

Custom components and CI/CD for TFX pipelines

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ML Solutions Engineer, Google Cloud

Agenda

TFX custom components

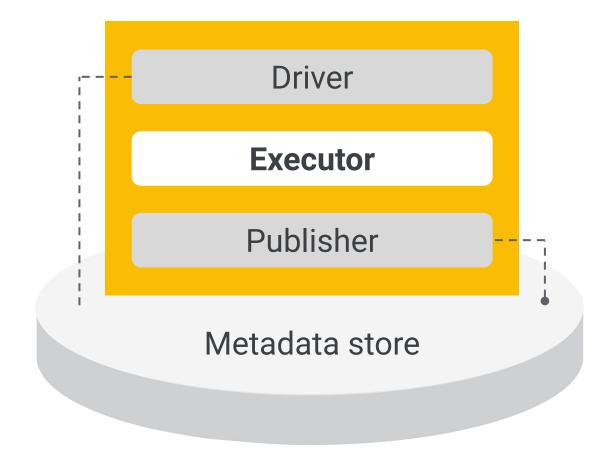
CI/CD for TFX pipeline workflows





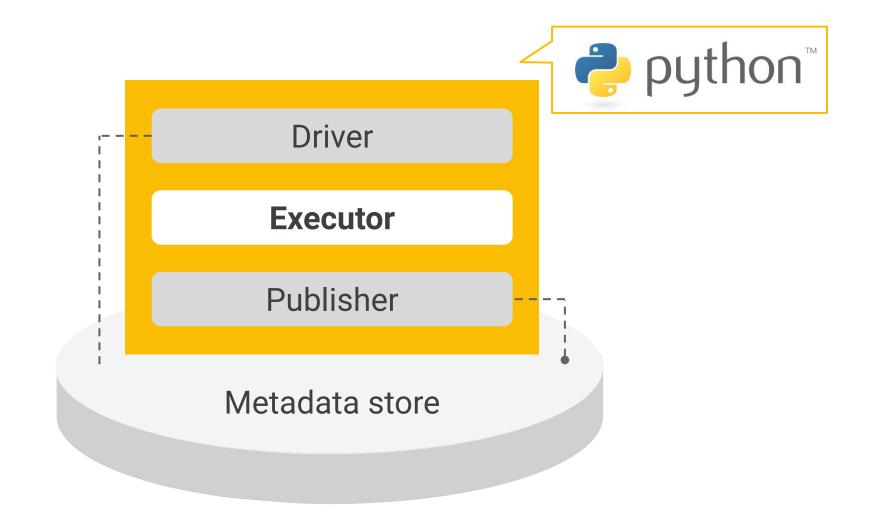
Create new custom components

- 1. Python functions
- 2. Containers
- 3. Extending existing component classes





Create custom components faster from Python functions, decorators, and type annotations.





```
from tfx.dsl.component.experimental.annotations import OutputDict
from tfx.dsl.component.experimental.annotations import InputArtifact
from tfx.dsl.component.experimental.annotations import OutputArtifact
from tfx.dsl.component.experimental.annotations import Parameter
from tfx.dsl.component.experimental.decorators import component
from tfx.types.standard_artifacts import Examples
from tfx.types.standard_artifacts import Model
@component
def MyTrainerComponent(
    training_data: InputArtifact[Examples],
    model: OutputArtifact[Model],
    dropout_hyperparameter: float,
    num_iterations: Parameter[int] = 10
     -> OutputDict(loss=float, accuracy=float):
  '''My simple trainer component.''
  records = read_examples(training_data.uri)
  model_obj = train_model(records, num_iterations, dropout_hyperparameter)
  model_obj.write_to(model.uri)
  return {
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    examples=example_gen.outputs['examples'],
    dropout_hyperparameter=other_component.outputs['dropout'],
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pusher = Pusher(model=trainer.outputs['model'])
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Step 1: apply @component decorator to your Python function.



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Step 1: apply @component decorator to
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Step 2: annotate input artifact
types.



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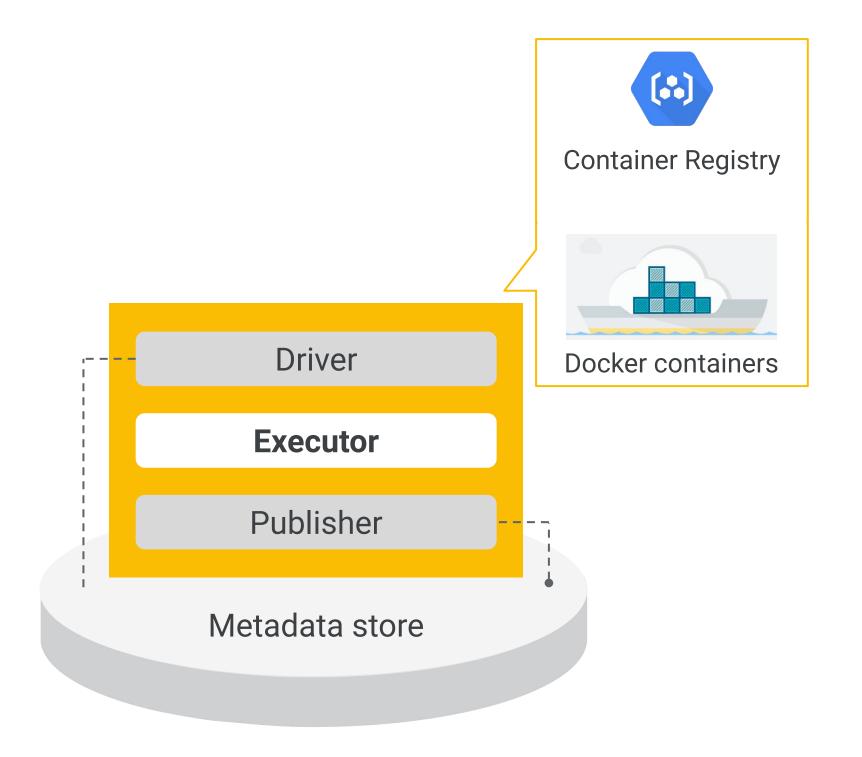
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```
Step 1: apply @component decorator to
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Step 2: annotate input artifact
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types.
Step 4: annotate output artifact
types.
Step 5: initialize custom component.
```



Option 2: Containers

Create custom components using pre-built Docker containers for flexibility to incorporate code in any language into your TFX pipeline.





Option 2: container-based components

```
from tfx.dsl.component.experimental import container_component
from tfx.dsl.component.experimental import placeholders
from tfx.types import standard_artifacts
grep_component = container_component.create_container_component(
    name='FilterWithGrep',
    inputs={ 'text': standard_artifacts.ExternalArtifact,},
    outputs={ 'filtered_text': standard_artifacts.ExternalArtifact,},
    parameters={'pattern': str, },
    # The component code uses gsutil to upload the data to Google Cloud Storage
    image='google/cloud-sdk:278.0.0',
    command=[
        'sh', '-exc',
          pattern="$1"
          text_uri="$3"
          text_path=$(mktemp)
          filtered_text_uri="$5"
          filtered_text_path=$(mktemp)
          # Step 1
          gsutil cp "$text_uri" "$text_path"
          # Step 2
          grep "$pattern" "$text_path" >"$filtered_text_path"
          # Step 3
          gsutil cp "$filtered_text_path" "$filtered_text_uri"
          placeholders.InputValuePlaceholder('pattern'),
        '--text', placeholders.InputUriPlaceholder('text'),
        '--filtered-text', placeholders.OutputUriPlaceholder('filtered_text'),
 '--pattern'
```

Create a component from an existing container image by wrapping it with create_container_component(). Its arguments:

Name: string component name.

Inputs: dictionary that maps input names to

artifact types.

Outputs: dictionary that maps output names

to artifact types.

Parameters: dictionary that maps names to

parameter types.

Image: Container image name with optional

tag.

Command: Container entrypoint command line.



