15-442/15-642: Machine Learning Systems

Attention Optimizations

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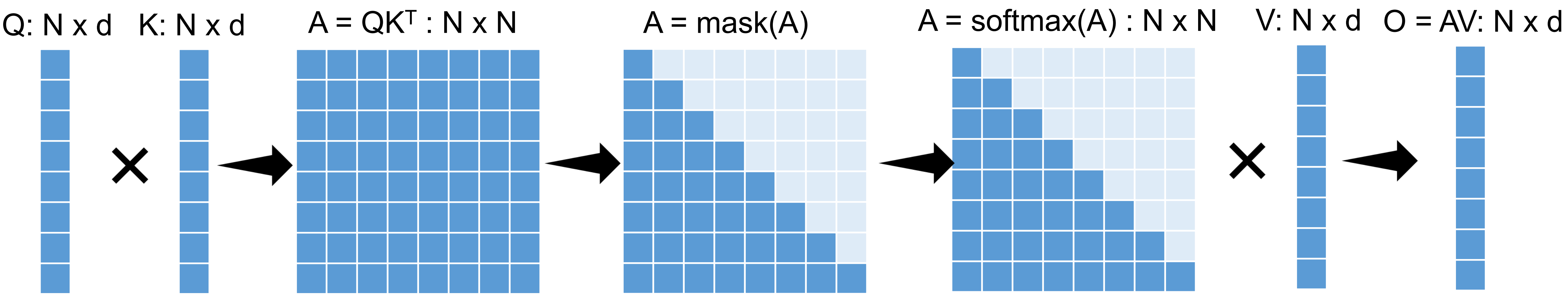
Attention: $O = \text{Softmax}(QK^T)\,V$



Challenges:

- Large intermediate results
- Repeated reads/writes from GPU device memory
- Cannot scale to long sequences due to O(N^2) intermediate results

Outline: Attention Optimizations

Part 1: LLM Training

- FlashAttention

Part 2: LLM Inference

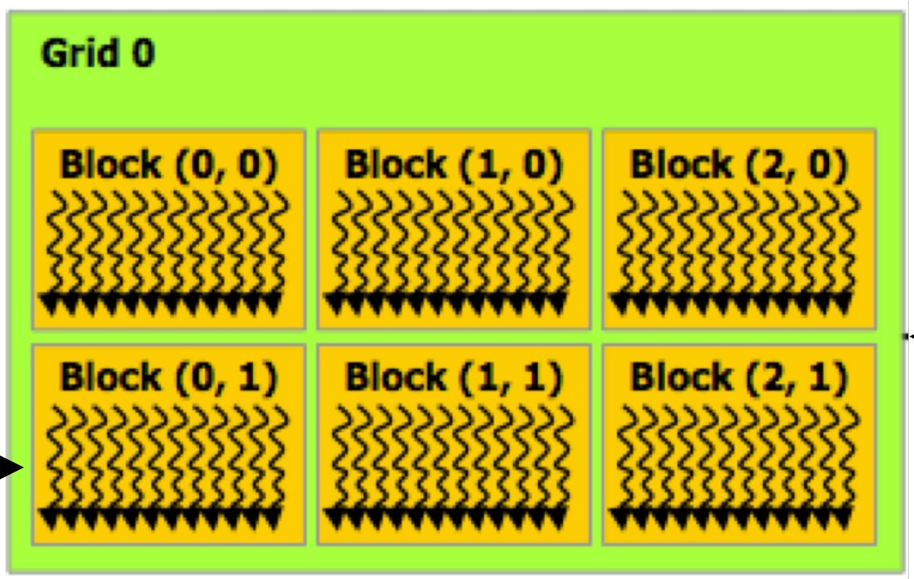
- Flash Decoding
- PagedAttention

These techniques are highly tailored for GPUs

Revisit: GPU Memory Hierarchy

Per-block **shared memory** (readable/writable by all threads in a block)

19 TB/s (20 MB)

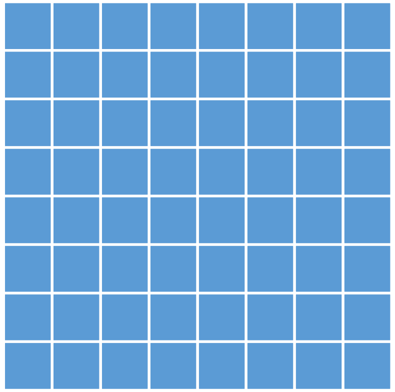


Device global memory (readable/writable by all threads)

1.5 TB/s (80 GB)

FlashAttention

$A = \text{softmax}(QK^T)$



Key idea: compute attention by blocks to reduce global memory access

Two main Techniques:

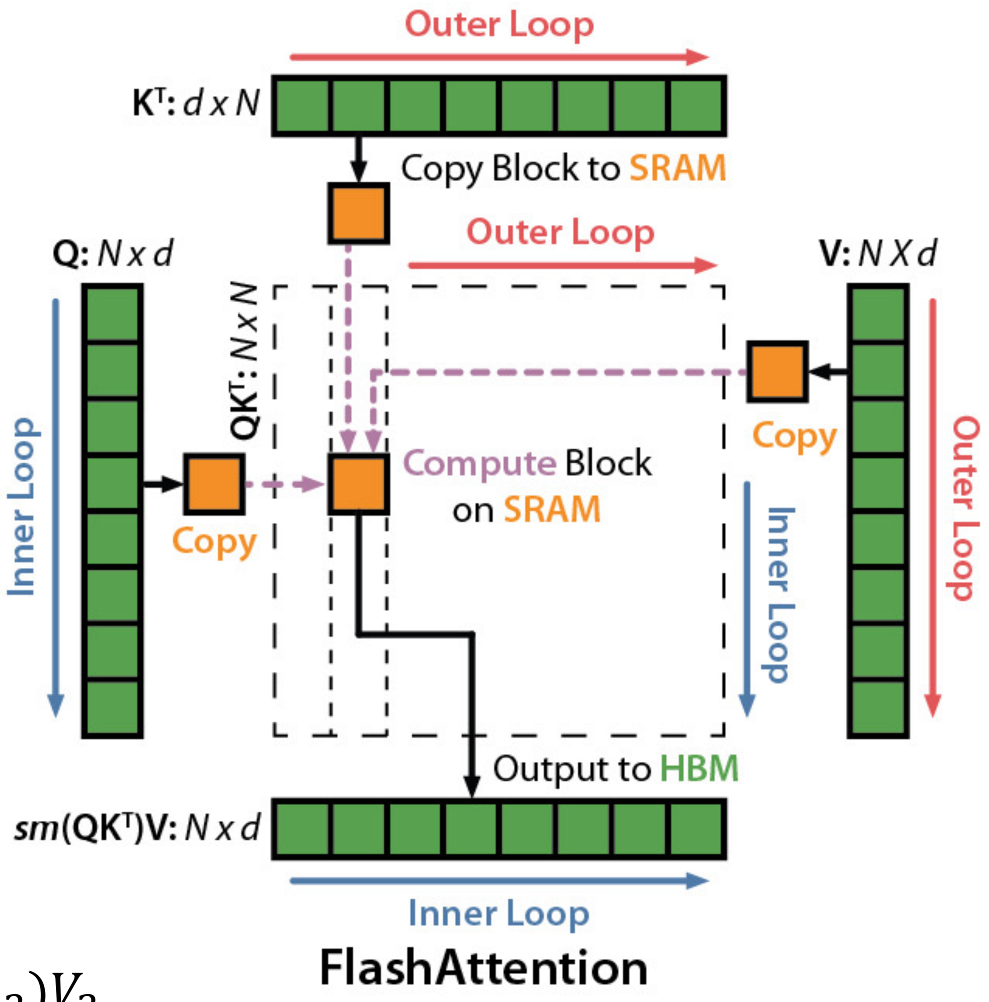
1. **Tiling:** restructure algorithm to load query/key/value block by block from global to shared memory

2. **Recomputation:** don’t store attention matrix from forward, recompute it in backward

* FlashAttention: Fast and Memory-Efficient Exact Attention with IO-Awareness

Tiling: Decompose Large Softmax into smaller ones by Scaling

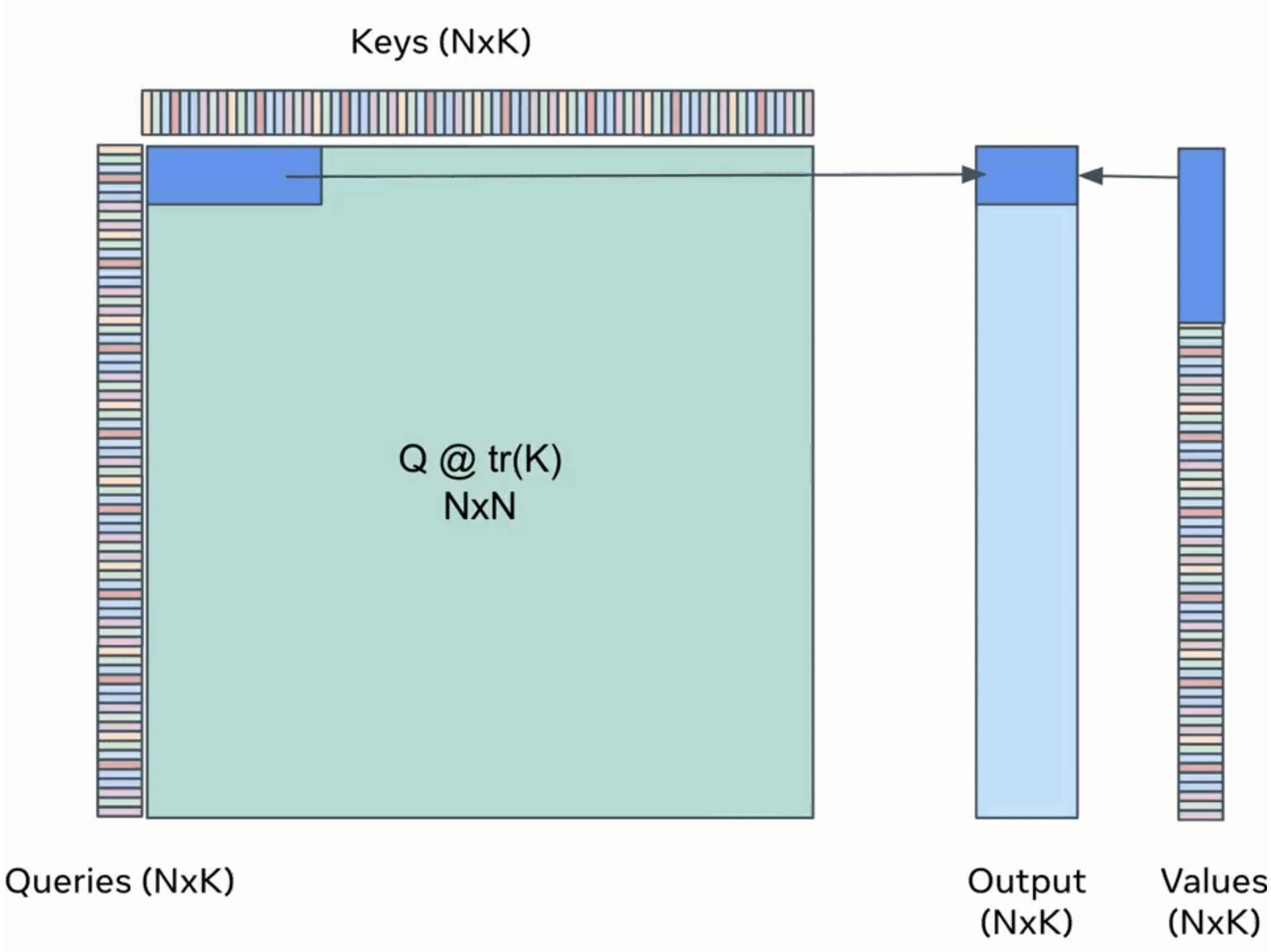
1. Load inputs by blocks from global to shared memory
2. On chip, compute attention output wrt the block
3. Update output in device memory by scaling



$$softmax([A_1, A_2]) = [\alpha \times softmax(A_1), \beta \times softmax(A_2)]$$

$$softmax([A_1, A_2]) \begin{bmatrix} V_1 \\ V_2 \end{bmatrix} = \alpha \times softmax(A_1)V_1 + \beta \times softmax(A_2)V_2$$

