AI Inferencing on the Edge Data Center with H615c and NVIDIA T4

NetApp HCI Solutions

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NVA-1144: NetApp HCI AI Inferencing at the Edge Data Center with H615c and NVIDIA T4

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This document describes how NetApp HCI can be designed to host artificial intelligence (AI) inferencing workloads at edge data center locations. The design is based on NVIDIA T4 GPU-powered NetApp HCI compute nodes, an NVIDIA Triton Inference Server, and a Kubernetes infrastructure built using NVIDIA DeepOps. The design also establishes the data pipeline between the core and edge data centers and illustrates implementation to complete the data lifecycle path.

Modern applications that are driven by AI and machine learning (ML) have pushed the limits of the internet. End users and devices demand access to applications, data, and services at any place and any time, with minimal latency. To meet these demands, data centers are moving closer to their users to boost performance, reduce back-and-forth data transfer, and provide cost-effective ways to meet user requirements.

In the context of AI, the core data center is a platform that provides centralized services, such as machine learning and analytics, and the edge data centers are where the real-time production data is subject to inferencing. These edge data centers are usually connected to a core data center. They provide end-user services and serve as a staging layer for data generated by IoT devices that need additional processing and that is too time sensitive to be transmitted back to a centralized core.
This document describes a reference architecture for AI inferencing that uses NetApp HCI as the base platform.

Customer Value

NetApp HCI offers differentiation in the hyperconverged market for this inferencing solution, including the following advantages:

- A disaggregated architecture allows independent scaling of compute and storage and lowers the virtualization licensing costs and performance tax on independent NetApp HCI storage nodes.
- NetApp Element storage provides quality of service (QoS) for each storage volume, which provides guaranteed storage performance for workloads on NetApp HCI. Therefore, adjacent workloads do not negatively affect inferencing performance.
- A data fabric powered by NetApp allows data to be replicated from core to edge to cloud data centers, which moves data closer to where application needs it.
- With a data fabric powered by NetApp and NetApp FlexCache software, AI deep learning models trained on NetApp ONTAP AI can be accessed from NetApp HCI without having to export the model.
- NetApp HCI can host inference servers on the same infrastructure concurrently with multiple workloads, either virtual-machine (VM) or container-based, without performance degradation.
- NetApp HCI is certified as NVIDIA GPU Cloud (NGC) ready for NVIDIA AI containerized applications.
- NGC-ready means that the stack is validated by NVIDIA, is purpose built for AI, and enterprise support is available through NGC Support Services.
- With its extensive AI portfolio, NetApp can support the entire spectrum of AI use cases from edge to core to cloud, including ONTAP AI for training and inferencing, Cloud Volumes Service and Azure NetApp Files for training in the cloud, and inferencing on the edge with NetApp HCI.

Next: Use Cases

Use Cases

Although all applications today are not AI driven, they are evolving capabilities that allow them to access the immense benefits of AI. To support the adoption of AI, applications need an infrastructure that provides them with the resources needed to function at an optimum level and support their continuing evolution.

For AI-driven applications, edge locations act as a major source of data. Available data can be used for training when collected from multiple edge locations over a period of time to form a training dataset. The trained model can then be deployed back to the edge locations where the data was collected, enabling faster inferencing without the need to repeatedly transfer production data to a dedicated inferencing platform.

The NetApp HCI AI inferencing solution, powered by NetApp H615c compute nodes with NVIDIA T4 GPUs and NetApp cloud-connected storage systems, was developed and verified by NetApp and NVIDIA. NetApp HCI simplifies the deployment of AI inferencing solutions at edge data centers by addressing areas of ambiguity, eliminating complexities in the design and ending guesswork.
This solution gives IT organizations a prescriptive architecture that:

- Enables AI inferencing at edge data centers
- Optimizes consumption of GPU resources
- Provides a Kubernetes-based inferencing platform for flexibility and scalability
- Eliminates design complexities

Edge data centers manage and process data at locations that are very near to the generation point. This proximity increases the efficiency and reduces the latency involved in handling data. Many vertical markets have realized the benefits of an edge data center and are heavily adopting this distributed approach to data processing.

The following table lists the edge verticals and applications.

Vertical	Applications
Medical	Computer-aided diagnostics assist medical staff in early disease detection
Oil and gas	Autonomous inspection of remote production facilities, video, and image analytics
Aviation	Air traffic control assistance and real-time video feed analytics
Media and entertainment	Audio/video content filtering to deliver family-friendly content
Business analytics	Brand recognition to analyze brand appearance in live-streamed televised events
E-Commerce	Smart bundling of supplier offers to find ideal merchant and warehouse combinations
Retail	Automated checkout to recognize items a customer placed in cart and facilitate digital payment
Smart city	Improve traffic flow, optimize parking, and enhance pedestrian and cyclist safety

Vertical	Applications
Manufacturing	Quality control, assembly-line monitoring, and defect identification
Customer service	Customer service automation to analyze and triage inquiries (phone, email, and social media)
Agriculture	Intelligent farm operation and activity planning, to optimize fertilizer and herbicide application

Target Audience

The target audience for the solution includes the following groups:

- Data scientists
- IT architects
- Field consultants
- Professional services
- IT managers
- Anyone else who needs an infrastructure that delivers IT innovation and robust data and application services at edge locations

Next: Architecture

Architecture

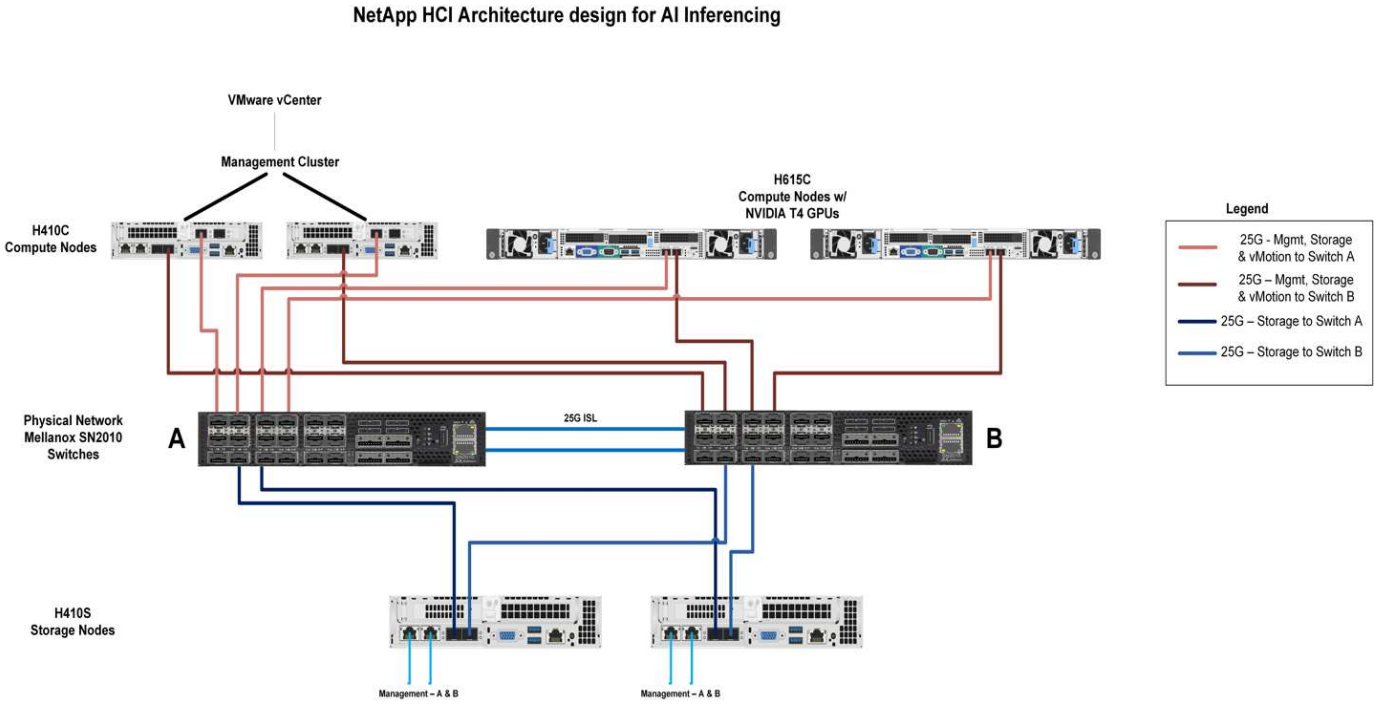
Solution Technology

This solution is designed with a NetApp HCI system that contains the following components:

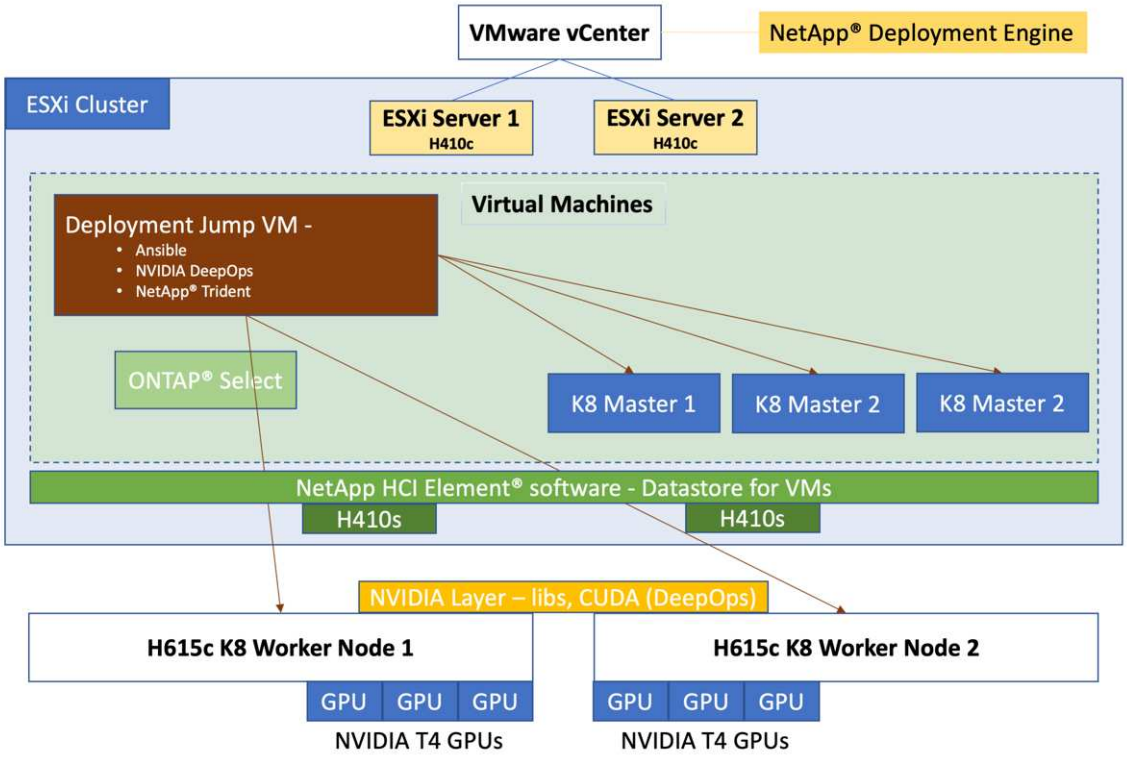
- Two H615c compute nodes with NVIDIA T4 GPUs
- Two H410c compute nodes
- Two H410s storage nodes
- Two Mellanox SN2010 10GbE/25GbE switches

Architectural Diagram

The following diagram illustrates the solution architecture for the NetApp HCI AI inferencing solution.



The following diagram illustrates the virtual and physical elements of this solution.



A VMware infrastructure is used to host the management services required by this inferencing solution. These services do not need to be deployed on a dedicated infrastructure; they can coexist with any existing workloads. The NetApp Deployment Engine (NDE) uses the H410c and H410s nodes to deploy the VMware infrastructure.

After NDE has completed the configuration, the following components are deployed as VMs in the virtual infrastructure:

- **Deployment Jump VM.** Used to automate the deployment of NVIDIA DeepOps. See NVIDIA DeepOps and storage management using NetApp Trident.
- **ONTAP Select.** An instance of ONTAP Select is deployed to provide NFS file services and persistent storage to the AI workload running on Kubernetes.
- **Kubernetes Masters.** During deployment, three VMs are installed and configured with a supported Linux distribution and configured as Kubernetes master nodes. After the management services have been set up, two H615c compute nodes with NVIDIA T4 GPUs are installed with a supported Linux distribution. These two nodes function as the Kubernetes worker nodes and provide the infrastructure for the inferencing platform.

Hardware Requirements

The following table lists the hardware components that are required to implement the solution. The hardware components that are used in any particular implementation of the solution might vary based on customer requirements.

Layer	Product Family	Quantity	Details
Compute	H615c	2	3 NVIDIA Tesla T4 GPUs per node
	H410c	2	Compute nodes for management infrastructure
Storage	H410s	2	Storage for OS and workload
Network	Mellanox SN2010	2	10G/25G switches

Software Requirements

The following table lists the software components that are required to implement the solution. The software components that are used in any particular implementation of the solution might vary based on customer requirements.

Layer	Software	Version
Storage	NetApp Element software	12.0.0.333
	ONTAP Select	9.7
	NetApp Trident	20.07
NetApp HCI engine	NDE	1.8
Hypervisor	Hypervisor	VMware vSphere ESXi 6.7U1
	Hypervisor Management System	VMware vCenter Server 6.7U1
Inferencing Platform	NVIDIA DeepOps	20.08
	NVIDIA GPU Operator	1.1.7
	Ansible	2.9.5
	Kubernetes	1.17.9

Layer	Software	Version
	Docker	Docker CE 18.09.7
	CUDA Version	10.2
	GPU Device Plugin	0.6.0
	Helm	3.1.2
	NVIDIA Tesla Driver	440.64.00
	NVIDIA Triton Inference Server	2.1.0 – NGC Container v20.07
K8 Master VMs	Linux	Any supported distribution across NetApp IMT, NVIDIA DeepOps, and GPUOperator Ubuntu 18.04.4 LTS was used in this solution Kernel version: 4.15
Host OS/ K8 Worker Nodes	Linux	Any supported distribution across NetApp IMT, NVIDIA DeepOps, and GPUOperator Ubuntu 18.04.4 LTS was used in this solution Kernel version: 4.15

Next: Design Considerations

Design Considerations

Network Design

The switches used to handle the NetApp HCI traffic require a specific configuration for successful deployment.

Consult the NetApp HCI Network Setup Guide for the physical cabling and switch details. This solution uses a two-cable design for compute nodes. Optionally, compute nodes can be configured in a six-node cable design affording options for deployment of compute nodes.

The diagram under Architecture depicts the network topology of this NetApp HCI solution with a two-cable design for the compute nodes.

Compute Design

The NetApp HCI compute nodes are available in two form factors, half-width and full-width, and in two rack unit sizes, 1 RU and 2 RU. The 410c nodes used in this solution are half-width and 1 RU and are housed in a chassis that can hold a maximum of four such nodes. The other compute node that is used in this solution is the H615c, which is a full-width node, 1 RU in size. The H410c nodes are based on Intel Skylake processors, and the H615c nodes are based on the second-generation Intel Cascade Lake processors. NVIDIA GPUs can be added to the H615c nodes, and each node can host a maximum of three NVIDIA Tesla T4 16GB GPUs.

The H615c nodes are the latest series of compute nodes for NetApp HCI and the second series that can support GPUs. The first model to support GPUs is the H610c node (full width, 2RU), which can support two

NVIDIA Tesla M10 GPUs.

