CS 0327

Pattern Recognition and Deep Learning

Lecture 6 Tensorflow Ops

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Agenda

Basic operations

Tensor types

Project speed dating

Placeholders and feeding inputs

Lazy loading

Fun with TensorBoard!!!

Your first TensorFlow program

```
import tensorflow as tf

a = tf.constant(2)

b = tf.constant(3)

x = tf.add(a, b)

with tf.Session() as sess:

    print sess.run(x)
```

Visualize it with TensorBoard

```
import tensorflow as tf

a = tf.constant(2)

b = tf.constant(3)

x = tf.add(a, b)

with tf.Session() as sess:

    # add this line to use TensorBoard.

    writer = tf.summary.FileWriter('./graphs, sess.graph)

    print sess.run(x)

writer.close() # close the writer when you’re done using it
```

Create the summary writer after graph definition and before running your session

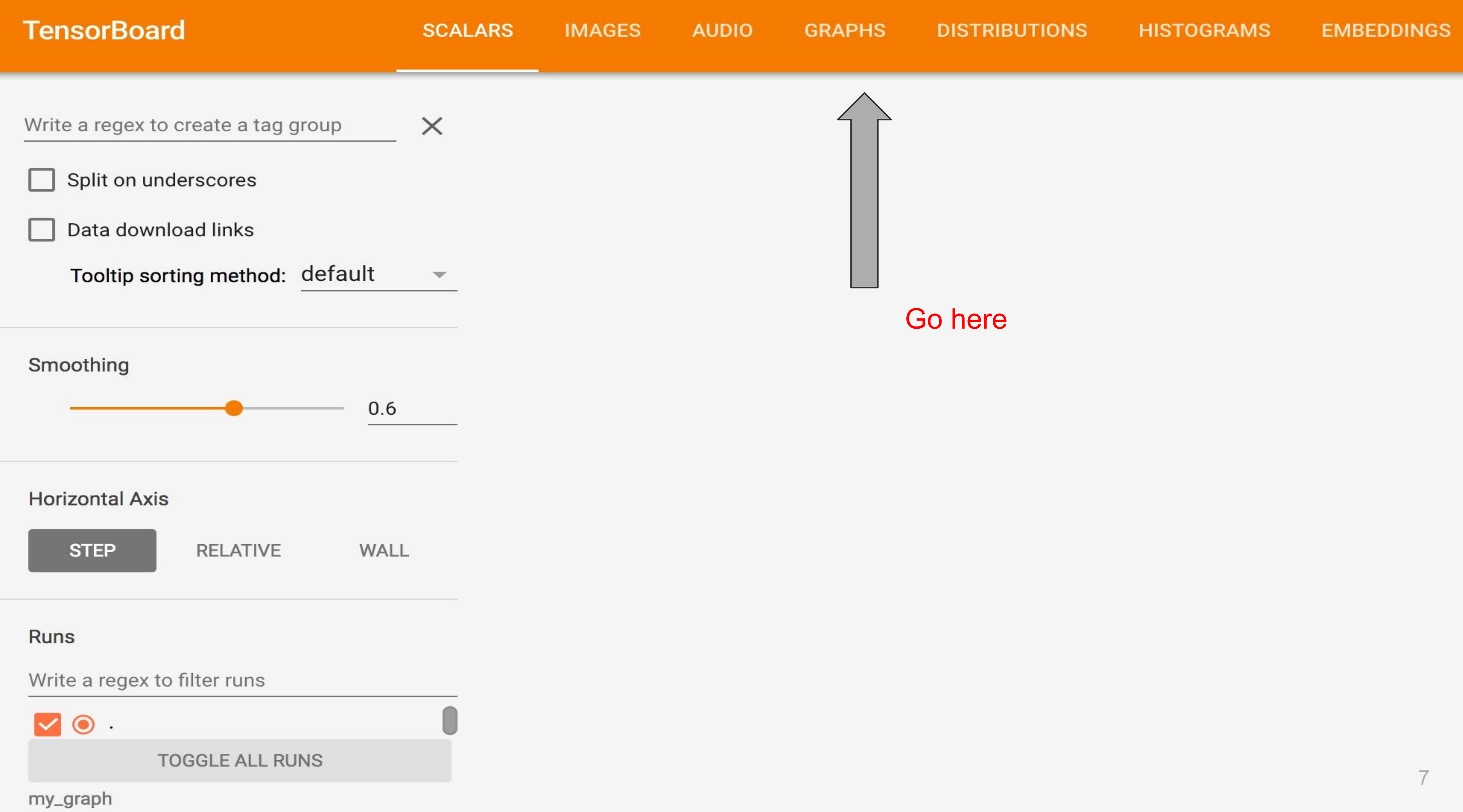
Where you want to keep your event files

Run it

Go to terminal, run:

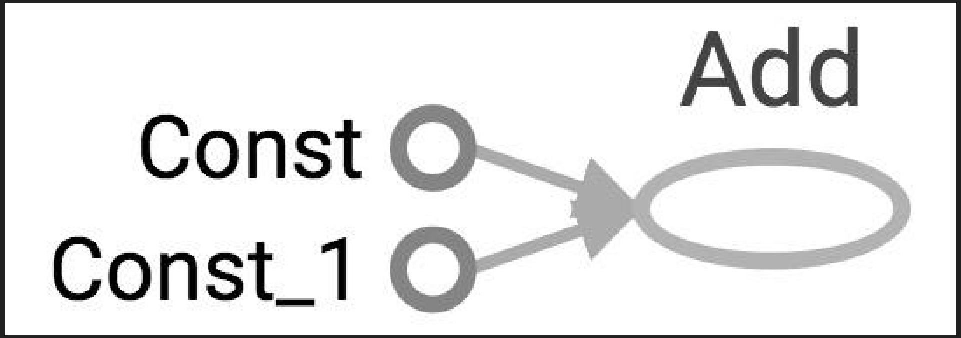
```
$ python [yourprogram].py

$ tensorboard --logdir="./graphs" --port 6006
```

