Courses 7 - Production ML Systems

Module 4: Designing High-Performance ML Systems

Lesson Title: **Introduction**

Format: Presenter

Presenter: Laurence Moroney

Video Name: T-PSML-O_4_I1_introduction

Google Cloud

Designing High Performance ML Systems

Laurence Moroney

Title Safe >

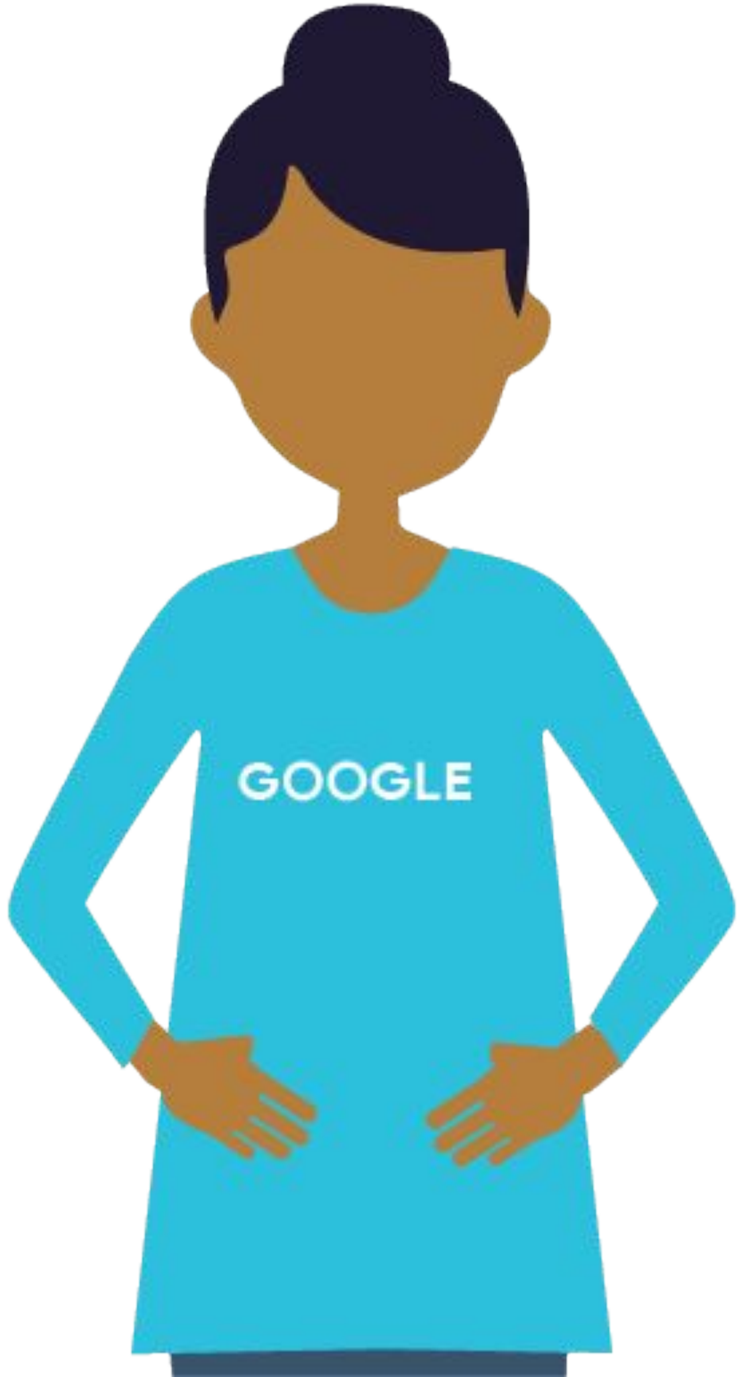
< Action Safe

Learn how to...

Identify performance considerations for ML models

Choose appropriate ML infrastructure

Select a distribution strategy

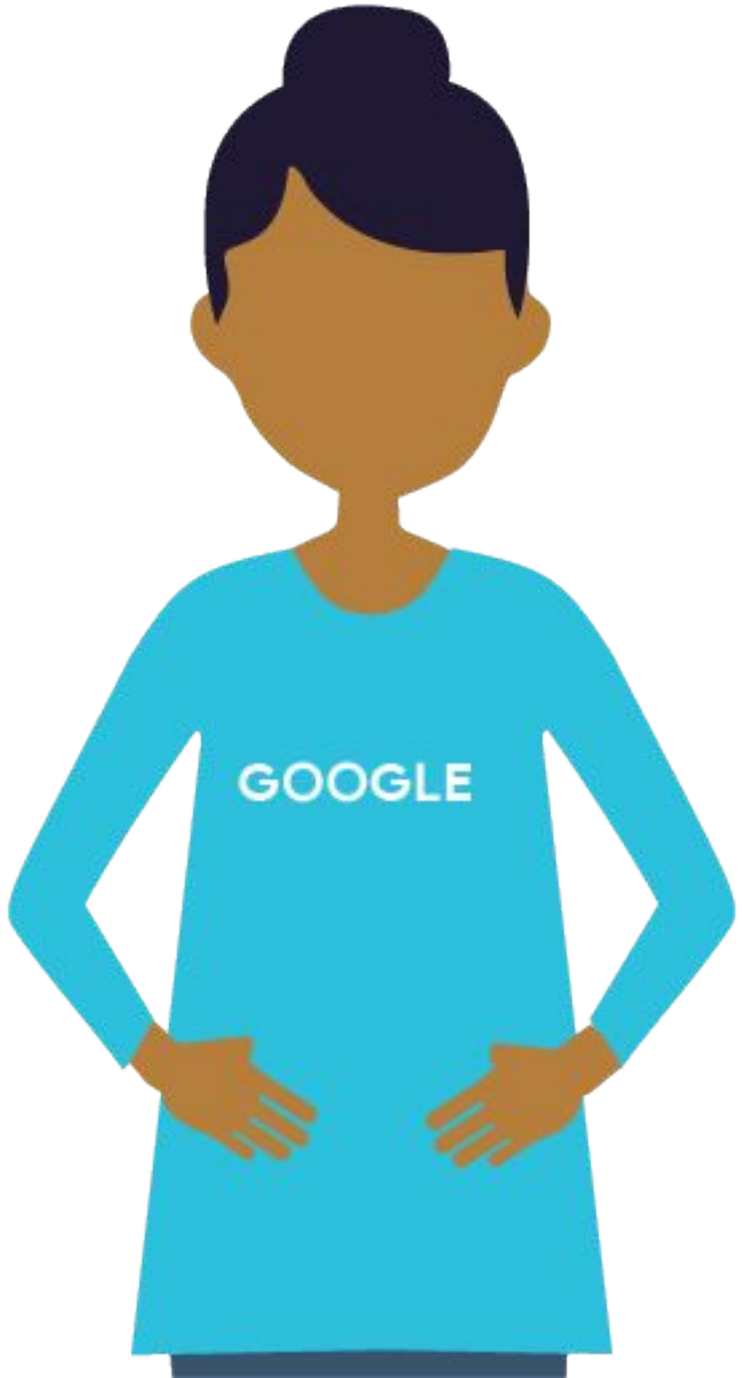


Learn how to...

Identify performance considerations for ML models

Choose appropriate ML infrastructure

Select a distribution strategy

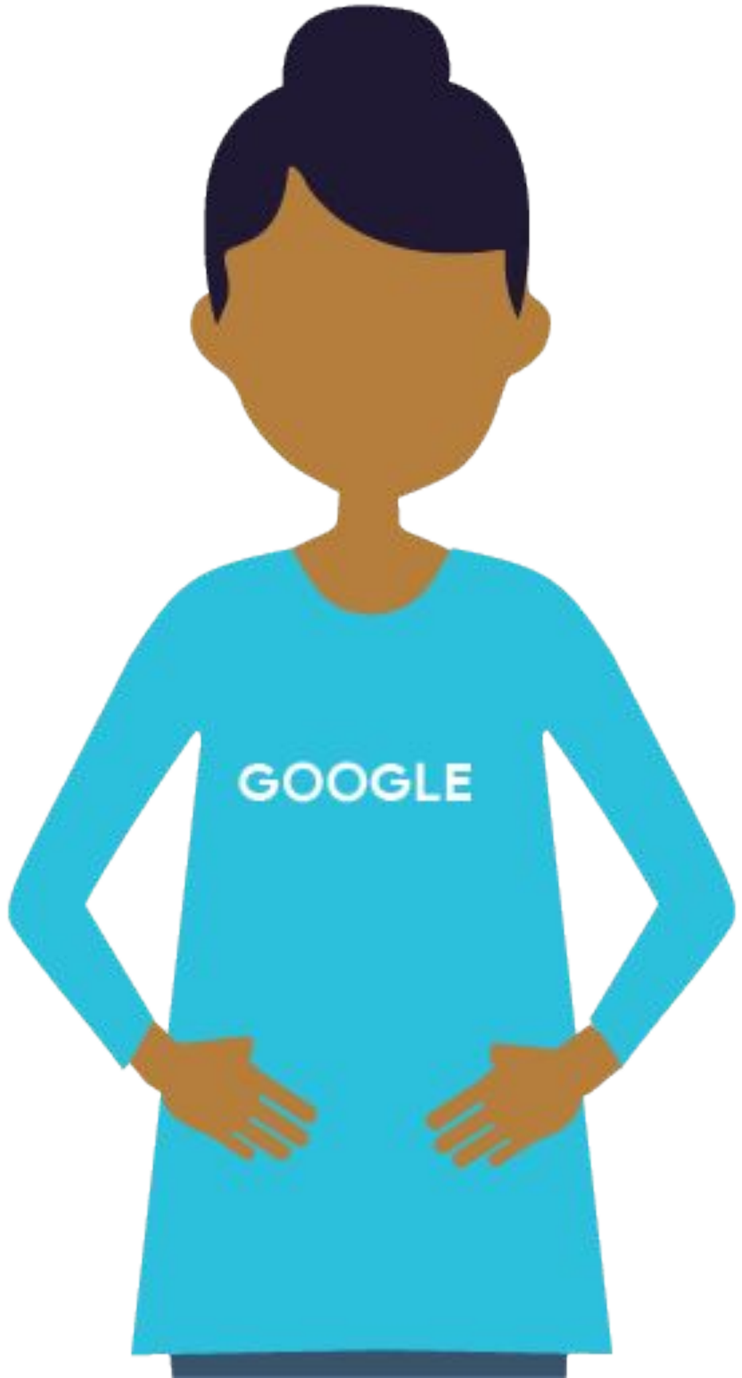


Learn how to...

Identify performance considerations for ML models

Choose appropriate ML infrastructure

Select a distribution strategy



Courses 7 - Production ML Systems

Module 4: Designing High-Performance ML Systems

Lesson Title: **Aspects of performance: Training**

Format: Presenter

Presenter: Laurence Moroney

Video Name: T-PSML-O_4_l2_aspects_of_performance:_training

Agenda

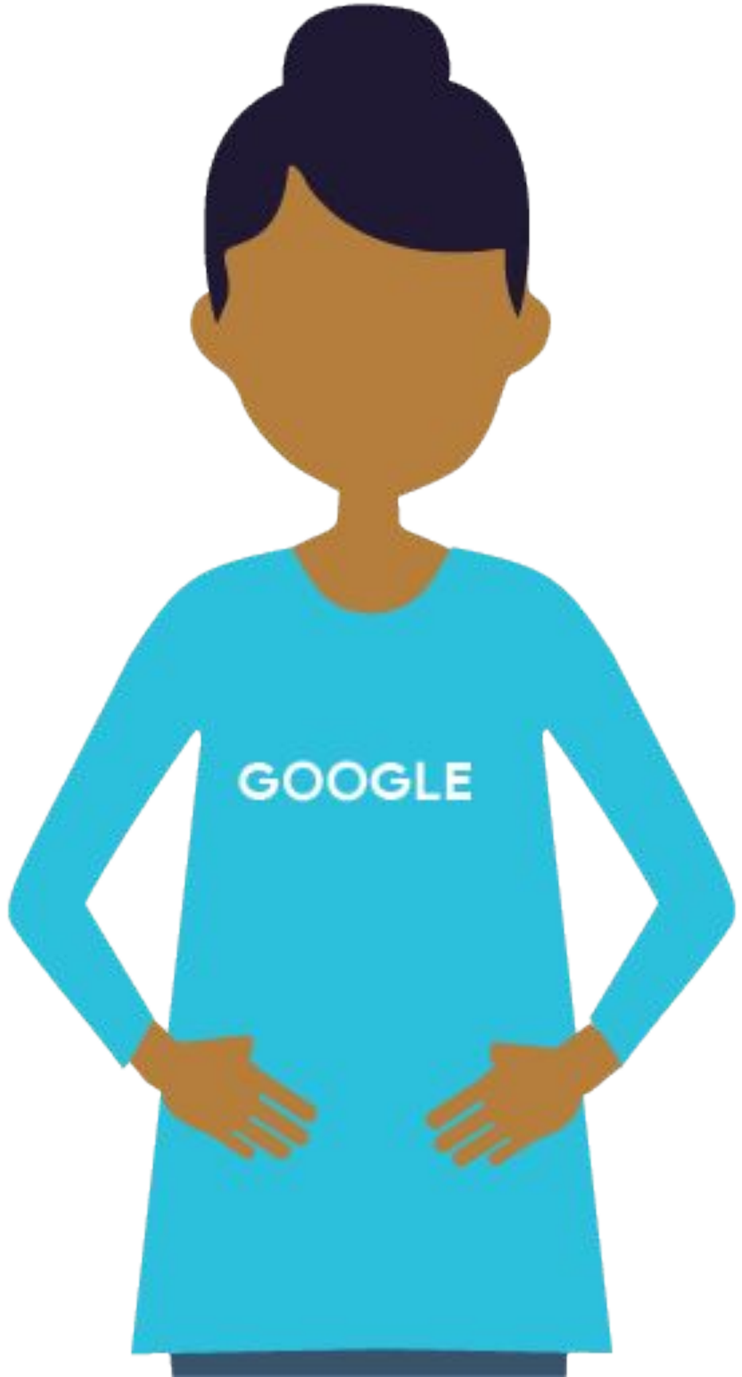
Distributed training

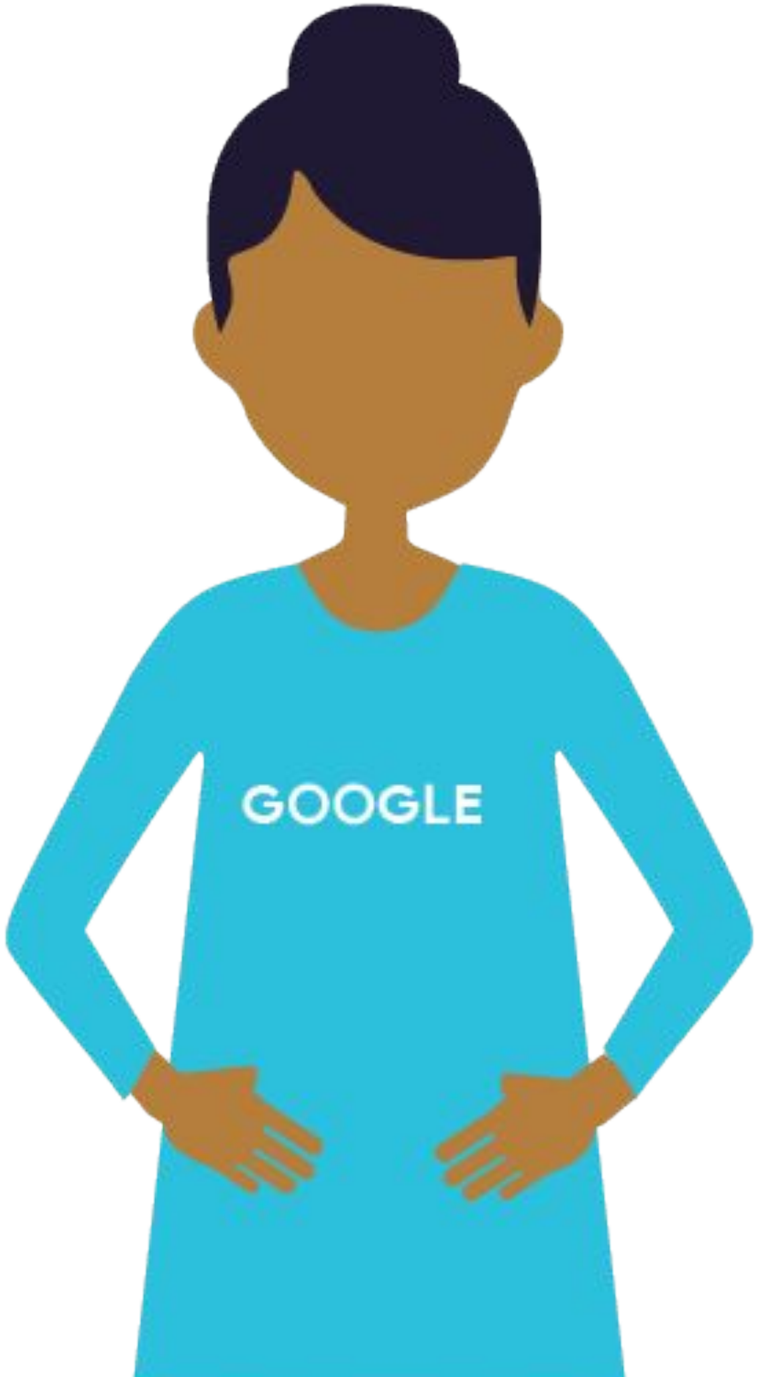
Faster input pipelines

Data parallelism (All Reduce)