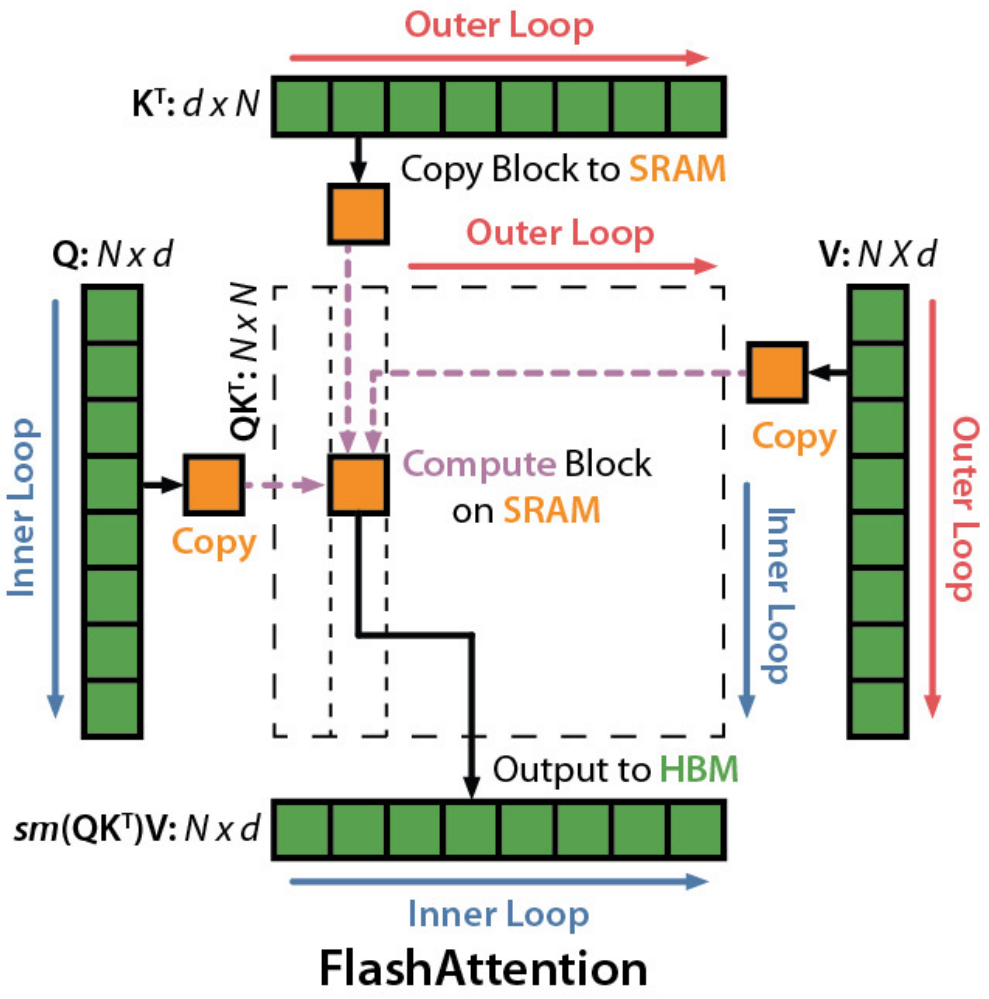
Tiling



Animation credit: Francisco Massa

Recomputation: Backward Pass

By storing softmax normalization factors from forward (size N), recompute attention in the backward from inputs in shared memory



Attention	Standard	FlashAttention
GFLOPs	66.6	75.2
Global mem access	40.3 GB	4.4 GB
Runtime	41.7 ms	7.3 ms

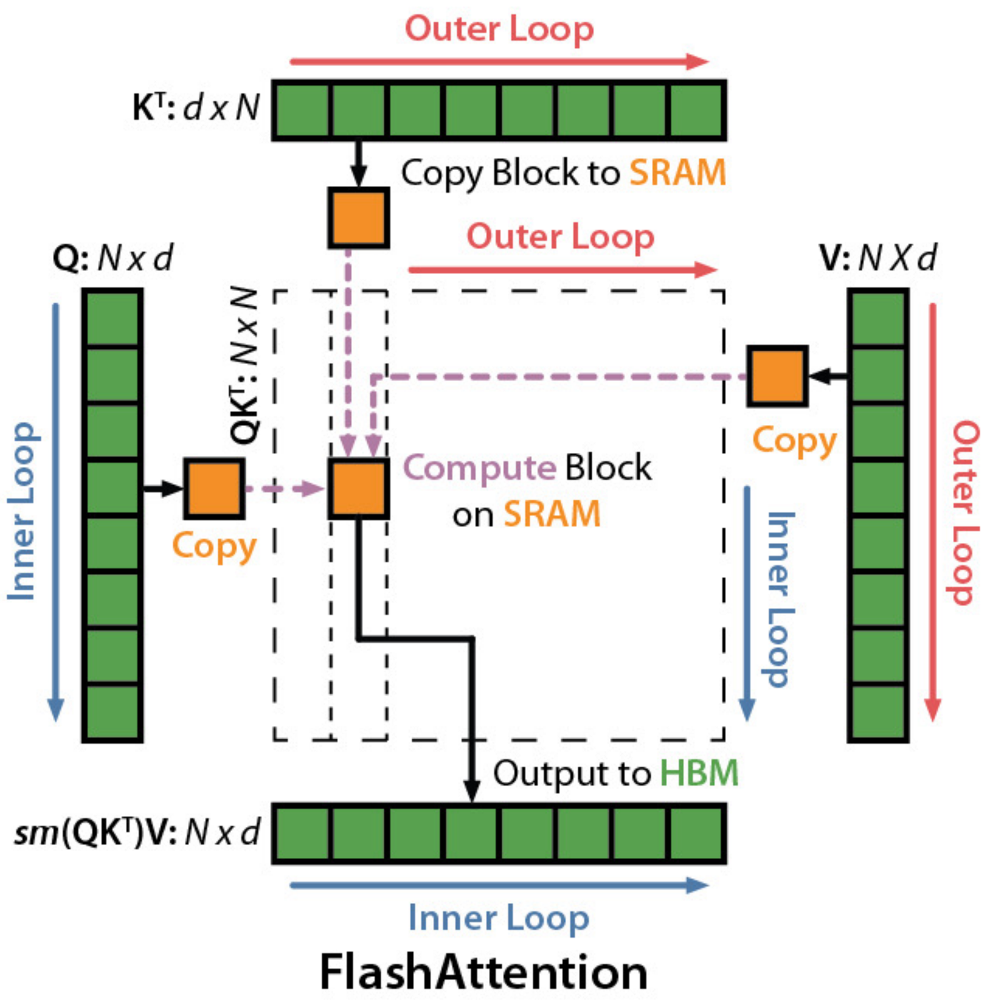
Speed up backward pass with increased FLOPs

FlashAttention: Threadblock-level Parallelism

How to partition FlasshAttention across thread blocks?

(An A100 has 108 SMMs -> 108 thread blocks)

- Step 1: assign different heads to different thread blocks (16-64 heads)



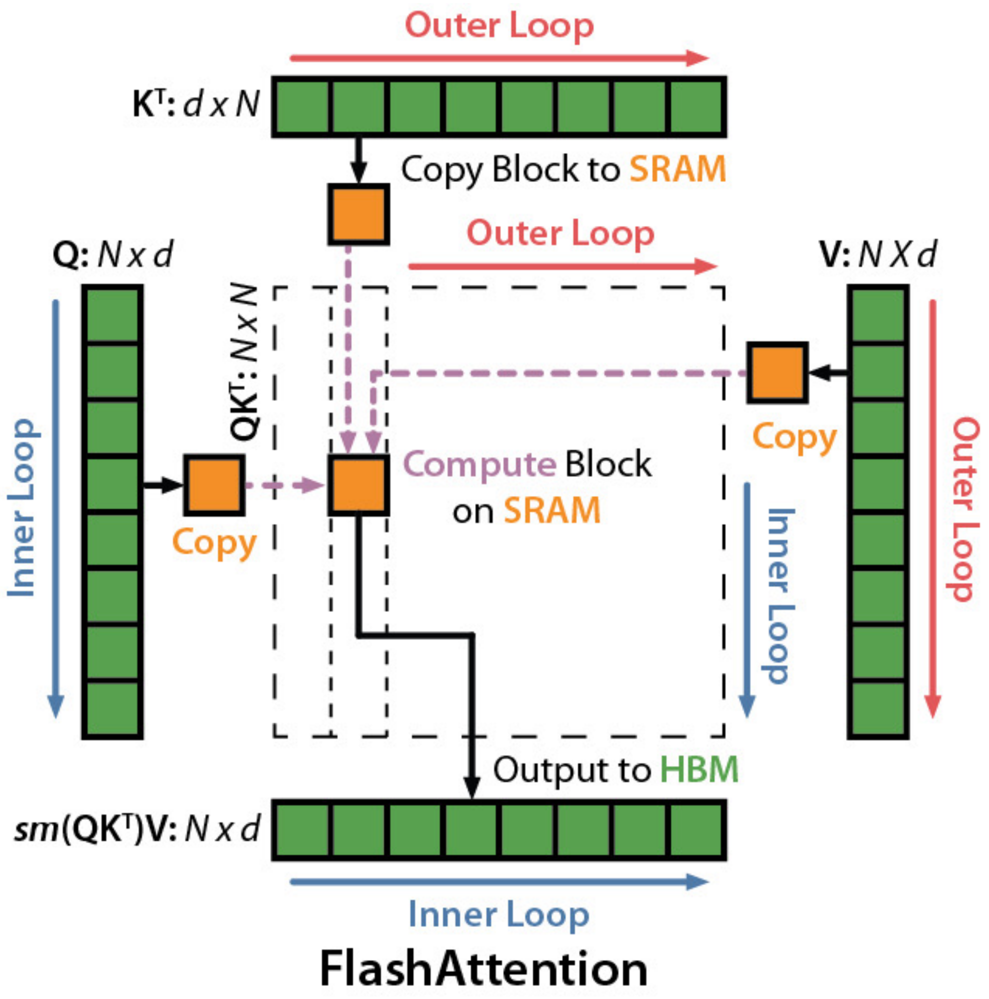
FlashAttention: Threadblock-level Parallelism

How to partition FlasshAttention across thread blocks?

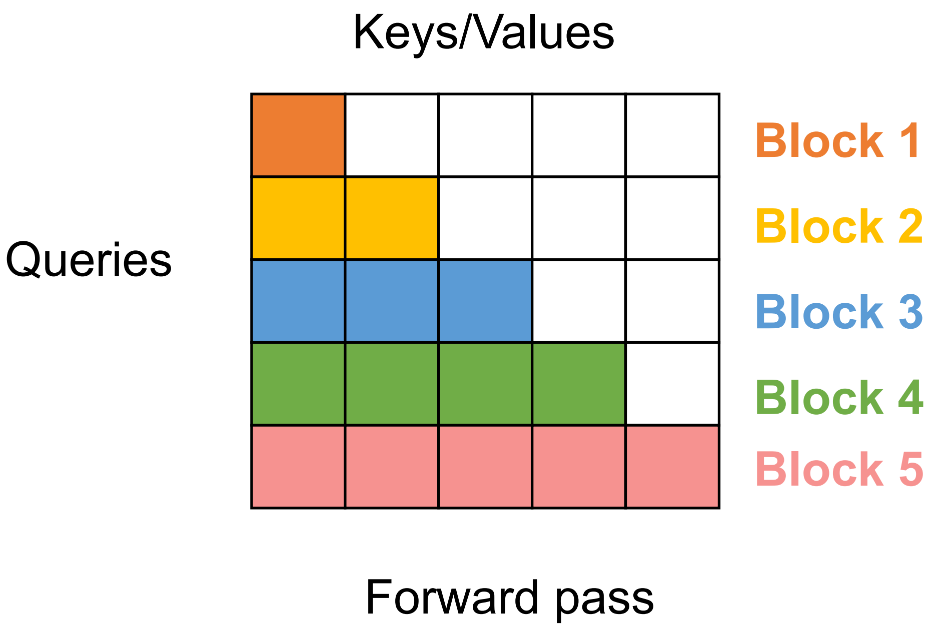
(An A100 has 108 SMMs -> 108 thread blocks)

- Step 1: assign different heads to different thread blocks (16-64 heads)
- Step 2: assign different queries to different thread blocks (Why?)

Thread blocks cannot communicate; cannot perform softmax when partitioning keys/values



FlashAttention: Threadblock-level Parallelism

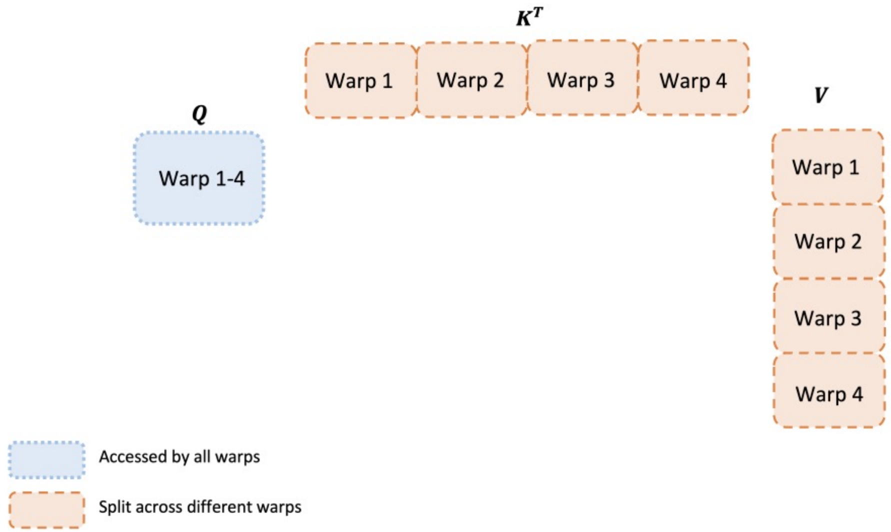


Do we need to handle workload imbalance?

