



# Microsoft Cloud Workshop

## MLOps with Azure Machine Learning

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# Welcome to this Virtual workshop!

## Agenda

Time	Description
09:00 – 11:30	<b>Presentation and Demo</b> <ul style="list-style-type: none"><li>• Introduction to Azure Machine Learning</li><li>• Brief overview, key features and MLOps</li><li>• Architecture E2E for Machine Learning and MLOps</li></ul> <b>Hands-on Lab – setup guide overview</b>
11:30 – 13:30	Personal Time / Lunch Break
13:30 – 16:30	<b>Hands-on Lab (self-paced)</b> <i>Possibly ad-hoc meeting to discuss common problems during lab execution</i> <i>Questions can be asked in Teams chat</i> <i>Individual calls with the proctors if needed during this time</i>
16:30 – 17:00	Wrap-up and Q&A

# Intro to Azure ML

# Machine Learning on Azure

## Domain specific pretrained models

To simplify solution development



Vision



Speech



Language



Web search



Decision

## Familiar Data Science tools

To simplify model development



Visual Studio Code



Azure Notebooks



Jupyter



Command line

## Popular frameworks

To build advanced deep learning solutions



PyTorch



TensorFlow



Scikit-Learn



ONNX

## Productive services

To empower data science and development teams



Azure Machine Learning



Azure Databricks



Machine Learning VMs

## Powerful infrastructure

To accelerate deep learning



CPU



GPU



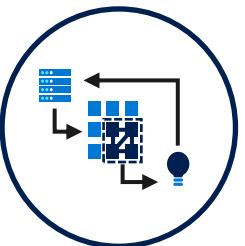
FPGA



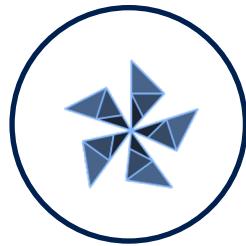
# AzureML



For all skill levels



Industry leading MLOps



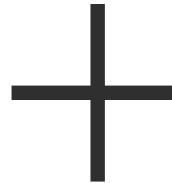
Open & Interoperable



Trusted

# What is Azure Machine Learning?

Set of Azure Cloud  
Services



Python  
SDK/CLI/UX

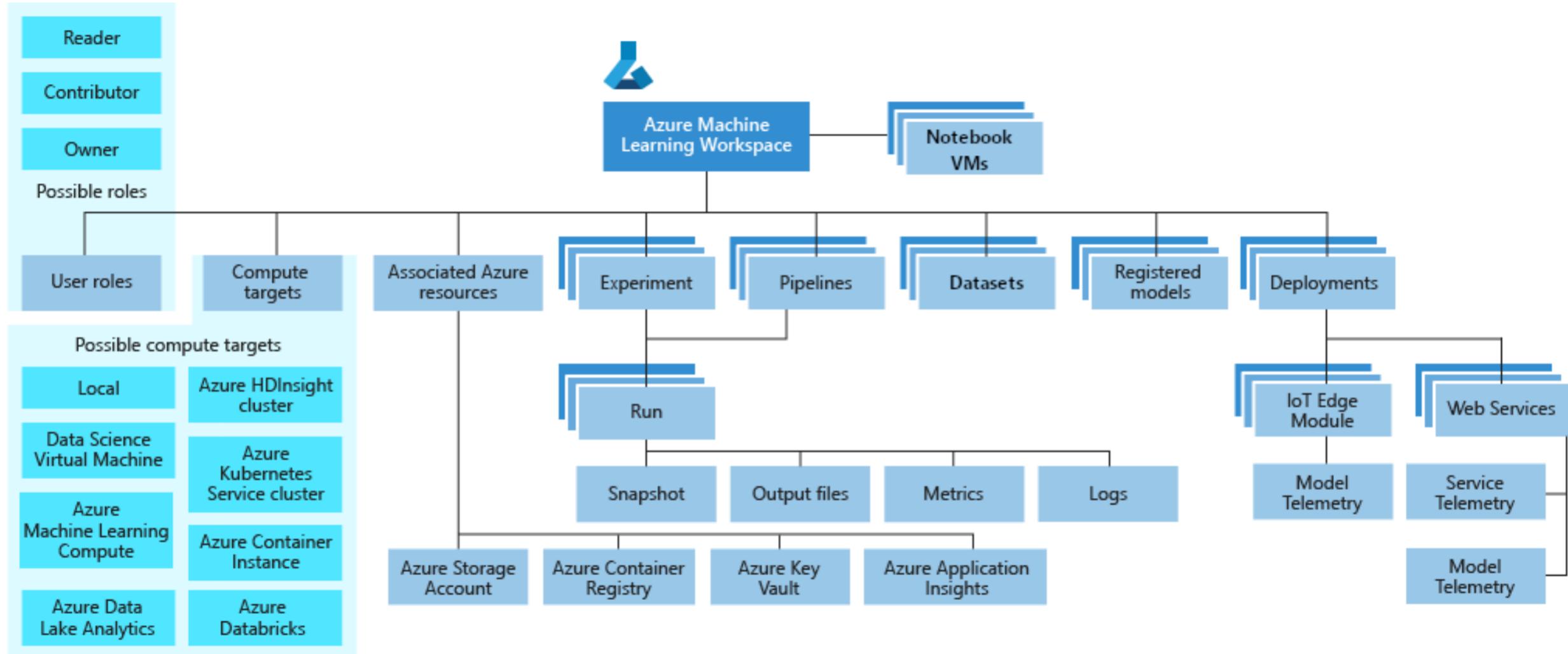
---

That enables  
you to:

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

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

# Key Artifacts of Azure Machine Learning



# Azure Machine Learning

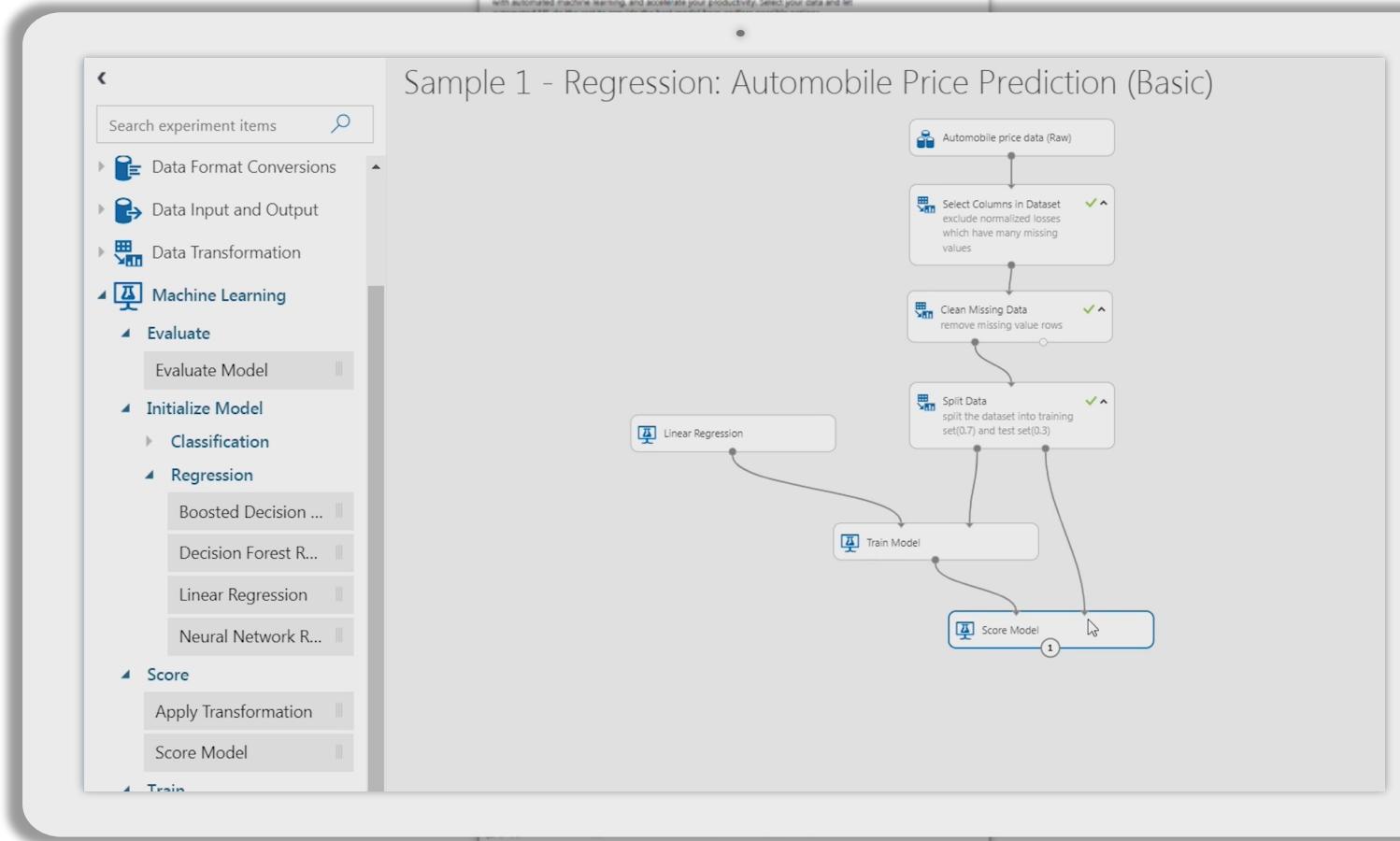
For all skill levels

Automated ML + drag & drop + code

Industry leading MLOps

Open & Interoperable

Trusted



A screenshot of a Jupyter Notebook titled "Distributed PyTorch with Horovod". The notebook contains the following text and code:

Copyright © Microsoft Corporation. All rights reserved.  
Licensed under the MIT License.

**Distributed PyTorch with Horovod**  
In this tutorial, you will train a PyTorch model on the [MNIST](#) dataset using distributed training via [Horovod](#) across a GPU cluster.

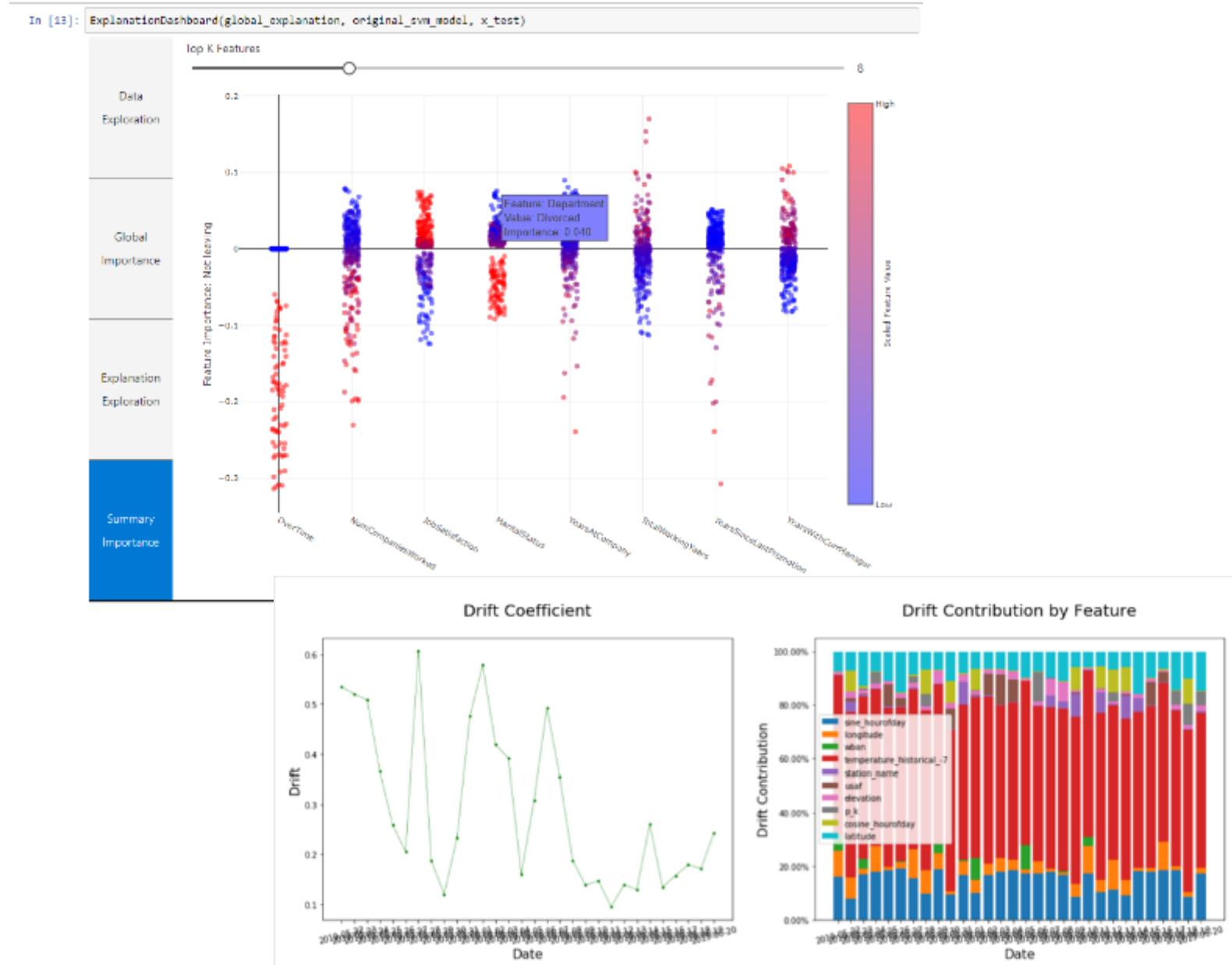
**Prerequisites**

- Go through the [Configuration](#) notebook to install the Azure Machine Learning Python SDK and create an Azure ML Workspace.
- Review the [tutorial on single-node PyTorch training using Azure Machine Learning](#).

```
# Check more DTF versions
# Import required modules
import tensorflow as tf
tf.__version__
```

# Azure Machine Learning

For all skill levels  
Industry leading MLOps  
Open & Interoperable  
Trusted  
Model explainability and fairness



# Azure ML Demos

## Overview and key features

- Compute Instance
- Experiment tracking
- Metrics Logging
- Datasets
- Model Register
- Model Deployment
- Designer
- AutoML

# Azure ML

Microsoft Azure | Machine learning

ntWBAutoMLField > Home

Welcome!

