Microsoft

Azure Machine Learning service:

A Technical Overview

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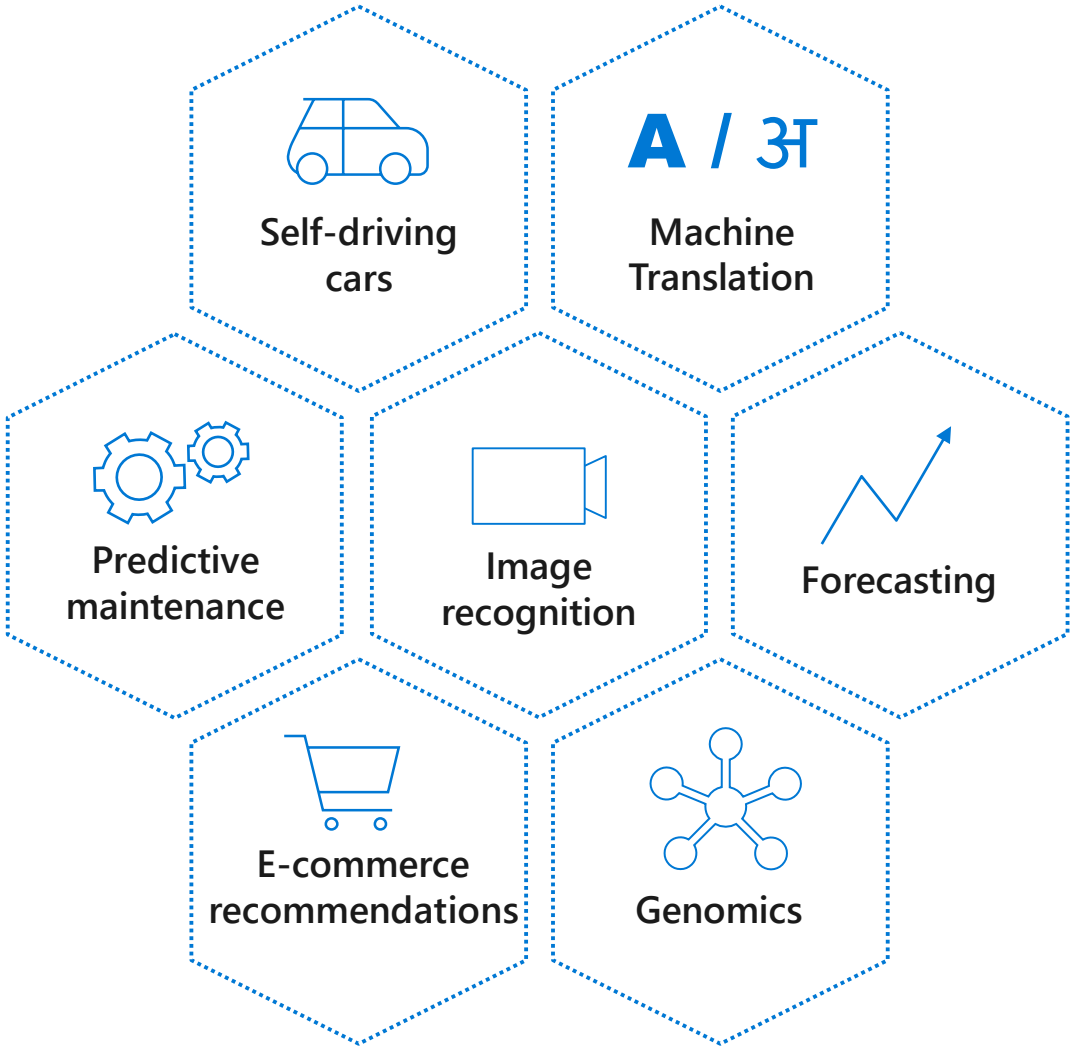
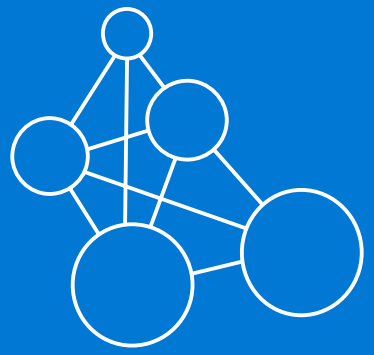
Machine Learning

Applications

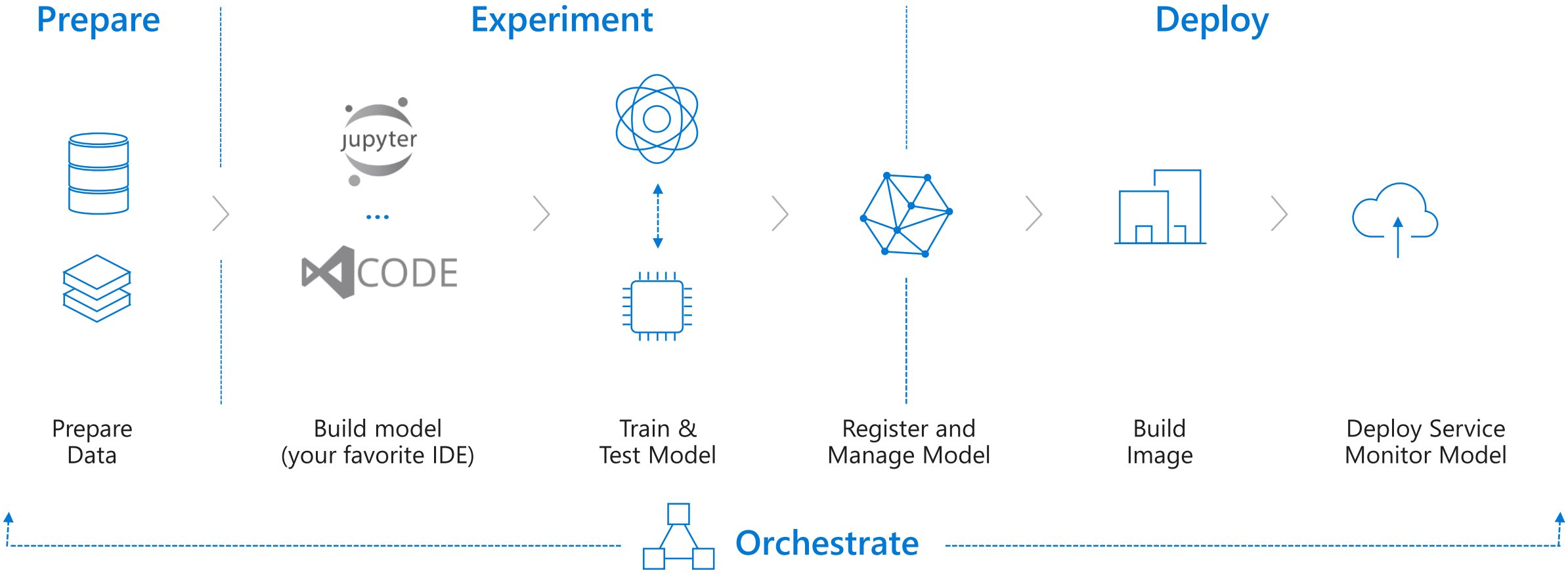




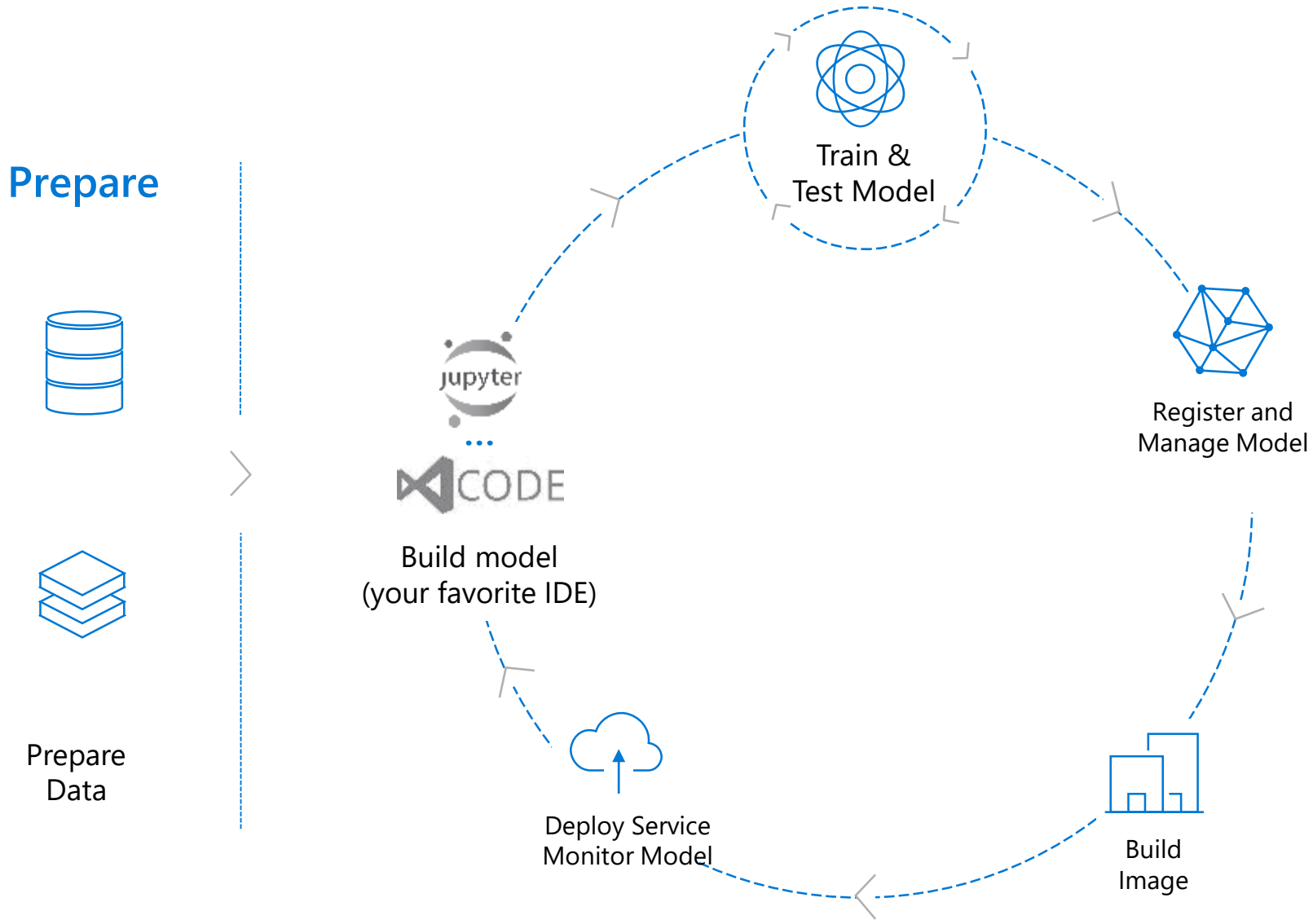
Requirements of an advanced ML Platform

Machine Learning

Typical E2E Process



DevOps loop for data science



Data Preparation

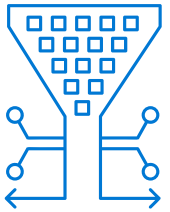
Requirements

Multiple Data Sources

SQL and NoSQL databases, file systems, network attached storage and cloud stores (such as Azure Blob Storage) and HDFS.

Multiple Formats

Binary, text, CSV, TS, ARFF, etc.



Cleansing

Detect and fix NULL values, outliers, out-of-range values, duplicate rows.

Transformation

General data transformation (transforming types) and ML-specific transformations (indexing, encoding, assembling into vectors, normalizing the vectors, binning, normalization and categorization).

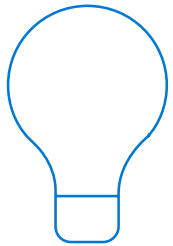
Model Building

Requirements

Choice of algorithms

Choice of language

Python



Choice of development tools

Browser-based, REPL-oriented, notebooks such as Jupyter, PyCharm and Spark Notebooks.

Desktop IDEs such as Visual Studio and R-Studio for R development.

Local Testing

To verify correctness before submitting to a more powerful (and expensive) training infrastructure.

Model Training

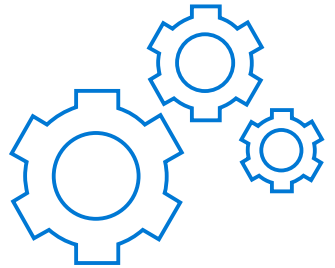
Requirements

Powerful Compute Environment

Choice should include scale-up VMs, auto-scaling scale-out clusters

Preconfigured

The compute environment should be pre-setup with all the correct versions ML frameworks, libraries, executables and container images.



Job Management

Data scientists should be able to easily start, stop, monitor and manage Jobs.

Automated Model and Parameter Selection

Solution should automatically select the best algorithms, and the corresponding best hyperparameters, for the desired outcome.

Model Registration and Management

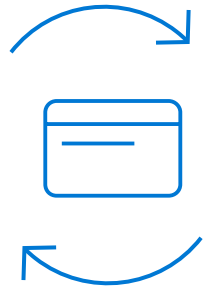
Requirements

Containerization

Automatically convert models to Docker containers so that they can be deployed into an execution environment.

Versioning

Assign versions numbers to models, to track changes over time, to identify and retrieve a specific version for deployment, for A/B testing, rolling back changes etc.



Model Repository

For storing and sharing models, to enable integration into CI/CD pipelines.

Track Experiments

For auditing, see changes over time and enable collaboration between team members.

Model Deployment

Requirements

Choice of Deployment Environments

Single VM, Cluster of VMs, Spark Clusters, Hadoop Clusters, In the cloud, On-premises

Edge Deployment

To enable predictions close to the event source-for quicker response and avoid unnecessary data transfer.

Security

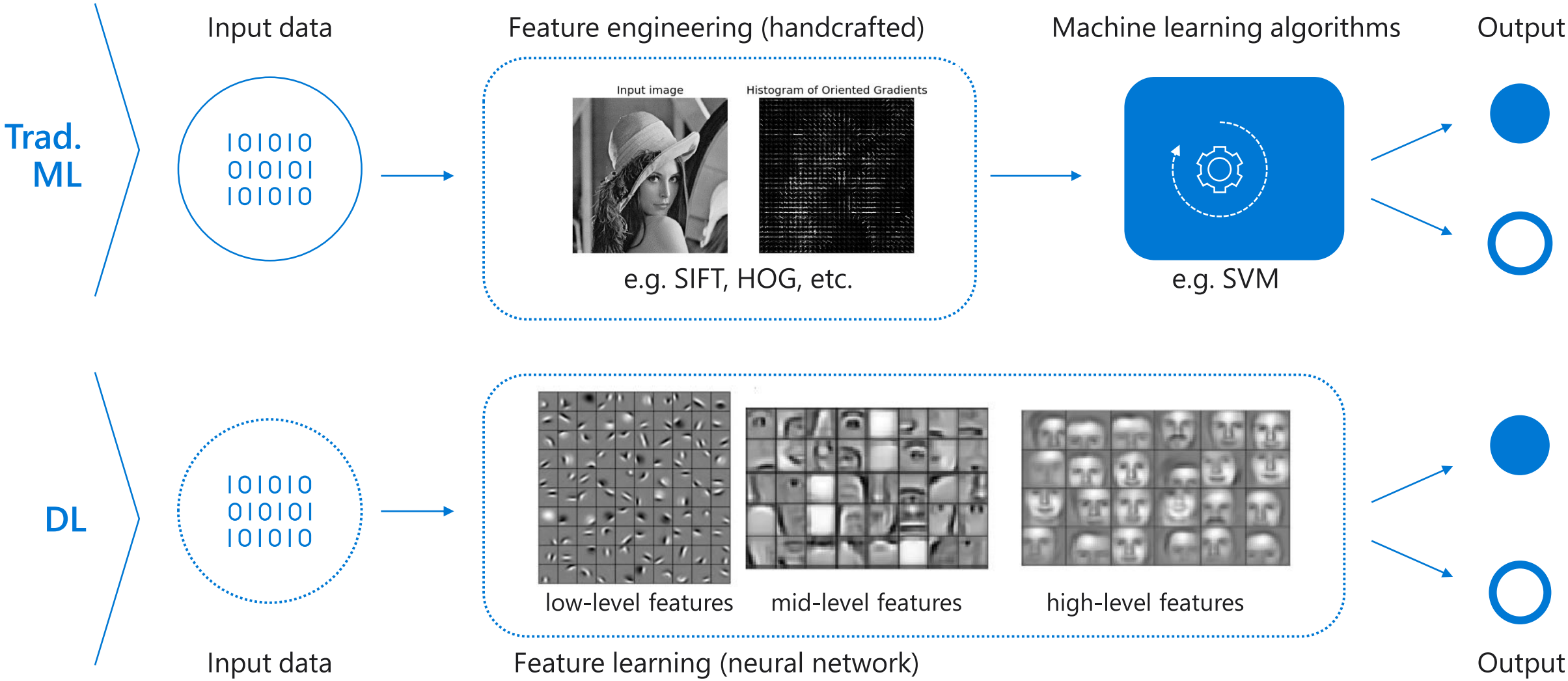
Even when deployed at the edge, the e2e security must be maintained. Models should be deployed and data transmitted only to secure, authenticated devices.