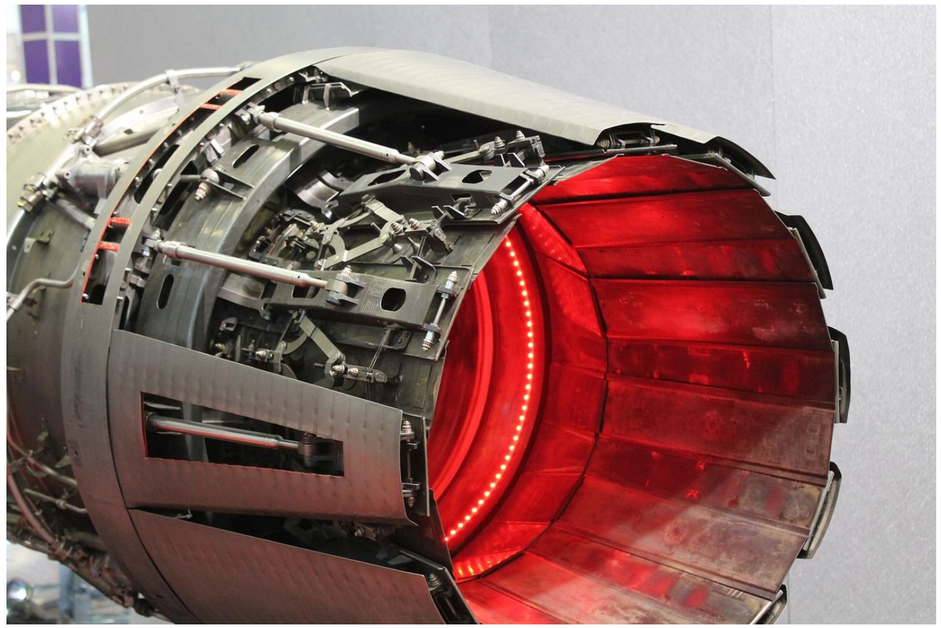
Parameter Server approach

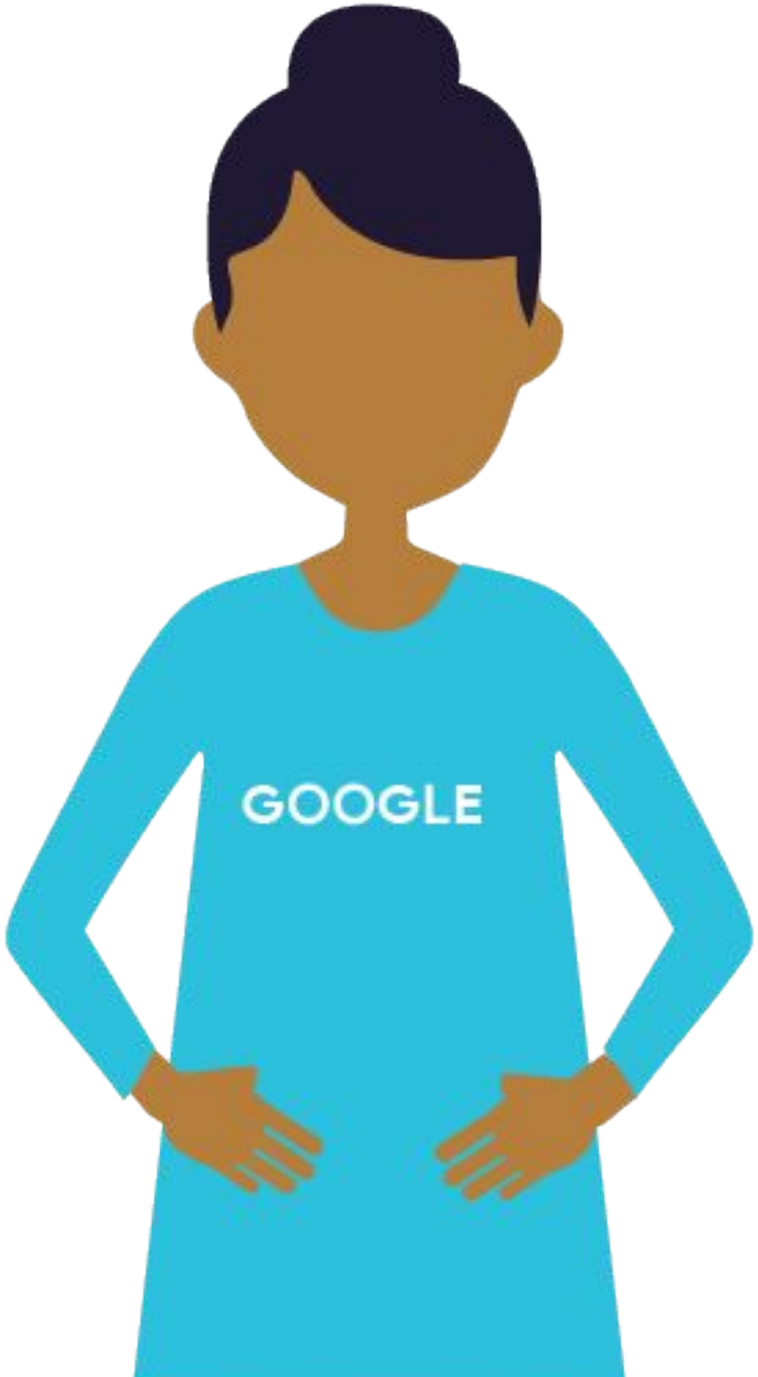
Inference



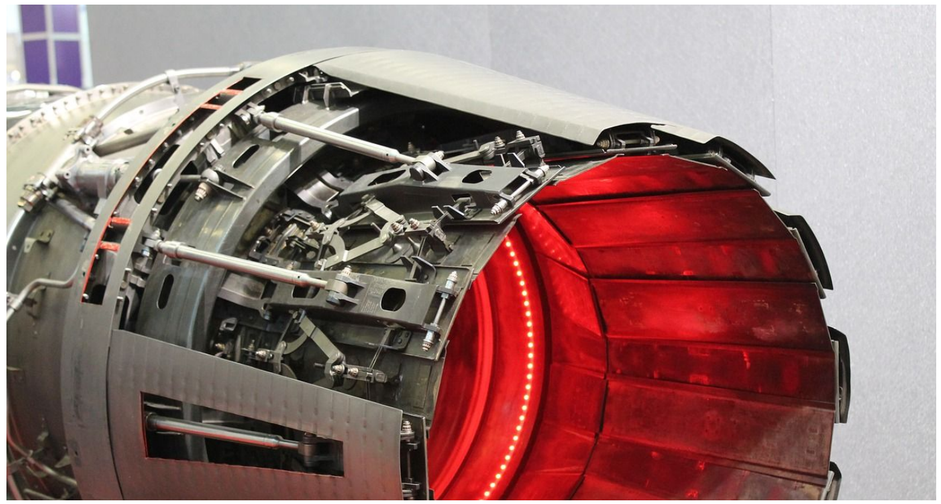


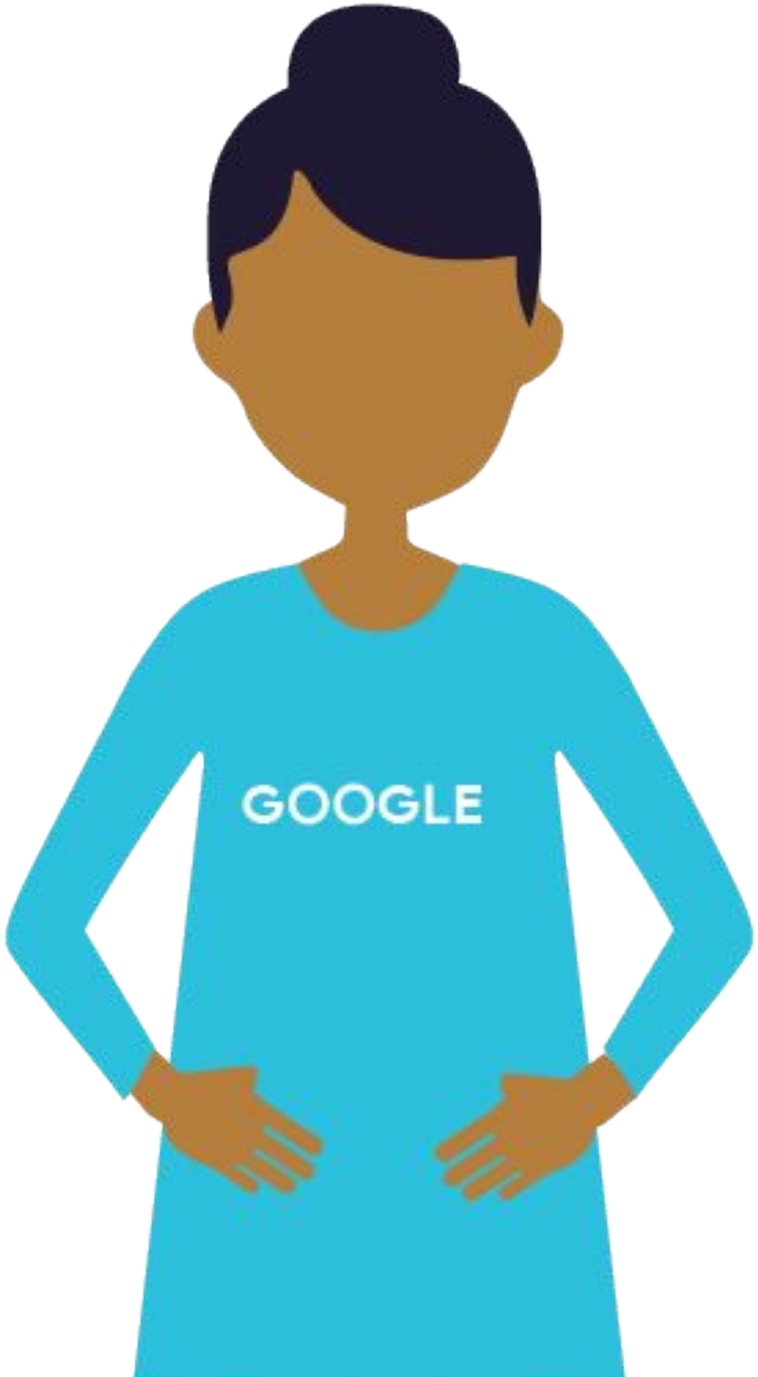
High Performance ML



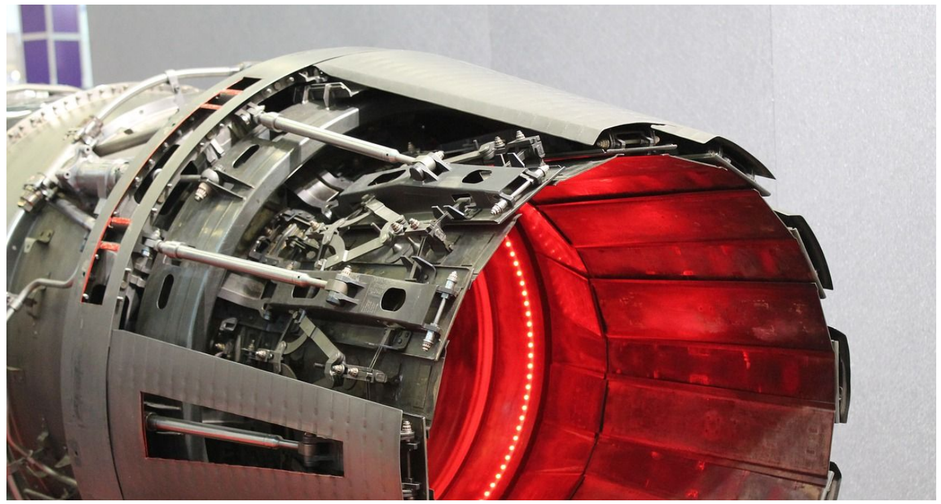


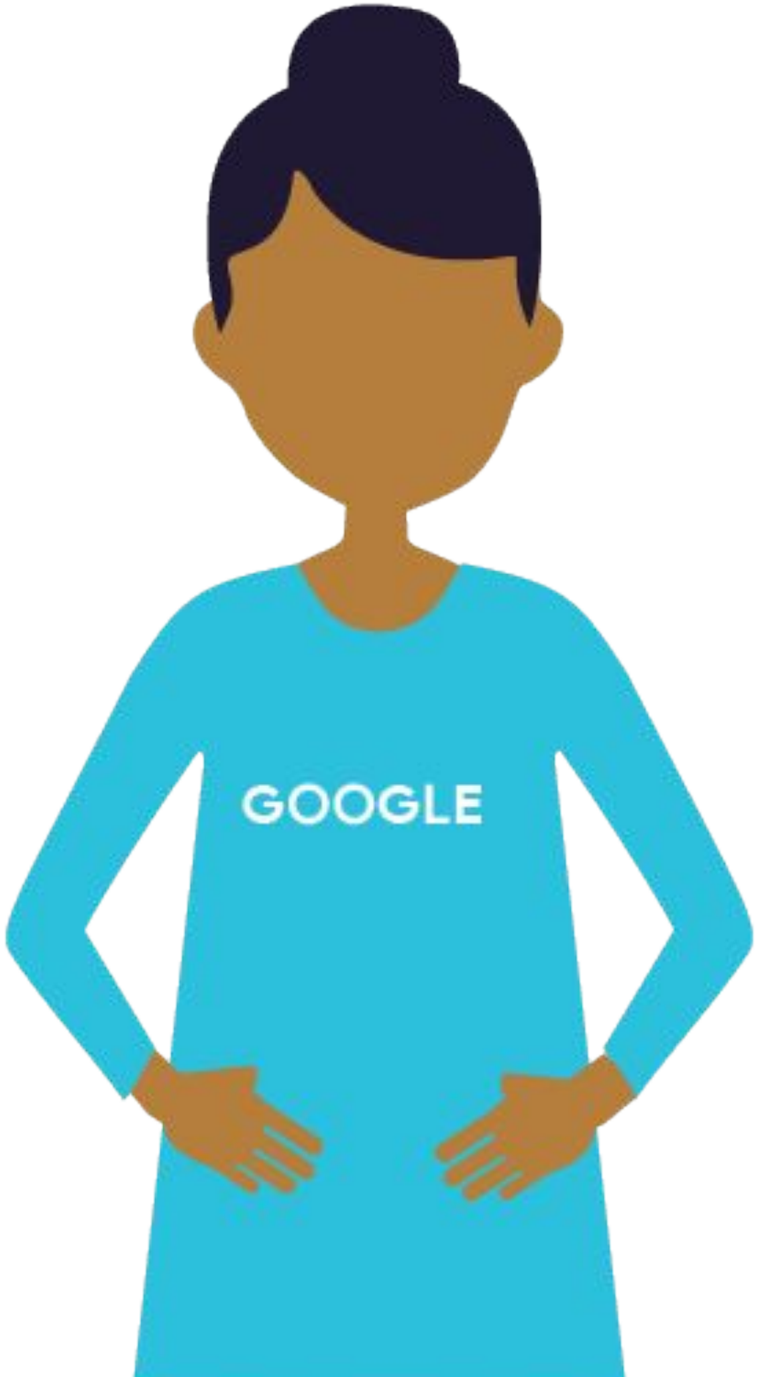
High Performance ML



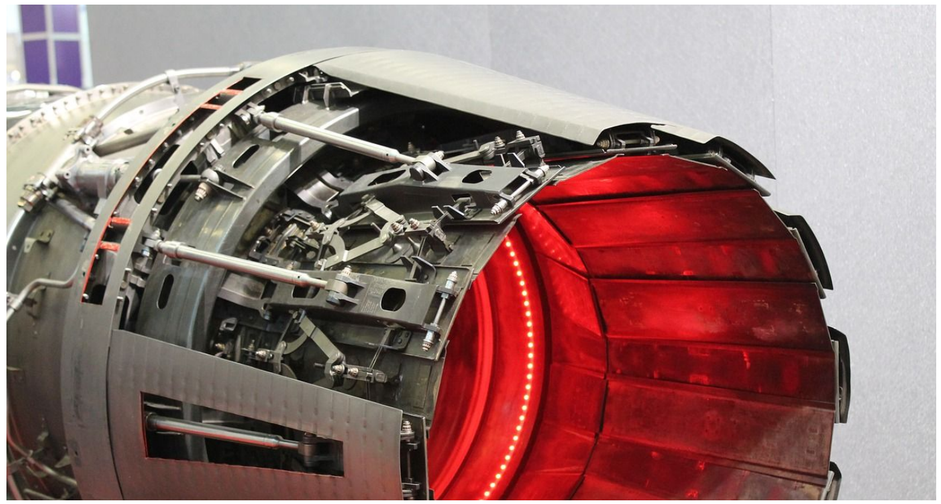


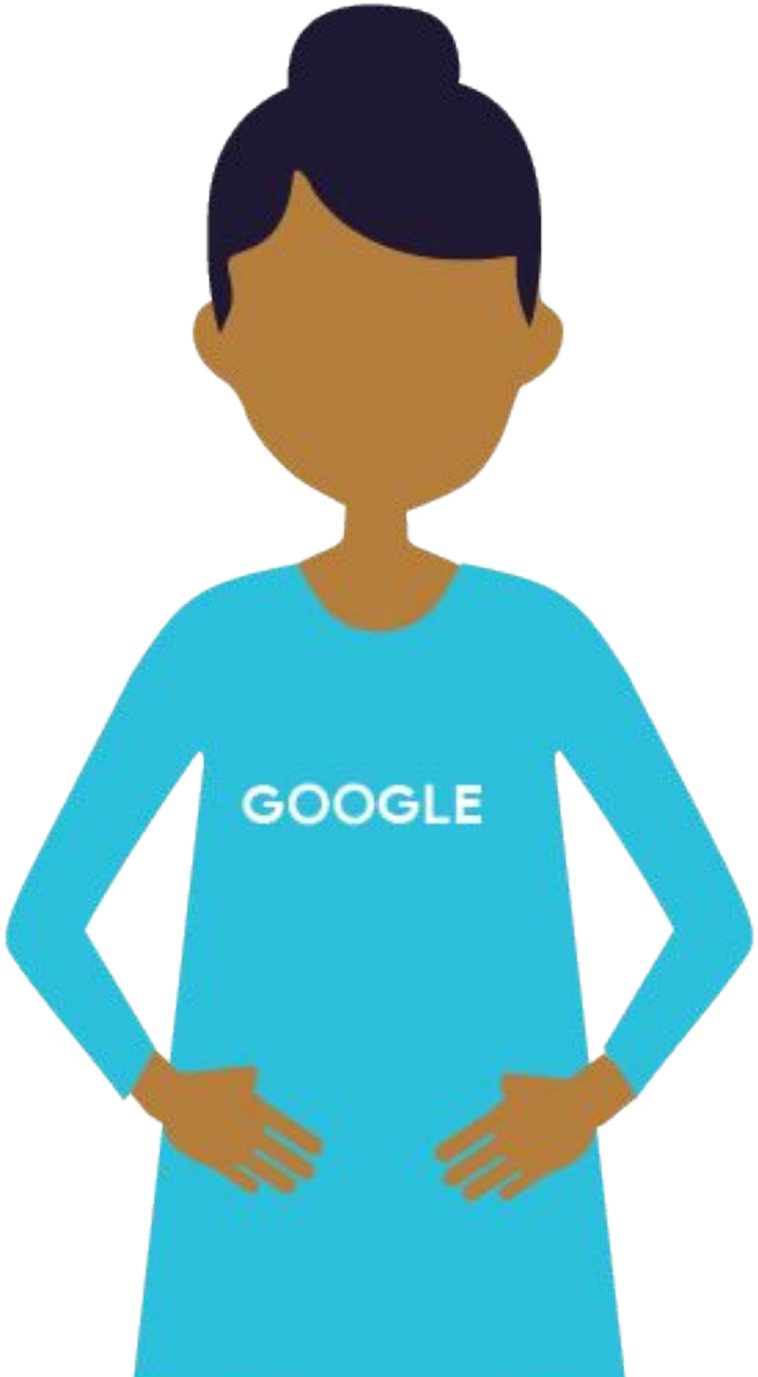
High Performance ML



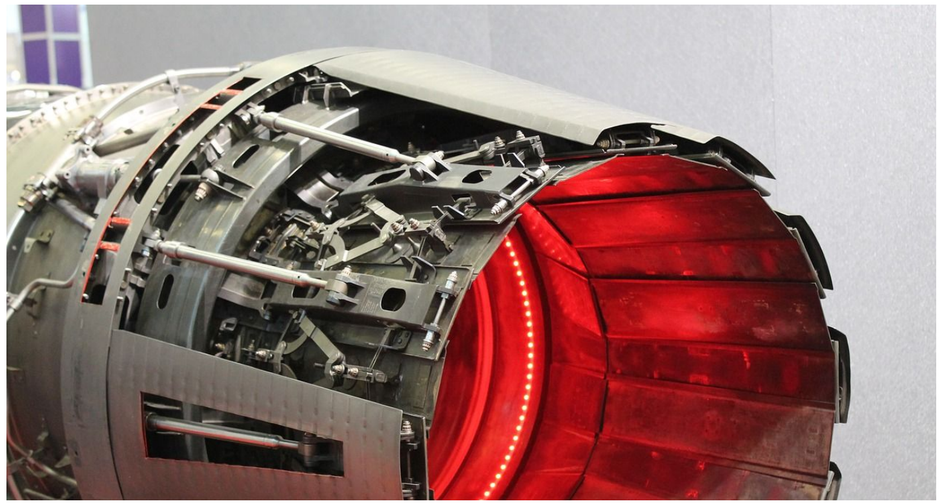


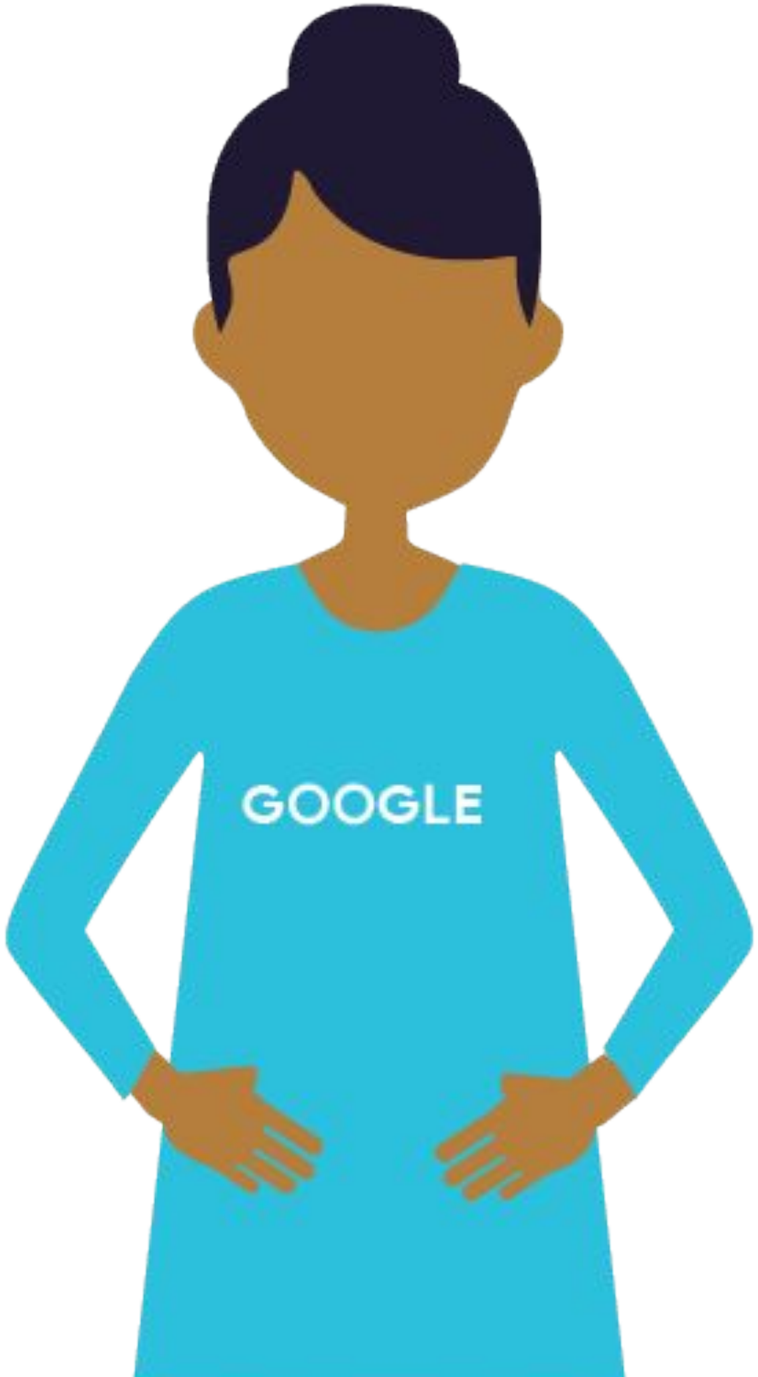
High Performance ML



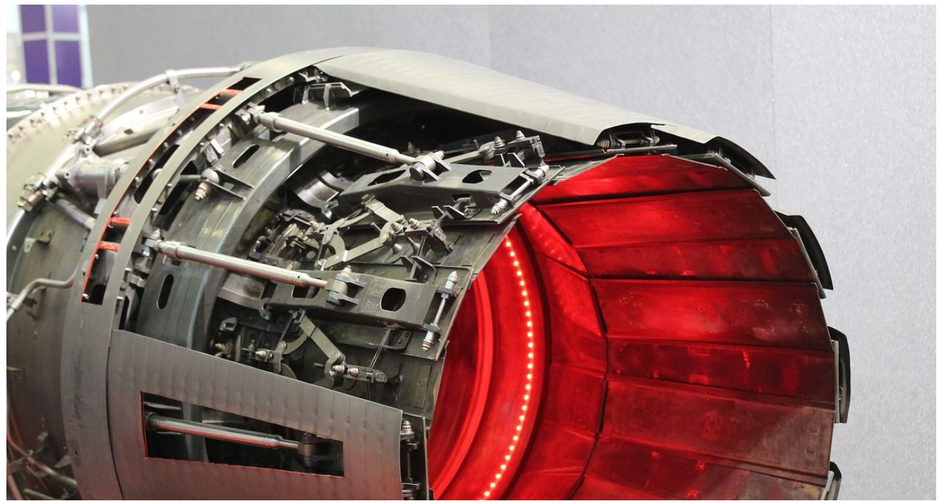


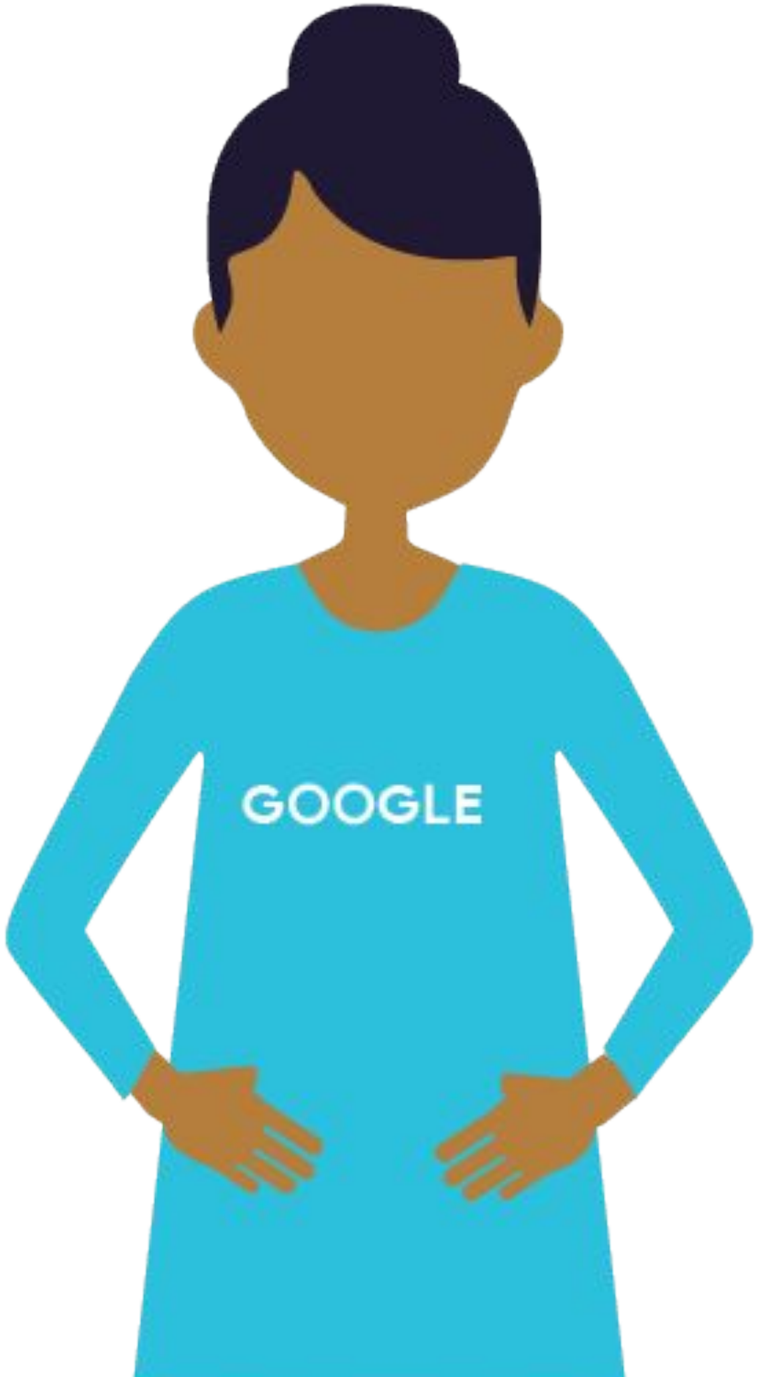
High Performance ML



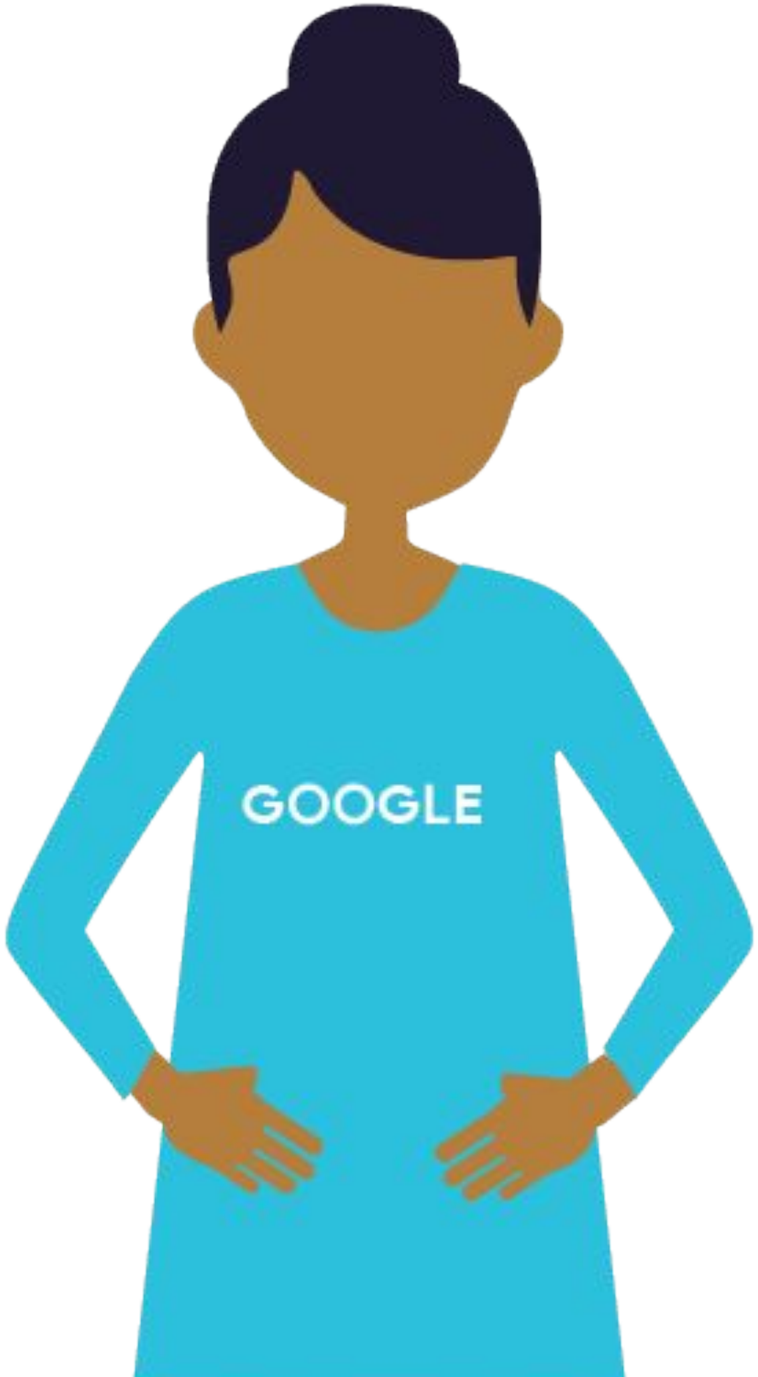


Model Training Time

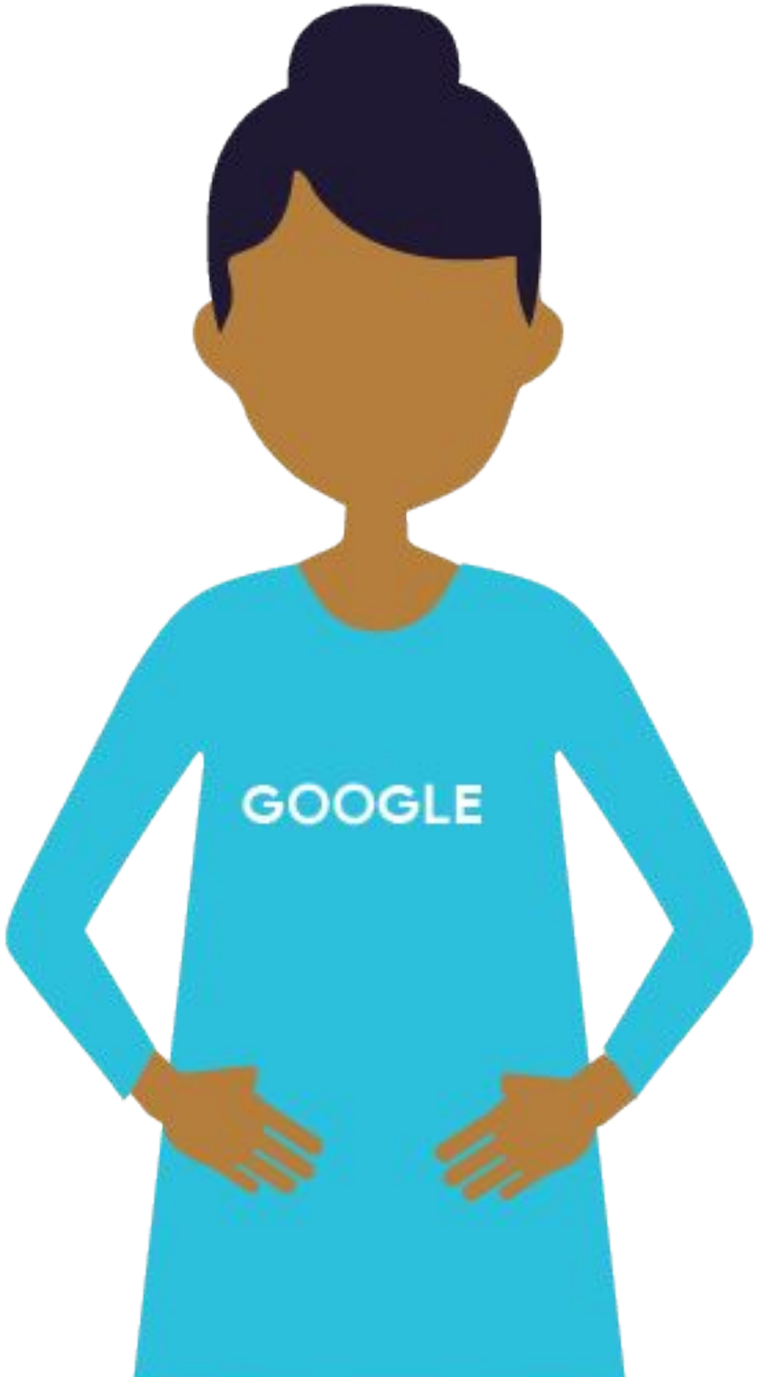




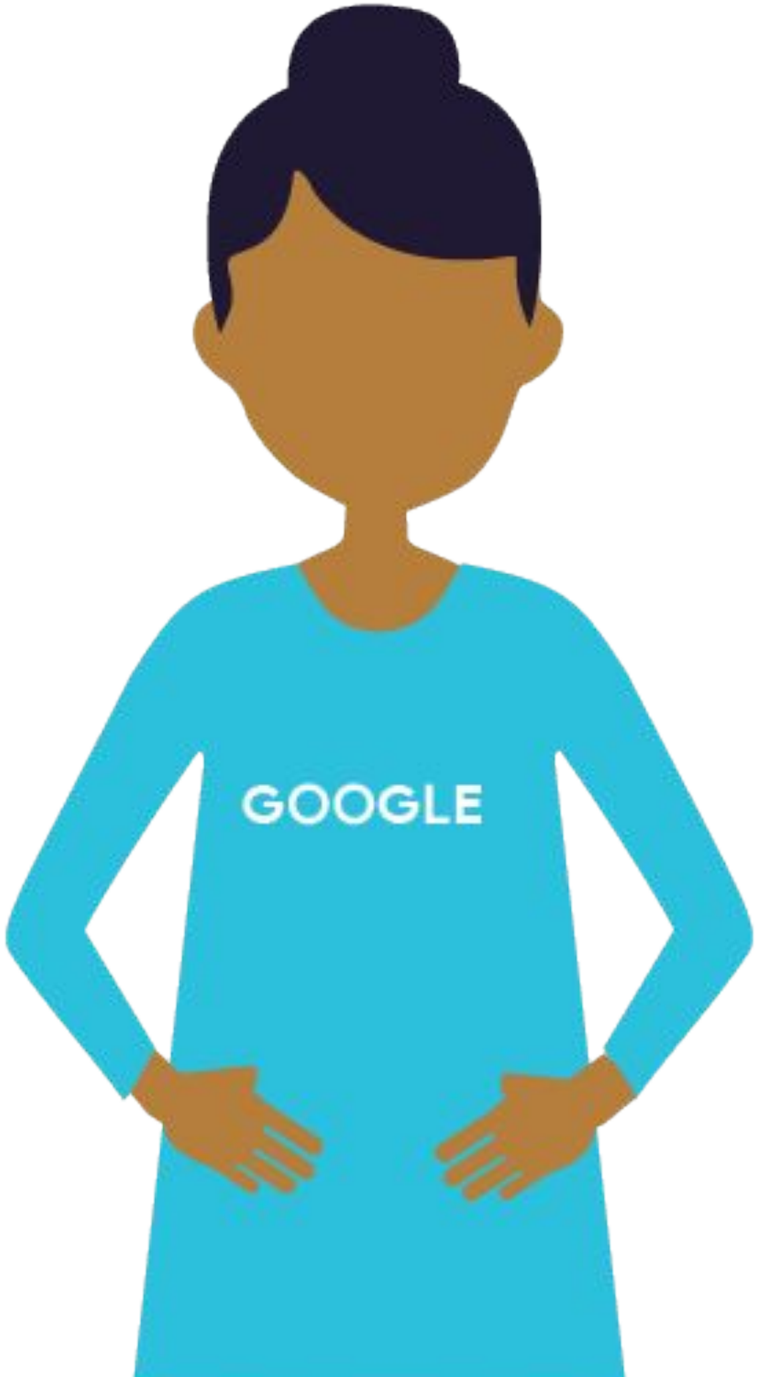
Model Training Time



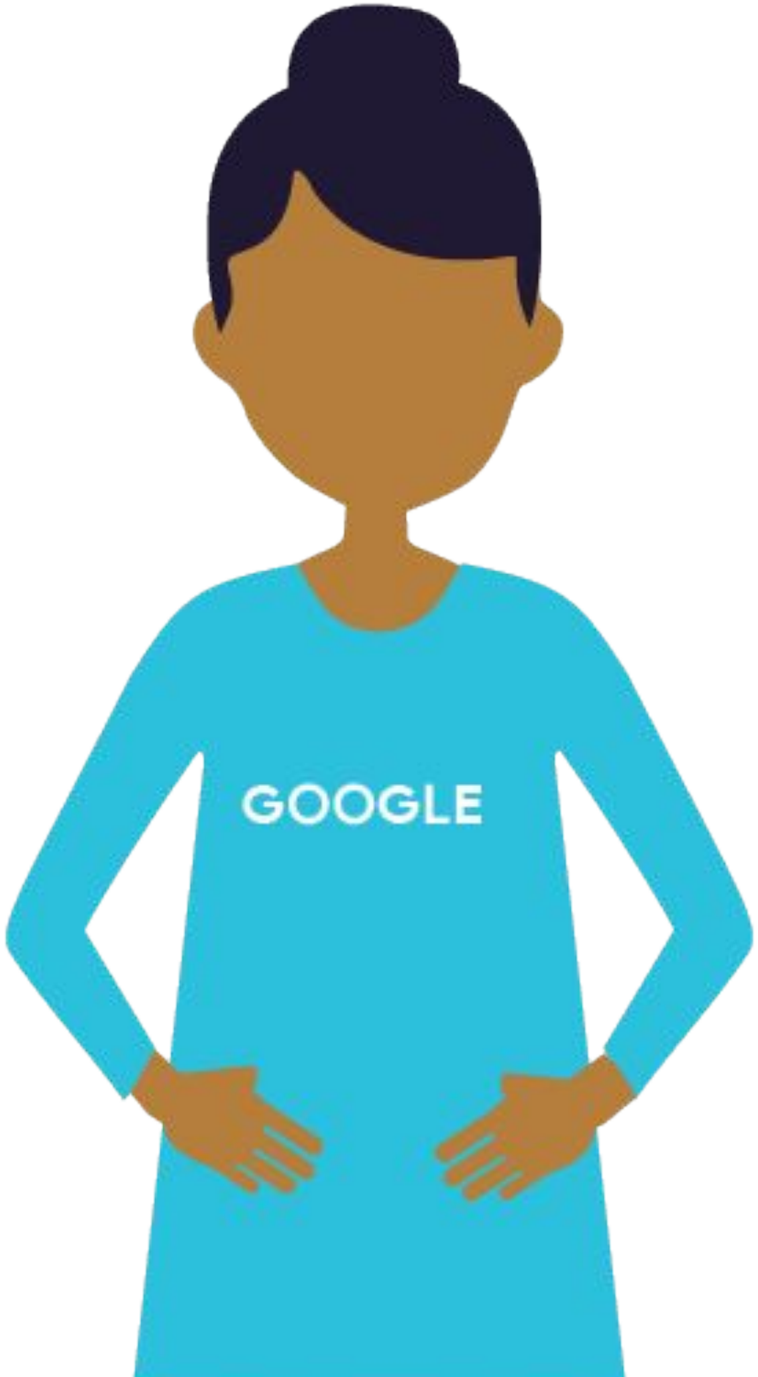
Model Training Time



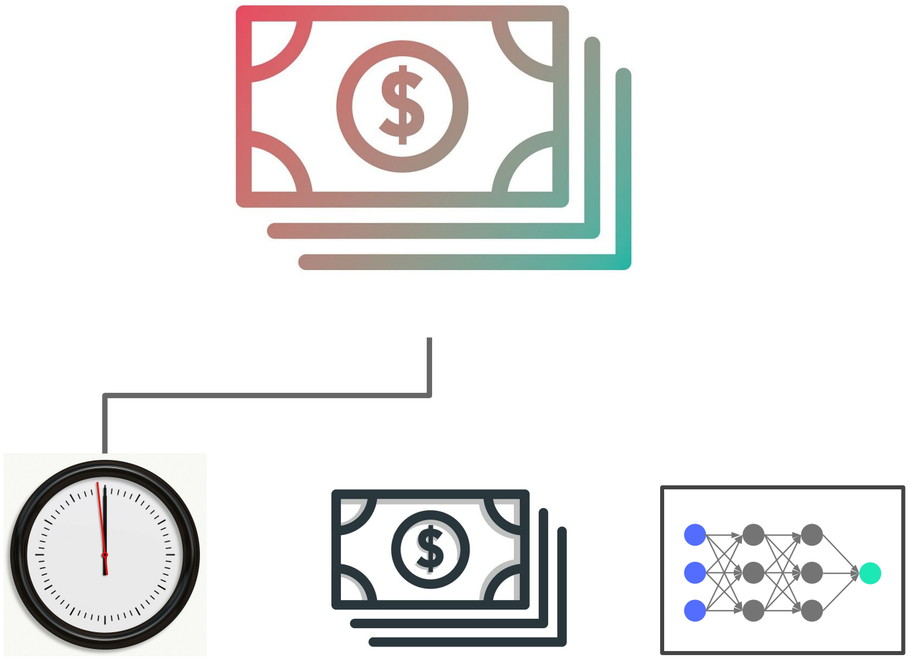
Model Training Time

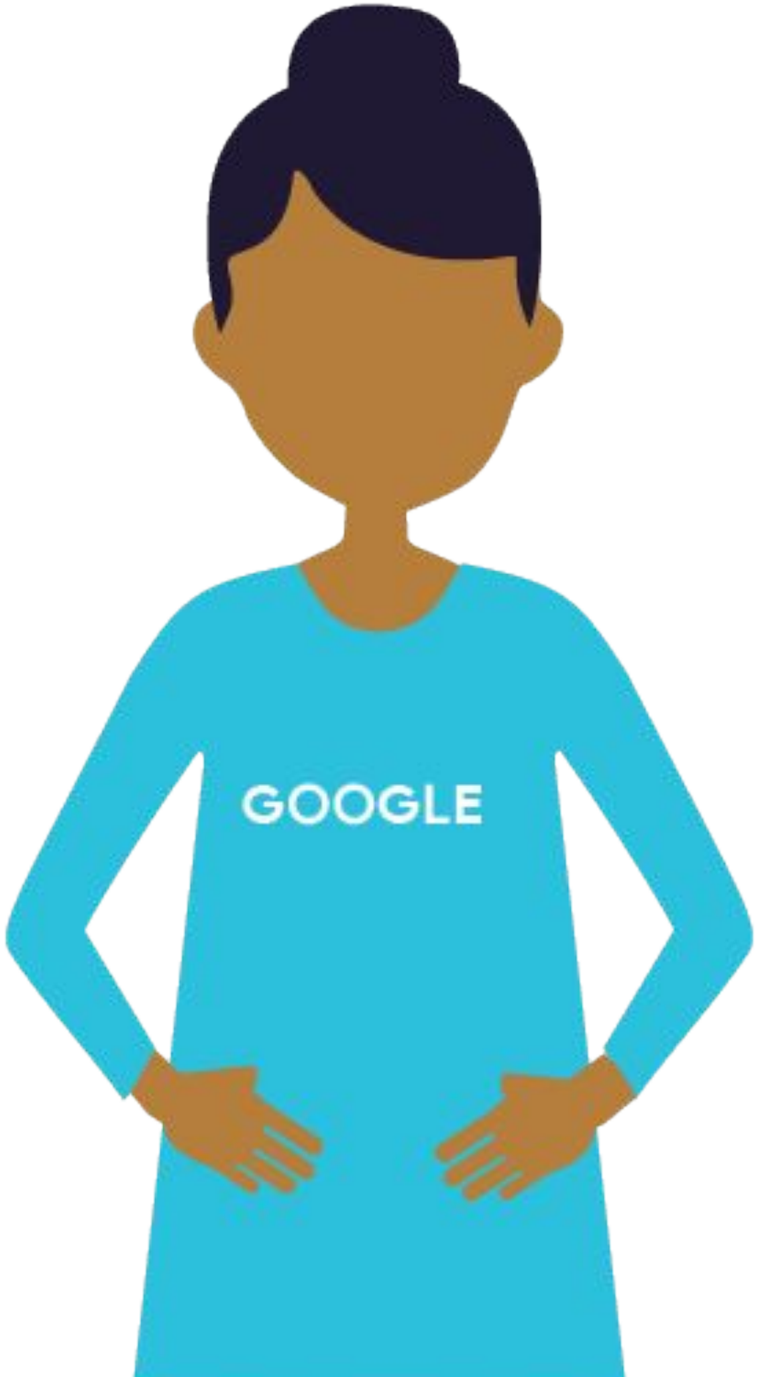


Optimizing your Training Budget

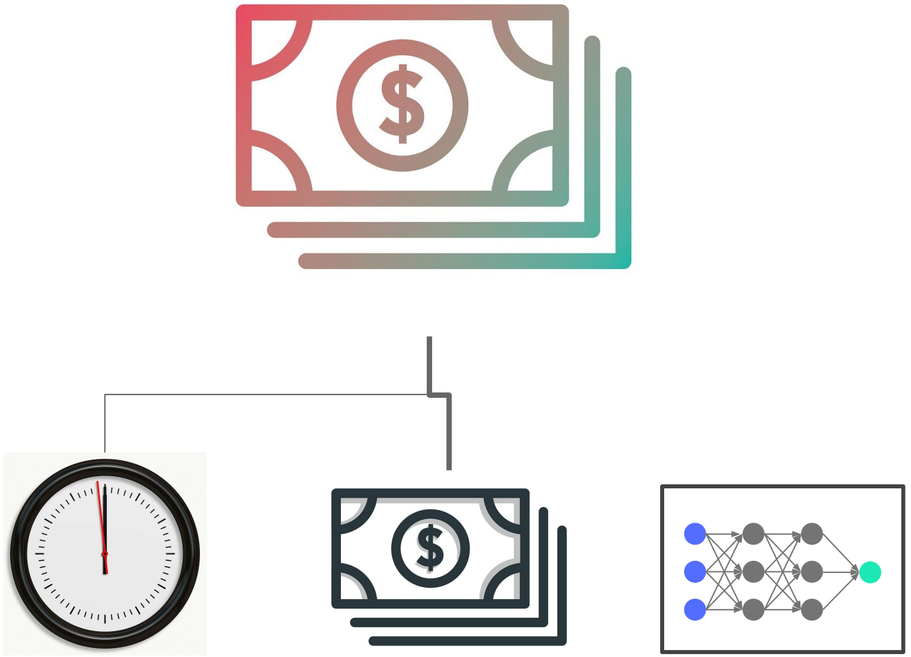


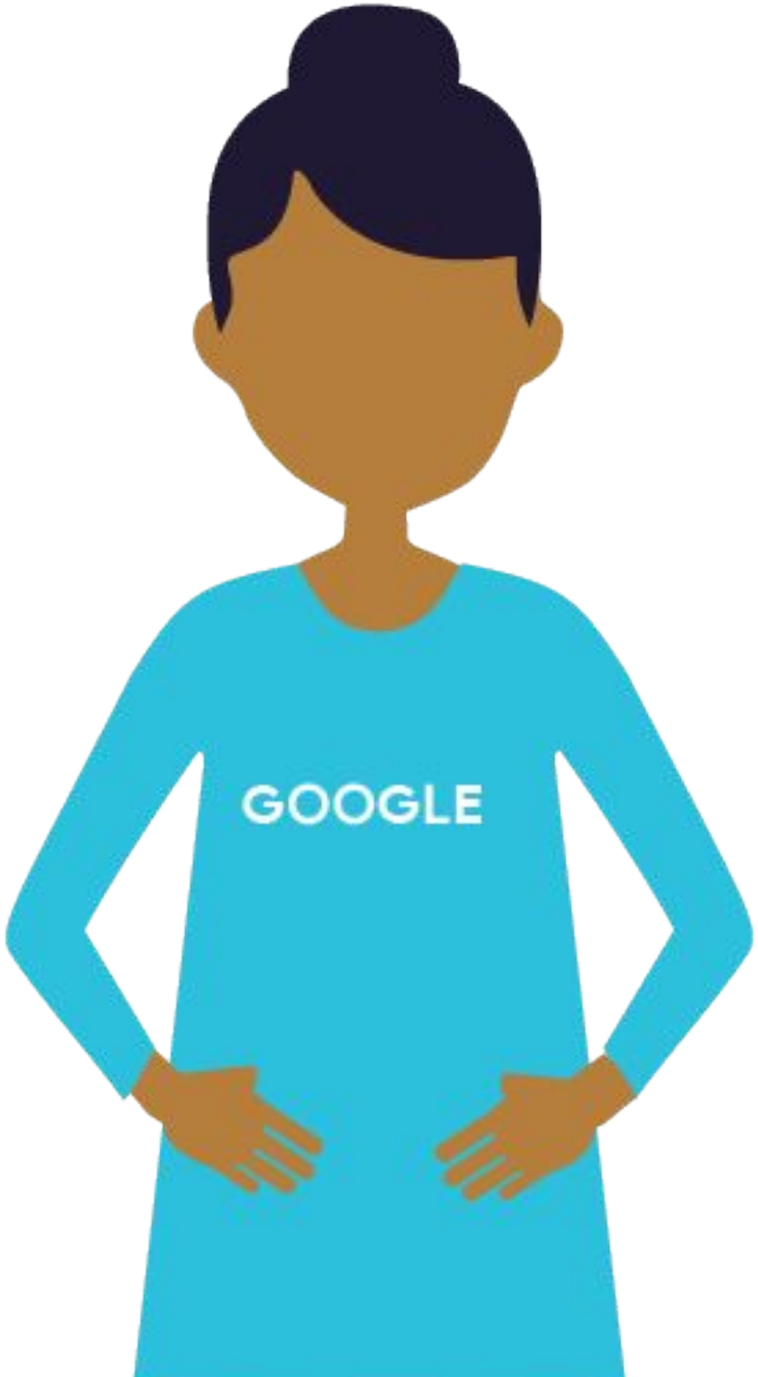
Optimizing your Training Budget



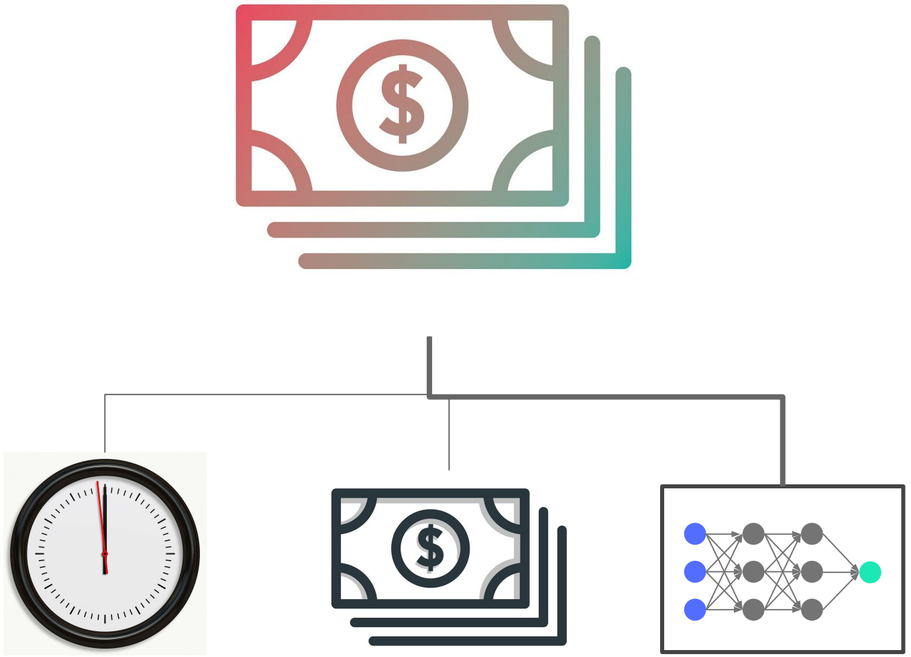


Optimizing your Training Budget

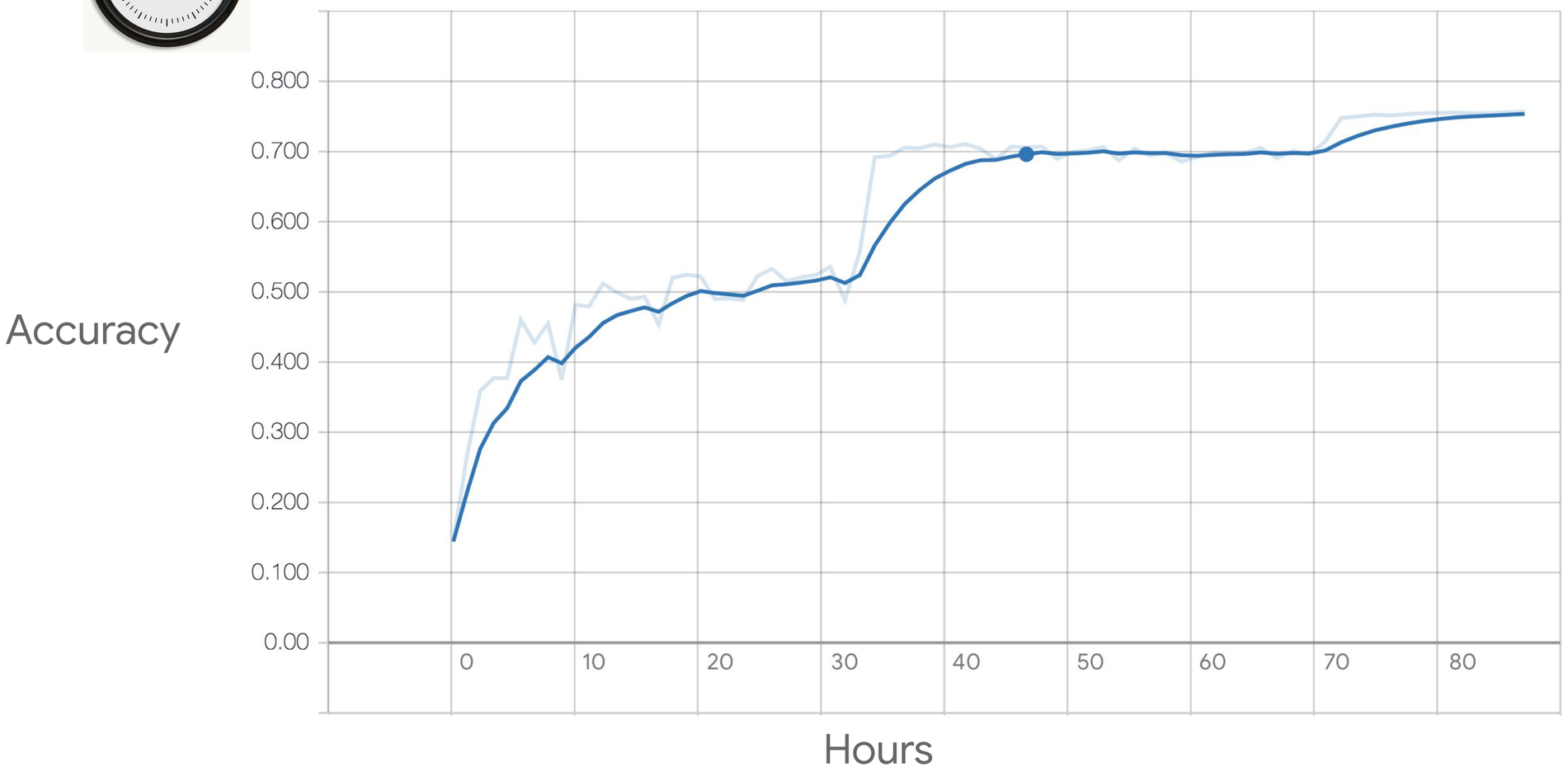




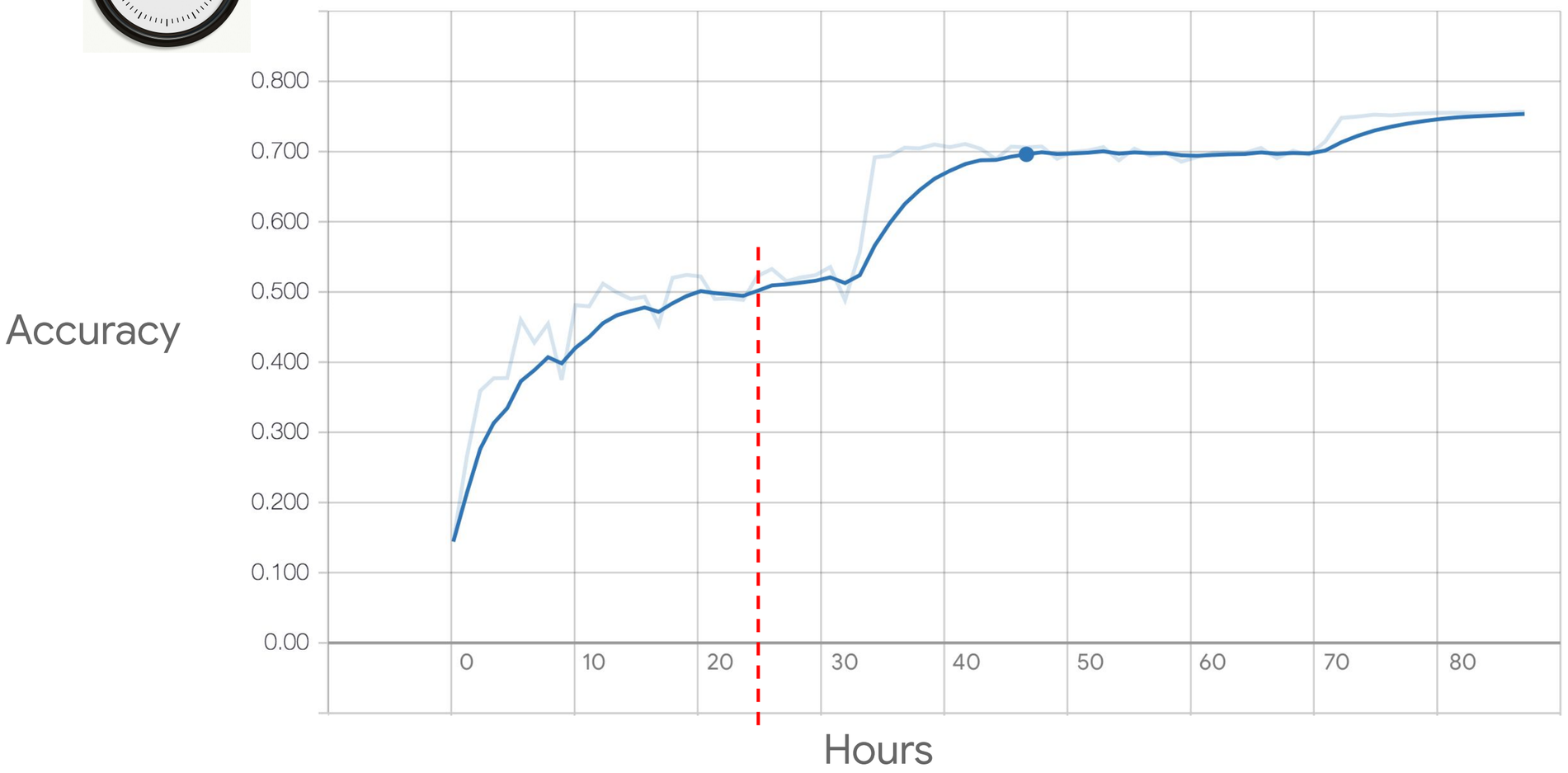
Optimizing your Training Budget



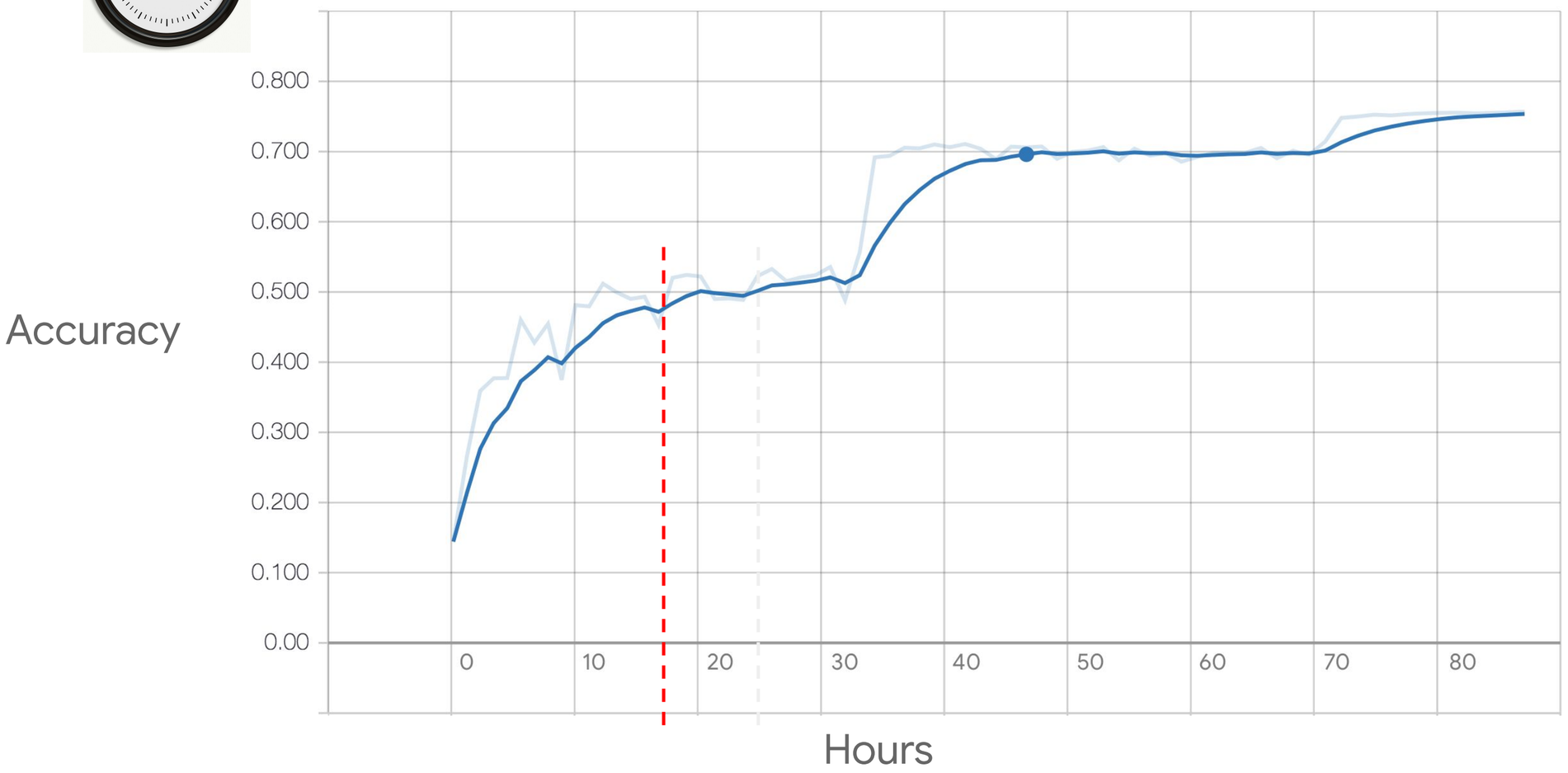
Model Training can take a long time

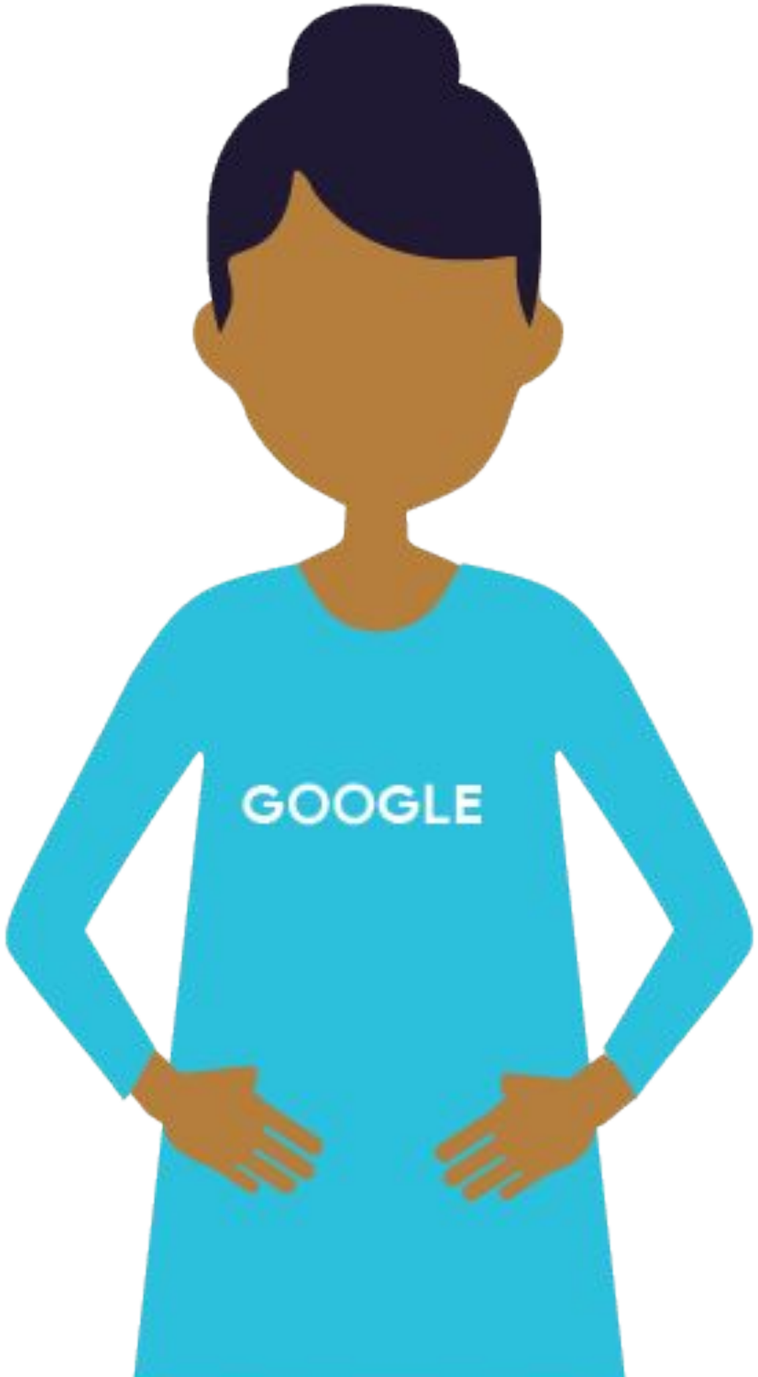


Model Training can take a long time

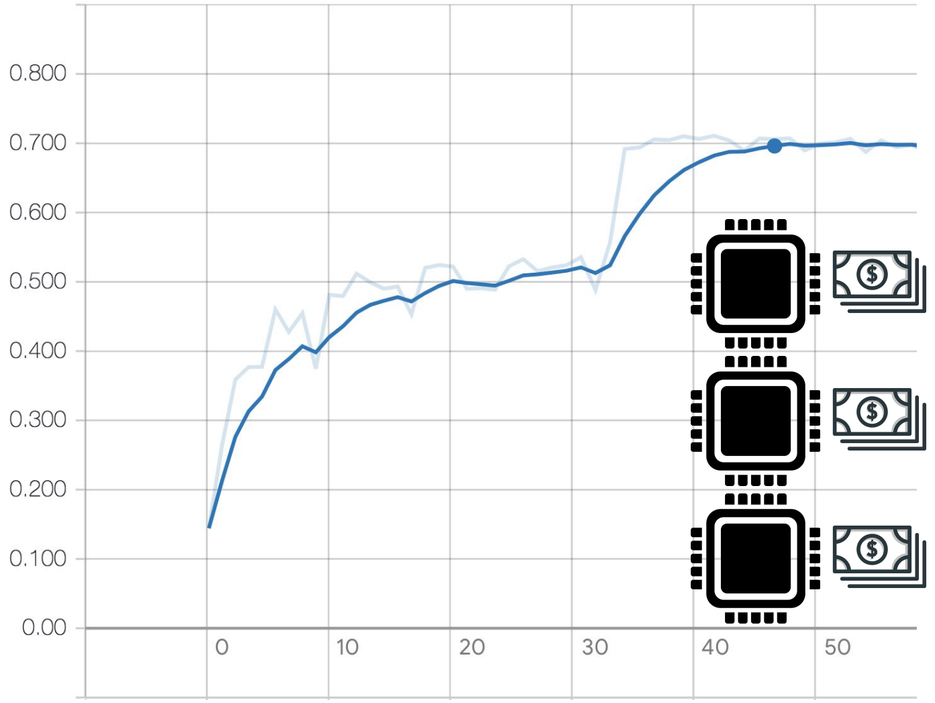


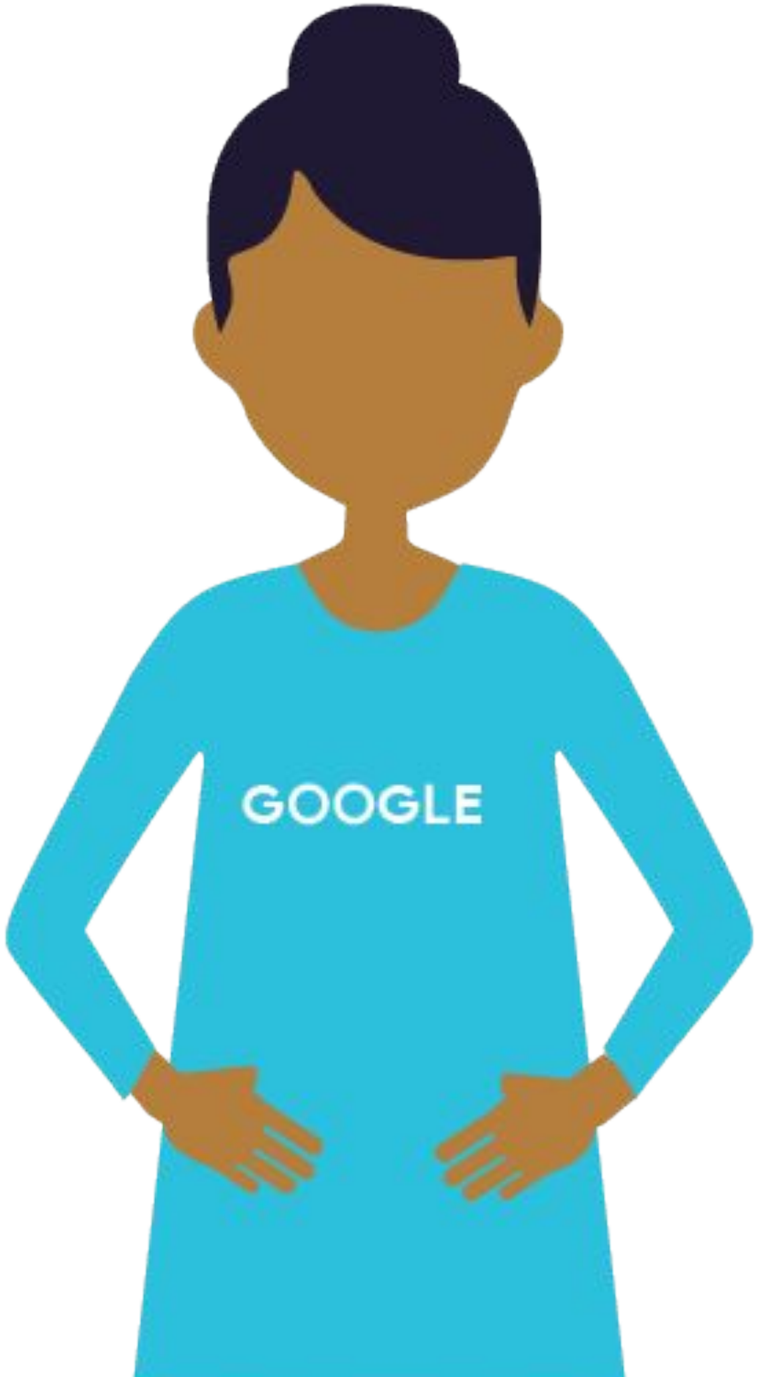
Model Training can take a long time



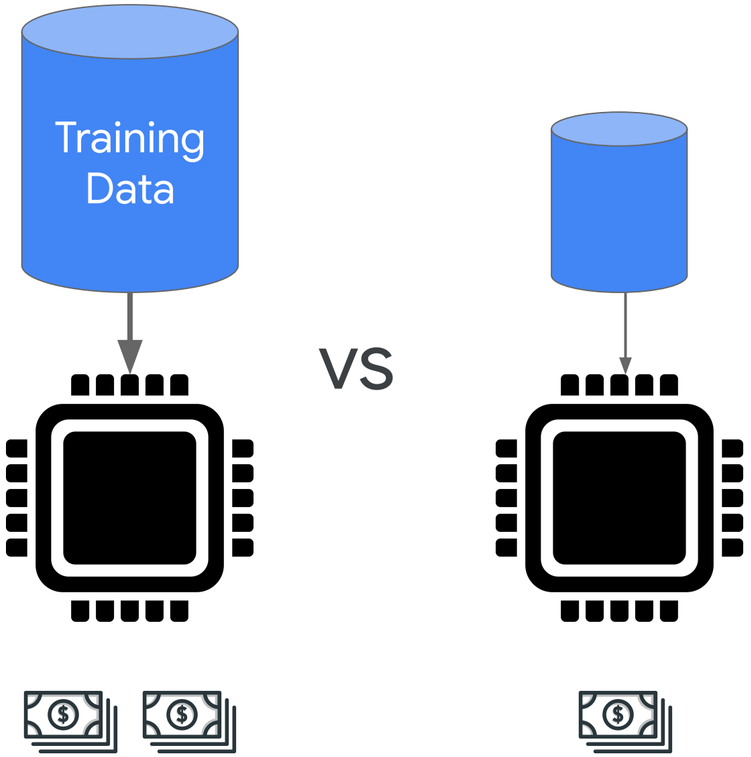


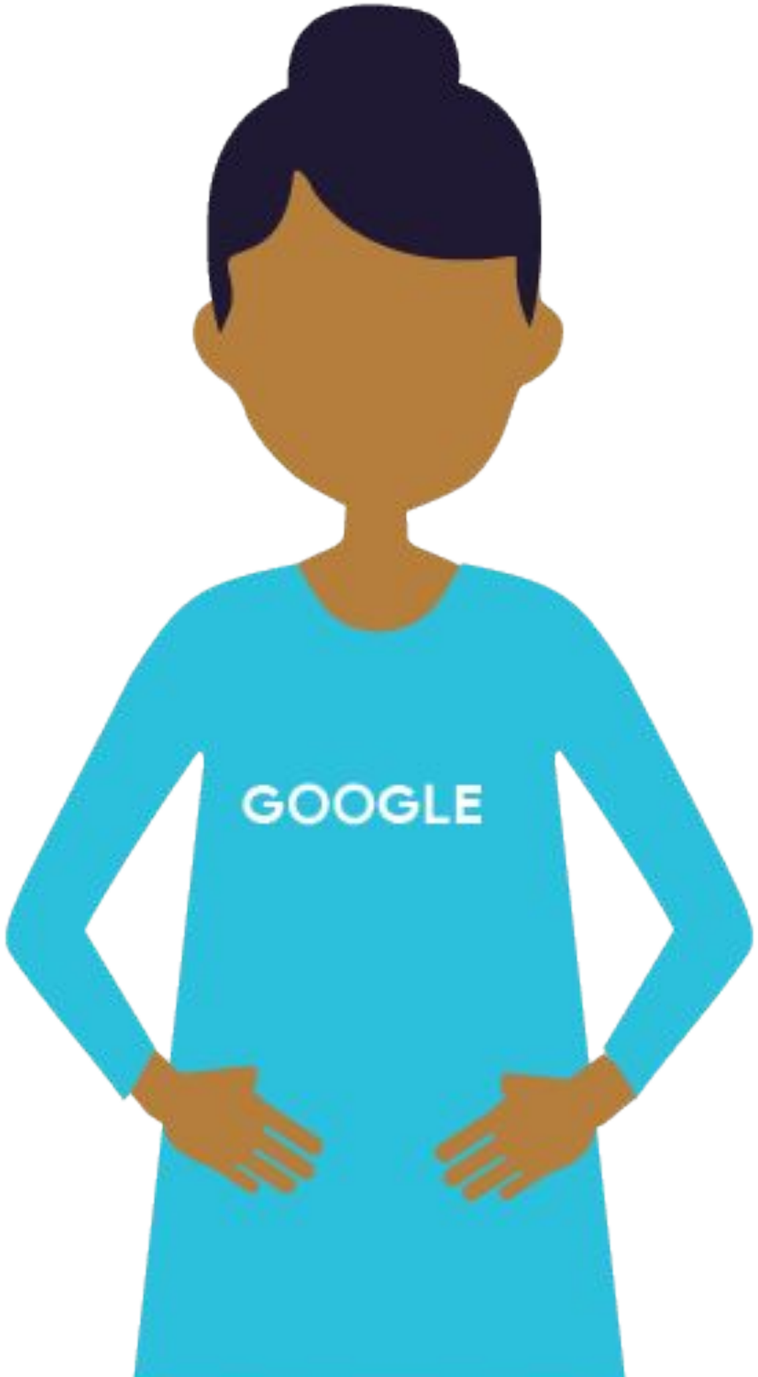
Analyze Benefit of Model vs Running Cost



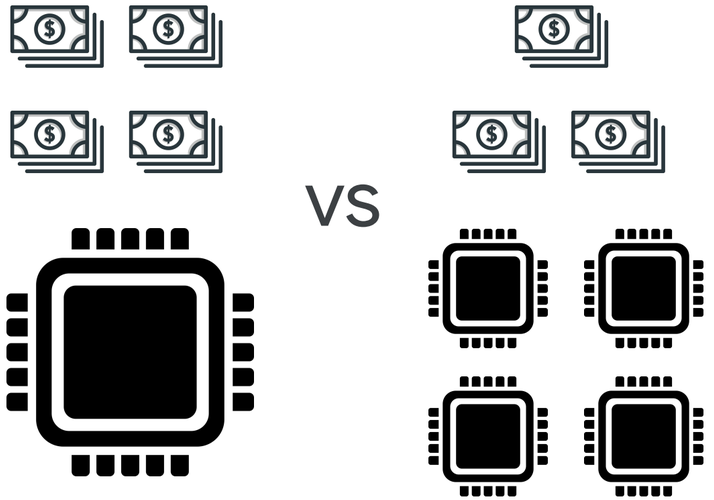


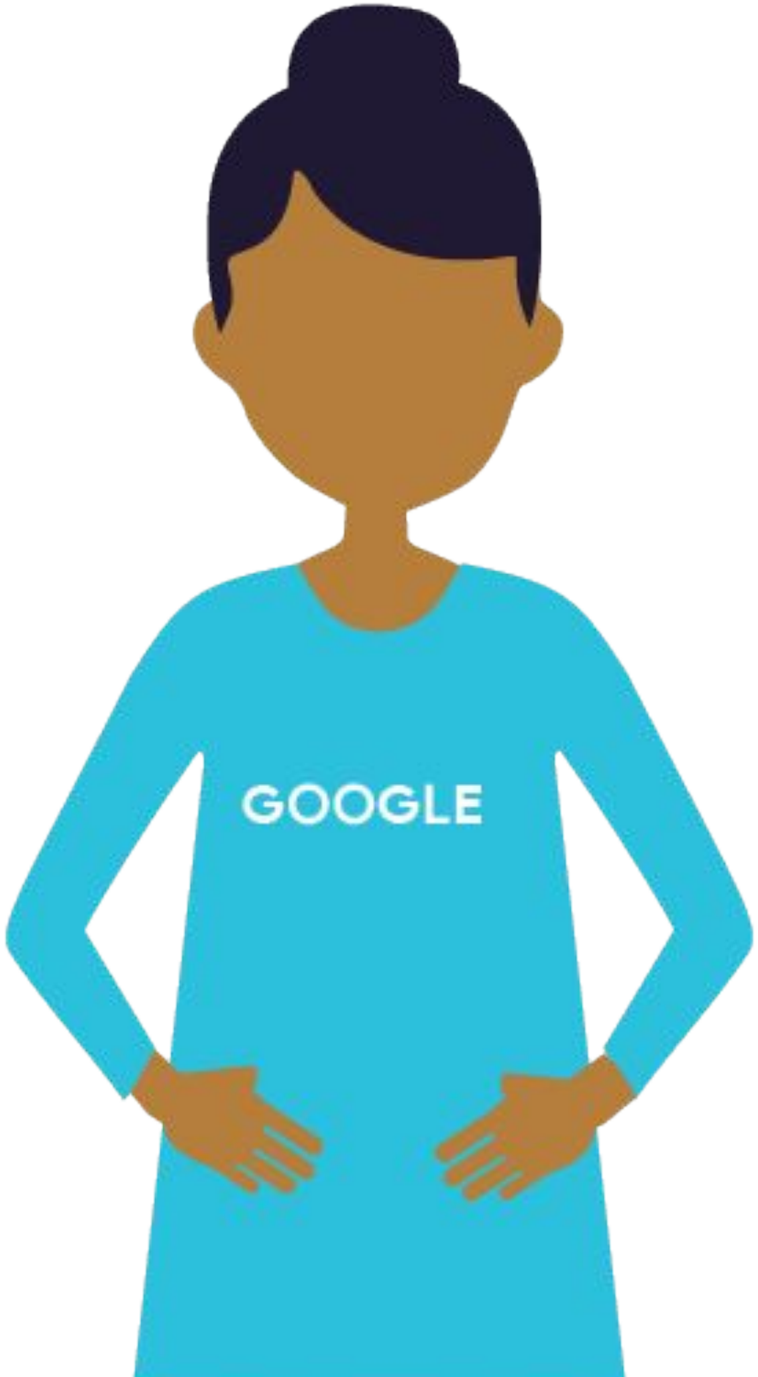
Optimize training dataset size



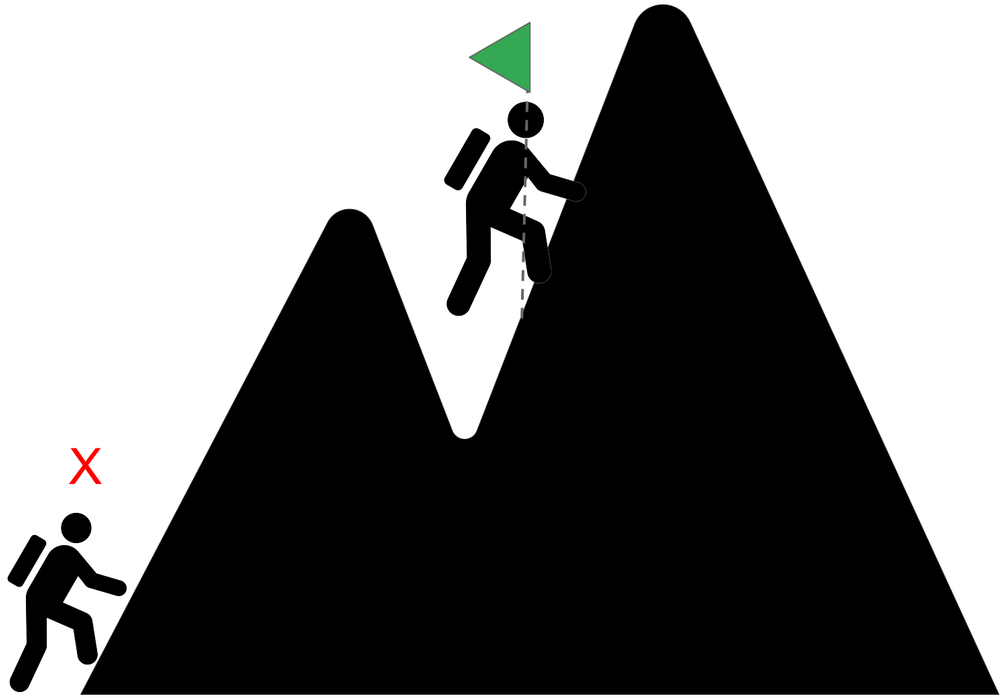


Choosing optimized infrastructure





Use earlier model checkpoints



Tuning Performance to reduce training time, reduce cost, and increase scale

Constraint	

Tuning Performance to reduce training time, reduce cost, and increase scale

Constraint	Input / Output

Tuning Performance to reduce training time, reduce cost, and increase scale

Constraint	Input / Output	CPU

Tuning Performance to reduce training time, reduce cost, and increase scale

Constraint	Input / Output	CPU	Memory

Tuning Performance to reduce training time, reduce cost, and increase scale

Constraint	Input / Output	CPU	Memory
Commonly Occurs	Large inputs Input requires parsing Small models		

Tuning Performance to reduce training time, reduce cost, and increase scale

Constraint	Input / Output	CPU	Memory
Commonly Occurs	Large inputs Input requires parsing Small models	Expensive computations Underpowered Hardware	

Tuning Performance to reduce training time, reduce cost, and increase scale

Constraint	Input / Output	CPU	Memory
Commonly Occurs	Large inputs Input requires parsing Small models	Expensive computations Underpowered Hardware	Large number of inputs Complex model

Tuning Performance to reduce training time, reduce cost, and increase scale

Constraint	Input / Output	CPU	Memory
Commonly Occurs	Large inputs Input requires parsing Small models	Expensive computations Underpowered Hardware	Large number of inputs Complex model
Take Action	Store efficiently Parallelize reads Consider batch size		

Tuning Performance to reduce training time, reduce cost, and increase scale

Constraint	Input / Output	CPU	Memory
Commonly Occurs	Large inputs Input requires parsing Small models	Expensive computations Underpowered Hardware	Large number of inputs Complex model
Take Action	Store efficiently Parallelize reads Consider batch size	Train on faster accel. Upgrade processor Run on TPUs Simplify model	

Tuning Performance to reduce training time, reduce cost, and increase scale

Constraint	Input / Output	CPU	Memory
Commonly Occurs	Large inputs Input requires parsing Small models	Expensive computations Underpowered Hardware	Large number of inputs Complex model
Take Action	Store efficiently Parallelize reads Consider batch size	Train on faster accel. Upgrade processor Run on TPUs Simplify model	Add more memory Use fewer layers Reduce batch size

Courses 7 - Production ML Systems

Module 4: Designing High-Performance ML Systems

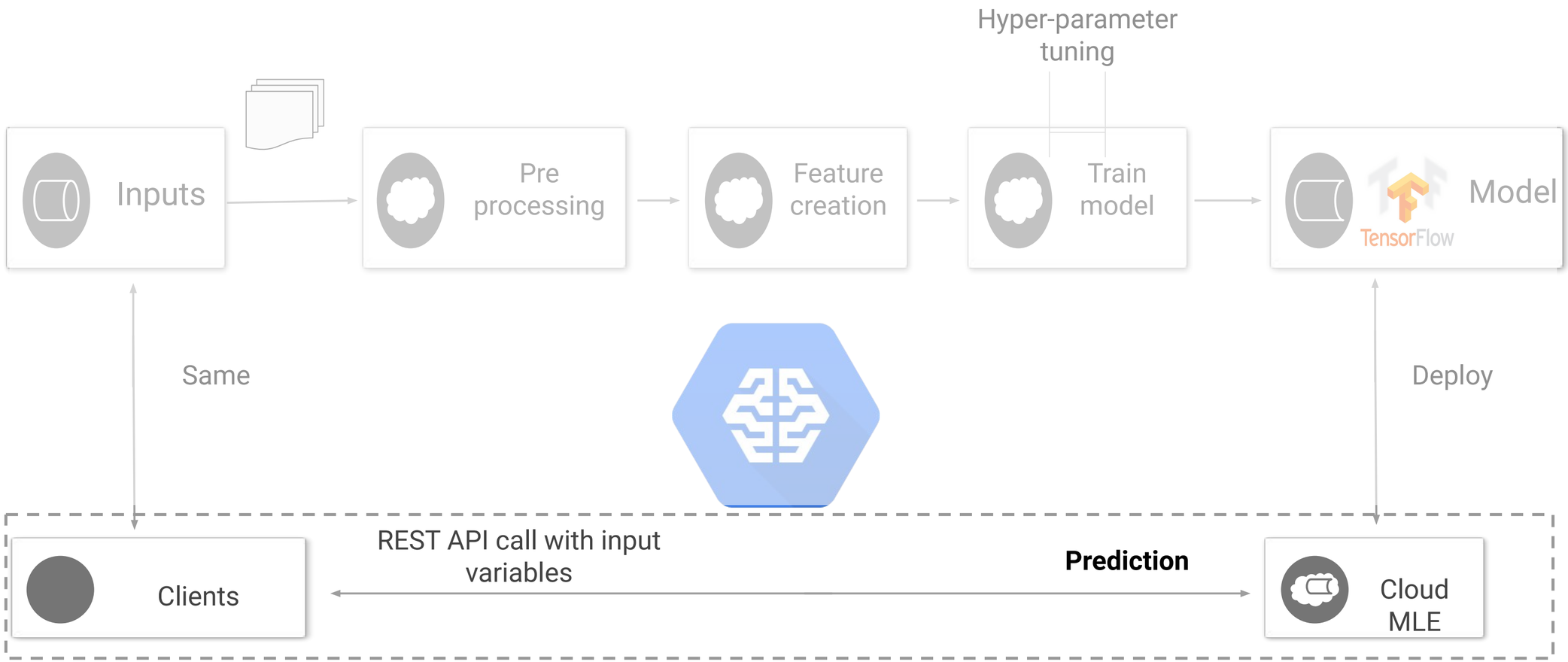
Lesson Title: **Aspects of Performance: Predictions**

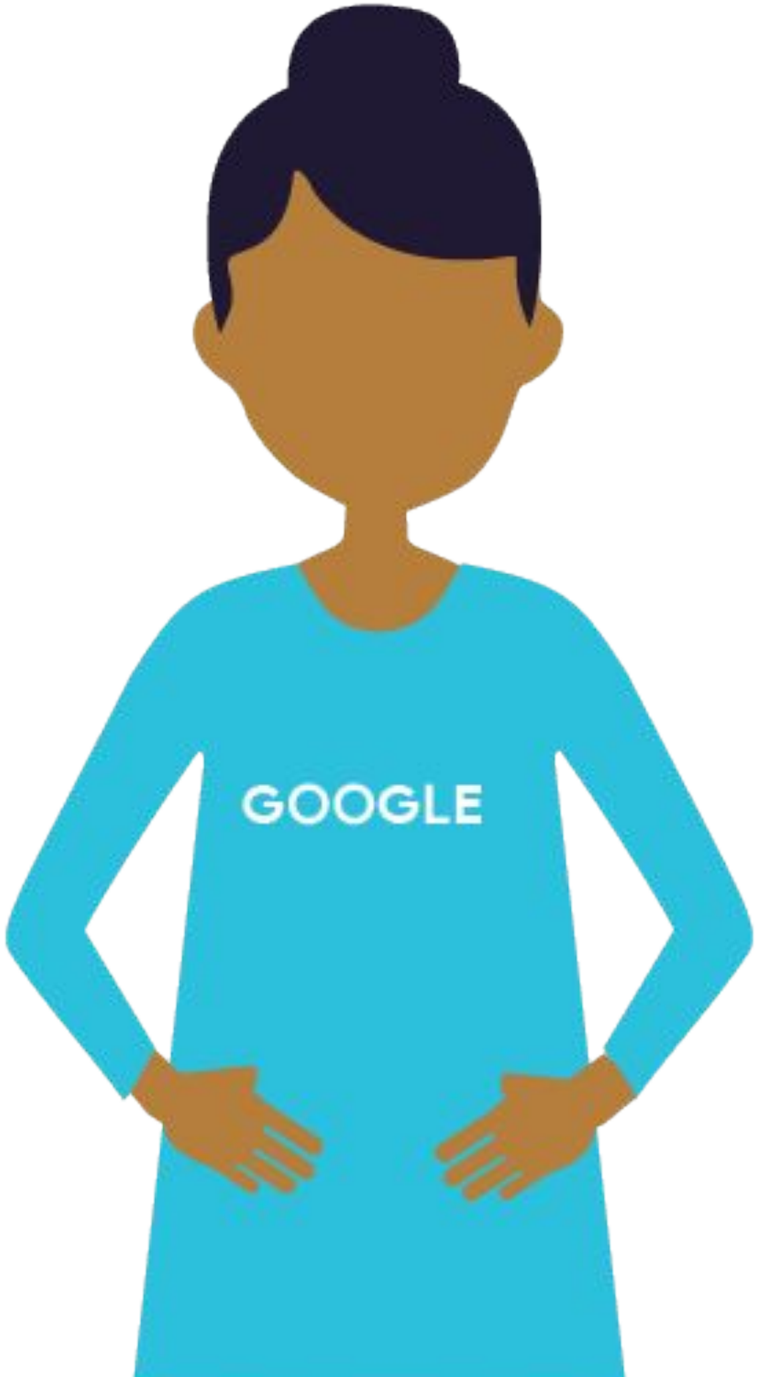
Format: Presenter

Presenter: Laurence Moroney

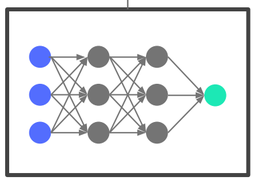
Video Name: T-PSML-O_4_I3_aspects_of_performance:_predictions

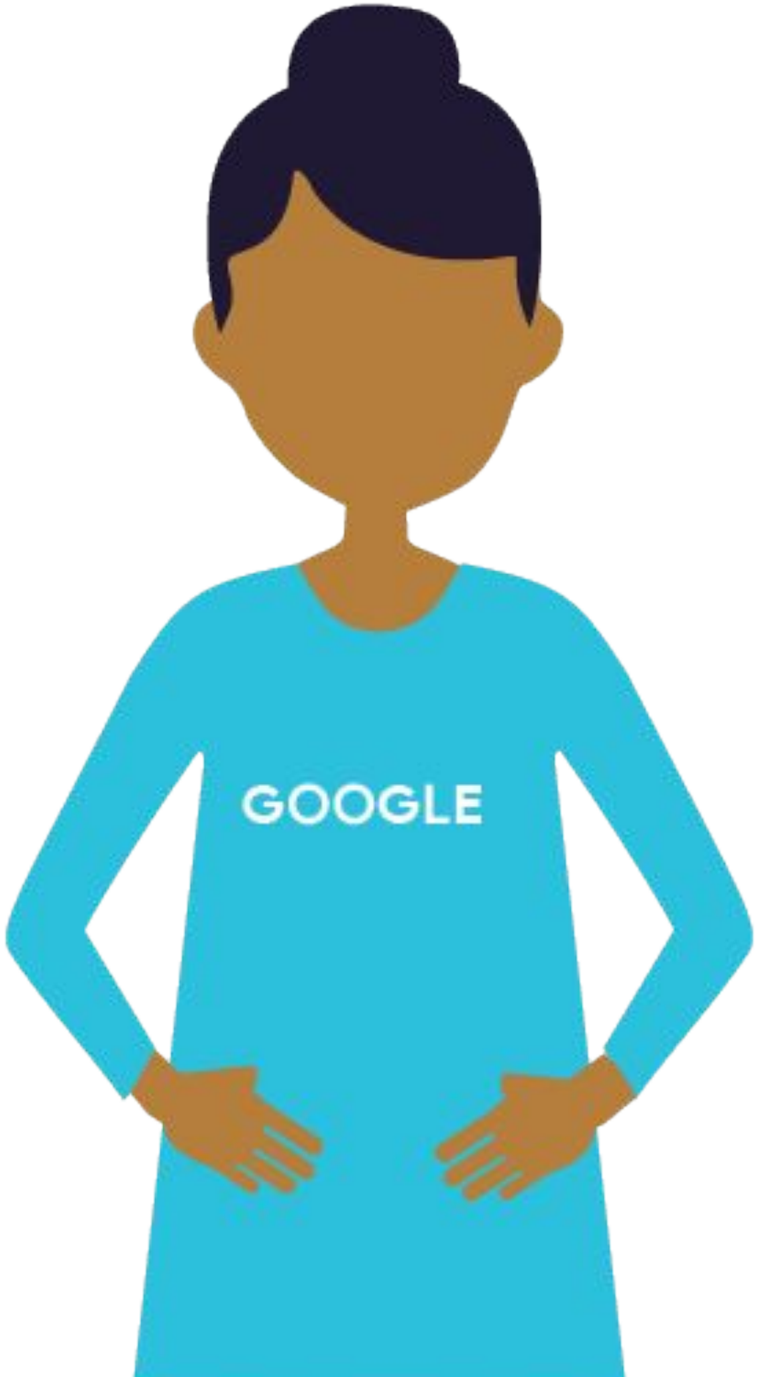
Performance must consider prediction-time, not just training



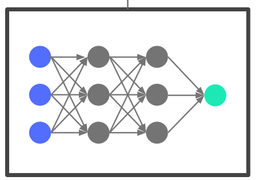


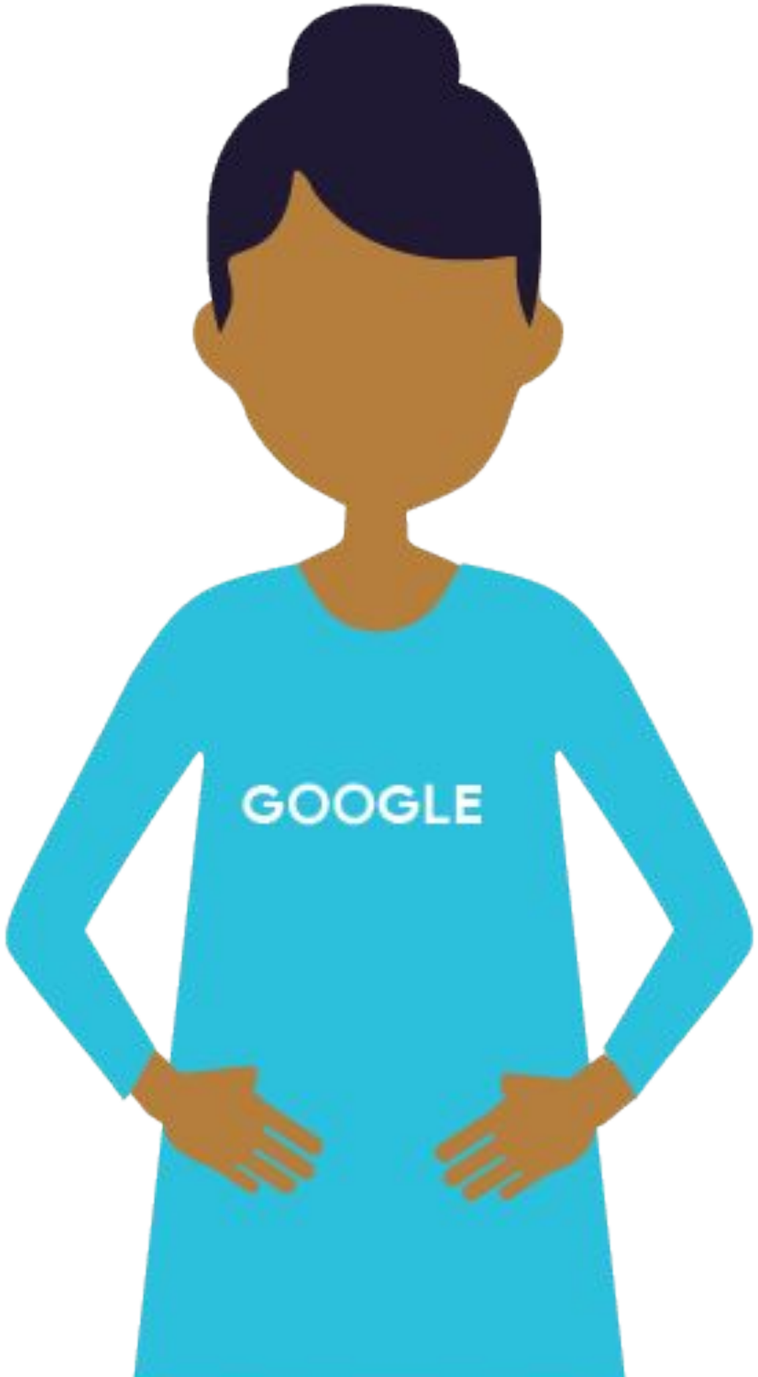
Optimizing your Batch Prediction



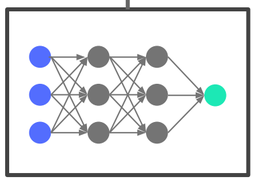


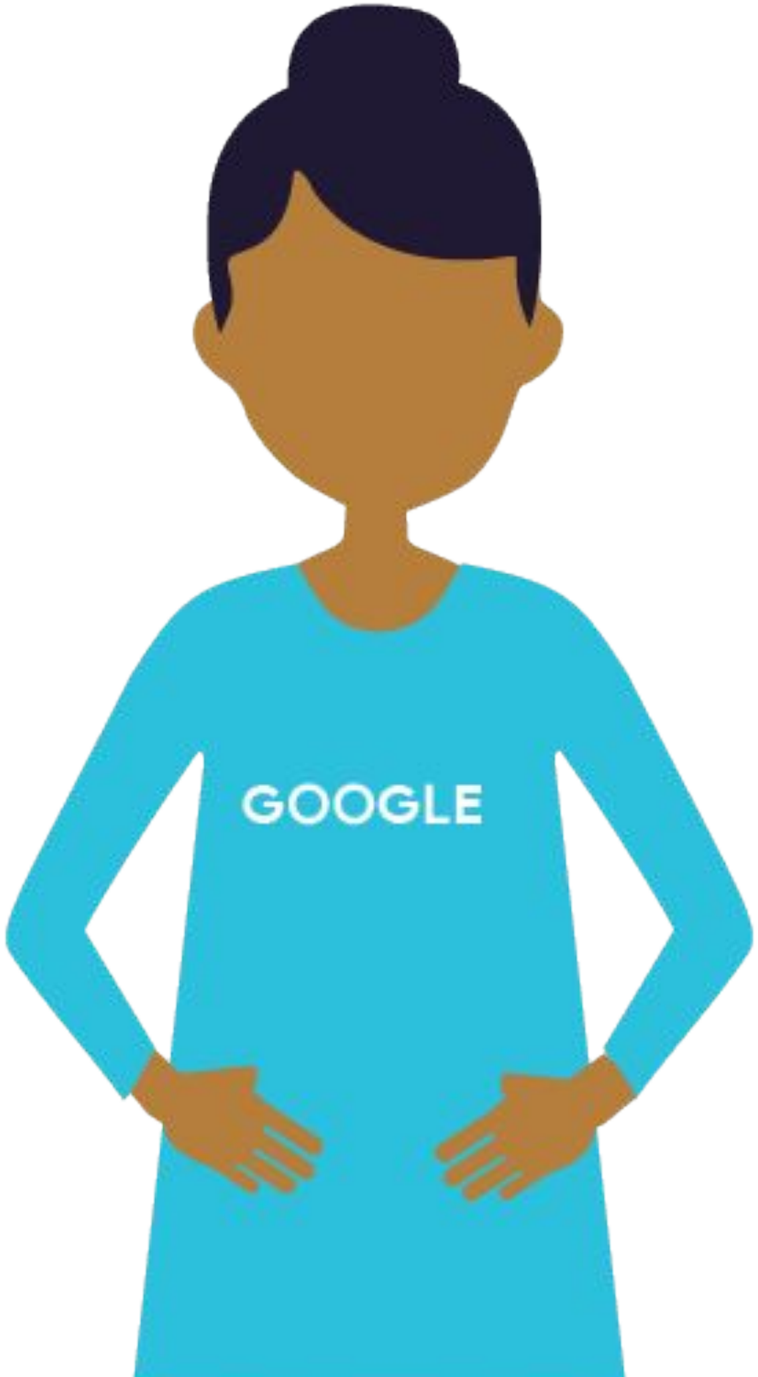
Optimizing your Batch Prediction



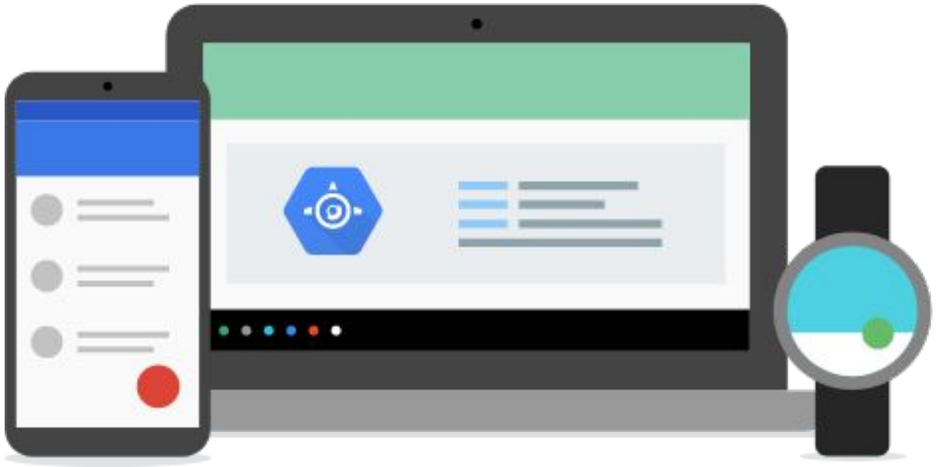


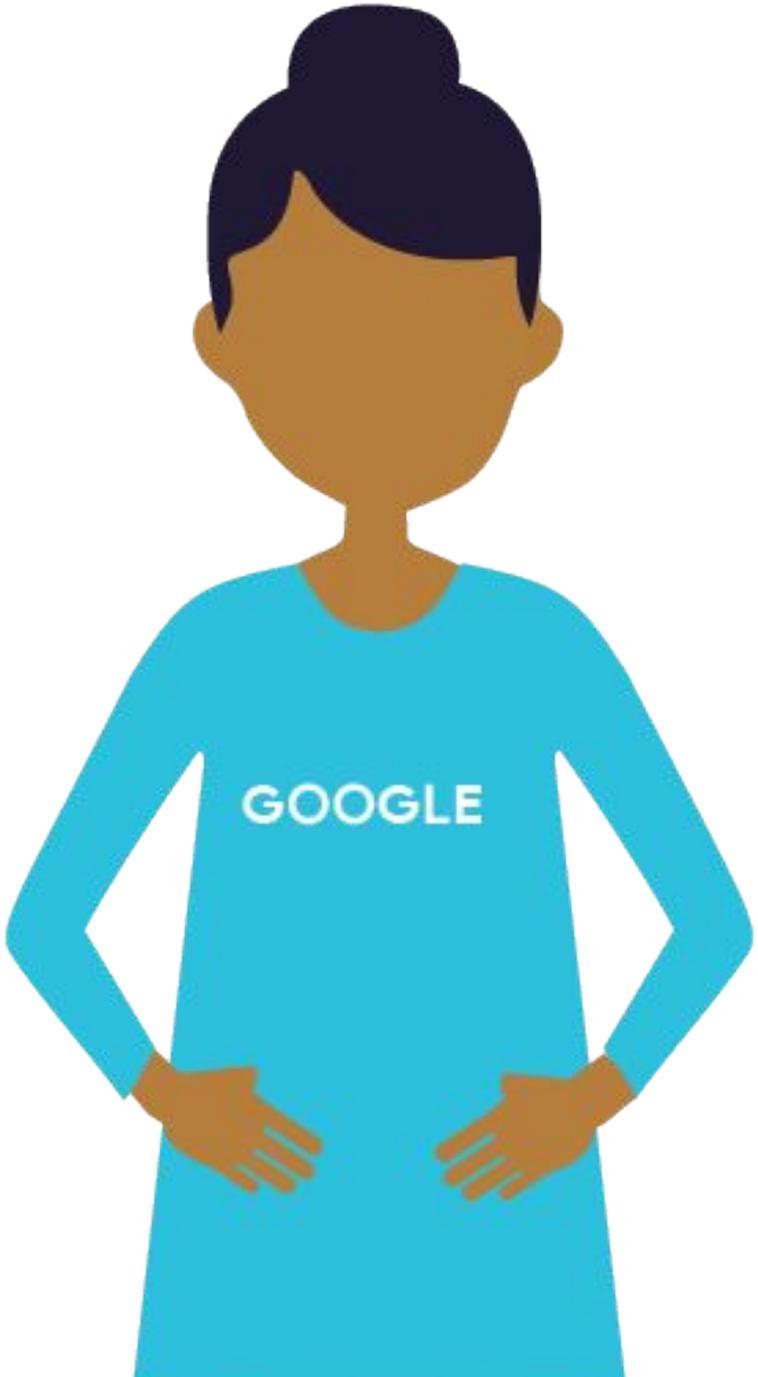
Optimizing your Batch Prediction



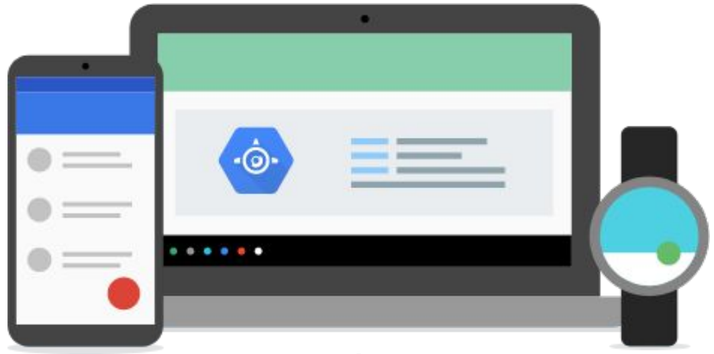


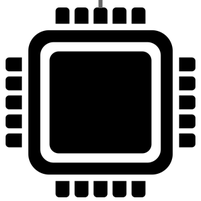
Optimizing your Online Predictions



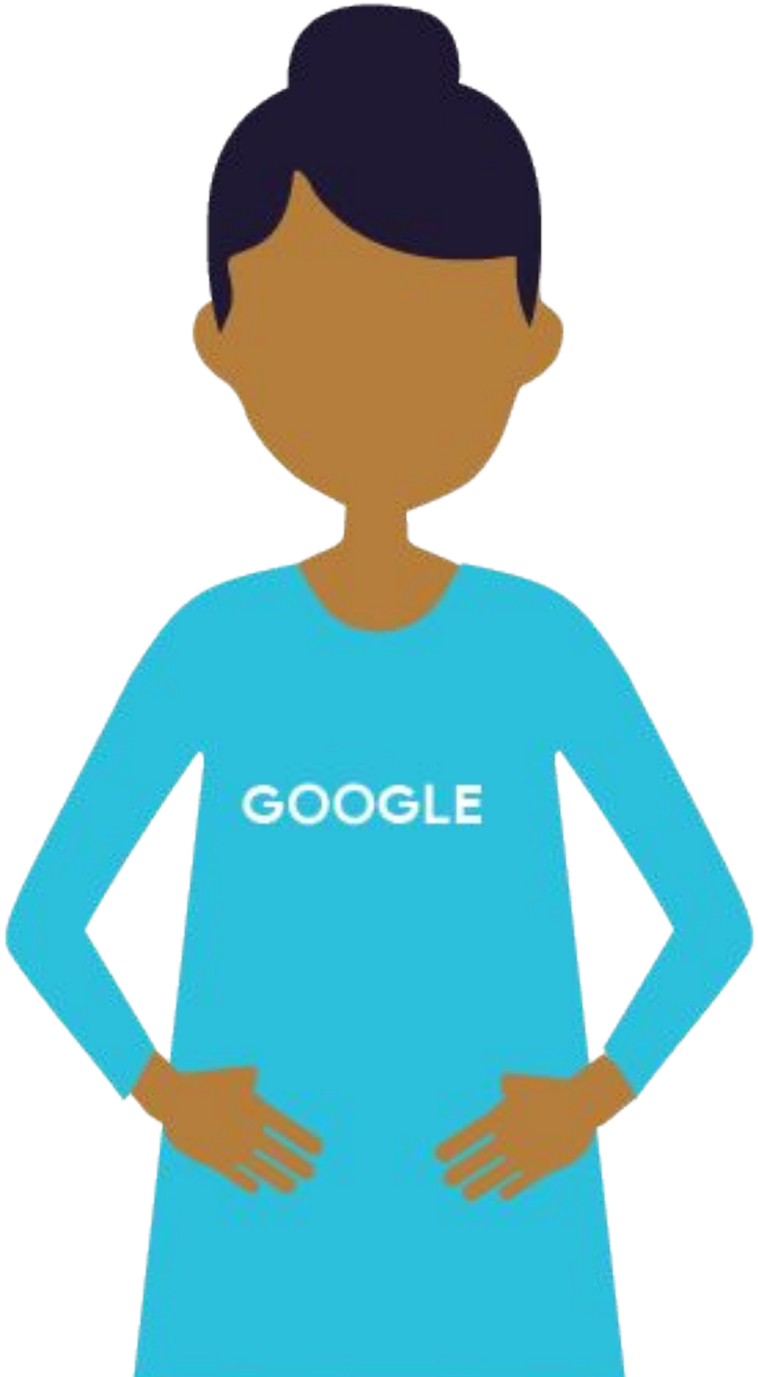


Optimizing your Online Predictions

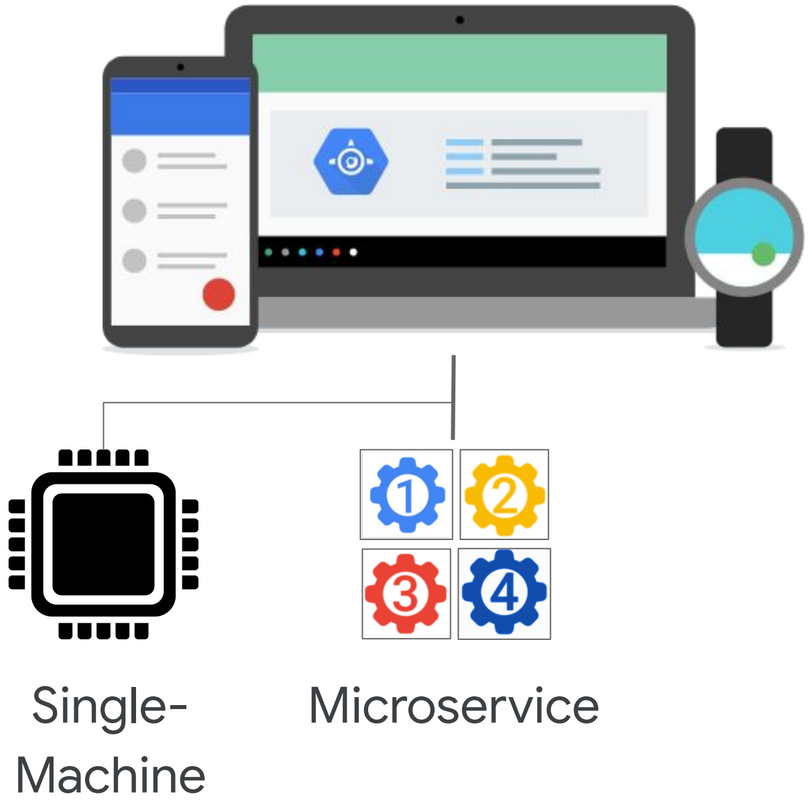




Single-Machine

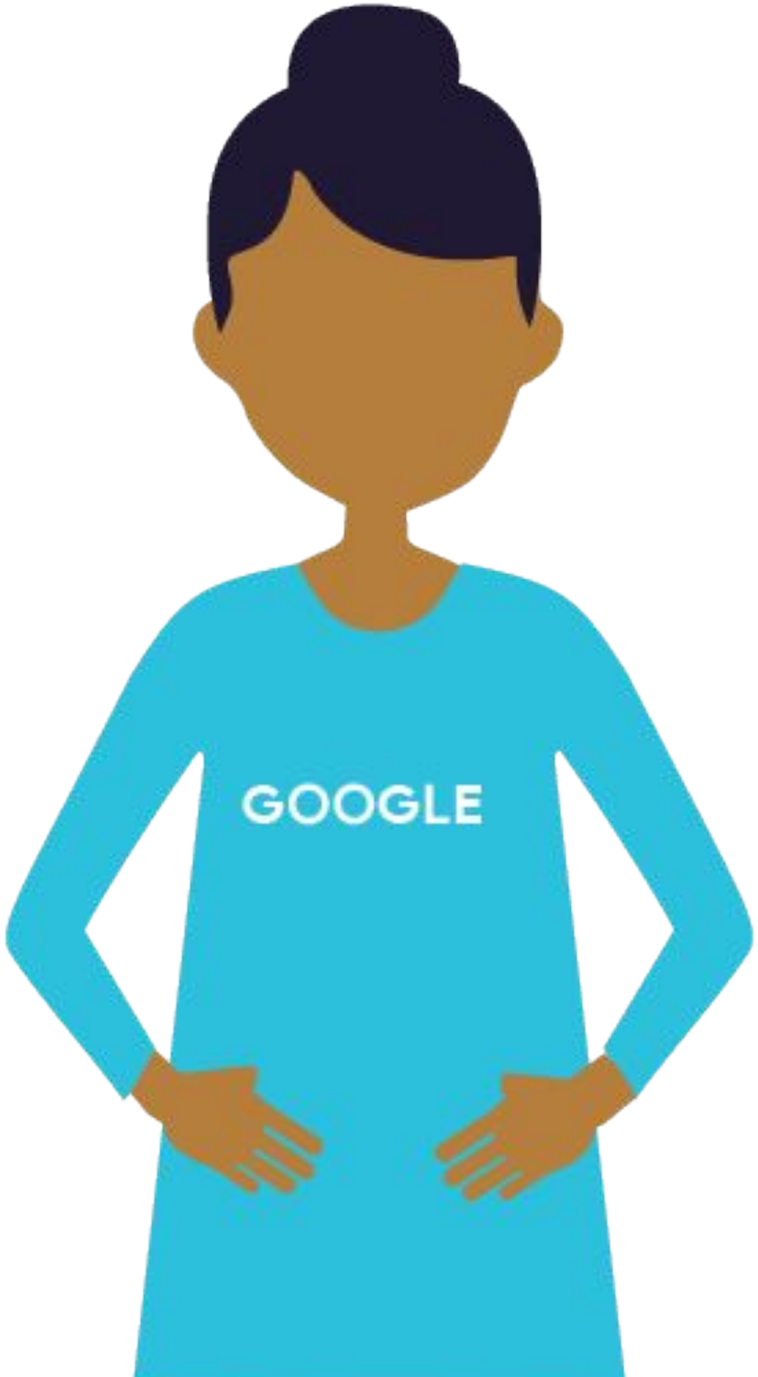


Optimizing your Online Predictions



Single-Machine

Microservice

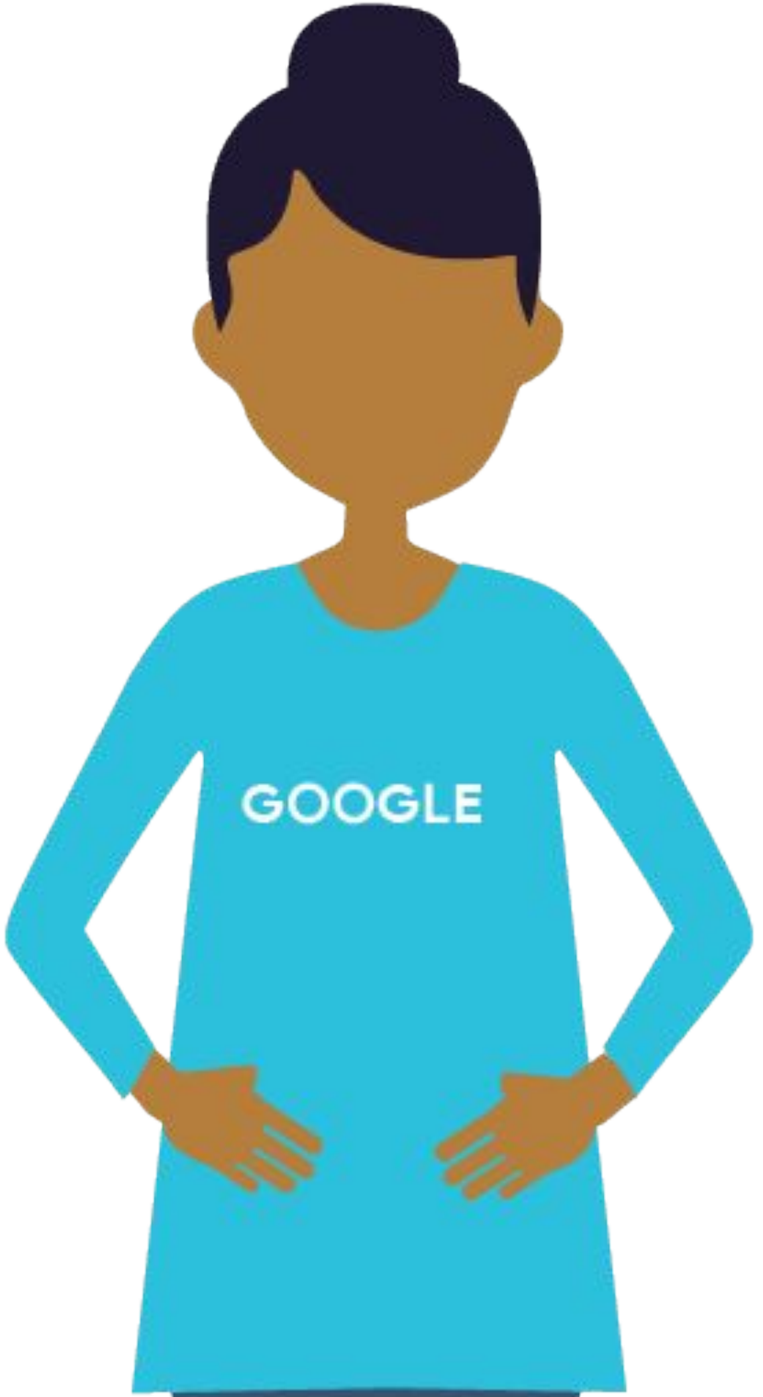


Optimizing your Online Predictions

Single-Machine

Microservice

QPS


GOOGLE

Courses 7 - Production ML Systems

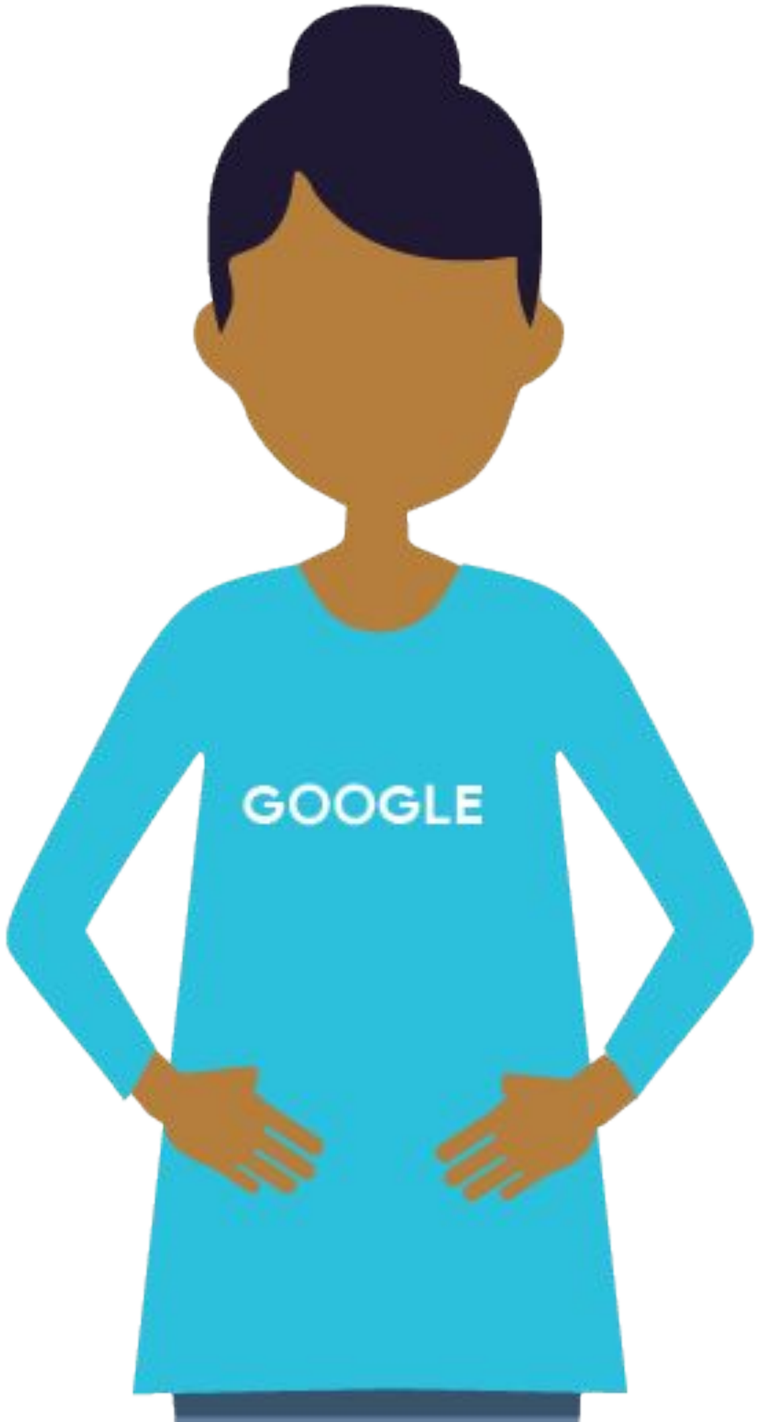
Module 4: Designing High-Performance ML Systems

