Kedro Vertex AI Plugin

Release 0.4.1

GetInData

Apr 14, 2022

CONTENTS:

CHAPTER ONE

INTRODUCTION

1.1 What is GCP VertexAI Pipelines?

Vertex AI Pipelines is a Google Cloud Platform service that aims to deliver Kubeflow Pipelines functionality in a fully managed fashion. Vertex AI Pipelines helps you to automate, monitor, and govern your ML systems by orchestrating your ML workflow in a serverless manner.

1.2 Why to integrate Kedro project with Vertex AI Pipelines?

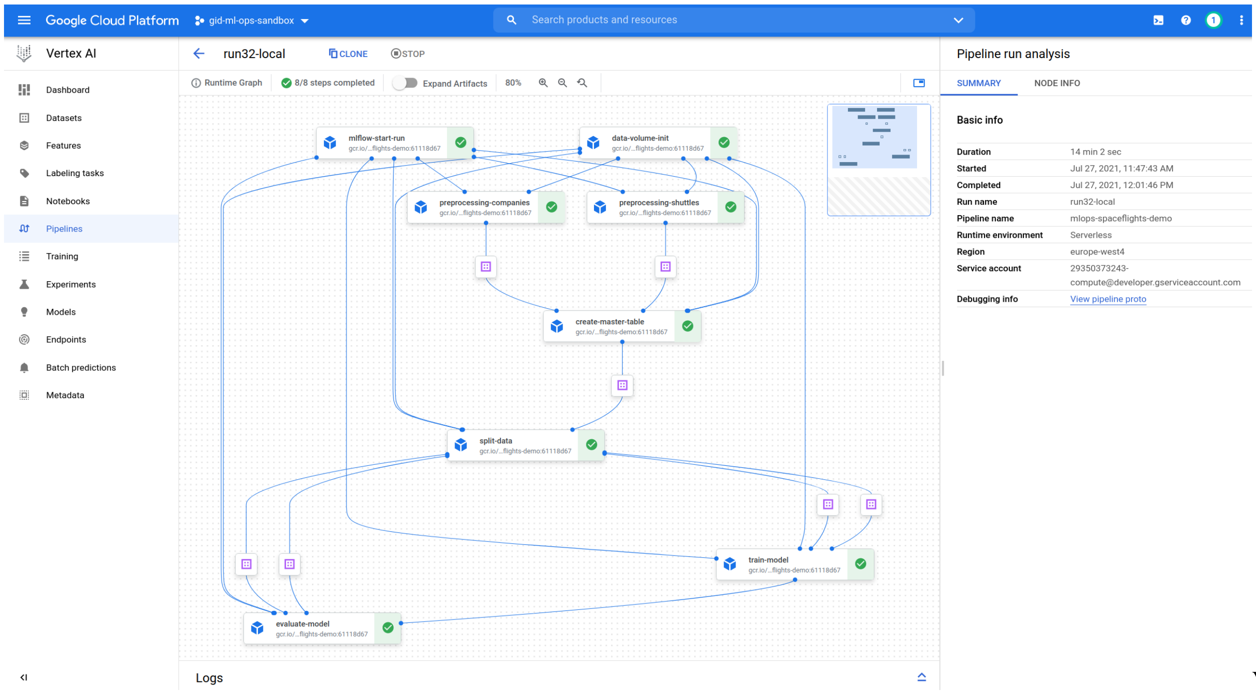
Throughout couple years of exploring ML Ops ecosystem as software developers we've been looking for a framework that enforces the best standards and practices regarding ML model development and Kedro Framework seems like a good fit for this position, but what happens next, once you've got the code ready?

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 kedro-kubeflow
- Airflow on Kubernetes kedro-airflow-k8s

And with this **kedro-vertexai** plugin, you can run your code on GCP Vertex AI Pipelines in a fully managed fashion



Basic info

Duration	14 min 2 sec
Started	Jul 27, 2021, 11:47:43 AM
Completed	Jul 27, 2021, 12:01:46 PM
Run name	run32-local
Pipeline name	mlops-spaceflights-demo
Runtime environment	Serverless
Region	europe-west4
Service account	29350373243-compute@developer.gserviceaccount.com
Debugging info	View pipeline proto

VertexAi

CHAPTER TWO

INSTALLATION

2.1 Installation guide

2.1.1 Kedro setup

First, you need to install base Kedro package

```
$ pip install "kedro>=0.16,<=0.18"
```

2.1.2 Plugin installation

Install from PyPI

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

```
pip install --upgrade kedro-vertexai
```

Install from sources

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

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

2.1.3 Available commands

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

```
$ kedro vertexai
Usage: kedro vertexai [OPTIONS] COMMAND [ARGS]...

  Interact with Google Cloud Platform :: Vertex AI Pipelines

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

Commands:
```