- Automated ML
- Visual Interface
- Notebooks

Assets

- Datasets
- Experiments
- Models
- Endpoints

Manage

- Compute
- Datastores
- Notebook VMs

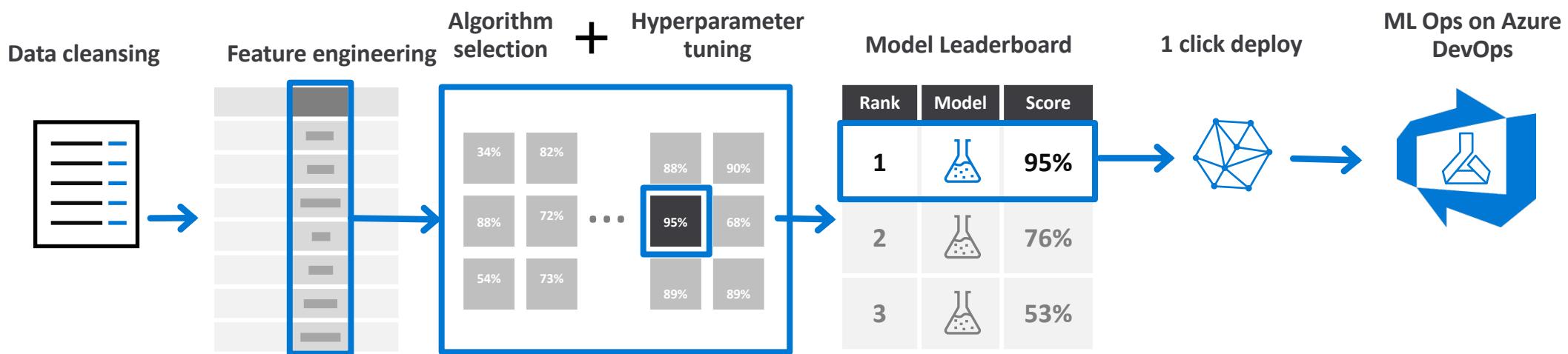
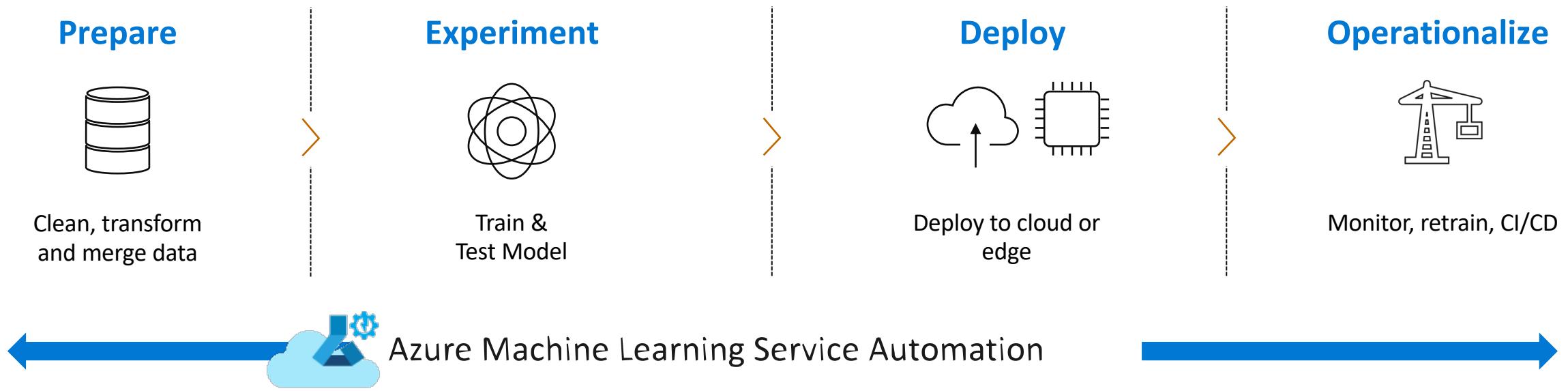
My recent resources

Run Number	Experiment	Status Updated Time	Status
a1b671dc-138...		9/25/2019, 11:06:12 PM	Completed
fefd8bd2-3435...		9/25/2019, 4:07:48 PM	Failed
AutoML_9c6b4...		9/24/2019, 1:33:22 PM	Completed

Compute

Name
ntWBAutoML
ntWBAutoMLEnv
wba-cluster

# The Machine Learning Workflow



# Azure ML – Designer

Preview Microsoft Azure Machine Learning

azuremlservice > Designer > Authoring

Training pipeline Real-time inference pipeline

Titanic visual interface Run Create inference pipeline Update inference pipeline Publish

Autosave on Run finished View run overview

Search

Datasets Data Input and Output Data Transformation Feature Selection Statistical Functions Machine Learning Algorithms Model Training Model Scoring & Evaluation Python Language R Language Text Analytics Recommendation Web Service

Home Notebooks Automated ML Designer Assets Datasets Experiments Pipelines Models Endpoints Manage Compute Datastores Data labeling

**Settings**

Default compute target StandardDS5V2 Select compute target

Pipeline parameters No parameters selected

Draft details

Draft name Titanic visual interface

Draft description (optional)

Summary: Description:

Created on 11/5/2019 09:06:34 AM

Created by Serge Retkowsky

Last edit time 11/7/2019 05:06:25 PM

Navigator

```
graph TD; A[Titanic.csv] --> B[Select Columns in Dataset]; B --> C[Two-Class Logistic Regression]; B --> D[Split Data]; C --> E[Train Model]; D --> F[Train Model]; E --> G[Score Model]; F --> H[Score Model]; G --> I[Score Model]; H --> I;
```

# Azure ML – AutoML

Preview Microsoft Azure Machine Learning

mlopsdb-AML-WS > Experiments > diabetesdemo > AutoML\_2139b739-b8a2-46af-9ec8-e5417eaf846a\_39

Run 42 Completed

Refresh Explain model Cancel

Model details Visualizations Explanations Logs Outputs

**Properties**

Algorithm name  
StandardScalerWrapper, XGBoostRegressor

Primary metric  
spearman\_correlation

Score  
0.6480102856769941

Sdk version  
1.0.72

Deploy status  
No deployment yet

**Status**

Status  
Completed

Run ID  
AutoML\_2139b739-b8a2-46af-9ec8-e5417eaf846a\_39

Input datasets  
Input name: input\_data, ID: 266b6614-94e5-426f-aa74-f3242da59408

Time started  
Mon Nov 04 2019 11:44:24 GMT+0100 (Central European Standard Time)

Duration  
00:01:26

**Deploy model** Download model

**Run Metrics**

normalized\_median\_absolute\_error  
0.12622

explained\_variance  
0.43638

root\_mean\_squared\_error  
57.310

median\_absolute\_error  
40.518

normalized\_root\_mean\_squared\_error  
0.17854

normalized\_root\_mean\_squared\_log\_error  
0.16446

Notebooks

Automated ML

Designer

Assets

Datasets

Experiments

Pipelines

Models

Endpoints

Compute

Datastores

Data labeling

# Distributed Training

You submit a model training ‘job’ – the infrastructure is managed for you.

Jobs run on a native VM or Docker container.

Supports Low priority (Cheaper) or Dedicated (Reliable) VMS.

Auto-scales: Just specify min and max number of nodes.

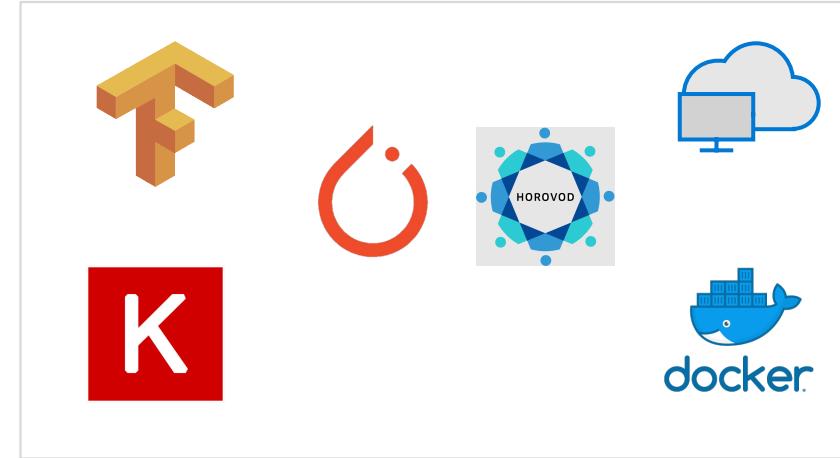
If min is set to zero, *cluster is deleted when no jobs are running; so pay only for job duration.*

Works with most popular frameworks and multiple languages.

Supports [distributed training with Horovod](#).

Cluster can be shared; multiple experiments can be run in parallel.

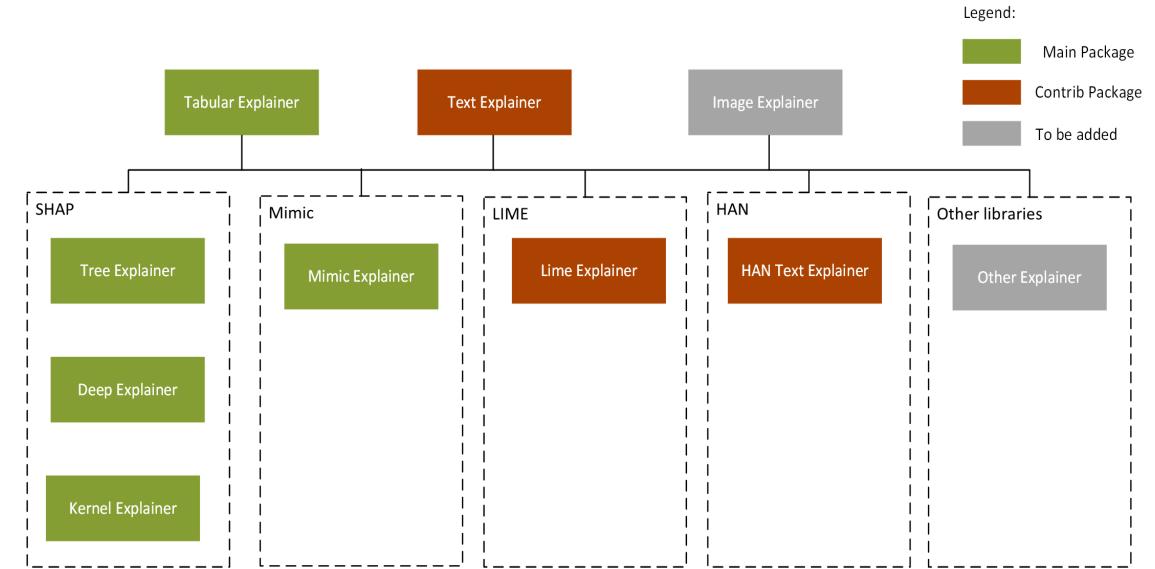
Supports most VM Families, including latest NVidia GPUs for DL model training.