Lesson Title: **Why distributed training?**

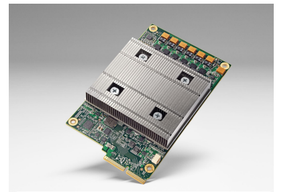
Format: Presenter

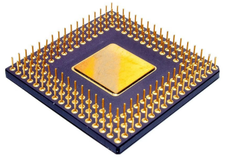
Presenter: Laurence Moroney

Video Name: T-PSML-O_4_I4_why_distributed_training

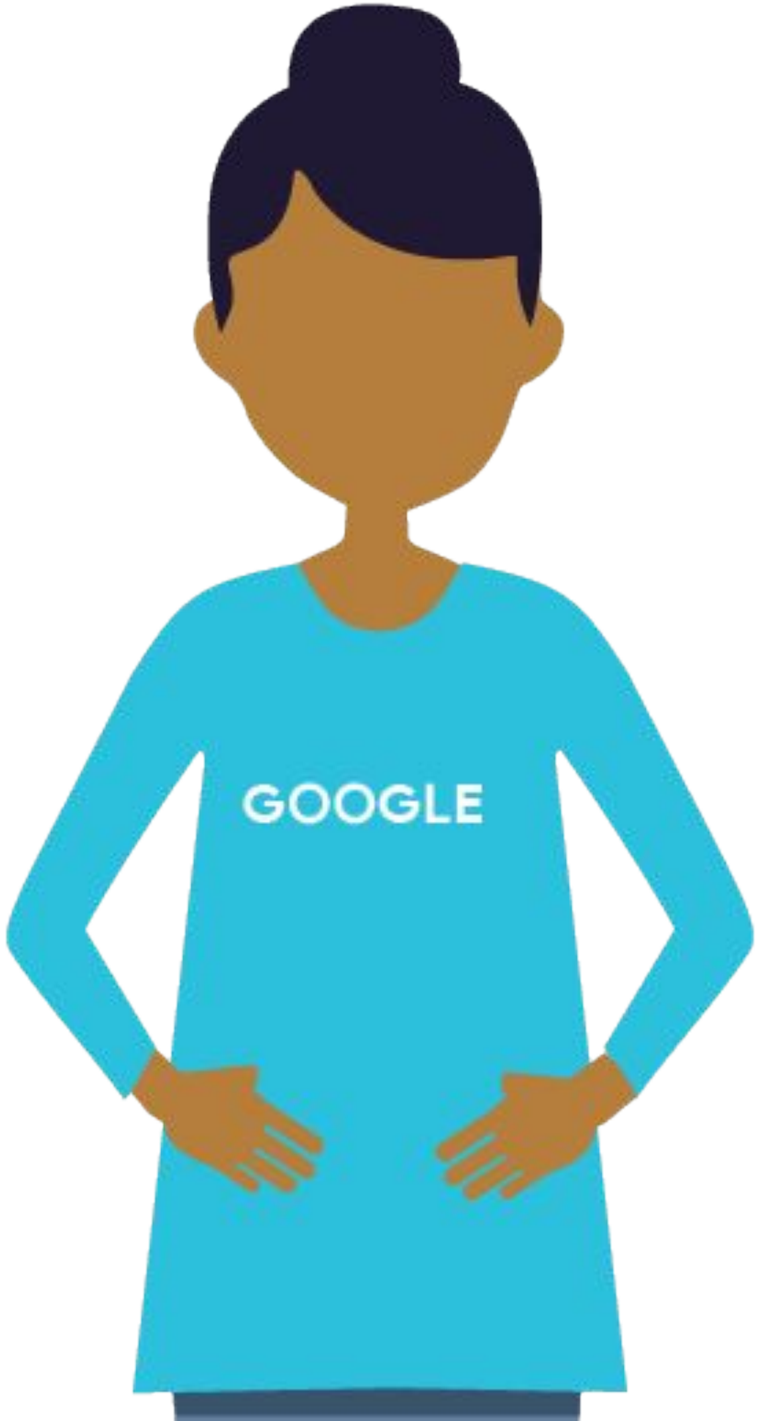


Improving performance also adds complexity

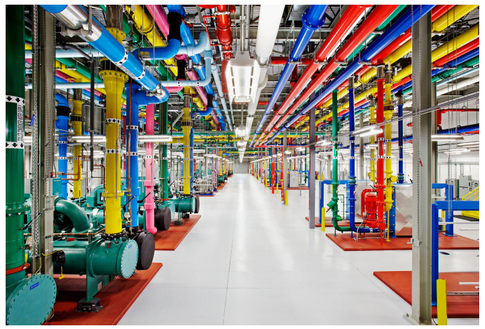




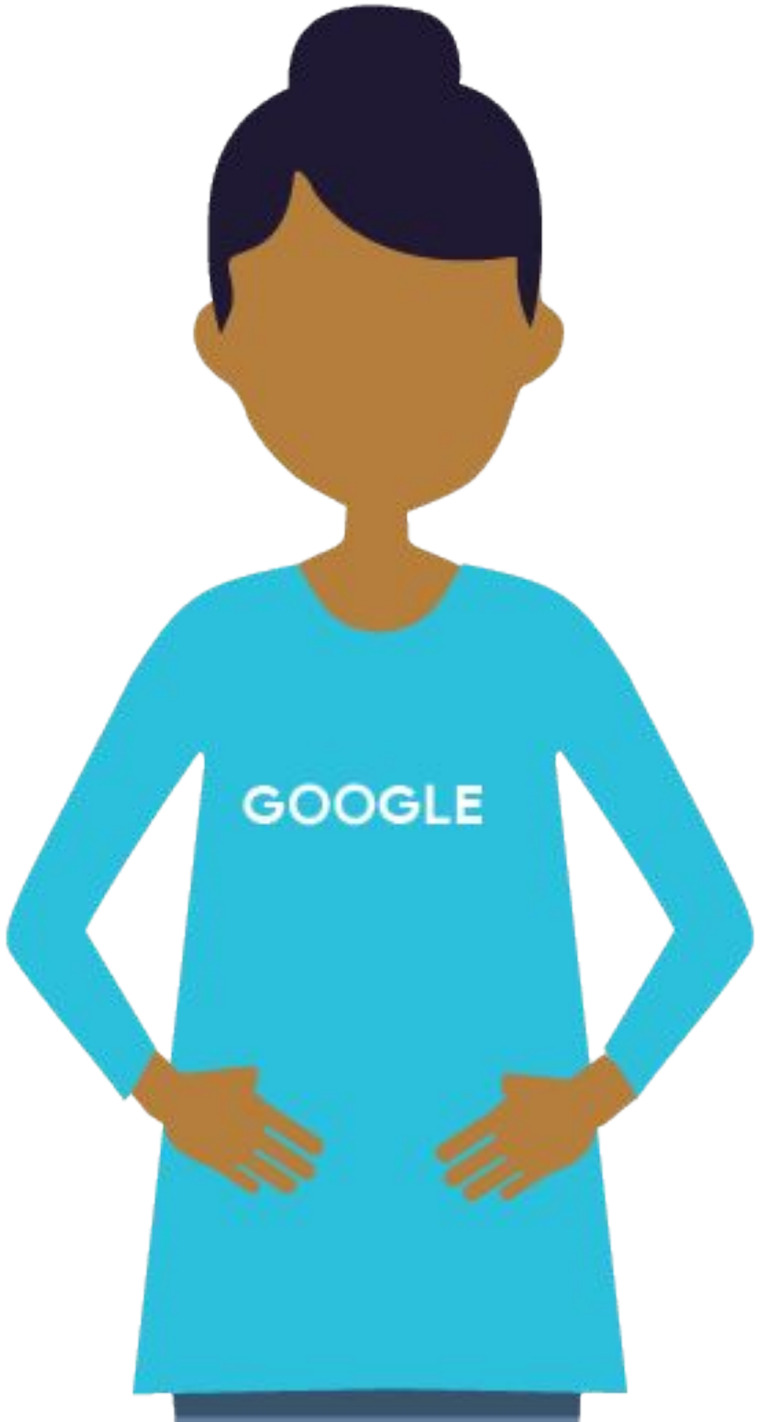
HETEROGENOUS SYSTEMS



Improving performance also adds complexity

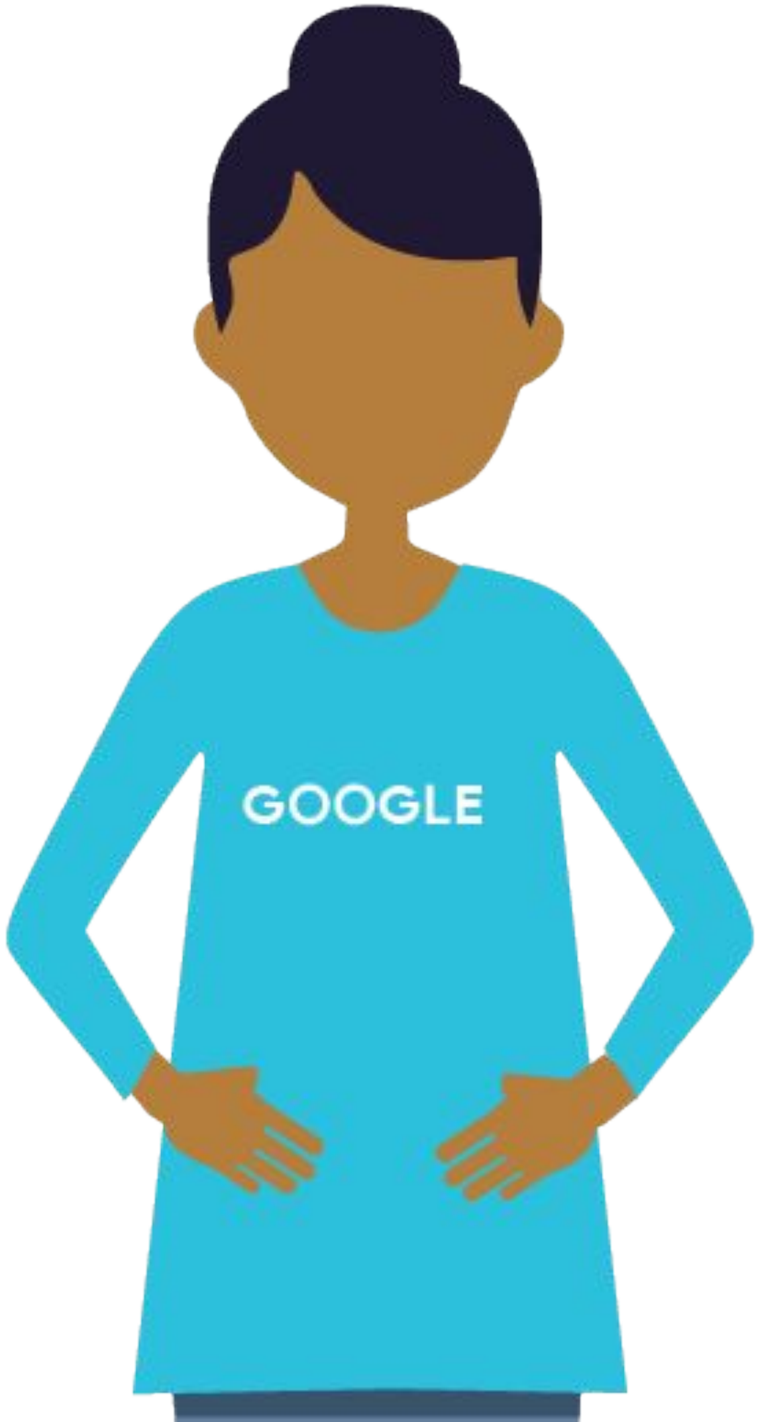


DISTRIBUTED SYSTEMS



Improving performance also adds complexity

MODEL ARCHITECTURES



Machine learning gets complex quickly

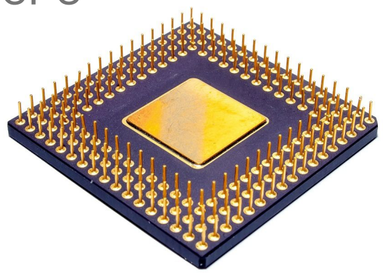
HETEROGENOUS SYSTEMS

DISTRIBUTED SYSTEMS

MODEL ARCHITECTURES

Heterogeneous systems require our code to work anywhere

CPU

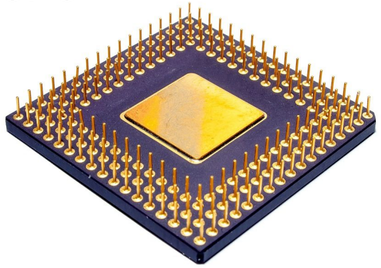


GPU

TPU

Heterogeneous systems require our code to work anywhere

CPU



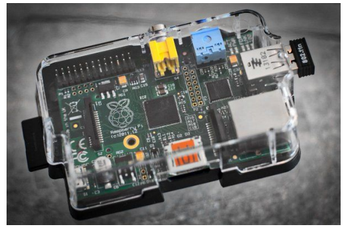
GPU

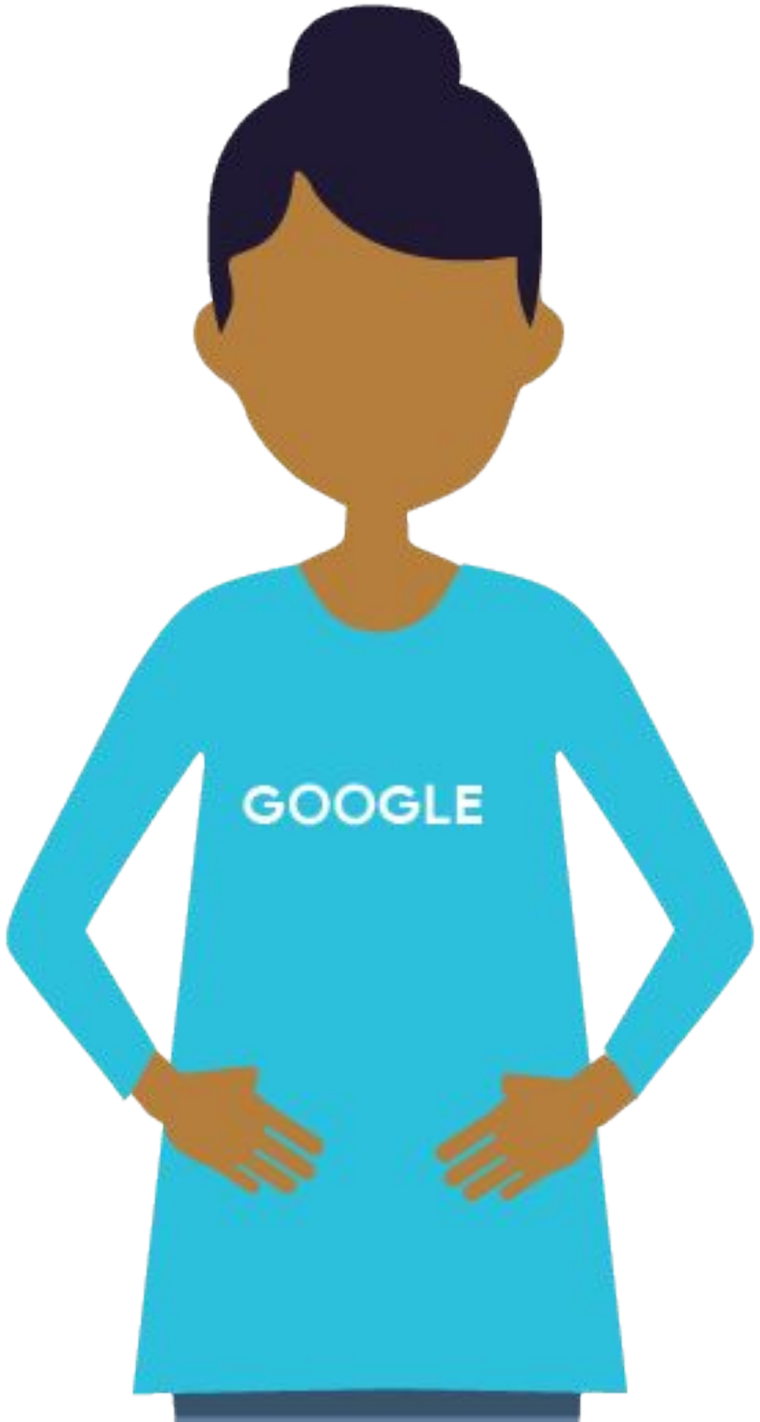
TPU

Android / iOS

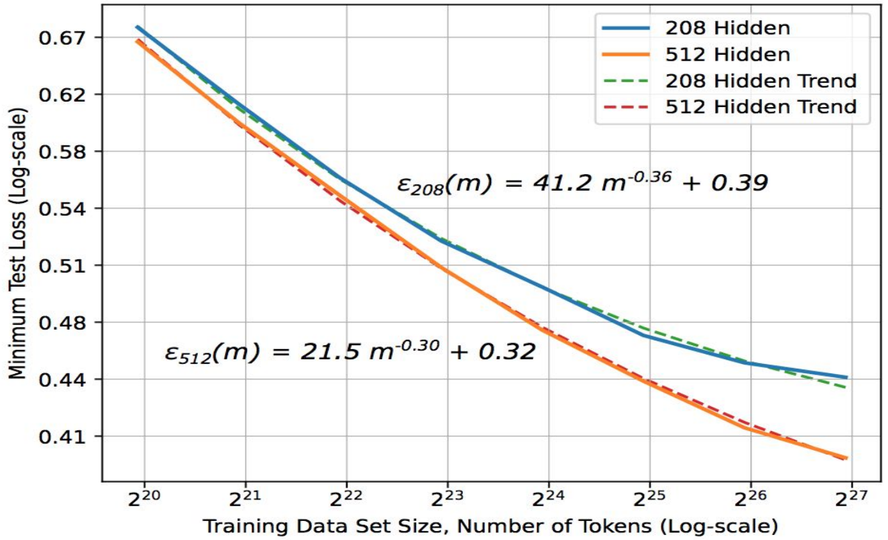
Edge
TPU

Raspberry Pi



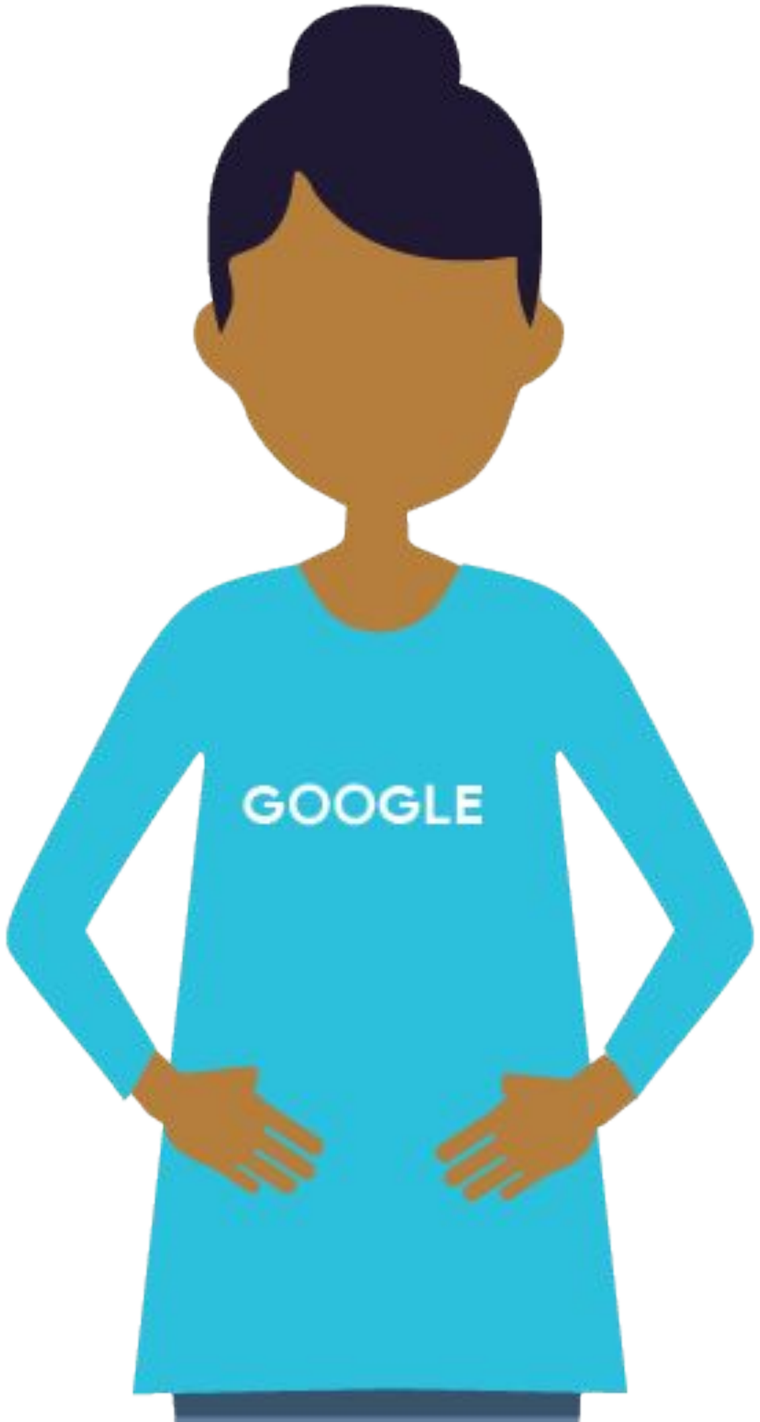


Deep learning works because datasets are large, but the compute required keeps increasing

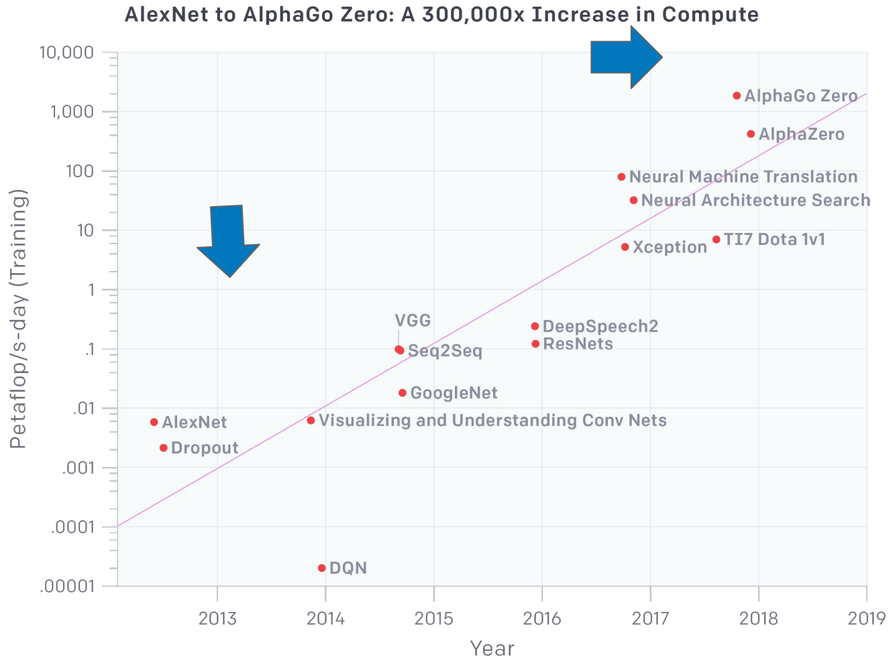


The unreasonable effectiveness of data
https://static.googleusercontent.com/media/research.google.com/en//pubs/archive/35179.pdf

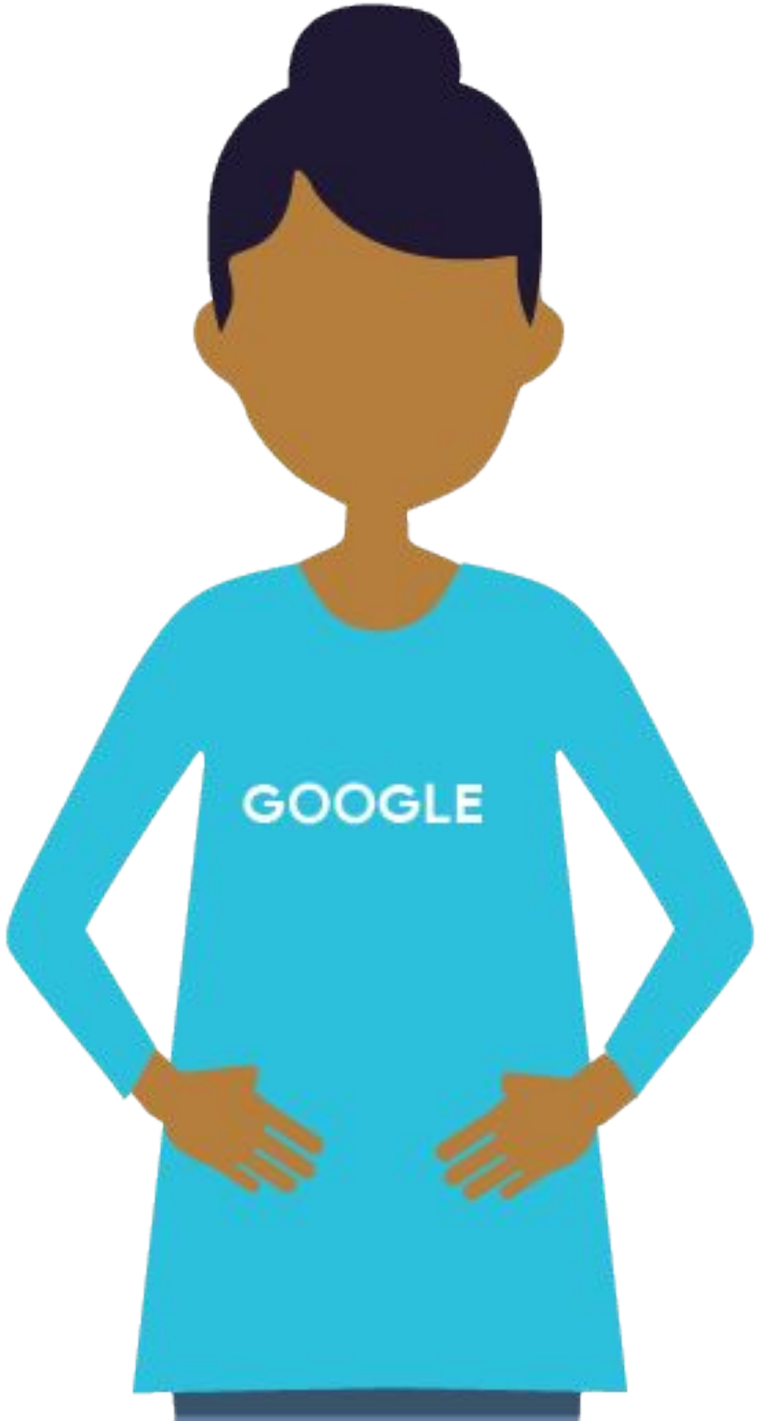
Deep Learning scaling is predictable, empirically
https://arxiv.org/abs/1712.00409



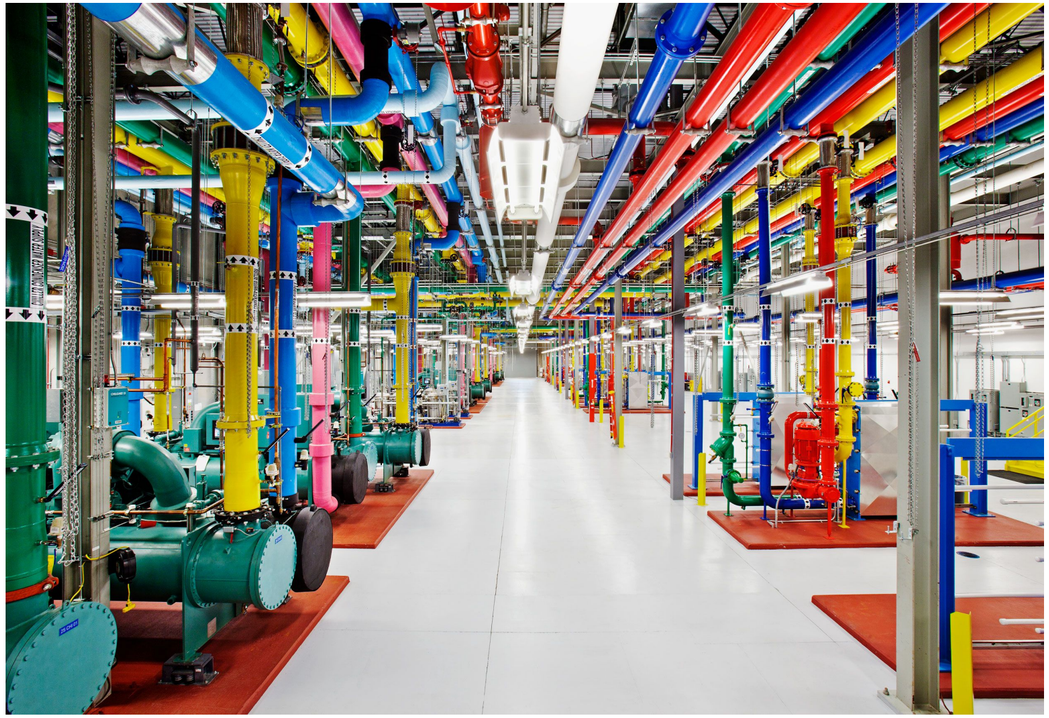
Deep learning works because datasets are large, but the compute required keeps increasing



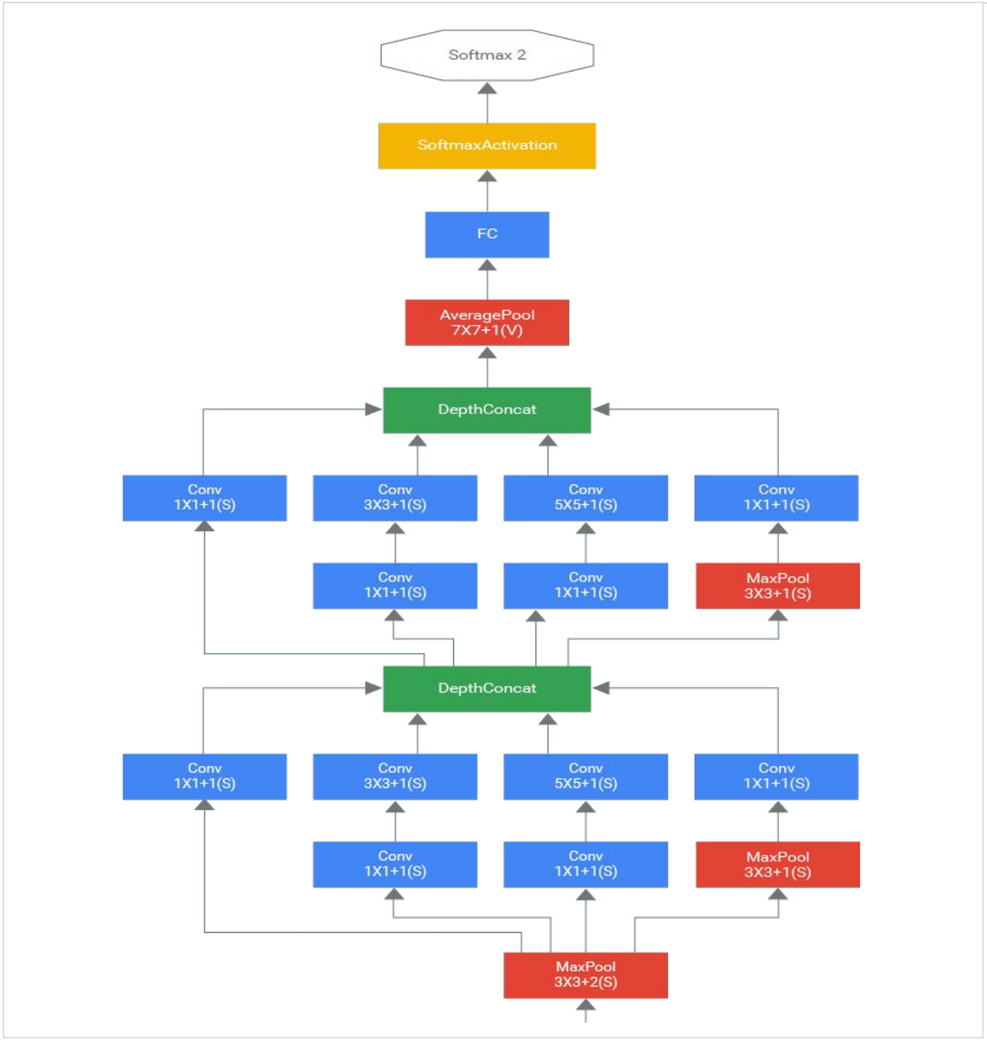
https://blog.openai.com/ai-and-compute/



Distributed systems are a necessity for managing complex models with large data volumes

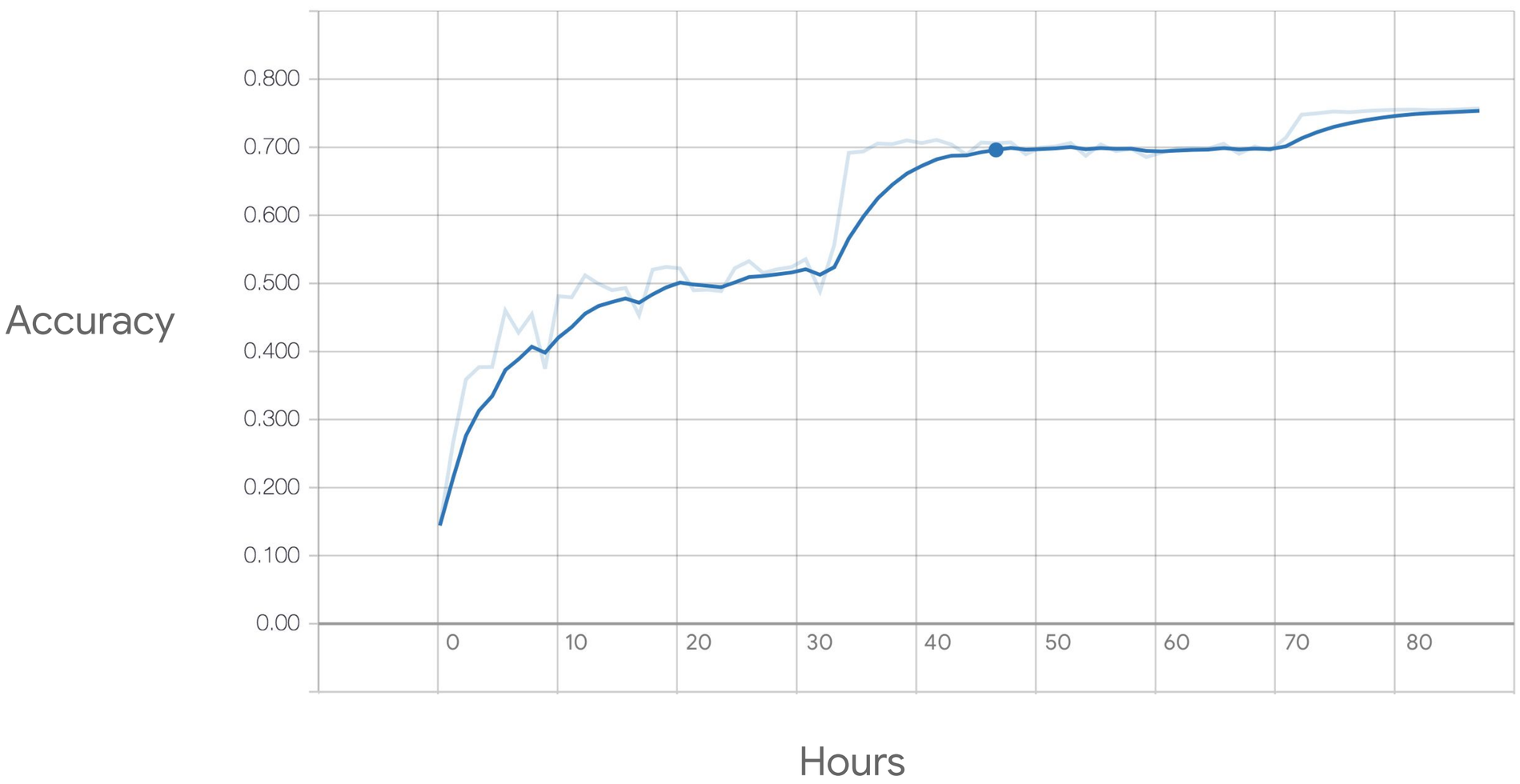


Large models could have millions of weights

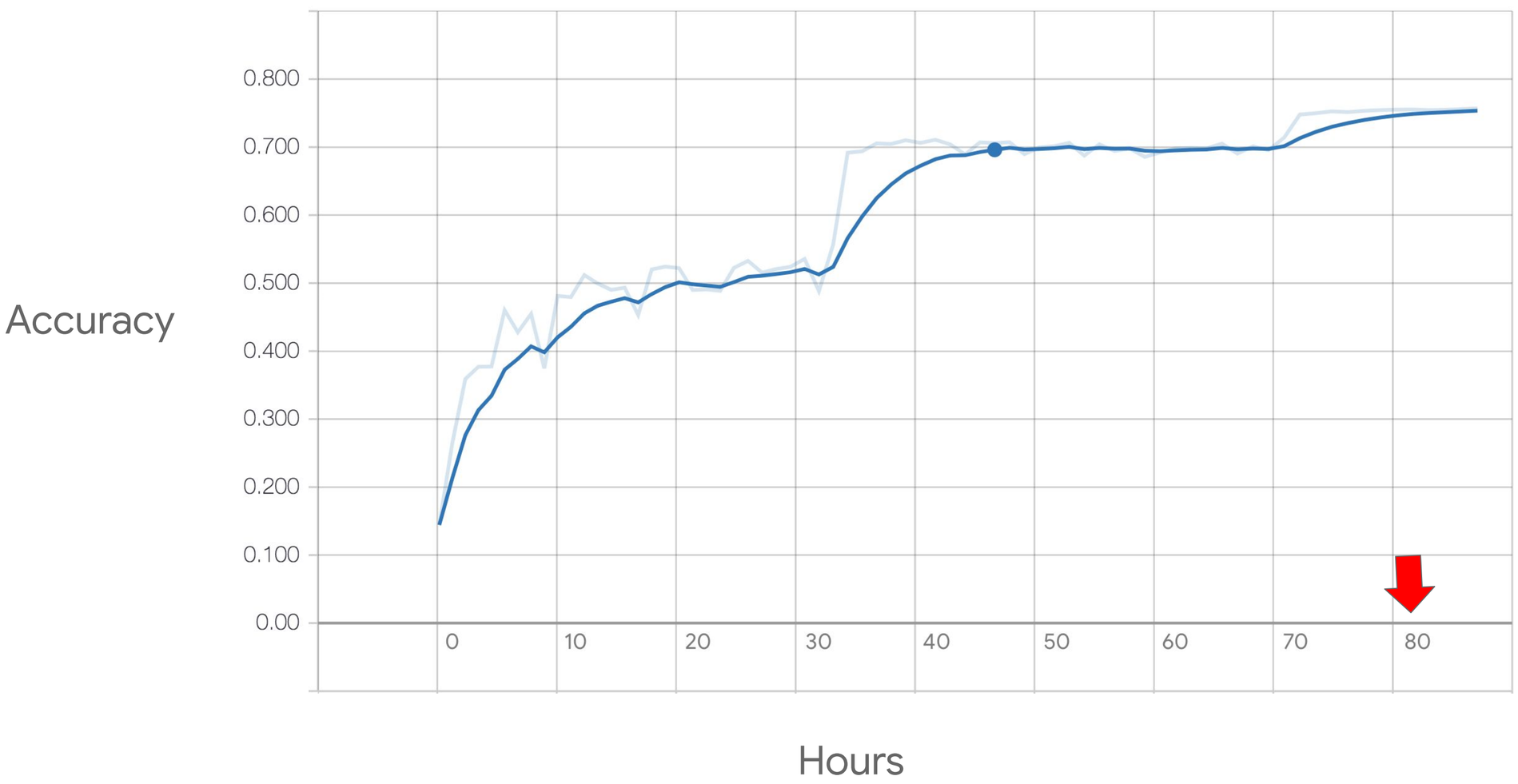


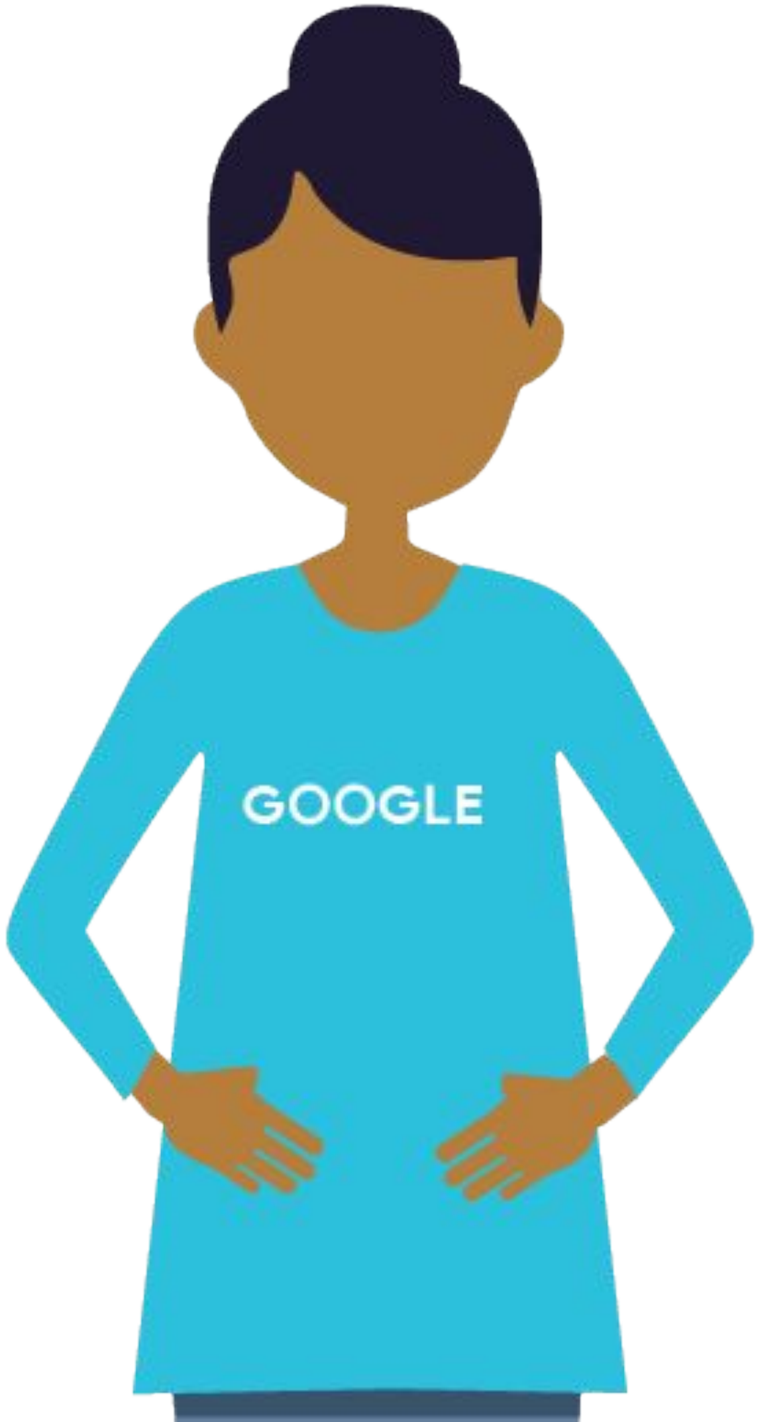
Model: Inception (2015)

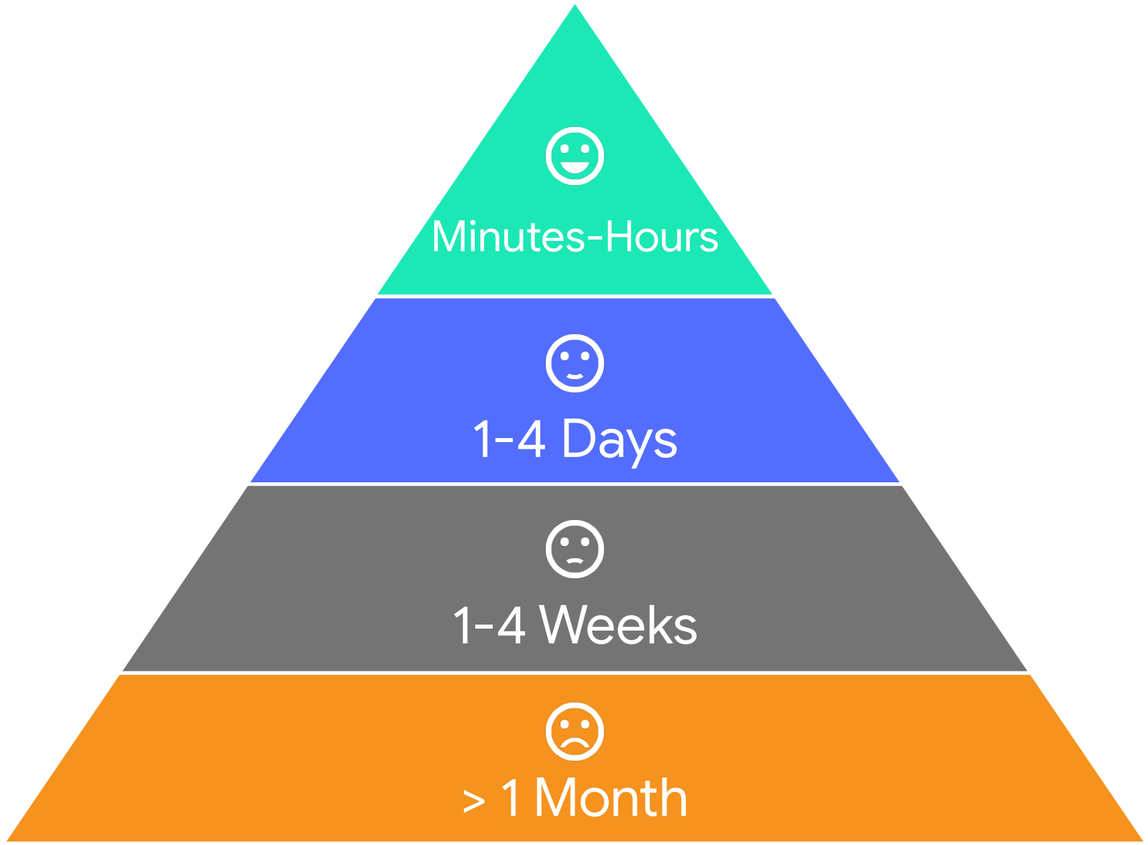
Training can take a long time

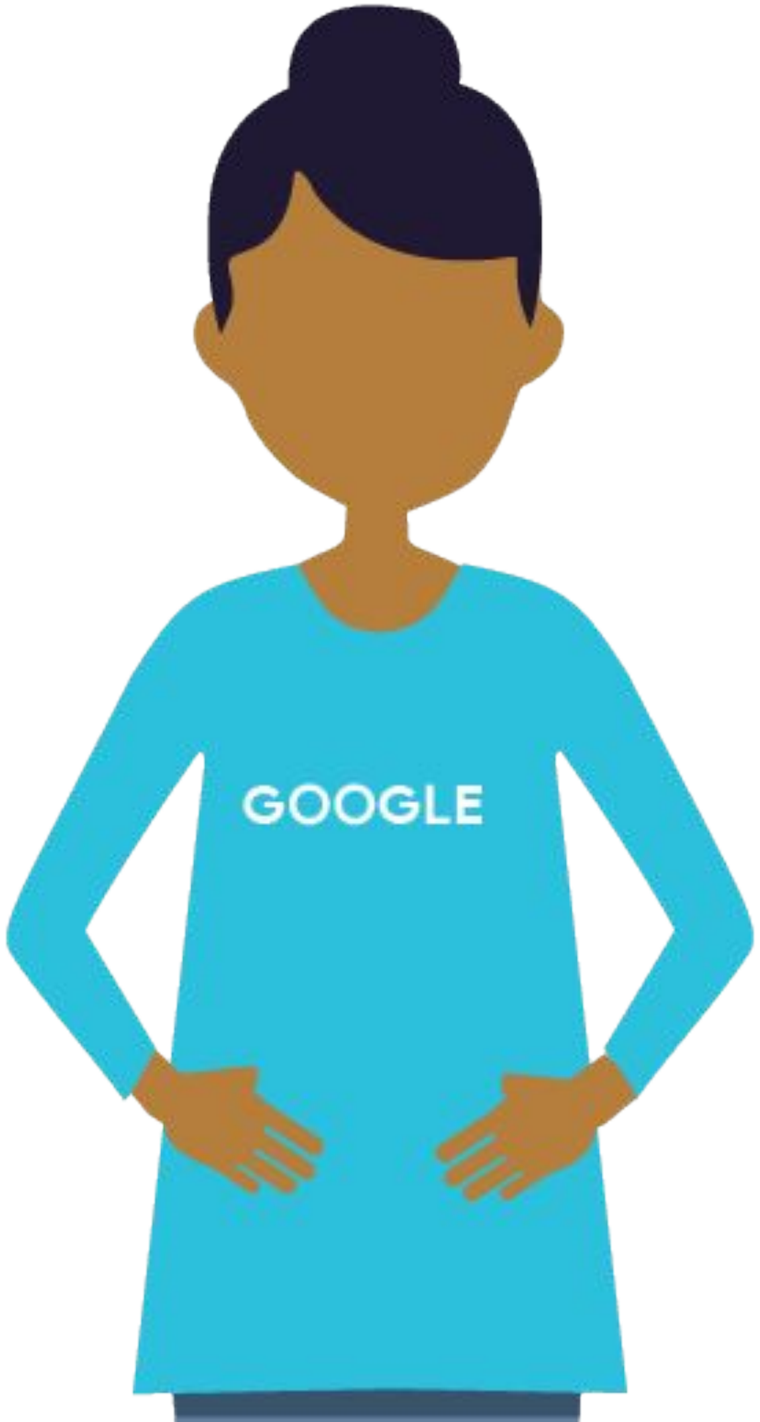


Training can take a long time

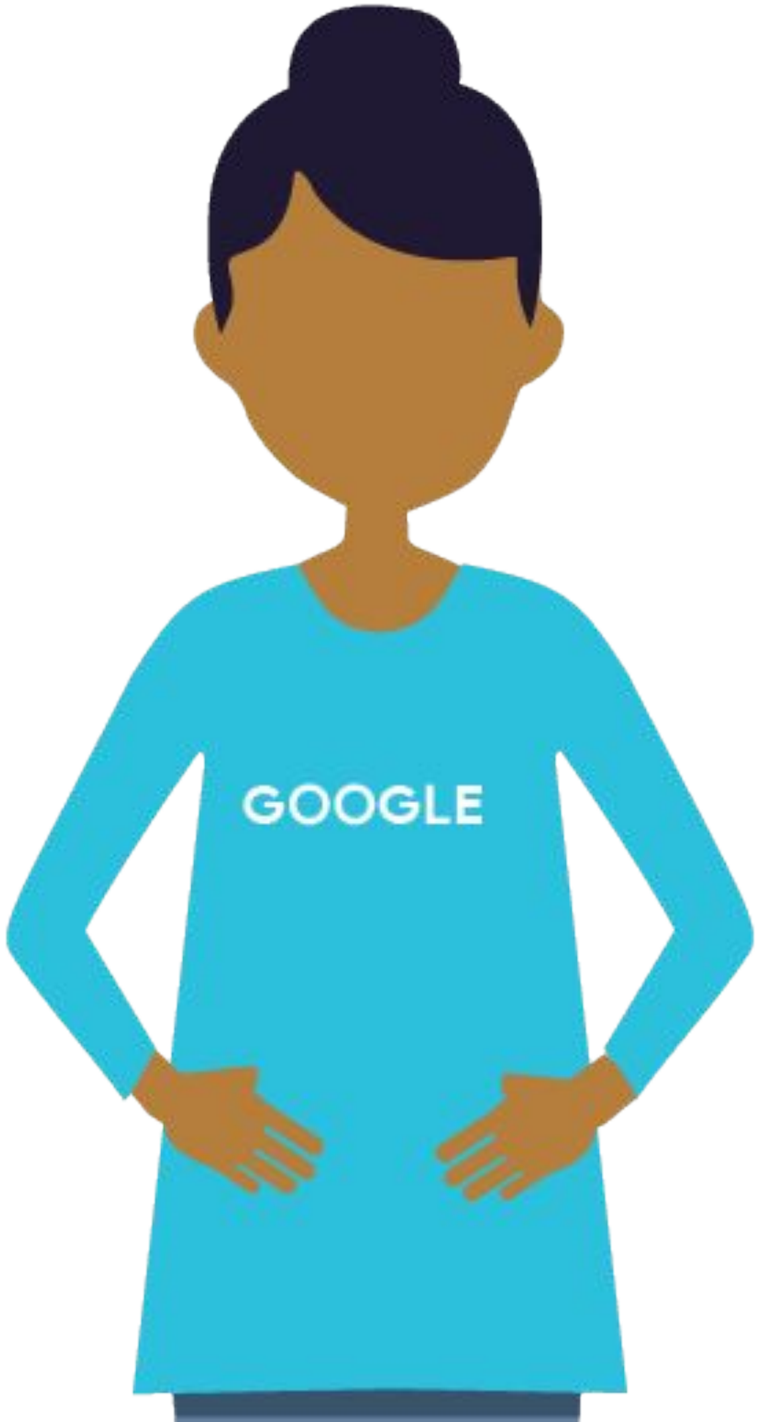



GOOGLE

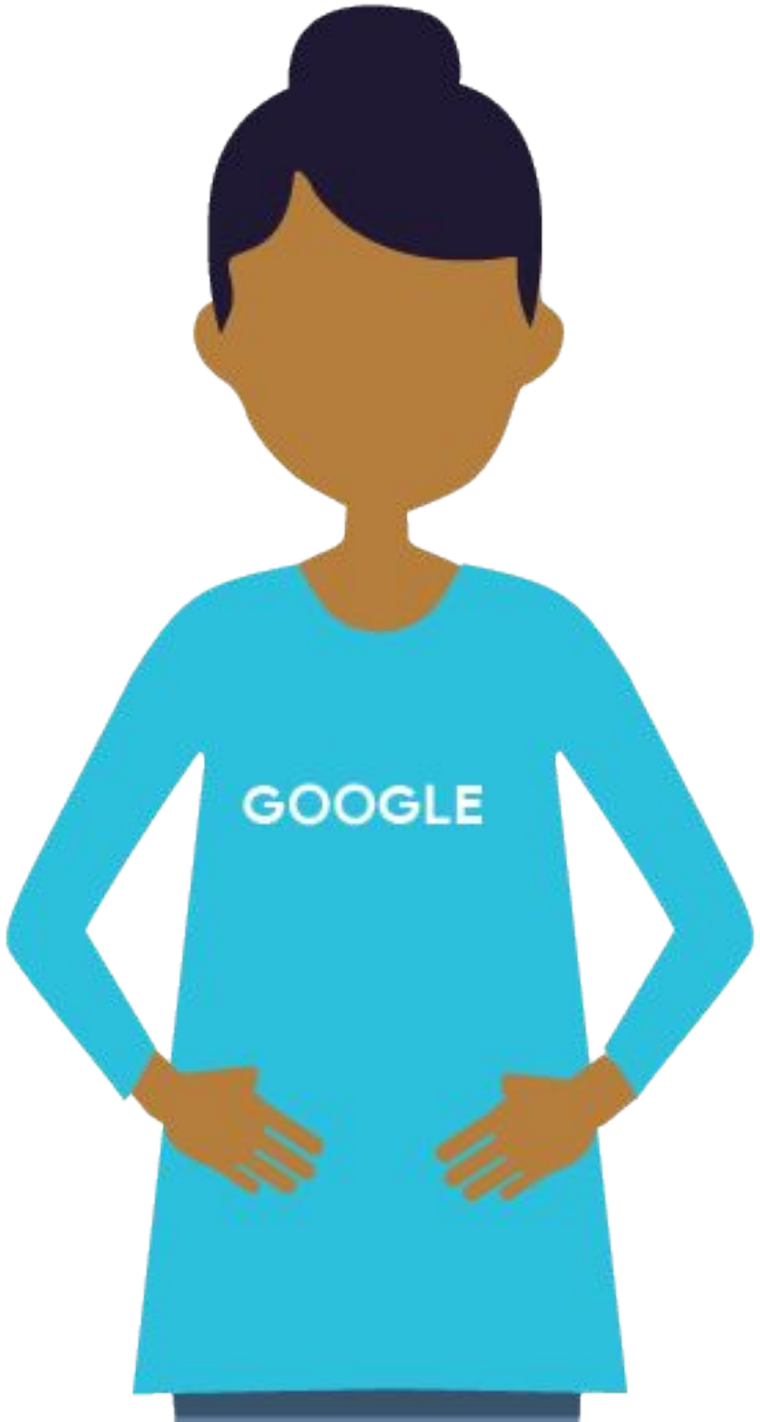

Minutes-Hours
1-4 Days
1-4 Weeks
> 1 Month



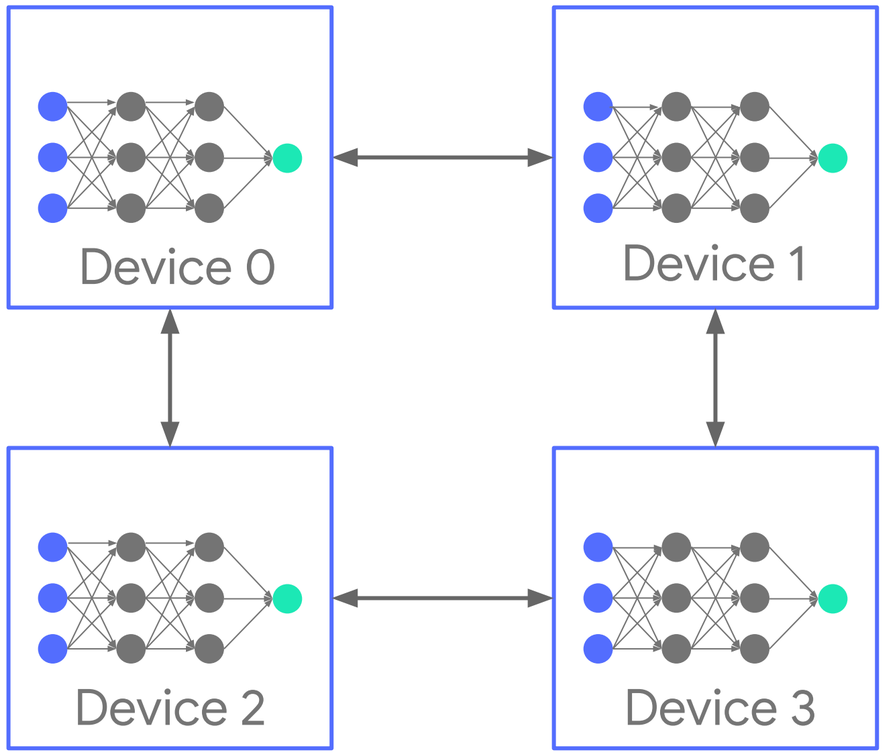
How can you make model training faster?

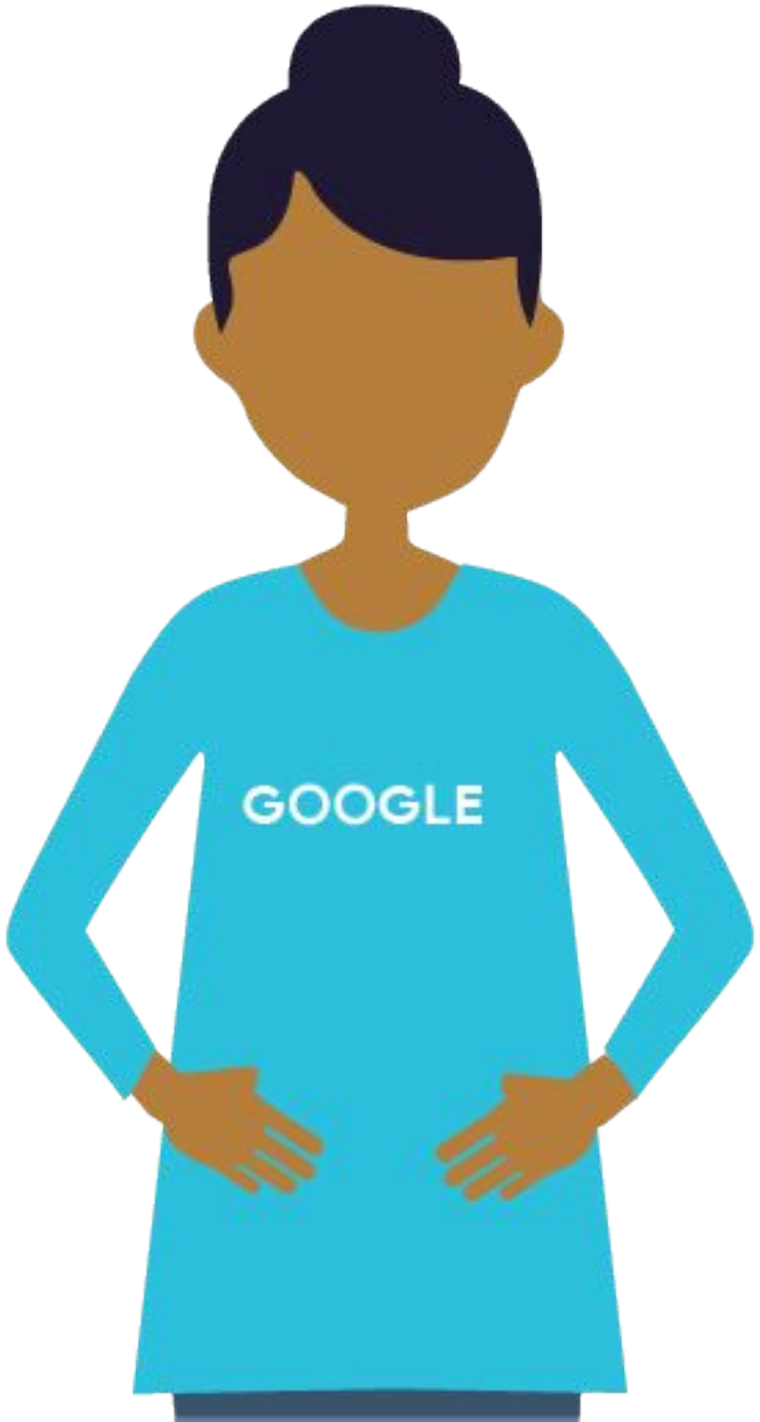


Gaining speed through parallel training



Gaining speed through parallel training





Scaling with Distributed Training

Courses 7 - Production ML Systems

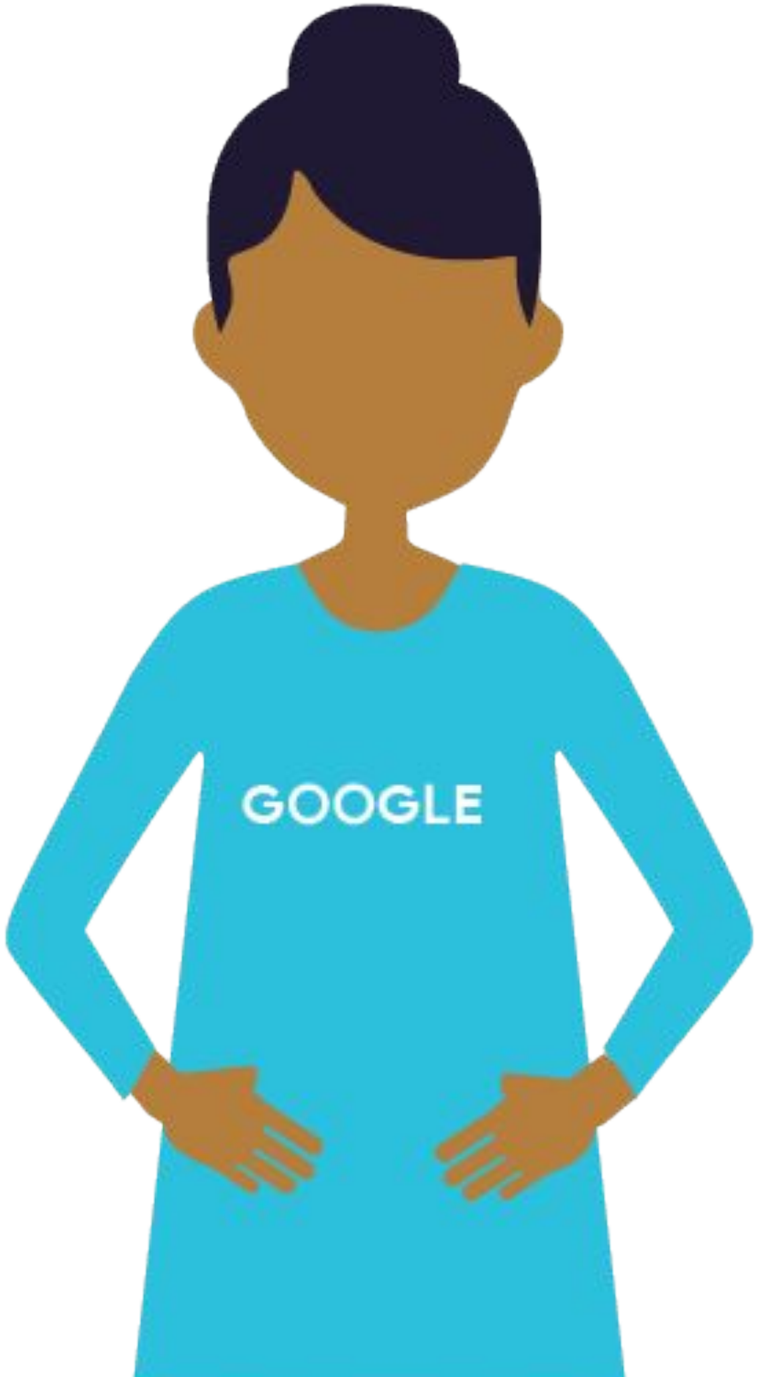
Module 4: Designing High-Performance ML Systems

Lesson Title: **Distributed training architectures**

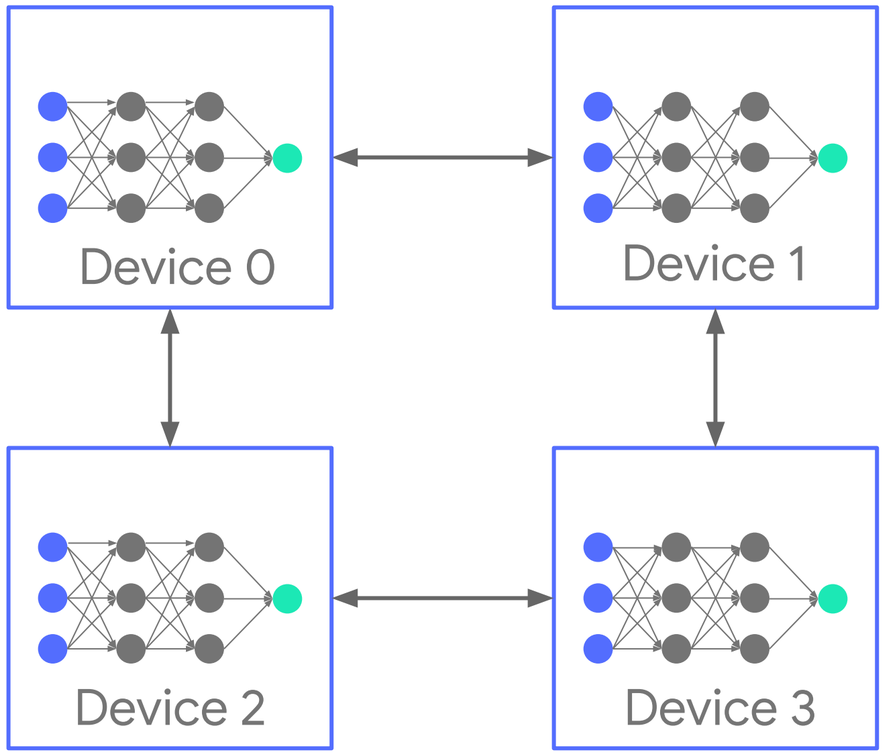
Format: Presenter

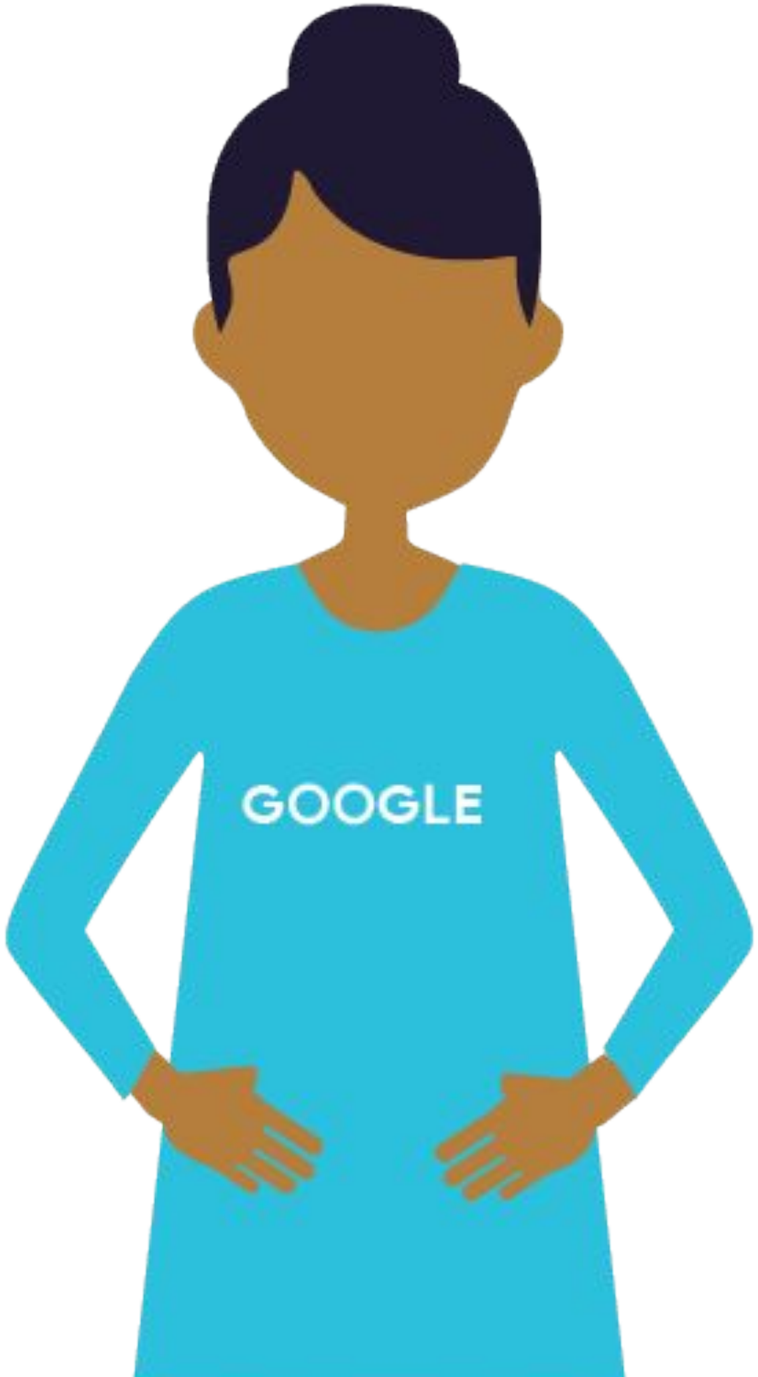
Presenter: Laurence Moroney

Video Name: T-PSML-O_4_l5_distributed_training_architectures

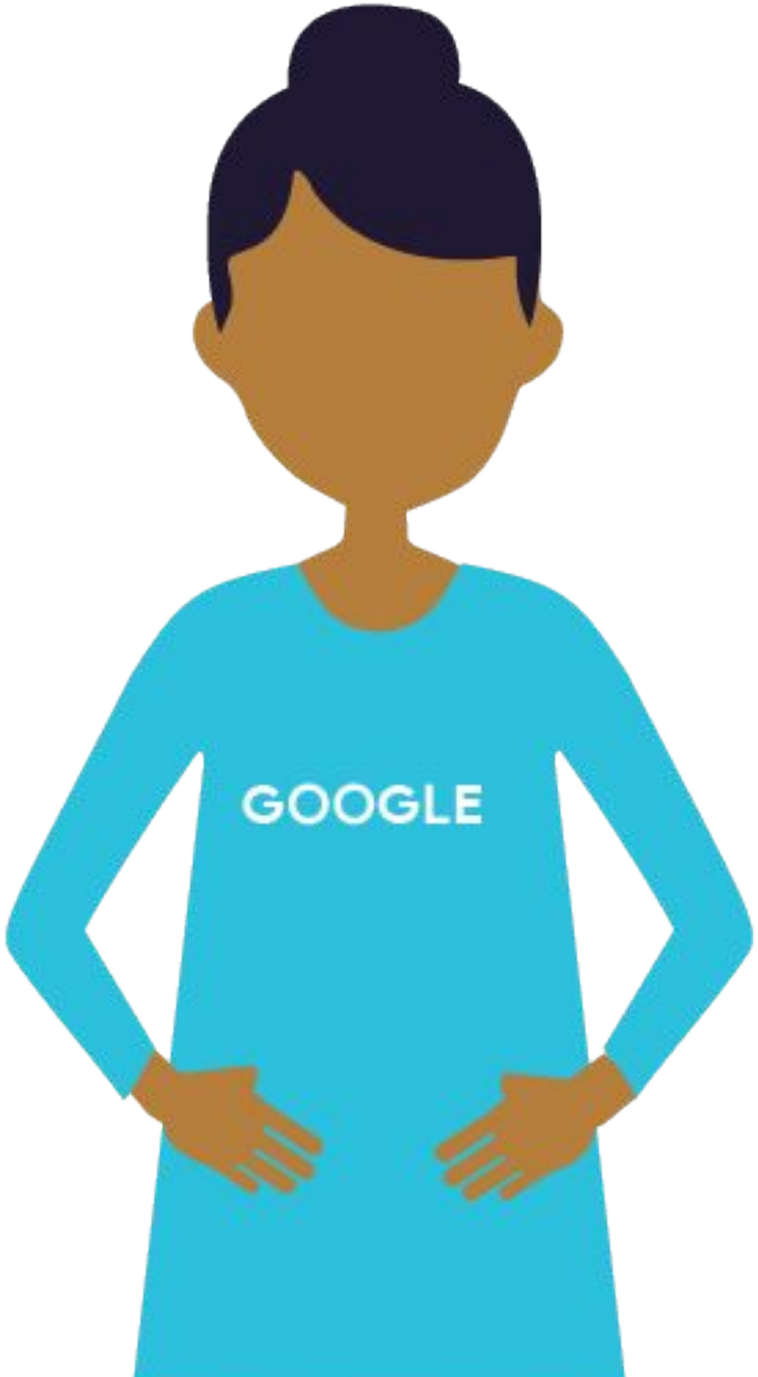


Distributed Training Architectures

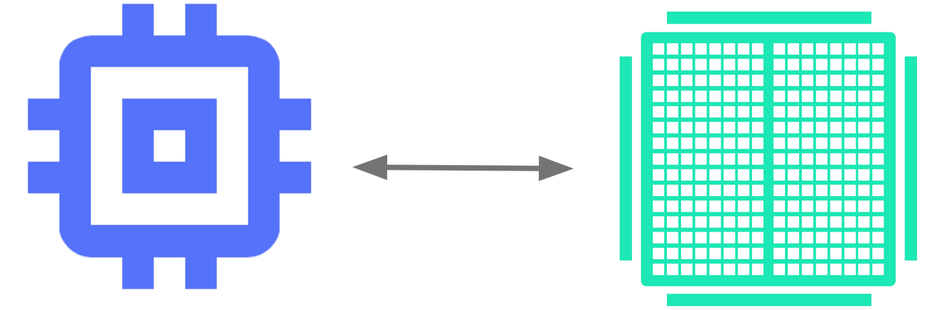




multi-core
CPU



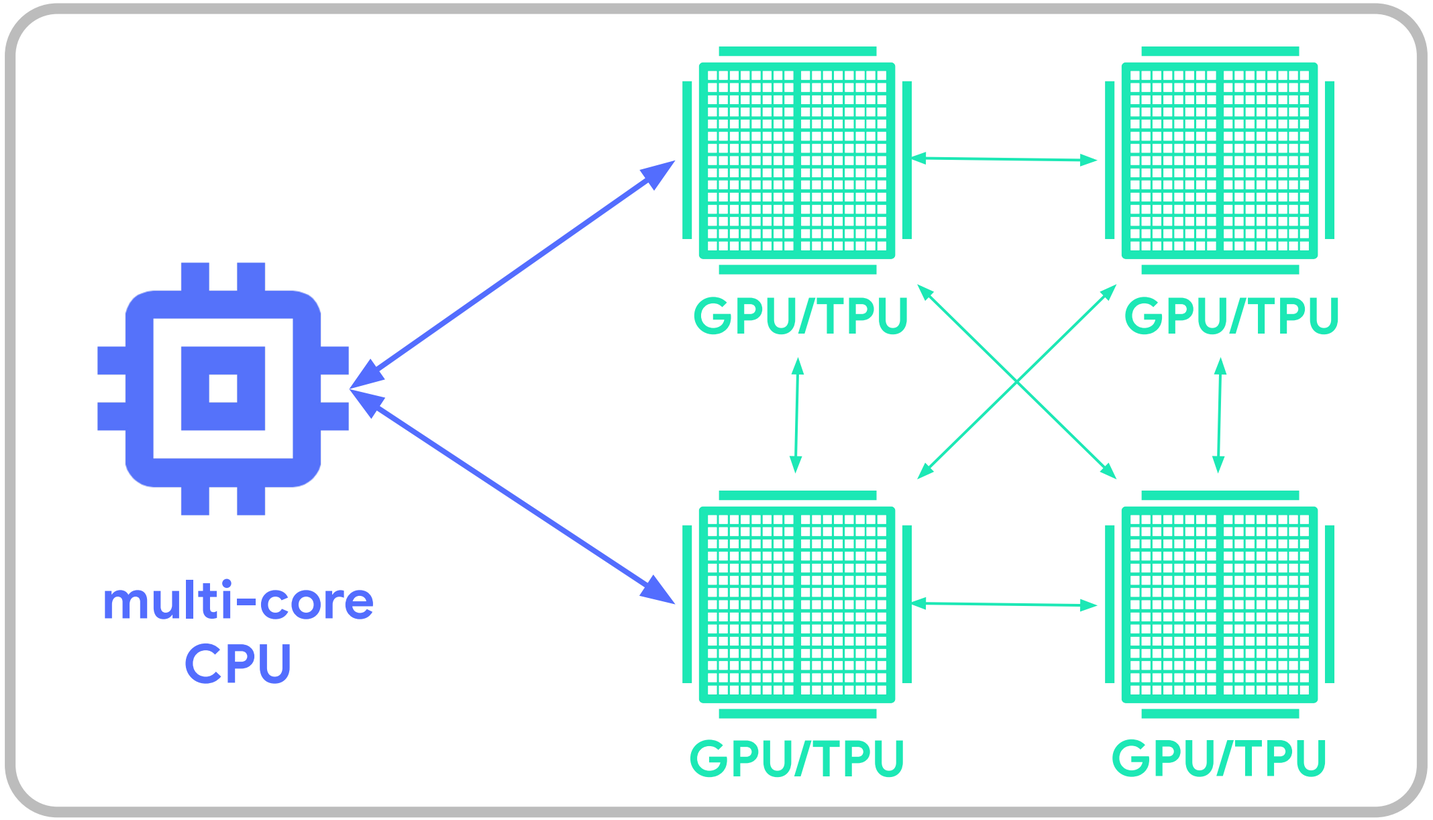
Adding a single accelerator



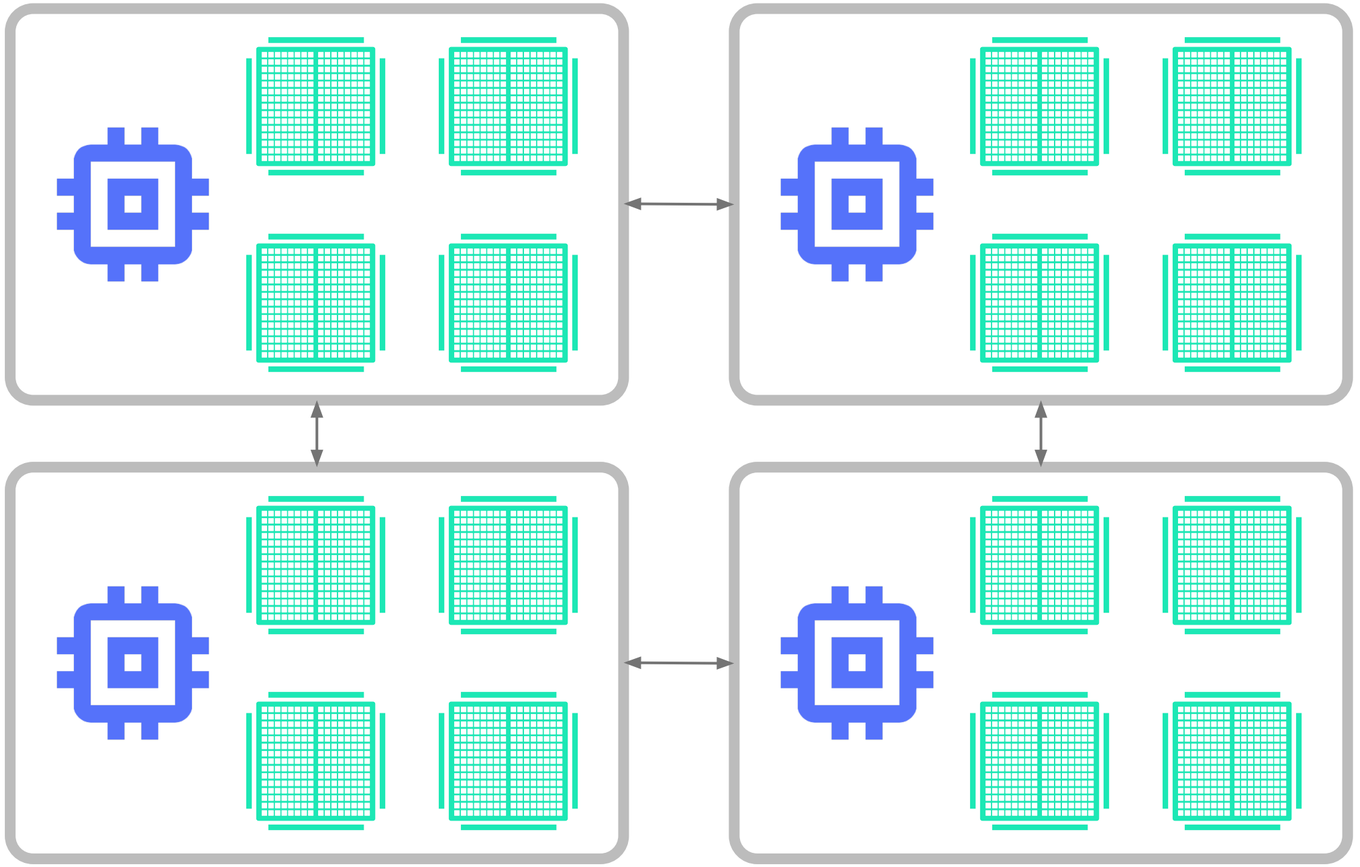
multi-core CPU

GPU/TPU

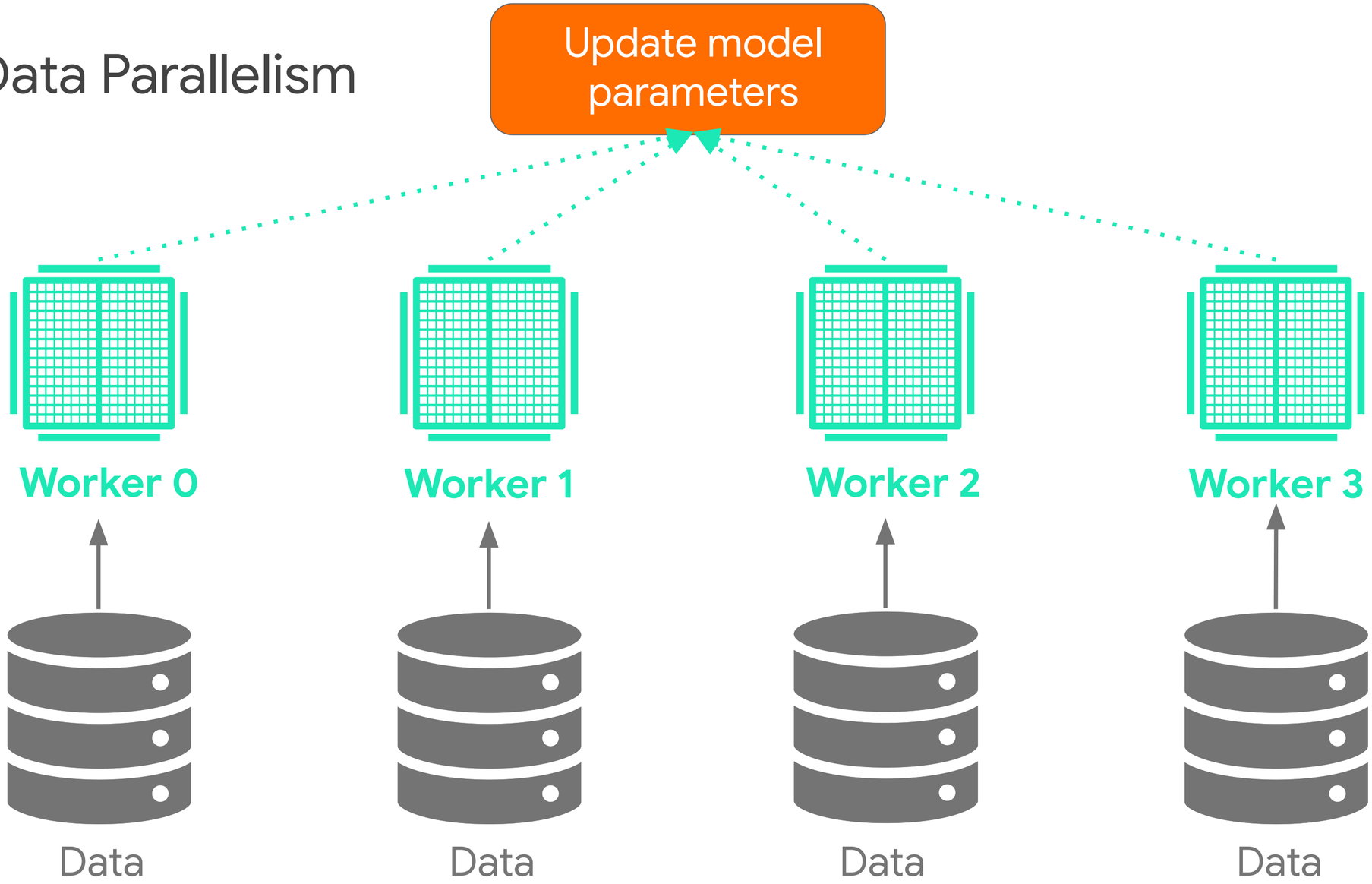
Adding many accelerators to a single device