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```
  compile         Translates Kedro pipeline into JSON file with VertexAI...
  init            Initializes configuration for the plugin
  list-pipelines  List deployed pipeline definitions
  run-once        Deploy pipeline as a single run within given experiment...
  schedule        Schedules recurring execution of latest version of the...
  ui              Open VertexAI Pipelines UI in new browser tab
```

`init`

`init` command takes two arguments: `PROJECT_ID` and `REGION`. This command generates a sample configuration file in `conf/base/vertexai.yaml`. The YAML file content is described in the Configuration section.

`ui`

`ui` command opens a web browser pointing to the currently configured Vertex AI Pipelines UI on GCP web console.

`list-pipelines`

`list-pipelines` uses Vertex AI API to retrieve list of all pipelines

`compile`

`compile` transforms Kedro pipeline into Vertex AI workflow. The resulting `json` file can be uploaded to Vertex AI Pipelines via Python Client e.g. from your CI/CD job.

`run-once`

`run-once` is all-in-one command to compile the pipeline and run it in the GCP Vertex AI Pipelines environment.

2.2 Configuration

Plugin maintains the configuration in the `conf/base/vertexai.yaml` file. Sample configuration can be generated using `kedro vertexai init`:

```yaml
# Configuration used to run the pipeline
project_id: my-gcp-mlops-project
region: europe-west1
run_config:
  # Name of the image to run as the pipeline steps
  image: eu.gcr.io/my-gcp-mlops-project/example_model:${commit_id}

  # Pull policy to be used for the steps. Use Always if you push the images
  # on the same tag, or Never if you use only local images
  image_pull_policy: IfNotPresent

  # Location of Vertex AI GCS root
```

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```yaml
root: bucket_name/gcs_suffix

# Name of the kubeflow experiment to be created
experiment_name: MyExperiment

# Name of the scheduled run, templated with the schedule parameters
scheduled_run_name: MyExperimentRun

# Optional pipeline description
#description: "Very Important Pipeline"

# How long to keep underlying Argo workflow (together with pods and data
# volume after pipeline finishes) [in seconds]. Default: 1 week
ttl: 604800

# What Kedro pipeline should be run as the last step regardless of the
# pipeline status. Used to send notifications or raise the alerts
# on_exit_pipeline: notify_via_slack

# Optional section allowing adjustment of the resources
# reservations and limits for the nodes
resources:

  # For nodes that require more RAM you can increase the "memory"
  data_import_step:
    memory: 2Gi

  # Training nodes can utilize more than one CPU if the algoritm
  # supports it
  model_training:
    cpu: 8
    memory: 1Gi

  # GPU-capable nodes can request 1 GPU slot
  tensorflow_step:
    nvidia.com/gpu: 1

  # Default settings for the nodes
  __default__:
    cpu: 200m
    memory: 64Mi

# Optional section allowing to generate config files at runtime,
# useful e.g. when you need to obtain credentials dynamically and store them in␣
↪credentials.yaml
# but the credentials need to be refreshed per-node
# (which in case of Vertex AI would be a separate container / machine)
# Example:
# dynamic_config_providers:
#  - cls: kedro_vertexai.auth.gcp.MLFlowGoogleOAuthCredentialsProvider
#    params:
#      client_id: iam-client-id
```

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```
  dynamic_config_providers: []
```

2.2.1 Dynamic configuration support

kedro-vertexai contains hook that enables TemplatedConfigLoader. It allows passing environment variables to configuration files. It reads all environment variables following KEDRO_CONFIG_<NAME> pattern, which you can later inject in configuration file using ${name} syntax.

This feature is especially useful for keeping the executions of the pipelines isolated and traceable by dynamically setting output paths for intermediate data in the **Data Catalog**, e.g.

```
# ...
train_x:
  type: pandas.CSVDataSet
  filepath: gs://<bucket>/kedro-vertexai/${run_id}/05_model_input/train_x.csv

train_y:
  type: pandas.CSVDataSet
  filepath: gs://<bucket>/kedro-vertexai/${run_id}/05_model_input/train_y.csv
# ...
```

In this case, the ${run_id} placeholder will be substituted by the unique run identifier from Vertex AI Pipelines.

There are two special variables KEDRO_CONFIG_COMMIT_ID, KEDRO_CONFIG_BRANCH_NAME with support specifying default when variable is not set, e.g. ${commit_id|dirty}

Disabling dynamic configuration hook

In current Kedro versions (<=0.18) only single configuration hook can be attached, which means if your project had a custom one, this plug-in will most likely overwrite it. You can disable this plugin's configuration hook by setting environment variable KEDRO_VERTEXAI_DISABLE_CONFIG_HOOK to true, e.g.:

```
export KEDRO_VERTEXAI_DISABLE_CONFIG_HOOK=true
```

Once set, the plugin will provide a clear warning with a reminder:

```
KEDRO_VERTEXAI_DISABLE_CONFIG_HOOK environment variable is set and␣
↪EnvTemplatedConfigLoader will not be used which means formatted config values like $
↪{run_id} will not be substituted at runtime
```

To make plugin-compatible custom config loader you can extend the class kedro_vertexai.context_helper.EnvTemplatedConfigLoader and register your own hook.

Dynamic config providers

When running the job in VertexAI it's possible to generate new configuration files **at runtime** if that's required, one example could be generating Kedro credentials on a Vertex AI's node level (the opposite would be supplying the credentials when starting the job).

Example:

```yaml
run_config:
  # ...
  dynamic_config_providers:
    - cls: kedro_vertexai.auth.gcp.MLFlowGoogleOAuthCredentialsProvider
      params:
        client_id: iam-client-id
```

The `cls` fields should contain a fully qualified reference to a class implementing abstract `kedro_vertexai.dynamic_config.DynamicConfigProvider`. All `params` will be passed as `kwargs` to the class's constructor. Two required methods are:

```python
@property
def target_config_file(self) -> str:
    return "name-of-the-config-file.yml"

def generate_config(self) -> dict:
    return {
        "layout": {
            "of-the-target": {
                "config-file": "value"
            }
        }
    }
```

First one - `target_config_file` should return the name of the configuration file to be generated (e.g. `credentials.yml`) and the `generate_config` should return a dictionary, which will be then serialized into the target file as YAML. If the target file already exists during the invocation, it will be merged (see method `kedro_vertexai.dynamic_config.DynamicConfigProvider.merge_with_existing`) with the existing one and then saved again. Note that the `generate_config` has access to an initialized plugin config via `self.config` property, so any values from the `vertexai.yml` configuration is accessible.

CHAPTER THREE

GETTING STARTED

3.1 Quickstart

3.1.1 Preprequisites

The quickstart assumes user have access to Vertex AI Pipelines service.

3.1.2 Install the toy project with Vertex AI Pipelines support

It is a good practice to start by creating a new virtualenv before installing new packages. Therefore, use `virtalenv` command to create new env and activate it:

```
$ virtualenv venv-demo
created virtual environment CPython3.8.12.final.0-64 in 764ms
  creator CPython3Posix(dest=/home/getindata/kedro/venv-demo, clear=False, no_vcs_
↪ignore=False, global=False)
  seeder FromAppData(download=False, pip=bundle, setuptools=bundle, wheel=bundle,␣
↪via=copy)
    added seed packages: pip==22.0.4, setuptools==60.9.3, wheel==0.37.1
  activators BashActivator,CShellActivator,FishActivator,NushellActivator,
↪PowerShellActivator,PythonActivator
$ source venv-demo/bin/activate
```

Then, `kedro` must be present to enable cloning the starter project, along with the latest version of `kedro-kubeflow` plugina and kedro-docker (required to build docker images with the Kedro pipeline nodes):

```
$ pip install 'kedro<0.18' kedro-vertexai kedro-docker
```

With the dependencies in place, let's create a new project:

```
$ kedro new --starter=spaceflights

Project Name:
=============
Please enter a human readable name for your new project.
Spaces and punctuation are allowed.
 [New Kedro Project]: Vertex AI Plugin Demo

Repository Name:
================
```

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```
Please enter a directory name for your new project repository.
Alphanumeric characters, hyphens and underscores are allowed.
Lowercase is recommended.
 [vertex-ai-plugin-demo]:

Python Package Name:
====================
Please enter a valid Python package name for your project package.
Alphanumeric characters and underscores are allowed.
Lowercase is recommended. Package name must start with a letter
or underscore.
 [vertex_ai_plugin_demo]:

Change directory to the project generated in /Users/getindata/vertex-ai-plugin-demo

A best-practice setup includes initialising git and creating a virtual environment␣
↪before running ``kedro install`` to install project-specific dependencies. Refer to␣
↪the Kedro documentation: https://kedro.readthedocs.io/
```

Finally, go the demo project directory and ensure that kedro-vertexai plugin is activated:

```
$ cd vertexai-plugin-demo/
$ pip install -r src/requirements.txt
(...)
Requirements installed!

$ kedro vertexai --help
Usage: kedro vertexai [OPTIONS] COMMAND [ARGS]...

  Interact with Google Cloud Platform :: Vertex AI Pipelines

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

Commands:
  compile         Translates Kedro pipeline into JSON file with VertexAI...
  init            Initializes configuration for the plugin
  list-pipelines  List deployed pipeline definitions
  run-once        Deploy pipeline as a single run within given experiment...
  schedule        Schedules recurring execution of latest version of the...
  ui              Open VertexAI Pipelines UI in new browser tab
```

3.1.3 Build the docker image to be used in Vertex AI Pipelines runs

First, initialize the project with `kedro-docker` configuration by running:

```
$ kedro docker init
```

