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

DSC 204A: Scalable Data Systems
Fall 2025

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Logistics

- **Fall 2025 Student Evaluations of Teaching were sent**
  - **Again: if 80% of you finish the evaluation, all will get 2 bonus points.**

  - **Completion rate as of today: 58%**

High-level Picture

Data

Model

Compute

✅ $\{x_i\}^n{}_{i=1}$

✅ Math primitives (mostly matmul)

❓ Make them run on (clusters of) different kinds of hardware

✅ A repr that expresses the computation using primitives

Focus of the rest of lectures

Data

✅ $\{x_i\}^n{}_{i=1}$

Model

✅ Math primitives (mostly matmul)

✅ A repr that expresses the computation using primitives

Compute

❓Make **LLMs** run on (**large clusters** of) **GPUs**

Large Language Models

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

Next Token Prediction

$$P(next\ word \mid prefix)$$

San Diego has very nice _	surfing	0.4
	weather	0.5
	snow	0.01
San Francisco is a city of _	innovation	0.6
	homeless	0.3

Next Token Prediction

Probability("San Diego has very nice weather")
= P("San Diego") P("has"|"San Diego")P("very"|"San Diego has")P("city"|…)…P("weather"|…)

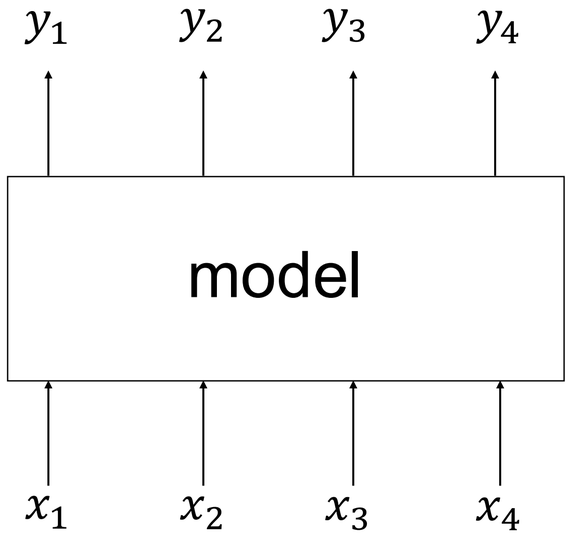
$$\text{Max}\, Prob(x_{1:T}) = \prod_{t=1}^{T} P(x_{t+1}|x_{1\ldots t})$$

MLE on observed data $x_{1:T}$,

This is next token prediction.
Predicting using seq2seq NNs.

Sequence Prediction

Take a set of input sequence, predict the output sequence



$\ldots$

$$\prod_{t=1}^{T} P(x_{t+1}|x_{1\ldots t})$$

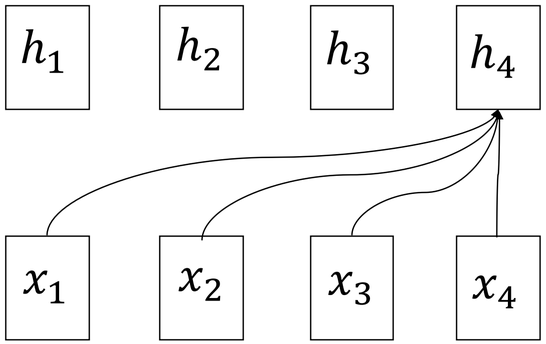
Predict each output based on history $y_t = f_\theta(x_{1:t})$

There are many ways to build up the predictive model

“Attention” Mechanism

Generally refers to the approach that weighted combine individual states

Attention output



Hidden states from previous layer

$$h_t = \sum_{i=1}^{t} s_i x_t$$

Intuitively s_i is “attention score” that computes how relevant the position i’s input is to this current hidden output

There are different methods to decide how attention score is being computed

Self-Attention Operation

Self attention refers to a particular form of attention mechanism.

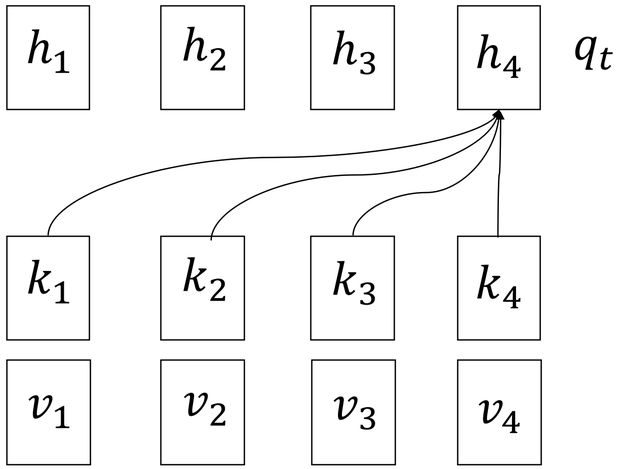
Given three inputs $Q, K, V \in \mathbb{R}^{T \times d}$ (“queries”, “keys”, “values”)

Define the self-attention as:

$$\text{SelfAttention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{d^{1/2}}\right)V$$

A Closer Look at Self-Attention

Use q_t, k_t, v_t to refers to row t of the K matrix



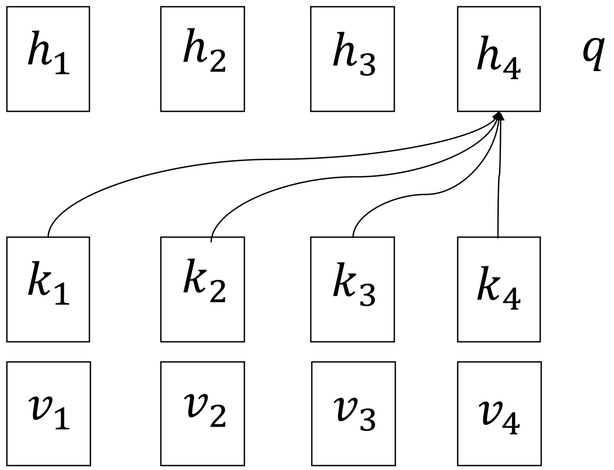
Ask the following question:

How to compute the output h_t, based on q_t, K, V one timestep t

To keep presentation simple, we will drop suffix t and just use q to refer to q_t in next few slide

A Closer Look at Self-Attention

Use q_t, k_t, v_t to refers to row t of the K matrix



Conceptually, we compute the output in the following two steps:

Pre-softmax "attention score"

$$s_i = \frac{1}{\sqrt{d}} q k_i^T$$

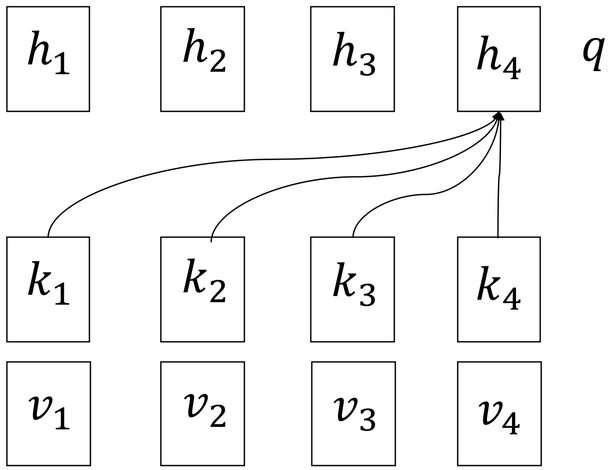
Weighed average via softmax

$$h = \sum_i \text{softmax}(s)_i v_i = \frac{\sum_i \exp(s_i) v_i}{\sum_j \exp(s_j)}$$

Intuition: s_i computes the relevance of k_i to the query q,
then we do weighted sum of values proportional to their relevance

Comparing the Matrix Form and the Decomposed Form

Use q_t, k_t, v_t to refers to row t of the K matrix



$$\text{SelfAttention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{d^{1/2}}\right)V$$

Pre-softmax "attention score"

$$S_{ti} = \frac{1}{\sqrt{d}} q_t k_i^T$$

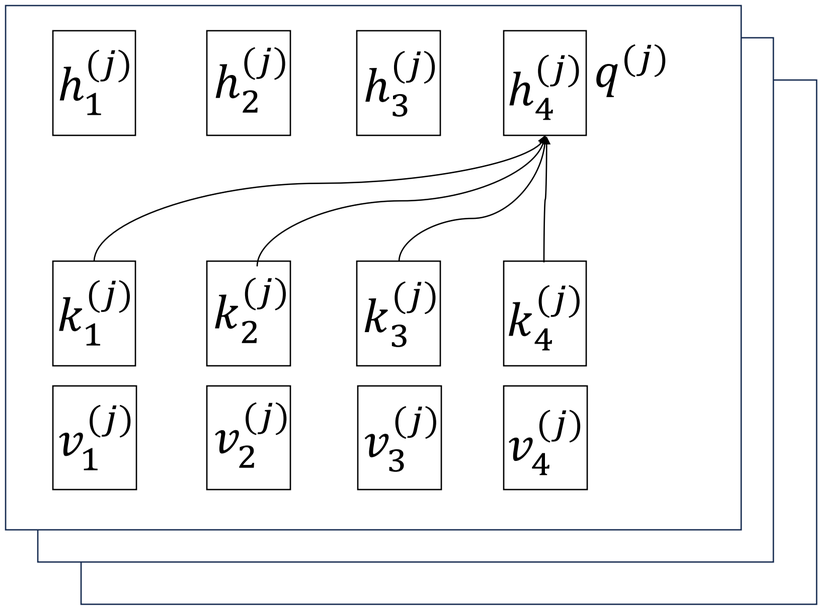
Weighed average via softmax

$$h_t = \sum_i \text{softmax}(S_{t,:})_i v_i = \text{softmax}(S_{t,:})V$$

Intuition: s_i computes the relevance of k_i to the query q,
then we do weighted sum of values proportional to their relevance

Multi-Head Attention

Have multiple “attention heads” $Q^{(j)}, K^{(j)}, V^{(j)}$ denotes j-th attention head



Apply self-attention in each attention head

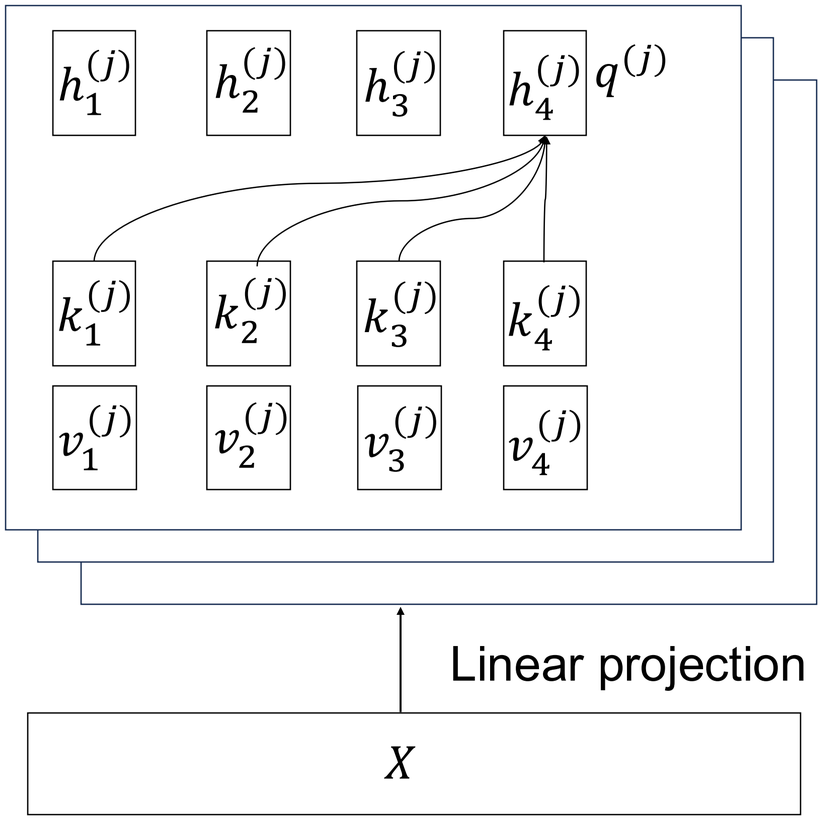
$$\text{SelfAttention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{d^{1/2}}\right)V$$

Concatenate all output heads together as output

Each head can correspond to different kind of information.
Sometimes we can share the heads: GQA(group query attention) all heads share K, V but have different Q

How to get Q K V?

Obtain Q, K, V from previous layer's hidden state X by linear projection



$$Q = XW_q$$
$$K = XW_K$$
$$V = XW_V$$

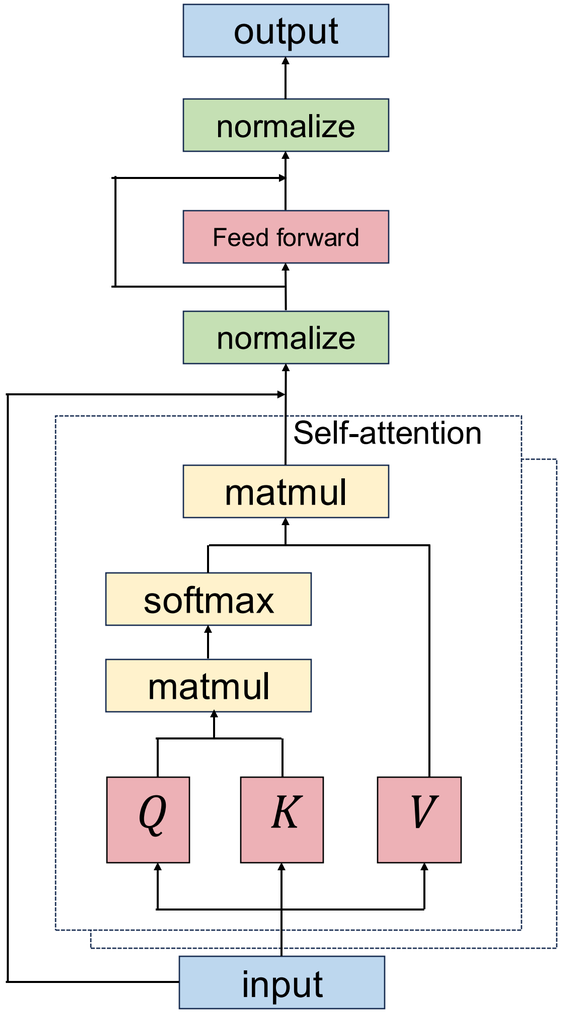
Can compute all heads and Q, K, V together then split/reshape out into individual Q, K, V with multiple heads

Transformer Block

A typical transformer block

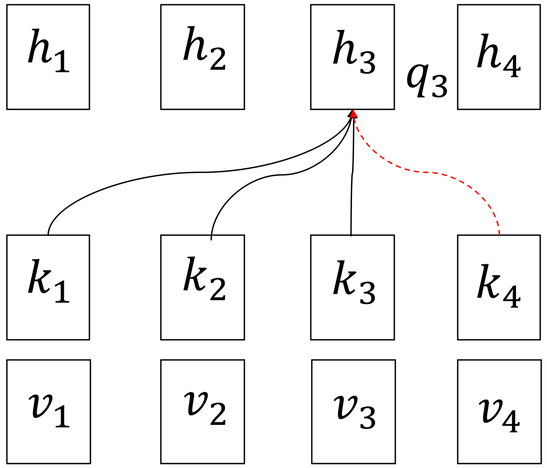
$$Z = \text{SelfAttention}(XW_K, XW_Q, XW_V)$$
$$Z = \text{LayerNorm}(X + Z)$$
$$H = \text{LayerNorm}(\text{ReLU}(ZW_1)W_2 + Z)$$

(multi-head) self-attention, followed by a linear layer and ReLU and some additional residual connections and normalization



Masked Self-Attention

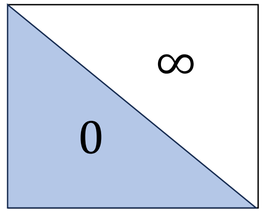
In the matrix form, we are computing weighted average over all inputs



In auto regressive models, usually it is good to maintain casual relation, and only attend to some of the inputs (e.g. skip the red dashed edge on the left). We can add "attention mask"

$$\text{MaskedSelfAttention}(Q,K,V) = \text{softmax}\left(\frac{QK^T}{d^{1/2}} - M\right)V$$

$$M_{ij} = \begin{cases} \infty, j > i \\ 0, j \le i \end{cases}$$

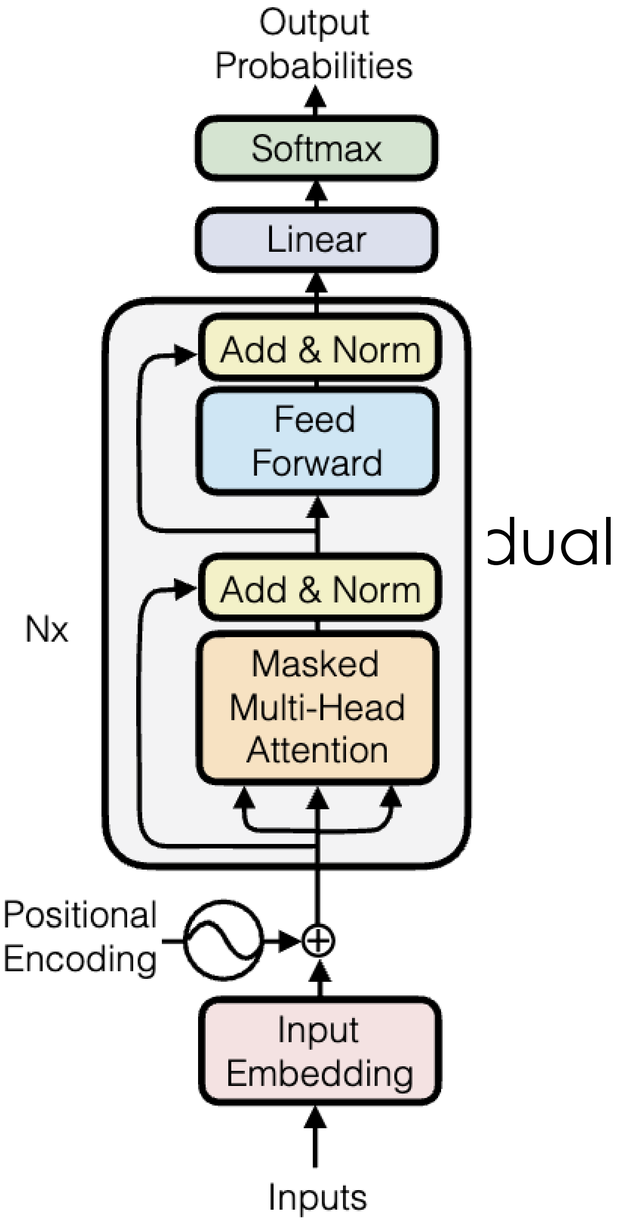


Only attend to previous inputs. Depending on input structure and model, attention mask can change.

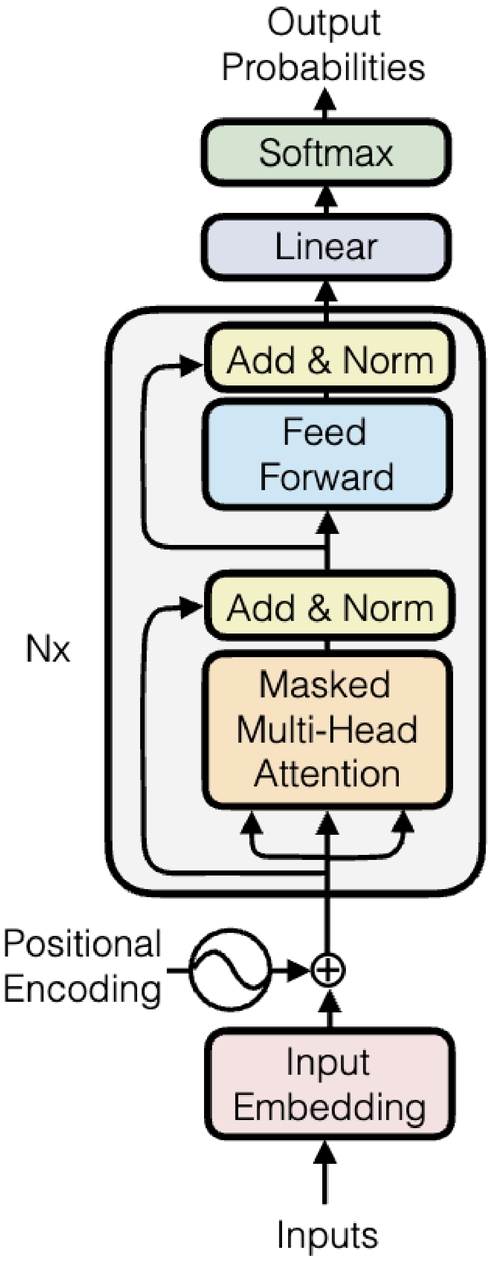
We can also simply skip the computation that are masked out if there is a special implementation to do so

Summary: Transformers

- Transformer decoders
  - Many of them
  - Really just: attentions + layernorm + MLPs + dual
- Word embeddings
- Position embeddings
  - Rotary embedding
- Loss function: cross entropy loss over a seque

