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KV-Cache Centric Inference

Building an Open Source LLM Serving Platform Around State

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- 30 yr tech career in enterprise and open source software
- Currently focusing on Cloud Native Computing and AI inference
- Core maintainer in LMCache
- Emeritus Helm core maintainer and TOC member
- Contributor to vLLM, llm-d, LMCache, Helm, Kubernetes, Open Telemetry, OpenStack
- Open source developer at IBM Research

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Maroon Ayoub

- Staff Research Scientist, IBM Research
- Co-lead of llm-d - an open source project for distributed LLM inference
  - KV-disaggregation SIG chair
- Focused on evolving agentic-inference
- Previously worked on Kubernetes, hybrid cloud, and distributed systems

LLM Scaling Inference Challenges

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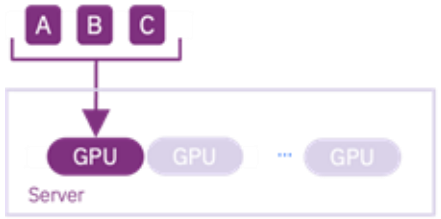
The challenge of scaling inference

Distributed inference is essential for cost-effective scaling of AI, but introduces unique **operationalization challenges**

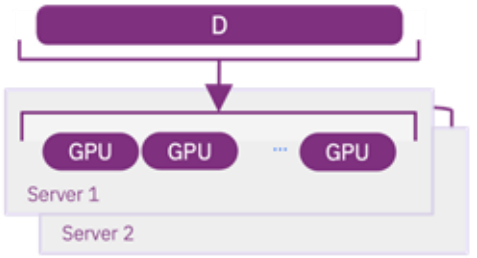
- Load balancing **variable, resource-heavy** and hardware-affinity nature of requests
- **Ensuring SLO** and maintaining low latency under multi-tenant traffic
- Leveraging and managing **heterogeneous hardware** for better cost-efficiency
- Managing distributed **KV cache state** at scale as key part in inference efficiency
- **Orchestrating** prefill and decode phases; and multi-node serving

Multiple small models
(e.g., granite-8b, mistral-7b, ...)

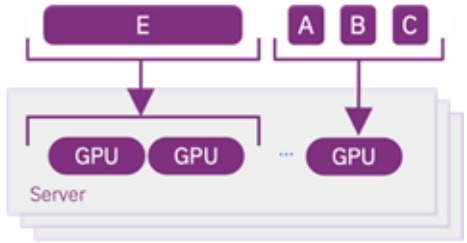


Single large model
(e.g., lama3-70b, llama4,

)



Mix of small and large models



KV cache management

KV cache reuse is essential to make prefix-heavy workloads **cost-effective**

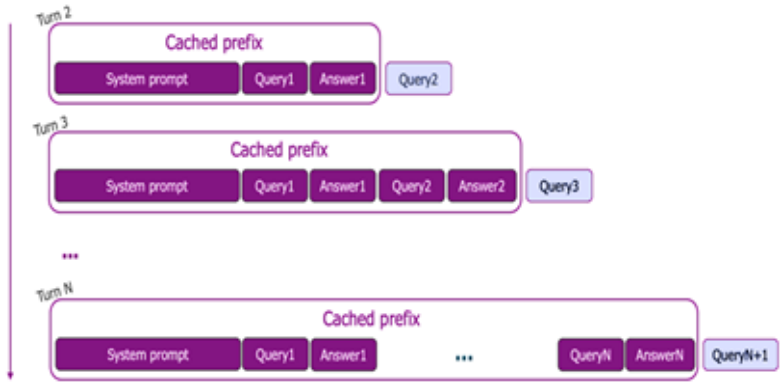
KV cache size grows linearly with context length and batch size

E.g., Llama 3.1 8B (fp8), 32K–128K context length results in 16–64 GB KV-cache size increase

KV cache grows to hundreds of terabytes for chatbot and agentic AI

Conversational AI

Large input-to-output ratio

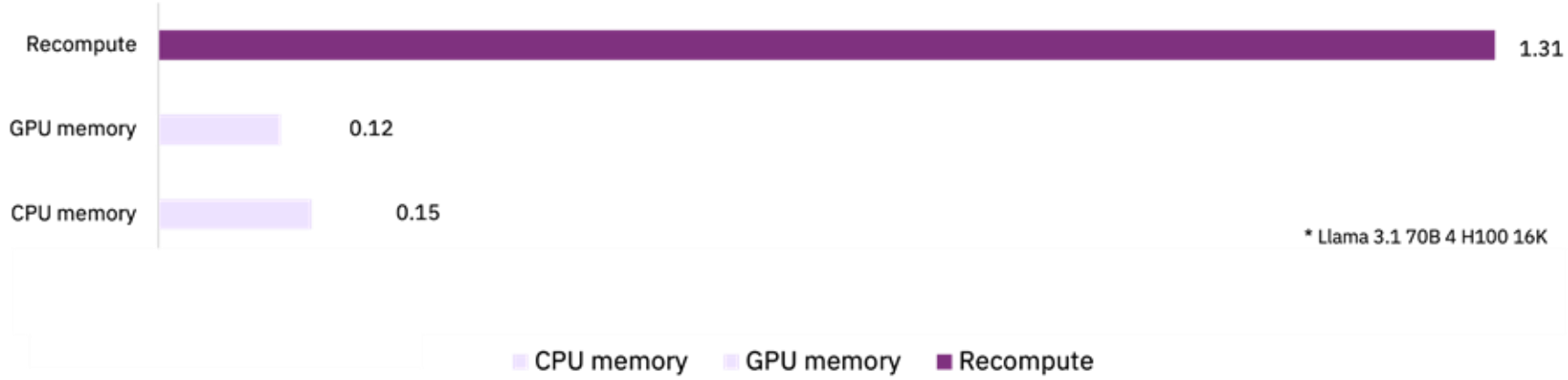


Agentic workflows

Very large input-to-output ratio (100:1)

Inference Time - TTFT (sec)

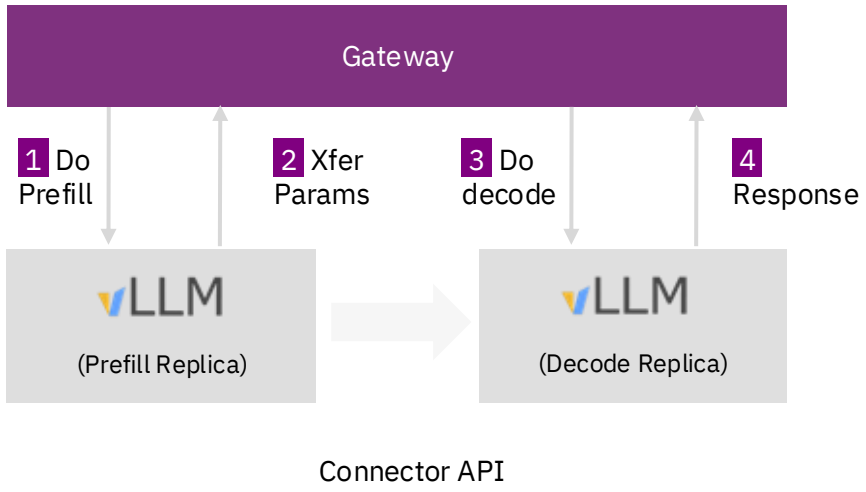
Inference speed-up with KV reuse



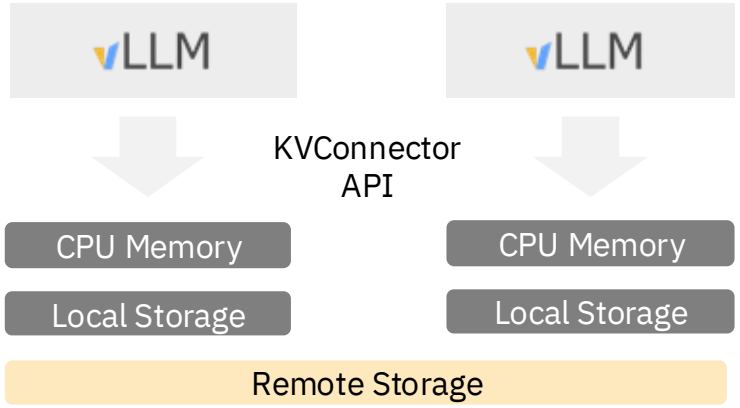
Pipeline imbalance: prefill and decode behave very differently