Monitoring

Monitor the status, performance and security.

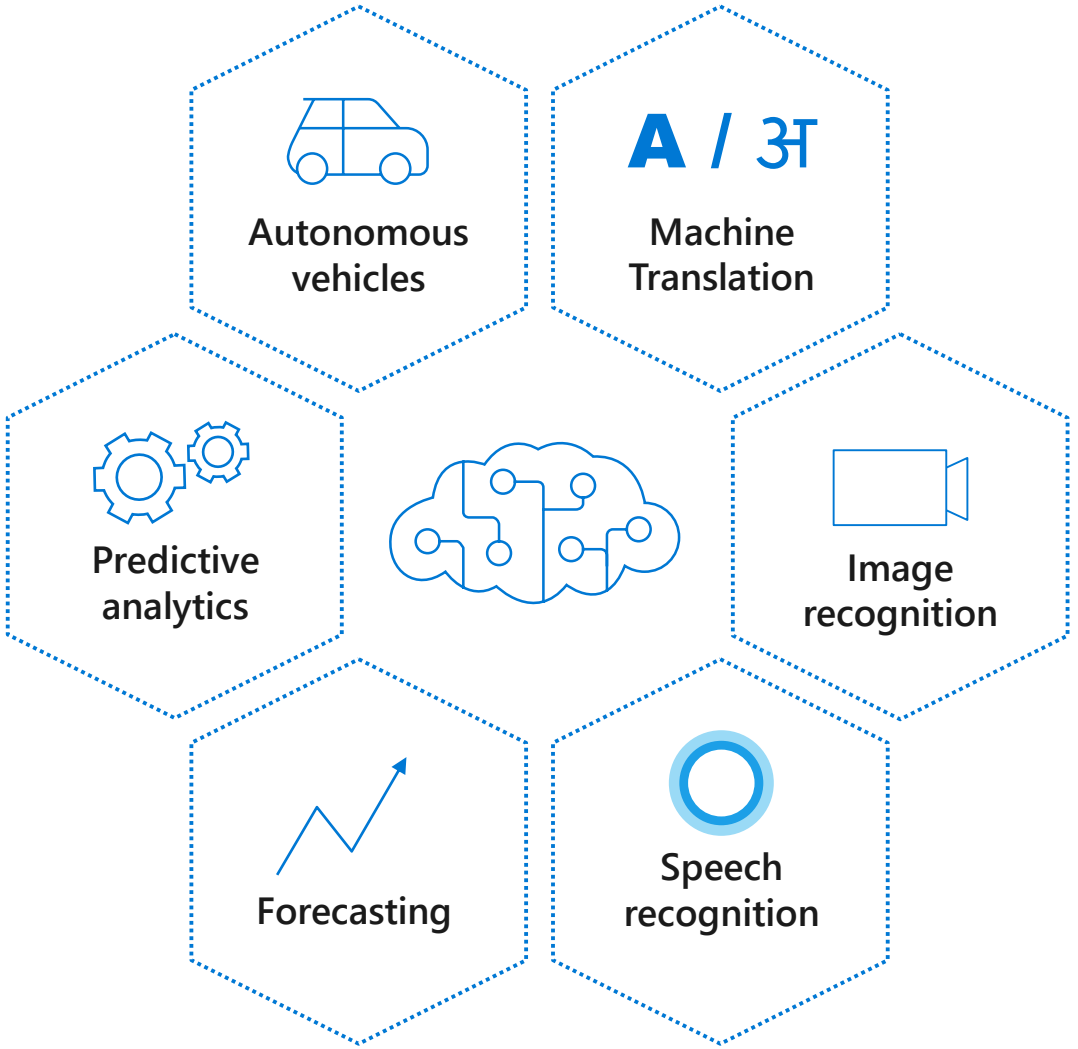
Deep Learning places additional requirements

Traditional ML versus DL

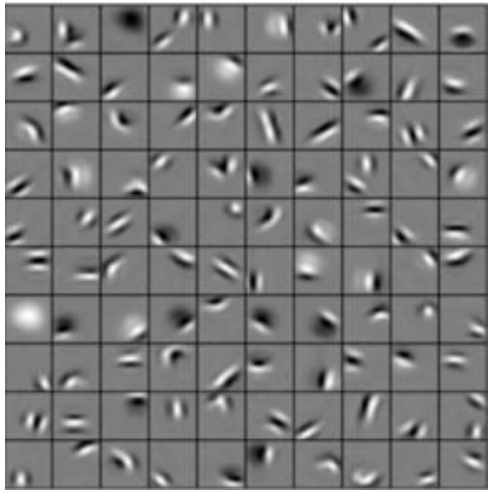


Top figure source;
Bottom figure from NVIDIA

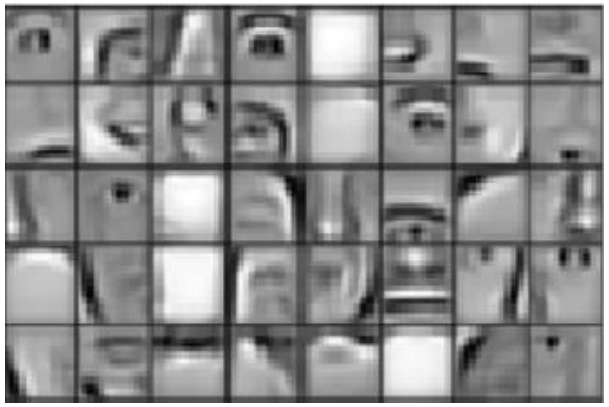
Some deep learning applications



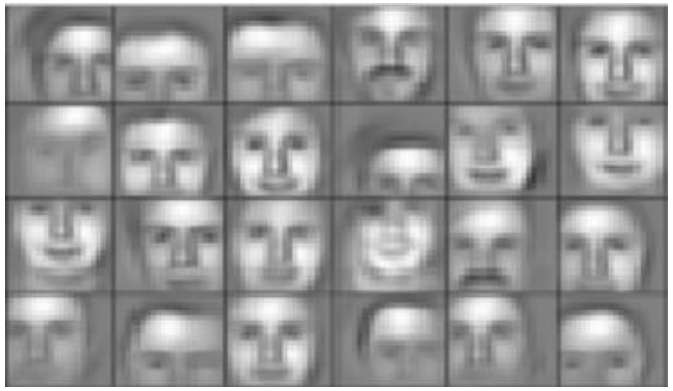
Neural networks



Low-level features



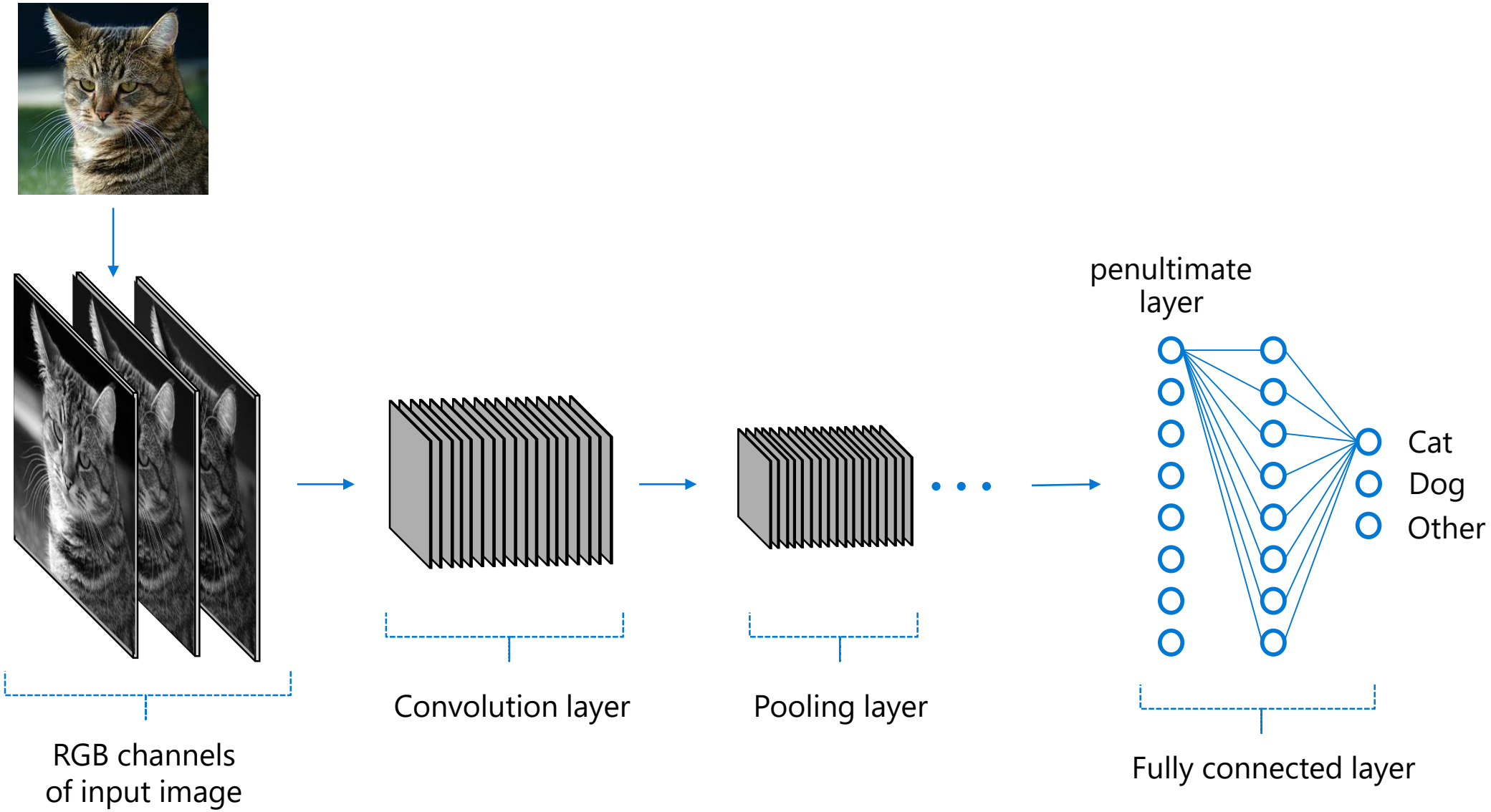
Mid-level features



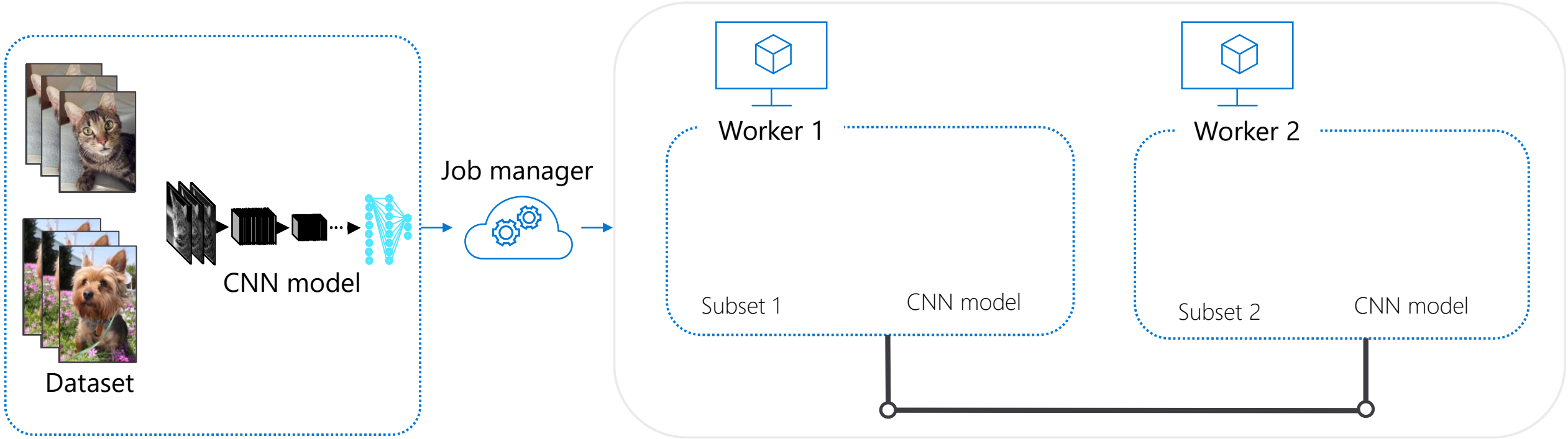
High-level features

Source

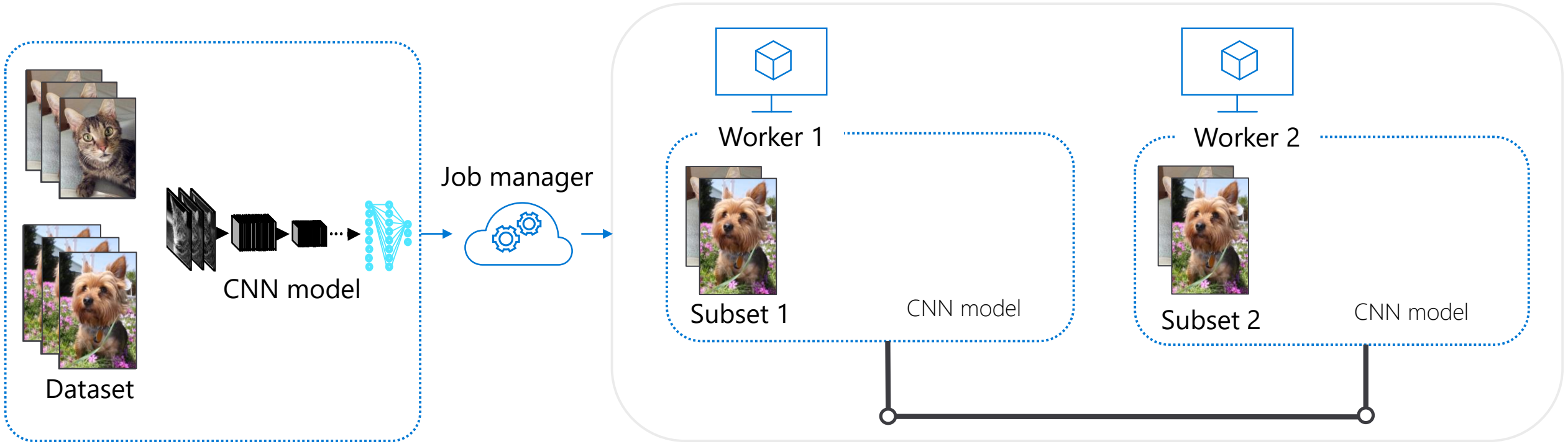
Convolutional neural network (CNN)



