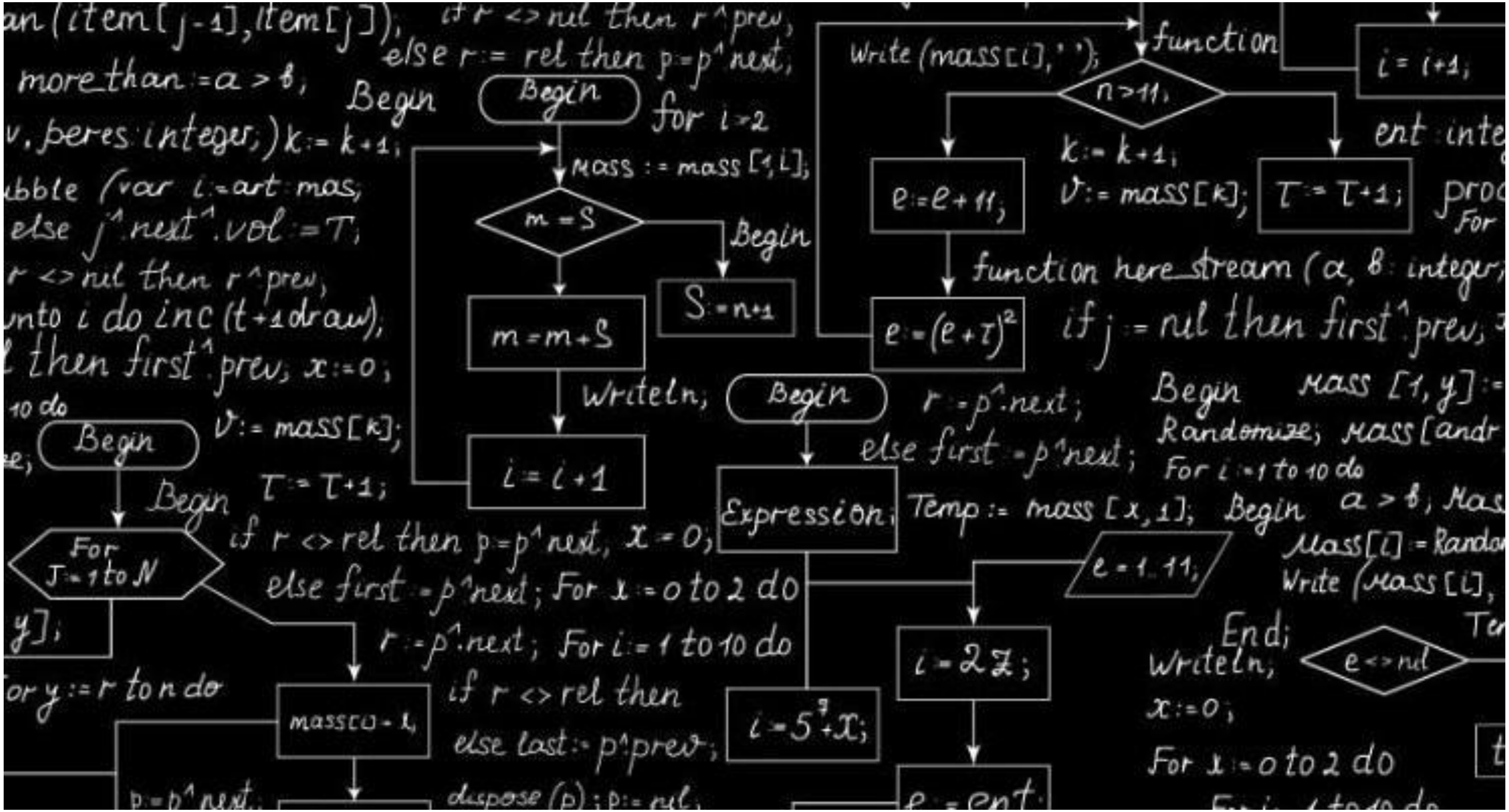
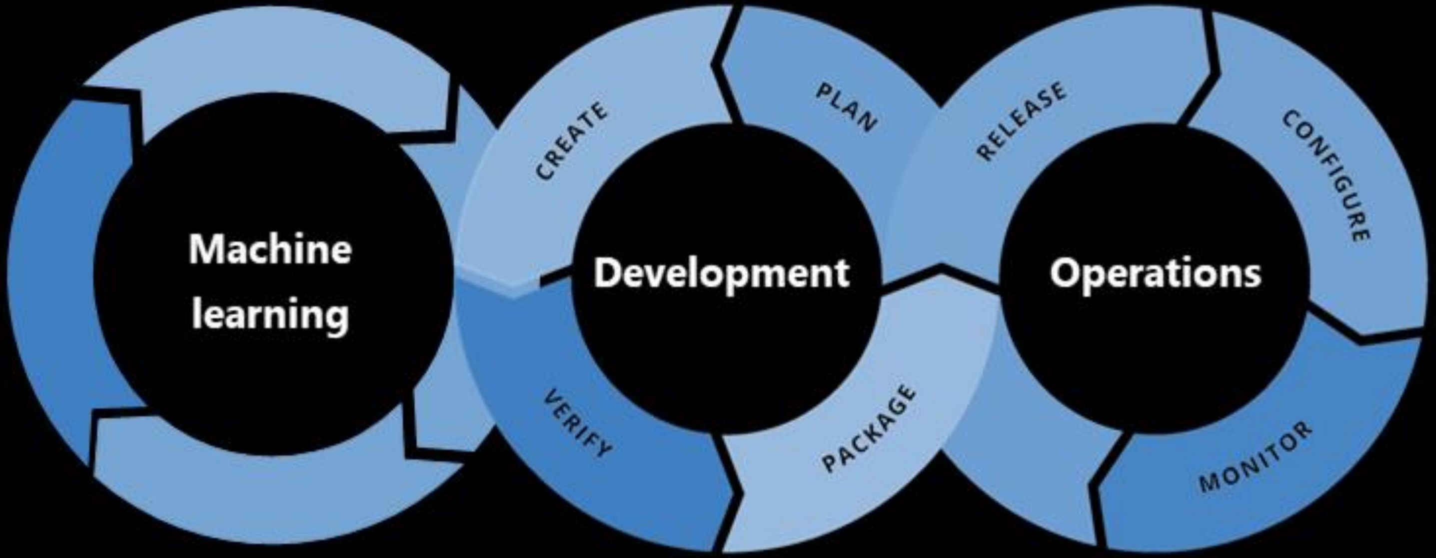


more than := a > b;
Begin
for i := 2
mass := mass [1, i];
m = S
Begin
S := n+1
m = m + S
Writeln;
i = i + 1
Write (mass[i], ' ');
function
n > 11
i = i+1;
k := k + 1;
V := mass [k];
e := e + 11;
T := T + 1;
function here_stream (a, b : integer);
e := (e + T)^2
if j = nil then first^.prev;
Begin
Randomize;
For i := 1 to 10 do
r := p^.next;
else first := p^.next;
Expression;
Temp := mass [x, 1];
Begin
e = 1..11;
i = 2Z;
i = 5^7 + X;
End;
Writeln;
x := 0;
For x := 0 to 2 do
e <> nil
Begin
For J = 1 to N
if r <> rel then p = p^.next; x = 0;
else first := p^.next; For x := 0 to 2 do
r := p^.next; For i := 1 to 10 do
if r <> rel then
else last := p^.prev;
dispose (p); p := nil;
mass[i] := 1;
V := mass [k];
T := T + 1;
for y := r to n do

