Quest: Query-Aware Sparsity for Efficient Long-Context LLM Inference

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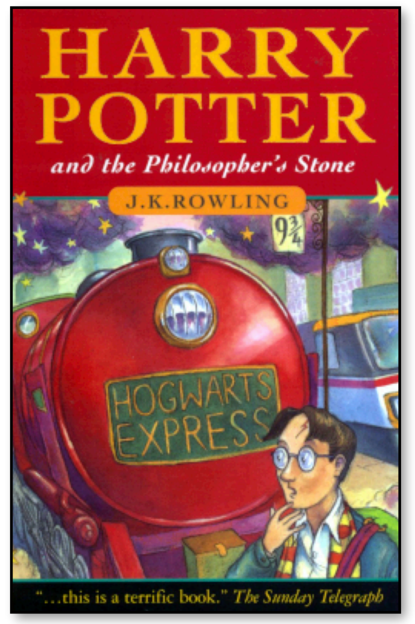
Motivation

Why Long Context LLMs?

What inputs can LLMs handle with different context lengths?

A short blog

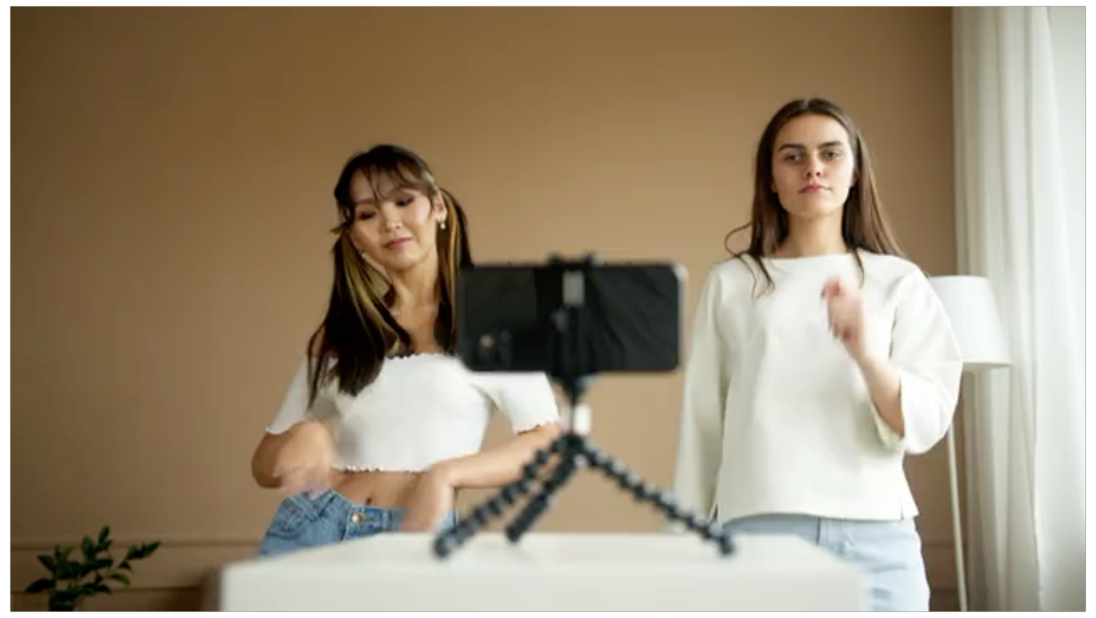


A Harry Potter book

The whole series of Harry Potter books

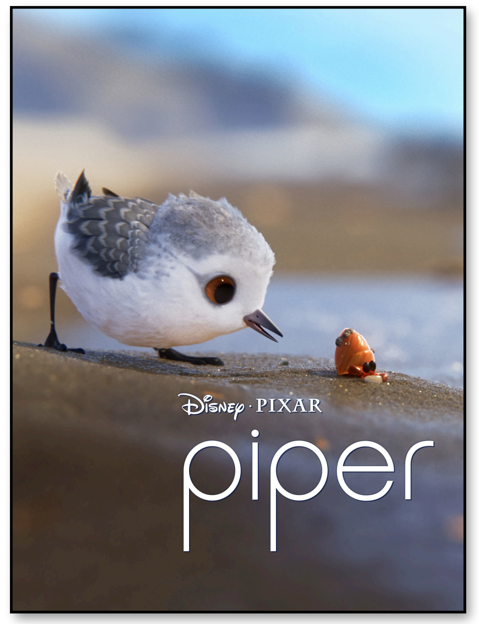
8,000 tokens | 128,000 tokens | 1,000,000 tokens — Context Length

What videos can multi-modal LLMs process (given a rate of 200 tokens per frame per second)?