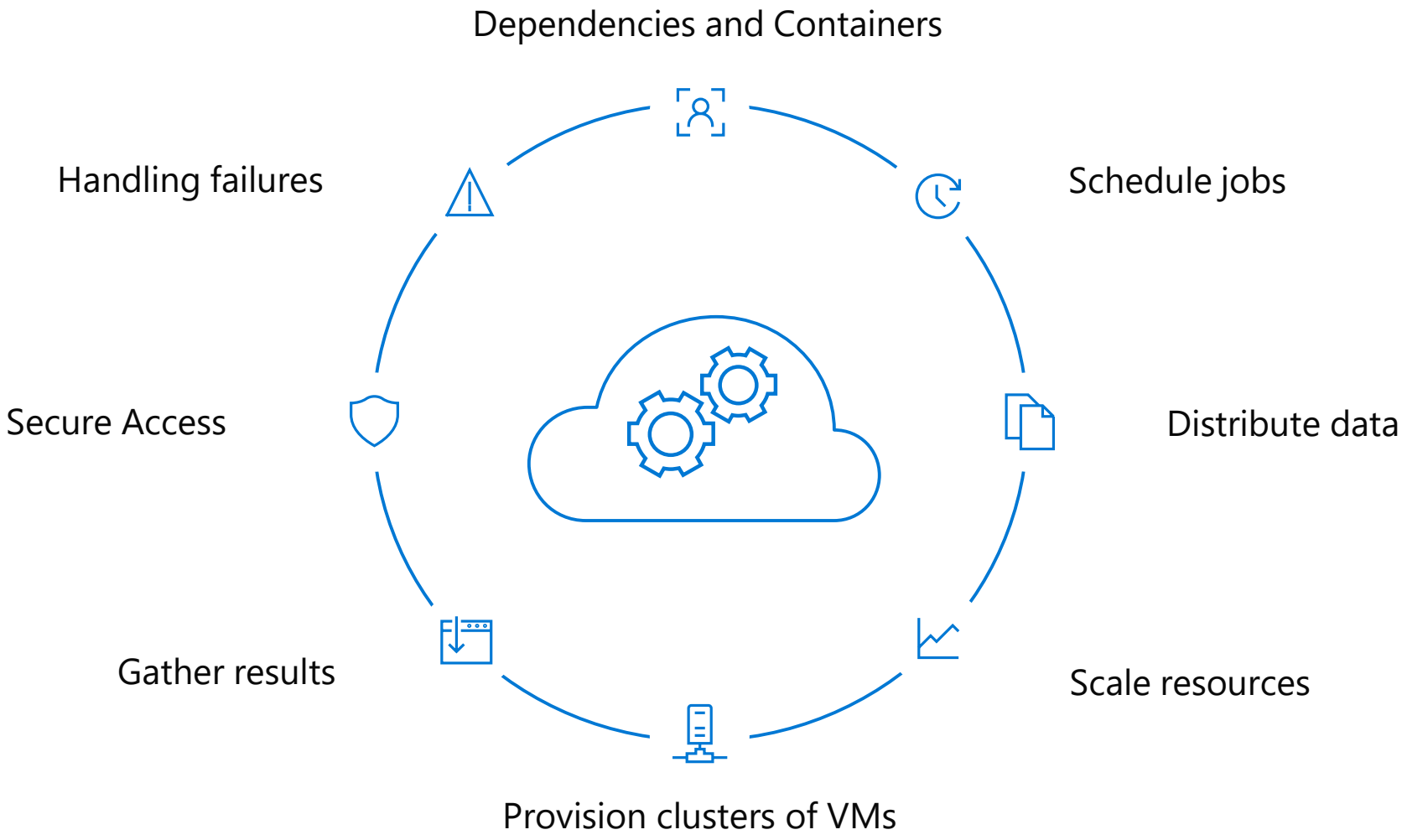
Distributed training mode: Data parallelism



Distributed training mode: Model parallelism



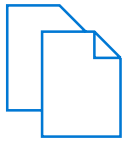
Challenges of distributed training



Training infrastructure

Dependencies and Containers

Leverage system-managed AML compute or bring your own compute



Distribute data

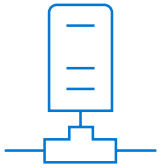
Manage and share resources across a workspace

Schedule jobs

Train at cloud scale using a framework of choice

Scale resources

Autoscale resources to only pay while running a job



Provision clusters

Use the latest NDv2 series VMs with the NVIDIA V100 GPUs

Required Deep Learning Frameworks

Popular Deep Learning Frameworks


TensorFlow


PyTorch

Scikit-Learn


MXNet


Chainer

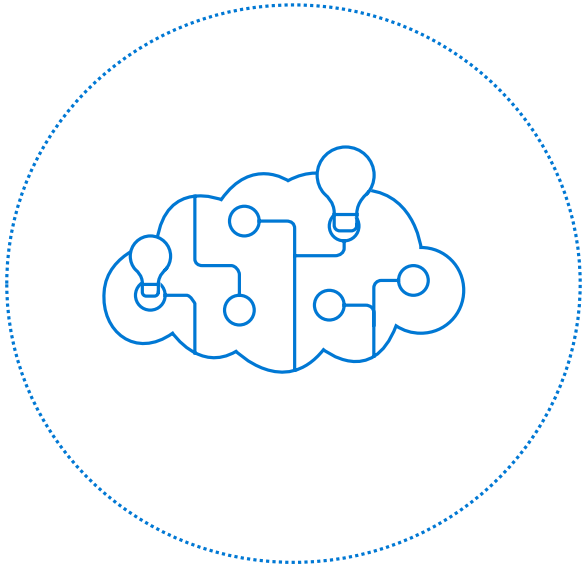
Keras


ONNX

Community project created by Facebook and Microsoft

Use the best tool for the job. Train in one framework and transfer to another for inference

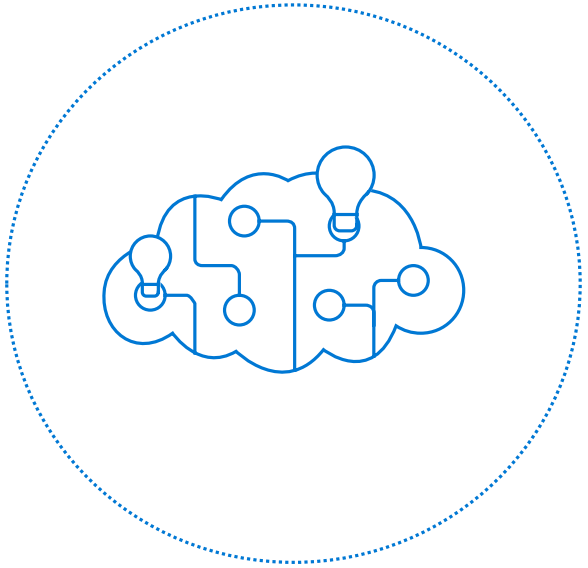
Characteristics of Deep Learning



- Massive amounts of training data
- Excels with raw, unstructured data
- Automatic feature extraction
- Computationally expensive

Deep Learning

Three Additional Requirements



1. Distributed Training on multi-node clusters
2. Support for advanced processors: TPUs GPUs FPGAs
3. Support for Deep Learning Frameworks:

Azure offers a comprehensive AI/ML platform that meets—and exceeds—requirements

Machine Learning on Azure

Domain specific pretrained models
To reduce time to market


Vision


Speech


Language


Search

Familiar Data Science tools
To simplify model development


PyCharm


Jupyter


Visual Studio Code


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 Databricks


Azure Machine Learning


Machine Learning VMs

Powerful infrastructure
To accelerate deep learning


CPU


GPU


FPGA


From the Intelligent Cloud to the Intelligent Edge


(Custom) Model Creation with Azure ML Platform

Development Tools



Languages

Frameworks




What is Azure Machine Learning service?

Set of Azure Cloud Services

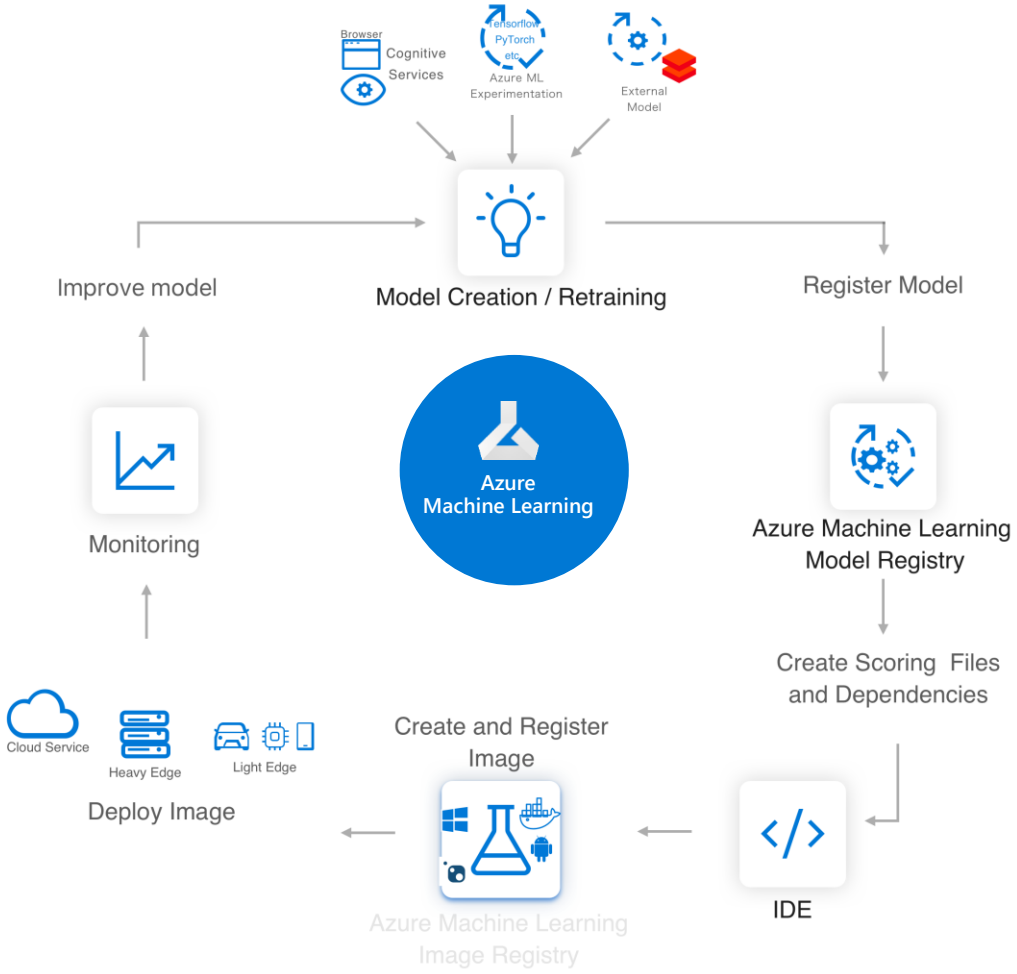
Python SDK

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.

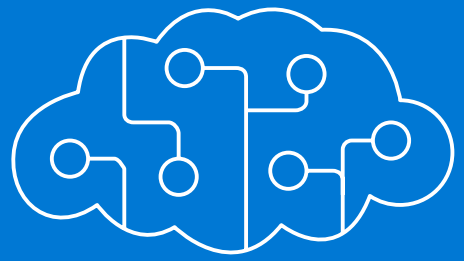
Query the experiment for logged metrics from the current and past runs. If the metrics do not indicate a desired outcome, loop back to step 1 and iterate on your scripts.

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.

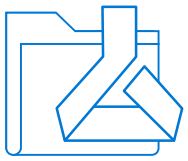
Deploy the image as a web service in Azure.



Azure Machine Learning: Technical Details

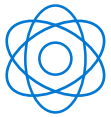
Azure ML service

Key Artifacts



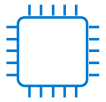
Workspace

Models



Experiments

Pipelines



Compute Target

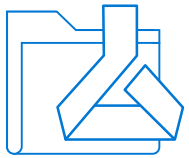
Images

Deployment

Data Stores

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.

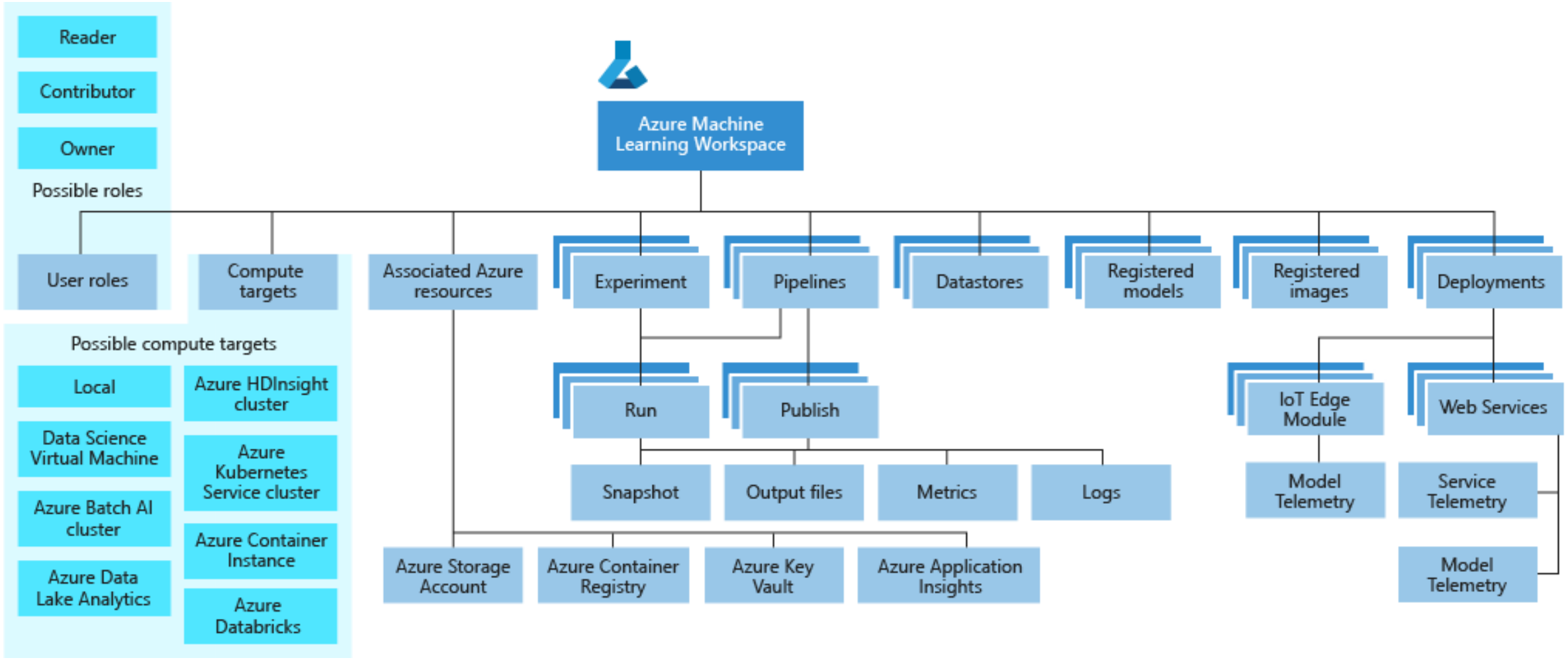
Models are registered with the workspace.

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:

- Azure Container Registry - Registers docker containers that are used during training and when deploying a model.
- Azure Storage - Used as the default datastore for the workspace.
- Azure Application Insights - Stores monitoring information about your models.
- Azure Key Vault - 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.

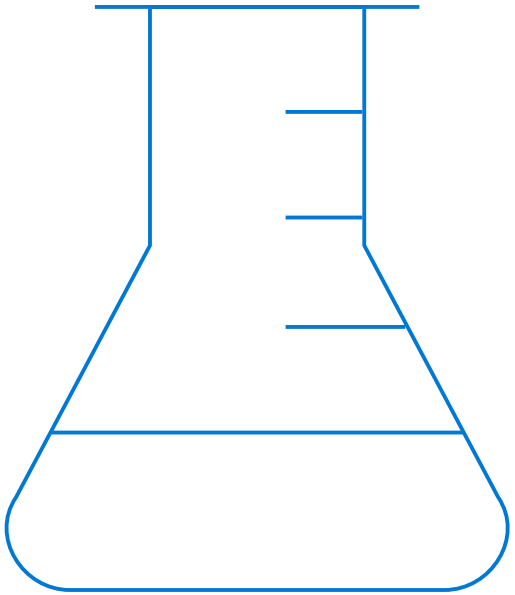
Models are identified by name and version.

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.

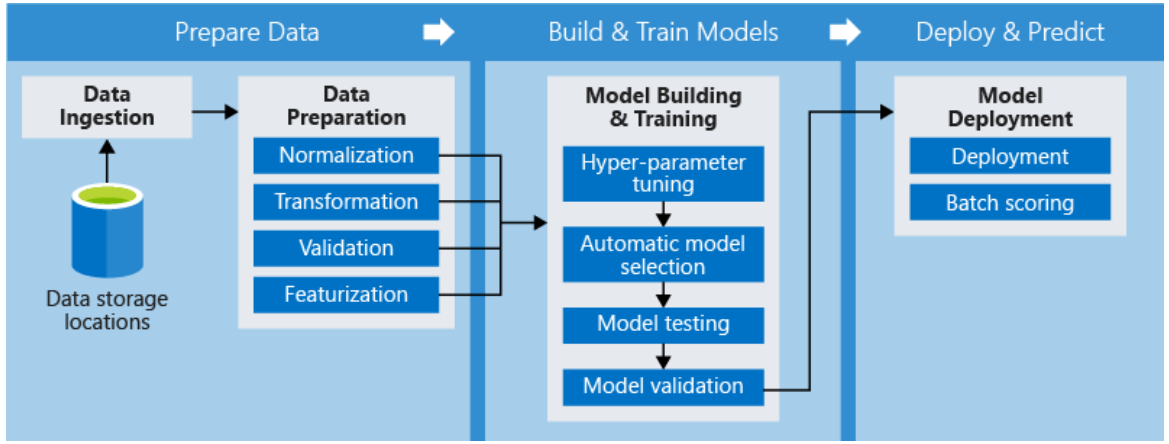
Azure ML Artifact

Pipeline

An Azure ML pipeline consists of a number of steps, where each step can be performed independently or as part of a single deployment command.

A step is a computational unit in the pipeline.

Diagram shows an example pipeline with multiple steps.



