CS 498: Machine Learning System Spring 2025

Minjia Zhang

The Grainger College of Engineering

Today

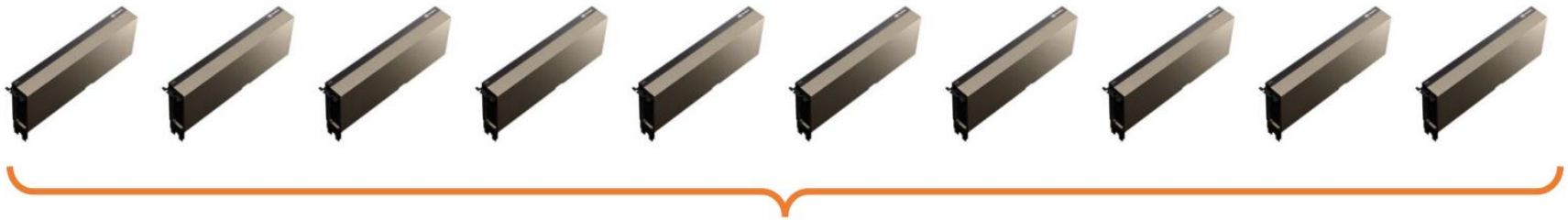
DL Inference

- LLM Inference Basic
- LLM Serving System
- Continuous Batching

Learning objectives

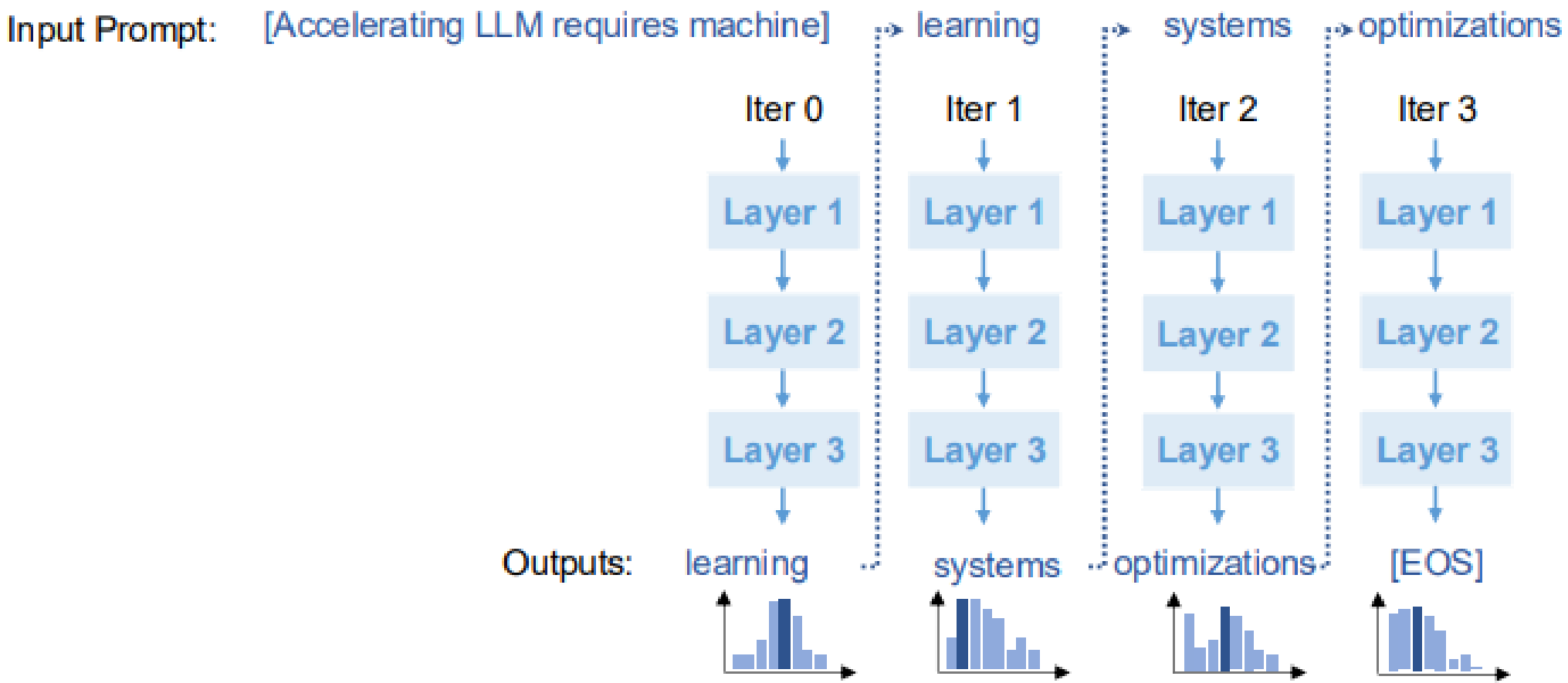
- Understand LLM inference basics
- Able to explain why sequence batching leads to inefficiencies
- Analyze how continuous batching and iteration-level scheduling improve GPU utilization

LLMs are Slow and Expensive to Serve



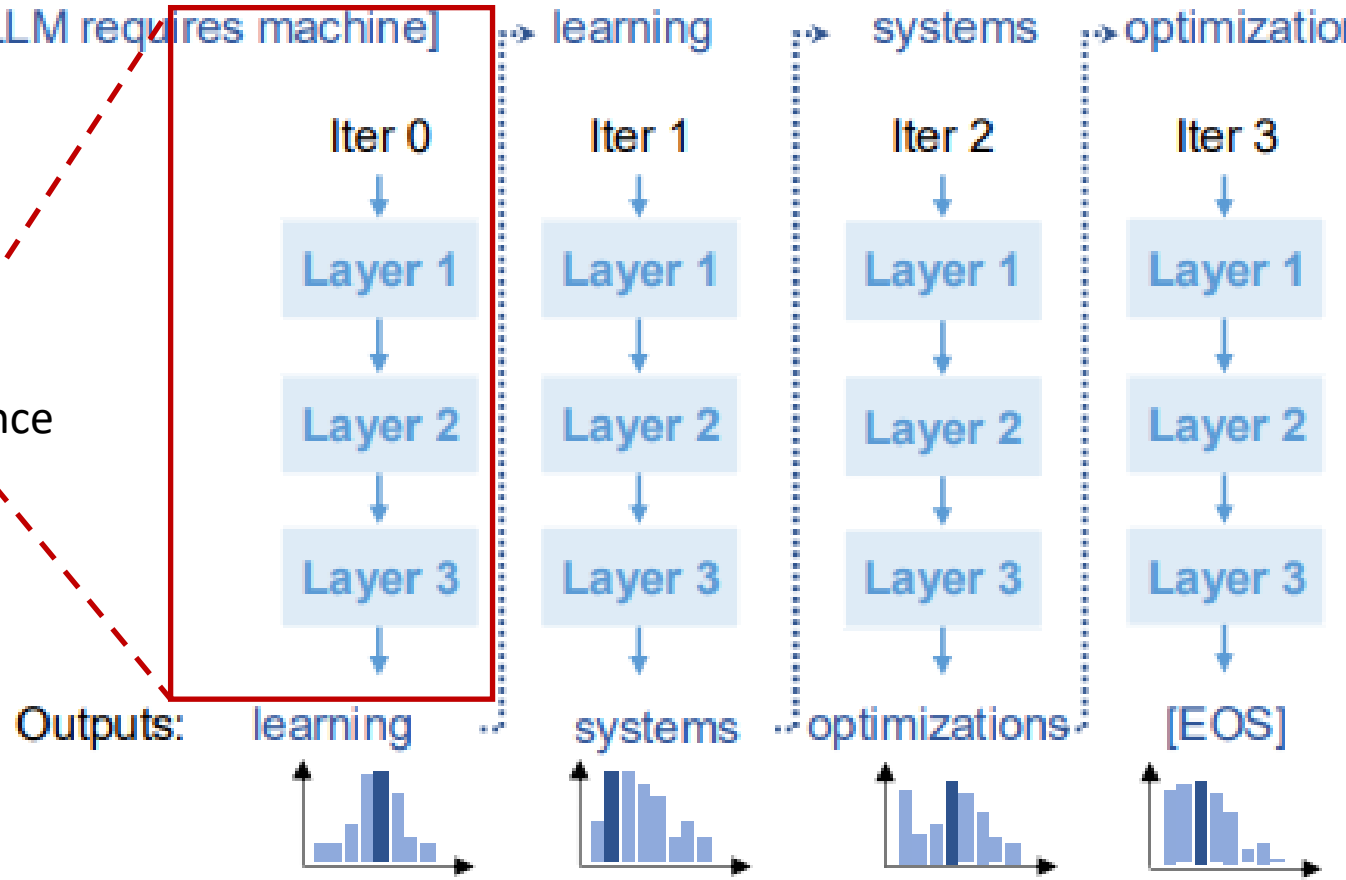
- At least ten A100-40GB GPUs to serve 175B GPT-3 in half-precision
- Generating 256 tokens takes ~20 seconds
- Cannot process requests in parallel
  - Per-request key-value cache takes 3GB GPU memory

Generative LLM Inference: Autoregressive Decoding



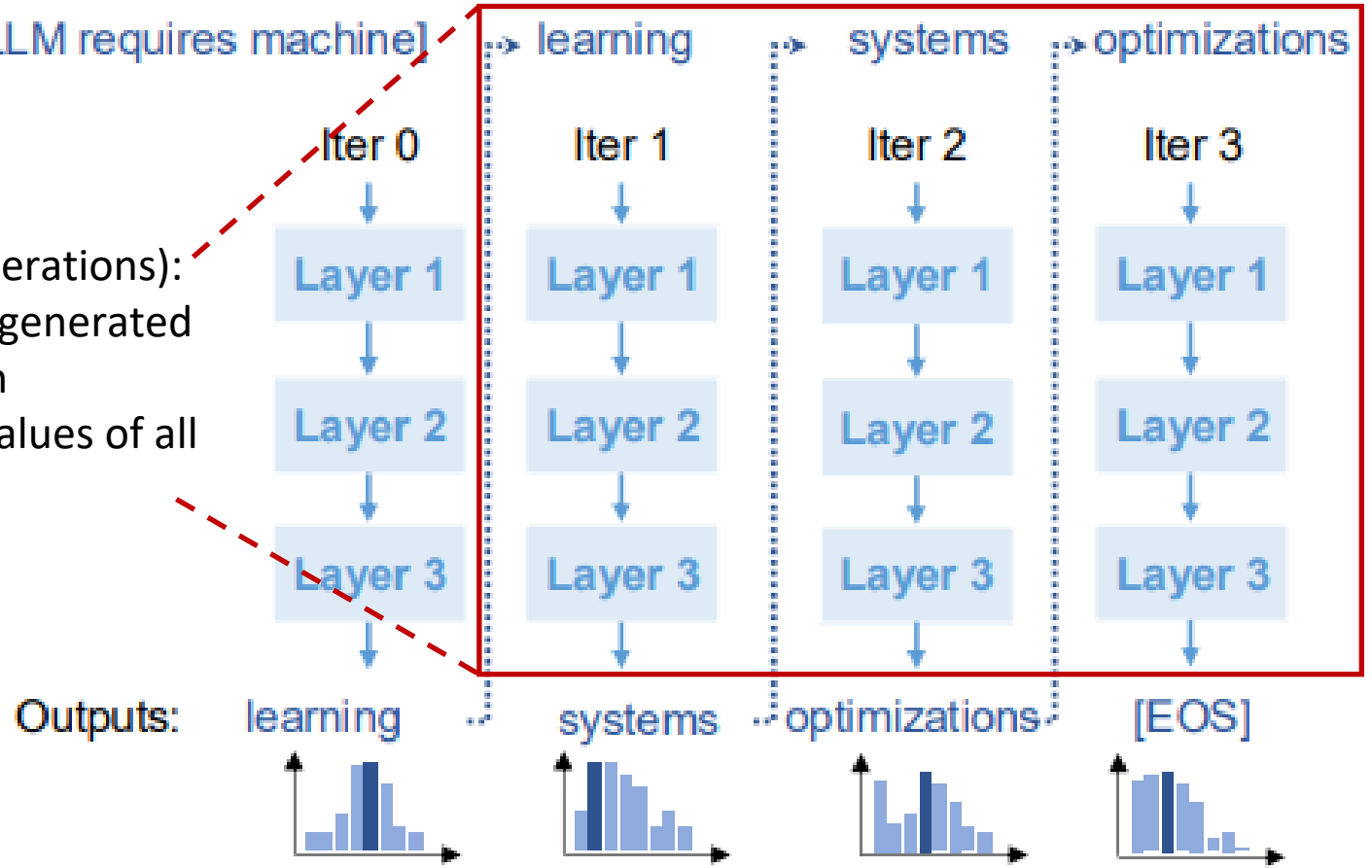
Generative LLM Inference: Autoregressive Decoding

- **Pre-filling phase** (0-th iteration):
  - Process **all** input tokens at once

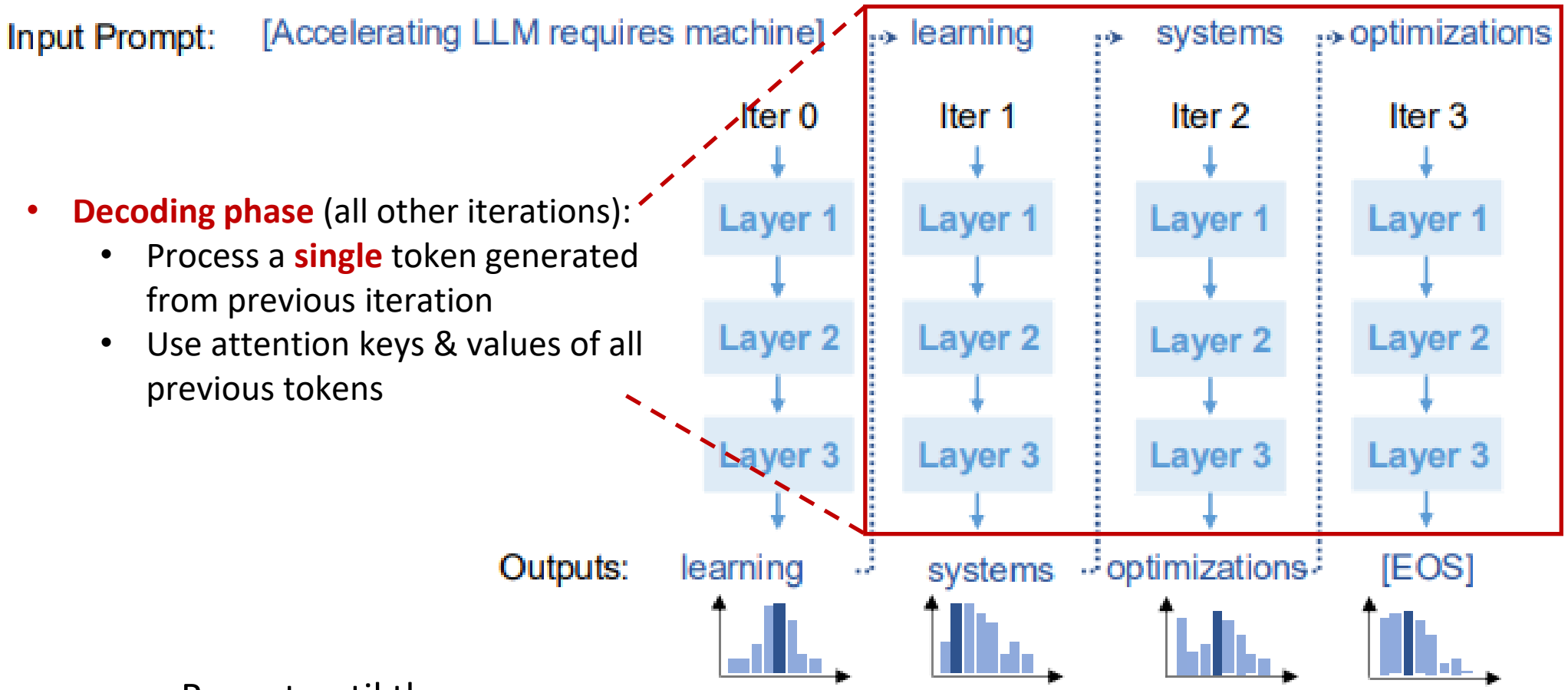


Generative LLM Inference: Autoregressive Decoding

- **Decoding phase** (all other iterations):
  - Process a **single** token generated from previous iteration
  - Use attention keys & values of all previous tokens



Generative LLM Inference: Autoregressive Decoding



- **Decoding phase** (all other iterations):
  - Process a **single** token generated from previous iteration
  - Use attention keys & values of all previous tokens

Repeat until the sequence

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

Generative LLM Inference: Important Metrics

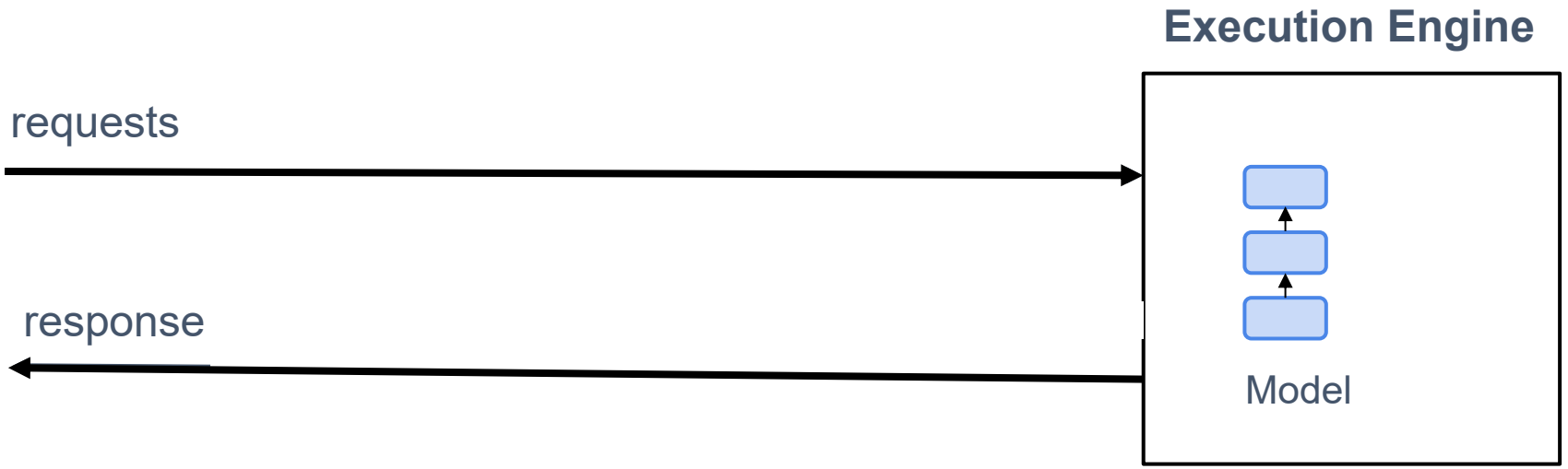
- **Time to First Token (TTFT)**: Measures how quickly users begin to see the model output token after submitting a query.
  - Critical for real-time interactions
  - Driven by prompt processing time and the generation of the first token
- **Time per Output Token (TPOT):** Time taken to generate each output token.
  - Impacts user perception of speed (e.g., 100ms/token = 10 tokens/second)
- **E2E Latency = TTFT + (TPOT * the number of generated tokens)**
  - Total time to generate the complete response
- **Throughput:** Number of tokens generated per second across all requests by the inference server

LLM Inference Performance Engineering: Best Practices | Databricks

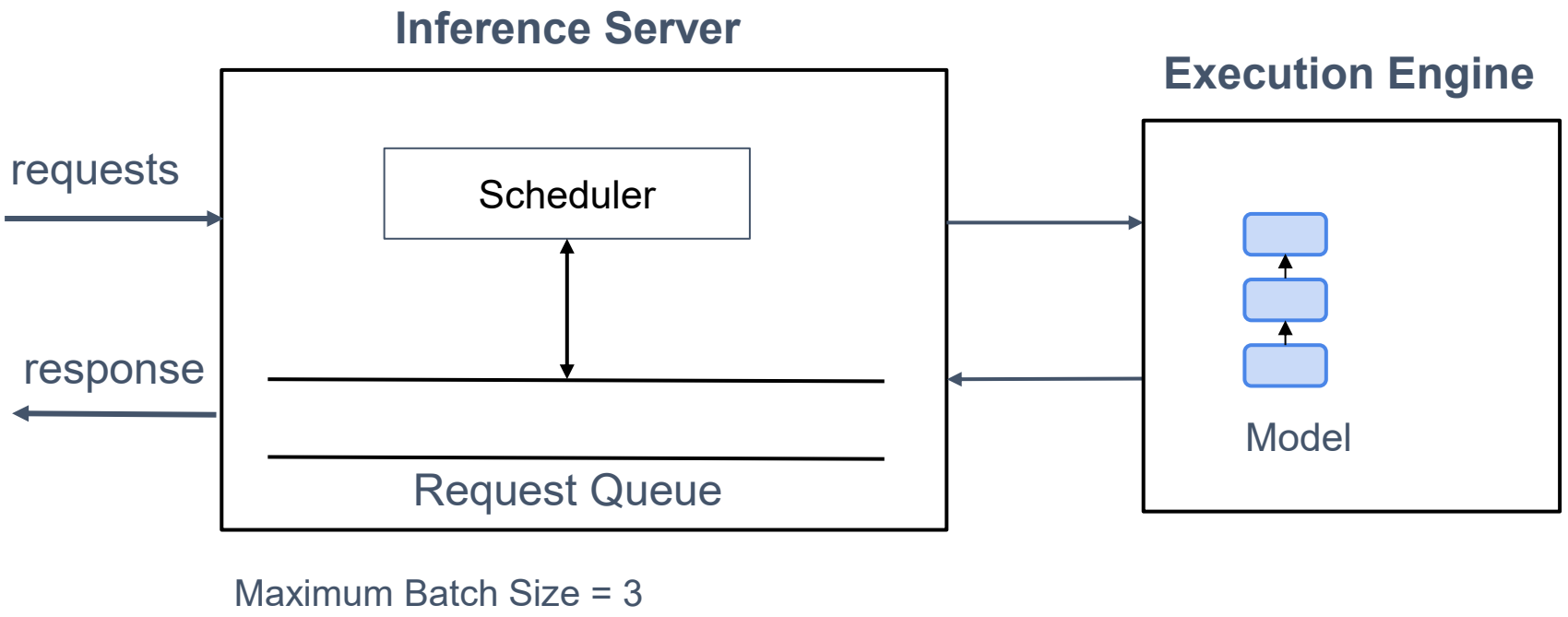
Optimizing LLM Inference: Goals and Tradeoffs

- **Goal:** Minimize TTFT, maximize throughput, and reduce TPOT
- **Throughput vs. TPOP Tradeoff**: Processing multiple queries concurrently increases throughput extends TPOT for each user.

