Data Pipelines, Data Lakes and Management

NetApp Solutions

NetApp
March 09, 2022

Table of Contents

Data Pipelines, Data Lakes and Management

NetApp AI Control Plane

TR-4798: NetApp AI Control Plane

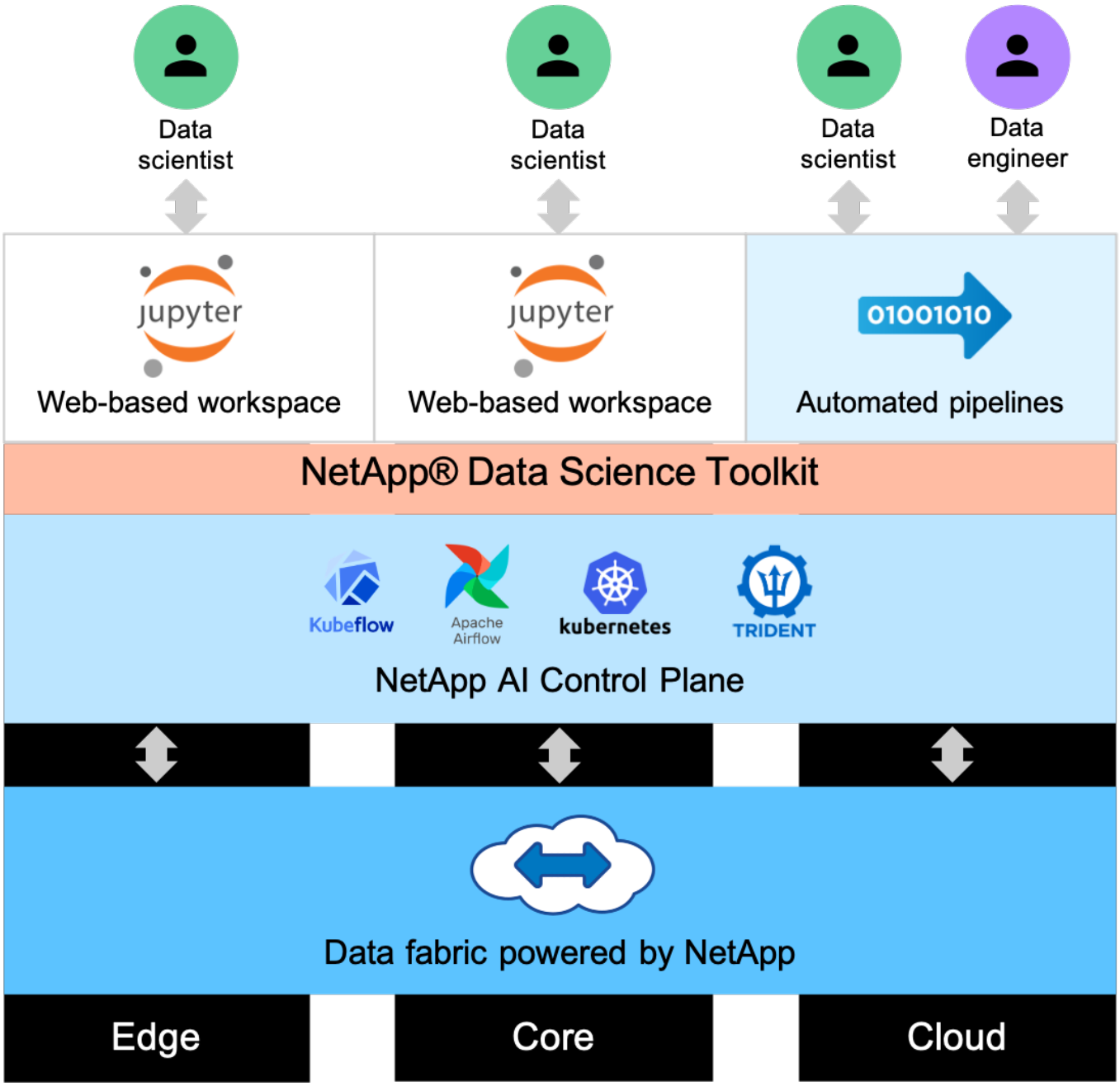
Mike Oglesby, NetApp

Companies and organizations of all sizes and across many industries are turning to artificial intelligence (AI), machine learning (ML), and deep learning (DL) to solve real-world problems, deliver innovative products and services, and to get an edge in an increasingly competitive marketplace. As organizations increase their use of AI, ML, and DL, they face many challenges, including workload scalability and data availability. This document demonstrates how you can address these challenges by using the NetApp AI Control Plane, a solution that pairs NetApp data management capabilities with popular open-source tools and frameworks.

This report shows you how to rapidly clone a data namespace. It also shows you how to seamlessly replicate data across sites and regions to create a cohesive and unified AI/ML/DL data pipeline. Additionally, it walks you through the defining and implementing of AI, ML, and DL training workflows that incorporate the near-instant creation of data and model baselines for traceability and versioning. With this solution, you can trace every model training run back to the exact dataset that was used to train and/or validate the model. Lastly, this document shows you how to swiftly provision Jupyter Notebook workspaces with access to massive datasets.

Note: For HPC style distributed training at scale involving a large number of GPU servers that require shared access to the same dataset, or if you require/prefer a parallel file system, check out TR-4890. This technical report describes how to include NetApp's fully supported parallel file system solution BeeGFS as part of the NetApp AI Control Plane. This solution is designed to scale from a handful of NVIDIA DGX A100 systems, up to a full blown 140 node SuperPOD.

The NetApp AI Control Plane is targeted towards data scientists and data engineers, and, thus, minimal NetApp or NetApp ONTAP® expertise is required. With this solution, data management functions can be executed using simple and familiar tools and interfaces. If you already have NetApp storage in your environment, you can test drive the NetApp AI Control plane today. If you want to test drive the solution but you do not have already have NetApp storage, visit cloud.netapp.com, and you can be up and running with a cloud-based NetApp storage solution in minutes. The following figure provides a visualization of the solution.



Next: Concepts and Components.

Concepts and Components

Artificial Intelligence

AI is a computer science discipline in which computers are trained to mimic the cognitive functions of the human mind. AI developers train computers to learn and to solve problems in a manner that is similar to, or even superior to, humans. Deep learning and machine learning are subfields of AI. Organizations are increasingly adopting AI, ML, and DL to support their critical business needs. Some examples are as follows:

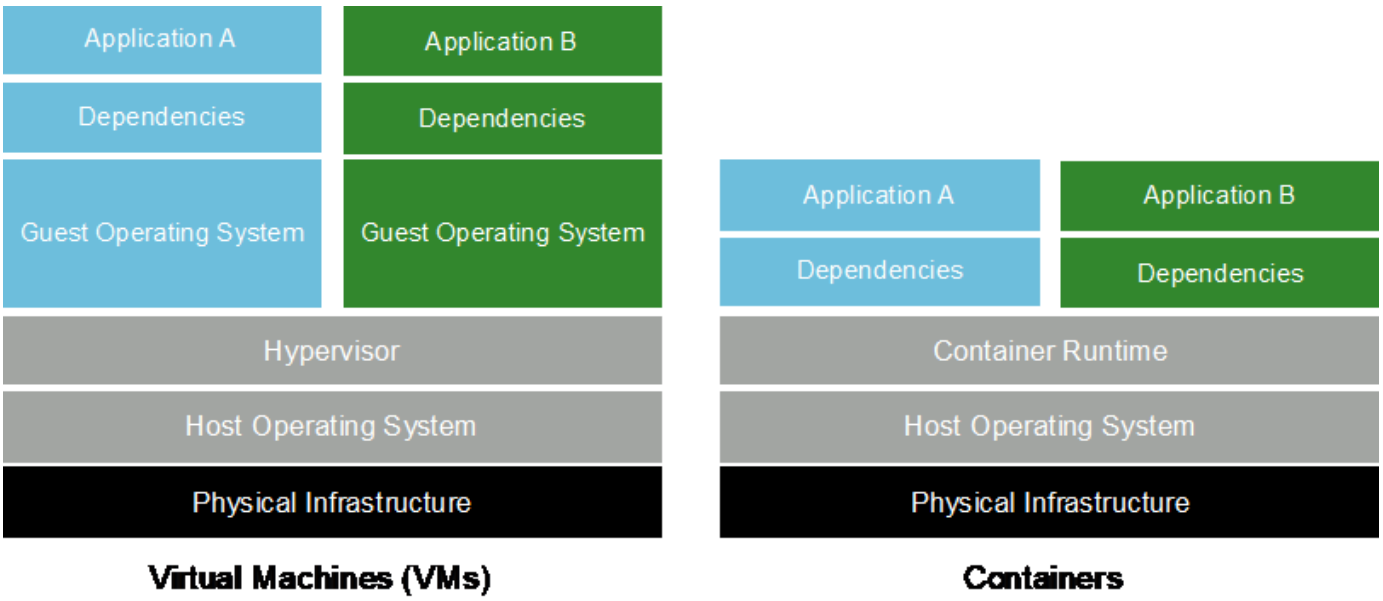
- Analyzing large amounts of data to unearth previously unknown business insights
- Interacting directly with customers by using natural language processing
- Automating various business processes and functions

Modern AI training and inference workloads require massively parallel computing capabilities. Therefore, GPUs are increasingly being used to execute AI operations because the parallel processing capabilities of GPUs are vastly superior to those of general-purpose CPUs.

Containers

Containers are isolated user-space instances that run on top of a shared host operating system kernel. The adoption of containers is increasing rapidly. Containers offer many of the same application sandboxing benefits that virtual machines (VMs) offer. However, because the hypervisor and guest operating system layers that VMs rely on have been eliminated, containers are far more lightweight. The following figure depicts a visualization of virtual machines versus containers.

Containers also allow the efficient packaging of application dependencies, run times, and so on, directly with an application. The most commonly used container packaging format is the Docker container. An application that has been containerized in the Docker container format can be executed on any machine that can run Docker containers. This is true even if the application's dependencies are not present on the machine because all dependencies are packaged in the container itself. For more information, visit the Docker website.



Kubernetes

Kubernetes is an open source, distributed, container orchestration platform that was originally designed by Google and is now maintained by the Cloud Native Computing Foundation (CNCF). Kubernetes enables the automation of deployment, management, and scaling functions for containerized applications. In recent years, Kubernetes has emerged as the dominant container orchestration platform. Although other container packaging formats and run times are supported, Kubernetes is most often used as an orchestration system for Docker containers. For more information, visit the Kubernetes website.

NetApp Trident

Trident is an open source storage orchestrator developed and maintained by NetApp that greatly simplifies the creation, management, and consumption of persistent storage for Kubernetes workloads. Trident, itself a Kubernetes-native application, runs directly within a Kubernetes cluster. With Trident, Kubernetes users (developers, data scientists, Kubernetes administrators, and so on) can create, manage, and interact with persistent storage volumes in the standard Kubernetes format that they are already familiar with. At the same time, they can take advantage of NetApp advanced data management capabilities and a data fabric that is

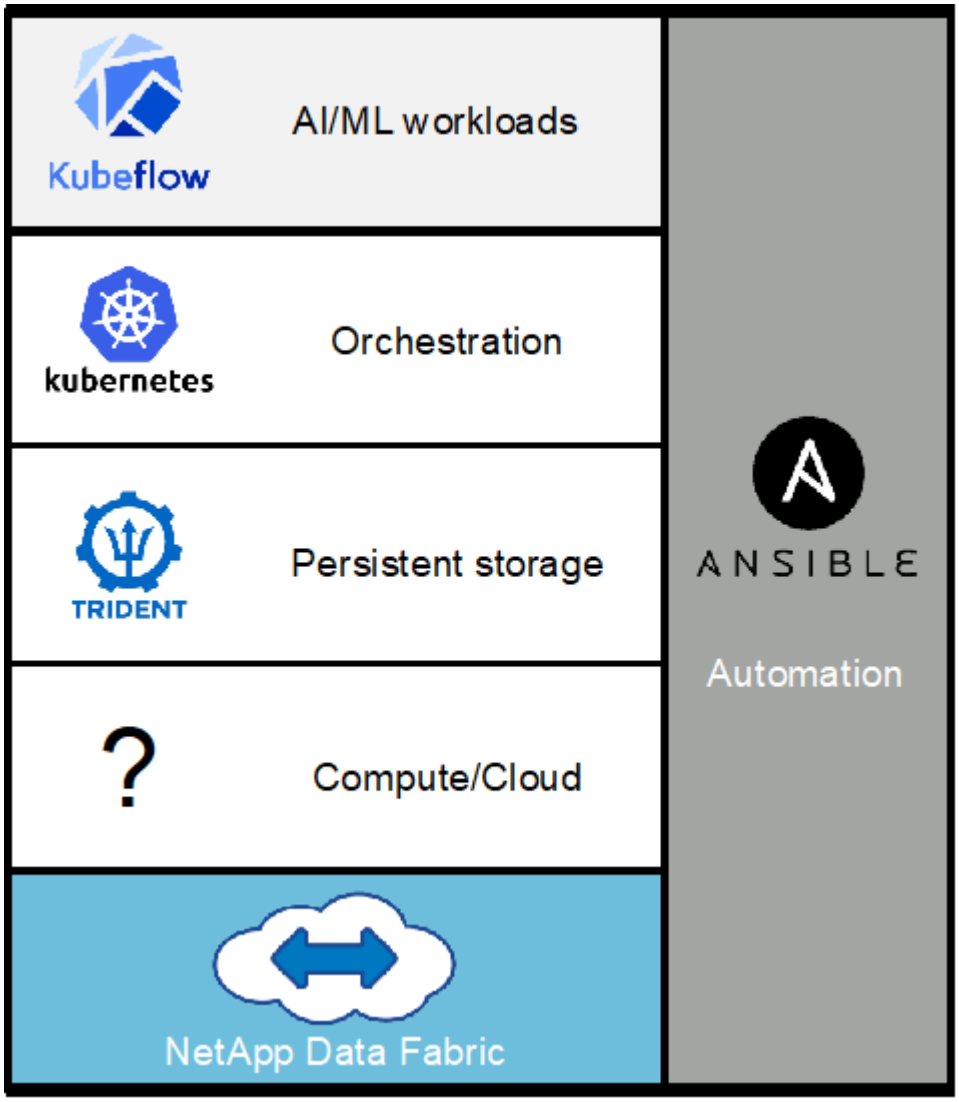
powered by NetApp technology. Trident abstracts away the complexities of persistent storage and makes it simple to consume. For more information, visit the Trident website.

NVIDIA DeepOps

DeepOps is an open source project from NVIDIA that, by using Ansible, automates the deployment of GPU server clusters according to best practices. DeepOps is modular and can be used for various deployment tasks. For this document and the validation exercise that it describes, DeepOps is used to deploy a Kubernetes cluster that consists of GPU server worker nodes. For more information, visit the DeepOps website.

Kubeflow

Kubeflow is an open source AI and ML toolkit for Kubernetes that was originally developed by Google. The Kubeflow project makes deployments of AI and ML workflows on Kubernetes simple, portable, and scalable. Kubeflow abstracts away the intricacies of Kubernetes, allowing data scientists to focus on what they know best—data science. See the following figure for a visualization. Kubeflow has been gaining significant traction as enterprise IT departments have increasingly standardized on Kubernetes. For more information, visit the Kubeflow website.



Kubeflow Pipelines

Kubeflow Pipelines are a key component of Kubeflow. Kubeflow Pipelines are a platform and standard for defining and deploying portable and scalable AI and ML workflows. For more information, see the official Kubeflow documentation.

Jupyter Notebook Server

A Jupyter Notebook Server is an open source web application that allows data scientists to create wiki-like documents called Jupyter Notebooks that contain live code as well as descriptive test. Jupyter Notebooks are widely used in the AI and ML community as a means of documenting, storing, and sharing AI and ML projects. Kubeflow simplifies the provisioning and deployment of Jupyter Notebook Servers on Kubernetes. For more information on Jupyter Notebooks, visit the Jupyter website. For more information about Jupyter Notebooks within the context of Kubeflow, see the official Kubeflow documentation.

Apache Airflow

Apache Airflow is an open-source workflow management platform that enables programmatic authoring, scheduling, and monitoring for complex enterprise workflows. It is often used to automate ETL and data pipeline workflows, but it is not limited to these types of workflows. The Airflow project was started by Airbnb but has since become very popular in the industry and now falls under the auspices of The Apache Software Foundation. Airflow is written in Python, Airflow workflows are created via Python scripts, and Airflow is designed under the principle of "configuration as code.” Many enterprise Airflow users now run Airflow on top of Kubernetes.

Directed Acyclic Graphs (DAGs)

In Airflow, workflows are called Directed Acyclic Graphs (DAGs). DAGs are made up of tasks that are executed in sequence, in parallel, or a combination of the two, depending on the DAG definition. The Airflow scheduler executes individual tasks on an array of workers, adhering to the task-level dependencies that are specified in the DAG definition. DAGs are defined and created via Python scripts.

NetApp ONTAP 9

NetApp ONTAP 9 is the latest generation of storage management software from NetApp that enables businesses like yours to modernize infrastructure and to transition to a cloud-ready data center. With industry-leading data management capabilities, ONTAP enables you to manage and protect your data with a single set of tools regardless of where that data resides. You can also move data freely to wherever you need it: the edge, the core, or the cloud. ONTAP 9 includes numerous features that simplify data management, accelerate and protect your critical data, and future-proof your infrastructure across hybrid cloud architectures.

Simplify Data Management

Data management is crucial for your enterprise IT operations so that you can use appropriate resources for your applications and datasets. ONTAP includes the following features to streamline and simplify your operations and reduce your total cost of operation:

- **Inline data compaction and expanded deduplication.** Data compaction reduces wasted space inside storage blocks, and deduplication significantly increases effective capacity.
- **Minimum, maximum, and adaptive quality of service (QoS).** Granular QoS controls help maintain performance levels for critical applications in highly shared environments.
- **ONTAP FabricPool.** This feature provides automatic tiering of cold data to public and private cloud storage options, including Amazon Web Services (AWS), Azure, and NetApp StorageGRID object-based storage.

Accelerate and Protect Data

ONTAP delivers superior levels of performance and data protection and extends these capabilities with the following features:

- **High performance and low latency.** ONTAP offers the highest possible throughput at the lowest possible latency.
- **NetApp ONTAP FlexGroup technology.** A FlexGroup volume is a high-performance data container that can scale linearly to up to 20PB and 400 billion files, providing a single namespace that simplifies data management.
- **Data protection.** ONTAP provides built-in data protection capabilities with common management across all platforms.
- **NetApp Volume Encryption.** ONTAP offers native volume-level encryption with both onboard and external key management support.

Future-Proof Infrastructure

ONTAP 9 helps meet your demanding and constantly changing business needs:

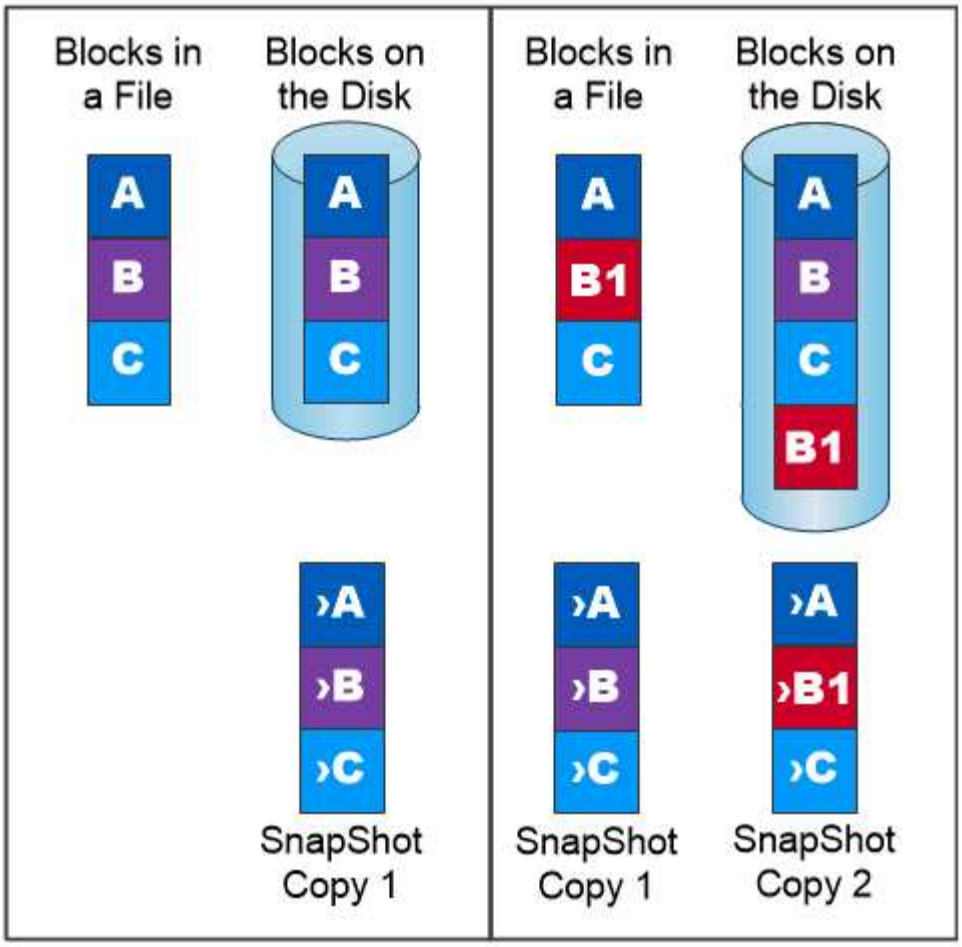
- **Seamless scaling and nondisruptive operations.** ONTAP supports the nondisruptive addition of capacity to existing controllers and to scale-out clusters. You can upgrade to the latest technologies, such as NVMe and 32Gb FC, without costly data migrations or outages.
- **Cloud connection.** ONTAP is one of the most cloud-connected storage management software, with options for software-defined storage (ONTAP Select) and cloud-native instances (NetApp Cloud Volumes Service) in all public clouds.
- **Integration with emerging applications.** By using the same infrastructure that supports existing enterprise apps, ONTAP offers enterprise-grade data services for next-generation platforms and applications such as OpenStack, Hadoop, and MongoDB.

NetApp Snapshot Copies

A NetApp Snapshot copy is a read-only, point-in-time image of a volume. The image consumes minimal storage space and incurs negligible performance overhead because it only records changes to files create since the last Snapshot copy was made, as depicted in the following figure.

Snapshot copies owe their efficiency to the core ONTAP storage virtualization technology, the Write Anywhere File Layout (WAFL). Like a database, WAFL uses metadata to point to actual data blocks on disk. But, unlike a database, WAFL does not overwrite existing blocks. It writes updated data to a new block and changes the metadata. It’s because ONTAP references metadata when it creates a Snapshot copy, rather than copying data blocks, that Snapshot copies are so efficient. Doing so eliminates the seek time that other systems incur in locating the blocks to copy, as well as the cost of making the copy itself.

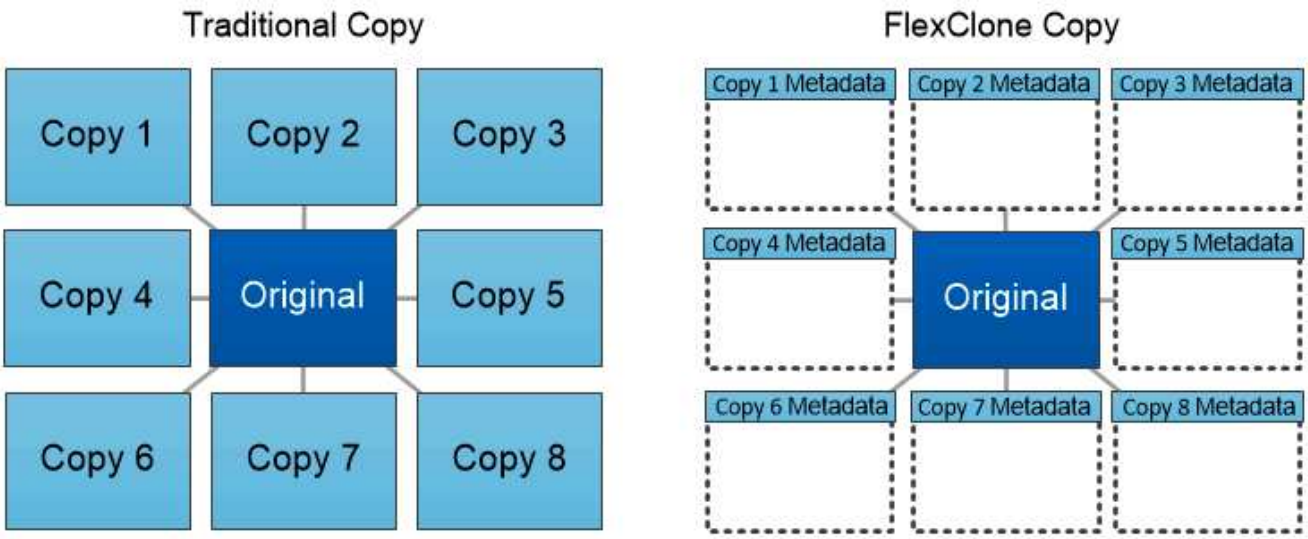
You can use a Snapshot copy to recover individual files or LUNs or to restore the entire contents of a volume. ONTAP compares pointer information in the Snapshot copy with data on disk to reconstruct the missing or damaged object, without downtime or a significant performance cost.



A Snapshot copy records only changes to the active file system since the last Snapshot copy.

NetApp FlexClone Technology

NetApp FlexClone technology references Snapshot metadata to create writable, point-in-time copies of a volume. Copies share data blocks with their parents, consuming no storage except what is required for metadata until changes are written to the copy, as depicted in the following figure. Where traditional copies can take minutes or even hours to create, FlexClone software lets you copy even the largest datasets almost instantaneously. That makes it ideal for situations in which you need multiple copies of identical datasets (a development workspace, for example) or temporary copies of a dataset (testing an application against a production dataset).

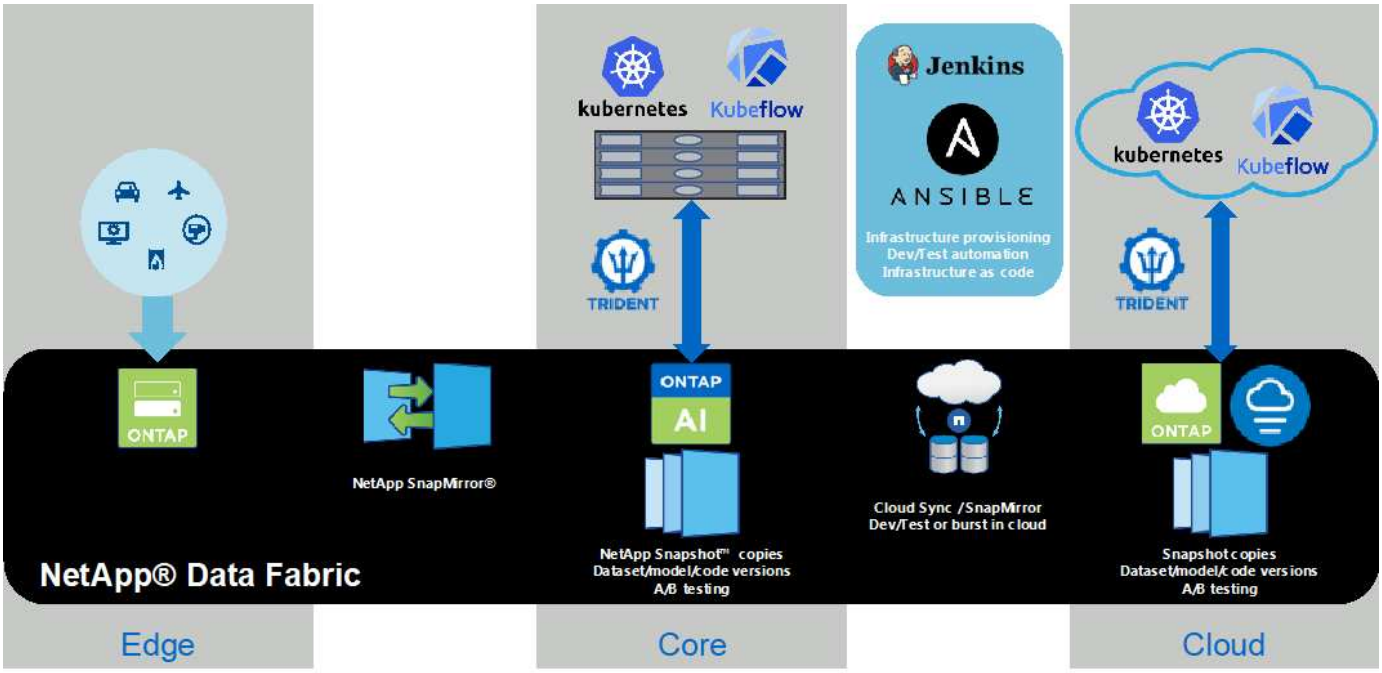


FlexClone copies share data blocks with their parents, consuming no storage except what is required for metadata.

NetApp SnapMirror Data Replication Technology

NetApp SnapMirror software is a cost-effective, easy-to-use unified replication solution across the data fabric. It replicates data at high speeds over LAN or WAN. It gives you high data availability and fast data replication for applications of all types, including business critical applications in both virtual and traditional environments. When you replicate data to one or more NetApp storage systems and continually update the secondary data, your data is kept current and is available whenever you need it. No external replication servers are required. See the following figure for an example of an architecture that leverages SnapMirror technology.

SnapMirror software leverages NetApp ONTAP storage efficiencies by sending only changed blocks over the network. SnapMirror software also uses built-in network compression to accelerate data transfers and reduce network bandwidth utilization by up to 70%. With SnapMirror technology, you can leverage one thin replication data stream to create a single repository that maintains both the active mirror and prior point-in-time copies, reducing network traffic by up to 50%.



NetApp Cloud Sync

Cloud Sync is a NetApp service for rapid and secure data synchronization. Whether you need to transfer files between on-premises NFS or SMB file shares, NetApp StorageGRID, NetApp ONTAP S3, NetApp Cloud Volumes Service, Azure NetApp Files, AWS S3, AWS EFS, Azure Blob, Google Cloud Storage, or IBM Cloud Object Storage, Cloud Sync moves the files where you need them quickly and securely.

After your data is transferred, it is fully available for use on both source and target. Cloud Sync can sync data on-demand when an update is triggered or continuously sync data based on a predefined schedule. Regardless, Cloud Sync only moves the deltas, so time and money spent on data replication is minimized.

