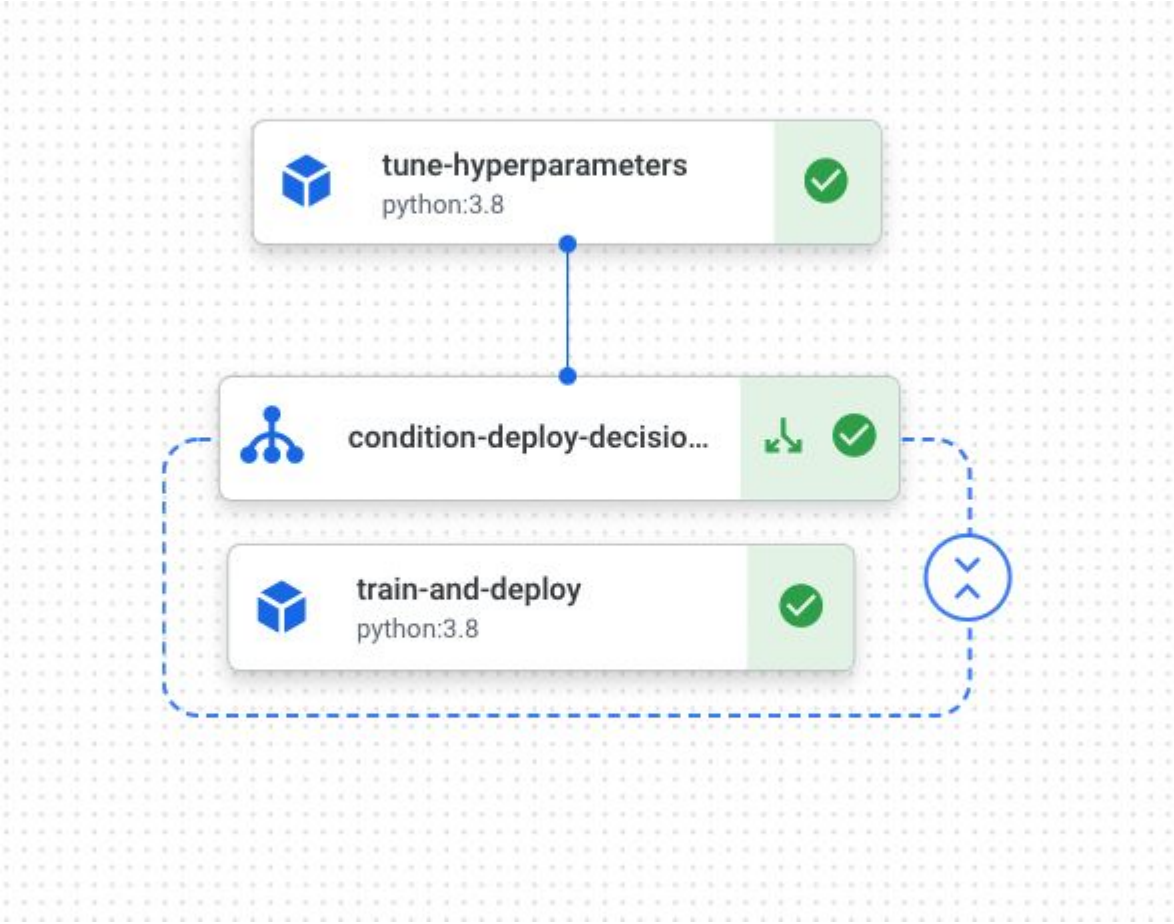
Kubeflow Pipelines on Vertex AI



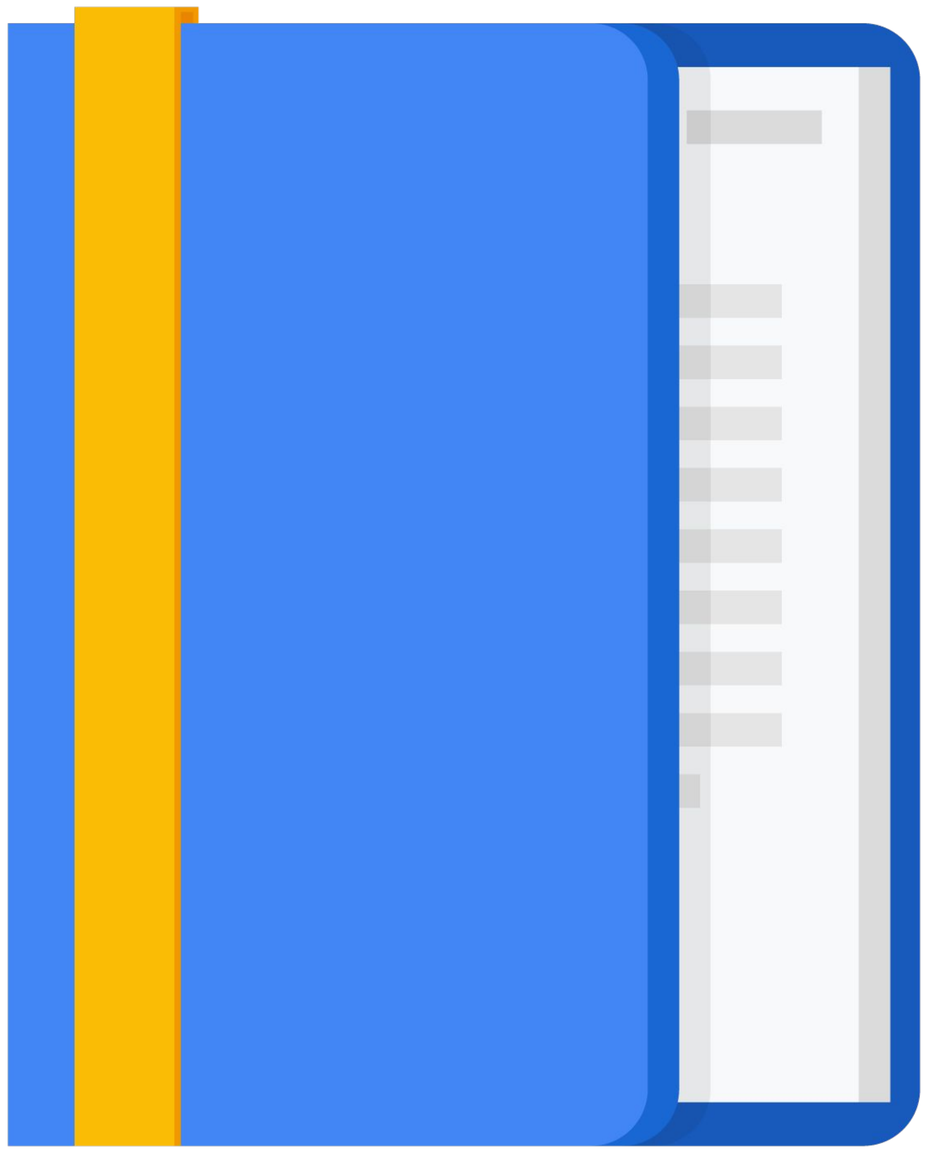
Level 0: All in the notebook

Level 1: Containerized Training

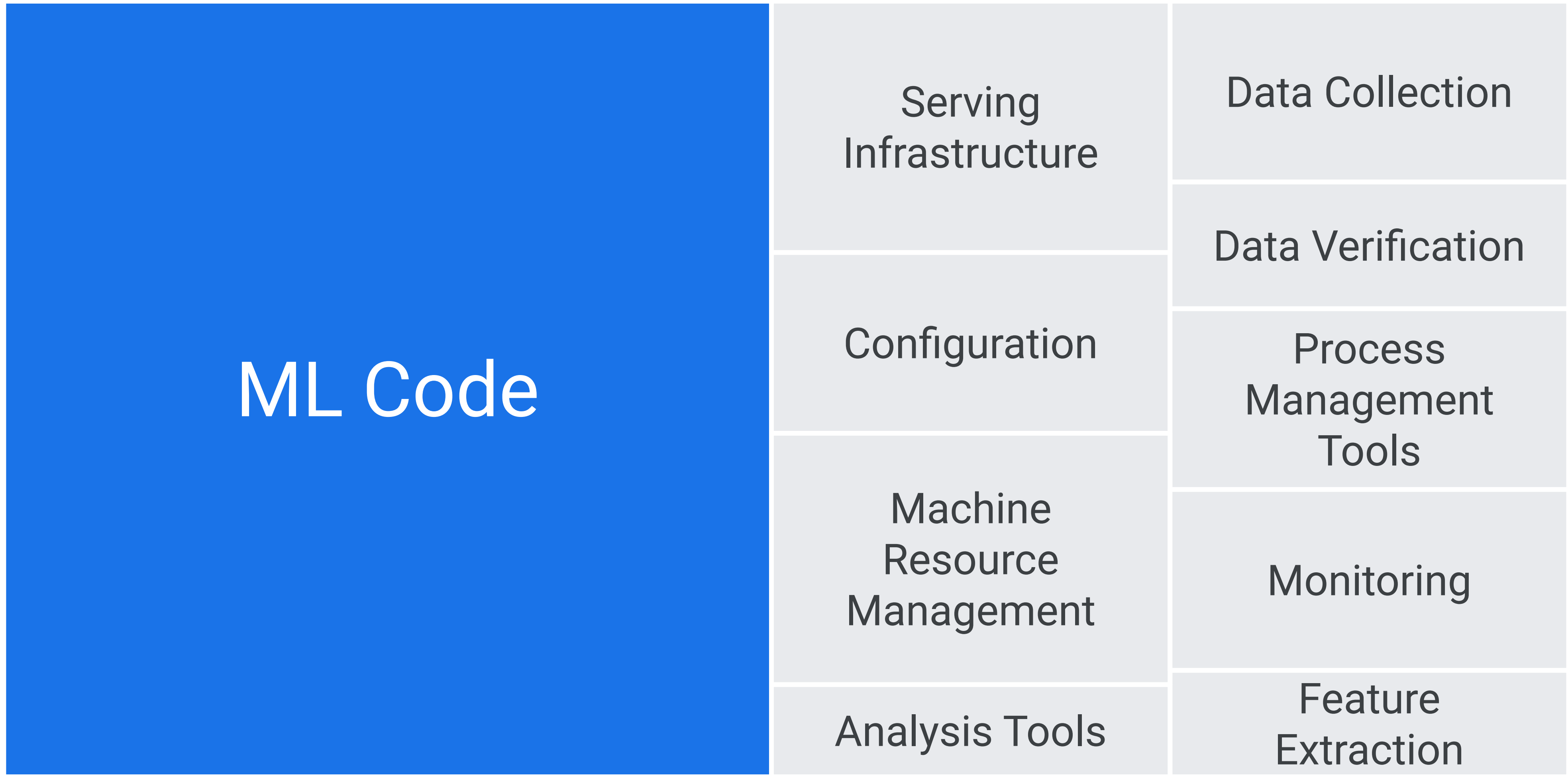
Level 2: ML Pipelines

Agenda

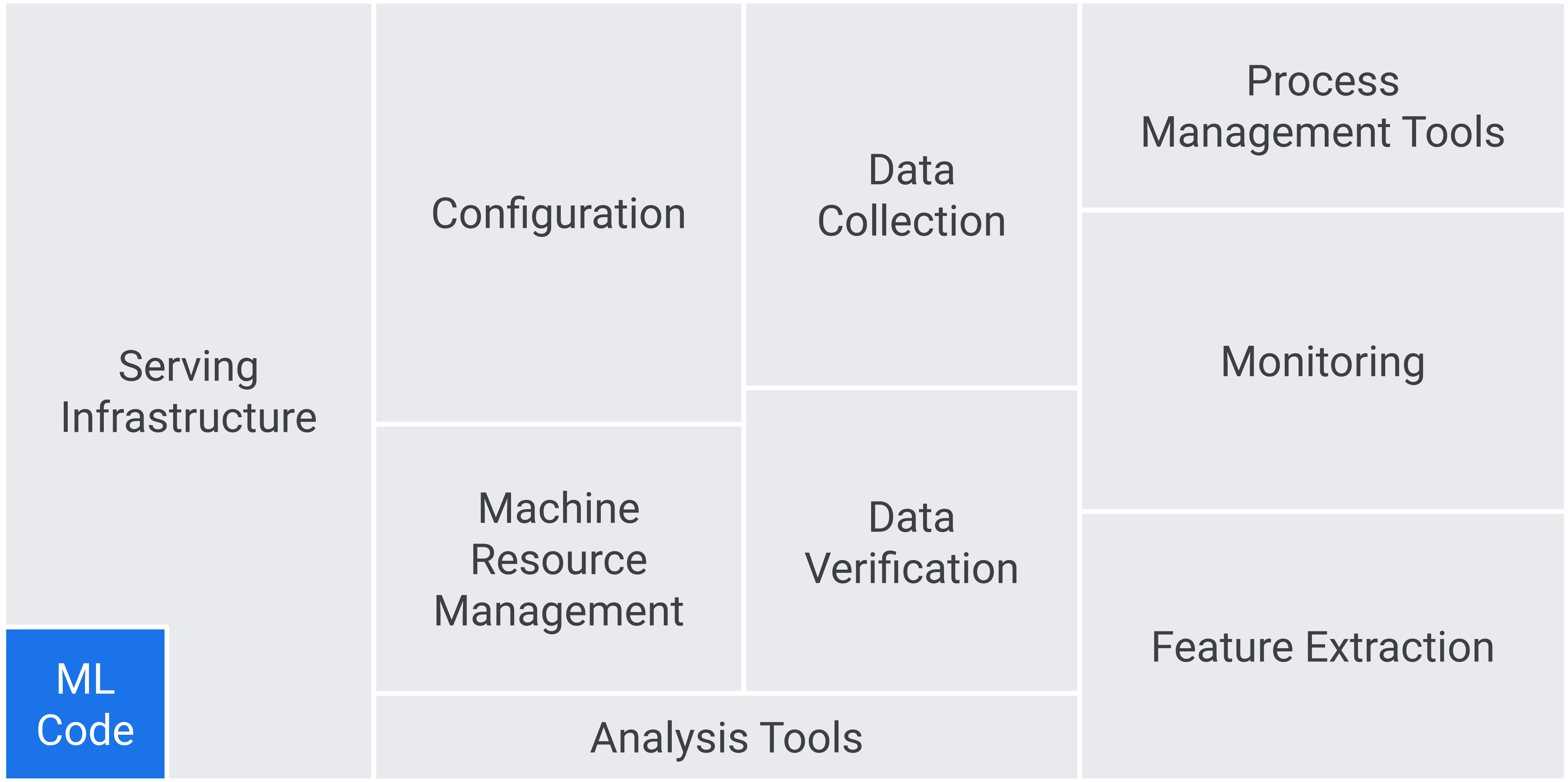
- System and Concept Overview
- Describing a Kubeflow Pipeline with KF DSL
- Compile, Upload, and Run