Option 2: container-based components

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          # Step 1
          gsutil cp "$text_uri" "$text_path"
          # Step 2
          grep "$pattern" "$text_path" >"$filtered_text_path"
          # Step 3
          gsutil cp "$filtered_text_path" "$filtered_text_uri"
        '--pattern', placeholders.InputValuePlaceholder('pattern'),
        '--text', placeholders.InputUriPlaceholder('text'),
        '--filtered-text', placeholders.OutputUriPlaceholder('filtered_text'),
```

Step 1: Use gsutil to copy ExternalArtifact text data into the container from text_uri directory.

Step 2: Filter text using grep command based on provided pattern.

Step 3: Use gsutil to copy data out of container into text_filtered_uri directory.



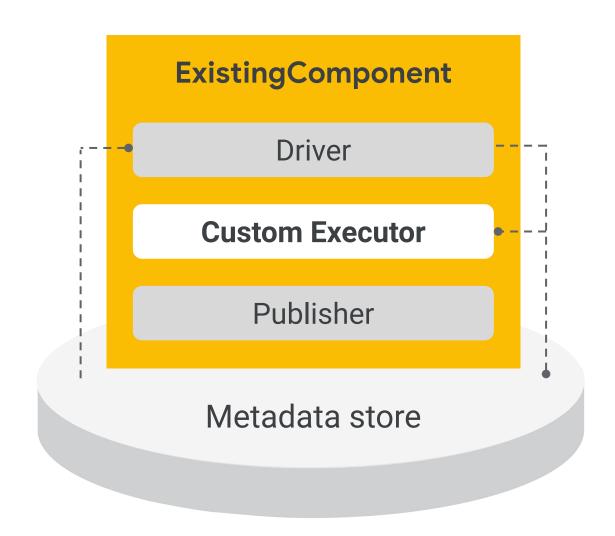
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          gsutil cp "$text_uri" "$text_path"
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        '--pattern', placeholders.InputValuePlaceholder('pattern'),
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```

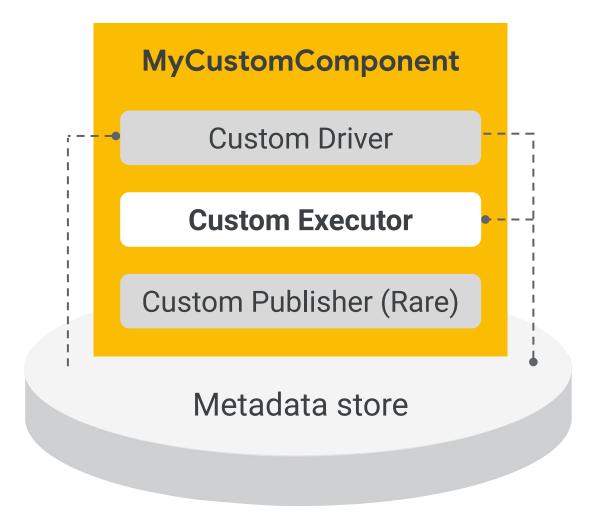
Placeholders are command-line arguments use in container component definitions that are replaced at runtime with artifact values or URIs.



Option 3: Extending existing components



Design Pattern # 1 (most common): Extend existing component executor



Design Pattern # 2: Full customization



Subclass ComponentSpec to customize component artifact linkage

```
class MyComponentSpec(types.ComponentSpec):

PARAMETERS = {
        'name': ExecutionParameter(type=Text),
}
INPUTS = {
        'input_data': ChannelParameter(type=standard_artifacts.Examples),
}
OUTPUTS = {
        'output_data': ChannelParameter(type=standard_artifacts.Examples),
}
```



Subclass BaseExecutor for custom computation



Customize BaseDriver to change interactions with ML Metadata

```
class MyDriver(base_driver.BaseDriver):
  """Custom driver for MyComponent."
 def resolve_input_artifacts(
      self,
      input_channels: Dict[Text, types.Channel],
      exec_properties: Dict[Text, Any],
      driver_args: data_types.DriverArgs,
      pipeline_info: data_types.PipelineInfo) -> Dict[Text, List[types.Artifact]]:
    """Overrides BaseDriver.resolve_input_artifacts()."""
   del driver_args 1
   del pipeline_info
   input_dict = channel_utils.unwrap_channel_dict(input_channels) 2
    for input_list in input_dict.values():
        for single_input in input_list:
            self._metadata_handler.publish_artifacts([single_input]) 3
            absl.logging.debug("Registered input: {}".format(single_input))
            absl.logging.debug("single_input.mlmd_artifact
                                "{}".format(single_input.mlmd_artifact)) 4
   return input_dict
```



Customize component interface to use fully custom component in pipeline