Cloud Sync is a software as a service (SaaS) tool that is extremely simple to set up and use. Data transfers that are triggered by Cloud Sync are carried out by data brokers. Cloud Sync data brokers can be deployed in AWS, Azure, Google Cloud Platform, or on-premises.

NetApp XCP

NetApp XCP is client-based software for any-to-NetApp and NetApp-to-NetApp data migrations and file system insights. XCP is designed to scale and achieve maximum performance by utilizing all available system resources to handle high-volume datasets and high-performance migrations. XCP helps you to gain complete visibility into the file system with the option to generate reports.

NetApp XCP is available in a single package that supports NFS and SMB protocols. XCP includes a Linux binary for NFS data sets and a windows executable for SMB data sets.

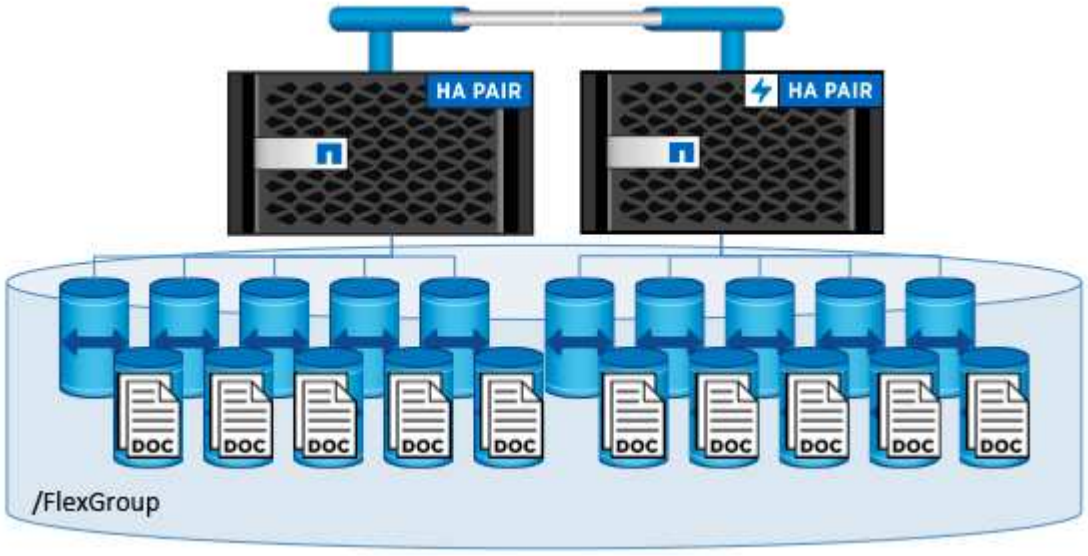
NetApp XCP File Analytics is host-based software that detects file shares, runs scans on the file system, and provides a dashboard for file analytics. XCP File Analytics is compatible with both NetApp and non-NetApp systems and runs on Linux or Windows hosts to provide analytics for NFS and SMB-exported file systems.

NetApp ONTAP FlexGroup Volumes

A training dataset can be a collection of potentially billions of files. Files can include text, audio, video, and other forms of unstructured data that must be stored and processed to be read in parallel. The storage system must store large numbers of small files and must read those files in parallel for sequential and random I/O.

A FlexGroup volume is a single namespace that comprises multiple constituent member volumes, as shown in the following figure. From a storage administrator viewpoint, a FlexGroup volume is managed and acts like a NetApp FlexVol volume. Files in a FlexGroup volume are allocated to individual member volumes and are not striped across volumes or nodes. They enable the following capabilities:

- FlexGroup volumes provide multiple petabytes of capacity and predictable low latency for high-metadata workloads.
- They support up to 400 billion files in the same namespace.
- They support parallelized operations in NAS workloads across CPUs, nodes, aggregates, and constituent FlexVol volumes.



Next: Hardware and Software Requirements.

Hardware and Software Requirements

The NetApp AI Control Plane solution is not dependent on this specific hardware. The solution is compatible with any NetApp physical storage appliance, software-defined instance, or cloud service, that is supported by Trident. Examples include a NetApp AFF storage system, Azure NetApp Files, NetApp Cloud Volumes Service, a NetApp ONTAP Select software-defined storage instance, or a NetApp Cloud Volumes ONTAP instance. Additionally, the solution can be implemented on any Kubernetes cluster as long as the Kubernetes version used is supported by Kubeflow and NetApp Trident. For a list of Kubernetes versions that are supported by Kubeflow, see the see the official Kubeflow documentation. For a list of Kubernetes versions that are supported by Trident, see the Trident documentation. See the following tables for details on the environment that was used to validate the solution.

Infrastructure Component	Quantity	Details	Operating System
Deployment jump host	1	VM	Ubuntu 20.04.2 LTS

Infrastructure Component	Quantity	Details	Operating System
Kubernetes master nodes	1	VM	Ubuntu 20.04.2 LTS
Kubernetes worker nodes	2	VM	Ubuntu 20.04.2 LTS
Kubernetes GPU worker nodes	2	NVIDIA DGX-1 (bare-metal)	NVIDIA DGX OS 4.0.5 (based on Ubuntu 18.04.2 LTS)
Storage	1 HA Pair	NetApp AFF A220	NetApp ONTAP 9.7 P6

Software Component	Version
Apache Airflow	2.0.1
Apache Airflow Helm Chart	8.0.8
Docker	19.03.12
Kubeflow	1.2
Kubernetes	1.18.9
NetApp Trident	21.01.2
NVIDIA DeepOps	Trident deployment functionality from master branch as of commit 61898cdfda; All other functionality from version 21.03

Support

NetApp does not offer enterprise support for Apache Airflow, Docker, Kubeflow, Kubernetes, or NVIDIA DeepOps. If you are interested in a fully supported solution with capabilities similar to the NetApp AI Control Plane solution, contact NetApp about fully supported AI/ML solutions that NetApp offers jointly with partners.

Next: Kubernetes Deployment.

Kubernetes Deployment

This section describes the tasks that you must complete to deploy a Kubernetes cluster in which to implement the NetApp AI Control Plane solution. If you already have a Kubernetes cluster, then you can skip this section as long as you are running a version of Kubernetes that is supported by Kubeflow and NetApp Trident. For a list of Kubernetes versions that are supported by Kubeflow, see the see the official Kubeflow documentation. For a list of Kubernetes versions that are supported by Trident, see the Trident documentation.

For on-premises Kubernetes deployments that incorporate bare-metal nodes featuring NVIDIA GPU(s), NetApp recommends using NVIDIA's DeepOps Kubernetes deployment tool. This section outlines the deployment of a Kubernetes cluster using DeepOps.

Prerequisites

Before you perform the deployment exercise that is outlined in this section, we assume that you have already

performed the following tasks:

1. You have already configured any bare-metal Kubernetes nodes (for example, an NVIDIA DGX system that is part of an ONTAP AI pod) according to standard configuration instructions.
2. You have installed a supported operating system on all Kubernetes master and worker nodes and on a deployment jump host. For a list of operating systems that are supported by DeepOps, see the DeepOps GitHub site.

Use NVIDIA DeepOps to Install and Configure Kubernetes

To deploy and configure your Kubernetes cluster with NVIDIA DeepOps, perform the following tasks from a deployment jump host:

1. Download NVIDIA DeepOps by following the instructions on the Getting Started page on the NVIDIA DeepOps GitHub site.
2. Deploy Kubernetes in your cluster by following the instructions on the Kubernetes Deployment Guide page on the NVIDIA DeepOps GitHub site.

Next: NetApp Trident Deployment and Configuration Overview.

NetApp Trident Deployment and Configuration

This section describes the tasks that you must complete to install and configure NetApp Trident in your Kubernetes cluster.

Prerequisites

Before you perform the deployment exercise that is outlined in this section, we assume that you have already performed the following tasks:

1. You already have a working Kubernetes cluster, and you are running a version of Kubernetes that is supported by Trident. For a list of supported versions, see the Trident documentation.
2. You already have a working NetApp storage appliance, software-defined instance, or cloud storage service, that is supported by Trident.

Install Trident

To install and configure NetApp Trident in your Kubernetes cluster, perform the following tasks from the deployment jump host:

1. Deploy Trident using one of the following methods:
    - If you used NVIDIA DeepOps to deploy your Kubernetes cluster, you can also use NVIDIA DeepOps to deploy Trident in your Kubernetes cluster. To deploy Trident with DeepOps, follow the Trident deployment instructions on the NVIDIA DeepOps GitHub site.
    - If you did not use NVIDIA DeepOps to deploy your Kubernetes cluster or if you simply prefer to deploy Trident manually, you can deploy Trident by following the deployment instructions in the Trident documentation. Be sure to create at least one Trident Backend and at least one Kubernetes StorageClass. For more information about Backends and StorageClasses, see the Trident documentation.

If you are deploying the NetApp AI Control Plane solution on an ONTAP AI pod, see Example Trident Backends for ONTAP AI Deployments for some examples of different Trident Backends that you might want to create and Example Kubernetes Storageclasses for ONTAP AI Deployments for some examples of different Kubernetes StorageClasses that you might want to create.

Next: Example Trident Backends for ONTAP AI Deployments.

NetApp Trident Deployment and Configuration

This section describes the tasks that you must complete to install and configure NetApp Trident in your Kubernetes cluster.

Prerequisites

Before you perform the deployment exercise that is outlined in this section, we assume that you have already performed the following tasks:

1. You already have a working Kubernetes cluster, and you are running a version of Kubernetes that is supported by Trident. For a list of supported versions, see the Trident documentation.
2. You already have a working NetApp storage appliance, software-defined instance, or cloud storage service, that is supported by Trident.

Install Trident

To install and configure NetApp Trident in your Kubernetes cluster, perform the following tasks from the deployment jump host:

1. Deploy Trident using one of the following methods:
   - If you used NVIDIA DeepOps to deploy your Kubernetes cluster, you can also use NVIDIA DeepOps to deploy Trident in your Kubernetes cluster. To deploy Trident with DeepOps, follow the Trident deployment instructions on the NVIDIA DeepOps GitHub site.
   - If you did not use NVIDIA DeepOps to deploy your Kubernetes cluster or if you simply prefer to deploy Trident manually, you can deploy Trident by following the deployment instructions in the Trident documentation. Be sure to create at least one Trident Backend and at least one Kubernetes StorageClass. For more information about Backends and StorageClasses, see the Trident documentation.

If you are deploying the NetApp AI Control Plane solution on an ONTAP AI pod, see Example Trident Backends for ONTAP AI Deployments for some examples of different Trident Backends that you might want to create and Example Kubernetes Storageclasses for ONTAP AI Deployments for some examples of different Kubernetes StorageClasses that you might want to create.

Next: Example Trident Backends for ONTAP AI Deployments.

Example Trident Backends for ONTAP AI Deployments

Before you can use Trident to dynamically provision storage resources within your Kubernetes cluster, you must create one or more Trident Backends. The examples that follow represent different types of Backends that you might want to create if you are

deploying the NetApp AI Control Plane solution on an ONTAP AI pod. For more information about Backends, see the Trident documentation.

1. NetApp recommends creating a FlexGroup-enabled Trident Backend for each data LIF (logical network interface that provides data access) that you want to use on your NetApp AFF system. This will allow you to balance volume mounts across LIFs

   The example commands that follow show the creation of two FlexGroup-enabled Trident Backends for two different data LIFs that are associated with the same ONTAP storage virtual machine (SVM). These Backends use the `ontap-nas-flexgroup` storage driver. ONTAP supports two main data volume types: FlexVol and FlexGroup. FlexVol volumes are size-limited (as of this writing, the maximum size depends on the specific deployment). FlexGroup volumes, on the other hand, can scale linearly to up to 20PB and 400 billion files, providing a single namespace that greatly simplifies data management. Therefore, FlexGroup volumes are optimal for AI and ML workloads that rely on large amounts of data.

   If you are working with a small amount of data and want to use FlexVol volumes instead of FlexGroup volumes, you can create Trident Backends that use the `ontap-nas` storage driver instead of the `ontap-nas-flexgroup` storage driver.

```
$ cat << EOF > ./trident-backend-ontap-ai-flexgroups-iface1.json
{
    "version": 1,
    "storageDriverName": "ontap-nas-flexgroup",
    "backendName": "ontap-ai-flexgroups-iface1",
    "managementLIF": "10.61.218.100",
    "dataLIF": "192.168.11.11",
    "svm": "ontapai_nfs",
    "username": "admin",
    "password": "ontapai"
}
EOF
$ tridentctl create backend -f ./trident-backend-ontap-ai-flexgroups-
iface1.json -n trident
+----------------------------+--------------------
+--------------------------------------+--------+---------+
|            NAME            |   STORAGE DRIVER    |
UUID                  | STATE  | VOLUMES |
+----------------------------+--------------------
+--------------------------------------+--------+---------+
| ontap-ai-flexgroups-iface1 | ontap-nas-flexgroup | b74cbddb-e0b8-40b7-
b263-b6da6dec0bdd | online |       0 |
+----------------------------+--------------------
+--------------------------------------+--------+---------+
$ cat << EOF > ./trident-backend-ontap-ai-flexgroups-iface2.json
{
    "version": 1,
    "storageDriverName": "ontap-nas-flexgroup",
    "backendName": "ontap-ai-flexgroups-iface2",
```

```
    "managementLIF": "10.61.218.100",
    "dataLIF": "192.168.12.12",
    "svm": "ontapai_nfs",
    "username": "admin",
    "password": "ontapai"
}
EOF
$ tridentctl create backend -f ./trident-backend-ontap-ai-flexgroups-
iface2.json -n trident
+----------------------------+--------------------
+--------------------------------------+--------+---------+
|            NAME            |   STORAGE DRIVER    |
UUID                  | STATE  | VOLUMES |
+----------------------------+--------------------
+--------------------------------------+--------+---------+
| ontap-ai-flexgroups-iface2 | ontap-nas-flexgroup | 61814d48-c770-436b-
9cb4-cf7ee661274d | online |       0 |
+----------------------------+--------------------
+--------------------------------------+--------+---------+
$ tridentctl get backend -n trident
+----------------------------+--------------------
+--------------------------------------+--------+---------+
|            NAME            |   STORAGE DRIVER    |
UUID                  | STATE  | VOLUMES |
+----------------------------+--------------------
+--------------------------------------+--------+---------+
| ontap-ai-flexgroups-iface1 | ontap-nas-flexgroup | b74cbddb-e0b8-40b7-
b263-b6da6dec0bdd | online |       0 |
| ontap-ai-flexgroups-iface2 | ontap-nas-flexgroup | 61814d48-c770-436b-
9cb4-cf7ee661274d | online |       0 |
+----------------------------+--------------------
+--------------------------------------+--------+---------+
```

2. NetApp also recommends creating one or more FlexVol- enabled Trident Backends. If you use FlexGroup volumes for training dataset storage, you might want to use FlexVol volumes for storing results, output, debug information, and so on. If you want to use FlexVol volumes, you must create one or more FlexVol-enabled Trident Backends. The example commands that follow show the creation of a single FlexVol-enabled Trident Backend that uses a single data LIF.

```
$ cat << EOF > ./trident-backend-ontap-ai-flexvols.json
{
    "version": 1,
    "storageDriverName": "ontap-nas",
    "backendName": "ontap-ai-flexvols",
    "managementLIF": "10.61.218.100",
    "dataLIF": "192.168.11.11",
    "svm": "ontapai_nfs",
    "username": "admin",
    "password": "ontapai"
}
EOF
$ tridentctl create backend -f ./trident-backend-ontap-ai-flexvols.json -n
trident
+----------------------------+--------------------
+--------------------------------------+--------+---------+
|            NAME            |   STORAGE DRIVER    |                 UUID
| STATE  | VOLUMES |
+----------------------------+--------------------
+--------------------------------------+--------+---------+
| ontap-ai-flexvols          | ontap-nas           | 52bdb3b1-13a5-4513-
a9c1-52a69657fabe | online |       0 |
+----------------------------+--------------------
+--------------------------------------+--------+---------+
$ tridentctl get backend -n trident
+----------------------------+--------------------
+--------------------------------------+--------+---------+
|            NAME            |   STORAGE DRIVER    |                 UUID
| STATE  | VOLUMES |
+----------------------------+--------------------
+--------------------------------------+--------+---------+
| ontap-ai-flexvols          | ontap-nas           | 52bdb3b1-13a5-4513-
a9c1-52a69657fabe | online |       0 |
| ontap-ai-flexgroups-iface1 | ontap-nas-flexgroup | b74cbddb-e0b8-40b7-
b263-b6da6dec0bdd | online |       0 |
| ontap-ai-flexgroups-iface2 | ontap-nas-flexgroup | 61814d48-c770-436b-
9cb4-cf7ee661274d | online |       0 |
+----------------------------+--------------------
+--------------------------------------+--------+---------+
```

Next: Example Kubernetes Storageclasses for ONTAP AI Deployments.

Example Kubernetes StorageClasses for ONTAP AI Deployments

Before you can use Trident to dynamically provision storage resources within your

Kubernetes cluster, you must create one or more Kubernetes StorageClasses. The examples that follow represent different types of StorageClasses that you might want to create if you are deploying the NetApp AI Control Plane solution on an ONTAP AI pod. For more information about StorageClasses, see the Trident documentation.

1. NetApp recommends creating a separate StorageClass for each FlexGroup-enabled Trident Backend that you created in the section Example Trident Backends for ONTAP AI Deployments, step 1. These granular StorageClasses enable you to add NFS mounts that correspond to specific LIFs (the LIFs that you specified when you created the Trident Backends) as a particular Backend that is specified in the StorageClass spec file. The example commands that follow show the creation of two StorageClasses that correspond to the two example Backends that were created in the section Example Trident Backends for ONTAP AI Deployments, step 1. For more information about StorageClasses, see the Trident documentation.

   So that a persistent volume isn't deleted when the corresponding PersistentVolumeClaim (PVC) is deleted, the following example uses a `reclaimPolicy` value of `Retain`. For more information about the `reclaimPolicy` field, see the official Kubernetes documentation.

```
$ cat << EOF > ./storage-class-ontap-ai-flexgroups-retain-iface1.yaml
apiVersion: storage.k8s.io/v1
kind: StorageClass
metadata:
  name: ontap-ai-flexgroups-retain-iface1
provisioner: netapp.io/trident
parameters:
  backendType: "ontap-nas-flexgroup"
  storagePools: "ontap-ai-flexgroups-iface1:.*"
reclaimPolicy: Retain
EOF
$ kubectl create -f ./storage-class-ontap-ai-flexgroups-retain-
iface1.yaml
storageclass.storage.k8s.io/ontap-ai-flexgroups-retain-iface1 created
$ cat << EOF > ./storage-class-ontap-ai-flexgroups-retain-iface2.yaml
apiVersion: storage.k8s.io/v1
kind: StorageClass
metadata:
  name: ontap-ai-flexgroups-retain-iface2
provisioner: netapp.io/trident
parameters:
  backendType: "ontap-nas-flexgroup"
  storagePools: "ontap-ai-flexgroups-iface2:.*"
reclaimPolicy: Retain
EOF
$ kubectl create -f ./storage-class-ontap-ai-flexgroups-retain-
iface2.yaml
storageclass.storage.k8s.io/ontap-ai-flexgroups-retain-iface2 created
$ kubectl get storageclass
NAME                                 PROVISIONER          AGE
ontap-ai-flexgroups-retain-iface1    netapp.io/trident    0m
ontap-ai-flexgroups-retain-iface2    netapp.io/trident    0m
```

2. NetApp also recommends creating a StorageClass that corresponds to the FlexVol-enabled Trident Backend that you created in the section Example Trident Backends for ONTAP AI Deployments, step 2. The example commands that follow show the creation of a single StorageClass for FlexVol volumes.

   In the following example, a particular Backend is not specified in the StorageClass definition file because only one FlexVol-enabled Trident backend was created. When you use Kubernetes to administer volumes that use this StorageClass, Trident attempts to use any available backend that uses the `ontap-nas` driver.

```
$ cat << EOF > ./storage-class-ontap-ai-flexvols-retain.yaml
apiVersion: storage.k8s.io/v1
kind: StorageClass
metadata:
  name: ontap-ai-flexvols-retain
provisioner: netapp.io/trident
parameters:
  backendType: "ontap-nas"
reclaimPolicy: Retain
EOF
$ kubectl create -f ./storage-class-ontap-ai-flexvols-retain.yaml
storageclass.storage.k8s.io/ontap-ai-flexvols-retain created
$ kubectl get storageclass
NAME                                  PROVISIONER         AGE
ontap-ai-flexgroups-retain-iface1   netapp.io/trident   1m
ontap-ai-flexgroups-retain-iface2   netapp.io/trident   1m
ontap-ai-flexvols-retain            netapp.io/trident   0m
```

3. NetApp also recommends creating a generic StorageClass for FlexGroup volumes. The following example commands show the creation of a single generic StorageClass for FlexGroup volumes.

   Note that a particular backend is not specified in the StorageClass definition file. Therefore, when you use Kubernetes to administer volumes that use this StorageClass, Trident attempts to use any available backend that uses the `ontap-nas-flexgroup` driver.

```
$ cat << EOF > ./storage-class-ontap-ai-flexgroups-retain.yaml
apiVersion: storage.k8s.io/v1
kind: StorageClass
metadata:
  name: ontap-ai-flexgroups-retain
provisioner: netapp.io/trident
parameters:
  backendType: "ontap-nas-flexgroup"
reclaimPolicy: Retain
EOF
$ kubectl create -f ./storage-class-ontap-ai-flexgroups-retain.yaml
storageclass.storage.k8s.io/ontap-ai-flexgroups-retain created
$ kubectl get storageclass
NAME                                 PROVISIONER         AGE
ontap-ai-flexgroups-retain          netapp.io/trident   0m
ontap-ai-flexgroups-retain-iface1   netapp.io/trident   2m
ontap-ai-flexgroups-retain-iface2   netapp.io/trident   2m
ontap-ai-flexvols-retain            netapp.io/trident   1m
```

Next: Kubeflow Deployment Overview.

Kubeflow Deployment

This section describes the tasks that you must complete to deploy Kubeflow in your Kubernetes cluster.

Prerequisites

Before you perform the deployment exercise that is outlined in this section, we assume that you have already performed the following tasks:

1. You already have a working Kubernetes cluster, and you are running a version of Kubernetes that is supported by Kubeflow. For a list of supported versions, see the official Kubeflow documentation.
2. You have already installed and configured NetApp Trident in your Kubernetes cluster as outlined in Trident Deployment and Configuration.

Set Default Kubernetes StorageClass

Before you deploy Kubeflow, you must designate a default StorageClass within your Kubernetes cluster. The Kubeflow deployment process attempts to provision new persistent volumes using the default StorageClass. If no StorageClass is designated as the default StorageClass, then the deployment fails. To designate a default StorageClass within your cluster, perform the following task from the deployment jump host. If you have already designated a default StorageClass within your cluster, then you can skip this step.

1. Designate one of your existing StorageClasses as the default StorageClass. The example commands that follow show the designation of a StorageClass named `ontap-ai- flexvols-retain` as the default StorageClass.

The `ontap-nas-flexgroup` Trident Backend type has a minimum PVC size that is fairly large. By default, Kubeflow attempts to provision PVCs that are only a few GBs in size. Therefore, you should not designate a StorageClass that utilizes the `ontap-nas-flexgroup` Backend type as the default StorageClass for the purposes of Kubeflow deployment.

```
$ kubectl get sc
NAME                                  PROVISIONER             AGE
ontap-ai-flexgroups-retain            csi.trident.netapp.io   25h
ontap-ai-flexgroups-retain-iface1     csi.trident.netapp.io   25h
ontap-ai-flexgroups-retain-iface2     csi.trident.netapp.io   25h
ontap-ai-flexvols-retain              csi.trident.netapp.io   3s
$ kubectl patch storageclass ontap-ai-flexvols-retain -p '{"metadata":
{"annotations":{"storageclass.kubernetes.io/is-default-class":"true"}}}'
storageclass.storage.k8s.io/ontap-ai-flexvols-retain patched
$ kubectl get sc
NAME                                   PROVISIONER             AGE
ontap-ai-flexgroups-retain             csi.trident.netapp.io   25h
ontap-ai-flexgroups-retain-iface1      csi.trident.netapp.io   25h
ontap-ai-flexgroups-retain-iface2      csi.trident.netapp.io   25h
ontap-ai-flexvols-retain (default)     csi.trident.netapp.io   54s
```

Use NVIDIA DeepOps to Deploy Kubeflow

NetApp recommends using the Kubeflow deployment tool that is provided by NVIDIA DeepOps. To deploy Kubeflow in your Kubernetes cluster using the DeepOps deployment tool, perform the following tasks from the deployment jump host.

> Alternatively, you can deploy Kubeflow manually by following the installation instructions in the official Kubeflow documentation

1. Deploy Kubeflow in your cluster by following the Kubeflow deployment instructions on the NVIDIA DeepOps GitHub site.
2. Note down the Kubeflow Dashboard URL that the DeepOps Kubeflow deployment tool outputs.

```
$ ./scripts/k8s/deploy_kubeflow.sh -x
…
INFO[0007] Applied the configuration Successfully!
filename="cmd/apply.go:72"
Kubeflow app installed to: /home/ai/kubeflow
It may take several minutes for all services to start. Run 'kubectl get
pods -n kubeflow' to verify
To remove (excluding CRDs, istio, auth, and cert-manager), run:
./scripts/k8s_deploy_kubeflow.sh -d
To perform a full uninstall : ./scripts/k8s_deploy_kubeflow.sh -D
Kubeflow Dashboard (HTTP NodePort): http://10.61.188.111:31380
```

3. Confirm that all pods deployed within the Kubeflow namespace show a `STATUS` of `Running` and confirm that no components deployed within the namespace are in an error state. It may take several minutes for all pods to start.

```
$ kubectl get all -n kubeflow
NAME                                                        READY
STATUS    RESTARTS   AGE
pod/admission-webhook-bootstrap-stateful-set-0              1/1
Running   0          95s
pod/admission-webhook-deployment-6b89c84c98-vrtbh           1/1
Running   0          91s
pod/application-controller-stateful-set-0                   1/1
Running   0          98s
pod/argo-ui-5dcf5d8b4f-m2wn4                                1/1
Running   0          97s
pod/centraldashboard-cf4874ddc-7hcr8                        1/1
Running   0          97s
pod/jupyter-web-app-deployment-685b455447-gjhh7             1/1
Running   0          96s
pod/katib-controller-88c97d85c-kgq66                        1/1
Running   1          95s
```

```
pod/katib-db-8598468fd8-5jw2c                                     1/1
Running   0          95s
pod/katib-manager-574c8c67f9-wtrf5                                1/1
Running   1          95s
pod/katib-manager-rest-778857c989-fjbzn                           1/1
Running   0          95s
pod/katib-suggestion-bayesianoptimization-65df4d7455-qthmw        1/1
Running   0          94s
pod/katib-suggestion-grid-56bf69f597-98vwn                        1/1
Running   0          94s
pod/katib-suggestion-hyperband-7777b76cb9-9v6dq                   1/1
Running   0          93s
pod/katib-suggestion-nasrl-77f6f9458c-2qzxq                       1/1
Running   0          93s
pod/katib-suggestion-random-77b88b5c79-l64j9                      1/1
Running   0          93s
pod/katib-ui-7587c5b967-nd629                                     1/1
Running   0          95s
pod/metacontroller-0                                              1/1
Running   0          96s
pod/metadata-db-5dd459cc-swzkm                                    1/1
Running   0          94s
pod/metadata-deployment-6cf77db994-69fk7                          1/1
Running   3          93s
pod/metadata-deployment-6cf77db994-mpbjt                          1/1
Running   3          93s
pod/metadata-deployment-6cf77db994-xg7tz                          1/1
Running   3          94s
pod/metadata-ui-78f5b59b56-qb6kr                                  1/1
Running   0          94s
pod/minio-758b769d67-llvdr                                        1/1
Running   0          91s
pod/ml-pipeline-5875b9db95-g8t2k                                  1/1
Running   0          91s
pod/ml-pipeline-persistenceagent-9b69ddd46-bt9r9                  1/1
Running   0          90s
pod/ml-pipeline-scheduledworkflow-7b8d756c76-7x56s                1/1
Running   0          90s
pod/ml-pipeline-ui-79ffd9c76-fcwpd                                1/1
Running   0          90s
pod/ml-pipeline-viewer-controller-deployment-5fdc87f58-b2t9r      1/1
Running   0          90s
pod/mysql-657f87857d-l5k9z                                        1/1
Running   0          91s
pod/notebook-controller-deployment-56b4f59bbf-8bvnr               1/1
Running   0          92s
```

```
pod/profiles-deployment-6bc745947-mrdkh                          2/2
Running   0          90s
pod/pytorch-operator-77c97f4879-hmlrv                            1/1
Running   0          92s
pod/seldon-operator-controller-manager-0                         1/1
Running   1          91s
pod/spartakus-volunteer-5fdfddb779-l7qkm                         1/1
Running   0          92s
pod/tensorboard-6544748d94-nh8b2                                 1/1
Running   0          92s
pod/tf-job-dashboard-56f79c59dd-6w59t                            1/1
Running   0          92s
pod/tf-job-operator-79cbfd6dbc-rb58c                             1/1
Running   0          91s
pod/workflow-controller-db644d554-cwrnb                          1/1
Running   0          97s
NAME                                                  TYPE
CLUSTER-IP      EXTERNAL-IP   PORT(S)             AGE
service/admission-webhook-service                     ClusterIP
10.233.51.169   <none>        443/TCP             97s
service/application-controller-service                ClusterIP
10.233.4.54     <none>        443/TCP             98s
service/argo-ui                                       NodePort
10.233.47.191   <none>        80:31799/TCP        97s
service/centraldashboard                              ClusterIP
10.233.8.36     <none>        80/TCP              97s
service/jupyter-web-app-service                       ClusterIP
10.233.1.42     <none>        80/TCP              97s
service/katib-controller                              ClusterIP
10.233.25.226   <none>        443/TCP             96s
service/katib-db                                      ClusterIP
10.233.33.151   <none>        3306/TCP            97s
service/katib-manager                                 ClusterIP
10.233.46.239   <none>        6789/TCP            96s
service/katib-manager-rest                            ClusterIP
10.233.55.32    <none>        80/TCP              96s
service/katib-suggestion-bayesianoptimization        ClusterIP
10.233.49.191   <none>        6789/TCP            95s
service/katib-suggestion-grid                         ClusterIP
10.233.9.105    <none>        6789/TCP            95s
service/katib-suggestion-hyperband                    ClusterIP
10.233.22.2     <none>        6789/TCP            95s
service/katib-suggestion-nasrl                        ClusterIP
10.233.63.73    <none>        6789/TCP            95s
service/katib-suggestion-random                       ClusterIP
10.233.57.210   <none>        6789/TCP            95s
```

```
service/katib-ui                                        ClusterIP
10.233.6.116    <none>        80/TCP              96s
service/metadata-db                                     ClusterIP
10.233.31.2     <none>        3306/TCP            96s
service/metadata-service                                ClusterIP
10.233.27.104   <none>        8080/TCP            96s
service/metadata-ui                                     ClusterIP
10.233.57.177   <none>        80/TCP              96s
service/minio-service                                   ClusterIP
10.233.44.90    <none>        9000/TCP            94s
service/ml-pipeline                                     ClusterIP
10.233.41.201   <none>        8888/TCP,8887/TCP   94s
service/ml-pipeline-tensorboard-ui                      ClusterIP
10.233.36.207   <none>        80/TCP              93s
service/ml-pipeline-ui                                  ClusterIP
10.233.61.150   <none>        80/TCP              93s
service/mysql                                           ClusterIP
10.233.55.117   <none>        3306/TCP            94s
service/notebook-controller-service                     ClusterIP
10.233.10.166   <none>        443/TCP             95s
service/profiles-kfam                                   ClusterIP
10.233.33.79    <none>        8081/TCP            92s
service/pytorch-operator                                ClusterIP
10.233.37.112   <none>        8443/TCP            95s
service/seldon-operator-controller-manager-service   ClusterIP
10.233.30.178   <none>        443/TCP             92s
service/tensorboard                                     ClusterIP
10.233.58.151   <none>        9000/TCP            94s
service/tf-job-dashboard                                ClusterIP
10.233.4.17     <none>        80/TCP              94s
service/tf-job-operator                                 ClusterIP
10.233.60.32    <none>        8443/TCP            94s
service/webhook-server-service                          ClusterIP
10.233.32.167   <none>        443/TCP             87s
NAME                                                    READY   UP-
TO-DATE   AVAILABLE   AGE
deployment.apps/admission-webhook-deployment            1/1     1
1           97s
deployment.apps/argo-ui                                 1/1     1
1           97s
deployment.apps/centraldashboard                        1/1     1
1           97s
deployment.apps/jupyter-web-app-deployment              1/1     1
1           97s
deployment.apps/katib-controller                        1/1     1
1           96s
```

```
deployment.apps/katib-db                                    1/1     1
1           97s
deployment.apps/katib-manager                               1/1     1
1           96s
deployment.apps/katib-manager-rest                          1/1     1
1           96s
deployment.apps/katib-suggestion-bayesianoptimization       1/1     1
1           95s
deployment.apps/katib-suggestion-grid                       1/1     1
1           95s
deployment.apps/katib-suggestion-hyperband                  1/1     1
1           95s
deployment.apps/katib-suggestion-nasrl                      1/1     1
1           95s
deployment.apps/katib-suggestion-random                     1/1     1
1           95s
deployment.apps/katib-ui                                    1/1     1
1           96s
deployment.apps/metadata-db                                 1/1     1
1           96s
deployment.apps/metadata-deployment                         3/3     3
3           96s
deployment.apps/metadata-ui                                 1/1     1
1           96s
deployment.apps/minio                                       1/1     1
1           94s
deployment.apps/ml-pipeline                                 1/1     1
1           94s
deployment.apps/ml-pipeline-persistenceagent                1/1     1
1           93s
deployment.apps/ml-pipeline-scheduledworkflow               1/1     1
1           93s
deployment.apps/ml-pipeline-ui                              1/1     1
1           93s
deployment.apps/ml-pipeline-viewer-controller-deployment    1/1     1
1           93s
deployment.apps/mysql                                       1/1     1
1           94s
deployment.apps/notebook-controller-deployment              1/1     1
1           95s
deployment.apps/profiles-deployment                         1/1     1
1           92s
deployment.apps/pytorch-operator                            1/1     1
1           95s
deployment.apps/spartakus-volunteer                         1/1     1
1           94s
```