EDSP - MLOPS

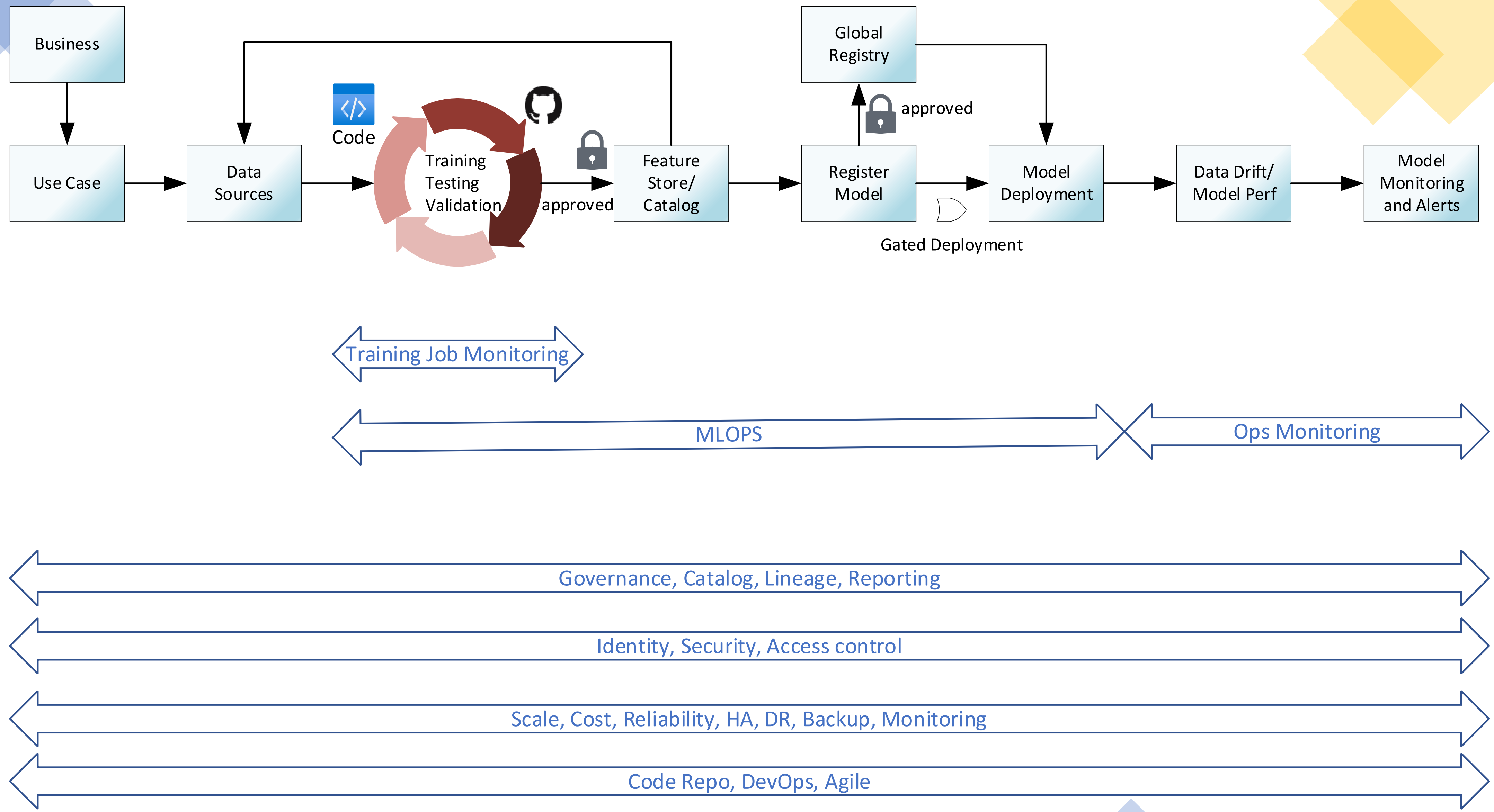
Machine learning operations: Machine learning plus development and operations



Experiment
Data acquisition
Business understanding
Initial modeling

Develop
Modeling and testing
Continuous integration
Continuous deployment

Operate
Continuous delivery
Data feedback loop
System and model monitoring


Business
Use Case
Data Sources
Code
Training Testing Validation
approved
Feature Store/ Catalog
Global Registry
approved
Register Model
Model Deployment
Gated Deployment
Data Drift/ Model Perf
Model Monitoring and Alerts
Training Job Monitoring
MLOPS
Ops Monitoring
Governance, Catalog, Lineage, Reporting
Identity, Security, Access control
Scale, Cost, Reliability, HA, DR, Backup, Monitoring
Code Repo, DevOps, Agile

Why do we Need MLOPS

- Streamline process
- IT Friendly
- IT Governance to manage and monitor multiple projects
- Framework for deployment
- Easy to use templates
- Structure to the code for deployment for various environments
- Common pattern across multiple projects

Azure Machine Learning (2 of 4)

Enterprise-grade machine learning service to build and deploy models faster

Structured data

Forecasting types
of ML scenarios

Unstructured data

All other ML scenarios;
NLP, Vision, IoT, etc.

Seamless studio experience for all skill levels

- Notebooks
- Automated ML UX
- Designer
- Tool Support i.e VS.Code, CLI

Comprehensive MLOPs capabilities

- Reproducibility
- Automation
- Deployment
- Re-training

Powerful compute

- CPU, GPU, FPGAs
- IoT Edge

Responsible ML capabilities

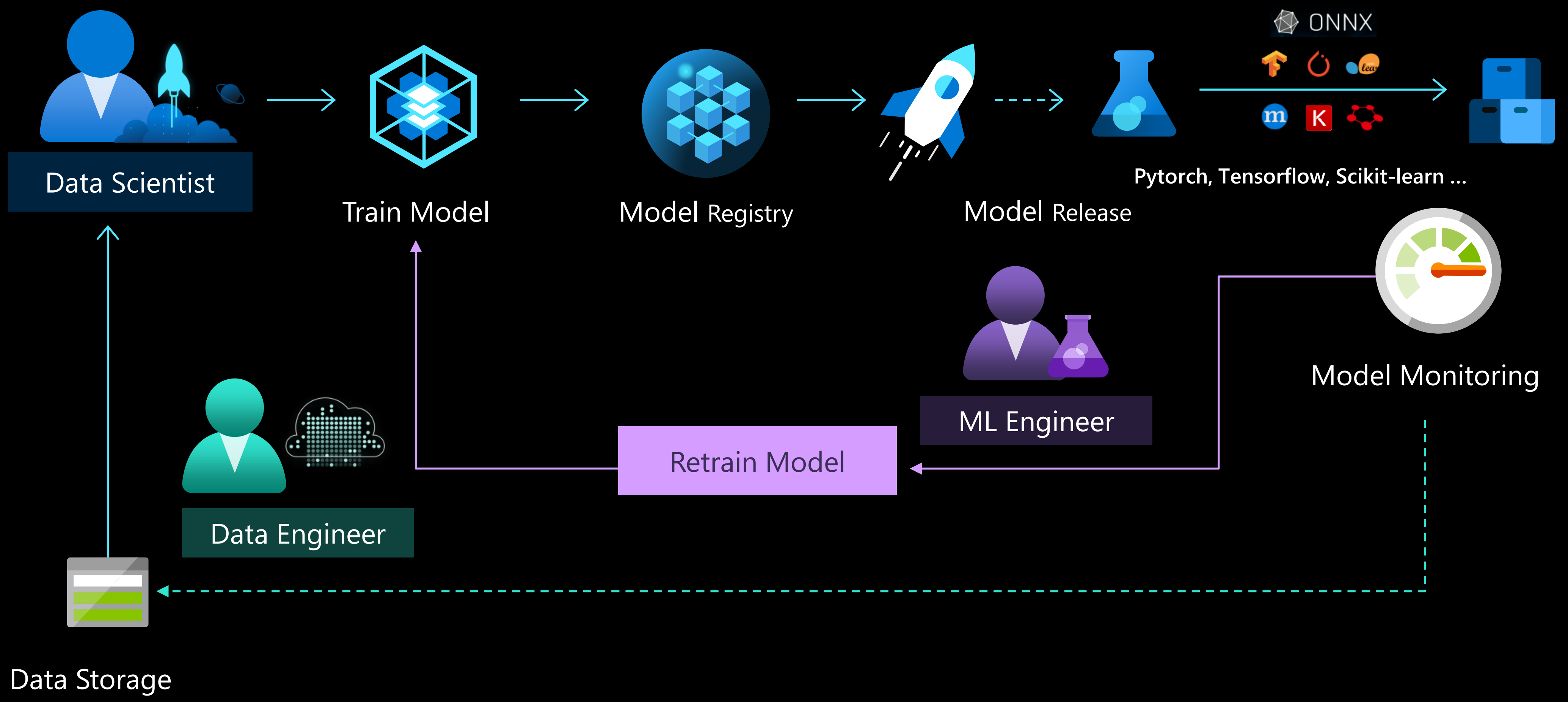
Apps

Models: AKS

Batch predictions: SQL DB

Analytics

The ML Lifecycle



What is Azure Machine Learning Service?