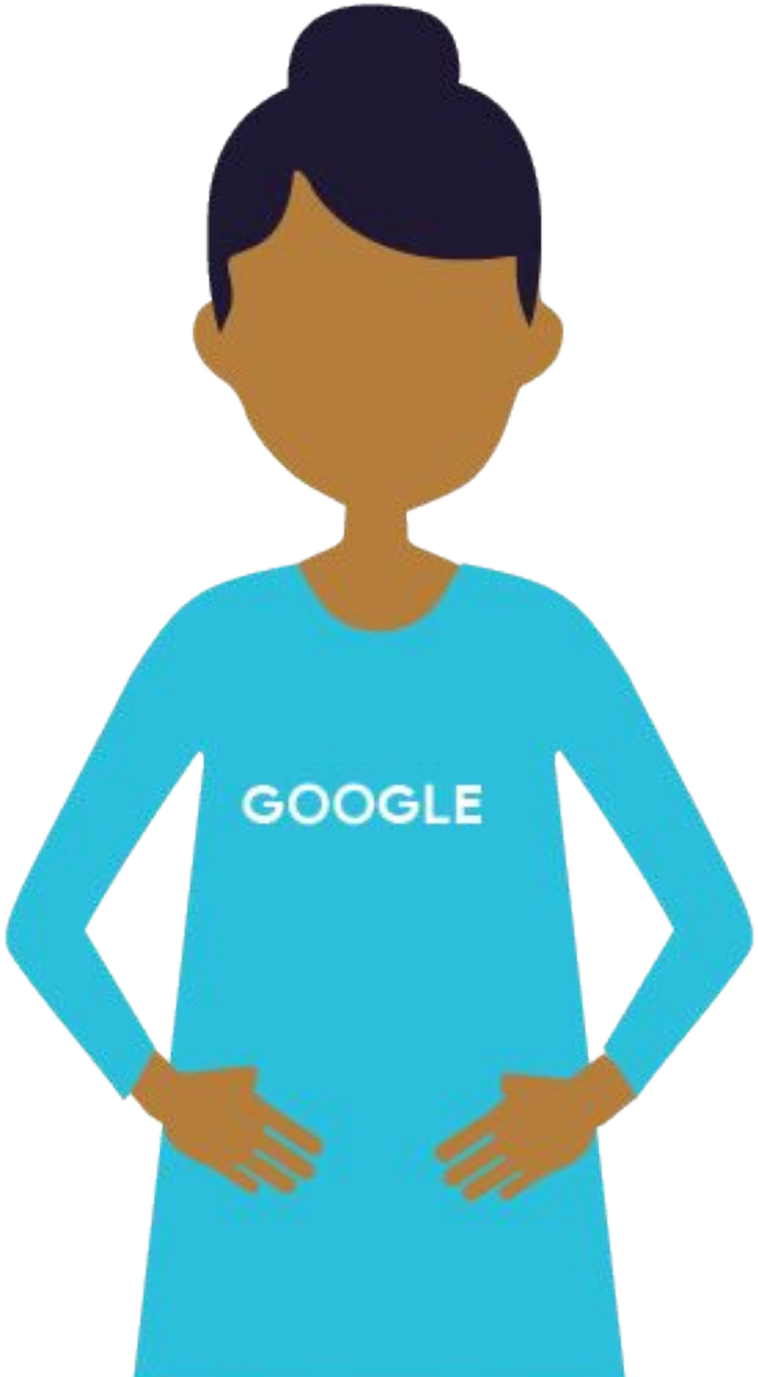


Adding many machines with many possible devices



Data Parallelism

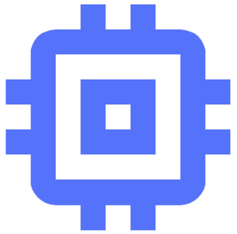




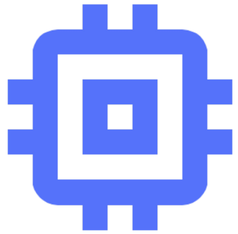
Two approaches to Data Parallelism

1. Parameter server
2. Sync Allreduce

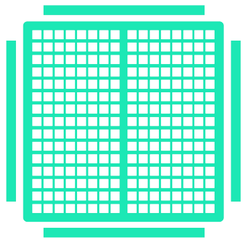
Async Parameter Server



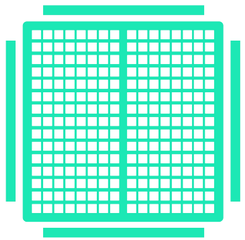
PS0



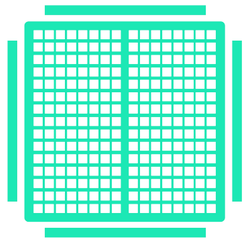
PS1



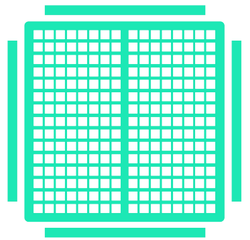
Worker 0



Worker 1

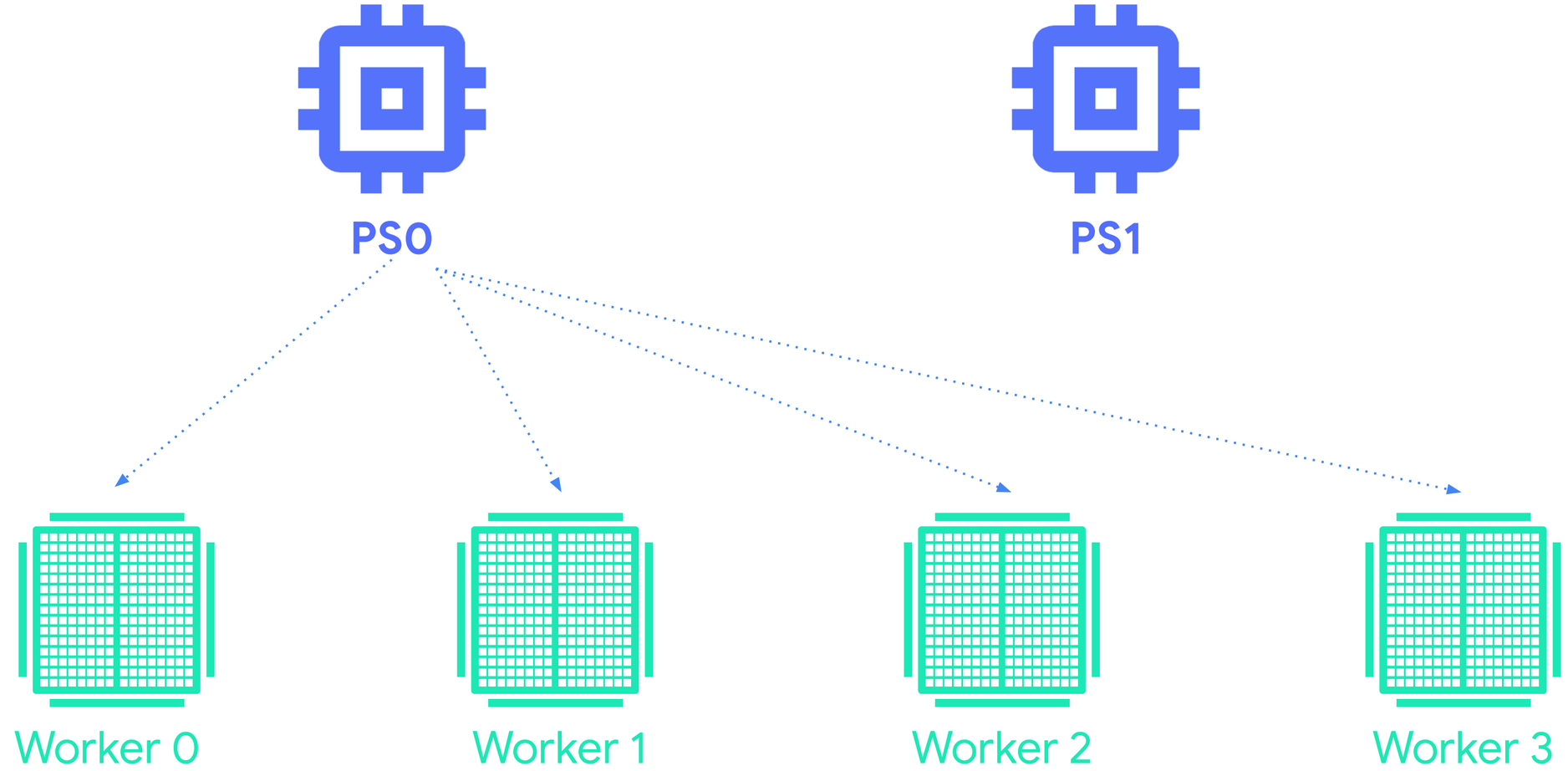


Worker 2

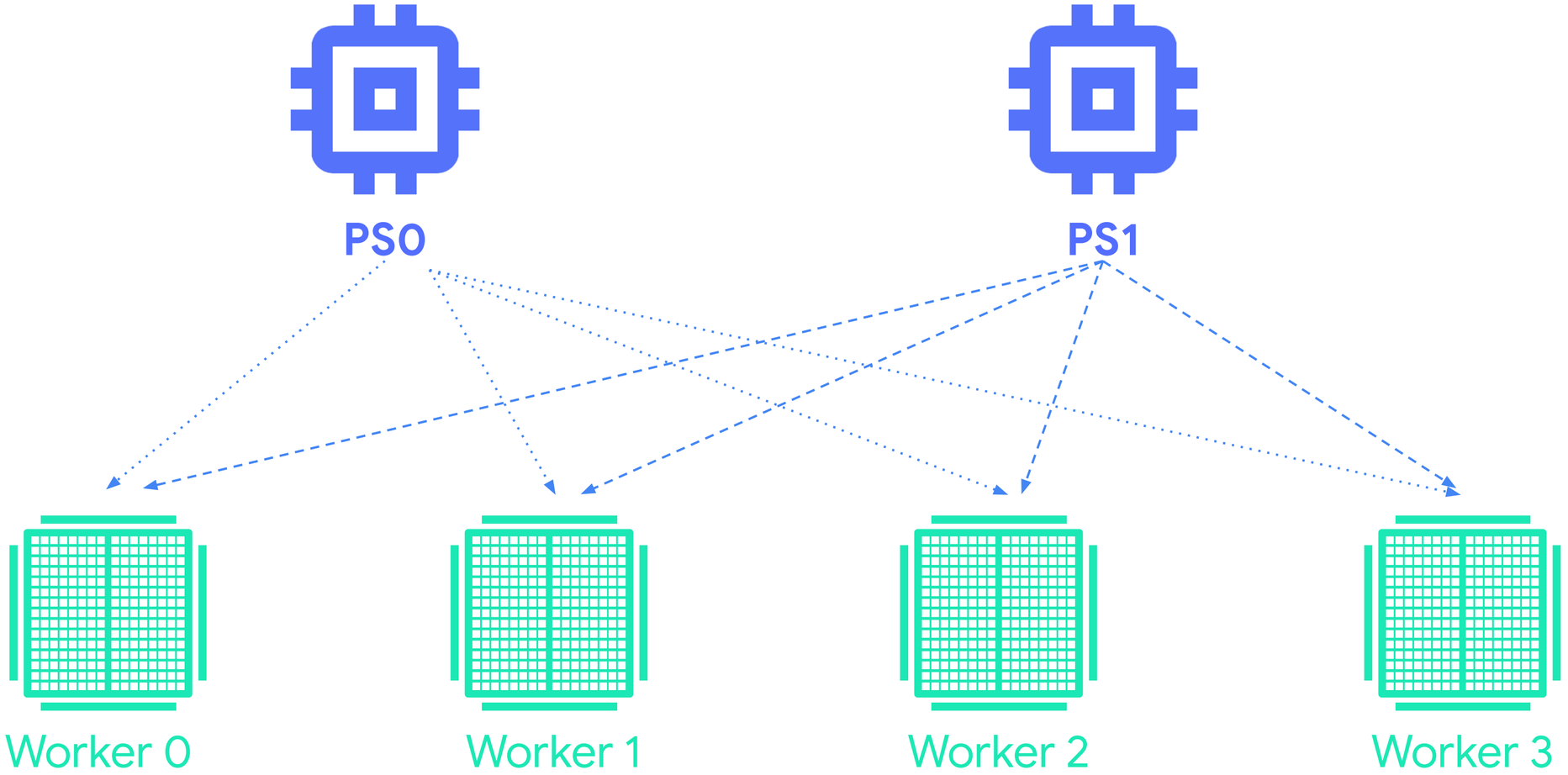


Worker 3

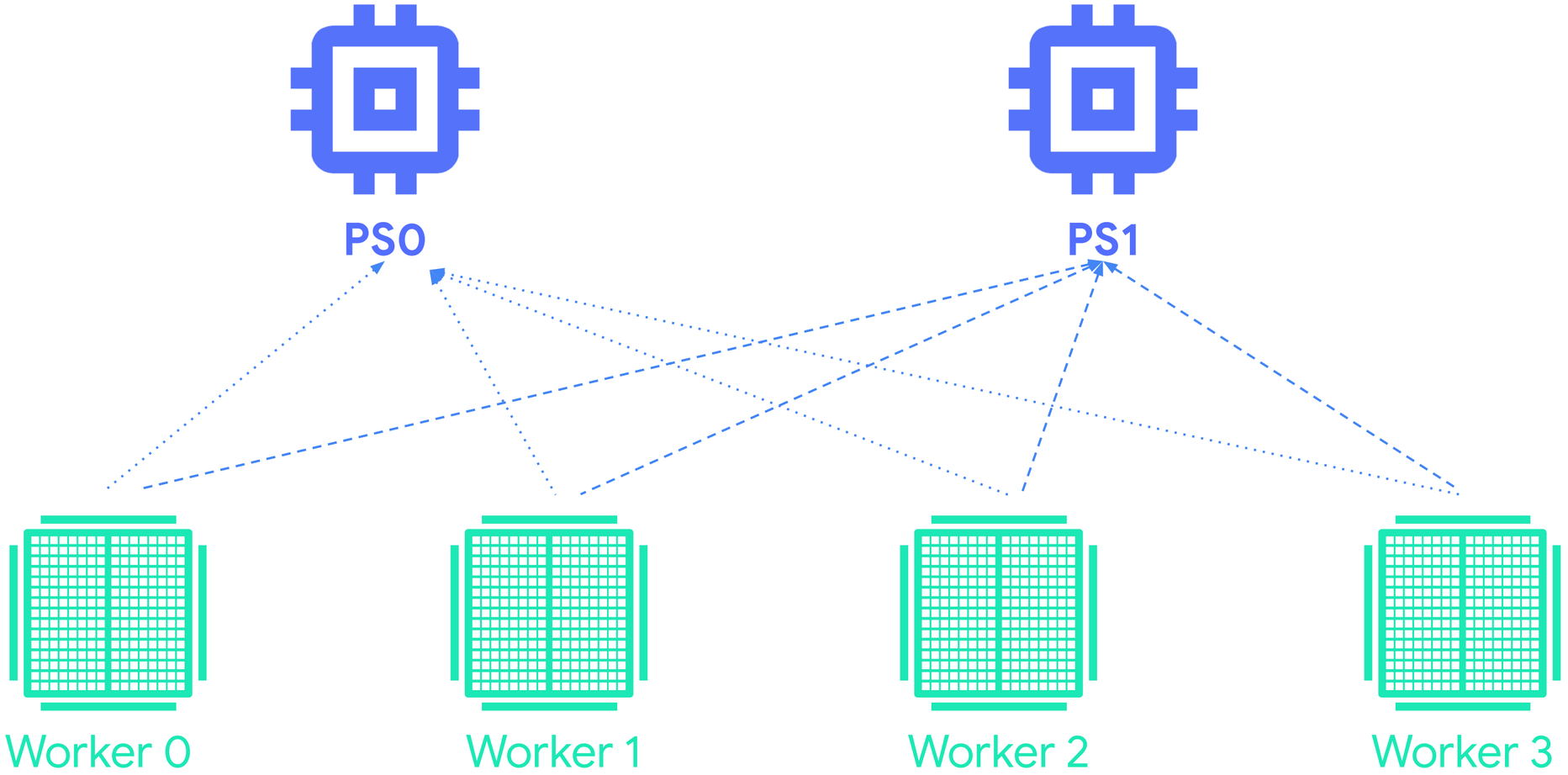
Async Parameter Server



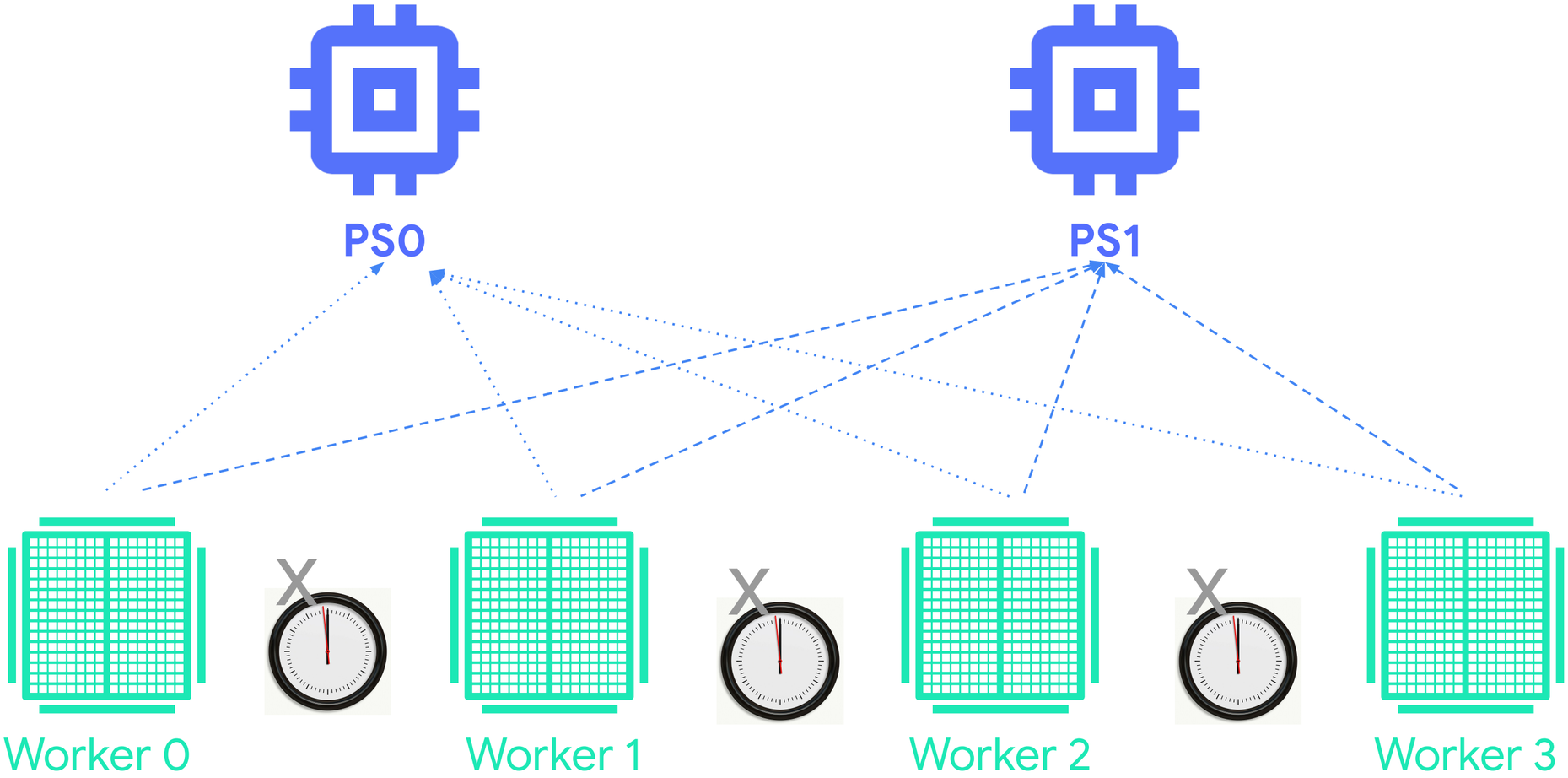
Async Parameter Server



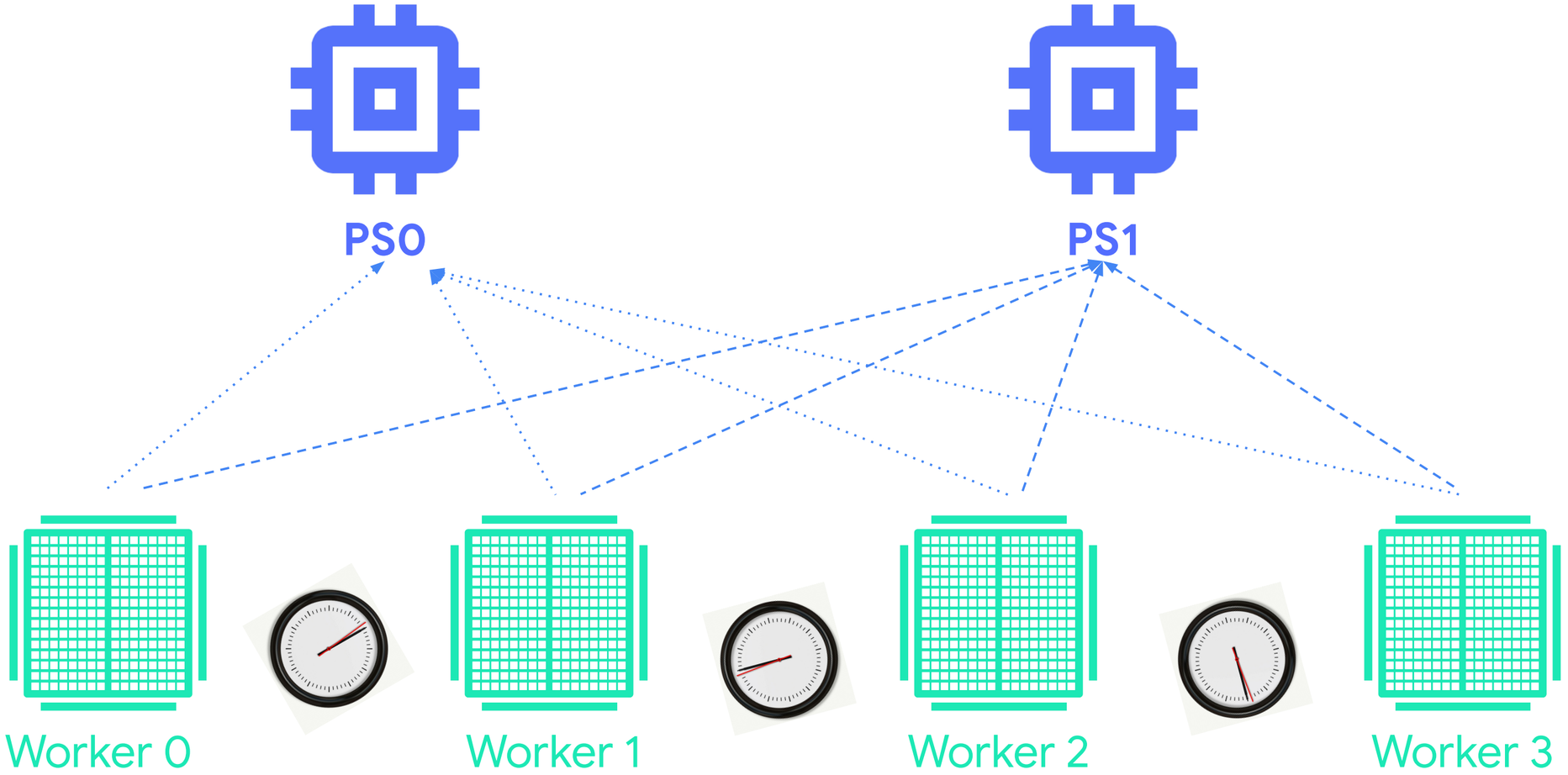
Async Parameter Server



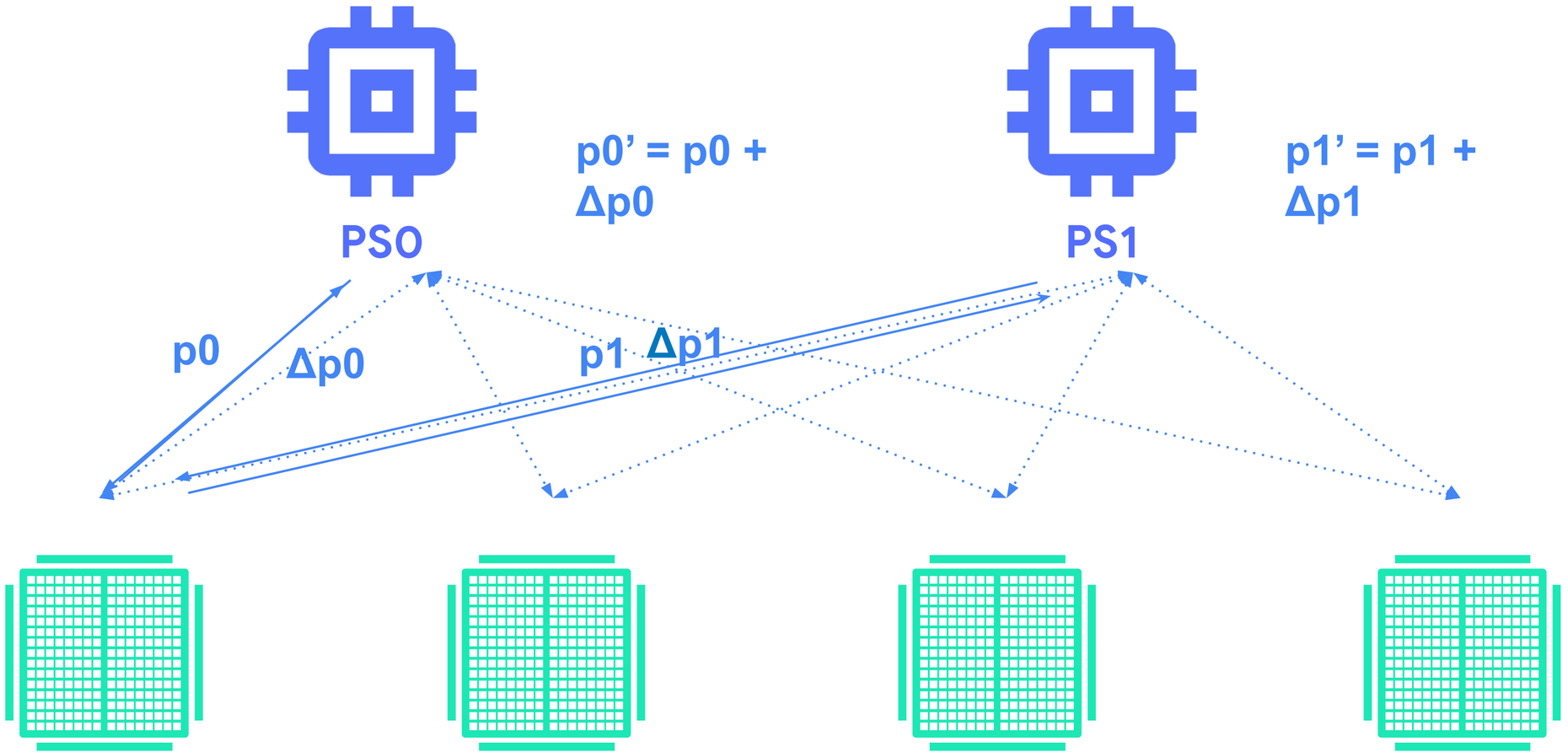
Async Parameter Server

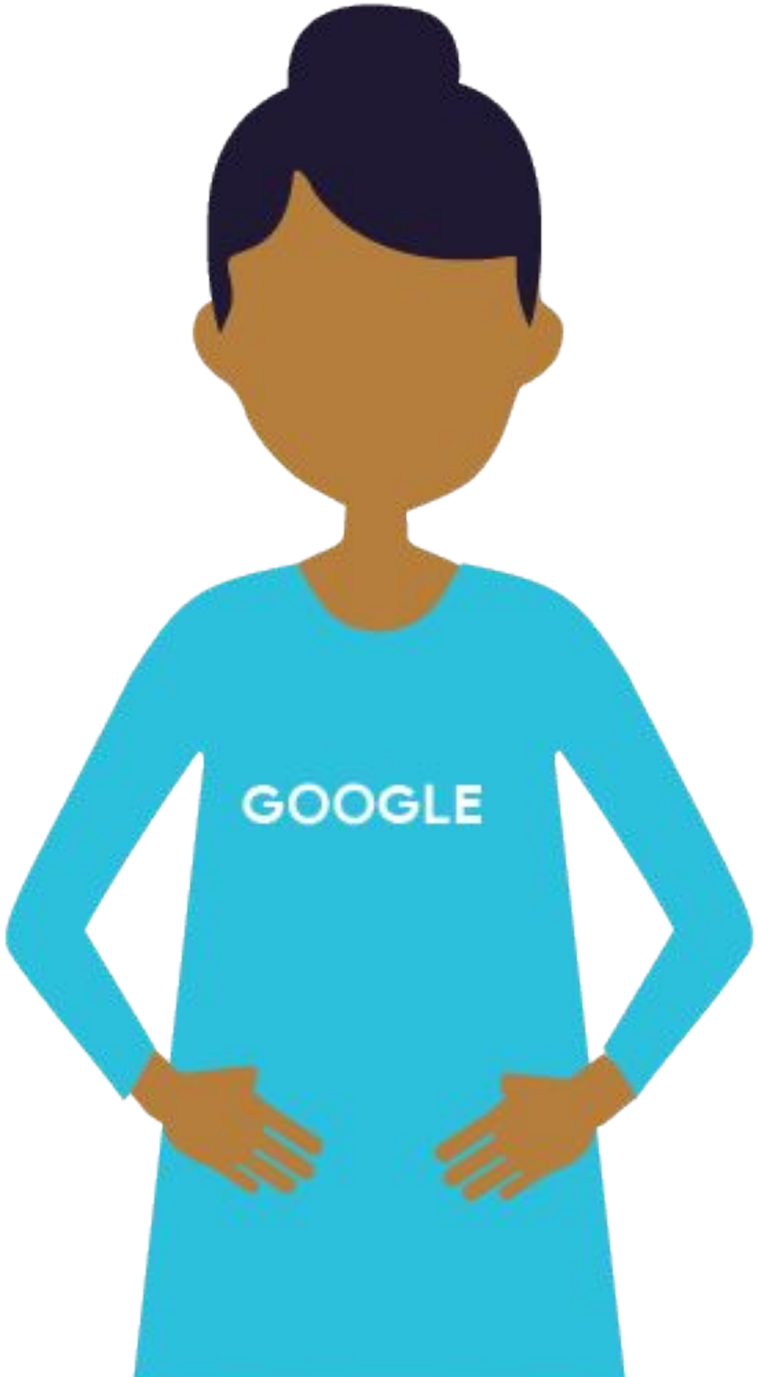


Async Parameter Server



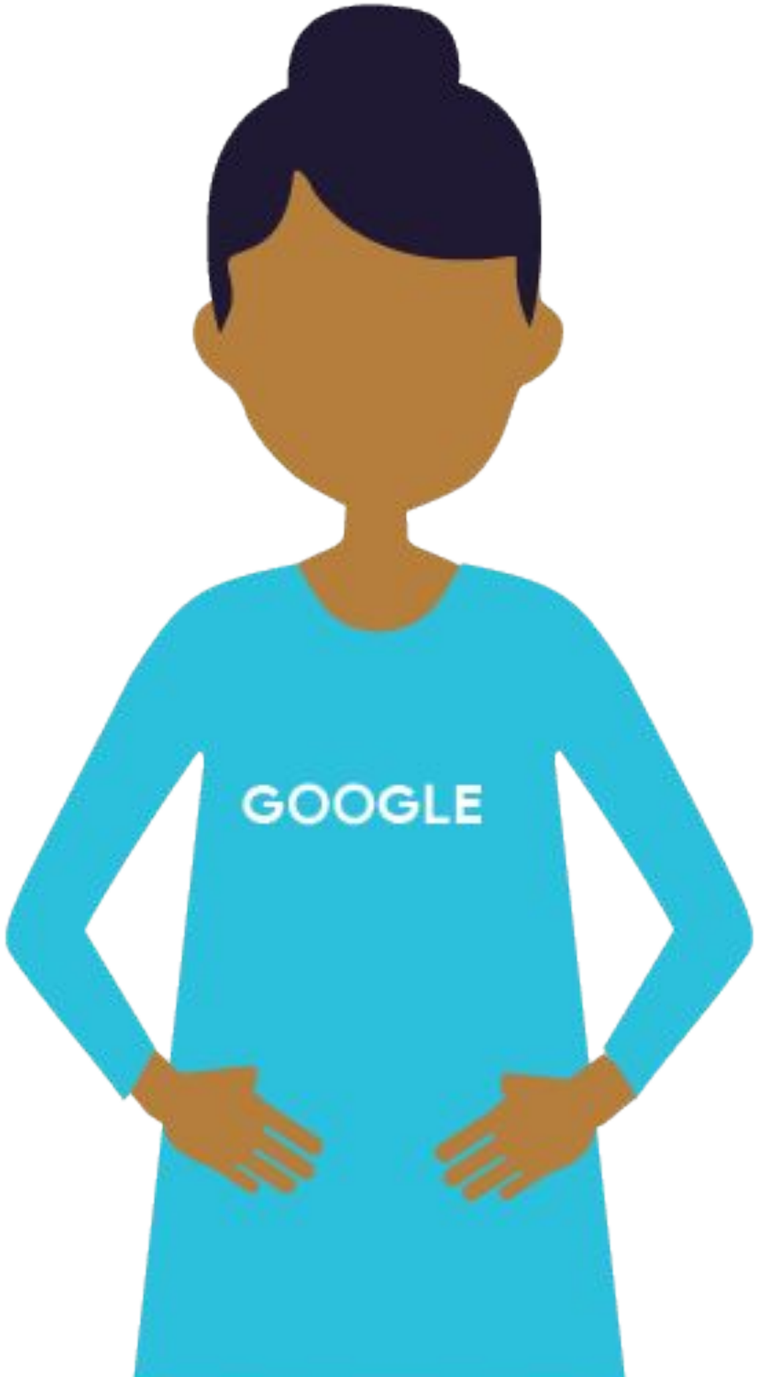
Async Parameter Server



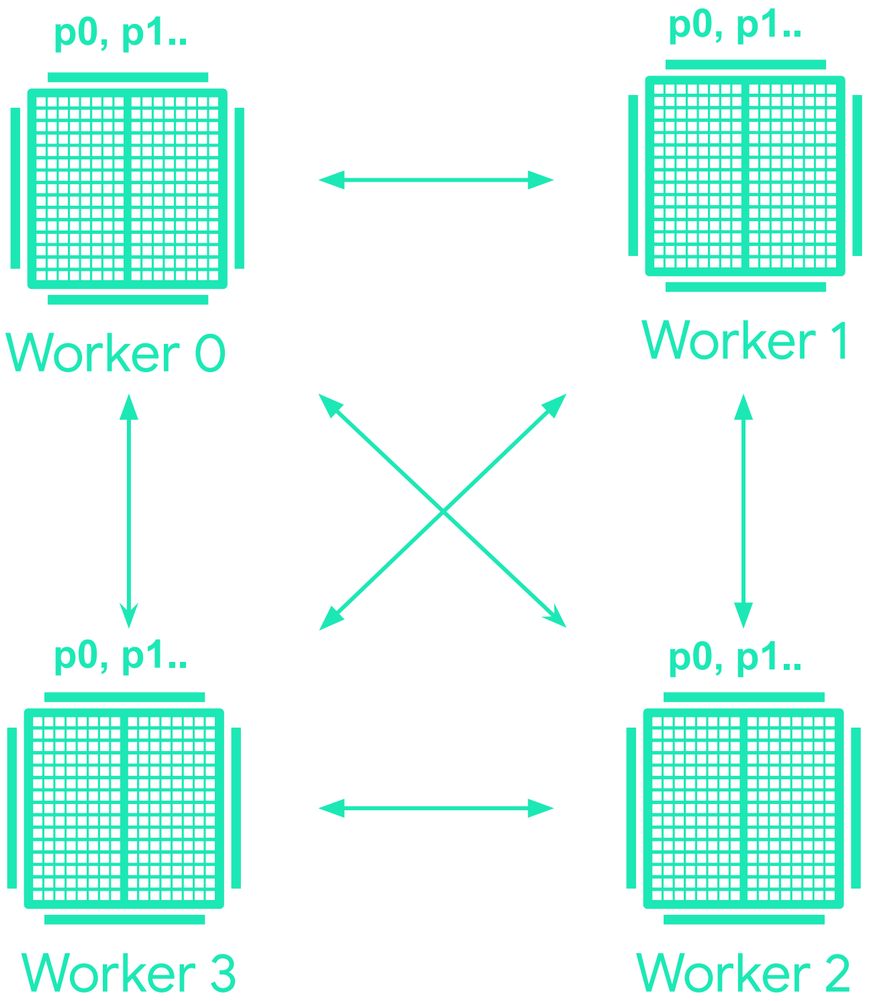


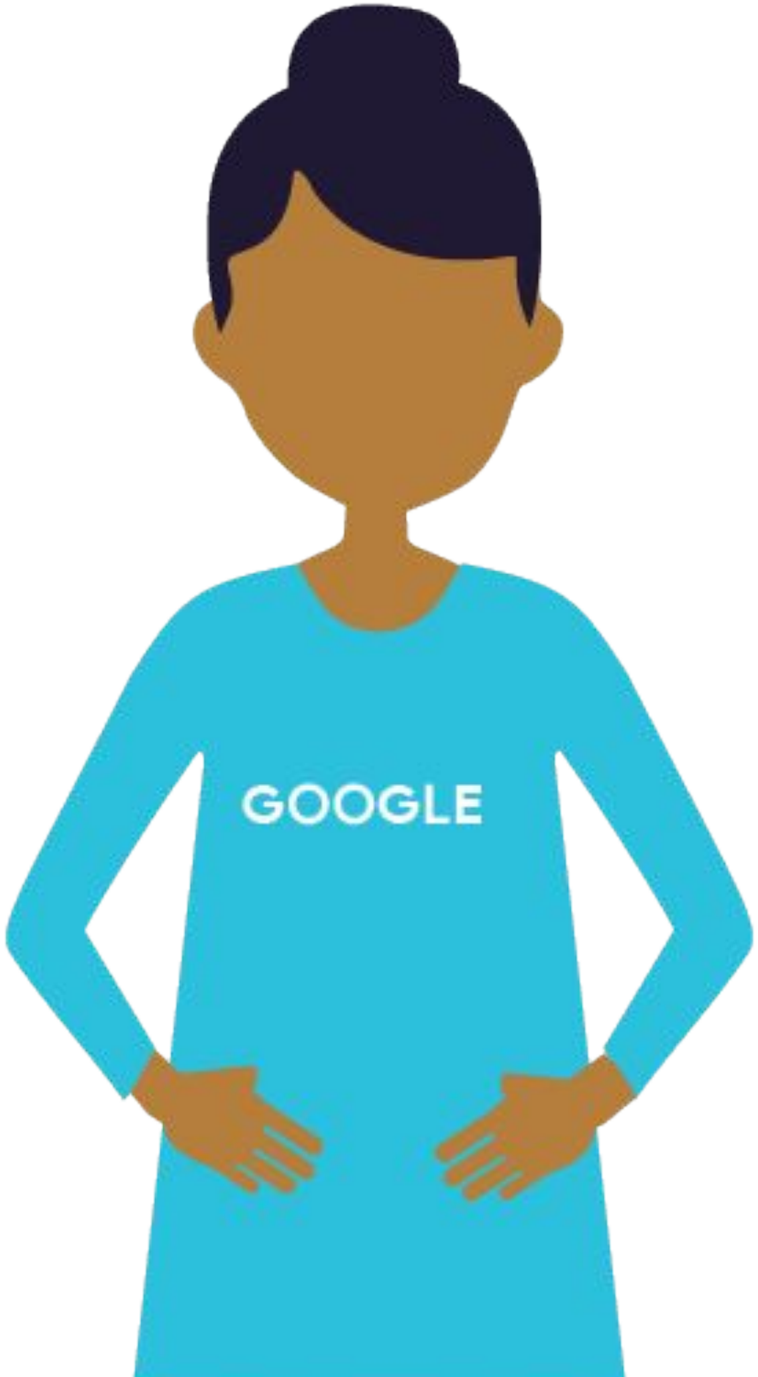
Two approaches to Data Parallelism

1. Parameter server
2. **Sync Allreduce**

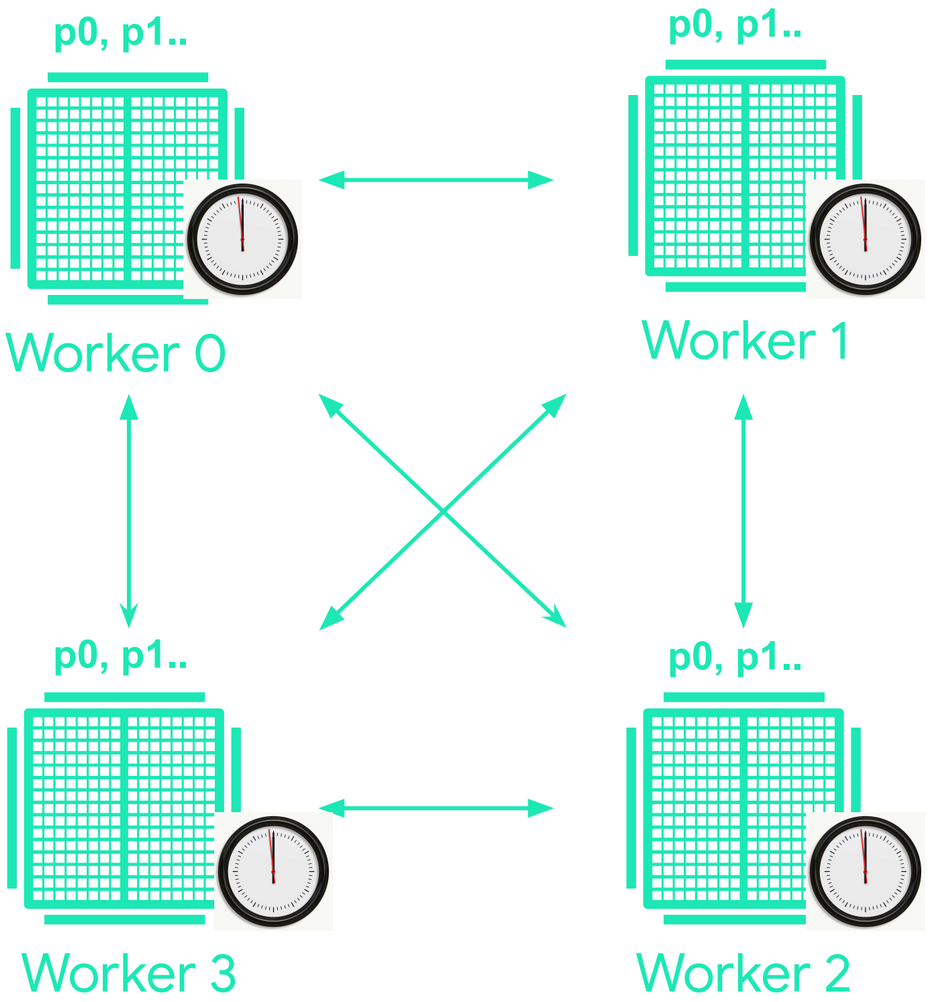


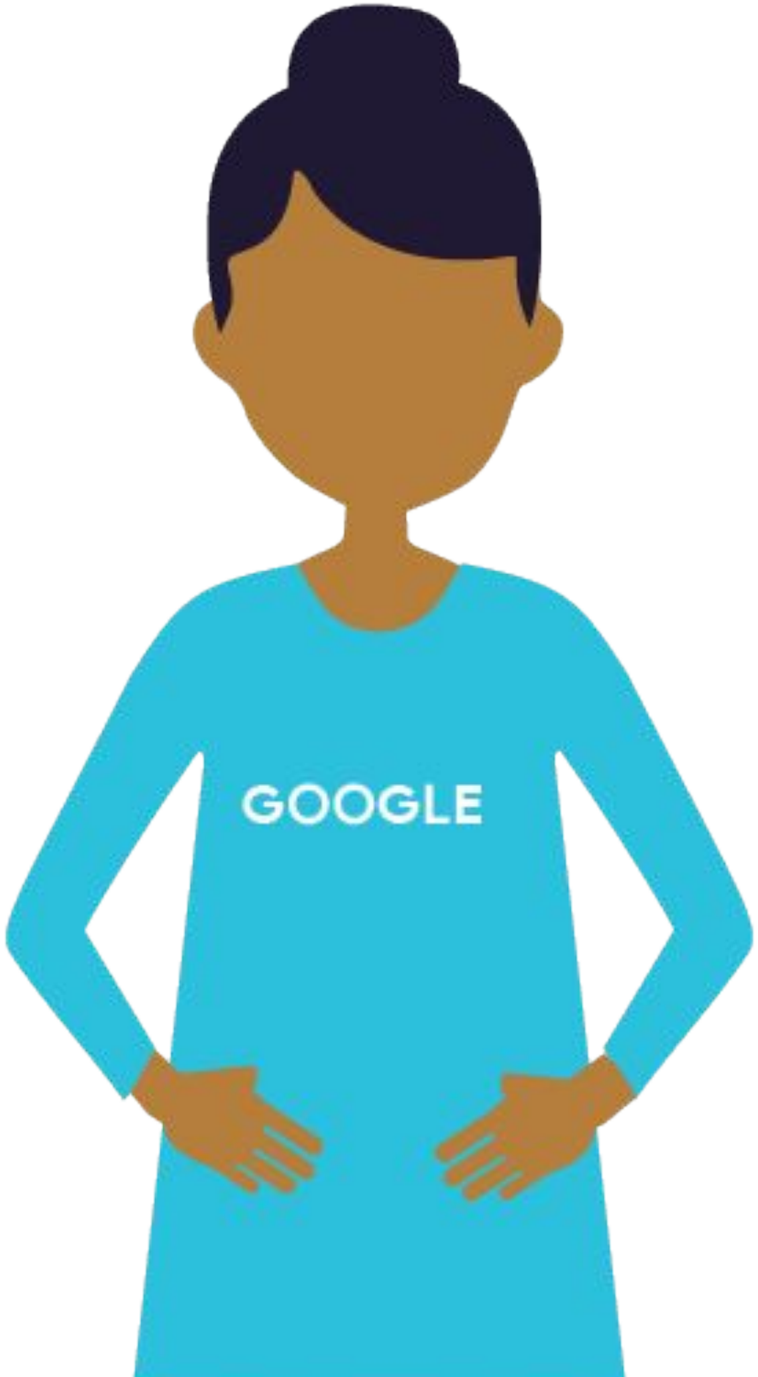
Sync Allreduce Architecture



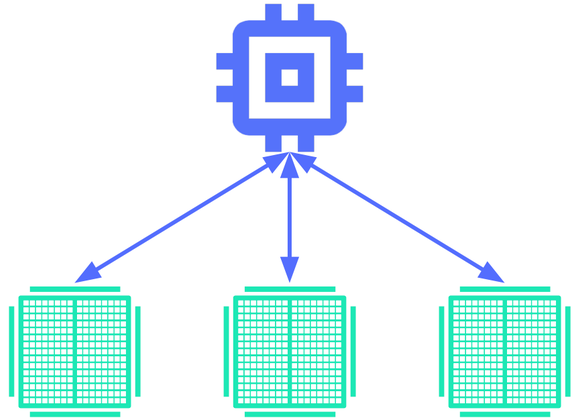


Sync Allreduce Architecture

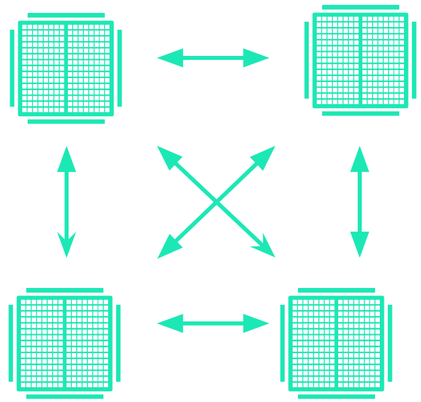




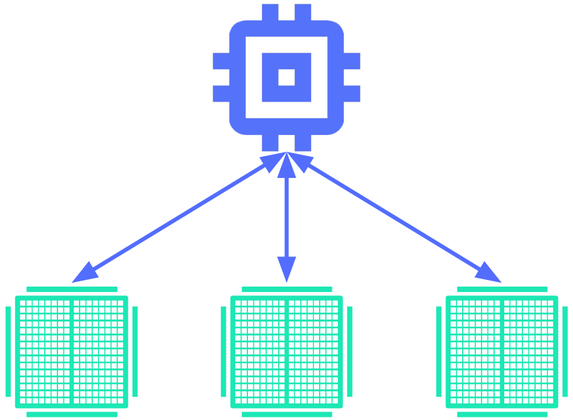
Async Parameter Server



Sync Allreduce

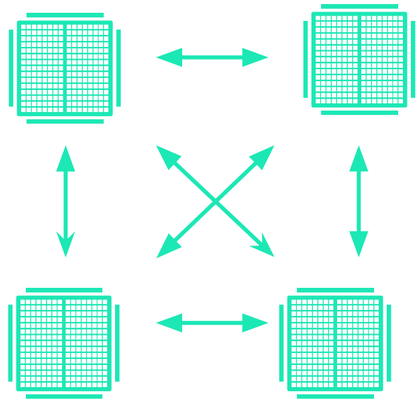


Consider Async Parameter Server if...

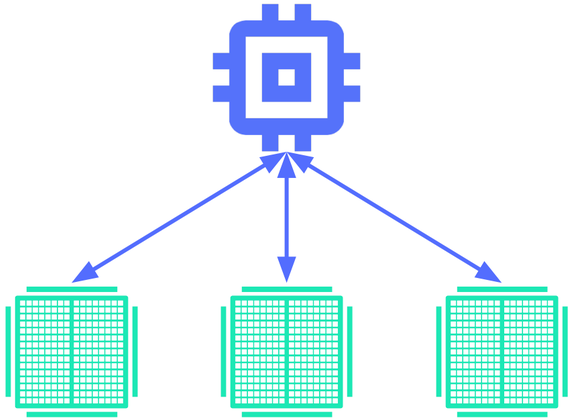


Many low-power
or unreliable workers

Consider Sync Allreduce if...

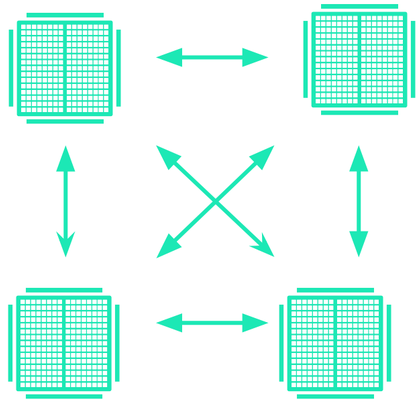


Consider Async Parameter Server if...



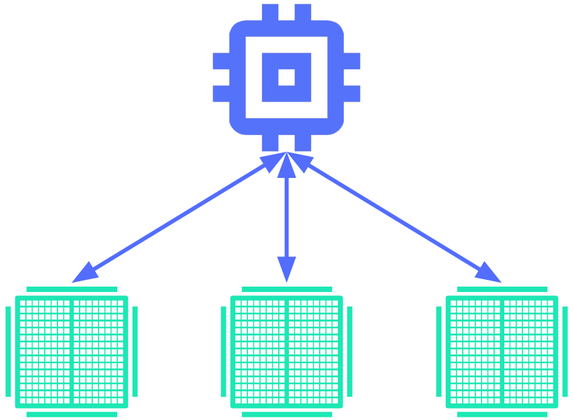
Many low-power
or unreliable workers

Consider Sync Allreduce if...



Multiple devices on one host
Fast devices with strong links (e.g. TPUs)

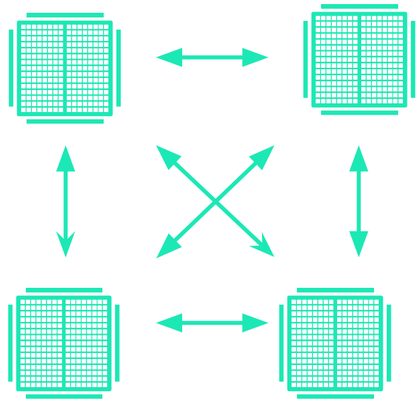
Consider Async Parameter Server if...



Many low-power
or unreliable workers

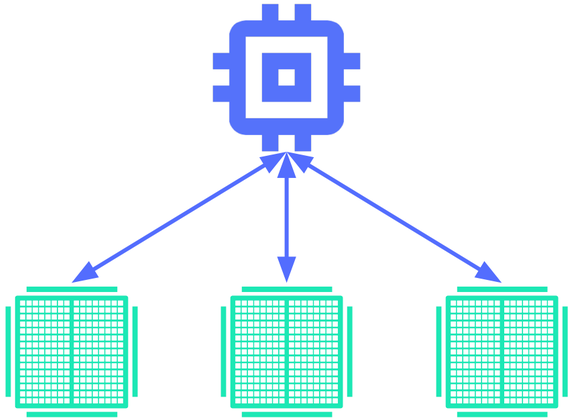
More mature approach

Consider Sync Allreduce if...



Multiple devices on one host
Fast devices with strong links (e.g. TPUs)

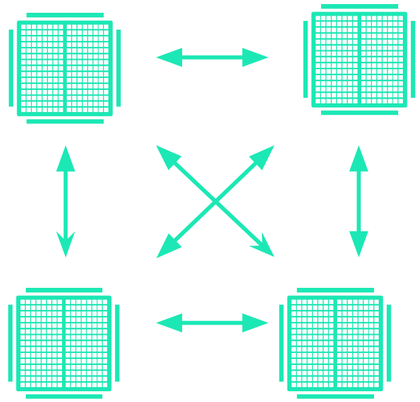
Consider Async Parameter Server if...



Many low-power
or unreliable workers

More mature approach

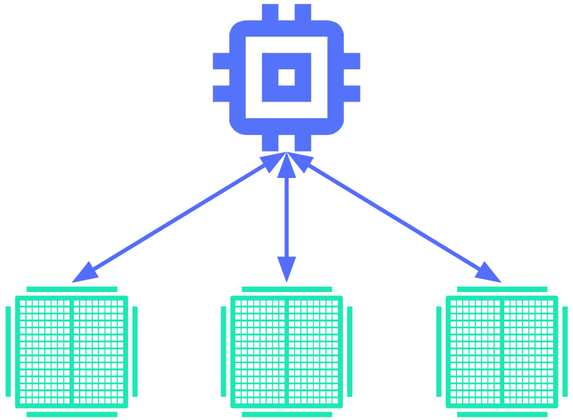
Consider Sync Allreduce if...



Multiple devices on one host
Fast devices with strong links (e.g. TPUs)

Better for multiple GPUs

Consider Async Parameter Server if...

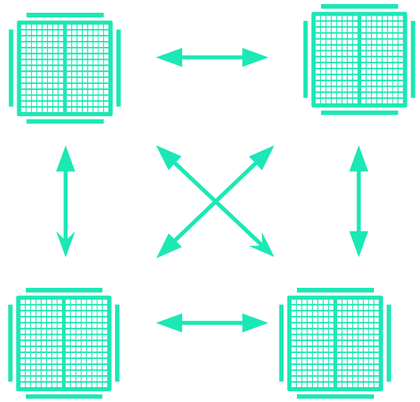


Many low-power
or unreliable workers

More mature approach

Constrained by I/O

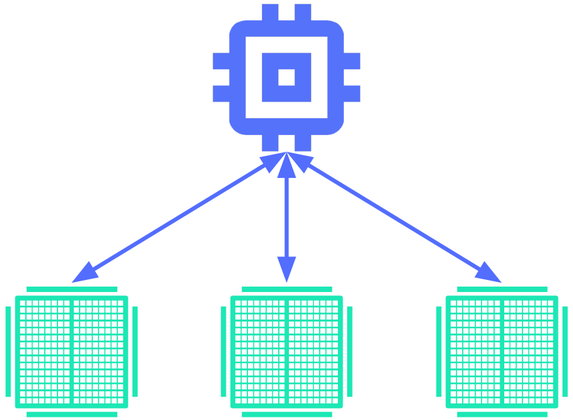
Consider Sync Allreduce if...



Multiple devices on one host
Fast devices with strong links (e.g. TPUs)

Better for multiple GPUs

Consider Async Parameter Server if...

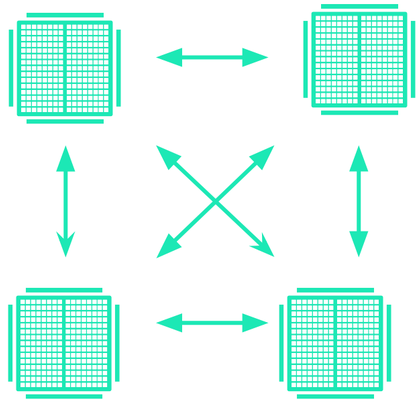


Many low-power
or unreliable workers

More mature approach

Constrained by I/O

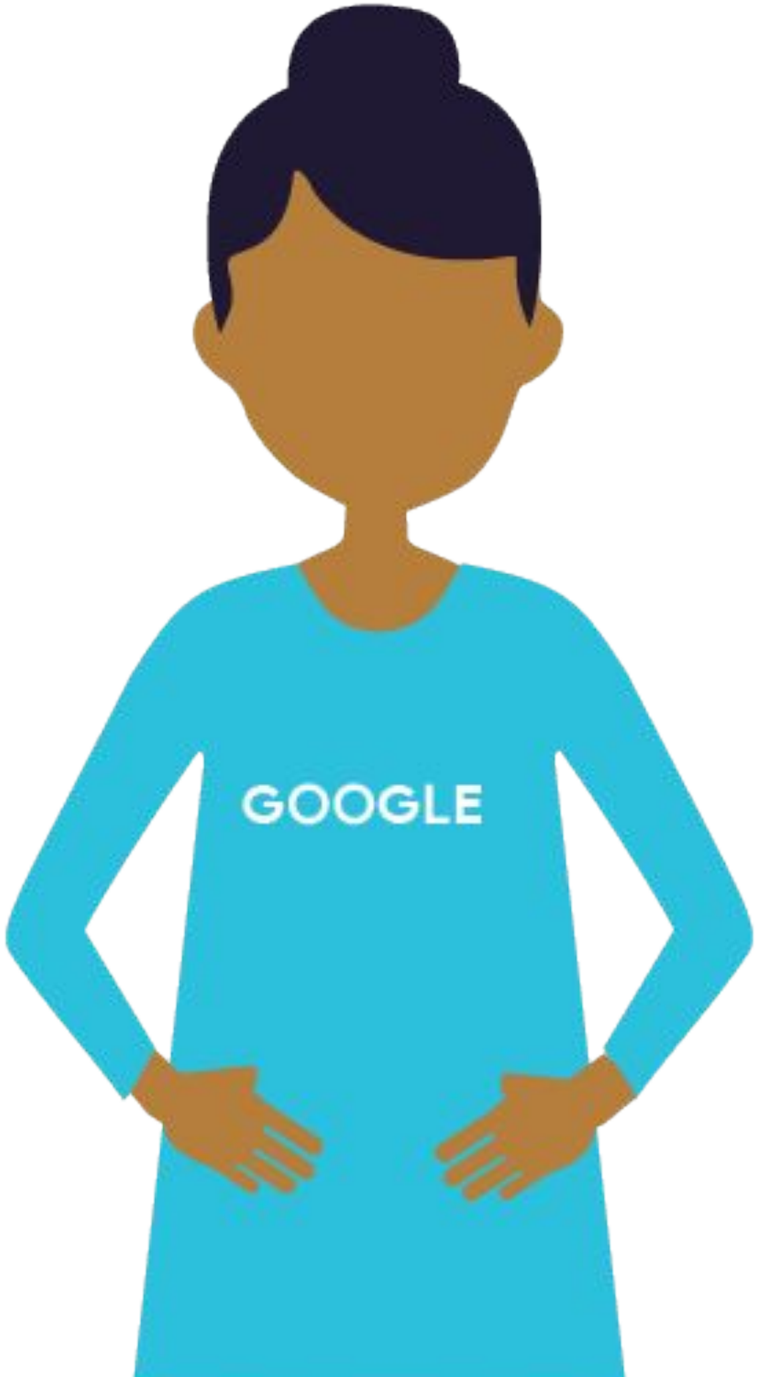
Consider Sync Allreduce if...



