FlexiCache

Leveraging Temporal Stability of Attention Heads for Efficient KV Cache Management

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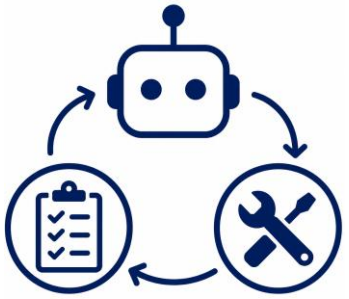
UCI University of California, Irvine

MLSys 2026 · Bellevue, WA, USA

Modern LLM Workloads Demand Long Context

Coding

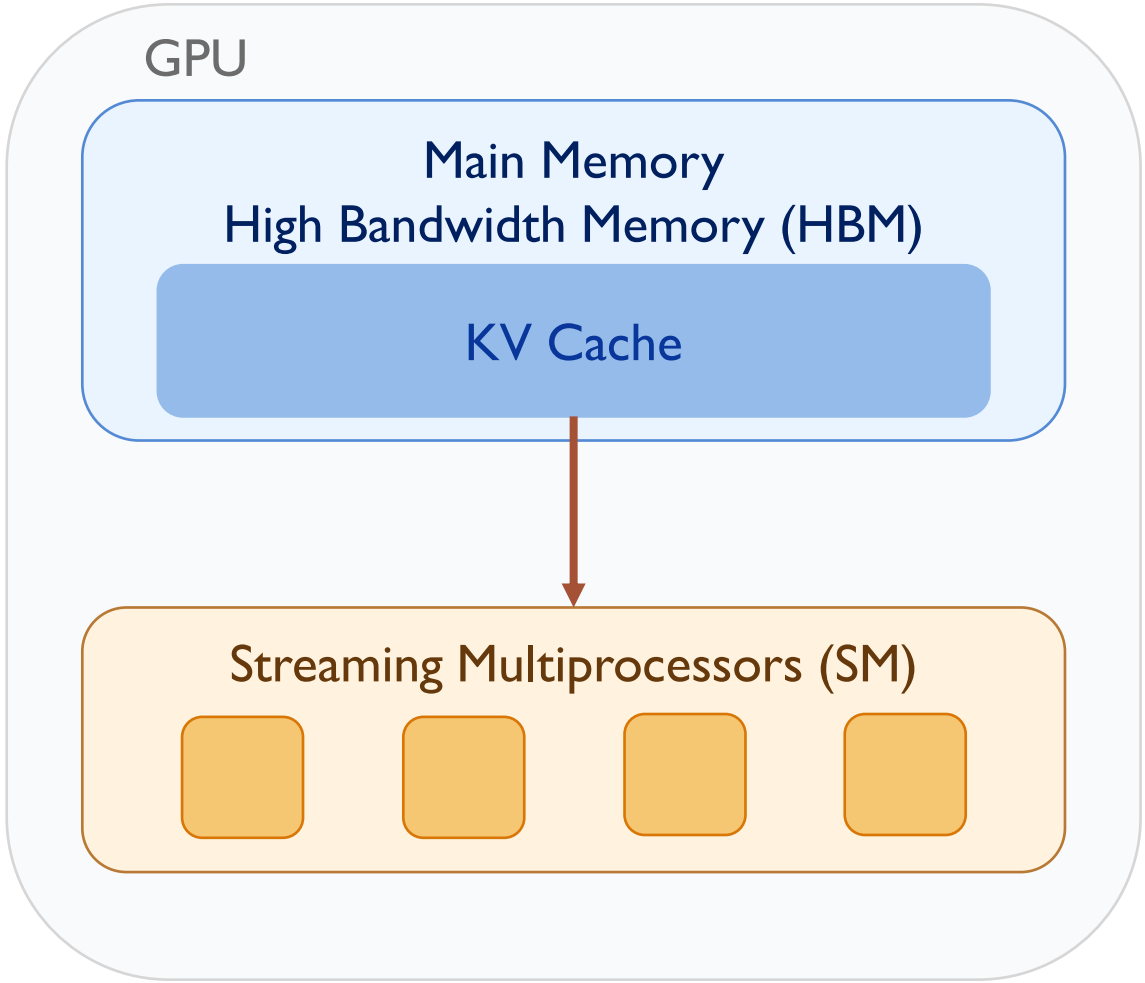
Long Document Q/A



Complex Agentic Workflows

Long Context → Large KV Cache

Issues of large KV Cache



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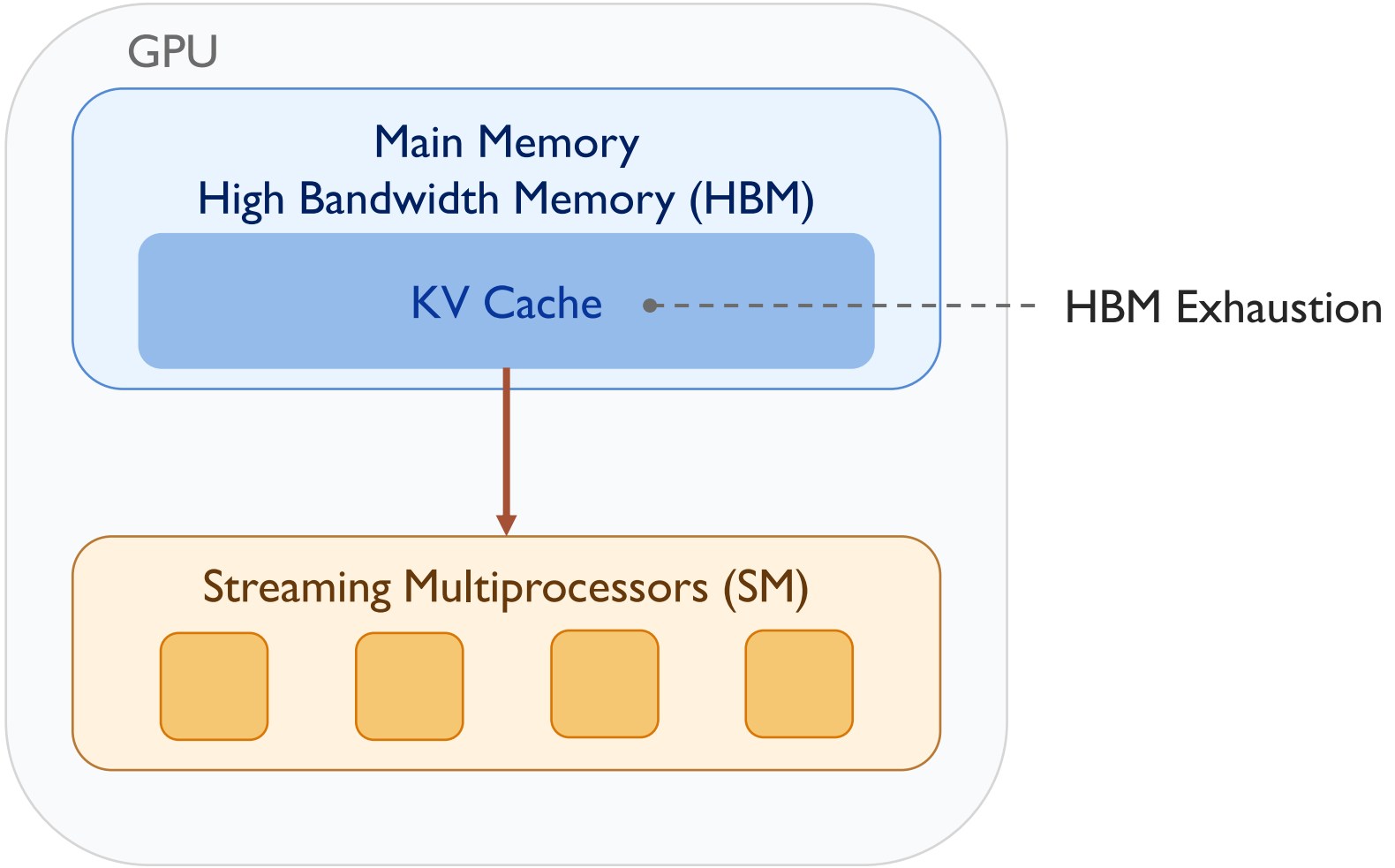

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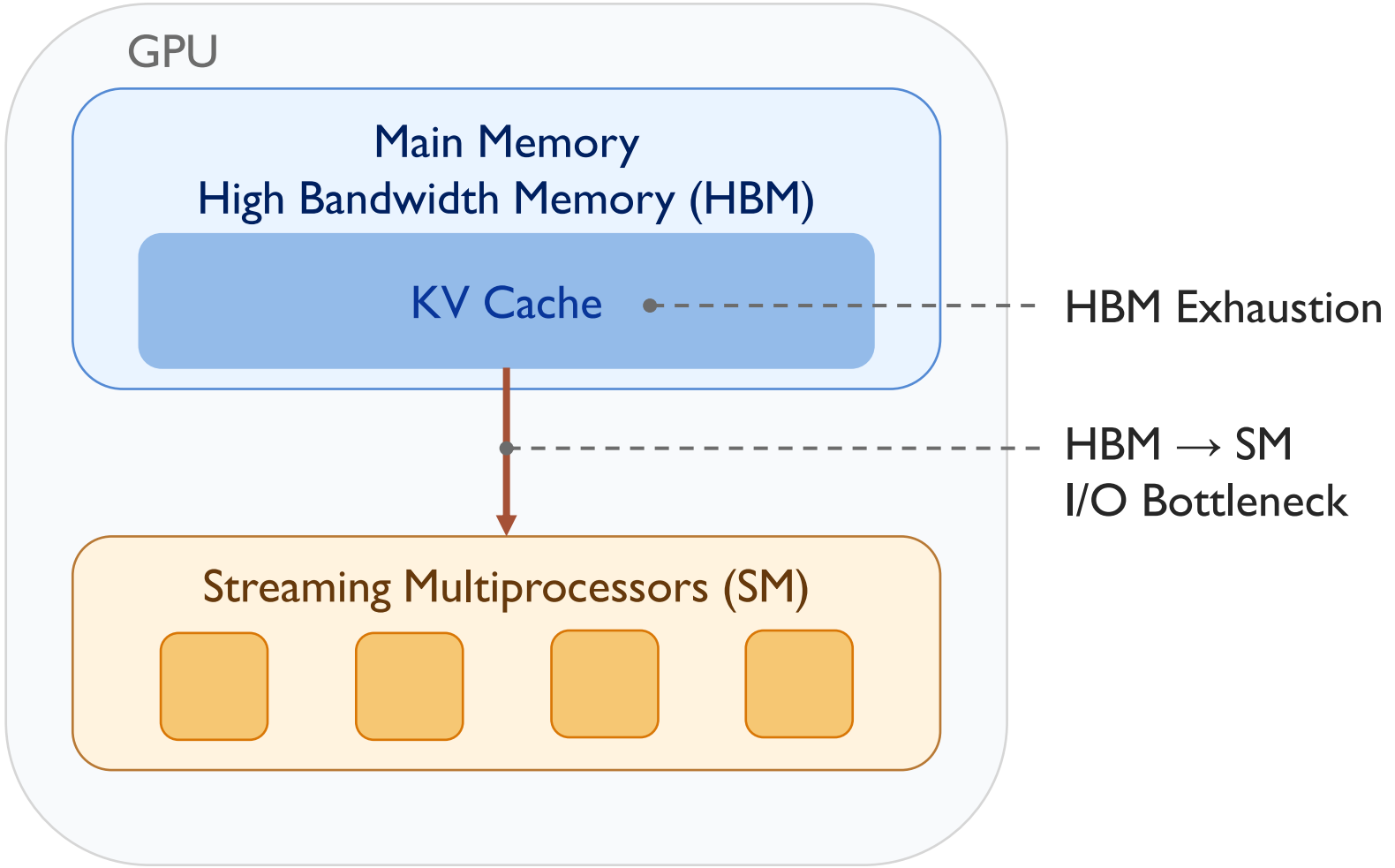

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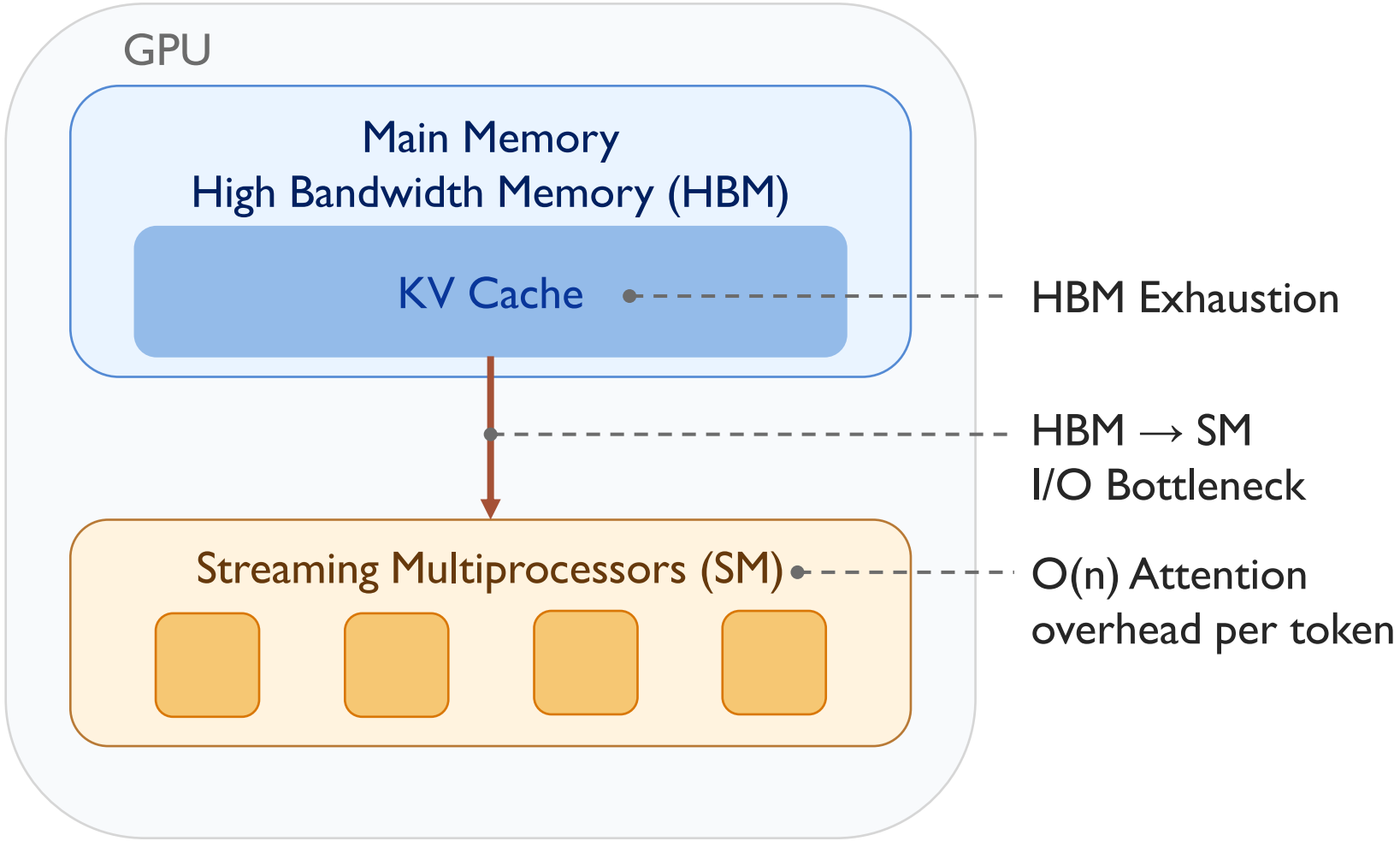
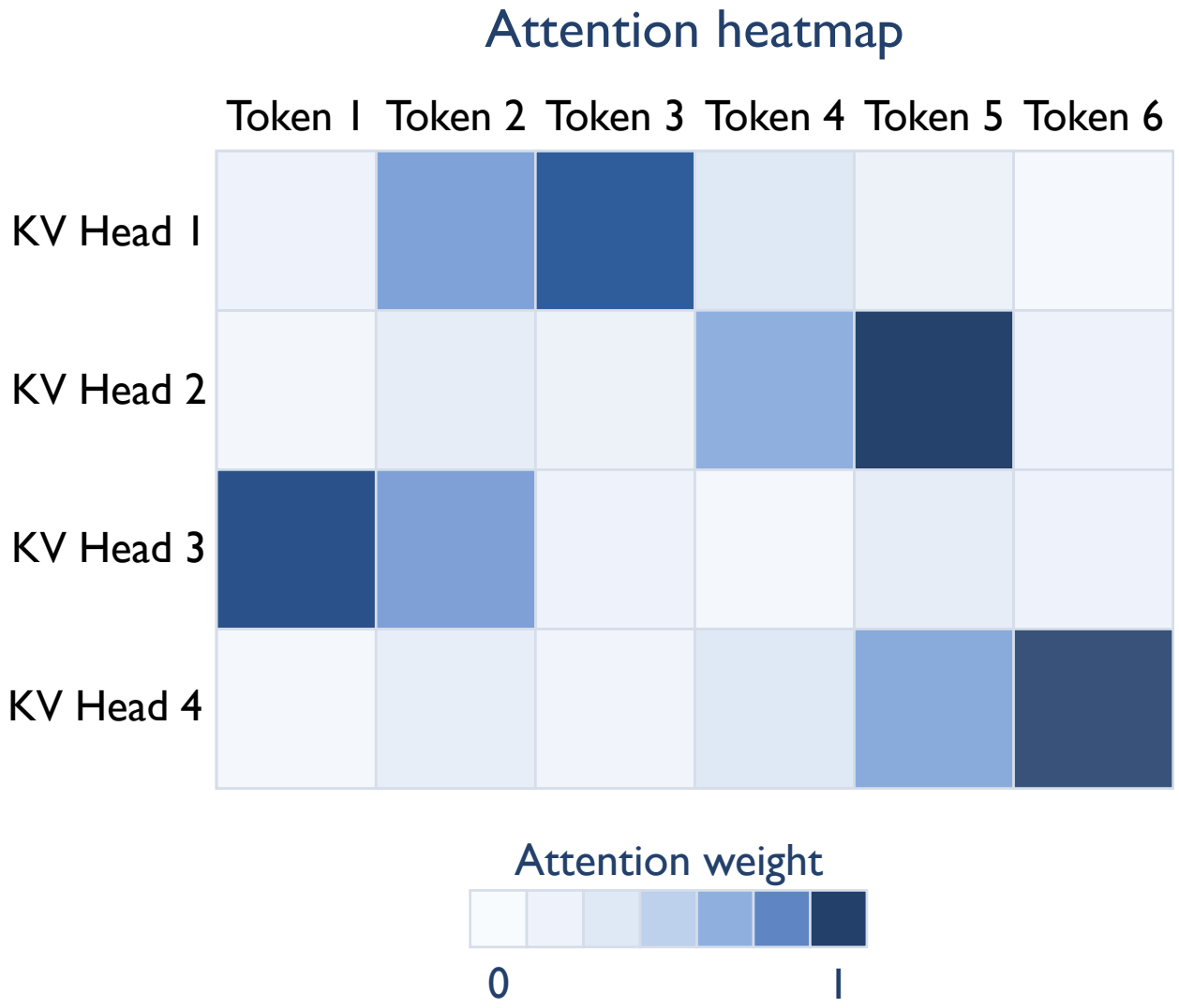
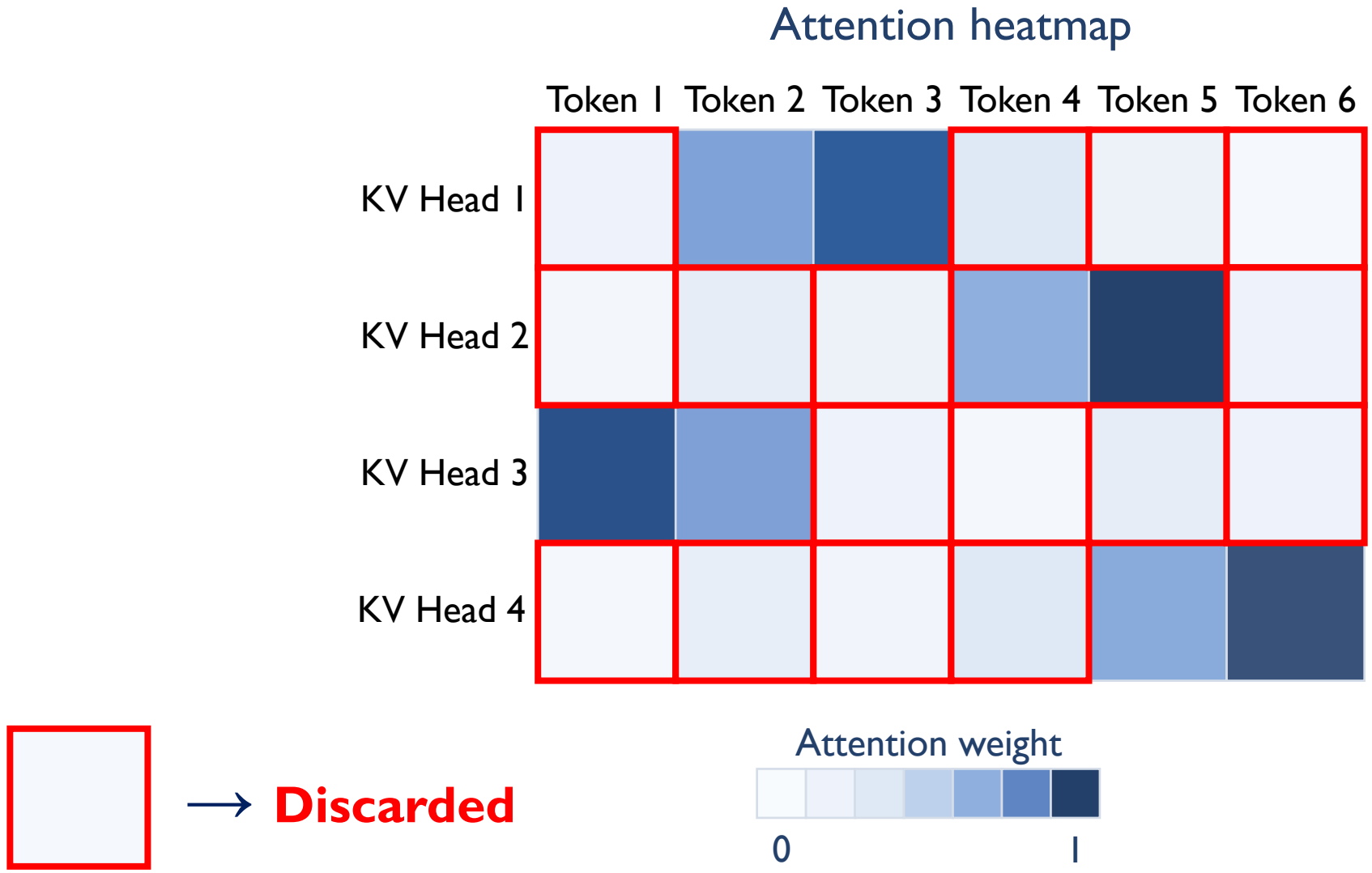