A short video vlog

~ 30 seconds



A short film – Piper

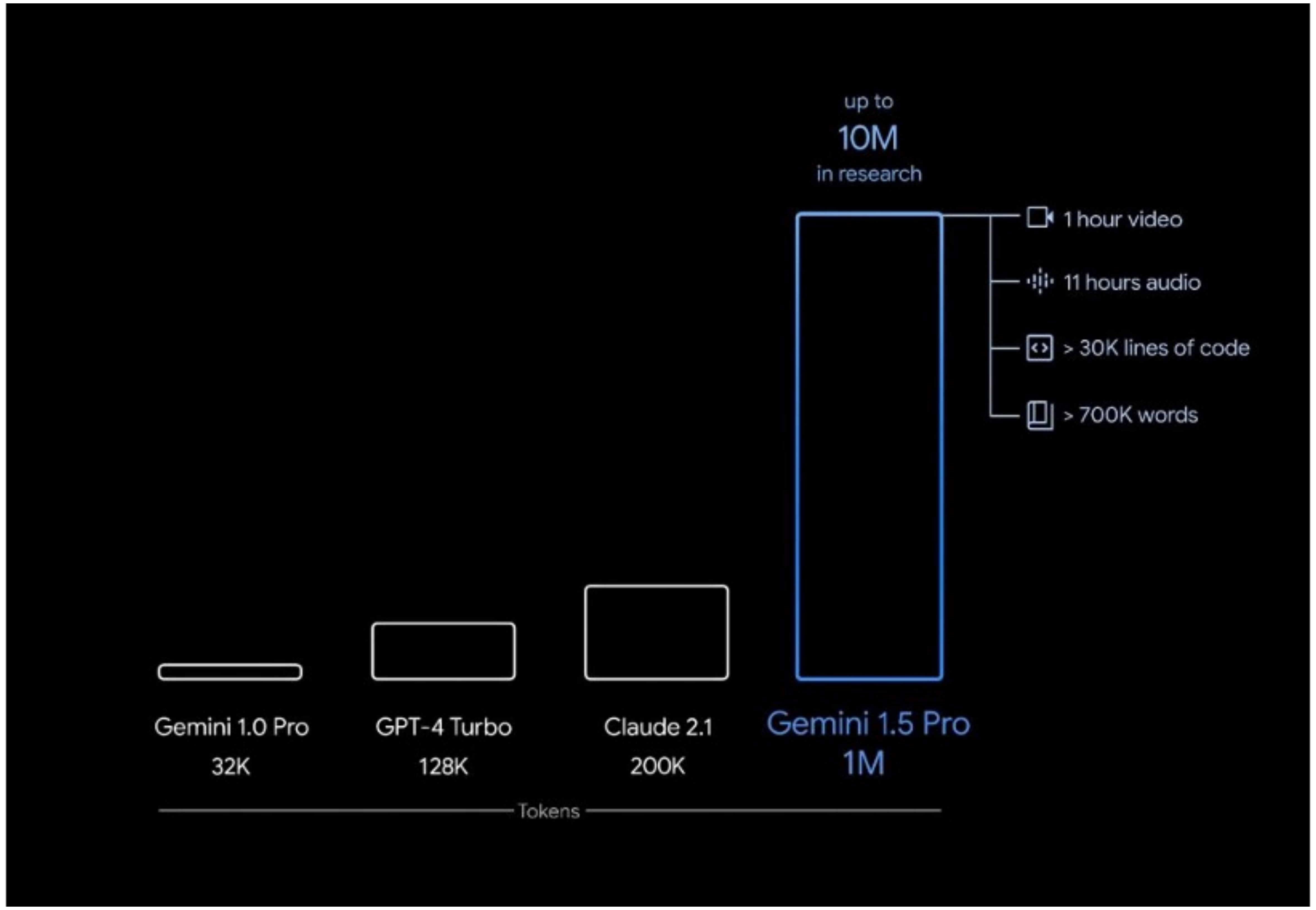
~ 10 minutes

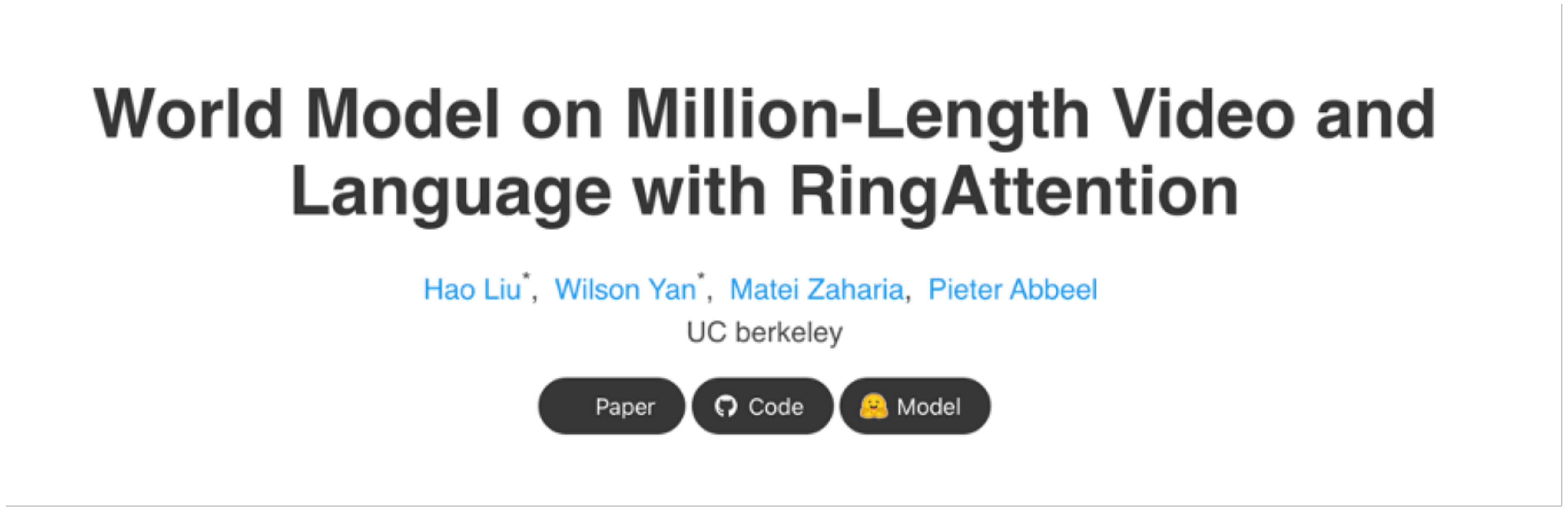
A film

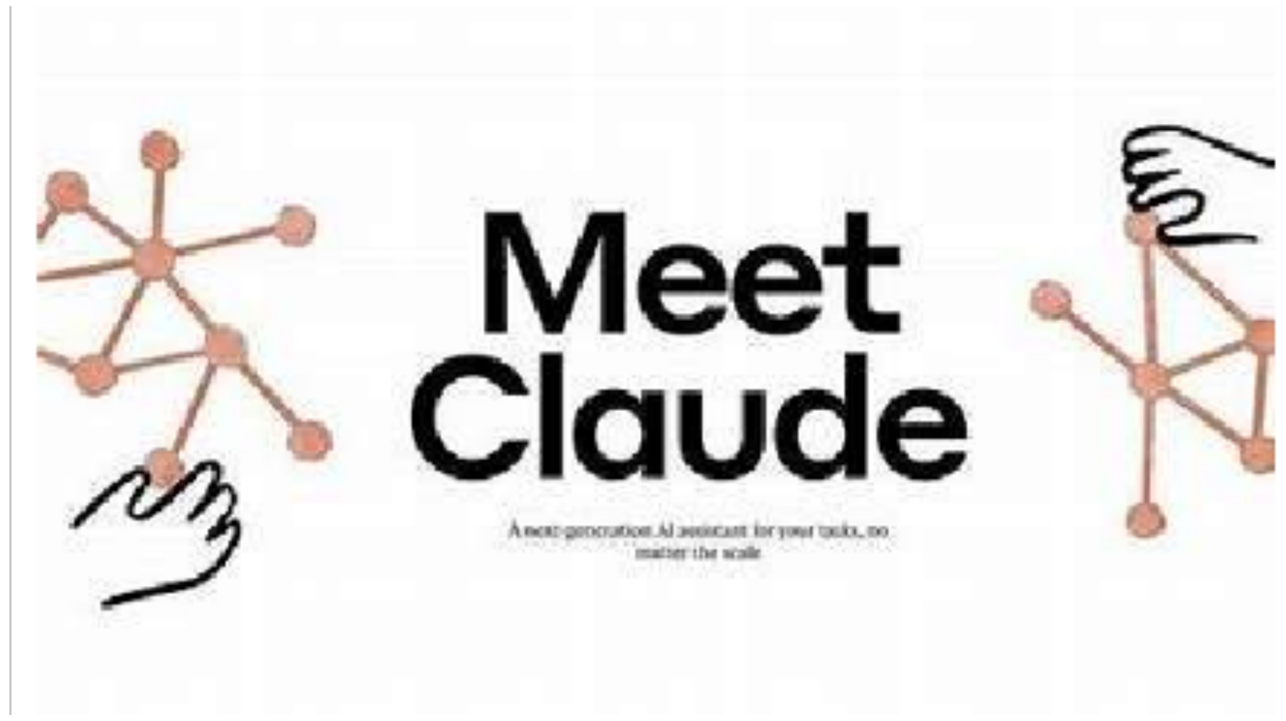
1 - 2 hours

Motivation

- As the demand for long-context large language models (LLMs) increases, models with context windows of up to 128k or even 1M tokens are becoming increasingly prevalent.



