Google Cloud

# Estimator API
# Introduction to TensorFlow

Martin Gorner

# Learn how to...

# Learn how to...

Create production-ready machine learning models the easy way

# Learn how to...

Create production-ready machine learning models the easy way

Train on large datasets that do not fit in memory

# Learn how to...

Create production-ready machine learning models the easy way

Train on large datasets that do not fit in memory

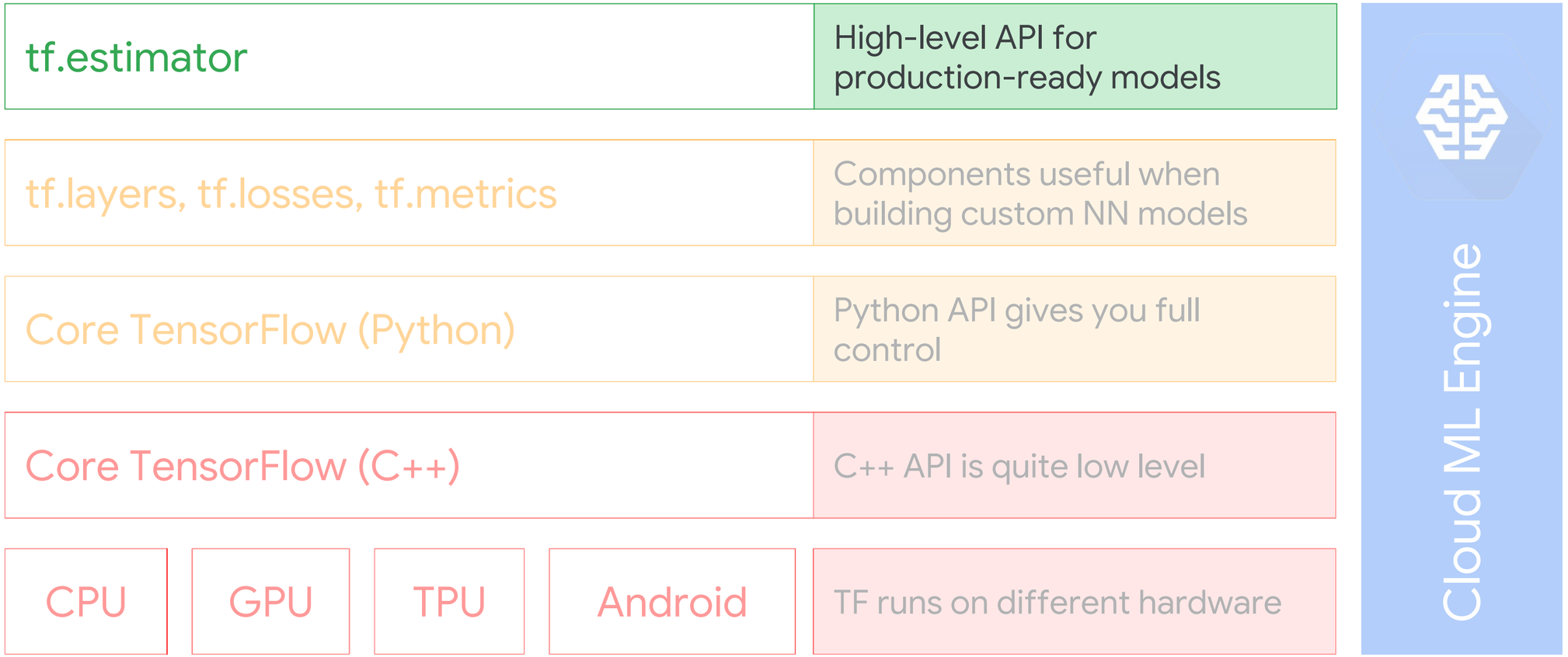
Monitor your training metrics in Tensorboard

Google Cloud

# Estimator API

Martin Gorner

# Estimators wrap up a large amount of boilerplate code, on top of the model itself



# From small to big to prod with the Estimator API

# From small to big to prod with the Estimator API

Quick model

# From small to big to prod with the Estimator API

Quick model

Checkpointing

# From small to big to prod with the Estimator API

Quick model

Checkpointing

Out-of-memory datasets

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- Quick model
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- Train / eval / monitor

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# From small to big to prod with the Estimator API

- Quick model
- Checkpointing
- Out-of-memory datasets
- Train / eval / monitor
- Distributed training
- Hyper-parameter tuning on ML-Engine
- Production: serving predictions from a trained model

Pre-made estimators that can all be used in the same way

**tf.estimator.Estimator.**

Pre-made estimators that can all be used in the same way

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# Pre-made estimators that can all be used in the same way

**tf.estimator.Estimator.**

Pre-made regressors

```
LinearRegressor
DNNRegressor
DNNLinearCombinedRegressor
...
```

Pre-made classifiers

```
LinearClassifier
DNNClassifier
DNNLinearCombinedClassifier
```

your custom Estimator

```
...
```

# Pre-made estimators that can all be used in the same way

**tf.estimator.Estimator.**

Pre-made regressors

- `LinearRegressor`
- `DNNRegressor`
- `DNNLinearCombinedRegressor`
- `...`

Pre-made classifiers

- `LinearClassifier`
- `DNNClassifier`
- `DNNLinearCombinedClassifier`

your custom Estimator

- `...`

# Predict property value from historical data

# Predict property value from historical data

| “Features” | ??? |
| --- | --- |
| | ??? |

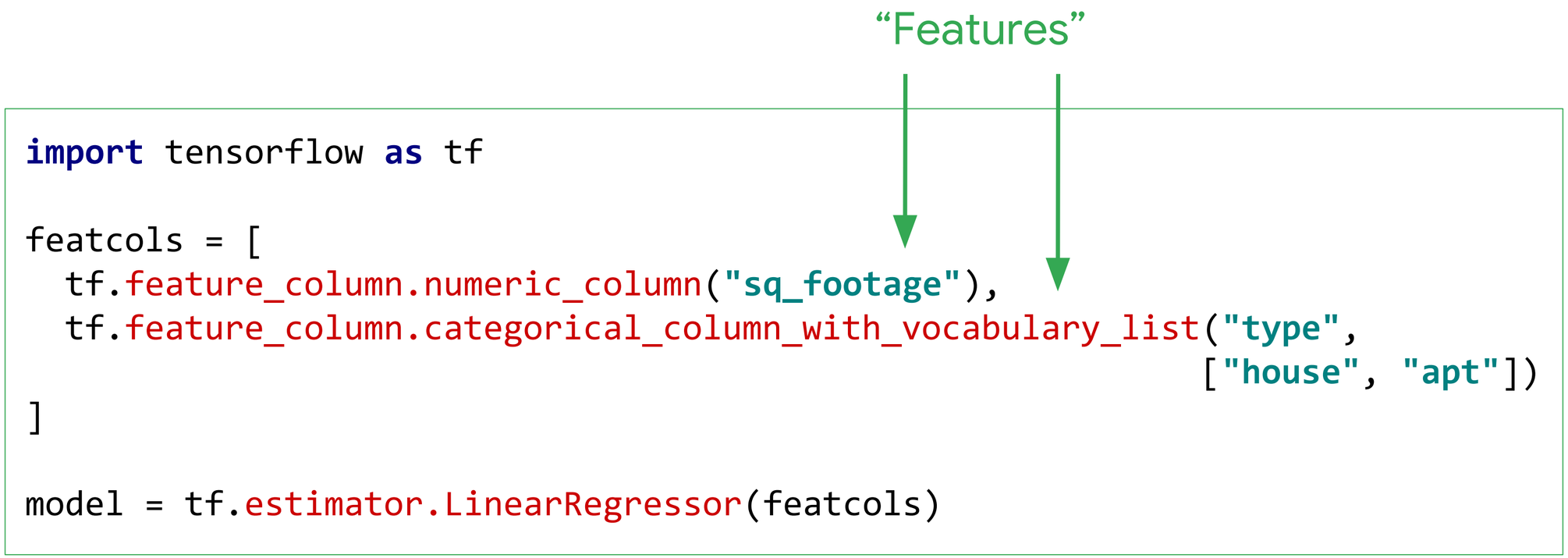
# Predict property value from historical data

| | |
|---|---|
| “Features” | Square footage<br>House / apartment |

**ML Model**

Output **Price:** $400,000

# Feature columns tell the model what inputs to expect



# Feature columns tell the model what inputs to expect

```
import tensorflow as tf

featcols = [
  tf.feature_column.numeric_column("sq_footage"),
  tf.feature_column.categorical_column_with_vocabulary_list("type",
                                                            ["house", "apt"])
]

model = tf.estimator.LinearRegressor(featcols)
```

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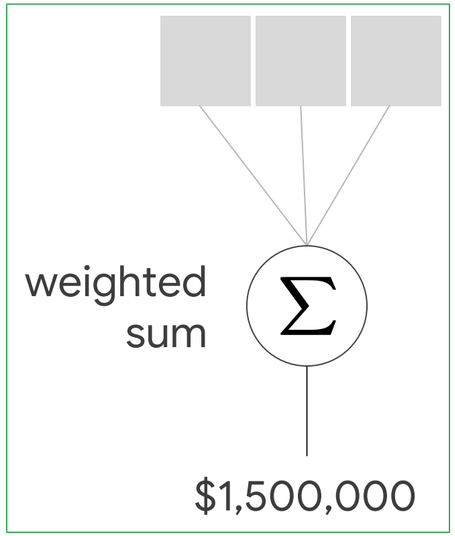
model = tf.estimator.LinearRegressor(featcols)
```

“Model”: predicts PRICE

# Under the hood: feature columns take care of packing the inputs into the input vector of the model




`tf.estimator.LinearRegressor`

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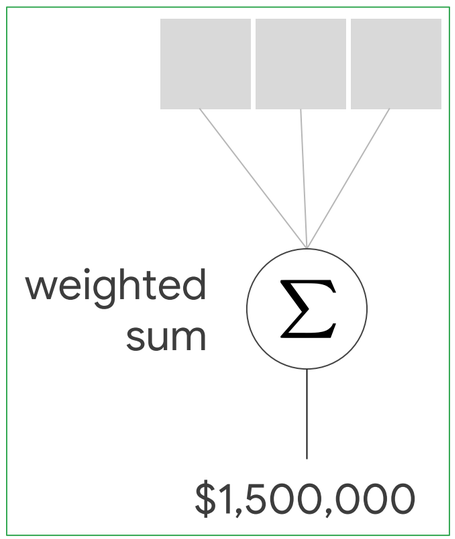
```




tf.estimator.LinearRegressor

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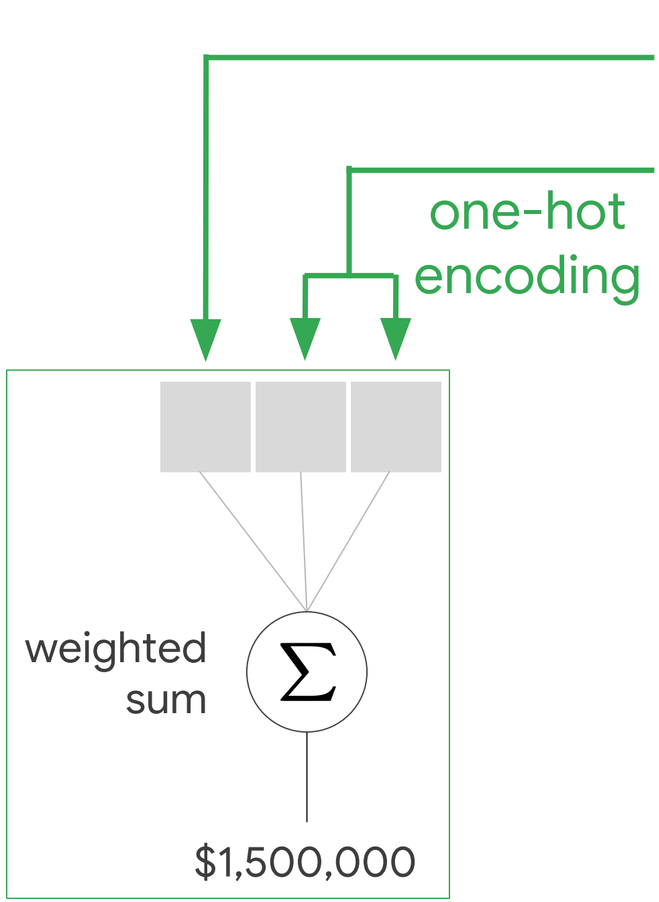



```
tf.feature_column.numeric_column("sq_footage")

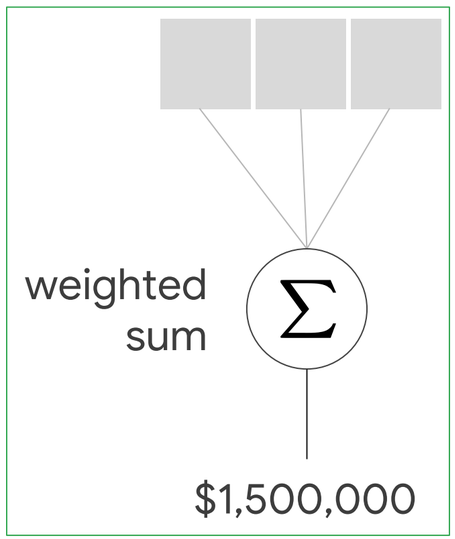
tf.feature_column.categorical_column_with_vocabulary_list(
    "type", ["house", "apt"])
```

“ house” -> 1, 0

“ apt” -> 0, 1

tf.estimator.LinearRegressor

# Under the hood: feature columns take care of packing the inputs into the input vector of the model




```
tf.feature_column.numeric_column("sq_footage")

tf.feature_column.categorical_column_with_vocabulary_list(
    "type", ["house", "apt"])
```

one-hot encoding

“ house” -> 1, 0

“ apt” -> 0, 1

`tf.estimator.LinearRegressor`

Many more...

```
tf.feature_column.bucketized_column
tf.feature_column.embedding_column
Tf.feature_column.crossed_column
Tf.feature_column.categorical_column
_with_hash_bucket
...
```

# Training: feed in training input data and train for 100 epochs

```
def train_input_fn():
   features = {"sq_footage": [ 1000,    2000,    3000,    1000,  2000,  3000],
               "type":       ["house", "house", "house", "apt", "apt", "apt"]}
                               # prices in thousands
   labels =                  [ 500,     1000,    1500,    700,   1300,  1900]
   return features, labels



model.train(train_input_fn, steps=100)
```

# Training: feed in training input data and train for 100 epochs

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def train_input_fn():
   features = {"sq_footage": [ 1000,    2000,    3000,    1000,  2000,  3000],
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   labels =                  [ 500,     1000,    1500,    700,   1300,  1900]
   return features, labels



model.train(train_input_fn, steps=100)
```

# Predictions: once trained, the model can be used for prediction

```
def predict_input_fn():
   features = {"sq_footage": [1500,    1800],
               "type":       ["house", "apt"]}
   return features


predictions = model.predict(predict_input_fn)
```

# Predictions: once trained, the model can be used for prediction

```
def predict_input_fn():
   features = {"sq_footage": [1500,    1800],
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# Predictions: once trained, the model can be used for prediction

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def predict_input_fn():
   features = {"sq_footage": [1500,    1800],
               "type":       ["house", "apt"]}
   return features


predictions = model.predict(predict_input_fn)
```

generator

```
print(next(predictions))
print(next(predictions))
```

```
{'predictions': array([855.93], dtype=float32)}
{'predictions': array([859.07], dtype=float32)}
```

# Pick an Estimator, train, predict

```
import tensorflow as tf

featcols = [
  tf.feature_column.numeric_column("sq_footage"),
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]