In this solution, H615c nodes are preferred over H610c nodes because of the following advantages:

- Reduced data center footprint, critical for edge deployments
- Support for a newer generation of GPUs designed for faster inferencing
- Reduced power consumption
- Reduced heat dissipation

NVIDIA T4 GPUs

The resource requirements of inferencing are nowhere close to those of training workloads. In fact, most modern hand-held devices are capable of handling small amounts of inferencing without powerful resources like GPUs. However, for mission-critical applications and data centers that are dealing with a wide variety of applications that demand very low inferencing latencies while subject to extreme parallelization and massive input batch sizes, the GPUs play a key role in reducing inference time and help to boost application performance.

The NVIDIA Tesla T4 is an x16 PCIe Gen3 single-slot low-profile GPU based on the Turing architecture. The T4 GPUs deliver universal inference acceleration that spans applications such as image classification and tagging, video analytics, natural language processing, automatic speech recognition, and intelligent search. The breadth of the Tesla T4's inferencing capabilities enables it to be used in enterprise solutions and edge devices.

These GPUs are ideal for deployment in edge infrastructures due to their low power consumption and small PCIe form factor. The size of the T4 GPUs enables the installation of two T4 GPUs in the same space as a double-slot full-sized GPU. Although they are small, with 16GB memory, the T4s can support large ML models or run inference on multiple smaller models simultaneously.

The Turing- based T4 GPUs include an enhanced version of Tensor Cores and support a full range of precisions for inferencing FP32, FP16, INT8, and INT4. The GPU includes 2,560 CUDA cores and 320 Tensor Cores, delivering up to 130 tera operations per second (TOPS) of INT8 and up to 260 TOPS of INT4 inferencing performance. When compared to CPU-based inferencing, the Tesla T4, powered by the new Turing Tensor Cores, delivers up to 40 times higher inference performance.

The Turing Tensor Cores accelerate the matrix-matrix multiplication at the heart of neural network training and inferencing functions. They particularly excel at inference computations in which useful and relevant information can be inferred and delivered by a trained deep neural network based on a given input.

The Turing GPU architecture inherits the enhanced Multi-Process Service (MPS) feature that was introduced in the Volta architecture. Compared to Pascal-based Tesla GPUs, MPS on Tesla T4 improves inference performance for small batch sizes, reduces launch latency, improves QoS, and enables the servicing of higher numbers of concurrent client requests.

The NVIDIA T4 GPU is a part of the NVIDIA AI Inference Platform that supports all AI frameworks and provides comprehensive tooling and integrations to drastically simplify the development and deployment of advanced AI.

Storage Design: Element Software

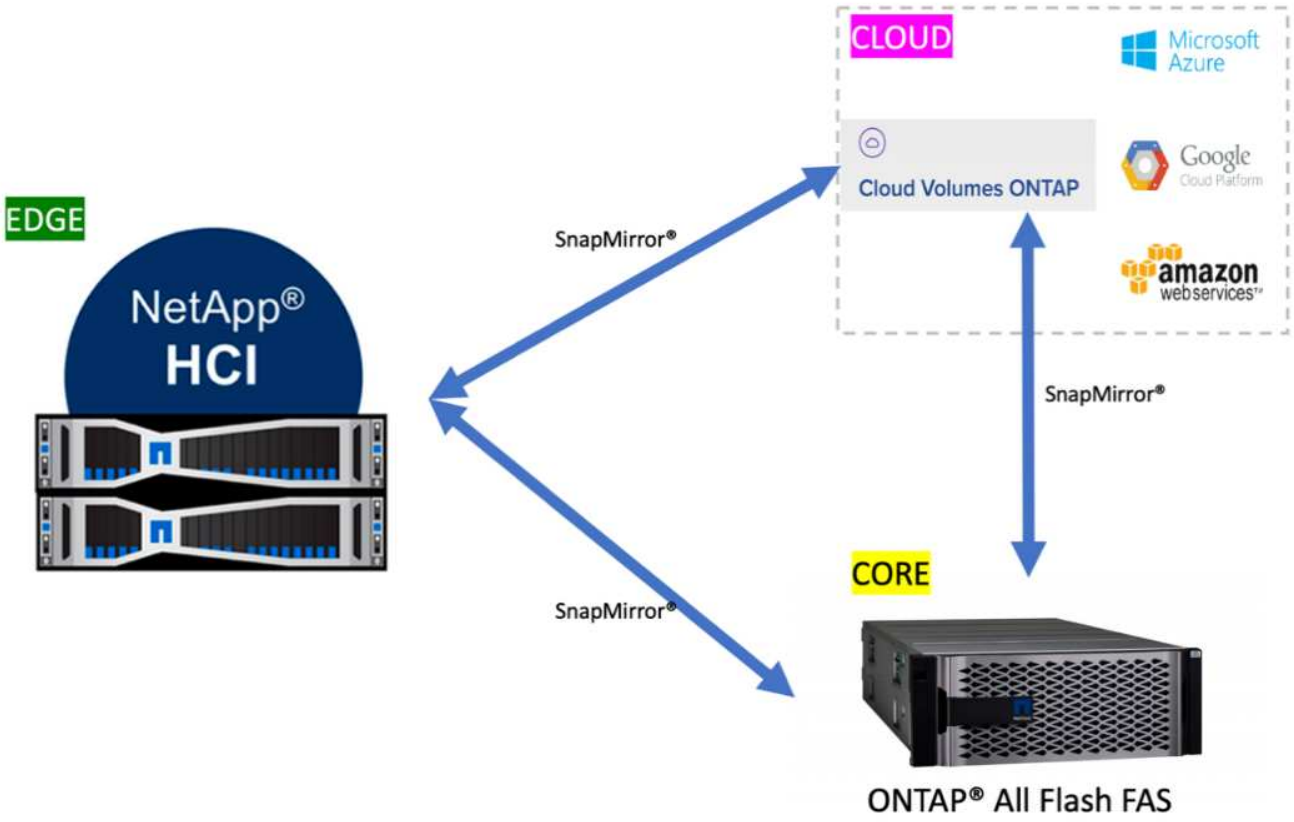
NetApp Element software powers the storage of the NetApp HCI systems. It delivers agile automation through scale-out flexibility and guaranteed application performance to accelerate new services.

Storage nodes can be added to the system non-disruptively in increments of one, and the storage resources are made available to the applications instantly. Every new node added to the system delivers a precise amount of additional performance and capacity to a usable pool. The data is automatically load balanced in the background across all nodes in the cluster, maintaining even utilization as the system grows.

Element software supports the NetApp HCI system to comfortably host multiple workloads by guaranteeing QoS to each workload. By providing fine-grained performance control with minimum, maximum, and burst settings for each workload, the software allows well-planned consolidations while protecting application performance. It decouples performance from capacity and allows each volume to be allocated with a specific amount of capacity and performance. These specifications can be modified dynamically without any interruption to data access.

As illustrated in the following figure, Element software integrates with NetApp ONTAP to enable data mobility between NetApp storage systems that are running different storage operating systems. Data can be moved from the Element software to ONTAP or vice versa by using NetApp SnapMirror technology. Element uses the same technology to provide cloud connectivity by integrating with NetApp Cloud Volumes ONTAP, which enables data mobility from the edge to the core and to multiple public cloud service providers.

In this solution, the Element-backed storage provides the storage services that are required to run the workloads and applications on the NetApp HCI system.

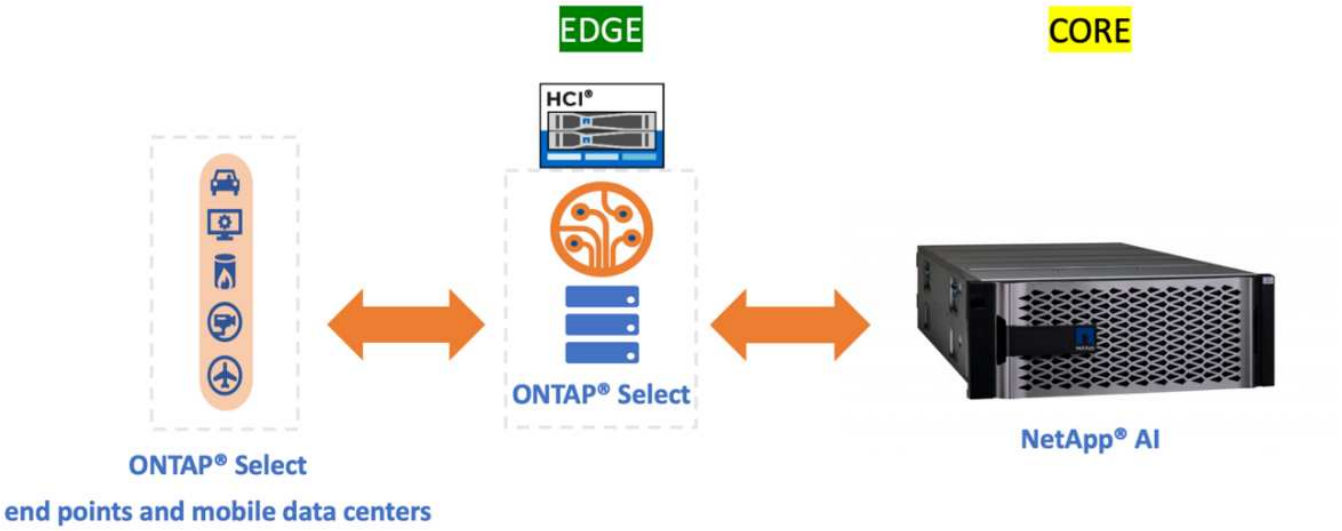


Storage Design: ONTAP Select

NetApp ONTAP Select introduces a software-defined data storage service model on top of NetApp HCI. It builds on NetApp HCI capabilities, adding a rich set of file and data services to the HCI platform while extending the data fabric.

Although ONTAP Select is an optional component for implementing this solution, it does provide a host of

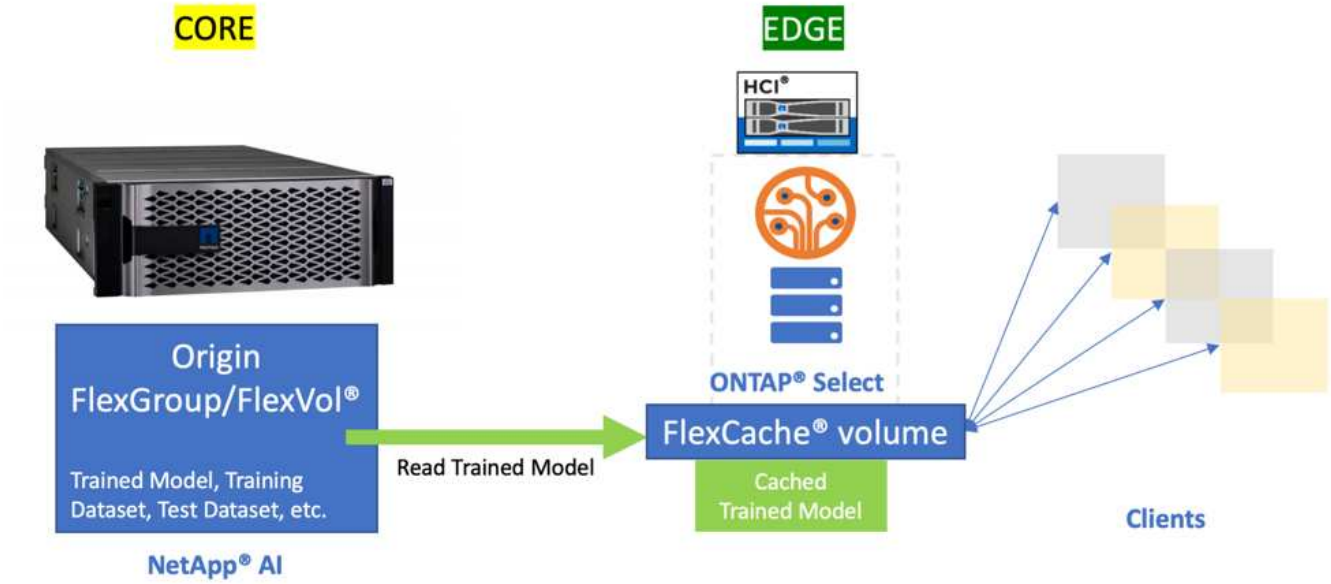
benefits, including data gathering, protection, mobility, and so on, that are extremely useful in the context of the overall AI data lifecycle. It helps to simplify several day-to-day challenges for data handling, including ingestion, collection, training, deployment, and tiering.



ONTAP Select can run as a VM on VMware and still bring in most of the ONTAP capabilities that are available when it is running on a dedicated FAS platform, such as the following:

- Support for NFS and CIFS
- NetApp FlexClone technology
- NetApp FlexCache technology
- NetApp ONTAP FlexGroup volumes
- NetApp SnapMirror software

ONTAP Select can be used to leverage the FlexCache feature, which helps to reduce data-read latencies by caching frequently read data from a back-end origin volume, as is shown in the following figure. In the case of high-end inferencing applications with a lot of parallelization, multiple instances of the same model are deployed across the inferencing platform, leading to multiple reads of the same model. Newer versions of the trained model can be seamlessly introduced to the inferencing platform by verifying that the desired model is available in the origin or source volume.



NetApp Trident

NetApp Trident is an open-source dynamic storage orchestrator that allows you to manage storage resources across all major NetApp storage platforms. It integrates with Kubernetes natively so that persistent volumes (PVs) can be provisioned on demand with native Kubernetes interfaces and constructs. Trident enables microservices and containerized applications to use enterprise-class storage services such as QoS, storage efficiencies, and cloning to meet the persistent storage demands of applications.

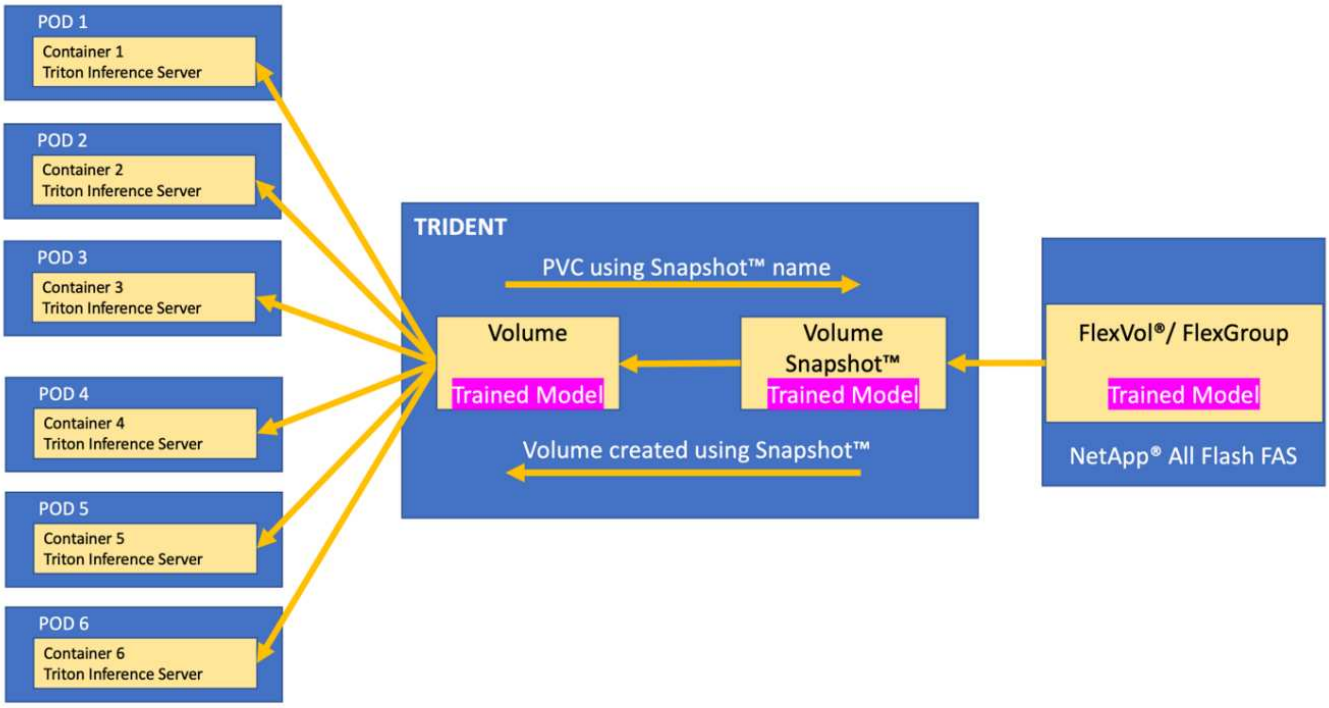
Containers are among the most popular methods of packaging and deploying applications, and Kubernetes is one of the most popular platforms for hosting containerized applications. In this solution, the inferencing platform is built on top of a Kubernetes infrastructure.

