Vertex AI, Training and Serving a Custom Model

Overview

In this experiment, you will use Vertex AI to train and serve a TensorFlow model using code in a custom container.

While we're using TensorFlow for the model code here, you could easily replace it with another framework.

What you learn

You'll learn how to:

Build and containerize model training code in Vertex Workbench

Submit a custom model training job to Vertex AI

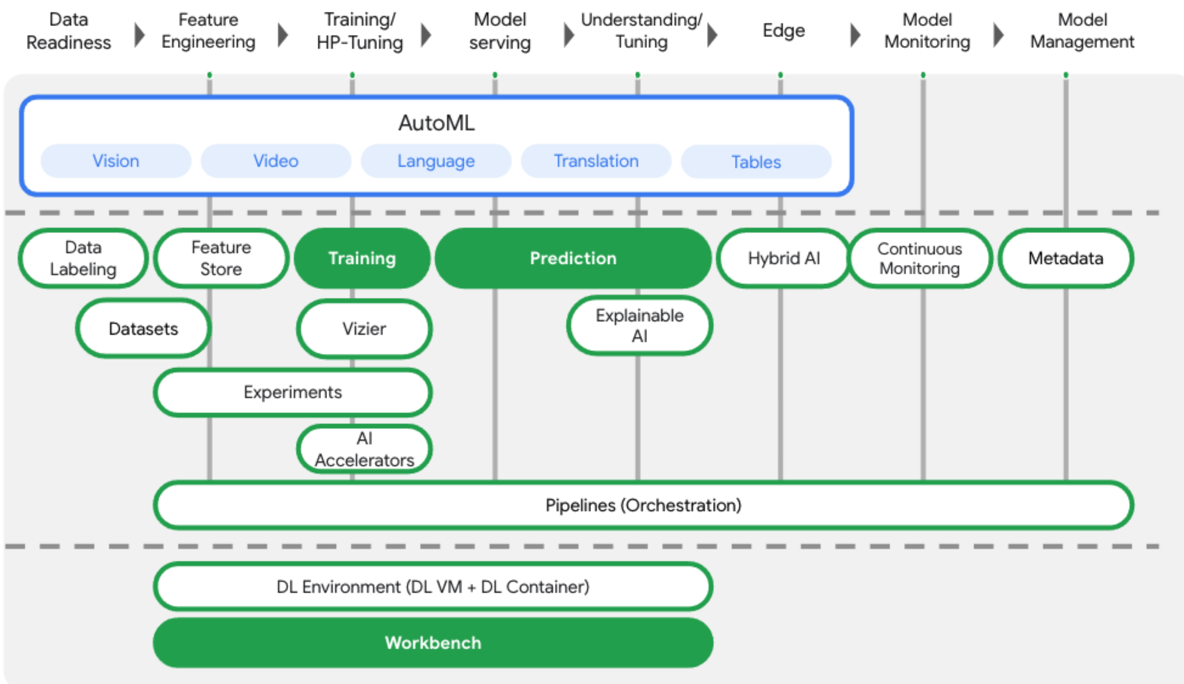
Deploy your trained model to an endpoint, and use that endpoint to get predictions

The total cost to run this lab on Google Cloud is about **$1**.

Intro to Vertex AI

This experiment uses the newest AI product offering available on Google Cloud. Vertex AI integrates the ML offerings across Google Cloud into a seamless development experience. Previously, models trained with AutoML and custom models were accessible via separate services. The new offering combines both into a single API, along with other new products. You can also migrate existing projects to Vertex AI.

Vertex AI includes many different products to support end-to-end ML workflows. This lab will focus on the products highlighted below: Training, Prediction, and Workbench.



Setup your environment

You'll need a Google Cloud Platform project with billing enabled to run this experiment. To create a project, follow the instructions here.

Step 1: Enable the Compute Engine API, if not already completed previously

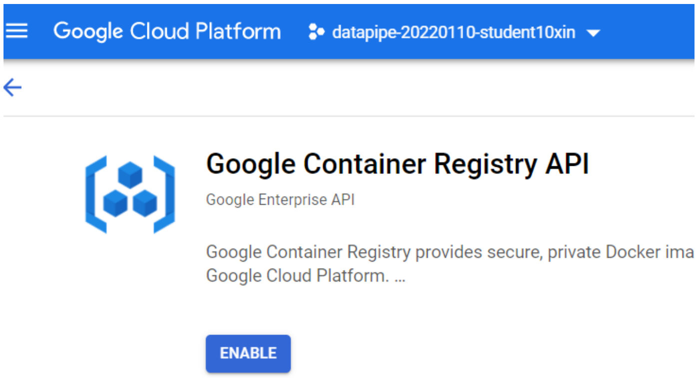
Navigate to Compute Engine and select **Enable** if it isn't already enabled. You'll need this to create your notebook instance.

Step 2: Enable the Vertex AI API, if not already completed previously

Navigate to Vertex AI and select **Enable Vertex AI API** if it isn't already enabled. You'll need this to create your notebook instance.

Step 3: Enable the Container Registry API

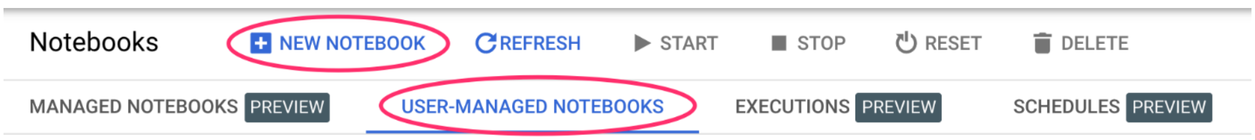
Navigate to the Container Registry and select **Enable** if it isn't already. You'll use this to create a container for your custom training job.



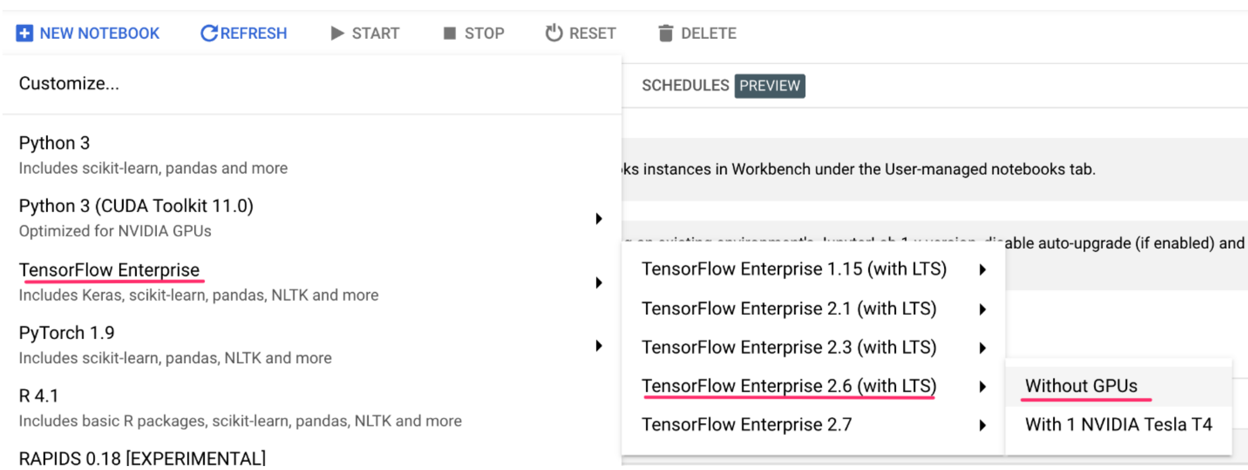
Step 4: Create a Vertex AI Workbench instance

From the Vertex AI section of your Cloud Console, click on Workbench:

From there, within **User-Managed Notebooks**, click **New Notebook**:

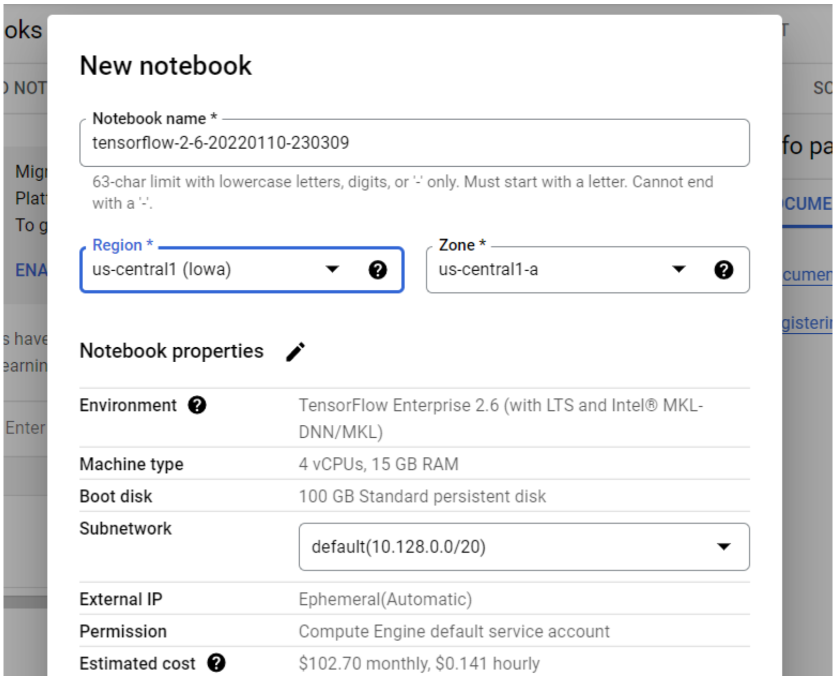


Then select the latest version of **TensorFlow Enterprise (with LTS)** instance type **without GPUs**:



Use the default options and then click **Create**.

