



<https://hao-ai-lab.github.io/dsc204a-f25/>

DSC 204A: Scalable Data Systems

Fall 2025

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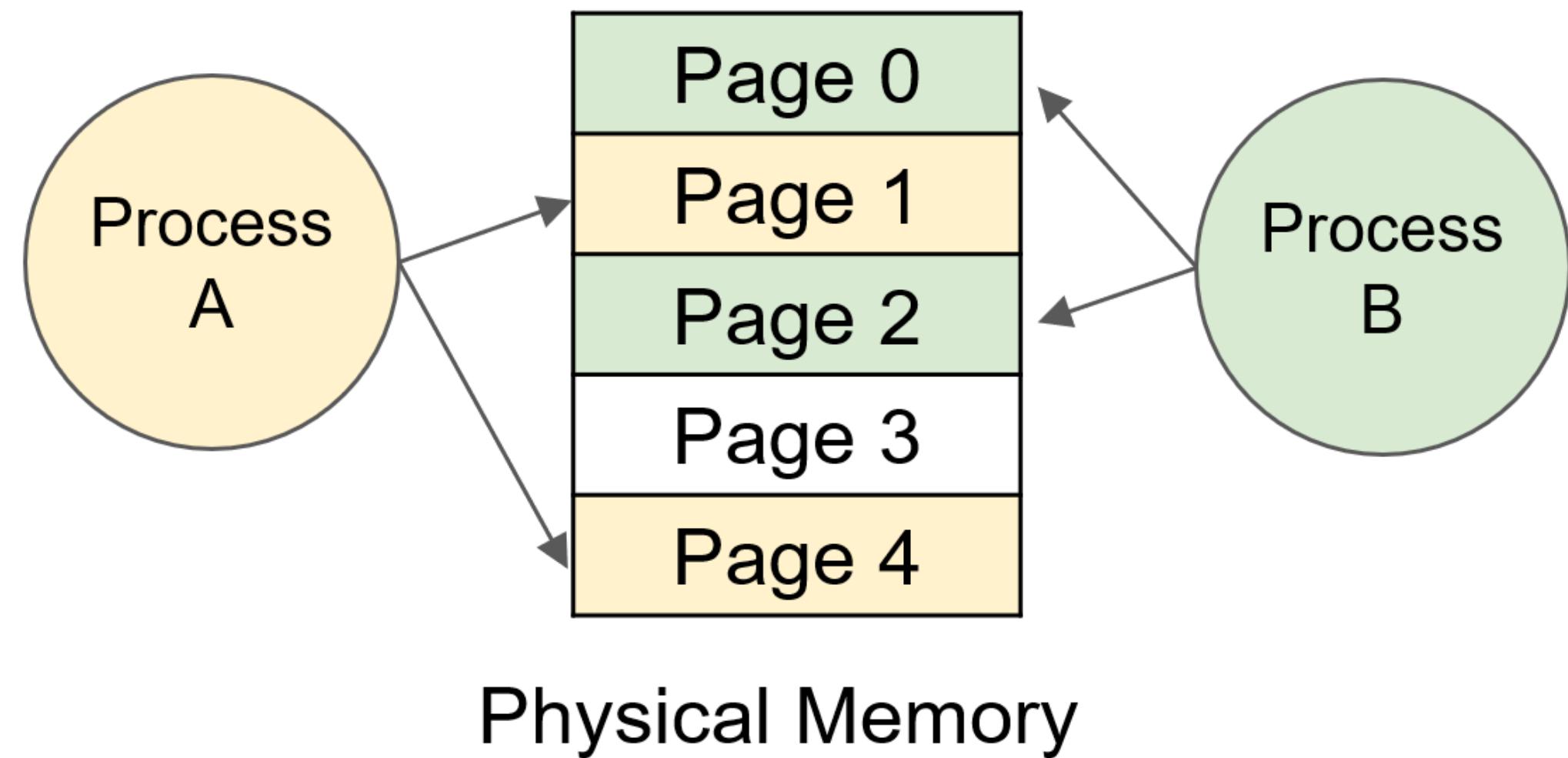
Large Language Models

- Transformers, Attentions
- **Serving and inference**
- Parallelization
- Attention optimization

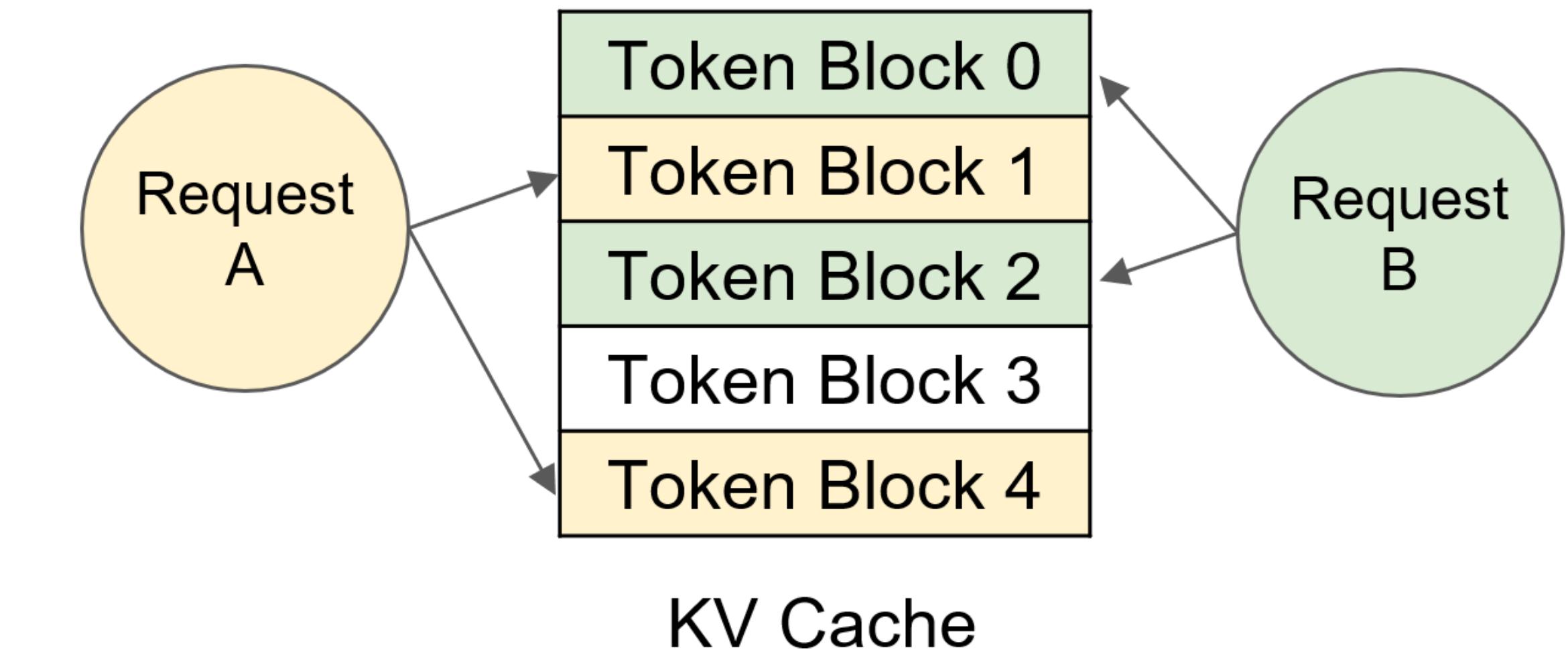
vLLM: Efficient memory management for LLM inference

Inspired by **virtual memory** and **paging**

Memory management in OS



Memory management in vLLM



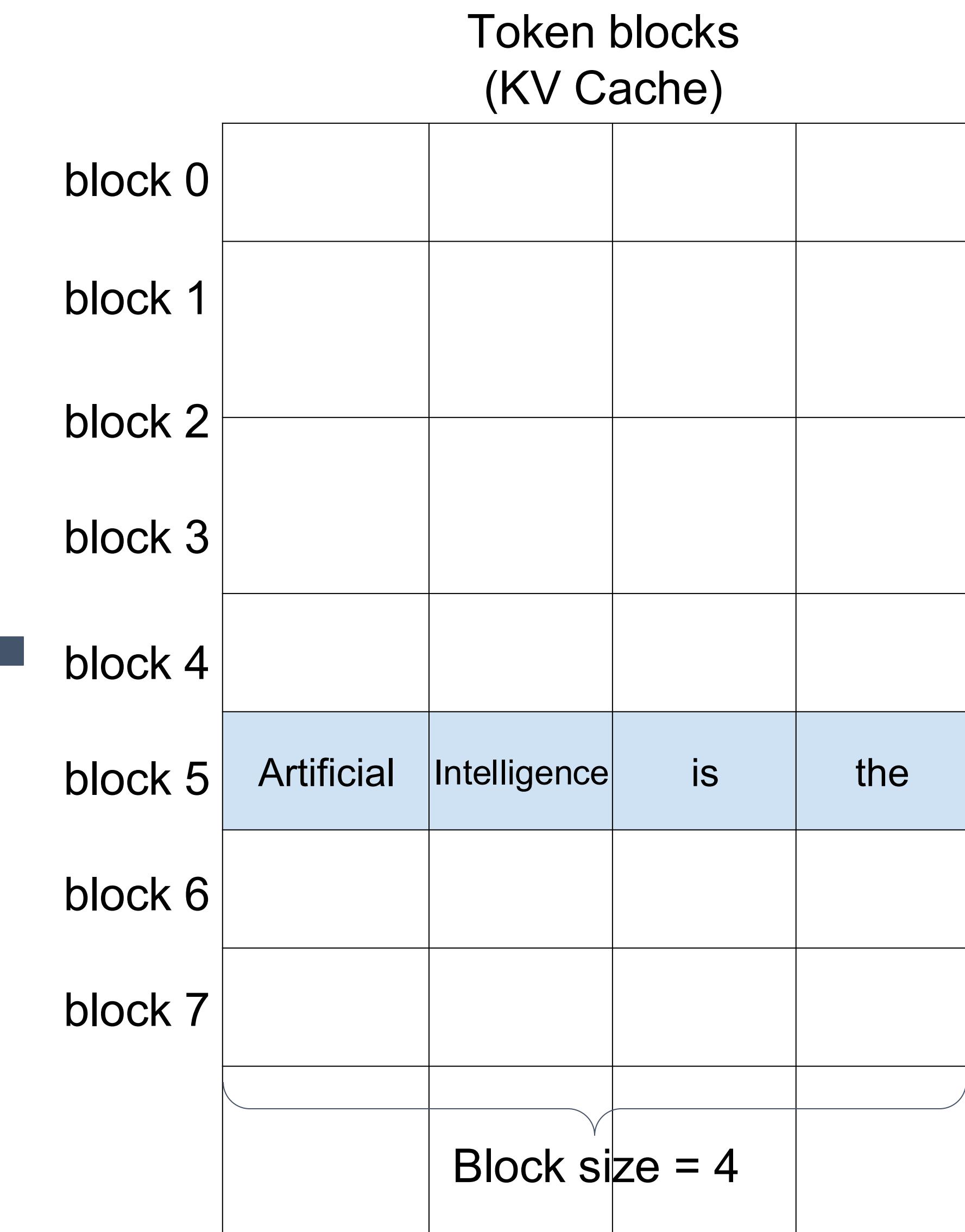
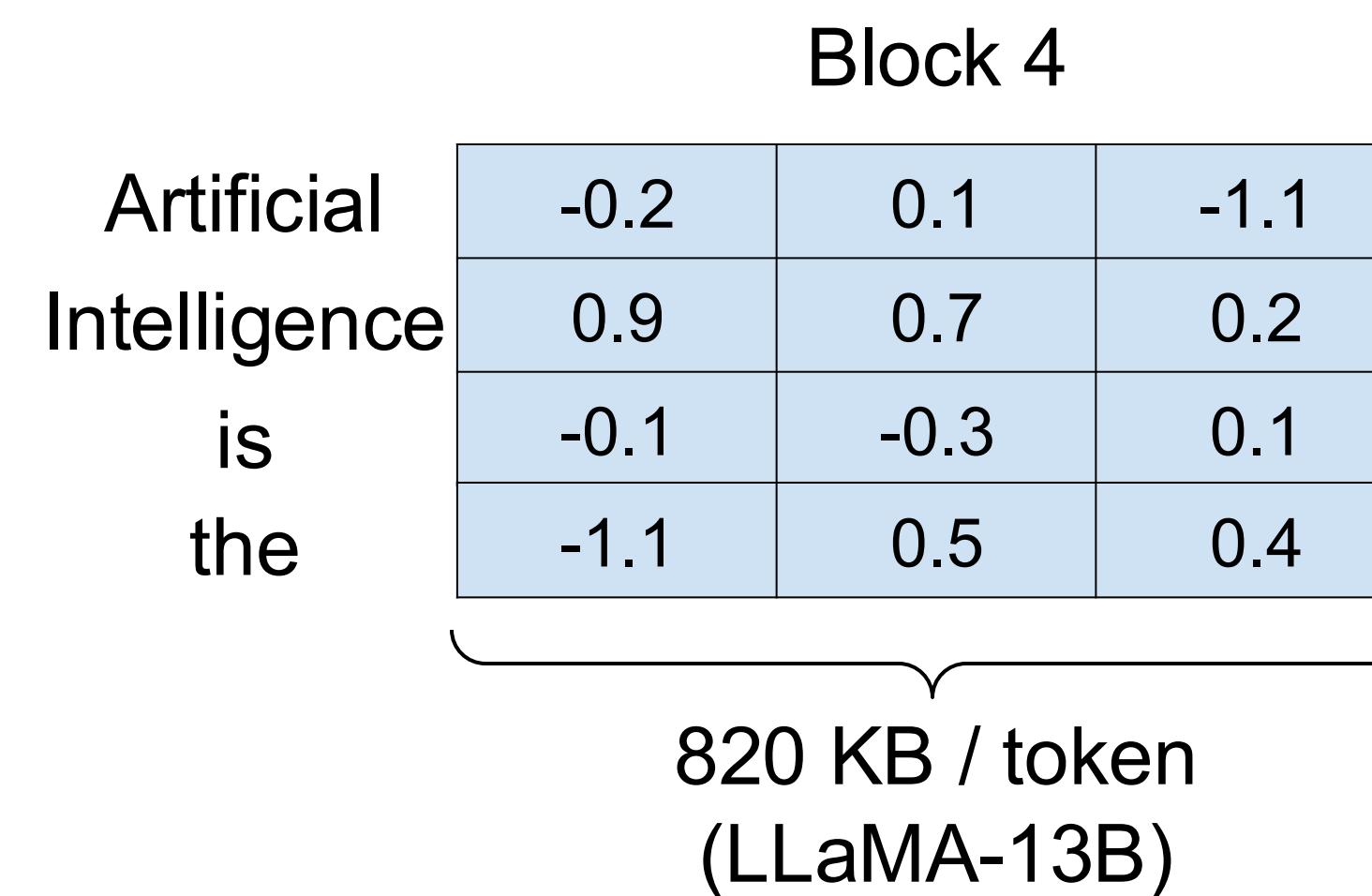
Token block