Trident currently supports storage orchestration across the following platforms:

- ONTAP: NetApp AFF, FAS, and Select
- Element software: NetApp HCI and NetApp SolidFire all-flash storage
- NetApp SANtricity software: E-Series and EF-series
- Cloud Volumes ONTAP
- Azure NetApp Files
- NetApp Cloud Volumes Service: AWS and Google Cloud

Trident is a simple but powerful tool to enable storage orchestration not just across multiple storage platforms, but also across the entire spectrum of the AI data lifecycle, ranging from the edge to the core to the cloud.

Trident can be used to provision a PV from a NetApp Snapshot copy that makes up the trained model. The following figure illustrates the Trident workflow in which a persistent volume claim (PVC) is created by referring to an existing Snapshot copy. Following this, Trident creates a volume by using the Snapshot copy.



This method of introducing trained models from a Snapshot copy supports robust model versioning. It simplifies the process of introducing newer versions of models to applications and switching inferencing between different versions of the model.

NVIDIA DeepOps

NVIDIA DeepOps is a modular collection of Ansible scripts that can be used to automate the deployment of a Kubernetes infrastructure. There are multiple deployment tools available that can automate the deployment of a Kubernetes cluster. In this solution, DeepOps is the preferred choice because it does not just deploy a Kubernetes infrastructure, it also installs the necessary GPU drivers, NVIDIA Container Runtime for Docker (nvidia-docker2), and various other dependencies for GPU-accelerated work. It encapsulates the best practices for NVIDIA GPUs and can be customized or run as individual components as needed.

DeepOps internally uses Kubespray to deploy Kubernetes, and it is included as a submodule in DeepOps. Therefore, common Kubernetes cluster management operations such as adding nodes, removing nodes, and cluster upgrades should be performed using Kubespray.

A software based L2 LoadBalancer using MetalLb and an Ingress Controller based on NGINX are also deployed as part of this solution by using the scripts that are available with DeepOps.

In this solution, three Kubernetes master nodes are deployed as VMs, and the two H615c compute nodes with NVIDIA Tesla T4 GPUs are set up as Kubernetes worker nodes.

NVIDIA GPU Operator

The GPU operator deploys the NVIDIA k8s-device-plugin for GPU support and runs the NVIDIA drivers as containers. It is based on the Kubernetes operator framework, which helps to automate the management of all NVIDIA software components that are needed to provision GPUs. The components include NVIDIA drivers, Kubernetes device plug-in for GPUs, the NVIDIA container runtime, and automatic node labeling, which is used in tandem with Kubernetes Node Feature Discovery.

The GPU operator is an important component of the NVIDIA EGX software-defined platform that is designed to make large-scale hybrid-cloud and edge operations possible and efficient. It is specifically useful when the Kubernetes cluster needs to scale quickly—for example, when provisioning additional GPU-based worker nodes and managing the lifecycle of the underlying software components. Because the GPU operator runs everything as containers, including NVIDIA drivers, administrators can easily swap various components by simply starting or stopping containers.

NVIDIA Triton Inference Server

NVIDIA Triton Inference Server (Triton Server) simplifies the deployment of AI inferencing solutions in production data centers. This microservice is specifically designed for inferencing in production data centers. It maximizes GPU utilization and integrates seamlessly into DevOps deployments with Docker and Kubernetes.

Triton Server provides a common solution for AI inferencing. Therefore, researchers can focus on creating high-quality trained models, DevOps engineers can focus on deployment, and developers can focus on applications without the need to redesign the platform for each AI-powered application.

Here are some of the key features of Triton Server:

- **Support for multiple frameworks.** Triton Server can handle a mix of models, and the number of models is limited only by system disk and memory resources. It can support the TensorRT, TensorFlow GraphDef, TensorFlow SavedModel, ONNX, PyTorch, and Caffe2 NetDef model formats.
- *Concurrent model execution. *Multiple models or multiple instances of the same model can be run simultaneously on a GPU.
- **Multi-GPU support.** Triton Server can maximize GPU utilization by enabling inference for multiple models on one or more GPUs.
- **Support for batching.** Triton Server can accept requests for a batch of inputs and respond with the corresponding batch of outputs. The inference server supports multiple scheduling and batching algorithms that combine individual inference requests together to improve inference throughput. Batching algorithms are available for both stateless and stateful applications and need to be used appropriately. These scheduling and batching decisions are transparent to the client that is requesting inference.
- **Ensemble support.** An ensemble is a pipeline with multiple models with connections of input and output tensors between those models. An inference request can be made to an ensemble, which results in the execution of the complete pipeline.
- **Metrics.** Metrics are details about GPU utilization, server throughput, server latency, and health for auto scaling and load balancing.

NetApp HCI is a hybrid multi-cloud infrastructure that can host multiple workloads and applications, and the Triton Inference Server is well equipped to support the inferencing requirements of multiple applications.

In this solution, Triton Server is deployed on the Kubernetes cluster using a deployment file. With this method, the default configuration of Triton Server can be overridden and customized as required. Triton Server also provides an inference service using an HTTP or GRPC endpoint, allowing remote clients to request inferencing for any model that is being managed by the server.

A Persistent Volume is presented via NetApp Trident to the container that runs the Triton Inference Server and this persistent volume is configured as the model repository for the Inference server.

The Triton Inference Server is deployed with varying sets of resources using Kubernetes deployment files, and each server instance is presented with a LoadBalancer front end for seamless scalability. This approach also illustrates the flexibility and simplicity with which resources can be allocated to the inferencing workloads.

Next: Deploying NetApp HCI – AI Inferencing at the Edge

Overview

This section describes the steps required to deploy the AI inferencing platform using NetApp HCI. The following list provides the high-level tasks involved in the setup:

1. Configure network switches
2. Deploy the VMware virtual infrastructure on NetApp HCI using NDE
3. Configure the H615c compute nodes to be used as K8 worker nodes
4. Set up the deployment jump VM and K8 master VMs
5. Deploy a Kubernetes cluster with NVIDIA DeepOps
6. Deploy ONTAP Select within the virtual infrastructure
7. Deploy NetApp Trident
8. Deploy NVIDIA Triton inference Server
9. Deploy the client for the Triton inference server
10. Collect inference metrics from the Triton inference server

Next: Configure Network Switches

Configure Network Switches (Automated Deployment)

Prepare Required VLAN IDs

The following table lists the necessary VLANs for deployment, as outlined in this solution validation. You should configure these VLANs on the network switches prior to executing NDE.

Network Segment	Details	VLAN ID
Out-of-band management network	Network for HCI terminal user interface (TUI)	16
In-band management network	Network for accessing management interfaces of nodes, hosts, and guests	3488
VMware vMotion	Network for live migration of VMs	3489
iSCSI SAN storage	Network for iSCSI storage traffic	3490
Application	Network for Application traffic	3487
NFS	Network for NFS storage traffic	3491
IPL*	Interpeer link between Mellanox switches	4000
Native	Native VLAN	2

*Only for Mellanox switches

Switch Configuration

This solution uses Mellanox SN2010 switches running Onyx. The Mellanox switches are configured using an

Ansible playbook. Prior to running the Ansible playbook, you should perform the initial configuration of the switches manually:

1. Install and cable the switches to the uplink switch, compute, and storage nodes.
2. Power on the switches and configure them with the following details:
   a. Host name
   b. Management IP and gateway
   c. NTP
3. Log into the Mellanox switches and run the following commands:

```
configuration write to pre-ansible
configuration write to post-ansible
```

   The `pre-ansible` configuration file created can be used to restore the switch's configuration to the state before the Ansible playbook execution.

   The switch configuration for this solution is stored in the `post-ansible` configuration file.

4. The configuration playbook for Mellanox switches that follows best practices and requirements for NetApp HCI can be downloaded from the NetApp HCI Toolkit.

   The HCI Toolkit also provides a playbook to setup Cisco Nexus switches with similar best practices and requirements for NetApp HCI.

   Additional guidance on populating the variables and executing the playbook is available in the respective switch README.md file.

5. Fill out the credentials to access the switches and variables needed for the environment. The following text is a sample of the variable file for this solution.

```
# vars file for nar_hci_mellanox_deploy
#These set of variables will setup the Mellanox switches for NetApp HCI
that uses a 2-cable compute connectivity option.
#Ansible connection variables for mellanox
ansible_connection: network_cli
ansible_network_os: onyx
#--------------------
# Primary Variables
#--------------------
#Necessary VLANs for Standard NetApp HCI Deployment [native, Management,
iSCSI_Storage, vMotion, VM_Network, IPL]
#Any additional VLANs can be added to this in the prescribed format
below
netapp_hci_vlans:
- {vlan_id: 2 , vlan_name: "Native" }
- {vlan_id: 3488 , vlan_name: "IB-Management" }
```

```
- {vlan_id: 3490 , vlan_name: "iSCSI_Storage" }
- {vlan_id: 3489 , vlan_name: "vMotion" }
- {vlan_id: 3491 , vlan_name: "NFS " }
- {vlan_id: 3487 , vlan_name: "App_Network" }
- {vlan_id: 4000 , vlan_name: "IPL" }#Modify the VLAN IDs to suit your
environment
#Spanning-tree protocol type for uplink connections.
#The valid options are 'network' and 'normal'; selection depends on the
uplink switch model.
uplink_stp_type: network
#----------------------
# IPL variables
#----------------------
#Inter-Peer Link Portchannel
#ipl_portchannel to be defined in the format - Po100
ipl_portchannel: Po100
#Inter-Peer Link Addresses
#The IPL IP address should not be part of the management network. This
is typically a private network
ipl_ipaddr_a: 10.0.0.1
ipl_ipaddr_b: 10.0.0.2
#Define the subnet mask in CIDR number format. Eg: For subnet /22, use
ipl_ip_subnet: 22
ipl_ip_subnet: 24
#Inter-Peer Link Interfaces
#members to be defined with Eth in the format. Eg: Eth1/1
peer_link_interfaces:
  members: ['Eth1/20', 'Eth1/22']
  description: "peer link interfaces"
#MLAG VIP IP address should be in the same subnet as that of the
switches' mgmt0 interface subnet
#mlag_vip_ip to be defined in the format - <vip_ip>/<subnet_mask>. Eg:
x.x.x.x/y
mlag_vip_ip: <<mlag_vip_ip>>
#MLAG VIP Domain Name
#The mlag domain must be unique name for each mlag domain.
#In case you have more than one pair of MLAG switches on the same
network, each domain (consist of two switches) should be configured with
different name.
mlag_domain_name: MLAG-VIP-DOM
#----------------------
# Interface Details
#----------------------
#Storage Bond10G Interface details
#members to be defined with Eth in the format. Eg: Eth1/1
#Only numerical digits between 100 to 1000 allowed for mlag_id
```

```
#Operational link speed [variable 'speed' below] to be defined in terms
of bytes.
#For 10 Gigabyte operational speed, define 10G. [Possible values - 10G
and 25G]
#Interface descriptions append storage node data port numbers assuming
all Storage Nodes' Port C -> Mellanox Switch A and all Storage Nodes'
Port D -> Mellanox Switch B
#List the storage Bond10G interfaces, their description, speed and MLAG
IDs in list of dictionaries format
storage_interfaces:
- {members: "Eth1/1", description: "HCI_Storage_Node_01", mlag_id: 101,
speed: 25G}
- {members: "Eth1/2", description: "HCI_Storage_Node_02", mlag_id: 102,
speed: 25G}
#In case of additional storage nodes, add them here
#Storage Bond1G Interface
#Mention whether or not these Mellanox switches will also be used for
Storage Node Mgmt connections
#Possible inputs for storage_mgmt are 'yes' and 'no'
storage_mgmt: <<yes or no>>
#Storage Bond1G (Mgmt) interface details. Only if 'storage_mgmt' is set
to 'yes'
#Members to be defined with Eth in the format. Eg: Eth1/1
#Interface descriptions append storage node management port numbers
assuming all Storage Nodes' Port A -> Mellanox Switch A and all Storage
Nodes' Port B -> Mellanox Switch B
#List the storage Bond1G interfaces and their description in list of
dictionaries format
storage_mgmt_interfaces:
- {members: "Ethx/y", description: "HCI_Storage_Node_01"}
- {members: "Ethx/y", description: "HCI_Storage_Node_02"}
#In case of additional storage nodes, add them here
#LACP load balancing algorithm for IP hash method
#Possible options are: 'destination-mac', 'destination-ip',
'destination-port', 'source-mac', 'source-ip', 'source-port', 'source-
destination-mac', 'source-destination-ip', 'source-destination-port'
#This variable takes multiple options in a single go
#For eg: if you want to configure load to be distributed in the port-
channel based on the traffic source and destination IP address and port
number, use 'source-destination-ip source-destination-port'
#By default, Mellanox sets it to source-destination-mac. Enter the
values below only if you intend to configure any other load balancing
algorithm
#Make sure the load balancing algorithm that is set here is also
replicated on the host side
#Recommended algorithm is source-destination-ip source-destination-port
```

```
#Fill the lacp_load_balance variable only if you are using configuring
interfaces on compute nodes in bond or LAG with LACP
lacp_load_balance: "source-destination-ip source-destination-port"
#Compute Interface details
#Members to be defined with Eth in the format. Eg: Eth1/1
#Fill the mlag_id field only if you intend to configure interfaces of
compute nodes into bond or LAG with LACP
#In case you do not intend to configure LACP on interfaces of compute
nodes, either leave the mlag_id field unfilled or comment it or enter NA
in the mlag_id field
#In case you have a mixed architecture where some compute nodes require
LACP and some don't,
#1. Fill the mlag_id field with appropriate MLAG ID for interfaces that
connect to compute nodes requiring LACP
#2. Either fill NA or leave the mlag_id field blank or comment it for
interfaces connecting to compute nodes that do not require LACP
#Only numerical digits between 100 to 1000 allowed for mlag_id.
#Operational link speed [variable 'speed' below] to be defined in terms
of bytes.
#For 10 Gigabyte operational speed, define 10G. [Possible values - 10G
and 25G]
#Interface descriptions append compute node port numbers assuming all
Compute Nodes' Port D -> Mellanox Switch A and all Compute Nodes' Port E
-> Mellanox Switch B
#List the compute interfaces, their speed, MLAG IDs and their
description in list of dictionaries format
compute_interfaces:
- members: "Eth1/7"#Compute Node for ESXi, setup by NDE
  description: "HCI_Compute_Node_01"
  mlag_id: #Fill the mlag_id only if you wish to use LACP on interfaces
towards compute nodes
  speed: 25G
- members: "Eth1/8"#Compute Node for ESXi, setup by NDE
  description: "HCI_Compute_Node_02"
  mlag_id: #Fill the mlag_id only if you wish to use LACP on interfaces
towards compute nodes
  speed: 25G
#In case of additional compute nodes, add them here in the same format
as above- members: "Eth1/9"#Compute Node for Kubernetes Worker node
  description: "HCI_Compute_Node_01"
  mlag_id: 109 #Fill the mlag_id only if you wish to use LACP on
interfaces towards compute nodes
  speed: 10G
- members: "Eth1/10"#Compute Node for Kubernetes Worker node
  description: "HCI_Compute_Node_02"
  mlag_id: 110 #Fill the mlag_id only if you wish to use LACP on
```

```
interfaces towards compute nodes
  speed: 10G
#Uplink Switch LACP support
#Possible options are 'yes' and 'no' - Set to 'yes' only if your uplink
switch supports LACP
uplink_switch_lacp: <<yes or no>>
#Uplink Interface details
#Members to be defined with Eth in the format. Eg: Eth1/1
#Only numerical digits between 100 to 1000 allowed for mlag_id.
#Operational link speed [variable 'speed' below] to be defined in terms
of bytes.
#For 10 Gigabyte operational speed, define 10G. [Possible values in
Mellanox are 1G, 10G and 25G]
#List the uplink interfaces, their description, MLAG IDs and their speed
in list of dictionaries format
uplink_interfaces:
- members: "Eth1/18"
  description_switch_a: "SwitchA:Ethx/y -> Uplink_Switch:Ethx/y"
  description_switch_b: "SwitchB:Ethx/y -> Uplink_Switch:Ethx/y"
  mlag_id: 118  #Fill the mlag_id only if 'uplink_switch_lacp' is set to
'yes'
  speed: 10G
  mtu: 1500
```

The fingerprint for the switch's key must match with that present in the host machine from where the playbook is being executed. To ensure this, add the key to `/root/.ssh/known_host` or any other appropriate location.

