

With TF 1.0!

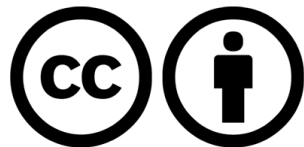


Lab 9

NN for XOR

Sung Kim <hunkim+ml@gmail.com>

Code: <https://github.com/hunkim/DeepLearningZeroToAll/>



Call for comments

Please feel free to add comments directly on these slides

Other slides: <https://goo.gl/jPtVNT>



With TF 1.0!

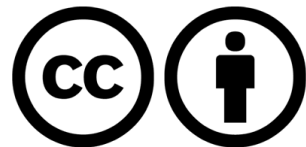


Lab 9-I

NN for XOR

Sung Kim <hunkim+ml@gmail.com>

Code: <https://github.com/hunkim/DeepLearningZeroToAll/>



<https://github.com/hunkim/DeepLearningZeroToAll/>



zeran4

1 commit / 5 ++ / 4 --

#11



jennykang

19 commits / 940 ++ / 253 --

#2



GzuPark

14 commits / 41 ++ / 31 --

#3



kkweon

5 commits / 372 ++ / 296 --

#4



BlueMelon715

4 commits / 45 ++ / 34 --

#5



jin-chong

2 commits / 4 ++ / 4 --

#6



FuZer

2 commits / 37 ++ / 30 --

#7



cynthia

1 commit / 28 ++ / 28 --

#8



keon

1 commit / 3 ++ / 3 --

#9

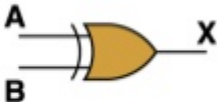


allieus

1 commit / 55 ++ / 59 --

#10

XOR data set

Boolean Expression	Logic Diagram Symbol	Truth Table															
$X = A \oplus B$		<table><tr><th>A</th><th>B</th><th>X</th></tr><tr><td>0</td><td>0</td><td>0</td></tr><tr><td>0</td><td>1</td><td>1</td></tr><tr><td>1</td><td>0</td><td>1</td></tr><tr><td>1</td><td>1</td><td>0</td></tr></table>	A	B	X	0	0	0	0	1	1	1	0	1	1	1	0
A	B	X															
0	0	0															
0	1	1															
1	0	1															
1	1	0															

```
x_data = np.array([[0, 0], [0, 1], [1, 0], [1, 1]], dtype=np.float32)
y_data = np.array([[0], [1], [1], [0]], dtype=np.float32)
```

XOR with logistic regression?

```
x_data = np.array([[0, 0], [0, 1], [1, 0], [1, 1]], dtype=np.float32)
y_data = np.array([[0], [1], [1], [0]], dtype=np.float32)
```

```
X = tf.placeholder(tf.float32)
Y = tf.placeholder(tf.float32)
W = tf.Variable(tf.random_normal([2, 1]), name='weight')
b = tf.Variable(tf.random_normal([1]), name='bias')
```

```
# Hypothesis using sigmoid: tf.div(1., 1. + tf.exp(tf.matmul(X, W)))
hypothesis = tf.sigmoid(tf.matmul(X, W) + b)
```

```
# cost/loss function
cost = -tf.reduce_mean(Y * tf.log(hypothesis) + (1 - Y) * tf.log(1 - hypothesis))
train = tf.train.GradientDescentOptimizer(learning_rate=0.1).minimize(cost)
```

```
# Accuracy computation
# True if hypothesis>0.5 else False
predicted = tf.cast(hypothesis > 0.5, dtype=tf.float32)
accuracy = tf.reduce_mean(tf.cast(tf.equal(predicted, Y), dtype=tf.float32))
```

```
# Launch graph
with tf.Session() as sess:
    # Initialize TensorFlow variables
    sess.run(tf.global_variables_initializer())
```

```
for step in range(10001):
    sess.run(train, feed_dict={X: x_data, Y: y_data})
    if step % 100 == 0:
        print(step, sess.run(cost, feed_dict={X: x_data, Y: y_data}), sess.run(W))
```

```
# Accuracy report
h, c, a = sess.run([hypothesis, predicted, accuracy], feed_dict={X: x_data, Y: y_data})
print("\nHypothesis: ", h, "\nCorrect: ", c, "\nAccuracy: ", a)
```

XOR with logistic regression?

But

it doesn't work!

```
x_data = np.array([[0, 0], [0, 1], [1, 0], [1, 1]], dtype=np.float32)
y_data = np.array([[0], [1], [1], [0]], dtype=np.float32)
```

```
X = tf.placeholder(tf.float32)
Y = tf.placeholder(tf.float32)
W = tf.Variable(tf.random_normal([2, 1]), name='weight')
b = tf.Variable(tf.random_normal([1]), name='bias')
```

```
# Hypothesis using sigmoid: tf.div(1., 1. + tf.exp(tf.matmul(X, W)))
hypothesis = tf.sigmoid(tf.matmul(X, W) + b)
```

```
# cost/loss function
cost = -tf.reduce_mean(Y * tf.log(hypothesis) + (1 - Y) * tf.log(1 - hypothesis))
train = tf.train.GradientDescentOptimizer(learning_rate=0.1).minimize(cost)
```

```
# Accuracy computation
# True if hypothesis>0.5 else False
predicted = tf.cast(hypothesis > 0.5, dtype=tf.float32)
accuracy = tf.reduce_mean(tf.cast(tf.equal(predicted, Y), dtype=tf.float32))
```

```
# Launch graph
with tf.Session() as sess:
    # Initialize TensorFlow variables
    sess.run(tf.global_variables_initializer())

    for step in range(10001):
        sess.run(train, feed_dict={X: x_data, Y: y_data})
        if step % 100 == 0:
            print(step, sess.run(cost, feed_dict={X: x_data, Y: y_data}), sess.run(W))
```

```
# Accuracy report
h, c, a = sess.run([hypothesis, predicted, accuracy], feed_dict={X: x_data, Y: y_data})
print("\nHypothesis: ", h, "\nCorrect: ", c, "\nAccuracy: ", a)
```

Hypothesis:

[[0.5]

[0.5]

[0.5]

[0.5]]

Correct:

[[0.]

[0.]

[0.]

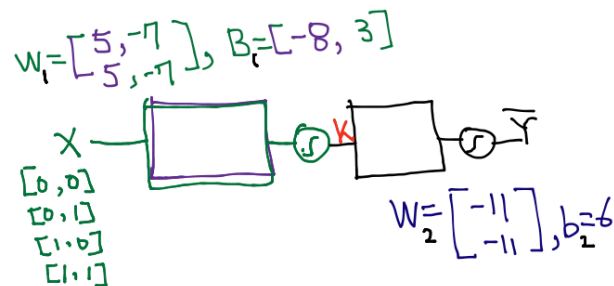
[0.]

Accuracy: 0.5

Neural Net

```
W = tf.Variable(tf.random_normal([2, 1]), name='weight')  
b = tf.Variable(tf.random_normal([1]), name='bias')
```

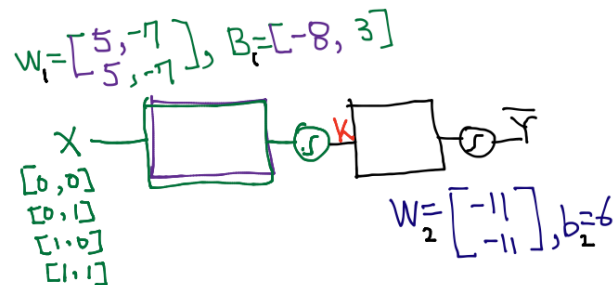
```
# Hypothesis using sigmoid: tf.div(1., 1. + tf.exp(tf.matmul(X, W)))  
hypothesis = tf.sigmoid(tf.matmul(X, W) + b)
```



Neural Net

```
W = tf.Variable(tf.random_normal([2, 1]), name='weight')
b = tf.Variable(tf.random_normal([1]), name='bias')
```

```
# Hypothesis using sigmoid: tf.div(1., 1. + tf.exp(tf.matmul(X, W)))
hypothesis = tf.sigmoid(tf.matmul(X, W) + b)
```



```
W1 = tf.Variable(tf.random_normal([2, 2]), name='weight1')
b1 = tf.Variable(tf.random_normal([2]), name='bias1')
layer1 = tf.sigmoid(tf.matmul(X, W1) + b1)
```

```
W2 = tf.Variable(tf.random_normal([2, 1]), name='weight2')
b2 = tf.Variable(tf.random_normal([1]), name='bias2')
hypothesis = tf.sigmoid(tf.matmul(layer1, W2) + b2)
```

```
x_data = np.array([[0, 0], [0, 1], [1, 0], [1, 1]], dtype=np.float32)
y_data = np.array([[0], [1], [1], [0]], dtype=np.float32)
X = tf.placeholder(tf.float32)
Y = tf.placeholder(tf.float32)
```

```
W1 = tf.Variable(tf.random_normal([2, 2]), name='weight1')
b1 = tf.Variable(tf.random_normal([2]), name='bias1')
layer1 = tf.sigmoid(tf.matmul(X, W1) + b1)
```

```
W2 = tf.Variable(tf.random_normal([2, 1]), name='weight2')
b2 = tf.Variable(tf.random_normal([1]), name='bias2')
hypothesis = tf.sigmoid(tf.matmul(layer1, W2) + b2)
```

```
# cost/loss function
cost = -tf.reduce_mean(Y * tf.log(hypothesis) + (1 - Y) * tf.log(1 - hypothesis))
train = tf.train.GradientDescentOptimizer(learning_rate=0.1).minimize(cost)

# Accuracy computation
# True if hypothesis>0.5 else False
predicted = tf.cast(hypothesis > 0.5, dtype=tf.float32)
accuracy = tf.reduce_mean(tf.cast(tf.equal(predicted, Y), dtype=tf.float32))

# Launch graph
with tf.Session() as sess:
    # Initialize TensorFlow variables
    sess.run(tf.global_variables_initializer())
    for step in range(10001):
        sess.run(train, feed_dict={X: x_data, Y: y_data})
        if step % 100 == 0:
            print(step, sess.run(cost, feed_dict={X: x_data, Y: y_data}), sess.run([W1, W2]))

# Accuracy report
h, c, a = sess.run([hypothesis, predicted, accuracy],
                    feed_dict={X: x_data, Y: y_data})
print("\nHypothesis: ", h, "\nCorrect: ", c, "\nAccuracy: ", a)
```

NN for XOR

Hypothesis:
[[0.01338218]
[0.98166394]
[0.98809403]
[0.01135799]]

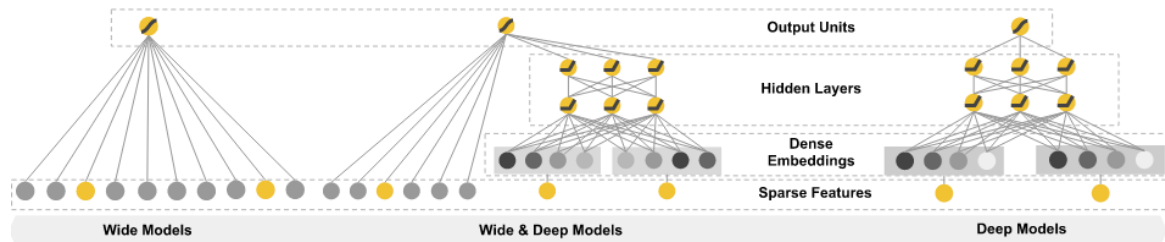
Correct:
[[0.]
[1.]
[1.]
[0.]]

Accuracy: 1.0

Wide NN for XOR

```
W1 = tf.Variable(tf.random_normal([2, 10]), name='weight1')
b1 = tf.Variable(tf.random_normal([10]), name='bias1')
layer1 = tf.sigmoid(tf.matmul(X, W1) + b1)
```

```
W2 = tf.Variable(tf.random_normal([10, 1]), name='weight2')
b2 = tf.Variable(tf.random_normal([1]), name='bias2')
hypothesis = tf.sigmoid(tf.matmul(layer1, W2) + b2)
```



[2,10], [10,1]

Hypothesis:

[[0.00358802]
[0.99366933]
[0.99204296]
[0.0095663]]

Correct:

[[0.]
[1.]
[1.]
[0.]]