Azure ML pipelines enables data scientists, data engineers, and IT professionals to collaborate on the steps involved in: Data preparation, Model training, Model evaluation, Deployment

How pipelines help?

- ✓ Using distinct steps makes it possible to rerun only the steps you need as you tweak and test your workflow.
- ✓ When you rerun a pipeline, the run jumps to the steps that need to be rerun, such as an updated training script, and skips what hasn't changed.
  - ✓ The same holds true for unchanged scripts used for the execution of the step
- ✓ You can use various toolkits and frameworks for each step in your pipeline. Azure coordinates between the various compute targets you use so that your intermediate data can be shared with the downstream compute targets easily.

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

The Azure Machine Learning SDK offers imperative constructs for sequencing and parallelizing the steps in your pipelines when no data dependency is present.

Using declarative data dependencies, you can optimize your tasks.

The SDK includes a framework of pre-built modules for common tasks such as data transfer and model publishing.

The framework can be extended to model your own conventions by implementing custom steps that are reusable across pipelines.

Compute targets and storage resources can also be managed directly from the SDK.

Pipelines can be saved as templates and can be deployed to a REST endpoint so you can schedule batch-scoring or retraining jobs

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	✓	
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
Local computer	Maybe		✓	
Data Science Virtual Machine (DSVM)	✓	✓	✓	✓
Azure ML compute	✓	✓	✓	✓
Azure Databricks	✓		✓	✓
Azure Data Lake Analytics				✓
Azure HDInsight				✓

https://docs.microsoft.com/en-us/azure/machine-learning/service/how-to-set-up-training-targets#supported-compute-targets

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.

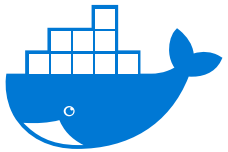


Image Registry

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

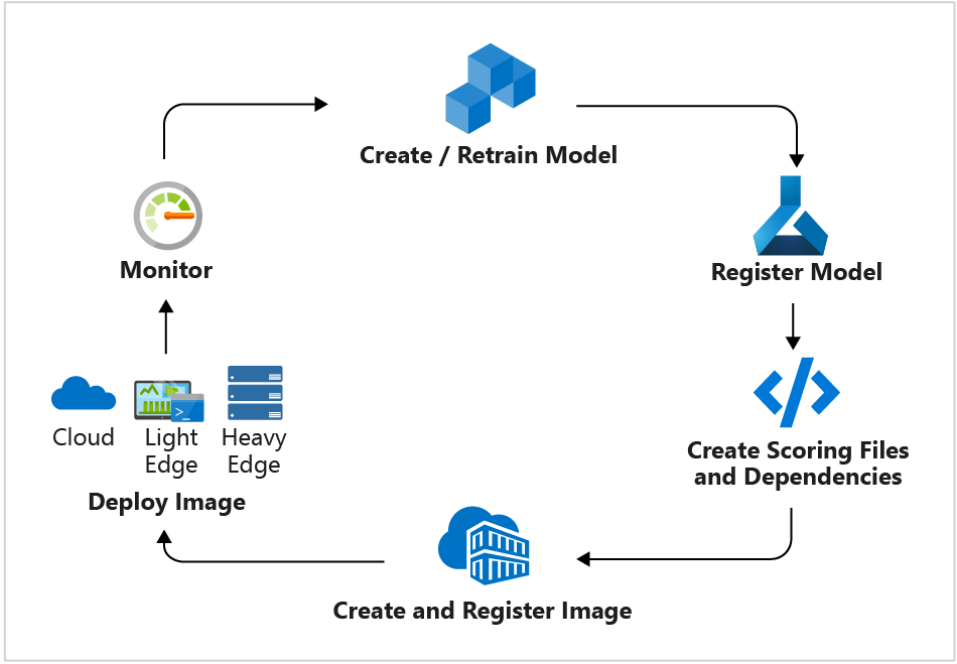
Model Management in Azure ML usually involves these four steps

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

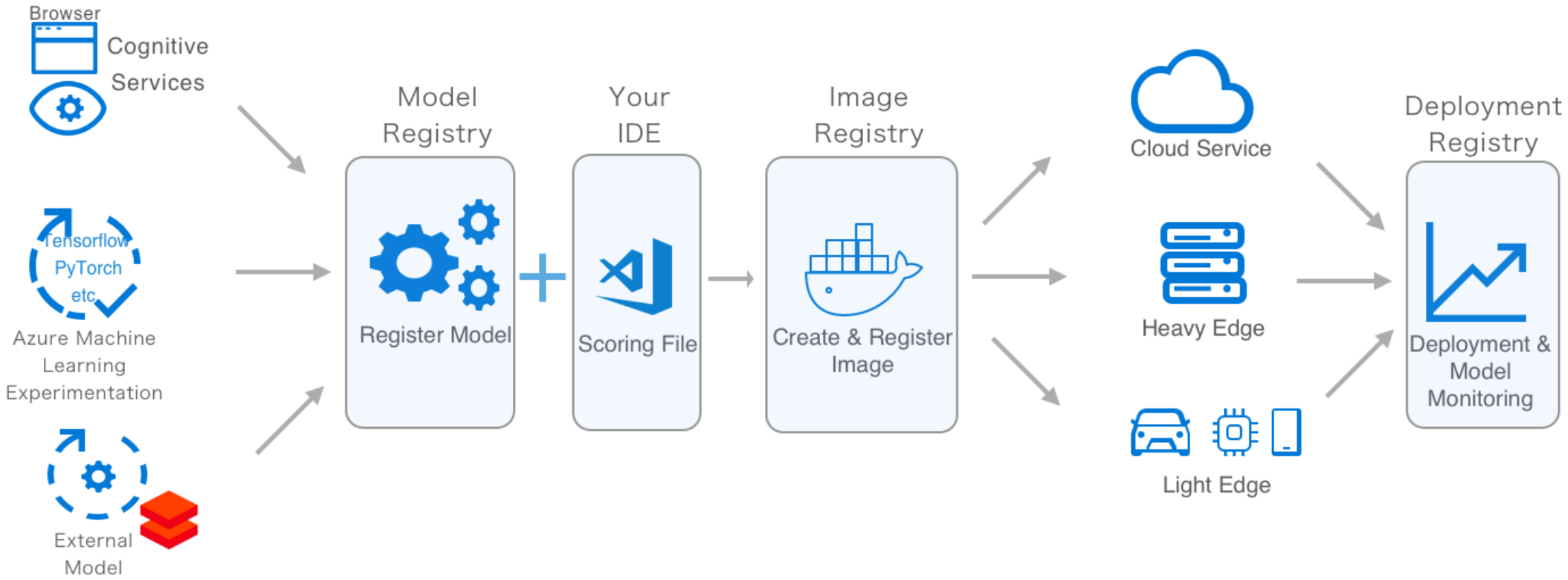
A deployed IoT Module is a Docker container that includes the model, associated script and additional dependencies.

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

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

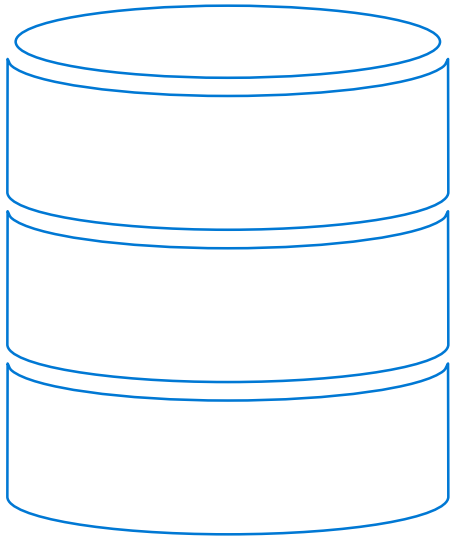
Azure IoT Edge will ensure that your module is running and monitor the device that is hosting it.

Azure ML: How to deploy models at scale



Azure ML Artifact

Datastore



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.

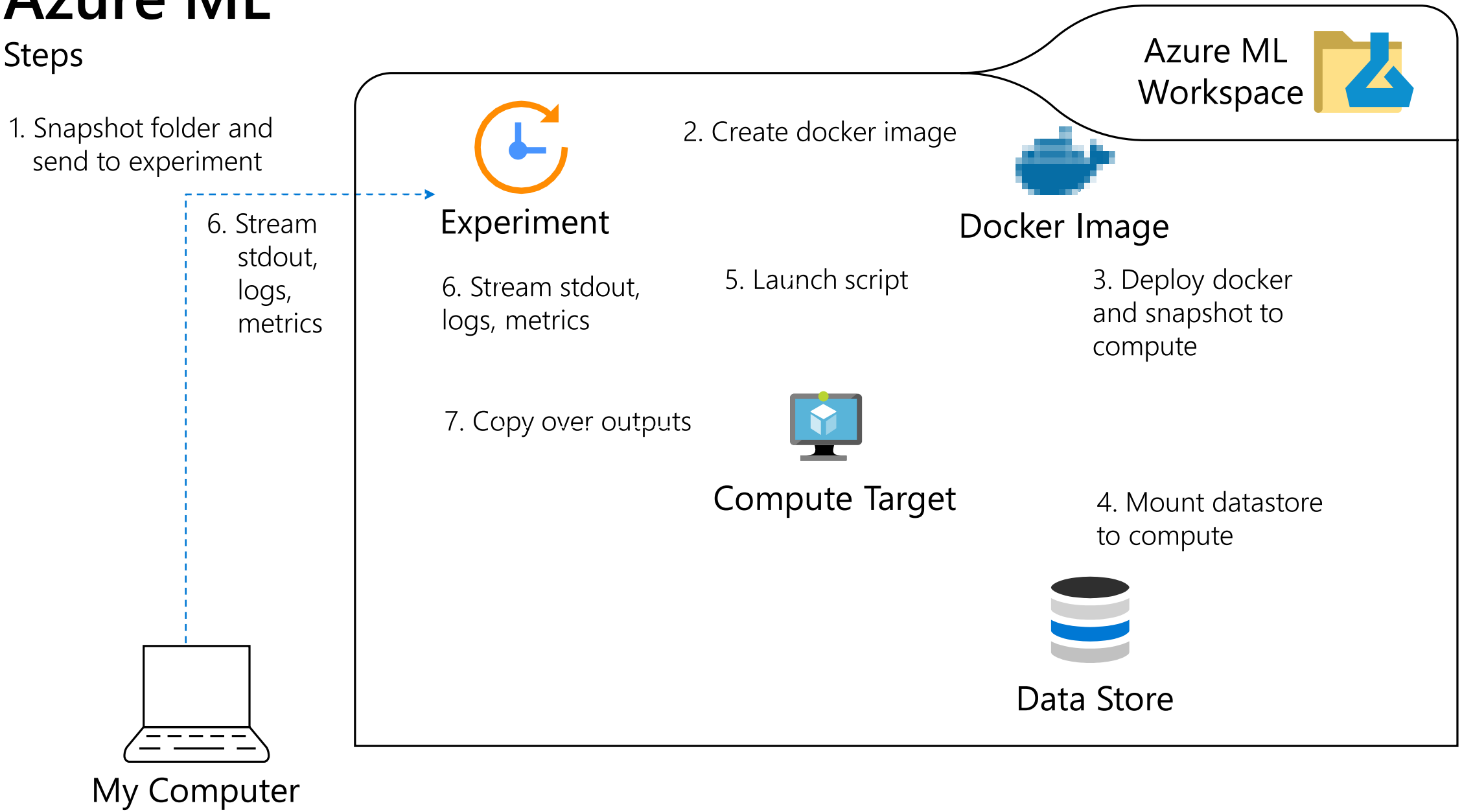
Each workspace has a default datastore, and you may register additional datastores.

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

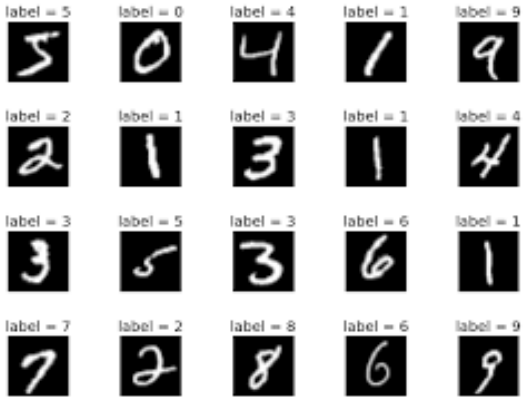


Setup for Code Example

This tutorial trains a simple logistic regression using the MNIST dataset and scikit-learn with Azure Machine Learning service.

MNIST is a dataset consisting of 70,000 grayscale images.

- Each image is a handwritten digit of 28x28 pixels, representing a number from 0 to 9.
- The goal is to create a multi-class classifier to identify the digit a given image represents.



Step 1 – Create a workspace

```
from azureml.core import Workspace
ws = Workspace.create(name='myworkspace',
                      subscription_id='<azure-subscription-id>',
                      resource_group='myresourcegroup',
                      create_resource_group=True,
                      location='eastus2' # or other supported Azure region
                     )

# see workspace details
ws.get_details()
```

Step 2 – Create an Experiment

Create an experiment to track the runs in the workspace. A workspace can have multiple experiments

```
experiment_name = ‘my-experiment-1'

from azureml.core import Experiment
exp = Experiment(workspace=ws, name=experiment_name)
```

Step 3 – Create remote compute target

```
# choose a name for your cluster, specify min and max nodes
compute_name = os.environ.get("BATCHAI_CLUSTER_NAME", "cpucluster")
compute_min_nodes = os.environ.get("BATCHAI_CLUSTER_MIN_NODES", 0)
compute_max_nodes = os.environ.get("BATCHAI_CLUSTER_MAX_NODES", 4)

# This example uses CPU VM. For using GPU VM, set SKU to STANDARD_NC6
vm_size = os.environ.get("BATCHAI_CLUSTER_SKU", "STANDARD_D2_V2")

provisioning_config = AmlCompute.provisioning_configuration(
                                vm_size = vm_size,
                                min_nodes = compute_min_nodes,
                                max_nodes = compute_max_nodes)
# create the cluster
print(‘ creating a new compute target... ')
compute_target = ComputeTarget.create(ws, compute_name, provisioning_config)

# You can poll for a minimum number of nodes and for a specific timeout.
# if no min node count is provided it will use the scale settings for the cluster
compute_target.wait_for_completion(show_output=True,
                                   min_node_count=None, timeout_in_minutes=20)
```

Zero is the default. If min is zero then the cluster is automatically deleted when no jobs are running on it.

Step 4 – Upload data to the cloud

First load the compressed files into numpy arrays. Note the '*load_data*' is a custom function that simply parses the compressed files into numpy arrays.

```
# note that while loading, we are shrinking the intensity values (X) from 0-255 to 0-1 so that the
model converge faster.
X_train = load_data('./data/train-images.gz', False) / 255.0
y_train = load_data('./data/train-labels.gz', True).reshape(-1)

X_test = load_data('./data/test-images.gz', False) / 255.0
y_test = load_data('./data/test-labels.gz', True).reshape(-1)
```

Now make the data accessible remotely by uploading that data from your local machine into Azure so it can be accessed for remote training. The files are uploaded into a directory named mnist at the root of the datastore.

```
ds = ws.get_default_datastore()
print(ds.datastore_type, ds.account_name, ds.container_name)

ds.upload(src_dir='./data', target_path='mnist', overwrite=True, show_progress=True)
```

We now have everything you need to start training a model.