This command creates a several files, including `.dockerignore`. This file ensures that transient files are not included in the docker image and it requires small adjustment. Open it in your favourite text editor and extend the section `# except the following` by adding there:

```
!data/01_raw
```

Ensure right requirements.txt

You need to make sure that before you build the docker image and submit the job to Vertex AI Pipelines, all of your project's Python package requirements are properly saved in `requirements.txt`, that includes **this plugin**. Ensure that the `src/requirements.txt` contains this line

```
kedro-vertexai
```

Adjusting Data Catalog to be compatible with Vertex AI

This change enforces raw data existence in the image. Also, one of the limitations of running the Kedro pipeline on Vertex AI (and not on local environment) is inability to use `MemoryDataSets`, as the pipeline nodes do not share memory, so every artifact should be stored as file in a location that can be accessed by the service (e.g. GCS bucket). The `spaceflights` demo configures datasets to output into local `data` folder, so let's change the behaviour by creating a temporary GCS bucket (referred to as `STAGING_BUCKET`) and modifying `conf/base/catalog.yml`:

```
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
  load_args:
    engine: openpyxl

model_input_table:
  type: pandas.CSVDataSet
  filepath: gs://STAGING_BUCKET/${run_id}/03_primary/model_input_table.csv
  layer: primary

### catalog entries required starter version <= 0.17.6
preprocessed_companies:
```

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```yaml
  type: pandas.CSVDataSet
  filepath: gs://STAGING_BUCKET/${run_id}/02_intermediate/preprocessed_companies.csv
  layer: intermediate

preprocessed_shuttles:
  type: pandas.CSVDataSet
  filepath: gs://STAGING_BUCKET/${run_id}/02_intermediate/preprocessed_shuttles.csv
  layer: intermediate

X_train:
  type: pickle.PickleDataSet
  filepath: gs://STAGING_BUCKET/${run_id}/05_model_input/X_train.pickle
  layer: model_input

y_train:
  type: pickle.PickleDataSet
  filepath: gs://STAGING_BUCKET/${run_id}/05_model_input/y_train.pickle
  layer: model_input

X_test:
  type: pickle.PickleDataSet
  filepath: gs://STAGING_BUCKET/${run_id}/05_model_input/X_test.pickle
  layer: model_input

y_test:
  type: pickle.PickleDataSet
  filepath: gs://STAGING_BUCKET/${run_id}/05_model_input/y_test.pickle
  layer: model_input

regressor:
  type: pickle.PickleDataSet
  filepath: gs://STAGING_BUCKET/${run_id}/06_models/regressor.pickle
  versioned: true
  layer: models

### catalog entries required for starter version >= 0.17.7
data_processing.preprocessed_companies:
  type: pandas.CSVDataSet
  filepath: gs://STAGING_BUCKET/${run_id}/02_intermediate/preprocessed_companies.csv
  layer: intermediate

data_processing.preprocessed_shuttles:
  type: pandas.CSVDataSet
  filepath: gs://STAGING_BUCKET/${run_id}/02_intermediate/preprocessed_shuttles.csv
  layer: intermediate

data_science.active_modelling_pipeline.X_train:
  type: pickle.PickleDataSet
  filepath: gs://STAGING_BUCKET/${run_id}/05_model_input/X_train.pickle
  layer: model_input

data_science.active_modelling_pipeline.y_train:
```

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```
  type: pickle.PickleDataSet
  filepath: gs://STAGING_BUCKET/${run_id}/05_model_input/y_train.pickle
  layer: model_input

data_science.active_modelling_pipeline.X_test:
  type: pickle.PickleDataSet
  filepath: gs://STAGING_BUCKET/${run_id}/05_model_input/X_test.pickle
  layer: model_input

data_science.active_modelling_pipeline.y_test:
  type: pickle.PickleDataSet
  filepath: gs://STAGING_BUCKET/${run_id}/05_model_input/y_test.pickle
  layer: model_input

data_science.active_modelling_pipeline.regressor:
  type: pickle.PickleDataSet
  filepath: gs://STAGING_BUCKET/${run_id}/06_models/regressor.pickle
  versioned: true
  layer: models

data_science.candidate_modelling_pipeline.X_train:
  type: pickle.PickleDataSet
  filepath: gs://STAGING_BUCKET/${run_id}/05_model_input/X_train.pickle
  layer: model_input

data_science.candidate_modelling_pipeline.y_train:
  type: pickle.PickleDataSet
  filepath: gs://STAGING_BUCKET/${run_id}/05_model_input/y_train.pickle
  layer: model_input

data_science.candidate_modelling_pipeline.X_test:
  type: pickle.PickleDataSet
  filepath: gs://STAGING_BUCKET/${run_id}/05_model_input/X_test.pickle
  layer: model_input

data_science.candidate_modelling_pipeline.y_test:
  type: pickle.PickleDataSet
  filepath: gs://STAGING_BUCKET/${run_id}/05_model_input/y_test.pickle
  layer: model_input

data_science.candidate_modelling_pipeline.regressor:
  type: pickle.PickleDataSet
  filepath: gs://STAGING_BUCKET/${run_id}/06_models/regressor.pickle
  versioned: true
  layer: models
```

We're investigating ways to stop enforcing explicit data catalog definitions for intermediate datasets, follow the issue here https://github.com/getindata/kedro-vertexai/issues/8.

