Kedro Azure ML Plugin

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GetInData

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CHAPTER ONE

INTRODUCTION

1.1 What Azure ML Pipelines?

An Azure Machine Learning pipeline is an independently executable workflow of a complete machine learning task. An Azure Machine Learning pipeline helps to standardize the best practices of producing a machine learning model, enables the team to execute at scale, and improves the model building efficiency.

1.2 Why to integrate Kedro project with Azure ML Pipelines?

Throughout couple years of exploring ML Ops ecosystem as software developers we've been looking for a framework that enforces the best standards and practices regarding ML model development and Kedro Framework seems like a good fit for this position, but what happens next, once you've got the code ready?

It seems like the ecosystem grown up enough so you no longer need to release models you've trained with Jupyter notebook on your local machine on Sunday evening. In fact there are many tools now you can use to have an elegant model delivery pipeline that is automated, reliable and in some cases can give you a resource boost that's often crucial when handling complex models or a load of training data. With the help of some plugins **You can develop your ML training code with Kedro and execute it using multiple robust services** without changing the business logic.

We currently support:

- Kubeflow Pipelines kedro-kubeflow
- Airflow on Kubernetes kedro-airflow-k8s
- GCP Vertex AI Pipelines kedro-vertexai

And with this **kedro-azureml** plugin, you can run your code on Azure ML Pipelines in a fully managed fashion

Azure ML Pipelines

CHAPTER

TWO

INSTALLATION GUIDE

2.1 Prerequisites

- a tool to manage Python virtual environments (e.g. venv, conda, virtualenv).
- Docker
- Azure CLI

2.2 Kedro setup

First, you need to install base Kedro package

```
$ pip install "kedro>=0.18.1,<0.19.0"
```

2.3 Plugin installation

2.3.1 Install from PyPI

You can install `kedro-azureml` plugin from `PyPi` with `pip`:

```
pip install --upgrade kedro-azureml
```

Optionally, extra can be specified: `kedro-azureml[mlflow]`.

2.3.2 Install from sources

You may want to install the develop branch which has unreleased features:

```
pip install git+https://github.com/getindata/kedro-azureml.git@develop
```

2.4 Available commands

You can check available commands by going into project directory and running:

```
kedro azureml

Usage: kedro azureml [OPTIONS] COMMAND [ARGS]...

Options:
  -e, --env TEXT  Environment to use.
  -h, --help      Show this message and exit.

Commands:
  compile  Compiles the pipeline into YAML format
  init     Creates basic configuration for Kedro AzureML plugin
  run      Runs the specified pipeline in Azure ML Pipelines
```

CHAPTER

THREE

QUICKSTART

You can go through the written quickstart here or watch the video on YouTube:

Before you start, make sure that you have the following resources created in Azure and have their **names** ready to input to the plugin:

- Azure Subscription ID
- Azure Resource Group
- Azure ML workspace
- Azure ML Compute Cluster
- Azure Storage Account and Storage Container
- Azure Storage Key (will be used to execute the pipeline)
- Azure Container Registry

1. Make sure that you're logged into Azure (`az login`).
2. Prepare new virtual environment with Python >=3.8. Install the packages

```
pip install "kedro>=0.18.2,<0.19" "kedro-docker" "kedro-azureml"
```

2. Create new project (e.g. from starter)

```
kedro new --starter=spaceflights

Project Name
============
Please enter a human readable name for your new project.
Spaces, hyphens, and underscores are allowed.
 [Spaceflights]: kedro_azureml_demo

The project name 'kedro_azureml_demo' has been applied to:
- The project title in /Users/marcin/Dev/tmp/kedro-azureml-demo/README.md
- The folder created for your project in /Users/marcin/Dev/tmp/kedro-azureml-demo
- The project's python package in /Users/marcin/Dev/tmp/kedro-azureml-demo/src/kedro_
↪azureml_demo
```