A screenshot of a GitHub repository page for 'Azure / BatchAI'. The repository has 30 stars, 57 forks, and 44 issues. It contains 174 commits, 7 branches, 0 releases, and 18 contributors. The repository is described as 'Repo for publishing code Samples and CLI samples for BatchAI service'. The commit history shows several recent updates, including a pull request from 'lliamsft' and changes to documentation, recipes, and schemas. The repository is licensed under MIT.

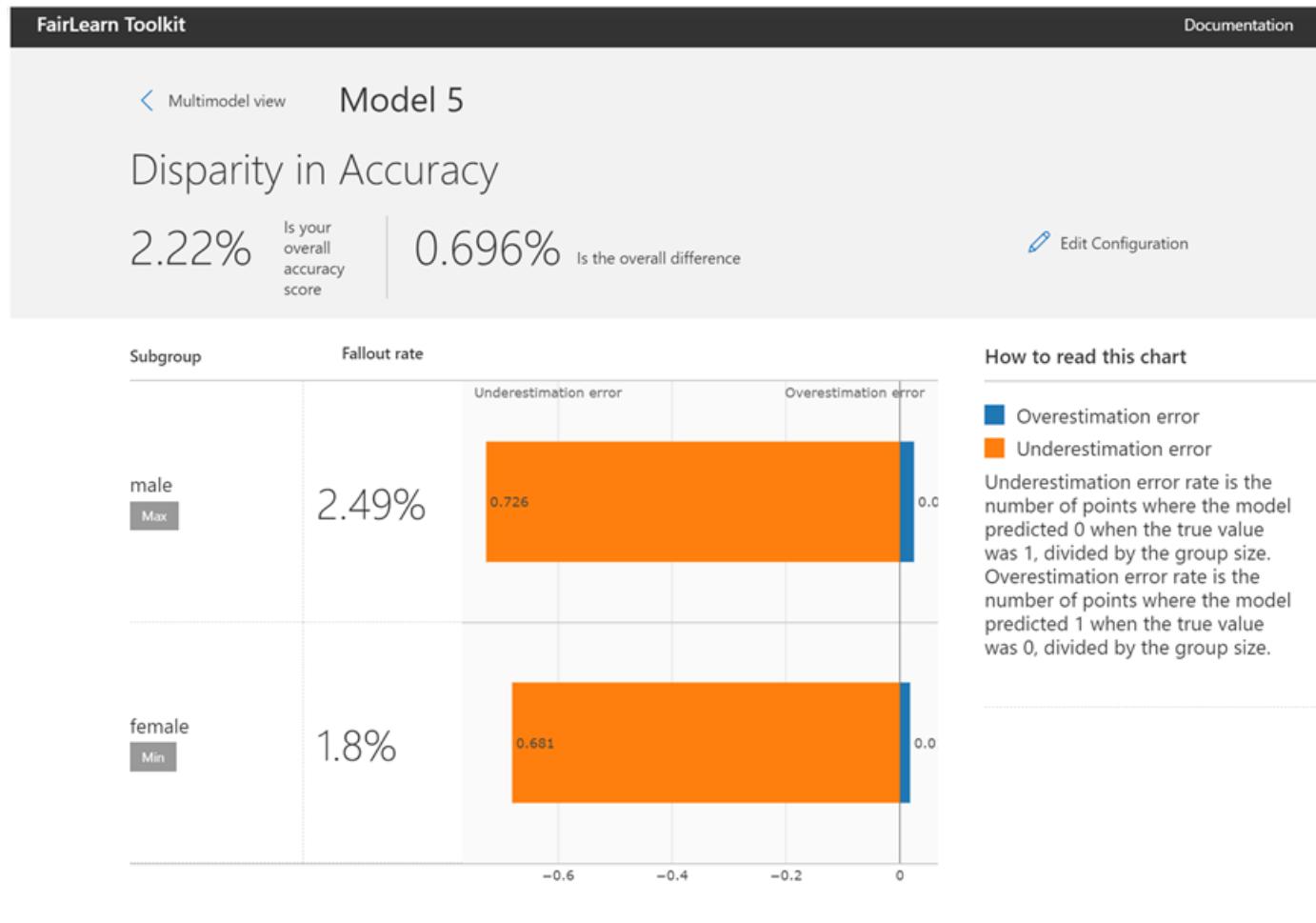
# Azure ML – Model Interpretability

- Explain ML models **globally on all data, or locally on a specific data point** using the state-of-art technologies in an easy-to-use and scalable fashion.
- Incorporate cutting-edge interpretability solutions **developed by Microsoft** and leverages **proven third-party libraries**
- Create a **common API and data structure** across the integrated libraries and integrates AML services



# Azure ML – Fairness

- Fairlearn is a new open source unfairness assessment and mitigation tool that assists business stakeholders, executives, developers, and data scientists to get insights about the unfairness in their model predictions.**



# Azure ML – Data Drift

## What is Data Drift

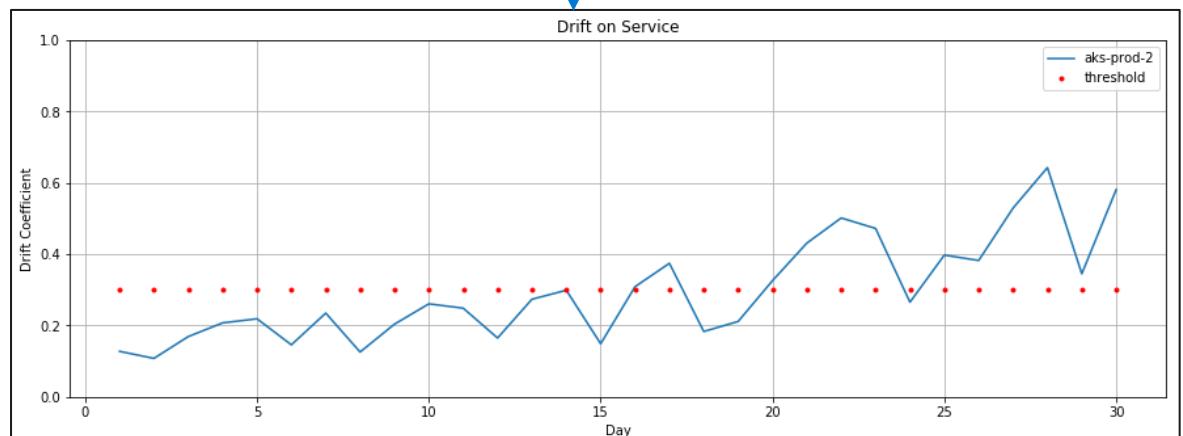
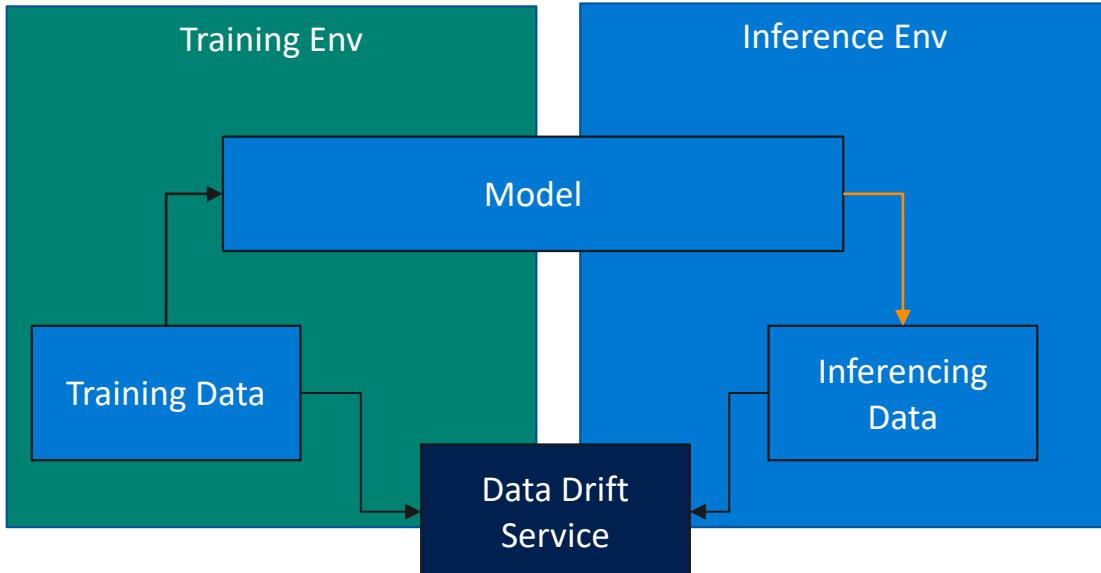
- When the inference data varies enough from the training data to cause model degradation, we consider it data drift

## Why is Data Drift important

- in absence of labels, data drift can be used as a proxy for model performance metrics

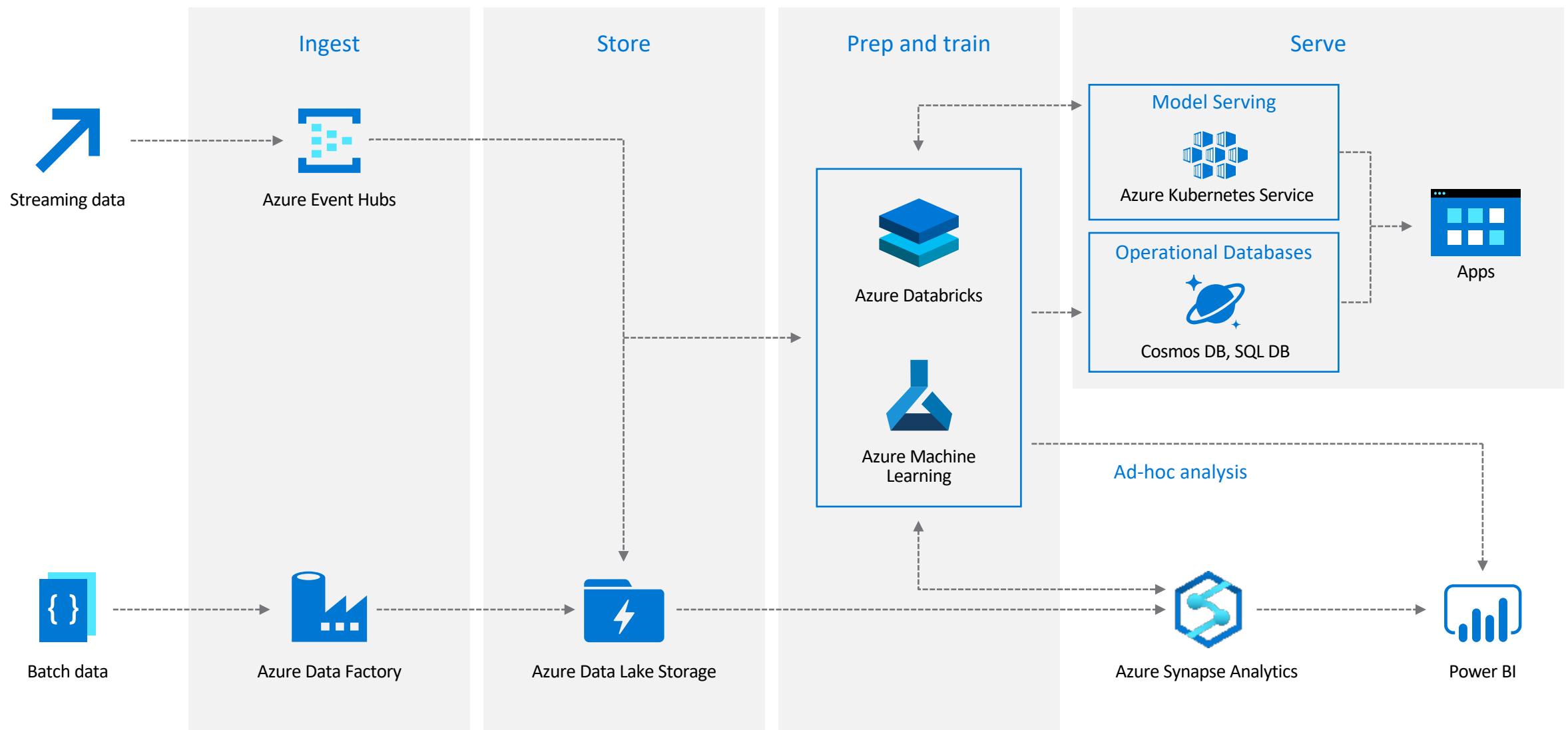
## What can I expect from data drift service

- Alerting and Insights in Previews**
- Drift Coefficient** - measures magnitude of drift
- Drift Contribution by Feature** - measures feature that caused data drift
- Distance Metrics by Feature** - distance metrics on features
- Distribution Visualization** - capture and visualize change in distributions over time