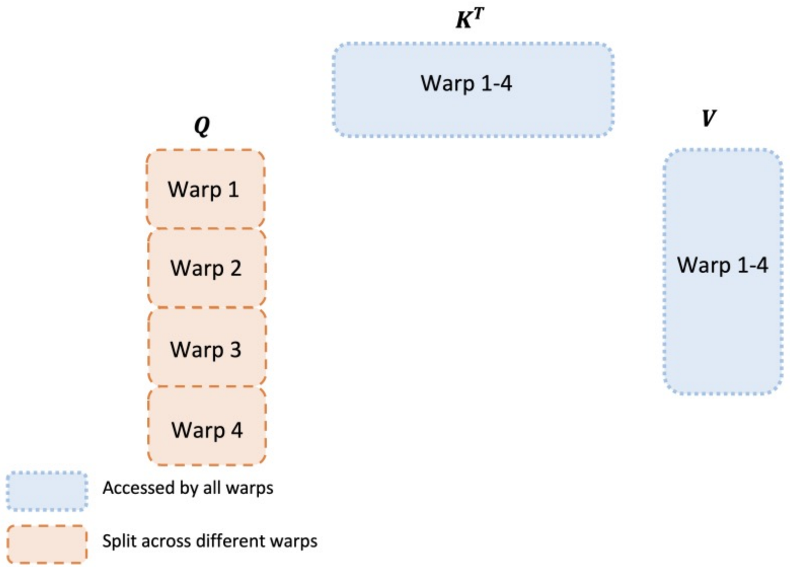
No. GPU scheduler automatically loads the next block once the current one completes.

FlashAttention: Warp-Level Parallelism

- How to partition FlashAttention across warps within a thread block?



(a) FlashAttention

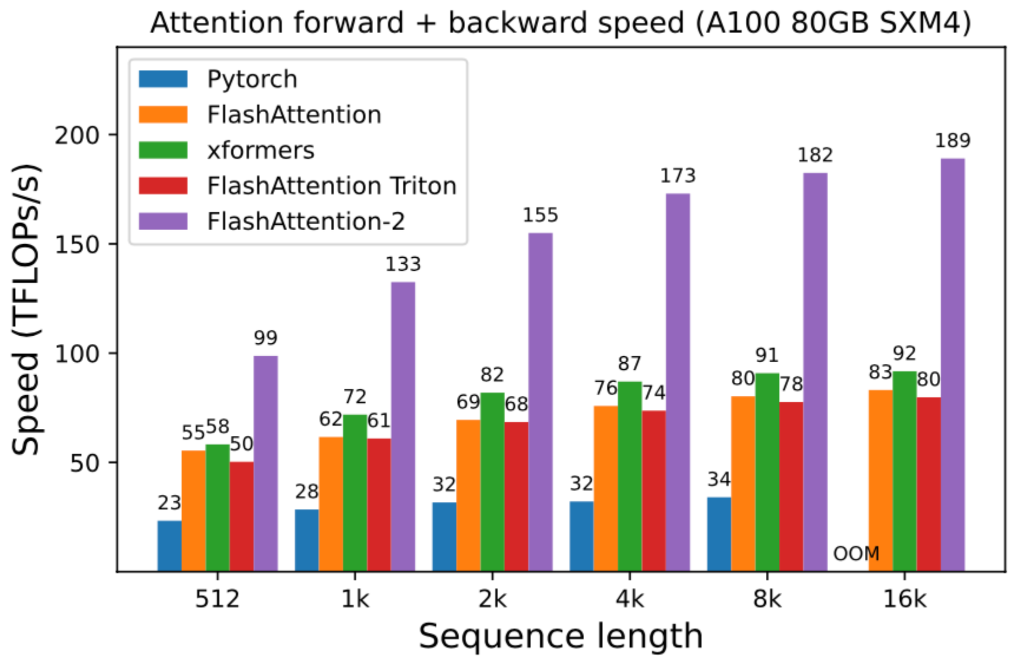


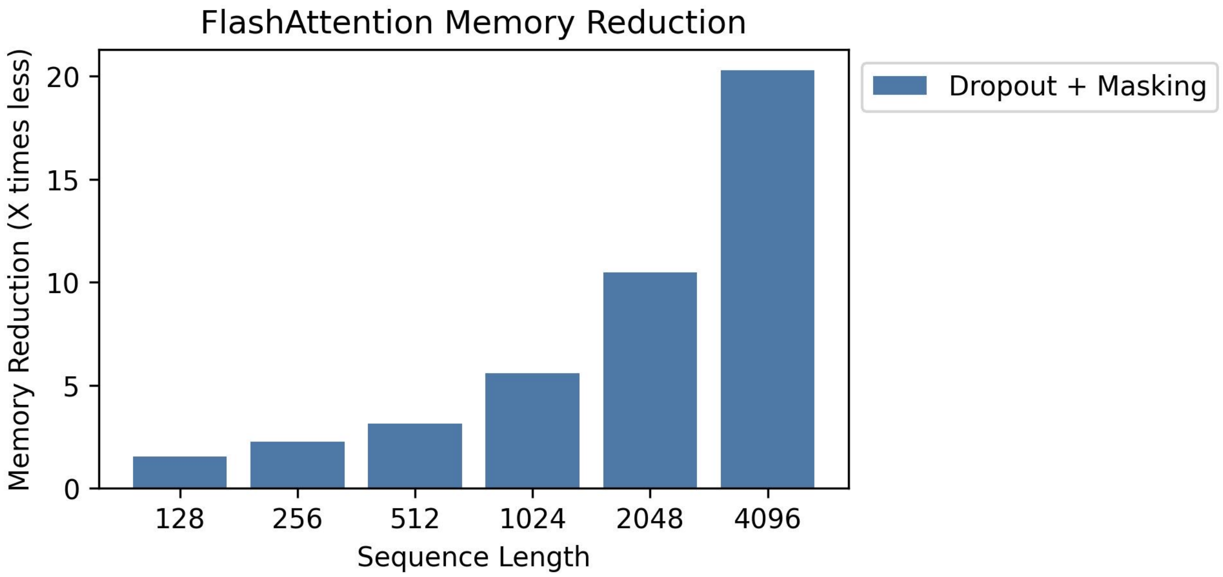
(b) FlashAttention-2

☹ Splitting across K/V requires communication to add results

Splitting across Q avoids communications ☺

FlashAttention: 2-4x speedup, 10-20x memory reduction





Memory linear in sequence length

Outline: Attention Optimizastions

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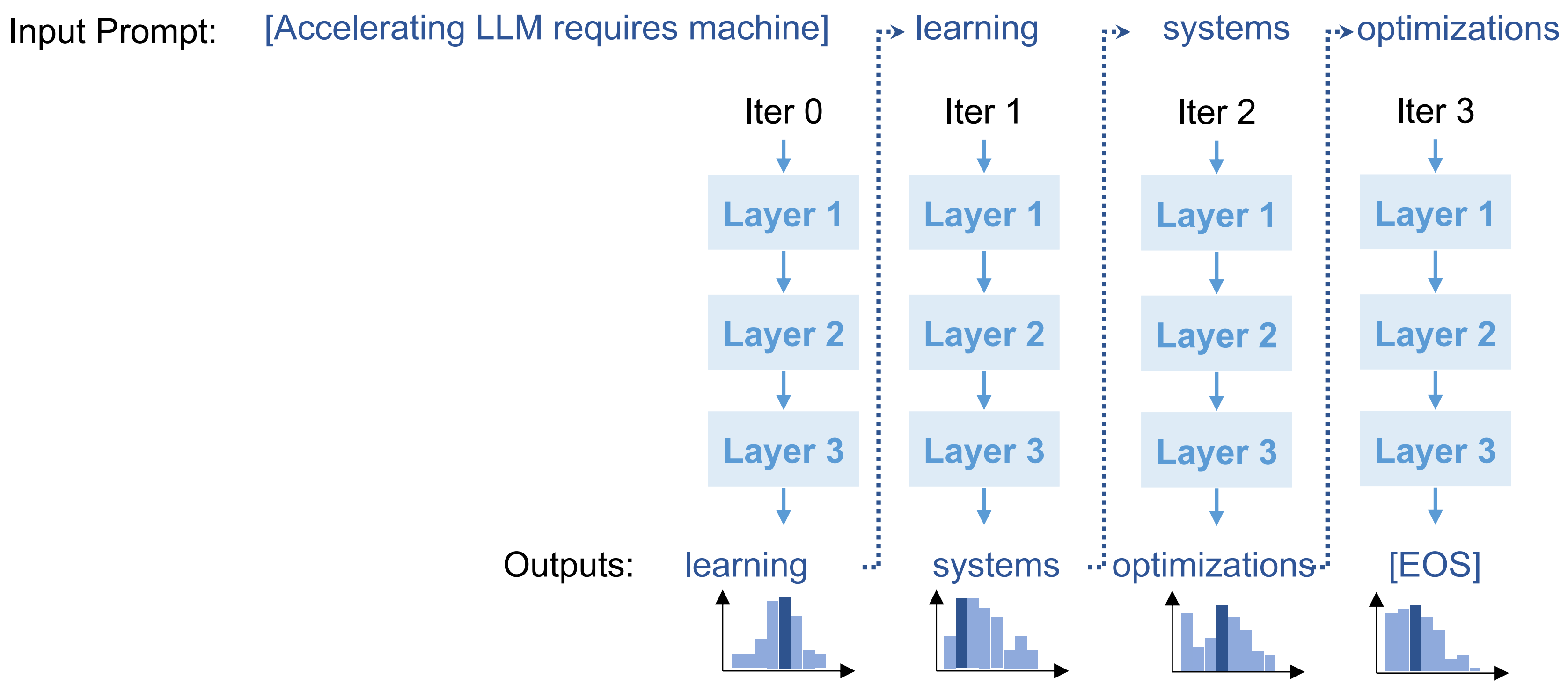
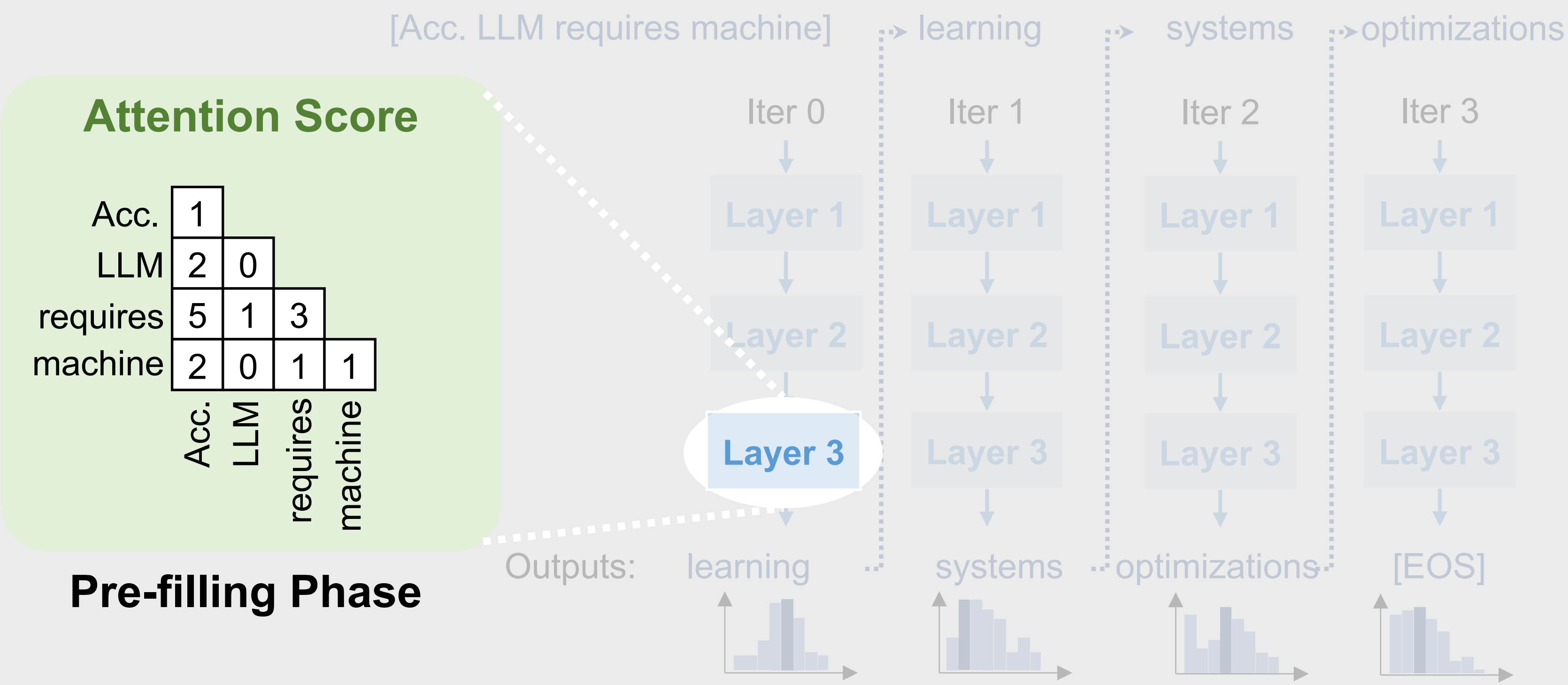
Part 2: LLM Inference (Auto-regressive Decoding)

