# Table of Contents

Open Source MLOps with NetApp ......................................................... 1
Open Source MLOps with NetApp ......................................................... 1
Technology Overview ................................................................. 2
Architecture .............................................................................. 9
NetApp Astra Trident Configuration ............................................... 10
Apache Airflow ....................................................................... 16
JupyterHub ............................................................................. 20
MLflow .................................................................................... 26
Kubeflow ............................................................................... 28
Example Astra Trident Operations .............................................. 33
Example High-performance Jobs for AIPod Deployments ............... 36
Companies and organizations of all sizes and across many industries are turning to artificial intelligence (AI) to solve real-world problems, deliver innovative products and services, and to get an edge in an increasingly competitive marketplace. Many organizations are turning to open-source MLOps tools in order to keep up with the rapid pace of innovation in the industry. These open-source tools offer advanced capabilities and cutting-edge features, but often don’t account for data availability and data security. Unfortunately, this means that highly-skilled data scientists are forced to spend a significant amount of time waiting to gain access to data or waiting for rudimentary data-related operations to complete. By pairing popular open-source MLOps tools with an intelligent data infrastructure from NetApp, organizations can accelerate their data pipelines, which, in turn, accelerates their AI initiatives. They can unlock value from their data while ensuring that it remains protected and secure. This solution demonstrates the pairing of NetApp data management capabilities with several popular open-source tools and frameworks in order to address these challenges.

The following list highlights some key capabilities that are enabled by this solution:

- Users can rapidly provision new high-capacity data volumes and development workspaces that are backed by high-performance, scale-out NetApp storage.

- Users can near-instantaneously clone high-capacity data volumes and development workspaces in order to enable experimentation or rapid iteration.

- Users can near-instantaneously save snapshots of high-capacity data volumes and development workspaces for backup and/or traceability/baselining.
A typical MLOps workflow incorporates development workspaces, usually taking the form of Jupyter Notebooks; experiment tracking; automated training pipelines; data pipelines; and inference/deployment. This solution highlights several different tools and frameworks that can be used independently or in conjunction to address the different aspects of the workflow. We also demonstrate the pairing of NetApp data management capabilities with each of these tools. This solution is intended to offer building blocks from which an organization can construct a customized MLOps workflow that is specific to their use cases and requirements.

The following tools/frameworks are covered in this solution:

- **Apache Airflow**
- **JupyterHub**
- **Kubeflow**
- **MLflow**

The following list describes common patterns for deploying these tools independently or in conjunction.

- Deploy JupyterHub, MLflow, and Apache Airflow in conjunction - JupyterHub for Jupyter Notebooks, MLflow for experiment tracking, and Apache Airflow for automated training and data pipelines.
- Deploy Kubeflow and Apache Airflow in conjunction - Kubeflow for Jupyter Notebooks, experiment tracking, automated training pipelines, and inference; and Apache Airflow for data pipelines.
- Deploy Kubeflow as an all-in-one MLOps platform solution for Jupyter Notebooks, experiment tracking, automated training and data pipelines, and inference.

**Technology Overview**

This section focuses on the technology overview for OpenSource MLOps with NetApp.

**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](https://www.docker.com).

![Virtual Machines (VMs) vs Containers Diagram](image_url)

**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. For more information, visit the [Kubernetes website](https://kubernetes.io).
### NetApp Astra Trident

Astra Trident enables consumption and management of storage resources across all popular NetApp storage platforms, in the public cloud or on premises, including ONTAP (AFF, FAS, Select, Cloud, Amazon FSx for NetApp ONTAP), Azure NetApp Files service, and Google Cloud NetApp Volumes. Astra Trident is a Container Storage Interface (CSI) compliant dynamic storage orchestrator that natively integrates with Kubernetes.

### NetApp DataOps Toolkit

The NetApp DataOps Toolkit is a Python-based tool that simplifies the management of development/training workspaces and inference servers that are backed by high-performance, scale-out NetApp storage. Key capabilities include:

- Rapidly provision new high-capacity workspaces that are backed by high-performance, scale-out NetApp storage.
- Near-instantly clone high-capacity workspaces in order to enable experimentation or rapid iteration.
- Near-instantly save snapshots of high-capacity workspaces for backup and/or traceability/baselining.
- Near-instantly provision, clone, and snapshot high-capacity, high-performance data volumes.

### 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.

### Jupyter Notebook

Jupyter Notebooks are wiki-like documents that contain live code as well as descriptive text. Jupyter Notebooks are widely used in the AI and ML community as a means of documenting, storing, and sharing AI and ML projects. For more information on Jupyter Notebooks, visit the Jupyter website.

#### Jupyter Notebook Server

A Jupyter Notebook Server is an open source web application that allows users to create Jupyter Notebooks.

#### JupyterHub

JupyterHub is a multi-user application that enables an individual user to provision and access their own Jupyter Notebook server. For more information on JupyterHub, visit the JupyterHub website.
MLflow

MLflow is a popular open source AI lifecycle management platform. Key features of MLflow include AI/ML experiment tracking and an AI/ML model repository. For more information on MLflow, visit the MLflow 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 is a good open-source option for organizations that prefer an all-in-one MLOps platform. 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.

