System for Artificial Intelligence

Attention Optimizations

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Attention: O = Softmax(QK^T) V

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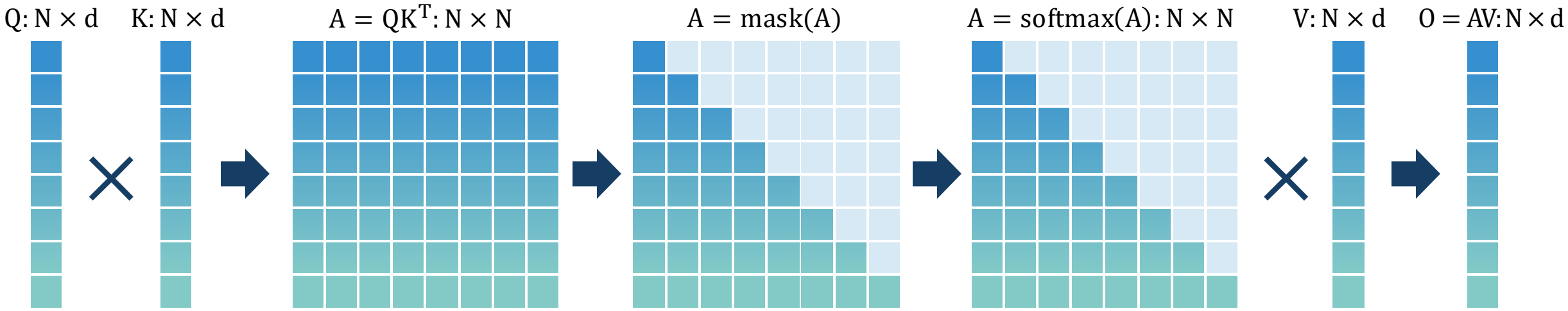

Challenges:

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

OUTLINE

01 LLM Training

02 LLM Inference

01

LLM Training

Revisit: GPU Memory Hierarchy

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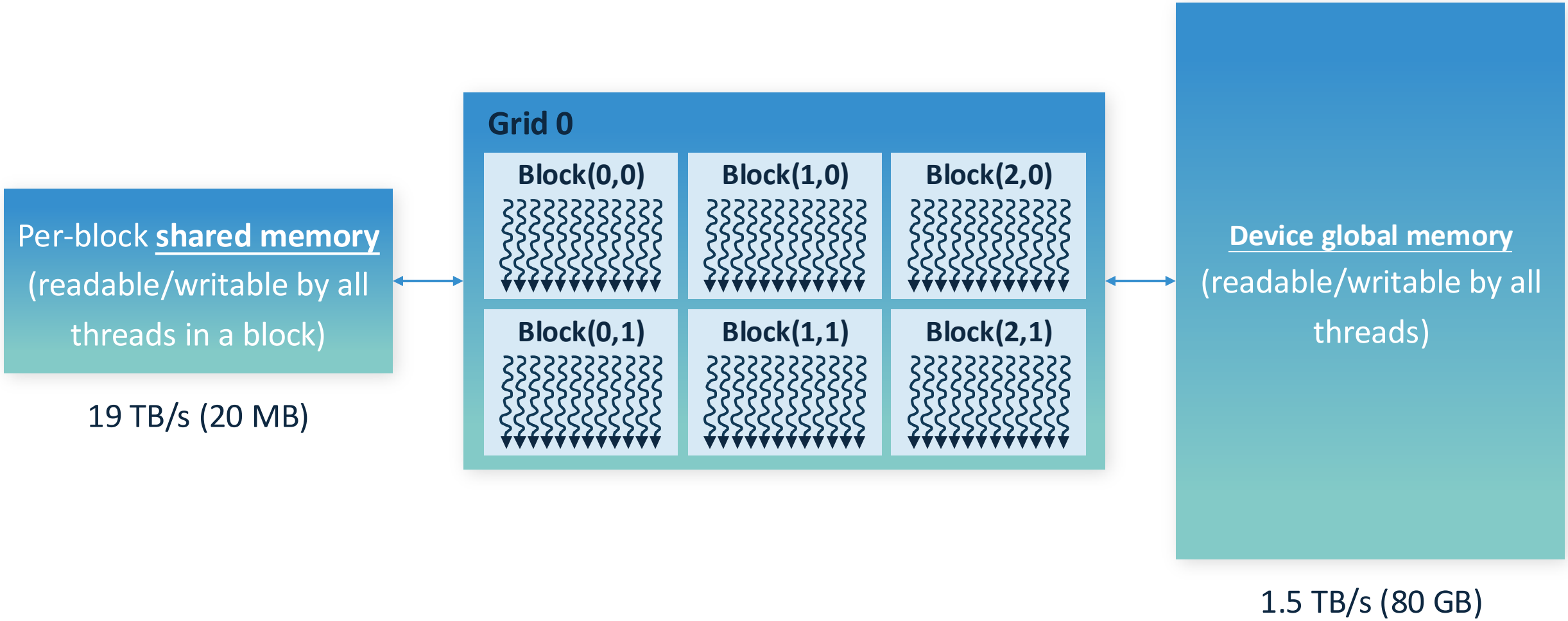

FlashAttention

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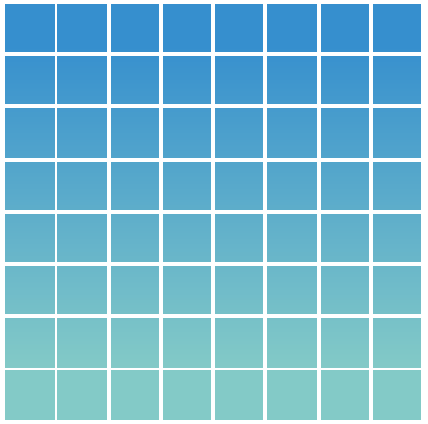
$$A = \text{softmax}(QK^T)$$