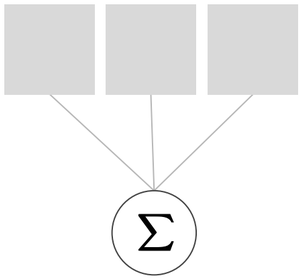
model = tf.estimator.LinearRegressor(featcols)

model.train(train_input_fn, steps=100)

predictions = model.predict(predict_input_fn)
```

To use a different pre-made estimator, just change the class name and supply appropriate parameters

```
model = tf.estimator.DNNRegressor(featcols,
                                  hidden_units=[3, 2])
```




tf.estimator.
LinearRegressor

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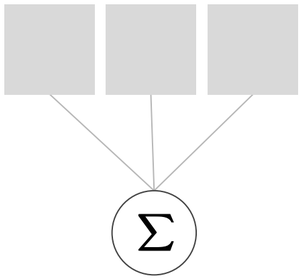


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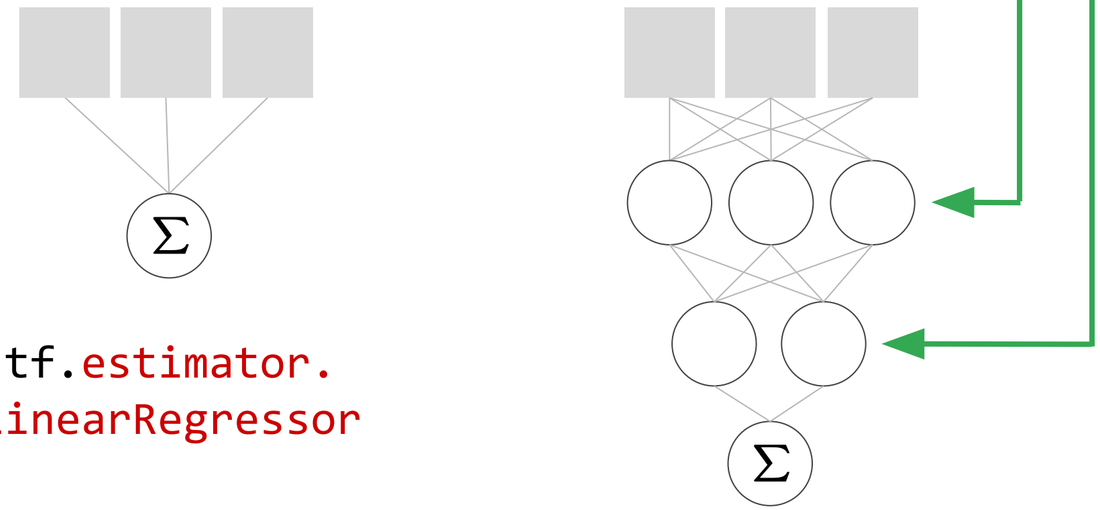


tf.estimator.
LinearRegressor

# For example, here are some of the things you can change about the DNN Regressor

```
tf.estimator.DNNRegressor(feature_columns=...,
                          hidden_units=[10, 5],
```

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tf.estimator.DNNRegressor(feature_columns=...,
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```

# For example, here are some of the things you can change about the DNN Regressor

```
tf.estimator.DNNRegressor(feature_columns=...,
                          hidden_units=[10, 5],
                          activation_fn=tf.nn.relu,
                          dropout=0.2,
                          optimizer="Adam")
```

# Model checkpoints

1 Continue training

# Model checkpoints

1 Continue training

2 Resume on failure

# Model checkpoints

1. Continue training
2. Resume on failure
3. Predict from trained model

# Estimators automatically checkpoint training

Where to put the checkpoints

```
model = tf.estimator.LinearRegressor(featcols, './model_trained')

model.train(train_input_fn, steps=100)
```

```
%ls model_trained

checkpoint                                      model.ckpt-100.meta
graph.pbtxt                                     model.ckpt-1.data-00000-of-00001
model.ckpt-100.data-00000-of-00001              model.ckpt-1.index
model.ckpt-100.index                            model.ckpt-1.meta
```

# We can now restore and predict with the model

```
trained_model = tf.estimator.LinearRegressor(featcols, './model_trained')

predictions = trained_model.predict(pred_input_fn)
```

```
INFO:tensorflow:Restoring parameters from
model_trained/model.ckpt-100
```

```
{'predictions': array([855.93], dtype=float32)}
{'predictions': array([859.07], dtype=float32)}
```

# Training also resumes from the last checkpoint

```
model = tf.estimator.LinearRegressor(featcols, './model_trained')

model.train(train_input_fn, steps=100)
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Training continues

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Training continues

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INFO:tensorflow:Restoring parameters from
model_trained/model.ckpt-100
```

# In memory data: usually numpy arrays or Pandas dataframes - you can use them directly

```
def numpy_train_input_fn(sqft, prop_type, price):  #np arrays
   return tf.estimator.inputs.numpy_input_fn(
       x = {"sq_footage": sqft, "type": prop_type},
       y = price,
       batch_size=128,
       num_epochs=10,
       shuffle=True,
       queue_capacity=1000
   )
```

```
def pandas_train_input_fn(df):  # a Pandas dataframe
   return tf.estimator.inputs.pandas_input_fn(
       x = df, # “sq_footage”, “type” selected
               # automatically because of feature
               # columns definition
       y = df['price'],
       batch_size=128,
       num_epochs=10,
       shuffle=True,
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       y = df['price'],
       batch_size=128,
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       shuffle=True,
       queue_capacity=1000
   )
```

# Training happens until input is exhausted or number of steps is reached

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def pandas_train_input_fn(df):  # a Pandas dataframe
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   )

model.train(pandas_train_input_fn(df))
```

Trains until input exhausted (10 epochs) starting from checkpoint

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def pandas_train_input_fn(df):  # a Pandas dataframe
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       num_epochs=10,
       shuffle=True
   )

model.train(pandas_train_input_fn(df))

model.train(pandas_train_input_fn(df), steps=1000)
```

Trains until input exhausted (10 epochs) starting from checkpoint

1000 additional steps from checkpoint

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   )

model.train(pandas_train_input_fn(df))

model.train(pandas_train_input_fn(df), steps=1000)

model.train(pandas_train_input_fn(df), max_steps=1000)
```

Trains until input exhausted (10 epochs) starting from checkpoint

1000 additional steps from checkpoint

1000 steps - might be nothing if checkpoint already there

# To add a new feature, add it to the list of feature columns and make sure it is present in data frame

```
featcols = [
   tf.feature_column.numeric_column("sq_footage"),
   tf.feature_column.categorical_column_with_vocabulary_list("type",
                                                             ["house", "apt"])

]

model = tf.estimator.LinearRegressor(featcols)

def train_input_fn(df):  # a Pandas dataframe
   return tf.estimator.inputs.pandas_input_fn(
       x = df,
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       batch_size=128, num_epochs=10, shuffle=True
   )

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```

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   tf.feature_column.categorical_column_with_vocabulary_list("type",
                                                             ["house", "apt"])
   tf.feature_column.numeric_column("nbeds"),
]

model = tf.estimator.LinearRegressor(featcols)

def train_input_fn(df):  # a Pandas dataframe
   return tf.estimator.inputs.pandas_input_fn(
       x = df,
       y = df['price'],
       batch_size=128, num_epochs=10, shuffle=True
   )

model.train(train_input_fn(df))
```

# Lab

Implementing a Machine Learning model in TensorFlow using Estimator API

Google Cloud

# Train on large datasets with Dataset API

Lak Lakshmanan

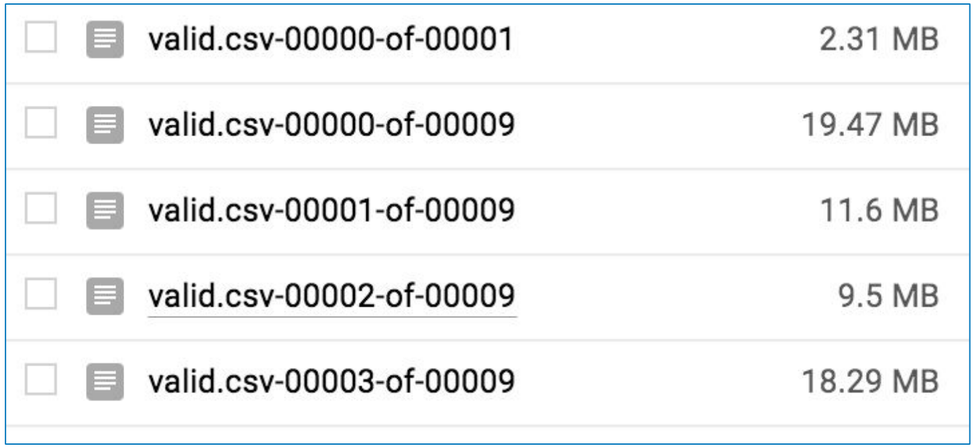
# Real World ML Models

| **Problem** | **Solution** |
| --- | --- |
| Out of memory data | ? |
| Distribution | ? |
| Need to evaluate during training | ? |
| Deployments that scale | ? |

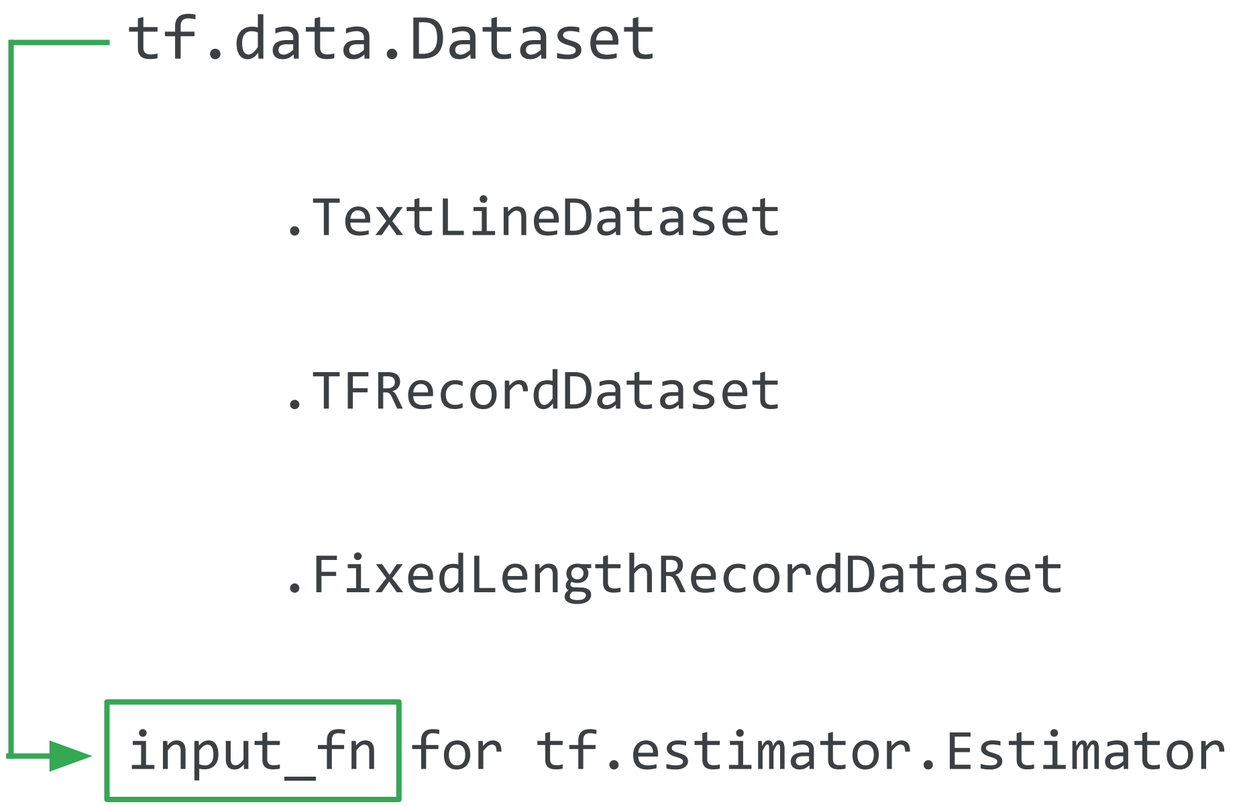
# Real World ML Models

| **Problem** | **Solution** |
| --- | --- |
| Out of memory data | Use the Dataset API |
| Distribution | ? |
| Need to evaluate during training | ? |
| Deployments that scale | ? |

# Out-of-memory datasets tend to be sharded into multiple files

Datasets can be created from different file formats.
They generate input functions for Estimators.



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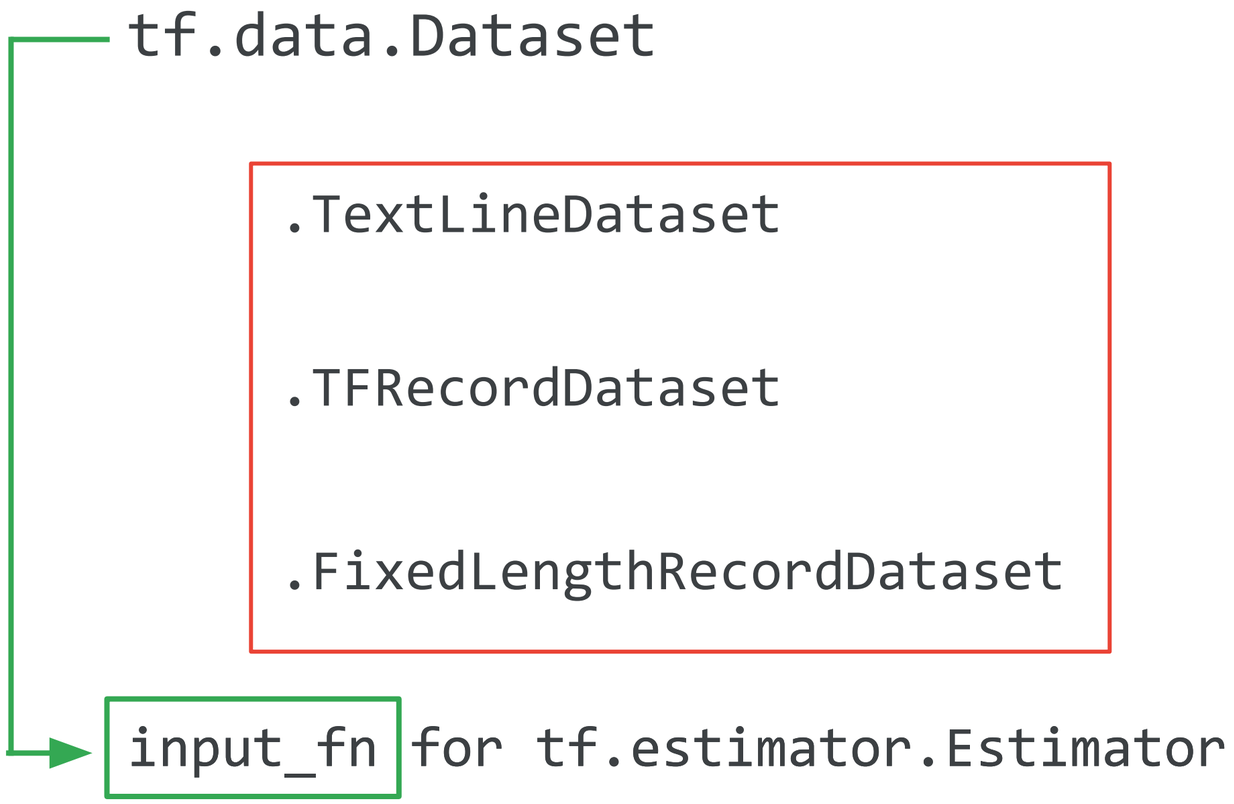

