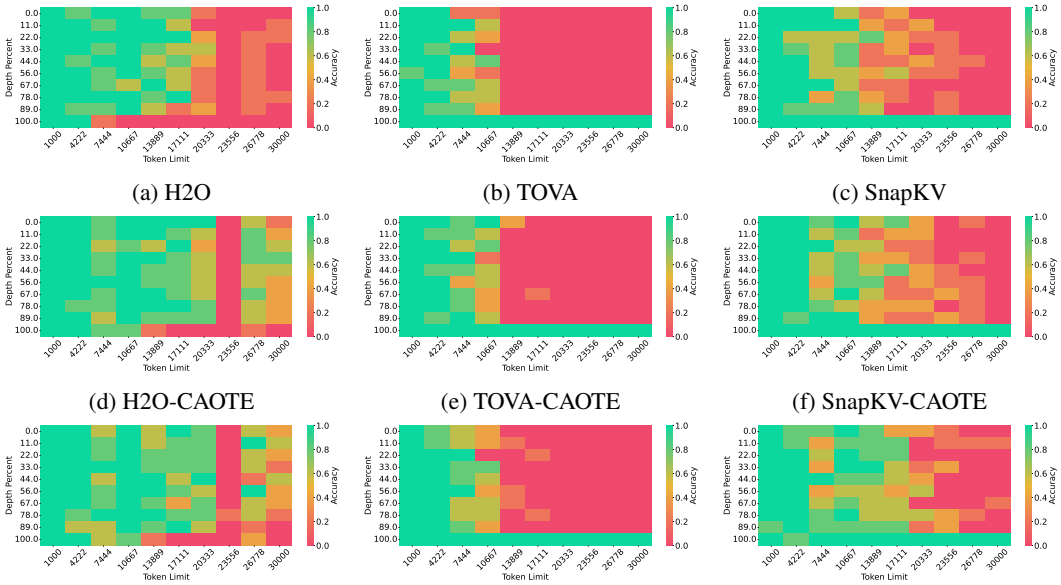
Table 3: **LongBench results for Qwen 2.5-7B/2.5-3B-Instruct.** Higher number is better. We highlight the best performing methods within a given budget with **bold** and the second best with underline.

		Single Doc. QA			Multi Doc. QA			Summarization			Fewshot Learning			Synthetic		Code		
		Narrative QA	Qasper	MF-en	HotpotQA	2WikiMQA	Musique	GovReport	QMSum	MultiNews	TREC	TriviaQA	SAMSum	PCount	PR-en	Lcc	RB-P	Avg.
	Qwen 2.5-7B	15.75	16.94	32.38	11.89	11.88	7.95	34.33	19.91	22.67	65.5	87.05	44.75	4.22	93.08	57.74	61.84	36.74
2k	H2O	2.39	7.29	12.42	8.55	11.06	2.73	3.62	6.6	15.69	42.5	28.21	10.63	0.65	0	35.1	18.77	12.89
	+ CAOTE	4.55	**14.30**	27.58	11.33	**13.55**	7.76	26.65	15.62	22.93	57.0	49.78	27.74	1.54	11.08	51.45	32.7	23.47
	+ FastCAOTE	4.8	12.79	**28.72**	12.94	13.25	7.53	27.06	14.46	22.84	**59.0**	48.23	26.4	2.53	11.54	52.85	32.93	23.62
	TOVA	8.49	14.01	21.04	14	11.51	5.09	27.43	17.84	22.83	56.5	79.56	40.55	2.43	9.29	55.99	56.15	27.67
	+ CAOTE	10.46	14.82	25.06	14.62	11.73	6.01	27.66	18.02	22.78	**57.5**	79.39	40.87	2.50	11.25	56.22	56.51	28.46
	+ FastCAOTE	10.08	13.58	25.28	14.44	12.14	5.24	27.34	18.31	**23.11**	55.5	78.51	**41.67**	2.70	10.54	**56.56**	**58.05**	28.32
	SnapKV	11.6	12.45	23.66	12.38	10.64	7.03	27.57	18.27	22.85	58.0	**81.78**	41.13	**3.76**	19.42	55.83	56.53	28.93
	+ CAOTE	**14.02**	12.23	24.55	**16.45**	10.35	**8.59**	27.77	**18.91**	22.87	56.0	80.58	40.43	2.38	21.52	55.17	56.03	29.24
	+ FastCAOTE	**14.26**	14.11	24.11	15.31	11.35	7.88	**27.95**	18.86	22.74	56.5	80.92	**41.49**	**3.80**	**22.42**	55.89	57.43	**29.69**
4k	H2O	1.99	11.92	19.88	10.24	10.12	4.73	9.08	10.14	20.85	51.00	37.37	20.57	3.16	6.43	52.14	29.09	18.67
	+ CAOTE	4.78	**18.06**	32.49	16.23	**17.28**	9.57	29.81	18.04	22.86	**59.5**	63.05	36.91	2.7	28.25	55.13	42.42	28.57
	+ FastCAOTE	5.69	16.99	**32.62**	18.22	16.58	**10.48**	**30.30**	17.71	**22.88**	**59.5**	62.95	36.29	2.1	27.65	56.30	40.65	28.56
	TOVA	12.83	17.03	27.01	16.8	13.37	8.05	29.21	19.05	22.73	58.5	82.67	42.71	1.67	15	56.69	56.59	29.99
	+ CAOTE	12.97	14.99	27.53	17.94	12.93	9.21	29.76	19.70	**22.92**	58	82.03	**43.14**	2.15	17.25	57.32	**59.37**	30.98
	+ FastCAOTE	14.52	16.71	26.97	**18.73**	13.84	9.59	29.47	19.45	22.87	**59.5**	**82.96**	42.42	2.60	20.33	57.22	58.42	30.98
	SnapKV	14.35	13.45	28.28	16.33	11.74	8.12	29.71	19.18	22.82	57	83.8	**43.27**	2.41	39.83	**58.12**	58.67	31.69
	+ CAOTE	15.07	14.34	28.70	16.7	12.89	**10.54**	30.03	19.58	22.73	**59.5**	83.12	42.56	3.17	**55.92**	57.34	58.85	**33.19**
	+ FastCAOTE	**17.12**	14.69	27.6	17.52	13.69	9.96	**30.24**	**20.02**	**22.88**	58.5	81.13	42.31	**4.06**	53.33	57.51	58.77	33.08
	Qwen 2.5-3B	18.08	22.49	39.72	27.86	20.45	18.93	32.8	23.74	24.89	67.5	85.05	43.88	5	40.97	51.91	47.53	35.68
2k	H2O	1.8	9.18	11.62	8.54	7.31	2.77	5.93	6.99	16.89	38	21.87	7.69	1	3	37.36	22.9	12.68
	+ CAOTE	6.9	**22.71**	28.09	15.23	**18.19**	4.95	**29.53**	17.68	24.74	52.5	45.81	26.95	1.92	6.16	45.81	36.48	23.98
	+ FastCAOTE	7.03	22.37	**28.88**	15.34	16.95	5.19	29.13	18.06	**25.03**	54.5	46.35	25.35	2.23	7.22	45.7	36.59	24.12
	TOVA	11.69	14.94	25.33	17.29	12.58	5.91	26.67	21.49	24.78	51.5	68.8	41.79	0.23	6	49.79	48.6	26.71
	+ CAOTE	11.17	15.23	27.42	18.94	13.1	6.94	27.01	21.62	24.86	57.5	68.38	42.11	0.82	4.88	49.36	48.13	27.34
	+ FastCAOTE	11.04	15.36	27.72	**19.80**	13.65	6.37	27.17	**22.08**	24.64	57	69.13	42.48	0.77	5.25	48.36	48.58	27.46
	SnapKV	11.7	13.91	24.28	14.8	10.89	7.42	27.4	21.63	24.64	54.5	75.35	42.72	2.5	18.33	49.65	50.59	28.14
	+CAOTE	**12.69**	14.88	26.16	13.93	12.21	7.07	27.48	20.99	24.75	61.0	**75.58**	42.08	**4**	**21.29**	**49.94**	**52.38**	**29.15**
	+FastCAOTE	12.03	14.56	24.82	14.66	10.83	**7.89**	27.51	20.98	24.67	**62.5**	**75.51**	41.53	2	17	49.02	50.83	28.52
	H2O	2.82	17.34	23.27	10.18	10.47	3.03	11.06	10.73	22.93	50.75	34.93	18.03	4.35	7.32	47.74	29.42	19.02
	+CAOTE	7.63	**24.16**	**35.29**	20.17	**17.67**	**12.61**	**31.14**	19.04	**25.01**	62.5	64.84	34.19	4.25	18.37	49.79	41.45	29.26
	+FastCAOTE	8.58	23.45	33.14	**21.72**	16.11	12.26	**31.11**	19.76	**25.04**	62	65.01	35.15	**4.60**	17.88	50.05	40.03	29.12
4k	TOVA	12.19	18.31	32.56	20.58	13.8	7.74	28.82	22.27	24.98	59	80.66	43.05	1.11	9.56	49.93	46.74	29.46
	+CAOTE	13.16	18.67	30.74	19.33	15.7	7.32	28.93	22.14	24.91	59.5	78.54	**43.57**	1.55	8.25	49.4	47.31	29.31
	+FastCAOTE	12.2	18.55	32.29	19.3	15.13	7.23	29.12	22.44	24.97	60	78.8	43.12	1.5	10.25	49.6	47.74	29.52
	SnapKV	12.98	2.21	31.77	18.33	14.41	10.83	29.14	**22.38**	24.89	61	**84.17**	42.63	3.75	**25.42**	50.22	48.77	30.18
	+CAOTE	13.65	20.35	32.62	19.36	15.27	11.42	29.47	**22.44**	24.78	64.0	82.6	43	4.25	24.46	**50.37**	49.28	**31.71**
	+FastCAOTE	**13.46**	19.92	32.53	20.44	13.64	8.44	29.56	22.14	24.93	**64.5**	82.73	43.26	2	24.58	50.14	**50.08**	31.40