Then open your browser and go to: `http://localhost:6006/`


TensorBoard
SCALARS
IMAGES
AUDIO
GRAPHS
DISTRIBUTIONS
HISTOGRAMS
EMBEDDINGS
Write a regex to create a tag group
Split on underscores
Data download links
Tooltip sorting method: default
Smoothing
0.6
Horizontal Axis
STEP
RELATIVE
WALL
Runs
Write a regex to filter runs
.
TOGGLE ALL RUNS
my_graph
Go here

Visualize it with TensorBoard

```
import tensorflow as tf

a = tf.constant(2)

b = tf.constant(3)

x = tf.add(a, b)

# add this line to use TensorBoard

writer = tf.summary.FileWriter("./graphs", sess.graph)

with tf.Session() as sess:

     print sess.run(x)
```



Visualize it with TensorBoard

```
import tensorflow as tf

a = tf.constant(2)

b = tf.constant(3)

x = tf.add(a, b)

writer = tf.summary.FileWriter("./graphs", sess.graph)

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    print sess.run(x)
```
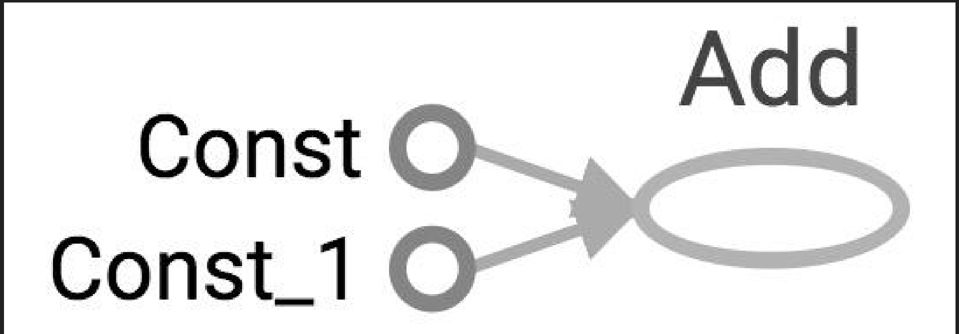
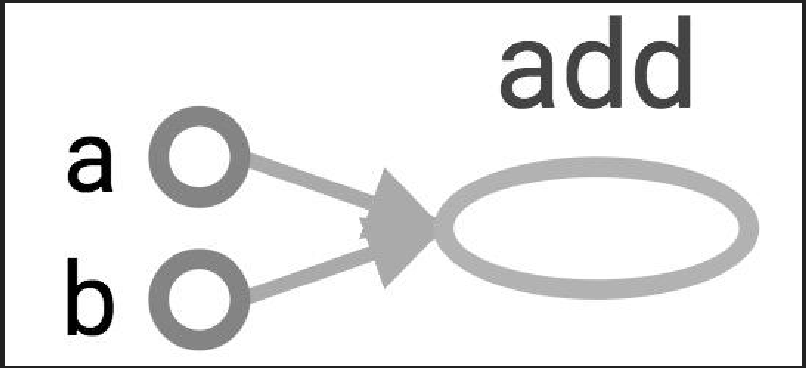



Question:
How to change Const, Const_1 to the names we give the variables?

Explicitly name them

```
import tensorflow as tf

a = tf.constant(2, name="a")

b = tf.constant(3, name="b")

x = tf.add(a, b, name="add")

writer = tf.summary.FileWriter("./graphs", sess.graph)

with tf.Session() as sess:

     print sess.run(x) # >> 5
```

Explicitly name them




```
import tensorflow as tf

a = tf.constant(2, name="a")

b = tf.constant(3, name="b")

x = tf.add(a, b, name="add")

writer = tf.summary.FileWriter("./graphs", sess.graph)

with tf.Session() as sess:

	print sess.run(x) # >> 5
```

Learn to use TensorBoard well and often.
It will help a lot when you build complicated models.

More constants

```
tf.constant(value, dtype=None, shape=None,
    name='Const', verify_shape=False)
```

More constants

```
import tensorflow as tf

a = tf.constant([2, 2], name="a")

b = tf.constant([[0, 1], [2, 3]], name="b")

x = tf.add(a, b, name="add")

y = tf.mul(a, b, name="mul")

with tf.Session() as sess:

      x, y = sess.run([x, y])

      print x, y

# >> [5 8] [6 12]
```

```
tf.constant(value, dtype=None, shape=None, name='Const', verify_shape=False)
```

Similar to how you can create constants in numpy

Tensors filled with a specific value

```
tf.zeros(shape, dtype=tf.float32, name=None)
```

creates a tensor of shape and all elements will be zeros (when ran in session)

Similar to numpy.zeros

```
tf.zeros([2, 3], tf.int32) ==> [[0, 0, 0], [0, 0, 0]]
```

more compact than other constants in the graph def
→ faster startup (esp.in distributed)

Tensors filled with a specific value

```
tf.zeros_like(input_tensor, dtype=None, name=None, optimize=True)
```

creates a tensor of shape and type (unless type is specified) as the input_tensor but all elements are zeros.

Similar to numpy.zeros_like

```
# input_tensor is [0, 1], [2, 3], [4, 5]]

tf.zeros_like(input_tensor) ==> [[0, 0], [0, 0], [0, 0]]
```

Tensors filled with a specific value

Same:

```
tf.ones(shape, dtype=tf.float32, name=None)

tf.ones_like(input_tensor, dtype=None, name=None, optimize=True)
```

Similar to numpy.ones,
numpy.ones_like

Tensors filled with a specific value

```
tf.fill(dims, value, name=None)
```

creates a tensor filled with a scalar value.

