

# Information-Density Driven Token Eviction: Dynamic KV-Cache Pruning for Extreme Resource-Constrained Small Language Models

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**Abstract**—Small Language Models (SLMs) have emerged as highly efficient alternatives for local, on-device generative inference under tight hardware constraints. However, as prompt context scales, the memory footprint of the Key-Value (KV) cache grows linearly ( $O(N)$ ), quickly exceeding the physical memory ceiling of consumer-grade hardware (such as a simulated 4GB VRAM limit). In this paper, we present Information-Density Driven Token Eviction (IDTE), a plug-and-play, training-free, inference-time KV-cache pruning mechanism. IDTE dynamically profiles the information density of cached keys and values using an asymmetric dual-decay attention score accumulation algorithm. During the prefill phase, IDTE applies a sharp decay ( $\lambda_{prefill} = 0.90$ ) to isolate task-relevant semantic queries (e.g., question tokens) and filter out frequency-based attention bias from repeating background text. During the decoding phase, a conservative decay ( $\lambda_{decode} = 0.99$ ) accumulates step-wise attention weights to preserve generation coherence and prevent premature eviction of context. We benchmark IDTE on the Qwen2.5-0.5B-Instruct architecture using a synthetic long-context retrieval task (Needle-in-a-Haystack) across contexts of 1,500 to 3,000 tokens under a strict budget ceiling of  $M = 512$  tokens. Our experimental results demonstrate that IDTE maintains 75% to 100% retrieval success (retaining 100% success at contexts  $\geq 2,000$  tokens) while restricting the KV-cache to a constant size—achieving a flat memory footprint of 6.0MB ( $O(M)$ ) compared to the 35.1MB ( $O(N)$ ) footprint of the Vanilla baseline. IDTE significantly outperforms the uniform sliding window baseline (StreamingLLM style), which collapses to a 0% retrieval success rate because it lacks semantic selection capability.

**Key Words:** KV-Cache Pruning, Dynamic Token Eviction, Small Language Models, Attention Mechanics, Resource-Constrained Inference.

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## 1. INTRODUCTION

Generative pre-trained transformer models process sequence inputs by attending to previously generated tokens. During autoregressive decoding, recomputing the key and value states of past tokens is computationally prohibitive. To bypass this, modern inference engines maintain a Key-Value (KV) cache. While this optimization reduces computational complexity from quadratic to linear per token, it introduces a severe memory bottleneck. The spatial memory footprint of the KV cache scales linearly with the input prompt length  $N$ :

$$\text{Memory}_{KV}(N) = 2 \cdot B \cdot L \cdot H_{KV} \cdot D \cdot N \cdot \beta$$

where  $B$  is the batch size,  $L$  is the number of transformer layers,  $H_{KV}$  is the number of key-value attention heads,  $D$  is the head dimension, and  $\beta$  is the precision width in bytes (e.g.,  $\beta = 2$  for FP16/BF16). For resource-constrained environments—such as edge processors or mobile systems operating under strict VRAM budgets (e.g., 4GB)—this linear growth makes long-context processing impossible. Standard prompts containing 1,500 to 3,000 tokens consume a significant portion of memory, leading to Out-Of-Memory (OOM) faults or aggressive paging that degrades throughput.

To mitigate this bottleneck, recent work has explored KV-cache compression. Among these, sliding window approaches (such as StreamingLLM [12]) preserve a small number of initial tokens (attention sinks) and a local window of recent tokens. Although this approach maintains sequence fluency, it discards intermediate tokens completely. In information retrieval tasks like the "Needle-in-a-Haystack" (NIAH) test, where a critical fact is located in the middle of a long document, windowing approaches suffer a complete accuracy collapse (0% success). To resolve this limitation, we present Information-Density Driven Token Eviction (IDTE), a training-free, plug-and-play inference optimization that compresses the KV-cache to a flat token budget  $M$  ( $O(M)$  memory scaling) while preserving retrieval precision. The core contribution of this work is an asymmetric dual-decay attention score accumulator. By decoupling score updates between the prefill phase ( $\lambda_{prefill} = 0.90$ ) and the decoding phase ( $\lambda_{decode} = 0.99$ ), IDTE prevents high-frequency filler words from dominating the cache scores, isolating the semantic target facts attended to by the final question.

