

Managed ML Model Training and Serving

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Machine Learning at Scale



Serverless, no-ops, ML training and serving platform

Distributed training infrastructure that supports CPUs, GPUs, and TPUs

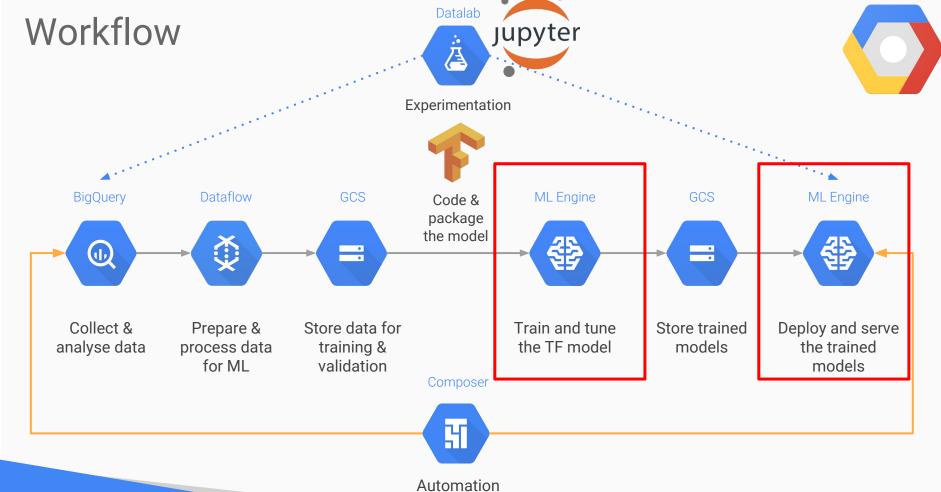
Automatic hyperparameter tuning

Train, tune, and serve TensorFlow models (batch and online prediction)

Train and serve Scikit-learn and XGBoost models for online predictions

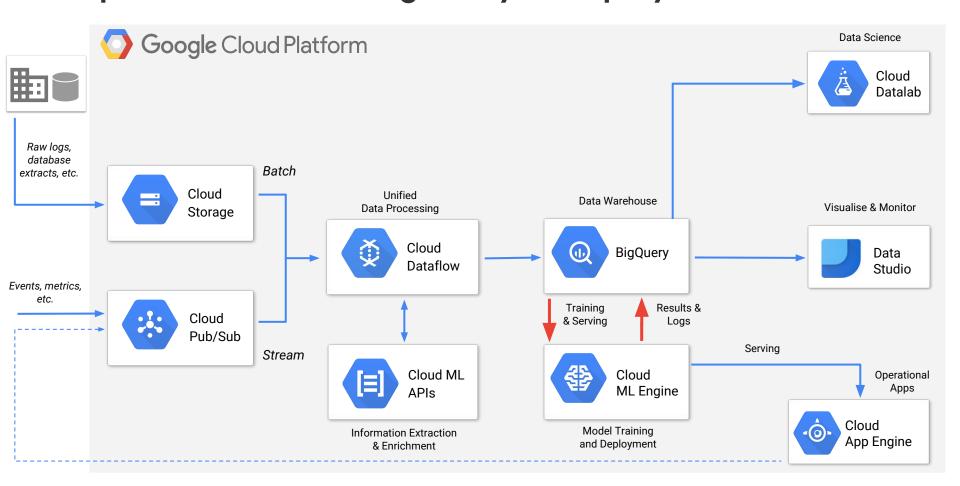
TPUs for training TensorFlow models (Beta)





Google Cloud

Example Architecture: BigQuery to deployed model API



Training locally



```
train locally
                                      Local path
gcloud ml-engine local train \
  --module-name trainer.task --package-path trainer/ \
  --train-files $TRAIN_DATA --eval-files $EVAL_DATA --job-dir $MODEL_DIR
                                            evaluation
```





Training in the cloud

with single node GCS location train in the cloud region gcloud ml-engine jobs submit training \$JOB_NAME --job-dir \$OUTPUT_PATH \ --runtime-version 1.10 --module-name trainer.task --package-path trainér --region \$REGION \ --scale-tier BASIC single worker --train-files \$TRAIN_DATA --eval-files \$EVAL_DATA --num-epoch 1000 --learning-rate 0.01 GCS Locations