If you already have a Notebook instance it may display in the **New notebook** dialog for the creation.

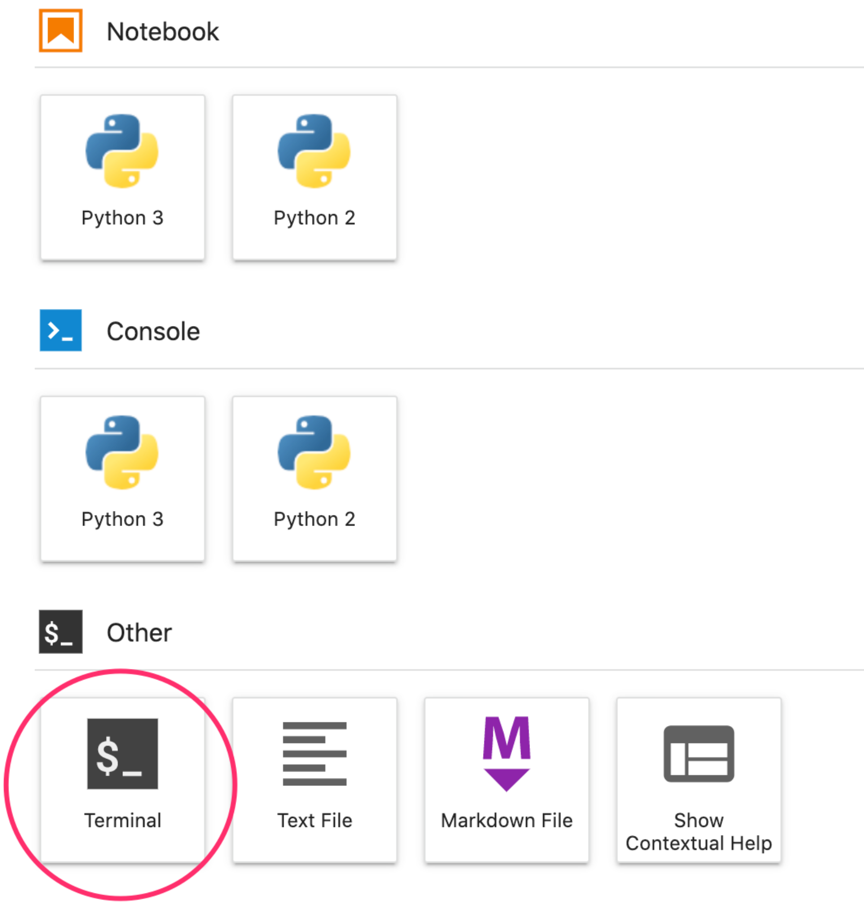


The model we'll be training and serving in this experiment is built upon Tensorflow notebook instance. The experiment uses the Auto MPG dataset from Kaggle to predict the fuel efficiency of a vehicle.

Containerize training code

We'll submit this training job to Vertex by putting our training code in a Docker container and pushing this container to Google Container Registry. Using this approach, we can train a model built with any framework.

To start, from the Launcher menu, open a Terminal window in your notebook instance:



Create a new directory called mpg and cd into it:

```
mkdir mpg
cd mpg
```

Step 1: Create a Dockerfile

Our first step in containerizing our code is to create a Dockerfile. In our Dockerfile we'll include all the commands needed to run our image. It'll install all the libraries we're using and set up the entry point for our training code. From your Terminal, create an empty Dockerfile:

```
touch Dockerfile
```

Open the Dockerfile and copy the following into it:

```
FROM gcr.io/deeplearning-platform-release/tf2-cpu.2-6
WORKDIR /

# Copies the trainer code to the docker image.
```

```
COPY trainer /trainer

# Sets up the entry point to invoke the trainer.
ENTRYPOINT ["python", "-m", "trainer.train"]
```

This Dockerfile uses the Deep Learning Container TensorFlow Enterprise 2.3 Docker image. The Deep Learning Containers on Google Cloud come with many common ML and data science frameworks pre-installed. The one we're using includes TF Enterprise 2.3, Pandas, Scikit-learn, and others. After downloading that image, this Dockerfile sets up the entrypoint for our training code. We haven't created these files yet – in the next step, we'll add the code for training and exporting our model.

Step 2: Create a Cloud Storage bucket

In our training job, we'll export our trained TensorFlow model to a Cloud Storage Bucket. Vertex will use this to read our exported model assets and deploy the model. From your Terminal, run the following to define an env variable for your project, making sure to replace your-cloud-project with the ID of your project:

You can get your project ID by running

```
gcloud config list --format 'value(core.project)'
```

datapipe-20220110-student10xin

in your terminal, update this command to reflect your project id for the PROJECT_ID environment variable definition.

```
PROJECT_ID='datapipe-cloud-project-id'
```

Next, run the following in your Terminal to create a new bucket in your project, if the bucket does not already exist. The -l (location) flag is important since this needs to be in the same region where you deploy a model endpoint later in the tutorial:

```
BUCKET_NAME="gs://${PROJECT_ID}-bucket"
gsutil mb -l us-central1 $BUCKET_NAME
```

Step 3: Add model training code

From your Terminal, run the following to create a directory for our training code and a Python file where we'll add the code:

```
mkdir trainer
touch trainer/train.py
```

You should now have the following in your mpg/ directory:

```
+ Dockerfile
+ trainer/
    + train.py
```

Next, open the train.py file you just created and copy the code below.

At the beginning of the file, update the BUCKET variable with the name of the Storage Bucket you created in the previous step:

```
import numpy as np
import pandas as pd
import pathlib
import tensorflow as tf

from tensorflow import keras
from tensorflow.keras import layers

print(tf.__version__)

"""## The Auto MPG dataset

The dataset is available from the [UCI Machine Learning
Repository](https://archive.ics.uci.edu/ml/).

### Get the data
First download the dataset.
"""

dataset_path = keras.utils.get_file("auto-mpg.data",
"http://archive.ics.uci.edu/ml/machine-learning-databases/auto-mpg/auto-
mpg.data")
dataset_path

"""Import it using pandas"""

column_names = ['MPG','Cylinders','Displacement','Horsepower','Weight',
                'Acceleration', 'Model Year', 'Origin']
dataset = pd.read_csv(dataset_path, names=column_names,
                      na_values = "?", comment='\t',
                      sep=" ", skipinitialspace=True)

dataset.tail()

# TODO: replace `your-gcs-bucket` with the name of the Storage bucket you
created earlier
BUCKET = 'gs://your-gcs-bucket'

"""### Clean the data

The dataset contains a few unknown values.
"""
```

```python
dataset.isna().sum()

"""To keep this initial tutorial simple drop those rows."""

dataset = dataset.dropna()

"""The `"Origin"` column is really categorical, not numeric. So convert
that to a one-hot:"""

dataset['Origin'] = dataset['Origin'].map({1: 'USA', 2: 'Europe', 3:
'Japan'})

dataset = pd.get_dummies(dataset, prefix='', prefix_sep='')
dataset.tail()

"""### Split the data into train and test

Now split the dataset into a training set and a test set.

We will use the test set in the final evaluation of our model.
"""

train_dataset = dataset.sample(frac=0.8,random_state=0)
test_dataset = dataset.drop(train_dataset.index)

"""### Inspect the data

Have a quick look at the joint distribution of a few pairs of columns from
the training set.

Also look at the overall statistics:
"""

train_stats = train_dataset.describe()
train_stats.pop("MPG")
train_stats = train_stats.transpose()
train_stats

"""### Split features from labels

Separate the target value, or "label", from the features. This label is
the value that you will train the model to predict.
"""

train_labels = train_dataset.pop('MPG')
test_labels = test_dataset.pop('MPG')

"""### Normalize the data

Look again at the `train_stats` block above and note how different the
ranges of each feature are.

It is good practice to normalize features that use different scales and
ranges. Although the model *might* converge without feature normalization,
```

```
it makes training more difficult, and it makes the resulting model
dependent on the choice of units used in the input.

Note: Although we intentionally generate these statistics from only the
training dataset, these statistics will also be used to normalize the test
dataset. We need to do that to project the test dataset into the same
distribution that the model has been trained on.
"""

def norm(x):
  return (x - train_stats['mean']) / train_stats['std']
normed_train_data = norm(train_dataset)
normed_test_data = norm(test_dataset)

"""This normalized data is what we will use to train the model.

Caution: The statistics used to normalize the inputs here (mean and
standard deviation) need to be applied to any other data that is fed to
the model, along with the one-hot encoding that we did earlier.  That
includes the test set as well as live data when the model is used in
production.

## The model

### Build the model

Let's build our model. Here, we'll use a `Sequential` model with two
densely connected hidden layers, and an output layer that returns a
single, continuous value. The model building steps are wrapped in a
function, `build_model`, since we'll create a second model, later on.
"""

def build_model():
  model = keras.Sequential([
    layers.Dense(64, activation='relu',
input_shape=[len(train_dataset.keys())]),
    layers.Dense(64, activation='relu'),
    layers.Dense(1)
  ])

  optimizer = tf.keras.optimizers.RMSprop(0.001)

  model.compile(loss='mse',
                optimizer=optimizer,
                metrics=['mae', 'mse'])
  return model

model = build_model()

"""### Inspect the model

Use the `.summary` method to print a simple description of the model
"""
```

```
model.summary()

"""Now try out the model. Take a batch of `10` examples from the training
data and call `model.predict` on it.

It seems to be working, and it produces a result of the expected shape and
type.

### Train the model

Train the model for 1000 epochs, and record the training and validation
accuracy in the `history` object.

Visualize the model's training progress using the stats stored in the
`history` object.

This graph shows little improvement, or even degradation in the validation
error after about 100 epochs. Let's update the `model.fit` call to
automatically stop training when the validation score doesn't improve.
We'll use an *EarlyStopping callback* that tests a training condition
for  every epoch. If a set amount of epochs elapses without showing
improvement, then automatically stop the training.

You can learn more about this callback
[here](https://www.tensorflow.org/api_docs/python/tf/keras/callbacks/Early
Stopping).


"""

model = build_model()

EPOCHS = 1000

# The patience parameter is the amount of epochs to check for improvement
early_stop = keras.callbacks.EarlyStopping(monitor='val_loss',
patience=10)

early_history = model.fit(normed_train_data, train_labels,
                    epochs=EPOCHS, validation_split = 0.2,
                    callbacks=[early_stop])


# Export model and save to GCS
model.save(BUCKET + '/mpg/model')
```