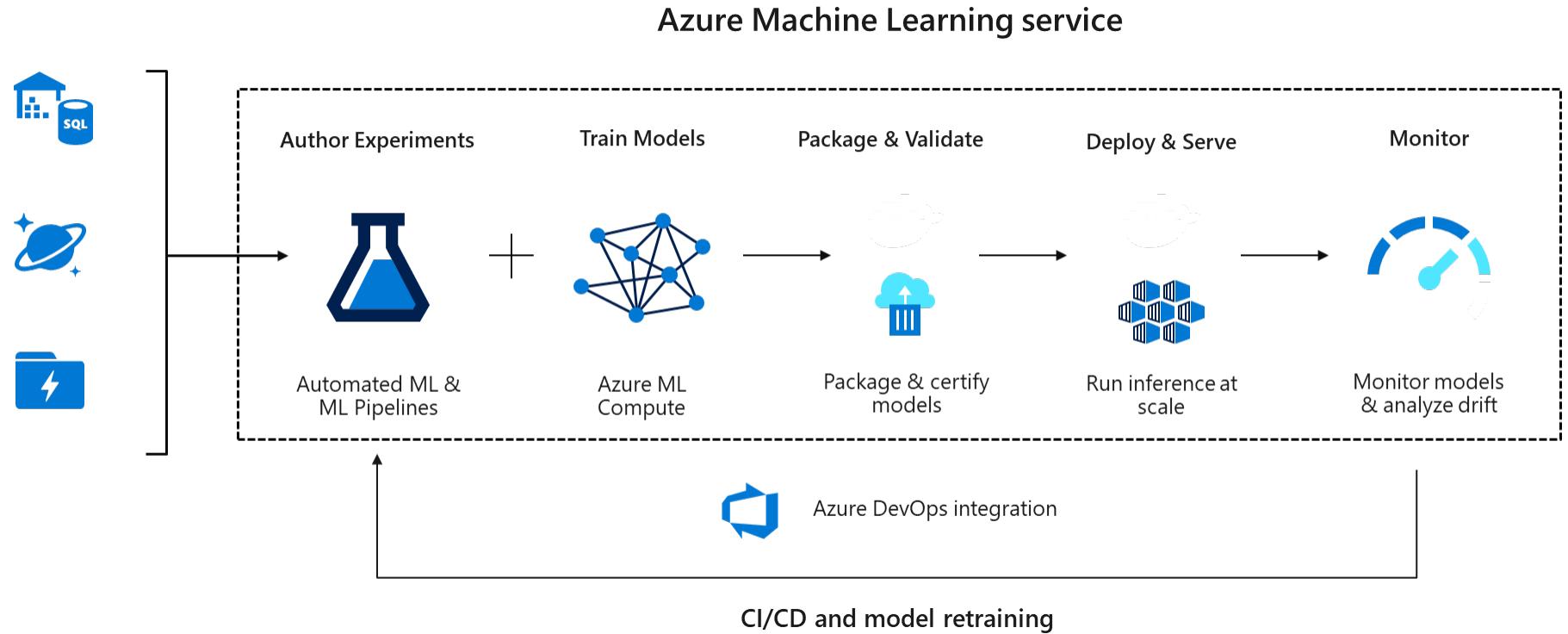
# Reference Architecture

# Machine learning



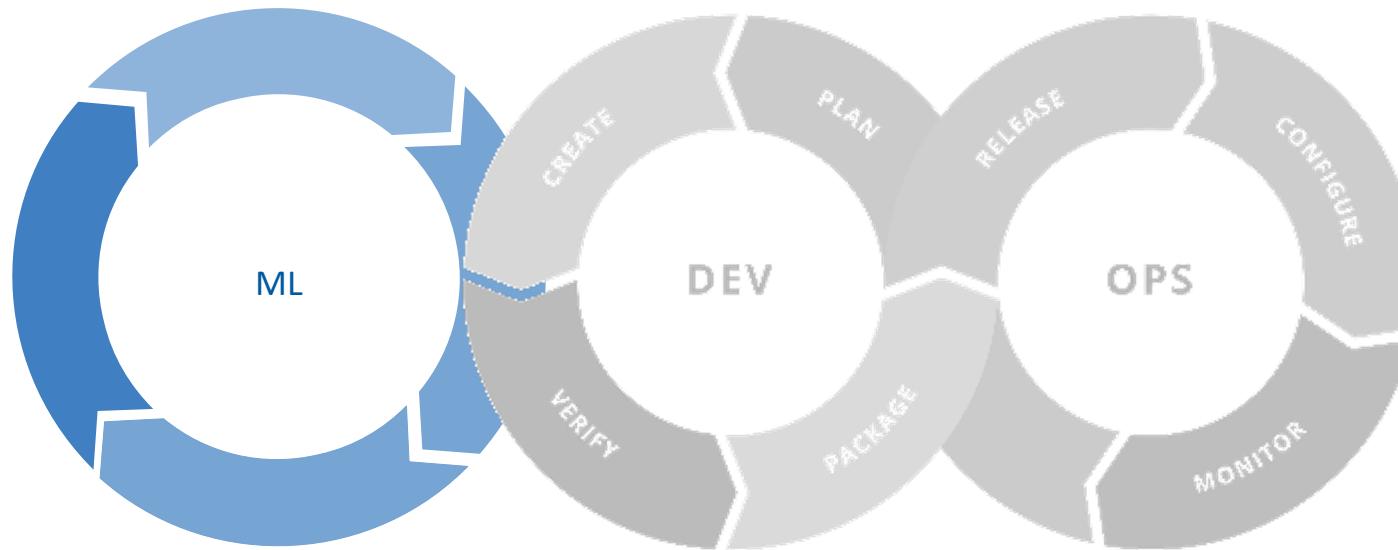
# MLOps

# MLOps



**MLOps = ML + DEV + OPS**

**Help bring models to production**



## **Experiment**

Data Acquisition  
Business Understanding  
Initial Modeling

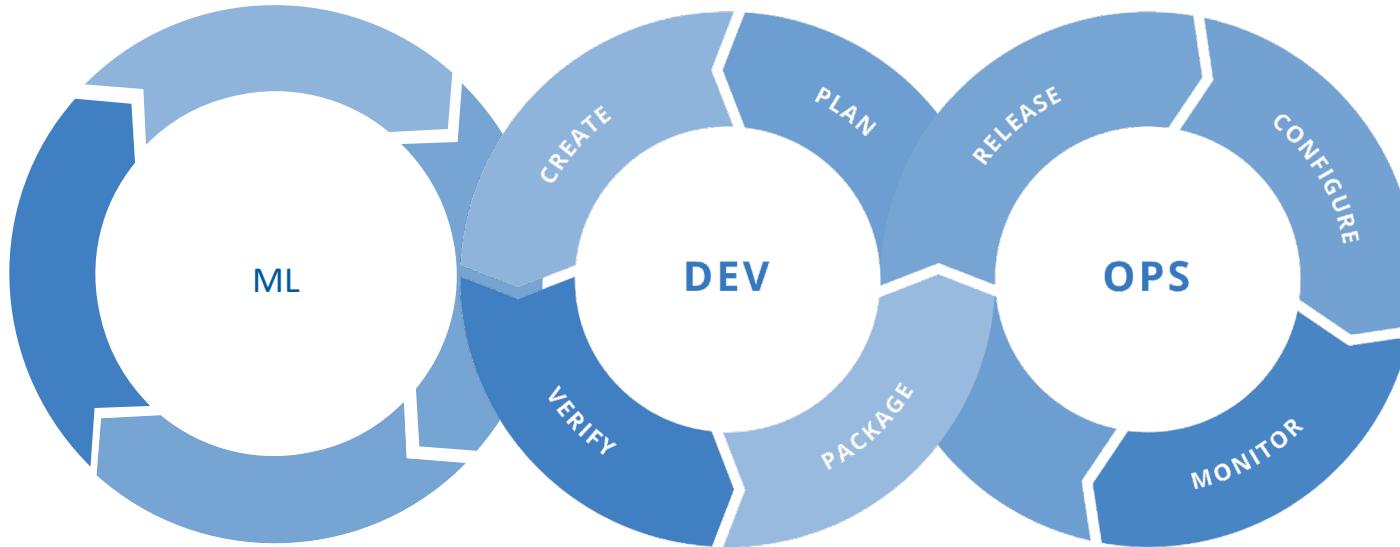
## **Develop**

Modeling + Testing  
Continuous Integration  
Continuous Deployment

## **Operate**

Continuous Delivery  
Data Feedback Loop  
System + Model Monitoring

# MLOps = ML + DEV + OPS



## Experiment

Data Acquisition  
Business Understanding  
Initial Modeling

## Develop

Modeling + Testing  
Continuous Integration  
Continuous Deployment

## Operate

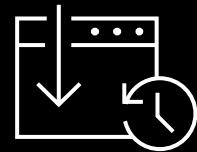
Continuous Delivery  
Data Feedback Loop  
System + Model Monitoring

# MLOps – Focus Areas

Challenge	How to solve – Best Practices
<b>Reproducibility &amp; versioning</b>	Track, snapshot & manage assets used to create the model Enable collaboration and sharing of ML pipelines
<b>Auditability &amp; explainability</b>	Maintain asset integrity & persist access control logs Certify model behavior meets regulatory & adversarial standards
<b>Packaging &amp; validation</b>	Support model portability across a variety of platforms Certify model performance meets functional requirements
<b>Deployment &amp; monitoring</b>	Release models with confidence Monitor & know when to retrain

# MLOps == How to bring ML to production

Bring together **people**, **process**, and **platform** to automate ML-infused software delivery & provide continuous value to our users.



