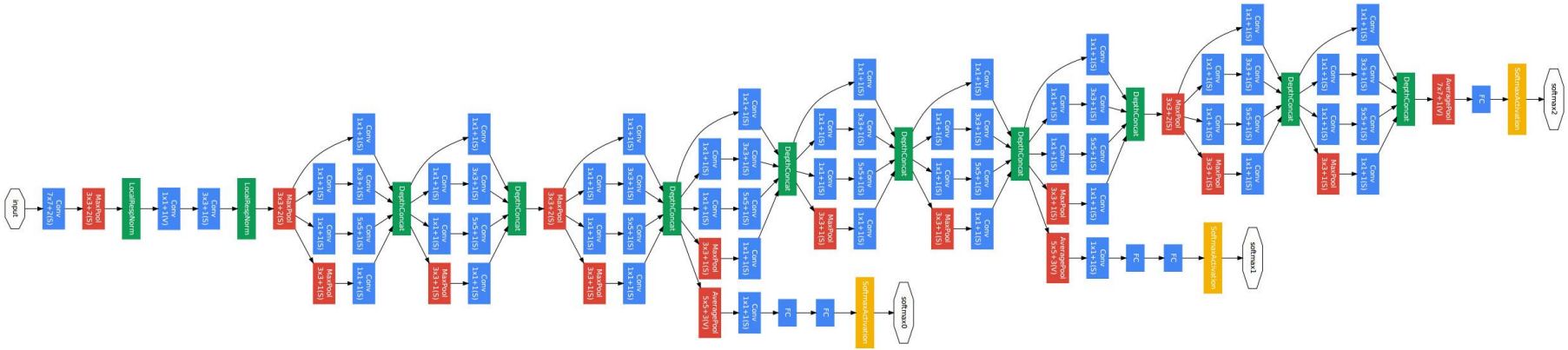
A multidimensional array.

A graph of operations.

Machine learning gets complex quickly

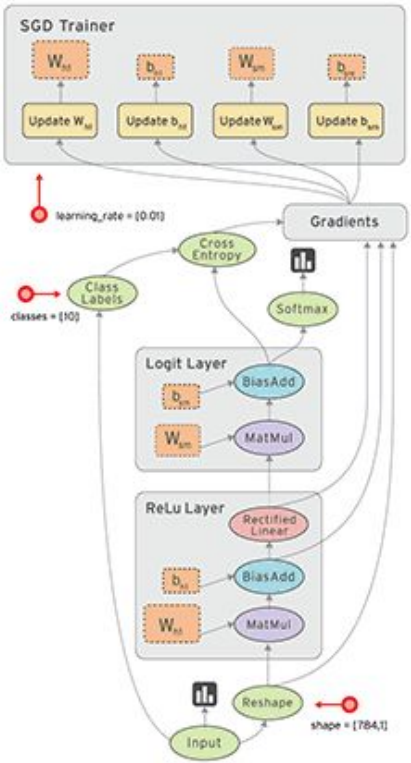


Modeling complexity

The TensorFlow Graph

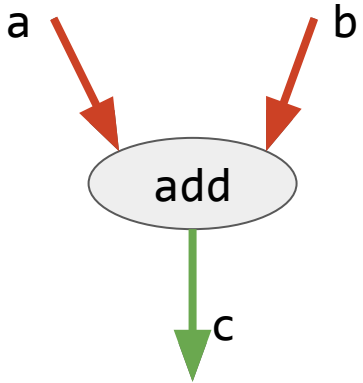
Computation is defined as a graph

- Graph is defined in high-level language (Python)
- Graph is compiled and optimized
- Graph is executed (in parts or fully) on available low level devices (CPU, GPU, TPU)
- Nodes represent computations and state
- Data (tensors) flow along edges