Step 4: Build and test the container locally

From your Terminal, define a variable with the URI of your container image in Google Container Registry:

```
IMAGE_URI="gcr.io/$PROJECT_ID/mpg:v1"
```

Then, build the container by running the following from the root of your mpg directory:

```
docker build ./ -t $IMAGE_URI
```

Run the container within your notebook instance to ensure it's working correctly:

```
docker run $IMAGE_URI
```

The model should finish training in 1-2 minutes with a validation accuracy around 72% (exact accuracy may vary). When you've finished running the container locally, push it to Google Container Registry:

```
docker push $IMAGE_URI
```

With our container pushed to Container Registry, we're now ready to kick off a custom model training job.

Note: Double check to see that you had success and not an error. In the event we missed the step to enable the Container Registry API in setup we would see something similar to below on our **docker push** command.

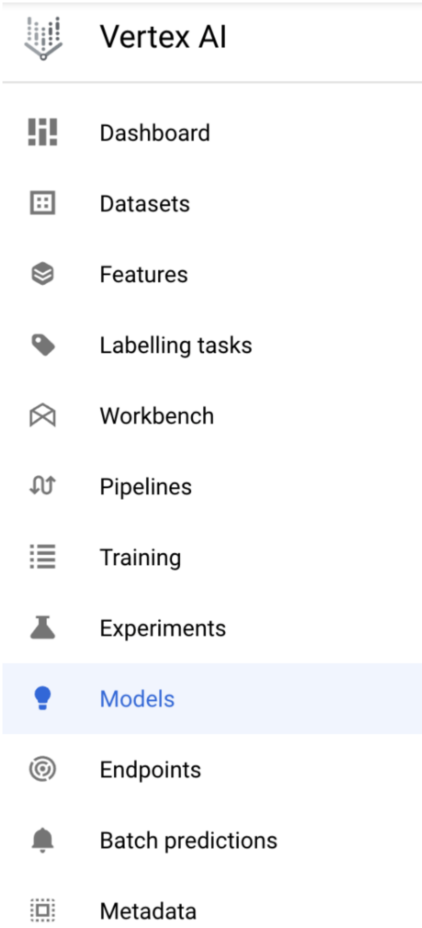
```
unknown: Service 'containerregistry.googleapis.com' is not enabled for
consumer 'project:datapipe-20220110-student10xin'.
```

Run a training job on Vertex AI

Vertex AI gives you two options for training models:

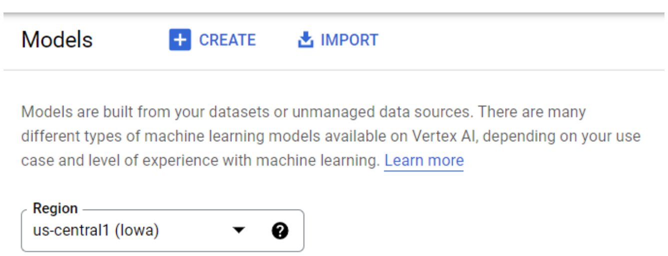
- **AutoML**: Train high-quality models with minimal effort and ML expertise.
- **Custom training**: Run your custom training applications in the cloud using one of Google Cloud's pre-built containers or use your own.

In this lab, we're using custom training via our own custom container on Google Container Registry. To start, navigate to the **Models** section in the Vertex section of your Cloud console:

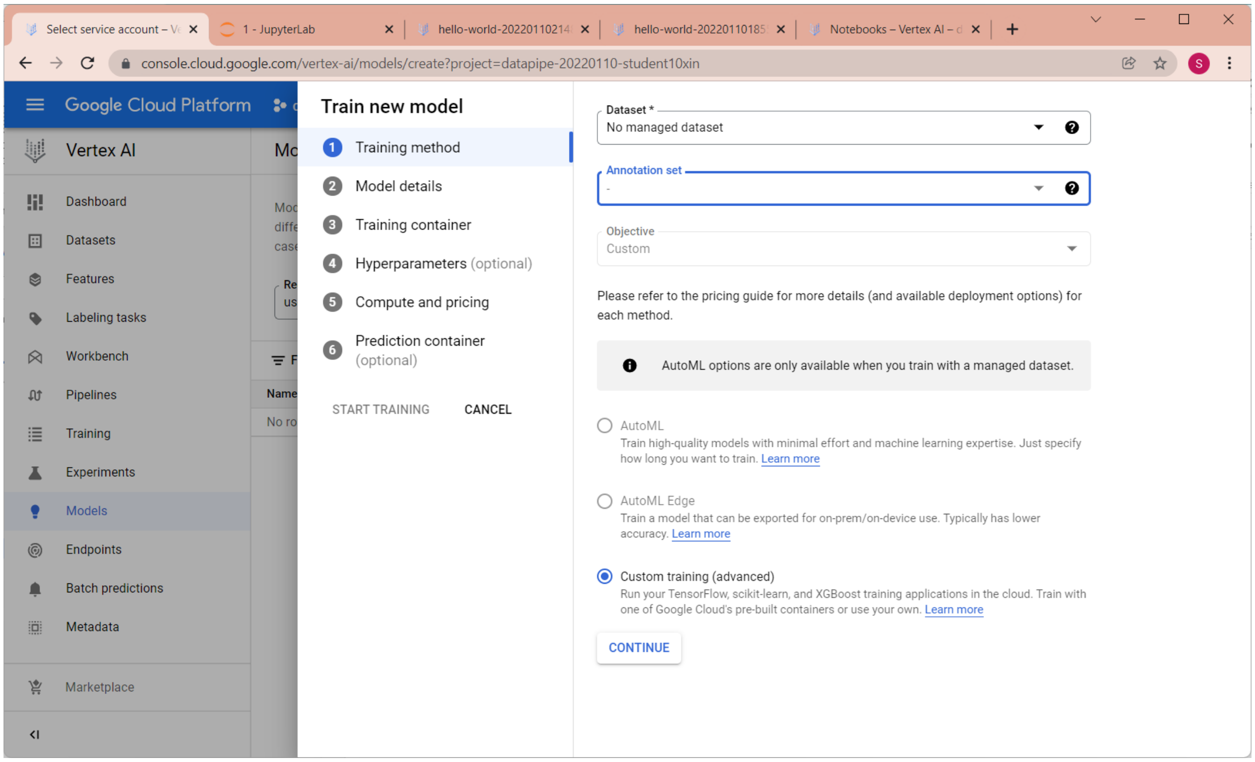


Step 1: Kick off the training job

Click **Create**

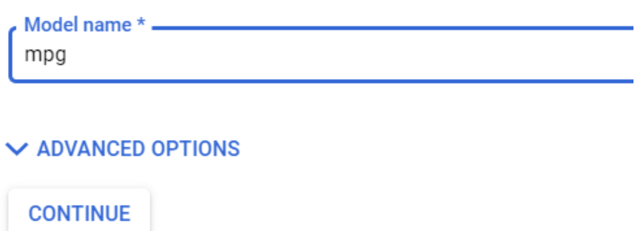


Enter the parameters for your training job and deployed model:



- Under **Dataset**, select **No managed dataset**
- Then select **Custom training (advanced)** as your training method.
- Click **Continue**

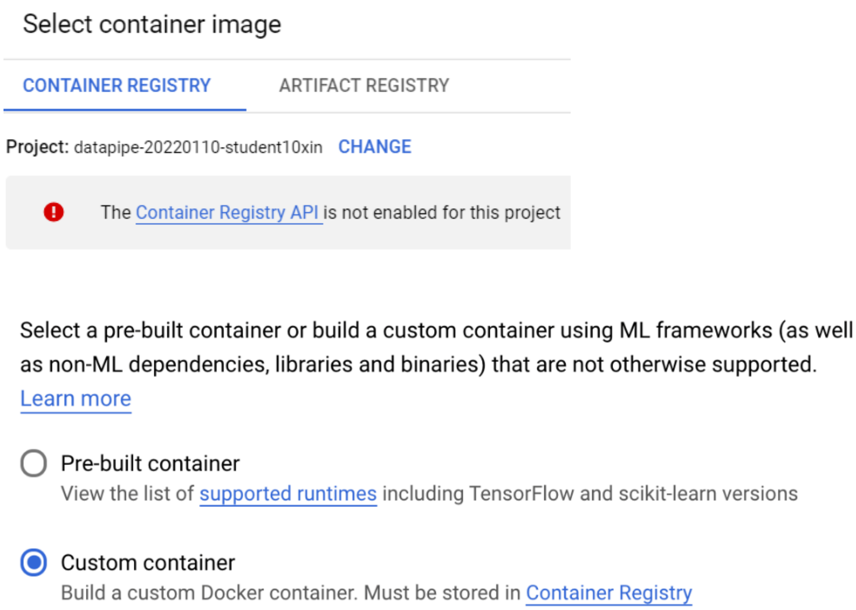
In the next step, enter **mpg** (or whatever you'd like to call your model) for **Model name**.



