vLLM

V1 Update & Q1 Roadmap

The vLLM Meetup at Google Cloud

The vLLM Team

Agenda

- V1 Deep Dive (Woosuk)
- vLLM’s Q1 Roadmap (Simon)

vLLM's Goal

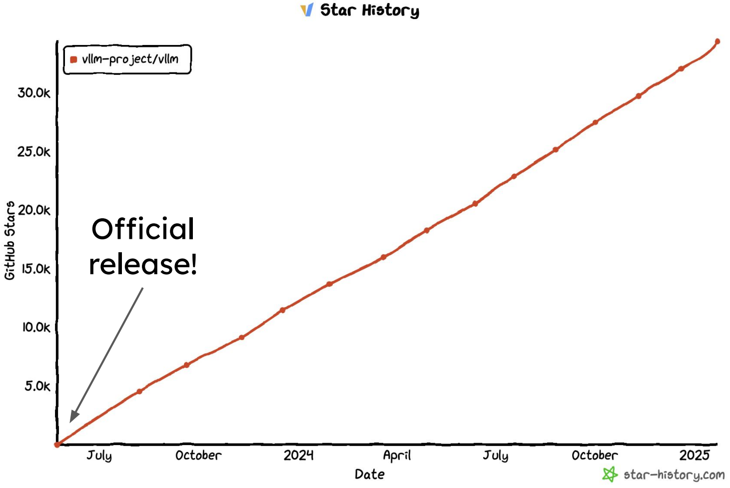
Build the fastest and easiest-to-use open-source LLM inference & serving engine

vLLM Today

https://github.com/vllm-project/vllm

`$ pip install vllm`

34.5K Stars



vLLM API (1): `LLM` class

A Python interface for offline batched inference

```python
from vllm import LLM

# Example prompts.
prompts = ["Hello, my name is", "The capital of France is"]
# Create an LLM with HF model name.
llm = LLM(model="meta-llama/Meta-Llama-3.1-8B")
# Generate texts from the prompts.
outputs = llm.generate(prompts) # also llm.chat(messages)]
```

vLLM API (2): OpenAI-compatible server

A FastAPI-based server for online serving

Server

```
$ vllm serve meta-llama/Meta-Llama-3.1-8B
```

Client

```
$ curl http://localhost:8000/v1/completions \
    -H "Content-Type: application/json" \
    -d '{
        "model": "meta-llama/Meta-Llama-3.1-8B",
        "prompt": "San Francisco is a",
        "max_tokens": 7,
        "temperature": 0
    }'
```

vLLM V1

Woosuk Kwon

What is vLLM V1?

Re-architect the "core" of vLLM

based on the lessons from V0 (current version)

Unchanged

- **User-level APIs**
- **Models**
- GPU Kernels
- Utility functions
- …

Changed

- Scheduler
- Memory Manager
- Model Runner
- API Server
- …

Why vLLM V1?

- Main goals:
    - Simple & easy-to-hack codebase
    - High performance with near-zero CPU overheads
    - Combining all key optimizations & enabling them by default

Key changes in vLLM V1

1. Optimized engine loop & API server

2. Simplified scheduler

3. Clean implementation of distributed inference

4. Piecewise CUDA graphs

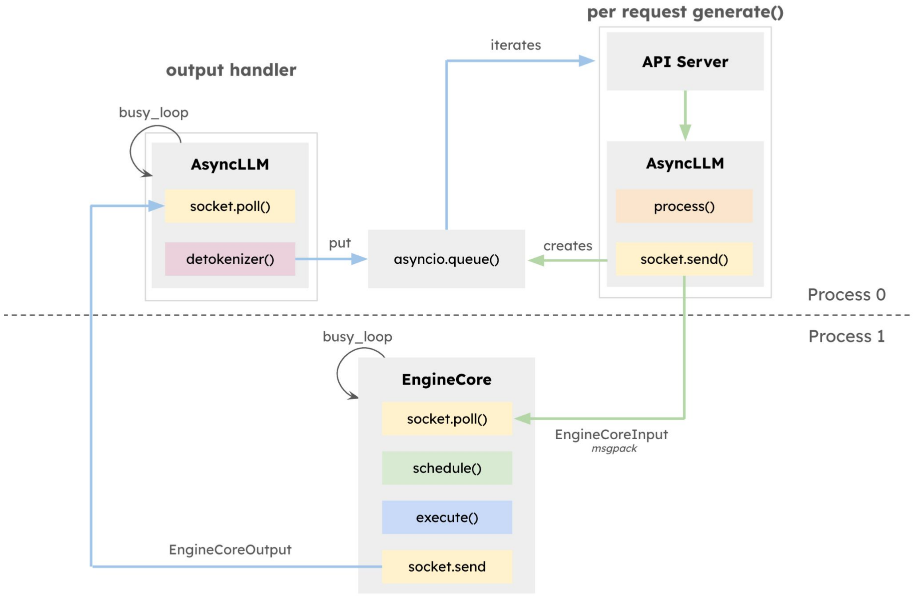
Optimized Engine Loop & API Server

Goal: Make sure GPU is not stalled

- By pre-processing
  - E.g., converting JPEG images into input tensors (resizing, cropping, …)
- By post-processing
  - E.g., de-tokenizing output token IDs into output strings
- By HTTP request handling
  - E.g., streaming outputs to 100s of concurrent users

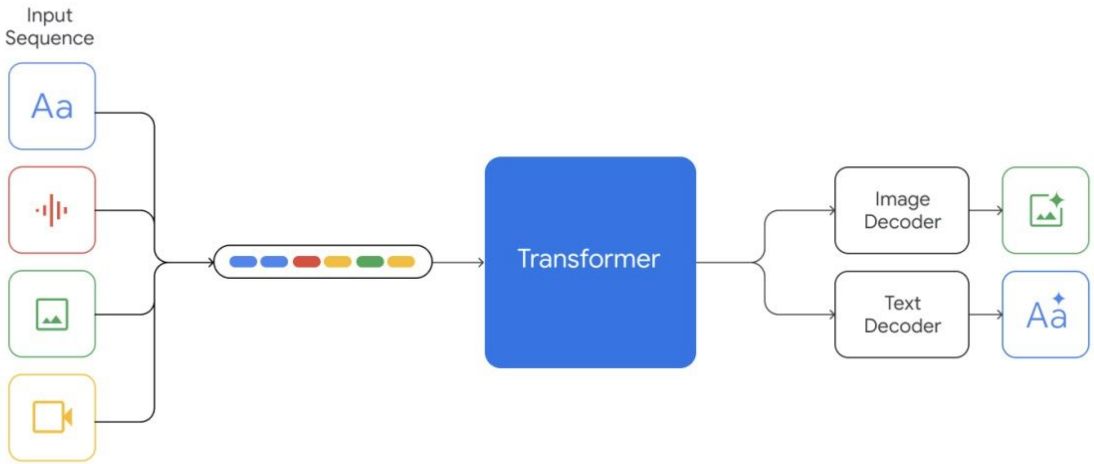
Optimized Engine Loop & API Server (cont'd)