forms best for 4k budget. The gains in precision are especially high for the 4 k budget for the `Llama3.1-8B-Instruct`, with an increase of up to $30 - 60\%$. We can see in Figure 2 that

Table 4: **Perplexity difference between different eviction methods with dense baseline.** The lower is better. Negative entry in table means the method performs better than dense baseline. The PPL of Llama 3.2-3B-Instruct and Llama 3.1-8B-Instruct is 15.4911 and 9.833 respectively.

Budget	H2O			TOVA			SnapKV		
		+CAOTE	+FastCAOTE		+CAOTE	+FastCAOTE		+CAOTE	+FastCAOTE
Llama 3.1-8B-Instruct									
2k	2.007	1.884	1.891	-0.046	-0.088	-0.085	-0.019	-0.097	**-0.098**
4k	1.284	1.079	1.061	-0.047	-0.060	-0.058	-0.0483	**-0.080**	-0.079
6k	0.843	0.716	0.703	-0.035	-0.0366	**-0.085**	-0.036	-0.043	-0.045
Llama 3.2-3B-Instruct									
2k	3.814	3.561	3.563	0.493	0.442	**0.432**	0.555	0.451	0.435
4k	2.460	2.142	2.128	0.175	0.150	**0.144**	0.223	0.152	0.144
6k	1.369	1.219	1.187	0.065	0.057	0.057	0.076	0.056	**0.044**
8k	0.589	0.462	0.448	0.023	0.012	0.011	0.020	0.007	**0.005**



(a) H2O (b) TOVA (c) SnapKV

(d) H2O-CAOTE (e) TOVA-CAOTE (f) SnapKV-CAOTE

(g) H2O-FastCAOTE (h) TOVA-FastCAOTE (i) SnapKV-FastCAOTE

Figure 2: Needle-In-A-Haystack accuracies of Llama 3.1-8B-Instruct with token eviction with 6k cache budget.

CAOTE improves the state-of-the-art eviction method and is able to predict beyond their budget constraints. Results for `Qwen2.5` models are shown in Table 13 in Appendix F.4. These results demonstrate that CAOTE significantly enhances retrieval precision under tight memory constraints, outperforming existing methods across models and budgets.

4.1 Compute Overhead

We theoretically measure CAOTE's efficiency across context lengths (4k–32k) and compare it to baseline attention FLOPs. Computing c_j requires one lightweight aggregation to form X_{attn} and $O((b{+}1)d_{\text{head}})$ vector norms, which is negligible relative to attention operations. CAOTE adds $<$0.1% of prefill FLOPs and incurs minimal per-step cost during generation. Table 6a, 6b reports FLOPs and latency overhead for different sequence lengths, showing that CAOTE's impact remains nearly constant and insignificant compared to total inference cost (see Appendix E for full breakdown).