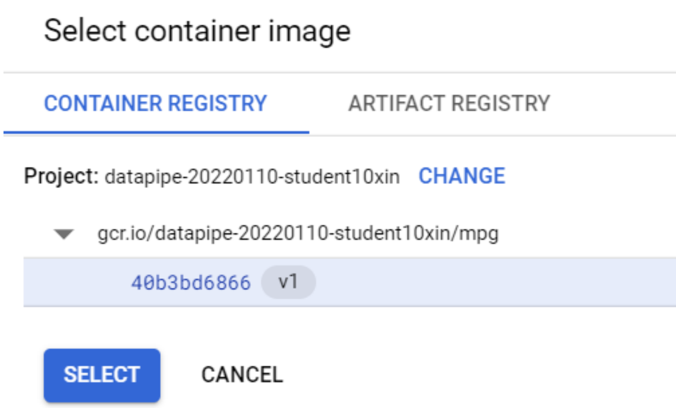
Click **Continue**

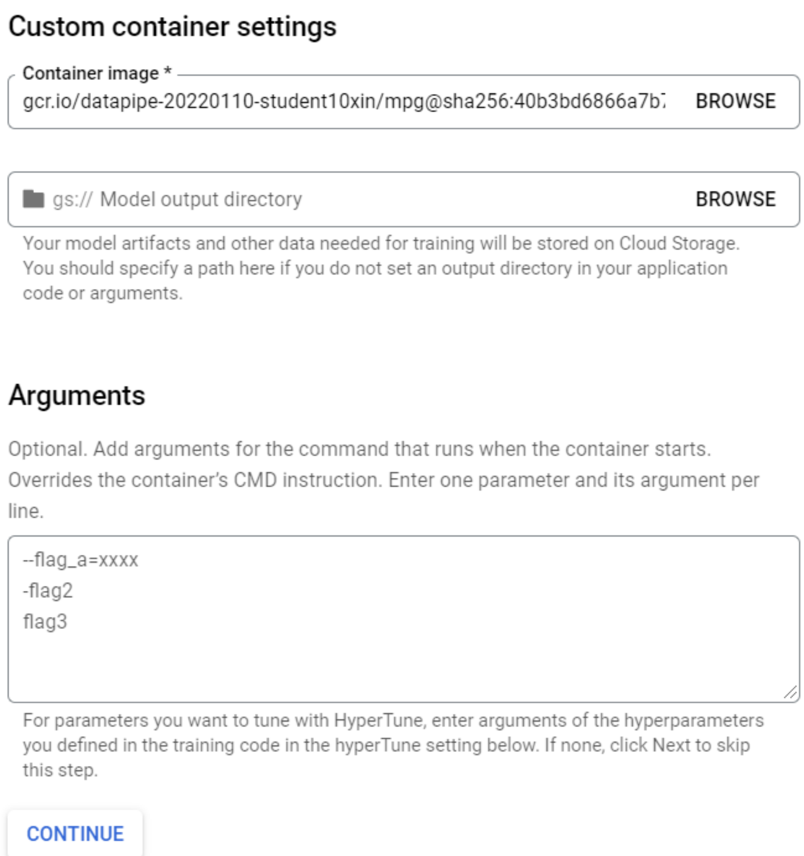
Now select **Custom container** and Browse for the container we created earlier in this experiment.

Note: If you see this, we missed the step to enable the Container Registry API. We can do that now.

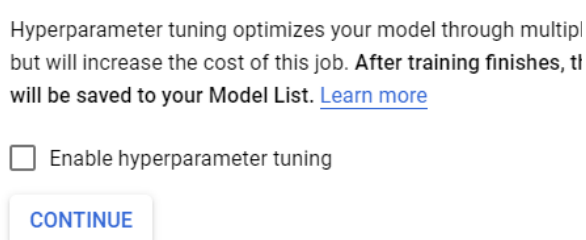


In the **Container image** text box, click **Browse** and find the Docker image you just uploaded to Container Registry. Leave the rest of the fields blank and click **Continue**.

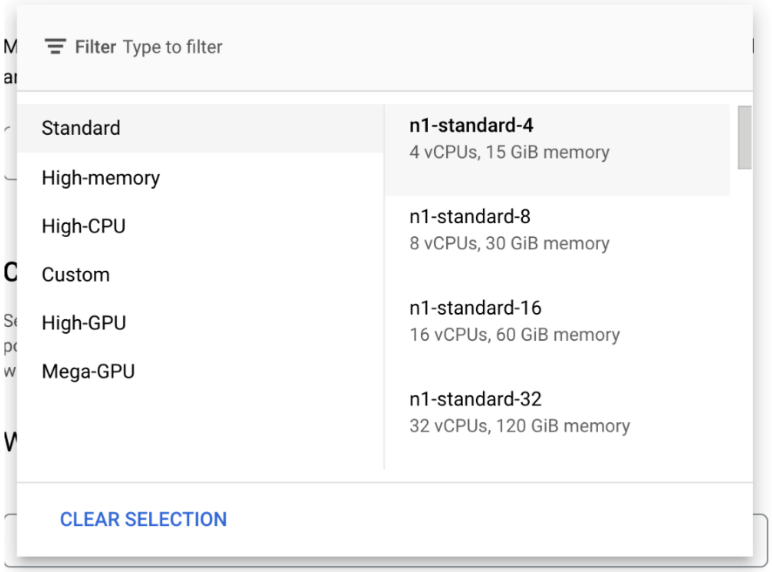


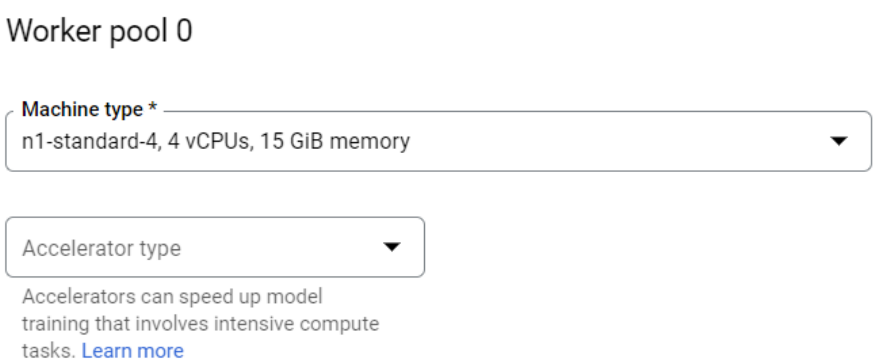


We won't use hyperparameter tuning in this tutorial, so leave the Enable hyperparameter tuning box **unchecked** and click **Continue**.



In **Compute and pricing**, leave the selected region as-is and choose **n1-standard-4** as your machine type:

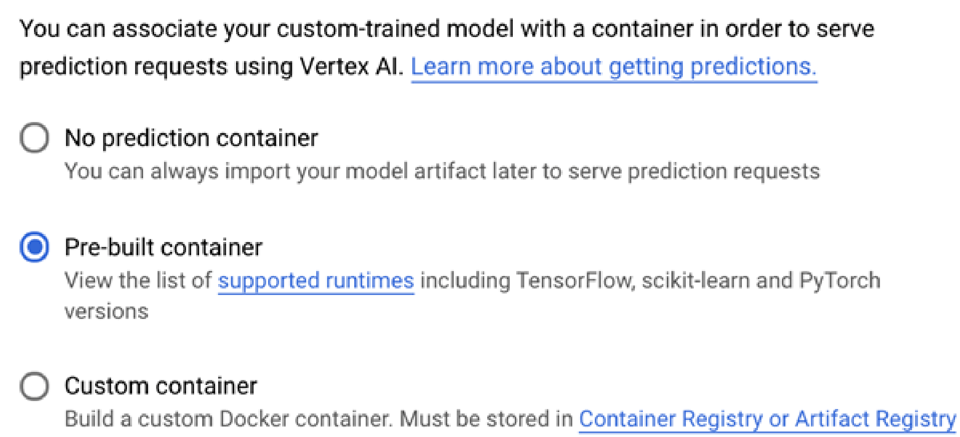




Leave the accelerator fields blank and select **Continue**. Because the model in this demo trains quickly, we're using a smaller machine type.