Training in the cloud at scale

with multiple workers



https://cloud.google.com/ml-engine/docs/tensorflow/machine-types





Manually Distributing the Training

```
"worker": [
                                                             "worker0.example.com:2222",
                                                             "worker1.example.com:2222",
with tf.device("/job:ps/task:0"):
                                                             "worker2.example.com:2222"
  weights_1 = tf.Variable(...)
  biases_1 = tf.Variable(...)
                                                          "ps":
                                                             "ps0.example.com:2222",
with tf.device("/job:ps/task:1"):
                                                             "ps1.example.com:2222"
  weights_2 = tf.Variable(...)
                                                         ]})
  biases_2 = tf.Variable(...)
with tf.device("/job:worker/task:7"):
  input, labels = ...
  layer_1 = tf.nn.relu(tf.matmul(input, weights_1) + biases_1)
  logits = tf.nn.relu(tf.matmul(layer_1, weights_2) + biases_2)
  # ...
  train_op = ...
with tf.Session("grpc://worker7.example.com:2222") as sess:
  for _ in range(10000):
    sess.run(train_op)
```

tf.train.ClusterSpec construction

tf.train.ClusterSpec({

tf.train.ClusterSpec({"local": ["localhost:2222", "localhost:2223"]

Training in the cloud at scale

with GPUs (K80/P100/V100 - availability by region)



https://cloud.google.com/ml-engine/docs/tensorflow/machine-types





CMLE Machine **Types**

BASIC A single worker instance. This tier is suitable for learning how to use Cloud ML Engine and for experimenting with new models using small datasets. Compute Engine machine name: n1-standard-4 STANDARD_1 One master instance, plus four workers and three parameter servers. Compute Engine machine name, master: n1-highcpu-8, workers: n1-highcpu-8, parameter servers: n1-standard-4 PREMIUM_1 One master instance, plus 19 workers and 11 parameter servers. parameter servers: n1-highmem-8 graphics processing units (GPUs), see the section on training with GPUs.

Compute Engine machine name, master: n1-highcpu-16, workers: n1-highcpu-16, BASIC_GPU A single worker instance with a single NVIDIA Tesla K80 GPU. To learn more about Compute Engine machine name: n1-standard-8 with one k80 GPU

according to these guidelines:

BASIC_TPU (Beta)

Cloud ML Engine scale tier

A master VM and a Cloud TPU. See how to use TPUs for your training job.

Compute Engine machine name, master: n1-standard-4, workers: Cloud TPU

The CUSTOM tier is not a set tier, but rather enables you to use your own cluster specification. When you use this tier, set values to configure your processing cluster

CMLE Custom **Options**



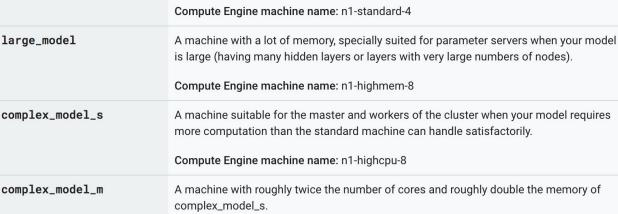


Cloud ML Engine machine name

datasets.

complex_model_m.

GPUs.

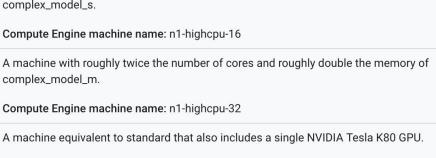


complex_model_1

standard_gpu

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complex_model_m_gpu



Compute Engine machine name: n1-standard-8 with one k80 GPU

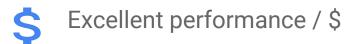
Compute Engine machine name: n1-standard-16-k80x4

A machine equivalent to complex_model_m that also includes four NVIDIA Tesla K80

A basic machine configuration suitable for training simple models with small to moderate

Cloud TPUs





- Train in days instead of weeks
- No more fighting with drivers
- Flexibility and scale
- Fully-managed in the cloud

Supported models for TPUs





Image recognition & object detection

Image recognition:

AmoebaNet-D ResNet-50/101/152/200 Inception v2/v3/v4 DenseNet

Object detection:

RetinaNet

Low-resource models:

MobileNet SqueezeNet



Machine translation and language modeling

Models:

Machine translation Language modeling Sentiment analysis Question-answering (all transformer-based)