- Flash Decoding
- PagedAttention

Generative LLM Inference: Autoregressive Decoding

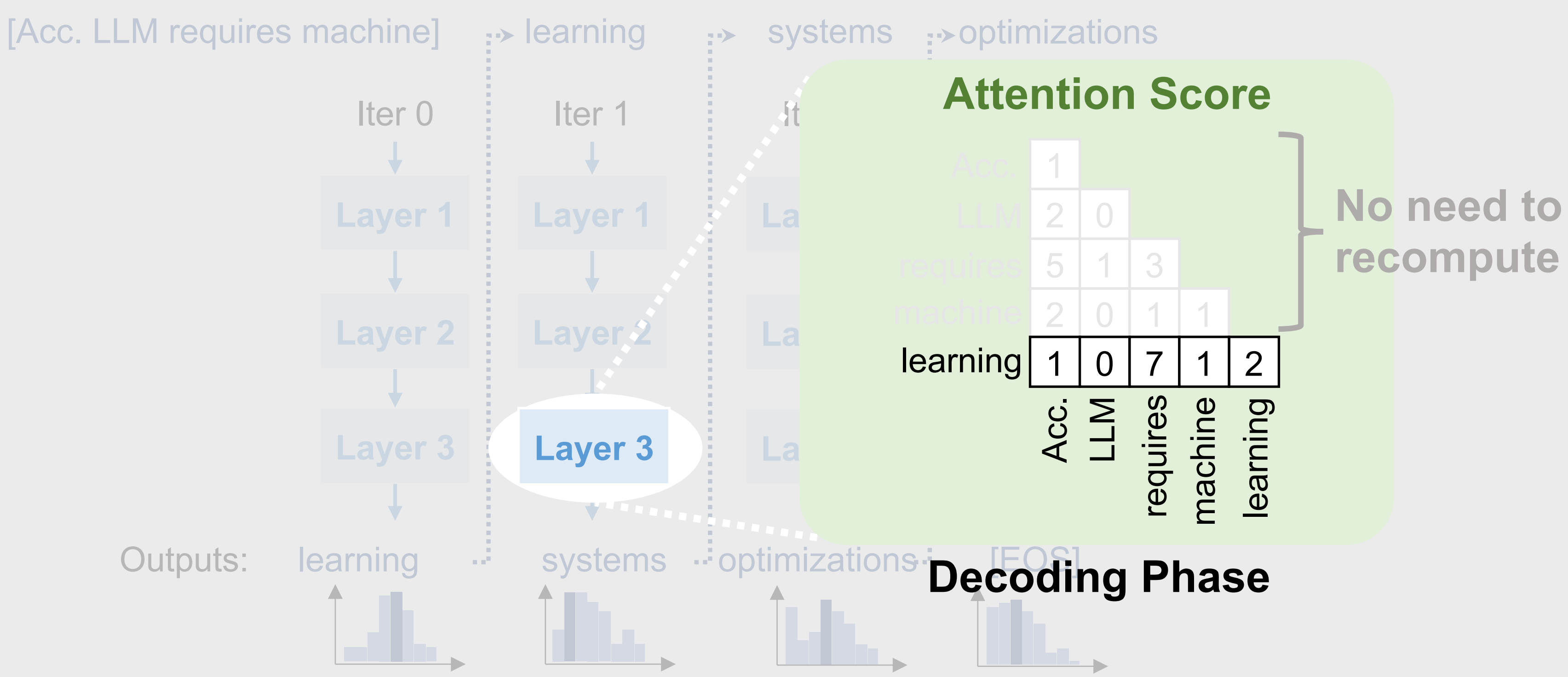


Generative LLM Inference: Autoregressive Decoding



Pre-filling Phase

Generative LLM Inference: Autoregressive Decoding



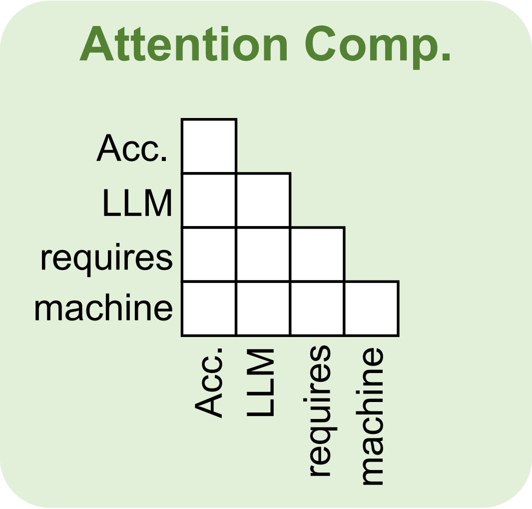
	Acc.	LLM	requires	machine	learning
Acc.	1				
LLM	2	0			
requires	5	1	3		
machine	2	0	1	1	
learning	1	0	7	1	2

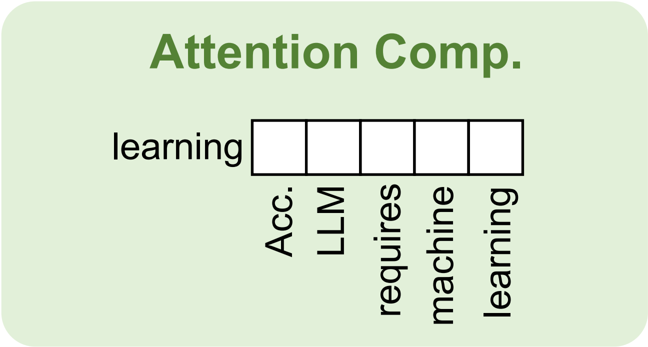
Generative LLM Inference: Autoregressive Decoding

- **Pre-filling phase** (0-th iteration):
  - Process ***all*** input tokens at once
- **Decoding phase** (all other iterations):
  - Process a ***single*** token generated from previous iteration
  - Use attention keys & values of all previous tokens

- Key-value cache:
  - Save attention keys and values for the following iterations to avoid recomputation

Can We Apply FlashAttention to LLM Inference?





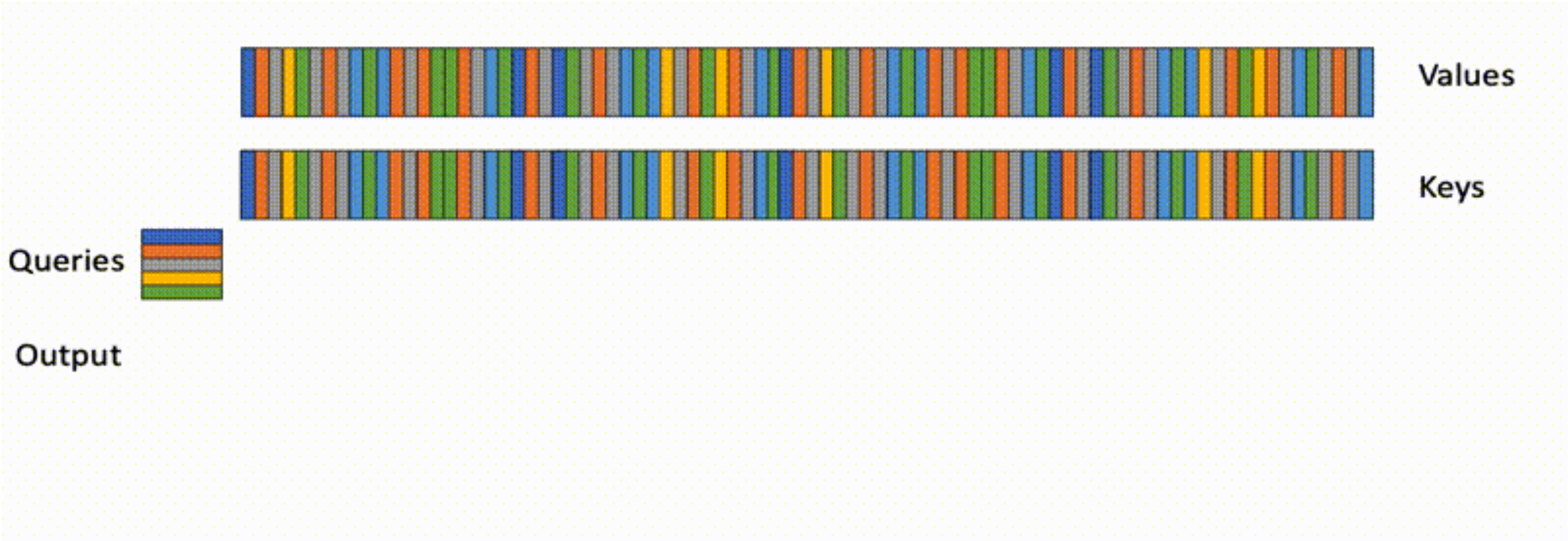
Pre-filling phase:

- Yes, compute different queries using different thread blocks/warps

Decoding phase:

- No, there is a single query in the decoding phase

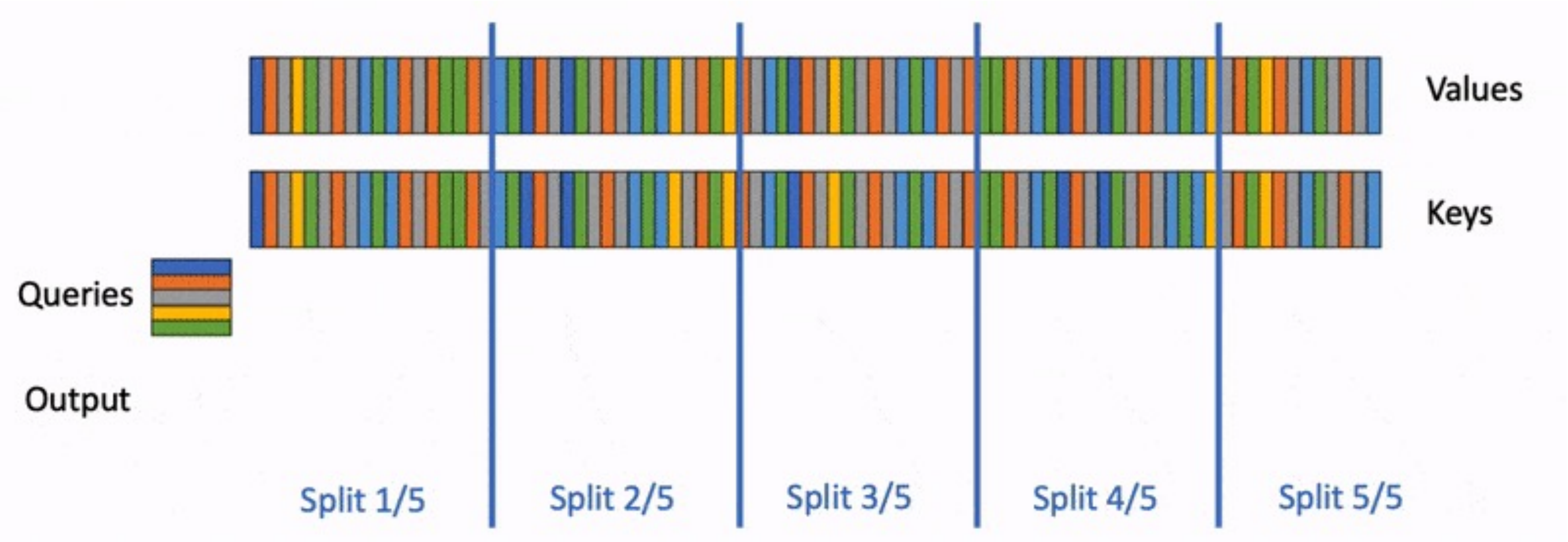
FlashAttention Processes K/V Sequentially



Inefficient for requests with long context (many keys/values)