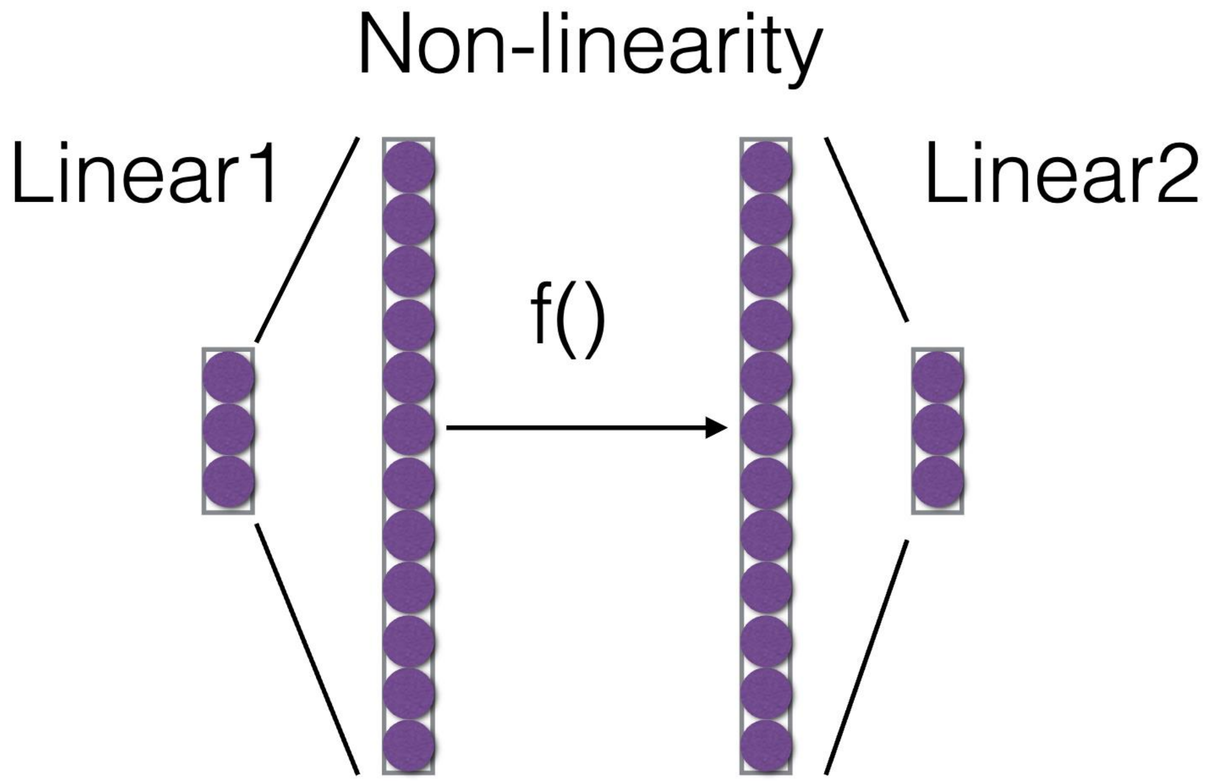


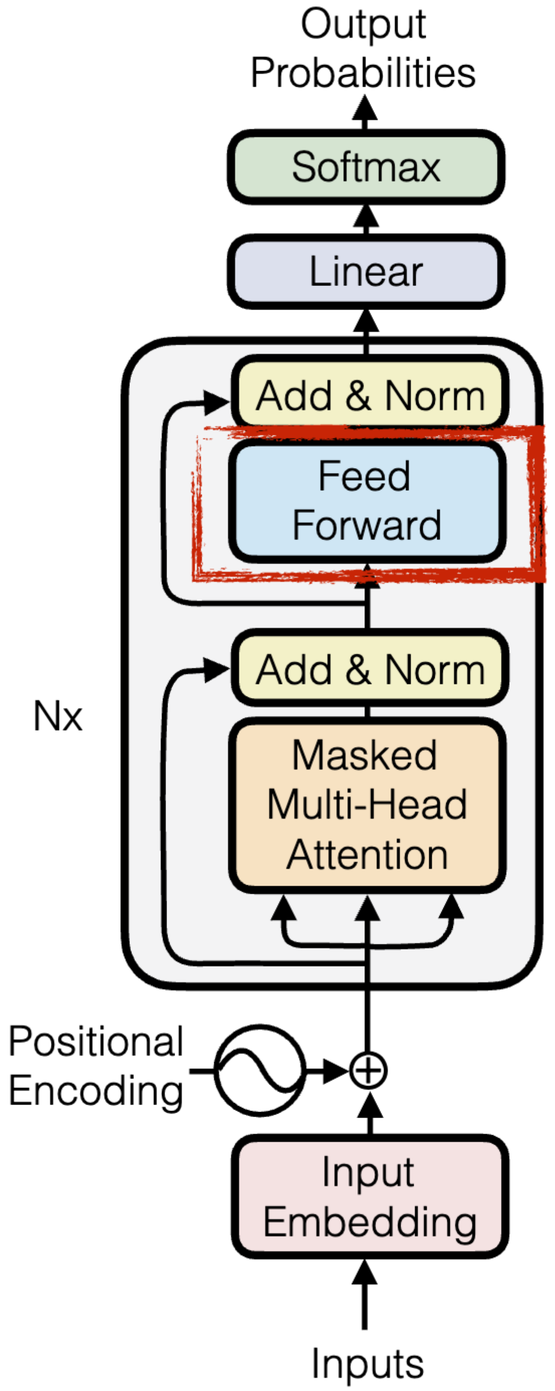
Transformers



Feedforward Layers

$$\mathrm{FFN}(x; W_1, \mathbf{b}_1, W_2, \mathbf{b}_2) = f(\mathbf{x}W_1 + \mathbf{b}_1)W_2 + \mathbf{b}_2$$

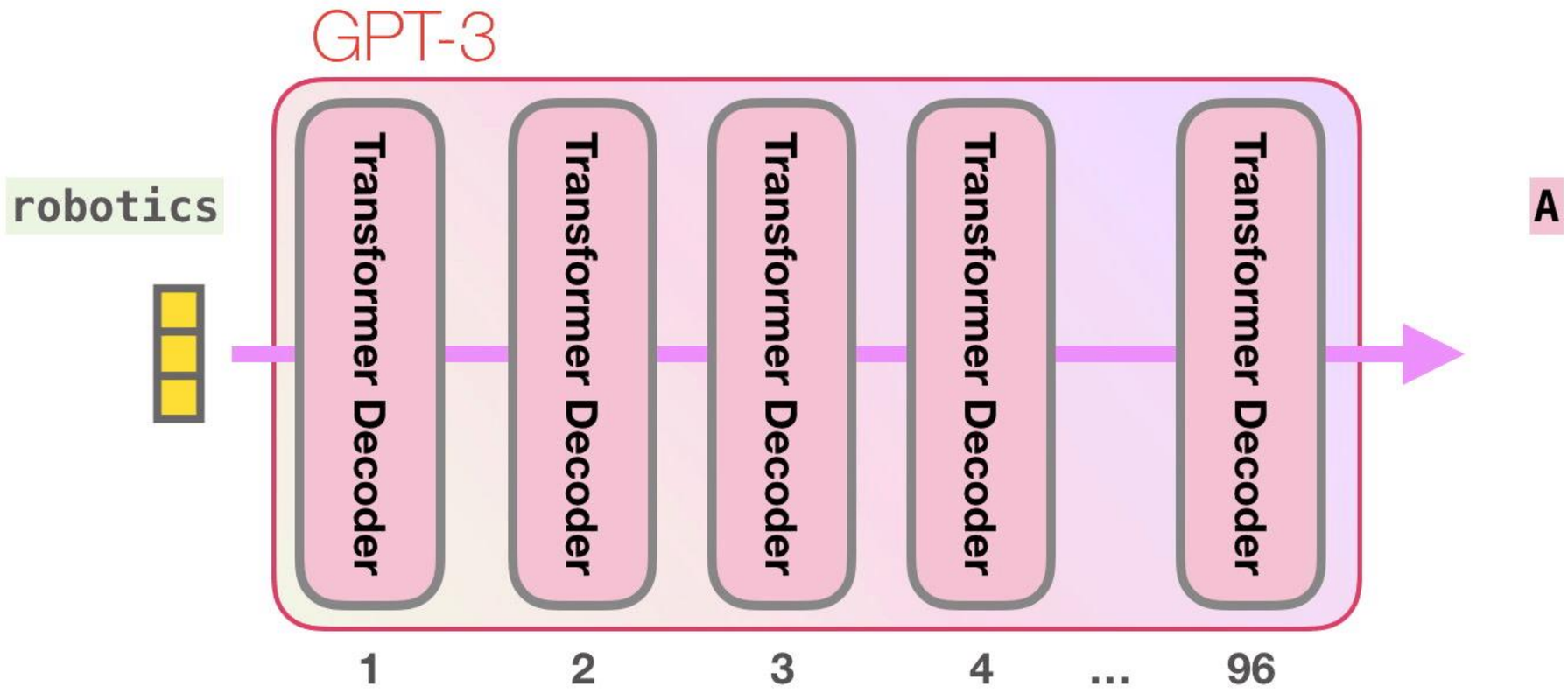




Computing Components in LLMs?

- Transformer decoders (many of them)
  - self-attentions (slow)
  - layernorm, residual (fast)
  - MLPs (slow)
  - Nonlinear (fast)
- Word embeddings (fast)
- Position embeddings (fast)
- Loss function: cross entropy loss over a sequence of words

LLMs

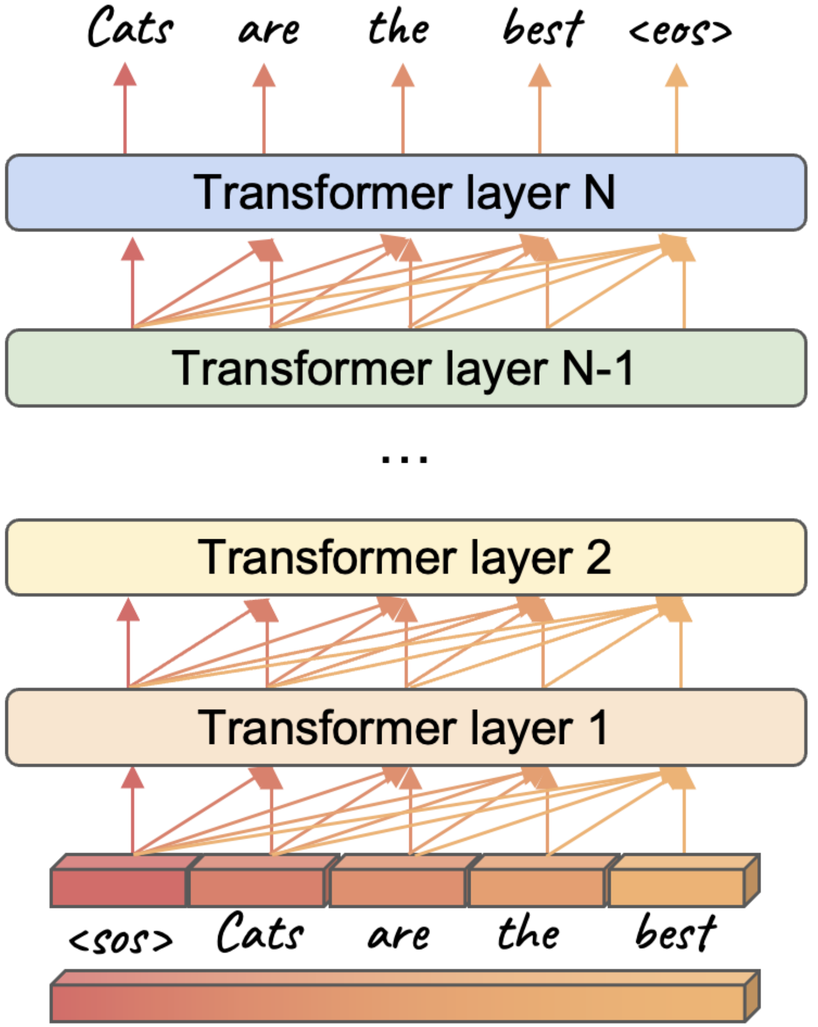

GPT-3
robotics
Transformer Decoder
Transformer Decoder
Transformer Decoder
Transformer Decoder
Transformer Decoder
A
1
2
3
4
...
96

Original Transformer vs. LLM today

	Vaswani et al.	LLaMA
Norm Position	Post	Pre
Norm Type	LayerNorm	RMSNorm
Non-linearity	ReLU	SiLU
Positional Encoding	Sinusoidal	RoPE

Training LLMs

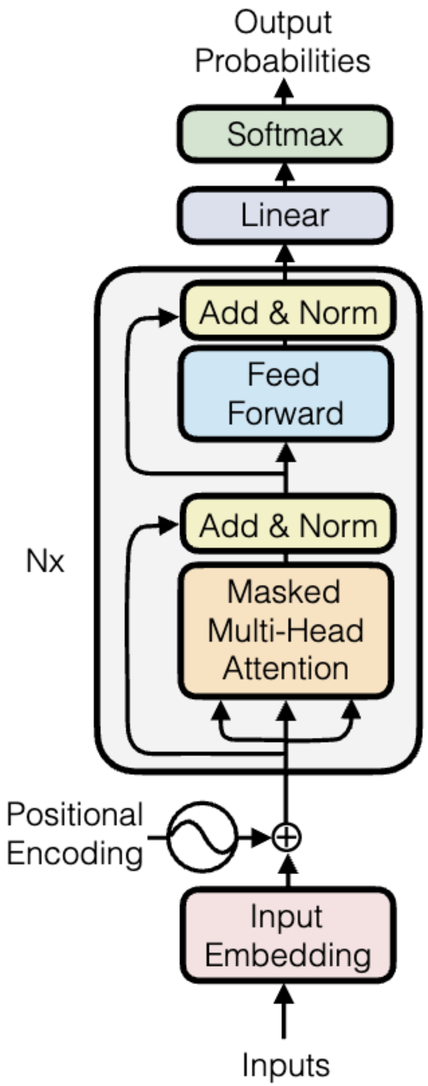
- Sequences are **known a priori**
- For each position, look at [1, 2, …, t-1] words to predict word t, and calculate the loss at t
- Parallelize the computation across all token positions, and then apply masking



Connecting the Dots: Compute/Comm characteristic of LLMs

Key characteristics: compute, memory, communication

- calculate the number of parameters of an LLM?
  - memory, communication
- calculate the flops needed to train an LLM?
  - compute
- calculate the memory needed to train an LLM?
  - memory, communication



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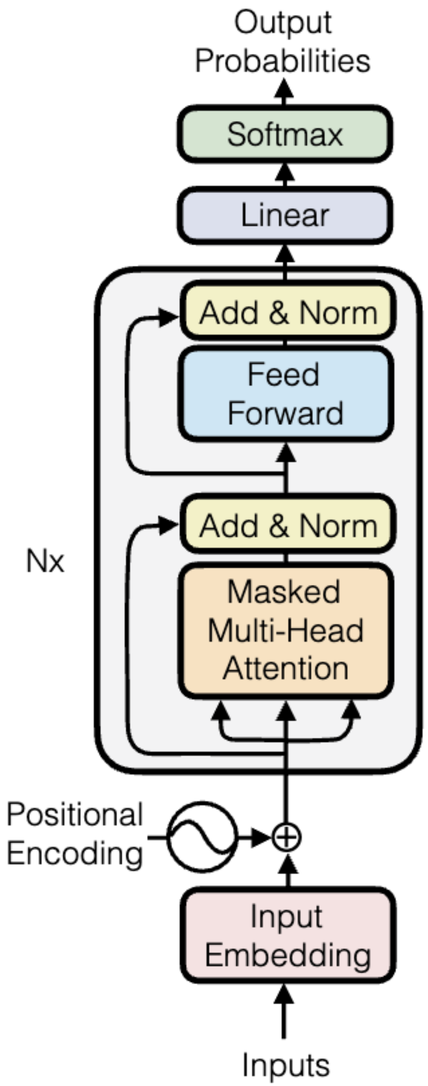
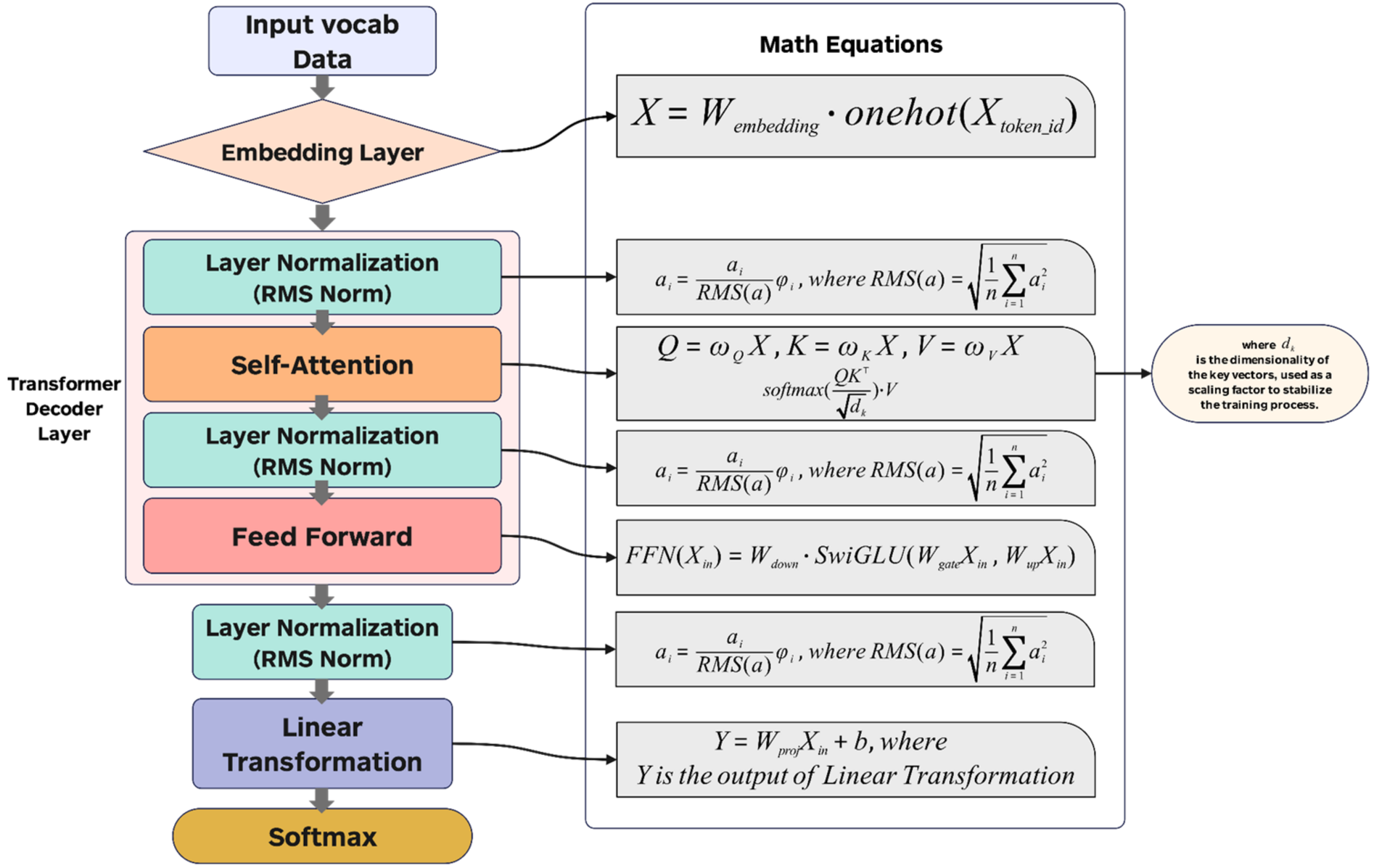



Input vocab Data
Embedding Layer
Transformer Decoder Layer
Layer Normalization (RMS Norm)
Self-Attention
Layer Normalization (RMS Norm)
Feed Forward
Layer Normalization (RMS Norm)
Linear Transformation
Softmax
Math Equations
$X = W_{embedding} \cdot onehot(X_{token\_id})$
$a_i = \frac{a_i}{RMS(a)} \varphi_i$, where $RMS(a) = \sqrt{\frac{1}{n}\sum_{i=1}^{n} a_i^2}$
$Q = \omega_Q X, K = \omega_K X, V = \omega_V X$
$softmax(\frac{QK^T}{\sqrt{d_k}}) \cdot V$
where d_k is the dimensionality of the key vectors, used as a scaling factor to stabilize the training process.
$a_i = \frac{a_i}{RMS(a)} \varphi_i$, where $RMS(a) = \sqrt{\frac{1}{n}\sum_{i=1}^{n} a_i^2}$
$FFN(X_{in}) = W_{down} \cdot SwiGLU(W_{gate} X_{in}, W_{up} X_{in})$
$a_i = \frac{a_i}{RMS(a)} \varphi_i$, where $RMS(a) = \sqrt{\frac{1}{n}\sum_{i=1}^{n} a_i^2}$
$Y = W_{proj} X_{in} + b$, where
Y is the output of Linear Transformation

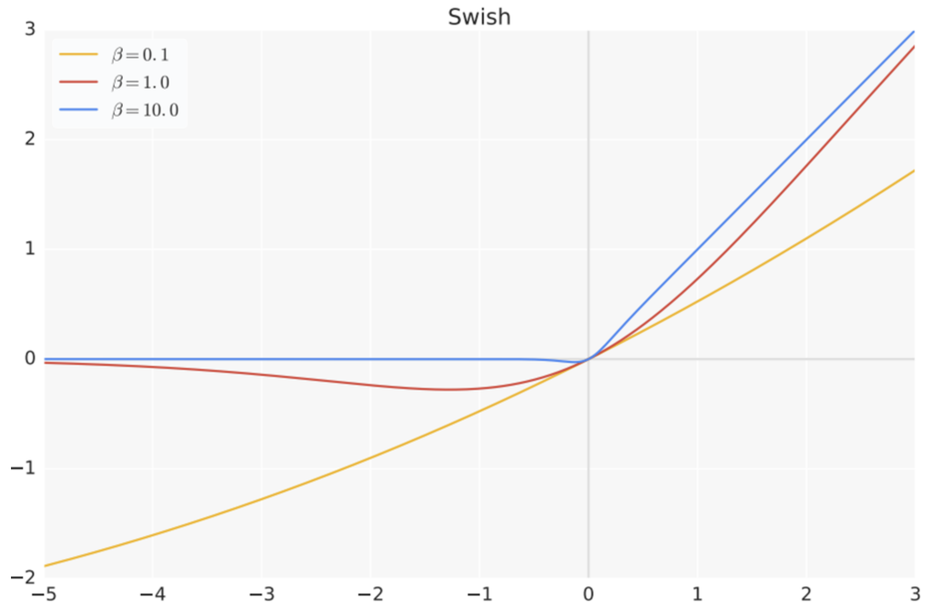
Feed Forward SwiGLU

The general formula for SwiGLU is:

$$\mathrm{SwiGLU}(x) = \mathrm{Swish}(xW_1 + b_1) \odot (xW_2 + b_2)$$

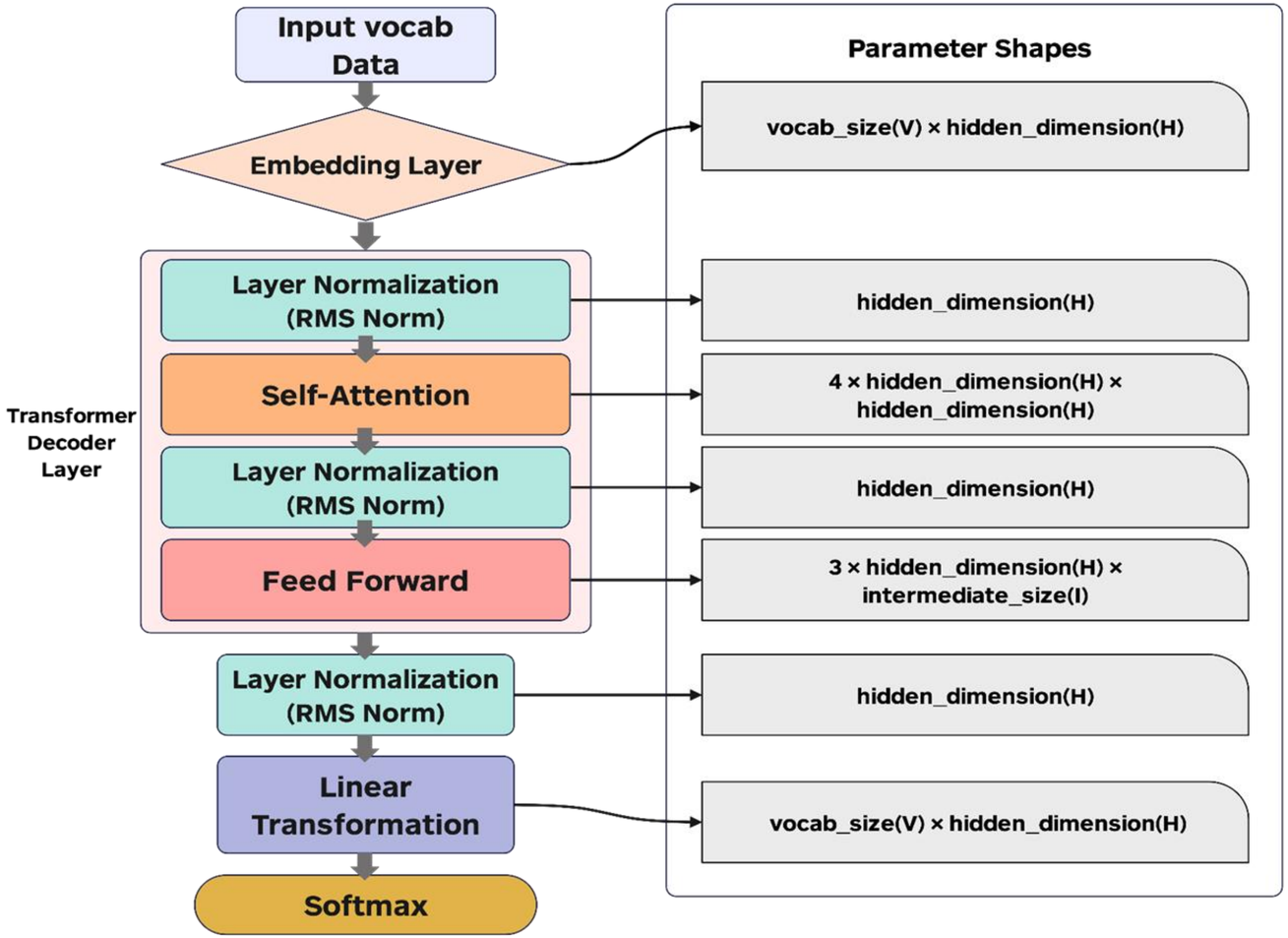
Swish is the activation function applied to one branch, defined as:

$$\mathrm{Swish}(z) = z \cdot \sigma(z)$$



- SwiGLU helps the model capture more complex patterns by selectively gating information
- Swish is smoother than traditional activations ReLU