- Two-process approach
  - Process 0 (Frontend): Pre-/post-processing & API Server
    - Importantly, de-tokenization happens in Process 0
  - Process 1 (EngineCore): Schedule & execute the model every step
    - A busy loop that is NOT blocked by Process 0



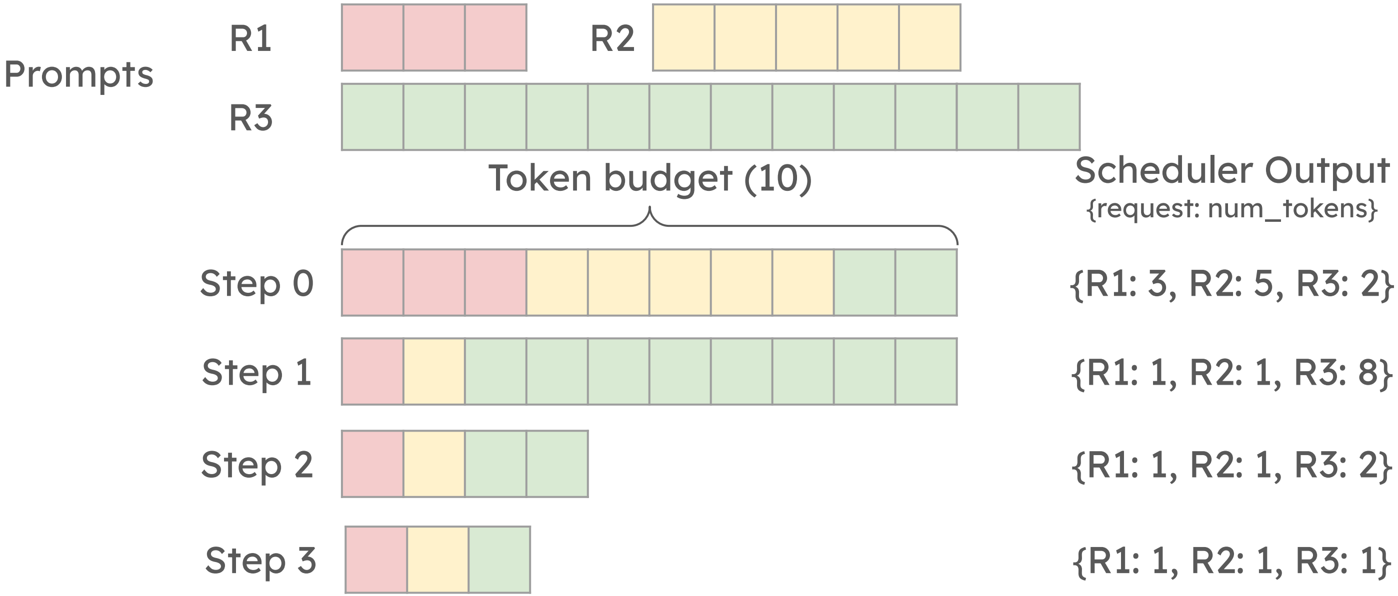
Optimized Engine Loop & API Server (cont'd 2)

- We are not there yet!
  - How to handle emerging modalities such as videos and audios?
  - It would be increasingly difficult to build a fast & reliable server
- We would like to solicit for more community engagement & contributions



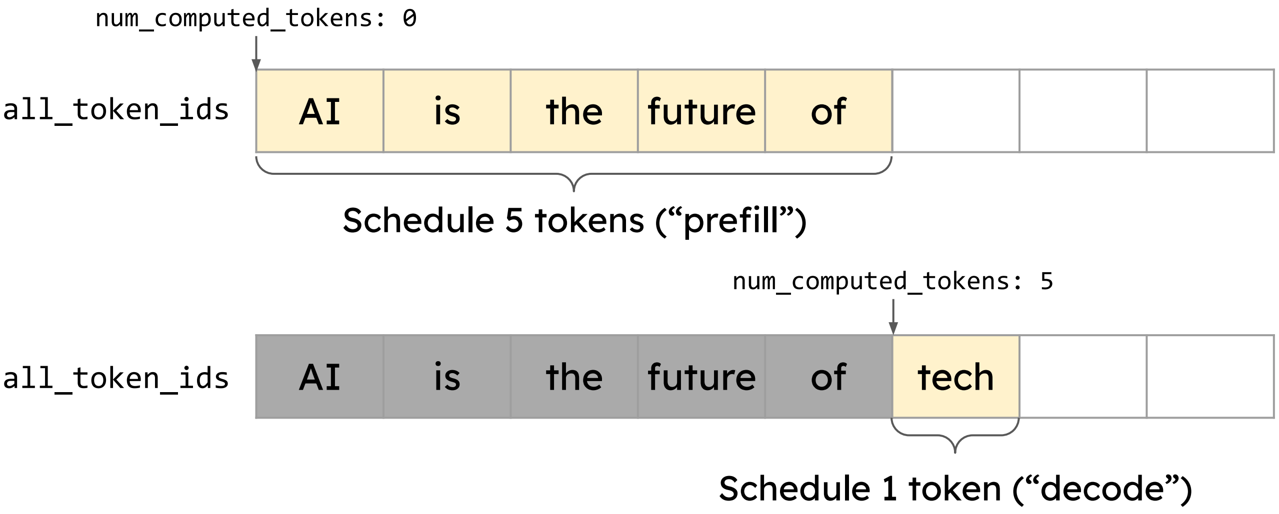
Simplified Scheduler

- Synchronous single-step scheduler
- Chunked prefills (aka Dynamic SplitFuse) by default
    - The scheduling decision is simply represented as a dictionary of `{request_id: num_tokens}`



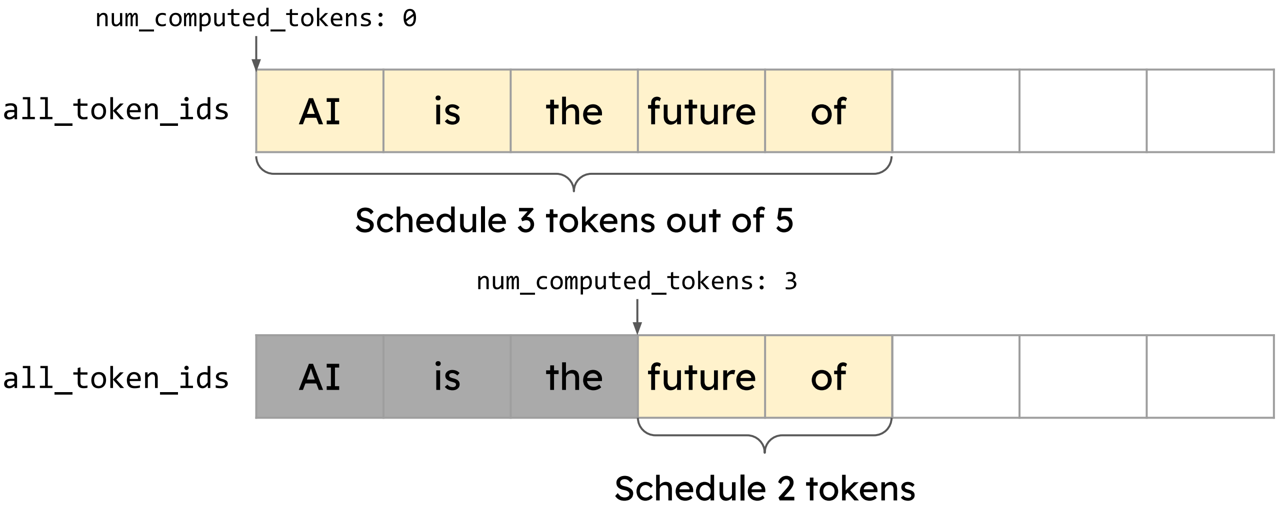
Simplified Scheduler (cont'd)