```
from tfx.components.base import base_component
from tfx import types
from tfx.types import channel_utils
class MyComponent(base_component.BaseComponent):
    """Custom MyComponent.""
    SPEC_CLASS = MyComponentSpec
    EXECUTOR_SPEC = executor_spec.ExecutorClassSpec(MyExecutor)
    DRIVER_CLASS = MyDriver
    def __init__(self, input, output_data=None, name=None):
        if not output_data:
            examples_artifact = standard_artifacts.Examples()
            examples_artifact.split_names = \
                artifact_utils.encode_split_names(['train', 'eval'])
            output_data = channel_utils.as_channel([examples_artifact])
        spec = MySpec(input=input,
examples=output_data,
name=name)
        super(MyComponent, self).__init__(spec=spec)
```



Exercise: Custom Component Brainstorm

Reflect on what you learned about building custom TFX components.

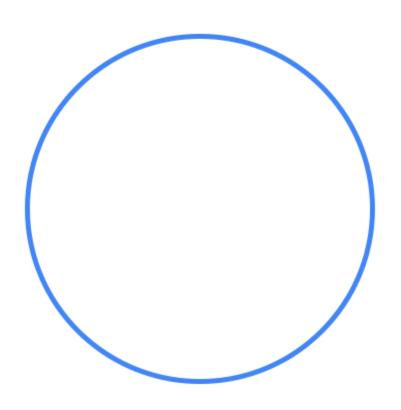
Option 1: Can you think of a part of your ML workflow that you would build a custom component for?

Option 2: How would you build a custom ExampleGen to convert image directories to TF Records?

Describe the following pieces of your custom component:

- ComponentSpec()
- Executor()
- Component() interface





Agenda

TFX custom components

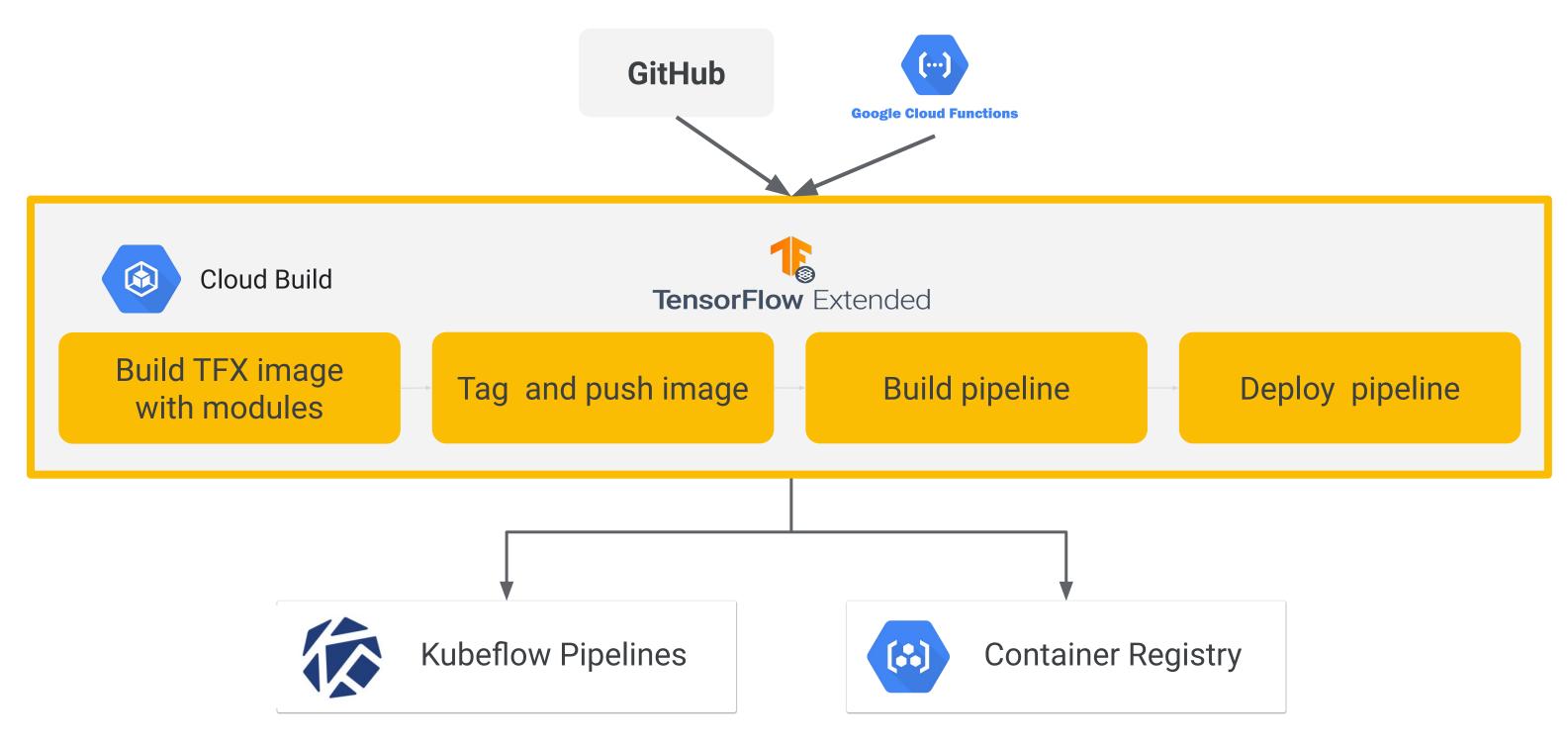
CI/CD for TFX pipeline workflows





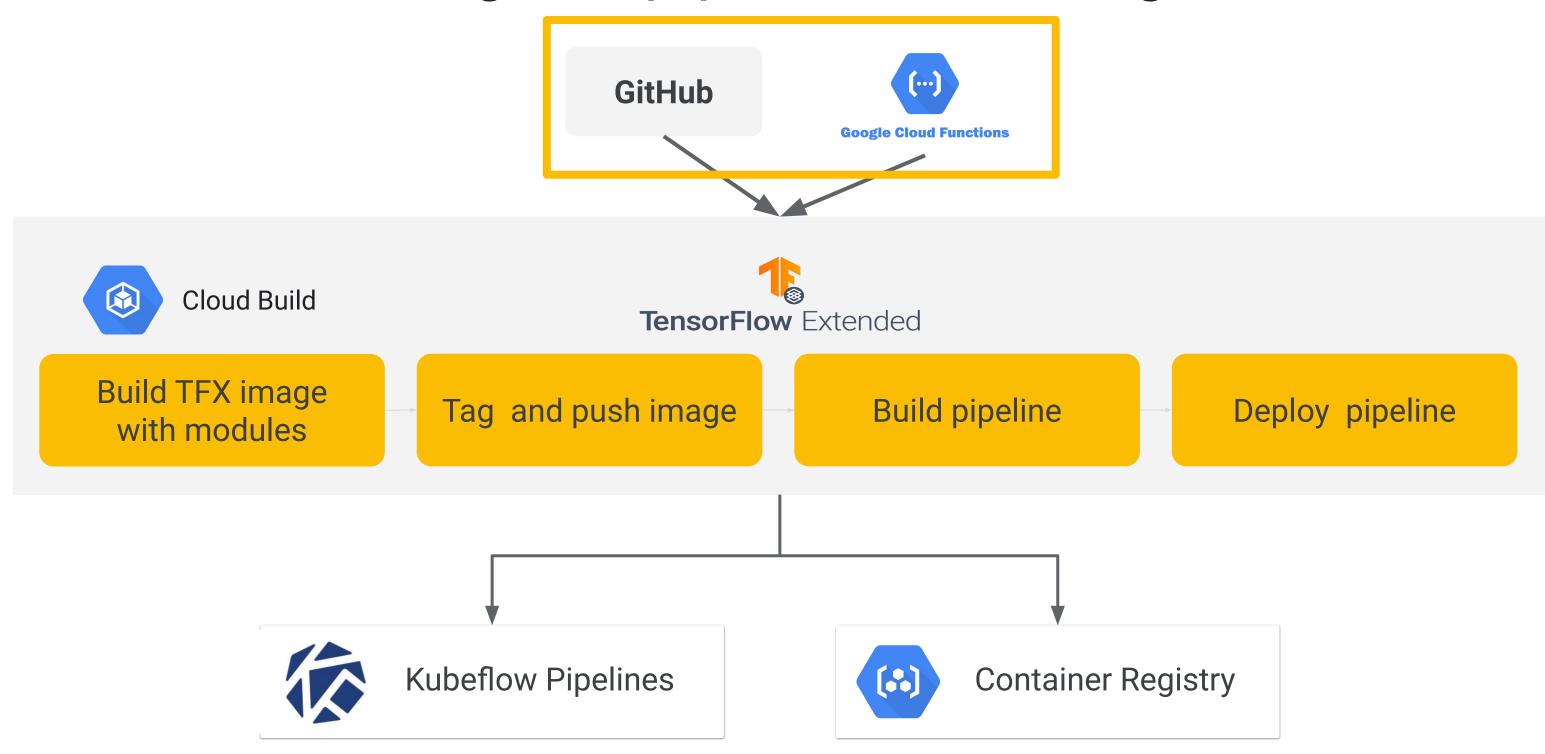
Review: TFX brings DevOps best practices to ML workflows

CI/CD for training TFX pipelines on Google Cloud





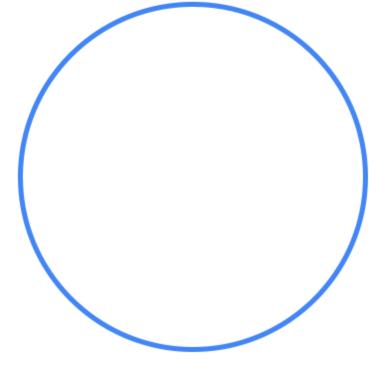
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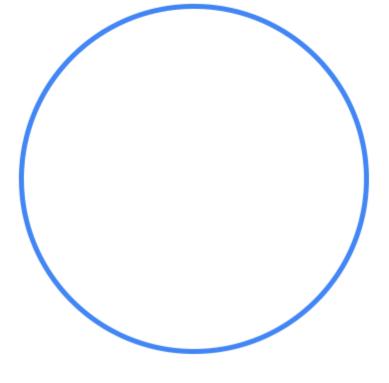
Clone Repo gcr.io/cloud-builders/git — clonehttps://githib.com/mlops-on-gcp/tfx-examples.git tfx-cicd-pipeline —dept	2 sec h 1verbose	16
Run Unit Tests python:3.6-slim-jessie – components/tests.sh	11 sec	~
	2 sec	~
	2 sec	~
✓ Update Component Spec Images gcr.io/ml-cicd-template/kfp-util:latest — pipeline/helper.py update-specs —repo_url gcr.io/ml-cicd-template {_TAG}	34 sec -image_tag	
Compile Pipeline gcr.io/ml-cicd-template/kfp-util:latest — -py pipeline/workflow.pyoutput pipeline/pipeline.tar.gzdisable	2 sec -type-check	~
✓ Upload Pipeline to GCS gcr.io/cloud-builders/gsutil — cp pipeline.tar.gz settings.yaml gs://ml-cicd-template/helloworld/pipelines/l	5 sec	~
✓ Deploy & Run Pipeline gcr.io/ml-cicd-template/kfp-util:latest — -c "/builder/kubectl.bash; python3 helper.py deploy-pipeline package_path=pipeline.tar.gzversion=\"latest\"experiment=\"helloworld-dev\"run"	8 sec	~





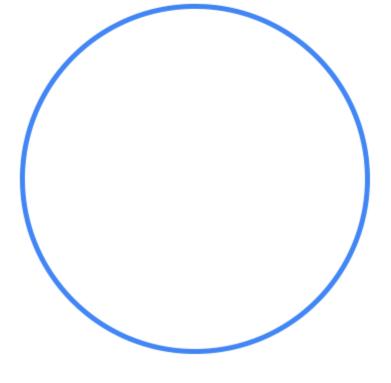
Build steps expand all Clone Repo 2 sec V gcr.io/cloud-builders/git — clonehttps://githib.com/mlops-on-gcp/tfx-examples.git tfx-cicd-pipeline --depth 1 --verbose Run Unit Tests 11 sec ∨ python:3.6-slim-jessie - components/tests.sh Build my_add Image 2 sec V gcr.io/cloud-builders/docker - build -t gcr.io/ml-cicd-template/my_add:latest Build my_divide Image 2 sec V gcr.io/cloud-builders/docker — build -t gcr.io/ml-cicd-template/my_divide:latest . Update Component Spec Images 34 sec V gcr.io/ml-cicd-template/kfp-util:latest - pipeline/helper.py update-specs --repo_url gcr.io/ml-cicd-template --image_tage {_TAG} Compile Pipeline 2 sec v gcr.io/ml-cicd-template/kfp-util:latest — --py pipeline/workflow.py --output pipeline/pipeline.tar.gz --disable-type-check Upload Pipeline to GCS 5 sec v gcr.io/cloud-builders/gsutil - cp pipeline.tar.gz settings.yaml gs://ml-cicd-template/helloworld/pipelines/latest/ Deploy & Run Pipeline 8 sec V gcr.io/ml-cicd-template/kfp-util:latest - -c "/builder/kubectl.bash; python3 helper.py deploy-pipeline -package_path=pipeline.tar.gz --version=\"latest\" --experiment=\"helloworld-dev\" --run"