- A **fixed-size** contiguous chunk of memory that can store token states **from left to right**



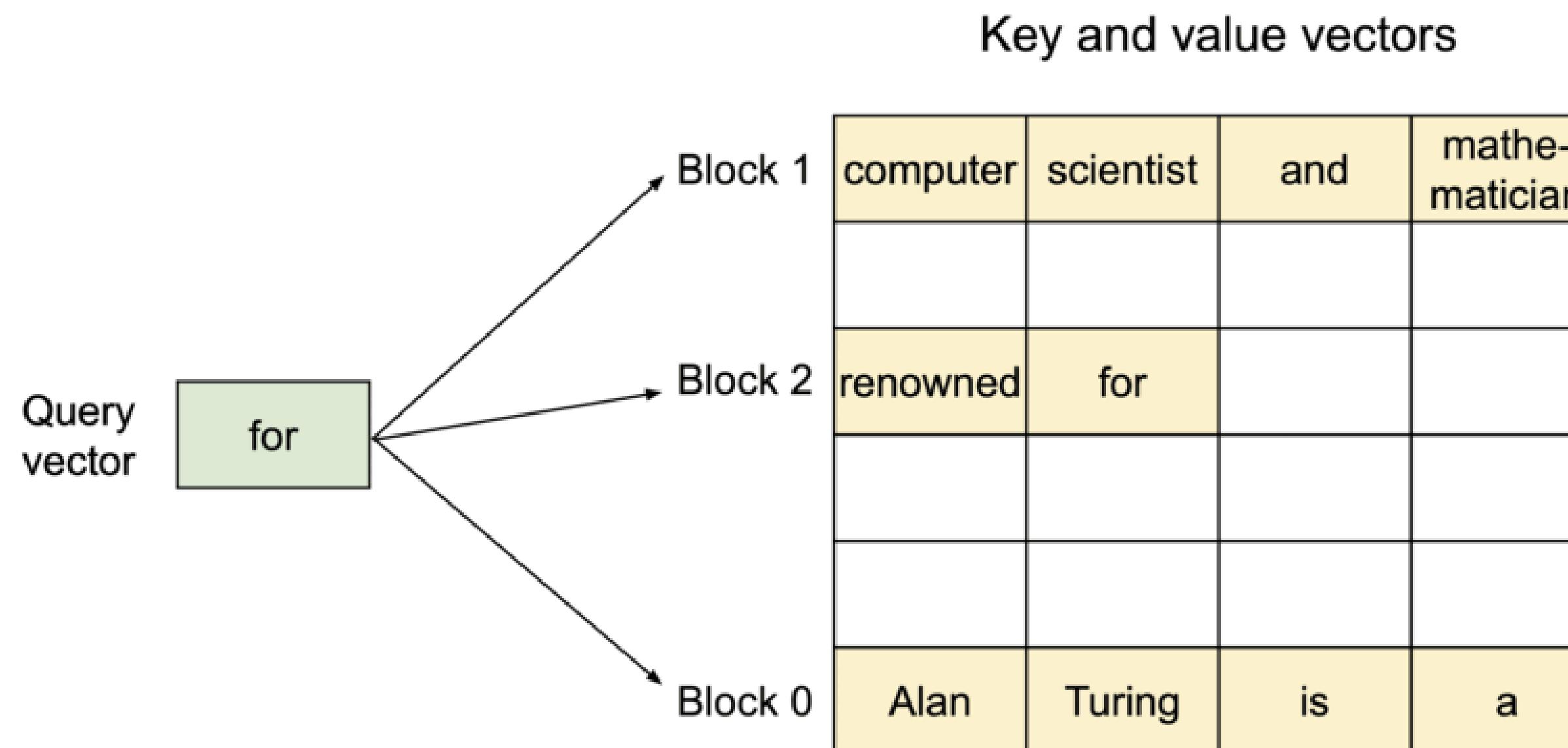
Token block

- A **fixed-size** contiguous chunk of memory that can store token states **from left to right**

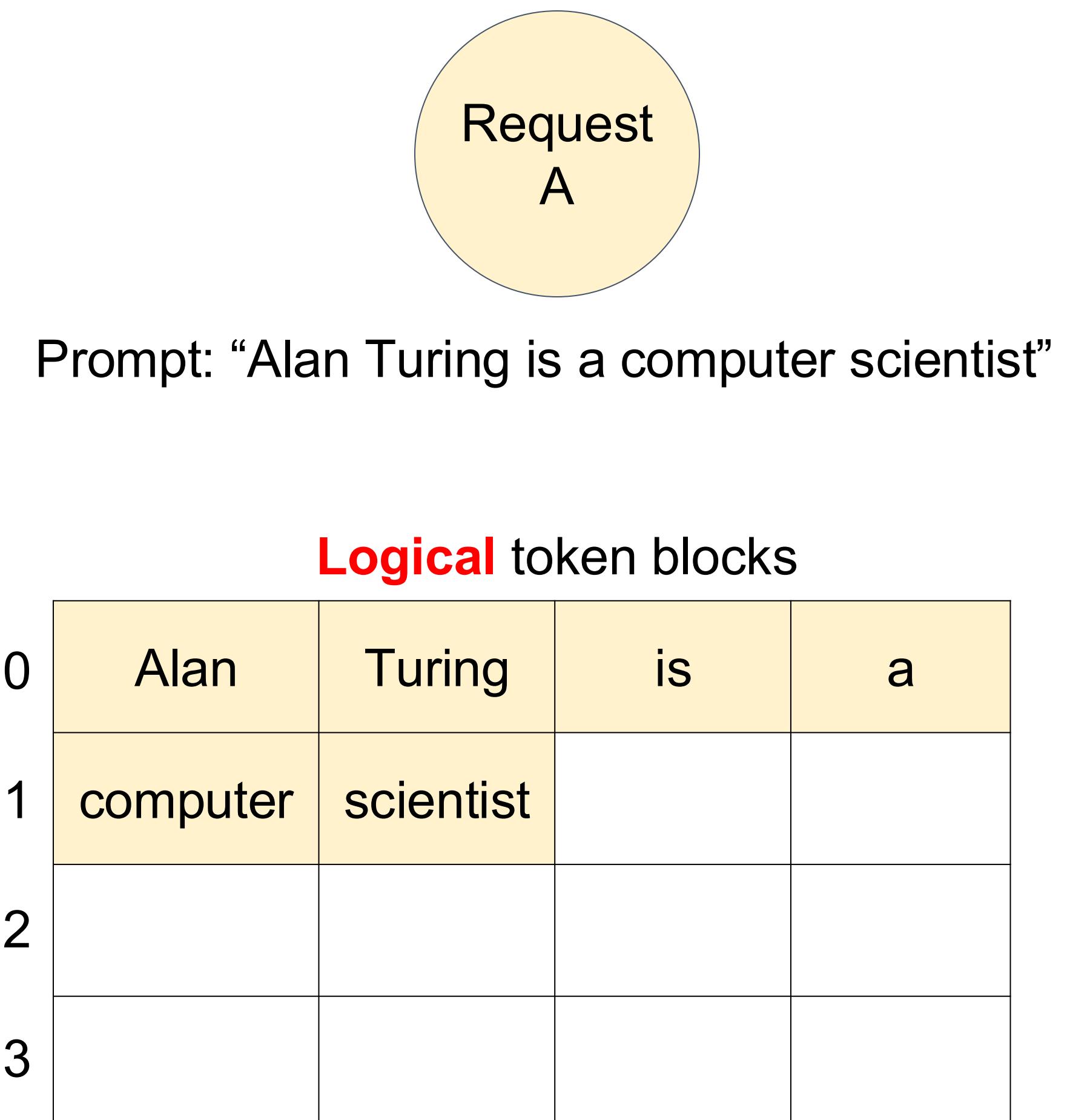


Paged Attention

- An attention algorithm that allows for storing continuous keys and values in non-contiguous memory space



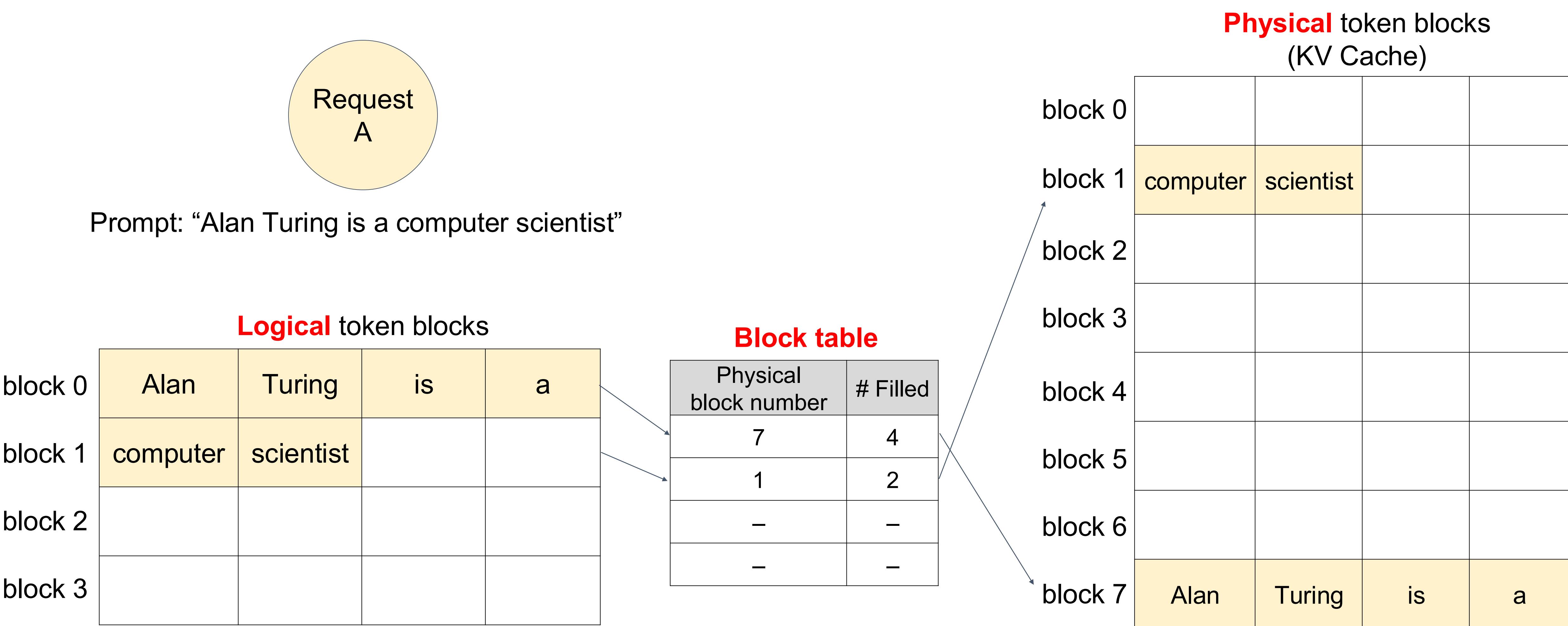
Logical & physical token blocks



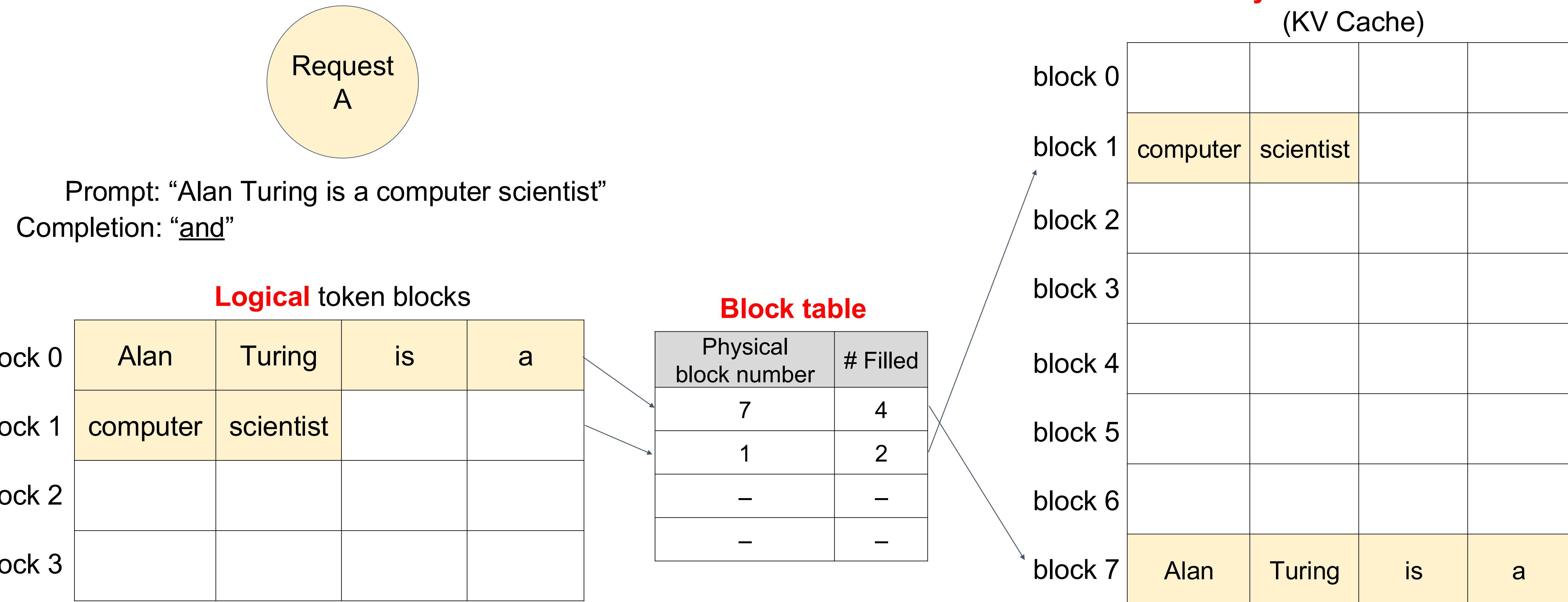
Physical token blocks (KV Cache)

block 0			
block 1			
block 2			
block 3			
block 4			
block 5			
block 6			
block 7			

