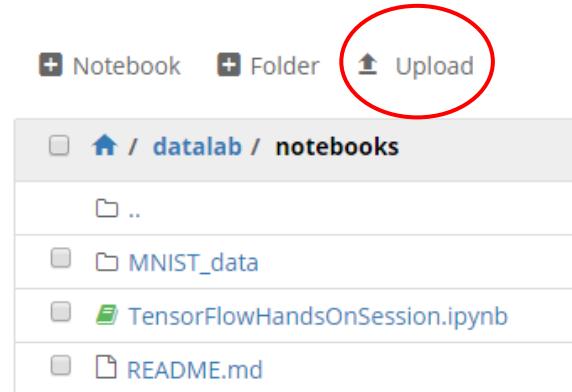


- Step 1: Create a [Google Cloud Platform Account](#) linked with your visa (12 month free trial)
- Step 2: Follow [this tutorial](#) to set up Cloud Datalab
- Step 3: [Download](#) the IPython notebooks containing the assignments and the solution code
- Step 4: Upload the notebook with the code in Datalab



* The slides of the presentation will appear here after the session

ML6

Hands-On Introduction to TensorFlow



Frederic Stallaert - Data Scientist @ML6 - Contact me! @ frederic.stallaert@ml6.eu

Nicolas DeRuytter - CEO @ML6

Erwin Huizenga - Machine Learning Specialist @Google

bit.ly/2yglnD0

Google Cloud

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Agenda

- 1 Machine Learning on Google Cloud Platform
- 2 Introduction to TensorFlow
- 3 tf.in.practice

Hi, how can I help?



“We will move from **mobile first** to an **AI first world**. We see huge opportunities to dramatically improve how people work.”

