Tensor Flow

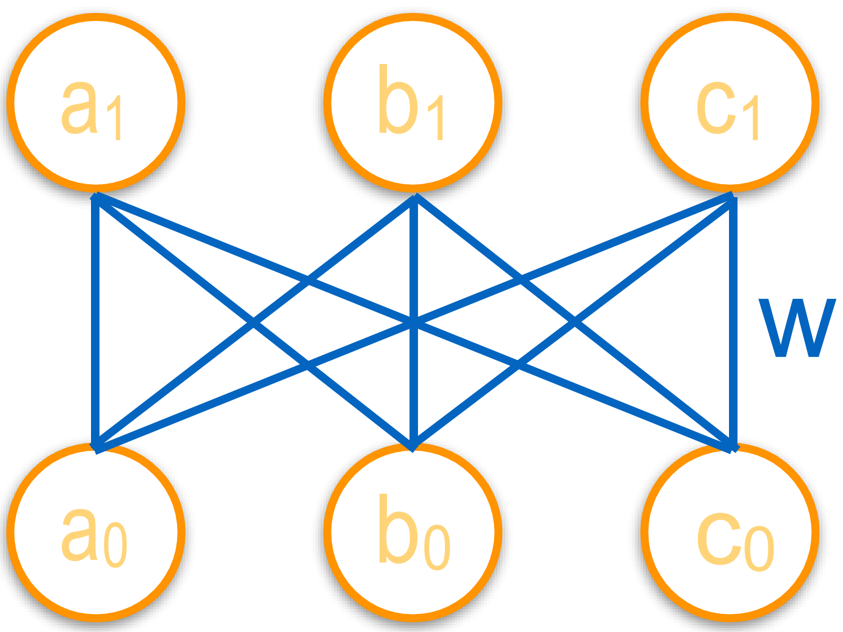
Tensors: n-dimensional arrays

- Vector: 1-D tensor
- Matrix: 2-D tensor

Deep learning process are flows of tensors

- A sequence of tensor operations
- Can represent also many machine learning algorithms

A simple ReLU network



$a_1 = a_0 w_{a,a} + b_0 w_{b,a} + c_0 w_{c,a}$

$b_1 = a_0 w_{a,b} + b_0 w_{b,b} + c_0 w_{c,b}$

$c_1 = a_0 w_{a,c} + b_0 w_{b,c} + c_0 w_{c,c}$

Apply relu(...) on a_1, b_1, c_1

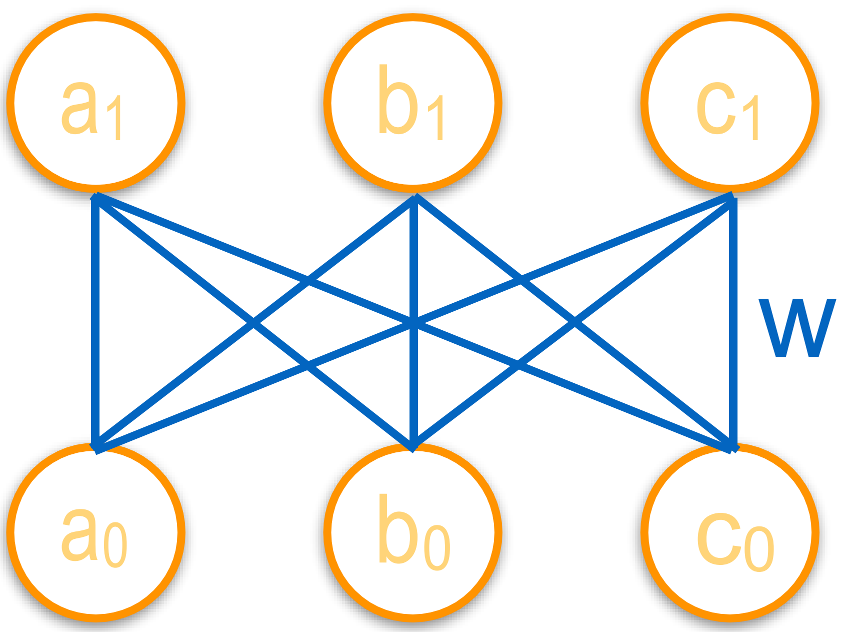
Slower approach

- Per-neuron operation

More efficientapproach

- Matrix operation

As matrix operations



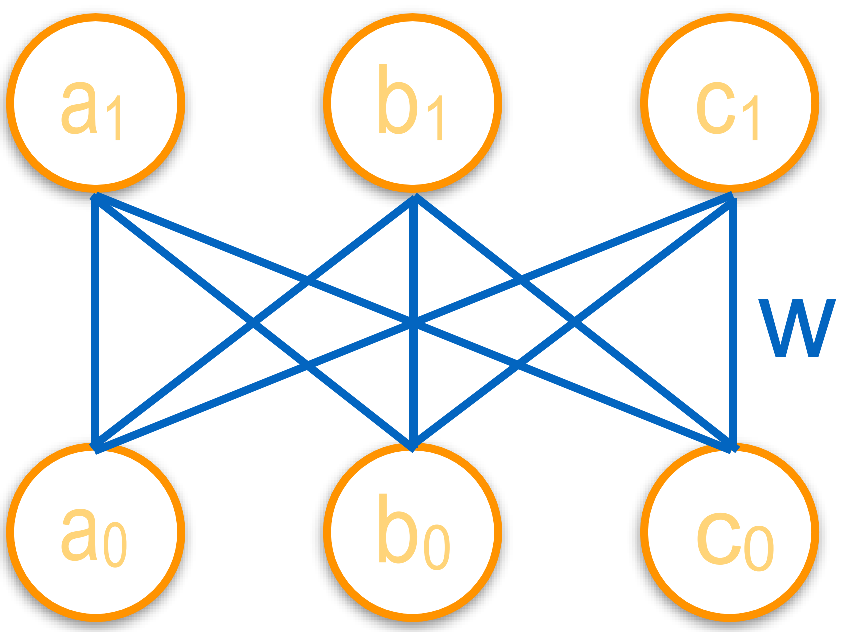
$$\begin{bmatrix} a_0 & b_0 & c_0 \end{bmatrix} \cdot \begin{bmatrix} w_{a,a} & w_{a,b} & w_{a,c} \\ w_{b,a} & w_{b,b} & w_{b,c} \\ w_{c,a} & w_{c,b} & w_{c,c} \end{bmatrix} = \begin{bmatrix} a_1 & b_1 & c_1 \end{bmatrix}$$

$$\boxed{a_1} = relu(\boxed{a_1})$$

$$\boxed{b_1} = relu(\boxed{b_1})$$

$$\boxed{c_1} = relu(\boxed{c_1})$$

With TensorFlow




```
import tensorflow as tf
```

$$\begin{array}{ccccc} x & & w & & \\ \begin{bmatrix} a_0 & b_0 & c_0 \end{bmatrix} & \cdot & \begin{bmatrix} w_{a,a} & w_{a,b} & w_{a,c} \\ w_{b,a} & w_{b,b} & w_{b,c} \\ w_{c,a} & w_{c,b} & w_{c,c} \end{bmatrix} & = & \begin{bmatrix} a_1 & b_1 & c_1 \end{bmatrix} \end{array}$$

```
y = tf.matmul(x, w)
```

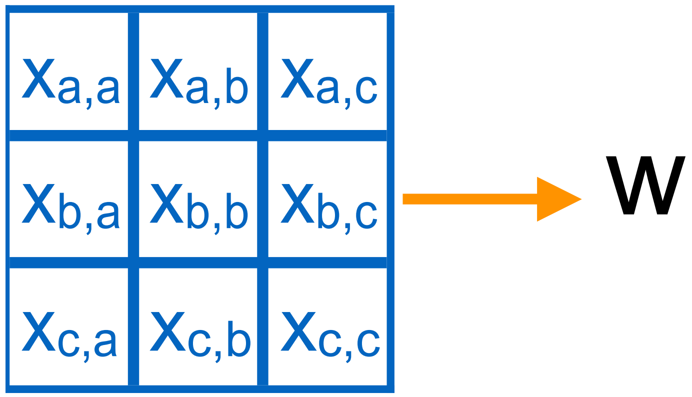
$$\boxed{a_1} = \mathrm{relu}(\boxed{a_1})$$

$$\boxed{b_1} = \mathrm{relu}(\boxed{b_1})$$

$$\boxed{c_1} = \mathrm{relu}(\boxed{c_1})$$

```
out = tf.nn.relu(y)
```

Define Tensors



Variable(<initial-value>,
name=<optional-name>)

```
import tensorflow as tf
w = tf.Variable(tf.random_normal([3, 3]),
name='w') y = tf.matmul(x, w)
relu_out = tf.nn.relu(y)
```