Accuracy: 1.0

[2,2], [2,1]

Hypothesis:

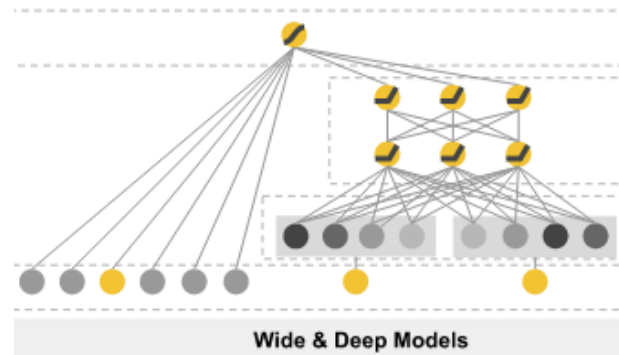
[[0.01338218]
[0.98166394]
[0.98809403]
[0.01135799]]

Correct:

[[0.]
[1.]
[1.]
[0.]]

Accuracy: 1.0

Deep NN for XOR



```
W1 = tf.Variable(tf.random_normal([2, 10]), name='weight1')
b1 = tf.Variable(tf.random_normal([10]), name='bias1')
layer1 = tf.sigmoid(tf.matmul(X, W1) + b1)
```

```
W2 = tf.Variable(tf.random_normal([10, 10]), name='weight2')
b2 = tf.Variable(tf.random_normal([10]), name='bias2')
layer2 = tf.sigmoid(tf.matmul(layer1, W2) + b2)
```

```
W3 = tf.Variable(tf.random_normal([10, 10]), name='weight3')
b3 = tf.Variable(tf.random_normal([10]), name='bias3')
layer3 = tf.sigmoid(tf.matmul(layer2, W3) + b3)
```

```
W4 = tf.Variable(tf.random_normal([10, 1]), name='weight4')
b4 = tf.Variable(tf.random_normal([1]), name='bias4')
hypothesis = tf.sigmoid(tf.matmul(layer3, W4) + b4)
```

4 layers

Hypothesis:

```
[[ 7.80e-04]
 [ 9.99e-01]
 [ 9.98e-01]
 [ 1.55e-03]]
```

Correct:

```
[[ 0.]
 [ 1.]
 [ 1.]
 [ 0.]]
```

Accuracy: 1.0

2 layers

Hypothesis:

```
[[ 0.01338218]
 [ 0.98166394]
 [ 0.98809403]
 [ 0.01135799]]
```

Correct:

```
[[ 0.]
 [ 1.]
 [ 1.]
 [ 0.]]
```

Accuracy: 1.0

Exercise

- Wide and Deep NN for MNIST



With TF 1.0!

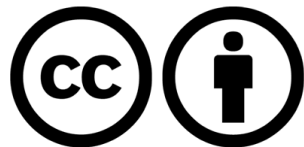


Lab 9-2

Tensorboard for XOR NN

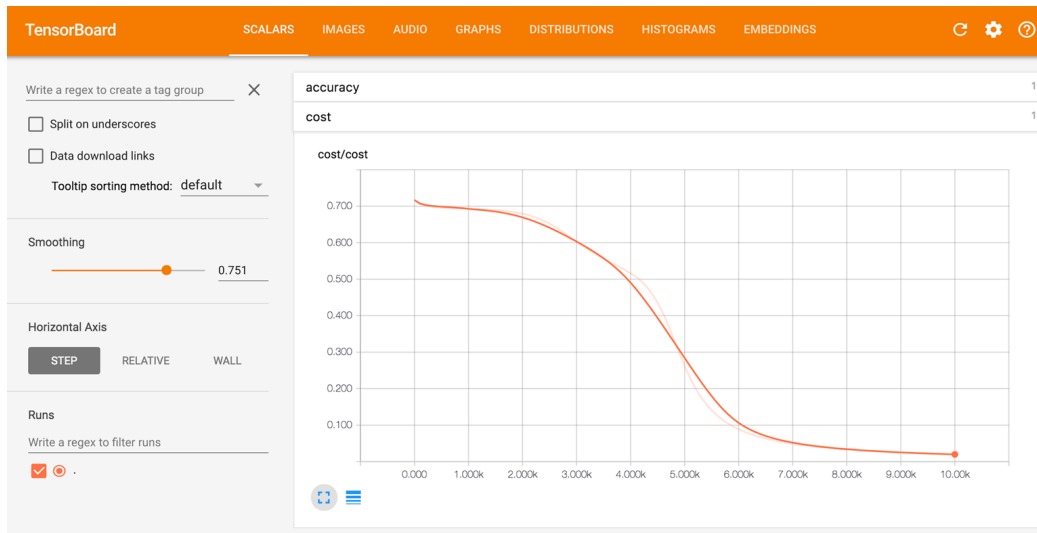
Sung Kim <hunkim+ml@gmail.com>

Code: <https://github.com/hunkim/DeepLearningZeroToAll/>



TensorBoard: TF logging/debugging tool

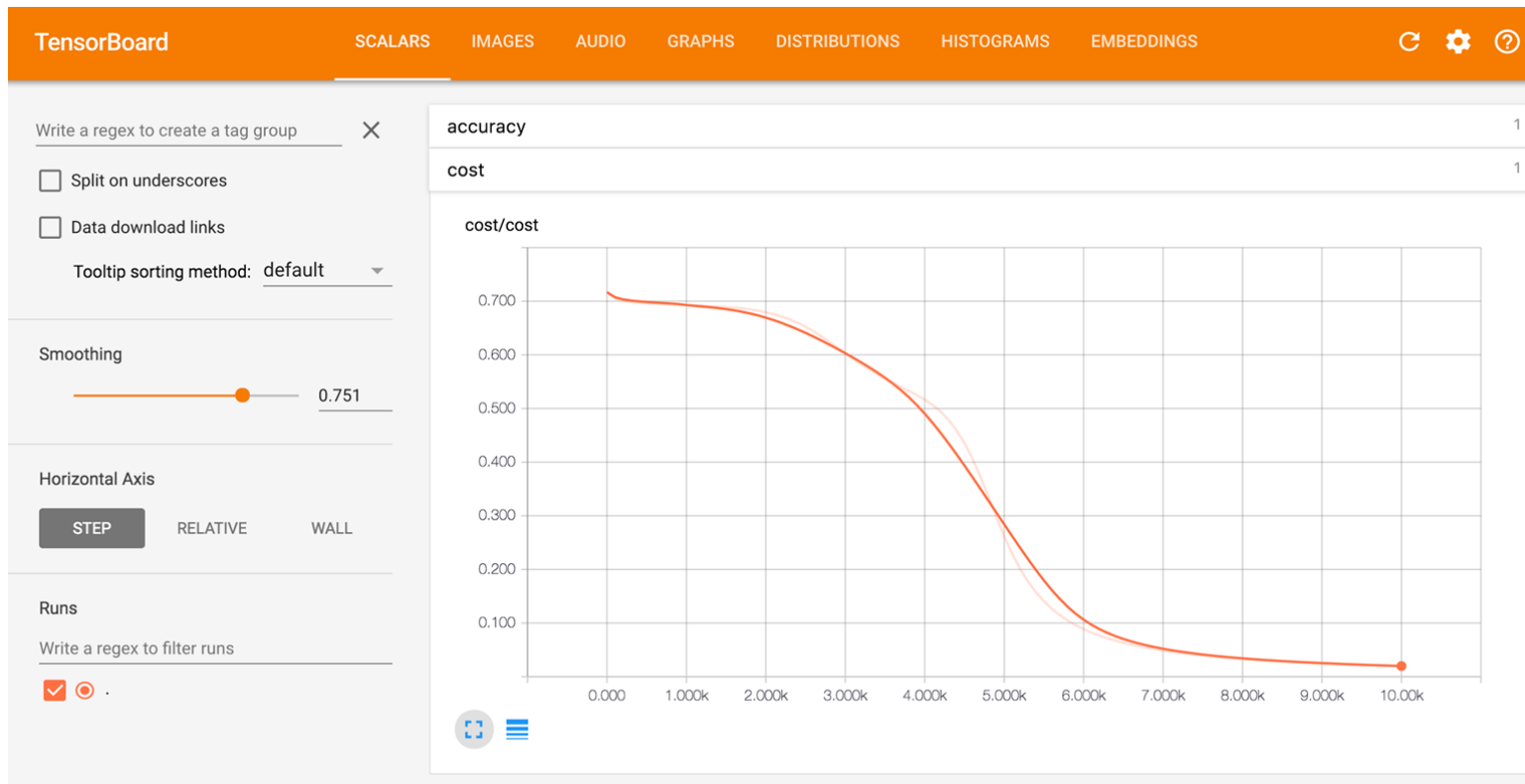
- Visualize your TF graph
- Plot quantitative metrics
- Show additional data



Old fashion: print, print, print

```
9400 0.0151413 [array([[ 6.21692038,  6.05913448],
      [-6.33773184, -5.75189114]], dtype=float32), array([[ 9.93581772],
      [-9.43034935]], dtype=float32)]
9500 0.014909 [array([[ 6.22498751,  6.07049847],
      [-6.34637976, -5.76352596]], dtype=float32), array([[ 9.96414757],
      [-9.45942593]], dtype=float32)]
9600 0.0146836 [array([[ 6.23292685,  6.08166742],
      [-6.35489035, -5.77496052]], dtype=float32), array([[ 9.99207973],
      [-9.48807526]], dtype=float32)]
9700 0.0144647 [array([[ 6.24074268,  6.09264851],
      [-6.36326933, -5.78619957]], dtype=float32), array([[ 10.01962471],
      [-9.51631165]], dtype=float32)]
9800 0.0142521 [array([[ 6.24843407,  6.10344648],
      [-6.37151814, -5.79724932]], dtype=float32), array([[ 10.04679298],
      [-9.54414845]], dtype=float32)]
9900 0.0140456 [array([[ 6.25601053,  6.11406422],
      [-6.3796401 , -5.80811596]], dtype=float32), array([[ 10.07359505],
      [-9.57159519]], dtype=float32)]
10000 0.0138448 [array([[ 6.26347113,  6.12451124],
      [-6.38764334, -5.81880617]], dtype=float32), array([[ 10.10004139],
      [-9.59866238]], dtype=float32)]
```


New way!



5 steps of using TensorBoard

1 From TF graph, decide which tensors you want to log

```
w2_hist = tf.summary.histogram("weights2", W2)
cost_summ = tf.summary.scalar("cost", cost)
```

2 Merge all summaries

```
summary = tf.summary.merge_all()
```

3 Create writer and add graph

```
# Create summary writer
writer = tf.summary.FileWriter('./logs')
writer.add_graph(sess.graph)
```

4 Run summary merge and add_summary

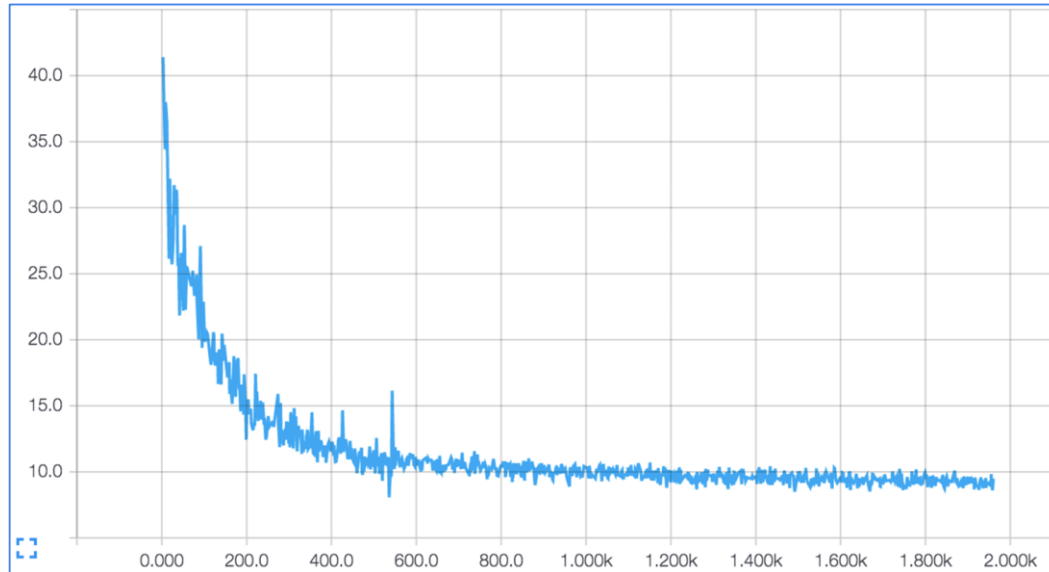
```
s, _ = sess.run([summary, optimizer], feed_dict=feed_dict)
writer.add_summary(s, global_step=global_step)
```

