Lecture 8: Advanced Training Workflows

AC215

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Outline

1. Recap
2. Experiment Tracking
3. Tutorial: Experiment Tracking
4. Vertex AI, Serverless Training
5. Tutorial: Serverless Training
6. Multi GPU Training

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Recap: Motivation

The 3 components for better Deep Learning

More Data

- Extraction
- Transformation
- Labeling
- Versioning
- Storage

- Processing
- Input to Training

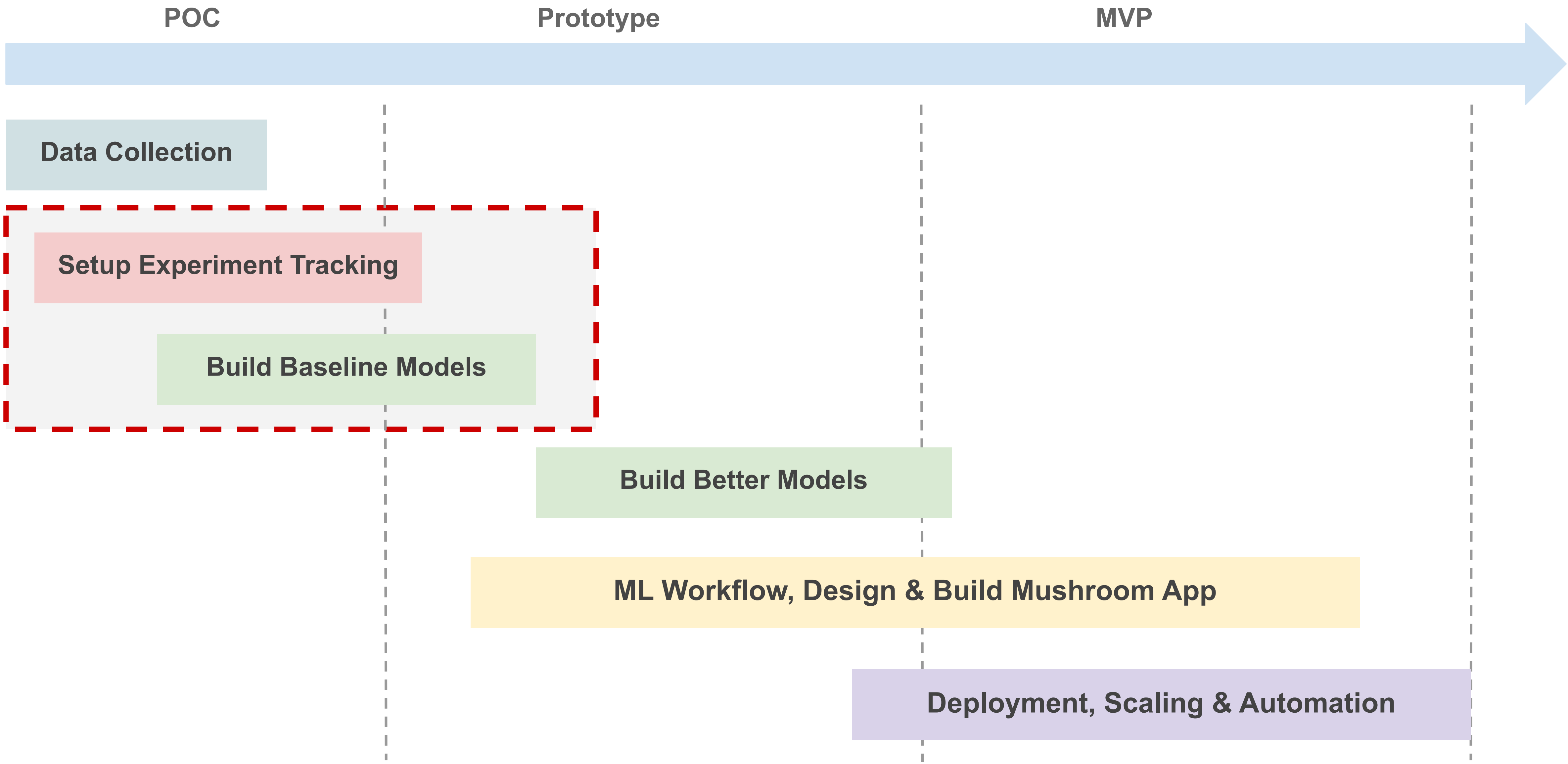
Better/Faster Models

- SOTA Models
- Transfer Learning
- Distillation
- Compression

Faster Hardware

- Scaling data processing
- GPU, TPU
- Multi GPU Server Training

Recap: Project Workflow


POC
Prototype
MVP
Data Collection
Setup Experiment Tracking
Build Baseline Models
Build Better Models
ML Workflow, Design & Build Mushroom App
Deployment, Scaling & Automation