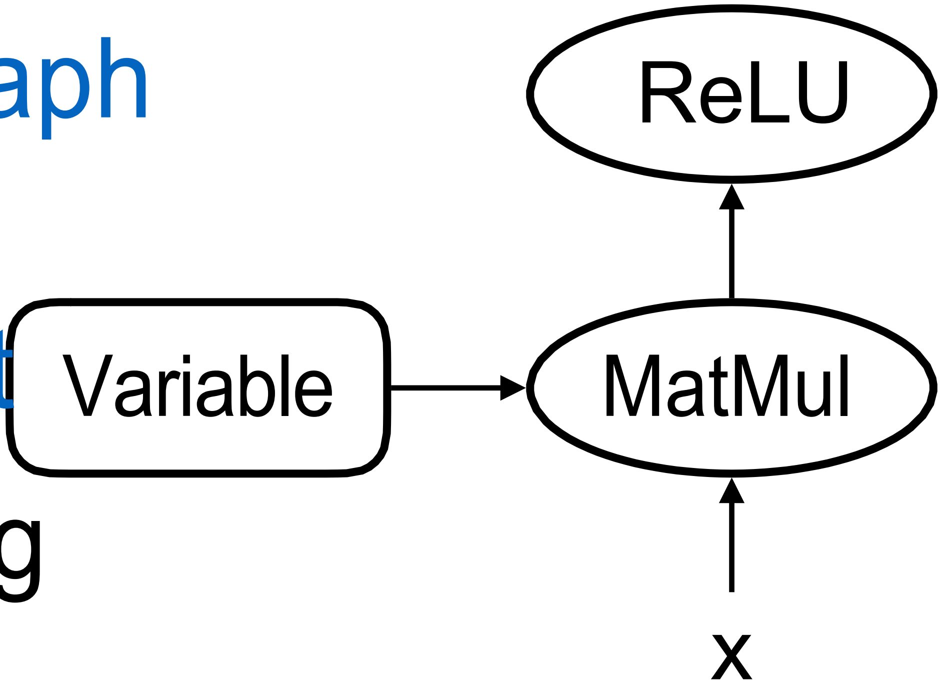
Variable stores the state of current execution

Others are operations

TensorFlow

Code so far defines a data flow graph

- Each variable corresponds to a node in the graph, not the result
- Can be confusing at the beginning

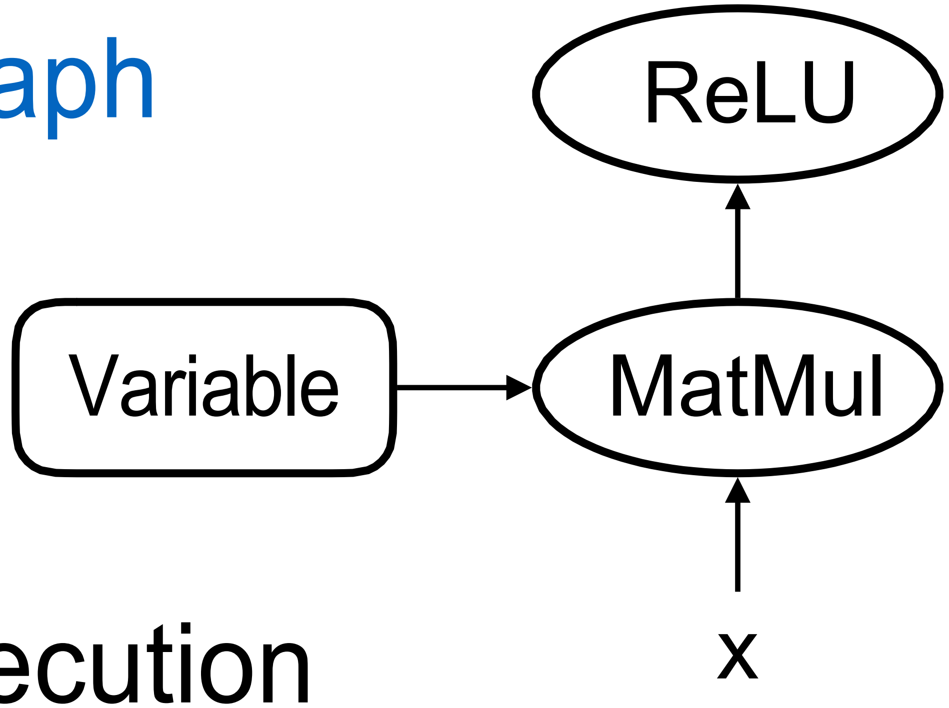



```
import tensorflow as tf
w = tf.Variable(tf.random_normal([3, 3]), name='w')
y = tf.matmul(x, w)
relu_out = tf.nn.relu(y)
```

TensorFlow

Code so far defines a data flow graph

Needs to specify how we want to execute the graph



Session

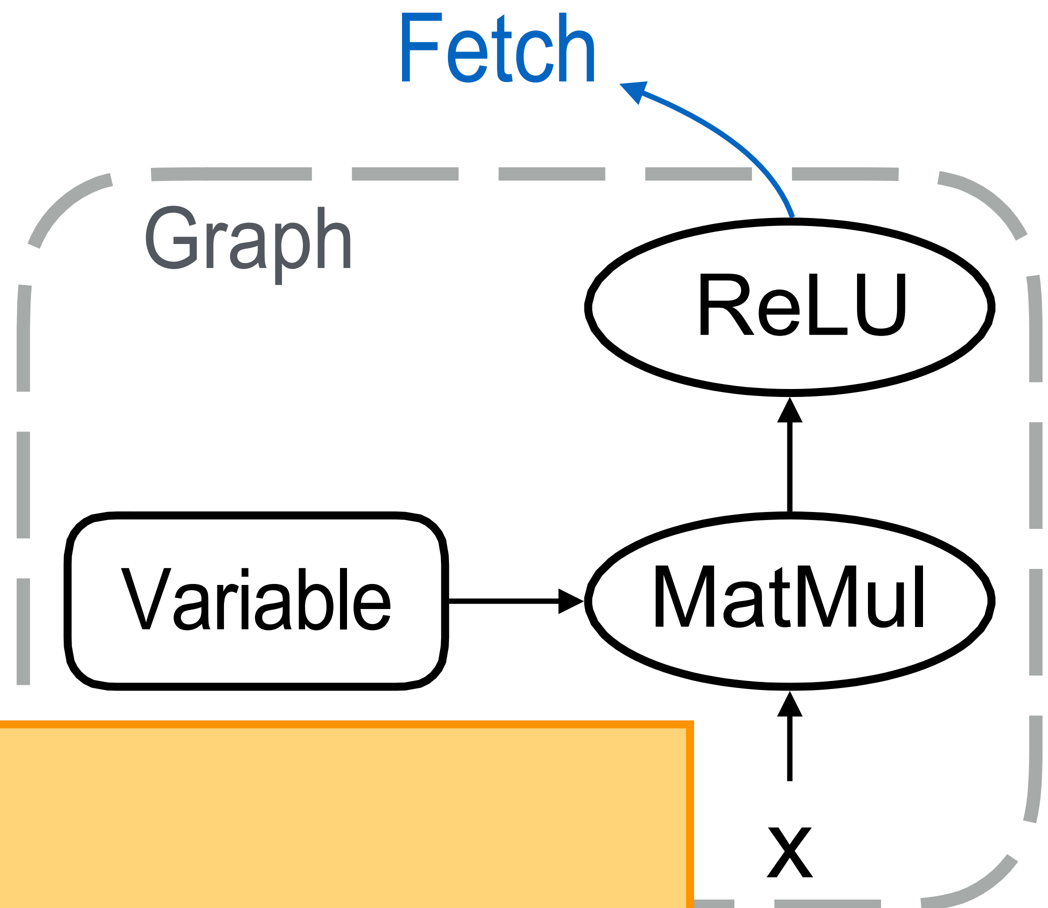
Manage resource for graph execution

```
import tensorflow as tf
sess = tf.Session()
w = tf.Variable(tf.random_normal([3, 3]), name='w')
y = tf.matmul(x, w)
relu_out = tf.nn.relu(y)
result = sess.run(relu_out)
```