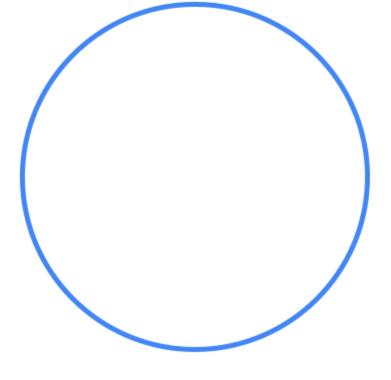
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✓ Upload Pipeline to GCS gcr.io/cloud-builders/gsutil — cp pipeline.tar.gz settings.yaml gs://ml-cicd-template/helloworld/pipelines/la	5 sec	~
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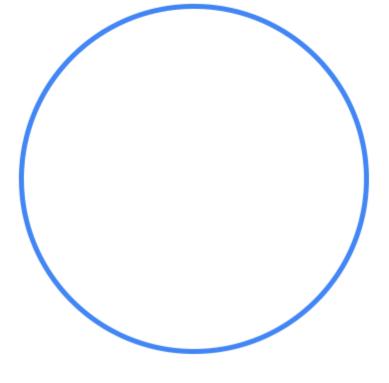
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Build my_add Image gcr.io/cloud-builders/docker — build -t gcr.io/ml-cicd-template/my_add:latest .	2 sec	~
Build my_divide Image gcr.io/cloud-builders/docker — build -t gcr.io/ml-cicd-template/my_divide:latest.	2 sec	~
Update Component Spec Images	34 sec	~
gcr.io/ml-cicd-template/kfp-util:latest — pipeline/helper.py update-specs –repo_url gcr.io/ml-cicd-template {_TAG}		
gcr.io/ml-cicd-template/kfp-util:latest — pipeline/helper.py update-specs –repo_url gcr.io/ml-cicd-template	image_tag	е
gcr.io/ml-cicd-template/kfp-util:latest — pipeline/helper.py update-specs —repo_url gcr.io/ml-cicd-template {_TAG} Compile Pipeline	2 sec type-check 5 sec	e ~





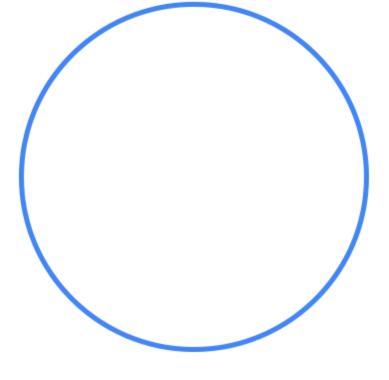
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Compile Pipeline gcr.io/ml-cicd-template/kfp-util:latest —py pipeline/workflow.pyoutput pipeline/pipeline.tar.gzdisable	2 sec ✓ -type-check
✓ Upload Pipeline to GCS gcr.io/cloud-builders/gsutil — cp pipeline.tar.gz settings.yaml gs://ml-cicd-template/helloworld/pipelines/l	5 sec ✓ atest/
✓ Deploy & Run Pipeline gcr.io/ml-cicd-template/kfp-util:latest — -c "/builder/kubectl.bash; python3 helper.py deploy-pipeline package_path=pipeline.tar.gzversion=\"latest\"experiment=\"helloworld-dev\"run"	8 sec ∨





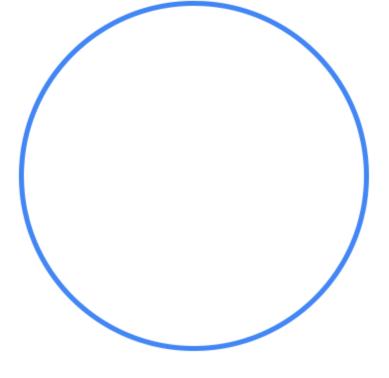
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Update Component Spec Images gcr.io/ml-cicd-template/kfp-util:latest — pipeline/helper.py update-specsrepo_url gcr.io/ml-cicd-template (_TAG)	34 sec eimage_tag	
Compile Pipeline gcr.io/ml-cicd-template/kfp-util:latest —py pipeline/workflow.pyoutput pipeline/pipeline.tar.gzdisable	2 sec e-type-check	~
Upload Pipeline to GCS gcr.io/cloud-builders/gsutil — cp pipeline.tar.gz settings.yaml gs://ml-cicd-template/helloworld/pipelines/	5 sec	~
Deploy & Run Pipeline gcr.io/ml-cicd-template/kfp-util:latest — -c "/builder/kubectl.bash; python3 helper.py deploy-pipeline package_path=pipeline.tar.gzversion=\"latest\"experiment=\"helloworld-dev\"run"	8 sec	~





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Update Component Spec Images gcr.io/ml-cicd-template/kfp-util:latest — pipeline/helper.py update-specs —repo_url gcr.io/ml-cicd-template {_TAG}	34 sec image_tag	
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Level-0 ML process automation: TFX pipeline prototyping in notebooks

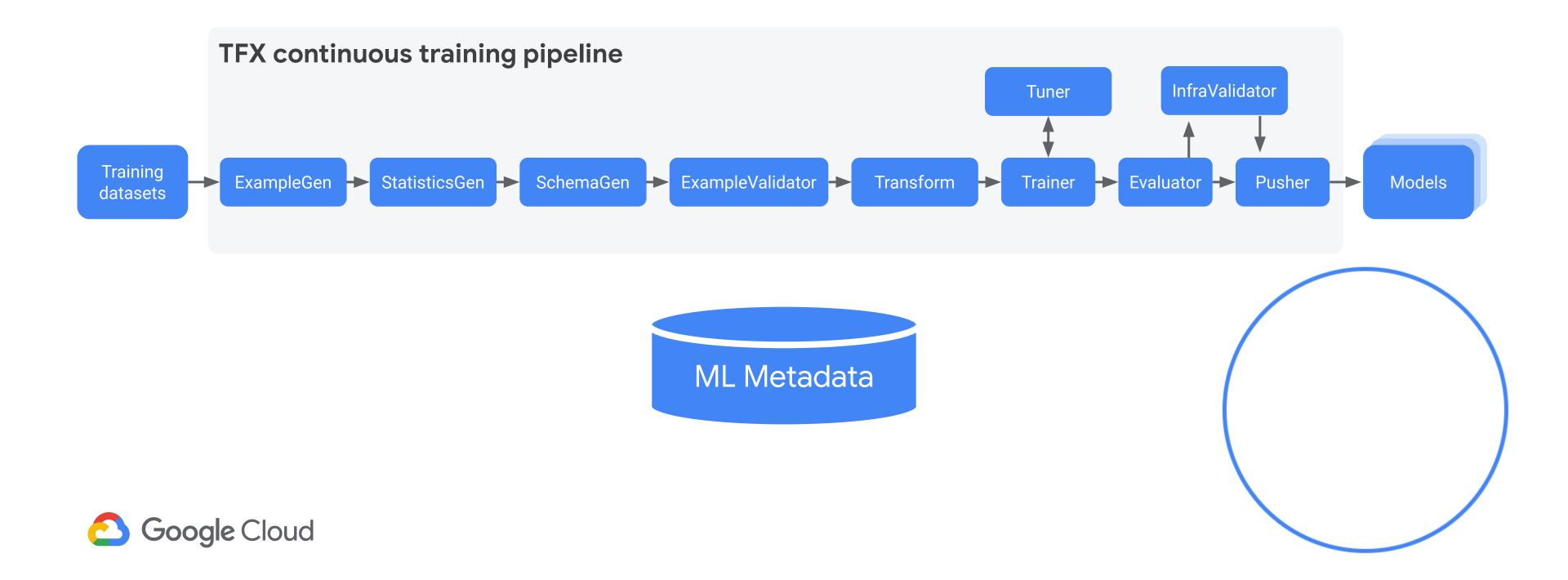
```
context = InteractiveContext()