Set of Azure Cloud Services

+

Python SDK

AND/OR

CLI

+

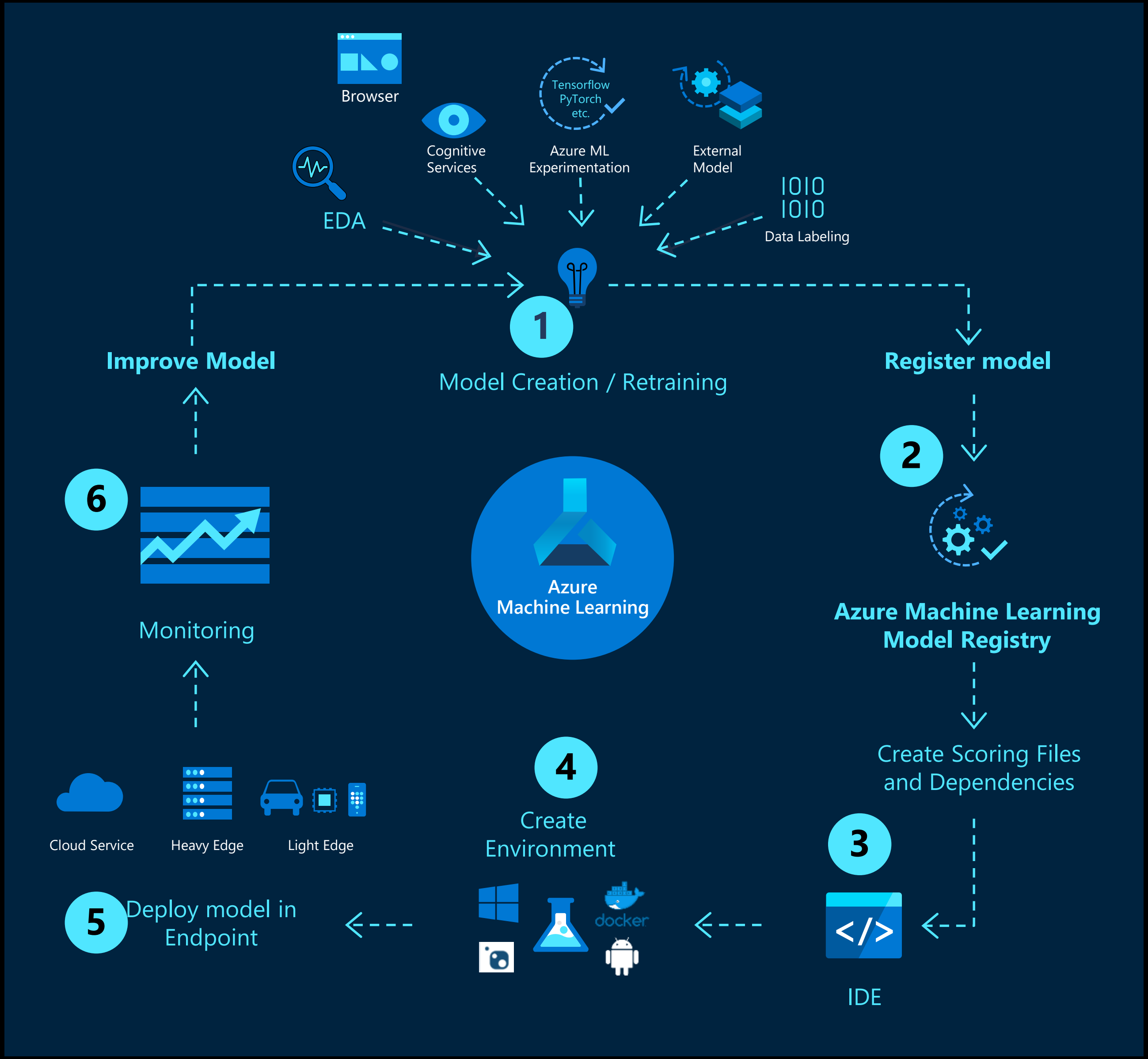
AML Studio or Interface of your choice

(Notebooks, Designer, AutoML, DSVM, VS Code)

That enables you to:

✓ Prepare Data	✓ Manage Models
✓ Build Models	✓ Track Experiments
✓ Train Models	✓ Deploy Models

Azure ML Service can implement the end-to-end ML lifecycle



Workflow Steps

1.
   a) Develop machine learning training scripts in R, Java, Julia or C# using an editor of your choice - Designer, Notebooks, VS Code, Jupyter etc.
   b) Alternatively, use AutoML for no code
   c) Create and configure a compute target
   d) Submit the scripts to the compute target to run in that environment. The script runs are saved to an experiment.
   e) Review experiment for logged metrics from the current and past runs. If the metrics do not indicate a desired outcome, loop back to step a) and iterate on your scripts.

2. Once a satisfactory run is found, register the persisted model in the model registry.
3. Develop a scoring script.
4. Create an Azure ML environment that captures the dependencies to deploy the model.
5. Deploy the model using Endpoints
6. Monitor the model in production and identify when further improvements / adjustments are needed including model and data drift.

HOW THE ROLES FUNCTION IN CUSTOMER

RACI

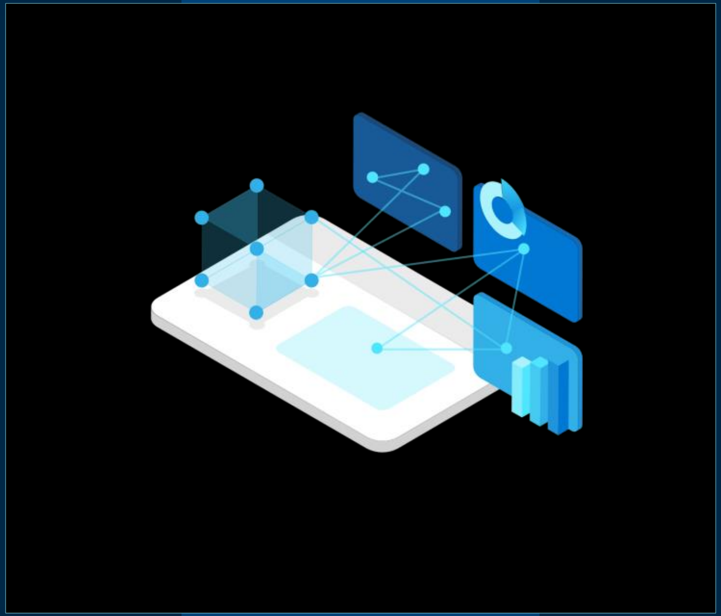
Matrix

If you take a look at the RACI chart for EDSP you'll notice two things immediately – first, the Account team is involved in every stage in the process, they should never be kept out of the loop. Second, accountability for the process is spread across several different roles, so teamwork and communication is essential. Although there are certain prescribed points information handoff, this process will work best with non-sensitive information being granted as freely as possible to all involved.

R Responsible A Accountable C Consulted I Informed

	Data Scientist	Business SME	Data Engineer	Business Owner	ML Engineer/CI /CD	IT – Azure/ Security
Data Engineering	C	C	R	I	I	I
ML Model	R	A	I	A	I	I
Prod Code	I	I	C	I	R	I
MLOps	I	I	A	I	R	C
Business analyst/ Validate	A	R	A	R	I	I
Prod Deploy	C	I	I	I	R	A

MLOps



MLOps == How to bring ML to production

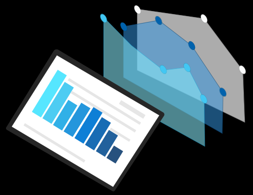
Bring together people, process, and platform to automate ML-infused software delivery & provide continuous value to our users.

People

Blend together the work of individual engineers in a repository.

Each time you commit, your work is automatically built and tested, and bugs are detected faster.

Code, data, models and training pipelines are shared to accelerate innovation.



Process

Provide templates to bootstrap your infrastructure and model development environment, expressed as code.

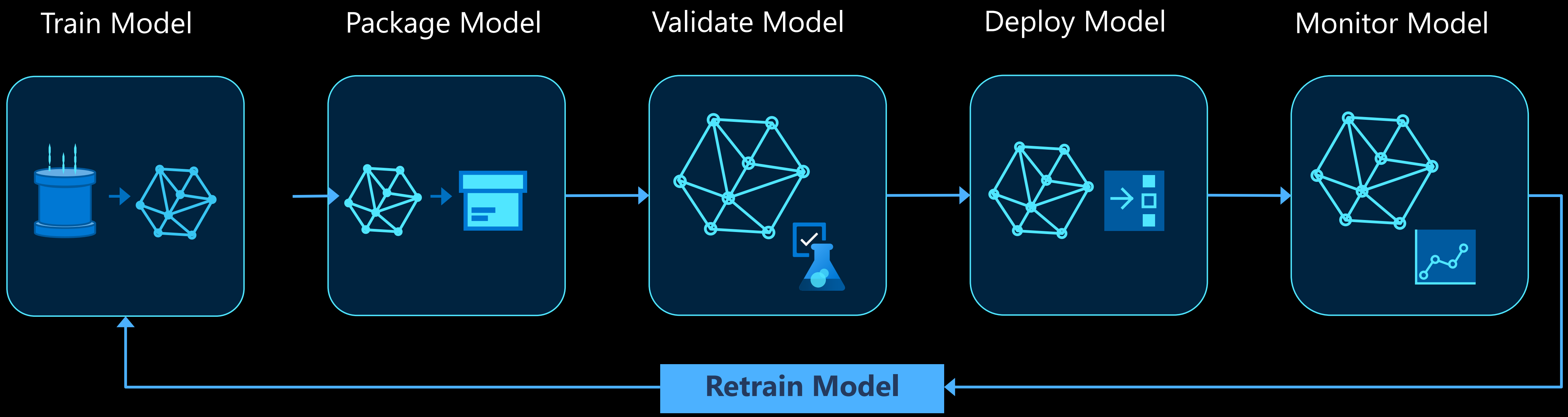
Automate the entire process from code commit to production.

