

Google  Extended



Simplifying LLM Serving Pipelines with GKE Inference Gateway

Efficient, Scalable, and Secure LLM Inference with GKE



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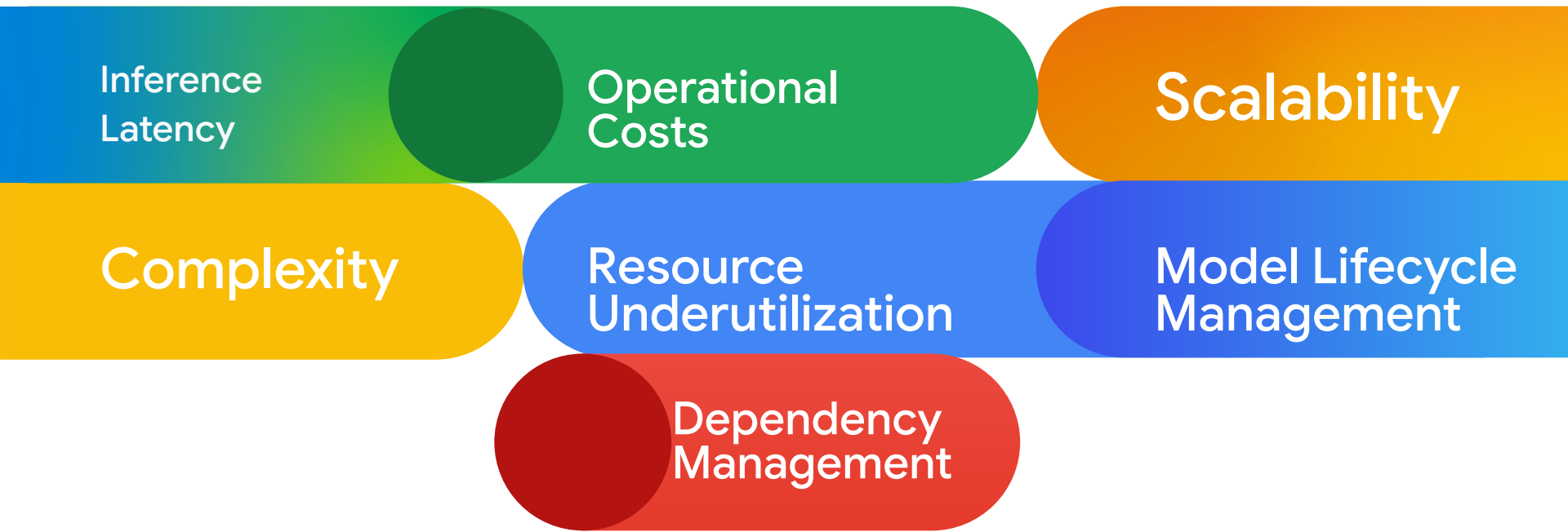




“By leveraging GKE Inference Gateway, organizations can **automate** traffic management, scale LLM inference workloads **efficiently**, and enforce **robust security**—simplifying the operational complexity of production AI pipelines.”

Introduction - The Challenge of AI Inference

AI models are increasingly complex, demanding significant computational resources.

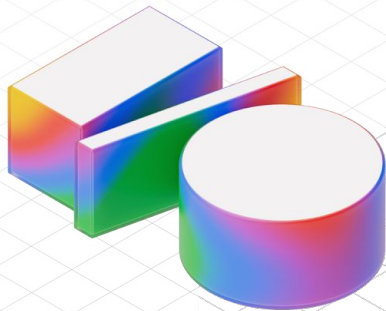


The Challenges

- Organizations deploy Large Language Models (LLMs) for applications like conversational AI, semantic search, and content generation. Production LLM serving introduces challenges:
 - Orchestrating **complex** deployment pipelines for model hosting and inference
 - **Dynamically scaling** compute resources (CPU, GPU, TPU) for bursty traffic
 - Enforcing **secure** authentication, authorization, and network isolation
 - **Optimizing** resource allocation to control costs and maintain performance
 - Integrating monitoring, logging, and tracing for **observability**
 - A managed, cloud-native solution is needed to abstract these complexities, enabling efficient, secure, scalable LLM inference in production.

