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ArkVale: Efficient Generative LLM Inference with Recallable Key-Value Eviction

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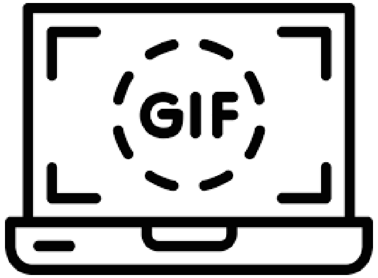
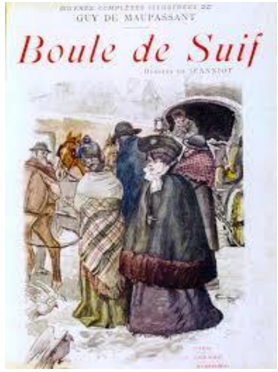
Long-form Contents

There are various long-form contents in our daily lives.

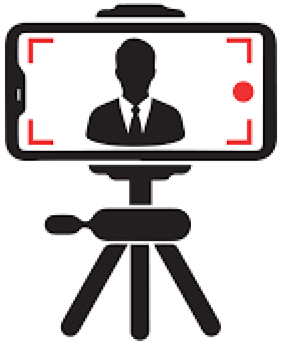
A research paper



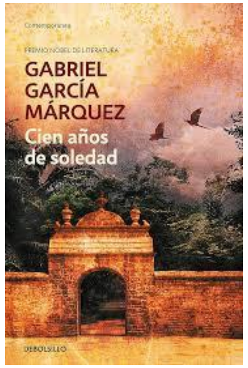
A gif meme



A novella



A short video



A novel

An EP of an anime

~8k tokens

~32k tokens

~128k tokens

Long Context LLMs

