DuoAttention: Efficient Long-Context LLM Inference with Retrieval and Streaming Heads

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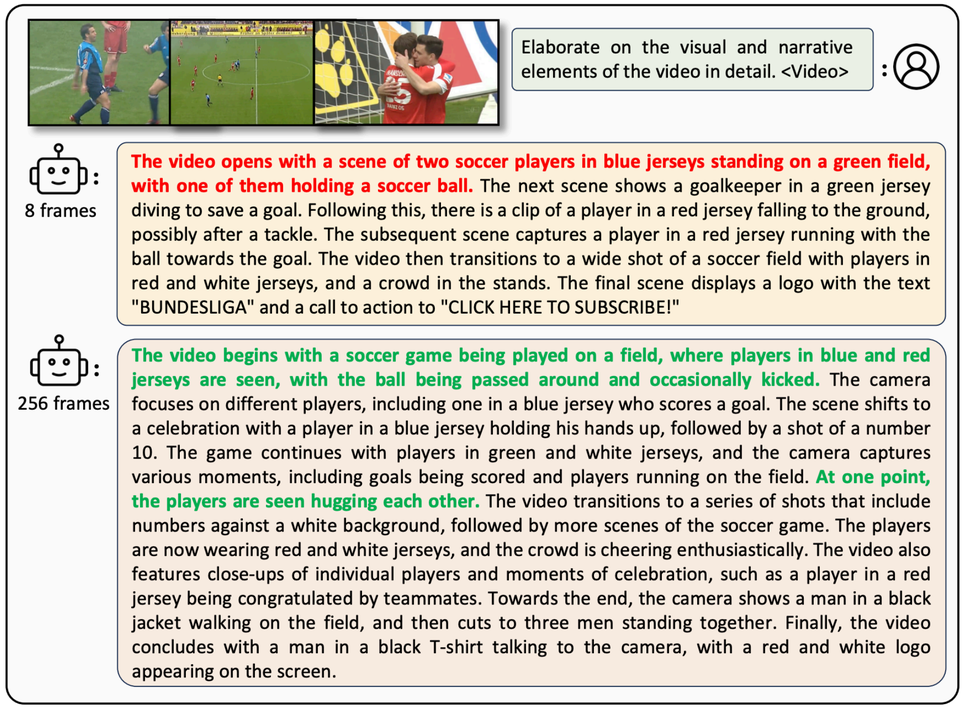
Motivation

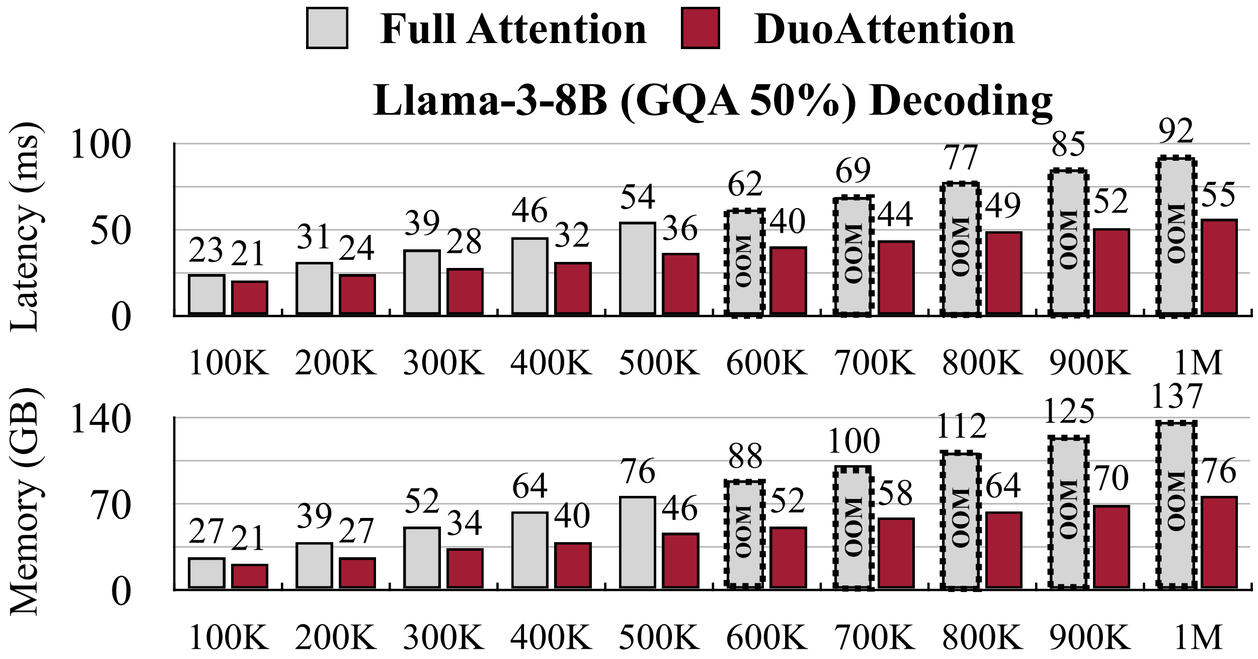
Deploying Long-Context LLMs is Crucial But Challenging

- LLMs need to handle long-context like summarizing long texts and processing images/videos.
- Memory and latency increase dramatically with context length.



a 224×224 image = 256 tokens

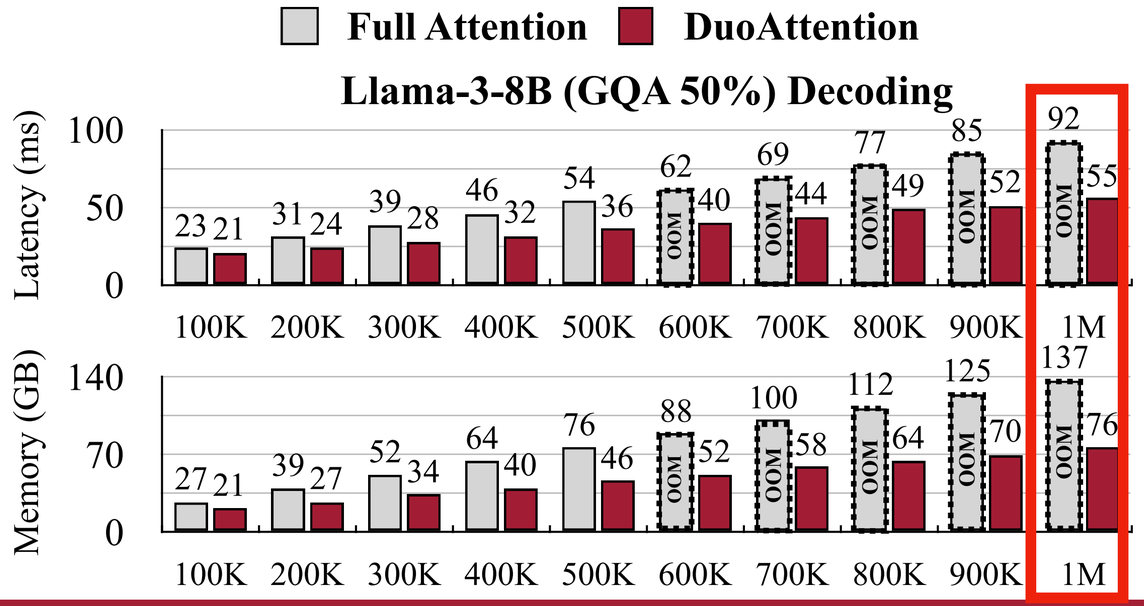
a 1-hour video at 1 FPS = **1 million tokens**

