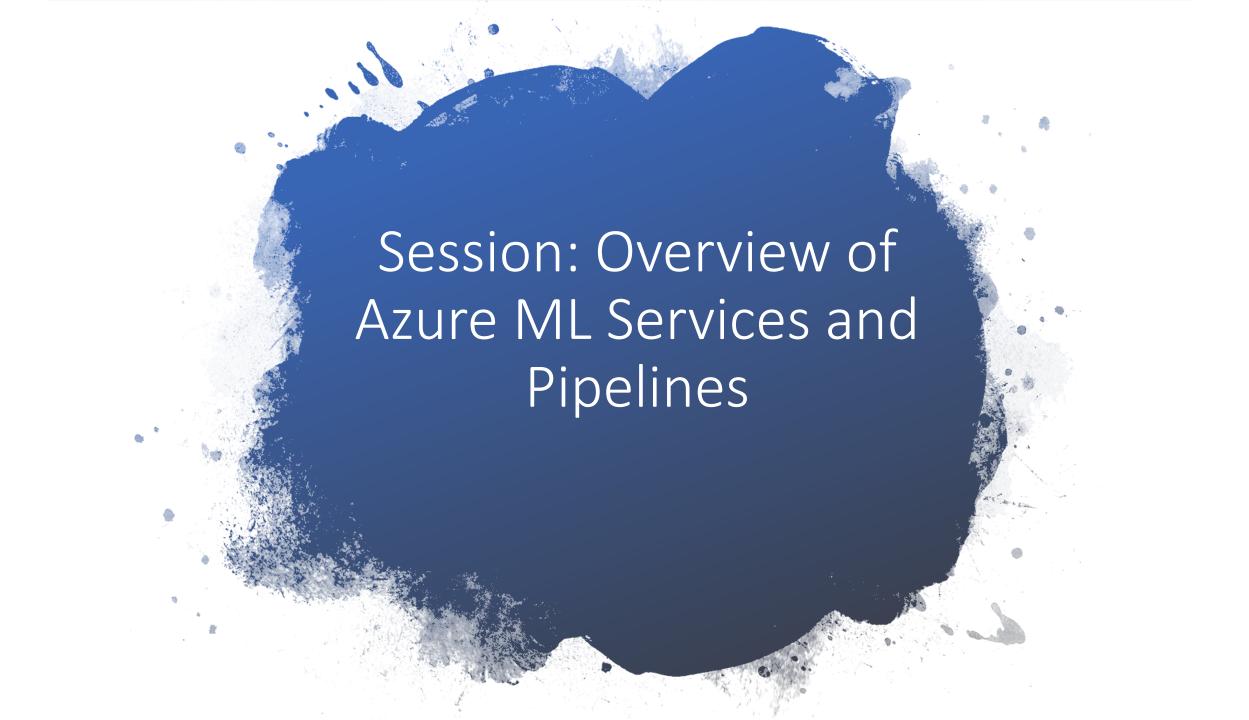
Al & DevOps Workshop June 24, 2019

Agenda

Time	Topic	Presenter
8:30 – 9:00	Breakfast & Registration	
9:00 – 9:10	Welcome	Hyun
9:10 - 10:00	Session: Overview of AML Pipelines	Giovanni
10:00 - 11:00	Session: Intro to Lifecycle Management with Azure DevOps/YAML	Prashant
11:00 - 12:00	Session: YAML and AML Pipeline Integration	Sanjeev & Kate
12:00 – 1:00	Lunch	
1:00 – 3:30	Lab: Implement Build, Retrain, Deployment Pipelines	Kate
3:30 – 4:00	Wrap-up	



MLOps Reference Architecture {New data location} Schedule-driven Azure Machine Learning Metrics-driven Azure Storage pipeline endpoint Azure Machine Learning Create Create Publish **Pipelines** Azure Machine Learning Publish machine Data sanity machine machine machine retraining pipeline learning pipeline Unit test learning learning learning test workspace compute pipeline Train Runs for new code One-time run Model Azure DevOps build pipeline Evaluate Operationalize model Model Register Model Azure Machine Learning Azure Machine Learning Package **Pipelines** Azure Deploy Deploy G Model Container model as model as Test web Test web Registry web service service web service service Manual Azure Container trigger on ACI on AKS release Azure Machine Learning Registry Compute Staging, QA Production Azure DevOps release gate Monitoring Azure Container Azure Kubernetes Azure App Insights Instances Service Scoring services

What is Azure Machine Learning service?



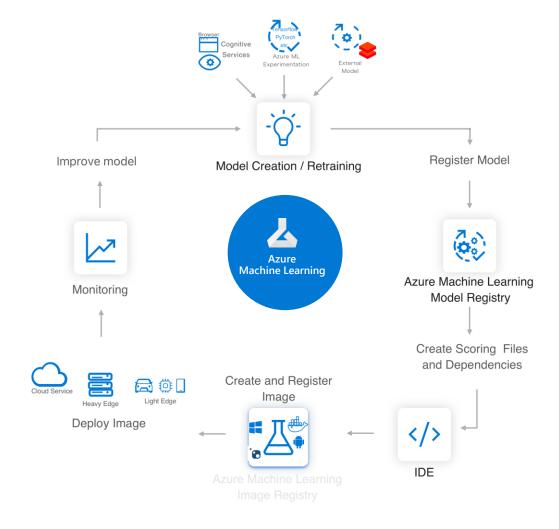
That enables you to:

- ✓ Prepare Data
- ✓ Build Models
- ✓ Train Models

- ✓ Manage Models
- ✓ Track Experiments
- ✓ Deploy Models

Azure ML service

Lets you easily implement this AI/ML Lifecycle



Workflow Steps

Develop machine learning training scripts in Python.

Create and configure a compute target.

Submit the scripts to the configured compute target to run in that environment. During training, the compute target stores run records to a datastore. There the records are saved to an experiment.

Query the experiment for logged metrics from the current and past runs. If the metrics do not indicate a desired outcome, loop back to step 1 and iterate on your scripts.

Once a satisfactory run is found, register the persisted model in the model registry.

Develop a scoring script.

Create an Image and register it in the image registry.