# Read one CSV file using TextLineDataset

```
def decode_line(row):
   cols = tf.decode_csv(row, record_defaults=[[0],['house'],[0]])
   features = {'sq_footage': cols[0], 'type': cols[1]}
   label = cols[2] # price
   return features, label

dataset = tf.data.TextLineDataset("train_1.csv") \
                 .map(decode_line)

dataset = dataset.shuffle(1000) \
                 .repeat(15)    \
                 .batch(128)

def input_fn():
   features, label = dataset.make_one_shot_iterator().get_next()
   return features, label

model.train(input_fn)
```

property type

sq_footage PRICE in K$

```
1001, house,  501
2001, house, 1001
3001, house, 1501
1001, apt,    701
2001, apt,   1301
3001, apt,   1901
1101, house,  526
2101, house, 1026
```

# Datasets handle shuffling, epochs, batching, ...

Shuffle buffer size

```
dataset = dataset.shuffle(1000) \
                 .repeat(15) \
                 .batch(128)
```

Nb of epochs

property type

| sq_footage | | PRICE in K$ |
|---|---|---|
| 1001, | house, | 501 |
| 2001, | house, | 1001 |
| 3001, | house, | 1501 |
| 1001, | apt, | 701 |
| 2001, | apt, | 1301 |
| 3001, | apt, | 1901 |
| 1101, | house, | 526 |
| 2101, | house, | 1026 |

# They support arbitrary transformations with `map()`

```
def decode_line(txt_line):
    cols = tf.decode_csv(txt_line, record_defaults=[[0],['house'],[0]])
    features = {'sq_footage': cols[0], 'type': cols[1]}
    label = cols[2] # price
    return features, label

dataset = tf.data.TextLineDataset("train_1.csv") \
                 .map(decode_line)
```

Dataset of text lines

property type

sq_footage PRICE in K$

```
1001, house,  501
2001, house, 1001
3001, house, 1501
1001, apt,    701
2001, apt,   1301
3001, apt,   1901
1101, house,  526
2101, house, 1026
```

# They support arbitrary transformations with `map()`

```
def decode_line(txt_line):
   cols = tf.decode_csv(txt_line, record_defaults=[[0],['house'],[0]])
   features = {'sq_footage': cols[0], 'type': cols[1]}
   label = cols[2] # price
   return features, label

dataset = tf.data.TextLineDataset("train_1.csv") \
                 .map(decode_line)
```

Dataset of pairs
(features, label)

property type

sq_footage PRICE in K$

```
1001, house,  501
2001, house, 1001
3001, house, 1501
1001, apt,    701
2001, apt,   1301
3001, apt,   1901
1101, house,  526
2101, house, 1026
```

# Datasets help create `input_fn`'s for Estimators

```
dataset = ...



def input_fn():
   features, label = dataset.make_one_shot_iterator().get_next()
   return features, label

model.train(input_fn)
```

property type

sq_footage PRICE in K$

```
1001, house,  501
2001, house, 1001
3001, house, 1501
1001, apt,    701
2001, apt,   1301
3001, apt,   1901
1101, house,  526
2101, house, 1026
```

# Datasets help create `input_fn`'s for Estimators

```
dataset = ...


def input_fn():
   features, label = dataset.make_one_shot_iterator().get_next()
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property type

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2001, house, 1001
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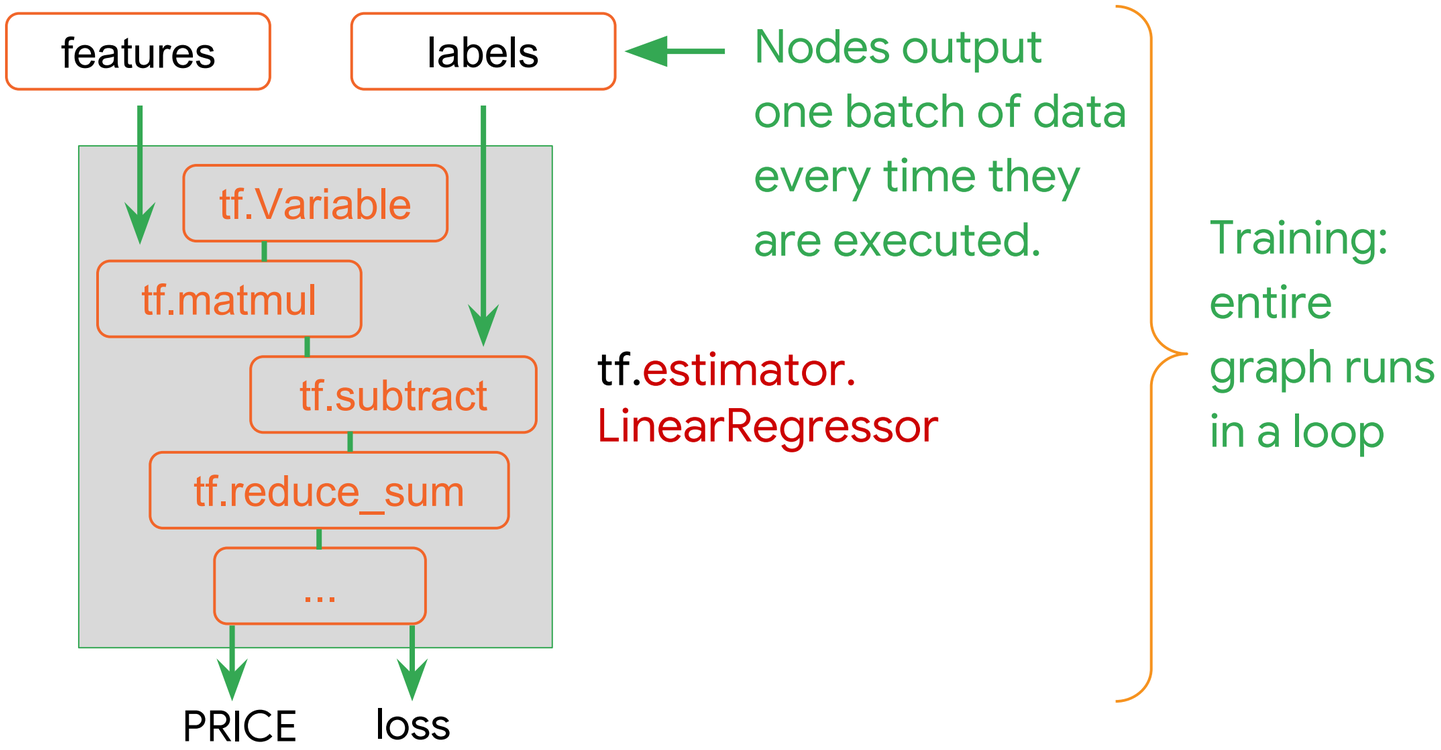
1001, apt,    701
2001, apt,   1301
3001, apt,   1901
1101, house,  526
2101, house, 1026
```

All the tf. commands that you write in Python **do not actually process any data**, they just build graphs

# Under the hood: what does an input function do ?

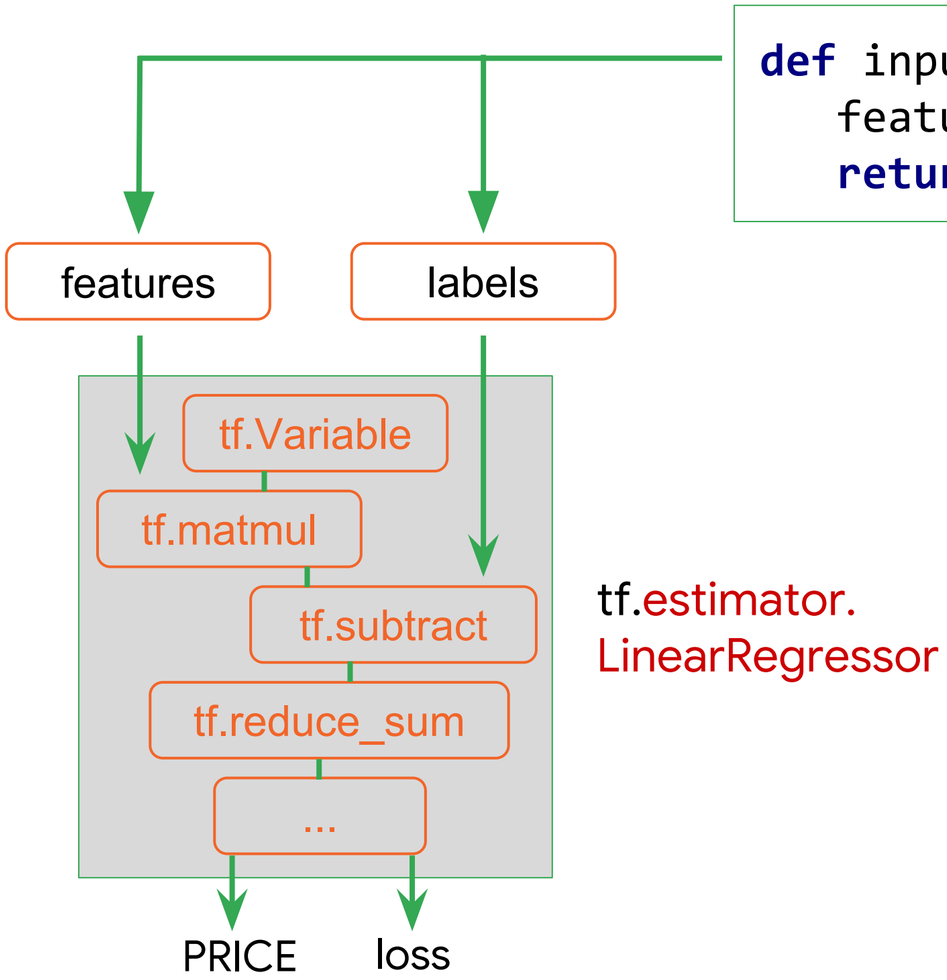



Nodes output one batch of data every time they are executed.

tf.estimator.
LinearRegressor

Training: entire graph runs in a loop

# Under the hood: what does an input function do ?



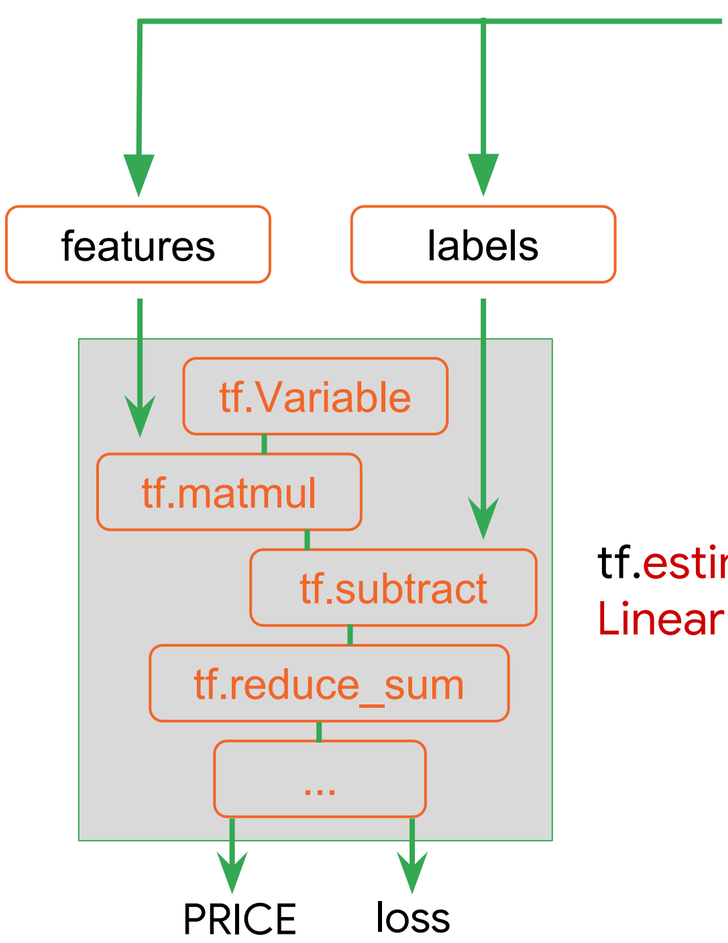

```
def input_fn():
   features, labels = ...
   return features, labels
```

Executed once

Returns Tensorflow nodes

tf.estimator.
LinearRegressor

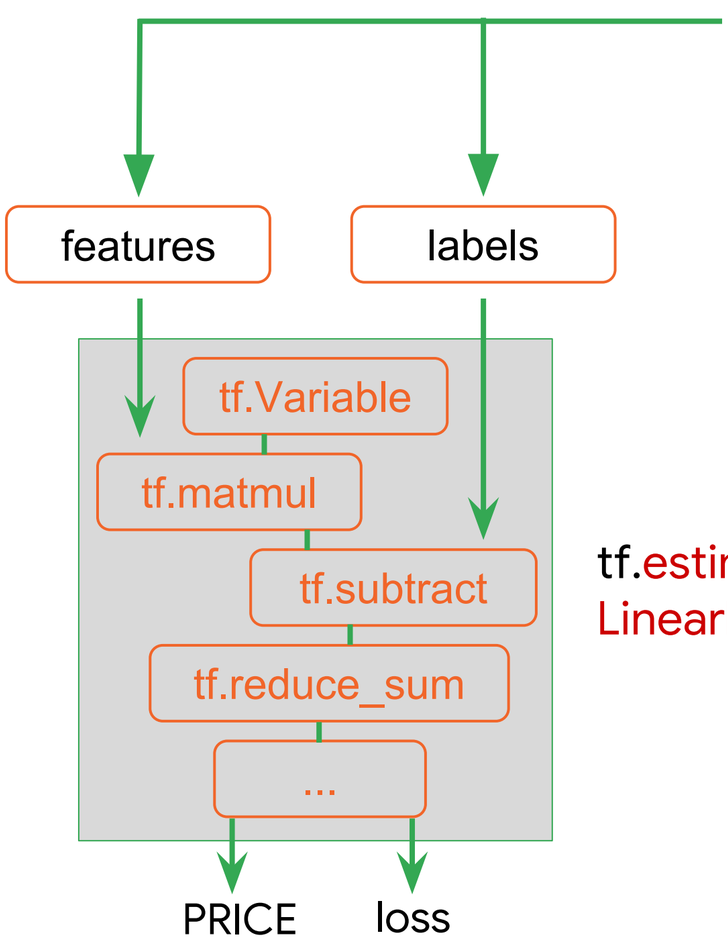
# Under the hood: Dataset API




```
def input_fn():
   features, label =
     dataset.make_one_shot_iterator().get_next()
   return features, labels
```

tf.estimator.
LinearRegressor

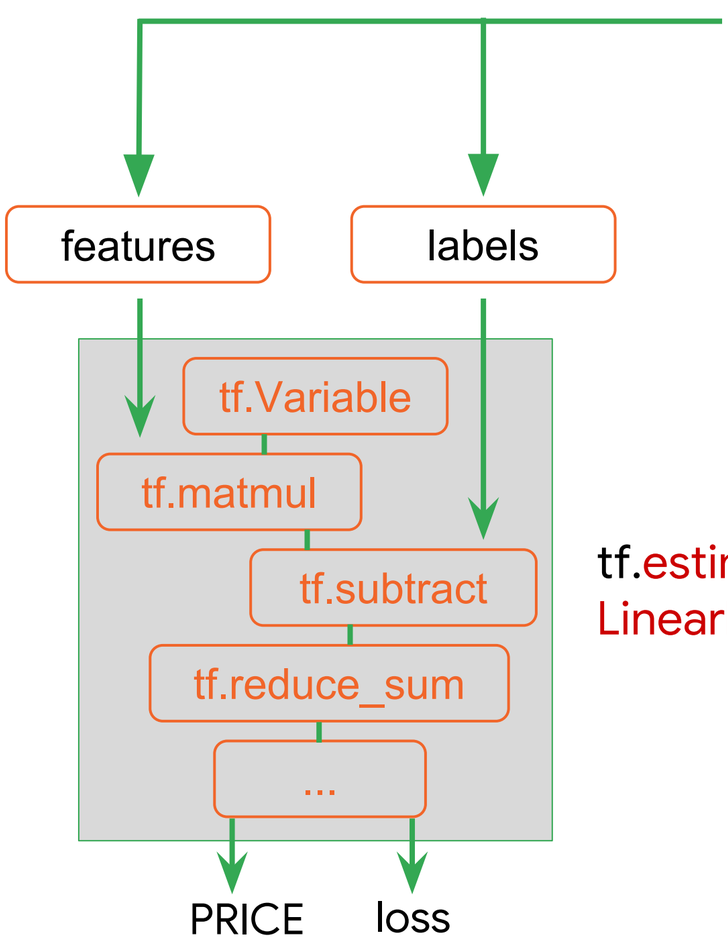
# Under the hood: Dataset API




```
def input_fn():
    features, label =
      dataset.make_one_shot_iterator().get_next()
    return features, labels
```