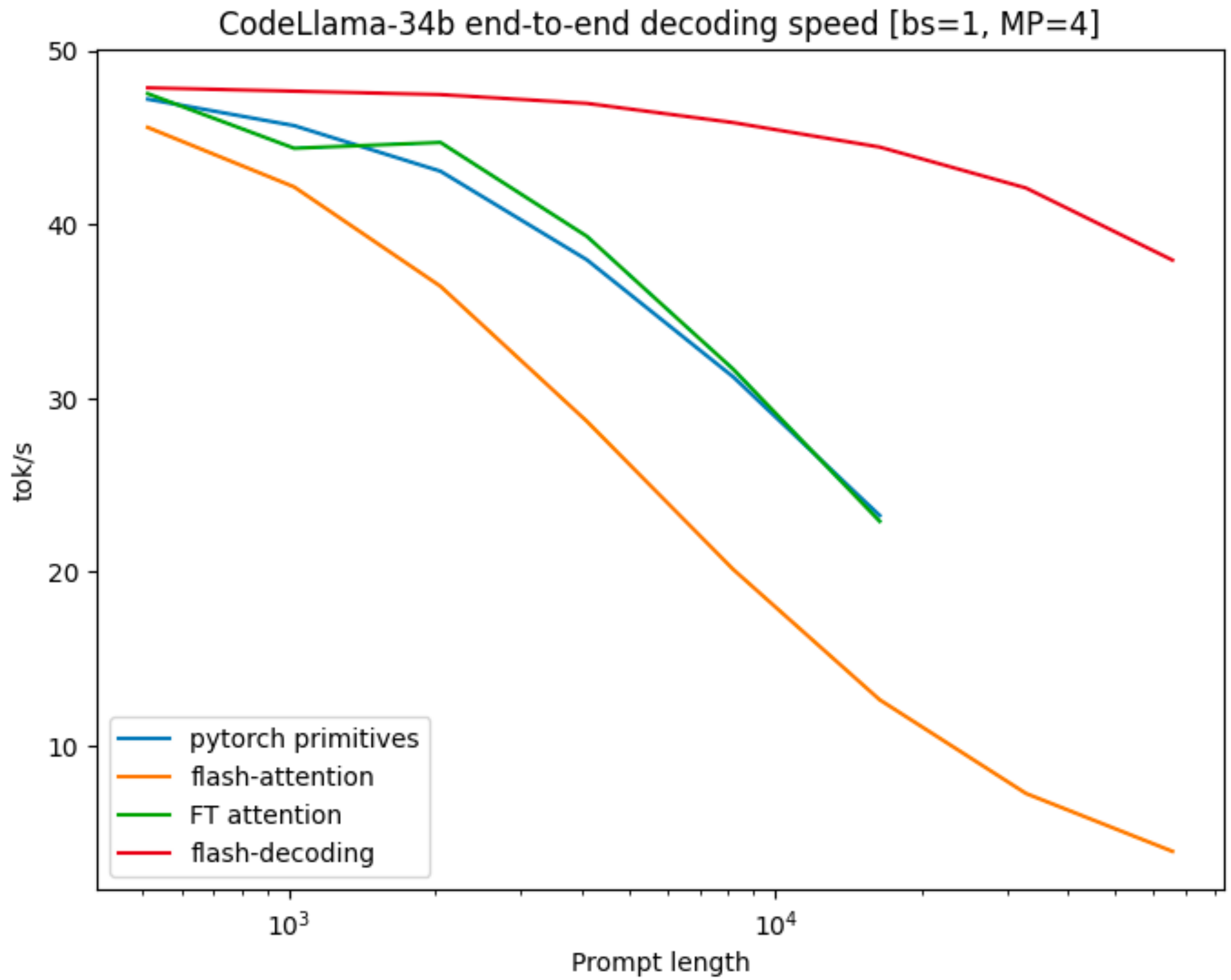
Flash-Decoding Parallelizes Across Keys/Values

1. Split keys/values into small chunks
2. Compute attention with these splits using FlashAttention
3. Reduce overall all splits



Key insight: attention is associative and commutative

Flash-Decoding is up to 8x faster than prior work



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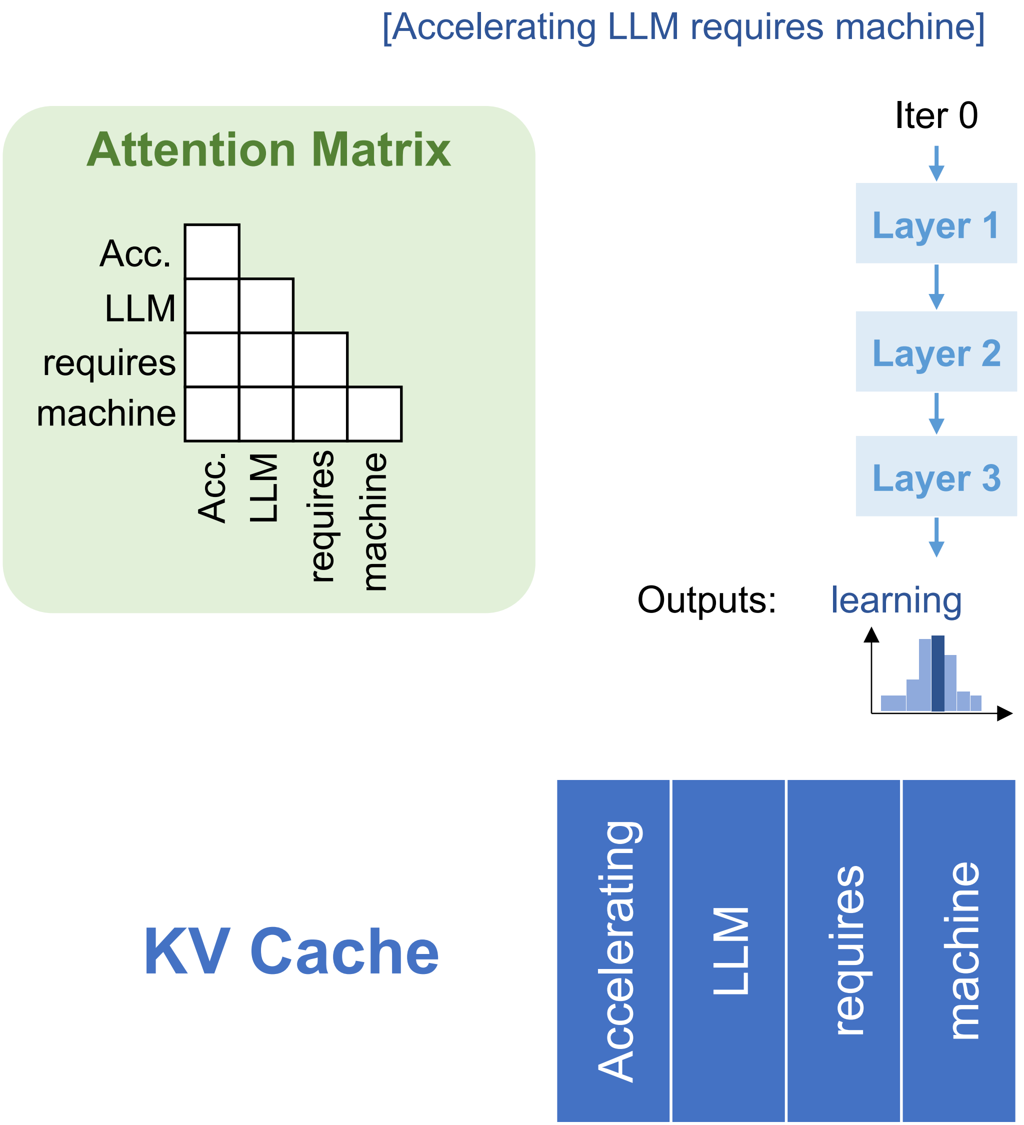
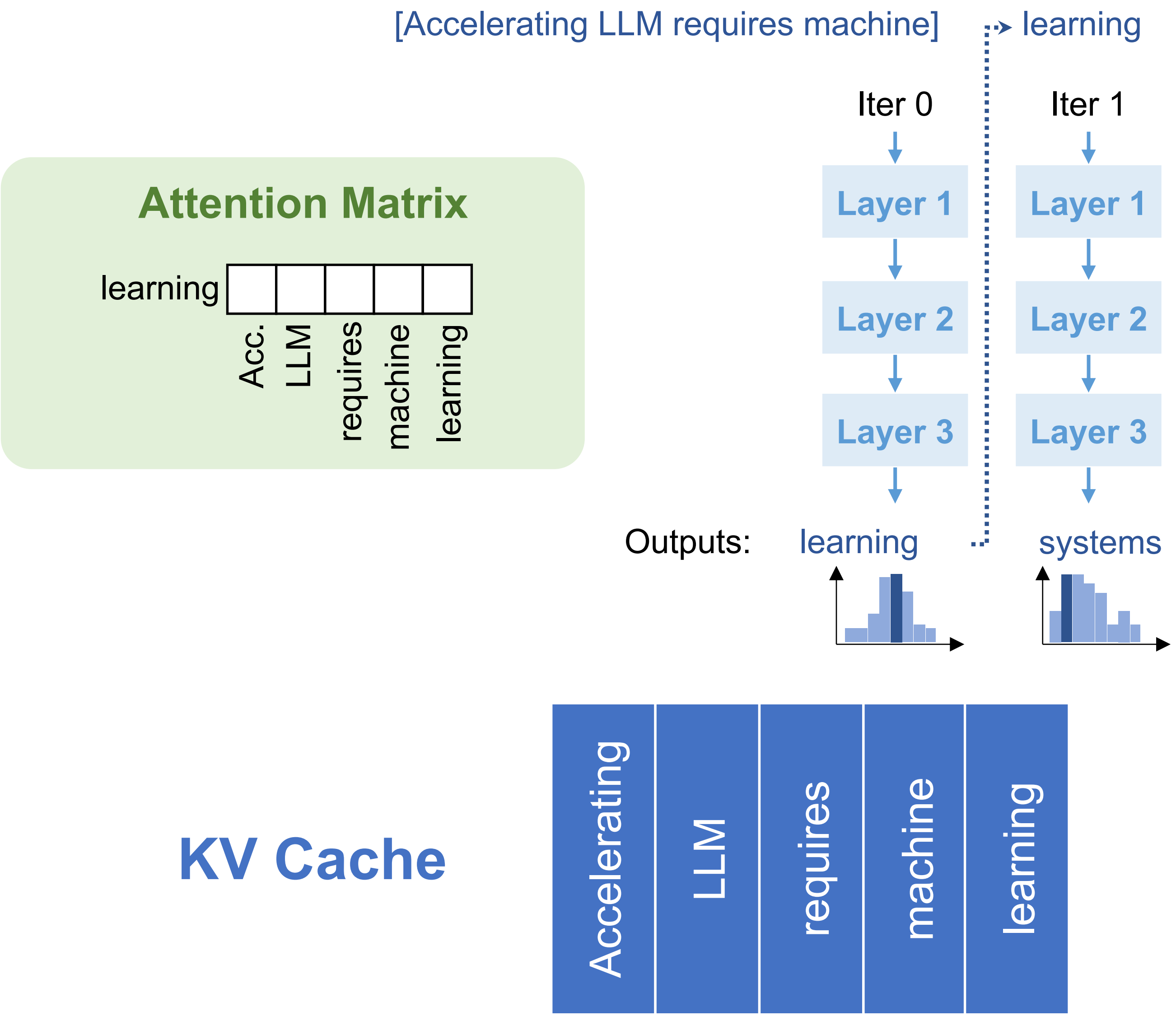
Part 2: LLM Inference (Auto-regressive Decoding)

- Flash-Decoding
- **PagedAttention**

KV Cache Dynamically Grows and Shrinks



KV Cache Dynamically Grows and Shrinks



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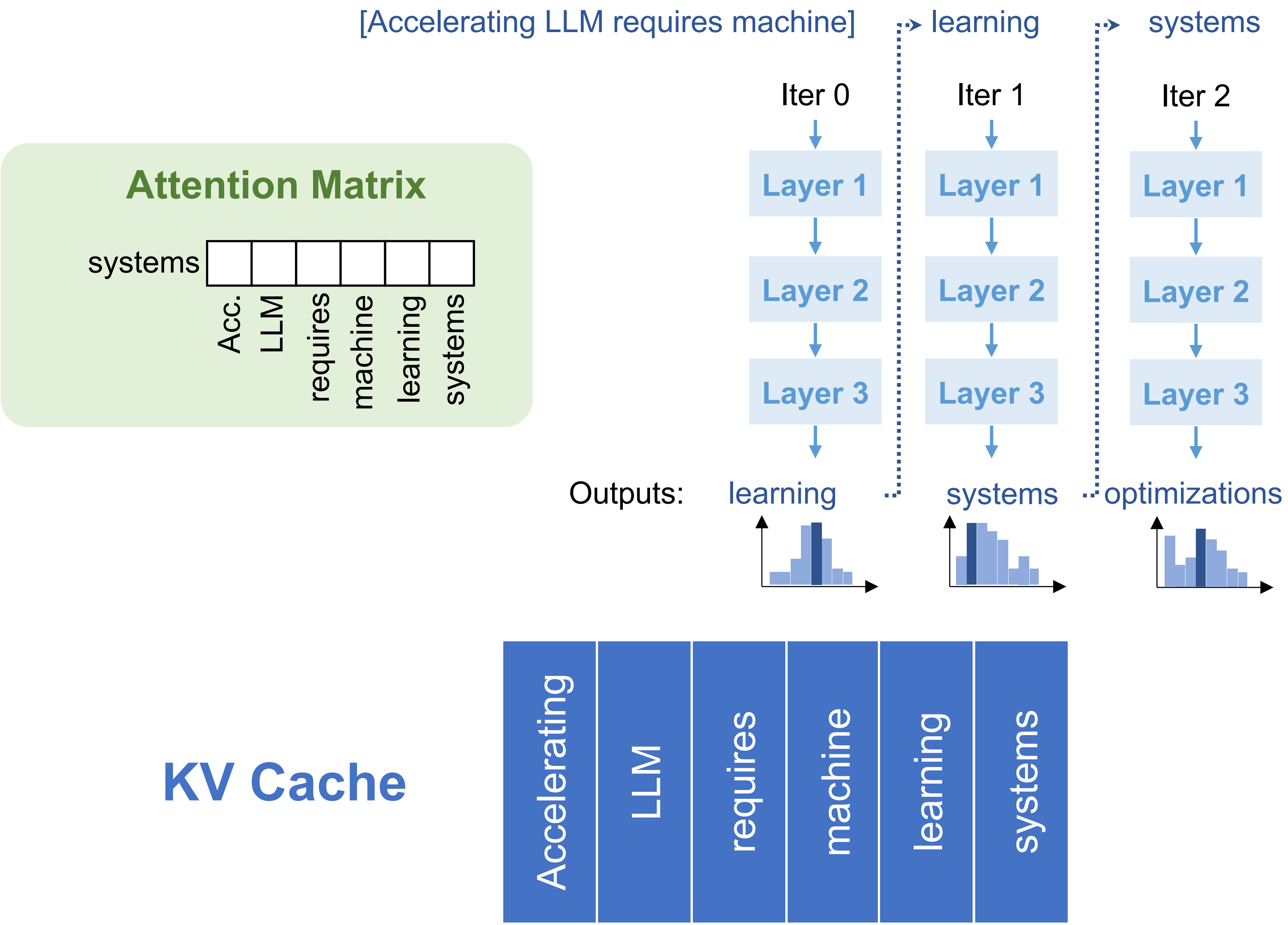