Sundar Pichai
CEO, Google

At Google, we've been applying Machine Learning for a long time



Search

Search ranking
Speech recognition



Android

Keyboard & speech input



Play

App recommendations
Game developer experience



Gmail

Smart Reply
Spam classification



Drive

Suggested visualization
and insights



Chrome

Search by Image



Photos

Photos search



YouTube

Video recommendations
Better thumbnails



Maps

Street View image
Parsing Local Search



Translate

Text, graphic, and
speech translations



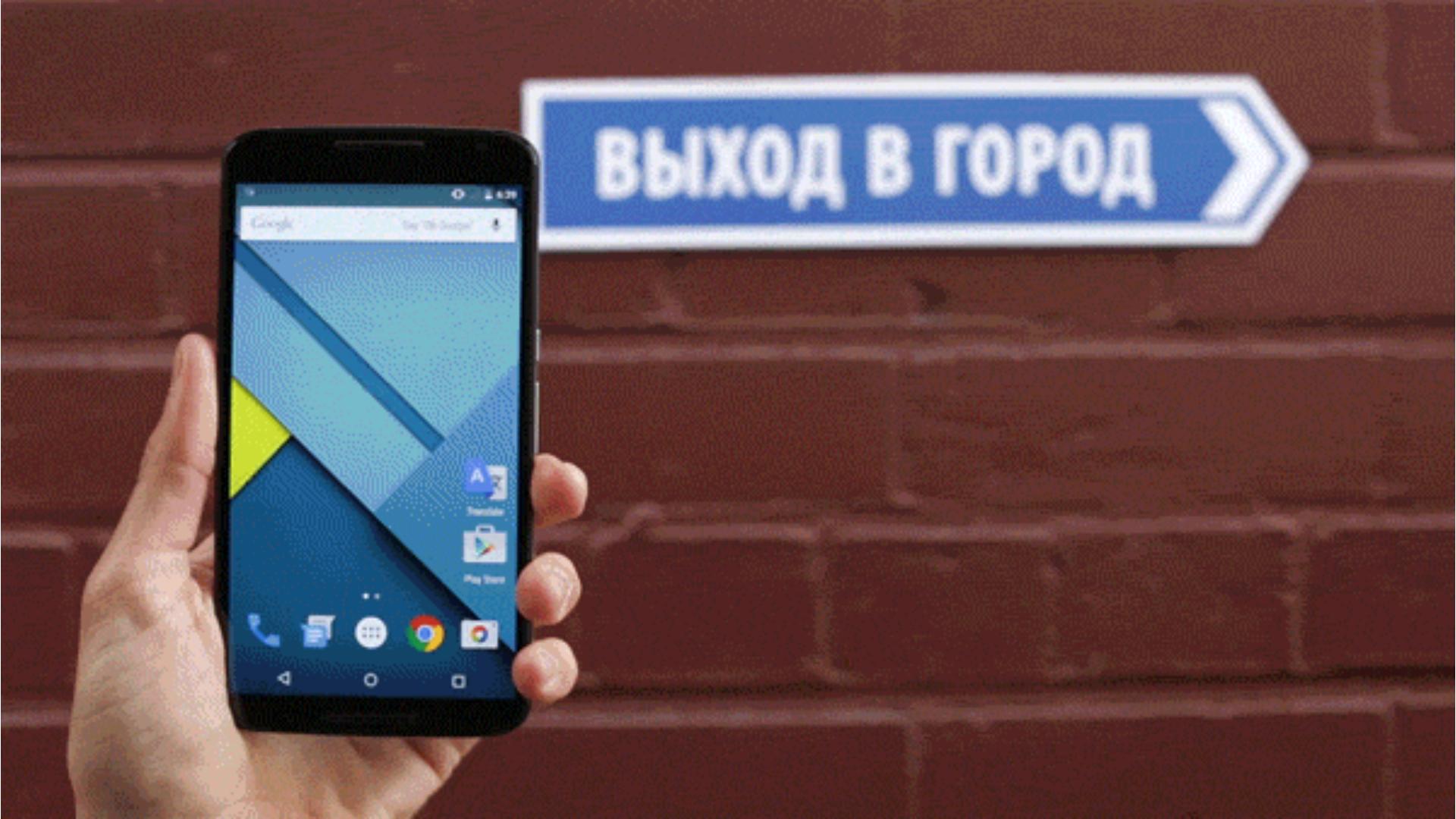
Cardboard

Smart stitching



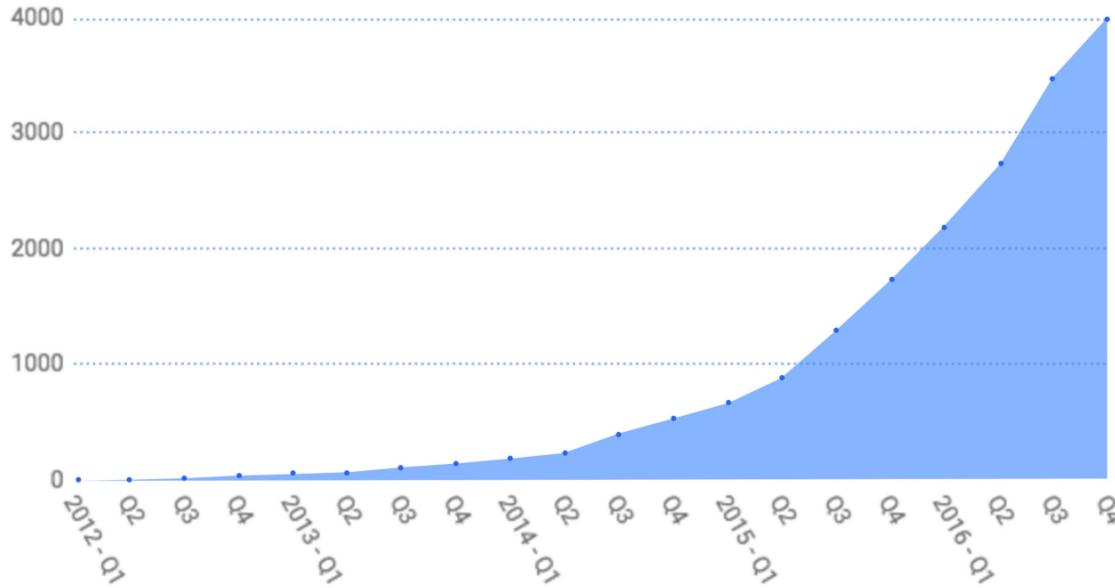
Ads

Richer Text Ads
Automated Bidding

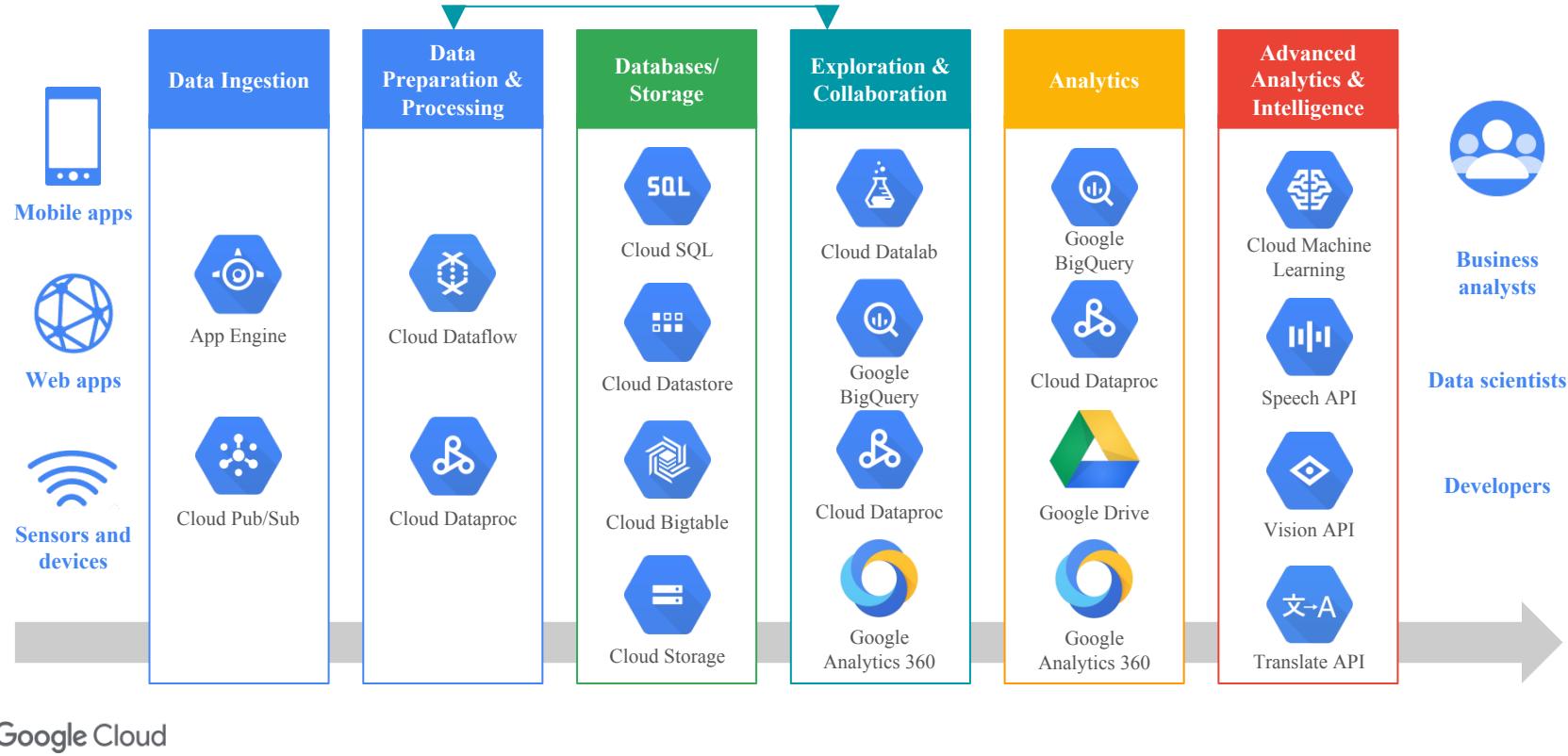


ВЫХОД В ГОРОД

Rapid accelerated use of Machine Learning at Google



Transform Data into Actions



Google Cloud the end-to-end AI Platform

Industry Use-cases

In-loop inferencing for trained models



Cloud AI products

Pre-trained ML APIs to
Building custom ML models



ML Framework

Industry-standard & widely adopted



Infrastructure

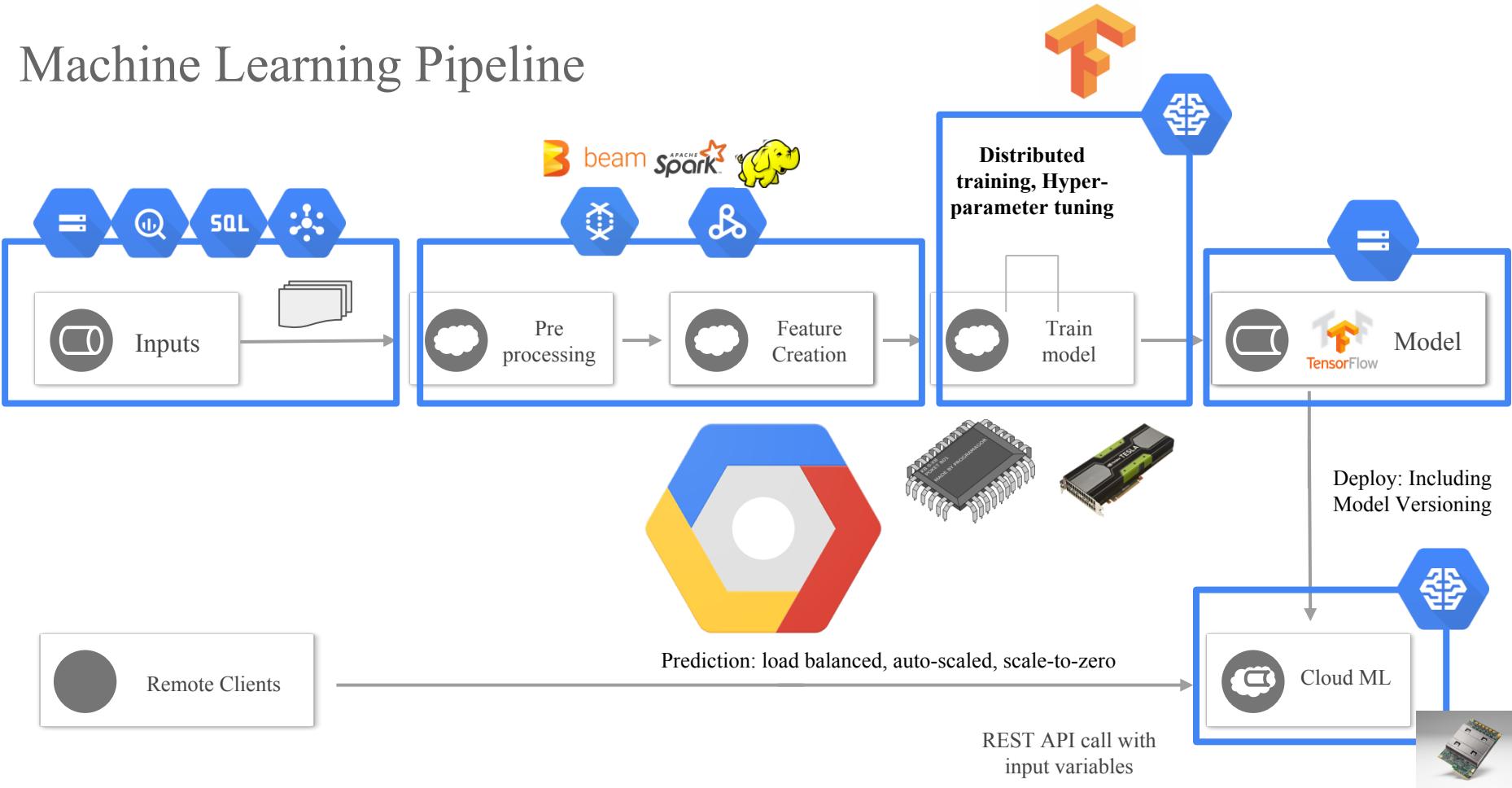
Best-in class processors for ML/DL

CPU

GPU

TPU

Machine Learning Pipeline



Google Cloud

Results Enabled by Google Cloud

- **Faster Time to Insights** - Customer and product analytics up to 35x faster
- **Increased Customer Stickiness** - Used to only have weekly playlists. Now users can get up to seven playlists customized for them per day.

“Queries that used to take 20 minutes now take seconds. Faster results means more queries can be done, resulting in more finely tuned recommendations.”

Wouter De Bie, Data Architect, Spotify





THURSDAY 19 OCT. - GOOGLE



Google Cloud Platform



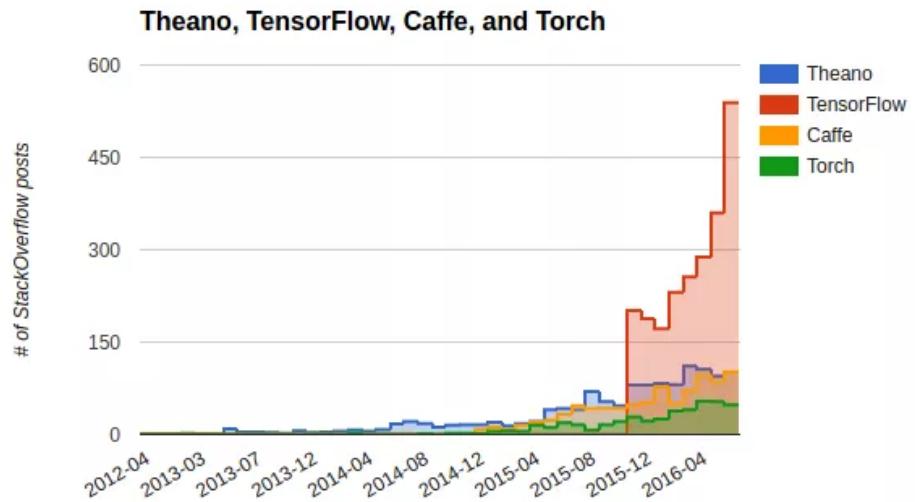
Who is ML6?