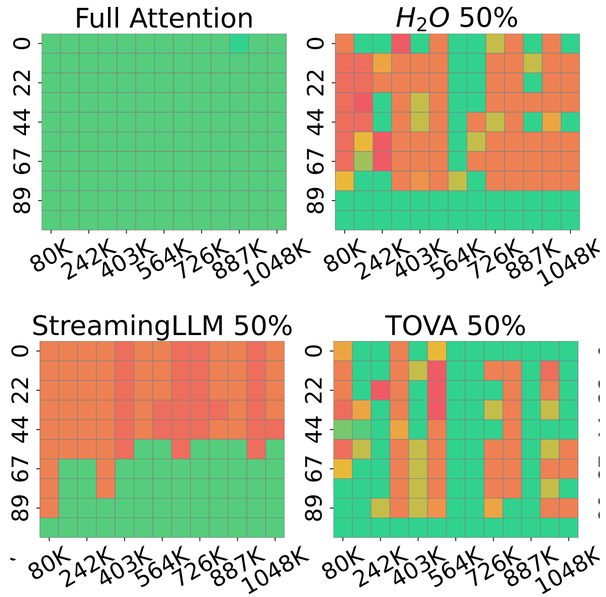


Key Challenges

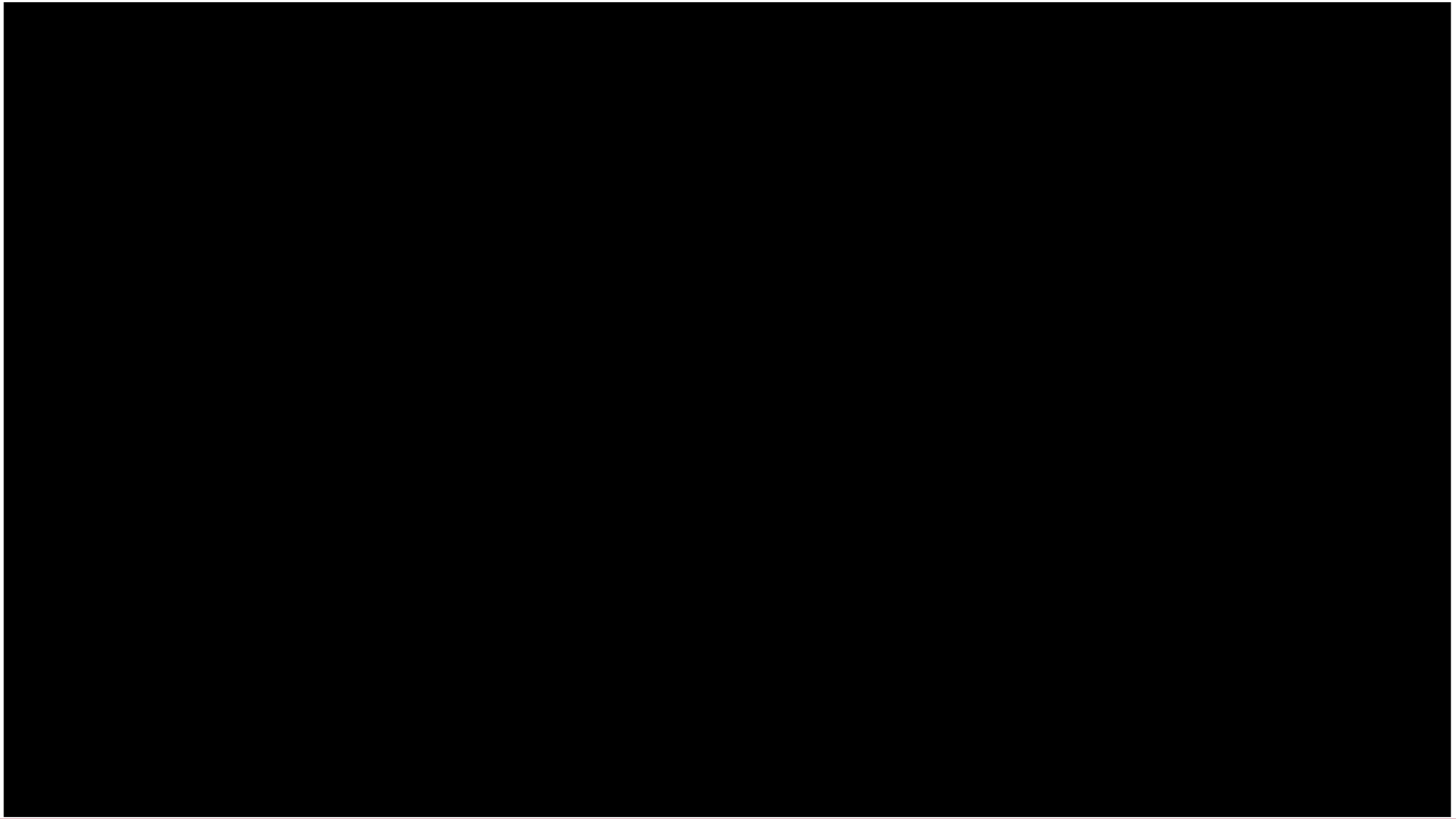
Memory, Latency, and Long-Context Accuracy

- **Memory Bottleneck:** Storing KV states across all tokens consumes massive memory (e.g., 137 GB for 1 million context in Llama-3-8B).
- **Decoding Latency:** Decoding time grows linearly with sequence length (e.g., 92 ms per token for 1 million context in Llama-3-7B).
- Existing KV cache compression methods **damages** LLMs' long-context ability.