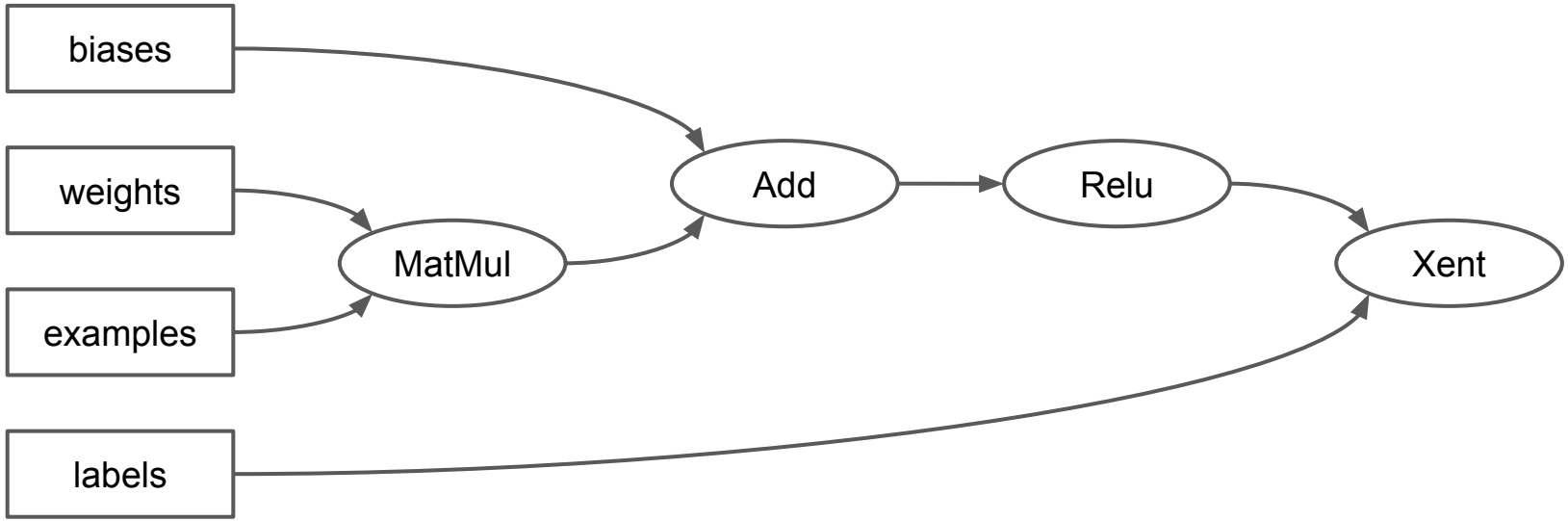


Build a graph; then run it.

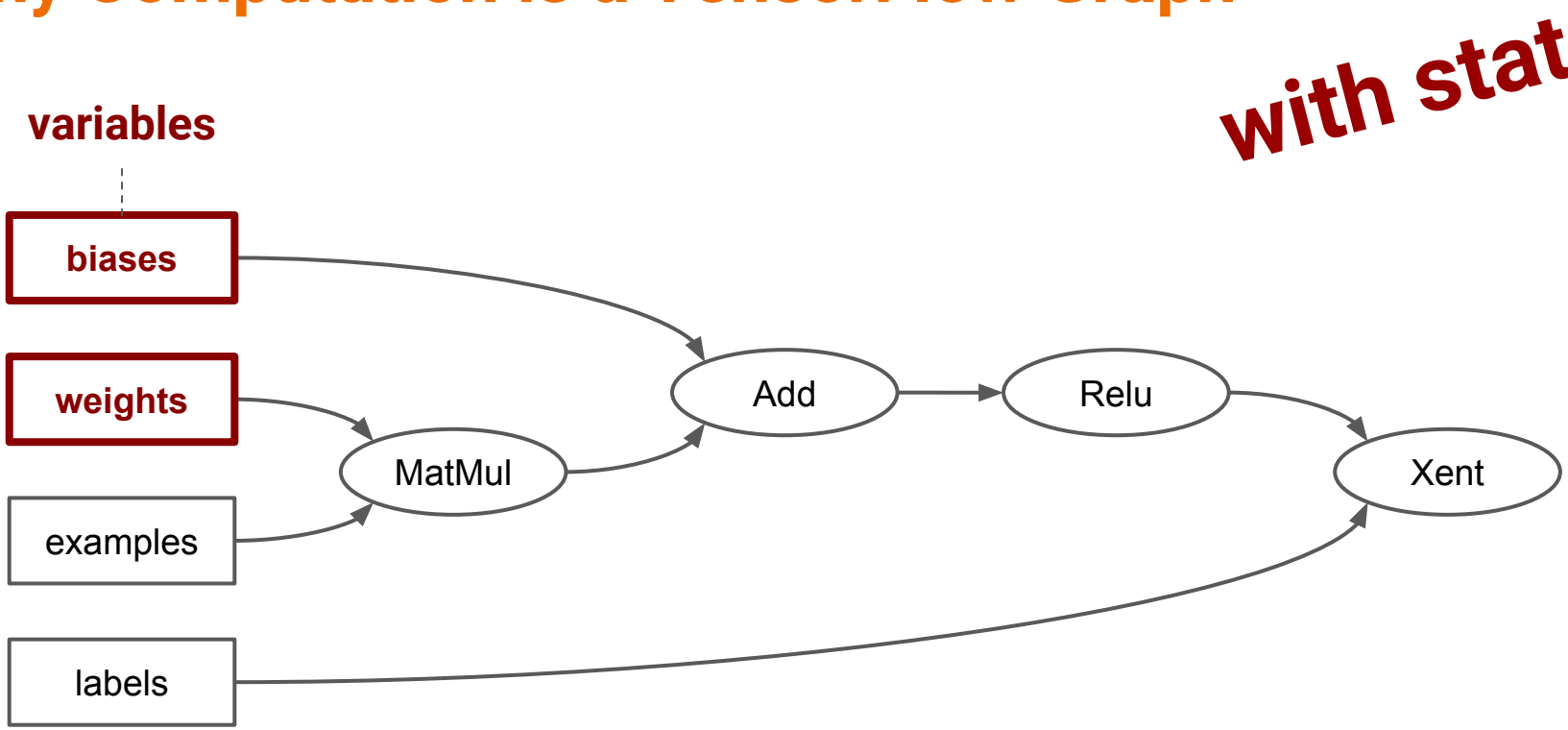
```
...
c = tf.add(a, b)


...

session = tf.Session()
value_of_c = session.run(c, {a=1, b=2})
```