5 Launch TensorBoard

```
tensorboard --logdir=./logs
```

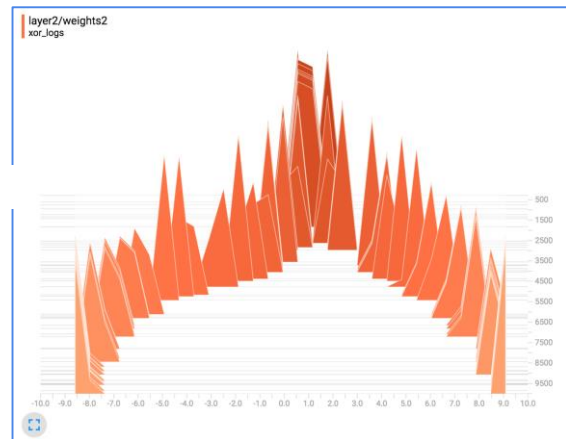
Scalar tensors

```
cost_summ = tf.summary.scalar("cost", cost)
```



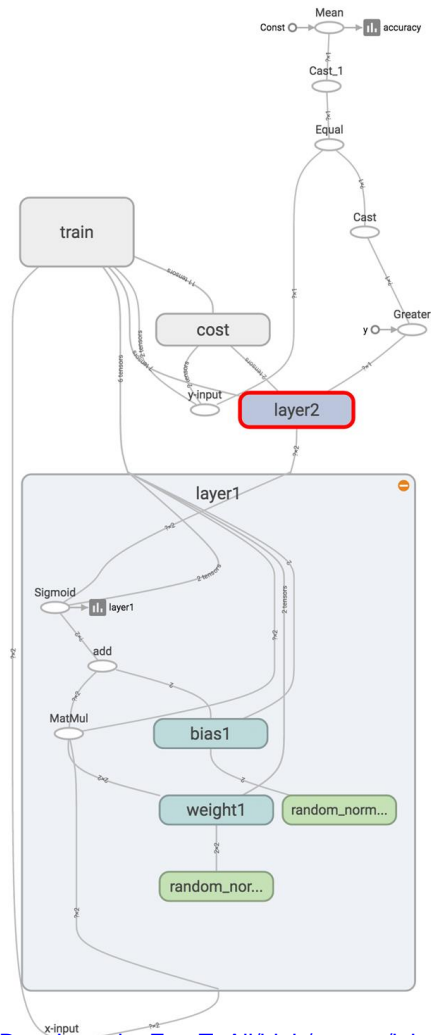
Histogram (multi-dimensional tensors)

```
W2 = tf.Variable(tf.random_normal([2, 1]), name='weight2')  
b2 = tf.Variable(tf.random_normal([1]), name='bias2')  
hypothesis = tf.sigmoid(tf.matmul(layer1, W2) + b2)  
  
w2_hist = tf.summary.histogram("weights2", W2)  
b2_hist = tf.summary.histogram("biases2", b2)  
hypothesis_hist = tf.summary.histogram("hypothesis", hypothesis)
```



Add scope for better graph hierarchy

```
with tf.name_scope("layer1") as scope:  
    W1 = tf.Variable(tf.random_normal([2, 2]), name='weight1')  
    b1 = tf.Variable(tf.random_normal([2]), name='bias1')  
    layer1 = tf.sigmoid(tf.matmul(X, W1) + b1)  
  
    w1_hist = tf.summary.histogram("weights1", W1)  
    b1_hist = tf.summary.histogram("biases1", b1)  
    layer1_hist = tf.summary.histogram("layer1", layer1)  
  
with tf.name_scope("layer2") as scope:  
    W2 = tf.Variable(tf.random_normal([2, 1]), name='weight2')  
    b2 = tf.Variable(tf.random_normal([1]), name='bias2')  
    hypothesis = tf.sigmoid(tf.matmul(layer1, W2) + b2)  
  
    w2_hist = tf.summary.histogram("weights2", W2)  
    b2_hist = tf.summary.histogram("biases2", b2)  
    hypothesis_hist = tf.summary.histogram("hypothesis", hypothesis)
```



2 Merge summaries and create writer

3 after creating session

Summary

```
summary = tf.summary.merge_all()
```

initialize

```
sess = tf.Session()
```

```
sess.run(tf.global_variables_initializer())
```

Create summary writer

```
writer = tf.summary.FileWriter(TB_SUMMARY_DIR)
```

```
writer.add_graph(sess.graph) # Add graph in the tensorboard
```

4 Run merged summary and write (add summary)

```
s, _ = sess.run([summary, optimizer], feed_dict=feed_dict)
writer.add_summary(s, global_step=global_step)
global_step += 1
```

5 Launch tensorboard (local)

```
writer = tf.summary.FileWriter("./logs/xor_logs")
```

```
$ tensorboard --logdir=./logs/xor_logs
```

Starting TensorBoard b'41' on port 6006
(You can navigate to <http://127.0.0.1:6006>)

5 Launch tensorboard (remote server)

```
ssh -L local_port:127.0.0.1:remote_port username@server.com
```

```
local> $ ssh -L 7007:121.0.0.0:6006 hunkim@server.com  
server> $ tensorboard --logdir=./logs/xor_logs
```

(You can navigate to <http://127.0.0.1:7007>)

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

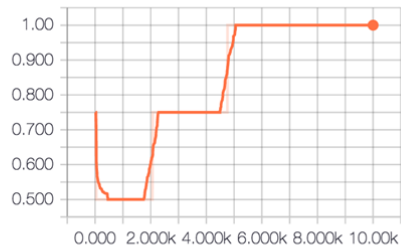
Runs

Write a regex to filter runs

☒ xor_logs☐ xor_logs_r0_01

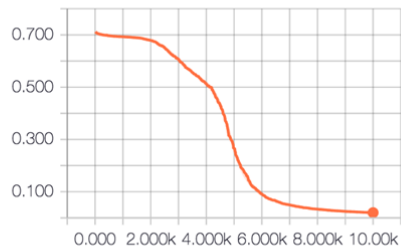
accuracy

accuracy



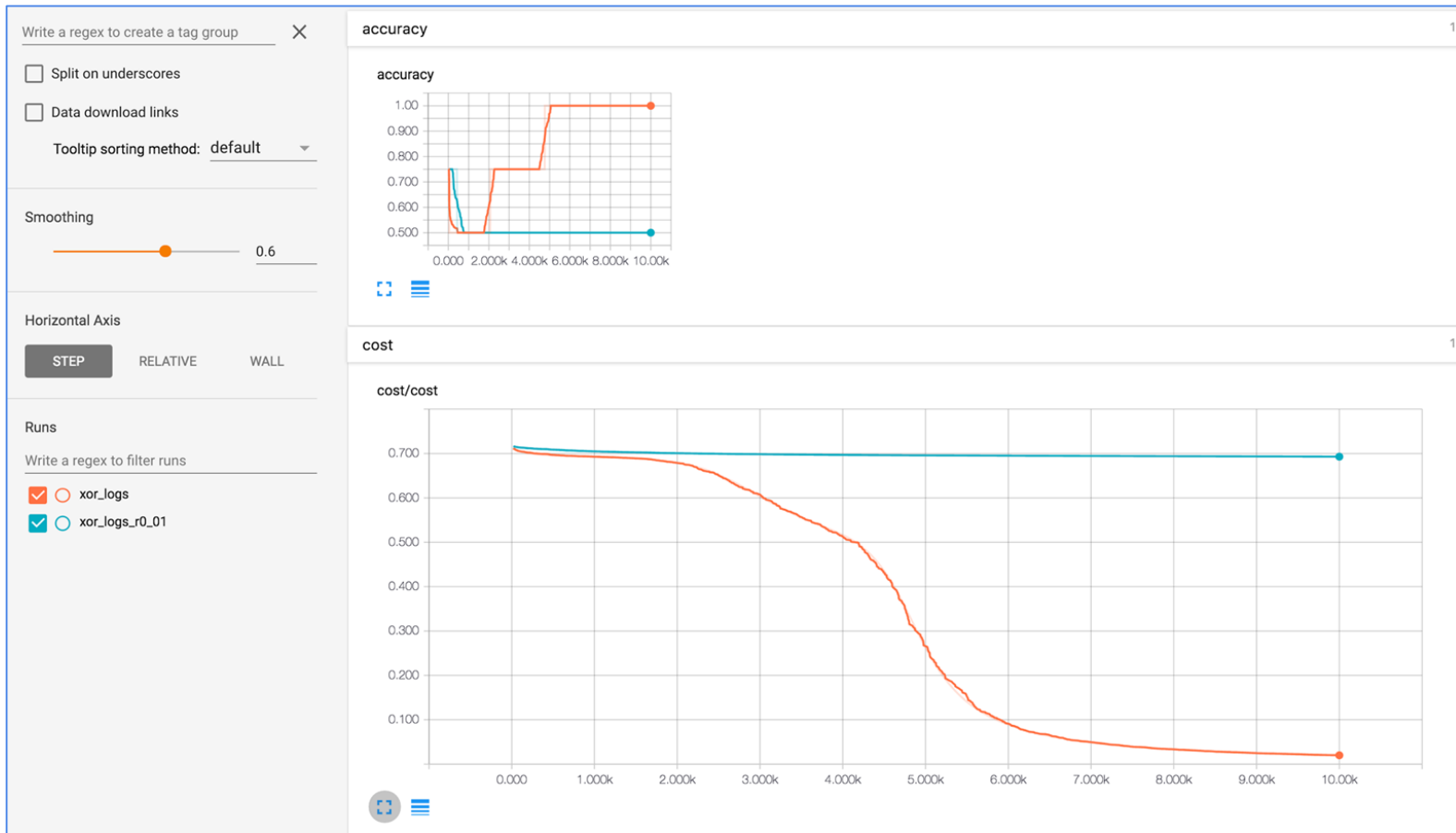
cost

cost/cost



Multiple runs

learning_rate=0.1 VS learning_rate=0.01



Multiple runs

```
tensorboard --logdir=./logs/xor_logs
```

```
train = tf.train.GradientDescentOptimizer(learning_rate=0.1).minimize(cost)
```

```
...
```

```
writer = tf.summary.FileWriter("./logs/xor_logs")
```

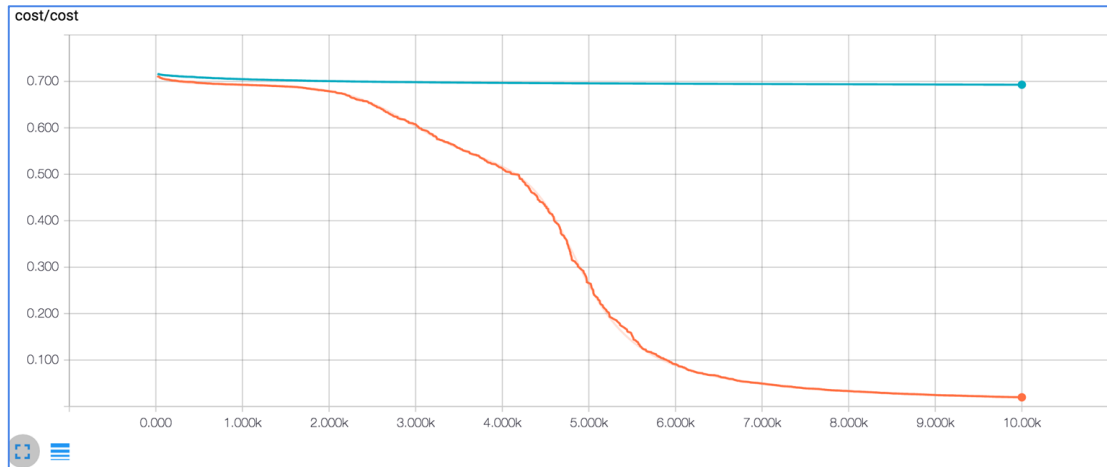
```
tensorboard --logdir=./logs/xor_logs_r0_01
```

```
train = tf.train.GradientDescentOptimizer(learning_rate=0.01).minimize(cost)
```