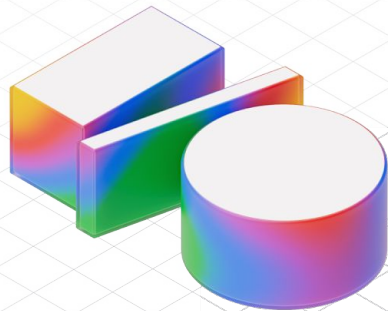
Real-Time Customer Support Chatbot

A company deploys an LLM-powered chatbot to handle customer inquiries on their website. GKE Inference Gateway enables seamless scaling and secure access, ensuring fast, reliable responses even during peak traffic.

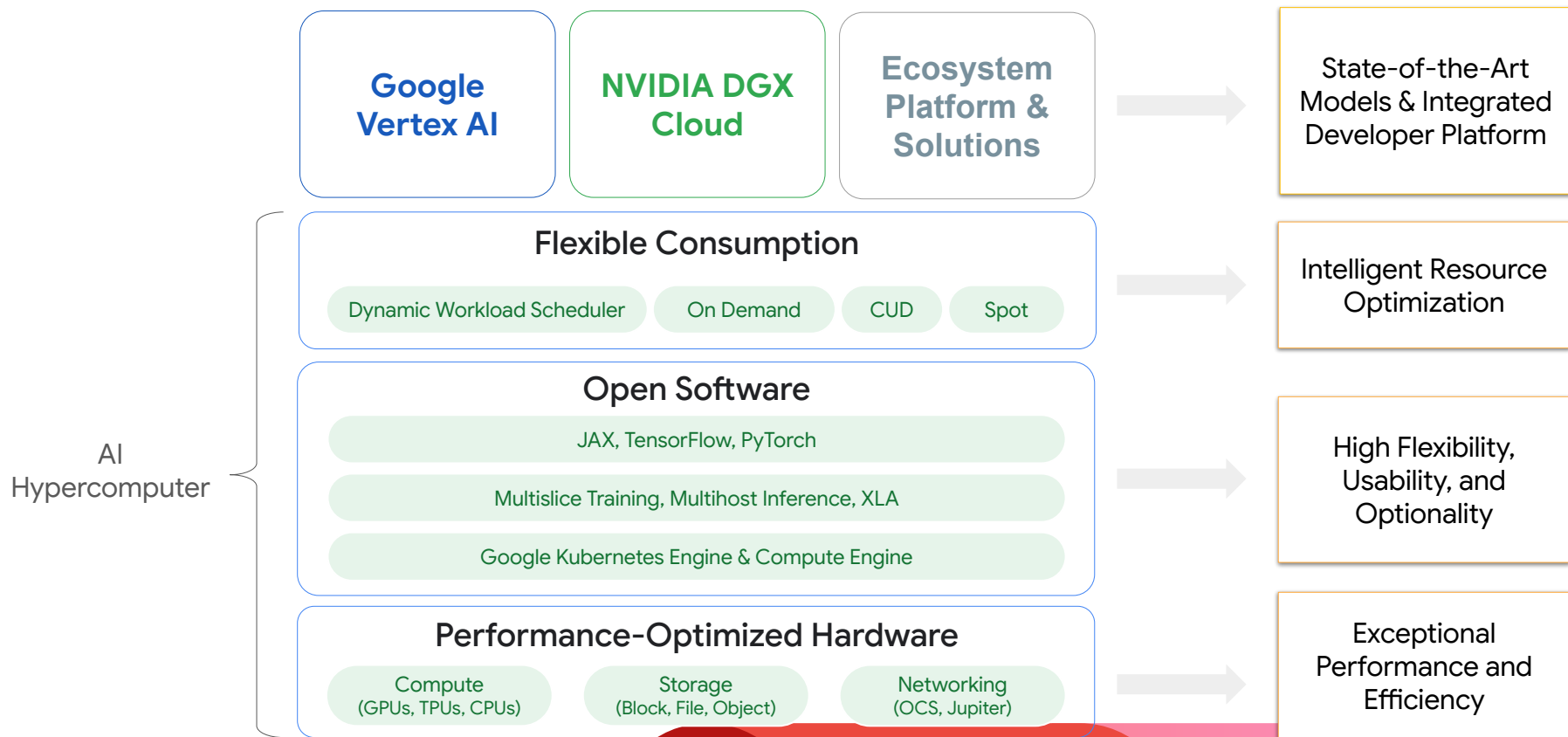


Key Takeaways

- Understand how GKE Inference Gateway **reduces complexity** in deploying and managing LLM serving pipelines.
- Learn best practices for **scalable, secure, and cost-effective** LLM inference on Kubernetes.
- Discover how to leverage managed **traffic routing, autoscaling, and observability** features for production workloads.
- Gain practical insights from real-world deployment examples and actionable steps for your own LLM projects.



AI Hypercomputer Architecture



Google Cloud AI Hypercomputer

Flexible Consumption

Dynamic Workload Scheduler

On Demand

CUD

Spot

Open Software

JAX, TensorFlow, PyTorch

Multislice Training, Multihost Inference, XLA

Google Kubernetes Engine & Compute Engine

Performance-Optimized Hardware

Compute
(GPUs, TPUs, CPUs)

Storage
(Block, File, Object)

Networking
(OCS, Jupiter)

Optimizing system-level co-design streamlines the entire AI lifecycle—from training to tuning and serving



Google Kubernetes Engine

cloud native infrastructure for AI training and inference

- **Limitless Scale:** Deploy AI at industry-leading scale, supporting thousands of TPUs and nodes.