5 Related Work

Sparse and efficient attention methods reduce compute or memory via linear approximations Katharopoulos et al. (2020), KV-compression with merged summaries Dong et al. (2024), or constant-memory architectures such as Landmark attention Mohtashami & Jaggi (2023), but these require retraining and are not directly applicable to post-training caching.

Table 5: **Needle-in-haystack accuracy** for Llama 3.2-3B/3.1-8B-Instruct using baseline eviction methods with(out) *CAOTE*. Higher is better, maximum accuracy is 1.0.

Budget	H2O			TOVA			SnapKV		
		+CAOTE	+FastCAOTE		+CAOTE	+FastCAOTE		+CAOTE	+FastCAOTE
Llama 3.1-8B-Instruct									
2k	0.174	**0.270**	0.264	0.196	0.204	0.202	0.214	0.226	0.242
4k	0.330	0.538	**0.568**	0.286	0.298	0.292	0.360	0.392	0.420
6k	0.544	**0.698**	0.676	0.370	0.402	0.396	0.490	0.550	0.580
Llama 3.2-3B-Instruct									
2k	0.104	0.160	**0.172**	**0.172**	0.150	0.166	0.154	**0.172**	0.168
4k	0.198	0.262	**0.294**	0.220	0.232	0.232	0.226	0.222	0.232
6k	0.258	0.308	**0.322**	0.258	0.278	0.270	0.272	0.264	0.312
8k	0.324	0.414	**0.404**	0.338	0.364	0.344	0.342	0.336	0.366

Table 6: Compute overhead ratios for CAOTE and FastCAOTE.

(a) Prefill phase

Sequence Length	Ratio	
	with CAOTE	with FastCAOTE
4k	1.6e-4	8.9e-5
8k	9.25e-5	5.28e-5
32k	6.45e-5	3.69e-5

(b) Generation phase

Sequence Length	Ratio	
	with CAOTE	*with FastCAOTE*
512	0.08	0.046
1024	0.15	0.087

Post-training KV-eviction methods instead rank tokens under a fixed cache budget. Approaches such as StreamingLLM Xiao et al. (2024b), H2O Zhang et al. (2024c), TOVA Oren et al. (2024), SNAPKV Li et al. (2024), and ROCO Ren & Zhu (2024) rely primarily on attention-score heuristics. StreamingLLM additionally exploits attention-sink behavior; however, its sliding-window strategy performs worse than recent methods on long-context benchmarks (see Appendix Table Table 10).

These attention-aligned approaches ignore value-vector contributions to the attention output. CAOTE provides a complementary value-aware criterion by estimating the change in attention output caused by evicting a token. It augments approximate methods such as QUEST Tang et al. (2024) and CaM Zhang et al. (2024b), and integrates naturally with strong modern baselines like SNAPKV. Other orthogonal directions—layer-wise budgeting Feng et al. (2024), token-characteristic prioritization Ge et al. (2023), and head-selection methods like DuoAttention Xiao et al. (2024a)—remain compatible with CAOTE. Concurrent work such as AhaKV Gu et al. (2025) also leverages value-vector information for eviction scoring, whereas our method focuses on minimizing attention-output error as the retention objective.

6 Conclusion

We propose a post-training KV cache eviction method that can be seamlessly integrated with any existing eviction strategies. Our approach, CAOTE, introduces an optimization objective aimed at minimizing the alteration in attention output when evicting a token. This objective ensures the incorporation of both attention scores and value vectors in the eviction decision process. Our formulation allows for the parallel computation of the CAOTE score for all tokens. Additionally, we present an efficient variant, FastCAOTE. Through extensive evaluations across various downstream tasks, we demonstrate that eviction methods equipped with CAOTE consistently deliver superior performance.

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A CAOTE FORMULATION PROOFS

Theorem A.1. *Given a new input token that exceeds the budget (b) by* 1*. A token needs to be evicted. For any token j being evicted, given the retention scores pre-eviction and post-eviction for any token $i \neq j$ as α_i and α_i' respectively, then the following relation holds:*

$$\alpha_i' = \frac{\alpha_i}{1 - \alpha_j} \tag{9}$$

Proof. Let the last input token has index n, then we define

$$S \triangleq \sum_{l=1}^{n} \exp(q_n^T k_l) \tag{10}$$

$$S_j' \triangleq S - \exp(q_n^T k_j) \tag{11}$$

The retention score for token i after evicting token j is

$$\alpha_i' = \frac{\exp(q_n^T k_i)}{S_j'} = \frac{\exp(q_n^T k_i)}{S - \exp(q_n^T k_j)} = \frac{\alpha_i}{1 - \alpha_j} \tag{12}$$

□

Theorem A.2. *Given a new input token that exceeds the budget (b) by* 1*. A token needs to be evicted. For any token j being evicted, the CAOTE score is equivalent to the eviction error:*

$$c_j = e_{eviction,j} \tag{13}$$

Proof. Using Theorem A.1, we can rewrite post-eviction attention output as:

$$\begin{aligned} \tilde{X}_{\text{attn},j} =& \frac{1}{1 - \alpha_j}\big(\alpha_1 v_1 + \cdots + \alpha_{j-1} v_{j-1} \\ &+ \alpha_{j+1} v_{j+1} + \ldots \alpha_{b+1} v_{b+1}\big) \end{aligned} \tag{14}$$

$$= \frac{1}{1 - \alpha_j}\big(X_{\text{attn}} - \alpha_j v_j\big) \tag{15}$$

Replacing Eq. (15) in Eq. (13), we get

$$\begin{aligned} e_{\text{eviction},j} =& ||X_{\text{attn}} - \tilde{X}_{\text{attn},j}||_2 \\ =& ||X_{\text{attn}} - \frac{1}{1 - \alpha_j}(X_{\text{attn}} - \alpha_j v_j)||_2 \\ =& \frac{\alpha_j}{1 - \alpha_j}||v_j - X_{\text{attn}}||_2 \\ =& c_j \end{aligned} \tag{16}$$