Summary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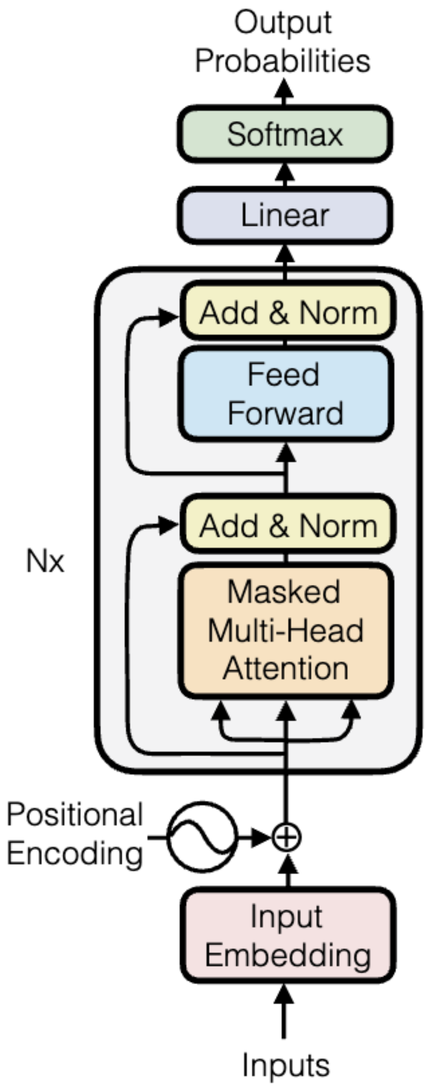
Linear Transformation
Softmax
Parameter Shapes
vocab_size(V) × hidden_dimension(H)
hidden_dimension(H)
4 × hidden_dimension(H) × hidden_dimension(H)
hidden_dimension(H)
3 × hidden_dimension(H) × intermediate_size(I)
hidden_dimension(H)
vocab_size(V) × hidden_dimension(H)

Connecting the Dots: Compute/Comm characteristic of LLMs

Key characteristics: compute, memory, communication

- calculate the number of parameters of an LLM?
- calculate the flops needed to train an LLM?
- calculate the memory needed to train an LLM?

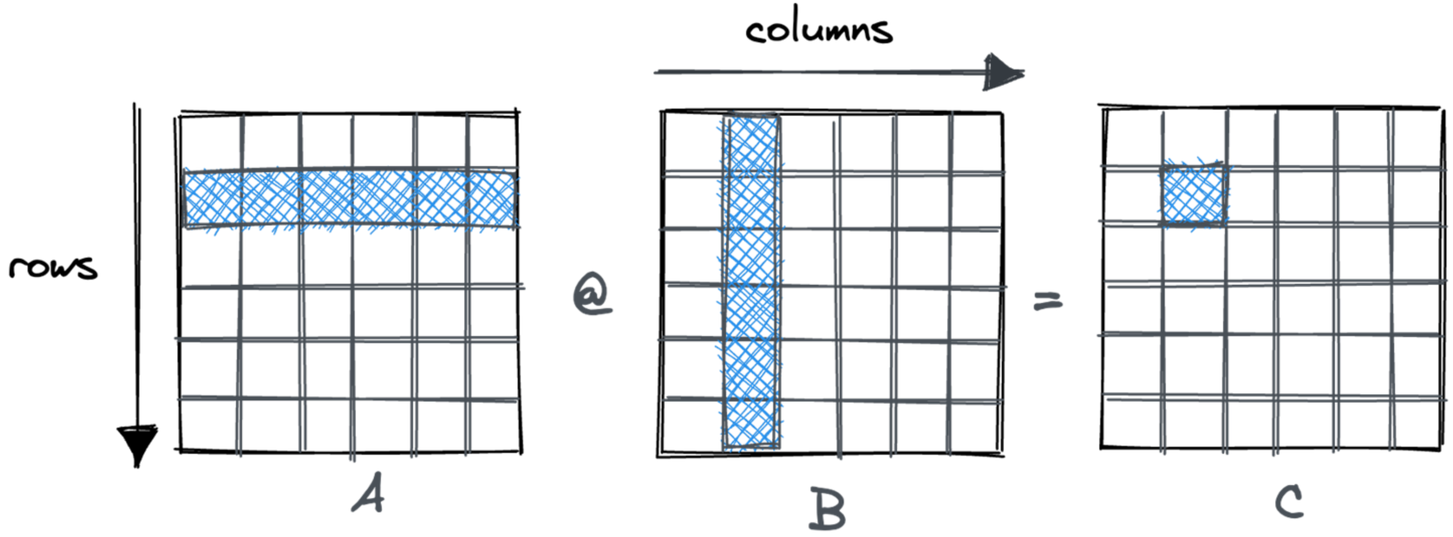


Estimate the Compute: FLOPs

The FLOPs for multiplying two matrices of dimensions m×n and n×h can be calculated as follows:

$$\text{FLOPs} = m \times h \times (2n - 1)$$

So the total number of FLOPs is roughly FLOPs ≈ 2m × n × h



LLama 2 7B Flops Forward Calculation (Training)

Hyperparameters:

Batch size: b

Sequence length: s

The number of attention heads: n

Hidden state size of one head: d

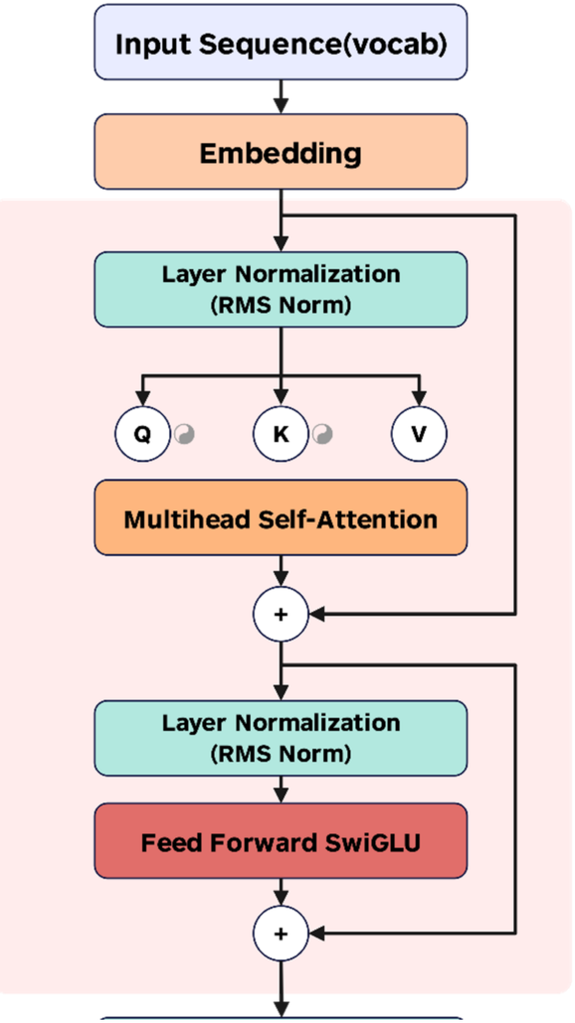
Hidden state size: h (h = n * d)

SwiGLU proj dim: i

Vocab size: v

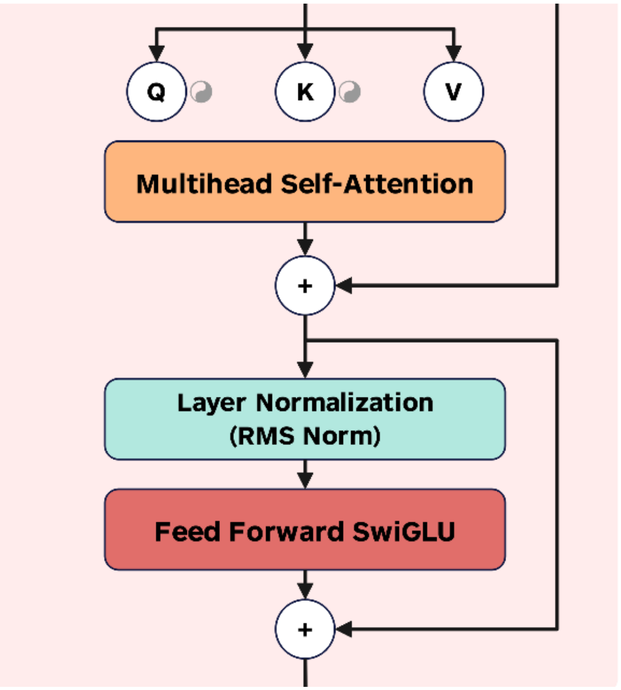
Input:	Output Shape:	FLOPs
X	(b, s, h)	0
Self Attention:		
XW_Q, XW_K, XW_V	(b, s, h)	$3 * 2bsh^2$
RoPE	(b, n, s, d)	$3bsnd$
$P = Softmax(QK^T/\sqrt{d})$	(b, n, s, s)	$2bs^2nd + 3bs^2n$
PV	(b, n, s, d)	$2bs^2nd$
AW_O	(b, s, h)	$2bsh^2$
Residual Connection:		
	(b, s, h)	bsh

Batch size: b
Sequence length: s
# of attention heads: n
Hidden state dim of one head: d
Hidden state dim: h



Batch size: b
Sequence length: s
Hidden state dim: h
SwiGLU proj dim: i

Output from Self Attn:	Output Shape:	FLOPs
X	(b, s, h)	0
Feed-Forward SwiGLU:		
XW_{gate}, XW_{up}	(b, s, i)	2 * 2bshi
Swish Activation	(b, s, i)	4bsi
Element-wise *	(b, s, i)	bsi
XW_{down}	(b, s, h)	2bshi
RMS Norm:		
	(b, s, h)	4bsh + 2bs



1. **Calculate Root Mean Square:**
   - $\text{RMS}(x) = \sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2}$
2. **Normalize:**
   - $\text{RMSNorm}(x) = \frac{x}{\text{RMS}(x)+\epsilon} \cdot \gamma$

$$\text{SwiGLU}(x) = \text{Swish}(xW_1 + b_1) \odot (xW_2 + b_2)$$

LLama 2 7B Flops Forward (Training)

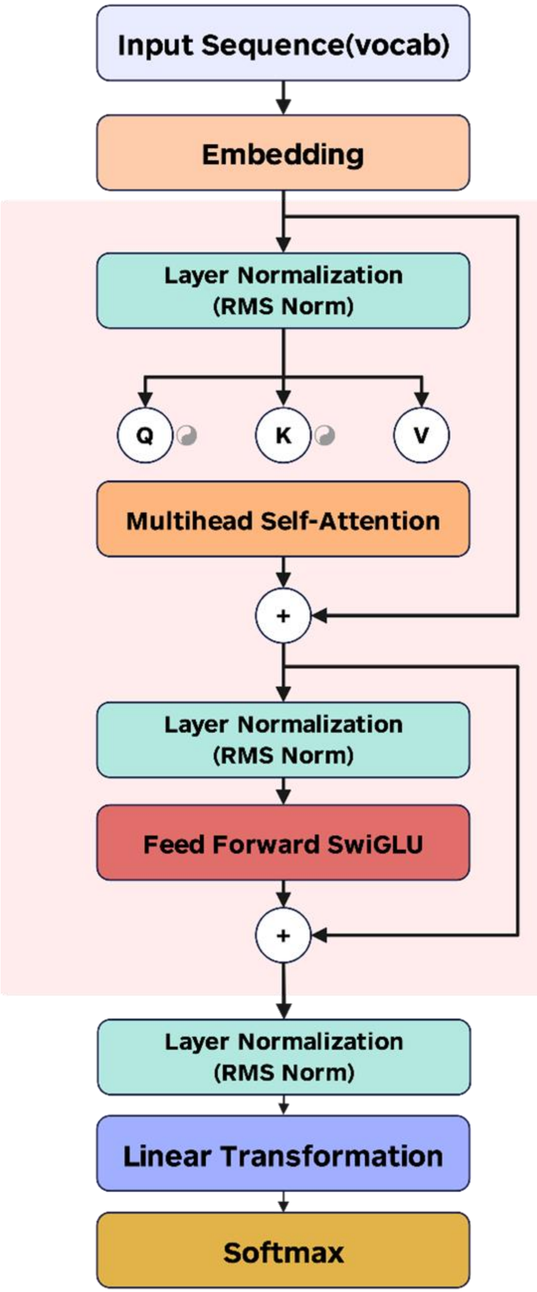
Total Flops ≈ #num_layers * (Attention block + SwiGLU block)

+ Prediction head

= #num_layers * ($6bsh^2 + 4bs^2h + 3bs^2n + 2bsh^2$)

+ #num_layers (6bshi)

+ 2 bshv



LLama 2 7B Flops Forward Calculation (Training)

Hyperparameters:

Batch size: b=1

Sequence length: s=4096

The number of attention heads: n=32

Hidden state size of one head: d=128

Hidden state size: h =4096

SwiGLU proj dim: i=11008

Vocab size: v=32000

The number of layers: N=32

$$\text{Total Flops} \approx N * (6bsh^2 + 4bs^2h + 3bs^2n + 2bsh^2)$$

$$+ N\,(6bshi)$$

$$+ 2\,bshv$$

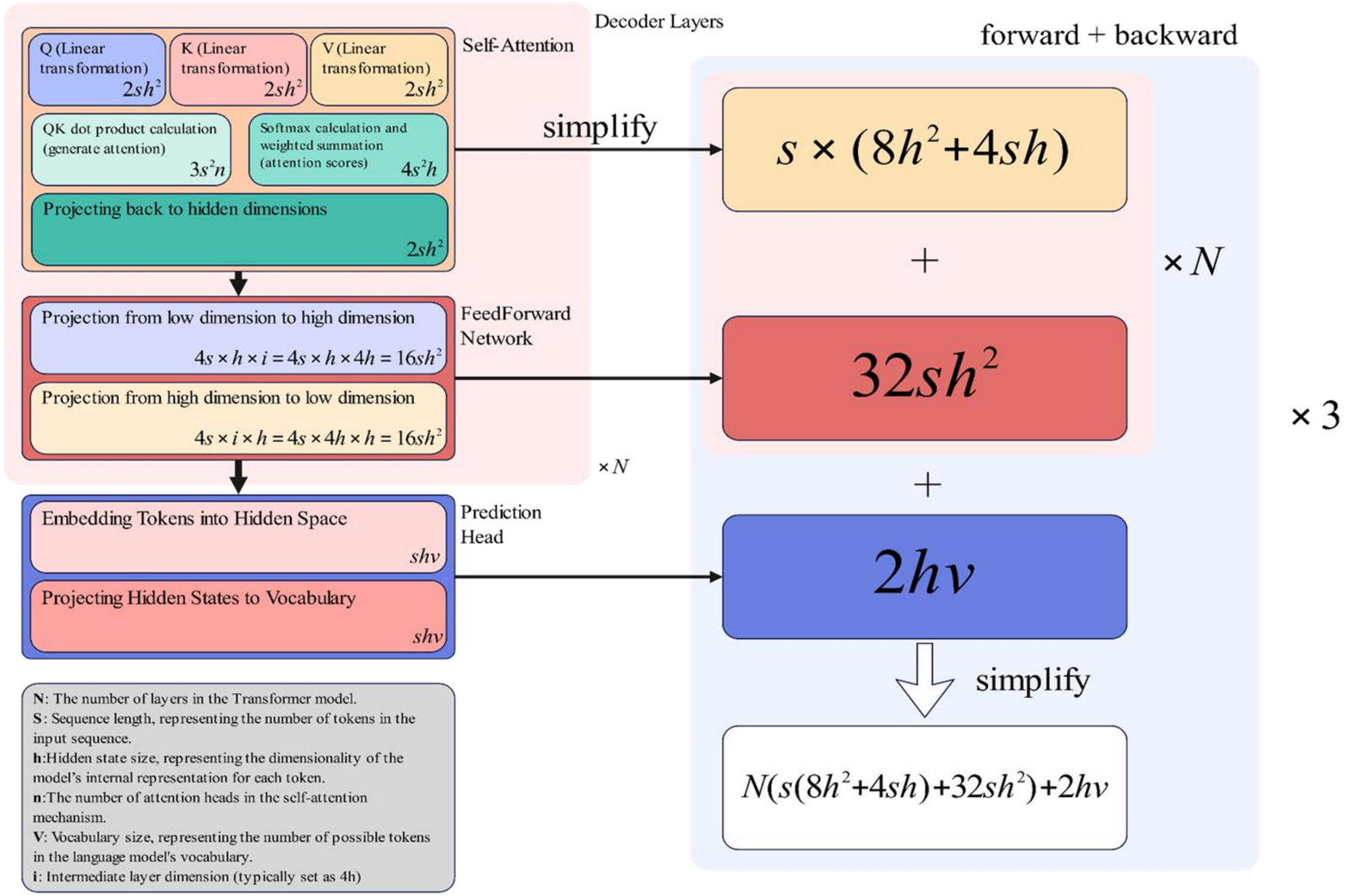
$$\approx 63 \text{ TFLOPs}$$

Flops Distribution

Training Computational Costs Breakdown:

- **Total Training TeraFLOPs:** 192.17 TFLOPs
- **FLOP Distribution by Layer:**
  - **Embedding Layer:** 1.676%
  - **Normalization:** 0.007%
  - **Residual:** 0.003%
  - **Attention:** 41.276%
  - **MLP (Multi-Layer Perceptron):** 55.361%
  - **Linear:** 1.676%

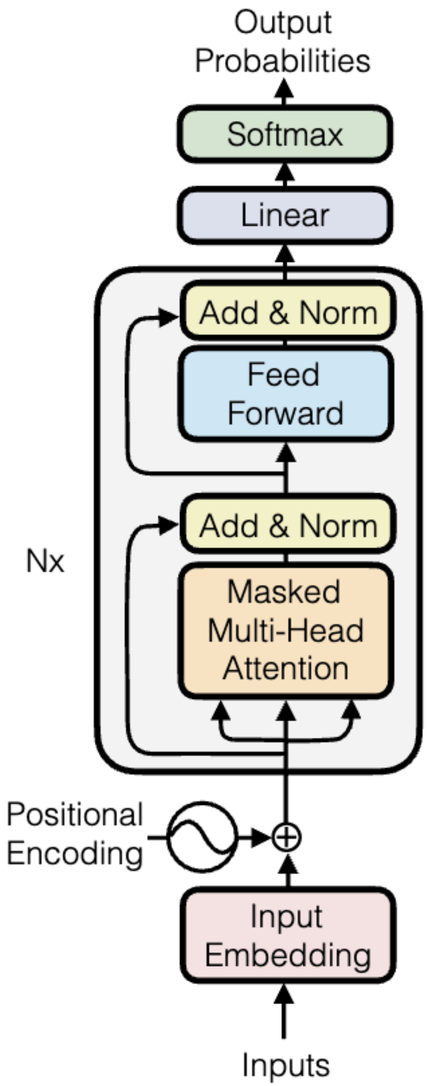
Scaling Up: Where is the Potential Bottleneck?



Connecting the Dots: Compute/Comm characteristic of LLMs

Key characteristics: compute, memory, communication

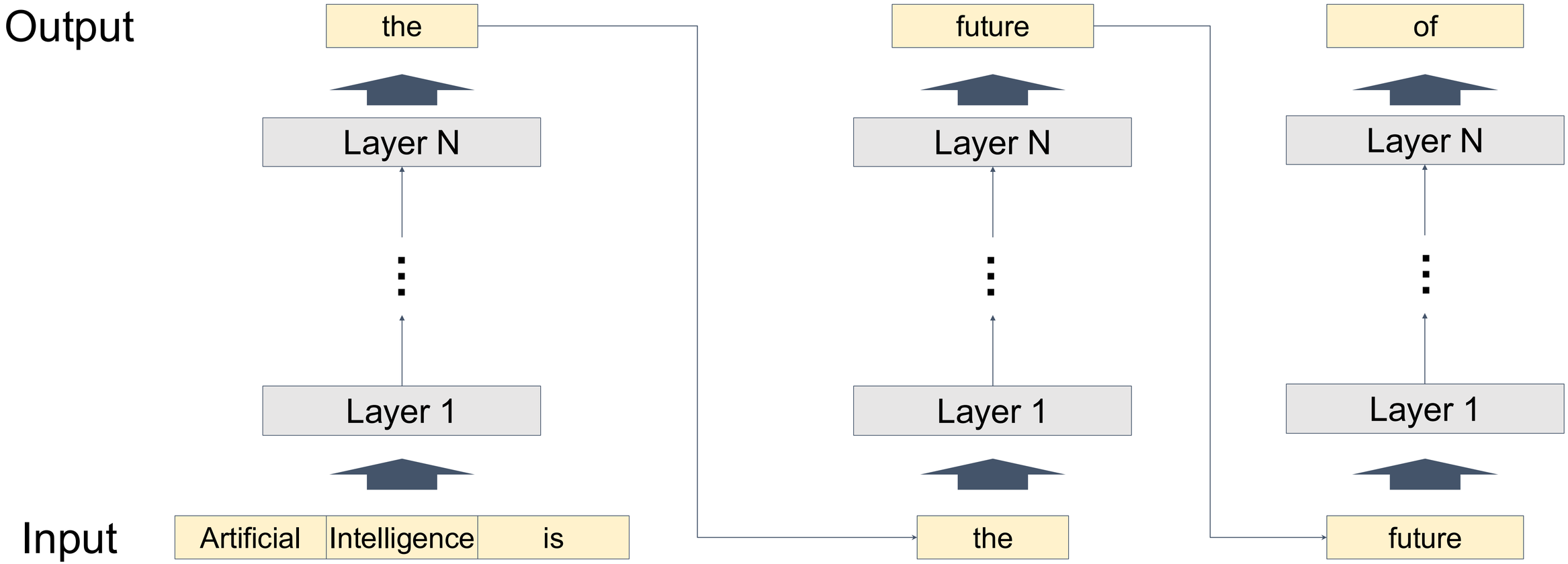
- calculate the number of parameters of an LLM?
- calculate the flops needed to train an LLM?
- calculate the memory needed to train an LLM?