- **Cost-Efficient Performance:** Maximize price-performance with smart GPU/TPU use, job queuing, and fast provisioning.
- **Effortless Ops:** Focus on models, not infra, with GKE Autopilot's managed, optimized Kubernetes.
- **Enterprise Reliability:** Trust AI workloads to the leading Kubernetes contributor's cloud-native infra.



Google Kubernetes Engine

Open Software and Frameworks

JAX, TensorFlow, PyTorch, XLA

Jupyter, Ray, KubeFlow, Spark

Distributed Training

Kueue Job Queuing

High Throughput Scaling

Scaled Inference

Autopilot

Pod Fast Starts

Node Provisioning and Autoscaling

Dynamic Workload Scheduler

Flexible Consumption (On-Demand, CUD, Spot)

Google Cloud Infrastructure (CPU / GPU / TPU)

Why Google Kubernetes Engine for AI

1

Portability & Customizability

Choice of frameworks and ecosystem tools that are portable

2

Performance & Scalability

Scale the platform for supercomputer scale training and inference

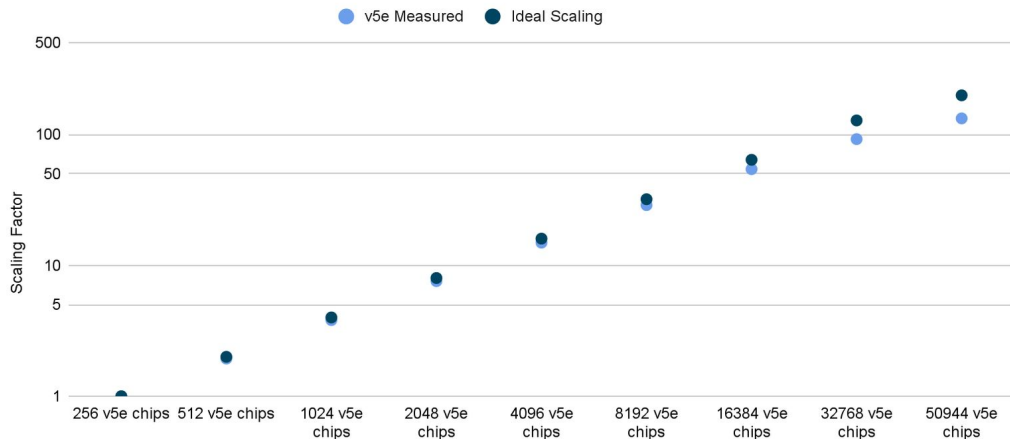
3

Cost-Efficiency

Increase utilization of valuable resources while reducing operational overhead

World's largest distributed training job on GKE with TPU Multislice Training

TPU v5e Efficient Scaling with 32B LLM



Scaled to
50,000+
TPU v5e chips

Google Internal data for TPU v5e As of November, 2023: All numbers normalized per chip. seq-len=2048 for 32 billion parameter decoder only language model implemented using MaxText. *2

What is GKE Inference Gateway?