Hence proved. □

B Extending CAOTE to Multi-token Eviction

We start with simple example, without loss of generality consider evicting two tokens in the order $i = 1, j = 2$. From (6) single token eviction error for token 1 is

$$c_1 = \frac{\alpha_1}{1 - \alpha_1}||X_{\text{attn}} - v_1||_2 \tag{17}$$

After evicting token 1, the updated attention output becomes:

$$X_{\text{attn},1}^{'} = \Sigma_{i=2}^{n+1} \alpha_i^{'} v_i, \text{ where } \alpha_i^{'} = \frac{\alpha_i}{1 - \alpha_1} \tag{18}$$

Now, evicting token 2 from updated attention output above yields

$$X_{\text{attn},[1,2]}^{''} = \Sigma_{i=3}^{n+1} \alpha_i^{''} v_i, \tag{19}$$

$$\text{where } \alpha_i^{''} = \frac{\alpha_i^{'}}{1 - \alpha_2^{'}} = \frac{\alpha_i}{1 - \alpha_1 - \alpha_2} \tag{20}$$

This leads to the following insights:

- The updated attention output can be expressed as

$$X_{\text{attn},[1,2]}^{''} = \frac{1}{1 - \alpha_2^{'}}(X_{\text{attn},1}^{'} - \alpha_2^{'} v_2) \tag{21}$$

- Eviction error of removing token 2 after removing token 1 is

$$c_{[1,2]} = ||X_{\text{attn},1}^{'} - X_{\text{attn},[1,2]}^{''}||_2 \tag{22}$$

- Substituting the expressions above, we obtain a **closed-form joint eviction score**:

$$c_{[1,2]} = \frac{1}{1-\alpha_1-\alpha_2}||\alpha_1(X_{\text{attn}} - v_1) + \alpha_2(X_{\text{attn}} - v_2)||_2 \tag{23}$$

This formulation generalizes to evicting m tokens jointly (assuming first m tokens here without loss of generality)

$$c_{[1,\ldots,m]} = \frac{1}{1-\Sigma_{i=1}^{m}\alpha_i}||\Sigma_{i=1}^{m}\alpha_i(X_{\text{attn}} - v_i)||_2 \tag{24}$$

This expression highlights the combinatorial nature of multi-token eviction: for n tokens with m-token eviction, there are $\binom{n}{m}$ possible combinations. This makes exact computation intractable for large m, motivating the need for approximate or greedy strategies.

Importantly, existing token eviction methods typically rely only on attention scores and assume independence between tokens. As a result, the relative ranking of tokens remains unchanged even after evictions, which limits their effectiveness in multi-token settings.

In contrast, CAOTE explicitly models the interplay between attention scores and value vectors, capturing how evicting one token affects the contribution of others. This introduces interdependencies between tokens during eviction, which are critical for accurate multi-token decisions.

C Additional Proofs

C.1 H2O scores

Theorem C.1. *Given H2O scores for $b+1$ tokens as $[h_1, \ldots, h_{b+1}]$, the summation of all h_i, $\forall i \in \{1, \ldots, b+1\}$ is greater than* 1

$$\Sigma_{i=1}^{b+1} h_i > 1 \tag{25}$$

Proof. Assuming that only $b+1$ tokens are present and are propagated through the model at the same time. The causal attention mask $A \in [0,1]^{b+1\times b+1}$, will have all entries on upper triangle excluding diagonal is 0. The first token will attend to itself have attention score as 1

$$A_{1,1} = 1 \tag{26}$$
$$A_{1,>1} = 0 \tag{27}$$

H2O score for token 1 is defined as the sum of attention score to token 1 by all future tokens:

$$h_1 = A_{1,1} + A_{2,1} + \cdots + A_{b+1,1} = \Sigma_{i=1}^{b+1} A_{i,1} \tag{28}$$

In general for a token j, the H2O score is defined as

$$h_j = A_{j,j} + A_{j+1,j} + \cdots + A_{b+1,j} \tag{29}$$
$$= \underbrace{A_{1,j} + \cdots + A_{j-1,j}}_{=0 \text{ causal mask}} + A_{j,j} \cdots + A_{b+1,j} \tag{30}$$
$$= \Sigma_{i=1}^{b+1} A_{i,j} \tag{31}$$

Using Eq. (31) and summing for all H2O scores, we get

$$\Sigma_{j=1}^{b+1} h_j = \Sigma_{j=1}^{b+1}\Sigma_{i=1}^{b+1} A_{i,j} \tag{32}$$
$$= \Sigma_{i=1}^{b+1}\Sigma_{j=1}^{b+1} A_{i,j} \tag{33}$$
$$= \Sigma_{i=1}^{b+1}\Big(\underbrace{\Sigma_{j=1}^{i} A_{i,j}}_{=1 \text{ due to softmax}} + \underbrace{\Sigma_{j=j+1}^{b+1} A_{i,j}}_{=0 \text{ for causal mask}} \Big) \tag{34}$$
$$= b+1 > 1 \tag{35}$$

Hence proved.

□

C.2 Relation of CAOTE score to output logits

We show that evicting token based on CAOTE score can lead to smaller discrepancy in final logits which affect the downstream performance. As CAOTE score is the eviction error during generation phase, we instead show the relation between eviction error and logits. We start by showing for a single attention layer (single head) based network, its extension to multiple heads and, finally a transformer layer (self-attention and feed-forward-network). For simplicity we ignore layer-norms. Some definitions which will used are given below. We assume a budget of b, with current token sequence having $b+1$ tokens (superscript denotes layer):

$$X^0 \triangleq [x_1, x_2, \ldots, x_{b+1}],\ X^0_{b+1} \triangleq x_{b+1} \tag{36}$$

The attention output for a sequence of $b+1$ tokens is (for layer m)

$$X^m_{A,b+1} \triangleq \Sigma_{j=1}^{b+1} \alpha^m_j W^m_v X^m_j \tag{37}$$

The logits with and without eviction for token j are defined as $l_j, \hat{l}_j$ respectively.

(Case 1) Single self-attention layer with single head: The logits for dense baseline is:

$$X^1_{b+1} = X^0_{b+1} + W_O X^0_{A,b+1} \tag{38}$$

$$l_{b+1} = W_H X^1_{b+1} = W_H(X^0_{b+1} + W_O \Sigma_j \alpha_j W_V X^0_j) \tag{39}$$

where W_H, W_O, W_V are the LM-head, output projection, and value projection respectively. X^1_{b+1} is the output after the residual connection.

