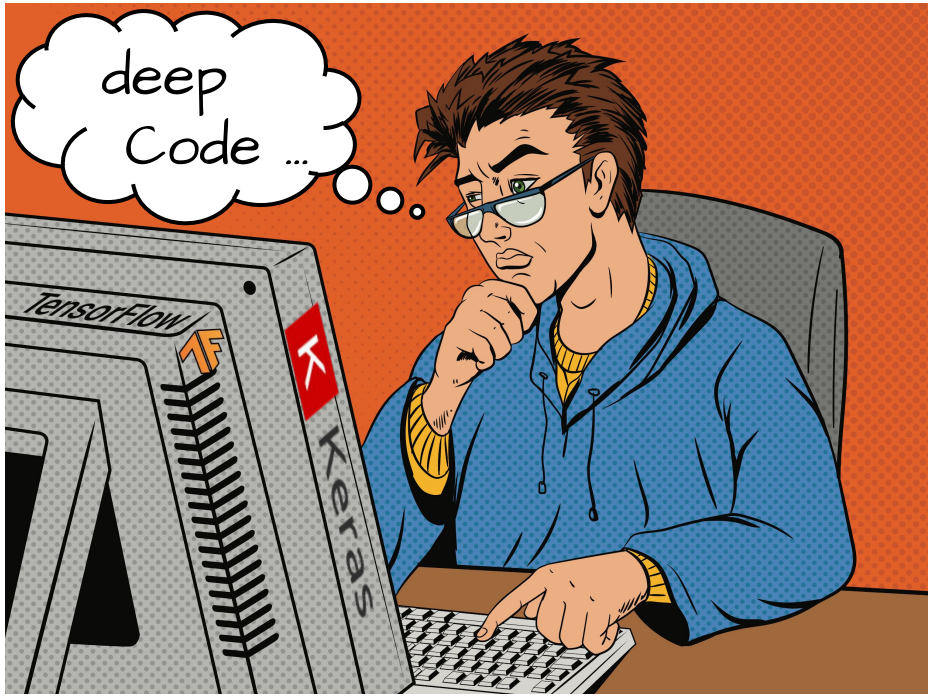
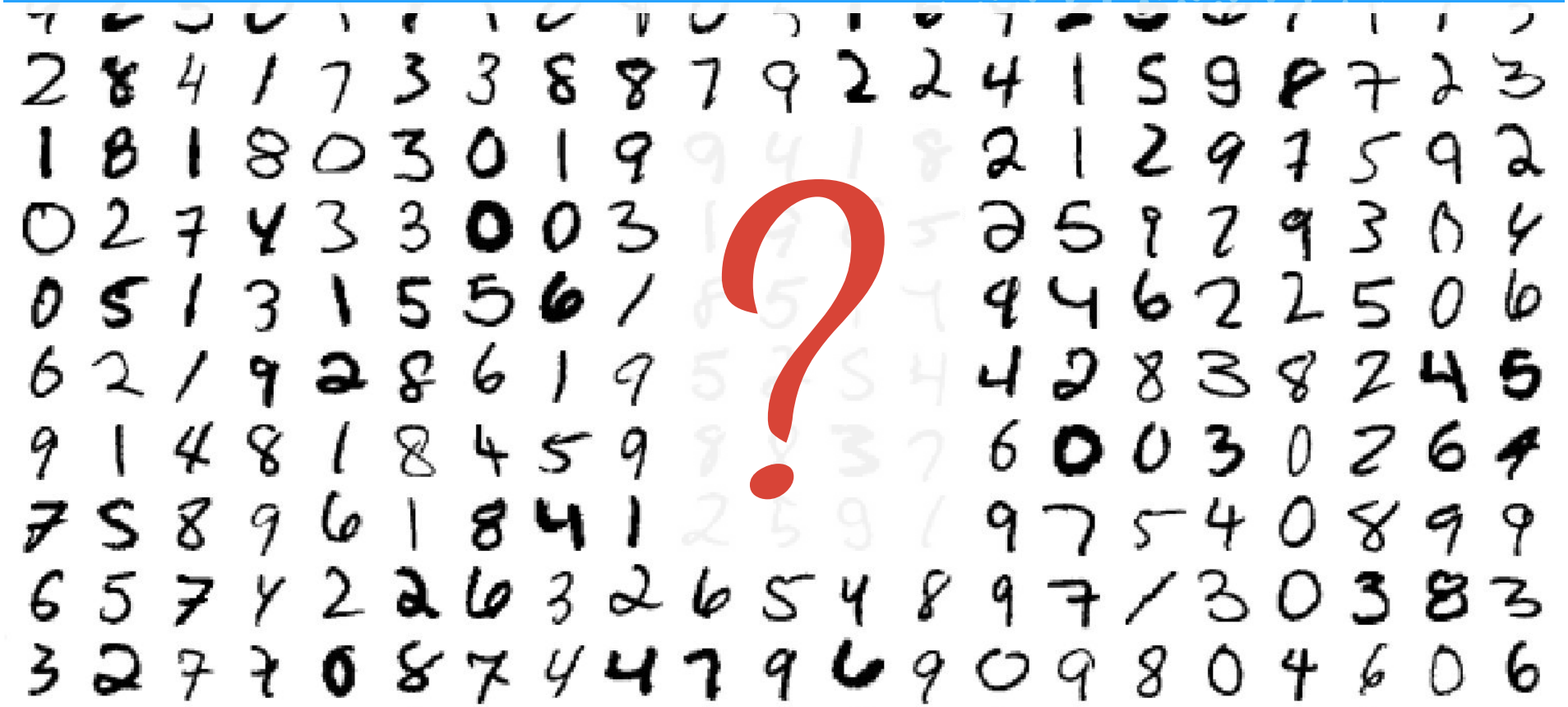
>TensorFlow, Keras and deep learning_

without a PhD

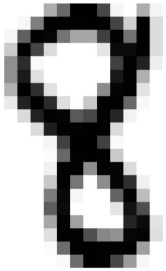


Hello World: handwritten digits classification - MNIST

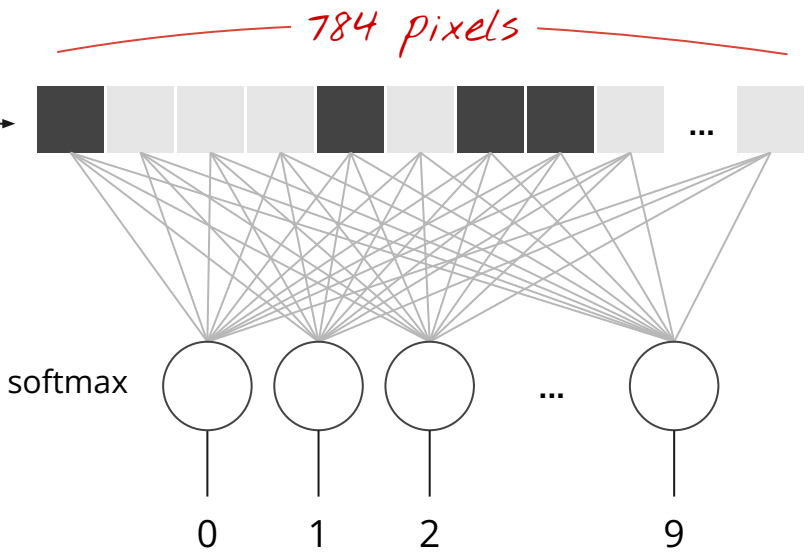


MNIST = Mixed National Institute of Standards and Technology - Download the dataset at http://yann.lecun.com/exdb/mnist/

Very simple model: softmax classification



28x28 pixels

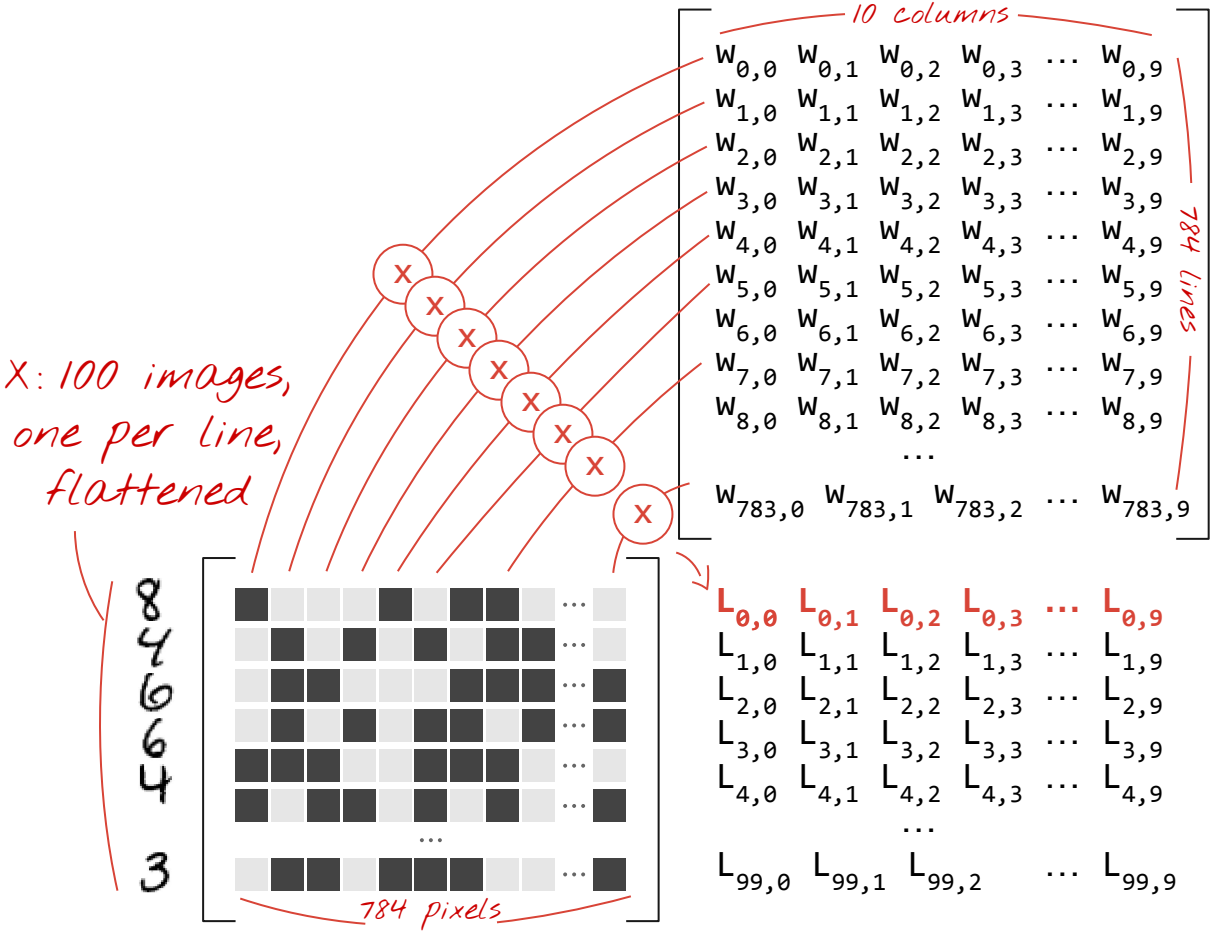


weighted sum of all pixels + bias

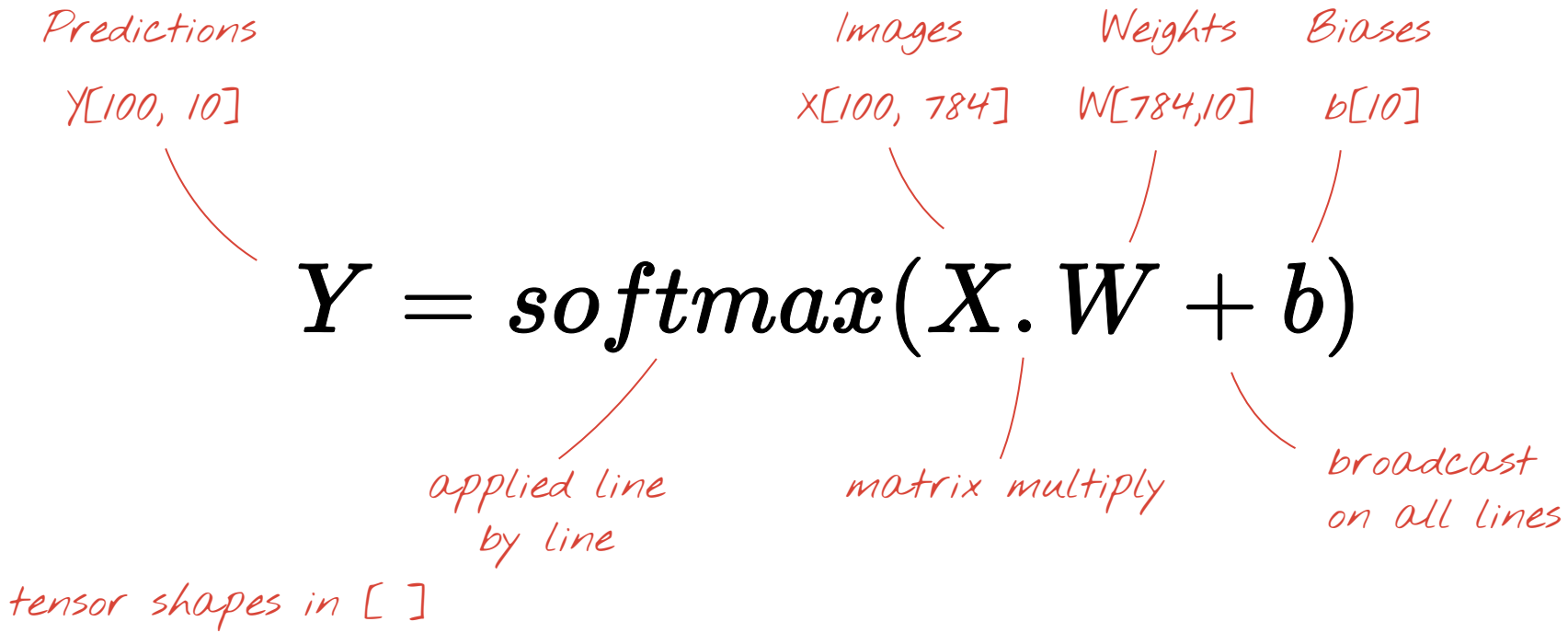
$$softmax(L_n) = \frac{e^{L_n}}{||e^{L}||}$$

neuron outputs

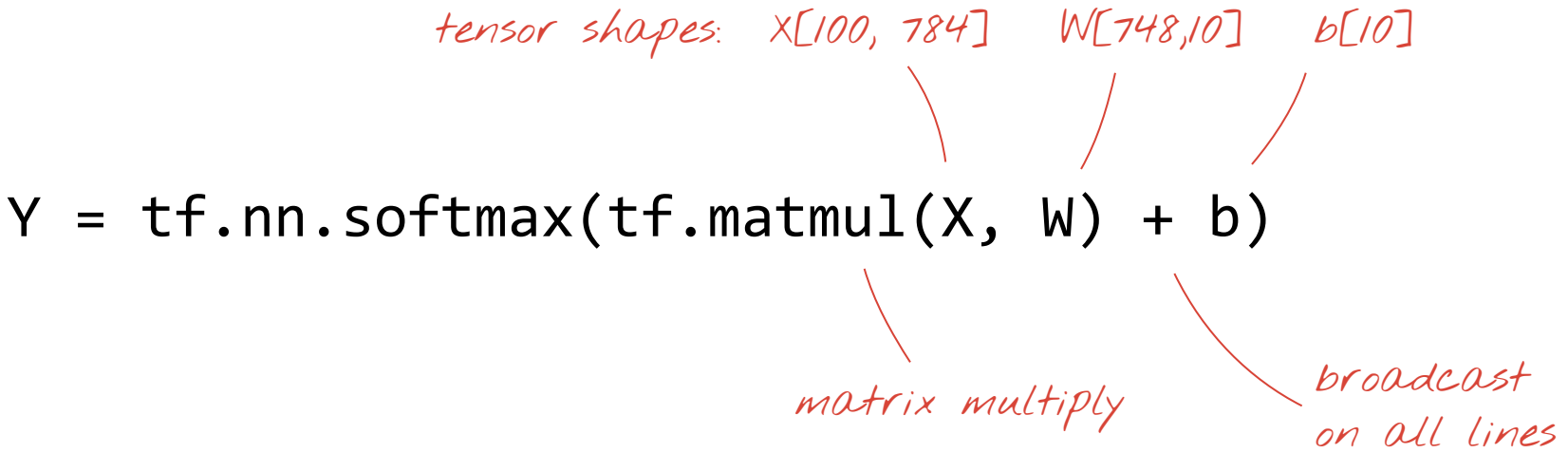
In matrix notation, 100 images at a time