Managed Inference Serving Layer

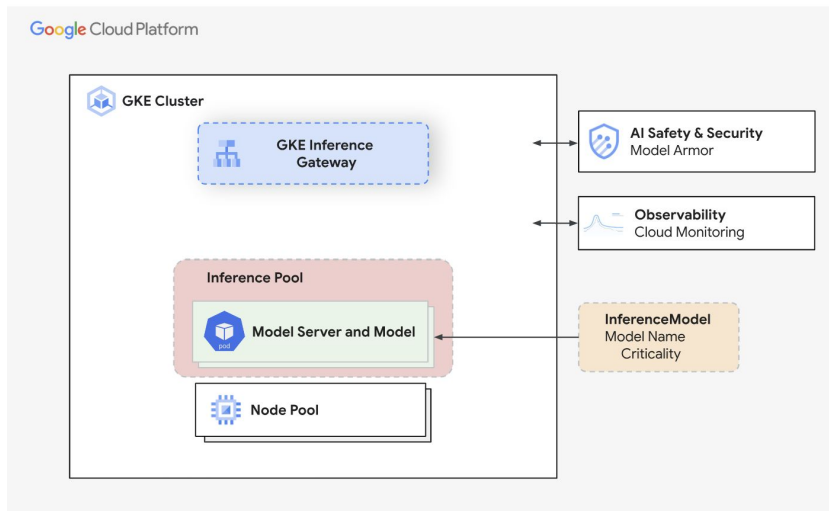
GKE Inference Gateway provides a fully managed, scalable layer for serving machine learning model inferences on Google Kubernetes Engine.

Simplified Traffic Routing

It automatically routes inference requests to the appropriate model endpoints, supporting versioning and canary deployments with minimal configuration.

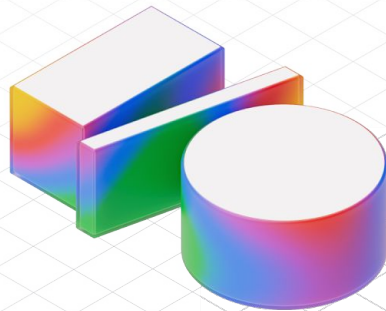
Integrated Security and Observability

The gateway offers built-in authentication, authorization, and monitoring features, enabling secure and observable model serving out of the box.



How the Request Works?

- **Client Request**
 - Client sends a request in **OpenAI API format** to the GKE Inference Gateway.
- **Body-Based Routing Extension**
 - Extracts **model ID** from the request body.
 - Routes request via **Gateway API HTTPRoute** using this identifier.
 - Enables flexible, content-aware routing.
- **Security Extension**
 - Applies **Model Armor** or third-party security policies.
 - Performs **content filtering, threat detection, sanitization, and logging**.
 - Secures both request and response paths.
- **Endpoint Picker Extension**
 - Monitors **KV-cache**, queue lengths, and **LoRA adapter status**.
 - Selects **optimal model replica** based on real-time metrics.
 - Maximizes throughput and reduces inference latency.
- **Final Routing**
 - Request is forwarded to the **chosen model replica** in the **InferencePool**.
 - Model processes and returns the inference result.