The logits with eviction will have a perturbation due to error in attention output (CAOTE score or eviction error), and is given as:

$$\hat{X}^1_{b+1} = X^0_{b+1} + W_O X^0_{A,b+1} + W_O \Delta^0_A \tag{40}$$

$$\hat{l}_{b+1} = W_H \hat{X}^1_{b+1} \tag{41}$$

$$= W_H(X^0_{b+1} + W_O X_{A,b+1} + W_O \Delta^0_A) \tag{42}$$

$$= l_{b+1} + \Delta_{l,b+1} \tag{43}$$

where the logit error is $\Delta_{l,b+1} = W_H W_O \Delta_{A,b+1}$, $\Delta_{A,b+1} = e_{\text{eviction}}$ from (13).

(Case 2) Multiple attention heads: this is trivial and can be achieved by replacing $\Delta_A = \text{concat}(\Delta^1_A, \ldots, \Delta^h_A)$, where super-script denotes head number.

(Case 3) Single self-attention and feedforward-network (FFN): we still assume single head without layer-norms. The dense logit is given as

$$X^{1/2}_{b+1} = X^0_{b+1} + W_O X^0_{A,b+1} \tag{44}$$

$$X^1_{b+1} = X^{1/2}_{b+1} + W_{FFN} X^{1/2}_{b+1} \tag{45}$$

$$= X^0_{b+1} + W_O X^0_{A,b+1} + W_{FFN} X^0_{b+1} + W_{FFN} W_O X^0_{A,b+1} \tag{46}$$

$$l_{b+1} = W_H X^1_{b+1} \tag{47}$$

where, for simplicity we assume feedforward network to subsumed within W_{FFN}.

The perturbed logit due to eviction is given as:

$$\hat{X}^{1/2}_{b+1} = X^0_{b+1} + W_O X^0_{A,b+1} + W_O \Delta^0_A \tag{48}$$

$$\hat{X}^1_{b+1} = \hat{X}^{1/2}_{b+1} + W_{FFN} \hat{X}^{1/2}_{b+1} \tag{49}$$

$$= X^0_{b+1} + W_O X^0_{A,b+1} + W_O \Delta^0_A + W_{FFN} X^0_{b+1} + W_{FFN} W_O X^0_{A,b+1} + W_{FFN} W_O \Delta^0_A \tag{50}$$

$$\hat{l}_{b+1} = W_H \hat{X}^1_{b+1} \tag{51}$$

$$= l_{b+1} + \Delta_{l,b+1} \tag{52}$$

Table 7: Spearman's correlation between CAOTE and *FastCAOTE* on `Llama3.2-3B-Instruct` using sample from NarrativeQA

Layer	1	2	3	4	5	6	7	8	9	10	11	12	13	14
	0.99	0.98	0.91	0.97	0.92	0.88	0.85	0.82	0.81	0.90	0.84	0.92	0.83	0.86

layer	15	16	17	18	19	20	21	22	23	24	25	26	27	28
	0.91	0.88	0.94	0.96	0.92	0.95	0.99	0.99	0.96	0.98	0.98	0.88	0.99	0.96

where, the logit error $\Delta_{l,b+1} = W_H(W_O\Delta_A^0 + W_{FFN}W_O\Delta_A^0)$. Thus, the above analysis shows that error in attention output can cause discrepancy in logit space which can affect performance on downstream tasks.

Note that for multiple layers, each layer would have its own eviction error which will keep compounding; however, this computing the exact compounded error is non-trivial due to the presence of output layer-norms.

D Relation between CAOTE and *FastCAOTE*

We empirically show in Table 7 that CAOTE and *FastCAOTE* are correlated, therefore, showing the efficacy of *FastCAOTE*

E Inference Latency

We analyze the computational overhead of CAOTE and *FastCAOTE* during both prefill and generation phases. The overhead is minimal, especially for *FastCAOTE*.

Let s be sequence length, d the hidden dimension, d_{KV} the KV hidden dimension, d_{FFN} the intermediate dimension, d_V the vocabulary size, and L the number of hidden layers. The total floating-point Operation count are as follows:

$$\text{prefill flops} : 2Lsd(d + d_{KV} + d_{FFN} + 2s + 6) + dd_V \tag{53}$$

$$\text{generation flops} : 2Ld(d + d_{KV} + d_{FFN} + 2s + 6) + dd_V \tag{54}$$

$$\text{CAOTE flops} : Ls(7d + 3) \tag{55}$$

$$\textit{FastCAOTE} \text{ flops} : Ls(4d + 3) + L \tag{56}$$

We compute the relative overhead for `Llama3`.1-8B model with different sequence lengths and show the ratio between prefill (and generation) flops to CAOTE flops in Table 6a, 6b

F Additional Results

F.1 Task context and generation lengths

Table 8: Task Input Sizes

Task Type	**Input Size (tokens)**
QA tasks	4k – 16k
Summarization	2.1k – 16k
Few-shot learning	5.2k – 22.4k
Synthetic tasks	7k – 11k
Code	1.5k – 4.2k
Needle-in-the-haystack	up to 32k

We show the average context and generation lengths of different tasks in Table 8, 9 respectively.

Table 9: Generation Lengths

Task Type	Generation Length (tokens)
QA tasks	100 – 300
Summarization	300 – 800
Multi-document reasoning	500 – 1000
Code	∼500

Table 10: **LongBench results for Llama 3.1-8B and Llama 3.2-3B-Instruct.** Higher number is better. We highlight the best performing methods within a given budget with **bold** and the second best with underline.

