Vertex Al for Easier ML Deployments

GFSA 2021 India

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\$whoami



- I call model.fit() @ Carted
- I contribute to TensorFlow Hub, Keras Examples
- Netflix Nerd ••
- My coordinates are here <u>sayak.dev</u>

Acknowledgements

Sara Robinson (@SRobTweets)
Karl Weinmeister (@kweinmeister)
Chansung Park (@algo_diver)

Agenda

01 Challenges in MLOps

02 Tooling for MLOps

03 Vertex AI for building MLOps stack

04 Q&A

Some questions ...

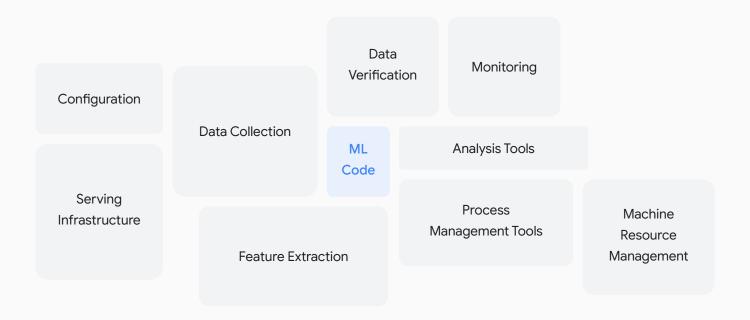
- Do train ML models continuously on new data?
- Do you deploy ML models continuously?
- Do you deploy multiple kinds of models?
- Are you training model training and deployment as a CI/CD system?
- Do you perform model monitoring at frequent intervals?
- Are your models equipped with auto-scaling?
- Are you managing the artifacts of all the steps of your ML workflow?
- ...

What is MLOps, though?

An ML engineering culture and practice that aims at **unifying** ML system development (Dev) and ML system operation (Ops).

- Google Cloud

It's hard stuff ...



Courtesy: Google Cloud

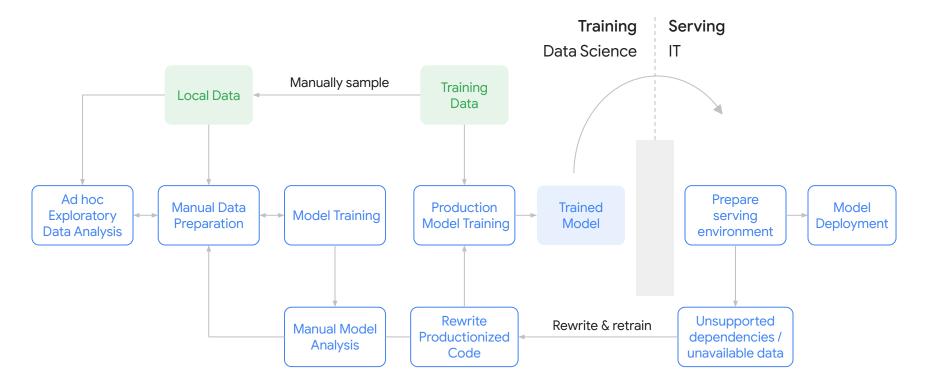
But it's important stuff too

MLOps can help you productionize and standardize

ML systems rapidly and reliably.

- Google Cloud

What's happening today: Data Science and IT (Ops) are isolated



The Challenges on Productionizing ML

ML challenges

- Governance of data, features, models, pipelines and experiments
- Continuous training and deployment
- Training-serving skew
- Data validation
- Model analysis
- Fairness and Explainability



Production system challenges

- Scalability
- Availability
- Portability
- Reproducibility
- Modularity
- Monitoring and Alerting
- Security
- Hosted or Serverless

Enter Vertex Al!



Vertex Al is a managed ML platform for every practitioner to speed up the rate of experimentation and accelerate deployment of ML models.