tf.estimator.
LinearRegressor

# Common Misconceptions about `input_fn`




```
def input_fn():
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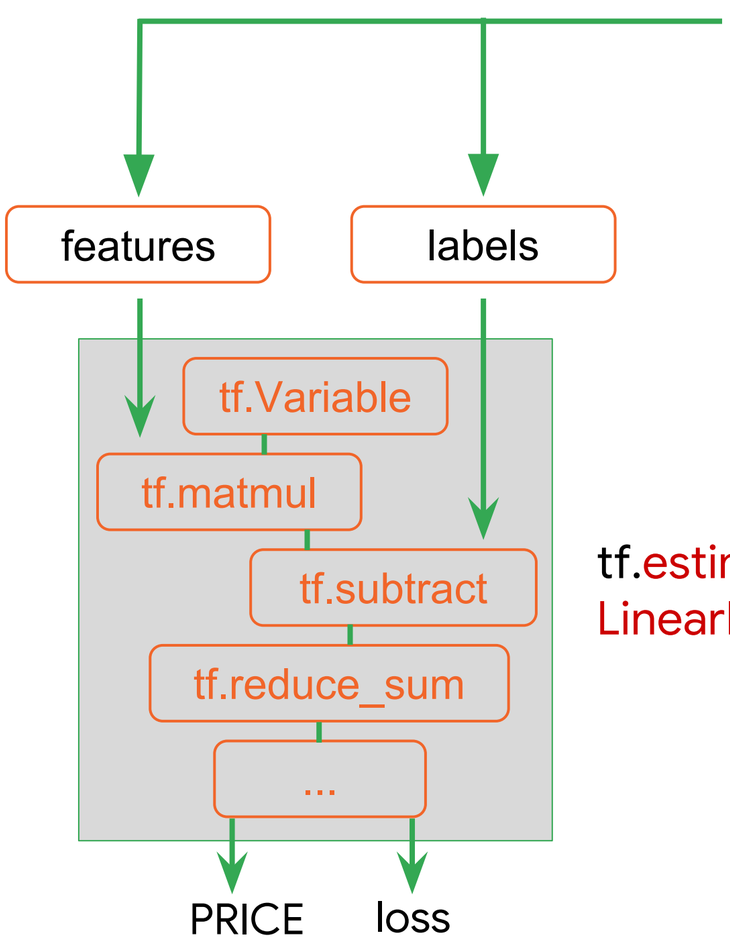
```

tf.estimator.
LinearRegressor

# Common Misconceptions about `input_fn`




```
def input_fn():
   features, label =
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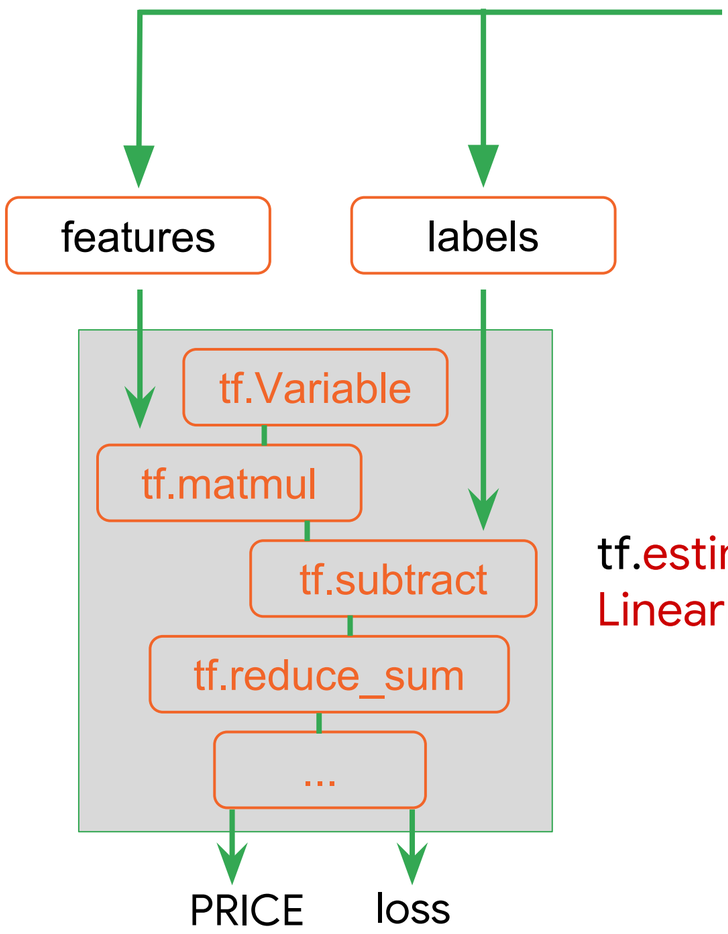
   return features, labels
```

1. Input functions called only once

tf.estimator.
LinearRegressor

# Common Misconceptions about `input_fn`

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def input_fn():
   features, label =
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   return features, labels
```

tf.estimator.
LinearRegressor

1. Input functions called only once
2. Input functions return Tf nodes (not data)

# Read one CSV file using `TextLineDataset`

```
def decode_line(row):
   cols = tf.decode_csv(row, record_defaults=[[0],['house'],[0]])
   features = {'sq_footage': cols[0], 'type': cols[1]}
   label = cols[2] # price
   return features, label

dataset = tf.data.TextLineDataset("train_1.csv") \
                 .map(decode_line)

dataset = dataset.shuffle(1000) \
                 .repeat(15)    \
                 .batch(128)

def input_fn():
   features, label = dataset.make_one_shot_iterator().get_next()
   return features, label

model.train(input_fn)
```

property type

sq_footage PRICE in K$

```
1001, house,  501
2001, house, 1001
3001, house, 1501
1001, apt,    701
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3001, apt,   1901
1101, house,  526
2101, house, 1026
```

# Read a set of sharded CSV files using `TextLineDataset`

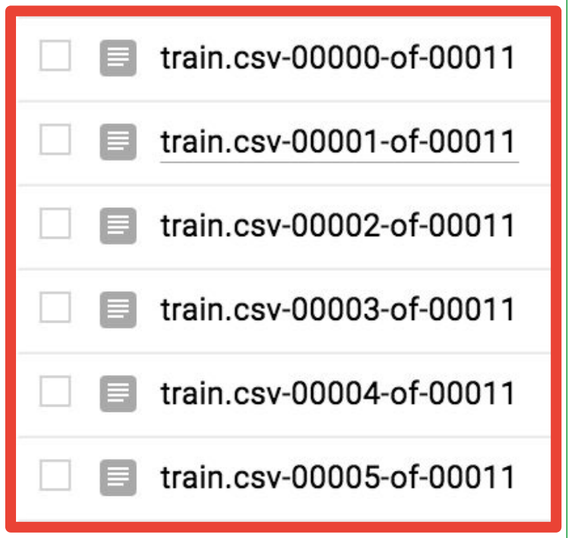
```
def decode_line(row):
   cols = tf.decode_csv(row, record_defaults=[[0],['house'],[0]])
   features = {'sq_footage': cols[0], 'type': cols[1]}
   label = cols[2] # price
   return features, label

dataset = tf.data.Dataset.list_files("train.csv-*")    \
                         .flat_map(tf.data.TextLineDataset) \
                         .map(decode_line)

dataset = dataset.shuffle(1000) \
                 .repeat(15)    \
                 .batch(128)

def input_fn():
   return dataset.make_one_shot_iterator().get_next()

model.train(input_fn)
```



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def decode_line(row):
   cols = tf.decode_csv(row, record_defaults=[[0],['house'],[0]])
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   label = cols[2] # price
   return features, label

dataset = tf.data.Dataset.list_files("train.csv-*")    \
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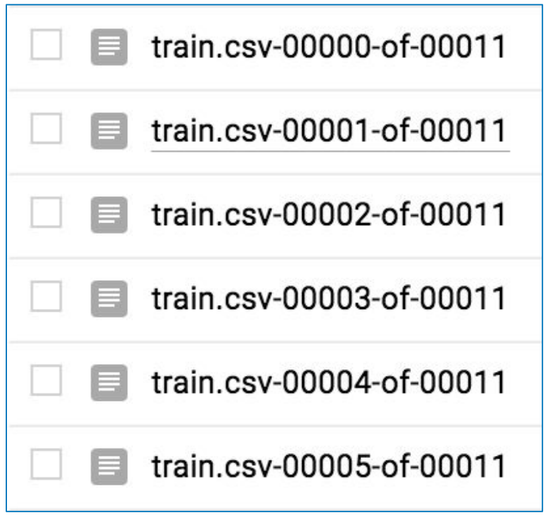
```



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def input_fn():
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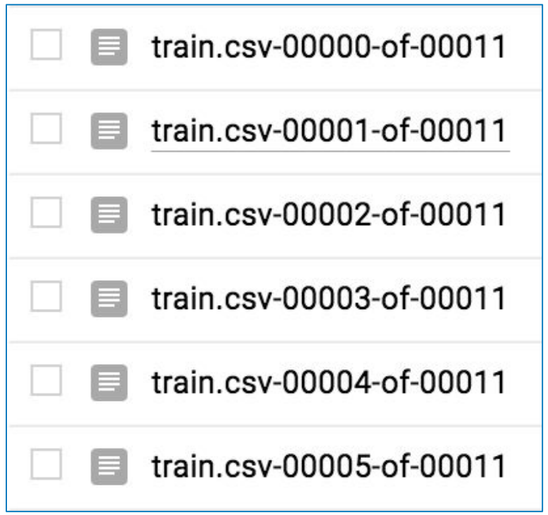
model.train(input_fn)
```



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def input_fn():
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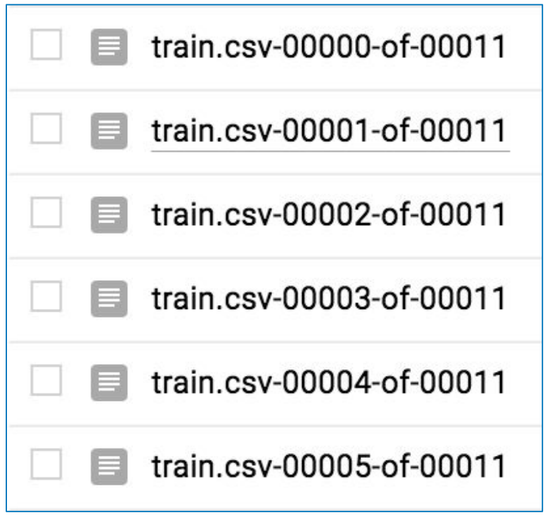
model.train(input_fn)
```



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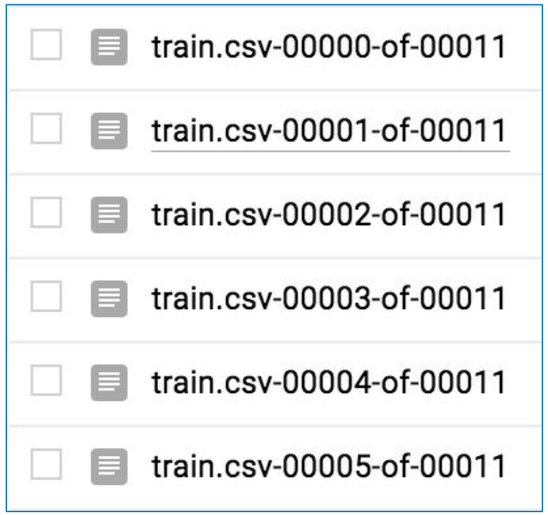
def input_fn():
   return dataset.make_one_shot_iterator().get_next()

model.train(input_fn)
```



# The real benefit of Dataset is that you can do more than just ingest data

```
dataset =
tf.data.TextLineDataset(filename)\
          .skip(num_header_lines)\
          .map(add_key)\
          .map(decode_csv)\
          .map(lambda feats,
               labels: preproc(feats), labels)
          .filter(is_valid)\
          .cache()
```

# LAB

Scaling up TensorFlow ingest using batching

Google Cloud

# Big Jobs, Distributed training

Martin Gorner

# Real World ML Models

| Problem | Solution |
| --- | --- |
| Out of memory data | Use the Dataset API |
| Distribution | Use `train_and_evaluate` |
| Need to evaluate during training | ? |
| Deployments that scale | ? |

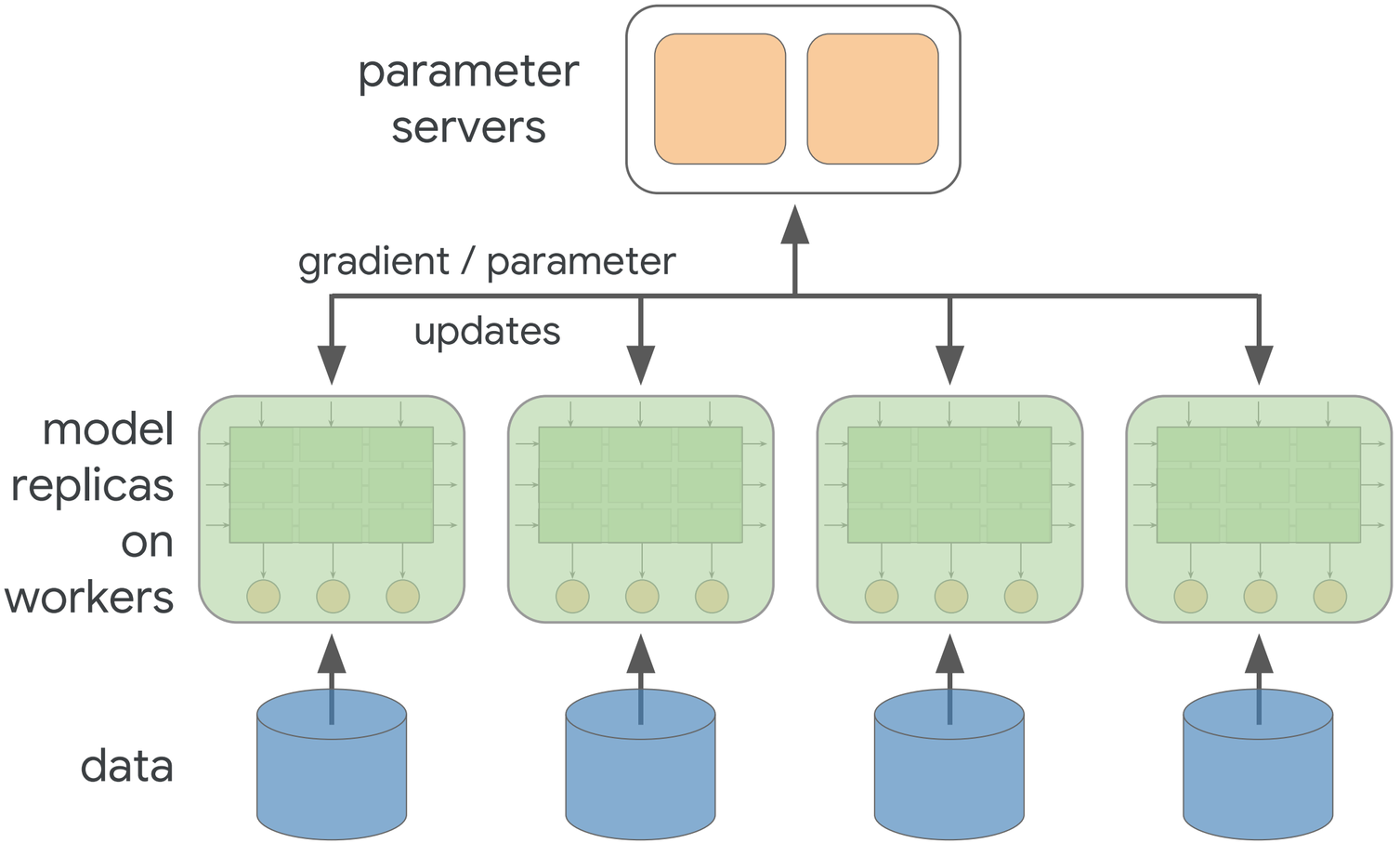
# `estimator.train_and_evaluate` is the preferred method for training real-world models