Kubeflow Notebooks

Kubeflow simplifies the provisioning and deployment of Jupyter Notebook Servers on Kubernetes. For more information about Jupyter Notebooks within the context of Kubeflow, see the official Kubeflow documentation.

Katib

Katib is a Kubernetes-native project for automated machine learning (AutoML). Katib supports hyperparameter tuning, early stopping and neural architecture search (NAS). Katib is the project which is agnostic to machine learning (ML) frameworks. It can tune hyperparameters of applications written in any language of the users’ choice and natively supports many ML frameworks, such as TensorFlow, MXNet, PyTorch, XGBoost, and others. Katib supports a lot of various AutoML algorithms, such as Bayesian optimization, Tree of Parzen Estimators, Random Search, Covariance Matrix Adaptation Evolution Strategy, Hyperband, Efficient Neural Architecture Search, Differentiable Architecture Search and many more. For more information about Jupyter Notebooks within the context of Kubeflow, see the official Kubeflow documentation.

NetApp ONTAP

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

Simplify data management

Data management is crucial to enterprise IT operations and data scientists so that appropriate resources are used for AI applications and training AI/ML datasets. The following additional information about NetApp technologies is out of scope for this validation but might be relevant depending on your deployment.

ONTAP data management software includes the following features to streamline and simplify 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. This applies to data stored locally and data tiered to the cloud.

- Minimum, maximum, and adaptive quality of service (AQoS). Granular quality of service (QoS) controls help maintain performance levels for critical applications in highly shared environments.

- NetApp FabricPool. Provides automatic tiering of cold data to public and private cloud storage options, including Amazon Web Services (AWS), Azure, and NetApp StorageGRID storage solution. For more information about FabricPool, see TR-4598: FabricPool best practices.

**Accelerate and protect data**

ONTAP delivers superior levels of performance and data protection and extends these capabilities in the following ways:

- Performance and lower latency. ONTAP offers the highest possible throughput at the lowest possible latency.

- Data protection. ONTAP provides built-in data protection capabilities with common management across all platforms.

- NetApp Volume Encryption (NVE). ONTAP offers native volume-level encryption with both onboard and External Key Management support.

- Multitenancy and multifactor authentication. ONTAP enables sharing of infrastructure resources with the highest levels of security.

**Future-proof infrastructure**

ONTAP helps meet demanding and constantly changing business needs with the following features:

- Seamless scaling and nondisruptive operations. ONTAP supports the nondisruptive addition of capacity to existing controllers and to scale-out clusters. Customers can upgrade to the latest technologies without costly data migrations or outages.

- Cloud connection. ONTAP is the most cloud-connected storage management software, with options for software-defined storage and cloud-native instances in all public clouds.

- Integration with emerging applications. ONTAP offers enterprise-grade data services for next generation platforms and applications, such as autonomous vehicles, smart cities, and Industry 4.0, by using the same infrastructure that supports existing enterprise apps.

**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.
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).

A Snapshot copy records only changes to the active file system since the last Snapshot copy.
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 BlueXP Copy and Sync

BlueXPCopy and 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, BlueXP Copy and 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. BlueXP Copy and Sync can sync data on-demand when an update is triggered or continuously sync data based on a predefined schedule. Regardless, BlueXP Copy and Sync only moves the deltas, so time and money spent on data replication is minimized.

BlueXP Copy and Sync is a software as a service (SaaS) tool that is extremely simple to set up and use. Data transfers that are triggered by BlueXP Copy and Sync are carried out by data brokers. BlueXP Copy and 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 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.

Architecture

This solution is not dependent on specific hardware. The solution is compatible with any NetApp physical storage appliance, software-defined instance, or cloud service, that is supported by NetApp Astra Trident. Examples include a NetApp AFF storage system, Amazon FSx for NetApp ONTAP, Azure NetApp Files, Google Cloud NetApp Volumes, 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 NetApp Astra Trident and the other solution components that are being implemented. For
a list of Kubernetes versions that are supported by Trident, see the Trident documentation. See the following tables for details on the environments that were used to validate the various components of this solution.

### Apache Airflow Validation Environment

<table>
<thead>
<tr>
<th>Software Component</th>
<th>Version</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apache Airflow</td>
<td>2.0.1, deployed via Apache Airflow Helm chart 8.0.8</td>
</tr>
<tr>
<td>Kubernetes</td>
<td>1.18</td>
</tr>
<tr>
<td>NetApp Astra Trident</td>
<td>21.01</td>
</tr>
</tbody>
</table>

### JupyterHub Validation Environment

<table>
<thead>
<tr>
<th>Software Component</th>
<th>Version</th>
</tr>
</thead>
<tbody>
<tr>
<td>JupyterHub</td>
<td>4.1.5, deployed via JupyterHub Helm chart 3.3.7</td>
</tr>
<tr>
<td>Kubernetes</td>
<td>1.29</td>
</tr>
<tr>
<td>NetApp Astra Trident</td>
<td>24.02</td>
</tr>
</tbody>
</table>

