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

3.1 Video-tutorial

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

3.2 Prerequisites

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

Depending on the type of flow you want to use, you might also need: - Azure Storage Account and Storage Container - Azure Storage Key (will be used to execute the pipeline) - Azure Container Registry

3.3 Project initialization

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>=0.18.5,<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
```

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```
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).

   There are two options, which determine how you should initialize the plugin (don't worry, you can change it later):

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

```
Usage: kedro azureml init [OPTIONS] SUBSCRIPTION_ID RESOURCE_GROUP
                          WORKSPACE_NAME EXPERIMENT_NAME CLUSTER_NAME

  Creates basic configuration for Kedro AzureML plugin

Options:
  --azureml-environment, --aml-env TEXT
                                  Azure ML environment to use with code flow
  -d, --docker-image TEXT         Docker image to use
  -a, --storage-account-name TEXT
                                  Name of the storage account (if you want to
                                  use Azure Blob Storage for temporary data)
  -c, --storage-container TEXT    Name of the storage container (if you want
                                  to use Azure Blob Storage for temporary
                                  data)
  --use-pipeline-data-passing     (flag) Set, to use EXPERIMENTAL pipeline
                                  data passing
```

For **docker image flow** (1.), use the following `init` command:

```
kedro azureml init <AZURE_SUBSCRIPTION_ID> <AZURE_RESOURCE_GROUP> <AML_
↪WORKSPACE_NAME> <EXPERIMENT_NAME> <COMPUTE_NAME> \
 --docker-image <YOUR_ARC>.azurecr.io/<IMAGE_NAME>:latest -a <STORAGE_ACCOUNT_
↪NAME> -c <STORAGE_CONTAINER_NAME>
```

For **code upload flow** (2.), use the following `init` command:

```
kedro azureml init <AZURE_SUBSCRIPTION_ID> <AZURE_RESOURCE_GROUP> <AML_
↪WORKSPACE_NAME> <EXPERIMENT_NAME> <COMPUTE_NAME> \
```

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```
 --aml-env <YOUR_ARC>.azurecr.io/<IMAGE_NAME>:latest -a <STORAGE_ACCOUNT_NAME>␣
↪-c <STORAGE_CONTAINER_NAME>
```

Note: If you want to pass data between nodes using the built-in Azure ML pipeline data passing, specify option `--use-pipeline-data-passing` instead of *-a* and *-c* options.

Note that pipeline data passing feature is experimental See 04_data_assets for more information about this.

3.4 Adjusting the Data Catalog

8. Adjust the Data Catalog - the default one stores all data locally, whereas the plugin will automatically use Azure Blob Storage / Azure ML built-in storage (if *pipeline data passing* was enabled). Only input data is required to be read locally.

   Final `conf/base/catalog.yml` should look like this:

```yaml
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
```

3.5 Pick your deployment option

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

9. 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.

3.5.1 (Option 1) Docker image flow

This option is also shown in the video-tutorial above.

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.

10. 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
```

11. 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.

12. Invoke docker build:

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

13. 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>
```

3.5.2 (Option 2) Code upload flow

10. 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.

```
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
```

11. Ensure `code_directory: "."` is set in the `azureml.yml` config file (it's set if you've used `--aml_env` during `init` above).

12. 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
```

12. 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
```

13. 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.

3.6 Run the pipeline

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

```
kedro azureml run
```

If you're using Azure Blob Storage for temporary data (`-a`, `-c` options during init), 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).

If you're using *pipeline data passing* (`--use-pipeline-data-passing` option during init), you're already set.

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
```

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```
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
[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
```

|Kedro AzureML Pipeline execution|

3.7 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`.

3.8 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(
    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!

3.9 Run customization

In case you need to customize pipeline run context, modifying configuration files is not always the most convinient option. Therefore, `kedro azureml run` command provides a few additional options you may find useful:

- `--subscription_id` overrides Azure Subscription ID,
- `--azureml_environment` overrides the configured Azure ML Environment,
- `--image` modifies the Docker image used during the execution,
- `--pipeline` allows to select a pipeline to run (by default, the `__default__` pipeline is started),
- `--params` takes a JSON string with parameters override (JSONed version of `conf/*/parameters.yml`, not the Kedro's `params:` syntax),

- `--env-var KEY=VALUE` sets the OS environment variable injected to the steps during runtime (can be used multiple times).

