

Connect

I servizi di inferenza per l'Al con HPE e Red Hat Openshift

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Agenda

HPE STRATEGY

HPE MACHINE LEARNING INFERENCE SOFTWARE

HPE | RED HAT OCP INFRASTRUCTURE BLUEPRINT

HPE | RED HAT OCP GPUS CONCURRENCY MODEL

Q&A





HPE Strategy – The key Pillars of Digital Enterprise

Edge

Connect your edge

Control and harness data to innovate at the edge

Data

Turn data into intelligence make smart decisions

Cloud

Create your hybrid cloud

Achieve the cloud experience everywhere

Securit

Secure your data

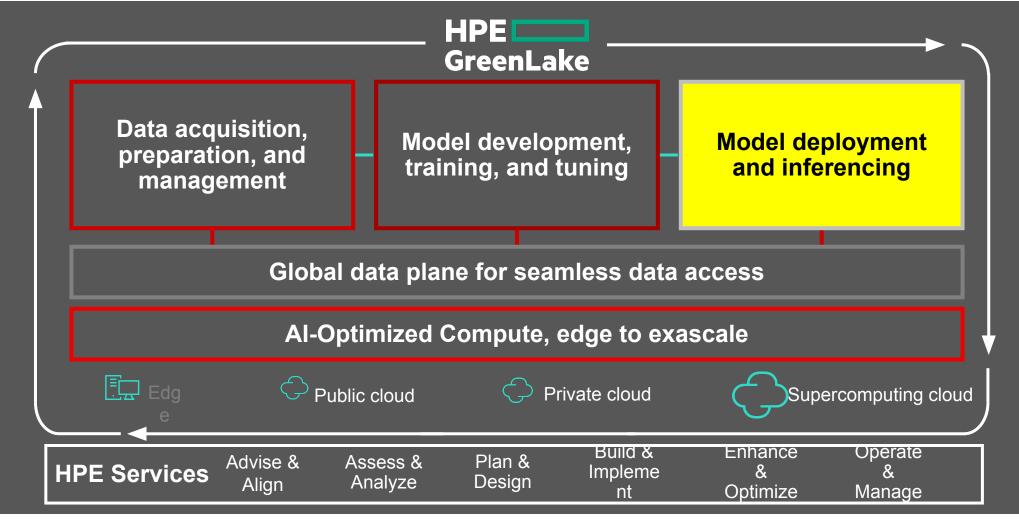
Secure your data from edge to cloud

Sustainability as a catalyst





Unlock your competitive advantage with responsible AI at any scale

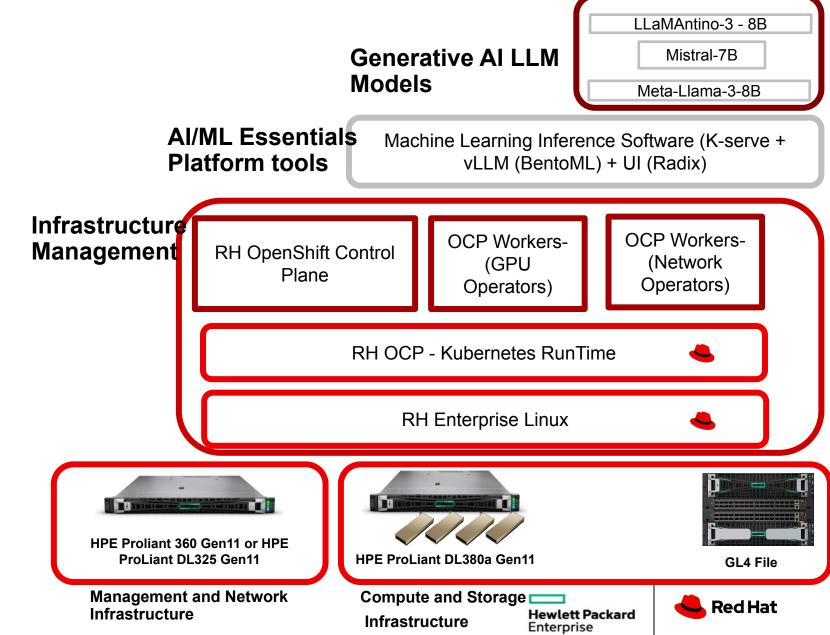




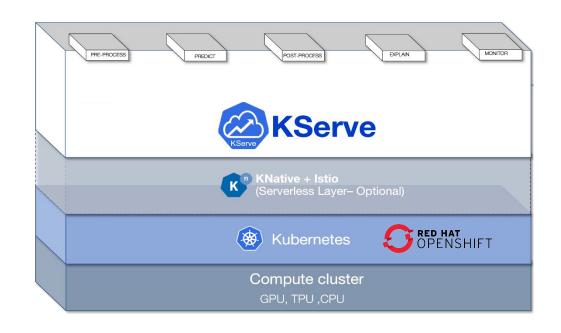


NVIDIA MIG to share the GPUs inside RH OCP

- HW Compute stack based on HPE Proliant Gen11 architecture
- HW Network stack switch at 100GB/s based on Aruba 8325 Switch for data and 6300 Switch for Mgmt at 1GB/s
- HW Storage based on latest GL4File NFS/S3 standard density rack
- Gen Al models choice either import from custom model or foundation models trained
- AI/ML Platform sw tools: choice of HPE MLIS (Machine Learning Inference Software)
- Services: HPE Deployment Inference Startup Service (DIY)

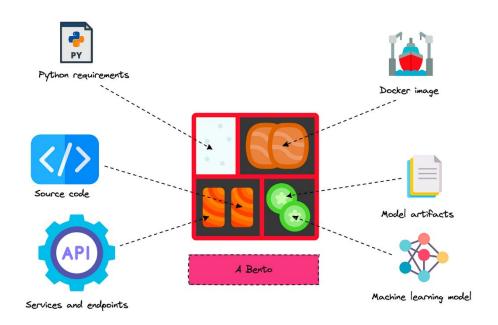


HPE MLIS Open source Components



KServe

- Kubernetes-based platform for deploying models at scale
- Autoscaling, canary rollouts, and batch inferencing capabilities



BentoML

- SDK for standardizing model packaging for services
- Serving standards for REST interfaces, logging, metrics