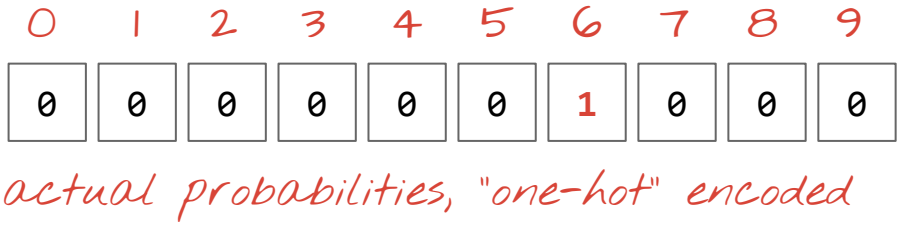
Softmax, on a batch of images



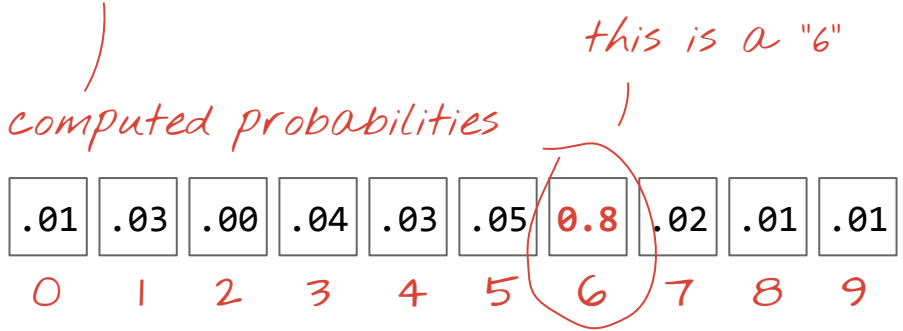
Now in TensorFlow (Python)



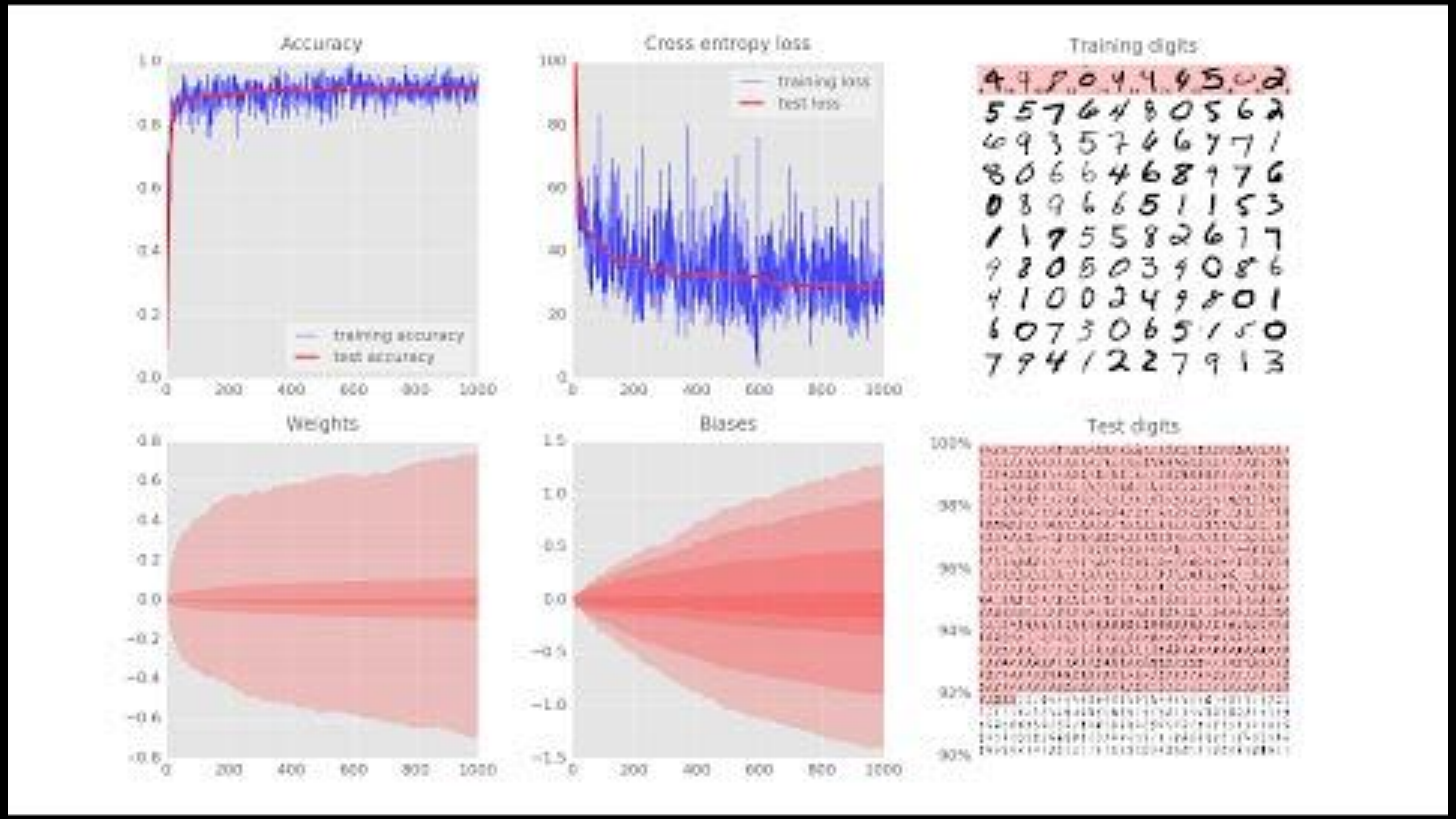
Success ?

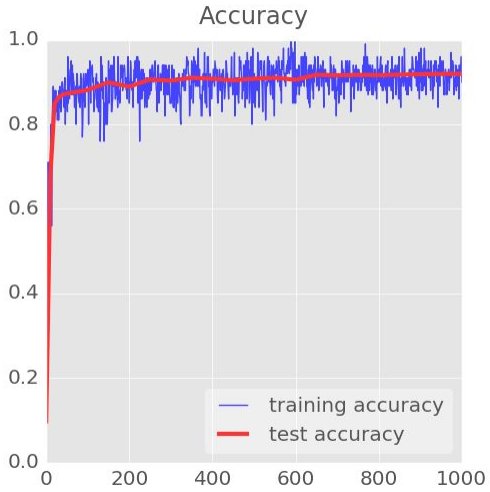


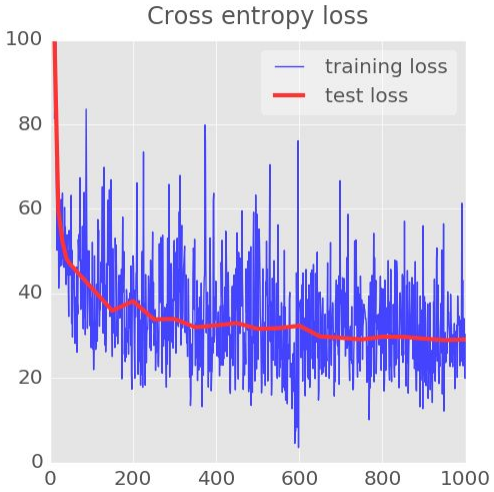
Cross entropy: $-\sum Y_i' . log(Y_i)$

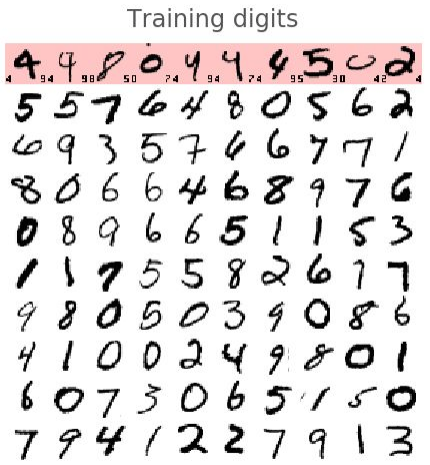


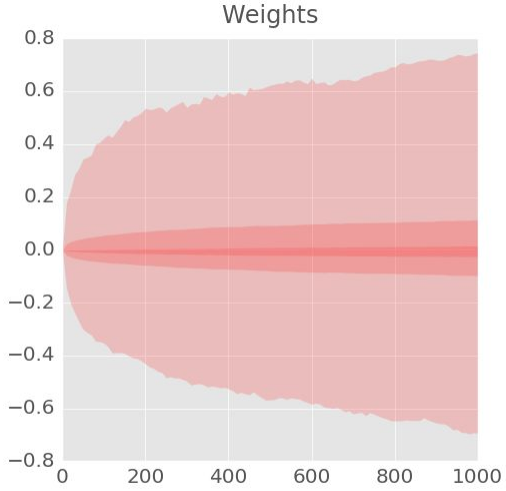
Demo

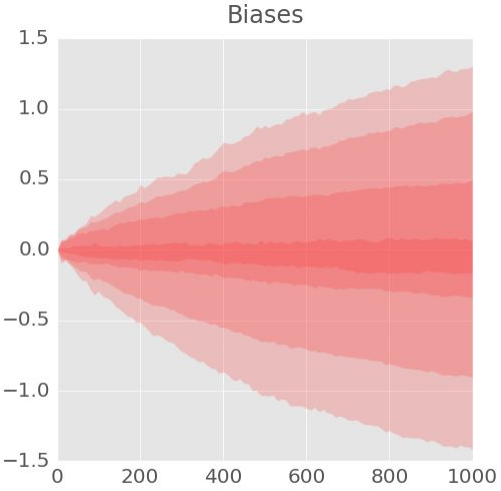

Accuracy
training accuracy
test accuracy
Cross entropy loss
training loss
test loss
Training digits
Weights
Biases
Test digits

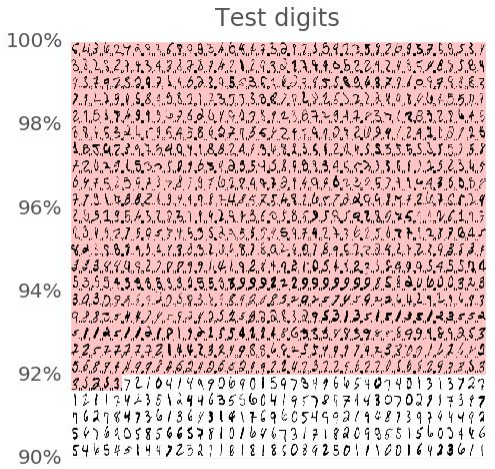

Accuracy
training accuracy
test accuracy


Cross entropy loss
training loss
test loss


Training digits


Weights


Biases


Test digits

92%

TensorFlow - initialisation

```
import tensorflow as tf

X = tf.placeholder(tf.float32, [None, 28, 28, 1])
W = tf.Variable(tf.zeros([784, 10]))
b = tf.Variable(tf.zeros([10]))

init = tf.initialize_all_variables()
```

this will become the batch size, 100

28 x 28 grayscale images

Training = computing variables W and b

TensorFlow - success metrics

flattening images

```
# model
Y = tf.nn.softmax(tf.matmul(tf.reshape(X, [-1, 784]), W) + b)
# placeholder for correct answers
Y_ = tf.placeholder(tf.float32, [None, 10])

# loss function
cross_entropy = -tf.reduce_sum(Y_ * tf.log(Y))

# % of correct answers found in batch
is_correct = tf.equal(tf.argmax(Y,1), tf.argmax(Y_,1))
accuracy = tf.reduce_mean(tf.cast(is_correct, tf.float32))
```

"one-hot" encoded

"one-hot" decoding

TensorFlow - training

learning rate

```
optimizer = tf.train.GradientDescentOptimizer(0.003)
train_step = optimizer.minimize(cross_entropy)
```

loss function

TensorFlow - run !