Rollback the Switch Configuration

1. In case of any timeout failures or partial configuration, run the following command to roll back the switch to the initial state.

```
configuration switch-to pre-ansible
```

This operation requires a reboot of the switch.

2. Switch the configuration to the state before running the Ansible playbook.

```
configuration delete post-ansible
```

3. Delete the post-ansible file that had the configuration from the Ansible playbook.

```
configuration write to post-ansible
```

4. Create a new file with the same name post-ansible, write the pre-ansible configuration to it, and switch to the new configuration to restart configuration.

IP Address Requirements

The deployment of the NetApp HCI inferencing platform with VMware and Kubernetes requires multiple IP addresses to be allocated. The following table lists the number of IP addresses required. Unless otherwise indicated, addresses are assigned automatically by NDE.

IP Address Quantity	Details	VLAN ID	IP Address
One per storage and compute node*	HCI terminal user interface (TUI) addresses	16	
One per vCenter Server (VM)	vCenter Server management address	3488	
One per management node (VM)	Management node IP address		
One per ESXi host	ESXi compute management addresses		
One per storage/witness node	NetApp HCI storage node management addresses		
One per storage cluster	Storage cluster management address		
One per ESXi host	VMware vMotion address	3489	
Two per ESXi host	ESXi host initiator address for iSCSI storage traffic	3490	
Two per storage node	Storage node target address for iSCSI storage traffic		
Two per storage cluster	Storage cluster target address for iSCSI storage traffic		
Two for mNode	mNode iSCSI storage access		

The following IPs are assigned manually when the respective components are configured.

IP Address Quantity	Details	VLAN ID	IP Address
One for Deployment Jump Management network	Deployment Jump VM to execute Ansible playbooks and configure other parts of the system – management connectivity	3488	
One per Kubernetes master node – management network	Kubernetes master node VMs (three nodes)	3488	
One per Kubernetes worker node – management network	Kubernetes worker nodes (two nodes)	3488	
One per Kubernetes worker node – NFS network	Kubernetes worker nodes (two nodes)	3491	
One per Kubernetes worker node – application network	Kubernetes worker nodes (two nodes)	3487	
Three for ONTAP Select – management network	ONTAP Select VM	3488	
One for ONTAP Select – NFS network	ONTAP Select VM – NFS data traffic	3491	
At least two for Triton Inference Server Load Balancer – application network	Load balancer IP range for Kubernetes load balancer service	3487	

*This validation requires the initial setup of the first storage node TUI address. NDE automatically assigns the TUI address for subsequent nodes.

DNS and Timekeeping Requirement

Depending on your deployment, you might need to prepare DNS records for your NetApp HCI system. NetApp HCI requires a valid NTP server for timekeeping; you can use a publicly available time server if you do not have one in your environment.

This validation involves deploying NetApp HCI with a new VMware vCenter Server instance using a fully qualified domain name (FQDN). Before deployment, you must have one Pointer (PTR) record and one Address (A) record created on the DNS server.

Next: Virtual Infrastructure with Automated Deployment

Deploy VMware Virtual Infrastructure on NetApp HCI with NDE (Automated Deployment)

NDE Deployment Prerequisites

Consult the NetApp HCI Prerequisites Checklist to see the requirements and recommendations for NetApp HCI before you begin deployment.

1. Network and switch requirements and configuration
2. Prepare required VLAN IDs
3. Switch configuration
4. IP Address Requirements for NetApp HCI and VMware
5. DNS and time-keeping requirements
6. Final preparations

NDE Execution

Before you execute the NDE, you must complete the rack and stack of all components, configuration of the network switches, and verification of all prerequisites. You can execute NDE by connecting to the management address of a single storage node if you plan to allow NDE to automatically configure all addresses.

NDE performs the following tasks to bring an HCI system online:

1. Installs the storage node (NetApp Element software) on a minimum of two storage nodes.
2. Installs the VMware hypervisor on a minimum of two compute nodes.
3. Installs VMware vCenter to manage the entire NetApp HCI stack.
4. Installs and configures the NetApp storage management node (mNode) and NetApp Monitoring Agent.

   > This validation uses NDE to automatically configure all addresses. You can also set up DHCP in your environment or manually assign IP addresses for each storage node and compute node. These steps are not covered in this guide.

   As mentioned previously, this validation uses a two-cable configuration for compute nodes.

   Detailed steps for the NDE are not covered in this document.

   For step-by-step guidance on completing the deployment of the base NetApp HCI platform, see the Deployment guide.

5. After NDE has finished, login to the vCenter and create a Distributed Port Group `NetApp HCI VDS 01-NFS_Network` for the NFS network to be used by ONTAP Select and the application.

Next: Configure NetApp H615c (Manual Deployment)

Configure NetApp H615c (Manual Deployment)

In this solution, the NetApp H615c compute nodes are configured as Kubernetes worker nodes. The Inferencing workload is hosted on these nodes.

Deploying the compute nodes involves the following tasks:

- Install Ubuntu 18.04.4 LTS.

- Configure networking for data and management access.
- Prepare the Ubuntu instances for Kubernetes deployment.

Install Ubuntu 18.04.4 LTS

The following high-level steps are required to install the operating system on the H615c compute nodes:

1. Download Ubuntu 18.04.4 LTS from Ubuntu releases.
2. Using a browser, connect to the IPMI of the H615c node and launch Remote Control.
3. Map the Ubuntu ISO using the Virtual Media Wizard and start the installation.
4. Select one of the two physical interfaces as the `Primary network interface` when prompted.

   An IP from a DHCP source is allocated when available, or you can switch to a manual IP configuration later. The network configuration is modified to a bond-based setup after the OS has been installed.

5. Provide a hostname followed by a domain name.
6. Create a user and provide a password.
7. Partition the disks according to your requirements.
8. Under Software Selection, select `OpenSSH server` and click Continue.
9. Reboot the node.

Configure Networking for Data and Management Access

The two physical network interfaces of the Kubernetes worker nodes are set up as a bond and VLAN interfaces for management and application, and NFS data traffic is created on top of it.

The inferencing applications and associated containers use the application network for connectivity.

1. Connect to the console of the Ubuntu instance as a user with root privileges and launch a terminal session.
2. Navigate to `/etc/netplan` and open the `01-netcfg.yaml` file.
3. Update the netplan file based on the network details for the management, application, and NFS traffic in your environment.

   The following template of the netplan file was used in this solution:

```
# This file describes the network interfaces available on your system
# For more information, see netplan(5).
network:
  version: 2
  renderer: networkd
  ethernets:
    enp59s0f0: #Physical Interface 1
      match:
        macaddress: <<mac_address Physical Interface 1>>
      set-name: enp59s0f0
```

```
    mtu: 9000
  enp59s0f1: # Physical Interface 2
    match:
      macaddress: <<mac_address Physical Interface 2>>
    set-name: enp59s0f1
    mtu: 9000
bonds:
    bond0:
      mtu: 9000
      dhcp4: false
      dhcp6: false
      interfaces: [ enp59s0f0, enp59s0f1 ]
      parameters:
        mode: 802.3ad
        mii-monitor-interval: 100
vlans:
  vlan.3488: #Management VLAN
    id: 3488
    xref:{relative_path}bond0
    dhcp4: false
    addresses: [ipv4_address/subnet]
    routes:
    - to: 0.0.0.0/0
      via: 172.21.232.111
      metric: 100
      table: 3488
    - to: x.x.x.x/x # Additional routes if any
      via: y.y.y.y
      metric: <<metric>>
      table: <<table #>>
    routing-policy:
    - from: 0.0.0.0/0
      priority: 32768#Higher Priority than table 3487
      table: 3488
    nameservers:
      addresses: [nameserver_ip]
      search: [ search_domain ]
    mtu: 1500
  vlan.3487:
    id: 3487
    xref:{relative_path}bond0
    dhcp4: false
    addresses: [ipv4_address/subnet]
    routes:
    - to: 0.0.0.0/0
      via: 172.21.231.111
```

```
        metric: 101
        table: 3487
      - to: x.x.x.x/x
        via: y.y.y.y
        metric: <<metric>>
        table: <<table #>>
      routing-policy:
      - from: 0.0.0.0/0
        priority: 32769#Lower Priority
        table: 3487
      nameservers:
        addresses: [nameserver_ip]
        search: [ search_domain ]
      mtu: 1500    vlan.3491:
      id: 3491
      xref:{relative_path}bond0
      dhcp4: false
      addresses: [ipv4_address/subnet]
      mtu: 9000
```

4. Confirm that the priorities for the routing policies are lower than the priorities for the main and default tables.
5. Apply the netplan.

```
sudo netplan --debug apply
```

6. Make sure that there are no errors.
7. If Network Manager is running, stop and disable it.

```
systemctl stop NetworkManager
systemctl disable NetworkManager
```

8. Add a host record for the server in DNS.
9. Open a VI editor to `/etc/iproute2/rt_tables` and add the two entries.

```
#
# reserved values
#
255     local
254     main
253     default
0       unspec
#
# local
#
#1      inr.ruhep
101     3488
102     3487
```

10. Match the table number to what you used in the netplan.
11. Open a VI editor to `/etc/sysctl.conf` and set the value of the following parameters.

```
net.ipv4.conf.default.rp_filter=0
net.ipv4.conf.all.rp_filter=0net.ipv4.ip_forward=1
```

12. Update the system.

```
sudo apt-get update && sudo apt-get upgrade
```

13. Reboot the system
14. Repeat steps 1 through 13 for the other Ubuntu instance.

Next: Set Up the Deployment Jump and the Kubernetes Master Node VMs (Manual Deployment)

Set Up the Deployment Jump VM and the Kubernetes Master Node VMs (Manual Deployment)

A Deployment Jump VM running a Linux distribution is used for the following purposes:

- Deploying ONTAP Select using an Ansible playbook
- Deploying the Kubernetes infrastructure with NVIDIA DeepOps and GPU Operator
- Installing and configuring NetApp Trident

Three more VMs running Linux are set up; these VMs are configured as Kubernetes Master Nodes in this solution.

Ubuntu 18.04.4 LTS was used in this solution deployment.

1. Deploy the Ubuntu 18.04.4 LTS VM with VMware tools

You can refer to the high-level steps described in section Install Ubuntu 18.04.4 LTS.

2. Configure the in-band management network for the VM. See the following sample netplan template:

```
# This file describes the network interfaces available on your system
# For more information, see netplan(5).
network:
  version: 2
  renderer: networkd
  ethernets:
    ens160:
      dhcp4: false
      addresses: [ipv4_address/subnet]
      routes:
      - to: 0.0.0.0/0
        via: 172.21.232.111
        metric: 100
        table: 3488
      routing-policy:
      - from: 0.0.0.0/0
        priority: 32768
        table: 3488
      nameservers:
        addresses: [nameserver_ip]
        search: [ search_domain ]
      mtu: 1500
```

This template is not the only way to setup the network. You can use any other approach that you prefer.

3. Apply the netplan.

```
sudo netplan --debug apply
```

4. Stop and disable Network Manager if it is running.

```
systemctl stop NetworkManager
systemctl disable NetworkManager
```

5. Open a VI editor to `/etc/iproute2/rt_tables` and add a table entry.

```
#
# reserved values
#
255     local
254     main
253     default
0       unspec
#
# local
#
#1      inr.ruhep
101     3488
```

6. Add a host record for the VM in DNS.
7. Verify outbound internet access.
8. Update the system.

```
sudo apt-get update && sudo apt-get upgrade
```

9. Reboot the system.
10. Repeat steps 1 through 9 to set up the other three VMs.

Next: Deploy a Kubernetes Cluster with NVIDIA DeepOps (Automated Deployment)

Deploy a Kubernetes Cluster with NVIDIA DeepOps Automated Deployment

To deploy and configure the Kubernetes Cluster with NVIDIA DeepOps, complete the following steps:

1. Make sure that the same user account is present on all the Kubernetes master and worker nodes.
2. Clone the DeepOps repository.

```
git clone https://github.com/NVIDIA/deepops.git
```

3. Check out a recent release tag.

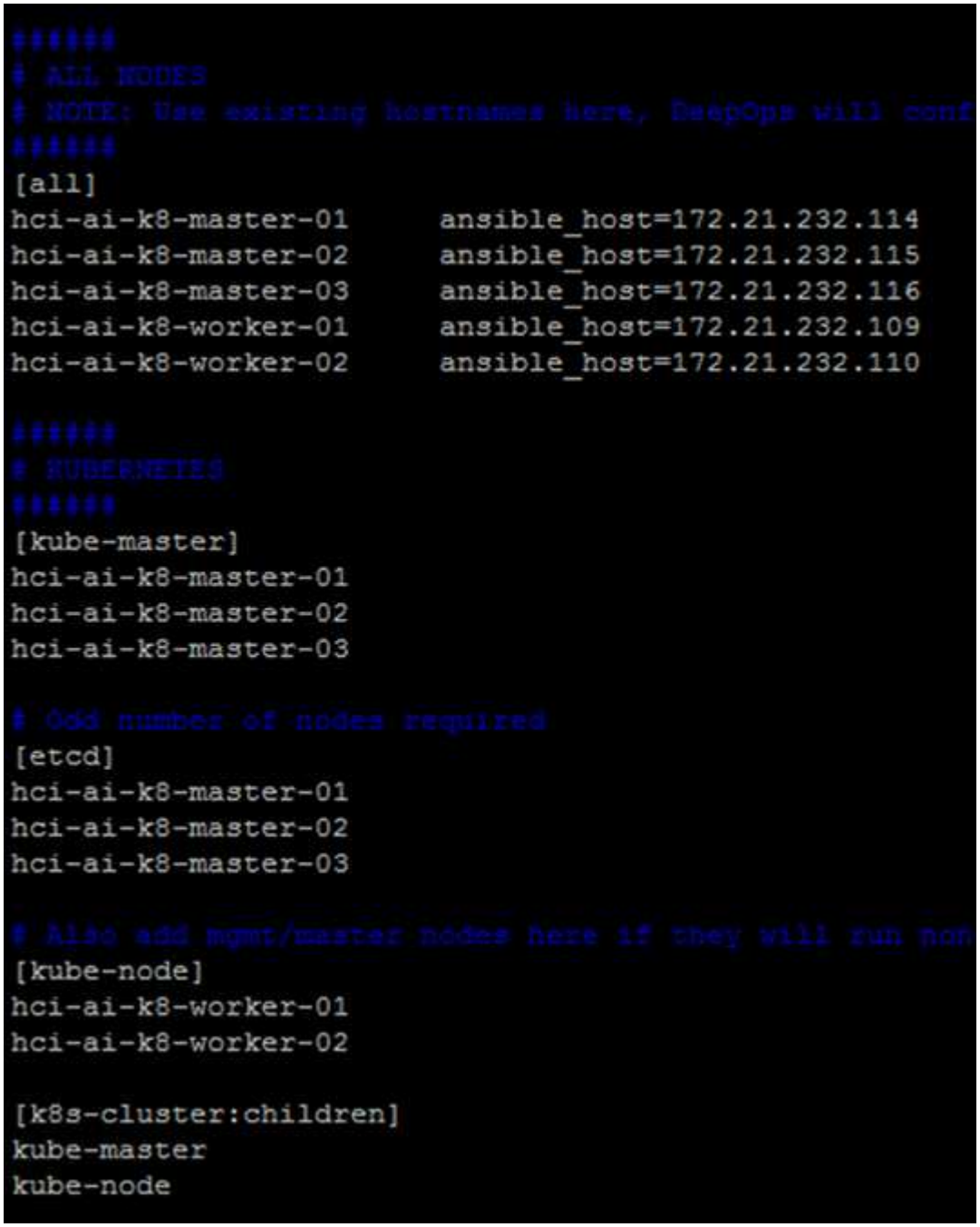
```
cd deepops
git checkout tags/20.08
```

If this step is skipped, the latest development code is used, not an official release.