Platform

Safely deliver features to your customers as soon as they're ready.

Monitor your pipelines, infrastructure and products in production and know when they aren't behaving as expected.

What does MLOps look like?



Develop & train model that solves a real business problem

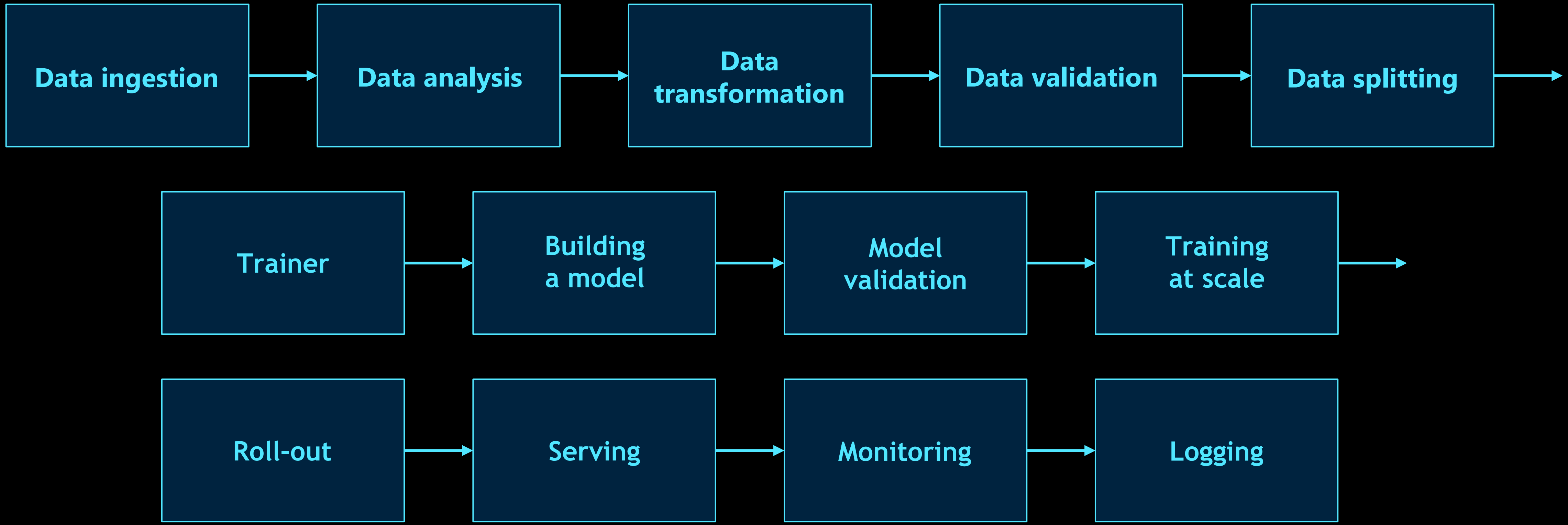
Package model so you can use it somewhere else

Validate model behavior functionally, in terms of responsiveness & regulatory compliance

Deploy model use the model to make predictions

Monitor model behavior & business value, know **when to replace / deprecate a stale model**

Components of the MLOps lifecycle



MLOps Benefits

Automation / Observability

Generate and deploy code drives

Pipelines are reproducible and verifiable

You can tag and audit all artifacts.

Validation

SWE Best Practices for Quality Control

Offline comparison of model quality

Minimize bias and provide descriptiveness

Reproducibility/Auditability

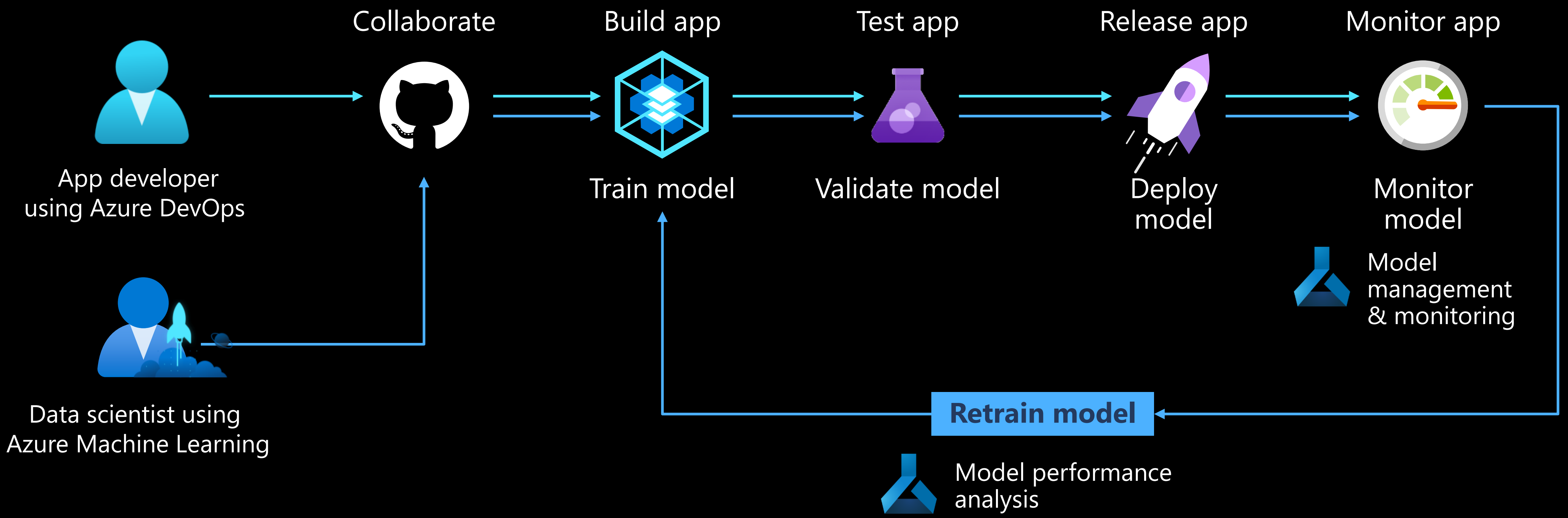
Controlled rollout capabilities

Live comparison of predicted and expected performance

Results feedback to monitor drift and improve model

== VELOCITY and SECURITY (For ML)