### MLflow Validation Environment

<table>
<thead>
<tr>
<th>Software Component</th>
<th>Version</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLflow</td>
<td>2.14.1, deployed via MLflow Helm chart 1.4.12</td>
</tr>
<tr>
<td>Kubernetes</td>
<td>1.29</td>
</tr>
<tr>
<td>NetApp Astra Trident</td>
<td>24.02</td>
</tr>
</tbody>
</table>

### Kubeflow Validation Environment

<table>
<thead>
<tr>
<th>Software Component</th>
<th>Version</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kubeflow</td>
<td>1.7, deployed via deployKF 0.1.1</td>
</tr>
<tr>
<td>Kubernetes</td>
<td>1.26</td>
</tr>
<tr>
<td>NetApp Astra Trident</td>
<td>23.07</td>
</tr>
</tbody>
</table>

### Support

NetApp does not offer enterprise support for Apache Airflow, JupyterHub, MLflow, Kubeflow, or Kubernetes. If you are interested in a fully supported MLOps platform, contact NetApp about fully supported MLOps solutions that NetApp offers jointly with partners.

### NetApp Astra Trident Configuration
Example Astra Trident Backends for NetApp AIPod Deployments

Before you can use Astra 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 components of this solution on a NetApp AIPod. For more information about Backends, and for example backends for other platforms/environments, see the Astra Trident documentation.

1. NetApp recommends creating a FlexGroup-enabled Trident Backend for your AIPod.

   The example commands that follow show the creation of a FlexGroup-enabled Trident Backend for an AIPod storage virtual machine (SVM). This Backend uses 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.
2. NetApp also recommends creating a FlexVol-enabled Trident Backend. You may want to use FlexVol volumes for hosting persistent applications, 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.
Example Kubernetes StorageClasses for NetApp AIPod Deployments

Before you can use Astra 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 components of this solution on a NetApp AIPod. For more information about StorageClasses, and for example StorageClasses for other
1. NetApp recommends creating a StorageClass for the FlexGroup-enabled Trident Backend that you created in the section Example Astra Trident Backends for NetApp AIPod Deployments, step 1. The example commands that follow show the creation of multiple StorageClasses that corresponds to the two example Backend that was created in the section Example Astra Trident Backends for NetApp AIPod Deployments, step 1 - one that utilizes NFS over RDMA and one that does not.

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.

Note: The following example StorageClasses use a maximum transfer size of 262144. To use this maximum transfer size, you must configure the maximum transfer size on your ONTAP system accordingly. Refer to the ONTAP documentation for details.

Note: To use NFS over RDMA, you must configure NFS over RDMA on your ONTAP system. Refer to the ONTAP documentation for details.

Note: In the following example, a specific Backend is not specified in the storagePool field in StorageClass definition file.
```shell
$ cat << EOF > ./storage-class-aipod-flexgroups-retain.yaml
apiVersion: storage.k8s.io/v1
kind: StorageClass
metadata:
  name: aipod-flexgroups-retain
  provisioner: csi.trident.netapp.io
  mountOptions: ["vers=4.1", "nconnect=16", "rsize=262144",
  "wsize=262144"]
parameters:
  backendType: "ontap-nas-flexgroup"
  storagePools: "aipod-flexgroups-iface1:."
reclaimPolicy: Retain
EOF
$ kubectl create -f ./storage-class-aipod-flexgroups-retain.yaml
storageclass.storage.k8s.io/aipod-flexgroups-retain created
$ cat << EOF > ./storage-class-aipod-flexgroups-retain-rdma.yaml
apiVersion: storage.k8s.io/v1
kind: StorageClass
metadata:
  name: aipod-flexgroups-retain-rdma
  provisioner: csi.trident.netapp.io
  mountOptions: ["vers=4.1", "proto=rdma", "max_connect=16",
  "rsize=262144", "wsize=262144"]
parameters:
  backendType: "ontap-nas-flexgroup"
  storagePools: "aipod-flexgroups-iface1:."
reclaimPolicy: Retain
EOF
$ kubectl create -f ./storage-class-aipod-flexgroups-retain-rdma.yaml
storageclass.storage.k8s.io/aipod-flexgroups-retain-rdma created
$ kubectl get storageclass
NAME                  PROVISIONER               AGE
aipod-flexgroups-retain csi.trident.netapp.io 0m
aipod-flexgroups-retain-rdma csi.trident.netapp.io 0m
```

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

Note: In the following example, a particular Backend is not specified in the storagePool field in StorageClass definition file. When you use Kubernetes to administer volumes using this StorageClass, Trident attempts to use any available backend that uses the ontap-nas driver.
Apache Airflow

Apache Airflow Deployment

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 Astra Trident in your Kubernetes cluster. For more details on Astra Trident, refer to the [Astra Trident documentation](#).

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 Kubeflow Deployment section. 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.