- Pre-built Components
- Lightweight Python Components
- AutoML Vertex Pipelines



Perception: ML products are mostly about ML

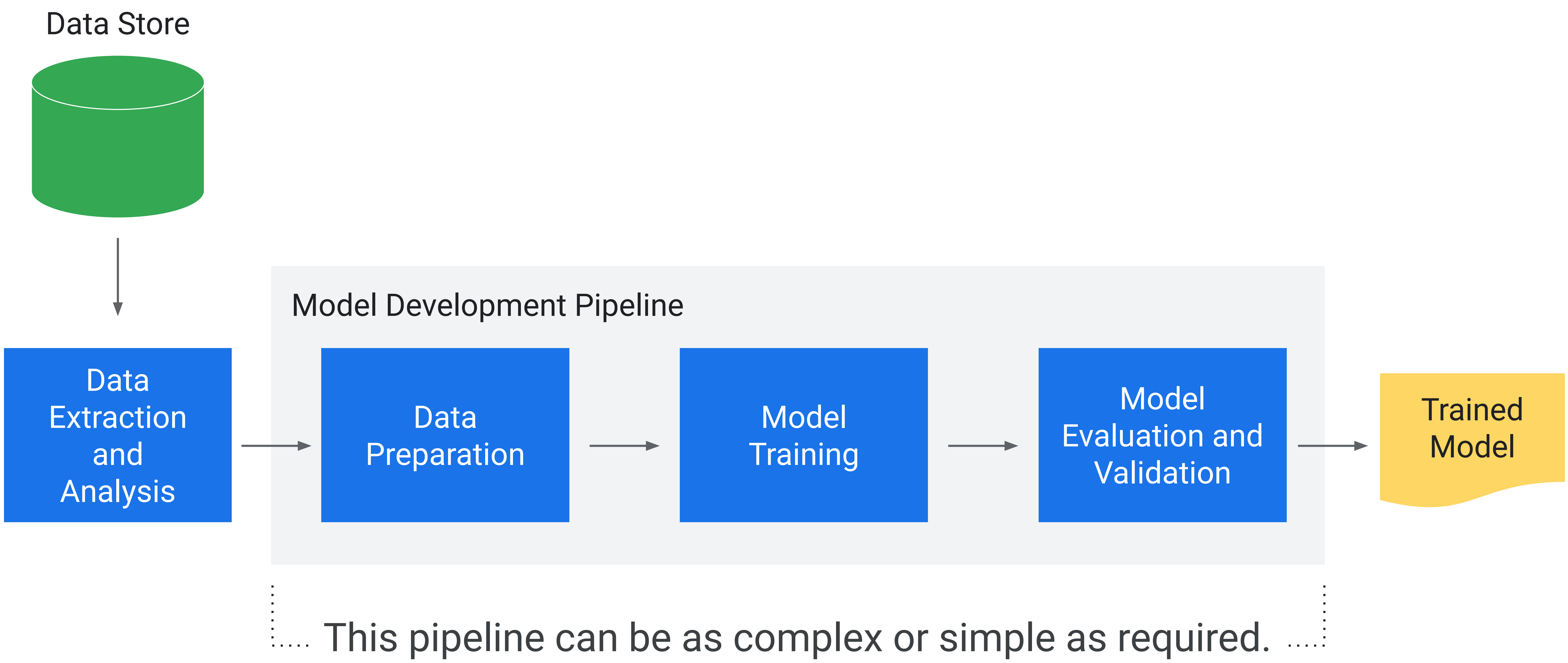


Reality: ML Requires lots of DevOps

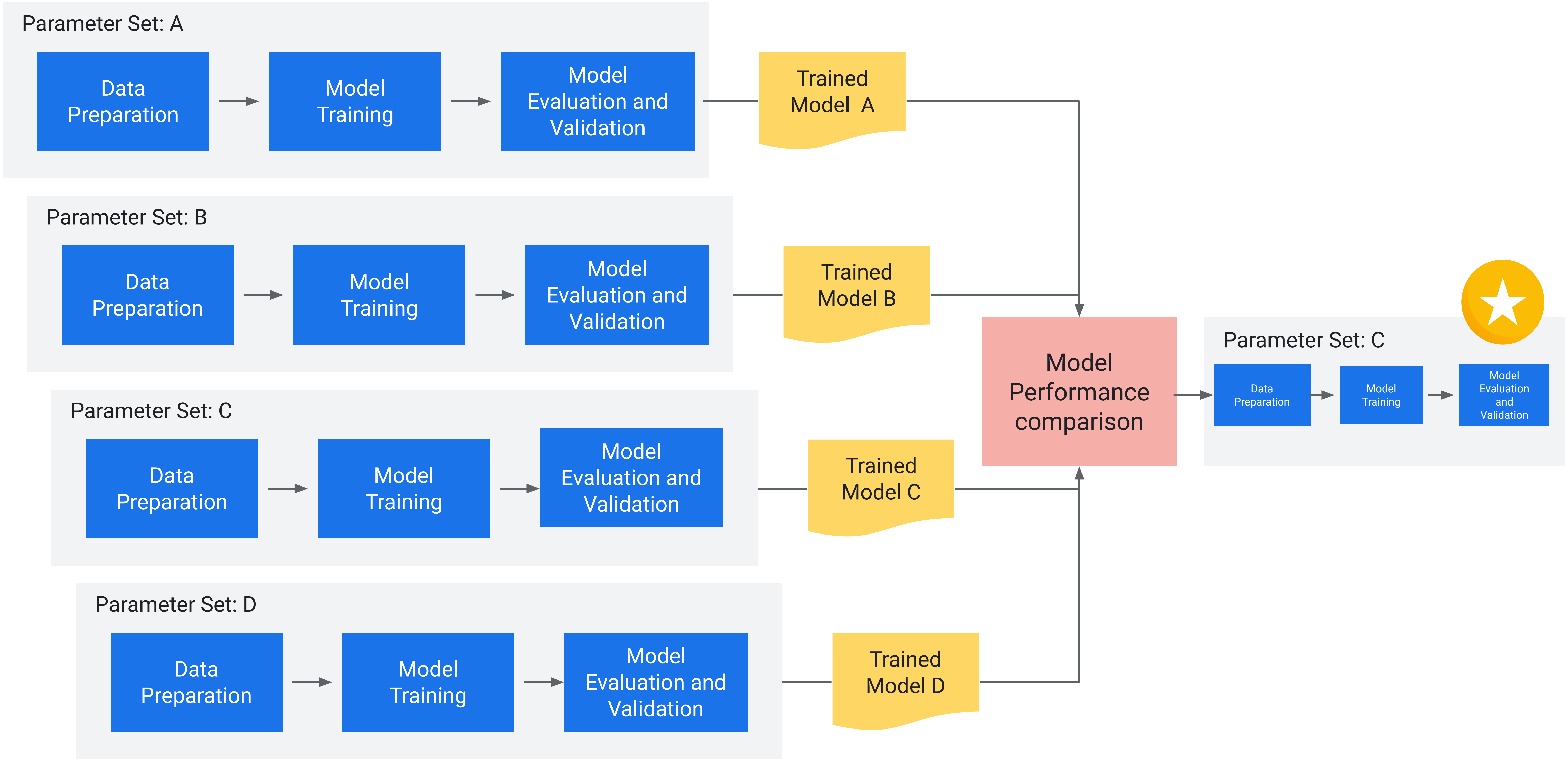


Source: Sculley et al.: Hidden Technical Debt in Machine Learning Systems

The ML process



Machine learning is all about experimentation!