Context-length supported by LLMs also grows rapidly

GPT-3.5

LLAMA 2

MISTRAL AI_

Qwen

OpenAI ChatGPT 4.0

Claude 3.5 Sonnet

Llama 3

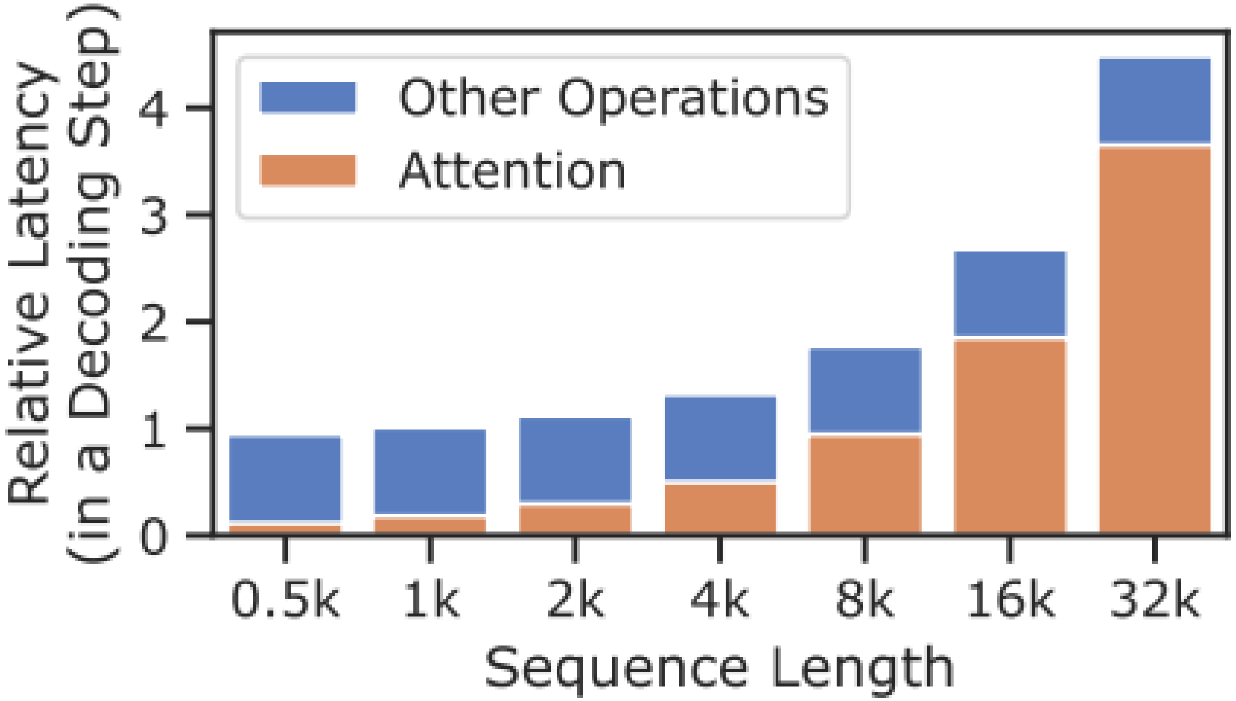
4k tokens

32k tokens

128k tokens

Impact of Long Context

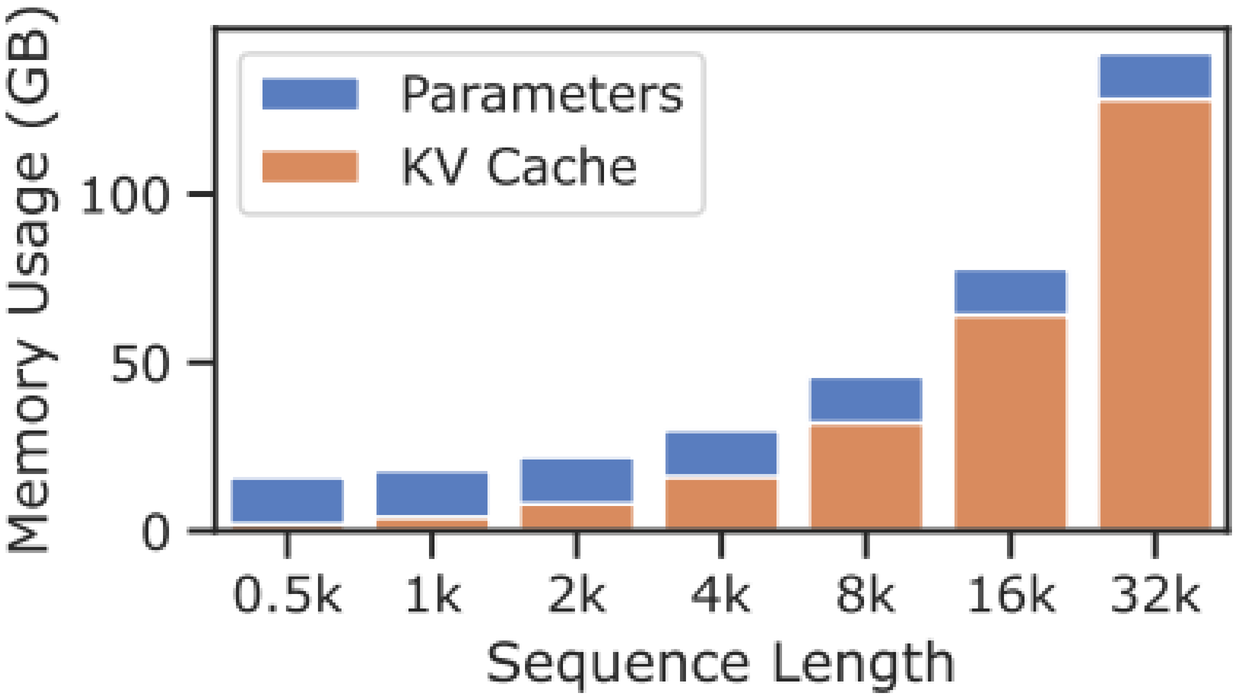
Long context attention can be the latency bottleneck of LLM decoding



LongChat-7b-v1.5-32k (batch-size=8)

Impact of Long Context

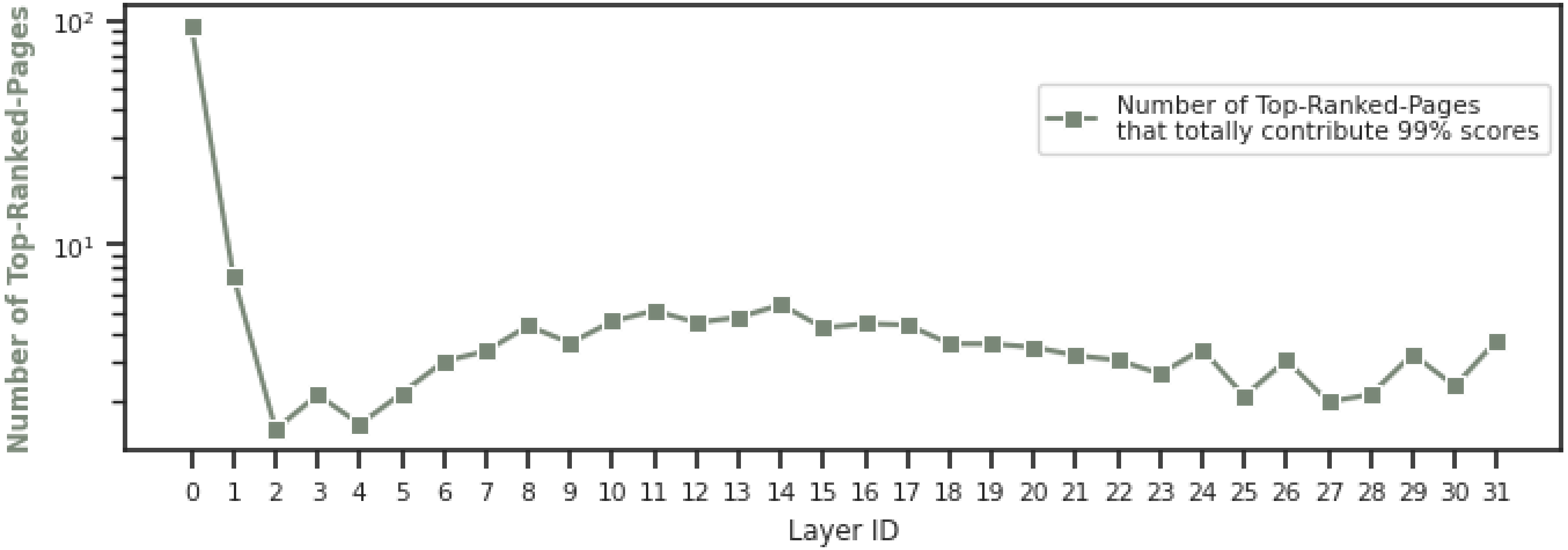
Long context can be the memory bottleneck of LLM decoding, which hampers the use of larger batch-size for serving.