Talk is cheap, show me code

```
job = aiplatform.CustomTrainingJob(
    display name=JOB NAME,
    script path="task.py",
    container uri=TRAIN IMAGE,
    requirements=["tensorflow datasets==1.3.0"],
    model serving container image uri=DEPLOY IMAGE,
MODEL DISPLAY NAME = "cifar10-" + TIMESTAMP
# Start the training
if TRAIN GPU:
   model = job.run(
        model display name=MODEL DISPLAY NAME,
        args=CMDARGS,
        replica count=1,
        machine type=TRAIN COMPUTE,
        accelerator type=TRAIN GPU.name,
        accelerator count=TRAIN NGPU,
```

Asynchronous Training

```
DEPLOYED_NAME = "cifar10_deployed-" + TIMESTAMP

TRAFFIC_SPLIT = {"0": 100}

MIN_NODES = 1
MAX_NODES = 1

if DEPLOY_GPU:
    endpoint = model.deploy(
        deployed_model_display_name=DEPLOYED_NAME,
        traffic_split=TRAFFIC_SPLIT,
        machine_type=DEPLOY_COMPUTE,
        accelerator_type=DEPLOY_GPU.name,
        accelerator_count=DEPLOY_NGPU,
        min_replica_count=MIN_NODES,
        max_replica_count=MAX_NODES,
)
```

Deployment for Online Predictions

Talk is cheap, show me code

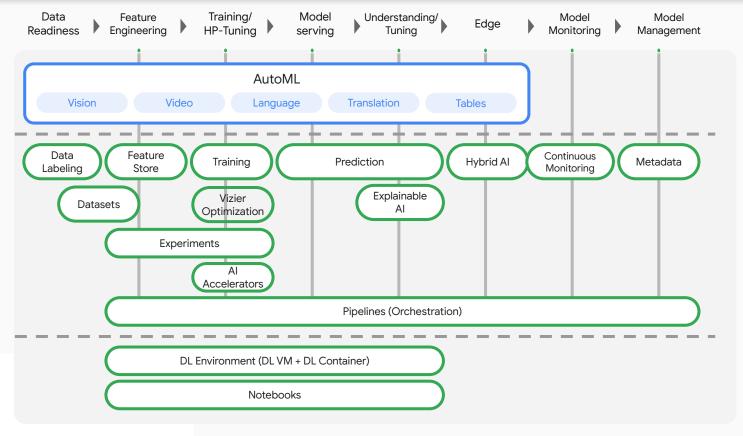
```
job = aiplatform.CustomTrainingJob(
    display name=JOB NAME,
    script path="task.py",
    container uri=TRAIN IMAGE,
    requirements=["tensorflow datasets==1.3.0"],
    model serving container image uri=DEPLOY IMAGE,
MODEL DISPLAY NAME = "cifar10-" + TIMESTAMP
# Start the training
if TRAIN GPU:
   model = job.run(
        model display name=MODEL DISPLAY NAME,
        args=CMDARGS,
        replica count=1,
        machine type=TRAIN COMPUTE,
        accelerator type=TRAIN GPU.name,
        accelerator count=TRAIN NGPU,
```

Asynchronous Training

```
# Make SDK batch_predict method call
batch_prediction_job = model.batch_predict(
    instances_format="jsonl",
    predictions_format="jsonl",
    job_display_name=BATCH_PREDICTION_JOB_NAME,
    gcs_source=BATCH_PREDICTION_GCS_SOURCE,
    gcs_destination_prefix=BATCH_PREDICTION_GCS_DEST_PREFIX,
    model_parameters=None,
    machine_type=DEPLOY_COMPUTE,
    accelerator_type=DEPLOY_GPU,
    accelerator_count=DEPLOY_NGPU,
    starting_replica_count=MIN_NODES,
    max_replica_count=MAX_NODES,
    sync=True,
)
```

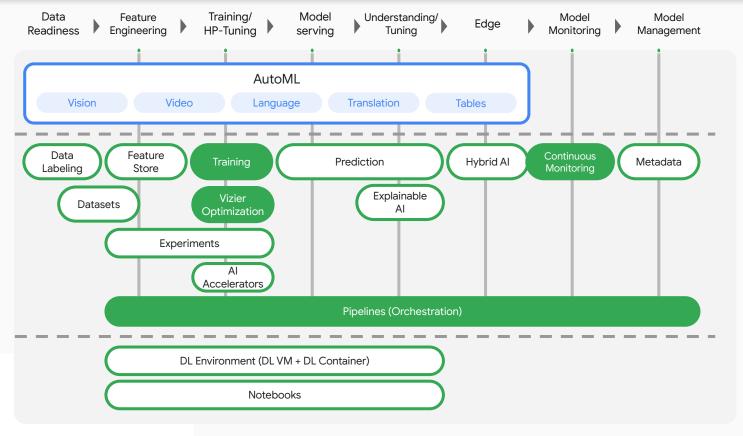
Running **Batch** Predictions

What's included in Vertex Al?