- + Team of Data Engineers, Data Scientists and Machine Learning Experts
- + Partner of Google Cloud
- + Artificial Intelligence Agency
- + Agile prototypes and robust solutions across various industries

info@ml6.eu

www.ML6.eu

Use case to illustrate what we actually do.

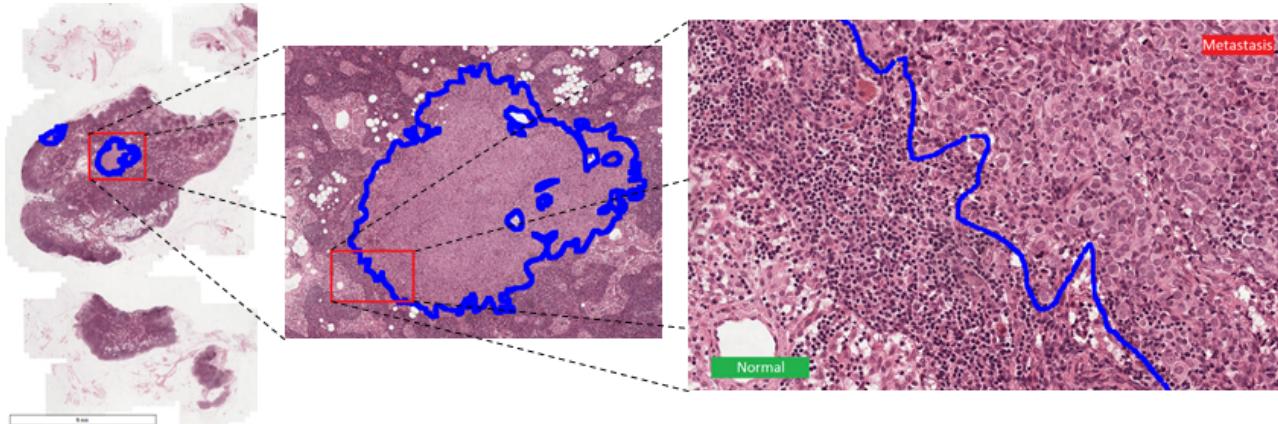


MEDICAL IMAGE CLASSIFICATION

TECHNICAL DETAILS - DATA

Camelyon16: ISBI challenge on cancer metastasis detection in lymph node

Training & Evaluation: 110 tumor slides, 160 normal slides, 130 evaluation slides



MEDICAL IMAGE CLASSIFICATION

TECHNICAL DETAILS - CHALLENGE BREAKDOWN

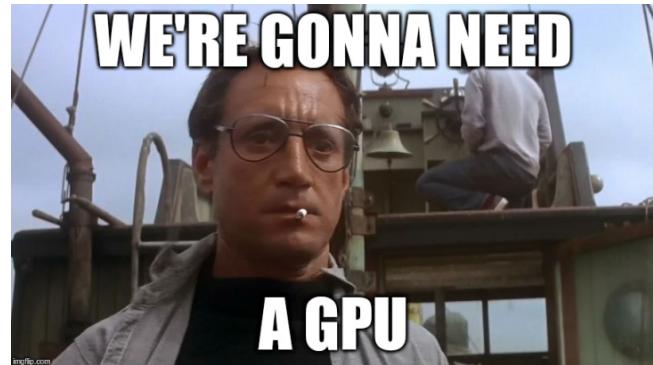
Not just another standard image classifier...

Training set construction

Computing environment

Network architecture

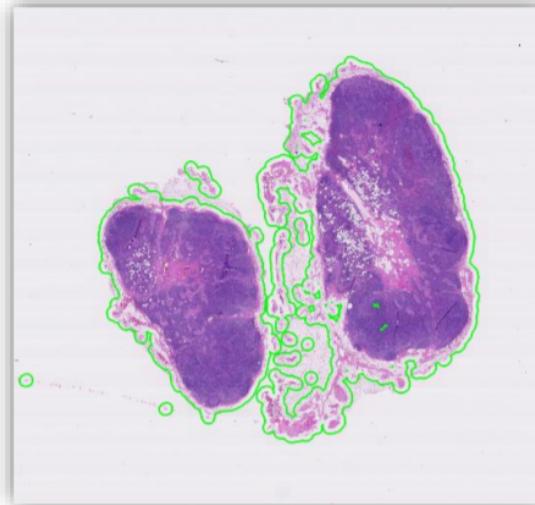
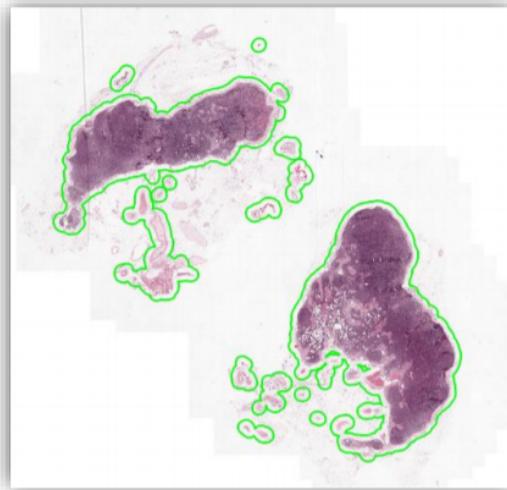
Post-processing (classification and segmentation)



MEDICAL IMAGE CLASSIFICATION

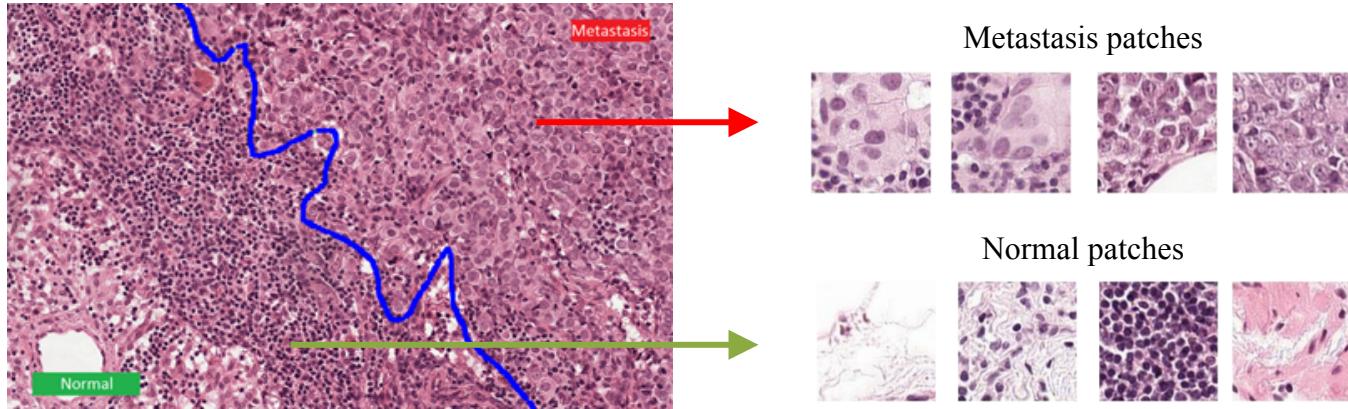
TECHNICAL DETAILS - PREPROCESSING

Tissue region segmentation with Otsu's method
allows for removing > 80% of image region on average



MEDICAL IMAGE CLASSIFICATION

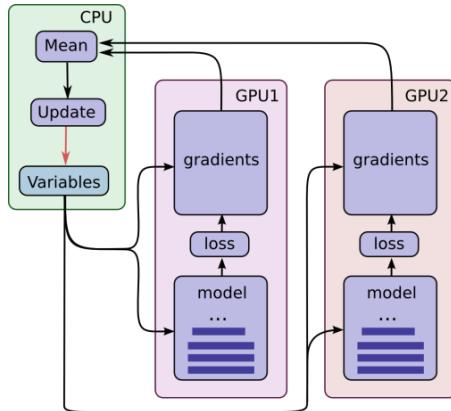
TECHNICAL DETAILS - PREPROCESSING



Millions of training examples are generated by sampling normal and metastasis regions of high-resolution whole-slide-images

MEDICAL IMAGE CLASSIFICATION

TECHNICAL DETAILS - MULTIPLE GPUs



Multiple GPUs were used to calculate **model updates**

- ▷ individual model replica on each GPU
- ▷ all GPUs process a batch of data and send update of model parameters to CPU, which performs a synchronized update