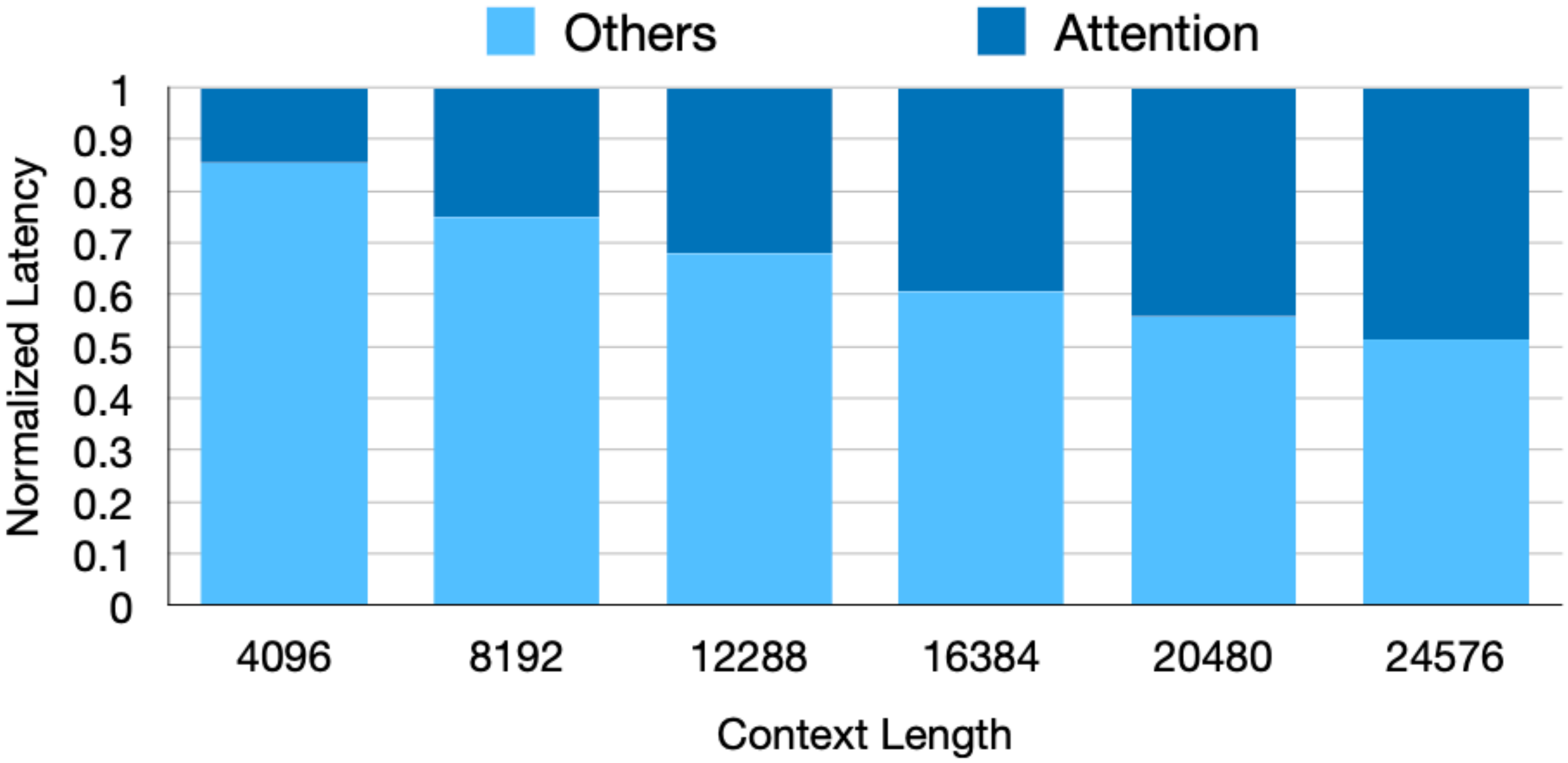




The Problem of Long Context: Large KV Cache

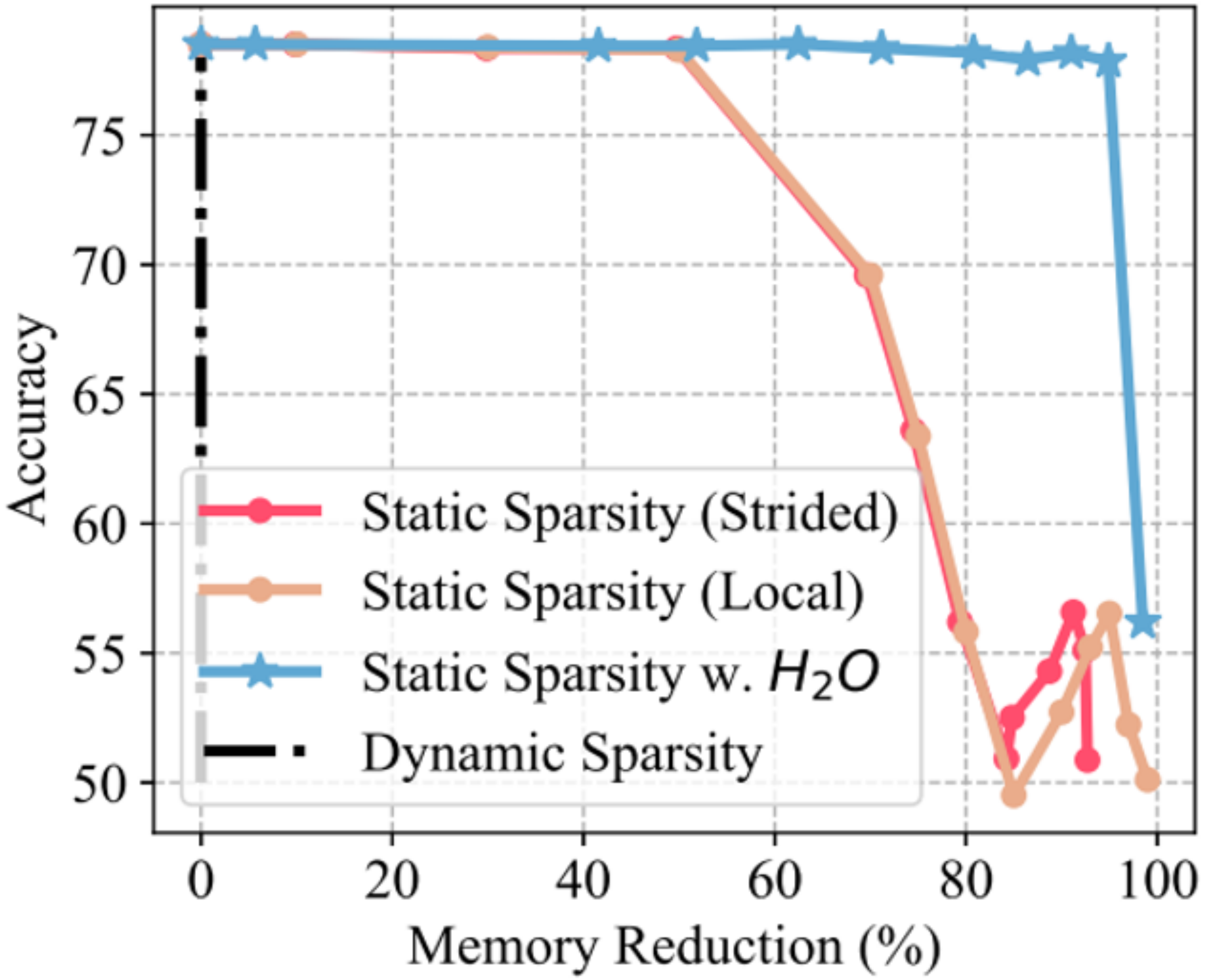
Large KV cache slows down long context inference