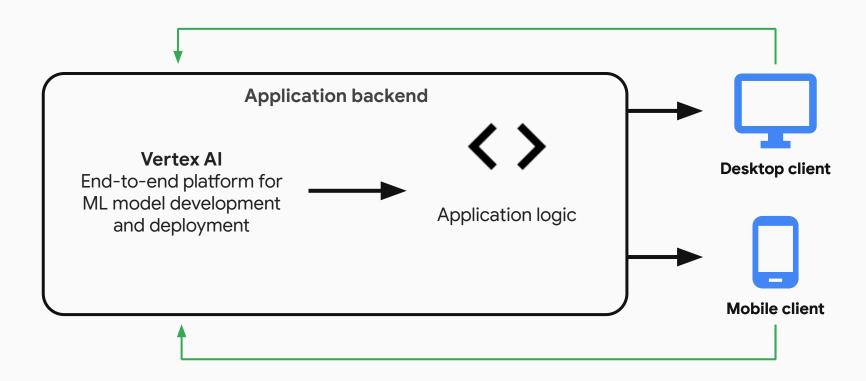
Courtesy: Google Cloud

What's included in Vertex Al?



Courtesy: Google Cloud

How does MLOps fit into app development?



My model deployment is done at scale. Let's now go on a trip





My model deployment is done at scale. Let's now go on a trip





But ...

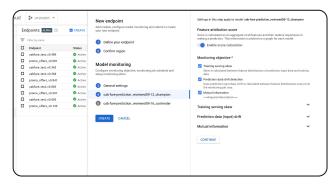
A deployed model is only the beginning

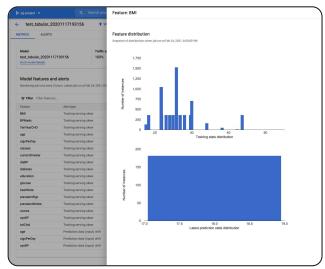
To avoid **concept** and **model drift**, ML models often need to be continuously monitored, retrained, and updated.

Pipelines can help automate this workflow.

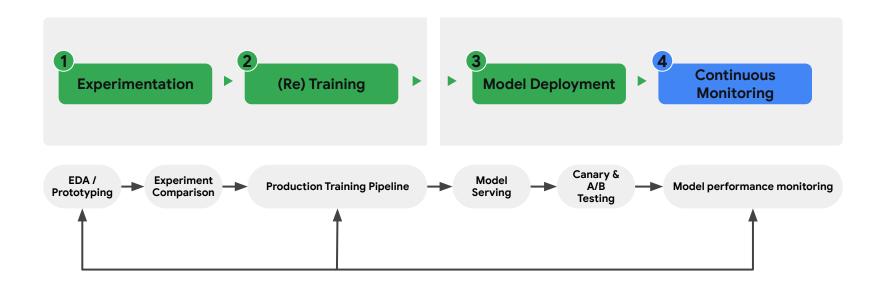
Model Monitoring

- Automatically alert your data scientists and ML engineers when model performance changes
- Detect drift and training-serving skew
- Provides confidence in model reliability



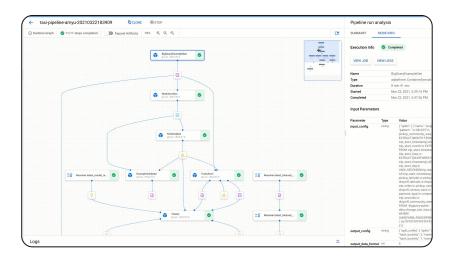


But how do we do this continuously?