LLM Inference



LLM Serving System



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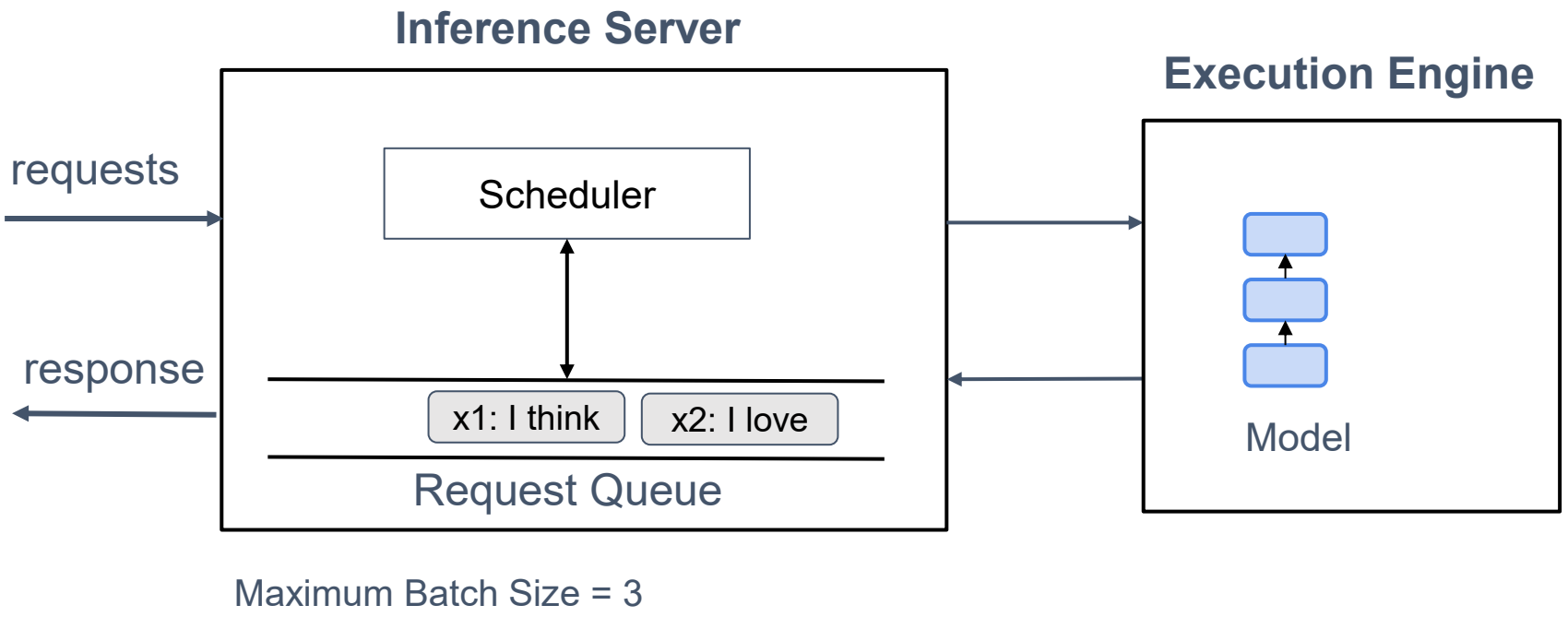

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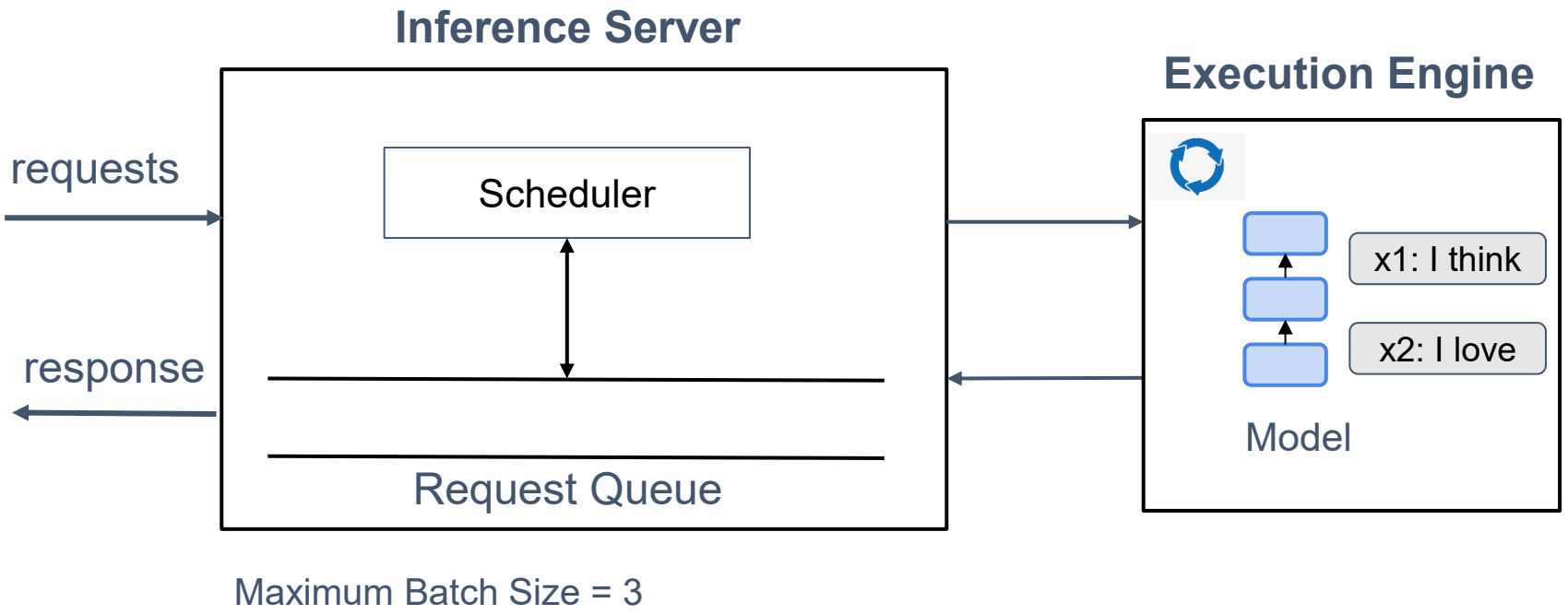

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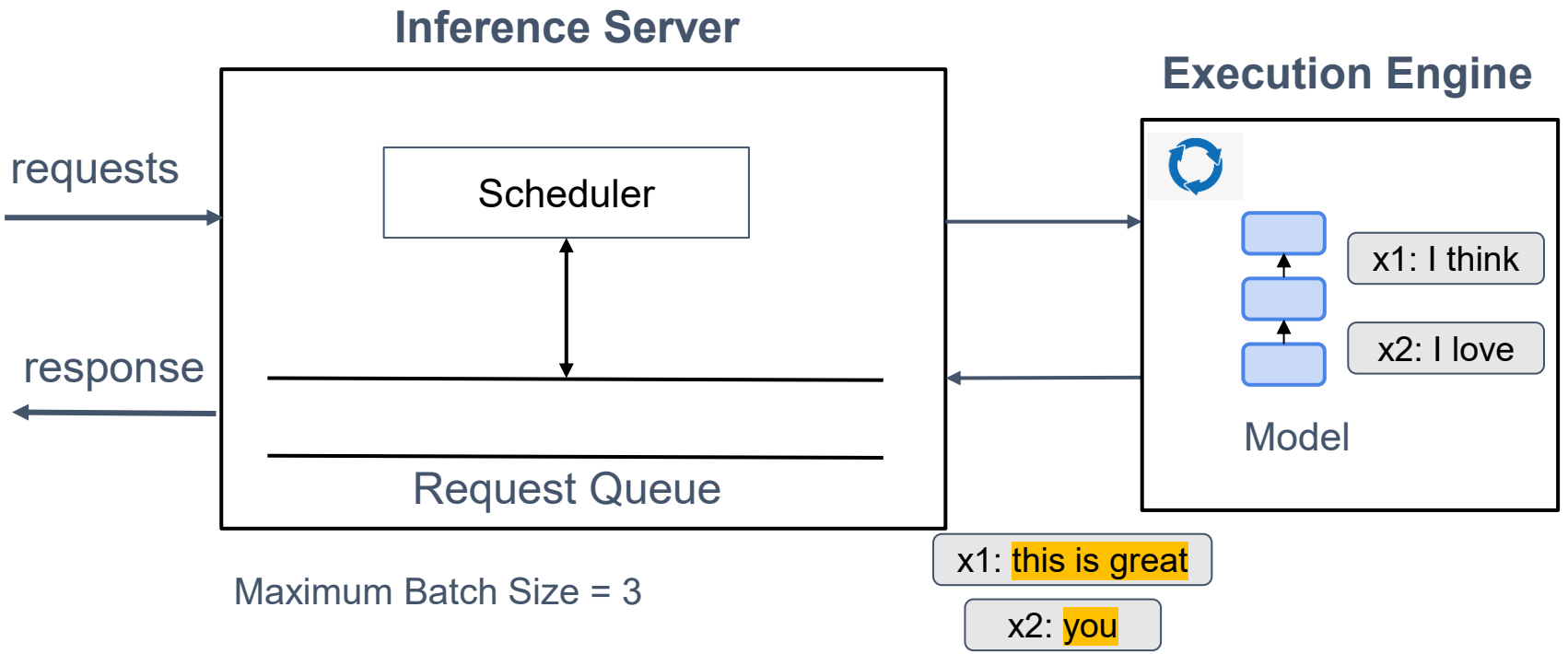

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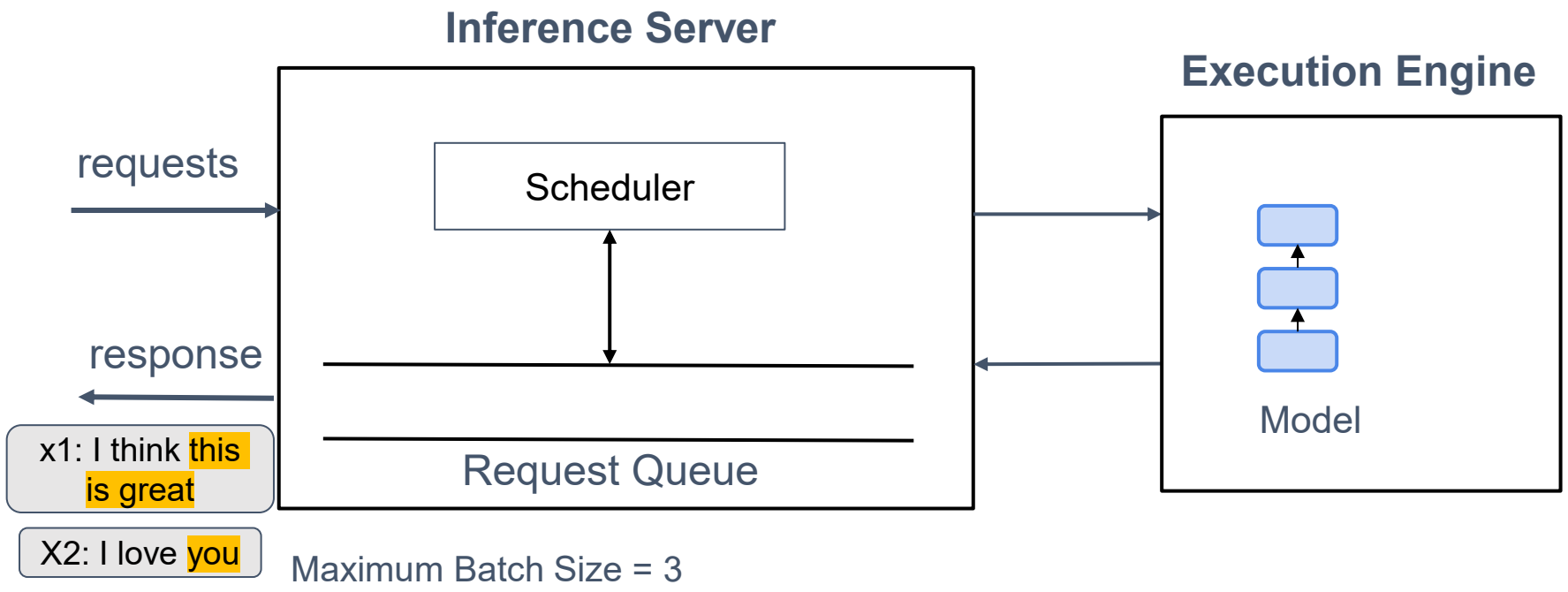
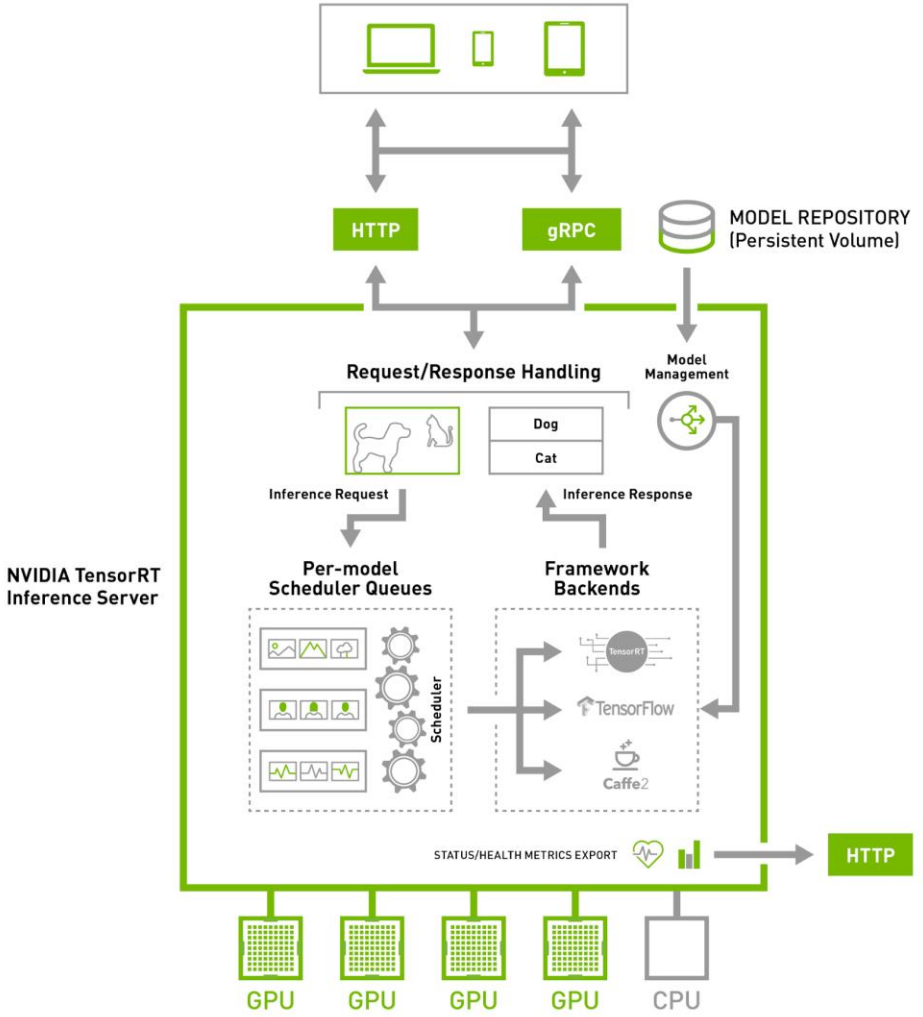
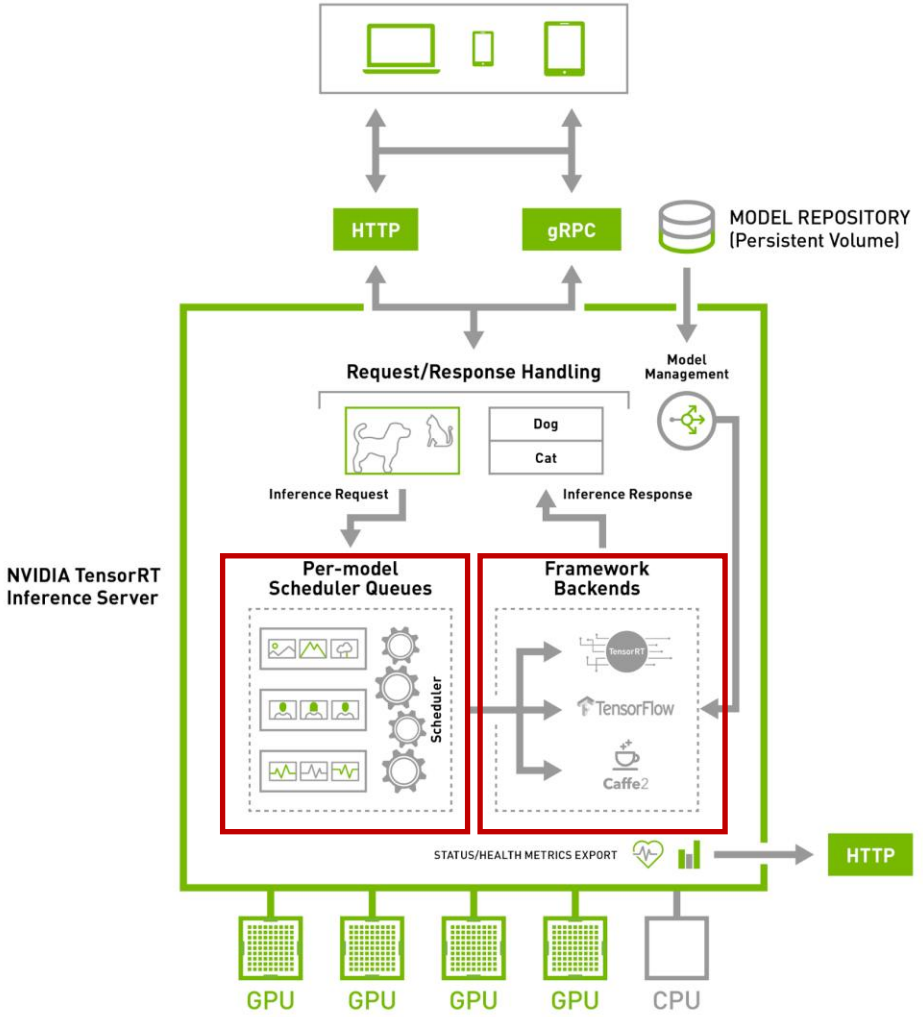