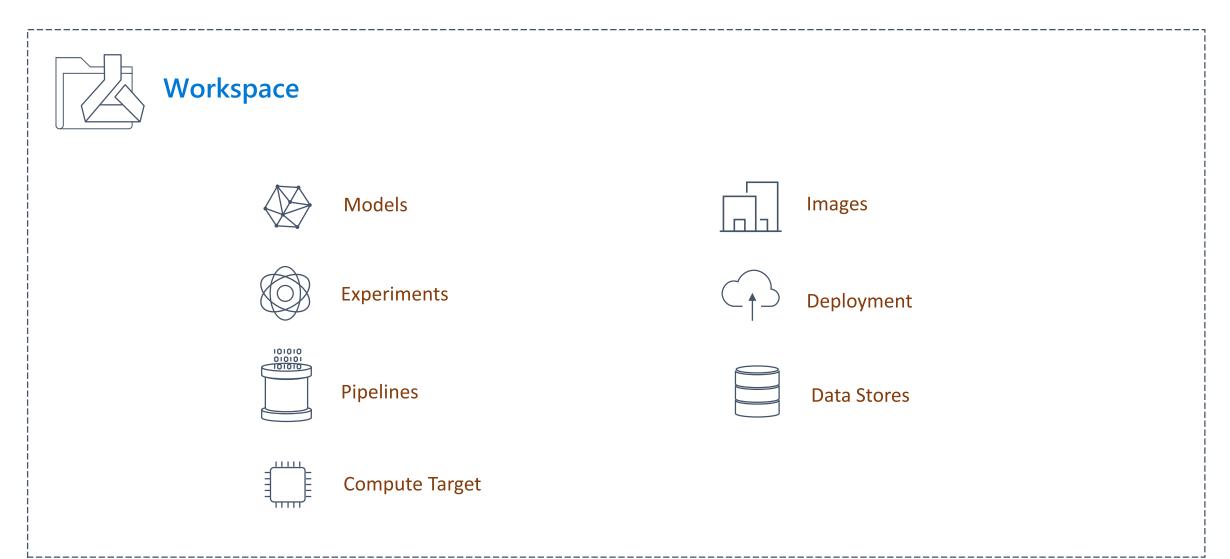
Deploy the image as a web service in Azure.



Azure Machine Learning: Technical Details

Azure ML service

Key Artifacts



Azure ML service Artifact

Workspace

The workspace is the **top-level resource** for the Azure Machine Learning service. It provides a centralized place to work with all the artifacts you create when using Azure Machine Learning service.

The workspace keeps a list of compute targets that can be used to train your model. It also keeps a history of the training runs, including logs, metrics, output, and a snapshot of your scripts.

Models are registered with the workspace.

You can create multiple workspaces, and each workspace can be shared by multiple people.

When you create a new workspace, it automatically creates these Azure resources:

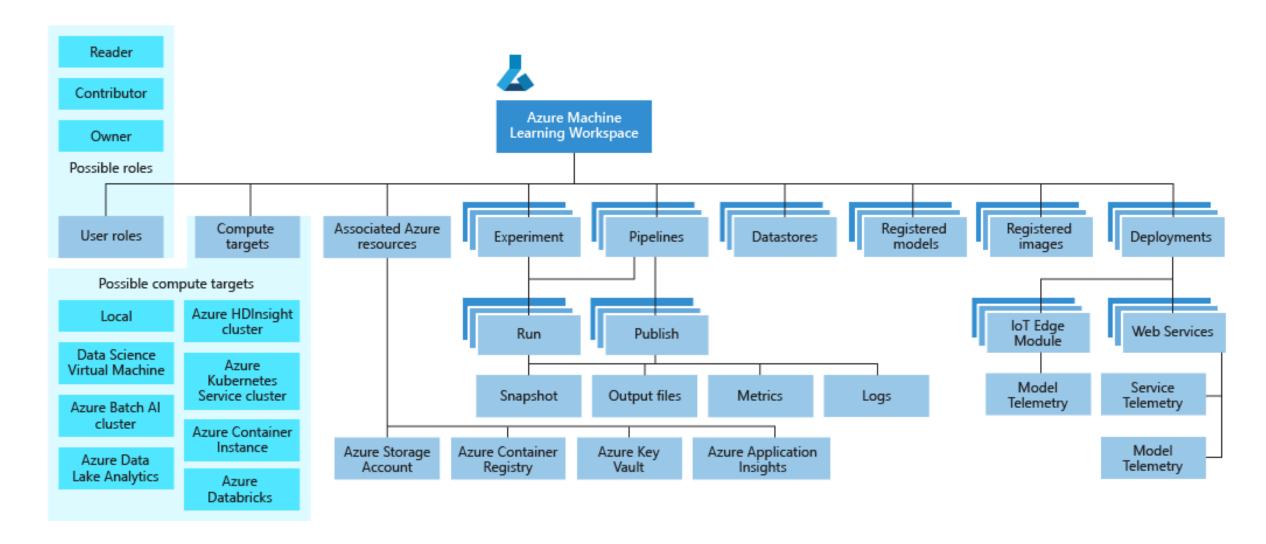
<u>Azure Container Registry</u> - Registers docker containers that are used during training and when deploying a model.

Azure Storage - Used as the default datastore for the workspace.

<u>Azure Application Insights</u> - Stores monitoring information about your models.

<u>Azure Key Vault</u> - Stores secrets used by compute targets and other sensitive information needed by the workspace.

Azure ML service Workspace Taxonomy



Azure ML service Artifacts

Models and Model Registry



Model

A machine learning model is an artifact that is created by your training process. You use a model to get predictions on new data.

A model is produced by a **run** in Azure Machine Learning.

Note: You can also use a model trained outside of Azure Machine Learning.

Azure Machine Learning service is framework agnostic — you can use any popular machine learning framework when creating a model.

A model can be registered under an Azure Machine Learning service workspace



Model Registry

Keeps track of all the models in your Azure Machine Learning service workspace.

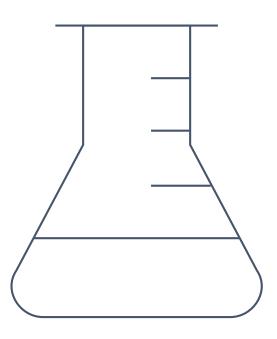
Models are identified by name and version.

You can provide additional metadata tags when you register the model, and then use these tags when searching for models.

You cannot delete models that are being used by an image.

Azure ML Artifacts

Runs and Experiments



Experiment

Grouping of many runs from a given script.

Always belongs to a workspace.

Stores information about runs

Run

Produced when you submit a script to train a model. Contains:

Metadata about the run (timestamp, duration etc.)

Metrics logged by your script.