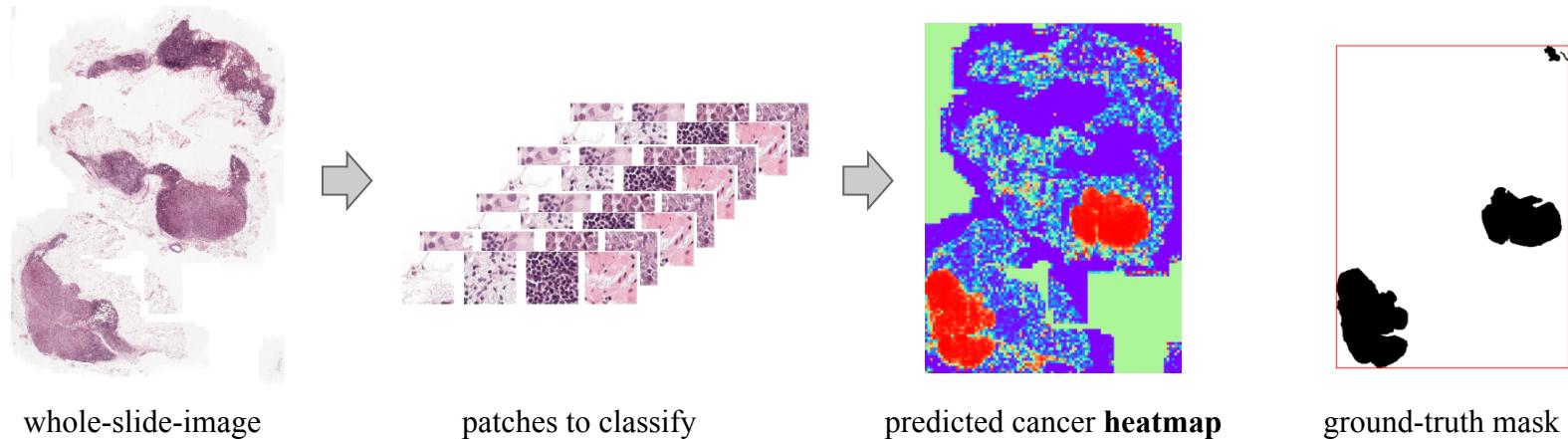
Approach was extended to **Cloud ML Engine GPUs** during Healthcare Hackathon to build a dermatology POC in 1 day (by starting from a.o. pretrained VGG16)



MEDICAL IMAGE CLASSIFICATION

TECHNICAL DETAILS - FIRST RESULTS

By **scanning the patches** of a WSI, a **heatmap** can be generated



First results of short training period seem **promising**

Longer training can lead to better results + extended **postprocessing** necessary

(e.g. extract higher level features from low level heatmaps, for tumor probability and location estimation)