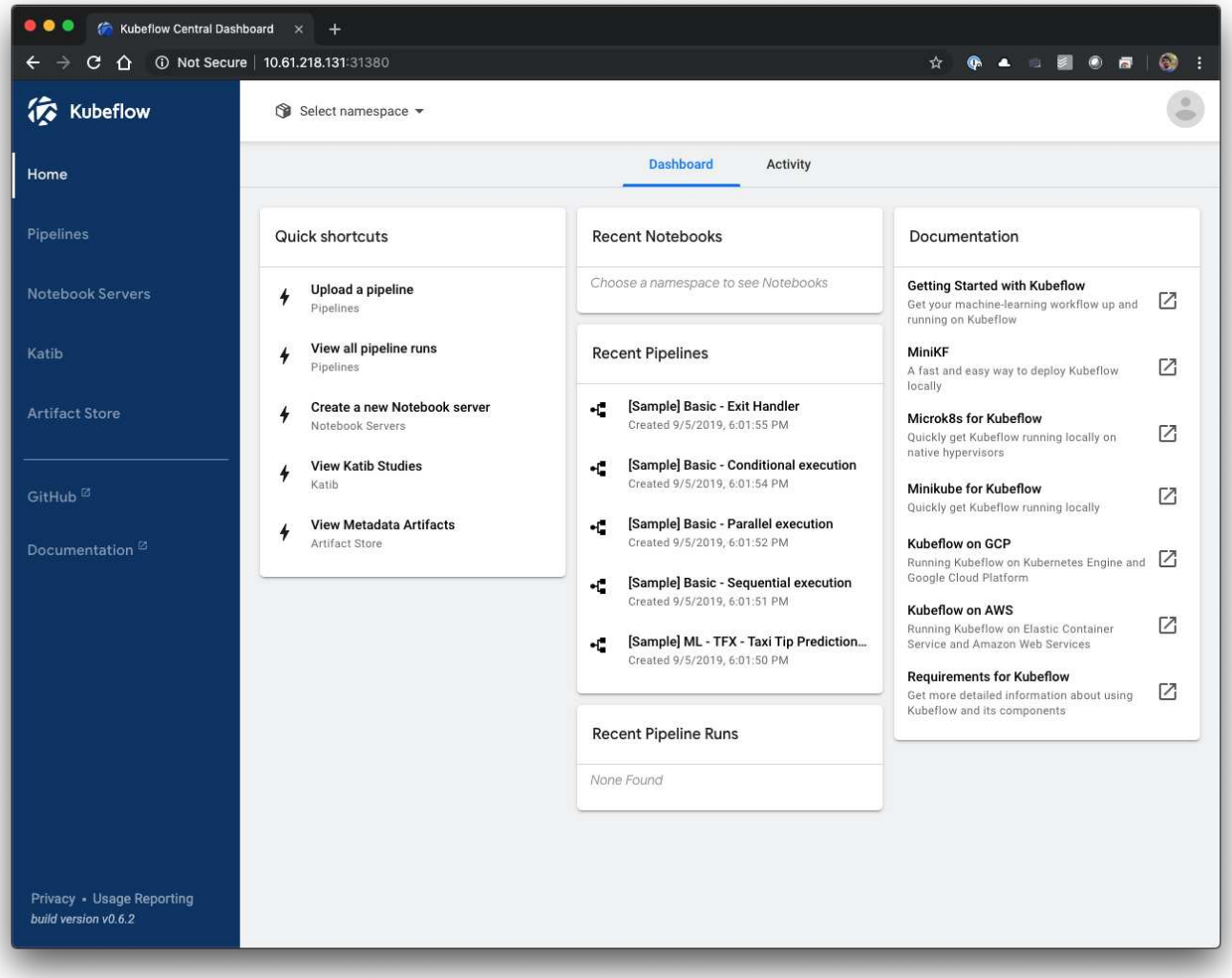
```
deployment.apps/tensorboard                                  1/1     1
1           94s
deployment.apps/tf-job-dashboard                             1/1     1
1           94s
deployment.apps/tf-job-operator                              1/1     1
1           94s
deployment.apps/workflow-controller                          1/1     1
1           97s
NAME
DESIRED   CURRENT   READY   AGE
replicaset.apps/admission-webhook-deployment-6b89c84c98              1
1         1       97s
replicaset.apps/argo-ui-5dcf5d8b4f                                  1
1         1       97s
replicaset.apps/centraldashboard-cf4874ddc                           1
1         1       97s
replicaset.apps/jupyter-web-app-deployment-685b455447                1
1         1       97s
replicaset.apps/katib-controller-88c97d85c                           1
1         1       96s
replicaset.apps/katib-db-8598468fd8                                  1
1         1       97s
replicaset.apps/katib-manager-574c8c67f9                             1
1         1       96s
replicaset.apps/katib-manager-rest-778857c989                        1
1         1       96s
replicaset.apps/katib-suggestion-bayesianoptimization-65df4d7455     1
1         1       95s
replicaset.apps/katib-suggestion-grid-56bf69f597                     1
1         1       95s
replicaset.apps/katib-suggestion-hyperband-7777b76cb9                1
1         1       95s
replicaset.apps/katib-suggestion-nasrl-77f6f9458c                    1
1         1       95s
replicaset.apps/katib-suggestion-random-77b88b5c79                   1
1         1       95s
replicaset.apps/katib-ui-7587c5b967                                  1
1         1       96s
replicaset.apps/metadata-db-5dd459cc                                 1
1         1       96s
replicaset.apps/metadata-deployment-6cf77db994                       3
3         3       96s
replicaset.apps/metadata-ui-78f5b59b56                               1
1         1       96s
replicaset.apps/minio-758b769d67                                     1
1         1       93s
```

```
replicaset.apps/ml-pipeline-5875b9db95                              1
1         1       93s
replicaset.apps/ml-pipeline-persistenceagent-9b69ddd46              1
1         1       92s
replicaset.apps/ml-pipeline-scheduledworkflow-7b8d756c76            1
1         1       91s
replicaset.apps/ml-pipeline-ui-79ffd9c76                            1
1         1       91s
replicaset.apps/ml-pipeline-viewer-controller-deployment-5fdc87f58  1
1         1       91s
replicaset.apps/mysql-657f87857d                                    1
1         1       92s
replicaset.apps/notebook-controller-deployment-56b4f59bbf           1
1         1       94s
replicaset.apps/profiles-deployment-6bc745947                       1
1         1       91s
replicaset.apps/pytorch-operator-77c97f4879                         1
1         1       94s
replicaset.apps/spartakus-volunteer-5fdfddb779                      1
1         1       94s
replicaset.apps/tensorboard-6544748d94                              1
1         1       93s
replicaset.apps/tf-job-dashboard-56f79c59dd                         1
1         1       93s
replicaset.apps/tf-job-operator-79cbfd6dbc                          1
1         1       93s
replicaset.apps/workflow-controller-db644d554                       1
1         1       97s
NAME                                                          READY   AGE
statefulset.apps/admission-webhook-bootstrap-stateful-set   1/1     97s
statefulset.apps/application-controller-stateful-set        1/1     98s
statefulset.apps/metacontroller                             1/1     98s
statefulset.apps/seldon-operator-controller-manager         1/1     92s
$ kubectl get pvc -n kubeflow
NAME             STATUS   VOLUME
CAPACITY   ACCESS MODES   STORAGECLASS               AGE
katib-mysql      Bound    pvc-b07f293e-d028-11e9-9b9d-00505681a82d
10Gi       RWO            ontap-ai-flexvols-retain   27m
metadata-mysql   Bound    pvc-b0f3f032-d028-11e9-9b9d-00505681a82d
10Gi       RWO            ontap-ai-flexvols-retain   27m
minio-pv-claim   Bound    pvc-b22727ee-d028-11e9-9b9d-00505681a82d
20Gi       RWO            ontap-ai-flexvols-retain   27m
mysql-pv-claim   Bound    pvc-b2429afd-d028-11e9-9b9d-00505681a82d
20Gi       RWO            ontap-ai-flexvols-retain   27m
```

4. In your web browser, access the Kubeflow central dashboard by navigating to the URL that you noted

down in step 2.

The default username is `admin@kubeflow.org`, and the default password is `12341234`. To create additional users, follow the instructions in the official Kubeflow documentation.



Next: Example Kubeflow Operations and Tasks.

Example Kubeflow Operations and Tasks

This section includes examples of various operations and tasks that you may want to perform using Kubeflow.

Next: Provision a Jupyter Notebook Workspace for Data Scientist or Developer Use.

Example Kubeflow Operations and Tasks

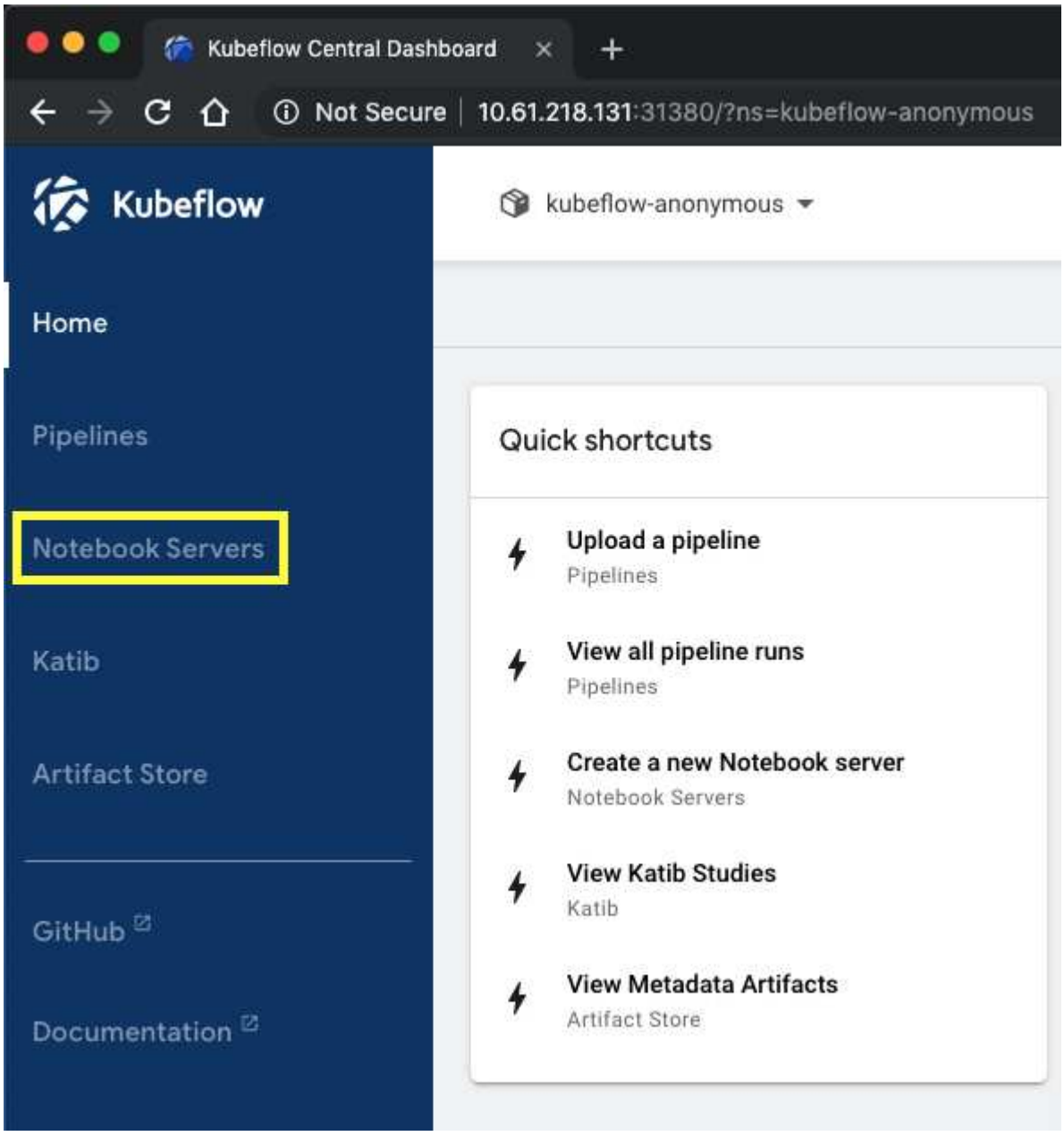
This section includes examples of various operations and tasks that you may want to perform using Kubeflow.

Next: Provision a Jupyter Notebook Workspace for Data Scientist or Developer Use.

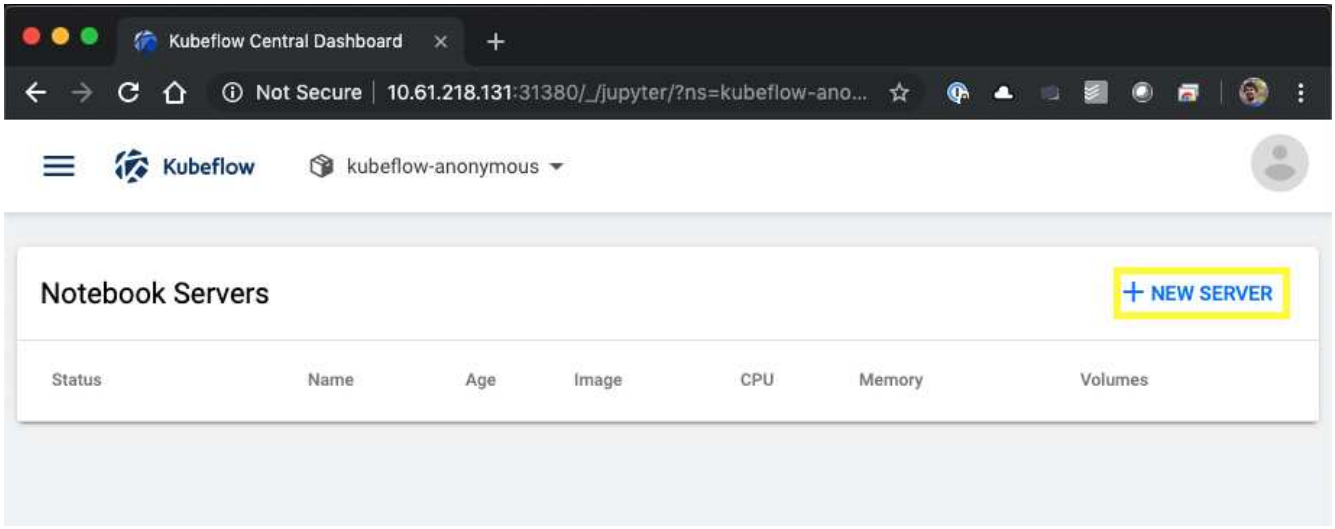
Provision a Jupyter Notebook Workspace for Data Scientist or Developer Use

Kubeflow is capable of rapidly provisioning new Jupyter Notebook servers to act as data scientist workspaces. To provision a new Jupyter Notebook server with Kubeflow, perform the following tasks. For more information about Jupyter Notebooks within the Kubeflow context, see the official Kubeflow documentation.

1. From the Kubeflow central dashboard, click Notebook Servers in the main menu to navigate to the Jupyter Notebook server administration page.

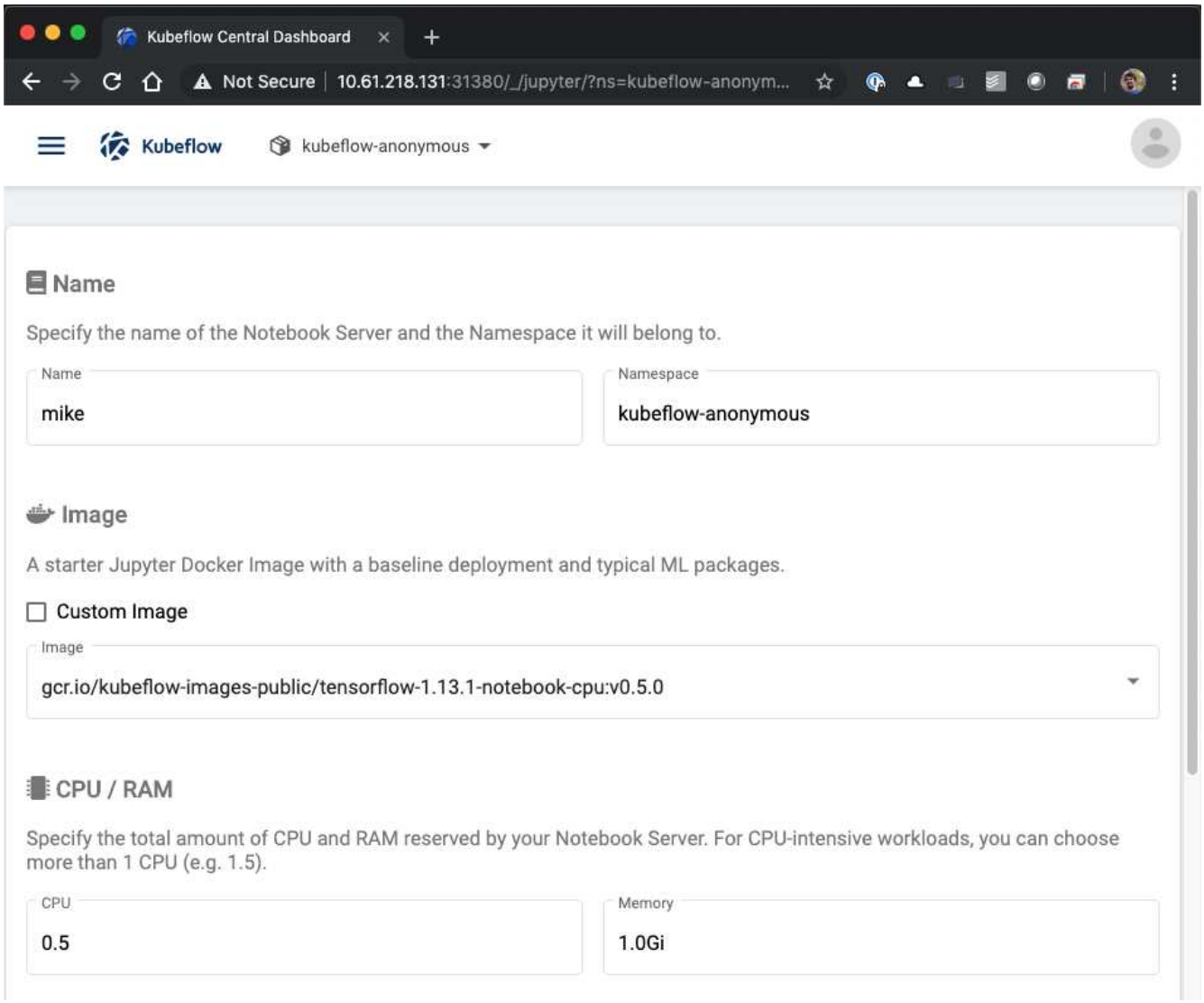


2. Click New Server to provision a new Jupyter Notebook server.

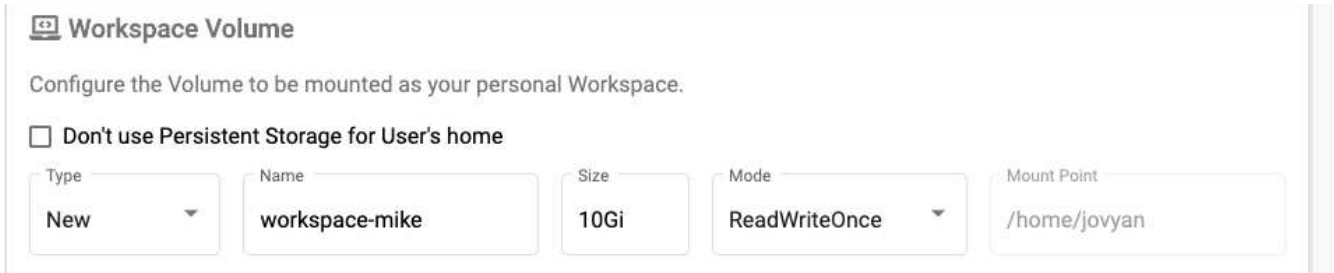


3. Give your new server a name, choose the Docker image that you want your server to be based on, and specify the amount of CPU and RAM to be reserved by your server. If the Namespace field is blank, use the Select Namespace menu in the page header to choose a namespace. The Namespace field is then auto-populated with the chosen namespace.

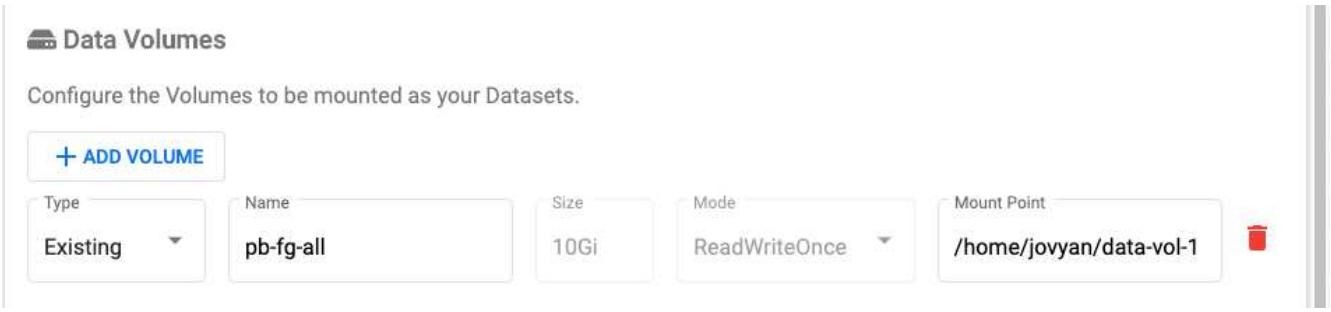
   In the following example, the `kubeflow-anonymous` namespace is chosen. In addition, the default values for Docker image, CPU, and RAM are accepted.



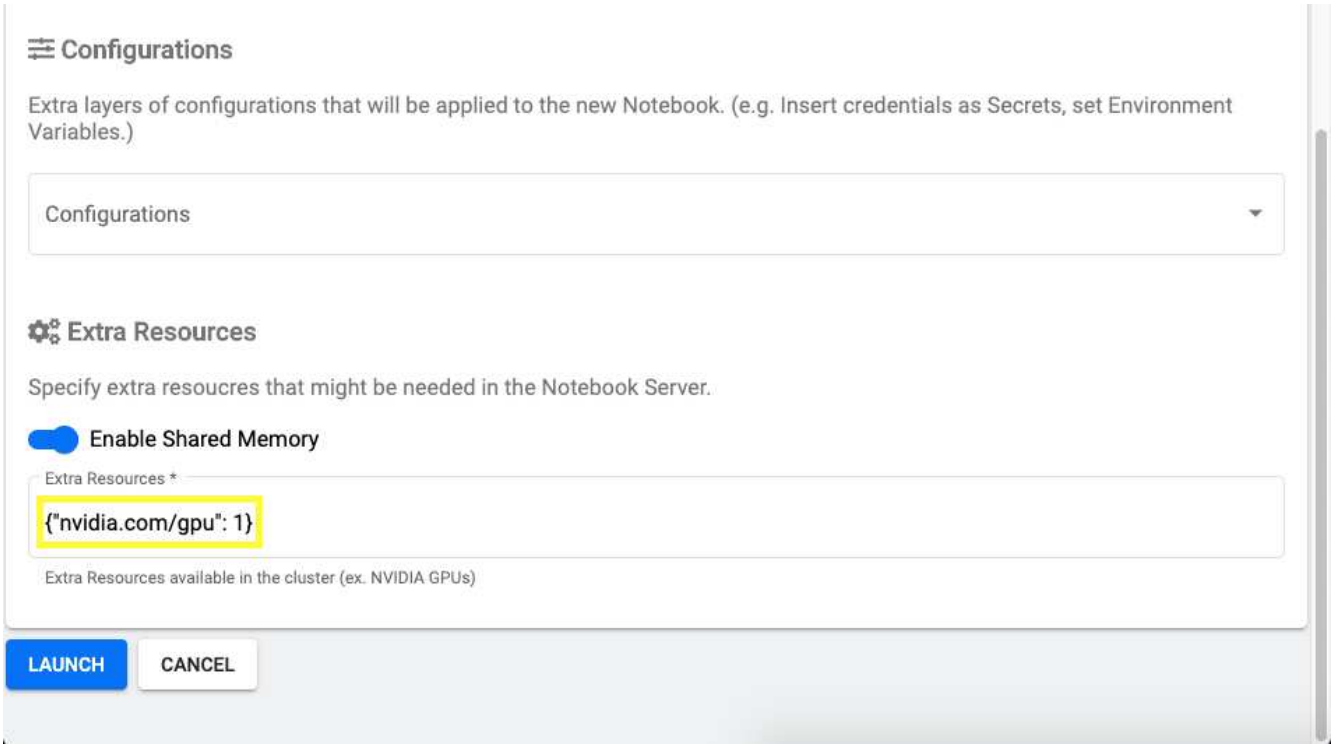
4. Specify the workspace volume details. If you choose to create a new volume, then that volume or PVC is provisioned using the default StorageClass. Because a StorageClass utilizing Trident was designated as the default StorageClass in the section Kubeflow Deployment, the volume or PVC is provisioned with Trident. This volume is automatically mounted as the default workspace within the Jupyter Notebook Server container. Any notebooks that a user creates on the server that are not saved to a separate data volume are automatically saved to this workspace volume. Therefore, the notebooks are persistent across reboots.



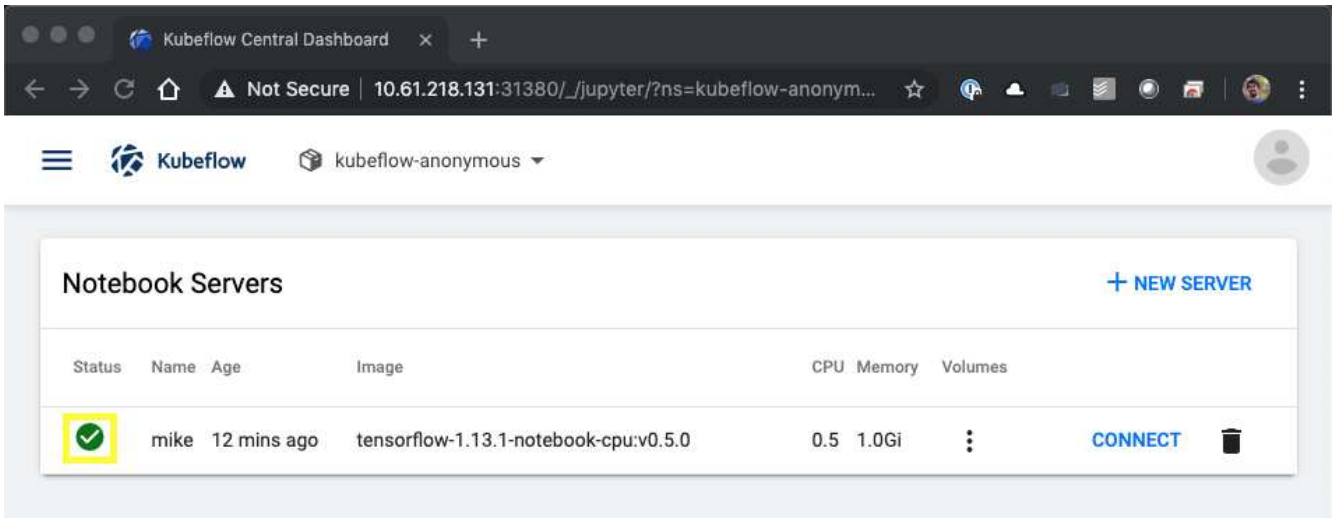
5. Add data volumes. The following example specifies an existing PVC named 'pb-fg-all' and accepts the default mount point.



