ScaleLLM: A Resource-Frugal LLM Serving Framework by Optimizing End-to-End Efficiency

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Overview of ScaleLLM Serving System

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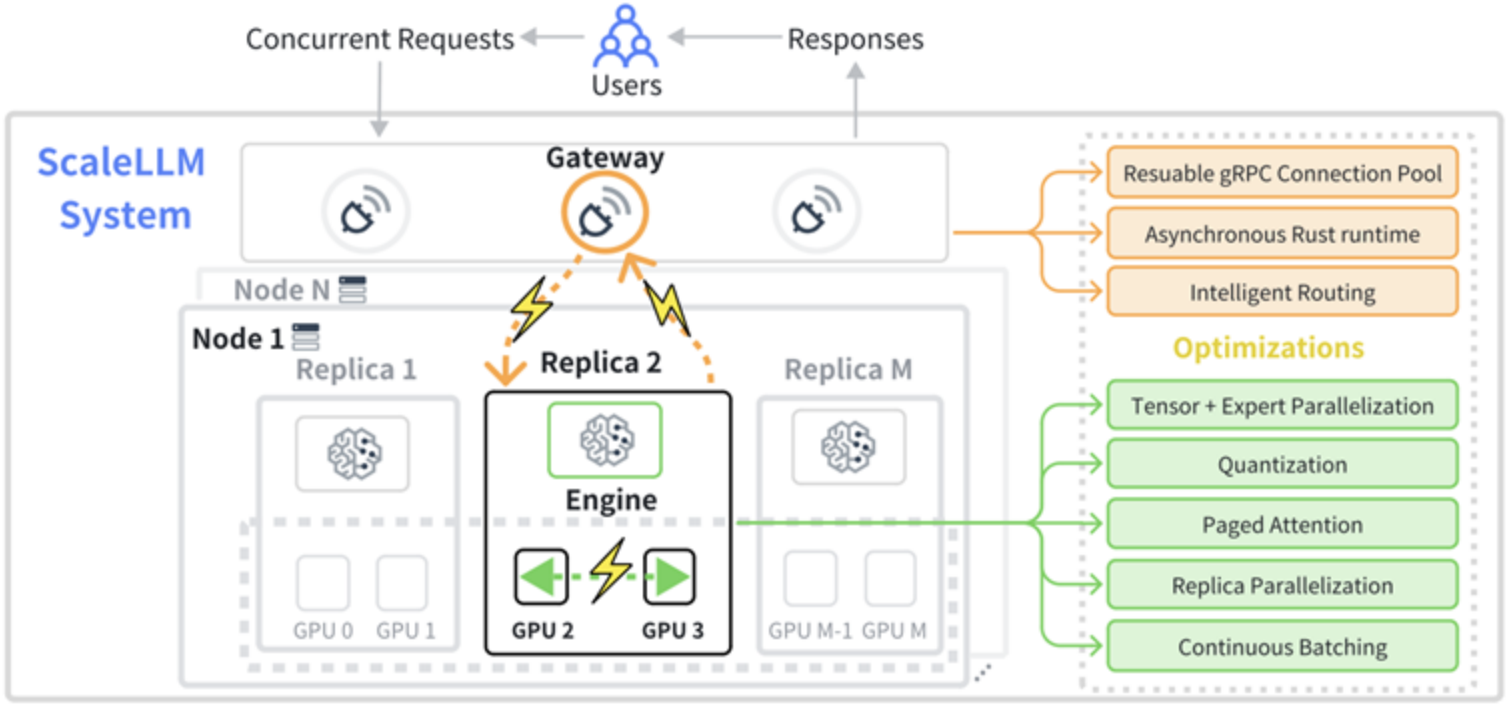

Gateway and serving engine are the key components.