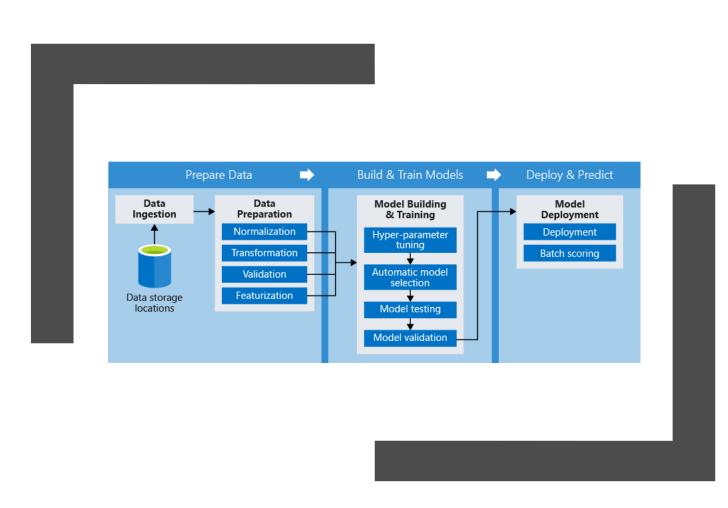
Output files autocollected by the experiment, or explicitly uploaded by you.

A snapshot of the directory that contains your scripts, prior to the run.

Run configuration

A set of instructions that defines how a script should be run in a given compute target.

Azure ML Artifacts Pipelines

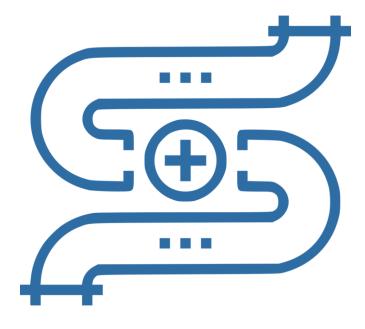


- Pipelines consist of steps
 - Steps can be independent
 - Or in sequence, part of a deployment

Azure ML Pipelines Advantages

Advantage	Description		
Unattended runs	Schedule a few steps to run in parallel or in sequence in a reliable and unattended manner. Since data prep and modeling can last days or weeks, you can now focus on other tasks while your pipeline is running.		
Mixed and diverse compute	Use multiple pipelines that are reliably coordinated across heterogeneous and scalable computes and storages. Individual pipeline steps can be run on different compute targets, such as HDInsight, GPU Data Science VMs, and Databricks.		
Reusability	Pipelines can be templatized for specific scenarios such as retraining and batch scoring. They can be triggered from external systems via simple REST calls.		
Tracking and versioning	Instead of manually tracking data and result paths as you iterate, use the pipelines SDK to explicitly name and version your data sources, inputs, and outputs as well as manage scripts and data separately for increased productivity		

Azure ML Pipeline Python SDK



- Imperative constructs for sequencing or parallelizing the steps
- Declarative data dependencies
- Pre-built modules for common tasks
- Extensible
- Compute targets and storage resources can be managed directly from the SDK.
- Pipelines can be saved as templates and deployed to a REST endpoint

Azure ML Artifact Compute Target

Compute Targets are the compute resources used to run training scripts or host your model when deployed as a web service.

They can be created and managed using the Azure Machine Learning SDK or CLI.

You can attach to existing resources.

You can start with local runs on your machine, and then scale up and out to other environments.

Currently supported compute targets

Compute Target	Training	Deployment
Local Computer	✓	
A Linux VM in Azure (such as the Data Science Virtual Machine)	√	
Azure ML Compute	√	
Azure Databricks	\checkmark	
Azure Data Lake Analytics	√	
Apache Spark for HDInsight	√	
Azure Container Instance		✓
Azure Kubernetes Service		✓
Azure IoT Edge		√
Field-programmable gate array (FPGA)		✓

Azure ML Currently Supported Compute Targets

Compute target	GPU acceleration	Hyperdrive	Automated model selection	Can be used in pipelines
<u>Local computer</u>	Maybe		\checkmark	
<u>Data Science Virtual Machine</u> (<u>DSVM</u>)	√	✓	\checkmark	✓
Azure ML compute	√	✓	√	✓
Azure Databricks	√		\checkmark	✓
Azure Data Lake Analytics				✓
Azure HDInsight				✓

Azure ML service Artifacts

Image and Registry



Image contains

- 1. A model.
- 2. A scoring script used to pass input to the model and return the output of the model.
- 3. Dependencies needed by the model or scoring script/application.

Two types of images

- **1. FPGA image**: Used when deploying to a field-programmable gate array in the Azure cloud.
- 2. **Docker image**: Used when deploying to compute targets such as Azure Container Instances and Azure Kubernetes Service.



Image Registry

Keeps track of images created from models.

Metadata tags can be attached to images. Metadata tags are stored by the image registry and can be used in image searches

Azure ML Concept

Model Management

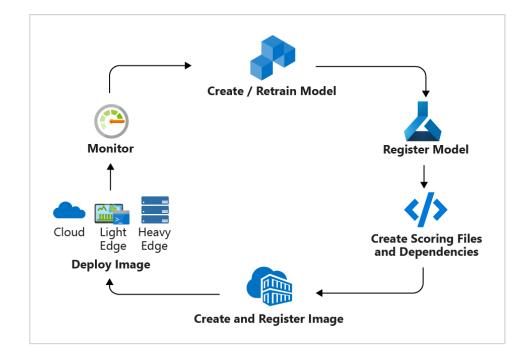
Model Management in Azure ML usually involves these four steps

Step 1: Register Model using the Model Registry

Step 2: Register Image using the Image Registry (the Azure Container Registry)

Step 3: Deploy the Image to cloud or to edge devices

Step 4: Monitor models—you can monitor input, output, and other relevant data from your model.



Azure ML Artifact Deployment

Deployment is an instantiation of an image. Two options:

Web service

A deployed web service can run on Azure Container Instances, Azure Kubernetes Service, or field-programmable gate arrays (FPGA).

Can receive scoring requests via an exposed a load-balanced, HTTP endpoint.

Can be monitored by collecting Application Insight telemetry and/or model telemetry.

Azure can automatically scale deployments.