Any Computation is a TensorFlow Graph



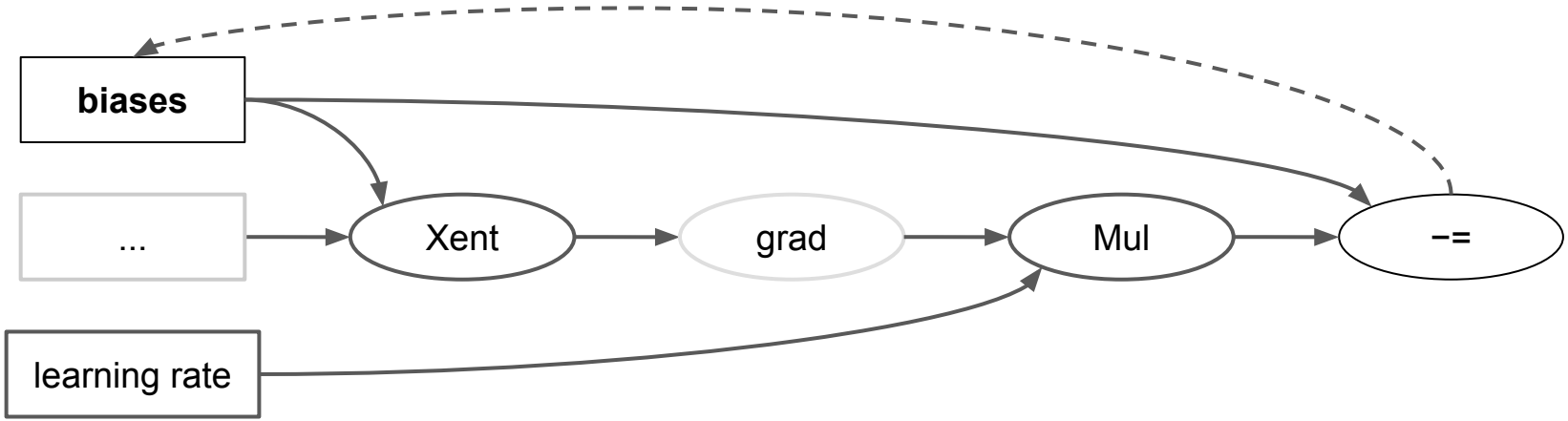
Any Computation is a TensorFlow Graph



Any Computation is a TensorFlow Graph

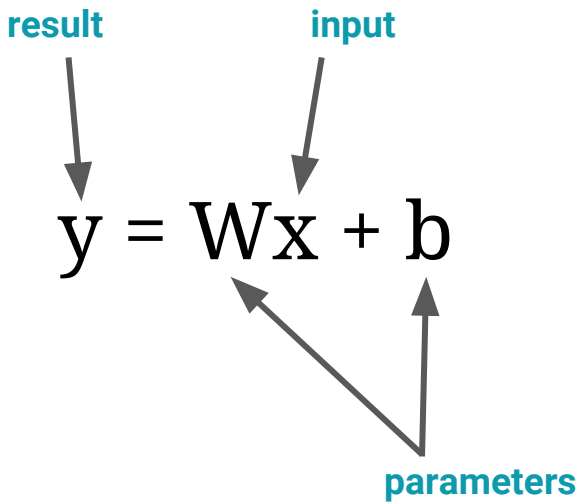
Simple gradient descent:

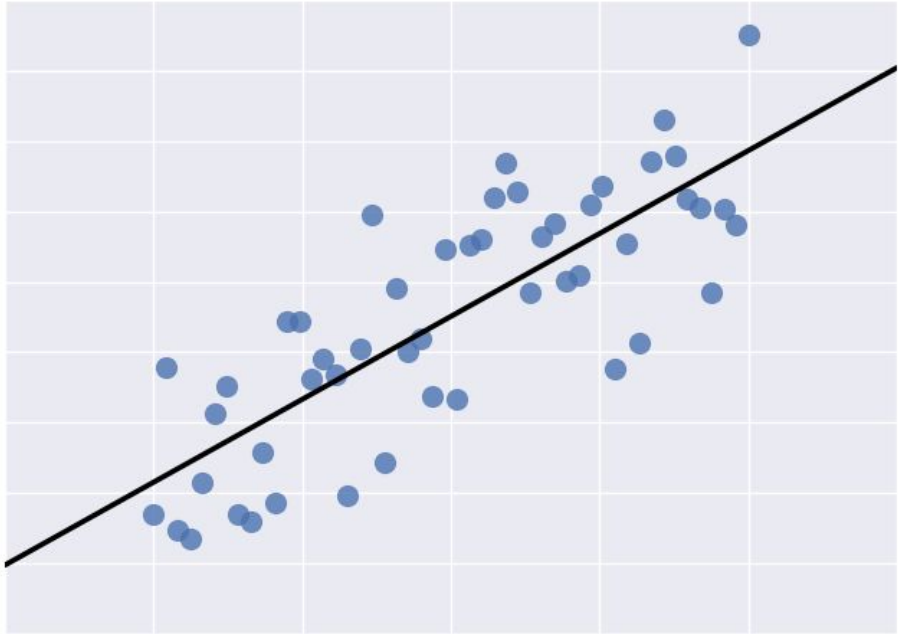
with state



Linear Regression

Linear Regression





What are we trying to do?