Fetch

Retrieve content from a node

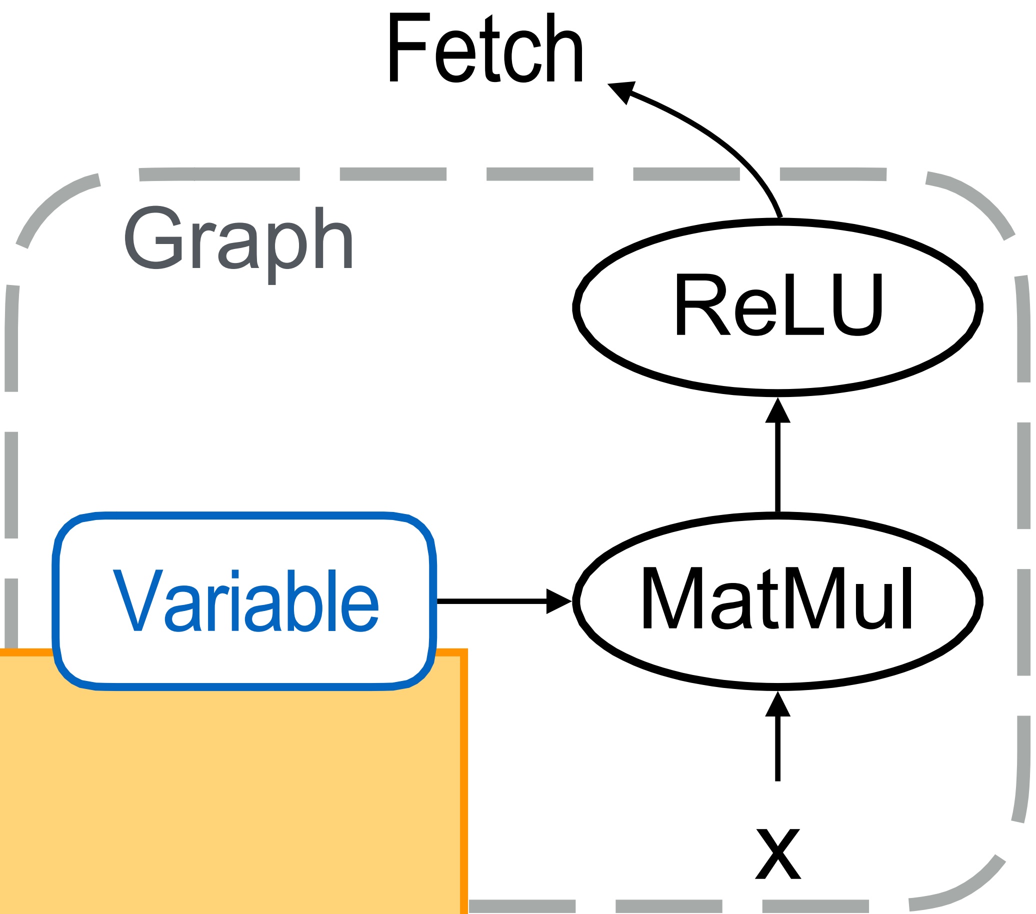
- We have assembled the pipes
- Fetch the liquid




```
import tensorflow as tf
sess = tf.Session()
w = tf.Variable(tf.random_normal([3, 3]), name='w')
y = tf.matmul(x, w)
relu_out = tf.nn.relu(y)
print sess.run(relu_out)
```

Initialize Variable

Variable is an empty node
  - Fill in the content of a Variable node



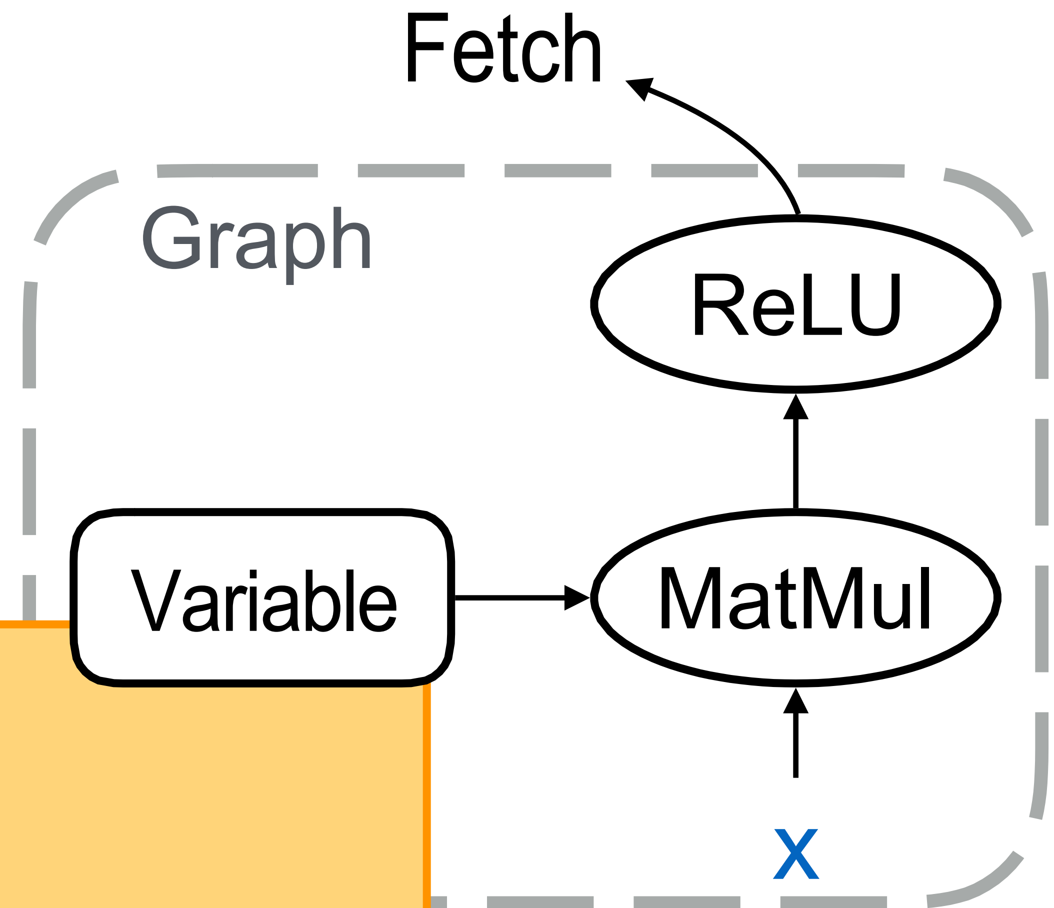

```
import tensorflow as tf
sess = tf.Session()
w = tf.Variable(tf.random_normal([3, 3]), name='w')
y = tf.matmul(x, w)
relu_out = tf.nn.relu(y)
sess.run(tf.global_variables_initializer())
print sess.run(relu_out)
```

Placeholder

How about x?

```
placeholder(<data type>,
            shape=<optional-shape>,
            name=<optional-name>)
```

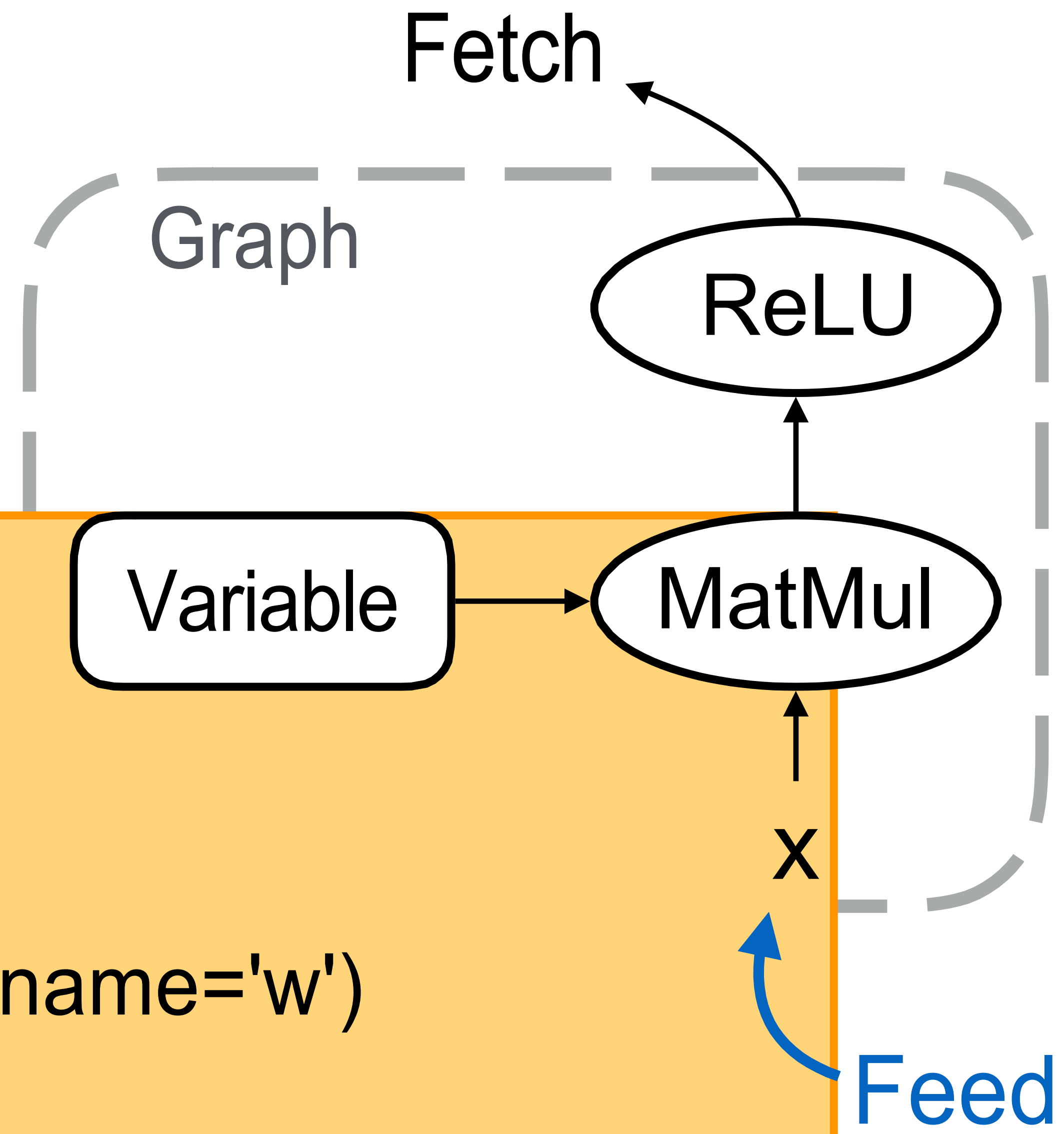
Its content will be fed




```
import tensorflow as tf
sess = tf.Session()
x = tf.placeholder("float", [1, 3])
w = tf.Variable(tf.random_normal([3, 3]), name='w')
y = tf.matmul(x, w)
relu_out = tf.nn.relu(y)
sess.run(tf.global_variables_initializer())
print sess.run(relu_out)
```