Example: TensorRT Inference Server



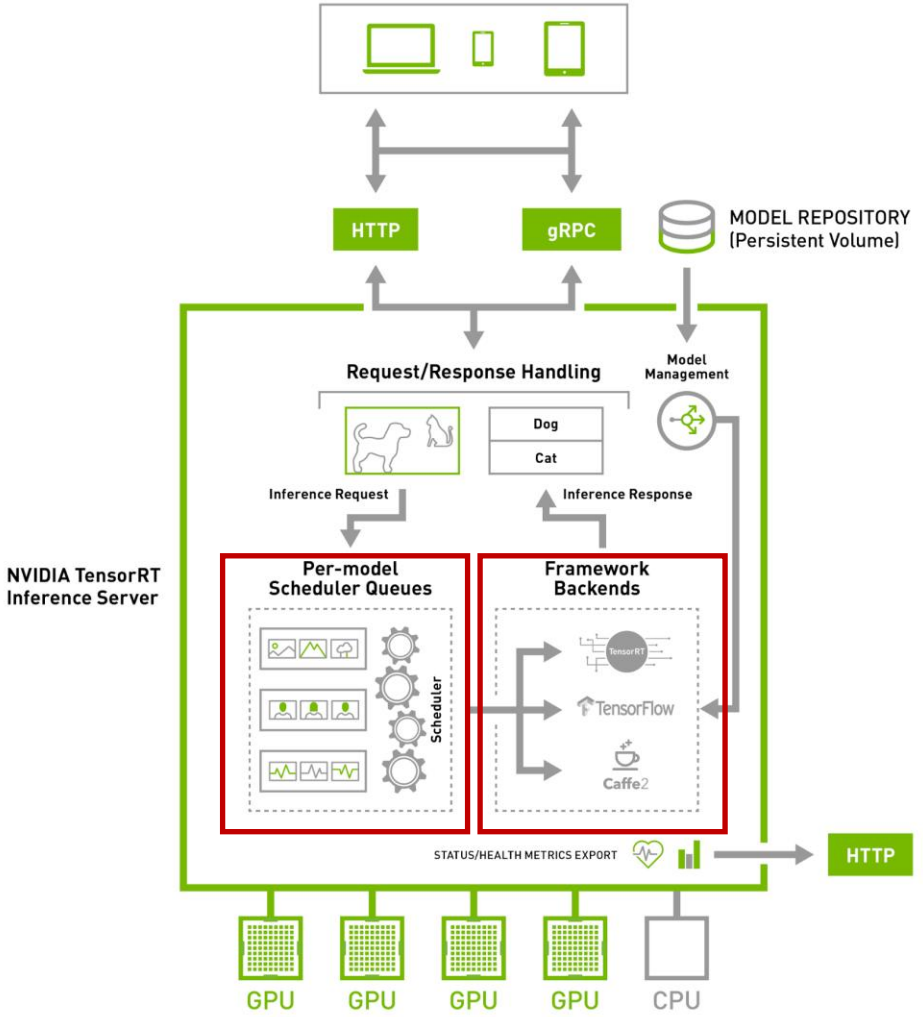
Example: TensorRT Inference Server

- Separates implementation of serving layer and execution layer



Example: TensorRT Inference Server

- Separates implementation of serving layer and execution layer
- Implements scheduling and batching algorithms
  - Sequence Batching
  - Continuous Batching



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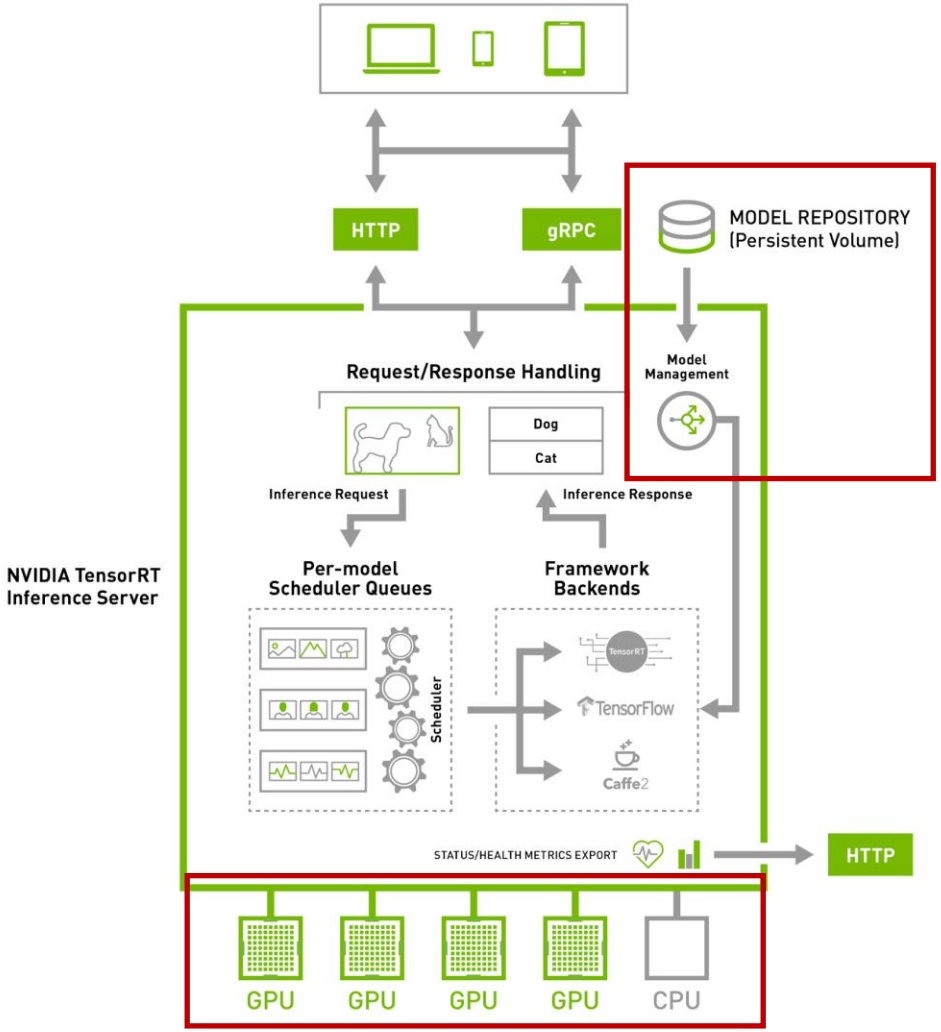
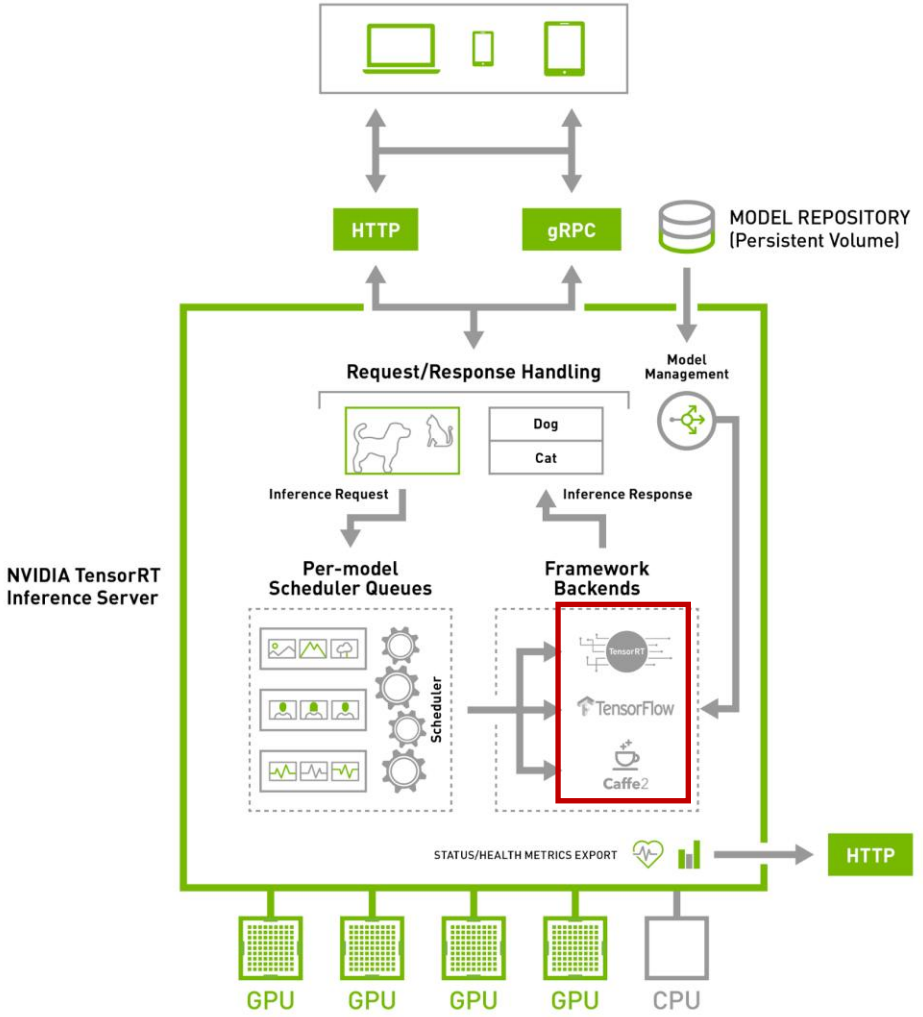
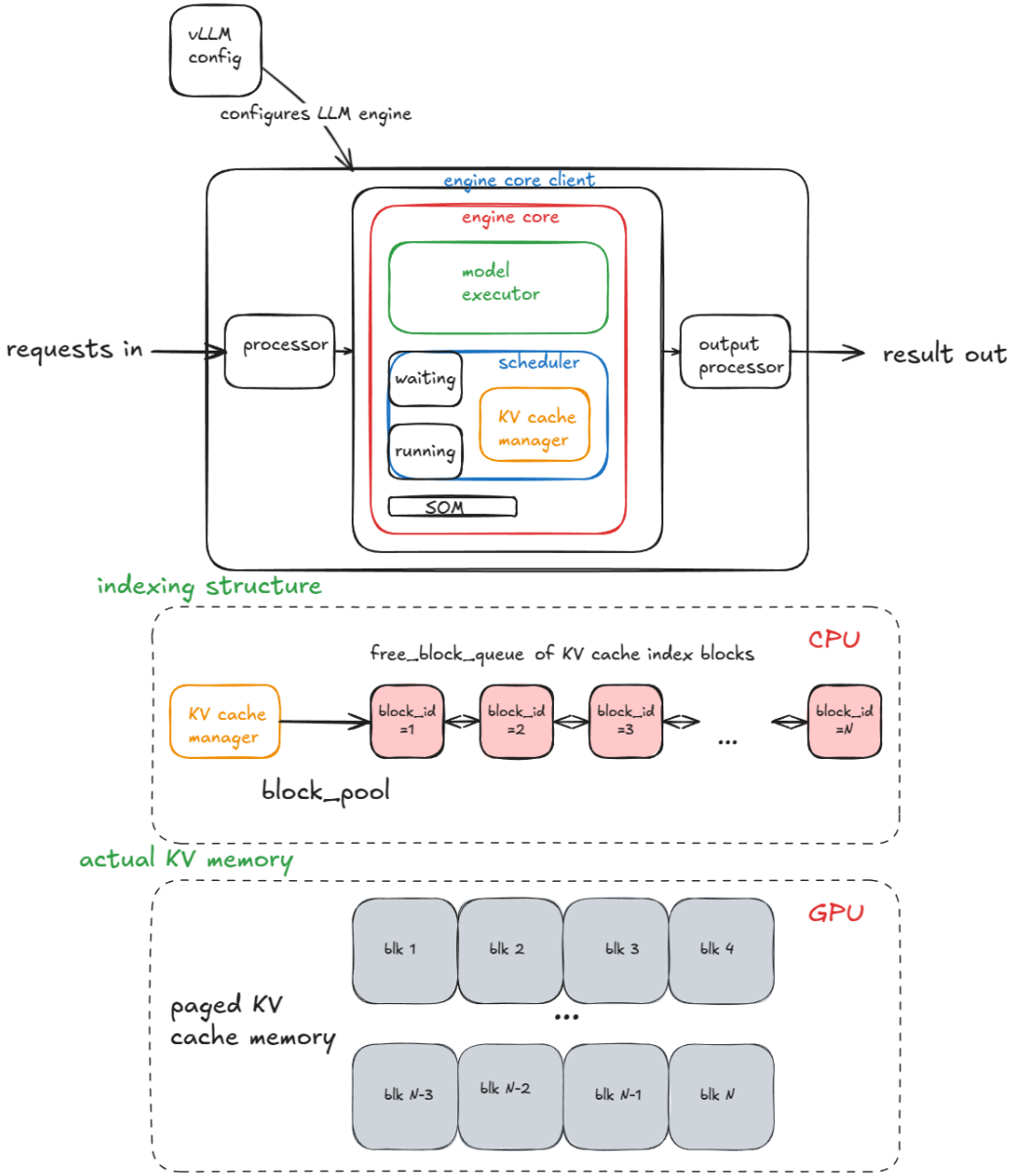


Example: TensorRT Inference Server

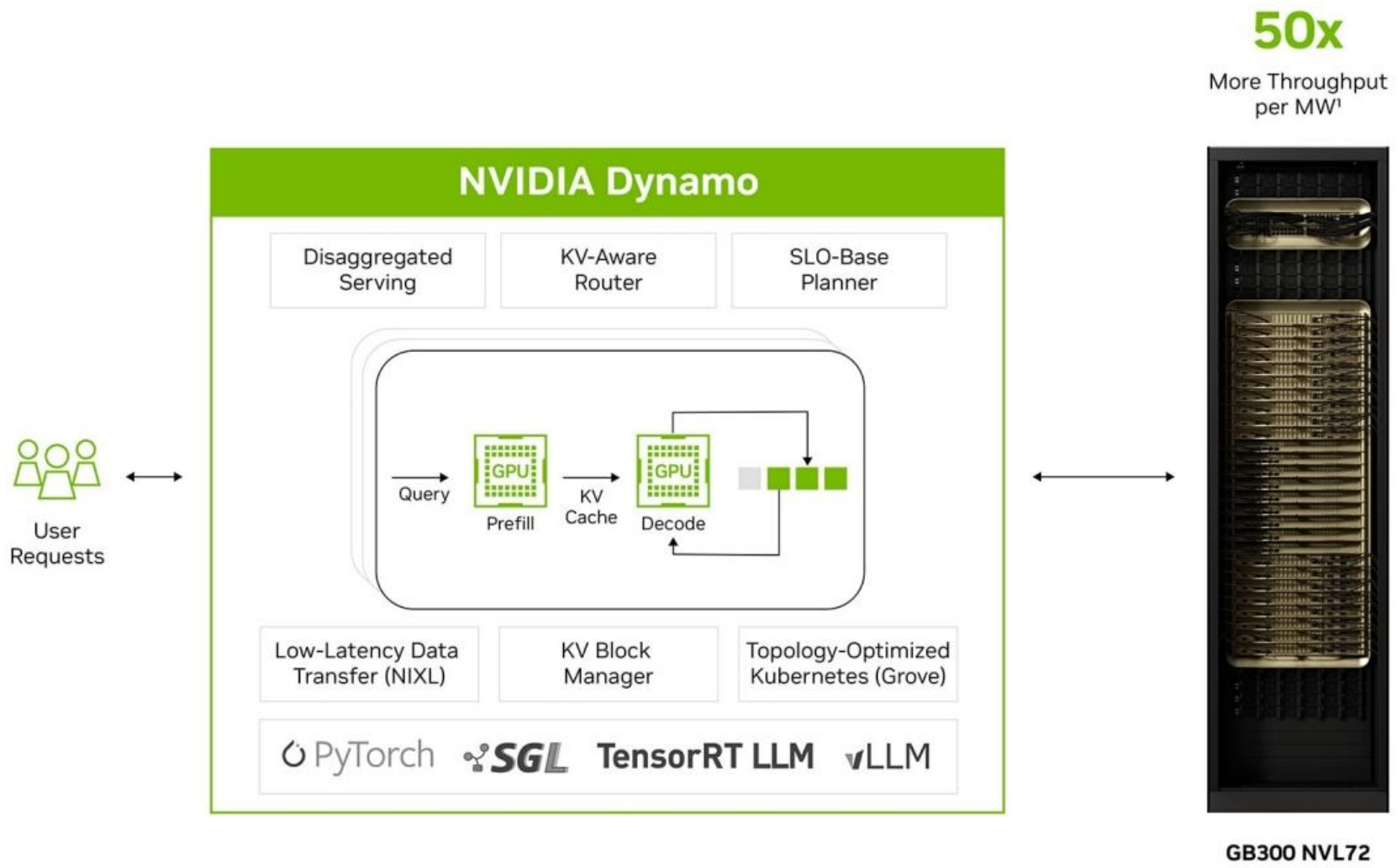
- Separates implementation of serving layer and execution layer
- Implements scheduling and batching algorithms
  - Sequence Batching
  - Continuous Batching
- Allows multiple models to concurrently execute
- Supports multiple frameworks
  - PyTorch
  - TensorFlow
  - ONNX
  - vLLM backend



Example: vLLM Server



Example: NVIDIA Dynamo



1- SemiAnalysis InferenceXv2 02/16/2026. NVIDIA GB300 NVL72 vs. H200. DeepSeek R1, TensorRT-LLM, 1k/1k

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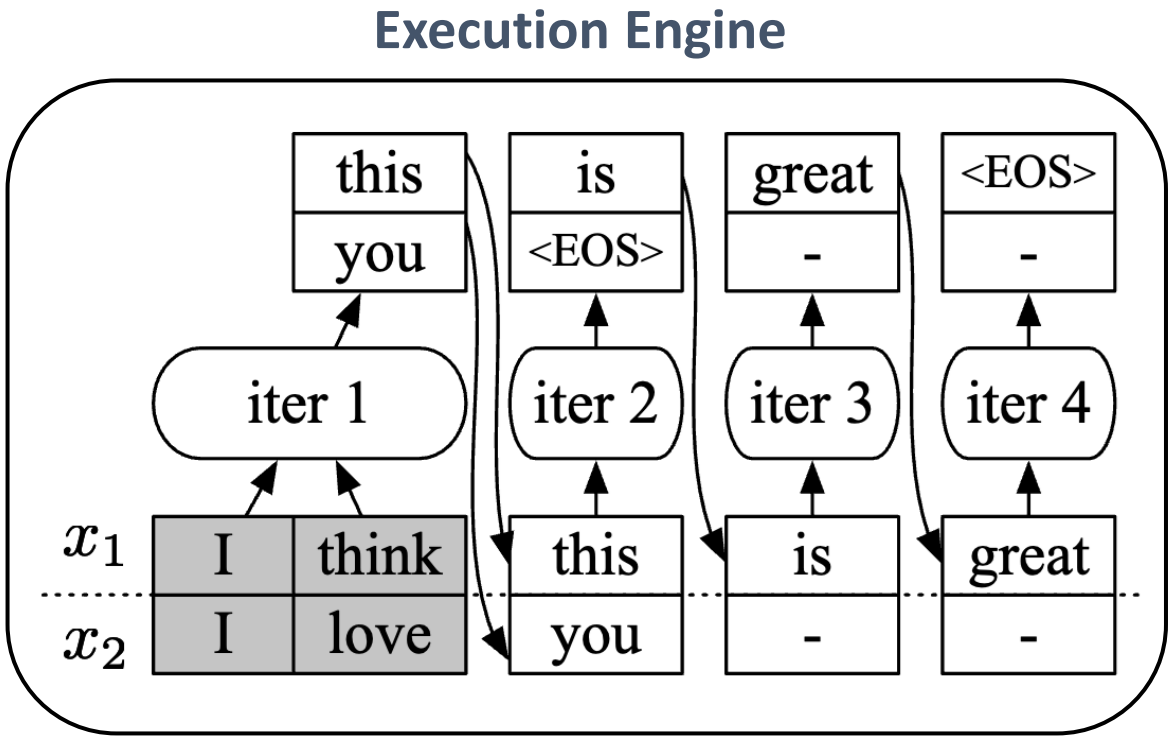
  - Continuous batching

Question: Can we use the batching scheme (sequence batching) during training for inference?