   ```bash
   $ 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
   EOF
   ```
## 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-web -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

<table>
<thead>
<tr>
<th>NAME</th>
<th>READY</th>
<th>STATUS</th>
<th>RESTARTS</th>
<th>AGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>airflow-flower-b5656d44f-h8qjk</td>
<td>1/1</td>
<td>Running</td>
<td>0</td>
<td>2h</td>
</tr>
<tr>
<td>airflow-postgresql-0</td>
<td>1/1</td>
<td>Running</td>
<td>0</td>
<td>2h</td>
</tr>
<tr>
<td>airflow-redis-master-0</td>
<td>1/1</td>
<td>Running</td>
<td>0</td>
<td>2h</td>
</tr>
<tr>
<td>airflow-scheduler-9d95fcd9f-clf4b</td>
<td>2/2</td>
<td>Running</td>
<td>2</td>
<td>2h</td>
</tr>
<tr>
<td>airflow-web-59c94db9c5-z7rg4</td>
<td>1/1</td>
<td>Running</td>
<td>0</td>
<td>2h</td>
</tr>
<tr>
<td>airflow-worker-0</td>
<td>2/2</td>
<td>Running</td>
<td>2</td>
<td>2h</td>
</tr>
</tbody>
</table>

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.

```bash
$ 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}")
$ export NODE_PORT=$(kubectl get --namespace airflow -o jsonpath="{.items[0].status.addresses[0].nodePort}"

$ echo http://$NODE_IP:$NODE_PORT/
```

4. Confirm that you can access the Airflow web service.
Use the NetApp DataOps Toolkit with Airflow

The NetApp DataOps Toolkit for Kubernetes can be used in conjunction with Airflow. Using the NetApp DataOps Toolkit with Airflow enables you to incorporate NetApp data management operations, such as creating snapshots and clones, into automated workflows that are orchestrated by Airflow.

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

JupyterHub

JupyterHub Deployment

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

It is possible to deploy JupyterHub on platforms other than Kubernetes. Deploying JupyterHub 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 Astra Trident in your Kubernetes cluster. For more details on Astra Trident, refer to the Astra Trident documentation.

Install Helm
JupyterHub is deployed using Helm, a popular package manager for Kubernetes. Before you deploy JupyterHub, you must install Helm on your Kubernetes control node. To install Helm, follow the installation instructions in the official Helm documentation.

Set Default Kubernetes StorageClass
Before you deploy JupyterHub, you must designate a default StorageClass within your Kubernetes cluster. To designate a default StorageClass within your cluster, follow the instructions outlined in the Kubeflow Deployment section. If you have already designated a default StorageClass within your cluster, then you can skip this step.

Deploy JupyterHub
After completing the steps above, you are now ready to deploy JupyterHub. JupyterHub deployment requires the following steps:

Configure JupyterHub Deployment
Before deployment it is a good practice to optimize the JupyterHub deployment for your respective environment. You can create a config.yaml file and utilize it during deployment using the Helm chart.

An example config.yaml file can be found at https://github.com/jupyterhub/zero-to-jupyterhub-k8s/blob/HEAD/jupyterhub/values.yaml

In this config.yaml file, you can set the (singleuser.storage.dynamic.storageClass) parameter for the NetApp Trident StorageClass. This is the storage class that will be used to provision the volumes for individual user workspaces.

Adding Shared Volumes
If you want to use a shared volume for all JupyterHub users you can adjust your config.yaml accordingly. For example, if you have a shared PersistentVolumeClaim called jupyterhub-shared-volume you could mount it as /home/shared in all user pods as:
singleuser:
  storage:
    extraVolumes:
      - name: jupyterhub-shared
        persistentVolumeClaim:
          claimName: jupyterhub-shared-volume
    extraVolumeMounts:
      - name: jupyterhub-shared
        mountPath: /home/shared

This is an optional step, you can adjust these parameters to your needs.

Deploy JupyterHub with Helm Chart

Make Helm aware of the JupyterHub Helm chart repository.

```
helm repo add jupyterhub https://hub.jupyter.org/helm-chart/
helm repo update
```

This should show output like:

Hang tight **while** we grab the latest from your chart repositories...
...Skip local chart repository
...Successfully got an update from the "stable" chart repository
...Successfully got an update from the "jupyterhub" chart repository
Update Complete. ⬜️ Happy Helming!⬜️

Now install the chart configured by your config.yaml by running this command from the directory that contains your config.yaml:

```
helm upgrade --cleanup-on-fail
  --install my-jupyterhub jupyterhub/jupyterhub
  --namespace my-namespace
  --create-namespace
  --values config.yaml
```

In this example:

<helm-release-name> is set to my-jupyterhub, which will be the name of your JupyterHub release.
<k8s-namespace> is set to my-namespace, which is the namespace where you want to install JupyterHub.
The --create-namespace flag is used to create the namespace if it does not already exist.
The --values flag specifies the config.yaml file that contains your desired configuration options.
Check Deployment

While step 2 is running, you can see the pods being created from the following command:

```
kubectl get pod --namespace <k8s-namespace>
```

Wait for the hub and proxy pod to enter the Running state.