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

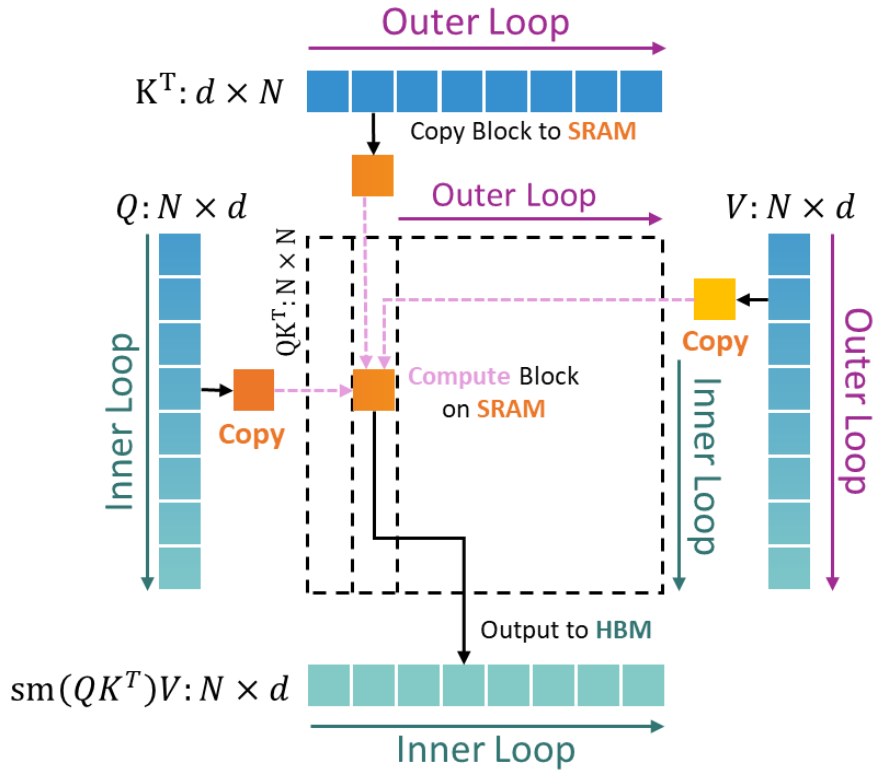
- **Two main Techniques:**

  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

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

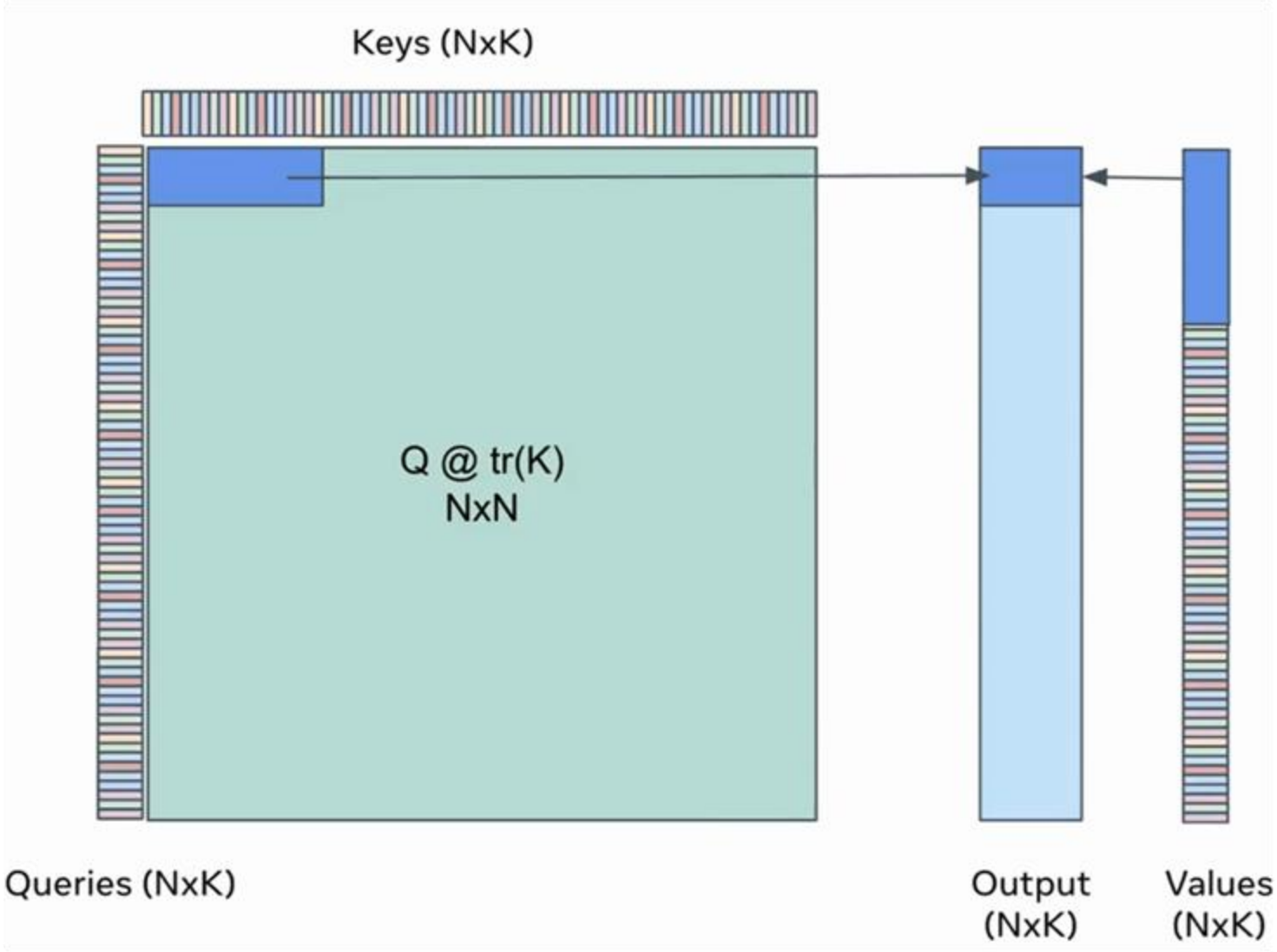


FlashAttention

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

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

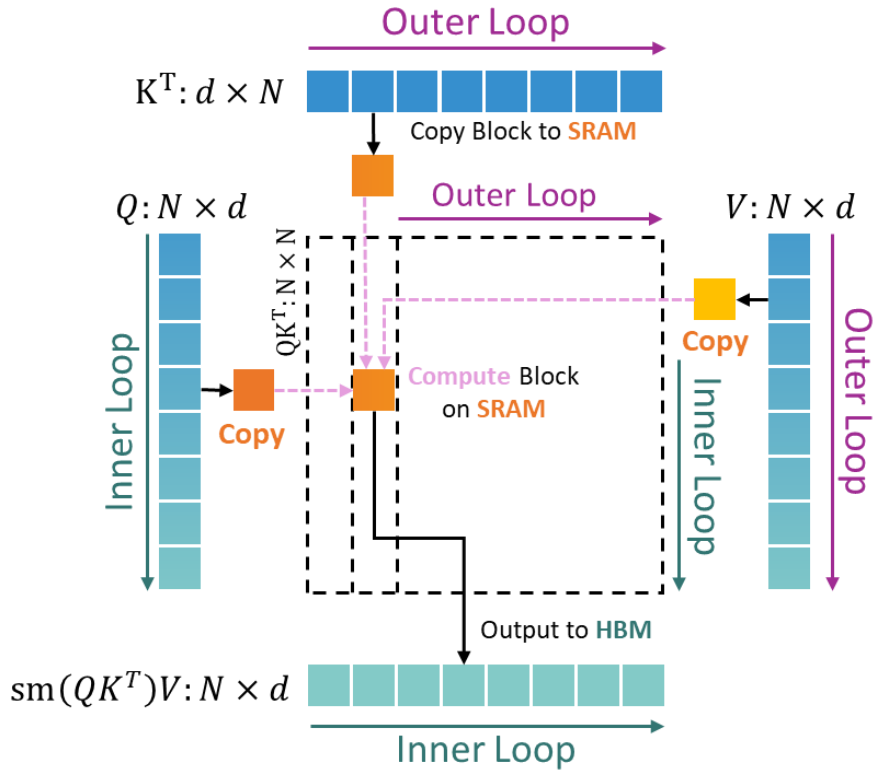
Tiling



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



FlashAttention

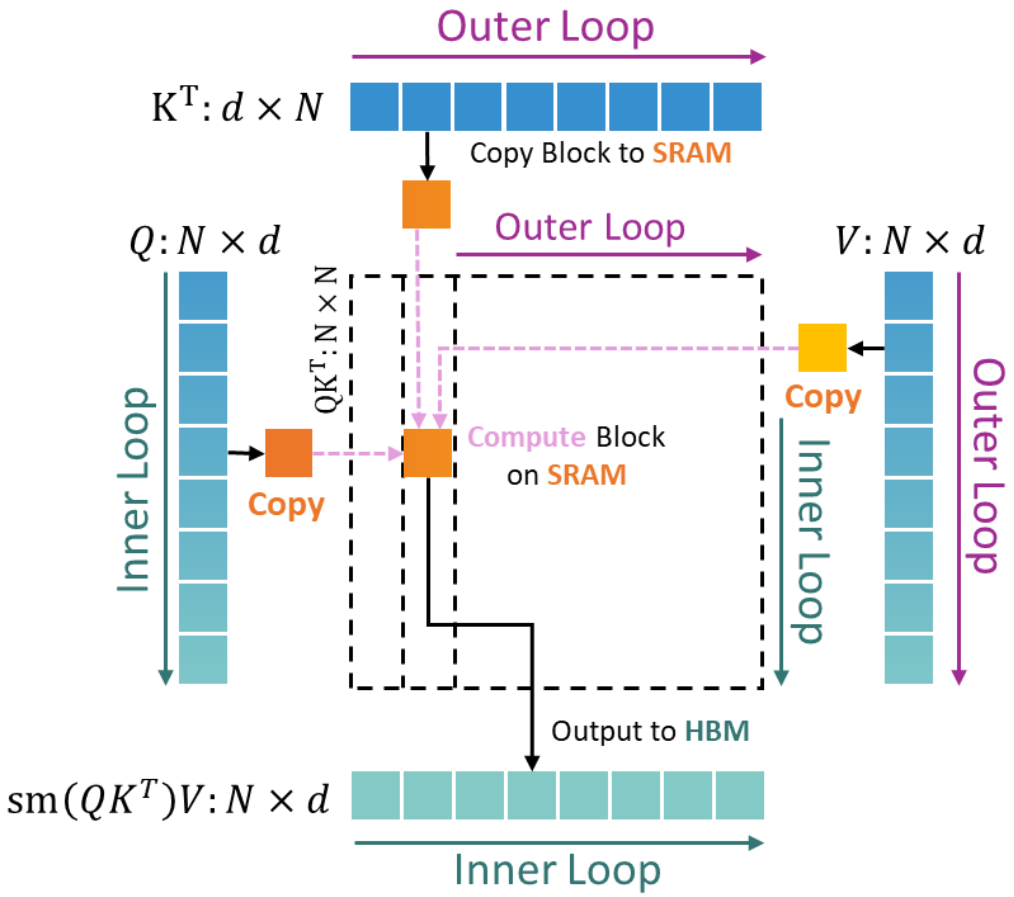
Speed up backward pass with increased FLOPs

FlashAttention: Threadblock-level Parallelism

How to partition FlashAttention across thread blocks?

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

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



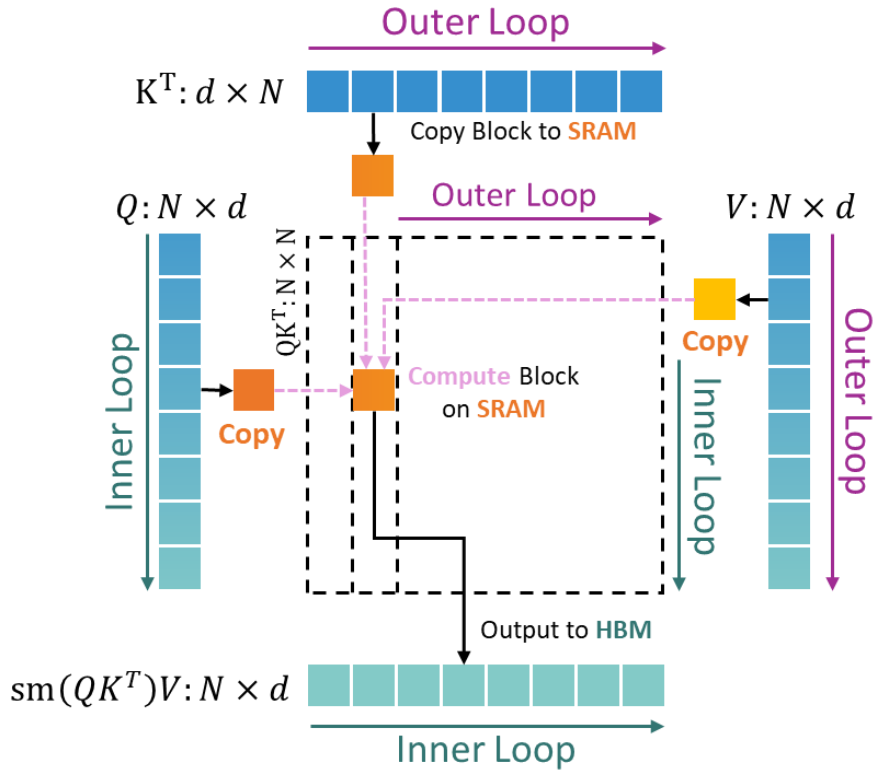
FlashAttention

FlashAttention: Threadblock-level Parallelism

How to partition FlashAttention across thread blocks?

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

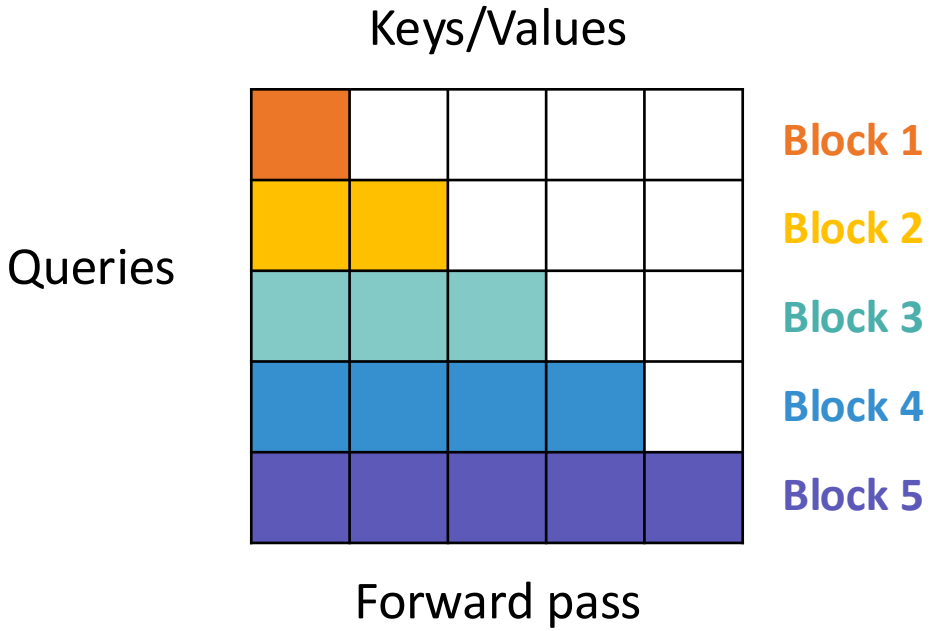
- Step 1: assign different heads to different thread blocks (16-64 heads)
- Step 2: assign different queries to different thread blocks (Why?)



FlashAttention

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

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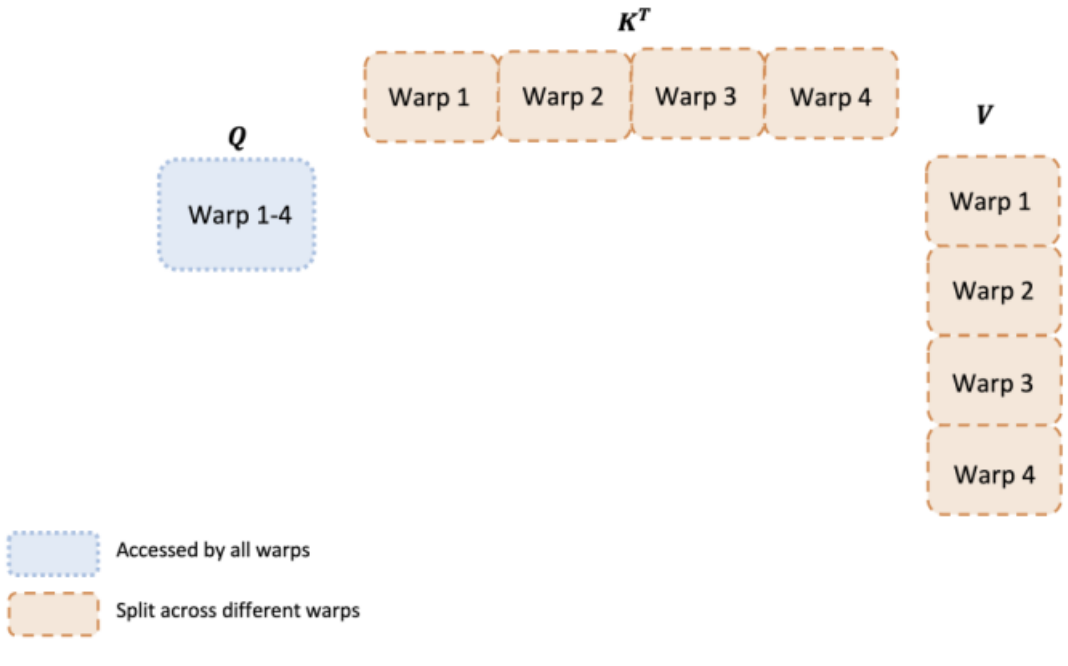
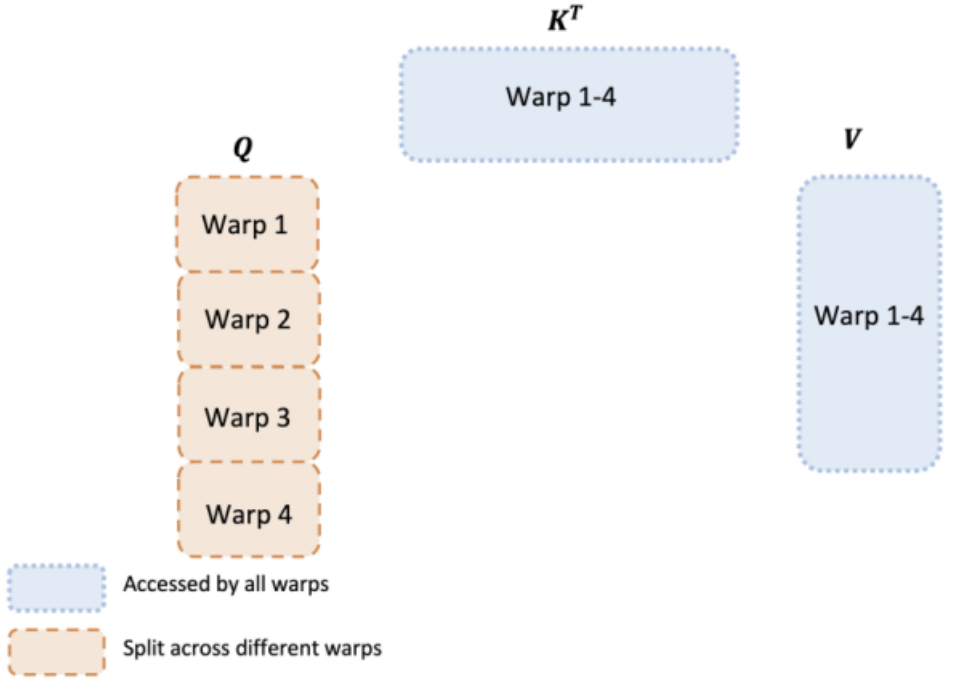
- How to partition FlashAttention across warps within a thread block?