Problem 1: Request Level Scheduling



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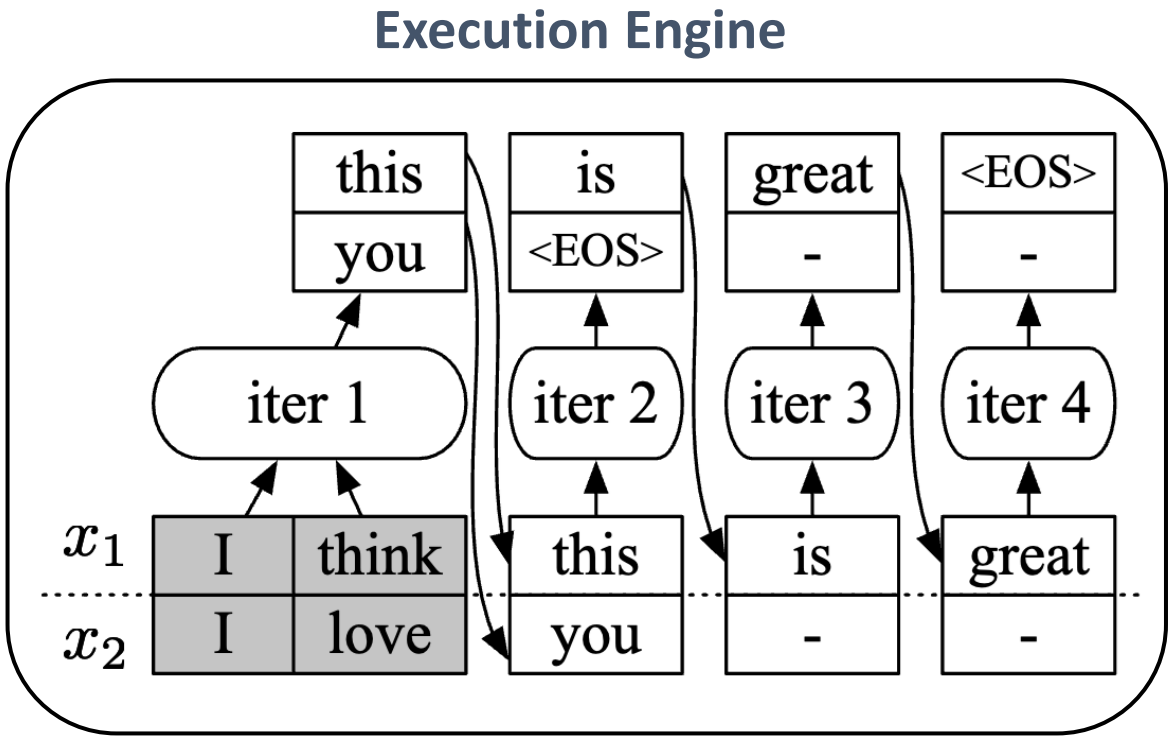
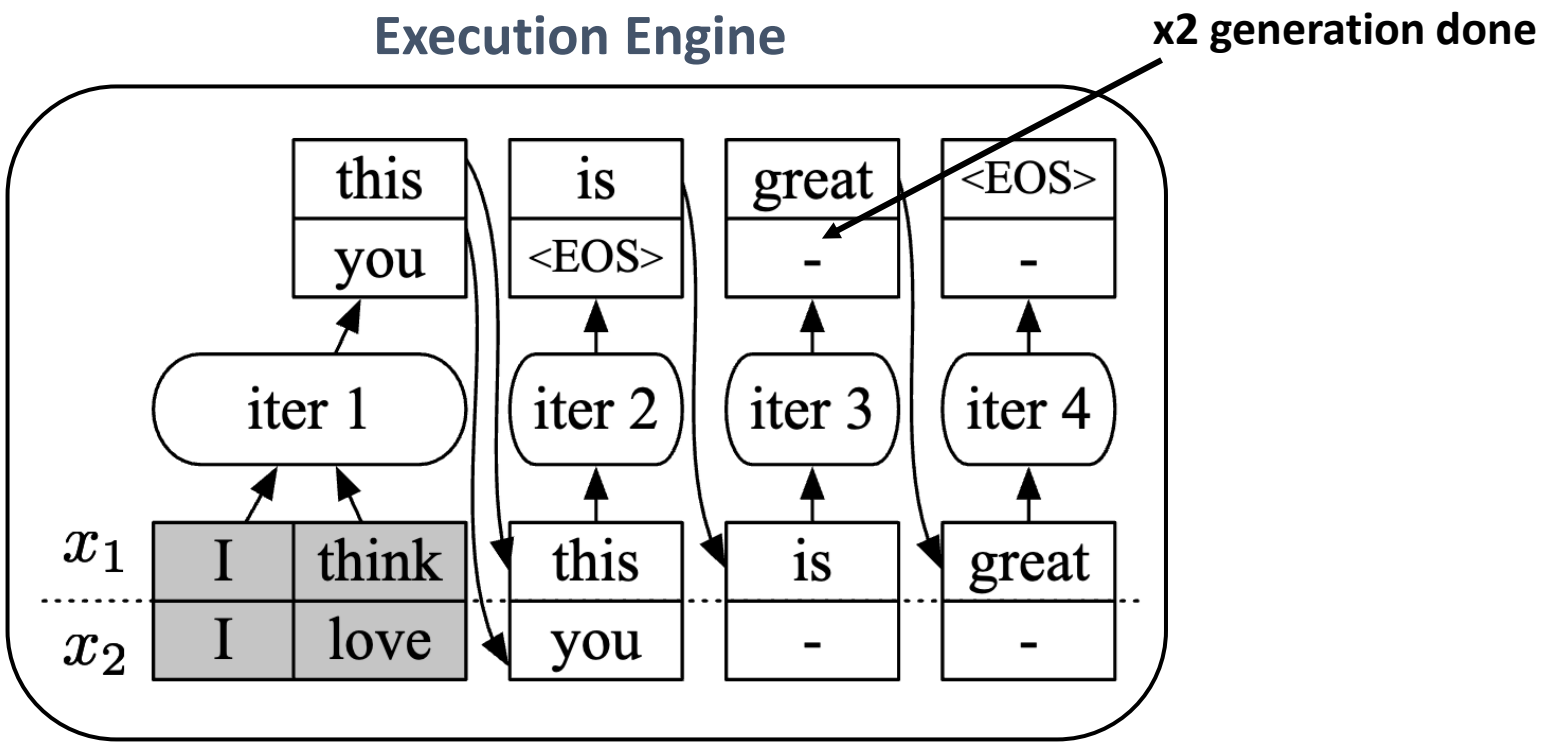


Do you see any problem?

Problem 1: Request Level Scheduling



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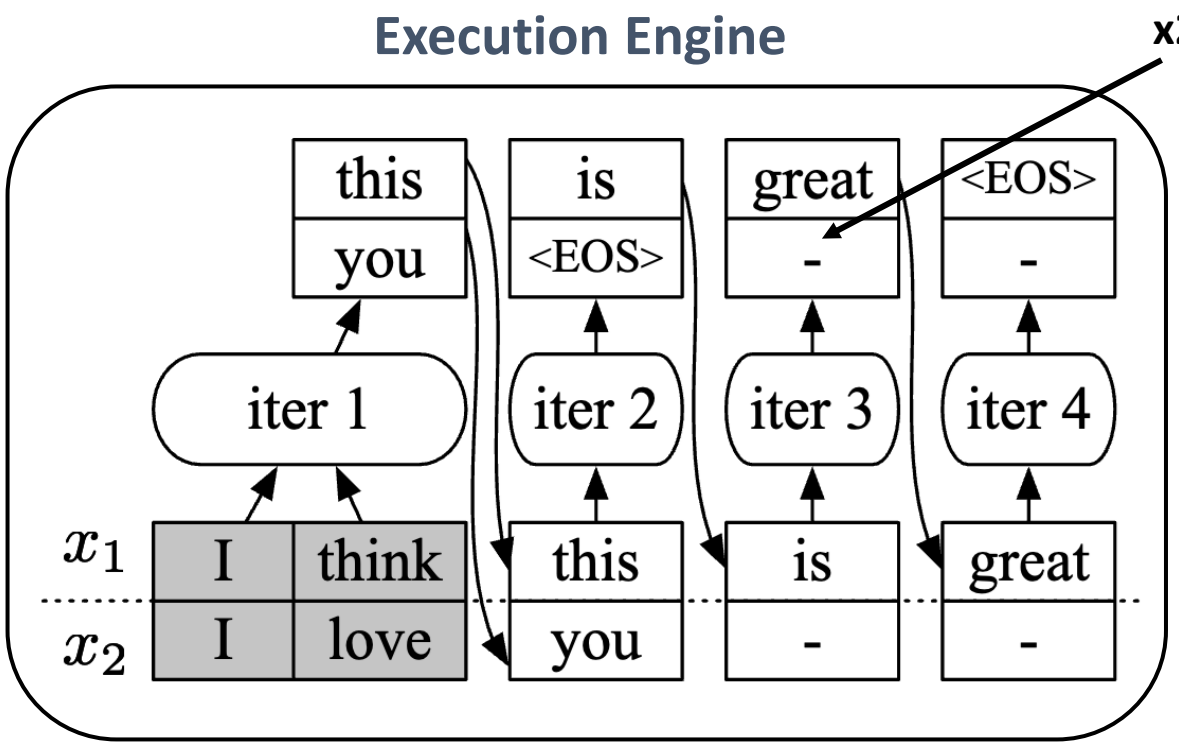

Early finished requests cannot return to the inference server → Latency increase

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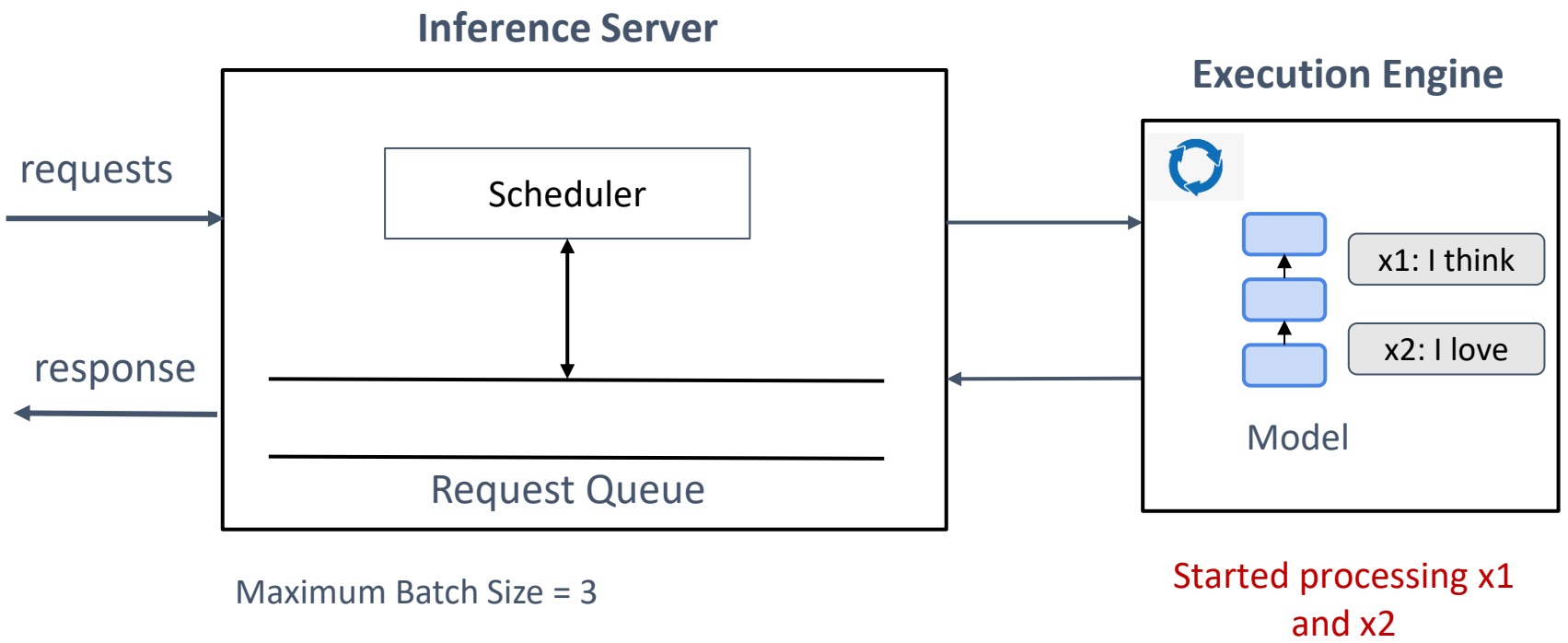

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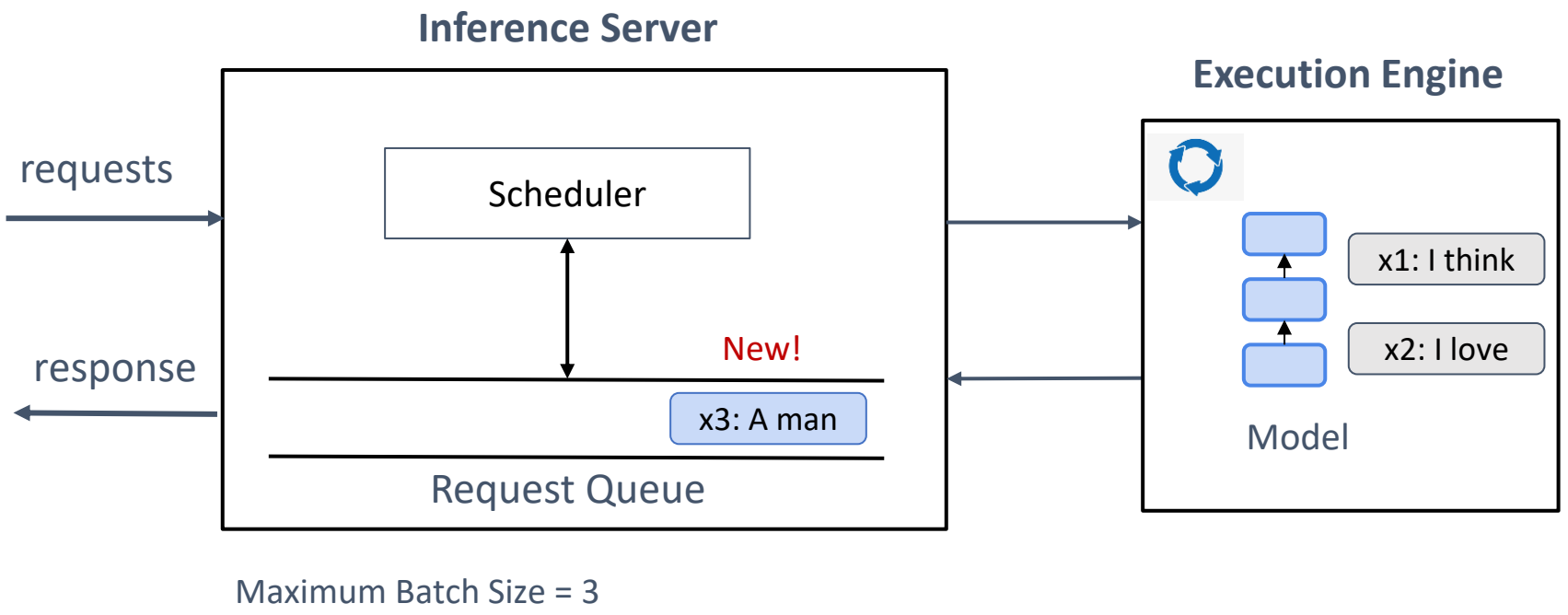

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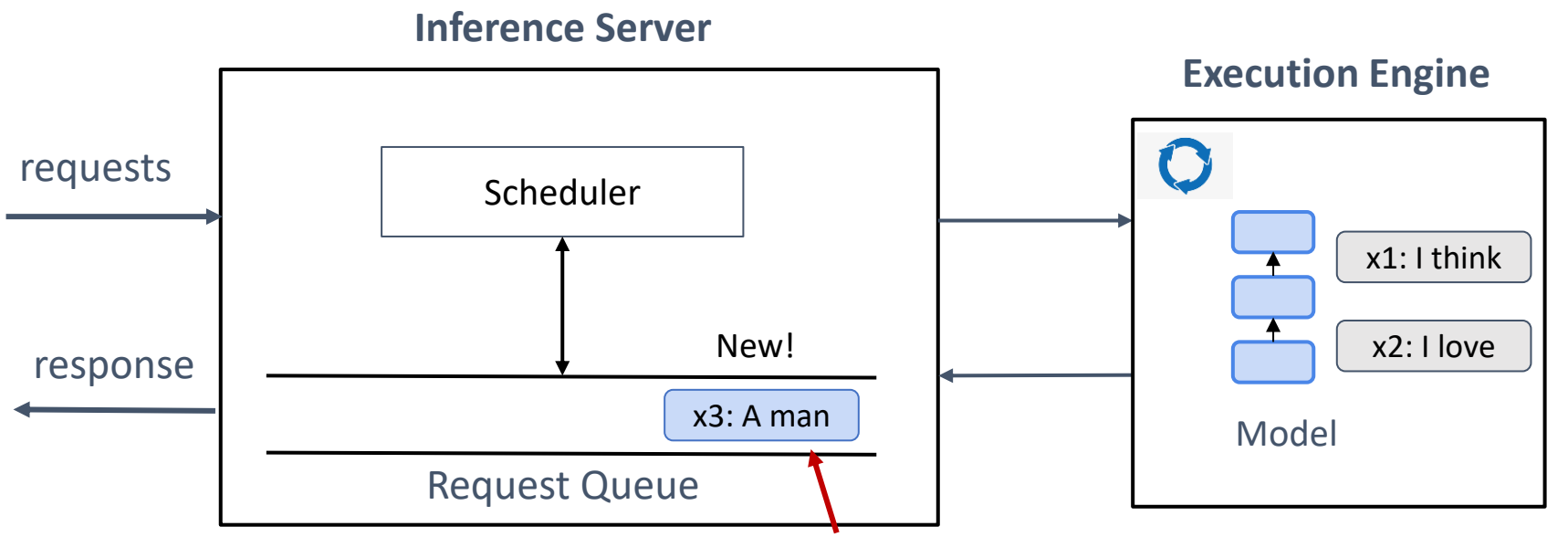