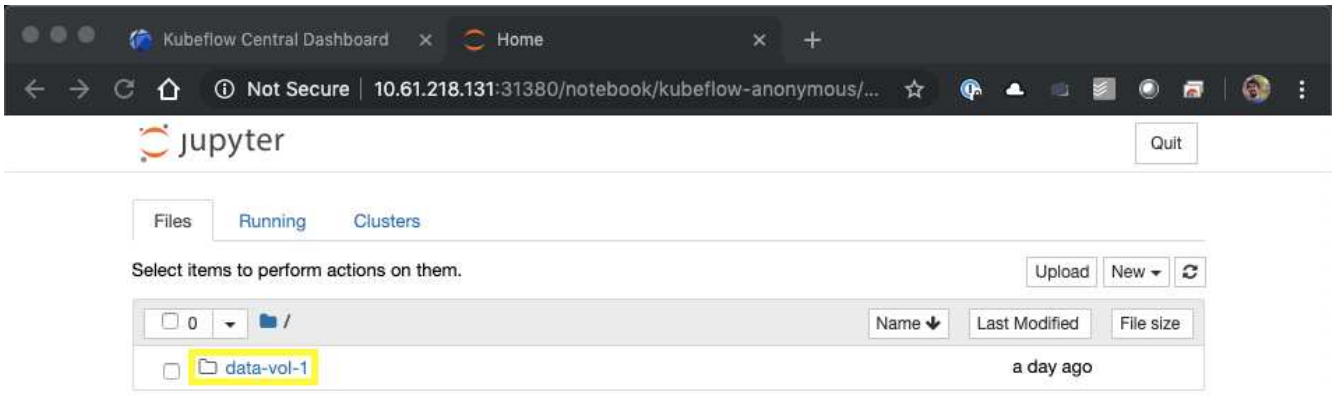
6. **Optional:** Request that the desired number of GPUs be allocated to your notebook server. In the following example, one GPU is requested.

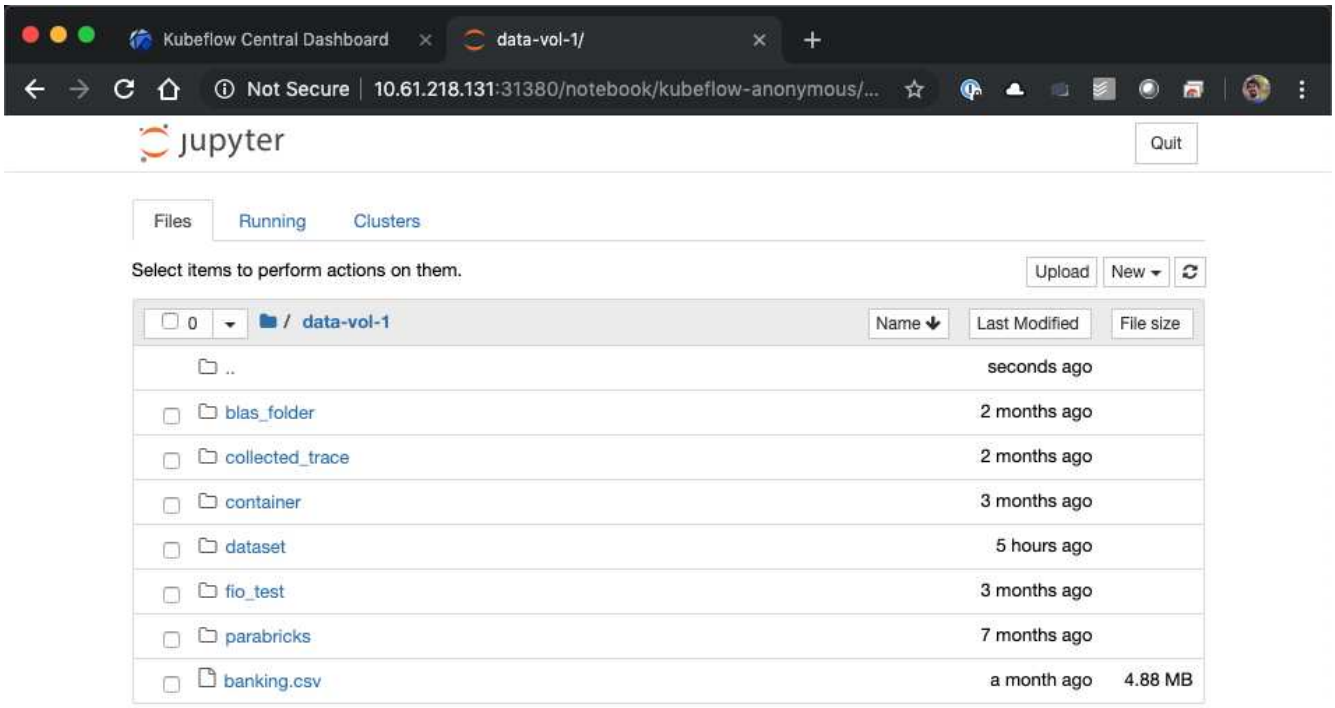


7. Click Launch to provision your new notebook server.
8. Wait for your notebook server to be fully provisioned. This can take several minutes if you have never provisioned a server using the Docker image that you specified because the image needs to be downloaded. When your server has been fully provisioned, you see a green check mark in the Status column on the Jupyter Notebook server administration page.



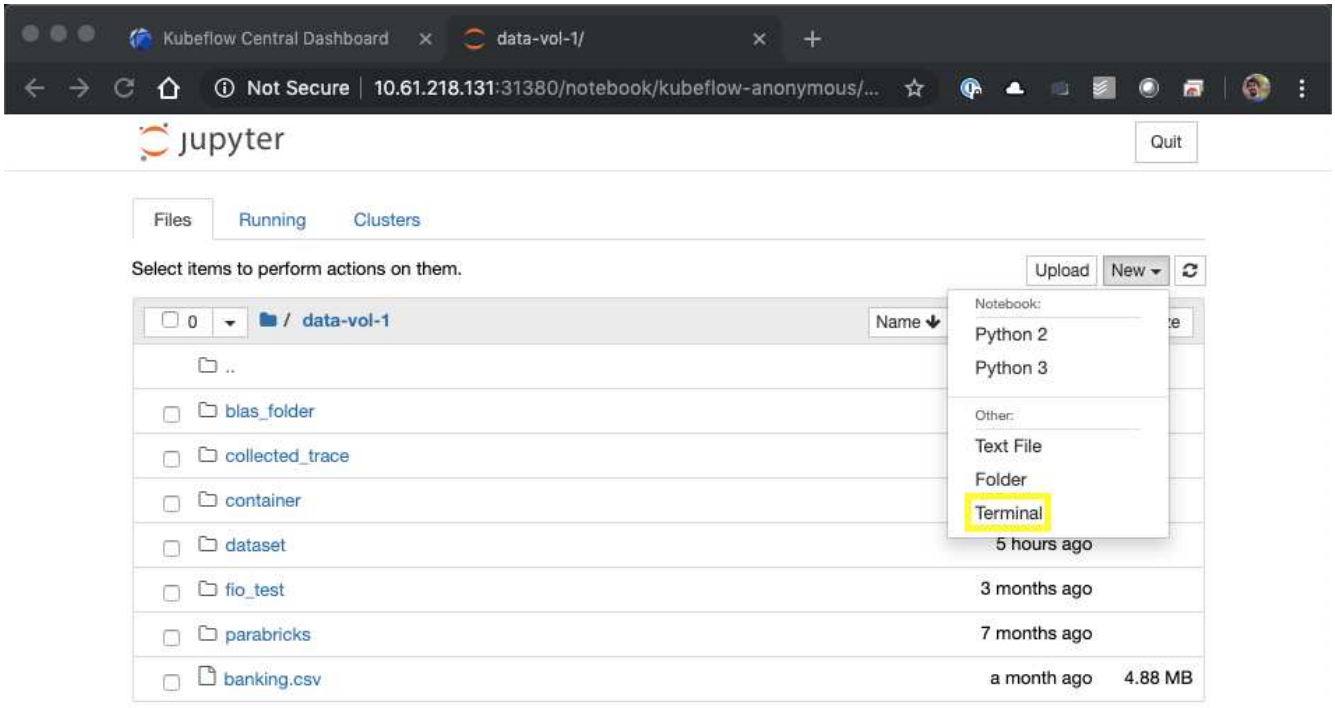
9. Click Connect to connect to your new server web interface.
10. Confirm that the dataset volume that was specified in step 6 is mounted on the server. Note that this volume is mounted within the default workspace by default. From the perspective of the user, this is just another folder within the workspace. The user, who is likely a data scientist and not an infrastructure expert, does not need to possess any storage expertise in order to use this volume.

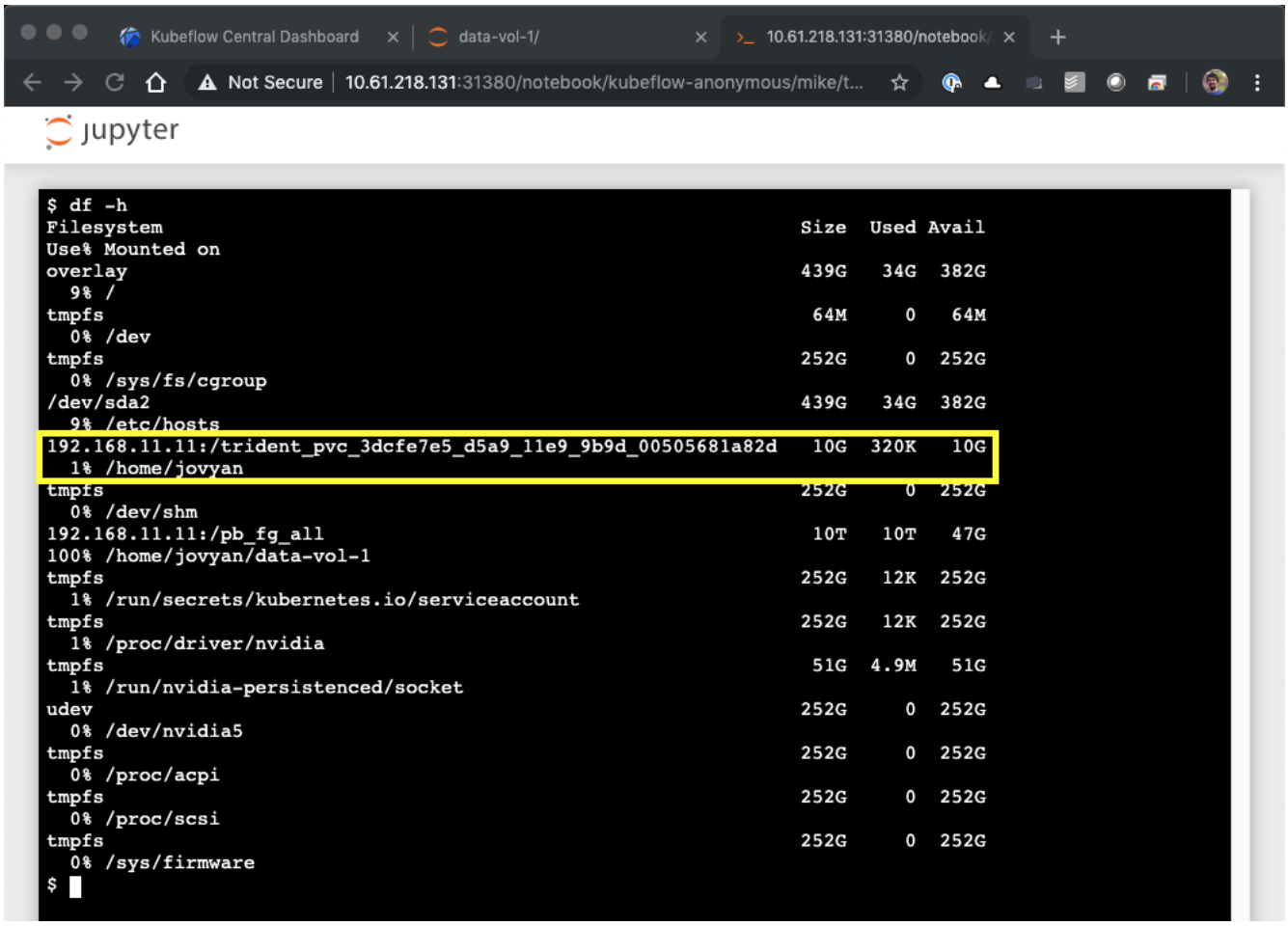




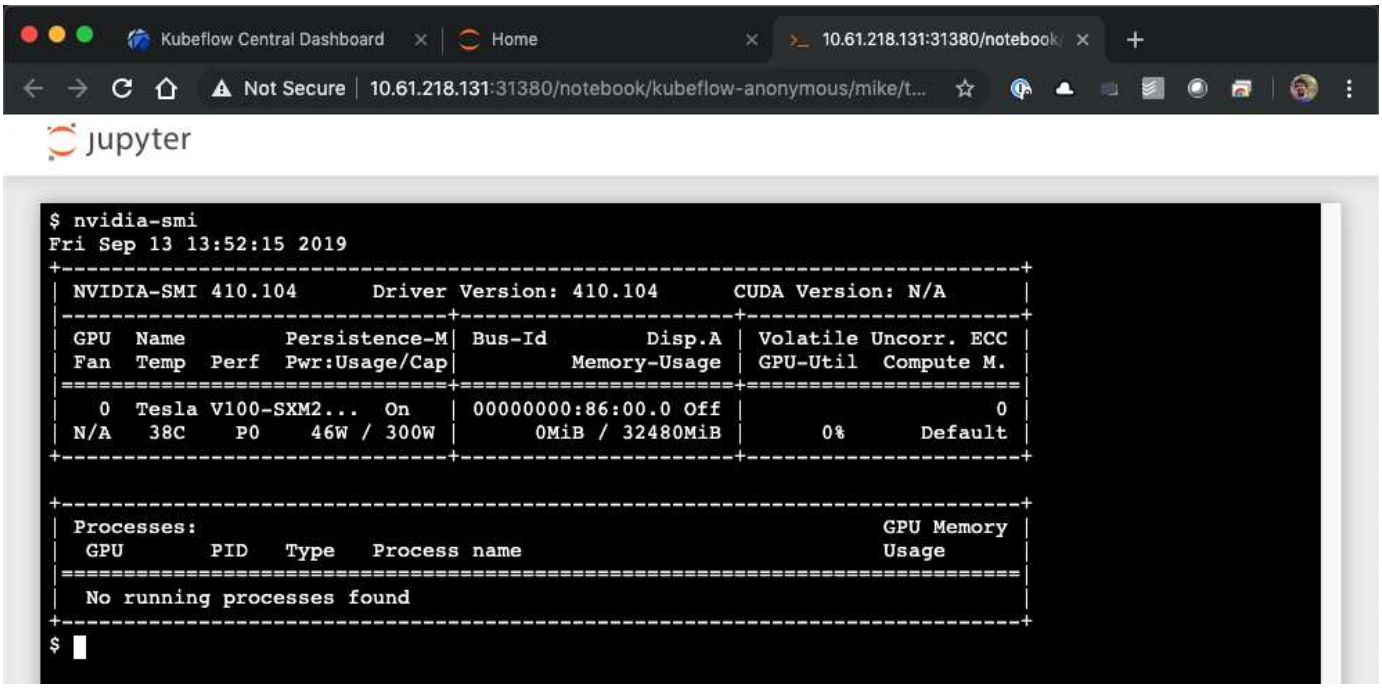
11. Open a Terminal and, assuming that a new volume was requested in step 5, execute `df -h` to confirm that a new Trident-provisioned persistent volume is mounted as the default workspace.

    The default workspace directory is the base directory that you are presented with when you first access the server's web interface. Therefore, any artifacts that you create by using the web interface are stored on this Trident-provisioned persistent volume.





12. Using the terminal, run `nvidia-smi` to confirm that the correct number of GPUs were allocated to the notebook server. In the following example, one GPU has been allocated to the notebook server as requested in step 7.



Next: Example Notebooks and Pipelines.

Example Notebooks and Pipelines

The NetApp Data Science Toolkit for Kubernetes can be used in conjunction with Kubeflow. Using the NetApp Data Science Toolkit with Kubeflow provides the following benefits:

- Data scientists can perform advanced NetApp data management operations directly from within a Jupyter Notebook.
- Advanced NetApp data management operations can be incorporated into automated workflows using the Kubeflow Pipelines framework.

Refer to the Kubeflow Examples section within the NetApp Data Science Toolkit GitHub repository for details on using the toolkit with Kubeflow.

Next: Apache Airflow Deployment.

Apache Airflow Deployment

NetApp recommends running Apache Airflow on top of Kubernetes. This section describes the tasks that you must complete to deploy Airflow in your Kubernetes cluster.

It is possible to deploy Airflow on platforms other than Kubernetes. Deploying Airflow on platforms other than Kubernetes is outside of the scope of this solution.

Prerequisites

Before you perform the deployment exercise that is outlined in this section, we assume that you have already performed the following tasks:

1. You already have a working Kubernetes cluster.
2. You have already installed and configured NetApp Trident in your Kubernetes cluster as outlined in the section “NetApp Trident Deployment and Configuration.”

Install Helm

Airflow is deployed using Helm, a popular package manager for Kubernetes. Before you deploy Airflow, you must install Helm on the deployment jump host. To install Helm on the deployment jump host, follow the installation instructions in the official Helm documentation.

Set Default Kubernetes StorageClass

Before you deploy Airflow, you must designate a default StorageClass within your Kubernetes cluster. The Airflow deployment process attempts to provision new persistent volumes using the default StorageClass. If no StorageClass is designated as the default StorageClass, then the deployment fails. To designate a default StorageClass within your cluster, follow the instructions outlined in the section Kubeflow Deployment. If you have already designated a default StorageClass within your cluster, then you can skip this step.

Use Helm to Deploy Airflow

To deploy Airflow in your Kubernetes cluster using Helm, perform the following tasks from the deployment jump host:

1. Deploy Airflow using Helm by following the deployment instructions for the official Airflow chart on the

Artifact Hub. The example commands that follow show the deployment of Airflow using Helm. Modify, add, and/or remove values in the `custom- values.yaml` file as needed depending on your environment and desired configuration.

```
$ cat << EOF > custom-values.yaml
#####################################
# Airflow - Common Configs
#####################################
airflow:
  ## the airflow executor type to use
  ##
  executor: "CeleryExecutor"
  ## environment variables for the web/scheduler/worker Pods (for
airflow configs)
  ##
  #
#####################################
# Airflow - WebUI Configs
#####################################
web:
  ## configs for the Service of the web Pods
  ##
  service:
    type: NodePort
#####################################
# Airflow - Logs Configs
#####################################
logs:
  persistence:
    enabled: true
#####################################
# Airflow - DAGs Configs
#####################################
dags:
  ## configs for the DAG git repository & sync container
  ##
  gitSync:
    enabled: true
    ## url of the git repository
    ##
    repo: "git@github.com:mboglesby/airflow-dev.git"
    ## the branch/tag/sha1 which we clone
    ##
    branch: master
    revision: HEAD
    ## the name of a pre-created secret containing files for ~/.ssh/
```

```
    ##
    ## NOTE:
    ## - this is ONLY RELEVANT for SSH git repos
    ## - the secret commonly includes files: id_rsa, id_rsa.pub,
known_hosts
    ## - known_hosts is NOT NEEDED if `git.sshKeyscan` is true
    ##
    sshSecret: "airflow-ssh-git-secret"
    ## the name of the private key file in your `git.secret`
    ##
    ## NOTE:
    ## - this is ONLY RELEVANT for PRIVATE SSH git repos
    ##
    sshSecretKey: id_rsa
    ## the git sync interval in seconds
    ##
    syncWait: 60
EOF
$ helm install airflow airflow-stable/airflow -n airflow --version 8.0.8
--values ./custom-values.yaml
...
Congratulations. You have just deployed Apache Airflow!
1. Get the Airflow Service URL by running these commands:
   export NODE_PORT=$(kubectl get --namespace airflow -o
jsonpath="{.spec.ports[0].nodePort}" services airflow-web)
   export NODE_IP=$(kubectl get nodes --namespace airflow -o
jsonpath="{.items[0].status.addresses[0].address}")
   echo http://$NODE_IP:$NODE_PORT/
2. Open Airflow in your web browser
```

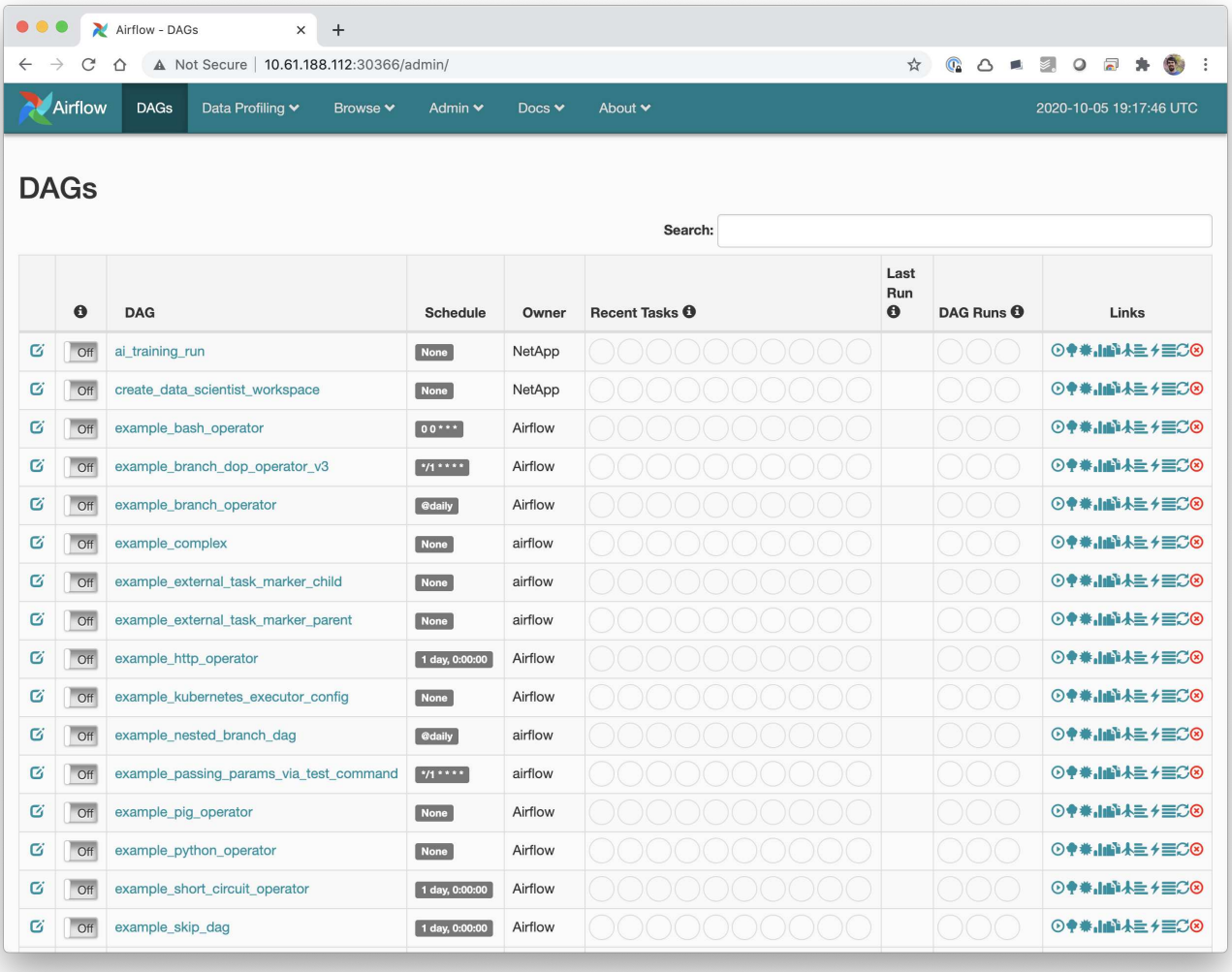
2. Confirm that all Airflow pods are up and running. It may take a few minutes for all pods to start.

```
$ kubectl -n airflow get pod
NAME                                READY   STATUS    RESTARTS   AGE
airflow-flower-b5656d44f-h8qjk      1/1     Running   0          2h
airflow-postgresql-0                1/1     Running   0          2h
airflow-redis-master-0              1/1     Running   0          2h
airflow-scheduler-9d95fcdf9-clf4b   2/2     Running   2          2h
airflow-web-59c94db9c5-z7rg4        1/1     Running   0          2h
airflow-worker-0                    2/2     Running   2          2h
```

3. Obtain the Airflow web service URL by following the instructions that were printed to the console when you deployed Airflow using Helm in step 1.

```
$ export NODE_PORT=$(kubectl get --namespace airflow -o
jsonpath="{.spec.ports[0].nodePort}" services airflow-web)
$ export NODE_IP=$(kubectl get nodes --namespace airflow -o
jsonpath="{.items[0].status.addresses[0].address}")
$ echo http://$NODE_IP:$NODE_PORT/
```

4. Confirm that you can access the Airflow web service.



Next: Example Apache Airflow Workflows.

Example Apache Airflow Workflows

The NetApp Data Science Toolkit for Kubernetes can be used in conjunction with Airflow. Using the NetApp Data Science Toolkit with Airflow enables you to incorporate NetApp data management operations into automated workflows that are orchestrated by Airflow.

Refer to the Airflow Examples section within the NetApp Data Science Toolkit GitHub repository for details on using the toolkit with Airflow.

Next: Example Trident Operations.

Example Trident Operations

This section includes examples of various operations that you may want to perform with Trident.

Import an Existing Volume

If there are existing volumes on your NetApp storage system/platform that you want to mount on containers within your Kubernetes cluster, but that are not tied to PVCs in the cluster, then you must import these volumes. You can use the Trident volume import functionality to import these volumes.

The example commands that follow show the importing of the same volume, named `pb_fg_all`, twice, once for each Trident Backend that was created in the example in the section Example Trident Backends for ONTAP AI Deployments, step 1. Importing the same volume twice in this manner enables you to mount the volume (an existing FlexGroup volume) multiple times across different LIFs, as described in the section Example Trident Backends for ONTAP AI Deployments, step 1. For more information about PVCs, see the official Kubernetes documentation. For more information about the volume import functionality, see the Trident documentation.

An `accessModes` value of `ReadOnlyMany` is specified in the example PVC spec files. For more information about the `accessMode` field, see the official Kubernetes documentation.

The Backend names that are specified in the following example import commands correspond to the Backends that were created in the example in the section Example Trident Backends for ONTAP AI Deployments, step 1. The StorageClass names that are specified in the following example PVC definition files correspond to the StorageClasses that were created in the example in the section Example Kubernetes StorageClasses for ONTAP AI Deployments, step 1.

```
$ cat << EOF > ./pvc-import-pb_fg_all-iface1.yaml
kind: PersistentVolumeClaim
apiVersion: v1
metadata:
  name: pb-fg-all-iface1
  namespace: default
spec:
  accessModes:
    - ReadOnlyMany
  storageClassName: ontap-ai-flexgroups-retain-iface1
EOF
$ tridentctl import volume ontap-ai-flexgroups-iface1 pb_fg_all -f ./pvc-
import-pb_fg_all-iface1.yaml -n trident
+---------------------------------+--------
+-----------------------------------+----------
+-------------------------------------------+--------+---------+
|          NAME                   |  SIZE  |       STORAGE CLASS
| PROTOCOL |             BACKEND UUID                          | STATE  |
MANAGED |
+---------------------------------+--------
```

```
+-----------------------------------+----------
+-----------------------------------------+--------+---------+
| default-pb-fg-all-iface1-7d9f1 | 10 TiB | ontap-ai-flexgroups-retain-
iface1 | file     | b74cbddb-e0b8-40b7-b263-b6da6dec0bdd | online | true
|
+-----------------------------------+--------
+-----------------------------------+----------
+-----------------------------------------+--------+---------+
$ cat << EOF > ./pvc-import-pb_fg_all-iface2.yaml
kind: PersistentVolumeClaim
apiVersion: v1
metadata:
  name: pb-fg-all-iface2
  namespace: default
spec:
  accessModes:
    - ReadOnlyMany
  storageClassName: ontap-ai-flexgroups-retain-iface2
EOF
$ tridentctl import volume ontap-ai-flexgroups-iface2 pb_fg_all -f ./pvc-
import-pb_fg_all-iface2.yaml -n trident
+-----------------------------------+--------
+-----------------------------------+----------
+-----------------------------------------+--------+---------+
|          NAME                   |  SIZE  |       STORAGE CLASS
| PROTOCOL |             BACKEND UUID                          | STATE  |
MANAGED |
+-----------------------------------+--------
+-----------------------------------+----------
+-----------------------------------------+--------+---------+
| default-pb-fg-all-iface2-85aee | 10 TiB | ontap-ai-flexgroups-retain-
iface2 | file     | 61814d48-c770-436b-9cb4-cf7ee661274d | online | true
|
+-----------------------------------+--------
+-----------------------------------+----------
+-----------------------------------------+--------+---------+
$ tridentctl get volume -n trident
+-----------------------------------+---------
+-----------------------------------+----------
+-----------------------------------------+--------+---------+
|               NAME                |  SIZE   |           STORAGE CLASS
| PROTOCOL |             BACKEND UUID             | STATE  | MANAGED |
+-----------------------------------+---------
+-----------------------------------+----------
+-----------------------------------------+--------+---------+
| default-pb-fg-all-iface1-7d9f1   | 10 TiB  | ontap-ai-flexgroups-retain-
```

```
iface1 | file     | b74cbddb-e0b8-40b7-b263-b6da6dec0bdd | online | true
|
| default-pb-fg-all-iface2-85aee   | 10 TiB  | ontap-ai-flexgroups-retain-
iface2 | file     | 61814d48-c770-436b-9cb4-cf7ee661274d | online | true
|
+----------------------------------+---------
+----------------------------------+----------
+--------------------------------------+--------+---------+
$ kubectl get pvc
NAME                  STATUS   VOLUME                                  CAPACITY
ACCESS MODES   STORAGECLASS                        AGE
pb-fg-all-iface1      Bound    default-pb-fg-all-iface1-7d9f1
10995116277760   ROX            ontap-ai-flexgroups-retain-iface1   25h
pb-fg-all-iface2      Bound    default-pb-fg-all-iface2-85aee
10995116277760   ROX            ontap-ai-flexgroups-retain-iface2   25h
```

Provision a New Volume

You can use Trident to provision a new volume on your NetApp storage system or platform. The following example commands show the provisioning of a new FlexVol volume. In this example, the volume is provisioned using the StorageClass that was created in the example in the section Example Kubernetes StorageClasses for ONTAP AI Deployments, step 2.