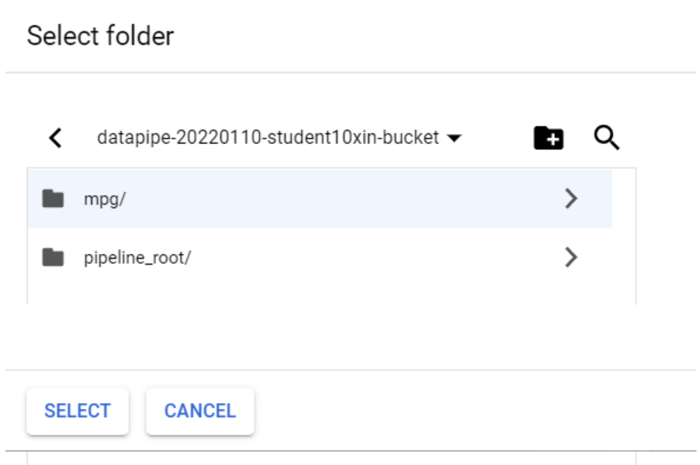
Note: You are welcome to experiment with larger machine types and GPUs if you'd like. If you use GPUs, you'll need to use a GPU-enabled base container image.

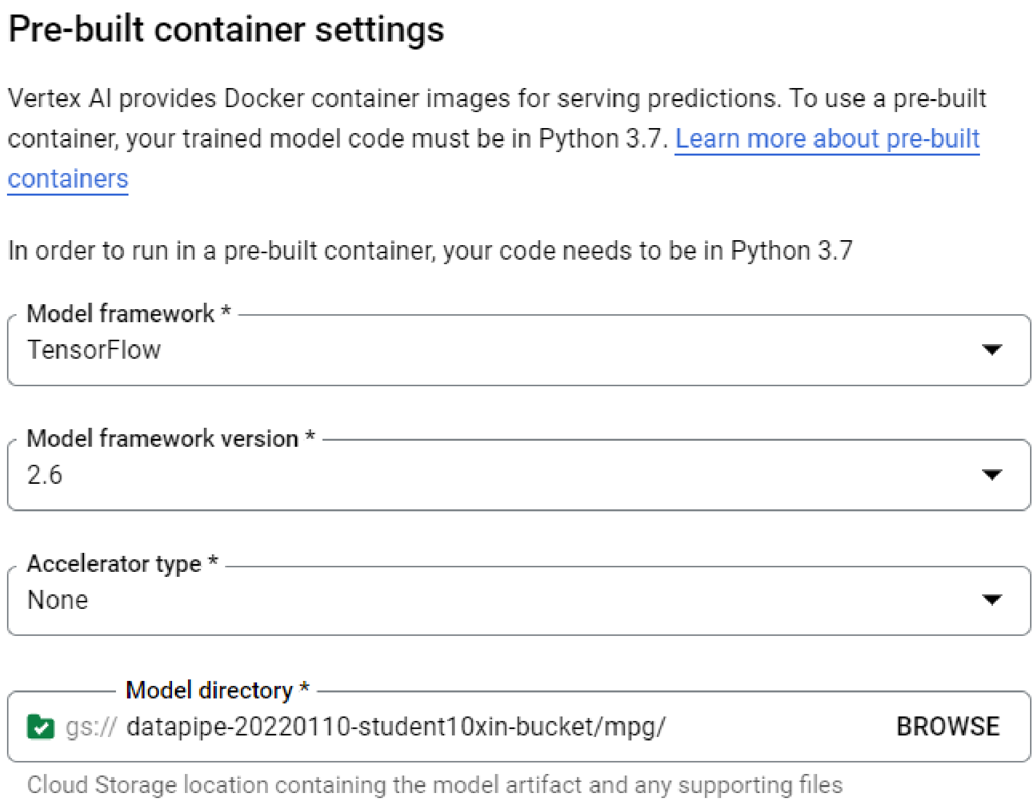
Under the **Prediction container** step, select **Pre-built container**



Then select **TensorFlow 2.6**.

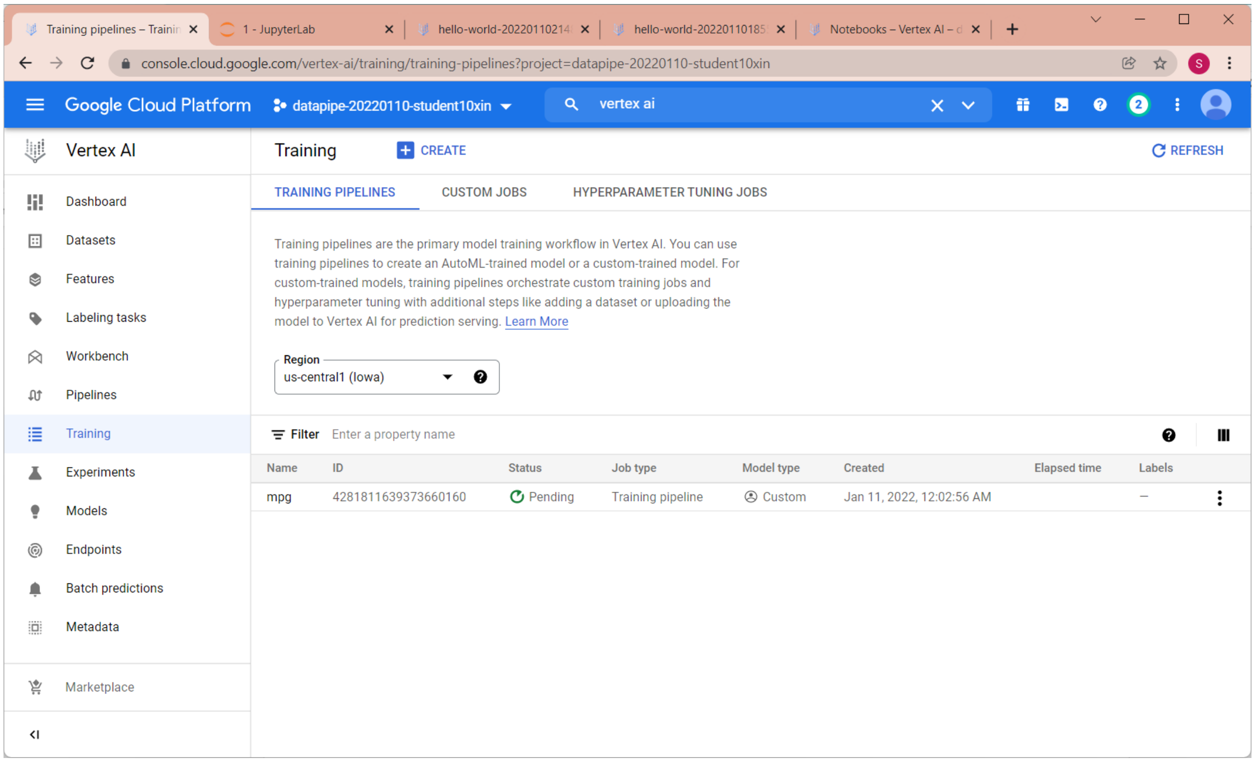
Leave the default settings for the pre-built container as is. Under **Model directory**, enter your GCS bucket with the **mpg** subdirectory. This is the path in your model training script where you export your trained model:



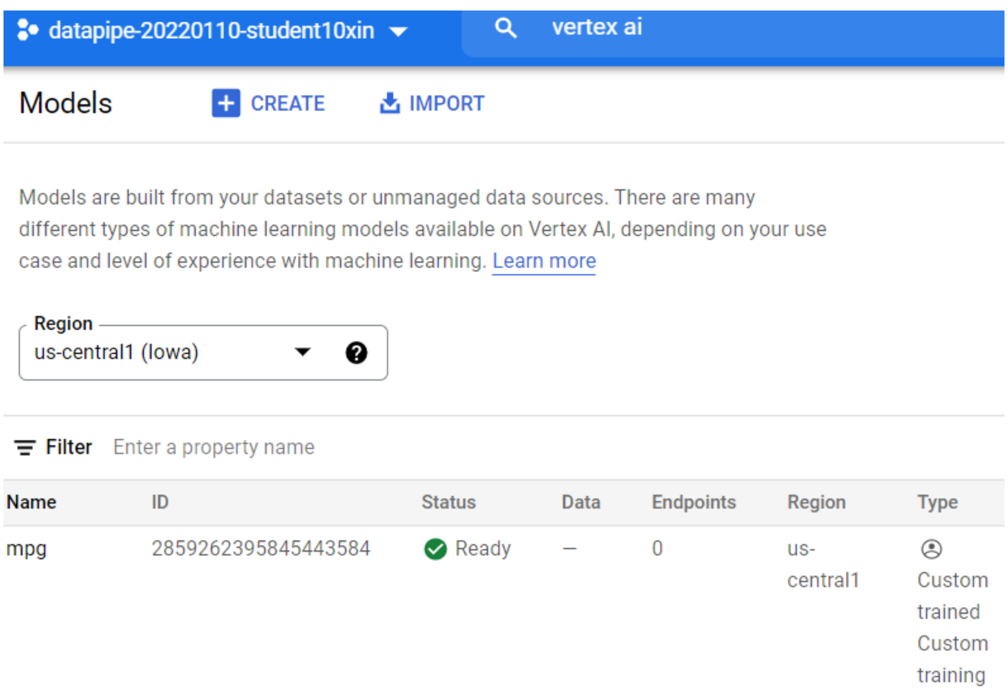


We use the folder that we created earlier in this experiment **`BUCKET_NAME`**. Vertex will look in this location when it deploys your model. Now you're ready for training!