- OpenLLM Support for optimized LLM deployments
- vLLM tackles the bottleneck of slow LLM inference, optimizing performance RedHat

HPE Developed software Components

• UI/UX

• Interface for managing and monitoring models, services, deployments, access tokens.

Security and authentication

- User management
- Auth integration and access token management

Deployment APIs

- Reduce Kubernetes deployment friction
- CLI and Python-native calls

Inferencing databases

- (Optionally) Capture data predictions
- Integrated logging
- Metrics and Operations
- LLM deployment and support





HPE MLIS Stack

Platform -Kubernetes (v1.20+) -Helm (v3.0+)Knative **External Users** Internal Users e.g., LoB -Istio Feedback Serving **ML Engineer** -Kserve (v0.11+) (MLE) ▼ Services Experimental -BentoML Trained Model Write Service **Build Service** Deploy Service Serving -OpenLLM (Source: MLDE, Logging Hugging Face, NGC −l oki etc.) Metrics -Prometheus **ML Operations** Production Deploy Service (MLOps) -Grafana Serving IT Operations (ITOps) Security **BentoML MLIS KServe** -Dex

• UI

-Radix





Inference Service Deployment for an LLM in 5 steps: 1) connect to a registry Connect to

existing registries:

Connect to your model registry

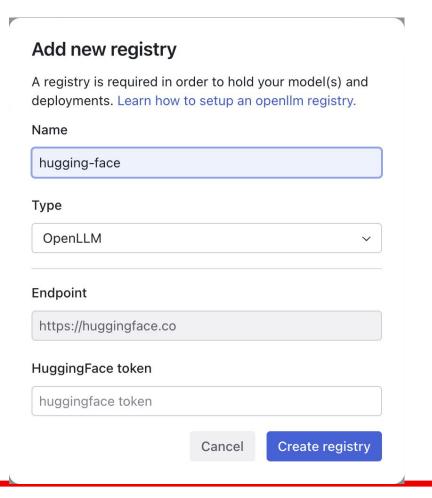
Select model

Configure Resources

Configure Scaling

Interact with your model

- NVIDIA NIM (NGC)
- OpenLLM (Hugging Face)
- AWS S3Bucket
- MinioRegistry







Inference Service Deployment for an LLM in 5 steps: 2) select model from a registry

Connect to your model registry

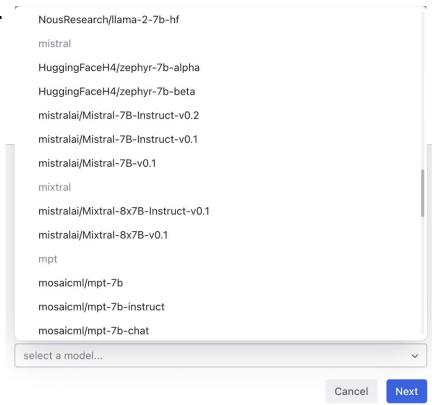
Select model

Configure Resources

Configure Scaling

Interact with your model

Select a model from the registry.