People



101010  
010101  
101010

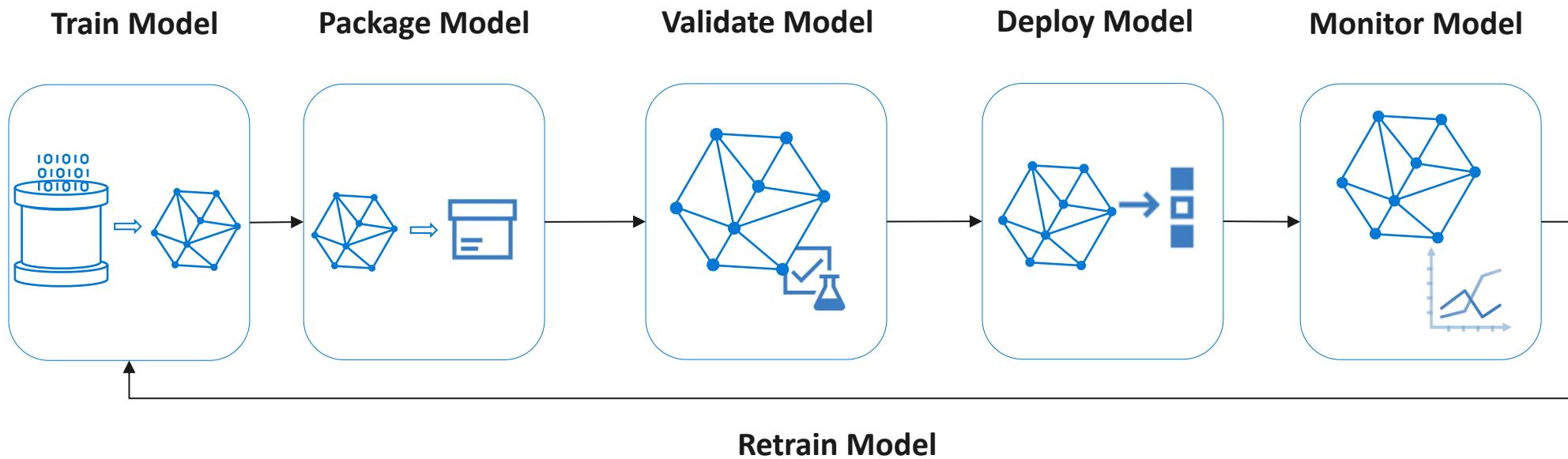
Process



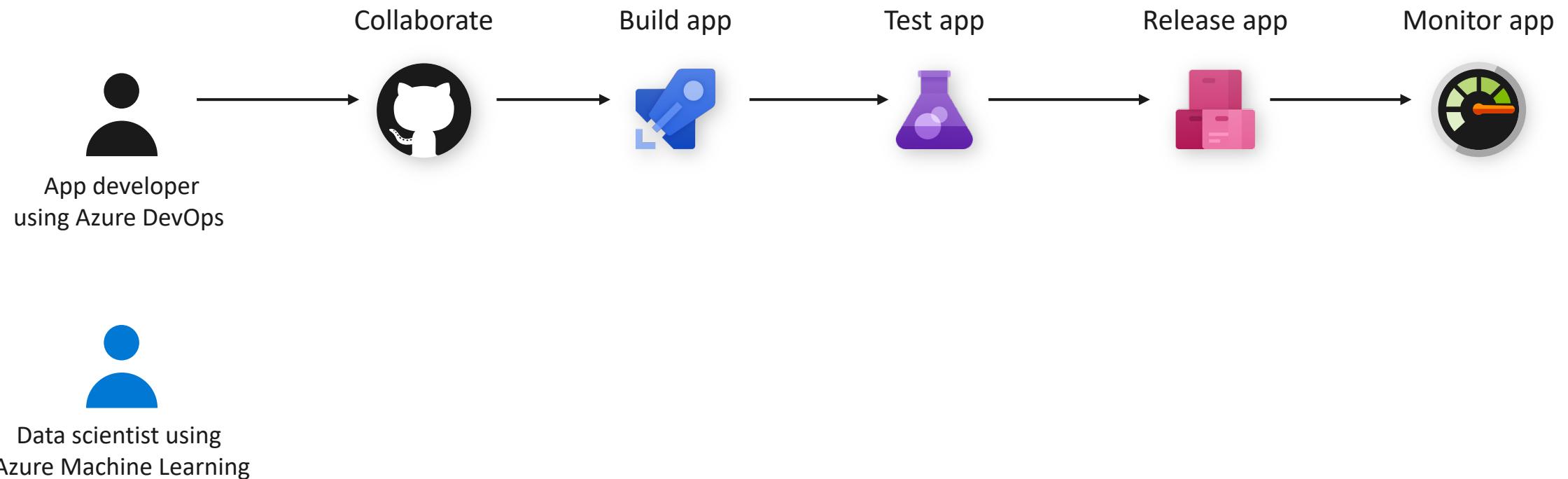
Platform

# What is the E2E ML lifecycle?

- **Develop & train model** with reusable ML pipelines
- **Package model** using containers to capture runtime dependencies for inference
- **Validate model behavior**—functionally, in terms of responsiveness, in terms of regulatory compliance
- **Deploy model**—to cloud & edge, for use in real-time/streaming/batch processing
- **Monitor model** behavior & business value, know **when to replace/deprecate a stale model**