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

for i in range(1000):
    # load batch of images and correct answers
    batch_X, batch_Y = mnist.train.next_batch(100)
    train_data={X: batch_X, Y_: batch_Y}

    # train
    sess.run(train_step, feed_dict=train_data)

    # success ?
    a,c = sess.run([accuracy, cross_entropy], feed_dict=train_data)

    # success on test data ?
    test_data={X: mnist.test.images, Y_: mnist.test.labels}
    a,c = sess.run([accuracy, cross_entropy], feed=test_data)
```

running a Tensorflow computation, feeding placeholders

Tip: do this every 100 iterations

TensorFlow - full python code

initialisation

```
import tensorflow as tf


X = tf.placeholder(tf.float32, [None, 28, 28, 1])
W = tf.Variable(tf.zeros([784, 10]))
b = tf.Variable(tf.zeros([10]))
init = tf.initialize_all_variables()
```

model

```
# model
Y=tf.nn.softmax(tf.matmul(tf.reshape(X,[-1, 784]), W) + b)

# placeholder for correct answers
Y_ = tf.placeholder(tf.float32, [None, 10])
```

success metrics

```
# loss function
cross_entropy = -tf.reduce_sum(Y_ * tf.log(Y))

# % of correct answers found in batch
is_correct = tf.equal(tf.argmax(Y,1), tf.argmax(Y_,1))
accuracy = tf.reduce_mean(tf.cast(is_correct,tf.float32))
```

training step

```
optimizer = tf.train.GradientDescentOptimizer(0.003)
train_step = optimizer.minimize(cross_entropy)


sess = tf.Session()
sess.run(init)

for i in range(10000):
      # load batch of images and correct answers
      batch_X, batch_Y = mnist.train.next_batch(100)
      train_data={X: batch_X, Y_: batch_Y}

      # train
      sess.run(train_step, feed_dict=train_data)

      # success ? add code to print it
      a,c = sess.run([accuracy, cross_entropy], feed=train_data)

      # success on test data ?
      test_data={X:mnist.test.images, Y_:mnist.test.labels}
      a,c = sess.run([accuracy, cross_entropy], feed=test_data)
```

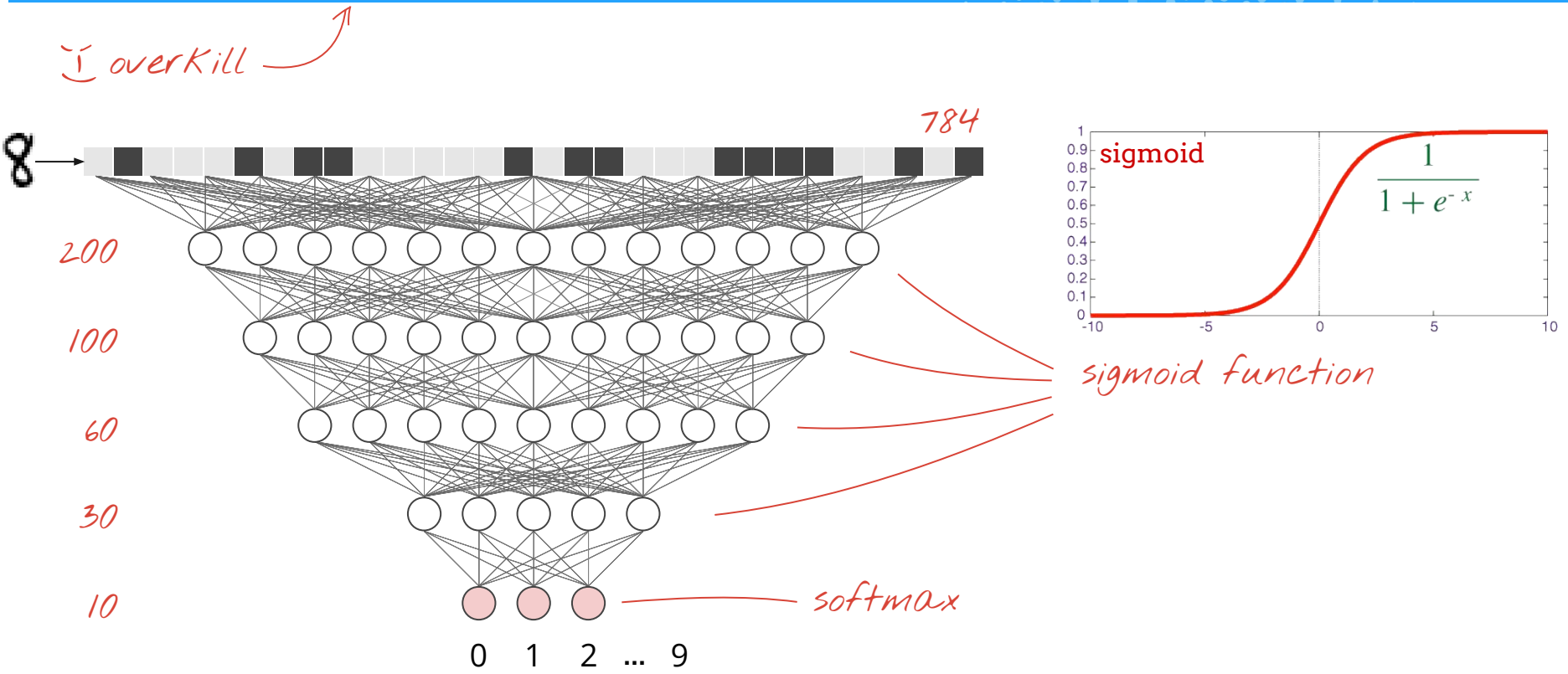
Run

Cookbook

Softmax
Cross-entropy
Mini-batch


Go deep !

Let's try 5 fully-connected layers !



TensorFlow - initialisation

```
K = 200
L = 100
M = 60
N = 30
```

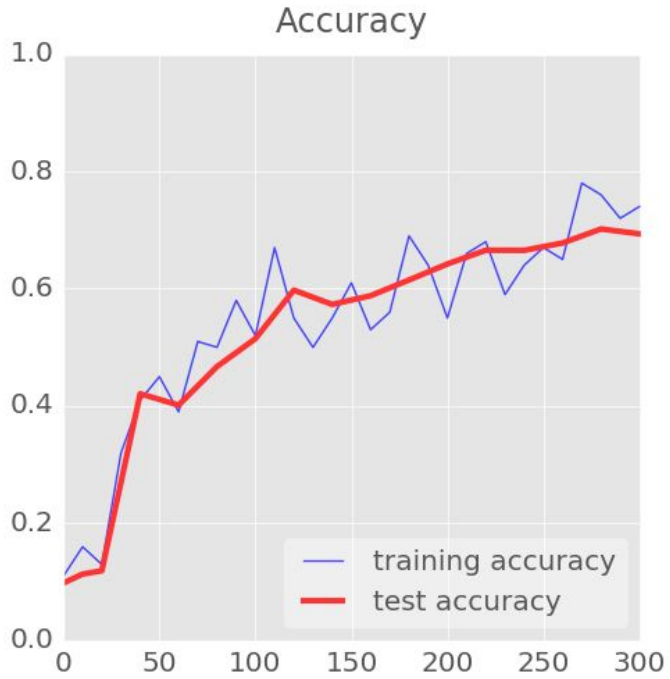
weights initialised with random values

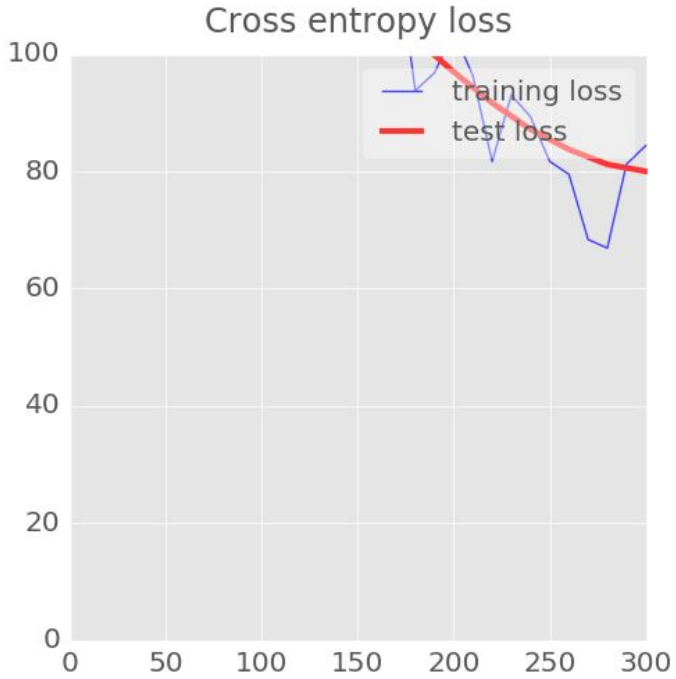
```
W1 = tf.Variable(tf.truncated_normal([28*28, K] ,stddev=0.1))
B1 = tf.Variable(tf.zeros([K]))

W2 = tf.Variable(tf.truncated_normal([K, L], stddev=0.1))
B2 = tf.Variable(tf.zeros([L]))

W3 = tf.Variable(tf.truncated_normal([L, M], stddev=0.1))
B3 = tf.Variable(tf.zeros([M]))
W4 = tf.Variable(tf.truncated_normal([M, N], stddev=0.1))
B4 = tf.Variable(tf.zeros([N]))
W5 = tf.Variable(tf.truncated_normal([N, 10], stddev=0.1))
B5 = tf.Variable(tf.zeros([10]))
```

TensorFlow - the model


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

Y1 = tf.nn.sigmoid(tf.matmul(X, W1) + B1)
Y2 = tf.nn.sigmoid(tf.matmul(Y1, W2) + B2)
Y3 = tf.nn.sigmoid(tf.matmul(Y2, W3) + B3)
Y4 = tf.nn.sigmoid(tf.matmul(Y3, W4) + B4)
Y = tf.nn.softmax(tf.matmul(Y4, W5) + B5)
```

Demo - slow start ?

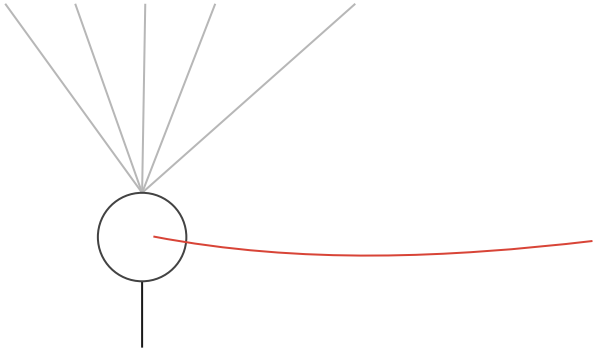


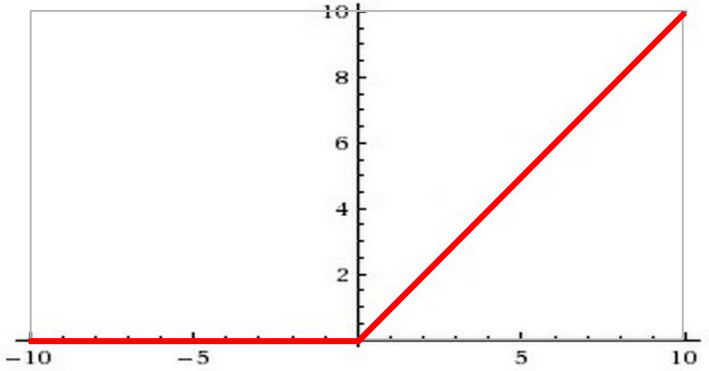



Relu !

RELU

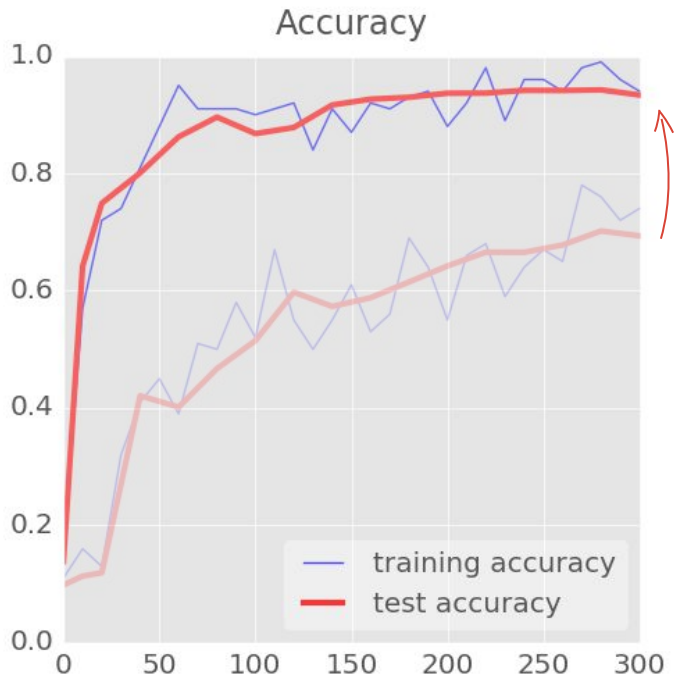
RELU = Rectified Linear Unit

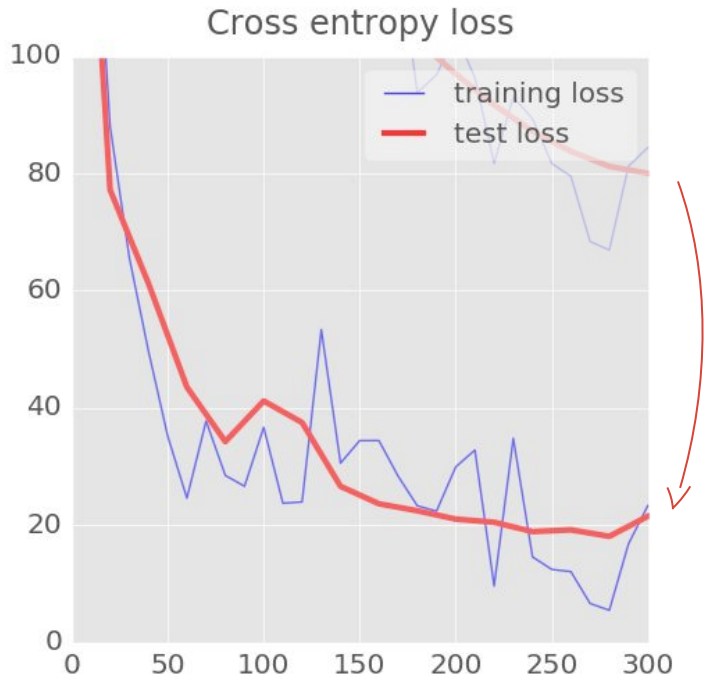




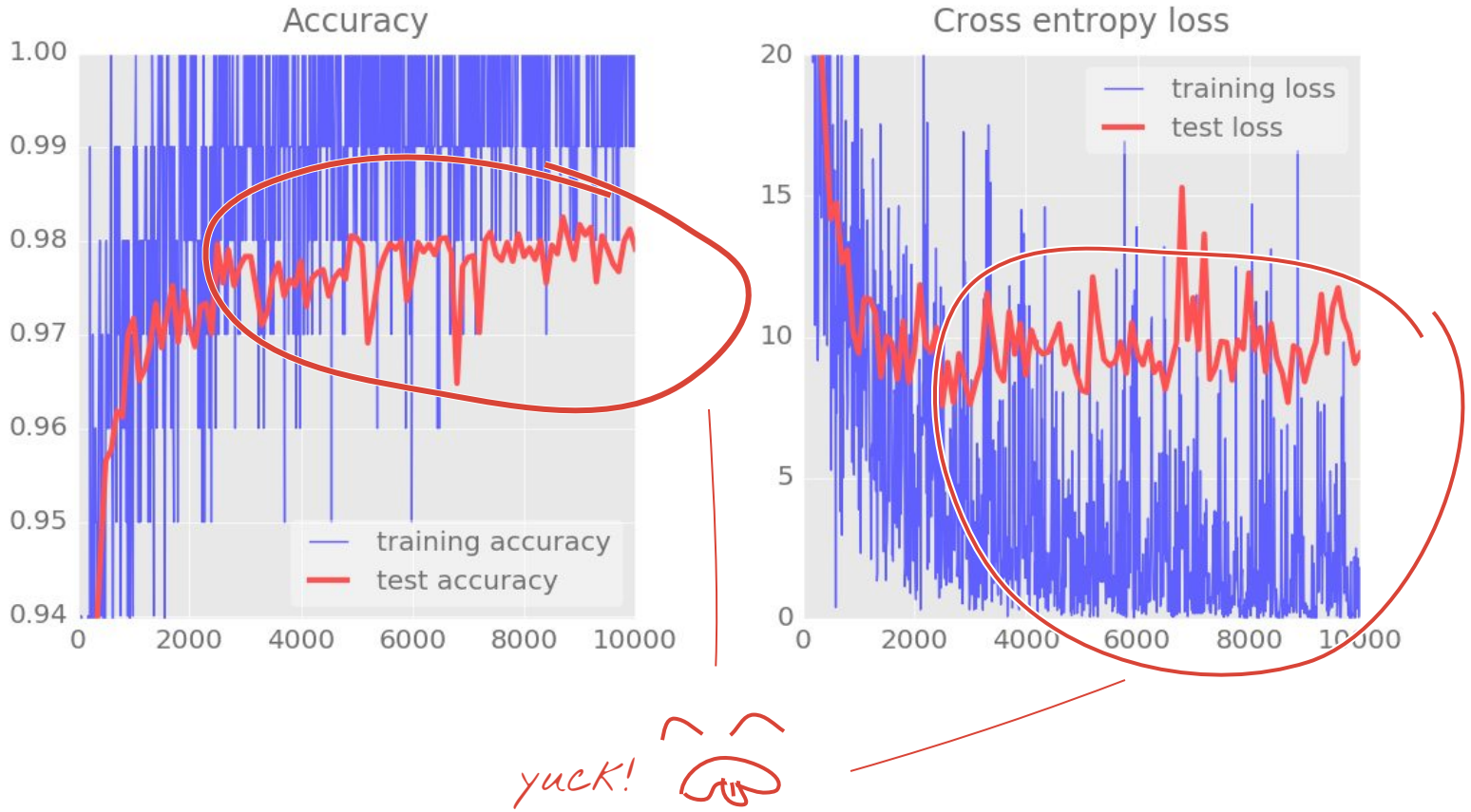

```
Y = tf.nn.relu(tf.matmul(X, W) + b)
```