LongChat-7b-v1.5-32k (batch-size=8)

Observation: Token-level Sparsity of KV Cache

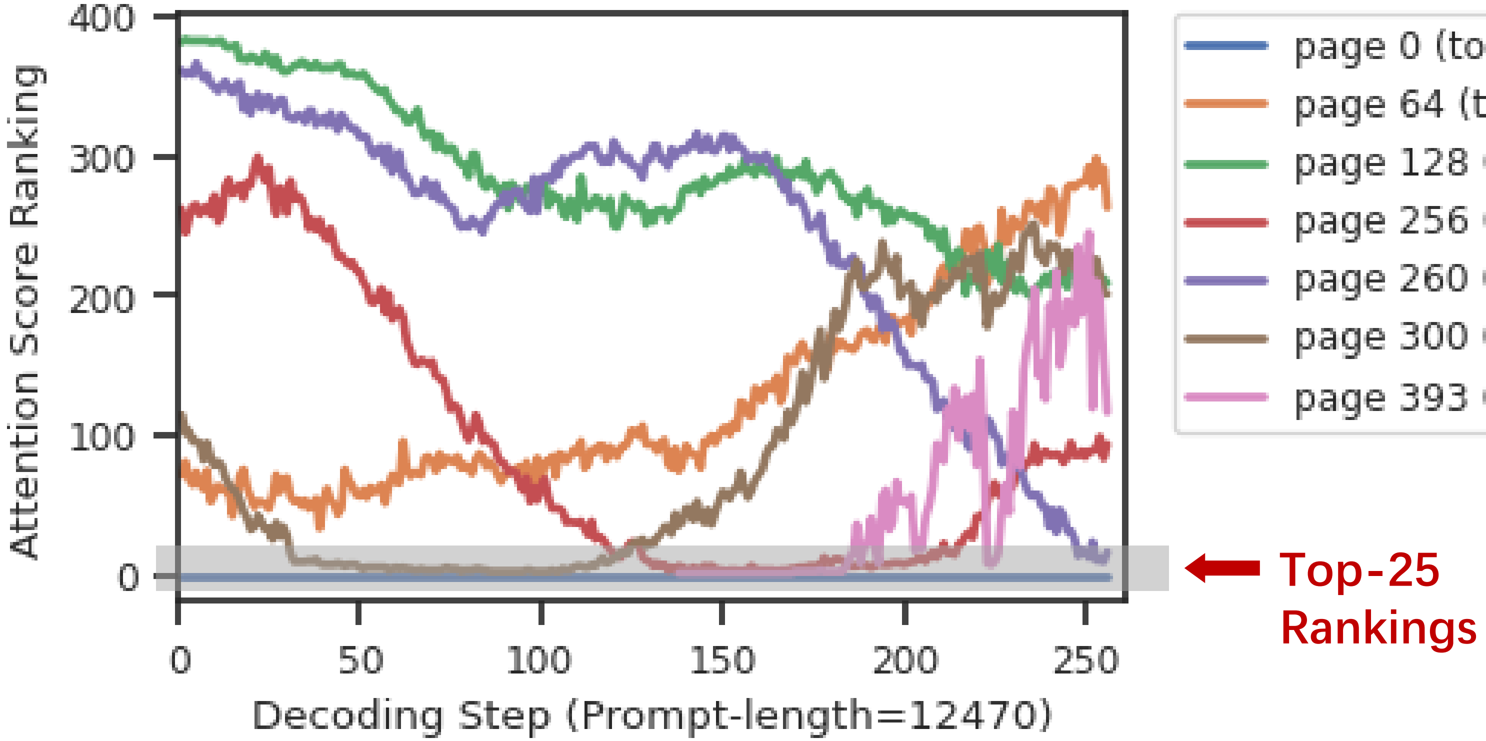
- In most LLM layers, less than 10 KV-cache pages (page-size=32) contributing over 99% of attention scores.



We can only keep those important tokens to save memory and make attention computation more efficient.