Mystery equation: `y = 0.1 * x + 0.3 + noise`

Model: `y = W * x + b`

Objective: Given enough (`x`, `y`) value samples, figure out the value of `W` and `b`.

y = Wx + b in TensorFlow

```
import tensorflow as tf
```

A TensorFlow graph consists of the following parts which will be detailed below:

1.Placeholder variables used to change the input to the graph.

2.Model variables that are going to be optimized so as to make the model perform better.

3The model which is essentially just a mathematical function that calculates some output given the input in the placeholder variables and the model variables.

4.A cost measure that can be used to guide the optimization of the variables.

5.An optimization method which updates the variables of the model.

y = Wx + b in TensorFlow

```
import tensorflow as tf

x = tf.placeholder(shape=[None],
                   dtype=tf.float32, name="x")
```

Placeholder variables serve as the input to the graph that we may change each time we execute the graph.

y = Wx + b in TensorFlow

```
import tensorflow as tf

x = tf.placeholder(shape=[None],
                   dtype=tf.float32, name=”x”)

W = tf.get_variable(shape=[], name=”W”)
```

Apart from the placeholder variables that were defined above and which serve as feeding input data into the model, there are also some model variables that must be changed by TensorFlow so as to make the model perform better on the training data.

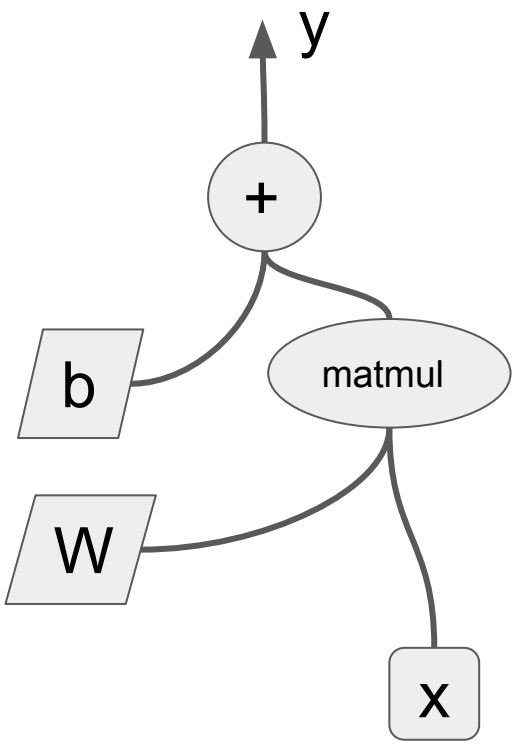
y = Wx + b in TensorFlow

```
import tensorflow as tf

x = tf.placeholder(shape=[None],
                   dtype=tf.float32, name=”x”)

W = tf.get_variable(shape=[], name=”W”)

b = tf.get_variable(shape=[], name=”b”)
```

Text

y = Wx + b in TensorFlow

```
import tensorflow as tf

x = tf.placeholder(shape=[None],
                   dtype=tf.float32, name="x")

W = tf.get_variable(shape=[], name="W")

b = tf.get_variable(shape=[], name="b")

y = W * x + b
```