(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

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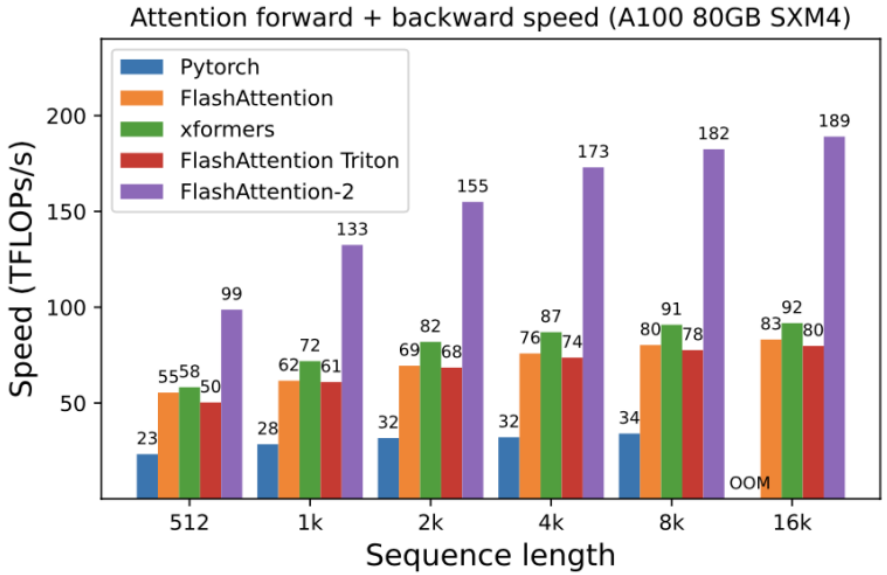
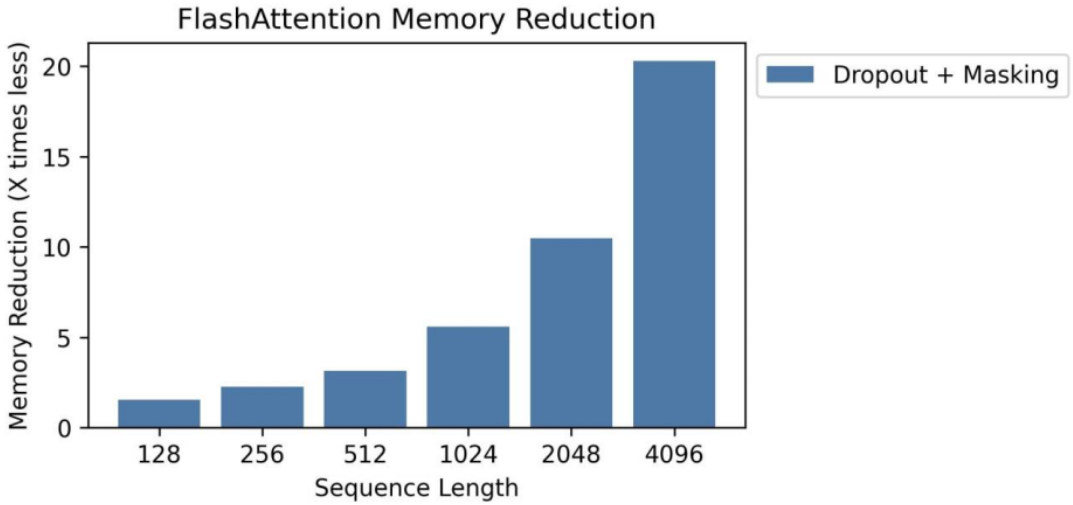


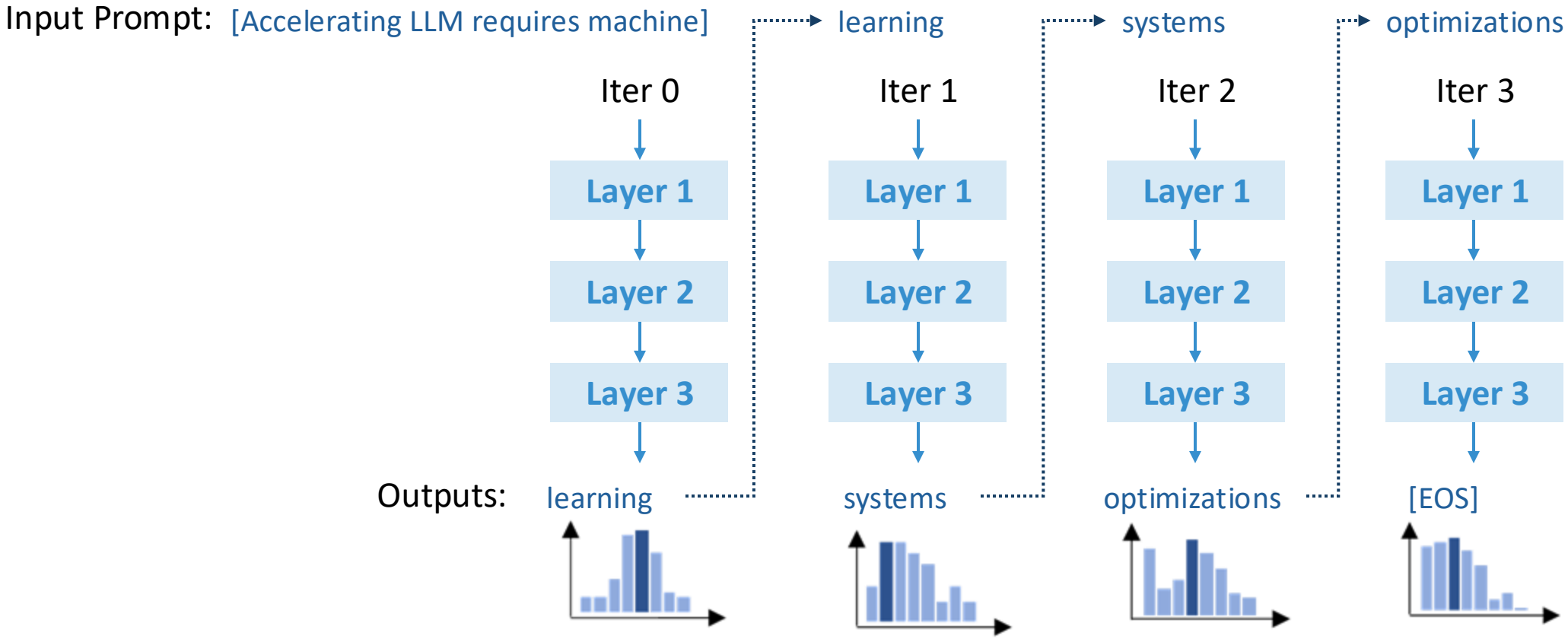


- **Memory linear in sequence length**

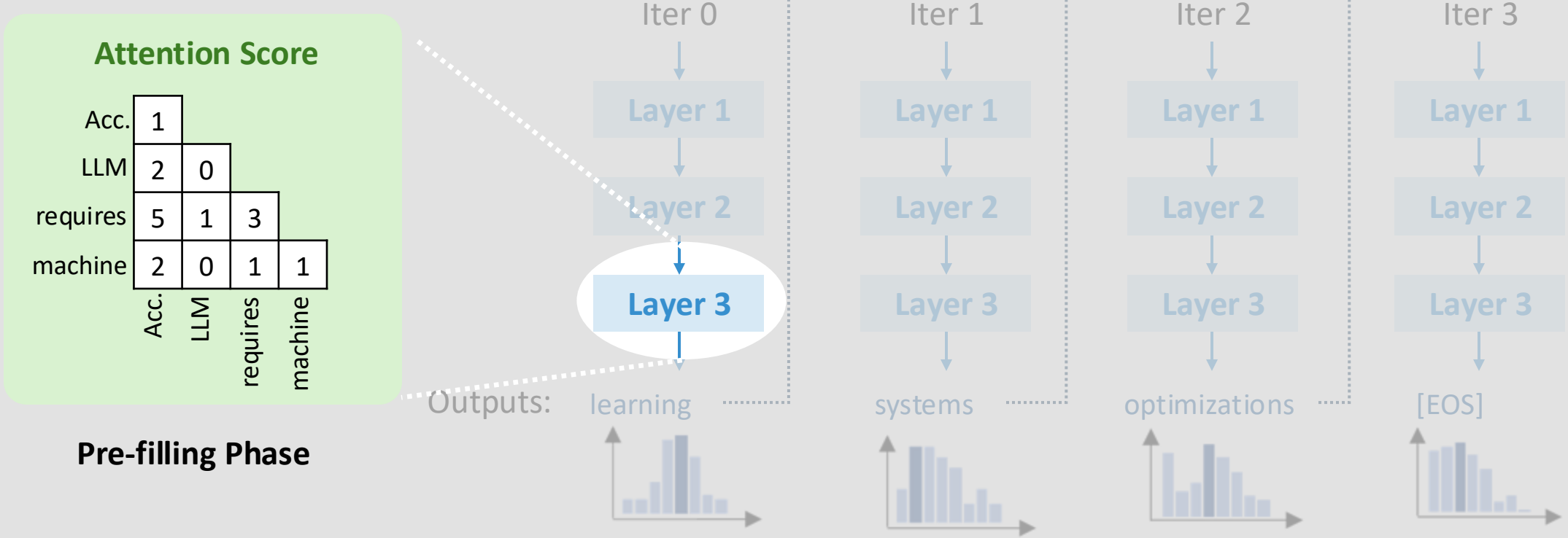
02

LLM Inference (Auto-regressive Decoding)