IoT Module

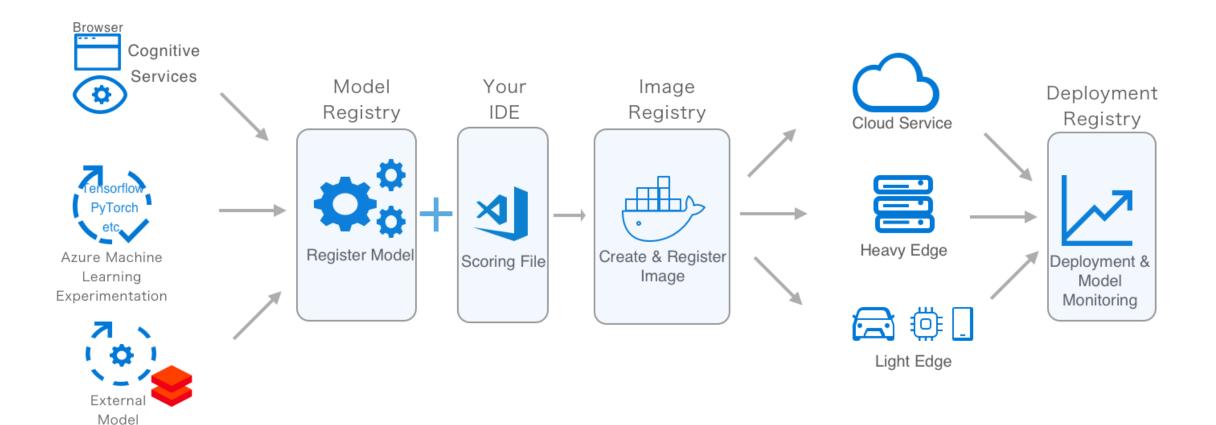
A deployed IoT Module is a Docker container that includes the model, associated script and additional dependencies.

Is deployed using **Azure IoT Edge** on edge devices.

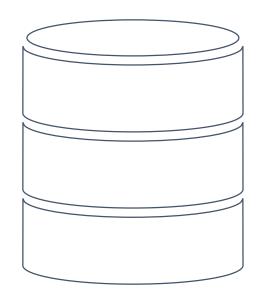
Can be monitored by collecting Application Insight telemetry and/or model telemetry.

Azure IoT Edge will ensure that your module is running and monitor the device that is hosting it.

Azure ML: How to deploy models at scale



Azure ML Artifact



A datastore is a storage abstraction over an Azure Storage Account.

The datastore can use either an Azure blob container or an Azure file share as the backend storage.

Each workspace has a default datastore, and you may register additional datastores.

Use the Python SDK API or Azure Machine Learning CLI to store and retrieve files from the datastore.



How to use the Azure Machine Learning service:

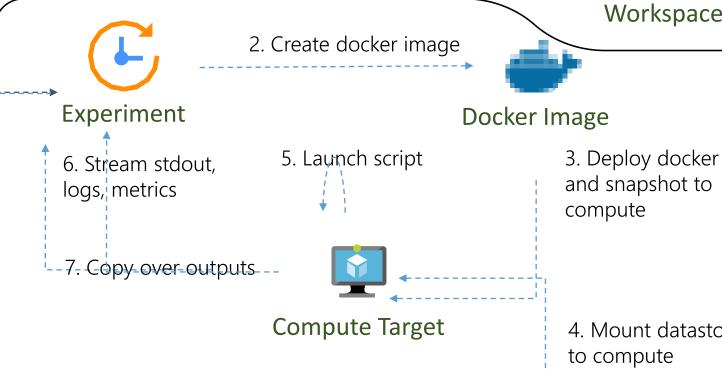
E2E coding example using the SDK

Azure ML Steps

1. Snapshot folder and send to experiment

My Computer

6. Stream stdout, logs, metrics



Azure ML Workspace



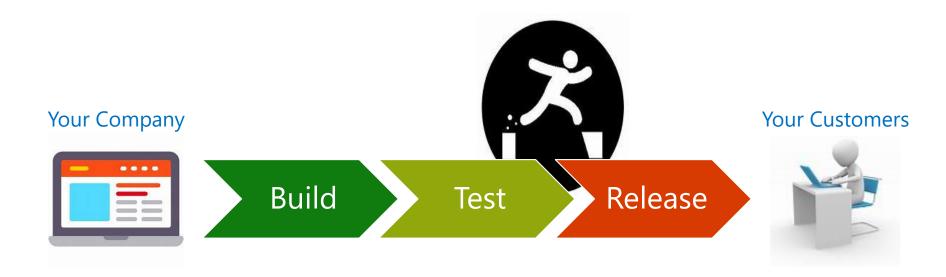
4. Mount datastore to compute



Data Store



Why DevOps





DevOps

- Improved Deliveries
 - Speed
 - Reliability
- Improved Collaboration
 - Security
 - Scale

DevOps Main Principles

- Develop and test in an environment identical or at least similar to production
- Build and Deploy Frequently
- Validate Quality Continuously

DevOps

DevOps best practices:

Continuous Integration (CI):

- Merges followed by automated builds and tests.
- Improve scale and quality

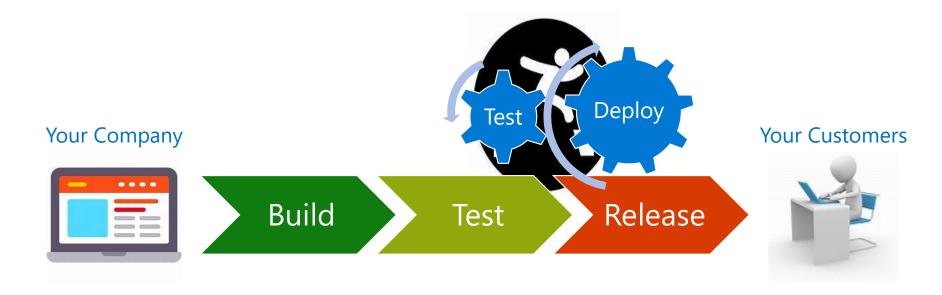
Continuous Delivery (CD):

- Changes are automatically built, tested, and prepared for a release to production.
- Changes are deployed to testing/staging and production.
- Deployment ready product built from the latest code changes, that has passed standardized testing, is always available

• Infrastructure as Code:

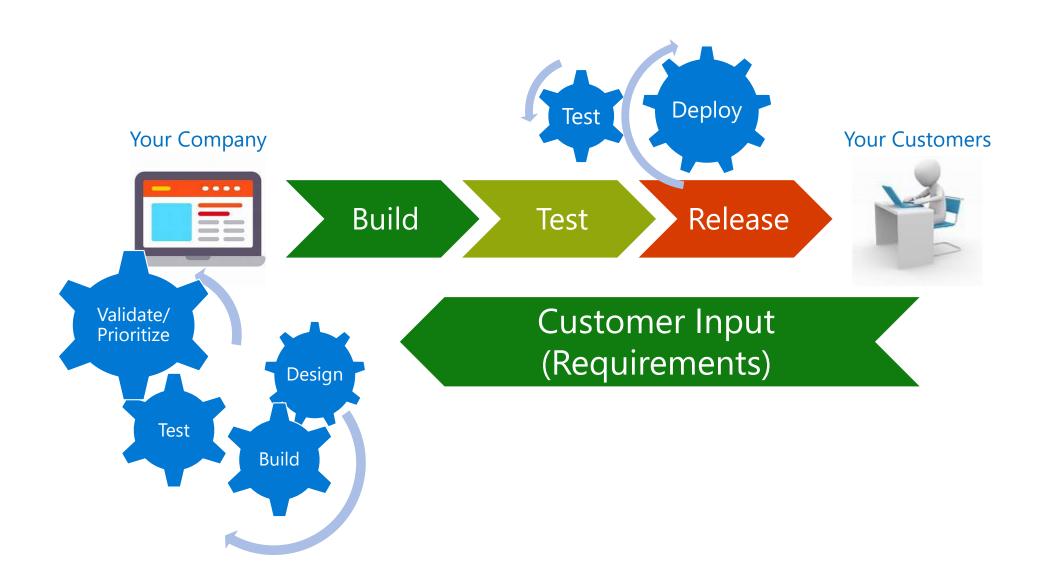
- Infrastructure provisioned and managed using code.
- Controlled with version control and Cl.
- Elimination of manual steps improves scale.
- Deployment is faster and repeatable. Just in time creation also improves security as it comes with the latest updates and patches.
- Microservices
- Monitoring
- Collaboration

How DevOps

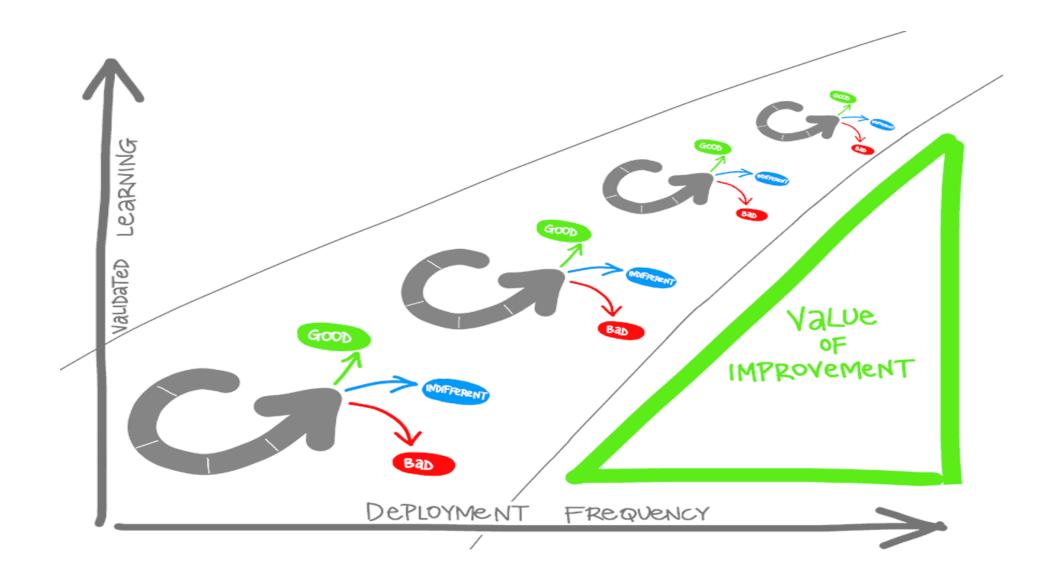




Agile?



Value of Improvement



Understand CI/CD

Continuous integration (CI)	Continuous delivery (CD)	
Increase code coverage.	Automatically deploy code to production.	
Build faster by splitting test and build runs.	Ensure deployment targets have latest code.	
Automatically ensure you don't ship broken code.	Use tested code from CI process.	
Run tests continually.		

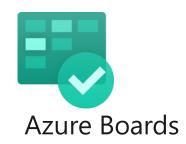
When and When Not

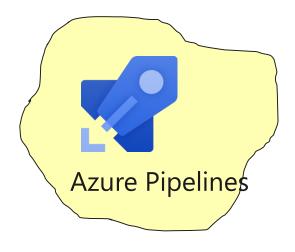
- DevOPs, CI/ CD makes sense in most cases
- May need modification/ gates/ additional loops and controls
 - High Risk
 - Financial
 - Banking
 - Markets
 - Life
 - Medical
 - Emergency Services
 - Operational
 - Power, Nuclear, Chemical
 - Autonomous Systems (Aircrafts, Automobiles, Trains, Industrial Robots)
 - High Value/ Low Frequency
 - Space Exploration
 - Elections
 - Regulatory

Azure DevOps (ADO)