ML6

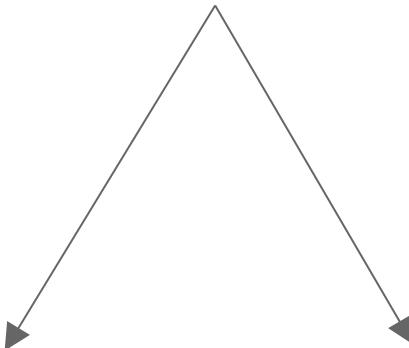


Key Machine Learning Concepts



Supervised vs. Unsupervised Learning

Regression



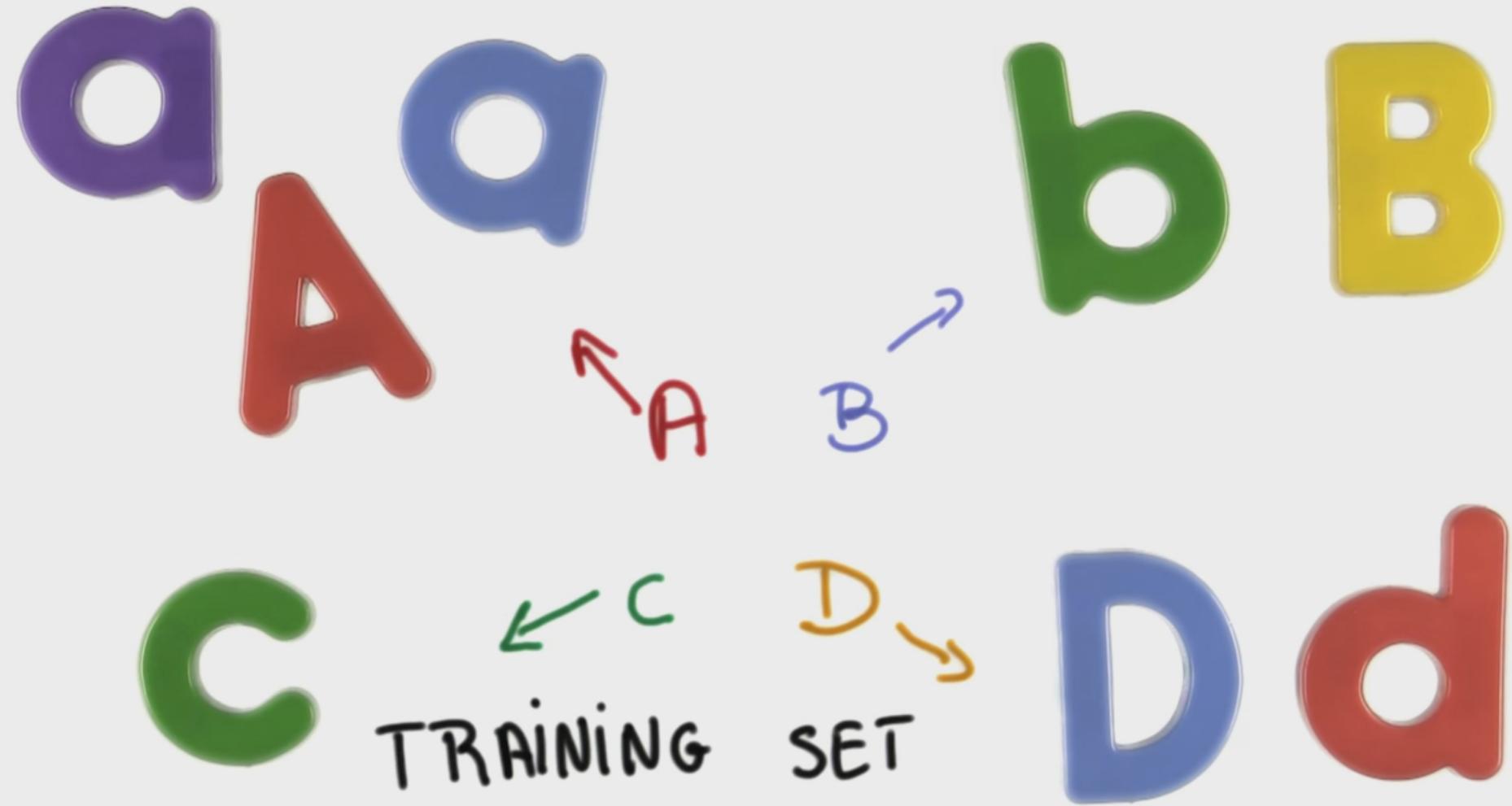
Classification



TRAINING

VALIDATION

TESTING

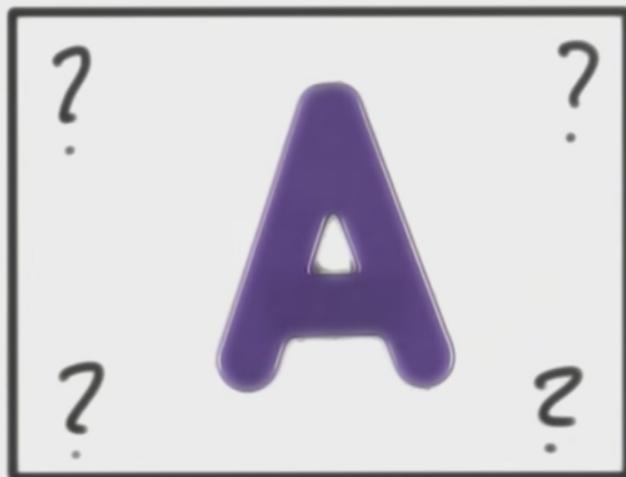


a

a

A

c



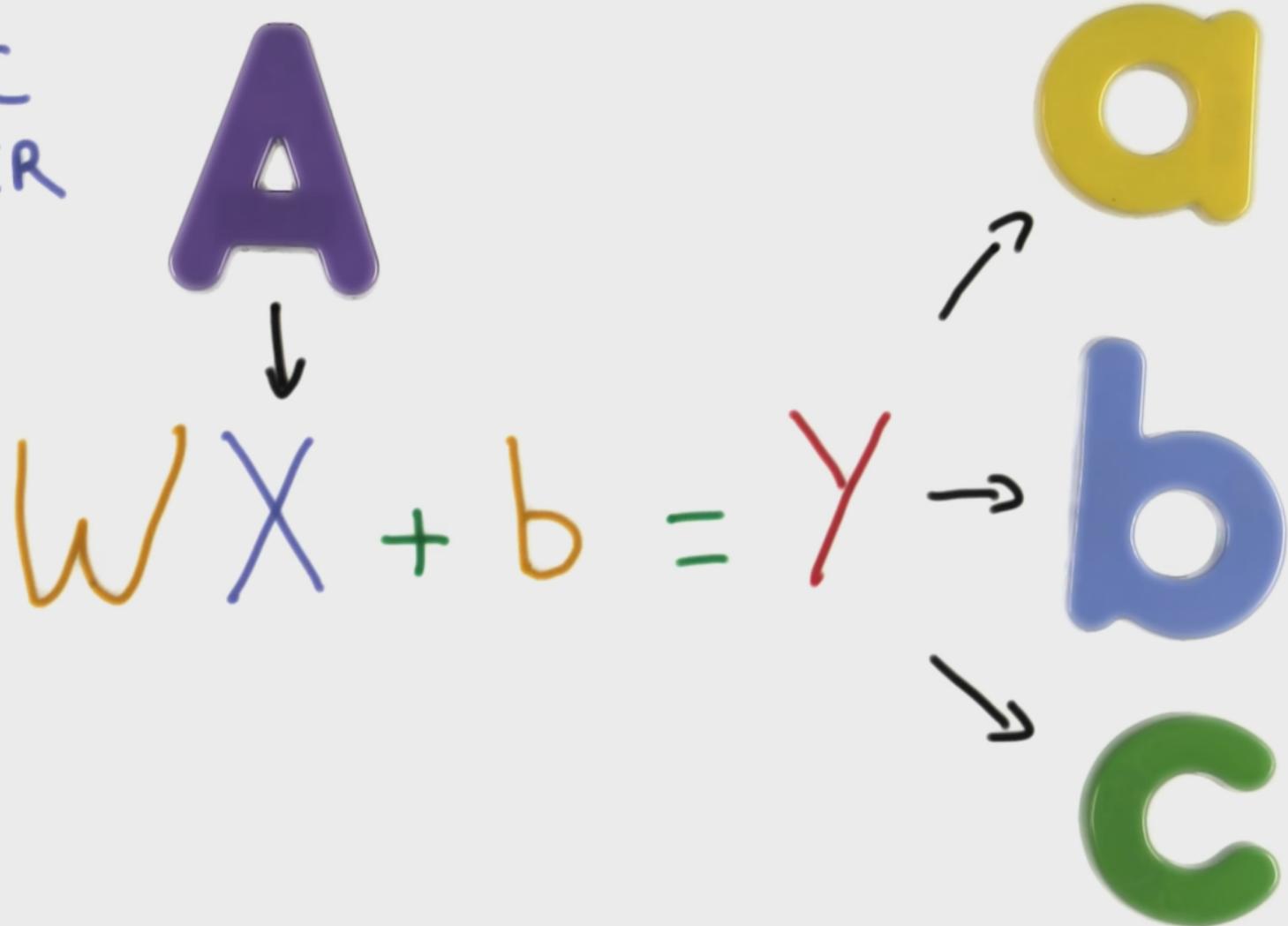
b

B

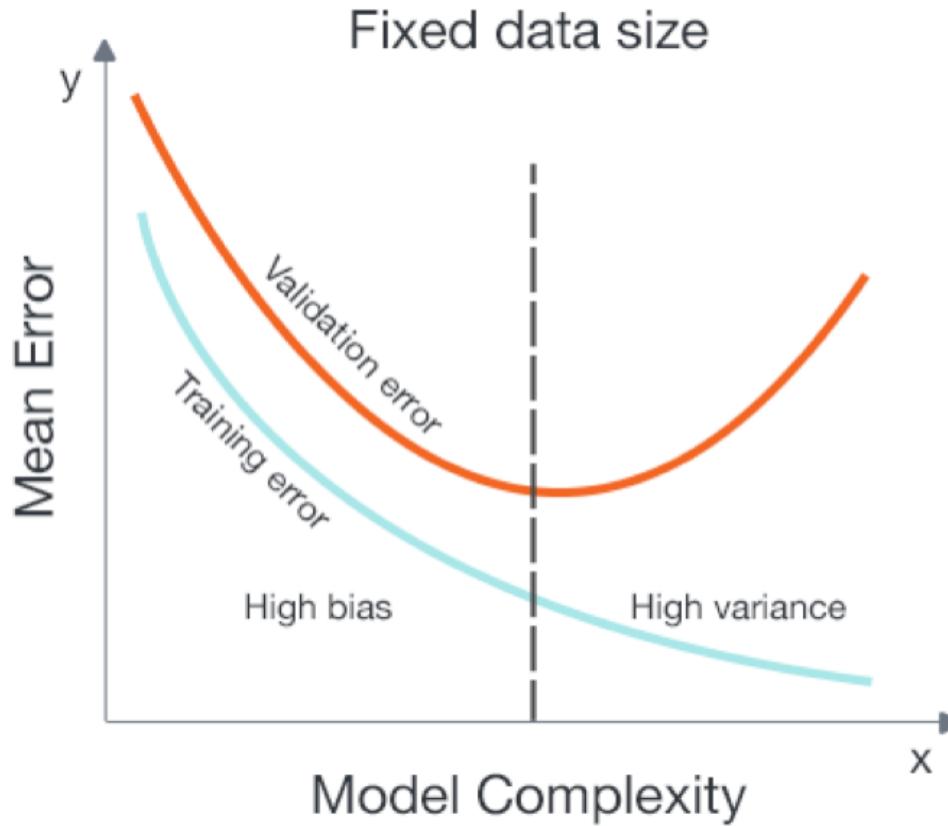
D d

d

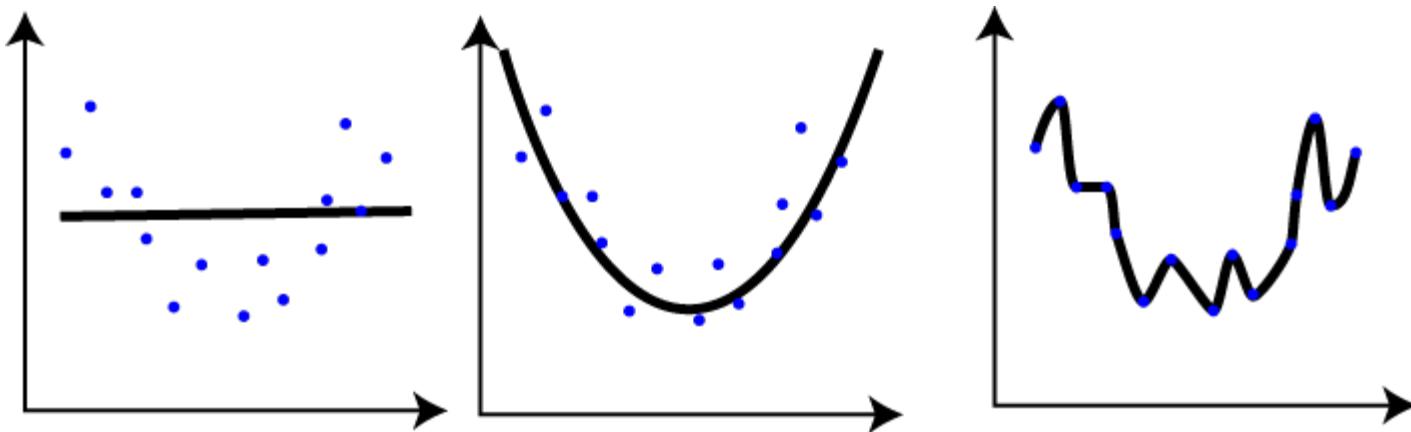
LOGISTIC CLASSIFIER



Model Evaluation



Under-/Overfitting



A

$s(y)$



0.7

0.2

0.1

'ONE-HOT'
ENCODING



1.0

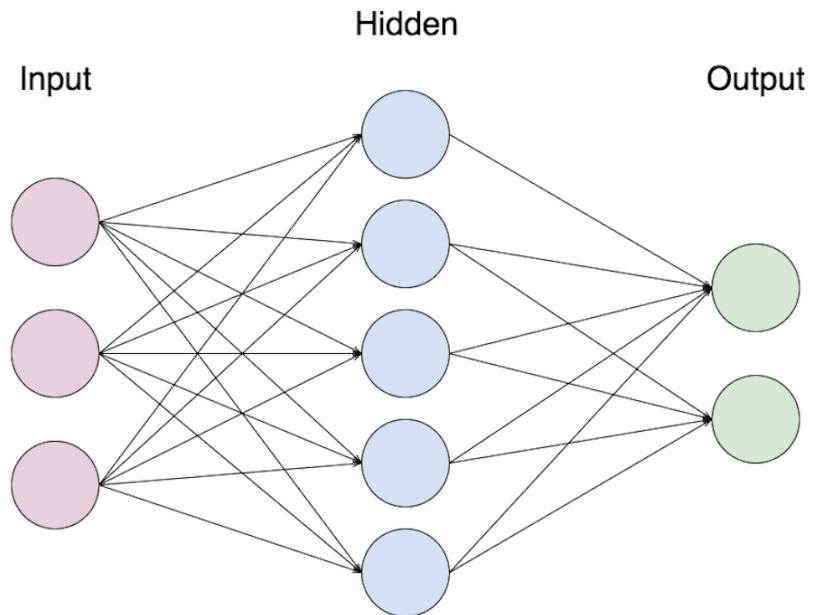
0.0

0.0



Neural Networks

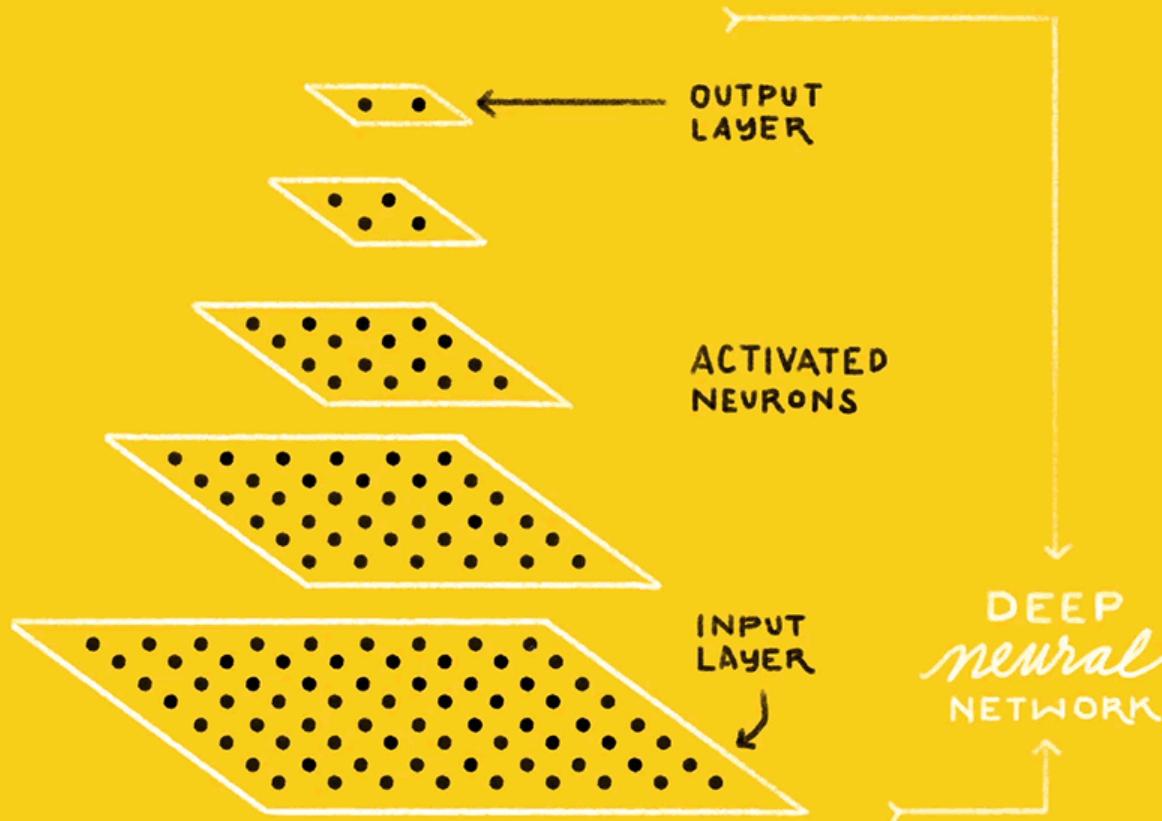
- Multiple layers of nodes
- Multiple nodes in each layer
- Node = function with parameters
- Training in 2 phases
 - feed forward
 - backpropagation
- Optimizer