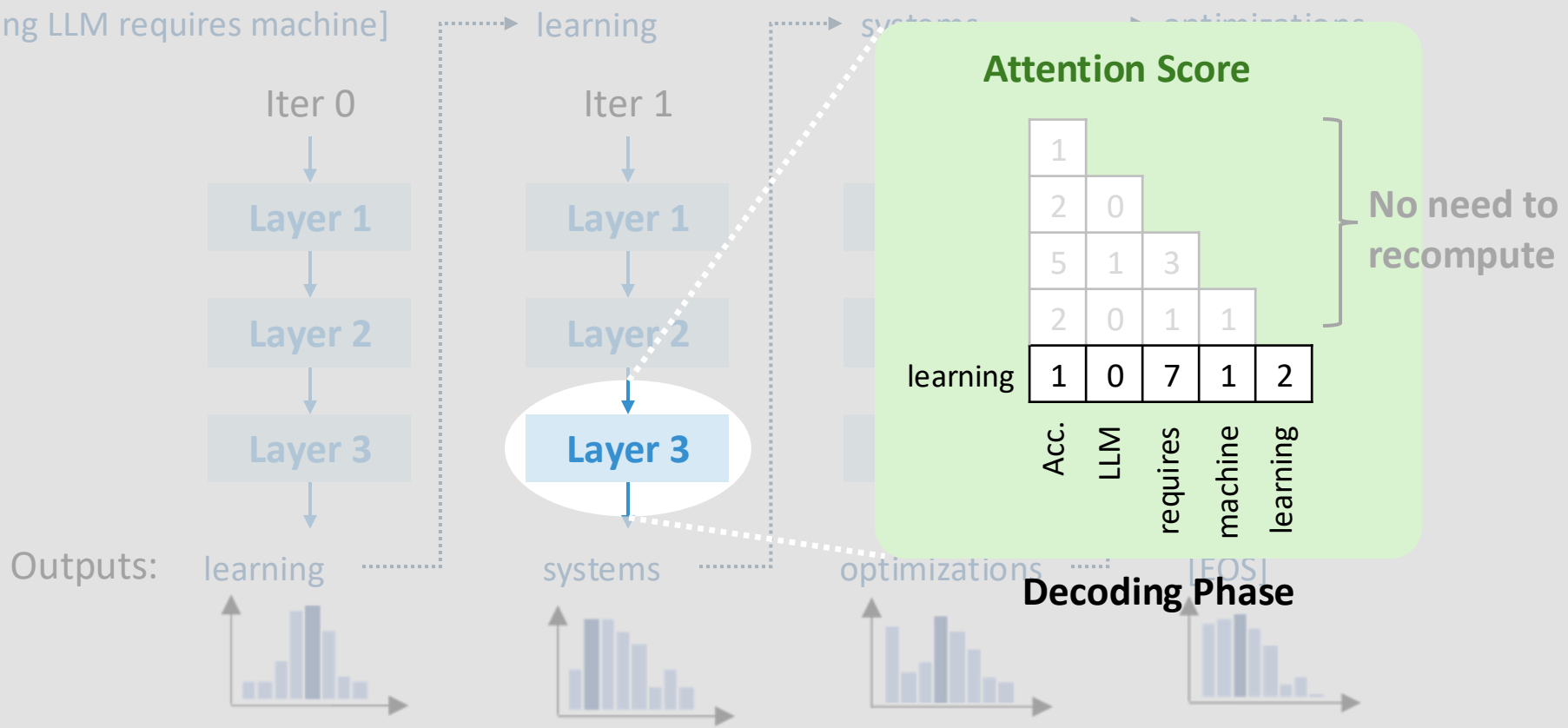
Generative LLM Inference: Autoregressive Decoding



Generative LLM Inference: Autoregressive Decoding



Generative LLM Inference: Autoregressive Decoding



Generative LLM Inference: Autoregressive Decoding

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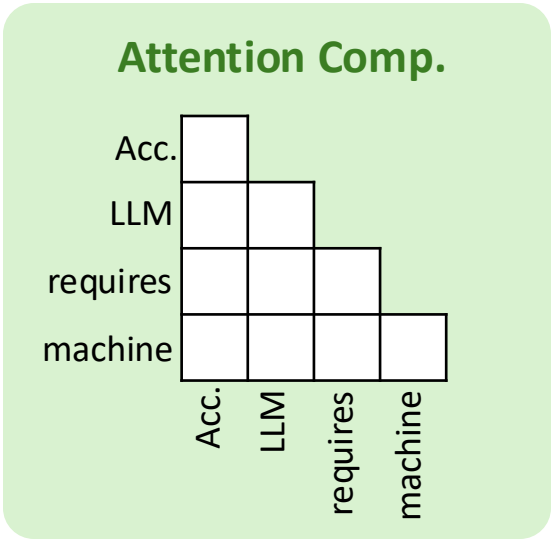
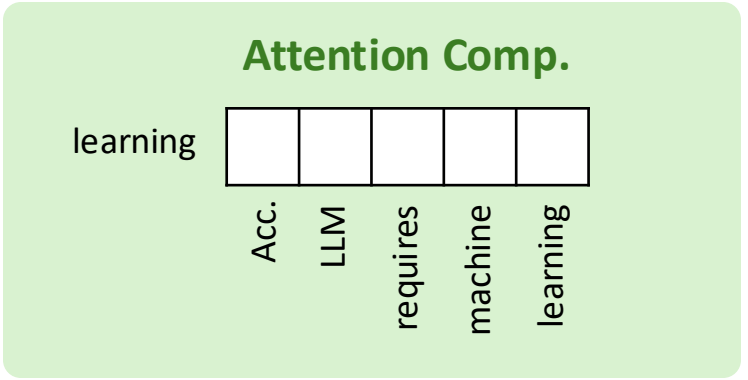
- **Pre-filling phase** (0-th iteration):
  - Process ***all*** input tokens at once
- **Decoding phase** (all other iterations):
  - Process a ***single*** token generated from previous iteration
  - Use attention keys & values of all previous tokens

- 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

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

FlashAttention Processes K/V Sequentially

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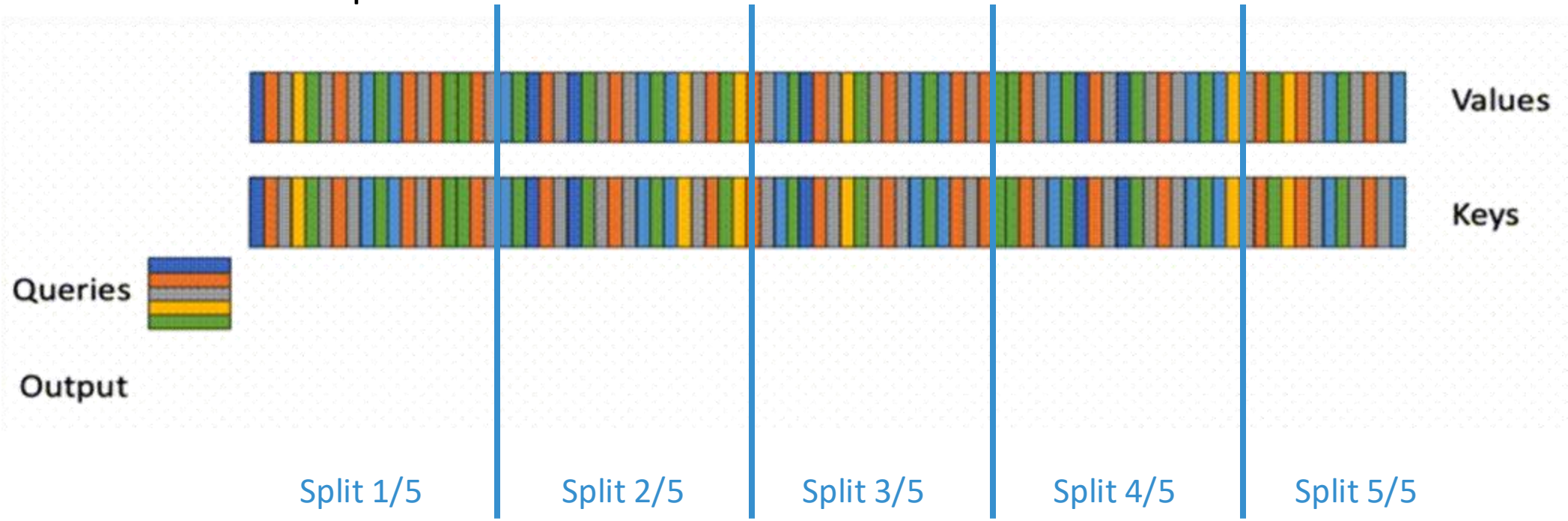
1. Split keys/values into small chunks
2. Compute attention with these splits using FlashAttention
3. Reduce overall all splits



Key insight: attention is associative and commutative

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

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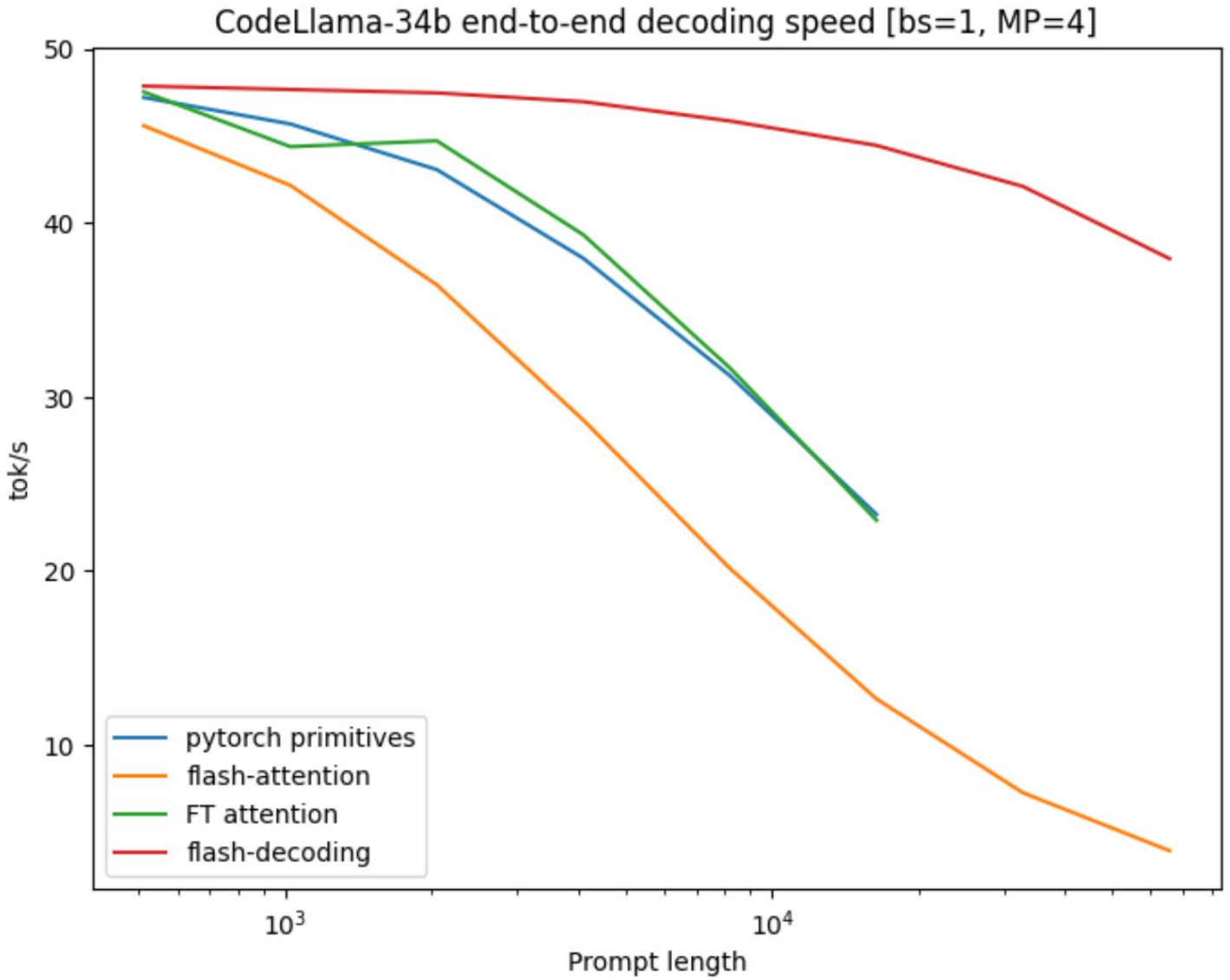
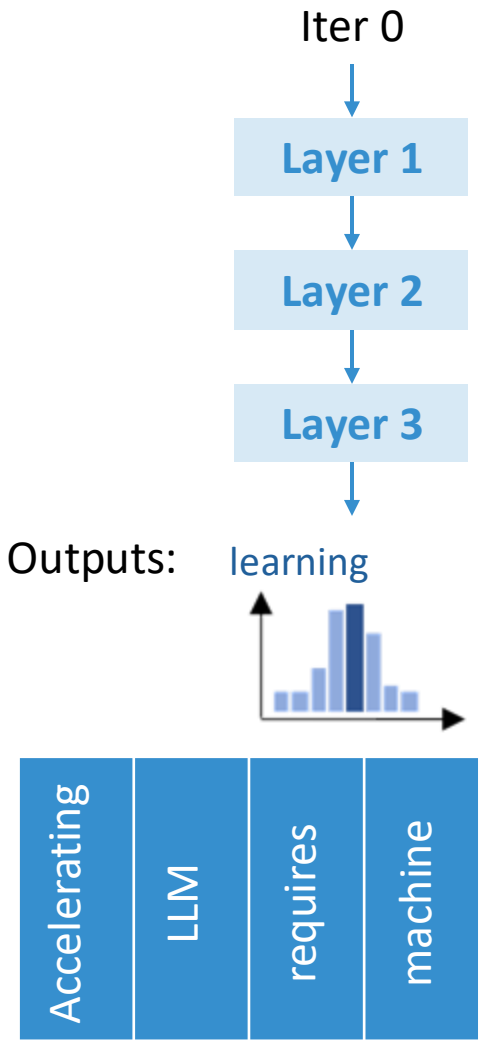