An `accessModes` value of `ReadWriteMany` is specified in the following example PVC definition file. For more information about the `accessMode` field, see the official Kubernetes documentation.

```
$ cat << EOF > ./pvc-tensorflow-results.yaml
kind: PersistentVolumeClaim
apiVersion: v1
metadata:
  name: tensorflow-results
spec:
  accessModes:
    - ReadWriteMany
  resources:
    requests:
      storage: 1Gi
  storageClassName: ontap-ai-flexvols-retain
EOF
$ kubectl create -f ./pvc-tensorflow-results.yaml
persistentvolumeclaim/tensorflow-results created
$ kubectl get pvc
NAME                                 STATUS    VOLUME
CAPACITY         ACCESS MODES   STORAGECLASS                          AGE
pb-fg-all-iface1                     Bound     default-pb-fg-all-iface1-7d9f1
10995116277760   ROX            ontap-ai-flexgroups-retain-iface1   26h
pb-fg-all-iface2                     Bound     default-pb-fg-all-iface2-85aee
10995116277760   ROX            ontap-ai-flexgroups-retain-iface2   26h
tensorflow-results                   Bound     default-tensorflow-results-
2fd60   1073741824       RWX            ontap-ai-flexvols-retain
25h
```

Next: Example High-Performance Jobs for ONTAP AI Deployments Overview.

Example High-performance Jobs for ONTAP AI Deployments

This section includes examples of various high-performance jobs that can be executed when Kubernetes is deployed on an ONTAP AI pod.

Next: Execute a Single-Node AI Workload.

Example High-performance Jobs for ONTAP AI Deployments

This section includes examples of various high-performance jobs that can be executed when Kubernetes is deployed on an ONTAP AI pod.

Next: Execute a Single-Node AI Workload.

Execute a Single-Node AI Workload

To execute a single-node AI and ML job in your Kubernetes cluster, perform the following tasks from the deployment jump host. With Trident, you can quickly and easily make a

data volume, potentially containing petabytes of data, accessible to a Kubernetes workload. To make such a data volume accessible from within a Kubernetes pod, simply specify a PVC in the pod definition. This step is a Kubernetes-native operation; no NetApp expertise is required.

> This section assumes that you have already containerized (in the Docker container format) the specific AI and ML workload that you are attempting to execute in your Kubernetes cluster.

1. The following example commands show the creation of a Kubernetes job for a TensorFlow benchmark workload that uses the ImageNet dataset. For more information about the ImageNet dataset, see the ImageNet website.

   This example job requests eight GPUs and therefore can run on a single GPU worker node that features eight or more GPUs. This example job could be submitted in a cluster for which a worker node featuring eight or more GPUs is not present or is currently occupied with another workload. If so, then the job remains in a pending state until such a worker node becomes available.

   Additionally, in order to maximize storage bandwidth, the volume that contains the needed training data is mounted twice within the pod that this job creates. Another volume is also mounted in the pod. This second volume will be used to store results and metrics. These volumes are referenced in the job definition by using the names of the PVCs. For more information about Kubernetes jobs, see the official Kubernetes documentation.

   An `emptyDir` volume with a `medium` value of `Memory` is mounted to `/dev/shm` in the pod that this example job creates. The default size of the `/dev/shm` virtual volume that is automatically created by the Docker container runtime can sometimes be insufficient for TensorFlow's needs. Mounting an `emptyDir` volume as in the following example provides a sufficiently large `/dev/shm` virtual volume. For more information about `emptyDir` volumes, see the official Kubernetes documentation.

   The single container that is specified in this example job definition is given a `securityContext > privileged` value of `true`. This value means that the container effectively has root access on the host. This annotation is used in this case because the specific workload that is being executed requires root access. Specifically, a clear cache operation that the workload performs requires root access. Whether or not this `privileged: true` annotation is necessary depends on the requirements of the specific workload that you are executing.

```
$ cat << EOF > ./netapp-tensorflow-single-imagenet.yaml
apiVersion: batch/v1
kind: Job
metadata:
  name: netapp-tensorflow-single-imagenet
spec:
  backoffLimit: 5
  template:
    spec:
      volumes:
      - name: dshm
        emptyDir:
          medium: Memory
      - name: testdata-iface1
```

```
        persistentVolumeClaim:
          claimName: pb-fg-all-iface1
      - name: testdata-iface2
        persistentVolumeClaim:
          claimName: pb-fg-all-iface2
      - name: results
        persistentVolumeClaim:
          claimName: tensorflow-results
      containers:
      - name: netapp-tensorflow-py2
        image: netapp/tensorflow-py2:19.03.0
        command: ["python", "/netapp/scripts/run.py", "--
dataset_dir=/mnt/mount_0/dataset/imagenet", "--dgx_version=dgx1", "--
num_devices=8"]
        resources:
          limits:
            nvidia.com/gpu: 8
        volumeMounts:
        - mountPath: /dev/shm
          name: dshm
        - mountPath: /mnt/mount_0
          name: testdata-iface1
        - mountPath: /mnt/mount_1
          name: testdata-iface2
        - mountPath: /tmp
          name: results
        securityContext:
          privileged: true
      restartPolicy: Never
EOF
$ kubectl create -f ./netapp-tensorflow-single-imagenet.yaml
job.batch/netapp-tensorflow-single-imagenet created
$ kubectl get jobs
NAME                                    COMPLETIONS   DURATION   AGE
netapp-tensorflow-single-imagenet       0/1           24s        24s
```

2. Confirm that the job that you created in step 1 is running correctly. The following example command confirms that a single pod was created for the job, as specified in the job definition, and that this pod is currently running on one of the GPU worker nodes.

```
$ kubectl get pods -o wide
NAME                                                READY   STATUS
RESTARTS   AGE
IP              NODE            NOMINATED NODE
netapp-tensorflow-single-imagenet-m7x92          1/1     Running     0
3m    10.233.68.61    10.61.218.154   <none>
```

3. Confirm that the job that you created in step 1 completes successfully. The following example commands confirm that the job completed successfully.

```
$ kubectl get jobs
NAME                                                COMPLETIONS   DURATION
AGE
netapp-tensorflow-single-imagenet                   1/1           5m42s
10m
$ kubectl get pods
NAME                                                      READY   STATUS
RESTARTS   AGE
netapp-tensorflow-single-imagenet-m7x92                   0/1     Completed
0          11m
$ kubectl logs netapp-tensorflow-single-imagenet-m7x92
[netapp-tensorflow-single-imagenet-m7x92:00008] PMIX ERROR: NO-
PERMISSIONS in file gds_dstore.c at line 702
[netapp-tensorflow-single-imagenet-m7x92:00008] PMIX ERROR: NO-
PERMISSIONS in file gds_dstore.c at line 711
Total images/sec = 6530.59125
================ Clean Cache !!! ==================
mpirun -allow-run-as-root -np 1 -H localhost:1 bash -c 'sync; echo 1 >
/proc/sys/vm/drop_caches'
==========================================
mpirun -allow-run-as-root -np 8 -H localhost:8 -bind-to none -map-by
slot -x NCCL_DEBUG=INFO -x LD_LIBRARY_PATH -x PATH python
/netapp/tensorflow/benchmarks_190205/scripts/tf_cnn_benchmarks/tf_cnn_be
nchmarks.py --model=resnet50 --batch_size=256 --device=gpu
--force_gpu_compatible=True --num_intra_threads=1 --num_inter_threads=48
--variable_update=horovod --batch_group_size=20 --num_batches=500
--nodistortions --num_gpus=1 --data_format=NCHW --use_fp16=True
--use_tf_layers=False --data_name=imagenet --use_datasets=True
--data_dir=/mnt/mount_0/dataset/imagenet
--datasets_parallel_interleave_cycle_length=10
--datasets_sloppy_parallel_interleave=False --num_mounts=2
--mount_prefix=/mnt/mount_%d --datasets_prefetch_buffer_size=2000
--datasets_use_prefetch=True --datasets_num_private_threads=4
--horovod_device=gpu >
/tmp/20190814_105450_tensorflow_horovod_rdma_resnet50_gpu_8_256_b500_ima
genet_nodistort_fp16_r10_m2_nockpt.txt 2>&1
```

4. **Optional:** Clean up job artifacts. The following example commands show the deletion of the job object that was created in step 1.

   When you delete the job object, Kubernetes automatically deletes any associated pods.

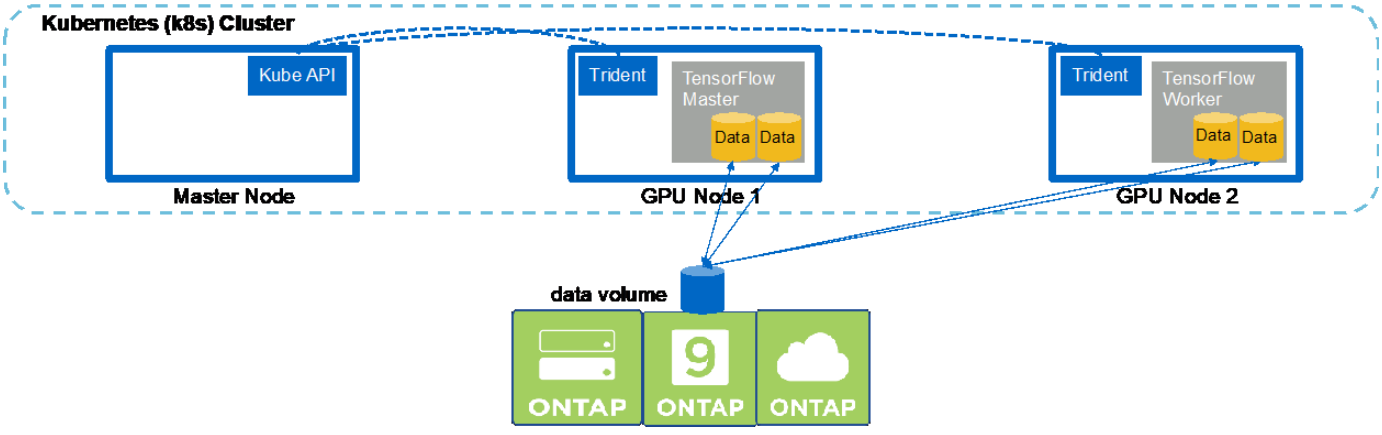
```
$ kubectl get jobs
NAME                                                COMPLETIONS   DURATION
AGE
netapp-tensorflow-single-imagenet                   1/1           5m42s
10m
$ kubectl get pods
NAME                                                      READY   STATUS
RESTARTS   AGE
netapp-tensorflow-single-imagenet-m7x92                   0/1     Completed
0          11m
$ kubectl delete job netapp-tensorflow-single-imagenet
job.batch "netapp-tensorflow-single-imagenet" deleted
$ kubectl get jobs
No resources found.
$ kubectl get pods
No resources found.
```

Next: Execute a Synchronous Distributed AI Workload.

Execute a Synchronous Distributed AI Workload

To execute a synchronous multinode AI and ML job in your Kubernetes cluster, perform the following tasks on the deployment jump host. This process enables you to take advantage of data that is stored on a NetApp volume and to use more GPUs than a single worker node can provide. See the following figure for a depiction of a synchronous distributed AI job.

Synchronous distributed jobs can help increase performance and training accuracy compared with asynchronous distributed jobs. A discussion of the pros and cons of synchronous jobs versus asynchronous jobs is outside the scope of this document.



1. The following example commands show the creation of one worker that participates in the synchronous distributed execution of the same TensorFlow benchmark job that was executed on a single node in the example in the section Execute a Single-Node AI Workload. In this specific example, only a single worker

is deployed because the job is executed across two worker nodes.

This example worker deployment requests eight GPUs and thus can run on a single GPU worker node that features eight or more GPUs. If your GPU worker nodes feature more than eight GPUs, to maximize performance, you might want to increase this number to be equal to the number of GPUs that your worker nodes feature. For more information about Kubernetes deployments, see the official Kubernetes documentation.

A Kubernetes deployment is created in this example because this specific containerized worker would never complete on its own. Therefore, it doesn't make sense to deploy it by using the Kubernetes job construct. If your worker is designed or written to complete on its own, then it might make sense to use the job construct to deploy your worker.

The pod that is specified in this example deployment specification is given a `hostNetwork` value of `true`. This value means that the pod uses the host worker node's networking stack instead of the virtual networking stack that Kubernetes usually creates for each pod. This annotation is used in this case because the specific workload relies on Open MPI, NCCL, and Horovod to execute the workload in a synchronous distributed manner. Therefore, it requires access to the host networking stack. A discussion about Open MPI, NCCL, and Horovod is outside the scope of this document. Whether or not this `hostNetwork: true` annotation is necessary depends on the requirements of the specific workload that you are executing. For more information about the `hostNetwork` field, see the official Kubernetes documentation.

```
$ cat << EOF > ./netapp-tensorflow-multi-imagenet-worker.yaml
apiVersion: apps/v1
kind: Deployment
metadata:
  name: netapp-tensorflow-multi-imagenet-worker
spec:
  replicas: 1
  selector:
    matchLabels:
      app: netapp-tensorflow-multi-imagenet-worker
  template:
    metadata:
      labels:
        app: netapp-tensorflow-multi-imagenet-worker
    spec:
      hostNetwork: true
      volumes:
      - name: dshm
        emptyDir:
          medium: Memory
      - name: testdata-iface1
        persistentVolumeClaim:
          claimName: pb-fg-all-iface1
      - name: testdata-iface2
        persistentVolumeClaim:
          claimName: pb-fg-all-iface2
```

```
      - name: results
        persistentVolumeClaim:
          claimName: tensorflow-results
      containers:
      - name: netapp-tensorflow-py2
        image: netapp/tensorflow-py2:19.03.0
        command: ["bash", "/netapp/scripts/start-slave-multi.sh",
"22122"]
        resources:
          limits:
            nvidia.com/gpu: 8
        volumeMounts:
        - mountPath: /dev/shm
          name: dshm
        - mountPath: /mnt/mount_0
          name: testdata-iface1
        - mountPath: /mnt/mount_1
          name: testdata-iface2
        - mountPath: /tmp
          name: results
        securityContext:
          privileged: true
EOF
$ kubectl create -f ./netapp-tensorflow-multi-imagenet-worker.yaml
deployment.apps/netapp-tensorflow-multi-imagenet-worker created
$ kubectl get deployments
NAME                                        DESIRED   CURRENT   UP-TO-DATE
AVAILABLE   AGE
netapp-tensorflow-multi-imagenet-worker   1         1         1
1           4s
```

2. Confirm that the worker deployment that you created in step 1 launched successfully. The following example commands confirm that a single worker pod was created for the deployment, as indicated in the deployment definition, and that this pod is currently running on one of the GPU worker nodes.

```
$ kubectl get pods -o wide
NAME                                                          READY
STATUS    RESTARTS   AGE
IP              NODE            NOMINATED NODE
netapp-tensorflow-multi-imagenet-worker-654fc7f486-v6725   1/1
Running   0          60s   10.61.218.154   10.61.218.154   <none>
$ kubectl logs netapp-tensorflow-multi-imagenet-worker-654fc7f486-v6725
22122
```

3. Create a Kubernetes job for a master that kicks off, participates in, and tracks the execution of the

synchronous multinode job. The following example commands create one master that kicks off, participates in, and tracks the synchronous distributed execution of the same TensorFlow benchmark job that was executed on a single node in the example in the section Execute a Single-Node AI Workload.

This example master job requests eight GPUs and thus can run on a single GPU worker node that features eight or more GPUs. If your GPU worker nodes feature more than eight GPUs, to maximize performance, you might want to increase this number to be equal to the number of GPUs that your worker nodes feature.

The master pod that is specified in this example job definition is given a `hostNetwork` value of `true`, just as the worker pod was given a `hostNetwork` value of `true` in step 1. See step 1 for details about why this value is necessary.

```
$ cat << EOF > ./netapp-tensorflow-multi-imagenet-master.yaml
apiVersion: batch/v1
kind: Job
metadata:
  name: netapp-tensorflow-multi-imagenet-master
spec:
  backoffLimit: 5
  template:
    spec:
      hostNetwork: true
      volumes:
      - name: dshm
        emptyDir:
          medium: Memory
      - name: testdata-iface1
        persistentVolumeClaim:
          claimName: pb-fg-all-iface1
      - name: testdata-iface2
        persistentVolumeClaim:
          claimName: pb-fg-all-iface2
      - name: results
        persistentVolumeClaim:
          claimName: tensorflow-results
      containers:
      - name: netapp-tensorflow-py2
        image: netapp/tensorflow-py2:19.03.0
        command: ["python", "/netapp/scripts/run.py", "--
dataset_dir=/mnt/mount_0/dataset/imagenet", "--port=22122", "--
num_devices=16", "--dgx_version=dgx1", "--
nodes=10.61.218.152,10.61.218.154"]
        resources:
          limits:
            nvidia.com/gpu: 8
        volumeMounts:
        - mountPath: /dev/shm
```

```
          name: dshm
        - mountPath: /mnt/mount_0
          name: testdata-iface1
        - mountPath: /mnt/mount_1
          name: testdata-iface2
        - mountPath: /tmp
          name: results
        securityContext:
          privileged: true
      restartPolicy: Never
EOF
$ kubectl create -f ./netapp-tensorflow-multi-imagenet-master.yaml
job.batch/netapp-tensorflow-multi-imagenet-master created
$ kubectl get jobs
NAME                                        COMPLETIONS   DURATION   AGE
netapp-tensorflow-multi-imagenet-master   0/1           25s        25s
```

4. Confirm that the master job that you created in step 3 is running correctly. The following example command confirms that a single master pod was created for the job, as indicated in the job definition, and that this pod is currently running on one of the GPU worker nodes. You should also see that the worker pod that you originally saw in step 1 is still running and that the master and worker pods are running on different nodes.

```
$ kubectl get pods -o wide
NAME                                                              READY
STATUS    RESTARTS   AGE
IP              NODE            NOMINATED NODE
netapp-tensorflow-multi-imagenet-master-ppwwj                     1/1
Running   0          45s   10.61.218.152   10.61.218.152   <none>
netapp-tensorflow-multi-imagenet-worker-654fc7f486-v6725   1/1
Running   0          26m   10.61.218.154   10.61.218.154   <none>
```

5. Confirm that the master job that you created in step 3 completes successfully. The following example commands confirm that the job completed successfully.

```
$ kubectl get jobs
NAME                                        COMPLETIONS   DURATION   AGE
netapp-tensorflow-multi-imagenet-master   1/1           5m50s      9m18s
$ kubectl get pods
NAME                                                              READY
STATUS      RESTARTS   AGE
netapp-tensorflow-multi-imagenet-master-ppwwj                     0/1
Completed   0          9m38s
netapp-tensorflow-multi-imagenet-worker-654fc7f486-v6725   1/1
Running     0          35m
$ kubectl logs netapp-tensorflow-multi-imagenet-master-ppwwj
```

```
[10.61.218.152:00008] WARNING: local probe returned unhandled
shell:unknown assuming bash
rm: cannot remove '/lib': Is a directory
[10.61.218.154:00033] PMIX ERROR: NO-PERMISSIONS in file gds_dstore.c at
line 702
[10.61.218.154:00033] PMIX ERROR: NO-PERMISSIONS in file gds_dstore.c at
line 711
[10.61.218.152:00008] PMIX ERROR: NO-PERMISSIONS in file gds_dstore.c at
line 702
[10.61.218.152:00008] PMIX ERROR: NO-PERMISSIONS in file gds_dstore.c at
line 711
Total images/sec = 12881.33875
================ Clean Cache !!! ==================
mpirun -allow-run-as-root -np 2 -H 10.61.218.152:1,10.61.218.154:1 -mca
pml ob1 -mca btl ^openib -mca btl_tcp_if_include enp1s0f0 -mca
plm_rsh_agent ssh -mca plm_rsh_args "-p 22122" bash -c 'sync; echo 1 >
/proc/sys/vm/drop_caches'
=========================================
mpirun -allow-run-as-root -np 16 -H 10.61.218.152:8,10.61.218.154:8
-bind-to none -map-by slot -x NCCL_DEBUG=INFO -x LD_LIBRARY_PATH -x PATH
-mca pml ob1 -mca btl ^openib -mca btl_tcp_if_include enp1s0f0 -x
NCCL_IB_HCA=mlx5 -x NCCL_NET_GDR_READ=1 -x NCCL_IB_SL=3 -x
NCCL_IB_GID_INDEX=3 -x
NCCL_SOCKET_IFNAME=enp5s0.3091,enp12s0.3092,enp132s0.3093,enp139s0.3094
-x NCCL_IB_CUDA_SUPPORT=1 -mca orte_base_help_aggregate 0 -mca
plm_rsh_agent ssh -mca plm_rsh_args "-p 22122" python
/netapp/tensorflow/benchmarks_190205/scripts/tf_cnn_benchmarks/tf_cnn_be
nchmarks.py --model=resnet50 --batch_size=256 --device=gpu
--force_gpu_compatible=True --num_intra_threads=1 --num_inter_threads=48
--variable_update=horovod --batch_group_size=20 --num_batches=500
--nodistortions --num_gpus=1 --data_format=NCHW --use_fp16=True
--use_tf_layers=False --data_name=imagenet --use_datasets=True
--data_dir=/mnt/mount_0/dataset/imagenet
--datasets_parallel_interleave_cycle_length=10
--datasets_sloppy_parallel_interleave=False --num_mounts=2
--mount_prefix=/mnt/mount_%d --datasets_prefetch_buffer_size=2000 --
datasets_use_prefetch=True --datasets_num_private_threads=4
--horovod_device=gpu >
/tmp/20190814_161609_tensorflow_horovod_rdma_resnet50_gpu_16_256_b500_im
agenet_nodistort_fp16_r10_m2_nockpt.txt 2>&1
```

6. Delete the worker deployment when you no longer need it. The following example commands show the deletion of the worker deployment object that was created in step 1.

   When you delete the worker deployment object, Kubernetes automatically deletes any associated worker pods.

```
$ kubectl get deployments
NAME                                        DESIRED   CURRENT   UP-TO-DATE
AVAILABLE   AGE
netapp-tensorflow-multi-imagenet-worker   1         1         1
1           43m
$ kubectl get pods
NAME                                                          READY
STATUS      RESTARTS   AGE
netapp-tensorflow-multi-imagenet-master-ppwwj                 0/1
Completed   0          17m
netapp-tensorflow-multi-imagenet-worker-654fc7f486-v6725   1/1
Running     0          43m
$ kubectl delete deployment netapp-tensorflow-multi-imagenet-worker
deployment.extensions "netapp-tensorflow-multi-imagenet-worker" deleted
$ kubectl get deployments
No resources found.
$ kubectl get pods
NAME                                             READY   STATUS
RESTARTS   AGE
netapp-tensorflow-multi-imagenet-master-ppwwj   0/1     Completed   0
18m
```

7. **Optional:** Clean up the master job artifacts. The following example commands show the deletion of the master job object that was created in step 3.

   When you delete the master job object, Kubernetes automatically deletes any associated master pods.

```
$ kubectl get jobs
NAME                                       COMPLETIONS   DURATION   AGE
netapp-tensorflow-multi-imagenet-master   1/1           5m50s      19m
$ kubectl get pods
NAME                                             READY   STATUS
RESTARTS   AGE
netapp-tensorflow-multi-imagenet-master-ppwwj   0/1     Completed   0
19m
$ kubectl delete job netapp-tensorflow-multi-imagenet-master
job.batch "netapp-tensorflow-multi-imagenet-master" deleted
$ kubectl get jobs
No resources found.
$ kubectl get pods
No resources found.
```

Next: Performance Testing.

Performance Testing

We performed a simple performance comparison as part of the creation of this solution. We executed several standard NetApp AI benchmarking jobs by using Kubernetes, and we compared the benchmark results with executions that were performed by using a simple Docker run command. We did not see any noticeable differences in performance. Therefore, we concluded that the use of Kubernetes to orchestrate containerized AI training jobs does not adversely affect performance. See the following table for the results of our performance comparison.

Benchmark	Dataset	Docker Run (images/sec)	Kubernetes (images/sec)
Single-node TensorFlow	Synthetic data	6,667.2475	6,661.93125
Single-node TensorFlow	ImageNet	6,570.2025	6,530.59125
Synchronous distributed two-node TensorFlow	Synthetic data	13,213.70625	13,218.288125
Synchronous distributed two-node TensorFlow	ImageNet	12,941.69125	12,881.33875

Next: Conclusion.

Conclusion

Companies and organizations of all sizes and across all industries are turning to artificial intelligence (AI), machine learning (ML), and deep learning (DL) to solve real-world problems, deliver innovative products and services, and to get an edge in an increasingly competitive marketplace. As organizations increase their use of AI, ML, and DL, they face many challenges, including workload scalability and data availability. These challenges can be addressed through the use of the NetApp AI Control Plane solution.

This solution enables you to rapidly clone a data namespace. Additionally, it allows you to define and implement AI, ML, and DL training workflows that incorporate the near-instant creation of data and model baselines for traceability and versioning. With this solution, you can trace every single model training run back to the exact dataset(s) that the model was trained and/or validated with. Lastly, this solution enables you to swiftly provision Jupyter Notebook workspaces with access to massive datasets.

Because this solution is targeted towards data scientists and data engineers, minimal NetApp or NetApp ONTAP expertise is required. With this solution, data management functions can be executed using simple and familiar tools and interfaces. Furthermore, this solution utilizes fully open-source and free components. Therefore, if you already have NetApp storage in your environment, you can implement this solution today. If you want to test drive this solution but you do not have already have NetApp storage, visit cloud.netapp.com, and you can be up and running with a cloud-based NetApp storage solution in no time.

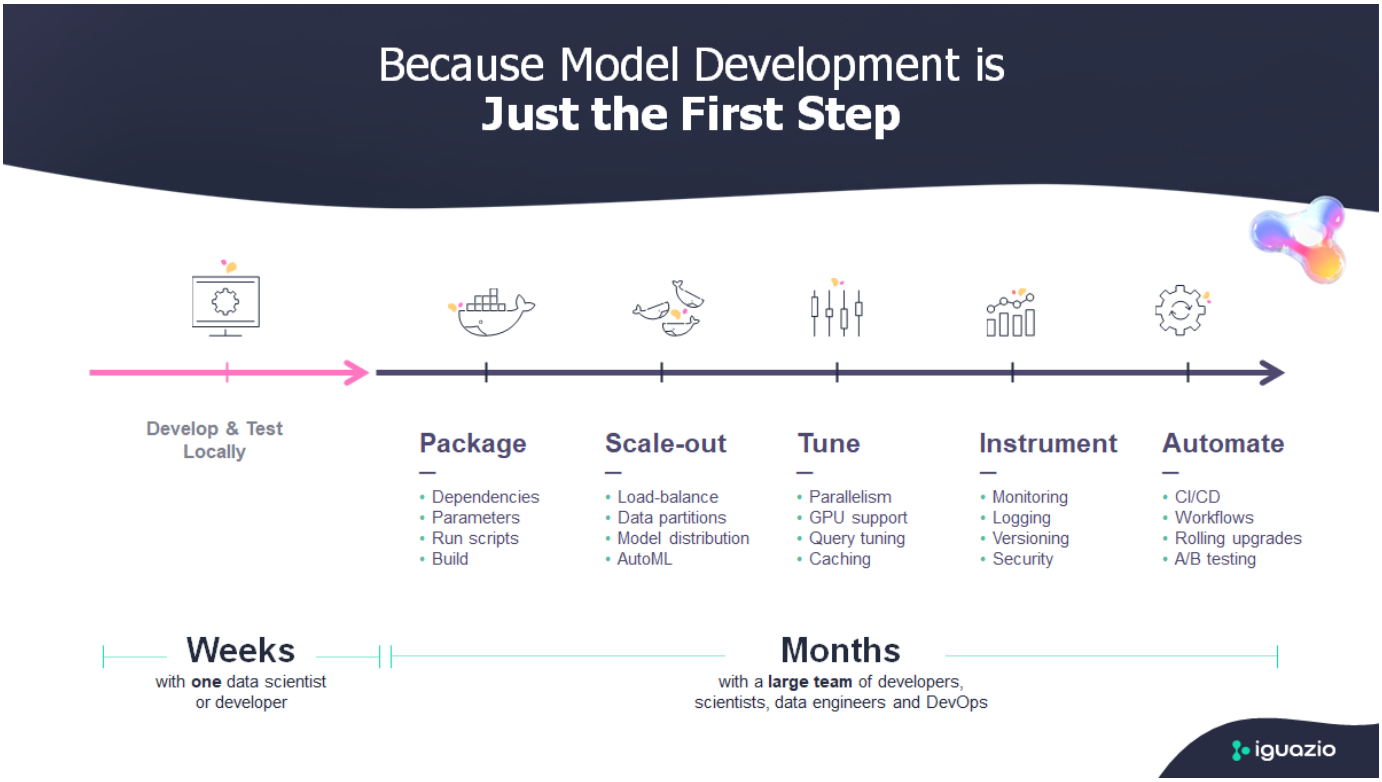
MLRun Pipeline with Iguazio

TR-4834: NetApp and Iguazio for MLRun Pipeline

Rick Huang, David Arnette, NetApp
Marcelo Litovsky, Iguazio

This document covers the details of the MLRun pipeline using NetApp ONTAP AI, NetApp AI Control Plane, NetApp Cloud Volumes software, and the Iguazio Data Science Platform. We used Nuclio serverless function, Kubernetes Persistent Volumes, NetApp Cloud Volumes, NetApp Snapshot copies, Grafana dashboard, and other services on the Iguazio platform to build an end-to-end data pipeline for the simulation of network failure detection. We integrated Iguazio and NetApp technologies to enable fast model deployment, data replication, and production monitoring capabilities on premises as well as in the cloud.