Late join requests need to wait until engine finishes execution

→ Latency Increase

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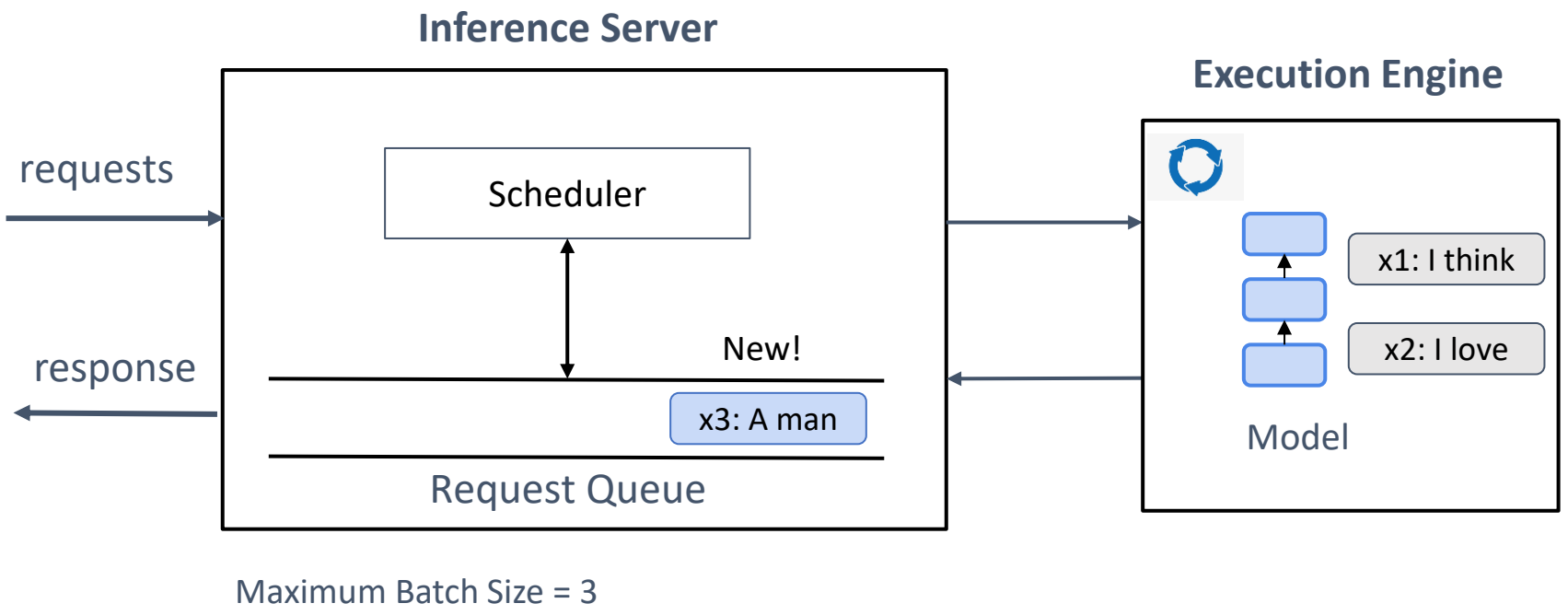
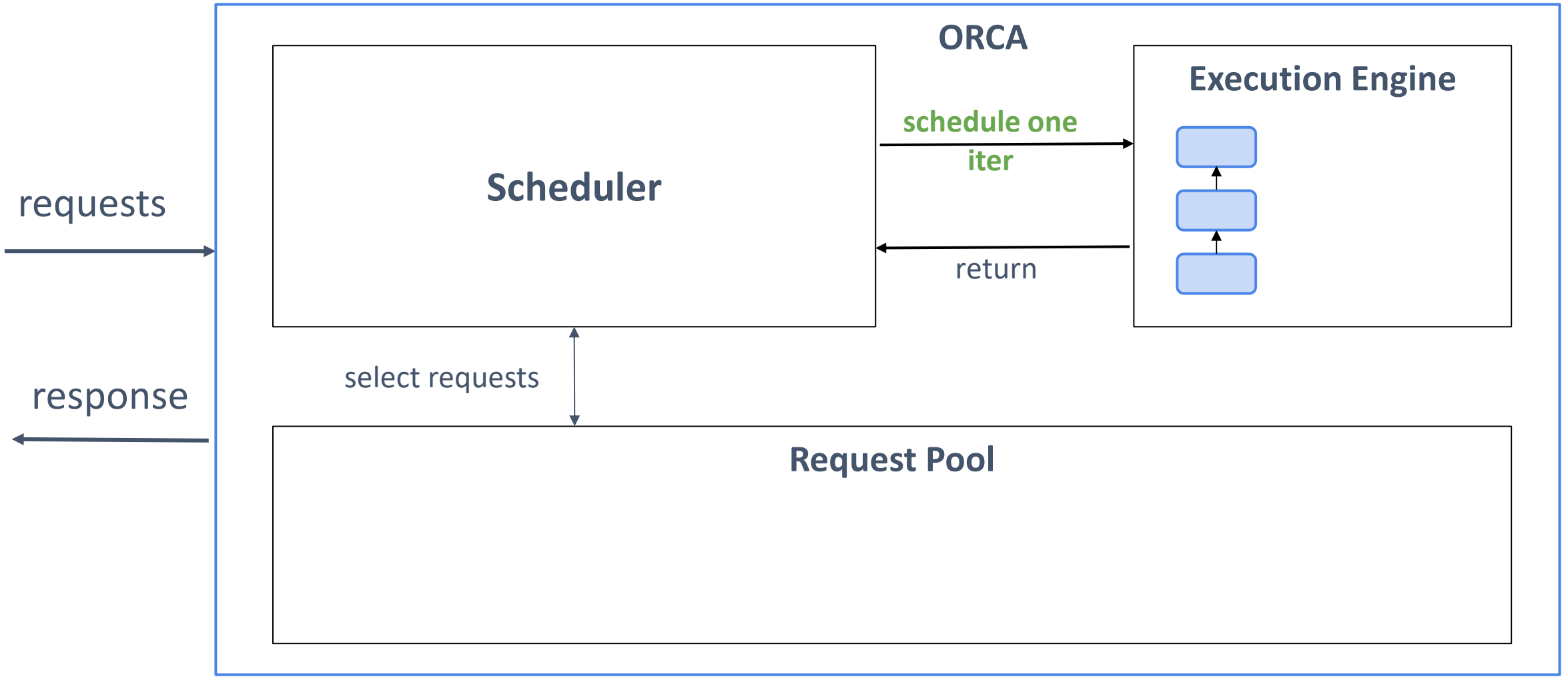


Question: How can we avoid redundant computation and ensure late-arriving requests to be processed more promptly?

Solution 1: Iteration Level Scheduling



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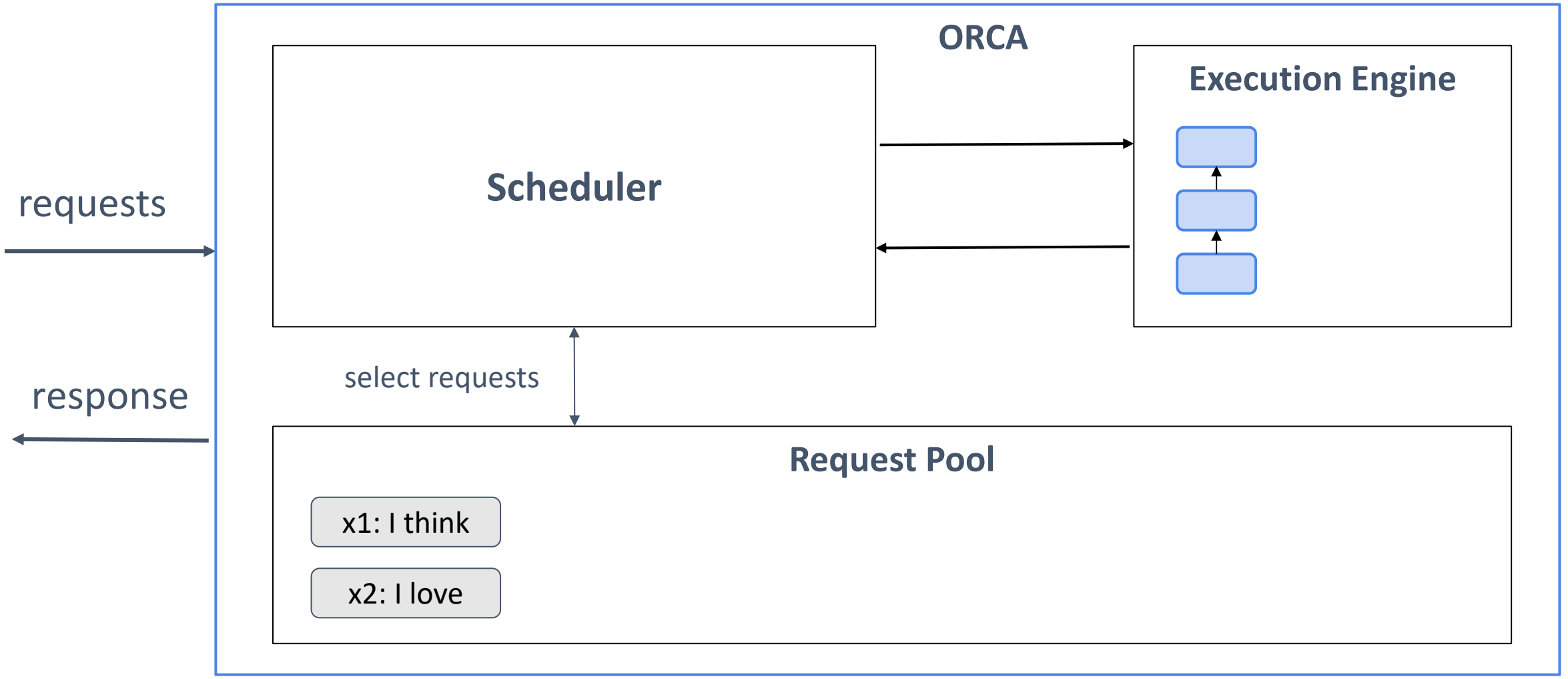

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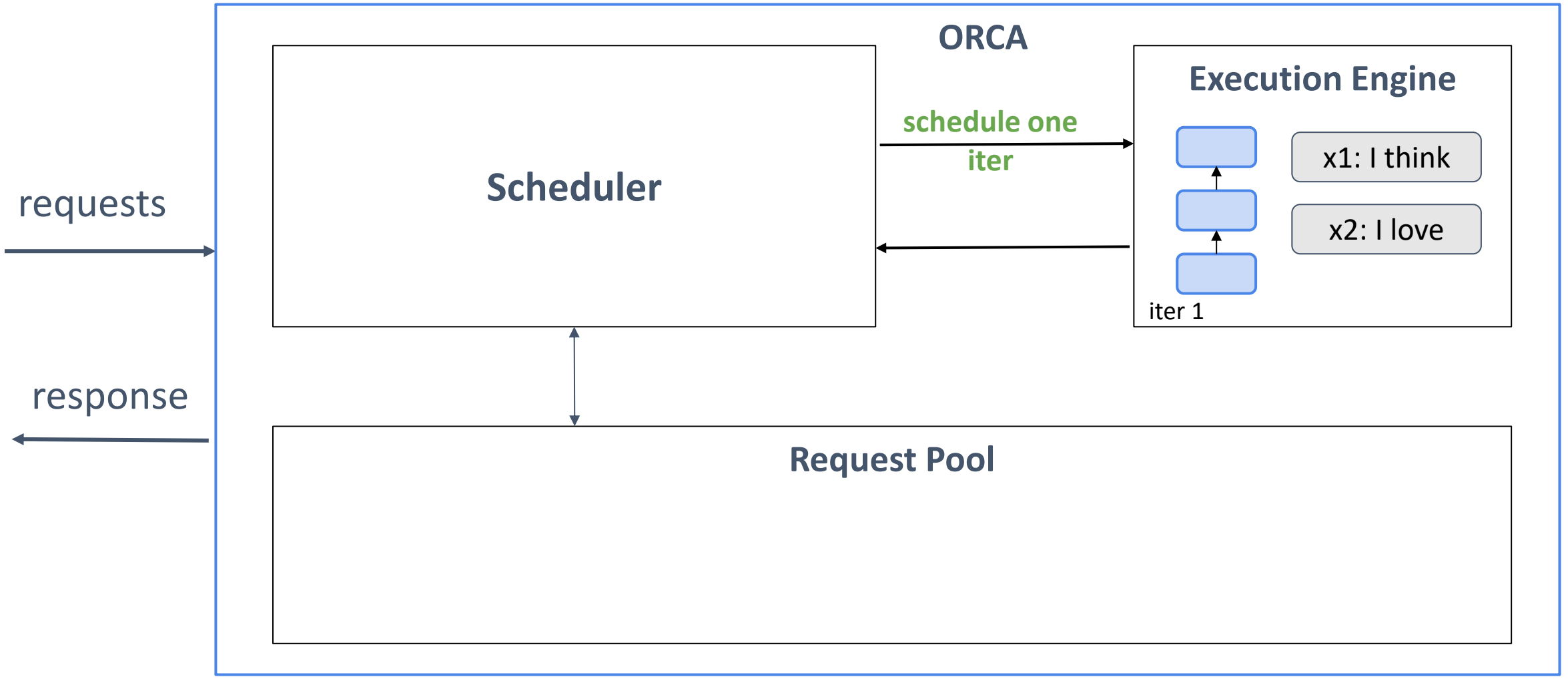

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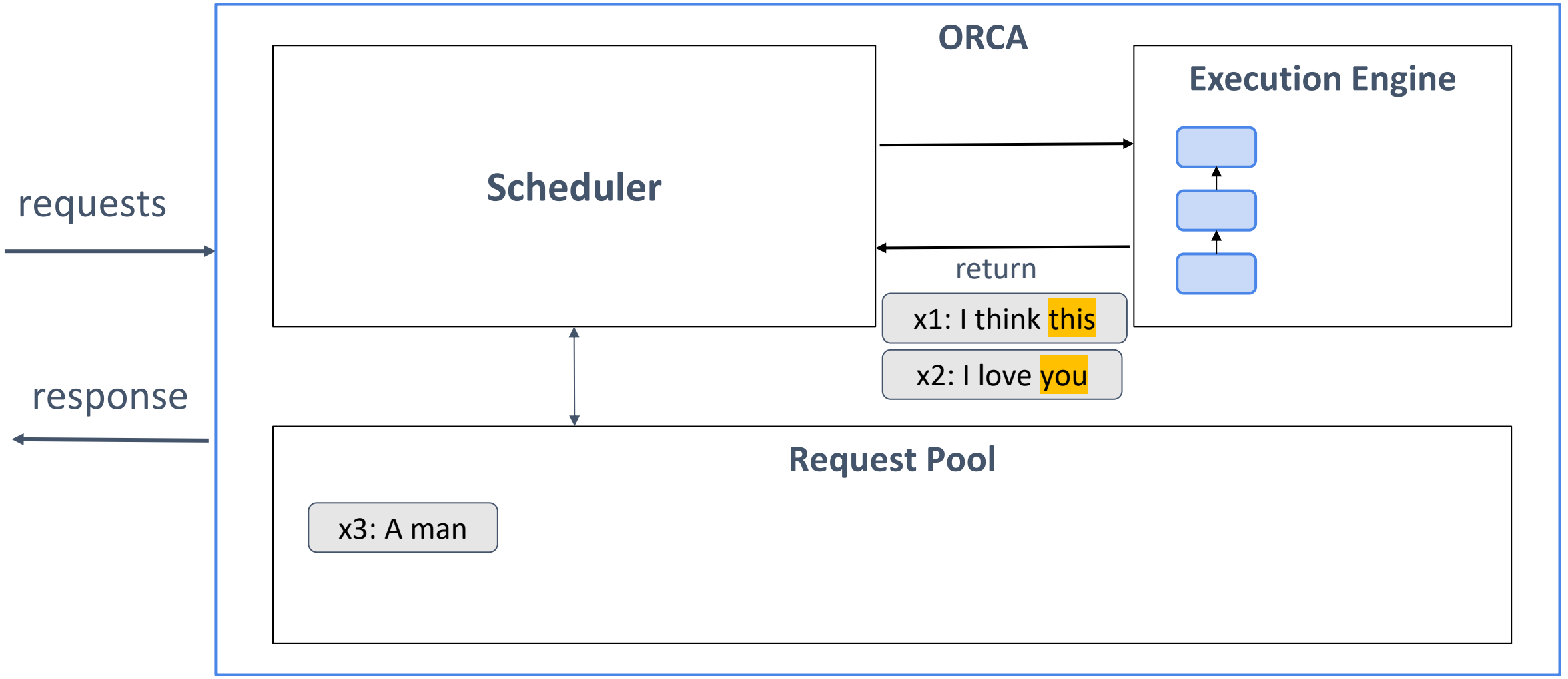

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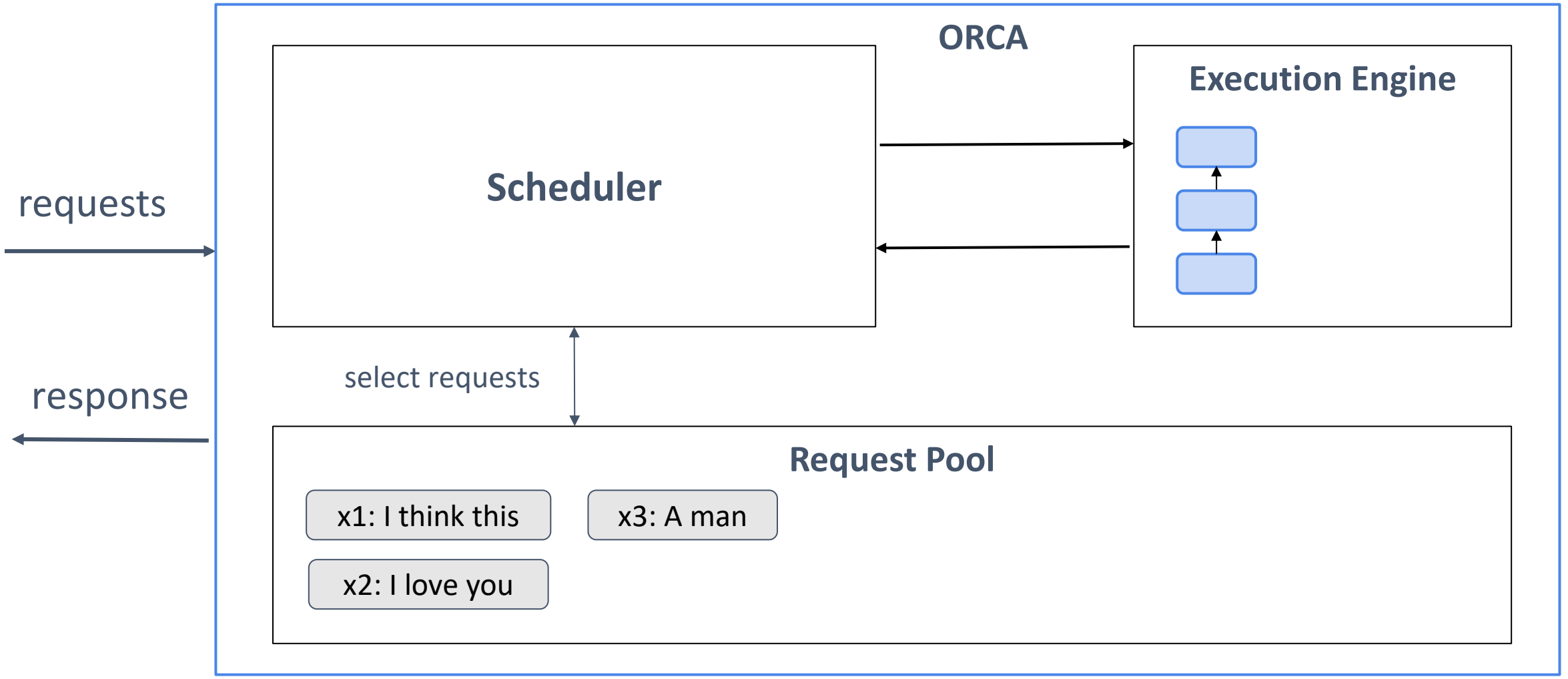