Speech recognition

Model:

ASR Transformer (LibriSpeech)



Image generation

Models:

Image Transformer DCGAN



Training Scikit-learn & XGBoost models



Key parameters to scikit-learn and XGBoost training on CMLE

```
gcloud ml-engine jobs submit training $JOB_NAME --job-dir $OUTPUT_PATH \
    --runtime-version 1.9 --python-version 2.7 --scale-tier BASIC \
    --module-name sklearn_trainer.task --package-path sklearn_trainer --region $REGION \
    -- \
    --train-files $TRAIN_DATA --eval-files $EVAL_DATA --num-epoch 1000 --learning-rate 0.01
```





Keras: what is happening?



- Compatibility module introduced in TensorFlow: tf.keras
- Write your custom estimator model_fn using tf.keras.layers and/or tf.layers (mix-and-match)
- Convert your compiled keras model to tf.estimator using tf.keras.estimator.model_to_estimator
- With TensorFlow, Keras users gain access to new features:
 - Distributed training
 - Multiple GPUs
 - Cloud ML
 - Hyperparameter tuning
 - TF-Serving







Keras example

```
F
```

```
y train = ...
y test = ...
model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=input_shape))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool size=(2, 2)))
model.add(Dropout(0.25))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num classes, activation='softmax'))
model.compile(loss=keras.losses.categorical crossentropy,
             optimizer=keras.optimizers.Adadelta(), metrics=['accuracy'])
model.fit(x train, y train, batch size=batch size, epochs=epochs,
         validation data=(x test, y test))
score = model.evaluate(x test, y test, verbose=0)
```





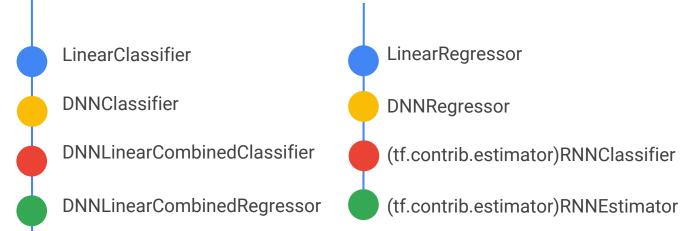


Premade Estimators





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(tf.contrib.kernel_methods.) KernelLinearClassifier

(tf.contrib.factorization.) KMeansClustering

(tf.contrib.timeseries.) ARRegressor

BoostedTreesClassifier

BoostedTreesRegressor

Hyperparameter tuning



```
gcloud ml-engine jobs submit training $JOB_NAME --job-dir $OUTPUT_PATH \
    --runtime-version 1.7 --module-name trainer.task --package-path trainer/ --region $REGION \
    --scale-tier PREMIUM_1 --config hyperparams.yaml
    -- \
    --train-files $TRAIN_DATA --eval-files $EVAL_DATA
```





Hyperparameter tuning



hyperparams.yaml

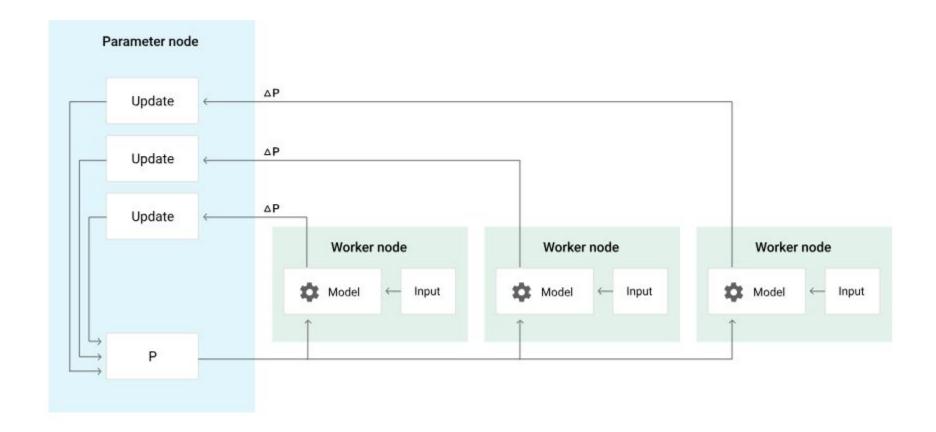
```
trainingInput:
hyperparameters:
    goal: MAXIMIZE
hyperparameterMetricTag: accuracy
maxTrials: 40
    enableTrialEarlyStopping: True
maxParallelTrials: 2
    algorithm: UNSPECIFIED
params:
    - parameterName: learning-rate
    type: FLOAT
    minValue: 0.001
    maxValue: 0.1
    scaleType: UNIT_LOG_SCALE
```