Click **Start training** to kick off the training job. In the Training section of your console, you'll see something like this:



The training job will take about 10-15 minutes to complete.



Deploy a model endpoint

When we set up our training job, we specified where Vertex AI should look for our exported model assets. As part of our training pipeline, Vertex will create a model resource based on this asset path. The model resource itself isn't a deployed model, but once you have a model you're ready to deploy it to an endpoint. To learn more about Models and Endpoints in Vertex AI, check out the documentation.

In this step we'll create an endpoint for our trained model. We can use this to get predictions on our model via the Vertex AI API.

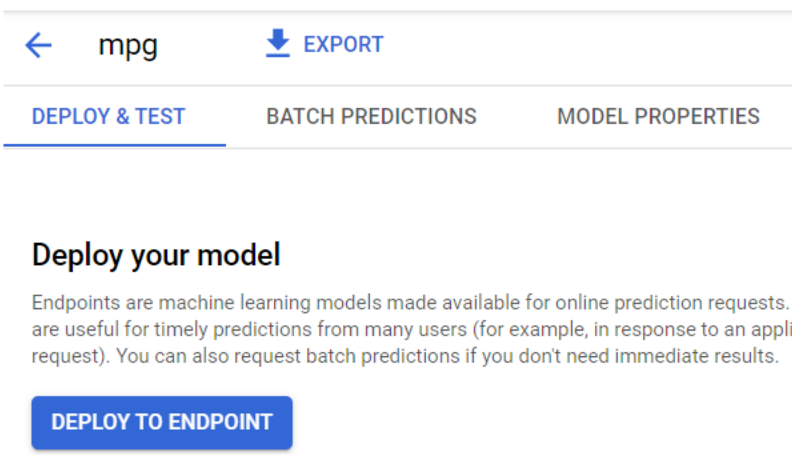
Step 1: Deploy an endpoint

When your training job completes, you should see a model named **mpg** (or whatever you named it) in the **Models** section of your console:

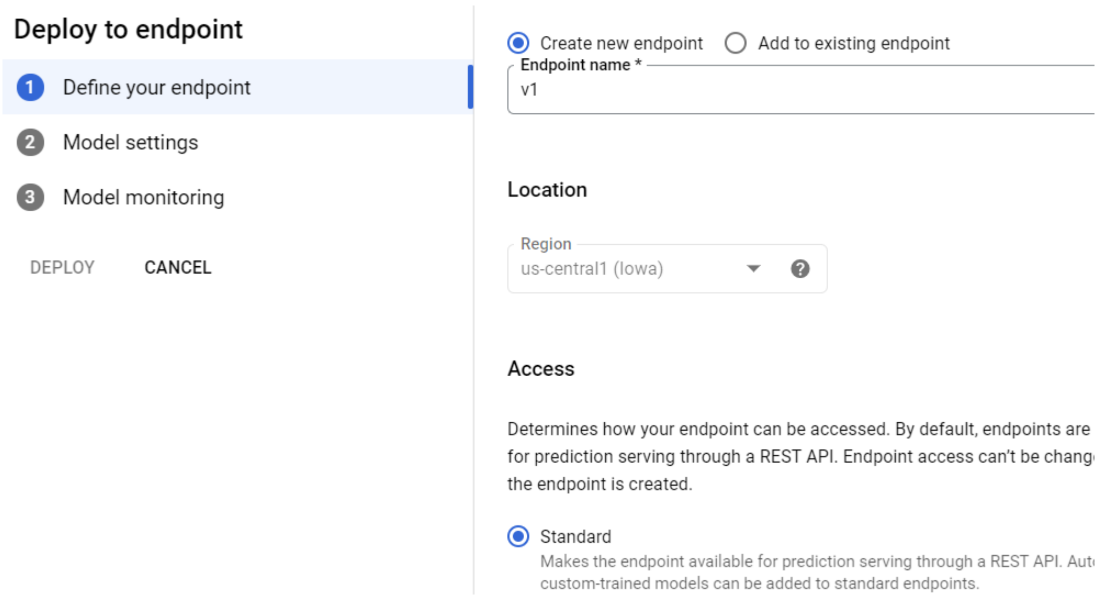
Filter Enter a property name

Name	ID	Status	Data	Endpoints	Region	Type
mpg	2859262395845443584	Ready	—	0	us-central1	Custom trained Custom training

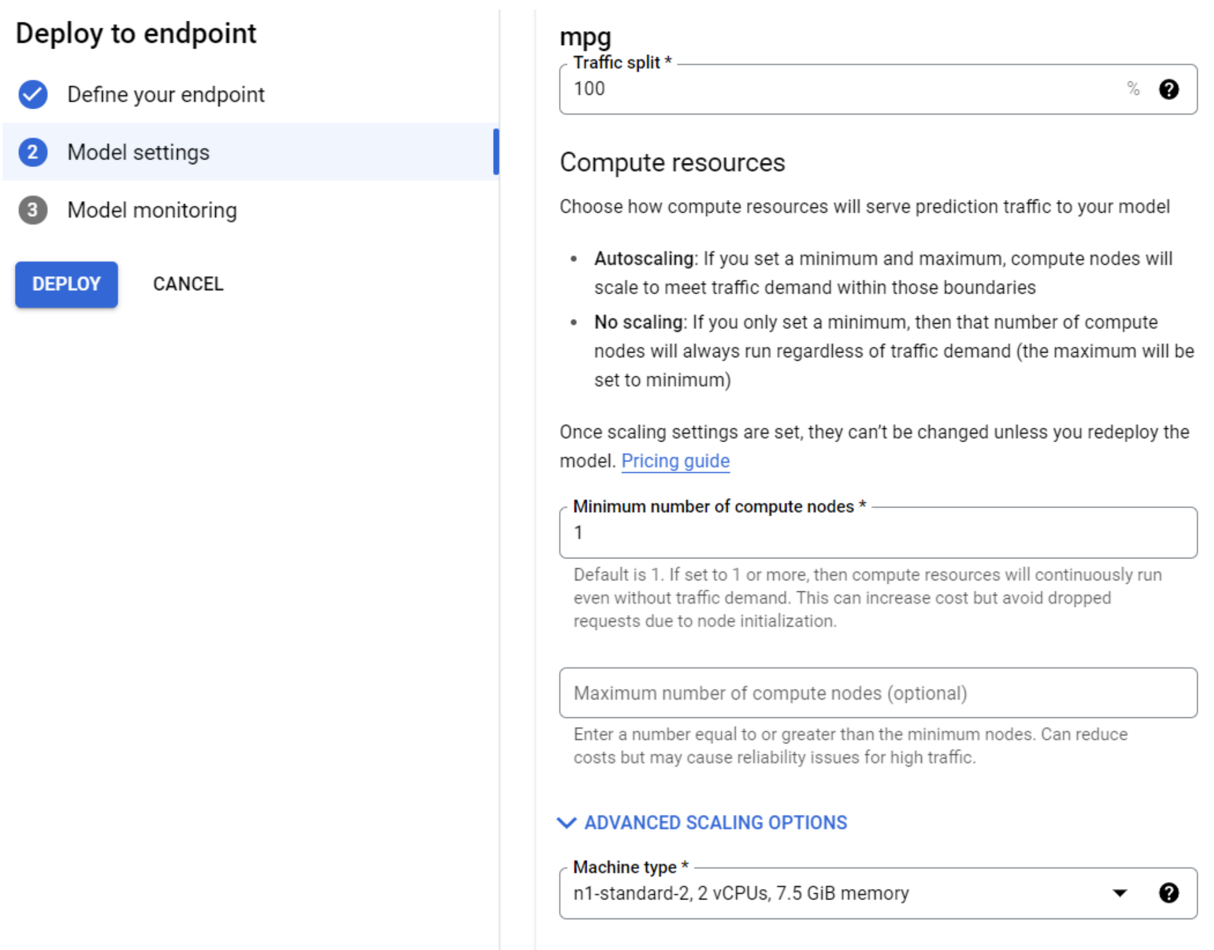
When your training job ran, Vertex created a model resource for you. In order to use this model, you need to deploy an endpoint. You can have many endpoints per model. Click on the hyperlinked model name (**mpg**) and then click **Deploy to endpoint**.



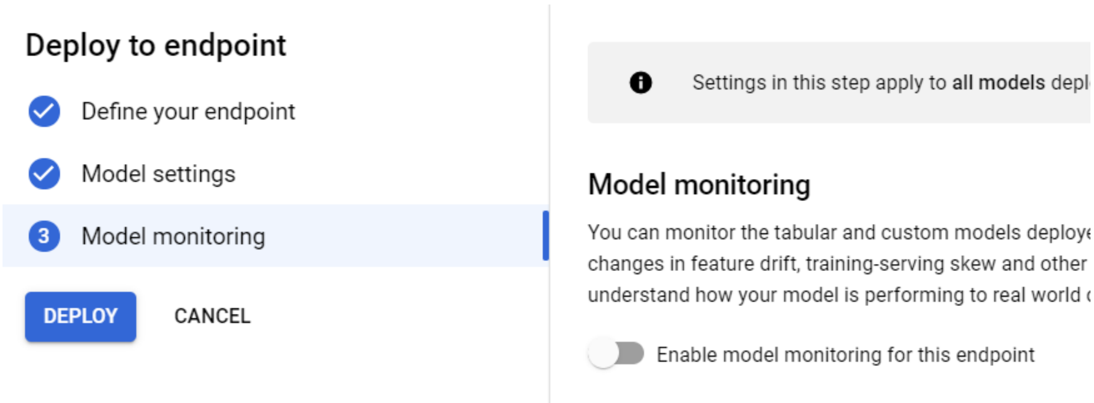
Select **Create new endpoint** and give it a name, **v1**. Leave **Standard** selected for Access and then click **Continue**.