3. Go to the project's directory: `cd kedro-azureml-demo`
4. Add `kedro-azureml` to `src/requirements.txt`

5. (optional) Remove `kedro-telemetry` from `src/requirements.txt` or set appropriate settings (https://github.com/kedro-org/kedro-plugins/tree/main/kedro-telemetry).
6. Install the requirements `pip install -r src/requirements.txt`
7. Initialize Kedro Azure ML plugin, it requires the Azure resource names as stated above. Experiment name can be anything you like (as long as it's allowed by Azure ML). The environment name is the name of the Azure ML Environment to be created in the next steps. You can use the syntax `<environment_name>@latest` for the latest version or `<environment-name>:<version>` for a specific version.

```
#Usage: kedro azureml init [OPTIONS] RESOURCE_GROUP WORKSPACE_NAME
#                          EXPERIMENT_NAME CLUSTER_NAME STORAGE_ACCOUNT_NAME
#                          STORAGE_CONTAINER ENVIRONMENT_NAME
kedro azureml init <resource-group-name> <workspace-name> <experiment-name> <compute-
↪cluster-name> <storage-account-name> <storage-container-name> <environment-name>
```

8. Adjust the Data Catalog - the default one stores all data locally, whereas the plugin will automatically use Azure Blob Storage. Only input data is required to be read locally. Final `conf/base/catalog.yml` should look like this:

```
companies:
  type: pandas.CSVDataSet
  filepath: data/01_raw/companies.csv
  layer: raw

reviews:
  type: pandas.CSVDataSet
  filepath: data/01_raw/reviews.csv
  layer: raw

shuttles:
  type: pandas.ExcelDataSet
  filepath: data/01_raw/shuttles.xlsx
  layer: raw
```

9. Prepare an Azure ML Environment for the project:

   For the project's code to run on Azure ML it needs to have an environment with the necessary dependencies.

You have 2 options for executing your pipeline in Azure ML

1. Use code upload (default) - more suitable for Data Scientists' experimentation and pipeline development
2. Use docker image flow (shown in the Quickstart video) - more suitable for MLOps processes with better experiment repeatability guarantees

Start by executing the following command:

```
kedro docker init
```

This command creates a several files, including `Dockerfile` and `.dockerignore`. These can be adjusted to match the workflow for your project.

Depending on whether you want to use code upload when submitting an experiment or not, you would need to add the code and any possible input data to the Docker image.

9.1. **If using code upload** (default)

Everything apart from the section “install project requirements” can be removed from the `Dockerfile`. This plugin automatically creates empty `.amlignore` file (see the official docs) which means that all of the files (including potentially sensitive ones!) will be uploaded to Azure ML. Modify this file if needed.

Ensure `code_directory: "."` is set in the `azureml.yml` config file (it’s set by default).

```
ARG BASE_IMAGE=python:3.9
FROM $BASE_IMAGE

# install project requirements
COPY src/requirements.txt /tmp/requirements.txt
RUN pip install -r /tmp/requirements.txt && rm -f /tmp/requirements.txt
```

Build the image:

```
kedro docker build --docker-args "--build-arg=BASE_IMAGE=python:3.9" --image=<acr repo␣
↪name>.azurecr.io/kedro-base-image:latest
```

Login to ACR and push the image:

```
az acr login --name <acr repo name>
docker push <acr repo name>.azurecr.io/kedro-base-image:latest
```

Register the Azure ML Environment:

```
az ml environment create --name <environment-name> --image <acr repo name>.azurecr.io/
↪kedro-base-image:latest
```

Now you can re-use this environment and run the pipeline without the need to build the docker image again (unless you add some dependencies to your environment, obviously :-)).

Warning:

Azure Code upload feature has issues with empty folders as identified in GitHub #33, where empty folders or folders with empty files might not get uploaded to Azure ML, which might result in the failing pipeline.
We recommend to:
- make sure that Kedro environments you intent to use in Azure have at least one non-empty file specified
- gracefully handle folder creation in your pipeline’s code (e.g. if your code depends on an existence of some folder)

The plugin will do it’s best to handle some of the edge-cases, but the fact that some of your files might not be captured by Azure ML SDK is out of our reach.

9.2. **If using docker image flow** (shown in the Quickstart video)

Note:

Note that using docker image flow means that every time you change your pipeline’s code,
you will need to build and push the docker image to ACR again.
We recommend this option for CI/CD-automated MLOps workflows.

Ensure that in the `azureml.yml` you have `code_directory` set to null, and `docker.image` is filled:

```
code_directory: ~
# rest of the azureml.yml file
docker:
   image: your-container-registry.azurecr.io/kedro-azureml:latest
```

Keep the sections in the `Dockerfile` and adjust the `.dockerignore` file to include any other files to be added to the Docker image, such as `!data/01_raw` for the raw data files.