4. Prepare the Deployment Jump by installing the necessary prerequisites.

```
./scripts/setup.sh
```

5. Create and edit the Ansible inventory by opening a VI editor to `deepops/config/inventory`.
   a. List all the master and worker nodes under [all].
   b. List all the master nodes under [kube-master]
   c. List all the master nodes under [etcd]
   d. List all the worker nodes under [kube-node]



6. Enable GPUOperator by opening a VI editor to `deepops/config/group_vars/k8s-cluster.yml`.

```
# Provide option to use GPU Operator instead of setting up NVIDIA driver and
# Docker configuration.
deepops_gpu_operator_enabled: true
```

7. Set the value of `deepops_gpu_operator_enabled` to true.
8. Verify the permissions and network configuration.

```
ansible all -m raw -a "hostname" -k -K
```

   - If SSH to the remote hosts requires a password, use -k.
   - If sudo on the remote hosts requires a password, use -K.

9. If the previous step passed without any issues, proceed with the setup of Kubernetes.

```
ansible-playbook --limit k8s-cluster playbooks/k8s-cluster.yml -k -K
```

10. To verify the status of the Kubernetes nodes and the pods, run the following commands:

```
kubectl get nodes
```

```
rarvind@deployment-jump:~/deepops$ kubectl get nodes
NAME                 STATUS   ROLES    AGE     VERSION
hci-ai-k8-master-01   Ready    master   2d19h   v1.17.6
hci-ai-k8-master-02   Ready    master   2d19h   v1.17.6
hci-ai-k8-master-03   Ready    master   2d19h   v1.17.6
hci-ai-k8-worker-01   Ready    <none>   2d19h   v1.17.6
hci-ai-k8-worker-02   Ready    <none>   2d19h   v1.17.6
```

```
kubectl get pods -A
```

It can take a few minutes for all the pods to run.

```
rarvind@deployment-jump:~/deepops$ kubectl get pods -A
NAMESPACE                NAME                                                              READY   STATUS
default                  gpu-operator-74c97448d9-ppdlc                                     1/1     Running
default                  nvidia-gpu-operator-node-feature-discovery-master-ffccb57dx9wtl   1/1     Running
default                  nvidia-gpu-operator-node-feature-discovery-worker-2lr9t           1/1     Running
default                  nvidia-gpu-operator-node-feature-discovery-worker-616x7           1/1     Running
default                  nvidia-gpu-operator-node-feature-discovery-worker-jf696           1/1     Running
default                  nvidia-gpu-operator-node-feature-discovery-worker-tmtwv           1/1     Running
default                  nvidia-gpu-operator-node-feature-discovery-worker-z4nlh           1/1     Running
gpu-operator-resources   nvidia-container-toolkit-daemonset-7jbl4                          1/1     Running
gpu-operator-resources   nvidia-container-toolkit-daemonset-x5ktb                          1/1     Running
gpu-operator-resources   nvidia-dcgm-exporter-5x94p                                        1/1     Running
gpu-operator-resources   nvidia-dcgm-exporter-7cbrl                                        1/1     Running
gpu-operator-resources   nvidia-device-plugin-daemonset-n8vrk                              1/1     Running
gpu-operator-resources   nvidia-device-plugin-daemonset-z7j6s                              1/1     Running
gpu-operator-resources   nvidia-device-plugin-validation                                   0/1     Completed
gpu-operator-resources   nvidia-driver-daemonset-7h752                                     1/1     Running
gpu-operator-resources   nvidia-driver-daemonset-v4rbj                                     1/1     Running
gpu-operator-resources   nvidia-driver-validation                                          0/1     Completed
kube-system              calico-kube-controllers-777478f4ff-jknxg                          1/1     Running
kube-system              calico-node-2j9mr                                                 1/1     Running
kube-system              calico-node-czk76                                                 1/1     Running
kube-system              calico-node-jpdxn                                                 1/1     Running
kube-system              calico-node-nwnvn                                                 1/1     Running
kube-system              calico-node-ssjrx                                                 1/1     Running
kube-system              coredns-76798d84dd-5pvgf                                          1/1     Running
kube-system              coredns-76798d84dd-w7l2j                                          1/1     Running
kube-system              dns-autoscaler-85f898cd5c-qqrbp                                   1/1     Running
kube-system              kube-apiserver-hci-ai-k8-master-01                                1/1     Running
kube-system              kube-apiserver-hci-ai-k8-master-02                                1/1     Running
kube-system              kube-apiserver-hci-ai-k8-master-03                                1/1     Running
kube-system              kube-controller-manager-hci-ai-k8-master-01                       1/1     Running
kube-system              kube-controller-manager-hci-ai-k8-master-02                       1/1     Running
kube-system              kube-controller-manager-hci-ai-k8-master-03                       1/1     Running
kube-system              kube-proxy-5znxk                                                  1/1     Running
kube-system              kube-proxy-fk6h6                                                  1/1     Running
kube-system              kube-proxy-hphfb                                                  1/1     Running
kube-system              kube-proxy-qzxhr                                                  1/1     Running
kube-system              kube-proxy-rkjds                                                  1/1     Running
kube-system              kube-scheduler-hci-ai-k8-master-01                                1/1     Running
kube-system              kube-scheduler-hci-ai-k8-master-02                                1/1     Running
kube-system              kube-scheduler-hci-ai-k8-master-03                                1/1     Running
kube-system              kubernetes-dashboard-5fcff756f-dmswt                              1/1     Running
kube-system              kubernetes-metrics-scraper-747b4fd5cd-4q4p2                       1/1     Running
kube-system              nginx-proxy-hci-ai-k8-worker-01                                   1/1     Running
kube-system              nginx-proxy-hci-ai-k8-worker-02                                   1/1     Running
kube-system              nodelocaldns-2dmjr                                                1/1     Running
kube-system              nodelocaldns-b7xrw                                                1/1     Running
kube-system              nodelocaldns-jrhs2                                                1/1     Running
kube-system              nodelocaldns-jztzs                                                1/1     Running
kube-system              nodelocaldns-wgx84                                                1/1     Running
```

11. Verify that the Kubernetes setup can access and use the GPUs.

```
./scripts/k8s_verify_gpu.sh
```

Expected sample output:

```
rarvind@deployment-jump:~/deepops$ ./scripts/k8s_verify_gpu.sh
job_name=cluster-gpu-tests
Node found with 3 GPUs
Node found with 3 GPUs
total_gpus=6
Creating/Deleting sandbox Namespace
updating test yml
downloading containers ...
```

```
job.batch/cluster-gpu-tests condition met
executing ...
Mon Aug 17 16:02:45 2020
+-----------------------------------------------------------------------------
------+
| NVIDIA-SMI 440.64.00    Driver Version: 440.64.00    CUDA Version:
10.2     |
|-------------------------------+----------------------
+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile
Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util
Compute M. |
|===============================+======================+================
======|
|   0  Tesla T4            On   | 00000000:18:00.0 Off |
0 |
| N/A   38C    P8    10W /  70W |      0MiB / 15109MiB |      0%
Default |
+-------------------------------+----------------------
+----------------------+
+-----------------------------------------------------------------------------
------+
| Processes:                                                       GPU
Memory |
|  GPU       PID   Type   Process name                             Usage
|
|=============================================================================
======|
|  No running processes found
|
+-----------------------------------------------------------------------------
------+
Mon Aug 17 16:02:45 2020
+-----------------------------------------------------------------------------
------+
| NVIDIA-SMI 440.64.00    Driver Version: 440.64.00    CUDA Version:
10.2     |
|-------------------------------+----------------------
+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile
Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util
Compute M. |
|===============================+======================+================
======|
```

```
|   0  Tesla T4            On   | 00000000:18:00.0 Off |
0 |
| N/A   38C    P8    10W /  70W |      0MiB / 15109MiB |      0%
Default |
+-------------------------------+----------------------
+----------------------+
+-----------------------------------------------------------------------------
------+
| Processes:                                                       GPU
Memory |
|  GPU       PID   Type   Process name                             Usage
|
|=============================================================================
======|
|  No running processes found
|
+-----------------------------------------------------------------------------
------+
Mon Aug 17 16:02:45 2020
+-----------------------------------------------------------------------------
------+
| NVIDIA-SMI 440.64.00    Driver Version: 440.64.00    CUDA Version:
10.2     |
|-------------------------------+----------------------
+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile
Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util
Compute M. |
|===============================+======================+================
======|
|   0  Tesla T4            On   | 00000000:18:00.0 Off |
0 |
| N/A   38C    P8    10W /  70W |      0MiB / 15109MiB |      0%
Default |
+-------------------------------+----------------------
+----------------------+
+-----------------------------------------------------------------------------
------+
| Processes:                                                       GPU
Memory |
|  GPU       PID   Type   Process name                             Usage
|
|=============================================================================
======|
|  No running processes found
```

```
|
+-----------------------------------------------------------------------------
------+
Mon Aug 17 16:02:45 2020
+-----------------------------------------------------------------------------
------+
| NVIDIA-SMI 440.64.00    Driver Version: 440.64.00    CUDA Version:
10.2     |
|-------------------------------+----------------------
+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile
Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util
Compute M. |
|===============================+======================+===============
======|
|   0  Tesla T4            On   | 00000000:18:00.0 Off |
0 |
| N/A   38C    P8    10W /  70W |      0MiB / 15109MiB |      0%
Default |
+-------------------------------+----------------------
+----------------------+
+-----------------------------------------------------------------------------
------+
| Processes:                                                                GPU
Memory |
|  GPU       PID   Type   Process name                                  Usage
|
|=============================================================================
======|
|  No running processes found
|
+-----------------------------------------------------------------------------
------+
Mon Aug 17 16:02:45 2020
+-----------------------------------------------------------------------------
------+
| NVIDIA-SMI 440.64.00    Driver Version: 440.64.00    CUDA Version:
10.2     |
|-------------------------------+----------------------
+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile
Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util
Compute M. |
|===============================+======================+===============
```

```
======|
|   0  Tesla T4            On   | 00000000:18:00.0 Off |
0 |
| N/A   38C    P8    10W /  70W |      0MiB / 15109MiB |      0%
Default |
+-------------------------------+----------------------
+----------------------+
+-----------------------------------------------------------------------
------+
| Processes:                                                       GPU
Memory |
|  GPU       PID   Type   Process name                             Usage
|
|=======================================================================
======|
|  No running processes found
|
+-----------------------------------------------------------------------
------+
Mon Aug 17 16:02:45 2020
+-----------------------------------------------------------------------
------+
| NVIDIA-SMI 440.64.00    Driver Version: 440.64.00    CUDA Version:
10.2     |
|-------------------------------+----------------------
+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile
Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util
Compute M. |
|===============================+======================+===============
======|
|   0  Tesla T4            On   | 00000000:18:00.0 Off |
0 |
| N/A   38C    P8    10W /  70W |      0MiB / 15109MiB |      0%
Default |
+-------------------------------+----------------------
+----------------------+
+-----------------------------------------------------------------------
------+
| Processes:                                                       GPU
Memory |
|  GPU       PID   Type   Process name                             Usage
|
|=======================================================================
======|
```

```
|  No running processes found
|
+-----------------------------------------------------------------------------
------+
Number of Nodes: 2
Number of GPUs: 6
6 / 6 GPU Jobs COMPLETED
job.batch "cluster-gpu-tests" deleted
namespace "cluster-gpu-verify" deleted
```

12. Install Helm on the Deployment Jump.

```
./scripts/install_helm.sh
```

13. Remove the taints on the master nodes.

```
kubectl taint nodes --all node-role.kubernetes.io/master-
```

This step is required to run the LoadBalancer pods.

14. Deploy LoadBalancer.
15. Edit the `config/helm/metallb.yml` file and provide a range of IP ddresses in the `Application Network` to be used as LoadBalancer.

```
---
# Default address range matches private network for the virtual cluster
# defined in virtual/.
# You should set this address range based on your site's infrastructure.
configInline:
  address-pools:
  - name: default
    protocol: layer2
    addresses:
    - 172.21.231.130-172.21.231.140#Application Network
controller:
  nodeSelector:
    node-role.kubernetes.io/master: ""
```

16. Run a script to deploy LoadBalancer.

```
./scripts/k8s_deploy_loadbalancer.sh
```

17. Deploy an Ingress Controller.

```
./scripts/k8s_deploy_ingress.sh
```

Next: Deploy and Configure ONTAP Select in the VMware Virtual Infrastructure (Automated Deployment)

Deploy and Configure ONTAP Select in the VMware Virtual Infrastructure (Automated Deployment)

To deploy and configure an ONTAP Select instance within the VMware Virtual Infrastructure, complete the following steps:

1. From the Deployment Jump VM, login to the NetApp Support Site and download the ONTAP Select OVA for ESXi.
2. Create a directory OTS and obtain the Ansible roles for deploying ONTAP Select.

```
mkdir OTS
cd OTS
git clone https://github.com/NetApp/ansible.git
cd ansible
```

3. Install the prerequisite libraries.

```
pip install requests
pip install pyvmomi
Open a VI Editor and create a playbook ``ots_setup.yaml`' with the below
content to deploy the ONTAP Select OVA and initialize the ONTAP cluster.
---
- name: Create ONTAP Select Deploy VM from OVA (ESXi)
  hosts: localhost
  gather_facts: false
  connection: 'local'
  vars_files:
    - ots_deploy_vars.yaml
  roles:
    - na_ots_deploy
- name: Wait for 1 minute before starting cluster setup
  hosts: localhost
  gather_facts: false
  tasks:
  - pause:
      minutes: 1
- name: Create ONTAP Select cluster (ESXi)
  hosts: localhost
  gather_facts: false
  vars_files:
  - ots_cluster_vars.yaml
  roles:
    - na_ots_cluster
```

4. Open a VI editor, create a variable file `ots_deploy_vars.yaml`, and fill in hte following parameters:

```
target_vcenter_or_esxi_host: "10.xxx.xx.xx"# vCenter IP
host_login: "yourlogin@yourlab.local"  # vCenter Username
ovf_path: "/run/deploy/ovapath/ONTAPdeploy.ova"# Path to OVA on
Deployment Jump VM
datacenter_name: "your-Lab"# Datacenter name in vCenter
esx_cluster_name: "your Cluster"# Cluster name in vCenter
datastore_name: "your-select-dt"# Datastore name in vCenter
mgt_network: "your-mgmt-network"# Management Network to be used by OVA
deploy_name: "test-deploy-vm"# Name of the ONTAP Select VM
deploy_ipAddress: "10.xxx.xx.xx"# Management IP Address of ONTAP Select
VM
deploy_gateway: "10.xxx.xx.1"# Default Gateway
deploy_proxy_url: ""# Proxy URL (Optional and if used)
deploy_netMask: "255.255.255.0"# Netmask
deploy_product_company: "NetApp"# Name of Organization
deploy_primaryDNS: "10.xxx.xx.xx"# Primary DNS IP
deploy_secondaryDNS: ""# Secondary DNS (Optional)
deploy_searchDomains: "your.search.domain.com"# Search Domain Name
```

Update the variables to match your environment.