In numpy, this takes two step:

1. Create a numpy array a
2. a.fill(value)

```
tf.fill([2, 3], 8) ==> [[8, 8, 8], [8, 8, 8]]
```

Constants as sequences

```
tf.linspace(start, stop, num, name=None) # slightly different from np.linspace

tf.linspace(10.0, 13.0, 4) ==> [10.0 11.0 12.0 13.0]

tf.range(start, limit=None, delta=1, dtype=None, name='range')

# 'start' is 3, 'limit' is 18, 'delta' is 3

tf.range(start, limit, delta) ==> [3, 6, 9, 12, 15]

# 'limit' is 5

tf.range(limit) ==> [0, 1, 2, 3, 4]
```

Tensor objects are not iterable

```
for _ in tf.range(4): # TypeError
```

Randomly Generated Constants

```
tf.random_normal(shape, mean=0.0, stddev=1.0, dtype=tf.float32, seed=None, name=None)

tf.truncated_normal(shape, mean=0.0, stddev=1.0, dtype=tf.float32, seed=None,
name=None)

tf.random_uniform(shape, minval=0, maxval=None, dtype=tf.float32, seed=None,
name=None)

tf.random_shuffle(value, seed=None, name=None)

tf.random_crop(value, size, seed=None, name=None)

tf.multinomial(logits, num_samples, seed=None, name=None)

tf.random_gamma(shape, alpha, beta=None, dtype=tf.float32, seed=None, name=None)
```

Randomly Generated Constants

```
tf.set_random_seed(seed)
```

Operations

Category	Examples
Element-wise mathematical operations	Add, Sub, Mul, Div, Exp, Log, Greater, Less, Equal, ...
Array operations	Concat, Slice, Split, Constant, Rank, Shape, Shuffle, ...
Matrix operations	MatMul, MatrixInverse, MatrixDeterminant, ...
Stateful operations	Variable, Assign, AssignAdd, ...
Neural network building blocks	SoftMax, Sigmoid, ReLU, Convolution2D, MaxPool, ...
Checkpointing operations	Save, Restore
Queue and synchronization operations	Enqueue, Dequeue, MutexAcquire, MutexRelease, ...
Control flow operations	Merge, Switch, Enter, Leave, NextIteration

*Table from “Fundamental of Deep Learning”

Operations

```
a = tf.constant([3, 6])

b = tf.constant([2, 2])

tf.add(a, b) # >> [5 8]

tf.add_n([a, b, b]) # >> [7 10]. Equivalent to a + b + b

tf.mul(a, b) # >> [6 12] because mul is element wise

tf.matmul(a, b) # >> ValueError

tf.matmul(tf.reshape(a, [1, 2]), tf.reshape(b, [2, 1])) # >> [[18]]

tf.div(a, b) # >> [1 3]

tf.mod(a, b) # >> [1 0]
```

Pretty standard, quite similar to numpy.
See TensorFlow documentation

TensorFlow Data Types

TensorFlow takes Python natives types: boolean, numeric (int, float), strings

0-d tensor, or "scalar"

```
t_0 = 19
tf.zeros_like(t_0) # ==> 0
tf.ones_like(t_0) # ==> 1
```

TensorFlow Data Types

TensorFlow takes Python natives types: boolean, numeric (int, float), strings

0-d tensor, or "scalar"

```
t_0 = 19
tf.zeros_like(t_0) # ==> 0
tf.ones_like(t_0) # ==> 1
```

1-d tensor, or "vector"

```
t_1 = ['apple', 'peach', 'banana']
tf.zeros_like(t_1) # ==> ???????
```

TensorFlow Data Types

TensorFlow takes Python natives types: boolean, numeric (int, float), strings

0-d tensor, or "scalar"

```
t_0 = 19
tf.zeros_like(t_0) # ==> 0
tf.ones_like(t_0) # ==> 1
```

1-d tensor, or "vector"

```
t_1 = ['apple', 'peach', 'banana']
tf.zeros_like(t_1) # ==> ['' '' '']
tf.ones_like(t_1) # ==> ????????
```

TensorFlow Data Types

TensorFlow takes Python natives types: boolean, numeric (int, float), strings

0-d tensor, or "scalar"

```
t_0 = 19
tf.zeros_like(t_0) # ==> 0
tf.ones_like(t_0) # ==> 1
```

1-d tensor, or "vector"

```
t_1 = ['apple', 'peach', 'banana']
tf.zeros_like(t_1) # ==> ['' '' '']
tf.ones_like(t_1) # ==> TypeError: Expected string, got 1 of type 'int' instead.
```

2x2 tensor, or "matrix"

```
t_2 = [[True, False, False],
       [False, False, True],
       [False, True, False]]
tf.zeros_like(t_2) # ==> 2x2 tensor, all elements are False
tf.ones_like(t_2) # ==> 2x2 tensor, all elements are True
```

TensorFlow Data Types

Data type	Python type	Description
DT_FLOAT	tf.float32	32 bits floating point.
DT_DOUBLE	tf.float64	64 bits floating point.
DT_INT8	tf.int8	8 bits signed integer.
DT_INT16	tf.int16	16 bits signed integer.
DT_INT32	tf.int32	32 bits signed integer.
DT_INT64	tf.int64	64 bits signed integer.
DT_UINT8	tf.uint8	8 bits unsigned integer.
DT_UINT16	tf.uint16	16 bits unsigned integer.
DT_STRING	tf.string	Variable length byte arrays. Each element of a Tensor is a byte array.
DT_BOOL	tf.bool	Boolean.
DT_COMPLEX64	tf.complex64	Complex number made of two 32 bits floating points: real and imaginary parts.
DT_COMPLEX128	tf.complex128	Complex number made of two 64 bits floating points: real and imaginary parts.
DT_QINT8	tf.qint8	8 bits signed integer used in quantized Ops.
DT_QINT32	tf.qint32	32 bits signed integer used in quantized Ops.
DT_QUINT8	tf.quint8	8 bits unsigned integer used in quantized Ops.

TF vs NP Data Types

TensorFlow integrates seamlessly with NumPy

```
tf.int32 == np.int32 # True
```

Can pass numpy types to TensorFlow ops

```
tf.ones([2, 2], np.float32) # ⇒ [[1.0 1.0], [1.0 1.0]]
```

For **`tf.Session.run(fetches)`**:

If the requested fetch is a Tensor , then the output of will be a NumPy ndarray.

TensorFlow Data Types

Do not use Python native types for tensors because TensorFlow has to infer Python type

TensorFlow Data Types

Beware when using NumPy arrays because NumPy and TensorFlow might become not so compatible in the future!

What’s wrong with constants?

What’s wrong with constants?