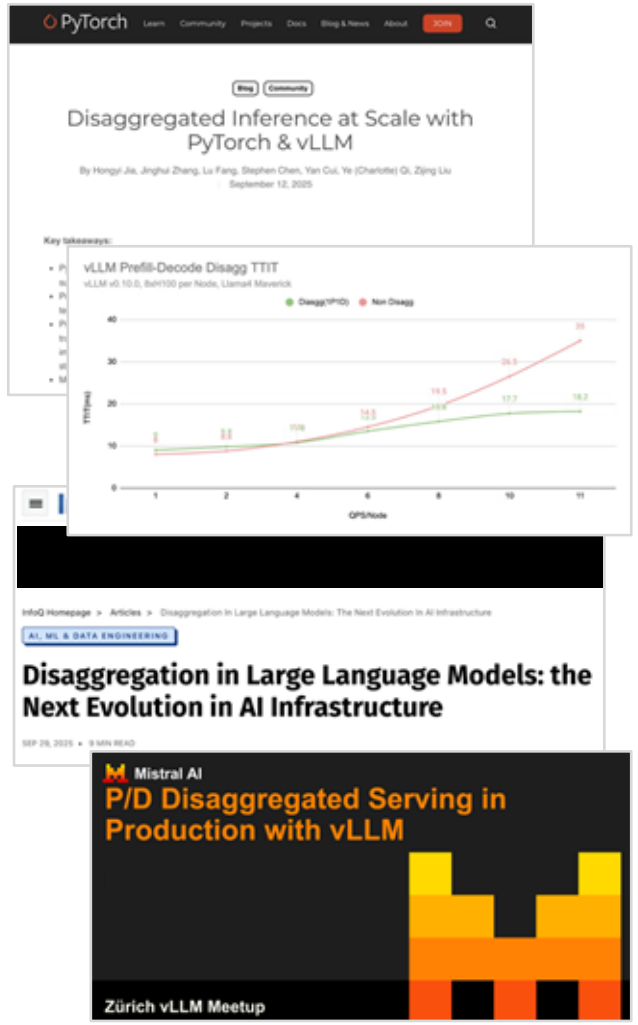
P/D disaggregation, from exploration to production operation

Prefill/Decode Disaggregation



KV Cache Offloading





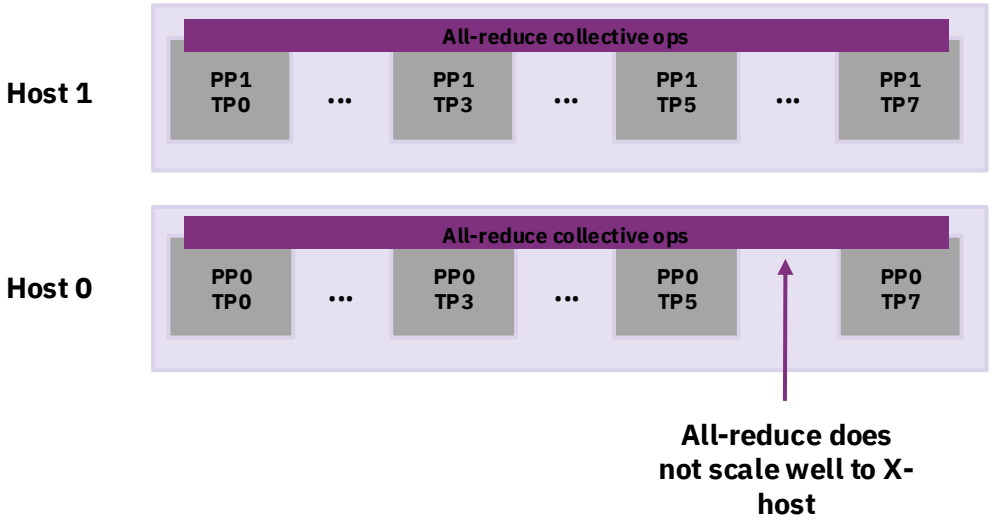
Key challenges on implementing and standardizing the optimizations/APIs needed for **disaggregated serving orchestration**

The communication wall: scaling MoE across nodes

Sparse MoE architectures scale to multi-node: this enables running **very large models** efficiently

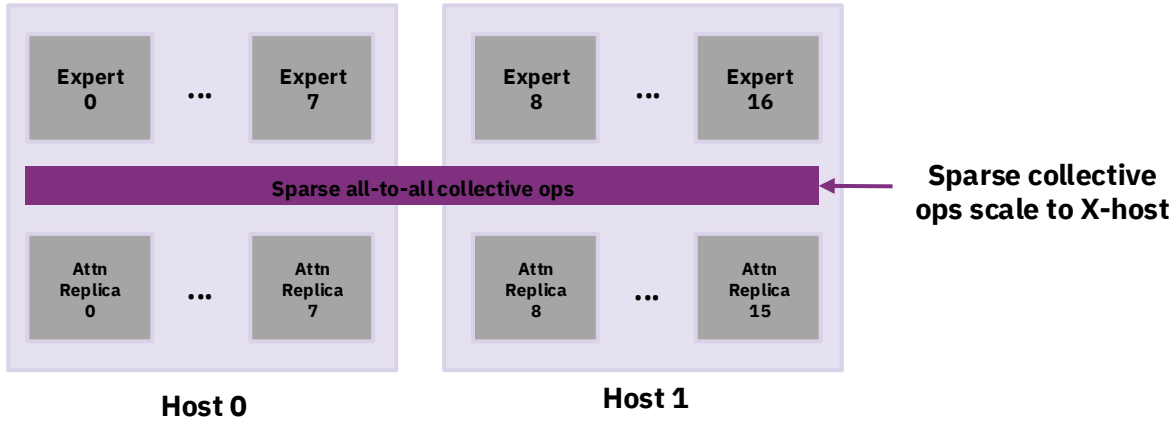
Dense: Tensor + Pipeline Parallel

e.g. Llama-405B



Sparse MoE: Data + Expert Parallel

e.g. DeepSeek-R1



Key challenges is on building a platform that can orchestrate these distributed systems behaviors with **operational simplicity**