The work of a data scientist should be focused on the training and tuning of machine learning (ML) and artificial intelligence (AI) models. However, according to research by Google, data scientists spend ~80% of their time figuring out how to make their models work with enterprise applications and run at scale, as shown in the following image depicting model development in the AI/ML workflow.



To manage end-to-end AI/ML projects, a wider understanding of enterprise components is needed. Although DevOps have taken over the definition, integration, and deployment these types of components, machine learning operations target a similar flow that includes AI/ML projects. To get an idea of what an end-to-end AI/ML pipeline touches in the enterprise, see the following list of required components:

- Storage
- Networking
- Databases
- File systems
- Containers
- Continuous integration and continuous deployment (CI/CD) pipeline
- Development integrated development environment (IDE)
- Security
- Data access policies
- Hardware

- Cloud
- Virtualization
- Data science toolsets and libraries

In this paper, we demonstrate how the partnership between NetApp and Iguazio drastically simplifies the development of an end-to-end AI/ML pipeline. This simplification accelerates the time to market for all of your AI/ML applications.

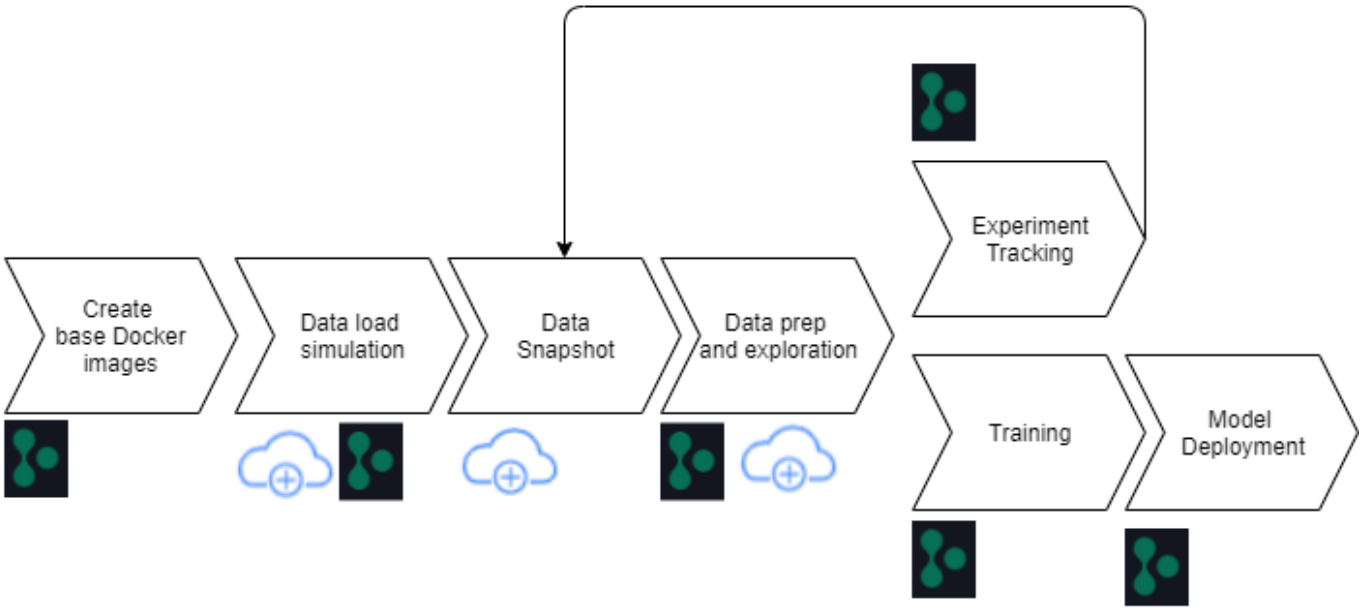
Target Audience

The world of data science touches multiple disciplines in information technology and business.

- The data scientist needs the flexibility to use their tools and libraries of choice.
- The data engineer needs to know how the data flows and where it resides.
- A DevOps engineer needs the tools to integrate new AI/ML applications into their CI/CD pipelines.
- Business users want to have access to AI/ML applications. We describe how NetApp and Iguazio help each of these roles bring value to business with our platforms.

Solution Overview

This solution follows the lifecycle of an AI/ML application. We start with the work of data scientists to define the different steps needed to prep data and train and deploy models. We follow with the work needed to create a full pipeline with the ability to track artifacts, experiment with execution, and deploy to Kubeflow. To complete the full cycle, we integrate the pipeline with NetApp Cloud Volumes to enable data versioning, as seen in the following image.



iguazio

Cloud Volumes ONTAP

Next: Technology Overview

Technology Overview

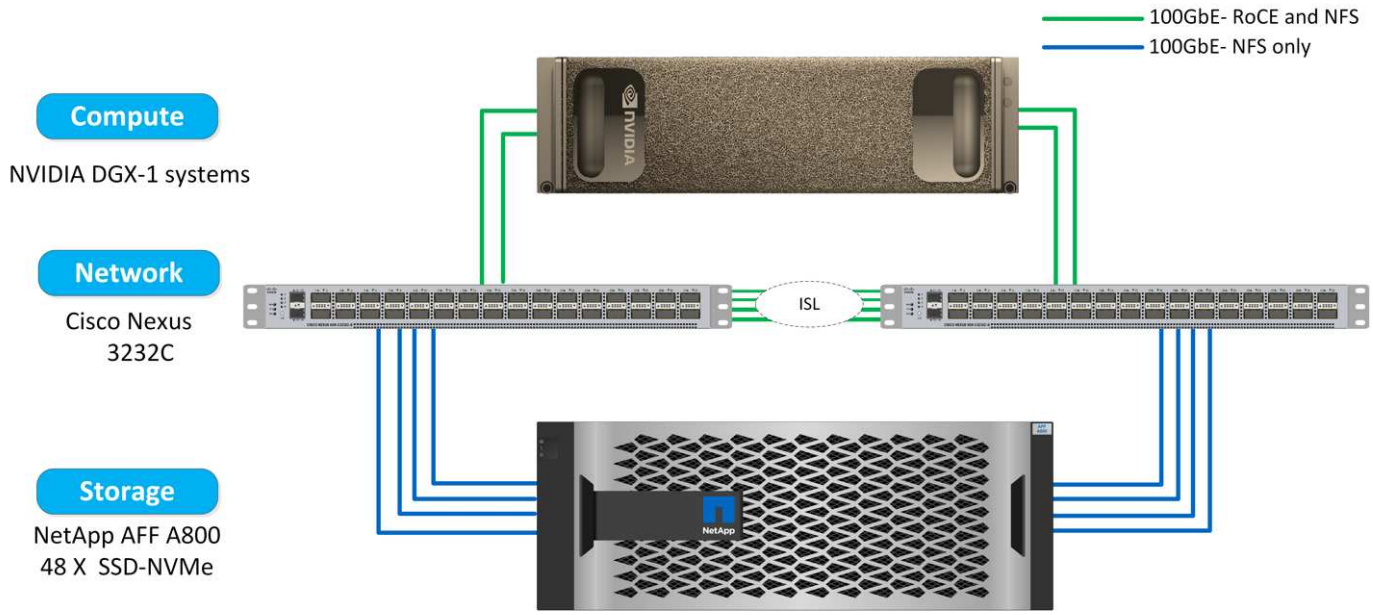
NetApp Overview

NetApp is the data authority for the hybrid cloud. NetApp provides a full range of hybrid cloud data services that simplify management of applications and data across cloud and on-premises environments to accelerate digital transformation. Together with our partners, NetApp empowers global organizations to unleash the full potential of their data to expand customer touch points, foster greater innovation, and optimize their operations.

NetApp ONTAP AI

NetApp ONTAP AI, powered by NVIDIA DGX systems and NetApp cloud-connected all-flash storage, streamlines the flow of data reliably and speeds up analytics, training, and inference with your data fabric that spans from edge to core to cloud. It gives IT organizations an architecture that provides the following benefits:

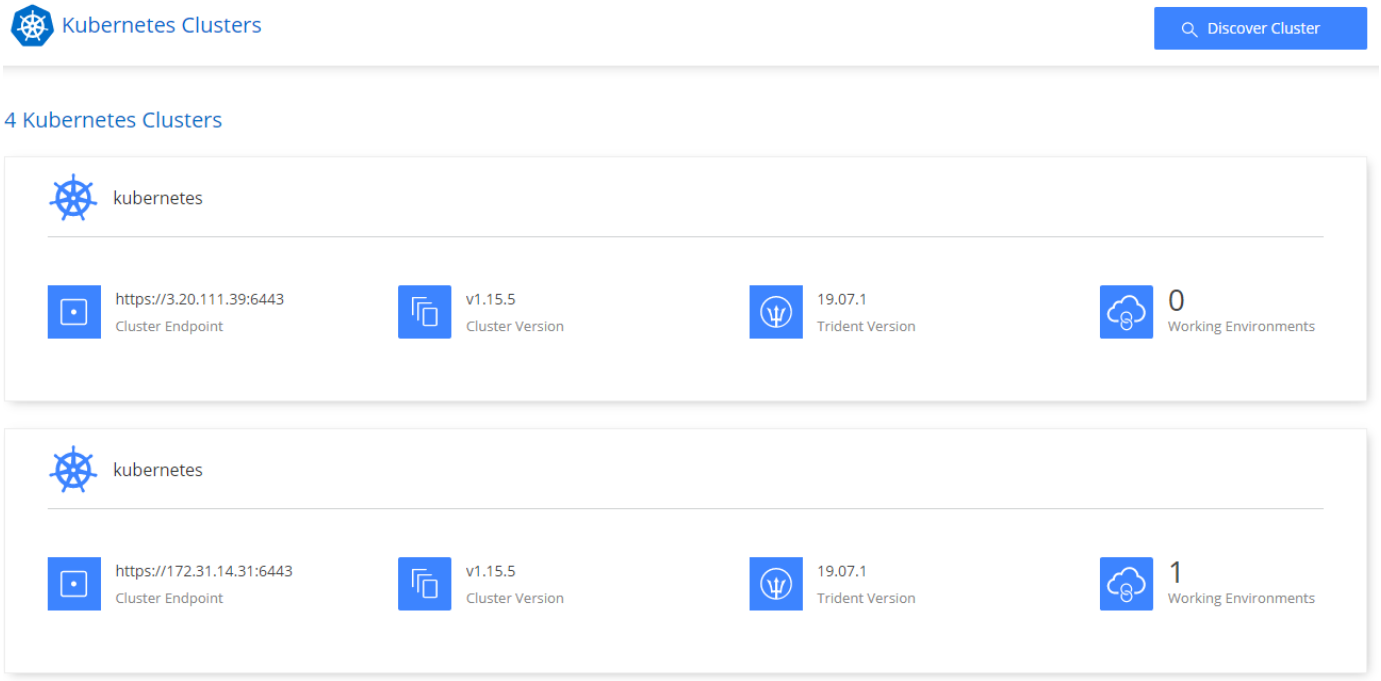
- Eliminates design complexities
- Allows independent scaling of compute and storage
- Enables customers to start small and scale seamlessly
- Offers a range of storage options for various performance and cost pointsNetApp ONTAP AI offers converged infrastructure stacks incorporating NVIDIA DGX-1, a petaflop-scale AI system, and NVIDIA Mellanox high-performance Ethernet switches to unify AI workloads, simplify deployment, and accelerate ROI. We leveraged ONTAP AI with one DGX-1 and NetApp AFF A800 storage system for this technical report. The following image shows the topology of ONTAP AI with the DGX-1 system used in this validation.

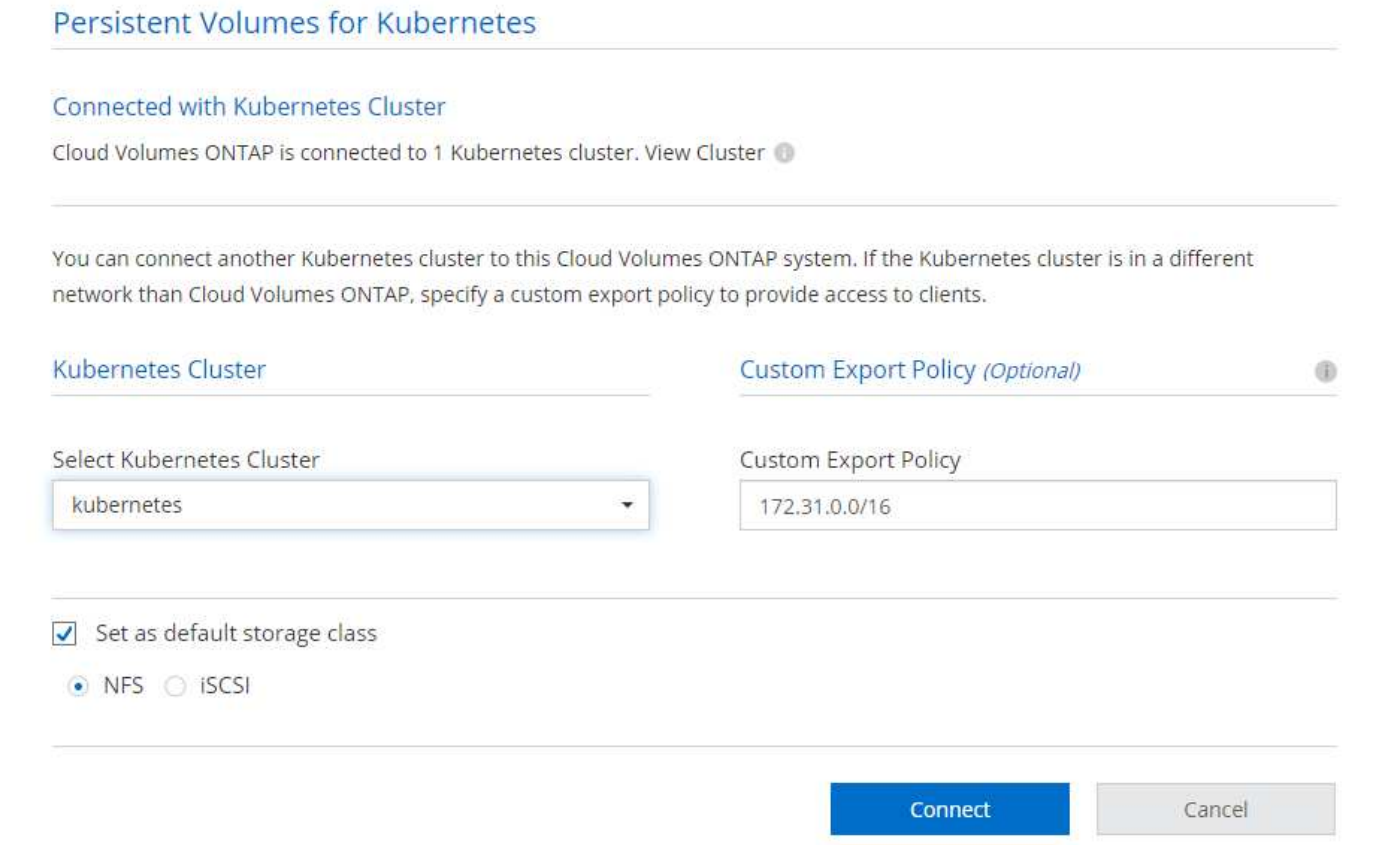


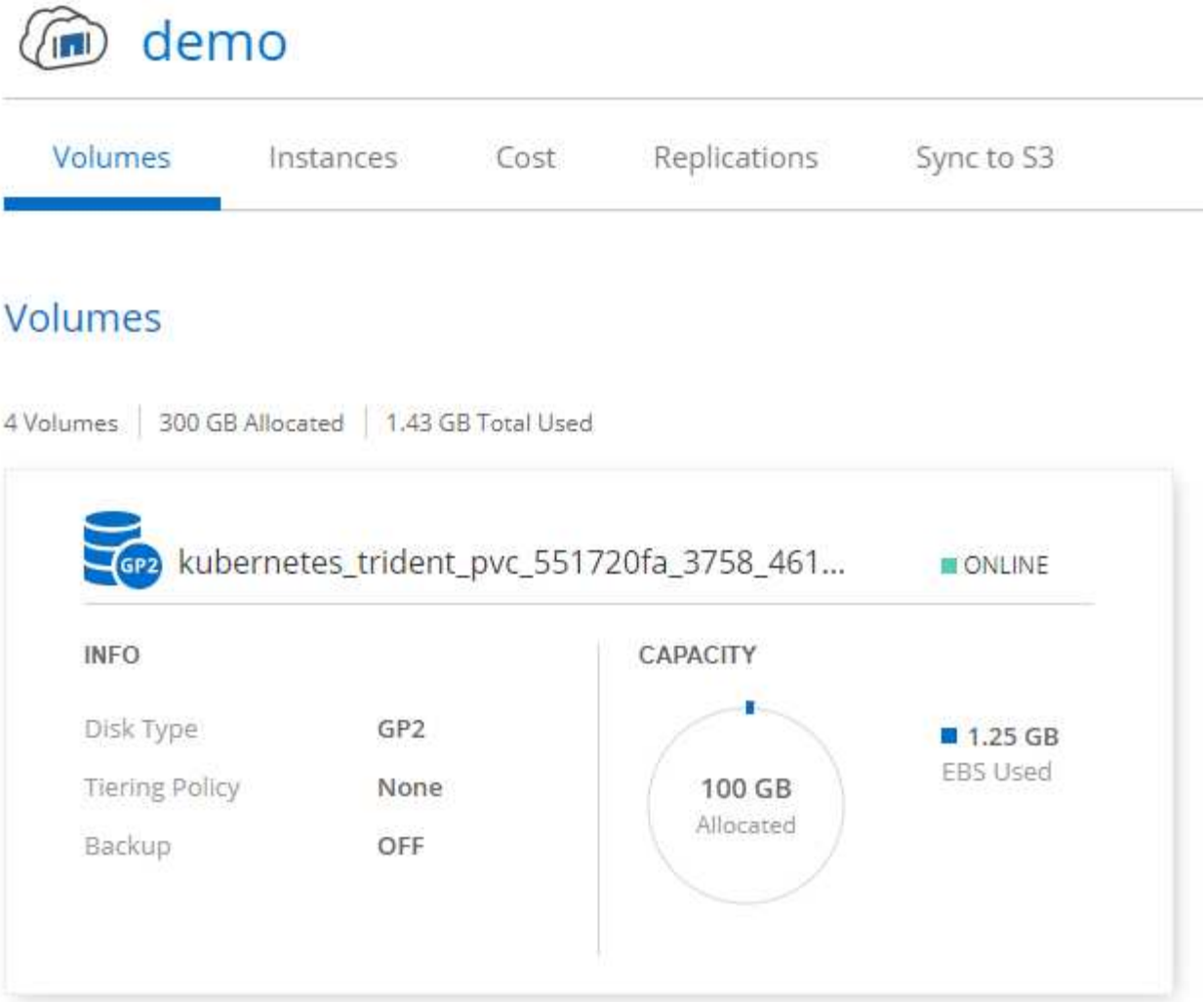
NetApp AI Control Plane

The NetApp AI Control Plane enables you to unleash AI and ML with a solution that offers extreme scalability, streamlined deployment, and nonstop data availability. The AI Control Plane solution integrates Kubernetes and Kubeflow with a data fabric enabled by NetApp. Kubernetes, the industry-standard container orchestration platform for cloud-native deployments, enables workload scalability and portability. Kubeflow is an open-source machine-learning platform that simplifies management and deployment, enabling developers to do more data science in less time. A data fabric enabled by NetApp offers uncompromising data availability and portability to make sure that your data is accessible across the pipeline, from edge to core to cloud. This technical report

uses the NetApp AI Control Plane in an MLRun pipeline. The following image shows Kubernetes cluster management page where you can have different endpoints for each cluster. We connected NFS Persistent Volumes to the Kubernetes cluster, and the following images show an Persistent Volume connected to the cluster, where NetApp Trident offers persistent storage support and data management capabilities.



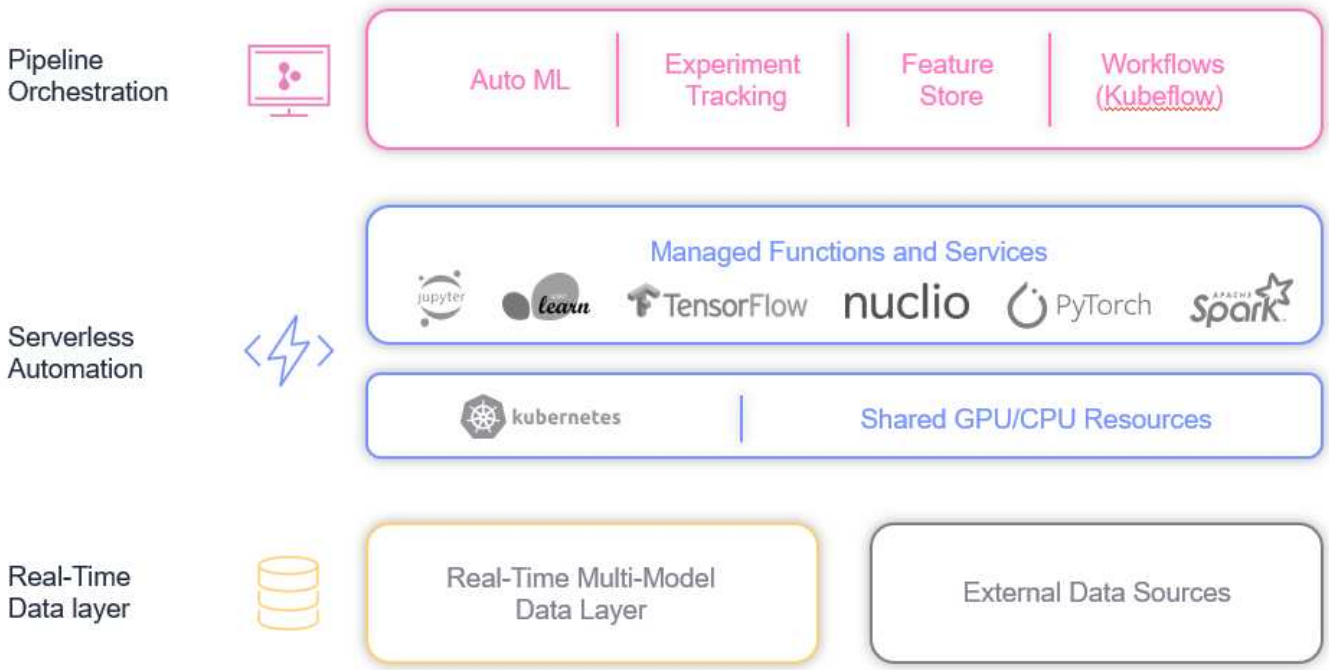




Iguazio Overview

The Iguazio Data Science Platform is a fully integrated and secure data- science platform as a service (PaaS) that simplifies development, accelerates performance, facilitates collaboration, and addresses operational challenges. This platform incorporates the following components, and the Iguazio Data Science Platform is presented in the following image:

- A data-science workbench that includes Jupyter Notebooks, integrated analytics engines, and Python packages
- Model management with experiments tracking and automated pipeline capabilities
- Managed data and ML services over a scalable Kubernetes cluster
- Nuclio, a real-time serverless functions framework
- An extremely fast and secure data layer that supports SQL, NoSQL, time-series databases, files (simple objects), and streaming
- Integration with third-party data sources such as NetApp, Amazon S3, HDFS, SQL databases, and streaming or messaging protocols
- Real-time dashboards based on Grafana



Next: Software and Hardware Requirements

Software and Hardware Requirements

Network Configuration

The following is the network configuration requirement for setting up in the cloud:

- The Iguazio cluster and NetApp Cloud Volumes must be in the same virtual private cloud.
- The cloud manager must have access to port 6443 on the Iguazio app nodes.
- We used Amazon Web Services in this technical report. However, users have the option of deploying the solution in any Cloud provider.For on-premises testing in ONTAP AI with NVIDIA DGX-1, we used the Iguazio hosted DNS service for convenience.

Clients must be able to access dynamically created DNS domains. Customers can use their own DNS if desired.

Hardware Requirements

You can install Iguazio on-premises in your own cluster. We have verified the solution in NetApp ONTAP AI with an NVIDIA DGX-1 system. The following table lists the hardware used to test this solution.

Hardware	Quantity
DGX-1 systems	1
NetApp AFF A800 system	1 high-availability (HA) pair, includes 2 controllers and 48 NVMe SSDs (3.8TB or above)
Cisco Nexus 3232C network switches	2

The following table lists the software components required for on-premise testing:

Software	Version or Other Information
NetApp ONTAP data management software	9.7
Cisco NX-OS switch firmware	7.0(3)I6(1)
NVIDIA DGX OS	4.4 - Ubuntu 18.04 LTS
Docker container platform	19.03.5
Container version	20.01-tf1-py2
Machine learning framework	TensorFlow 1.15.0
Iguazio	Version 2.8+
ESX Server	6.5

This solution was fully tested with Iguazio version 2.5 and NetApp Cloud Volumes ONTAP for AWS. The Iguazio cluster and NetApp software are both running on AWS.

Software	Version or Type
Iguazio	Version 2.8+
App node	M5.4xlarge
Data node	I3.4xlarge

Next: Network Device Failure Prediction Use Case Summary

Network Device Failure Prediction Use Case Summary

This use case is based on an Iguazio customer in the telecommunications space in Asia. With 100K enterprise customers and 125k network outage events per year, there was a critical need to predict and take proactive action to prevent network failures from affecting customers. This solution provided them with the following benefits:

- Predictive analytics for network failures
- Integration with a ticketing system
- Taking proactive action to prevent network failuresAs a result of this implementation of Iguazio, 60% of failures were proactively prevented.

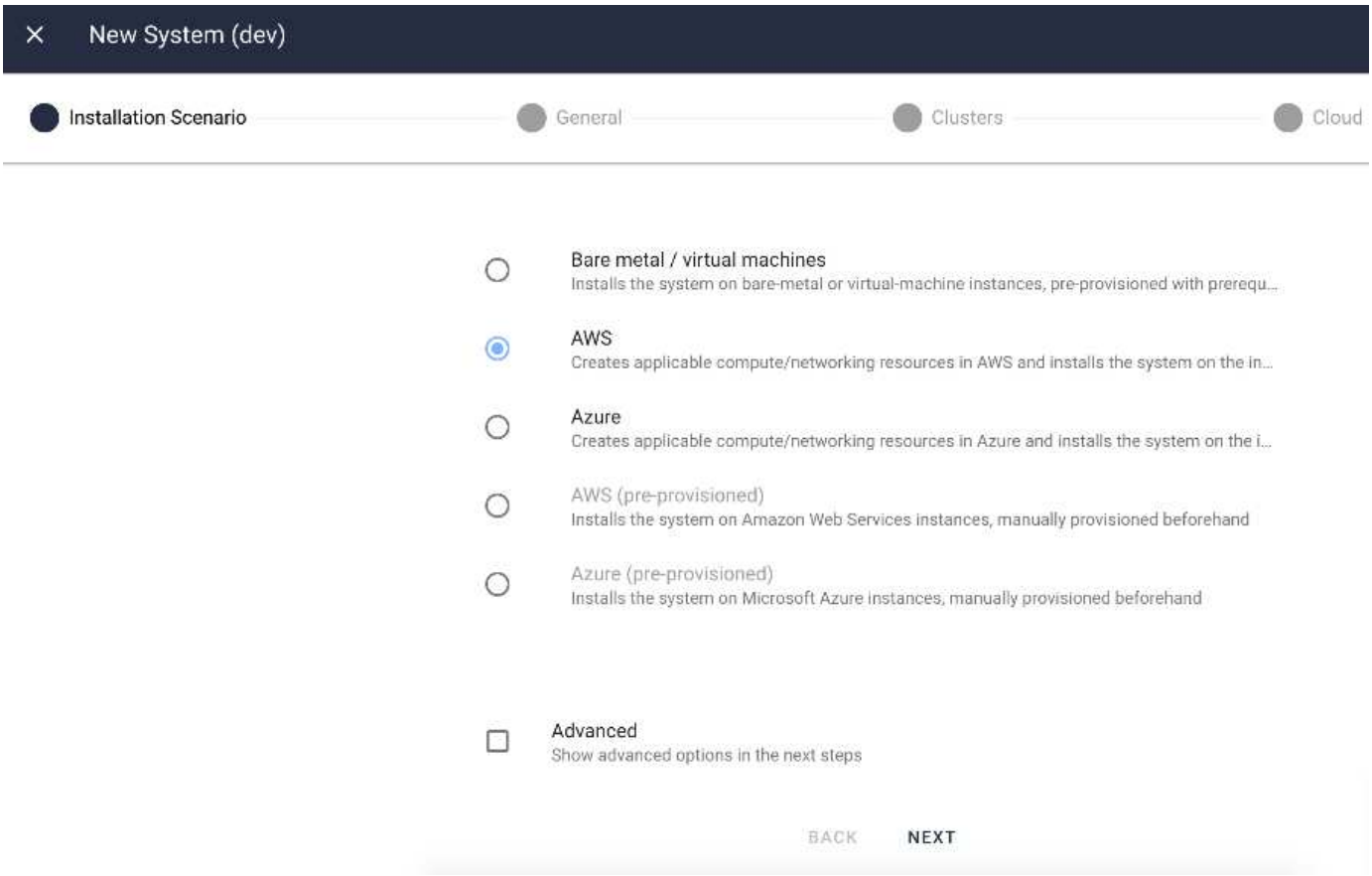
Next: Setup Overview

Setup Overview

Iguazio Installation

Iguazio can be installed on-premises or on a cloud provider. Provisioning can be done as a service and managed by Iguazio or by the customer. In both cases, Iguazio provides a deployment application (Provazio) to deploy and manage clusters.

For on-premises installation, please refer to NVA-1121 for compute, network, and storage setup. On-premises deployment of Iguazio is provided by Iguazio without additional cost to the customer. See this page for DNS and SMTP server configurations. The Provazio installation page is shown as follows.