Large Language Models

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

Inference process of LLMs



Repeat until the sequence

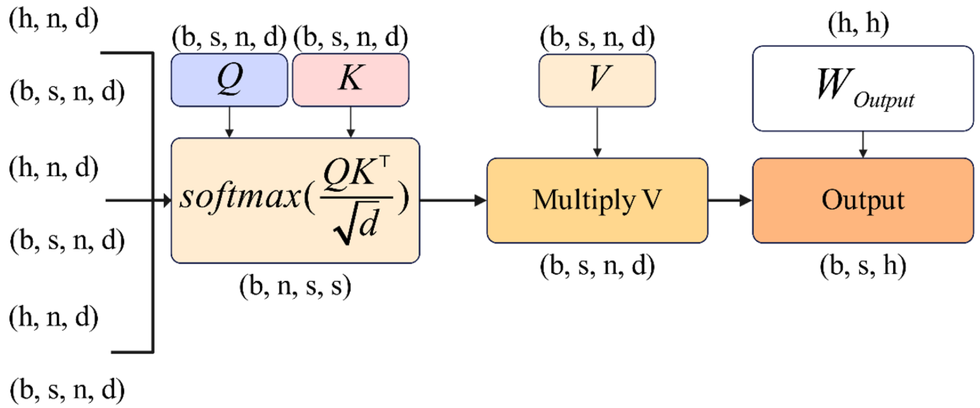
- Reaches its pre-defined maximum length (e.g., 2048 tokens)
- Generates certain tokens (e.g., “<|*end of sequence*|>”)

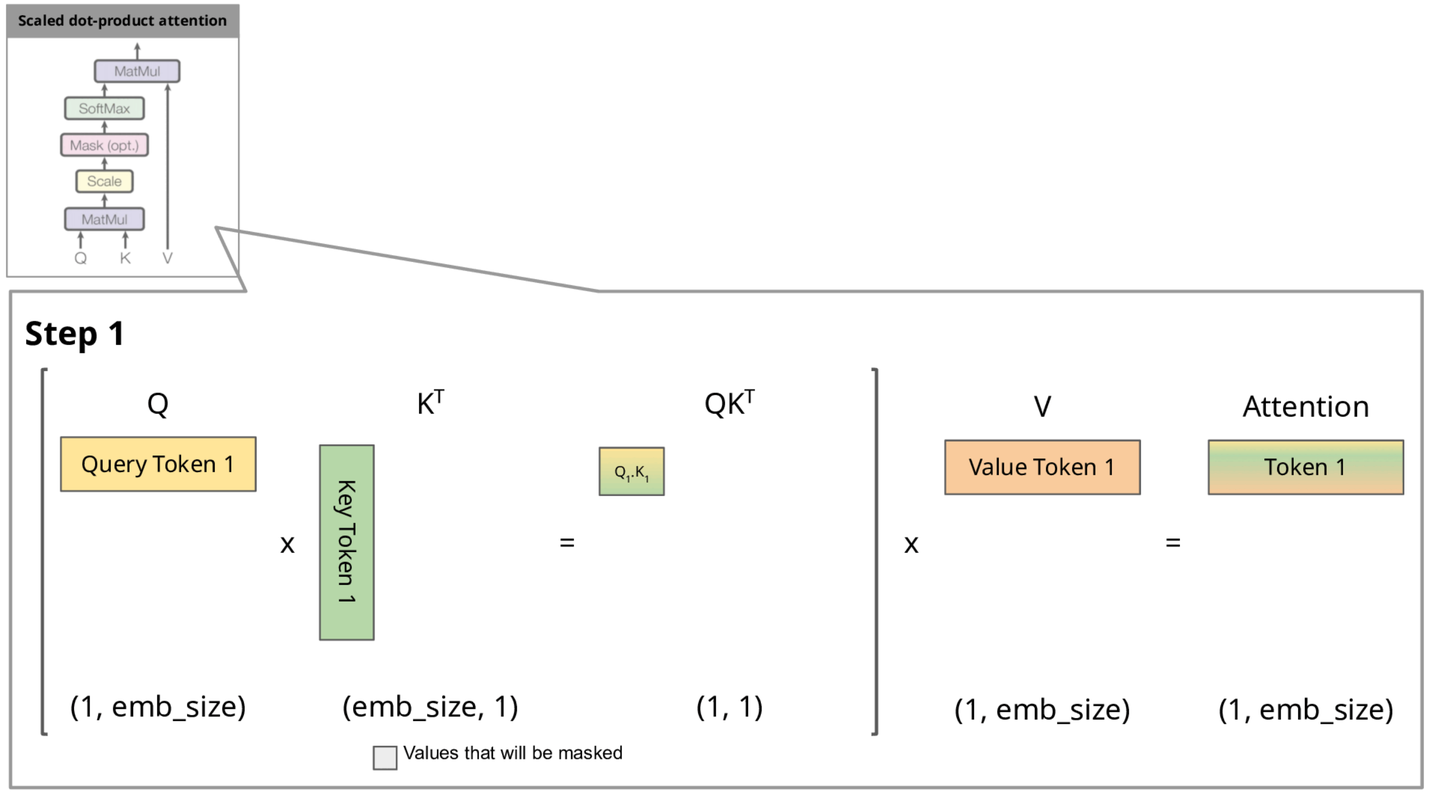
Generative LLM Inference: Autoregressive Decoding

- 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

- Key-value cache:
  - Save attention keys and values for the following iterations to avoid recomputation
  - what is KV cache essentially?

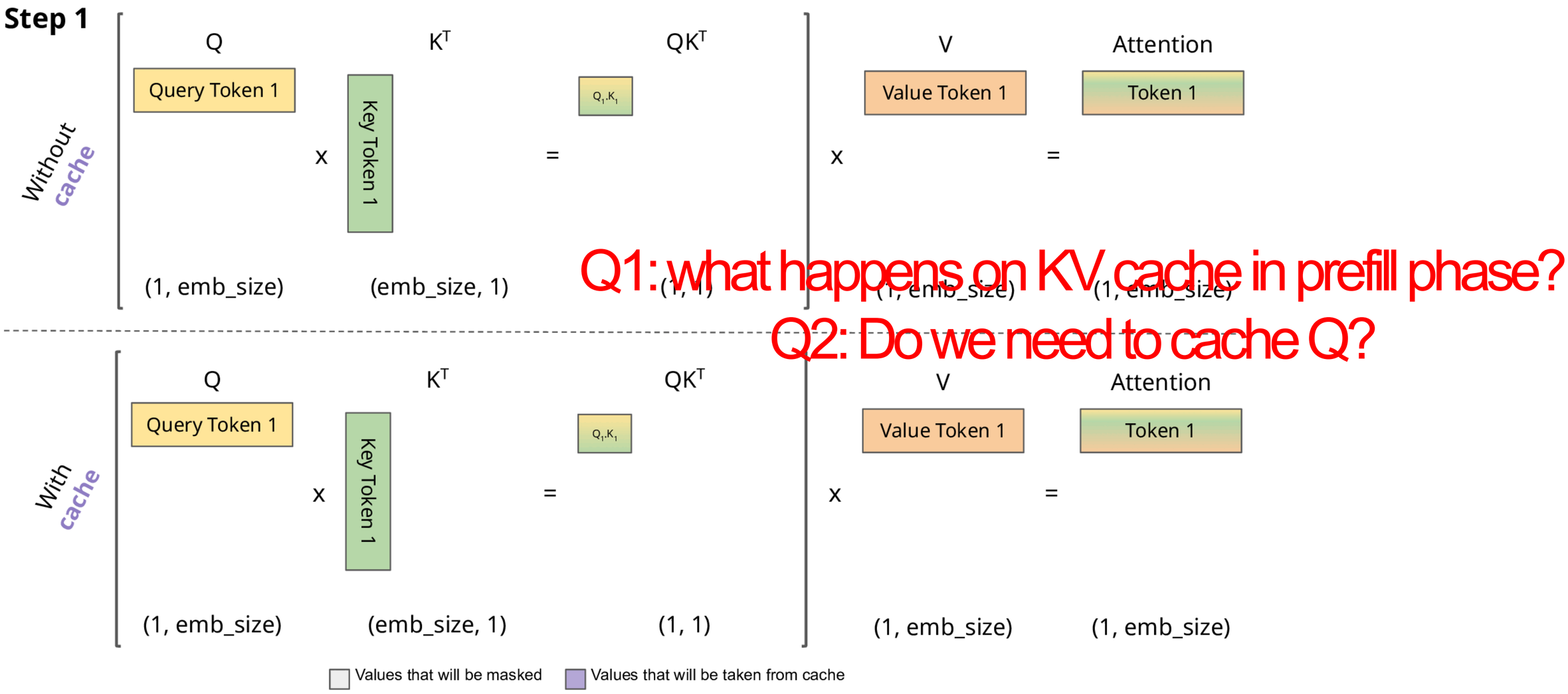
w/ KV Cache vs. w/o KV Cache





Zoom-in! (simplified without Scale and Softmax)

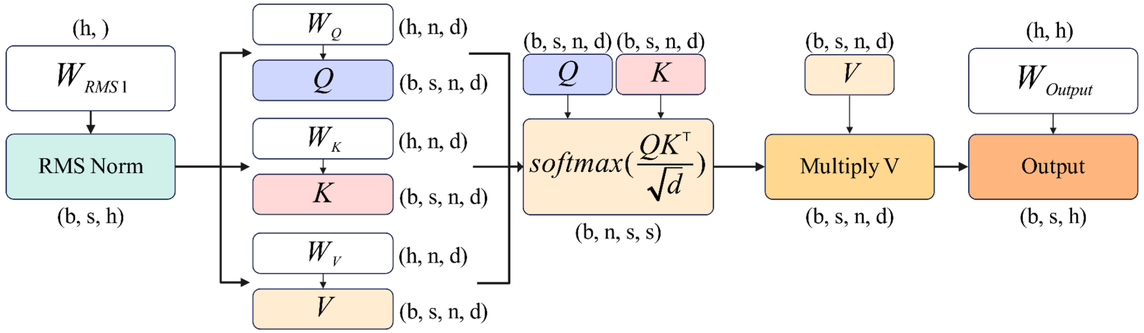
w/ KV Cache vs. w/o KV Cache

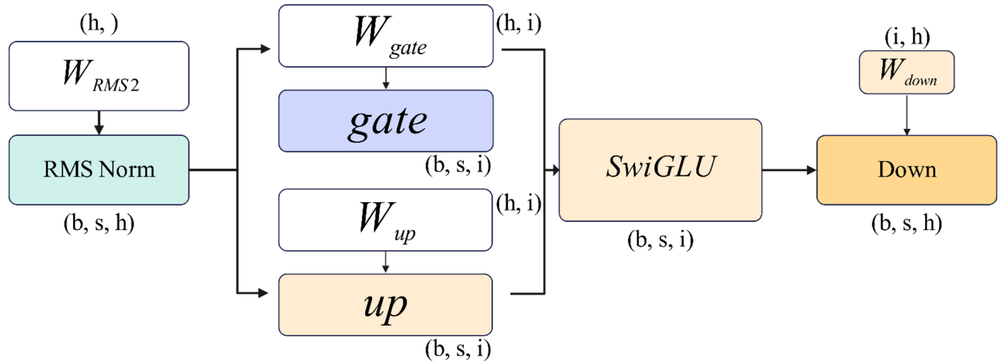


Q1: what happens on KV cache in prefill phase?

Q2: Do we need to cache Q?

Potential Bottleneck of LLM Inference?





- Compute:
  - Prefill: largely same with training
  - Decode: s = 1
- Memory
  - New: KV cache
- Communication
  - mostly same with training

Q? how about batch size b?

Serving vs. Inference

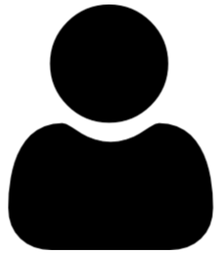
large b

Serving: many requests, online traffic, emphasize cost-per-query.

s.t. some mild latency constraints

emphasize **throughput**

b = 1

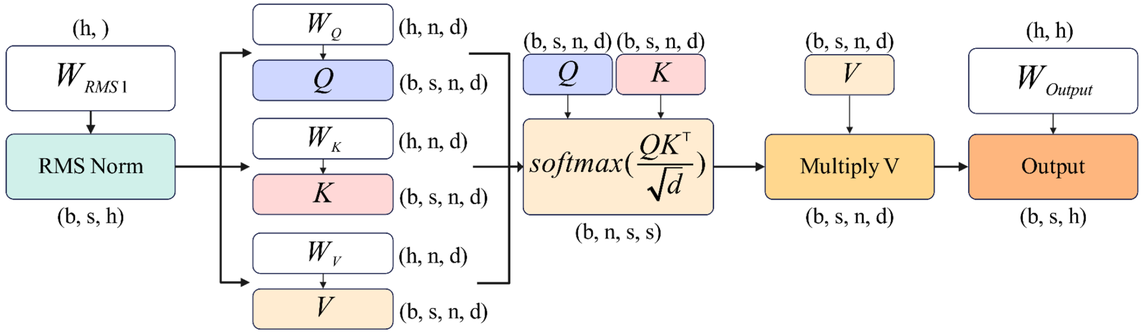


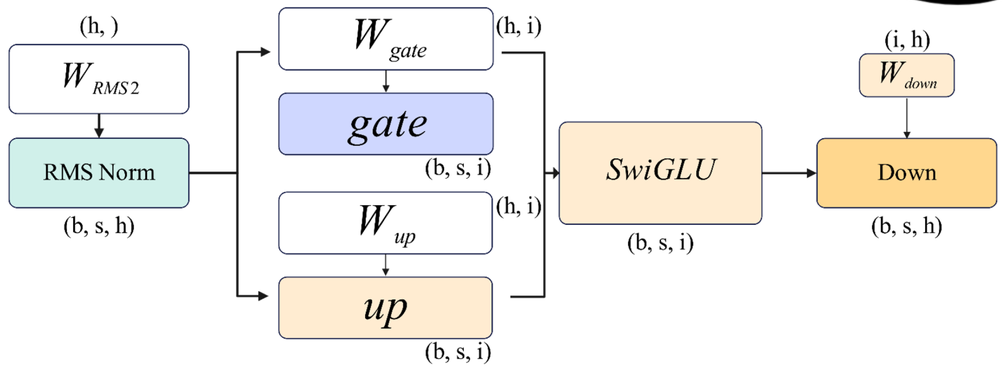
Inference: fewer request, low or offline traffic,

emphasize **latency**

large b

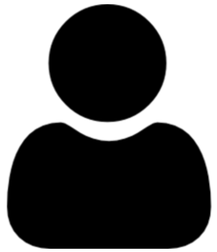
Potential Bottleneck of LLM Inference in Serving



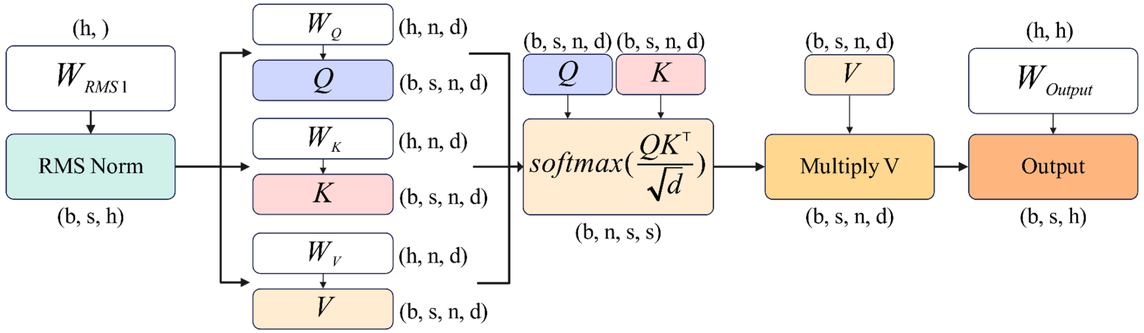


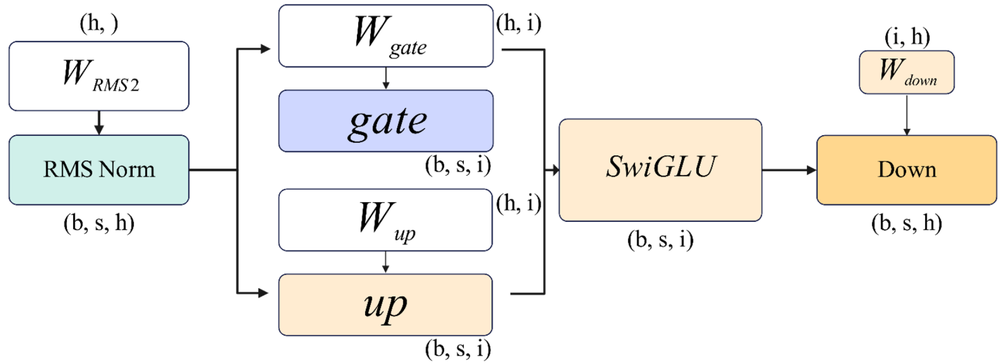
- Compute:
  - Prefill:
    - Different prompts have different length: how to batch?
  - Decode
    - Different prompts have different, unknown #generated tokens
    - s = 1, b is large
- Memory
  - New: KV cache
  - b is large -> KV is linear with b -> will KVs be large?
- Communication
  - mostly same with training

b=1



Potential Bottleneck of LLM Inference in Serving



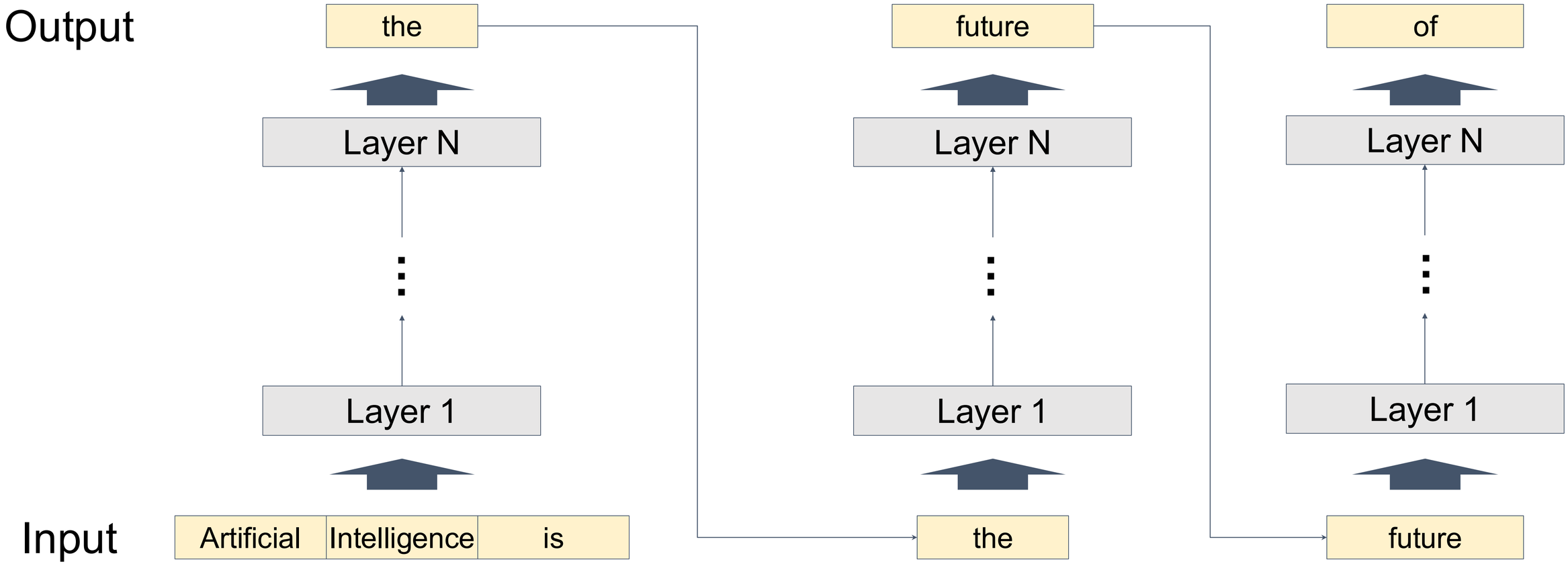


- Compute:
  - Prefill:
    - ~~Different prompts have different length: how to batch?~~
  - Decode
    - Different prompts have different, unknown #generated tokens
    - s = 1, b=1
- Memory
  - New: KV cache
  - ~~b =1 -> KV is linear with b -> will KVs be large?~~
- Communication
  - mostly same with training

Problems of bs = 1

max AI = #ops / #bytes

Recap: Inference process of LLMs

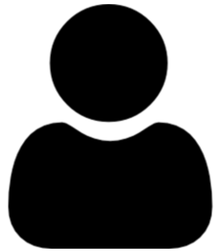


Repeat until the sequence

- Reaches its pre-defined maximum length (e.g., 2048 tokens)
- Generates certain tokens (e.g., “<|*end of sequence*|>”)