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Experiment Tracking

Why

- Organize your work(data collection/model training)
- Reproducibility
- Logging

Experiment Tracking

What

- Environments
- Scripts (Code)
- Data (version, train/validate/test split)
- Data pre-processing logic
- Model hyper parameters / configurations
- Evaluation metrics
- Model weights
- Performance results
- Sample predictions

Training Code

```
# Training Params
learning_rate = 0.001
batch_size = 32
epochs = 10

# Data
train_data, validation_data = get_dataset(...)
# Model
model = build_model(...)

# Train
training_results = model.fit(...)
```

Training Code using WandB

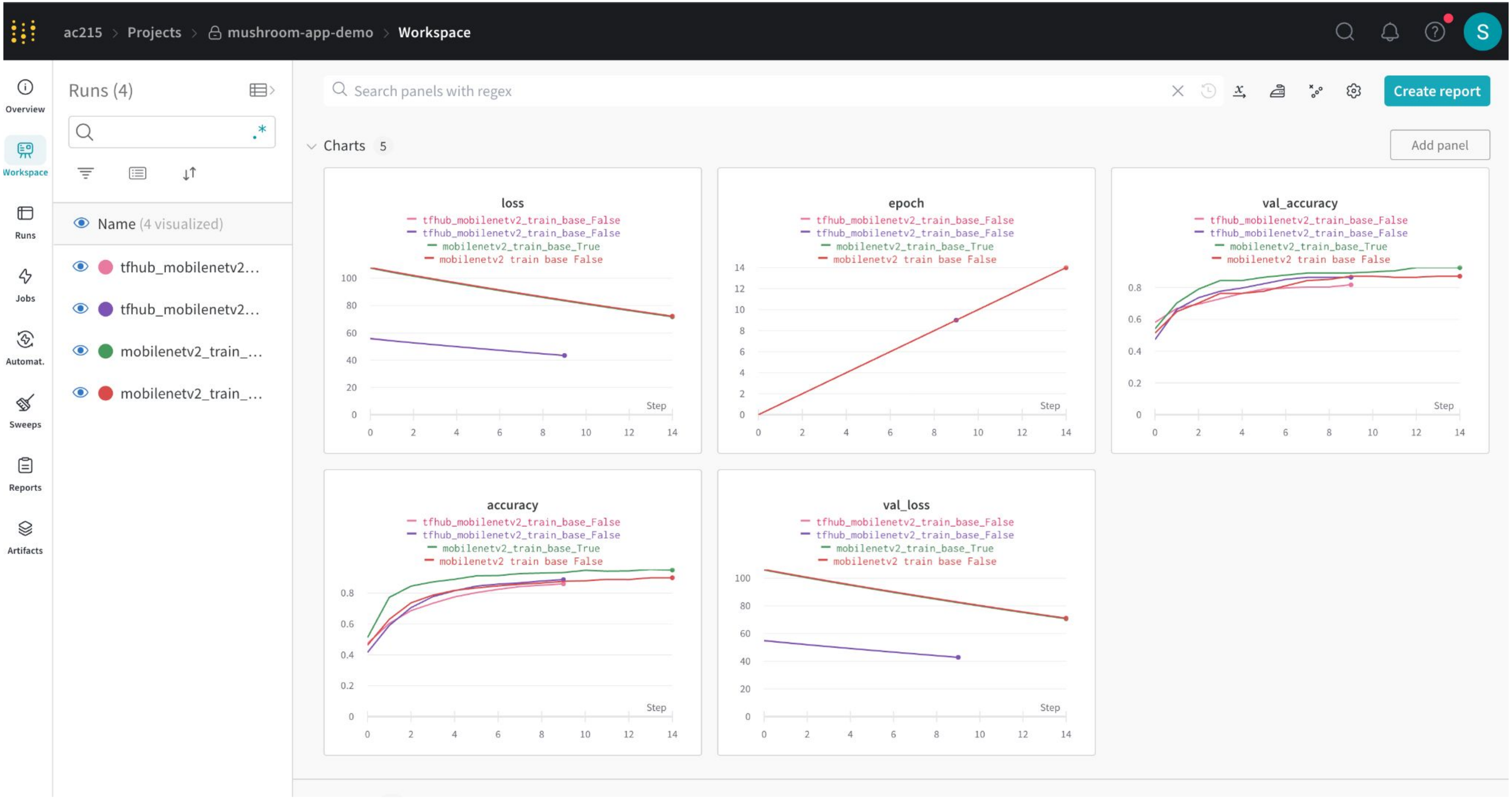
```
# Training Params
learning_rate = 0.001
batch_size = 32
epochs = 10

# Data
train_data, validation_data = get_dataset(...)
# Model
model = build_model(...)

# Initialize a W&B run
wandb.init(...)
# Train
training_results = model.fit(...,callbacks=[WandbCallback()])
# Close the W&B run
wandb.run.finish()
```