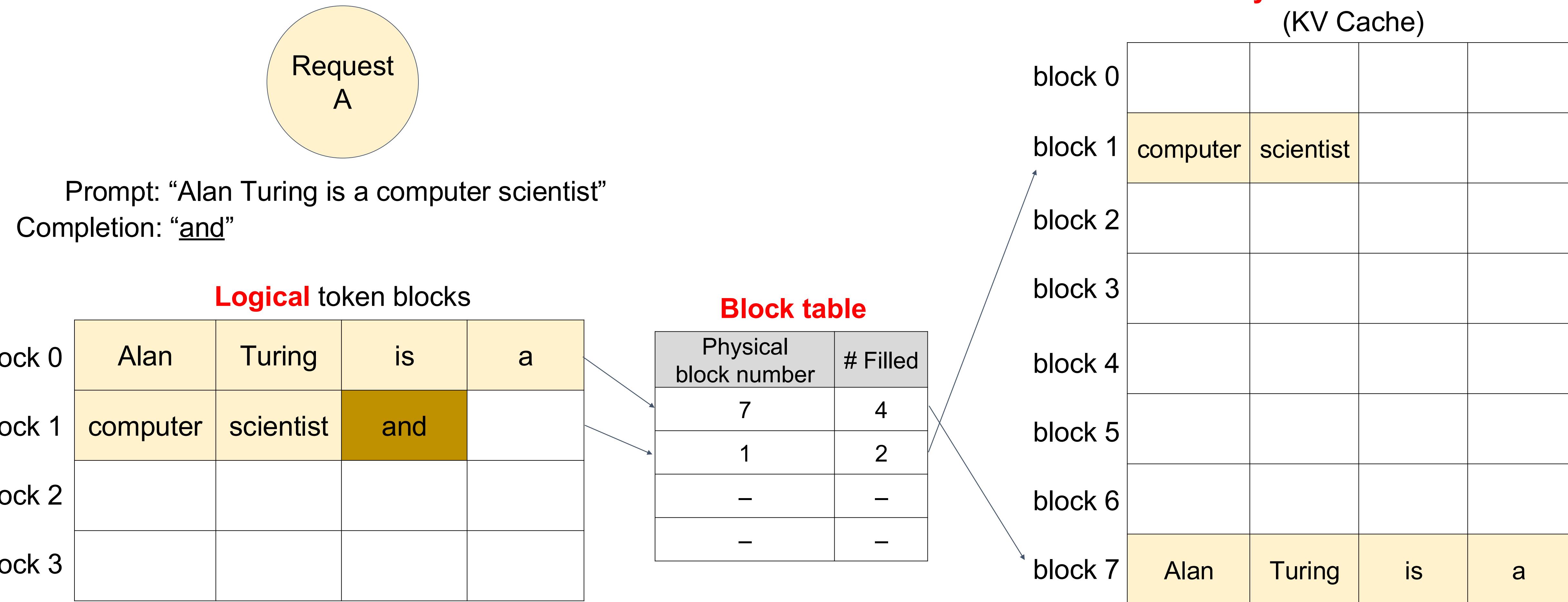
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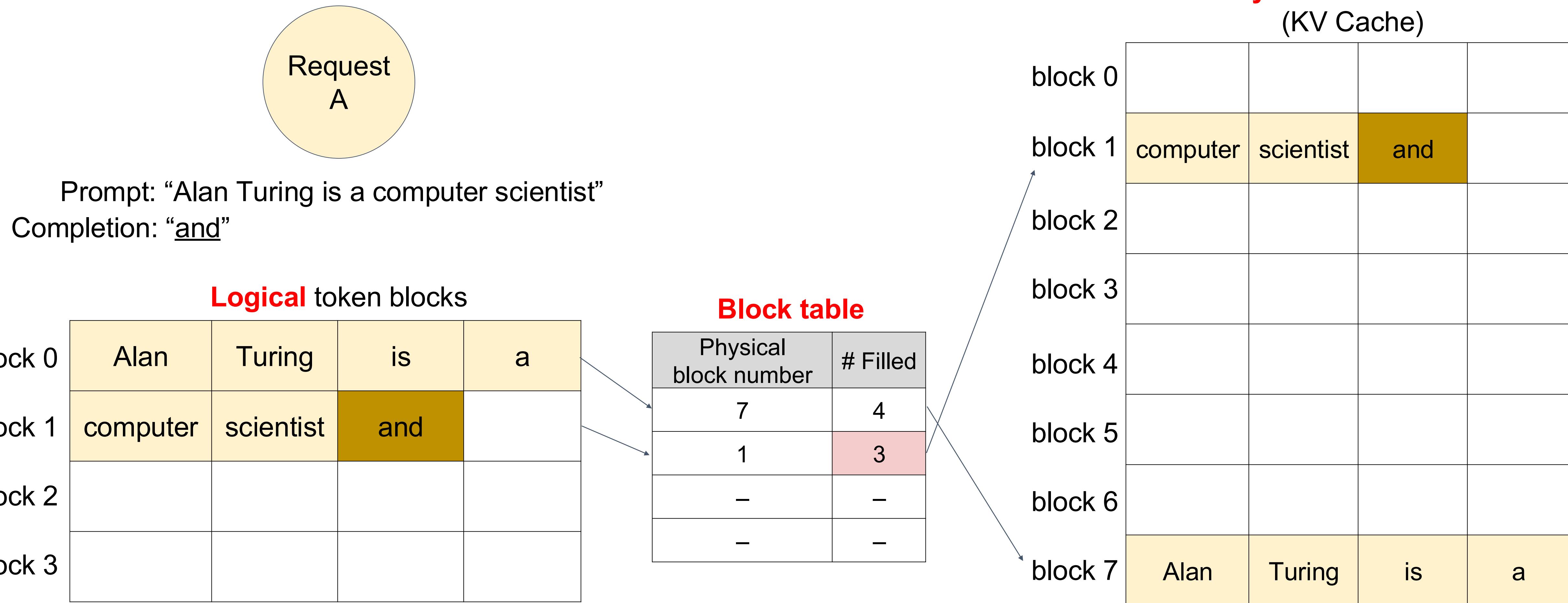
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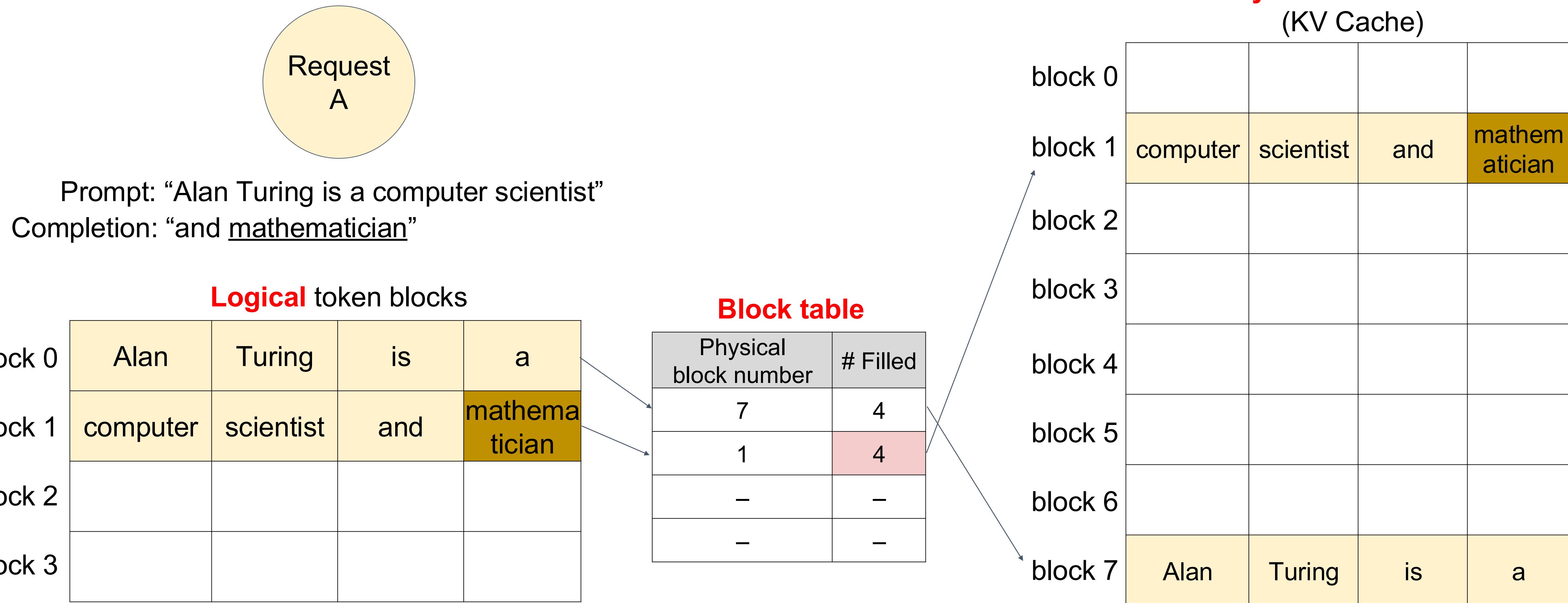
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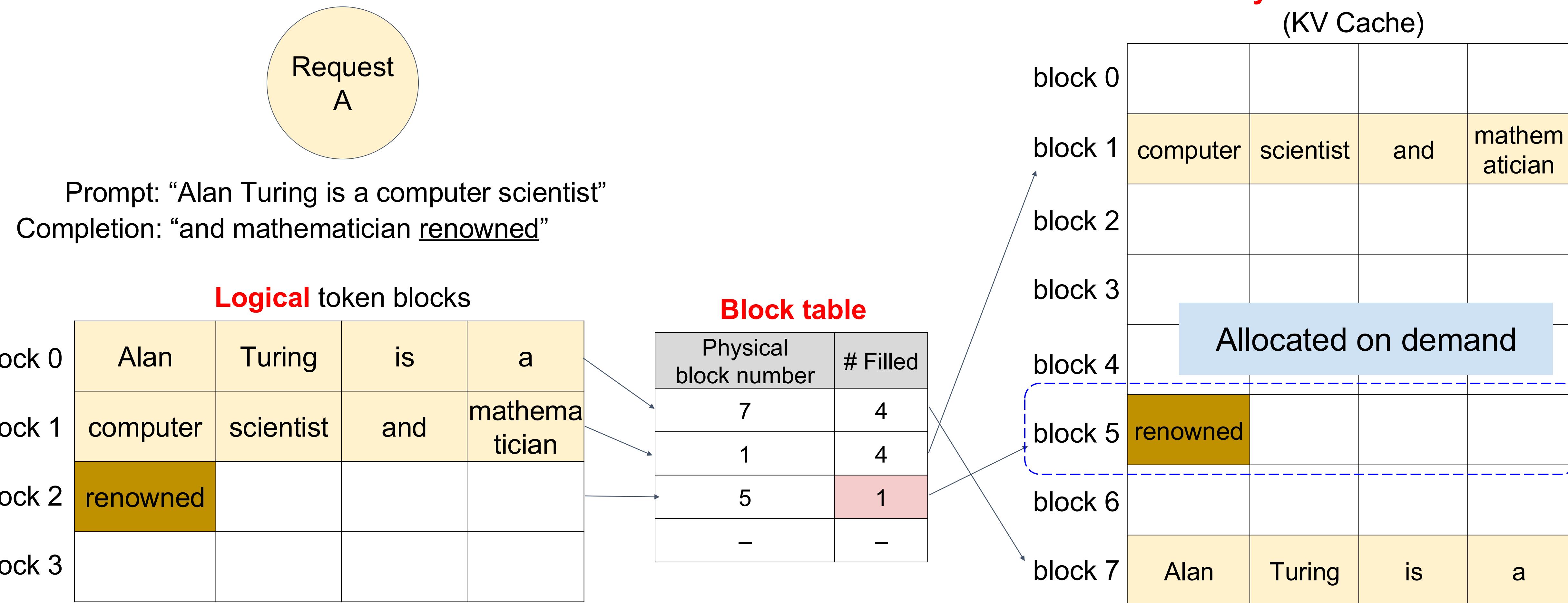
Logical & physical token blocks