Problem of bs = 1

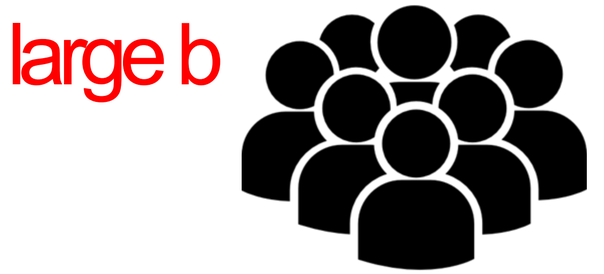
b=1



Latency = step latency * # steps

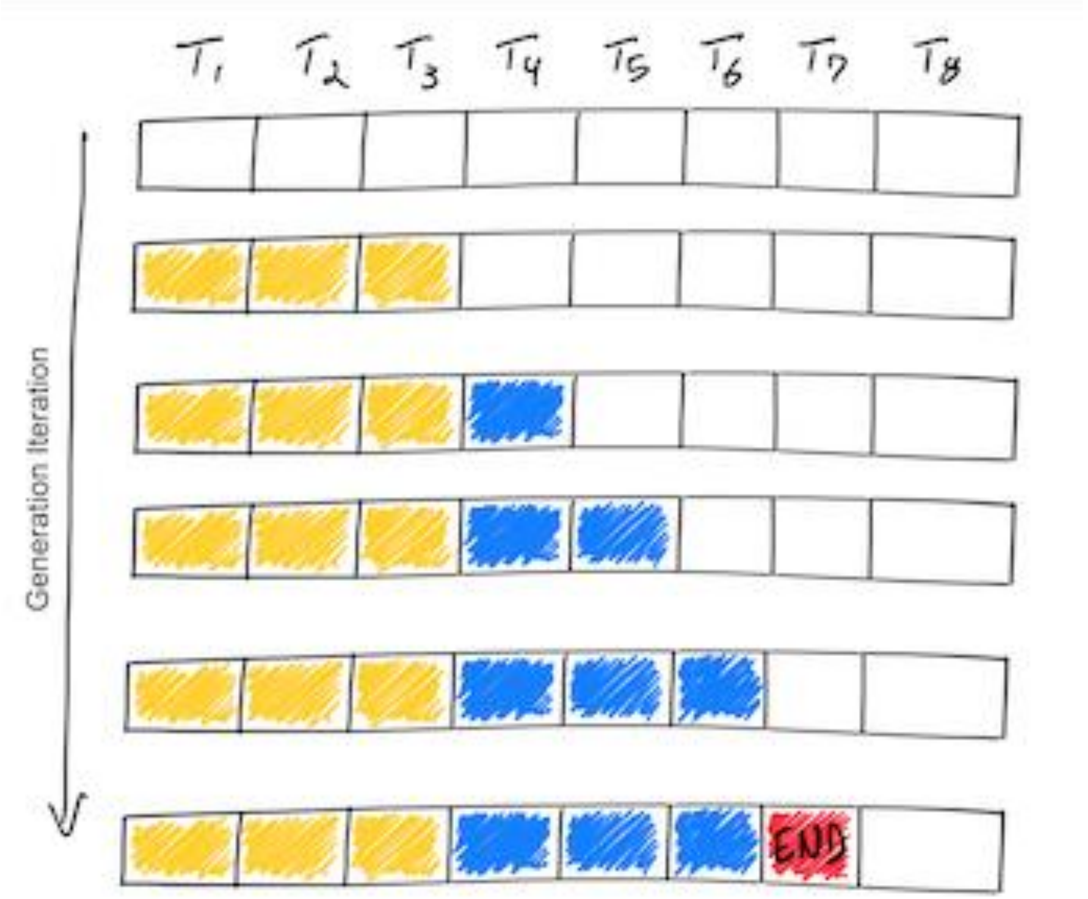
Speculative decoding reduces this, hence amortize the memory moving cost (but it may increase compute cost)

Large Language Models

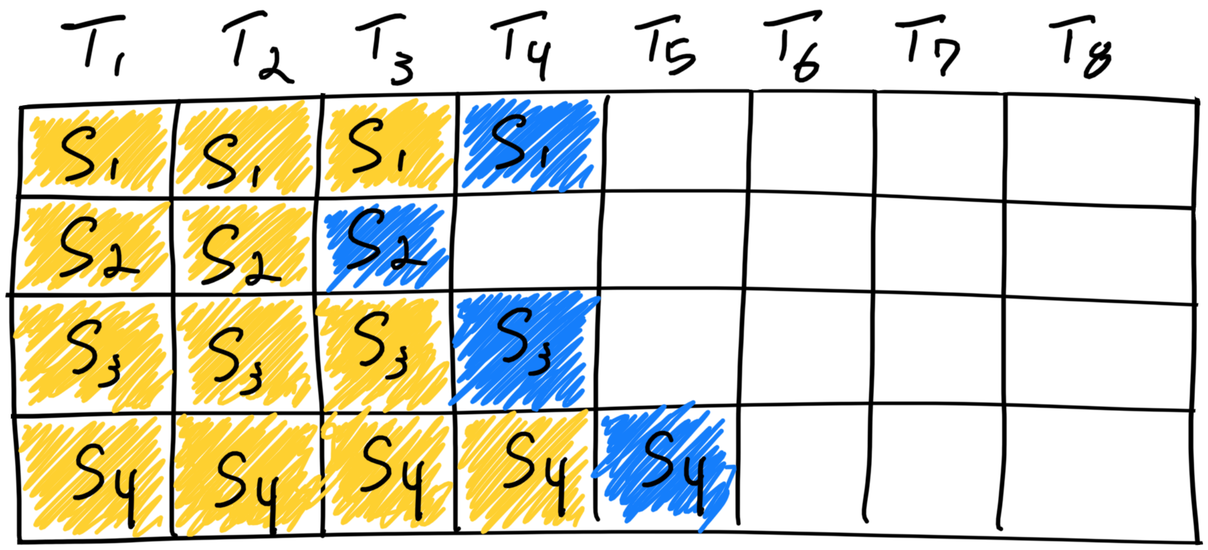


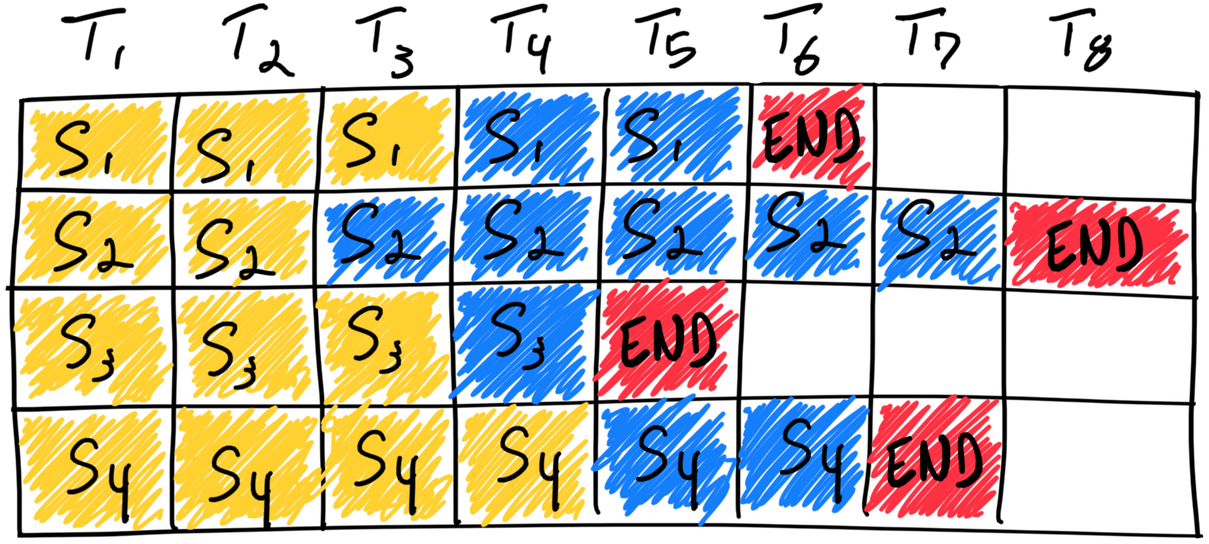
- Serving and inference optimization
  - **Continuous batching and Paged attention**
  - Speculative decoding (Guest Lecture)

LLM Decoding Timeline



Batching Requests to Improve GPU Performance

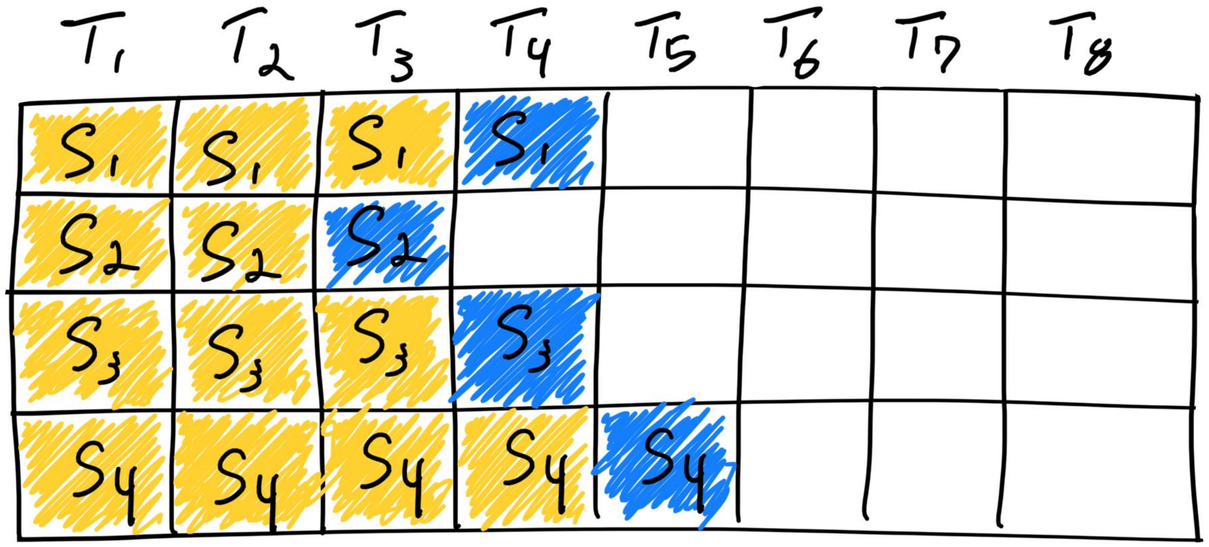


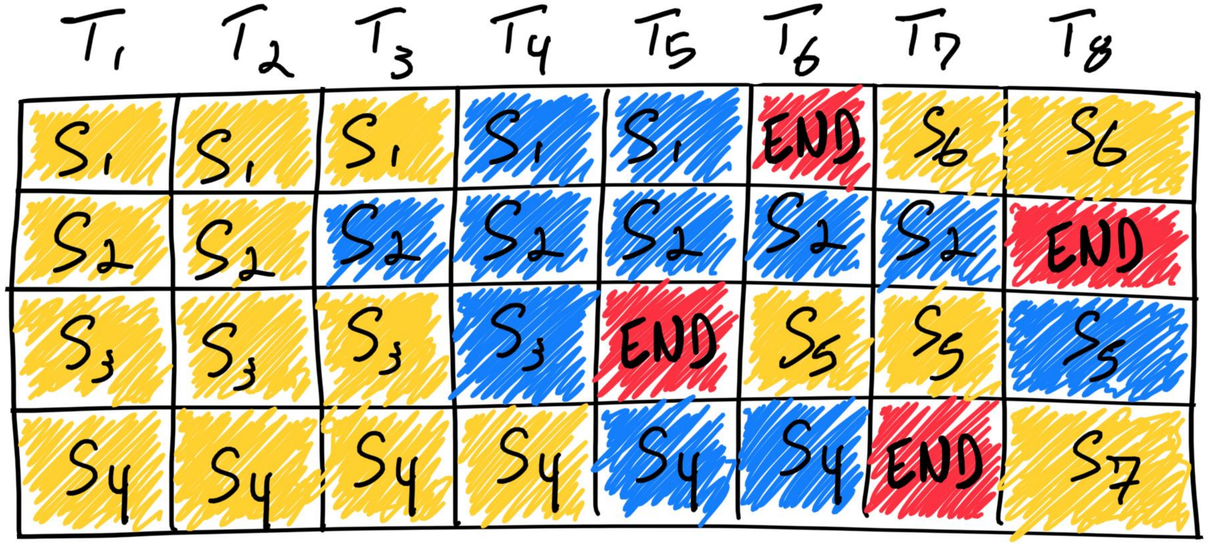


Issues with static batching:

- Requests may complete at different iterations
- Idle GPU cycles
- New requests cannot start immediately

Continuous Batching



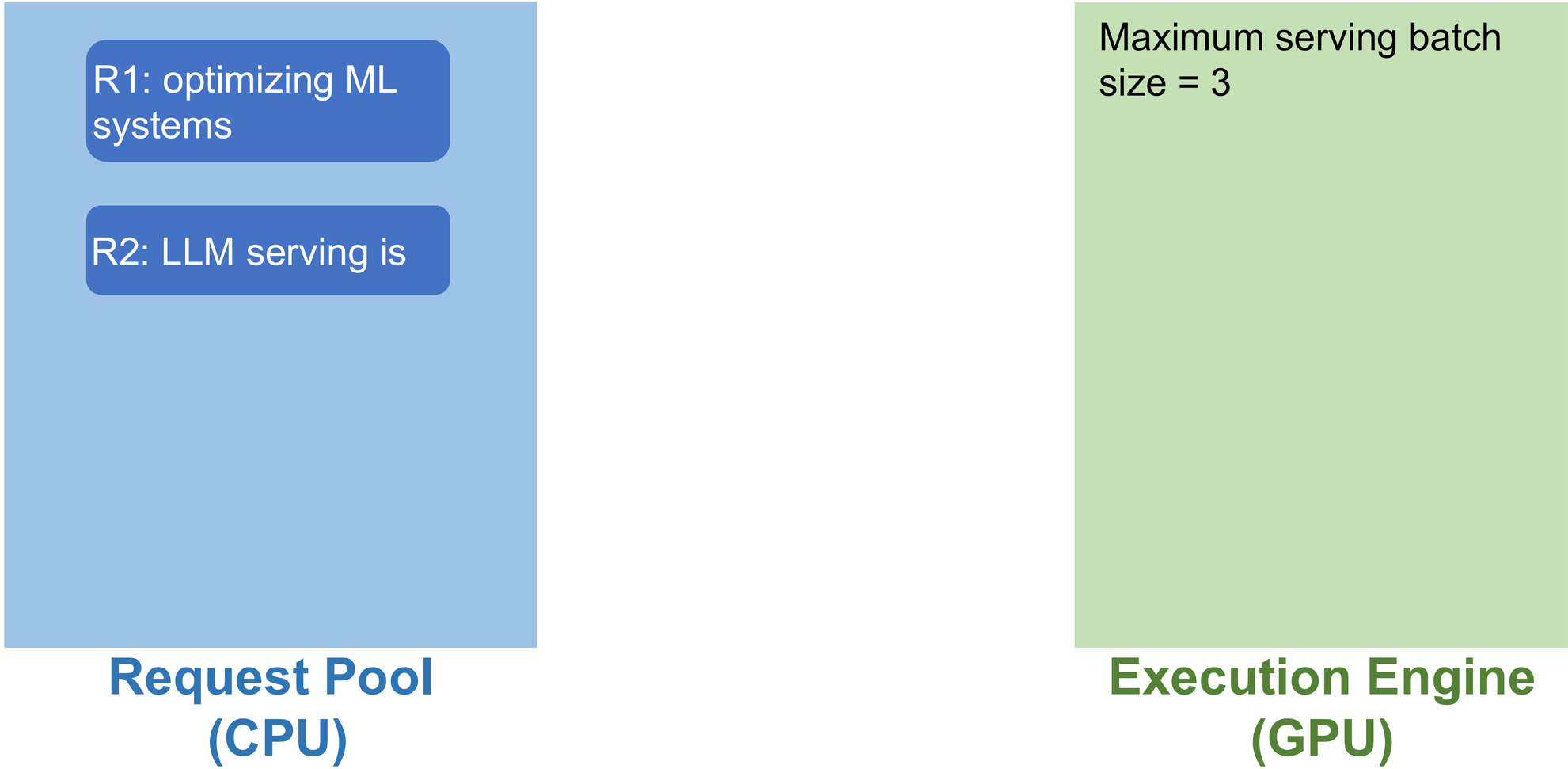


Benefits:

- Higher GPU utilization
- New requests can start immediately

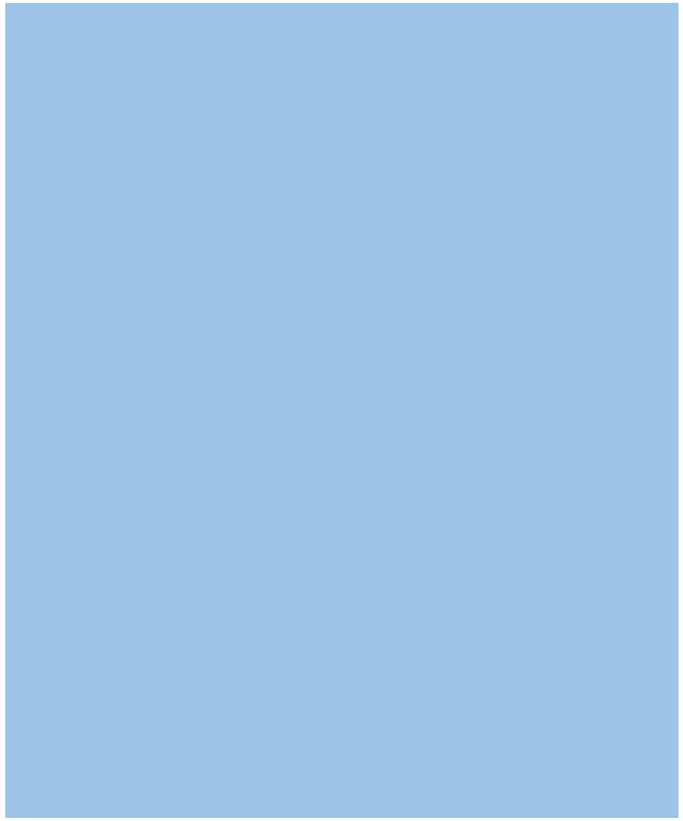
Continuous Batching Step-by-Step

- Receives two new requests R1 and R2



Continuous Batching Step-by-Step

- Iteration 1: decode R1 and R2



Request Pool (CPU)

Maximum serving batch size = 3

R1: optimizing ML systems

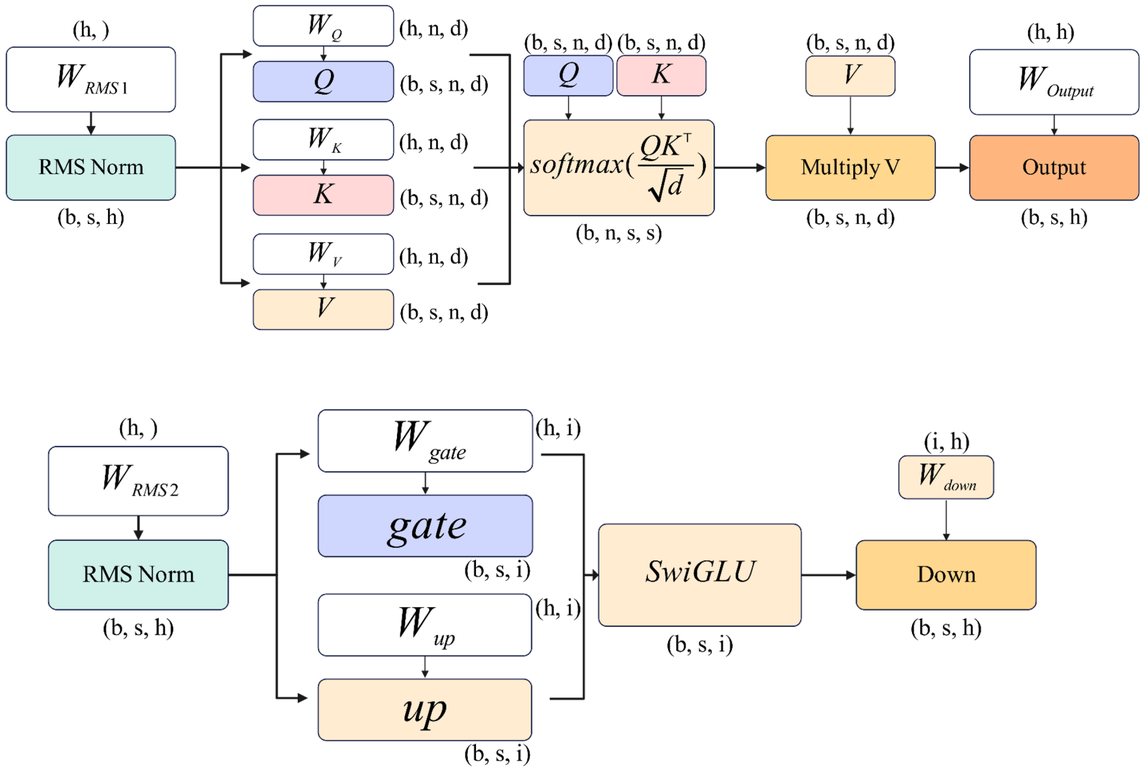
R2: LLM serving is

Execution Engine (GPU)

Iteration 1

Continuous Batching Step-by-Step

- Iteration 1: decode R1 and R2



Q: How to batch these?