Attention is Sparse

Each KV head focuses on a small subset of tokens



Leveraging Sparsity: Discard KV of Unimportant Tokens



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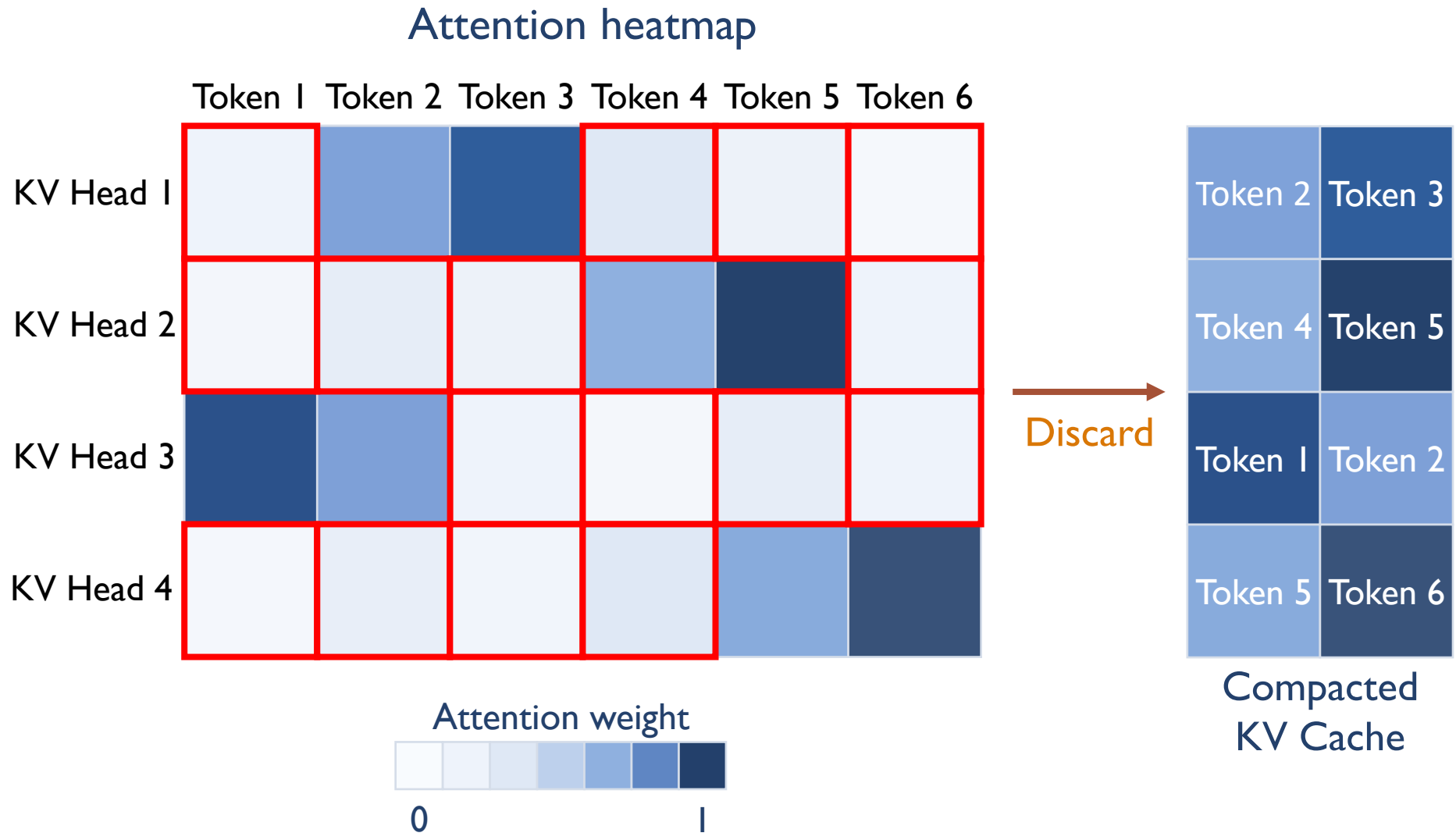
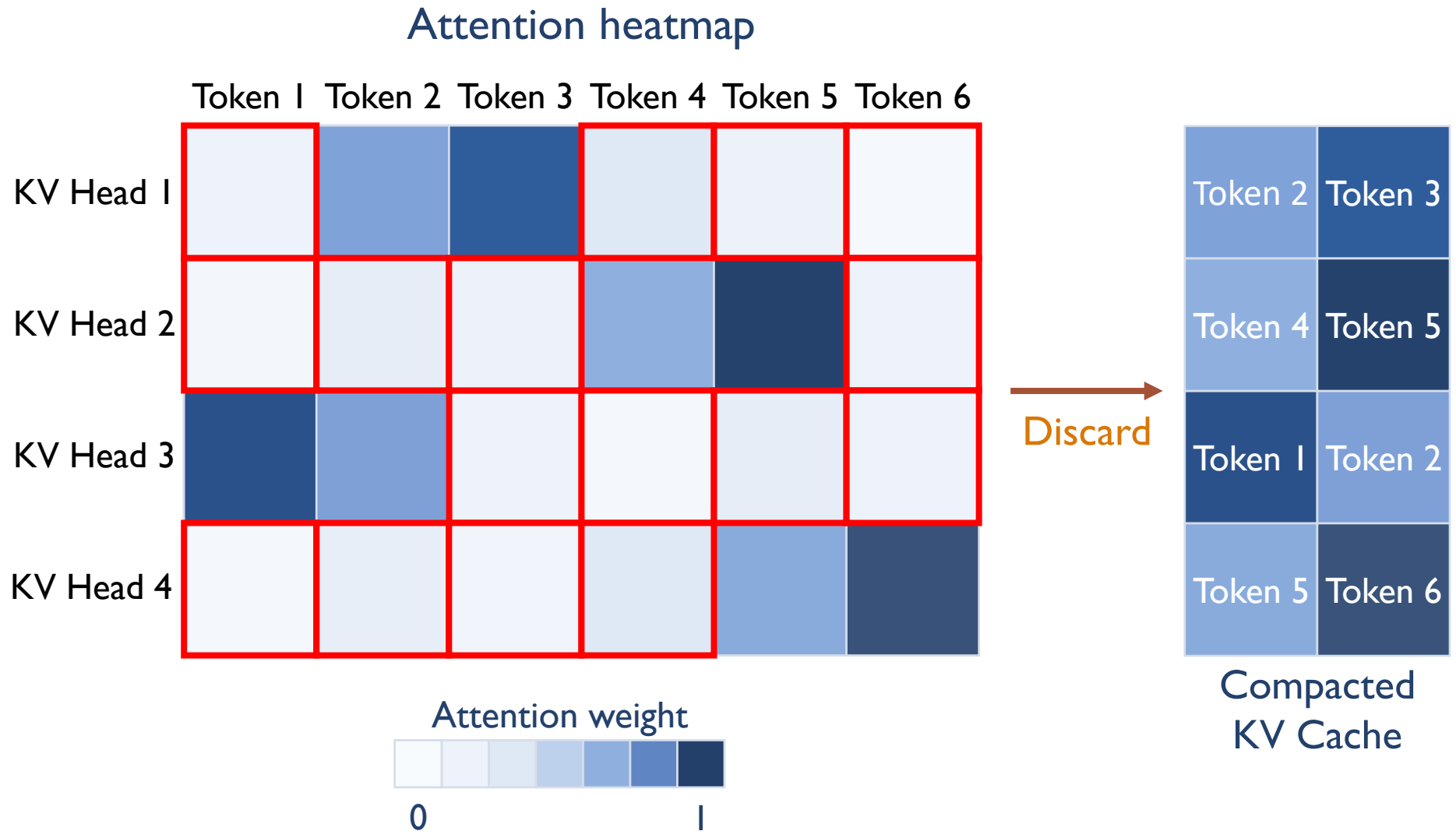


Leveraging Sparsity: Discard KV of Unimportant Tokens

- HBM usage ↓



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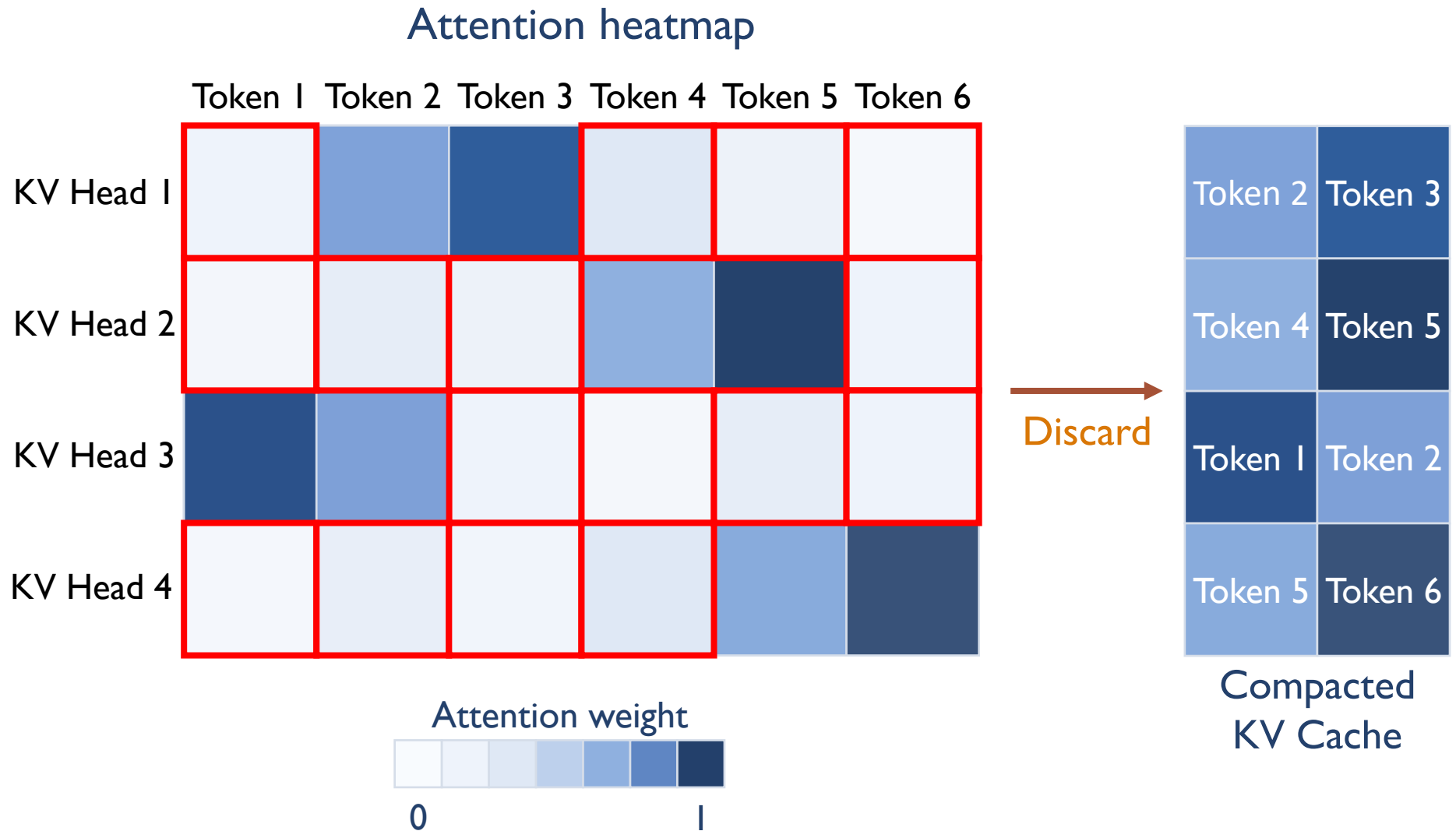

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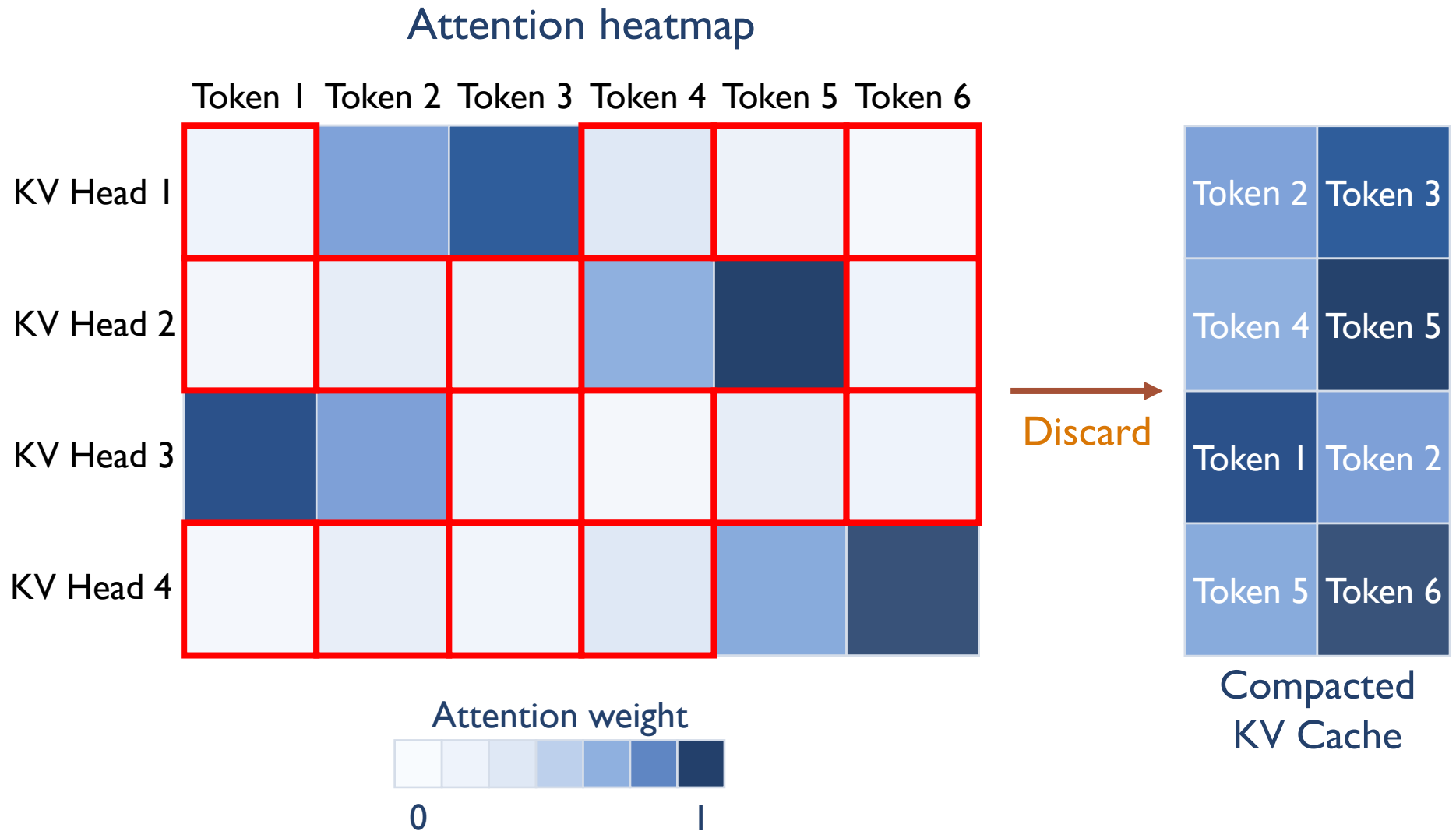
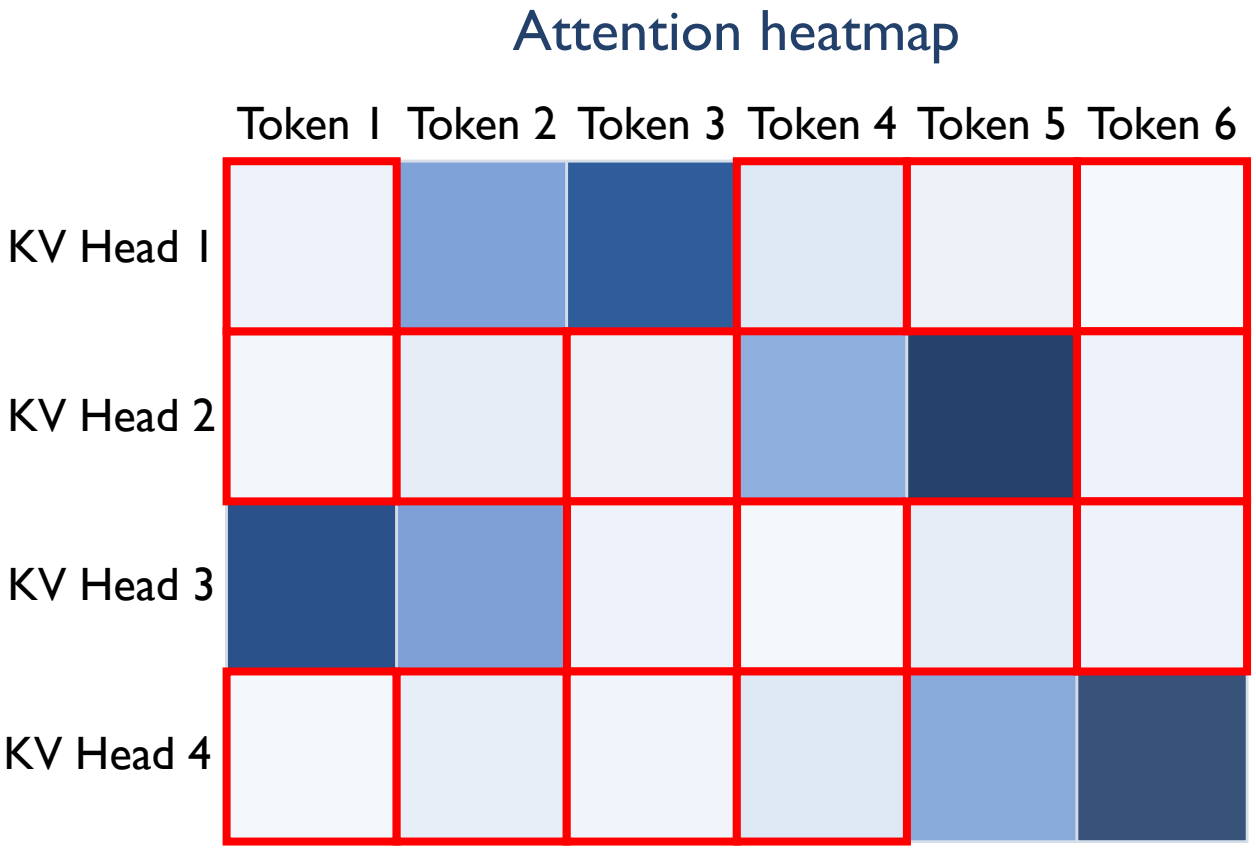


Problem: Discarding is irreversible



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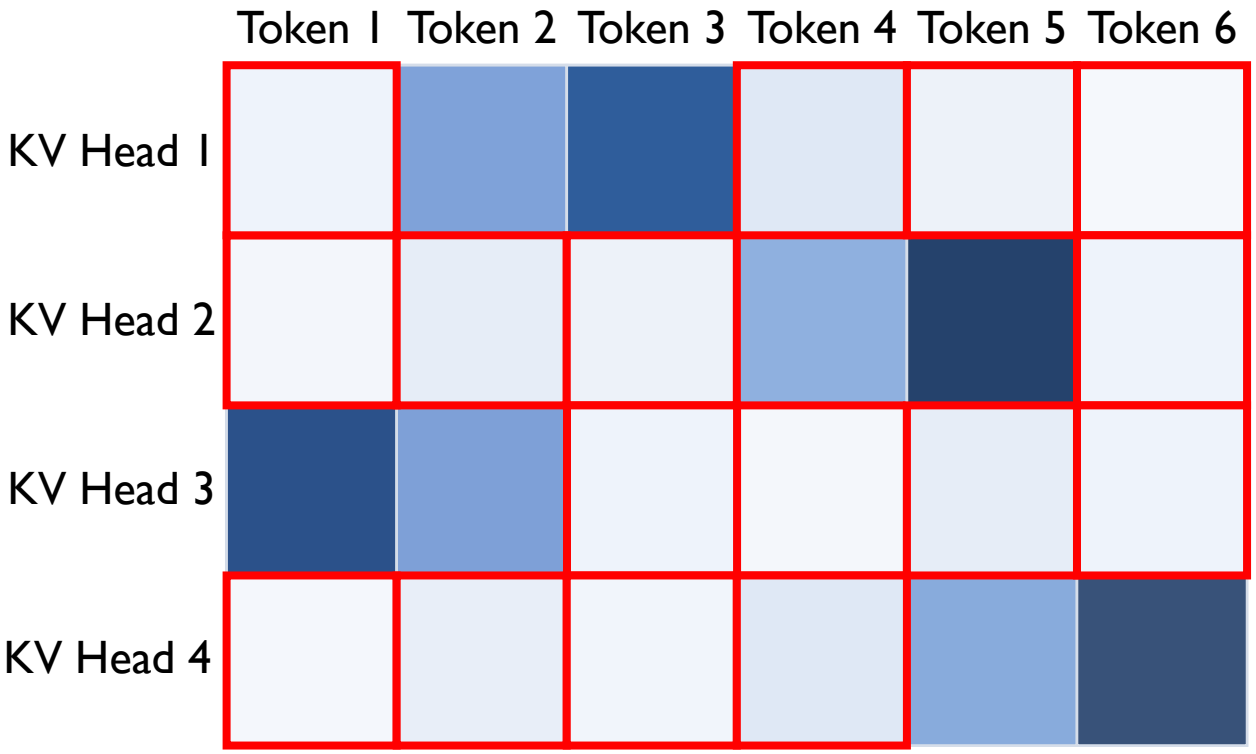
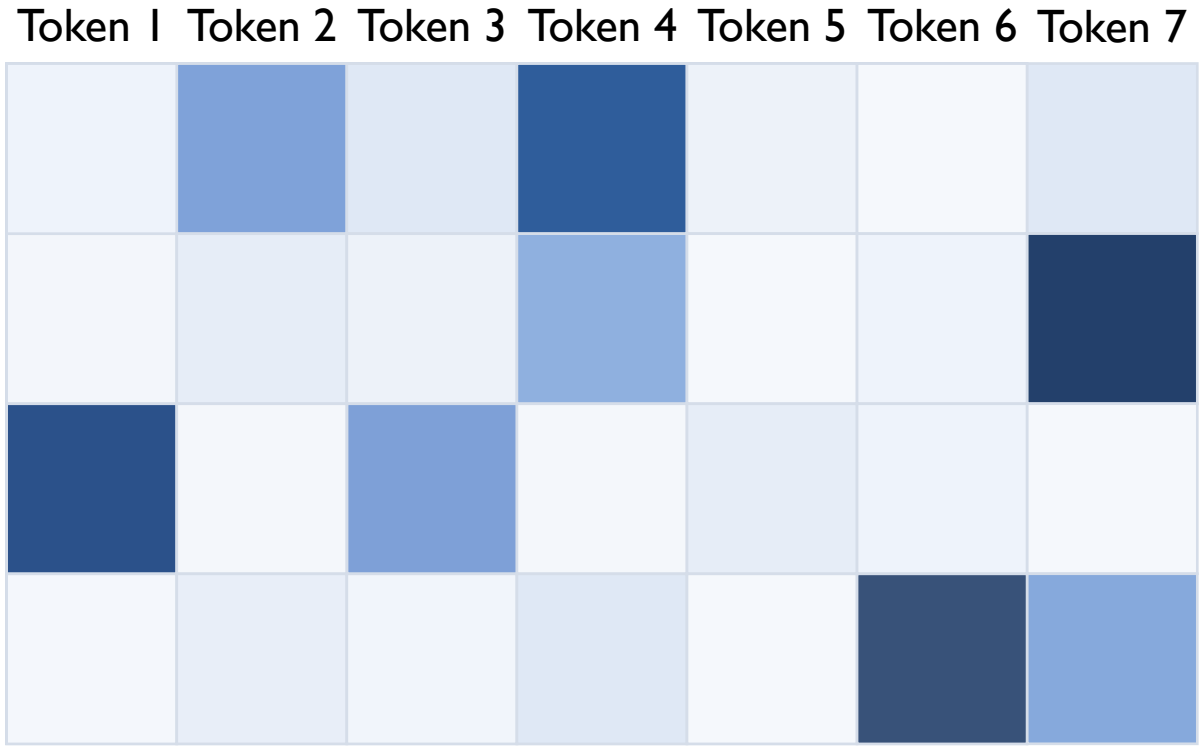
Attention heatmap



Attention heatmap for next decode step



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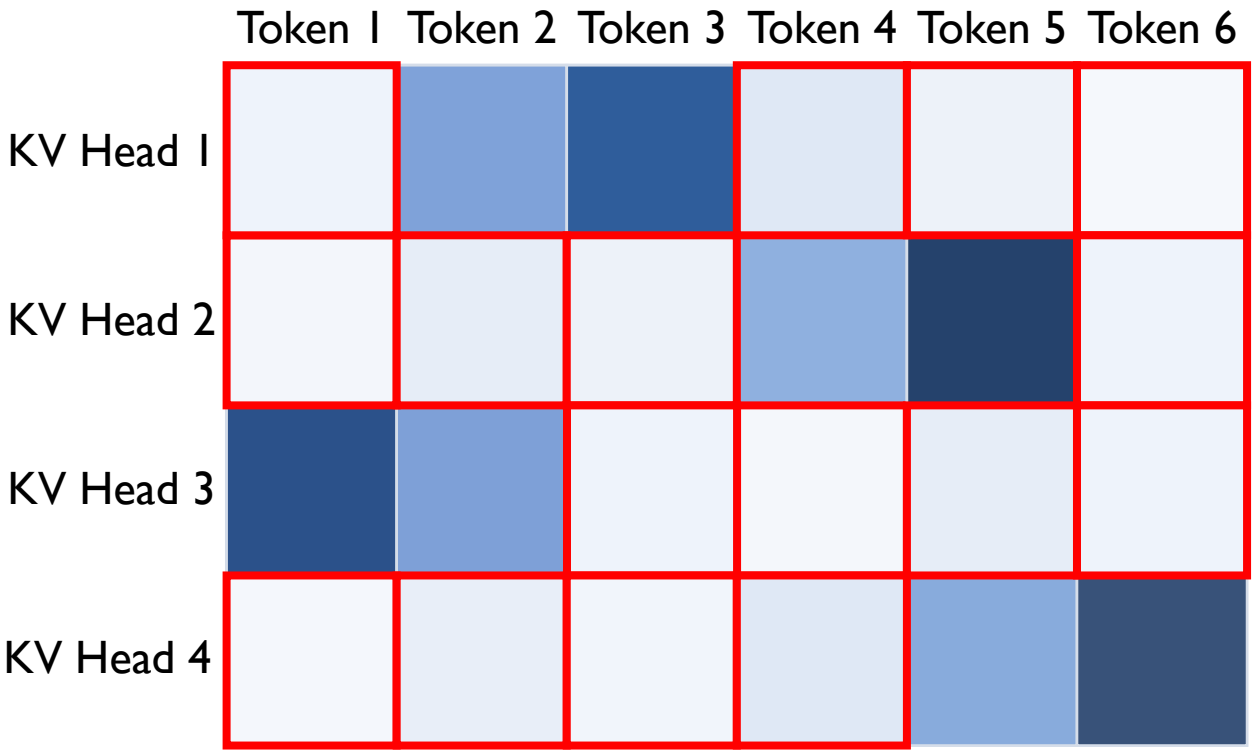