# MLOps Workflow



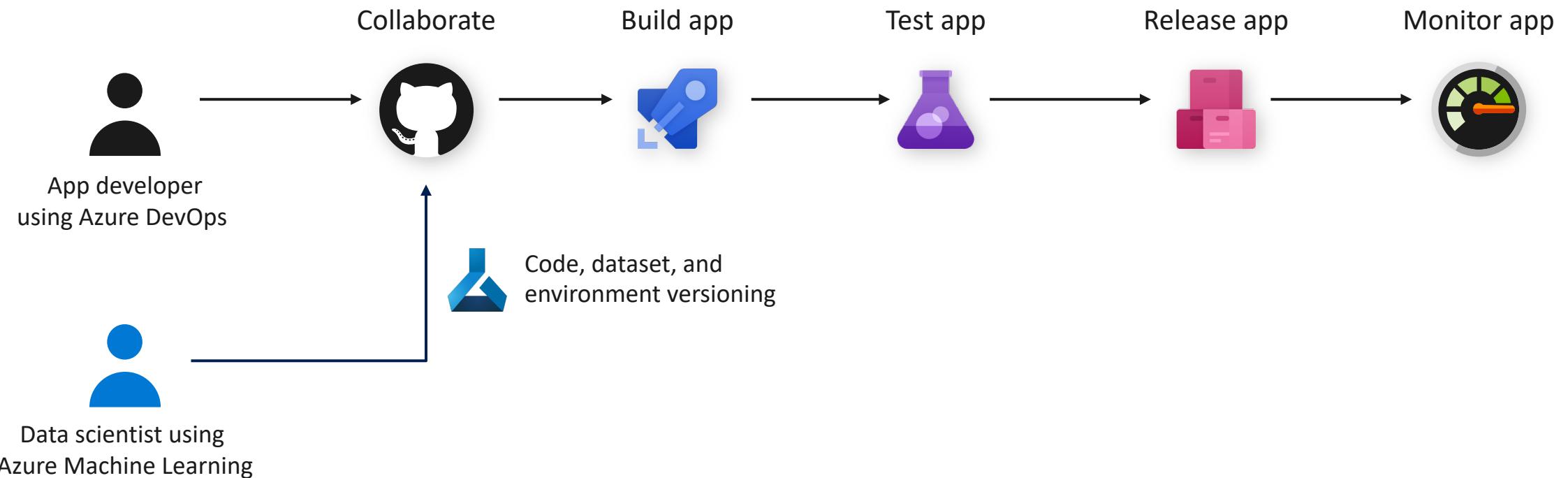
✗ Model reproducibility

✗ Model validation

✗ Model deployment

✗ Model retraining

# MLOps Workflow



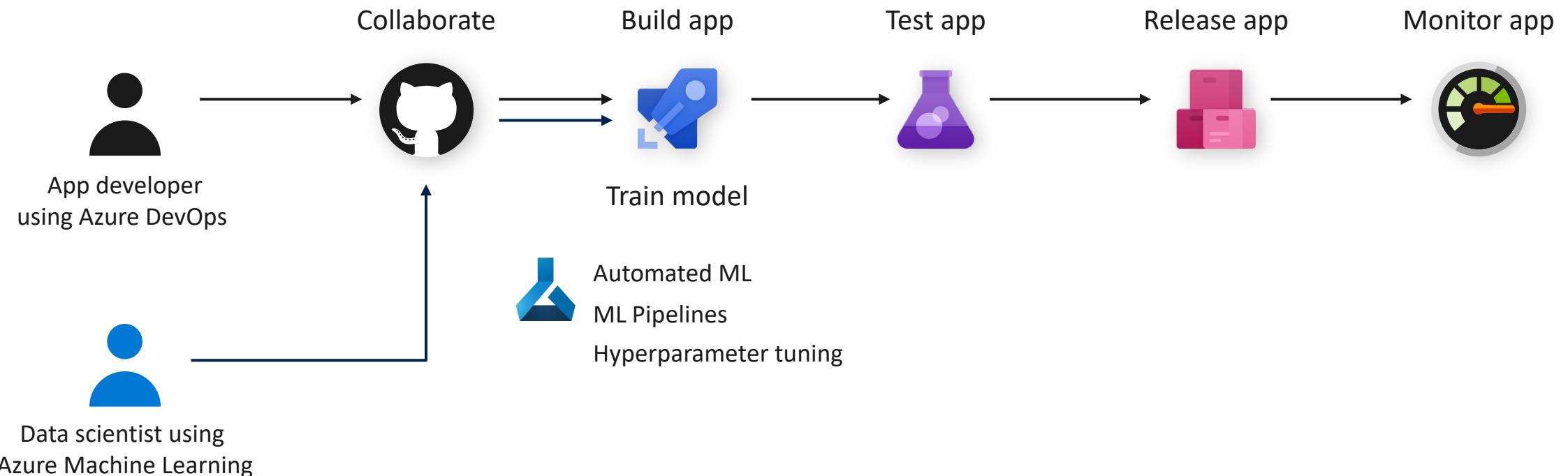
✓ Model reproducibility

✗ Model validation

✗ Model deployment

✗ Model retraining

# MLOps Workflow



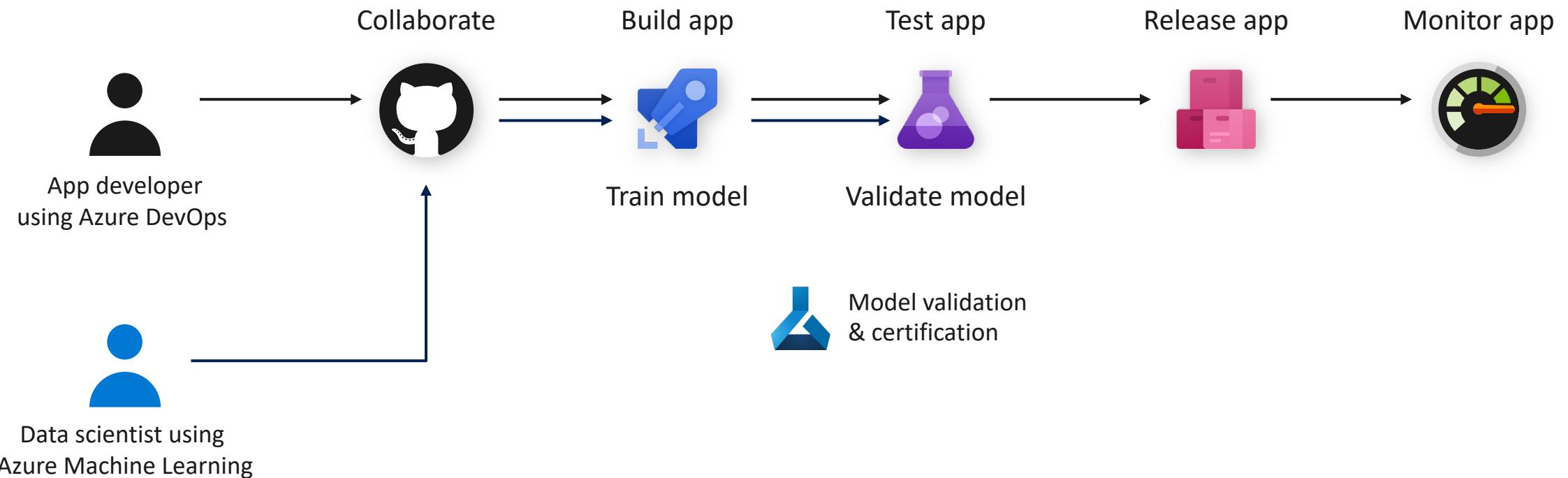
✓ Model reproducibility

✗ Model validation

✗ Model deployment

✗ Model retraining

# MLOps Workflow



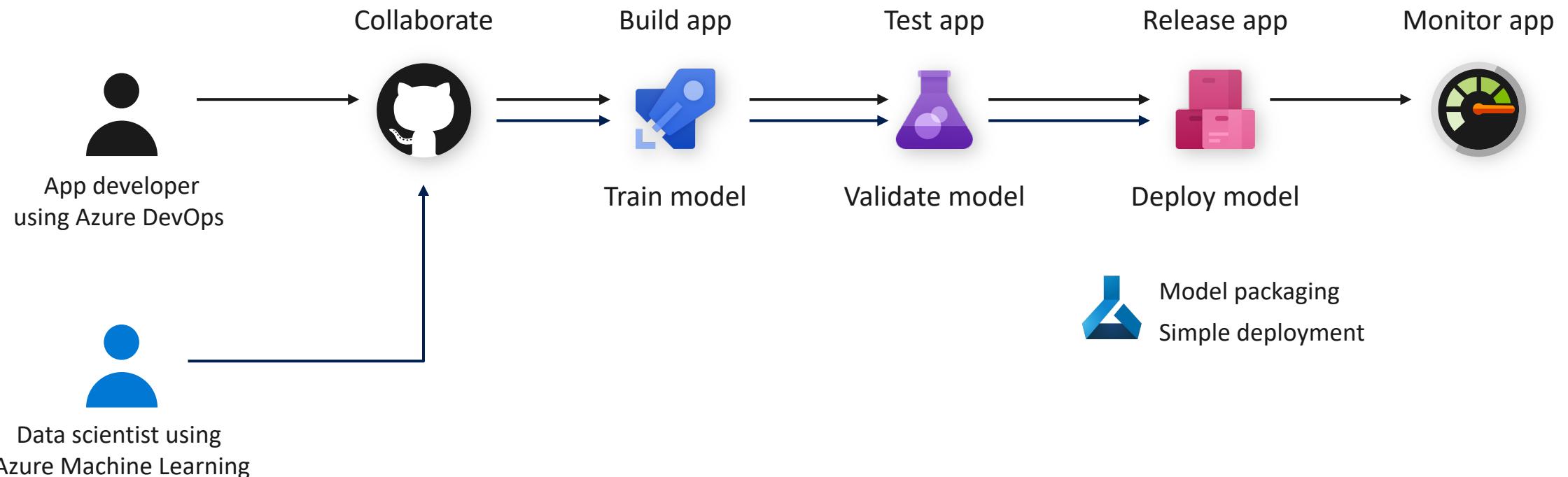
✓ Model reproducibility

✓ Model validation

✗ Model deployment

✗ Model retraining

# MLOps Workflow



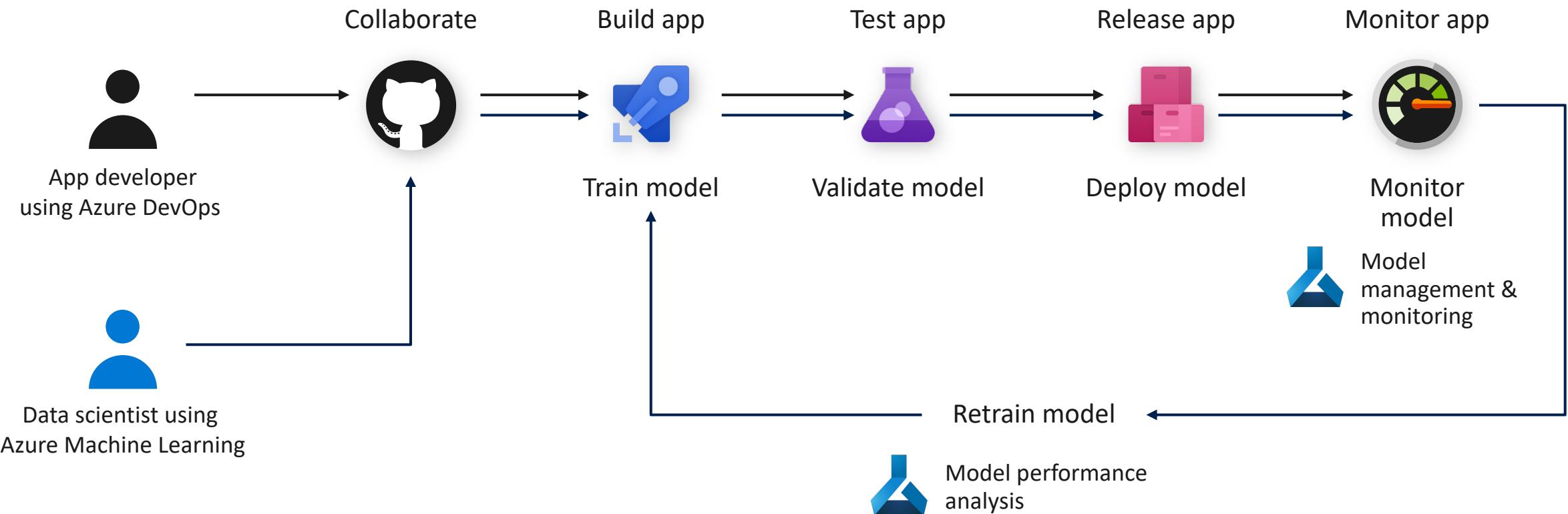
✓ Model reproducibility

✓ Model validation

✓ Model deployment

✗ Model retraining

# MLOps with Azure Machine Learning



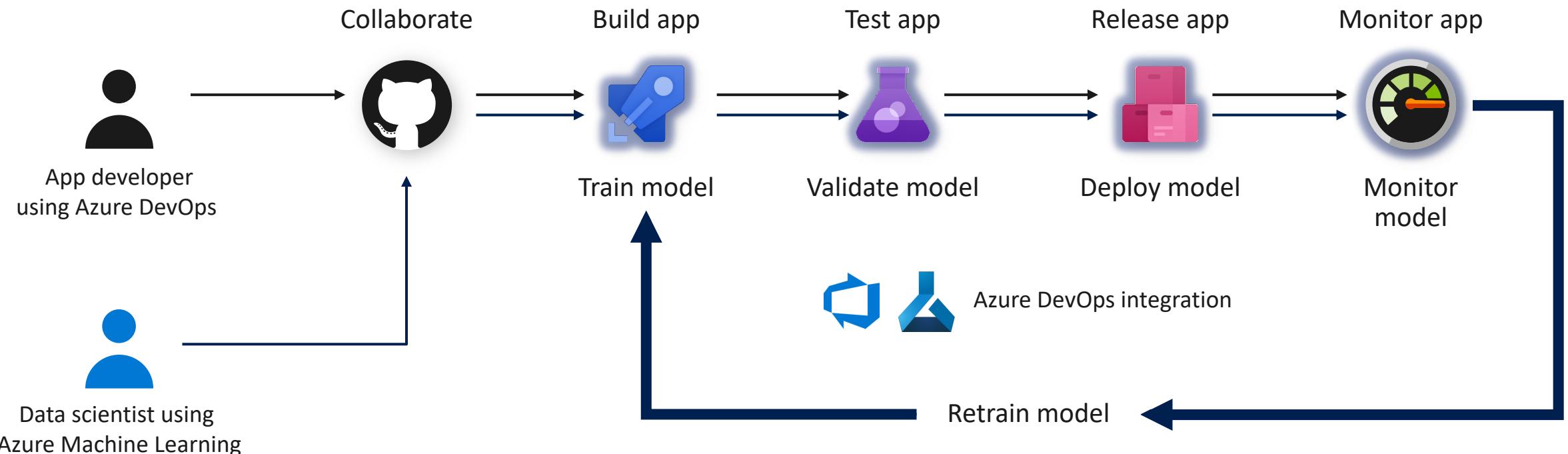
✓ Model reproducibility

✓ Model validation

✓ Model deployment

✓ Model retraining

# MLOps with Azure Machine Learning



✓ Model reproducibility

✓ Model validation

✓ Model deployment

✓ Model retraining

# MLOps Process

Enterprise ready machine learning development



Data Engineer



Data Scientist

Azure Data Factory

Prepare Data

Data Catalog

Azure Machine Learning

Build Model

Featurize

Train

Evaluate

register

Model Registry

Data Lake

Code Repo



ML Engineer

Release Model

Package

Validate

Profile

Approve

Deploy

release

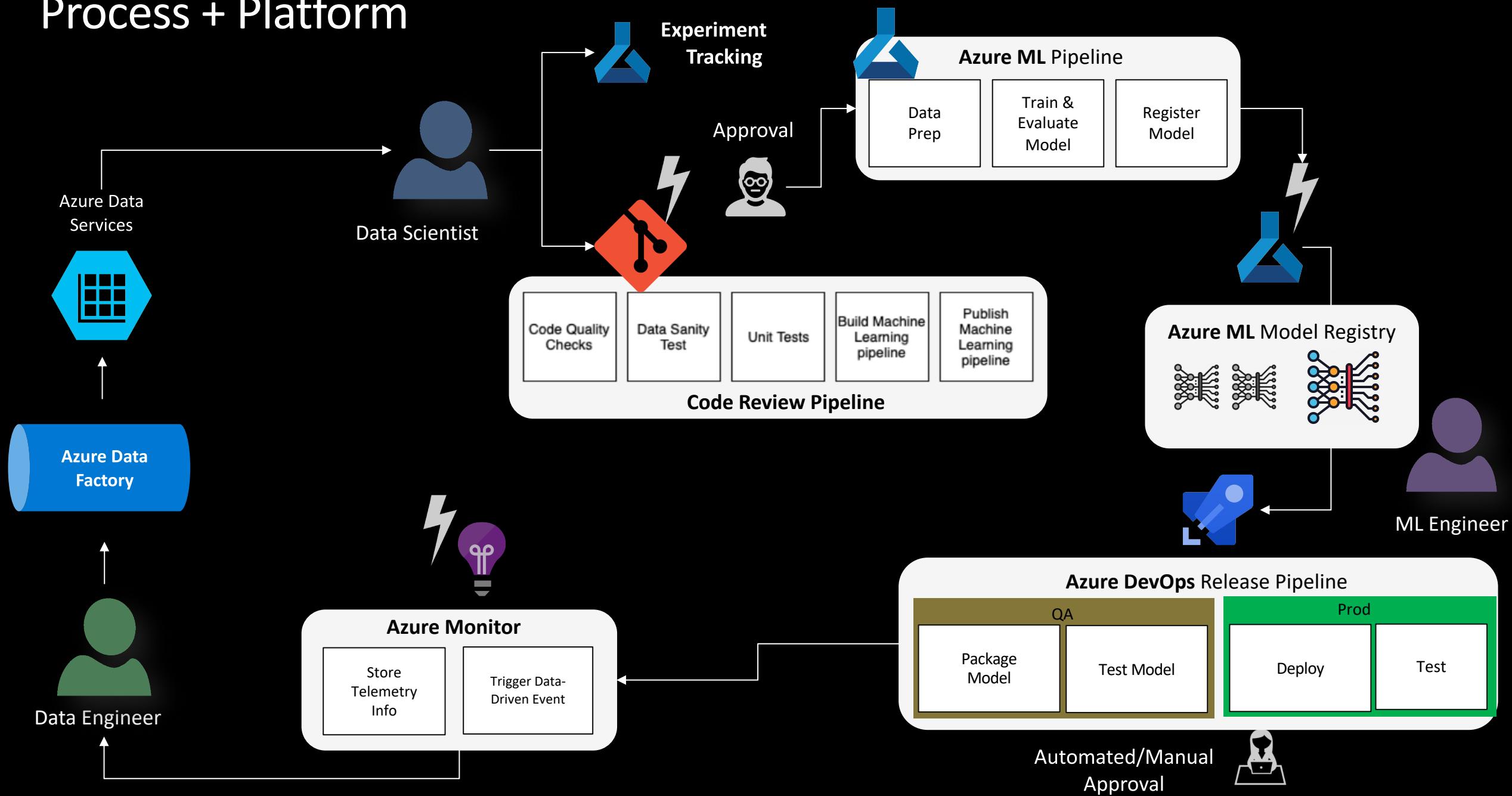


Azure DevOps

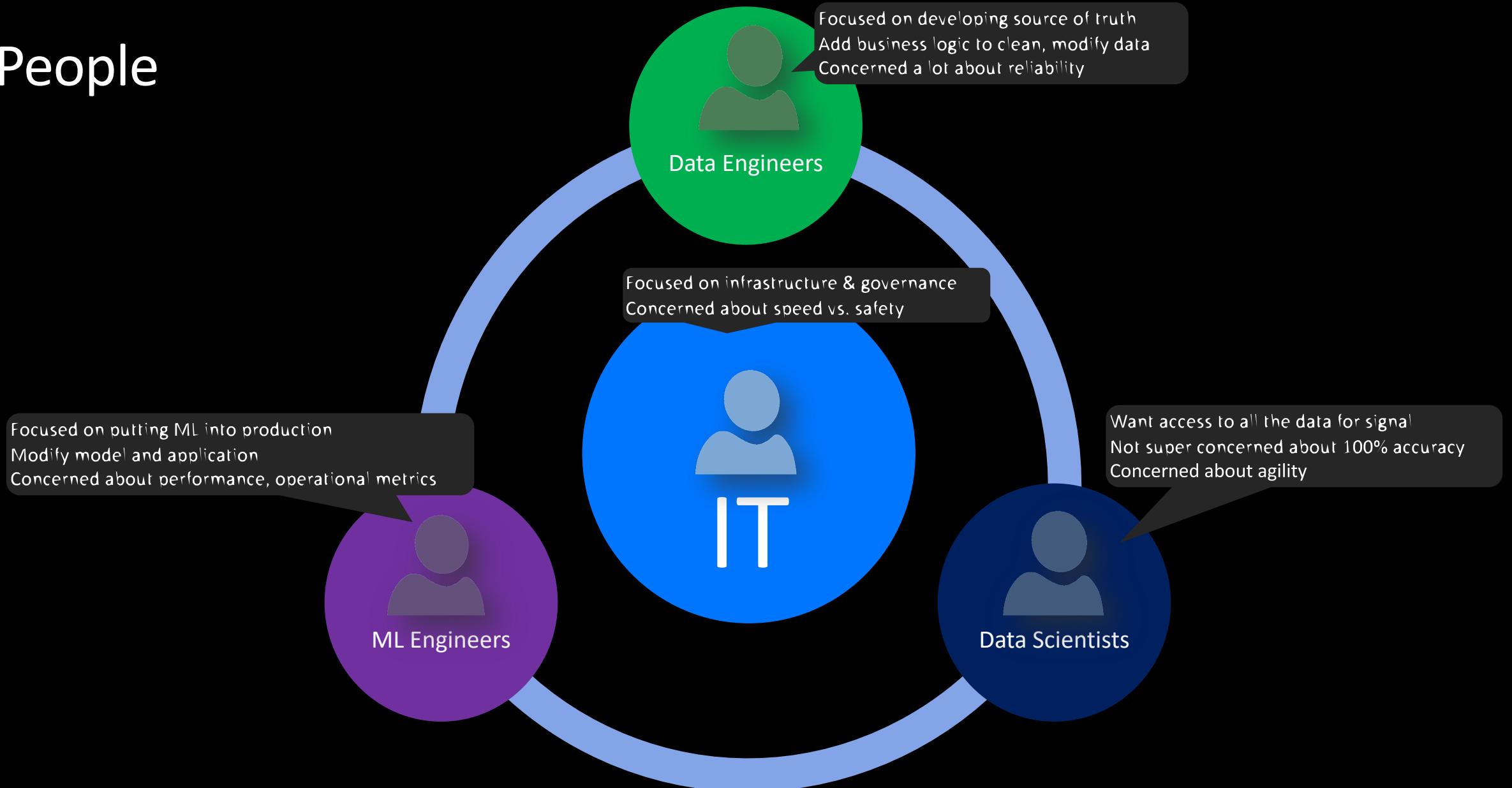
collect

# MLOps Demo

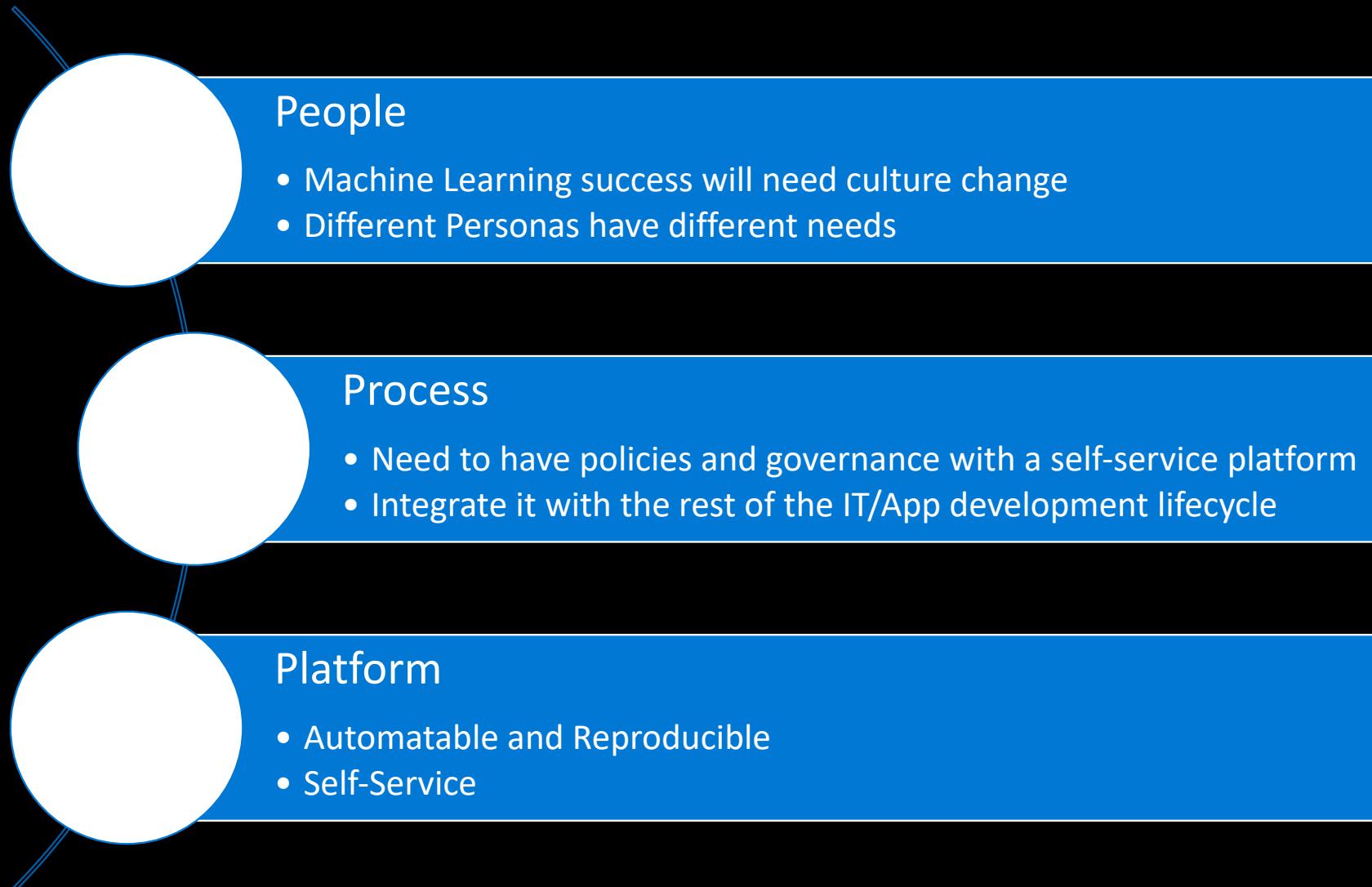
# Process + Platform



# People



# Summary



# MLOps Benefits

## Reproducibility / Auditability

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- Code drives **generation** and **deployments**
- Pipelines are **reproducible** and **verifiable**
- All artifacts can be **tagged** and **audited**

## Validation

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- SWE best practices for quality control
- Offline comparisons of model **quality**
- Minimize **bias** and enable **explainability**

## Automation / Observability

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- Controlled rollout capabilities
- Live comparison of predicted vs. expected performance
- Results fed back to watch for drift and improve model

# MLOps

Some additional capabilities...

# Azure ML Event Grid integration

Fully managed event routing for all activities in the ML lifecycle

Let's look at some examples...

The screenshot shows the Azure Machine Learning studio interface for managing events. The left sidebar lists various resources: Overview, Activity log, Access control (IAM), Tags, Diagnose and solve problems, Events (selected), Authoring (Preview) (Automated machine learning, Notebook VMs, Visual interface), Assets (Experiments, Pipelines, Compute, Models, Images, Deployments, Activities). The main content area is titled "mlopsign-AML-WS - Events" and "Machine Learning". It features a "Get Started" tab and an "Event Subscriptions" tab. A large text area says "Events, automated." and "Build reactive, event-driven apps with a fully managed event routing service that is built into Azure. Event Grid helps you build automation into your cloud infrastructure, create serverless apps, and integrate across services and clouds." Below this are sections for "TOPIC DETAILS" (Topic Type: Machine Learning, Topic Resource: mlopsign-AML-WS), "EVENT TYPES" (4 selected: Model registered, Model deployed, Run completed, Dataset drift detected), and "ENDPOINT DETAILS" (Endpoint Type: not specified).

# Send emails / hit a webhook whenever a run completes

Streamline model reuse & consumption