Maximum serving batch size = 3

R1: optimizing ML systems

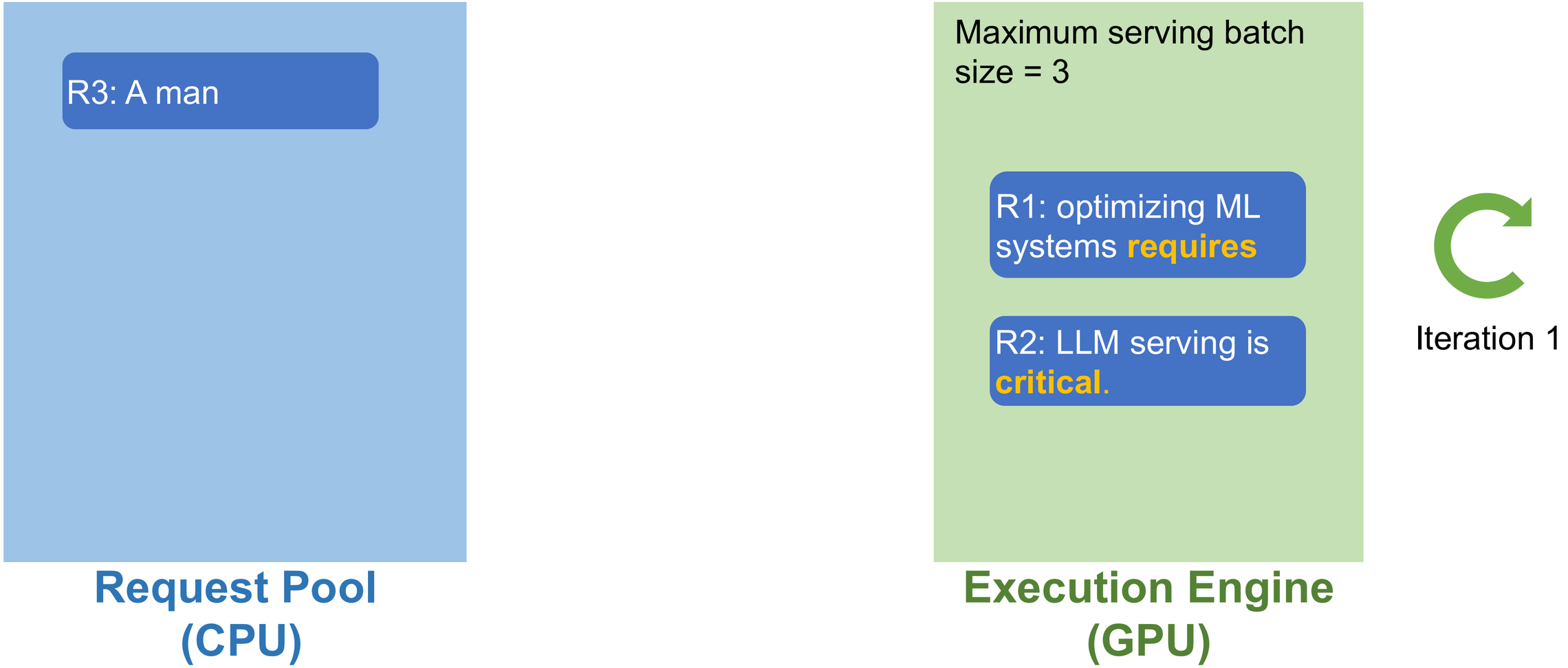
R2: LLM serving is

Iteration 1

Execution Engine (GPU)

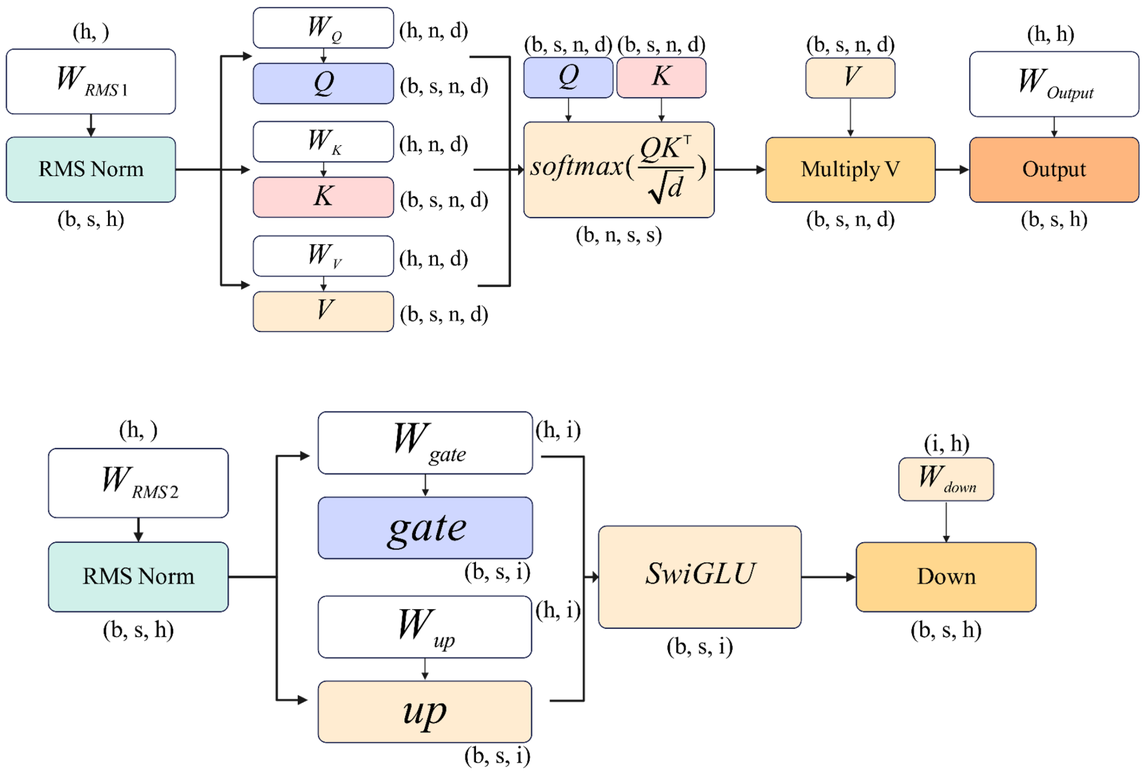
Continuous Batching Step-by-Step

- Receive a new request R3; finish decoding R1 and R2



Continuous Batching Step-by-Step

- Receive a new request R3; finish decoding R1 and R2



Q: How to batch these?

Maximum serving batch size = 3

R1: optimizing ML systems **requires**

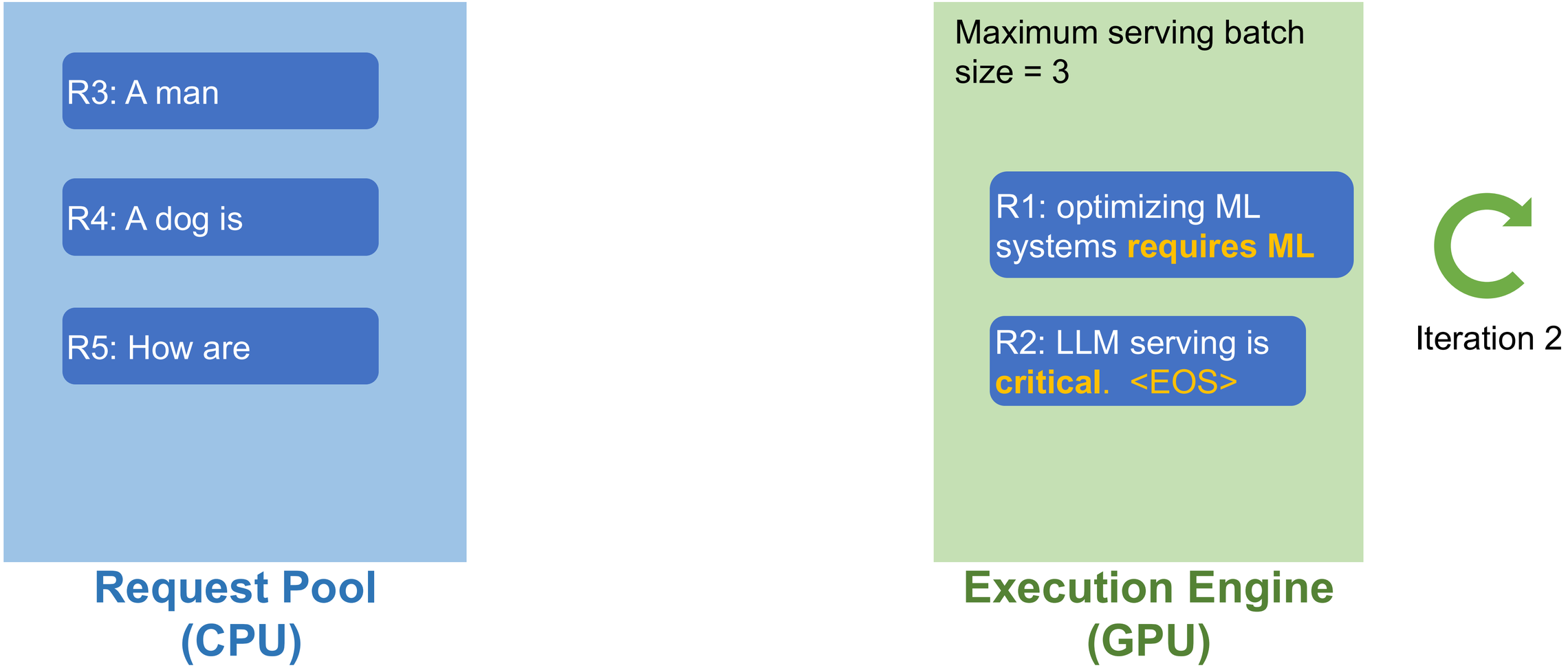
R2: LLM serving is **critical**.

Iteration 1

Execution Engine (GPU)

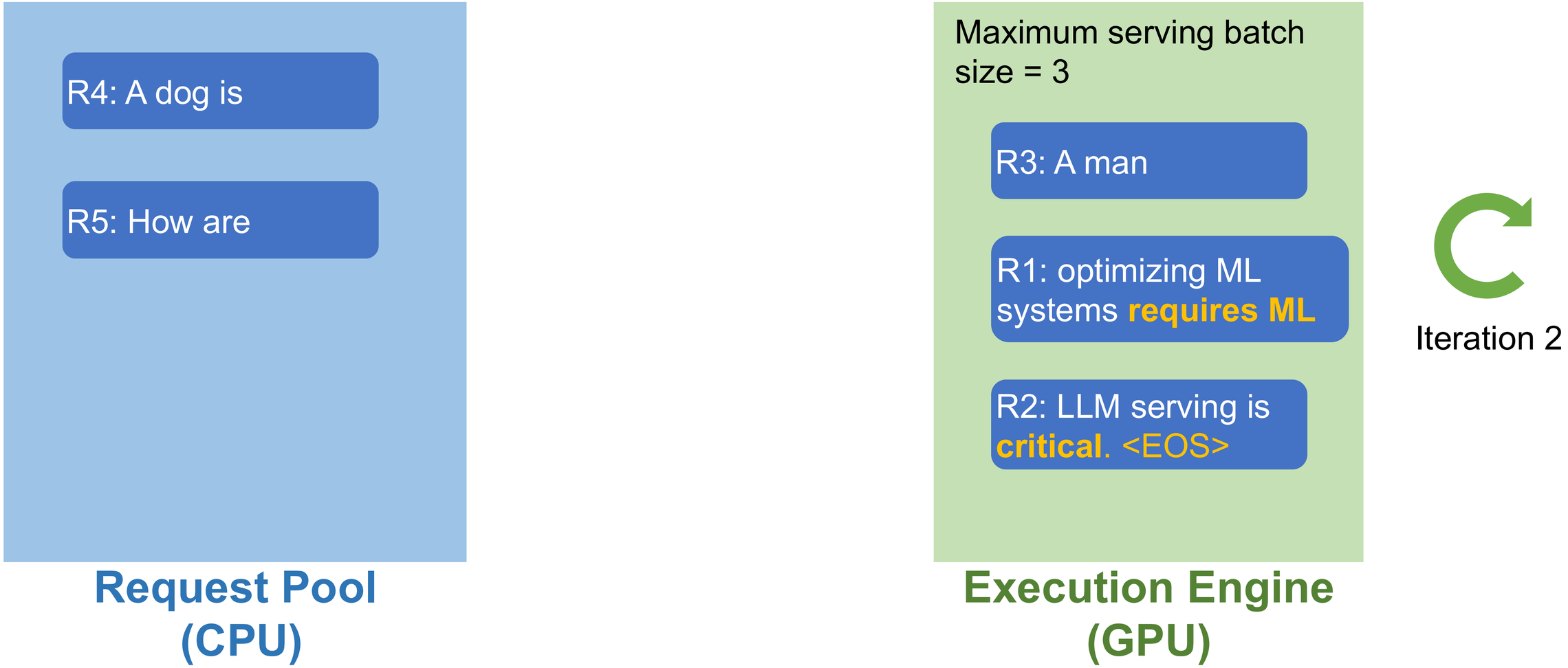
Traditional Batching

- Receive a new request R3; finish decoding R1 and R2



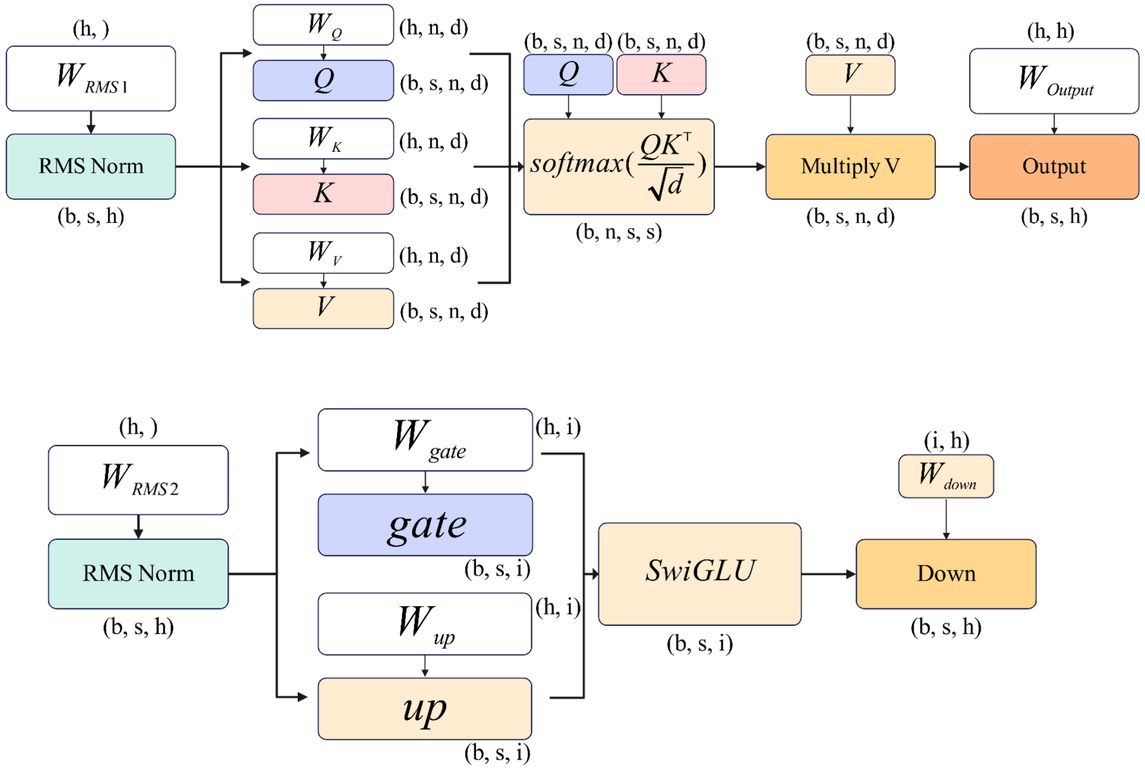
Continuous Batching

- Iteration 2: decode R1, R2, R3; receive R4, R5; R2 completes

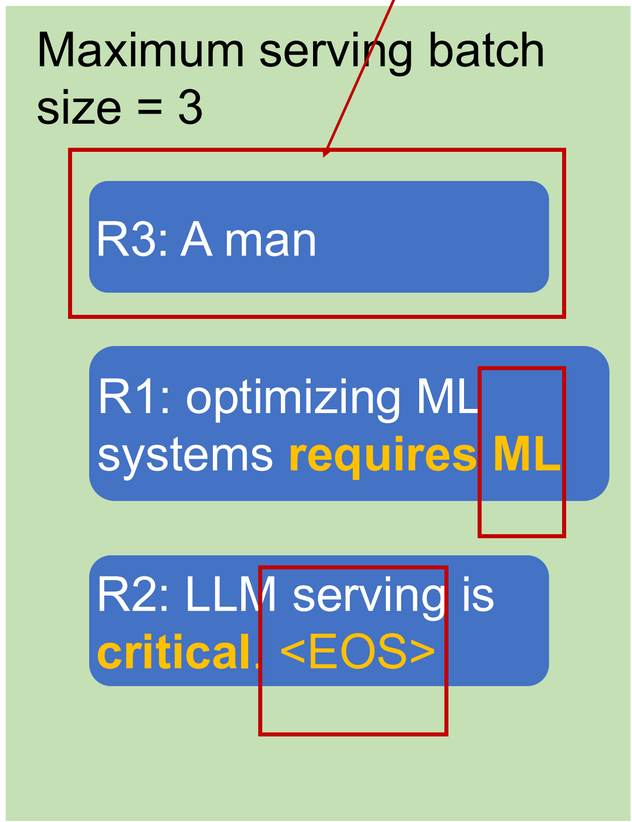


Continuous Batching

- Iteration 2: decode R1, R2, R3; receive R4, R5; R2 completes



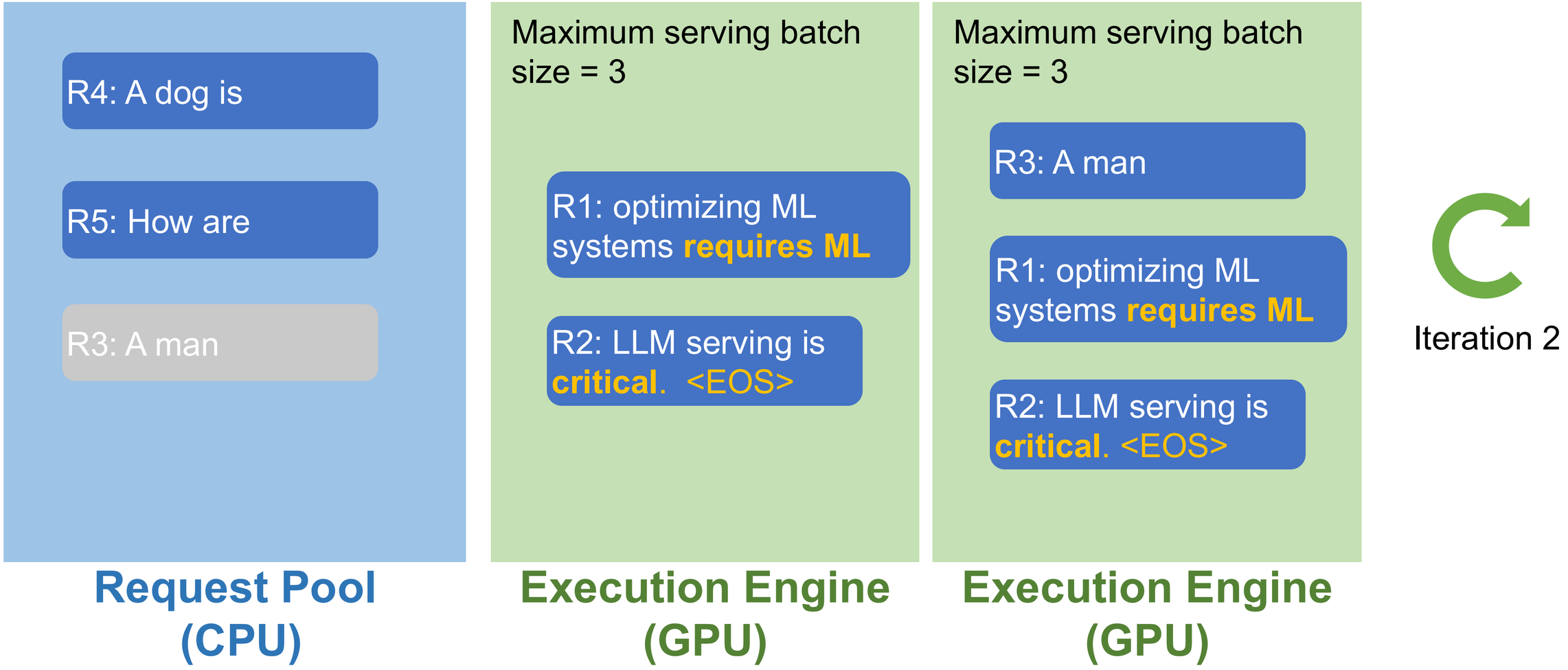
Q: How to batch these?