- Unification of "prefill" and "decode"
  - In V1, there's no concept of prefill and decode
  - Schedule based on the difference between `num_compute_tokens` and `len(all_token_ids)`
- Ex1) "Prefill" & "Decode"



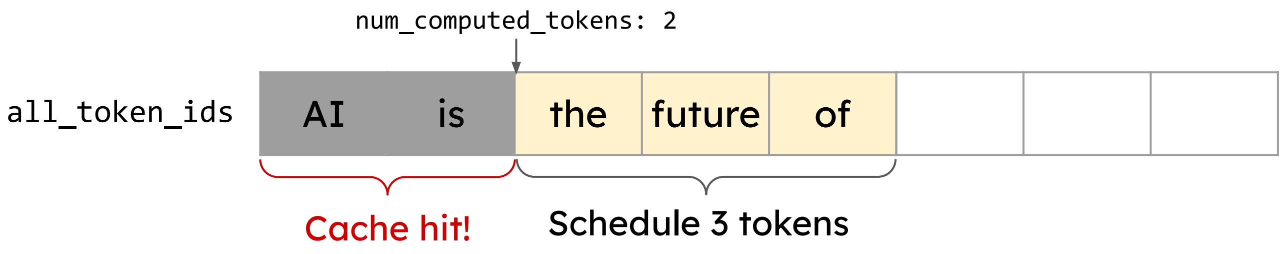
Simplified Scheduler (cont'd)

- Unification of "prefill" and "decode"
  - In V1, there's no concept of prefill and decode
  - Schedule based on the difference between `num_compute_tokens` and `len(all_token_ids)`
- Ex2) Chunked prefills



Simplified Scheduler (cont'd)

- Unification of "prefill" and "decode"
  - In V1, there's no concept of prefill and decode
  - Schedule based on the difference between `num_compute_tokens` and `len(all_token_ids)`
- Ex3) Prefix caching



Simplified Scheduler: Next Steps

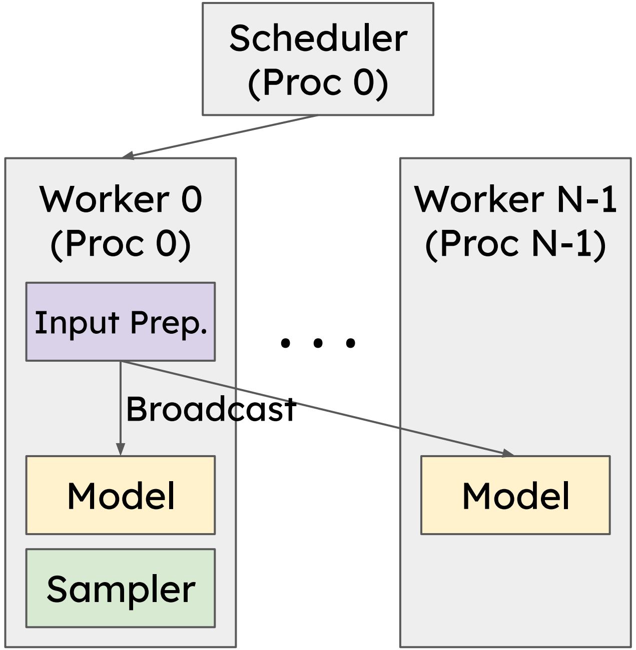
- Current: First-come-first-served policy is baked in the scheduler

- Next step 1: Support various scheduling policies
  - Priority-based scheduling
  - Fair scheduling
  - Predictive scheduling

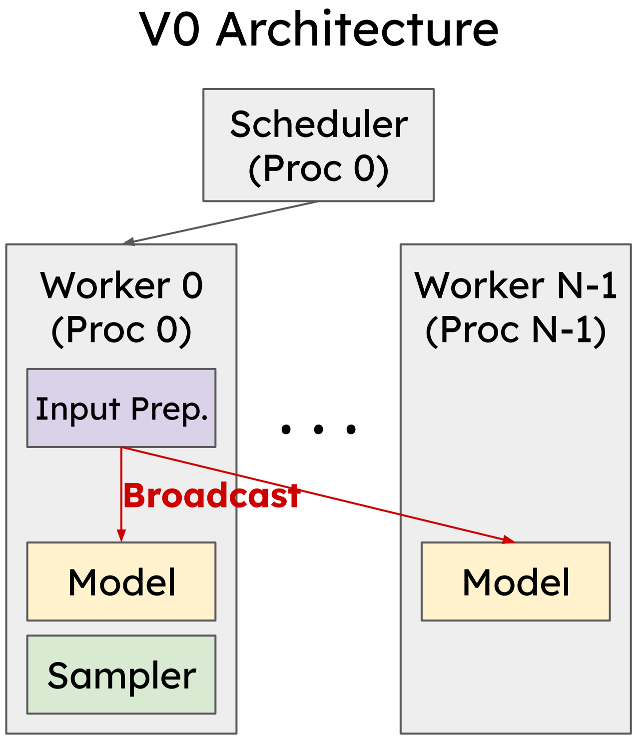
- Next step 2: Pluggable scheduler
  - E.g., workload-specific scheduler
  - E.g., different schedulers for different hardware backends