Kubeflow provides a standardized platform for building ML pipelines

- Leverage containers and Kubernetes so that in ML pipelines can be run on a cloud or on-premises with Anthos on GKE.
- Kubeflow is a cloud-native, multi-cloud solution for ML.
- Kubeflow provides a platform for composable, portable, and scalable ML pipelines.
- If you have a Kubernetes-conformant cluster, you can run Kubeflow.

Kubeflow pipelines enable:

ML workflow orchestration

Share, re-use, and compose

Rapid, reliable experimentation

What constitutes a Kubeflow pipeline?

Containerized implementations of ML tasks

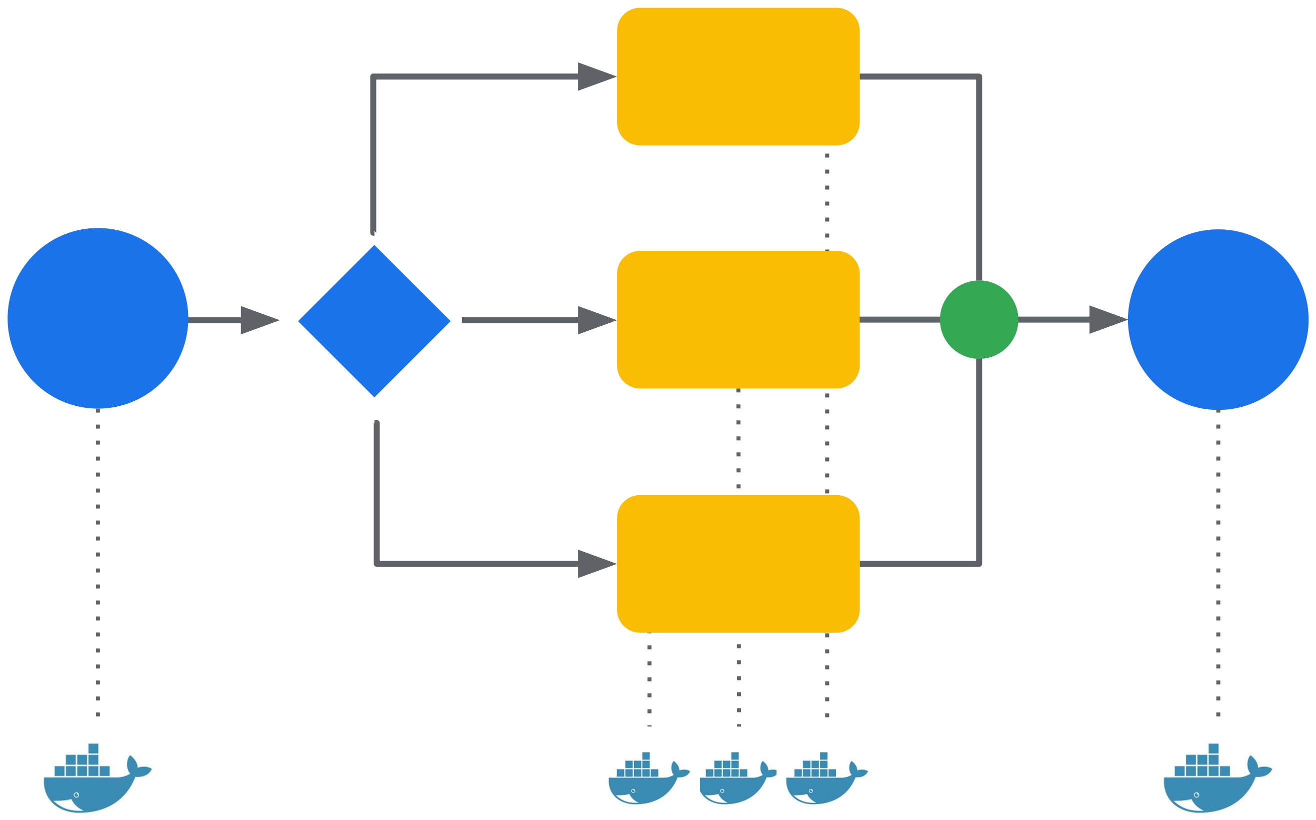
- Example of ML tasks: Data import, training, serving, model evaluation
- Containers provide portability, repeatability, and encapsulation.
- A containerized task can invoke other services, such as Vertex AI, Dataflow, or Dataproc.

Specification of the sequence of steps

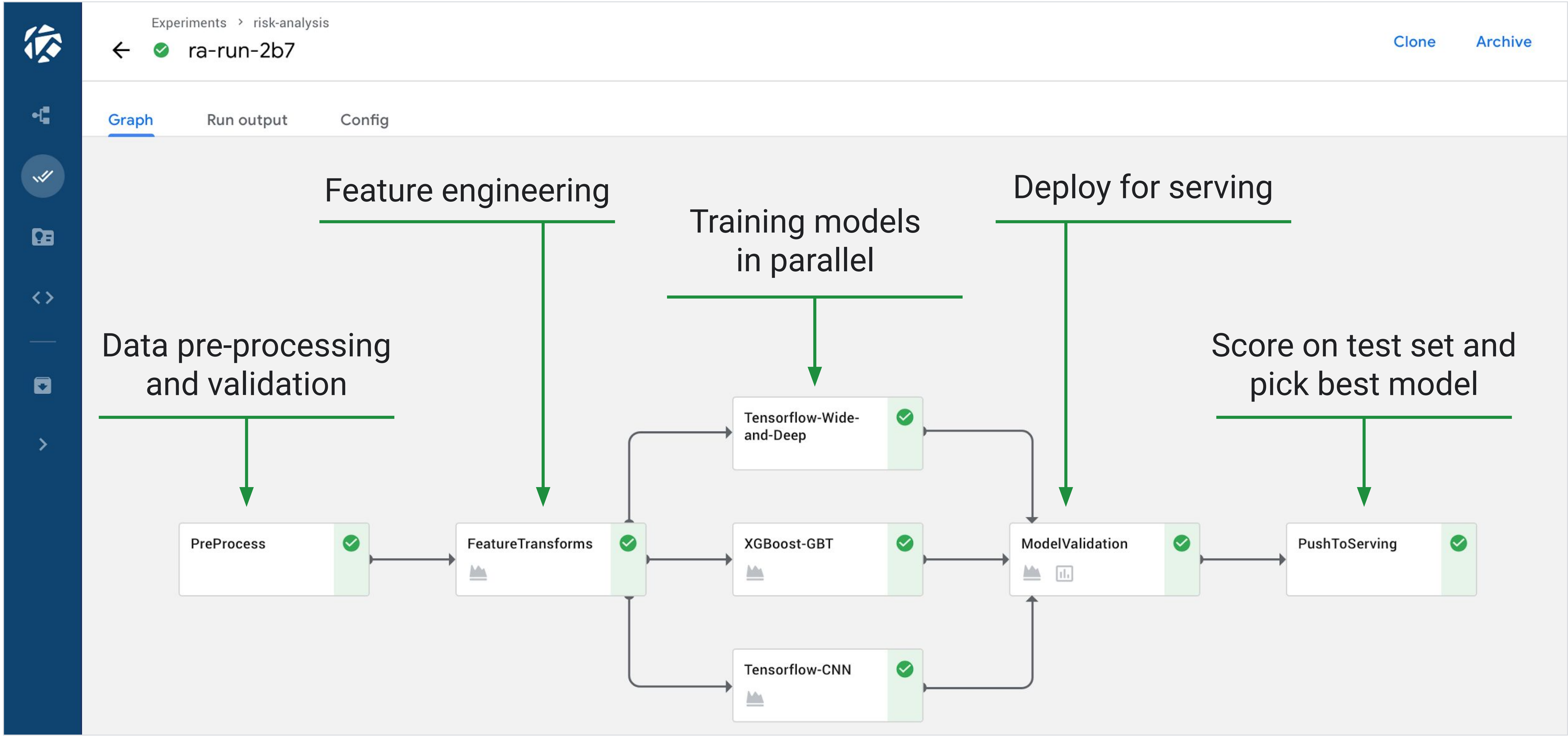
- Specified via Python SDK

Input parameters

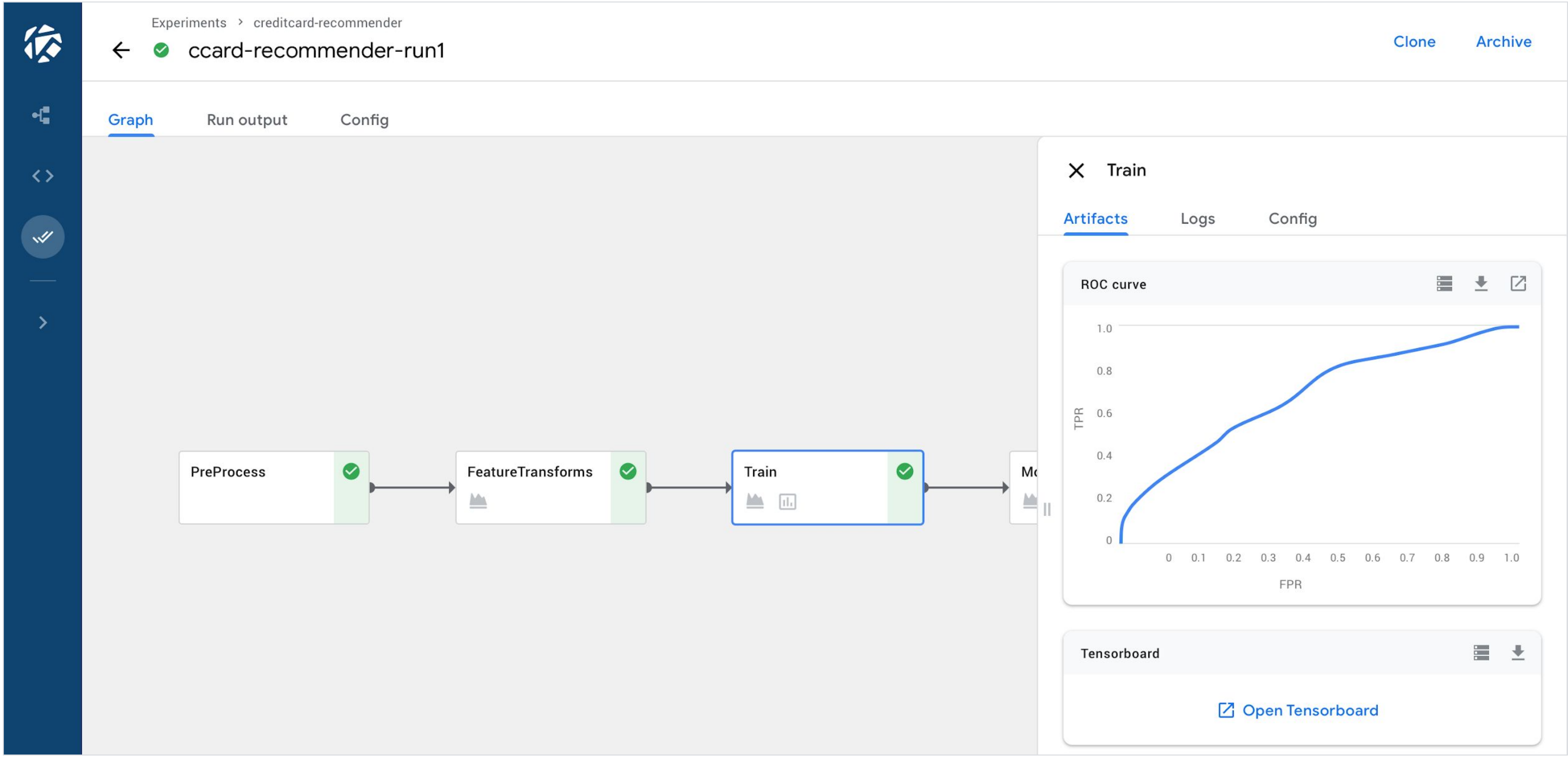
- A “Job” is a pipeline invoked w/specific parameters