Variables Must be Initialized

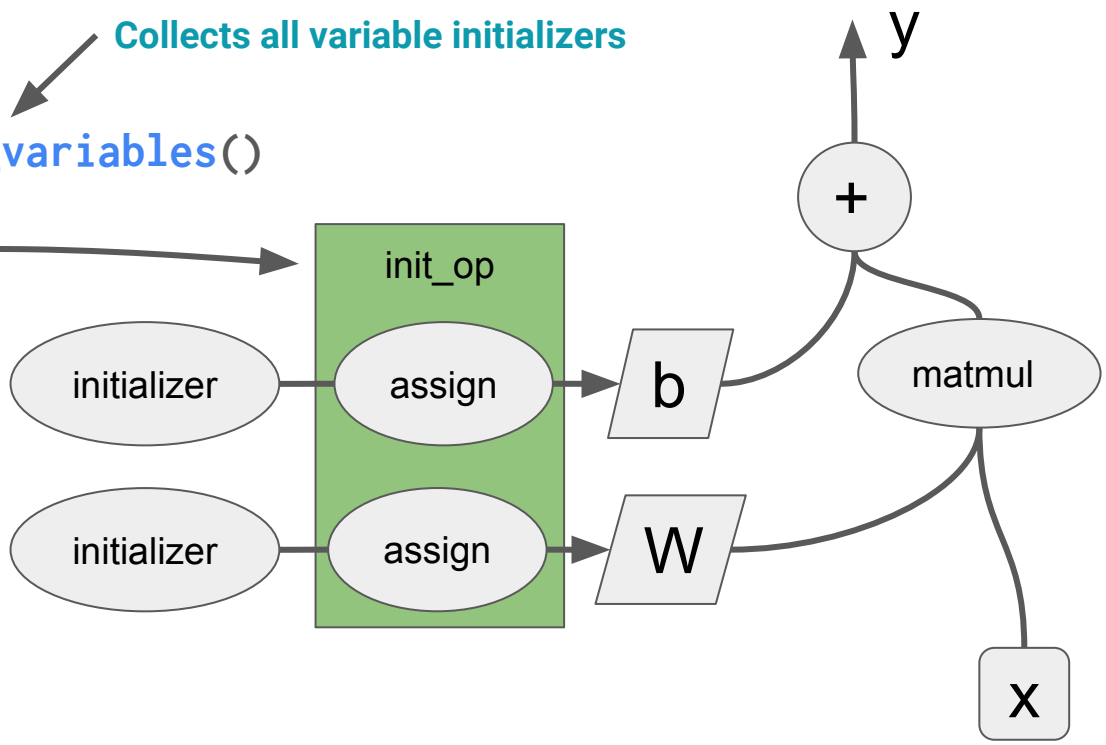
Collects all variable initializers

```
init_op = tf.initialize_all_variables()
```

Makes an execution environment

```
sess = tf.Session()

sess.run(init_op)
```

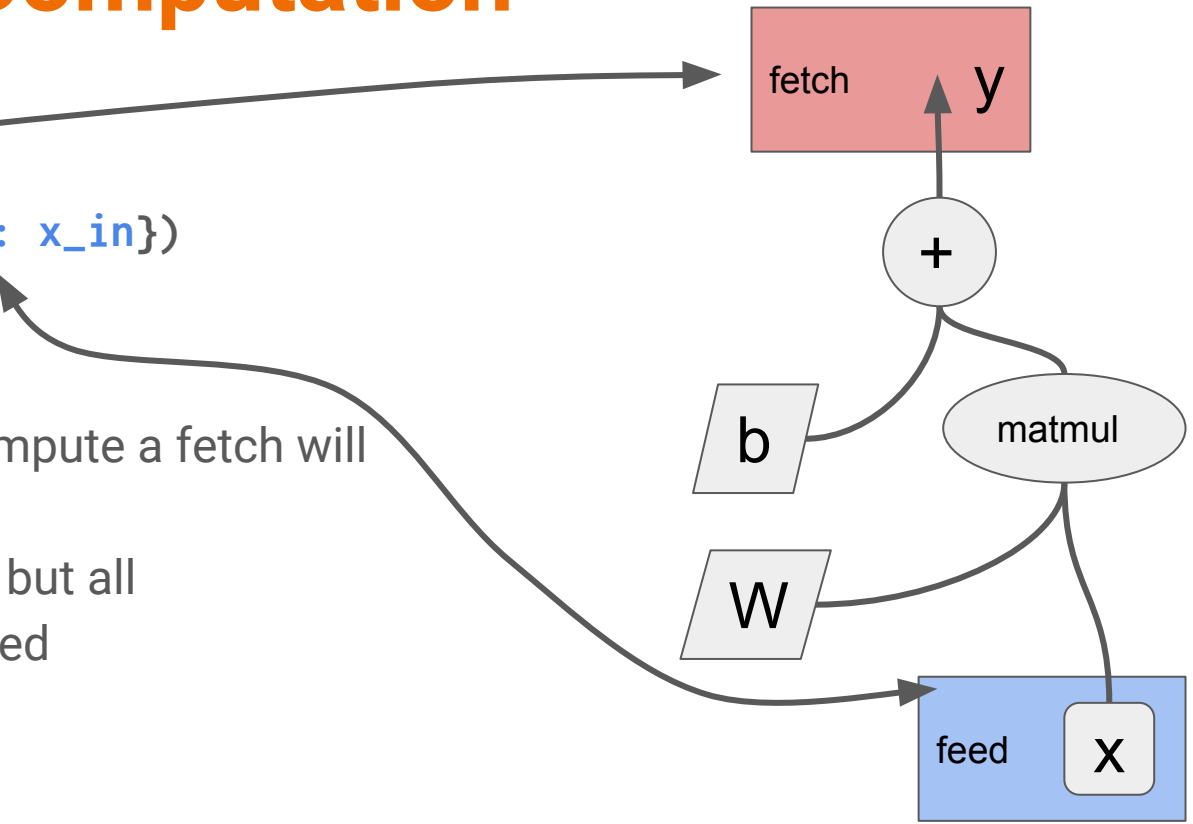
Actually initialize the variables



Running the Computation

```
x_in = 3

sess.run(y, feed_dict={x: x_in})
```

- Only what's used to compute a fetch will be evaluated
- All Tensors can be fed, but all placeholders must be fed