KV Cache Dynamically Grows and Shrinks

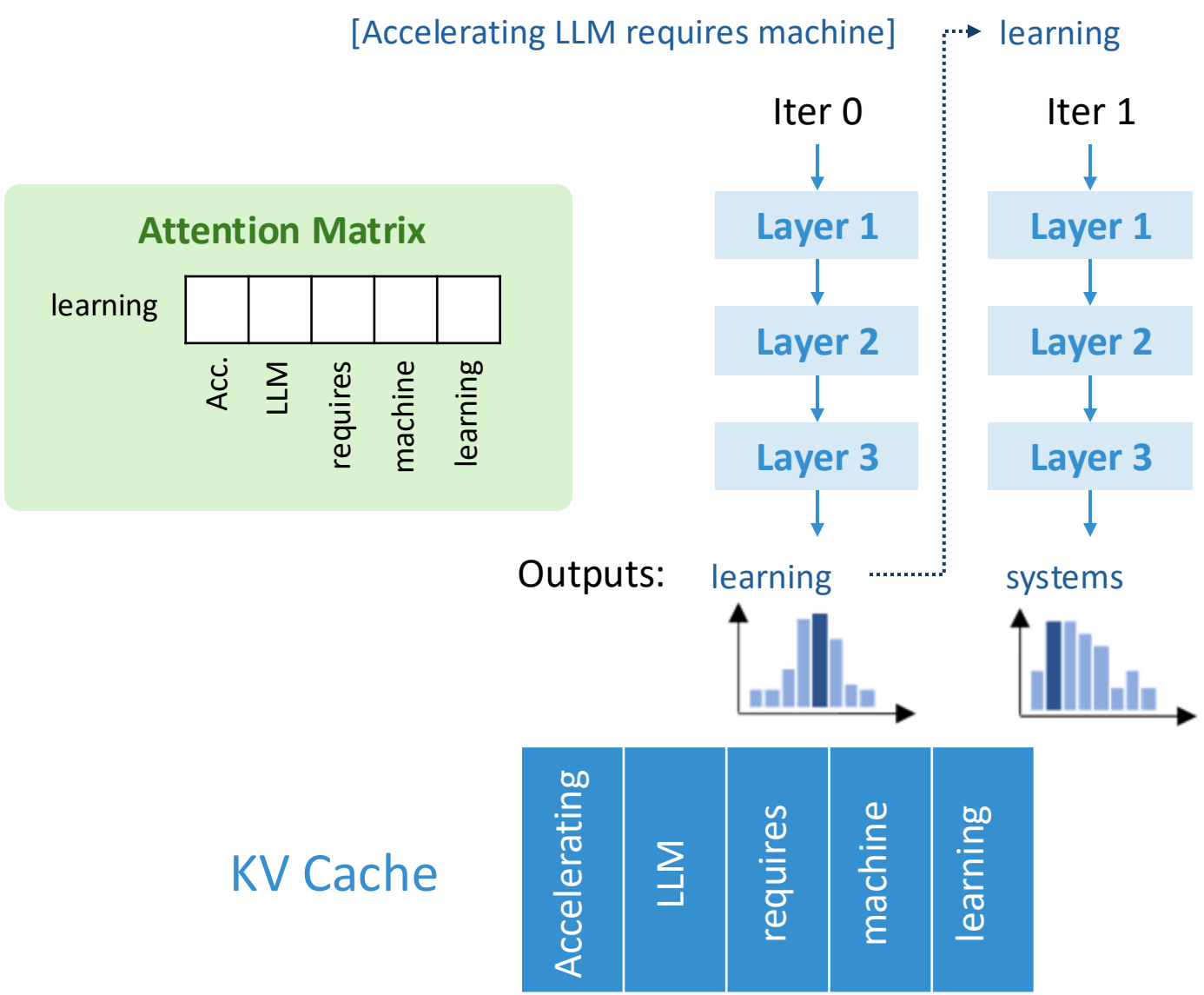
[Accelerating LLM requires machine]

Attention Matrix

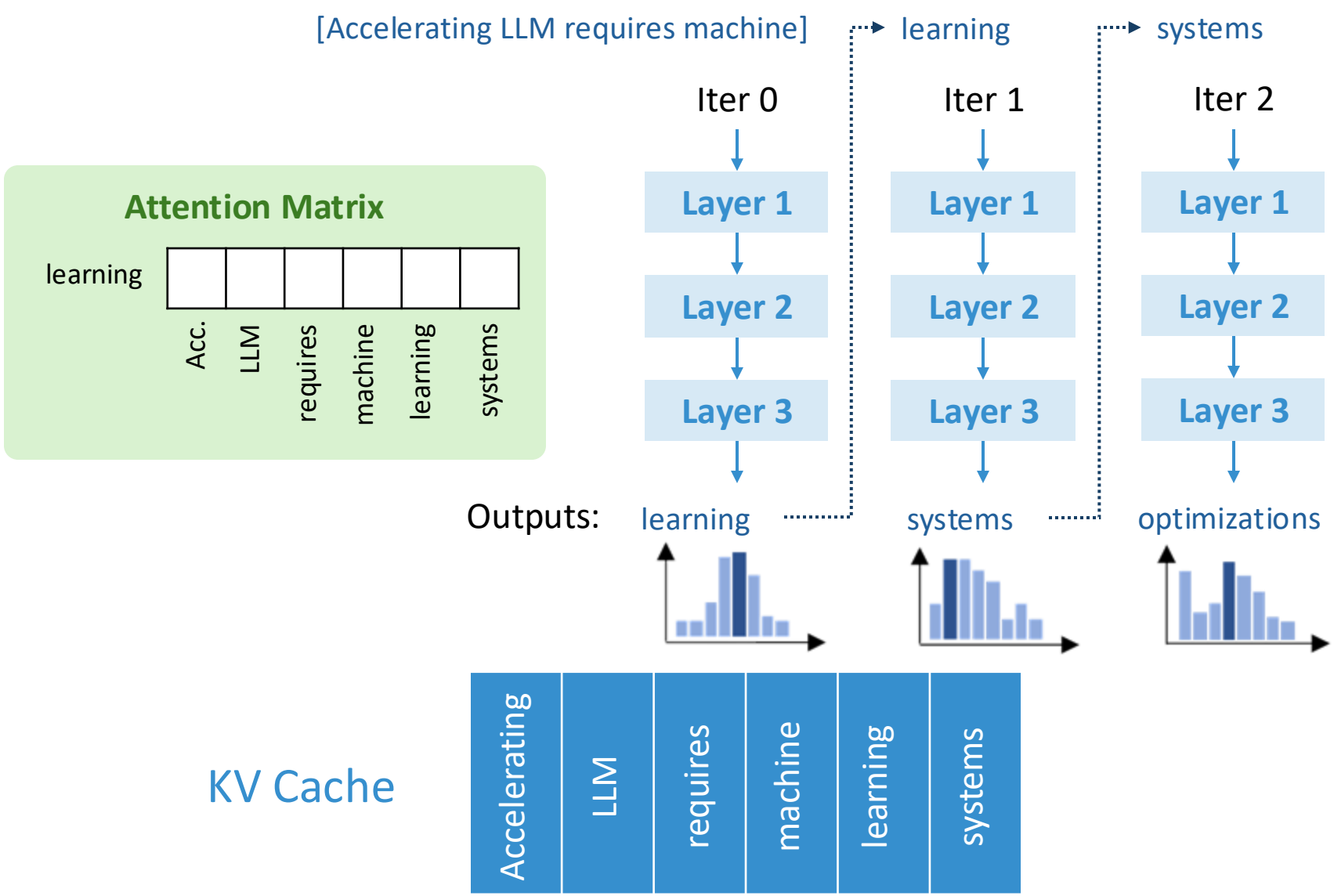
	Acc.	LLM	requires	machine
Acc.	1			
LLM	2	0		
requires	5	1	3	
machine	2	0	1	1