MLOps Workflow



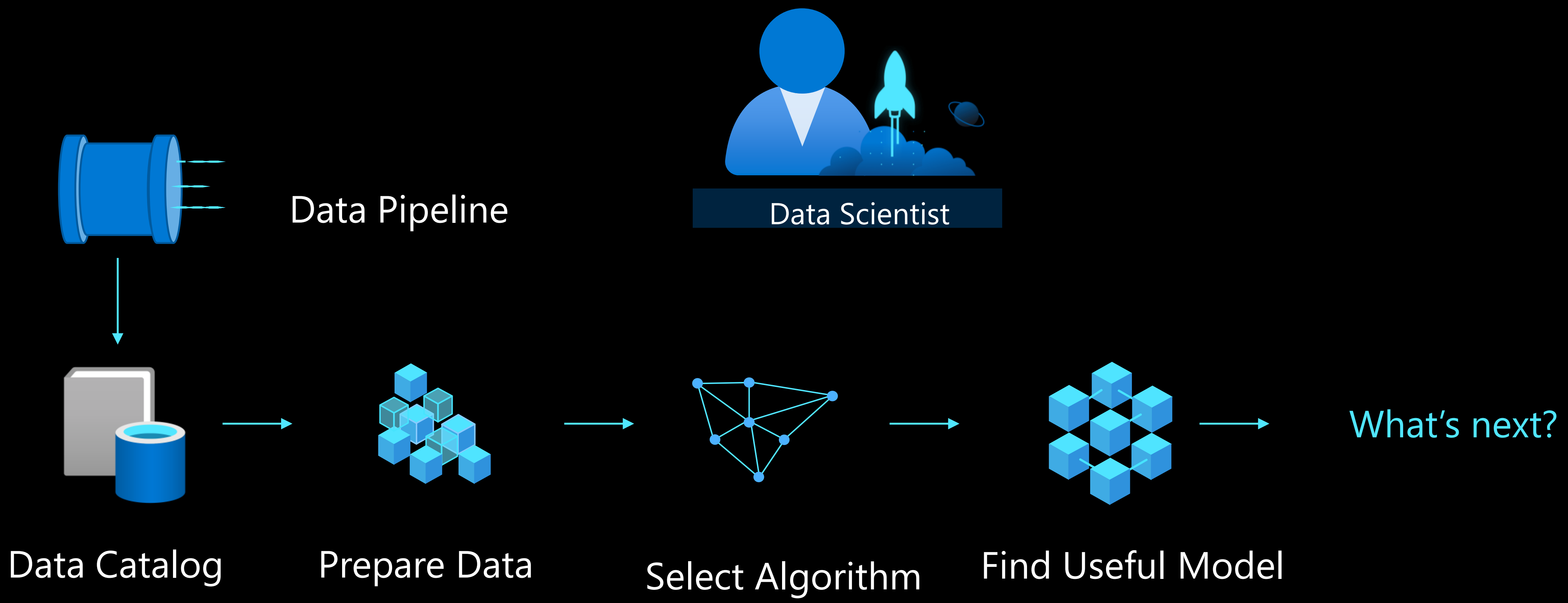
- Model reproducibility
- Model validation
- Model deployment
- Model retraining

MLOps Maturity stages

Maturity Level	Training Process	Release Process	Integration into app
Level 1 – No MLOps	Untracked, file is provided for handoff	Manual, hand-off	Manual, heavily DS driven
Level 2- Training Operationalized	Tracked, run results and model artifacts are captured in a repeatable way	Manual release,clean handoff process, managed by SWE team	Manual, heavily DS driven, basic integration tests added
Level 3 – Release Operationalized	Tracked, run results and model artifacts are captured in a repeatable way	Automated, CI/CD pipeline set up, everything is version controlled	Semi-automated, unit and integration tests added, still needs human signoff
Level 4 – Training & Release Operationalized Together	Tracked, run results and model artifacts are captured in a repeatable way, **retraining set up** based on metrics from app	Automated, CI/CD pipeline set up, everything is version controlled, A/B testing has been added	Semi-automated, unit and integration tests added, **may** need human signoff

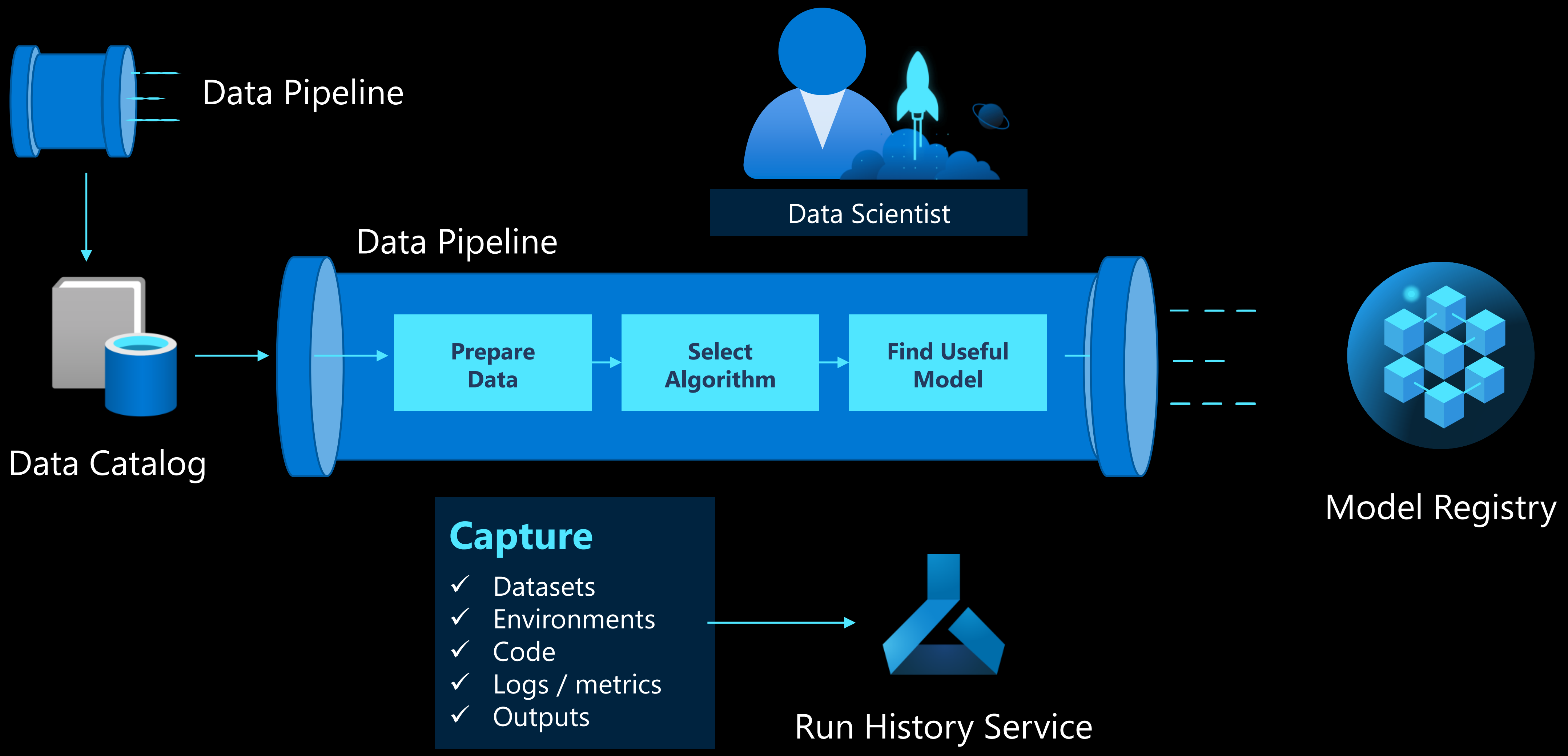
Level 1 – No MLOps

Interactive, exploratory, get to something useful.