RELU

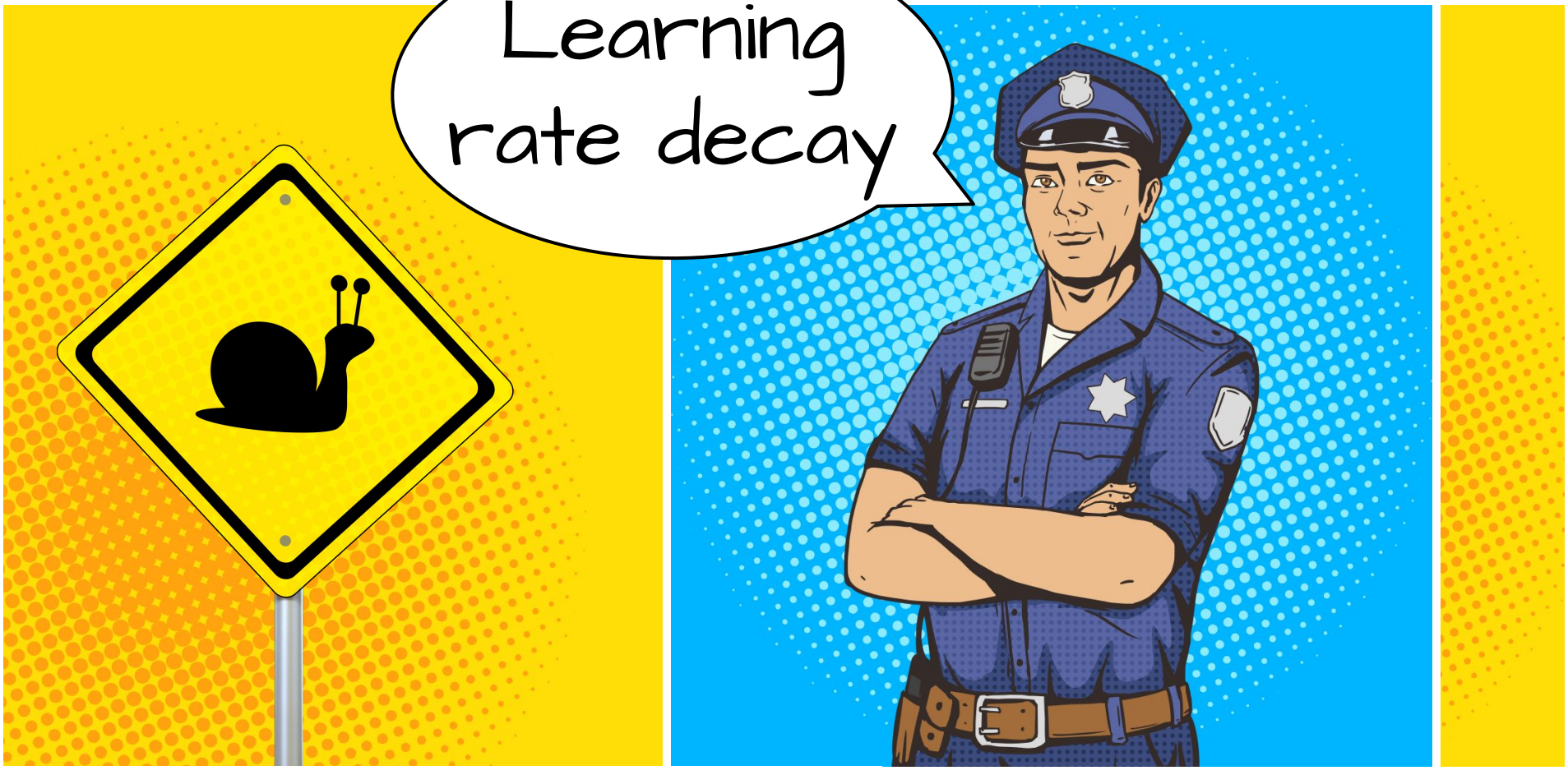

Accuracy
1.0
0.8
0.6
0.4
0.2
0.0
0
50
100
150
200
250
300
training accuracy
test accuracy


Cross entropy loss
100
80
60
40
20
0
0
50
100
150
200
250
300
training loss
test loss

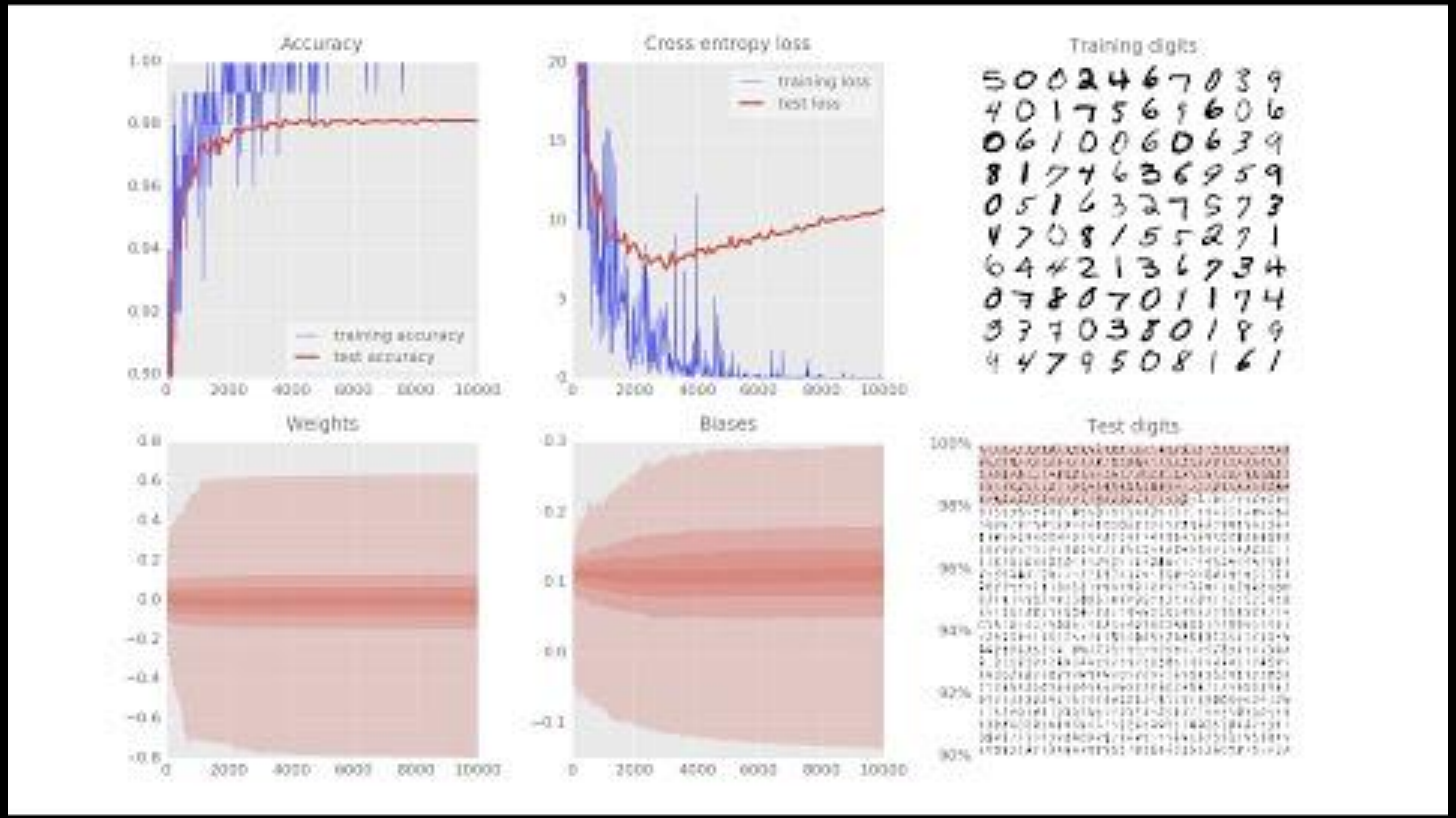
Demo - noisy accuracy curve ?

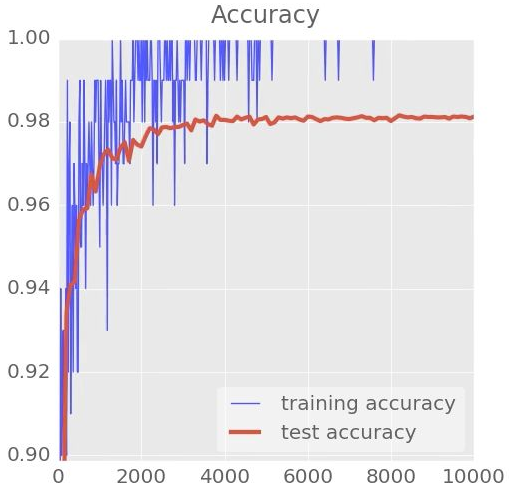


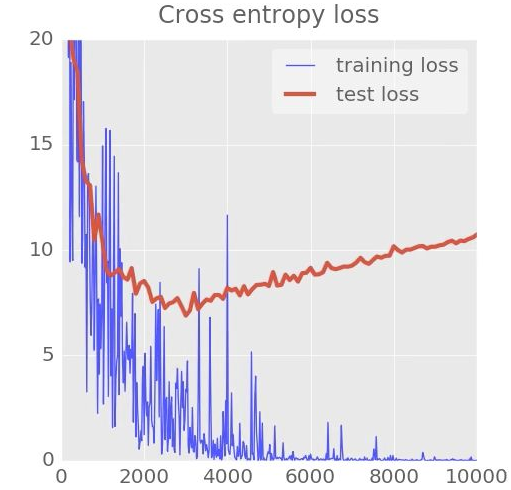
Slow down...

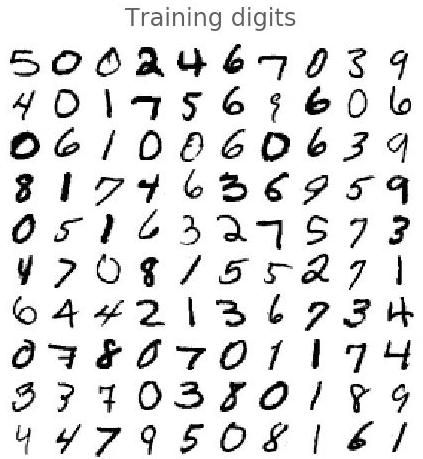


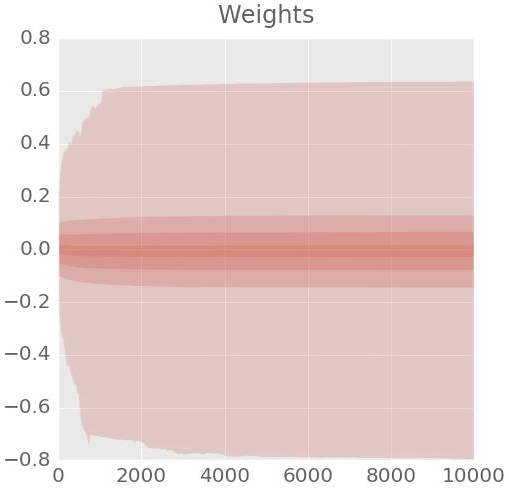
Demo

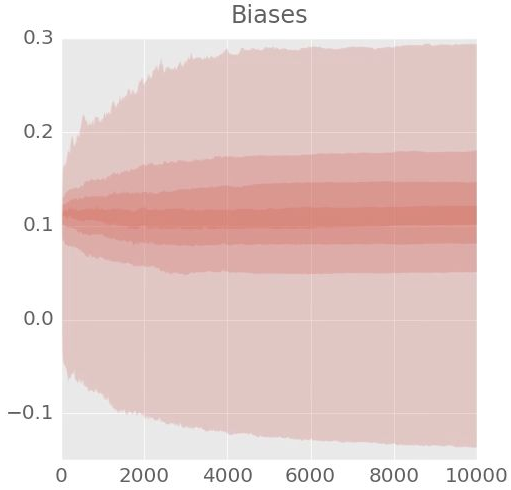

Accuracy
training accuracy
test accuracy
Cross entropy loss
training loss
test loss
Training digits
Weights
Biases
Test digits

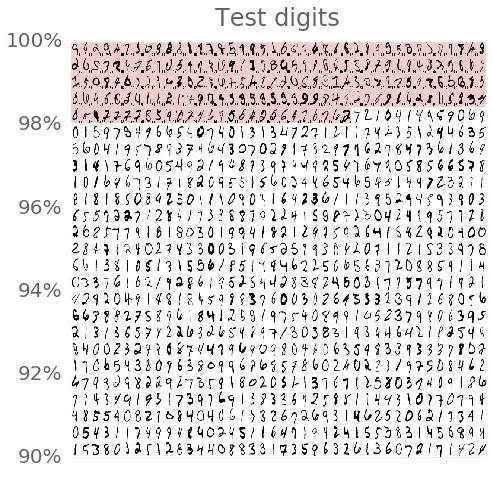

Accuracy
1.00
0.98
0.96
0.94
0.92
0.90
0
2000
4000
6000
8000
10000
training accuracy
test accuracy