Running LLMs with 3.3 Million Contextual Tokens on an A100 GPU

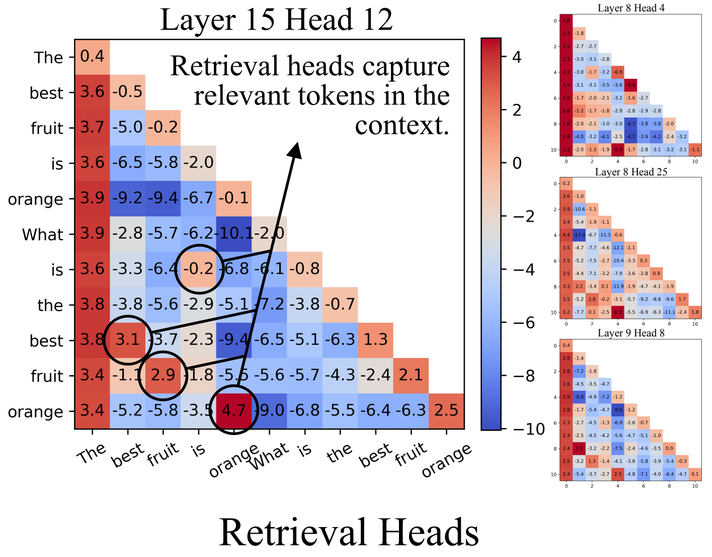


Retrieval vs. Streaming Heads

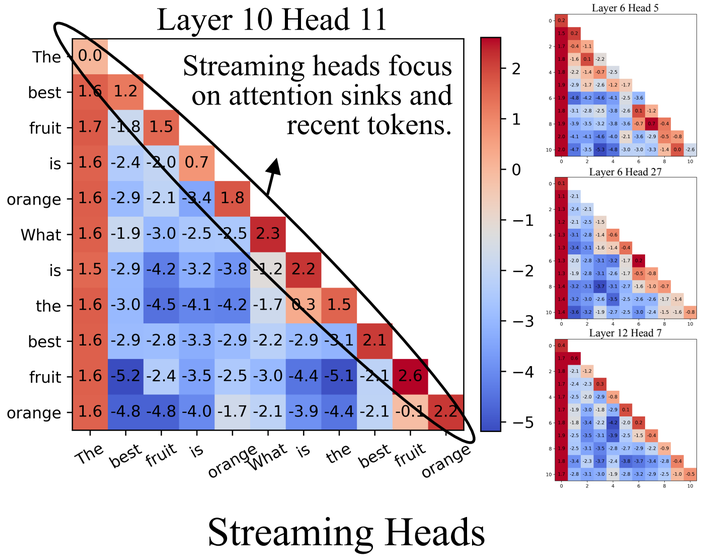
Retrieval Heads vs. Streaming Heads

- **Retrieval Heads:**
  - Capture contextually important tokens from earlier in the sequence.
  - Require full attention across all tokens in the context.
  - Compressing their KV cache would cause a significant loss in performance.

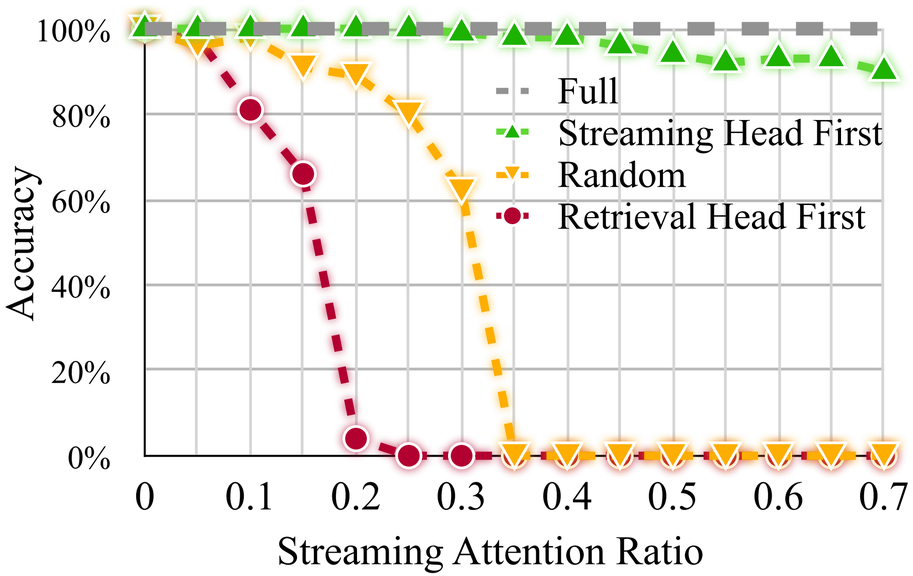
- **Streaming Heads:**
  - Focus on recent tokens and attention sinks.
  - Use a reduced KV cache that only stores recent tokens.
  - Reducing their cache size has minimal impact on performance.



Retrieval Heads



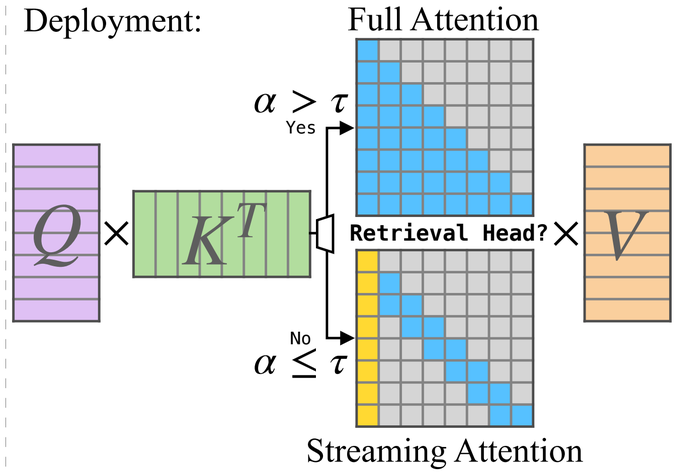
Streaming Heads

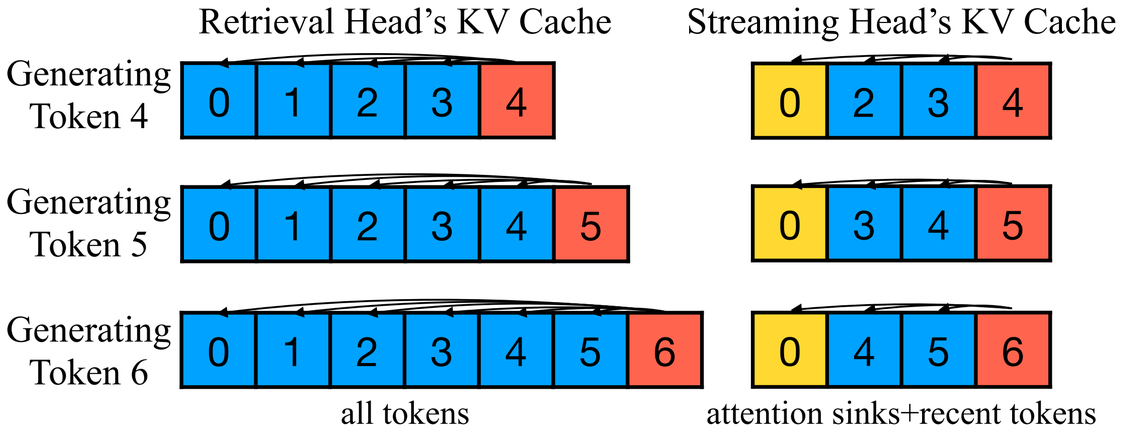


Streaming Attention Ratio

DuoAttention Framework Overview

- **Key Insight: Not all attention heads in a model need full attention across the entire context.**
  - **Retrieval Heads** focus on important tokens from earlier in the sequence and need full KV cache.
  - **Streaming Heads** focus on recent tokens and attention sinks, needing only a reduced KV cache.
- **Solution**: DuoAttention only applies full KV cache to Retrieval Heads, and uses lightweight, constant-length caches for Streaming Heads. Reduces memory and decoding latency while preserving long-context capabilities.