Feed

Pump liquid into the pipe




```python
import numpy as np
import tensorflow as tf
sess =tf.Session()
x = tf.placeholder("float", [1, 3])
w = tf.Variable(tf.random_normal([3, 3]), name='w')
y = tf.matmul(x, w)
relu_out = tf.nn.relu(y)
sess.run(tf.global_variables_initializer())
print sess.run(relu_out, feed_dict={x:np.array([[1.0, 2.0, 3.0]])})
```

Session management

Needs to release resource after use

```
sess.close()
```

Common usage

```
with tf.Session() as sess:
    ...
```

Interactive

```
sess = InteractiveSession()
```

Prediction

Softmax

Make predictions for n targets that sum to 1

```
import numpy as np
import tensorflow as tf

with tf.Session() as sess:
  x = tf.placeholder("float", [1, 3])
  w = tf.Variable(tf.random_normal([3, 3]), name='w')
  relu_out = tf.nn.relu(tf.matmul(x, w))
  softmax = tf.nn.softmax(relu_out)
  sess.run(tf.global_variables_initializer())
  print sess.run(softmax, feed_dict={x:np.array([[1.0, 2.0, 3.0]])})
```

Prediction Difference

```
import numpy as np
import tensorflow as tf

with tf.Session() as sess:
  x = tf.placeholder("float", [1, 3])
  w = tf.Variable(tf.random_normal([3, 3]), name='w')
  relu_out = tf.nn.relu(tf.matmul(x, w))
  softmax = tf.nn.softmax(relu_out)
  sess.run(tf.global_variables_initializer())
  answer = np.array([[0.0, 1.0, 0.0]])
  print answer - sess.run(softmax, feed_dict={x:np.array([[1.0, 2.0, 3.0]])})
```

Learn parameters: Loss

Define loss function

Loss function for softmax

softmax_cross_entropy_with_logits(
logits, labels, name=<optional-name>)

```
labels = tf.placeholder("float", [1, 3])
cross_entropy =
    tf.nn.softmax_cross_entropy_with_logits( relu_out,
    labels, name='xentropy')
```

Learn parameters: Optimization

Gradient descent

class GradientDescentOptimizer

GradientDescentOptimizer(learning rate)

learning rate = 0.1

```
labels = tf.placeholder("float", [1, 3])
cross_entropy =
    tf.nn.softmax_cross_entropy_with_logits( relu_out,
    labels, name='xentropy')
optimizer = tf.train.GradientDescentOptimizer(0.1)
train_op = optimizer.minimize(cross_entropy)
sess.run(train_op,
         feed_dict={x:np.array([[1.0,2.0,3.0]]),labels:answer})
```

Iterative update

Gradient descent usually needs more than one step

- Run multiple times

```
labels = tf.placeholder("float", [1, 3])
cross_entropy =
    tf.nn.softmax_cross_entropy_with_logits( relu_out,
    labels, name='xentropy')
optimizer = tf.train.GradientDescentOptimizer(0.1)
train_op =optimizer.minimize(cross_entropy)
for step in range(10):
  sess.run(train_op,
           feed_dict={x:np.array([[1.0,2.0,3.0]]),labels:answer})
```

Add parameters for Softmax

Do not want to use only non-negative input

- Softmax layer

```
…
softmax_w = tf.Variable(tf.random_normal([3, 3]))
logit = tf.matmul(relu_out, softmax_w)
softmax = tf.nn.softmax(logit)
…
cross_entropy =
    tf.nn.softmax_cross_entropy_with_logits( logit, labels,
    name='xentropy')
…
```

Add biases

Biases initialized to zero

```
…
w = tf.Variable(tf.random_normal([3, 3]))
b = tf.Variable(tf.zeros([1,3]))
relu_out = tf.nn.relu(tf.matmul(x, w) + b)
softmax_w = tf.Variable(tf.random_normal([3, 3]))
softmax_b = tf.Variable(tf.zeros([1, 3]))
logit = tf.matmul(relu_out, softmax_w) + softmax_b
softmax = tf.nn.softmax(logit)
…
```

Make it deep

Add layers

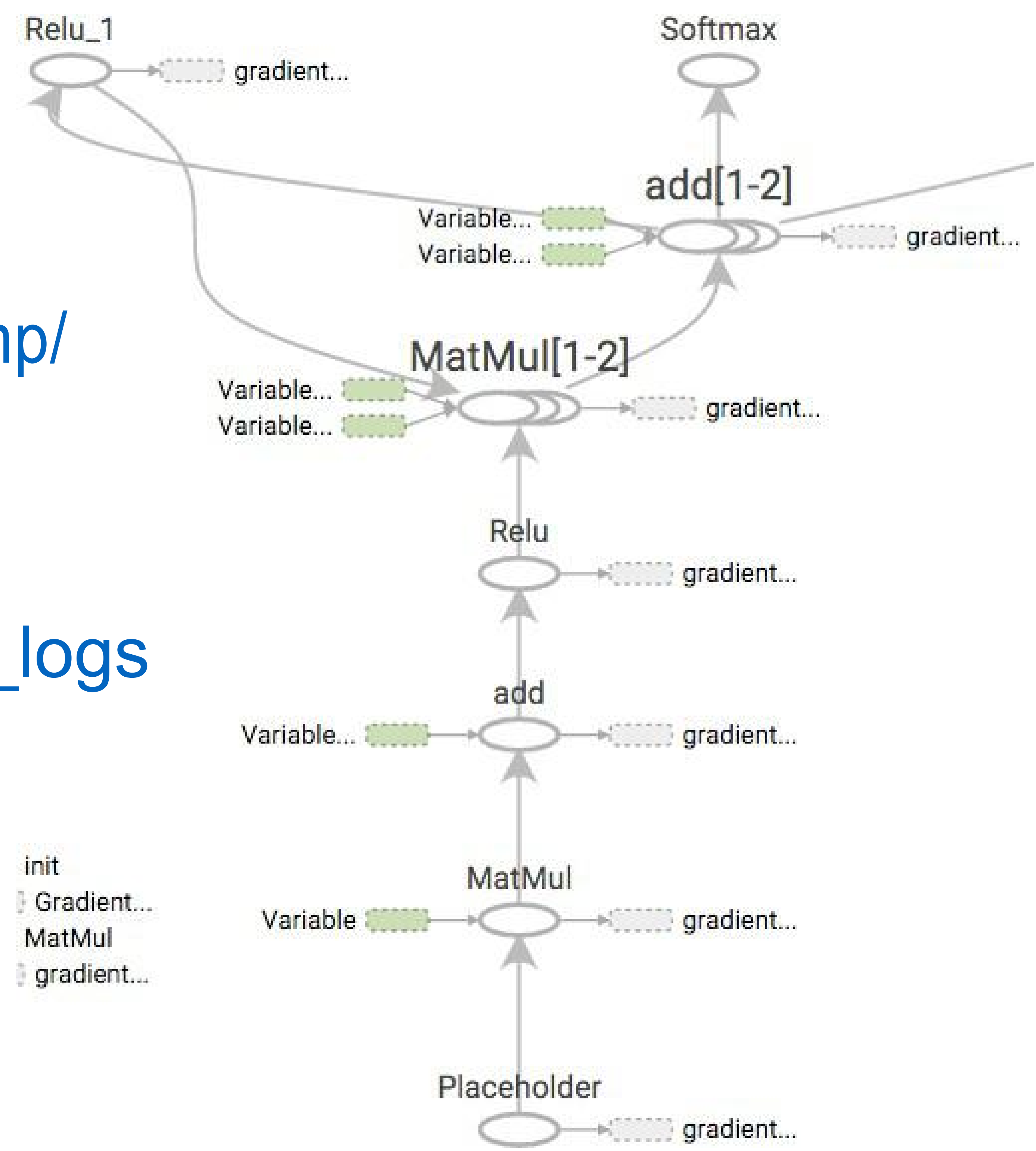
```
…
x = tf.placeholder("float", [1, 3])
relu_out = x
num_layers = 2
for layer in range(num_layers):
  w = tf.Variable(tf.random_normal([3, 3]))
  b = tf.Variable(tf.zeros([1,3]))
  relu_out = tf.nn.relu(tf.matmul(relu_out, w) + b)
…
```