Clean Implementation of Distributed Inference

V0 Architecture

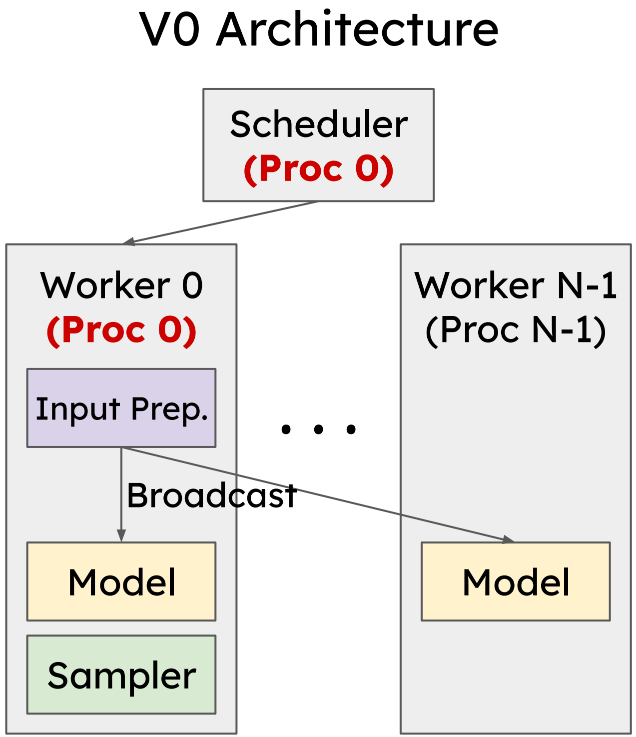


Clean Implementation of Distributed Inference



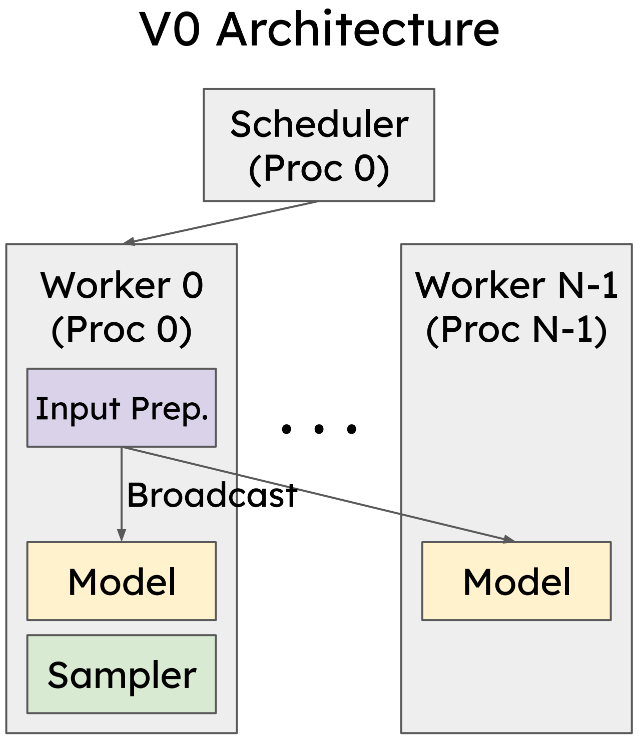
- Problem 1: Broadcasting whole input tensors every step
  - Significant communication overheads

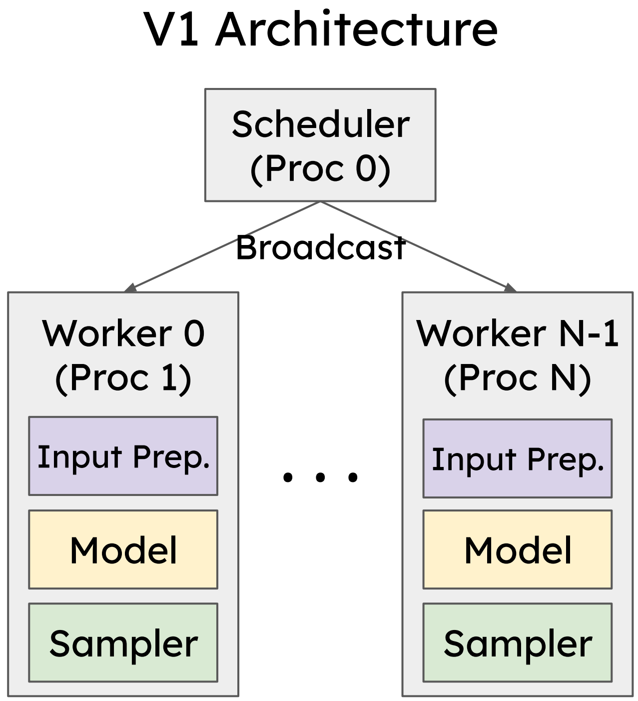
Clean Implementation of Distributed Inference



- Problem 1: Broadcasting whole input tensors every step
  - Significant communication overheads
- Problem 2: Scheduler and Worker 0 share the same process
  - Increased complexity due to the asymmetric architecture

Clean Implementation of Distributed Inference

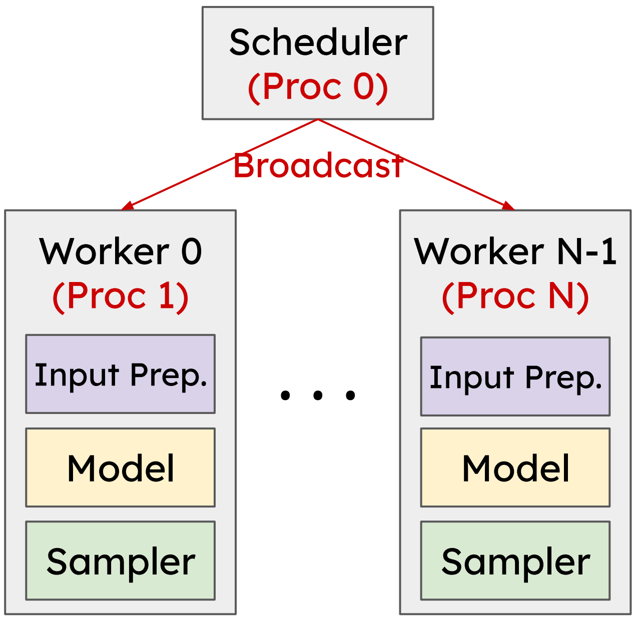




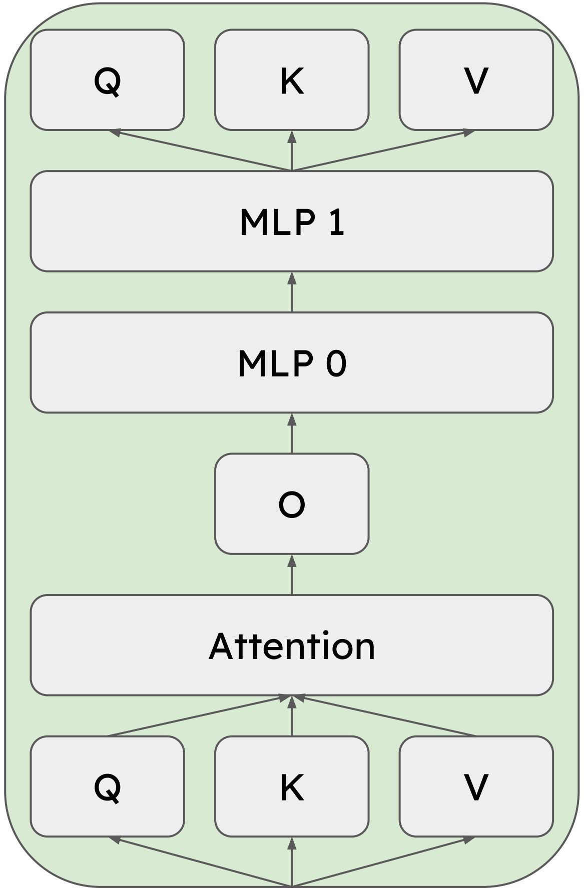
Clean Implementation of Distributed Inference