component = MyComponent(...)
context.run(component)
context.show(component.outputs['my_output'])
```

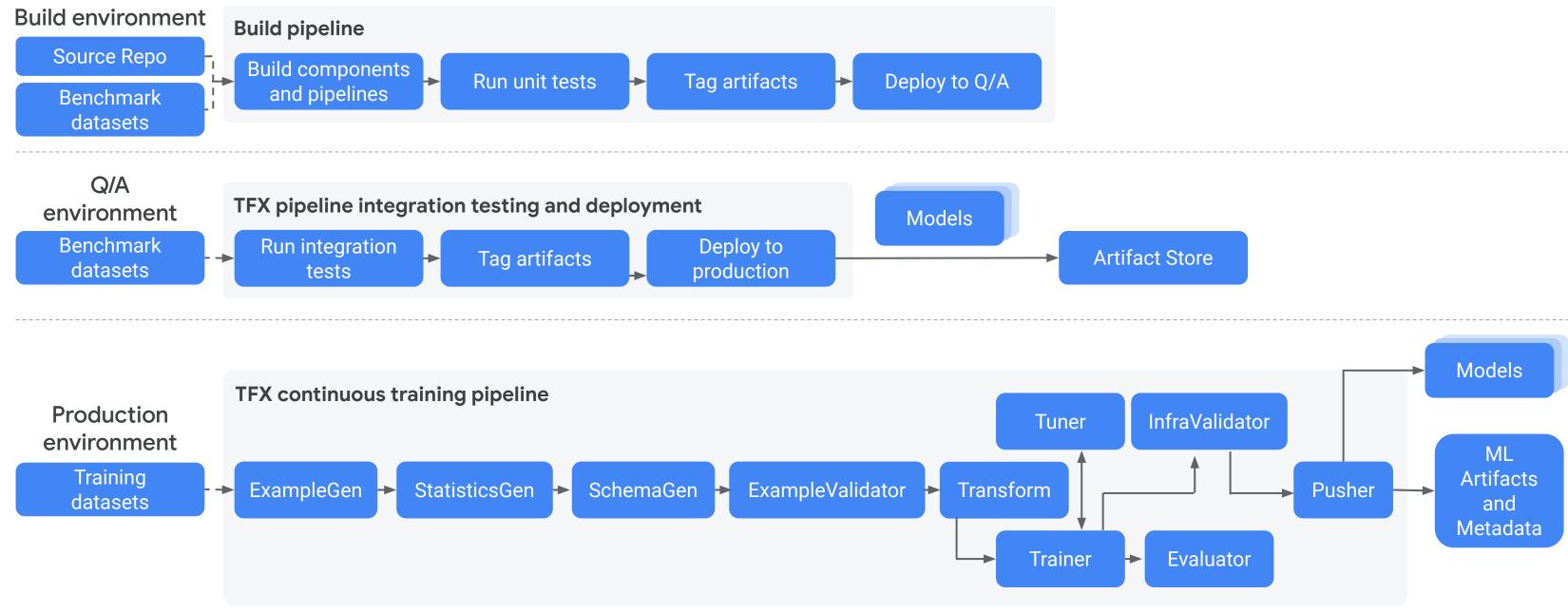
Prototype-to-production: notebook can be converted into an orchestratable pipeline file



Level-1 ML development automation: TFX pipeline continuous training

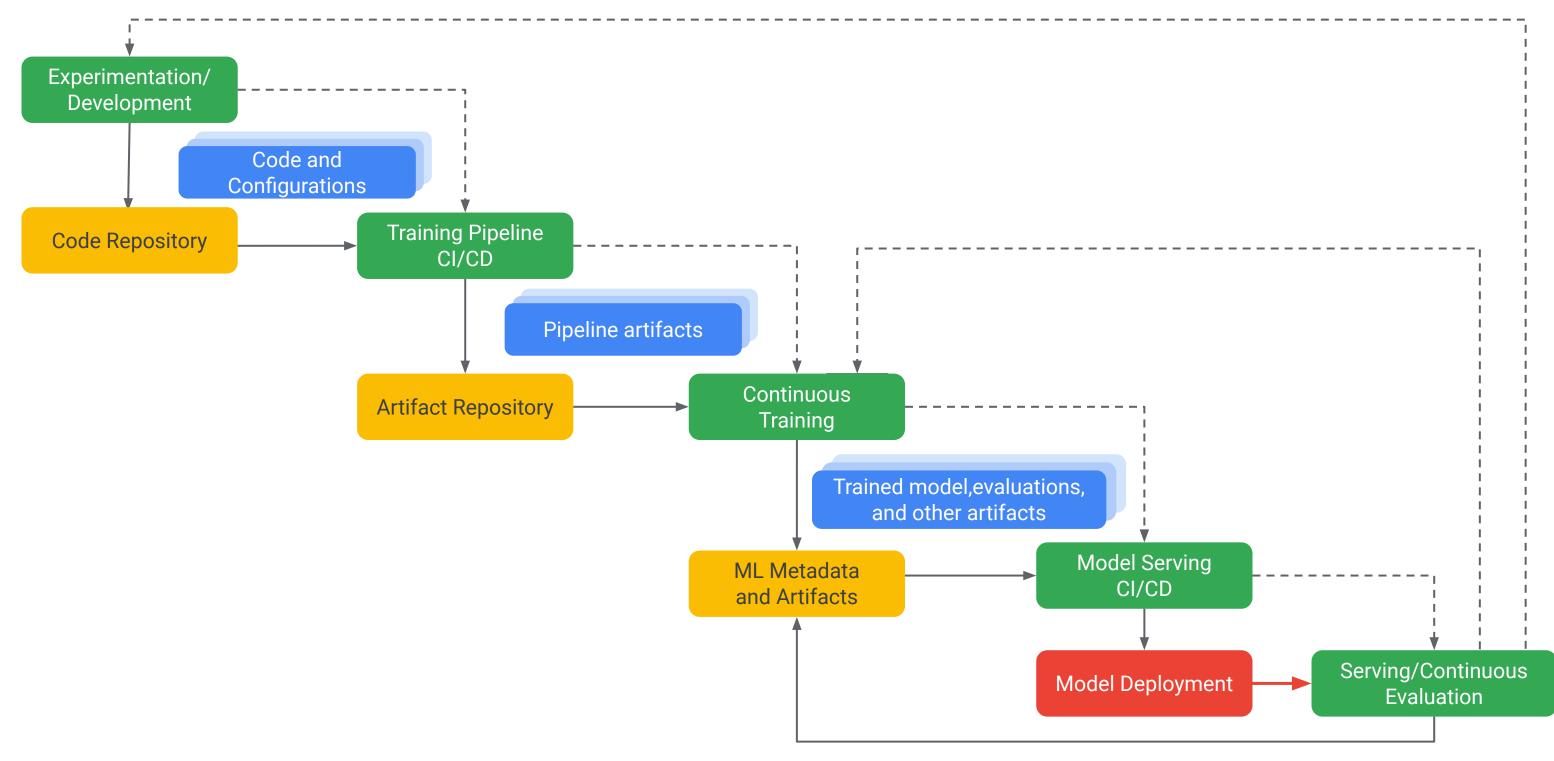


Level-2 ML development automation: TFX CI/CD pipelines



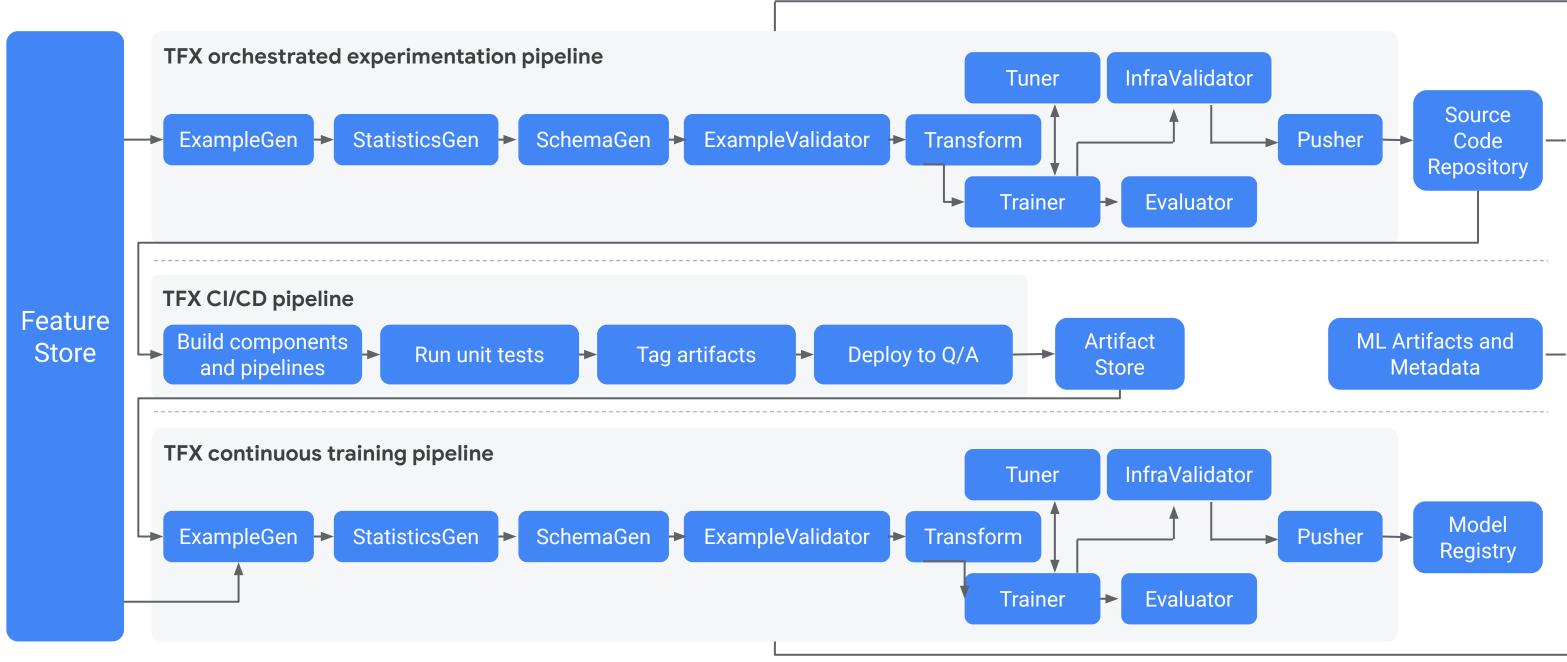


End-to-end TFX MLOps workflow



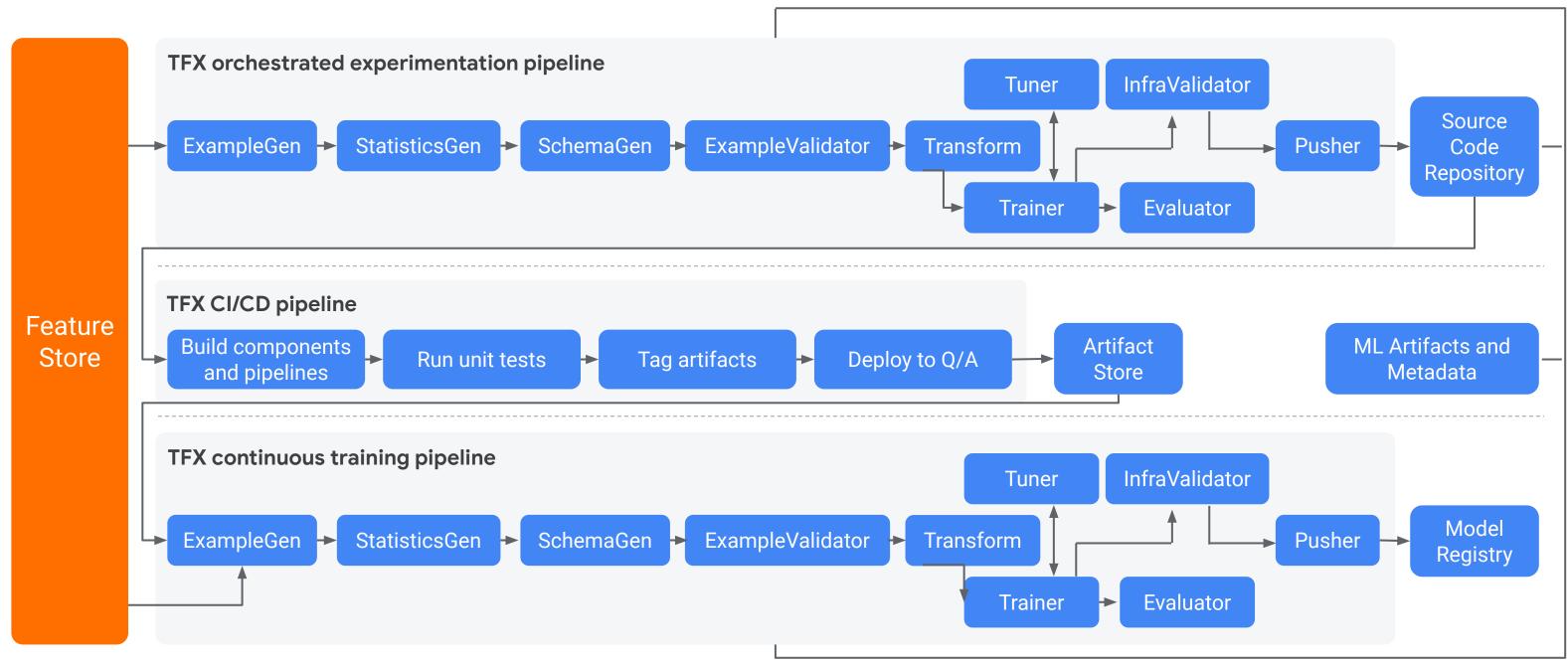


Future state of ML development: Fully automated TFX MLOps pipeline development



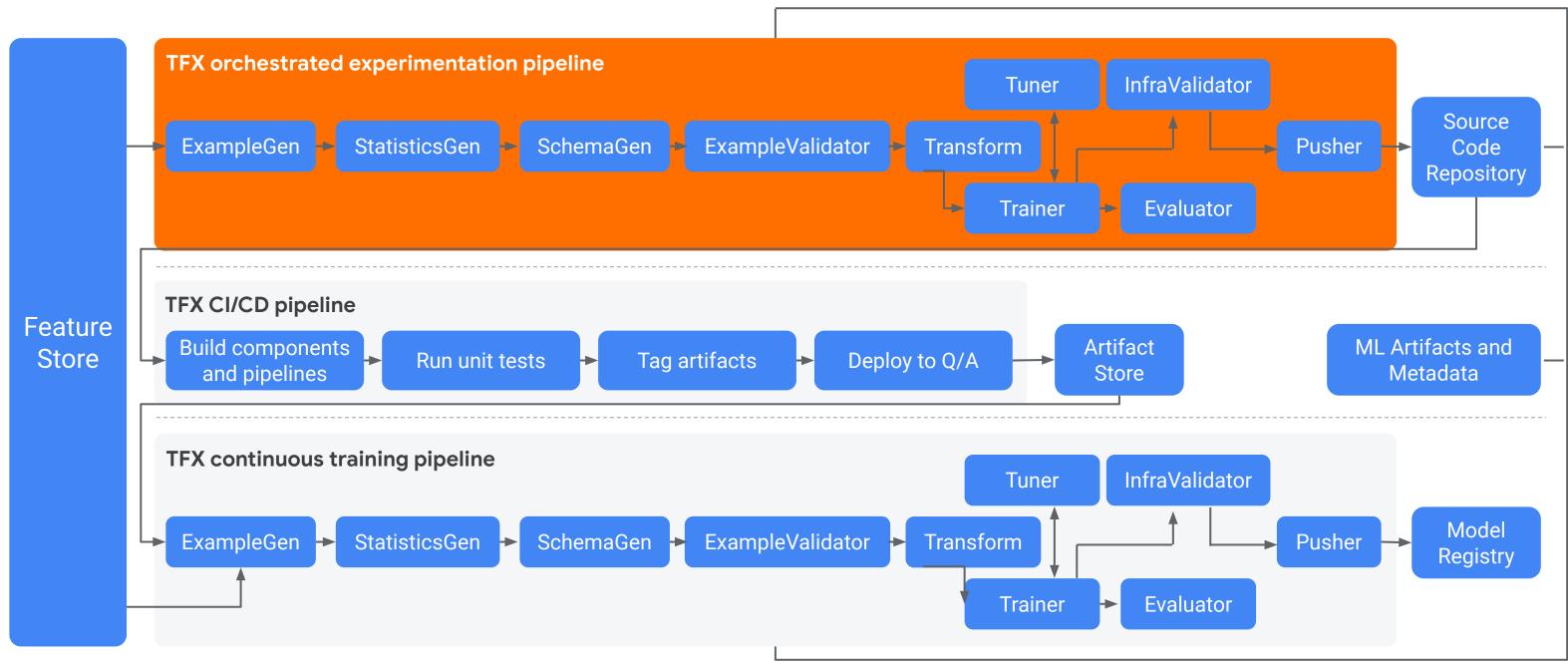


Future state of ML development: Fully automated TFX MLOps pipeline development





Future state of ML development: Fully automated TFX MLOps pipeline development





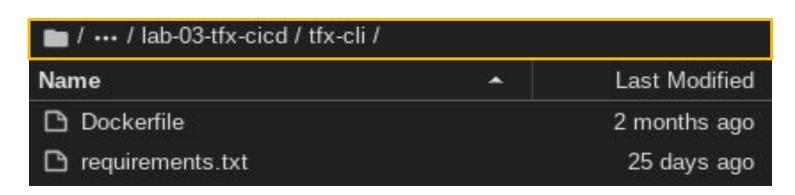
Lab Walkthrough

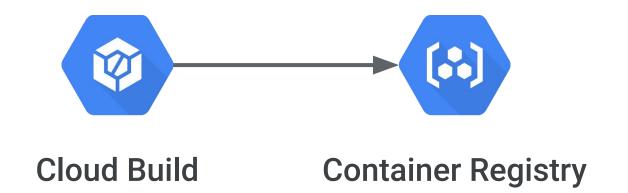
CI/CD for TFX pipelines





Use Cloud Build to build and submit TFX CLI to Container Registry





Dockerfile