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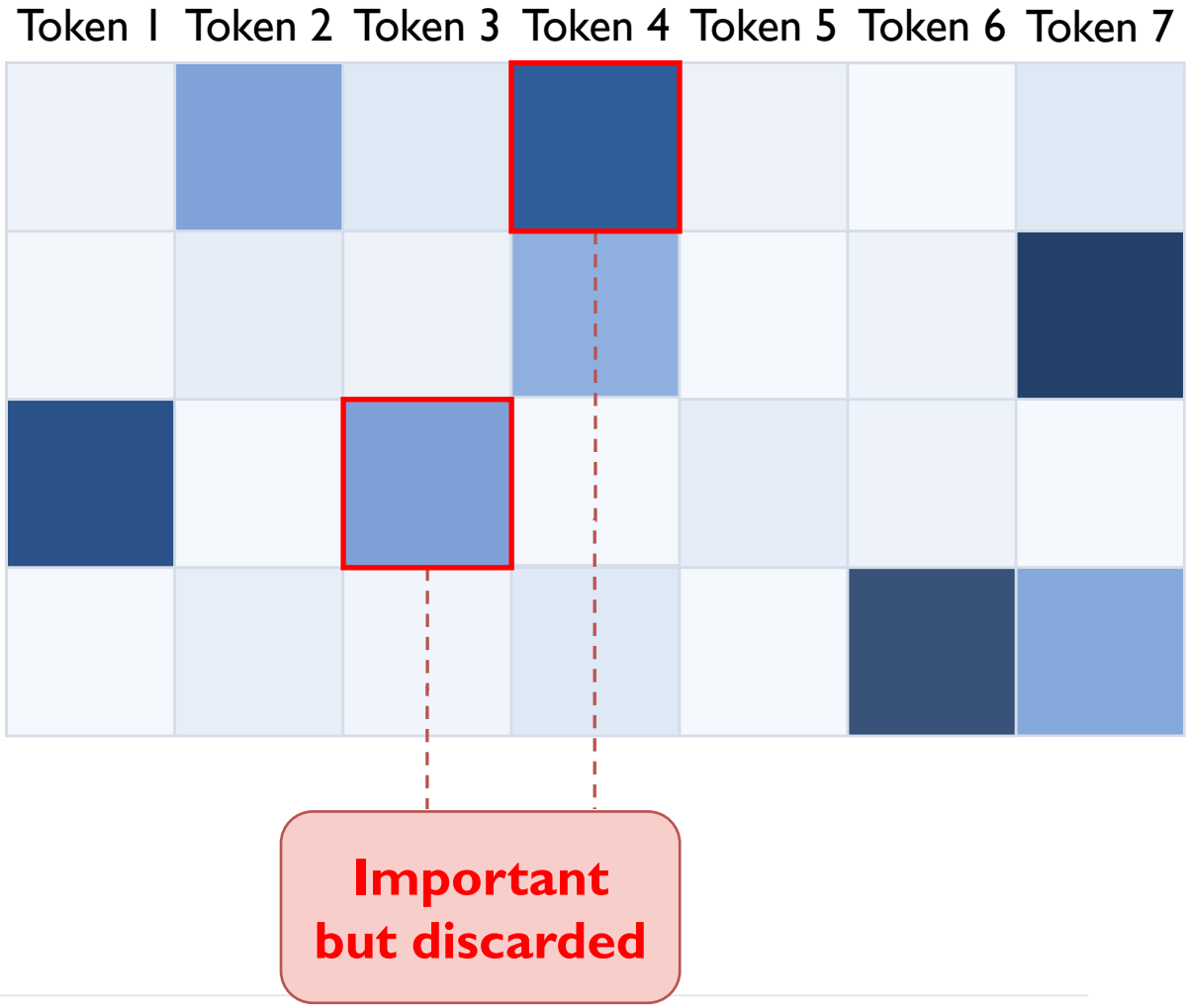

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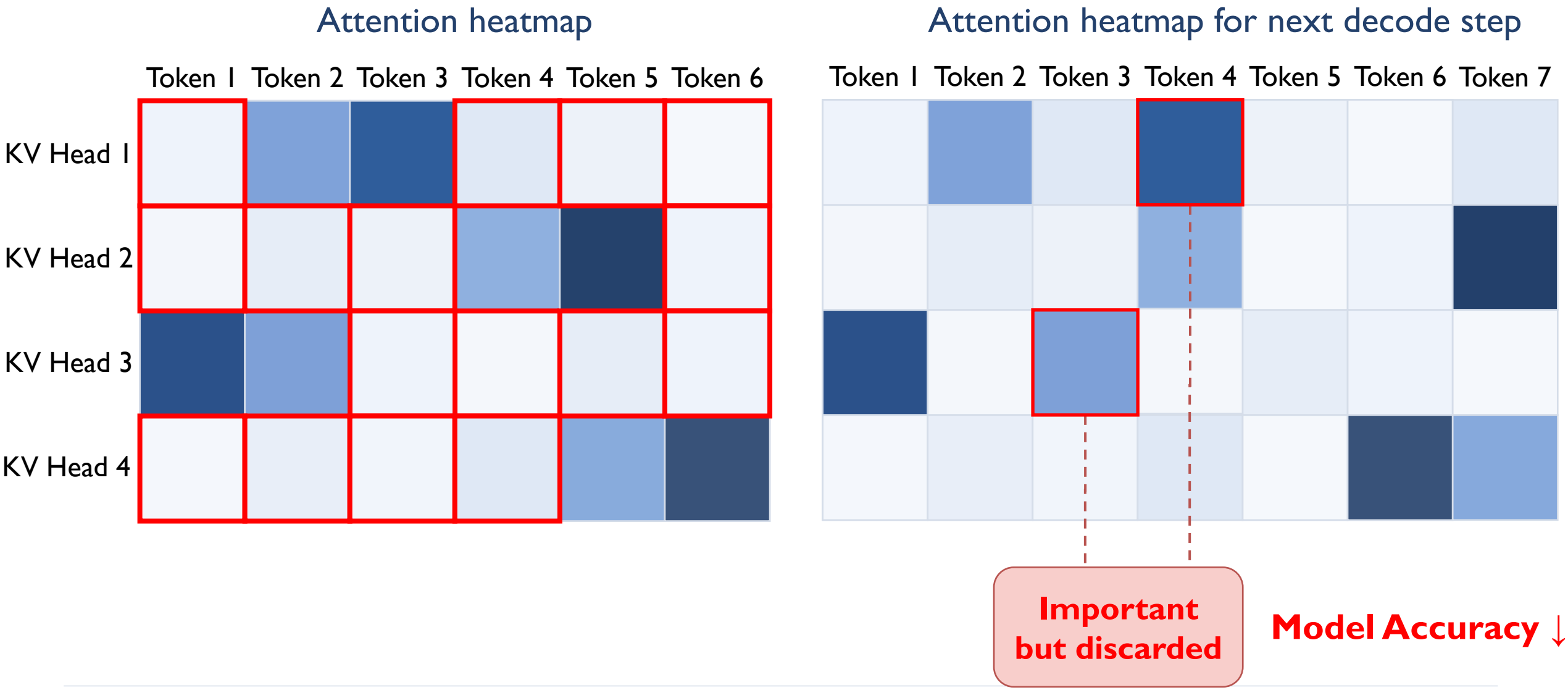
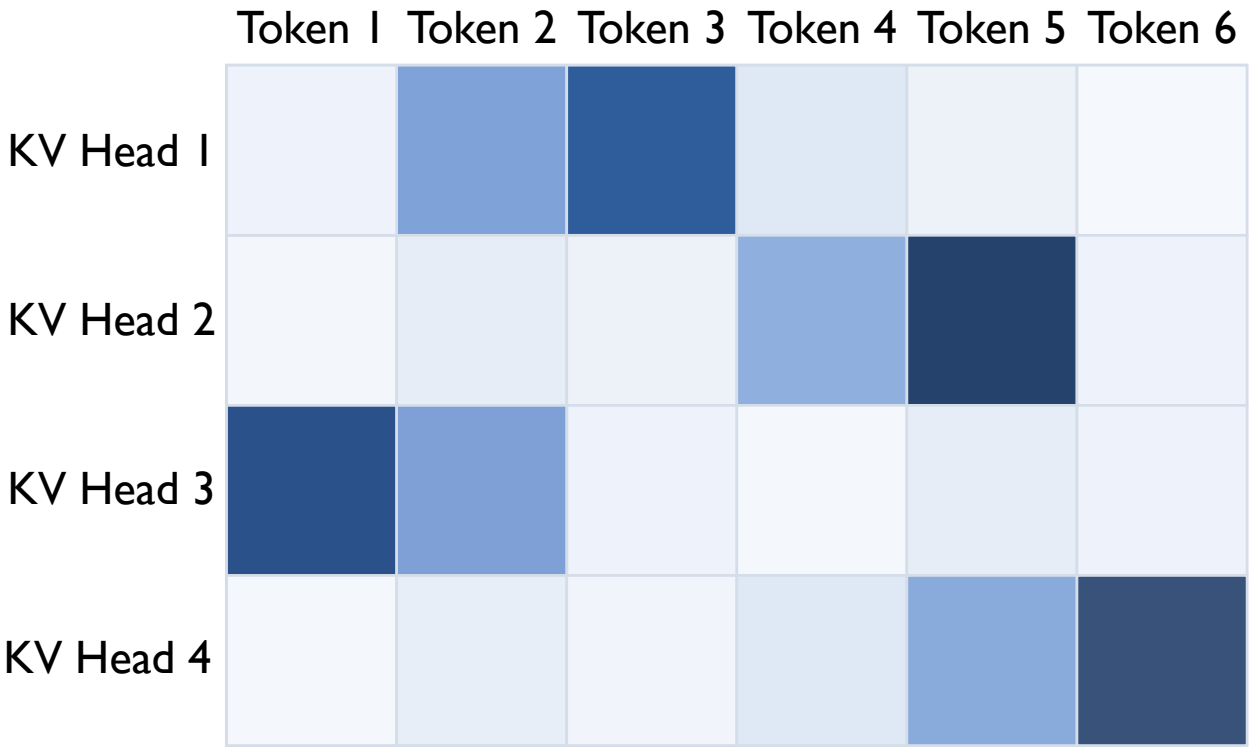


Leveraging Sparsity: Query Aware KV Selection

Attention heatmap



At each decode step, the current query vector is used to select the most important KV

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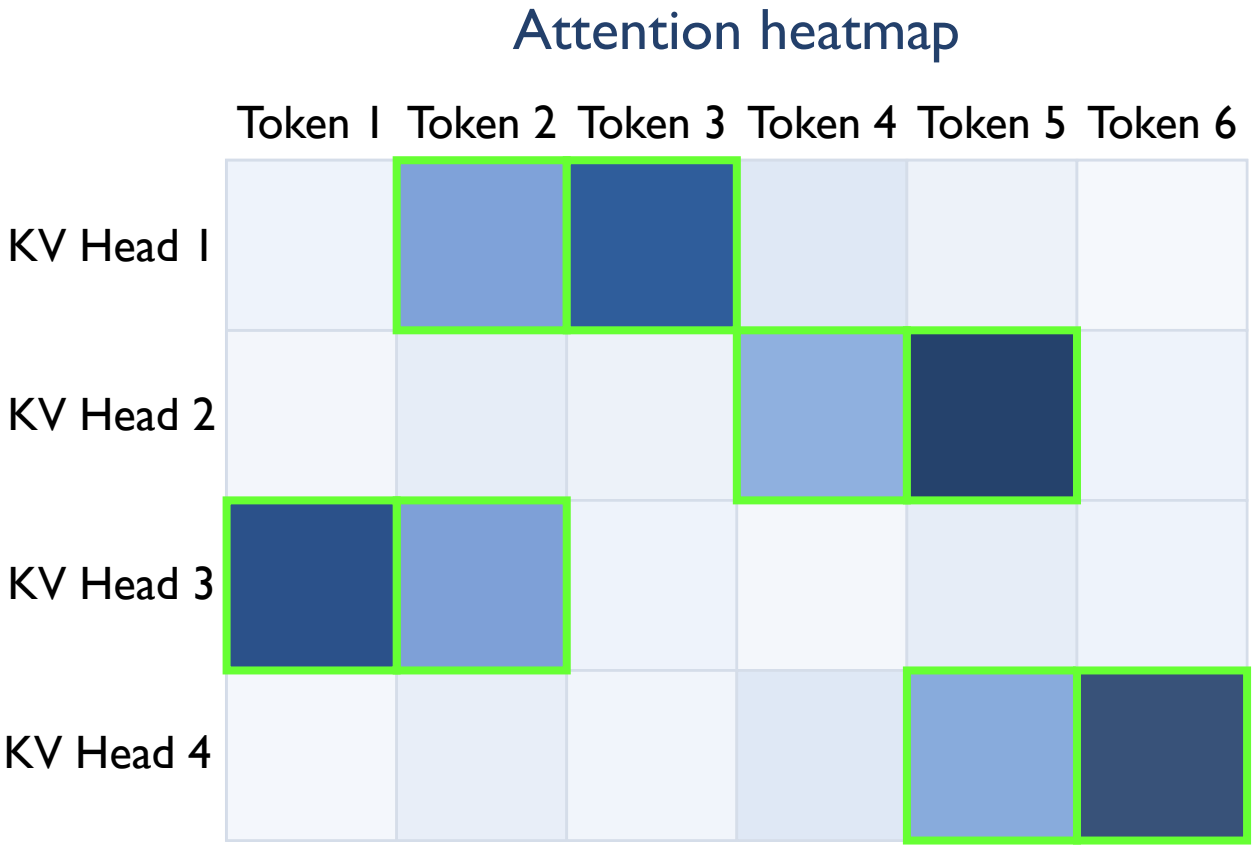

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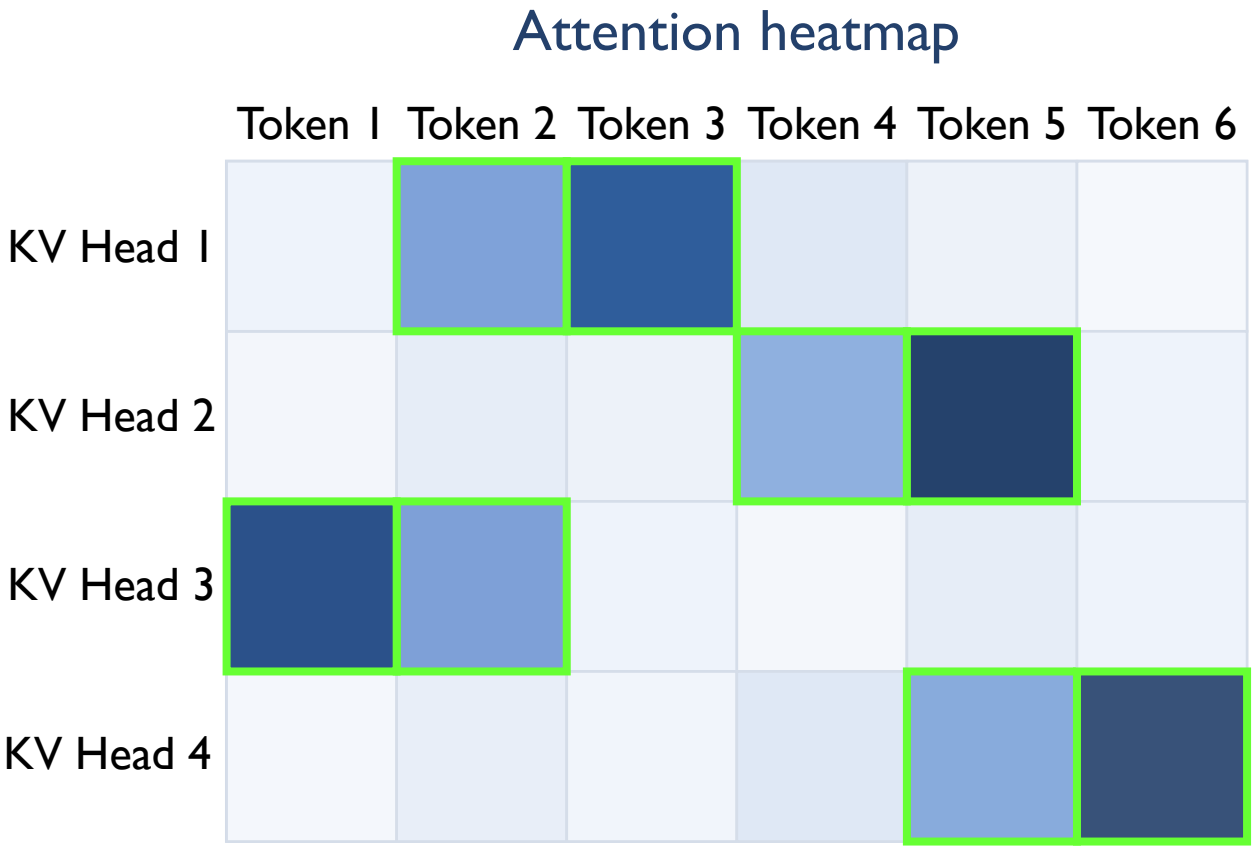

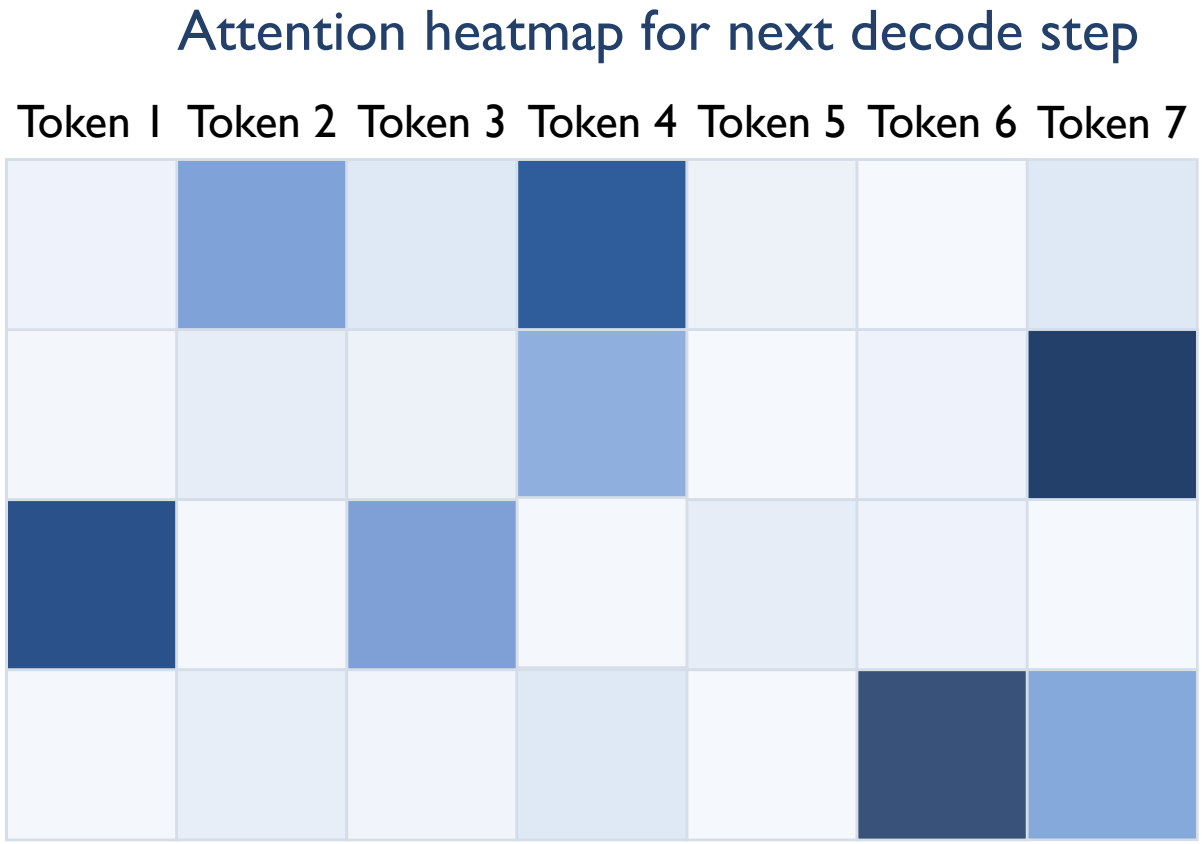

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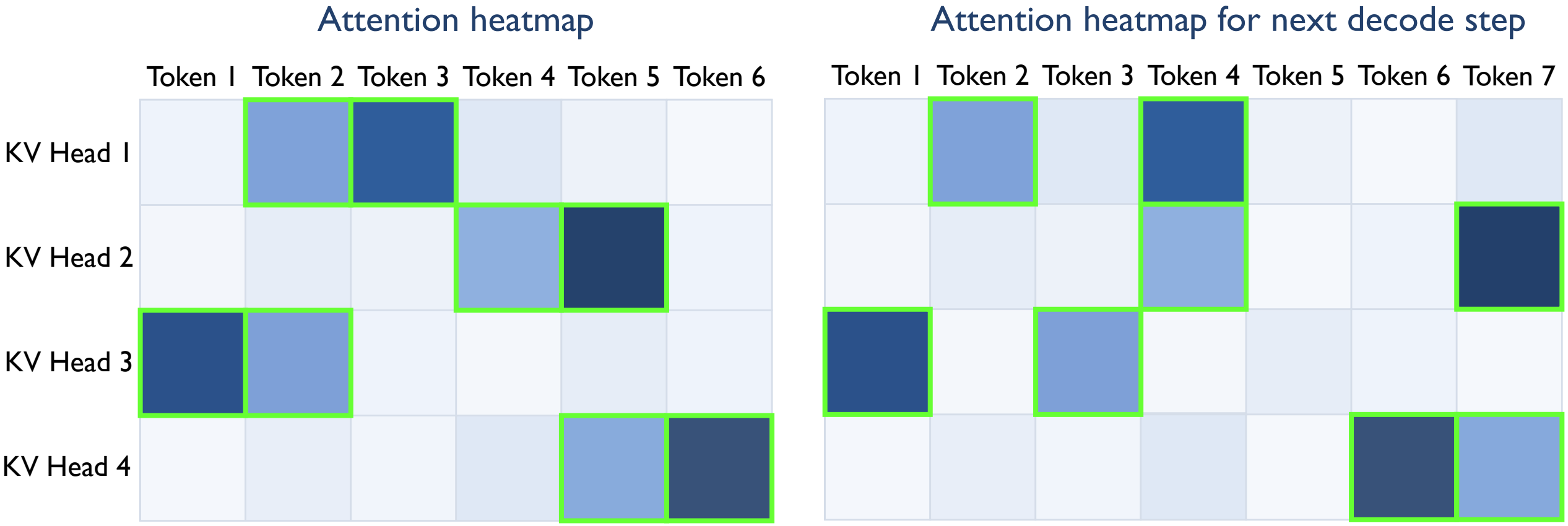

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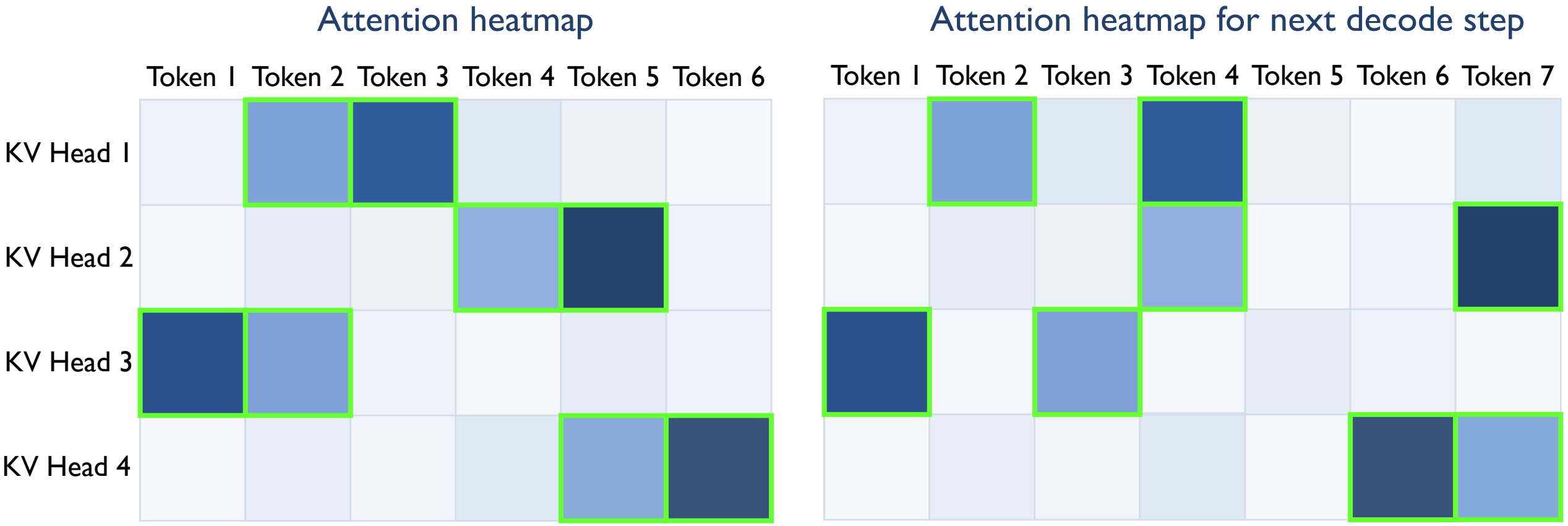