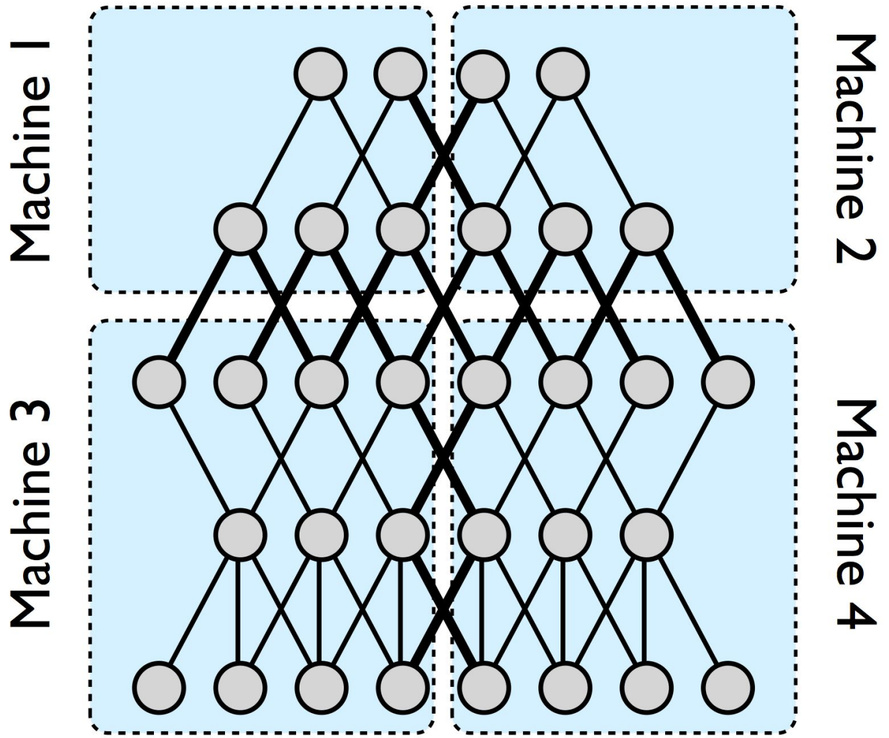
Multiple devices on one host
Fast devices with strong links (e.g. TPUs)

Better for multiple GPUs

Constrained by compute power



Model Parallelism



Courses 7 - Production ML Systems

Module 4: Designing High-Performance ML Systems

Lesson Title: **Faster input pipelines**

Format: Presenter

Presenter: Laurence Moroney

Video Name: T-PSML-O_4_l6_faster_input_pipelines

Agenda

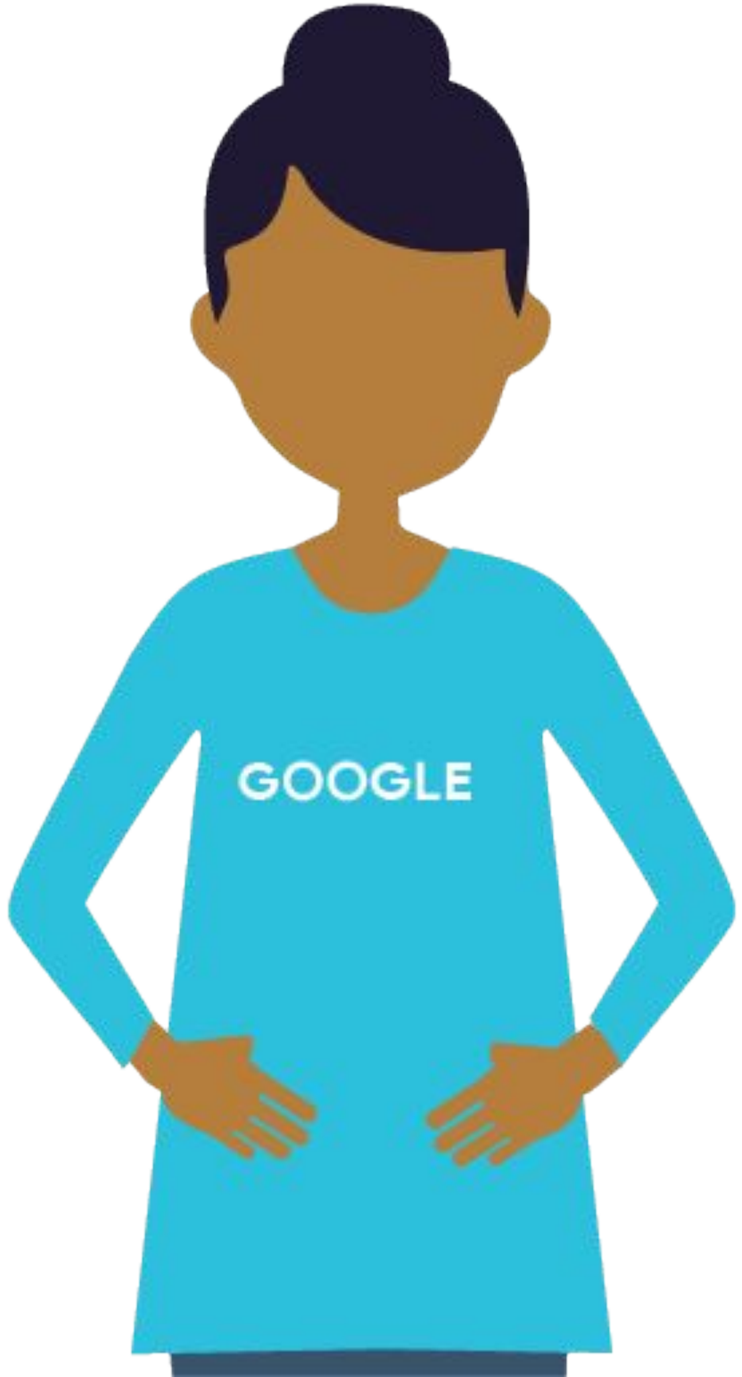
Distributed training

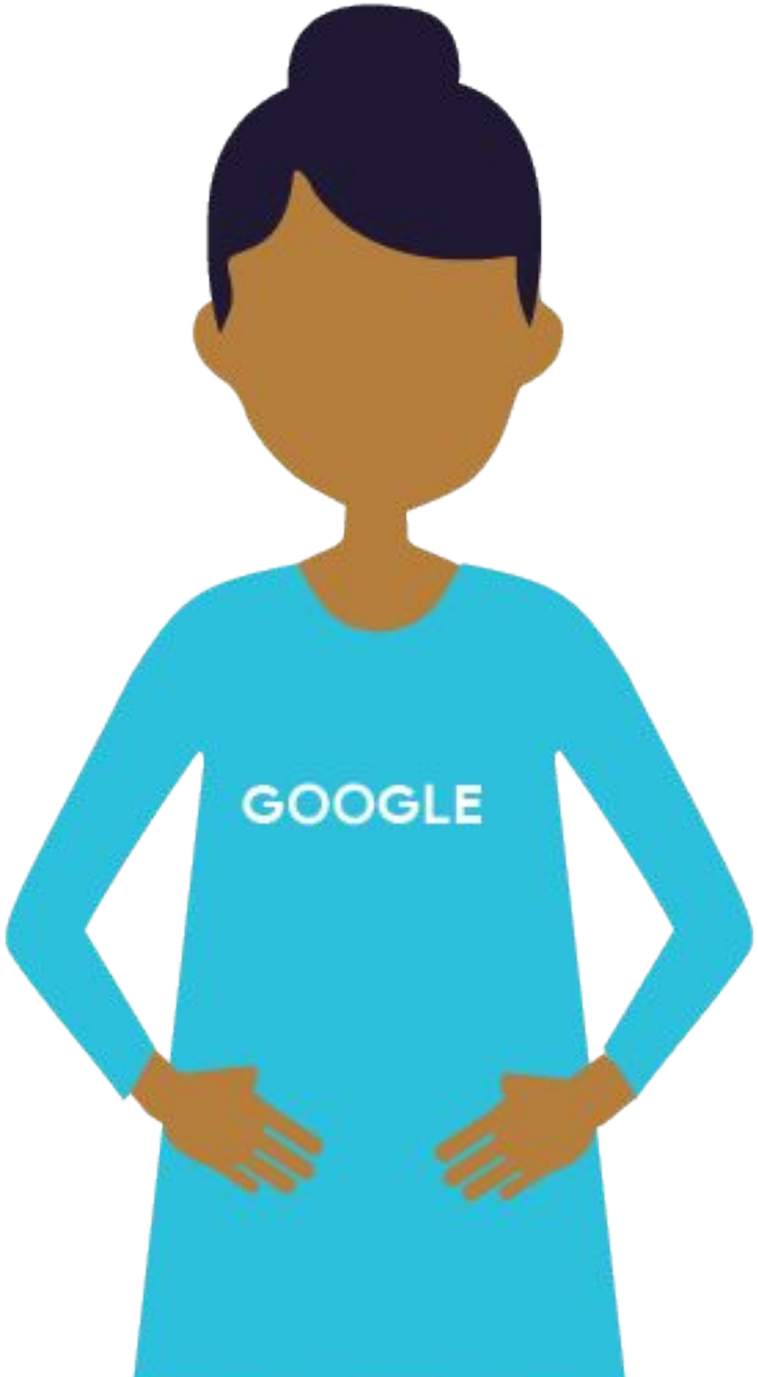
Faster input pipelines

Data parallelism (All Reduce)

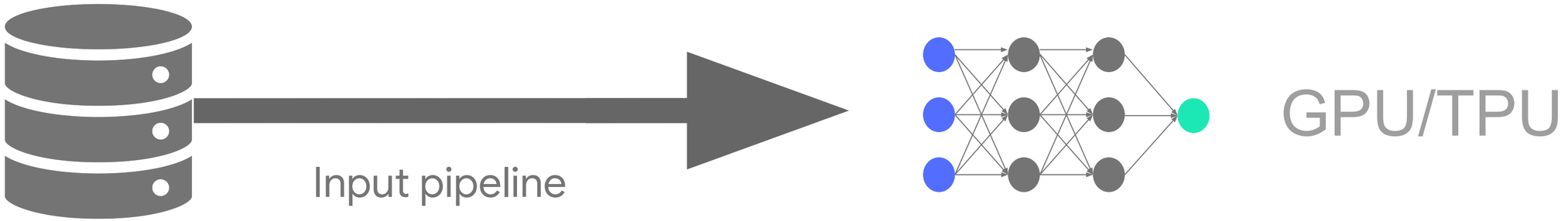
Parameter Server approach

Inference

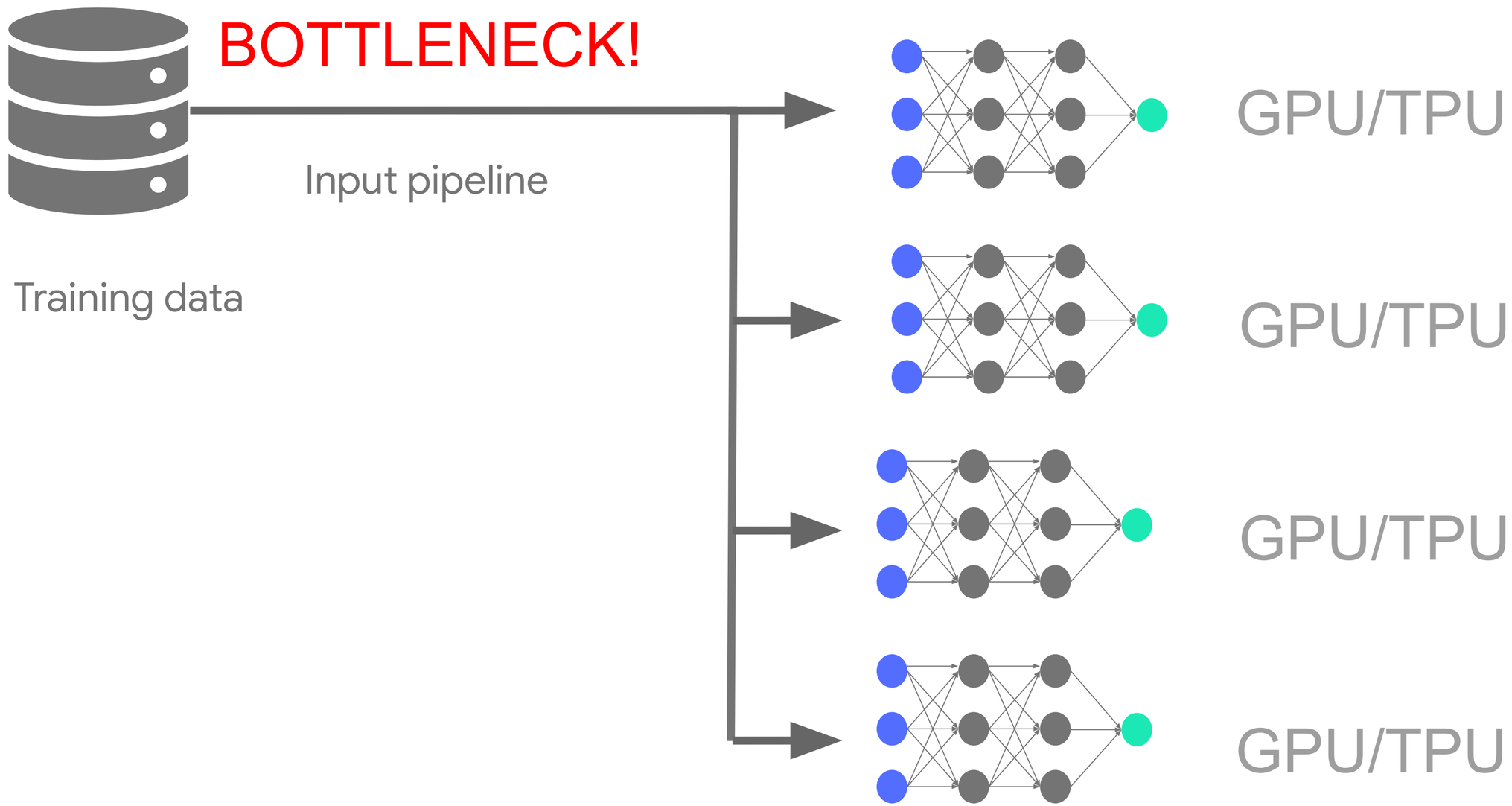


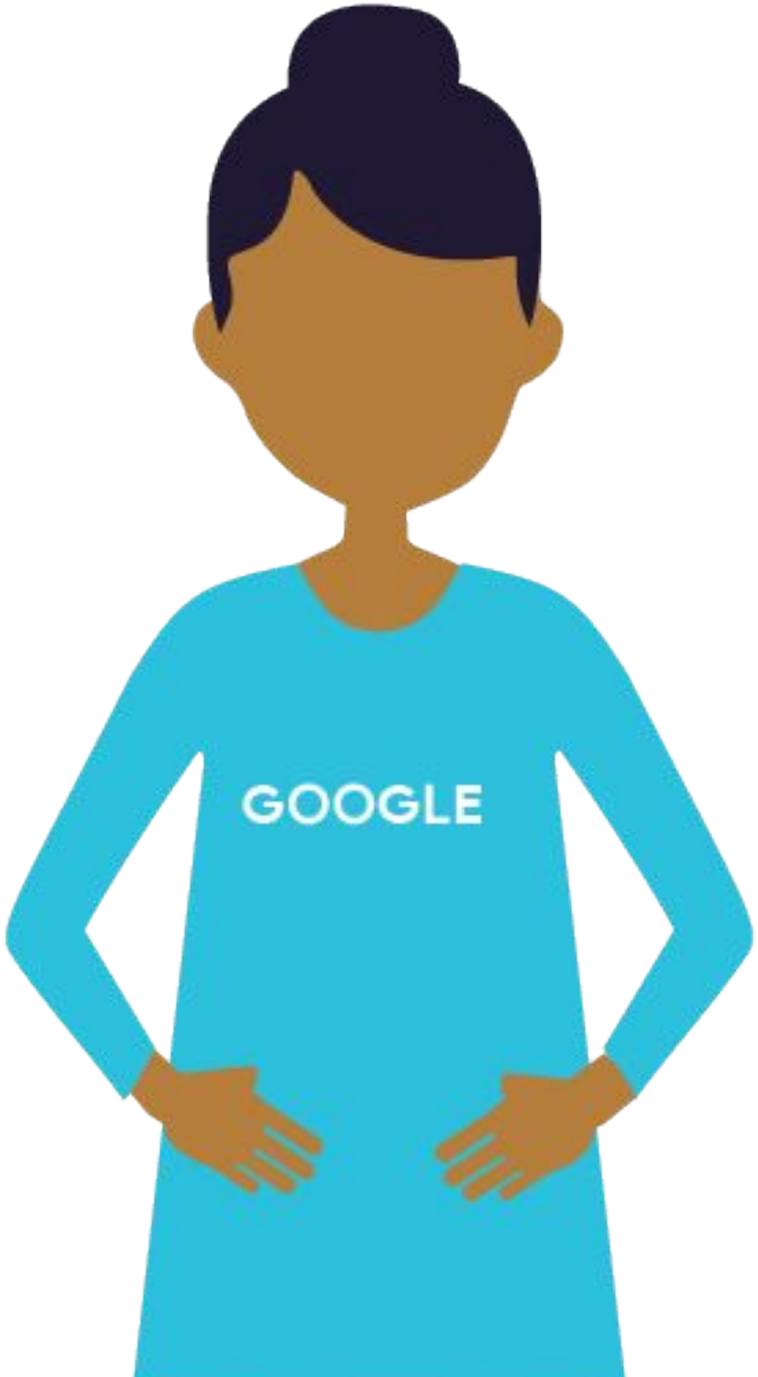


Faster input pipelines

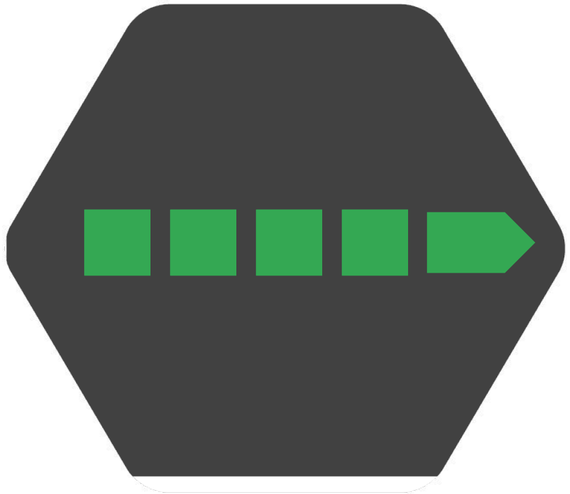


Training data

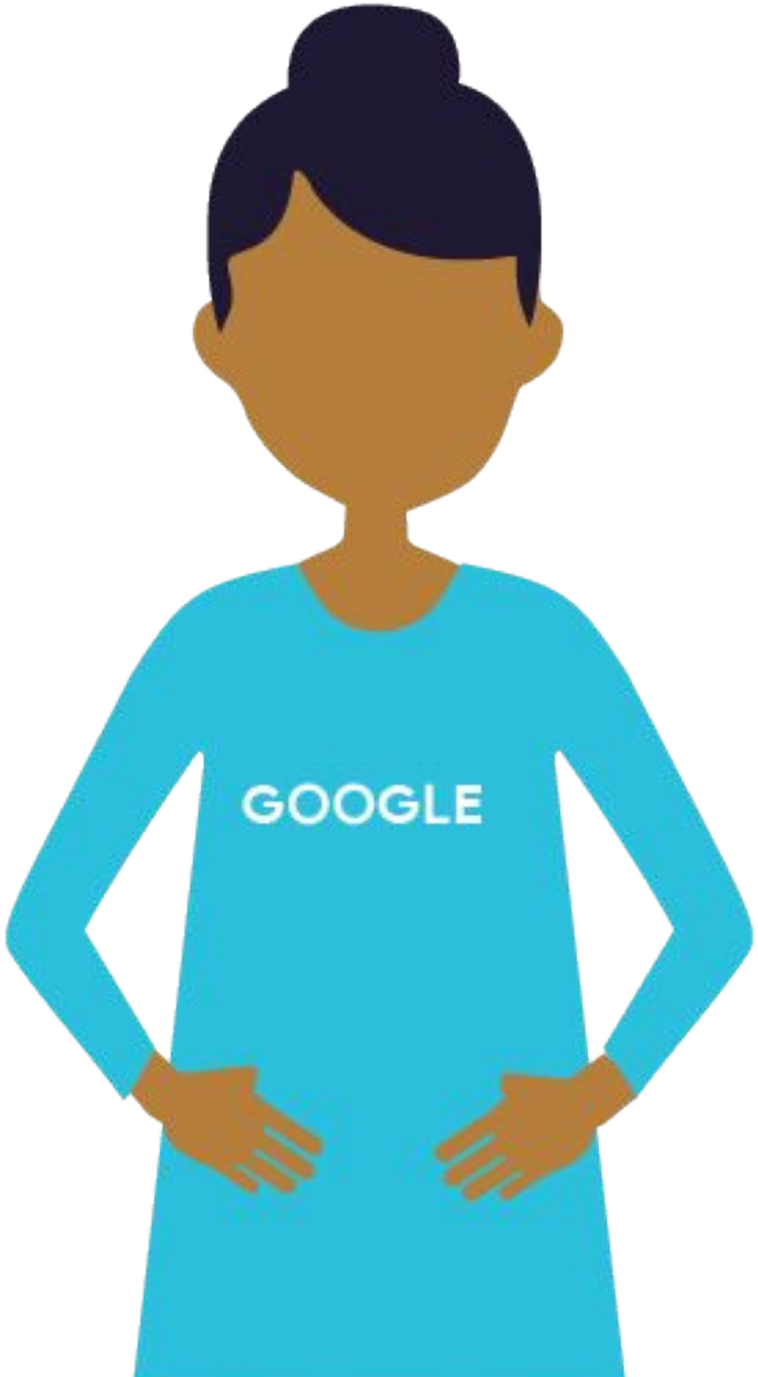

BOTTLENECK!
Input pipeline
Training data
GPU/TPU
GPU/TPU
GPU/TPU
GPU/TPU



Reading Data into TensorFlow

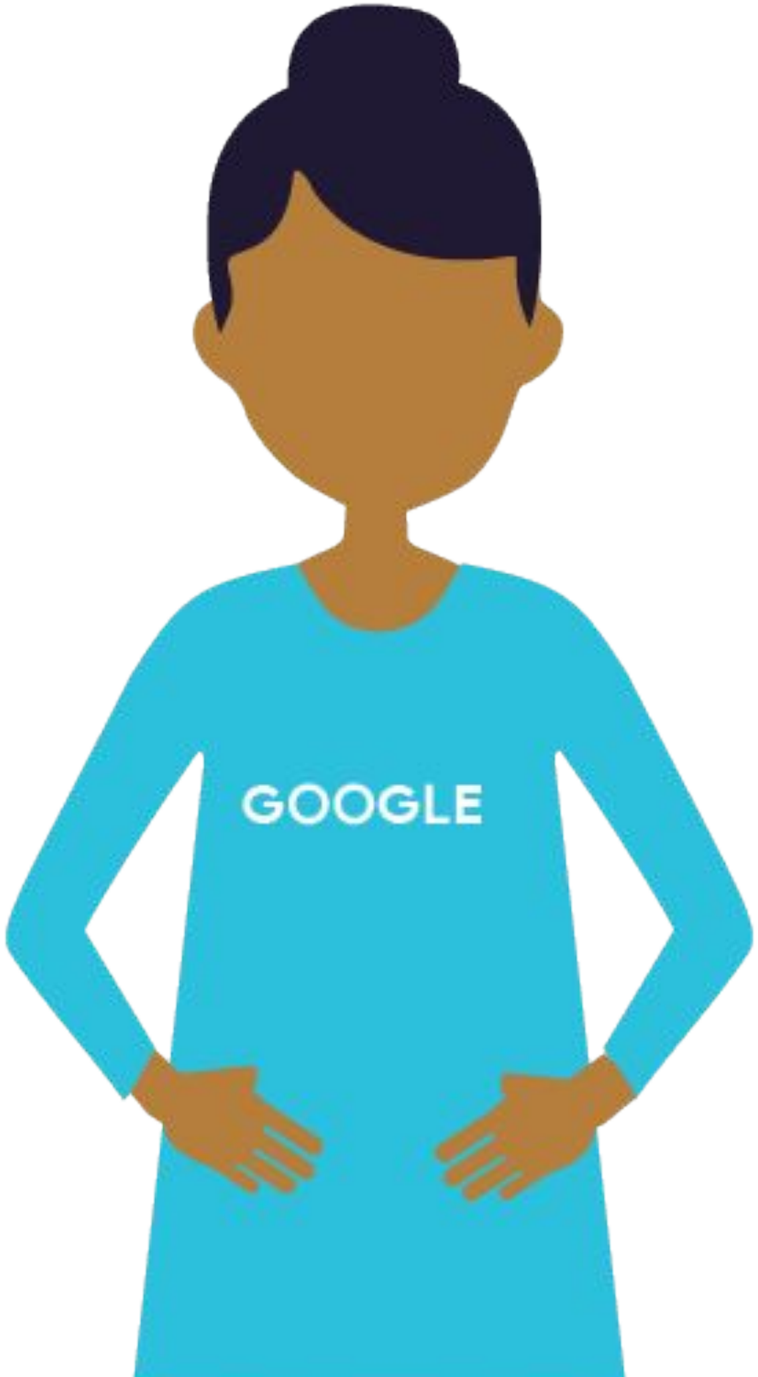


1. Directly feed from Python



Reading Data into TensorFlow

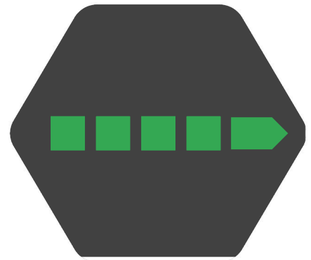
2. Native TensorFlow Ops



Reading Data into TensorFlow

3. Read transformed tf records

1. Feed TensorFlow directly from Python



```
def get_input_fn(data_set, num_epochs = None):
  return tf.estimator.inputs.pandas_input_fn(
      x = pd.DataFrame({k: data_set[k].values for k in FEATURES}),
      y = pd.Series(data_set[LABEL].values),
      num_epochs = num_epochs,
      shuffle = True, batch_size = 128)
```

Entire dataset in memory

Shuffle the data

Courses 7 - Production ML Systems

Module 4: Designing High-Performance ML Systems

Lesson Title: **Native TensorFlow Operations**

Format: Screencast

Presenter: Laurence Moroney

Video Name: T-PSML-O_4_l7_native_tensorflow_operations

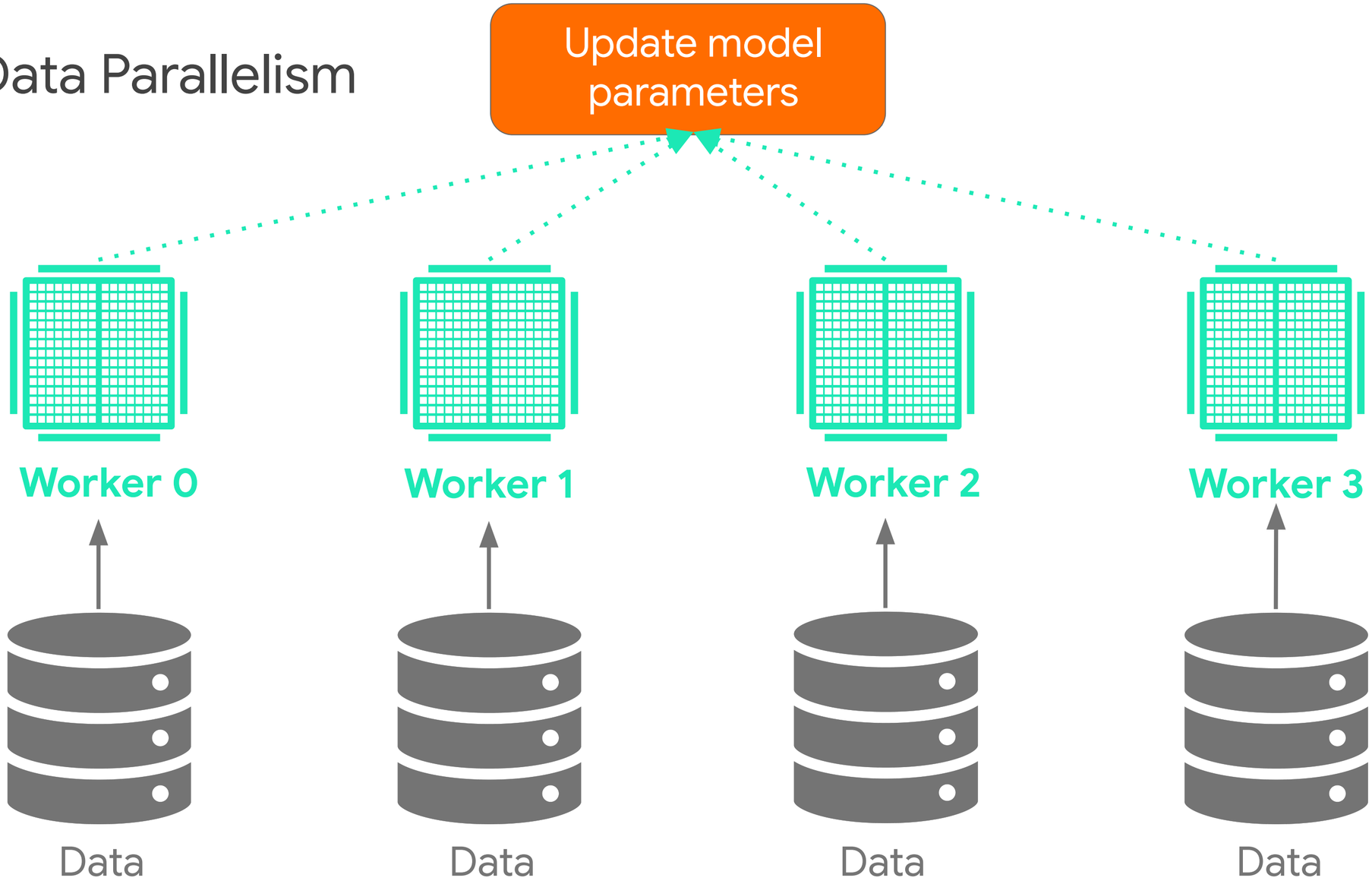
2. Using native TensorFlow ops to read CSV files


```
CSV_COLUMNS = ['fare_amount', 'pickuplon','pickuplat',..., 'key']
LABEL_COLUMN = 'fare_amount'
DEFAULTS = [[0.0], [-74.0], [40.0], [-74.0], [40.7], [1.0], ['nokey']]

def read_dataset(filename, mode, batch_size = 512):
  def _input_fn():
    def decode_csv(value_column):
      columns = tf.decode_csv(value_column, record_defaults = DEFAULTS)
      features = dict(zip(CSV_COLUMNS, columns))
      label = features.pop(LABEL_COLUMN)
      return features, label

    file_list = tf.gfile.Glob(filename) # create list of files that match pattern
    dataset = tf.data.TextLineDataset(file_list).map(decode_csv) # create dataset from file list
    if mode == tf.estimator.ModeKeys.TRAIN:
        num_epochs = None # indefinitely
        dataset = dataset.shuffle(buffer_size = 10 * batch_size)
    else:
        num_epochs = 1 # end-of-input after this

    dataset = dataset.repeat(num_epochs).batch(batch_size)
    return dataset.make_one_shot_iterator().get_next()
  return _input_fn
```

2. Using native TensorFlow ops to read CSV files


```
CSV_COLUMNS = ['fare_amount', 'pickuplon','pickuplat',..., 'key']
LABEL_COLUMN = 'fare_amount'
DEFAULTS = [[0.0], [-74.0], [40.0], [-74.0], [40.7], [1.0], ['nokey']]

def read_dataset(filename, mode, batch_size = 512):
  def _input_fn():
    def decode_csv(value_column):
      columns = tf.decode_csv(value_column, record_defaults = DEFAULTS)
      features = dict(zip(CSV_COLUMNS, columns))
      label = features.pop(LABEL_COLUMN)
      return features, label

    file_list = tf.gfile.Glob(filename) # create list of files that match pattern
    dataset = tf.data.TextLineDataset(file_list).map(decode_csv) # create dataset from file list
    if mode == tf.estimator.ModeKeys.TRAIN:
        num_epochs = None # indefinitely
        dataset = dataset.shuffle(buffer_size = 10 * batch_size)
    else:
        num_epochs = 1 # end-of-input after this

    dataset = dataset.repeat(num_epochs).batch(batch_size)
    return dataset.make_one_shot_iterator().get_next()
  return _input_fn
```

Data Parallelism



2. Using native TensorFlow ops to read images


```
# Reads an image from a file, decodes it into a dense tensor, and resizes it to a fixed shape.
def _parse_function(filename, label):
  image_string = tf.read_file(filename)
  image_decoded = tf.image.decode_image(image_string)
  image_resized = tf.image.resize_images(image_decoded, [299, 299])
  return image_resized, label

# A vector of filenames.
file_list = tf.gfile.Glob(filename)
filenames = tf.constant(file_list)

# labels[i] is the label for the image in filenames[i].
labels = tf.constant(label_list)
dataset = tf.data.Dataset.from_tensor_slices((filenames, labels))
dataset = dataset.map(_parse_function)
```

Courses 7 - Production ML Systems

Module 4: Designing High-Performance ML Systems

Lesson Title: **TensorFlow Records**

Format: Screencast

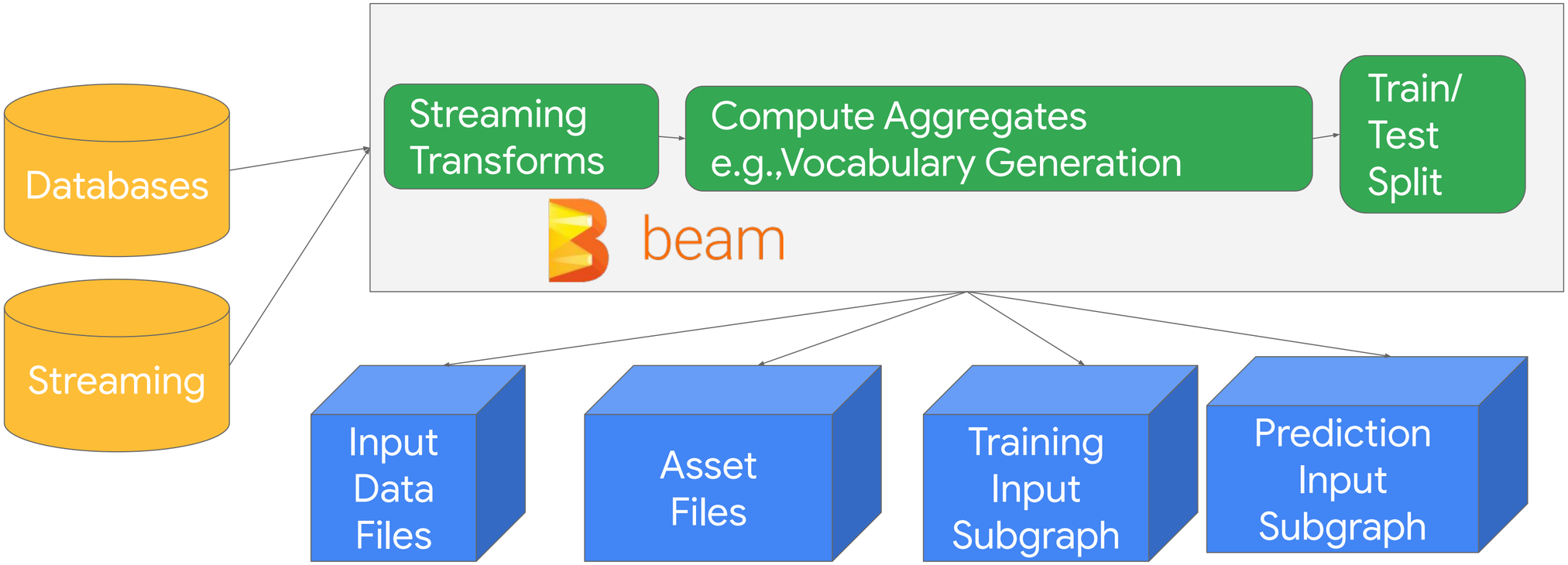
Presenter: Laurence Moroney

Video Name: T-PSML-O_4_l8_tensorflow_records

3. Preprocess data into TFRecord

```
def convert_to_example(csvline, categories):
  filename, label = csvline.encode('ascii', 'ignore').split(',')
  if label in categories:
    coder = ImageCoder()
    image_buffer, height, width = _get_image_data(filename, coder)
    example = _convert_to_example(filename, image_buffer,
                                  categories.index(label), label, height, width)
    yield example.SerializeToString()

LABELS = ['nails', 'screws']
(p
 | beam.FlatMap(lambda line: convert_to_example(line, LABELS))
 | beam.io.tfrecordio.WriteToTFRecord(os.path.join(OUTPUT_DIR, 'train')))
)

# https://github.com/tensorflow/tpu/blob/master/tools/datasets/jpeg_to_tf_record.py
```

3. Can use Tensorflow Transform to create tf records



3. Writing TFRecord from Spark


```
import org.apache.spark.sql.DataFrame


df.write.format("tfrecords").option("recordType", "Example").save(path)
```

Warning! Because preprocessing is carried out on DataFrame using Spark, you need to repeat the preprocessing during prediction using Spark Streaming (the code is different).

3. Read TFRecord produced by tf.transform or Spark

```
from tensorflow_transform.saved import input_fn_maker
def gzip_reader_fn():
  return tf.TFRecordReader(options=tf.python_io.TFRecordOptions(
      compression_type=tf.python_io.TFRecordCompressionType.GZIP))

def get_input_fn(transformed_metadata, transformed_data_paths, batch_size, mode):
  return input_fn_maker.build_training_input_fn(
      metadata=transformed_metadata,
      file_pattern=(
          transformed_data_paths[0] if len(transformed_data_paths) == 1
          else transformed_data_paths),
      training_batch_size=batch_size,
      label_keys=[TARGET_FEATURE_COLUMN],
      reader=gzip_reader_fn,
      key_feature_name=KEY_FEATURE_COLUMN,
      reader_num_threads=4,
      queue_capacity=batch_size * 2,
      randomize_input=(mode != tf.contrib.learn.ModeKeys.EVAL),
      num_epochs=(1 if mode == tf.contrib.learn.ModeKeys.EVAL else None))
```

gzipped files

tf.transform writes out the TFRecords with metadata

Each read is of Batch_SIZE recs

Courses 7 - Production ML Systems

Module 4: Designing High-Performance ML Systems

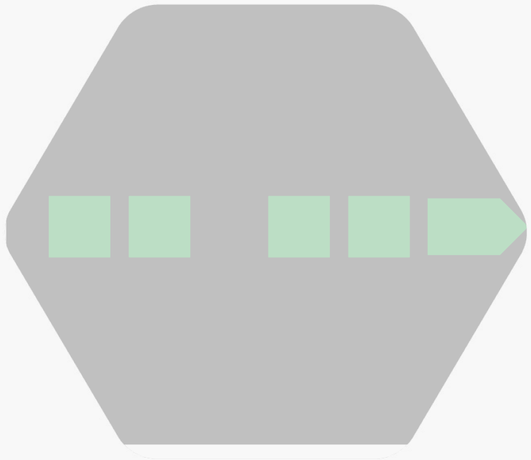
Lesson Title: **Parallel pipelines**

Format: Screencast

Presenter: Laurence Moroney

Video Name: T-PSML-O_4_l9_parallel_pipelines

Three approaches to reading data into TensorFlow



Directly feed from Python

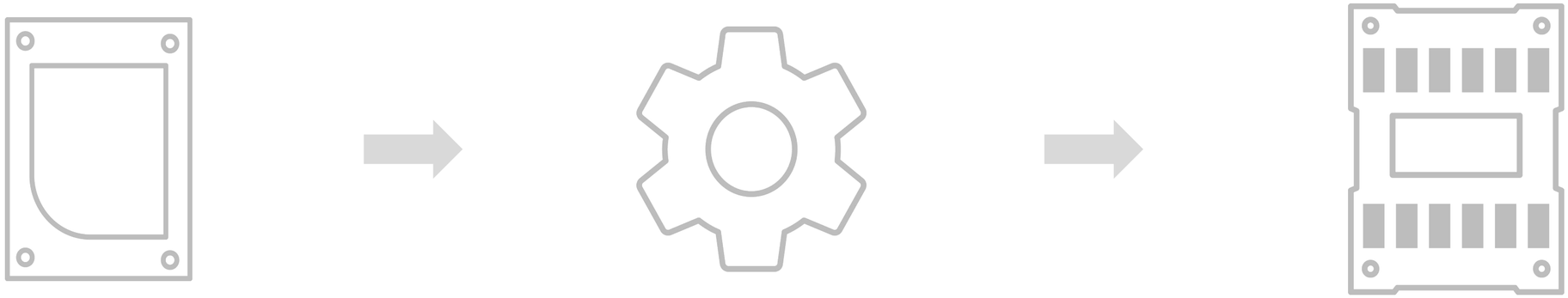
Native TensorFlow ops

Read transformed tf records

A simple input pipeline for an image model


```
def input_fn(batch_size):
  files = tf.data.Dataset.list_files(file_pattern)
  dataset = tf.data.TFRecordDataset(files)
  dataset = dataset.shuffle(10000)
  dataset = dataset.repeat(NUM_EPOCHS)
  dataset = dataset.map(preproc_fn)
  dataset = dataset.batch(batch_size)
  return dataset
```

Input pipeline as an ETL Process



Extract

Transform

Load

A simple input pipeline for an image model

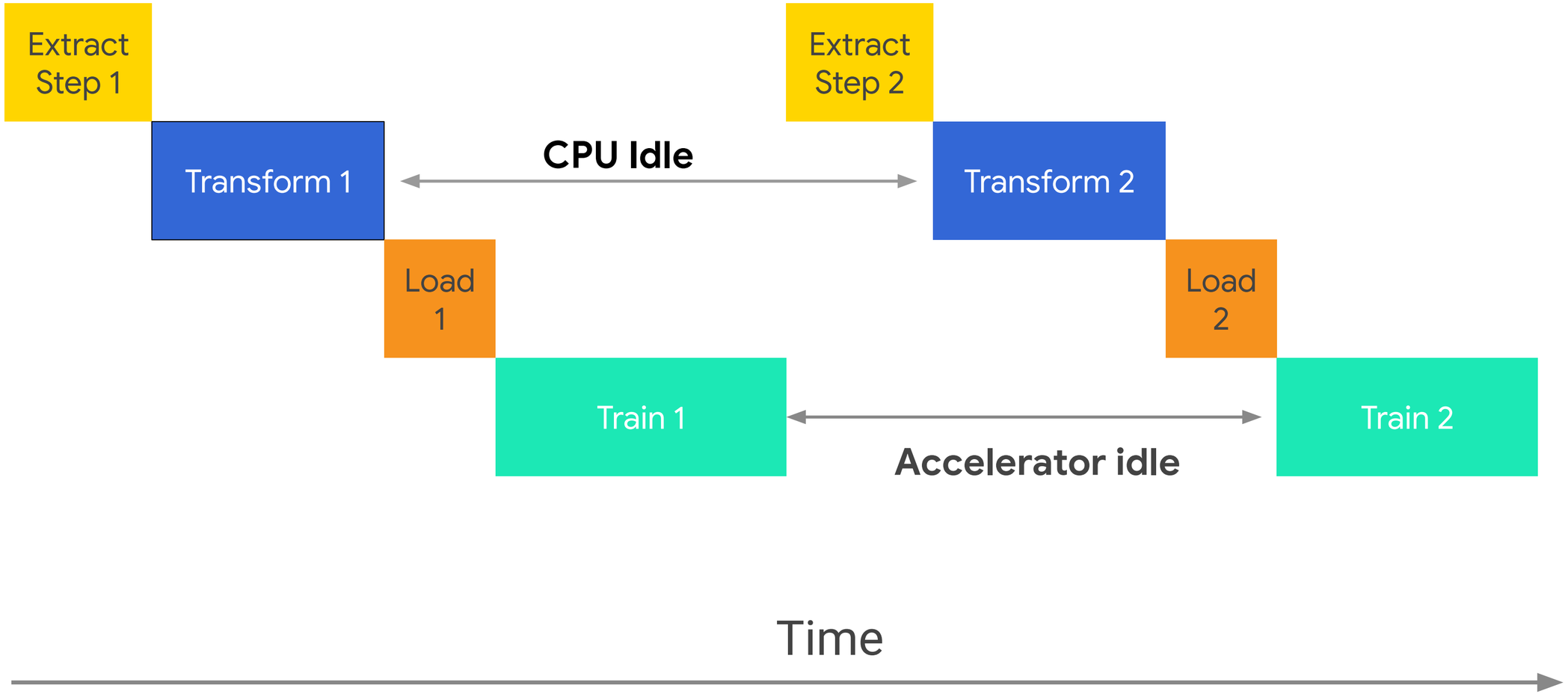
E

T

L

```
def input_fn(batch_size):
  files = tf.data.Dataset.list_files(file_pattern)
  dataset = tf.data.TFRecordDataset(files)

  dataset = dataset.shuffle(10000)
  dataset = dataset.repeat(NUM_EPOCHS)
  dataset = dataset.map(preproc_fn)
  dataset = dataset.batch(batch_size)

  return dataset
```

Input pipeline bottleneck



1. Parallelize file reading


```
def input_fn(batch_size):
  files = tf.data.Dataset.list_files(file_pattern)
  dataset = tf.data.TFRecordDataset(files, num_parallel_reads=40)
  dataset = dataset.shuffle(buffer_size=10000)
  dataset = dataset.repeat(NUM_EPOCHS)
  dataset = dataset.map(preproc_fn)
  dataset = dataset.batch(batch_size)
  return dataset
```

Parallelize file reading from Google Cloud Storage

2. Parallelize map for transformations


```
def input_fn(batch_size):
  files = tf.data.Dataset.list_files(file_pattern)
  dataset = tf.data.TFRecordDataset(files, num_parallel_reads=40)
  dataset = dataset.shuffle(buffer_size=10000)
  dataset = dataset.repeat(NUM_EPOCHS)
  dataset = dataset.map(preproc_fn, num_parallel_calls=40)
  dataset = dataset.batch(batch_size)
  return dataset
```

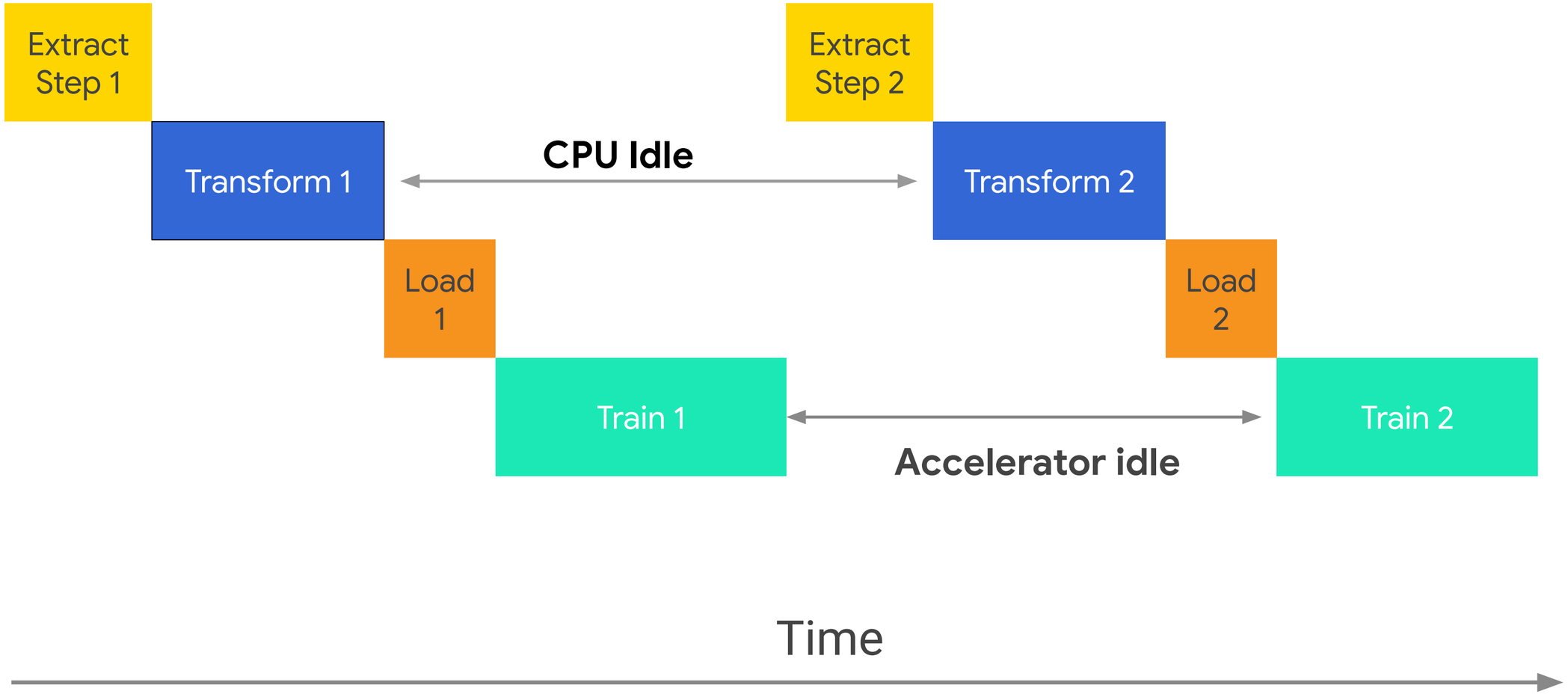
Parallelize across many CPU cores

3. Pipelining with prefetching

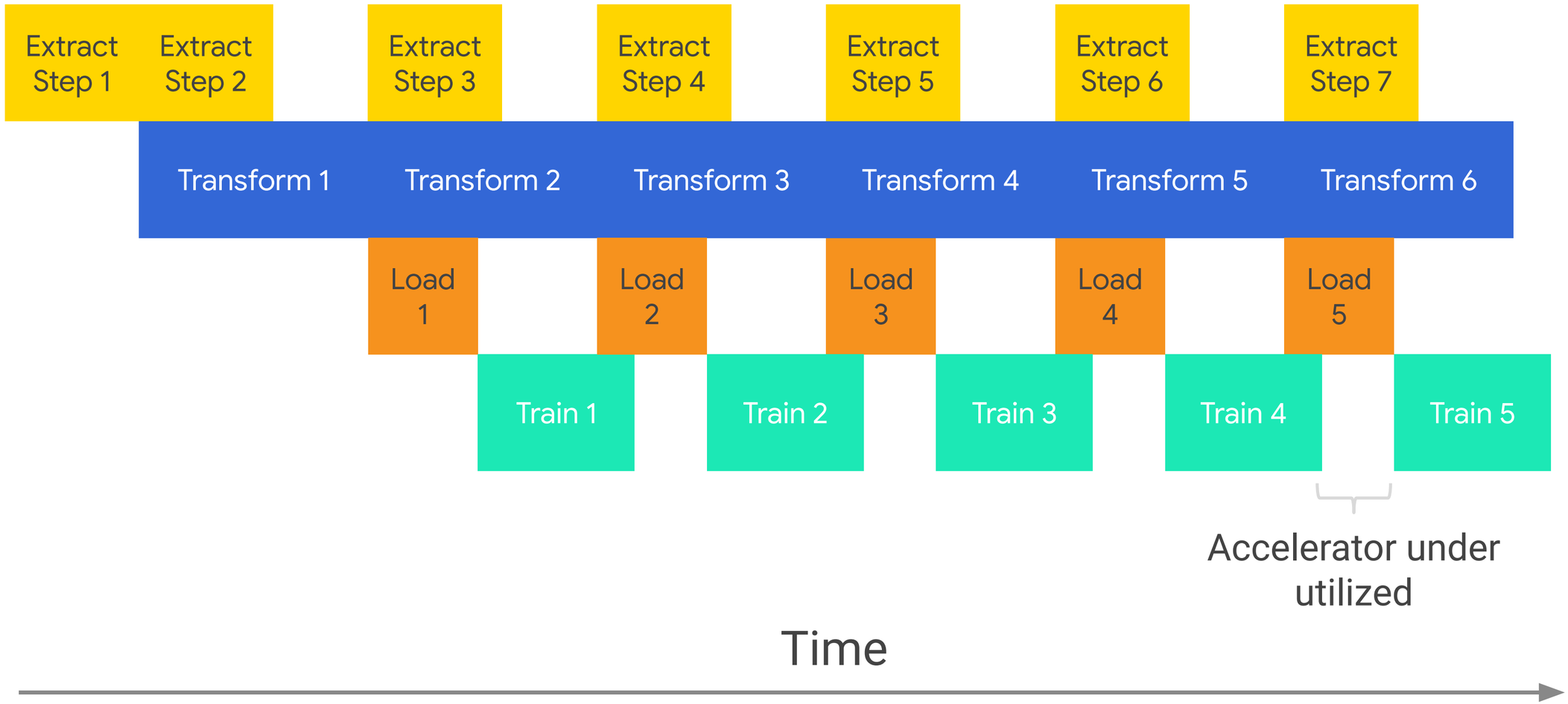

```
def input_fn(batch_size):
  files = tf.data.Dataset.list_files(file_pattern)
  dataset = tf.data.TFRecordDataset(files, num_parallel_reads=40)
  dataset = dataset.shuffle(buffer_size=10000)
  dataset = dataset.repeat(NUM_EPOCHS)
  dataset = dataset.map(preproc_fn, num_parallel_calls=40)
  dataset = dataset.batch(batch_size)
  dataset = dataset.prefetch(buffer_size=1)
  return dataset
```

Prefetch pipelines everything above with the accelerator training

Input pipeline bottleneck



Updated Input pipeline



4. Using fused transformation ops


```
def input_fn(batch_size):
  files = tf.data.Dataset.list_files(file_pattern)
  dataset = tf.data.TFRecordDataset(files, num_parallel_reads=40)
  dataset = dataset.shuffle(buffer_size=10000)
  dataset = dataset.repeat(NUM_EPOCHS)
  dataset = dataset.map(preproc_fn, num_parallel_calls=40)
  dataset = dataset.batch(batch_size)
  dataset = dataset.prefetch(buffer_size=1)
  return dataset
```

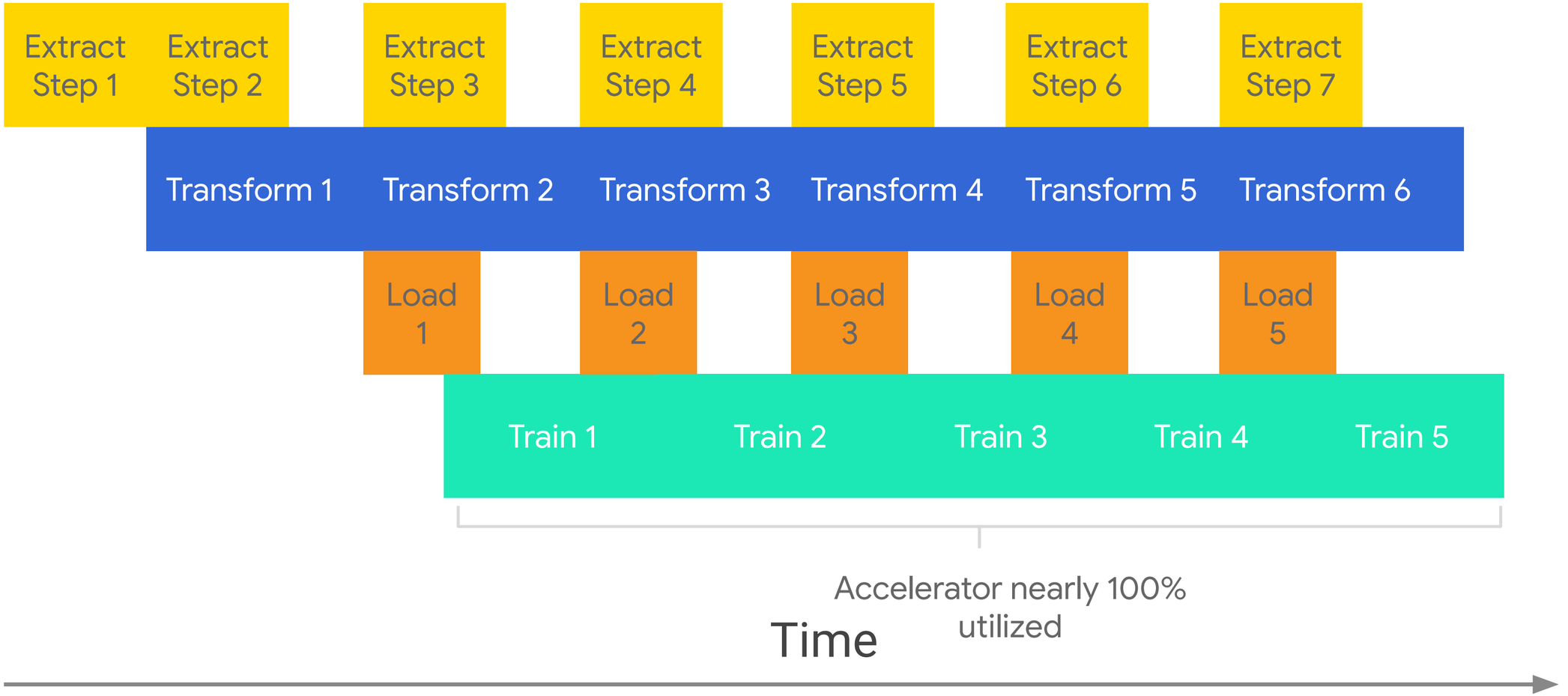
4. Using fused transformation ops


```
def input_fn(batch_size):
  files = tf.data.Dataset.list_files(file_pattern)
  dataset = tf.data.TFRecordDataset(files, num_parallel_reads=40)
  dataset = dataset.shuffle(buffer_size=10000)
  dataset = dataset.repeat(NUM_EPOCHS)
  dataset = dataset.map(preproc_fn, num_parallel_calls=40)
  dataset = dataset.batch(batch_size)
  dataset = dataset.prefetch(buffer_size=1)
  return dataset
```

4. Using fused transformation ops


```
def input_fn(batch_size):
  files = tf.data.Dataset.list_files(file_pattern)
  dataset = tf.data.TFRecordDataset(files, num_parallel_reads=40)

  dataset = dataset.apply(
      tf.contrib.data.shuffle_and_repeat(buffer_size=10000, NUM_EPOCHS))

  dataset = dataset.apply(
      tf.contrib.data.map_and_batch(parser_fn, batch_size))

  dataset = dataset.prefetch(buffer_size=1)
  return dataset
```

Updated Input pipeline



Courses 7 - Production ML Systems

Module 4: Designing High-Performance ML Systems

Lesson Title: **Data parallelism with All Reduce**

Format: On-Camera Screencast

Presenter: Laurence Moroney

Video Name: T-PSML-O_4_l10_data_parallelism_with_all_reduce

Agenda

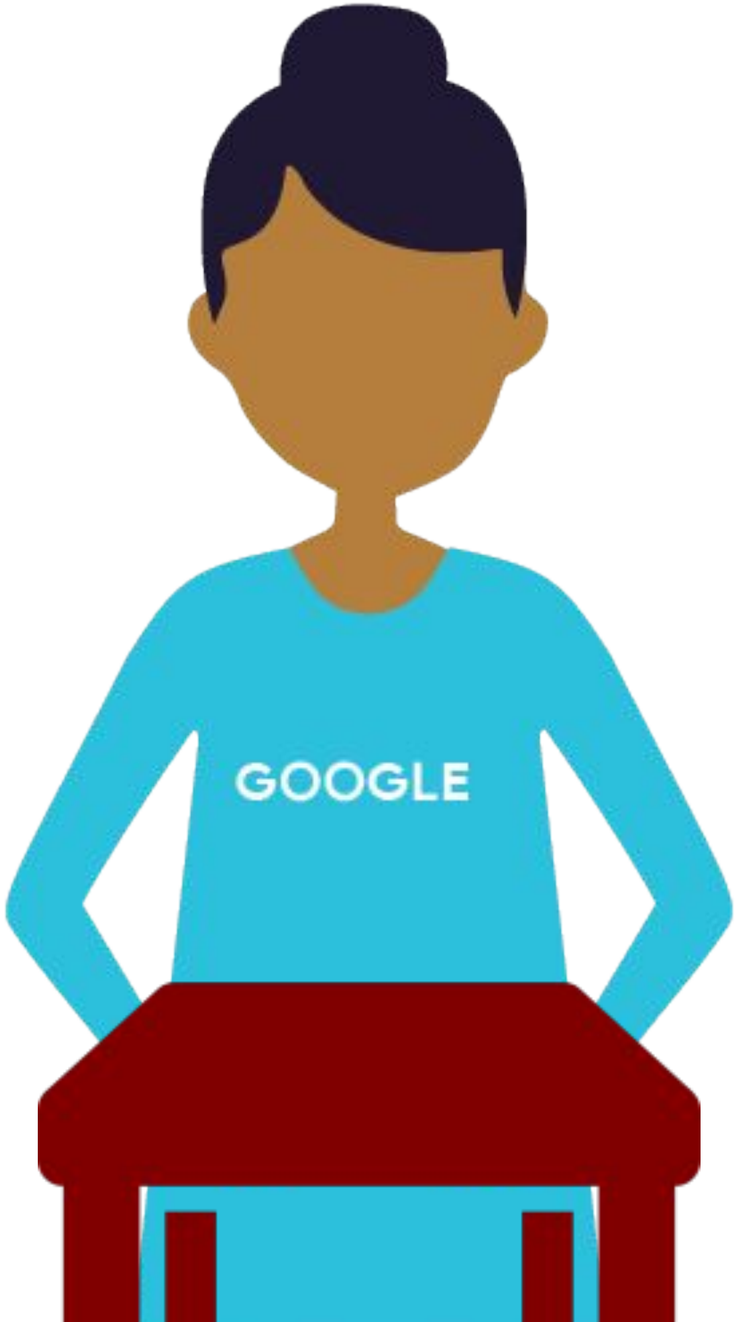
Distributed training

Faster input pipelines

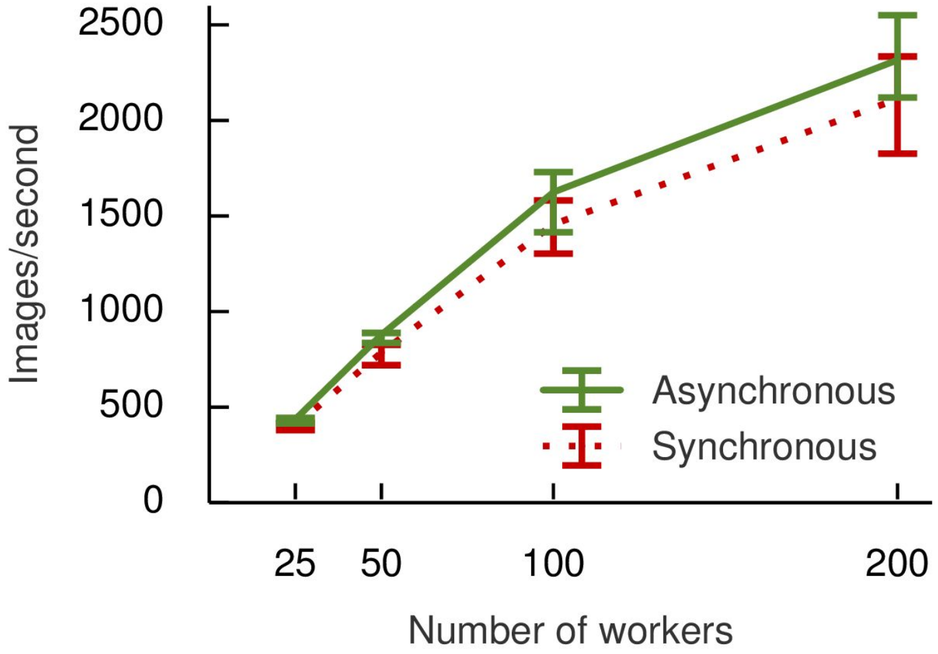
Data parallelism (All Reduce)

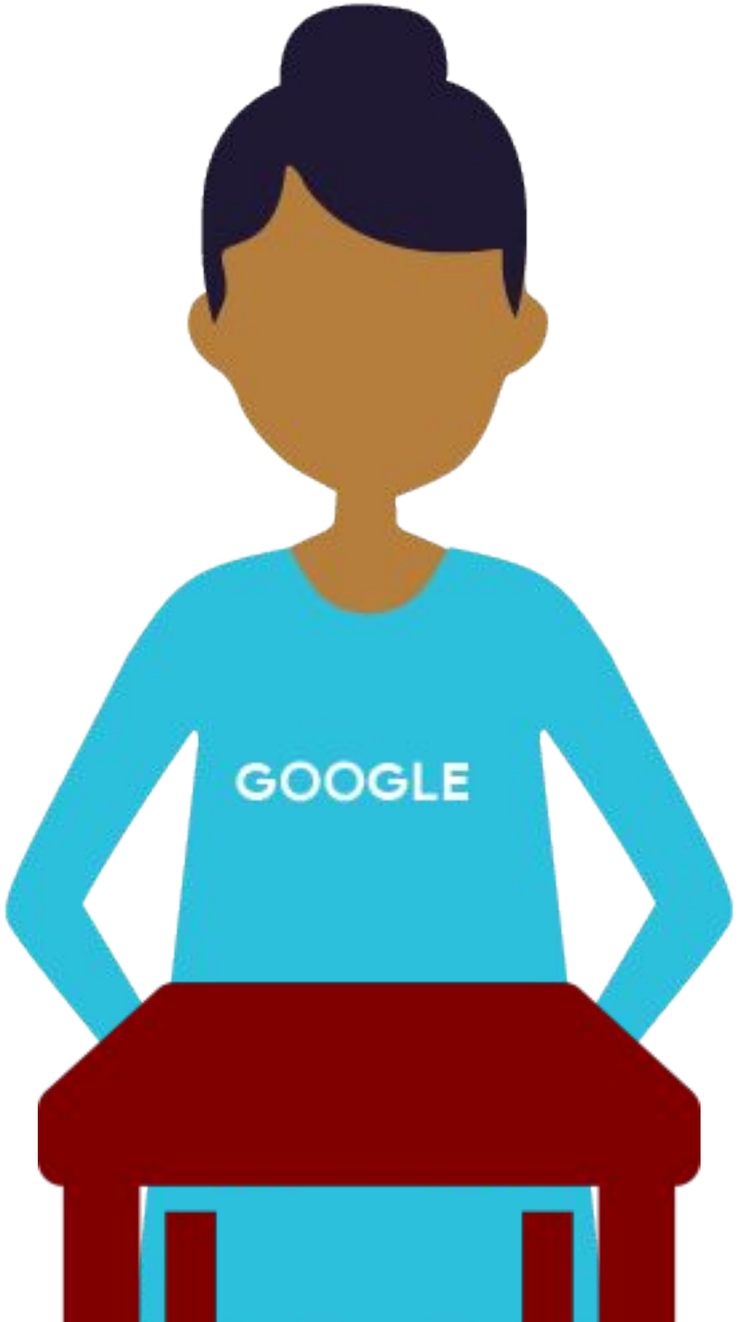
Parameter Server approach

Inference



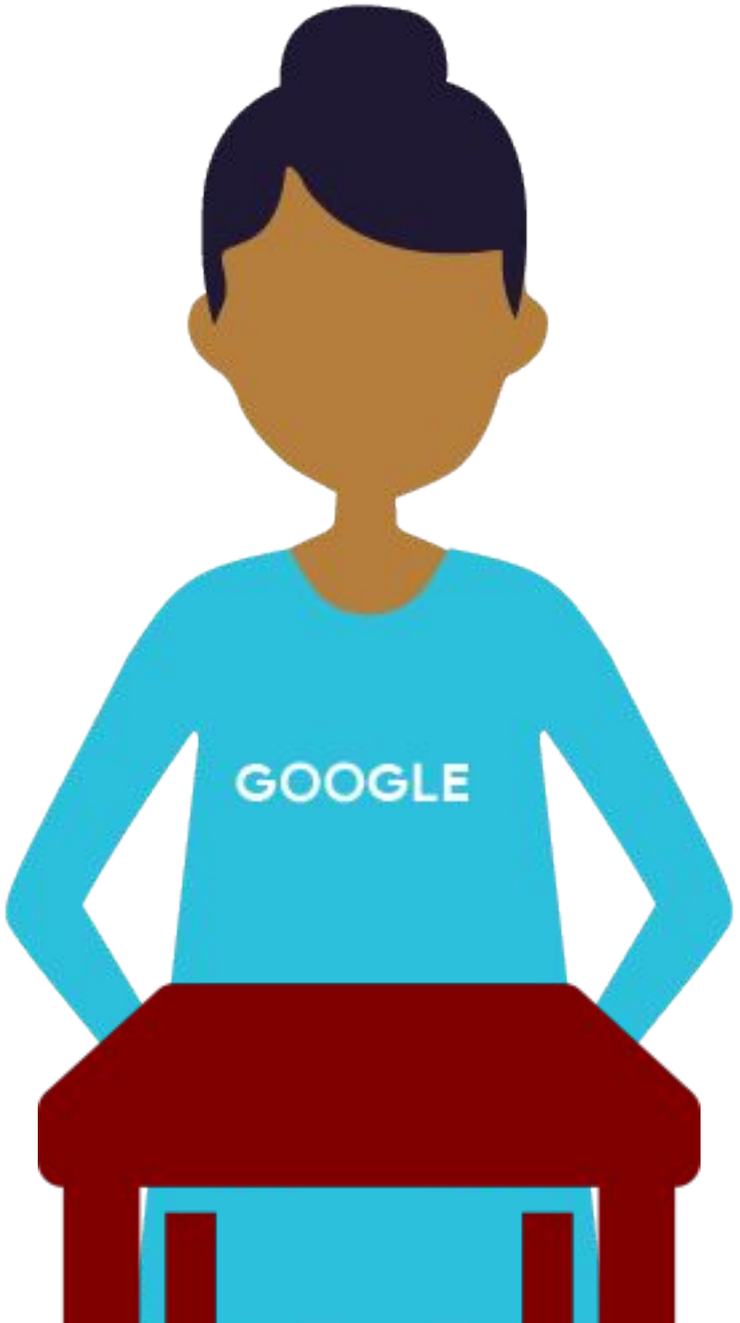
Data parallelism is a way to increase training throughput





Distribution API Strategy

```
with tf.device("/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
with tf.device("/gpu:0"):
  output = tf.matmul(input, W) + b
  loss = f(output)
```



Distribution API Strategy

Easy to use

Fast to train

Training with Estimator API

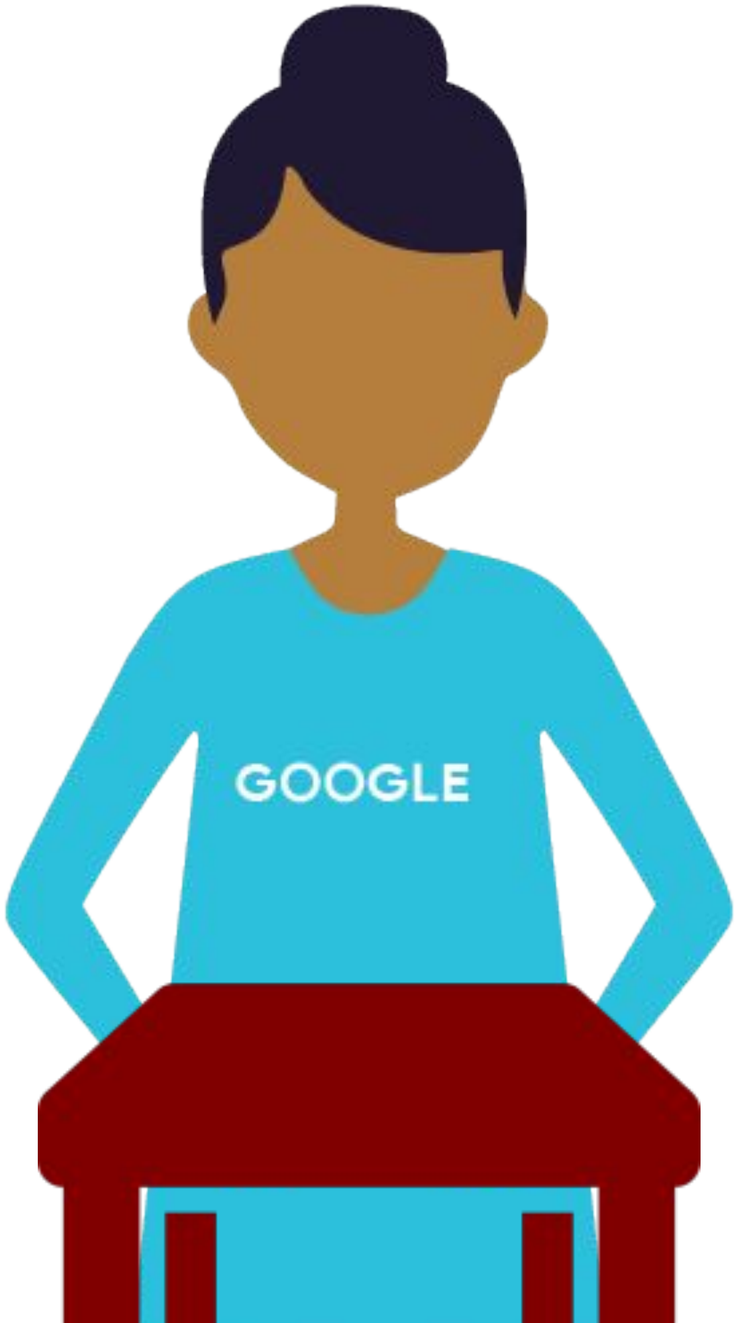

```
run_config = tf.estimator.RunConfig()


classifier = tf.estimator.Estimator(
    model_fn=model_function,
    model_dir=model_dir,
    config=run_config)

classifier.train(input_fn=input_function)
```

Training with Estimator API

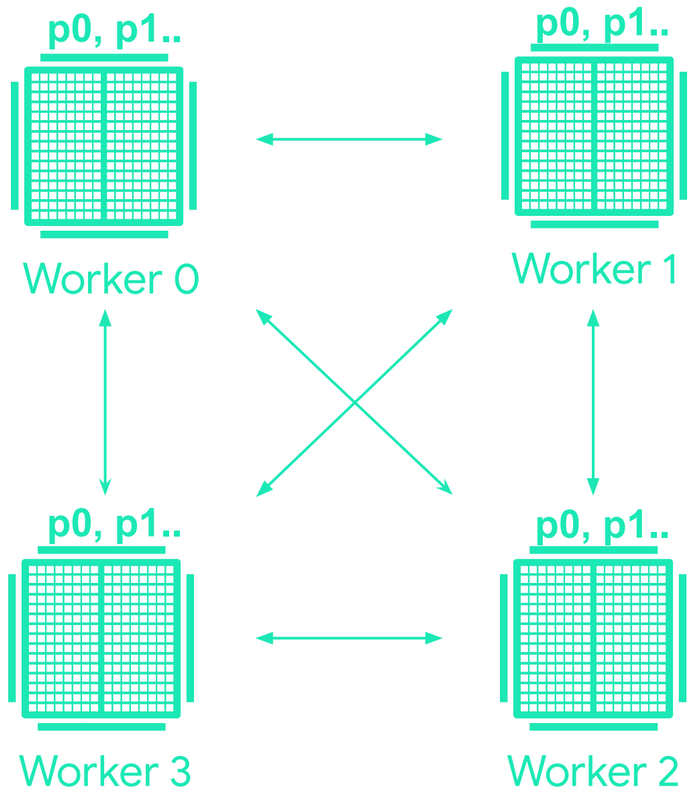

```
distribution = tf.contrib.distribute.MirroredStrategy()


run_config = tf.estimator.RunConfig(train_distribute=distribution)


classifier = tf.estimator.Estimator(
    model_fn=model_function,
    model_dir=model_dir,
    config=run_config)

classifier.train(input_fn=input_function)
```

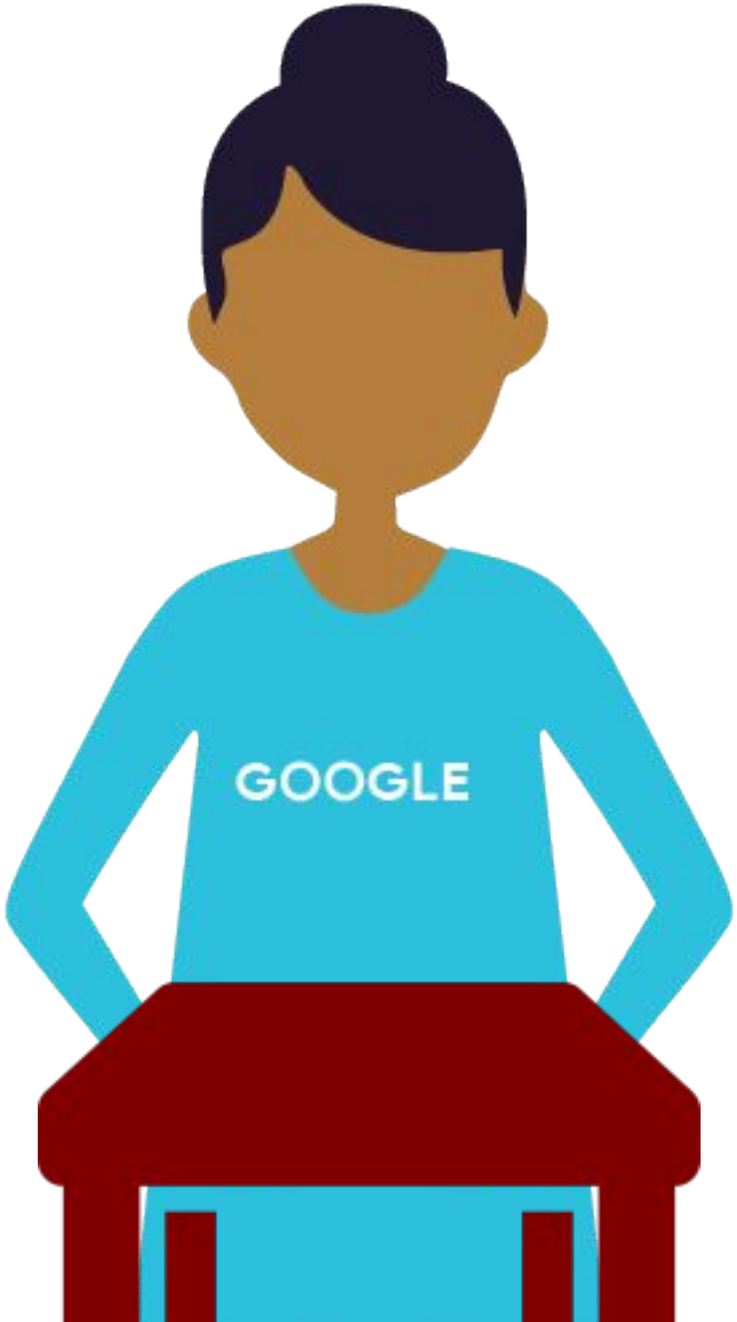
MirroredStrategy for multi GPU distribution

Pass the distribution to RunConfig



Mirrored Strategy





Mirrored Strategy

- No change to the model or training loop
- No change to input function (requires tf.data.Dataset)
- Checkpoints and summaries are seamless

Mirrored Strategy Demo

Demo goes here

Training Time

All Submissions

Objective: Time taken to train an image classification model to a top-5 validation accuracy of 93% or greater on ImageNet.