Step 5 – Train a local model

Train a simple logistic regression model using scikit-learn locally. This should take a minute or two.

```
%%time from sklearn.linear_model import LogisticRegression
clf = LogisticRegression()
clf.fit(X_train, y_train)

# Next, make predictions using the test set and calculate the accuracy
y_hat = clf.predict(X_test)
print(np.average(y_hat == y_test))
```

You should see the local model accuracy displayed. [It should be a number like 0.915]

Step 6 – Train model on remote cluster

To submit a training job to a remote you have to perform the following tasks:

- 6.1: Create a directory
- 6.2: Create a training script
- 6.3: Create an estimator object
- 6.4: Submit the job

Step 6.1 – Create a directory

Create a directory to deliver the required code from your computer to the remote resource.

```
import os
script_folder = './sklearn-mnist' os.makedirs(script_folder, exist_ok=True)
```

Step 6.2 – Create a Training Script (1/2)

```
%%writefile $script_folder/train.py
# load train and test set into numpy arrays
# Note: we scale the pixel intensity values to 0-1 (by dividing it with 255.0) so the model can
# converge faster.
# 'data_folder' variable holds the location of the data files (from datastore)
Reg = 0.8 # regularization rate of the logistic regression model.
X_train = load_data(os.path.join(data_folder, 'train-images.gz'), False) / 255.0
X_test  = load_data(os.path.join(data_folder, 'test-images.gz'), False) / 255.0
y_train = load_data(os.path.join(data_folder, 'train-labels.gz'), True).reshape(-1)
y_test  = load_data(os.path.join(data_folder, 'test-labels.gz'), True).reshape(-1)
print(X_train.shape, y_train.shape, X_test.shape, y_test.shape, sep = '\n')
# get hold of the current run
run = Run.get_context()
#Train a logistic regression model with regularizaion rate of' 'reg'
clf = LogisticRegression(C=1.0/reg, random_state=42)
clf.fit(X_train, y_train)
```

Step 6.2 – Create a Training Script (2/2)

```
print('Predict the test set’)
y_hat = clf.predict(X_test)

# calculate accuracy on the prediction
acc = np.average(y_hat == y_test)
print('Accuracy is', acc)


run.log('regularization rate', np.float(args.reg))
run.log('accuracy', np.float(acc)) os.makedirs('outputs', exist_ok=True)


# The training script saves the model into a directory named ‘outputs’. Note files saved in the
# outputs folder are automatically uploaded into experiment record. Anything written in this
# directory is automatically uploaded into the workspace.
joblib.dump(value=clf, filename='outputs/sklearn_mnist_model.pkl')
```

Step 6.3 – Create an Estimator

An estimator object is used to submit the run.

```
from azureml.train.estimator import Estimator

script_params = { '--data-folder': ds.as_mount(), '--regularization': 0.8 }

est = Estimator(source_directory=script_folder,
                script_params=script_params,
                compute_target=compute_target,
                entry_script='train.py',
                conda_packages=['scikit-learn'])
```

The directory that contains the scripts. All the files in this directory are uploaded into the cluster nodes for execution

Name of estimator

Python Packages needed for training

Training Script Name

Compute target (Batch AI in this case)

Parameters required from the training script

Step 6.4 – Submit the job to the cluster for training

```
run = exp.submit(config=est)
run
```

What happens after you submit the job?

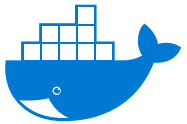


Image creation

A Docker image is created matching the Python environment specified by the estimator. The image is uploaded to the workspace. Image creation and uploading takes about 5 minutes.

This happens once for each Python environment since the container is cached for subsequent runs. During image creation, logs are streamed to the run history. You can monitor the image creation progress using these logs.

Scaling

If the remote cluster requires more nodes to execute the run than currently available, additional nodes are added automatically. Scaling typically takes about 5 minutes.

Running

In this stage, the necessary scripts and files are sent to the compute target, then data stores are mounted/copied, then the entry_script is run. While the job is running, stdout and the ./logs directory are streamed to the run history. You can monitor the run's progress using these logs.

Post-Processing

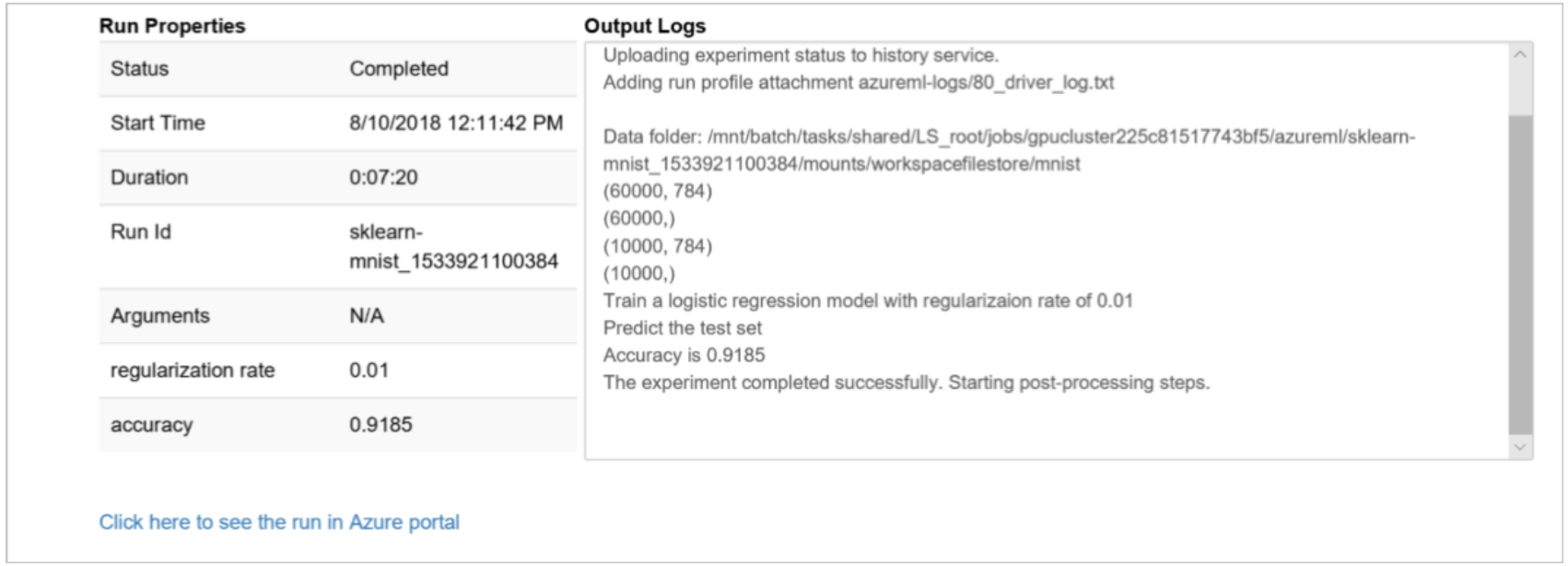
The ./outputs directory of the run is copied over to the run history in your workspace so you can access these results.

Step 7 – Monitor a run

You can watch the progress of the run with a Jupyter widget. The widget is asynchronous and provides live updates every 10-15 seconds until the job completes.

```
from azureml.widgets import RunDetails
RunDetails(run).show()
```

Here is a still snapshot of the widget shown at the end of training:



Run Properties

Status	Completed
Start Time	8/10/2018 12:11:42 PM
Duration	0:07:20
Run Id	sklearn-mnist_1533921100384
Arguments	N/A
regularization rate	0.01
accuracy	0.9185

Output Logs

```
Uploading experiment status to history service.
Adding run profile attachment azureml-logs/80_driver_log.txt

Data folder: /mnt/batch/tasks/shared/LS_root/jobs/gpucluster225c81517743bf5/azureml/sklearn-mnist_1533921100384/mounts/workspacefilestore/mnist
(60000, 784)
(60000,)
(10000, 784)
(10000,)
Train a logistic regression model with regularizaion rate of 0.01
Predict the test set
Accuracy is 0.9185
The experiment completed successfully. Starting post-processing steps.
```

Click here to see the run in Azure portal

Step 8 – See the results

As model training and monitoring happen in the background. Wait until the model has completed training before running more code. Use *wait_for_completion* to show when the model training is complete

Specify 'True' for a verbose log

```
run.wait_for_completion(show_output=False)

# now there is a trained model on the remote cluster
print(run.get_metrics())
```

Displays the accuracy of the model. You should see an output that looks like this.

```
{'regularization rate': 0.8, 'accuracy': 0.9204}
```

Step 9 – Register the model

Recall that the last step in the training script is:

```
joblib.dump(value=clf, filename='outputs/sklearn_mnist_model.pkl')
```

This wrote the file 'outputs/sklearn_mnist_model.pkl' in a directory named 'outputs' in the VM of the cluster where the job is executed.

- outputs is a special directory in that all content in this directory is automatically uploaded to your workspace.
- This content appears in the run record in the experiment under your workspace.
- Hence, the model file is now also available in your workspace.

```
# register the model in the workspace
model = run.register_model (
                                model_name='sklearn_mnist',
                                model_path='outputs/sklearn_mnist_model.pkl')
```

The model is now available to query, examine, or deploy

Step 9 – Deploy the Model

Deploy the model registered in the previous slide, to Azure Container Instance (ACI) as a Web Service

There are 4 steps involved in model deployment

Step 9.1 – Create scoring script

Step 9.2 – Create environment file

Step 9.3 – Create configuration file

Step 9.4 – Deploy to ACI!

Step 9.1 – Create the scoring script

Create the scoring script, called score.py, used by the web service call to show how to use the model. It requires two functions – init() and run (input data)

```
from azureml.core.model import Model

def init():
      global model
      # retreive the path to the model file using the model name
      model_path = Model.get_model_path('sklearn_mnist’)
      model = joblib.load(model_path)

def run(raw_data):
      data = np.array(json.loads(raw_data)['data’])
      # make prediction
      y_hat = model.predict(data) return json.dumps(y_hat.tolist())
```

The init() function, typically loads the model into a global object. This function is run only once when the Docker container is started.

The run(input_data) function uses the model to predict a value based on the input data. Inputs and outputs to the run typically use JSON for serialization and de-serialization, but other formats are supported

Step 9.2 – Create environment file

Create an environment file, called *myenv.yml*, that specifies all of the script's package dependencies. This file is used to ensure that all of those dependencies are installed in the Docker image. This example needs scikit-learn and azureml-sdk.

```
from azureml.core.conda_dependencies import CondaDependencies

myenv = CondaDependencies()
myenv.add_conda_package("scikit-learn")

with open("myenv.yml","w") as f:
        f.write(myenv.serialize_to_string())
```

Step 9.3 – Create configuration file

Create a deployment configuration file and specify the number of CPUs and gigabyte of RAM needed for the ACI container. Here we will use the defaults (1 core and 1 gigabyte of RAM)

```
from azureml.core.webservice import AciWebservice

aciconfig = AciWebservice.deploy_configuration(cpu_cores=1, memory_gb=1,
                                               tags={"data": "MNIST", "method" : "sklearn"},
                                               description='Predict MNIST with sklearn')
```

Step 9.4 – Deploy the model to ACI

```
%%time
from azureml.core.webservice import Webservice
from azureml.core.image import ContainerImage

# configure the image
image_config = ContainerImage.image_configuration(
                                    execution_script ="score.py",
                                    runtime ="python",
                                    conda_file ="myenv.yml")

service = Webservice.deploy_from_model(workspace=ws, name='sklearn-mnist-svc’,
                                       deployment_config=aciconfig, models=[model],
                                       image_config=image_config)

service.wait_for_deployment(show_output=True)
```

Build an image using:
- The scoring file (score.py)
- The environment file (myenv.yml)
- The model file

Register that image under the workspace and send the image to the ACI container.

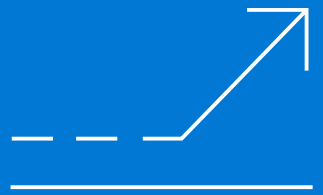
Start up a container in ACI using the image

Step 10 – Test the deployed model using the HTTP end point

Test the deployed model by sending images to be classified to the HTTP endpoint

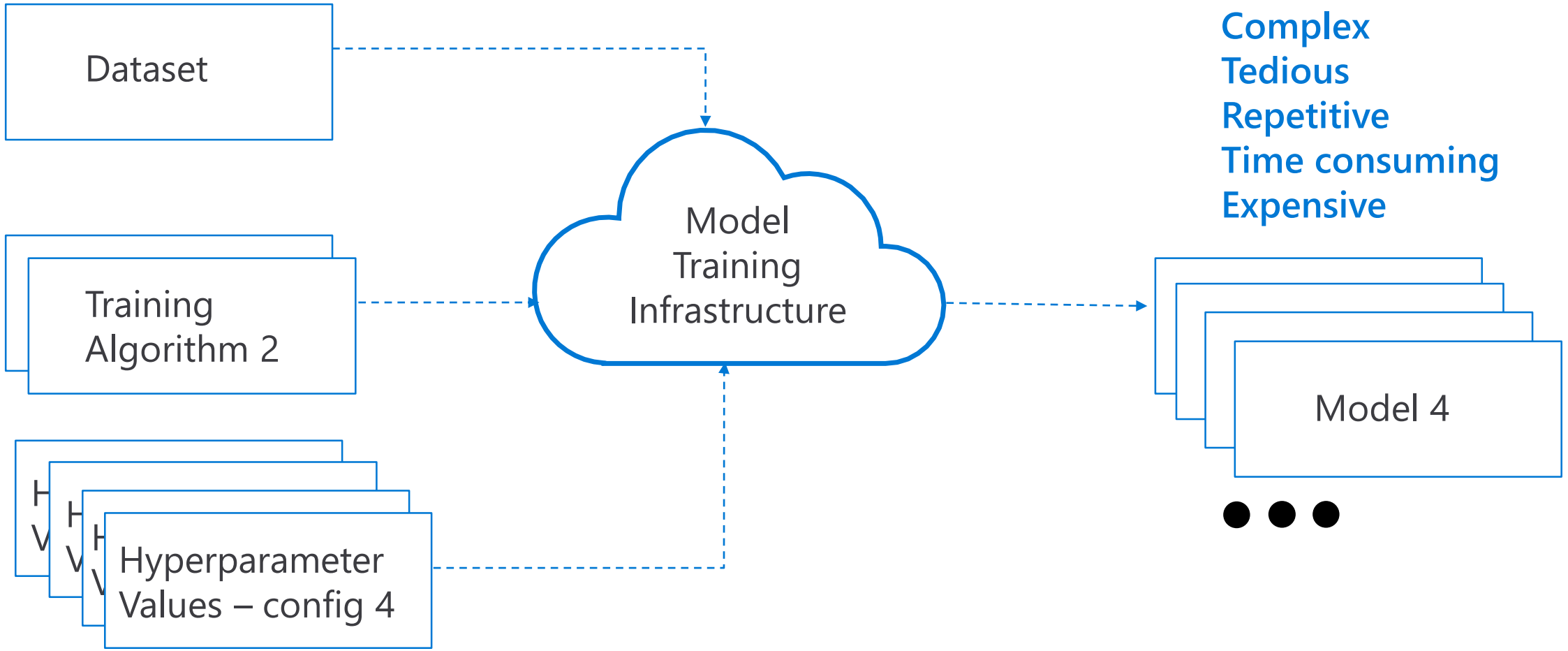
```
import requests
import json

# send a random row from the test set to score
random_index = np.random.randint(0, len(X_test)-1)
input_data = "{\"data\": [" + str(list(X_test[random_index])) + "]}"

headers = {'Content-Type':'application/json’}

resp = requests.post(service.scoring_uri, input_data, headers=headers)

print("POST to url", service.scoring_uri)
#print("input data:", input_data)
print("label:", y_test[random_index])
print("prediction:", resp.text)
```

Send the data to the HTTP end-point for scoring



Azure Automated Machine Learning ‘simplifies’ the creation and selection of the optimal model

Typical ‘manual’ approach to hyperparameter tuning

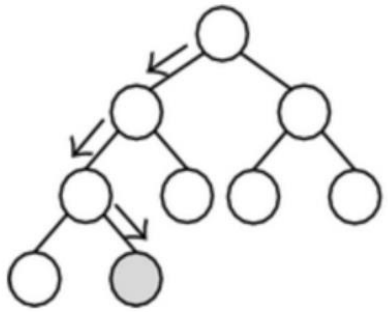


What are Hyperparameters?

Adjustable parameters that govern model training

Chosen prior to training, stay constant during training

Model performance heavily depends on hyperparameter



Setting
Number Of Leaves
Minimum Leaf Instances
Learning Rate
Number Of Trees

Number of leaves	Minimum leaf instances	Learning rate	Number of trees
8	10	0.1	500
8	1	0.05	500
8	1	0.2	100
32	1	0.05	100
8	10	0.2	100
32	1	0.025	500
8	10	0.05	500
32	1	0.1	100
8	1	0.025	500
8	50	0.05	500
32	10	0.025	500
8	50	0.025	500
32	10	0.05	100
8	10	0.025	500
32	10	0.2	20
8	1	0.1	500
32	10	0.1	100
8	1	0.1	100
8	10	0.1	100

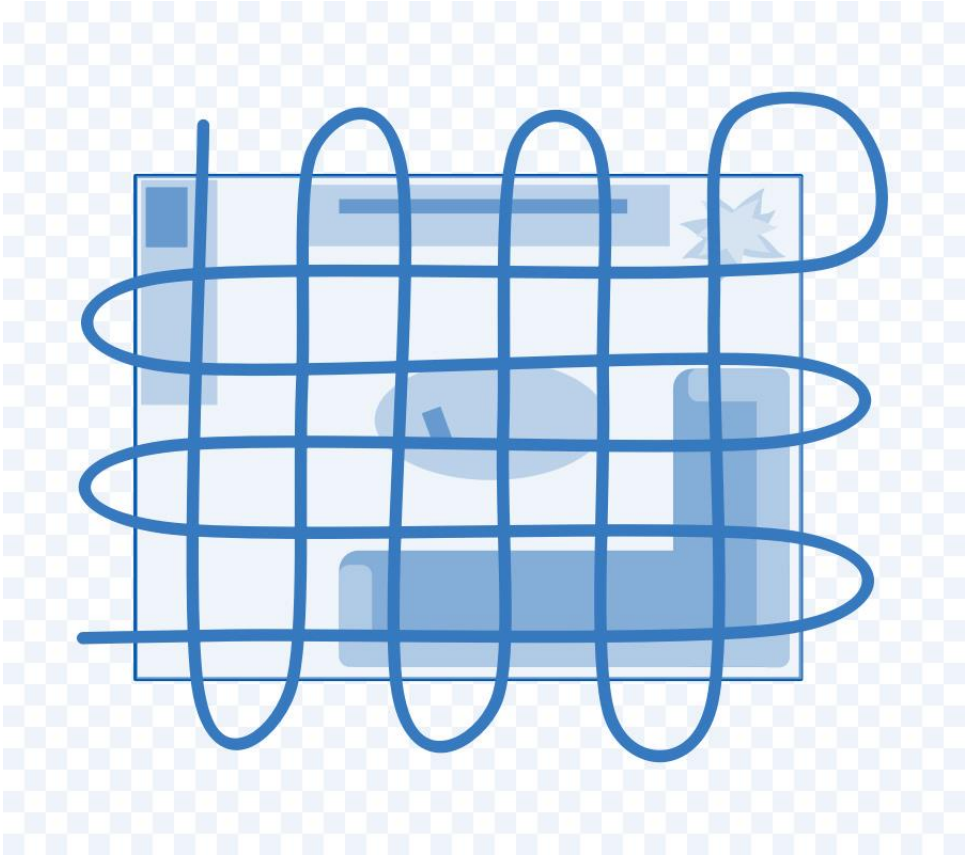
Challenges with Hyperparameter Selection

The search space to explore—i.e. evaluating all possible combinations—is huge.