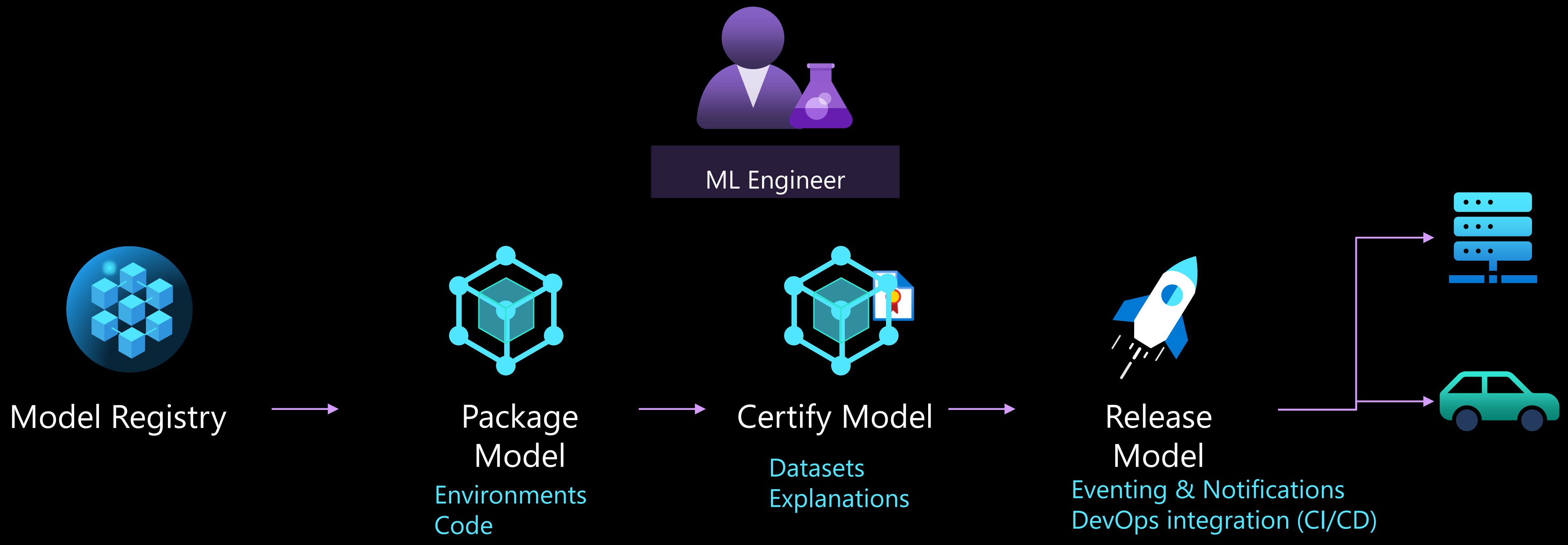
Level 2 – Reproducible Model Training

Version code, data, ensure model can be recreated

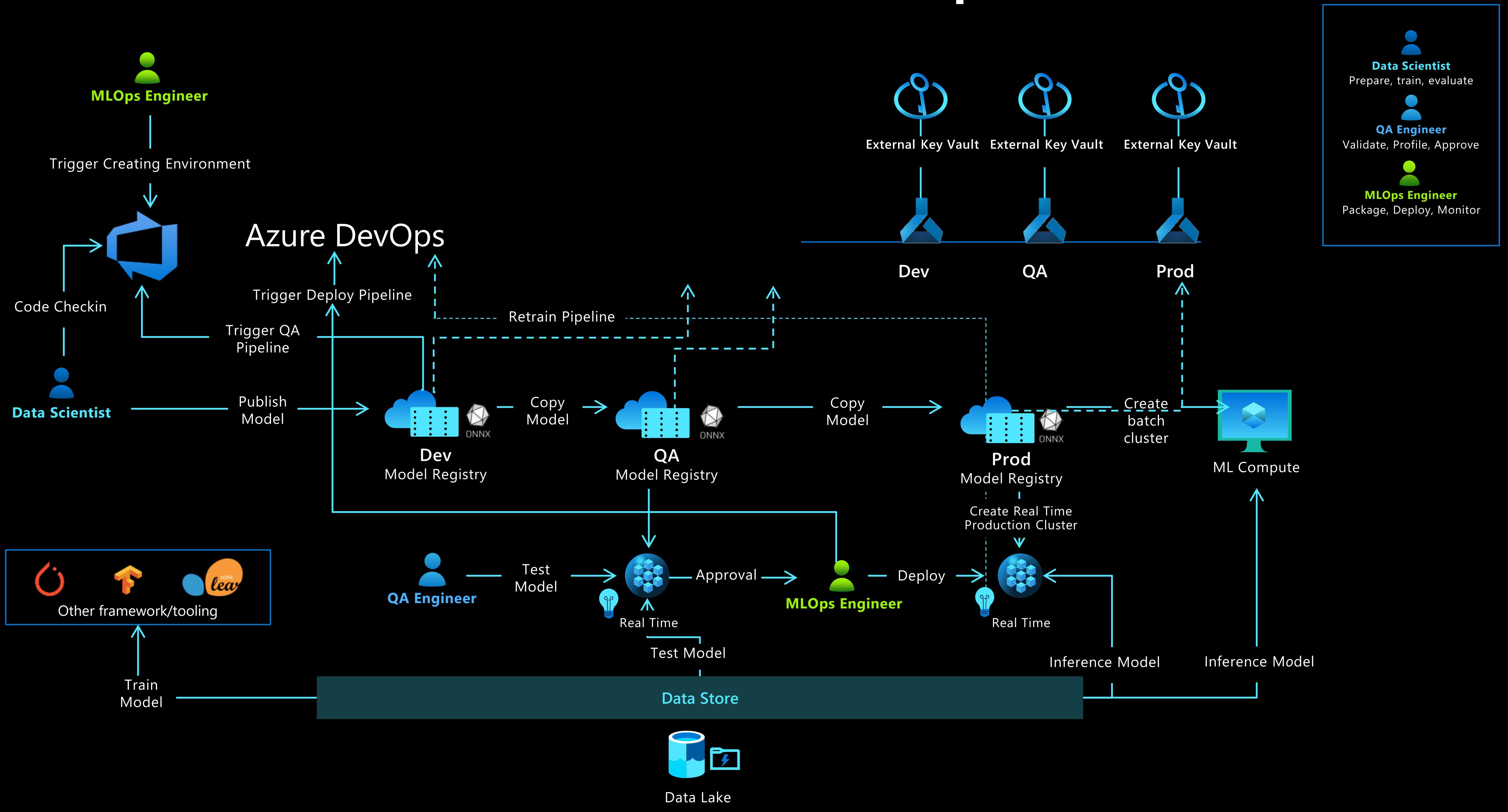


Level 3 – Managed Model Operationalization

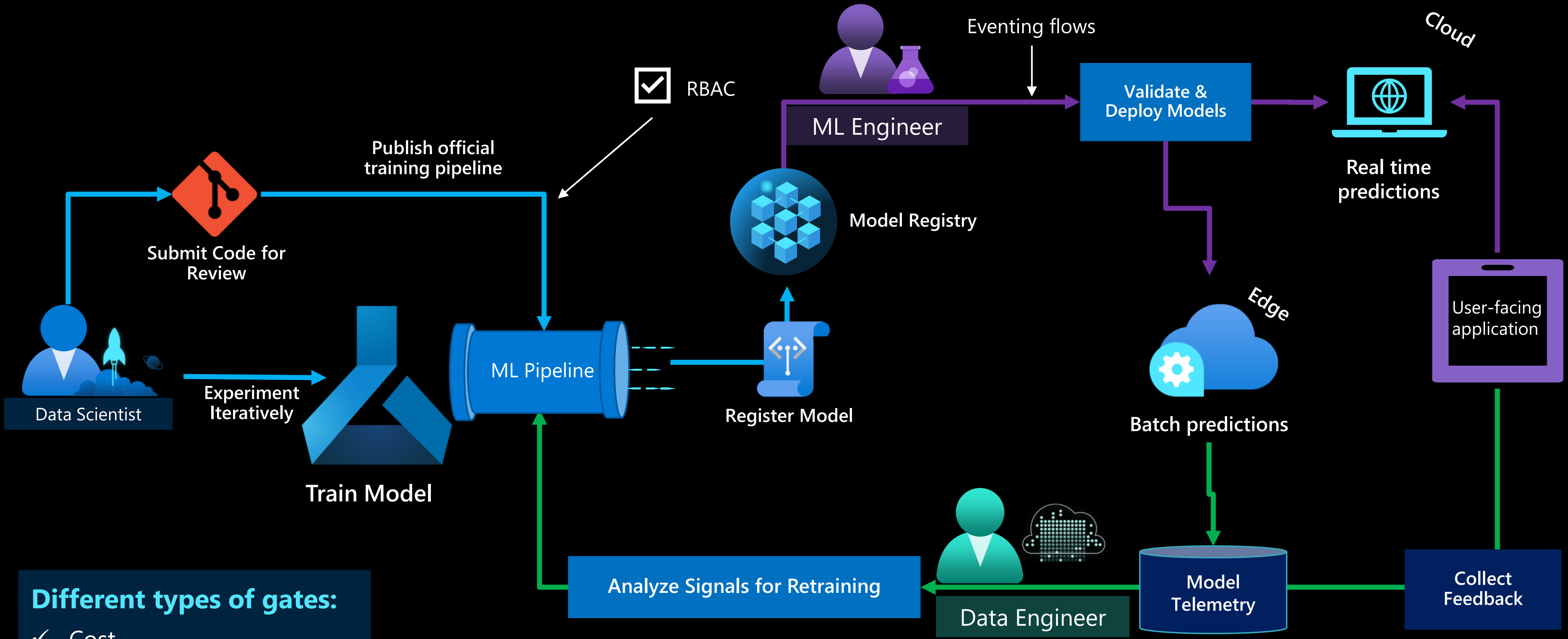
Package, certify, deploy



Level 4 – E2E MLOps

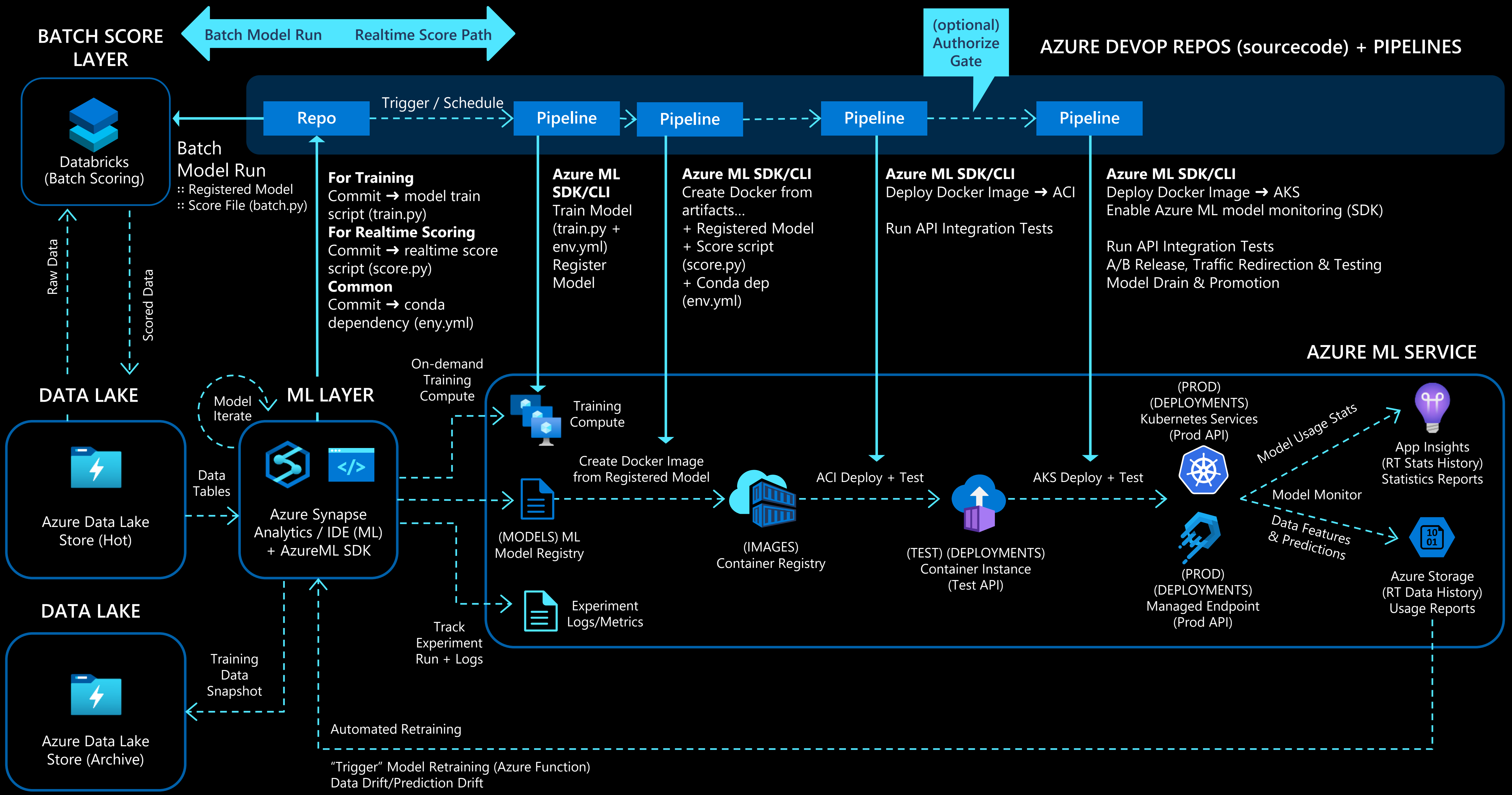


Generalized DS MLOps process



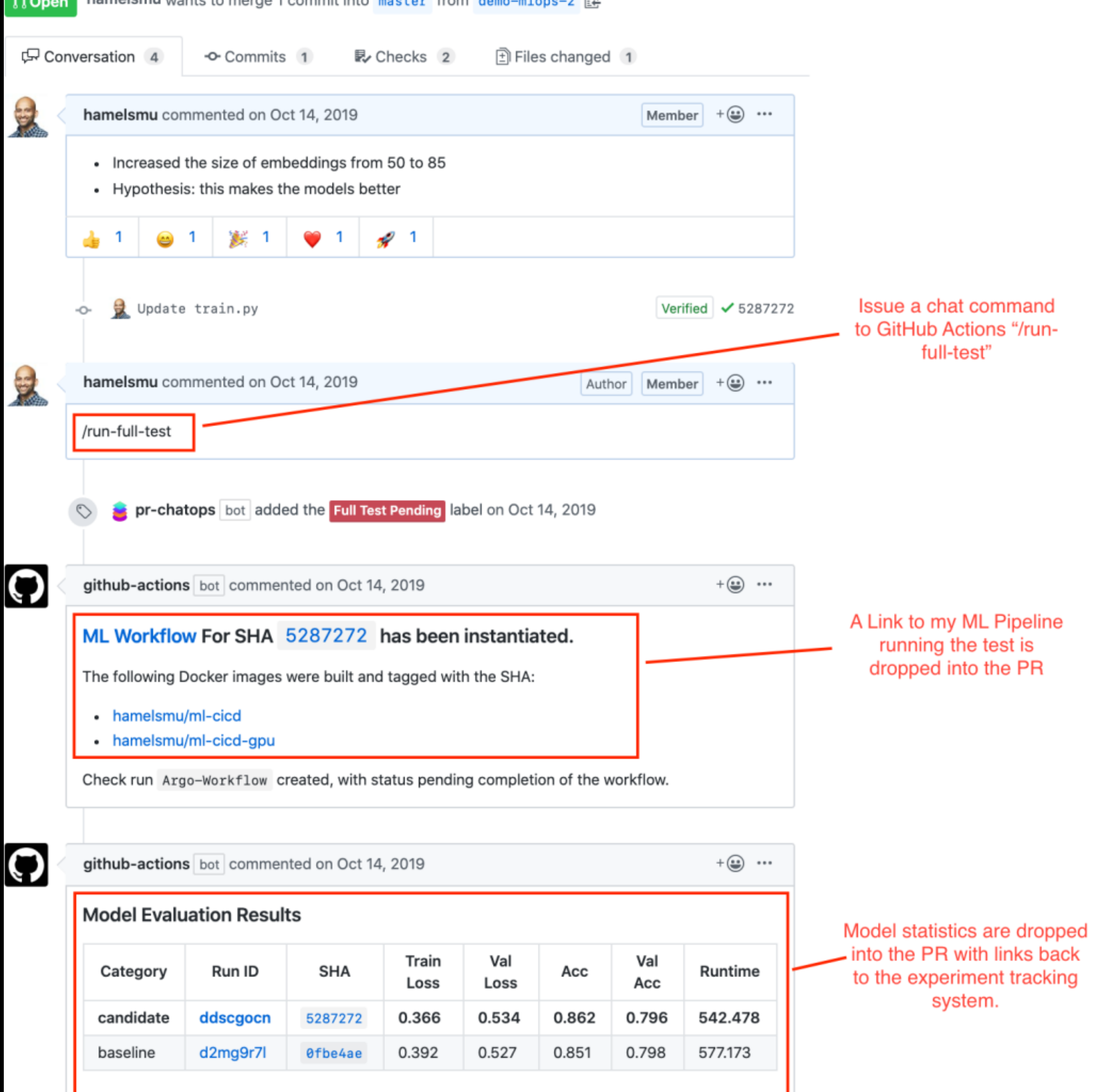
Different types of gates:

- ✓ Cost
- ✓ Compliance
- ✓ Quota


BATCH SCORE LAYER
Batch Model Run
Realtime Score Path
(optional) Authorize Gate
AZURE DEVOP REPOS (sourcecode) + PIPELINES
Databricks (Batch Scoring)
Repo
Trigger / Schedule
Pipeline
Pipeline
Pipeline
Pipeline
Batch Model Run
:: Registered Model
:: Score File (batch.py)
For Training
Commit ➔ model train script (train.py)
For Realtime Scoring
Commit ➔ realtime score script (score.py)
Common
Commit ➔ conda dependency (eny.yml)
Azure ML SDK/CLI
Train Model (train.py + env.yml)
Register Model
Azure ML SDK/CLI
Create Docker from artifacts...
+ Registered Model
+ Score script (score.py)
+ Conda dep (env.yml)