Rank	Time to 93% Accuracy	Model	Hardware	Framework
1 Apr 2018	0:30:43	ResNet50 *Google* source	Half of a TPUv2 Pod	TensorFlow 1.8.0-rc1
2 Apr 2018	1:06:32	AmoebaNet-D N6F256 *Google* source	1/4 of a TPUv2 Pod	TensorFlow 1.8.0-rc1
3 Apr 2018	1:58:24	AmoebaNet-D N6F256 *Google* source	1/16 of a TPUv2 Pod	TensorFlow 1.8.0-rc1
4 Apr 2018	2:57:28	Resnet 50 *fast.ai + students team: Jeremy Howard, Andrew Shaw, Brett Koonce, Sylvain Gugger* source	8 * V100 (AWS p3.16xlarge)	fastai / pytorch
5 Apr 2018	3:25:55	ResNet50 *Intel(R) Corporation* source	128 nodes with Xeon Platinum 8124M / 144 GB / 36 Cores (Amazon EC2 [c5.18xlarge])	Intel(R) Optimized Caffe

https://dawn.cs.stanford.edu/benchmark/

Courses 7 - Production ML Systems

Module 4: Designing High-Performance ML Systems

Lesson Title: **Parameter Server Approach**

Format: Presenter

Presenter: Laurence Moroney

Video Name: T-PSML-O_4_l11_parameter_server_approach

Agenda

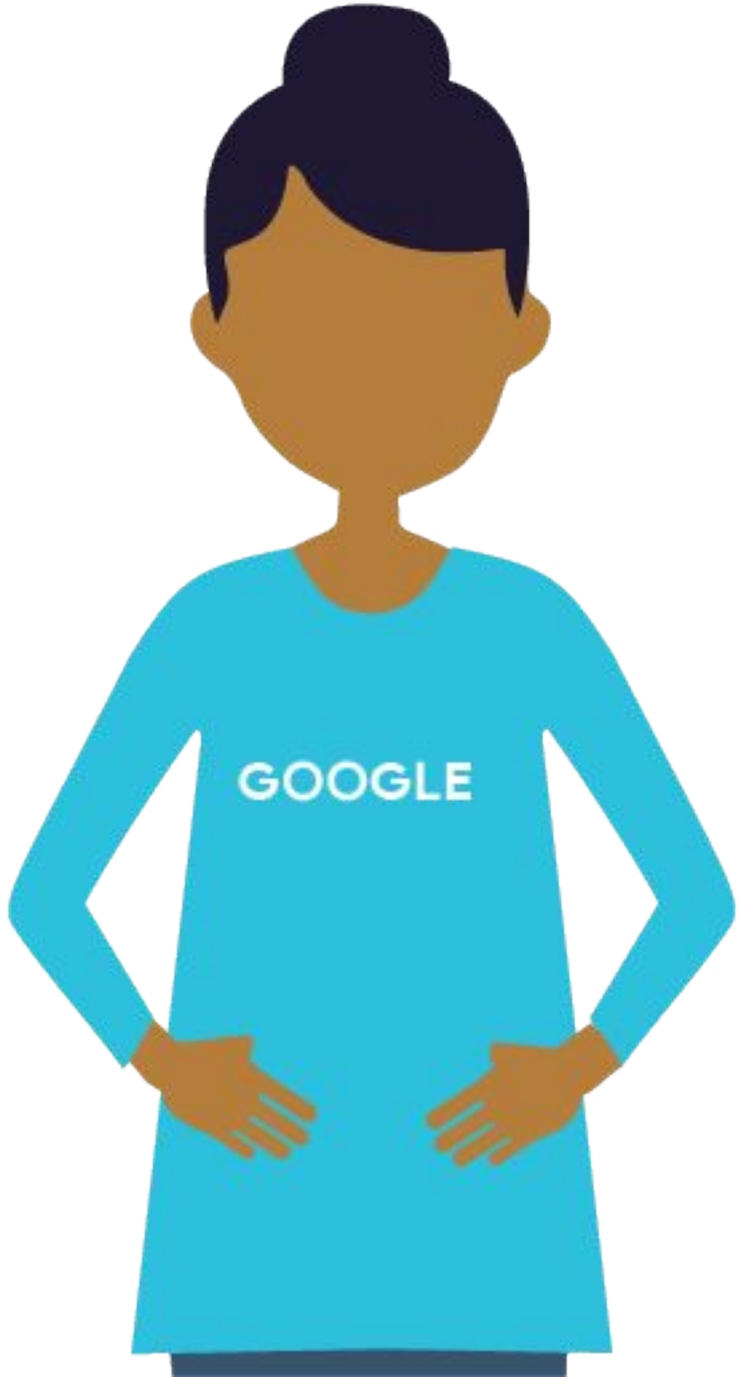
Distributed training

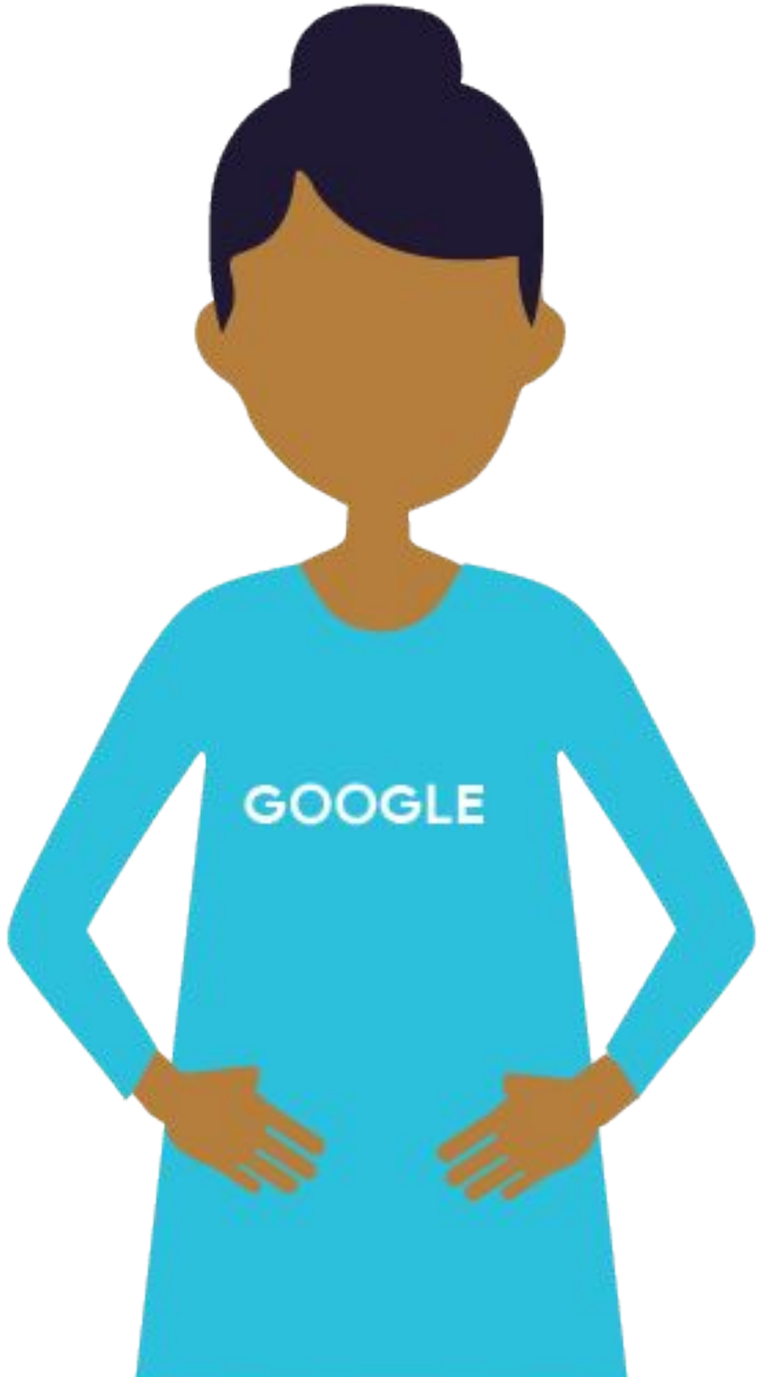
Faster input pipelines

Data parallelism (All Reduce)

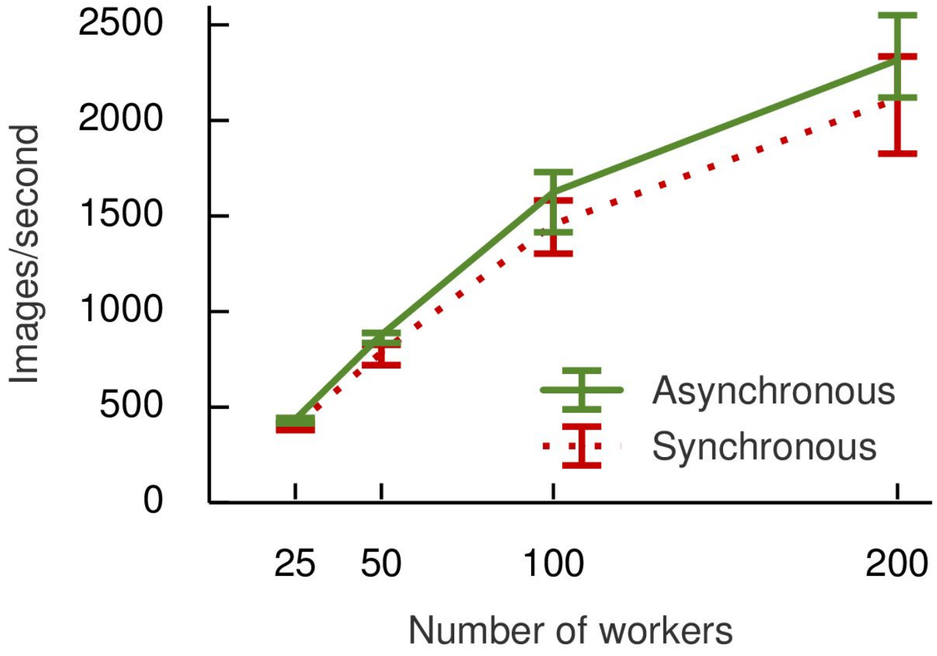
Parameter Server approach

Inference

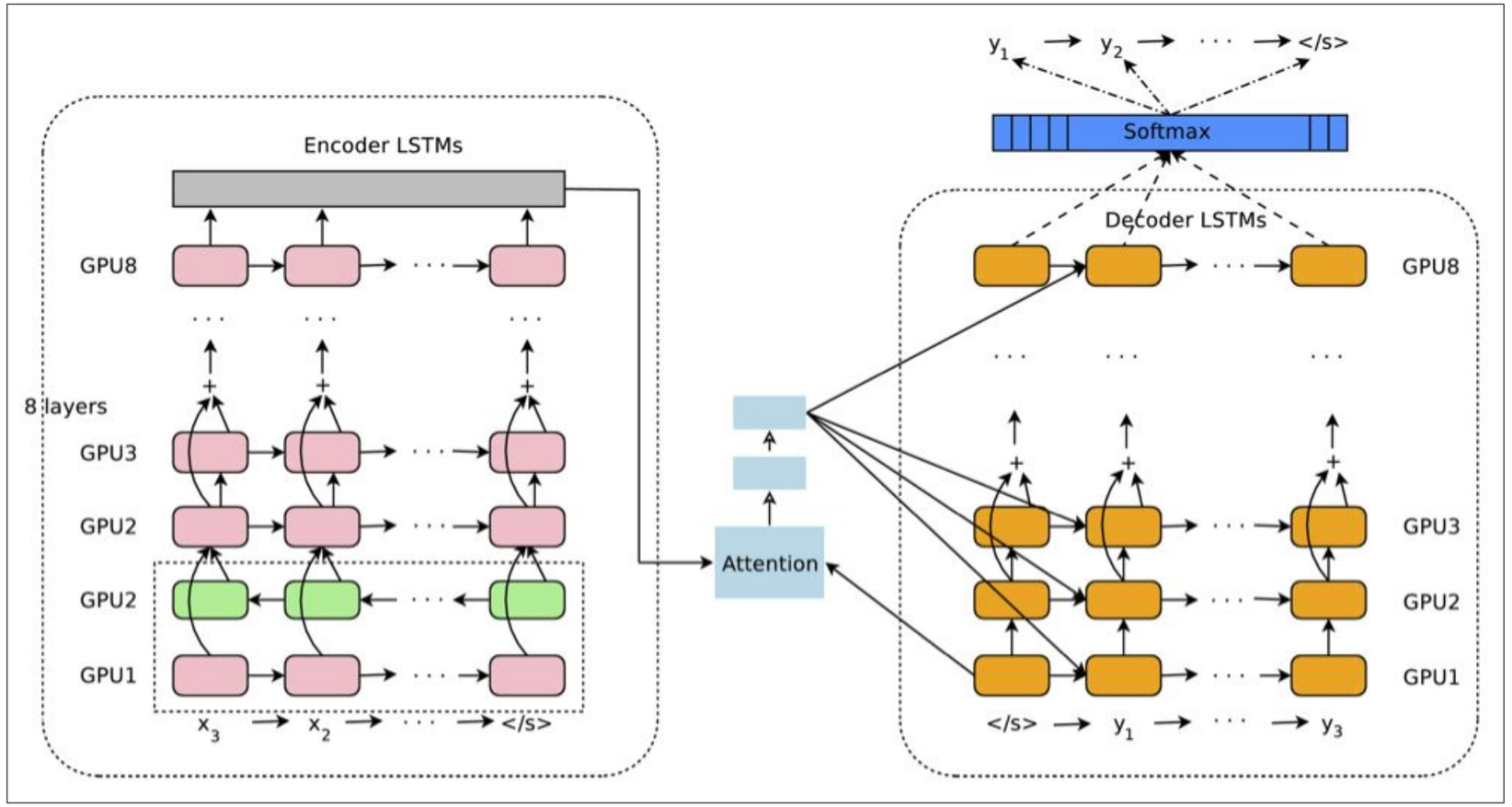


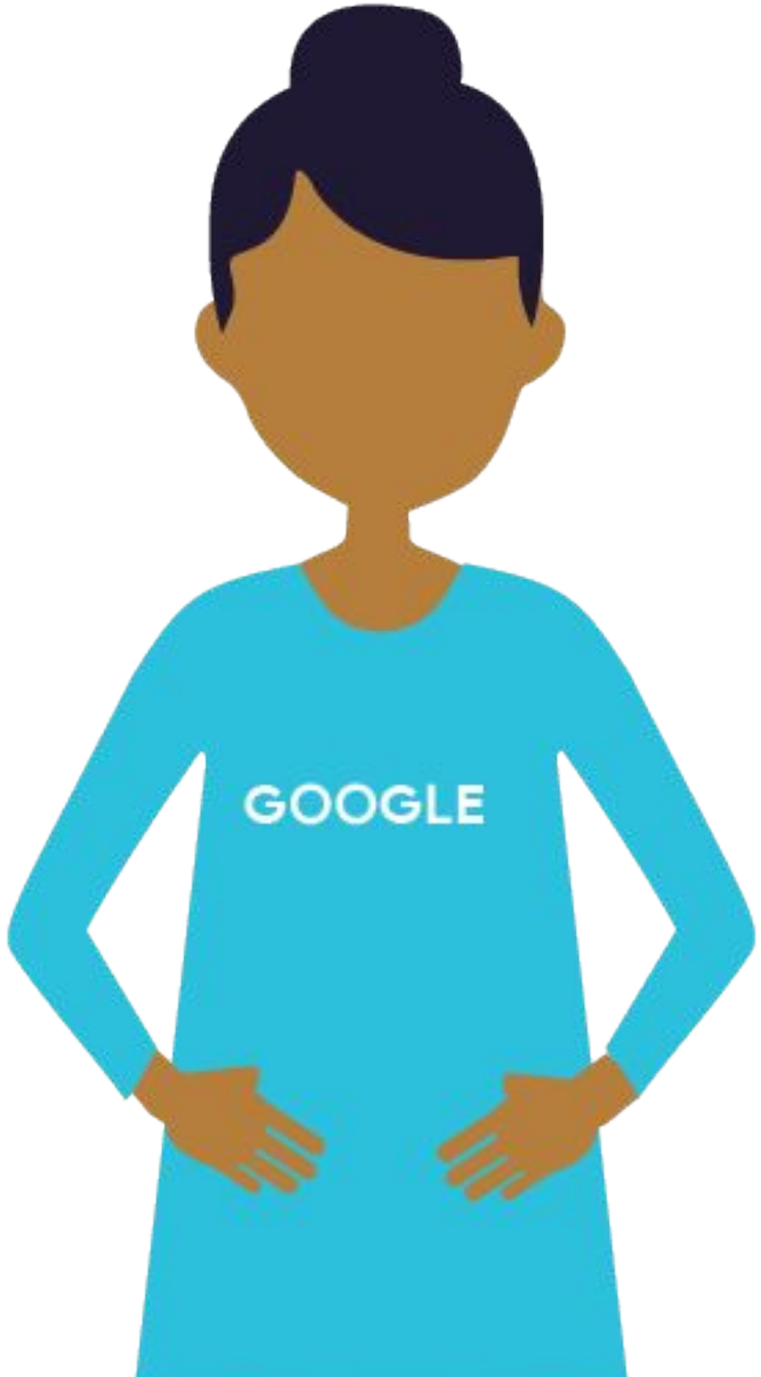


Data parallelism is a way to increase training throughput

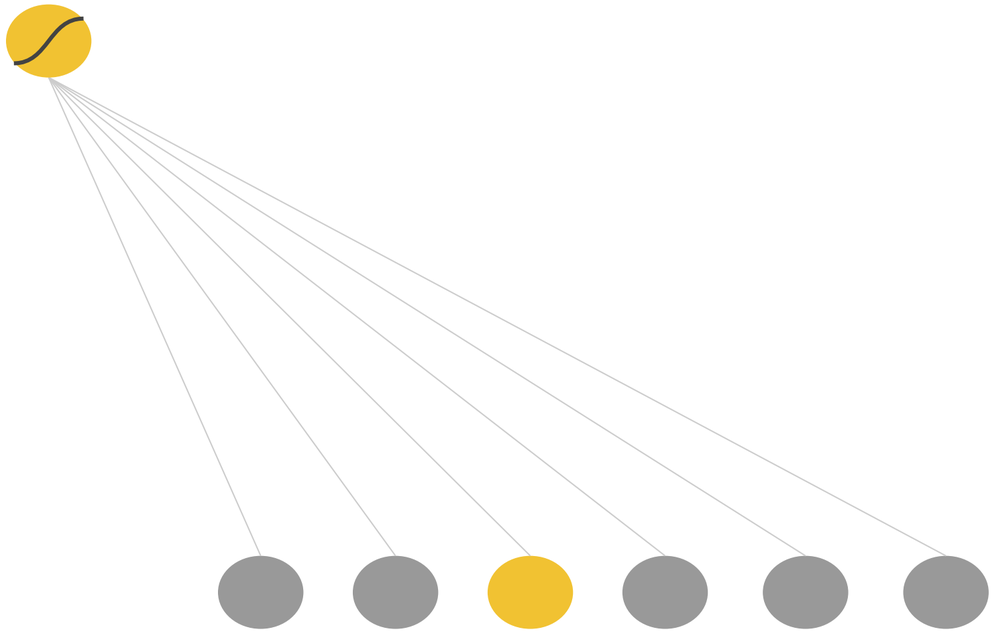


Model parallelism lets you distribute a model across GPUs

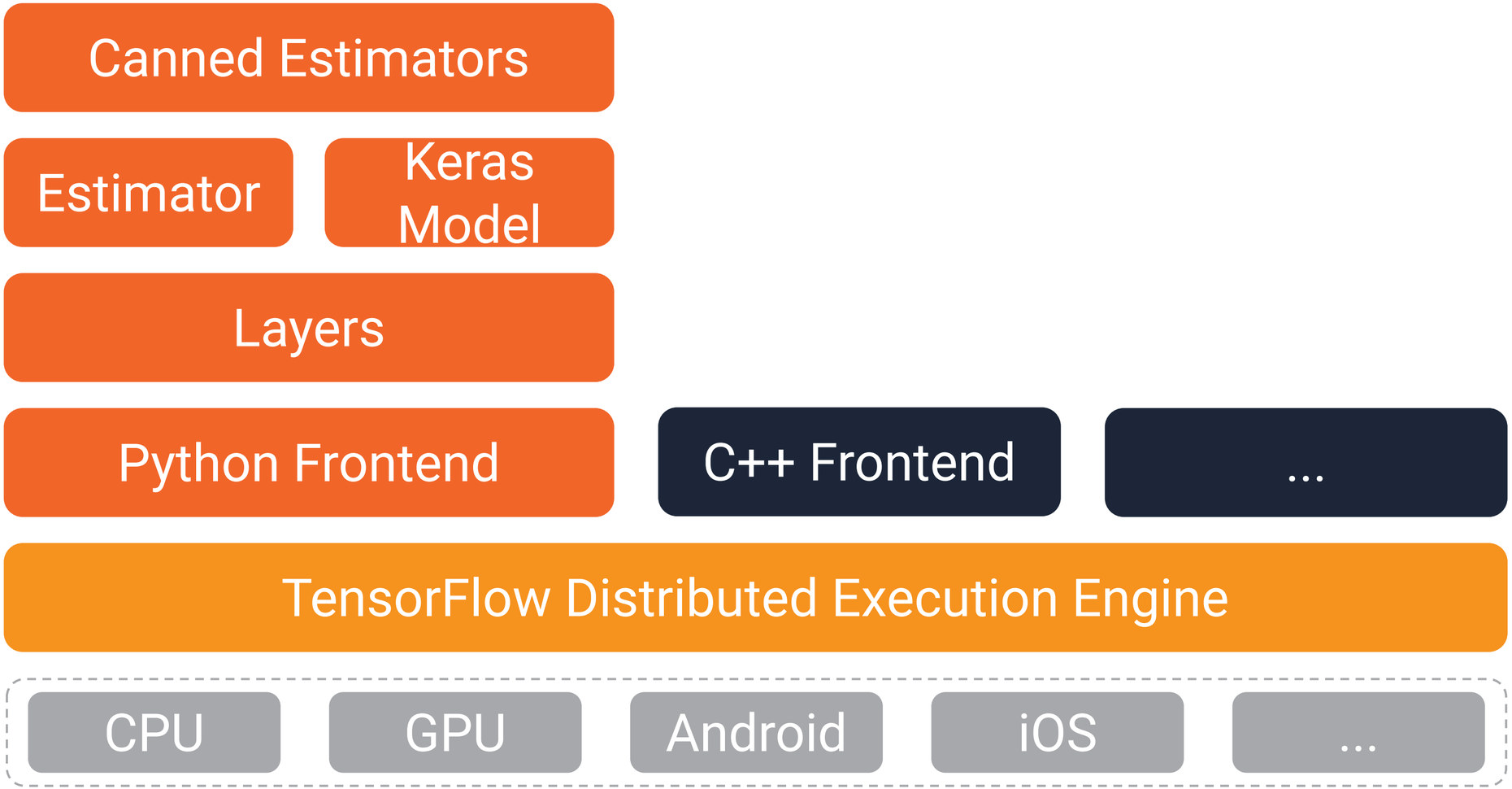




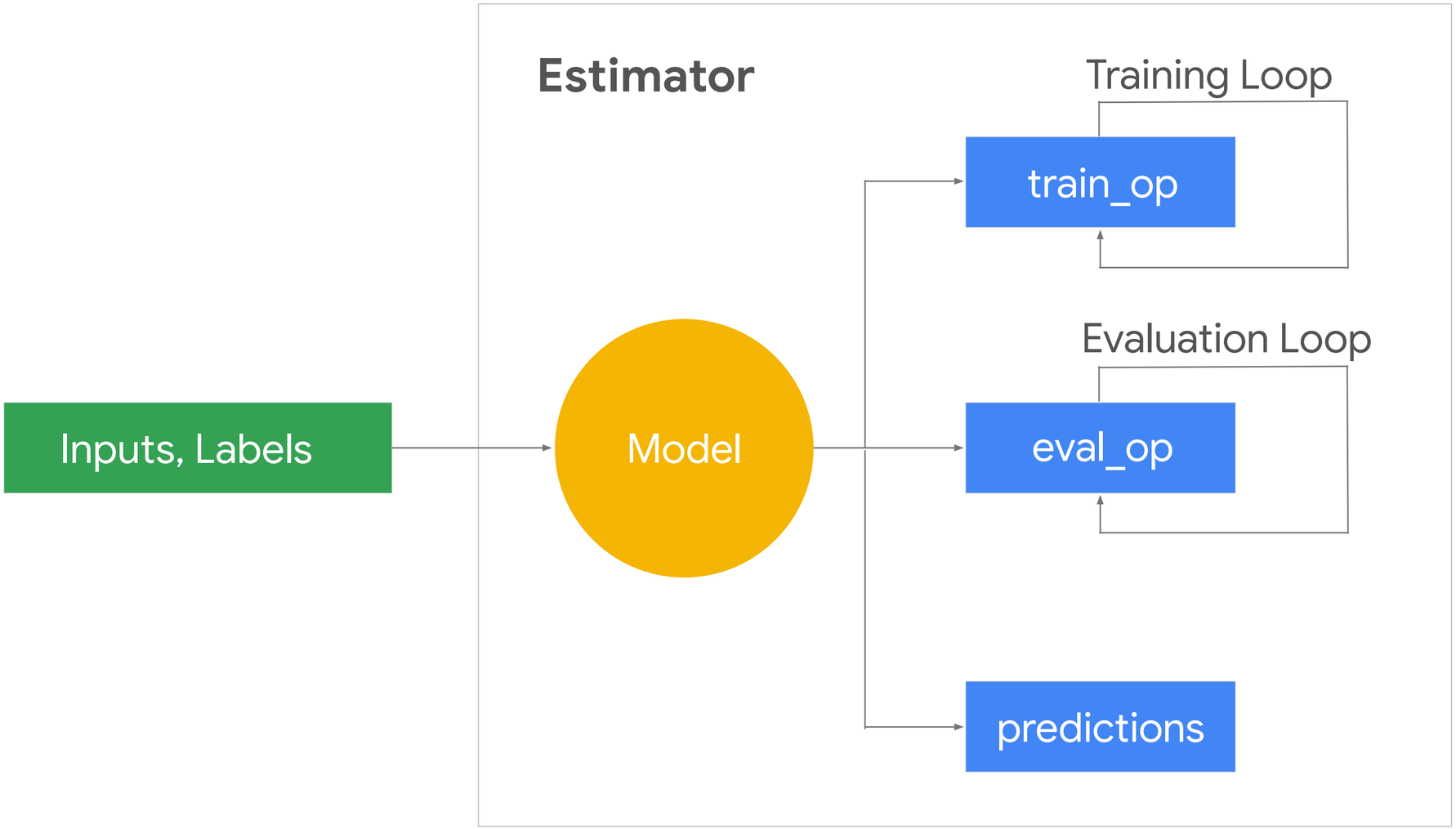
Large embeddings need multiple machines to map sparse data



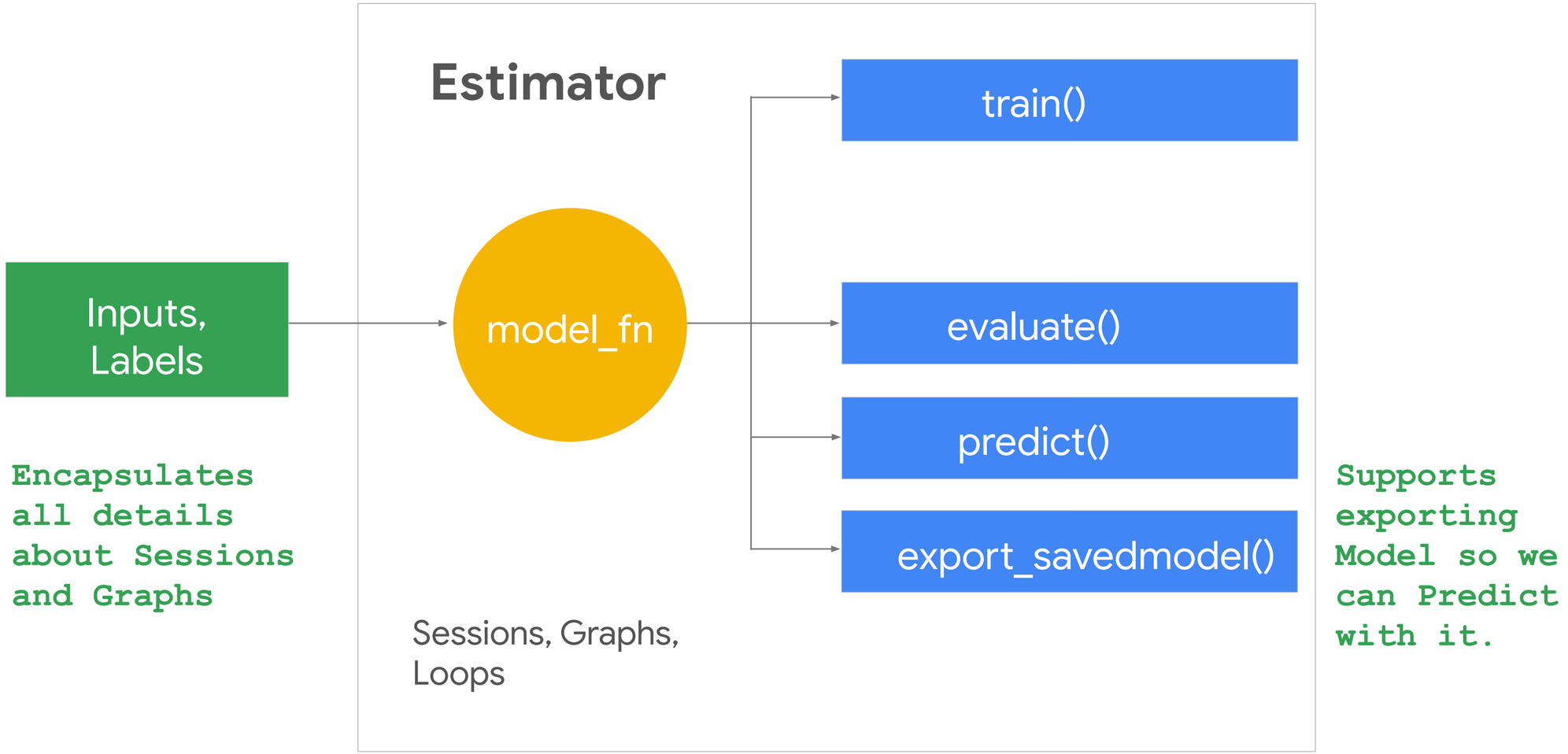
Estimator train_and_evaluate() handles all this



Estimator contains the implementation of three functions



By encapsulating details about sessions and graphs,
it also supports exporting the model for serving



Encapsulates all details about Sessions and Graphs

Supports exporting Model so we can Predict with it.

train_and_evaluate bundles together a distributed workflow


```
def train_and_evaluate(output_dir, config, params):
  features = [tf.feature_column.embedding_column(...),
              tf.feature_column.bucketized_column(...)]
  estimator = tf.estimator.Estimator(model_fn = simple_rnn,
                          model_dir = output_dir)
  train_spec = tf.estimator.TrainSpec(input_fn = get_train(),
                                      max_steps = 1000)
  exporter = tf.estimator.LatestExporter('exporter', serving_input_fn)
  eval_spec = tf.estimator.EvalSpec(input_fn = get_valid(),
                                    steps = None,
                                    exporters = exporter)
  tf.estimator.train_and_evaluate(estimator, train_spec, eval_spec)


train_and_evaluate(output_dir)
```

Runs training, evaluation, etc. on Cloud ML

Courses 7 - Production ML Systems

Module 4: Designing High-Performance ML Systems

Lesson Title: **Inference**

Format: Presenter

Presenter: Laurence Moroney

Video Name: T-PSML-O_4_I12_inference

Agenda

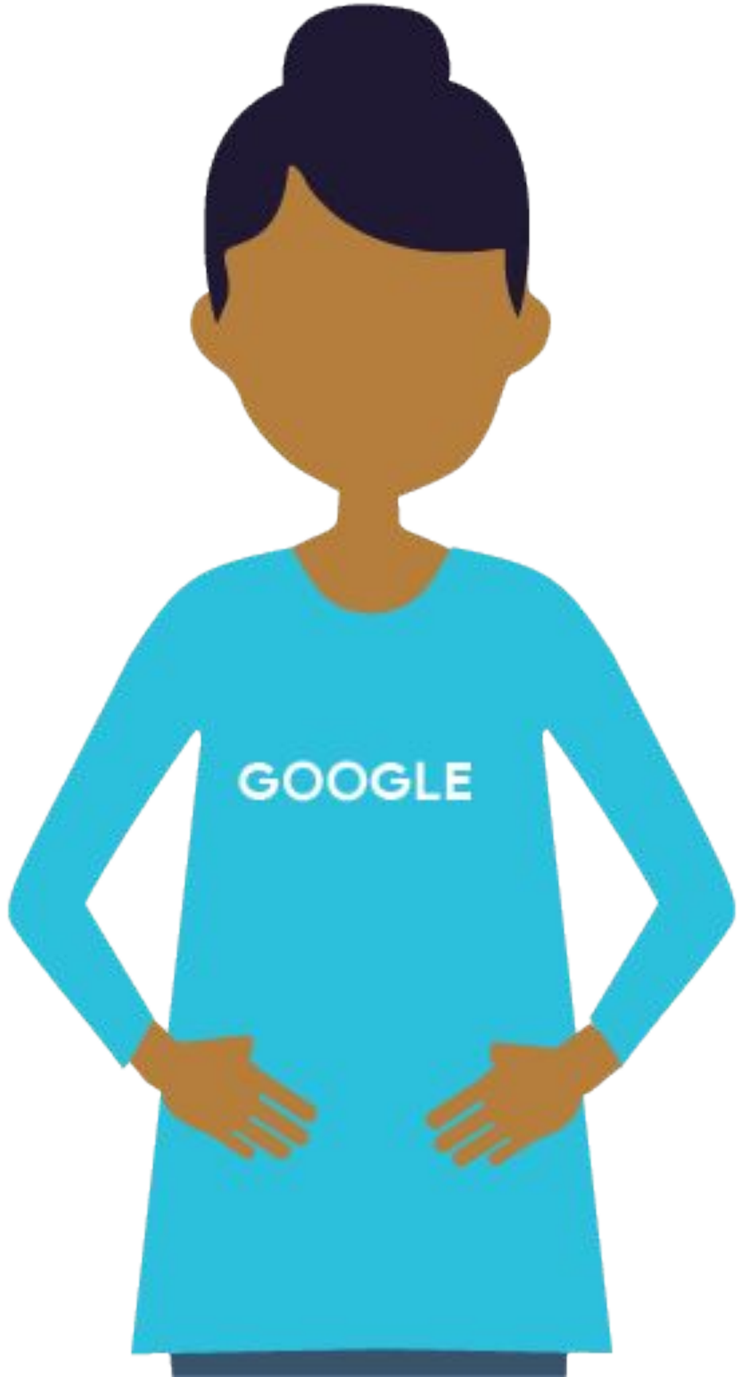
Distributed training

Faster input pipelines

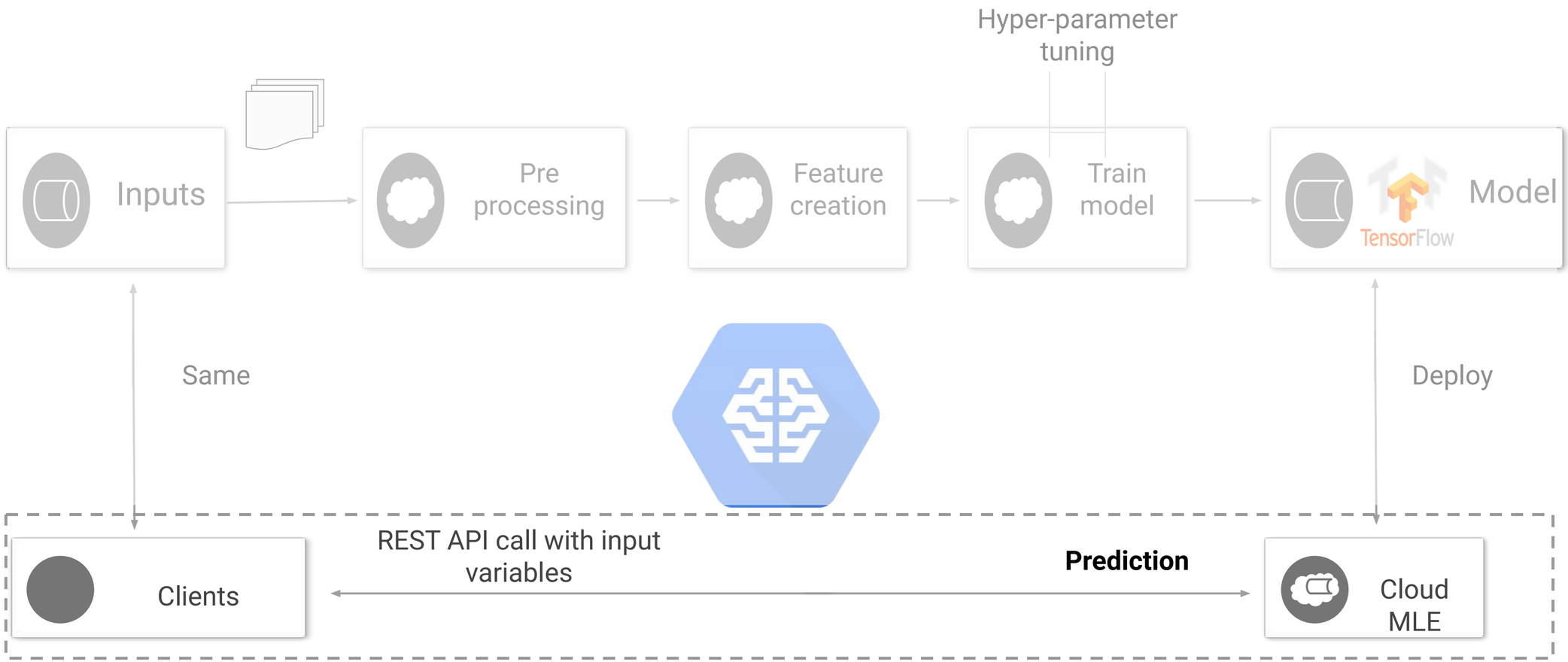
Data parallelism (All Reduce)

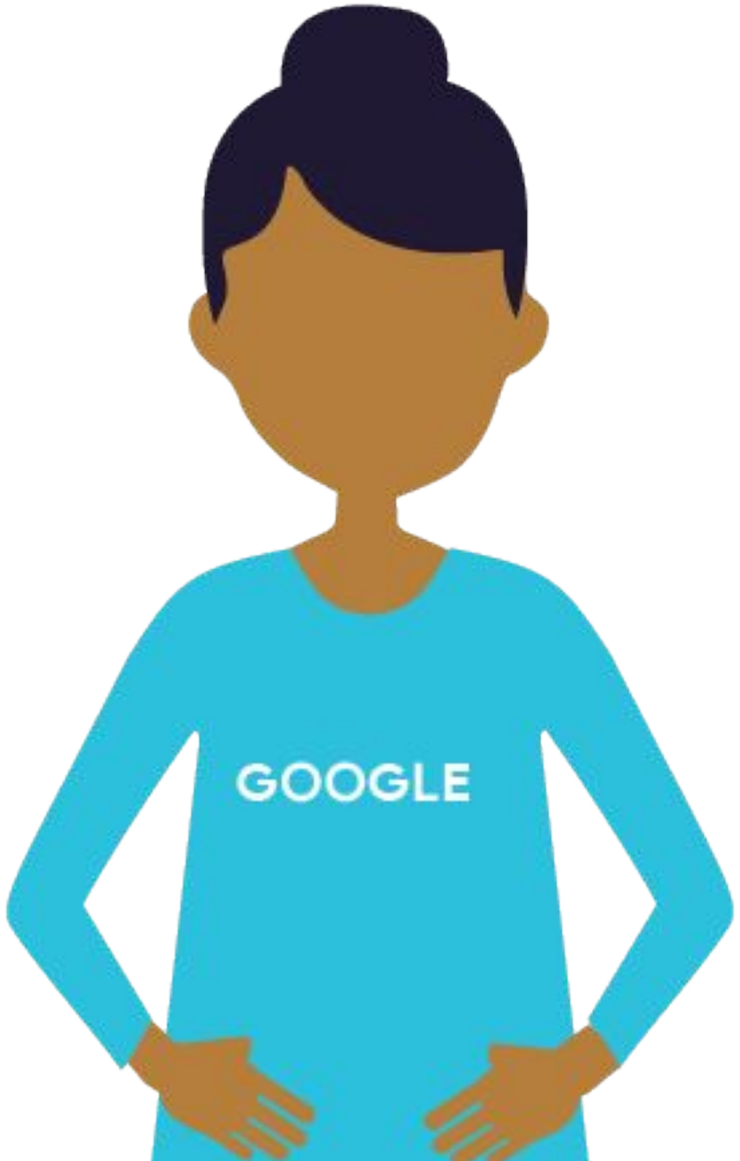
Parameter Server approach

Inference

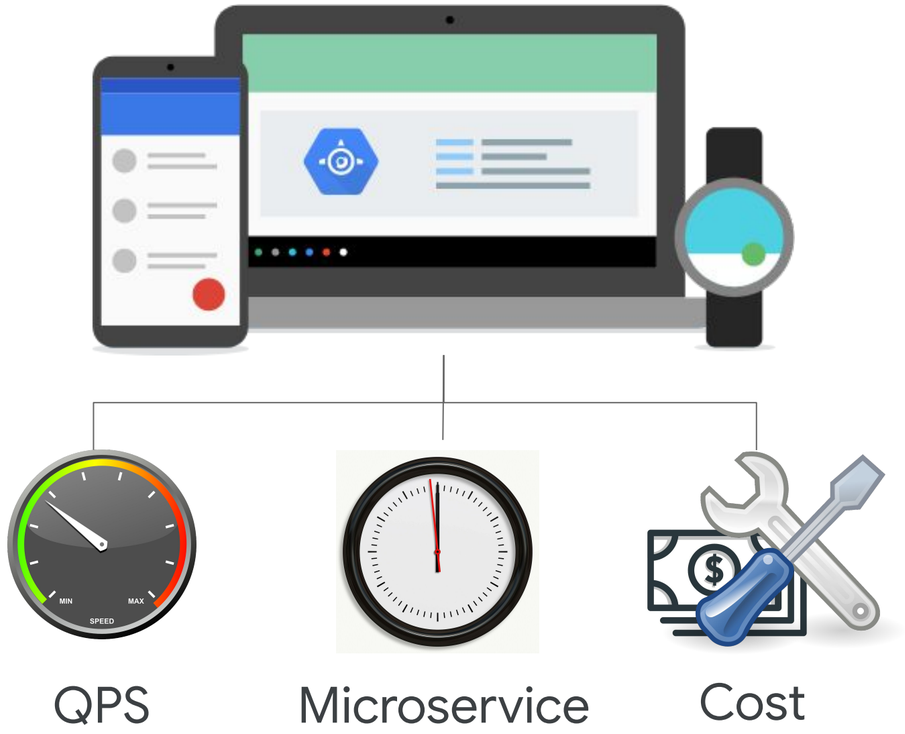


Performance must consider prediction-time, not just training

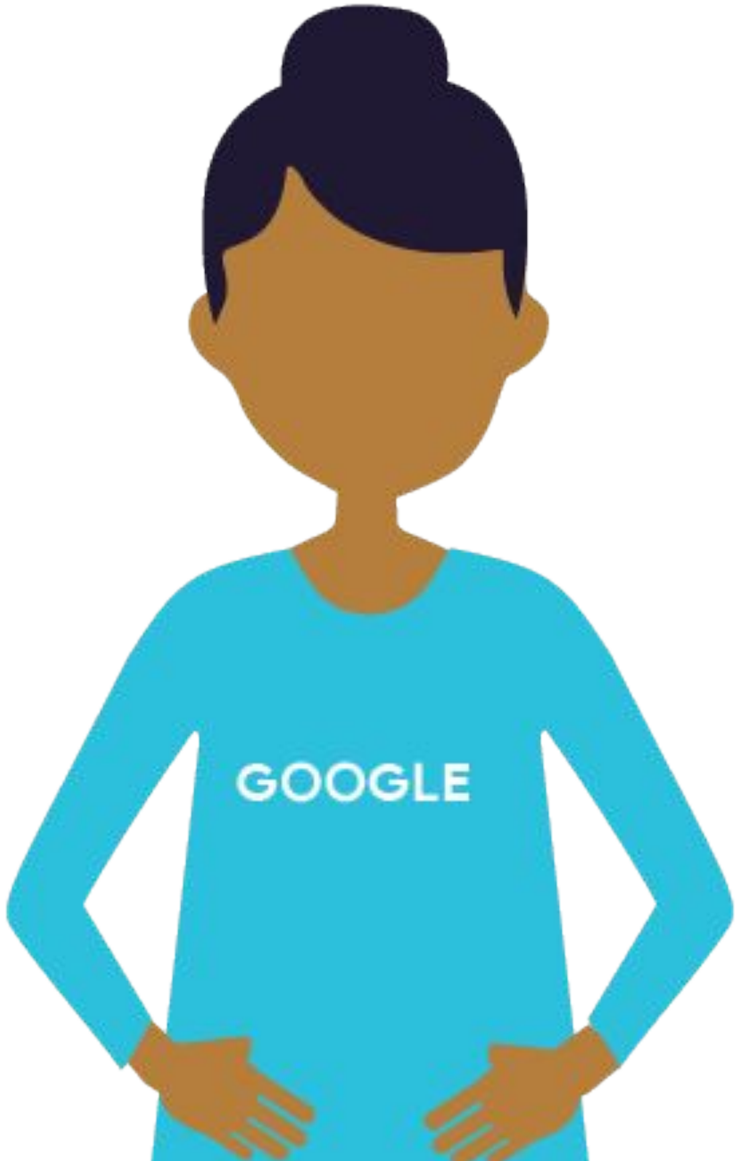




Aspects of performance during inference



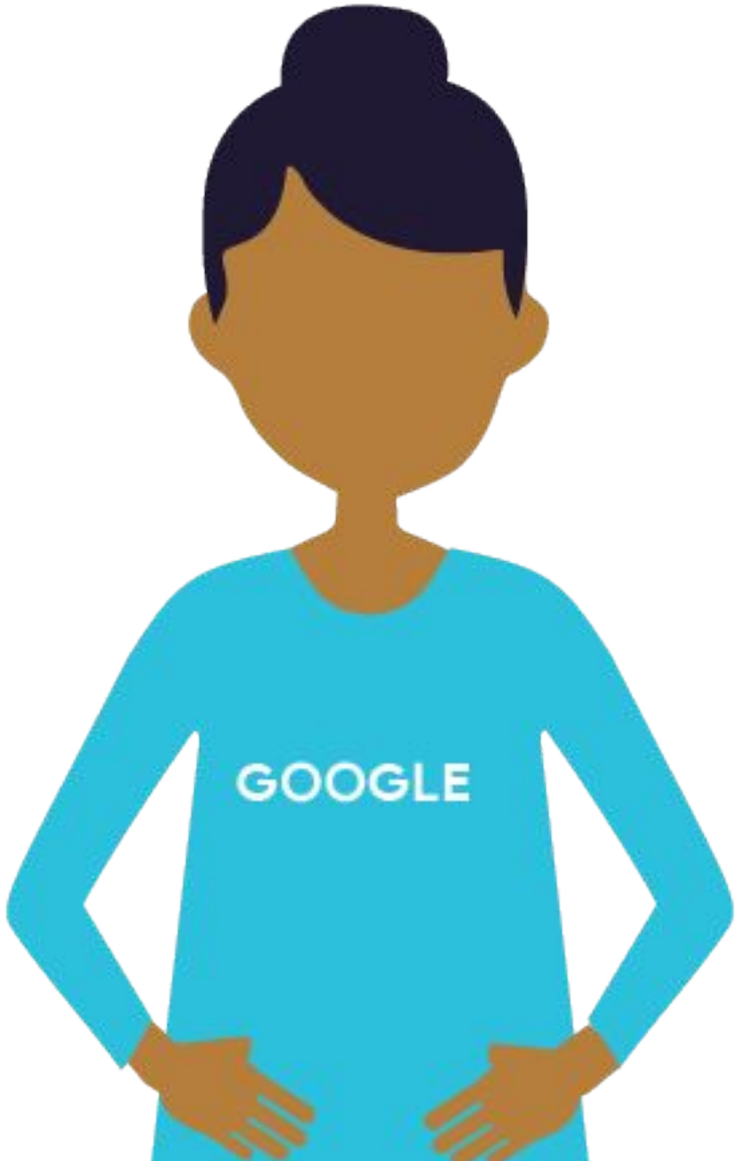
QPS Microservice Cost



Implementation Options

REST/HTTP API

For Streaming Pipelines



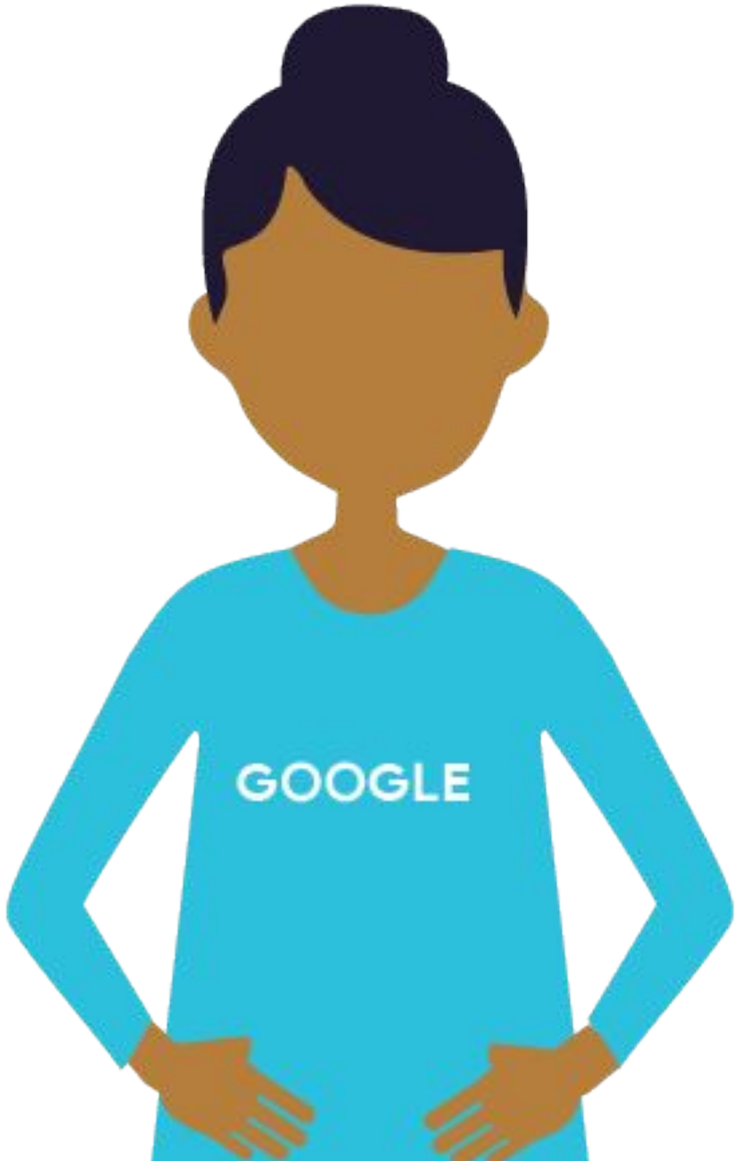
Implementation Options

REST/HTTP API

For Streaming Pipelines

Cloud Machine Learning Engine

For Batch Pipelines



Implementation Options

REST/HTTP API

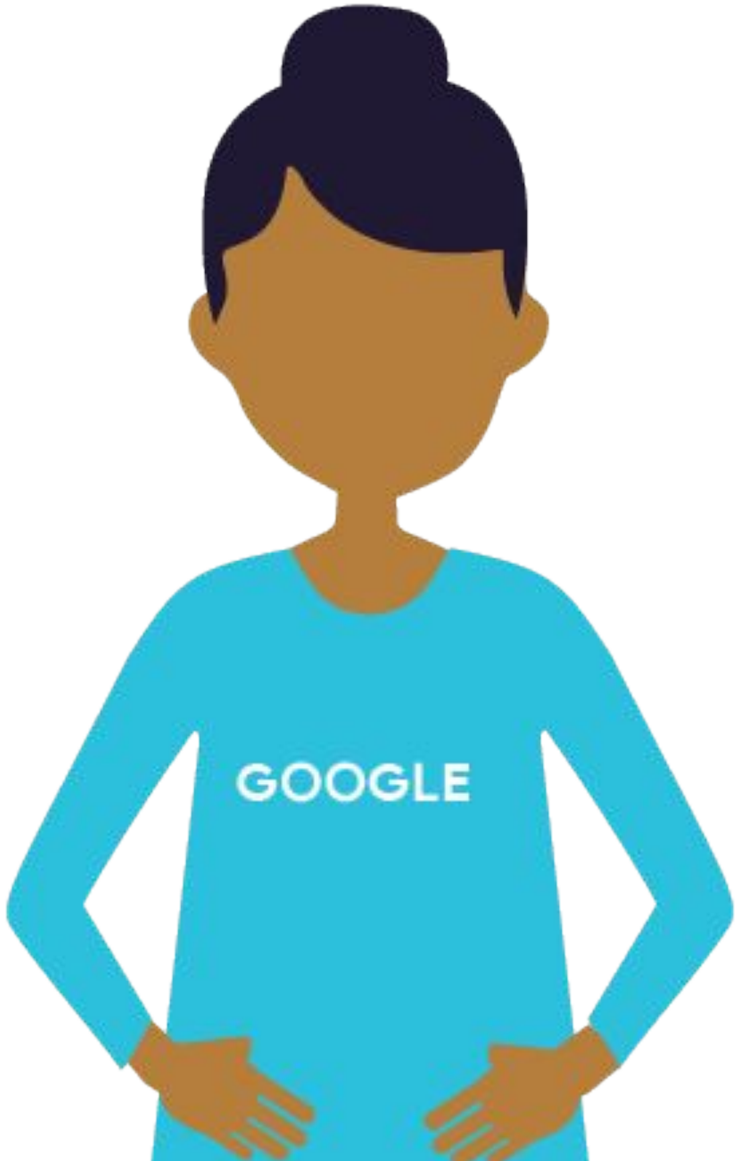
For Streaming Pipelines

Cloud Machine Learning Engine

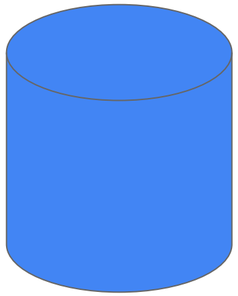
For Batch Pipelines

Cloud Dataflow

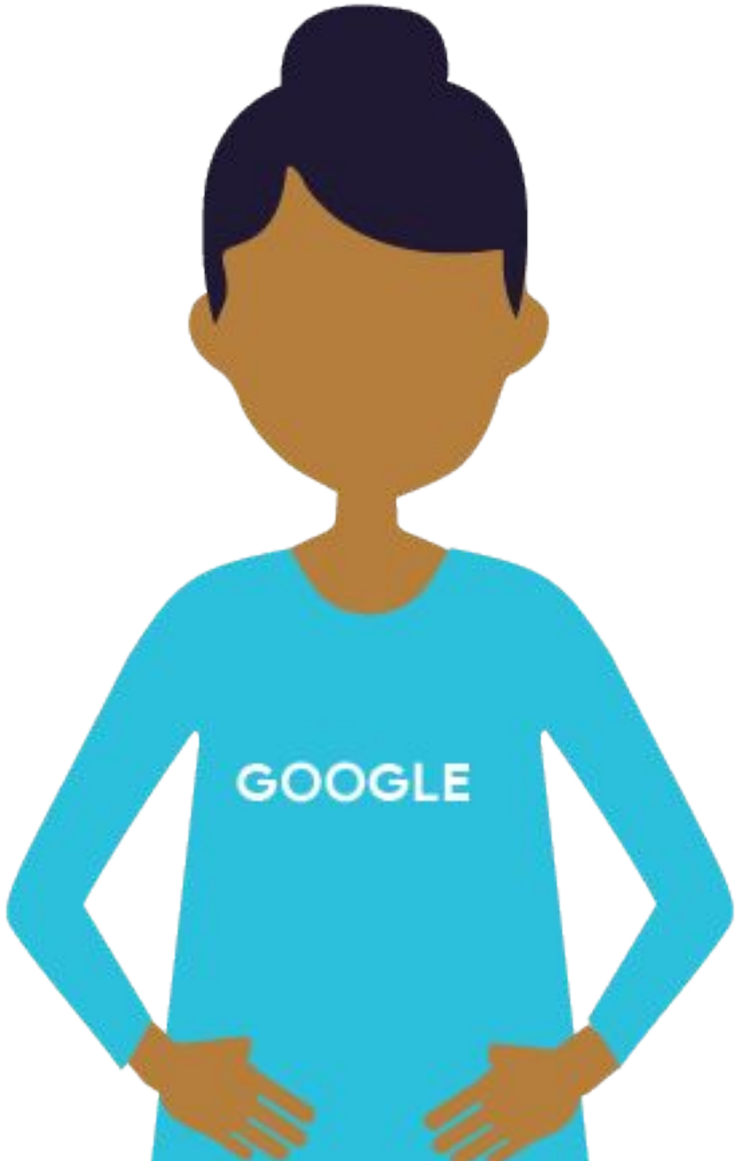
For Batch and Streaming Pipelines

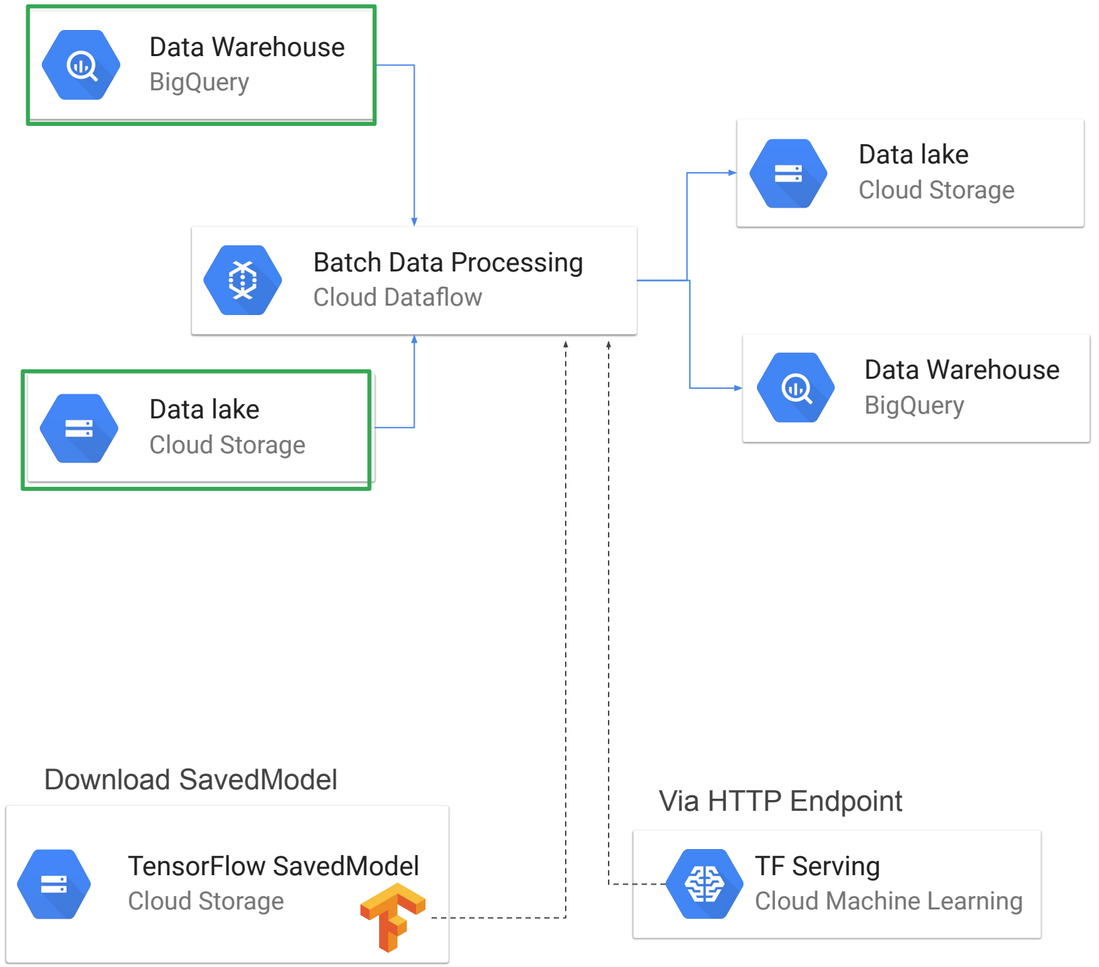


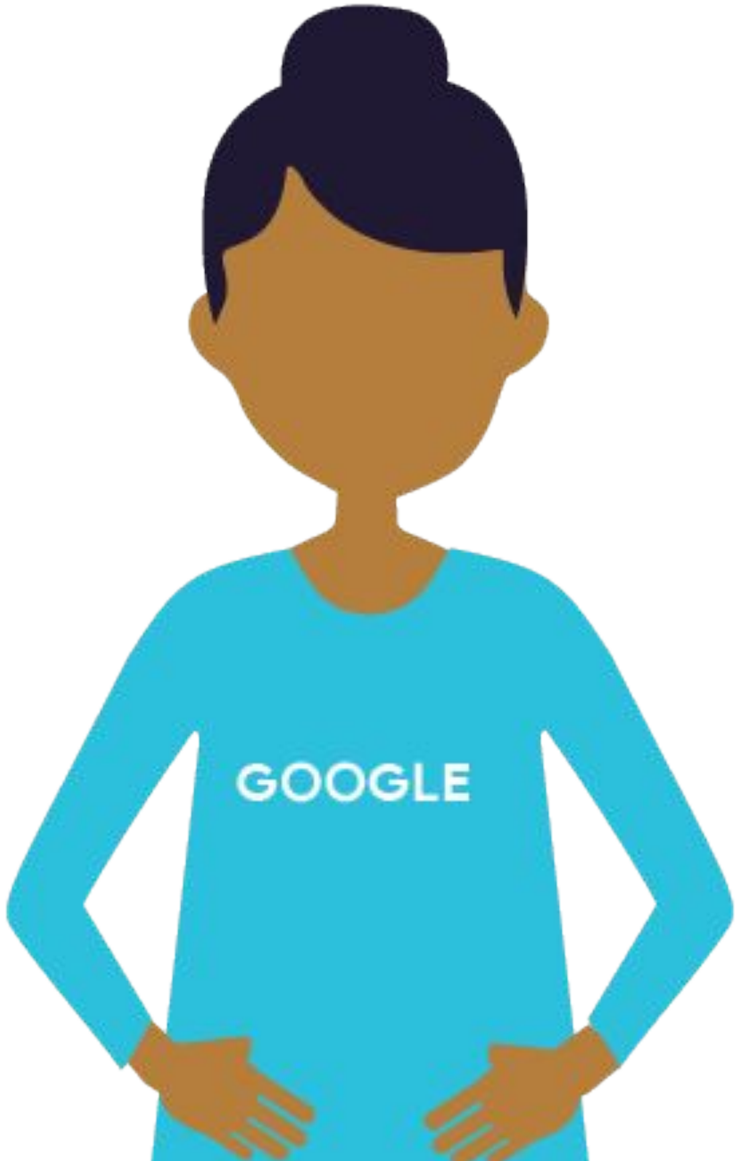
Batch = Bounded Dataset

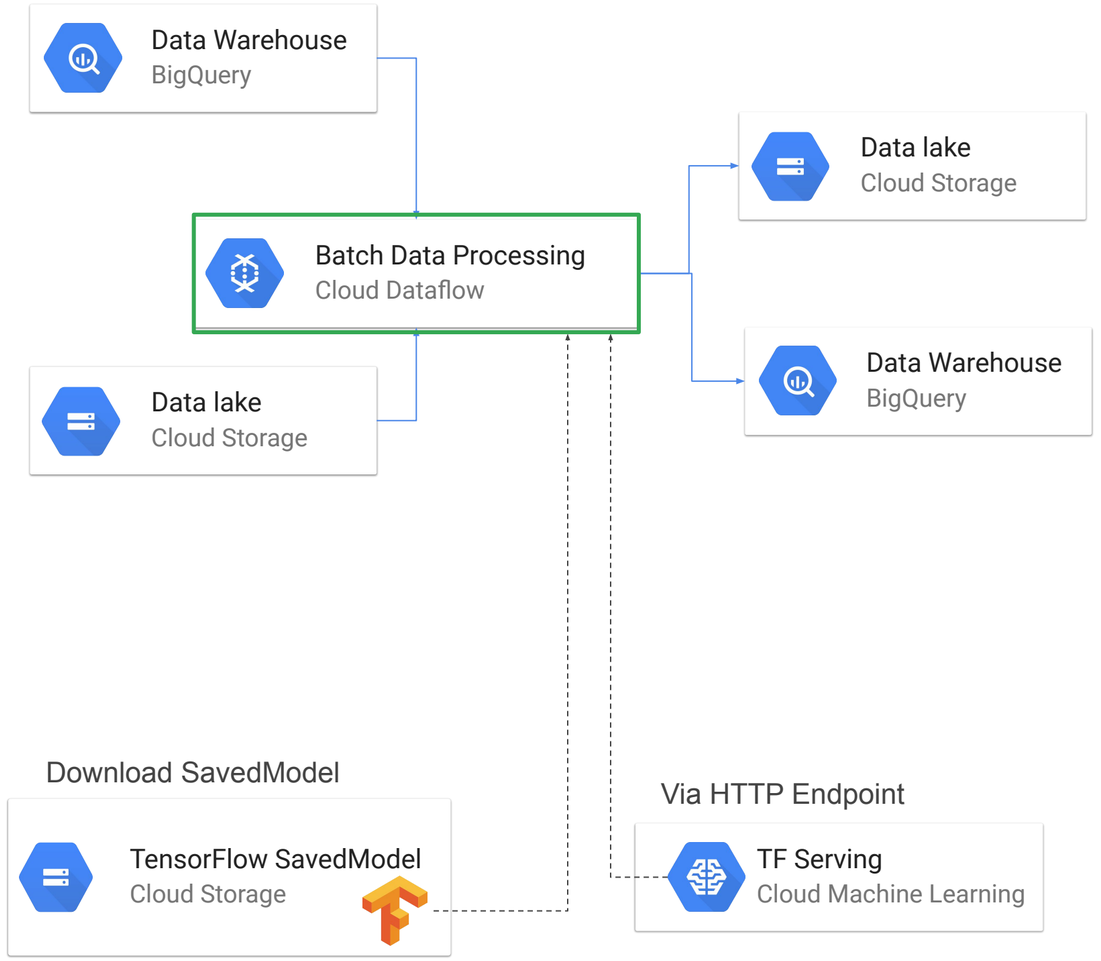


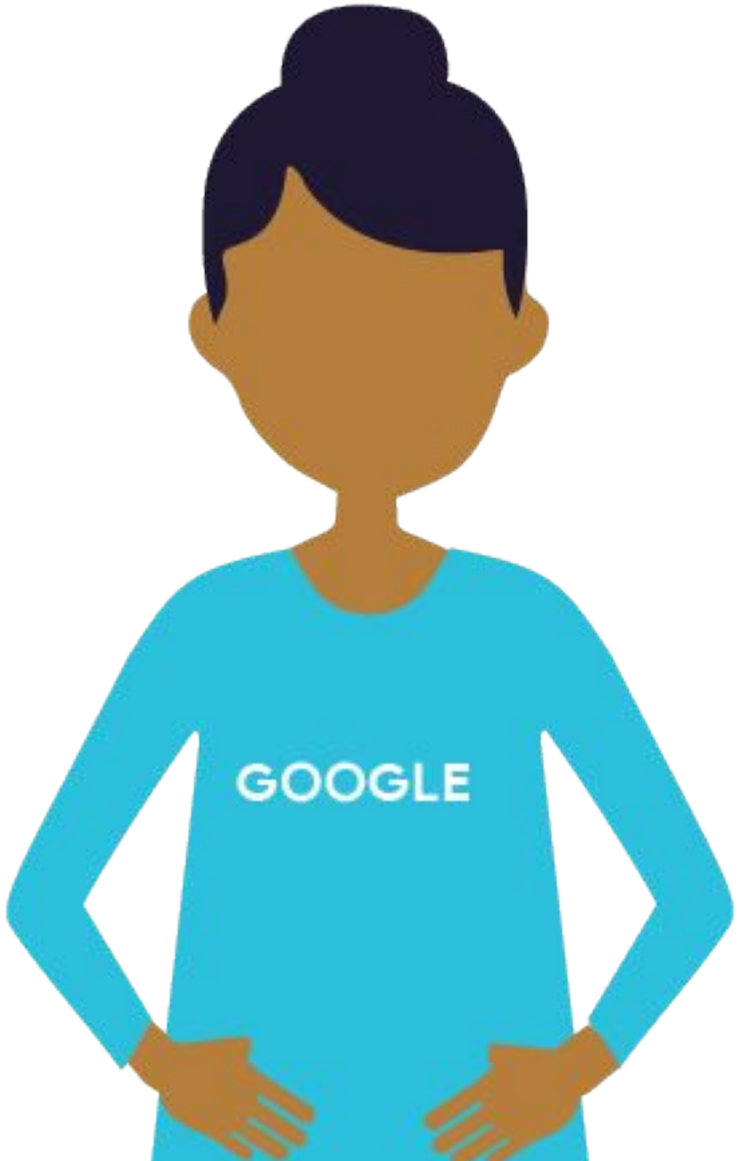
```
SELECT * FROM sales
WHERE date = '2018-01-01'
```

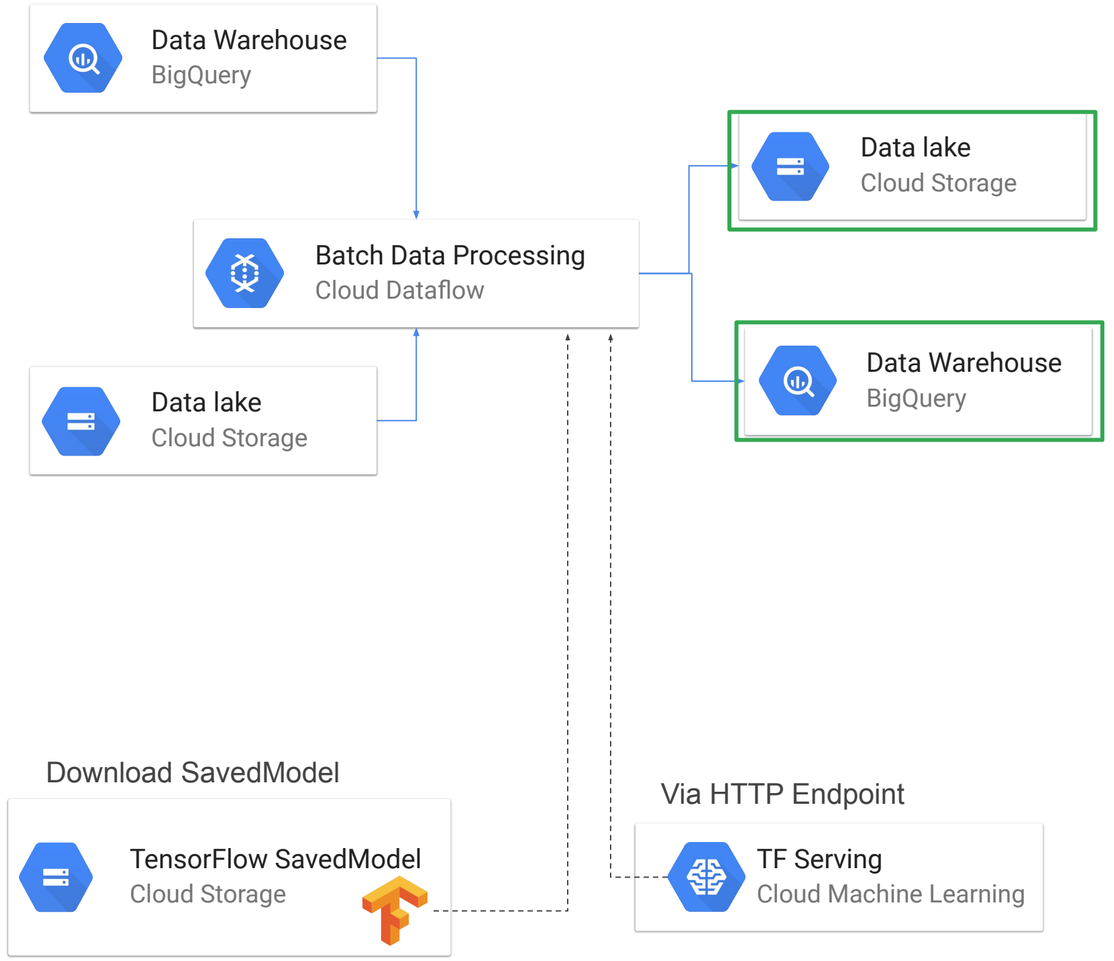

GOOGLE

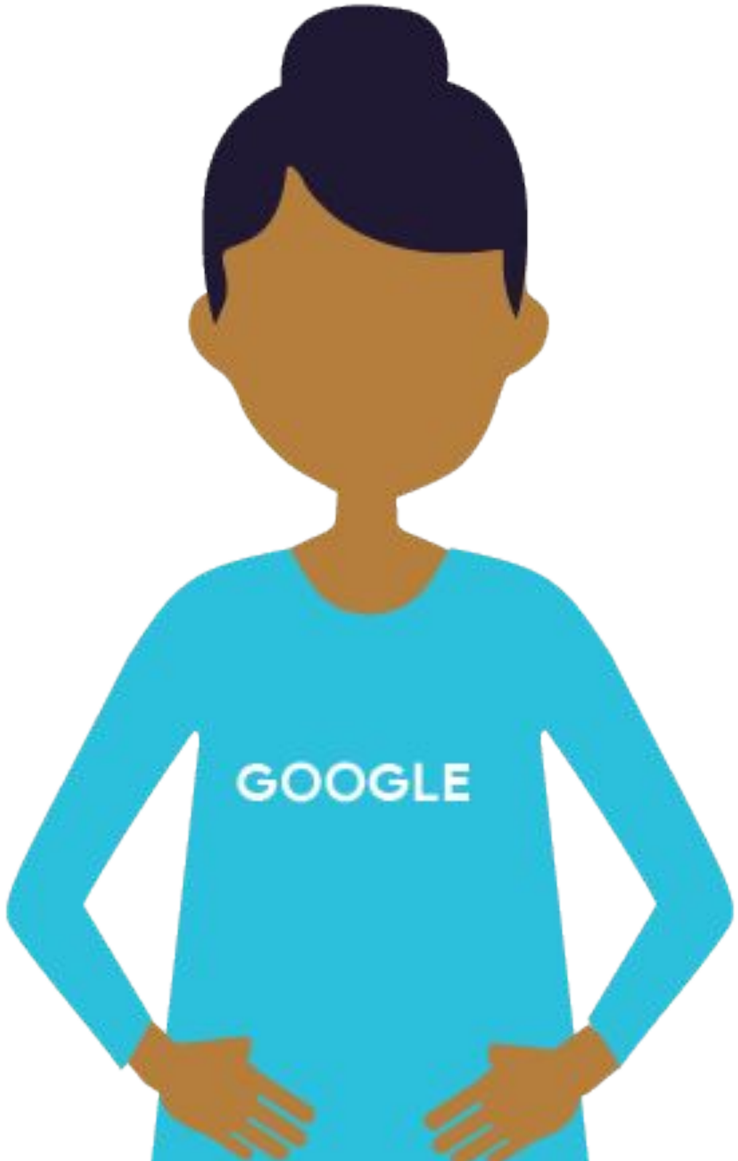

Data Warehouse
BigQuery
Batch Data Processing
Cloud Dataflow
Data lake
Cloud Storage
Data lake
Cloud Storage
Data Warehouse
BigQuery
Download SavedModel
TensorFlow SavedModel
Cloud Storage
Via HTTP Endpoint
TF Serving
Cloud Machine Learning


GOOGLE


Data Warehouse
BigQuery
Data lake
Cloud Storage
Batch Data Processing
Cloud Dataflow
Data lake
Cloud Storage
Data Warehouse
BigQuery
Download SavedModel
TensorFlow SavedModel
Cloud Storage
Via HTTP Endpoint
TF Serving
Cloud Machine Learning


GOOGLE


Data Warehouse
BigQuery
Batch Data Processing
Cloud Dataflow
Data lake
Cloud Storage
Data lake
Cloud Storage
Data Warehouse
BigQuery
Download SavedModel
TensorFlow SavedModel
Cloud Storage
Via HTTP Endpoint
TF Serving
Cloud Machine Learning