Inference Service Deployment for an LLM in 5 steps: 3) Configure model's resources

Connect to your model registry

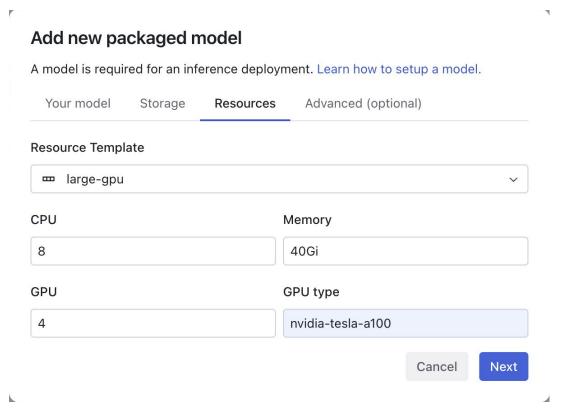
Select model

Configure Resources

Configure Scaling

Interact with your model

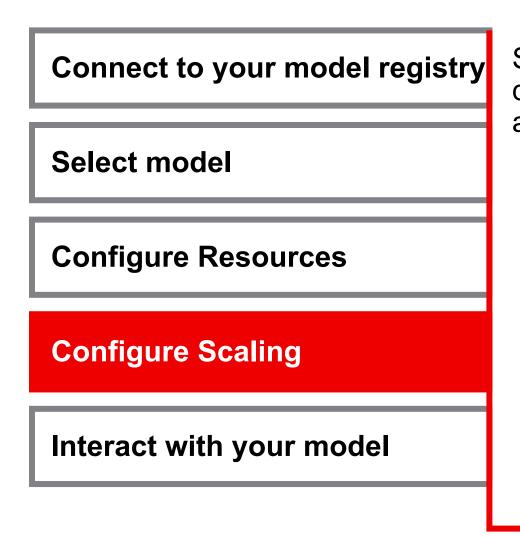
Easily configure resources in the UI.







Inference Service Deployment for an LLM in 5 steps: 4) Set deployment scaling

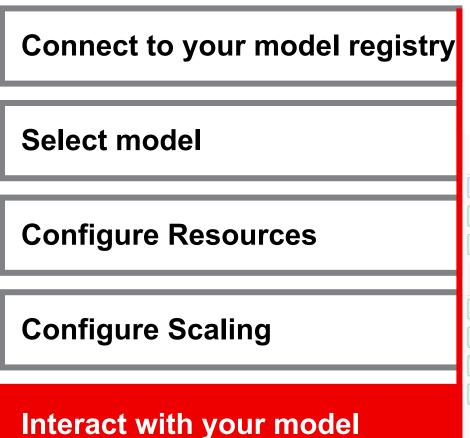


Set your deployment to scale according to load.
Create new deployment A deployment is a running instance of a packaged model. Learn how to setup a deployment. Deployment Packaged Model Infrastructure Scaling Advanced (optional) Auto scaling targets template @ scale-0-to-8-rps-20 Minimum instance Maximum instances 0 8 Auto scaling target 20 rps v Back Next

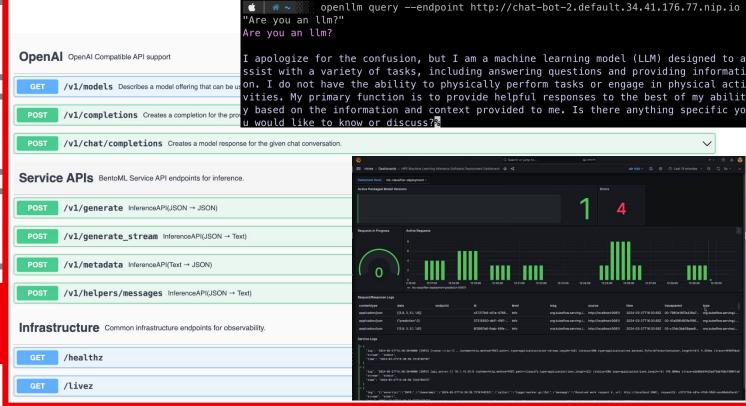




Inference Service Deployment for an LLM in 5 steps: 5) Retrieve model predictions