Visualize the graph

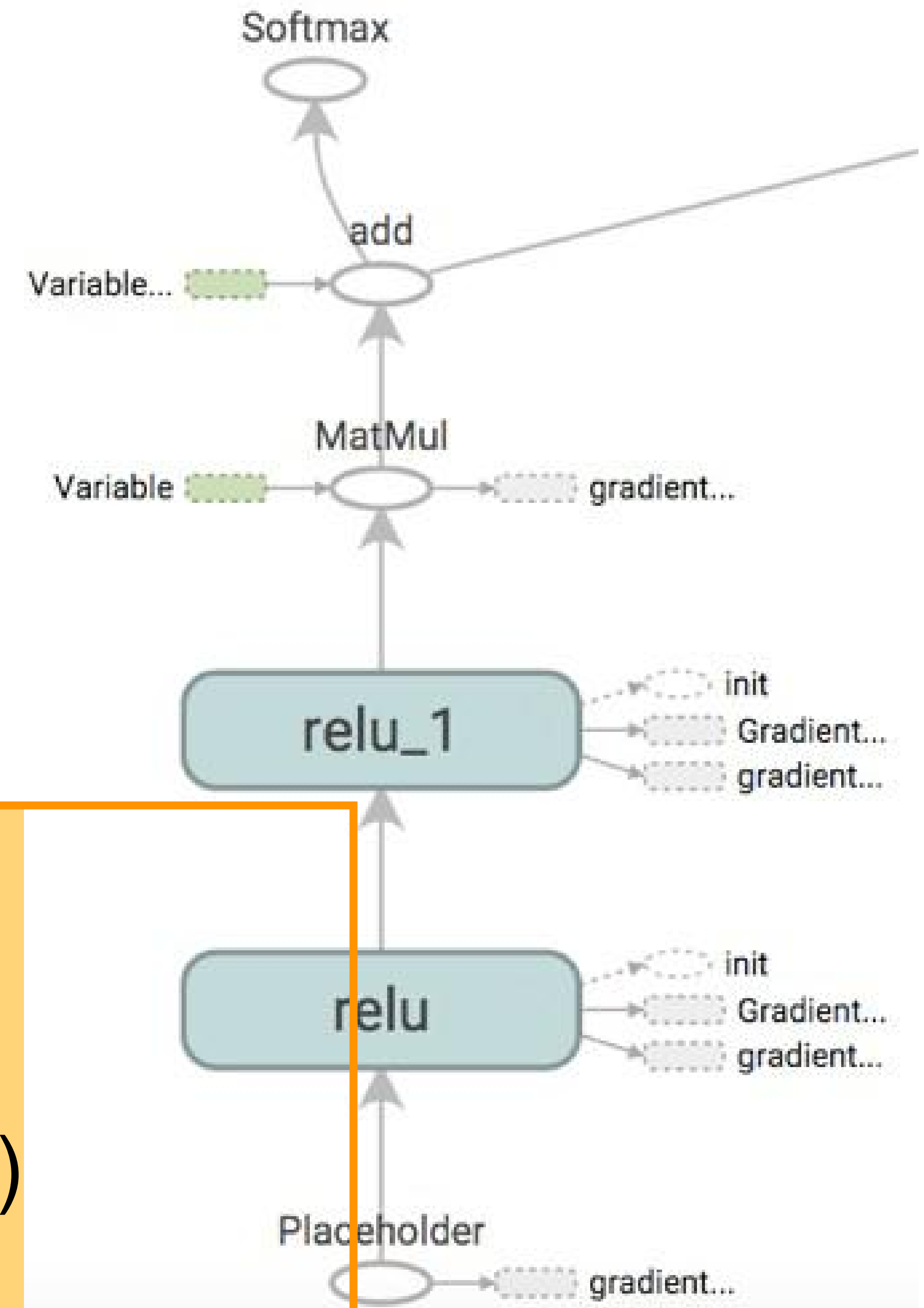
TensorBoard

writer=
    tf.summary.FileWriter('/tmp/
    tf_logs', sess.graph_def)

tensorboard --logdir=/tmp/tf_logs



Improve naming, improve visualization



name_scope(name)

Help specify hierarchical names

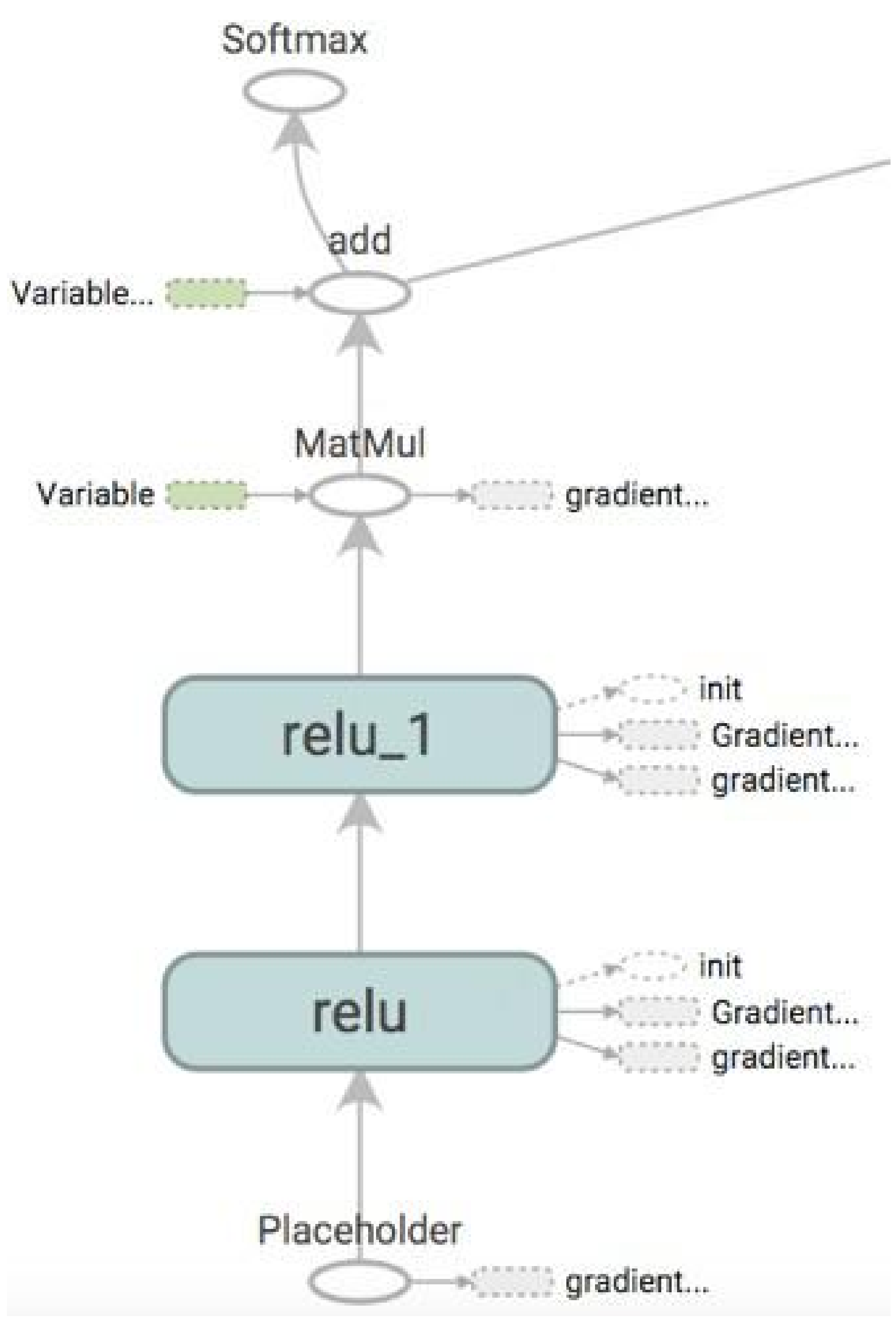
Will help visualizer to better understand hierarchical relation

```
...
for layer in range(num_layers):
  with tf.name_scope('relu'):
    w = tf.Variable(tf.random_normal([3, 3]))
    b = tf.Variable(tf.zeros([1,3]))
    relu_out = tf.nn.relu(tf.matmul(relu_out, w) + b)
...
```