IS THIS A
CAT or DOG?

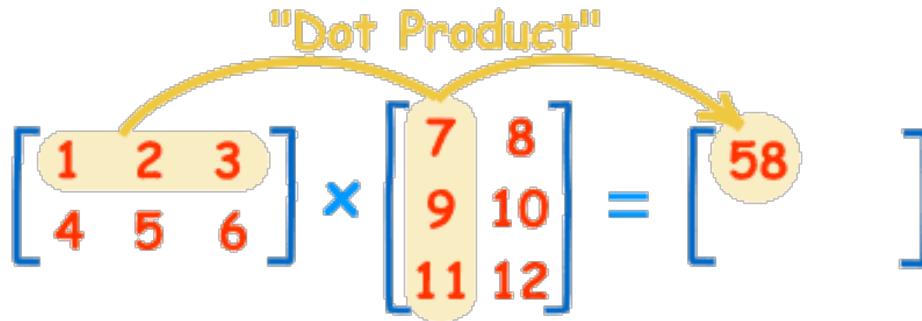


CAT DOG



Calculations with Matrices

Basic Recap



$$\begin{bmatrix} 1 & 4 \\ -2 & 3 \end{bmatrix} \cdot \begin{bmatrix} 1 & 3 & -4 \\ 6 & 8 & 0 \end{bmatrix}$$

$(2 \times 2) \cdot (2 \times 3)$

same

$$\begin{bmatrix} 5 & -3 \\ 4 & 1 \\ 7 & -2 \end{bmatrix} \cdot \begin{bmatrix} 8 \\ 2 \end{bmatrix}$$

$(3 \times 2) \cdot (2 \times 1)$

same



- Open-source machine- and deep learning library
- Numerical computations using data flow graphs
 - Nodes: Mathematical operations
 - Edges: Multidimensional data arrays called tensors
- Flexible architecture allows computations on multiple CPU's or GPU's



TensorFlow

Are you ready?

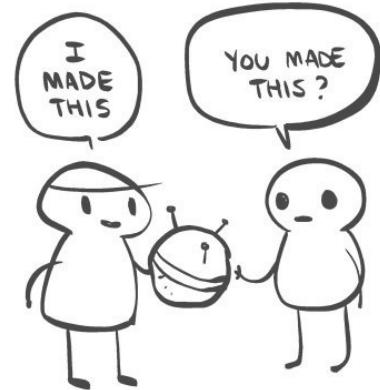




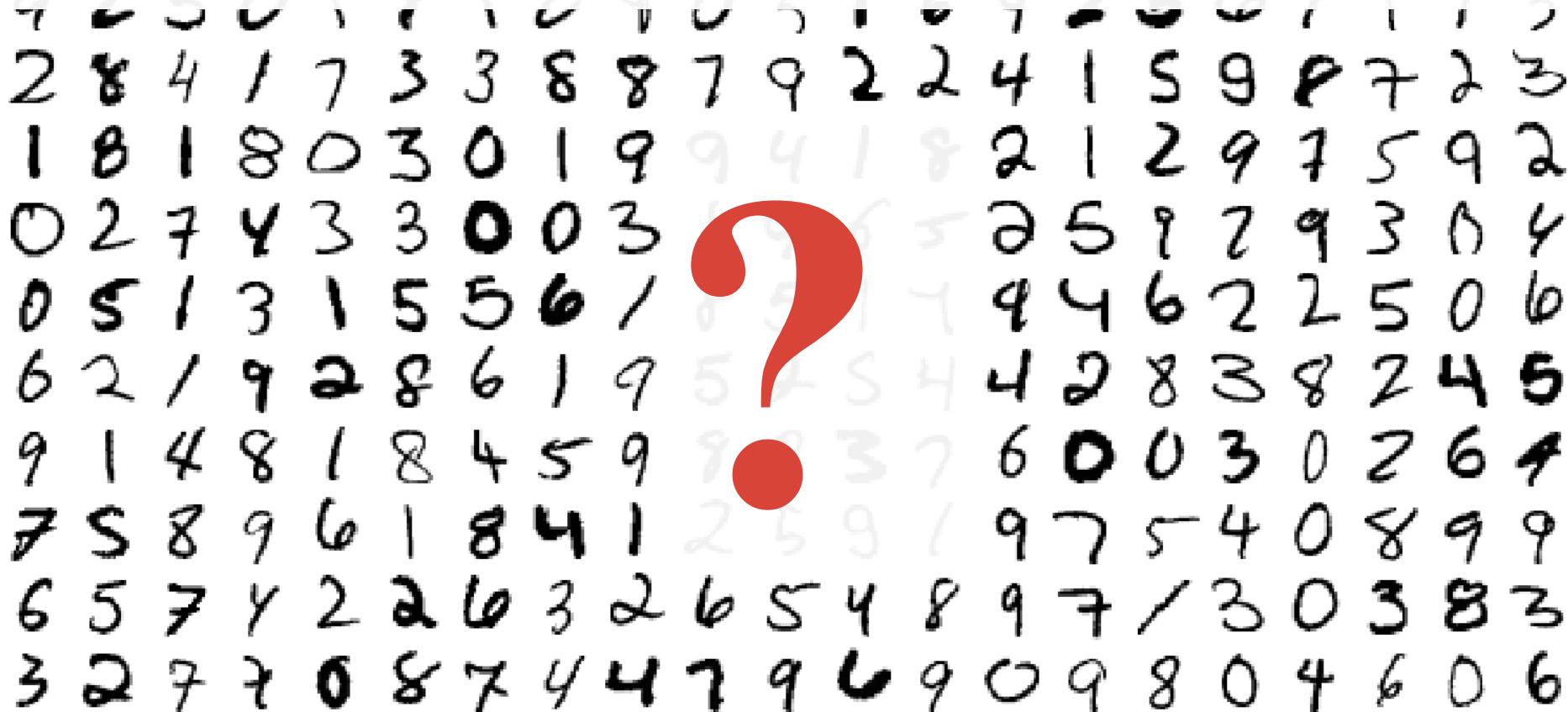
Let's get started!