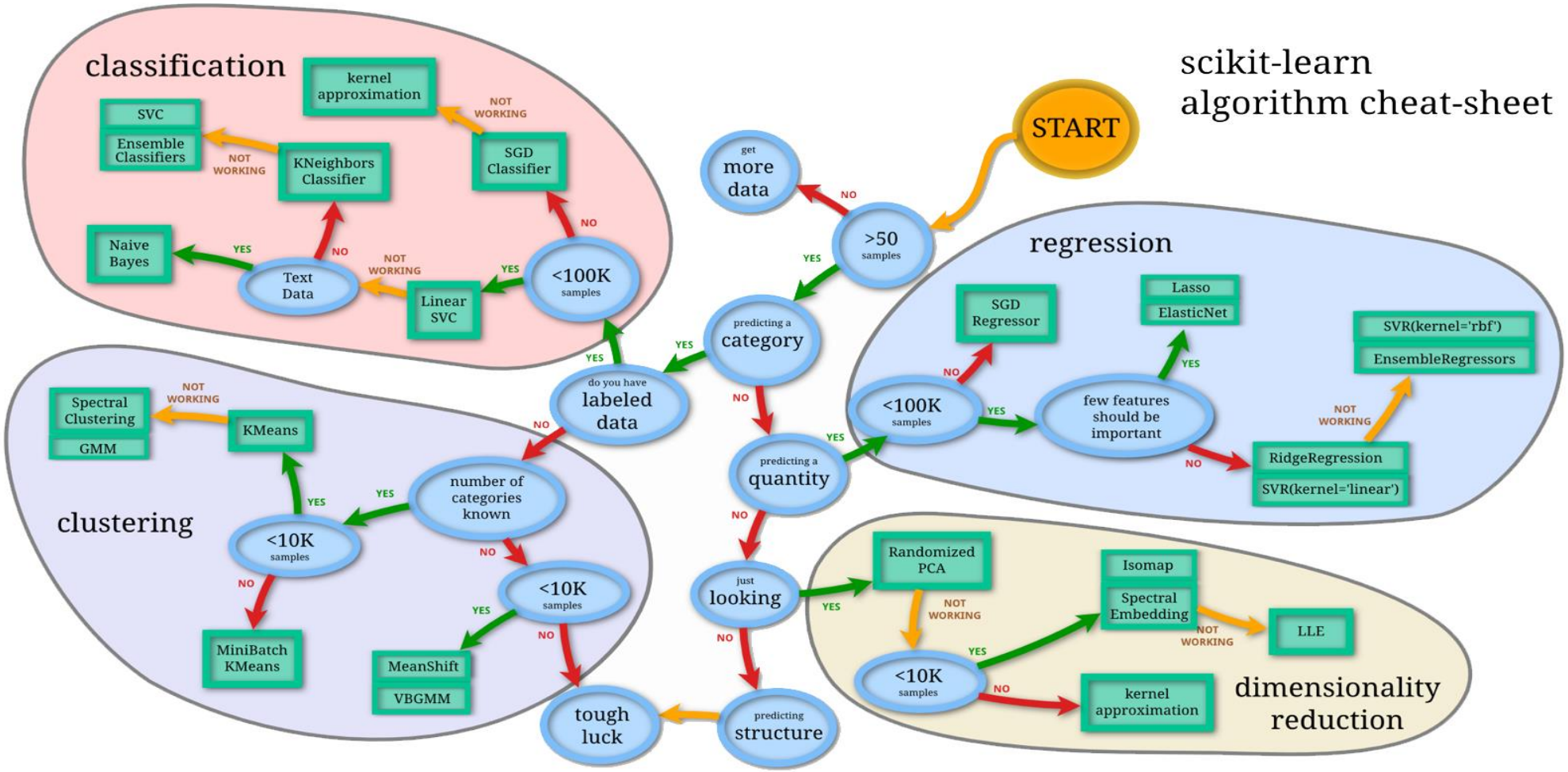
Sparsity of good configurations.
Very few of all possible configurations are optimal.

Evaluating each configuration is resource and time consuming.

Time and resources are limited.



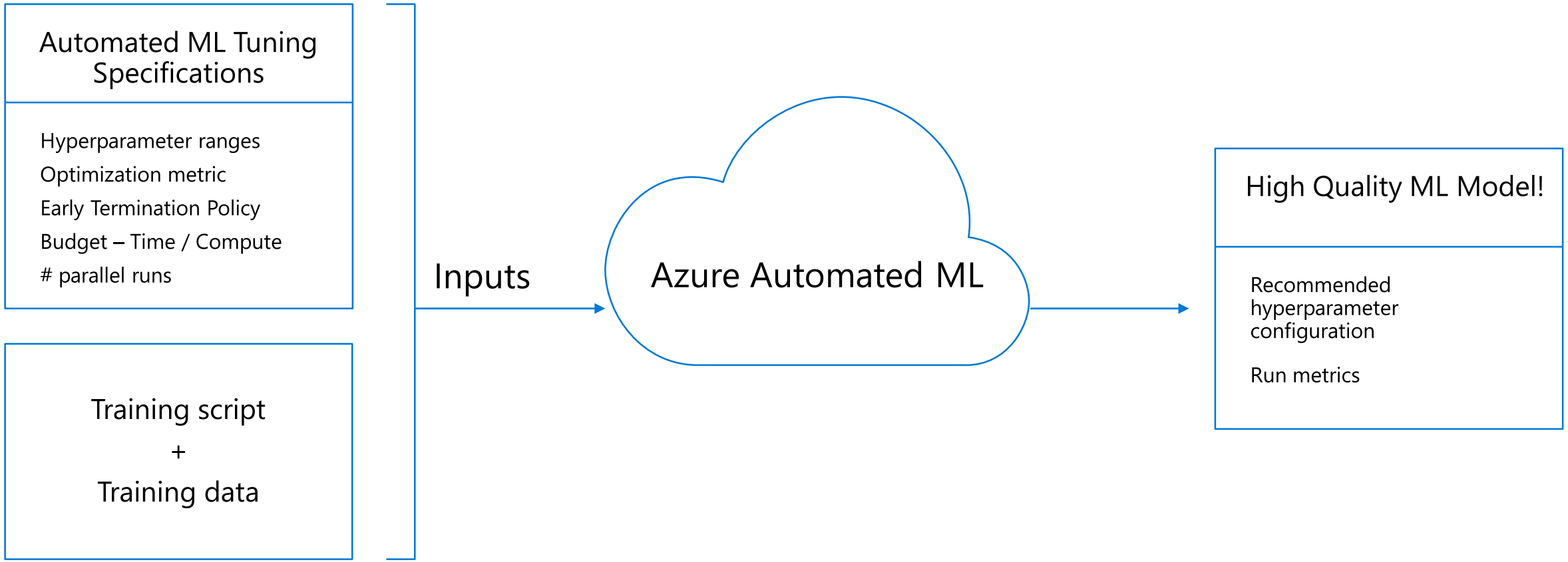
Complexity of Machine Learning



Source: http://scikit-learn.org/stable/tutorial/machine_learning_map/index.html

Azure Automated ML

Conceptual Overview



Azure Automated ML

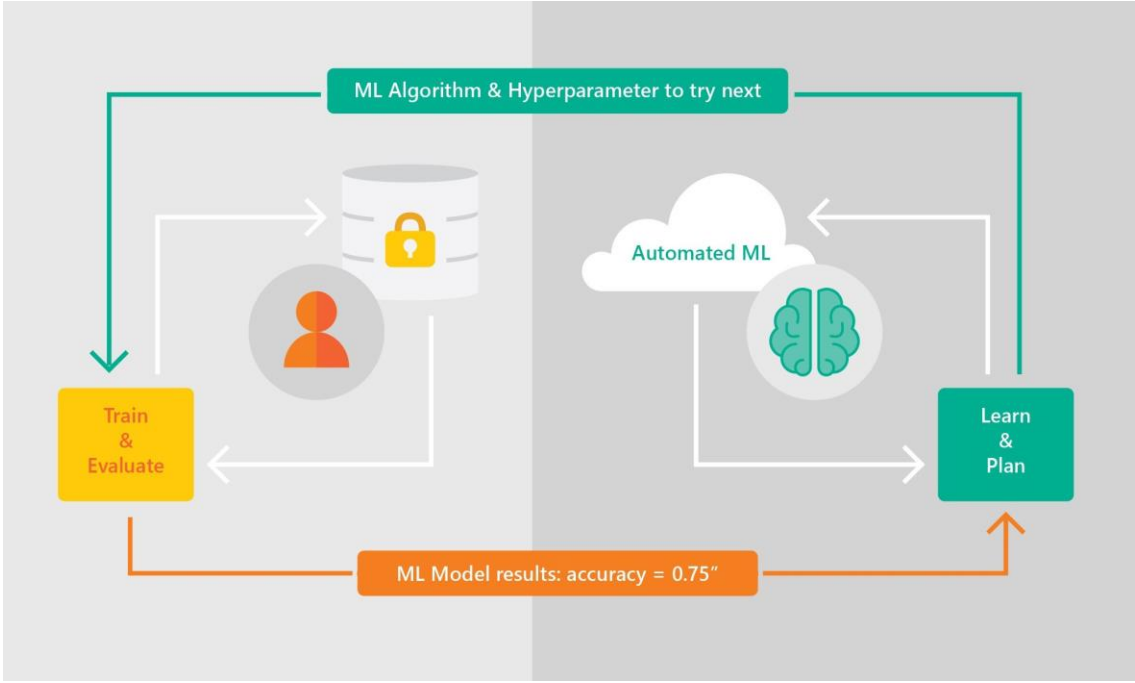
Benefits Overview

Azure Automated ML lets you

- Automate the exploration process
- Use resources more efficiently
- Optimize model for desired outcome
- Control resource budget

Apply it to different models and learning domains

- Pick training frameworks of choice
- Visualize all configurations in one place



Azure Automated ML

Current Capabilities

Category		Value
ML Problem Spaces		Classification Regression Forecasting
Frameworks		Scikit Learn
Languages		Python
Data Type and Data Formats		Numerical Text Scikit-learn supported data formats (Numpy, Pandas)
Data sources		Local Files, Azure Blob Storage
Compute Target	Automated Hyperparameter Tuning	Azure ML Compute (Batch AI), Azure Databricks
	Automated Model Selection	Local Compute, Azure ML Compute (Batch AI), Azure Databricks

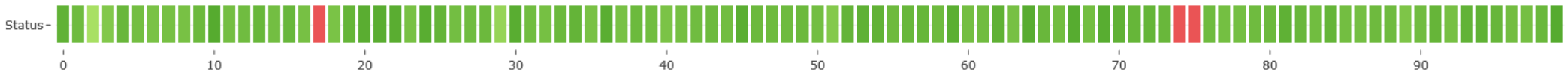
Azure Automated ML

Algorithms Supported

Classification	Regression
sklearn.linear_model.LogisticRegression	sklearn.linear_model.ElasticNet
sklearn.linear_model.SGDClassifier	sklearn.ensemble.GradientBoostingRegressor
sklearn.naive_bayes.BernoulliNB	sklearn.tree.DecisionTreeRegressor
sklearn.naive_bayes.MultinomialNB	sklearn.neighbors.KNeighborsRegressor
sklearn.svm.SVC	sklearn.linear_model.LassoLars
sklearn.svm.LinearSVC	sklearn.linear_model.SGDRegressor
sklearn.calibration.CalibratedClassifierCV	sklearn.ensemble.RandomForestRegressor
sklearn.neighbors.KNeighborsClassifier	sklearn.ensemble.ExtraTreesRegressor
sklearn.tree.DecisionTreeClassifier	lightgbm.LGBMRegressor
sklearn.ensemble.RandomForestClassifier	
sklearn.ensemble.ExtraTreesClassifier	
sklearn.ensemble.GradientBoostingClassifier	
lightgbm.LGBMClassifier	

Azure Automated ML – Sample Output

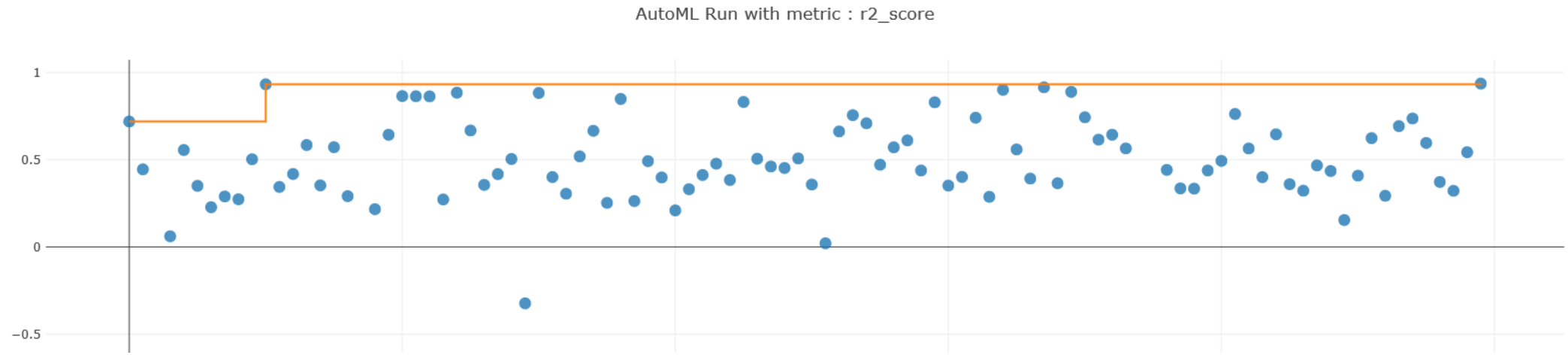
AutoML_ab755820-4bfd-4e8a-8b4b-9e0a2446b1c2:
Status: Completed



Iteration	Pipeline	Iteration metric	Best metric	Status	Duration	Started	Run Id
99	Ensemble	0.93702349	0.93702349	Completed	0:02:18	Dec 4, 2018 12:18 AM	
10	MaxAbsScaler, LightGBM	0.93289307	0.93289307	Completed	0:01:22	Dec 3, 2018 7:49 PM	
67	SparseNormalizer, LightGBM	0.9154763	0.93289307	Completed	0:01:31	Dec 3, 2018 10:19 PM	
64	MaxAbsScaler, LightGBM	0.90148724	0.93289307	Completed	0:01:24	Dec 3, 2018 10:09 PM	
69	MaxAbsScaler, LightGBM	0.88975241	0.93289307	Completed	0:00:55	Dec 3, 2018 10:22 PM	