Observation: Dynamism of Token Importance

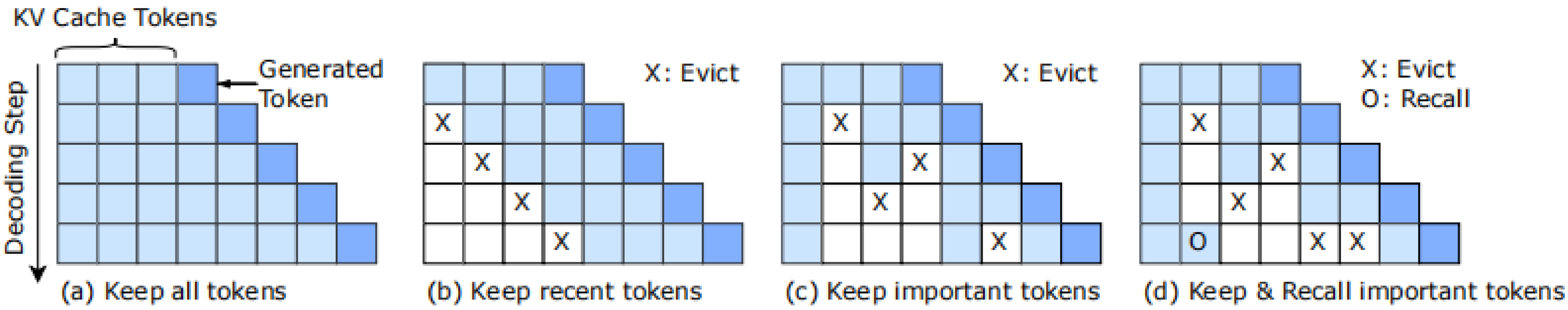
Importance of KV-cache token/page can dynamically change overtime



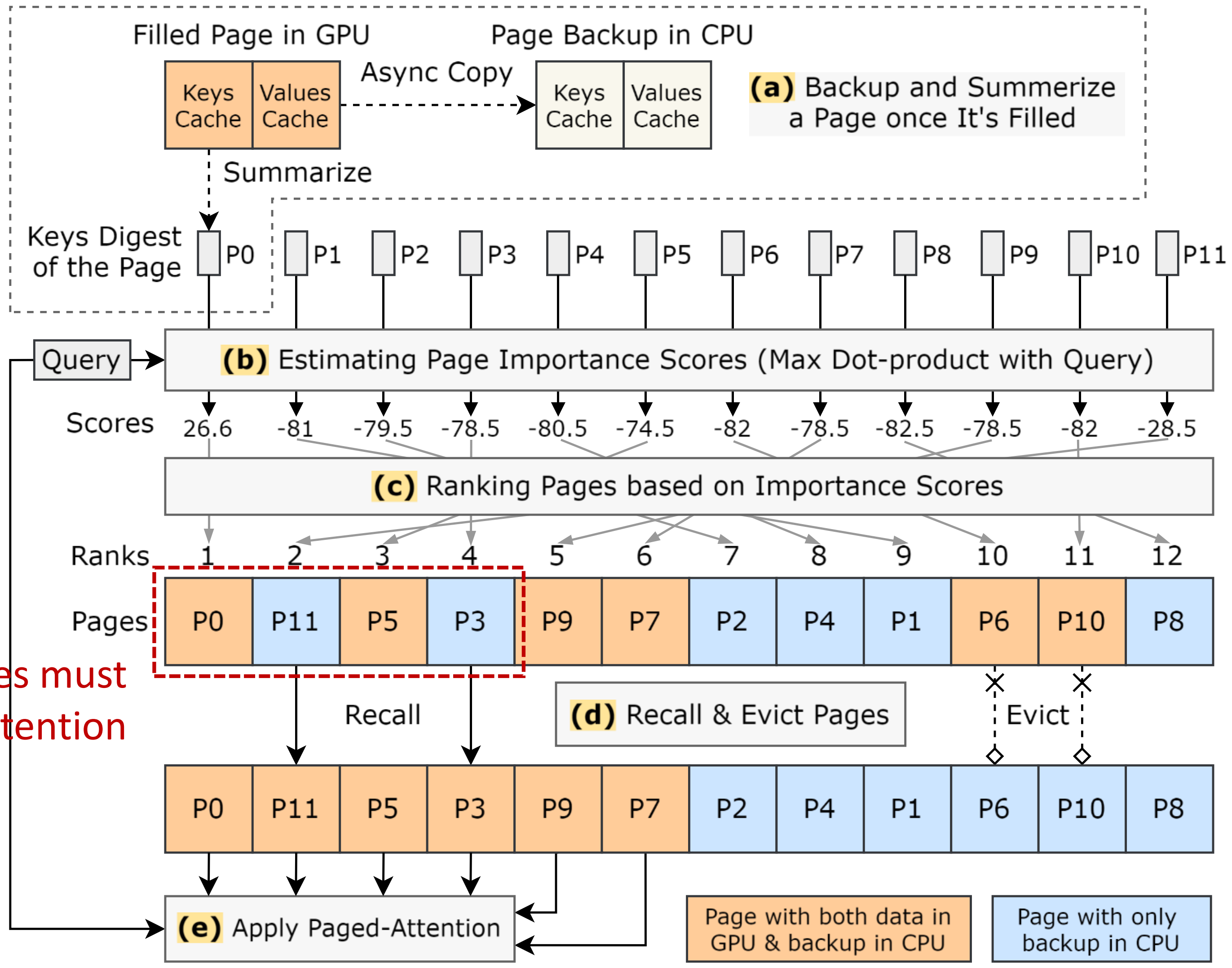
The attention score ranking of different KV-cache pages over decoding steps.

Observation: Dynamism of Token Importance

- Previous works permanently evict unimportant tokens based on history attention scores, but the evicted tokens may be important in the future.
- We propose a method named ArkVale to properly recall important tokens as well as evict unimportant ones during LLM decoding.