```
FROM gcr.io/deeplearning-platform-release/tf2-cpu.2-3
COPY requirements.txt .
RUN python -m pip install -U -r requirements.txt
ENTRYPOINT ["tfx"]
```

```
IMAGE_NAME='tfx-cli'
TAG='latest'
IMAGE_URI='gcr.io/{}/{}:{}'.format(PROJECT_ID,
IMAGE_NAME, TAG)
```

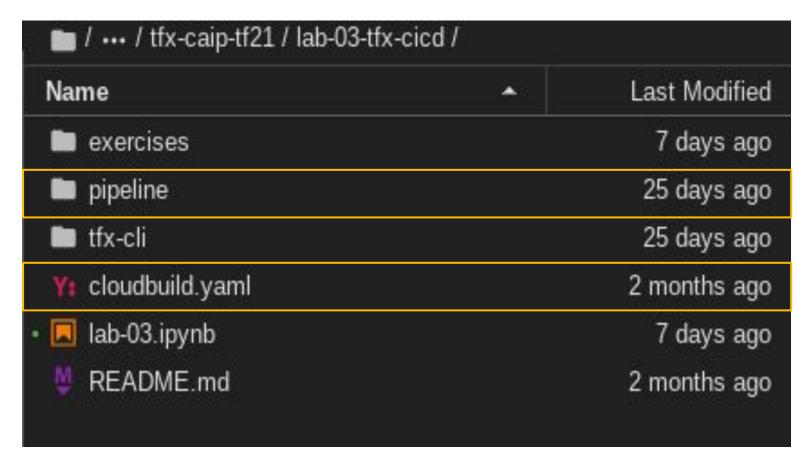
requirements.txt