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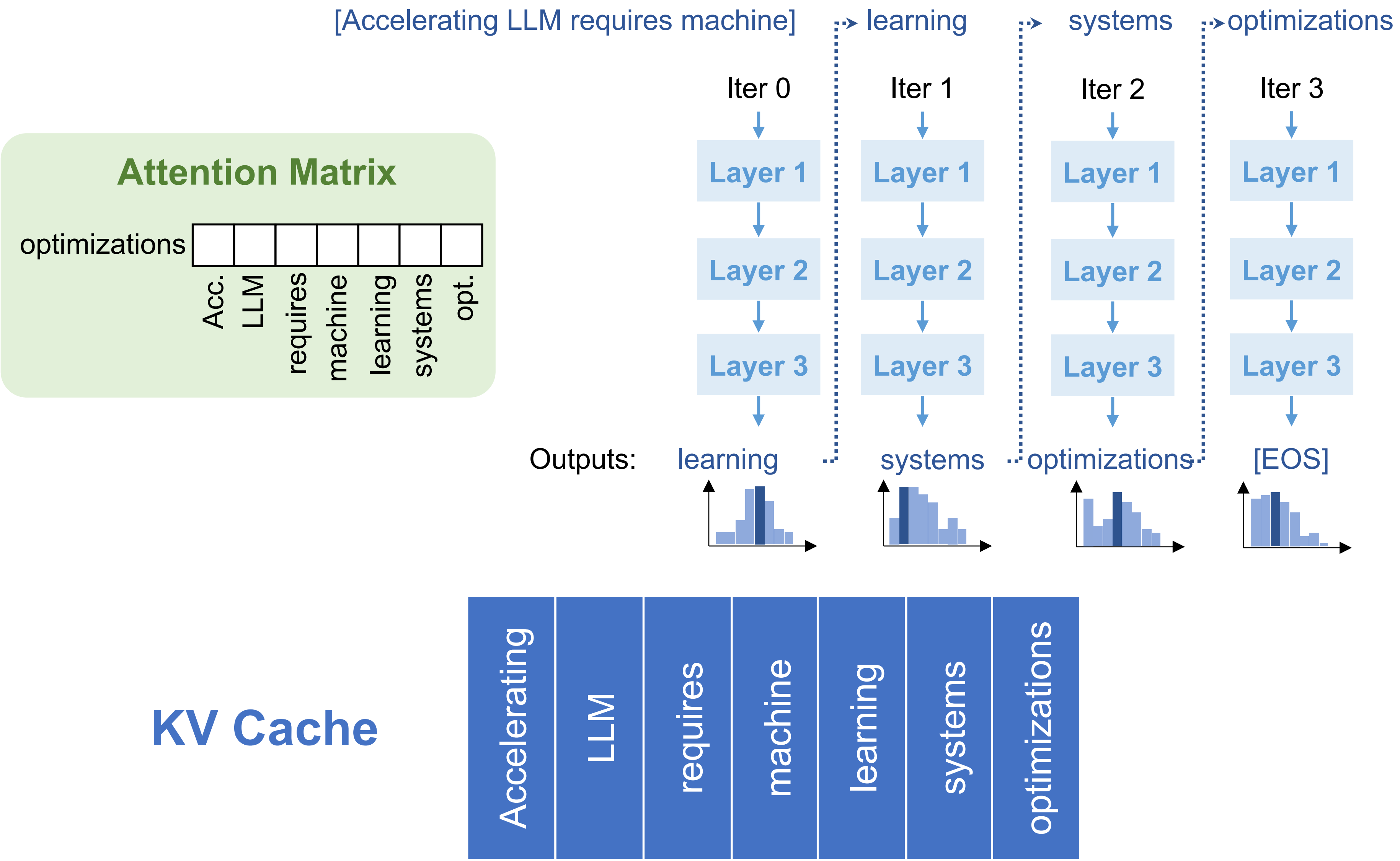
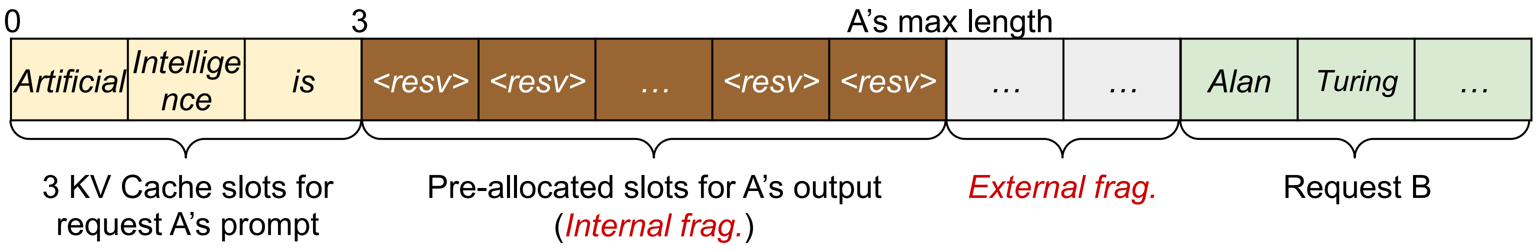


Static KV Cache Management Wastes Memory

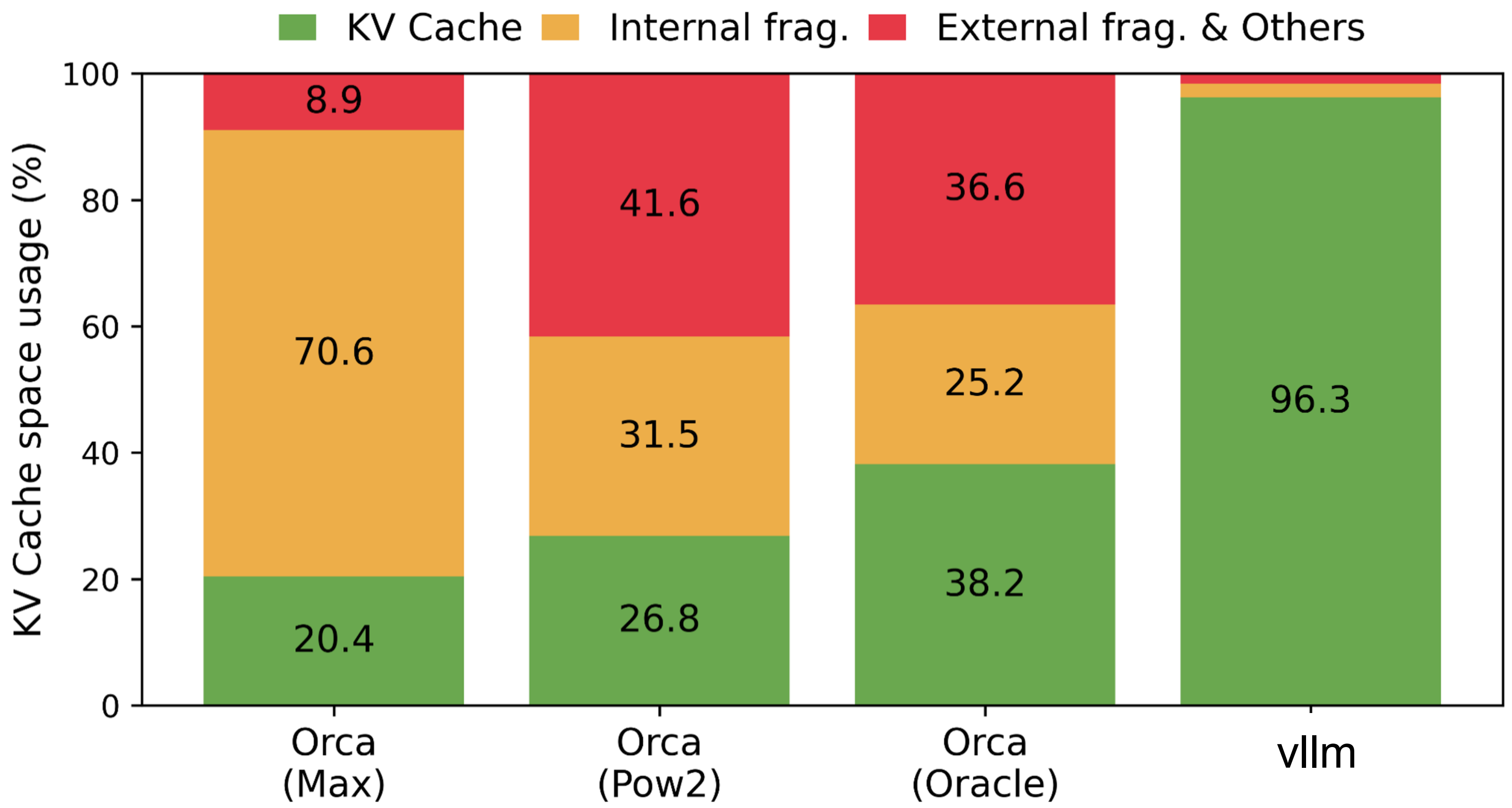


- **Pre-allocates contiguous** space of memory to the request’s maximum length

- Memory fragmentation
  - **Internal fragmentation** due to unknown output length
  - **External fragmentation** due to non-uniform per-request max lengths

Significant Memory Waste in KV Cache

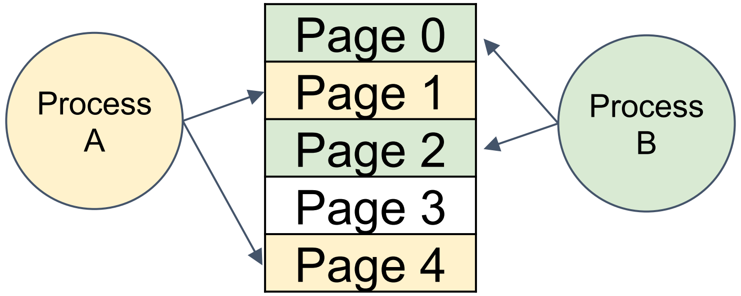
- Only 20-40% of KV cache is utilized to store actual token states



PagedAttention

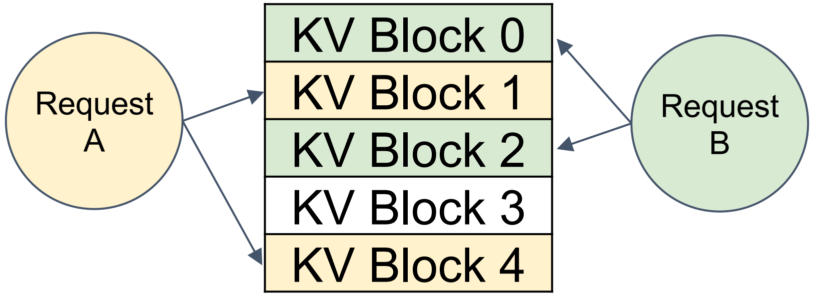
- Application-level memory paging and virtualization for KV cache