Disable telemetry or ensure consent

Latest version of Kedro starters come with the `kedro-telemetry` installed, which by default prompts the user to allow or deny the data collection. Before submitting the job to Vertex AI Pipelines you have two options:

- allow the telemetry by setting `consent: true` in the `.telemetry` file in the project root directory
- disable telemetry by removing `kedro-telemetry` from the `src/requirements.txt`.

If you leave the `.telemetry` file with default `consent: false`, the pipeline will crash in runtime in Vertex AI, because `kedro-telemetry` will spawn an interactive prompt and ask for the permission to collect the data.

The usage of `${run_id}` is described in section Dynamic configuration support.

Build the image

Execute:

```
kedro docker build --build-arg BASE_IMAGE=python:3.8-buster
```

When execution finishes, your docker image is ready. If you don't use local cluster, you should push the image to the remote repository:

```
docker tag vertex-ai-plugin-demo:latest remote.repo.url.com/vertex-ai-plugin-demo:latest
docker push remote.repo.url.com/vertex-ai-plugin-demo:latest
```

3.1.4 Run the pipeline on Vertex AI

First, run `init` script to create the sample configuration. There are 2 parameters:

- `PROJECT_ID` which is ID of your Google Cloud Platform project - can be obtained from GCP Console or from command line (`gcloud config get-value project`)
- `REGION` - Google Cloud Platform region in which the Vertex AI pipelines should be executed (e.g. `europe-west1`).

```
kedro vertexai init <GCP PROJECT ID> <GCP REGION>
(...)
Configuration generated in /Users/getindata/vertex-ai-plugin-demo/conf/base/vertexai.yaml
```

Then adjust the `conf/base/vertexai.yaml`, especially:

- `image:` key should point to the full image name (like `remote.repo.url.com/vertex-ai-plugin-demo:latest` if you pushed the image at this name).
- `root:` key should point to the GCS bucket that will be used internally by Vertex AI, e.g. `your_bucket_name/subfolder-for-vertexai`

Finally, everything is set to run the pipeline on Vertex AI Pipelines. Execute `run-once` command:

```
$ kedro vertexai run-once
2022-03-18 13:44:27,667 - kedro_vertexai.client - INFO - Generated pipeline definition␣
↪was saved to /var/folders/0b/mdxthmvd74x90fp84zl4mb5h0000gn/T/kedro-vertexai2jyrt89b.
↪json
See the Pipeline job here: https://console.cloud.google.com/vertex-ai/locations/europe-
↪west1/pipelines/runs/vertex-ai-plugin-demo-20220318124425?project=gid-ml-ops-sandbox
```

As you can see, the pipeline was compiled and started in Vertex AI Pipelines. When you visit the link shown in logs you can observe the running pipeline:

Kedro pipeline running in Vertex AI Pipelines

3.2 GCP AI Platform support

Google Cloud's AI Platform offers couple services that simplify Machine Learning tasks with use of Kubeflow based components.

3.2.1 Using `kedro` with AI Platform Notebooks

AI Platform Notebooks provides an easy way to manage and host JupyterLab based data science workbench environment. What we've found out is that the default images provided by a service cause some dependency conflicts. To avoid this issues make sure you use isolated virtual environment, e.g. virtualenv. New virual environment can be created by simply invoking `python -m virtualenv venv` command.

3.2.2 Using `kedro-kubeflow` with AI Platform Pipelines

AI Platform Pipelines is a service that allows to easily deploy Kubeflow Pipelines on new or existing Google Kubernetes Engine clusters.

In general `kedro-kubeflow` plugin should work with AI Platform Pipelines out of the box, with the only exception is that it requires authentication. Note that the `host` variable should point to a dashbard URL generated by AI Platform Pipelines service (e.g. https://653hddae86eb7b0-dot-europe-west1.pipelines.googleusercontent.com/), just open the dashboard from the service page and copy url from the browser.

Below is the list of authentication scenarios supported so far:

1. Connecting to AI Pipelines from AI Platform Notebooks

In this scenario authentication works out of the box with *default credentials* mechanism.

2. Authentication to AI Pipelines from local environment

To interact with AI Platform Pipelines from local environment you can use the mechanisms provided by Google Cloud SDK. After installing the SDK run `google cloud application-default login` to initialize *default credentials* on your local machine.