Introducing llm-d

High Performance distributed scalable LLM inference platform

github.com/llm-d/llm-d

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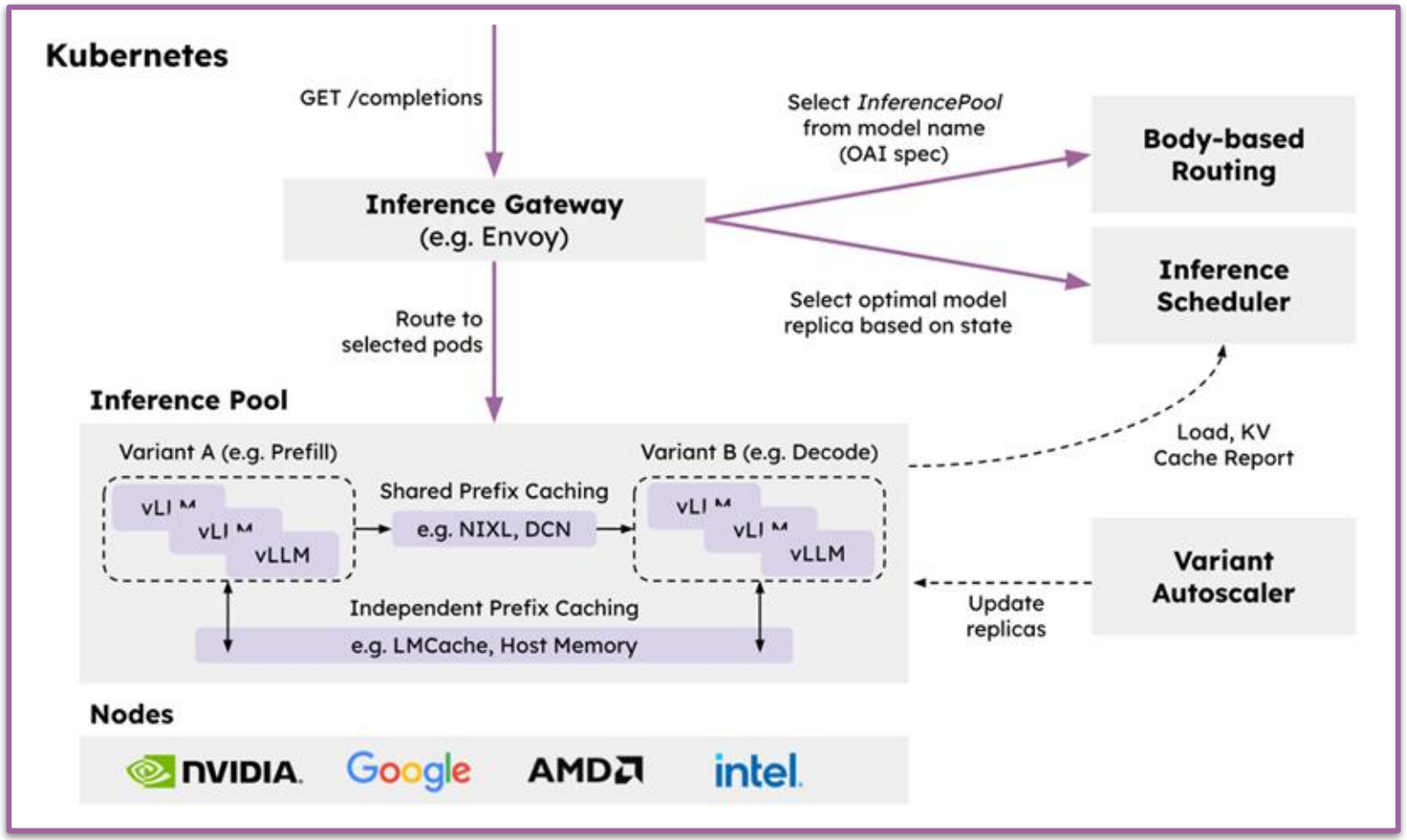
vLLM llm-d kubernetes



Operationalizability

- Modular and resilient architecture with native integration into Kubernetes via Inference Gateway API

Flexibility

- Cross-platform with extensible implementations of key composable layers of the stack

Performance

- Leverage distributed optimizations like prefix-aware routing and disaggregation to achieve the highest throughput while meeting SLOs

What are the Key llm-d Capabilities for Enhanced Distributed LLM Workloads?

https://llm-d.ai/docs/guides

01

Intelligent Inference Scheduling

Prefix-aware + load-aware routing
via pluggable EPP scorers

02

KV Cache Management

GPU → CPU → Remote Storage tiers
with global prefix index

03

Prefill / Decode Disaggregation

Separate compute-optimized prefill
from bandwidth-optimized decode fleets

04

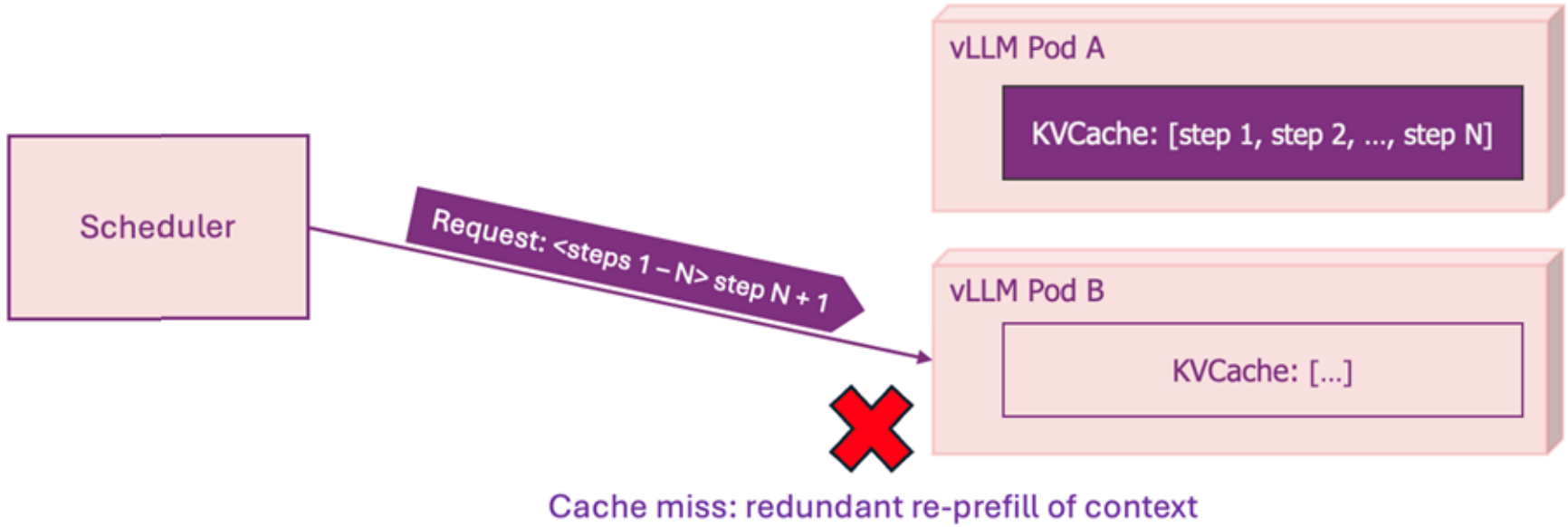
Wide Expert Parallelism

Kubernetes-native MoE routing
with DP-aware EPP

Where Standard Load-Balancing Fails

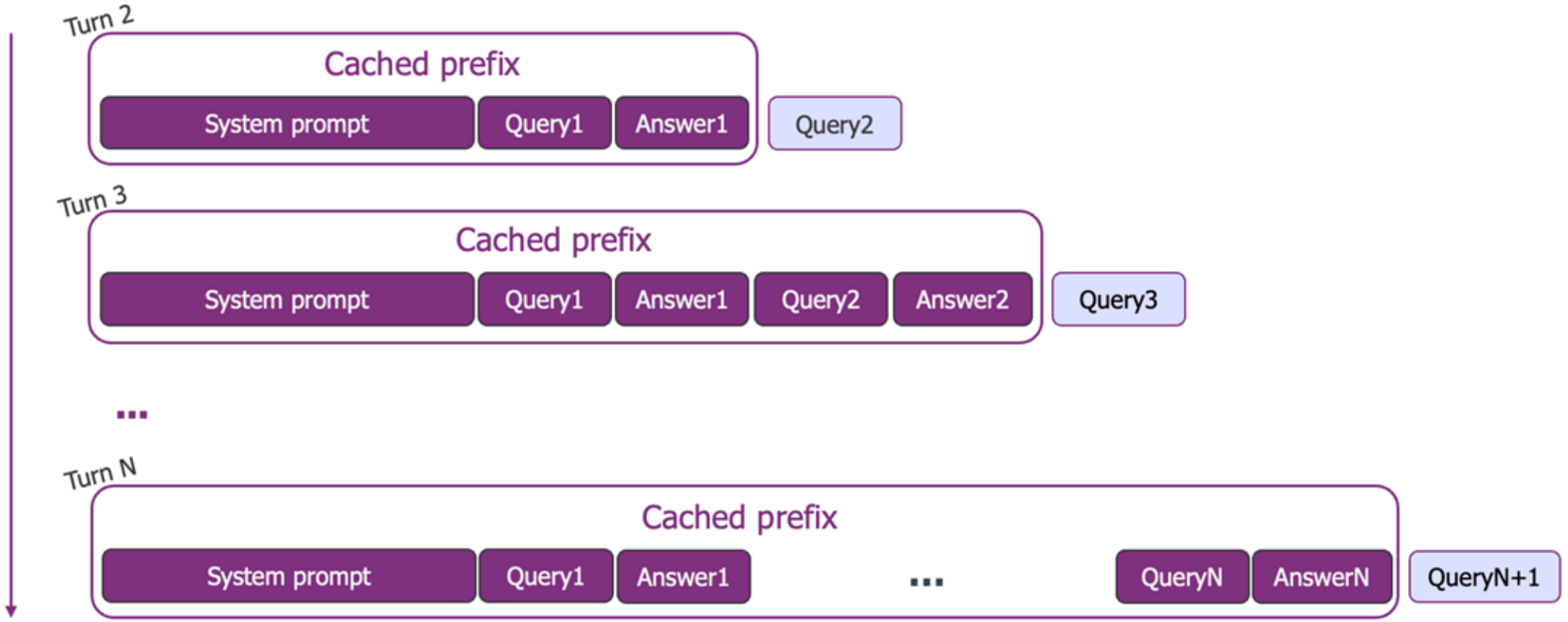
Production AI inference involves multiple vLLM instances and replicas