Data Warehouse
BigQuery

Data lake
Cloud Storage

Batch Data Processing
Cloud Dataflow

Data lake
Cloud Storage

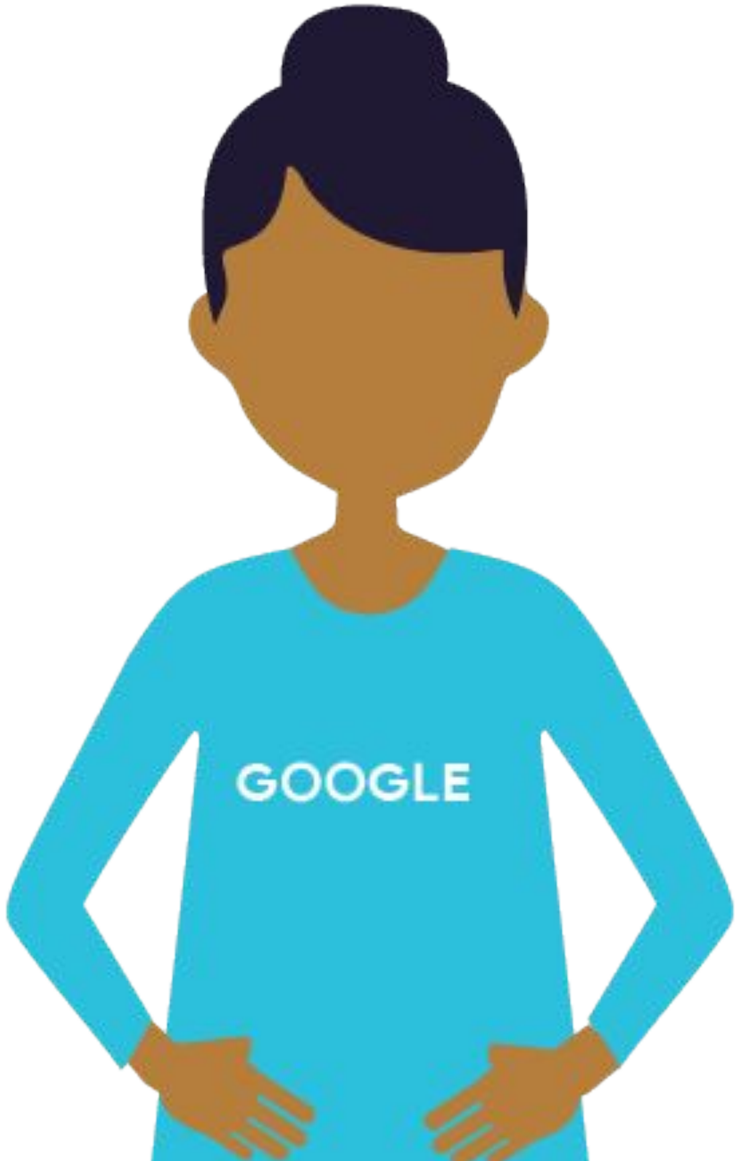
Data Warehouse
BigQuery

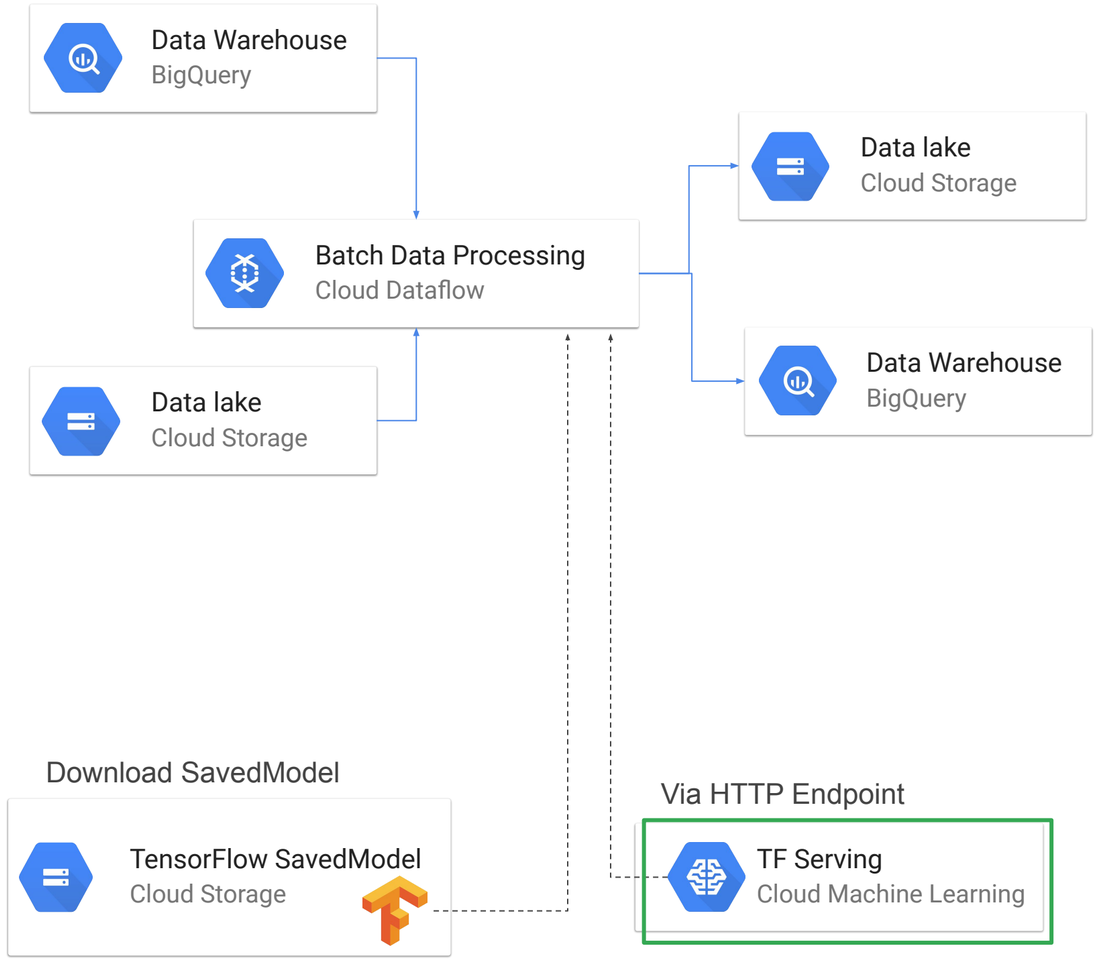
Download SavedModel

TensorFlow SavedModel
Cloud Storage

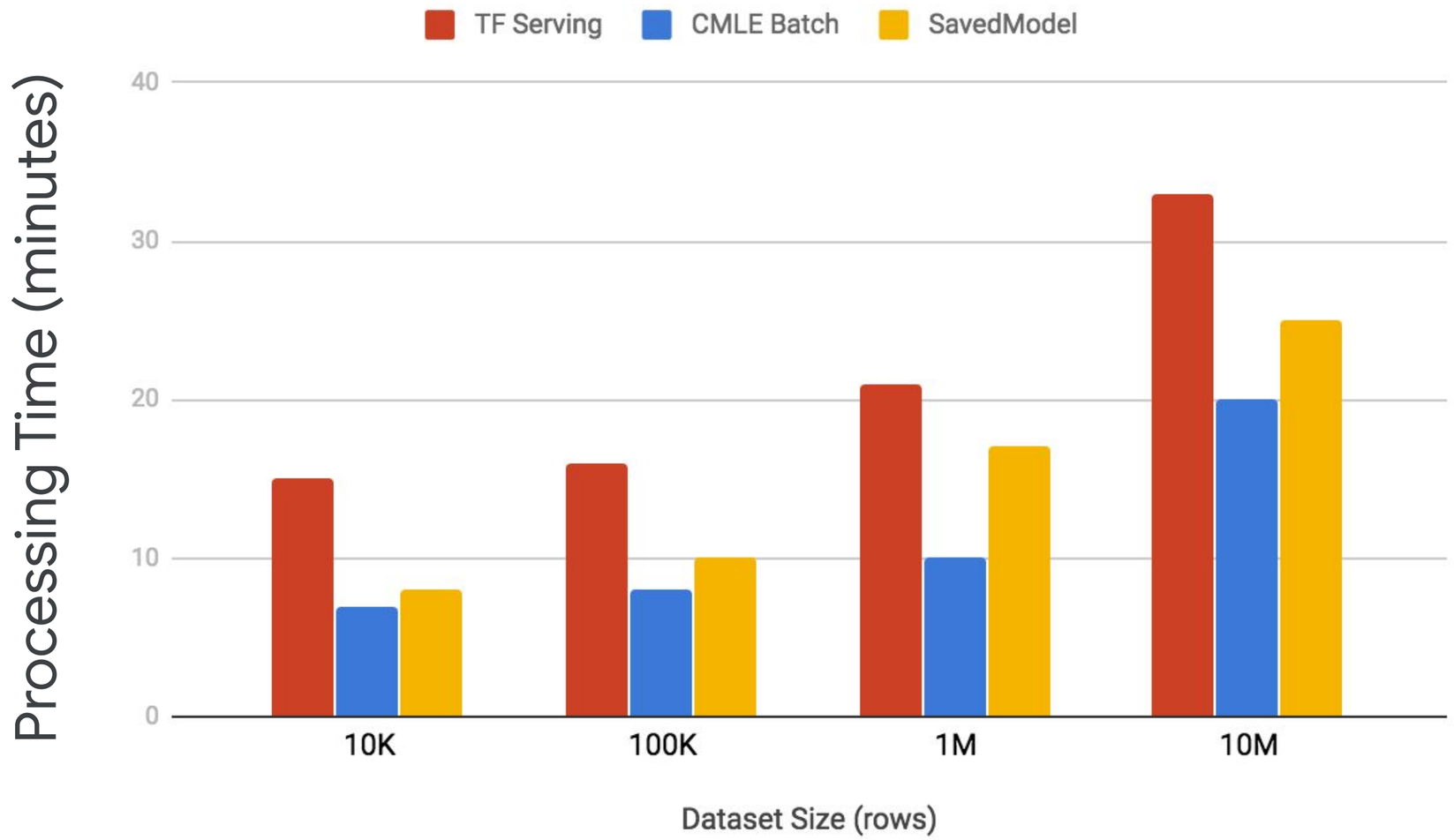
Via HTTP Endpoint

TF Serving
Cloud Machine Learning


GOOGLE

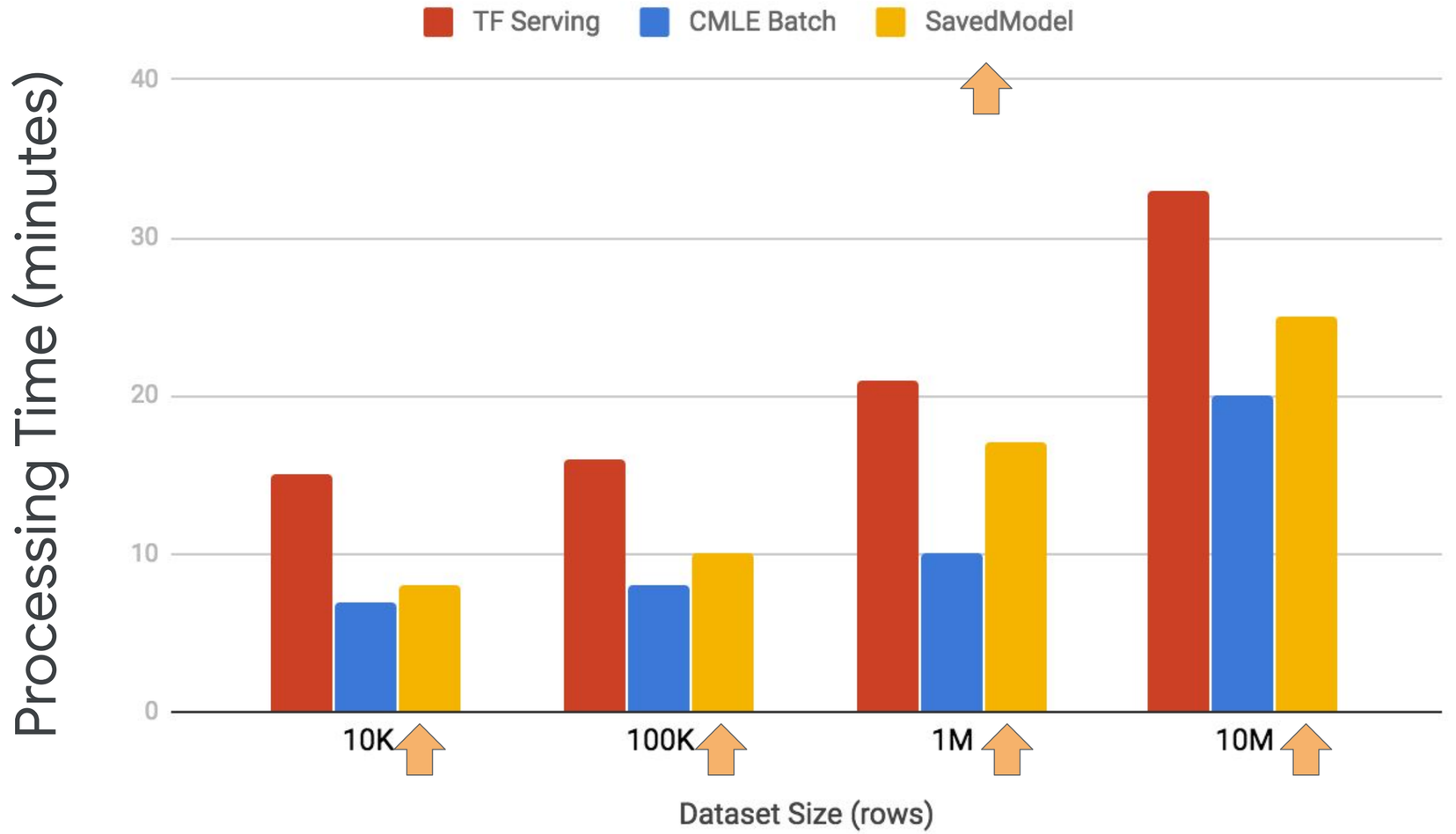

Data Warehouse
BigQuery
Batch Data Processing
Cloud Dataflow
Data lake
Cloud Storage
Data lake
Cloud Storage
Data Warehouse
BigQuery
Download SavedModel
TensorFlow SavedModel
Cloud Storage
Via HTTP Endpoint
TF Serving
Cloud Machine Learning

Performance for Batch Pipelines

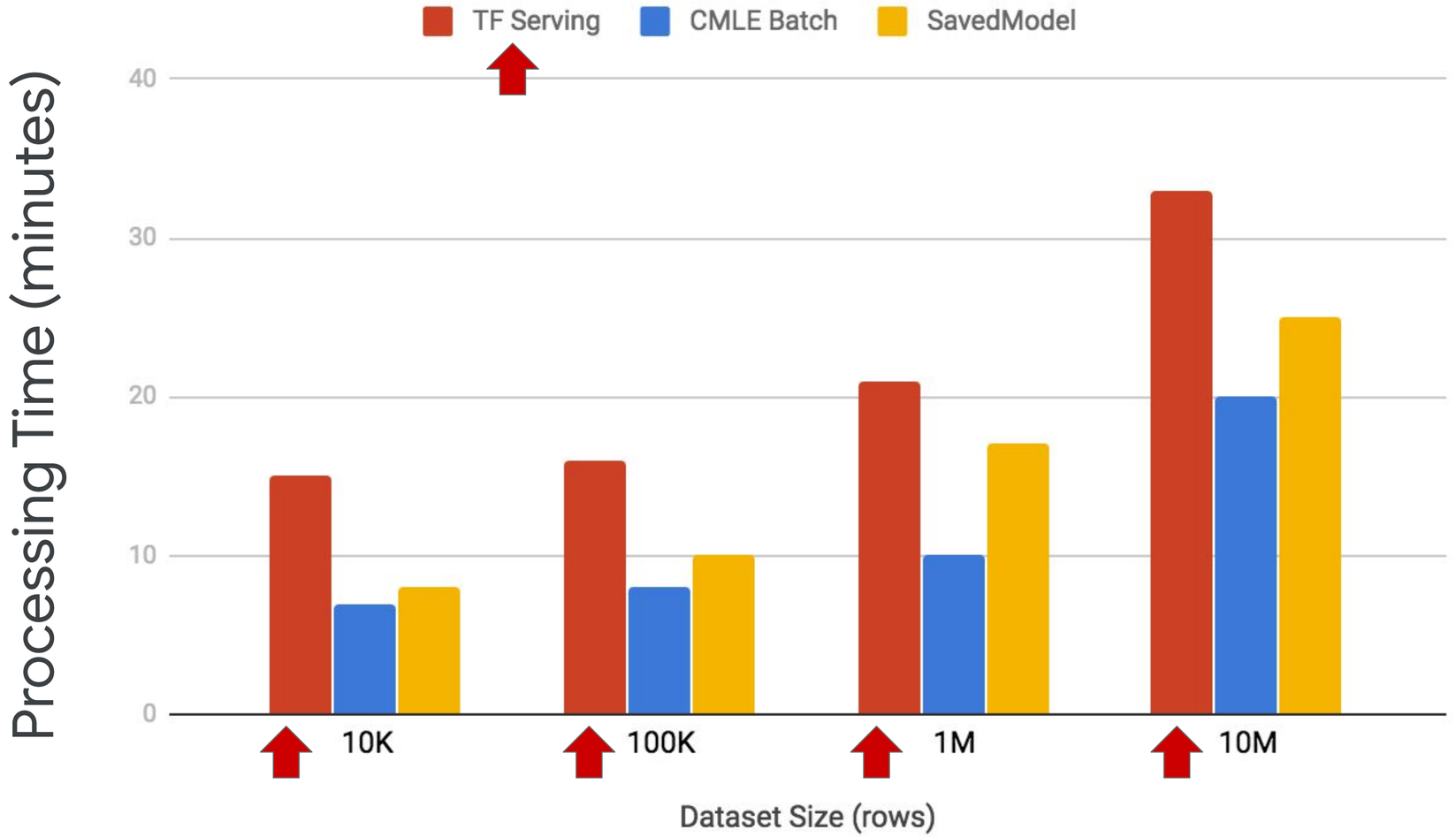


Performance for Batch Pipelines

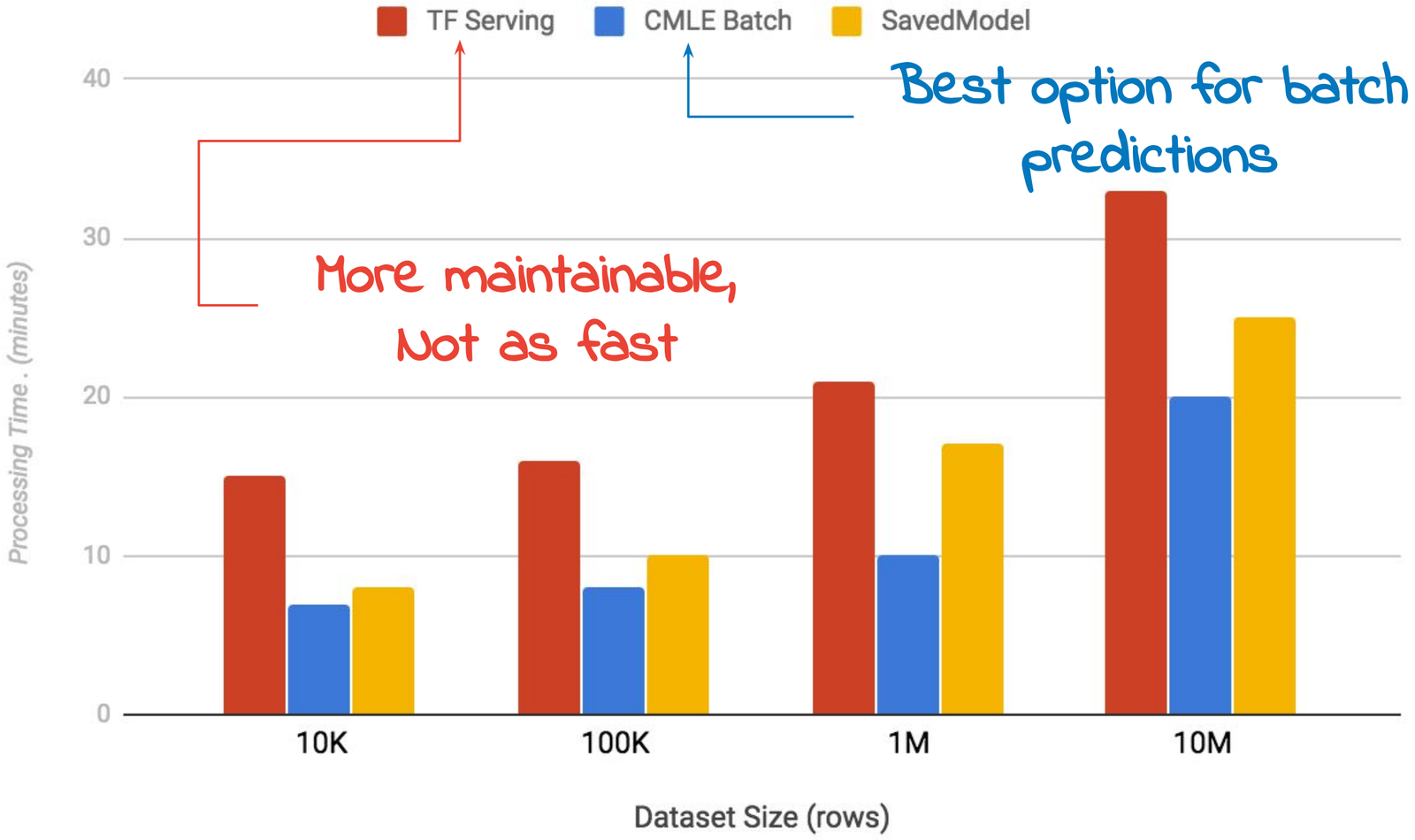
Performance for Batch Pipelines

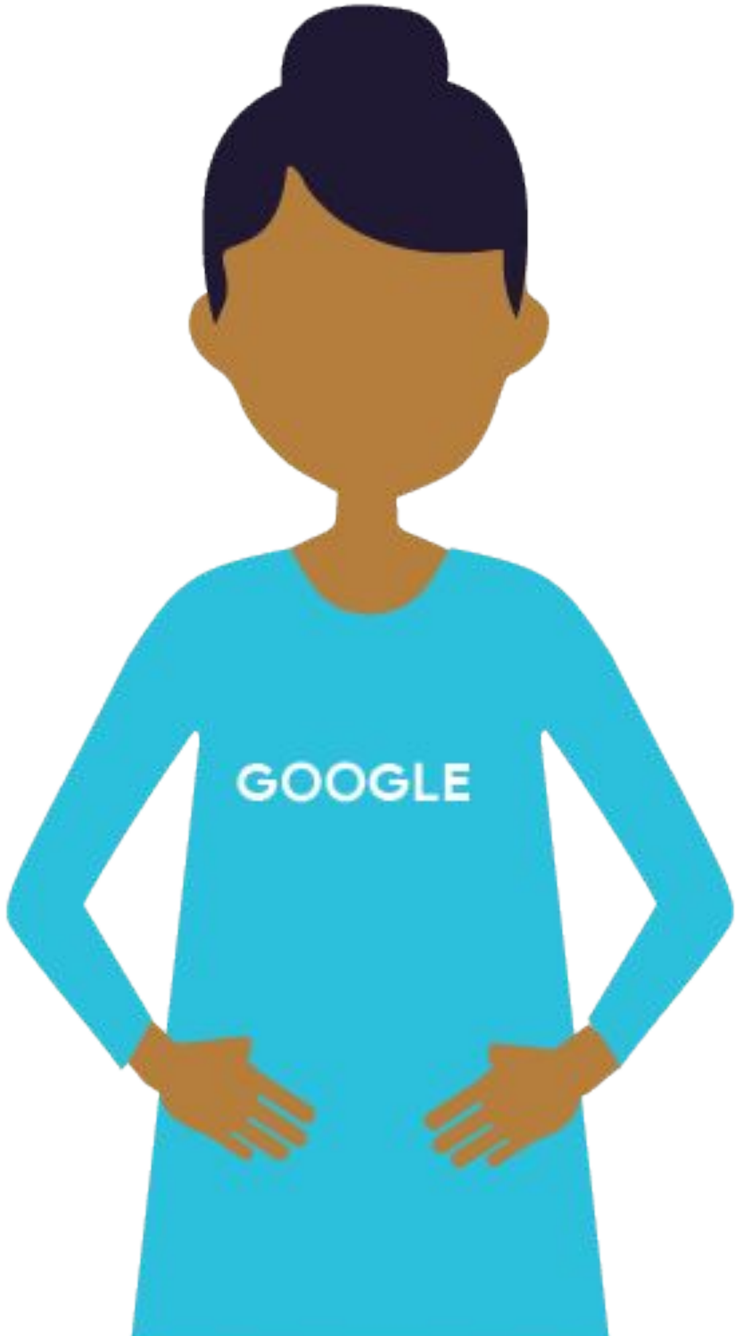


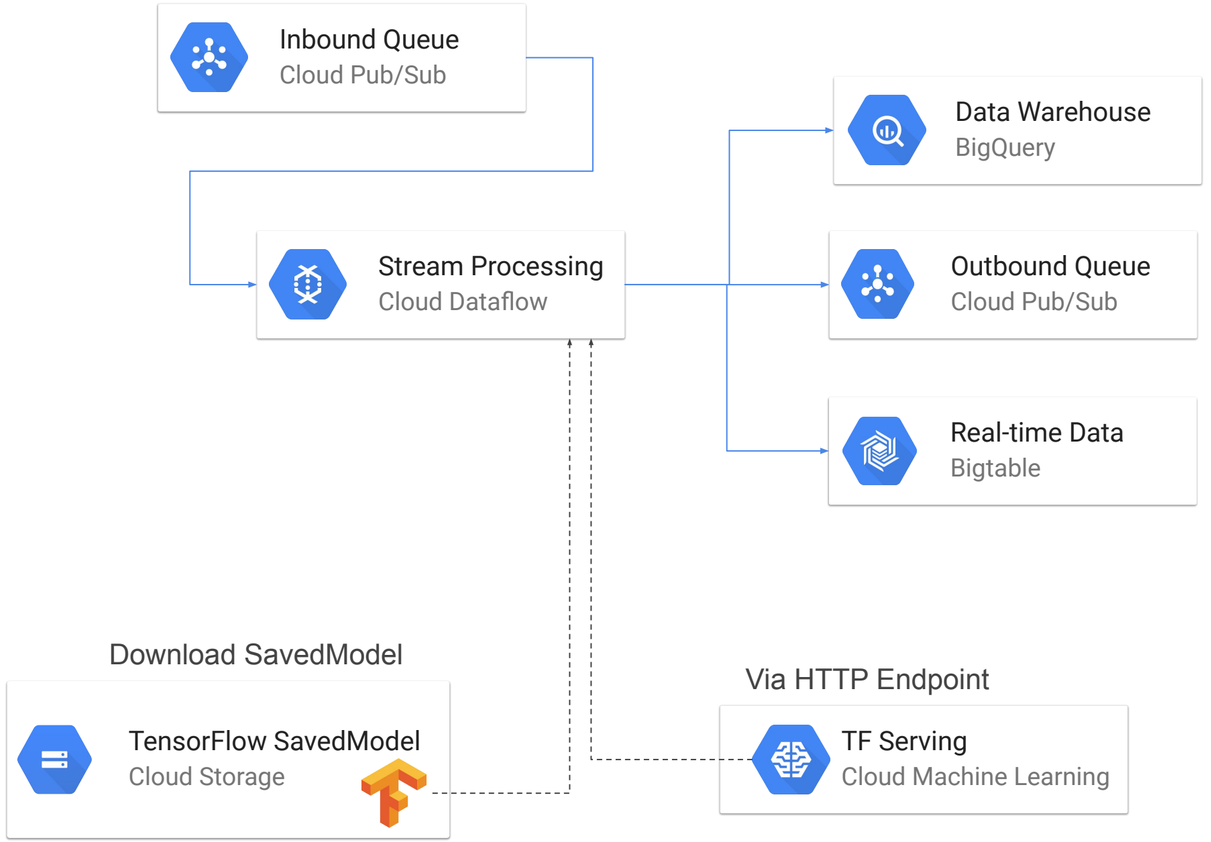
Performance for Batch Pipelines



Performance for Batch Pipelines

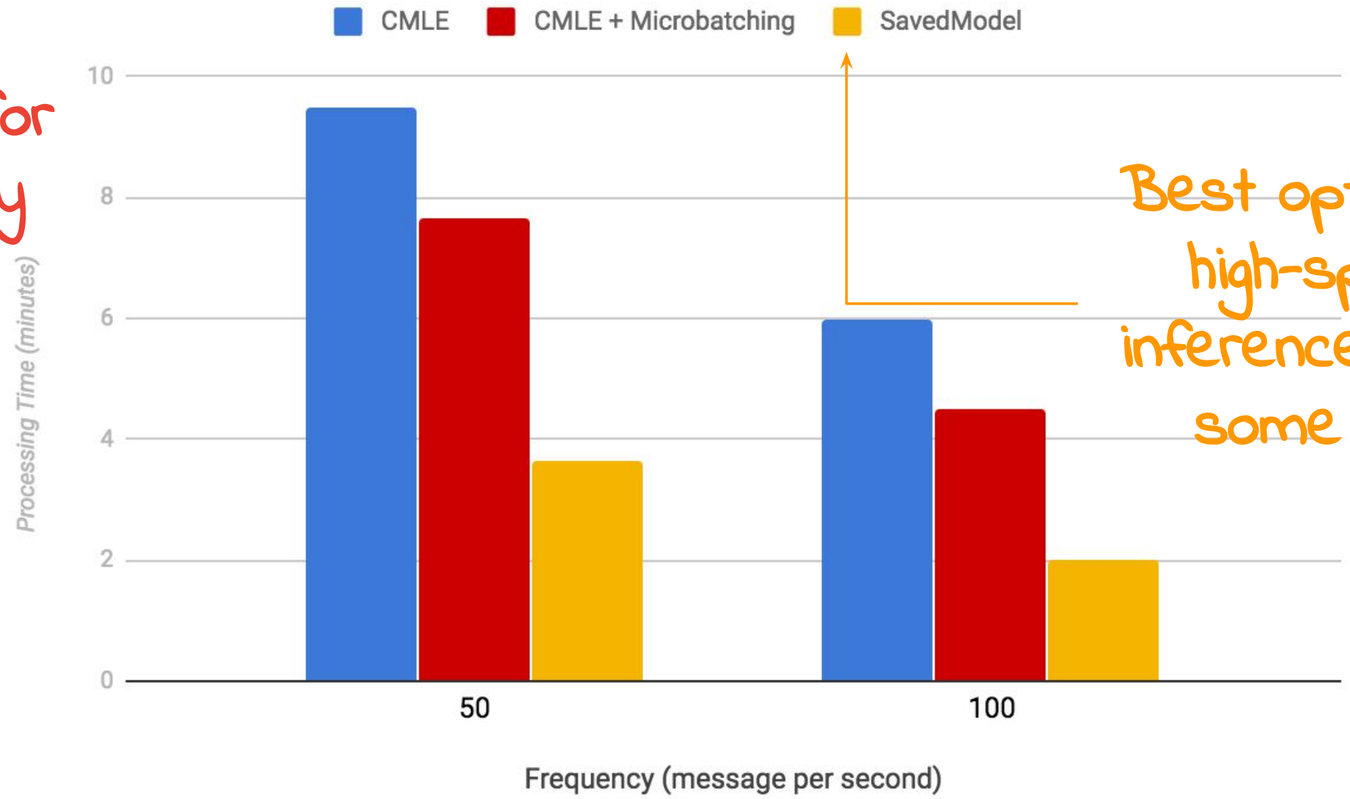



GOOGLE


Inbound Queue
Cloud Pub/Sub
Stream Processing
Cloud Dataflow
Data Warehouse
BigQuery
Outbound Queue
Cloud Pub/Sub
Real-time Data
Bigtable
Download SavedModel
TensorFlow SavedModel
Cloud Storage
Via HTTP Endpoint
TF Serving
Cloud Machine Learning

Performance for Streaming Pipelines

Best option for maintainability and speed



Best option for high-speed inference below some limit

Courses 7 - Production ML Systems

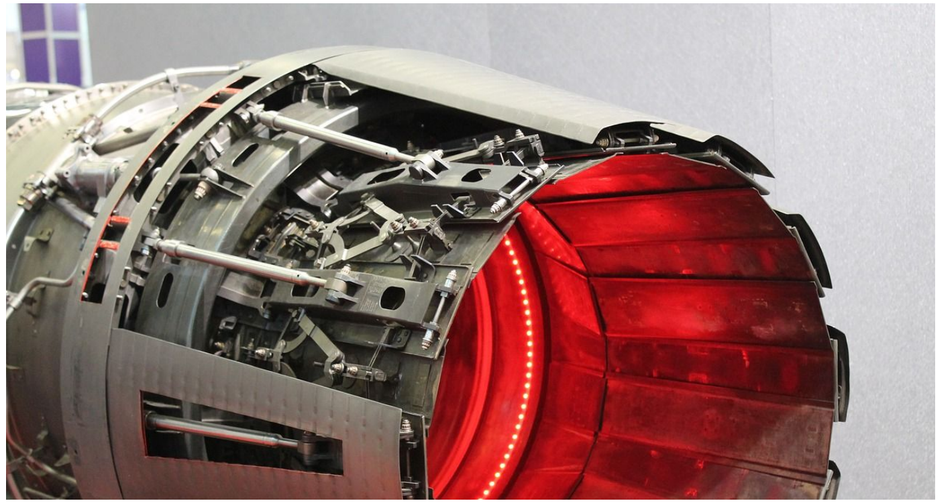
Module 4: Designing High-Performance ML Systems

Lesson Title: **Summary**

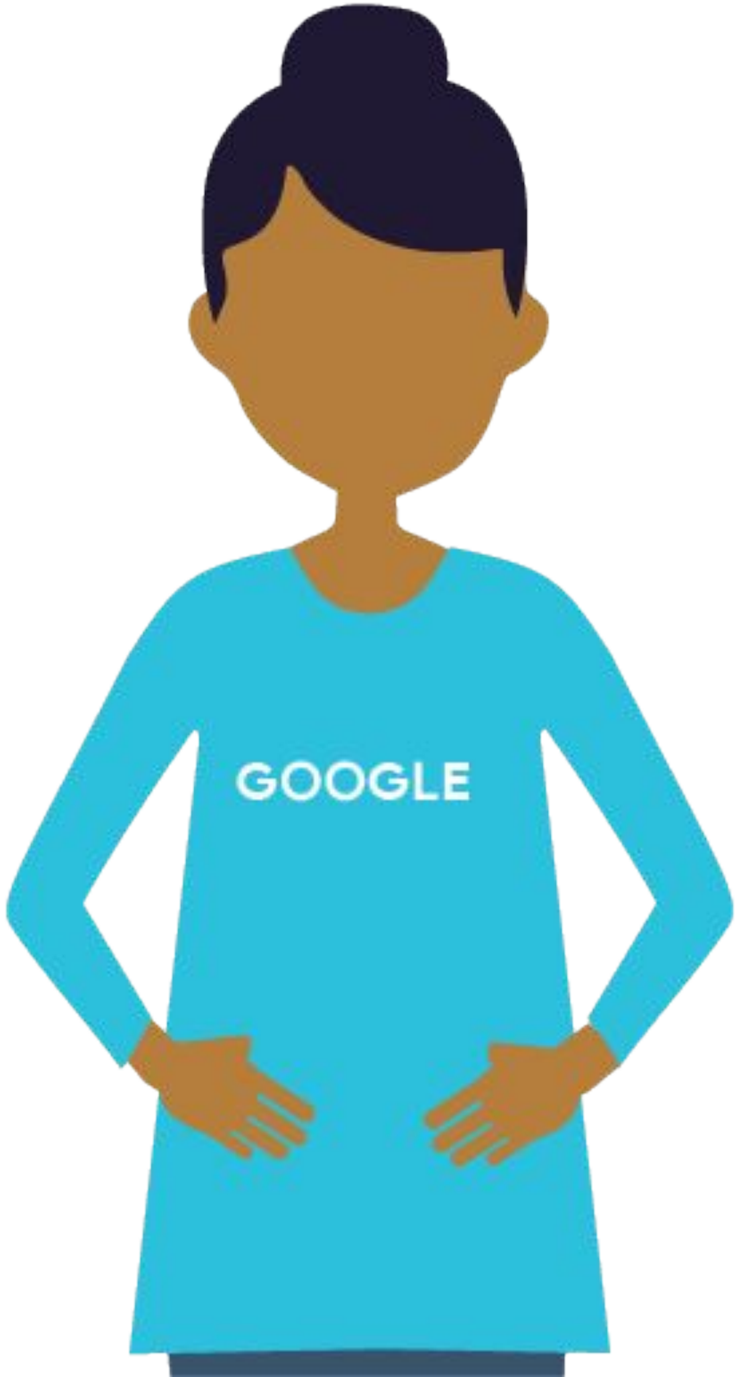
Format: Presenter

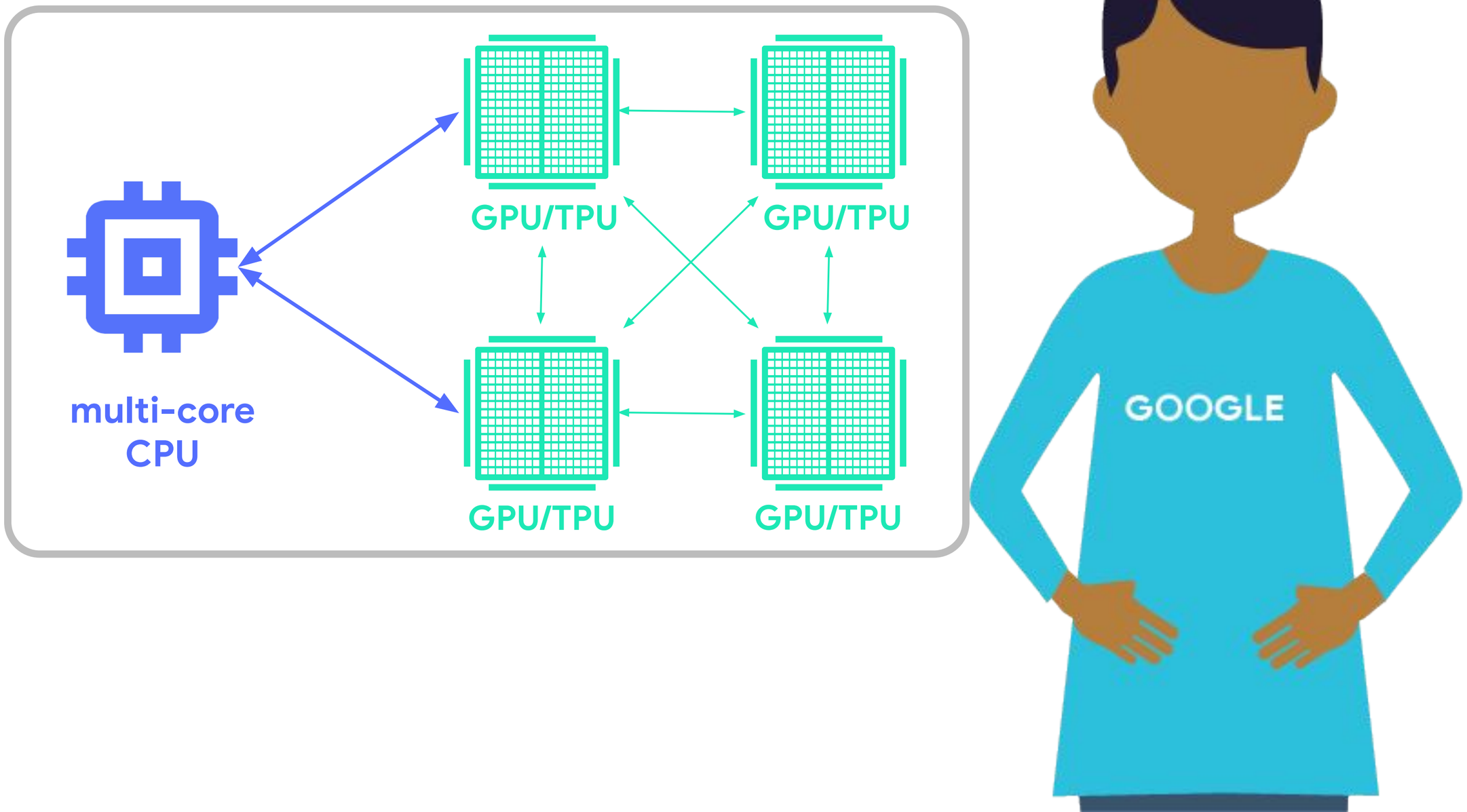
Presenter: Laurence Moroney

Video Name: T-PSML-O_4_I13_summary

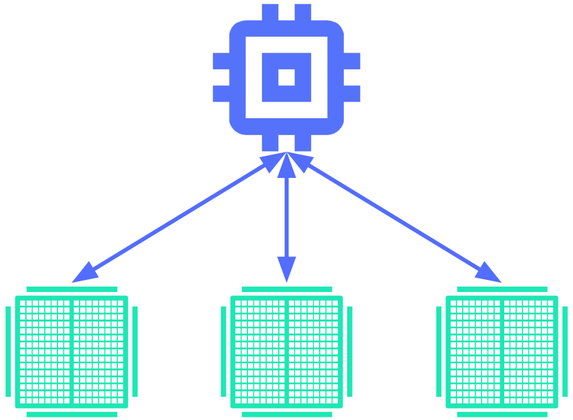



MIN
MAX
SPEED


GOOGLE


multi-core
CPU
GPU/TPU
GPU/TPU
GPU/TPU
GPU/TPU
GOOGLE

Consider Async Parameter Server if...

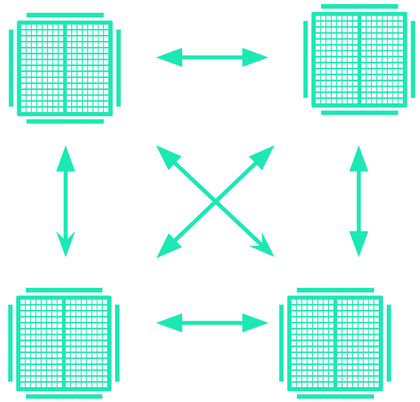


Many low-power
or unreliable workers

More mature approach

Constrained by I/O

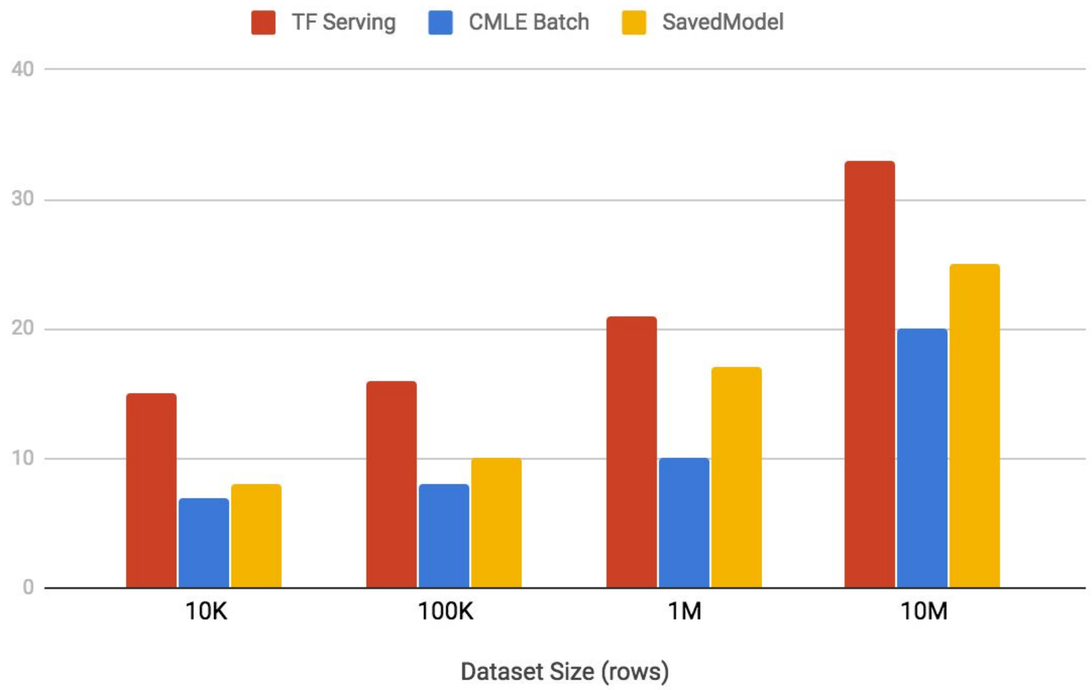
Consider Sync Allreduce if...

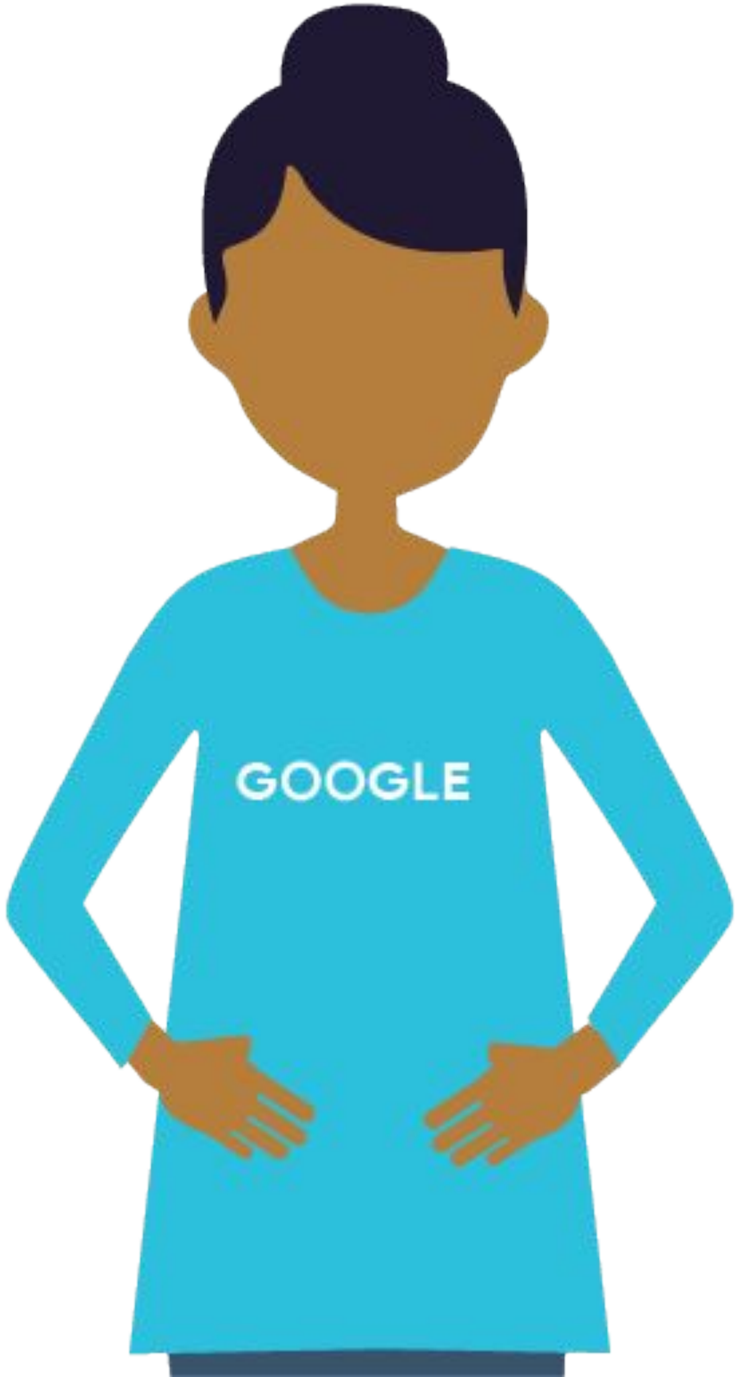


Multiple devices on one host
Fast devices with strong links (e.g. TPUs)

Better for multiple GPUs

Constrained by compute power


TF Serving
CMLE Batch
SavedModel
40
30
20
10
0
10K
100K
1M
10M
Dataset Size (rows)


GOOGLE

Courses 7 - Production ML Systems

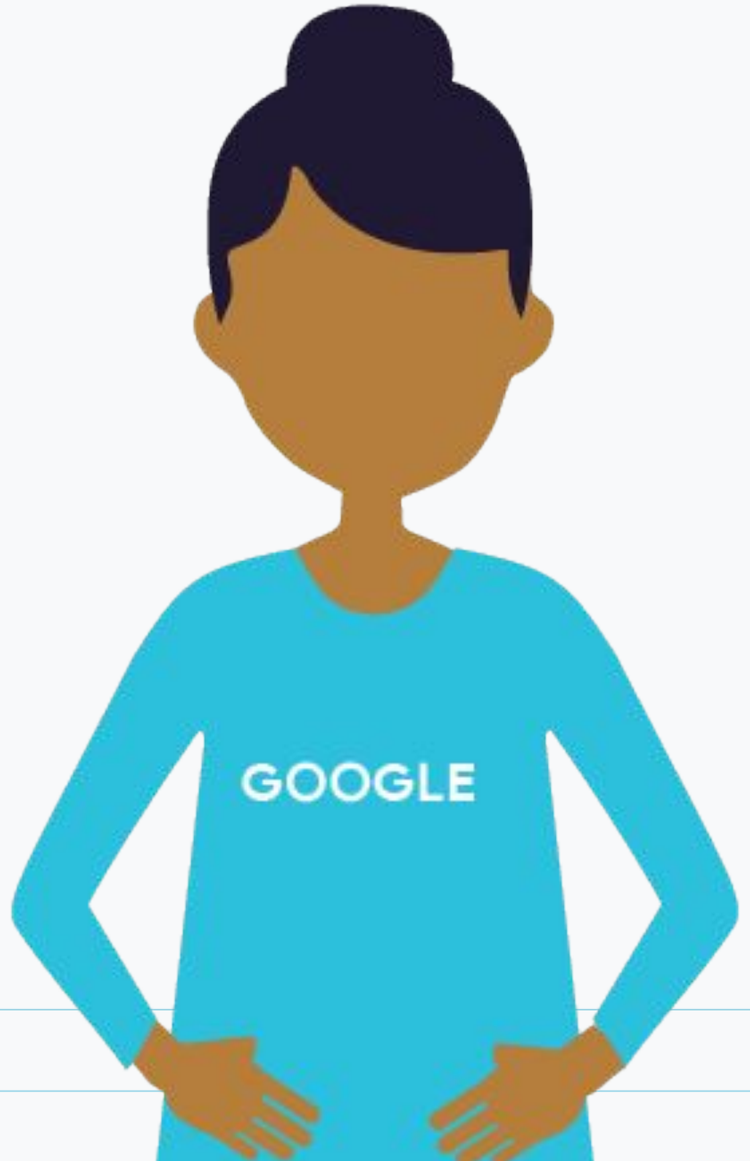
Module 4: Designing High-Performance ML Systems

Lesson Title: **Minimalist Core [optional]**

Format: Presenter

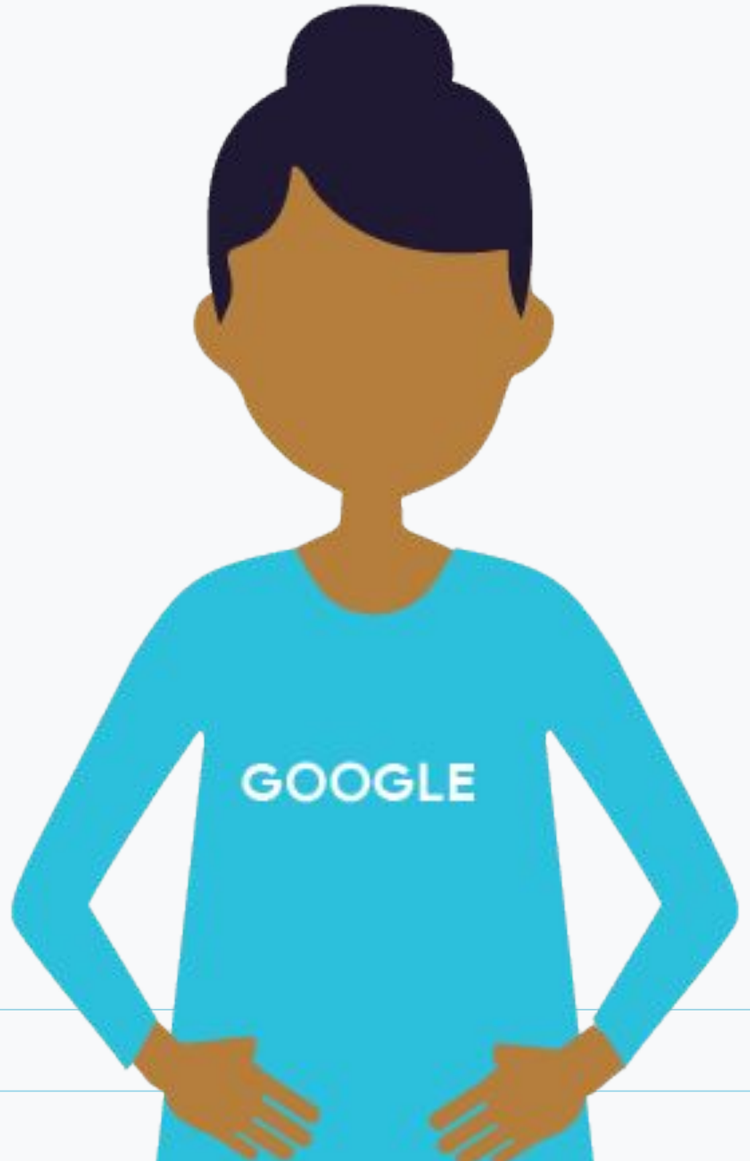
Presenter: Laurence Moroney

Video Name: T-PSML-O_4_l14_minimalist_core_[optional]



Title Safe >

< Action Safe

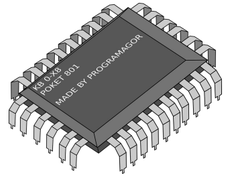


Distributed TensorFlow has a minimalist core. The core can be done on a single machine.

Client

/job:worker/task:0/

cpu:0



gpu:0

Title Safe >

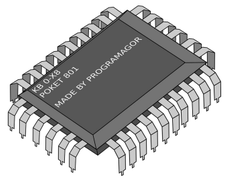
< Action Safe

Distributed TensorFlow has a minimalist core
The core can be done on a single machine.

Client

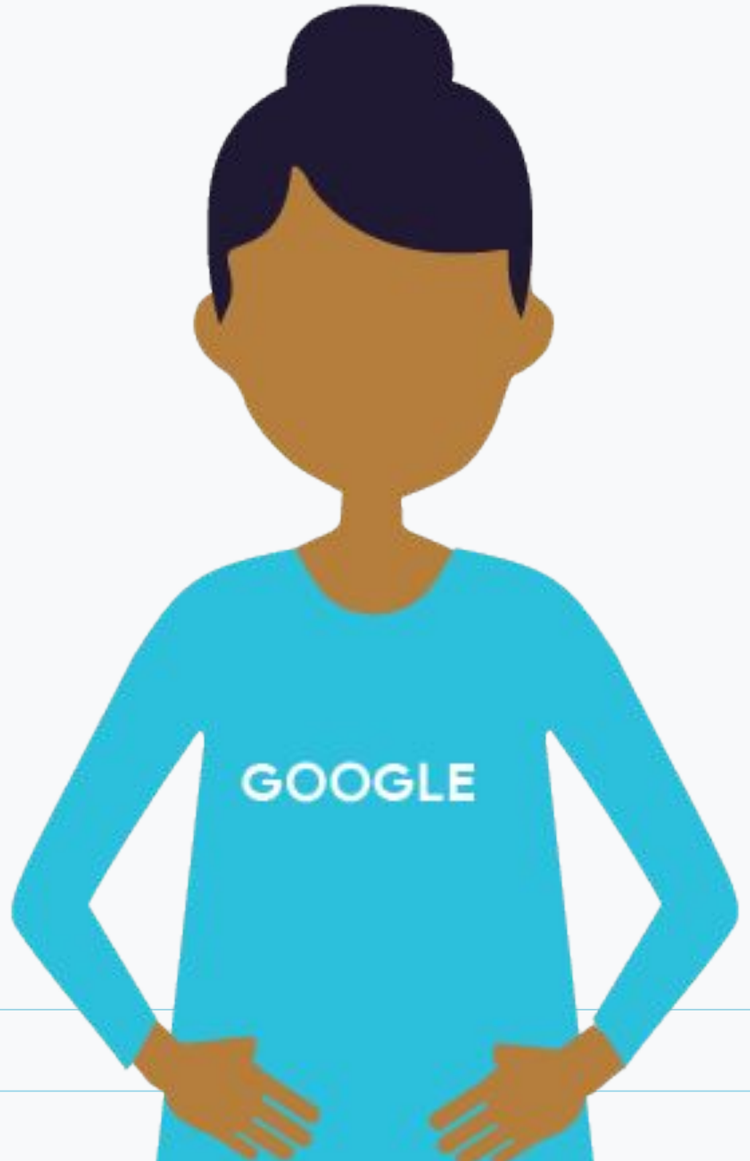
/job:worker/task:0/

cpu:0



gpu:0

You can assign variables to devices

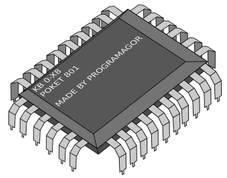



```
with tf.device("/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
with tf.device("/gpu:0"):
  output = tf.matmul(input, W) + b
  loss = f(output)
```

Client

/job:worker/task:0/

cpu:0



gpu:0

Title Safe >

< Action Safe

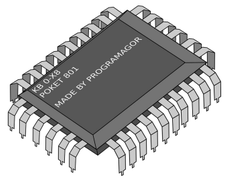
You can assign variables to devices

```
with tf.device("/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
with tf.device("/gpu:0"):
  output = tf.matmul(input, W) + b
  loss = f(output)
```

Client

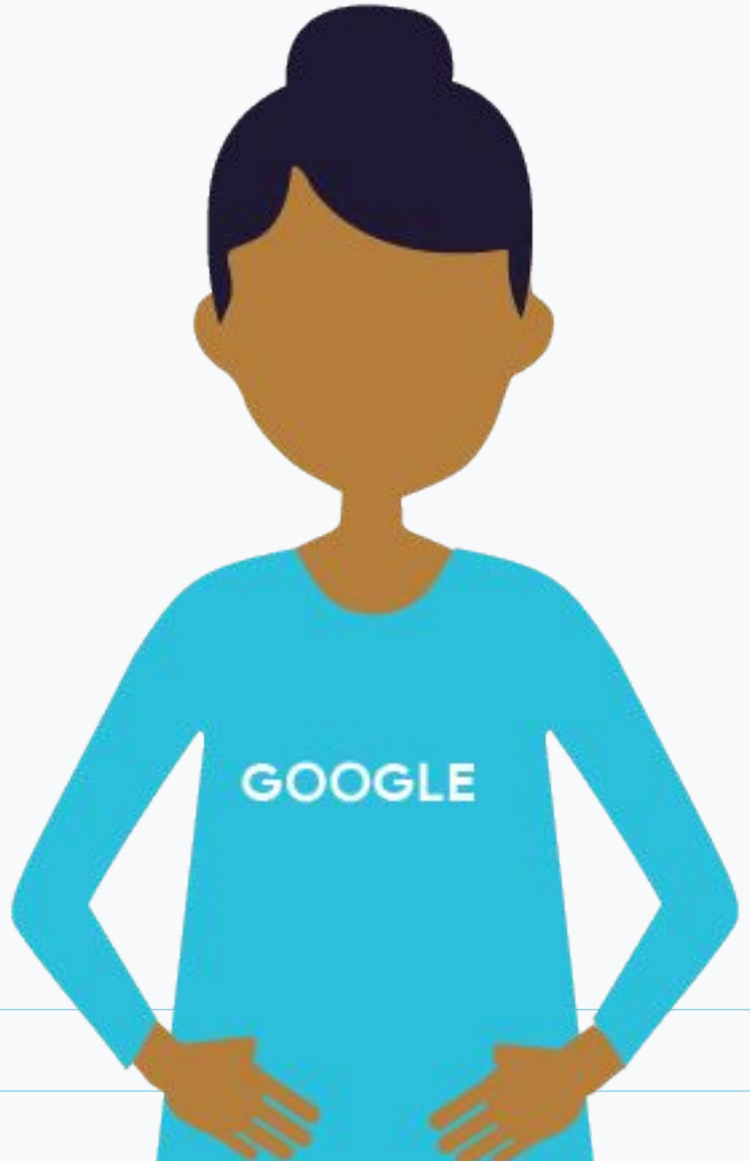
/job:worker/task:0/

cpu:0



gpu:0

TensorFlow inserts necessary data transfers

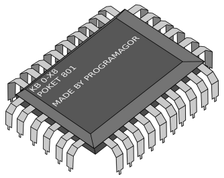



```
with tf.device("/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
with tf.device("/gpu:0"):
  output = tf.matmul(input, W) + b
  loss = f(output)
```

Client

/job:worker/task:0/

cpu:0



gpu:0

Title Safe >

< Action Safe

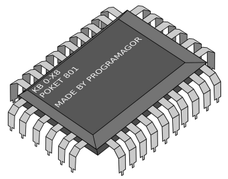
TensorFlow inserts necessary data transfers

```
with tf.device("/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
with tf.device("/gpu:0"):
  output = tf.matmul(input, W) + b
  loss = f(output)
```

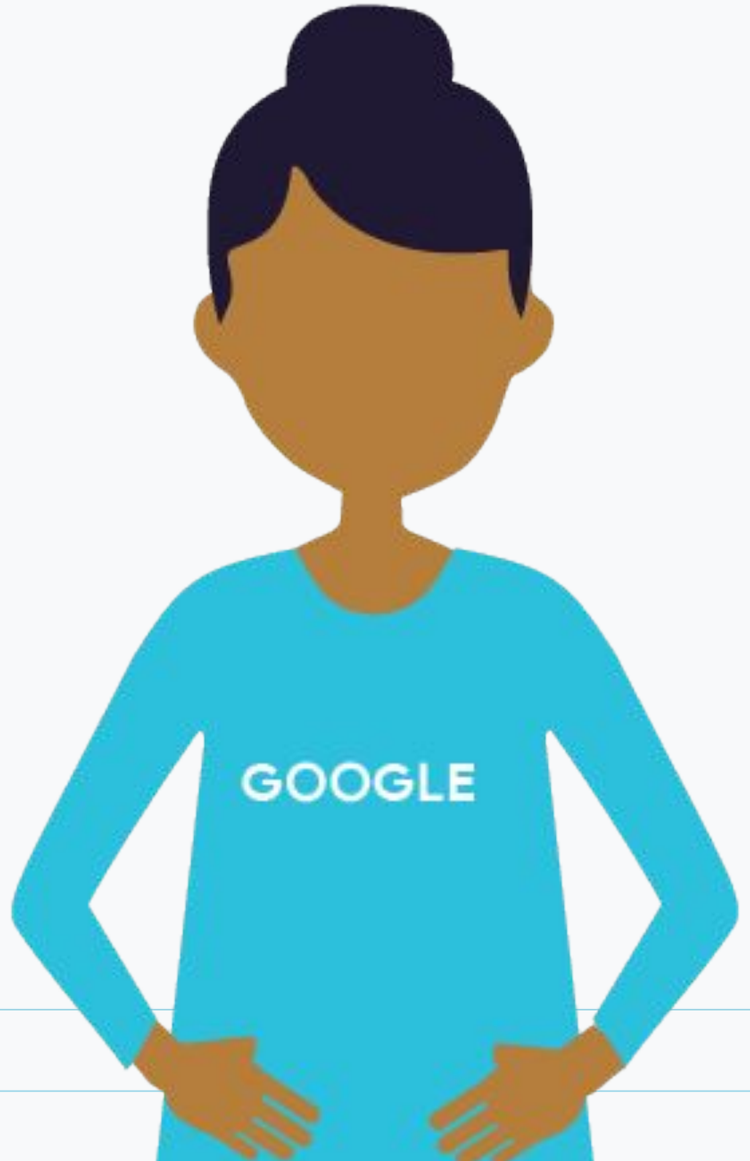
Client

/job:worker/task:0/

cpu:0



gpu:0



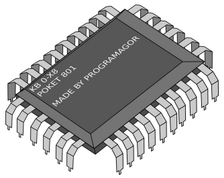
What if you have a second machine?

```
with tf.device("/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
with tf.device("/gpu:0"):
  output = tf.matmul(input, W) + b
  loss = f(output)
```

Client

/job:worker/task:0/

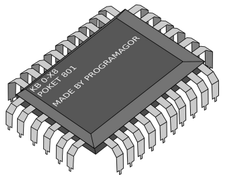
cpu:0



gpu:0

/job:ps/task:0/

cpu:0



Title Safe >

< Action Safe

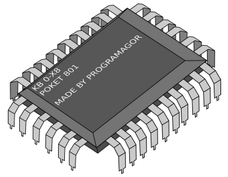
What if you have a second machine?

```
with tf.device("/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
with tf.device("/gpu:0"):
  output = tf.matmul(input, W) + b
  loss = f(output)
```

Client

/job:worker/task:0/

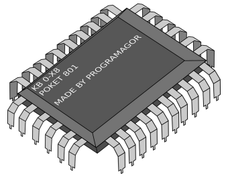
cpu:0

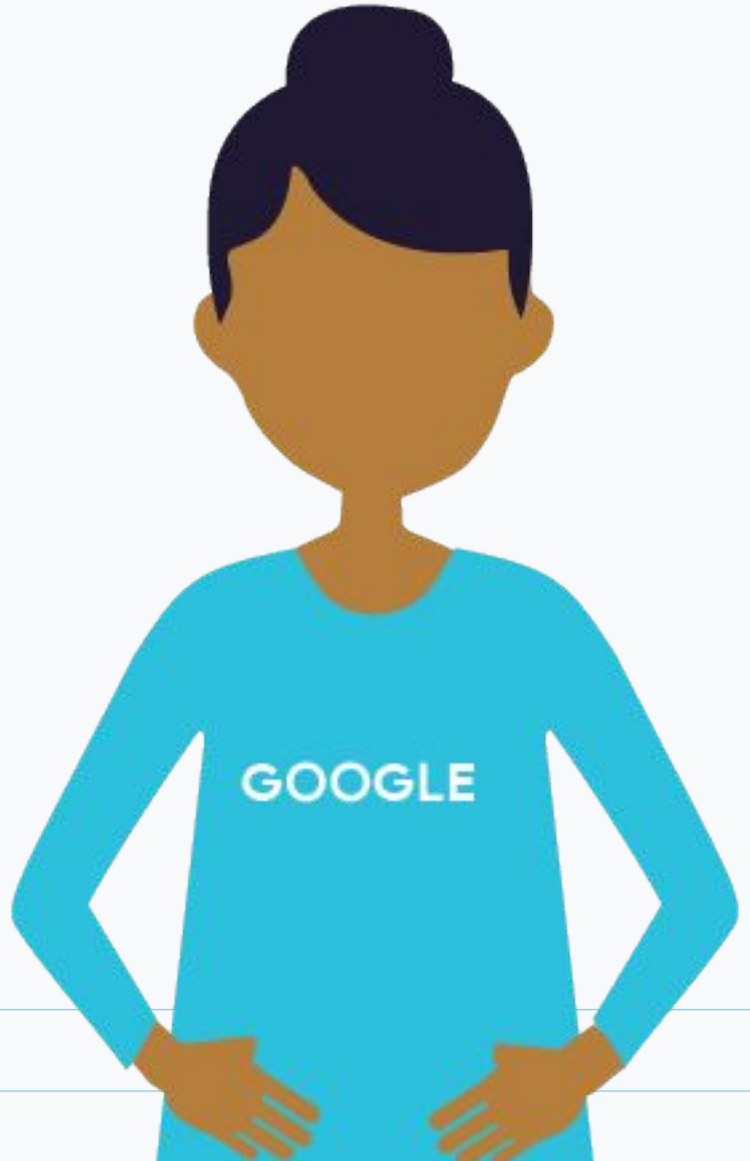


gpu:0

/job:ps/task:0/

cpu:0





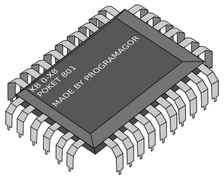
Assign different tasks to different machines

```
with tf.device("/job:ps/task:0/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
with tf.device("/job:worker/task:0/gpu:0"):
  output = tf.matmul(input, W) + b
  loss = f(output)
```

Client

/job:worker/task:0/

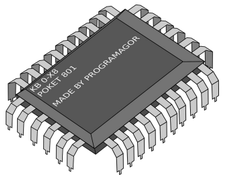
cpu:0



gpu:0

/job:ps/task:0/

cpu:0



Title Safe >

< Action Safe

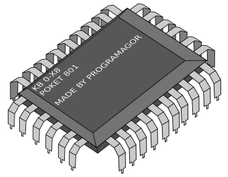
Assign different tasks to different machines

```
with tf.device("/job:ps/task:0/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
with tf.device("/job:worker/task:0/gpu:0"):
  output = tf.matmul(input, W) + b
  loss = f(output)
```

Client

/job:worker/task:0/

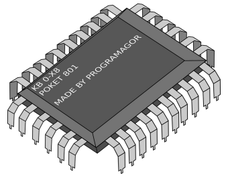
cpu:0

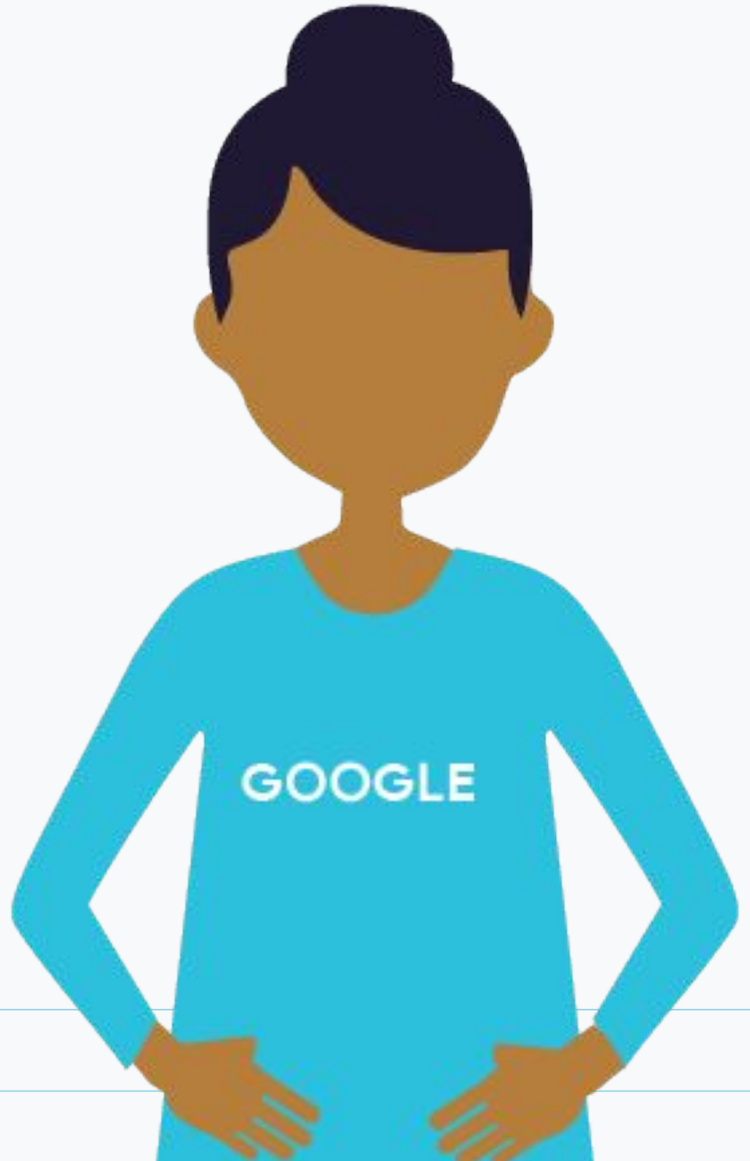


gpu:0

/job:ps/task:0/

cpu:0

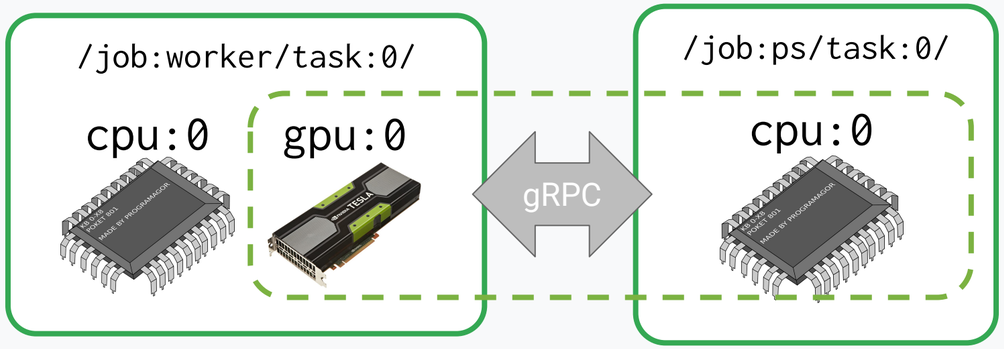




Now, the graph is split between two processes ...

```
with tf.device("/job:ps/task:0/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
with tf.device("/job:worker/task:0/gpu:0"):
  output = tf.matmul(input, W) + b
  loss = f(output)
```

Client



Title Safe >

< Action Safe

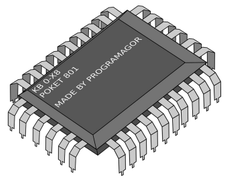
Now, the graph is split between two processes ...

```
with tf.device("/job:ps/task:0/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
with tf.device("/job:worker/task:0/gpu:0"):
  output = tf.matmul(input, W) + b
  loss = f(output)
```

Client

/job:worker/task:0/

cpu:0

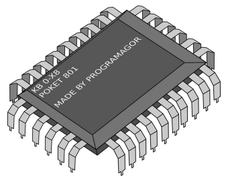


gpu:0

gRPC

/job:ps/task:0/

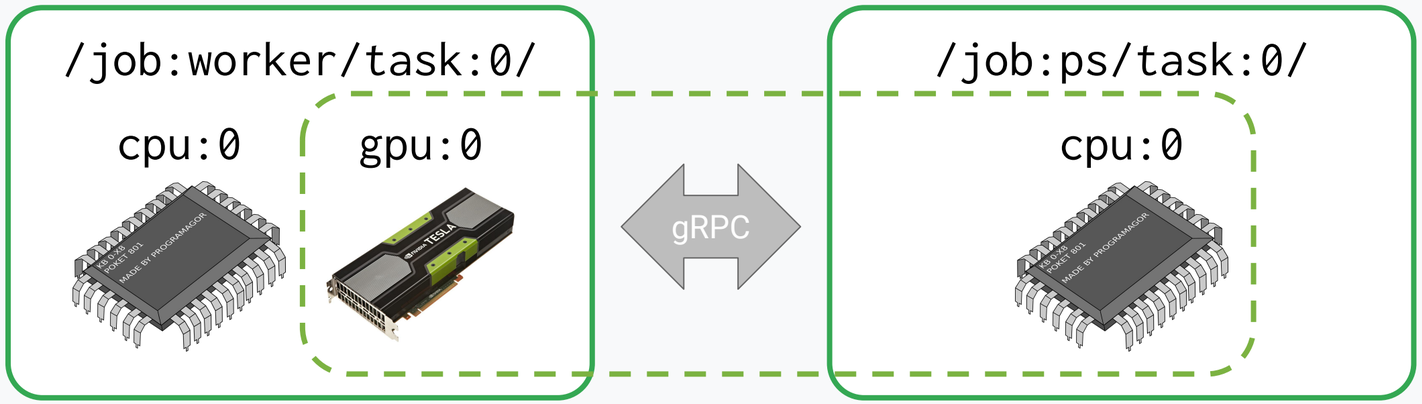
cpu:0



... we just get need to get the device placements right

```
with tf.device("/job:ps/task:0/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
with tf.device("/job:worker/task:0/gpu:0"):
  output = tf.matmul(input, W) + b
  loss = f(output)
```