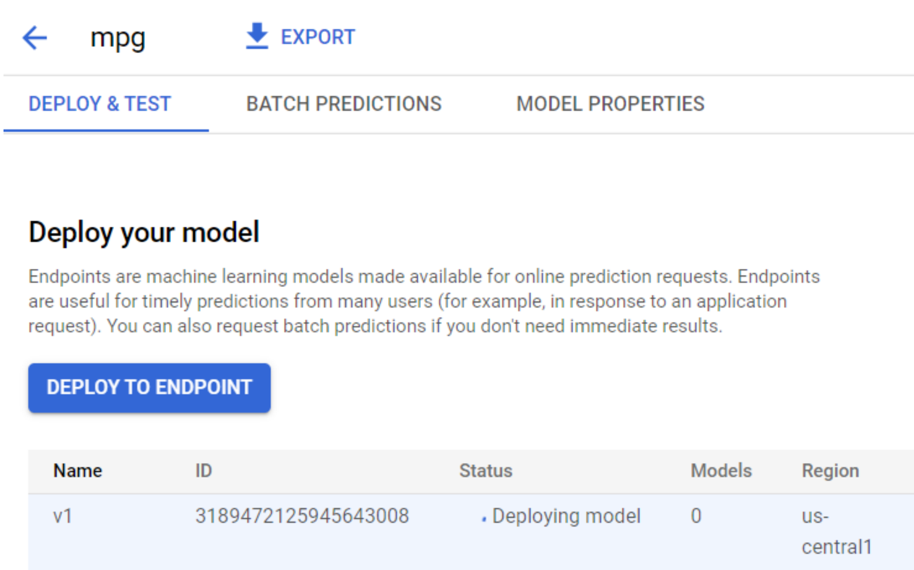
Leave **Traffic split** at 100 and enter 1 for **Minimum number of compute nodes**. Under **Machine type**, select **n1-standard-2** (or any machine type you'd like). Leave the rest of the defaults selected and then click **Continue**.



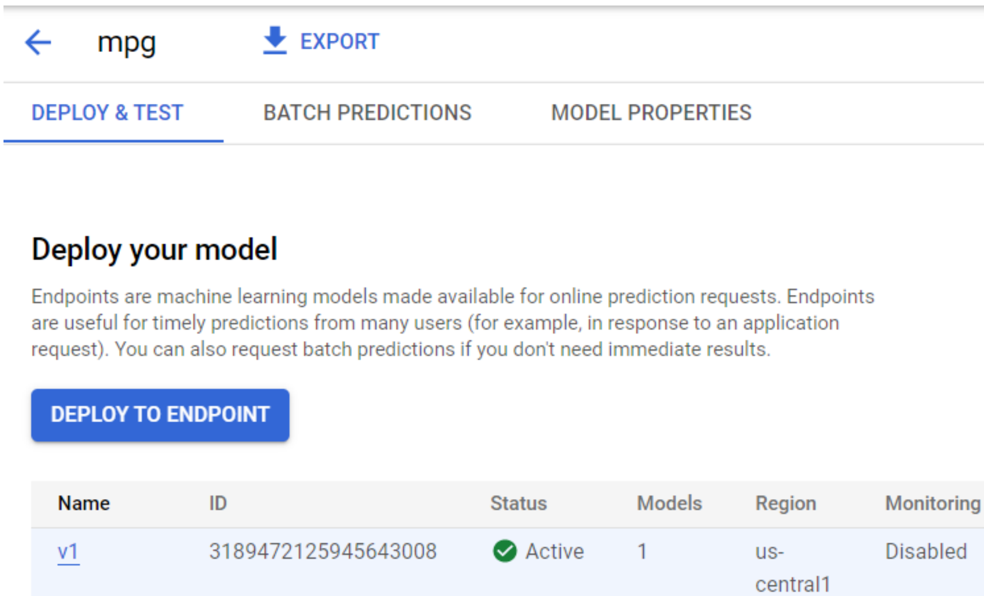
We won't enable monitoring for this model, so next click **Deploy** to kick off the endpoint deployment.



Deploying the endpoint will take 10-15 minutes, and an email will be sent when the deploy completes, although since we're using training accounts we won't receive that email.

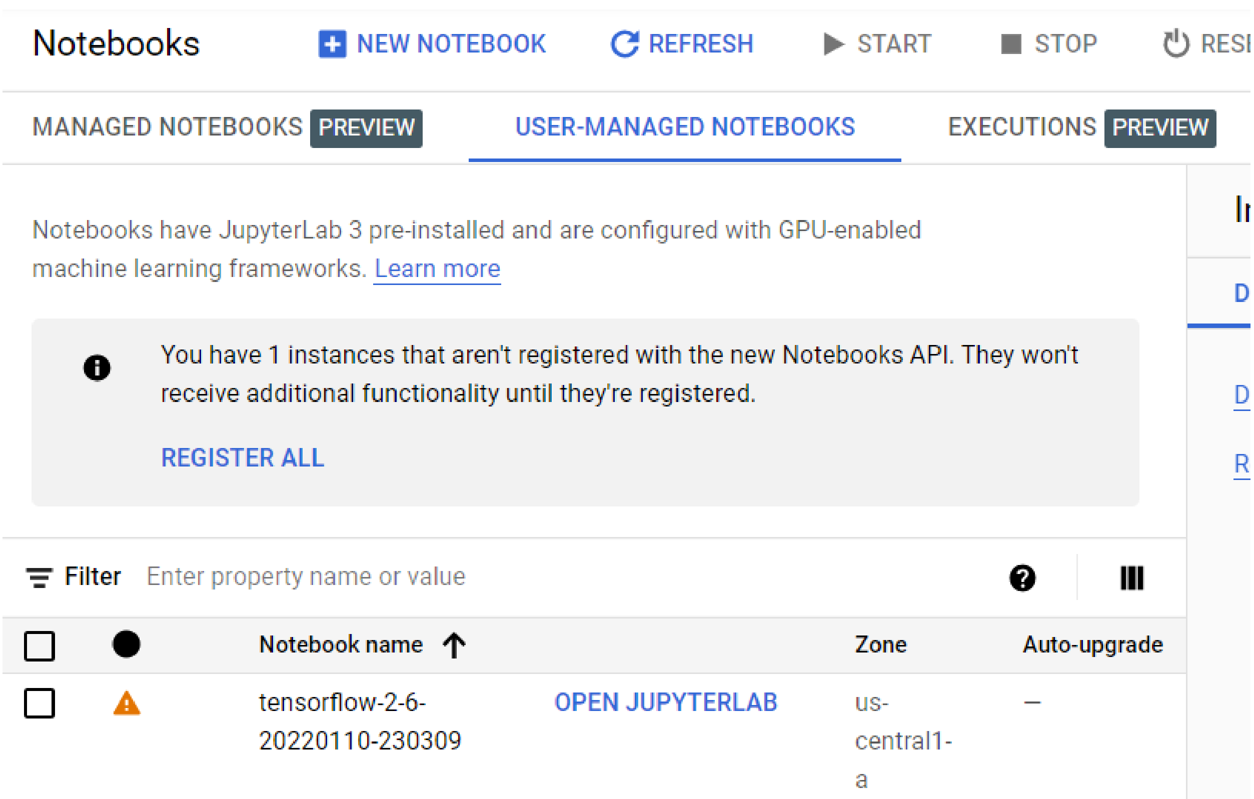


When the endpoint has finished deploying, you'll see the following, which shows one endpoint deployed under your Model resource:



Step 2: Get predictions on the deployed model

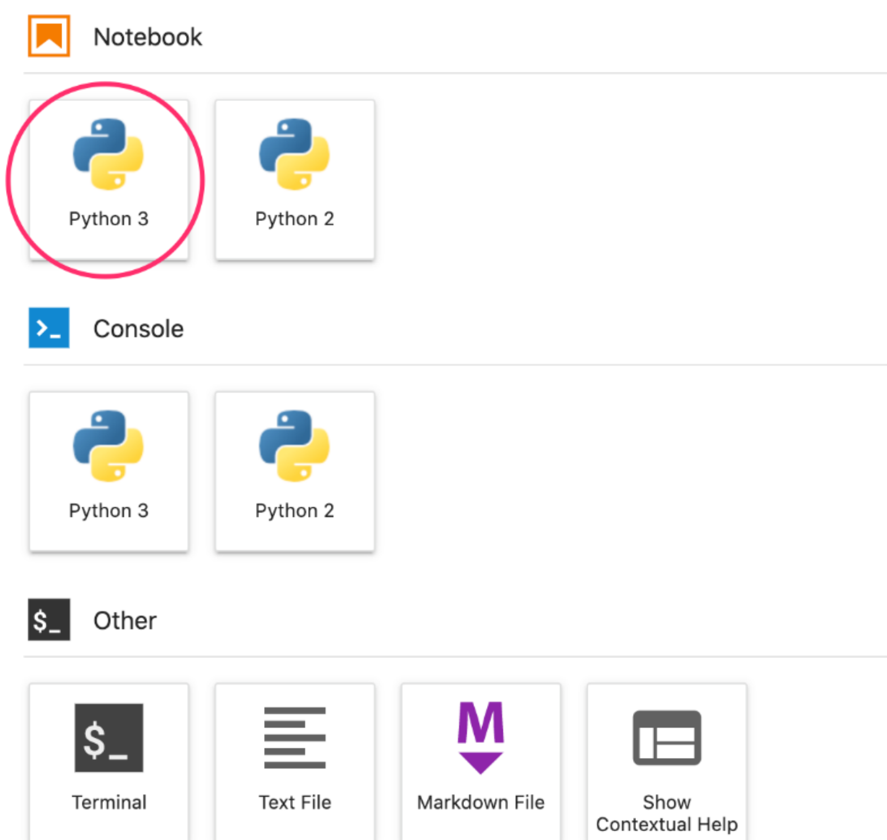
We'll get predictions on our trained model from a Python notebook, using the Vertex Python API.