Iteration 2

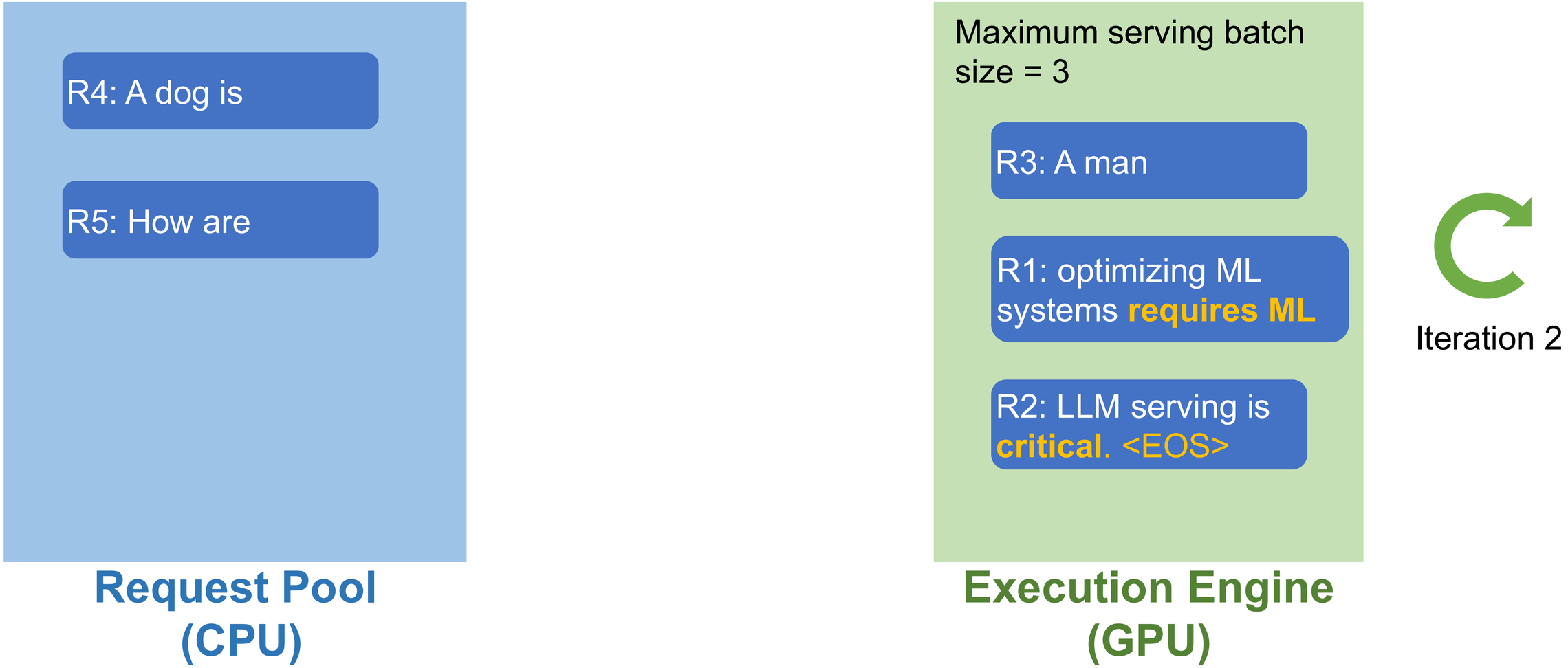
Traditional vs. Continuous Batching

- Iteration 2: decode R1, R2, R3; receive R4, R5; R2 completes



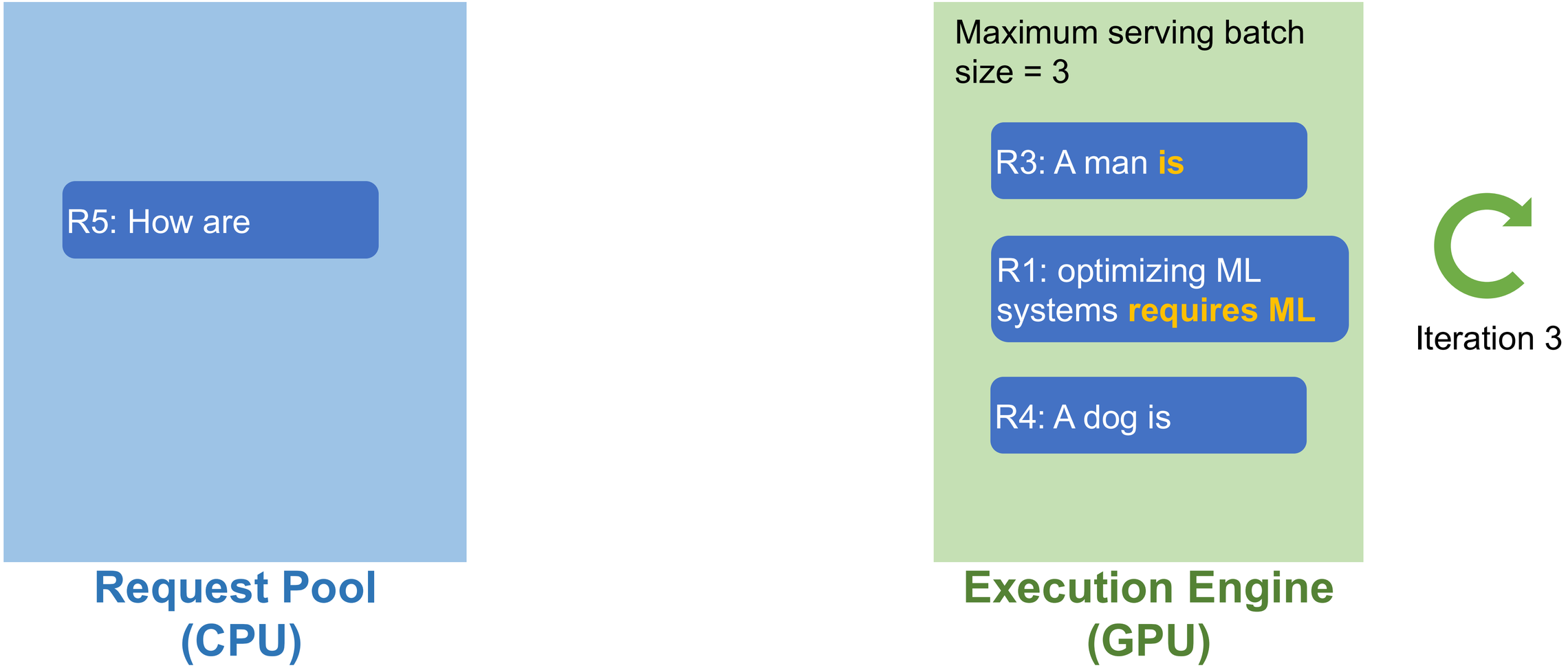
Continuous Batching

- Iteration 2: decode R1, R2, R3; receive R4, R5; R2 completes



Continuous Batching Step-by-Step

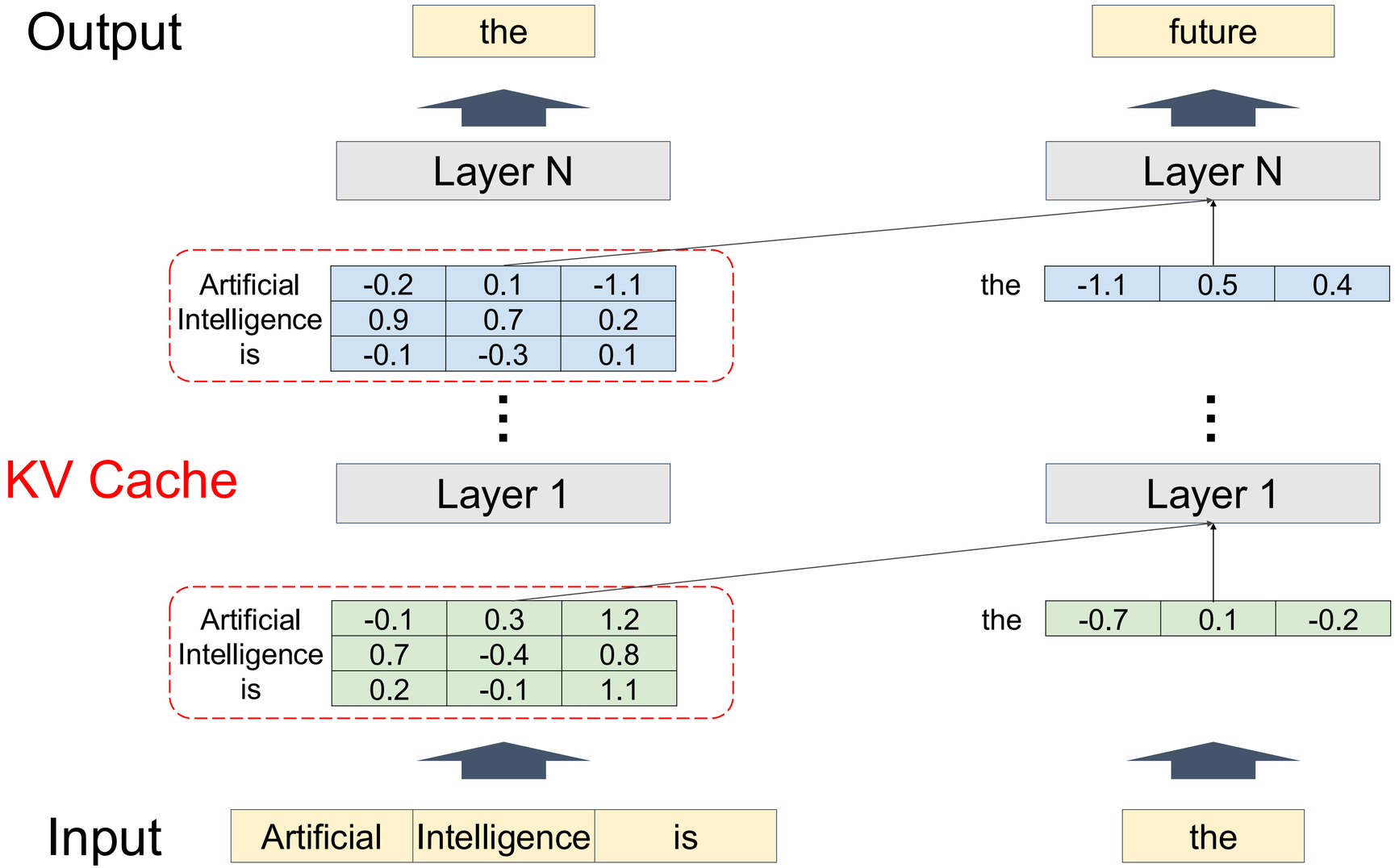
- Iteration 3: decode R1, R3, R4



Summary: Continuous Batching

- Handle early-finished and late-arrived requests more efficiently
- Improve GPU utilization
- Key observation
  - MLP kernels are agnostic to the sequence dimension

KV Cache


Output
the
future
Layer N
Layer N
Artificial
Intelligence
is
-0.2
0.1
-1.1
0.9
0.7
0.2
-0.1
-0.3
0.1
the
-1.1
0.5
0.4
KV Cache
Layer 1
Layer 1
Artificial
Intelligence
is
-0.1
0.3
1.2
0.7
-0.4
0.8
0.2
-0.1
1.1
the
-0.7
0.1
-0.2
Input
Artificial
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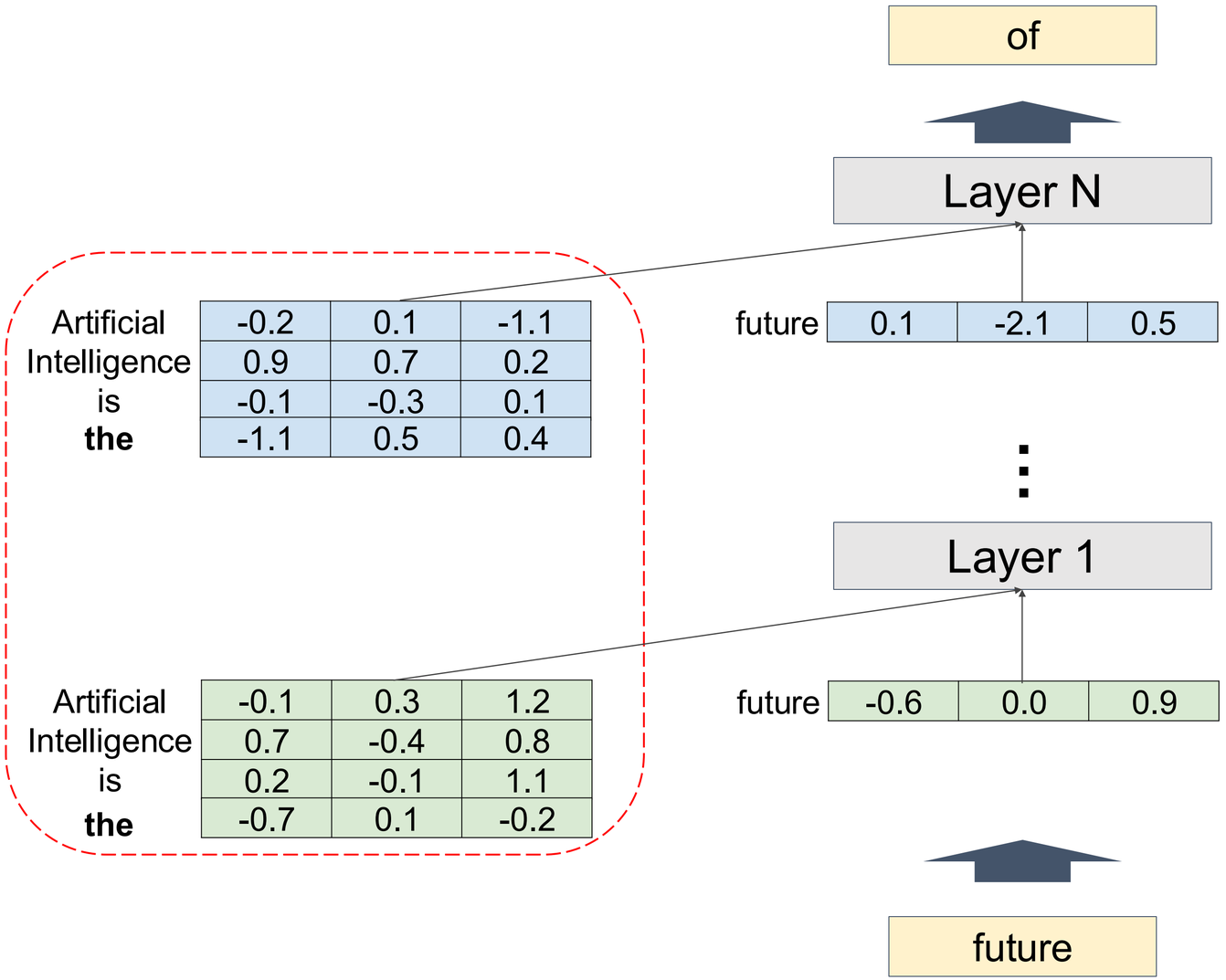
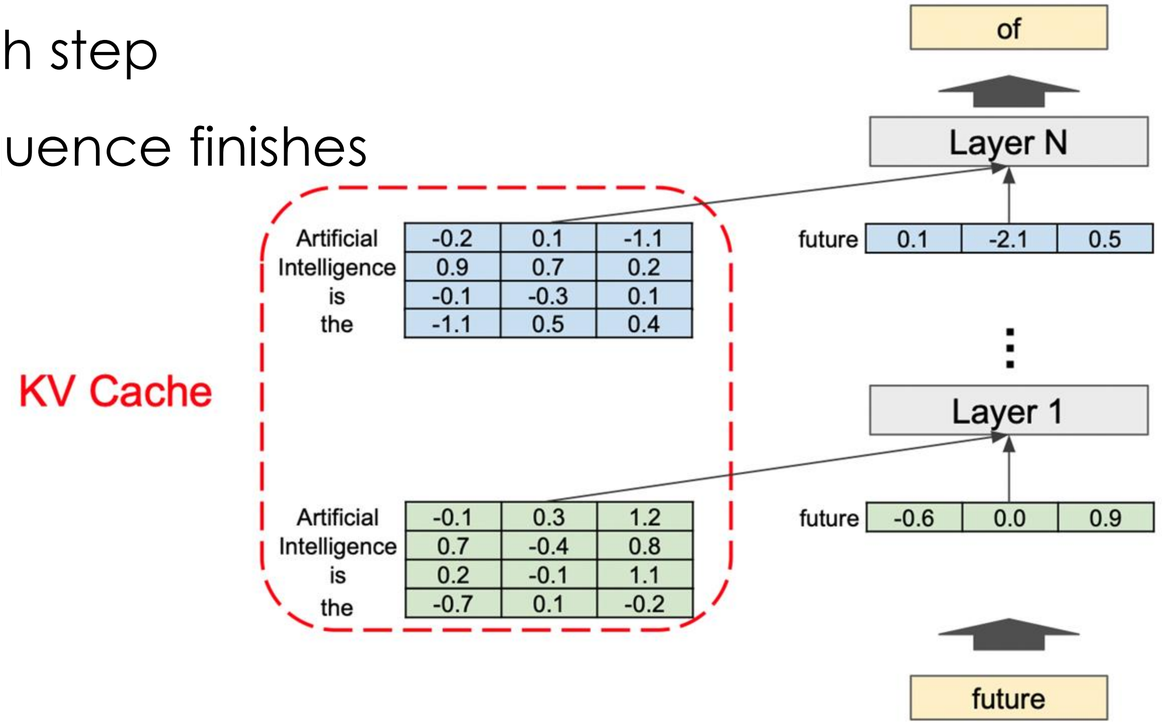
Output



Input

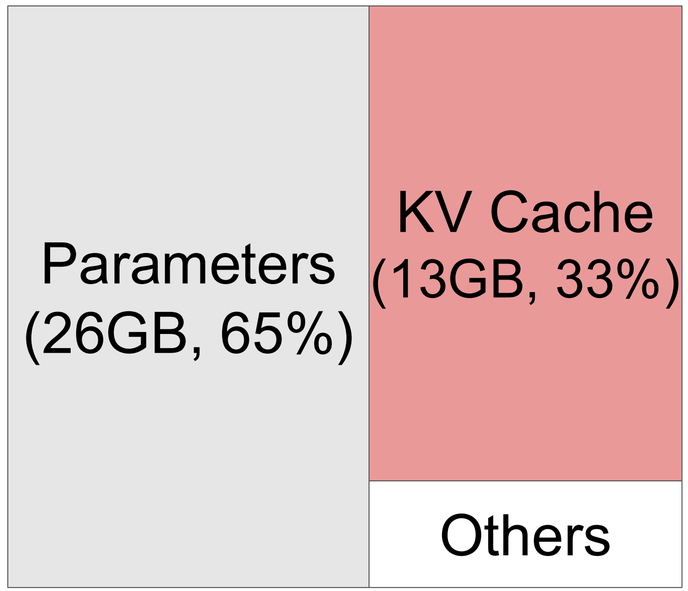
KV Cache

- Memory space to store intermediate vector representations of tokens
  - **Working set** rather than a "cache"
- The size of KV Cache dynamically grows and shrinks
  - A new token is appended in each step
  - Tokens are deleted once the sequence finishes

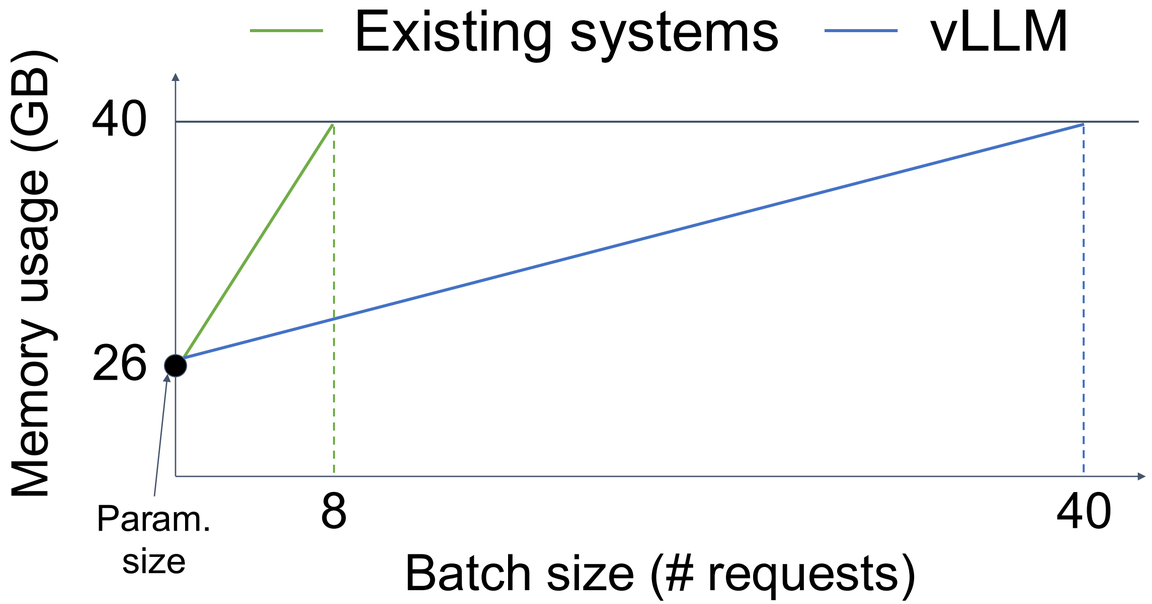


Key insight

Efficient management of KV cache is crucial for high-throughput LLM serving

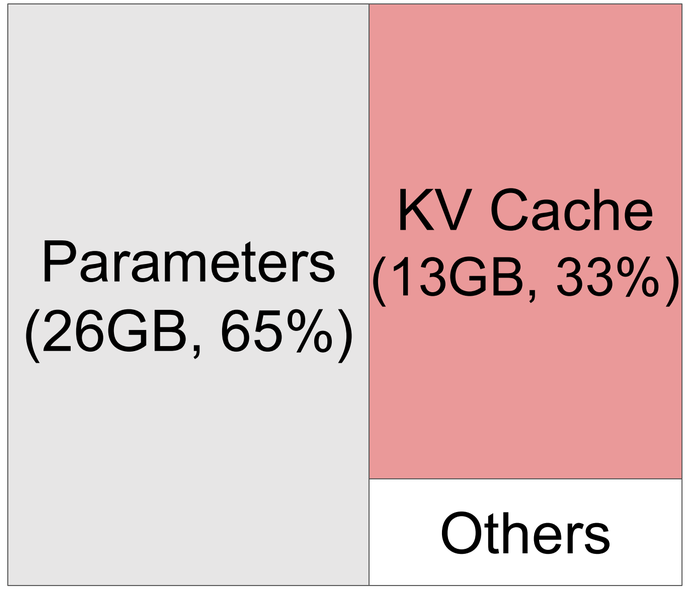


13B LLM on A100-40GB

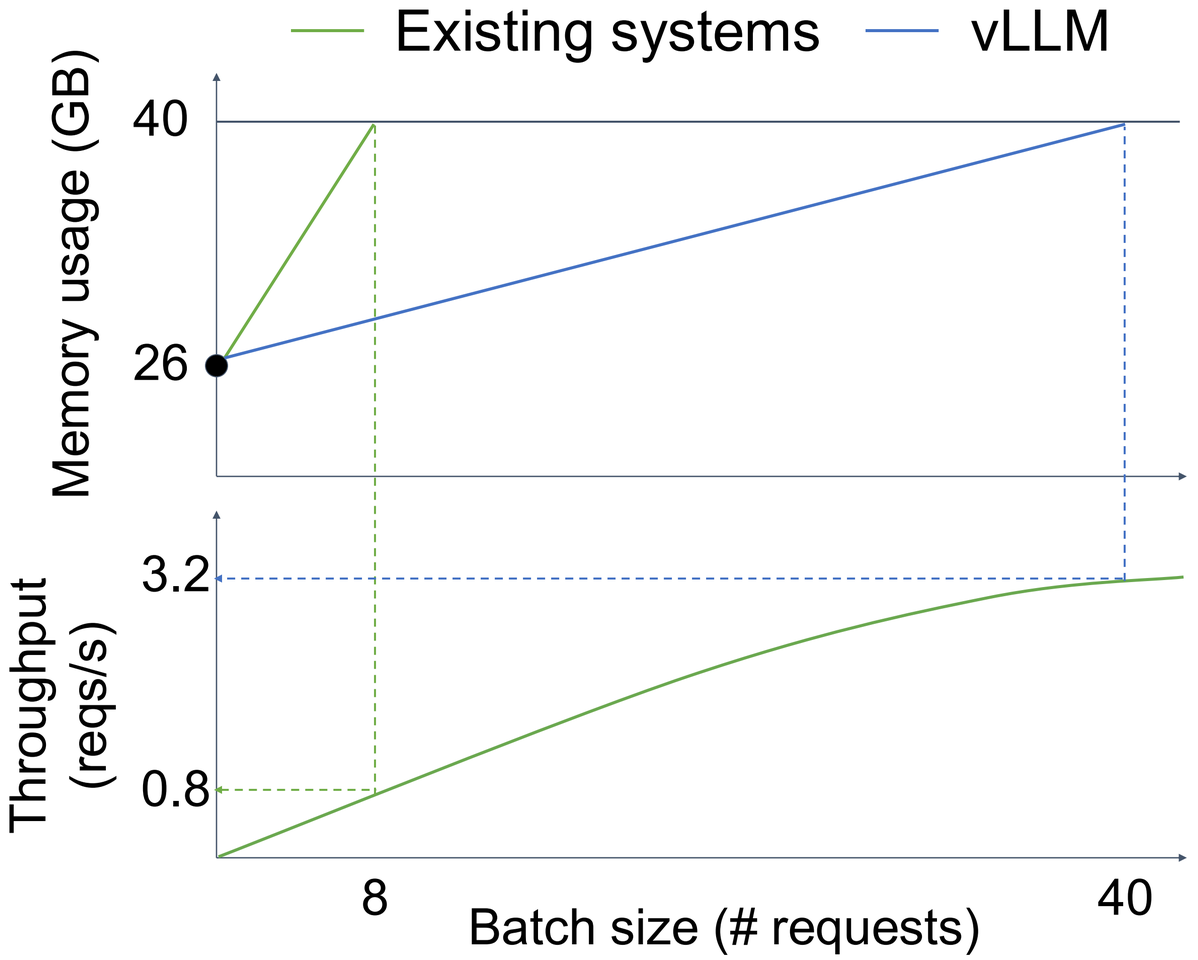


Key insight

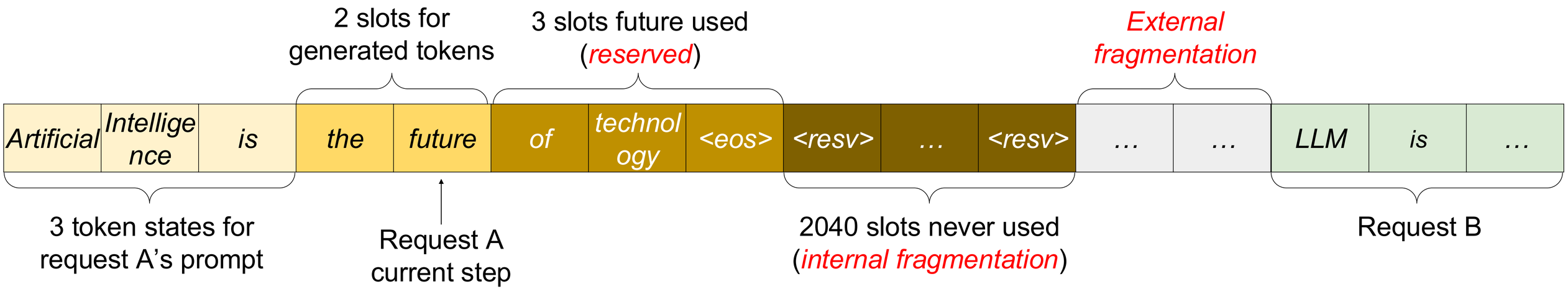
Efficient management of KV cache is crucial for high-throughput LLM serving