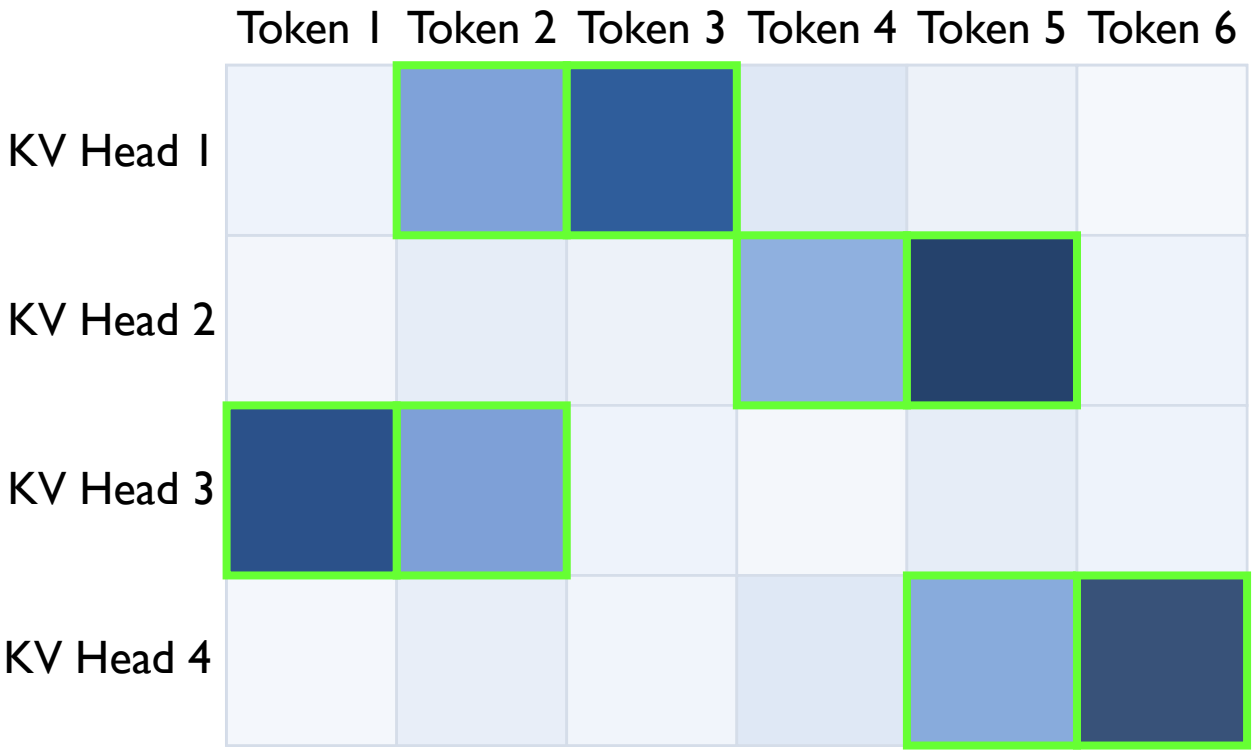
Model Accuracy Preserved

HBM → SM I/O ↓

Attention Compute ↓

Leveraging Sparsity: Query Aware KV Selection

Attention heatmap



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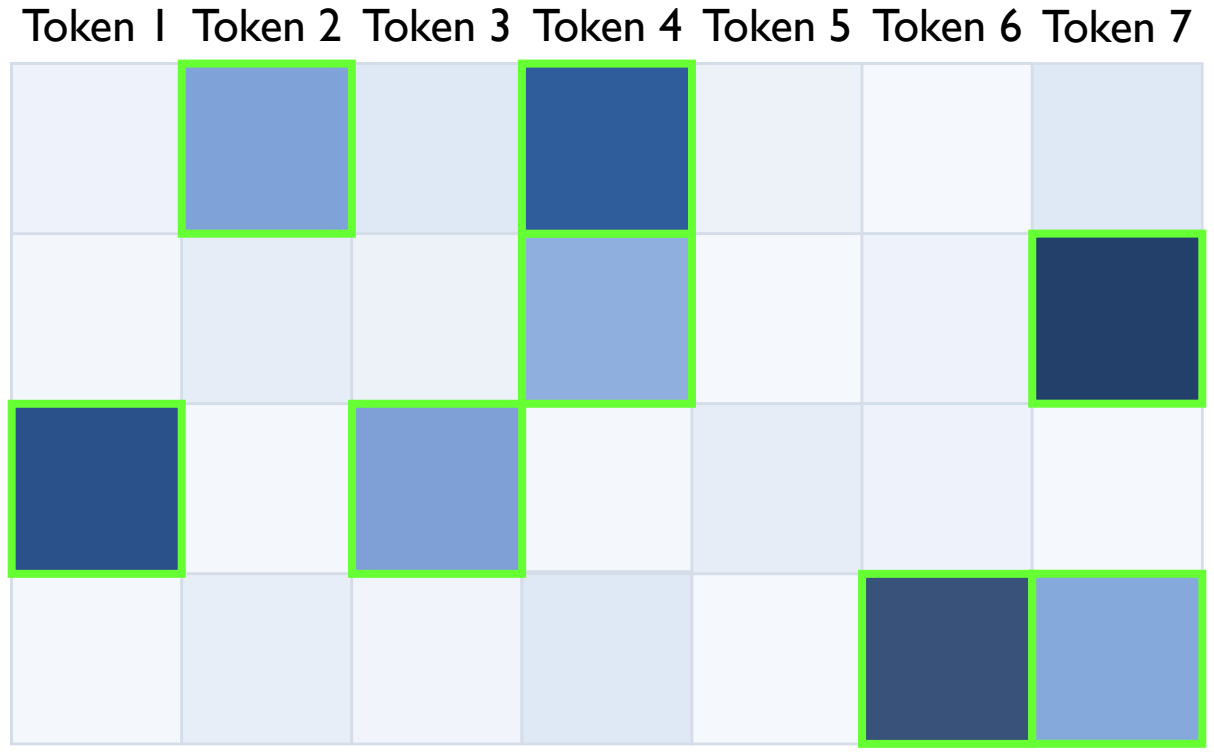
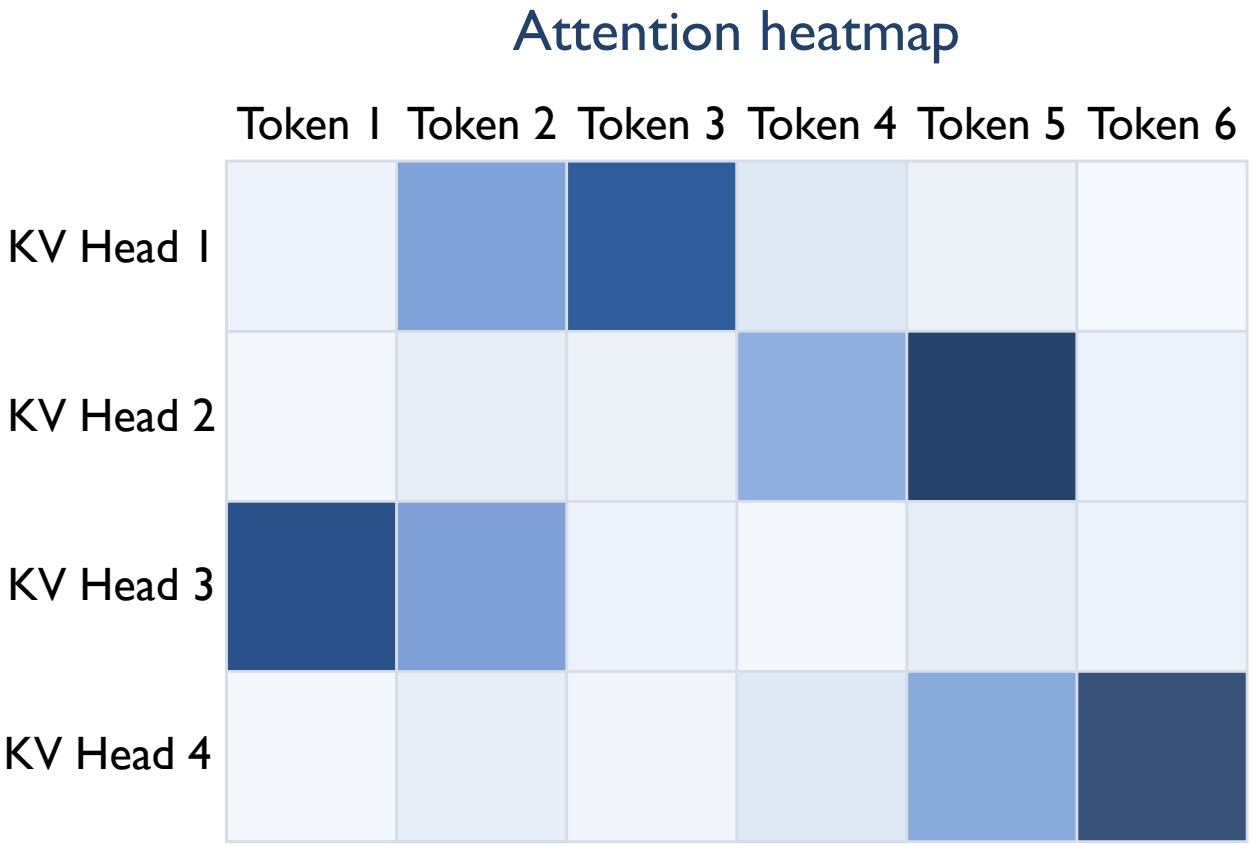


HBM usage unchanged

Leveraging Sparsity: Offloading + Query Aware Selection



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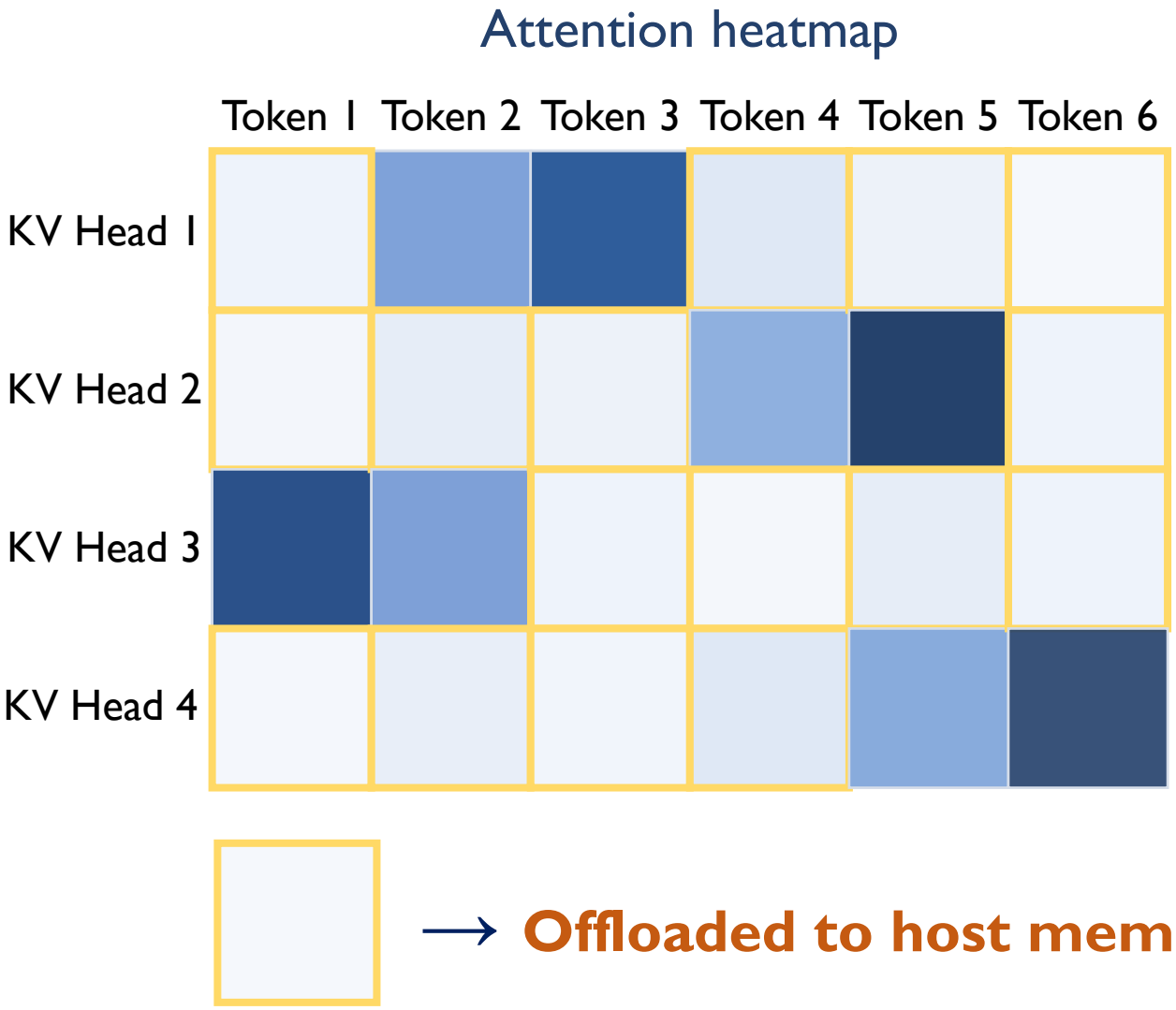

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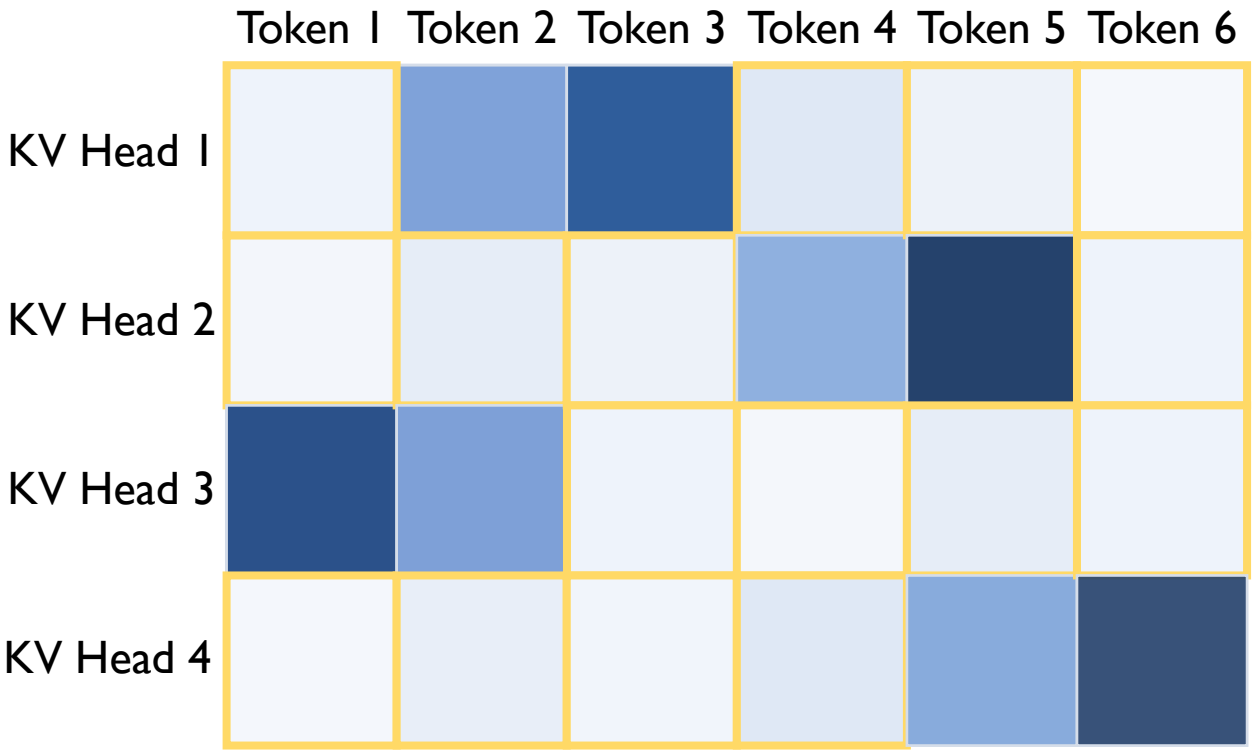

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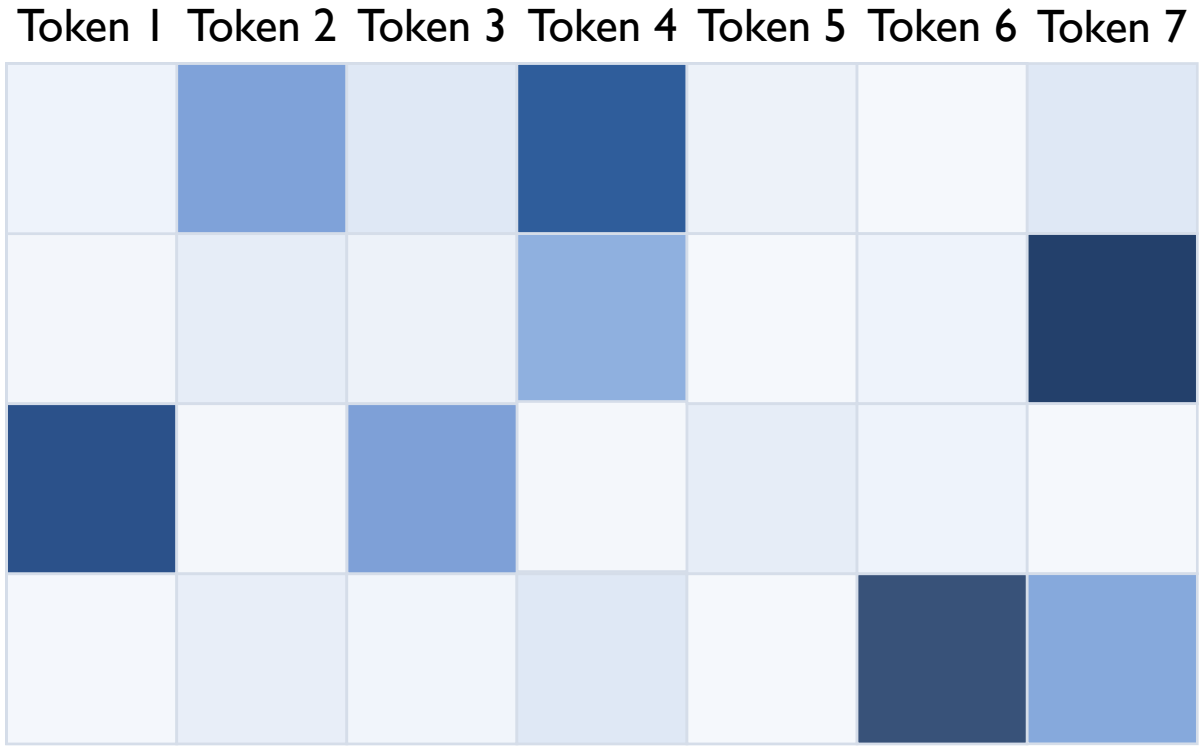

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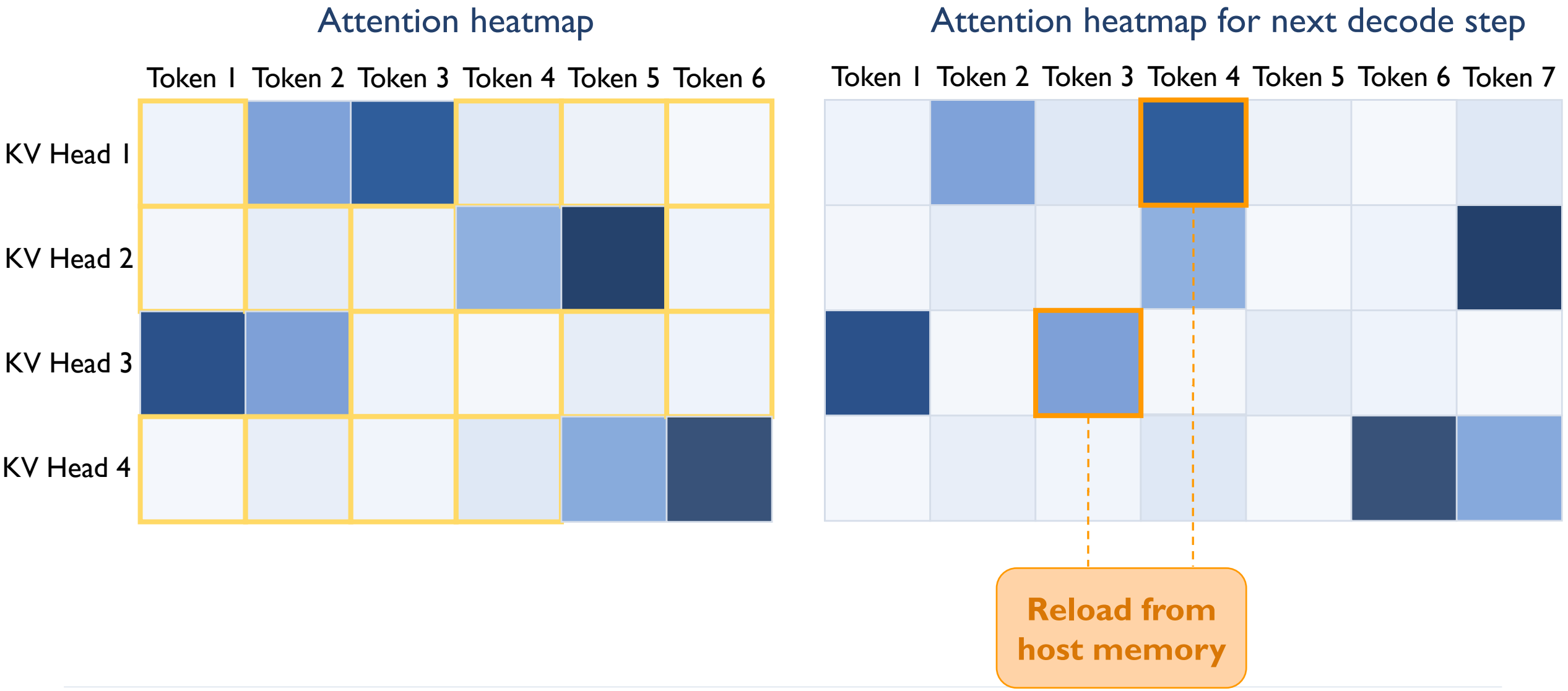

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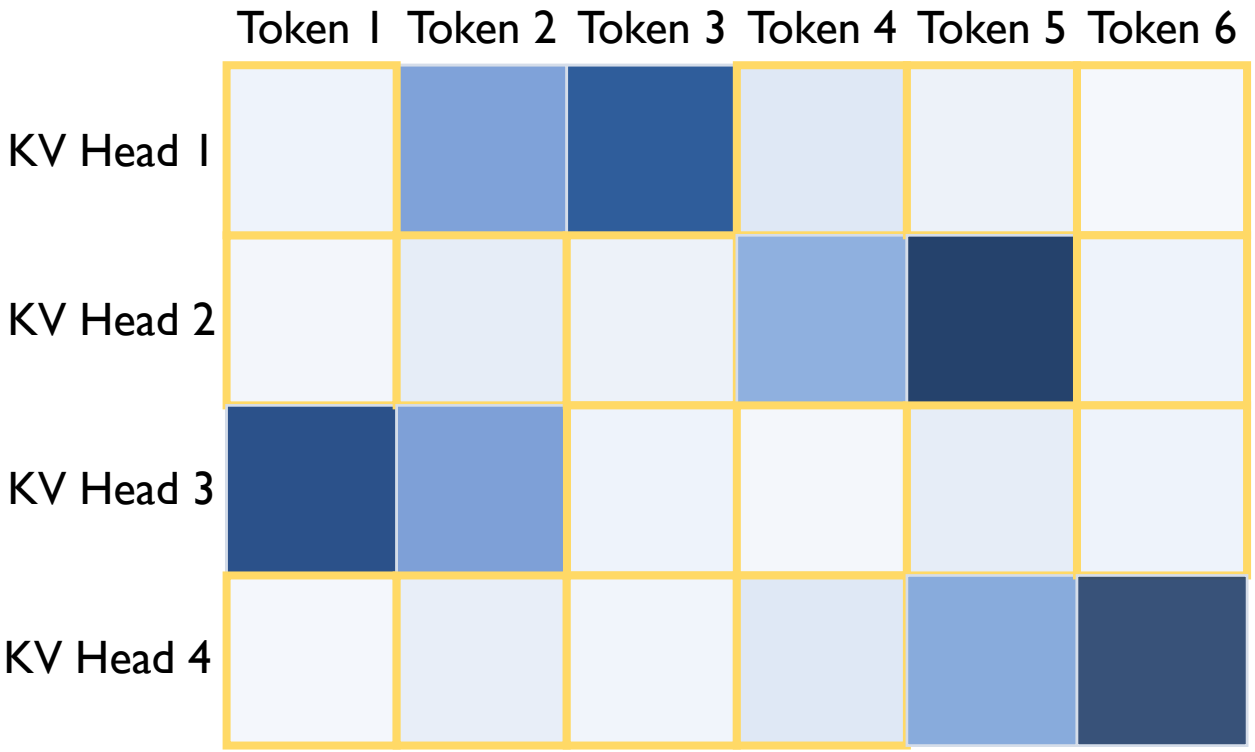