The screenshot shows the Logic Apps Designer interface with a dark theme. At the top, the navigation bar includes 'Save As', 'Discard', 'Designer', 'Code view', 'Templates', 'Connectors', and 'Help'. The main workspace displays a workflow titled 'When a resource event occurs' connected to an 'Azure Event Grid' trigger. The trigger configuration specifies a Tenant (Microsoft) and a connection to 'Create a new release' in 'MLOps' under 'Project Name'. The 'Create a new release' step is highlighted with a blue border. This step has fields for 'Account Name' (aidemos), 'Project Name' (MLOps), and 'Release Definition Id' (deploy workshop model). A description notes 'Deployment triggered because a new model meeting prefix constraints is in place.' Below this, there are sections for 'Is Draft' (set to 'ContinuousIntegration') and 'Reason'. A note at the bottom states 'Connected to jordan@bing.com. Change connection.' At the bottom of the workspace, there are buttons for '+ New step' and 'Update a work item' (Azure DevOps). To the right, a sidebar lists 'Server', 'Functions', 'Office 365', and 'Outlook' with their respective counts (0, 0, 0, 0). The background of the slide features a scenic landscape of mountains and water.

# Set up a data drift monitor...

Compare datasets over time  
Determine when to take a closer look

## Monitor settings

Settings for the data drift scheduled pipeline that will monitor the target dataset and send an email alert if the data drift percentage is above the set threshold.

### Enable

Monitor enabled

### Latency (hrs) i

1

### Email addresses i

abc@example.com;bcd@example.com

### Threshold i



20%

The screenshot shows the Azure ML workspace interface. On the left, there's a sidebar with options like Home, Automated ML, Visual Interface, Notebooks, Assets, Datasets (selected), Experiments, Models, Endpoints, Compute, Datastores, and Notebook VMs. The main area is titled 'Drift overview'. It features two charts: 'Data drift magnitude' (a line graph showing the percentage of data drift over time from January 1, 2019, to September 1, 2019) and 'Drift contribution by feature' (a bar chart showing the percentage contribution of various features to the drift, with bars for temperature, windAngle, latitude, longitude, stationName, countryOrRegion, precipTime, snowDepth, and elevation). Below the charts, there are sections for 'Feature details' and 'Select feature: Select metrics:'.

# Trigger Data Factory when data drift is detected

Now every time data drift is detected, your data factory pipeline will automatically be triggered. View details on your data drift run and machine learning pipeline on the [new workspace portal](#).

The screenshot shows the Azure Data Factory workspace portal. At the top, there's a message about data drift detection. Below it, the 'Endpoints' section has tabs for 'Real-time endpoints' and 'Pipeline endpoints'. Under 'Pipeline endpoints', there are two entries: 'My\_New\_Pipeline' (Published Pipeline) and 'DataDriftPipeline-68d4de40f' (Pipeline for run\_invoker.py). Both entries show their last run status and modification details.

The screenshot shows the Azure Logic Apps designer interface. It starts with a trigger 'When a resource event occurs' set to 'Microsoft.MachineLearningServices.Workspaces'. This triggers an 'Actions' step, which is a 'Create a pipeline run' action from 'Azure Data Factory'. The action step is highlighted with a red border. Below the logic app, the main Data Factory workspace is visible, showing the 'Training Pipeline' with its 'Copy data' activity and 'ML Execute Pipeline' activity.

When a resource event occurs

\* Subscription: [dropdown]

\* Resource Type: Microsoft.MachineLearningServices.Workspaces

\* Resource Name: [dropdown]

Event Type Item - 1

+ Add new item

Add new parameter

Connected to shipatel@microsoft.com

When a resource event occurs

Choose an action

Search: azure data factory

For You All Built-in Standard Enterprise Custom

Azure Data Factory

Triggers Actions

Create a pipeline run Azure Data Factory

Create a pipeline run Azure Data Factory

Data Factory Publish all Validate all Refresh Discard all Data flow debug ARM template

Factory Resources Pipelines 1 Training Pipeline Datasets 1 new\_dataset Data flows 0

Activities Search activities Copy data Data flow Azure Data Explorer Azure Function Batch Service Data Lake Analytics