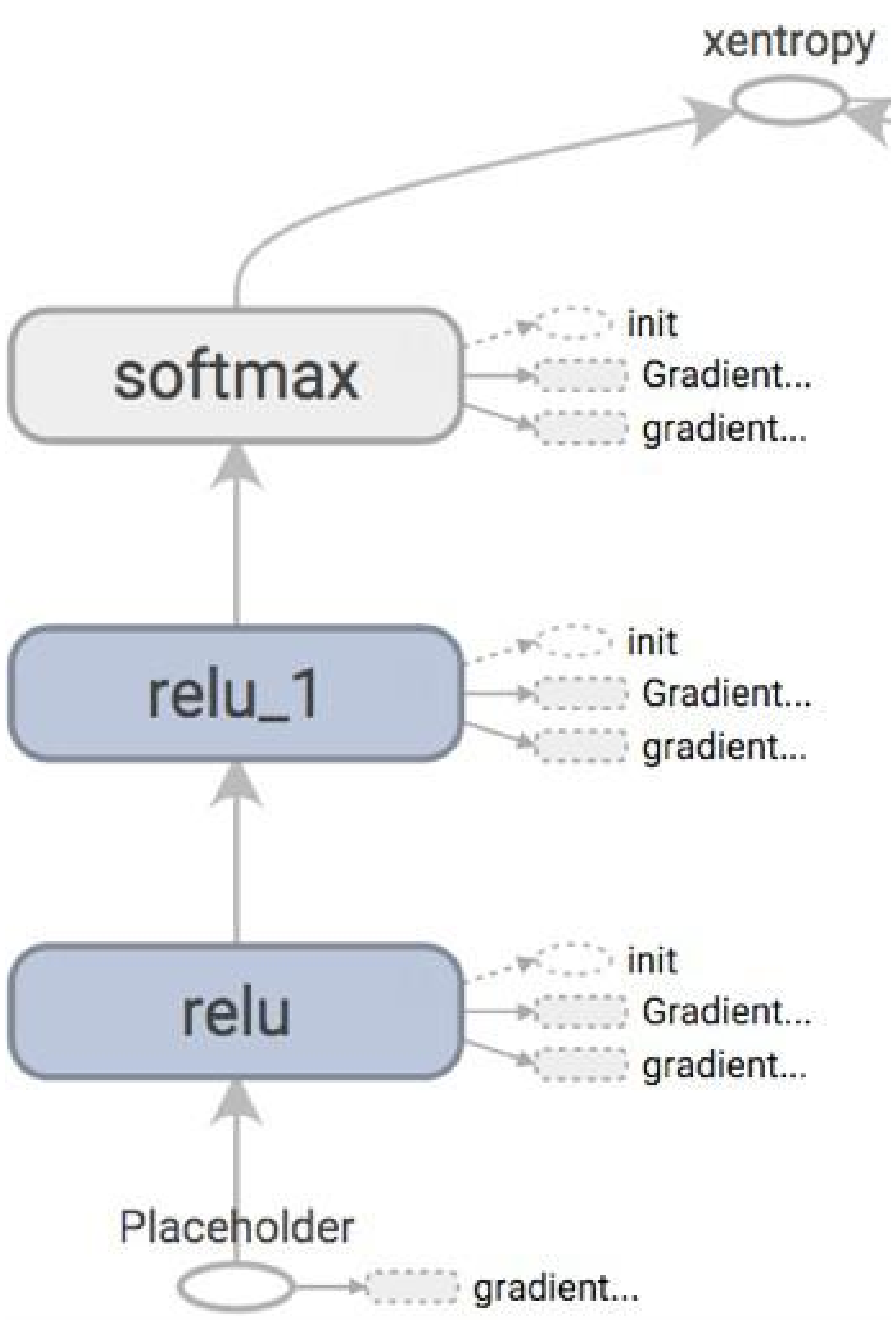
Move to outside the loop?

Add name_scope for softmax

Before



After



Add regularization to the loss

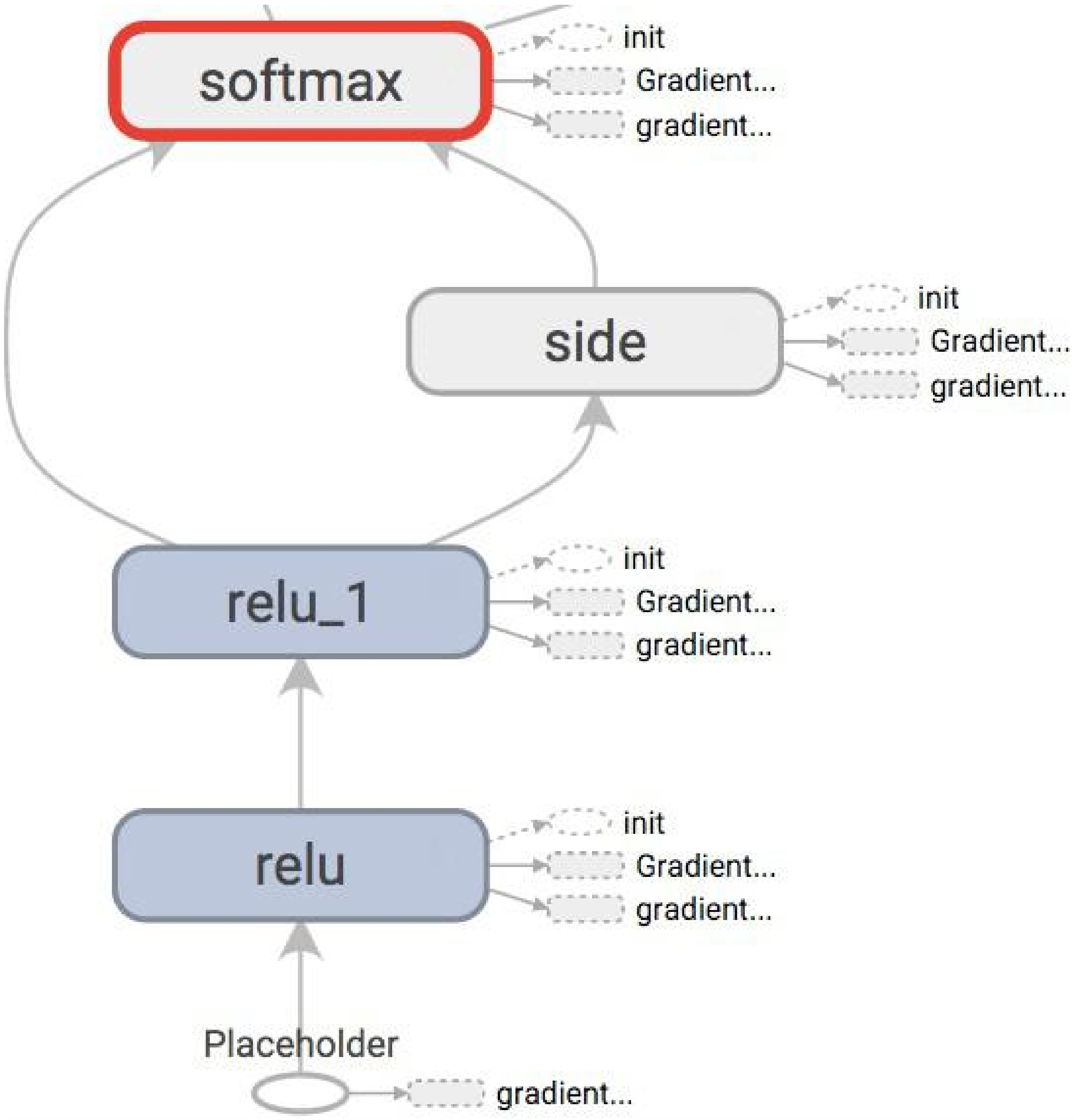
eg. L2 regularize on the Softmax layer parameters