Putting it all together

```
import tensorflow as tf
x = tf.placeholder(shape=[None],
                   dtype=tf.float32,
                   name='x')
W = tf.get_variable(shape=[], name='W')
b = tf.get_variable(shape=[], name='b')
y = W * x + b

with tf.Session() as sess:

  sess.run(tf.initialize_all_variables())

  print(sess.run(y, feed_dict={x: x_in}))
```

Build the graph

Prepare execution environment

Initialize variables

Run the computation (usually often)

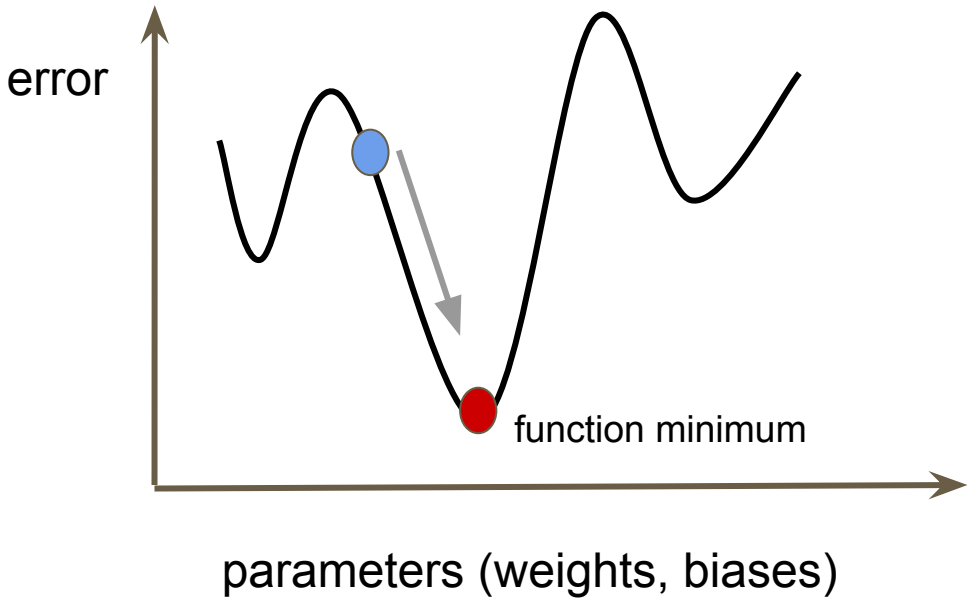
Define a Loss

Given x, y compute a loss, for instance:

$$L = (y - y_{label})^2$$

```
# create an operation that calculates loss.
loss = tf.reduce_mean(tf.square(y - y_data))
```

Minimize loss: optimizers




```
tf.train.AdadeltaOptimizer

tf.train.AdagradOptimizer

tf.train.AdagradDAOptimizer

tf.train.AdamOptimizer

…
```

Train

Feed (x, y_{label}) pairs and adjust W and b to decrease the loss.

$$W \leftarrow W - \eta \left(dL/dW \right)$$

$$b \leftarrow b - \eta \left(dL/db \right)$$

TensorFlow computes gradients automatically

```
# Create an optimizer

optimizer = tf.train.GradientDescentOptimizer(0.5)

# Create an operation that minimizes loss.

train = optimizer.minimize(loss)
```

Learning rate

Putting it all together

```
loss = tf.reduce_mean(tf.square(y - y_label))
optimizer = tf.train.GradientDescentOptimizer(0.5)
train = optimizer.minimize(loss)
with tf.Session() as sess:
  sess.run(tf.initialize_all_variables())
  for i in range(1000):
    sess.run(train, feed_dict={x: x_in[i],
                               y_label: y_in[i]})
```