<table>
<thead>
<tr>
<th>NAME</th>
<th>READY</th>
<th>STATUS</th>
<th>RESTARTS</th>
<th>AGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>hub-5d4ffd57cf-k68z8</td>
<td>1/1</td>
<td>Running</td>
<td>0</td>
<td>37s</td>
</tr>
<tr>
<td>proxy-7cb9bc4cc-9bdlp</td>
<td>1/1</td>
<td>Running</td>
<td>0</td>
<td>37s</td>
</tr>
</tbody>
</table>

Access JupyterHub

Find the IP we can use to access the JupyterHub. Run the following command until the EXTERNAL-IP of the proxy-public service is available like in the example output.

```
(kubectl --namespace <k8s-namespace> get service proxy-public)
```

<table>
<thead>
<tr>
<th>NAME</th>
<th>TYPE</th>
<th>CLUSTER-IP</th>
<th>EXTERNAL-IP</th>
<th>PORT(S)</th>
</tr>
</thead>
<tbody>
<tr>
<td>proxy-public</td>
<td>NodePort</td>
<td>10.51.248.230</td>
<td>104.196.41.97</td>
<td>80:30000/TCP</td>
</tr>
</tbody>
</table>

To use JupyterHub, enter the external IP for the proxy-public service in to a browser.

**Use the NetApp DataOps Toolkit with JupyterHub**

The NetApp DataOps Toolkit for Kubernetes can be used in conjunction with JupyterHub. Using the NetApp DataOps Toolkit with JupyterHub enables end users to create volume snapshots for workspace backup and/or dataset-to-model traceability directly from within a Jupyter Notebook.

**Initial Setup**

Before you can use the DataOps Toolkit with JupyterHub, you must grant appropriate permissions to the Kubernetes service account that JupyterHub assigns to individual user Jupyter Notebook Server pods. JupyterHub uses the service account that is specified by the `singleuser.serviceAccountName` variable in your JupyterHub Helm chart configuration file.
Create Cluster Role for DataOps Toolkit

First, create a cluster role named 'netapp-dataops' that has the required Kubernetes API permissions for creating volume snapshots.

```
$ vi clusterrole-netapp-dataops-snapshots.yaml
---
kind: ClusterRole
apiVersion: rbac.authorization.k8s.io/v1
metadata:
  name: netapp-dataops-snapshots
rules:
- apiGroups: [""
  resources: ["persistentvolumeclaims", "persistentvolumeclaims/status", "services"]
  verbs: ["get", "list"]
- apiGroups: ["snapshot.storage.k8s.io"]
  resources: ["volumesnapshots", "volumesnapshots/status", "volumesnapshotcontents", "volumesnapshotcontents/status"]
  verbs: ["get", "list", "create"]
```

```
$ kubectl create -f clusterrole-netapp-dataops-snapshots.yaml
clusterrole.rbac.authorization.k8s.io/netapp-dataops-snapshots created
```

Assign Cluster Role to Notebook Server Service Account

Create a role binding that assigns the 'netapp-dataops-snapshots' cluster role to the appropriate service account in the appropriate namespace. For example, if you installed JupyterHub in the 'jupyterhub' namespace, and you specified the 'default' service account via the `singleuser.serviceAccountName` variable, you would assign the the 'netapp-dataops-snapshots' cluster role to the 'default' service account in the 'jupyterhub' namespace as shown in the following example.

```
$ kubectl create -f rolebinding-netapp-dataops-snapshots.yaml
rolebinding.rbac.authorization.k8s.io/rolebinding-netapp-dataops-snapshots created
```

```bash
$ kubectl get all -n jupyterhub
```

---

24
$ vi rolebinding-jupyterhub-netapp-dataops-snapshots.yaml
---
kind: RoleBinding
apiVersion: rbac.authorization.k8s.io/v1
metadata:
  name: jupyterhub-netapp-dataops-snapshots
  namespace: jupyterhub # Replace with your JupyterHub namespace
subjects:
  - kind: ServiceAccount
    name: default # Replace with your JupyterHub singleuser.serviceAccountName
    namespace: jupyterhub # Replace with your JupyterHub namespace
roleRef:
  kind: ClusterRole
  name: netapp-dataops-snapshots
  apiGroup: rbac.authorization.k8s.io

$ kubectl create -f ./rolebinding-jupyterhub-netapp-dataops-snapshots.yaml
rolebinding.rbac.authorization.k8s.io/jupyterhub-netapp-dataops-snapshots
created

Create Volume Snapshots Within Jupyter Notebook

Now, JupyterHub users can use the NetApp DataOps Toolkit to create volume snapshots directly from within a Jupyter Notebook as shown in the following example.

Execute NetApp DataOps Toolkit operations within JupyterHub

This notebook demonstrates the execution of NetApp DataOps Toolkit operations from within a Jupyter Notebook running on JupyterHub

Install NetApp DataOps Toolkit for Kubernetes (only run once)

Note: This cell only needs to be run once. This is a one-time task

[1]:

```
$ pip install --user netapp-dataops-k8s
```

Import NetApp DataOps Toolkit for Kubernetes functions

[1]:

```
from netapp_dataops.k8s import list_volumes, list_volume_snapshots, create_volume_snapshot
```

Create Volume Snapshot for User Workspace Volume

The following example shows the execution of a "create volume snapshot" operation for my user workspace volume.