13B LLM on A100-40GB

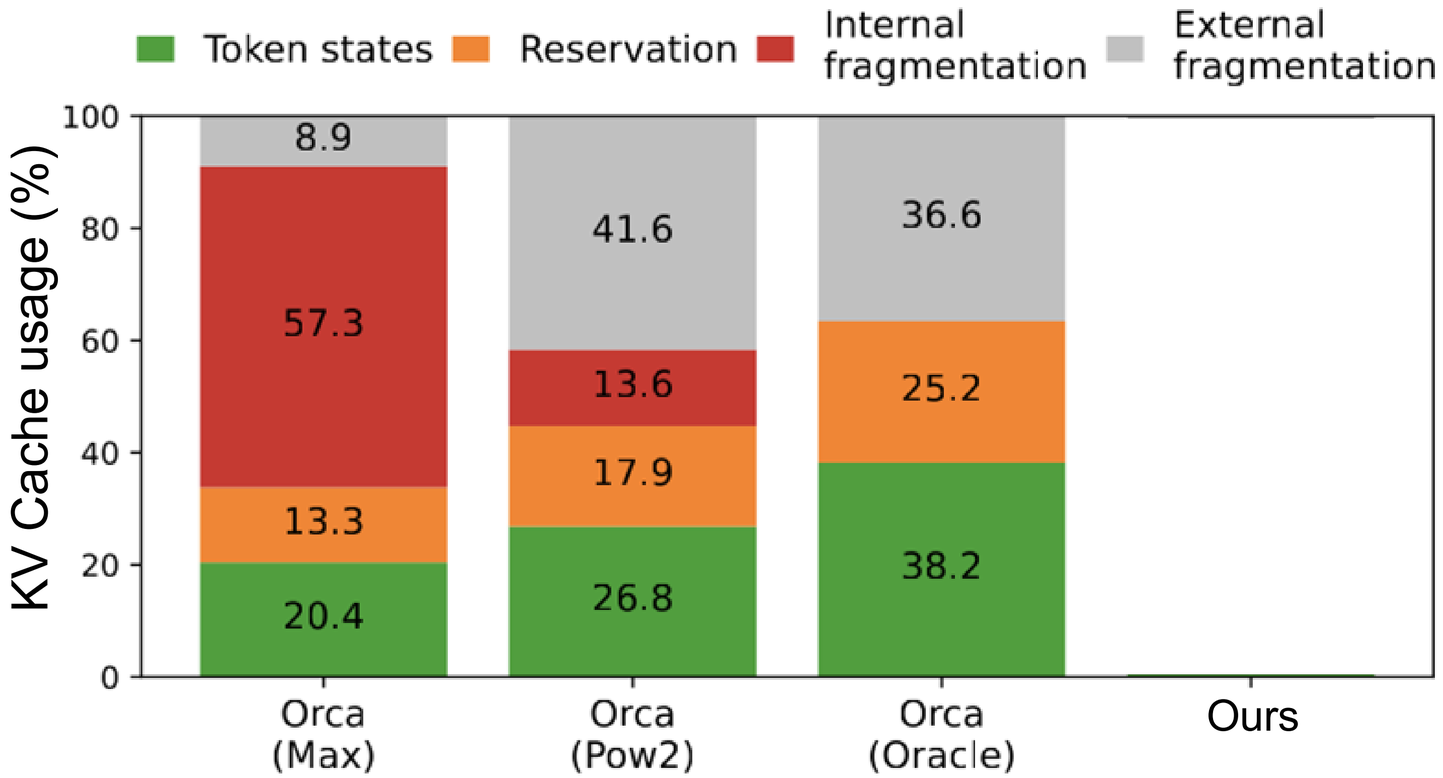


Memory waste in KV Cache



- Reservation: not used at the current step, but used in the future
- Internal fragmentation: over-allocated due to the unknown output length.

Memory waste in KV Cache

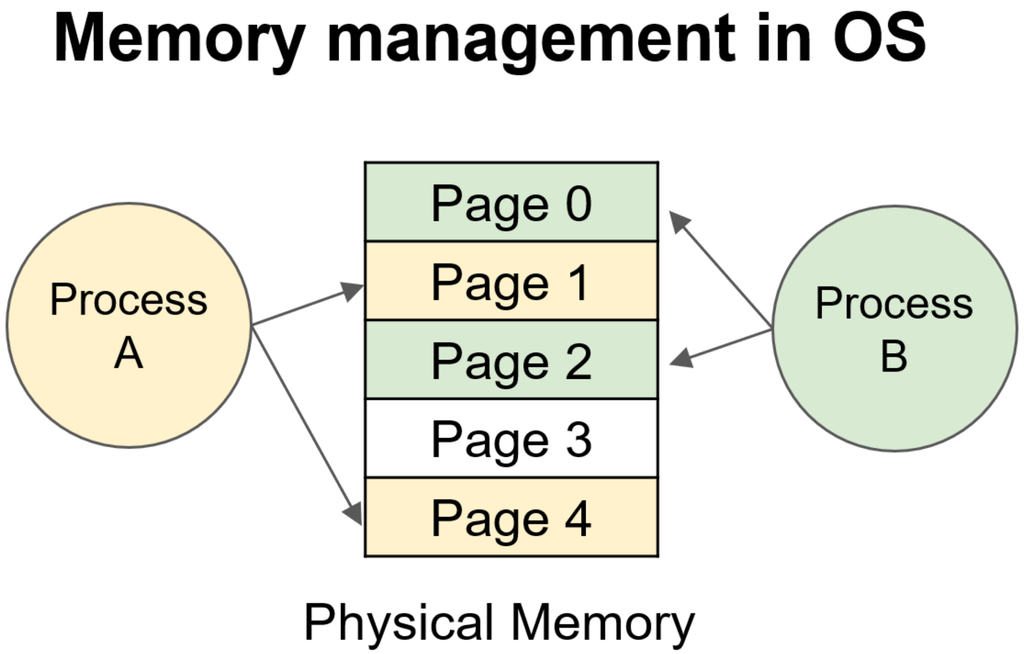


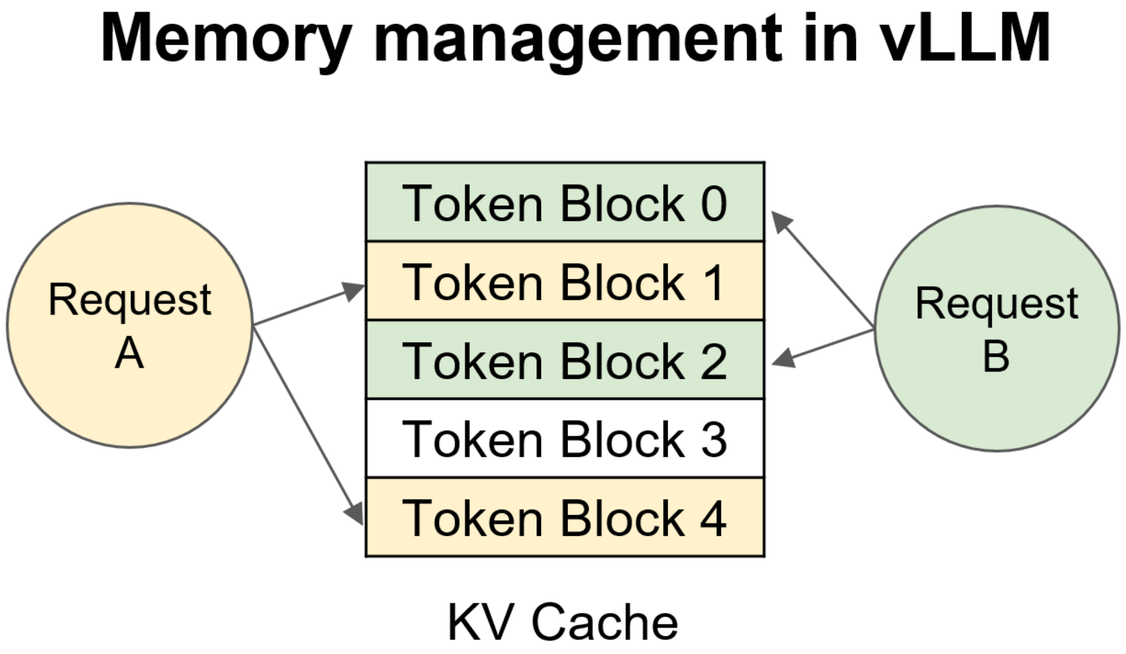
Only **20–40%** of KV cache is utilized to store token states

* Yu, G. I., Jeong, J. S., Kim, G. W., Kim, S., Chun, B. G. “Orca: A Distributed Serving System for Transformer-Based Generative Models” (OSDI 22).

vLLM: Efficient memory management for LLM inference

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





Token block

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

Token block

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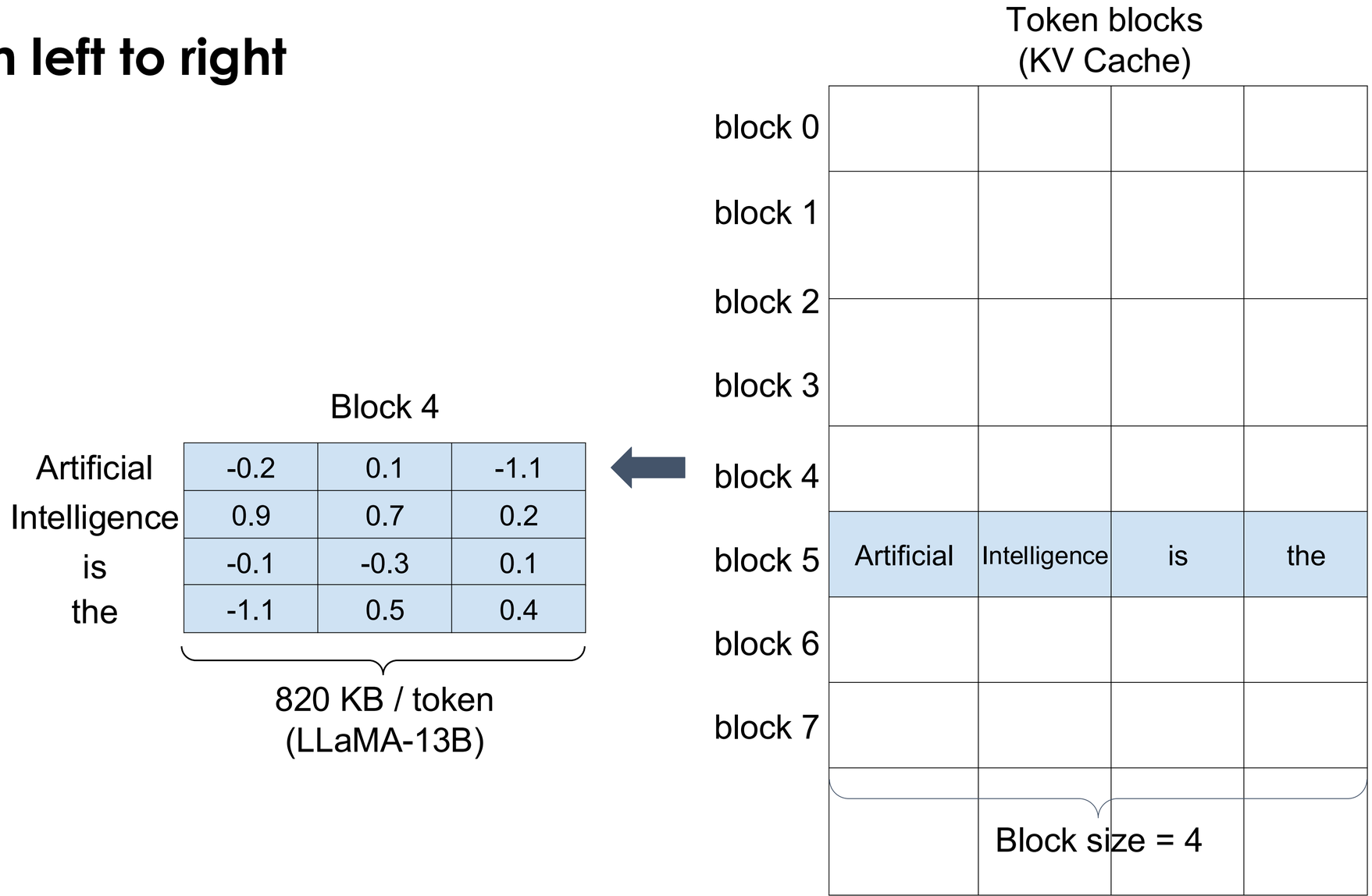
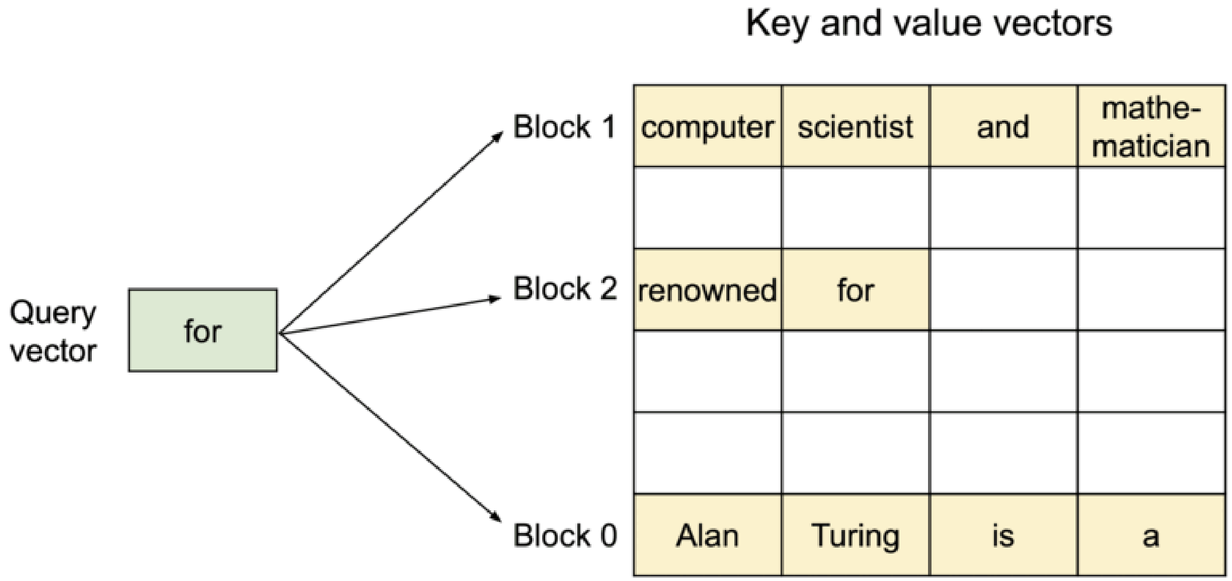


Paged Attention

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



Logical & physical token blocks

Request A

Prompt: “Alan Turing is a computer scientist”

Logical token blocks

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

Physical token blocks (KV Cache)

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

Logical & physical token blocks

Request A

Prompt: “Alan Turing is a computer scientist”

Logical token 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 token blocks (KV Cache)

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

Logical & physical token blocks

Request A

Prompt: “Alan Turing is a computer scientist”
Completion: “and”

Logical token 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 token blocks (KV Cache)

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

Logical & physical token blocks

Request A

Prompt: “Alan Turing is a computer scientist”
Completion: “and”

Logical token blocks

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

Block table

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

Physical token blocks (KV Cache)

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

Logical & physical token blocks

Request A

Prompt: “Alan Turing is a computer scientist”
Completion: “and”

Logical token blocks

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

Block table

Physical block number	# Filled
7	4
1	3
–	–
–	–

Physical token blocks (KV Cache)

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

Logical & physical token blocks

Request A

Prompt: “Alan Turing is a computer scientist”
Completion: “and mathematician”

Logical token blocks

block 0	Alan	Turing	is	a
block 1	computer	scientist	and	mathema tician
block 2				
block 3				

Block table

Physical block number	# Filled
7	4
1	4
–	–
–	–

Physical token blocks (KV Cache)

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

Logical & physical token blocks

Request A

Prompt: “Alan Turing is a computer scientist”
Completion: “and mathematician renowned”

Logical token blocks

block 0	Alan	Turing	is	a
block 1	computer	scientist	and	mathema tician
block 2	renowned			
block 3				

Block table

Physical block number	# Filled
7	4
1	4
5	1
–	–

Physical token blocks (KV Cache)

block 0				
block 1	computer	scientist	and	mathem atician
block 2				
block 3				
block 4				
block 5	renowned			
block 6				
block 7	Alan	Turing	is	a

Allocated on demand

Serving multiple requests

Request A

Block Table

Logical token blocks

Alan	Turing	is	a
computer	scientist	and	mathematician
renowned			

Physical token blocks
(KV Cache)

computer	scientist	and	mathematician
Artificial	Intelligence	is	the
renowned			
future	of	technology	
Alan	Turing	is	a

Block Table

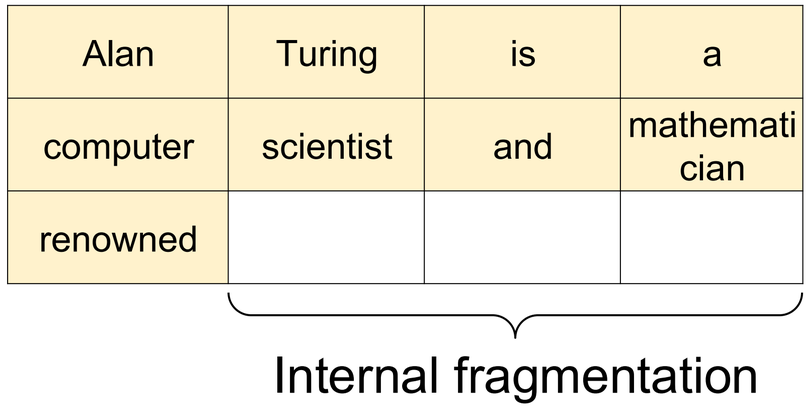
Request B

Logical token blocks

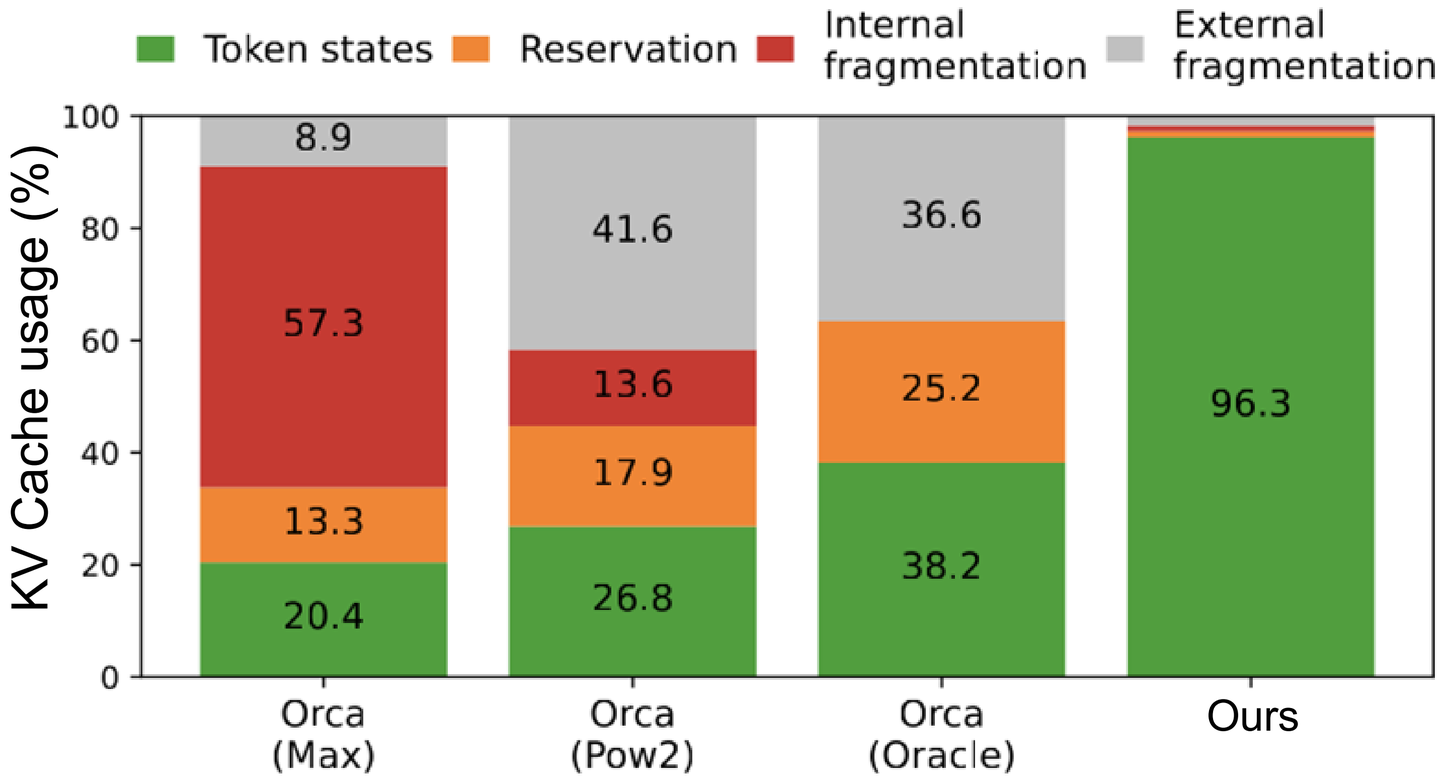
Artificial	Intelligence	is	the
future	of	technology	

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



Effectiveness of PagedAttention



96.3% KV cache utilization