Constants are stored in the graph definition

Print out the graph def

```
import tensorflow as tf

my_const = tf.constant([1.0, 2.0], name="my_const")

with tf.Session() as sess:

     print sess.graph.as_graph_def()

# you will see value of my_const stored in the graph’s definition
```

This makes loading graphs expensive when constants are big

Only use constants for primitive types. Use variables or readers for more data that requires more memory

Variables?

```
# create variable a with scalar value
a = tf.Variable(2, name="scalar")

# create variable b as a vector
b = tf.Variable([2, 3], name="vector")

# create variable c as a 2x2 matrix
c = tf.Variable([[0, 1], [2, 3]], name="matrix")

# create variable W as 784 x 10 tensor, filled with zeros
W = tf.Variable(tf.zeros([784,10]))
```

Variables?

```
# create variable a with scalar value
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c = tf.Variable([[0, 1], [2, 3]], name="matrix")

# create variable W as 784 x 10 tensor, filled with zeros
W = tf.Variable(tf.zeros([784,10]))
```

Why tf.constant but tf.Variable and not tf.variable?

How about variables?

```
# create variable a with scalar value
a = tf.Variable(2, name="scalar")

# create variable b as a vector
b = tf.Variable([2, 3], name="vector")

# create variable c as a 2x2 matrix
c = tf.Variable([[0, 1], [2, 3]], name="matrix")

# create variable W as 784 x 10 tensor, filled with zeros
W = tf.Variable(tf.zeros([784,10]))
```

tf.Variable is a class, but tf.constant is an op

How about variables?

```
# create variable a with scalar value
a = tf.Variable(2, name="scalar")

# create variable b as a vector
b = tf.Variable([2, 3], name="vector")

# create variable c as a 2x2 matrix
c = tf.Variable([[0, 1], [2, 3]], name="matrix")

# create variable W as 784 x 10 tensor, filled with zeros
W = tf.Variable(tf.zeros([784,10]))
```

tf.Variable holds several ops:

```
x = tf.Variable(...)

x.initializer # init op
x.value() # read op
x.assign(...) # write op
x.assign_add(...) # and more
```

You have to initialize your variables

The easiest way is initializing all variables at once:

```
init = tf.global_variables_initializer()
with tf.Session() as sess:
      sess.run(init)
```

You have to initialize your variables

The easiest way is initializing all variables at once:

```
init = tf.global_variables_initializer()
with tf.Session() as sess:
      sess.run(init)
```

Initialize only a subset of variables:

```
init_ab = tf.variables_initializer([a, b], name="init_ab")
with tf.Session() as sess:
      sess.run(init_ab)
```

You have to initialize your variables

The easiest way is initializing all variables at once:

```
init = tf.global_variables_initializer()
with tf.Session() as sess:
      sess.run(init)
```

Initialize only a subset of variables:

```
init_ab = tf.variables_initializer([a, b], name="init_ab")
with tf.Session() as sess:
      sess.run(init_ab)
```

Initialize a single variable

```
W = tf.Variable(tf.zeros([784,10]))
with tf.Session() as sess:
      sess.run(W.initializer)
```

Eval() a variable

```
# W is a random 700 x 100 variable object
W = tf.Variable(tf.truncated_normal([700, 10]))
with tf.Session() as sess:
      sess.run(W.initializer)
      print W

>> Tensor("Variable/read:0", shape=(700, 10), dtype=float32)
```

Eval() a variable

```
# W is a random 700 x 100 variable object
W = tf.Variable(tf.truncated_normal([700, 10]))
with tf.Session() as sess:
      sess.run(W.initializer)
      print W.eval()

>> [[-0.76781619 -0.67020458  1.15333688 ..., -0.98434633 -1.25692499
  -0.90904623]
 [-0.36763489 -0.65037876 -1.52936983 ...,  0.19320194 -0.38379928
   0.44387451]
 [ 0.12510735 -0.82649058  0.4321366  ..., -0.3816964   0.70466036
   1.33211911]
 ...,
 [ 0.9203397  -0.99590844  0.76853162 ..., -0.74290705  0.37568584
   0.64072722]
 [-0.12753558  0.52571583  1.03265858 ...,  0.59978199 -0.91293705
  -0.02646019]
 [ 0.19076447 -0.62968266 -1.97970271 ..., -1.48389161  0.68170643
   1.46369624]]
```

tf.Variable.assign()

```
W = tf.Variable(10)
W.assign(100)
with tf.Session() as sess:
     sess.run(W.initializer)
     print W.eval() # >> ????
```

What do you think this will return?

tf.Variable.assign()

```
W = tf.Variable(10)
W.assign(100)
with tf.Session() as sess:
     sess.run(W.initializer)
     print W.eval() # >> 10
```

Uh, why?

tf.Variable.assign()

```
W = tf.Variable(10)
W.assign(100)
with tf.Session() as sess:
     sess.run(W.initializer)
     print W.eval() # >> 10
```

W.assign(100) doesn’t assign the value 100 to W. It creates an assign op, and that op needs to be run to take effect.

tf.Variable.assign()

```
W = tf.Variable(10)
W.assign(100)
with tf.Session() as sess:
     sess.run(W.initializer)
     print W.eval() # >> 10

--------

W = tf.Variable(10)
assign_op = W.assign(100)
with tf.Session() as sess:
     sess.run(W.initializer)
     sess.run(assign_op)
print W.eval() # >> 100
```

tf.Variable.assign()

```
W = tf.Variable(10)
W.assign(100)
with tf.Session() as sess:
     sess.run(W.initializer)
     print W.eval() # >> 10

--------

W = tf.Variable(10)
assign_op = W.assign(100)
with tf.Session() as sess:
     sess.run(assign_op)
     print W.eval() # >> 100
```

You don’t need to initialize variable because assign_op does it for you

tf.Variable.assign()

```
W = tf.Variable(10)
W.assign(100)
with tf.Session() as sess:
     sess.run(W.initializer)
     print W.eval() # >> 10

--------

W = tf.Variable(10)
assign_op = W.assign(100)
with tf.Session() as sess:
     sess.run(assign_op)
     print W.eval() # >> 100
```

In fact, initializer op is the assign op that assigns the variable’s initial value to the variable itself.