Client



GKE Cluster

1

Client request



2

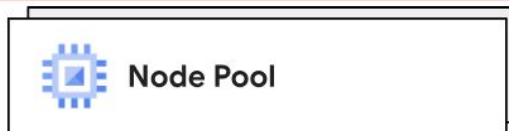
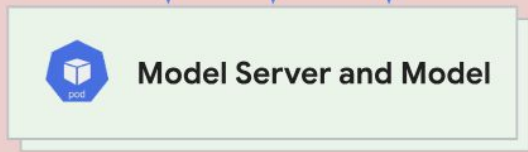
Inference Extensions



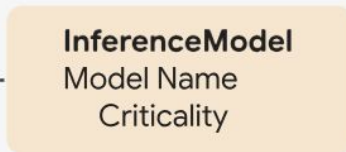
Model-aware request routing

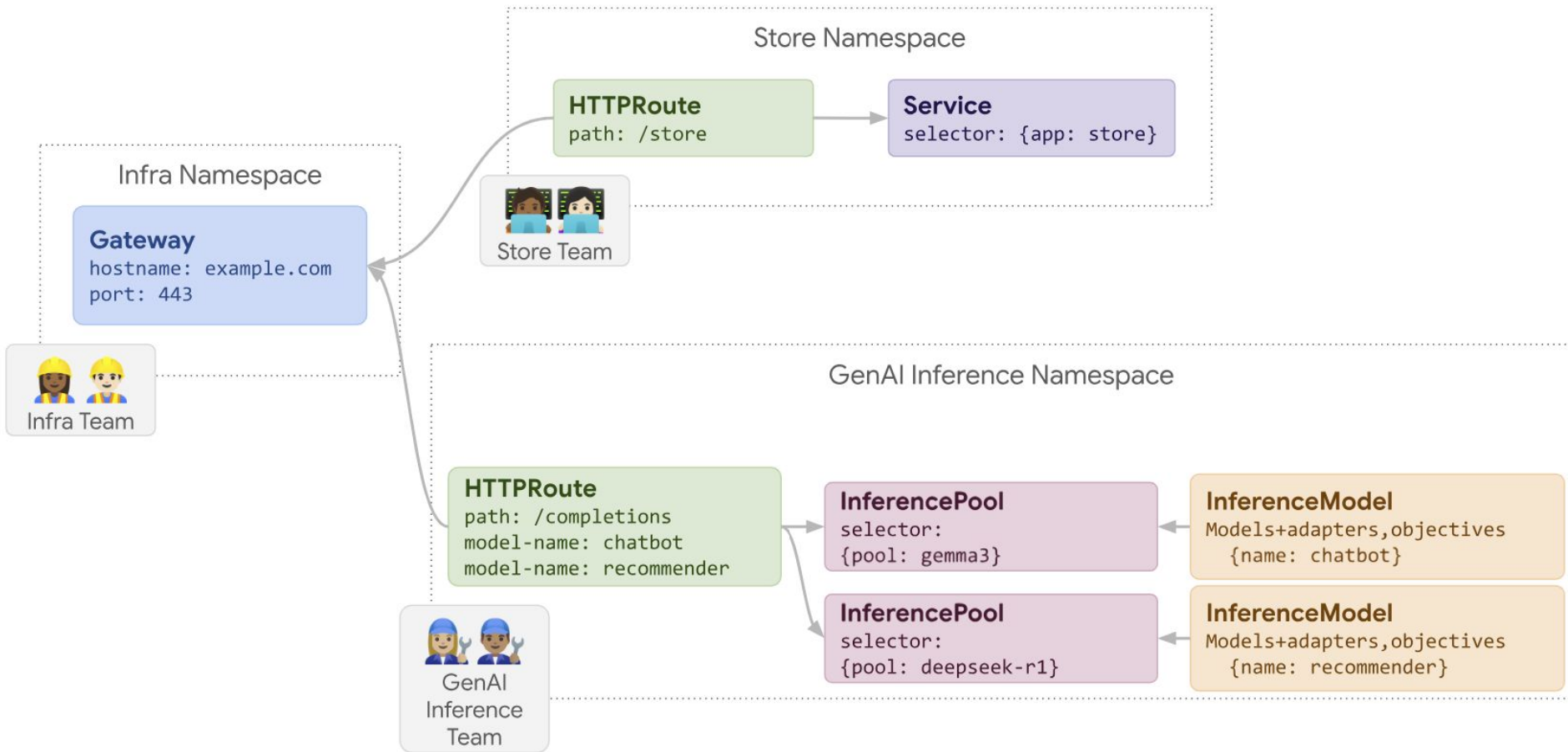
3

Inference Pool



Model server load report





To create an **InferencePool** using Helm, perform the following steps:

```
helm install vllm-llama3-8b-instruct \  
  --set inferencePool.modelServers.matchLabels.app=vllm-llama3-8b-instruct \  
  --set provider.name=gke \  
  --version v0.3.0 \  
  oci://registry.k8s.io/gateway-api-inference-extension/charts/inferencepool
```