Cross entropy loss
20
15
10
5
0
2000
4000
6000
8000
10000
training loss
test loss

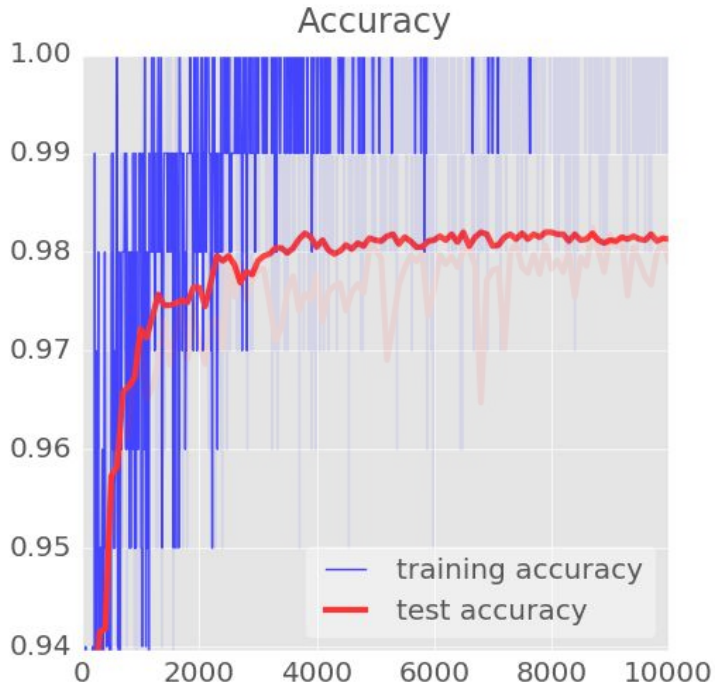

Training digits

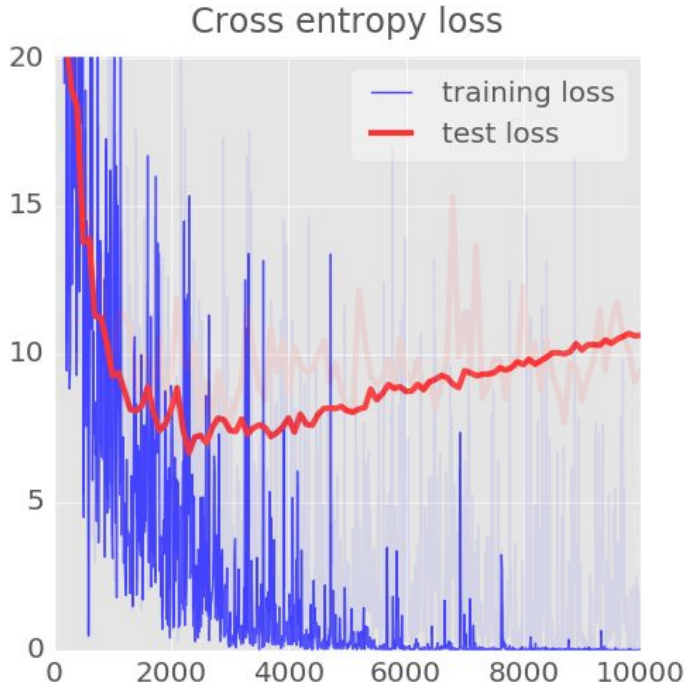

Weights
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
−0.8
0
2000
4000
6000
8000
10000


Biases
0.3
0.2
0.1
0.0
−0.1
0
2000
4000
6000
8000
10000


Test digits
100%
98%
96%
94%
92%
90%
98%

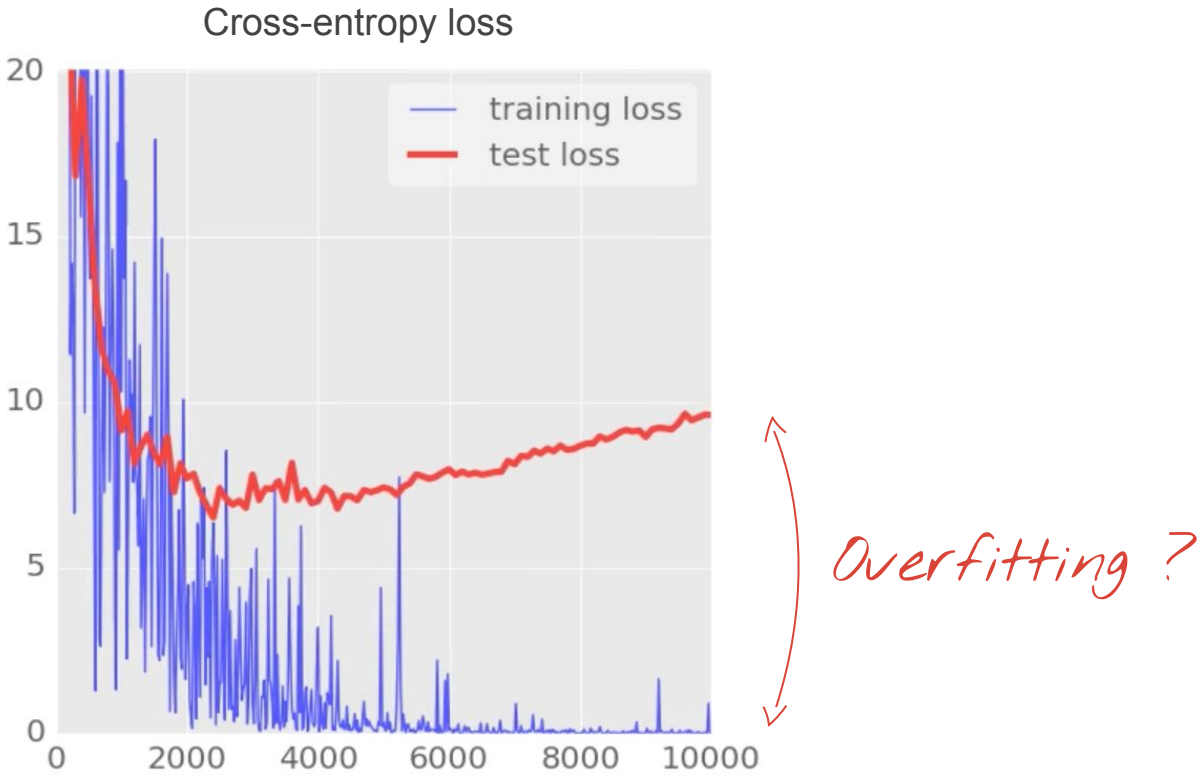
Learning rate decay

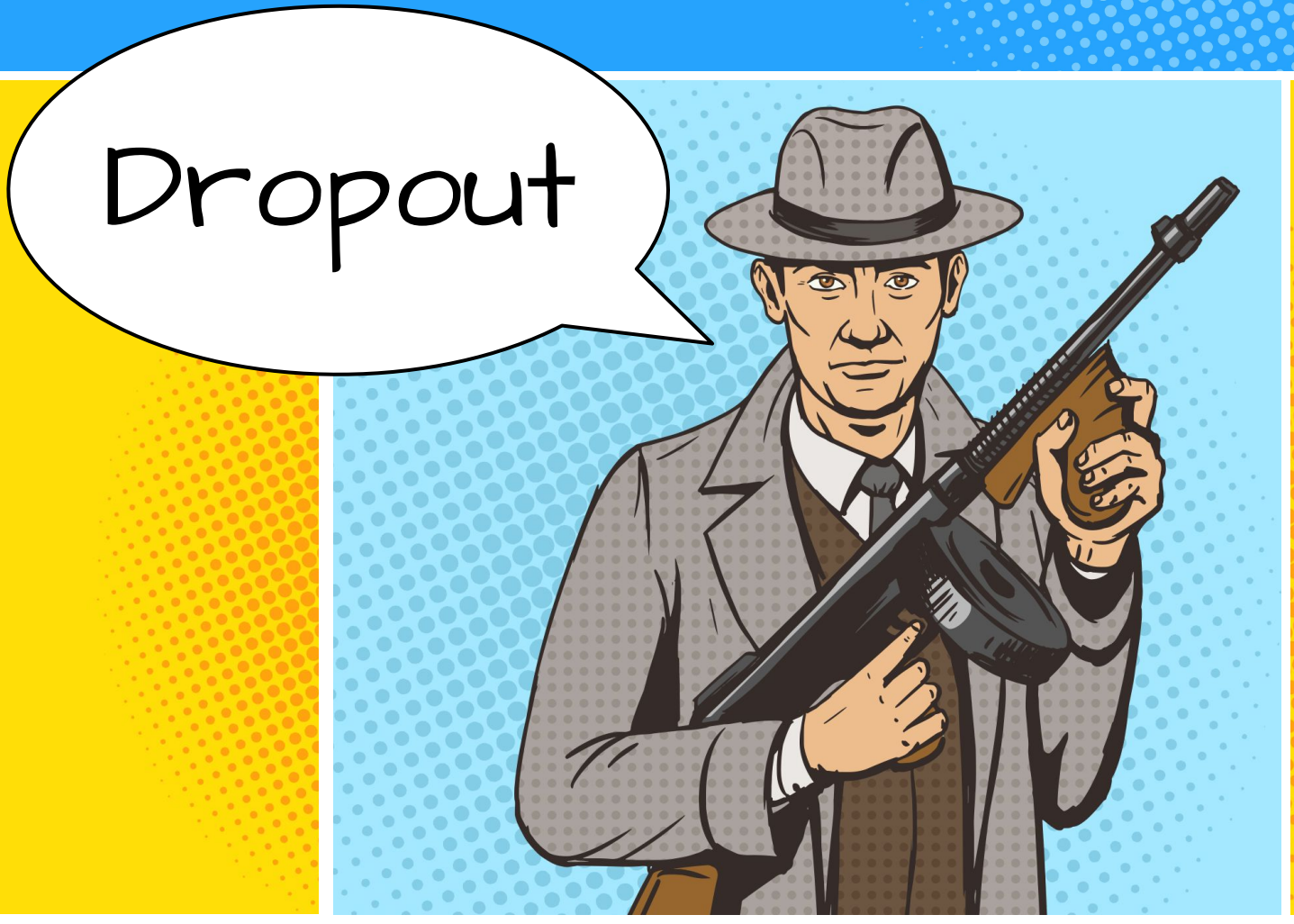




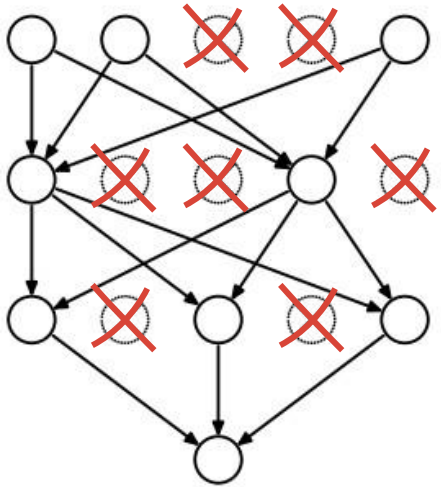
Learning rate 0.003 at start then dropping exponentially to 0.0001

Overfitting

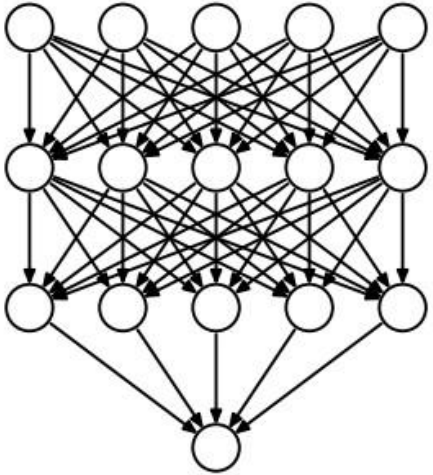



Dropout

Dropout



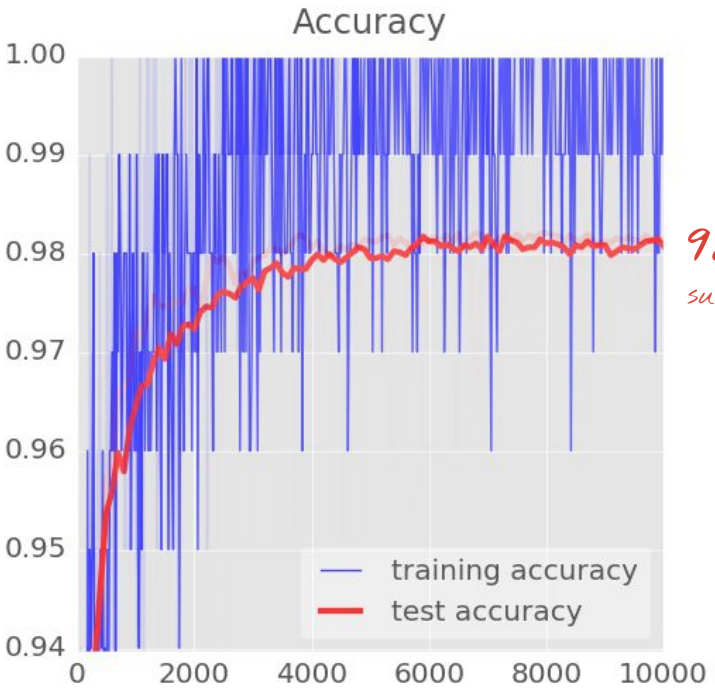
TRAINING
rate=0.5



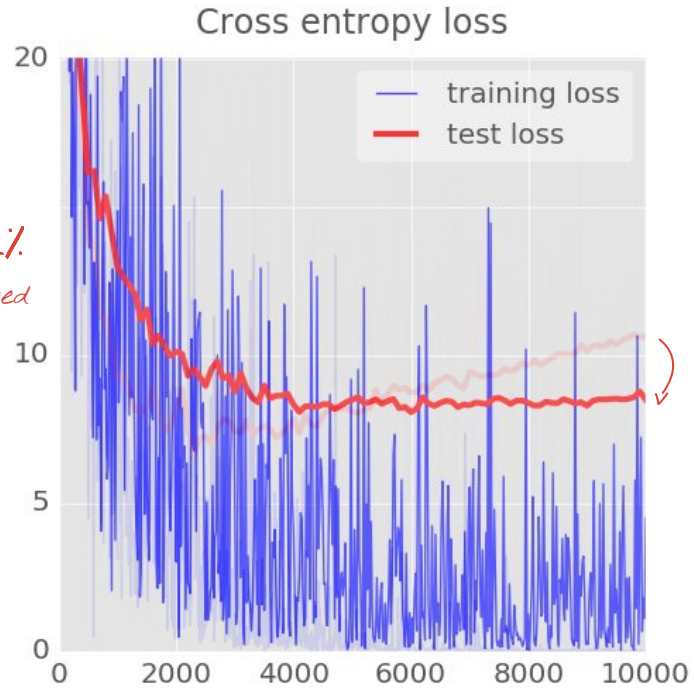
EVALUATION
rate=0

```
pkeep =
tf.placeholder(tf.float32)

Yf = tf.nn.relu(tf.matmul(X, W) + B)
Y  = tf.nn.dropout(Yf, pkeep)
```