		Single Doc. QA			Multi Doc. QA			Summarization			Fewshot Learning			Synthetic		Code		
		Narrative QA	Qasper	MF-en	HotpotQA	2WikiMQA	Musique	GovReport	QMSum	MultiNews	TREC	TriviaQA	SAMSum	PCount	PR-en	Lcc	RB-P	Avg.
	Llama 3.1-8B	30.05	47.00	56.12	57.33	47.81	32.25	34.86	25.32	27.02	73.00	91.61	43.37	8.33	99.50	61.66	51.94	49.20
6k	Sink	25.41	47.40	44.13	47.39	45.73	21.90	32.53	22.19	26.87	72.00	91.25	43.41	3.08	52.50	62.22	56.24	43.39
	H2O	8.52	43.31	44.80	40.03	42.46	21.68	11.85	8.78	26.03	62.00	56.39	25.72	5.75	45.50	58.62	29.53	33.19
	+ CAOTE	25.77	46.45	54.99	50.57	47.7	31.93	33.99	22.86	27.01	71	87.05	41.29	6.67	54	60.48	43.23	44.06
	+ FastCAOTE	27.02	46.46	55.4	51.32	47.4	32.89	34.08	23.69	27.03	71	86.25	42.14	9	48.5	60.49	42.94	44.10
	TOVA	24.59	45.93	53.92	55.09	47.43	25.07	32.33	24.10	27.00	68.50	90.81	43.89	4.25	67.00	61.50	52.39	45.24
	+ CAOTE	24.23	45.88	53.5	52.96	49.59	27.02	32.62	23.86	27.08	70	90.98	43.45	3	74.5	61.46	51.76	45.74
	+ FastCAOTE	24.17	46.07	53.8	53.53	48.11	26.49	32.64	23.88	27.01	70	90.81	43.53	3	73	61.49	51.43	45.56
	SnapKV	24.10	45.57	50.44	53.12	48.41	24.27	33.43	23.53	27.03	71.50	92.28	43.58	5.25	98.00	61.32	52.16	47.12
	+ CAOTE	25.97	46.09	51.54	55.19	47.41	26.48	33.32	24	27.05	71.5	91.11	43.55	6.83	99.5	61.11	51.45	<u>47.63</u>
	+ FastCAOTE	24.77	46.06	52.18	56.72	47.01	26.24	33.41	23.8	26.99	73	91.31	43.6	5.92	99.5	61.5	51.37	**47.71**
8k	Sink	23.53	46.63	48.68	49.61	47.16	21.14	33.10	23.20	26.92	72.00	91.29	43.79	3.25	66.00	62.18	56.43	44.68
	H2O	13.85	44.94	47.81	43.64	44.90	23.65	18.78	11.35	26.49	69.50	69.05	33.41	5.25	62.50	59.74	36.26	38.20
	+ CAOTE	27.74	46.67	54.97	52.71	48.28	33.66	34.51	24.73	26.99	73	86.8	42.86	5	66.5	61.06	48.29	45.86
	+ FastCAOTE	28.8	47.08	54.67	52.95	47.13	34.36	34.21	24.53	27.04	72	87.87	43.03	5.5	69.5	61.06	49.69	46.21
	TOVA	24.86	46.78	54.83	54.52	49.00	26.40	33.44	24.76	27.00	71.00	91.11	43.29	6.25	87.00	61.49	51.79	47.09
	+ CAOTE	25.65	46.88	54.5	55.42	48.73	26.54	33.47	24.8	27.02	72	91.11	43.26	6.25	87	61.36	51.3	47.21
	+ FastCAOTE	25.25	46.75	54.76	56.29	48.94	26.25	33.37	24.81	27.01	71.5	91.11	43.24	5.25	89	61.32	52.1	**48.58**
	SnapKV	25.15	46.55	53.39	56.00	48.75	27.82	33.67	24.85	27.01	72.50	91.78	43.54	5.08	100.00	61.48	51.41	48.06
	+ CAOTE	27.06	46.42	53.76	56.51	47.79	28.13	33.87	24.93	27.02	73	91.38	43.29	6.75	99.5	61.49	51.99	48.31
	+ FastCAOTE	26.91	46.59	53.47	56.63	48.54	29.27	33.91	24.86	27.01	73	91.38	43.49	6.75	100	61.49	51.78	<u>48.44</u>
	Llama 3.2-3B	23.76	40.23	50.09	50.69	42.29	26.84	33.09	24.30	25.21	72.50	90.11	42.58	3.00	96.50	56.22	56.52	45.87
6k	Sink	19.33	40.29	37.95	46.48	40.29	15.31	30.43	21.35	25.14	71.50	88.93	42.04	3.50	47.00	56.55	54.11	40.01
	H2O	4.62	38.81	39.06	34.66	35.52	15.21	10.51	10.01	24.25	61.50	53.23	27.37	0.50	13.00	54.55	32.29	28.44
	+CAOTE	16.14	41.68	49.36	46.7	43.36	22.75	32.07	21	25.07	69	80.02	39.33	1.5	26	55.82	49.05	38.68
	+FastCAOTE	16.31	41.94	49.17	45.64	41.83	21.68	32.07	20.73	25.02	68.5	80.34	39.88	3.5	24	55.83	48.7	38.45
	TOVA	20.22	39.78	45.86	49.08	41.54	20.43	30.50	22.17	25.11	66.50	89.00	42.50	4.00	46.50	55.57	57.53	41.02
	+CAOTE	21.17	39.69	47.21	48.82	41.7	20.59	30.72	22.36	25.1	68	89	42.38	3.5	52.5	55.6	57.09	41.59
	+FastCAOTE	21.48	39.66	47.02	47.56	41.95	19.91	30.8	21.98	25.17	67.5	89.5	42.06	4	53	55.6	57.39	41.54
	SnapKV	20.83	39.65	44.48	49.30	40.18	20.28	31.27	22.73	25.09	69.00	89.95	41.47	4.00	85.00	55.69	57.82	43.55
	+CAOTE	20.23	39.65	44.91	50.16	40.58	21.32	31.23	22.51	25.13	69	90	41.83	5	89.5	55.84	57.24	<u>44.01</u>
	+FastCAOTE	20.09	40.02	44.58	48.57	42.12	22.51	31.25	22.89	25.15	71	90	41.83	4	89.5	55.83	57.25	**44.16**
8k	Sink	20.15	40.02	41.94	48.15	42.24	16.01	31.64	22.10	25.20	73.00	89.26	42.37	3.50	62.50	56.86	56.63	41.97
	H2O	9.65	39.66	43.20	38.09	40.41	21.46	17.80	13.28	24.67	70.00	64.30	32.19	2.00	24.50	55.00	39.09	33.46
	+CAOTE	20.07	40.73	47.76	47.25	42.88	23.19	32.41	22.01	25.15	71	83.58	40.8	3	43.5	55.45	53.35	40.76
	+FastCAOTE	20.81	40.54	48.1	47.35	43.4	25.13	32.73	22.31	25.18	71.5	84.91	40.6	4	45	55.84	52.89	41.27
	TOVA	21.08	40.67	49.07	48.69	41.93	23.05	31.64	22.85	25.21	69.00	89.25	42.19	2.50	71.00	55.77	57.47	43.21
	+CAOTE	21.97	40.66	49.37	50.1	41.29	24.05	31.65	22.85	25.16	69.5	89.5	42	3	78.5	55.82	57.16	43.91
	+FastCAOTE	22.73	40.51	49.36	50.18	42.26	24.45	31.68	23.09	25.16	69.5	89.5	42.28	4.5	80	55.79	57.16	44.26
	SnapKV	20.49	40.80	48.16	48.78	41.65	24.79	31.81	23.46	25.17	70.00	90.17	41.99	5.00	94.00	55.77	57.29	**44.96**
	+CAOTE	19.71	40.7	48.05	49.03	41.27	22.95	31.95	23.1	25.21	72	90	41.88	4	95	55.77	57.02	<u>44.85</u>
	+FastCAOTE	20.13	40.71	48.35	48.62	41.04	24.38	32.19	23.04	25.20	72	90	42.33	3.5	95	55.77	57.03	**44.96**