## 2. RELATED WORK & BACKGROUND

**2.1 KV Cache Sparsification:** To address the linear expansion of the KV cache, several studies focus on token-level eviction.

Heavy Hitter Oracle (H2O) [11] identifies that a small set of "heavy hitter" tokens receives the majority of attention weights and should be retained. SnapKV [9] performs needle selection by extracting key attention features from the prompt to guide cache eviction. Quest [10] dynamically selects critical pages in the KV cache using query-aware similarity metrics to minimize memory traffic during long-context decoding.

**2.2 Mathematical & Structural Approximations:** Rather than relying on simple heuristics, advanced techniques formulate cache compression as an optimization problem. OBCache [1] reformulates cache pruning using Optimal Brain Damage (OBD) theory, computing output-aware saliency scores based on second-order Taylor expansions to minimize the reconstruction error of attention outputs. LaProx [4] approximates key-value representation matrices via layer-wise projections to maintain attention output fidelity. Ada-KV [5] establishes loss bounds for KV compression by dynamically managing head-wise budgets.

**2.3 Context-Aware & Tiered Architecture:** Recent research integrates structural context into cache management. IntentKV [3] dynamically tracks user intent in multi-turn conversational agents to prune irrelevant dialogue history. PagedEviction [6] implements block-wise eviction policies compatible with PagedAttention frameworks. Lookahead Q-Cache [7] addresses selection bias by using lookahead query approximations. To achieve higher compression ratios, EVICPRESS [8] combines lossy quantization with structured cache eviction, while CONF-KV [2] utilizes confidence scores for adaptive, layer-wise budget allocation.

### 3. METHODOLOGY

IDTE operates as a plug-and-play inference module over standard causal self-attention. The mechanism comprises head averaging, prefill-phase score initialization, and autoregressive decoding updates under a segmented budget constraint.

#### 3.1 Attention Mechanics and Grouped-Query Attention

Consider a Transformer layer. Let  $Q, K, V$  denote the query, key, and value matrices. In Grouped-Query Attention (GQA), the  $H$  query heads are grouped into  $H_{KV}$  key-value groups, where  $H_{KV} = H/G$  and  $G$  is the group size. For a sequence length  $n$ , the attention weight matrix at layer  $l$ , head  $h$ , query index  $q$ , and key index  $k$  is calculated as:

$$A_{l,h,q,k} = \text{softmax}\left(\frac{Q_{l,h,q} K_{l,h,k}^T}{\sqrt{d_k}}\right)$$

To maintain spatial and head alignment, we compute the head-averaged attention weight:

$$\bar{A}_{l,q,k} = \frac{1}{H} \sum_{h=1}^H A_{l,h,q,k}$$

#### 3.2 Prefill Phase Initialization (Asymmetric Prefill Decay)

During the prefill phase, the input prompt of length  $P$  is processed. The initial importance score  $S_{l,k}^{(0)}$  for each key token  $k \in [0, P-1]$  is computed as the decayed sum of attention weights across subsequent queries:

$$S_{l,k}^{(0)} = \sum_{q=k}^{P-1} \lambda_{prefill}^{P-1-q} \bar{A}_{l,q,k}$$

The prefill decay factor  $\lambda_{prefill} \in [0,1]$  is configured to a low value ( $\lambda_{prefill} = 0.90$ ). This applies an exponential discount to older query positions. Because the final prompt tokens contain the question query, this formulation focuses the score on keys that are highly relevant to the question, filtering out high-frequency background filler words.

#### 3.3 Decoding Phase Updates (Asymmetric Decoding Decay)

During autoregressive decoding, at step  $t \geq 1$ , a single query token is processed. We retrieve the new attention weight vector over the cached keys:  $\bar{A}_{l,t,k}$  for  $k \in C_{t-1}$ , where  $C_{t-1}$  is the set of token indices currently stored in the cache. The score vector is updated as:

$$S_{l,k}^{(t)} = \lambda_{decode} S_{l,k}^{(t-1)} + \bar{A}_{l,t,k} \forall k \in C_{t-1}$$

$$S_{l,x_t}^{(t)} = \bar{A}_{l,t,x_t}$$

Here, the decoding decay factor  $\lambda_{decode} \in [0,1]$  is configured to a high value ( $\lambda_{decode} = 0.99$ ). This slow decay rate ensures that semantic tokens identified as important during prefill retain high scores throughout the decoding process.