tf.Variable.assign()

```
# create a variable whose original value is 2
my_var = tf.Variable(2, name="my_var")

# assign a * 2 to a and call that op a_times_two
my_var_times_two = my_var.assign(2 * my_var)

with tf.Session() as sess:
      sess.run(my_var.initializer)
      sess.run(my_var_times_two) # >> 4
```

tf.Variable.assign()

```
# create a variable whose original value is 2
my_var = tf.Variable(2, name="my_var")

# assign a * 2 to a and call that op a_times_two
my_var_times_two = my_var.assign(2 * my_var)

with tf.Session() as sess:
      sess.run(my_var.initializer)
      sess.run(my_var_times_two) # >> 4
      sess.run(my_var_times_two) # >> ?????
```

What do you think this will return?

tf.Variable.assign()

```
# create a variable whose original value is 2
my_var = tf.Variable(2, name="my_var")

# assign a * 2 to a and call that op a_times_two
my_var_times_two = my_var.assign(2 * my_var)

with tf.Session() as sess:
      sess.run(my_var.initializer)
      sess.run(my_var_times_two) # >> 4
      sess.run(my_var_times_two) # >> 8
      sess.run(my_var_times_two) # >> 16
```

It assign 2 * `my_var` to a every time `my_var_times_two` is fetched.

assign_add() and assign_sub()

```
my_var = tf.Variable(10)

With tf.Session() as sess:

     sess.run(my_var.initializer)

     # increment by 10

     sess.run(my_var.assign_add(10)) # >> 20

     # decrement by 2

     sess.run(my_var.assign_sub(2)) # >> 18
```

assign_add() and assign_sub() can't initialize the variable `my_var` for you because these ops need the original value of `my_var`

Each session maintains its own copy of variable

```
W = tf.Variable(10)

sess1 = tf.Session()
sess2 = tf.Session()

sess1.run(W.initializer)
sess2.run(W.initializer)

print sess1.run(W.assign_add(10)) # >> 20
print sess2.run(W.assign_sub(2)) # >> ?
```

Each session maintains its own copy of variable

```
W = tf.Variable(10)

sess1 = tf.Session()
sess2 = tf.Session()

sess1.run(W.initializer)
sess2.run(W.initializer)

print sess1.run(W.assign_add(10)) # >> 20
print sess2.run(W.assign_sub(2)) # >> 8
```

Each session maintains its own copy of variable

```
W = tf.Variable(10)

sess1 = tf.Session()
sess2 = tf.Session()

sess1.run(W.initializer)
sess2.run(W.initializer)

print sess1.run(W.assign_add(10)) # >> 20
print sess2.run(W.assign_sub(2)) # >> 8

print sess1.run(W.assign_add(100)) # >> 120
print sess2.run(W.assign_sub(50)) # >> -42

sess1.close()
sess2.close()
```

Use a variable to initialize another variable

Want to declare U = 2 * W

```
# W is a random 700 x 100 tensor
W = tf.Variable(tf.truncated_normal([700, 10]))
U = tf.Variable(2 * W)
```

Not so safe (but quite common)

Use a variable to initialize another variable

Want to declare U = W * 2

```
# W is a random 700 x 100 tensor
W = tf.Variable(tf.truncated_normal([700, 10]))
U = tf.Variable(2 * W.intialized_value())

# ensure that W is initialized before its value is used to initialize U
```

Safer

Session vs InteractiveSession

You sometimes see InteractiveSession instead of Session

The only difference is an InteractiveSession makes itself the default

```
sess = tf.InteractiveSession()
a = tf.constant(5.0)
b = tf.constant(6.0)
c = a * b
# We can just use 'c.eval()' without specifying the context 'sess'
print(c.eval())
sess.close()
```

Control Dependencies

`tf.Graph.control_dependencies(control_inputs)`

defines which ops should be run first

```
# your graph g have 5 ops: a, b, c, d, e
with g.control_dependencies([a, b, c]):
      # 'd' and 'e' will only run after 'a', 'b', and 'c' have executed.
      d = ...
      e = …
```

Project speed dating

Project Speed Dating

Placeholder

A quick reminder

A TF program often has 2 phases:

1. Assemble a graph
2. Use a session to execute operations in the graph.

Placeholders

A TF program often has 2 phases:

1. Assemble a graph
2. Use a session to execute operations in the graph.

⇒ Can assemble the graph first without knowing the values needed for computation

Placeholders

A TF program often has 2 phases:

1. Assemble a graph
2. Use a session to execute operations in the graph.

⇒ Can assemble the graph first without knowing the values needed for computation

Analogy:
Can define the function f(x, y) = x*2 + y without knowing value of x or y. x, y are placeholders for the actual values.

Why placeholders?

We, or our clients, can later supply their own data when they need to execute the computation.

Placeholders

tf.placeholder(dtype, shape=None, name=None)

```
# create a placeholder of type float 32-bit, shape is a vector of 3 elements
a = tf.placeholder(tf.float32, shape=[3])

# create a constant of type float 32-bit, shape is a vector of 3 elements
b = tf.constant([5, 5, 5], tf.float32)

# use the placeholder as you would a constant or a variable
c = a + b  # Short for tf.add(a, b)

with tf.Session() as sess:
      print sess.run(c) # Error because a doesn’t have any value
```

Feed the values to placeholders using a dictionary

Placeholders

`tf.placeholder(dtype, shape=None, name=None)`

```
# create a placeholder of type float 32-bit, shape is a vector of 3 elements
a = tf.placeholder(tf.float32, shape=[3])

# create a constant of type float 32-bit, shape is a vector of 3 elements
b = tf.constant([5, 5, 5], tf.float32)

# use the placeholder as you would a constant or a variable
c = a + b  # Short for tf.add(a, b)

with tf.Session() as sess:
      # feed [1, 2, 3] to placeholder a via the dict {a: [1, 2, 3]}
      # fetch value of c
      print sess.run(c, {a: [1, 2, 3]}) # the tensor a is the key, not the string ‘a’

# >> [6, 7, 8]
```

Placeholders

`tf.placeholder(dtype, shape=None, name=None)`

```
# create a placeholder of type float 32-bit, shape is a vector of 3 elements
a = tf.placeholder(tf.float32, shape=[3])

# create a constant of type float 32-bit, shape is a vector of 3 elements
b = tf.constant([5, 5, 5], tf.float32)

# use the placeholder as you would a constant or a variable
c = a + b  # Short for tf.add(a, b)

with tf.Session() as sess:
      # feed [1, 2, 3] to placeholder a via the dict {a: [1, 2, 3]}
      # fetch value of c
      print sess.run(c, {a: [1, 2, 3]})

# >> [6, 7, 8]
```