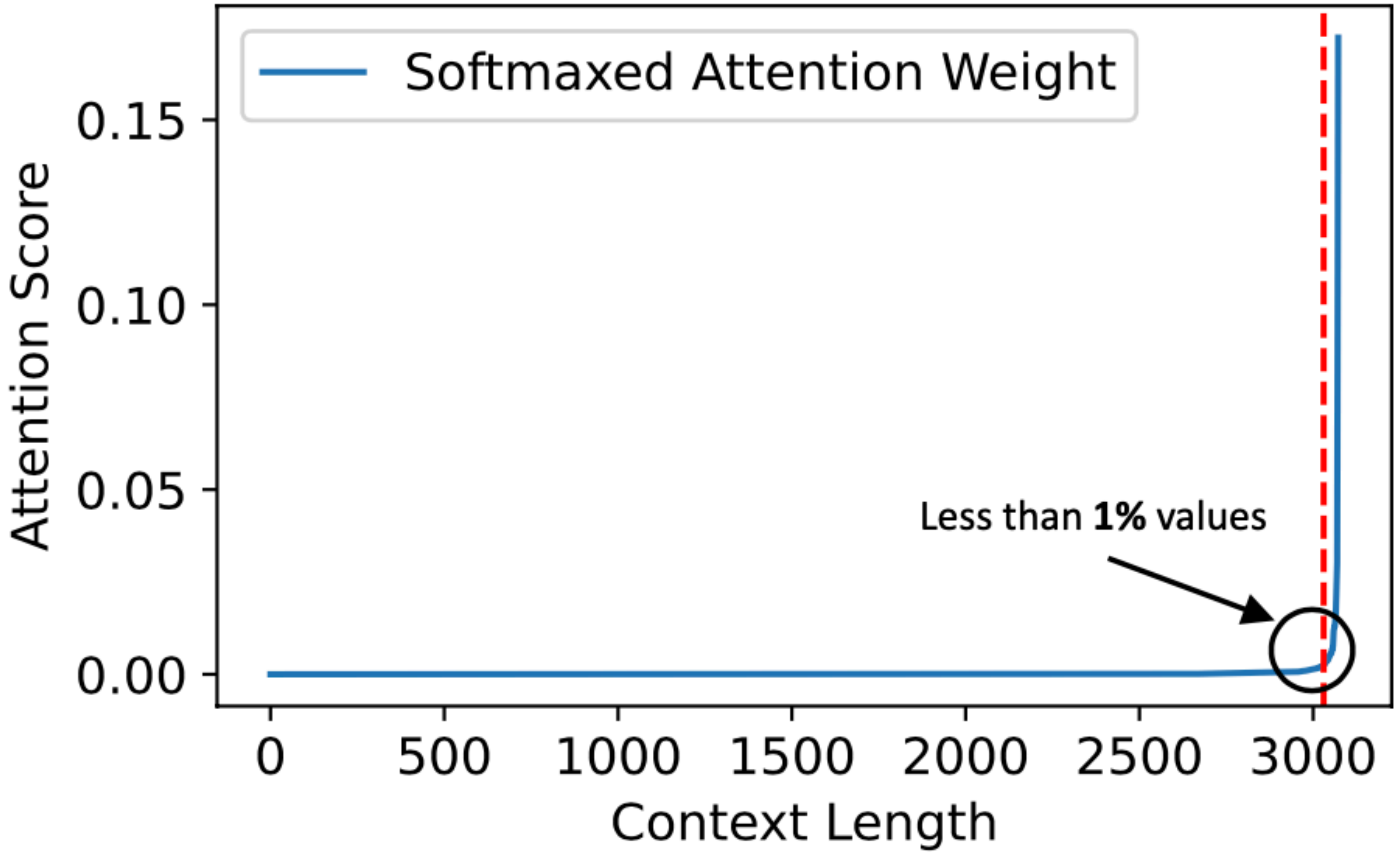
- However, long-context LLM inference is challenging since the **inference speed decreases significantly as the sequence length grows**.
- This slowdown is primarily caused by **loading a large KV cache during attention**.



The Sparsity in Attention Mechanism

- Previous research has highlighted the **inherent sparsity in attention mechanism**.
- Due to this property of self-attention, a small portion of tokens in the KV cache, called critical tokens, can accumulate sufficient attention scores, capturing the most important inter-token relationships.

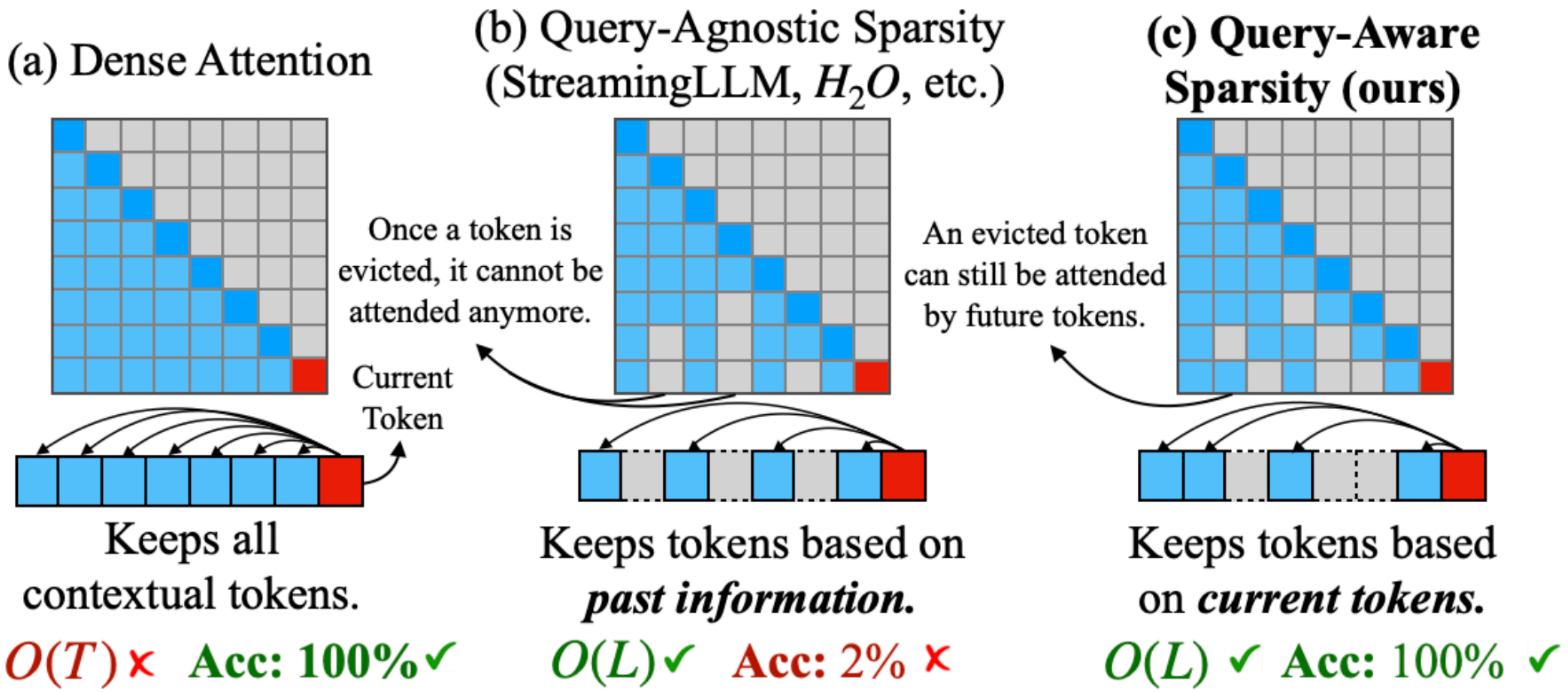




H2O: Heavy-Hitter Oracle for Efficient Generative Inference of Large Language Models. Zhang et al.