Naive load-balancing distributes traffic evenly across the pods -> destroying cache optimizations



Prefix-Cache Reuse in Production

Multi-Turn Chat



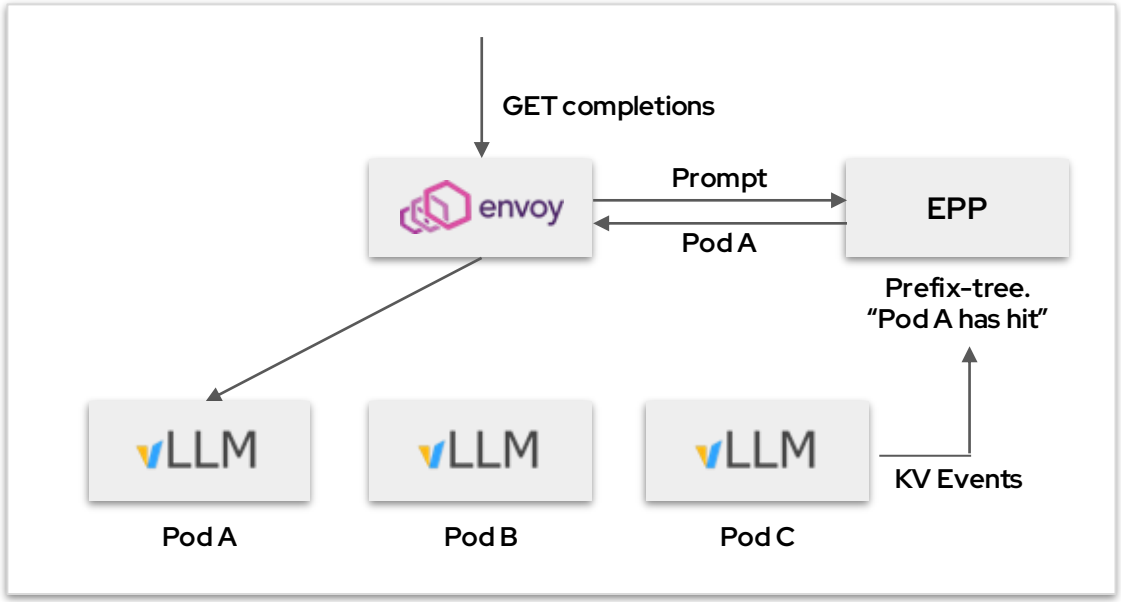
Prefix-Cache Reuse in Production

Linear Agents – Multi-Turn Tool Use

Intelligent Inference Scheduling

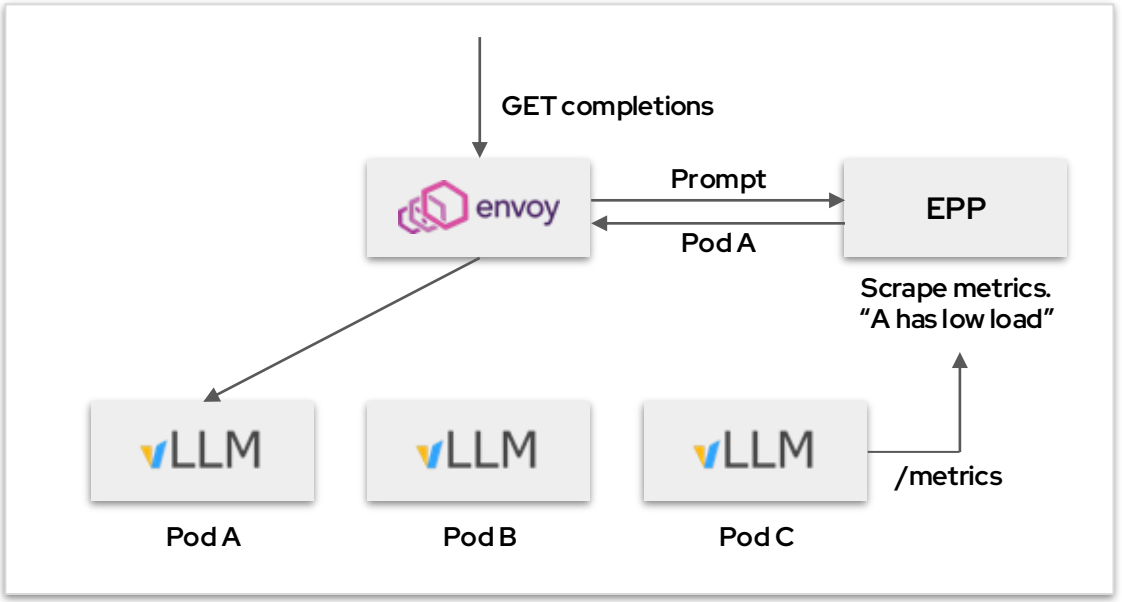
vLLM-aware load-balancing enables smarter request routing that improve SLOs