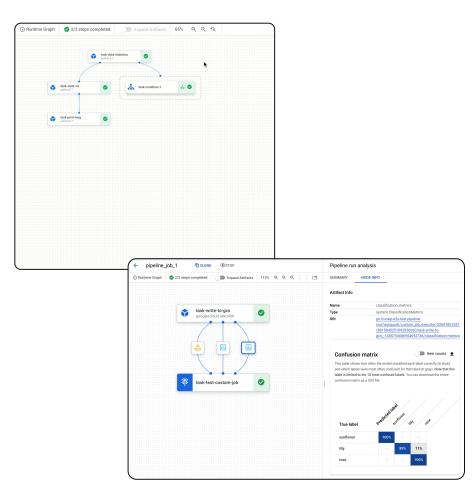
Managed Pipelines

- Build pipelines with familiar open-source Python SDKs like TFX and Kubeflow Pipelines
- Automated, scalable, serverless, cost effective: pay only for what you use



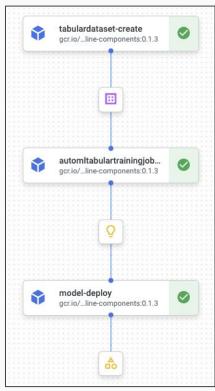
Managed Pipelines

- Add conditional logic and branches to your pipeline
- Store metadata for every artifact produced by the pipeline
- Track artifacts, lineage, metrics, and execution across your ML workflow
- Support for Cloud IAM, VPC-SC, and CMEK



Courtesy: Google Cloud

What does this look in code?

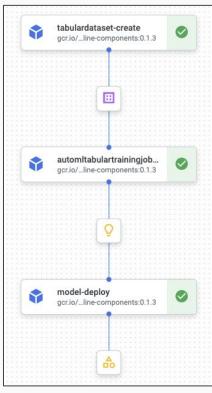


A common ML workflow

```
@kfp.dsl.pipeline(name="automl-tab-training-v2")
def pipeline(project: str = PROJECT ID):
   dataset create op = gcc aip.TabularDatasetCreateOp(
       project=project, display name="housing", gcs source=gcs csv path
   training op = gcc aip.AutoMLTabularTrainingJobRunOp(
        project=project,
       display name="train-housing-autom1 1",
       optimization prediction type="regression",
       optimization objective="minimize-rmse",
       column transformations=[
            {"numeric": {"column name": "longitude"}},
            {"numeric": {"column name": "latitude"}},
            {"numeric": {"column name": "housing median age"}},
            {"numeric": {"column name": "total rooms"}},
            {"numeric": {"column name": "total bedrooms"}},
            {"numeric": {"column name": "population"}},
            {"numeric": {"column name": "households"}},
            {"numeric": {"column name": "median income"}},
            {"numeric": {"column name": "median house value"}},
       dataset=dataset create op.outputs["dataset"],
        target column="median house value",
   deploy op = gcc aip.ModelDeployOp( # noga: F841
       model=training op.outputs["model"],
       project=project,
       machine type="n1-standard-4",
```

I. <u>Write the pipeline</u>

What does this look in code?



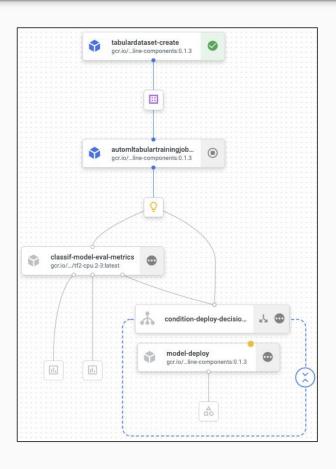
A common ML workflow

```
from kfp.v2 import compiler # noga: F811
compiler.Compiler().compile(
    pipeline func=pipeline, package path="tab regression pipeline.json"
The pipeline compilation generates the tab regression pipeline.json job spec file.
Next, instantiate an API client object:
from kfp.v2.google.client import AIPlatformClient # noqa: F811
api client = AIPlatformClient(project id=PROJECT ID, region=REGION)
Then, you run the defined pipeline like this:
response = api client.create run from job spec(
    "tab regression pipeline.json",
    pipeline root=PIPELINE ROOT,
    parameter values={"project": PROJECT ID},
```

2. <u>Compile and Run</u>

All from a Colab Notebook: bit.ly/vertex-automl

What about more complicated ones?