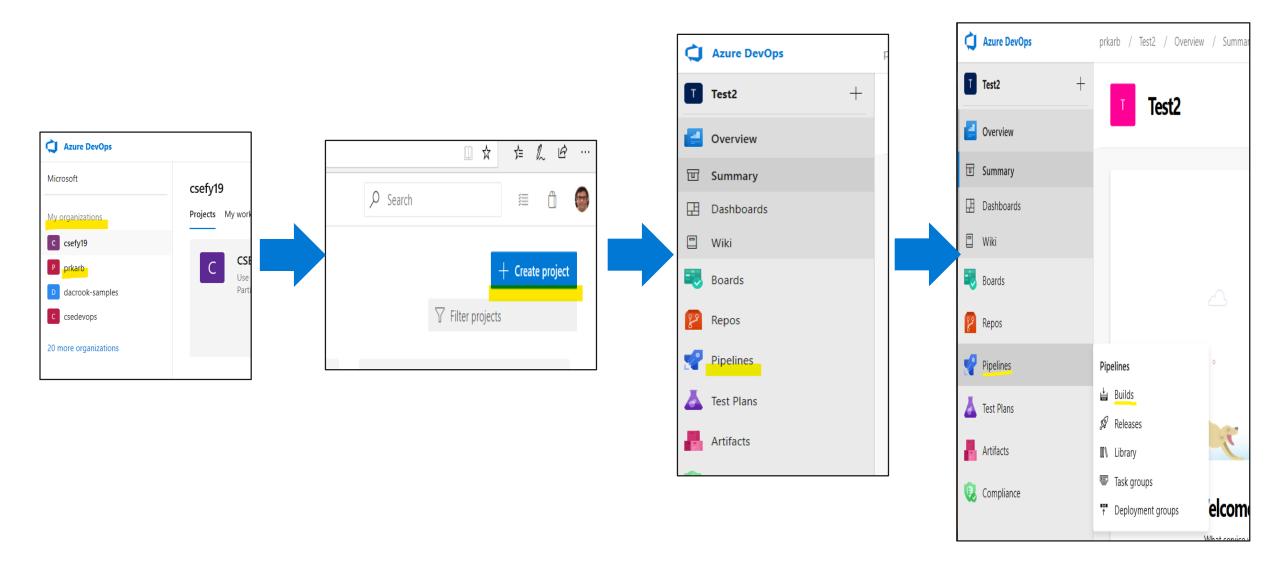




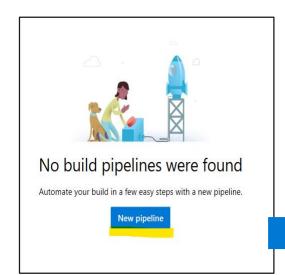


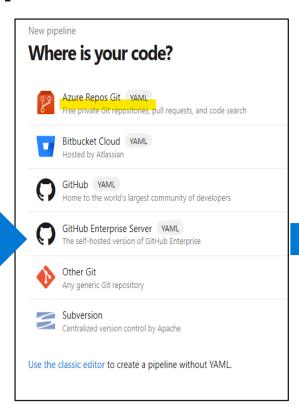
- •Work with any language or platform.
- •Deploy to different types of targets at the same time.
- •Integrate with Azure deployments.
- •Build on Windows, Linux, or Mac machines.
- •Integrate with GitHub.
- •Work with open-source projects.

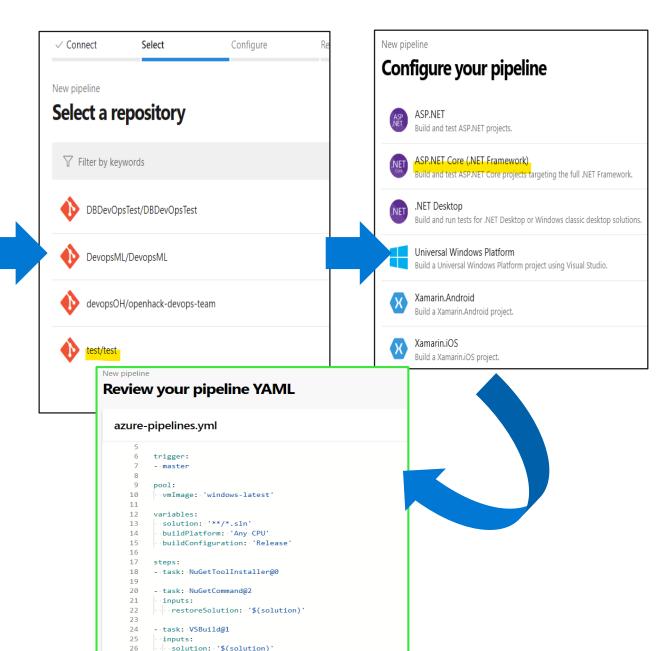
Creating a pipeline in ADO



Creating a pipeline in ADO







YAML?

YAML

- "YAML Ain't Markup Language" (started as Yet Another Markup Language)
- Is a human-readable data-serialization language
- Commonly used for configuration files
- Uses both Python-style indentation to indicate nesting
- Uses [] for lists and {} for map

Blocks

```
--- # Seattle Suburbs --- # Pet Animals
- Bellevue [dog, cat, hamster]
```

- Kirkland

- Redmond

Key-Value Pairs

```
--- # Indented Block
name: John Smith
age: 33
--- # Inline Block
{name: John Smith, age: 33}
```

YAML Pipeline

Structure

- •Pipeline Stage A
 - Job 1
 - Step 1.1
 - Step 1.2
 - ...
 - Job 2
 - Step 2.1
 - Step 2.2
 - ...
- •Stage B
 - ...

Example

```
name: $(Date:yyyyMMdd)$(Rev:.r)
variables:
```

var1: value1

jobs:

- job: One

steps:

- script: echo First step!

Stage

- Collection of related jobs.
- By default, stages run sequentially

```
stages:
```

```
stage: Buildjobs:job: BuildJobsteps:script: echo Building!
```

- stage: Test jobs:
 - job: TestOnWindows steps:
 - script: echo Testing on Windows!
 - job: TestOnLinux steps:
 - script: echo Testing on Linux!

Job

- Collection of steps to be run by an agent
- Can be run conditionally & May depend on earlier jobs
 jobs:

```
- job: MyJob
displayName: My First Job
continueOnError: true
steps:
- script: echo My first job
```

- script: echo My first job
- script: echo It's a YAML job

Job Strategies (Matrix, Parallel)

```
jobs:
- job: Build
strategy:
matrix:
Python35:
PYTHON_VERSION: '3.5'
Python36:
PYTHON_VERSION: '3.6'
Python37:
PYTHON_VERSION: '3.7'
maxParallel: 2
```

jobs:
- job: SliceItFourWays
strategy:
parallel: 4

Variables

variables:

- Hardcoded values can be added directly, or variable groups can be referenced.
- May be specified at the pipeline, stage, or job level

```
# pipeline-level
 MY_VAR: 'my value'
 ANOTHER_VAR: 'another value'
stages:
- stage: Build
 variables: # stage-level
  STAGE_VAR: 'that happened'
 jobs:
 - job: FirstJob
  variables: # job-level
   JOB_VAR: 'a job var'
  steps:
  - script: echo $(MY_VAR) $(STAGE_VAR) $(JOB_VAR)
```

Templates

- Reusable sections of a pipeline in a separate file.
- Four kinds of templates: [Stage, Job, Step, Variable]

```
# File: stages/test.yml
                                                    # File: azure-pipelines.yml
parameters:
                                                    stages:
                                                    - template: stages/test.yml # Template reference
 name: "
 testFile: "
                                                     parameters:
                                                      name: Mini
                                                      testFile: tests/miniSuite.js
stages:
- stage: Test_${{ parameters.name }}
 jobs:
                                                    - template: stages/test.yml # Template reference
                                                     parameters:
                                                      name: Full
                                                      testFile: tests/fullSuite.js
```

Pools

Specifies which Agent pool to use for a job of the pipeline

pool:

name: string # name of the pool to run this job in

demands: string | [string] ## see below

vmlmage: string # name of the vm image you want to use, only valid in the Microsoft-hosted

pool

Azure

pool:

vmlmage: ubuntu-16.04

Private Pool

pool:

name: MyPool

demands:

- myCustomCapability # check for existence of

capability

- agent.os -equals Darwin # check for specific string in

capability

Triggers

- Trigger to start a Pipeline
- Trigger Types: [Push, PR (pull request), Scheduled]

```
trigger:
batch: true
branches:
include:
- features/*
exclude:
- features/experimental/*
paths:
exclude:
- README.md
```

```
pr:
  branches:
  include:
  - features/*
  exclude:
  - features/experimental/*
  paths:
  exclude:
  - README.md
```

```
schedules:
- cron: "0 0 * * *"
 displayName: Daily midnight build
 branches:
  include:
  - master
  - releases/*
  exclude:
  releases/ancient/*
- cron: "0 12 * * 0"
 displayName: Weekly Sunday build
 branches:
  include:
  - releases/*
 always: true
```