Azure ML SDK/CLI
Deploy Docker Image ➔ ACI
Run API Integration Tests
Azure ML SDK/CLI
Deploy Docker Image ➔ AKS
Enable Azure ML model monitoring (SDK)
Run API Integration Tests
A/B Release, Traffic Redirection & Testing
Model Drain & Promotion
Raw Data
Scored Data
AZURE ML SERVICE
DATA LAKE
Model Iterate
ML LAYER
On-demand Training Compute
Training Compute
(PROD) (DEPLOYMENTS) Kubernetes Services (Prod API)
Model Usage Stats
App Insights (RT Stats History) Statistics Reports
Azure Data Lake Store (Hot)
Data Tables
Azure Synapse Analytics / IDE (ML) + AzureML SDK
Create Docker Image from Registered Model
ACI Deploy + Test
AKS Deploy + Test
Model Monitor
Data Features & Predictions
(MODELS) ML Model Registry
(IMAGES) Container Registry
(TEST) (DEPLOYMENTS) Container Instance (Test API)
(PROD) (DEPLOYMENTS) Managed Endpoint (Prod API)
Azure Storage (RT Data History) Usage Reports
Experiment Logs/Metrics
Track Experiment Run + Logs
DATA LAKE
Azure Data Lake Store (Archive)
Training Data Snapshot
Automated Retraining
“Trigger” Model Retraining (Azure Function)
Data Drift/Prediction Drift