<u>Quirk:</u>
shape=None means that tensor of any shape will be accepted as value for placeholder.

shape=None is easy to construct graphs, but nightmarish for debugging

Placeholders

```
tf.placeholder(dtype, shape=None, name=None)
```

```
# create a placeholder of type float 32-bit, shape is a vector of 3 elements
a = tf.placeholder(tf.float32, shape=[3])

# create a constant of type float 32-bit, shape is a vector of 3 elements
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# use the placeholder as you would a constant or a variable
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with tf.Session() as sess:
      # feed [1, 2, 3] to placeholder a via the dict {a: [1, 2, 3]}
      # fetch value of c
      print sess.run(c, {a: [1, 2, 3]})

# >> [6, 7, 8]
```

<u>Quirk:</u>
shape=None also breaks all following shape inference, which makes many ops not work because they expect certain rank.

Placeholders are valid ops

`tf.placeholder(dtype, shape=None, name=None)`

```
# create a placeholder of type float 32-bit, shape is a vector of 3 elements
a = tf.placeholder(tf.float32, shape=[3])

# create a constant of type float 32-bit, shape is a vector of 3 elements
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      # fetch value of c
      print sess.run(c, {a: [1, 2, 3]})

# >> [6, 7, 8]
```
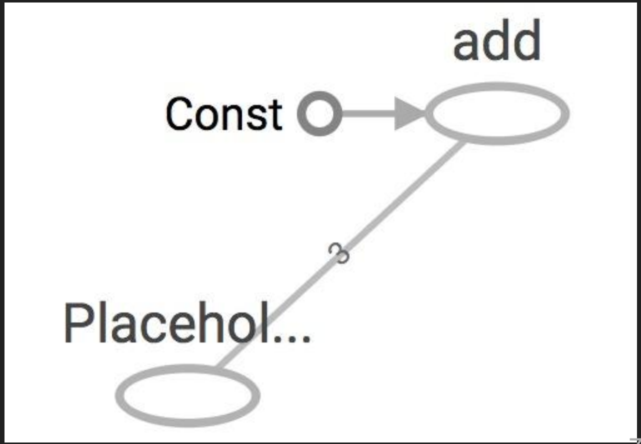



What if want to feed multiple data points in?

We feed all the values in, one at a time

```
with tf.Session() as sess:
     for a_value in list_of_values_for_a:
          print sess.run(c, {a: a_value})
```

You can feed_dict any feedable tensor. Placeholder is just a way to indicate that something must be fed

```
tf.Graph.is_feedable(tensor)
```

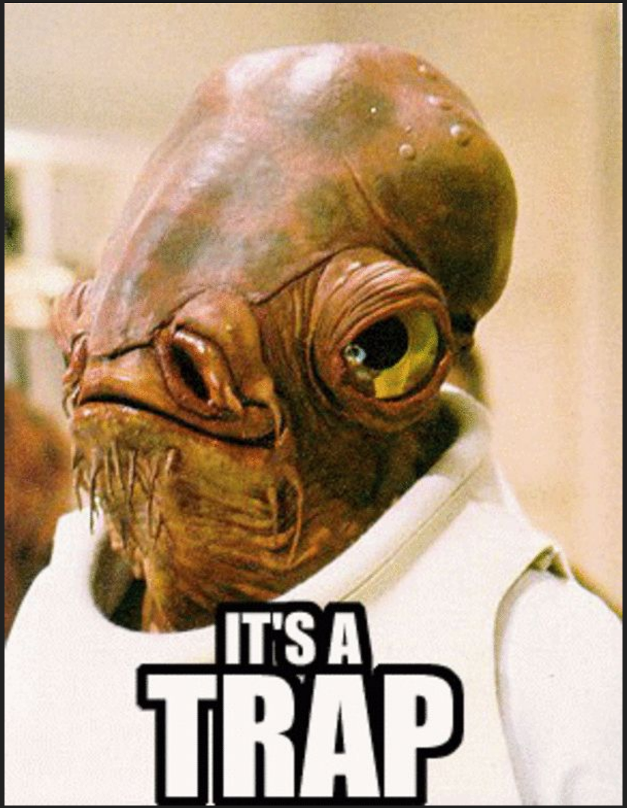
True if and only if tensor is feedable.

Feeding values to TF ops

```
# create operations, tensors, etc (using the default graph)
a = tf.add(2, 5)
b = tf.mul(a, 3)

with tf.Session() as sess:
     # define a dictionary that says to replace the value of 'a' with 15
     replace_dict = {a: 15}

     # Run the session, passing in 'replace_dict' as the value to 'feed_dict'
     sess.run(b, feed_dict=replace_dict) # returns 45
```

Extremely helpful for testing too

The trap of lazy loading*



*I might have made this term up

What’s lazy loading?

Defer creating/initializing an object until it is needed

Lazy loading Example

Normal loading:

```
x = tf.Variable(10, name='x')
y = tf.Variable(20, name='y')
z = tf.add(x, y) # you create the node for add node before executing the graph

with tf.Session() as sess:
      sess.run(tf.global_variables_initializer())
      writer = tf.summary.FileWriter('./my_graph/l2', sess.graph)
      for _ in range(10):
            sess.run(z)
      writer.close()
```