- Broadcasting the scheduler outputs (Python data structures)
  - Key optimization: Only sending the diff every step by caching the request states in the worker
- Symmetric architecture
  - Each worker has its own process
  - No code divergence between worker 0 and other workers
- Overall, most of the code for distributed inference is abstracted away

V1 Architecture



Piecewise CUDA Graphs



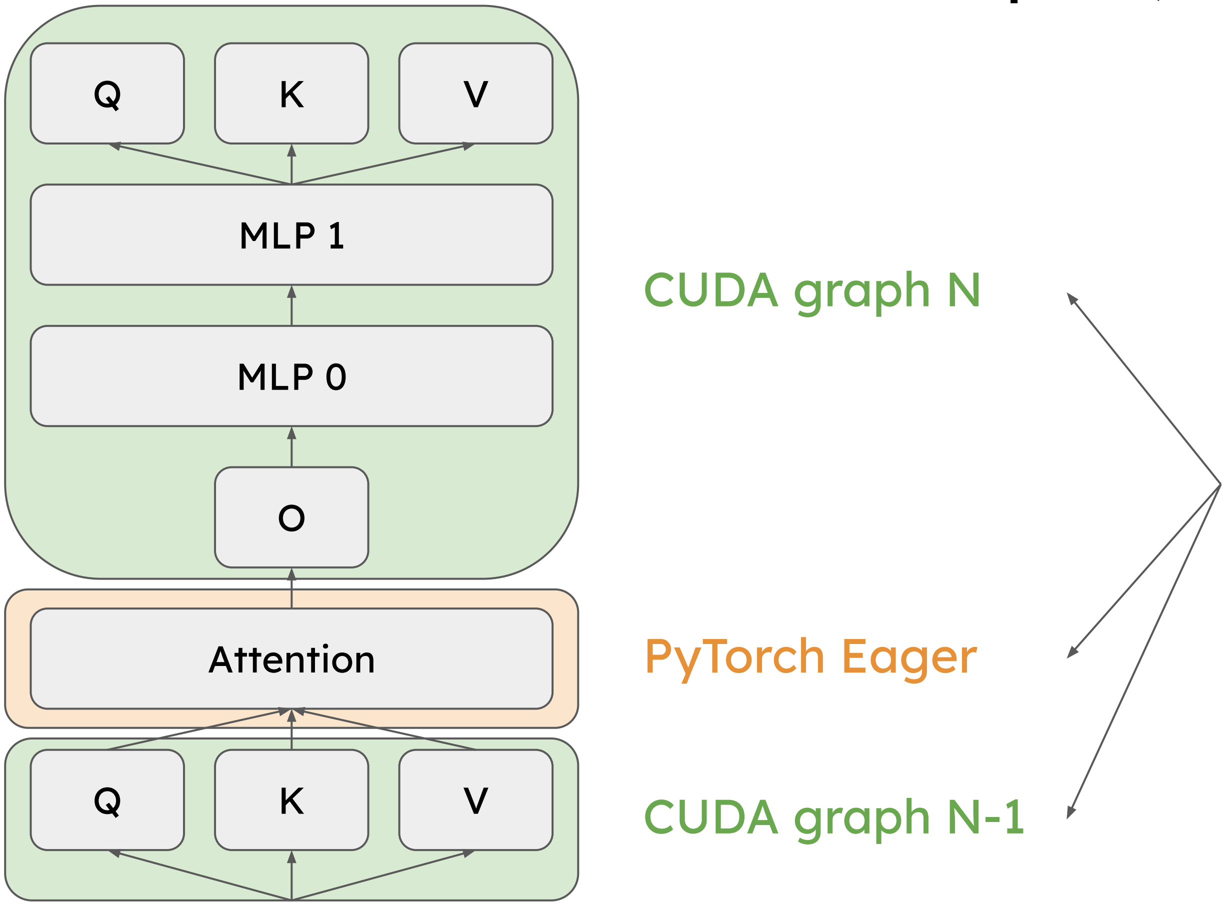
- V0: Single CUDA graph for the entire model

- Pros: Minimal CPU overheads in model execution

- Cons: Limited flexibility
  - Static shapes are required
  - No CPU operations are allowed

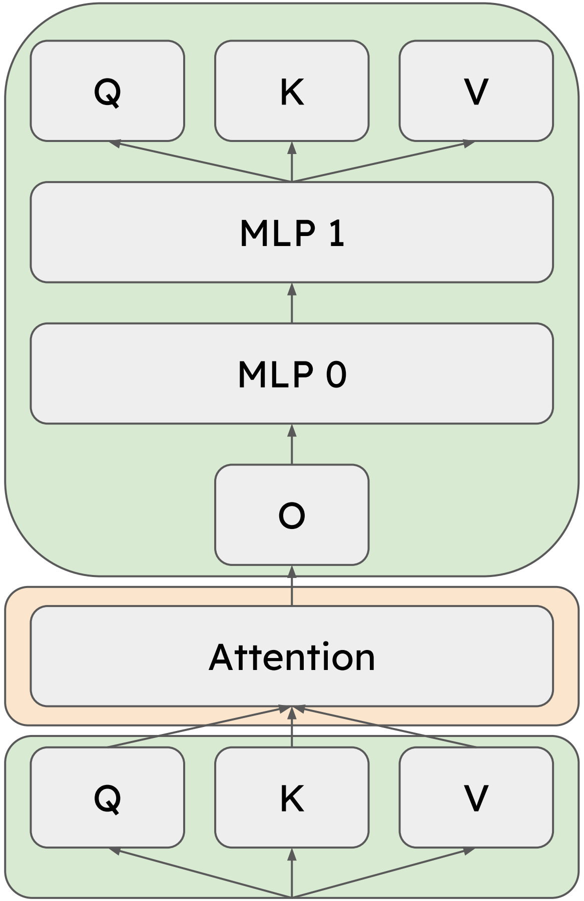
  → Increased development burden

Piecewise CUDA Graphs (cont'd)



Graph split using [torch.compile]()

Piecewise CUDA Graphs (cont'd)



- V1: Splits the model into pieces
  - Runs the attention op in eager-mode PyTorch
  - Runs other ops with CUDA graphs
    - Easy to capture, since the ops are token-wise
    - Critical to capture the all-reduce op

- Pros: Maximum freedom in implementing the attention op
  - No restriction on shapes
  - Any CPU operations are allowed

- Cons: CPU overheads unhidden by CUDA graphs could slow down the model execution
  - Negligible for 8B+ models on H100