Prefix-Aware Routing



Dramatically increase prefix-cache hit rate

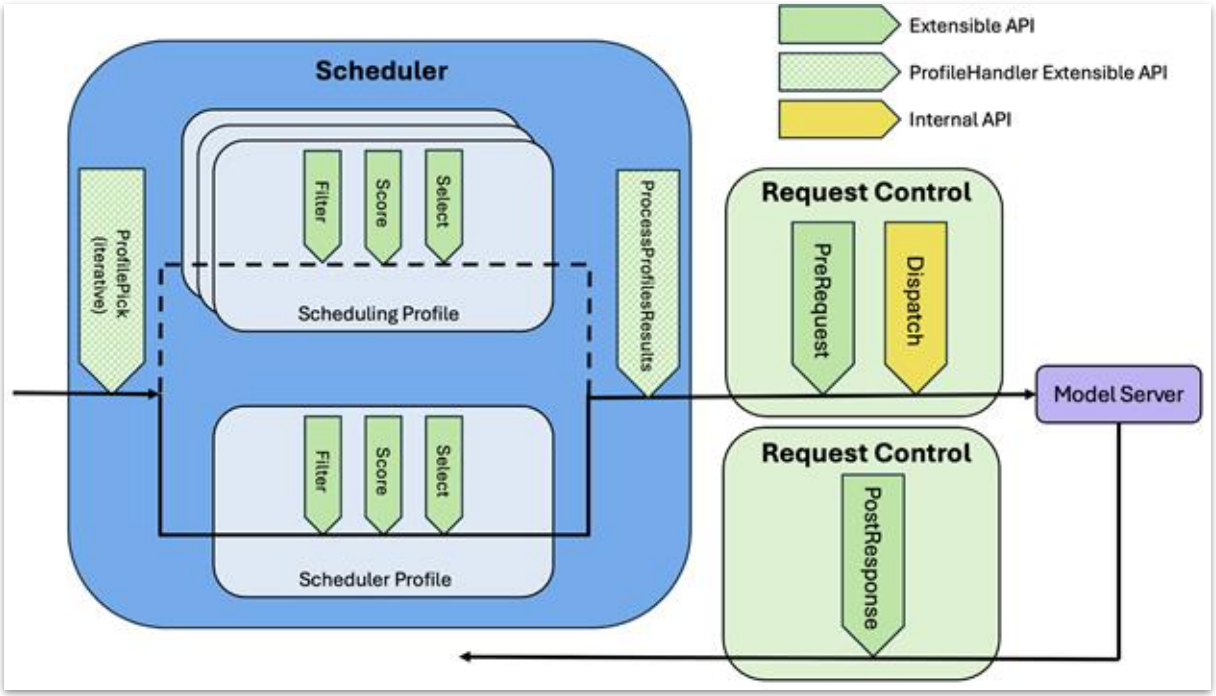
Load-Aware Routing



Load-balancing based on actual replica state

Intelligent Inference Scheduling

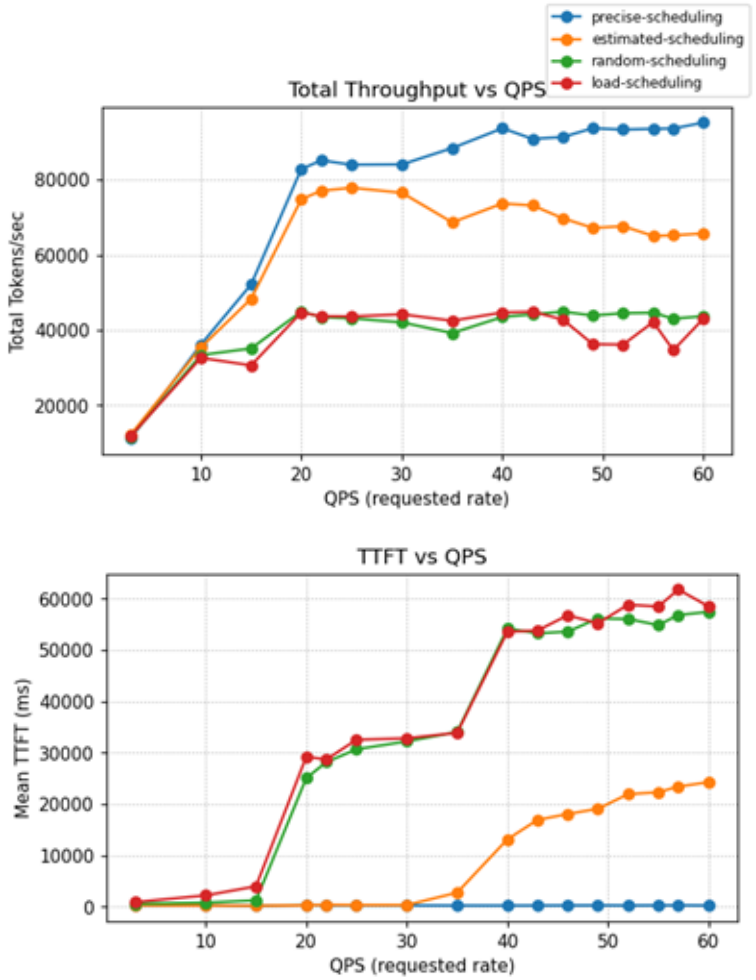
llm-d's pluggable architecture enables first-class composing and extending



- **Scorers** → Apply weights to signals
  - Configure relative weights
  - Add custom scorers as needed
- **Filters** → filter specific pods
- **Request Control** → queue requests until the server load is ready

Intelligent Inference Scheduling

Inference scheduling is a no-brainer optimization which can have huge impacts on repeated prompts

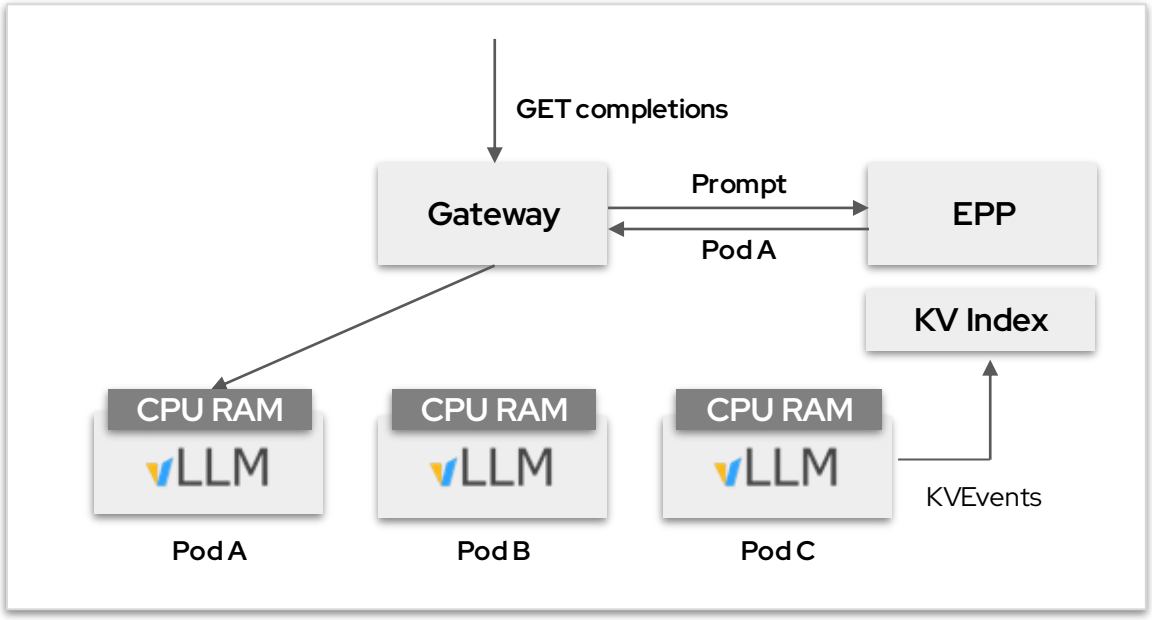


- llm-d provides different levels of **prefix-cache aware scheduling** capabilities in our **guides**
- In a workload that demands only 73% of a 16 H100 GPUs KV-cache capacity, **optimal performance is achieved**:
  - **x57 faster response time** than naive scheduling
  - **x2 throughput** than load-aware scheduling

KV Cache Management

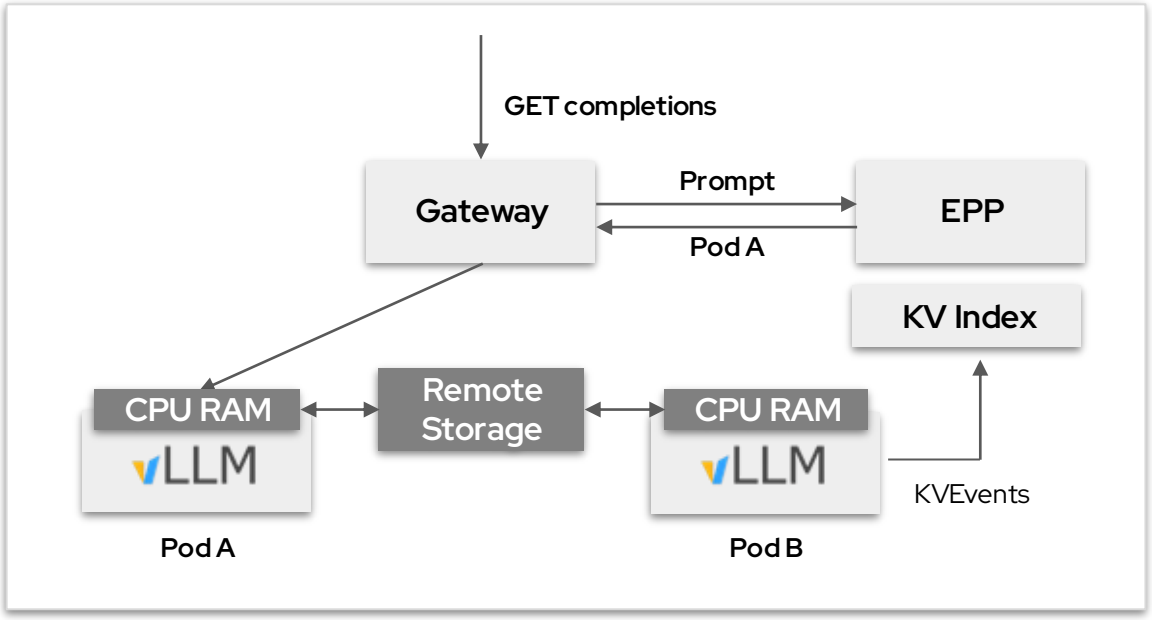
Leverage all system resources to maximize prefix cache hit rate within the cluster