```
estimator = tf.estimator.LinearRegressor(...)

tf.estimator.train_and_evaluate(estimator, ...)
```

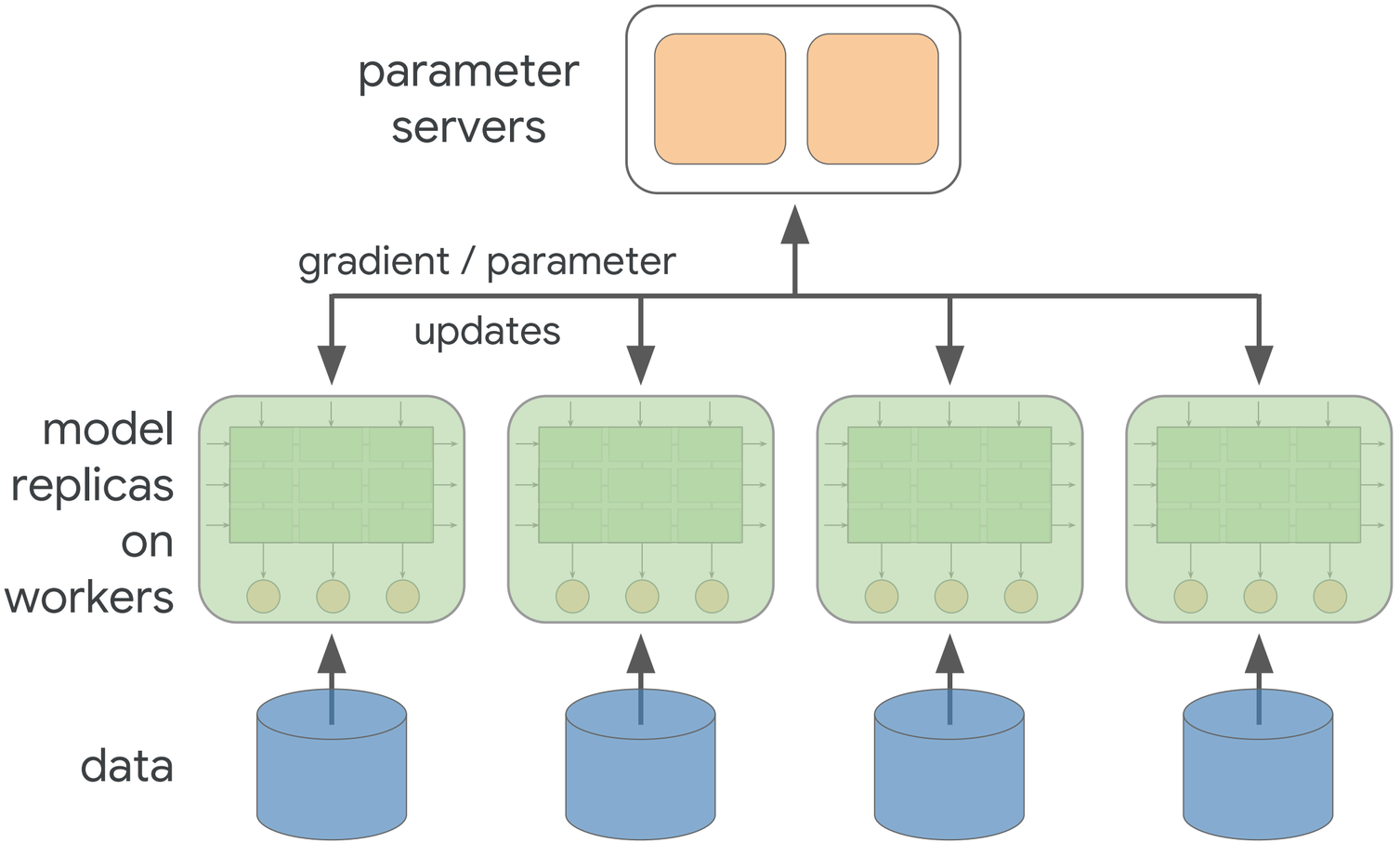
**data parallelism** =
replicate your model on
multiple workers

# Distributed training using “data parallelism”




- Distribute the graph
- Share variables
- Manage workers
- Handle exceptions / failures
- Create checkpoint files

# Distributed training using “data parallelism”




- Distribute the graph
- Share variables
- Manage workers
- Handle exceptions / failures
- Create checkpoint files

For free!

→ `tf.estimator.train_and_evaluate`

# `estimator.train_and_evaluate` is the preferred method for training real-world models

```
estimator = tf.estimator.LinearRegressor(
                      feature_columns=featcols,
                      config=run_config)

...

tf.estimator.train_and_evaluate(estimator,
                                train_spec,
                                eval_spec)
```

You need:

1. Estimator
2. Run Config
3. Train Spec
4. Eval Spec

# run_config tells the estimator where and how often to write Checkpoints and Tensorboard logs ("summaries")

```
run_config = tf.estimator.RunConfig(
                           model_dir=output_dir,
                           save_summary_steps=100,
                           save_checkpoints_steps=2000)

estimator = tf.estimator.LinearRegressor(config=run_config, ...)
```

# The TrainSpec tells the estimator how to get training data

Use Datasets

```
train_spec =
tf.estimator.TrainSpec(input_fn=train_input_fn, max_steps=50000)

...

tf.estimator.train_and_evaluate(estimator, train_spec, eval_spec)
```

# The EvalSpec controls the evaluation and the checkpointing of the model since they happen at the same time

```
eval_spec =
tf.estimator.EvalSpec(
           input_fn=eval_input_fn,
           steps=100, # evals on 100 batches
           throttle_secs=600 # eval no more than every 10 min
           exporters=...)

tf.estimator.train_and_evaluate(estimator, train_spec, eval_spec)
```

# The EvalSpec controls the evaluation and the checkpointing of the model since they happen at the same time

Use Datasets

```
eval_spec =
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tf.estimator.train_and_evaluate(estimator, train_spec, eval_spec)
```

# Recap with all the code

```
run_config =
tf.estimator.RunConfig(model_dir=output_dir, ...)

estimator =
tf.estimator.LinearRegressor(featcols, config=run_config)

train_spec =
tf.estimator.TrainSpec(input_fn=train_input_fn, max_steps=1000)

export_latest =
tf.estimator.LatestExporter(serving_input_receiver_fn=serving_input_fn)

eval_spec =
tf.estimator.EvalSpec(input_fn=eval_input_fn, exporters=export_latest)


tf.estimator.train_and_evaluate(estimator, train_spec, eval_spec)
```

# Recap with all the code

```
run_config =
tf.estimator.RunConfig(model_dir=output_dir, ...)

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train_spec =
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export_latest =
tf.estimator.LatestExporter(serving_input_receiver_fn=serving_input_fn)

eval_spec =
tf.estimator.EvalSpec(input_fn=eval_input_fn, exporters=export_latest)

tf.estimator.train_and_evaluate(estimator, train_spec, eval_spec)
```

# Shuffling is even more important in distributed training

```
dataset =
tf.data.Dataset.list_files("train.csv-*")  \
        .shuffle(100)                      \
        .flat_map(tf.data.TextLineDataset) \
        .map(decode_csv)

dataset = dataset.shuffle(1000) \
                 .repeat(15)    \
                 .batch(128)
```

# Shuffling is even more important in distributed training.

```
dataset =
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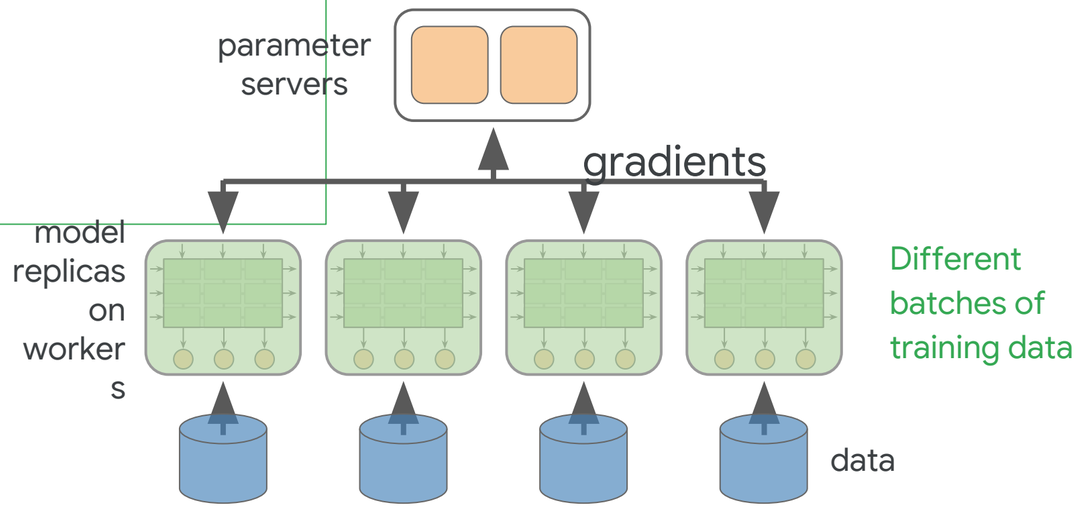


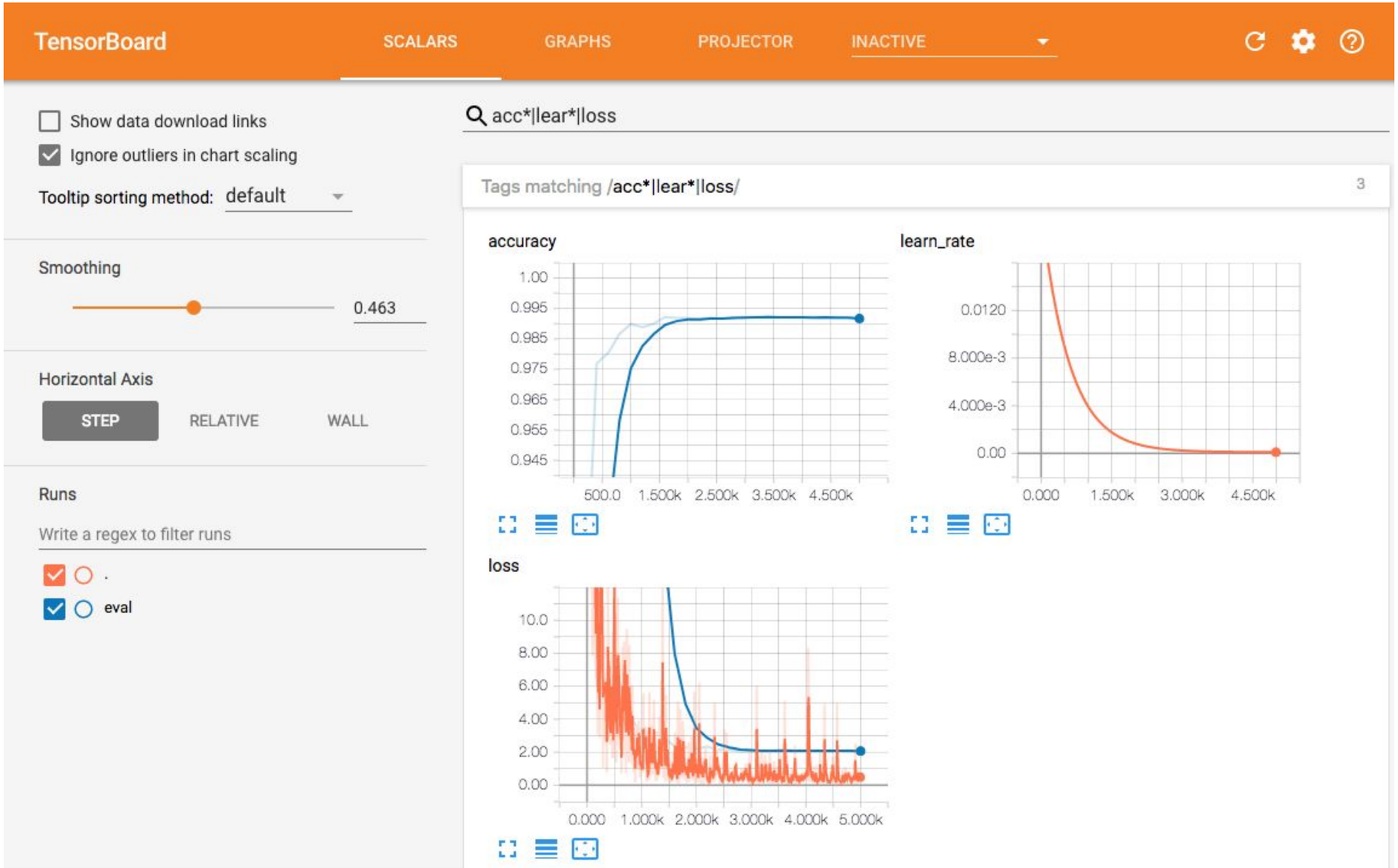
Google Cloud

# Monitoring with TensorBoard

Martin Gorner

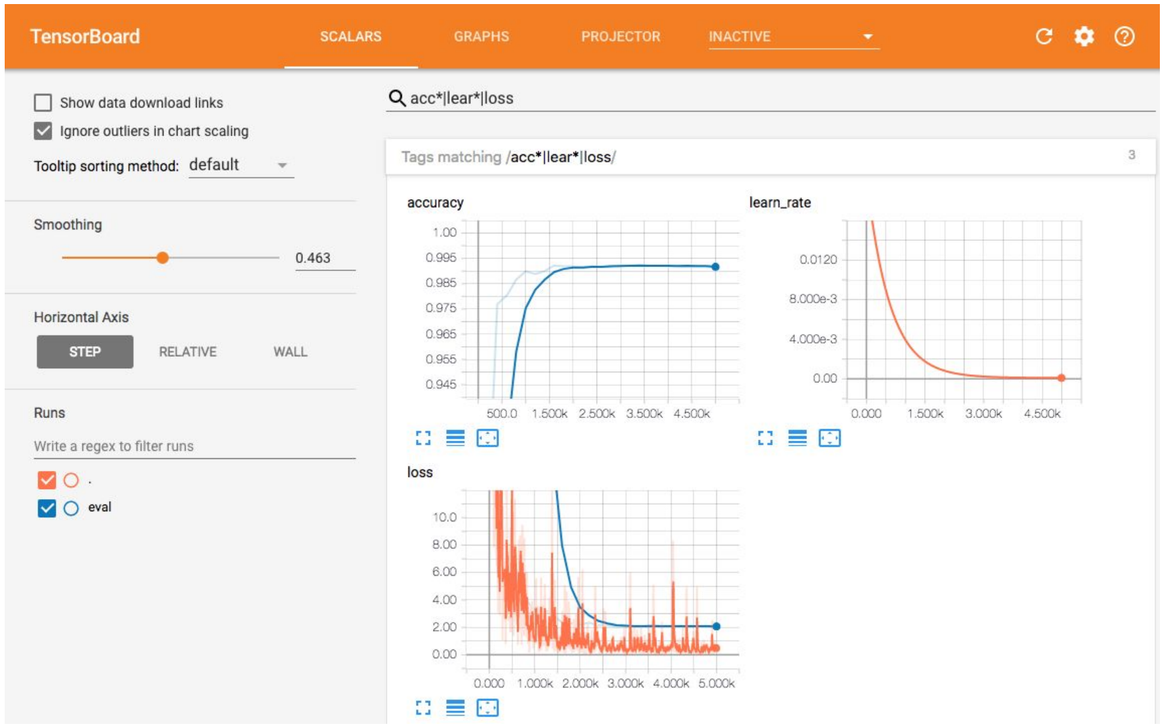
# Real World ML Models

| Problem | Solution |
| --- | --- |
| ✓ Out of memory data | Use the Dataset API |
| ✓ Distribution | Use `train_and_evaluate` |
| Need to evaluate during training | Use `train_and_evaluate` + TensorBoard |
| Deployments that scale | ? |