task.py

```
. . .
      # Initialise the optimizer for the DNN
      optimizer = tf.train.AdagradOptimizer(
             learning rate=hparams.learning rate)
parser.add_argument(
     '--learning-rate',
     help='Learning rate used by the DNN optimizer',
     default=0.01,
     type=float
```



Distributed Training







Consuming the deployed ML model API for predictions



Deploy the trained TF model



gcloud command line tool:

```
# Creating model
NAME=demo_classifier
gcloud ml-engine models create $NAME --regions $REGION
# Creating versions\
VERSION=v2.3
MODEL_DIR=qs://ksalama-qcs/trained_models/demo_classifier_output
gcloud ml-engine versions create $VERSION --model $NAME --origin $MODEL_DIR \
  --runtime-version 1.7 --config config.yaml
                                                         description: A free-form description of the version.
                                                         deploymentUri: qs://path/to/source
                                                          runtimeVersion: '1.7'
# List deployed models
                                                         manualScaling:
```

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gcloud ml-engine models list

deploymentUri: gs://path/to/source runtimeVersion: '1.7' manualScaling: nodes: 10 autoScaling: minNodes: 0

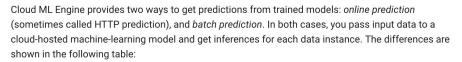


Predicting with TF Model

Online versus Batch Prediction

SEND FEEDBACK

Internal: Count: 1, Average: 5.0



Online prediction	Batch prediction
Optimized to minimize the latency of serving predictions.	Optimized to handle a high volume of instances in a job and to run more complex models.
Can process one or more instances per request.	Can process one or more instances per request.
Predictions returned in the response message.	Predictions written to output files in a Cloud Storage location that you specify.
Input data passed directly as a JSON string.	Input data passed indirectly as one or more URIs of files in Cloud Storage locations.
Returns as soon as possible.	Asynchronous request.
Accounts with the following IAM roles can request online predictions: Legacy Editor or Viewer Cloud ML Engine Admin or Developer	Accounts with the following IAM roles can request batch predictions: Legacy Editor Cloud ML Engine Admin or Developer
Runs on the runtime version and in the region selected when you deploy the model.	Can run in any available region, using any available runtime version. Though you should run with the defaults for deployed model versions.





Predicting with TF Model



gcloud command line tool:

```
gcloud ml-engine predict --model $NAME --version $VERSION --json-instances test.json
```

gcloud batch prediction:

```
gcloud ml-engine job submit prediction \
$JOB_NAME --model $NAME --version $VERSION \
data-format TEXT \
input-paths $GCS_DATA_DIR \
output-path $GCS_OUT_DIR \
```

Google Cloud

python code - REST API call - **online prediction**:

Deploy XGBoost & Scikit-learn models



```
from sklearn.externals import joblib joblib.dump(estimator, model.joblib)
```

Save and dump model to GCS

gsutil cp ./model.joblib \${MODEL_PATH}/model.joblib

```
deploy the model
to CMLE
```

```
gcloud ml-engine models create ${MODEL_NAME} --regions=${REGION}
```

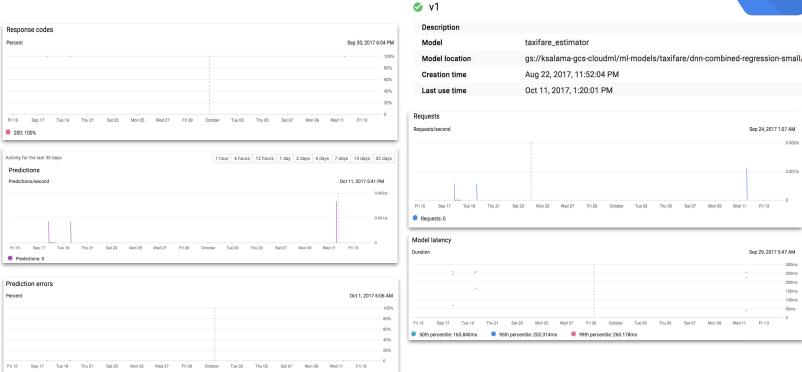
```
gcloud ml-engine versions create ${VERSION} --model=${MODEL_NAME} \
--origin=${MODEL_PATH} \
--runtime-version="1.4" \
--framework="SCIKIT_LEARN"
--pythonVersion="2.7"
```

https://cloud.google.com/blog/big-data/2018/04/serving-real-time-scikit-learn-and-xgboost-predictions