Optimize LLM Serving Engine

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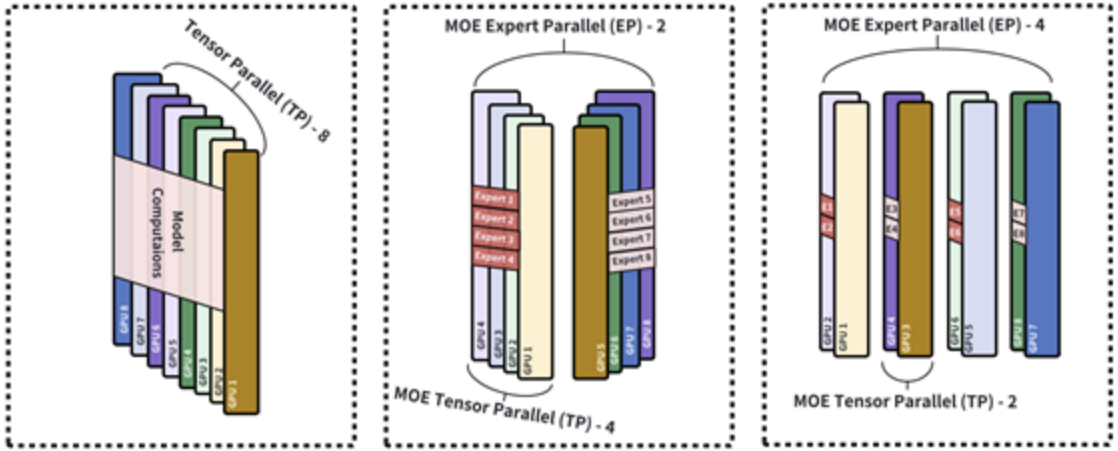
- Model Parallelization



- Model Quantization: fp8
- Continuous Batching and Batch Scheduler
- FlashAttention and PagedAttention

Evaluation of LLM Serving Latency

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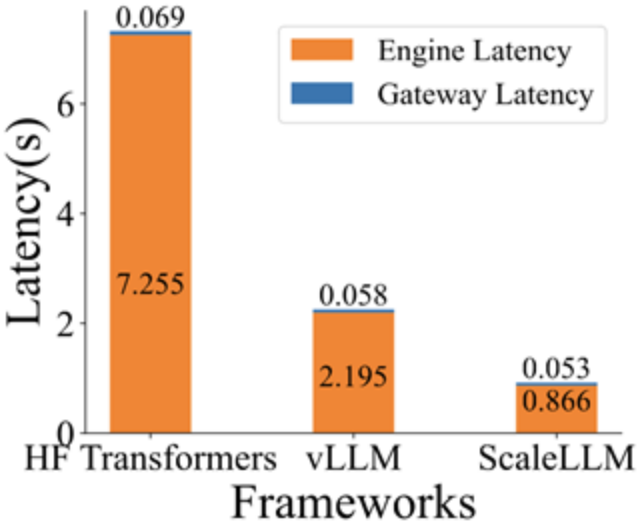
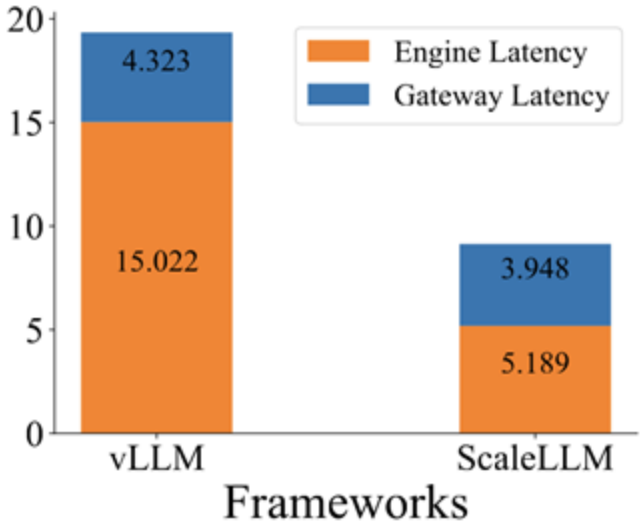


(a) Concurrency: 4.



(b) Concurrency: 256.

Comparisons with the two baseline solutions. ScaleLLM is applied without gateway optimization.