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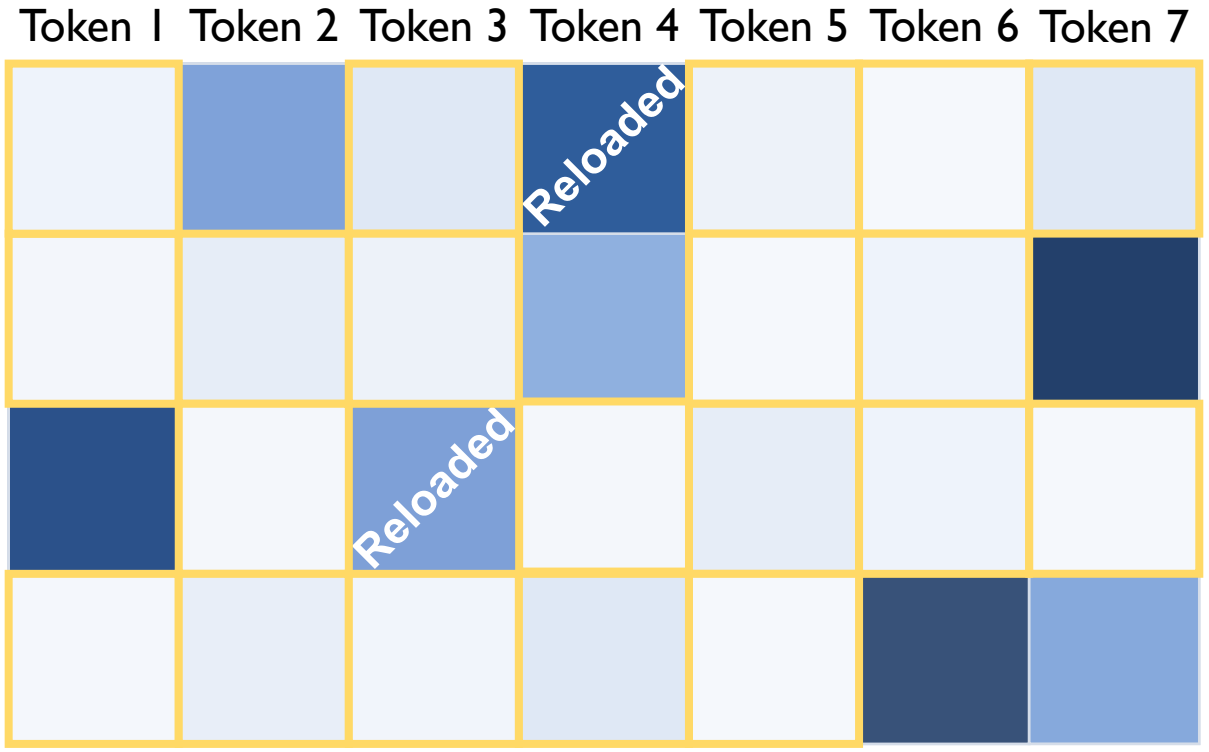

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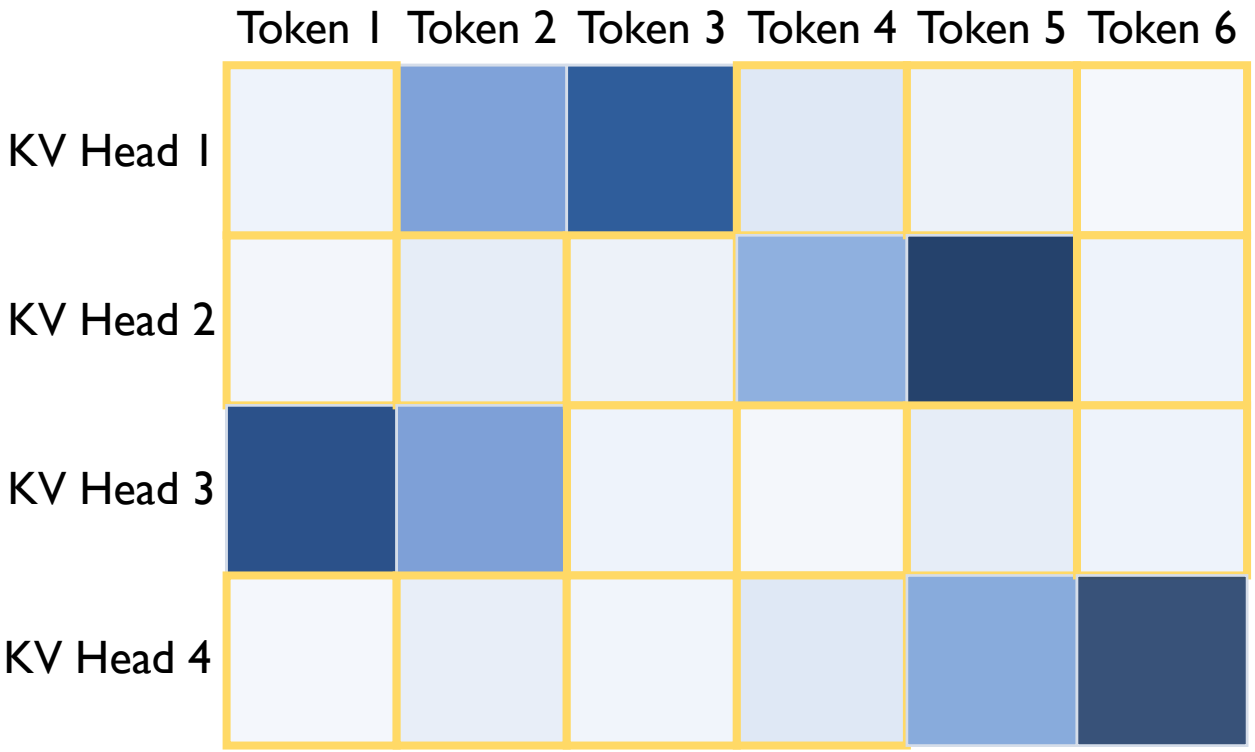

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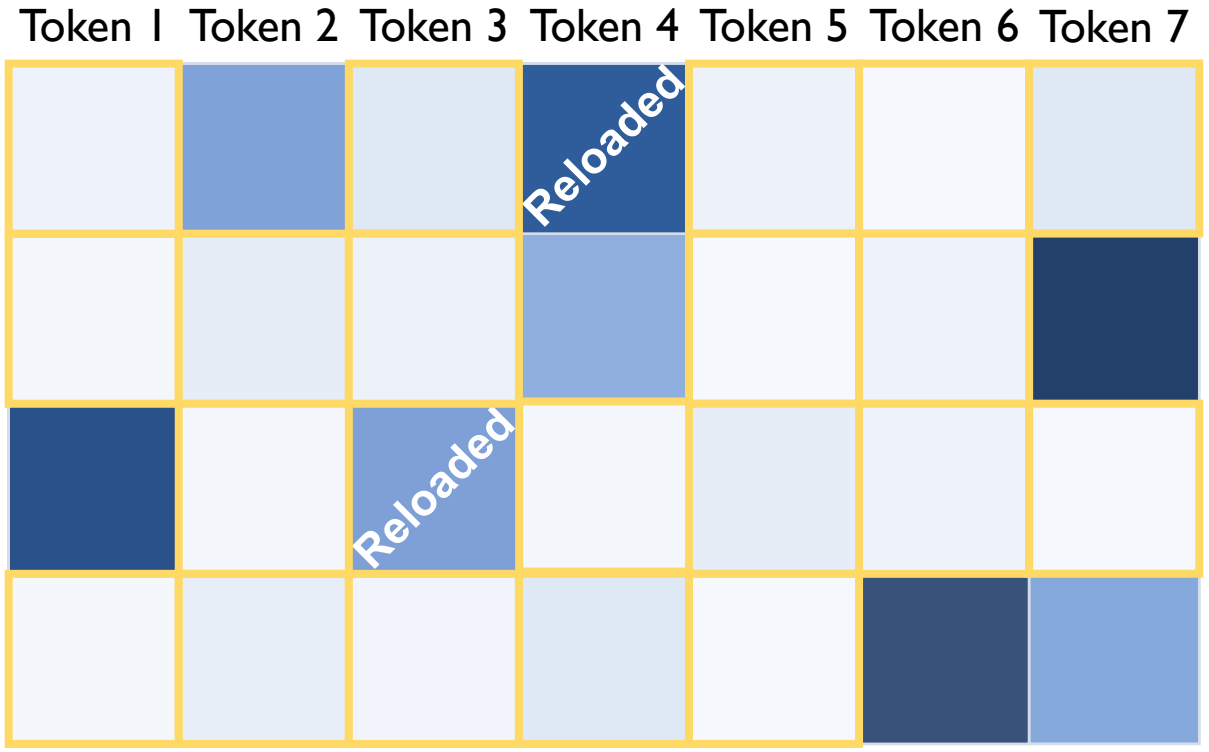

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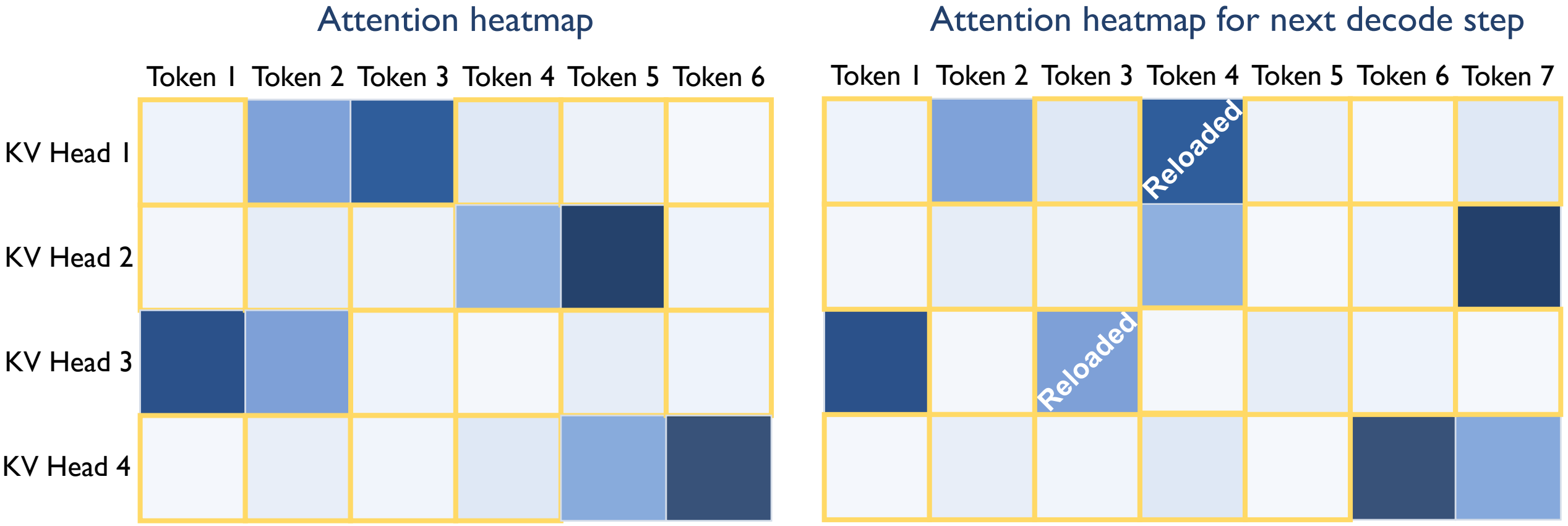

Host → GPU
I/O Bottleneck

Leveraging Sparsity: Summary

Method	HBM ↓	I/O ↓	Compute ↓	Accuracy Preserved

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Query Aware KV Selection	❌	✅	✅	✅
Offloading + Query Aware KV Selection	✅	❌	✅	✅

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Query Aware KV Selection	❌	✅	✅	✅
Offloading + Query Aware KV Selection	✅	❌	✅	✅
FlexiCache	✅	✅	✅	✅

FlexiCache achieves all four

Key Insight: Temporal stability

- **Temporal Stability:** How consistently an attention head keeps selecting the same Top-K KV across decode steps

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$$\mathrm{RCO}(s,t) = \frac{\frac{\left|S^{(s)} \cap S^{(t)}\right|}{K} - \frac{K}{N_t}}{1 - \frac{K}{N_t}}$$

where,

- $S^{(s)}$: Top−K KV set at decode step s
- $S^{(t)}$: Top−K KV set at decode step t
- $\frac{\left|S^{(s)} \cap S^{(t)}\right|}{K}$: **Fraction of Top-K KV set that remains the same across steps**

Key Insight: Temporal stability

- **Temporal Stability:** How consistently an attention head keeps selecting the same Top-K KV across decode steps

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- **Divide by $1 - \frac{K}{N_t}$: scale RCO between 0 and 1**

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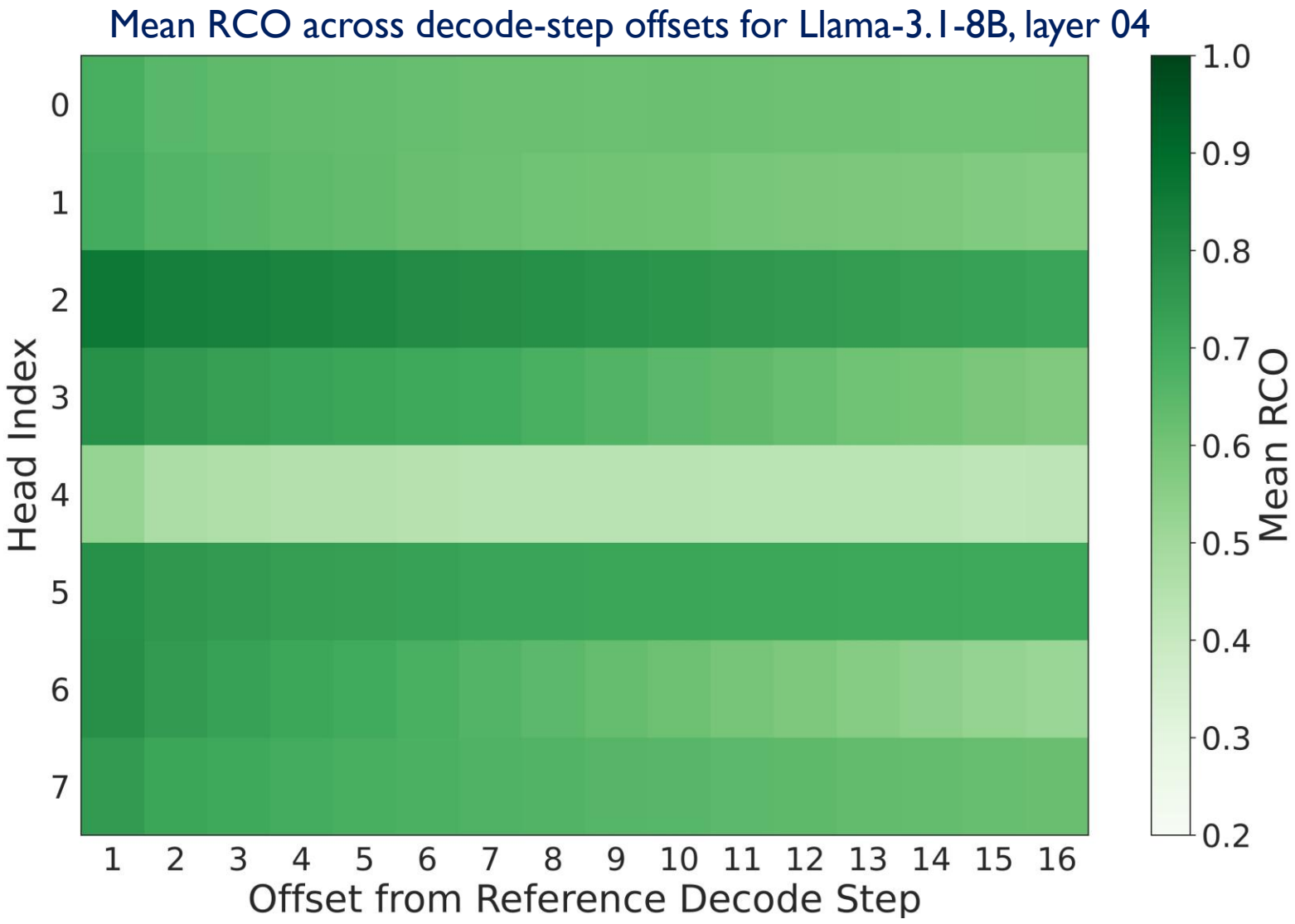
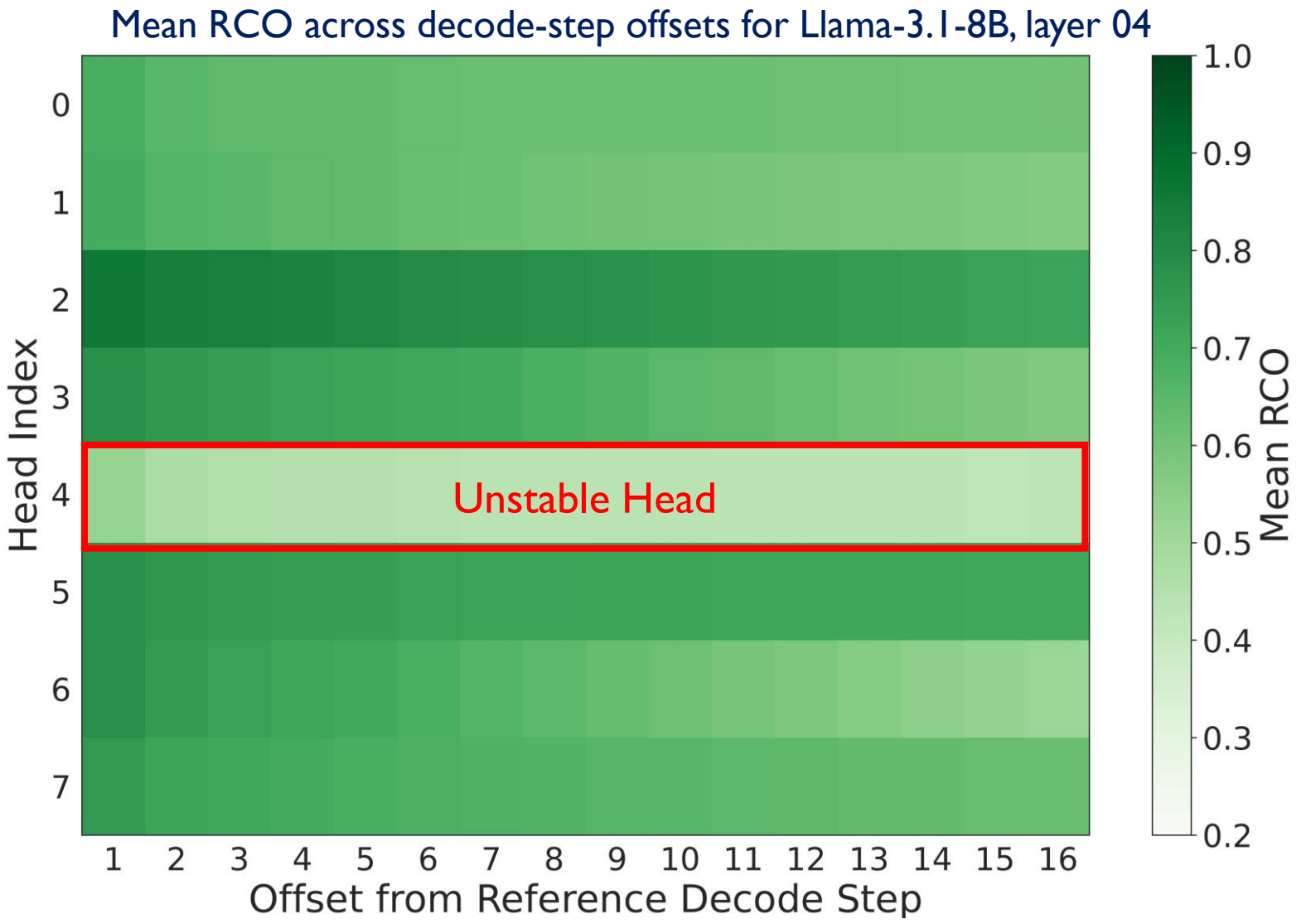
where,