5. Open a VI editor, create a variable file `ots_cluster_vars.yaml`, and fill it out with the following parameters:

```
node_count: 1#Number of nodes in the ONTAP Cluster
monitor_job: truemonitor_deploy_job: true
deploy_api_url: #Use the IP of the ONTAP Select VM
deploy_login: "admin"
vcenter_login: "administrator@vsphere.local"
vcenter_name: "172.21.232.100"
esxi_hosts:
  - host_name: 172.21.232.102
  - host_name: 172.21.232.103
cluster_name: "hci-ai-ots"# Name of ONTAP Cluster
cluster_ip: "172.21.232.118"# Cluster Management IP
cluster_netmask: "255.255.255.0"
cluster_gateway: "172.21.232.1"
cluster_ontap_image: "9.7"
cluster_ntp:
  - "10.61.186.231"
cluster_dns_ips:
  - "10.61.186.231"
cluster_dns_domains:
  - "sddc.netapp.com"
mgt_network: "NetApp HCI VDS 01-Management_Network"# Name of VM Port
Group for Mgmt Network
data_network: "NetApp HCI VDS 01-NFS_Network"# Name of VM Port Group for
NFS Network
internal_network: ""# Not needed for Single Node Cluster
instance_type: "small"
cluster_nodes:
  - node_name: "{{ cluster_name }}-01"
    ipAddress: 172.21.232.119# Node Management IP
    storage_pool: NetApp-HCI-Datastore-02 # Name of Datastore in vCenter
to use
    capacityTB: 1# Usable capacity will be ~700GB
    host_name: 172.21.232.102# IP Address of an ESXi host to deploy node
```

Update the variables to match your environment.

6. Start ONTAP Select setup.

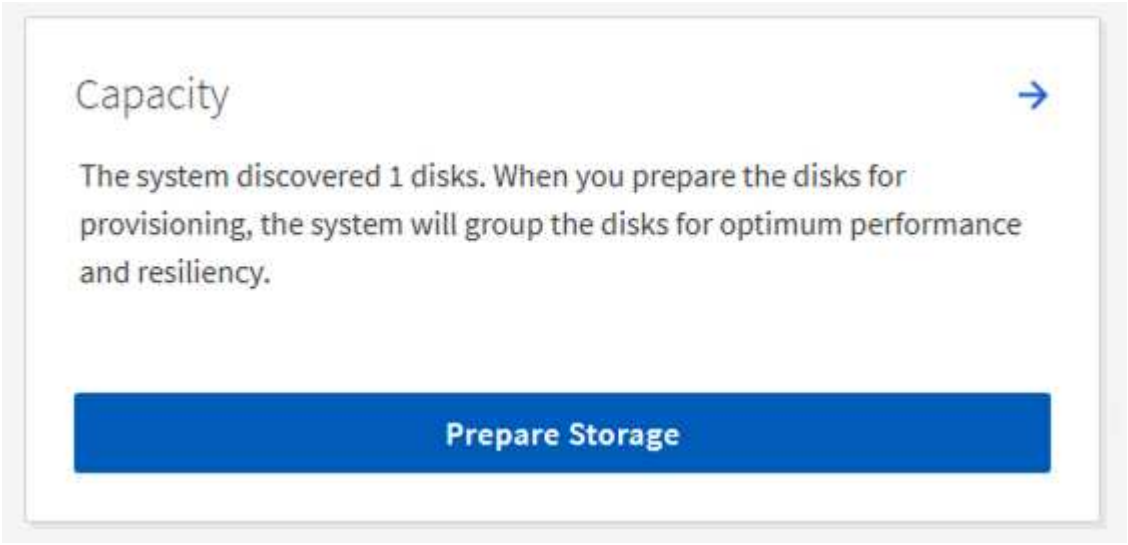
```
ansible-playbook ots_setup.yaml --extra-vars deploy_pwd=$'"P@ssw0rd"'
--extra-vars vcenter_password=$'"P@ssw0rd"' --extra-vars
ontap_pwd=$'"P@ssw0rd"' --extra-vars host_esx_password=$'"P@ssw0rd"'
--extra-vars host_password=$'"P@ssw0rd"' --extra-vars
deploy_password=$'"P@ssw0rd"'
```

7. Update the command with `deploy_pwd `(ONTAP Select VM instance), `vcenter_password`(vCenter), `ontap_pwd` (ONTAP login password), `host_esx_password` (VMware ESXi), `host_password` (vCenter), and `deploy_password` (ONTAP Select VM instance).

Configure the ONTAP Select Cluster – Manual Deployment

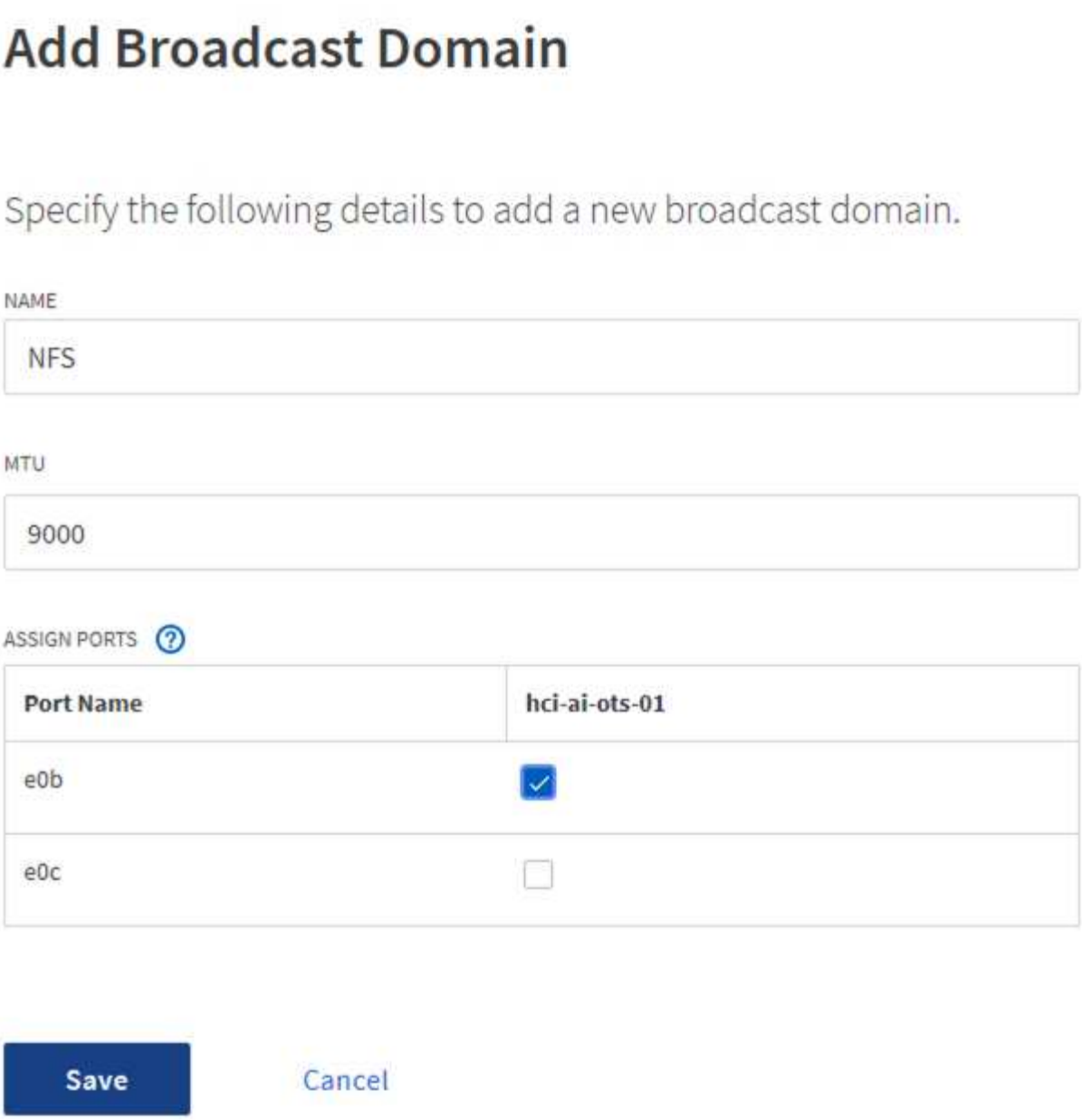
To configure the ONTAP Select cluster, complete the following steps:

1. Open a browser and log into the ONTAP cluster's System Manager using its cluster management IP.
2. On the DASHBOARD page, click Prepare Storage under Capacity.

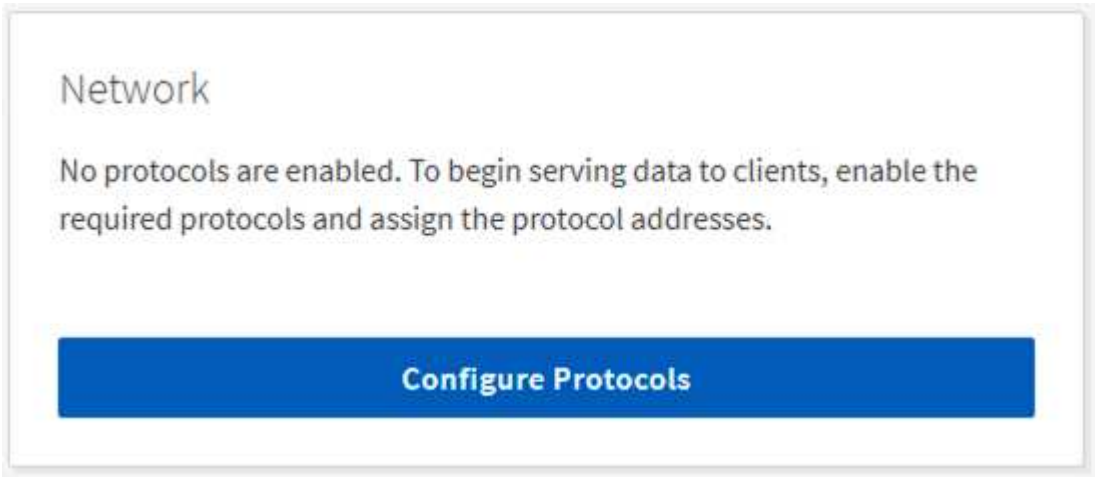


3. Select the radio button to continue without onboard key manager, and click Prepare Storage.
4. On the NETWORK page, click the + sign in the Broadcast Domains window.

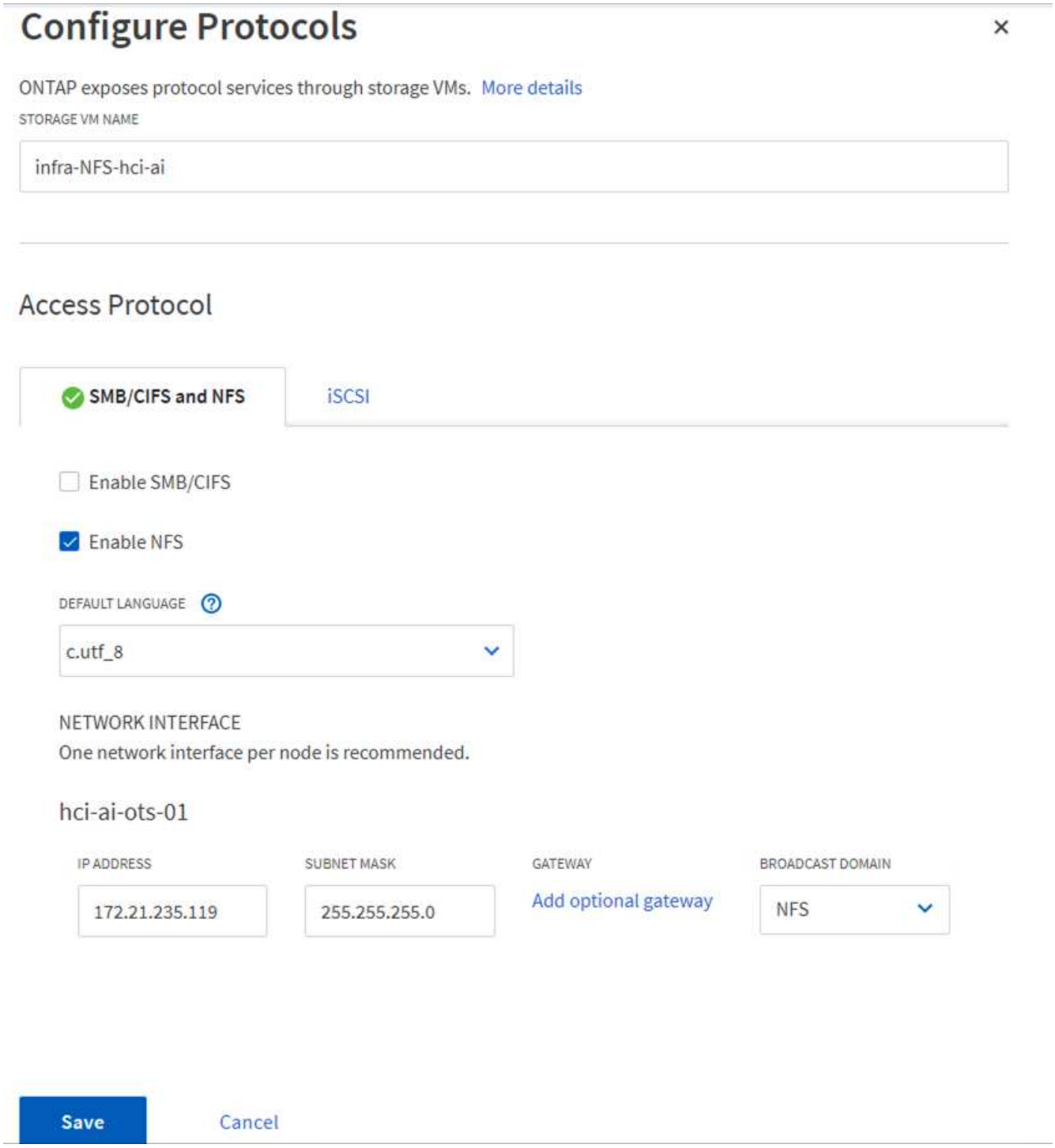
5. Enter the Name as `NFS`, set the MTU to `9000`, and select the port `e0b`. Click Save.



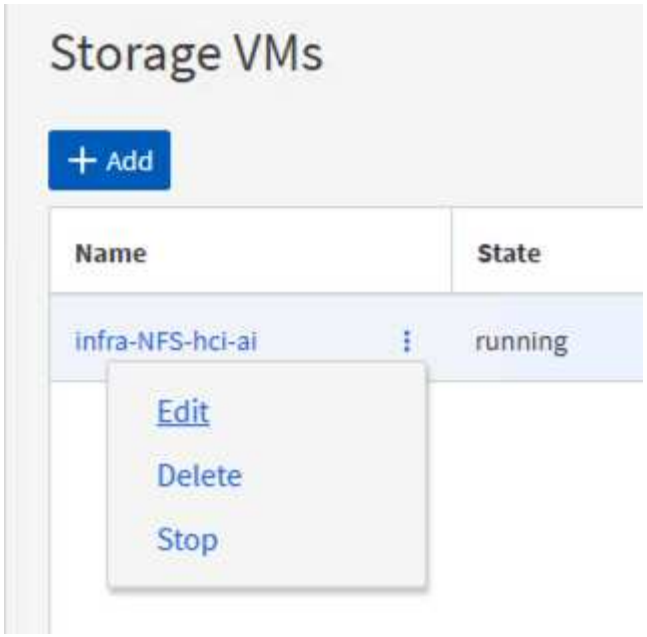
6. On the DASHBOARD page, click `Configure Protocols` under Network.