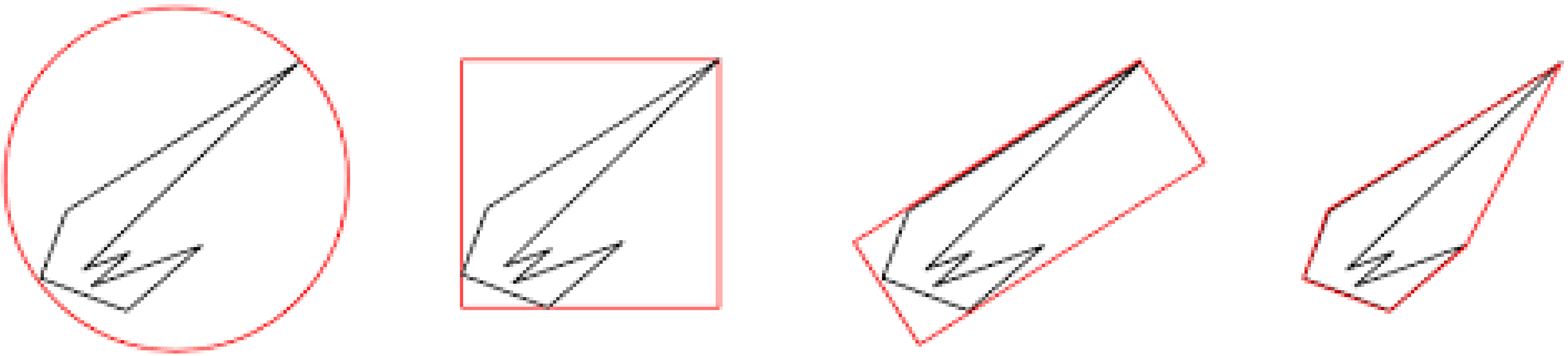
ArkVale: Workflow Overview



top-k (k=4) pages must participate attention

Page Summarization & Importance Estimation

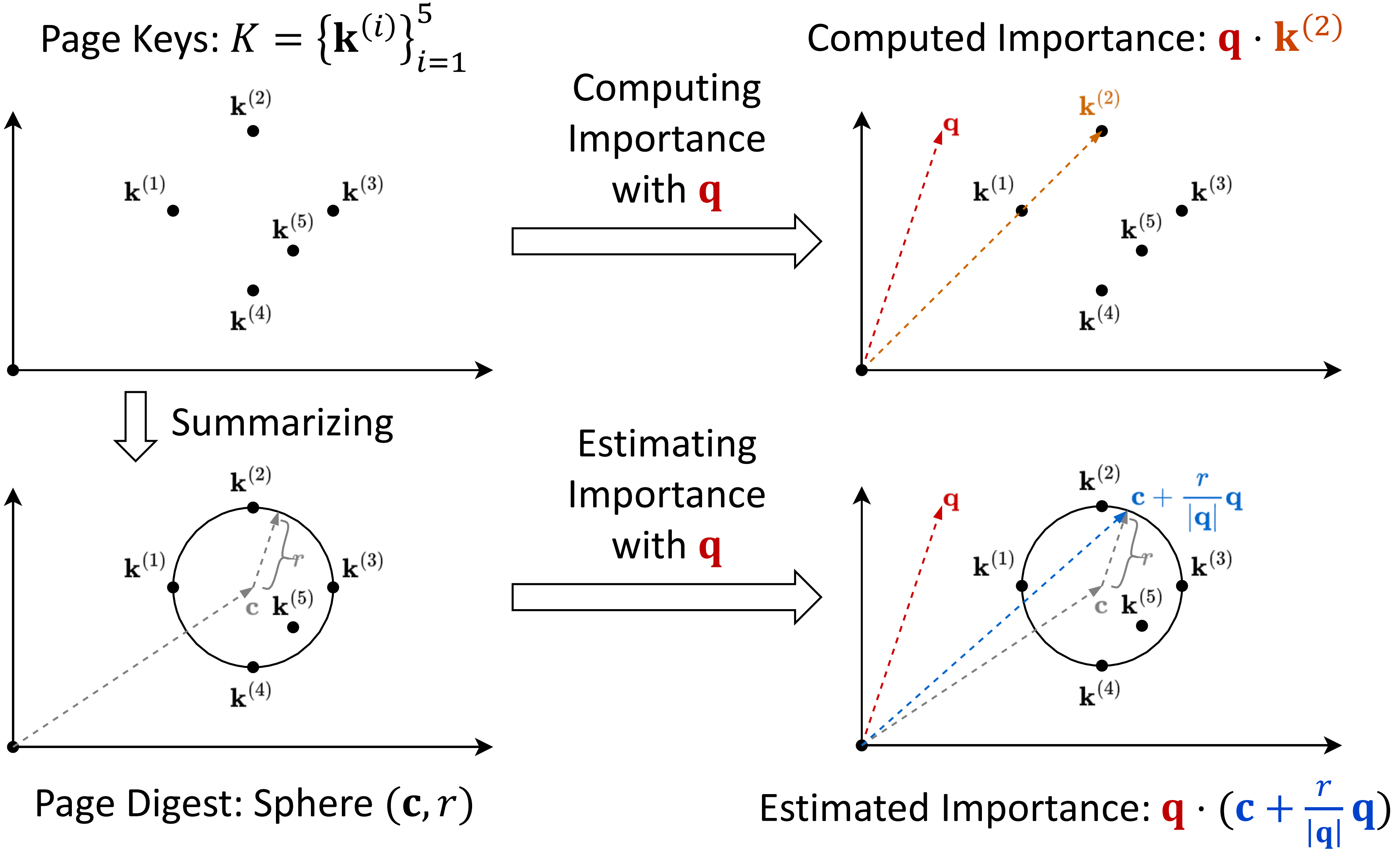
- **Definition:** For a page with keys $K = \{\mathbf{k}^{(i)}\}_{i=1}^{n} (\mathbf{k}^{(i)} \in \mathbb{R}^d)$, and a query $\mathbf{q} \in \mathbb{R}^d$, the *page importance* of K in terms of $\mathbf{q}$ is defined as $\max_{\mathbf{k} \in K} \mathbf{q} \cdot \mathbf{k}$
- **Observation:** $\mathbf{k}' = \operatorname{argmax}_{\mathbf{k} \in K} \mathbf{q} \cdot \mathbf{k}$ must be one of the "outmost" points of K
- **Solution:** We can use the concept of *bounding-volume* (from computer graphics area) for page summarization and importance estimation.