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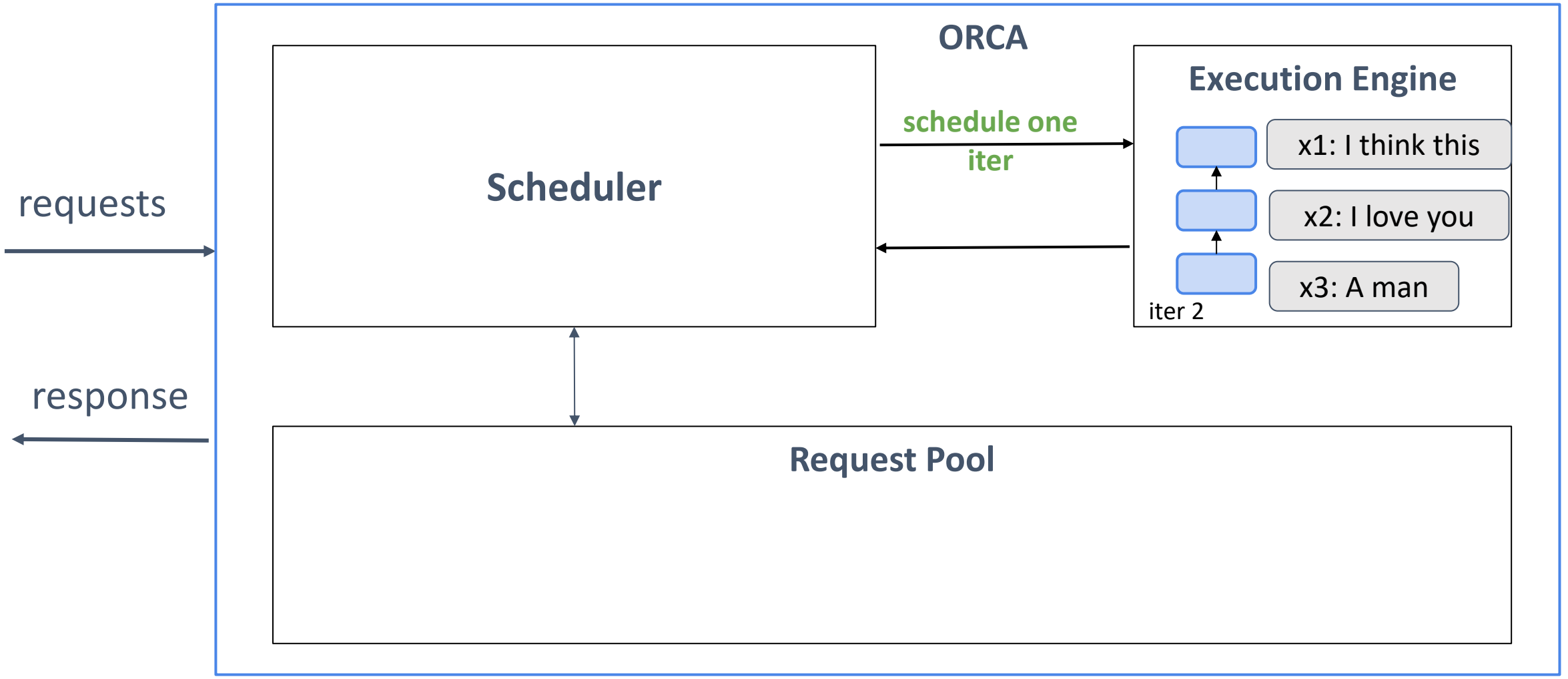

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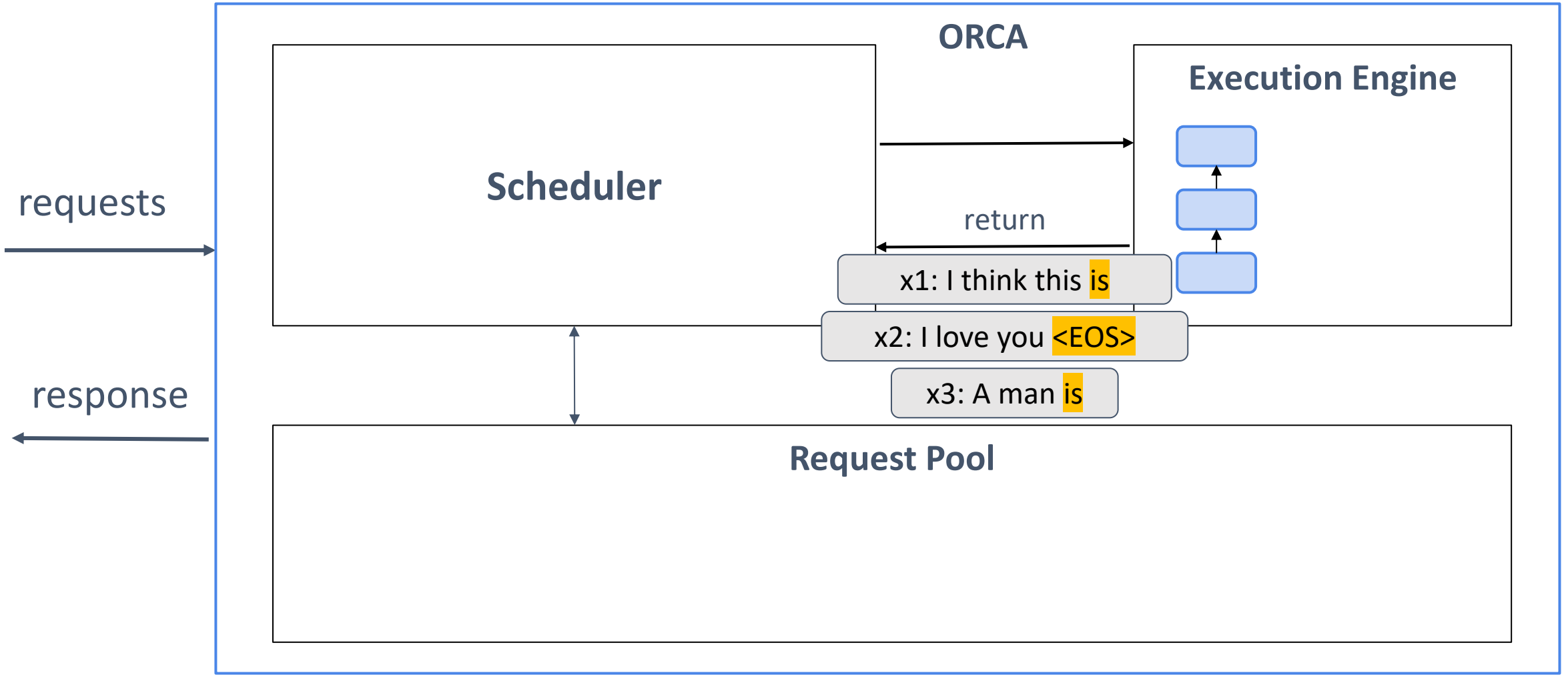

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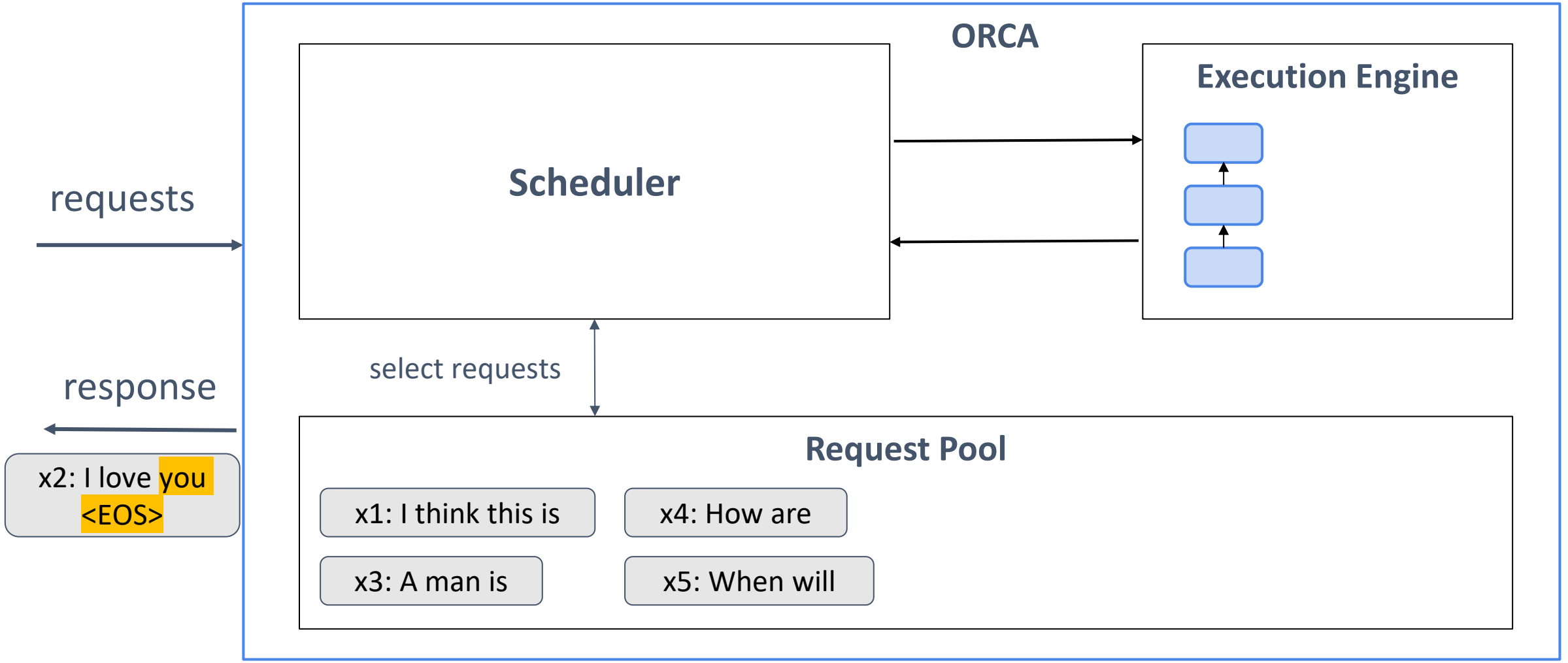

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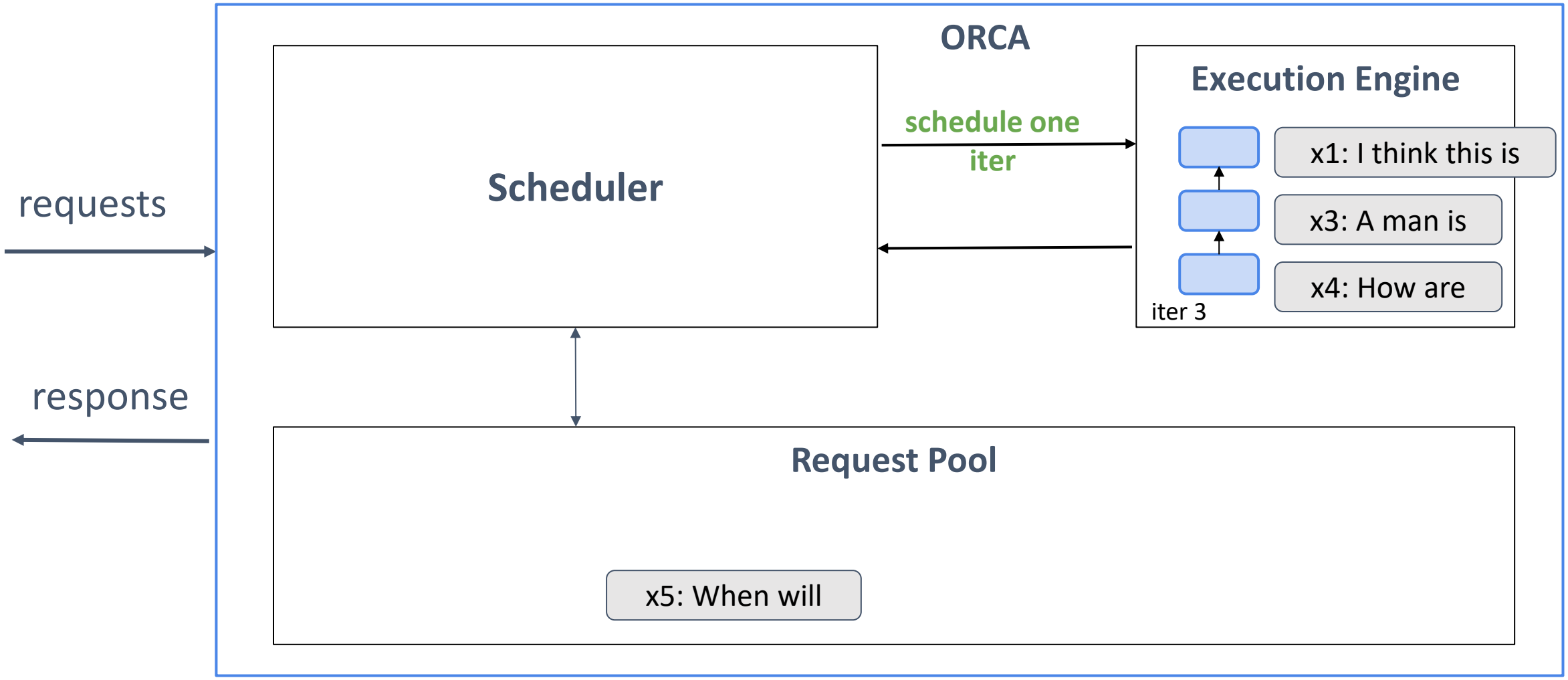


Solution 1: Iteration Level Scheduling

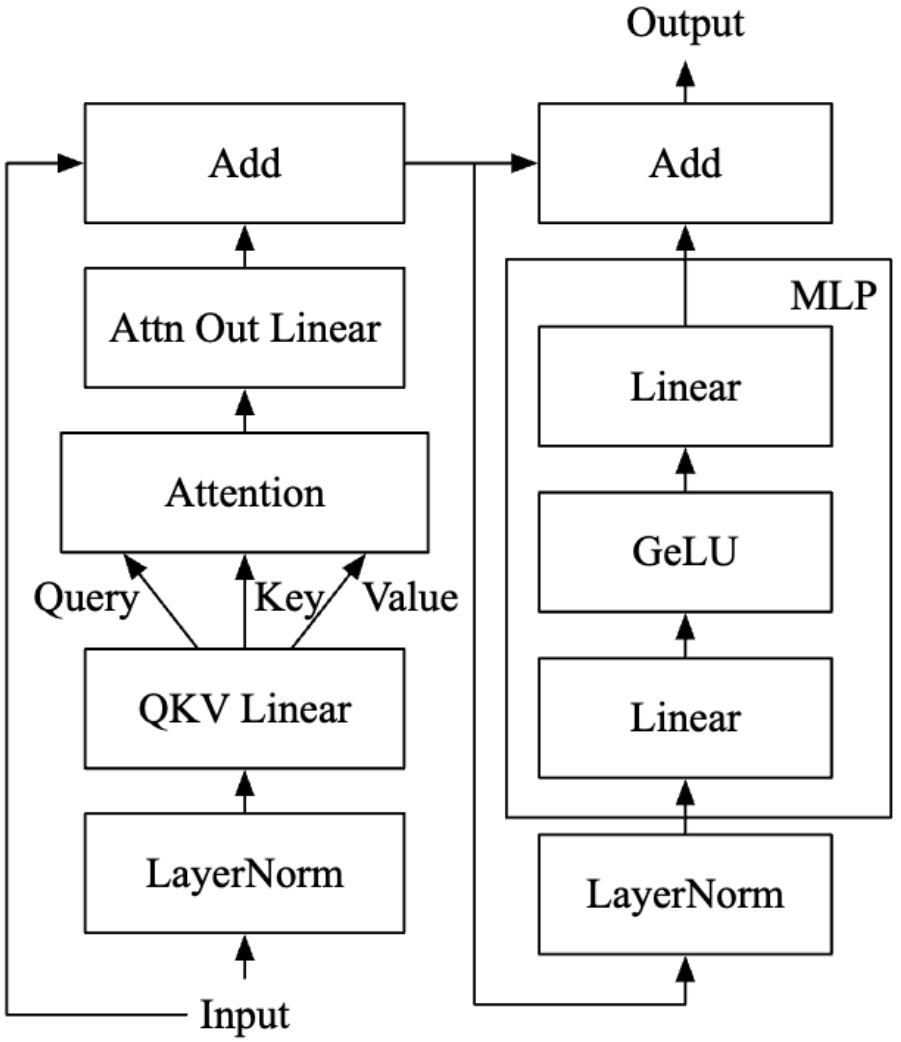
Problem 2: How to Batch Requests?

Let's assume Batch Size B = 1

Input Dimension: [L x H] (L=sequence length, H=hidden dim.)

Attention Operation:

1. **QK^T** : [LxH] x [HxL] → [L x L]
2. **P = softmax(QK^T)** : [L x L]
3. **O = PV** : [LxL] x [LxH] → [L x H]



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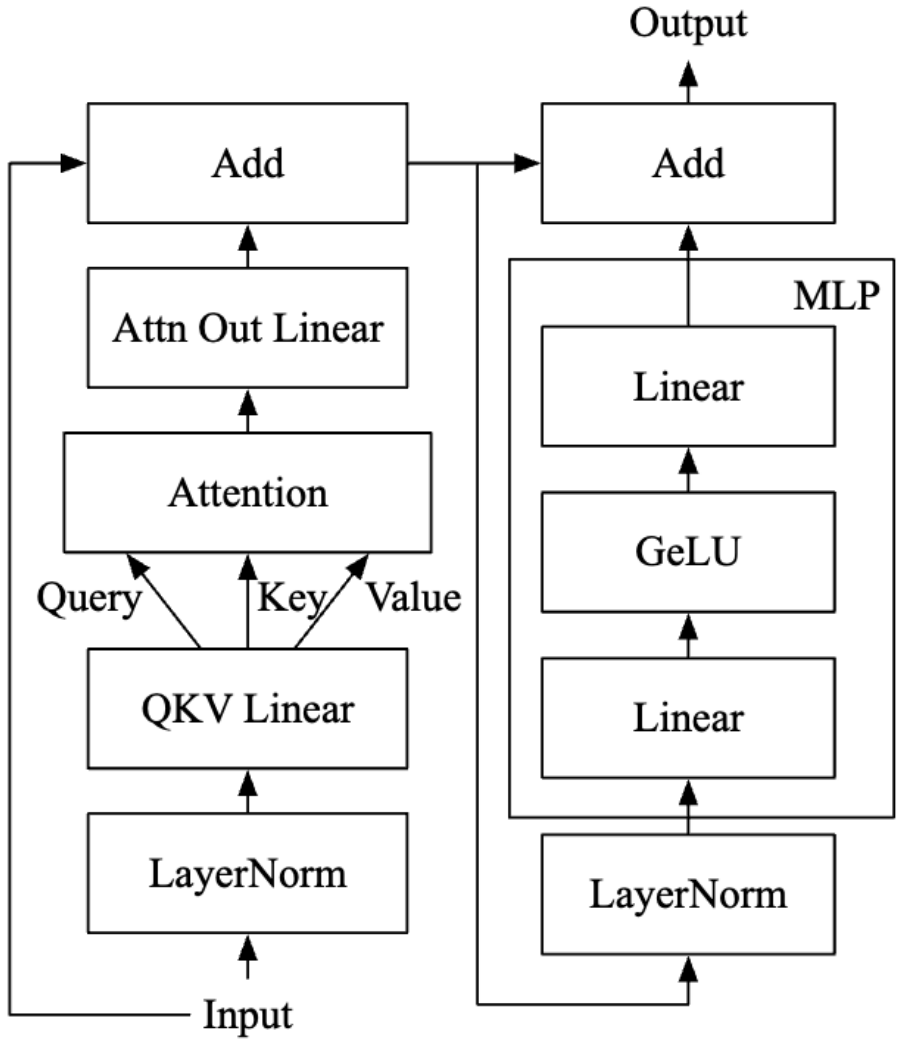