- Martin Görner
- How to set everything up?

bit.ly/2yg1nD0

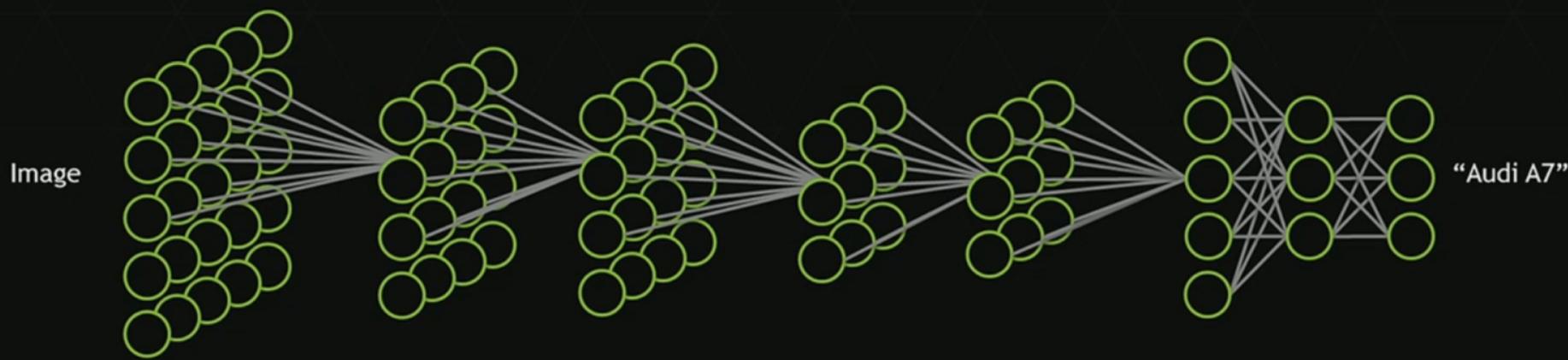


Hello World: handwritten digits classification - MNIST



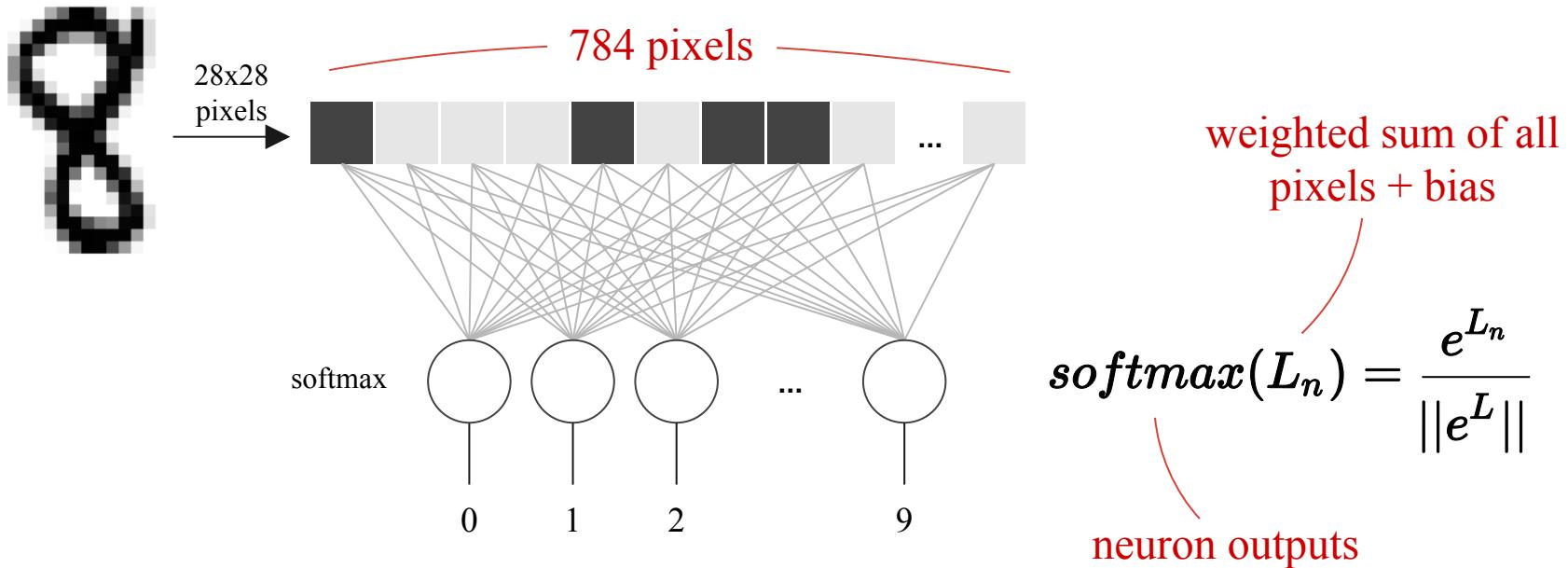
MNIST = Mixed National Institute of Standards and Technology - Download the dataset at <http://yann.lecun.com/exdb/mnist/>

HOW A DEEP NEURAL NETWORK SEES

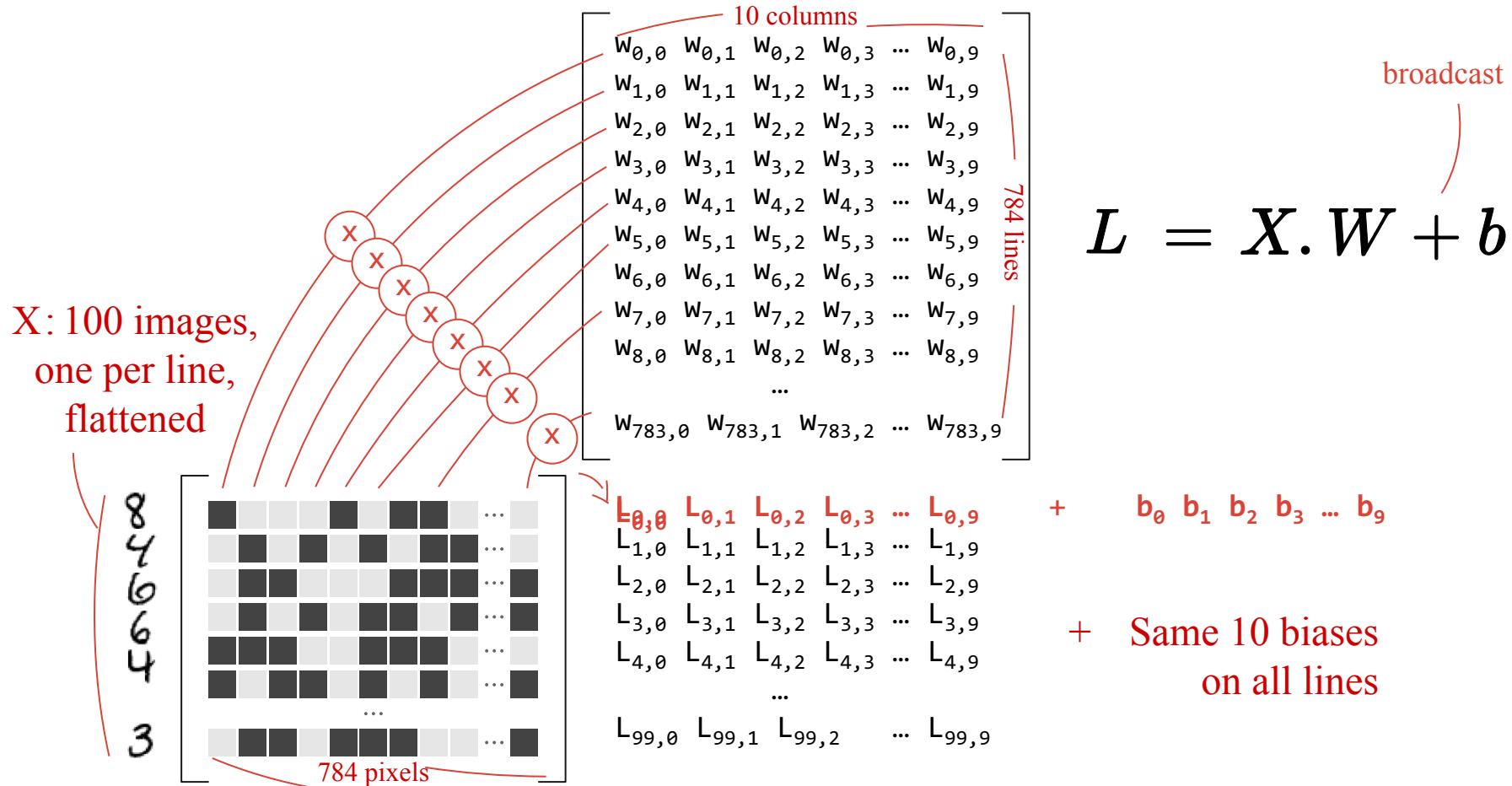


*Image source: "Unsupervised Learning of Hierarchical Representations with Convolutional Deep Belief Networks" ICML 2009 & Comm. ACM 2011.
Honglak Lee, Roger Grosse, Rajesh Ranganath, and Andrew Ng.*

Very simple model: softmax classification



In matrix notation, 100 images at a time



Softmax, on a batch of images

Predictions

$Y[100, 10]$

Images Weights Biases

$X[100, 784]$ $W[784, 10]$ $b[10]$

$$Y = \text{softmax}(X \cdot W + b)$$

applied line by
line

matrix multiply

broadcast on
all lines

tensor shapes in []

Now in TensorFlow (Python)

tensor shapes: X[100, 784] W[748,10] b[10]

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

matrix multiply

broadcast on
all lines

Success ?