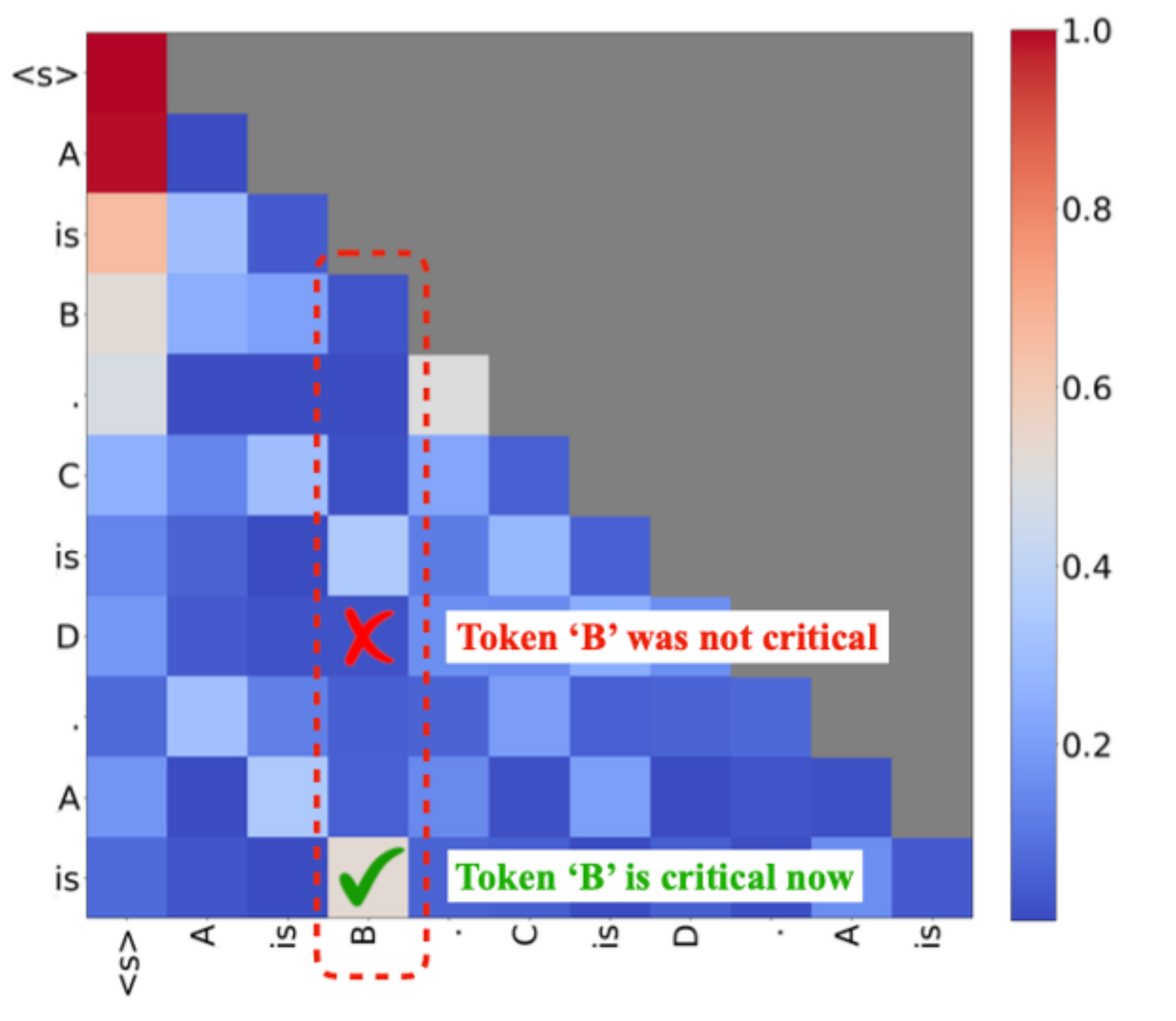
The Limits of Previous Methods

- Many previous efforts have been dedicated to compressing the size of the KV cache to accelerate attention and reduce memory usage.
- These methods decide which parts of the KV cache to discard based on historical information or current states, but **discarded tokens might be important for future tokens**, which may cause the loss of important information.