- RCO of 0 → random-selection level overlap
- RCO of 1 → perfect overlap

Key Insight: Non-uniform temporal stability

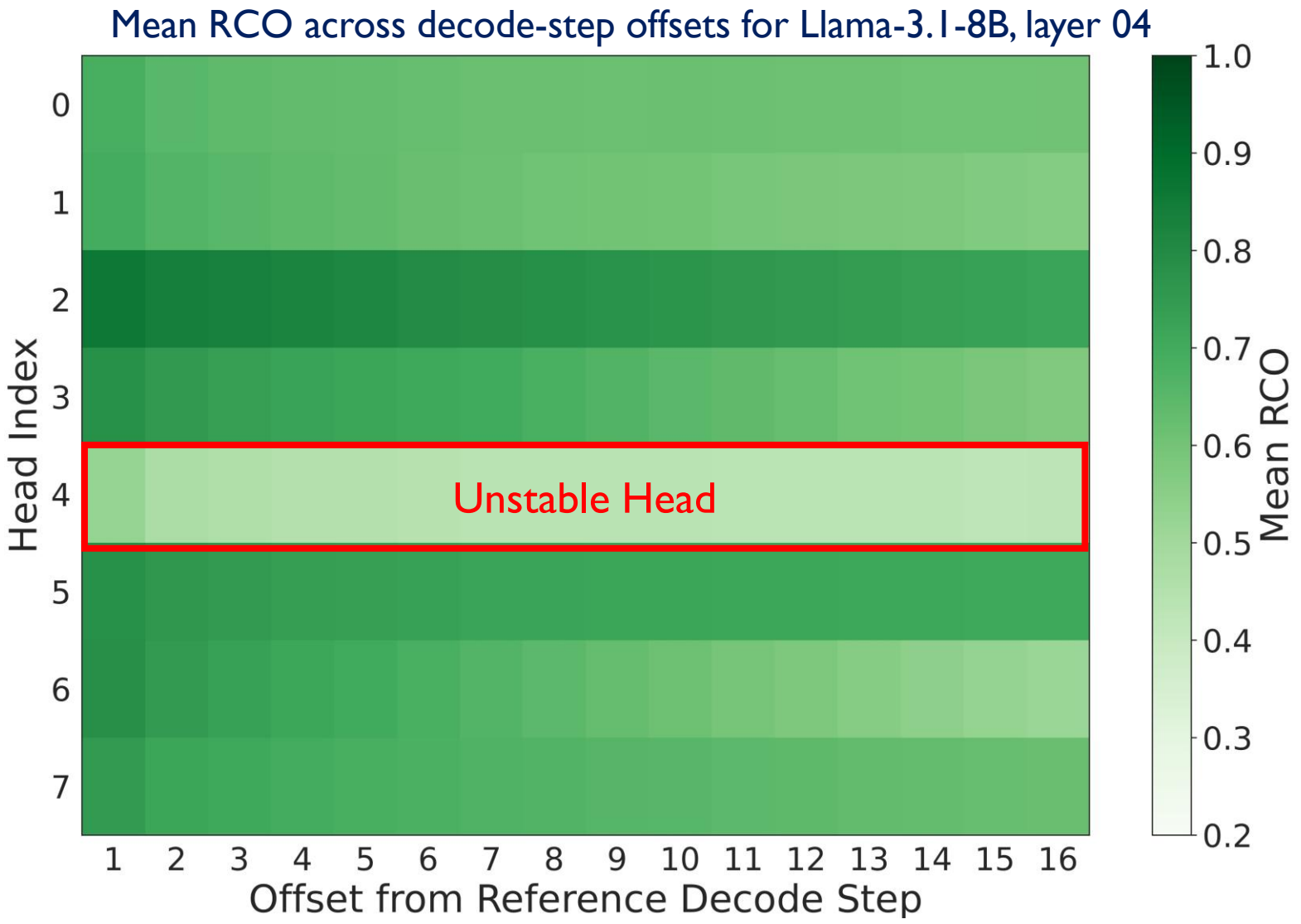


Key Insight: Unstable Heads



Key Insight: Unstable Heads

- For each KV head: Compute mean RCO across decode steps



Key Insight: Unstable Heads

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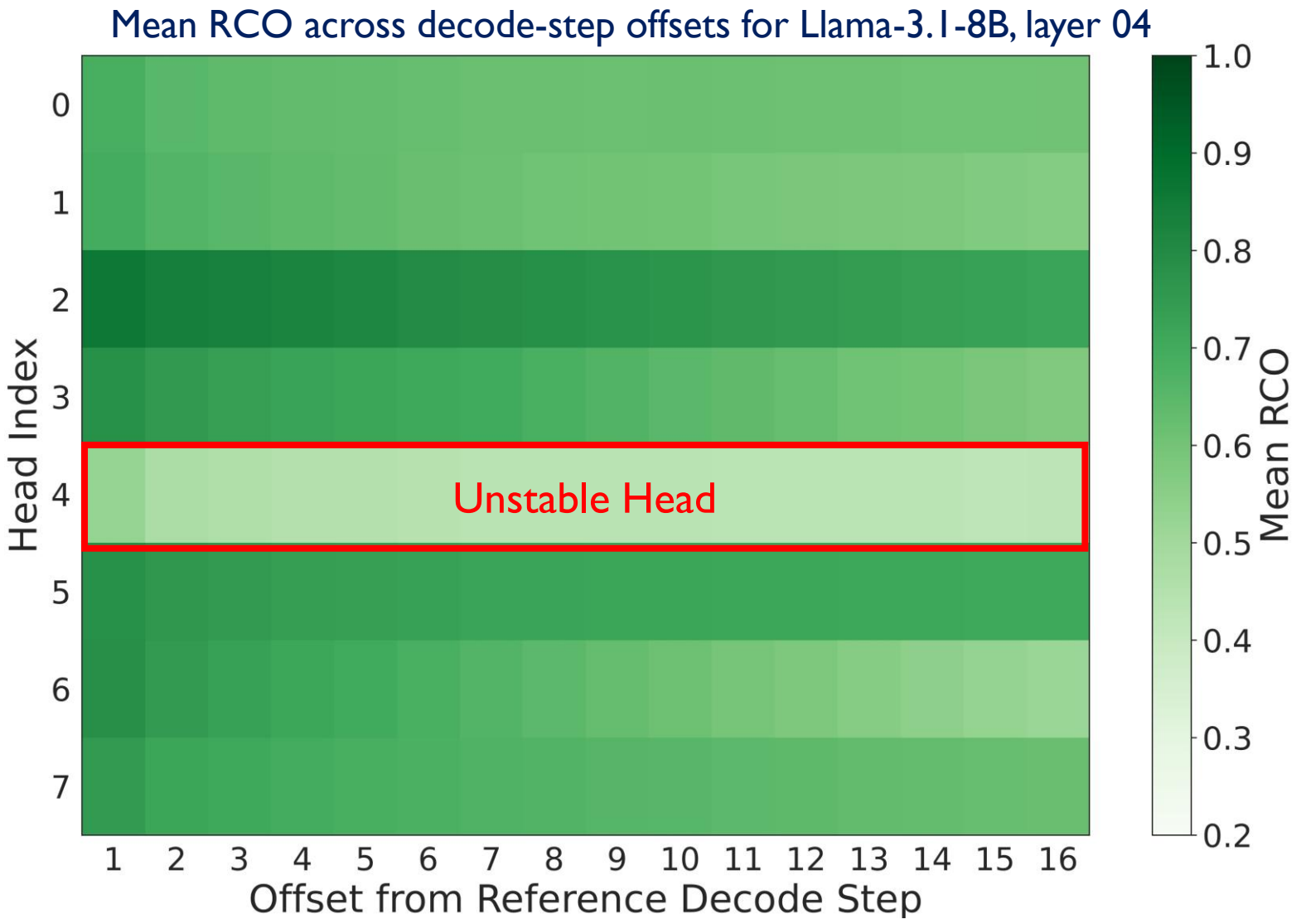
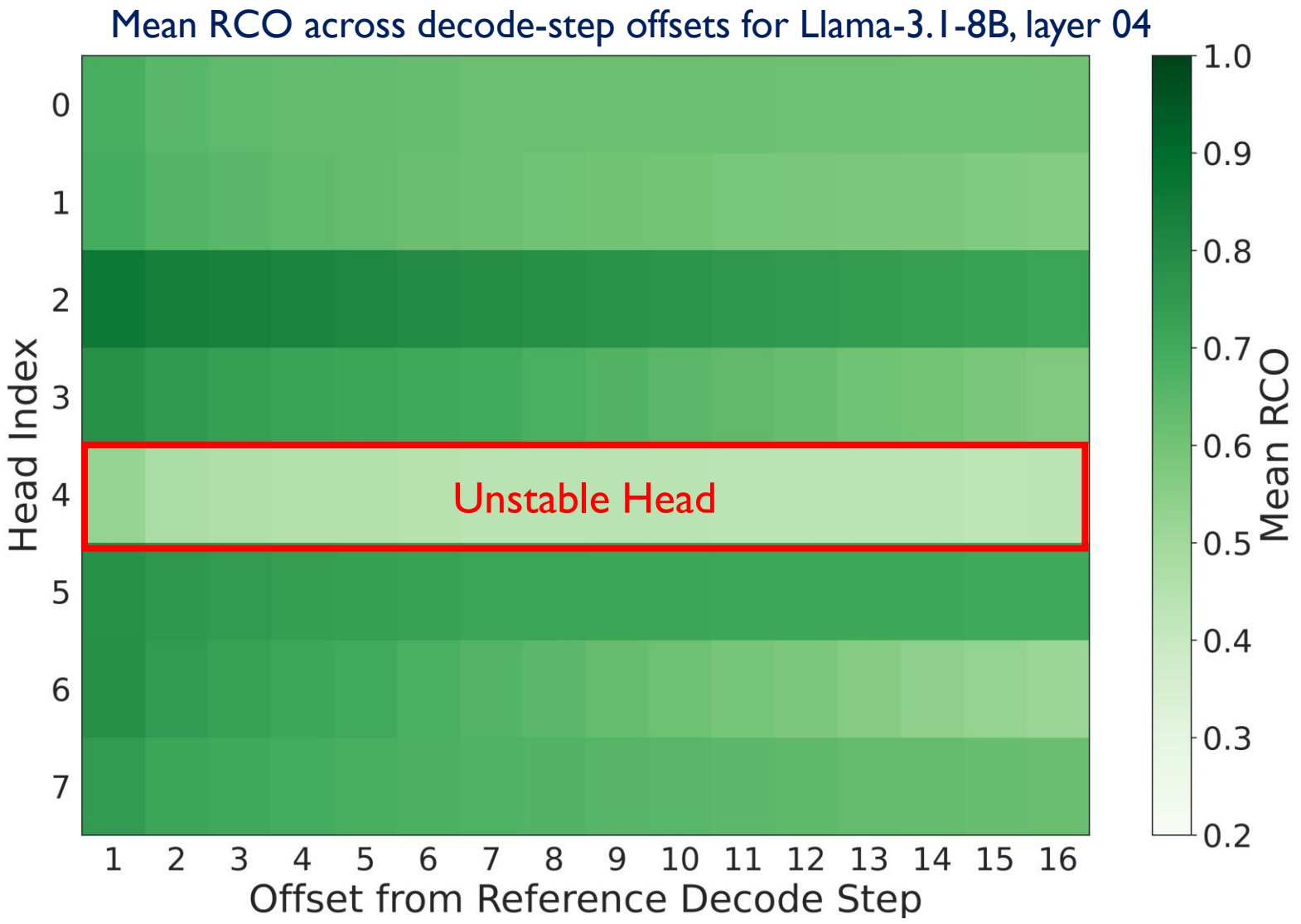


Key Insight: Unstable Heads

- For each KV head: Compute mean RCO across decode steps
- Rank KV heads by mean RCO
- Classify least stable 25% of KV heads as unstable



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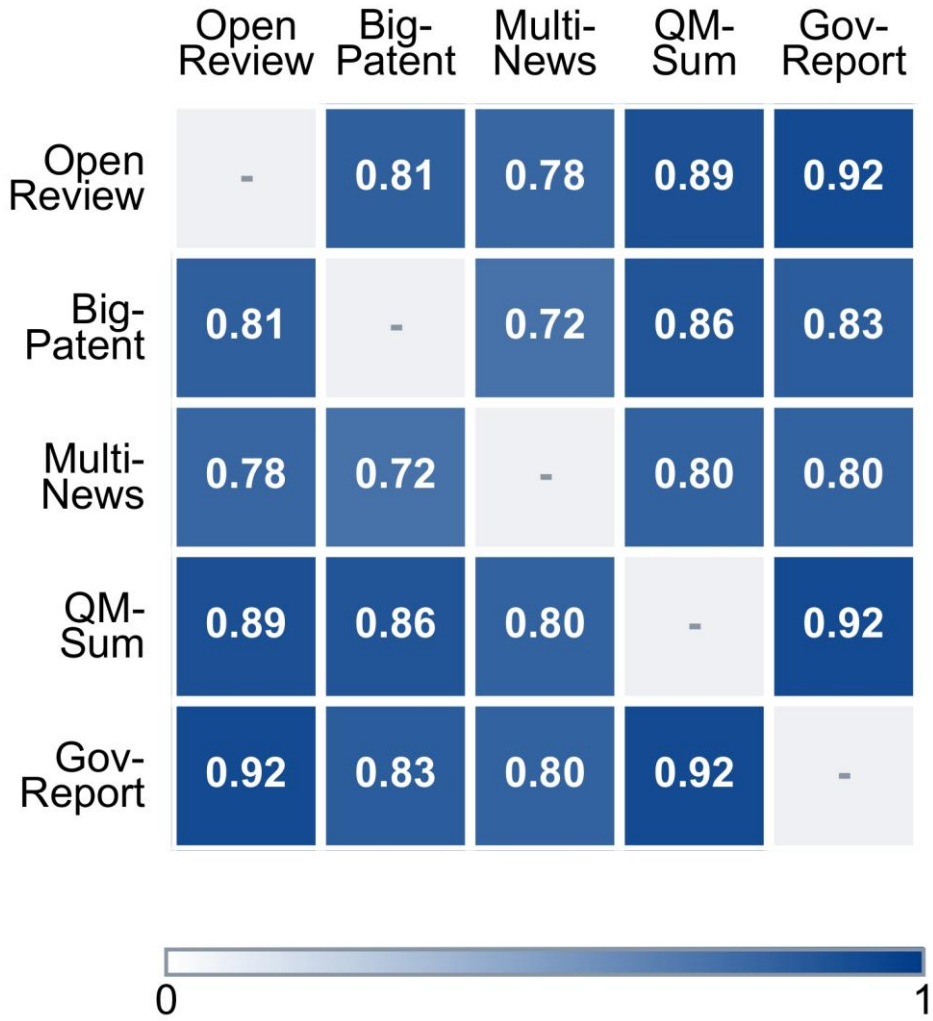
Cross-dataset overlap of unstable heads for Llama-3.1-8B-Instruct



Key Insight: Model Intrinsic Unstable Heads

- Identify unstable heads independently for several datasets
- High overlap → instability is model intrinsic
- Paper reports similar trends for more models & datasets

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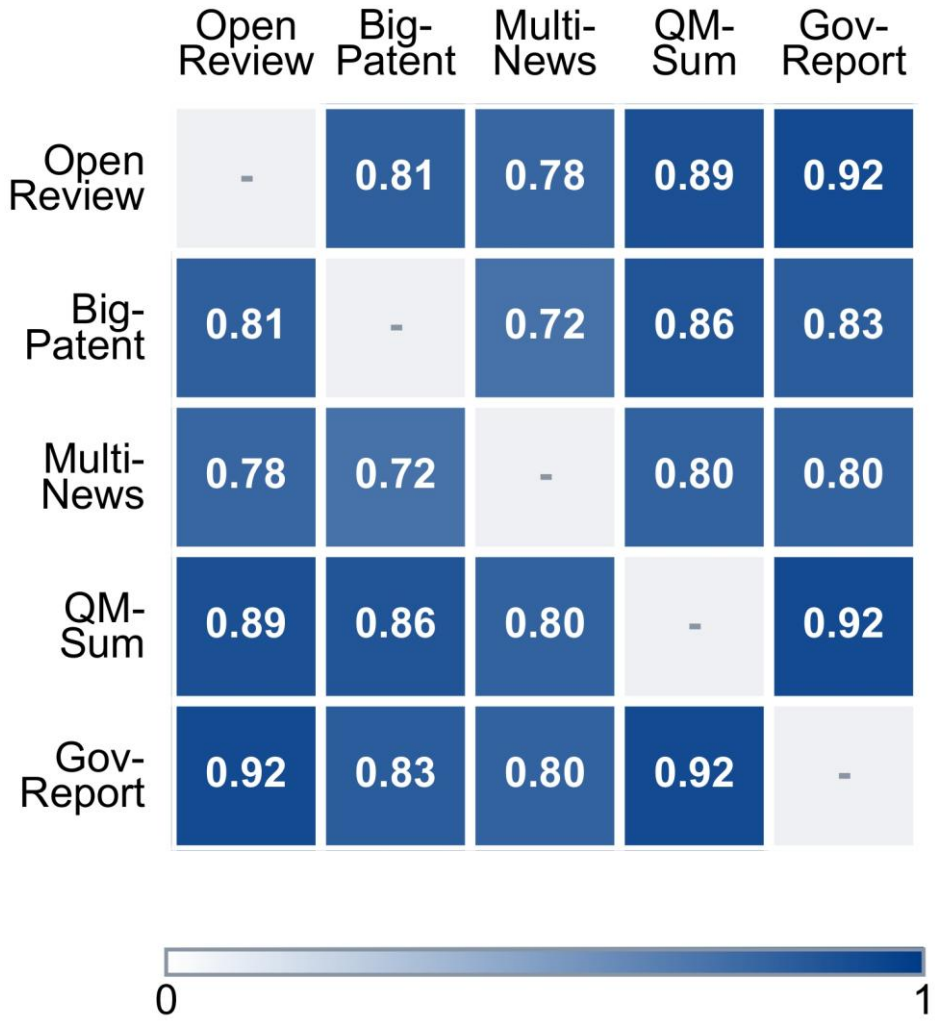
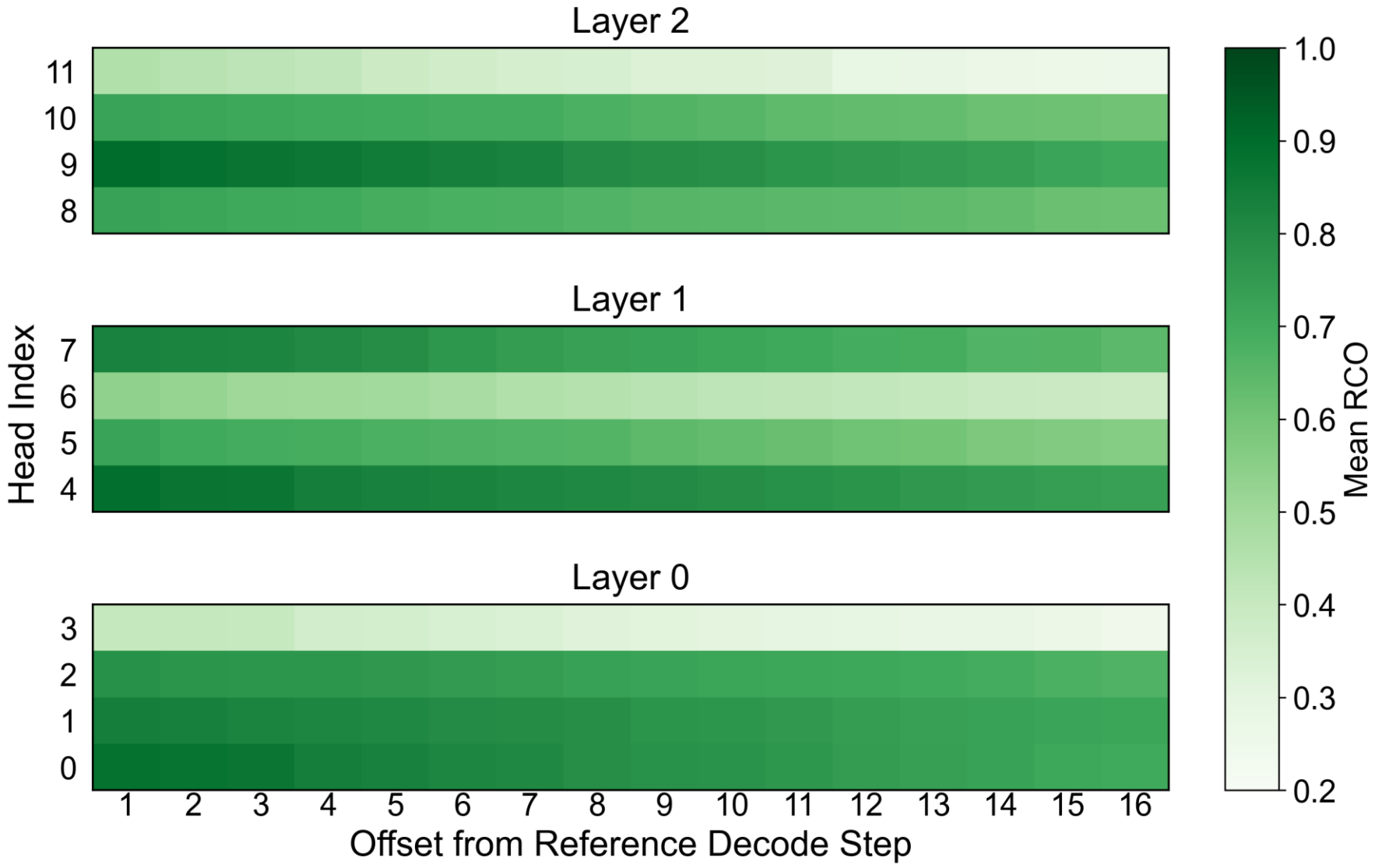


FlexiCache

Temporal Stability Aware Hierarchical KV Cache Management

FlexiCache: Offline KV Head Classification



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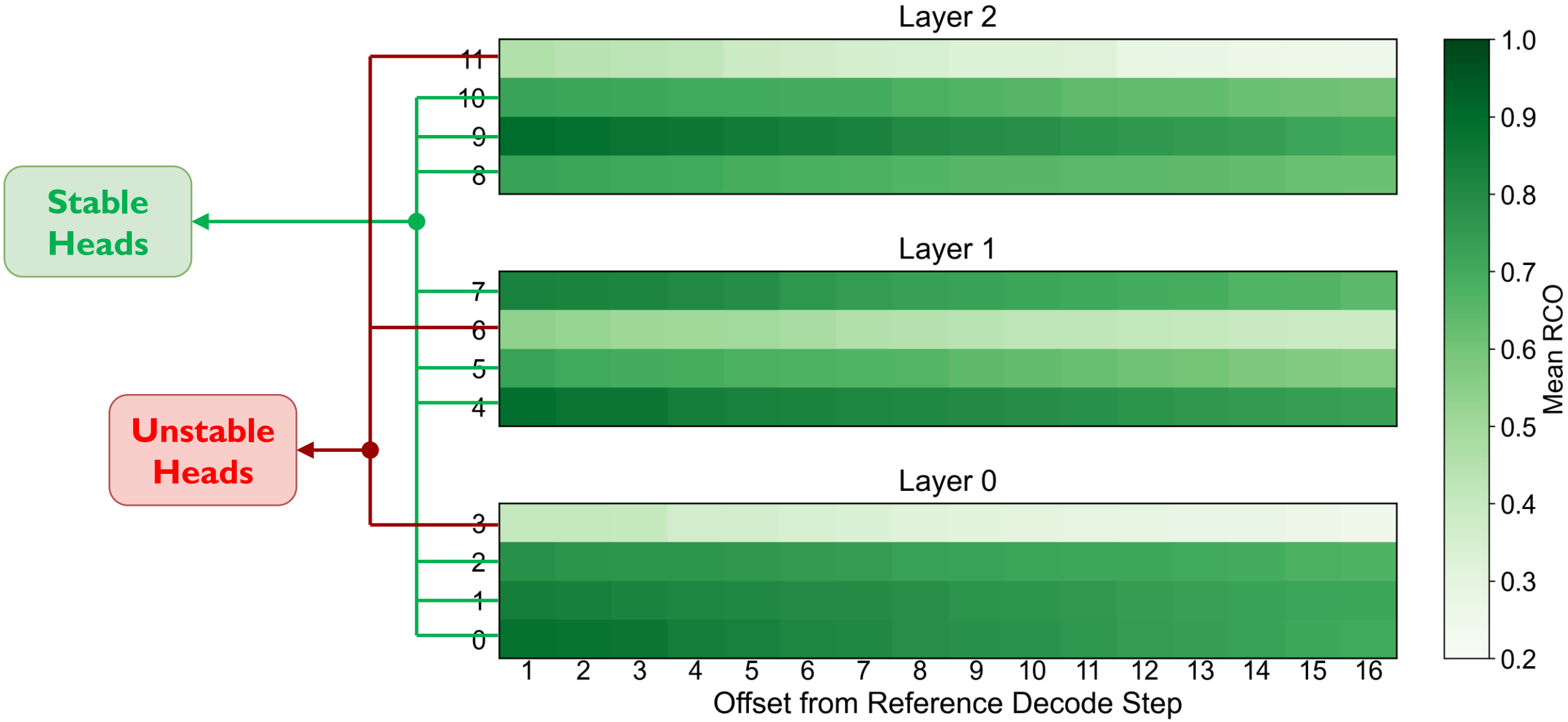
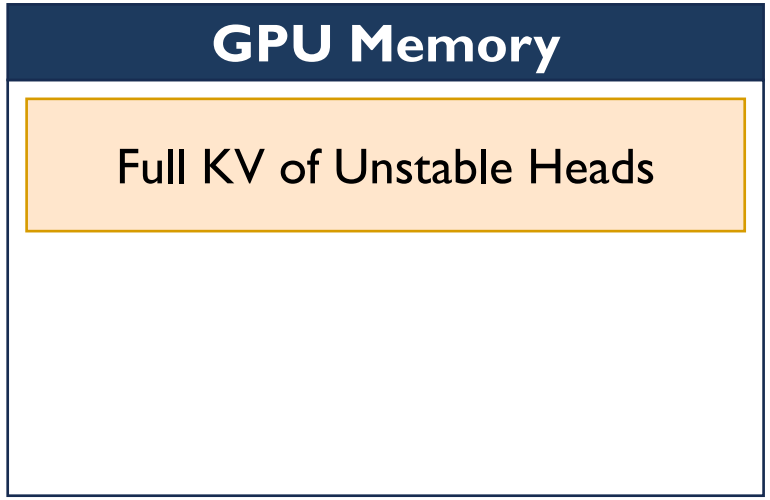


FlexiCache: Stability Aware Hierarchical KV Placement



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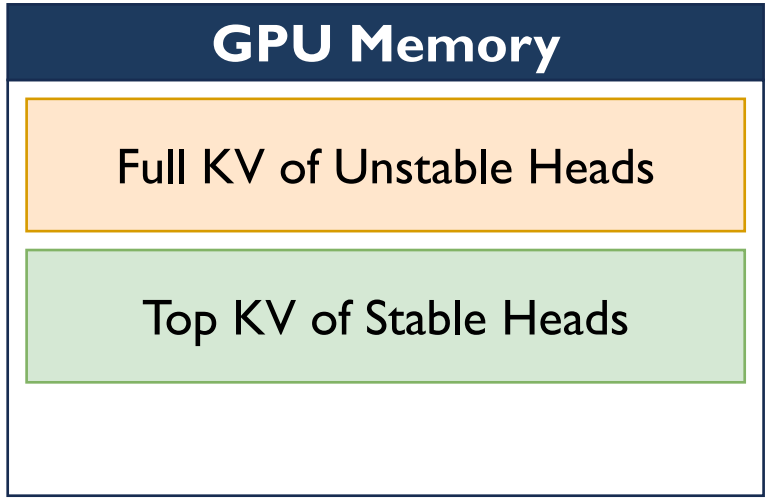