F.2 LONGBENCH

LongBench result for 6k and 8K for `Llama 3.2-3B-Instruct`/3.1-8B-Instruct and `Qwen 2.5-3B-Instruct`/8B-Instruct are shown in Table Table 10, Table 11 respectively. We also include Sink attention results Xiao et al. (2024b) with budget of 6k and 8k. For `Llama 3.1-8B-Instruct`, *TOVA-FastCAOTE* performs best for 6k budget, while *SnapKV-FastCAOTE* for 8k budget. For `Llama 3.2-3B-Instruct` *SnapKV-FastCAOTE* performs best for both 6k and 8k budget. On the other hand, for `Qwen 2.5-7B-Instruct`, *SnapKV-CAOTE* performs the best for both 6k and 8k, and for `Qwen 2.5-3B-Instruct`, *SnapKV-COATE* performs best for 6k budget, and *SnapKV-FastCAOTE* performs best for 8k budget. Additionally, note that all baseline token eviction methods achieve boost in accuracy when using CAOTE or *FastCAOTE*.

F.3 PERPLEXITY

We show perplexity results for `Qwen2.5` models in Table 12 for budget of 2k. *SnapKV-FastCAOTE* performs best for both `Qwen 2.5-3B-Instruct` and 2.5-7B-Instruct, and using CAOTE, all methods achieve improved perplexity.

Table 11: **LongBench results for Qwen 2.5-7B/2.5-3B-Instruct.** Higher number is better. We highlight the best performing methods within a given budget with **bold** and the second best with underline.