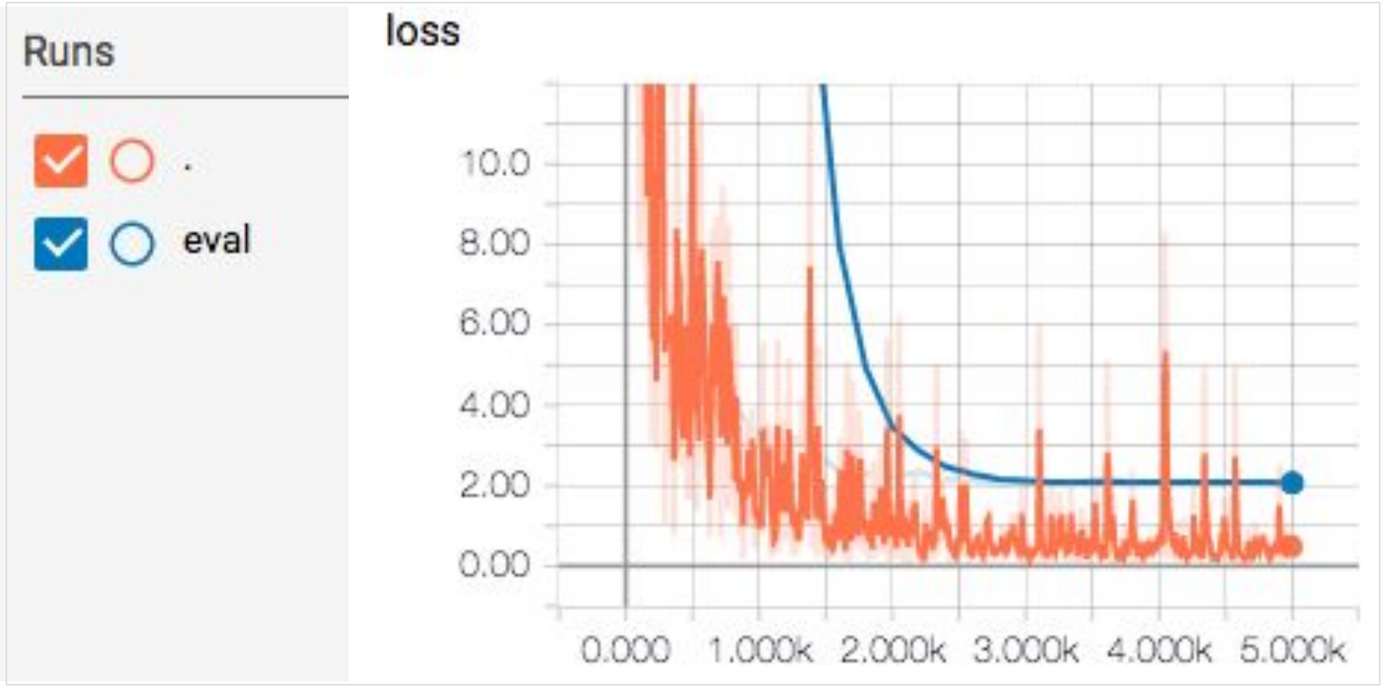

TensorBoard
SCALARS
GRAPHS
PROJECTOR
INACTIVE
Show data download links
Ignore outliers in chart scaling
Tooltip sorting method: default
Smoothing
0.463
Horizontal Axis
STEP
RELATIVE
WALL
Runs
Write a regex to filter runs
.
eval
acc*|lear*|loss
Tags matching /acc*|lear*|loss/
3
accuracy
1.00
0.995
0.985
0.975
0.965
0.955
0.945
500.0
1.500k
2.500k
3.500k
4.500k
learn_rate
0.0120
8.000e-3
4.000e-3
0.00
0.000
1.500k
3.000k
4.500k
loss
10.0
8.00
6.00
4.00
2.00
0.00
0.000
1.000k
2.000k
3.000k
4.000k
5.000k

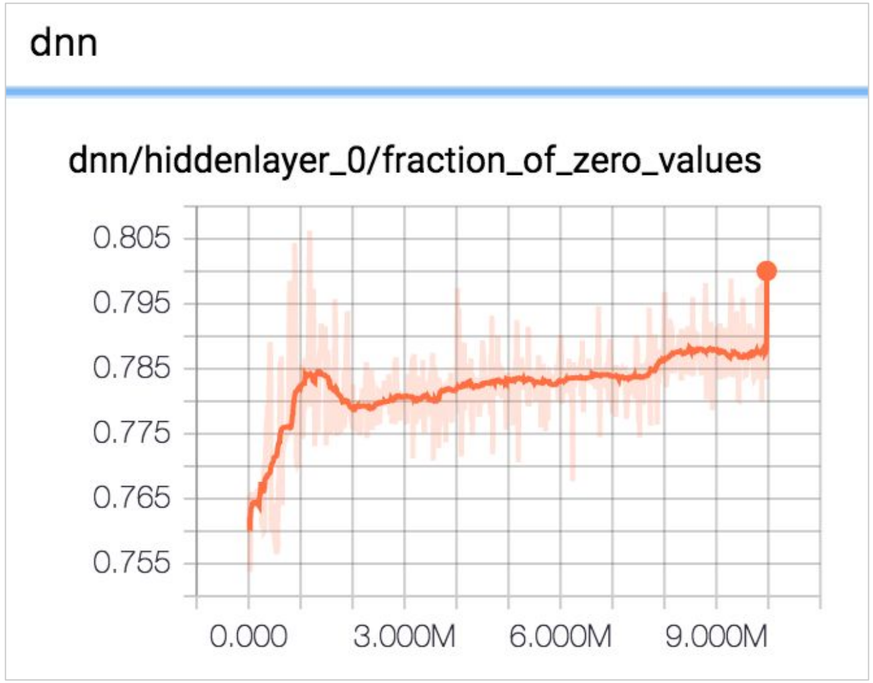
# Point Tensorboard to your output directory and the dashboards appear in your browser at localhost:6006

```
tf.estimator.RunConfig(model_dir='output_dir’)
> tensorboard --logdir output_dir
```

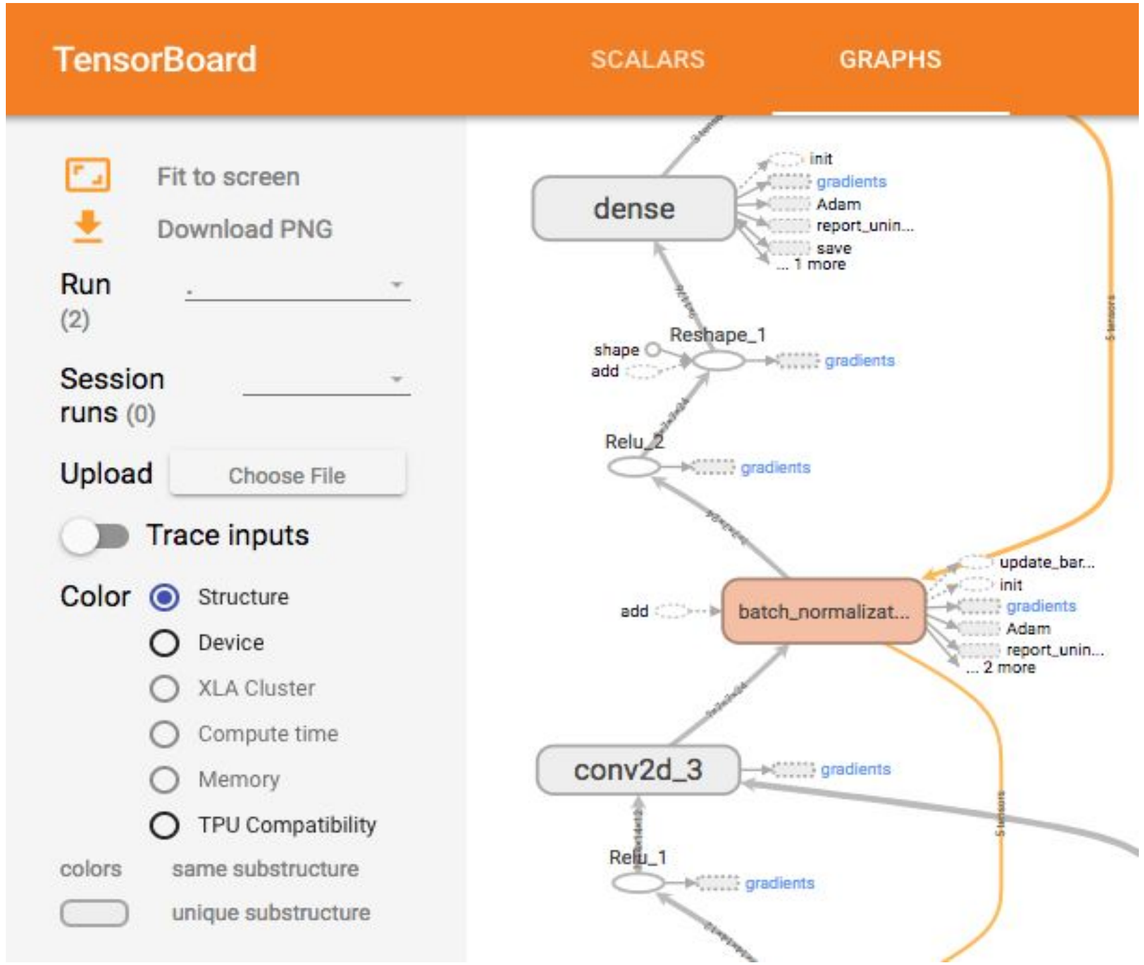


Pre-made Estimators export relevant metrics, embeddings, histograms, etc. for TensorBoard, so there is nothing more to do



# The dashboard for the graph



# If you are writing a custom Estimator model, you can add summaries for Tensorboard with a single line

```
tf.summary.scalar('meanVar1', tf.reduce_mean(var1))

...

tf.summary.text('outClass', stringvar))
```

these names will show up in TensorBoard

Sprinkle appropriate summary ops throughout your code:

`tf.summary.scalar`

`tf.summary.image`

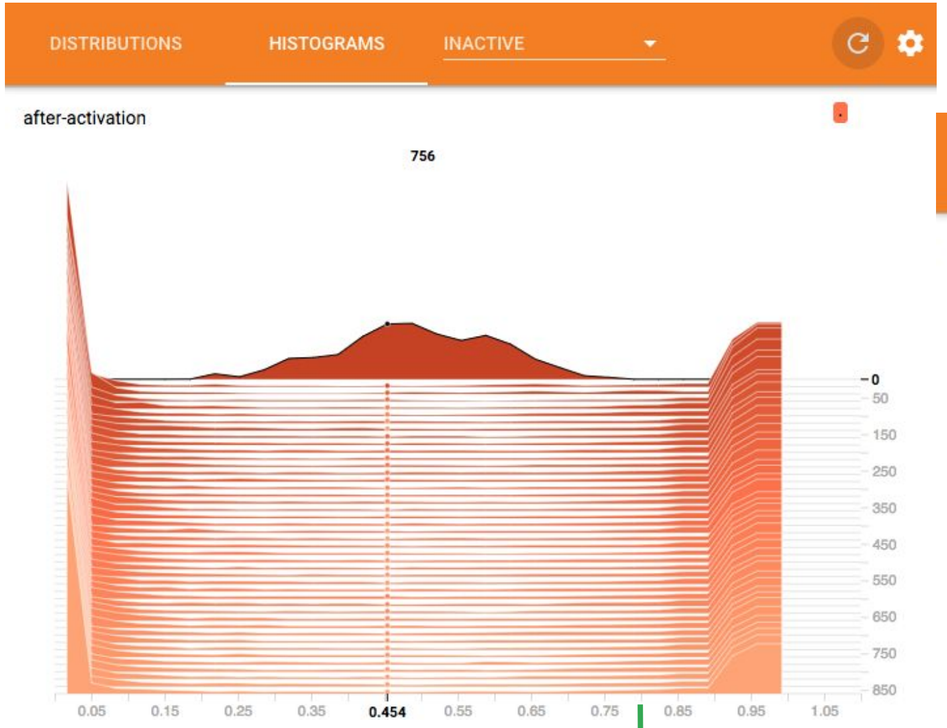
`tf.summary.audio`

`tf.summary.text`

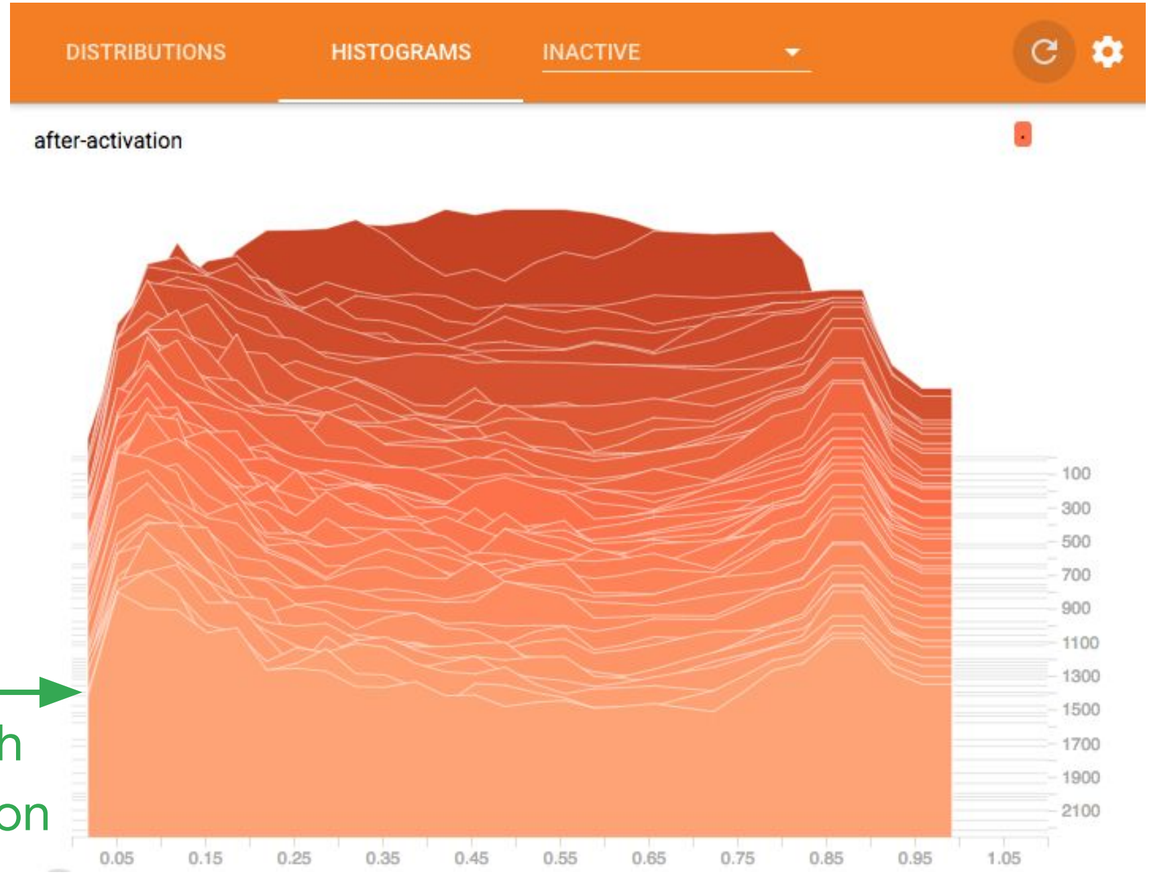
`tf.summary.histogram`

https://www.tensorflow.org/get_started/summaries_and_tensorboard

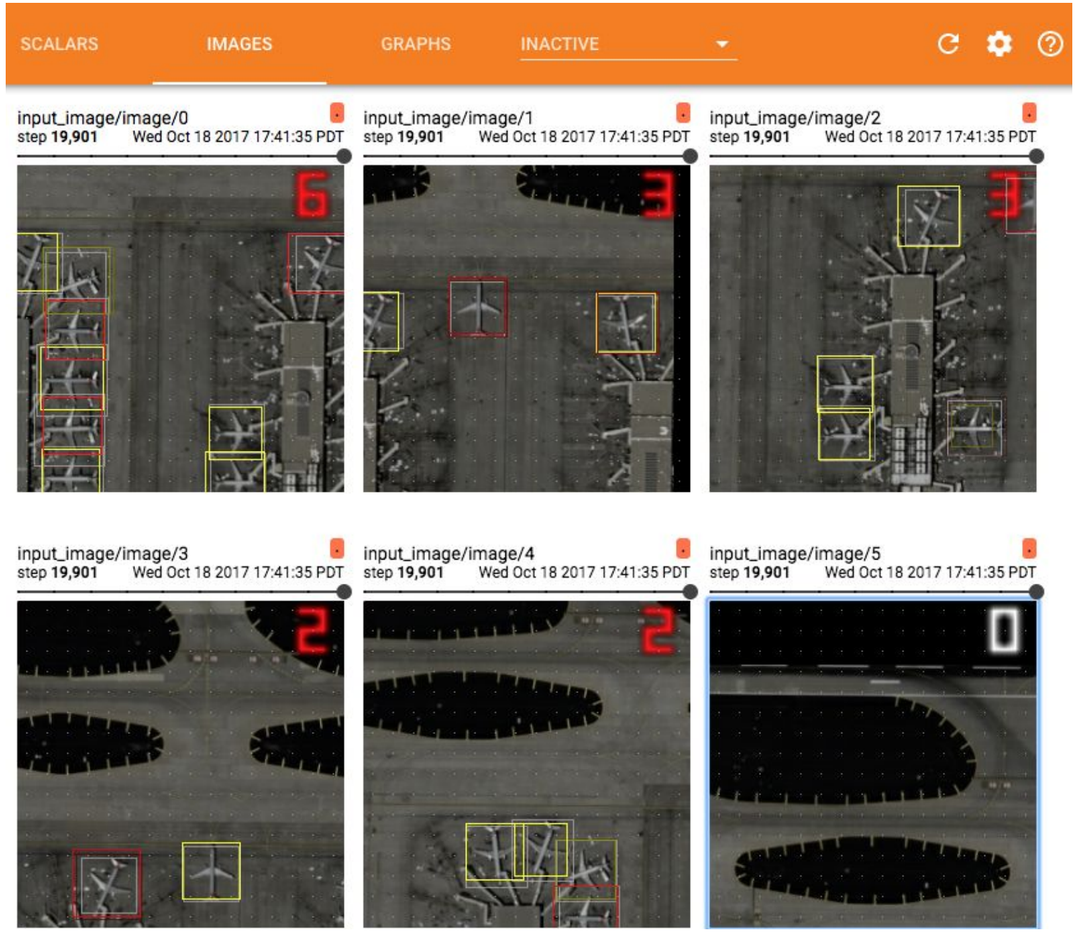
# The dashboard for histograms




After Batch Normalization



# Images and Audio have their own (non-scalar) summary ops

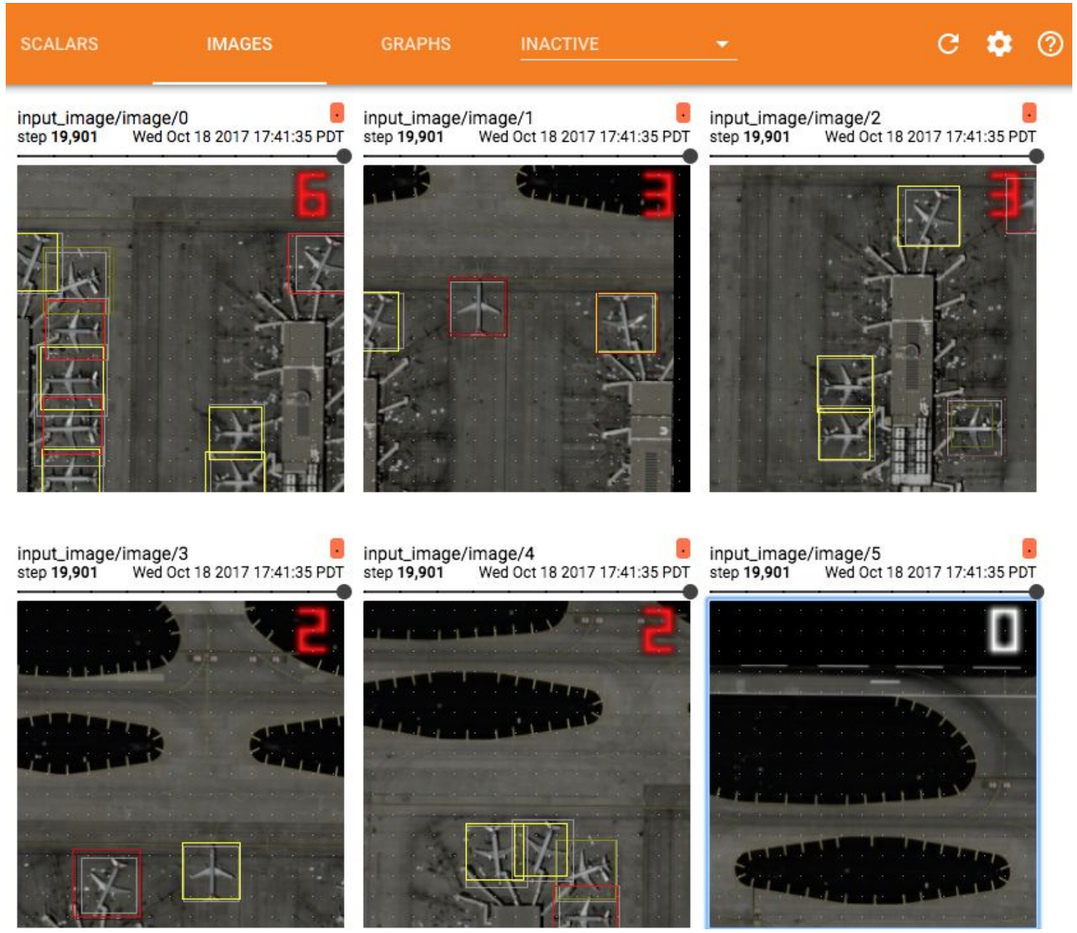


# Images and Audio have their own (non-scalar) summary ops

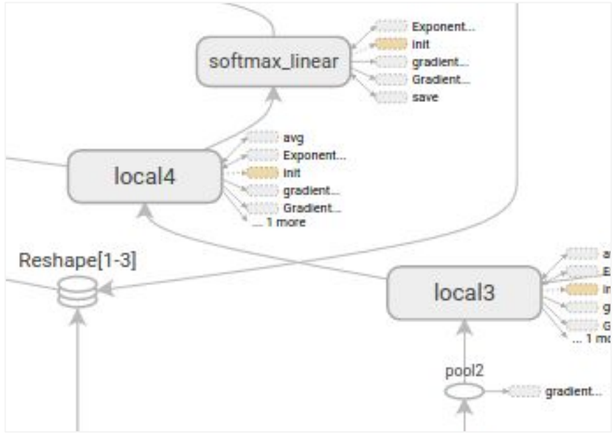
```
p = tf.placeholder("uint8", (None, ht, wd,num_channels))
s = tf.summary.image(“im1”, p)
```

```
p = tf.placeholder("float32",
            (None, duration_frames, num_channels))
s = tf.summary.audio(name='au1', tensor=p, sample_rate=4000)
```

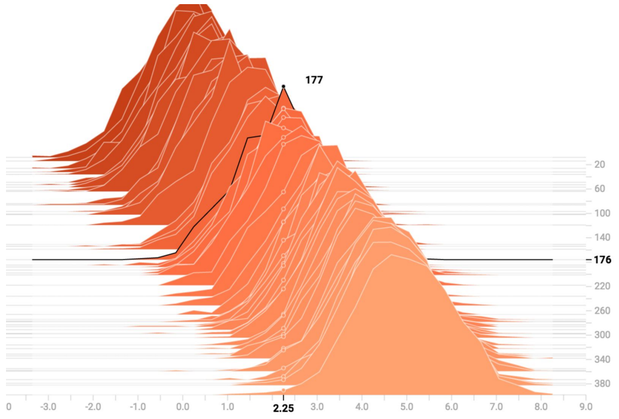
# Images and Audio have their own (non-scalar) summary ops



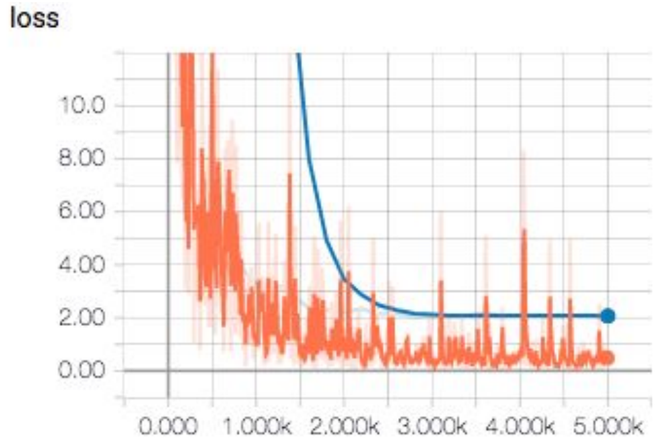
# TensorBoard has a suite of visualization tools to explore and explain your model and results




Graph Explorer




Histogram Dashboard




Scalar Dashboard

Many more including Audio, Image and Text Dashboards ...

# Real World ML Models

| Problem | Solution |
| --- | --- |
| Out of memory data | Use the Dataset API |
| Distribution | Use `train_and_evaluate` |
| Need to evaluate during training | Use `train_and_evaluate` + TensorBoard |
| Deployments that scale | Use serving input function |

# Recap with all the code

```
run_config =
tf.estimator.RunConfig(model_dir=output_dir, ...)

estimator =
tf.estimator.LinearRegressor(featcols, config=run_config)

train_spec =
tf.estimator.TrainSpec(input_fn=train_input_fn, max_steps=1000)

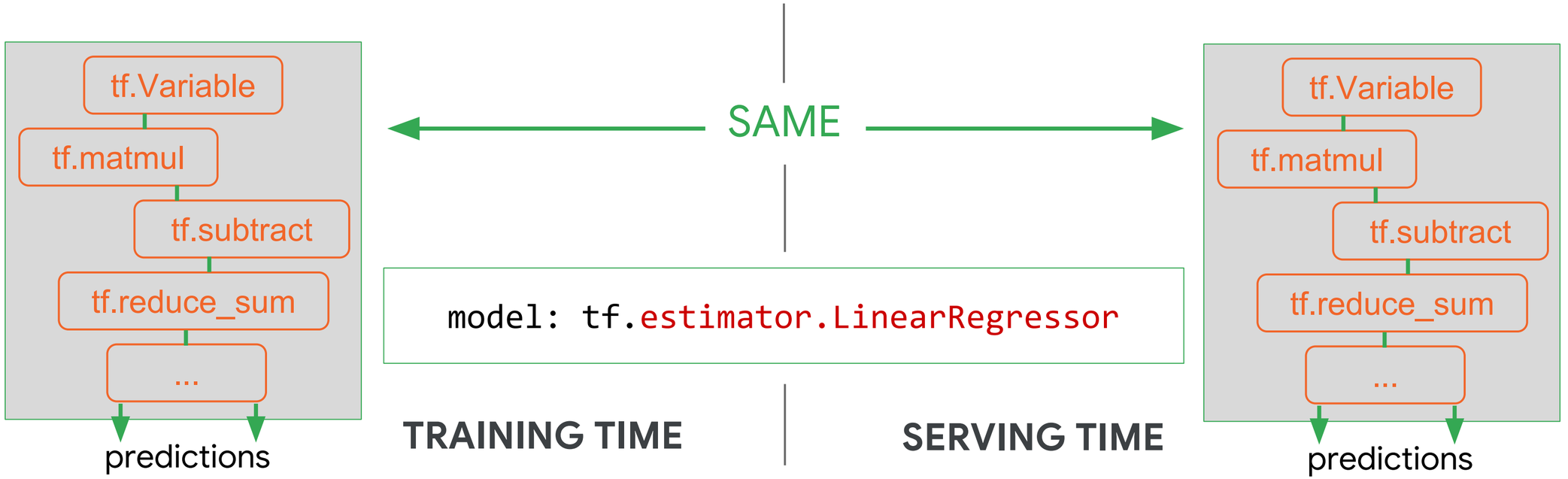
export_latest =
tf.estimator.LatestExporter(serving_input_receiver_fn=serving_input_fn)

eval_spec =
tf.estimator.EvalSpec(input_fn=eval_input_fn, exporters=export_latest)

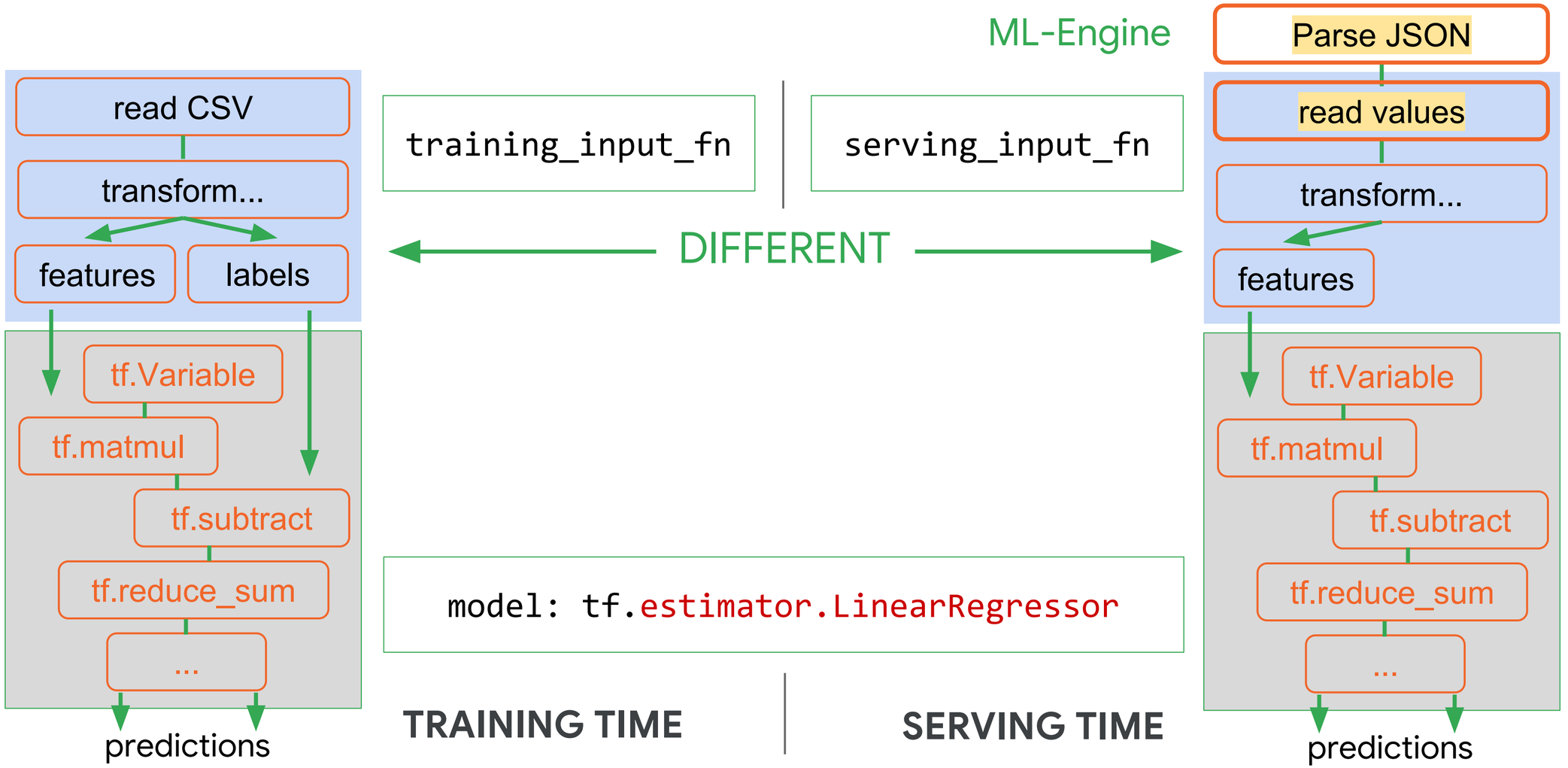

tf.estimator.train_and_evaluate(estimator, train_spec, eval_spec)
```