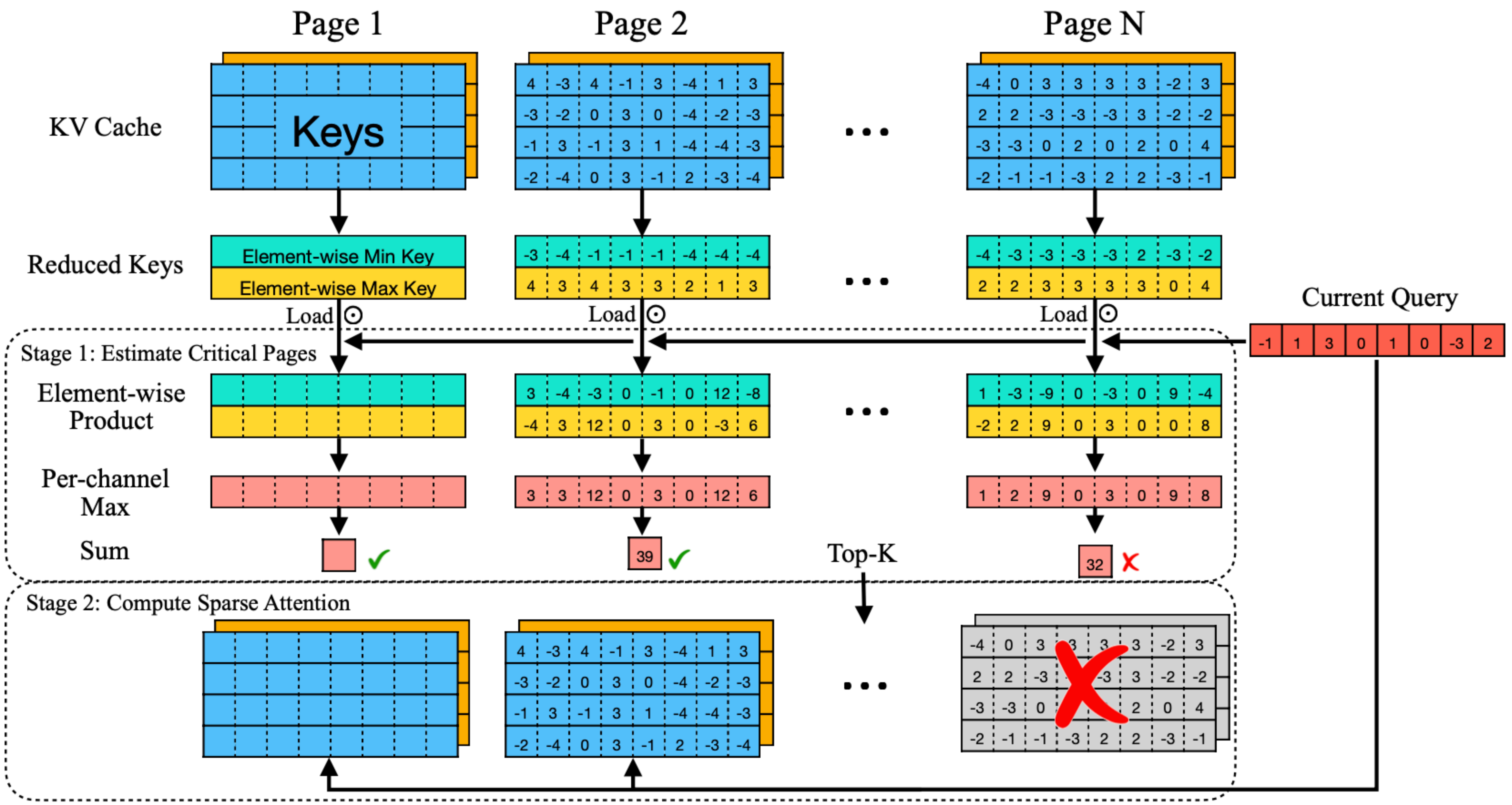
The Limits of Previous Methods

- The **criticality of the tokens is dynamic** and **highly dependent on the query vector Q**.
- Example: the token ‘B’ is critical to the current query ‘is’. Thus, it has a high attention score. However, before the final token ‘is’, ‘B’ is not critical for any previous query and has very low attention scores.



Quest: Using Query-aware Sparsity in Attention

- **Key Idea: preserve all KV cache**, and significantly accelerate inference by reducing the memory movement from the entire KV cache to selected constant K pages.



Quest: Using Query-aware Sparsity in Attention

- Our insight is that in order not to miss critical tokens, we should **select pages containing the tokens with the highest attention weights**.
- However, for an efficient selection of pages, we should **calculate an approximate attention score** following this insight.
- We found that the **upper bound attention weights within a page** can be used to approximate the highest attention score in the page.

When inserting new token to KV cache:
Input: Key vector K, Dimension of hidden states dim, Current maximal vector M_i, Current minimal vector m_i

for $i = 1$ **to** dim **do**
  $M_i = \max(M_i, k_i)$
  $m_i = \min(m_i, k_i)$
end for

When perform self-attention:
Input: Query vector Q, Dimension of hidden states dim, Current maximal vector M_i, Current minimal vector m_i

Initialize $score = 0$.
for $i = 1$ **to** dim **do**
  $score$ += $MAX(q_i * max, q_i * min)$
end for

Quest Performance

Needle-in-a-Haystack

- (i) Results of 10k length passkey retrieval test on LongChat-7b-v1.5-32k.
- (ii) Results of 100k length passkey retrieval test on Yarn-Llama-2-7b-128k.
- Quest can achieve nearly **perfect accuracy** with a KV cache of 64 and 1024 tokens, which is about **1% of the total sequence length**, demonstrating that Quest can effectively preserve the model's ability to handle long-dependency tasks.

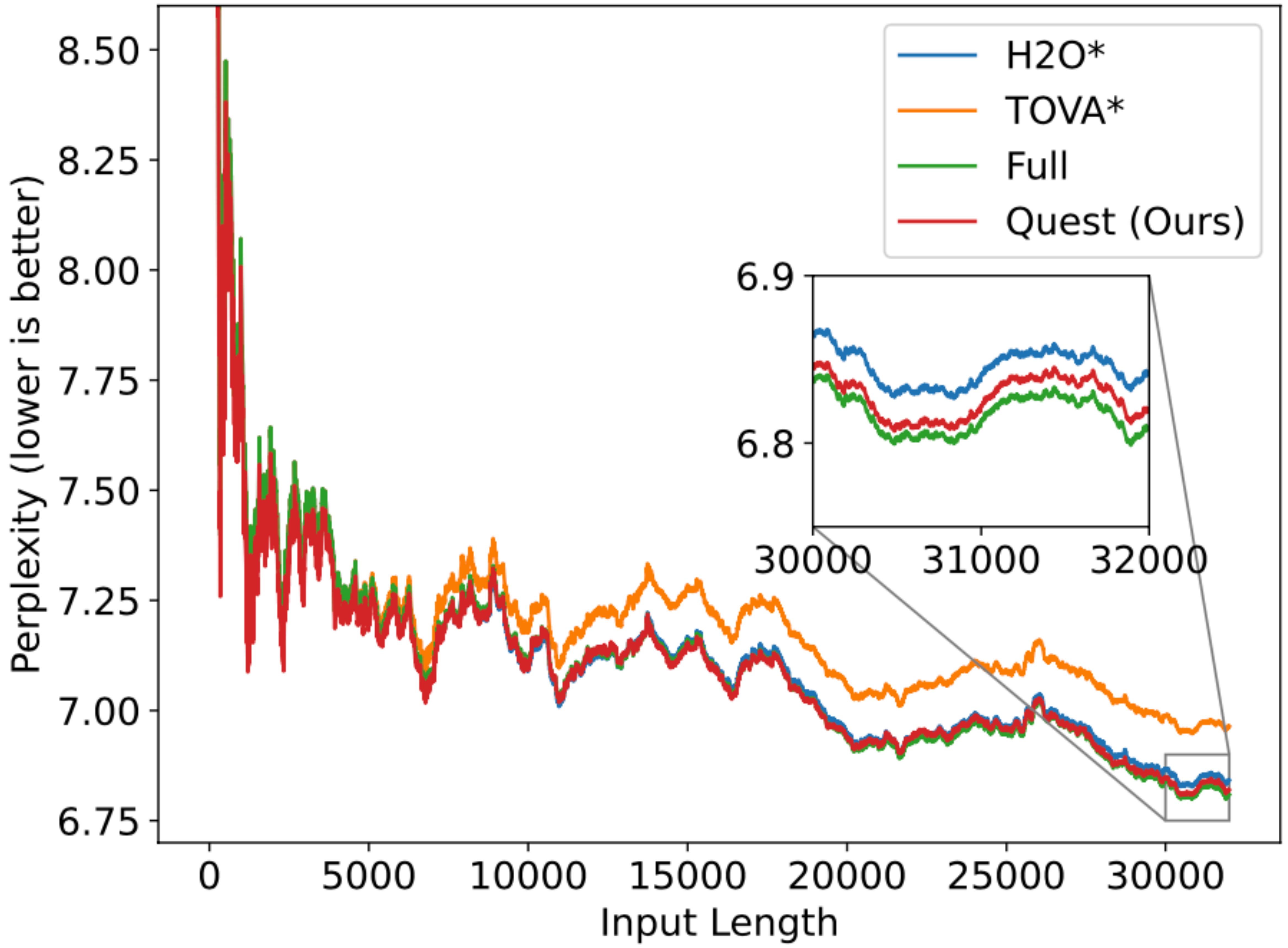
Method / Budget	32	64	128	256	512
H2O	0%	1%	1%	1%	3%
TOVA	0%	1%	1%	3%	8%
StreamingLLM	1%	1%	1%	3%	5%
Quest (ours)	**65%**	**99%**	**99%**	**99%**	**100%**

Method / Budget	256	512	1024	2048	4096
H2O	2%	2%	2%	2%	4%
TOVA	2%	2%	2%	2%	10%
StreamingLLM	1%	1%	1%	2%	4%
Quest (ours)	**88%**	**92%**	**96%**	**100%**	**100%**