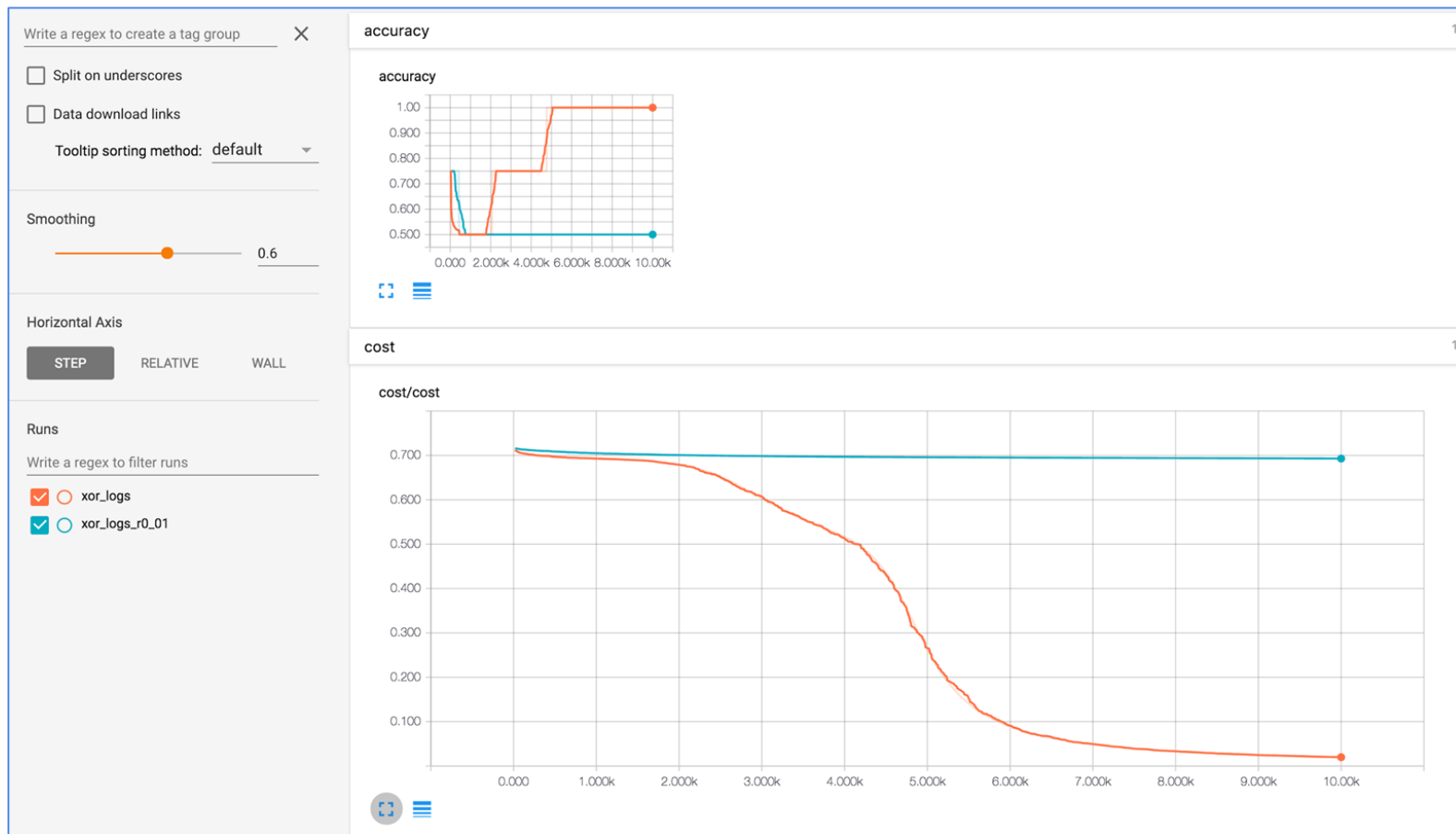
```
...
```

```
writer = tf.summary.FileWriter("./logs/xor_logs_r0_01")
```

```
tensorboard --logdir=./logs
```



Multiple runs



5 steps of using TensorBoard

1 From TF graph, decide which tensors you want to log

```
w2_hist = tf.summary.histogram("weights2", W2)
cost_summ = tf.summary.scalar("cost", cost)
```

2 Merge all summaries

```
summary = tf.summary.merge_all()
```

3 Create writer and add graph

```
# Create summary writer
writer = tf.summary.FileWriter('./logs')
writer.add_graph(sess.graph)
```

4 Run summary merge and add_summary

```
s, _ = sess.run([summary, optimizer], feed_dict=feed_dict)
writer.add_summary(s, global_step=global_step)
```

5 Launch TensorBoard

```
tensorboard --logdir=./logs
```

Exercise

- Wide and Deep NN for MNIST
- Add tensorboard



With TF 1.0!

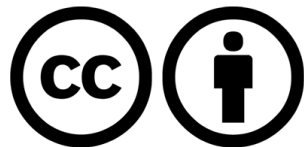


Lab 9-2-E

Tensorboard for MNIST

Sung Kim <hunkim+ml@gmail.com>

Code: <https://github.com/hunkim/DeepLearningZeroToAll/>

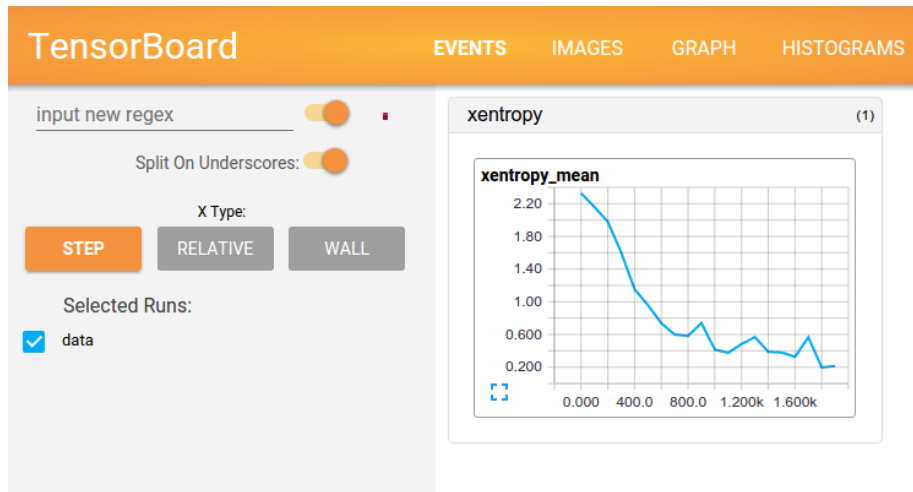


Visualizing your Deep learning using TensorBoard (TensorFlow)

Sung Kim <hunkim+ml@gmail.com>

TensorBoard: TF logging/debugging tool

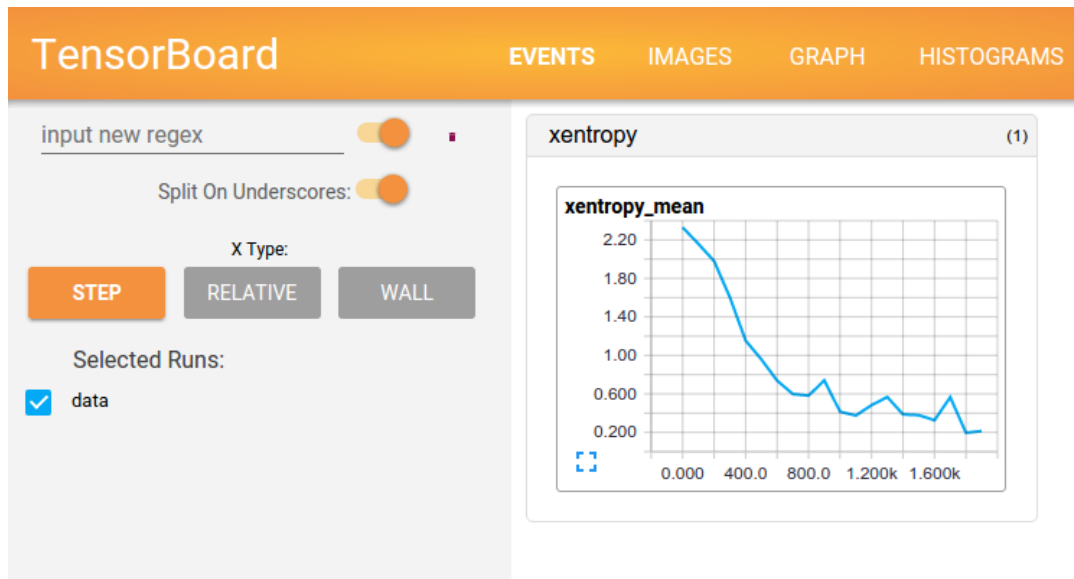
- Visualize your TF graph
- Plot quantitative metrics
- Show additional data



Old fashion: print, print, print

```
2000 [0.69364417, array([[ 0.50981331,  0.50592244],
      [ 0.37054271,  0.37088916],
      [ 0.6810087 ,  0.38607275],
      [ 0.54717511,  0.26581794]], dtype=float32), array([[ 0.50861073],
      [ 0.51602864],
      [ 0.4826754 ]],
      dtype=float32), array([[ 0.71915275, -0.48754135],
      [-0.56914777, -0.55209494]], dtype=float32), array([[ -0.44138899],
      [ 0.23536676]], dtype=float32), array([ 0.03925836,  0.02369077], dtype=float32), array([ 0.14039496], dtype=float32)]
4000 [0.69332385, array([[ 0.52235132,  0.50927138],
      [ 0.38598102,  0.37814924],
      [ 0.69650716,  0.39592981],
      [ 0.56881481,  0.27748841]], dtype=float32), array([[ 0.50748861],
      [ 0.51554251],
      [ 0.48338425],
      [ 0.49113813]], dtype=float32), array([[ 0.74125487, -0.45954311],
      [-0.55370271, -0.53450096]], dtype=float32), array([[ -0.42565805],
      [ 0.19686614]], dtype=float32), array([ 0.08946501,  0.03708982], dtype=float32), array([ 0.15204136], dtype=float32)]
6000 [0.69306737, array([[ 0.53439337,  0.51197231],
      [ 0.39961013,  0.38383543],
      [ 0.71191686,  0.40380618],
      [ 0.58899951,  0.2868301 ]], dtype=float32), array([[ 0.50660294],
      [ 0.51538038],
```

New way!



5 steps of using TensorBoard

- 1 From TF graph, decide which tensors you want to log

```
with tf.variable_scope('layer1') as scope:  
    tf.summary.image('input', x_image, 3)  
    tf.summary.histogram("layer", L1)  
    tf.summary.scalar("loss", cost)
```
- 2 Merge all summaries

```
summary = tf.summary.merge_all()
```
- 3 Create writer and add graph

```
# Create summary writer  
writer = tf.summary.FileWriter(TB_SUMMARY_DIR)  
writer.add_graph(sess.graph)
```
- 4 Run summary merge and add_summary

```
s, _ = sess.run([summary, optimizer], feed_dict=feed_dict)  
writer.add_summary(s, global_step=global_step)
```
- 5 Launch TensorBoard

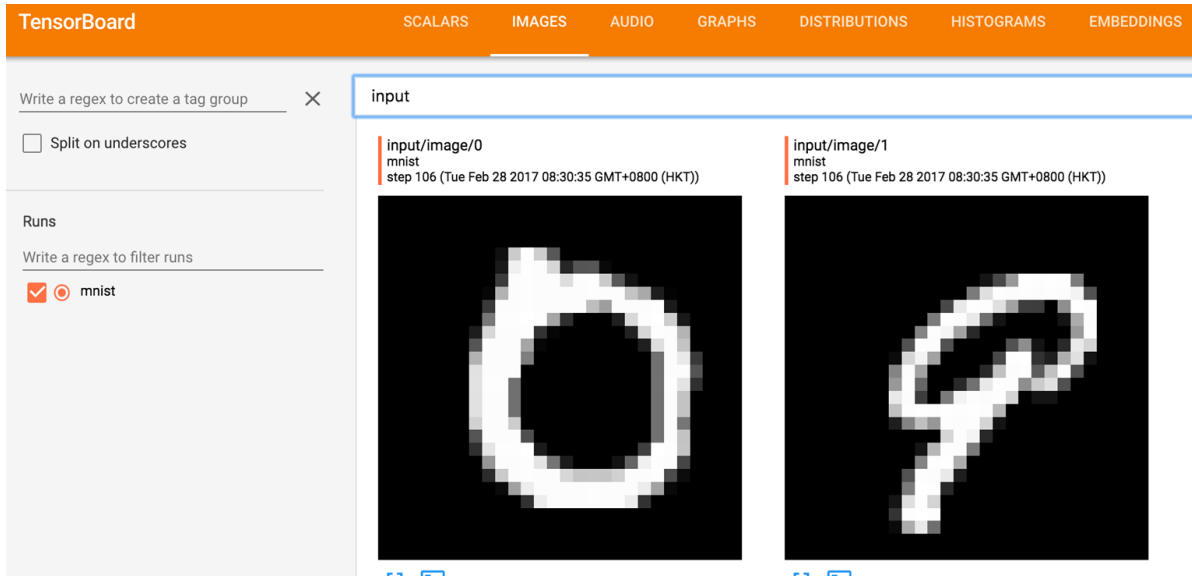
```
tensorboard --logdir=/tmp/mnist_logs
```