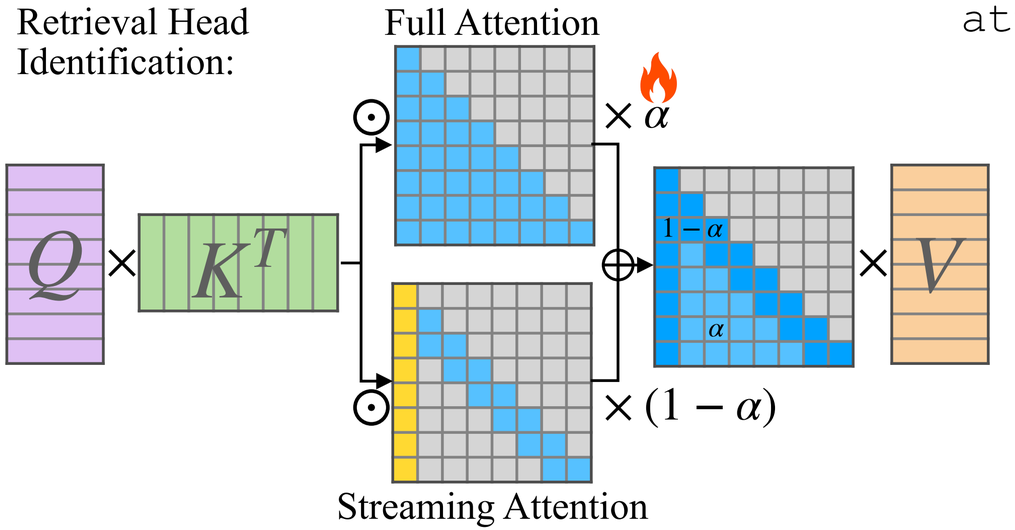


DuoAttention: Efficient Long-Context LLM Inference with Retrieval and Streaming Heads [Xiao et al., 2024]

Optimization-Based Identification of Retrieval Heads

Efficiently and Accurately identify Retrieval Heads

- **Challenge:** Precisely identifying which heads are critical for long-context processing is difficult.
- **Optimization-Based Approach:**
  - Assign a trainable gate value (α) to each head.
  - The gate value blends full attention and streaming attention, allowing the model to learn which heads are necessary.
  - Minimize output deviation from the full attention model to maintain accuracy.



$$\texttt{attn}_{i,j} = \alpha_{i,j} \cdot \texttt{full\_attn} + (1 - \alpha_{i,j}) \cdot \texttt{streaming\_attn}$$

$$\texttt{full\_attn} = \text{softmax}(\boldsymbol{Q}\boldsymbol{K}^T \odot \boldsymbol{M}_{\text{causal}})\boldsymbol{V},$$

$$\texttt{streaming\_attn} = \text{softmax}(\boldsymbol{Q}\boldsymbol{K}^T \odot \boldsymbol{M}_{\text{streaming}})\boldsymbol{V},$$

$$\mathcal{L}_{\text{distill}} = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=T-l+1}^{T}(\boldsymbol{H}_{\text{full}}^{(i)}[j] - \boldsymbol{H}_{\text{mixed}}^{(i)}[j])^2$$

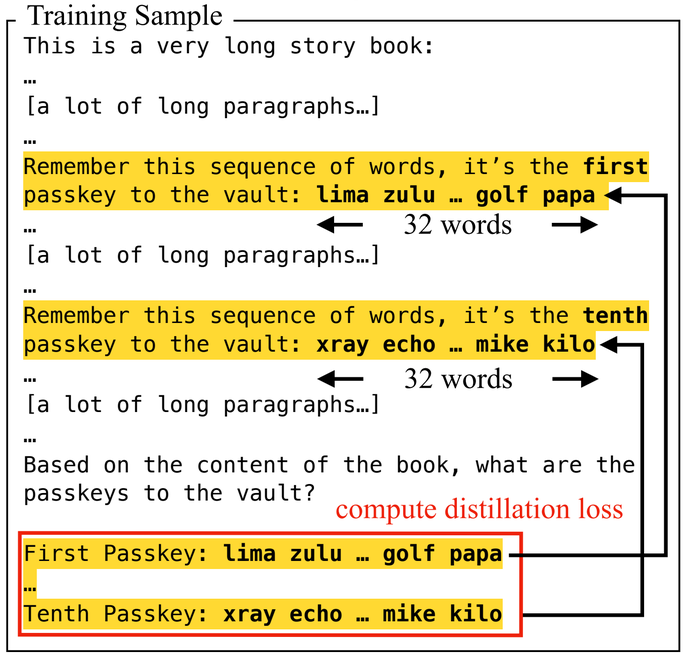
$$\mathcal{L}_{\text{reg}} = \sum_{i=1}^{L}\sum_{j=1}^{H}|\alpha_{i,j}|$$

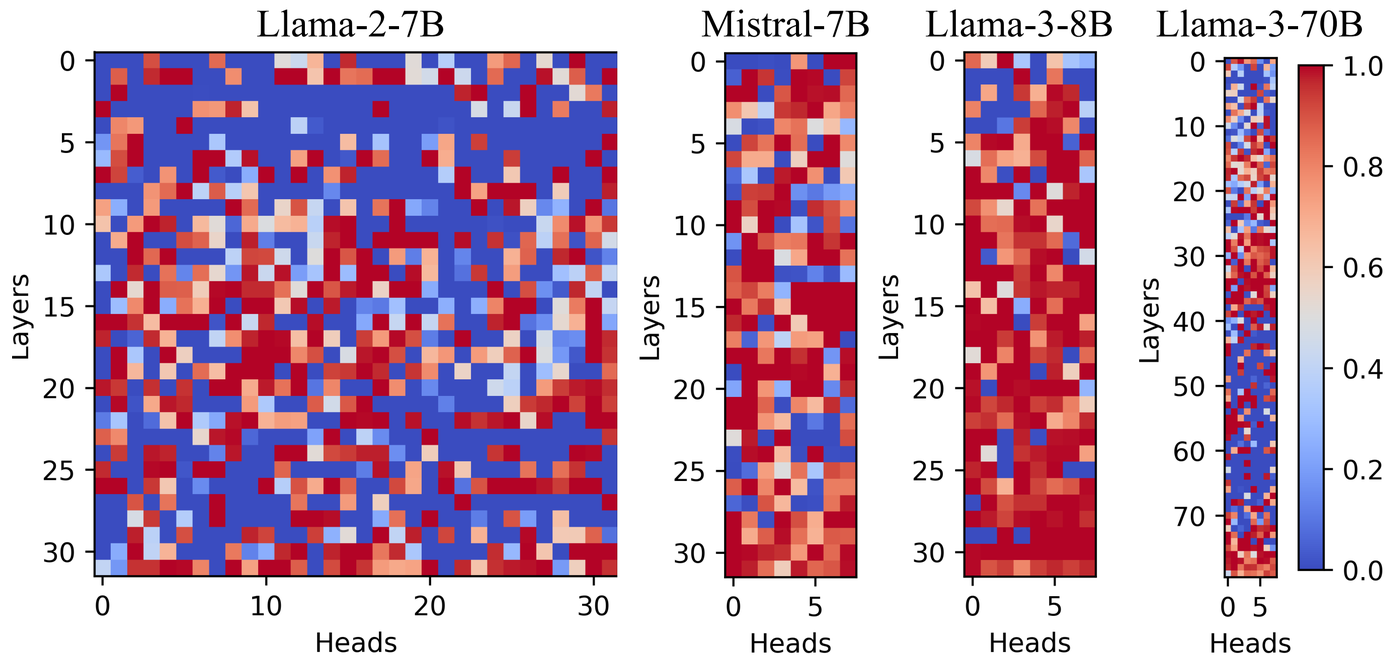
$$\mathcal{L} = \mathcal{L}_{\text{distill}} + \lambda\mathcal{L}_{\text{reg}}$$