North/South KV Management



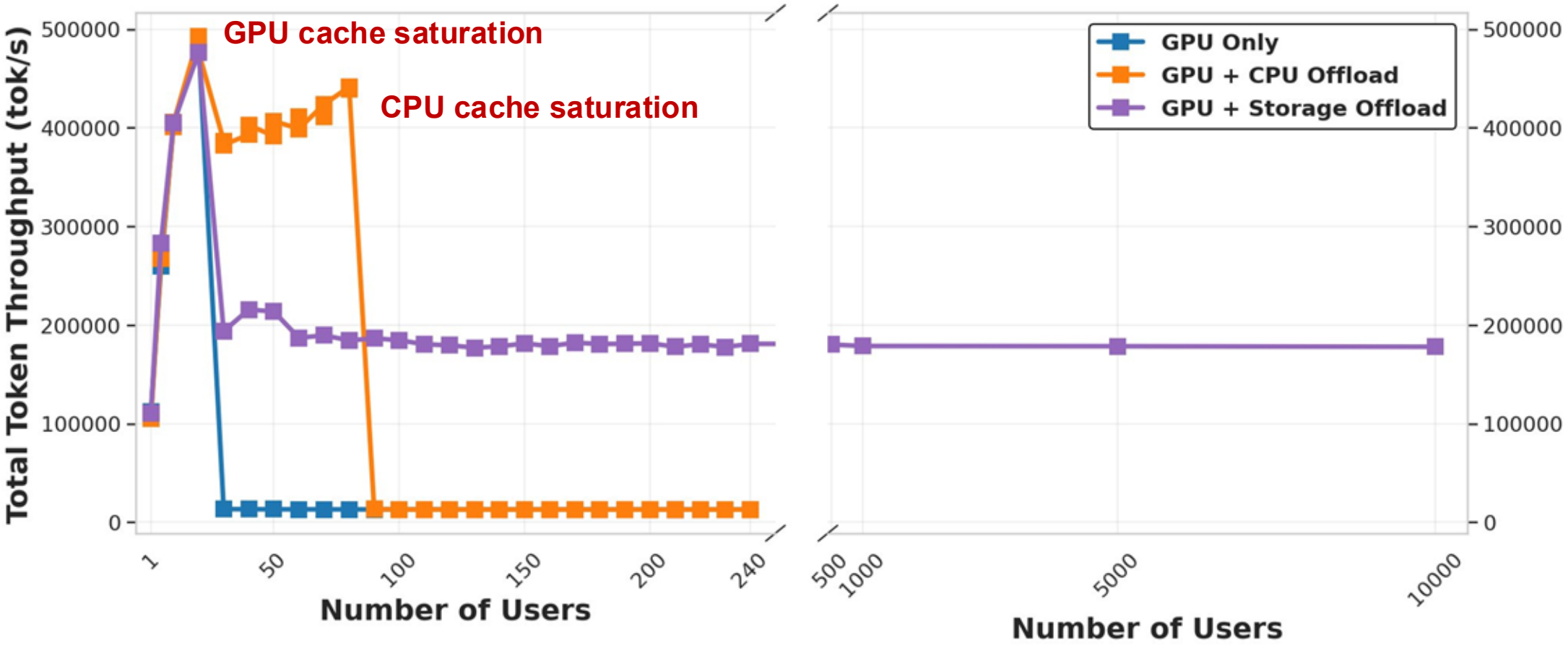
Offload KV caches to local memory with global index

East/West KV Management

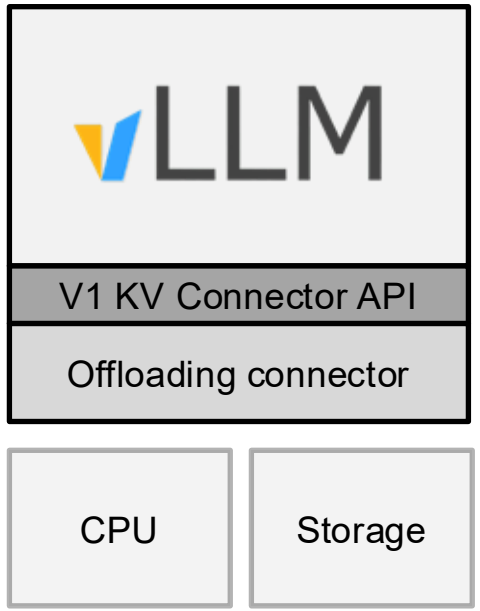


Offload KV caches to global shared remote storage

KV-Offloading Performance

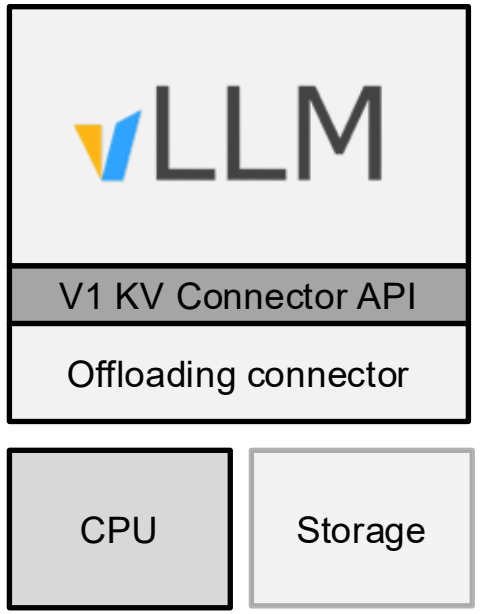


The KV Offloading Connector



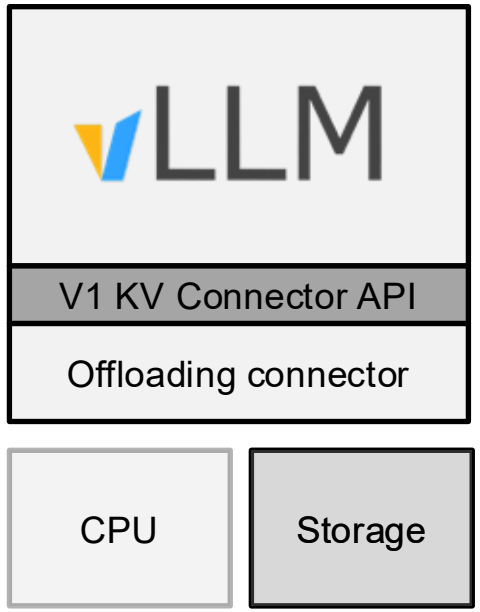
- **Bridges the vLLM V1 KV-Connector API** into a simple, unified offloading interface for **pluggable backends**
- Enables KV cache to live **beyond GPU memory** across CPU and storage tiers
- Improves **throughput** and **stability** by reducing GPU memory pressure