Gateway becomes the new bottleneck after optimizing the Seving Engine

Optimize Gateway Latency

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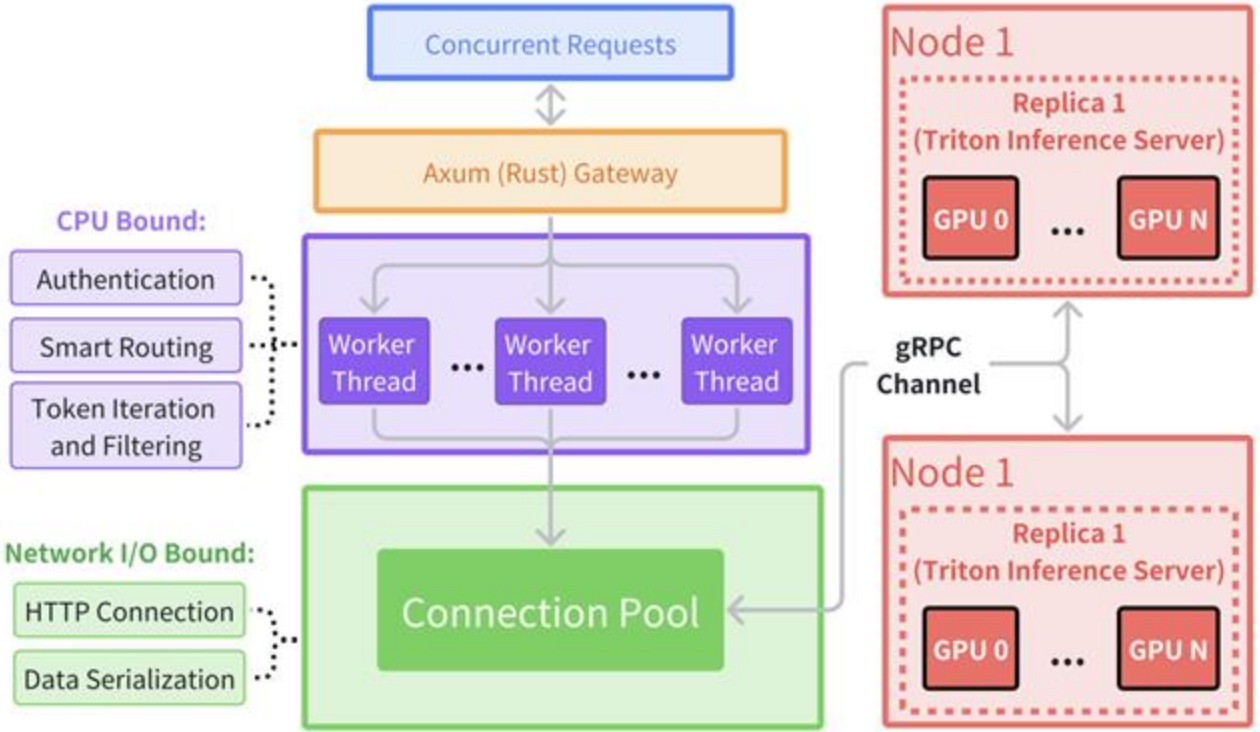

Key Features:

- CPU Bound Job Optimization
- Network I/O Bound Job Optimization

Evaluation of LLM Serving Latency

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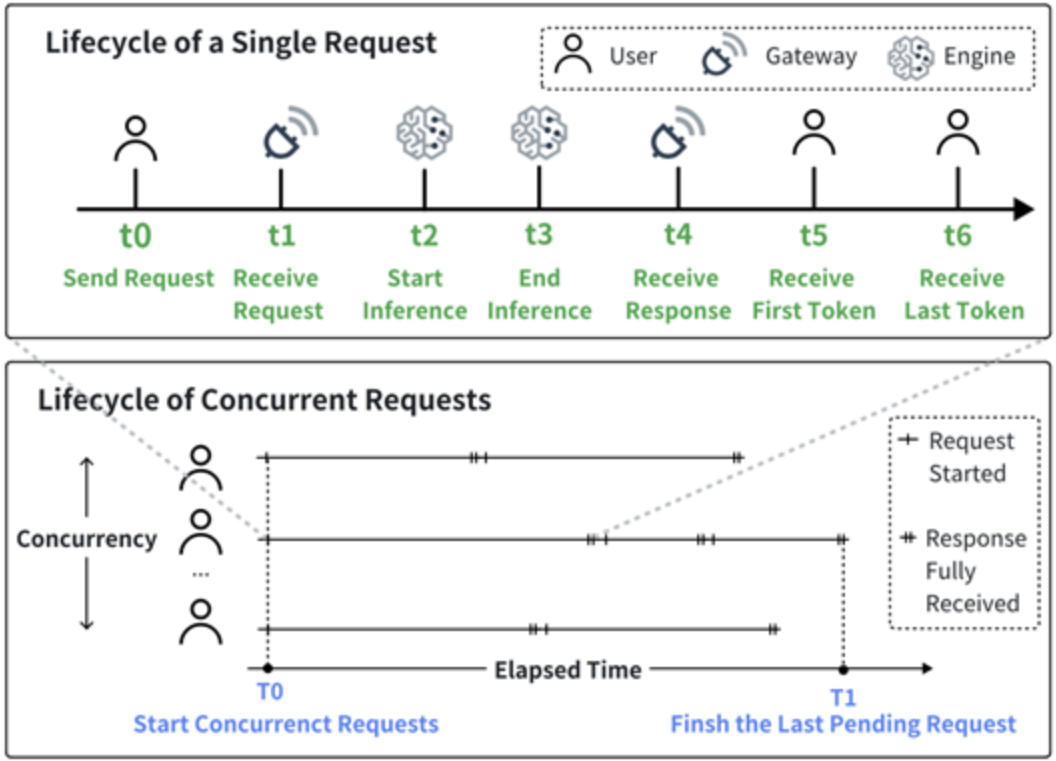