Quest Performance

Super Long Language Modeling

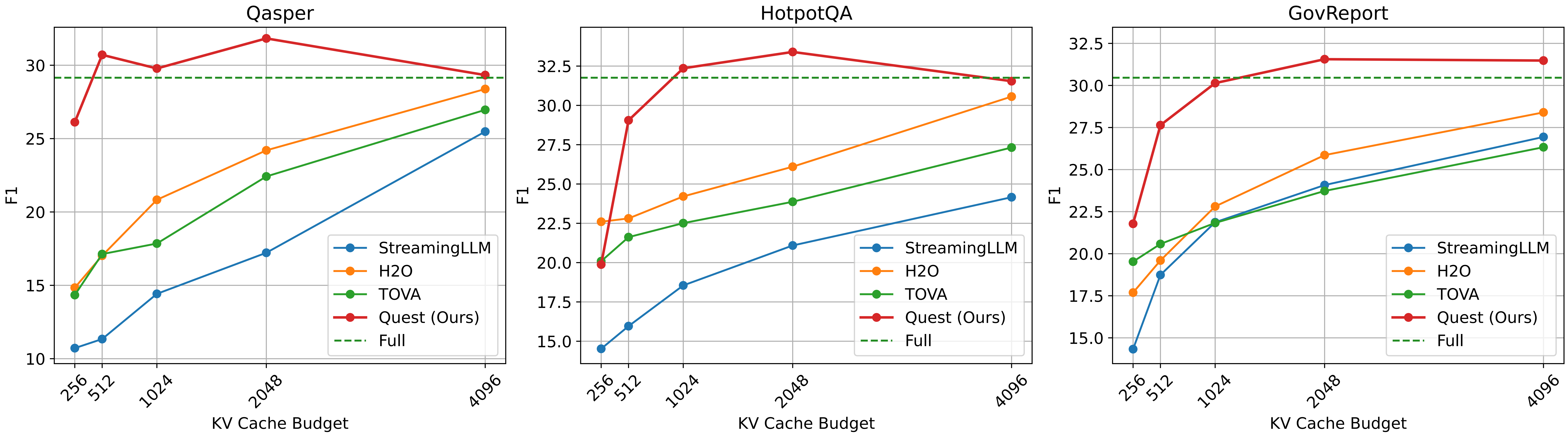
- Language modeling evaluation of Quest on PG19 dataset.
- Quest can **closely match the performance of the full cache model**.



Quest Performance

LongBench

- We evaluate LongChat-7b-v1.5-32k across a wide range of long-context datasets,
- Quest with **a budget of 2k tokens can achieve comparable performance as the model with full KV cache**, while other baselines still exhibit a notable gap from full cache performance even with a larger budget.
- Single-document QA: NarrativeQA, Qasper, MultiFieldQA; multi-document QA: HotpotQA; summarization: GovReport; few-shot learning: TriviaQA.



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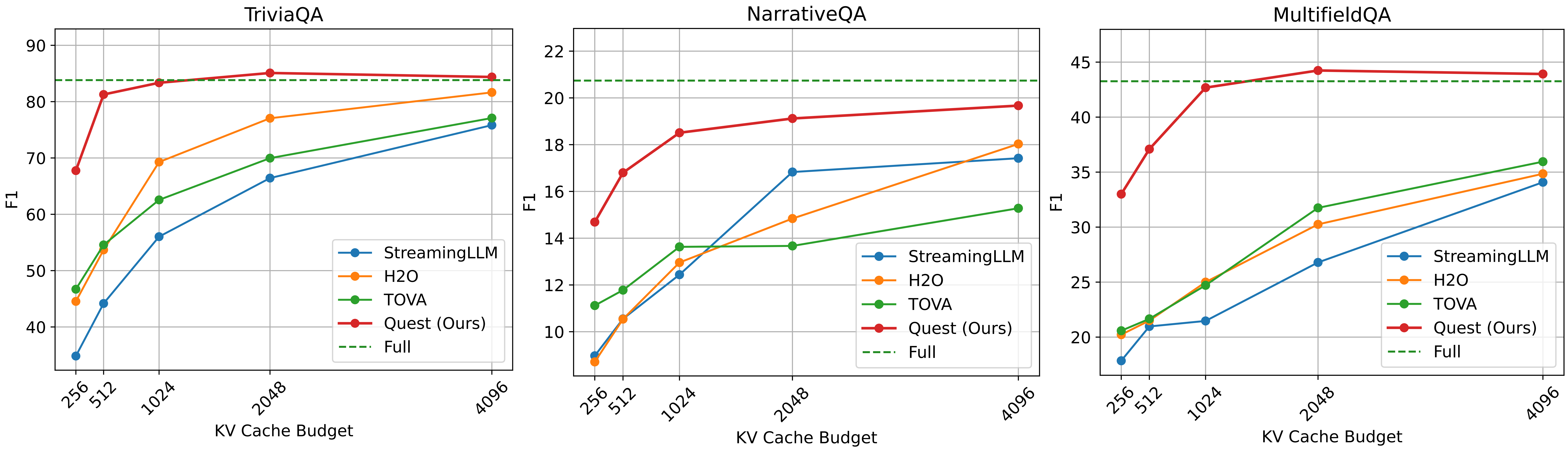
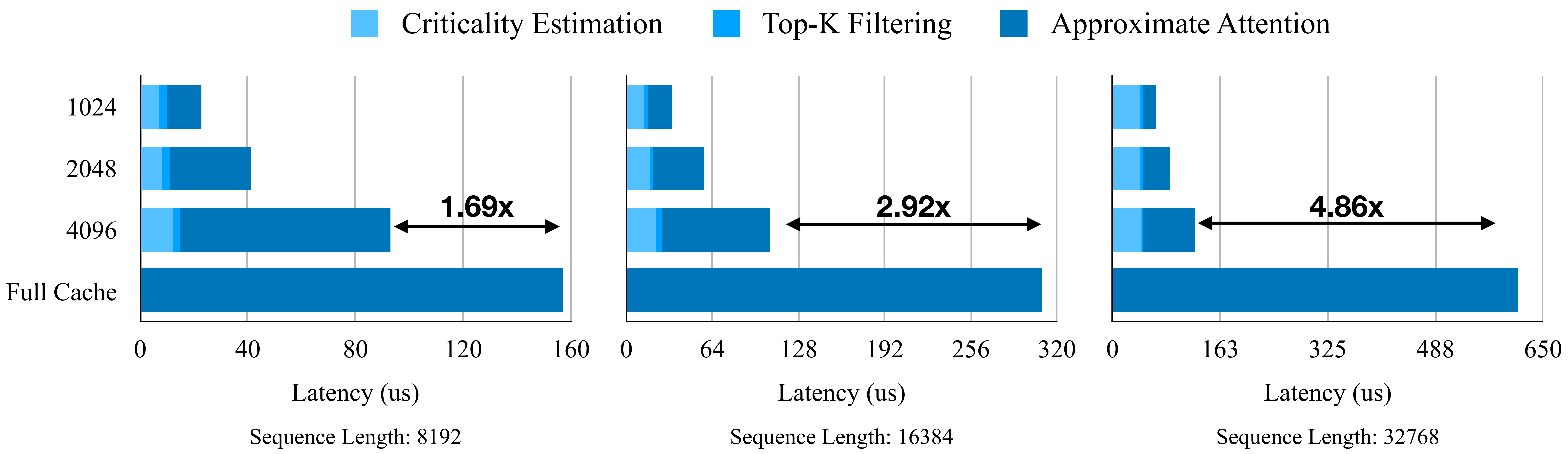