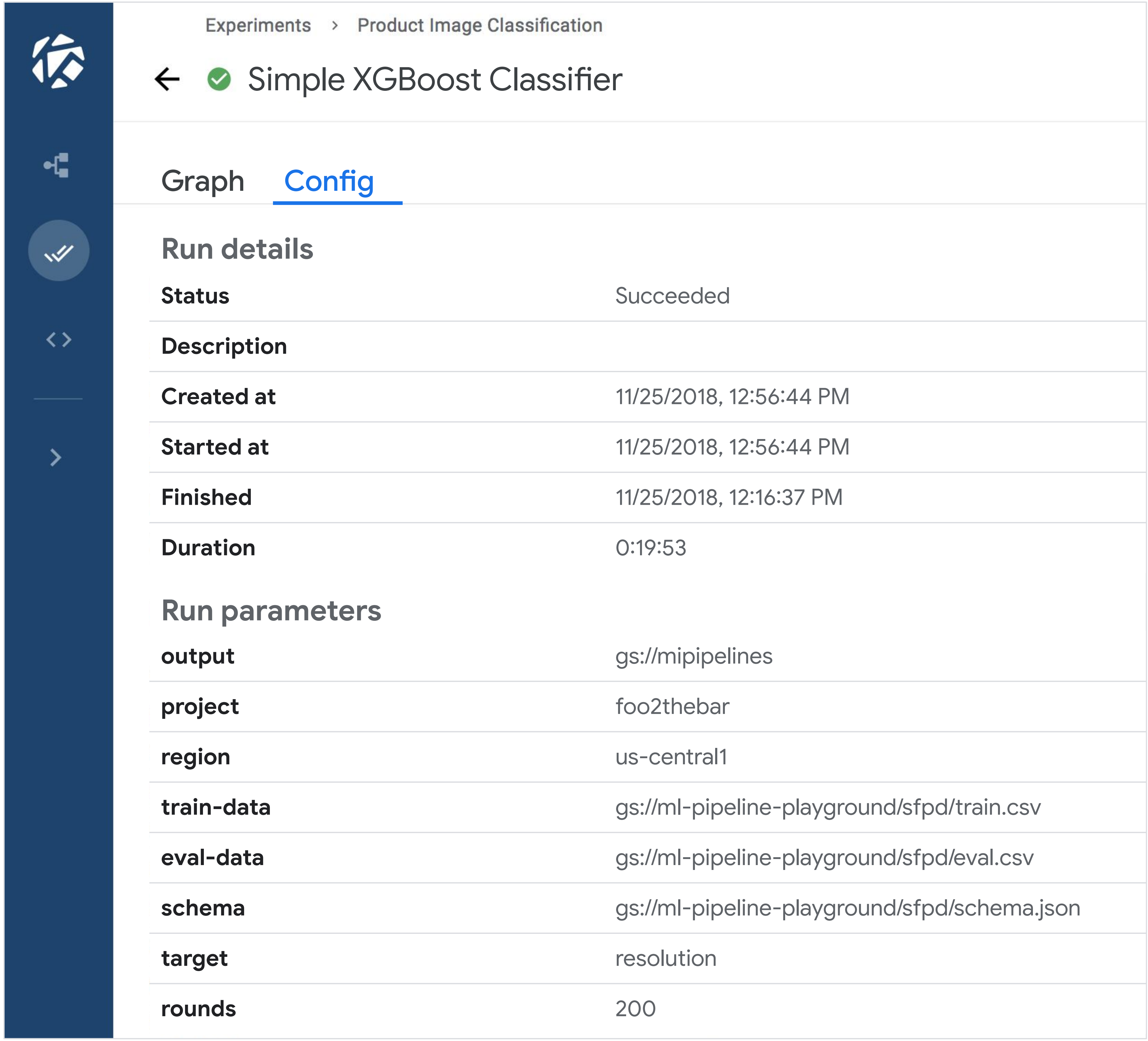
Visual depiction of pipeline topology



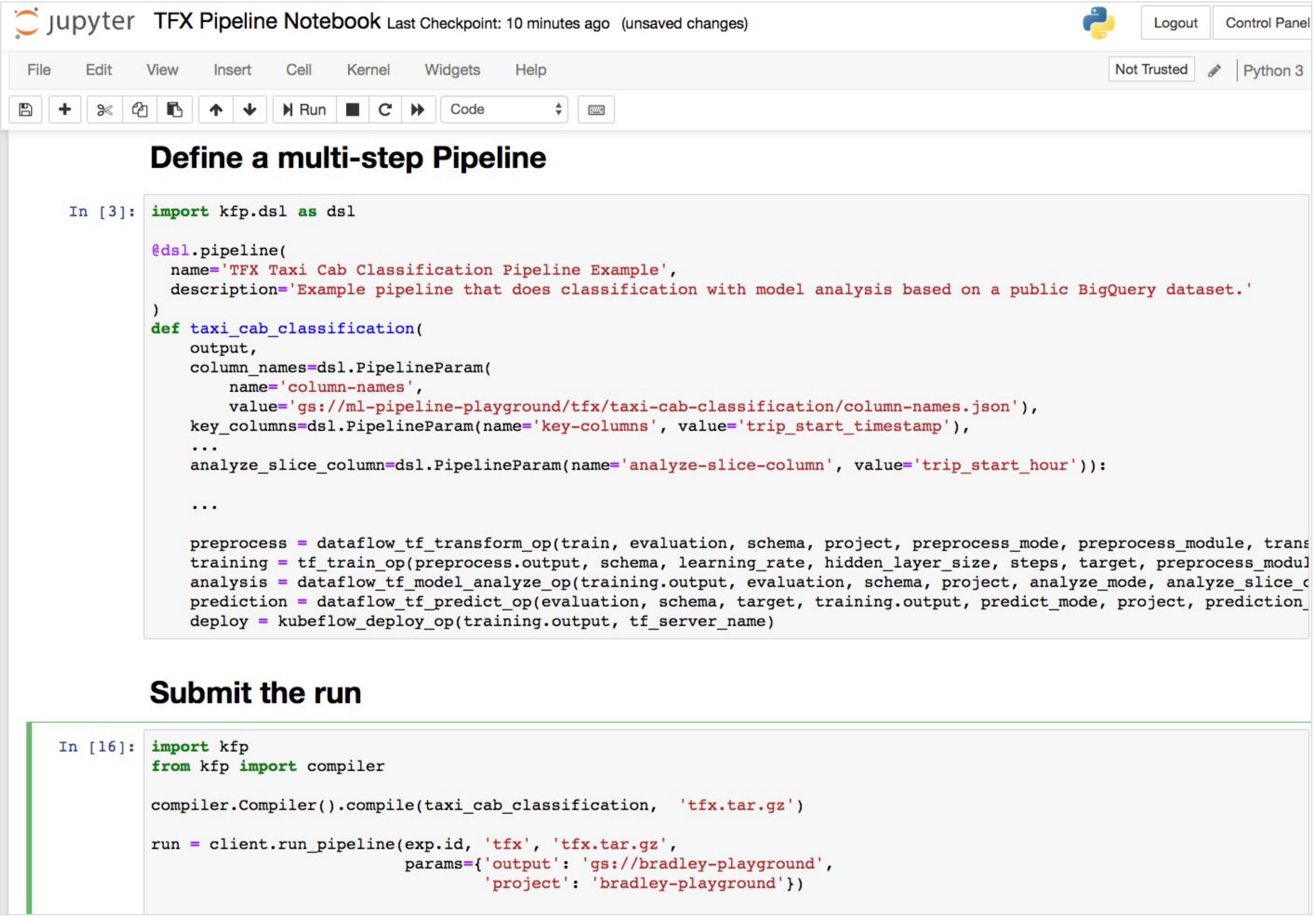
Rich visualization of metrics



View all configs, inputs, and outputs



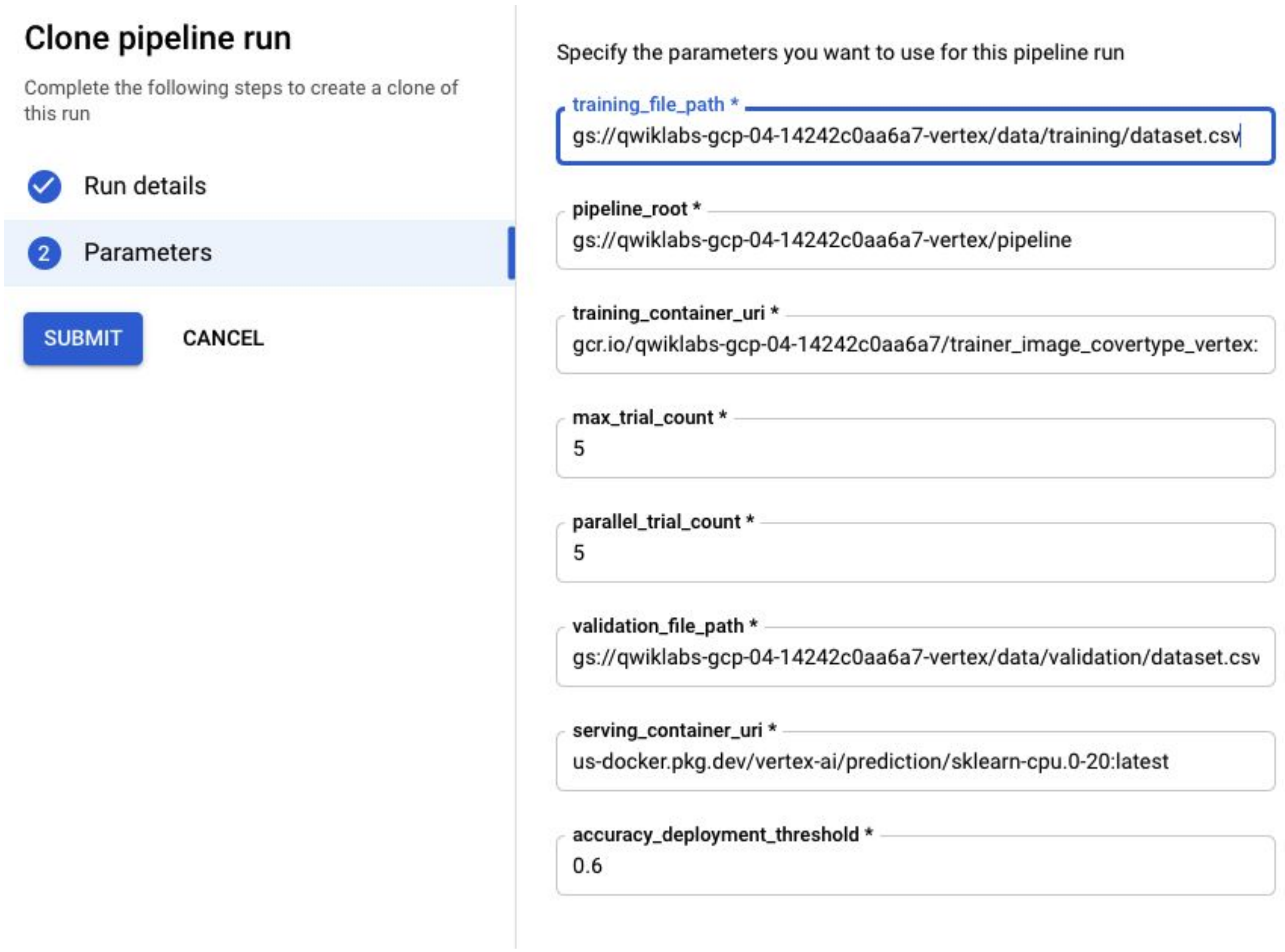
Author pipelines with an intuitive Python SDK



Package and share pipelines as zip files

- Upload and execute pipelines via UI (in addition to API/SDK).