Serving and training-time inputs are often very different

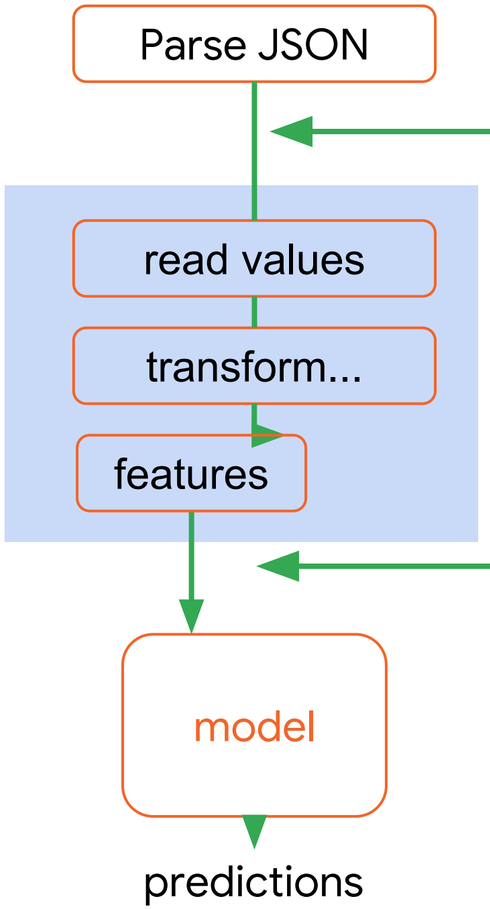
# Serving and training-time inputs are often very different



# Serving and training-time inputs are often very different



# Serving input function transforms from parsed JSON data to the data your model expects

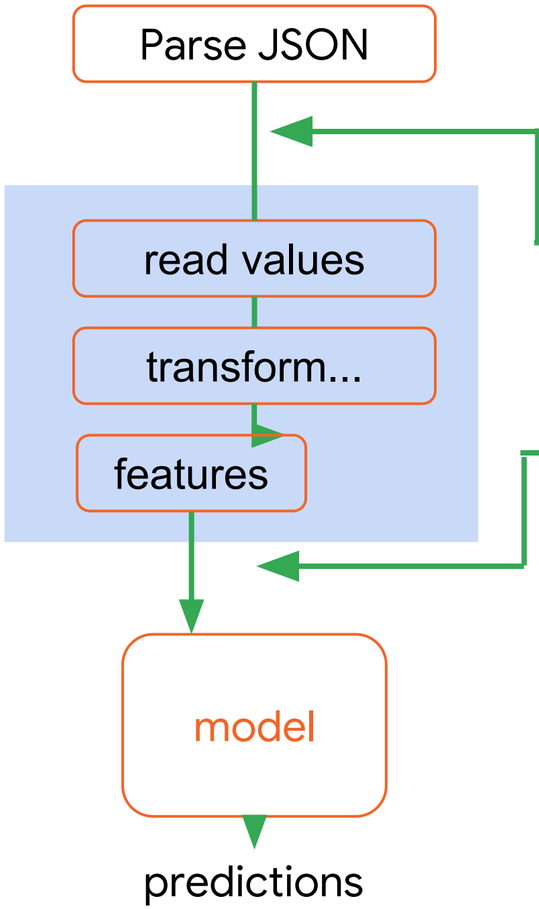



Batch size

```
def serving_input_fn():
    json = { 'sq_footage' : tf.placeholder(tf.int32, [None]),
             'prop_type'  : tf.placeholder(tf.string, [None])
           }
    # ... transformations ...
    features = { 'sq_footage': json['sq_footage'],
                 'type': json['prop_type'],
               }
    return tf.estimator.export.ServingInputReceiver(features,
                                                    json)


exp = tf.estimator.LatestExporter("pricing",
serving_input_fn)
eval_spec = tf.estimator.EvalSpec(exporters=exp, ...)
```

# Serving input function transforms from parsed JSON data to the data your model expects

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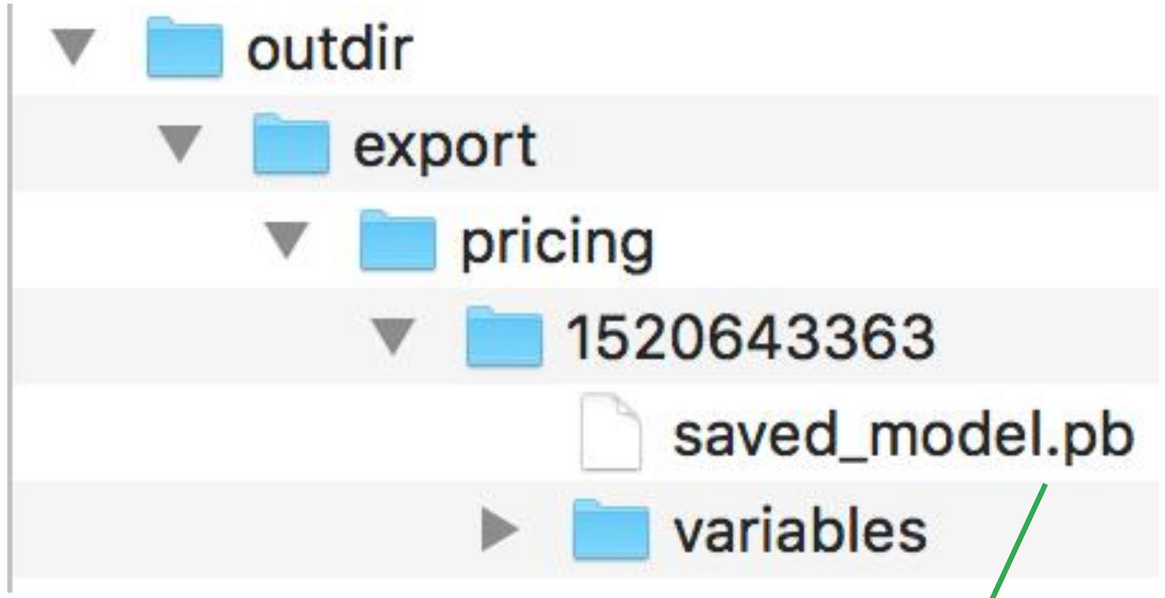
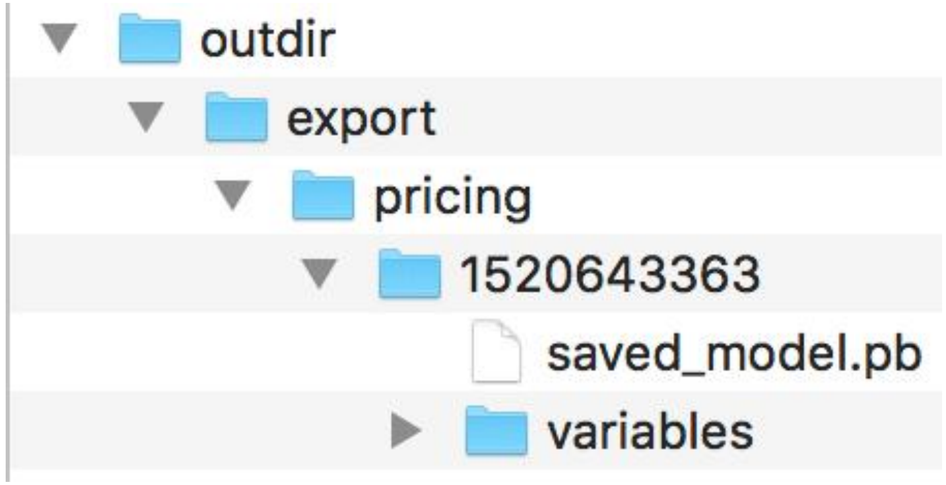
# The exported model is ready to deploy




One click deploy to ML Engine

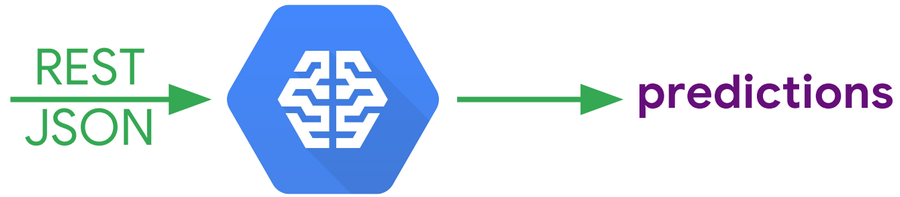
# The exported model is ready to deploy




```
gcloud ml-engine predict
--model <model_name>
--json-instances data.json
```

Online predictions :

```
{"instances":[
 {"sq_footage": 1520, "prop_type": "apt"},
 {"sq_footage": 1520, "prop_type": "house"}
]}
```



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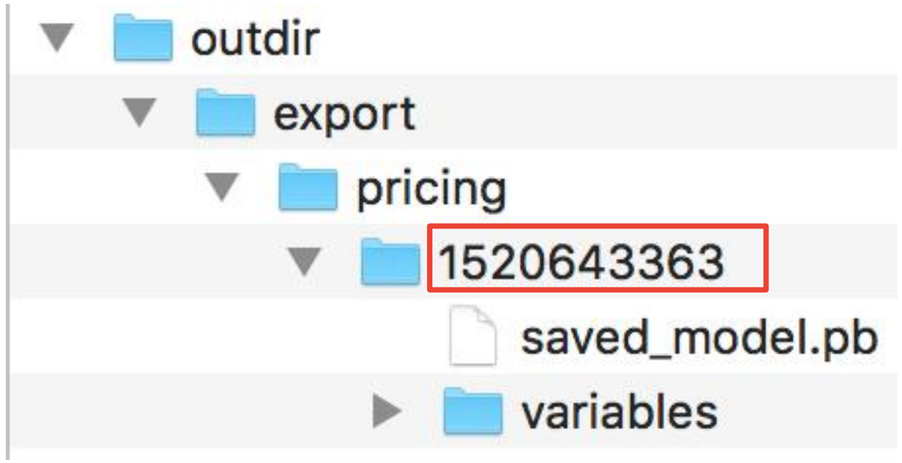


To test locally :

```
{"sq_footage": 1520, "prop_type": "apt"},
{"sq_footage": 1520, "prop_type": "house"}
```

model

```
gcloud ml-engine local predict \
   --model-dir outdir/export/pricing/1520643363 \
   --json-instances test_jsons.txt
```

# Example serving input function that decodes JPEGs

```
def serving_input_fn():
    json = {'jpeg_bytes': tf.placeholder(tf.string, [None])}

    def decode(jpeg):
        pixels = tf.image.decode_jpeg(jpeg, channels=3)
        return pixels

    pics = tf.map_fn(decode, json['jpeg_bytes'], dtype=tf.uint8)

    features = {'pics': pics}
    return tf.estimator.export.ServingInputReceiver(features, json)
```

Output shape:
[batch, width, height, 3]

# Example serving input function that decodes JPEGs

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def serving_input_fn():
    json = {'jpeg_bytes': tf.placeholder(tf.string, [None])}

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    return tf.estimator.export.ServingInputReceiver(features, json)
```

Output shape:
[batch, width, height, 3]

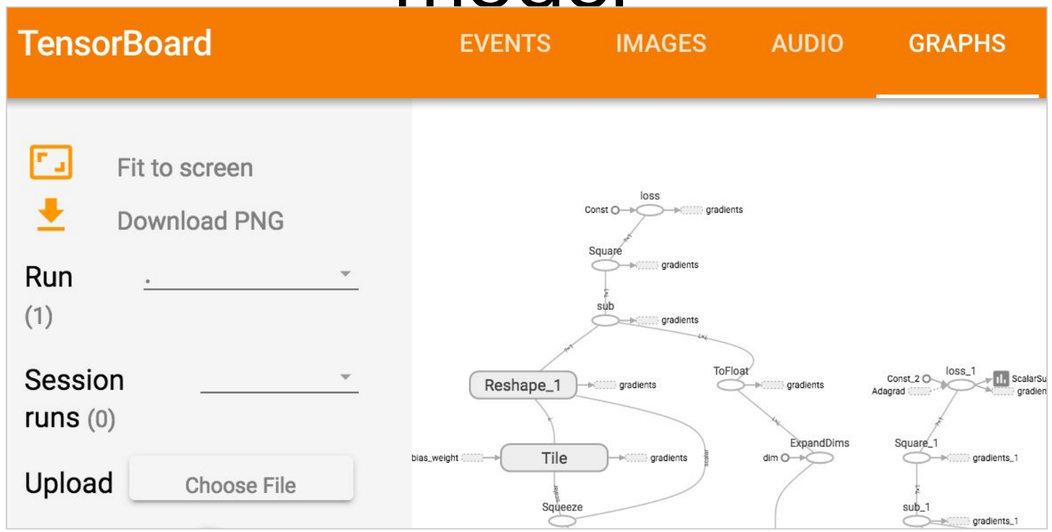
# Example serving input function that decodes JPEGs

JSON

```
{"jpeg_bytes":{"b64":"/9j/4DAwQDBAgEBAgQCwkLEBAQEBAQEQEB...”}}
```

Base 64: special syntax _bytes and b64

# Lab: Implementing a distributed TensorFlow model




- Use train_and_evaluate
- Monitor training using TensorBoard

| | Problem | Solution |
|---|---|---|
| ✓ | Out of memory data | Use the Dataset API |
| ✓ | Distribution | Use `train_and_evaluate` |
| ✓ | Need to evaluate during training | Use `train_and_evaluate` + TensorBoard |
| ✓ | Deployments that scale | Use serving input function |

cloud.google.com