Save the following sample manifest as inferencemodel.yaml:

```
apiVersion:
inference.networking.x-k8s.io/v1alpha2
kind: InferenceModel
metadata:
  name: inferencemodel-sample
spec:
  modelName: MODEL_NAME
  criticality: VALUE
  poolRef:
    name: INFERENCE_POOL_NAME
```

Apply the sample manifest to your cluster:

```
kubectl apply -f inferencemodel.yaml
```

Create an **InferenceModel** that serves the **food-review** LoRA model on the **vllm-llama3-8b-instruct** **InferencePool** with **Standard** criticality, while the base model is served with a Critical priority level.

```
apiVersion: inference.networking.x-k8s.io/v1alpha2
kind: InferenceModel
metadata:
  name: food-review
spec:
  modelName: food-review
  criticality: Standard
  poolRef:
    name: vllm-llama3-8b-instruct
  targetModels:
    - name: food-review
      weight: 100

---
apiVersion: inference.networking.x-k8s.io/v1alpha2
kind: InferenceModel
metadata:
  name: llama3-base-model
spec:
  modelName: meta-llama/Llama-3.1-8B-Instruct
  criticality: Critical
  poolRef:
    name: vllm-llama3-8b-instruct
```

Save the following sample manifest as gateway.yaml:

```
apiVersion: gateway.networking.k8s.io/v1
kind: Gateway
metadata:
  name: GATEWAY_NAME
spec:
  gatewayClassName: GATEWAY_CLASS
  listeners:
    - protocol: HTTP
      port: 80
      name: http
```

Apply the sample manifest to your cluster:

```
kubectl apply -f gateway.yaml
```


To create an HTTPRoute, save the following sample manifest as httproute.yaml:

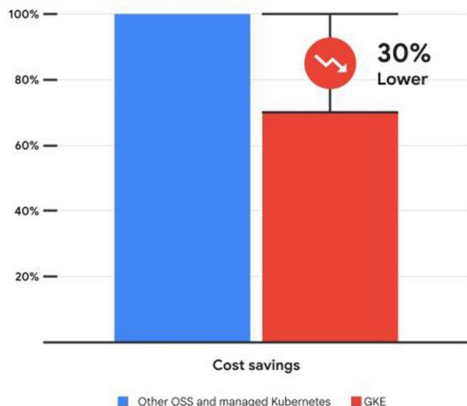
```
apiVersion: gateway.networking.k8s.io/v1
kind: HTTPRoute
metadata:
  name: HTTPROUTE_NAME
spec:
  parentRefs:
  - name: GATEWAY_NAME
  rules:
  - matches:
    - path:
        type: PathPrefix
        value: PATH_PREFIX
    backendRefs:
    - name: INFERENCE_POOL_NAME
      group: inference.networking.x-k8s.io
      kind: InferencePool
```

Apply the sample manifest to your cluster:

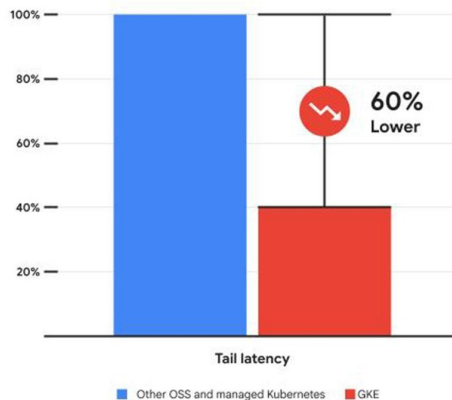
```
kubectl apply -f httproute.yaml
```

GKE Inference Performance

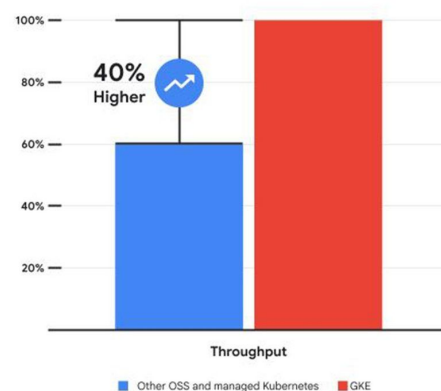
Cost to serve the same demand
(lower is better)



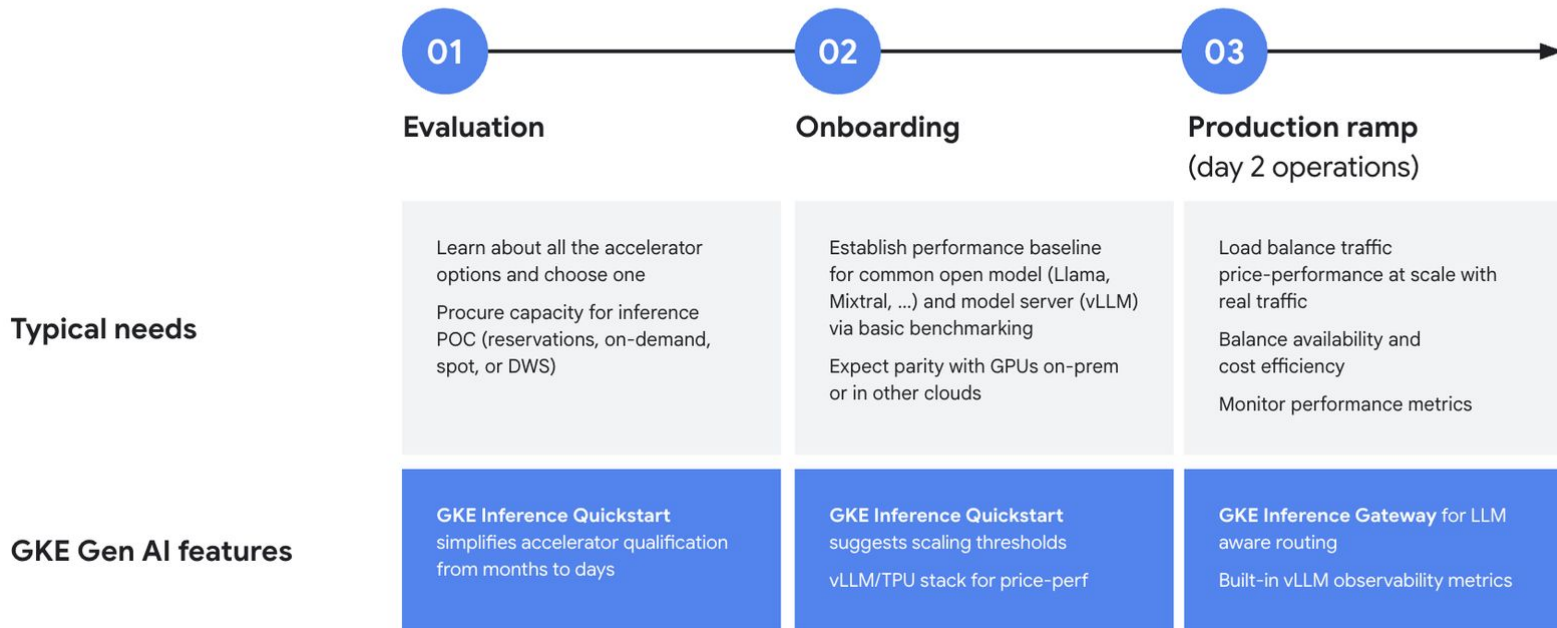
Tail latency of LLM (lower is better)



Throughput of LLM (higher is better)



Solution mapping to customer journey



QnA

(Answers Not Guaranteed)

Thank You