CPU Offloading Backend



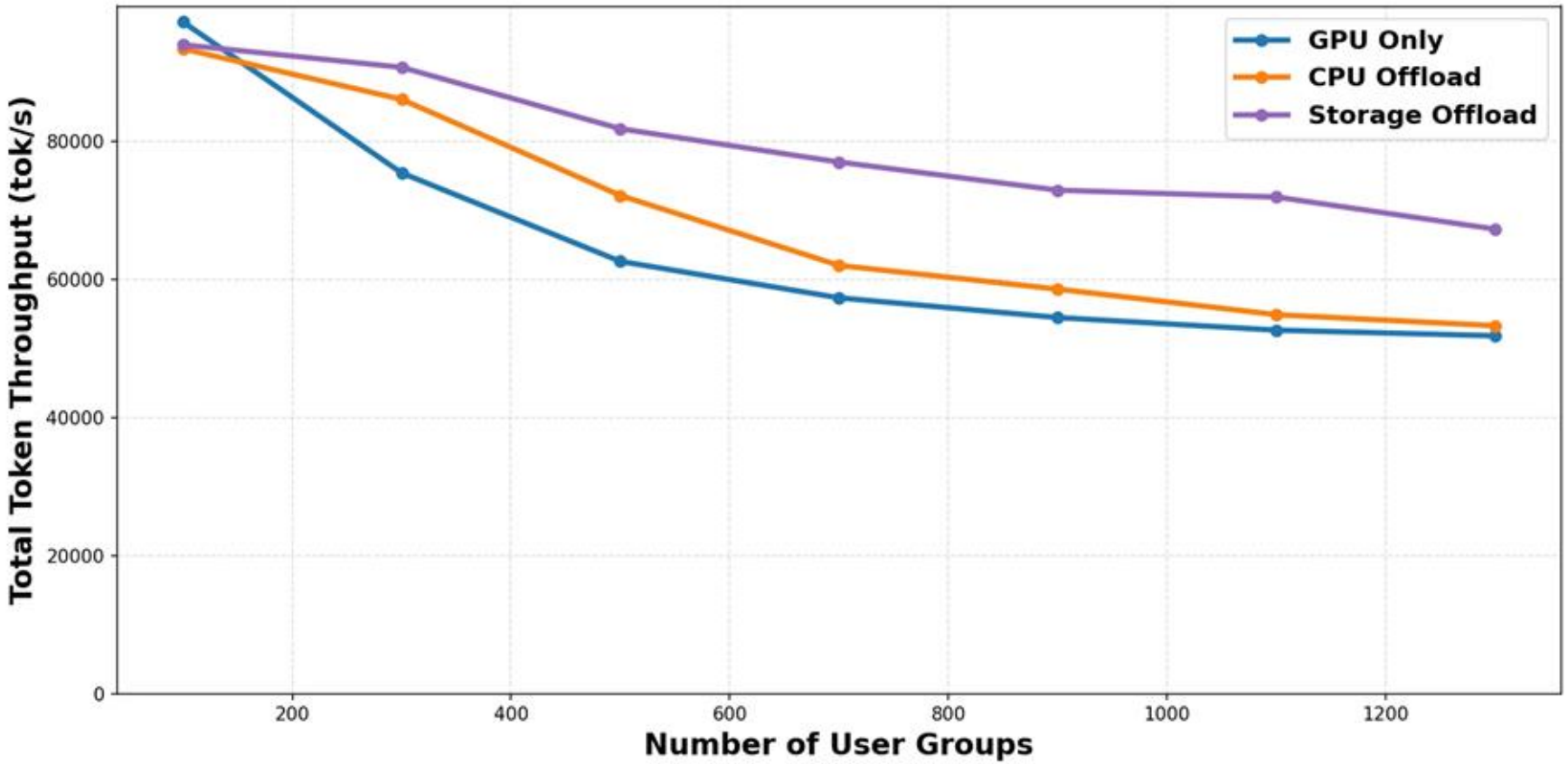
- KV blocks are **copied asynchronously** from GPU -> pinned CPU memory **using DMA**
- **CPU memory acts as a high-capacity KV cache tier** extending the number and lifespan of token sequences
- **When a request resumes, KV blocks are streamed back just-in-time** instead of recomputing attention from scratch

Storage Offloading Backend



- KV blocks are **copied asynchronously** from GPU -> shared storage using the same offloading connector (C++)
- **Storage acts as a cluster-wide KV cache pool** extending cache capacity beyond any single node's GPU or RAM
- **Any POSIX filesystem is immediately supported**