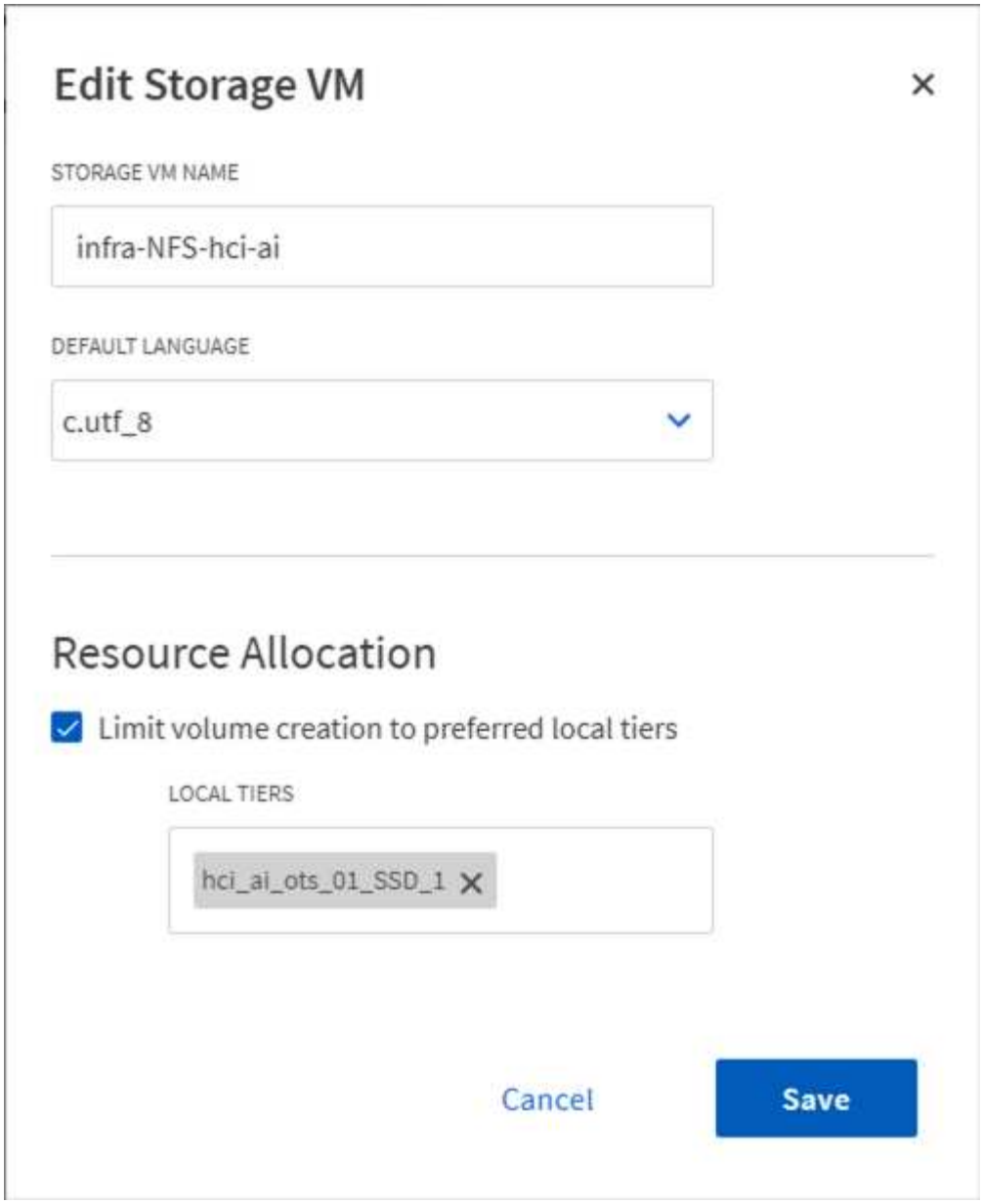
7. Enter a name for the SVM, select Enable NFS, provide an IP and subnet mask for the NFS LIF, set the Broadcast Domain to NFS, and click Save.



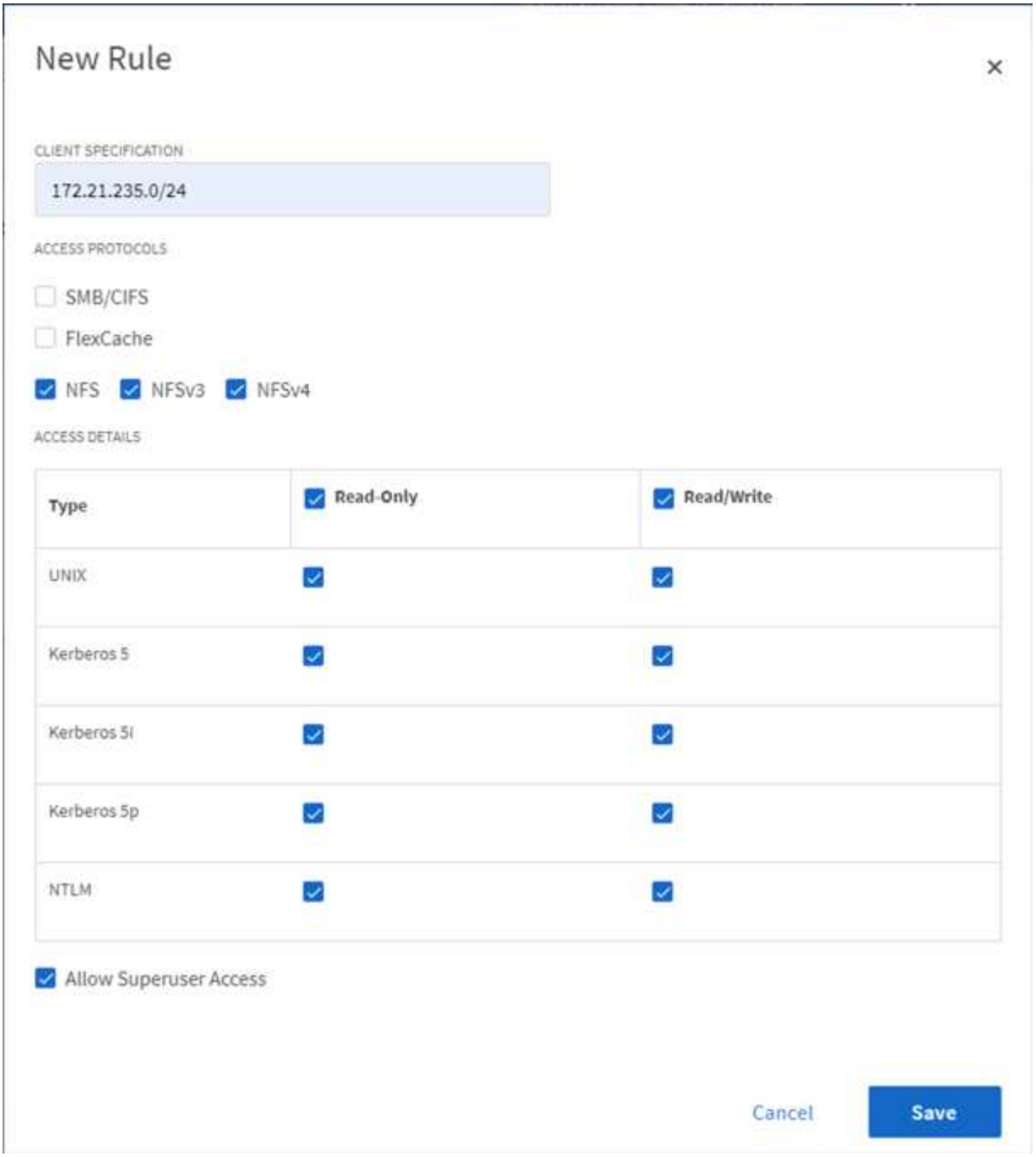
8. Click STORAGE in the left pane, and from the dropdown select Storage VMs
   a. Edit the SVM.



b. Select the checkbox under Resource Allocation, make sure that the local tier is listed, and click Save.



9. Click the SVM name, and on the right panel scroll down to Policies.
10. Click the arrow within the Export Policies tile, and click the default policy.
11. If there is a rule already defined, you can edit it; if no rule exists, then create a new one.
    a. Select NFS Network Clients as the Client Specification.
    b. Select the Read-Only and Read/Write checkboxes.
    c. Select the checkbox to Allow Superuser Access.



Next: Deploy NetApp Trident (Automated Deployment)

Deploy NetApp Trident (Automated Deployment)

NetApp Trident is deployed by using an Ansible playbook that is available with NVIDIA DeepOps. Follow these steps to set up NetApp Trident:

1. From the Deployment Jump VM, navigate to the DeepOps directory and open a VI editor to `config/group_vars/netapp-trident.yml`. The file from DeepOps lists two backends and two storage classes. In this solution only one backend and storage class are used.

   Use the following template to update the file and its parameters (highlighted in yellow) to match your environment.

```
---
# vars file for netapp-trident playbook
# URL of the Trident installer package that you wish to download and use
trident_version: "20.07.0"# Version of Trident desired
trident_installer_url:
"https://github.com/NetApp/trident/releases/download/v{{ trident_version
}}/trident-installer-{{ trident_version }}.tar.gz"
# Kubernetes version
# Note: Do not include patch version, e.g. provide value of 1.16, not
1.16.7.
# Note: Versions 1.14 and above are supported when deploying Trident
with DeepOps.
#   If you are using an earlier version, you must deploy Trident
manually.
k8s_version: 1.17.9# Version of Kubernetes running
# Denotes whether or not to create new backends after deploying trident
# For more info, refer to: https://netapp-
trident.readthedocs.io/en/stable-v20.04/kubernetes/operator-
install.html#creating-a-trident-backend
create_backends: true
# List of backends to create
# For more info on parameter values, refer to: https://netapp-
trident.readthedocs.io/en/stable-
v20.04/kubernetes/operations/tasks/backends/ontap.html
# Note: Parameters other than those listed below are not avaible when
creating a backend via DeepOps
#   If you wish to use other parameter values, you must create your
backend manually.
backends_to_create:
  - backendName: ontap-flexvol
    storageDriverName: ontap-nas # only 'ontap-nas' and 'ontap-nas-
flexgroup' are supported when creating a backend via DeepOps
    managementLIF: 172.21.232.118# Cluster Management IP or SVM Mgmt LIF
IP
    dataLIF: 172.21.235.119# NFS LIF IP
    svm: infra-NFS-hci-ai# Name of SVM
    username: admin# Username to connect to the ONTAP cluster
    password:  P@ssw0rd# Password to login
    storagePrefix: trident
    limitAggregateUsage: ""
    limitVolumeSize: ""
    nfsMountOptions: ""
    defaults:
      spaceReserve: none
      snapshotPolicy: none
      snapshotReserve: 0
```

```
      splitOnClone: false
      encryption: false
      unixPermissions: 777
      snapshotDir: false
      exportPolicy: default
      securityStyle: unix
      tieringPolicy: none
# Add additional backends as needed
# Denotes whether or not to create new StorageClasses for your NetApp
storage
# For more info, refer to: https://netapp-
trident.readthedocs.io/en/stable-v20.04/kubernetes/operator-
install.html#creating-a-storage-class
create_StorageClasses: true
# List of StorageClasses to create
# Note: Each item in the list should be an actual K8s StorageClass
definition in yaml format
# For more info on StorageClass definitions, refer to https://netapp-
trident.readthedocs.io/en/stable-
v20.04/kubernetes/concepts/objects.html#kubernetes-storageclass-objects.
storageClasses_to_create:
  - apiVersion: storage.k8s.io/v1
    kind: StorageClass
    metadata:
      name: ontap-flexvol
      annotations:
        storageclass.kubernetes.io/is-default-class: "true"
    provisioner: csi.trident.netapp.io
    parameters:
      backendType: "ontap-nas"
# Add additional StorageClasses as needed
# Denotes whether or not to copy tridenctl binary to localhost
copy_tridentctl_to_localhost: true
# Directory that tridentctl will be copied to on localhost
tridentctl_copy_to_directory: ../ # will be copied to 'deepops/'
directory
```

2. Setup NetApp Trident by using the Ansible playbook.

```
ansible-playbook -l k8s-cluster playbooks/netapp-trident.yml
```

3. Verify that Trident is running.

```
./tridentctl -n trident version
```

The expected output is as follows:

```
rarvind@deployment-jump:~/deepops$ ./tridentctl -n trident version
+----------------+----------------+
| SERVER VERSION | CLIENT VERSION |
+----------------+----------------+
| 20.07.0        | 20.07.0        |
+----------------+----------------+
```

Next: Deploy NVIDIA Triton Inference Server (Automated Deployment)

Deploy NVIDIA Triton Inference Server (Automated Deployment)

To set up automated deployment for the Triton Inference Server, complete the following steps:

1. Open a VI editor and create a PVC yaml file `vi pvc-triton-model- repo.yaml`.

```
kind: PersistentVolumeClaim
apiVersion: v1
metadata:
  name: triton-pvc  namespace: triton
spec:
  accessModes:
    - ReadWriteMany
  resources:
    requests:
      storage: 10Gi
  storageClassName: ontap-flexvol
```

2. Create the PVC.

```
kubectl create -f pvc-triton-model-repo.yaml
```

3. Open a VI editor, create a deployment for the Triton Inference Server, and call the file `triton_deployment.yaml`.

```
---
apiVersion: v1
kind: Service
metadata:
  labels:
    app: triton-3gpu
  name: triton-3gpu
```

```
  namespace: triton
spec:
  ports:
  - name: grpc-trtis-serving
    port: 8001
    targetPort: 8001
  - name: http-trtis-serving
    port: 8000
    targetPort: 8000
  - name: prometheus-metrics
    port: 8002
    targetPort: 8002
  selector:
    app: triton-3gpu
  type: LoadBalancer
---
apiVersion: v1
kind: Service
metadata:
  labels:
    app: triton-1gpu
  name: triton-1gpu
  namespace: triton
spec:
  ports:
  - name: grpc-trtis-serving
    port: 8001
    targetPort: 8001
  - name: http-trtis-serving
    port: 8000
    targetPort: 8000
  - name: prometheus-metrics
    port: 8002
    targetPort: 8002
  selector:
    app: triton-1gpu
  type: LoadBalancer
---
apiVersion: apps/v1
kind: Deployment
metadata:
  labels:
    app: triton-3gpu
  name: triton-3gpu
  namespace: triton
spec:
```

```
  replicas: 1
  selector:
    matchLabels:
      app: triton-3gpu      version: v1
  template:
    metadata:
      labels:
        app: triton-3gpu
        version: v1
    spec:
      containers:
      - image: nvcr.io/nvidia/tritonserver:20.07-v1-py3
        command: ["/bin/sh", "-c"]
        args: ["trtserver --model-store=/mnt/model-repo"]
        imagePullPolicy: IfNotPresent
        name: triton-3gpu
        ports:
        - containerPort: 8000
        - containerPort: 8001
        - containerPort: 8002
        resources:
          limits:
            cpu: "2"
            memory: 4Gi
            nvidia.com/gpu: 3
          requests:
            cpu: "2"
            memory: 4Gi
            nvidia.com/gpu: 3
        volumeMounts:
        - name: triton-model-repo
          mountPath: /mnt/model-repo      nodeSelector:
        gpu-count: “3”
      volumes:
      - name: triton-model-repo
        persistentVolumeClaim:
          claimName: triton-pvc---
apiVersion: apps/v1
kind: Deployment
metadata:
  labels:
    app: triton-1gpu
  name: triton-1gpu
  namespace: triton
spec:
  replicas: 3
```

```
  selector:
    matchLabels:
      app: triton-1gpu
      version: v1
  template:
    metadata:
      labels:
        app: triton-1gpu
        version: v1
    spec:
      containers:
      - image: nvcr.io/nvidia/tritonserver:20.07-v1-py3
        command: ["/bin/sh", "-c", "sleep 1000"]
        args: ["trtserver --model-store=/mnt/model-repo"]
        imagePullPolicy: IfNotPresent
        name: triton-1gpu
        ports:
        - containerPort: 8000
        - containerPort: 8001
        - containerPort: 8002
        resources:
          limits:
            cpu: "2"
            memory: 4Gi
            nvidia.com/gpu: 1
          requests:
            cpu: "2"
            memory: 4Gi
            nvidia.com/gpu: 1
        volumeMounts:
        - name: triton-model-repo
          mountPath: /mnt/model-repo      nodeSelector:
        gpu-count: "1"
      volumes:
      - name: triton-model-repo
        persistentVolumeClaim:
          claimName: triton-pvc
```

Two deployments are created here as an example. The first deployment spins up a pod that uses three GPUs and has replicas set to 1. The other deployment spins up three pods each using one GPU while the replica is set to 3. Depending on your requirements, you can change the GPU allocation and replica counts.