Click the **REGISTER ALL** in the notification on the notebook. Note the Information Icon next to our Tensorflow 2.6 notebook.

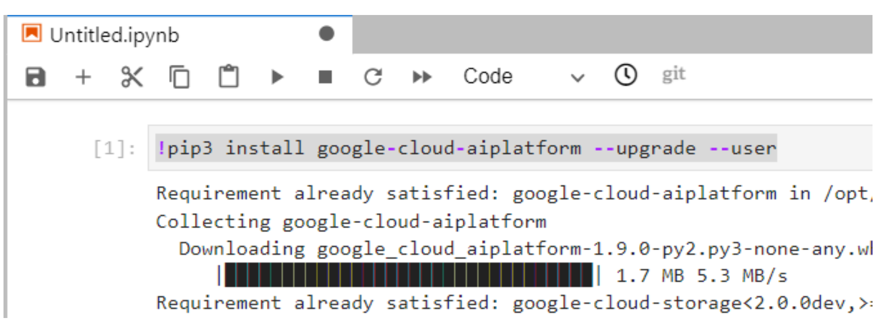
Choose **OPEN JUPYTERLAB**

Create a Python 3 notebook from the Launcher:



In your notebook, run the following in a cell to install the Vertex AI SDK:

```
!pip3 install google-cloud-aiplatform --upgrade --user
```

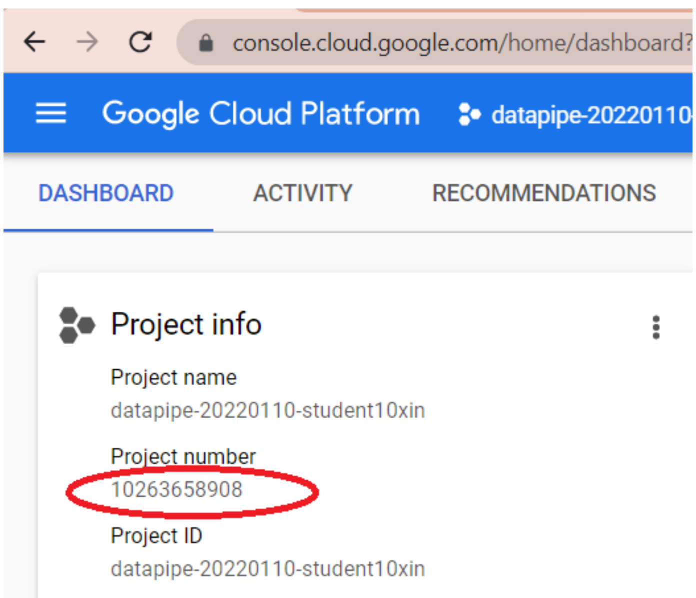


Then add a cell in your notebook to import the SDK and create a reference to the endpoint you just deployed:

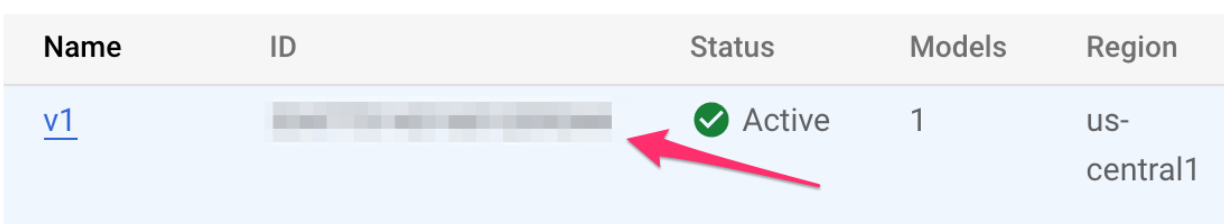
```
from google.cloud import aiplatform

endpoint = aiplatform.Endpoint(
    endpoint_name="projects/YOUR-PROJECT-NUMBER/locations/us-
central1/endpoints/YOUR-ENDPOINT-ID"
)
```

You'll need to replace two values in the endpoint_name string above with your project number and endpoint. You can find your project number by navigating to your project dashboard and getting the Project Number value.



You can find your endpoint ID in the endpoints section of the console here:



Finally, make a prediction to your endpoint by copying and running the code below in a new cell:

```
test_mpg = [1.4838871833555929,
 1.8659883497083019,
 2.234620276849616,
 1.0187816540094903,
 -2.530890710602246,
 -1.6046416850441676,
 -0.4651483719733302,
 -0.4952254087173721,
```

```
 0.7746763768735953]

response = endpoint.predict([test_mpg])

print('API response: ', response)

print('Predicted MPG: ', response.predictions[0][0])
```

This example already has normalized values, which is the format our model is expecting.

Run this cell, and you should see a prediction output around 16 miles per gallon.

```
[3]: test_mpg = [1.4838871833555929,
 1.8659883497083019,
 2.234620276849616,
 1.0187816540094903,
 -2.530890710602246,
 -1.6046416850441676,
 -0.4651483719733302,
 -0.4952254087173721,
 0.7746763768735953]

response = endpoint.predict([test_mpg])

print('API response: ', response)

print('Predicted MPG: ', response.predictions[0][0])
```

```
API response:  Prediction(predictions=[[15.8347549]],
Predicted MPG:  15.8347549
```

🎉 Congratulations! 🎉

You've learned how to use Vertex AI to:

- Train a model by providing the training code in a custom container. You used a TensorFlow model in this example, but you can train a model built with any framework using custom containers.
- Deploy a TensorFlow model using a pre-built container as part of the same workflow you used for training.
- Create a model endpoint and generate a prediction.

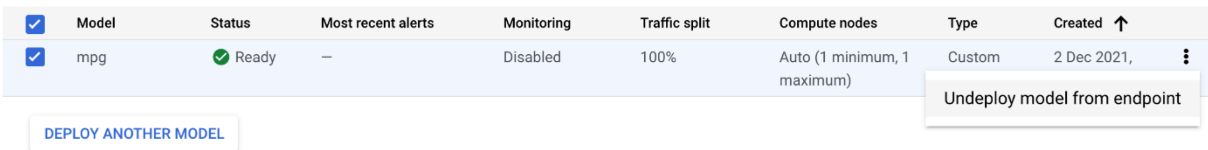
To learn more about different parts of Vertex, check out the documentation.

Cleanup

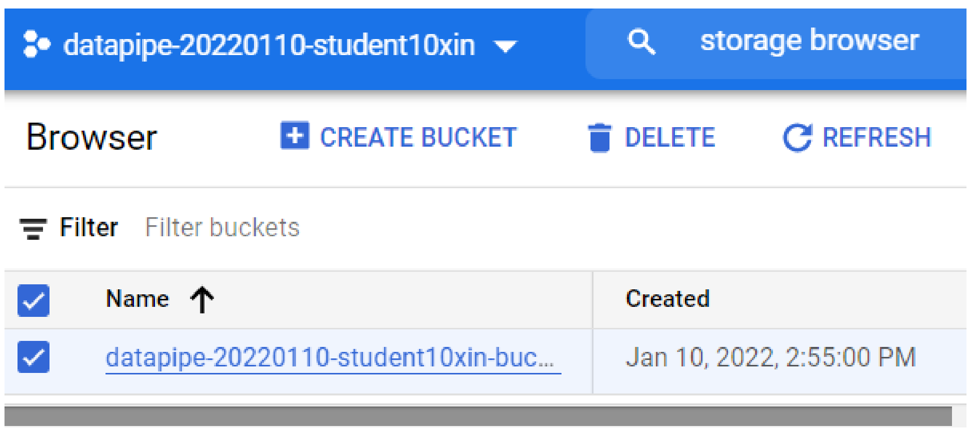
If you'd like to continue using the notebook you created in this lab, it is recommended that you turn it off when not in use. From the Workbench UI in your Cloud Console, select the notebook and then select **Stop**.

If you'd like to delete the notebook entirely, click the Delete button in the top right.

To delete the endpoint you deployed, navigate to the **Endpoints** section of your Vertex AI console, click on the endpoint you created, and then select **Undeploy model from endpoint**:



To delete the Storage Bucket, using the Navigation menu in your Cloud Console, browse to Storage, select your bucket, and click Delete:



Post note: You may have noticed when we enabled the Container Registry API. The default moving forward for containers will be the Artifact Registry. Using the Container Registry currently is fine, but incurs technical debt that will have to be addressed in the future.