Optimization-Based Identification of Retrieval Heads

Using Synthetic Data to Focus on LLMs' Retrieval Ability

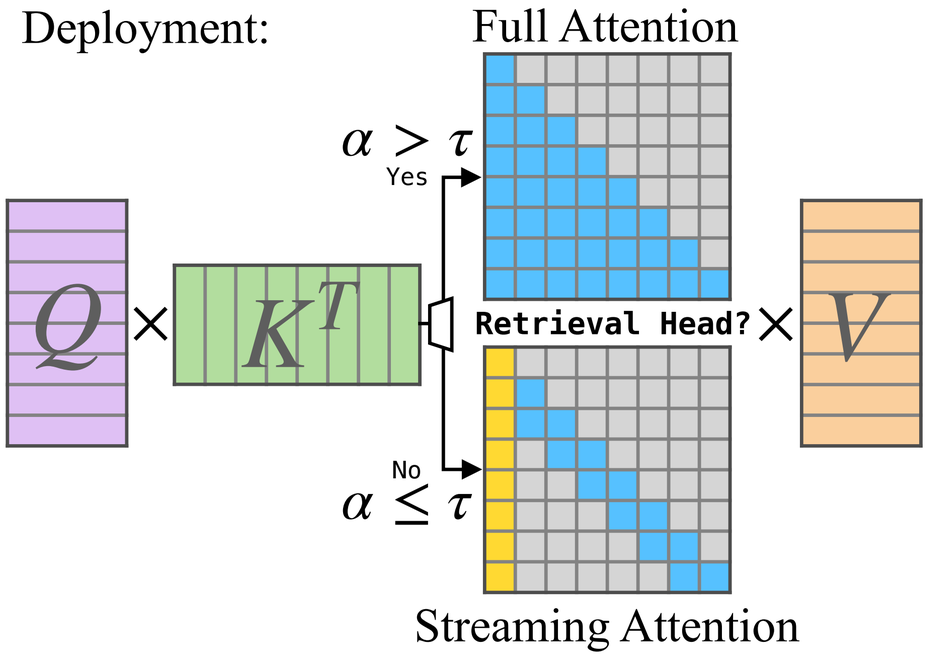
- **Synthetic Dataset:**
  - Embeds ten passkeys in a long context.
  - LLM recalls the passkeys to identify which heads need full attention for long-context retrieval.
- **Efficiency:**
  - Only ~1K gate values need to be trained. (e.g. 32 layers x 32 heads for llama2-7B)
  - The process is completed in a few hours on 8 A100 GPUs.