Publish

- Shortcut for the Publish Pipeline Artifact task
- Publish (upload) a file or folder as a pipeline artifact that can be consumed by other jobs and pipelines

steps:

- publish: \$(Build.SourcesDirectory)/build

artifact: WebApp

Download

- Shortcut for the Download Pipeline Artifact task
- Download one or more artifacts associated with the current run to \$(Pipeline.Workspace)

steps:

download: current artifact: WebApp patterns: '**/.js'

Task

- Tasks are the building blocks of a pipeline.
- There is a <u>catalog of tasks</u> available to choose from.

steps:

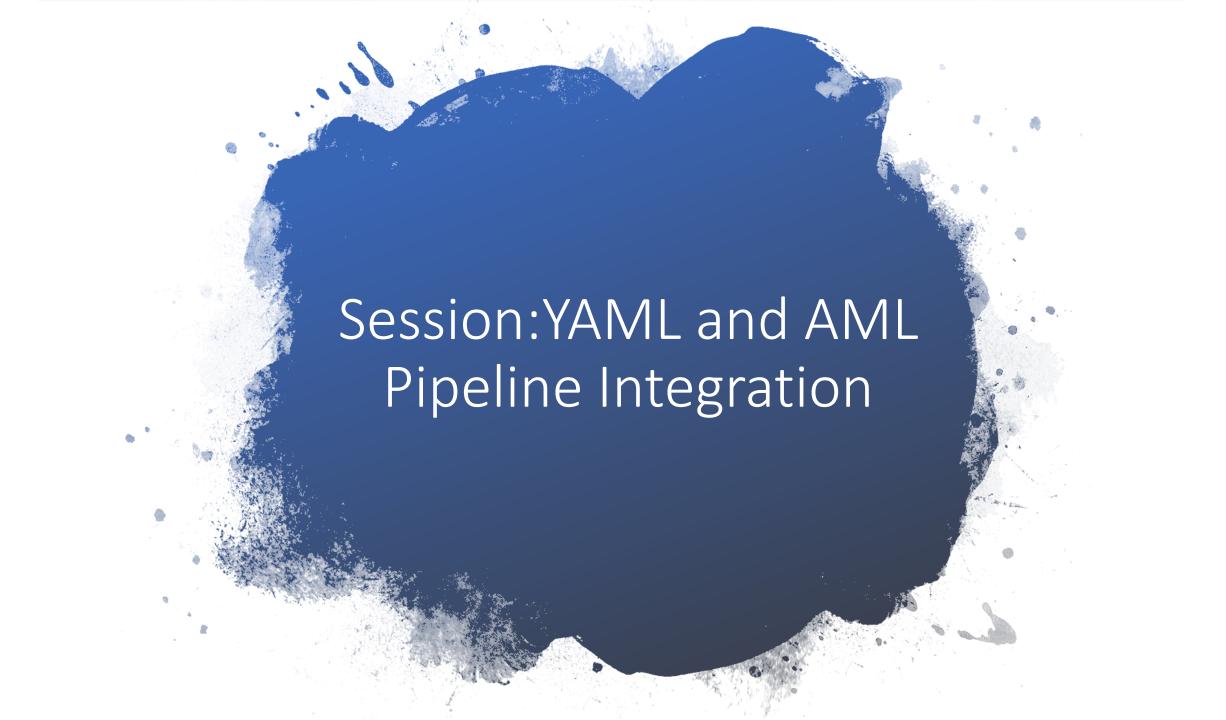
```
- task: string # reference to a task and version, e.g. "VSBuild@1" displayName: string # friendly name displayed in the UI name: string # identifier for this step (A-Z, a-z, 0-9, and underscore) condition: string continueOnError: boolean # should future steps run if this step fails? Default: 'false' enabled: boolean # whether or not to run this step; defaults to 'true' timeoutInMinutes: number inputs: { string: string } # task-specific inputs env: { string: string } # list of environment variables to add
```

steps:

task: VSBuild@1displayName: BuildtimeoutInMinutes: 120inputs:solution: '***.sIn'

Use Task Helpers to Edit a Pipeline

← openhack-devops-team Save openhack-devops-team / azure-pipelines.yml * Tasks -> #-Starter pipeline docker # Start with a minimal pipeline that you can customize to build and deploy your code. #-Add-steps-that-build, run-tests, deploy, and more: #-https://aka.ms/yaml Azure App Service deploy Deploy to Azure App Service a web, mobile, or AP... trigger: --master Azure Function for container 8 Update Function Apps with Docker containers pool: vmImage: 'ubuntu-latest' 10 11 Docker Build or push Docker images, login or logout, or r... 12 steps: --script: echo Hello, world! displayName: 'Run a one-line script' Docker CLI installer 15 Install Docker CLI on agent machine. --script: 16 ----echo-Add-other-tasks-to-build, test, and deploy-your-project. 17 Docker Compose echo See https://aka.ms/yaml 18 Build, push or run multi-container Docker applica... displayName: 'Run a multi-line script' 19 20 Service Fabric Compose deploy - task: DockerCompose@0 21 Deploy a Docker Compose application to an Azur... 22 ·inputs: 23 containerregistrytype: 'Azure Container Registry' azureSubscription: 'Jason Young''s Team(fdeb6cd6-9cac-474d-ad6b-d2000b9b0e0c)' 24 azureContainerRegistry: '{"loginServer":"prkcontreg.azurecr.io", "id" : "/subscriptions/fdeb@ 25 dockerComposeFile: '**/docker-compose.yml' 26 27 action: 'Run a Docker Compose command'



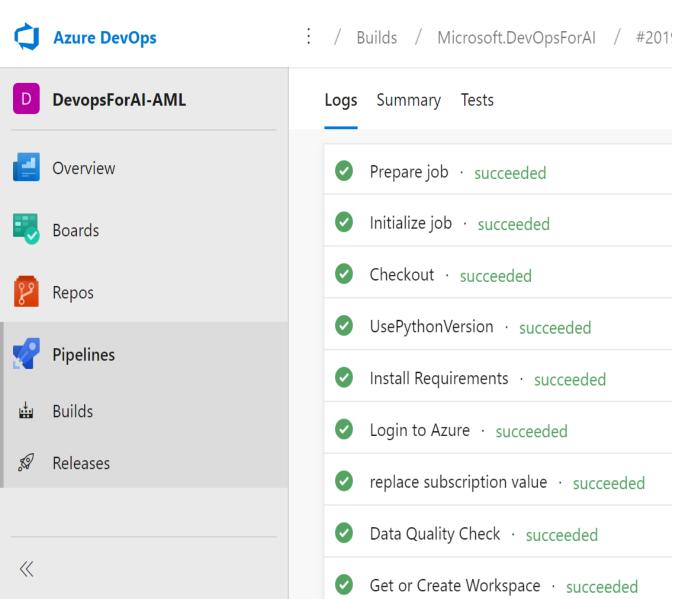
Session goals

- Project architecture
- · Build, Re-training, Deployment pipelines
- · Lab Setup