Client



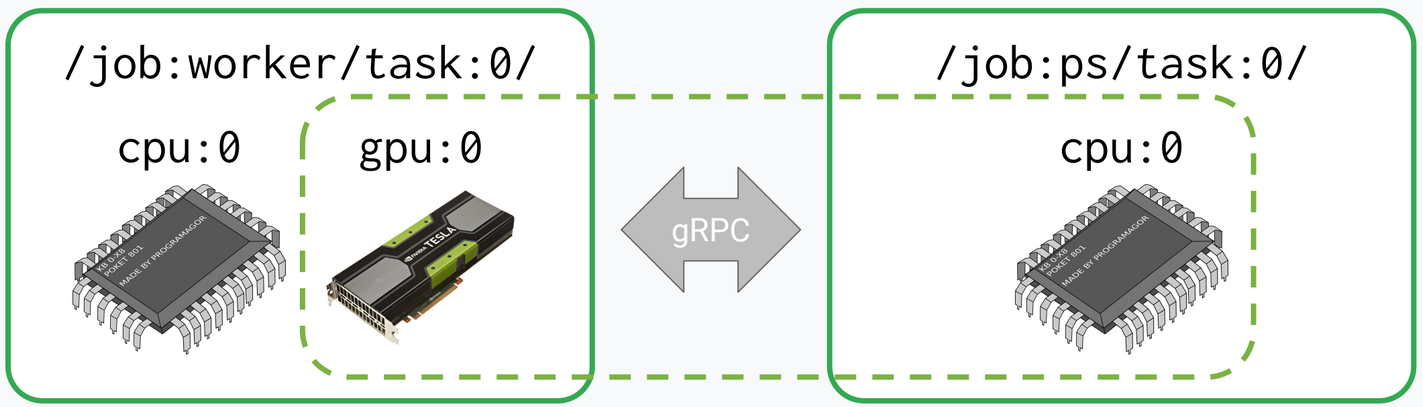
Title Safe >

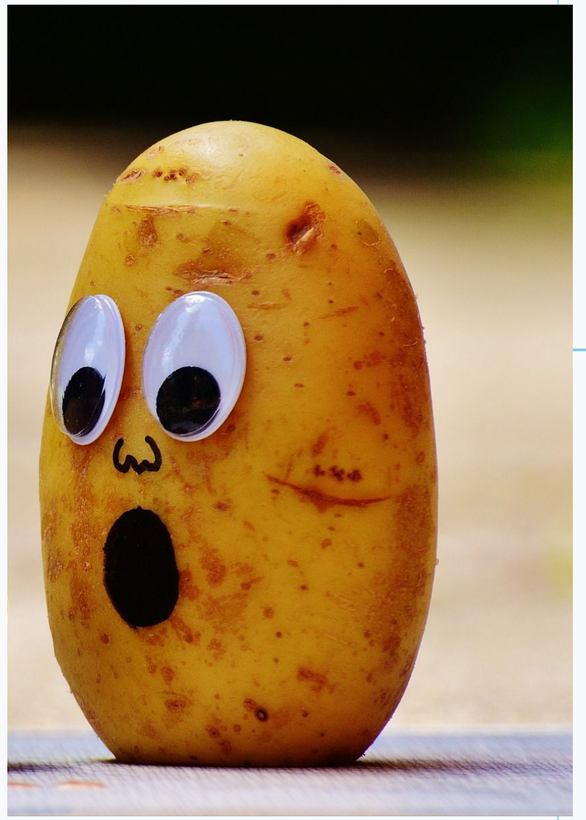
< Action Safe

... we just get need to get the device placements right

```
with tf.device("/job:ps/task:0/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
with tf.device("/job:worker/task:0/gpu:0"):
  output = tf.matmul(input, W) + b
  loss = f(output)
```

Client





Title Safe >

< Action Safe

Courses 7 - Production ML Systems

Module 4: Designing High-Performance ML Systems

Lesson Title: **Simplifying device placement [optional]**

Format: Screencast

Presenter: Laurence Moroney

Video Name:
T-PSML-O_4_I15_simplifying_device_placement_[optional]

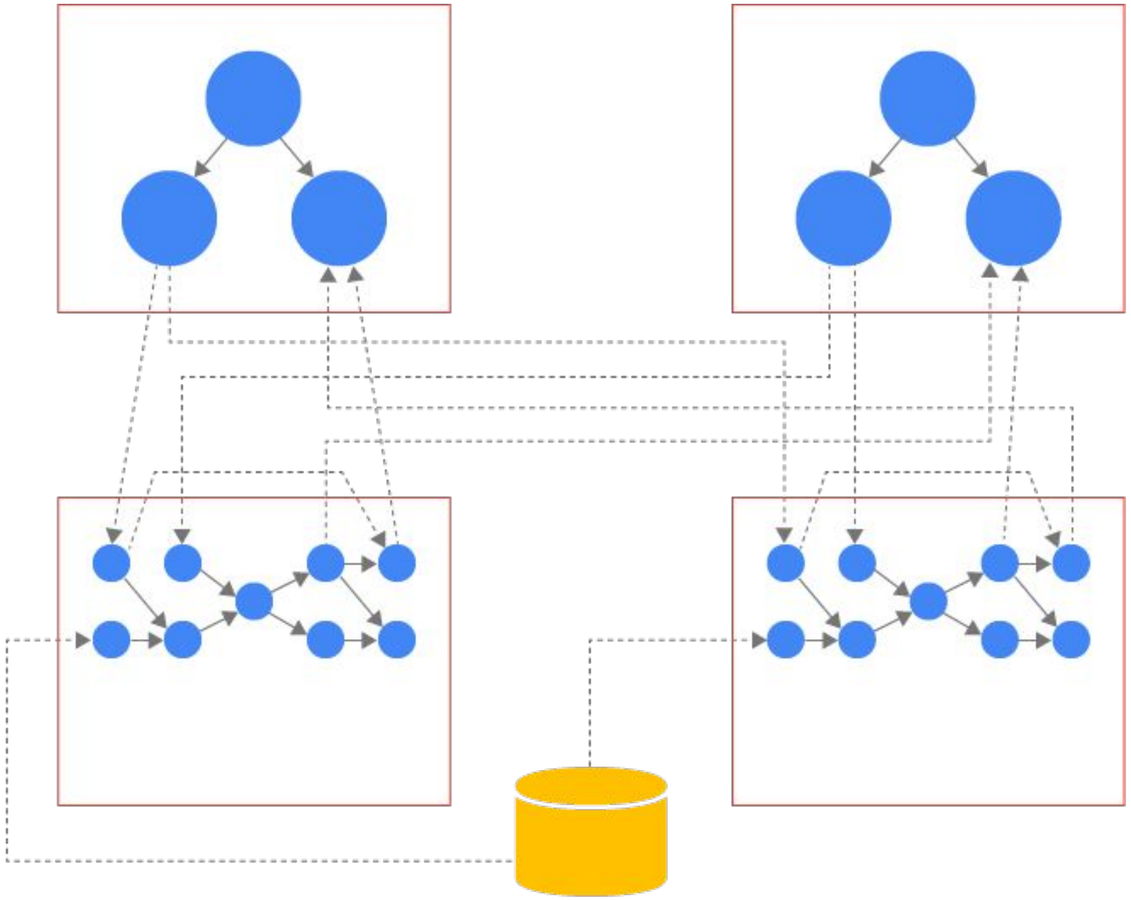
One way to simplify this is to think in terms of parameter servers and worker replicas

PS tasks

- Variables
- Update ops

Worker tasks

- Pre-processing
- Loss calculation
- Backpropagation



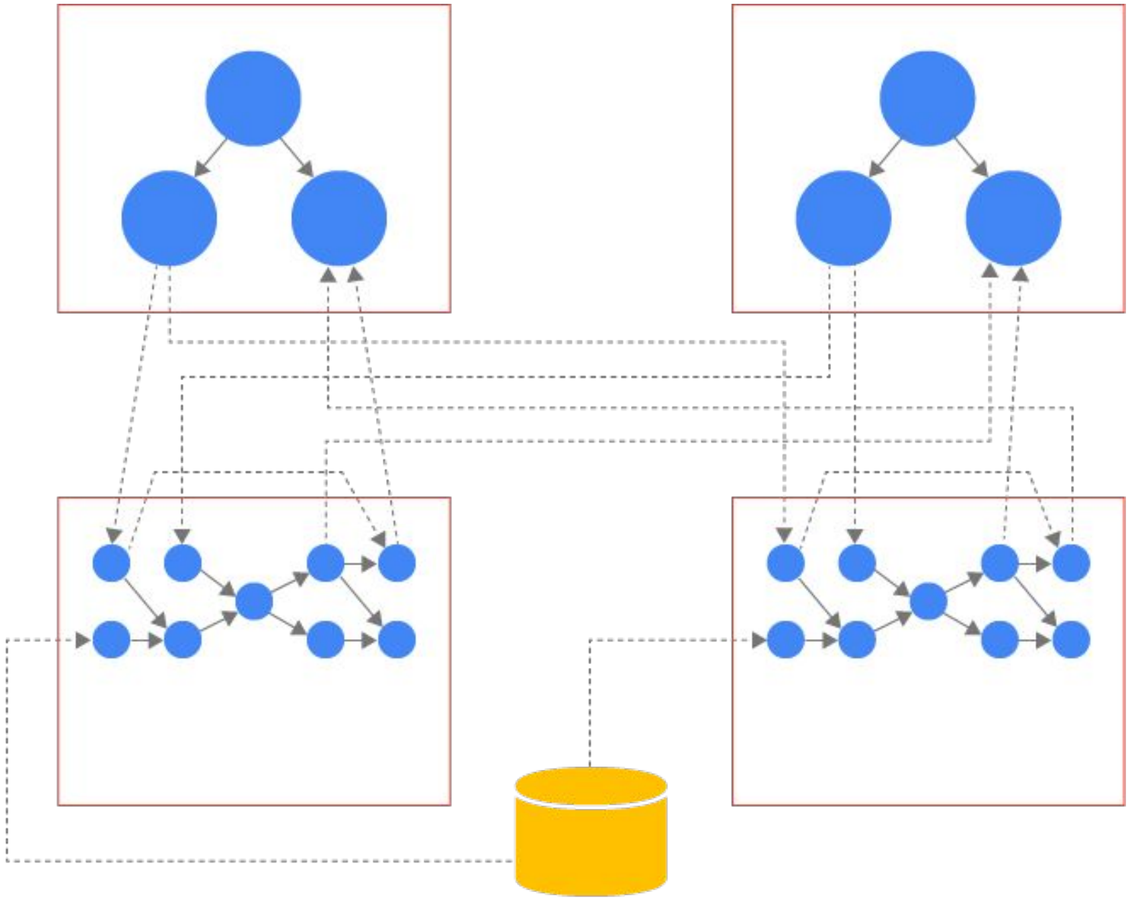
In TensorFlow, it's the same program for both

PS tasks

- Variables
- Update ops

Worker tasks

- Pre-processing
- Loss calculation
- Backpropagation



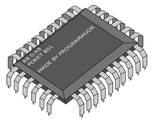
Use in-graph replication: if a single step can be done on a single machine

Each worker works on different subsets of the data

Client

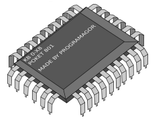
/job:worker/task:0/

cpu:0 gpu:0



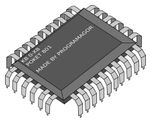

/job:ps/task:0/

cpu:0



/job:worker/task:1/

gpu:0 cpu:0

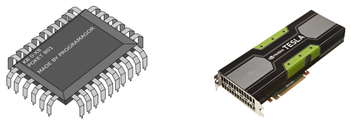
With in-graph replication, data is broken into equal-sized chunks and each worker works on a chunk

```
with tf.device("/job:ps/task:0/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
inputs = tf.split(0, num_workers, input)
outputs = []
for i in range(num_workers):
  with tf.device("/job:worker/task:%d/gpu:0" %
i):
    outputs.append(tf.matmul(input[i], W) + b)
loss = f(outputs)
```

Client

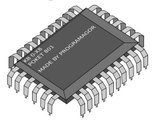
/job:worker/task:0/

cpu:0 gpu:0



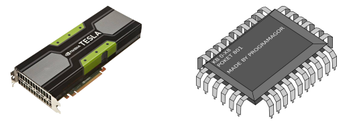
/job:ps/task:0/

cpu:0



/job:worker/task:1/

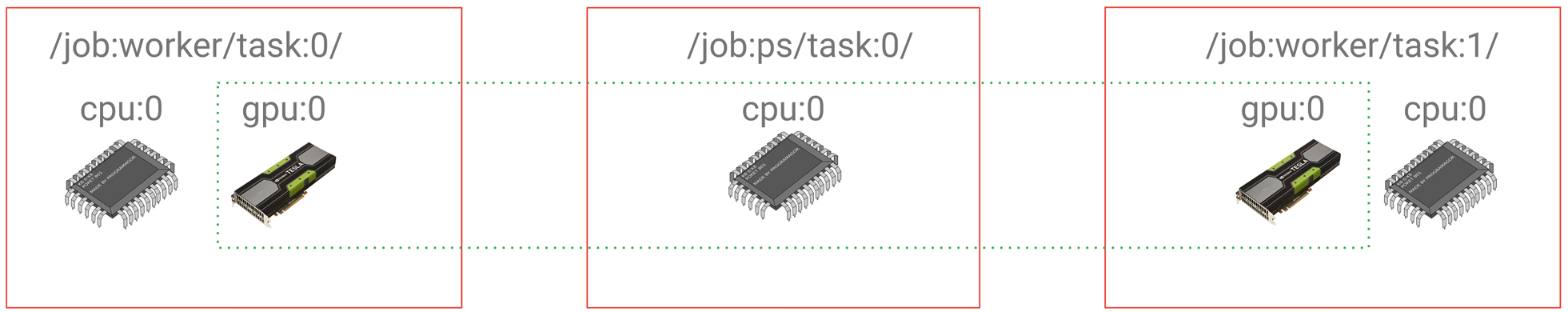
gpu:0 cpu:0



Replicas are run in parallel, and loss is averaged across workers

```
with tf.device("/job:ps/task:0/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
inputs = tf.split(0, num_workers, input)
outputs = []
for i in range(num_workers):
  with tf.device("/job:worker/task:%d/gpu:0" %
i):
    outputs.append(tf.matmul(input[i], W) + b)
loss = f(outputs)
```

Client



Courses 7 - Production ML Systems

Module 4: Designing High-Performance ML Systems

Lesson Title: **Between-graph replication [optional]**

Format: Screencast

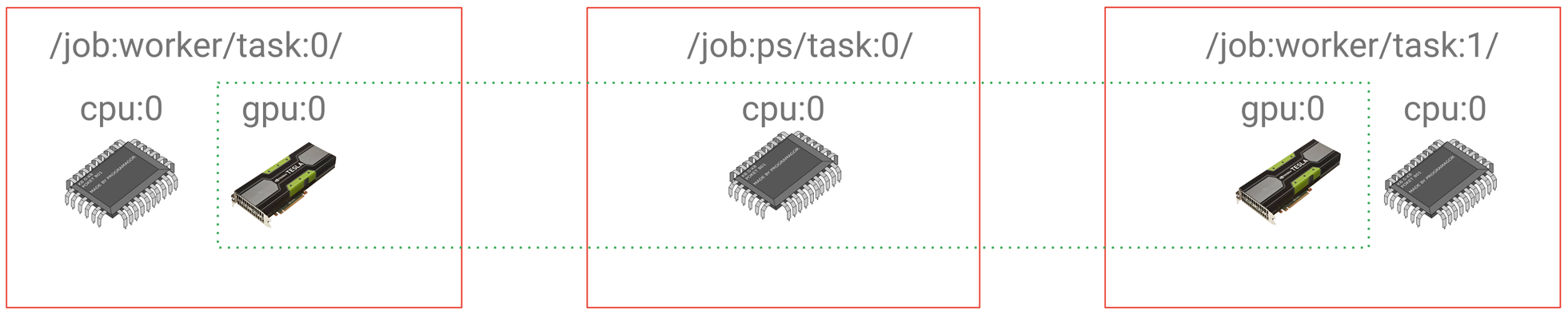
Presenter: Laurence Moroney

Video Name: T-PSML-O_4_l16_between-graph_replication_[optional]

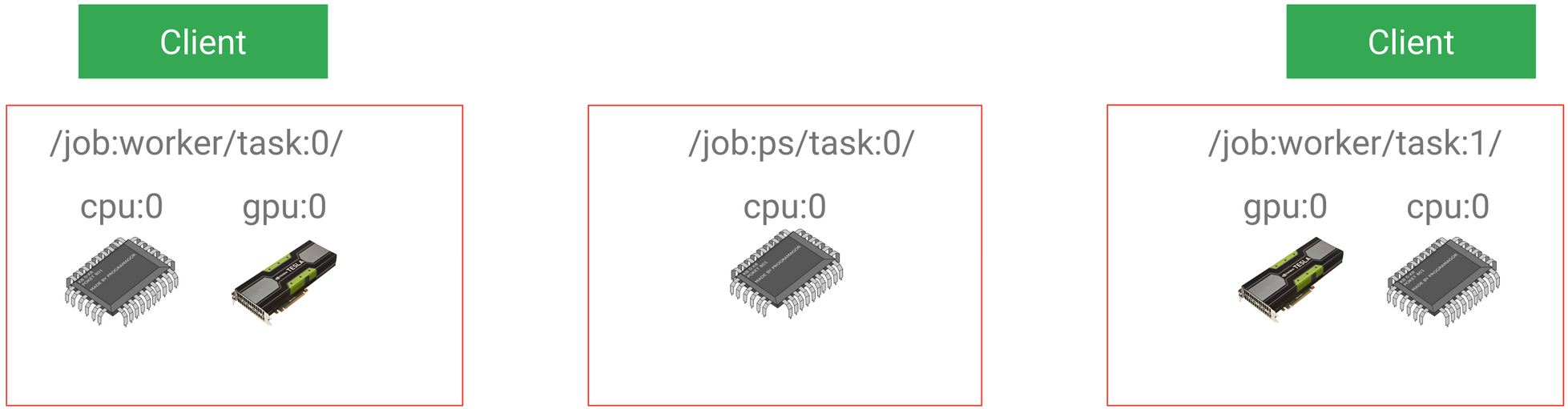
In-graph replication doesn't work for very large models

```
with tf.device("/job:ps/task:0/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
inputs = tf.split(0, num_workers, input)
outputs = []
for i in range(num_workers):
  with tf.device("/job:worker/task:%d/gpu:0" %
i):
    outputs.append(tf.matmul(input[i], W) + b)
loss = f(outputs)
```

Client



In between-graph replication, there are multiple client programs; this is the recommended approach in Cloud MLE



Both clients build the same graph

```
with tf.device("/job:ps/task:0/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
with tf.device("/job:worker/task:0/gpu:0"):
  output = tf.matmul(input, W) + b
  loss = f(output)
```

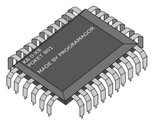
Client

```
with tf.device("/job:ps/task:0/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
with tf.device("/job:worker/task:1/gpu:0"):
  output = tf.matmul(input, W) + b
  loss = f(output)
```

Client

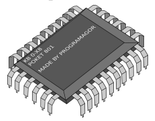
/job:worker/task:0/

cpu:0 gpu:0



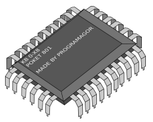

/job:ps/task:0/

cpu:0



/job:worker/task:1/

gpu:0 cpu:0

Local devices get a replica from “their” client

```
with tf.device("/job:ps/task:0/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
with tf.device("/job:worker/task:0/gpu:0"):
  output = tf.matmul(input, W) + b
  loss = f(output)
```

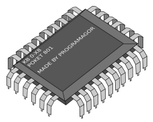
Client

```
with tf.device("/job:ps/task:0/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
with tf.device("/job:worker/task:1/gpu:0"):
  output = tf.matmul(input, W) + b
  loss = f(output)
```

Client

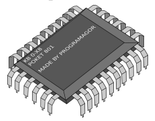
/job:worker/task:0/

cpu:0 gpu:0



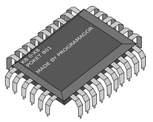

/job:ps/task:0/

cpu:0



/job:worker/task:1/

gpu:0 cpu:0

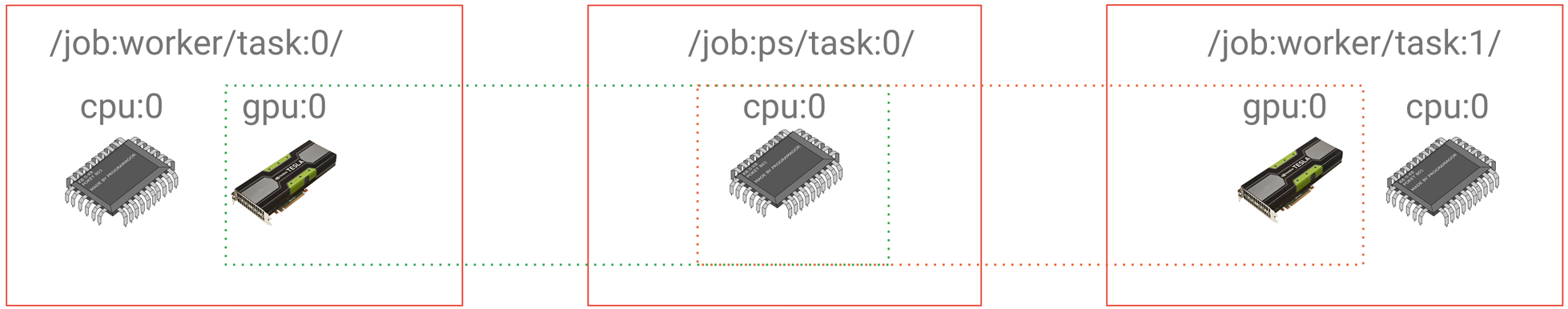
Machines without a client share variables, leading to shared storage

```
with tf.device("/job:ps/task:0/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
with tf.device("/job:worker/task:0/gpu:0"):
  output = tf.matmul(input, W) + b
  loss = f(output)
```

Client

```
with tf.device("/job:ps/task:0/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
with tf.device("/job:worker/task:1/gpu:0"):
  output = tf.matmul(input, W) + b
  loss = f(output)
```

Client



Here, weights and biases are shared, but loss is not

```
with tf.device("/job:ps/task:0/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
with tf.device("/job:worker/task:0/gpu:0"):
  output = tf.matmul(input, W) + b
  loss = f(output)
```

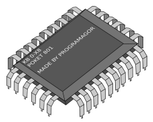
```
with tf.device("/job:ps/task:0/cpu:0"):
  W = tf.Variable(...)
  b = tf.Variable(...)
with tf.device("/job:worker/task:1/gpu:0"):
  output = tf.matmul(input, W) + b
  loss = f(output)
```

Client

Client

/job:worker/task:0/

cpu:0



gpu:0

/job:ps/task:0/

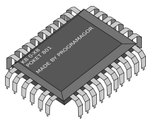
w

b

/job:worker/task:1/

gpu:0

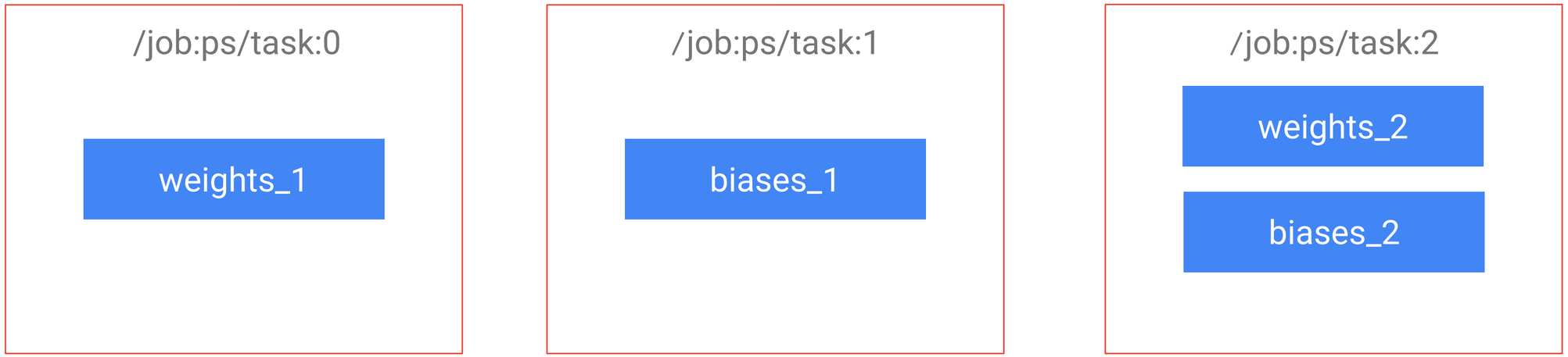
cpu:0



Defining variable placement with strings is brittle

```
with tf.device("/job:ps/task:0"):
  weights_1 = tf.get_variable("weights_1", [784, 100])
with tf.device("/job:ps/task:1"):
  biases_1 = tf.get_variable("biases_1", [100])
with tf.device("/job:ps/task:2"):
  weights_2 = tf.get_variable("weights_2", [100, 10])
  biases_2 = tf.get_variable("biases_2", [10])
```

Hardcoding strings in your program is a bad idea



Courses 7 - Production ML Systems

Module 4: Designing High-Performance ML Systems

Lesson Title: **Device Placement Strategies [optional]**

Format: Screencast

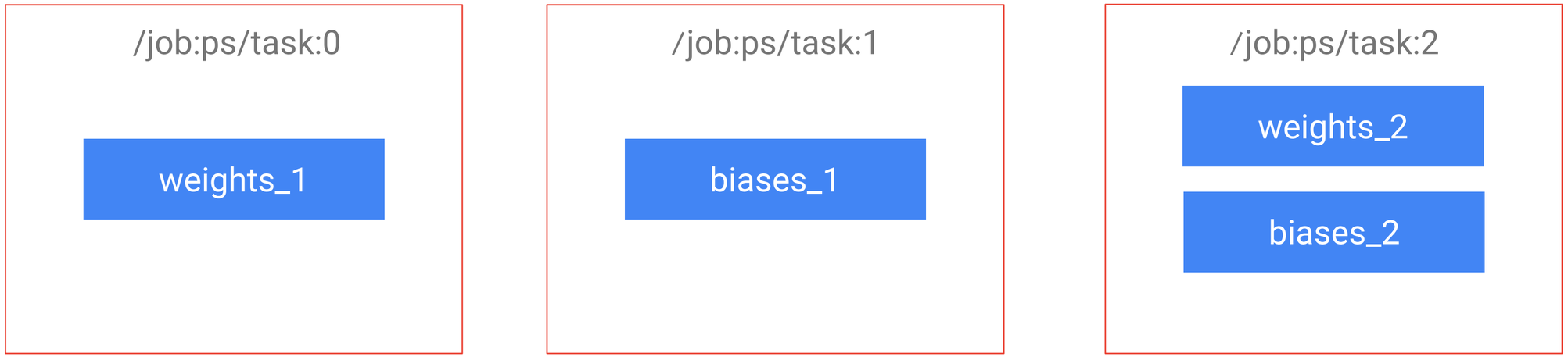
Presenter: Laurence Moroney

Video Name: T-PSML-O_4_I17_device_placement_strategies_[optional]

Defining variable placement with strings is brittle

```
with tf.device("/job:ps/task:0"):
  weights_1 = tf.get_variable("weights_1", [784, 100])
with tf.device("/job:ps/task:1"):
  biases_1 = tf.get_variable("biases_1", [100])
with tf.device("/job:ps/task:2"):
  weights_2 = tf.get_variable("weights_2", [100, 10])
  biases_2 = tf.get_variable("biases_2", [10])
```

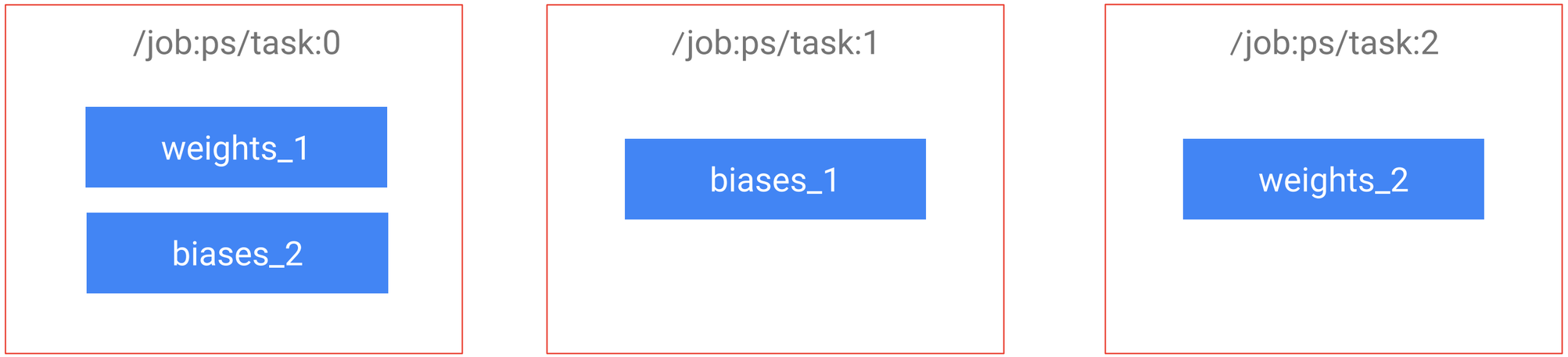
Hardcoding strings in your program is a bad idea



Use device placement functions instead

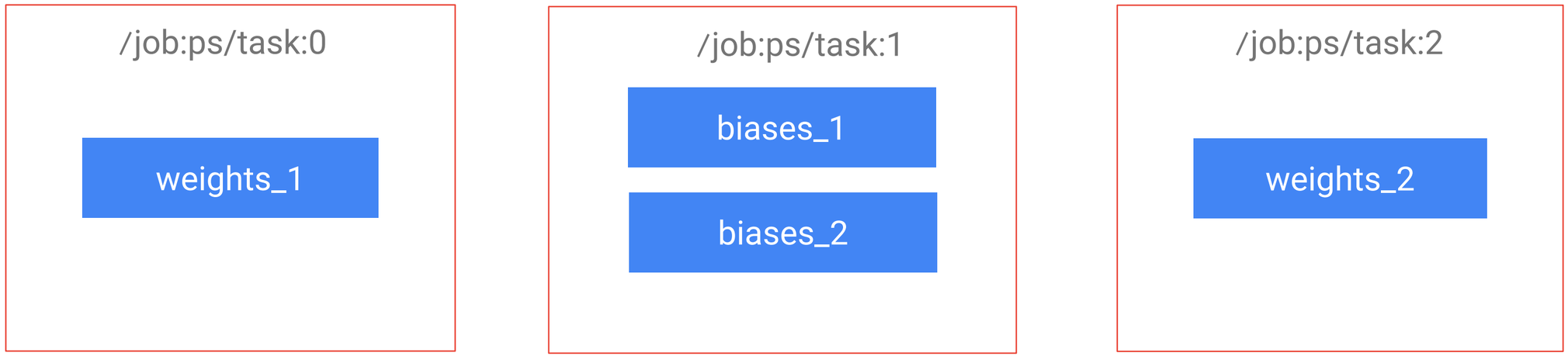
```
with
tf.device(tf.train.replica_device_setter(ps_tasks=3)):

  weights_1 = tf.get_variable("weights_1", [784, 100])
  biases_1 = tf.get_variable("biases_1", [100])
  weights_2 = tf.get_variable("weights_2", [100, 10])
  biases_2 = tf.get_variable("biases_2", [10])
```

Variables are assigned in round-robin fashion, so this is between-graph replication



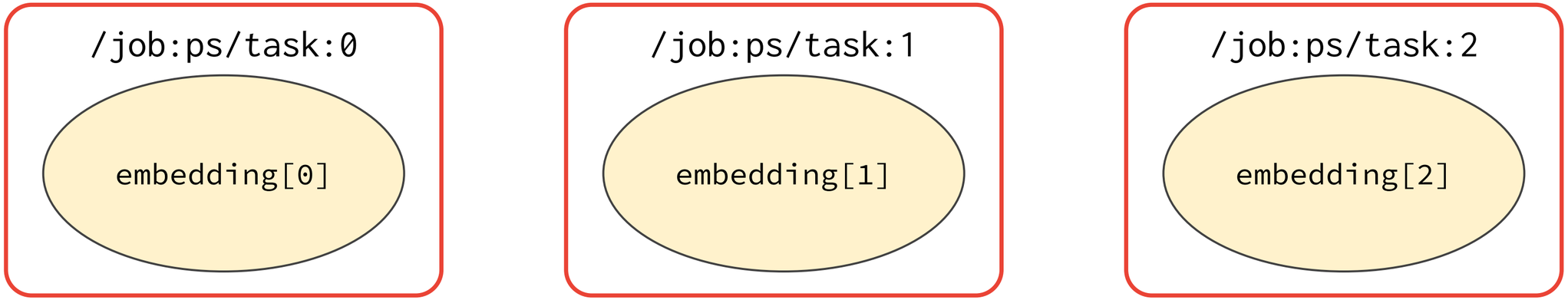
A load balancing strategy can improve performance

```
greedy = tf.contrib.training.GreedyLoadBalancingStrategy(...)
with tf.device(tf.train.replica_device_setter(
    ps_tasks=3, ps_strategy=greedy)):
  weights_1 = tf.get_variable("weights_1", [784, 100])
  biases_1 = tf.get_variable("biases_1", [100])
  weights_2 = tf.get_variable("weights_2", [100, 10])
  biases_2 = tf.get_variable("biases_2", [10])
```

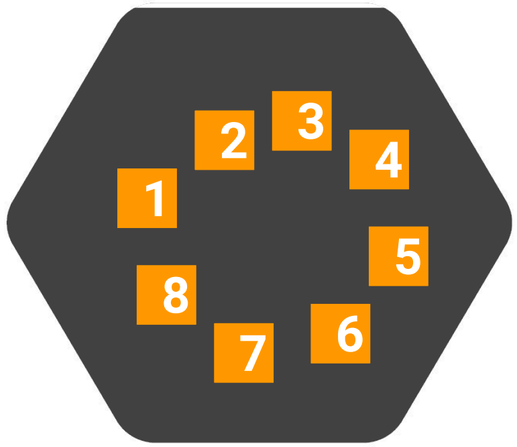


You can partition very large variables as needed

```
greedy = tf.contrib.training.GreedyLoadBalancingStrategy(...)
with tf.device(tf.train.replica_device_setter(
    ps_tasks=3, ps_strategy=greedy)):

  embedding = tf.get_variable(
      "embedding", [1000000000, 20],
      partitioner=tf.fixed_size_partitioner(3))
```

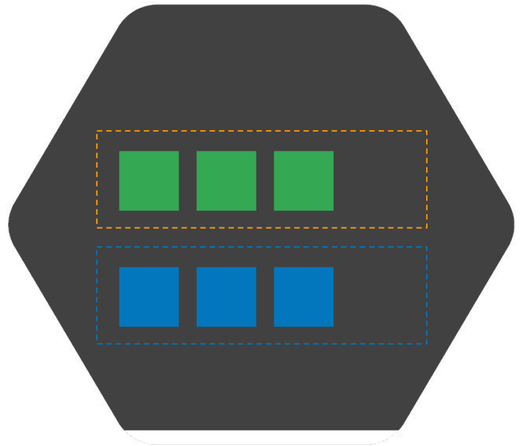


`replica_device_setter` provides a simple heuristic for between-graph partitioning



Round-robin variable placement by default

Add load balancing to improve weight placement across machines



Partition if your variables are too large to fit on a single machine

Courses 7 - Production ML Systems

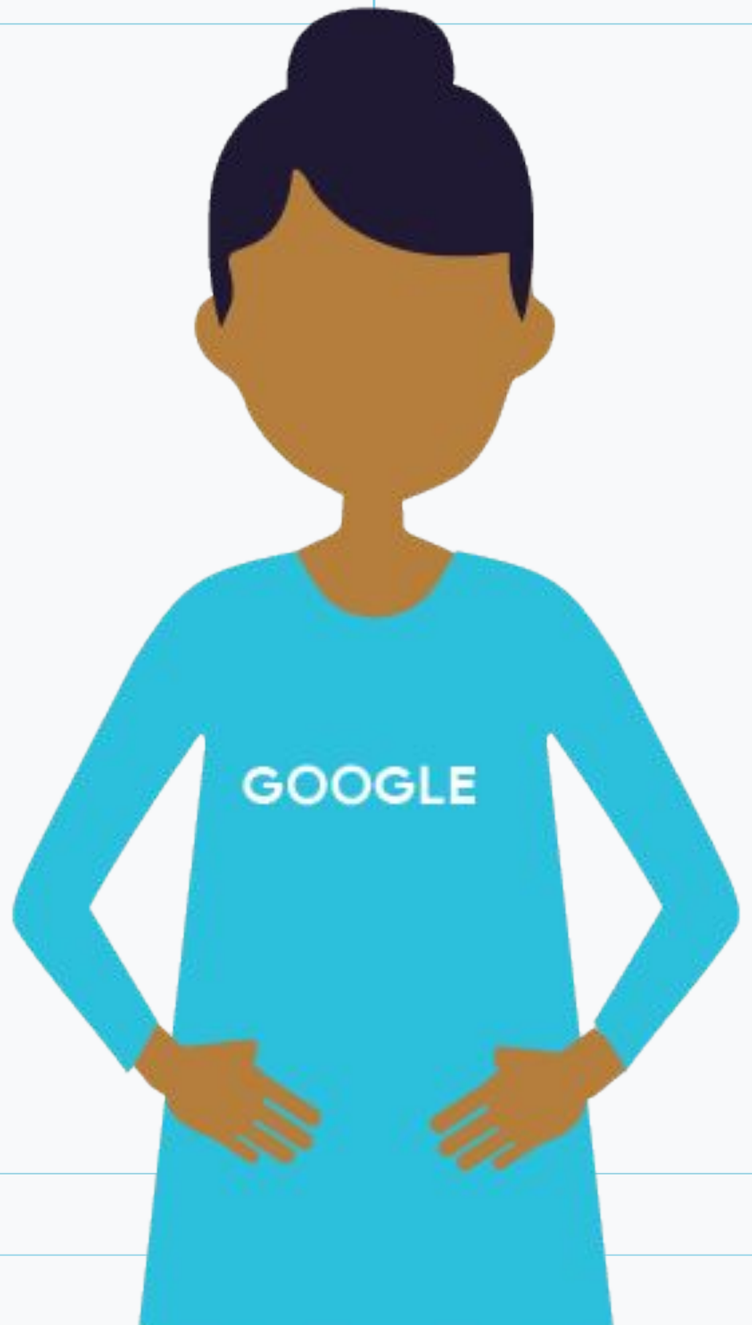
Module 4: Designing High-Performance ML Systems

Lesson Title: **Sessions and Servers [optional]**

Format: Presenter

Presenter: Laurence Moroney

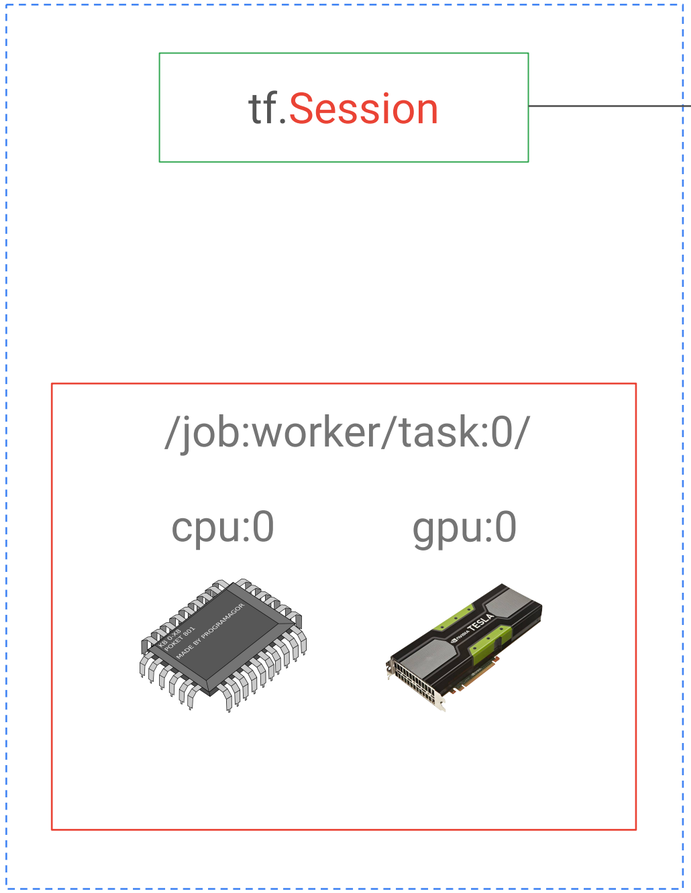
Video Name: T-PSML-O_4_I18_sessions_and_servers_[optional]



Title Safe >

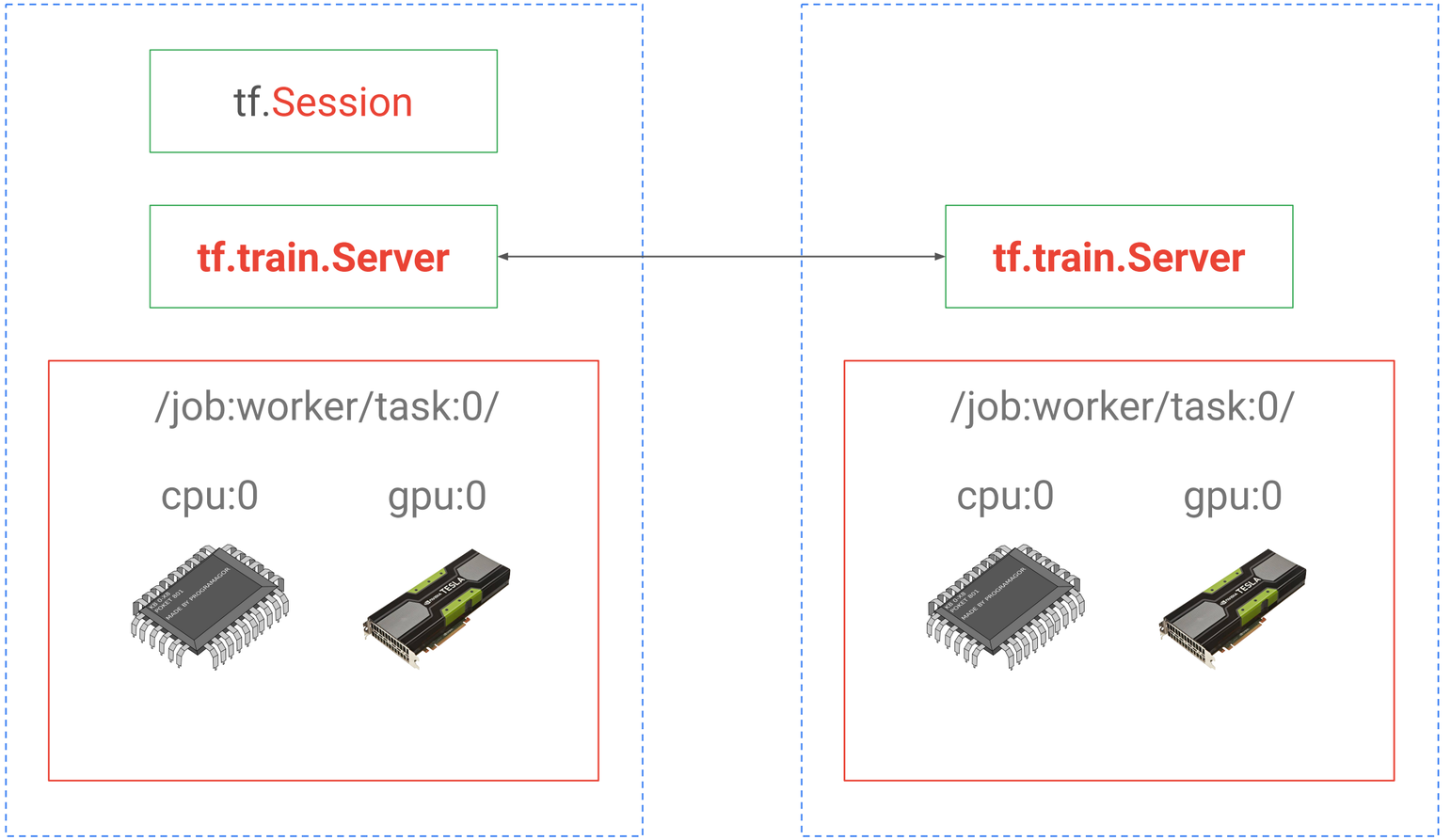
< Action Safe

Distributed TensorFlow runs on a cluster of servers, but `tf.Session` knows only about local devices




```
# Single-process code.
with tf.Session() as sess:
  sess.run(init_op)
  for _ in
range(NUM_STEPS):
    sess.run(train_op)
```

Create a TensorFlow server on each machine, and configure them to communicate over network



The setup is defined by a cluster spec that is identical for each machine in the cluster

```
                                    1. ClusterSpec: set of jobs (worker, ps)

# Distributed code for a worker task. 2. For each job, specify a list of tasks
cluster = tf.train.ClusterSpec({"worker": ["192.168.0.1:2222", ...],
                                "ps": ["192.168.1.1:2222", ...]})

                                       3. For each task, specify machine :
                                       network port to listen on

server = tf.train.Server(cluster, job_name="worker", task_index=0)

with tf.Session(server.target) as sess:
  # ...
```

tf.train.Server implements a task in cluster

```
# Distributed code for a worker task.
cluster = tf.train.ClusterSpec({"worker": ["192.168.0.1:2222", ...],
                                "ps": ["192.168.1.1:2222", ...]})

server = tf.train.Server(cluster, job_name="worker", task_index=0)

with tf.Session(server.target) as sess:
  # ...
```

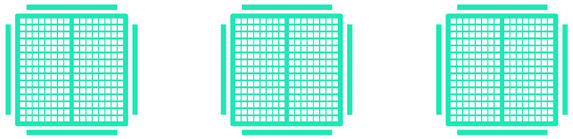
Which job, which task

Can run code on any device in cluster

A PS task simply needs to respond to workers

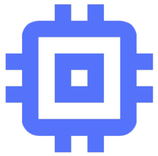
```
# Distributed code for a PS task.
cluster = tf.train.ClusterSpec({"worker": ["192.168.0.1:2222", ...],
                                "ps": ["192.168.1.1:2222", ...]})

server = tf.train.Server(cluster, job_name="ps", task_index=0)

# Wait for incoming connections forever.
server.join()
```

Recap: Create a cluster spec for two types of jobs



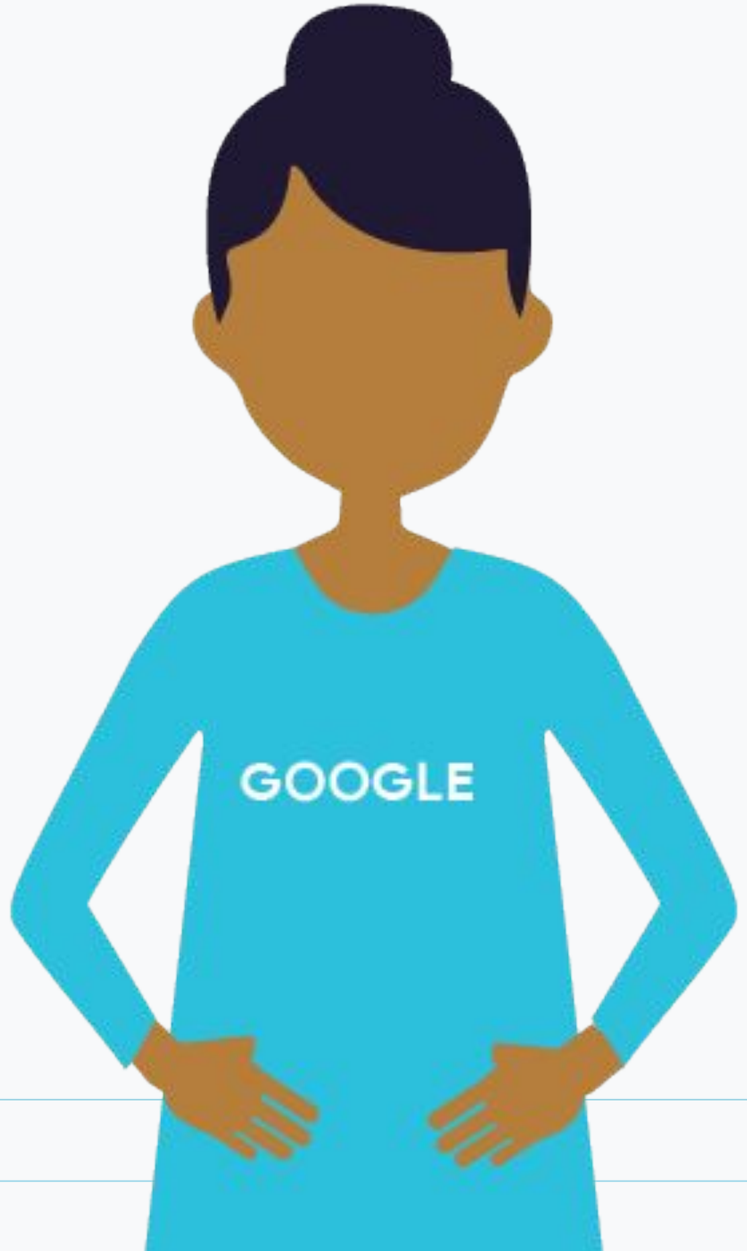
Worker jobs

- Each worker has a `tf.train.Server`.
- Specify the server's own address as the Session target.
- Can run code on any device in the cluster.



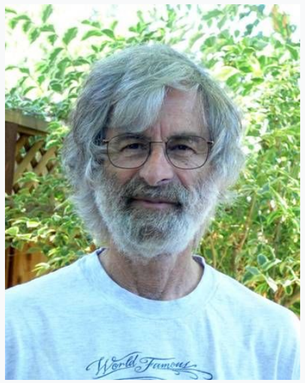
Parameter Server (PS) jobs

- Simply call `server.join()`



*"A **distributed system** is a system where I can't get my work done because a computer has failed that I've never even heard of."*

Leslie Lamport



Source
https://upload.wikimedia.org/wikipedia/commons/5/50/Leslie_Lamport.jpg

Title Safe >

< Action Safe

Courses 7 - Production ML Systems

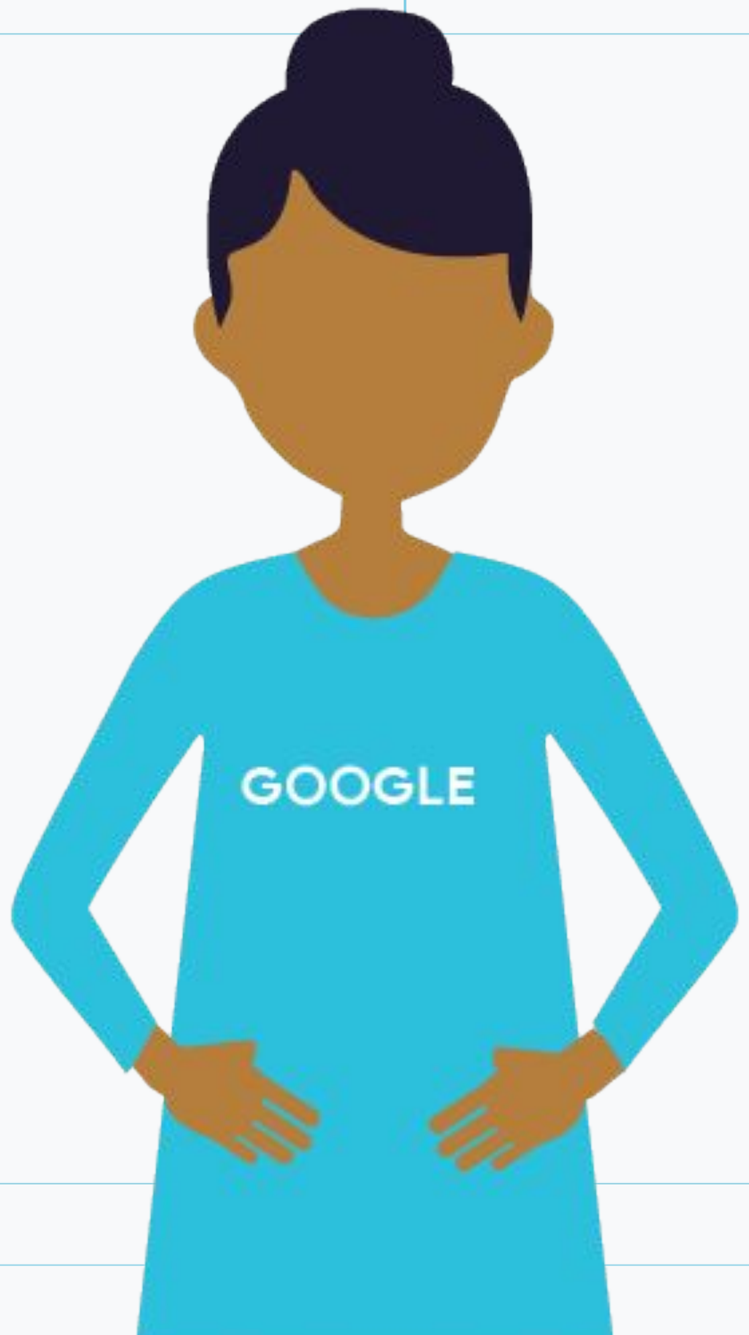
Module 4: Designing High-Performance ML Systems

Lesson Title: **Fault Tolerance [optional]**

Format: Presenter

Presenter: Laurence Moroney

Video Name: T-PSML-O_4_I19_fault_tolerance_[optional]



Title Safe >

< Action Safe

For fault tolerance, save sharded checkpoints to Google Cloud Storage

```
with tf.device(tf.train.replica_device_setter(ps_tasks=3)):
  weights_1 = tf.get_variable("weights_1", [784, 100])
  biases_1 = tf.get_variable("biases_1", [100])
  # ...

saver = tf.train.Saver(sharded=True)

with tf.Session(server.target) as sess:
  while True:
    # ...
    if step % 1000 == 0:
      saver.save(sess, "gs://mybucket/chk_{}".format(step))
```

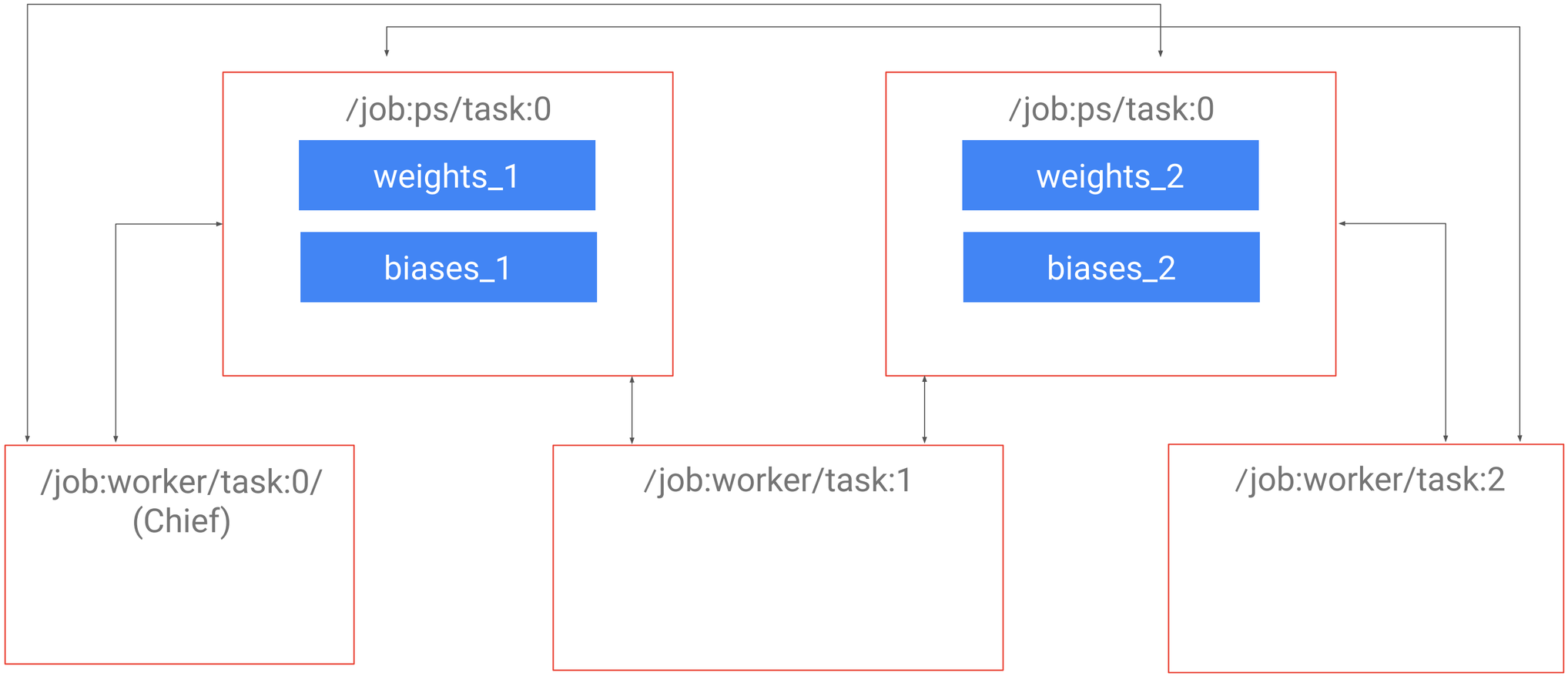
Each PS task writes "its" variables; together the shards form a checkpoint

Write to Cloud Storage

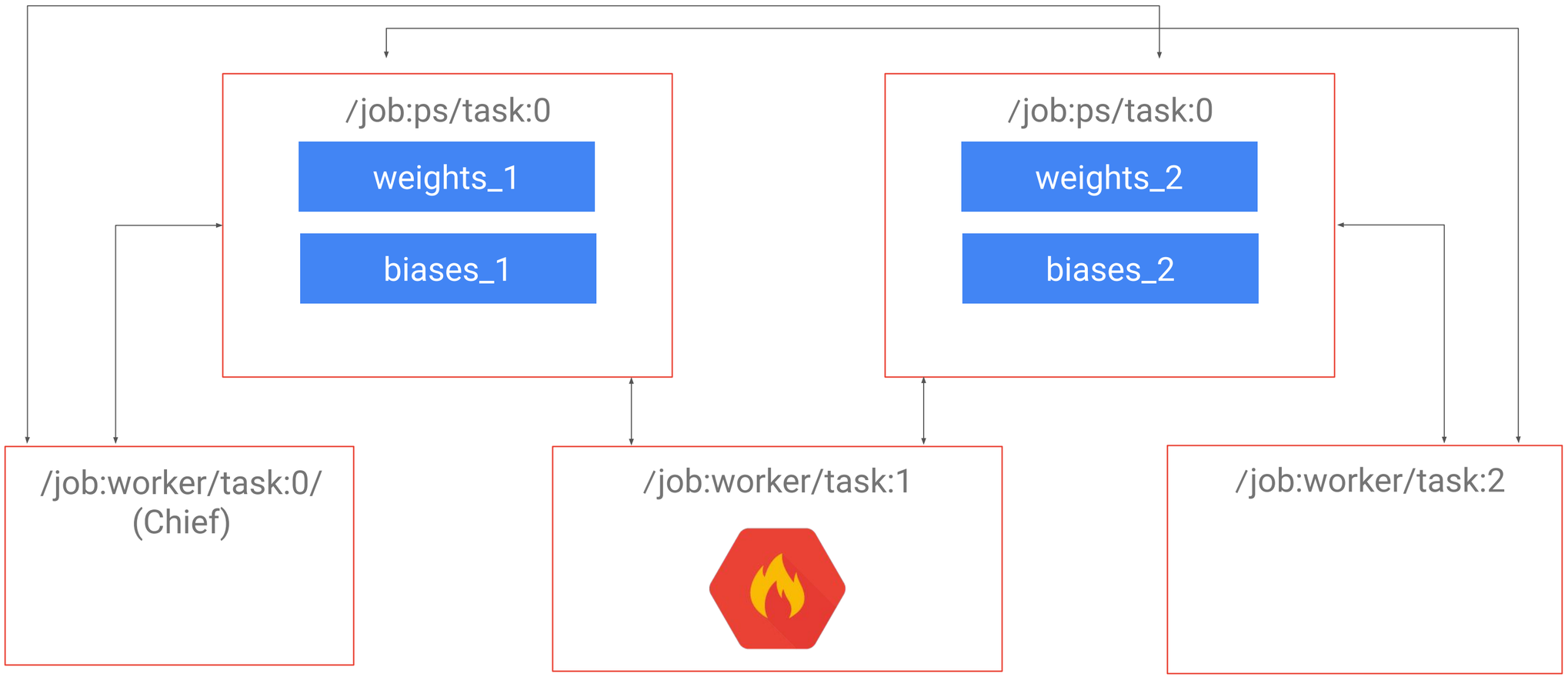
For between-graph replication, make worker 0 the one to write checkpoints

```
with tf.device(tf.train.replica_device_setter(ps_tasks=3)):
  weights_1 = tf.get_variable("weights_1", [784, 100])
  biases_1 = tf.get_variable("biases_1", [100])
  # ...

saver = tf.train.Saver(sharded=True)
is_chief = FLAGS.task_index == 0
with tf.Session(server.target) as sess:
  while True:
    # ...
    if is_chief and step % 1000 == 0:
      saver.save(sess, "gs://mybucket/chk_{}".format(step))
```

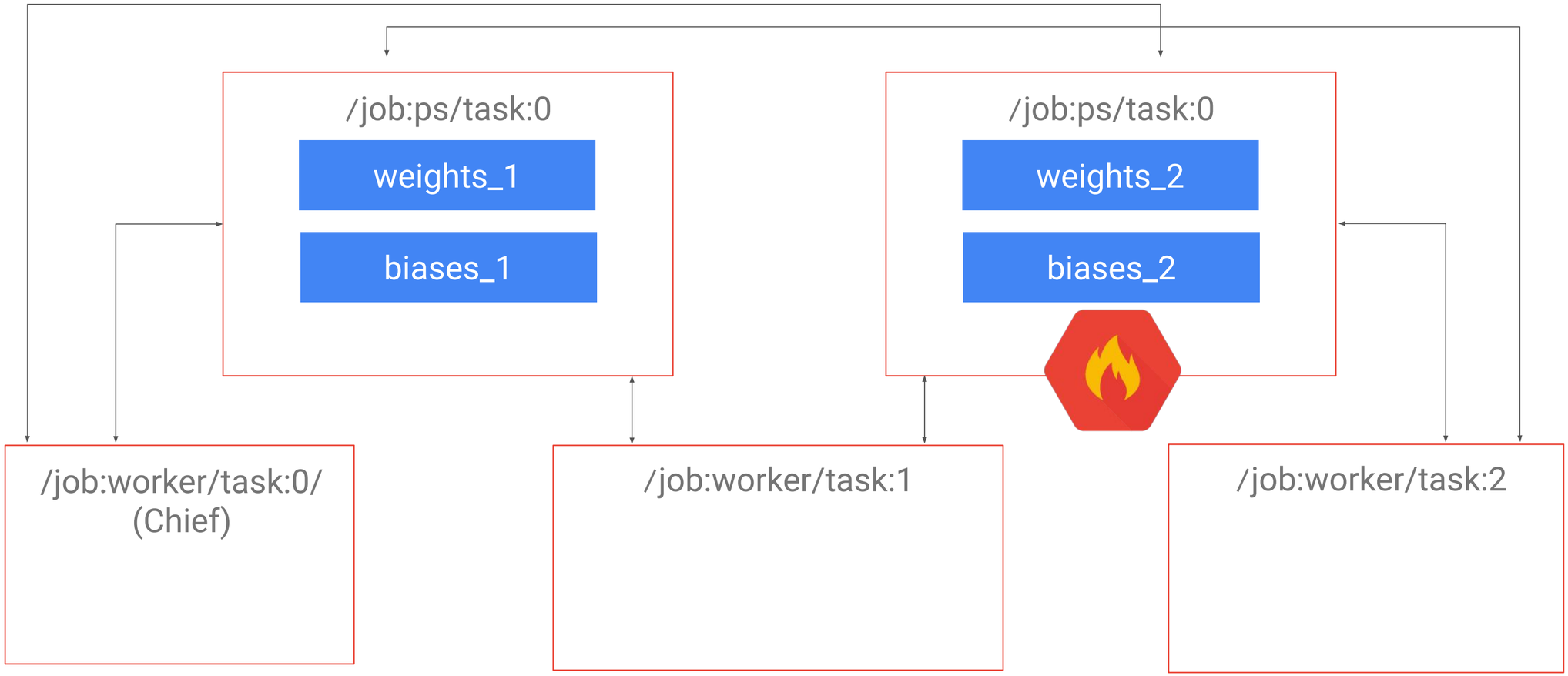
When a fault occurs,
the response is dependent on the failed task



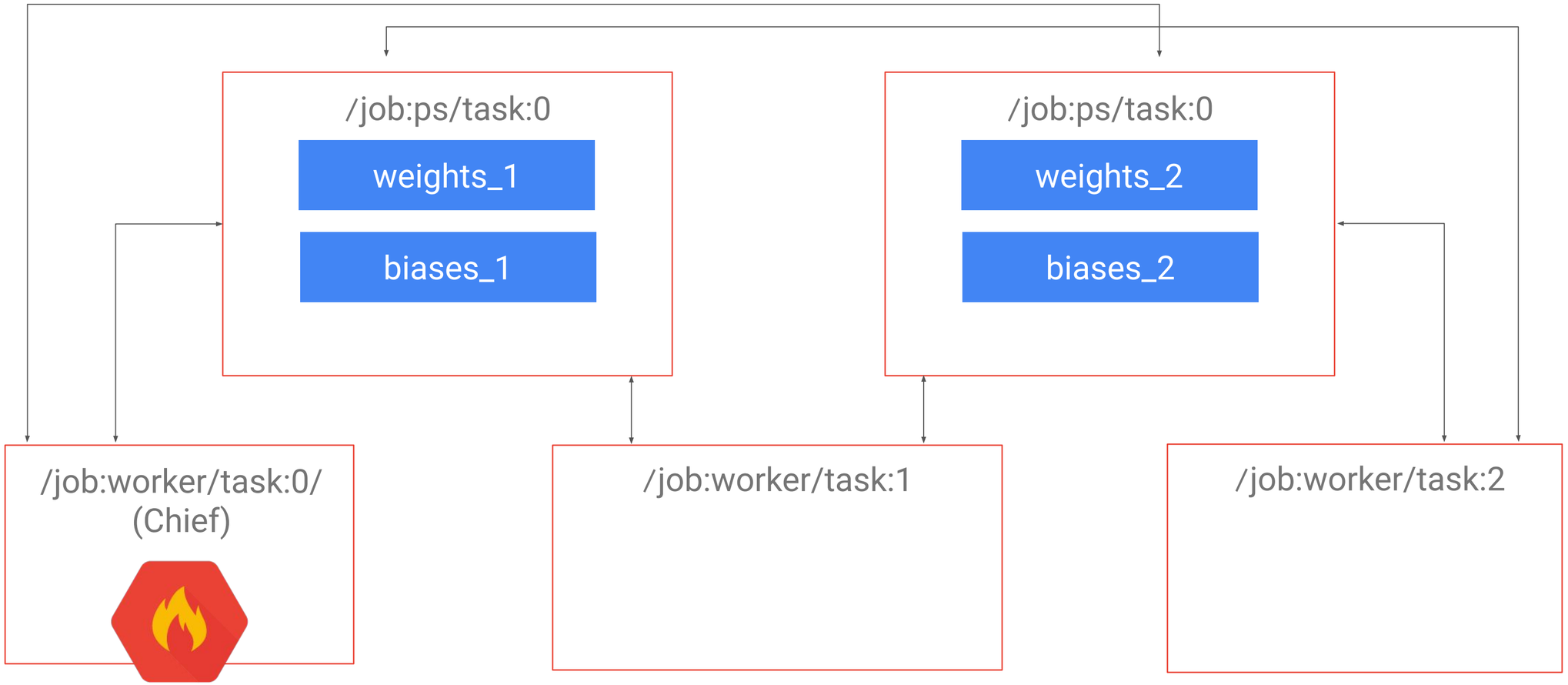
When a worker fails, it will recover and carry on



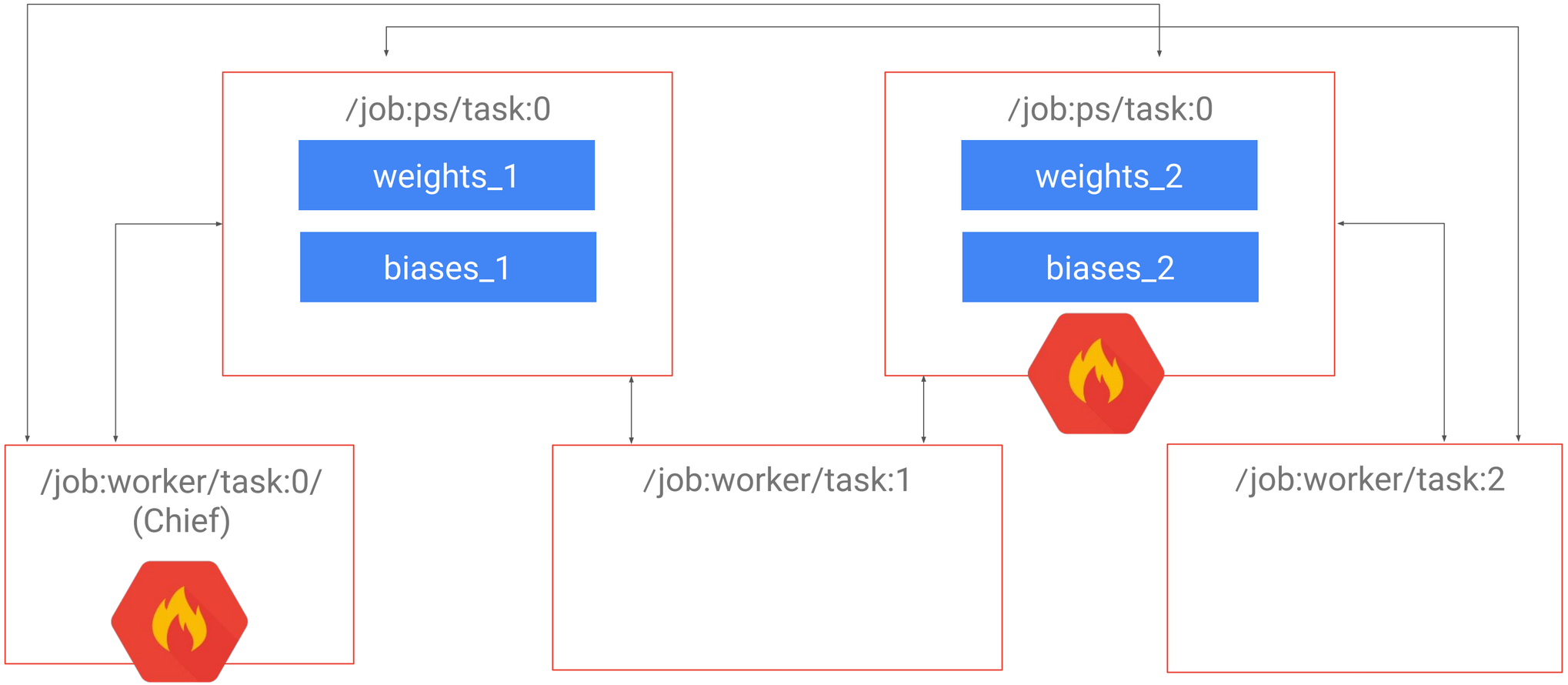
When a PS task fails, the chief interrupts training and restores PS tasks from the last checkpoint



When a chief fails, it doesn't know whether a PS task has failed



So, a chief interrupts training and restores from a checkpoint



With local training and `tf.Session()`, you have to manage initialization or restoring from a checkpoint

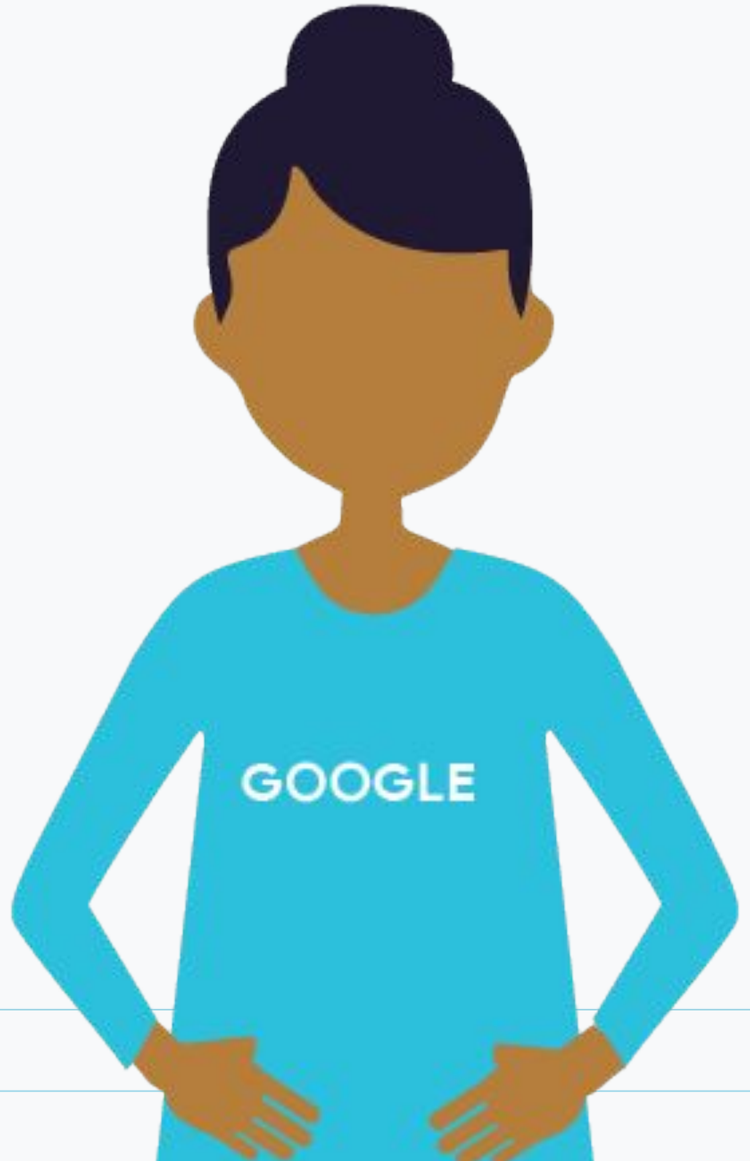
```
# Single-process code.
with tf.Session() as sess:
  sess.run(init_op)  # Or saver.restore(sess, ...)
  for _ in range(NUM_STEPS):
    sess.run(train_op)
```

MonitoredTrainingSession automates recovery process

Automatically initializes and/or restores variables

```
# Distributed code.
server = tf.train.Server(...)
is_chief = FLAGS.task_index == 0
with tf.train.MonitoredTrainingSession(server.target, is_chief) as sess:
  while not sess.should_stop():
    sess.run(train_op)
```

Recovers from PS failures, and can run additional code in hooks



Title Safe >

< Action Safe