[2]:

```
jupyterhub_namespace = "jupyterhub"
my_user_workspace_vol = "claim-moglesby"
create_volume_snapshot(namespace=jupyterhub_namespace, pvc_name=my_user_workspace_vol, print_output=True)
```

Creating VolumeSnapshot 'ntap-dsutil.20240726002955' for PersistentVolumeClaim (PVC) 'claim-moglesby' in namespace 'jupyterhub'.
VolumeSnapshot 'ntap-dsutil.20240726002955' created. Waiting for Trident to create snapshot on backing storage. Snapshot successfully created.
MLflow

MLflow Deployment

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

It is possible to deploy MLflow on platforms other than Kubernetes. Deploying MLflow 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 Astra Trident in your Kubernetes cluster. For more details on Astra Trident, refer to the Astra Trident documentation.

Install Helm

MLflow is deployed using Helm, a popular package manager for Kubernetes. Before you deploy MLflow, you must install Helm on your Kubernetes control node. To install Helm, follow the installation instructions in the official Helm documentation.

Set Default Kubernetes StorageClass

Before you deploy MLflow, you must designate a default StorageClass within your Kubernetes cluster. To designate a default StorageClass within your cluster, follow the instructions outlined in the Kubeflow Deployment section. If you have already designated a default StorageClass within your cluster, then you can skip this step.

Deploy MLflow

Once the pre-requisites have been met, you can start with MLflow deployment using the helm chart.

Configure MLflow Helm Chart Deployment.

Before we deploy MLflow using the Helm chart, we can configure the deployment to use NetApp Trident Storage Class and change other parameters to suit our needs using a config.yaml file. An example of config.yaml file can be found at: https://github.com/bitnami/charts/blob/main/bitnami/mlflow/values.yaml

You can set the Trident storageClass under the global.defaultStorageClass parameter in the config.yaml file (e.g. storageClass: "ontap-flexvol").

Installing the Helm Chart

The Helm chart can be installed with the custom config.yaml file for MLflow using the following command:
The command deploys MLflow on the Kubernetes cluster in the custom configuration via the provided `config.yaml` file. MLflow is deployed in the given namespace and a random release name is given via Kubernetes for the release.

### Check Deployment

After the Helm chart is done deploying, you can check if the service is accessible using:

```bash
kubectl get service -n jupyterhub
```

Replace `jupyterhub` with the namespace you used during deployment.

You should see the following services:

<table>
<thead>
<tr>
<th>NAME</th>
<th>TYPE</th>
<th>CLUSTER-IP</th>
<th>EXTERNAL-IP</th>
</tr>
</thead>
<tbody>
<tr>
<td>mlflow-1719843029-minio</td>
<td>ClusterIP</td>
<td>10.233.22.4</td>
<td>&lt;none&gt;</td>
</tr>
<tr>
<td>Port(8)TCP,9001/TCP 25d</td>
<td>ClusterIP</td>
<td>10.233.5.141</td>
<td>&lt;none&gt;</td>
</tr>
<tr>
<td>mlflow-1719843029-postgresql</td>
<td>ClusterIP</td>
<td>None</td>
<td>&lt;none&gt;</td>
</tr>
<tr>
<td>Port(5432)TCP 25d</td>
<td>ClusterIP</td>
<td>None</td>
<td>&lt;none&gt;</td>
</tr>
<tr>
<td>mlflow-1719843029-tracking</td>
<td>NodePort</td>
<td>10.233.2.158</td>
<td>&lt;none&gt;</td>
</tr>
<tr>
<td>Port(30002)TCP 25d</td>
<td>NodePort</td>
<td>10.233.2.158</td>
<td>&lt;none&gt;</td>
</tr>
</tbody>
</table>

We edited the `config.yaml` file to use NodePort service to access MLflow on port 30002.

### Access MLflow

Once all the services related to MLflow are up and running you can access it using the given NodePort or LoadBalancer IP address (e.g. `http://10.61.181.109:30002`)

### Dataset-to-model Traceability with NetApp and MLflow

The [NetApp DataOps Toolkit for Kubernetes](https://github.com/NetApp/NetApp-DataOps-Toolkit-Kubernetes) can be used in conjunction with MLflow's experiment tracking capabilities in order to implement dataset-to-model or workspace-to-model traceability.

To implement dataset-to-model or workspace-to-model traceability, simply create a snapshot of your dataset or workspace volume using the DataOps Toolkit as part of your training run, as shown the following example code snippet. This code will save the data volume name and snapshot name as tags associated with the specific training run that you are logging to your MLflow experiment tracking server.
from netapp_dataops.k8s import create_volume_snapshot

with mlflow.start_run() :
...

    namespace = "my_namespace"  # Kubernetes namespace in which dataset volume PVC resides
    dataset_volume_name = "project1"  # Name of PVC corresponding to dataset volume
    snapshot_name = "run1"  # Name to assign to your new snapshot

    # Create snapshot
    create_volume_snapshot(
        namespace=namespace,
        pvc_name=dataset_volume_name,
        snapshot_name=snapshot_name,
        printOutput=True
    )

    # Log data volume name and snapshot name as "tags"
    # associated with this training run in mlflow.
    mlflow.set_tag("data_volume_name", dataset_volume_name)
    mlflow.set_tag("snapshot_name", snapshot_name)