Initialize wandb run

Add a callback to monitor model

Let wandb know to finish the run

Experiment Tracking using WandB



Tutorial: Experiment Tracking

Goals of the tutorial are

- Explore models for mushroom classifications
- https://colab.research.google.com/drive/1N6UDx3fFdz7_IDa7Xsqx-V1KVN4ZxzZ-?usp=sharing
- Experiment Tracking using Weights & Bias

  https://colab.research.google.com/drive/1NP3crNooNnJZa1KLuOKDba_SMLRDqTyG?usp=sharing

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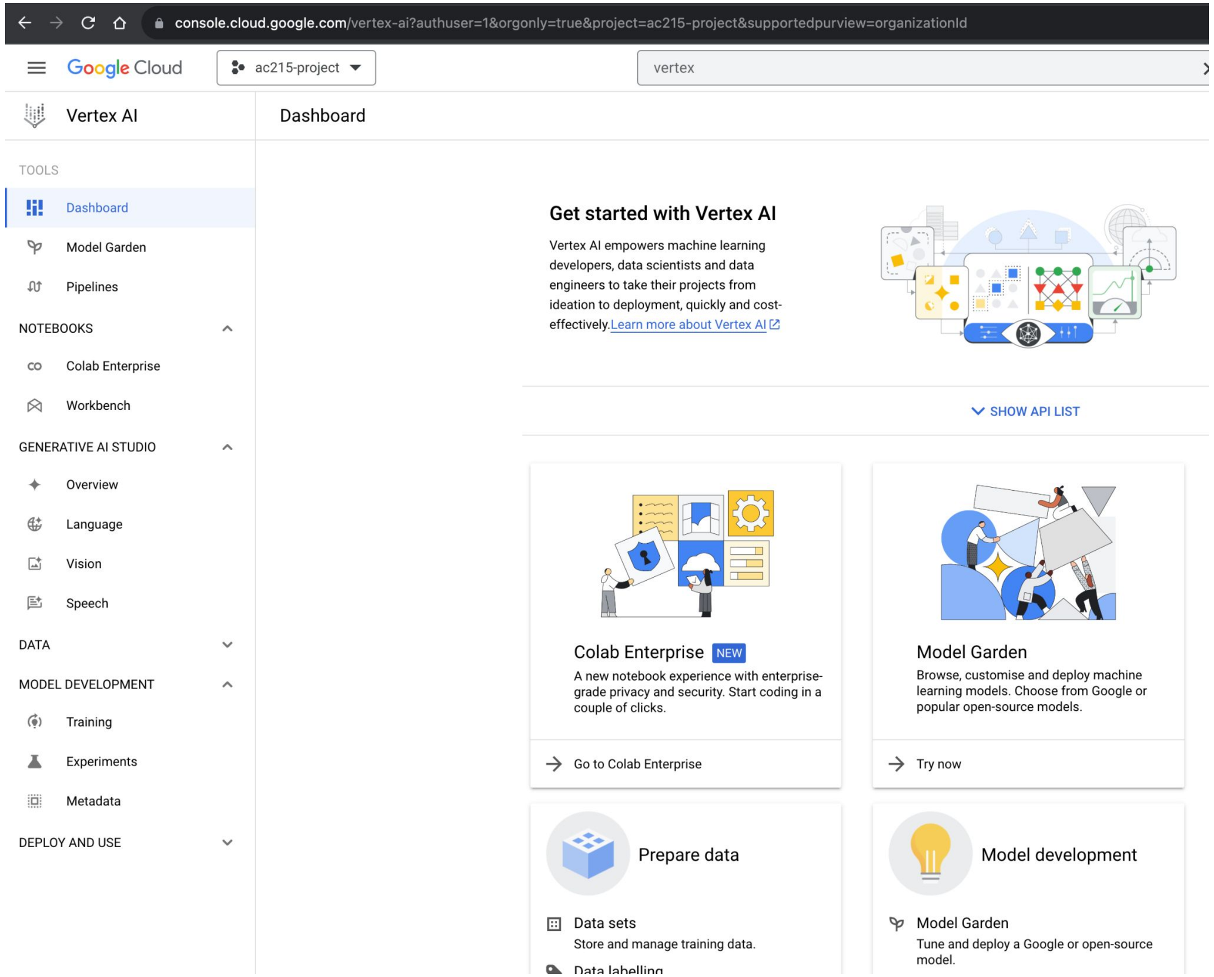
Vertex AI