- Pipeline steps can be authored as reusable components.



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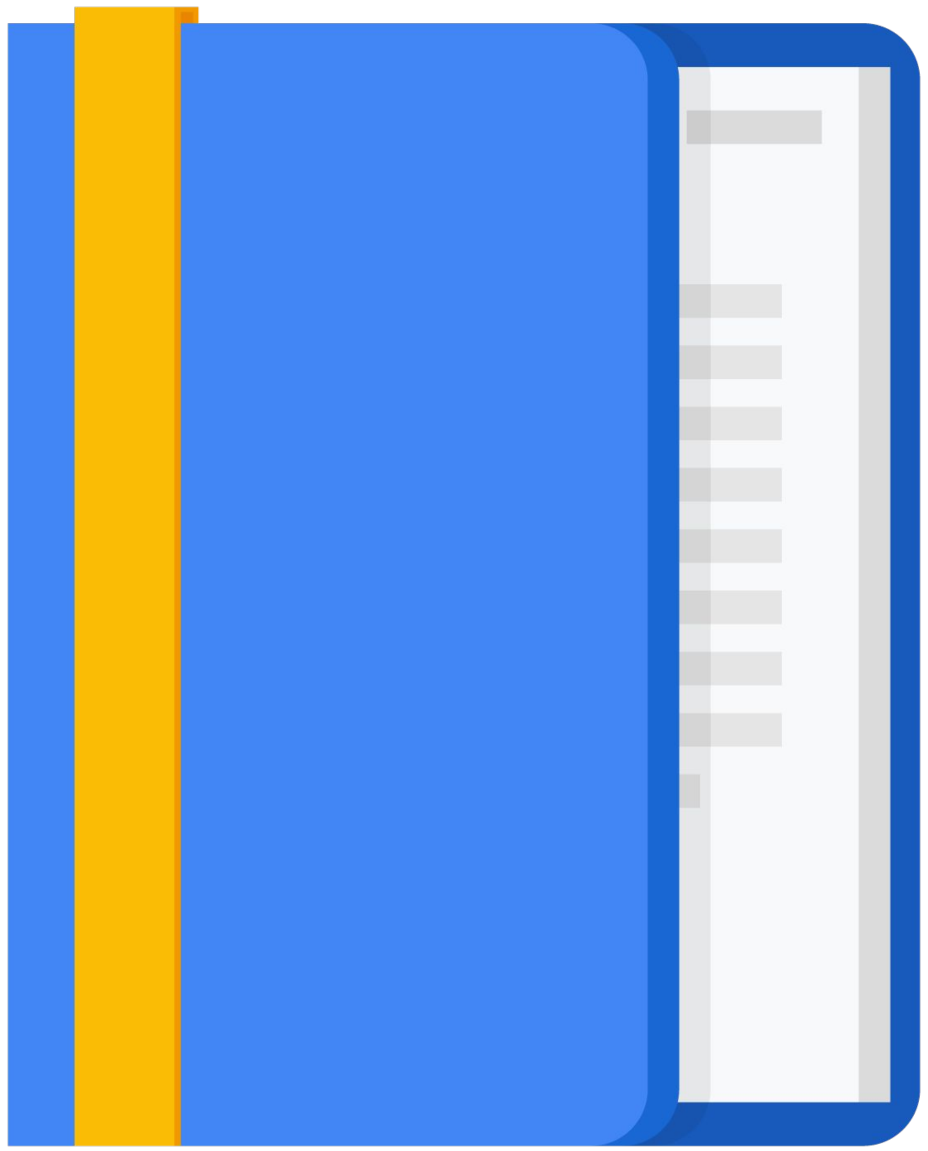


Kubeflow offers a Domain Specific Language (DSL) in Python that allows you to use Python code to describe Kubeflow tasks as they organize themselves in a Directed Acyclic Graph (DAG).

We describe this DSL next...

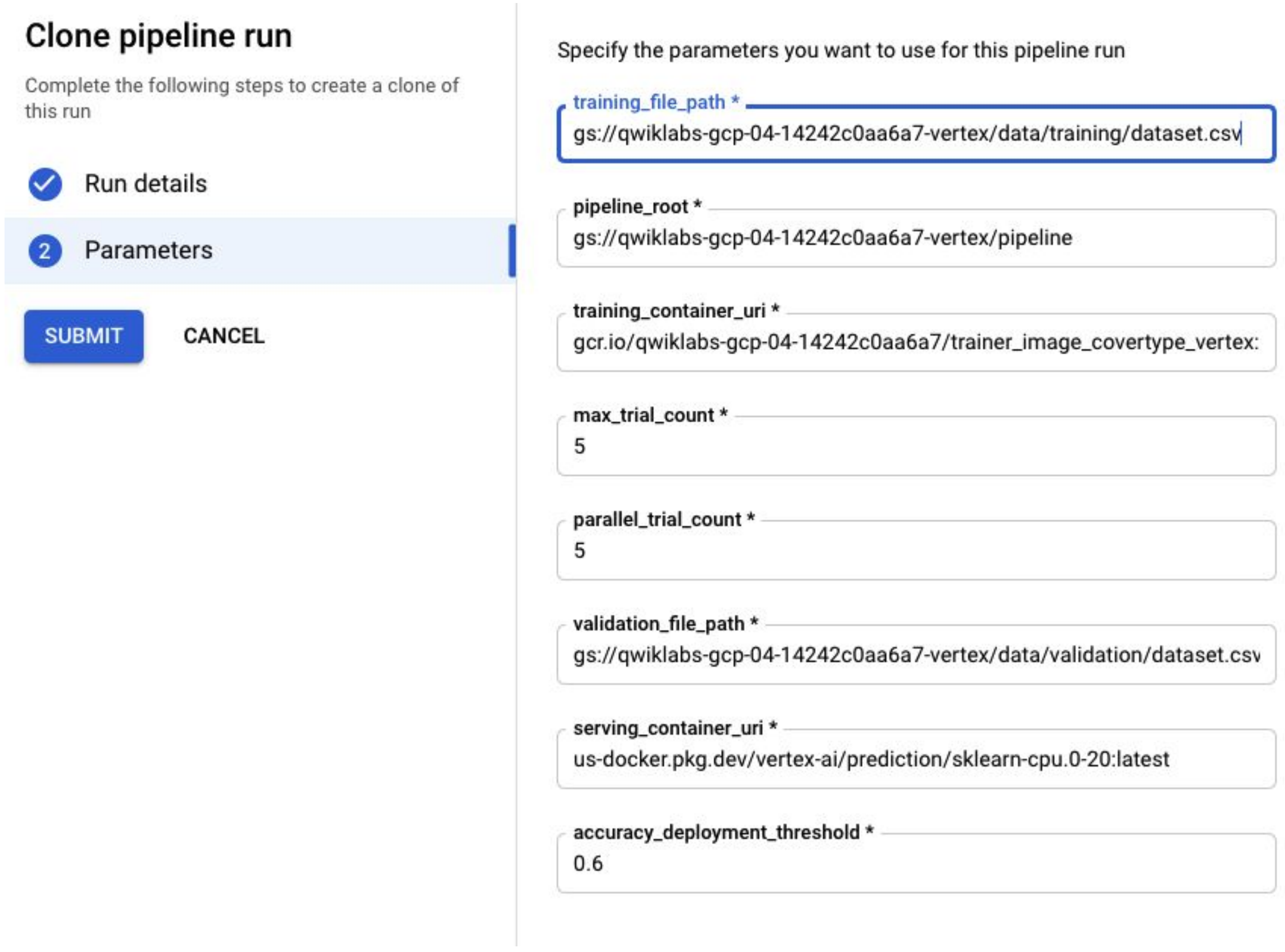
```python
import kfp

@kfp.dsl.pipeline(
    name="covertype-kfp-pipeline",
    description="The Covertype Classifier KFP Pipeline",
    pipeline_root=PIPELINE_ROOT,

)
def covertype_train(
    training_container_uri: str = TRAINING_CONTAINER_IMAGE_URI,
    serving_container_uri: str = SERVING_CONTAINER_IMAGE_URI,
    training_file_path: str = TRAINING_FILE_PATH,
    validation_file_path: str = VALIDATION_FILE_PATH,
    accuracy_deployment_threshold: float = THRESHOLD,
    max_trial_count: int = MAX_TRIAL_COUNT,
    parallel_trial_count: int = PARALLEL_TRIAL_COUNT,
    pipeline_root: str = PIPELINE_ROOT,
):
```

Pipeline Decorator

Pipeline Run Parameters




```
def covertype_train(
    training_container_uri: str = TRAINING_CONTAINER_IMAGE_URI,
    serving_container_uri: str = SERVING_CONTAINER_IMAGE_URI,
    training_file_path: str = TRAINING_FILE_PATH,
    validation_file_path: str = VALIDATION_FILE_PATH,
    accuracy_deployment_threshold: float = THRESHOLD,
    max_trial_count: int = MAX_TRIAL_COUNT,
    parallel_trial_count: int = PARALLEL_TRIAL_COUNT,
    pipeline_root: str = PIPELINE_ROOT,
):
```

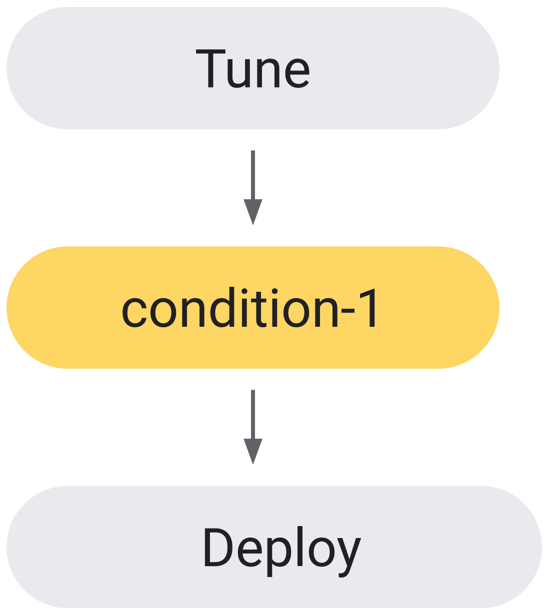
The Run Parameters are supplied at run time.