...
**Set Default Kubernetes StorageClass**

Before you deploy Kubeflow, we recommend designating a default StorageClass within your Kubernetes cluster. The Kubeflow deployment process may attempt to provision new persistent volumes using the default StorageClass. If no StorageClass is designated as the default StorageClass, then the deployment may fail. 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
   ```

**Kubeflow Deployment Options**

There are many different options for deploying Kubeflow. Refer to the [official Kubeflow documentation](https://kubeflow.org/docs/) for a list of deployment options, and choose the option that is the best fit for your needs.

For validation purposes, we deployed Kubeflow 1.7 using `deployKF 0.1.1`.

**Example Kubeflow Operations and Tasks**

**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. For more information about Jupyter Notebooks within the Kubeflow context, see the [official Kubeflow documentation](https://kubeflow.org/docs/).
Use the NetApp DataOps Toolkit with Kubeflow

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, such as creating snapshots and clones, directly from within a Jupyter Notebook.
- Advanced NetApp data management operations, such as creating snapshots and clones, 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.

Example Workflow - Train an Image Recognition Model Using Kubeflow and the NetApp DataOps Toolkit

This section describes the steps involved in training and deploying a Neural Network for Image Recognition using Kubeflow and the NetApp DataOps Toolkit. This is intended to serve as an example to show a training job that incorporates NetApp storage.

Prerequisites

Create a Dockerfile with the required configurations to use for the train and test steps within the Kubeflow pipeline.
Here is an example of a Dockerfile:
FROM pytorch/pytorch:latest
RUN pip install torchvision numpy scikit-learn matplotlib tensorboard
WORKDIR /app
COPY . /app
COPY train_mnist.py /app/train_mnist.py
CMD ["python", "train_mnist.py"]

Depending on your requirements, install all required libraries and packages needed to run the program. Before you train the Machine Learning model, it is assumed that you already have a working Kubeflow deployment.

**Train a Small NN on MNIST Data Using PyTorch and Kubeflow Pipelines**

We use the example of a small Neural Network trained on MNIST data. The MNIST dataset consists of handwritten images of digits from 0-9. The images are 28x28 pixels in size. The dataset is divided into 60,000 train images and 10,000 validation images. The Neural Network used for this experiment is a 2-layer feedforward network. Training is executed using Kubeflow Pipelines. Refer to the documentation [here](#) for more information. Our Kubeflow pipeline incorporates the docker image from the Prerequisites section.

---

**Visualize Results Using Tensorboard**

Once the model is trained, we can visualize the results using Tensorboard. Tensorboard is available as a feature on the Kubeflow Dashboard. You can create a custom tensorboard for your job. An example below shows the plot of training accuracy vs. number of epochs and training loss vs. number of epochs.
Experiment with Hyperparameters Using Katib

Katib is a tool within Kubeflow that can be used to experiment with the model hyperparameters. To create an experiment, define a desired metric/goal first. This is usually the test accuracy. Once the metric is defined, choose hyperparameters that you would like to play around with (optimizer/learning_rate/number of layers). Katib does a hyperparameter sweep with the user-defined values to find the best combination of parameters that satisfy the desired metric. You can define these parameters in each section in the UI. Alternatively, you could define a YAML file with the necessary specifications. Below is an illustration of a Katib experiment -
Use NetApp Snapshots to Save Data for Traceability

During the model training, we may want to save a snapshot of the training dataset for traceability. To do this, we can add a snapshot step to the pipeline as shown below. To create the snapshot, we can use the NetApp DataOps Toolkit for Kubernetes.

```python
@mll.pipeline
name = "MIST Classification Pipeline"

def mll_pipeline():
    mll.train_task = mll.train.up()
    mll.train_task.apply()
    mll.unpromt.mont_pvc('mll-data', 'mll-data-vol', '/mnt/data/')

    mll.test_task = mll.test_up()
    mll.test_task.apply()
    mll.unpromt.mont_pvc('mll-data', 'mll-data-vol', '/mnt/data/')

    volume_snapshot_name = 'mll-xyjrcsnapshott'
    dataset_snapshot = mll.containerpi:
        name = 'dataset-snapshot',
        image = 'python:3.9',
        command = ['sh', '-c'],
        arguments = [
            python = 'python "import netapp.k8s.create_volume_snapshot.k8s_all();
            echo "/volume_snapshot_name" = ""/volume_snapshot_name.txt" &
            netapp.k8s.create_volume_snapshot.k8s_all();"
            file_output("volume_snapshot_name" = ""/volume_snapshot_name.txt")
            file_output("namesp ace = ""/namespac e""");']
    dataset_snapshot.after = mll.train_task

    mll.test_task.after = mll.train_task
```

Refer to the NetApp DataOps Toolkit example for Kubeflow for more information.

Example Astra Trident Operations

This section includes examples of various operations that you may want to perform with Astra 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 a volume named `pb_fg_all`. 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.