Image Input

```
# Image input
```

```
x_image = tf.reshape(X, [-1, 28, 28, 1])
```

```
tf.summary.image('input', x_image, 3)
```

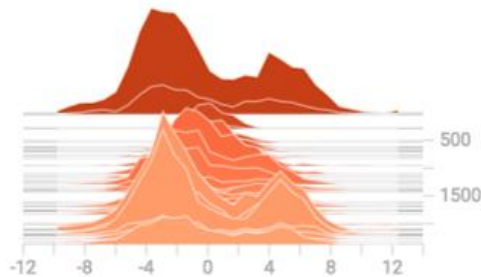


Histogram (multi-dimensional tensors)

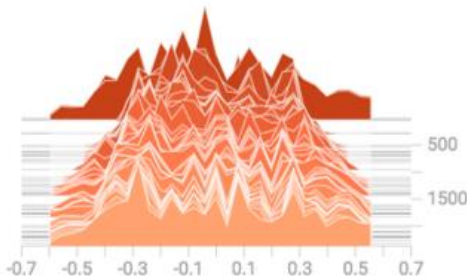
```
with tf.variable_scope('layer1') as scope:  
    W1 = tf.get_variable("W", shape=[784, 512])  
    b1 = tf.Variable(tf.random_normal([512]))  
    L1 = tf.nn.relu(tf.matmul(X, W1) + b1)  
    L1 = tf.nn.dropout(L1, keep_prob=keep_prob)
```

```
tf.summary.histogram("X", X)  
tf.summary.histogram("weights", W1)  
tf.summary.histogram("bias", b1)  
tf.summary.histogram("layer", L1)
```

layer2/layer

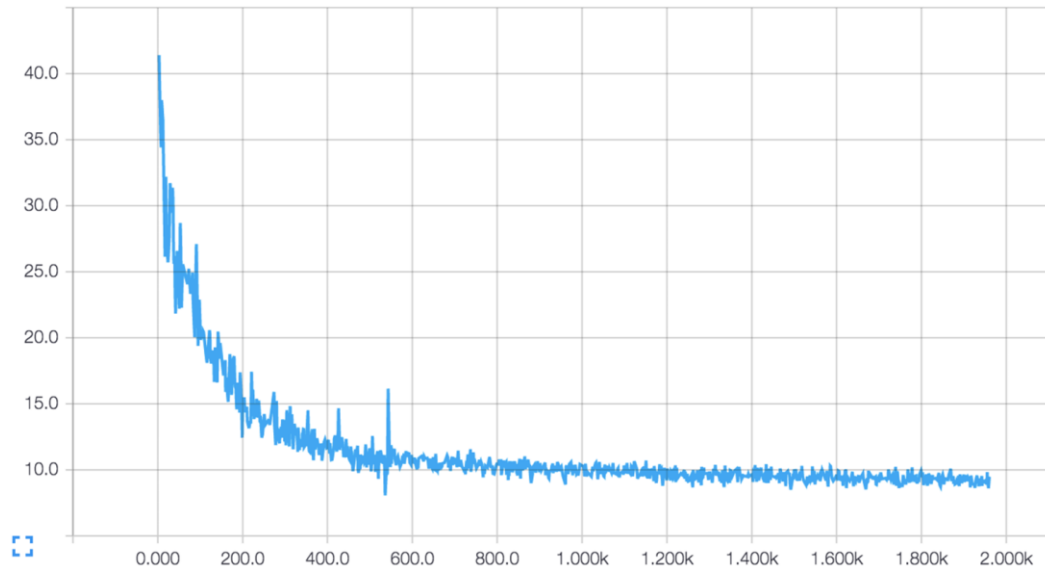


layer2/weights



Scalar tensors

```
tf.summary.scalar("loss", cost)
```



Add scope for better hierarchy

```
with tf.variable_scope('layer1') as scope:  
    W1 = tf.get_variable("W", shape=[784, 512], ...  
    b1 = tf.Variable(tf.random_normal([512]))  
    L1 = tf.nn.relu(tf.matmul(X, W1) + b1)  
    L1 = tf.nn.dropout(L1, keep_prob=keep_prob)
```

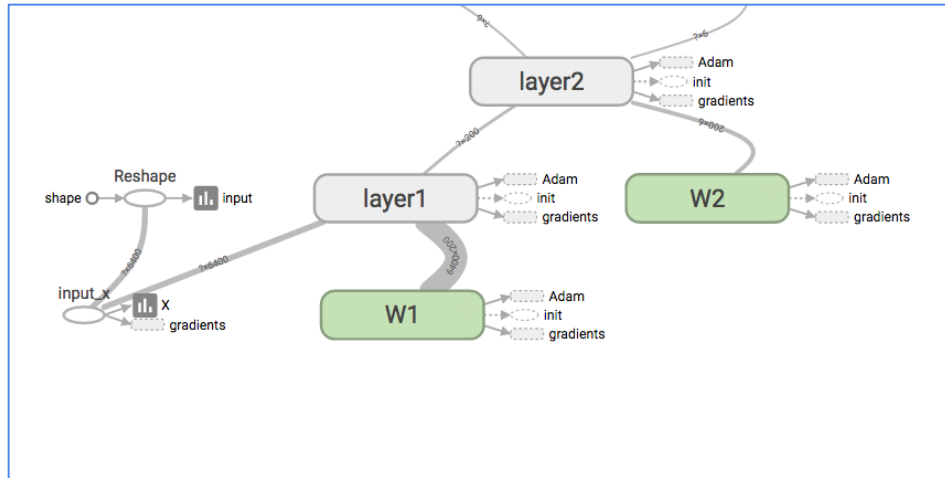
```
tf.summary.histogram("X", X)  
tf.summary.histogram("weights", W1)  
tf.summary.histogram("bias", b1)  
tf.summary.histogram("layer", L1)
```

```
with tf.variable_scope('layer2') as scope:  
    ...
```

```
with tf.variable_scope('layer3') as scope:  
    ...
```

```
with tf.variable_scope('layer4') as scope:  
    ...
```

```
with tf.variable_scope('layer5') as scope:  
    ...
```



2 Merge summaries and create writer

3 after creating session

Summary

```
summary = tf.summary.merge_all()
```

initialize

```
sess = tf.Session()
```

```
sess.run(tf.global_variables_initializer())
```

Create summary writer

```
writer = tf.summary.FileWriter(TB_SUMMARY_DIR)
```

```
writer.add_graph(sess.graph)
```

Run merged summary and write (add summary)

```
s, _ = sess.run([summary, optimizer], feed_dict=feed_dict)
writer.add_summary(s, global_step=global_step)
global_step += 1
```

Launch tensorboard (local)

```
writer = tf.summary.FileWriter("/tmp/mnist_logs")
```

```
$ tensorboard --logdir=/tmp/mnist_logs
```

Starting TensorBoard b'4I' on port 6006

(You can navigate to <http://127.0.0.1:6006>)

Launch tensorboard (remote server)

```
ssh -L local_port:127.0.0.1:remote_port username@server.com
```

```
local> $ ssh -L 7007:127.0.0.1:6006 hunkim@server.com  
server> $ tensorboard --logdir=/tmp/mnist_logs
```

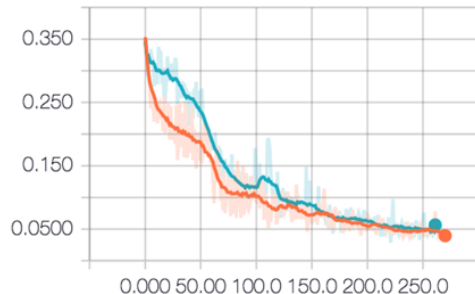
(You can navigate to <http://127.0.0.1:7007>)

Multiple runs

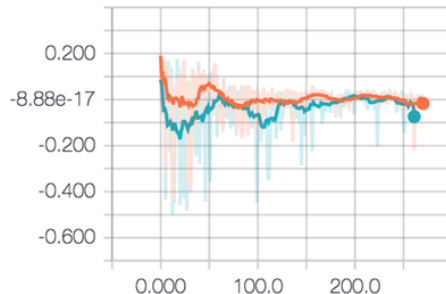
```
tensorboard --logdir=/tmp/mnist_logs/run1  
    writer = tf.summary.FileWriter("/tmp/mnist_logs/run1")  
tensorboard --logdir=/tmp/mnist_logs/run2  
    writer = tf.summary.FileWriter("/tmp/mnist_logs/run1")
```

```
tensorboard --logdir=/tmp/mnist_logs
```

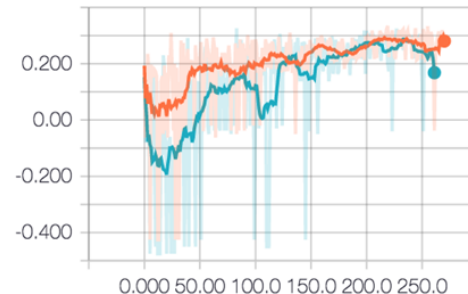
log_likelihood



loss



reward_1



5 steps of using TensorBoard

- 1 From TF graph, decide which tensors you want to log

```
with tf.variable_scope('layer1') as scope:  
    tf.summary.image('input', x_image, 3)  
    tf.summary.histogram("layer", L1)  
    tf.summary.scalar("loss", cost)
```

- 2 Merge all summaries

```
summary = tf.summary.merge_all()
```

- 3 Create writer and add graph

```
# Create summary writer  
writer = tf.summary.FileWriter(TB_SUMMARY_DIR)  
writer.add_graph(sess.graph)
```

- 4 Run summary merge and add_summary

```
s, _ = sess.run([summary, optimizer], feed_dict=feed_dict)  
writer.add_summary(s, global_step=global_step)
```

- 5 Launch TensorBoard

```
tensorboard --logdir=/tmp/mnist_logs
```

With TF 1.0!

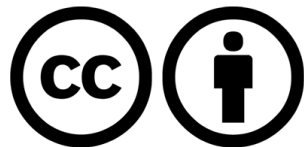


Lab 9-3 (optional)

NN Backpropagation

Sung Kim <hunkim+ml@gmail.com>

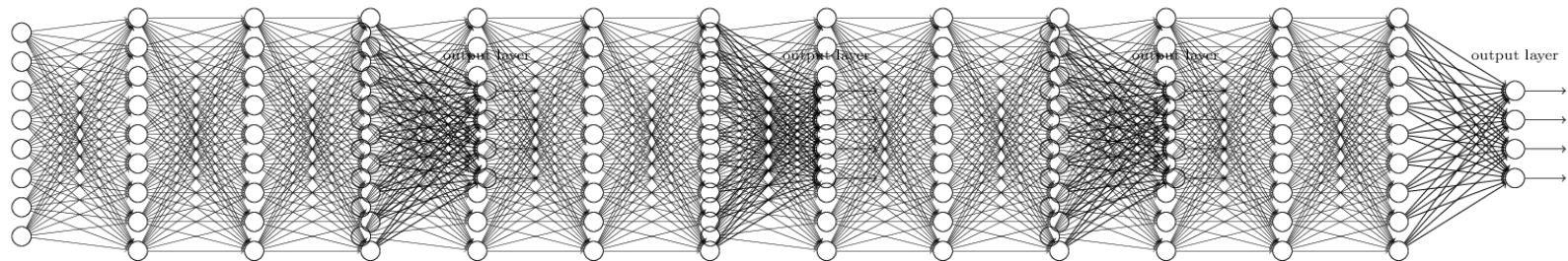
Code: <https://github.com/hunkim/DeepLearningZeroToAll/>



<https://github.com/hunkim/DeepLearningZeroToAll/>

 sxscience 1 commit / 350 ++ / 0 --	#12	 jennykang 19 commits / 940 ++ / 253 --	#2	 GzuPark 15 commits / 49 ++ / 39 --	#3	 kkweon 12 commits / 1,087 ++ / 340 --	#4
 BlueMelon715 5 commits / 55 ++ / 44 --	#5	 jihobak 3 commits / 244 ++ / 1,289 --	#6	 FuZer 2 commits / 37 ++ / 30 --	#7	 jin-chong 2 commits / 4 ++ / 4 --	#8
 zeran4 1 commit / 5 ++ / 4 --	#9	 cynthia 1 commit / 28 ++ / 28 --	#10	 kaka120011 1 commit / 1 ++ / 1 --	#11	 keon 1 commit / 3 ++ / 3 --	#12
 allieus 1 commit / 55 ++ / 59 --	#13	 togheppi 1 commit / 1,280 ++ / 0 --	#14	 davinnovation 1 commit / 64 ++ / 0 --	#15	 skyer9 1 commit / 94 ++ / 69 --	#16
 redongjun 1 commit / 78 ++ / 0 --	#17	 bkRyusim 1 commit / 1 ++ / 1 --	#18	 maestrojeong 1 commit / 50 ++ / 0 --	#19	 mjc92 1 commit / 1,215 ++ / 0 --	#13

How to train?