Efficiency Evaluation

Quest attention time breakdown

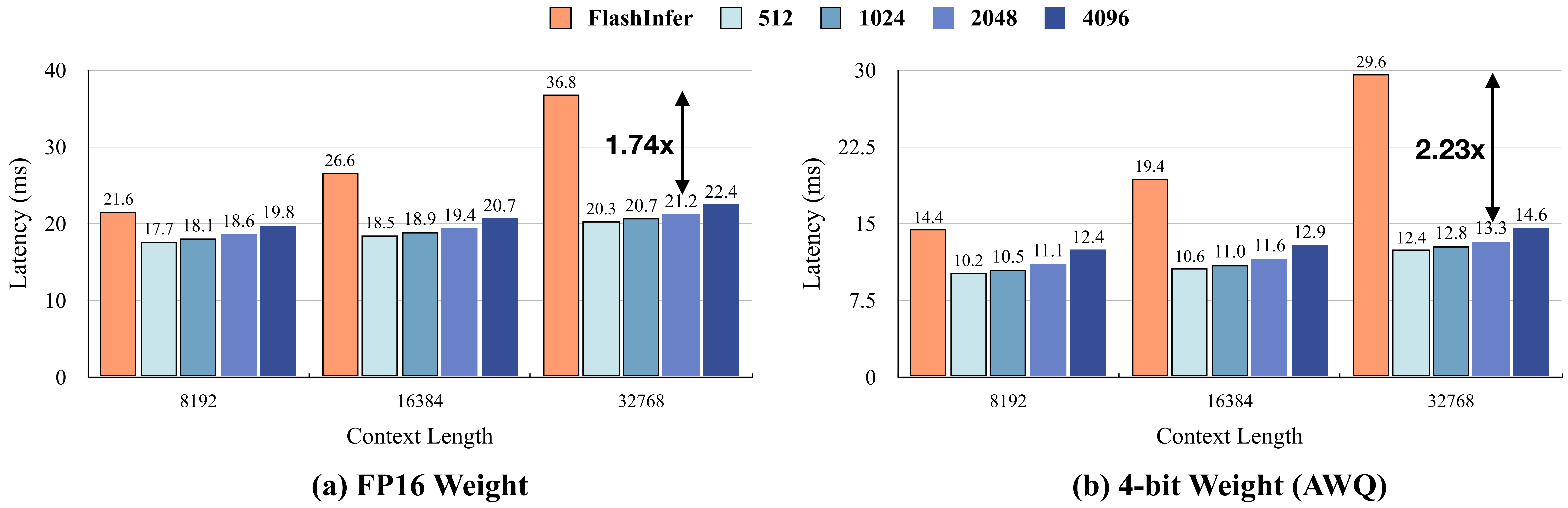
- At all sequence lengths, **Quest significantly outperforms FlashInfer**, as the memory movement is reduced.
- **Quest speeds up self-attention by 7.03×** at sequence length 32k with token budget 2048.



Efficiency Evaluation

End-to-end latency

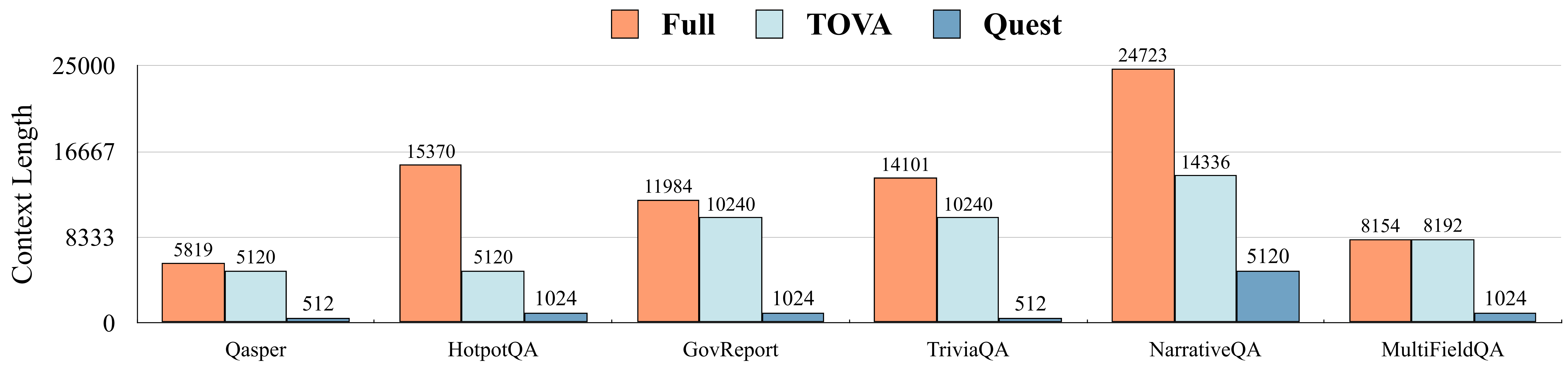
- For all sequence lengths, Quest significantly outperforms FlashInfer. Increasing the sequence lengths only slightly changes the latency of Quest.
- **Quest speedup end-to-end inference by 2.23×** with sequence length 30K, token budget 2048, 4-bit weight quantization.



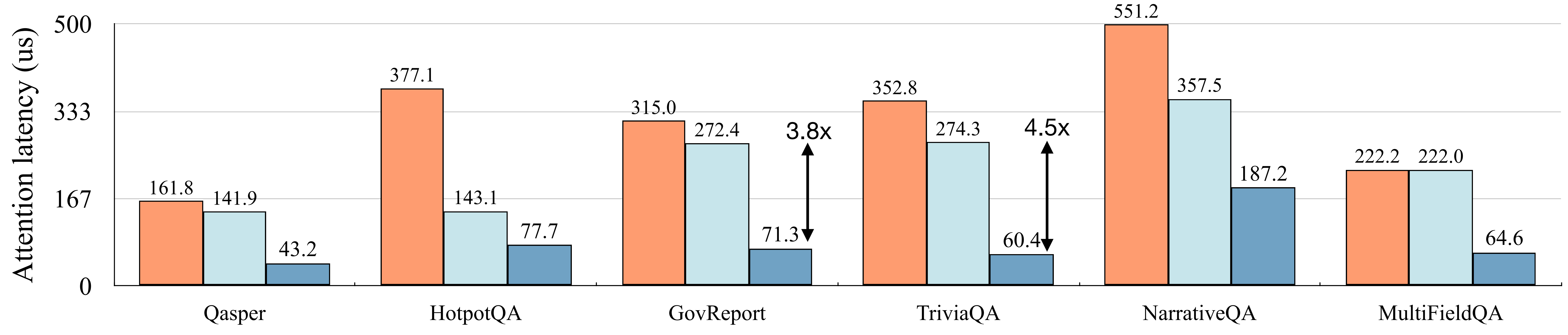
Efficiency Evaluation

Efficiency comparison with baselines

- Baselines need nearly full cache to achieve lossless performance on LongBench benchmarks.
- Therefore, **Quest outperforms the baseline by up to 4.54x with the same lossless accuracy.**



(a) Average context length for lossless accuracy of attention mechanisms



(b) Inference latency of different attention mechanism under benchmarks

Thanks for Listening!

- We propose Quest, an efficient long-context LLM inference framework that **leverages query-aware sparsity in the KV cache** to accelerate the attention mechanism.

- Code: https://github.com/mit-han-lab/Quest
- Paper: https://github.com/mit-han-lab/Quest/blob/main/assets/quest_paper.pdf
- Poster: https://github.com/mit-han-lab/Quest/blob/main/assets/quest_poster.pdf