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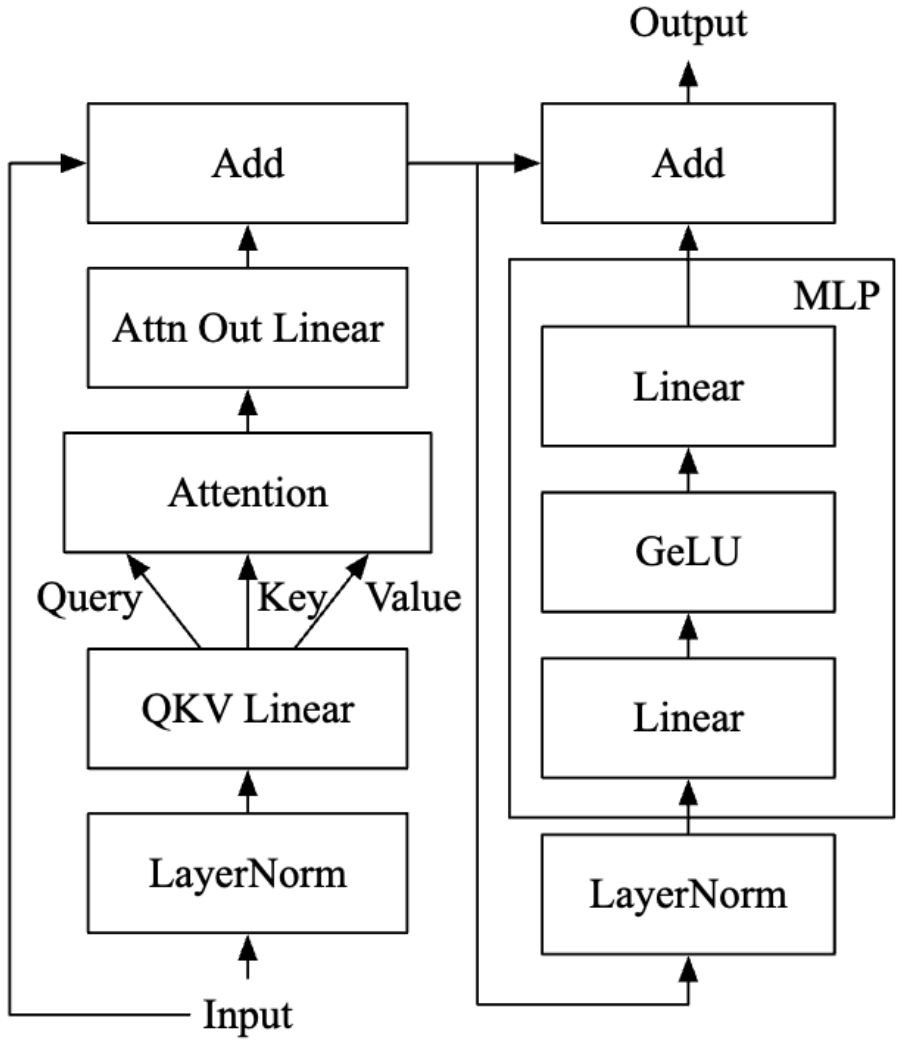
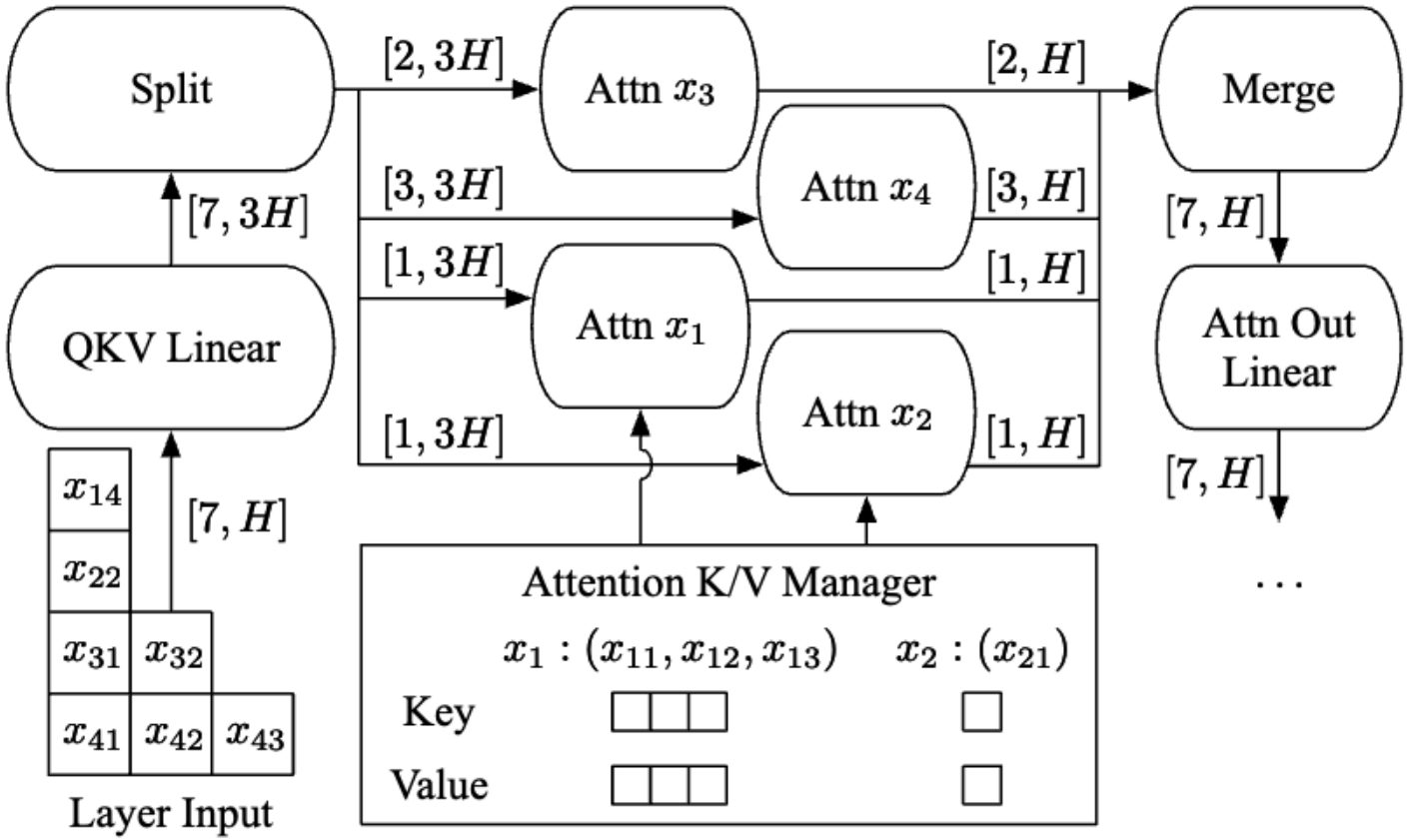
With different sequence lengths, QK^T cannot be easily computed



Solution 2: Selective Batching

Only **Attention operation** does not work with batching tensors with diff. L_i

Batch for other ops. (Layer Norm, GeLU, etc.)



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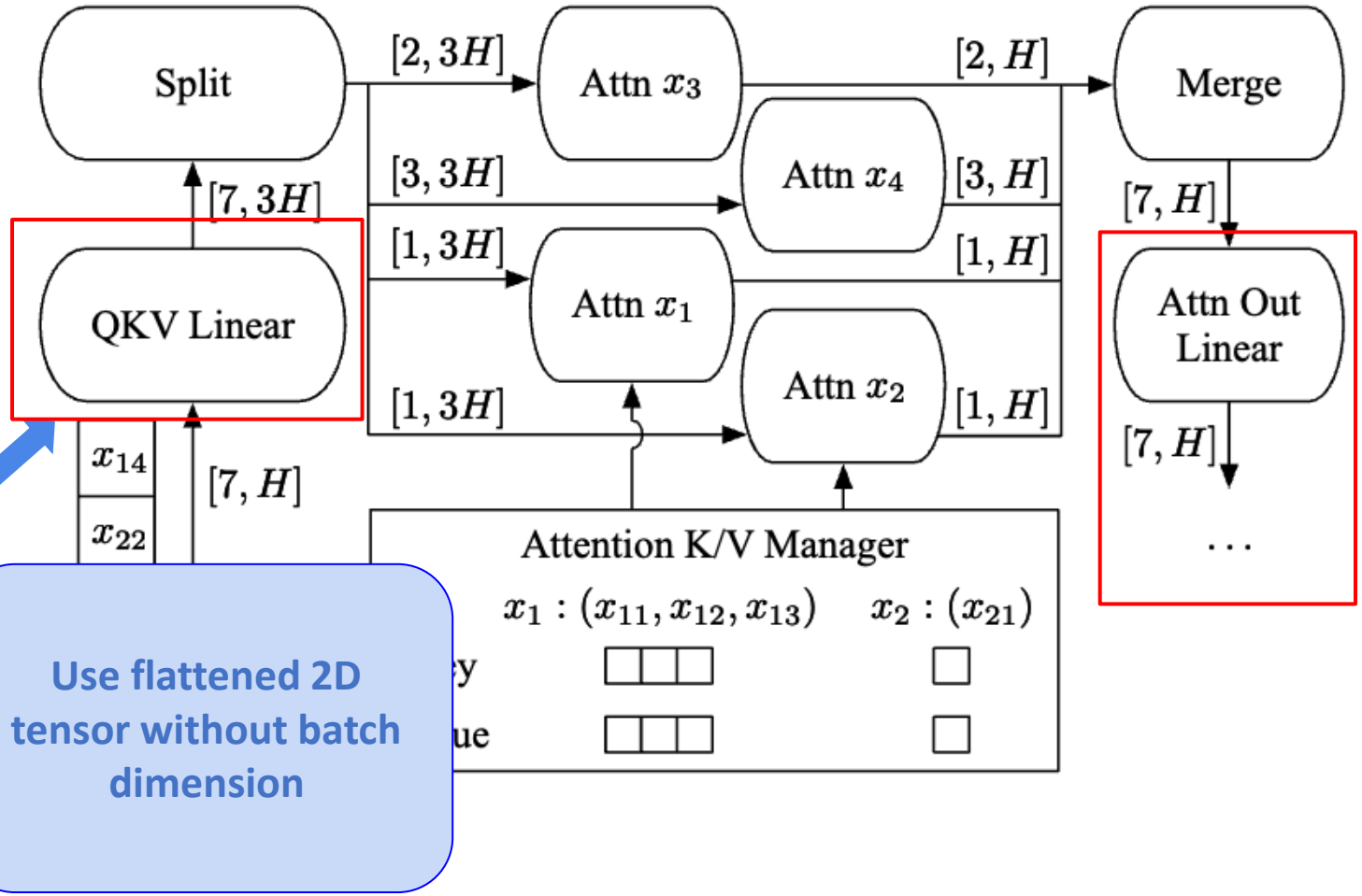
x1: [1,H]
x2: [1,H]
x3: [2,H]
x4: [3,H]

[7,H] tensor



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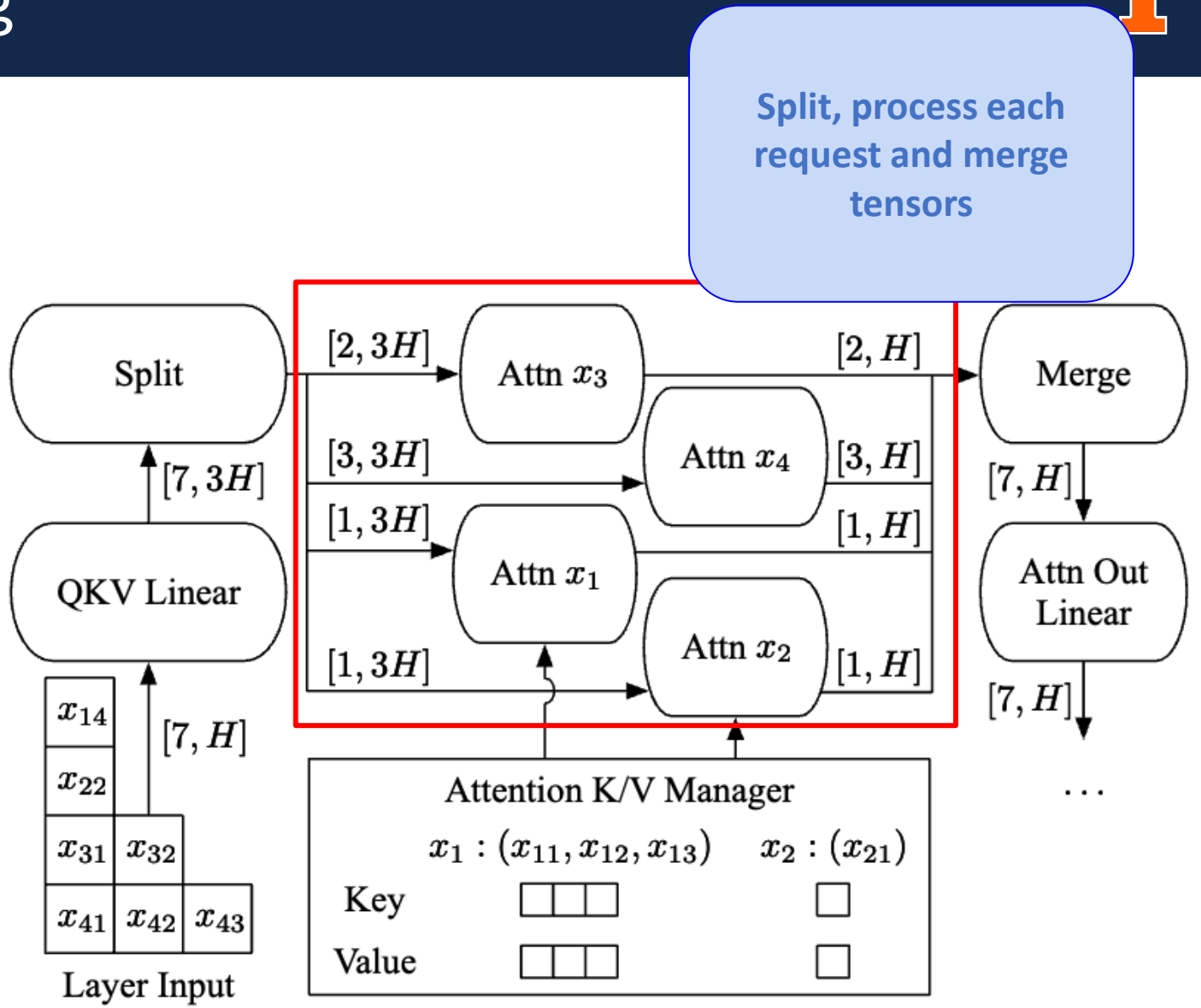
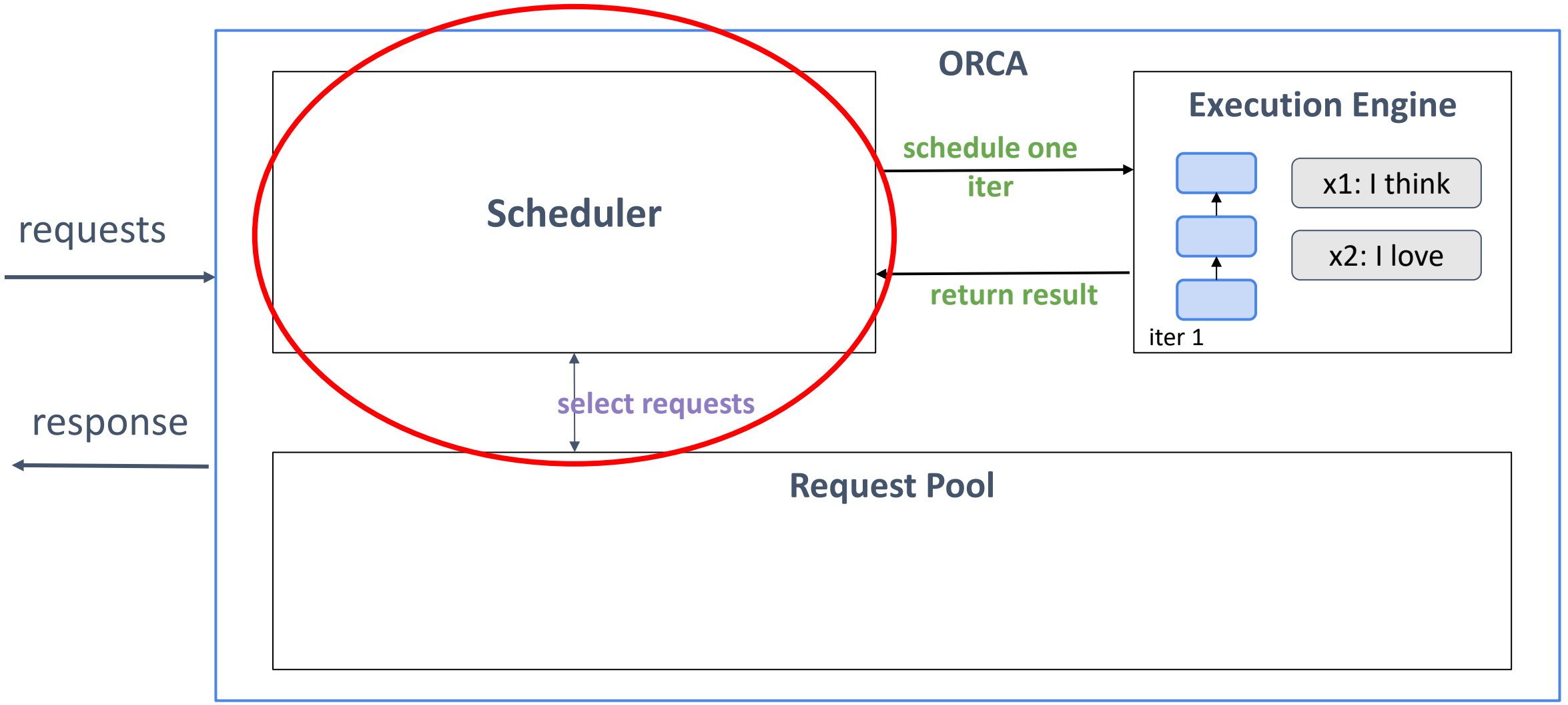


LLM Inference Scheduler



LLM Inference Scheduler

- Enforces iteration-level first-come-first-served (FCFS) property
- Maximum batch size → Throughput vs. Latency control knob
- Reserves max_tokens memory slots per request
- …

Throughput Experiments

- Question: When would continuous batching provide more benefits than sequence batching?