Use Case: Cascade Attention for System Prompts

- What is system prompt?
  - A text prefix describing the task, style, tools, safety rules, etc.
  - Typically shared for all requests to the model
  - The length varies a lot by models & applications
    - E.g., Copilot: ~570 tokens, ChatGPT-4o: ~1200 tokens, Sonnet 3.5: ~2400 tokens

```
You are an AI programming assistant.
When asked for your name, you must respond with "GitHub Copilot".
Follow the user's requirements carefully & to the letter.
Follow Microsoft content policies.
Avoid content that violates copyrights.
...
```

Use Case: Cascade Attention for System Prompts

- What is system prompt?
  - A text prefix describing the task, style, tools, safety rules, etc.
  - Typically shared for all requests to the model
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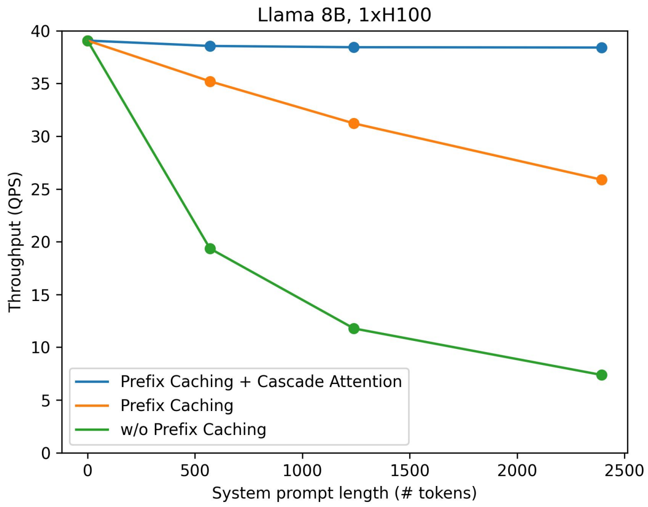
- What is cascade attention?
  - Proposed by Zihao Ye (UW) et al.
  - A GPU kernel trick to optimize attention with shared KV cache
  - Was difficult to integrate because the trick makes the kernel more dynamic, making it less compatible with CUDA graph

Use Case: Cascade Attention (cont'd)

- Thanks to piecewise CUDA graphs, vLLM V1 was able to smoothly integrate cascade attention and enable it by default
  - Automatically detects the system prompt & applies the optimization

- Performance improvements
  - ShareGPT + system prompts of varying lengths
  - 0–50% throughput increase
  - Makes the system prompt almost free



Potential Use Cases of Piecewise CUDA Graphs

Piecewise CUDA graphs will allow vLLM to easily integrate new optimizations such as:

- KV cache offloading to CPU memory (#11532)
- KV cache offloading to disk
- Sparse KV cache
- Brand-new attention algorithms
- . . .

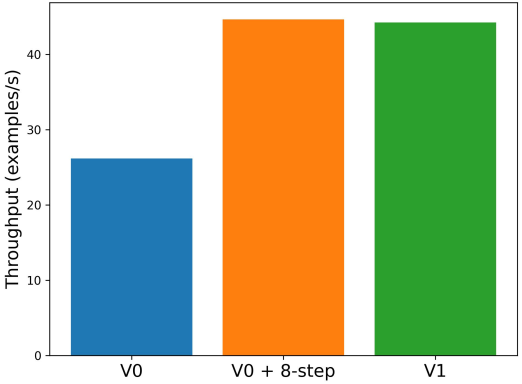
Other Important Enhancements in V1

- FlashAttention 3 integration
  - Also available in V0
- Prefix caching for image inputs
  - Useful for multi-turn chat with images
- Miscellaneous Python-level optimizations
  - Avoid frequently creating new objects
  - Minimize garbage-collection overhead
- . . .

V1 Engine Performance (Llama 3 8B)

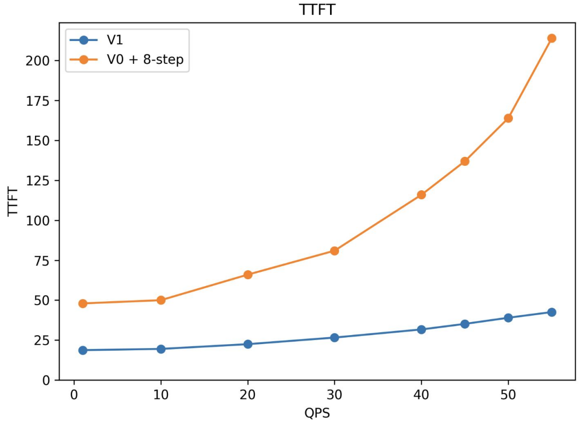
Offline Inference (ShareGPT)

Throughput

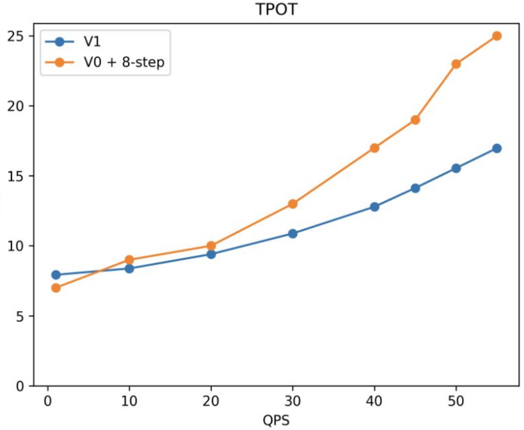


Online Serving (ShareGPT)

Time-to-first-token



Time-per-output-token



- Same throughput as V0 + 8-step scheduling
- Lower TTFT & TPOT than V0 + 8-step scheduling

V1 Current Status

- Will do **alpha** release very soon
  - The code can be found in [vllm/v1/]
- Set `VLLM_USE_V1=1` to use the V1 engine
  - Same end-user APIs as V0 (OpenAI server & `LLM` class)

- Supported models
  - Decoder-only Transformers (e.g., Llama, Mixtral)
  - Llava-style VLMs (e.g., Pixtral, Qwen2-VL)
- Features
  - Supported: chunked prefills, prefix caching, tensor parallelism
  - WIP: LoRA, spec decoding, pipeline parallelism, structured outputs
- Only supports NVIDIA GPUs for now
  - Actively working to also integrate other hardware backends

Q1 Roadmap

Simon Mo

vLLM 2025 Vision

1. Support **Emerging** Models
2. **Production** Deployments
3. **Open Architecture**

1. Support Emerging Models

...GPT4o level model in 1 GPU, and very large models

- **Small yet mighty models + large models coexist**
- **System Optimizations for:**
  - KV Cache
  - MoE
  - Long Context
- **Tailored Inference System for:**
  - Reasoning
  - Coding
  - Agents
  - Creative Writing
- **vLLM being used in data curation and RLHF**