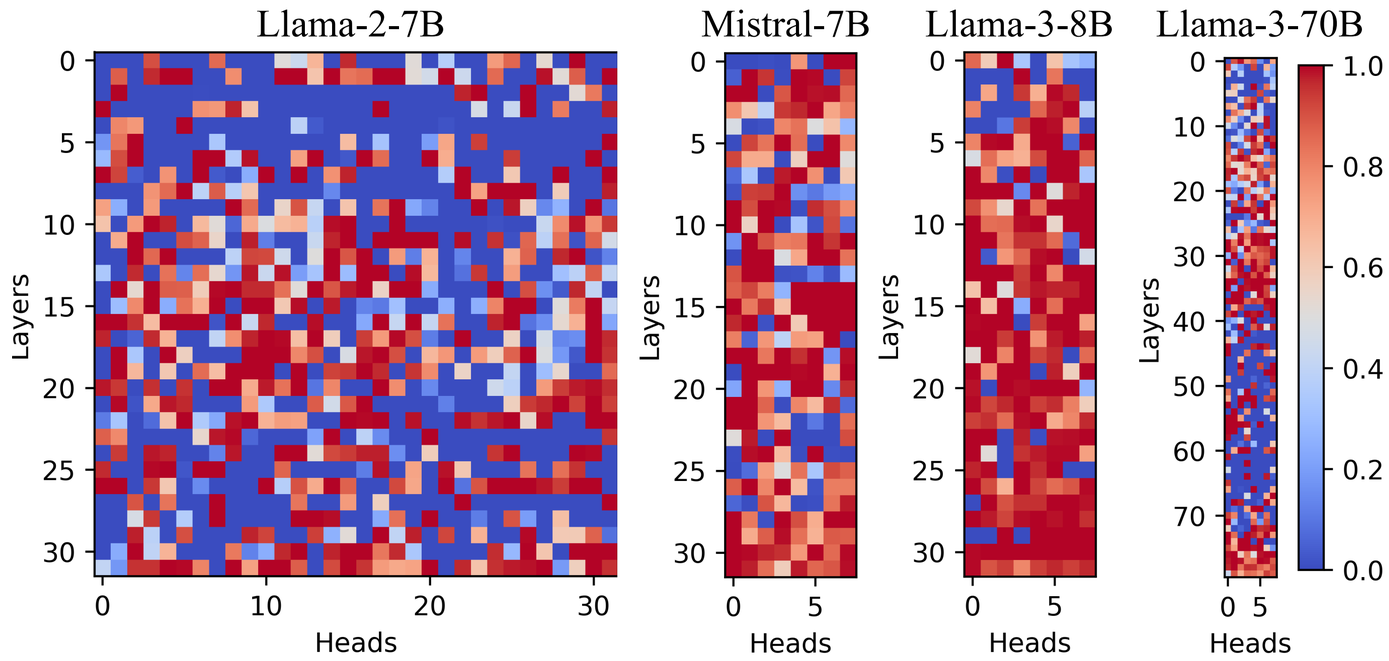




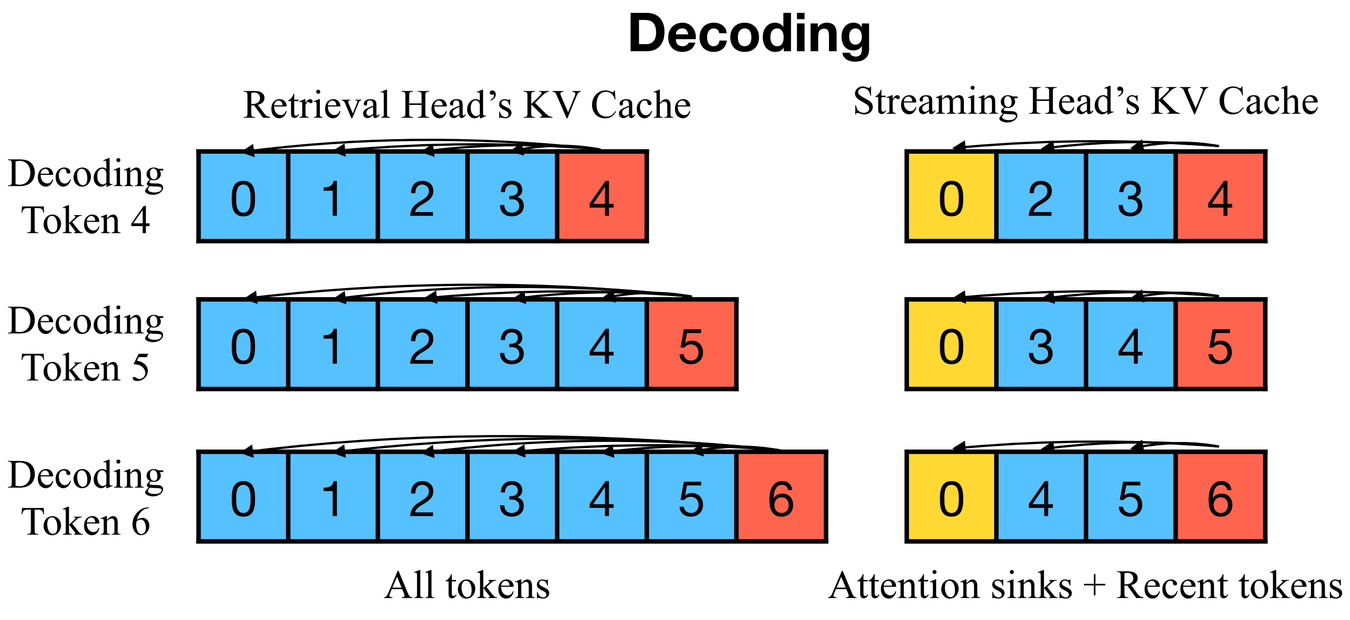
Deploying LLMs with DuoAttention

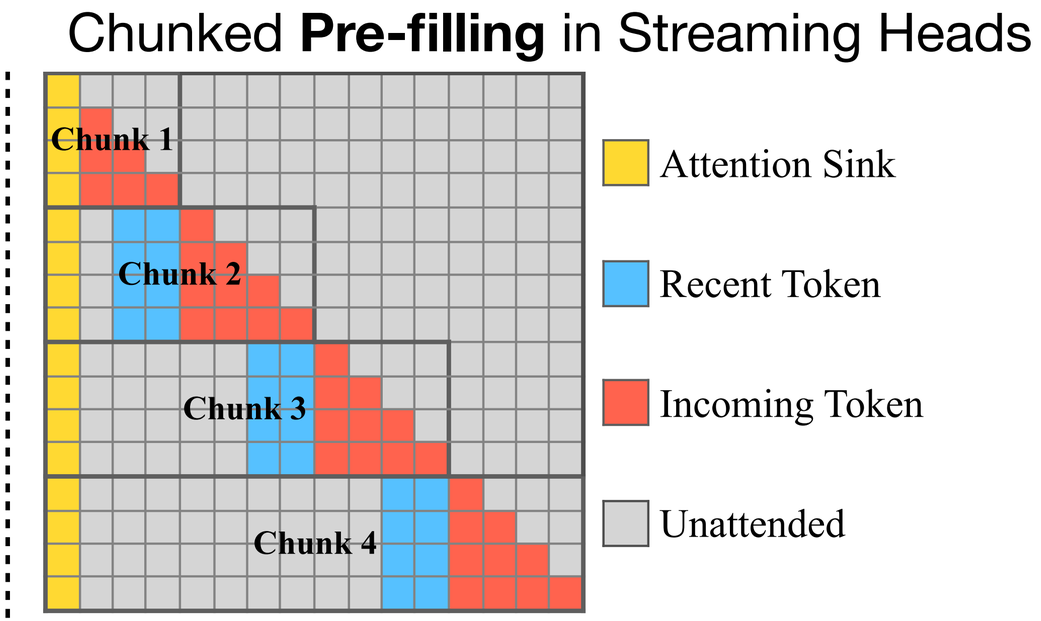
- **Binarizing Attention: During deployment, the trained gate values (α) are binarized to classify each head as either a Retrieval Head or a Streaming Head.**
- **Reordering Attention Heads:**
  - During deployment, attention heads are reordered into distinct clusters for efficient processing.
  - This allows for better slicing and concatenation of KV caches, improving inference speed.





Decoding and Chunked Pre-filling of DuoAttention





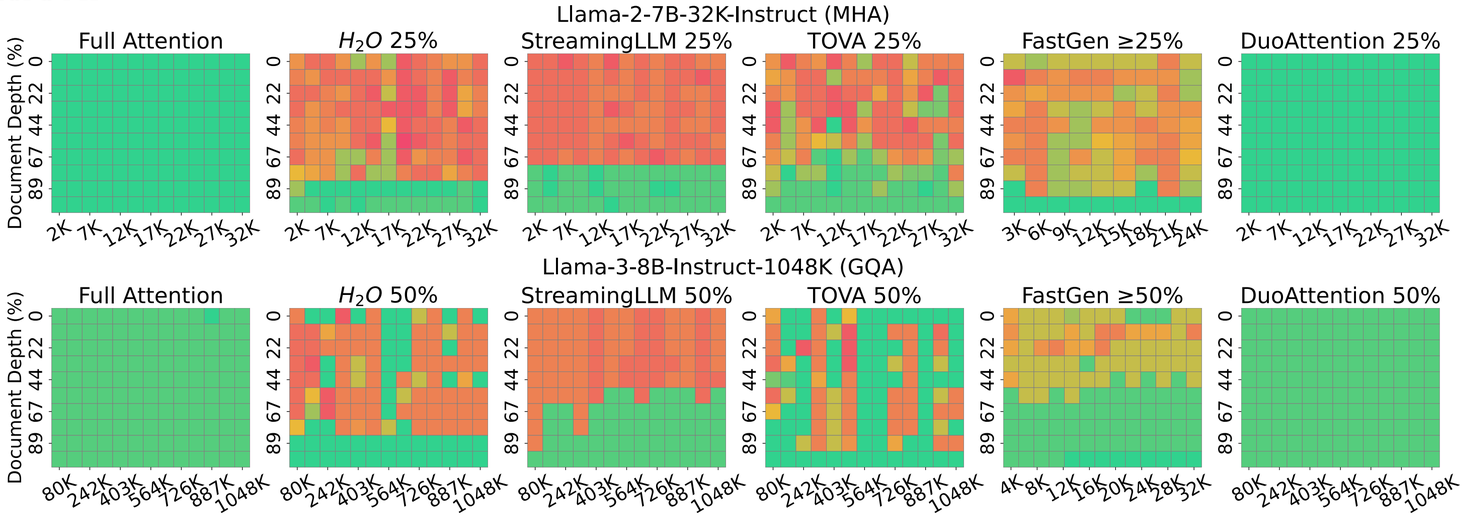
- **Two KV Caches:**
  - **Retrieval Head:** Stores all tokens.
  - **Streaming Head:** Stores attention sinks and recent tokens (constant memory).
- **Computation:**
  - Queries, keys, and values are split into retrieval and streaming heads.
  - Outputs from both heads are concatenated for the final projection.

- **Chunked Pre-filling splits sequence into fixed-length chunks.**
- **Streaming head's KV cache keeps only sink and recent tokens after each pre-filling chunk.**
- **Pre-filling Complexity on Streaming Heads:**
  - Time complexity reduced from $O(L^2)$ to $O(LK)$.
  - Memory complexity reduced from $O(L)$ to $O(K)$
  - L is sequence length and K is chunk size.