```
pandas>1.0.0
tfx==0.25.0
kfp==1.0.4
```

```
!gcloud builds submit --timeout 15m --tag {IMAGE_URI}
tfx-cli
```



Manually trigger CI/CD runs of TFX pipeline image



Use Cloud Build to create custom TFX pipeline container and push to Container Registry.

Use Cloud Build to trigger build of TFX pipeline image on Container Registry.



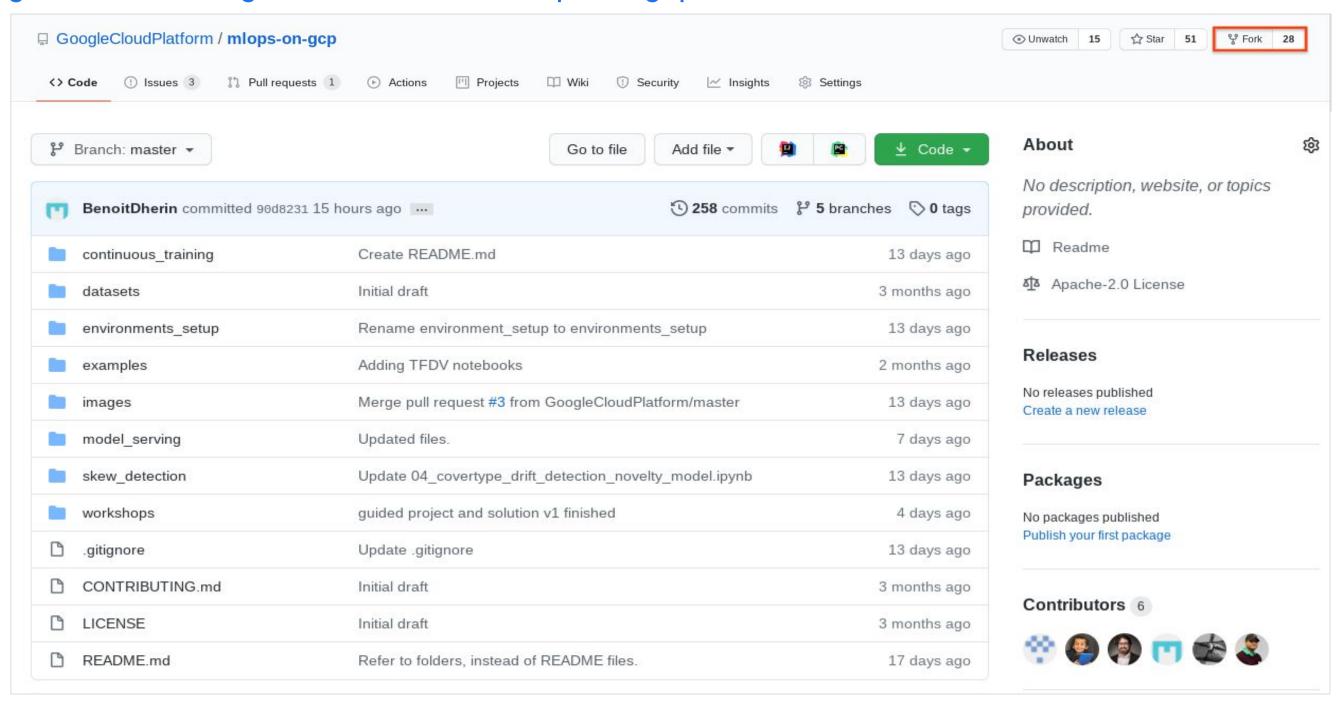
!gcloud builds submit .
--config cloudbuild.yaml
--substitutions {SUBSTITUTIONS}