Invoke docker build:

```
kedro docker build --docker-args "--build-arg=BASE_IMAGE=python:3.9" --image=<image tag␣
↪from conf/base/azureml.yml>
```

Once finished, login to ACR:

```
az acr login --name <acr repo name>
```

and push the image:

```
docker push <image tag from conf/base/azureml.yml>
```

10. Run the pipeline on Azure ML Pipelines. Here, the *Azure Subscription ID* and *Storage Account Key* will be used:

```
kedro azureml run -s <azure-subscription-id>
```

You will most likely see the following prompt:

```
Environment variable AZURE_STORAGE_ACCOUNT_KEY not set, falling back to CLI prompt
Please provide Azure Storage Account Key for storage account <azure-storage-account>:
```

Input the storage account key and press [ENTER] (input will be hidden).

11. Plugin will verify the configuration (e.g. the existence of the compute cluster) and then it will create a *Job* in the Azure ML. The URL to view the job will be displayed in the console output.

12. (optional) You can also use `kedro azureml run -s <azure-subscription-id> --wait-for-completion` to actively wait for the job to finish. Execution logs will be streamed to the console.

```
RunId: placid_pot_bdcyntnkvn
Web View: https://ml.azure.com/runs/placid_pot_bdcyntnkvn?wsid=/subscriptions/<redacted>/
↪resourcegroups/<redacted>/workspaces/ml-ops-sandbox

Streaming logs/azureml/executionlogs.txt
========================================

[2022-07-22 11:45:38Z] Submitting 2 runs, first five are: 1ee5f43f:8cf2e387-e7ec-44cc-
↪9615-2108891153f7,7d81aeeb:c8b837a9-1f79-4971-aae3-3191b29b42e8
[2022-07-22 11:47:02Z] Completing processing run id c8b837a9-1f79-4971-aae3-3191b29b42e8.
[2022-07-22 11:47:25Z] Completing processing run id 8cf2e387-e7ec-44cc-9615-2108891153f7.
[2022-07-22 11:47:26Z] Submitting 1 runs, first five are: 362b9632:7867ead0-b308-49df-
↪95ca-efa26f8583cb
[2022-07-22 11:49:27Z] Completing processing run id 7867ead0-b308-49df-95ca-efa26f8583cb.
[2022-07-22 11:49:28Z] Submitting 2 runs, first five are: 03b2293e:e9e210e7-10ab-4010-
↪91f6-4a40aabf3a30,4f9ccafb:3c00e735-cd3f-40c7-9c1d-fe53349ca8bc
```

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```
[2022-07-22 11:50:50Z] Completing processing run id e9e210e7-10ab-4010-91f6-4a40aabf3a30.
[2022-07-22 11:50:51Z] Submitting 1 runs, first five are: 7a88df7a:c95c1488-5f55-48fa-
↪80ce-971d5412f0fb
[2022-07-22 11:51:26Z] Completing processing run id 3c00e735-cd3f-40c7-9c1d-fe53349ca8bc.
[2022-07-22 11:51:26Z] Submitting 1 runs, first five are: a79effc8:0828c39a-6f02-43f5-
↪acfd-33543f0d6c74
[2022-07-22 11:52:38Z] Completing processing run id c95c1488-5f55-48fa-80ce-971d5412f0fb.
[2022-07-22 11:52:39Z] Submitting 1 runs, first five are: 0a18d6d6:cb9c8f61-e129-4394-
↪a795-ab70be74eb0f
[2022-07-22 11:53:03Z] Completing processing run id 0828c39a-6f02-43f5-acfd-33543f0d6c74.
[2022-07-22 11:53:04Z] Submitting 1 runs, first five are: 1af5c8de:2821dc44-3399-4a26-
↪9cdf-1e8f5b7d6b62
[2022-07-22 11:53:28Z] Completing processing run id cb9c8f61-e129-4394-a795-ab70be74eb0f.
[2022-07-22 11:53:51Z] Completing processing run id 2821dc44-3399-4a26-9cdf-1e8f5b7d6b62.