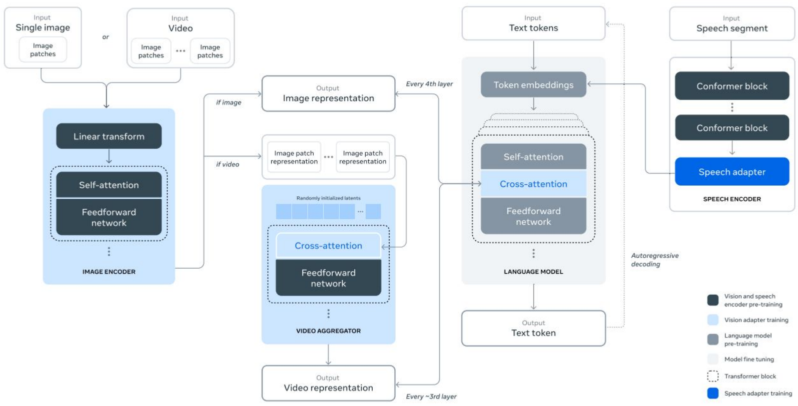
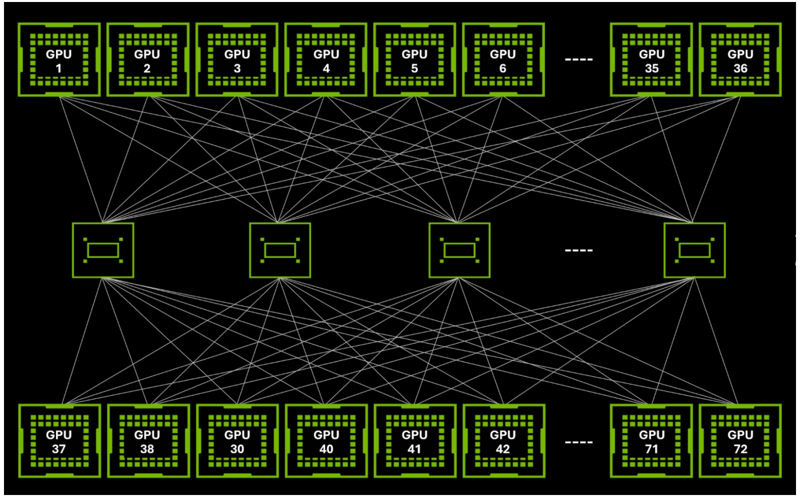


Illustration of adding multimodal capabilities to Llama 3

2. Production Deployment

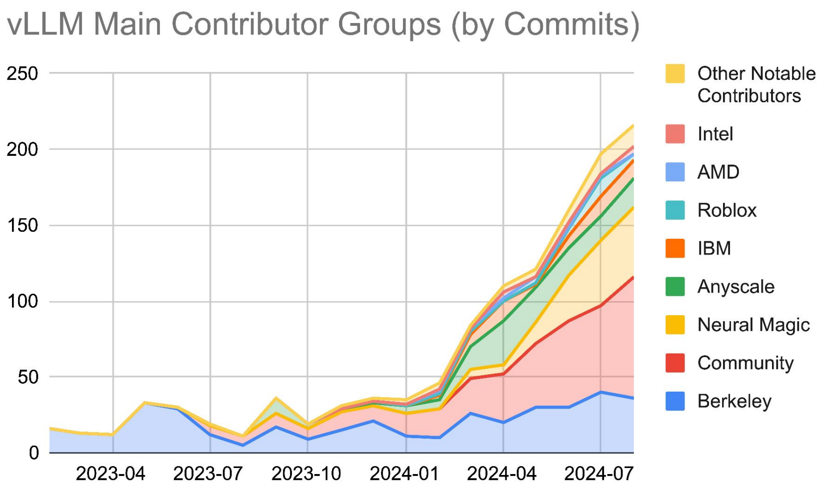
…hundreds of thousands of GPUs scale

- **The year of productionization of scaled deployments**
- **Recipes and ecosystems for routing, caching, and scaling**
- **High performance by default:**
  - Quantization (< FP8, KV Cache, Attention)
  - Speculative Decoding
  - Predicted and Structured Outputs
- **Cluster solutions increase in importance; support for prefill disaggregation**
- **vLLM being tuned for specific models, leading hardwares, and extreme workloads**



3. Open Architecture is Our Key to Adoption

- **A community of passionate users, adopters, and contributors**
- **vLLM can be easily extended and modified**
  - Forks and monetization are welcomed
- **Technically**
  - We will ship a performant yet modular V1 architecture.
  - torch.compile as an extension point for fusion
  - Researchers will build on it for new ideas
  - Users will extend it with private use cases
- **A coordinated engineering organization spanning multiple companies**
- **A positive ROI for everyone involved**



Our Q1 Roadmap

- roadmap.vllm.ai
- vLLM Core
- Emerging Features
- Ecosystem Projects

vLLM Core

- Ship a performant and modular V1 architecture
  - V1 on by default, spec decode, hybrid memory allocator and more!
- Support large and long context models
  - Sparsity in attention and MoEs
  - Disaggregated prefill support
- Improved performance in batch mode
  - RLHF
  - Long Generation

Built-in RLHF support

- If vLLM is an OS,
  - User requests are normal processes running on the OS
  - And the OS also provides "system call" to control the behavior of the system
- RLHF community has been a key driving-factor for adding new "system calls", and vLLM has been their primary inference engine
  - OpenRLHF, veRL, open_instruct, LLaMA-Factory , …
- vLLM provides built-in "system calls" that are difficult to implement out-of-tree
  - Sleep mode: unmap the kv cache and model weights, put vLLM in sleep mode. Give up GPU resource temporarily for training or other models.
- RLHF frameworks can also easily customize and add new "system calls"
  - Provide a new worker class, and use llm.collective_rpc to call the new functions.
  - For more details, please check the PR.

Features

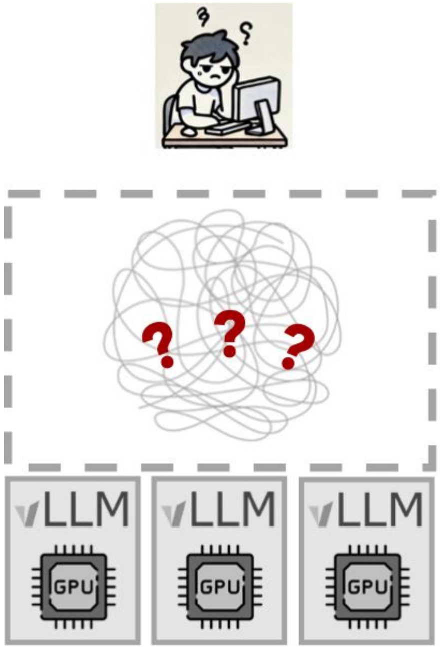
- Model Support
  - Arbitrary HF model
  - Alternative checkpoint format
- Hardware Support
  - Blackwell
  - Improved Tranium/Inferentia, Gaudi
  - Productionize and support large scale deployment of vLLM on TPU
  - Out of tree support for IBM Spyre, Ascend, Tenstorrent
- Optimizations
  - AsyncTP/Flux
  - FlashAttention
- Usability
  - Multi-platform wheels and distributions