Define a loss

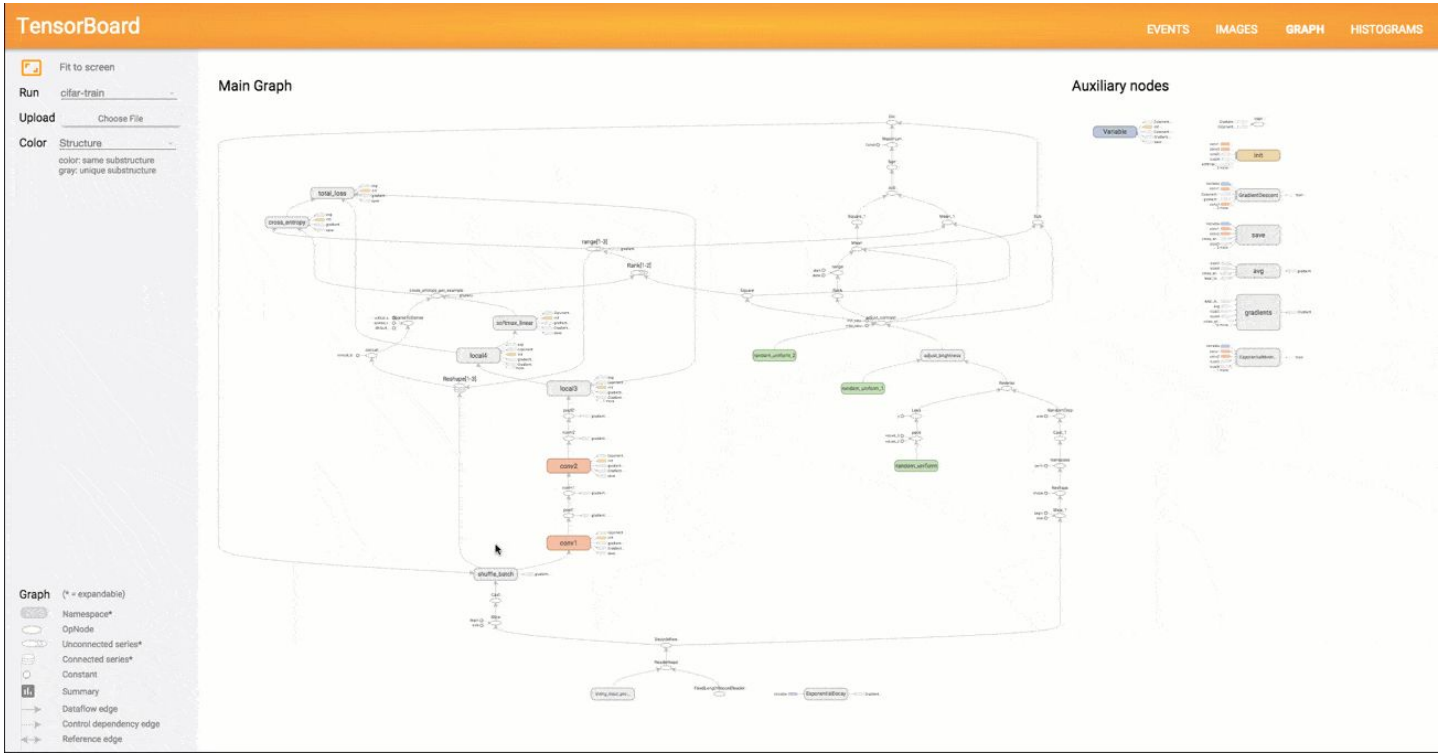
Create an optimizer

Op to minimize the loss

Initialize variables

Iteratively run the training op

TensorBoard



Deep Neural Network

IS THIS A

CAT or DOG?

CAT DOG

OUTPUT LAYER

ACTIVATED NEURONS

INPUT LAYER

DEEP *neural* NETWORK

Remember linear regression?

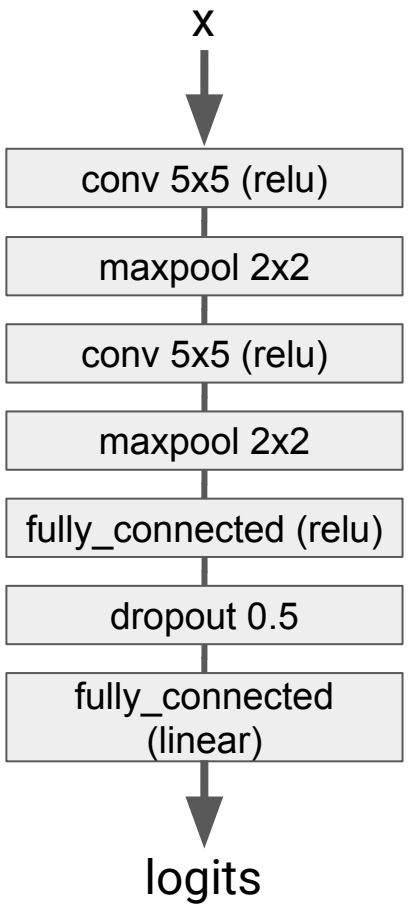
```
import tensorflow as tf
x = tf.placeholder(shape=[None],
                   dtype=tf.float32,
                   name='x')
W = tf.get_variable(shape=[], name='W')
b = tf.get_variable(shape=[], name='b')
y = W * x + b
```

Build the graph

```
loss = tf.reduce_mean(tf.square(y - y_label))

optimizer = tf.train.GradientDescentOptimizer(0.5)

train = optimizer.minimize(loss)

...
```