All the party tricks

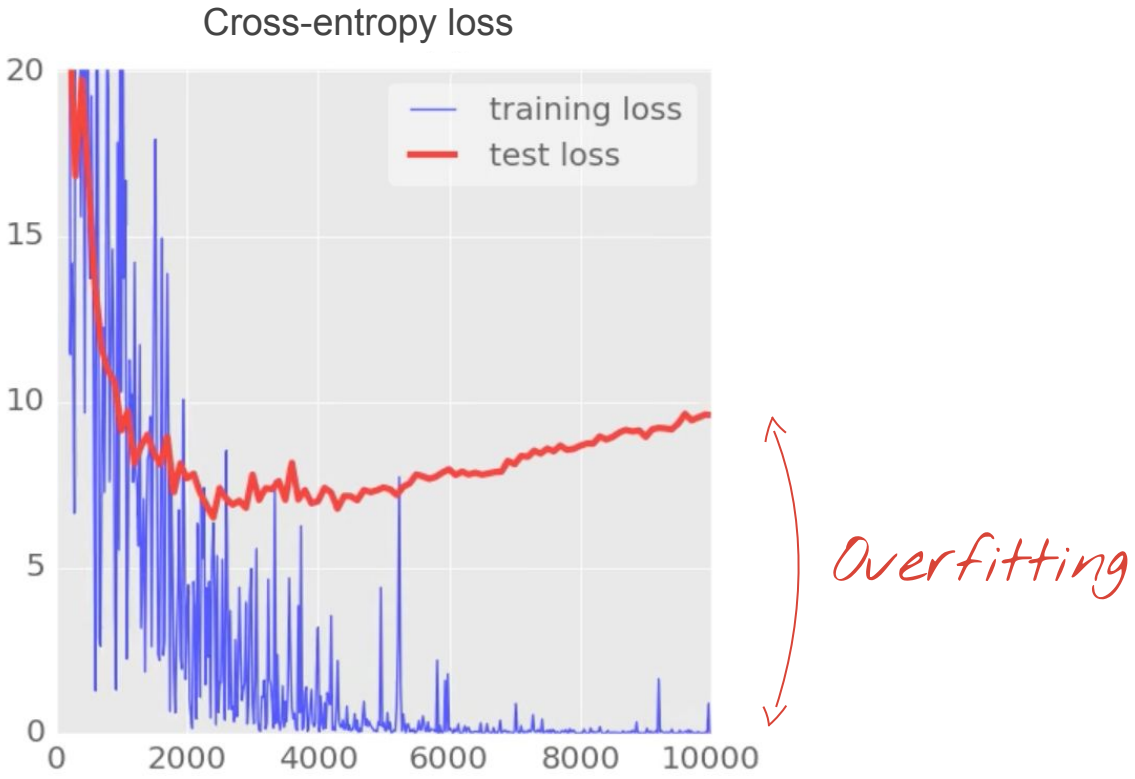


98.2% sustained



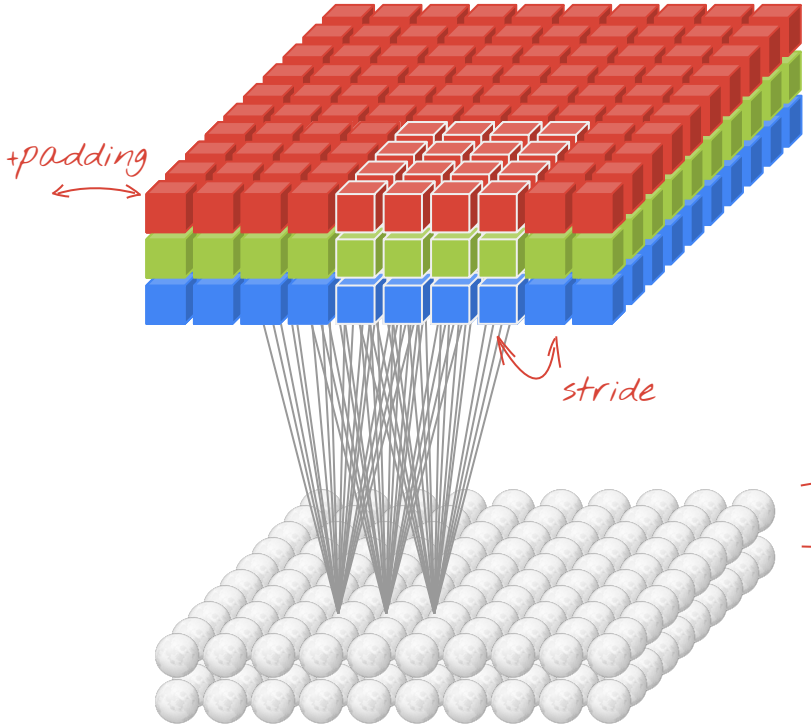
RELU, decaying learning rate 0.003 -> 0.0001 and dropout 0.75

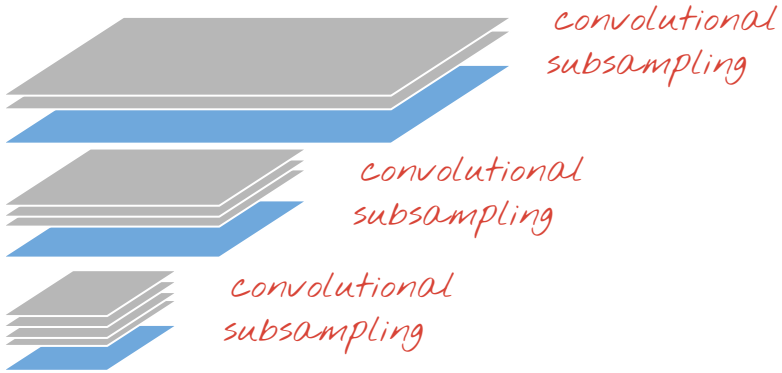
Overfitting




Overfitting
?!?
Too many
neurons
Not
enough
DATA
BAD
Network

Convolutional layer





$W_1[4, 4, 3]$

$W_2[4, 4, 3]$

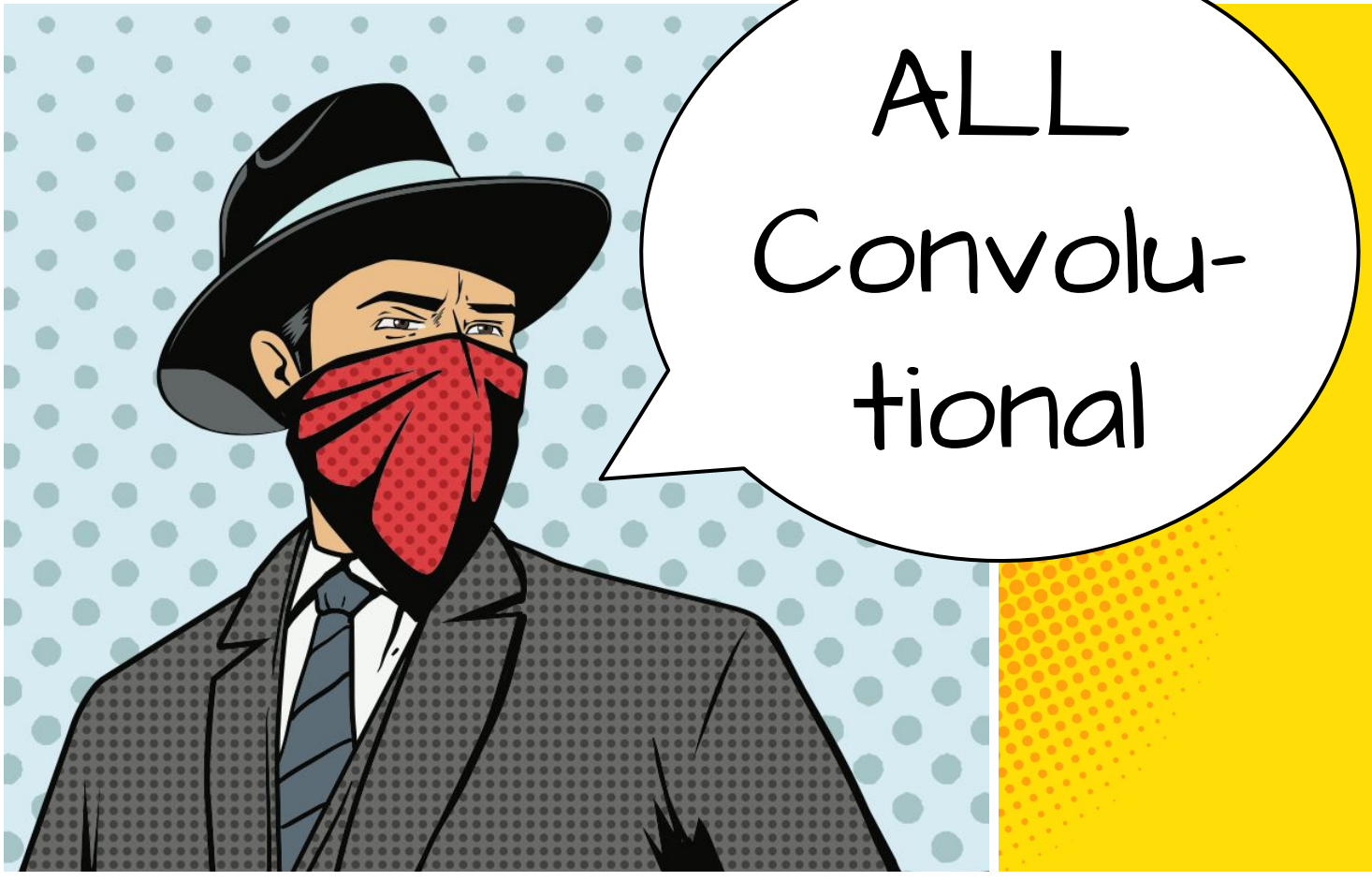
$W[4, 4, 3, 2]$

filter size

input channels

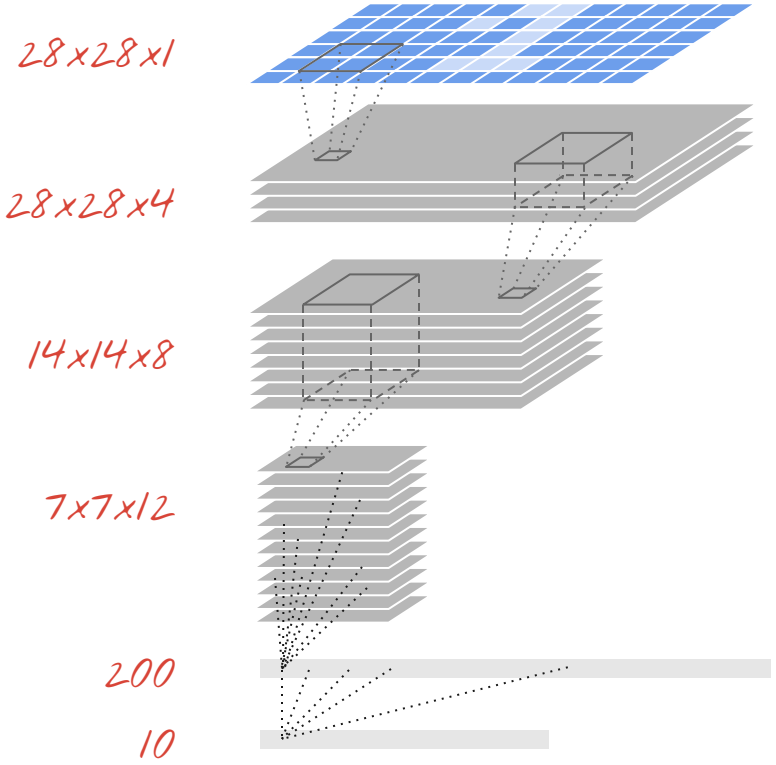
output channels

Hacker's tip



Convolutional neural network

+ biases on all layers



convolutional layer, 4 channels
W1[5, 5, 1, 4] stride 1

convolutional layer, 8 channels
W2[4, 4, 4, 8] stride 2

convolutional layer, 12 channels
W3[4, 4, 8, 12] stride 2

fully connected layer W4[7x7x12, 200]
softmax readout layer W5[200, 10]

Tensorflow - initialisation

filter size

input channels

output channels

```
K=4
L=8
M=12

W1 = tf.Variable(tf.truncated_normal([5, 5, 1, K] ,stddev=0.1))
B1 = tf.Variable(tf.ones([K])/10)
W2 = tf.Variable(tf.truncated_normal([5, 5, K, L] ,stddev=0.1))
B2 = tf.Variable(tf.ones([L])/10)
W3 = tf.Variable(tf.truncated_normal([4, 4, L, M] ,stddev=0.1))
B3 = tf.Variable(tf.ones([M])/10)

N=200

W4 = tf.Variable(tf.truncated_normal([7*7*M, N] ,stddev=0.1))
B4 = tf.Variable(tf.ones([N])/10)
W5 = tf.Variable(tf.truncated_normal([N, 10] ,stddev=0.1))
B5 = tf.Variable(tf.zeros([10])/10)
```

weights initialised with random values

Tensorflow - the model

input image batch
X[100, 28, 28, 1]