KV Cache Dynamically Grows and Shrinks



KV Cache Dynamically Grows and Shrinks



KV Cache Dynamically Grows and Shrinks

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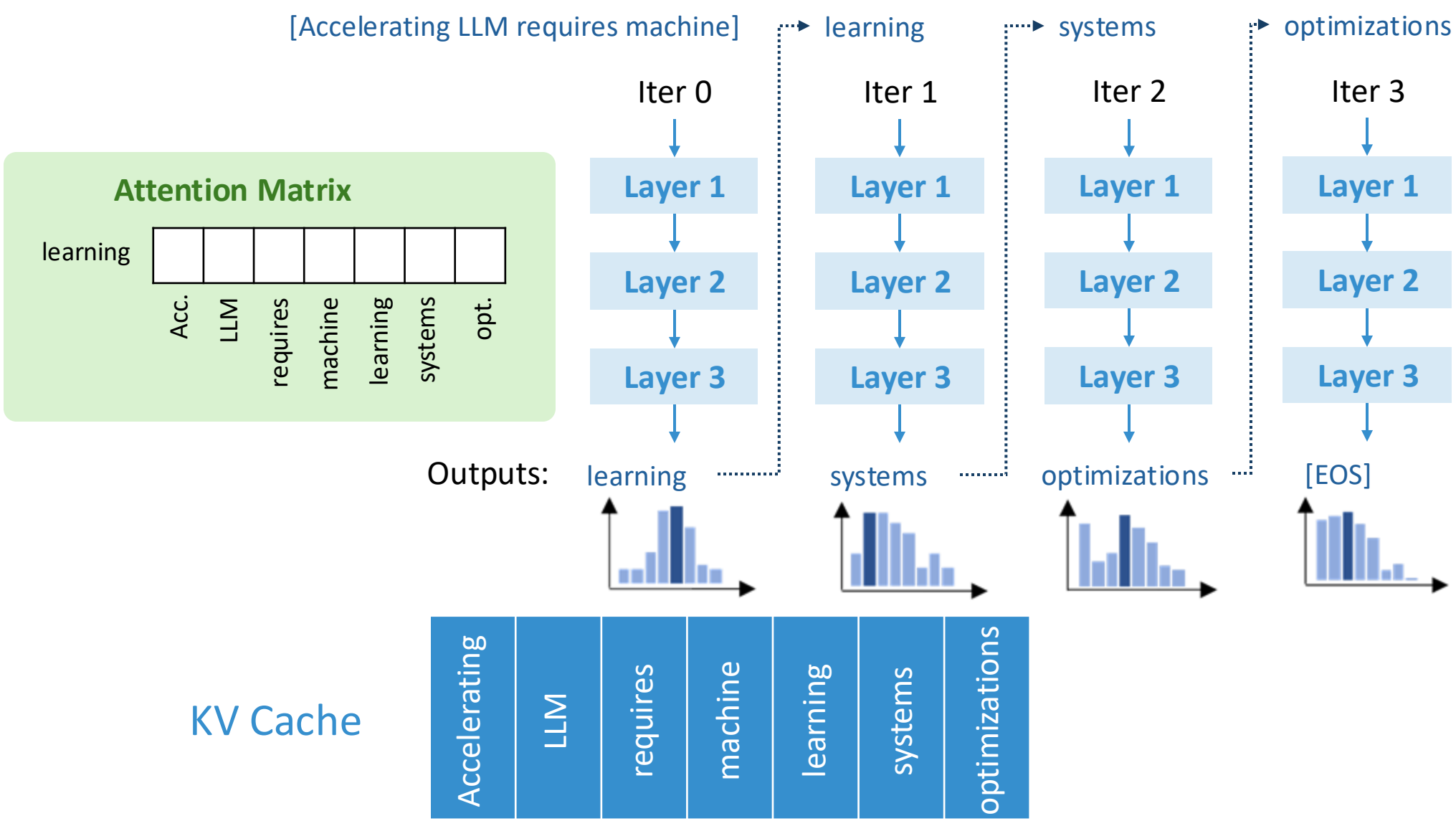
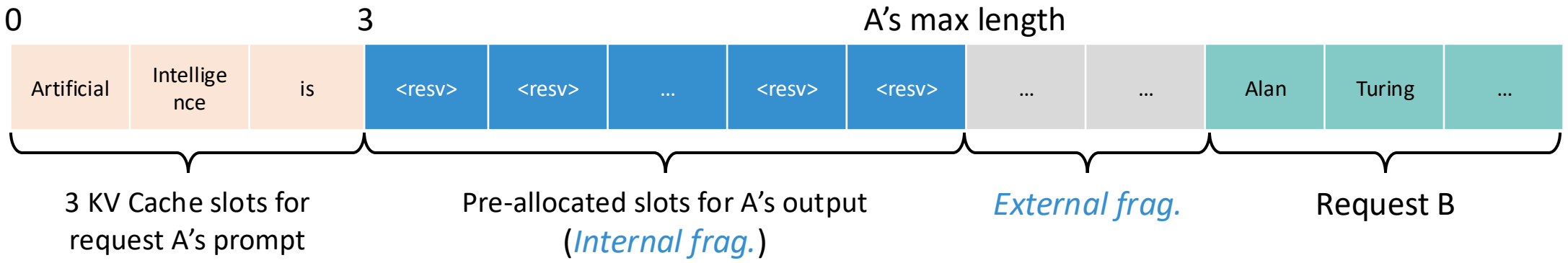


Static KV Cache Management Wastes Memory



- **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

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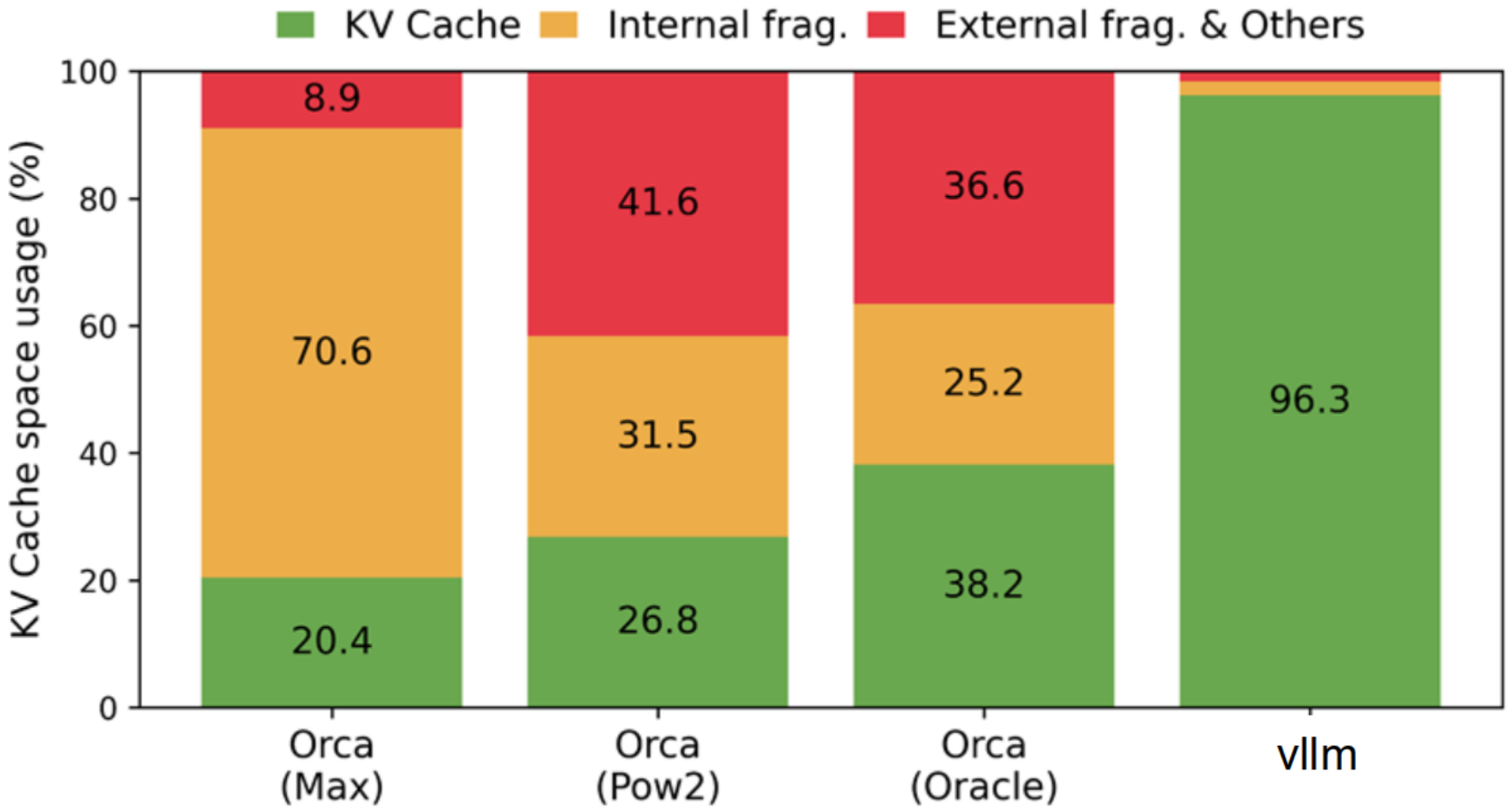
- Only 20-40% of KV cache is utilized to store actual token states



PagedAttention

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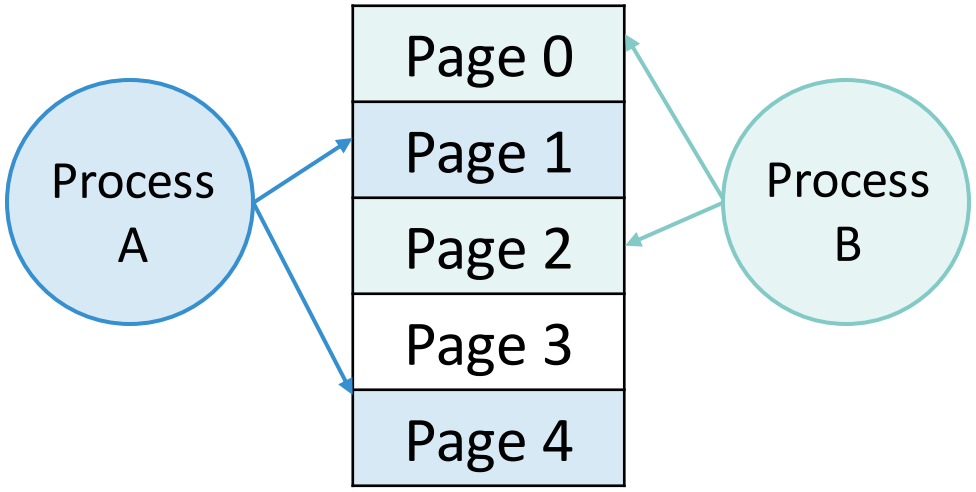
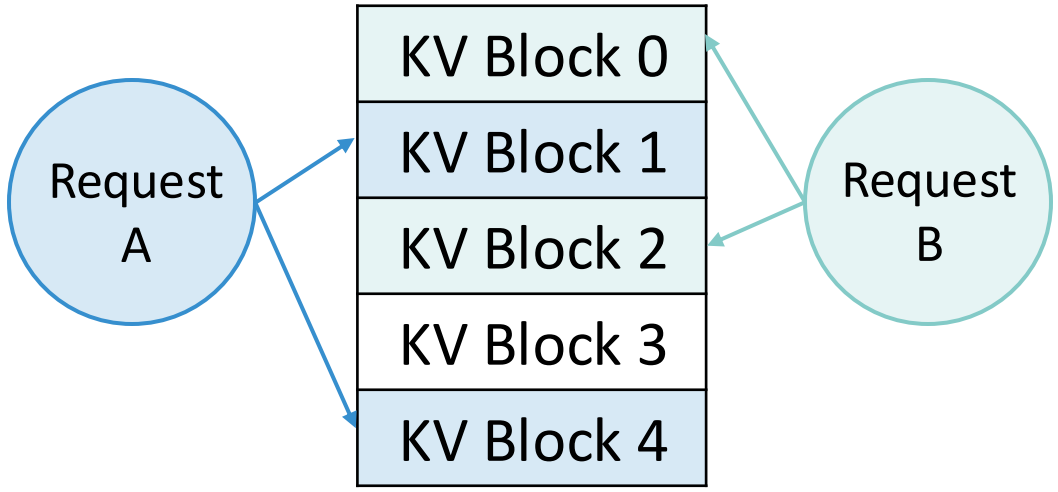
- Application-level memory paging and virtualization for KV cache

Memory management in OS



Physical Memory

PagedAttention



KV Cache

Paging KV Cache Space into KV Blocks*

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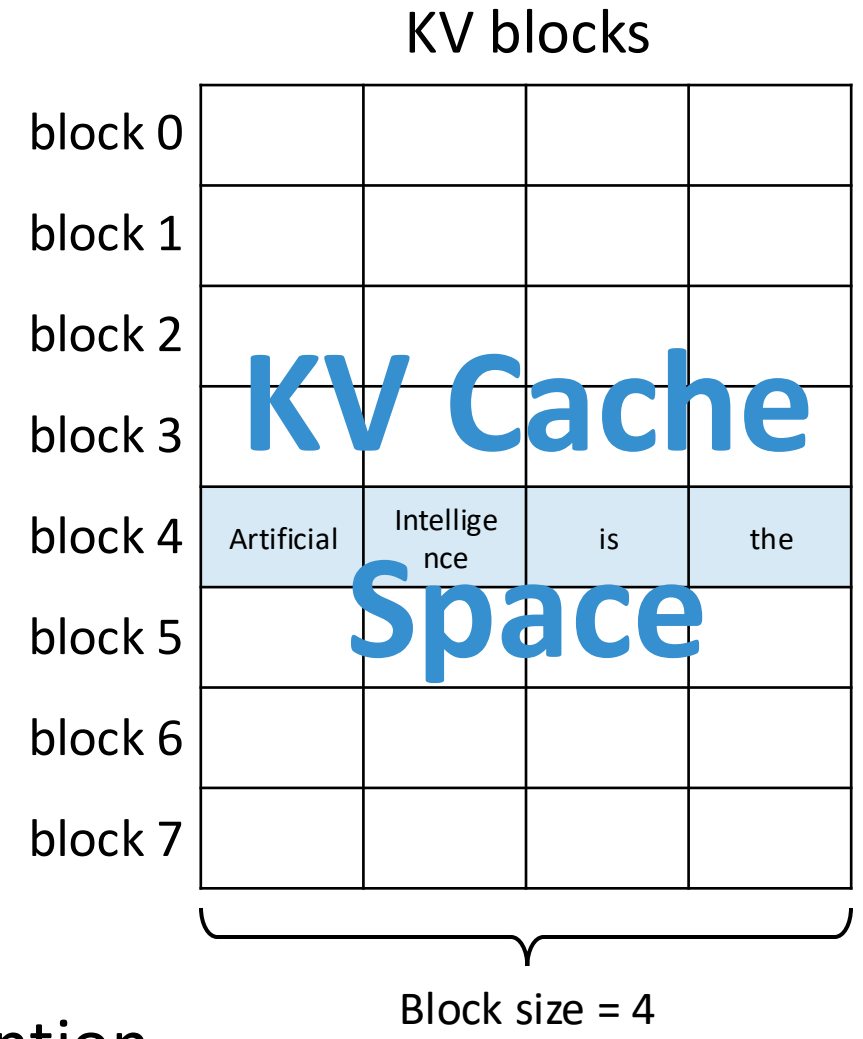
- KV block is a **fixed-size** contiguous chunk of memory that stores KV states from **left to right**