Gradient descent algorithm

$$W := W - \alpha \frac{1}{m} \sum_{i=1}^m (Wx^{(i)} - y^{(i)})x^{(i)}$$

$$w = w - \alpha \frac{\partial E}{\partial w}$$

Tensorflow Magic!



$$w = w - \alpha \frac{\partial E}{\partial w}$$

```
train = tf.train.GradientDescentOptimizer(learning_rate=0.1).minimize(cost)
```

“Yes you should understand backprop”

- “If you try to ignore how it works under the hood because *TensorFlow* *automagically makes my networks learn*”
 - “You will not be ready to wrestle with the dangers it presents”
 - “You will be much less effective at building and debugging neural networks.”
- “The good news is that backpropagation is not that difficult to understand”
 - “if presented properly.”

Back propagation (chain rule)

$$f = wx + b, \quad g = wx, \quad f = g + b$$

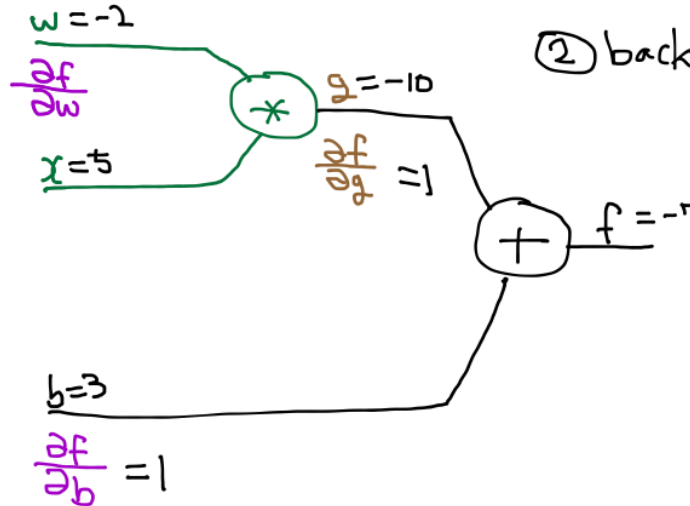
$\frac{\partial f}{\partial g} = 1, \quad \frac{\partial f}{\partial b} = 1$

$\hookrightarrow \frac{\partial g}{\partial w} = x$

① forward ($w = -2, x = 5, b = 3$)

② backward

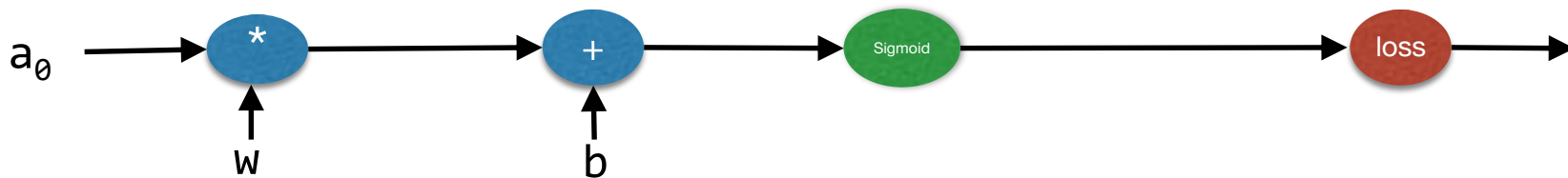
$$\frac{\partial f}{\partial w} = \frac{\partial f}{\partial g} \frac{\partial g}{\partial w} = 1 * x = 5$$



Back propagation (chain rule)

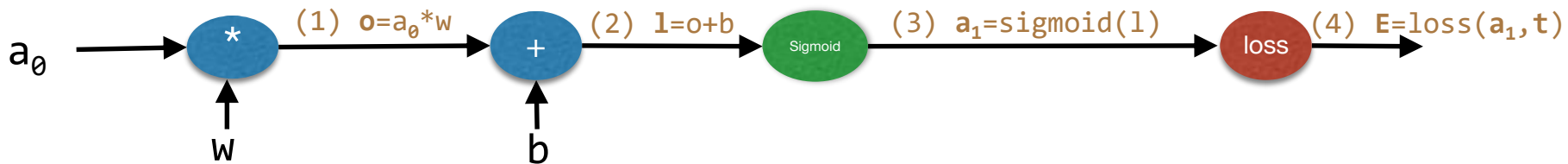
$$\frac{\partial f}{\partial w} = \frac{\partial f}{\partial g} \frac{\partial g}{\partial w} = 1 * x = 5$$

Logistic Regression Network



Network

forward



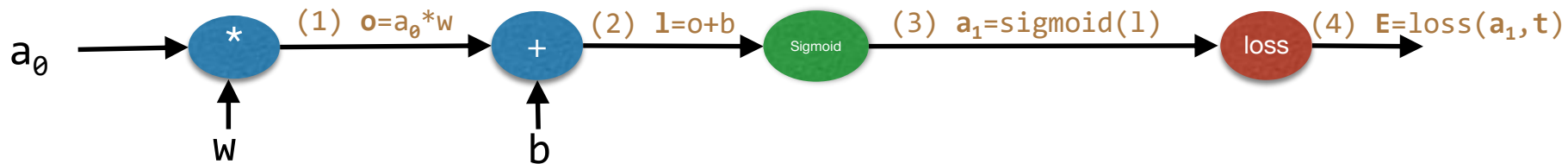
$$a_1 = \text{sigmoid}(a_0 * w + b)$$

$$E = \text{loss}(a_1, t) = - \sum t * \log(a_1) + (1 - t) * \log(1 - a_1)$$

Forward pass, OK? Just follow (1), (2), (3) and (4)

Network

forward



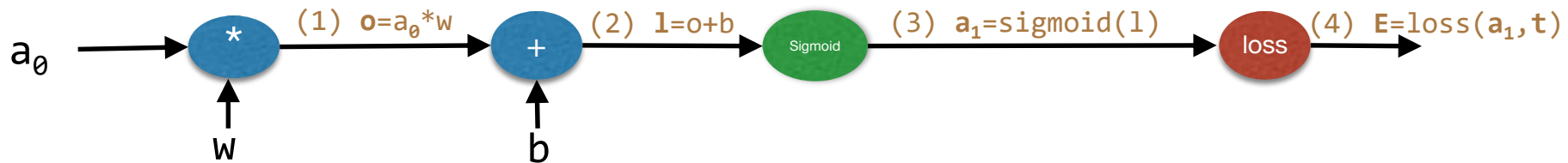
$$a_1 = \text{sigmoid}(a_0 * w + b)$$

$$E = \text{loss}(a_1, t) = - \sum t * \log(a_1) + (1 - t) * \log(1 - a_1)$$

$$a_0 = 0.1, t = 0, w = 0.1, b = 0.3$$

Network

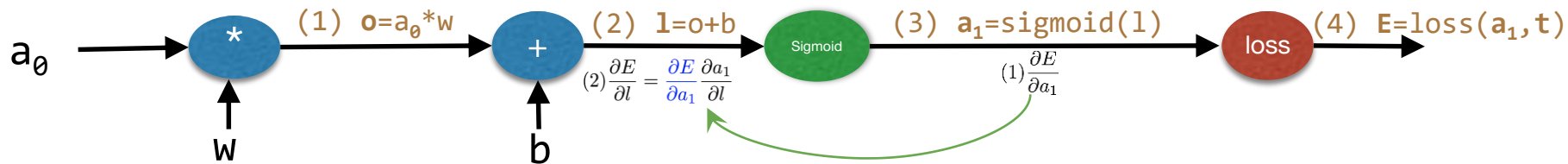
forward



$$w = w - \alpha \frac{\partial E}{\partial w}$$

Network

forward



backward prop

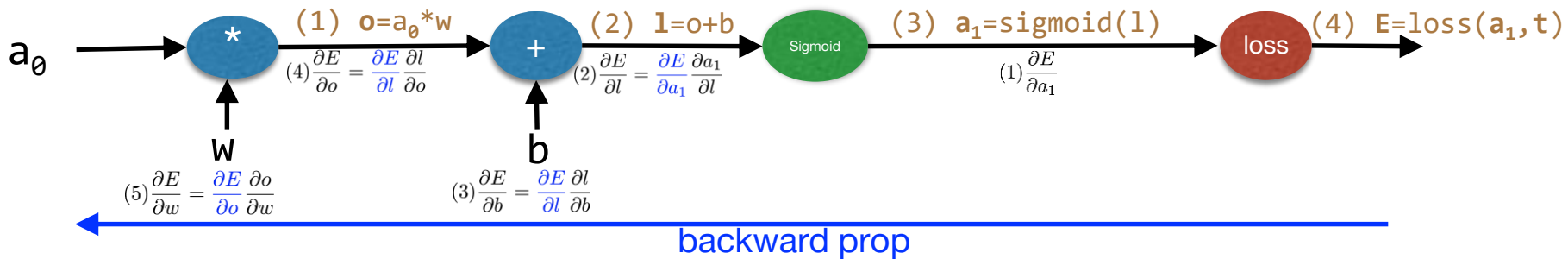
$$w = w - \alpha \frac{\partial E}{\partial w}$$

Let's do back propagation!

$(1) \frac{\partial E}{\partial a_1}$ will be given. What would be $(2) \frac{\partial E}{\partial l}$? We can use the chain rule.

Network

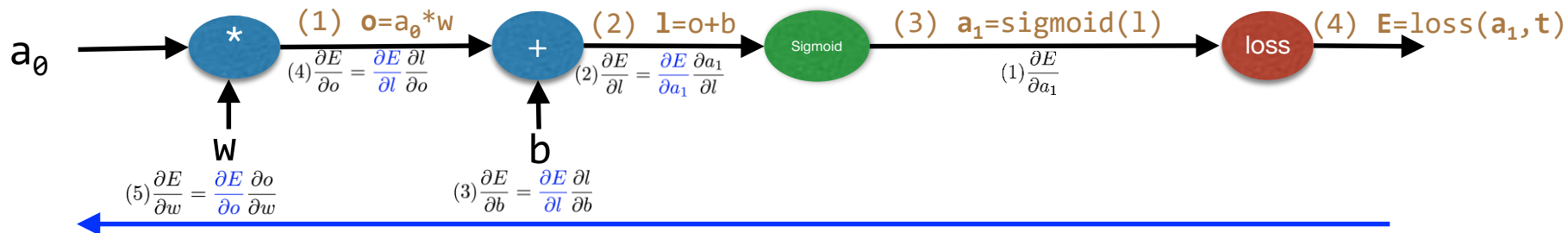
forward



In the same manner, we can get back prop (4), (3), (1) and (1)!

Network

forward



Gate derivatives

$$o = aw, \quad \frac{\partial o}{\partial w} = a, \quad \frac{\partial o}{\partial a} = w$$

$$l = o + b, \quad \frac{\partial l}{\partial o} = 1, \quad \frac{\partial l}{\partial b} = 1$$

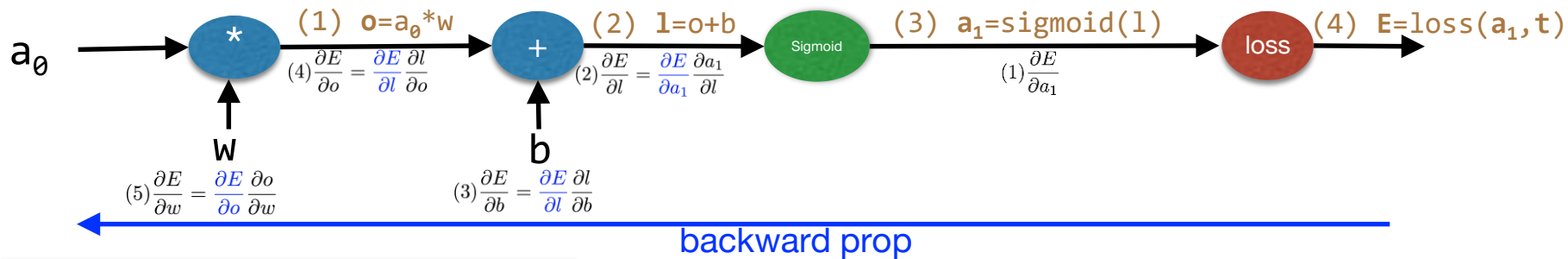
$$E = -\sum t \log(a) + (1 - t) \log(1 - a), \quad \frac{\partial E}{\partial a} = \frac{a - t}{a(1 - a)}$$

$$a = \text{sigmoid}(l) = \frac{1}{1 + e^{-l}}, \quad \frac{\partial a}{\partial l} = a(1 - a)$$

These derivatives for each gate will be given.
We can just use them in the chain rule.