Execution Summary
=================
RunId: placid_pot_bdcyntnkvn
```

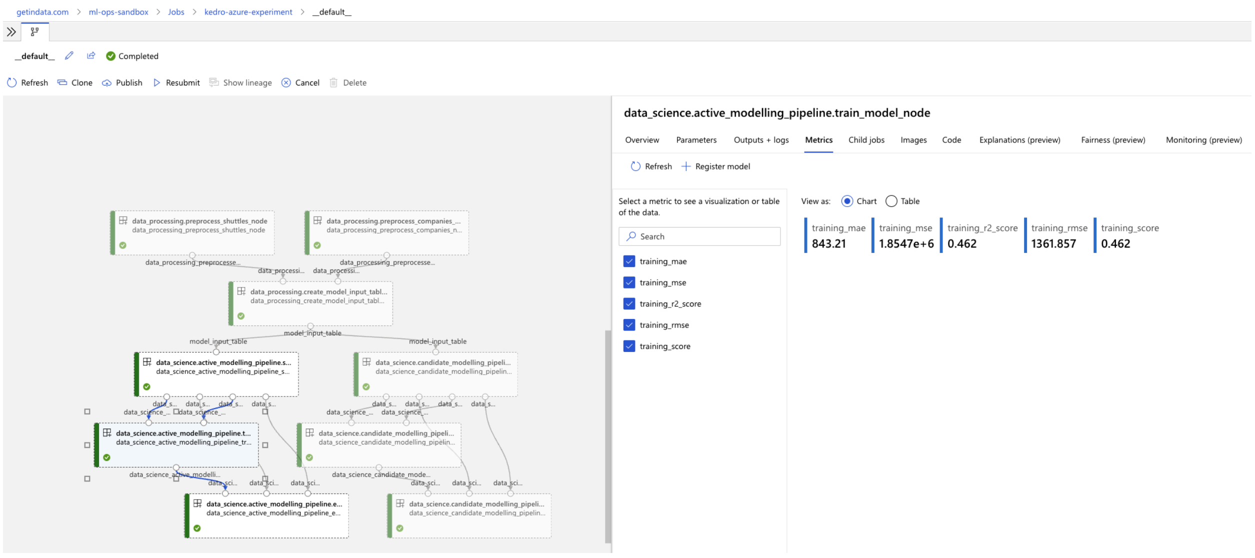
CHAPTER

FOUR

MLFLOW INTEGRATION

The plugin is compatible with `mlflow` (but not yet with `kedro-mlflow`). You can use native mlflow logging capabilities provided by Azure ML. See the guide here: https://docs.microsoft.com/en-us/azure/machine-learning/how-to-use-mlflow-cli-runs?tabs=azuremlsdk.

There is no additional configuration for MLflow required in order to use it with Azure ML pipelines. All the settings are provided automatically by the Azure ML service.


getindata.com > ml-ops-sandbox > Jobs > kedro-azure-experiment > __default__
__default__
Completed
Refresh
Clone
Publish
Resubmit
Show lineage
Cancel
Delete
data_processing.preprocess_shuttles_node
data_processing.preprocess_companies_...
data_processing.create_model_input_tabl...
model_input_table
data_science.active_modelling_pipeline.s...
data_science.candidate_modelling_pipeli...
data_science.active_modelling_pipeline.t...
data_science.active_modelling_pipeline.e...
Overview
Parameters
Outputs + logs
Metrics
Child jobs
Images
Code
Explanations (preview)
Fairness (preview)
Monitoring (preview)
Refresh
Register model
Select a metric to see a visualization or table of the data.
Search
View as: Chart Table

data_science.active_modelling_pipeline.train_model_node

Metrics: ✓ training_mae, ✓ training_mse, ✓ training_r2_score, ✓ training_rmse, ✓ training_score

training_mae	training_mse	training_r2_score	training_rmse	training_score
843.21	1.8547e+6	0.462	1361.857	0.462

CHAPTER

FIVE

USING A DIFFERENT COMPUTE CLUSTER FOR SPECIFIC NODES

For certain nodes it can make sense to run them on a different compute clusters (e.g. High Memory or GPU). This can be achieved using Node tags and adding additional compute targets in your `azureml.yml`.

After creating an additional compute cluster in your AzureML workspace, in this case the additional cluster is called `cpu-cluster-8`, we can add it in our `azureml.yml` under an alias (in this case `chunky`).