* The term “block” is overloaded in PagedAttention

Virtualizing KV Cache

Request A

Prompt: “Alan Turing is a computer scientist”

Logical KV blocks

block 0	Alan	Turing	is	a
block 1	computer	scientist		
block 2				
block 3				

Block table

Physical block number	# Filled
7	4
1	2
-	-
-	-

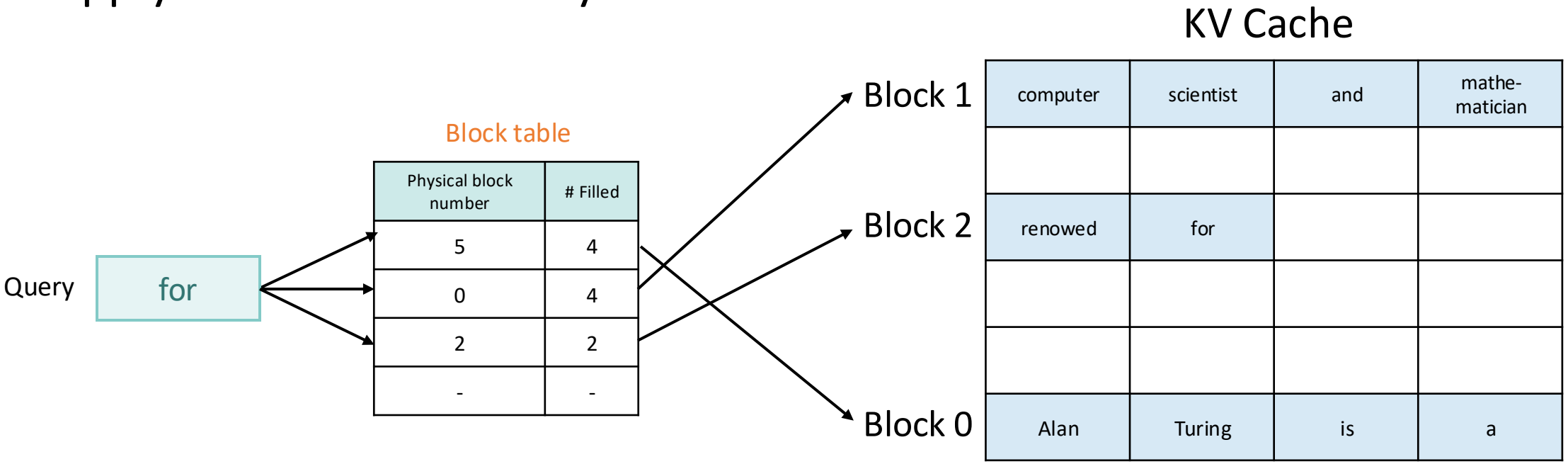
Physical KV blocks

block 0				
block 1	computer	scientist		
block 2				
block 3				
block 4				
block 5				
block 6				
block 7	Alan	Turing	is	a

Attention with Virtualized KV Cache

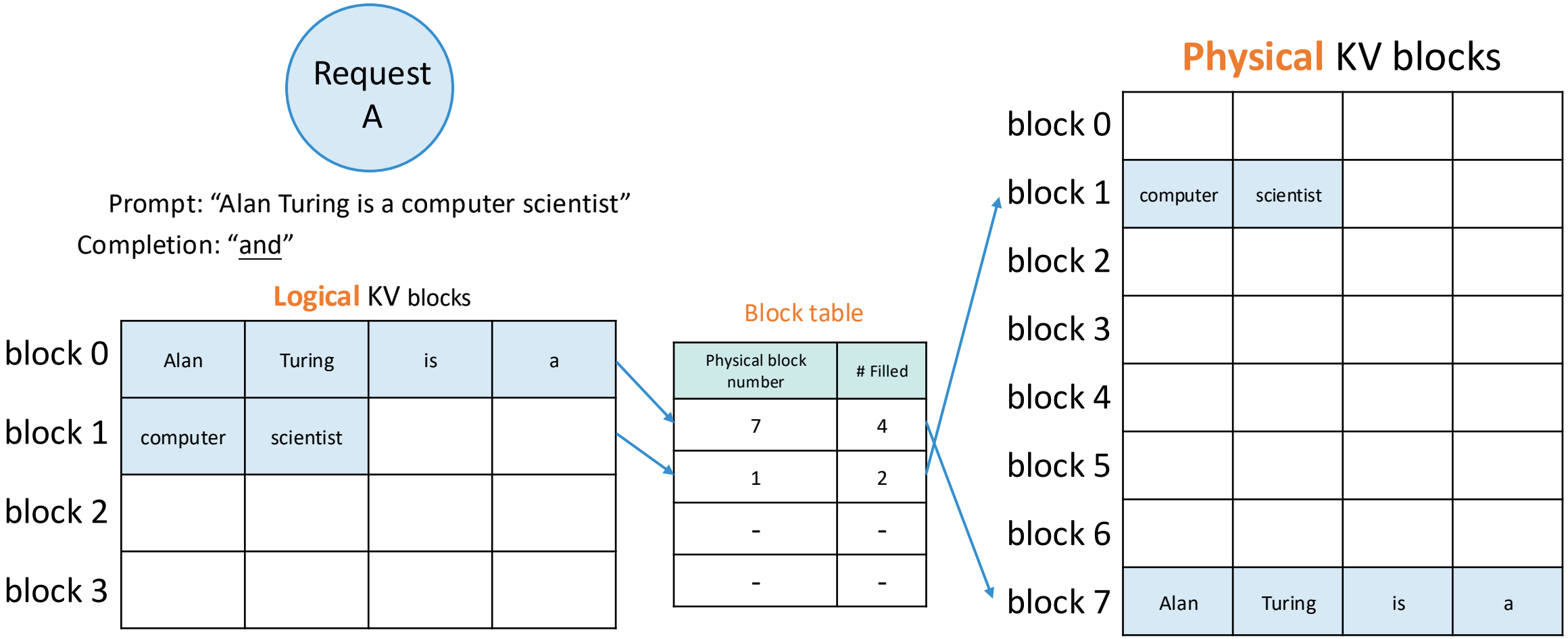
1. Fetch non-contiguous KV blocks using the block table