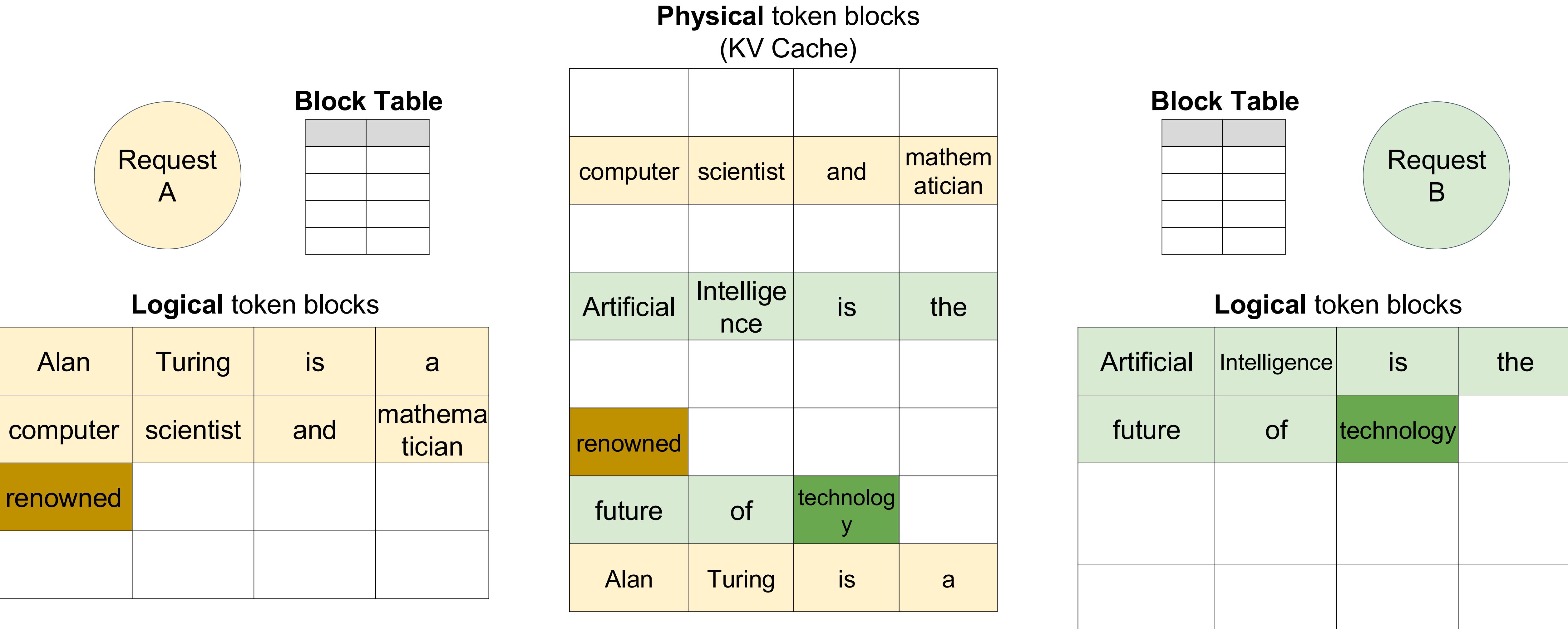
Logical & physical token blocks



Logical & physical token blocks



Serving multiple requests



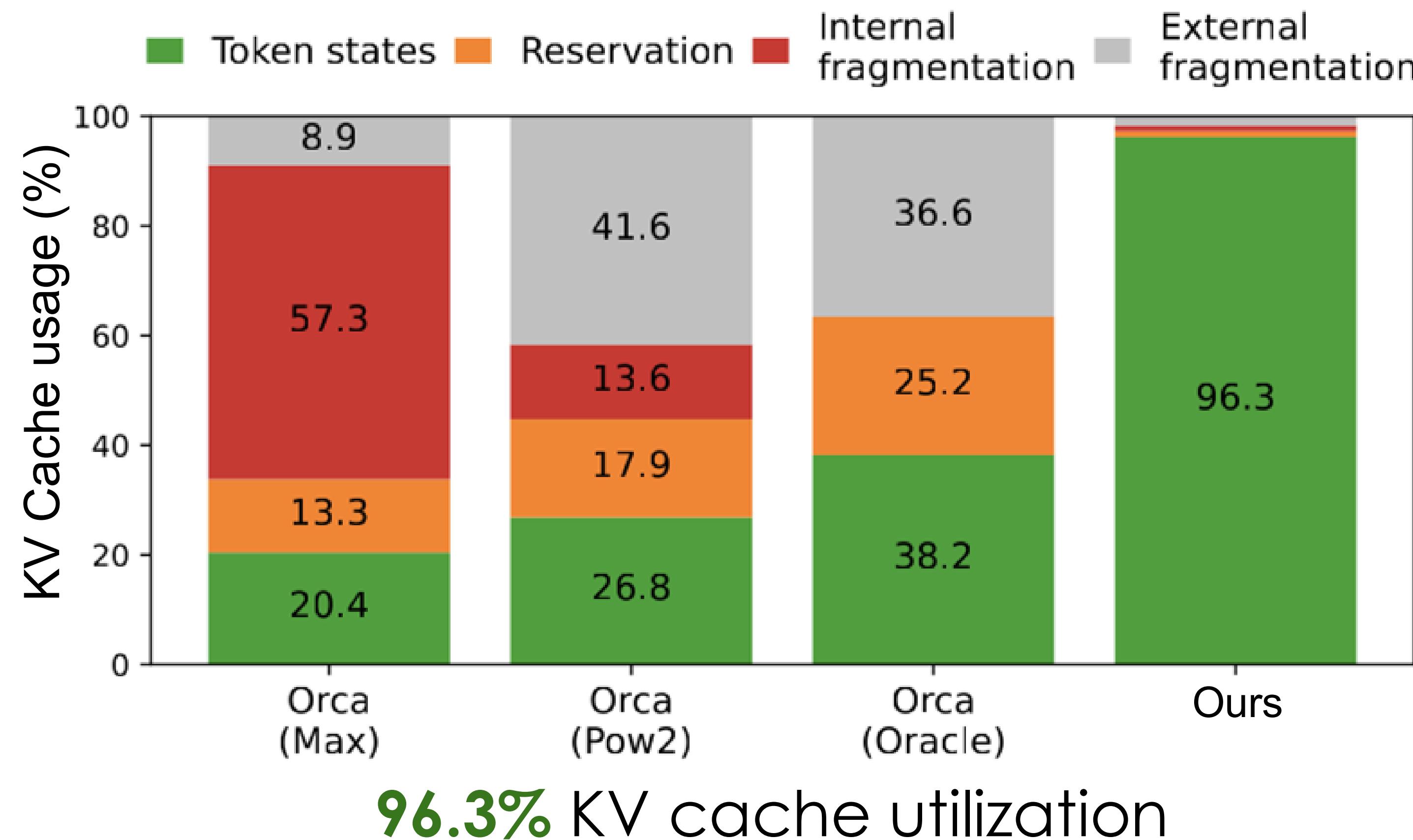
Memory efficiency of vLLM

- Minimal internal fragmentation
 - Only happens at the last block of a sequence
 - **# wasted tokens / seq < block size**
 - Sequence: $O(100) - O(1000)$ tokens
 - Block size: 16 or 32 tokens
- No external fragmentation

Alan	Turing	is	a
computer	scientist	and	mathematician
renowned			

Internal fragmentation

Effectiveness of PagedAttention

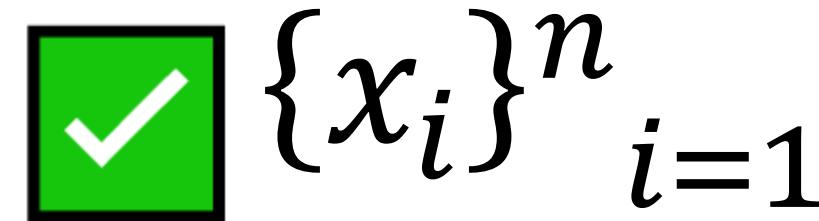


Other Inference Techniques

- Speculative Decoding
 - optimization for small bs, decoding multiple tokens per fwd pass
- Chunked prefill
 - Continuous batching enhancement
- Disaggregated Serving
- Prefix caching
- More...

Focus of the rest of lectures

Data



Model

Math primitives
(mostly matmul)