Ecosystem Projects

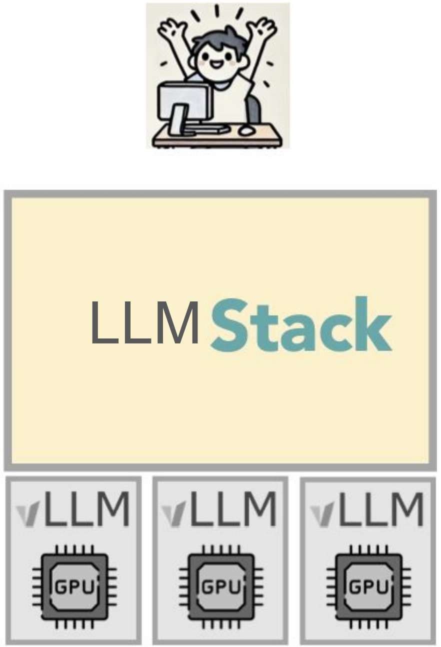
- Distributed batch inference
- Large scale serving
- Prefix aware router
- Multi-modality output

vLLM ecosystem project: LLM inference stack

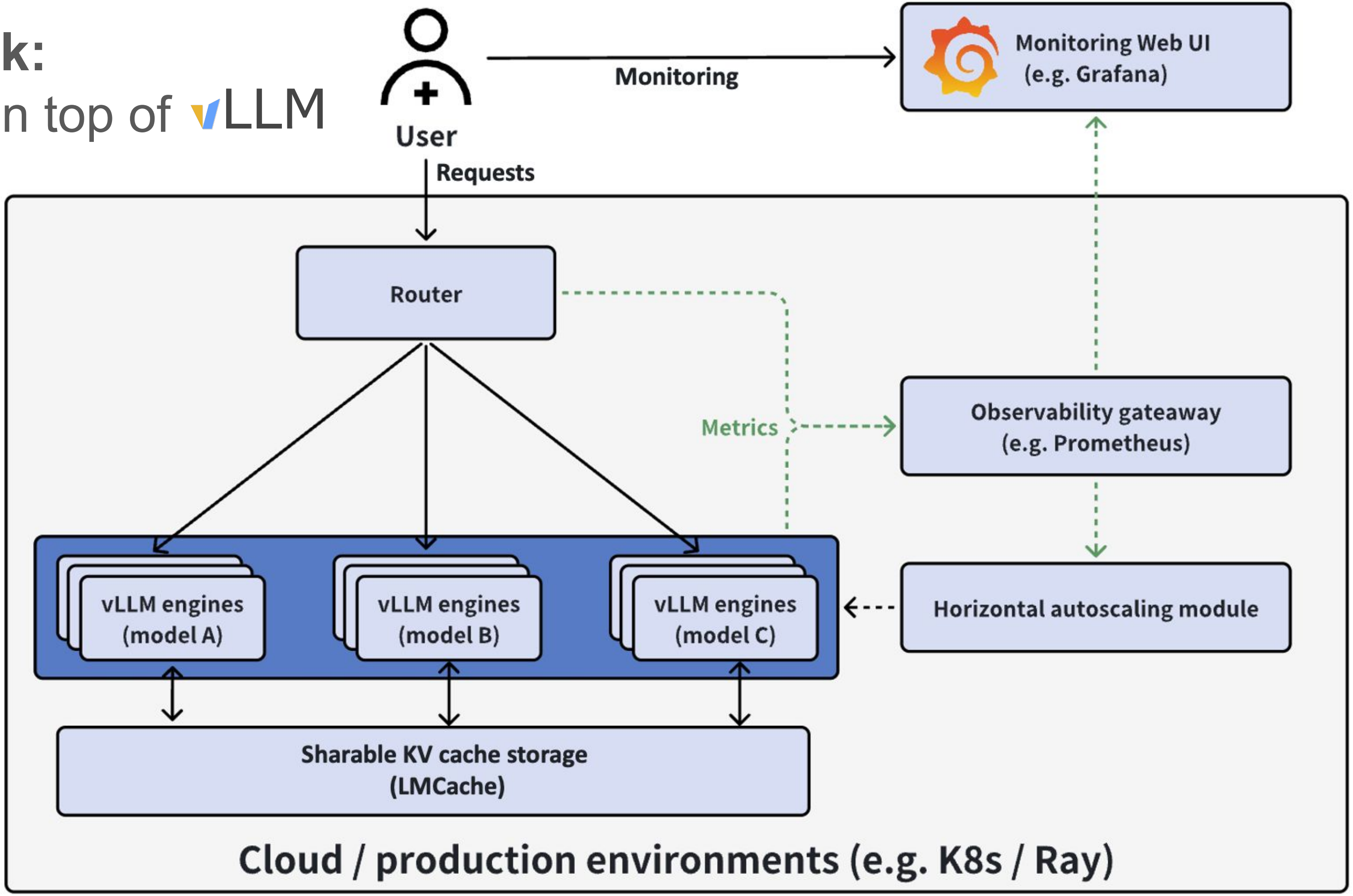
vLLM $\xrightarrow{???}$ LLM service



A stack on top of vLLM!



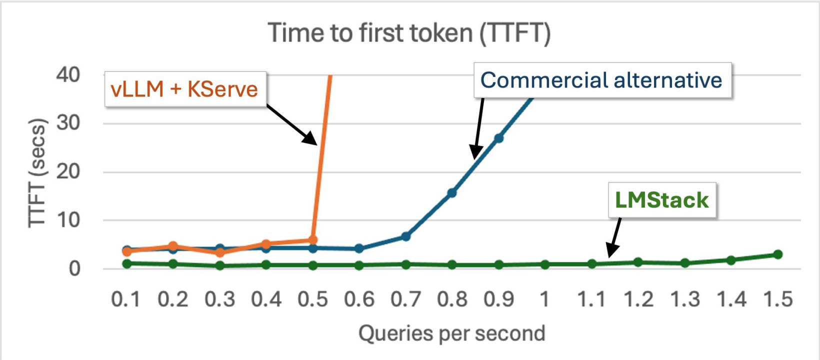
LLMStack:
A **Stack** on top of vLLM



Key features of **LLMStack**

- **One-click deployable** on kubernetes via `helm install`

- **Optimized performance**
  - **Smart router & KV cache offloading (LMCache)**
  - Handle **2x** more QPS with lower TTFT than commercial alternative!



- Cluster-wide **observability dashboard**

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Our Goal

Build the fastest and easiest-to-use open-source LLM inference & serving engine vLLM

Building the fastest and easiest-to-use open-source LLM inference & serving engine!

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https://twitter.com/vllm_project

https://slack.vllm.ai

https://opencollective.com/vllm