- Vertex AI is machine learning platform offered by Google in GCP.
- Vertex AI combines data engineering, data science, and ML engineering workflows, enabling your teams to collaborate using a common toolset and scale your applications using the benefits of Google Cloud.

Vertex AI

Vertex AI: https://console.cloud.google.com/vertex-ai



Get started with Vertex AI

Vertex AI empowers machine learning developers, data scientists and data engineers to take their projects from ideation to deployment, quickly and cost-effectively.Learn more about Vertex AI

Colab Enterprise NEW

A new notebook experience with enterprise-grade privacy and security. Start coding in a couple of clicks.

Model Garden

Browse, customise and deploy machine learning models. Choose from Google or popular open-source models.

Prepare data

Data sets

Store and manage training data.

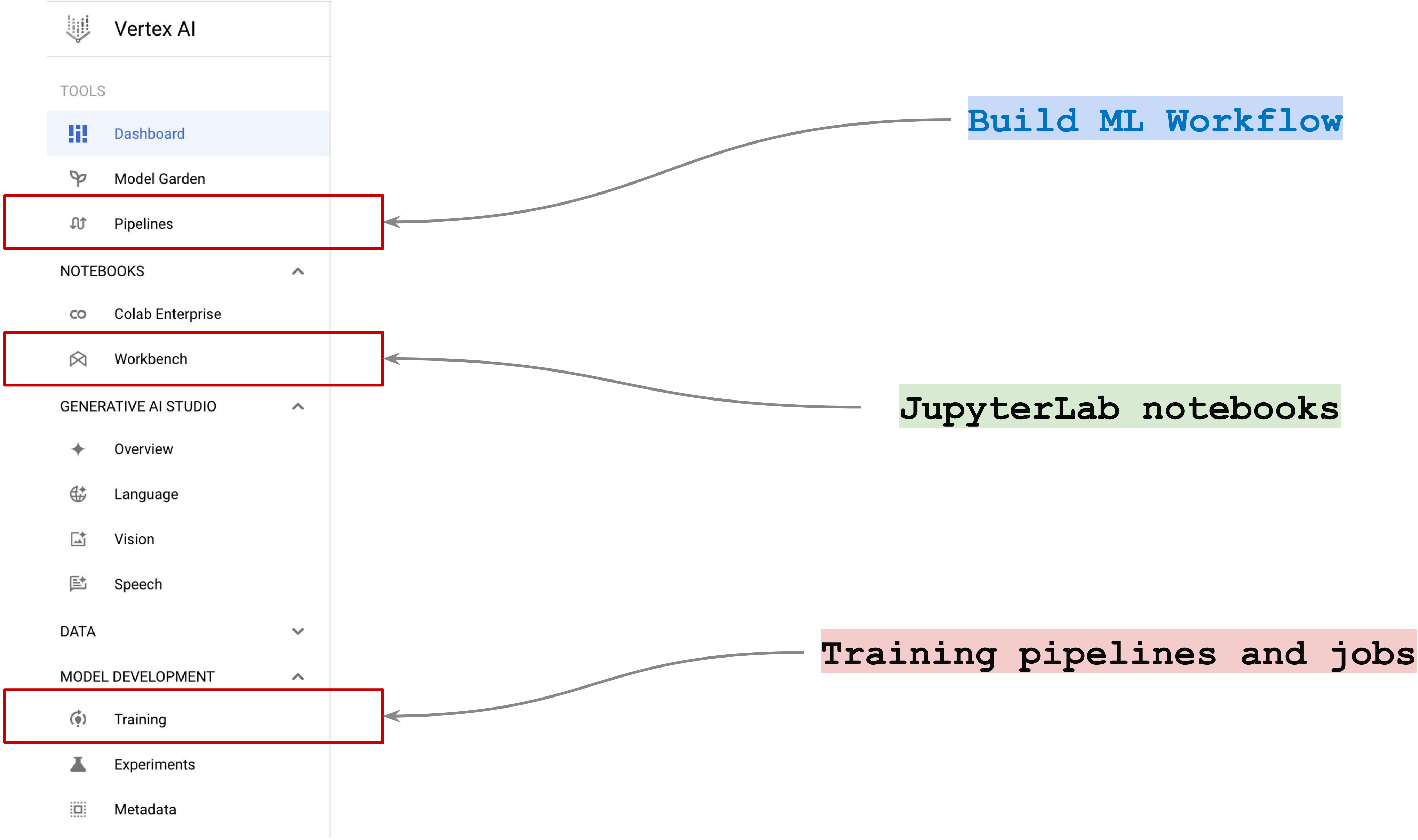
Data labelling

Model development

Model Garden

Tune and deploy a Google or open-source model.