You can use service account key for authentication as well. To make that work just set `GOOGLE_APPLICATION_CREDENTIALS` environment variable to the path of where the service account key file is stored.

3. Authenticating through IAP Proxy

Identity Aware Proxy is a product that allows securing your cloud based applications with Google Identity.

To authenticate with IAP find out which *oauth client ID* is the proxy configured with and then save it in `IAP_CLIENT_ID` environment variable. The authentication should work seamlessly assuming identity you are using has been granted access to the application.

The above will work if you are connecting from within GCP VM or locally with specified service account credentials. It will *NOT* work for credentials obtained with `google cloud application-default login`.

3.2.3 Using `kedro-kubeflow` with Vertex AI Pipelines (EXPERIMENTAL)

Vertex AI Pipelines is a fully managed service that allows to easily deploy Kubeflow Pipelines on a serverless Google service. Vertex AI Pipelines was still in a Preview mode when this plugin version was released, therefore plugin capability is also limited.

1. Preparing configuration

In order the plugin picks Vertex AI Pipelines as a target infrastructure, it has to be indicated in configuration. As the solution is serverless, no URL is to be provided. Instead, special set of parameters has to be passed, so that connection is established with proper GCP service.

```
host: vertex-ai-pipelines
project_id: hosting-project
region: europe-west4
run_config:
  root: vertex-ai-pipelines-accessible-gcs-bucket/pipelines-specific-path
```

If the pipeline requires access to services that are not exposed to public internet, you need to configure VPC peering between Vertex internal network and VPC that hosts the internal service and then set the VPC identifier in the configuration. Optionally, you can add custom host aliases:

```
run_config:
  vertex_ai_networking:
    vpc: projects/12345/global/networks/name-of-vpc
    host_aliases:
    - ip: 10.10.10.10
      hostnames: ['mlflow.internal']
    - ip: 10.10.20.20
      hostnames: ['featurestore.internal']
```

2. Preparing environment variables

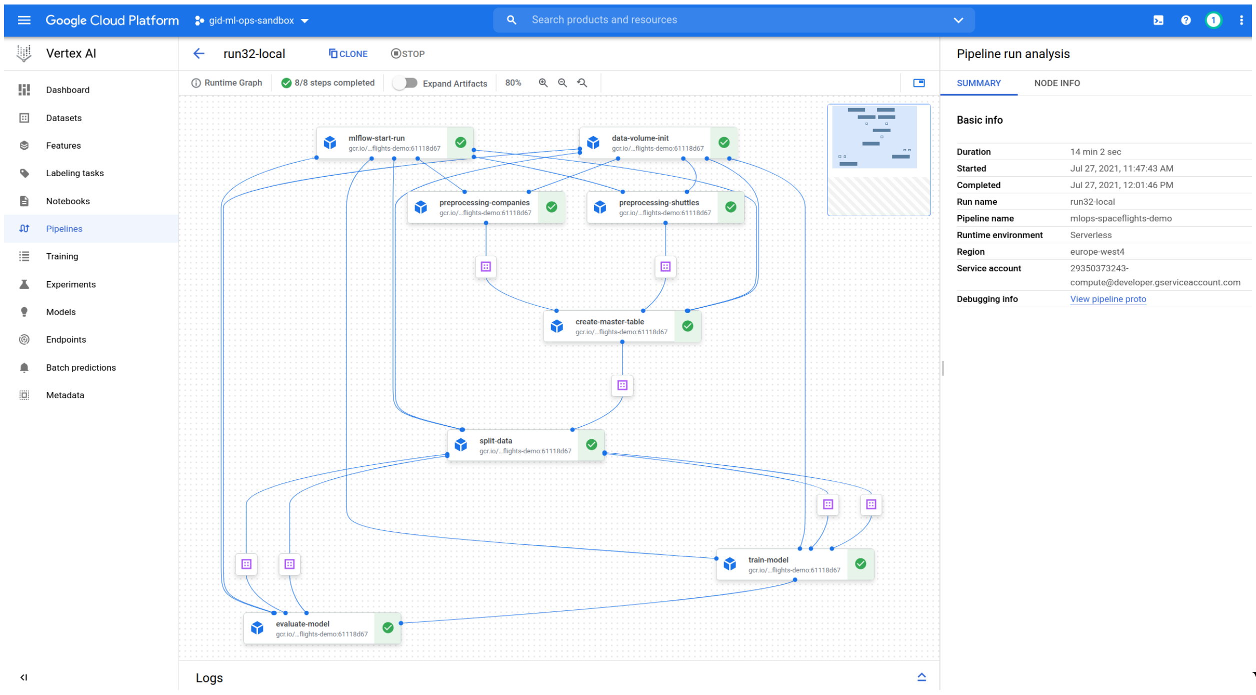
There're the following specific environment variables required for the pipeline to run correctly:

- SERVICE_ACCOUNT - full email of service account that job will use to run the pipeline. Account has to have access to `run_config.root` path. Variable is optional, if no given, project compute account is used
- MLFLOW_TRACKING_TOKEN - identity token required if MLFlow is used inside the project and mlflow access is protected. Token is passed as it is to kedro nodes in order to authenticate against MLFlow service. Can be generated via `gcloud auth print-identity-token` command.