Bounding-Sphere | Bounding-Cuboid (Axis-Aligned Bounding Box) | Oriented Bounding Box | Convex Hull

https://www.ncollide.org/bounding_volumes/

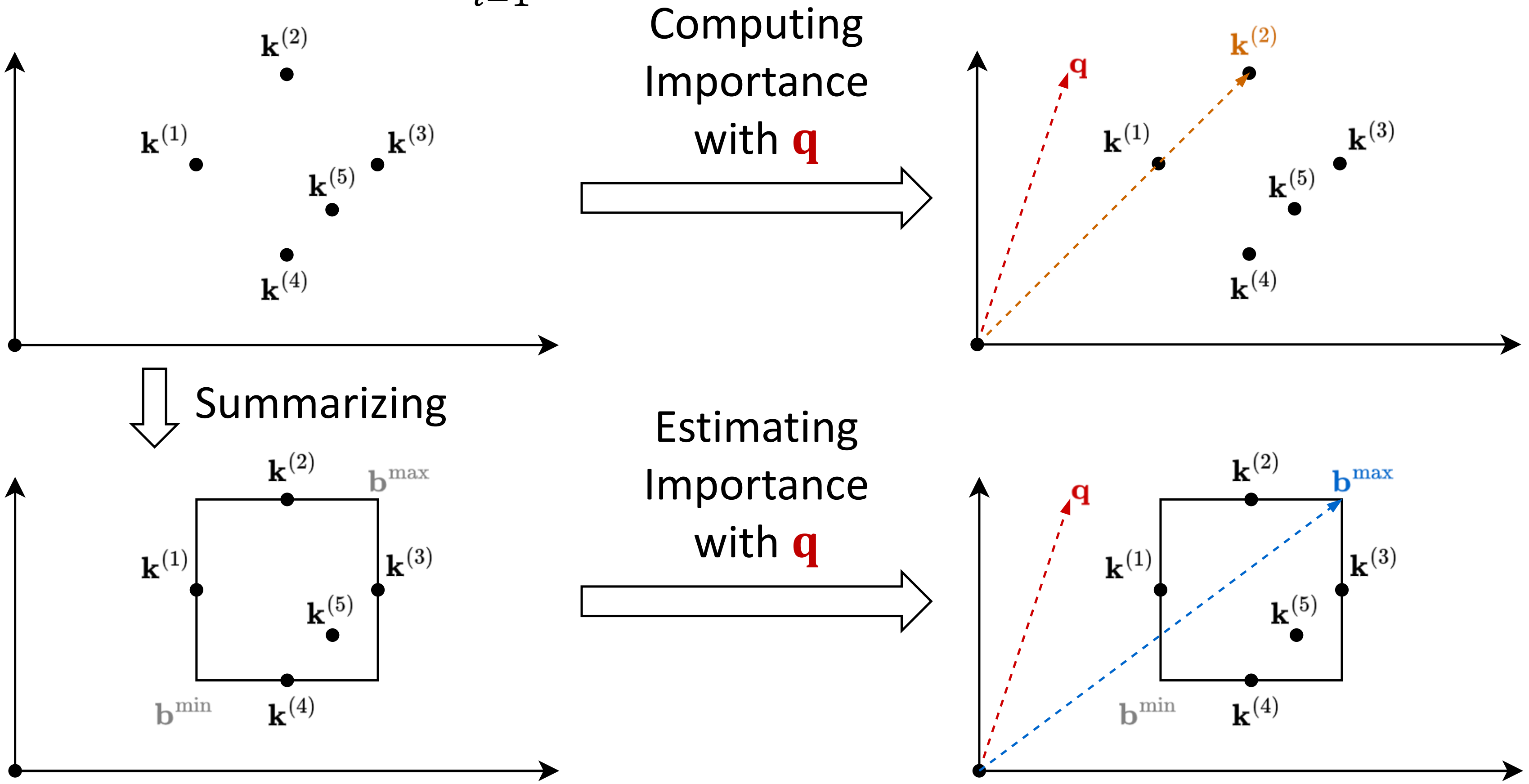
Bounding-Sphere for Summarization & Estimation