Throughput Experiments

- Hypothesis
  - Continuous batching performs better the more variance there is in sequence lengths

- Frameworks
- Setup – hardware/model
- Setup – data
- Results

Throughput Experiments: Frameworks

- Static batching
  - HuggingFace
  - NVIDIA FasterTransformer
- Continuous batching
  - HuggingFace text-generation-inference (TGI)
  - Ray Serve
  - vLLM

https://www.anyscale.com/blog/continuous-batching-llm-inference

Throughput Experiments: Hardware/model

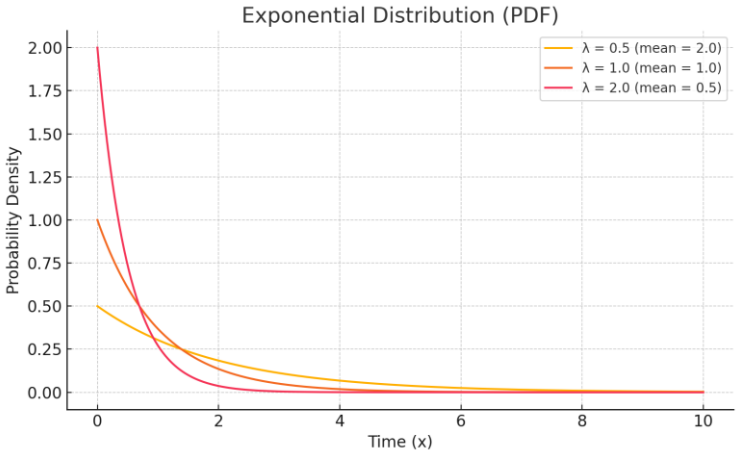
- NVIDIA A100-40GB
- Meta's OPT-13B
  - dtype = float16 → 26GB for parameters
- No tensor parallelism

https://www.anyscale.com/blog/continuous-batching-llm-inference

Throughput Experiments: Data

- Hypothesis
  - Continuous batching performs better the more variance there is in sequence lengths

- How to test?
  - Generate 1000 prompts each with 512 input tokens
  - Generate predetermined output length for each prompt, following an exponential distribution
  - Configure model to ignore EOS token



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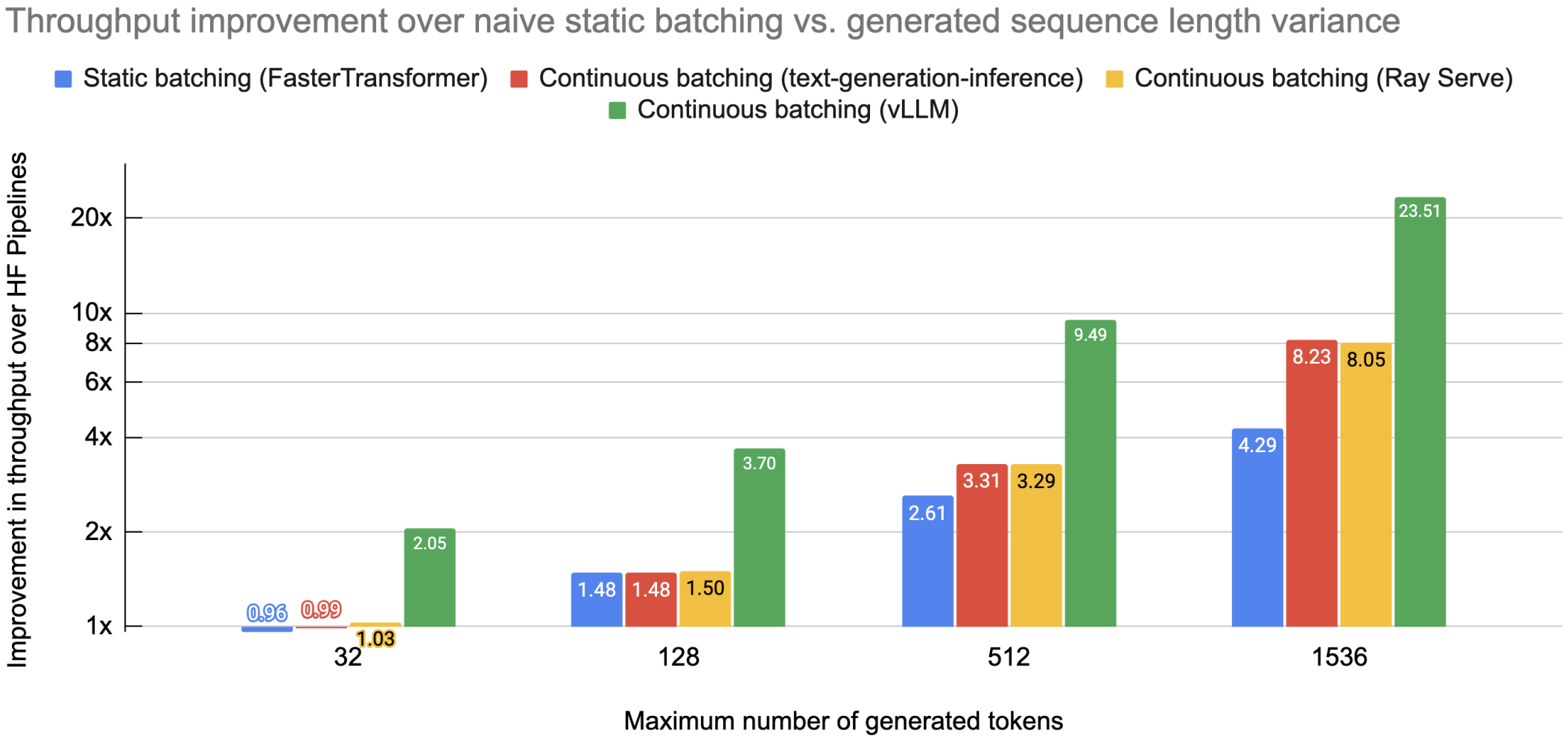
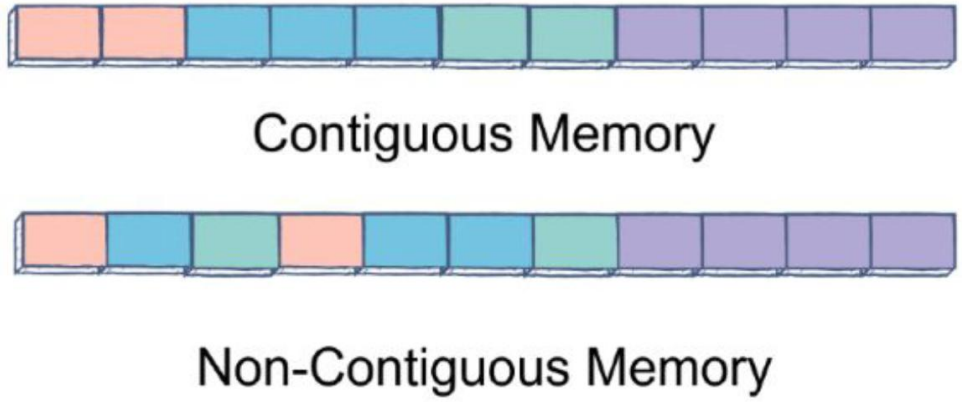
Throughput Improvement from Continuous Batching



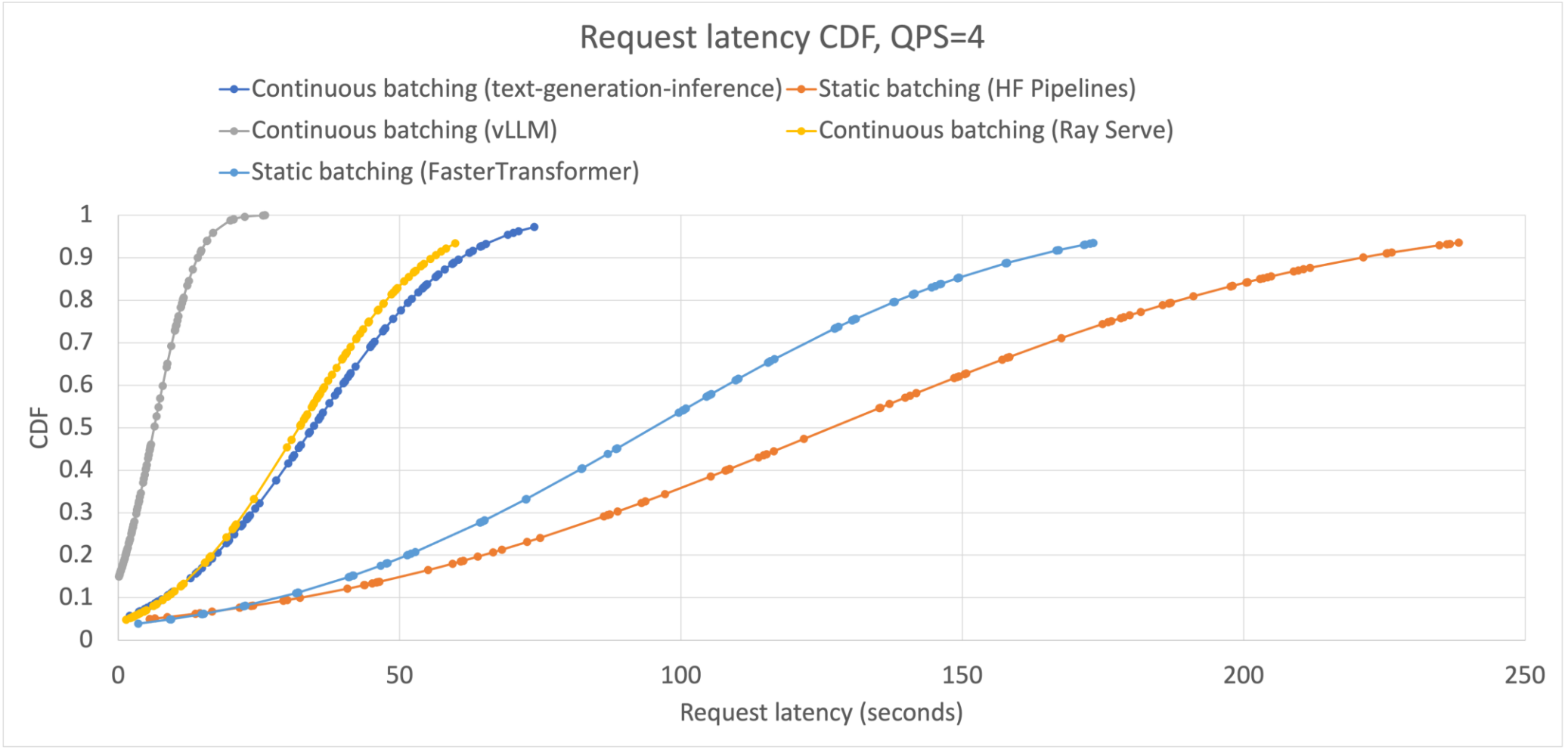
https://www.anyscale.com/blog/continuous-batching-llm-inference

How does vLLM beat TGI

- vLLM uses PagedAttention – extra batch size space



E2E Latency Experiments: Results

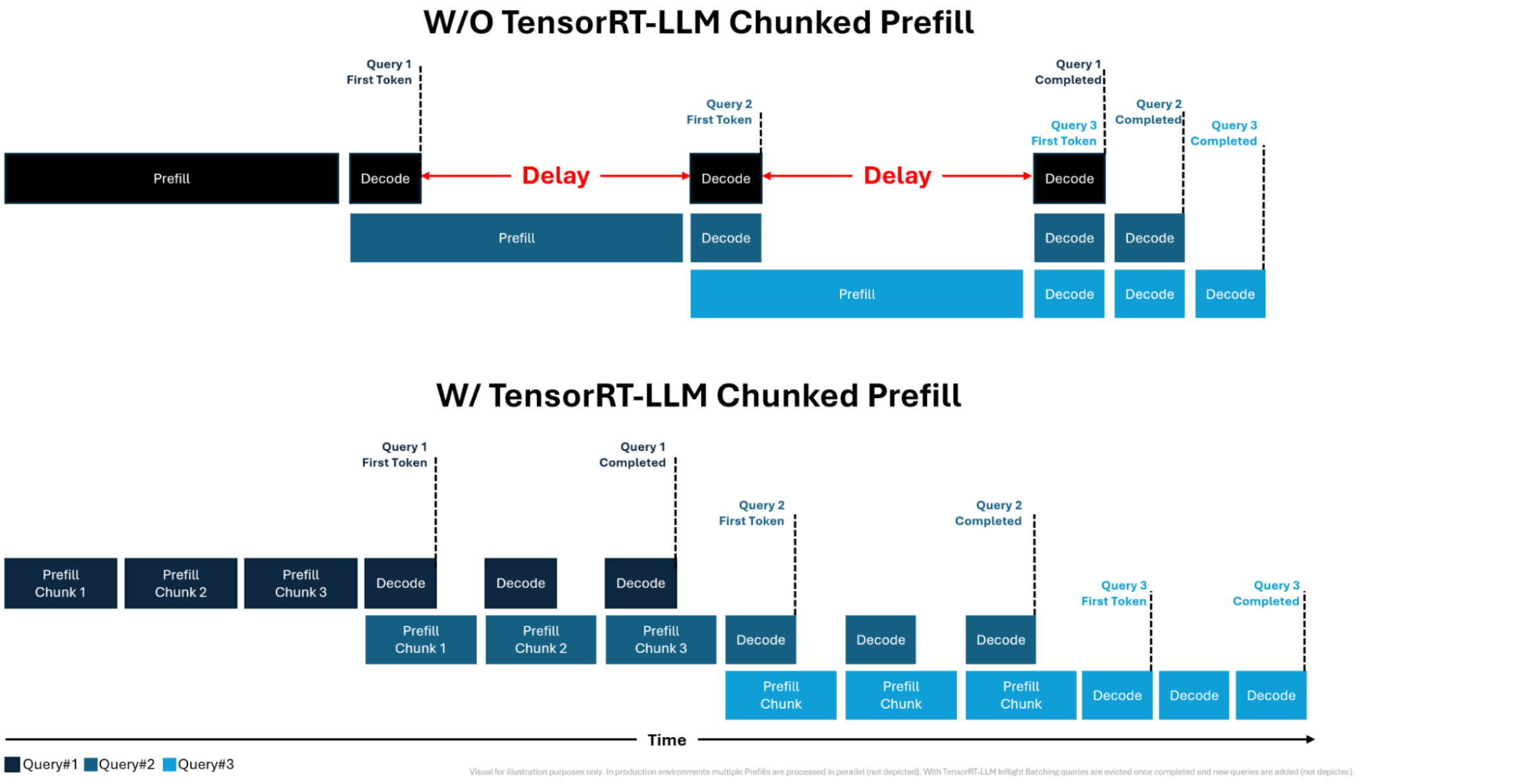


https://www.anyscale.com/blog/continuous-batching-llm-inference

Summary: Continuous Batching

- Continuous batching handles early-finished and late-arrived requests more efficiently
- Fills GPU capacity after each token generation
- As variance in sequence length increases, continuous batching increases GPU utilization

LLM Inference Scheduler: Chunked Prefill

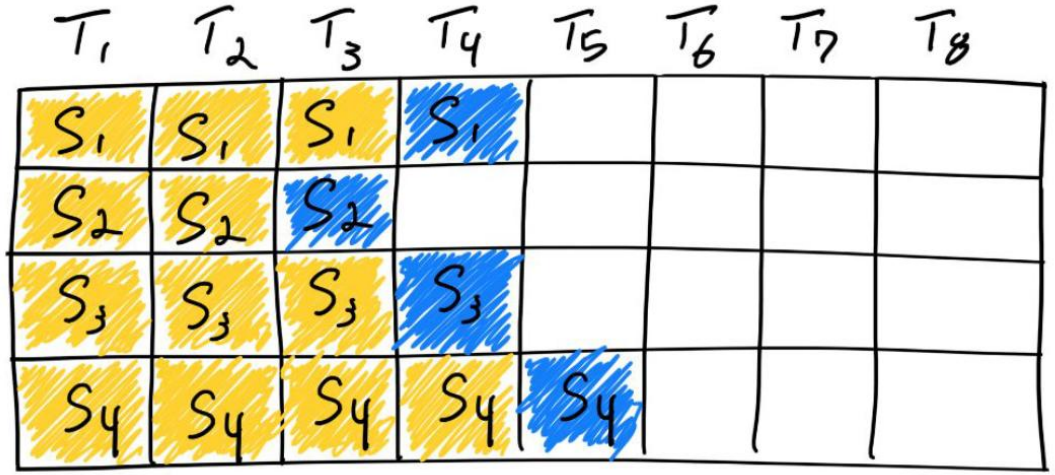


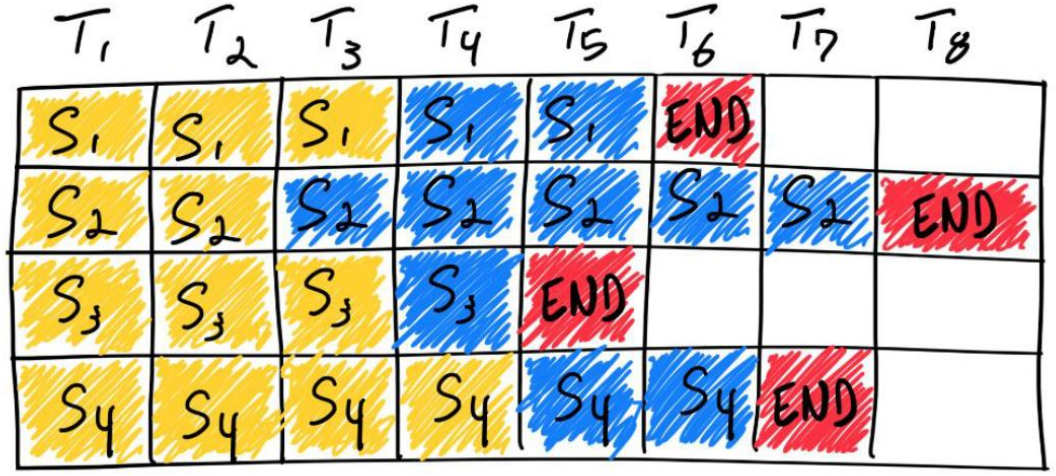
Visual for illustration purposes only. In production environments multiple Prefills are processed in parallel (not depicted). With TensorRT-LLM Inflight Batching queries are evicted once completed and new queries are added (not depictec).

Questions?

Sequence Batching (Static Batching)

- Batching multiple sequences on GPU, aka “static batching”
- Problem: GPU utilization drops as sequences complete





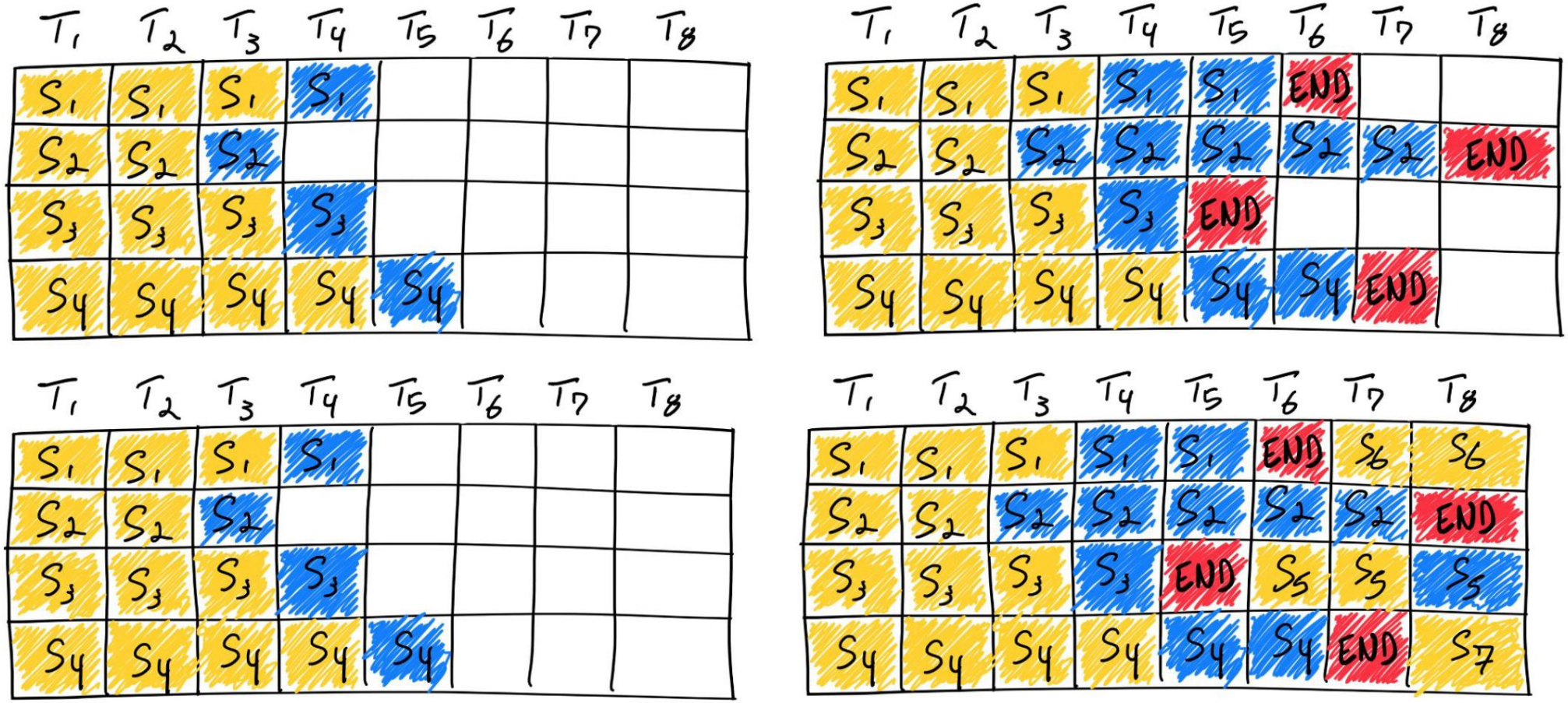
Legend:

- Yellow: prompt token
- Blue: generated token
- Red: end-of-sequence token

Continuous Batching

Top: static batching
Bottom: continuous batching

Legend:
- Yellow: prompt token
- Blue: generated token
- Red: end-of-sequence token



Throughput Experiments: Results

Throughput (token/s) vs. variance in generated sequence lengths	**Generation limit** (higher limit implies higher variance in output sequence lengths)			
	max 32 tokens	max 128 tokens	max 512 tokens	max 1536 tokens
Static batching (HF Pipelines)	2988	972	214	81
Static batching (FasterTransformer)	2869	1441	558	346
Continuous batching (Ray Serve)	3090	1460	703	650
Continuous batching (text-generation-inference)	2948	1442	707	665
Continuous batching (vLLM)	6121	3592	2029	1898

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