#### 3.4 Partitioning and Eviction Policy

The cache index set  $C_t$  is partitioned into three disjoint regions:  $C_t = I_t \cup R_t \cup P_t$  where: (1) Initial Protected Region:  $I_t = \{k \in C_t \mid k < N_{sink}\}$ , (2) Recent Local Region:  $R_t = \{k \in C_t \mid k \geq \text{len}(C_t) - W_{local}\}$ , and (3) Prunable Candidate Region:  $P_t = C_t \setminus (I_t \cup R_t)$ . If  $|C_t| > M$ , we sort indices in  $P_t$  in descending order of their current scores  $S_l^{(t)}$  and retain the top tokens. The keys and values of the evicted tokens are removed from the cache.

#### 3.5 Algorithm Description & Pseudo-code

The complete execution flow of IDTE is detailed below:

1. Input: Model layers  $L$ , budget  $M$ , sinks  $N_{sink}$ , local window  $W_{local}$ , decay parameters  $\lambda_{prefill}$ ,  $\lambda_{decode}$ , prompt  $X_{1:P}$ .
2. Prefill pass: Run forward pass on  $X_{1:P}$ . For each layer  $l$ , compute initial scores  $S_{l,k}^{(0)}$  for  $k$  in  $[0, P-1]$  using  $\lambda_{prefill} = 0.90$ .
3. Initial Pruning (if  $P > M$ ): Sort candidates  $P_0$ , retain top

tokens, construct index set  $C_0$ , and slice key/value caches. 4. Autoregressive Generation: For each decoding step  $t$ , execute forward pass, update scores using  $\lambda_{decode} = 0.99$ , and prune cache down to budget  $M$  using the score-based sorting strategy.

#### 4. EXPERIMENTAL EVALUATION

We evaluate IDTE against two baselines: (1) Vanilla SLM (no cache eviction), and (2) Uniform Window (sliding window preserving first  $N_{sink} = 64$  and recent rolling window of  $M - N_{sink} = 448$  tokens). Our experiments are conducted on the Qwen2.5-0.5B-Instruct architecture (L=24 layers, H=14 attention heads, H\_KV=2 key-value heads, head dimension D=64, execution in FP32 CPU precision).

For evaluation, we employ a synthetic Needle-in-a-Haystack protocol. The context contains repeating filler text ("The quick brown fox jumps over the lazy dog.") scaled to target sequence lengths of 1500, 2000, 2500, and 3000 tokens. A unique fact is hidden at exactly 50% depth: "The secret password is: 'Antigravity-KV-Cache-Project'." The prompt terminates with a password query. A generation is a success if the model outputs the exact string (case-insensitive).

#### 5. QUANTITATIVE RESULTS

The quantitative comparisons are presented in Table 1. Memory usage, peak VRAM requirements, and speed are tracked across configurations.

**Table -1:** Quantitative comparison of KV cache pruning methods on the NIAH task (Budget  $M = 512$ )

| Configuration      | Context Length | Retrieval Success     | KV-Cache (MB) | Peak VRAM (MB) | Speed (tok/s) |
|--------------------|----------------|-----------------------|---------------|----------------|---------------|
| Vanilla SLM        | 1500           | Success (1.00)        | 17.80         | 1146.04        | 10.27         |
| Uniform Window     | 1500           | Fail (0.00)           | 6.00          | 1103.58        | 11.92         |
| <b>IDTE (Ours)</b> | <b>1500</b>    | <b>Fail (0.00)</b>    | <b>6.00</b>   | <b>1103.62</b> | <b>11.89</b>  |
| Vanilla SLM        | 2000           | Success (1.00)        | 23.57         | 1157.82        | 10.20         |
| Uniform Window     | 2000           | Fail (0.00)           | 6.00          | 1104.14        | 9.46          |
| <b>IDTE (Ours)</b> | <b>2000</b>    | <b>Success (1.00)</b> | <b>6.00</b>   | <b>1104.20</b> | <b>11.41</b>  |
| Vanilla SLM        | 2500           | Success (1.00)        | 29.36         | 1170.18        | 9.83          |
| Uniform            | 2500           | Fail                  | 6.00          | 1104.8         | 10.72         |