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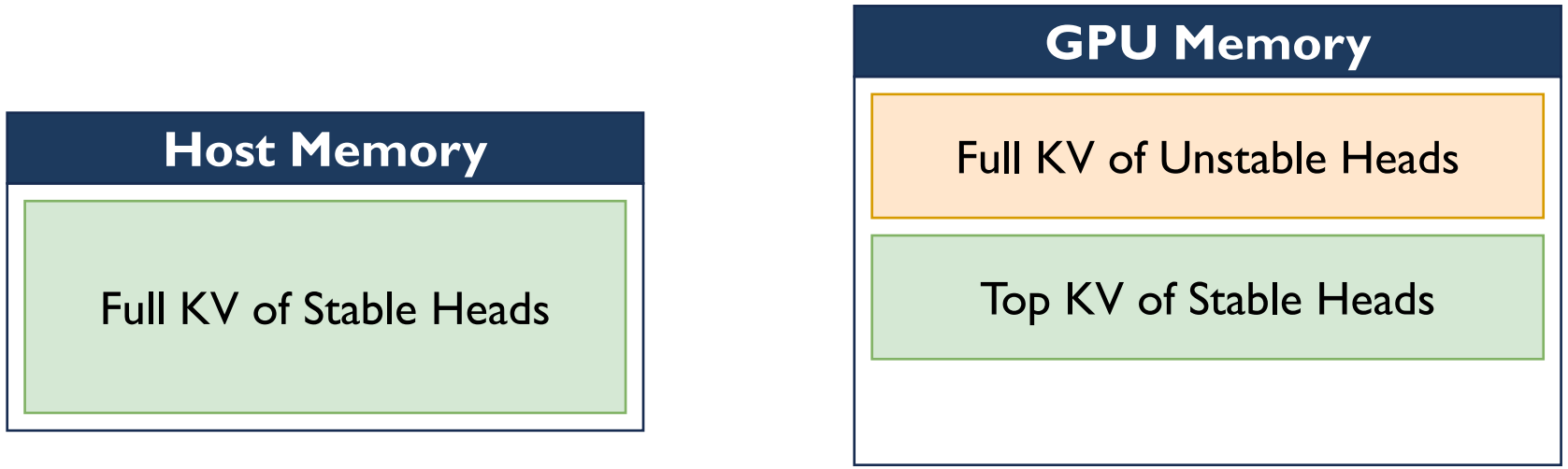

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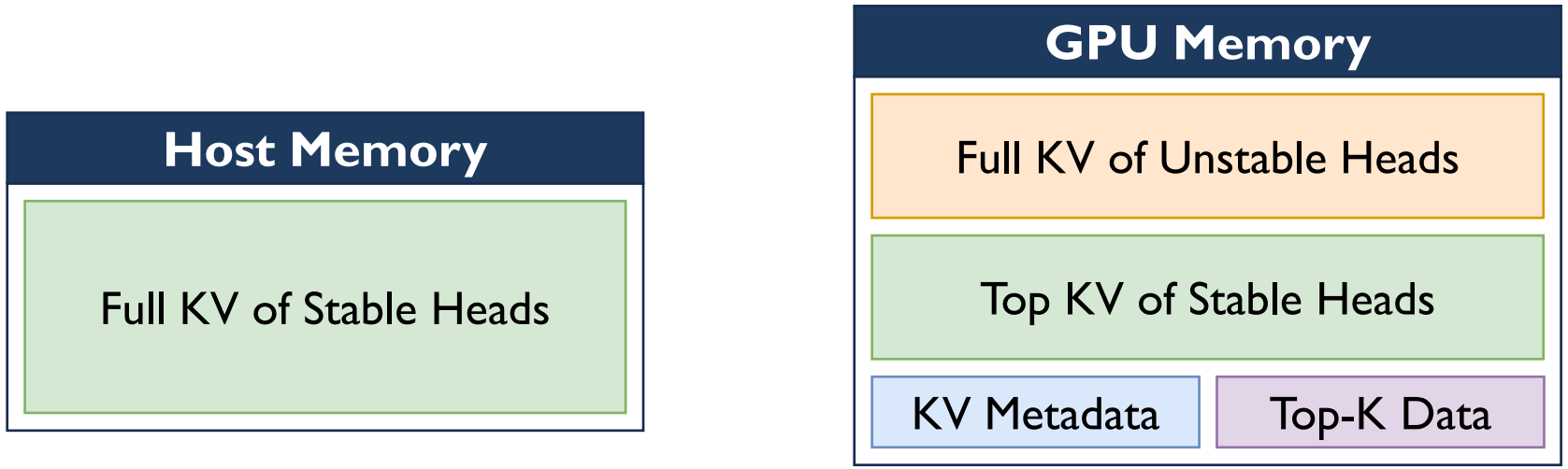
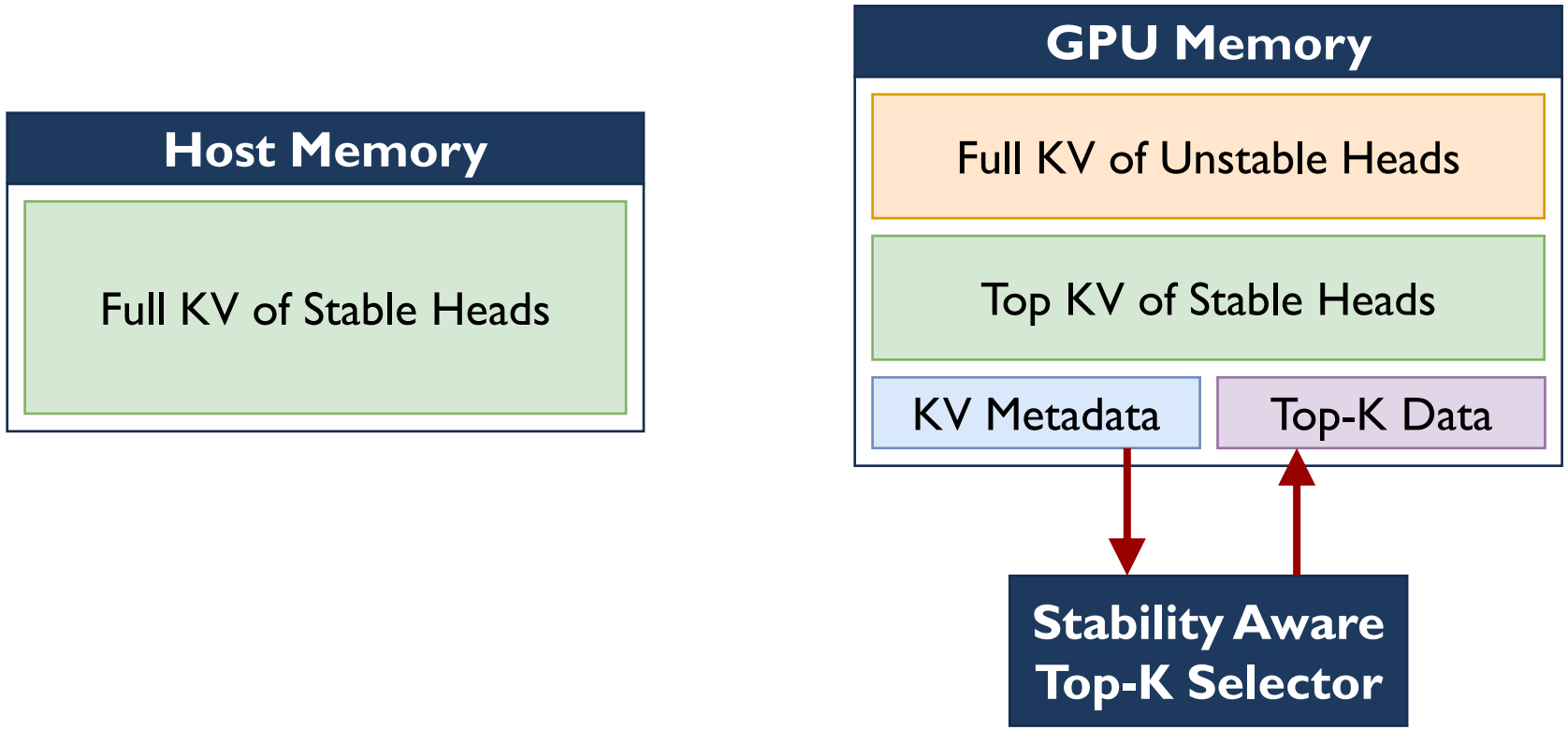


FlexiCache: Stability Aware Top-K KV Selector



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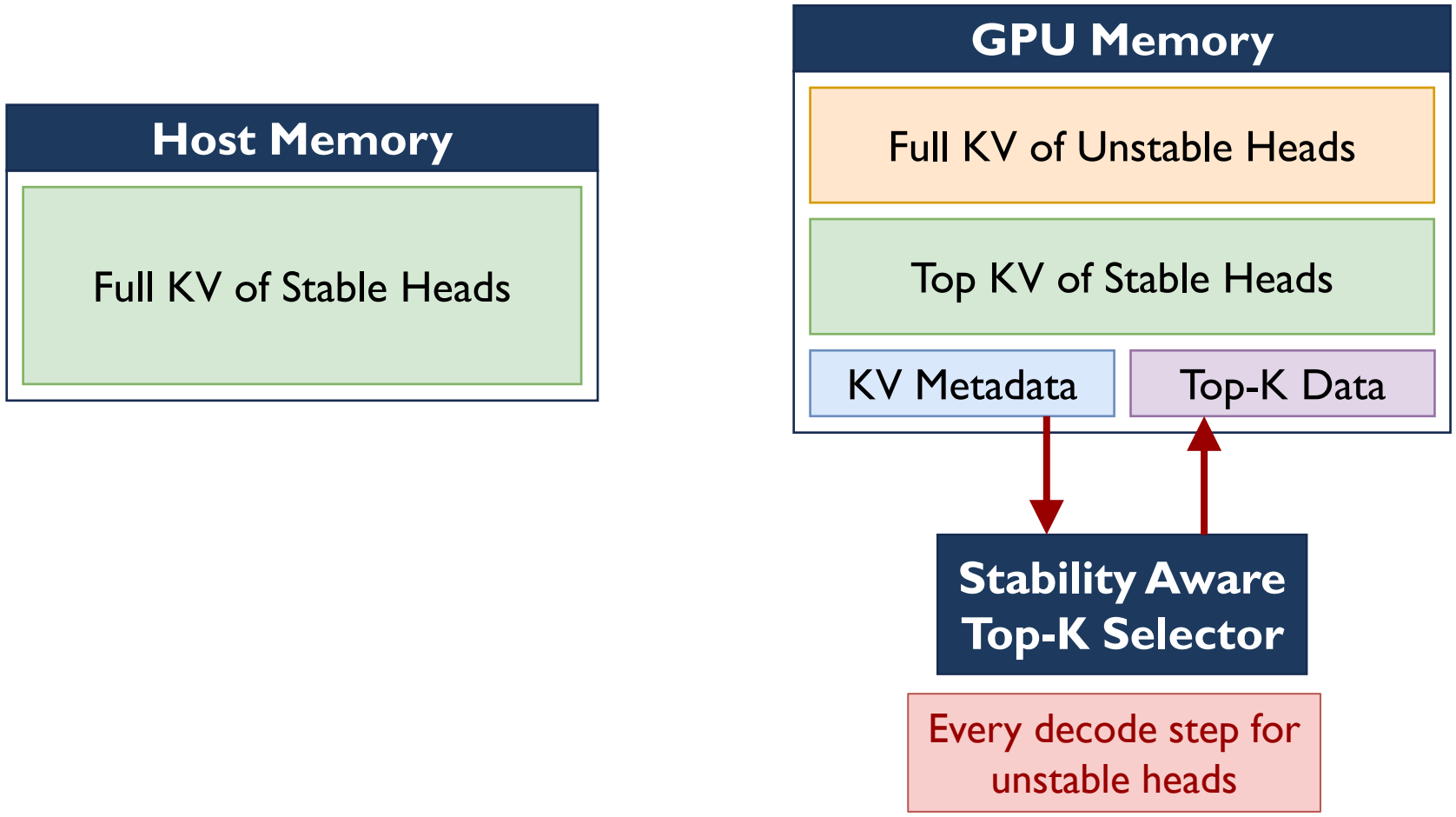

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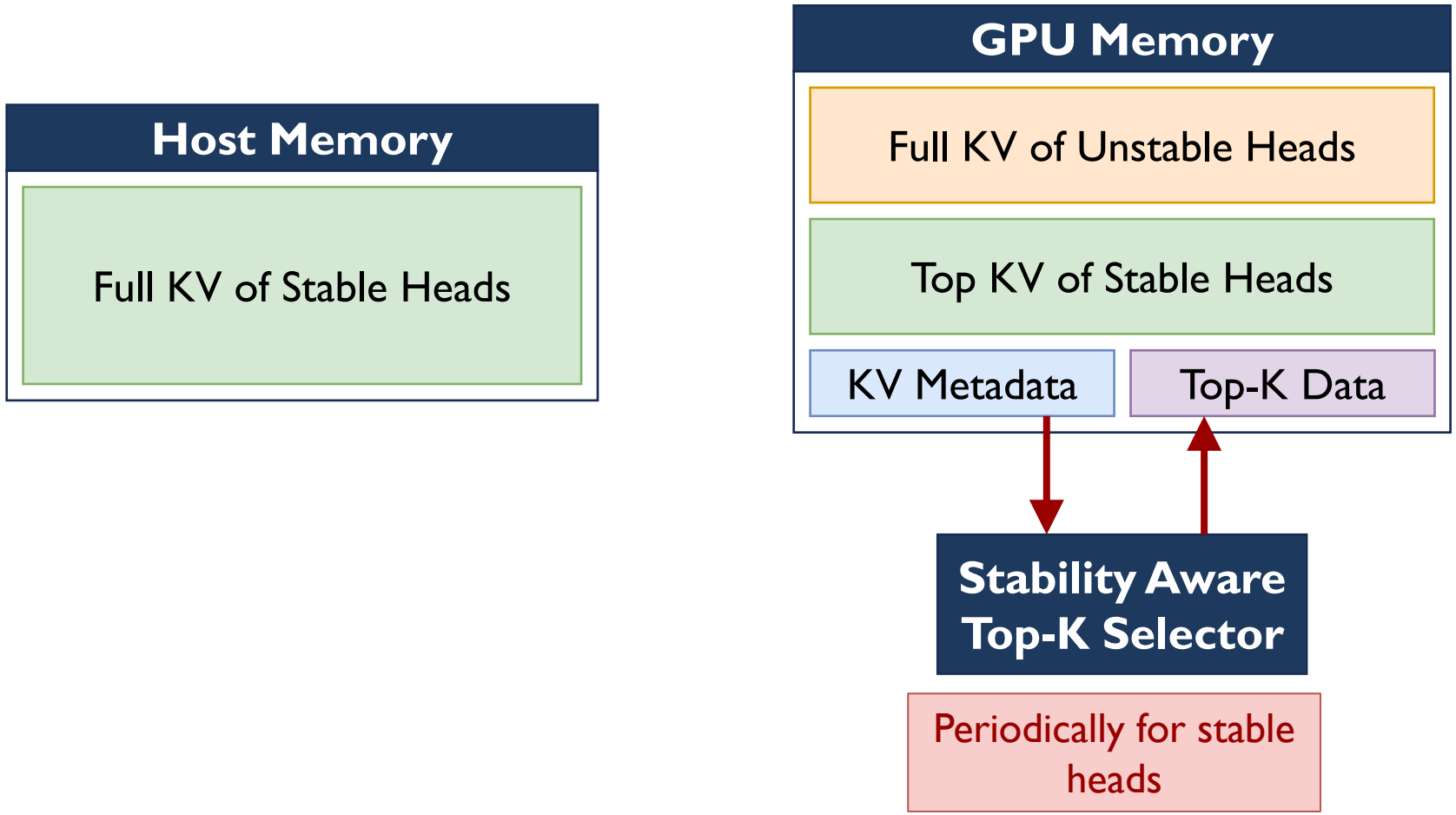

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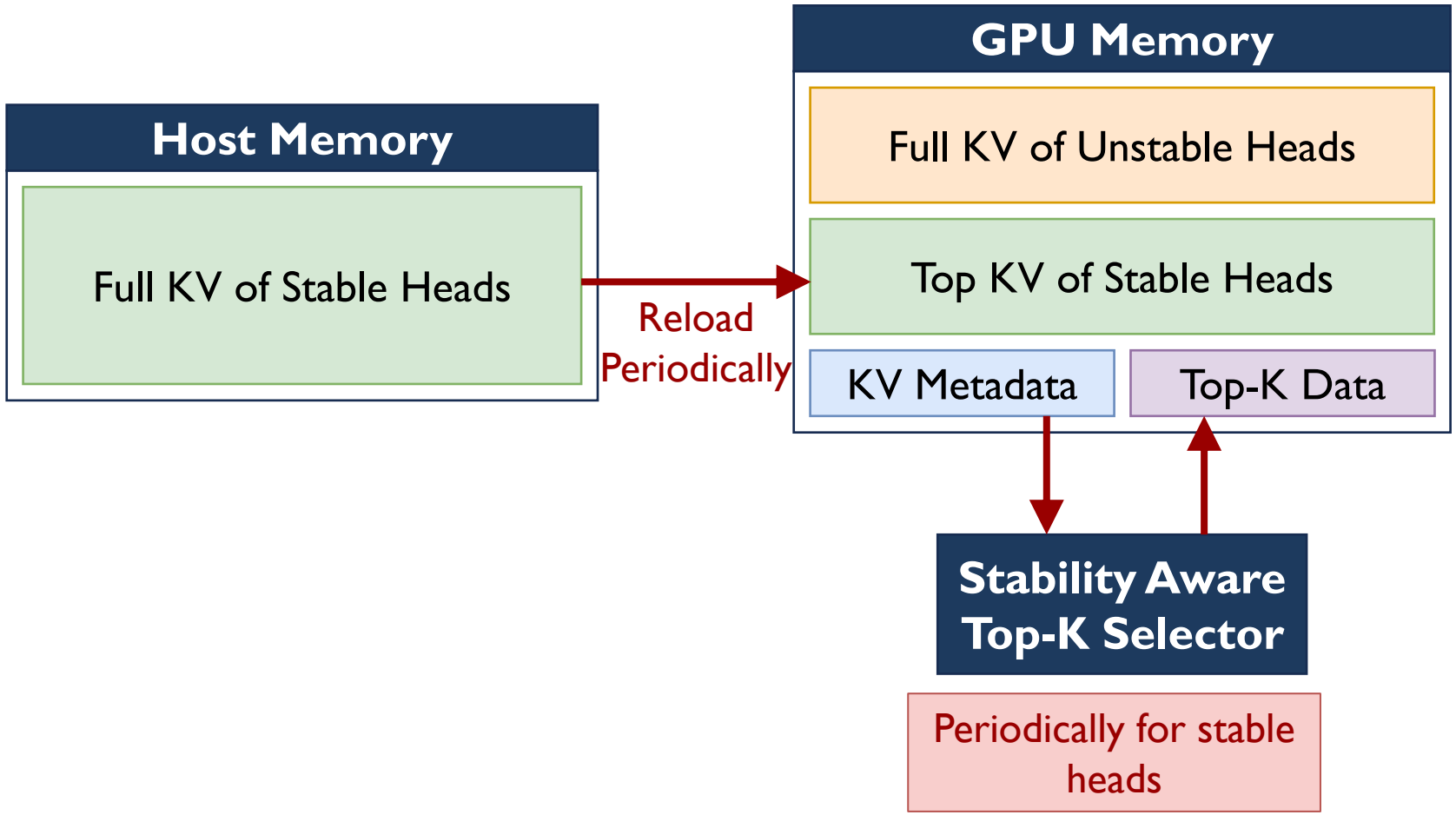
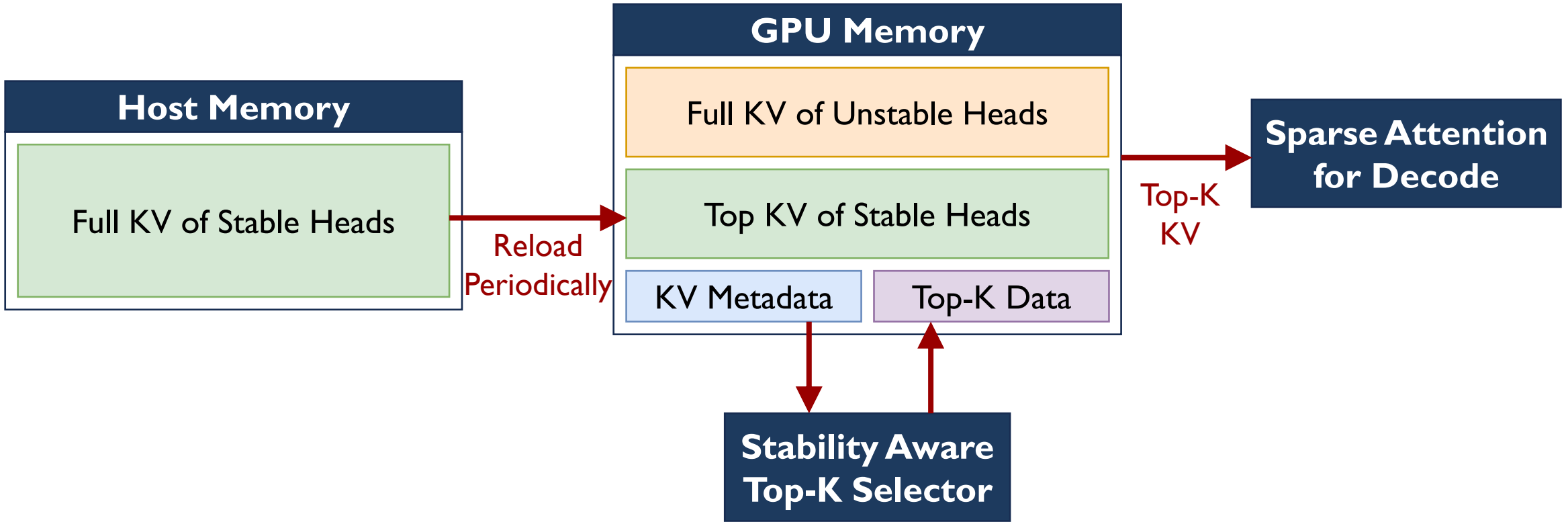


FlexiCache: Sparse Decode on Top-K KV



FlexiCache: Selecting Top-K KV

Query-aware page scoring

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FlexiCache: Selecting Top-K KV

Query-aware page scoring

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- **Stability-aware reranking**
  - Unstable heads: rerank every decode step
  - Stable heads: rerank periodically and reuse Top-K pages between reranks

FlexiCache: Other Optimizations

Efficient Host-GPU KV Movement

Efficient Block Table Management

More details in the paper …

Implementation

- Built on top of vLLM
- Modified Triton Flash-Decoding kernel
  - Decode attention only over selected Top-K KV pages
- Optimized KV movement with custom CUDA kernels
  - Overlap KV offload/reload with compute

Evaluation

- **Models**
  - Llama-3.1-8B-Instruct, Mistral-7B-Instruct-v0.2, Mistral-Small-24B, Qwen2.5-32B

- **Testbed:**
  - NVIDIA H100 GPU (94 GB) and 180 GB allocated on host memory for offloaded KV cache

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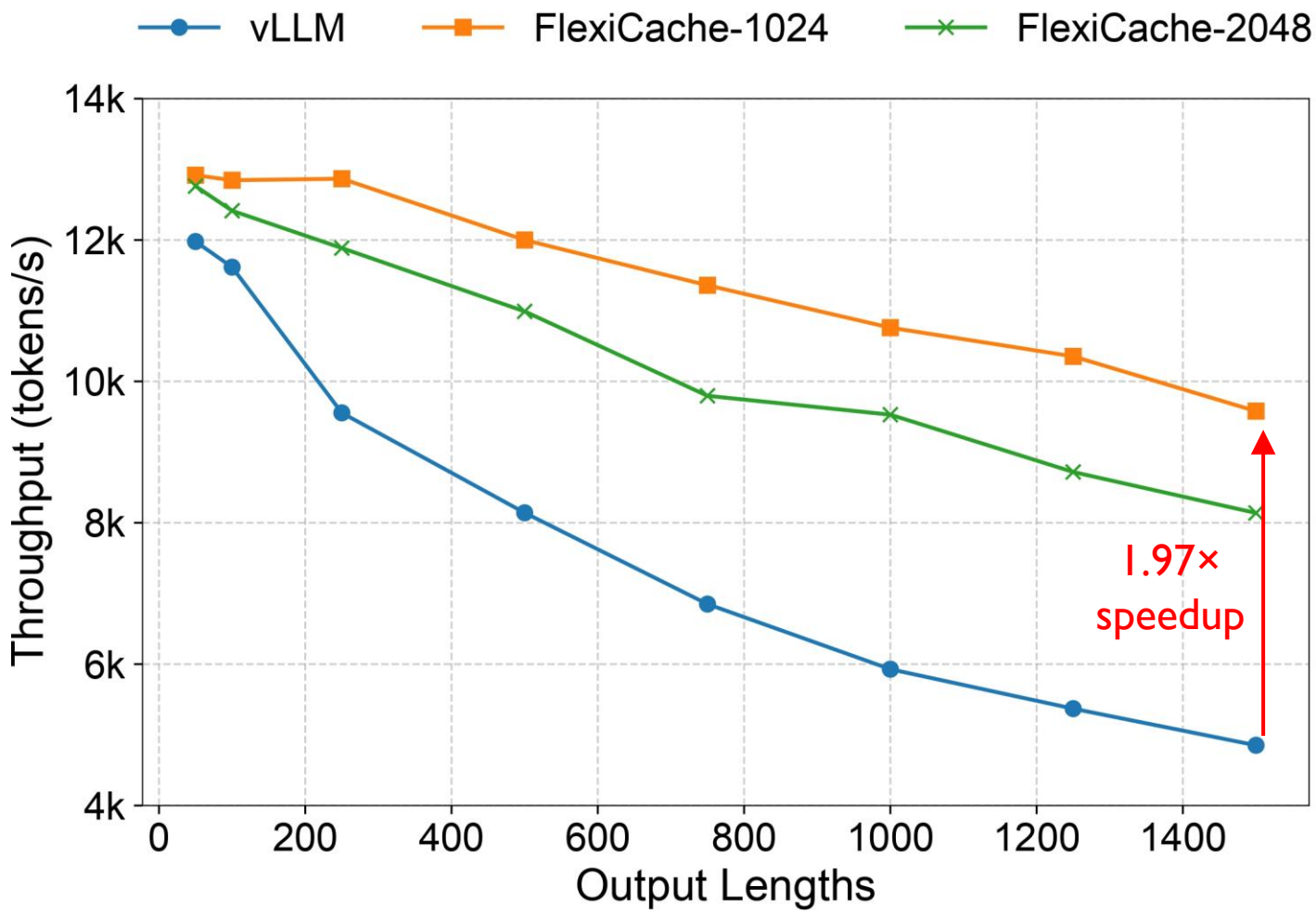
- FlexiCache consistently outperforms vLLM across output lengths