Pages: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 ... Next Last 5 per page

r2_score



Azure Automated ML

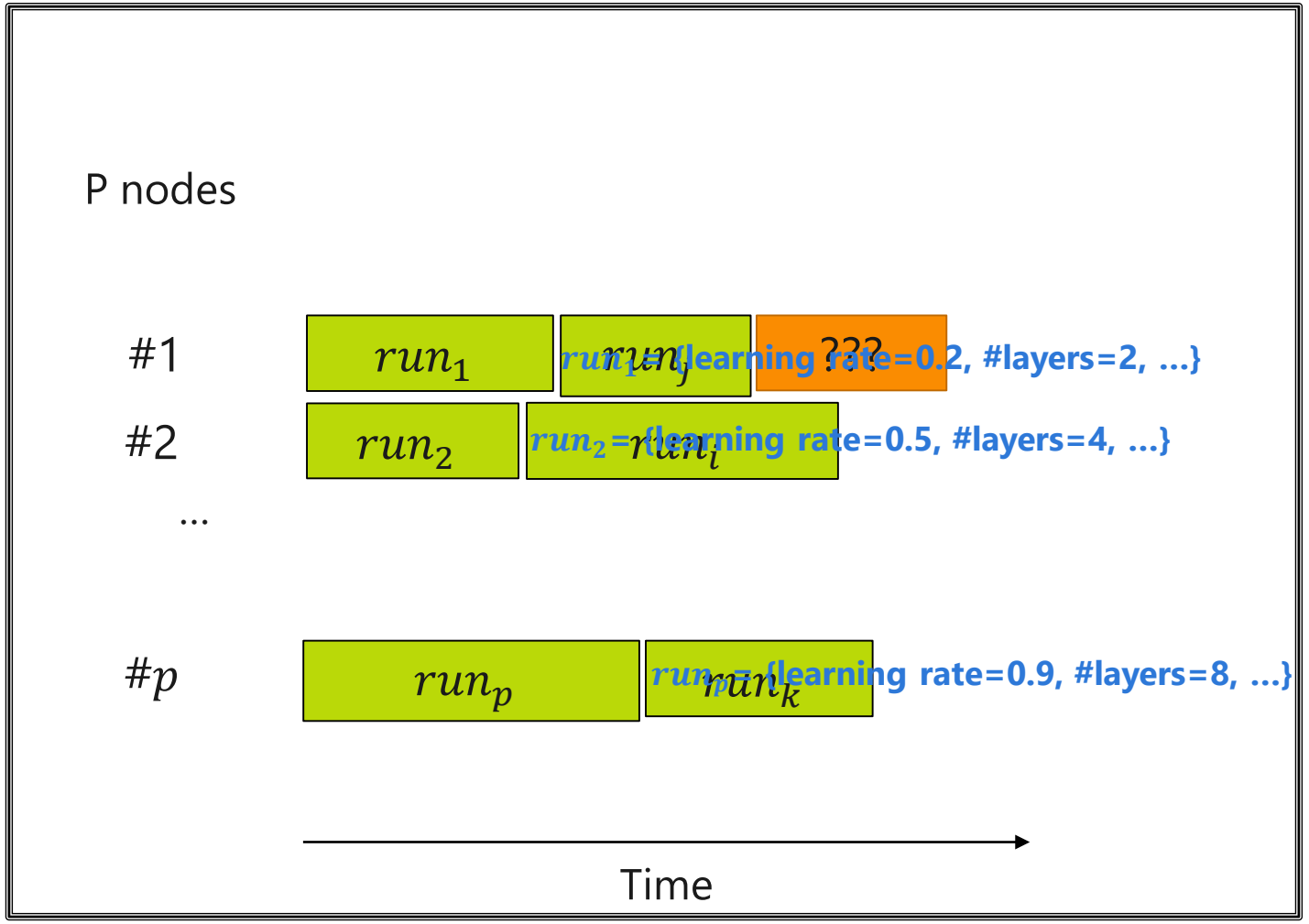
How it works

Launch multiple parallel training runs

(A) Generate new runs
- Which parameter configuration to explore?

(B) Manage resource usage of active runs
- How long to execute a run?

Hyperparameter Tuning runs in Azure ML



Azure Automated ML: Sampling to generate new runs

Define hyperparameter search space

```
{
    “learning_rate”: uniform(0, 1),
    “num_layers”: choice(2, 4, 8)
    …
}
```

Sampling algorithm

```
Config1= {“learning_rate”: 0.2,
“num_layers”: 2, …}

Config2= {“learning_rate”: 0.5,
“num_layers”: 4, …}

Config3= {“learning_rate”: 0.9,
“num_layers”: 8, …}

…
```

Supported sampling algorithms:
Grid Sampling
Random Sampling
Bayesian Optimization

Azure Automated ML

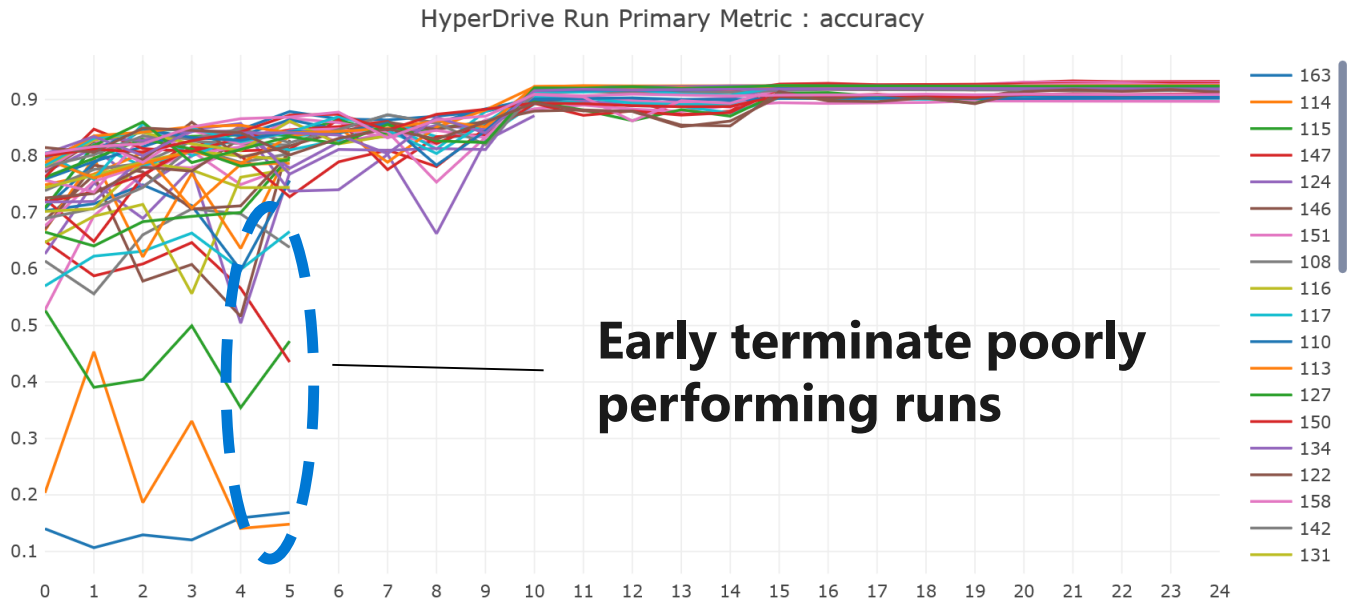
Manage Active Jobs

Evaluate training runs for specified primary metric

Use resources to explore new configurations

Early terminate poor performing training runs. Early termination policies include:

- Bandit policy
- Median Stopping policy
- Truncation Selection policy



Azure Automated ML

Use via the Python SDK

jupyter 102.auto-ml-regression (unsaved changes)

File Edit View Insert Cell Kernel Widgets Help Not Trusted Python [default]

Run Code

Instantiate Auto ML Regressor

Instantiate a AutoML Object This creates an Experiment in Azure ML. You can reuse this objects to trigger multiple runs. Each run will be part of the same experiment.

Property	Description
primary_metric	This is the metric that you want to optimize. Auto ML Regressor supports the following primary metrics *spearman_correlation* *normalized_root_mean_squared_error* *r2_score*
max_time_sec	Time limit in seconds for each iterations
iterations	Number of iterations. In each iteration Auto ML Classifier trains the data with a specific pipeline
num_cross_folds	Cross Validation split

In [5]:
```
from azureml.train.automl import AutoMLConfig

automl_config = AutoMLConfig(task = 'regression',
                             debug_log = 'automl_errors.log',
                             primary_metric = 'spearman_correlation',
                             max_time_sec = 12000,
                             iterations = 10,
                             n_cross_validations = 3,
                             verbosity = logging.INFO,
                             X = X,
                             y = y,
                             path=project_folder)
```

Training the Model

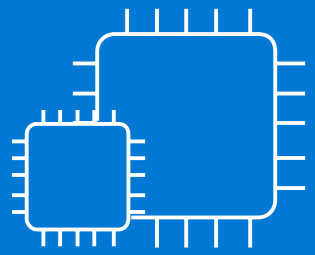
You can call the fit method on the AutoML instance and pass the run configuration. For Local runs the execution is synchronous. Depending on the data and number of iterations this can run for while. You will see the currently running iterations printing to the console.

fit method on Auto ML Regressor triggers the training of the model. It can be called with the following parameters

Parameter	Description
X	(sparse) array-like, shape = [n_samples, n_features]
y	(sparse) array-like, shape = [n_samples,], [n_samples, n_classes] Multi-class targets. An indicator matrix turns on multilabel classification.
compute_target	Indicates the compute used for training. *local* indicates train on the same compute which hosts the jupyter notebook. For DSVM and Batch AI please refer to the relevant notebooks.
show_output	True/False to turn on/off console output

In [6]:
```
local_run = experiment.submit(automl_config, show_output=True)
```

```
Parent Run ID: AutoML_e7a4236e-8935-4e93-888d-1ea8310a6b22
********************************************************************************************
ITERATION: The iteration being evaluated.
PIPELINE: A summary description of the pipeline being evaluated.
DURATION: Time taken for the current iteration.
METRIC: The result of computing score on the fitted pipeline.
BEST: The best observed score thus far.
********************************************************************************************

 ITERATION   PIPELINE                                       DURATION      METRIC      BEST
         0   Normalize extra trees regressor                0:00:12.069893   0.688     0.688
         1   Normalize lightGBM regressor                   0:00:11.192919   0.597     0.688
         2   Normalize Elastic net                          0:00:09.866233   0.689     0.689
         3   Scale 0/1 lightGBM regressor                   0:00:10.069764   0.656     0.689
         4   Robust Scaler kNN regressor                    0:00:09.090668   0.598     0.689
         5   Normalize lightGBM regressor                   0:00:12.562876   0.649     0.689
         6   Robust Scaler kNN regressor                    0:00:09.361137   0.600     0.689
         7   Normalize SGD regressor                        0:00:09.010672   0.070     0.689
         8   Scale 0/1 extra trees regressor                0:00:10.442752   0.685     0.689
         9   Robust Scaler Gradient boosting regres0:00:09.567582   0.651     0.689
```



Distributed Training with Azure ML Compute

Distributed Training with Azure ML Compute

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.

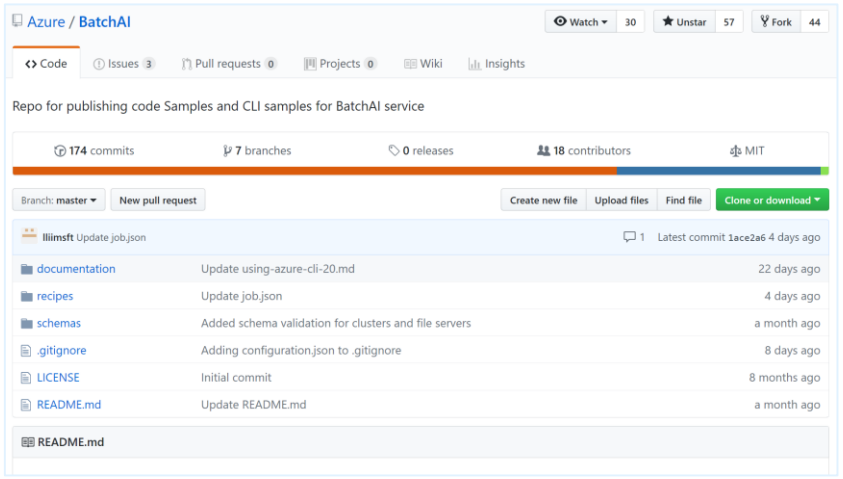
- If min is set to zero, *cluster is deleted when no jobs are running; so pay only for job duration*.

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.



Deploy to IoT Edge

IoT Edge Modules

An Azure IoT Edge device is a Linux or Windows-based device that runs the Azure IoT Edge runtime. Machine learning models can be deployed to these devices as **IoT Edge Modules**.

Benefits: Deploying a model to an IoT Edge device allows the device to use the model directly, instead of having to send data to the cloud for processing. You get faster response times and less data transfer

IoT Edge Modules

Azure IoT Edge modules are the smallest unit of computation managed by IoT Edge, and can contain Azure services or your own solution-specific code.

IoT Edge module images contain applications that take advantage of the management, security, and communication features of the IoT Edge runtime.

In implementation, modules images exist as container images in a repository, and module instances are containers on devices.

Deploying to IoT Edge Devices

Prerequisites

IoT Hub
IoT Edge Device with the IoT Egde runtime installed.
Docker Image based on the ML model and image configuration stored in the container registry.
This can be done as follows

```
from azureml.core.image import Image, ContainerImage

#Image configuration
image_config = ContainerImage.image_configuration (
                                    runtime = "python", execution_script ="score.py",
                                    conda_file = "myenv.yml",
                                    tags = {"attributes", "classification"},
                                    description = "Image with my model")

image = ContainerImage.create (name = "myimage",
                               models = [model], #this is the model object
                               image_config = image_config, workspace = ws )
```

Deploying to the IoT Edge

Steps

1. **Get the container registry credentials**: Azure IoT needs the credentials for the container registry that Azure Machine Learning service stores docker images in. You can get via the Azure Portal
2. Configure deployment manifest, a JSON document that describes which modules to deploy, how data flows between the modules, and desired properties of the module twins. You can use wizard in the Azure Portal to create this. The Wizard has 4 steps:
    1. Add Modules
    2. Specify Routes
    3. Review Deployment
    4. Submit
3. View Modules on device: Once you've deployed modules to your device, you can view all of them in the Device details page of the portal. This page displays the name of each deployed module, as well as useful information like the deployment status and exit code.

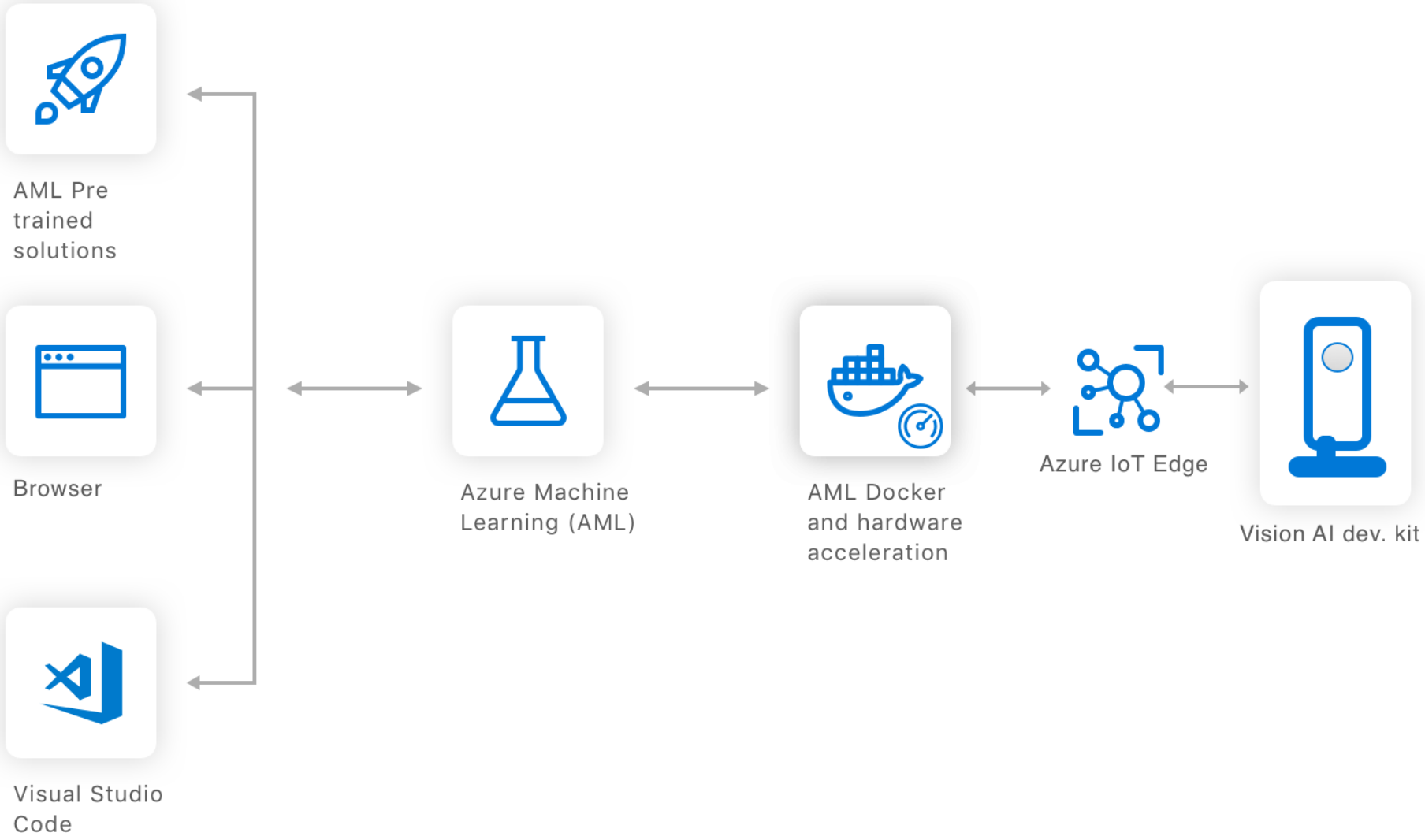
Edge Deployment

Light and Heavy

		Heavy Edge				Light Edge		
Description	An Azure host that spans from CPU to GPU and FPGA VMs	A server with slots to insert CPUs, GPUs, and FPGAs or a X64 or ARM system that needs to be plugged in to work **Cloud Consistent Hybrid Server**	**Servers**	**PC class devices**	**Gateway**	A Sensor with a SOC (ARM CPU, NNA, MCU) and memory that can operate on batteries **Smart Sensors + Ambient AI**		**Sensors**
Example	DSVM / ACI / AKS / Batch AI	- DataBox Edge - HPE - Azure Stack	- DataBox Edge	- Industrial PC	-Video Gateway -DVR	-Mobile Phones -VAIDK	-Mobile Phones -IP Cameras	-Azure Sphere - Appliances
What runs the model	CPU,GPU or FPGA	CPU,GPU or FPGA	CPU, GPU	x64 CPU	Multi-ARM CPU	Hw accelerated NNA	CPU/GPU	MCU