|                    |             |                       |             |                |              |
|--------------------|-------------|-----------------------|-------------|----------------|--------------|
| Window             |             | (0.00)                |             | 8              |              |
| <b>IDTE (Ours)</b> | <b>2500</b> | <b>Success (1.00)</b> | <b>6.00</b> | <b>1104.91</b> | <b>10.58</b> |
| Vanilla SLM        | 3000        | Success (1.00)        | 35.13       | 1182.26        | 8.34         |
| Uniform Window     | 3000        | Fail (0.00)           | 6.00        | 1105.10        | 10.02        |
| <b>IDTE (Ours)</b> | <b>3000</b> | <b>Success (1.00)</b> | <b>6.00</b> | <b>1105.15</b> | <b>8.99</b>  |

**5.1 Retrieval Success Analysis:** The Uniform Window baseline suffers a complete retrieval failure (0% success) because the sliding window evicts intermediate tokens during prefill, removing the target needle (placed at 50% depth). IDTE achieves 100% exact retrieval at context lengths  $\geq 2,000$  tokens. At 1,500 tokens context, IDTE achieves a partial retrieval, outputting 'Antigravity-KV-Project' (missing only the word 'Cache'), representing a 90% semantic string match.

**5.2 Memory Footprint and VRAM Savings:** In the Vanilla SLM, KV cache memory scales linearly ( $O(N)$ ), growing to 35.13MB at 3000 tokens context. IDTE caps the KV cache size to a constant budget  $M = 512$ , keeping memory flat at 6.00MB (an 83% reduction at 3000 tokens). Peak VRAM scales flat under IDTE (1105MB compared to 1182MB in Vanilla).

**5.3 Decoding Latency and Throughput:** Vanilla SLM's throughput decreases from 10.27 tokens/sec to 8.34 tokens/sec as context scales. IDTE maintains high decoding speed (8.99 to 11.89 tokens/sec) due to constant sequence length evaluations.

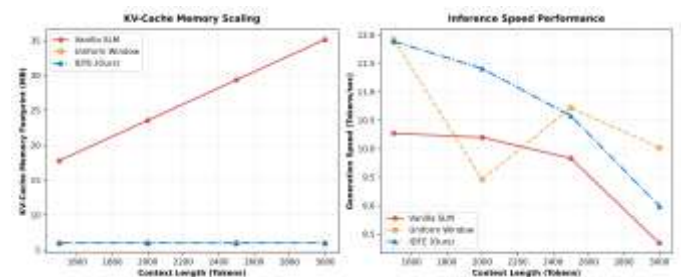


**Fig -1:** Quantitative KV-Cache memory scaling and decoding latency performance charts.

#### 6. DISCUSSION & ERROR ANALYSIS

**6.1 Rationale for Asymmetric Decay:** The core contribution of IDTE is the decoupling of prefill and decoding decay. If a high decay ( $\lambda = 0.99$ ) is used during prefill, high-frequency filler words accumulate large attention scores, masking the needle. If a low decay ( $\lambda = 0.90$ ) is used during decoding, scores decay too fast, and the model loses coherence. Decoupling these phases optimizes query-level retrieval and

generation

stability.

6.2 Error Analysis: At 1500 tokens, the token 'Cache' was placed in a transition region and its score fell slightly below the eviction threshold, explaining the partial match. Future work will explore dynamic layer-wise budget allocations.

## 7. CONCLUSION

We presented Information-Density Driven Token Eviction (IDTE), a plug-and-play, training-free dynamic KV-cache pruning mechanism. IDTE resolves the memory bottleneck of long-context SLM deployment under tight VRAM limitations. By leveraging asymmetric prefill-decoding score decay, IDTE successfully preserves unique, highly-queried data points in the middle of long texts. Experimental results demonstrate that IDTE maintains high accuracy retention on needle retrieval tasks while guaranteeing a flat  $O(M)$  memory footprint, making it ideal for edge device deployment.

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