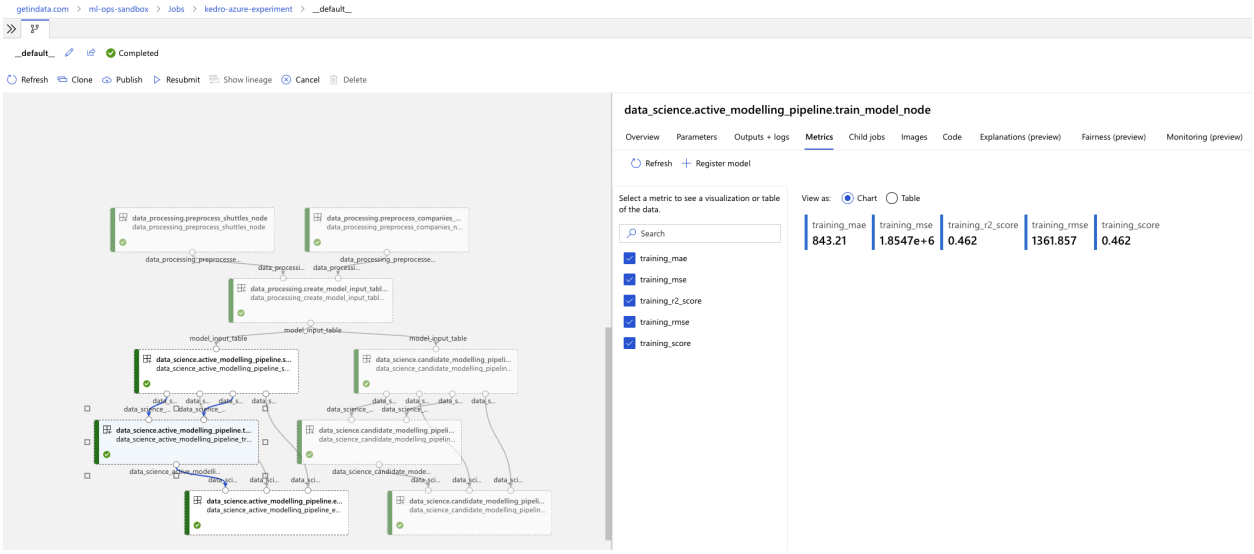
CHAPTER

FOUR

MLFLOW INTEGRATION

The plugin is compatible with `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 via environment variables.



CHAPTER

FIVE

AZURE DATA ASSETS

`kedro-azureml` adds support for two new datasets that can be used in the Kedro catalog. Right now we support both Azure ML v1 SDK (direct Python) and Azure ML v2 SDK (fsspec-based) APIs.

For v2 API (fspec-based) - use `AzureMLAssetDataSet` that enables to use Azure ML v2-sdk Folder/File datasets for remote and local runs.

For v1 API (deprecated) use the `AzureMLFileDataSet` and the `AzureMLPandasDataSet` which translate to File/Folder dataset and Tabular dataset respectively in Azure Machine Learning. Both fully support the Azure versioning mechanism and can be used in the same way as any other dataset in Kedro.

Apart from these, `kedro-azureml` also adds the `AzureMLPipelineDataSet` which is used to pass data between pipeline nodes when the pipeline is run on Azure ML and the *pipeline data passing* feature is enabled. By default, data is then saved and loaded using the `PickleDataSet` as underlying dataset. Any other underlying dataset can be used instead by adding a `AzureMLPipelineDataSet` to the catalog.

All of these can be found under the kedro_azureml.datasets module.

For details on usage, see the *API Reference* below

5.1 API Reference

5.1.1 Pipeline data passing

Cannot be used when run locally.

class kedro_azureml.datasets.**AzureMLPipelineDataSet**(*dataset: str | Type[AbstractDataSet] | Dict[str, Any]*, *root_dir: str = 'data'*, *filepath_arg: str = 'filepath'*)

Dataset to support pipeline data passing in Azure ML between nodes, using *kedro.io.AbstractDataSet* as base class. Wraps around an underlying dataset, which can be any dataset supported by Kedro, and adds the ability to modify the file path of the underlying dataset, to point to the mount paths on the Azure ML compute where the node is run.