Vertex AI



Build ML Workflow

JupyterLab notebooks

Training pipelines and jobs

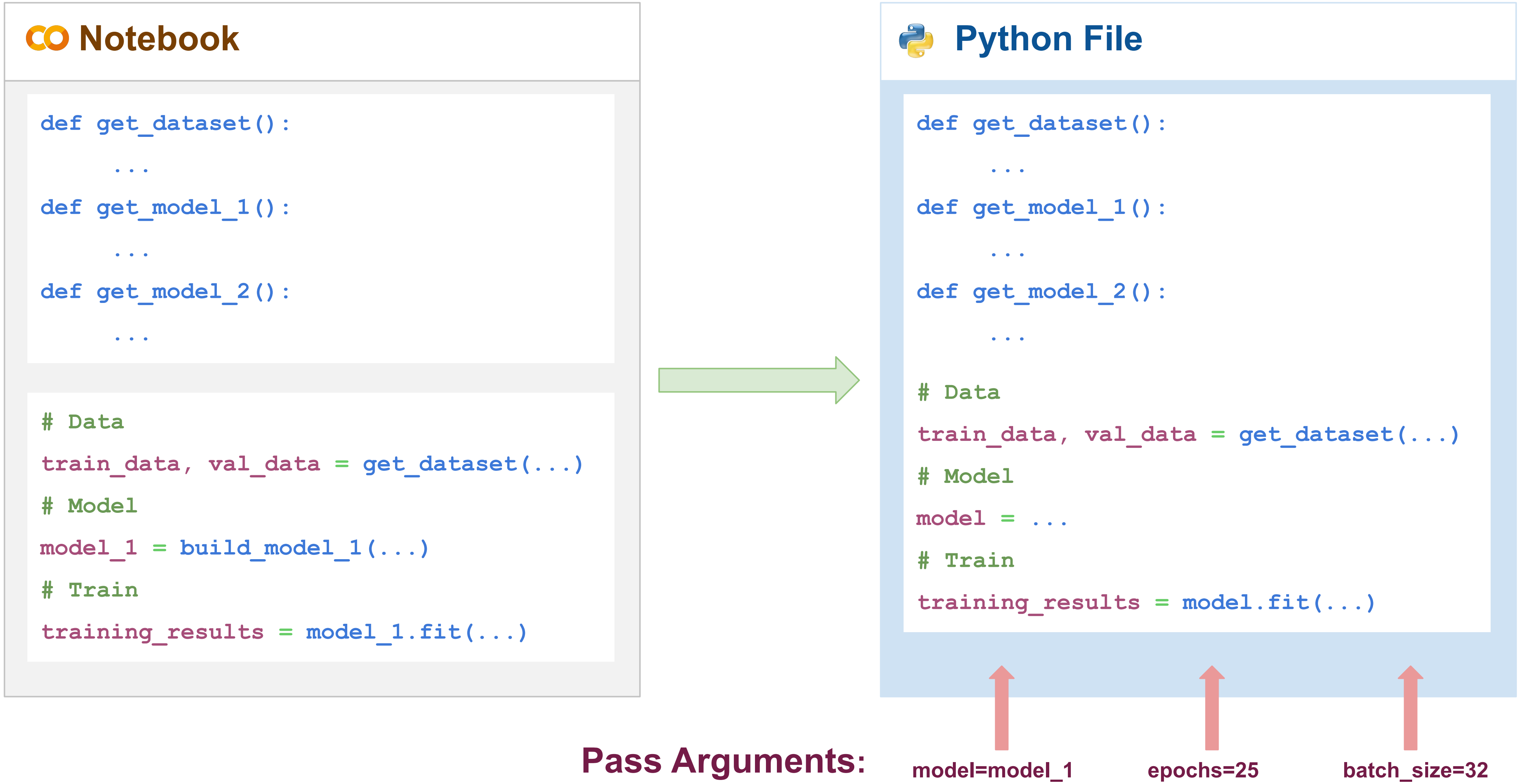
Serverless Training

What is serverless training?

- Execute training on an as-need basis
- Access GPU hardware only for the “training” step in a pipeline
- No setup of servers required
- Brings down training cost

Serverless Training

1 Move Code to Python File



Notebook

```
def get_dataset():
    ...