More code but certainly doable from a Colab Notebook:D

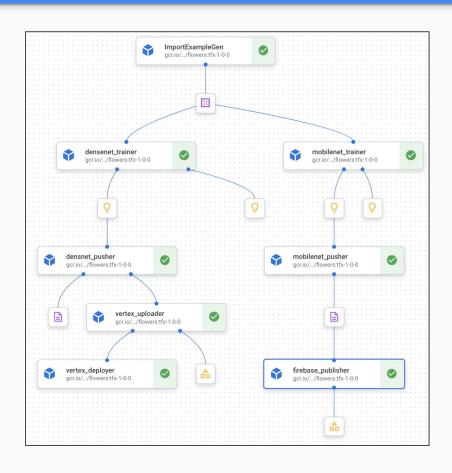
bit.ly/vertex-beans

Standard KFP components

- AutoMLImageTrainingJobRunOp(...)
- AutoMLTabularTrainingJobRunOp(...)
- AutoMLTextTrainingJobRunOp(...)
- AutoMLVideoTrainingJobRunOp(...)
- ModelBatchPredictOp(...)
- ModelDeployOp(...)

Full list is available here: bit.ly/kfp-gcp

What if I wanted to allow two different models?

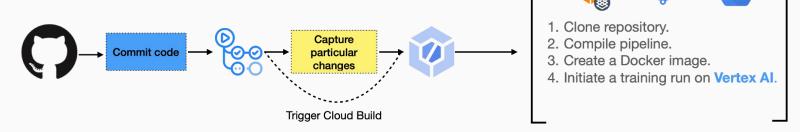


Sky's the limit!

bit.ly/dual-deployments

Can we incorporate CI/CD?

Scenario 1



bit.ly/ci-cd-vertex-2



Cloud Build



Vertex Al

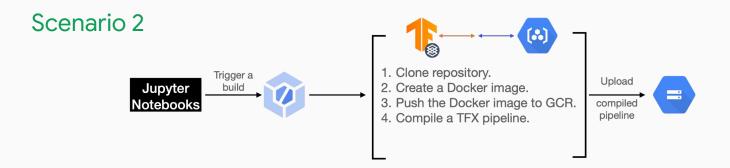


Google Container Registry



TensorFlow Extended

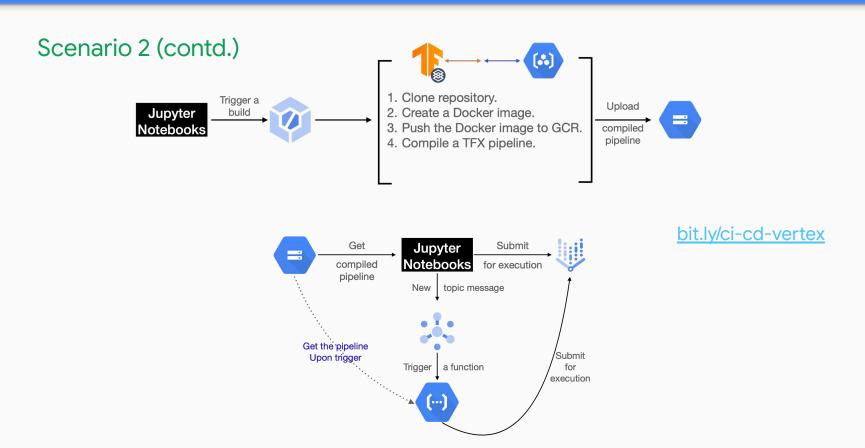
Can we incorporate CI/CD?





How the build looks like?

Can we incorporate CI/CD?