Memory management in OS



Physical Memory

PagedAttention

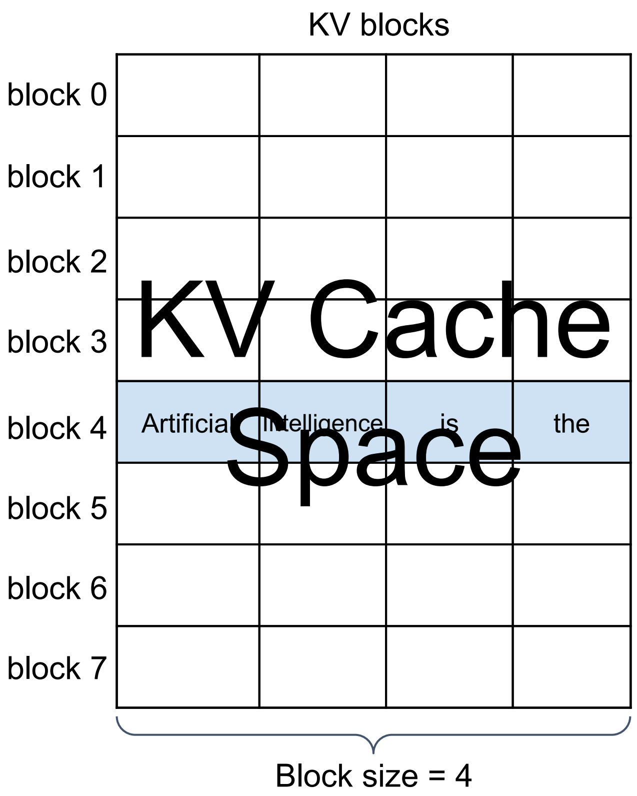


KV Cache

slides from vllm: Efficient Memory Management for Large Language Model Serving with PagedAttention

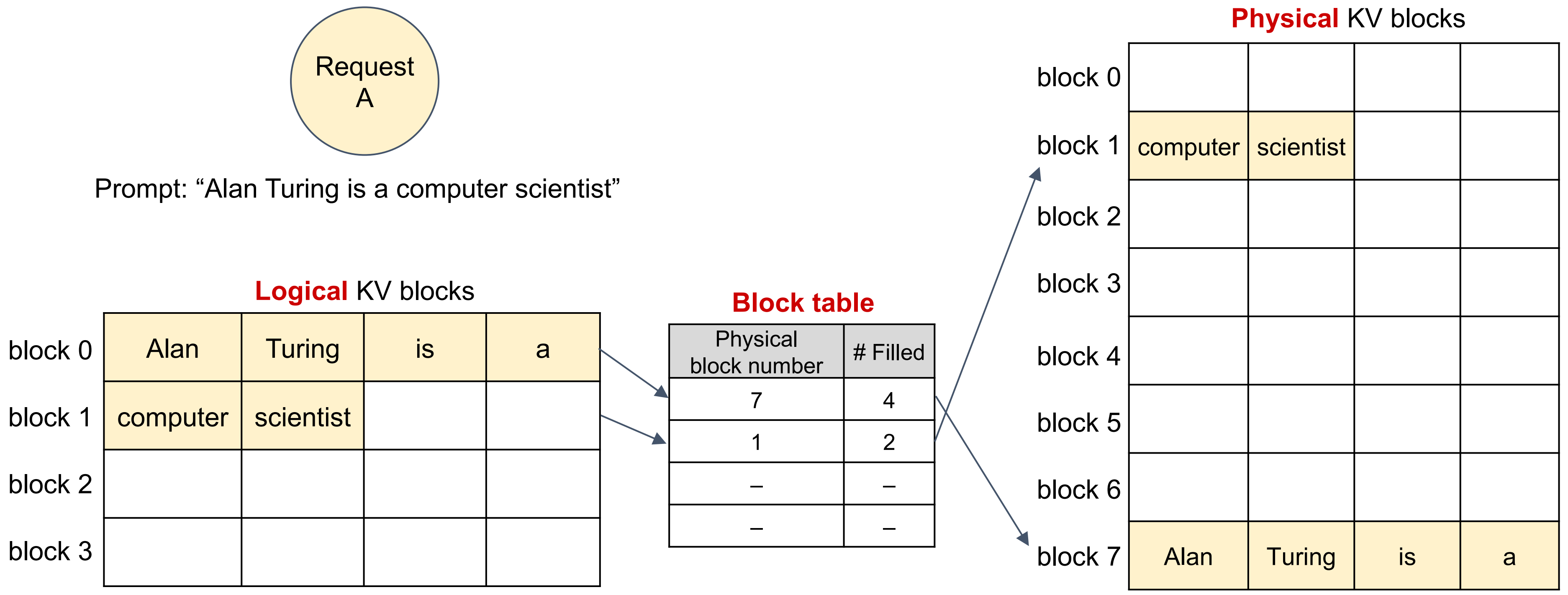
Paging KV Cache Space into KV Blocks*

- KV block is a **fixed-size** contiguous chunk of memory that stores KV states from **left to right**



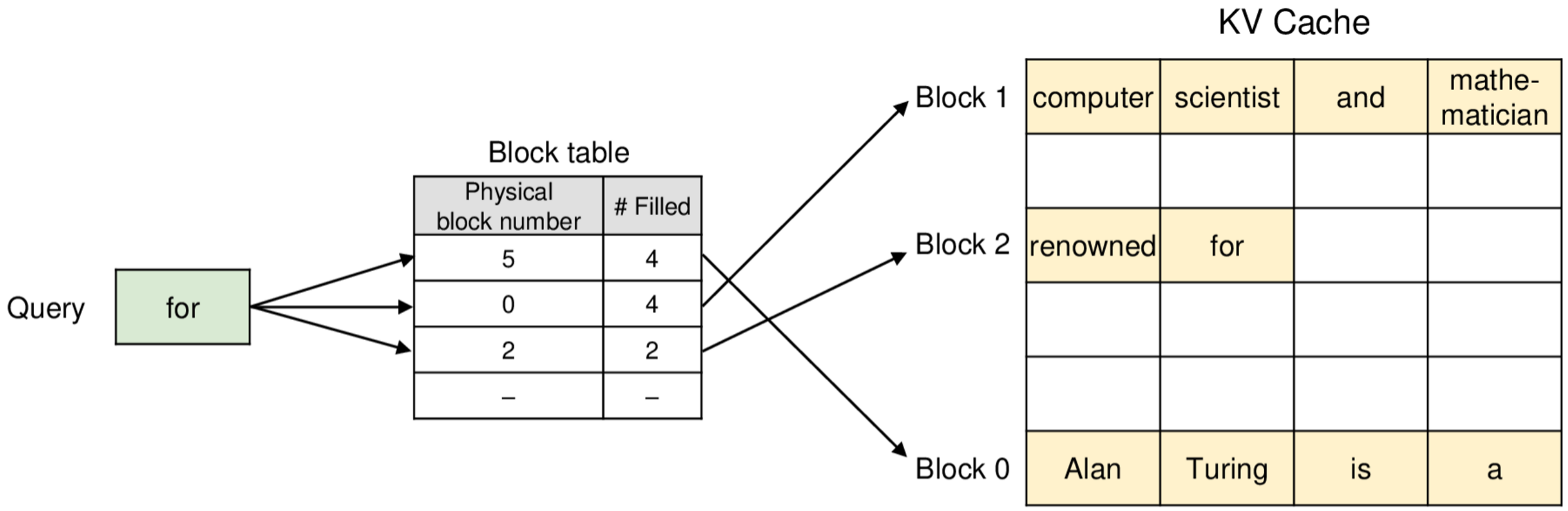
* The term ``block” is overloaded in PagedAttention