Next: Configuring Kubernetes Cluster

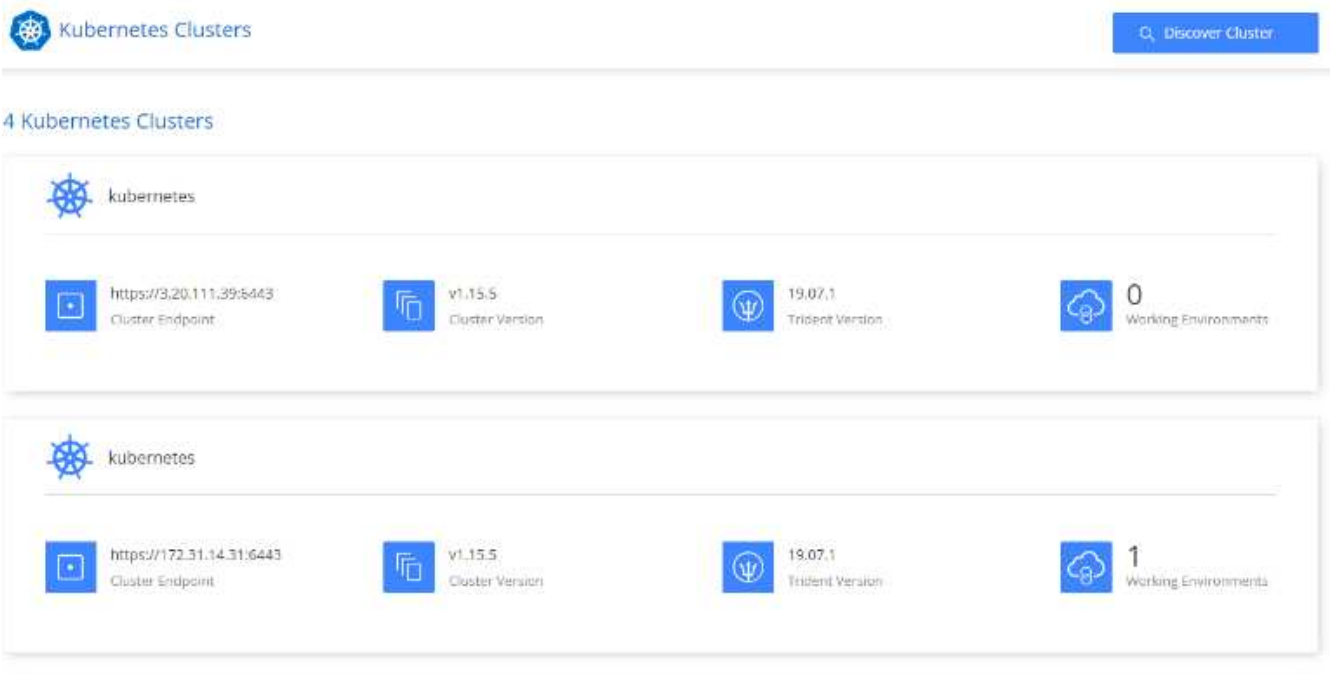
Configuring Kubernetes Cluster

This section is divided into two parts for cloud and on-premises deployment respectively.

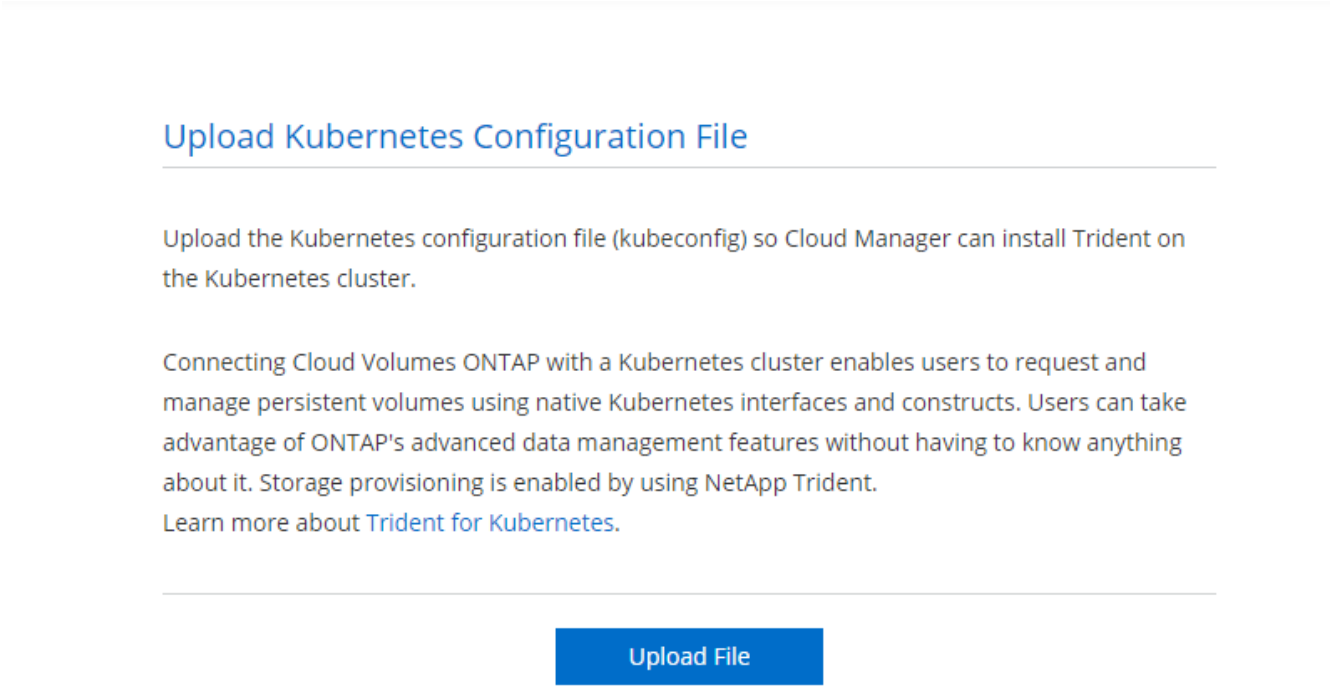
Cloud Deployment Kubernetes Configuration

Through NetApp Cloud Manager, you can define the connection to the Iguazio Kubernetes cluster. Trident requires access to multiple resources in the cluster to make the volume available.

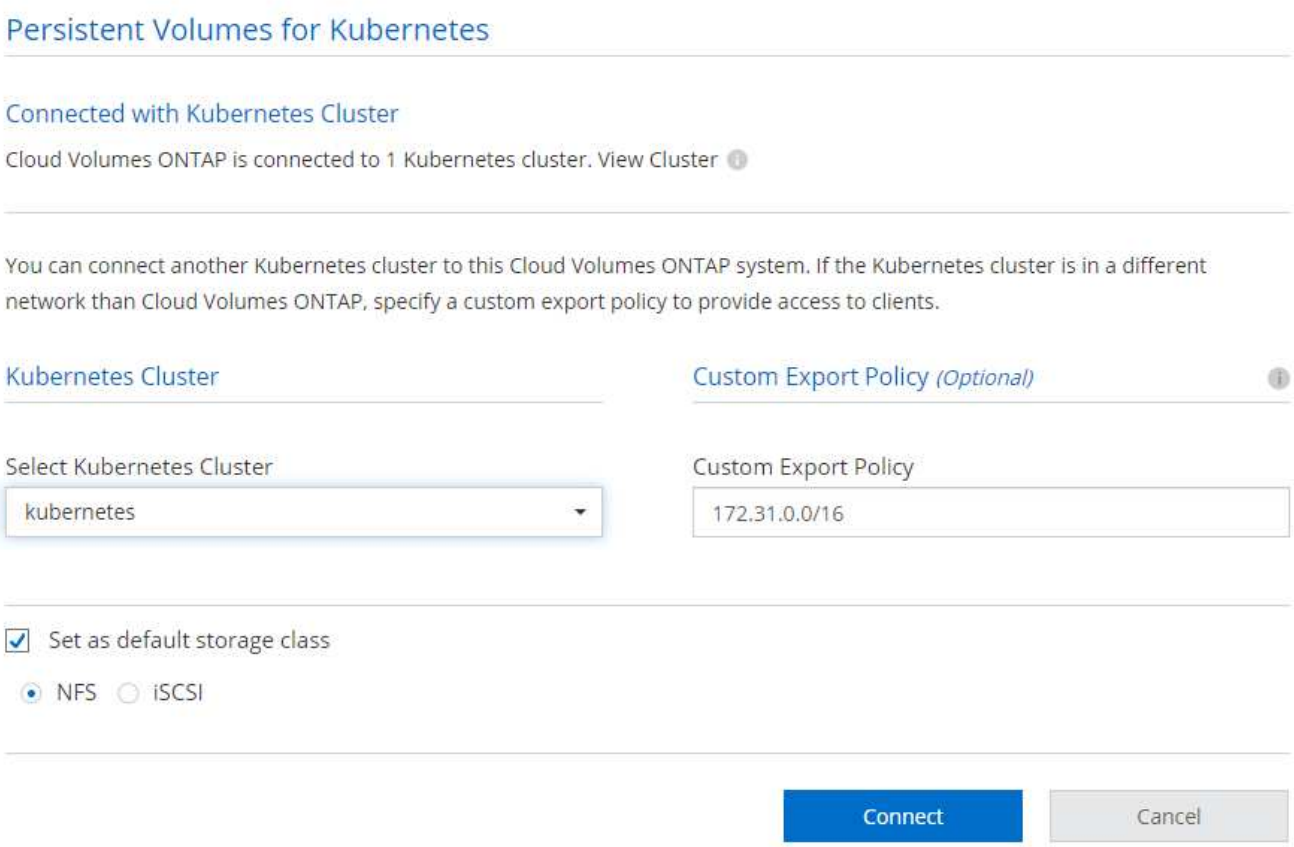
1. To enable access, obtain the Kubernetes config file from one the Iguazio nodes. The file is located under `/home/Iguazio/.kube/config`. Download this file to your desktop.
2. Go to Discover Cluster to configure.



3. Upload the Kubernetes config file. See the following image.



4. Deploy Trident and associate a volume with the cluster. See the following image on defining and assigning a Persistent Volume to the Iguazio cluster.This process creates a Persistent Volume (PV) in Iguazio's Kubernetes cluster. Before you can use it, you must define a Persistent Volume Claim (PVC).



On-Premises Deployment Kubernetes Configuration

For on-premises installation of NetApp Trident, see TR-4798 for details. After configuring your Kubernetes cluster and installing NetApp Trident, you can connect Trident to the Iguazio cluster to enable NetApp data management capabilities, such as taking Snapshot copies of your data and model.

Next: Define Persistent Volume Claim

Define Persistent Volume Claim

1. Save the following YAML to a file to create a PVC of type Basic.

```
kind: PersistentVolumeClaim
apiVersion: v1
metadata:
  name: basic
spec:
  accessModes:
    - ReadWriteOnce
  resources:
    requests:
      storage: 100Gi
  storageClassName: netapp-file
```

2. Apply the YAML file to your Iguazio Kubernetes cluster.

```
Kubectl -n default-tenant apply -f <your yaml file>
```

Attach NetApp Volume to the Jupyter Notebook

Iguazio offers several managed services to provide data scientists with a full end-to-end stack for development and deployment of AI/ML applications. You can read more about these components at the Iguazio Overview of Application Services and Tools.

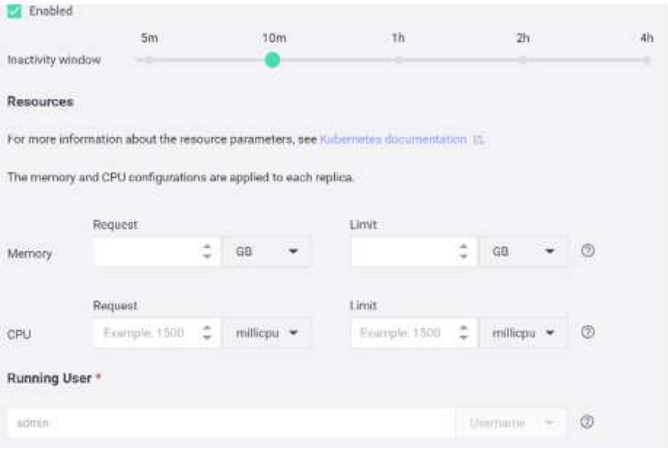
One of the managed services is Jupyter Notebook. Each developer gets its own deployment of a notebook container with the resources they need for development. To give them access to the NetApp Cloud Volume, you can assign the volume to their container and resource allocation, running user, and environment variable settings for Persistent Volume Claims is presented in the following image.

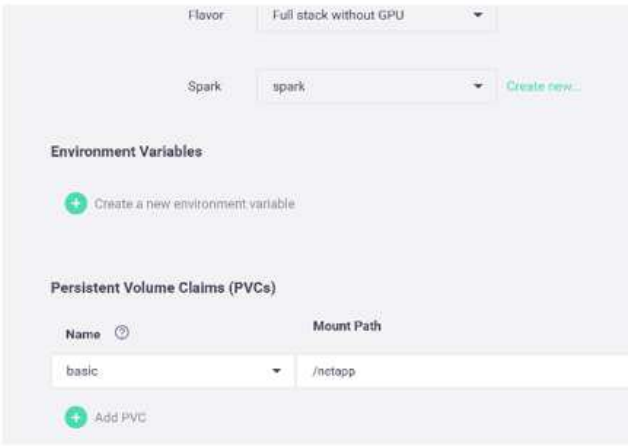
For an on-premises configuration, you can refer to TR-4798 on the Trident setup to enable NetApp ONTAP data management capabilities, such as taking Snapshot copies of your data or model for versioning control. Add the following line in your Trident back- end config file to make Snapshot directories visible:

```
{
    …
    "defaults": {
        "snapshotDir": "true"
    }
}
```

You must create a Trident back- end config file in JSON format, and then run the following Trident command to reference it:

```
tridentctl create backend -f <backend-file>
```





Next: Deploying the Application

Deploying the Application

The following sections describe how to install and deploy the application.

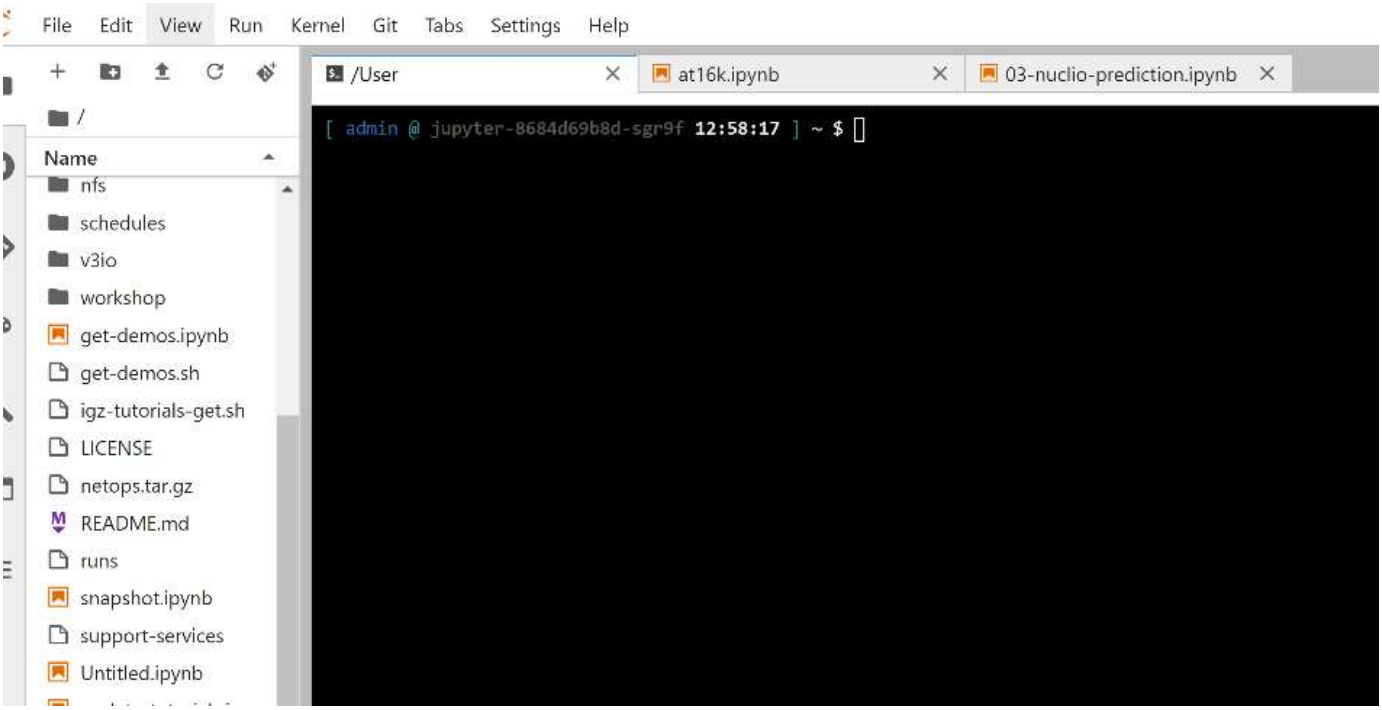
Next: Get Code from GitHub.

Get Code from GitHub

Now that the NetApp Cloud Volume or NetApp Trident volume is available to the Iguazio cluster and the developer environment, you can start reviewing the application.

Users have their own workspace (directory). On every notebook, the path to the user directory is `/User`. The Iguazio platform manages the directory. If you follow the instructions above, the NetApp Cloud volume is available in the `/netapp` directory.

Get the code from GitHub using a Jupyter terminal.



At the Jupyter terminal prompt, clone the project.

```
cd /User
git clone .
```

You should now see the `netops- netapp` folder on the file tree in Jupyter workspace.

Next: Configure Working Environment

Configure Working Environment

Copy the `Notebook set_env-Example.ipynb` as `set_env.ipynb`. Open and edit `set_env.ipynb`. This notebook sets variables for credentials, file locations, and

execution drivers.

If you follow the instructions above, the following steps are the only changes to make:

1. Obtain this value from the Iguazio services dashboard: `docker_registry`

   Example: `docker-registry.default-tenant.app.clusterq.iguaziodev.com:80`

2. Change `admin` to your Iguazio username:

   ```
   IGZ_CONTAINER_PATH = '/users/admin'
   ```

   The following are the ONTAP system connection details. Include the volume name that was generated when Trident was installed. The following setting is for an on-premises ONTAP cluster:

   ```
   ontapClusterMgmtHostname = '0.0.0.0'
   ontapClusterAdminUsername = 'USER'
   ontapClusterAdminPassword = 'PASSWORD'
   sourceVolumeName = 'SOURCE VOLUME'
   ```

   The following setting is for Cloud Volumes ONTAP:

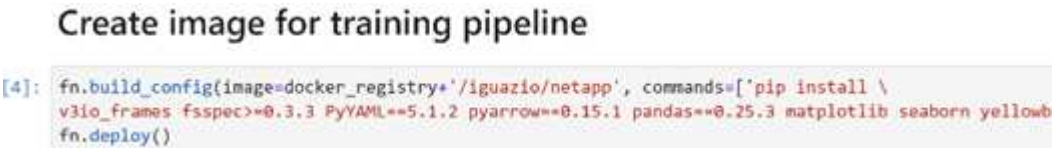
```
MANAGER=ontapClusterMgmtHostname
svm='svm'
email='email'
password=ontapClusterAdminPassword
weid="weid"
volume=sourceVolumeName
```

Create Base Docker Images

Everything you need to build an ML pipeline is included in the Iguazio platform. The developer can define the specifications of the Docker images required to run the pipeline and execute the image creation from Jupyter Notebook. Open the notebook `create- images.ipynb` and Run All Cells.

This notebook creates two images that we use in the pipeline.

- `iguazio/netapp`. Used to handle ML tasks.



- `netapp/pipeline`. Contains utilities to handle NetApp Snapshot copies.

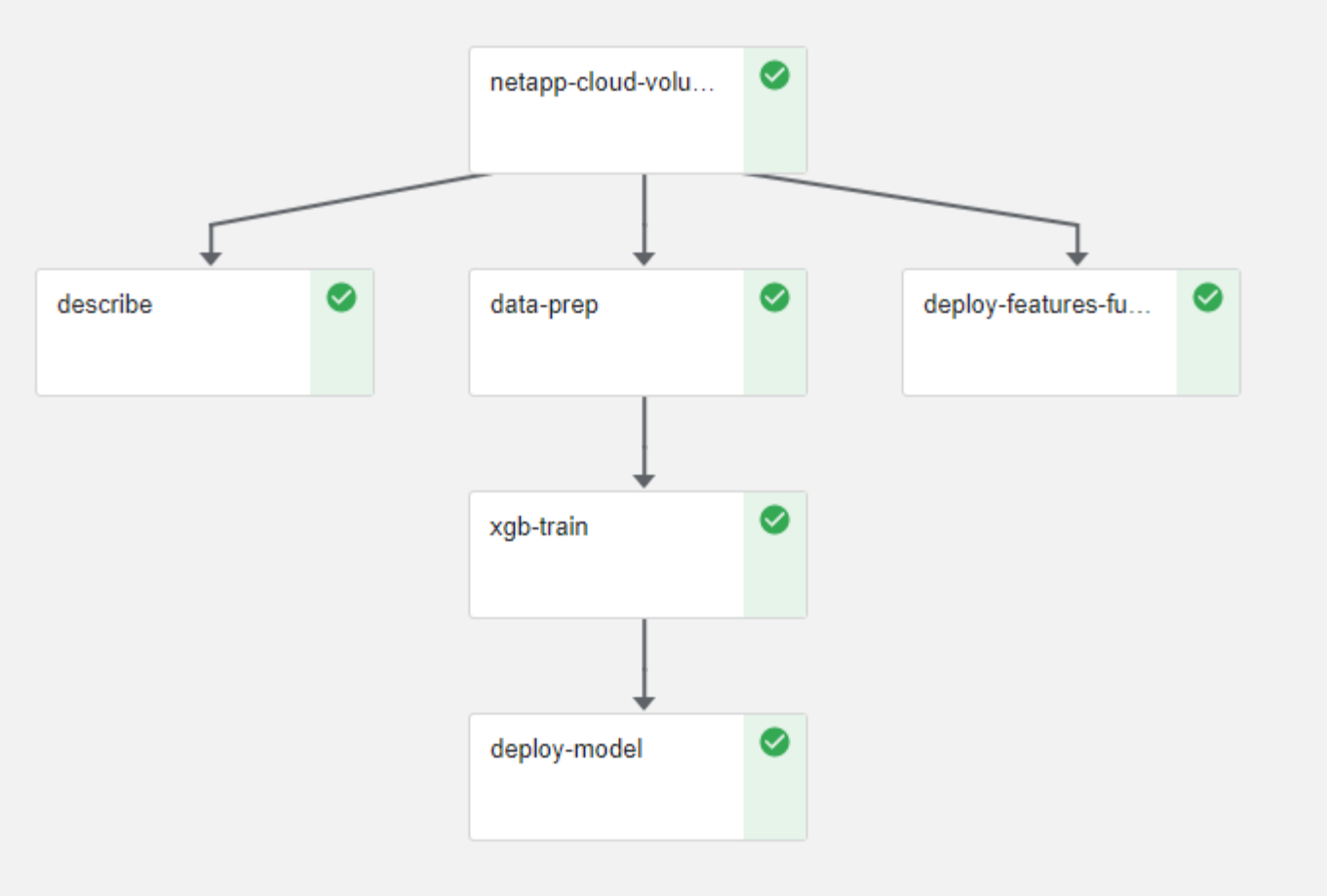
Review Individual Jupyter Notebooks

The following table lists the libraries and frameworks we used to build this task. All these components have been fully integrated with Iguazio's role- based access and security controls.

Libraries/Framework	Description
MLRun	An managed by Iguazio to enable the assembly, execution, and monitoring of an ML/AI pipeline.
Nuclio	A serverless functions framework integrated with Iguazio. Also available as an open-source project managed by Iguazio.
Kubeflow	A Kubernetes-based framework to deploy the pipeline. This is also an open-source project to which Iguazio contributes. It is integrated with Iguazio for added security and integration with the rest of the infrastructure.
Docker	A Docker registry run as a service in the Iguazio platform. You can also change this to connect to your registry.
NetApp Cloud Volumes	Cloud Volumes running on AWS give us access to large amounts of data and the ability to take Snapshot copies to version the datasets used for training.
Trident	Trident is an open-source project managed by NetApp. It facilitates the integration with storage and compute resources in Kubernetes.

We used several notebooks to construct the ML pipeline. Each notebook can be tested individually before being brought together in the pipeline. We cover each notebook individually following the deployment flow of this demonstration application.

The desired result is a pipeline that trains a model based on a Snapshot copy of the data and deploys the model for inference. A block diagram of a completed MLRun pipeline is shown in the following image.



Deploy Data Generation Function

This section describes how we used Nuclio serverless functions to generate network device data. The use case is adapted from an Iguazio client that deployed the pipeline and used Iguazio services to monitor and predict network device failures.

We simulated data coming from network devices. Executing the Jupyter notebook `data- generator.ipynb` creates a serverless function that runs every 10 minutes and generates a Parquet file with new data. To deploy the function, run all the cells in this notebook. See the Nuclio website to review any unfamiliar components in this notebook.

A cell with the following comment is ignored when generating the function. Every cell in the notebook is assumed to be part of the function. Import the Nuclio module to enable `%nuclio magic`.

```
# nuclio: ignore
import nuclio
```

In the spec for the function, we defined the environment in which the function executes, how it is triggered, and the resources it consumes.

```
spec = nuclio.ConfigSpec(config={"spec.triggers.inference.kind":"cron",

"spec.triggers.inference.attributes.interval" :"10m",
                                  "spec.readinessTimeoutSeconds" : 60,
                                  "spec.minReplicas" : 1},……
```

The `init_context` function is invoked by the Nuclio framework upon initialization of the function.

```
def init_context(context):
    ….
```

Any code not in a function is invoked when the function initializes. When you invoke it, a handler function is executed. You can change the name of the handler and specify it in the function spec.

```
def handler(context, event):
            …
```

You can test the function from the notebook prior to deployment.

```
%%time
# nuclio: ignore
init_context(context)
event = nuclio.Event(body='')
output = handler(context, event)
output
```

The function can be deployed from the notebook or it can be deployed from a CI/CD pipeline (adapting this code).

```
addr = nuclio.deploy_file(name='generator',project='netops',spec=spec,
tag='v1.1')
```

Pipeline Notebooks

These notebooks are not meant to be executed individually for this setup. This is just a review of each notebook. We invoked them as part of the pipeline. To execute them individually, review the MLRun documentation to execute them as Kubernetes jobs.

snap_cv.ipynb

This notebook handles the Cloud Volume Snapshot copies at the beginning of the pipeline. It passes the name of the volume to the pipeline context. This notebook invokes a shell script to handle the Snapshot copy. While running in the pipeline, the execution context contains variables to help locate all files needed for execution.

While writing this code, the developer does not have to worry about the file location in the container that executes it. As described later, this application is deployed with all its dependencies, and it is the definition of the pipeline parameters that provides the execution context.

```
command = os.path.join(context.get_param('APP_DIR'),"snap_cv.sh")
```

The created Snapshot copy location is placed in the MLRun context to be consumed by steps in the pipeline.

```
context.log_result('snapVolumeDetails',snap_path)
```

The next three notebooks are run in parallel.

data-prep.ipynb

Raw metrics must be turned into features to enable model training. This notebook reads the raw metrics from the Snapshot directory and writes the features for model training to the NetApp volume.

When running in the context of the pipeline, the input `DATA_DIR` contains the Snapshot copy location.

```
metrics_table = os.path.join(str(mlruncontext.get_input('DATA_DIR',
os.getenv('DATA_DIR','/netpp'))),
                             mlruncontext.get_param('metrics_table',
os.getenv('metrics_table','netops_metrics_parquet')))
```

describe.ipynb

To visualize the incoming metrics, we deploy a pipeline step that provides plots and graphs that are available through the Kubeflow and MLRun UIs. Each execution has its own version of this visualization tool.

```
ax.set_title("features correlation")
plt.savefig(os.path.join(base_path, "plots/corr.png"))
context.log_artifact(PlotArtifact("correlation",  body=plt.gcf()),
local_path="plots/corr.html")
```

deploy-feature-function.ipynb

We continuously monitor the metrics looking for anomalies. This notebook creates a serverless function that generates the features need to run prediction on incoming metrics. This notebook invokes the creation of the function. The function code is in the notebook `data- prep.ipynb`. Notice that we use the same notebook as a step in the pipeline for this purpose.

training.ipynb

After we create the features, we trigger the model training. The output of this step is the model to be used for inferencing. We also collect statistics to keep track of each execution (experiment).

For example, the following command enters the accuracy score into the context for that experiment. This value is visible in Kubeflow and MLRun.

```
context.log_result('accuracy',score)
```

deploy-inference-function.ipynb

The last step in the pipeline is to deploy the model as a serverless function for continuous inferencing. This notebook invokes the creation of the serverless function defined in `nuclio-inference- function.ipynb`.

Review and Build Pipeline

The combination of running all the notebooks in a pipeline enables the continuous run of experiments to reassess the accuracy of the model against new metrics. First, open the `pipeline.ipynb` notebook. We take you through details that show how NetApp and Iguazio simplify the deployment of this ML pipeline.

We use MLRun to provide context and handle resource allocation to each step of the pipeline. The MLRun API service runs in the Iguazio platform and is the point of interaction with Kubernetes resources. Each developer cannot directly request resources; the API handles the requests and enables access controls.

```
# MLRun API connection definition
mlconf.dbpath = 'http://mlrun-api:8080'
```

The pipeline can work with NetApp Cloud Volumes and on-premises volumes. We built this demonstration to use Cloud Volumes, but you can see in the code the option to run on-premises.

```
# Initialize the NetApp snap fucntion once for all functions in a notebook
if [ NETAPP_CLOUD_VOLUME ]:
    snapfn =
code_to_function('snap',project='NetApp',kind='job',filename="snap_cv.ipyn
b").apply(mount_v3io())
    snap_params = {
    "metrics_table" : metrics_table,
    "NETAPP_MOUNT_PATH" : NETAPP_MOUNT_PATH,
    'MANAGER' : MANAGER,
    'svm' : svm,
    'email': email,
    'password': password ,
    'weid': weid,
    'volume': volume,
    "APP_DIR" : APP_DIR
       }
else:
    snapfn =
code_to_function('snap',project='NetApp',kind='job',filename="snapshot.ipy
nb").apply(mount_v3io())
….
snapfn.spec.image = docker_registry + '/netapp/pipeline:latest'
snapfn.spec.volume_mounts =
[snapfn.spec.volume_mounts[0],netapp_volume_mounts]
      snapfn.spec.volumes = [ snapfn.spec.volumes[0],netapp_volumes]
```

The first action needed to turn a Jupyter notebook into a Kubeflow step is to turn the code into a function. A function has all the specifications required to run that notebook. As you scroll down the notebook, you can see that we define a function for every step in the pipeline.

Part of the Notebook	**Description**
<code_to_function> (part of the MLRun module)	Name of the function: Project name. used to organize all project artifacts. This is visible in the MLRun UI. Kind. In this case, a Kubernetes job. This could be Dask, mpi, sparkk8s, and more. See the MLRun documentation for more details. File. The name of the notebook. This can also be a location in Git (HTTP).
image	The name of the Docker image we are using for this step. We created this earlier with the create-image.ipynb notebook.
volume_mounts & volumes	Details to mount the NetApp Cloud Volume at run time.