Send X concurrent requests and record the latency

Latency with Streaming Output

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Concurrent Requests	Huggingface Endpoint		vLLM Endpoint		ScaleLLM	
	TTFT/ms	TBT/ms	TTFT/ms	TBT/ms	TTFT/ms	TBT/ms
1	315.6	83.4	48.4	16.5	25.0 (1.9x)	8.5 (1.9x)
2	637.2	218.3	51.9	16.7	25.3 (2.1x)	8.7 (1.9x)
4	1157.8	506.4	55.1	21.1	25.5 (2.2x)	10.4 (2.0x)
8	Timeout	Timeout	70.2	30.1	25.9 (2.7x)	12.2 (2.5x)
16	Timeout	Timeout	93.1	38.3	26.7 (3.5x)	13.4 (2.9x)
32	Timeout	Timeout	135.8	50.1	29.8 (4.5x)	14.6 (3.4x)
64	Timeout	Timeout	285.4	70.8	99.4 (2.9x)	16.5 (4.3x)

Smaller TTFT means faster response for the first token and smaller TBT means faster generation of tokens.
Timeout: 90% of the users' requests cannot complete in 60s.

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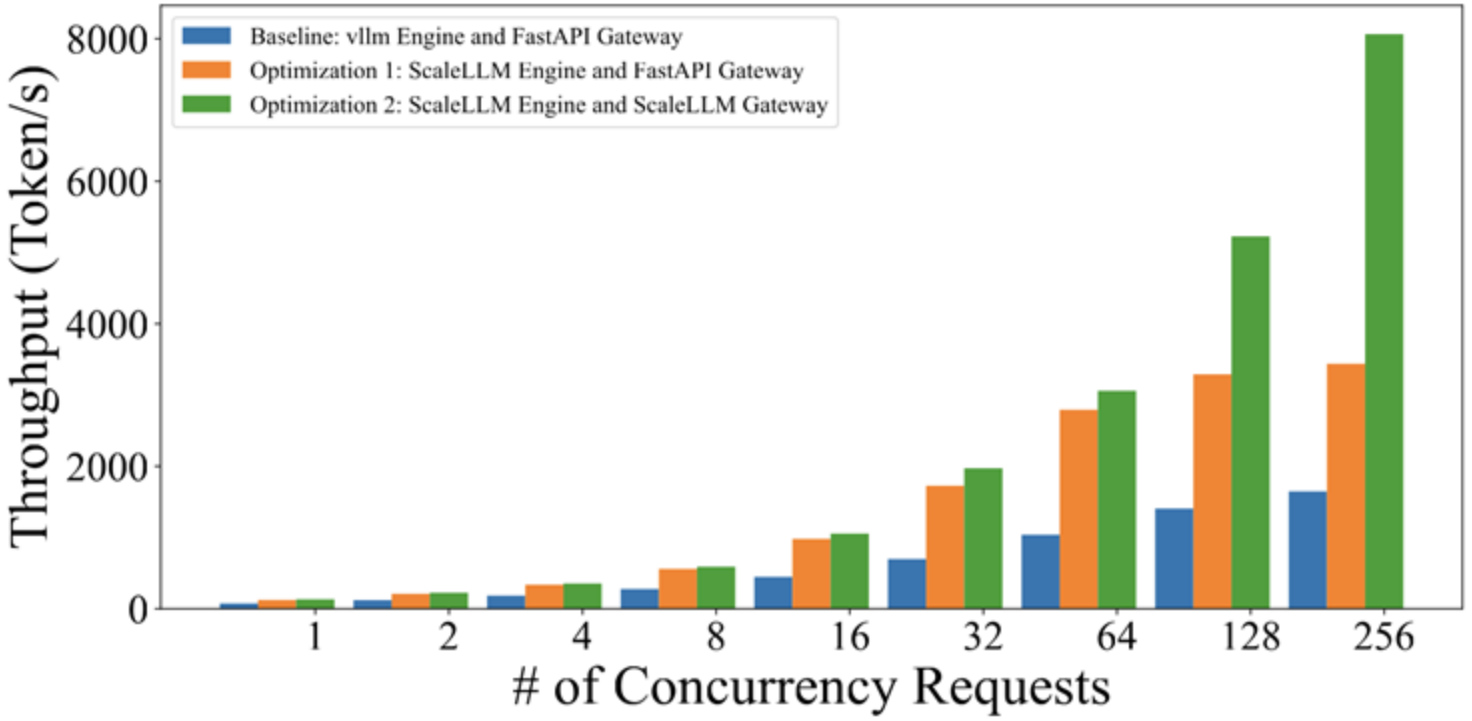
Throughput vs Number of Concurrent Requests.