2. Apply attention on the fly



Key insight: attention is associative and commutative

Memory Management with PagedAttention



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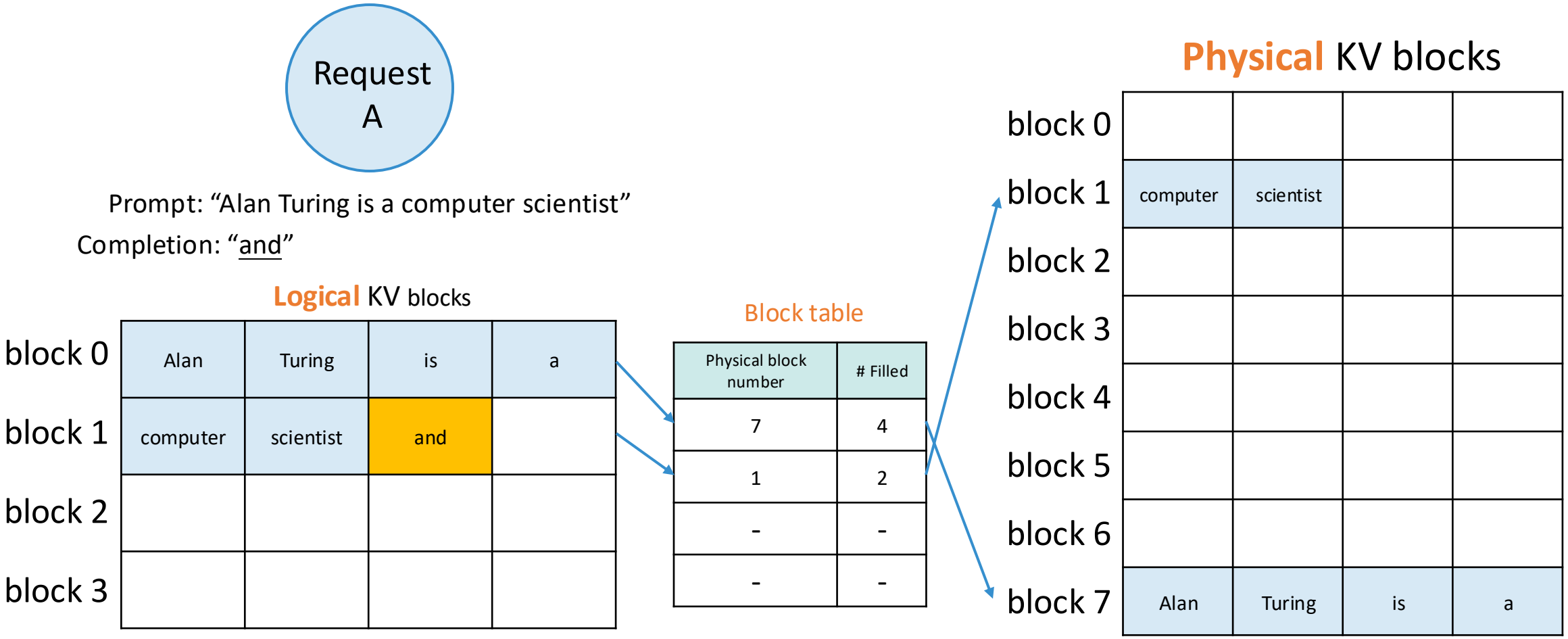
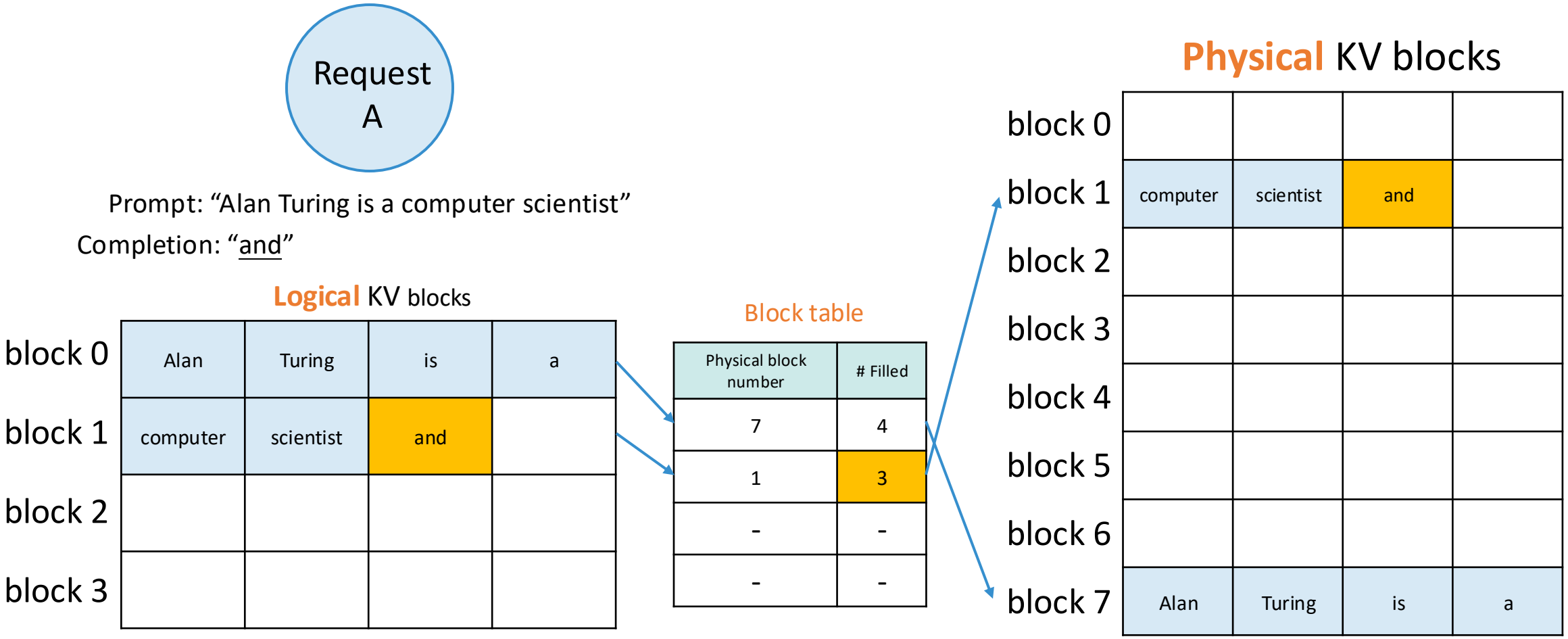
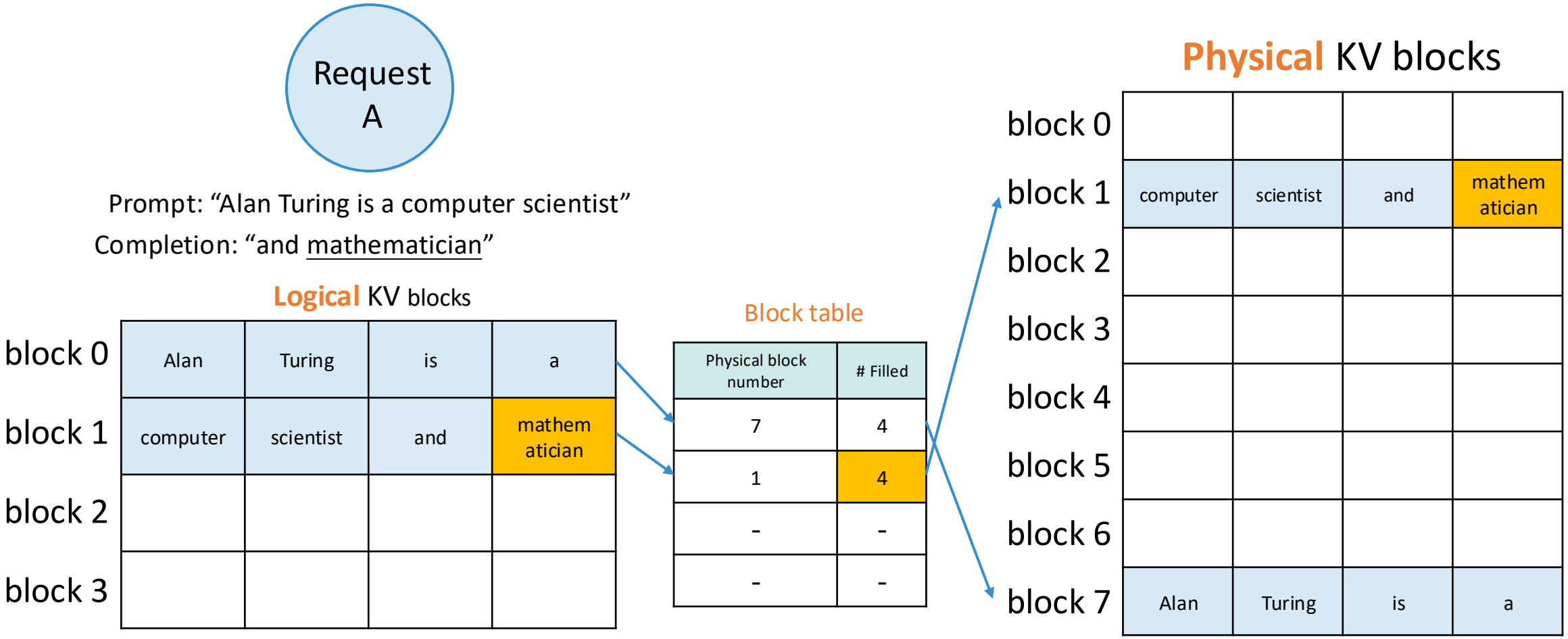


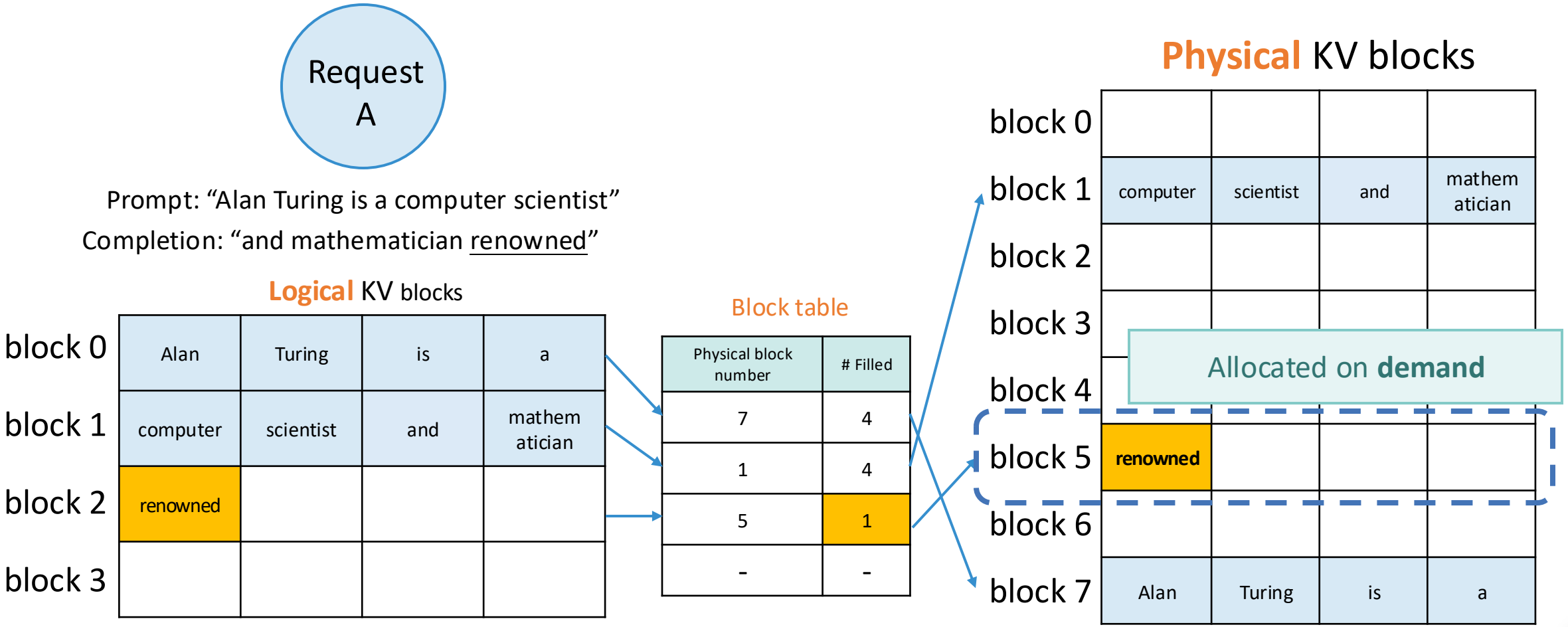
Memory Management with PagedAttention



Memory Management with PagedAttention



Memory Management with PagedAttention



Memory Efficiency of PagedAttention

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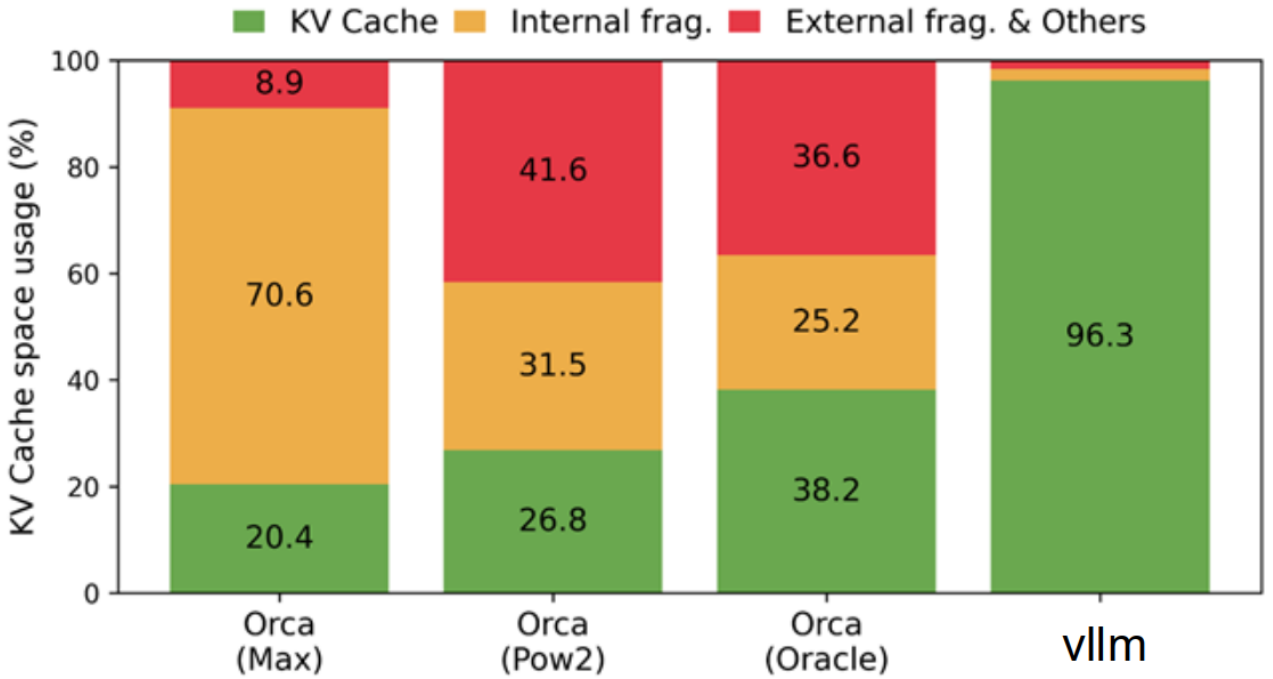
Minimal internal fragmentation

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

Alan	Turing	is	a
computer	scientist	and	mathematician
renowned			

Internal fragmentation

No external fragmentation



Recap: Techniques for Optimizing Attention

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- **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

Acknowledgement

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- Machine Learning Systems[15-442/15-642], by **Tianqi Chen** and **Zhihao Jia** at **CMU**.
- Advanced Topics in Machine Learning (Systems)[CS6216], by **Yao Lu** at **NUS**

While these materials provided a foundational blueprint and a wealth of insightful examples, all content herein has been adapted, modified, and curated to meet the specific learning objectives of our curriculum. Any errors, omissions, or shortcomings found in these course materials are entirely our own responsibility. We are profoundly grateful for the contributions of the educators listed above, whose dedication to teaching and knowledge-sharing has made the creation of this course possible.

System for Artificial Intelligence

Thanks

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