Both of the deployments use the PVC created earlier and this persistent storage is provided to the Triton inference servers as the model repository.

For each deployment, a service of type LoadBalancer is created. The Triton Inference Server can be

accessed by using the LoadBalancer IP which is in the application network.

A nodeSelector is used to ensure that both deployments get the required number of GPUs without any issues.

4. Label the K8 worker nodes.

```
kubectl label nodes hci-ai-k8-worker-01 gpu-count=3
kubectl label nodes hci-ai-k8-worker-02 gpu-count=1
```

5. Create the deployment.

```
kubectl apply -f triton_deployment.yaml
```

6. Make a note of the LoadBalancer service external LPS.

```
kubectl get services -n triton
```

The expected sample output is as follows:

```
rarvind@deployment-jump:~/triton-inference-server$ kubectl get services -n triton
NAME                  TYPE           CLUSTER-IP      EXTERNAL-IP      PORT(S)                                        AGE
triton-1gpu-v20-07-v1   LoadBalancer   10.233.21.185   172.21.231.133   8001:31238/TCP,8000:30171/TCP,8002:32348/TCP   10h
triton-3gpu-v20-07-v1   LoadBalancer   10.233.13.17    172.21.231.132   8001:31549/TCP,8000:30220/TCP,8002:31517/TCP   10h
```

7. Connect to any one of the pods that were created from the deployment.

```
kubectl exec -n triton --stdin --tty triton-1gpu-86c4c8dd64-545lx --
/bin/bash
```

8. Set up the model repository by using the example model repository.

```
git clone
cd triton-inference-server
git checkout r20.07
```

9. Fetch any missing model definition files.

```
cd docs/examples
./fetch_models.sh
```

10. Copy all the models to the model repository location or just a specific model that you wish to use.

```
cp -r model_repository/resnet50_netdef/ /mnt/model-repo/
```

In this solution, only the resnet50_netdef model is copied over to the model repository as an example.

11. Check the status of the Triton Inference Server.

```
curl -v <<LoadBalancer_IP_recorded earlier>>:8000/api/status
```

The expected sample output is as follows:

```
curl -v 172.21.231.132:8000/api/status
*   Trying 172.21.231.132...
* TCP_NODELAY set
* Connected to 172.21.231.132 (172.21.231.132) port 8000 (#0)
> GET /api/status HTTP/1.1
> Host: 172.21.231.132:8000
> User-Agent: curl/7.58.0
> Accept: */*
>
< HTTP/1.1 200 OK
< NV-Status: code: SUCCESS server_id: "inference:0" request_id: 9
< Content-Length: 1124
< Content-Type: text/plain
<
id: "inference:0"
version: "1.15.0"
uptime_ns: 377890294368
model_status {
  key: "resnet50_netdef"
  value {
    config {
      name: "resnet50_netdef"
      platform: "caffe2_netdef"
      version_policy {
        latest {
          num_versions: 1
        }
      }
      max_batch_size: 128
      input {
        name: "gpu_0/data"
        data_type: TYPE_FP32
        format: FORMAT_NCHW
        dims: 3
```

```
        dims: 224
        dims: 224
      }
      output {
        name: "gpu_0/softmax"
        data_type: TYPE_FP32
        dims: 1000
        label_filename: "resnet50_labels.txt"
      }
      instance_group {
        name: "resnet50_netdef"
        count: 1
        gpus: 0
        gpus: 1
        gpus: 2
        kind: KIND_GPU
      }
      default_model_filename: "model.netdef"
      optimization {
        input_pinned_memory {
          enable: true
        }
        output_pinned_memory {
          enable: true
        }
      }
    }
    version_status {
      key: 1
      value {
        ready_state: MODEL_READY
        ready_state_reason {
        }
      }
    }
  }
}
ready_state: SERVER_READY
* Connection #0 to host 172.21.231.132 left intact
```

Next: Deploy the Client for Triton Inference Server (Automated Deployment)

Deploy the Client for Triton Inference Server (Automated Deployment)

To deploy the client for the Triton Inference Server, complete the following steps:

1. Open a VI editor, create a deployment for the Triton client, and call the file `triton_client.yaml`.

```
---
apiVersion: apps/v1
kind: Deployment
metadata:
  labels:
    app: triton-client
  name: triton-client
  namespace: triton
spec:
  replicas: 1
  selector:
    matchLabels:
      app: triton-client
      version: v1
  template:
    metadata:
      labels:
        app: triton-client
        version: v1
    spec:
      containers:
      - image: nvcr.io/nvidia/tritonserver:20.07- v1- py3-clientsdk
        imagePullPolicy: IfNotPresent
        name: triton-client
        resources:
          limits:
            cpu: "2"
            memory: 4Gi
          requests:
            cpu: "2"
            memory: 4Gi
```

2. Deploy the client.

```
kubectl apply -f triton_client.yaml
```

Next: Collect Inference Metrics from Triton Inference Server

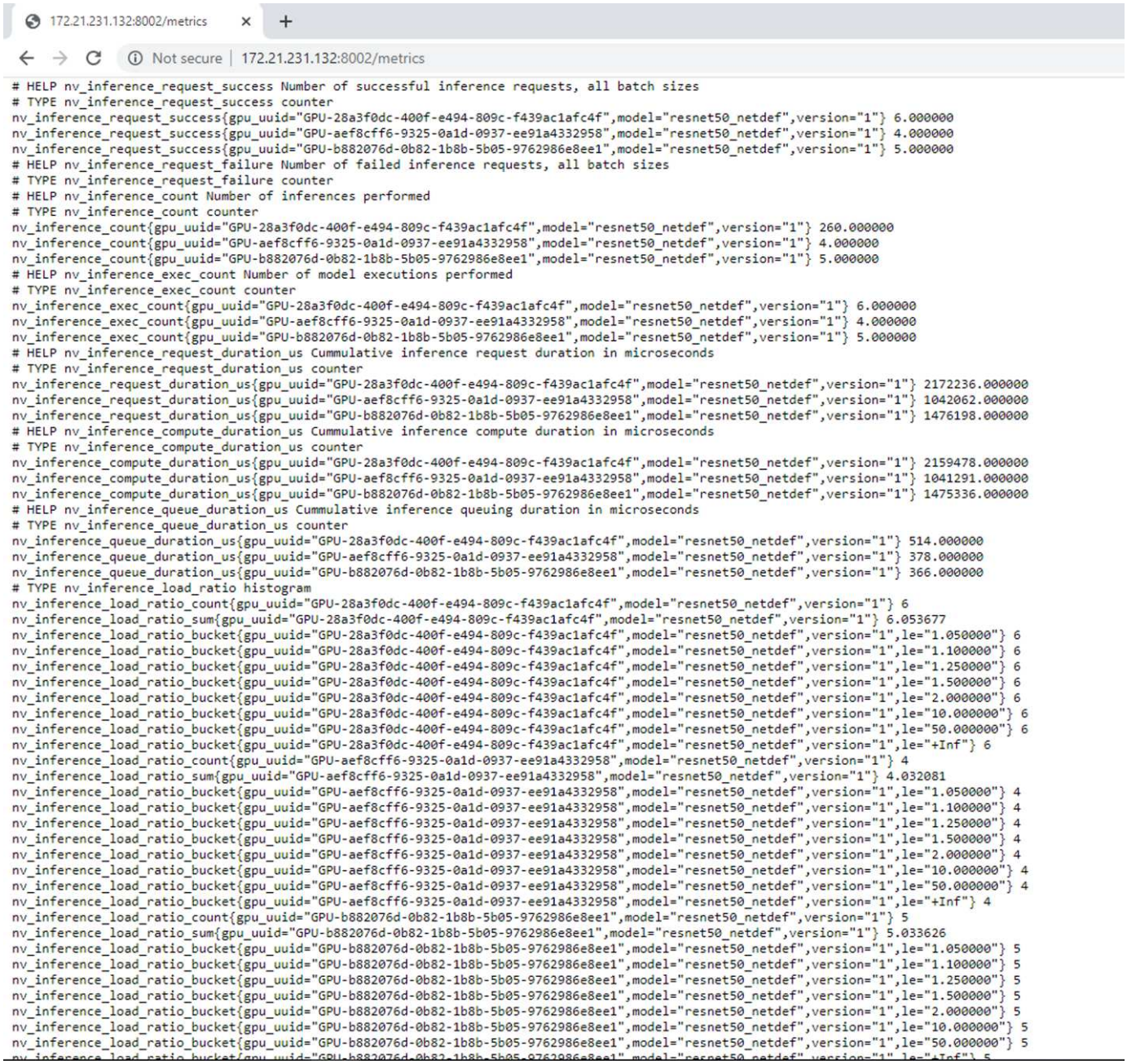
Collect Inference Metrics from Triton Inference Server

The Triton Inference Server provides Prometheus metrics indicating GPU and request statistics.

By default, these metrics are available at http://[triton_inference_server_IP]:8002/metrics.

The Triton Inference Server IP is the LoadBalancer IP that was recorded earlier.

The metrics are only available by accessing the endpoint and are not pushed or published to any remote server.



```
nv_inference_load_ratio_bucket{gpu_uuid="GPU-b882076d-0b82-1b8b-5b05-9762986e8ee1",model="resnet50_netdef",version="1",le="+Inf"} 5
# HELP nv_gpu_utilization GPU utilization rate [0.0 - 1.0)
# TYPE nv_gpu_utilization gauge
nv_gpu_utilization{gpu_uuid="GPU-b882076d-0b82-1b8b-5b05-9762986e8ee1"} 0.000000
nv_gpu_utilization{gpu_uuid="GPU-28a3f0dc-400f-e494-809c-f439ac1afc4f"} 0.000000
nv_gpu_utilization{gpu_uuid="GPU-aef8cff6-9325-0a1d-0937-ee91a4332958"} 0.000000
# HELP nv_gpu_memory_total_bytes GPU total memory, in bytes
# TYPE nv_gpu_memory_total_bytes gauge
nv_gpu_memory_total_bytes{gpu_uuid="GPU-b882076d-0b82-1b8b-5b05-9762986e8ee1"} 15843721216.000000
nv_gpu_memory_total_bytes{gpu_uuid="GPU-28a3f0dc-400f-e494-809c-f439ac1afc4f"} 15843721216.000000
nv_gpu_memory_total_bytes{gpu_uuid="GPU-aef8cff6-9325-0a1d-0937-ee91a4332958"} 15843721216.000000
# HELP nv_gpu_memory_used_bytes GPU used memory, in bytes
# TYPE nv_gpu_memory_used_bytes gauge
nv_gpu_memory_used_bytes{gpu_uuid="GPU-b882076d-0b82-1b8b-5b05-9762986e8ee1"} 1466236928.000000
nv_gpu_memory_used_bytes{gpu_uuid="GPU-28a3f0dc-400f-e494-809c-f439ac1afc4f"} 13004767232.000000
nv_gpu_memory_used_bytes{gpu_uuid="GPU-aef8cff6-9325-0a1d-0937-ee91a4332958"} 1466236928.000000
# HELP nv_gpu_power_usage GPU power usage in watts
# TYPE nv_gpu_power_usage gauge
nv_gpu_power_usage{gpu_uuid="GPU-b882076d-0b82-1b8b-5b05-9762986e8ee1"} 27.999000
nv_gpu_power_usage{gpu_uuid="GPU-28a3f0dc-400f-e494-809c-f439ac1afc4f"} 28.428000
nv_gpu_power_usage{gpu_uuid="GPU-aef8cff6-9325-0a1d-0937-ee91a4332958"} 27.632000
# HELP nv_gpu_power_limit GPU power management limit in watts
# TYPE nv_gpu_power_limit gauge
nv_gpu_power_limit{gpu_uuid="GPU-b882076d-0b82-1b8b-5b05-9762986e8ee1"} 70.000000
nv_gpu_power_limit{gpu_uuid="GPU-28a3f0dc-400f-e494-809c-f439ac1afc4f"} 70.000000
nv_gpu_power_limit{gpu_uuid="GPU-aef8cff6-9325-0a1d-0937-ee91a4332958"} 70.000000
# HELP nv_energy_consumption GPU energy consumption in joules since the Triton Server started
# TYPE nv_energy_consumption counter
nv_energy_consumption{gpu_uuid="GPU-b882076d-0b82-1b8b-5b05-9762986e8ee1"} 9796.449000
nv_energy_consumption{gpu_uuid="GPU-28a3f0dc-400f-e494-809c-f439ac1afc4f"} 9997.538000
nv_energy_consumption{gpu_uuid="GPU-aef8cff6-9325-0a1d-0937-ee91a4332958"} 9669.536000
```

Next: Validation Results

Validation Results

To run a sample inference request, complete the following steps:

1. Get a shell to the client container/pod.

```
kubectl exec --stdin --tty <<client_pod_name>> -- /bin/bash
```

2. Run a sample inference request.

```
image_client -m resnet50_netdef -s INCEPTION -u
<<LoadBalancer_IP_recorded earlier>>:8000 -c 3 images/mug.jpg
```

```
root@triton-client-v20-07-v1-5566895bc-zqz6w:/workspace# image_client -m resnet50_netdef -s INCEPTION -u 172.21.231.133:8000 -c 3 images/mug.jpg
Request 0, batch size 1
Image 'images/mug.jpg':
    504 (COFFEE MUG) = 0.723991
    968 (CUP) = 0.270953
    967 (ESPRESSO) = 0.00115996
```

This inferencing request calls the `resnet50_netdef` model that is used for image recognition. Other clients can also send inferencing requests concurrently by following a similar approach and calling out the appropriate model.

Next: Where to Find Additional Information

Additional Information

To learn more about the information that is described in this document, review the following documents and/or websites:

- NetApp HCI Theory of Operations

  https://www.netapp.com/us/media/wp-7261.pdf
- NetApp Product Documentation

  docs.netapp.com
- NetApp HCI Solution Catalog Documentation

  https://docs.netapp.com/us-en/hci/solutions/index.html
- HCI Resources page

  https://mysupport.netapp.com/info/web/ECMLP2831412.html
- ONTAP Select

  https://www.netapp.com/us/products/data-management-software/ontap-select-sds.aspx
- NetApp Trident

  https://netapp-trident.readthedocs.io/en/stable-v20.01/
- NVIDIA DeepOps

  https://github.com/NVIDIA/deepops
- NVIDIA Triton Inference Server

  https://docs.nvidia.com/deeplearning/sdk/triton-inference-server-master-branch-guide/docs/index.html

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