Vision AI Development kit

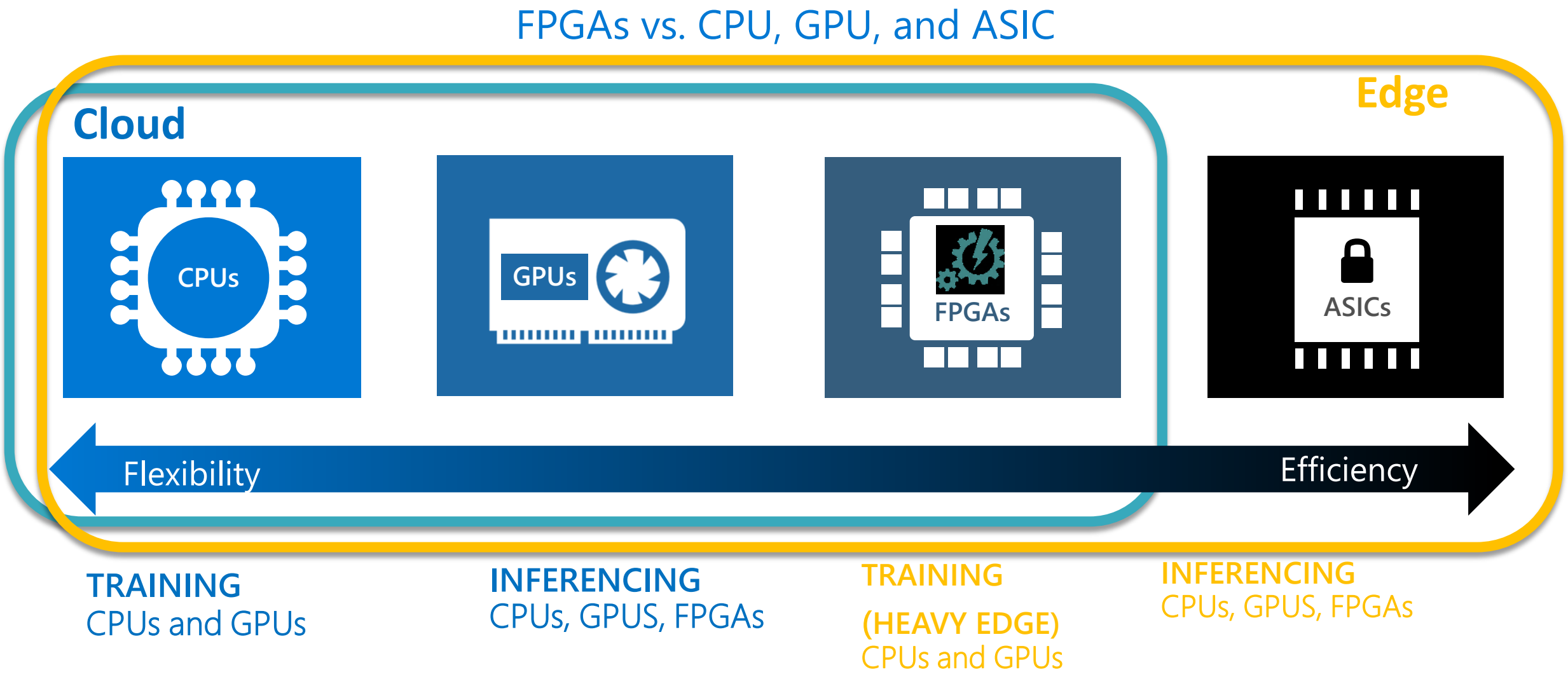
System Architecture



Deploy to FPGA

Azure ML

Silicon Alternatives



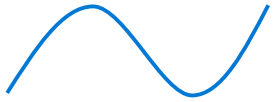
Project Brainwave on Azure

Enables real-time AI calculations using FPGAs. Benefits include:

Performance

Excellent inference at low batch sizes

Ultra-low latency | 10x < CPU/GPU

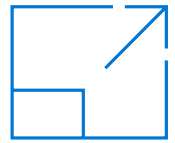


Flexibility

Rapidly adapt to evolving ML

Inference-optimized numerical precision

Exploit sparsity, deep compression



Scale

World's largest cloud investment in FPGAs

Multiple Exa-Ops of aggregate AI capacity

Runs on Microsoft's scale infrastructure

Low cost

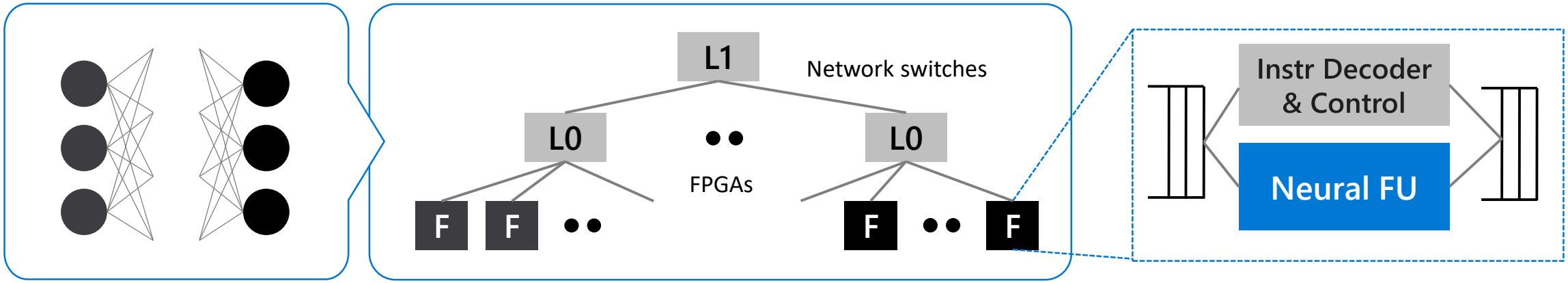
$0.21/million images on Azure FPGA

Project Brainwave on Azure

Capabilities Overview

A Scalable FPGA-Powered DNN Serving Platform

Fast: Ultra-low latency, high-throughput serving of DNN models at low batch sizes
Flexible: Future proof, adaptable to fast-moving AI space and evolving model types
Friendly: Turnkey deployment of TensorFlow/CNTK/Caffe/etc.



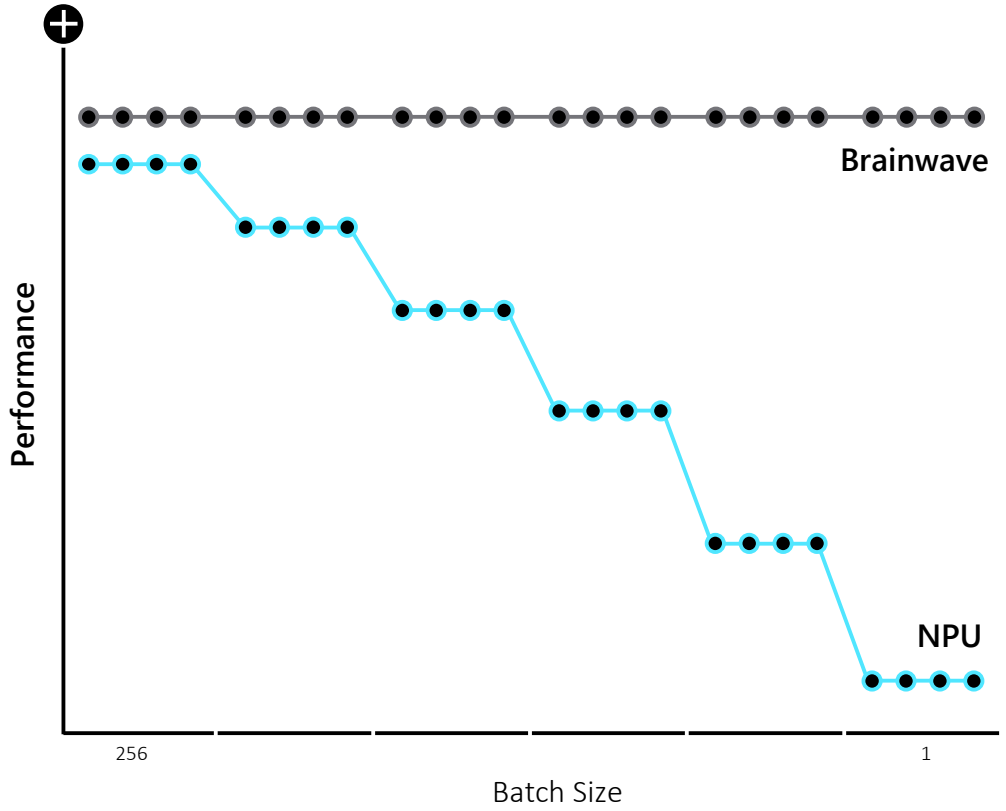
Pretrained DNN Model in TensorFlow, CNTK, etc.

Scalable DNN Hardware Microservice

BrainWave Soft DPU

Project Brainwave

Advantages



Brainwave delivers the ideal combination:

High hardware utilization

Low latency

Low batch sizes

What is currently supported on Azure?

Today, Project Brainwave supports

Image classification and recognition scenarios

TensorFlow deployment

DNNs: ResNet 50, ResNet 152, VGG-16, SSD-VGG, and DenseNet-121

Intel FPGA hardware

Using this FPGA-enabled hardware architecture, trained neural networks run quickly and with lower latency.

Project Brainwave can parallelize pre-trained deep neural networks (DNN) across FPGAs to scale out your service.

The DNNs can be pre-trained, as a deep featurizer for transfer learning, or fine-tuned with updated weights

Here is the workflow for creating an image recognition service in Azure using supported DNNs as a featurizer for deployment on Azure FPGAs:

Use the Azure Machine Learning SDK for Python to create a service definition, which is a file describing a pipeline of graphs (input, featurizer, and classifier) based on TensorFlow. The deployment command will automatically compress the definition and graphs into a ZIP file and upload the ZIP to Azure Blob storage. The DNN is already deployed on Project Brainwave to run on the FPGA.

Register the model using the SDK with the ZIP file in Azure Blob storage.

Deploy the service with the registered model using SDK

How to deploy to FPGAs on Azure

Workflow for creating an image recognition service in Azure using supported DNNs as a featurizer for deployment on Azure FPGAs:

Use the Azure Machine Learning SDK for Python to create a service definition

- A file describing a pipeline of graphs (input, featurizer, and classifier) based on TensorFlow.
- Deployment command automatically compresses the definition and graphs into a ZIP file
- Deployment command automatically uploads the ZIP to Azure Blob storage.
- The DNN is already deployed on Project Brainwave to run on the FPGA.
- Model registration using the SDK with the ZIP file in Azure Blob storage.
- Deploy the service with the registered model using SDK.

Customer story

Drone-based electric grid inspector powered by deep learning

Challenge

Traditional power line inspection services are costly

Demand for low cost image scoring and support for multiple concurrent customers

Needed powerful AI to execute on a drone solution

Solution

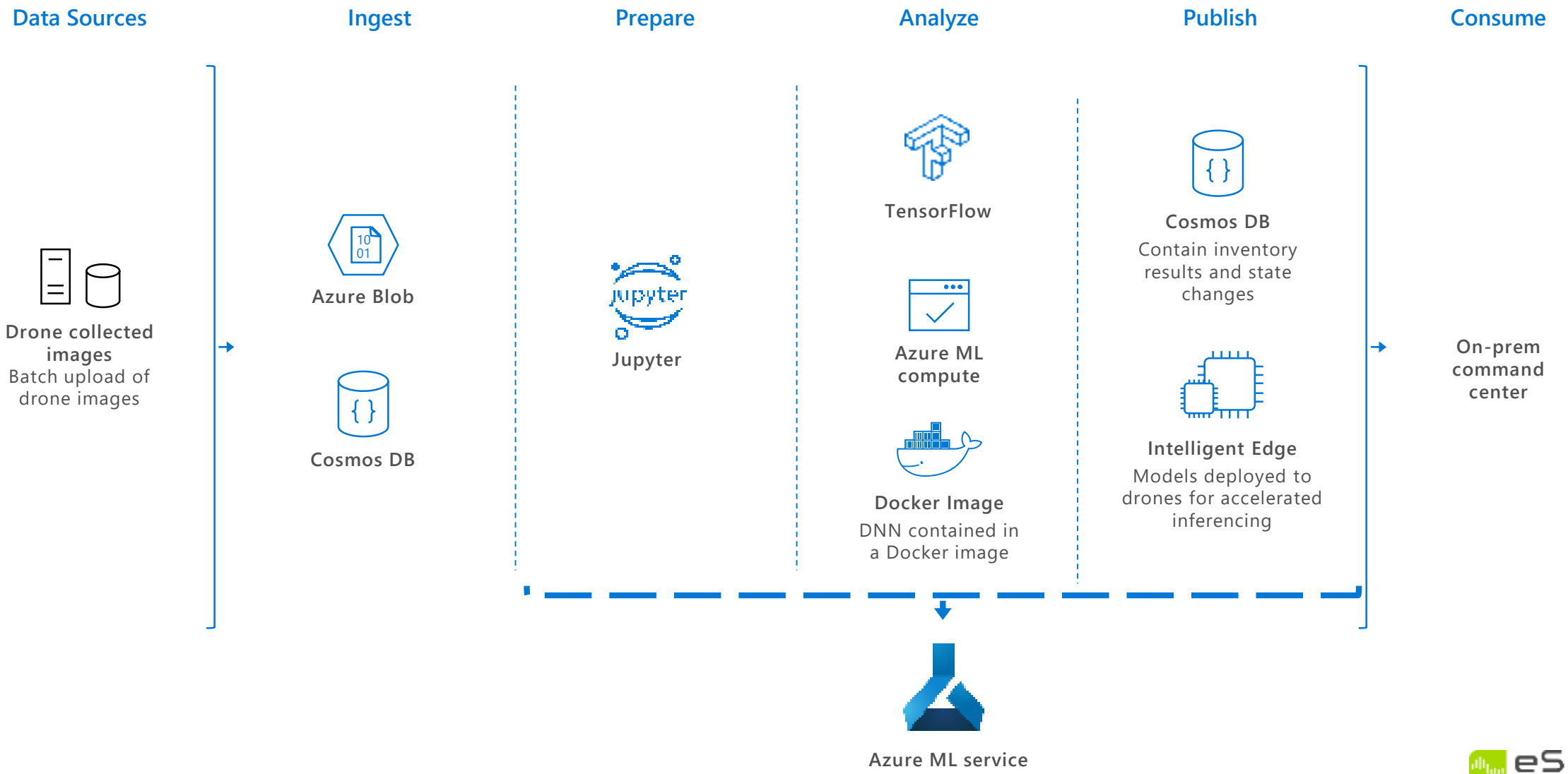
Deep learning to analyze multiple streaming data feeds

Azure GPUs support Single Shot multibox detectors

Reliable, consistent, and highly elastic scalability with Azure Batch Shipyards

eSmart SYSTEMS

eSmart architecture



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