Bounding-Cuboid for Summarization & Estimation

Page Keys: $K = \{\mathbf{k}^{(i)}\}_{i=1}^{5}$

Computed Importance: $\mathbf{q} \cdot \mathbf{k}^{(2)}$



$$\mathbf{b}^{\min} = \min_{\mathbf{k} \in K} \mathbf{k}$$

$$\mathbf{b}^{\max} = \max_{\mathbf{k} \in K} \mathbf{k}$$

Page Digest: Cuboid $(\mathbf{b}^{\min}, \mathbf{b}^{\max})$

Estimated Importance: $\mathbf{q} \cdot \mathbf{b}^{\max} = \mathrm{sum}(\max(\mathbf{q} \odot \mathbf{b}^{\min}, \mathbf{q} \odot \mathbf{b}^{\max}))$

Evaluation Setup

Platform
Intel(R) Xeon(R) Gold 6348 CPUs
NVIDIA A100 80GB PCIe GPU

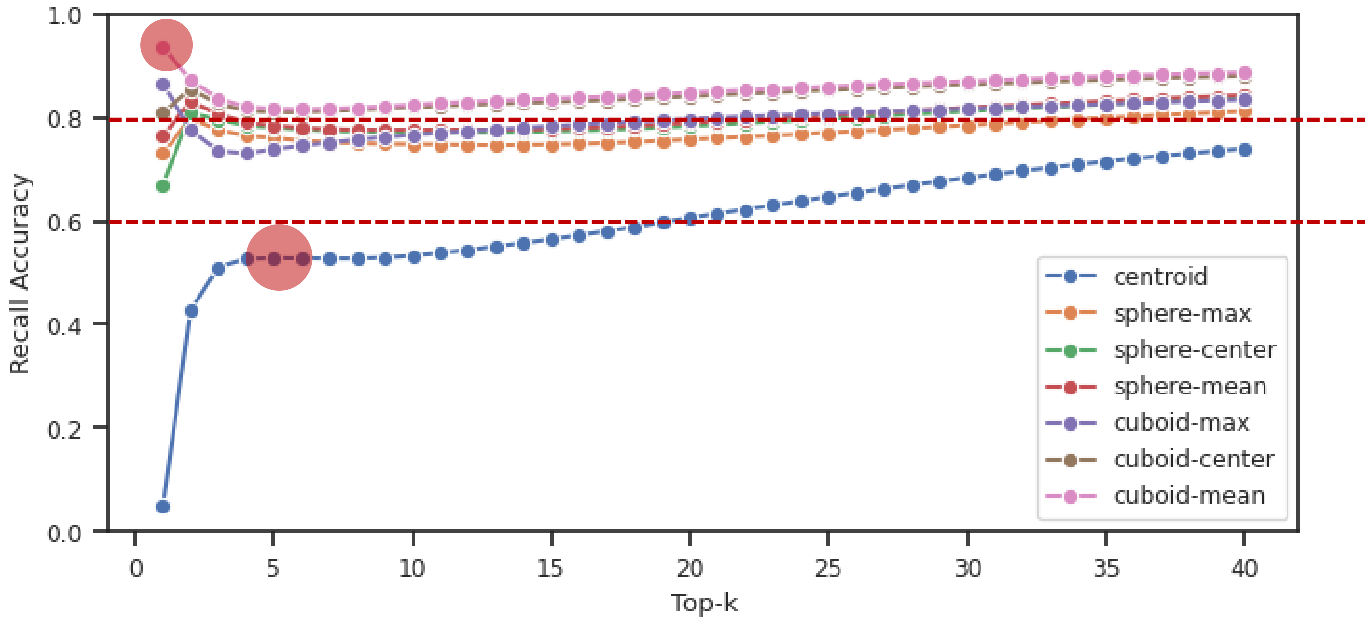
Baseline	Method
Origin/Full	Without KV-cache eviction
StreamingLLM (ICLR’23)	Retain initial tokens + recent tokens
H2O (NIPS’23)	Evict tokens based on history scores
TOVA	Evict tokens based on history scores