Copy data Copy data1 ML Execute Pipeline ML Execute Pipeline1

## NEW MLOPS CAPABILITIES

# Azure Machine Learning

Improved data management

ML pipelines YAML support

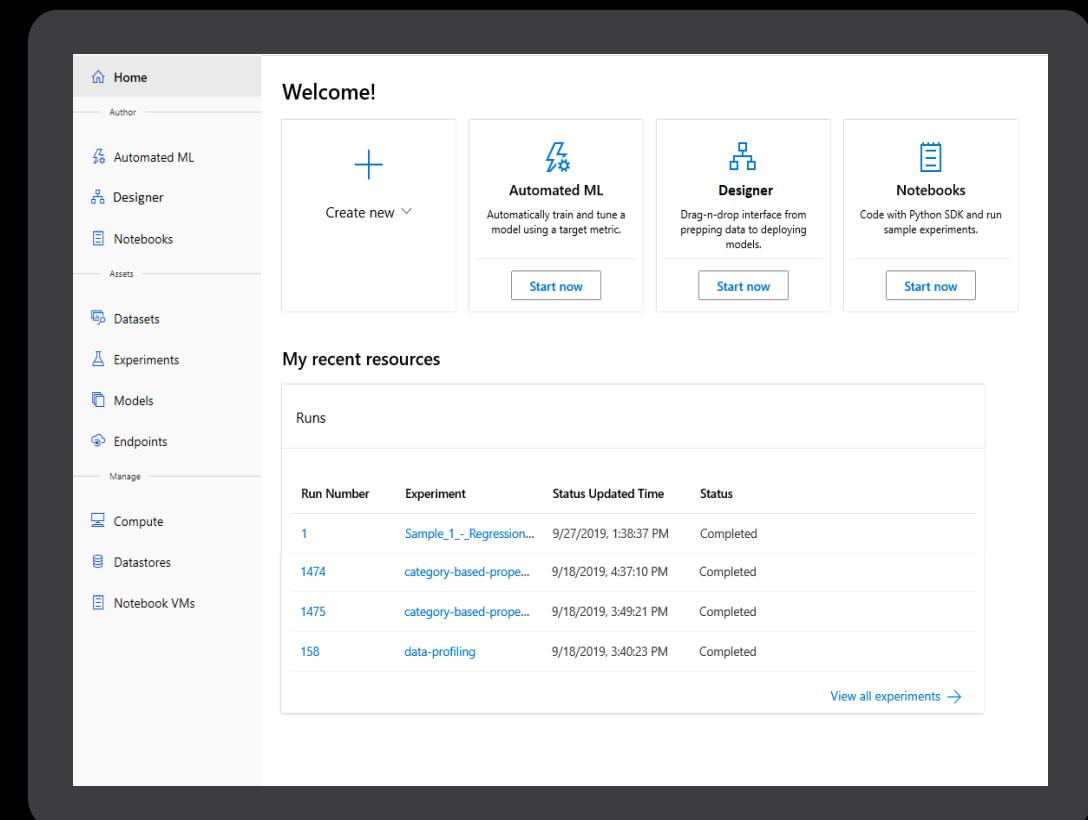
Event Grid integration

No-code model deployment

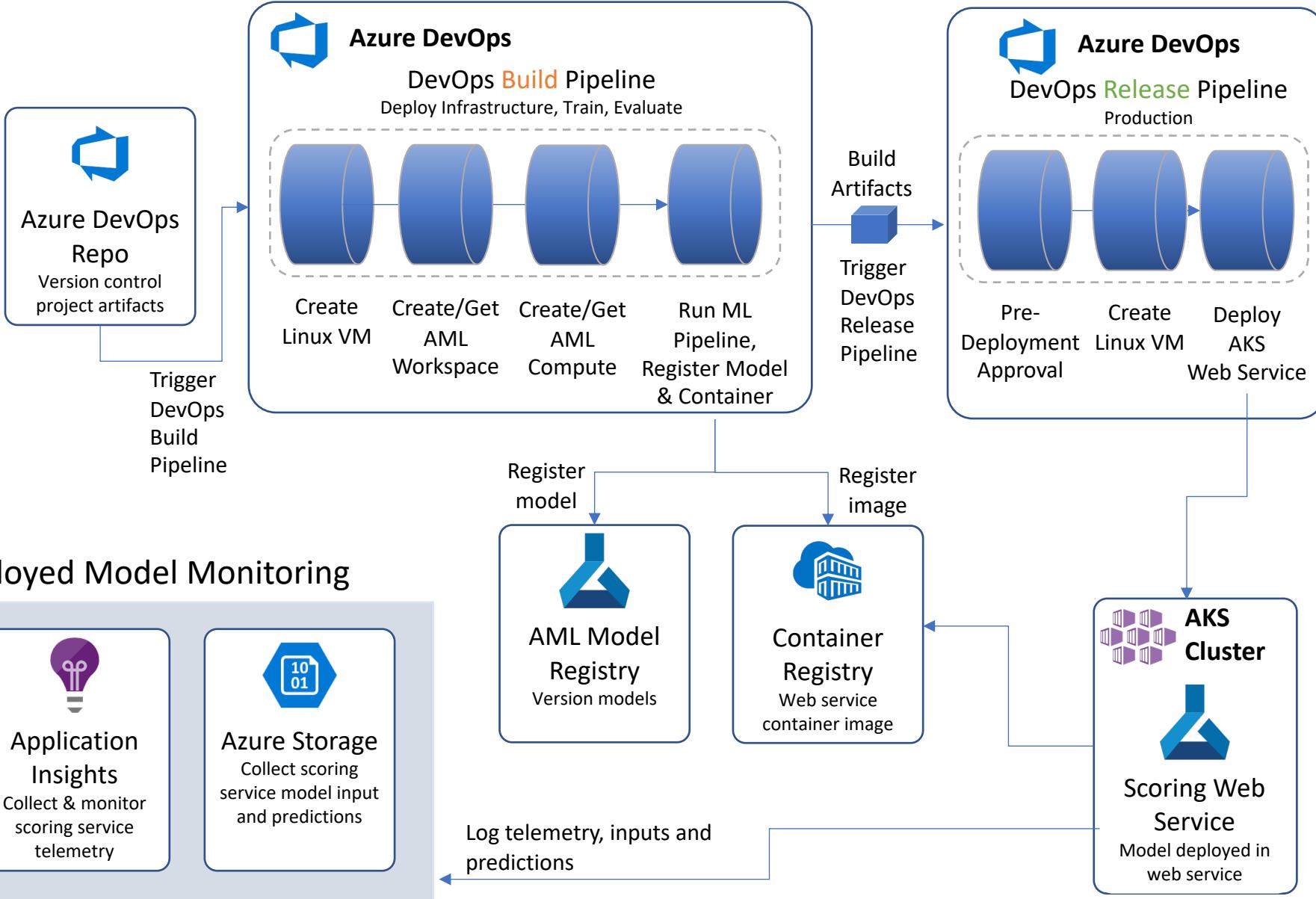
DevOps integration

Dataset drift analysis

Data Factory integration



# Hands-on Lab



# Hands-on Lab – setup guide overview

Full workshop content:

<https://github.com/tiagoh/MCW-ML-Ops-1Day>

How to get started ?

Follow-up the Before the hands-on lab setup guide

Potencial questions:

- AML Workspace ?
- AML Compute Instance ?
- Options to execute notebooks in Azure ?



# Wrap-up + Q&A

# Azure ML Components

## Experience

SDK, Notebooks, Drag-n-drop, Wizard

## MLOps

Reproducible, Automatable, GitHub, CLI, REST

## Datasets

Profiling, Drift, Labeling



## Training

Experiments, Runs



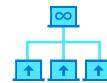
## Model Registry

Models, Images



## Inferencing

Batch, Realtime



## Compute

Jobs, Clusters, Instances



## IoT Edge

Security, Mgmt, Deployment



## Cloud

CPU, GPU, FPGA



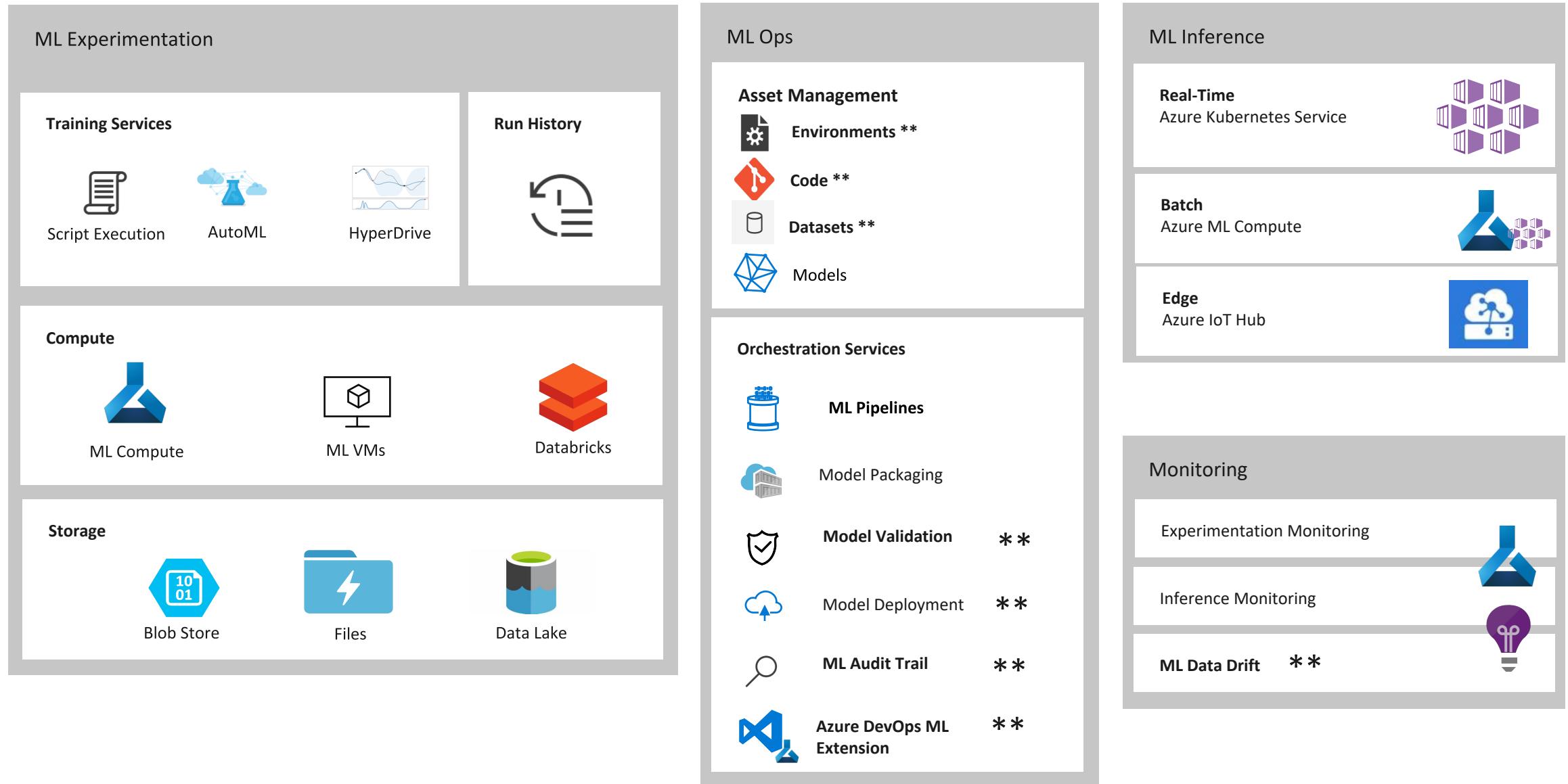
## Edge

CPU, GPU, NPU



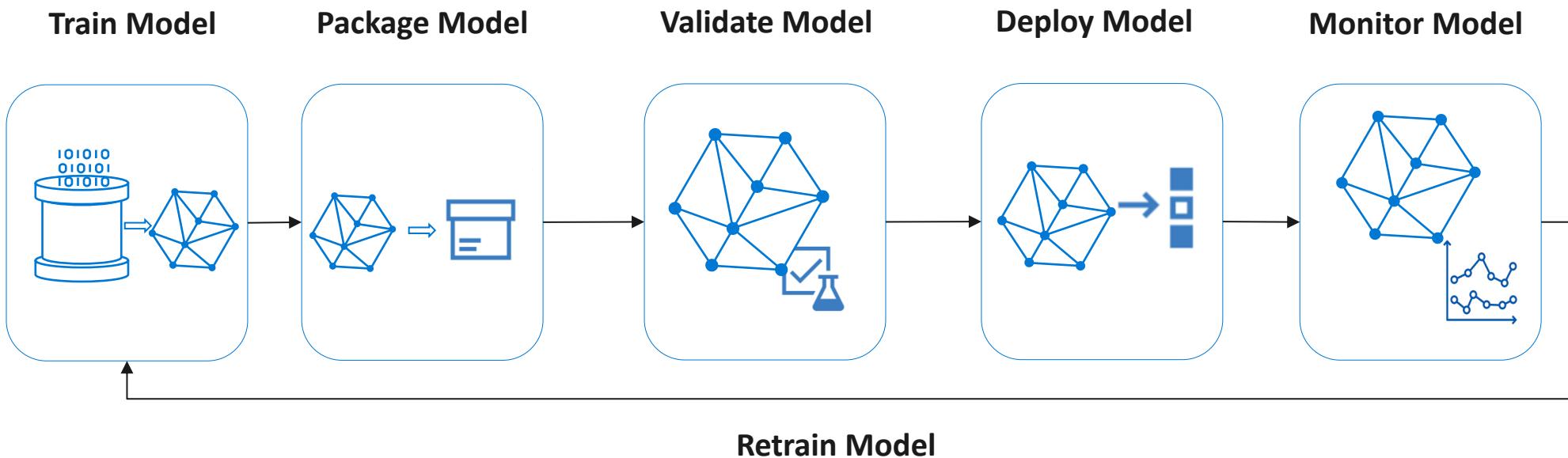
# New Capabilities - Azure MLOps

Asset management & orchestration services to help manage the ML lifecycle.



# Recap—E2E ML Lifecycle

- **Develop & train model** with reusable ML pipelines
- **Package model** using containers to capture runtime dependencies for inference
- **Validate model behavior**—functionally, in terms of responsiveness, in terms of regulatory compliance
- **Deploy model**—to cloud & edge, for use in real-time/streaming/batch processing
- **Monitor model** behavior & business value, know **when to replace/deprecate a stale model**



# MLOps accelerates going to Production

- We have pre-built solutions you can customize for your business
- We will continue to flesh these recipes out as we go
- Everything we build, we will build in the open!

# Conclusions

MLOps makes it possible to do production-grade ML

Azure is investing heavily in **MLOps**

Try Azure ML for MLOps **today!**

<https://aka.ms/mlops>

# Resources

Sources for this presentation:

- Ignite “Manage your end-to-end machine learning lifecycle with MLOps” | [BRK3035](#)
- Ignite: “Understanding enterprise readiness for machine learning solutions” | [BRK2017](#)

Related materials:

- R MLOps [presentation](#)



# Thank You!

ευχαριστώ

Salamat Po

متشکرم

شكراً

Grazie

благодаря

ありがとうございます

Kiitos Teşekkürler

謝謝

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Obrigado

شکریہ

Terima Kasih

Dziękuję

Hvala

Köszönöm

Tak

Dank u Wel

дякую

Tack

Mulțumesc

спасибо

Danke

Cám ơn

Gracias

多謝晒

Ďakujem

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Děkuji

감사합니다