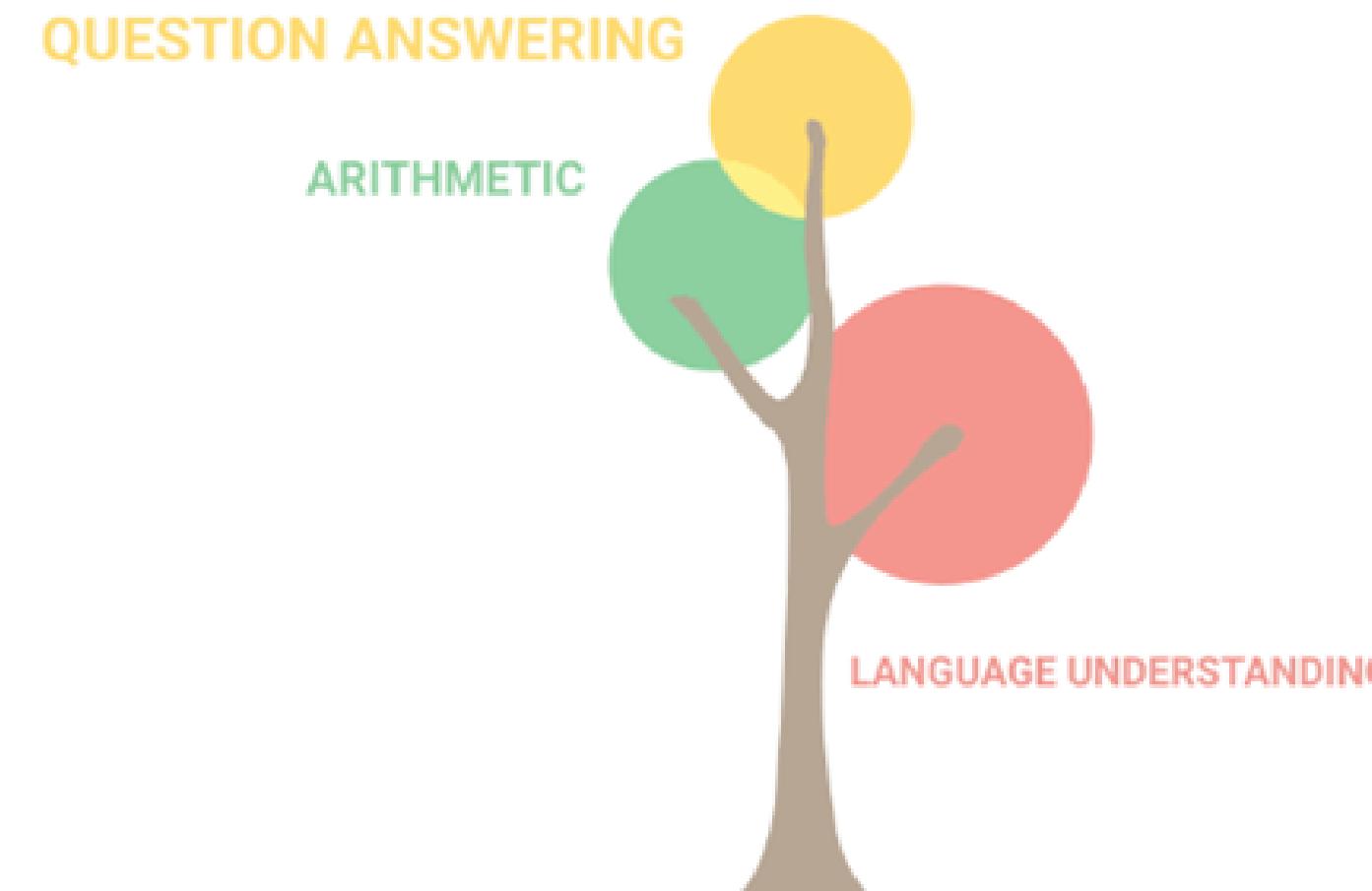


A repr that expresses the computation using primitives

Compute

❓ Make LLMs run on
(large clusters of) GPUs

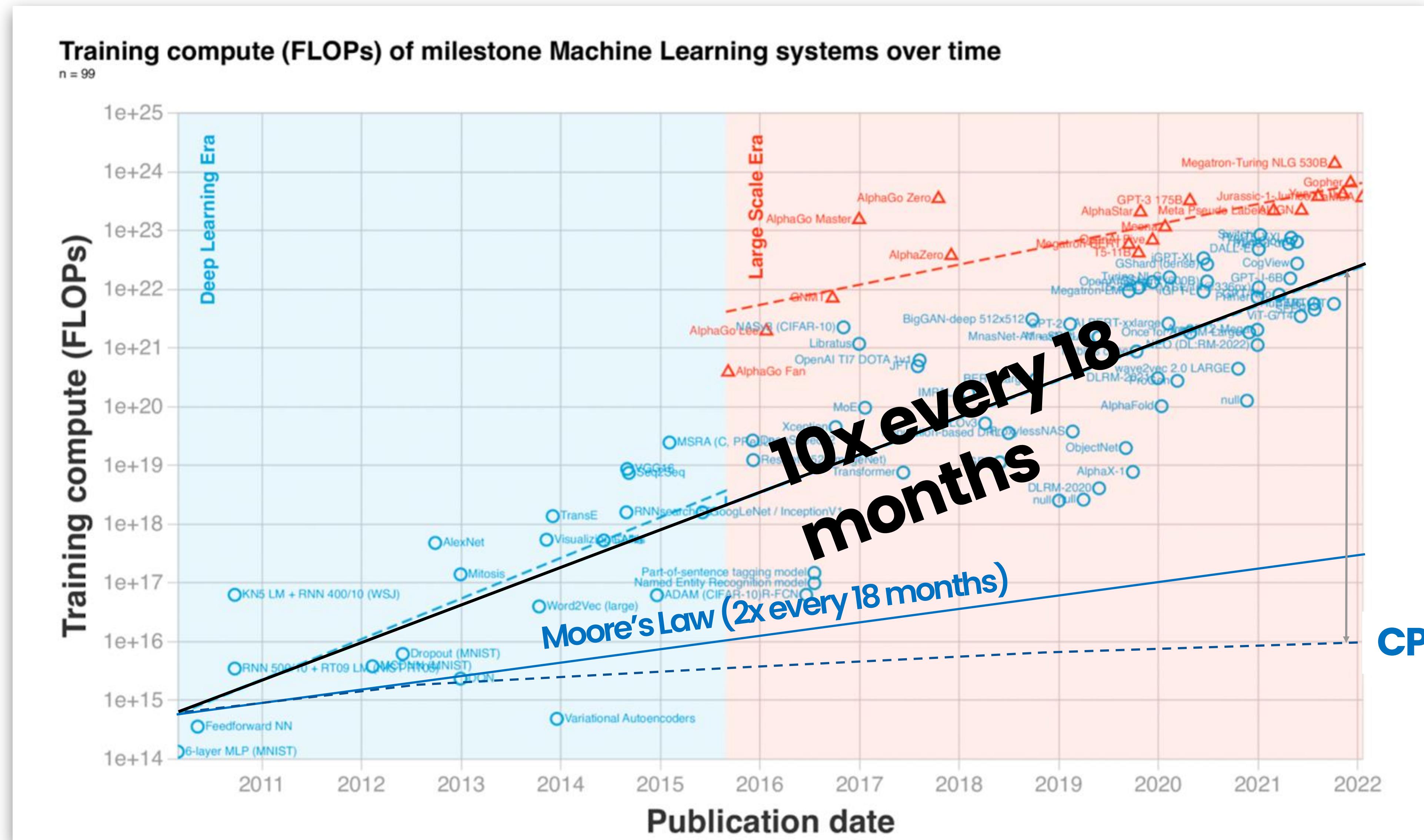
Big Models have Emergent capabilities



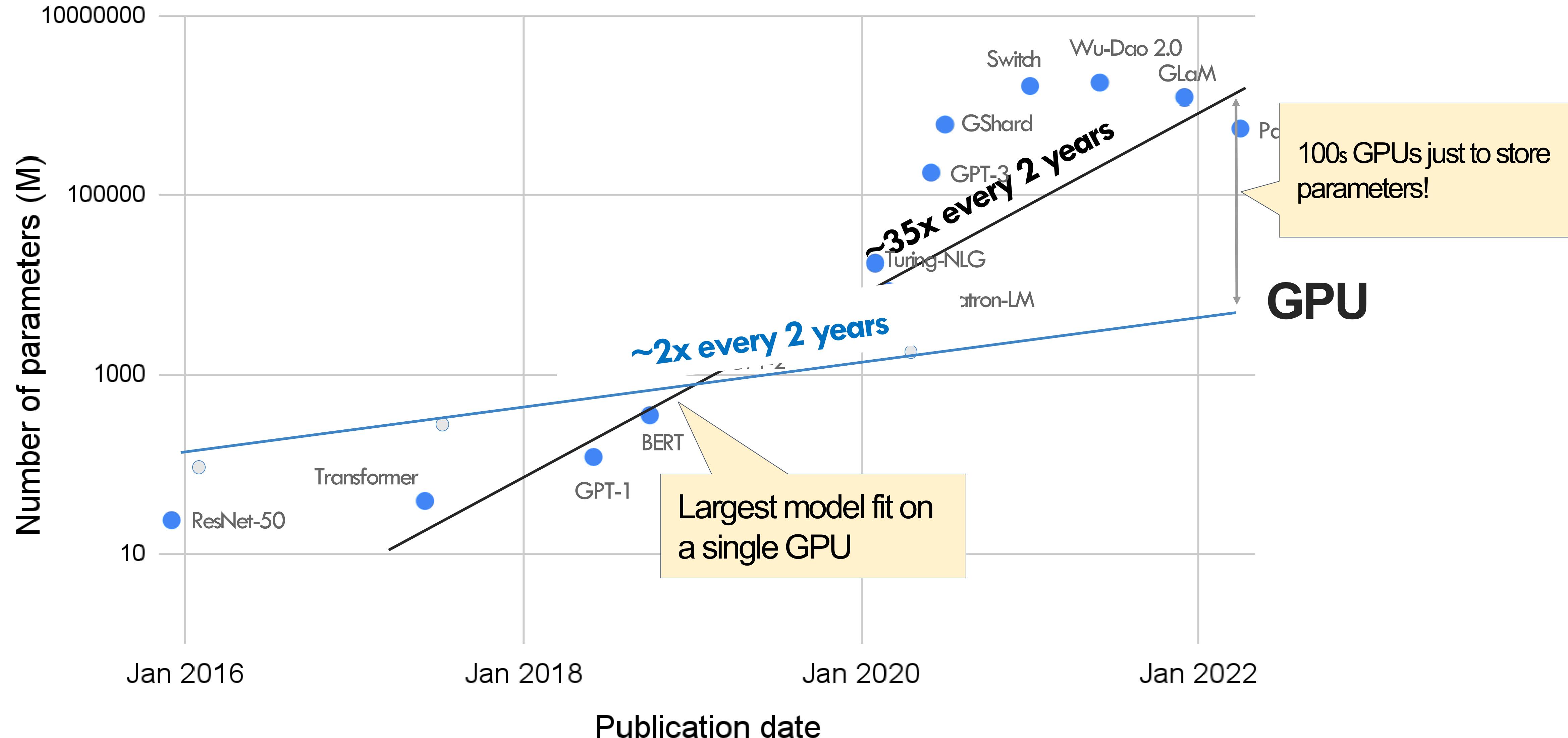
8 billion parameters

“Pathways Language Model (PaLM): Scaling to 540 Billion Parameters for Breakthrough Performance”,
S Narang, A Chowdhery et al, <https://ai.googleblog.com/2022/04/pathways-language-model-palm-scaling-to.html>

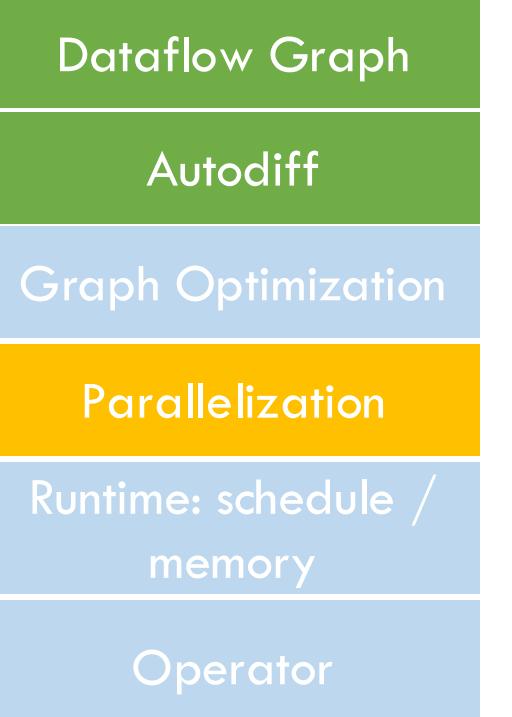
Growing gap between demand and supply



Growing gap between memory demand and supply



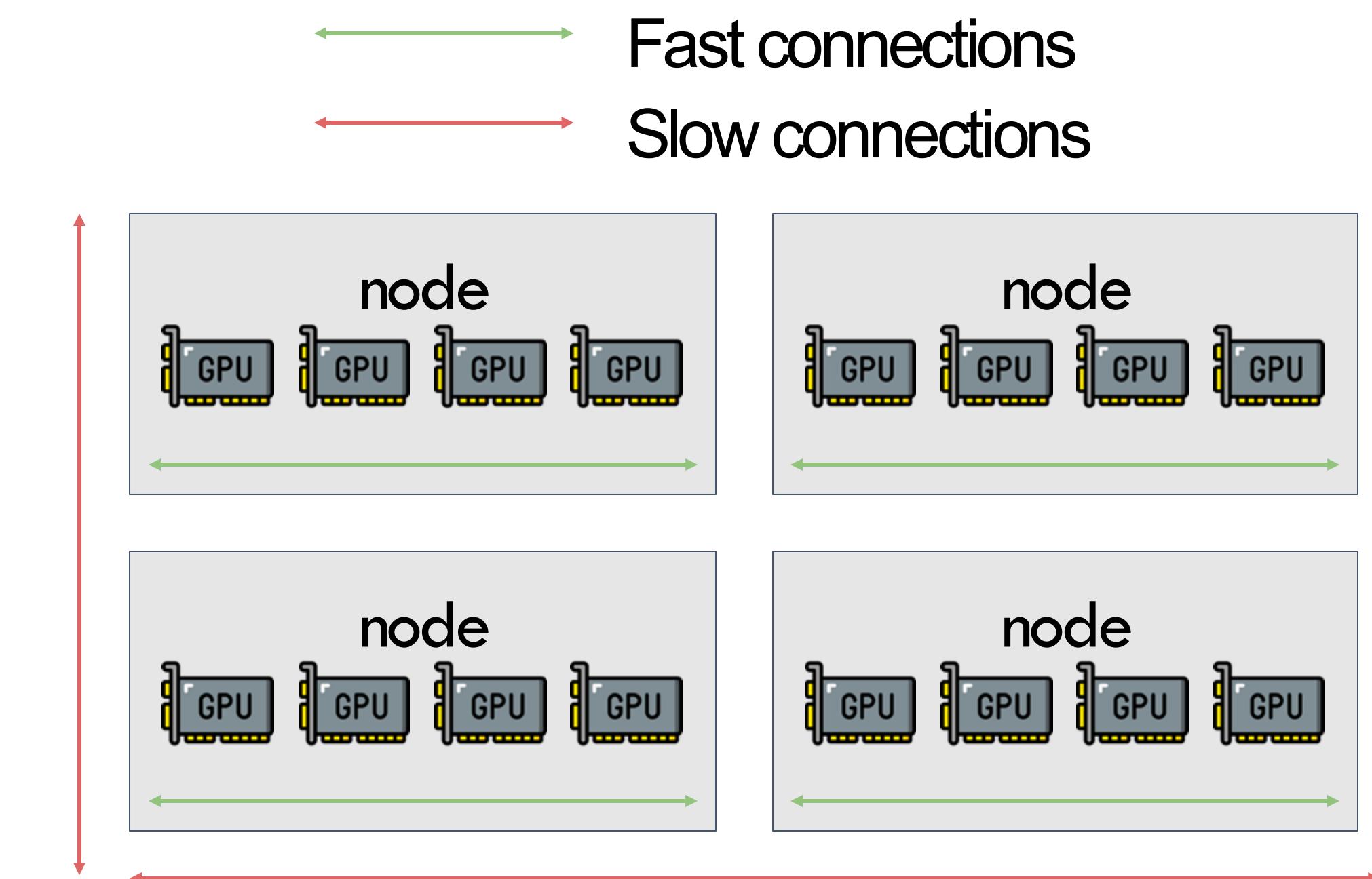
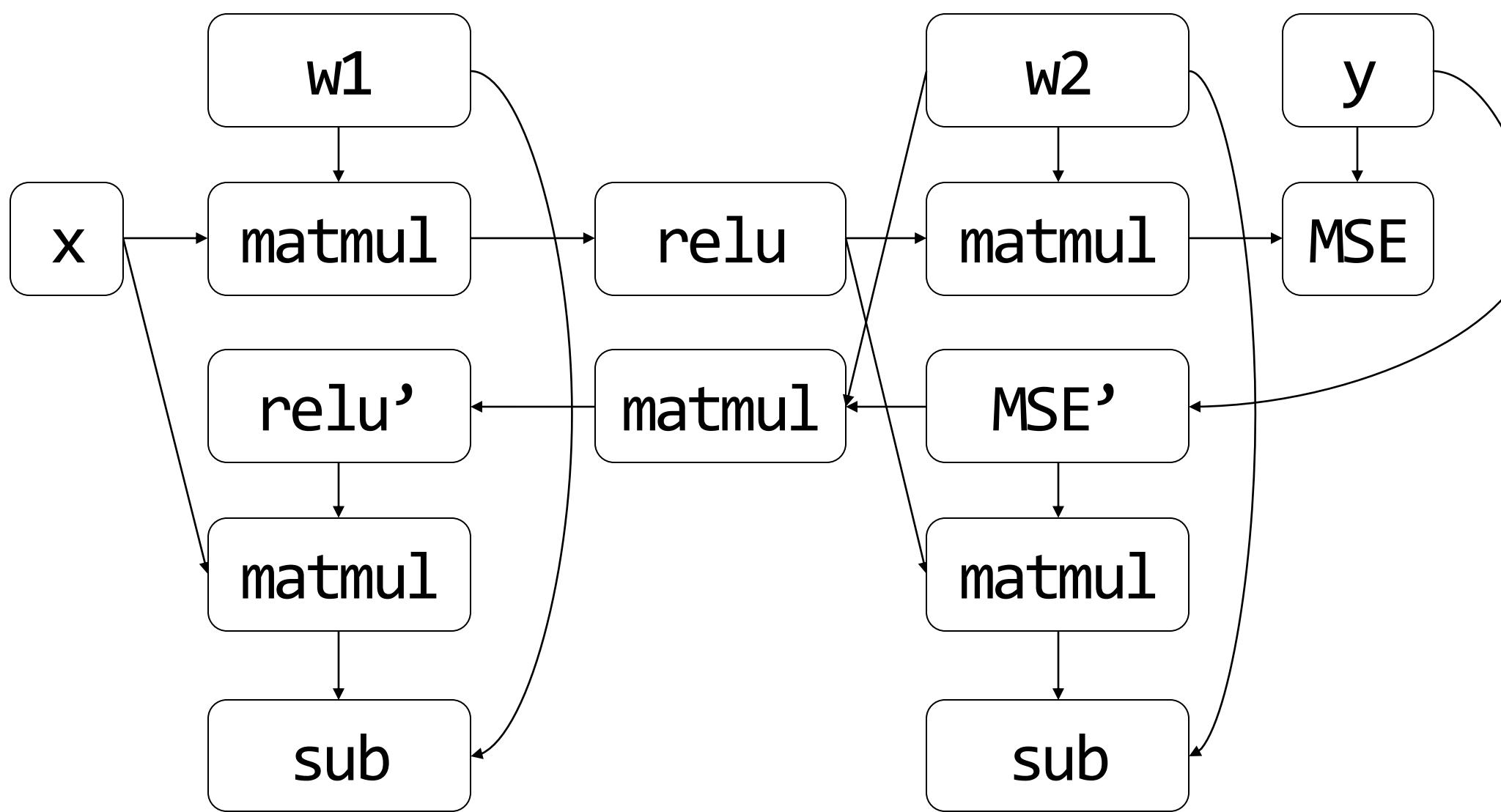
**No way out but to parallelize
these workloads !**

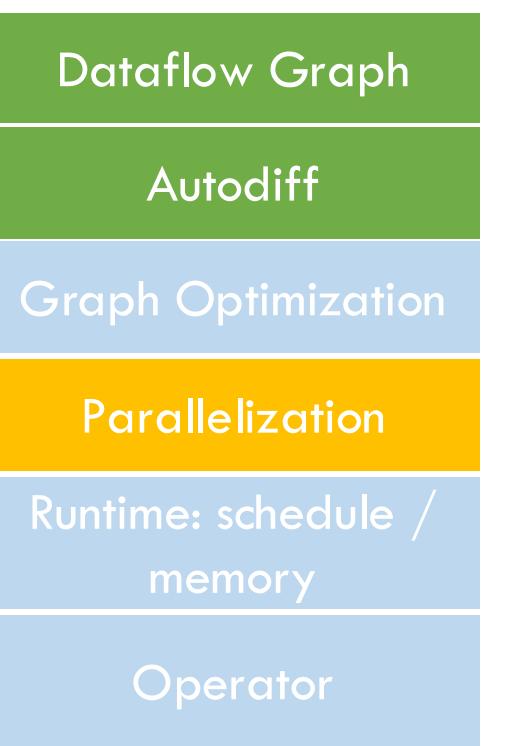


Parallelization

- Goal: parallelize the graph compute over multiple devices

How to partition the computational graph on the device cluster?