MLOps Reference Architecture {New data location} Schedule-driven Metrics-driven Azure Machine Learning Azure Storage pipeline endpoint Azure Machine Learning Azure **Pipelines** Create Create Publish Azure Machine Learning Publish machine Data sanity machine machine machine retraining pipeline learning pipeline Unit test learning learning test learning workspace compute pipeline Train Runs for new code Model One-time run Azure DevOps build pipeline Evaluate Operationalize model Model Register Model Azure Machine Learning Azure Machine Learning 2 Azure Package **Pipelines** Azure Deploy Deploy G Model Container model as Test web model as Test web Registry web service web service service service Manual Azure Container on ACI on AKS trigger release Azure Machine Learning Registry gate Compute Staging, QA Production Azure DevOps release gate Monitoring Azure Container Azure Kubernetes Azure App Insights Instances Service Scoring services

Model performance data

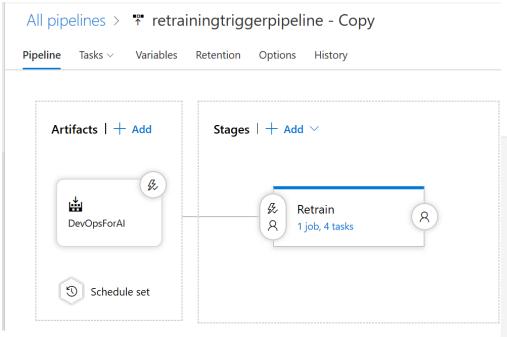
Build Pipeline



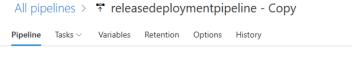
Create AML Compute Cluster · succeeded Create and Test AML Pipeline · succeeded Publish AML Pipeline as Endpoint · succeeded Copy Files to: \$(Build.ArtifactStagingDirectory) · succeeded Publish Artifact: devops-for-ai · succeeded Publish Artifact: AML Pipeline Config · succeeded Component Detection (auto-injected by policy) · succeede Post-job: Checkout · succeeded

Finalize Job · succeeded

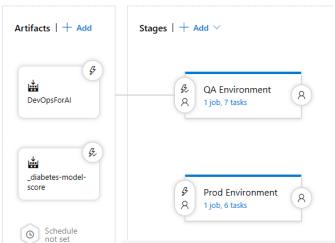
Re-training Pipeline



Agent job Pool: Hosted Ubuntu 1604 · Agent: Hosted Agent	Started: 6/21/2019, 5:20:41 PM 1m 51s
✓ Initialize job · succeeded	2s
✓ Download artifact - DevOpsForAl - devops-for-ai · succeeded	6s
Use Python 3.6 · succeeded	<1s
Install Requirements · succeeded	1m 33s
✓ Login to Azure Subscription · succeeded	2s
Run AML Pipeline · succeeded	6s
Finalize Job · succeeded	<1s

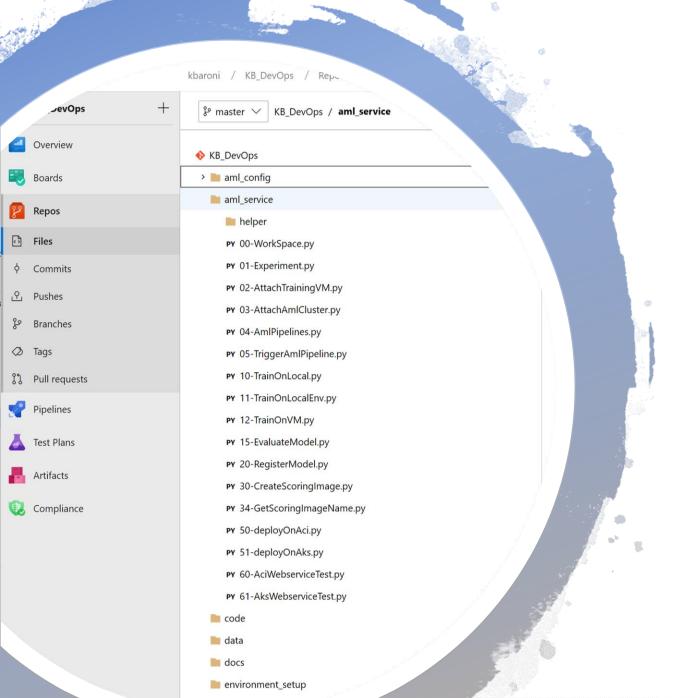


Deployment Pipeline



Agent job Started: 6/22/	Started: 6/22/2019, 10:26:38 AM	
Pool: Hosted Ubuntu 1604 · Agent: Hosted Agent	··· 5m 47s	
✓ Initialize job · succeeded	1s	
✓ Download artifact - DevOpsForAl - devops-f · succeeded	6s	
✓ Use Python 3.6 · succeeded	<1s	
	1m 31s	
✓ Login to Azure Subscription · succeeded	2s	
✓ Get Latest Scoring Image Name & Version · succeeded	3s	
✓ Deploy new image to ACI · succeeded	3m 57s	
✓ Test the image on ACI · succeeded	3s	
✓ Finalize Job · succeeded	<1s	

Agent job Pool: Hosted Ubuntu 1604 · Agent: Hosted Agent	Started: 6/22/2019, 10:37:08 AM 13m 59s
✓ Initialize job · succeeded	3s
Download artifact - DevOpsForAl - devops-f · succ	ceeded 6s
✓ Use Python 3.6 · succeeded	<1s
	1m 30s
✓ Login to Azure Subscription · succeeded	3s
✓ Get Latest Scoring Image Name & Version · succeede	ed 4s
✓ Deploy to AKS · succeeded	10m 57s
✓ Test AKS endpoint · succeeded	1m 13s
✓ Finalize Job · succeeded	<1s



Project Code

Lab Setup

Create new Azure DevOps project
Create Azure DevOps service connection
Setup variable group with secrets
Import repo into Azure DevOps