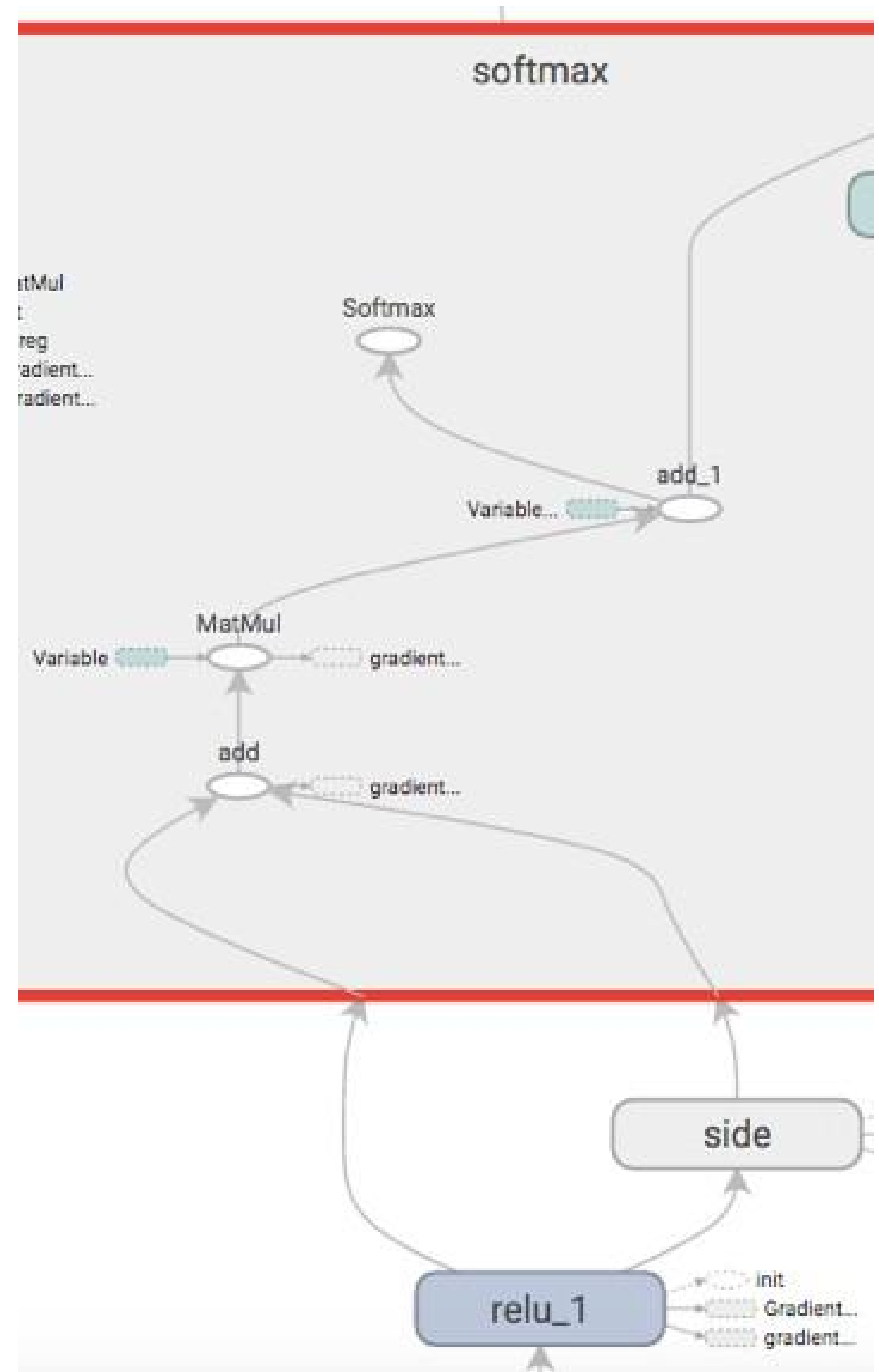
Add it to the loss

Automatic gradient calculation

```
…
l2reg = tf.reduce_sum(tf.square(softmax_w))
loss = cross_entropy + l2reg
train_op = optimizer.minimize(loss)
…
print sess.run(l2reg)
…
```