```
PIPELINE_NAME='tfx_covertype_continuous_training'
TAG_NAME='test'
TFX_IMAGE_NAME='lab-03-tfx-image'
DATA_ROOT_URI='gs://workshop-datasets/covertype/small'
MODEL_NAME='tfx_covertype_classifier'
PIPELINE_FOLDER='pipeline'
PIPELINE_DSL='runner.py'
RUNTIME_VERSION='2.3'
PYTHON_VERSION='3.7
USE_KFP_SA='False'
SUBSTITUTIONS="""
_ENDPOINT={},\
_GCP_REGION={},\
_ARTIFACT_STORE_URI={},\
_TFX_IMAGE_NAME={},\
_DATA_ROOT_URI={},\
_MODEL_NAME={},\
TAG_NAME={}, \
_PIPELINE_FOLDER={},\
_PIPELINE_DSL={},\
_PIPELINE_NAME={},\
_RUNTIME_VERSION={},\
_USE_KFP_SA={},\
_PYTHON_VERSION={}
""".format(ENDPOINT,
           GCP_REGION,
           ARTIFACT_STORE_URI,
           TFX_IMAGE_NAME,
           DATA_ROOT_URI,
           MODEL_NAME
           TAG_NAME,
           PIPELINE_FOLDER,
           PIPELINE_DSL,
           PIPELINE_NAME,
           RUNTIME_VERSION
           PYTHON_VERSION,
           USE_KFP_SA
           ).strip()
```



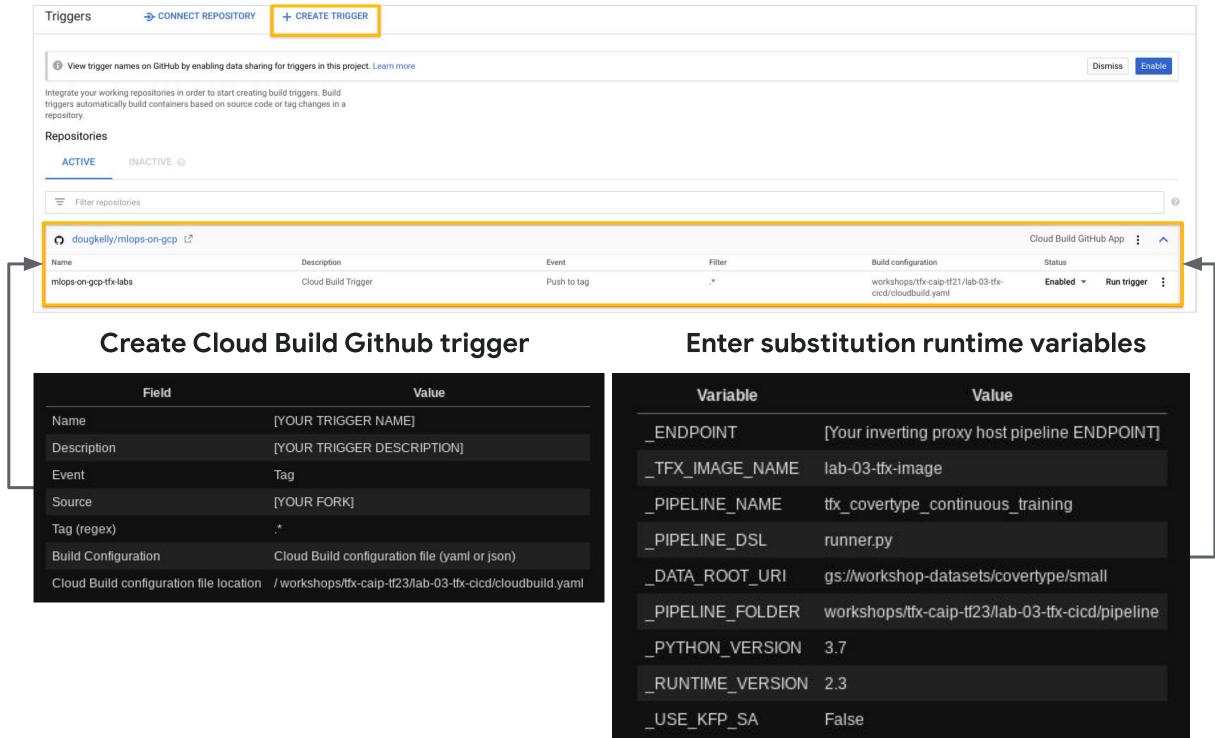
Fork mlops-on-gcp Github repository

https://github.com/GoogleCloudPlatform/mlops-on-gcp





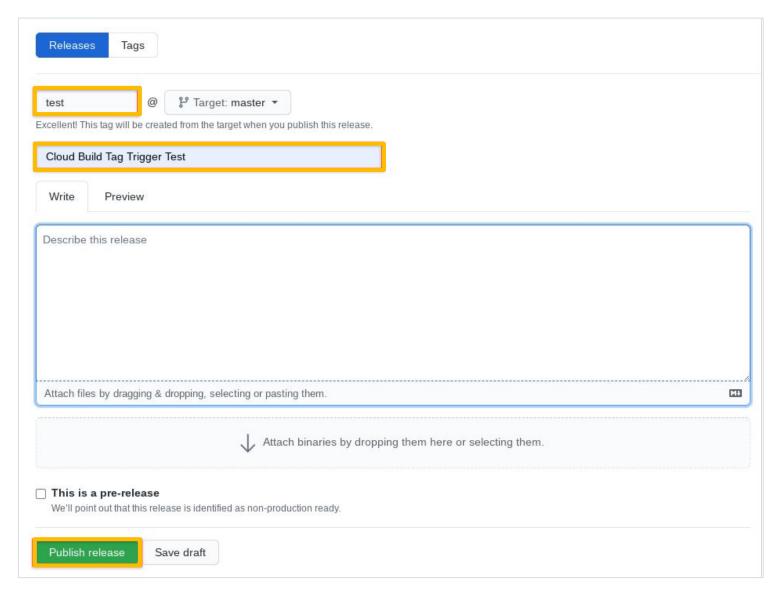
Create a Github App trigger with Cloud Build



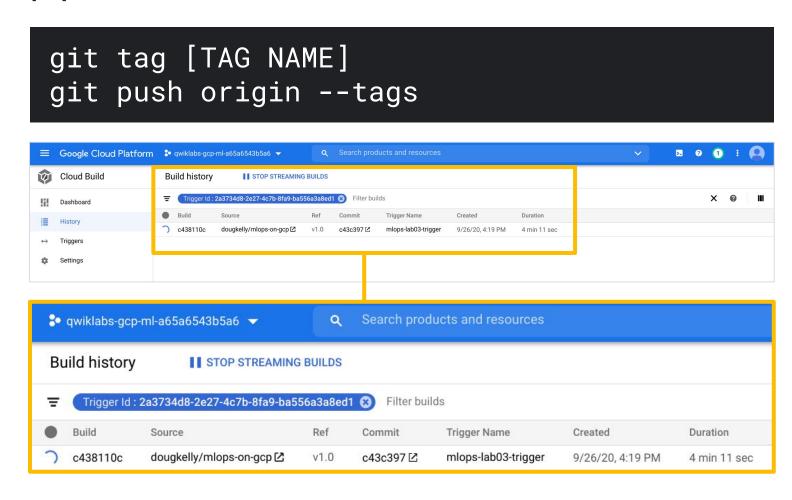


Trigger CI/CD run with Github release or Git

Create a release on Github to trigger pipeline run.



Add a release tag to trigger pipeline run via Git.





Verify pipeline run in Kubeflow Pipelines Ul