Network

forward



Derivatives (chain rule)

$$(1) \ \frac{\partial E}{\partial a_1} = \frac{a_1 - t}{a_1(1 - a_1)}$$

$$(2) \ \frac{\partial E}{\partial l} = \frac{\partial E}{\partial a_1} \frac{\partial a_1}{\partial l}$$

Given from the pre
computed derivative

Gate derivatives

$$o = aw, \quad \frac{\partial o}{\partial w} = a, \quad \frac{\partial o}{\partial a} = w$$

$$l = o + b, \quad \frac{\partial l}{\partial o} = 1, \quad \frac{\partial l}{\partial b} = 1$$

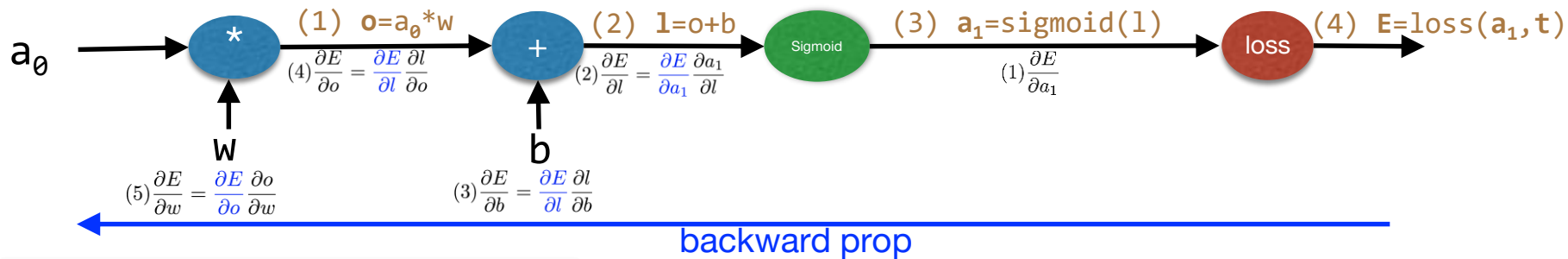
$$E = -\sum t \log(a) + (1 - t) \log(1 - a), \quad \frac{\partial E}{\partial a} = \frac{a - t}{a(1 - a)}$$

$$a = \text{sigmoid}(l) = \frac{1}{1 + e^{-l}}, \quad \frac{\partial a}{\partial l} = a(1 - a)$$

Just apply them one by one and solve each derivative one by one!

Network

forward



Derivatives (chain rule)

$$(1) \frac{\partial E}{\partial a_1} = \frac{a_1 - t}{a_1(1 - a_1)}$$

$$(2) \frac{\partial E}{\partial l} = \frac{\partial E}{\partial a_1} \frac{\partial a_1}{\partial l} = \frac{a_1 - t}{a_1(1 - a_1)} * a_1(1 - a_1) = a_1 - t$$

Given from the pre computed derivative

Given

Gate derivatives

$$o = aw, \quad \frac{\partial o}{\partial w} = a, \quad \frac{\partial o}{\partial a} = w$$

$$l = o + b, \quad \frac{\partial l}{\partial o} = 1, \quad \frac{\partial l}{\partial b} = 1$$

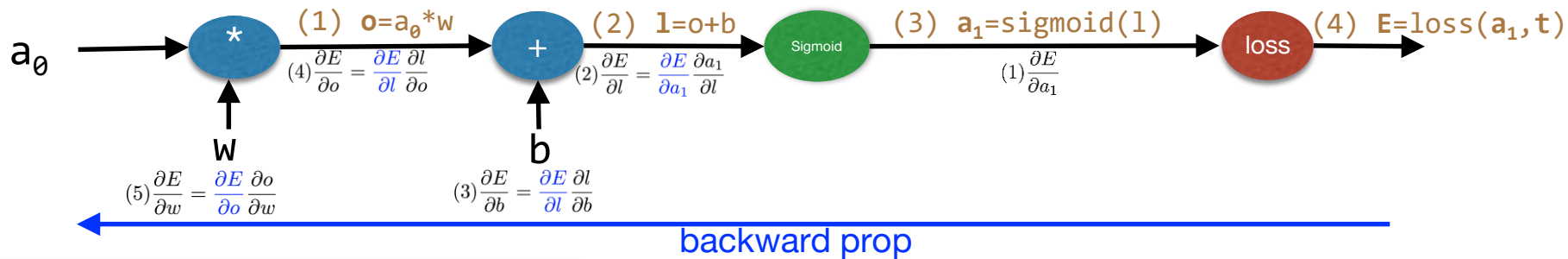
$$E = -\sum t \log(a) + (1 - t) \log(1 - a), \quad \frac{\partial E}{\partial a} = \frac{a - t}{a(1 - a)}$$

$$a = \text{sigmoid}(l) = \frac{1}{1 + e^{-l}}, \quad \frac{\partial a}{\partial l} = a(1 - a)$$

Just apply them one by one and solve each derivative one by one!

Network

forward



Derivatives (chain rule)

$$(1) \frac{\partial E}{\partial a_1} = \frac{a_1 - t}{a_1(1 - a_1)}$$

$$(2) \frac{\partial E}{\partial l} = \frac{\partial E}{\partial a_1} \frac{\partial a_1}{\partial l} = \frac{a_1 - t}{a_1(1 - a_1)} * a_1(1 - a_1) = a_1 - t$$

$$(3) \frac{\partial E}{\partial b} = \frac{\partial E}{\partial l} \frac{\partial l}{\partial b} = \frac{\partial E}{\partial l} * 1 = a_1 - t$$

$$(4) \frac{\partial E}{\partial o} = \frac{\partial E}{\partial l} \frac{\partial l}{\partial o} = \frac{\partial E}{\partial l} * 1 = a_1 - t$$

$$(5) \frac{\partial E}{\partial w} = \frac{\partial E}{\partial o} \frac{\partial o}{\partial w} = \frac{\partial E}{\partial o} a_0 = (a_1 - t) a_0$$

Given from the pre computed derivative

Given

Gate derivatives

$$o = aw, \quad \frac{\partial o}{\partial w} = a, \quad \frac{\partial o}{\partial a} = w$$

$$l = o + b, \quad \frac{\partial l}{\partial o} = 1, \quad \frac{\partial l}{\partial b} = 1$$

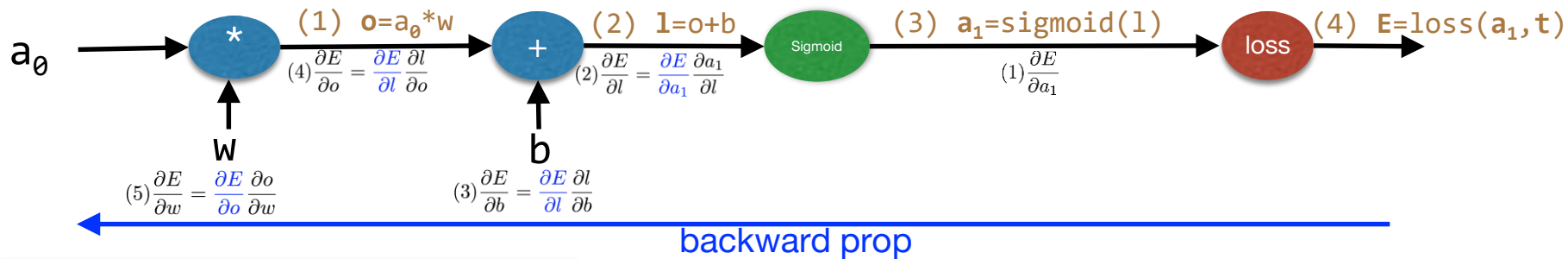
$$E = -\sum t \log(a) + (1 - t) \log(1 - a), \quad \frac{\partial E}{\partial a} = \frac{a - t}{a(1 - a)}$$

$$a = \text{sigmoid}(l) = \frac{1}{1 + e^{-l}}, \quad \frac{\partial a}{\partial l} = a(1 - a)$$

Just apply them one by one and solve each derivative one by one!

Network

forward



Derivatives (chain rule)

$$(1) \frac{\partial E}{\partial a_1} = \frac{a_1 - t}{a_1(1 - a_1)}$$

$$(2) \frac{\partial E}{\partial l} = \frac{\partial E}{\partial a_1} \frac{\partial a_1}{\partial l} = \frac{a_1 - t}{a_1(1 - a_1)} * a_1(1 - a_1) = a_1 - t$$

$$(3) \frac{\partial E}{\partial b} = \frac{\partial E}{\partial l} \frac{\partial l}{\partial b} = \frac{\partial E}{\partial l} * 1 = a_1 - t$$

$$(4) \frac{\partial E}{\partial o} = \frac{\partial E}{\partial l} \frac{\partial l}{\partial o} = \frac{\partial E}{\partial l} * 1 = a_1 - t$$

$$(5) \frac{\partial E}{\partial w} = \frac{\partial E}{\partial o} \frac{\partial o}{\partial w} = a_0^T \frac{\partial E}{\partial o} = a_0^T (a_1 - t)$$

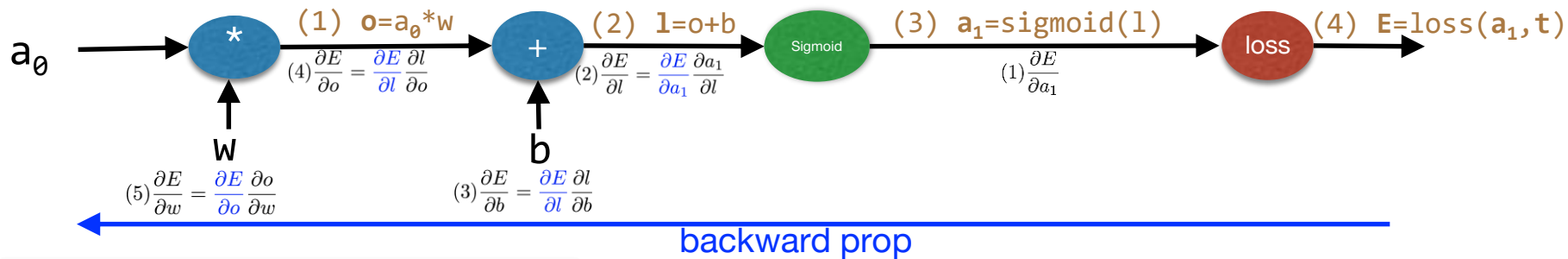
Matrix

$$\frac{\partial E}{\partial W} = \frac{\partial E}{\partial O} \frac{\partial O}{\partial W} = A^T \frac{\partial E}{\partial O}, \text{ where } O = AW$$

For Matrix: <http://cs231n.github.io/optimization-2/#staged>

Network

forward



Derivatives (chain rule)

$$(1) \frac{\partial E}{\partial a_1} = \frac{a_1 - t}{a_1(1 - a_1)}$$

$$(2) \frac{\partial E}{\partial l} = \frac{\partial E}{\partial a_1} \frac{\partial a_1}{\partial l} = \frac{a_1 - t}{a_1(1 - a_1)} * a_1(1 - a_1) = a_1 - t$$

$$(3) \frac{\partial E}{\partial b} = \frac{\partial E}{\partial l} \frac{\partial l}{\partial b} = \frac{\partial E}{\partial l} * 1 = a_1 - t$$

$$(4) \frac{\partial E}{\partial o} = \frac{\partial E}{\partial l} \frac{\partial l}{\partial o} = \frac{\partial E}{\partial l} * 1 = a_1 - t$$

$$(5) \frac{\partial E}{\partial w} = \frac{\partial E}{\partial o} \frac{\partial o}{\partial w} = a_0^T \frac{\partial E}{\partial o} = a_0^T (a_1 - t)$$