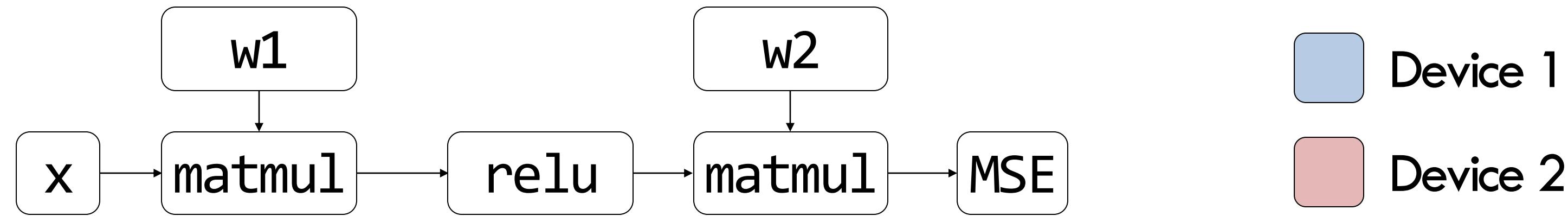




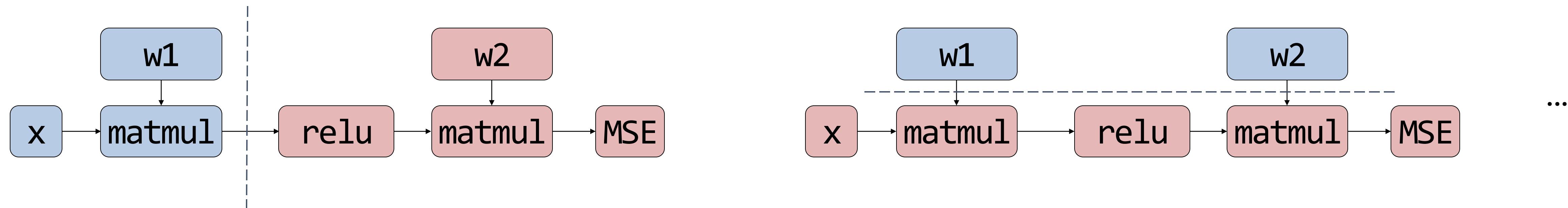
Parallelization Problems

- **How to partition**
- **How to communicate**
- **How to schedule**
- Consistency
- How to auto-parallelize?

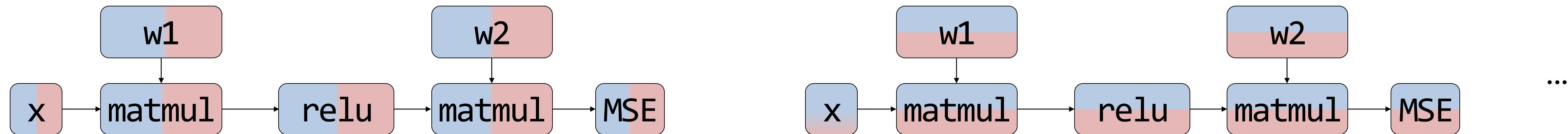
Partitioning Computation Graph



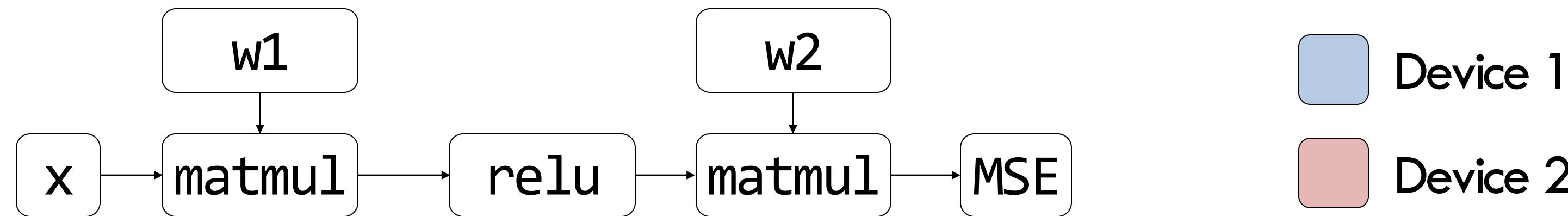
Strategy 1



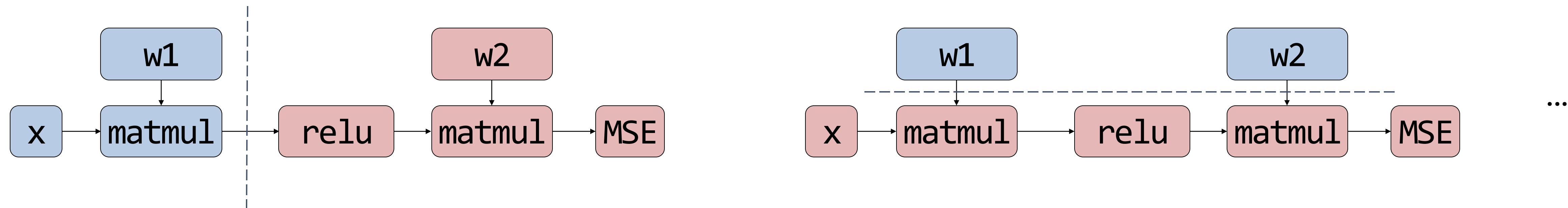
Strategy 2



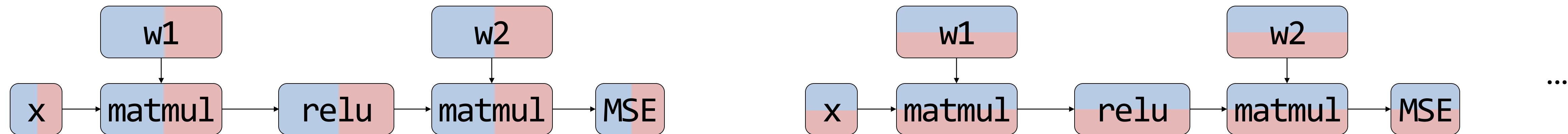
Partitioning Computation Graph



Strategy 1: Inter-operator Parallelism



Strategy 2: Intra-operator Parallelism



More Parallelisms...

Multiple intra-op strategies for a single node

Row-partitioned

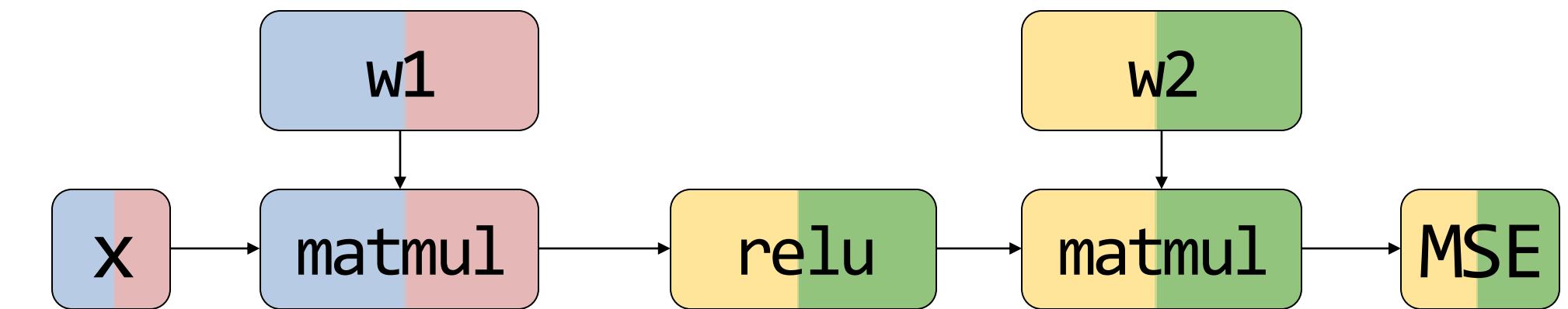
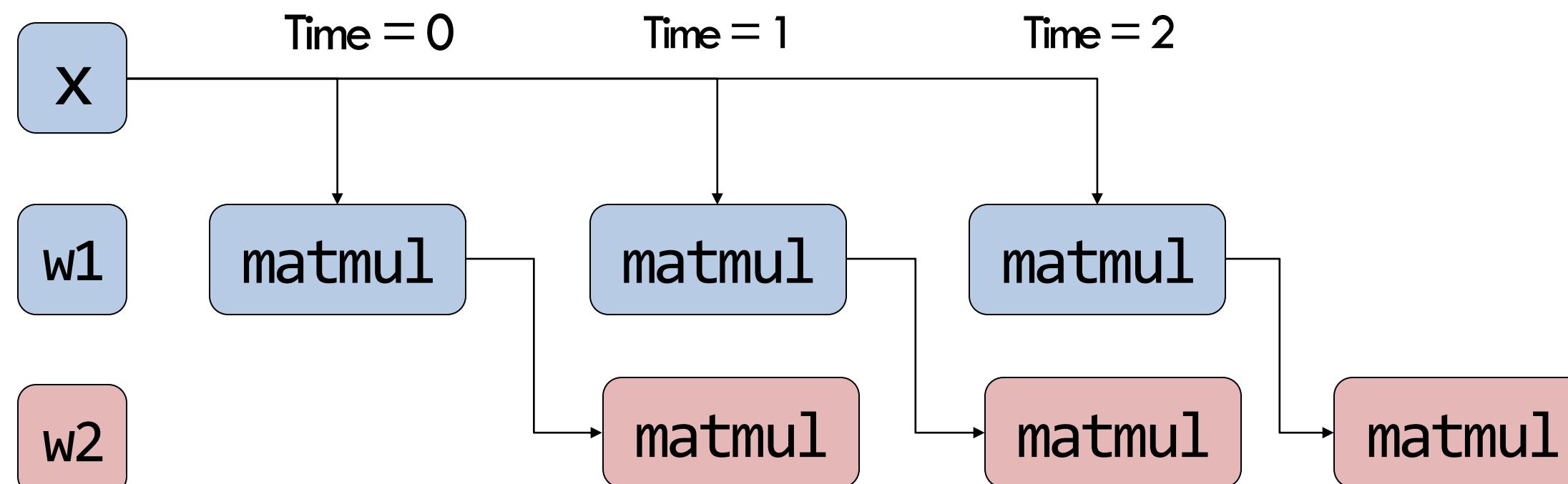
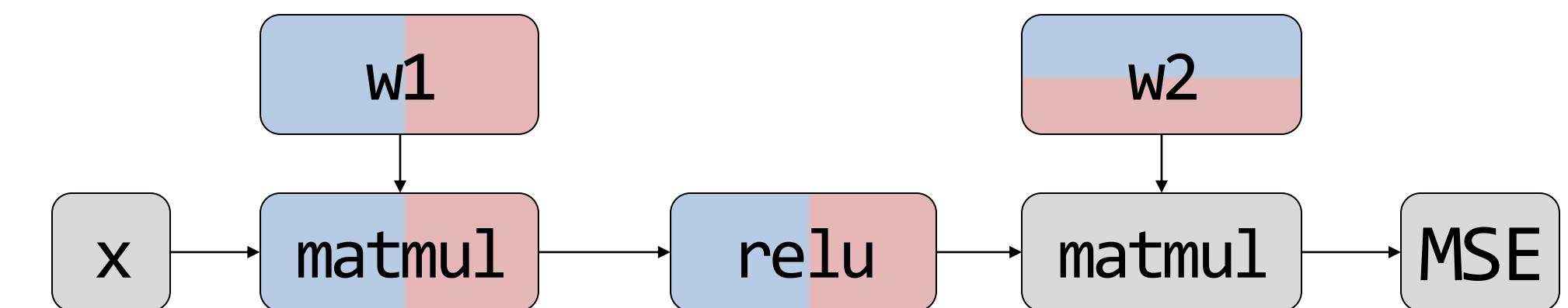
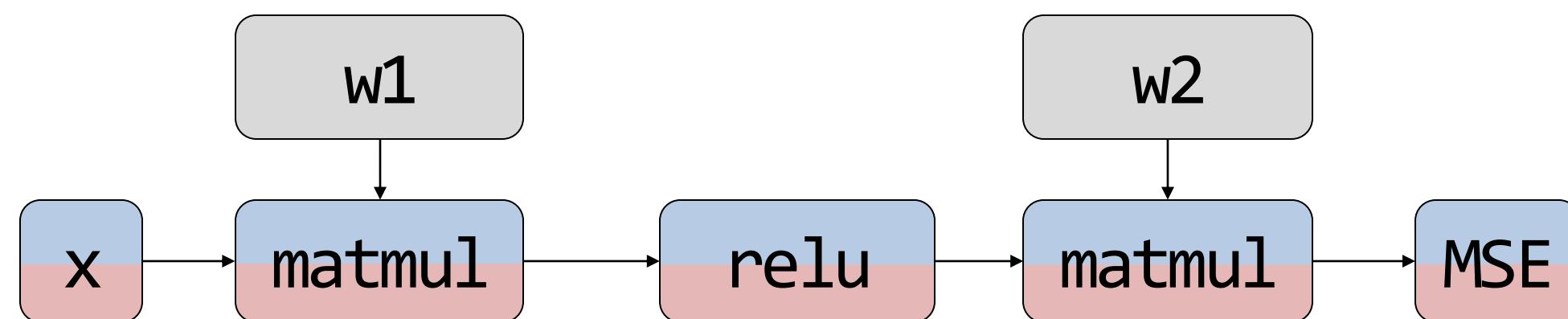
Column-partitioned

Replicated

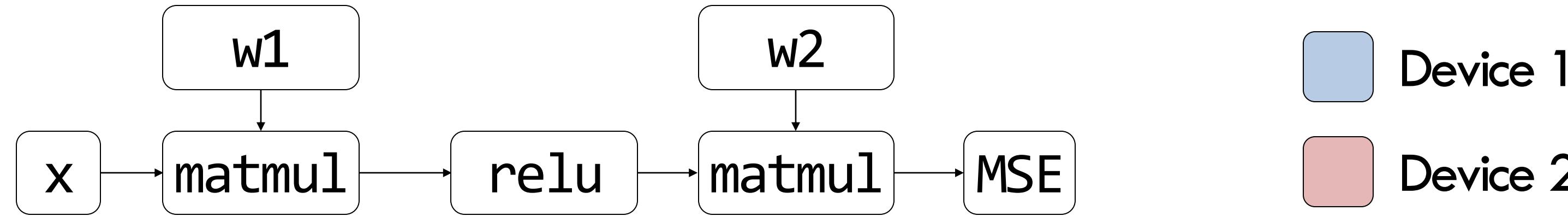
Device 3

Device 4

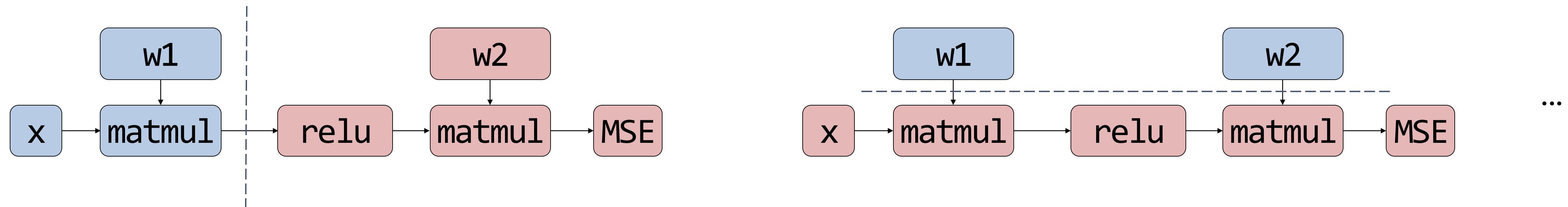
More strategies



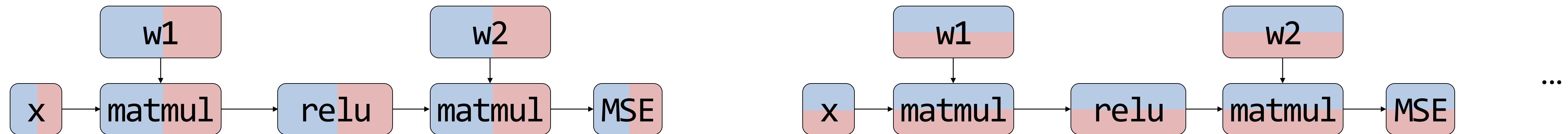
Summary: Inter-op and Intra-op Parallelisms



Inter-op parallelism: Assign different operators to different devices.