Optimizing gateway is as important as optimizing engine

ScaleLLM on Mixtral-8x7B

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https://tensoropera.ai/prod/model/mistralai/ScaleLLM-Mixtral-8x7B

A Bad Inference Optimization Strategy

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1. **Find something in the paper/arxiv/blog**

   May not suitable of the current system

1. **Spend time understand and integrate**

   Waste time in research/development

1. **Measure the speedup**

   Maybe the gain is less than 10%

A Good Inference Optimization Strategy

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1. **Apply the current infrastructure**

   Start with the current solution.

1. **Profile the efficiency bottleneck**

   Quantify the impact of each part in the endpoint

1. **Always solve the most inefficient bottleneck**

   Search for the right techniques and apply

Endpoints Throughput Evaluation

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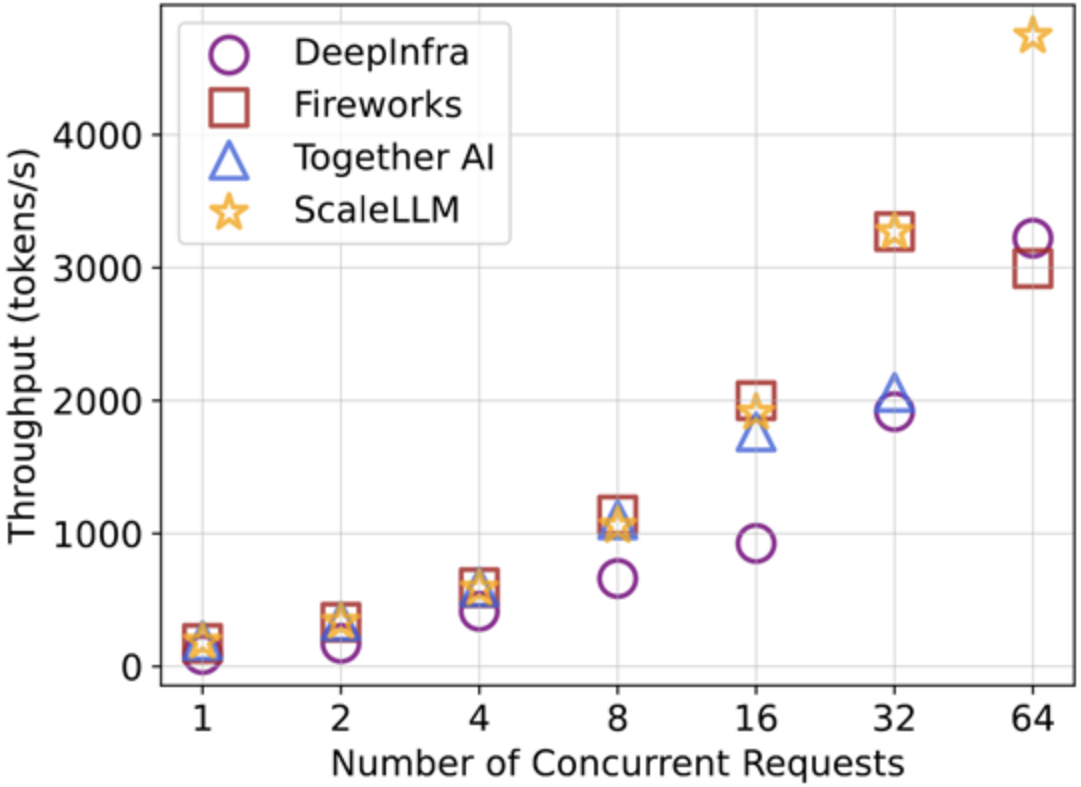
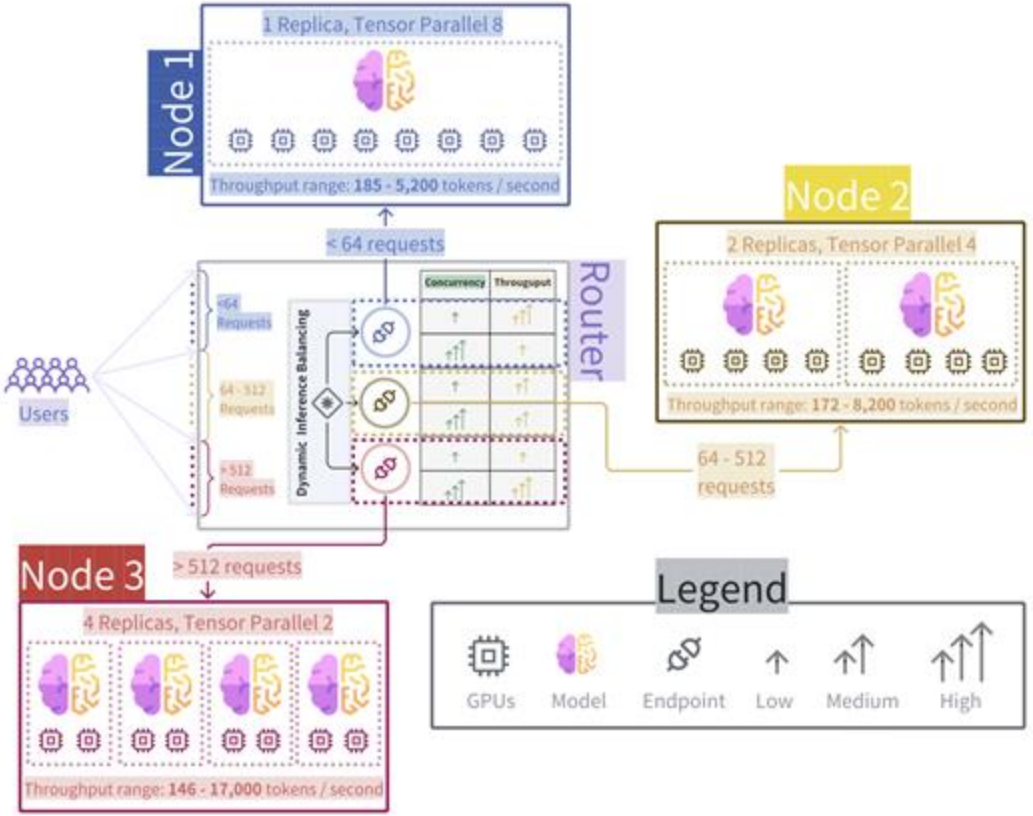


- Comparable with State-of-The-Art endpoints
- 1.5X faster when sending 64 concurrent requests

Blueprint: Dynamic Inference Load Balancing System



Low concurrency (< 64 requests)

Fewer replicas but higher tensor parallelism to optimize resource utilization for smaller batch computations.

High concurrency (≥ 64 requests)

More replicas but lower tensor parallelism effectively distributing the workload to squeeze everything out of available compute.

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