Args

- `dataset`: Underlying dataset definition. Accepted formats are: a) object of a class that inherits from `AbstractDataSet` b) a string representing a fully qualified class name to such class c) a dictionary with `type` key pointing to a string from b), other keys are passed to the Dataset initializer.
- `root_dir`: Folder (path) to prepend to the filepath of the underlying dataset. If unspecified, defaults to "data".
- `filepath_arg`: Underlying dataset initializer argument that will set the filepath. If unspecified, defaults to "filepath".

Example

Example of a catalog.yml entry:

```
processed_images:
  type: kedro_azureml.datasets.AzureMLPipelineDataSet
  root_dir: 'data/01_raw'
  dataset:
    type: pillow.ImageDataSet
    filepath: 'images.png'
```

5.1.2 V2 SDK

Use the dataset below when you're using Azure ML SDK v2 (fsspec-based).

Can be used for both remote and local runs.

class kedro_azureml.datasets.asset_dataset.**AzureMLAssetDataSet**(*azureml_dataset: str*, *dataset: str | Type[AbstractDataSet] | Dict[str, Any]*, *root_dir: str = 'data'*, *filepath_arg: str = 'filepath'*, *azureml_type: Literal['uri_file', 'uri_folder'] = 'uri_folder'*, *version: Version | None = None*)

AzureMLAssetDataSet enables kedro-azureml to use azureml v2-sdk Folder/File datasets for remote and local runs.

Args

- `azureml_dataset`: Name of the AzureML dataset.
- `dataset`: Definition of the underlying dataset saved in the Folder/Filedataset. ``e.g. Parquet, Csv etc.
- `root_dir`: The local folder where the dataset should be saved during local runs. ``Relevant for local execution via *kedro run*.
- `filepath_arg`: Filepath arg on the wrapped dataset, defaults to *filepath*
- `azureml_type`: Either *uri_folder* or *uri_file*
- `version`: Version of the AzureML dataset to be used in kedro format.

Example

Example of a catalog.yml entry:

```
my_folder_dataset:
  type: kedro_azureml.datasets.AzureMLAssetDataSet
  azureml_dataset: my_azureml_folder_dataset
  root_dir: data/01_raw/some_folder/
  versioned: True
  dataset:
    type: pandas.ParquetDataSet
    filepath: "."

my_file_dataset:
    type: kedro_azureml.datasets.AzureMLAssetDataSet
    azureml_dataset: my_azureml_file_dataset
    root_dir: data/01_raw/some_other_folder/
    versioned: True
    dataset:
        type: pandas.ParquetDataSet
        filepath: "companies.csv"
```

5.1.3 V1 SDK

Use the datasets below when you're using Azure ML SDK v1 (direct Python).

Deprecated - will be removed in future version of *kedro-azureml*.

class kedro_azureml.datasets.**AzureMLPandasDataSet**(*azureml_dataset: str*, *azureml_datastore: str | None = None*, *azureml_dataset_save_args: Dict[str, Any] | None = None*, *azureml_dataset_load_args: Dict[str, Any] | None = None*, *workspace: azureml.core.Workspace | None = None*, *workspace_args: Dict[str, Any] | None = None*)

AzureML tabular dataset integration with Pandas DataFrame and kedro. Can be used to save Pandas DataFrame to AzureML tabular dataset, and load it back to Pandas DataFrame.

Args

- `azureml_dataset`: Name of the AzureML file azureml_dataset.
- `azureml_datastore`: Name of the AzureML azureml_datastore. If not provided, the default azureml_datastore will be used.
- `azureml_dataset_save_args`: Additional arguments to pass to `TabularDatasetFactory.register_pandas_dataframe` method. Read more: register_pandas_dataframe
- `azureml_dataset_load_args`: Additional arguments to pass to `azureml.core.Dataset.get_by_name` method. Read more: Dataset.get_by_name
- `workspace`: AzureML Workspace. If not specified, will attempt to load the workspace automatically.
- `workspace_args`: Additional arguments to pass to `utils.get_workspace()`.