3. Supported commands

Following commands are supported:

```
kedro kubeflow compile
kedro kubeflow run-once
kedro kubeflow schedule
kedro kubeflow list-pipelines
```



Basic info

Duration	14 min 2 sec
Started	Jul 27, 2021, 11:47:43 AM
Completed	Jul 27, 2021, 12:01:46 PM
Run name	run32-local
Pipeline name	mlops-spaceflights-demo
Runtime environment	Serverless
Region	europe-west4
Service account	29350373243-compute@developer.gserviceaccount.com
Debugging info	View pipeline proto

Vertex_AI_Pipelin

3.3 Mlflow support

If you use MLflow and kedro-mlflow for the Kedro pipeline runs monitoring, the plugin will automatically enable support for:

- starting the experiment when the pipeline starts,
- logging all the parameters, tags, metrics and artifacts under unified MLFlow run.

To make sure that the plugin discovery mechanism works, add `kedro-mlflow` and `kedro-kubeflow` as a dependencies to `src/requirements.in` and run:

```
$ pip-compile src/requirements.in > src/requirements.txt
$ kedro install
$ kedro mlflow init
```

Then, adjust the kedro-mlflow configuration and point to the mlflow server by editing `conf/base/mlflow.yml` and adjusting `mlflow_tracking_uri` key. Then, build the image:

```
$ kedro docker build
```

And re-push the image to the remote registry. Finally, reupload the pipeline:

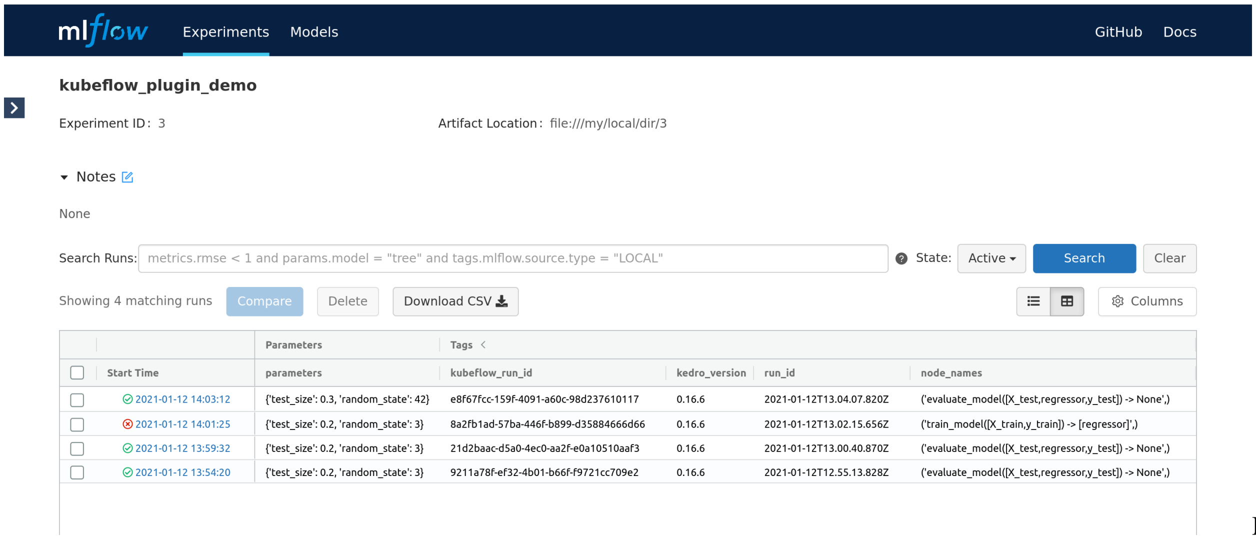
```
$ kedro kubeflow upload-pipeline
(...)
2021-01-12 13:05:56,879 - kedro_kubeflow.kfpclient - INFO - No IAP_CLIENT_ID provided,␣
↪skipping custom IAP authentication
2021-01-12 13:05:56,973 - kedro_kubeflow.kfpclient - INFO - New version of pipeline␣
↪created: ba3a05c2-2f19-40c5-809e-0ed7c2989000
2021-01-12 13:05:56,973 - kedro_kubeflow.kfpclient - INFO - Pipeline link: http://10.43.
↪54.89/#/pipelines/details/9a3e4e16-1897-48b5-9752-d350b1d1faac/version/ba3a05c2-2f19-
↪40c5-809e-0ed7c2989000
```