Monitoring model API serving health

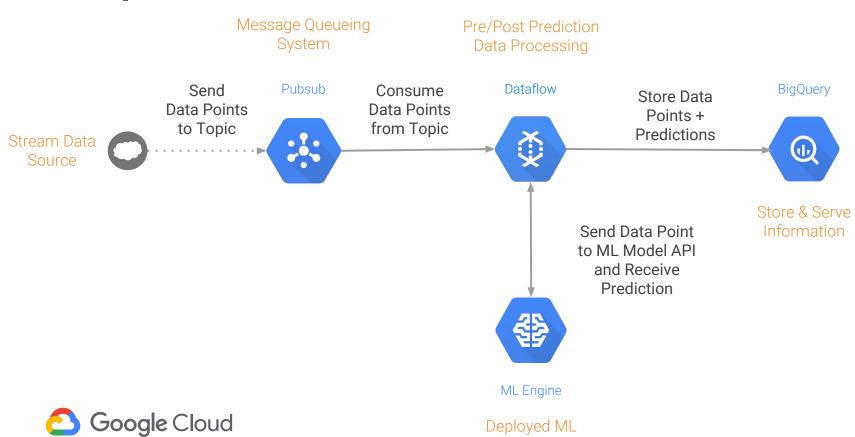






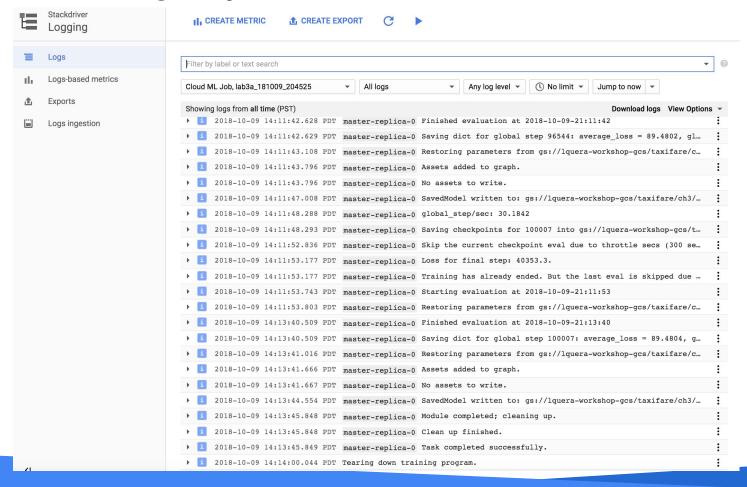
Prediction errors: 0

Example Production Workflow

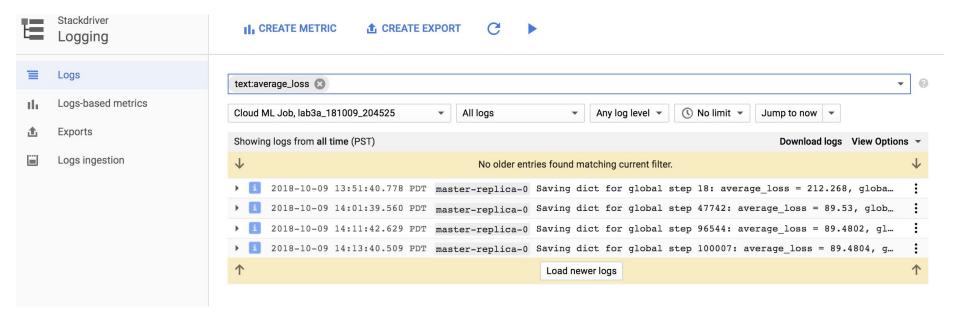


Model APIs

Monitor ML Engine job on Cloud Console



Monitor ML Engine job on Cloud Console



Thank you!