weights

stride

biases

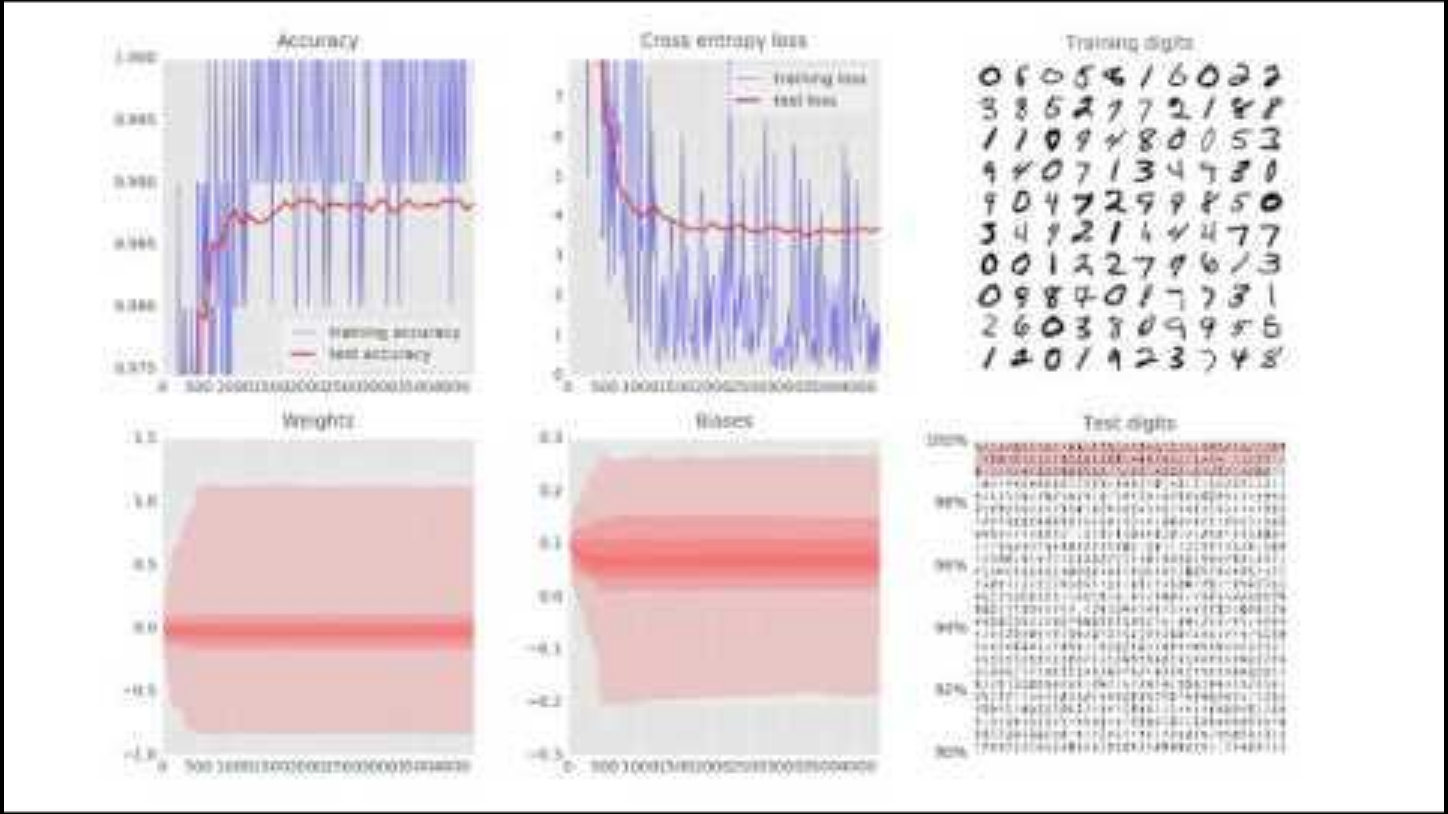
```
Y1 = tf.nn.relu(tf.nn.conv2d(X, W1, strides=[1, 1, 1, 1], padding='SAME') + B1)
Y2 = tf.nn.relu(tf.nn.conv2d(Y1, W2, strides=[1, 2, 2, 1], padding='SAME') + B2)
Y3 = tf.nn.relu(tf.nn.conv2d(Y2, W3, strides=[1, 2, 2, 1], padding='SAME') + B3)

YY = tf.reshape(Y3, shape=[-1, 7 * 7 * M])

Y4 = tf.nn.relu(tf.matmul(YY, W4) + B4)
Y  = tf.nn.softmax(tf.matmul(Y4, W5) + B5)
```

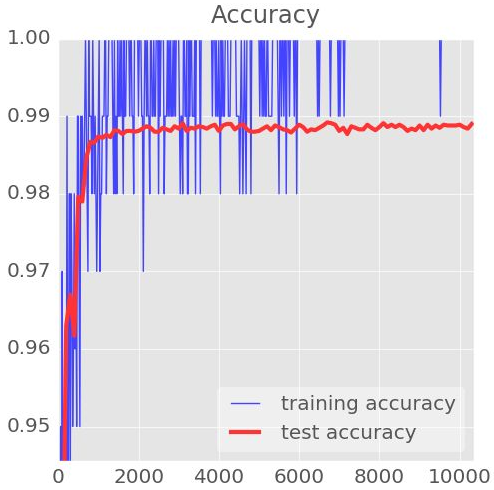
flatten all values for fully connected layer

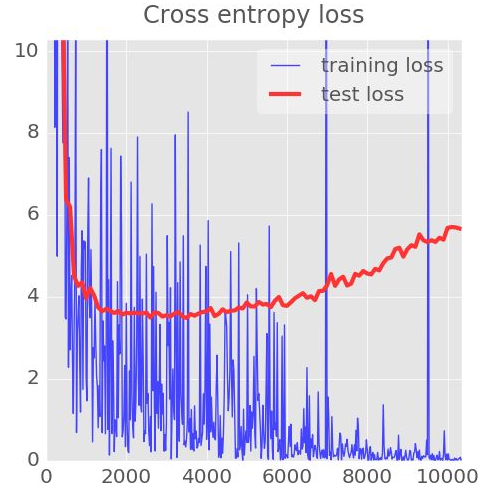
Y3 [100, 7, 7, 12]

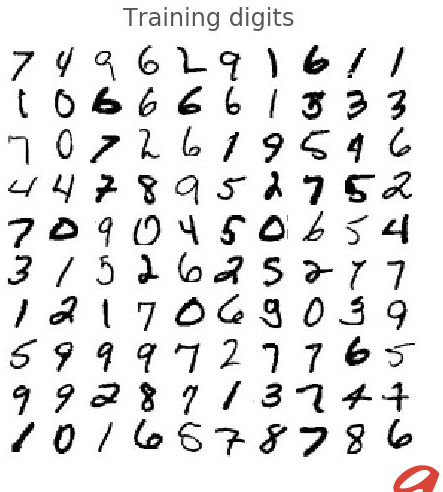
YY [100, 7x7x12]

Demo

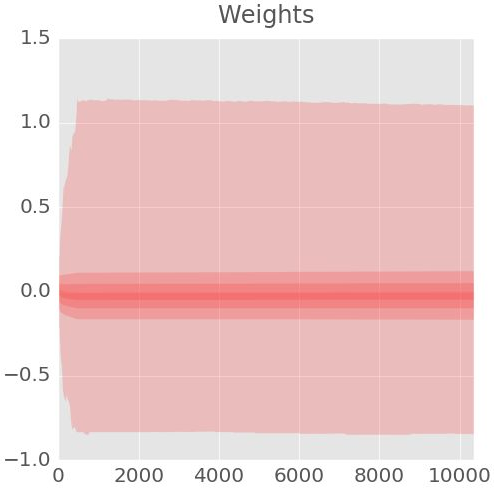

Accuracy
training accuracy
test accuracy
Cross entropy loss
training loss
test loss
Training digits
Weights
Biases
Test digits

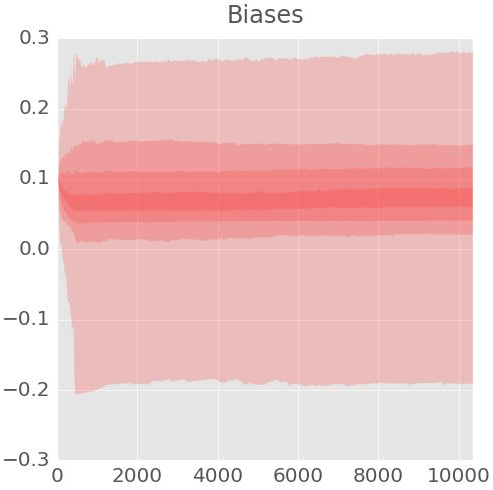

Accuracy
1.00
0.99
0.98
0.97
0.96
0.95
0
2000
4000
6000
8000
10000
training accuracy
test accuracy

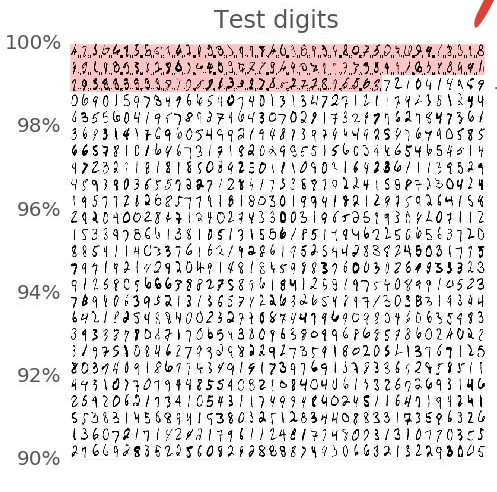

Cross entropy loss
10
8
6
4
2
0
0
2000
4000
6000
8000
10000
training loss
test loss


Training digits

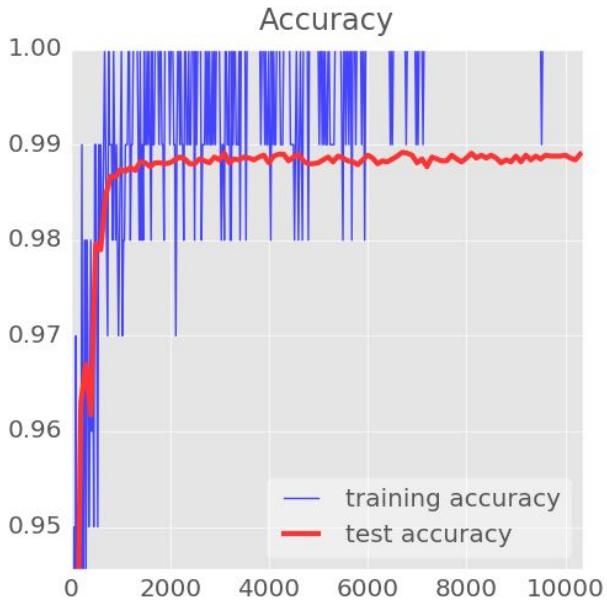
98.9%

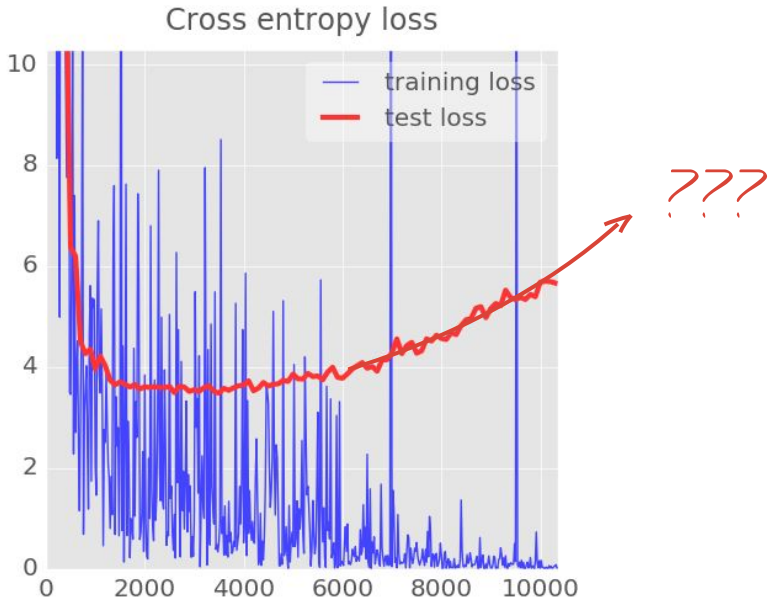

Weights
1.5
1.0
0.5
0.0
−0.5
−1.0
0
2000
4000
6000
8000
10000


Biases
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3
0
2000
4000
6000
8000
10000


Test digits
100%
98%
96%
94%
92%
90%

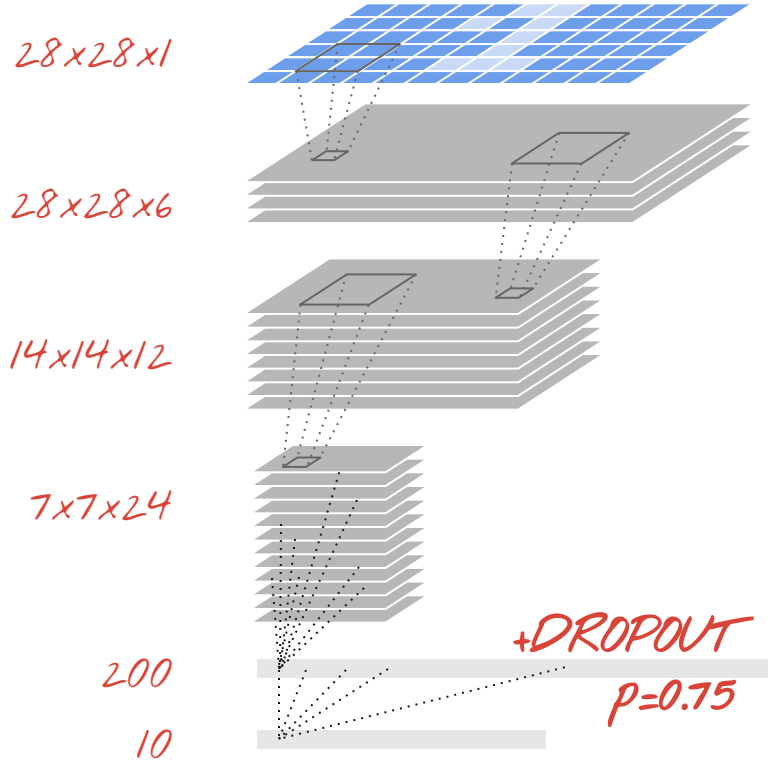
WTFH ???


Accuracy
1.00
0.99
0.98
0.97
0.96
0.95
0
2000
4000
6000
8000
10000
training accuracy
test accuracy


Cross entropy loss
10
8
6
4
2
0
0
2000
4000
6000
8000
10000
training loss
test loss
???