Lazy loading Example

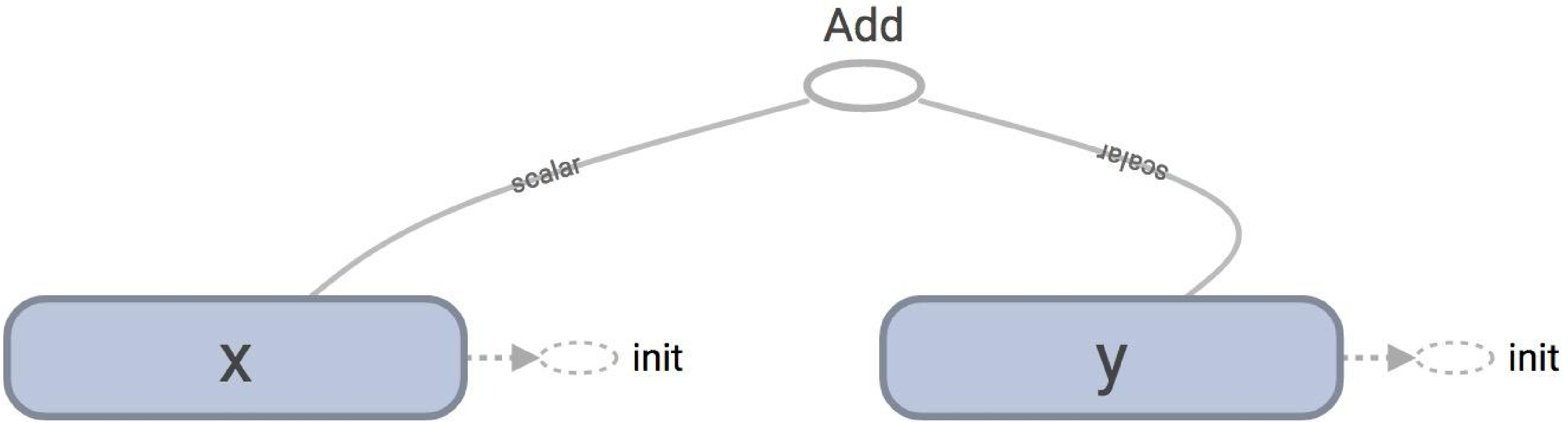
Lazy loading:

```
x = tf.Variable(10, name='x')
y = tf.Variable(20, name='y')

with tf.Session() as sess:
      sess.run(tf.global_variables_initializer())
      writer = tf.summary.FileWriter('./my_graph/l2', sess.graph)
      for _ in range(10):
            sess.run(tf.add(x, y)) # someone decides to be clever to save one line of code
      writer.close()
```

Both give the same value of z
What’s the problem?

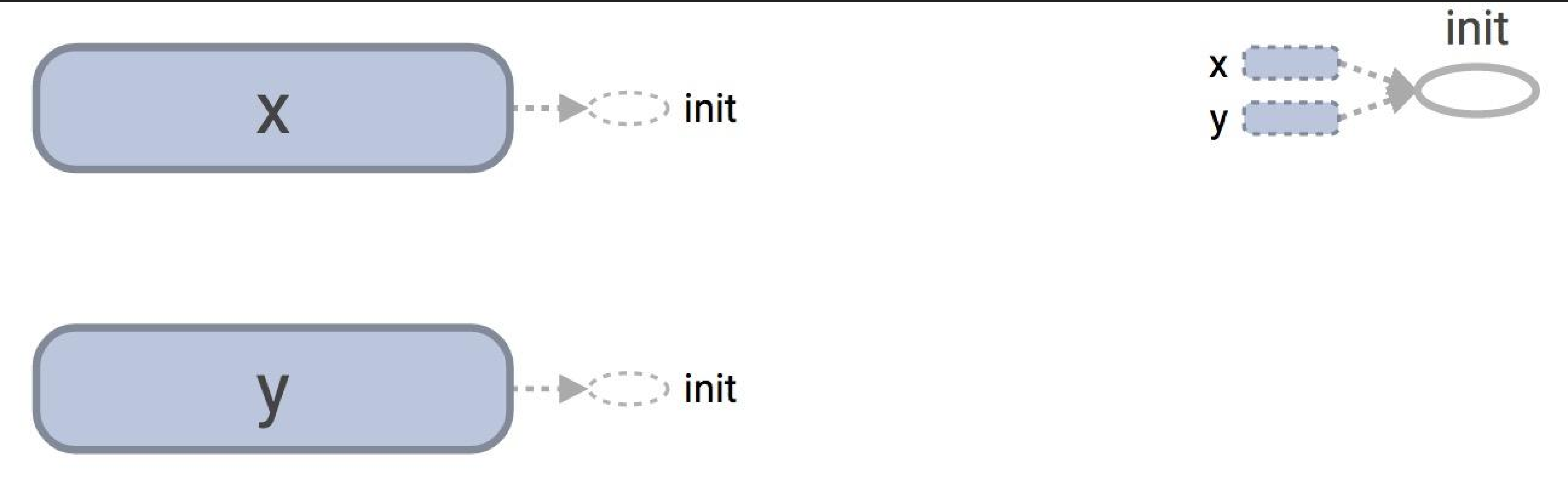
TensorBoard

Normal loading



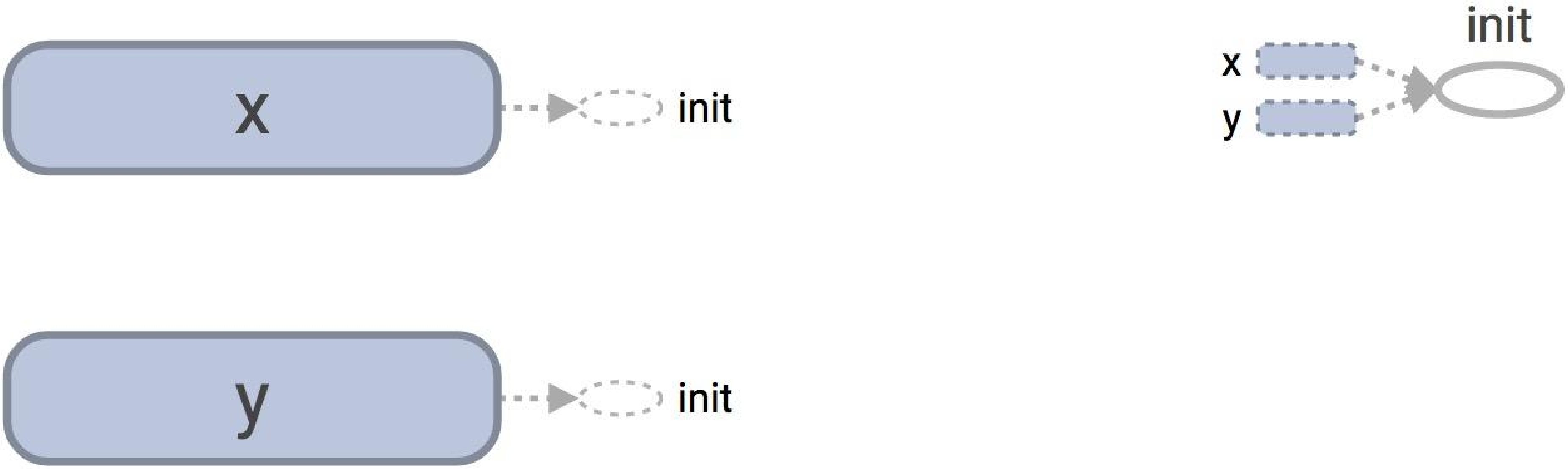
TensorBoard

Lazy loading (just missing the node Add, bad for reading graph, but not a bug)