End-to-end token throughput for Llama-3.1-8B-Instruct on L-Eval



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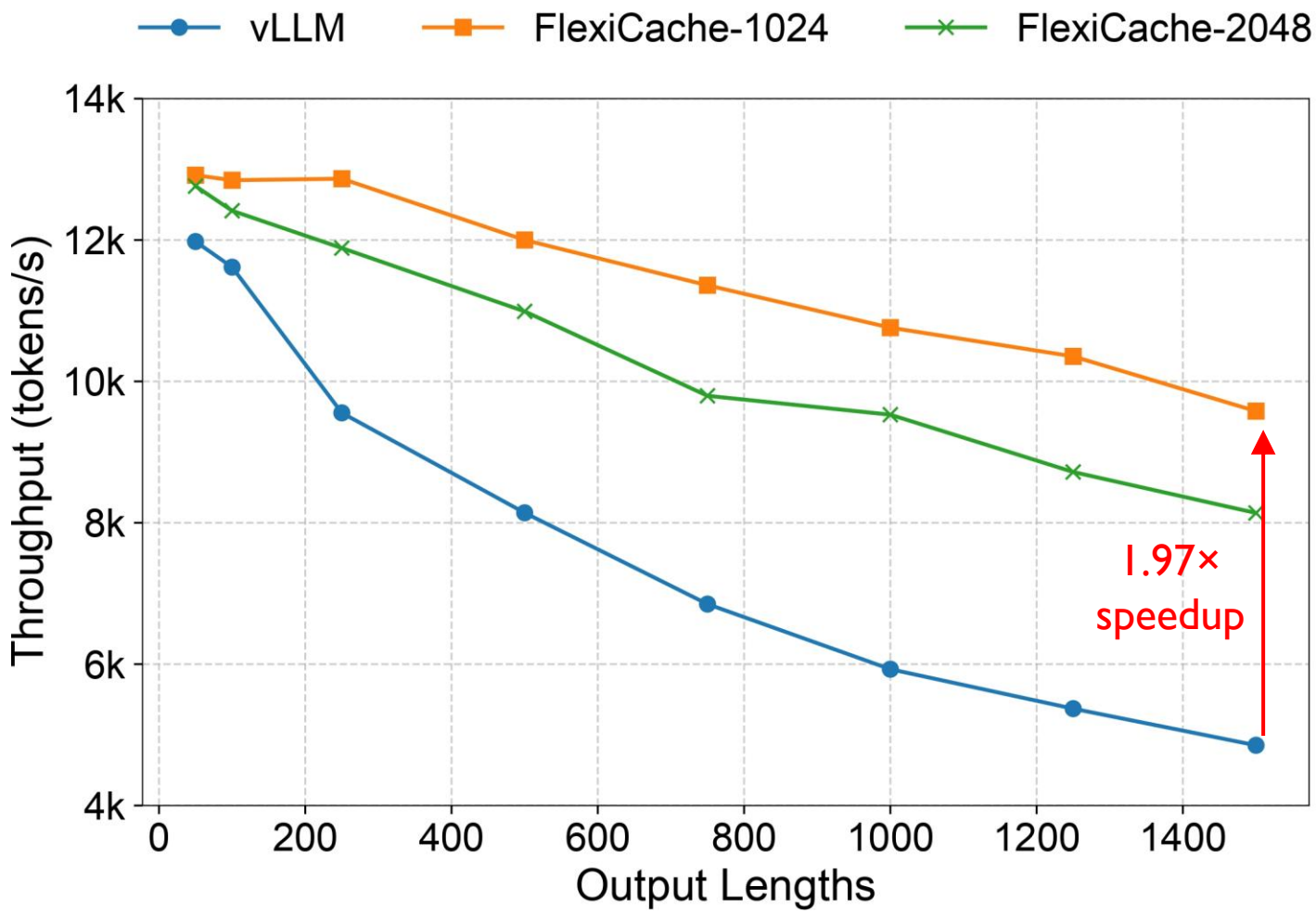

Offline Serving: Up to 1.97× Higher Throughput

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- Smaller Top-K budget → higher throughput
  FlexiCache-1024 > FlexiCache-2048

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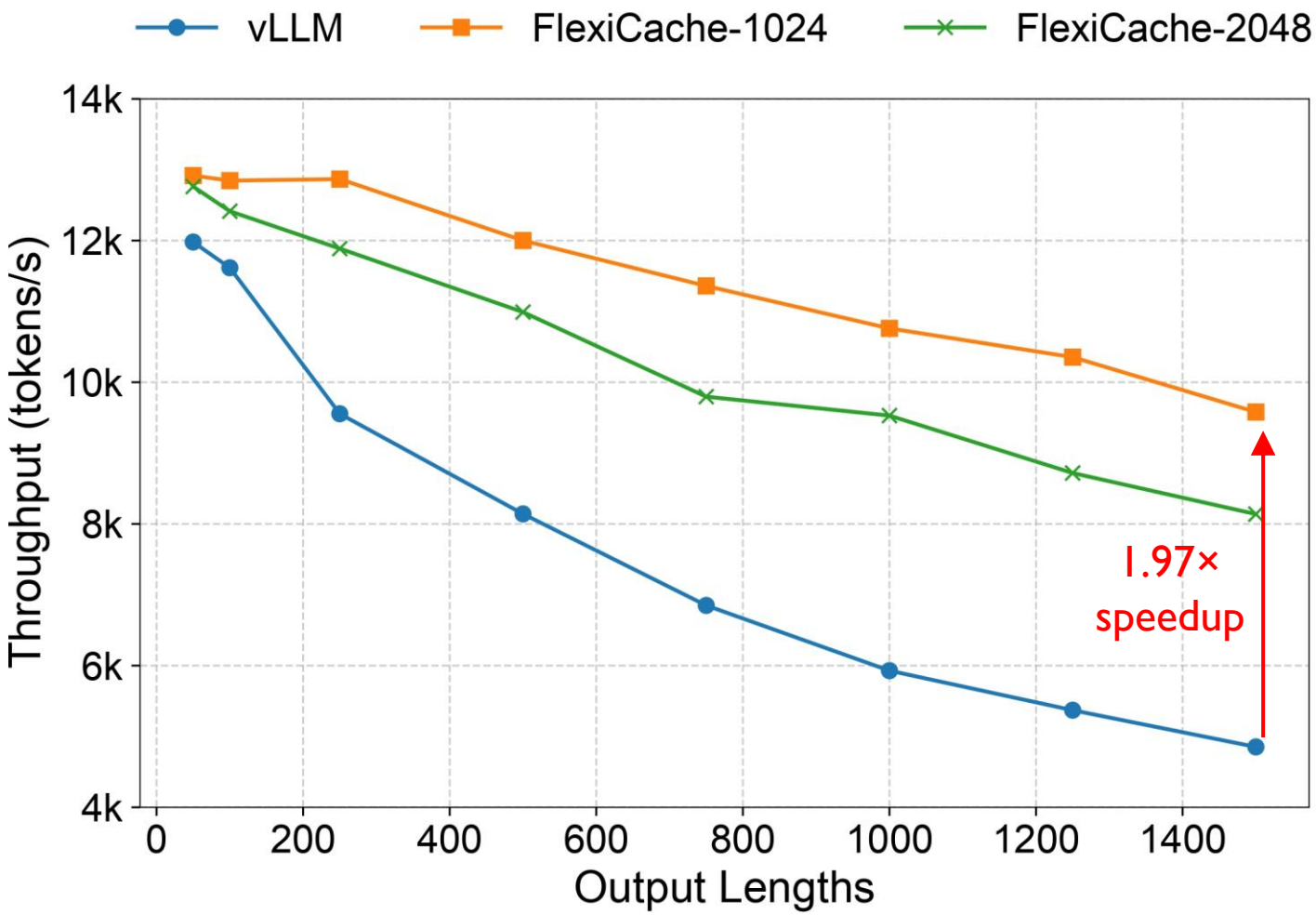

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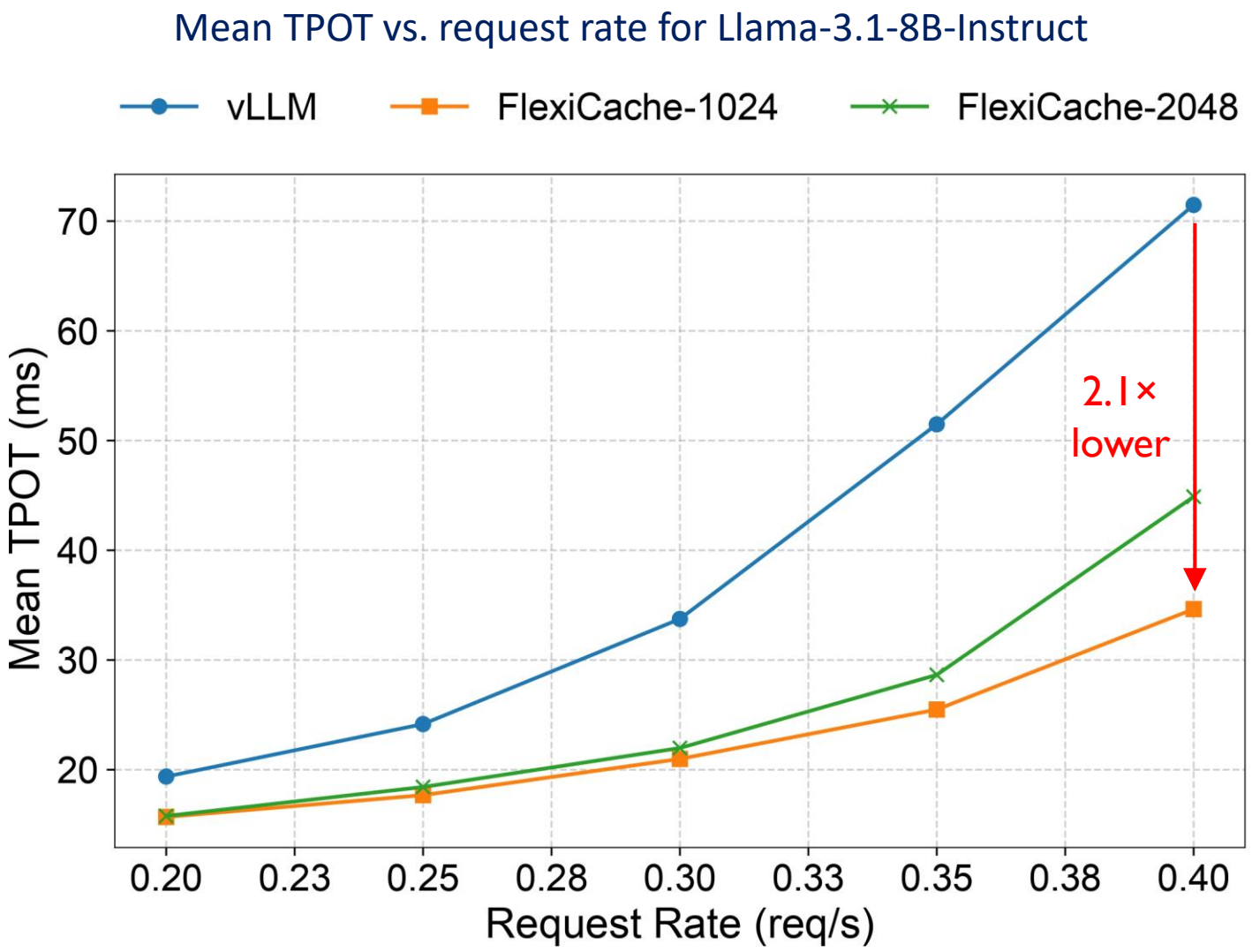

Online Serving: Up to 2.1× Lower TPOT

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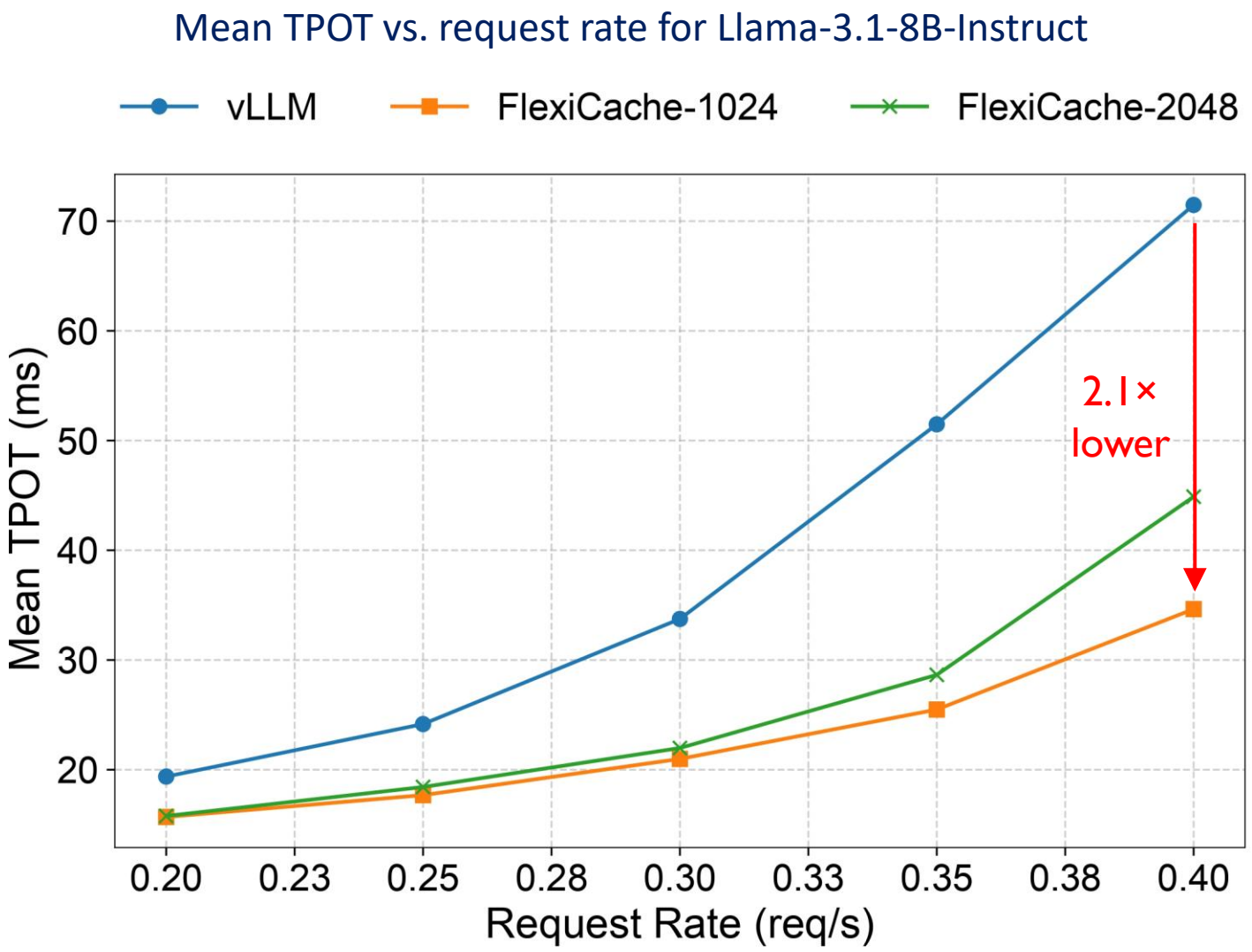
- Higher request rate → higher HBM pressure → larger FlexiCache gains



Accuracy Retention: ≈ Full-KV Accuracy

Accuracy retention on selected L-Eval tasks

Model	Method	Long-FQA	Gov-Report	CUAD	Multi-News	Retention Ratio Avg.
Llama 3.1 8B Instruct	Full KV	49.6	27.2	37.2	17.5	1.01
	FlexiCache	50.8	26.2	38.1	18.0	
Mistral 7B Instruct	Full KV	48.5	27.5	35.3	15.4	1.01
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- Paper reports similar accuracy retention across more models and datasets

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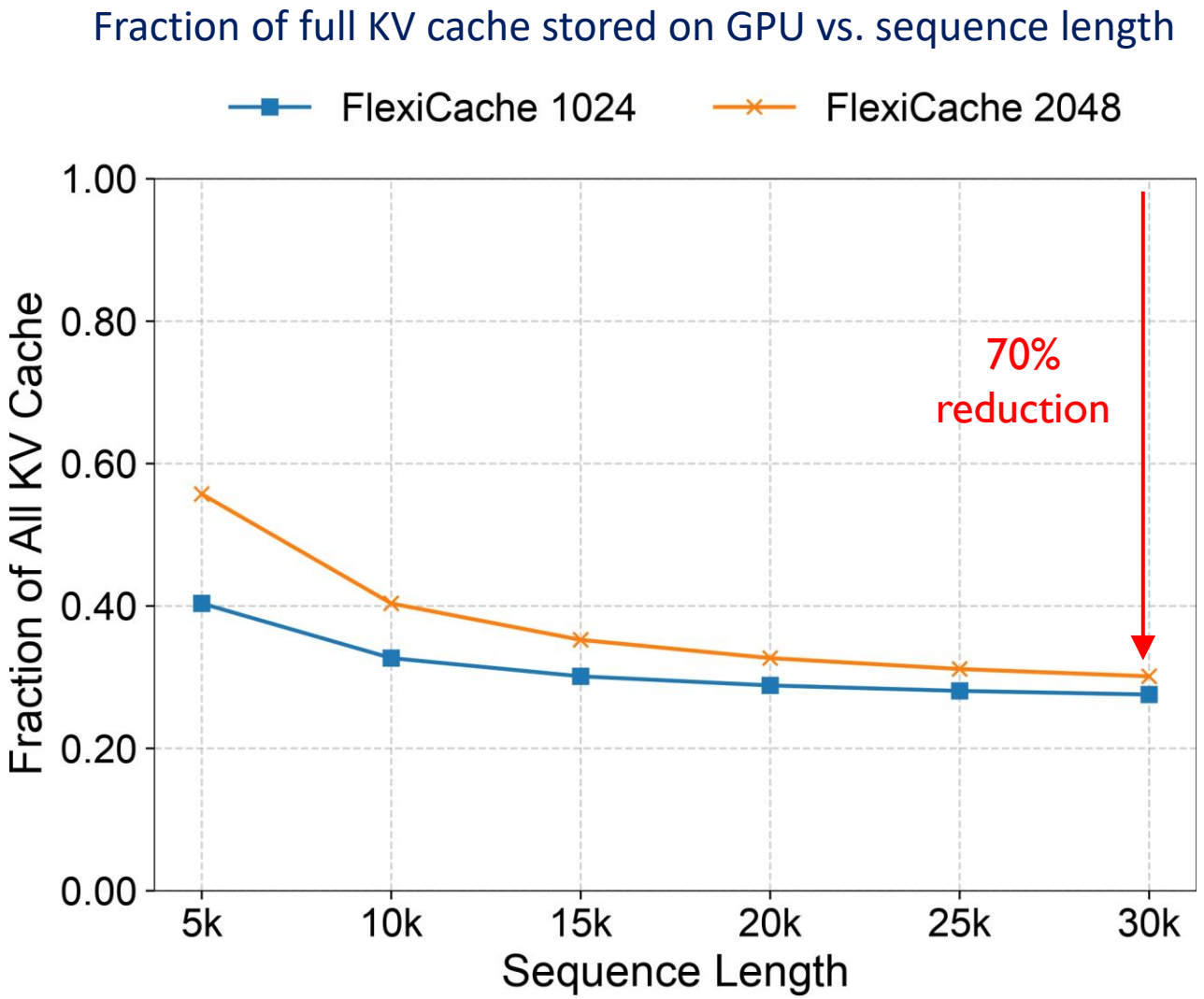

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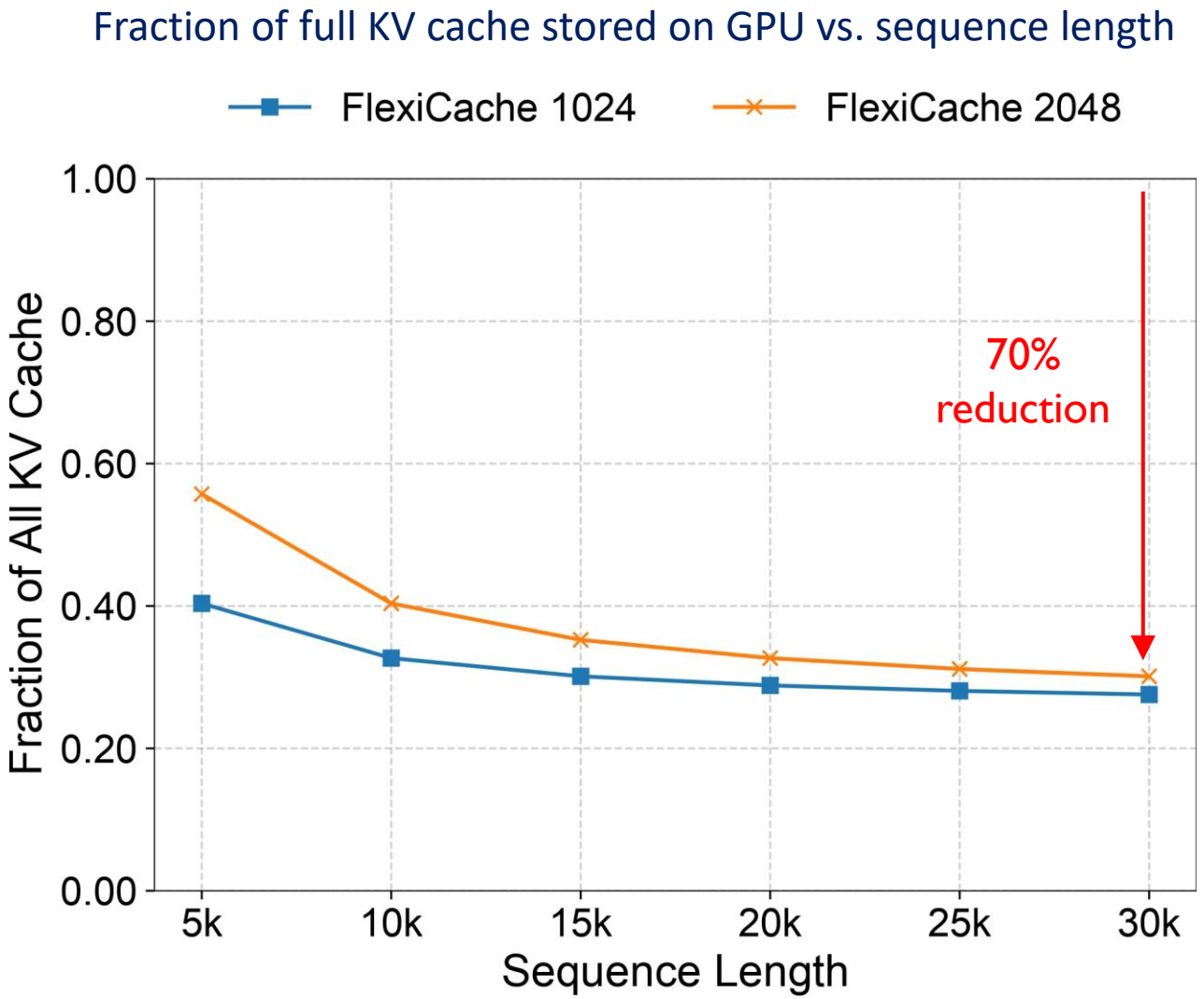
- With Top-K = 1024, FlexiCache achieves over 70% GPU memory savings beyond 20k tokens



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https://github.com/NazmulTakbir/FlexiCache