def get_model_1():
    ...
def get_model_2():
    ...
```

```
# Data
train_data, val_data = get_dataset(...)
# Model
model_1 = build_model_1(...)
# Train
training_results = model_1.fit(...)
```

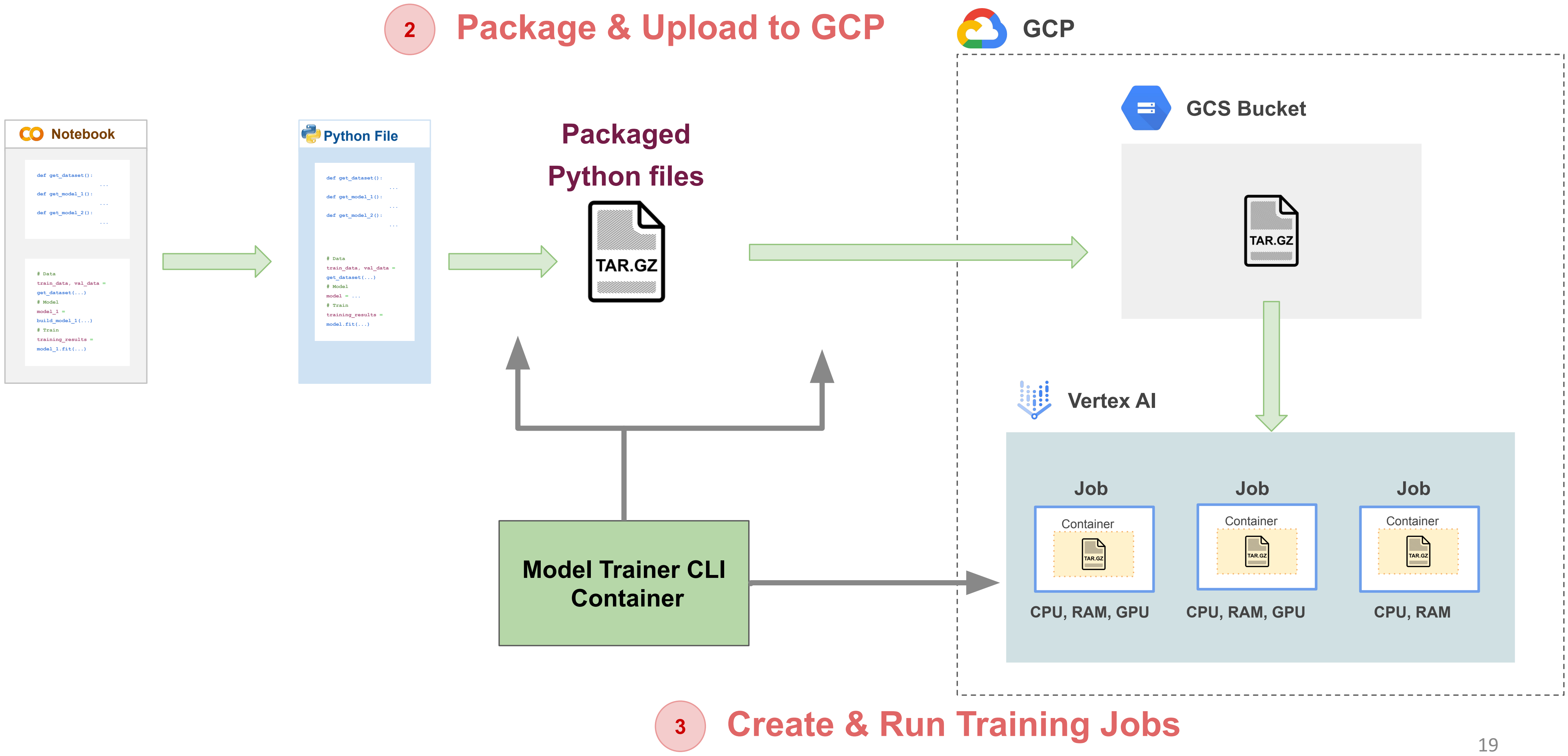
Python File

```
def get_dataset():
    ...
def get_model_1():
    ...
def get_model_2():
    ...

# Data
train_data, val_data = get_dataset(...)
# Model
model = ...
# Train
training_results = model.fit(...)
```