Benchmark
Long-Bench

Base Model
LongChat-v1.5-32k

Importance Estimation Accuracy

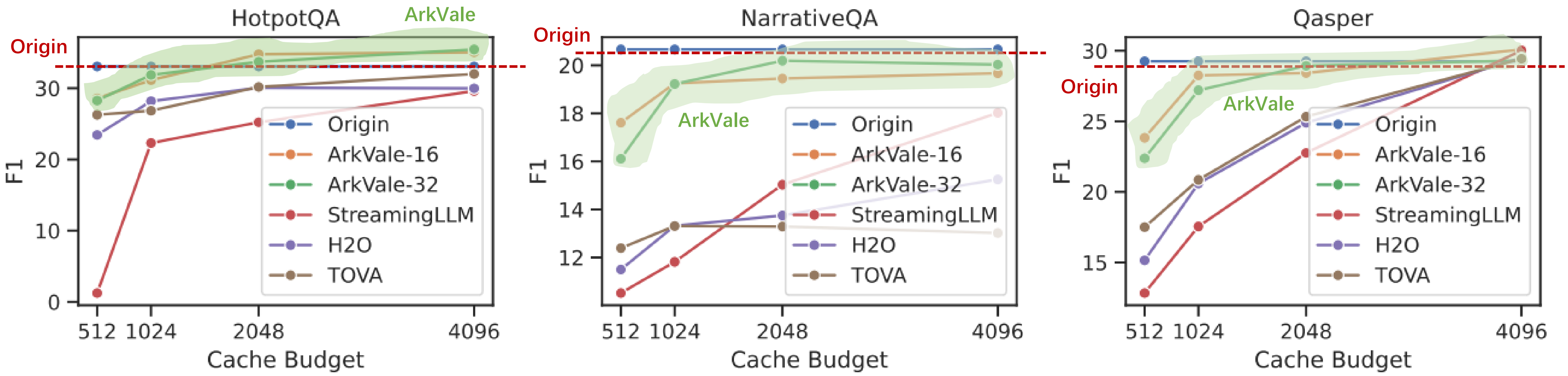
- Baseline method (centroid) cannot achieve even 60% top-5 recall accuracy.
- Our methods can achieve 60% top-k recall accuracy for all k.
- Our cuboid-mean method ensure 95% top-1 recall accuracy, and can achieve 80% top-k recall accuracy for all k.



Top-k recall accuracy of different importance estimation methods

Part of Evaluation Results on Long-Bench

- ◇ArkVale can surpass all baselines with different datasets and cache-budgets.
- ◇ArkVale can approach or even surpass “Origin”.
- ◇ArkVale-16 (page-size=16) usually outperforms ArkVale-32 (page-size=32).

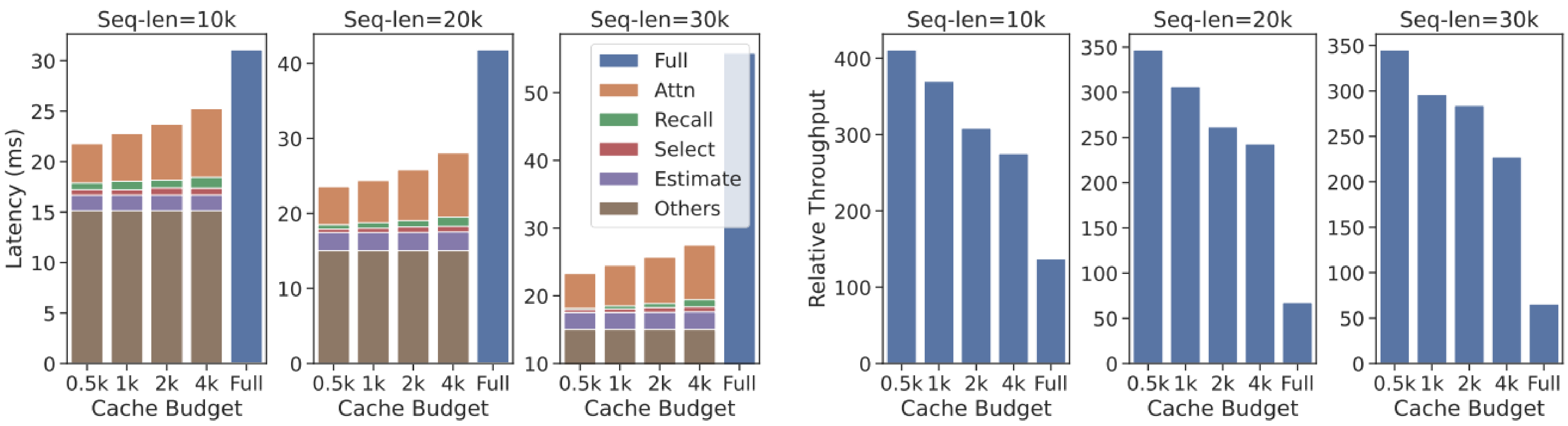


Performance Evaluation

◇Allocate 40 GB GPU memory for KV-cache (and page digests) in A100 GPU.

◇Compared to baseline, ArkVale can achieve up to 2.2x decoding speedup.

◇Compared to baseline, ArkVale can achieve up to 6x decoding throughput.



(a) Latency Breakdown (batch-size=4)

(b) Throughput Comparison

Summary

- ArkVale: Efficient Generative LLM Inference with Recallable Key-Value Eviction
  - Page-based KV-cache Eviction & Recall
  - Page Summarization & Importance Estimation based on Bounding-volume
- ArkVale performs well on various long context tasks with few accuracy loss under a cache budget of 2k~4k and speeds up decoding latency by 2.2× and boosts throughput to 6× in long-context scenarios.

Scan to access our code

Our code is now open-sourced at https://github.com/pku-liang/ArkVale

Thanks for listening! E-mail us to ask follow-up questions: crz@pku.edu.cn