Matrix

$$\frac{\partial E}{\partial W} = \frac{\partial E}{\partial O} \frac{\partial O}{\partial W} = A^T \frac{\partial E}{\partial O}, \text{ where } O = AW$$

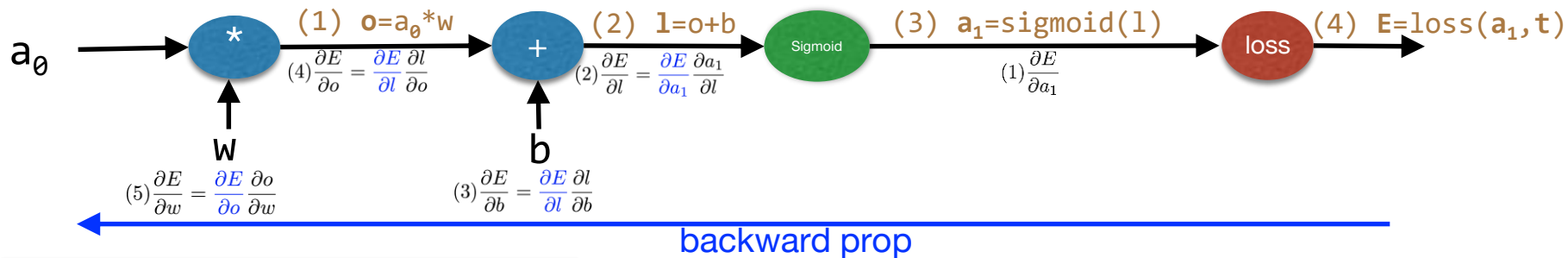
Network update (learning rate, alpha)

$$w = w - \alpha \frac{\partial E}{\partial w}$$

$$b = b - \alpha \frac{\partial E}{\partial b}$$

Network

forward



Derivatives (chain rule)

$$(1) \frac{\partial E}{\partial a_1} = \frac{a_1 - t}{a_1(1 - a_1)}$$

$$(2) \frac{\partial E}{\partial l} = \frac{\partial E}{\partial a_1} \frac{\partial a_1}{\partial l} = \frac{a_1 - t}{a_1(1 - a_1)} * a_1(1 - a_1) = a_1 - t$$

$$(3) \frac{\partial E}{\partial b} = \frac{\partial E}{\partial l} \frac{\partial l}{\partial b} = \frac{\partial E}{\partial l} * 1 = a_1 - t$$

$$(4) \frac{\partial E}{\partial o} = \frac{\partial E}{\partial l} \frac{\partial l}{\partial o} = \frac{\partial E}{\partial l} * 1 = a_1 - t$$

$$(5) \frac{\partial E}{\partial w} = \frac{\partial E}{\partial o} \frac{\partial o}{\partial w} = a_0^T \frac{\partial E}{\partial o} = a_0^T (a_1 - t)$$

Done! Let's update our network using derivatives!

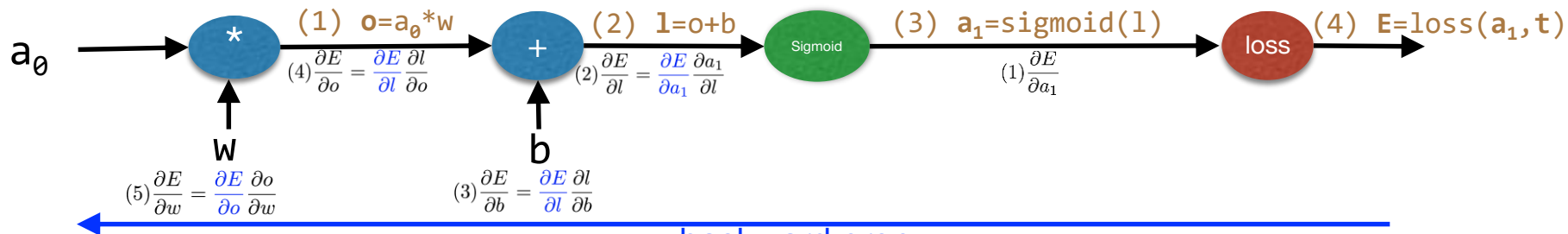
Network update (learning rate, alpha)

$$w = w - \alpha \frac{\partial E}{\partial w}$$

$$b = b - \alpha \frac{\partial E}{\partial b}$$

Network

forward



backward prop

Derivatives (chain rule)

$$(1) \frac{\partial E}{\partial a_1} = \frac{a_1 - t}{a_1(1 - a_1)}$$

$$(2) \frac{\partial E}{\partial l} = \frac{\partial E}{\partial a_1} \frac{\partial a_1}{\partial l} = \frac{a_1 - t}{a_1(1 - a_1)} * a_1(1 - a_1) = a_1 - t$$

$$(3) \frac{\partial E}{\partial b} = \frac{\partial E}{\partial l} \frac{\partial l}{\partial b} = \frac{\partial E}{\partial l} * 1 = a_1 - t$$

$$(4) \frac{\partial E}{\partial o} = \frac{\partial E}{\partial l} \frac{\partial l}{\partial o} = \frac{\partial E}{\partial l} * 1 = a_1 - t$$

$$(5) \frac{\partial E}{\partial w} = \frac{\partial E}{\partial o} \frac{\partial o}{\partial w} = a_0^T \frac{\partial E}{\partial o} = a_0^T (a_1 - t)$$

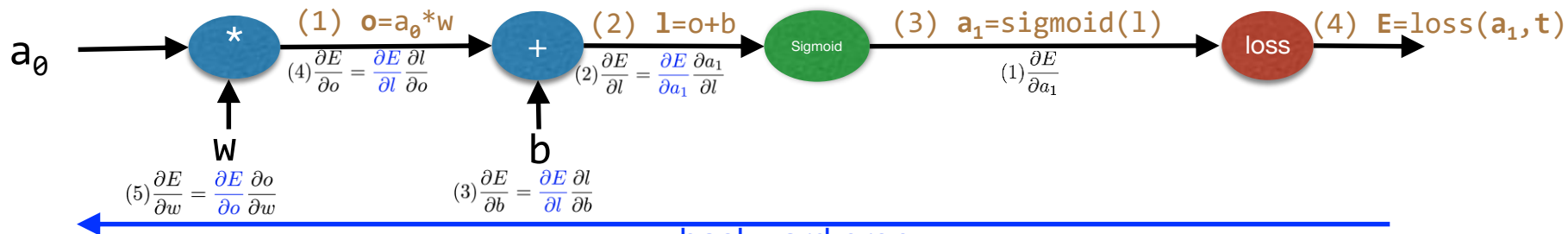
$$E = - \sum t \log(a) + (1 - t) \log(1 - a), \quad \frac{\partial E}{\partial a} = \frac{a - t}{a(1 - a)}$$

$$a = \text{sigmoid}(l) = \frac{1}{1 + e^{-l}}, \quad \frac{\partial a}{\partial l} = a(1 - a)$$

```
d_a1 = (a1 - t) / (a1 * (1. - t) + 1e-7)
d_sigma = a1 * (1 - a1) # sigma prime
d_l = d_a1 * d_sigma # (a1 - t)
d_b = d_l * 1
d_o = d_l * 1
d_W = tf.matmul(tf.transpose(a0), d_o)
```

Network

forward



backward prop

Derivatives (chain rule)

$$(1) \frac{\partial E}{\partial a_1} = \frac{a_1 - t}{a_1(1 - a_1)}$$

$$(2) \frac{\partial E}{\partial l} = \frac{\partial E}{\partial a_1} \frac{\partial a_1}{\partial l} = \frac{a_1 - t}{a_1(1 - a_1)} * a_1(1 - a_1) = a_1 - t$$

$$(3) \frac{\partial E}{\partial b} = \frac{\partial E}{\partial l} \frac{\partial l}{\partial b} = \frac{\partial E}{\partial l} * 1 = a_1 - t$$

$$(4) \frac{\partial E}{\partial o} = \frac{\partial E}{\partial l} \frac{\partial l}{\partial o} = \frac{\partial E}{\partial l} * 1 = a_1 - t$$

$$(5) \frac{\partial E}{\partial w} = \frac{\partial E}{\partial o} \frac{\partial o}{\partial w} = a_0^T \frac{\partial E}{\partial o} = a_0^T (a_1 - t)$$

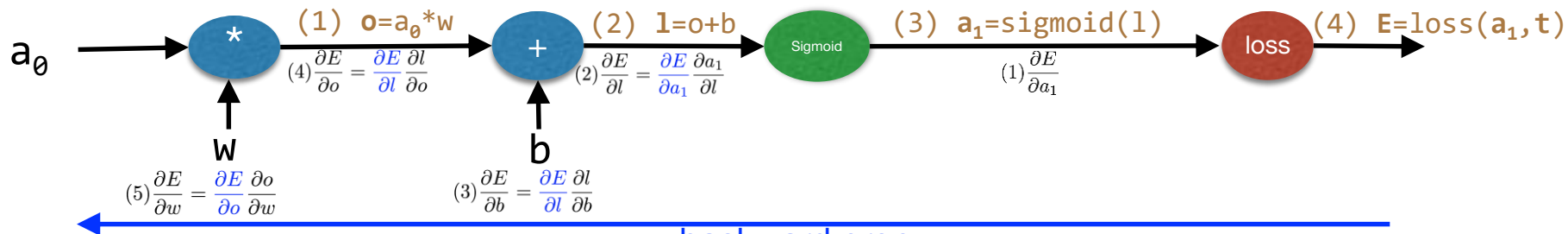
$$E = - \sum t \log(a) + (1 - t) \log(1 - a), \quad \frac{\partial E}{\partial a} = \frac{a - t}{a(1 - a)}$$

$$a = \text{sigmoid}(l) = \frac{1}{1 + e^{-l}}, \quad \frac{\partial a}{\partial l} = a(1 - a)$$

```
d_a1 = (a1 - t) / (a1 * (1. - a1) + 1e-7)
d_sigma = a1 * (1 - a1) # sigma prime
d_l = d_a1 * d_sigma # (a1 - t)
d_b = d_l * 1
d_o = d_l * 1
d_W = tf.matmul(tf.transpose(a0), d_o)
# Updating network using gradients
learning_rate = 0.01
train_step = [
    tf.assign(W, W - learning_rate * d_W),
    tf.assign(b, b - learning_rate * d_b)]
```

Network

forward



backward prop

Derivatives (chain rule)

$$(1) \frac{\partial E}{\partial a_1} = \frac{a_1 - t}{a_1(1 - a_1)}$$

$$(2) \frac{\partial E}{\partial l} = \frac{\partial E}{\partial a_1} \frac{\partial a_1}{\partial l} = \frac{a_1 - t}{a_1(1 - a_1)} * a_1(1 - a_1) = a_1 - t$$

$$(3) \frac{\partial E}{\partial b} = \frac{\partial E}{\partial l} \frac{\partial l}{\partial b} = \frac{\partial E}{\partial l} * 1 = a_1 - t$$

$$(4) \frac{\partial E}{\partial o} = \frac{\partial E}{\partial l} \frac{\partial l}{\partial o} = \frac{\partial E}{\partial l} * 1 = a_1 - t$$

$$(5) \frac{\partial E}{\partial w} = \frac{\partial E}{\partial o} \frac{\partial o}{\partial w} = a_0^T \frac{\partial E}{\partial o} = a_0^T (a_1 - t)$$

$$E = - \sum t \log(a) + (1 - t) \log(1 - a), \quad \frac{\partial E}{\partial a} = \frac{a - t}{a(1 - a)}$$

$$a = \text{sigmoid}(l) = \frac{1}{1 + e^{-l}}, \quad \frac{\partial a}{\partial l} = a(1 - a)$$

```
d_a1 = (a1 - t) / (a1 * (1. - a1) + 1e-7)
d_sigma = a1 * (1 - a1) # sigma prime
d_l = d_a1 * d_sigma # (a1 - t)
d_b = d_l * 1
d_o = d_l * 1
d_W = tf.matmul(tf.transpose(a0), d_o)
# Updating network using gradients
learning_rate = 0.01
train_step = [
    tf.assign(W, W - learning_rate * d_W / N), # sample size
    tf.assign(b, b - learning_rate * tf.reduce_sum(d_b))]
```

Exercise

- See more backprop code samples at <https://github.com/hunkim/DeepLearningZeroToAll>
- `https://github.com/hunkim/DeepLearningZeroToAll/blob/master/lab-09-7-sigmoid_back_prop.py`
- Solve XOR using NN backprop