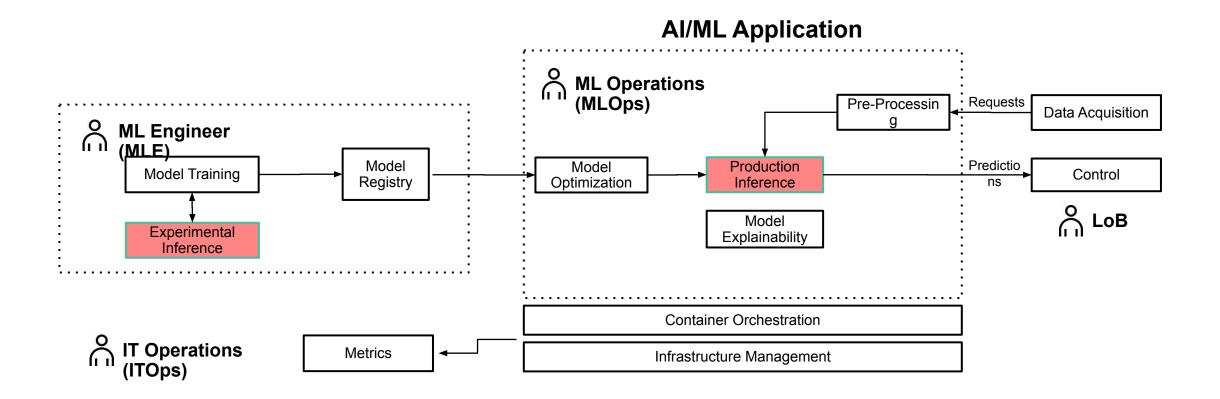
Retrieve model predictions through APIs, CLI, or applications.







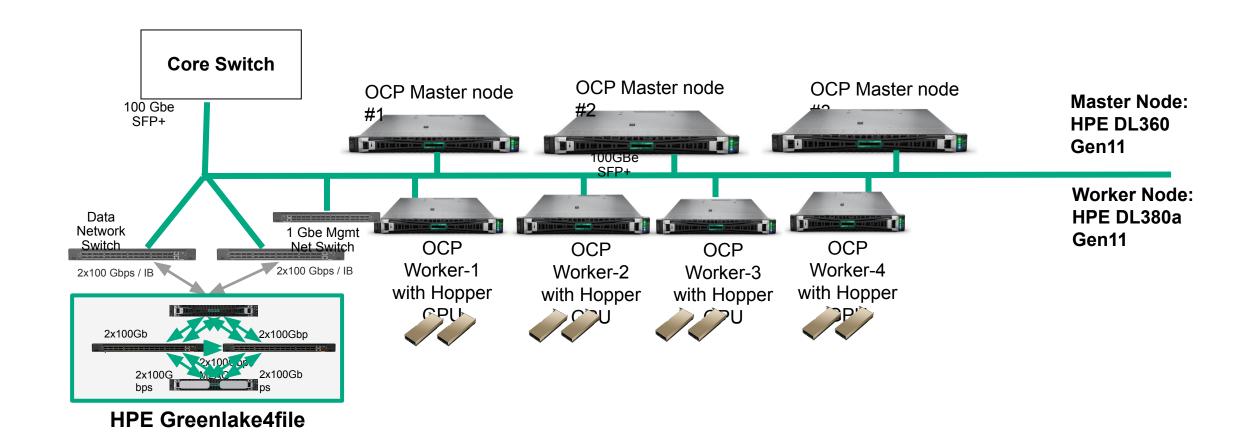
Deploying AI/ML Models into Production







Example of physical Architecture with RH Openshift





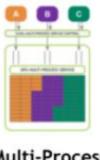
NVIDIA GPUs Concurrency choices

GPU "CONCURRENCY"

Choices



Single Process in CUDA



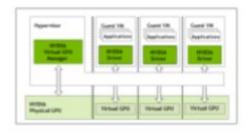
Multi-Process with CUDA MPS



Time-slicing



MIG



Virtualization with vGPU

Application level

(using the CUDA programming model APIs - CUDA streams)

GPU System Software / Hardware (Mostly transparent to CUDA applications)





NVIDIA GPUs Concurrency choices

	Streams	MPS	Time-Slicing	MIG	vGPU
Partition Type	Single process	Logical	Temporal (Single process)	Physical	Temporal & Physical – VMs
Max Partitions	Unlimited	48	Unlimited	7	Variable
SM Performance Isolation	No	Yes (by percentage, not partitioning)	Yes	Yes	Yes
Memory Protection	No	Yes	Yes	Yes	Yes
Memory Bandwidth QoS	No	No	No	Yes	Yes
Error Isolation	No	No	Yes	Yes	Yes
Cross-Partition Interop	Always	IPC	Limited IPC	Limited IPC	No
Reconfigure	Dynamic	At process launch	N/A	When idle	N/A
GPU Management (telemetry)	N/A	Limited GPU metrics	N/A	Yes - GPU metrics, support for containers	Yes – live migration and other industry virtualization tools
Target use cases (and when to use each)	Optimize for concurrency within a single application	Run multiple applications in parallel but can deal with limited resiliency	Run multiple applications that are not latency- sensitive or can tolerate jitter	Run multiple applications in parallel but need resiliency and QoS	Support multi- tenancy on the GPU through virtualization and need VM management benefits







Connect

Q&A







Connect

Thank you