Virtualizing KV Cache



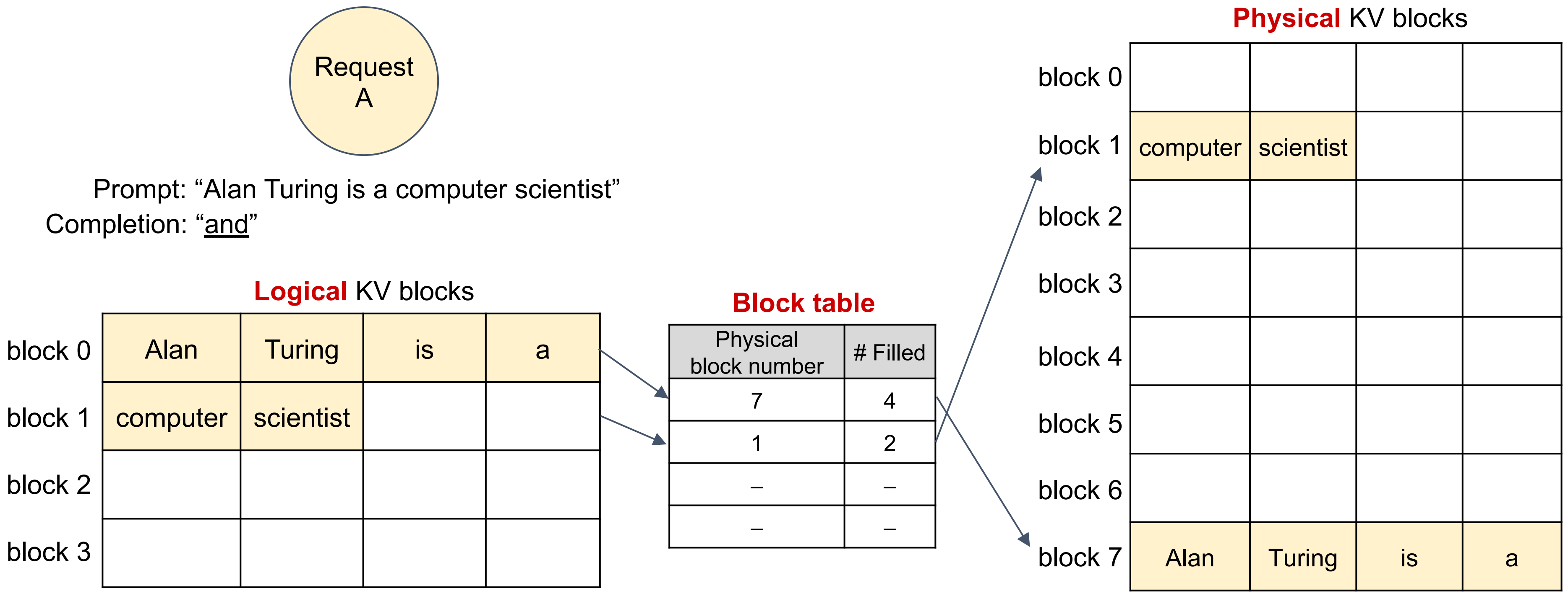
Attention with Virtualized KV Cache

1. Fetch non-contiguous KV blocks using the block table
2. Apply attention on the fly

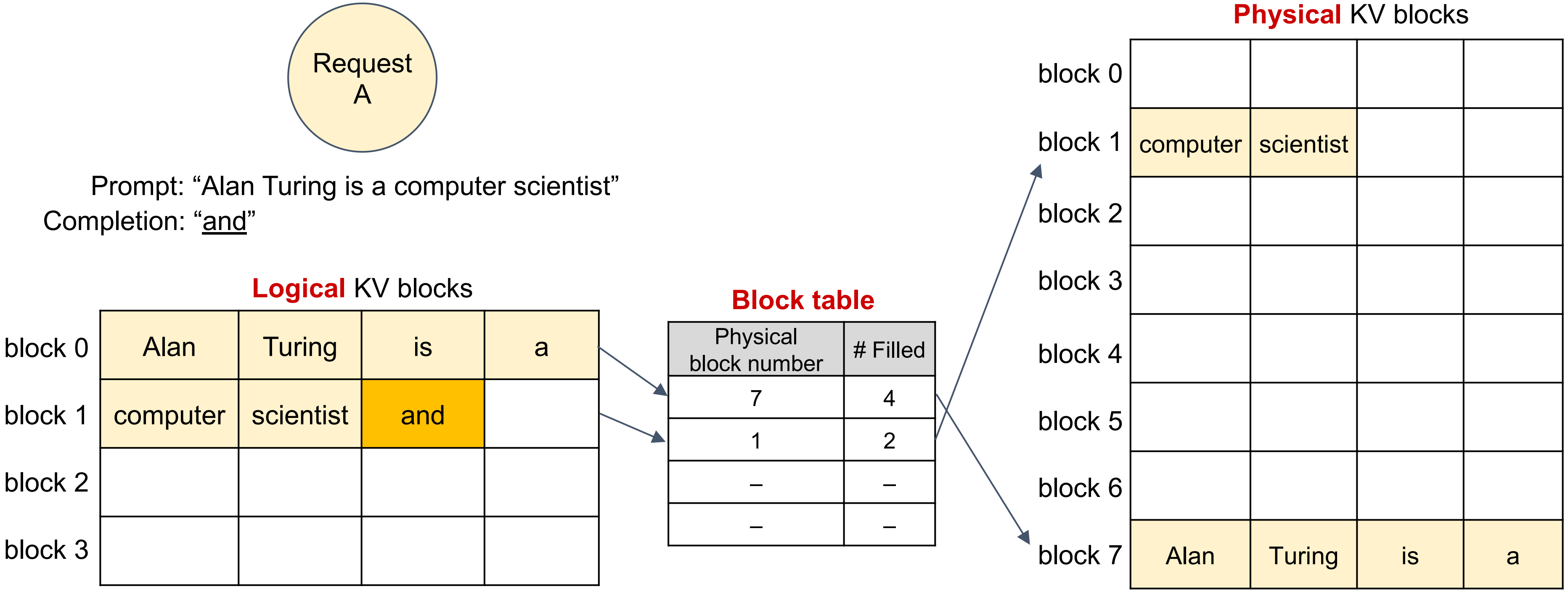


Key insight: attention is associative and commutative

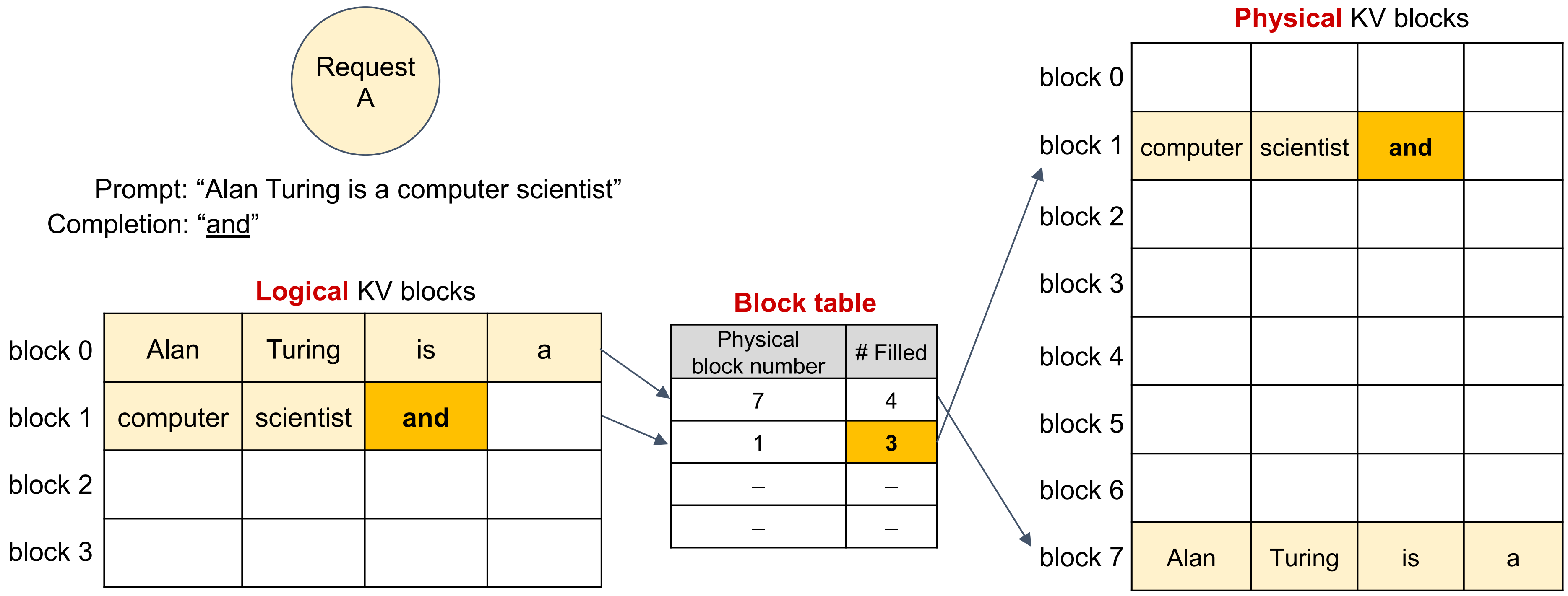
Memory Management with PagedAttention



Memory Management with PagedAttention



Memory Management with PagedAttention



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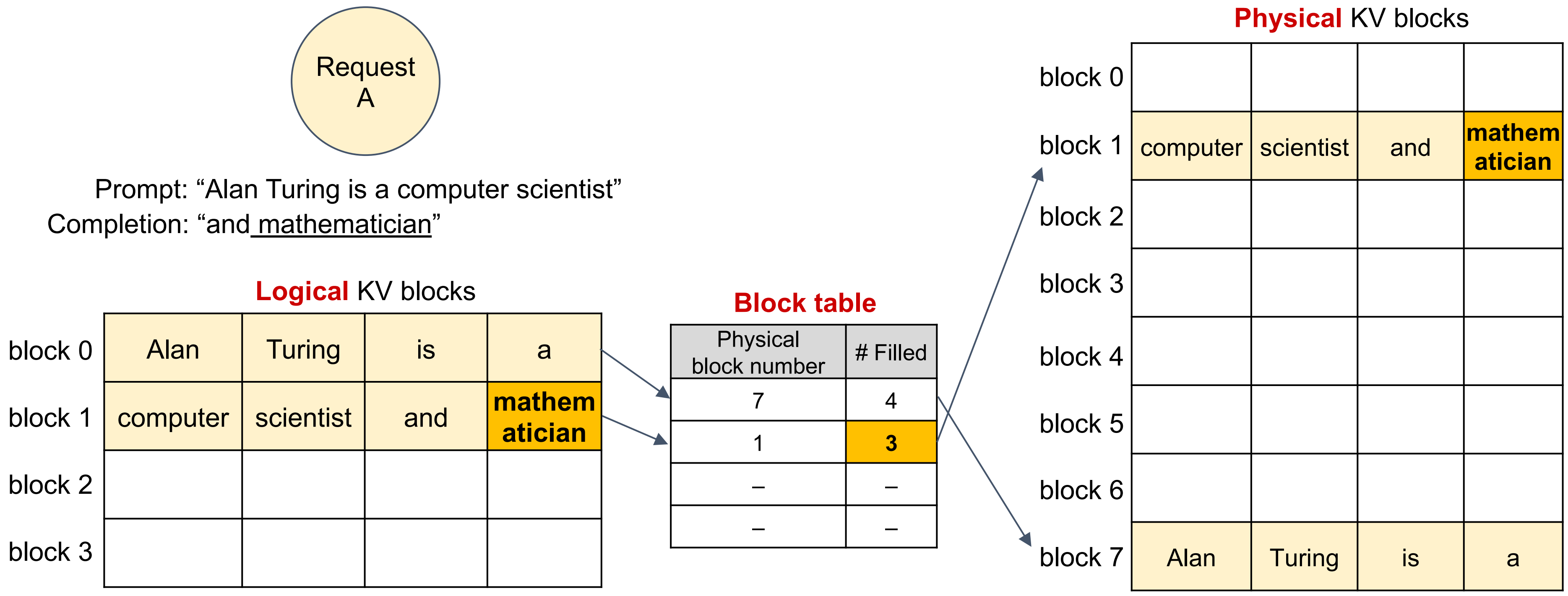
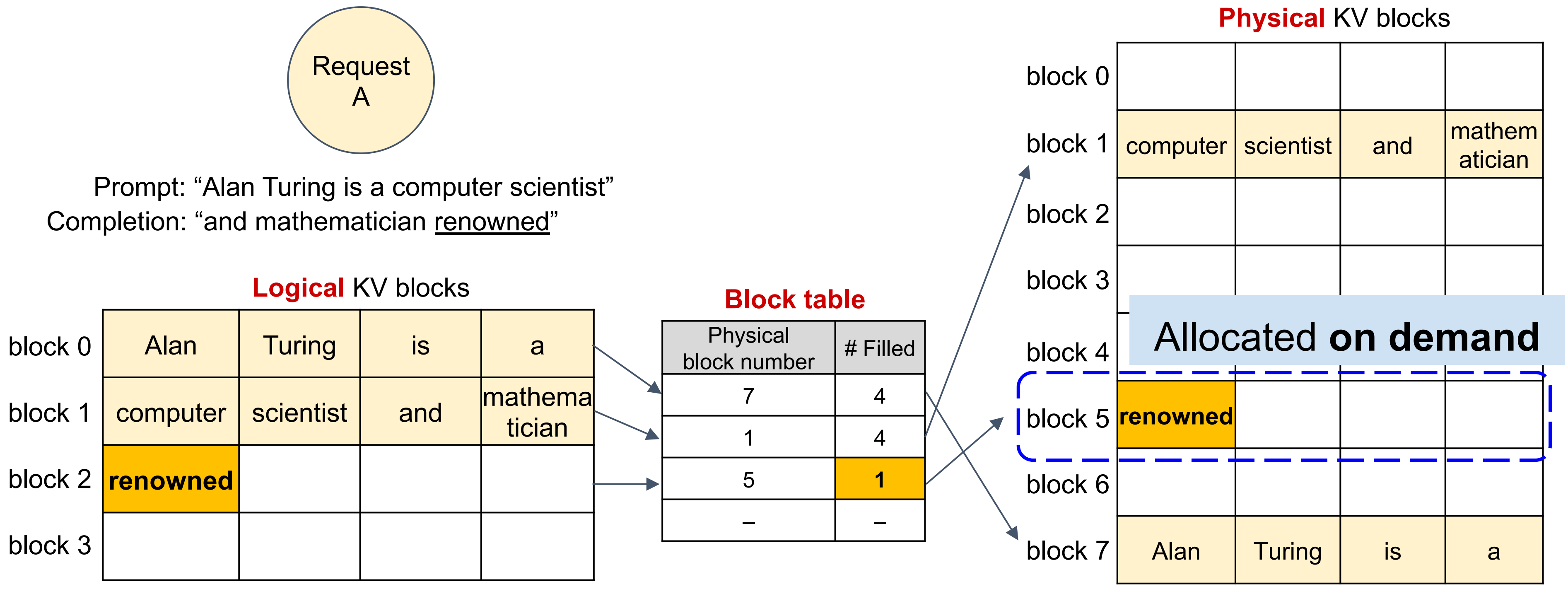


Memory Management with PagedAttention



Memory Efficiency of PagedAttention

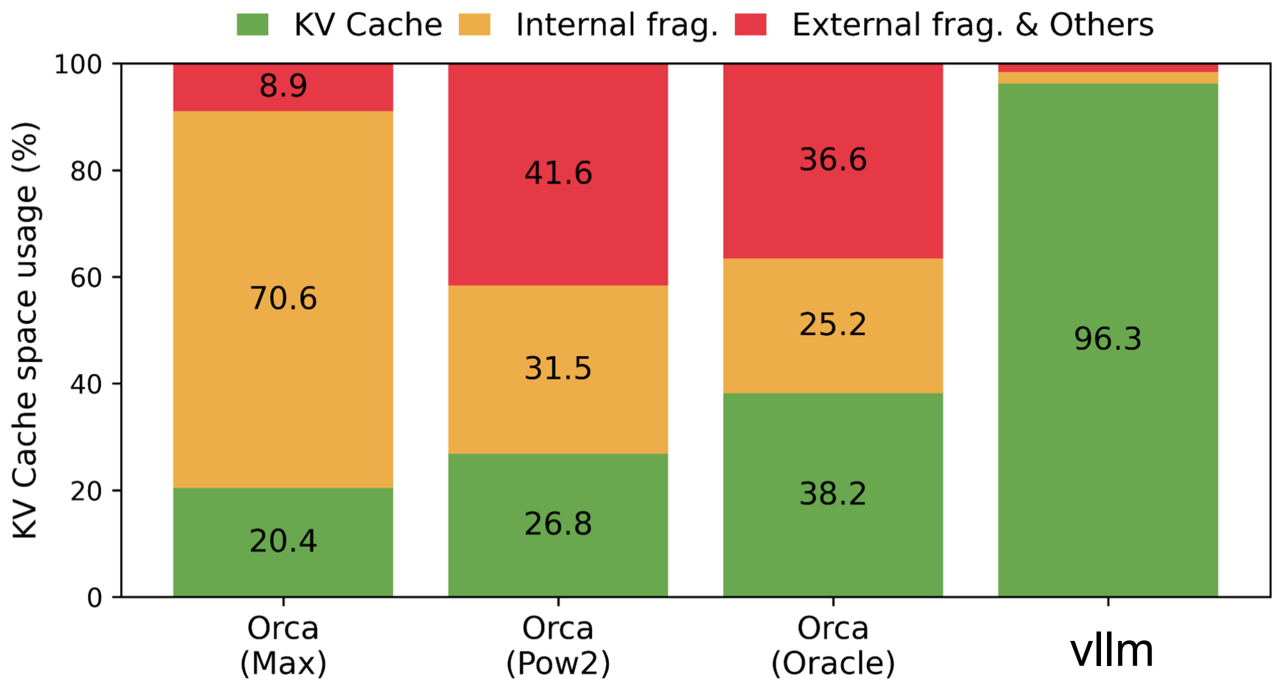
Minimal internal fragmentation

- Only happens at the last block of a sequence
- # wasted tokens / seq < block size

No external fragmentation

Alan	Turing	is	a
computer	scientist	and	mathemati cian
renowned			

Internal fragmentation



Recap: Techniques for Optimizing Attention

- **FlashAttention**: tiling to reduce GPU global memory access
- **Auto-regressive Decoding**: pre-filling and decoding phases, KV cache
- **FlashDecoding**: improving attention's parallelism by splitting keys/values
- **PagedAttention**: paging and virtualization to reduce KV cache's memory requirement