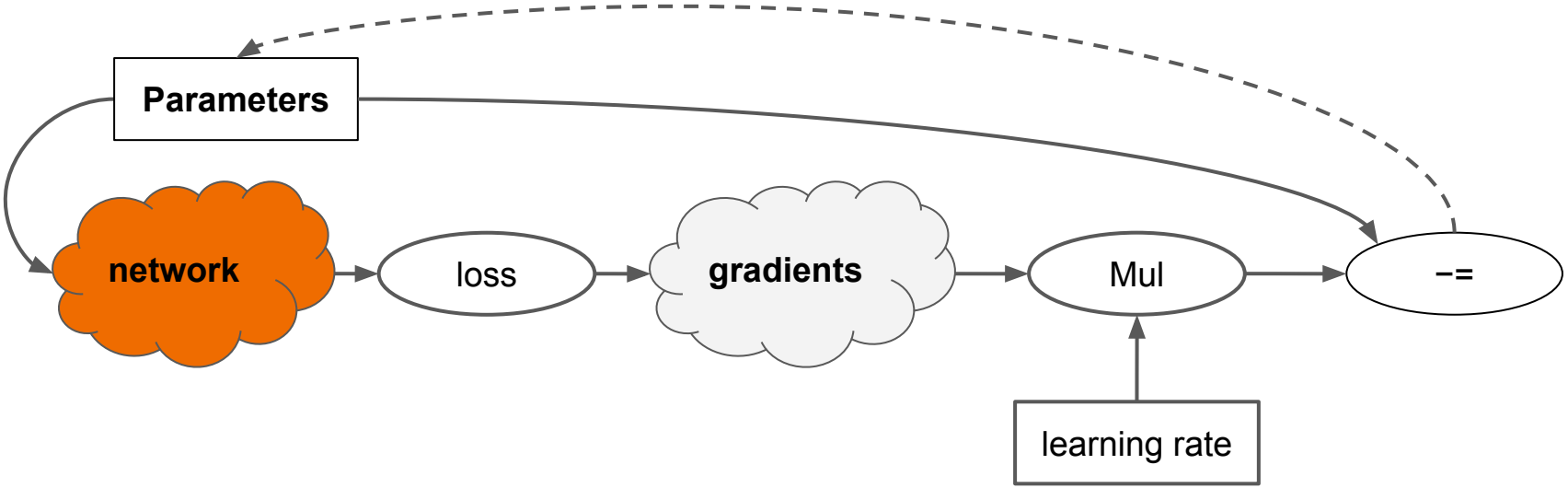
Convolutional DNN

```
x = tf.contrib.layers.conv2d(x, kernel_size=[5,5], ...)

x = tf.contrib.layers.max_pool2d(x, kernel_size=[2,2], ...)

x = tf.contrib.layers.conv2d(x, kernel_size=[5,5], ...)

x = tf.contrib.layers.max_pool2d(x, kernel_size=[2,2], ...)

x = tf.contrib.layers.fully_connected(x, activation_fn=tf.nn.relu)

x = tf.contrib.layers.dropout(x, 0.5)

logits = tf.config.layers.linear(x)
```



https://github.com/martinwicke/tensorflow-tutorial/blob/master/2_mnist.ipynb

Defining Complex Networks



Tutorials & Courses

Tutorials on tensorflow.org:

Image recognition: https://www.tensorflow.org/tutorials/image_recognition

Word embeddings: https://www.tensorflow.org/versions/word2vec

Language Modeling: https://www.tensorflow.org/tutorials/recurrent

Translation: https://www.tensorflow.org/versions/seq2seq

Deep Dream:
https://tensorflow.org/code/tensorflow/examples/tutorials/deepdream/deepdream.ipynb

Extras

Inception

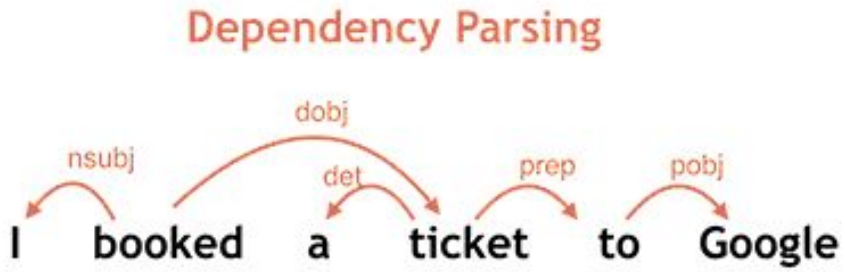
An Alaskan Malamute (left) and a Siberian Husky (right). Images from Wikipedia.

https://research.googleblog.com/2016/08/improving-inception-and-image.html

Show and Tell

https://research.googleblog.com/2016/09/show-and-tell-image-captioning-open.html

Parsey McParseface



https://research.googleblog.com/2016/05/announcing-syntaxnet-worlds-most.html

Text Summarization

Original text

- *Alice and Bob took the train to visit the zoo. They saw a **baby giraffe, a lion, and a flock of colorful tropical birds**.*

Abstractive summary

- *Alice and Bob visited the zoo and saw **animals and birds**.*

https://research.googleblog.com/2016/08/text-summarization-with-tensorflow.html

Mobile TensorFlow

TensorFlow was designed with mobile and embedded platforms in mind. We have sample code and build support you can try now for these platforms:

Android

iOS

Raspberry Pi

Many applications can benefit from on-device processing. Google Translate's instant visual translation is a great example. By running its processing locally, users get an incredibly responsive and interactive experience.

Mobile TensorFlow makes sense when there is a poor or missing network connection, or where sending continuous data to a server would be too expensive. We are working to help developers make lean mobile apps using TensorFlow, both by continuing to reduce the code footprint, and supporting quantization and lower precision arithmetic that reduce model size.

Claude Monet - Bouquet of Sunflowers
Images from the Metropolitan Museum of Art (with permission)

Image by @random_forests