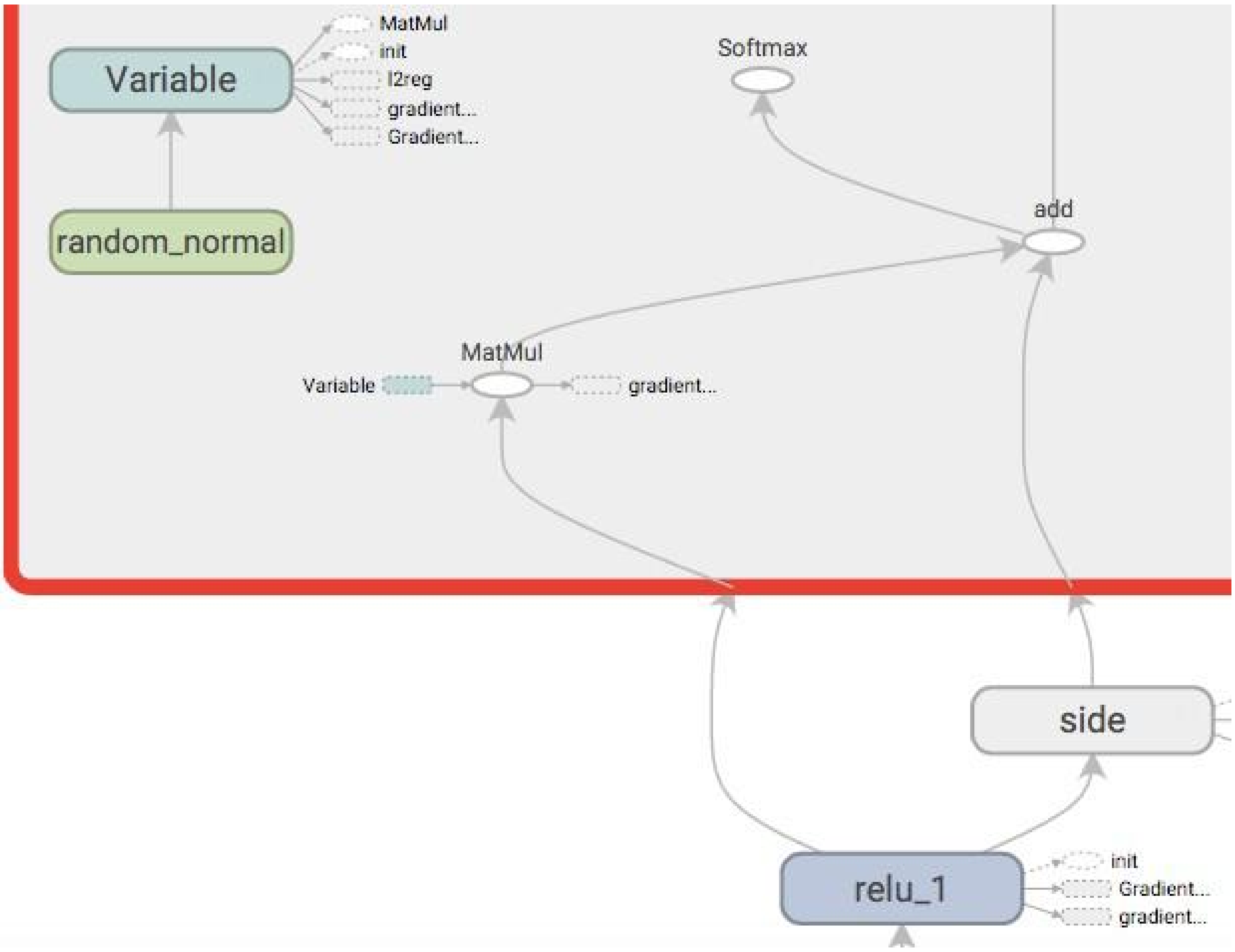
Add a parallel path





Use activation as bias

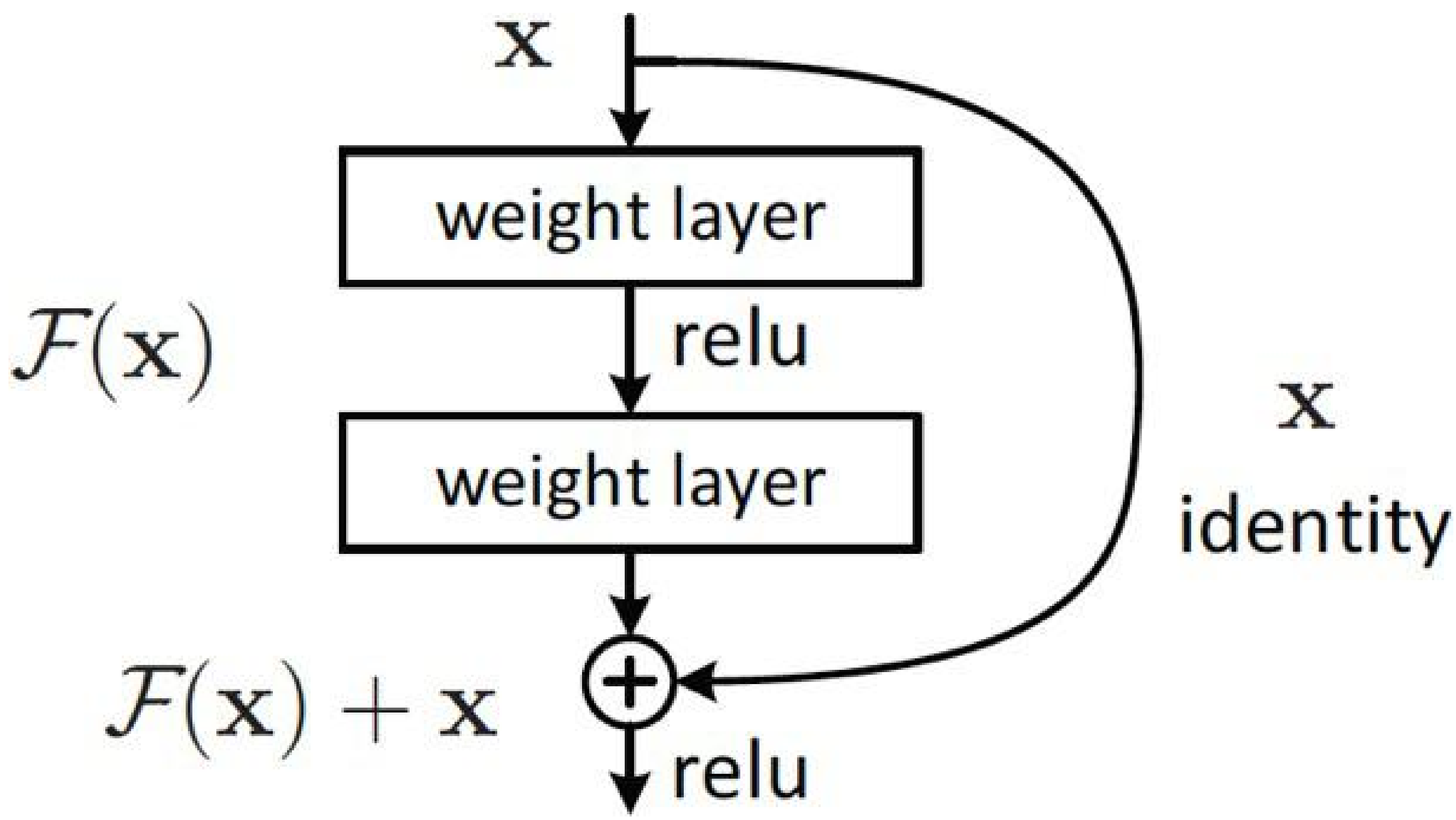
Everything is a tensor



Residual learning

He et al. 2015

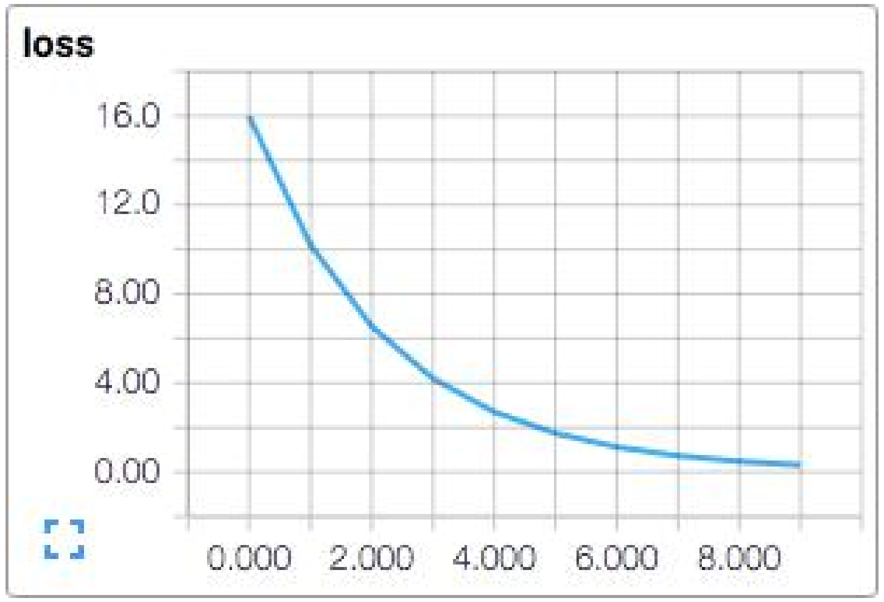
ILSVRC 2015 classification task winer



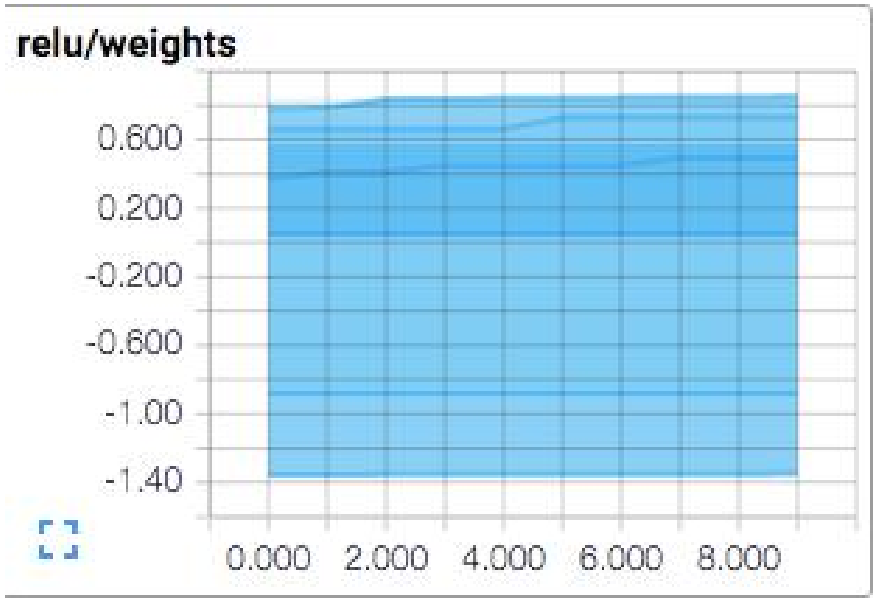
Visualize states

Add summaries

scalar_summary



histogram_summary




```
merged_summaries = tf.merge_all_summaries()
results = sess.run([train_op, merged_summaries],
                   feed_dict=…)
writer.add_summary(results[1], step)
```

Save and load models

tf.train.Saver(…)

Default will associate with all variables

all_variables()

save(sess, save_path, …)

restore(sess, save_path, …)

Replace initialization

That's why we need to run initialization separately

Convolution

conv2d(input, filter, strides, padding,
    use_cudnn_on_gpu=None, name=None)

LSTM

BasicLSTMCell

$$i_t = W_{ix}x_t + W_{ih}h_{t-1} + b_i$$
$$j_t = W_{jx}x_t + W_{jh}h_{t-1} + b_j$$
$$f_t = W_{fx}x_t + W_{fh}h_{t-1} + b_f$$
$$o_t = W_{ox}x_t + W_{oh}h_{t-1} + b_o$$
$$c_t = \sigma(f_t) \odot c_{t-1} + \sigma(i_t) \odot \tanh(j_t)$$
$$h_t = \sigma(o_t) \odot \tanh(c_t)$$

```
# Parameters of gates are concatenated into one multiply for efficiency.
c, h = array_ops.split(1, 2, state)
concat = linear([inputs, h], 4 * self._num_units, True)
# i = input_gate, j = new_input, f = forget_gate, o = output_gate
i, j, f, o = array_ops.split(1, 4, concat)
new_c = c * sigmoid(f + self._forget_bias) + sigmoid(i) * tanh(j)
new_h = tanh(new_c) * sigmoid(o)
```

Word2Vec with TensorFlow

```
# Look up embeddings for inputs.
embeddings = tf.Variable(
        tf.random_uniform([vocabulary_size, embedding_size], -1.0, 1.0))
embed = tf.nn.embedding_lookup(embeddings, train_inputs)
# Construct the variables for the NCE loss
nce_weights = tf.Variable(
        tf.truncated_normal([vocabulary_size, embedding_size],
                            stddev=1.0 / math.sqrt(embedding_size)))
nce_biases = tf.Variable(tf.zeros([vocabulary_size]))
# Compute the average NCE loss for the batch.
# tf.nce_loss automatically draws a new sample of the negative labels each
# time we evaluate the loss.
loss = tf.reduce_mean(
      tf.nn.nce_loss(nce_weights, nce_biases, embed, train_labels,
                     num_sampled, vocabulary_size))
```