```
compute:
  __default__:
    cluster_name: "cpu-cluster"
  chunky:
    cluster_name: "cpu-cluster-8"
```

Now we are able to reference this compute target in our kedro pipelines using kedro node tags:

```
[
    node(
        func=preprocess_companies,
        inputs="companies",
        outputs="preprocessed_companies",
        name="preprocess_companies_node",
        tags=["chunky"]
    ),
    node(
        func=preprocess_shuttles,
        inputs="shuttles",
        outputs="preprocessed_shuttles",
        name="preprocess_shuttles_node",
    ),
    node(
        func=create_model_input_table,
        inputs=["preprocessed_shuttles", "preprocessed_companies", "reviews"],
        outputs="model_input_table",
        name="create_model_input_table_node",
        tags=["chunky"]
    ),
],
```

When running our project, `preprocess_companies` and `create_model_input_table` will be run on `cpu-cluster-8` while all other nodes are run on the default `cpu-cluster`.

CHAPTER

SIX

DISTRIBUTED TRAINING

The plugins supports distributed training via native Azure ML distributed orchestration, which includes:

- MPI - https://learn.microsoft.com/en-us/azure/machine-learning/how-to-train-distributed-gpu#mpi
- PyTorch - https://learn.microsoft.com/en-us/azure/machine-learning/how-to-train-distributed-gpu#pytorch
- TensorFlow - https://learn.microsoft.com/en-us/azure/machine-learning/how-to-train-distributed-gpu#tensorflow

If one of your Kedro's pipeline nodes requires distributed training (e.g. you train a neural network with PyTorch), you can mark the node with `distributed_job` decorator from `kedro_azureml.distributed.decorators` and use native Kedro parameters to specify the number of nodes you want to spawn for the job. An example for PyTorch looks like this:

```
#                    | use appropriate framework
#                   \|/                       \/ specify the number of distributed nodes␣
↪to spawn for the job
@distributed_job(Framework.PyTorch, num_nodes="params:num_nodes")
def train_model_pytorch(
    X_train: pd.DataFrame, y_train: pd.Series, num_nodes: int, max_epochs: int
):
    # rest of the code
    pass
```

In the `pipeline` you would use this node like that:

```
node(
    func=train_model_pytorch,
    inputs=["X_train", "y_train", "params:num_nodes", "params:max_epochs"],
    outputs="regressor",
    name="train_model_node",
),
```

and that's it! The `params:` you use support namespacing as well as overriding at runtime, e.g. when launching the Azure ML job:

```
kedro azureml run -s <subscription id> --params '{"data_science": {"active_modelling_
↪pipeline": {"num_nodes": 4}}}'
```

The `distributed_job` decorator also supports "hard-coded" values for number of nodes:

```
@distributed_job(Framework.PyTorch, num_nodes=2) # no need to use Kedro params here
def train_model_pytorch(
```

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```
    X_train: pd.DataFrame, y_train: pd.Series, num_nodes: int, max_epochs: int
):
    # rest of the code
    pass
```

We have tested the implementation heavily with PyTorch (+PyTorch Lightning) and GPUs. If you encounter any problems, drop us an issue on GitHub!

CHAPTER SEVEN

DEVELOPMENT

7.1 Prerequisites

- poetry `1.1.14` (as of 2022-07-22)
- Python >= 3.9
- Azure CLI (https://docs.microsoft.com/en-us/cli/azure/install-azure-cli)

7.2 Local development

It's easiest to develop the plugin by having a side project created with Kedro (e.g. spaceflights starter), managed by Poetry (since there is no `pip install -e` support in Poetry). In the side project, just add the following entry in `pyproject.toml`:

```
[tool.poetry.dependencies]
kedro-azureml = { path = "<full path to the plugin on local machine>", develop = true,␣
↪extras = ["mlflow"]}
```

and invoke

```
poetry update
poetry install
```

and all of the changes made in the plugin will be immediately visible in the side project (just as with `pip install -e` option).

7.3 Starting the job from local machine

Since you need a docker container to run the job in Azure ML Pipelines, it needs to be build first. For fast local development I suggest the following:

1. Once you decide to test the plugin, run `poetry build`. It will create `dist` folder with `.tar.gz` file in it.
2. Go to the side project folder, create a hard-link to the `.tar.gz`: `ln <full path to the plugin on local machine>/dist/kedro-azureml-0.1.0.tar.gz kedro-azureml-0.1.0.tar.gz`
3. In the `Dockerfile` of the side project add

```
COPY kedro-azureml-0.1.0.tar.gz .
RUN pip install ./kedro-azureml-0.1.0.tar.gz
```

1. Build the docker with `:latest` tag (make sure that `:latest` is specified in the plugin's config `azureml.yml` in `conf`), push the image and run the plugin.
2. Done!

CHAPTER

EIGHT

INDICES AND TABLES

- genindex
- modindex
- search