TensorBoard

Lazy loading



tf.get_default_graph().as_graph_def()

Normal loading:

```
node {
  name: "Add"
  op: "Add"
  input: "x/read"
  input: "y/read"
  attr {
    key: "T"
    value {
      type: DT_INT32
    }
  }
}
```

Node “Add” added once to the graph definition

tf.get_default_graph().as_graph_def()

Lazy loading:

```
node {
  name: "Add"
  op: "Add"
  ...
  }
...
node {
  name: "Add_9"
  op: "Add"
  ...
}
```

Node “Add” added 10 times to the graph definition

Or as many times as you want to compute z

Imagine you want to compute an op thousands of times!

Your graph gets bloated
Slow to load
Expensive to pass around

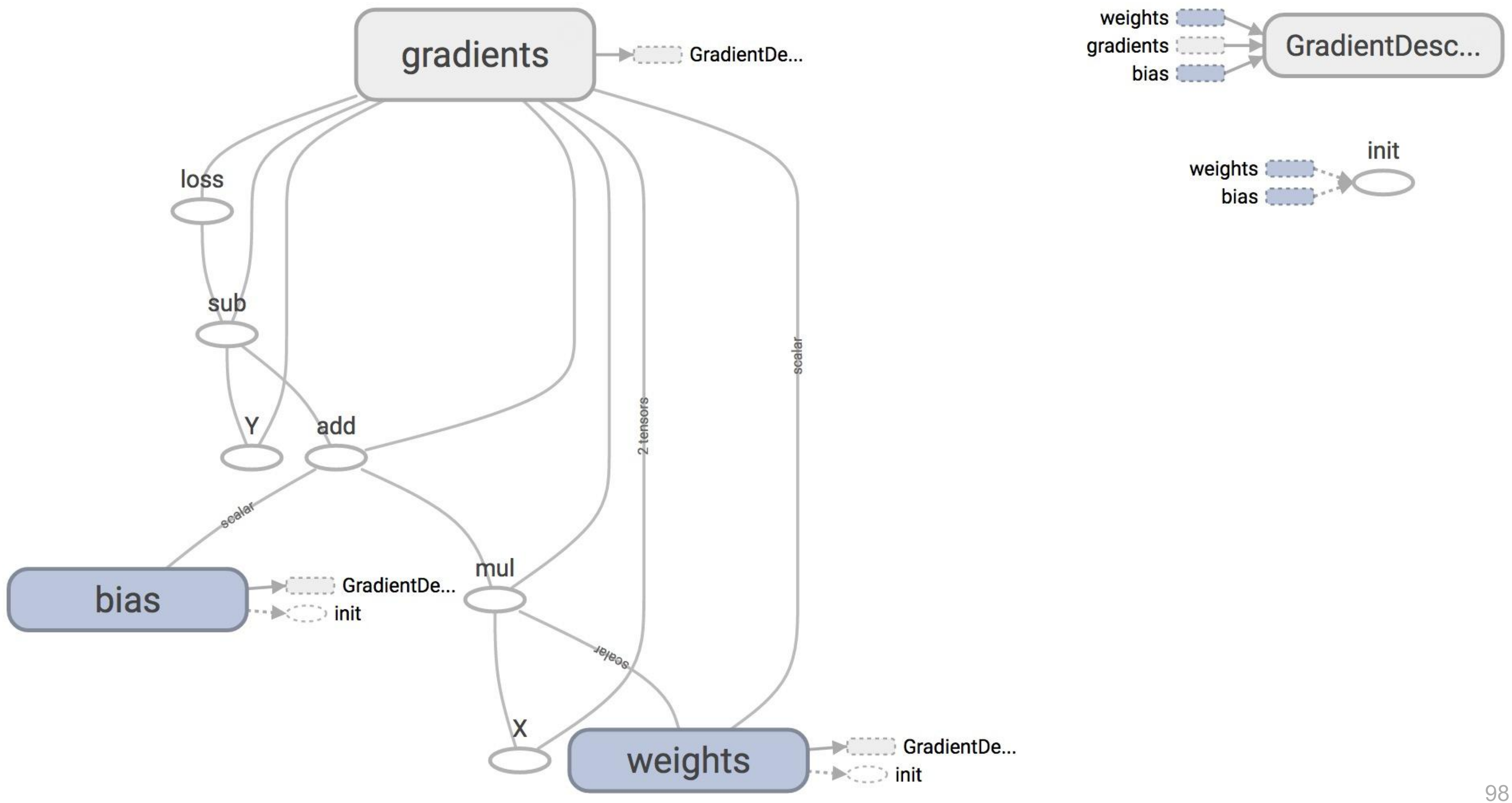
One of the most common TF non-bug bugs I’ve seen on GitHub

Solution

1. Separate definition of ops from computing/running ops
2. Use Python property to ensure function is also loaded once the first time it is called*

* This is not a Python class so I won't go into it here. But if you don't know how to use this property, you're welcome to ask me!

Putting it together:
A simple linear regression example


gradients
GradientDe...
weights
gradients
bias
GradientDesc...
init
weights
bias
loss
sub
Y
add
scalar
2 tensors
scalar
bias
GradientDe...
init
mul
scalar
X
weights
GradientDe...
init

We will construct this model next time!!

Next class

Linear regression in TensorFlow

Optimizers

Logistic regression on MNIST

Feedback: 49261200@qq.com

Thanks!