Pass Arguments: model=model_1 epochs=25 batch_size=32

Serverless Training



2 Package & Upload to GCP

Notebook

```
def get_dataset():
                    ...
def get_model_1():
                    ...
def get_model_2():
                    ...
```

```
# Data
train_data, val_data =
get_dataset(...)
# Model
model_1 =
build_model_1(...)
# Train
training_results =
model_1.fit(...)
```

Python File

```
def get_dataset():
                    ...
def get_model_1():
                    ...
def get_model_2():
                    ...
```

```
# Data
train_data, val_data =
get_dataset(...)
# Model
model = ...
# Train
training_results =
model.fit(...)
```

Packaged Python files

Model Trainer CLI Container

3 Create & Run Training Jobs

Tutorial: Serverless Training

Steps to perform **Serverless Training** on mushroom classification models:

- Create a GCS bucket to store packaged python training code.
- Get Weights & Bias API Key for experiment tracking.
- Package & Upload python code.
- Create Jobs in Vertex AI.
- For detailed instructions, please refer to the following link
  - Serverless Training. (https://github.com/dlops-io/model-training)
  - View Training Jobs. (https://console.cloud.google.com/vertex-ai/training/custom-jobs)
  - View Experiment Metrics. (https://wandb.ai/home)

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Multi GPU Training

How do we perform distributed training?

- What type of distribution:
  - ■ Single Machine, Single GPU [One Device Strategy]
  - ■ Single Machine, Multiple GPUs [Mirrored Strategy]
  - ■ Multiple Machine, Multiple GPUs [Multi Worker Mirrored Strategy]
- Organize code to apply the appropriate Strategy
- Train as usual

Training Code

```
# Training Params
learning_rate = 0.001
batch_size = 32
epochs = 10

# Data
train_data, validation_data = get_dataset(...)
# Model
model = build_model(...)

# Train
training_results = model.fit(...)
```

Training Code for Multi GPU

```
# Training Params
batch_size = 32
...
# Create distribution strategy
strategy = tf.distribute.MirroredStrategy()
num_workers = strategy.num_replicas_in_sync
# Data
train_data, validation_data = get_dataset(...,batch_size=batch_size * num_workers)
# Wrap model creation and compilation within scope of strategy
with strategy.scope():
    # Model
    model = build_model(...)

# Train
training_results = model.fit(...)
```

Create distribution Strategy

Adjust dataset batch size

Create & Compile model in strategy scope

THANK YOU