Define the task DAG within the pipeline function body

```
@kfp.dsl.pipeline(...)
def covertype_train(...):
    # Task DAG defined here
```

1. Create the “ops.”
2. Compose them into a DAG.

(OPs = components)



Creation and composition of ops

```
tuning_op = tune_hyperparameters_component(
    project=PROJECT_ID,
    location=REGION,
    container_uri=training_container_uri,
    # etc.
)
```

```
train_and_deploy_op = train_and_deploy_component(
    project=PROJECT_ID,
    location=REGION,
    alpha=tuning_op.outputs['best_alpha'],
    max_iter=tuning_op.outputs['best_max_iter'],
    # etc.
)
```

1. Ops creation
2. Ops composition

Some ops can be triggered conditionally to other ops output

```
# Deploy the model if the primary metric is higher than a given threshold

accuracy = tuning_op.outputs['best_accuracy']

with dsl.Condition(accuracy >= accuracy_deployment_threshold, name="deploy_decision"):
    train_and_deploy_op = train_and_deploy_component(
        project=PROJECT_ID,
        location=REGION,
        container_uri=training_container_uri,
        serving_container_uri=serving_container_uri,
        training_file_path=training_file_path,
        validation_file_path=validation_file_path,
        staging_bucket=staging_bucket,
        alpha=tuning_op.outputs['best_alpha'],
        max_iter=tuning_op.outputs['best_max_iter'],
    )
```

3 main types of Kubeflow components

01 Pre-built components

- Just load the component from its description and compose.

02 Lightweight Python components

- Implement the component code.

03 Custom components

- Implement the component code.
- Package it into a Docker container.
- Write the component description.

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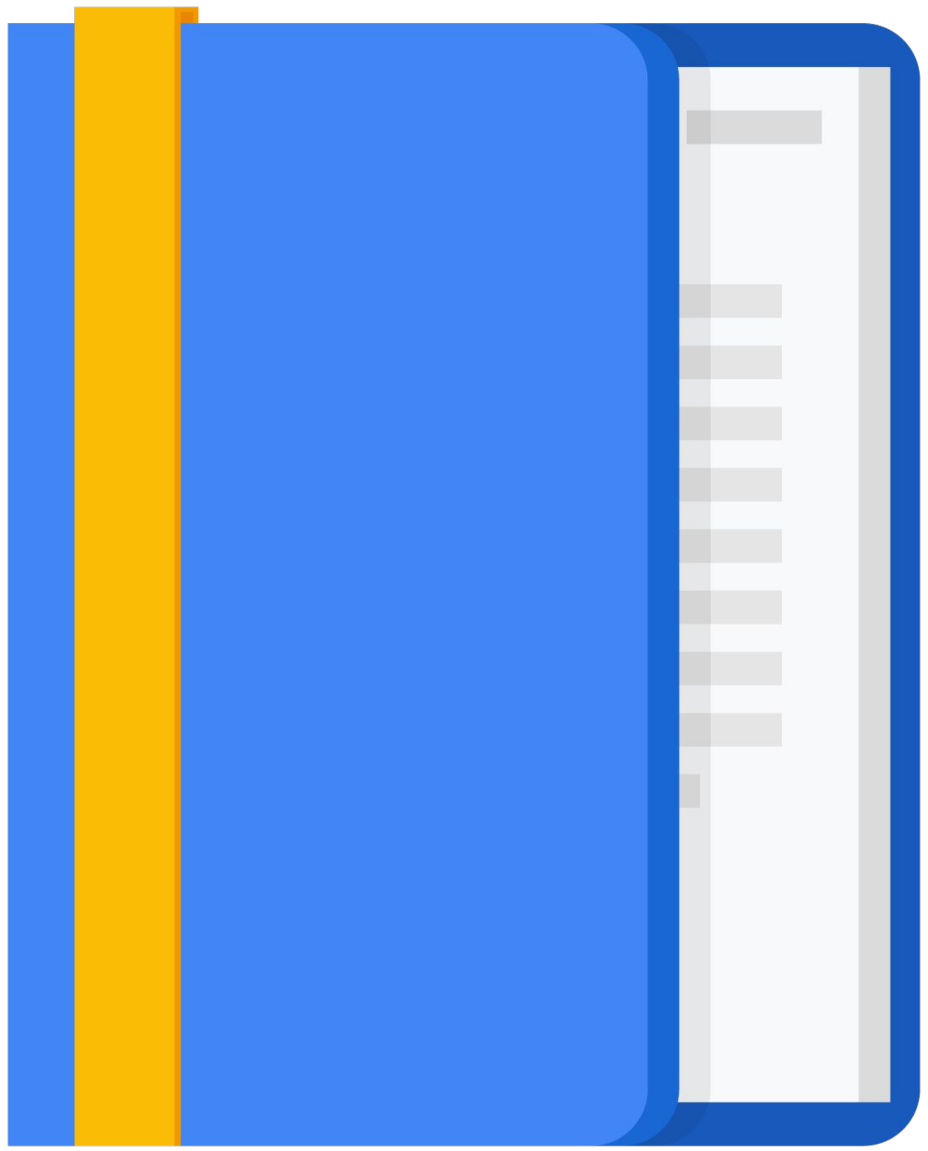

Step 1: Build and push the trainer container

trainer_image/Dockerfile

Required by Vertex AI Training

```
FROM gcr.io/deeplearning-platform-release/base-cpu
RUN pip install -U fire cloudml-hypertune scikit-learn==0.20.4 pandas==0.24.2

WORKDIR /app

COPY train.py .

ENTRYPOINT ["python", "train.py"]
```

```
TRAINER_IMAGE='gcr.io/PROJECT_ID/TRAINER_IMAGE_NAME:TAG'

gcloud builds submit --timeout 15m --tag $TRAINER_IMAGE trainer_image
```

Step 2: Compile the Kubeflow pipeline

```
dsl-compile-v2 --py pipeline_vertex/pipeline.py --output PIPELINE_JSON
```

[12]:
```
!head {PIPELINE_JSON}
```


```
{
  "pipelineSpec": {
    "components": {
      "comp-condition-deploy-decision-1": {
        "dag": {
          "tasks": {
            "train-and-deploy": {
              "cachingOptions": {
                "enableCache": true
              },
```


- The compilation produces a JSON description of the pipeline
- This JSON version will ultimately be converted by Vertex into a Kubeflow YAML argo file after upload to Vertex

Step 3: Upload and run on Vertex AI Pipeline

```
from google.cloud import aiplatform


aiplatform.init(project=PROJECT_ID, location=REGION)


pipeline = aiplatform.PipelineJob(
    display_name='covertype_kfp_pipeline',
    template_path=PIPELINE_JSON,
    enable_caching=False,
)


pipeline.run()
```

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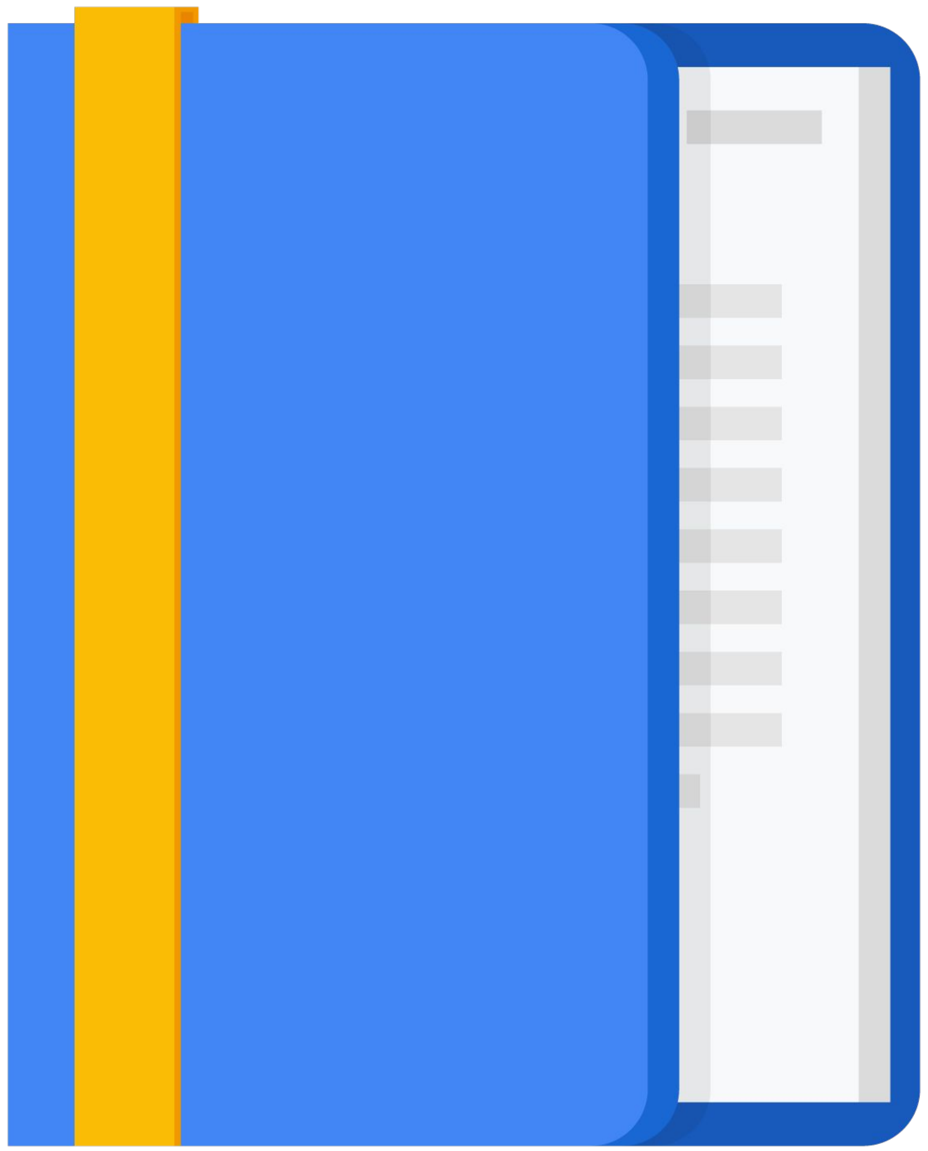

Importing Kubeflow pre-built components

Standard package

```
from google_cloud_pipeline_components.aiplatform
import (
    AutoMLTabularTrainingJobRunOp
    AutoMLImageTrainingJobRunOp
    AutoMLForecastingTrainingJobRunOp
    # etc.
    CustomContainerTrainingJobRunOp
    EndpointCreateOp,
    ModelDeployOp,
    ModelUploadOp,
)
```

Experimental Package

```
from google_cloud_pipeline_components.experimental.hyperparameter_tuning_job
import (
    HyperparameterTuningJobRunOp,
)

from google_cloud_pipeline_components.experimental.custom_job import (
    CustomTrainingJobOp,
)
```