Bigger convolutional network + dropout

+ biases on all layers



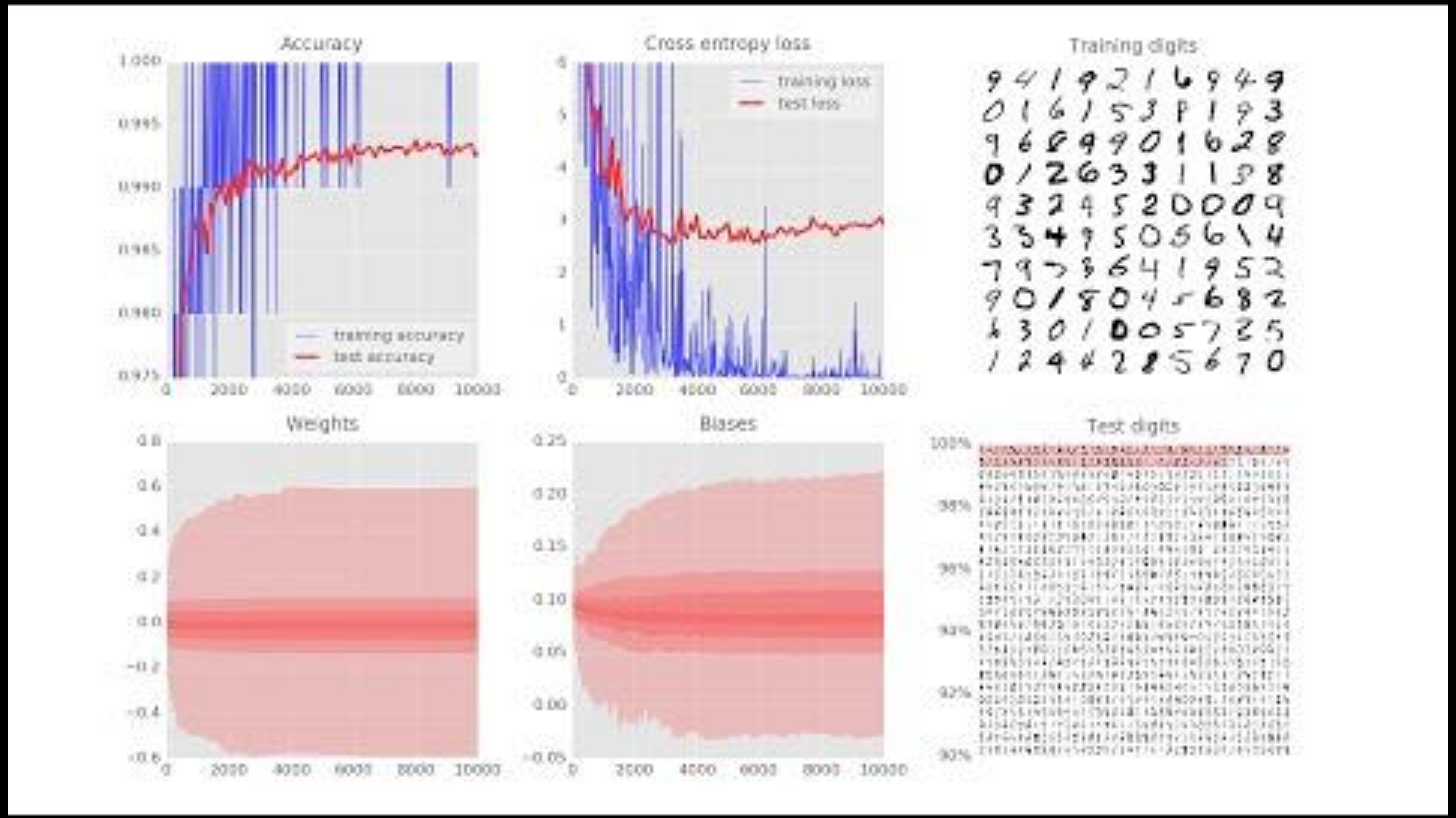
convolutional layer, **6 channels**
W1[6, 6, 1, 6] stride 1

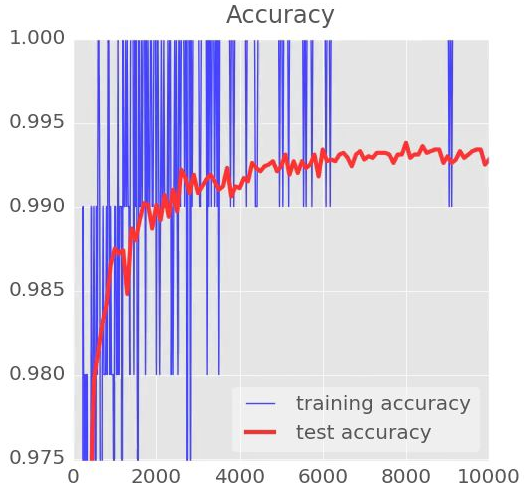
convolutional layer, **12 channels**
W2[5, 5, 6, 12] stride 2

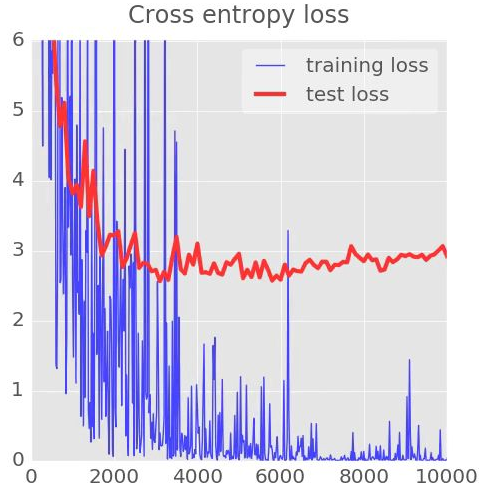
convolutional layer, **24 channels**
W3[4, 4, 12, 24] stride 2

fully connected layer W4[7x7x24, 200]
softmax readout layer W5[200, 10]

Demo

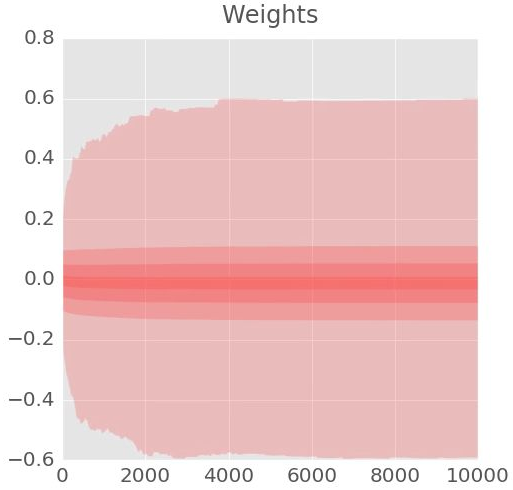

Accuracy
training accuracy
test accuracy
Cross entropy loss
training loss
test loss
Training digits
Weights
Biases
Test digits

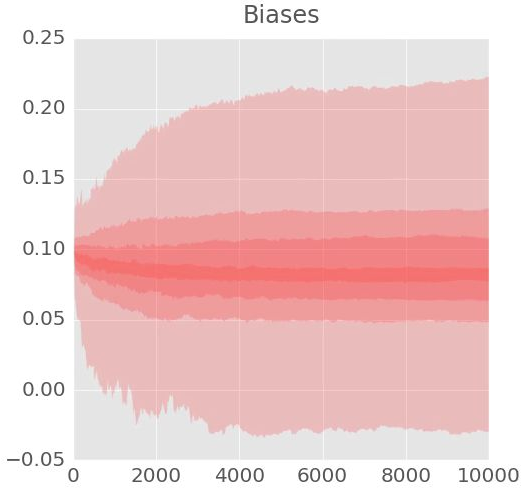

Accuracy
1.000
0.995
0.990
0.985
0.980
0.975
0
2000
4000
6000
8000
10000
training accuracy
test accuracy

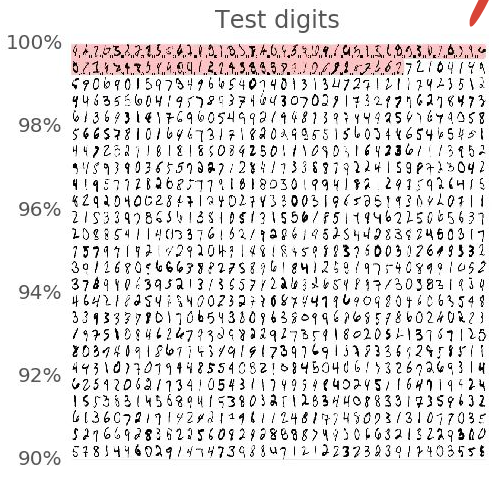

Cross entropy loss
6
5
4
3
2
1
0
2000
4000
6000
8000
10000
training loss
test loss


Training digits

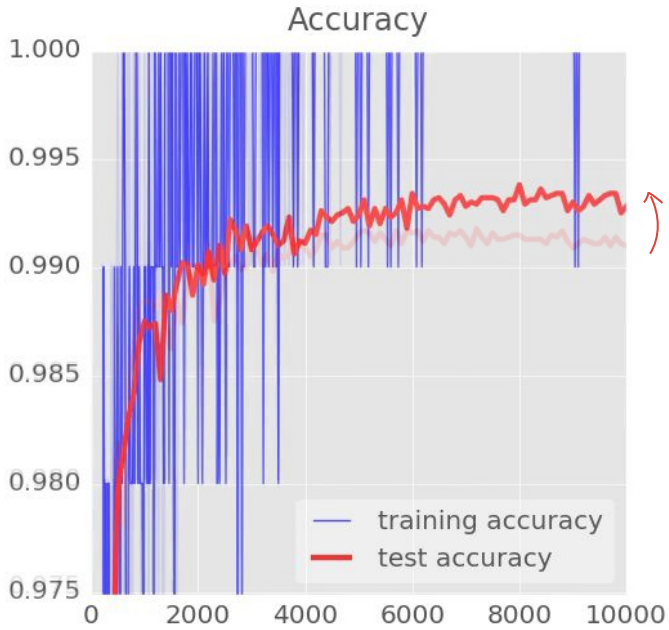
99.3%

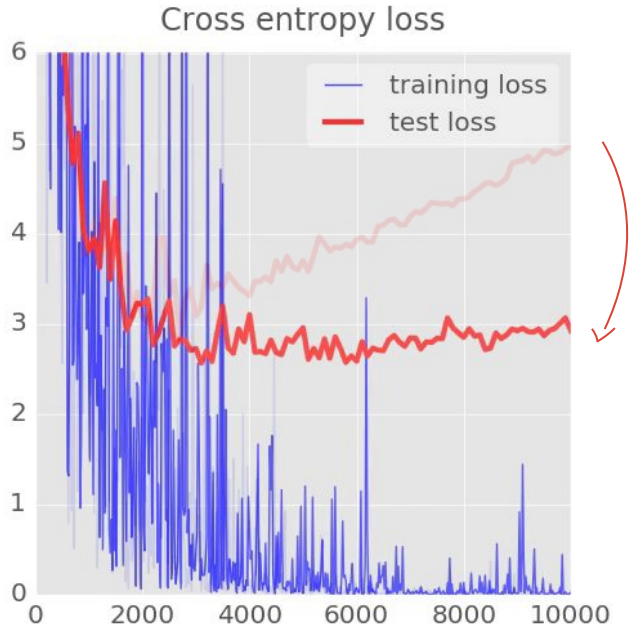

Weights
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
0
2000
4000
6000
8000
10000


Biases
0.25
0.20
0.15
0.10
0.05
0.00
−0.05
0
2000
4000
6000
8000
10000


Test digits
100%
98%
96%
94%
92%
90%

YEAH !





with dropout

Have fun !

Martin Görner

Google Developer relations

@martin_gorner

TensorFlow

Videos, slides, code:

github.com/GoogleCloudPlatform/tensorflow-without-a-phd

Cloud ML Engine
your TensorFlow models trained in Google's cloud.

Cloud Auto ML Vision ALPHA
Just bring your data

Cloud TPU
ML supercomputing

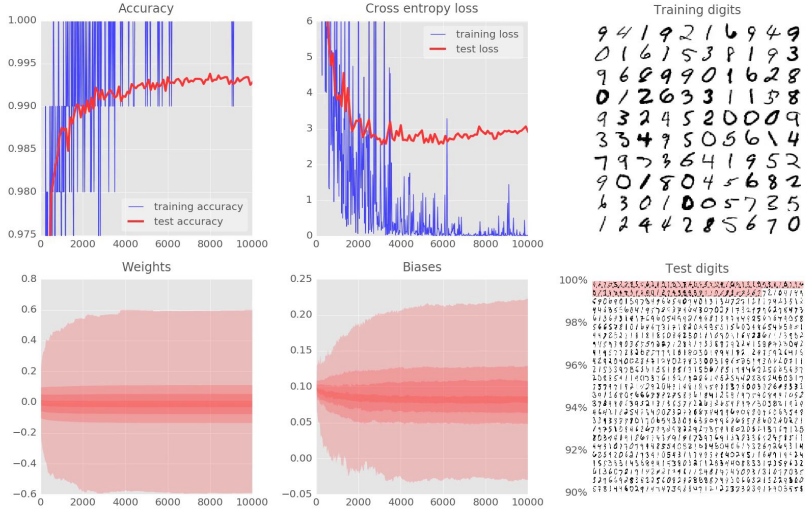
Pre-trained models:

- Cloud Vision API
- Cloud Speech API
- Natural Language API
- Google Translate API
- Video Intelligence API
- Cloud Jobs API BETA

Google Cloud


>TensorFlow and deep learning_
without a PhD
deep Science
#Tensorflow
>TensorFlow, deep learning and \
recurrent neural networks
without a PhD_
deep Science
#Tensorflow
>TensorFlow, deep learning and \
modern convolutional neural nets
without a PhD_
VGG
ResNet
BANG
#Tensorflow
>TensorFlow and \
deep reinforcement learning
without a PhD_
deep Science !
#Tensorflow
The superpower: batch normalisation
>TensorFlow, deep learning and \
modern RNN architectures
without a PhD_
EMBED
ENCODE
ATTEND
PREDICT
I ♥ neurons
Tensorflow and deep learning without a PhD
@martin_gorner
github.com/GoogleCloudPlatform/tensorflow-without-a-phd

Workshop



If training speed is an issue (it can happen in VirtualBox), consider displaying graph 3 while you wait instead of all the six graphs. You can also disable the visualisations altogether. There are instructions for that purpose at the end of each code sample.

Keyboard shortcuts for the visualisation GUI:

```
1 ......... display 1st graph only
2 ......... display 2nd graph only
3 ......... display 3rd graph only
4 ......... display 4th graph only
5 ......... display 5th graph only
6 ......... display 6th graph only
7 ......... display graphs 1 and 2
8 ......... display graphs 4 and 5
9 ......... display graphs 3 and 6
ESC or 0 .. back to displaying all graphs

SPACE ..... pause/resume
O ......... box zoom mode (then use mouse)
H ......... reset all zooms
Ctrl-S .... save current image
```

Workshop

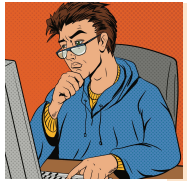
Self-paced code lab (summary below ↓): goo.gl/mVZloU
Code: github.com/martin-gorner/tensorflow-mnist-tutorial

1-5. Theory (install then sit back and listen or read)

Neural networks 101: softmax, cross-entropy, mini-batching, gradient descent, hidden layers, sigmoids, and how to implement them in Tensorflow

6. Practice (full instructions for this step)

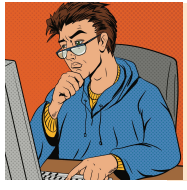
Open file: `mnist_1.0_softmax.py`
Run it, play with the visualisations (keyboard shortcuts on previous slide), read and understand the code as well as the basic structure of a Tensorflow program.



7. Practice (full instructions for this step)

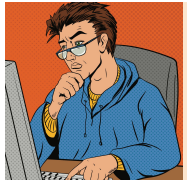
Start from the file `mnist_1.0_softmax.py` and add one or two hidden layers.

Solution in: `mnist_2.0_five_layers_sigmoid.py`



8. Practice (full instructions for this step)

Special care for deep neural networks: use RELU activation functions, use a better optimiser, initialise weights with random values and beware of the log(0)



9-10. Practice (full instructions for this step)

Use a decaying learning rate and then add dropout

Solution in: `mnist_2.2_five_layers_relu_lrdecay_dropout.py`

11. Theory (sit back and listen or read)

Convolutional networks

12. Practice (full instructions for this step)

Replace your model with a convolutional network, without dropout.

Solution in: `mnist_3.0_convolutional.py`

13. Challenge (full instructions for this step)

Try a bigger neural network (good hyperparameters on slide 43) and add dropout on the last layer to get >99%

Solution in: `mnist_3.0_convolutional_bigger_dropout.py`