We also define parameters for the steps.

```
params={   "FEATURES_TABLE":FEATURES_TABLE,
           "SAVE_TO" : SAVE_TO,
           "metrics_table" : metrics_table,
           'FROM_TSDB': 0,
           'PREDICTIONS_TABLE': PREDICTIONS_TABLE,
           'TRAIN_ON_LAST': '1d',
           'TRAIN_SIZE':0.7,
           'NUMBER_OF_SHARDS' : 4,
           'MODEL_FILENAME' : 'netops.v3.model.pickle',
           'APP_DIR' : APP_DIR,
           'FUNCTION_NAME' : 'netops-inference',
           'PROJECT_NAME' : 'netops',
           'NETAPP_SIM' : NETAPP_SIM,
           'NETAPP_MOUNT_PATH': NETAPP_MOUNT_PATH,
           'NETAPP_PVC_CLAIM' : NETAPP_PVC_CLAIM,
           'IGZ_CONTAINER_PATH' : IGZ_CONTAINER_PATH,
           'IGZ_MOUNT_PATH' : IGZ_MOUNT_PATH
            }
```

After you have the function definition for all steps, you can construct the pipeline. We use the `kfp` module to make this definition. The difference between using MLRun and building on your own is the simplification and shortening of the coding.

The functions we defined are turned into step components using the `as_step` function of MLRun.

Snapshot Step Definition

Initiate a Snapshot function, output, and mount v3io as source:

```
snap = snapfn.as_step(NewTask(handler='handler',params=snap_params),
name='NetApp_Cloud_Volume_Snapshot',outputs=['snapVolumeDetails','training
_parquet_file']).apply(mount_v3io())
```

Parameters	Details
NewTask	NewTask is the definition of the function run.
(MLRun module)	Handler. Name of the Python function to invoke. We used the name handler in the notebook, but it is not required. params. The parameters we passed to the execution. Inside our code, we use context.get_param (‘PARAMETER’) to get the values.

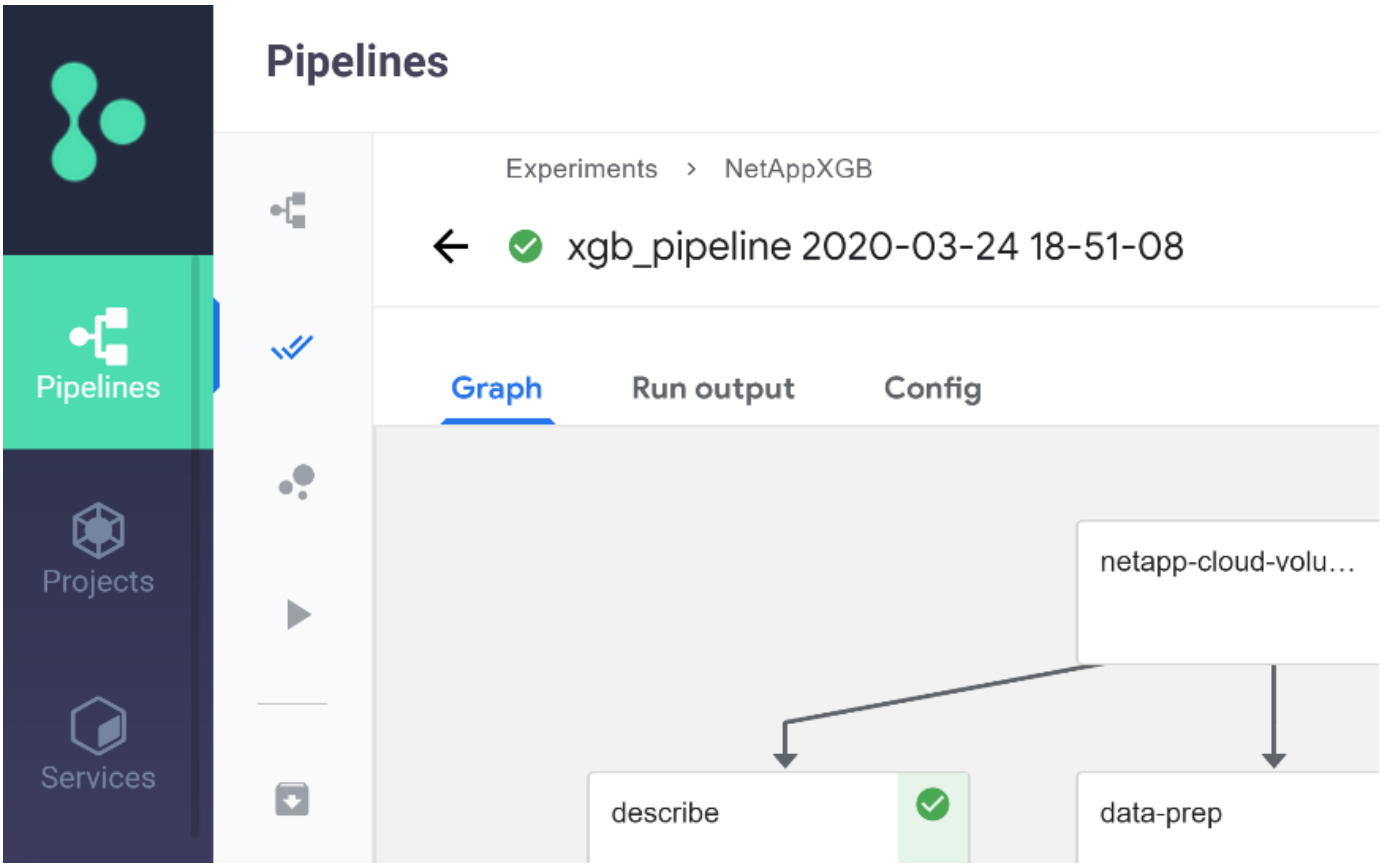
Parameters	Details
as_step	Name. Name of the Kubeflow pipeline step. outputs. These are the values that the step adds to the dictionary on completion. Take a look at the snap_cv.ipynb notebook. mount_v3io(). This configures the step to mount /User for the user executing the pipeline.

```
prep = data_prep.as_step(name='data-prep',
handler='handler',params=params,
                          inputs = {'DATA_DIR':
snap.outputs['snapVolumeDetails']} ,

out_path=artifacts_path).apply(mount_v3io()).after(snap)
```

Parameters	Details
inputs	You can pass to a step the outputs of a previous step. In this case, snap.outputs['snapVolumeDetails'] is the name of the Snapshot copy we created on the snap step.
out_path	A location to place artifacts generating using the MLRun module log_artifacts.

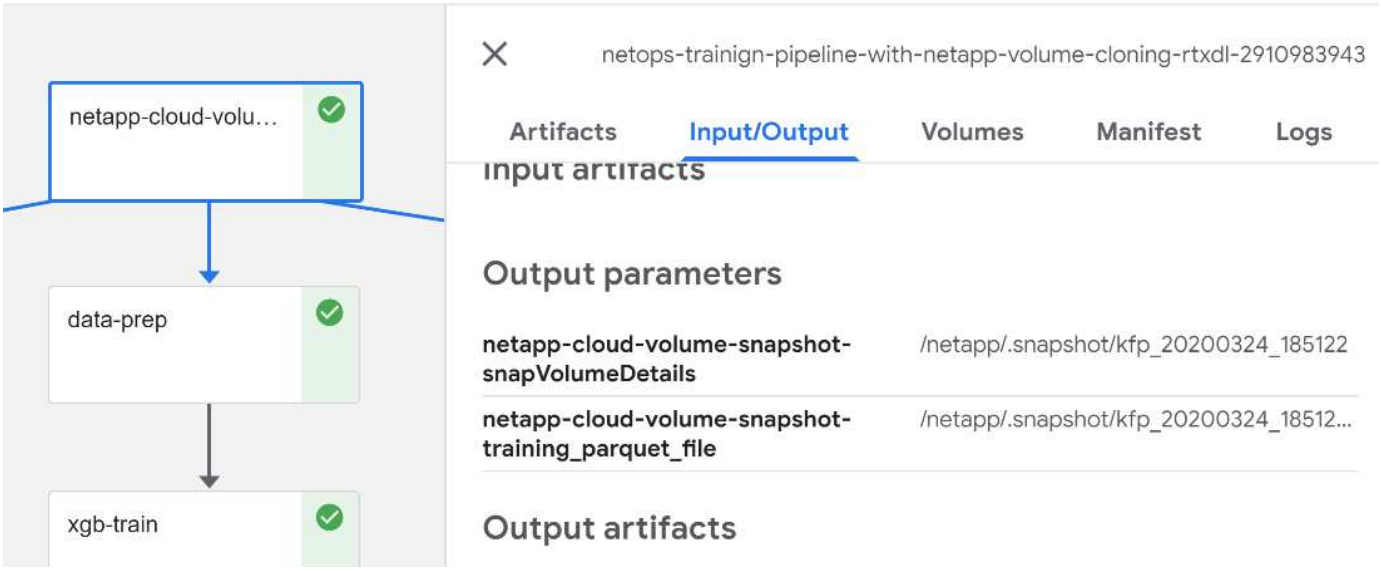
You can run `pipeline.ipynb` from top to bottom. You can then go to the Pipelines tab from the Iguazio dashboard to monitor progress as seen in the Iguazio dashboard Pipelines tab.



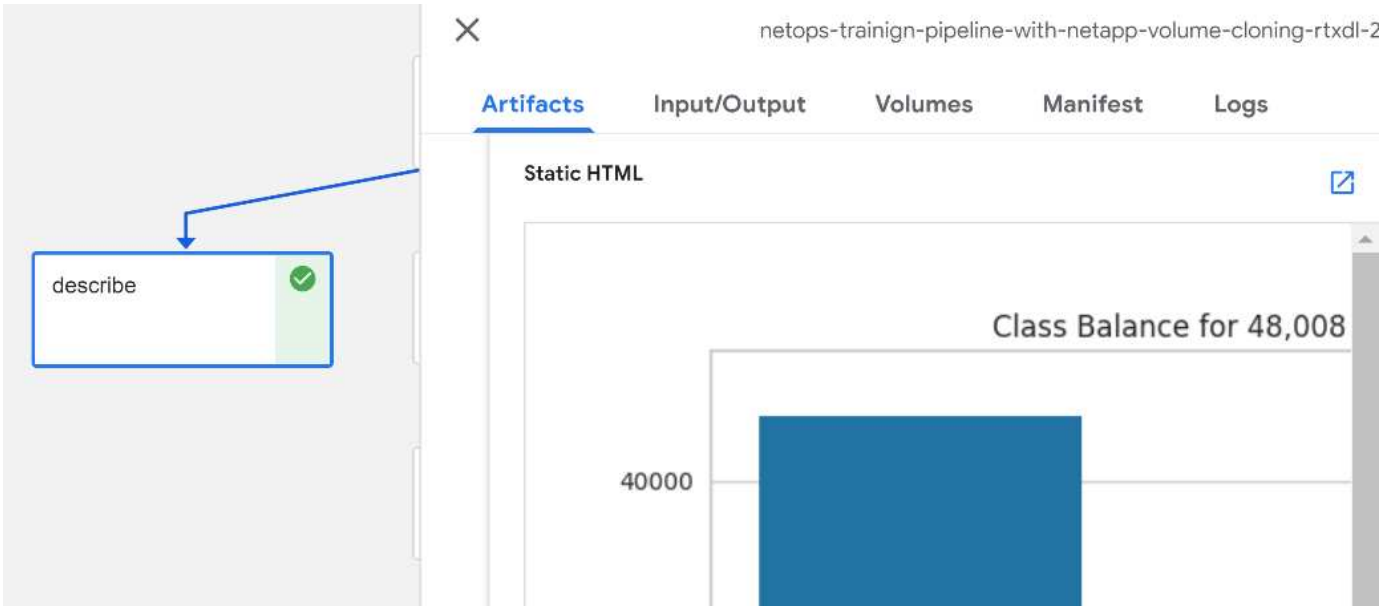
Because we logged the accuracy of training step in every run, we have a record of accuracy for each experiment, as seen in the record of training accuracy.

Run name	Status	Duration	Pipeline Version	Recurring …	Start time	accuracy
xgb_pipeline 2020-03-24 18-51-…	✓	0:08:43	[View pipeline]	-	3/24/2020, 2:51:09 PM	0.985
xgb_pipeline 2020-03-19 13-31-…	✓	0:08:14	[View pipeline]	-	3/19/2020, 9:31:19 AM	0.980
xgb_pipeline 2020-03-18 12-56-…	✓	0:08:11	[View pipeline]	-	3/18/2020, 8:56:08 AM	0.990
xgb_pipeline 2020-03-17 19-49-…	✓	0:08:03	[View pipeline]	-	3/17/2020, 3:49:31 PM	0.985
xgb_pipeline 2020-03-17 18-34-…	✓	0:05:54	[View pipeline]	-	3/17/2020, 2:34:56 PM	0.980
xgb_pipeline 2020-03-17 17-34-…	✓	0:04:48	[View pipeline]	-	3/17/2020, 1:34:16 PM	0.982
xgb_pipeline 2020-03-17 17-01-…	✓	0:05:25	[View pipeline]	-	3/17/2020, 1:01:58 PM	0.987
xgb_pipeline 2020-03-16 16-47-…	✓	0:06:08	[View pipeline]	-	3/16/2020, 12:47:19 …	0.983
xgb_pipeline 2020-03-16 13-57-…	✓	0:05:18	[View pipeline]	-	3/16/2020, 9:57:03 AM	0.980

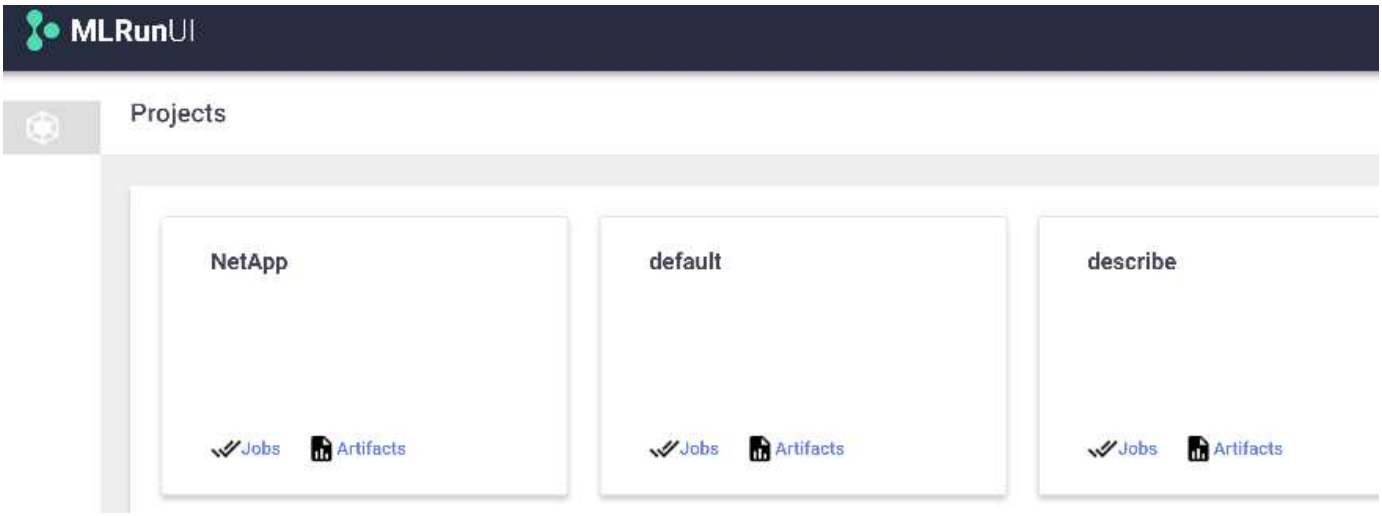
If you select the Snapshot step, you can see the name of the Snapshot copy that was used to run this experiment.



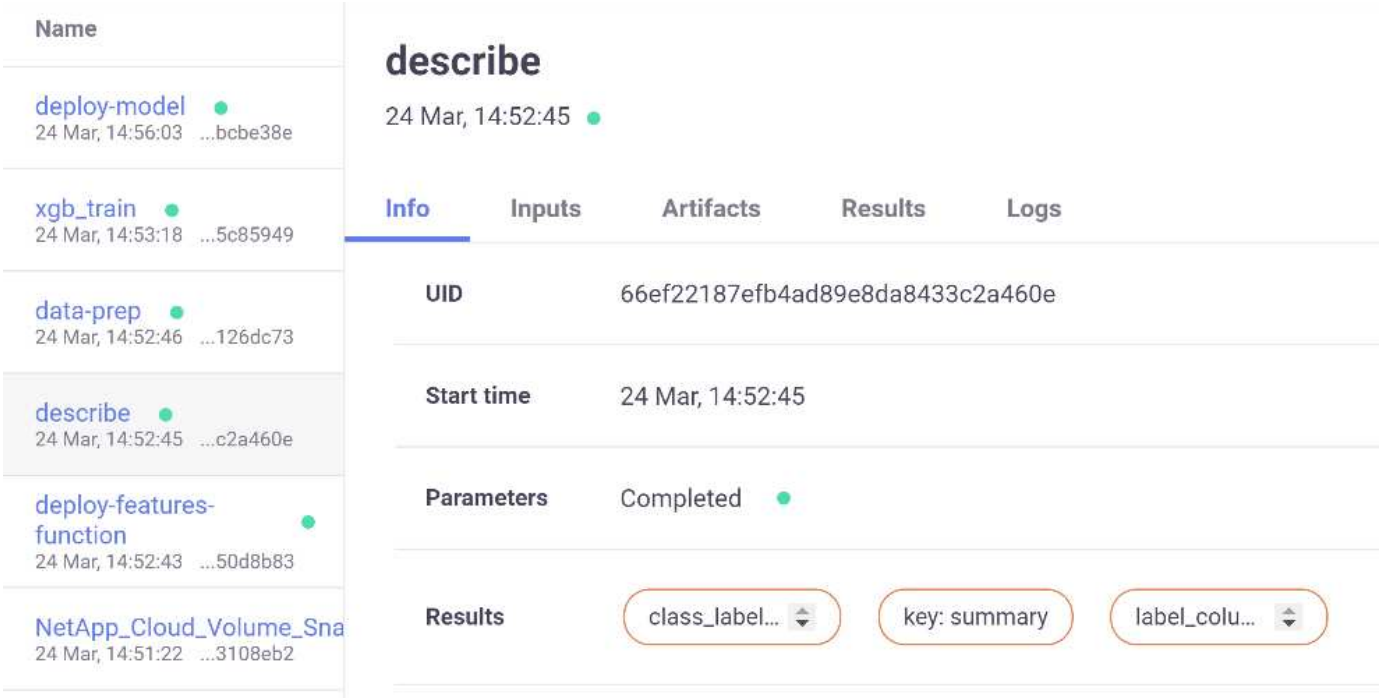
The described step has visual artifacts to explore the metrics we used. You can expand to view the full plot as seen in the following image.



The MLRun API database also tracks inputs, outputs, and artifacts for each run organized by project. An example of inputs, outputs, and artifacts for each run can be seen in the following image.



For each job, we store additional details.



There is more information about MLRun than we can cover in this document. AI artifacts, including the definition of the steps and functions, can be saved to the API database, versioned, and invoked individually or as a full project. Projects can also be saved and pushed to Git for later use. We encourage you to learn more at the MLRun GitHub site.

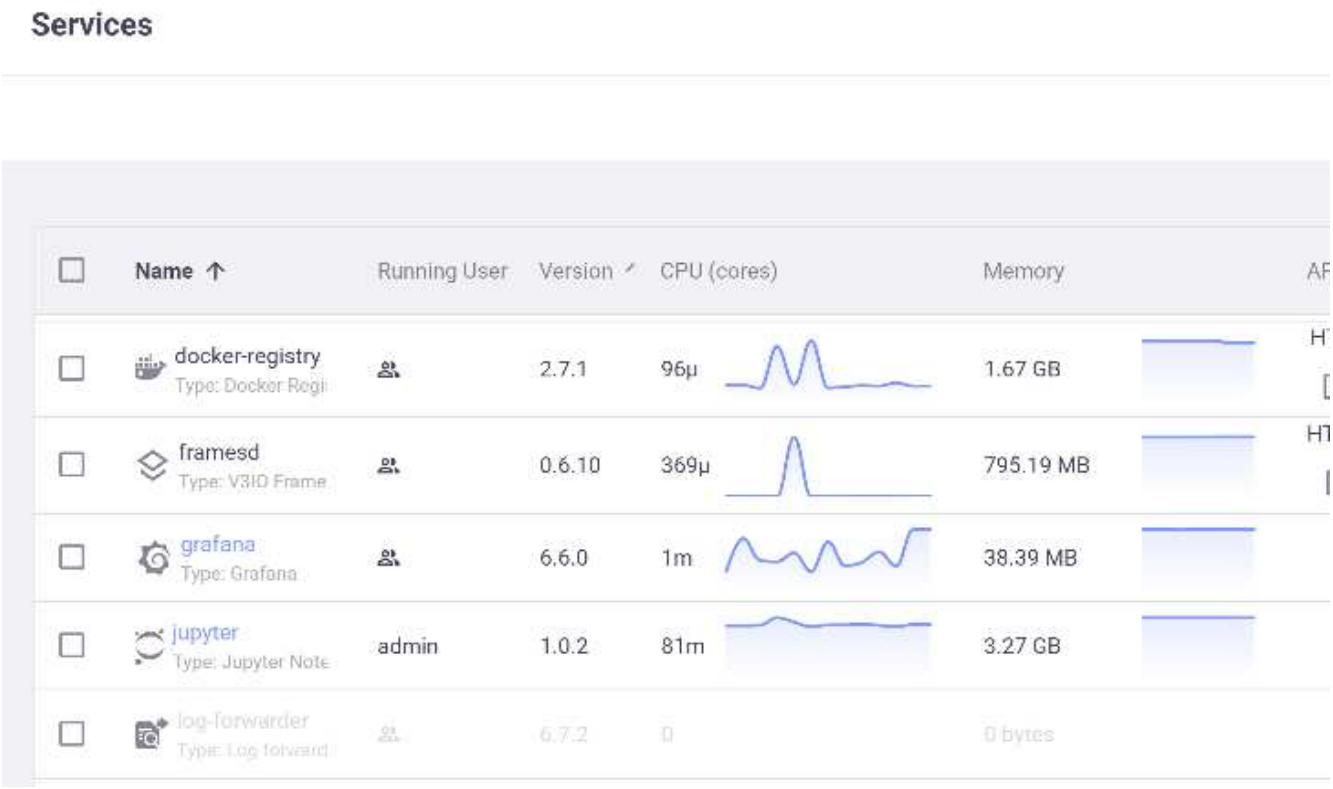
Next: Deploy Grafana Dashboard

Deploy Grafana Dashboard

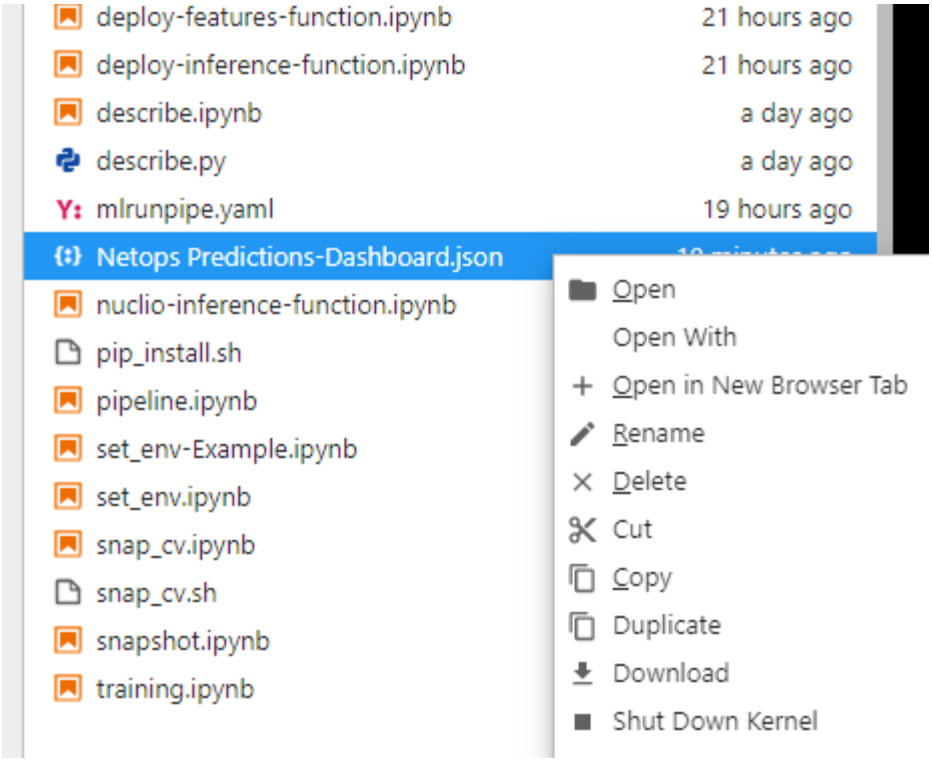
After everything is deployed, we run inferences on new data. The models predict failure on network device equipment. The results of the prediction are stored in an Iguazio TimeSeries table. You can visualize the results with Grafana in the platform integrated with Iguazio's security and data access policy.

You can deploy the dashboard by importing the provided JSON file into the Grafana interfaces in the cluster.

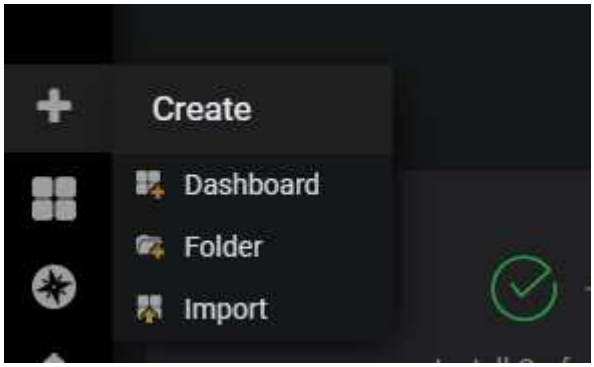
1. To verify that the Grafana service is running, look under Services.



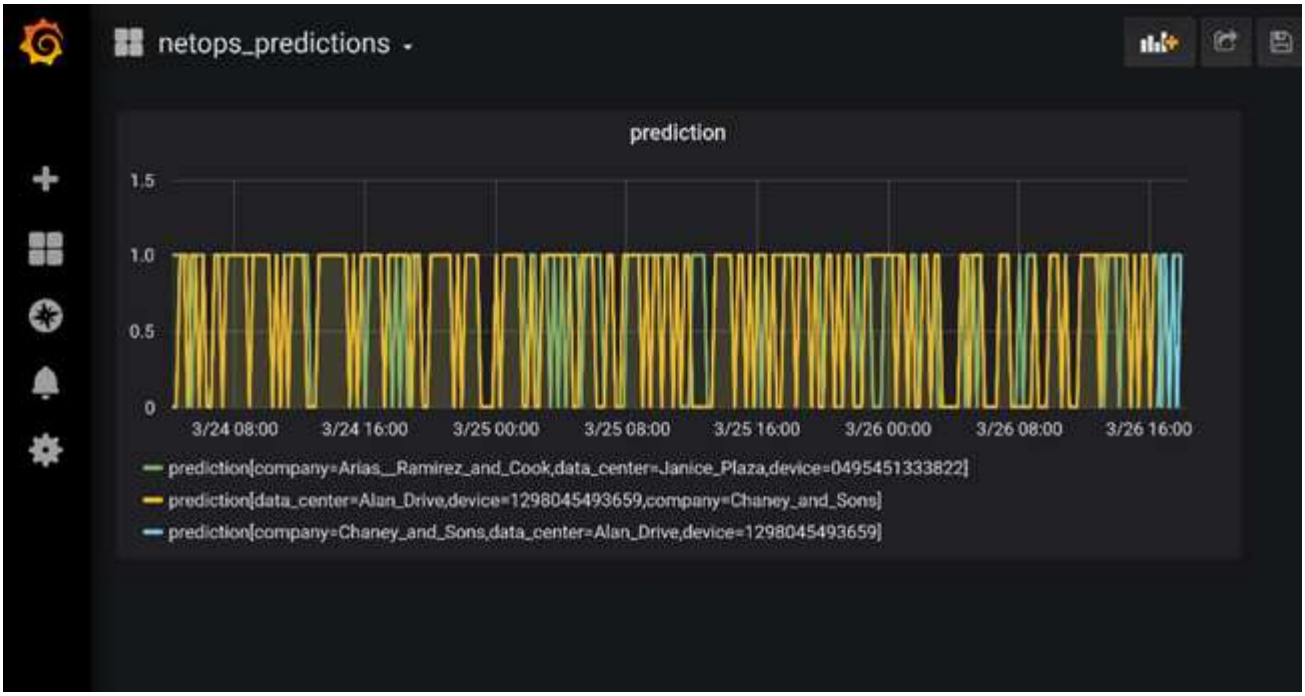
2. If it is not present, deploy an instance from the Services section:
   a. Click New Service.
   b. Select Grafana from the list.
   c. Accept the defaults.
   d. Click Next Step.
   e. Enter your user ID.
   f. Click Save Service.
   g. Click Apply Changes at the top.
3. To deploy the dashboard, download the file `NetopsPredictions-Dashboard.json` through the Jupyter interface.



4. Open Grafana from the Services section and import the dashboard.



5. Click Upload `*.json` File and select the file that you downloaded earlier (`NetopsPredictions-Dashboard.json`). The dashboard displays after the upload is completed.



Deploy Cleanup Function

When you generate a lot of data, it is important to keep things clean and organized. To do so, deploy the cleanup function with the `cleanup.ipynb` notebook.

Benefits

NetApp and Iguazio speed up and simplify the deployment of AI and ML applications by building in essential frameworks, such as Kubeflow, Apache Spark, and TensorFlow, along with orchestration tools like Docker and Kubernetes. By unifying the end-to-end data pipeline, NetApp and Iguazio reduce the latency and complexity inherent in many advanced computing workloads, effectively bridging the gap between development and operations. Data scientists can run queries on large datasets and securely share data and algorithmic models with authorized users during the training phase. After the containerized models are ready for production, you can easily move them from development environments to operational environments.

Next: Conclusion

Conclusion

When building your own AI/ML pipelines, configuring the integration, management, security, and accessibility of the components in an architecture is a challenging task. Giving developers access and control of their environment presents another set of challenges.

The combination of NetApp and Iguazio brings these technologies together as managed services to accelerate technology adoption and improve the time to market for new AI/ML applications.

Next: Where to Find Additional Information