GitHub Actions Integration

Create AzureML Workspace
Manage Azure Compute
Run Jobs in AzureML
Register Models in AzureML
Deploy Models in AzureML
http://mlops-github.com/actions



Getting started with Github Actions + MLOps

Azure/azureml-template: Official Azure Machine Learning template for GitHub

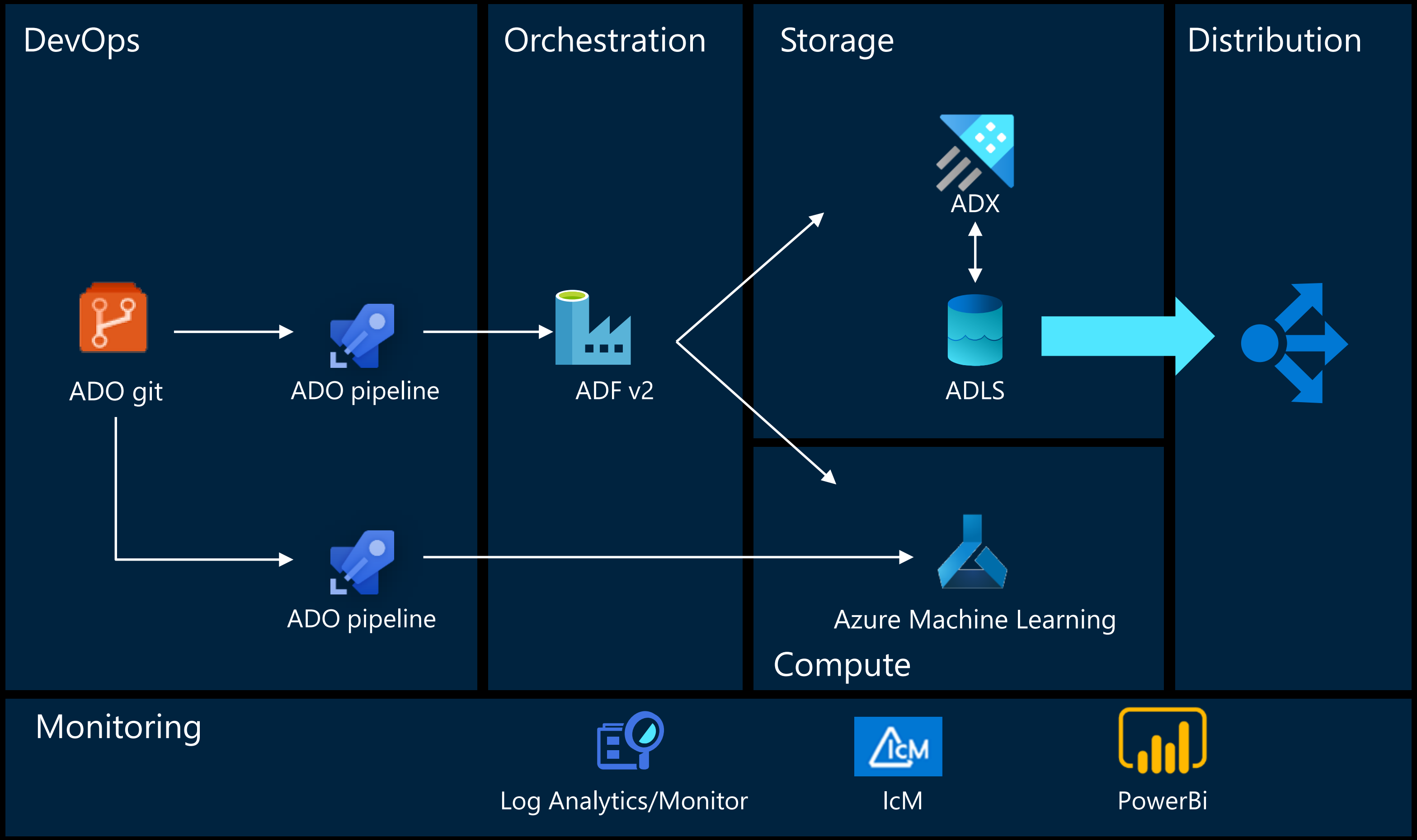
A light-weight template to use to demonstrate how to automate your ML lifecycle using Git hub actions.

Other examples: GitHub - Azure/azureml-examples: Official community-driven Azure Machine Learning examples, tested with GitHub Actions

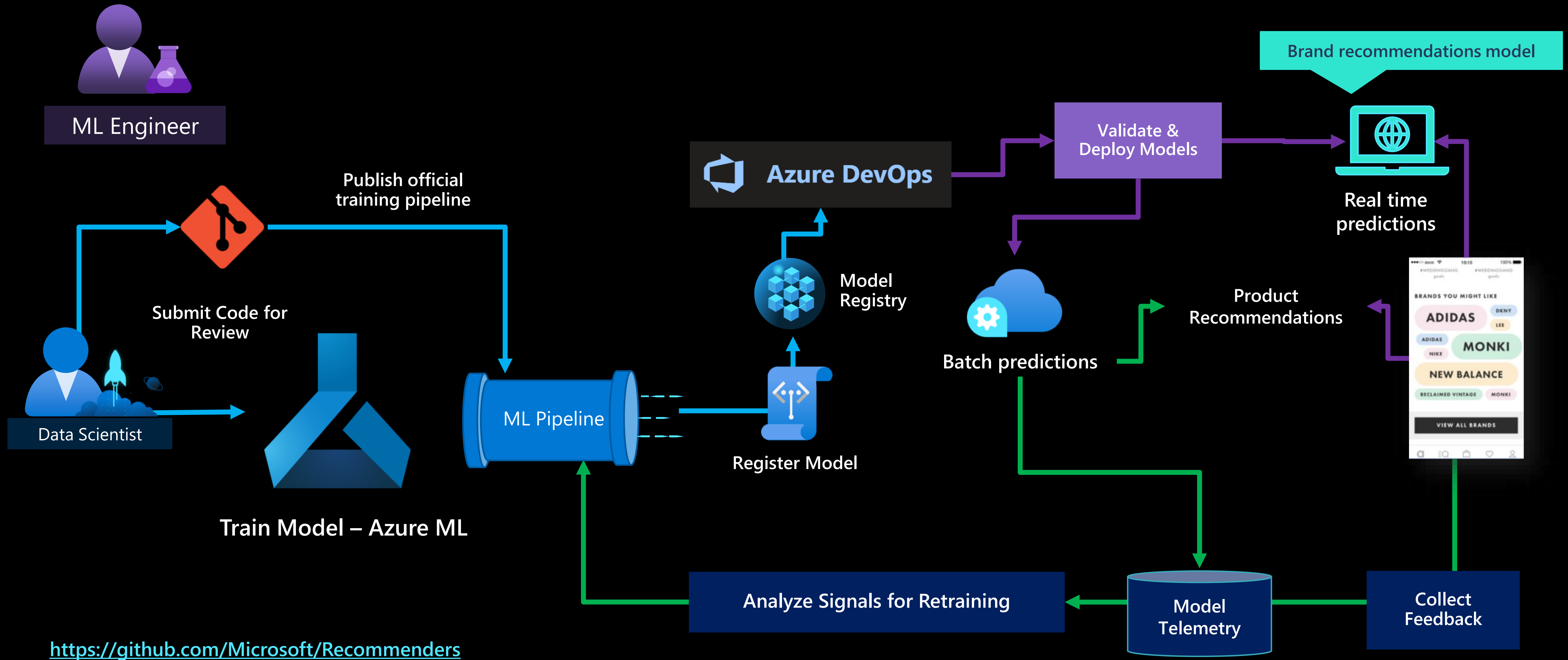
Examples of MLOps Deployment Patterns

Common Deployment& Orchestration Patterns

Data Factory | DataLake | DevOps Pipeline



Leveraging MLOps to ship recommender systems.



https://github.com/Microsoft/Recommenders

Azure Arc enabled Kubernetes GitOps Flow