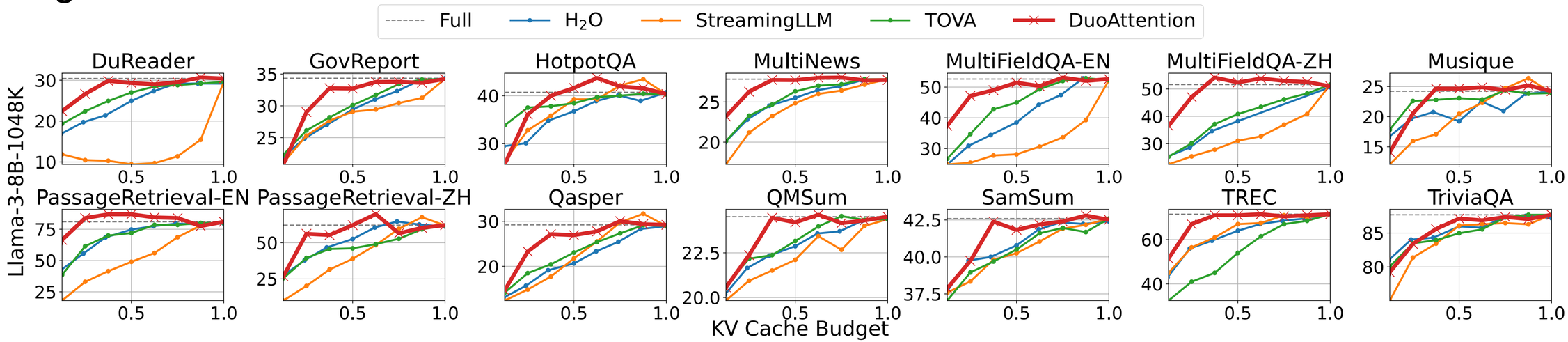
Results on Accuracy Benchmarks

Long-Context Benchmarks: Needle-in-a-Haystack and LongBench

- **Needle-in-a-Haystack:**



- **LongBench:**



Results on Accuracy Benchmarks

Short-Context Benchmarks: MBPP, MMLU, and MT-Bench

- **DuoAttention doesn't harm LLMs other general abilities.**

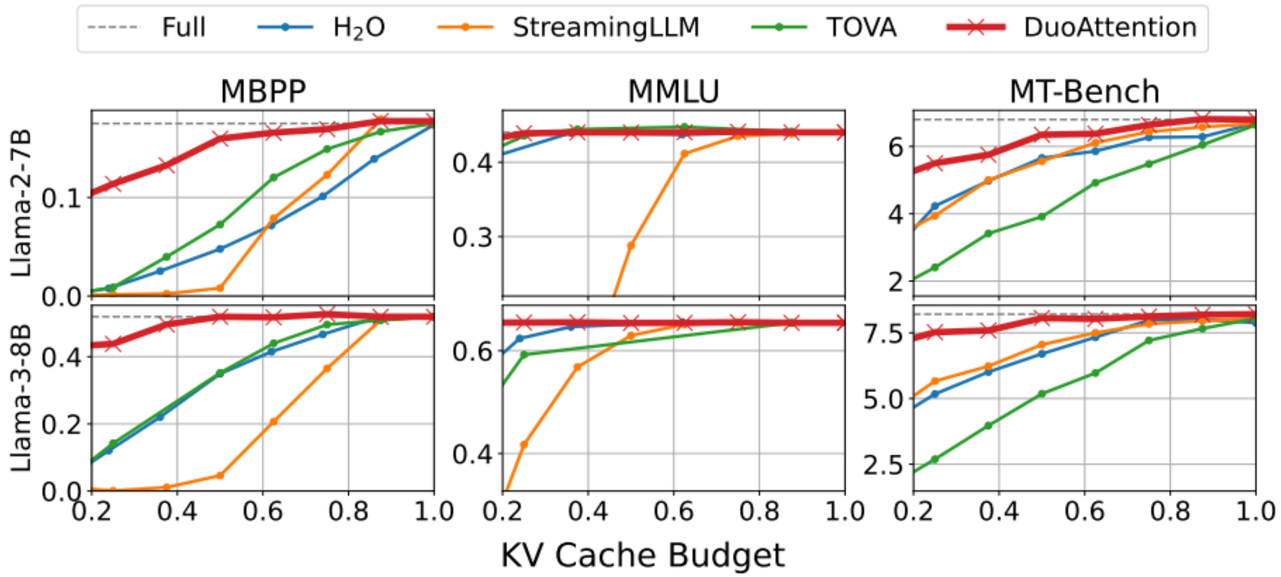


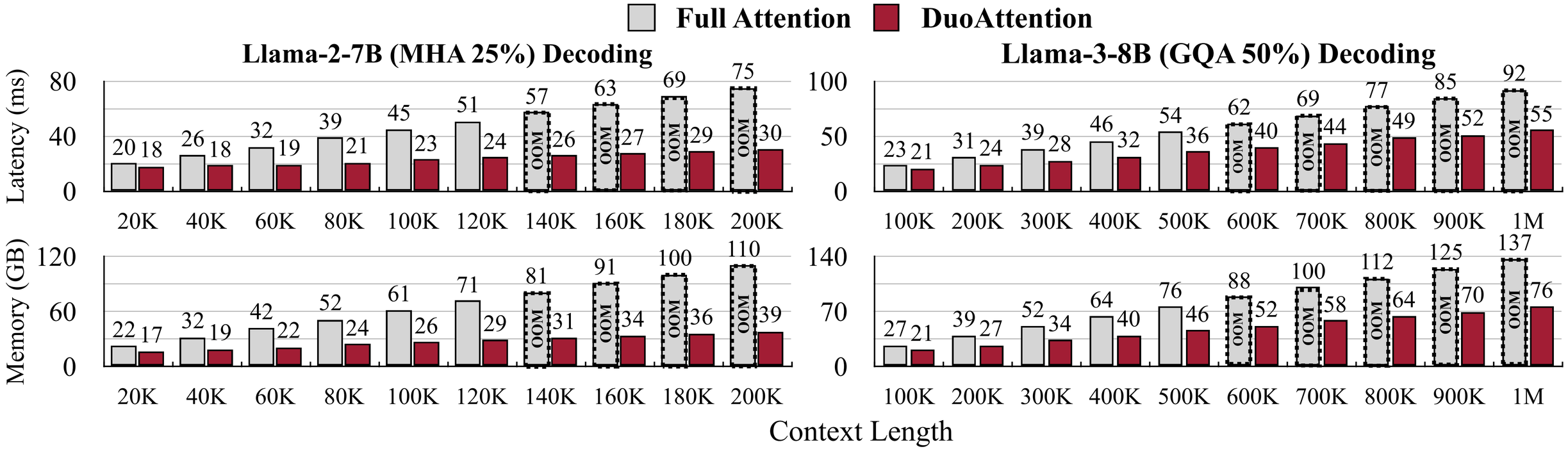
Figure 8: Results on short benchmarks.

Table 1: Llama-3-70B results on short benchmarks.