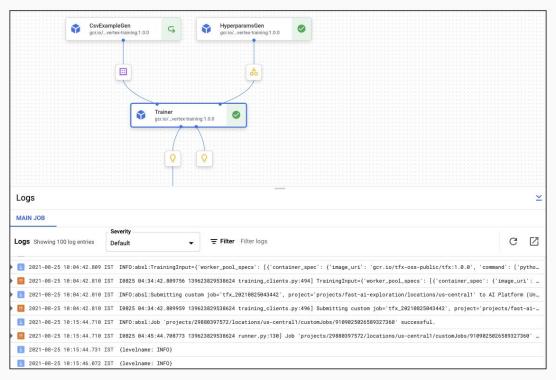


Operate effortlessly

pipeline-with-loops-and-conditions-spsayakpaul-20210722081841	• Failed	pipeline-with-loops-and-conditions-spsayakpaul				:
$\begin{tabular}{ll} \hline & pipeline-with-loops-and-conditions-spsayakpaul-20210722082539 \\ \hline \end{tabular}$	• Failed	pipeline-with-loops-and-conditions-spsayakpaul				:
pipeline-with-loops-and-conditions-spsayakpaul-20210722082831	Succeeded	pipeline-with-loops-and-conditions-spsayakpaul	8 min 6 sec	Jul 22, 2021, 1:58:32 PM	Jul 22, 2021, 2:06:38 PM	÷
automl-tab-beans-training-v2-20210722090230	Canceled	automl-tab-beans-training-v2	26 min 13 sec	Jul 22, 2021, 2:32:31 PM	Jul 22, 2021, 2:58:44 PM	÷
automl-image-training-v2-20210722093207	Canceled	automl-image-training-v2	5 min 49 sec	Jul 22, 2021, 3:02:08 PM	Jul 22, 2021, 3:07:57 PM	:
hello-world-v2-20210722115441	• Failed	hello-world-v2				:
hello-world-v2-20210722115629	Succeeded	hello-world-v2	5 min 2 sec	Jul 22, 2021, 5:26:30 PM	Jul 22, 2021, 5:31:32 PM	:
custom-cifar10-training-20210723022324	• Failed	custom-cifar10-training				:
custom-cifar10-training-20210723022432	• Failed	custom-cifar10-training	2 min 47 sec	Jul 23, 2021, 7:54:33 AM	Jul 23, 2021, 7:57:21 AM	:
automl-tab-training-v2-20210723033914	• Failed	automl-tab-training-v2				:
automl-tab-training-v2-20210723034427	Succeeded	automl-tab-training-v2	1 hr 28 min	Jul 23, 2021, 9:14:28 AM	Jul 23, 2021, 10:42:49 AM	:
penguin-vertex-pipelines-20210723050040	Succeeded	penguin-vertex-pipelines	27 min 48 sec	Jul 23, 2021, 10:30:41 AM	Jul 23, 2021, 10:58:30 AM	:

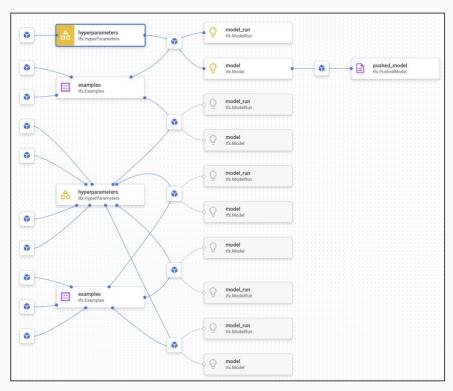
A central dashboard for all your pipelines

Operate effortlessly



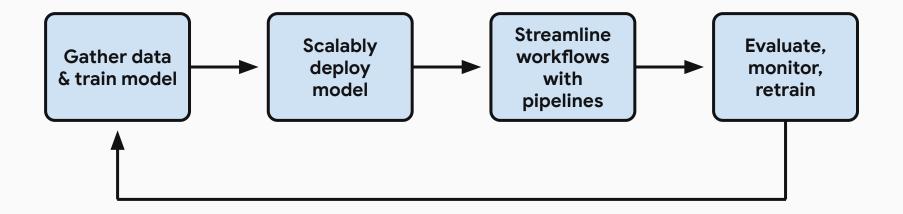
Automated logging at each step

Operate effortlessly



Track lineage of all the artifacts

Streamlining ML workflows with Vertex Al



Learning more

- Vertex Al documentation
- Goldmine of MLOps code
- Machine Learning Design Patterns [Book]
- Applied ML Summit from GCP
- Machine Learning Engineering for Production (MLOps)
 Specialization
- Made With ML: Home
- Full Stack Deep Learning





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