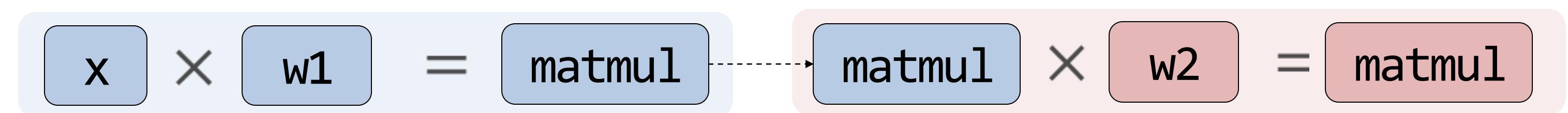
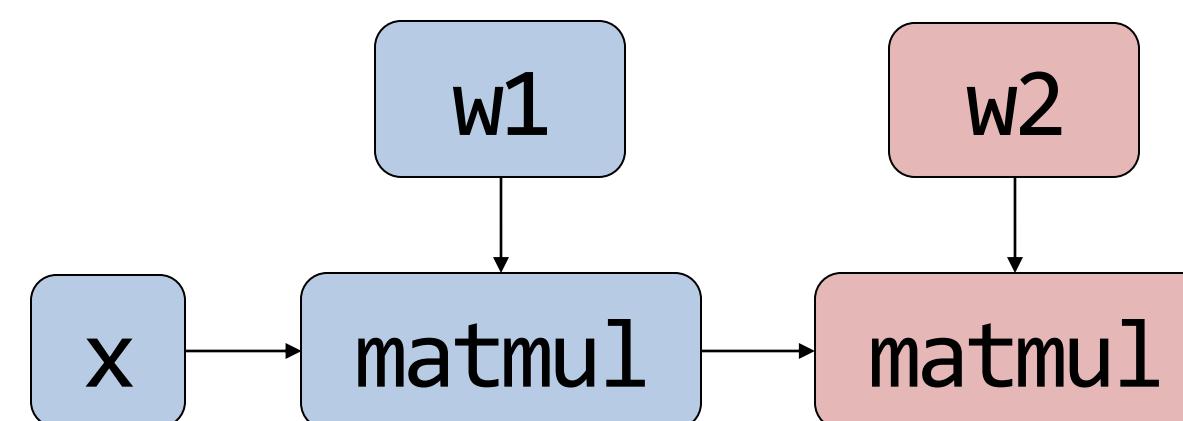
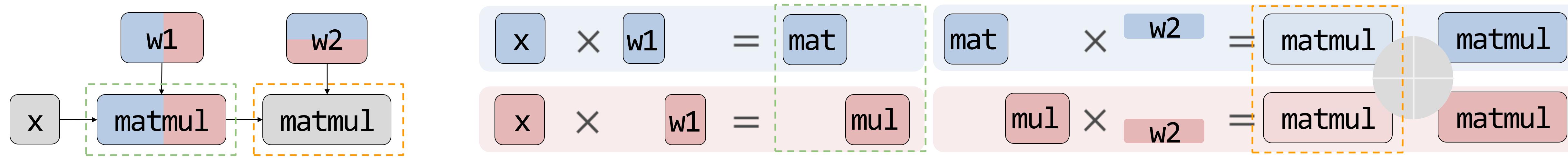
Intra-op parallelism: Assign different regions of a single operator to different devices.



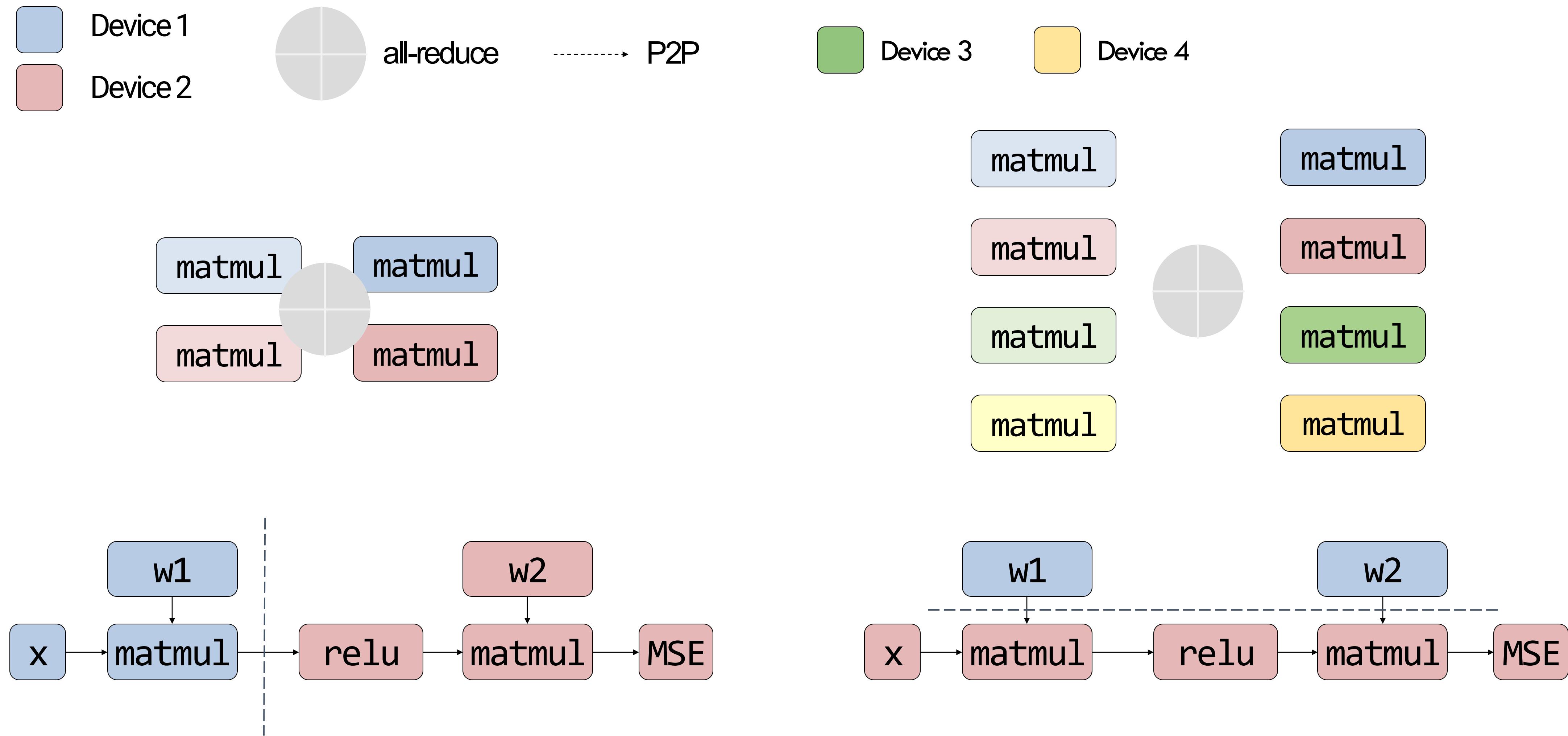
Inside Intra- and Inter-op Parallelism



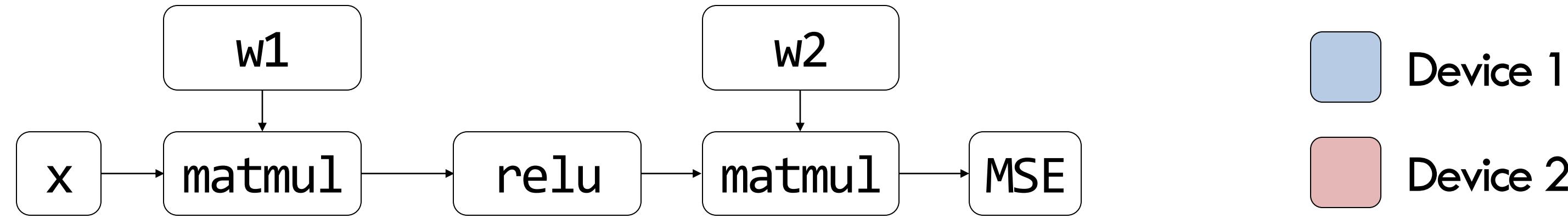
$$Y = X \cdot W_1 \cdot W_2 = X \cdot [W_1^{d1} \quad W_1^{d2}] \cdot \begin{bmatrix} W_2^{d1} \\ W_2^{d2} \end{bmatrix}$$



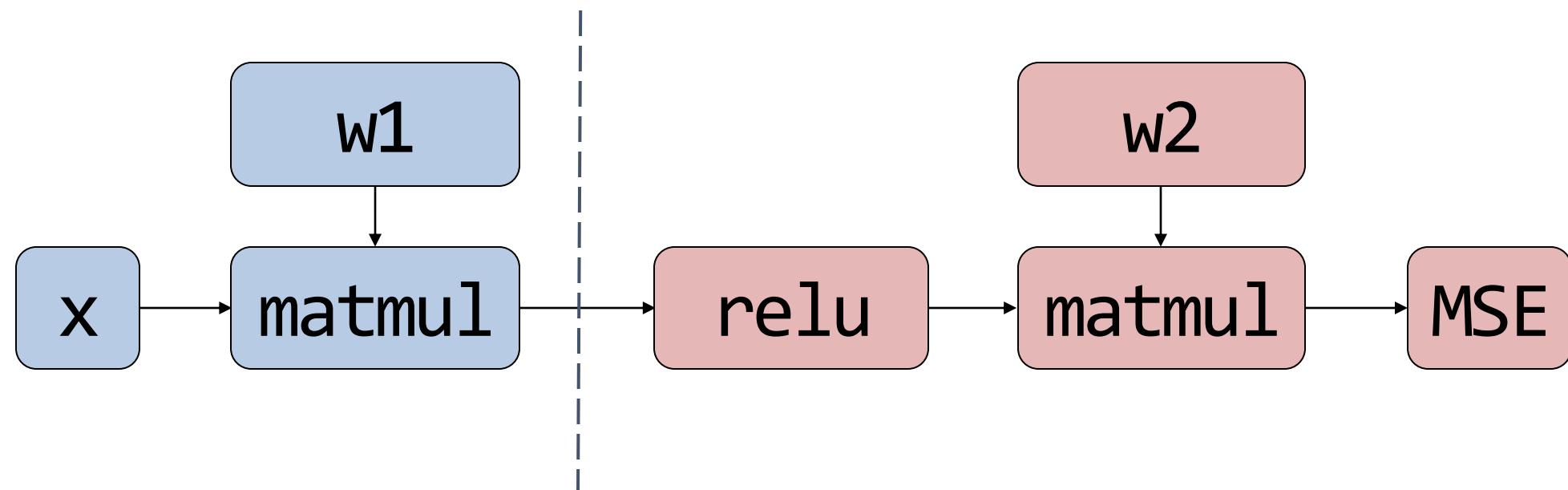
Looking Into the Communication



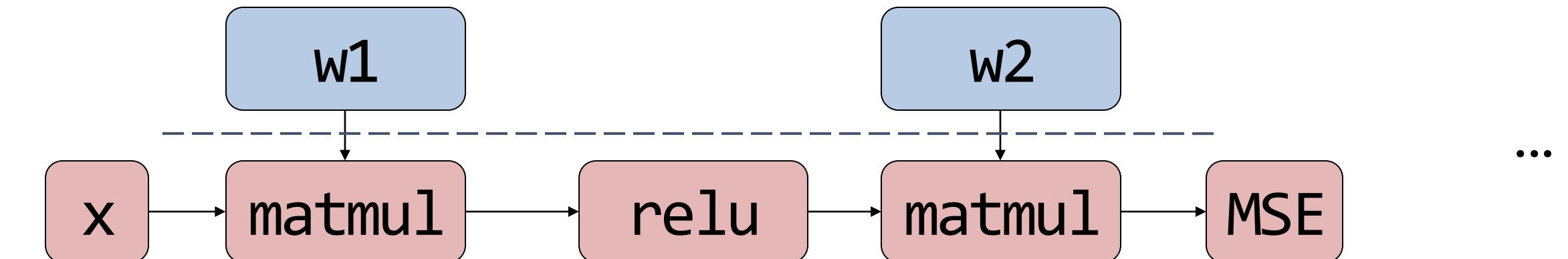
Parallelism: Key Characteristics



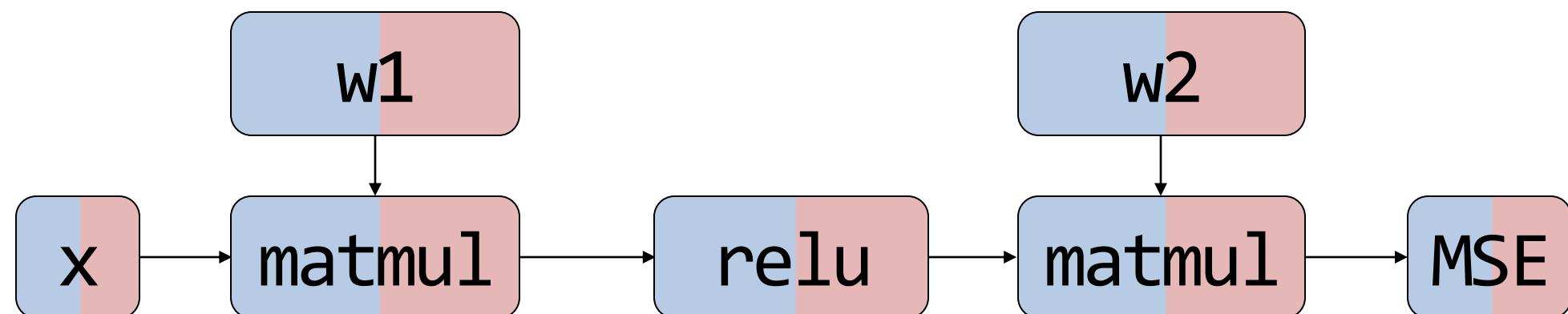
Inter-op parallelism:



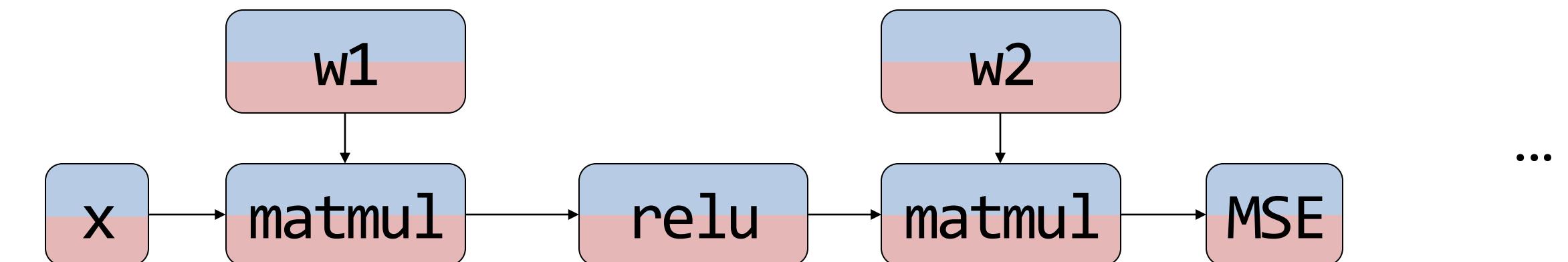
Requires point-to-point communication but results in device idle



Intra-op parallelism:

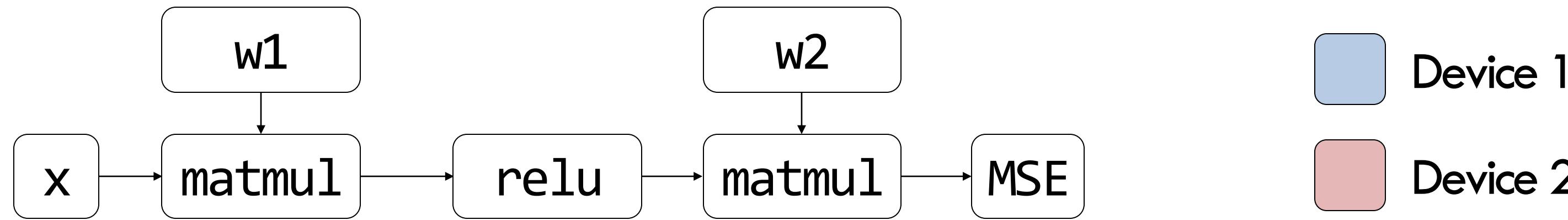


Devices are busy but requires collective communication

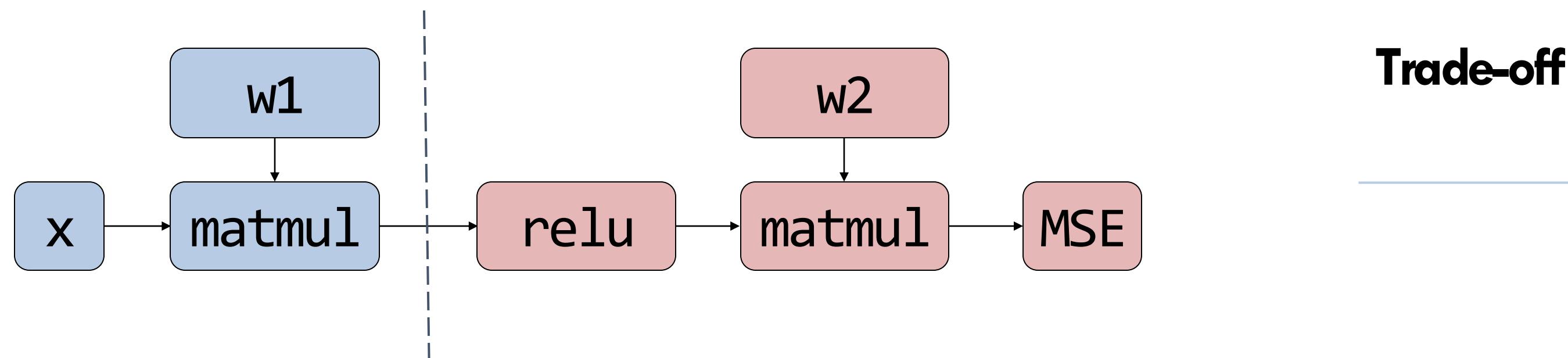


Inter-op and Intra-op Parallelism: Characteristics

[Important]



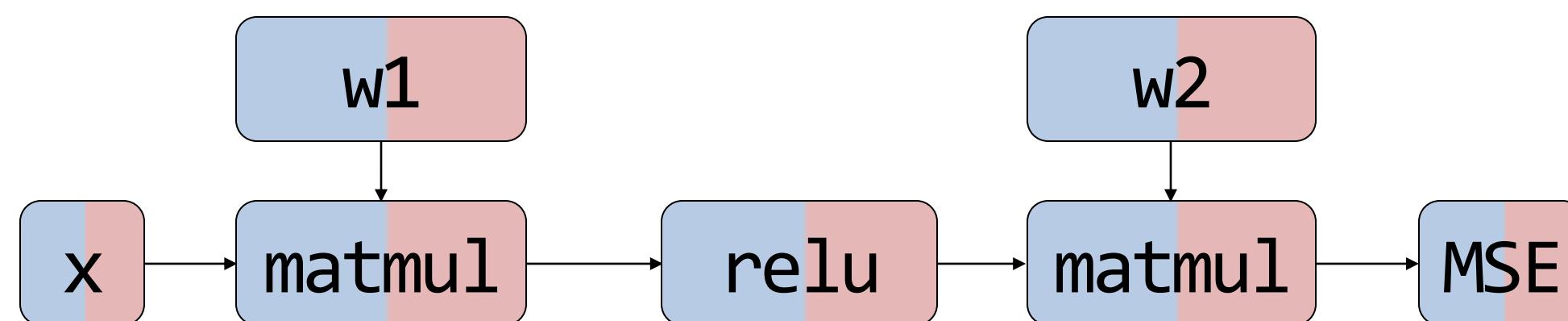
Inter-op parallelism



Trade-off

Inter-operator Parallelism Intra-operator Parallelism

Intra-op parallelism



Communication Less More

Device Idle Time More Less

Computational View of ML Parallelisms

Classic view

Data parallelism

Model parallelism

New view (this class)

Inter-op parallelism

Intra-op parallelism

Two Views of ML Parallelisms

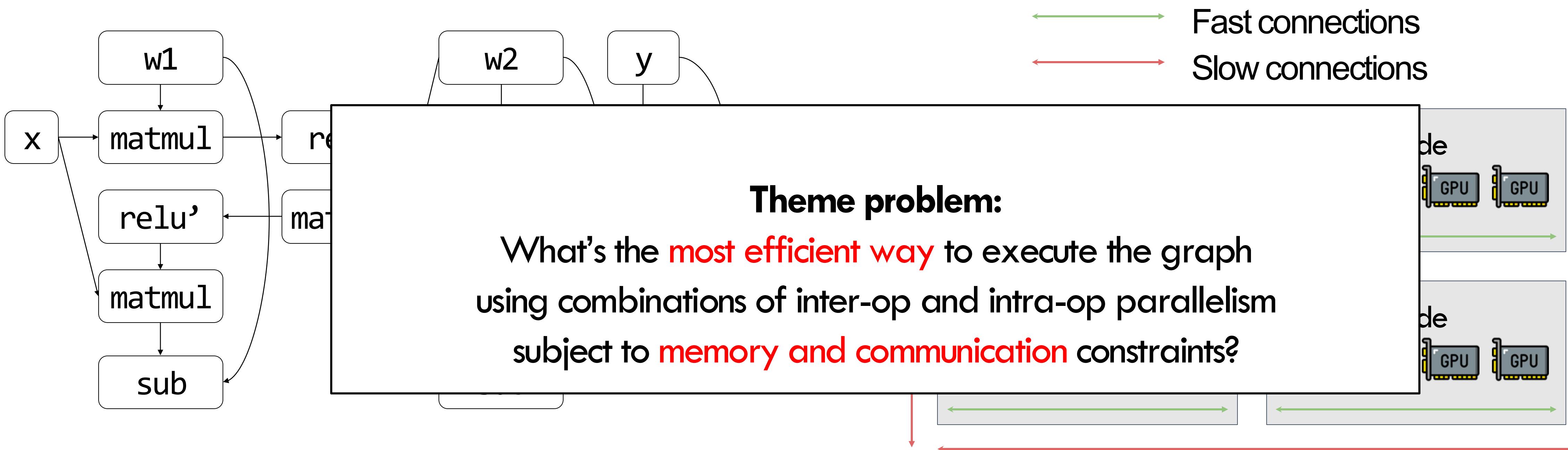
Data and model parallelism

- Two pillars: **data** and **model**.
-  “Data parallelism” is general and precise.
-  “Model parallelism” is vague.
-  The view creates ambiguity for methods that neither partitions data nor the model computation.

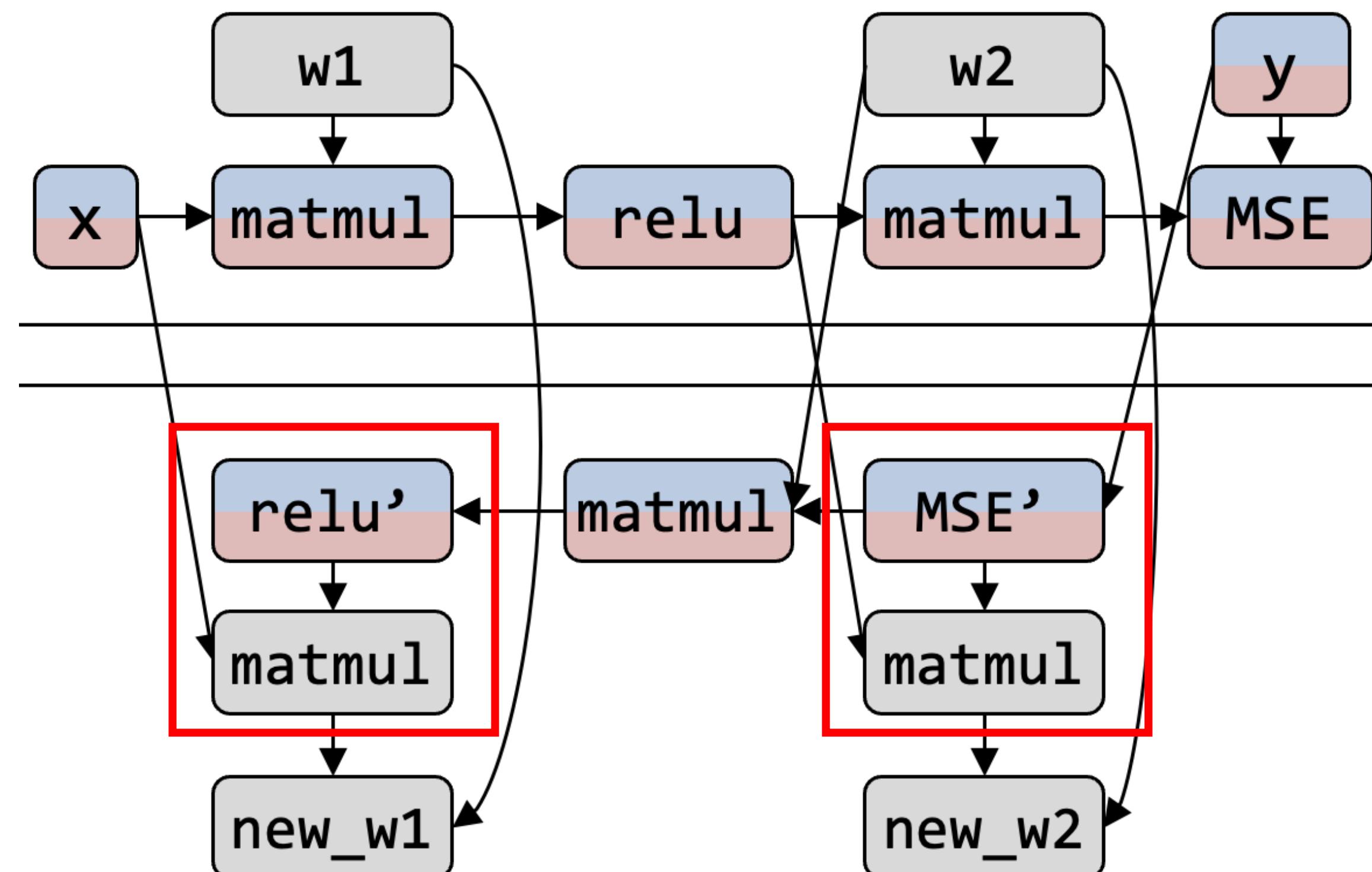
New: Inter-op and Intra-op parallelism.

- Two pillars: **computational graph** and **device cluster**
-  This view is based on their computing characteristics.
-  This view facilitates the development of new parallelism methods.

ML Parallelization under New View



Data Parallelism



How to implement this communication?

Two Solutions

- Parameter Server
- AllReduce
- Key assumption:
 - The model can fit into an (GPU) worker memory hence we can create many replica