	Budget	MMLU	MBPP	MT-B
Full	100%	79.38%	47.85%	8.93
H2O	50%	79.26%	32.12%	7.16
TOVA	50%	79.15%	36.09%	7.96
SLLM	50%	77.46%	5.57%	5.41
DuoAttn	50%	**79.35%**	**47.09%**	**9.14**

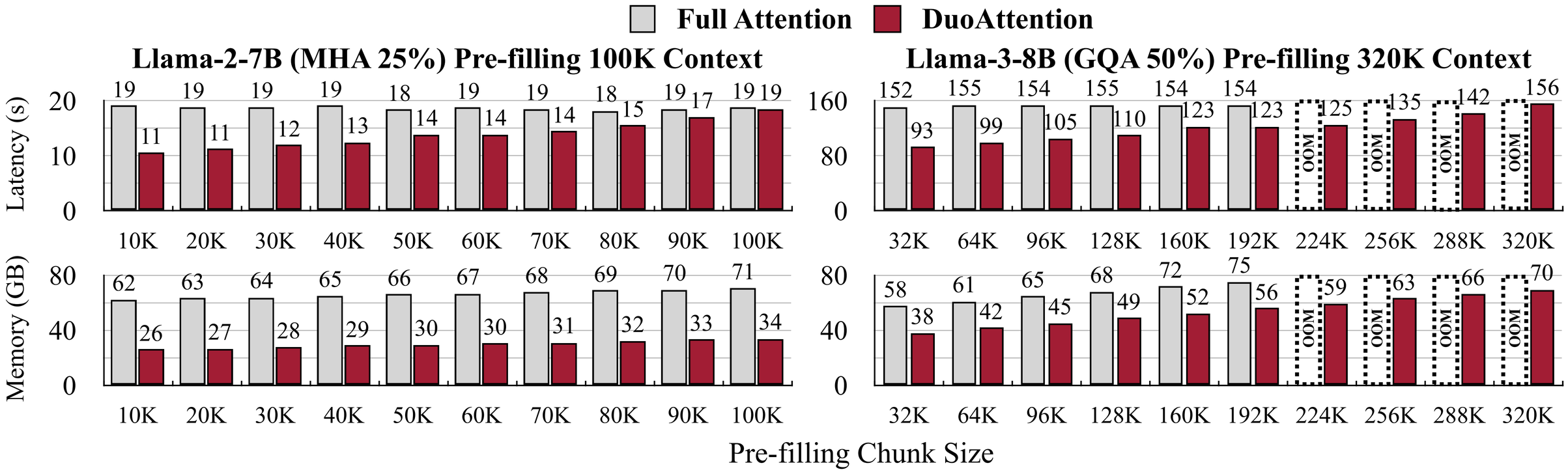
Decoding Memory and Latency Improvements

- **DuoAttention provides up to 2.45× memory reduction for MHA and 1.65× for GQA models, and up to 2.13× decoding latency improvement for MHA and 1.5× for GQA models.**



Pre-filling Memory and Latency Improvements

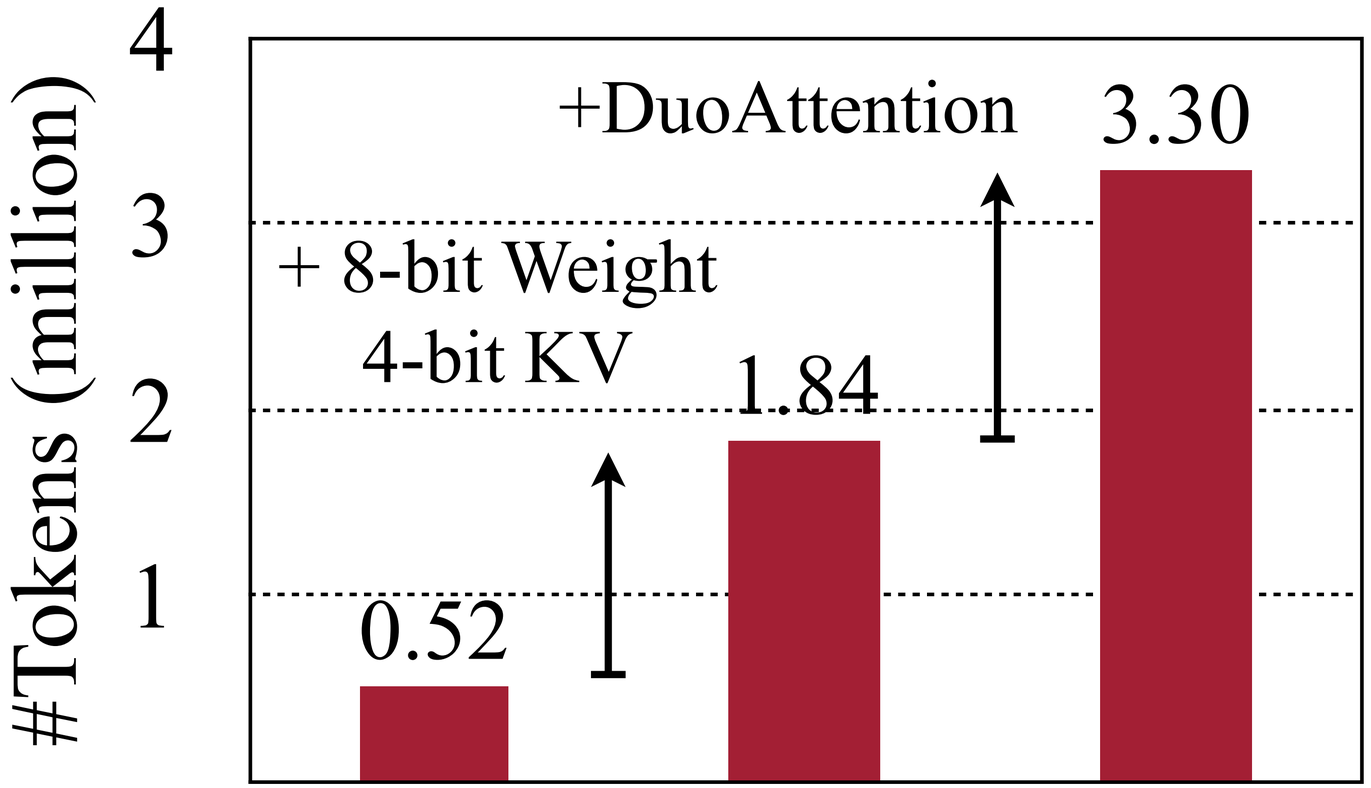
- **DuoAttention achieves up to 1.73x pre-filling latency reduction for MHA and 1.63x for GQA models, with memory reductions up to 2.38x for MHA and 1.53x for GQA models.**



Combination with KV Cache Quantization

Pushing the Limits of Context Length on Memory-constrained Devices

- **Up to 3.3 million tokens can be handled in a single A100 GPU using DuoAttention combined with 4-bit KV cache quantization.**



Conclusion

- **We introduce DuoAttention, an efficient framework that significantly reduces deployment memory and latency in long-context LLMs while maintaining their long-context ability.**
- **Paper:** https://arxiv.org/abs/2410.10819
- **Code:** https://github.com/mit-han-lab/duo-attention
- **Demo:** https://youtu.be/tyTkZOqKt6U