Using pre-built components for TUNING

```python
hp_tuning_task = HyperparameterTuningJobRunOp(
    display_name=f"{PIPELINE_NAME}-kfp-tuning-job",
    project=PROJECT_ID,
    location=REGION,
    worker_pool_specs=worker_pool_specs,
    study_spec_metrics=metric_spec,
    study_spec_parameters=parameter_spec,
    max_trial_count=MAX_TRIAL_COUNT,
    parallel_trial_count=PARALLEL_TRIAL_COUNT,
    base_output_directory=PIPELINE_ROOT,
)
```

```python
worker_pool_specs = [
    {
        "container_spec": {
            "image_uri": TRAINING_CONTAINER_IMAGE_URI,
            "args": [
                f"--training_dataset_path={TRAINING_FILE_PATH}",
                f"--validation_dataset_path={VALIDATION_FILE_PATH}",
                "--hptune",
            ],
        },
    }
]

metric_spec = hyperparameter_tuning_job.serialize_metrics(
    {"accuracy": "maximize"}
)

parameter_spec = hyperparameter_tuning_job.serialize_parameters(
    {
        "alpha": hpt.DoubleParameterSpec(
            min=1.0e-4, max=1.0e-1, scale="linear"
        ),
        "max_iter": hpt.DiscreteParameterSpec(
            values=[1, 2], scale="linear"
        ),
    }
)
```

Using pre-built components for TRAINING

```
training_task = CustomTrainingJobOp(
    project=PROJECT_ID,
    location=REGION,
    display_name=f"{PIPELINE_NAME}-kfp-training-job",
    worker_pool_specs=worker_pool_specs_task.output,
    base_output_directory=BASE_OUTPUT_DIR,
)
```

```
worker_pool_specs_task = GetWorkerPoolSpecsOp(
    best_hyperparameters=best_hyperparameters_task.output,
    worker_pool_specs=[
        {
            "machine_spec": {"machine_type": "n1-standard-4"},
            "replica_count": 1,
            "container_spec": {
                "image_uri": TRAINING_CONTAINER_IMAGE_URI,
                "args": [
                    f"--training_dataset_path={TRAINING_FILE_PATH}",
                    f"--validation_dataset_path={VALIDATION_FILE_PATH}",
                    "--nohptune",
                ],
            },
        }
    ],
)
```

When the container is run the environment variable

`AIP_MODEL_DIR` **will be set to** `BASE_OUTPUT_DIR/model`

It is then used in train.py to save the model:

train.py

```
AIP_MODEL_DIR = os.environ["AIP_MODEL_DIR"]
MODEL_FILENAME = "model.pkl"
```

Using pre-built components for SERVING

```
model_upload_task = ModelUploadOp(
    project=PROJECT_ID,
    display_name=f"{PIPELINE_NAME}-kfp-model-upload-job",
    artifact_uri=f"{BASE_OUTPUT_DIR}/model",
    serving_container_image_uri=SERVING_CONTAINER_IMAGE_URI,
)


endpoint_create_task = EndpointCreateOp(
    project=PROJECT_ID,
    display_name=f"{PIPELINE_NAME}-kfp-create-endpoint-job",
)


model_deploy_op = ModelDeployOp(
    model=model_upload_task.outputs["model"],
    endpoint=endpoint_create_task.outputs["endpoint"],
    deployed_model_display_name=MODEL_DISPLAY_NAME,
    dedicated_resources_machine_type=SERVING_MACHINE_TYPE,
    dedicated_resources_min_replica_count=1,
    dedicated_resources_max_replica_count=1,
)
```

Lab

Kubeflow Pipelines on Vertex AI

In this lab, you will learn how to use Vertex AI Pipelines to build a Kubeflow pipeline to train, tune, and serve a model using **Google pre-built components.**

kubeflow_pipelines/pipelines/labs/kfp_pipeline_vertex_prebuilt.ipynb

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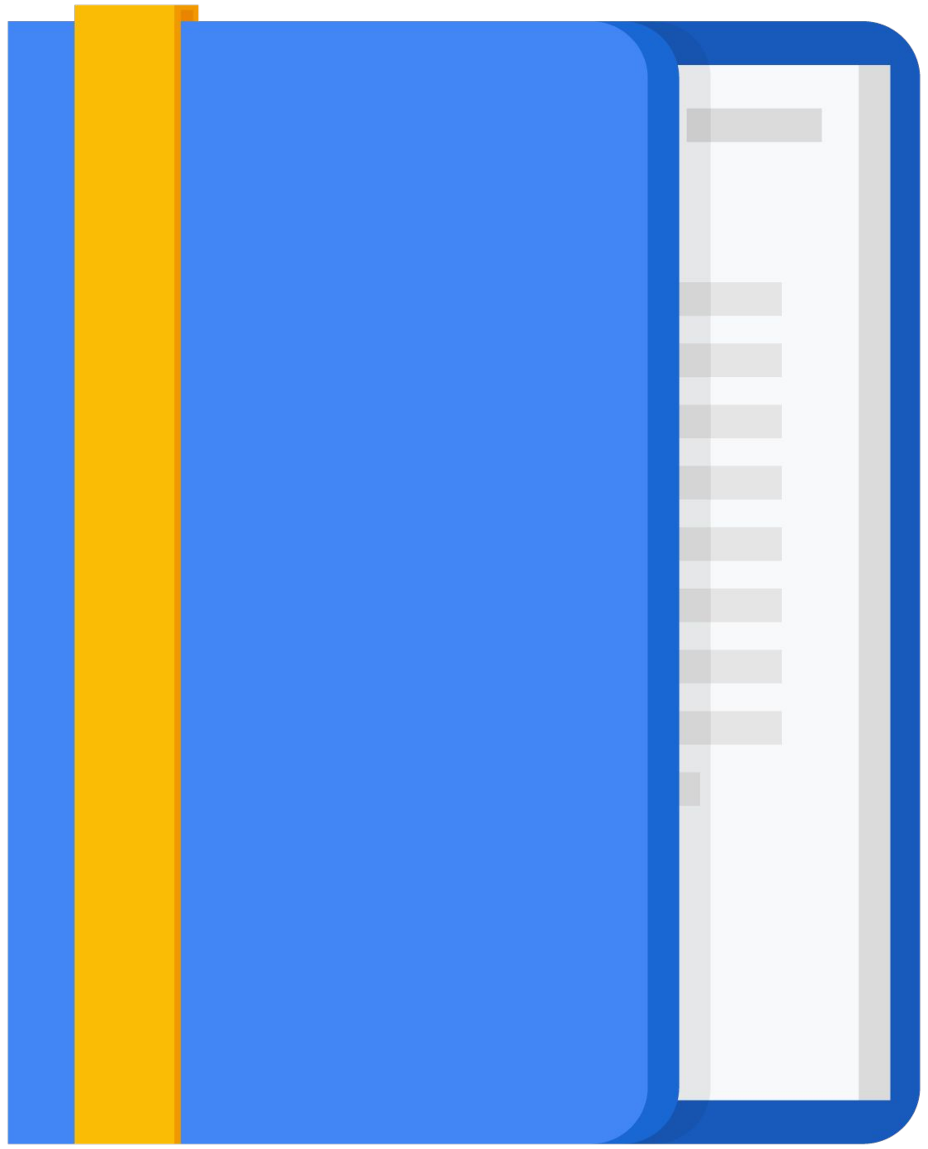

Wrap Python functions into KF components

training_lightweight_component.py

```
@component(base_image="python:3.8",
    output_component_file="covertype_kfp_train_and_deploy.yaml",
    packages_to_install=["google-cloud-aiplatform"])
def train_and_deploy(
        project: str,
        location: str,
        container_uri: str,
        serving_container_uri: str,
        training_file_path: str,
        validation_file_path: str,
        staging_bucket: str,
        alpha: float,
        max_iter: int,
):
```

Wrap Python functions into KF components

tuning_lightweight_component.py

```
from kfp.v2.dsl import component

@component(...)
def tune_hyperparameters(
        container_uri: str,
        # etc.
) -> NamedTuple("Outputs", [
    ("best_accuracy", float),
    ("best_alpha", float),
    ("best_max_iter", int)
]):

# etc.

return best_accuracy, best_alpha, best_max_iter
```

Use and compose the lightweight components as usual

```
tuning_op = tune_hyperparameters(
    project=PROJECT_ID,
    location=REGION,
    container_uri=training_container_uri,
    training_file_path=training_file_path,
    validation_file_path=validation_file_path,
    staging_bucket=staging_bucket,
    max_trial_count=max_trial_count,
    parallel_trial_count=parallel_trial_count,
)
```

Lab (Optional)

Kubeflow Pipelines on Vertex AI

In this lab, you will learn how to use Vertex AI Pipelines to build a Kubeflow pipeline to train, tune, and serve a model using your implementing **Python lightweight components.**