And verify how does it look in the Kubeflow UI. You should notice `mlflow-start-run` step on the very top:

`source/03_getting_started/pipeline_mlflow.png`

Pipeline with Mlflow

Finally, start the pipeline. While it executes, the new Mlflow run is started and it's constantly updated with the attributes provided by the next steps. Finally, the experiments runs page looks like:



kubeflow_plugin_demo

Experiment ID: 3 Artifact Location: file:///my/local/dir/3

Notes

None

Search Runs: metrics.rmse < 1 and params.model = "tree" and tags.mlflow.source.type = "LOCAL" State: Active Search Clear

Showing 4 matching runs Compare Delete Download CSV Columns

		Parameters	Tags			
☐	Start Time	parameters	kubeflow_run_id	kedro_version	run_id	node_names
☐	✓ 2021-01-12 14:03:12	{'test_size': 0.3, 'random_state': 42}	e8f67fcc-159f-4091-a60c-98d237610117	0.16.6	2021-01-12T13.04.07.820Z	('evaluate_model([X_test,regressor,y_test]) -> None',)
☐	⊗ 2021-01-12 14:01:25	{'test_size': 0.2, 'random_state': 3}	8a2fb1ad-57ba-446f-b899-d35884666d66	0.16.6	2021-01-12T13.02.15.656Z	('train_model([X_train,y_train]) -> [regressor]',)
☐	✓ 2021-01-12 13:59:32	{'test_size': 0.2, 'random_state': 3}	21d2baac-d5a0-4ec0-aa2f-e0a10510aaf3	0.16.6	2021-01-12T13.00.40.870Z	('evaluate_model([X_test,regressor,y_test]) -> None',)
☐	✓ 2021-01-12 13:54:20	{'test_size': 0.2, 'random_state': 3}	9211a78f-ef32-4b01-b66f-f9721cc709e2	0.16.6	2021-01-12T12.55.13.828Z	('evaluate_model([X_test,regressor,y_test]) -> None',)

Mlflow UI

The UI presents the pipeline stauts (in form of the icon) and latest node that was run (for failed runs in indicates at what step did the pipeline fail). Also, the `kubeflow_run_id` tag can be used to correlate Mlflow run with the Kubeflow pipeline execution.

3.4 Continuous Deployment

With kedro pipelines started on the remote Kubeflow Pipelnes clusters, changes in the code require re-building docker images and (sometimes) changing the pipeline structure. To simplify this workflow, Kedro-kubeflow plugin is capable of creating configuration for the most popular CI/CD automation tools.

The autogenerated configuration defines these actions:

- on any new push to the repository - image is re-built and the pipeline is started using `run-once`,
- on merge to master - image is re-built, the pipeline is registered in the Pipelines and scheduled to execute on the daily basis.

The behaviour and parameters (like schedule expression) can be adjusted by editing the genrated files. The configuration assumes that Google Container Registry is used to store the images, but users can freely adapt it to any (private or public) docker images registry.

3.4.1 Github Actions

If the Kedro project is stored on github (either in private or public repository), Github Actions can be used to automate the Continuous Deployment. To configure the repository, go to Settings->Secrets and add there:

- `GKE_PROJECT`: ID of the google project.
- `GKE_SA_KEY`: service account key, encoded with base64 (this service account must have access to push images into registry),
- `IAP_CLIENT_ID`: id of the IAP proxy client to communicate with rest APIs.

Next, re-configure the project using

```
kedro kubeflow init --with-github-actions https://<endpoint_name>.endpoints.<project-
↪name>.cloud.goog/pipelines
```

This command will generate Github Actions in `.github/workflows` directory. Then push the code to any branch and go to "Actions" tab in Github interface.

3.5 Authenticating to Kubeflow Pipelines API

Plugin supports 2 ways of authenticating to Kubeflow Pipelines API:

3.5.1 1. KFP behind IAP proxy on Google Cloud

It's already described in GCP AI Platform support chapter.

3.5.2 2. KFP behind Dex+authservice

Dex is the recommended authentication mechanism for on-premise Kubeflow clusters. The usual setup looks in a way that:

- oidc-autheservice redirect unauthenticated users to Dex,
- Dex authenticates user in remote system, like LDAP or OpenID and also acts as OpenID provider,
- oidc-autheservice asks Dex for token and creates the session used across entire Kubeflow.

In order to use `kedro-kubeflow` behind Dex-secured clusters, use the following manual:

1. Setup staticPassword authentication method and add a user that you're going to use as CI/CD account.
2. Point your Kedro project to `/pipeline` API on Kubeflow, for example: `https://kubeflow.local/pipeline`
3. Set environment variables `DEX_USERNAME` and `DEX_PASSWORD` before calling `kedro kubeflow`

CHAPTER

FOUR

INDICES AND TABLES

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