Example

Example of a catalog.yml entry:

```
my_pandas_dataframe_dataset:
  type: kedro_azureml.datasets.AzureMLPandasDataSet
  azureml_dataset: my_new_azureml_dataset

  # if version is not provided, the latest dataset version will be used
  azureml_dataset_load_args:
    version: 1
```

---

class kedro_azureml.datasets.**AzureMLFileDataSet**(*azureml_dataset: str*, *azureml_datastore: str | None = None*, *azureml_dataset_save_args: Dict[str, Any] | None = None*, *azureml_dataset_load_args: Dict[str, Any] | None = None*, *workspace: azureml.core.Workspace | None = None*, *workspace_args: Dict[str, Any] | None = None*, ***kwargs*)

AzureML file dataset integration with Kedro, using *kedro.io.PartitionedDataSet* as base class. Can be used to save (register) data stored in azure blob storage as an AzureML file dataset. The data can then be loaded from the AzureML file dataset into a convenient format (e.g. pandas, pillow image etc).

Args

- `azureml_dataset`: Name of the AzureML file dataset.

- `azureml_datastore`: Name of the AzureML datastore. If not provided, the default datastore will be used.

- `azureml_dataset_save_args`: Additional arguments to pass to `AbstractDataset.register` method. make sure to pass `create_new_version=True` to create a new version of an existing dataset. note: if there's no difference in file paths, a new version will not be created and the existing version will be overwritten, even if `create_new_version=True`. Read more: AbstractDataset.register.

- `azureml_dataset_load_args`: Additional arguments to pass to *azureml.core.Dataset.get_by_name* method. Read more: azureml.core.Dataset.get_by_name.

- `workspace`: AzureML Workspace. If not specified, will attempt to load the workspace automatically.

- `workspace_args`: Additional arguments to pass to `utils.get_workspace()`.

- `kwargs`: Additional arguments to pass to `PartitionedDataSet` constructor. make sure to not pass *path* argument, as it will be built from `azureml_datastore` argument.

Example

Example of a catalog.yml entry:

```yaml
processed_images:
  type: kedro_azureml.datasets.AzureMLFileDataSet
  dataset: pillow.ImageDataSet
  filename_suffix: '.png'
  azureml_dataset: processed_images
  azureml_dataset_save_args:
    create_new_version: true

  # if version is not provided, the latest dataset version will be used
  azureml_dataset_load_args:
    version: 1

  # optional, if not provided, the environment variable
  # `AZURE_STORAGE_ACCOUNT_NAME` and `AZURE_STORAGE_ACCOUNT_KEY` will be used
  credentials:
    account_name: my_storage_account_name
    account_key: my_storage_account_key
```

Example of Python API usage:

```python
import pandas as pd

# create dummy data
dict_df = {}
dict_df['path/in/azure/blob/storage/file_1'] = pd.DataFrame({'a': [1,2], 'b': [3,4]}
↪)
dict_df['path/in/azure/blob/storage/file_2'] = pd.DataFrame({'c': [3,4], 'd': [5,6]}
↪)

# init AzureMLFileDataSet
data_set = AzureMLFileDataSet(
    azureml_dataset='my_azureml_file_dataset_name',
    azureml_datastore='my_azureml_datastore_name',  # optional, if not provided,␣
↪the default datastore will be used  # noqa
    dataset='pandas.CSVDataSet',
    filename_suffix='.csv',  # optional, will add this suffix to the file names␣
↪(file_1.csv, file_2.csv)

    # optional - if not provided, will use the environment variables
    # AZURE_STORAGE_ACCOUNT_NAME and AZURE_STORAGE_ACCOUNT_KEY
    credentials={
        'account_name': 'my_storage_account_name',
        'account_key': 'my_storage_account_key',
    },

    # create version if the dataset already exists (otherwise, when trying to save,␣
↪will get an error)
    azureml_dataset_save_args={
        'create_new_version': True,
    }
```

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```
)

# this will create 2 blobs, one for each dataframe, in the following paths:
# <my_storage_account_name/my_container/path/in/azure/blob/storage/file_1.csv>
# <my_storage_account_name/my_container/path/in/azure/blob/storage/file_2.csv>
# also, it will register a corresponding AzureML file-dataset under the name <my_
↪azureml_file_dataset_name> # noqa
data_set.save(dict_df)

# this will create lazy load functions instead of loading data into memory␣
↪immediately.
loaded = data_set.load()

# load all the partitions
for file_path, load_func in loaded.items():
    df = load_func()

    # process pandas dataframe
    # ...
```

CHAPTER

SIX

DEVELOPMENT

6.1 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)

6.2 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).

6.3 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

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