kubeflow_pipelines/pipelines/labs/kfp_pipeline_vertex_lightweight.ipynb

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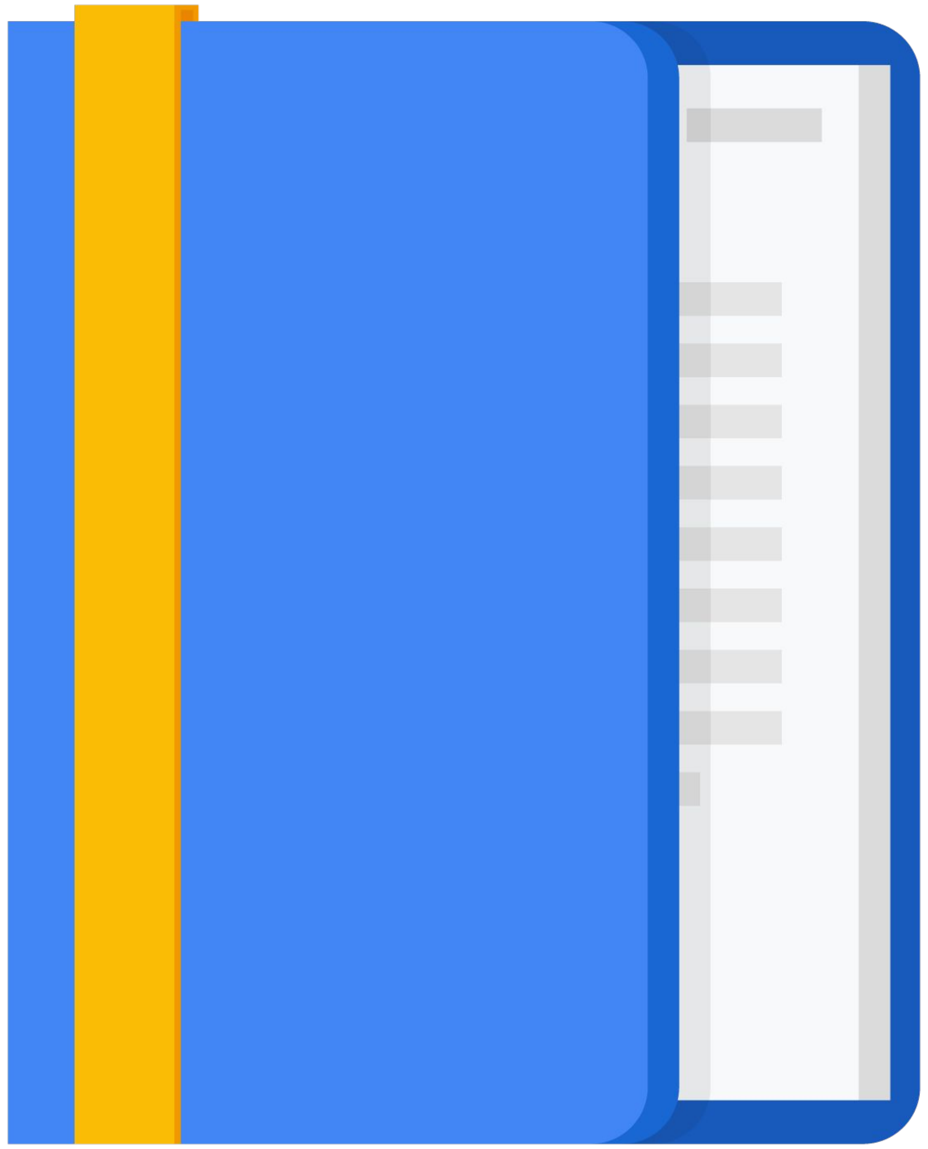
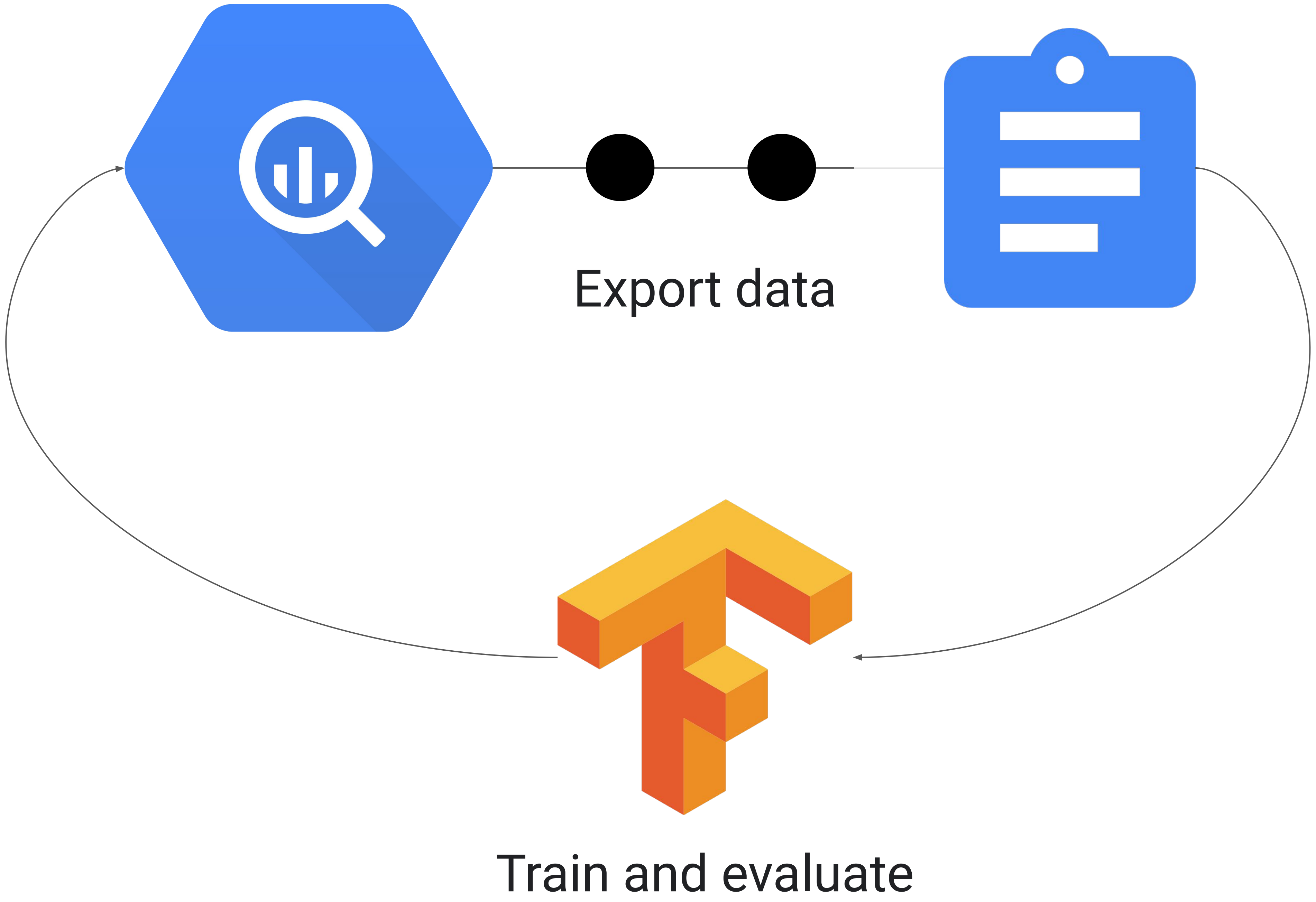
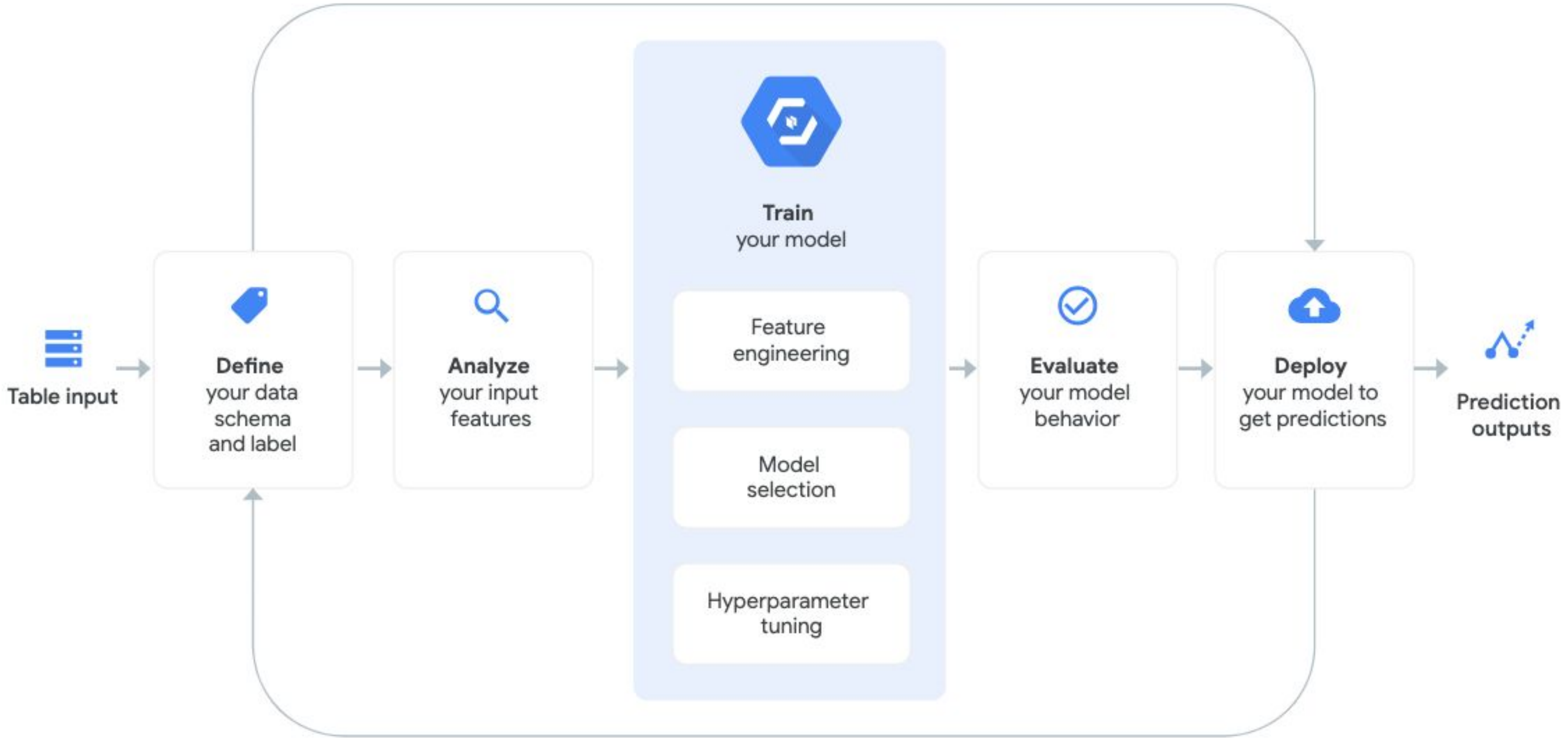


It can take days to months to create an ML model



Using AutoML within a Vertex Pipeline can speed up things!



AutoML can be launched using pre-built components

```
from google_cloud_pipeline_components.aiplatform import (
    TabularDatasetCreateOp,
    AutoMLTabularTrainingJobRunOp
    AutoMLImageTrainingJobRunOp
    AutoMLForecastingTrainingJobRunOp
    EndpointCreateOp,
    ModelDeployOp,

    # etc.
)
```

AutoML Vertex components exists for many input sources and ML problems

How to implement a AutoML Vertex Pipeline

Step 1: Create a Vertex Dataset for your data source

Step 2: Launch the AutoML training from the Vertex Dataset

Step 3: Upload and deploy the model as before

Step 1: Create a Vertex Dataset

```
dataset_create_task = TabularDatasetCreateOp(
    display_name=DISPLAY_NAME,
    bq_source=DATASET_SOURCE,
    project=PROJECT,
)
```

bq://project.dataset.table"

Step 2: Launch AutoML training

```
automl_training_task = AutoMLTabularTrainingJobRunOp(
    project=PROJECT,
    display_name=DISPLAY_NAME,
    optimization_prediction_type="classification",
    dataset=dataset_create_task.outputs["dataset"],
    target_column=TARGET_COLUMN,
)
```

The output `dataset_create_task.outputs["dataset"]` is an AutoML dataset

By setting the `dataset` argument as a `dataset_create_task.outputs["dataset"]` we are implicitly ordering the pipeline.

Step 3: Deploy the trained model as before

```
endpoint_create_task = EndpointCreateOp(
    project=PROJECT,
    display_name=DISPLAY_NAME,
)

model_deploy_task = ModelDeployOp(
    model=automl_training_task.outputs["model"],
    endpoint=endpoint_create_task.outputs["endpoint"],
    deployed_model_display_name=DISPLAY_NAME,
    dedicated_resources_machine_type=SERVING_MACHINE_TYPE,
    dedicated_resources_min_replica_count=1,
    dedicated_resources_max_replica_count=1,
)
```

Lab (Optional)

AutoML Pipelines on Vertex AI

In this lab, you will learn how to use Vertex AI Pipelines to build a **Vertex AutoML pipeline** to train, tune, and serve a model.

notebooks/kubeflow_pipelines/pipelines/solutions/kfp_pipeline_vertex_automl_online_predictions.ipynb cloud.google.com