```yaml
$ 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 | MANAGED |
|----------+----------------+---------|
| default-pb-fg-all-iface1-7d9f1 | 10 TiB | ontap-ai-flexgroups-retain-iface1 | file | b74cbddb-e0b8-40b7-b263-b6da6dec0bdd | online | true |
$ tridentctl get volume -n trident
+---------------------------------+---------+
|          NAME                   |  SIZE  |
| PROTOCOL | BACKEND UUID | MANAGED |
|----------+----------------+---------|
| default-pb-fg-all-iface1-7d9f1 | 10 TiB | ontap-ai-flexgroups-retain-iface1 | file | b74cbddb-e0b8-40b7-b263-b6da6dec0bdd | online | true |
```
Provision a New Volume

You can use Trident to provision a new volume on your NetApp storage system or platform.

Provision a New Volume Using `kubectl`

The following example commands show the provisioning of a new FlexVol volume using `kubectl`.

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](https://kubernetes.io/docs/concepts/storage/persistent-volumes/).

```
$ 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
tensorflow-results                Bound     default-tensorflow-results-2fd60           1073741824       RWX            ontap-ai-flexvols-retain             25h
```
Provision a New Volume Using the NetApp DataOps Toolkit

You can also use the NetApp DataOps Toolkit for Kubernetes to provision a new volume on your NetApp storage system or platform. The NetApp DataOps Toolkit for Kubernetes utilizes Trident to provision volumes but simplifies the process for the user. Refer to the documentation for details.

Example High-performance Jobs for AIPod Deployments

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 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
EOF
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_benchmarks.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=0 --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_imagenet_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.
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.

```yaml
$ 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:
EOF
```
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
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.

```yaml
$ 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   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
STATUS        RESTARTS   AGE
netapp-tensorflow-multi-imagenet-master-ppwwj Completed 0 9m38s
netapp-tensorflow-multi-imagenet-worker-654fc7f486-v6725 Running 0 35m

$ kubectl logs netapp-tensorflow-multi-imagenet-master-ppwwj
rm: cannot remove '/lib': Is a directory
[10.61.218.154:00033] PMIX ERROR: NO-PERMISSIONS in file gds_dstore.c at
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.
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.
Copyright information

Copyright © 2024 NetApp, Inc. All Rights Reserved. Printed in the U.S. No part of this document covered by copyright may be reproduced in any form or by any means—graphic, electronic, or mechanical, including photocopying, recording, taping, or storage in an electronic retrieval system—without prior written permission of the copyright owner.

Software derived from copyrighted NetApp material is subject to the following license and disclaimer:

THIS SOFTWARE IS PROVIDED BY NETAPP “AS IS” AND WITHOUT ANY EXPRESS OR IMPLIED WARRANTIES, INCLUDING, BUT NOT LIMITED TO, THE IMPLIED WARRANTIES OF MERCHANTABILITY AND FITNESS FOR A PARTICULAR PURPOSE, WHICH ARE HEREBY DISCLAIMED. IN NO EVENT SHALL NETAPP BE LIABLE FOR ANY DIRECT, INDIRECT, INCIDENTAL, SPECIAL, EXEMPLARY, OR CONSEQUENTIAL DAMAGES (INCLUDING, BUT NOT LIMITED TO, PROCUREMENT OF SUBSTITUTE GOODS OR SERVICES; LOSS OF USE, DATA, OR PROFITS; OR BUSINESS INTERRUPTION) HOWEVER CAUSED AND ON ANY THEORY OF LIABILITY, WHETHER IN CONTRACT, STRICT LIABILITY, OR TORT (INCLUDING NEGLIGENCE OR OTHERWISE) ARISING IN ANY WAY OUT OF THE USE OF THIS SOFTWARE, EVEN IF ADVISED OF THE POSSIBILITY OF SUCH DAMAGE.

NetApp reserves the right to change any products described herein at any time, and without notice. NetApp assumes no responsibility or liability arising from the use of products described herein, except as expressly agreed to in writing by NetApp. The use or purchase of this product does not convey a license under any patent rights, trademark rights, or any other intellectual property rights of NetApp.

The product described in this manual may be protected by one or more U.S. patents, foreign patents, or pending applications.

LIMITED RIGHTS LEGEND: Use, duplication, or disclosure by the government is subject to restrictions as set forth in subparagraph (b)(3) of the Rights in Technical Data -Noncommercial Items at DFARS 252.227-7013 (FEB 2014) and FAR 52.227-19 (DEC 2007).

Data contained herein pertains to a commercial product and/or commercial service (as defined in FAR 2.101) and is proprietary to NetApp, Inc. All NetApp technical data and computer software provided under this Agreement is commercial in nature and developed solely at private expense. The U.S. Government has a non-exclusive, non-transferrable, nonsublicensable, worldwide, limited irrevocable license to use the Data only in connection with and in support of the U.S. Government contract under which the Data was delivered. Except as provided herein, the Data may not be used, disclosed, reproduced, modified, performed, or displayed without the prior written approval of NetApp, Inc. United States Government license rights for the Department of Defense are limited to those rights identified in DFARS clause 252.227-7015(b) (FEB 2014).

Trademark information

NETAPP, the NETAPP logo, and the marks listed at http://www.netapp.com/TM are trademarks of NetApp, Inc. Other company and product names may be trademarks of their respective owners.