Azure ML Model Training Steps (Note: Does not include MLDevOps process or ML pipelines)

- Step 1 – Create a workspace
- Step 2 – Create an Experiment
- Step 3 – Create remote compute target
- Step 4 – Upload data to the cloud
- Step 5 – Train a local model ***or* Step 6**
- Step 6 – Train model on remote cluster
  - 6.1: Create a directory
  - 6.2: Create a training script
  - 6.3: Create an estimator object
  - 6.4: Submit the job
- Step 7 – Monitor a run
- Step 8 – See the results
- Step 9 – Register the model
- Step 9 – Deploy the Model (*for testing not production*)
  - 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 10 – Test the deployed model using the HTTP end point

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)
```

Step3 – 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.

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

```
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'])
```

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

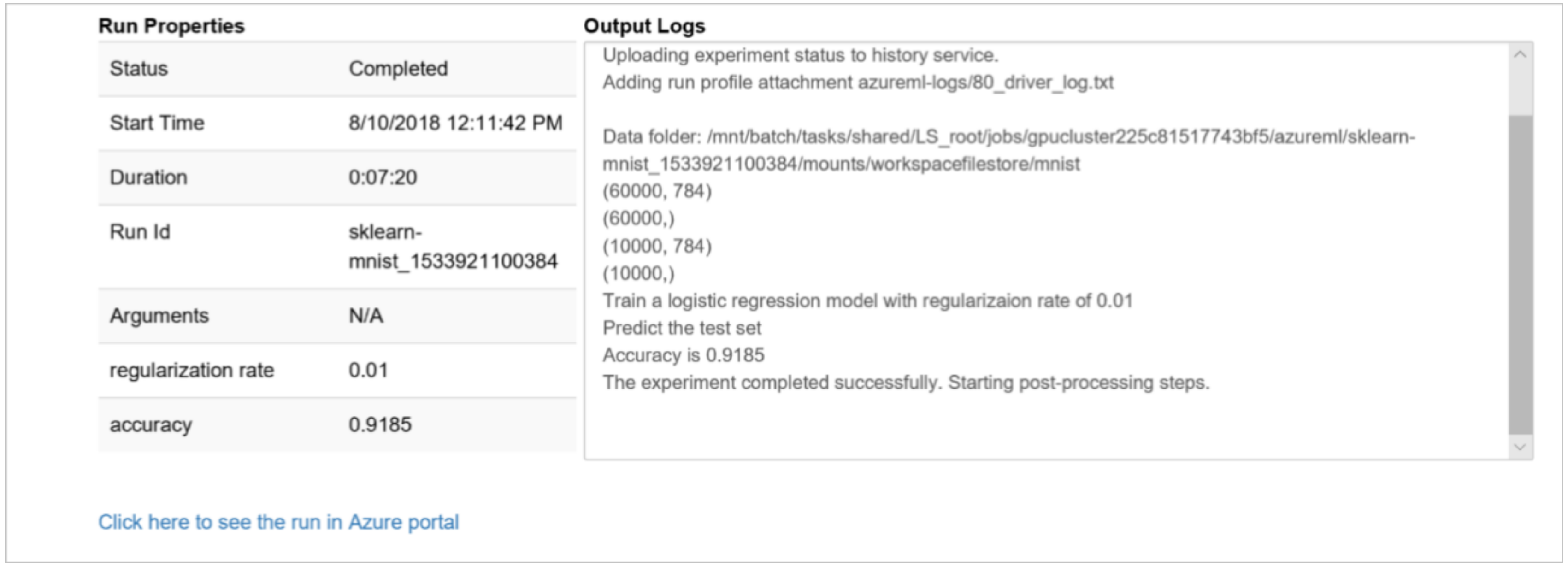
```
run = exp.submit(config=est)
run
```

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.

```python
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)

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

```
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 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

Build an image using:

- The scoring file (score.py)
- The environment file (myenv.yml)
- The model file

```
%%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")
```

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

```
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)
```

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