		Single Doc. QA			Multi Doc. QA			Summarization			Fewshot Learning			Synthetic		Code		
		Narrative QA	Qasper	MF-en	HotpotQA	2WikiMQA	Musique	GovReport	QMSum	MultiNews	TREC	TriviaQA	SAMSum	PCount	PR-en	Lcc	RB-P	Avg.
	Qwen 2.5-7B	15.75	16.94	32.38	11.89	11.88	7.95	34.33	19.91	22.67	65.5	87.05	44.75	4.22	93.08	57.74	61.84	36.74
6k	Sink	7.37	16.61	25.73	11.29	11.27	5.69	31.47	18.72	22.86	64.5	84.86	44.47	3.59	41.48	55.89	55.99	31.36
	H2O	3.34	14.79	23.94	11.45	11.3	5.52	14.63	14.27	22.06	55.75	51.99	28.01	1.39	9.41	54.68	38.32	22.55
	+ CAOTE	4.78	18.06	32.49	16.23	17.28	9.57	29.81	18.04	22.86	59.5	63.05	36.91	2.7	28.25	55.13	42.42	28.57
	+ FastCAOTE	5.69	16.99	32.62	18.22	16.58	10.48	30.3	17.71	22.88	59.5	62.95	36.29	2.1	27.65	56.3	40.65	28.56
	TOVA	15.77	15.33	30.31	19.3	13.78	9.11	30.4	19.95	22.91	61.5	83.47	42.9	1.15	21.775	57.68	57.99	31.46
	+ CAOTE	15.81	16.07	29.39	19.4	14.15	10.8	30.89	20.54	22.86	62	84.92	43.19	2.17	30	57.76	57.53	32.34
	+ FastCAOTE	15.67	16.23	30.4	19.45	13.32	10.18	30.77	20.2	22.82	61.5	83.29	43.3	1.5	28.75	57.71	58.1	32.07
	SnapKV	14.34	16.35	31.12	17.56	14.1	8.74	31.09	20.16	22.84	60	83.8	42.99	2.91	54.17	57.48	60.26	33.62
	+ CAOTE	12.77	16.3	31.33	19.74	14.06	11.07	31.02	20.85	22.91	61.5	83.79	42.97	4.8	68.25	57.54	61.08	**35.00**
	+ FastCAOTE	12.98	15.93	31.3	18.58	13.82	9.45	30.96	20.27	22.88	61.5	84.58	43.28	5.34	65.48	57.54	60.25	<u>34.63</u>
8k	H2O	6.1	15.55	28.29	12.37	14.65	6.24	20.78	17.22	22.44	59	58.74	33.05	1.82	15.73	55.63	44.56	25.76
	+ CAOTE	8.65	15.59	34.92	20.41	15.95	13.6	32.11	20.05	22.82	63.5	78.2	40.66	3.85	46.33	57.19	51.7	32.85
	+ FastCAOTE	6.76	15.88	34.3	20.75	16.2	16.82	31.95	20.67	22.81	62.5	77.33	41.02	3.03	47.08	57.23	50.48	32.8
	TOVA	15.69	15.55	33.09	18.37	13.99	11.26	31.33	20.17	22.82	62	84.49	43.01	2.78	30.33	57.45	58.96	32.58
	+ CAOTE	16.38	15.46	32.16	17.86	14.24	12.76	31.34	20.2	22.8	61	83.97	43.23	2.01	38.83	57.45	59.41	33.07
	+ FastCAOTE	17.06	15.55	32.32	17.57	14.14	13.03	31.43	20.3	22.78	62	84.86	43.3	2.41	41.58	57.41	58.93	33.42
	SnapKV	15.6	15.81	33.47	18.02	14.49	10.53	31.99	20.09	22.84	61	84.08	43.01	4.58	64.25	57.46	60.59	34.86
	+ CAOTE	15.55	15.57	33.89	21.08	14.43	12.38	31.41	20.73	22.83	61.5	85.11	43.39	5.22	75.75	57.44	60.35	**36.04**
	+ FastCAOTE	13.38	15.77	33.97	19.78	15.08	13.01	31.44	20.69	22.77	62	85.66	43.69	4.24	75.33	57.44	60.04	<u>35.89</u>
	Qwen 2.5-3B	18.08	22.49	39.72	27.86	20.45	18.93	32.8	23.74	24.89	67.5	85.05	43.88	5	40.97	51.91	47.53	35.68
6k	Sink	13.01	20.03	32.59	18.62	15.77	9.37	30.98	20.7	24.97	66.5	75.39	42.77	4	14.92	52.32	50.35	30.77
	H2O	5.52	18.62	27.93	12.61	15.07	4.26	14.92	13.89	24.21	58	45.94	24.93	2.91	9.1	49.5	34.54	22.62
	+ CAOTE	8.23	21.34	36.28	22.43	17.92	13.53	31.57	21.2	24.91	65	74.3	39.09	4.58	21.25	50.47	42.71	30.93
	+ FastCAOTE	9.29	20.47	35.8	21.67	18.14	13.65	31.34	20.52	24.82	64.5	75.88	39.16	5.72	20.42	50.6	44.38	31.02
	TOVA	13.62	19.56	34.64	21.67	16.25	8.47	30.17	23.1	24.94	63.5	81.88	42.97	1.16	10.58	51.3	47.7	30.72
	+ CAOTE	13.28	19.82	35.25	22.6	15.5	8.97	30.4	23.17	24.84	64.5	81.68	43.46	2.07	13.21	50.56	47.05	31.02
	+ FastCAOTE	13.34	19.71	35.58	22.02	15.65	8.76	30.49	23.26	24.82	65	80.92	43.66	1.75	13	51.45	47.74	31.07
	SnapKV	14.16	20.09	36.15	19.14	15.59	12.7	30.35	22.75	24.91	65	83.92	43.52	5.00	32.2	51.04	47.49	32.75
	+CAOTE	14.3	20.13	34.89	20.32	15.06	12.85	30.61	23.16	24.9	66.5	84.75	43.3	4.75	33.9	51.48	48.31	**33.08**
	+FastCAOTE	14.33	19.48	34.59	20.8	16.54	11.85	30.68	23.19	24.93	66.5	83.54	43.55	4.62	33	51.06	47.93	<u>32.91</u>
8k	H2O	6.16	19.84	32.32	16.01	17.74	4.99	20.21	16.49	24.54	64	56.1	32.56	3.13	11.61	50.61	38.8	25.94
	+CAOTE	11.53	21.59	38.02	25.62	20.19	15.11	32.18	21.82	24.81	67.5	79.32	41.2	5.15	25.5	50.72	45.27	32.85
	+FastCAOTE	11.65	21.2	37.92	24.47	20.32	13.25	32.11	21.75	24.84	67.5	78.07	40.27	5.17	25.21	50.17	46.37	32.52
	TOVA	14.66	20.93	37.77	22.57	17.08	9.63	31.12	23.17	24.83	67	84.11	43.55	2.06	13.08	51.32	47.64	31.91
	+CAOTE	13.98	21	36.91	22.97	17.05	9.93	31.25	23.45	24.9	66.5	84.14	43.86	3.07	13.92	51.14	47.883	32.00
	+FastCAOTE	14.84	20.66	37.45	23.05	17.07	10.16	31.2	23.47	24.85	66.5	84.01	43.41	3.31	13.25	51.19	48.11	32.03
	SnapKV	12.76	20.88	37.1	22.49	18.19	13.83	31.33	23.37	24.8	65.5	84.88	44.49	5.2	35.83	51.31	47.82	33.74
	+CAOTE	13.66	20.41	38.08	24.76	17.31	13.21	31.3	23.62	24.82	66.5	84.88	44.16	5.17	36.58	51.24	47.94	<u>33.98</u>
	+FastCAOTE	14.56	20.99	37.61	25.56	18.02	13.89	31.37	23.27	24.83	66.5	84.88	44.01	5	35.92	51.13	48.14	**34.11**

Table 12: **Perplexity difference between different eviction methods with dense baseline.** Lower is better. Negative entry in table means the method performs better than dense baseline. The PPL of Qwen 2.5-3B-Instruct and Qwen 2.5-7B-Instruct is 8.4547 and 7.3188 respectively.

Budget	H2O			TOVA			SnapKV		
		+CAOTE	+FastCAOTE		+CAOTE	+FastCAOTE		+CAOTE	+FastCAOTE
Qwen 2.5-7B-Instruct									
2k	0.4253	0.4422	0.3917	0.0567	0.059	0.1077	0.0369	0.0987	**0.0307**
Qwen 2.5-3B-Instruct									
2k	0.2585	0.2168	0.2154	0.0603	0.0513	0.0507	0.0278	0.0199	**0.0196**

F.4 NEEDLE IN A HAYSTACK

Table 13 shows Needle-in-haystack results for `Qwen2.5` models for budget=6k. *SnapKV-FastCAOTE* performs best for both `Qwen 2.5-3B-Instruct` and 2.5-7B-Instruct, and using CAOTE, all methods achieve improved accurracy.

G LIMITATION

CAOTE is a myopic (greedy) strategy and its scoring framework based on the assumption of evicting 1 token per iteration. This assumption breaks during prefilling stage, however, taking into account change in attention output due to multi-token eviction is non-trivial. Fortunately, we observe that even assuming multi-token eviction independently (without considering the effect of other tokens being evicted), CAOTE is still able to give boost in performance for all tasks. Due to this reason CAOTE's performance might further improve with smaller prompt filling block-size.

Table 13: **Needle-in-haystack accuracy** for Qwen 2.5-3B/2.5-7B-Instruct using baseline eviction methods with(out) *CAOTE*. Higher is better, maximum accuracy is 1.0.

Budget	H2O			TOVA			SnapKV		
		+CAOTE	+FastCAOTE		+CAOTE	+FastCAOTE		+CAOTE	+FastCAOTE
Qwen 2.5-7B-Instruct									
6k	0.206	0.312	0.3	0.292	0.292	0.286	0.32	0.33	**0.332**
Qwen 2.5-3B-Instruct									
6k	0.212	0.288	0.27	0.282	0.286	0.288	0.304	0.324	**0.336**