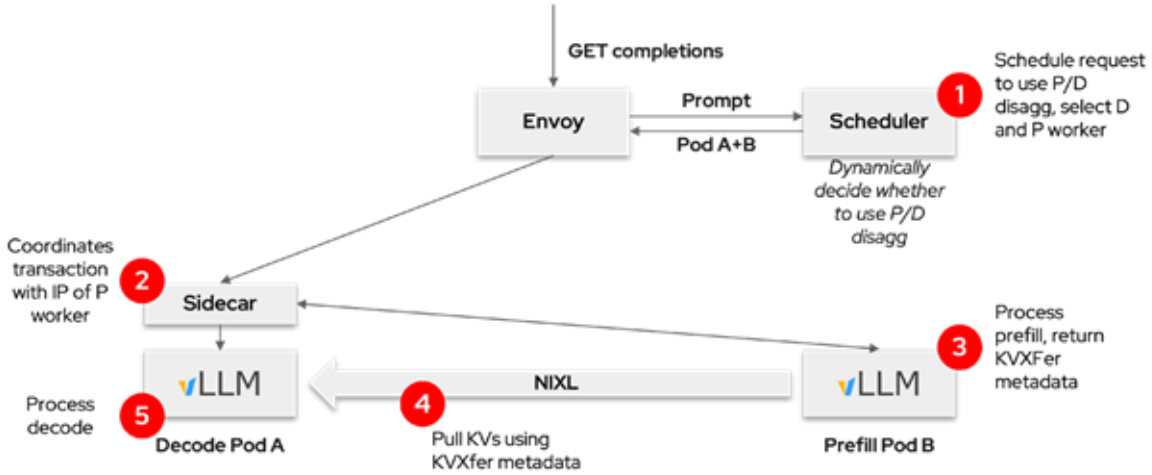
Offloading Performance

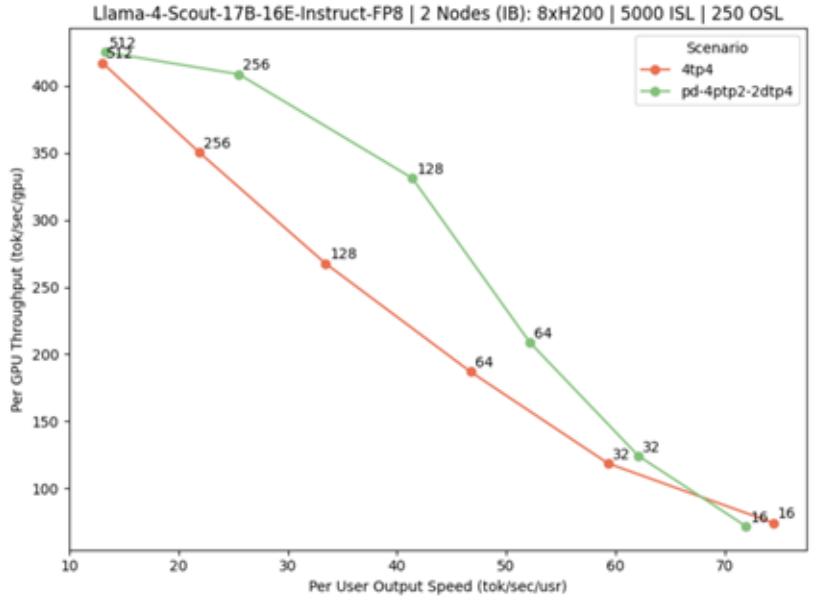


llm-d blog: Native KV Cache Offloading to Any Filesystem with llm-d

Prefill/Decode Disaggregation

llm-d composes vLLM and Gateway to enable P/D disaggregation



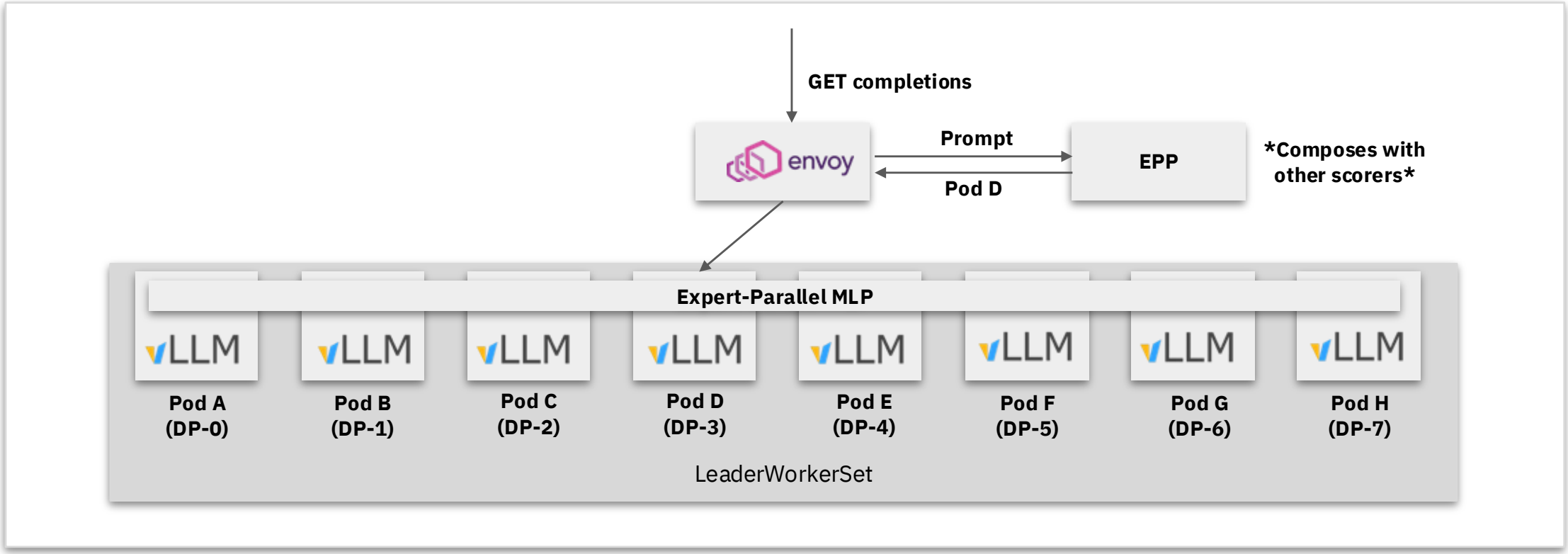


- Separate prefill and decode
- Allows specialization
- Dynamically decided
- Easier to meet TTFT and ITL SLO requirements

- Best for “medium” server load
- Typical: small prefillers, large decoders
- P/D benefits are most clear when jointly optimizing efficiency and interactivity

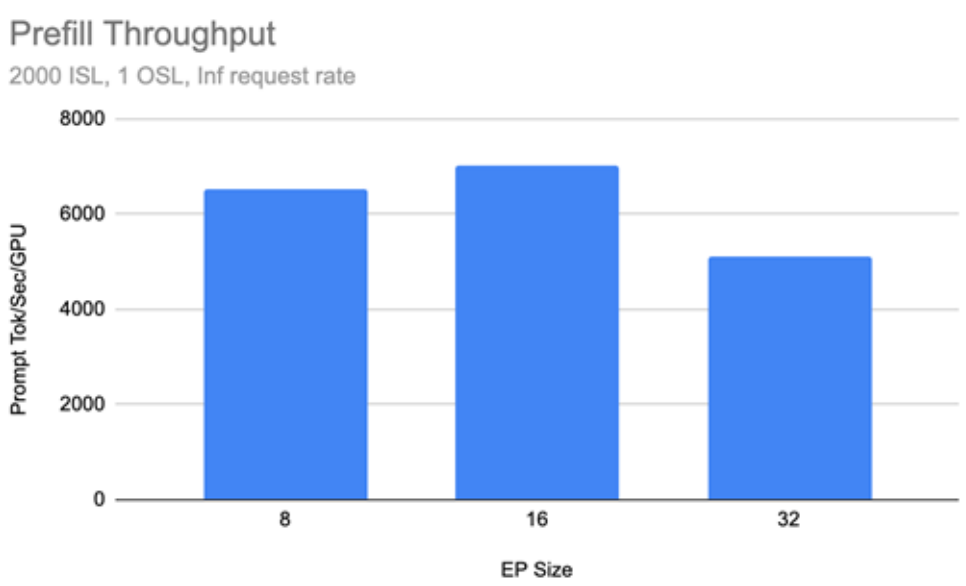
Wide Expert Parallelism

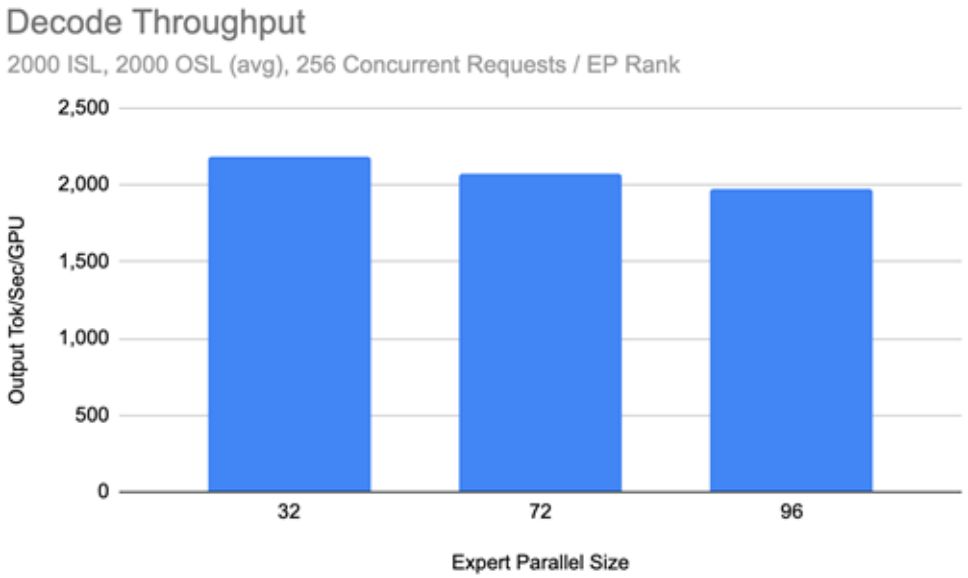
llm-d's K8s-native design integrates EP implementation directly with the broader system, including DP-aware load balancing



Wide Expert Parallelism

Reached **2.2k tokens/s per H200 GPU** for DeepSeek-R1 in community benchmarks on H200 clusters





State-of-The-Art performance from deep GPU and scheduler optimizations across the full inference stack

https://llm-d.ai/blog/llm-d-v0.3-expanded-hardware-faster-perf-and-igw-ga

To Conclude

Key Takeaways

01

KV-Cache Hit Rate Is the #1 Production Metric

A 10× cost gap separates cached from uncached tokens. Standard load balancing destroys this. It's not a nice-to-have — it's your inference margin.

02

llm-d Delivers Real Wins Out of the Box

Prefix-aware scheduling alone: 57× faster TTFT, 2× throughput. P/D disaggregation, expert parallelism, and KV offloading compound gains further.

03

Semantic KV-Cache Is the Next Frontier

Smart (semantic-aware) instead of just raw tokens .

Join the llm-d Community!

llm-d https://llm-d.ai/

Open source. Kubernetes-native.
Your contributions matter.

GitHub

github.com/llm-d/llm-d

github.com/llm-d/llm-d-kv-cache

github.com/llm-d/llm-d-inference-scheduler

Slack (llm-d workspace)

#sig-kv-disaggregation

#sig-inference-scheduler

Slack (vLLM workspace)

#feat-v1-cpu-offloading

#feat-kvcache-offloading

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