0	1	2	3	4	5	6	7	8	9
0	0	0	0	0	0	0	1	0	0

actual probabilities, “one-hot” encoded

Cross entropy:

$$-\sum Y'_i \cdot \log(Y_i)$$

computed probabilities

0.1	0.2	0.1	0.3	0.2	0.1	0.9	0.2	0.1	0.1
0	1	2	3	4	5	6	7	8	9

this is a “6”

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

```
# 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))
```

flattening images

“one-hot” encoded

“one-hot” decoding

TensorFlow - training

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

learning rate



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

```
import tensorflow as tf
```

initialisation

```
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
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))
```

Google Cloud

success metrics

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

training step

```
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

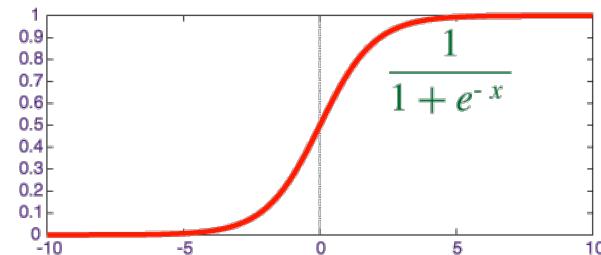
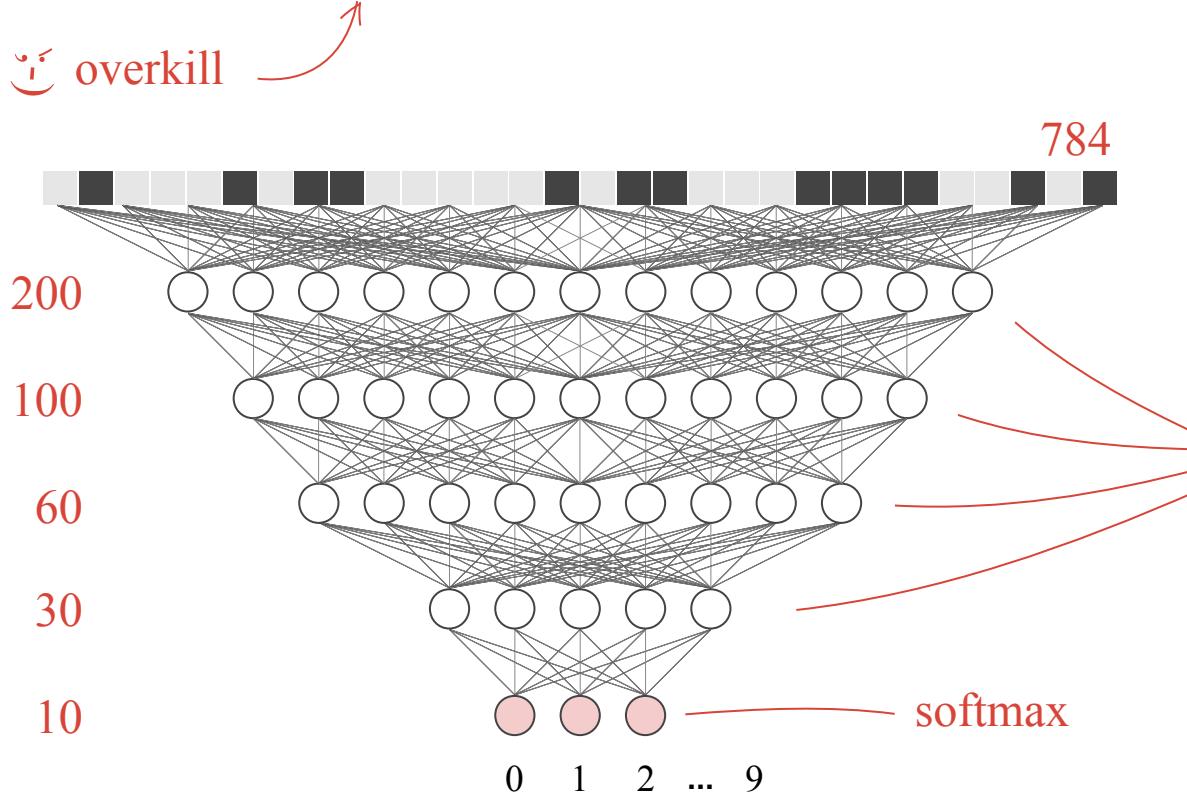
Softmax Cross-entropy Mini-batch





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]))
```

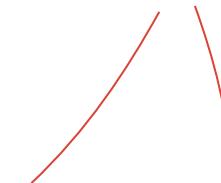
```
W2 = tf.Variable(tf.truncated_normal([K, L], stddev=0.1))  
B2 = tf.Variable(tf.zeros([L]))
```

```
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])
```

weights and biases



```
Y1 = tf.nn.sigmoid(tf.matmul(X, W1) + B1)
```

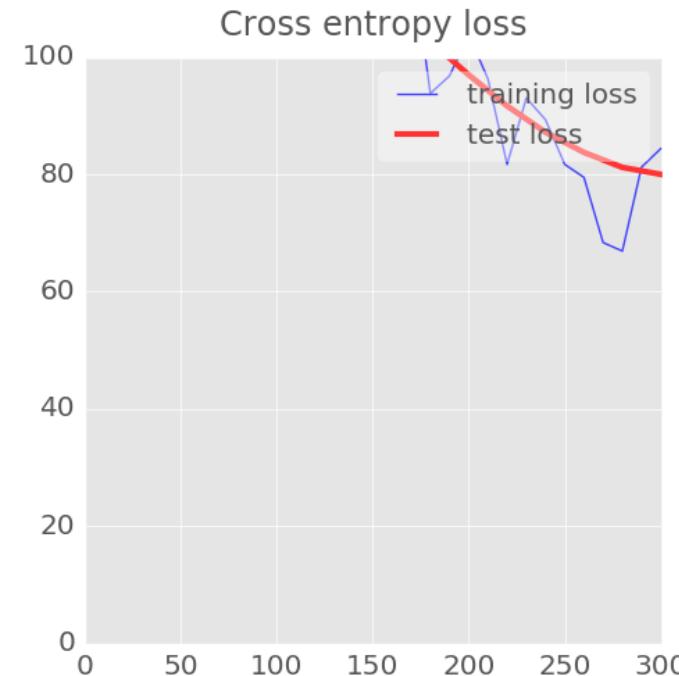
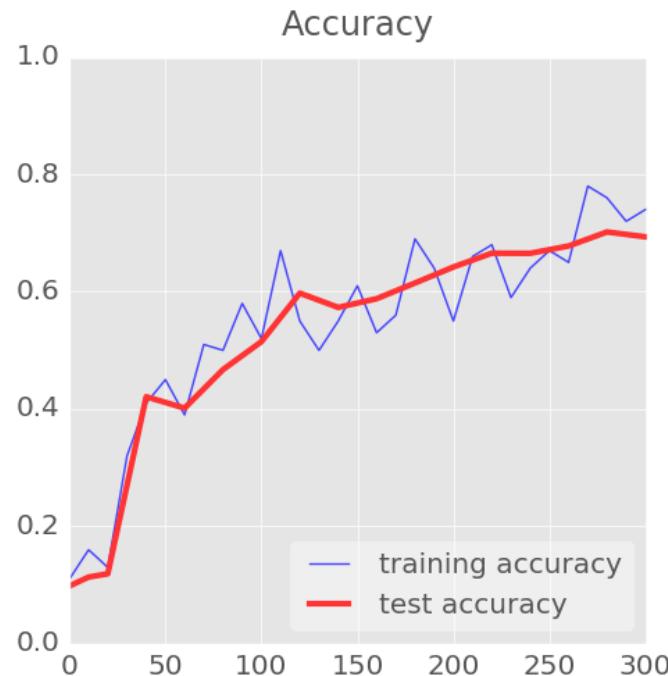
```
Y2 = tf.nn.sigmoid(tf.matmul(Y1, W2) + B2)
```

```
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 ?



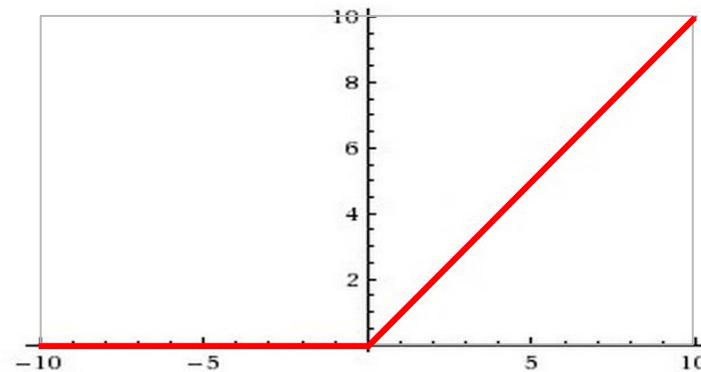
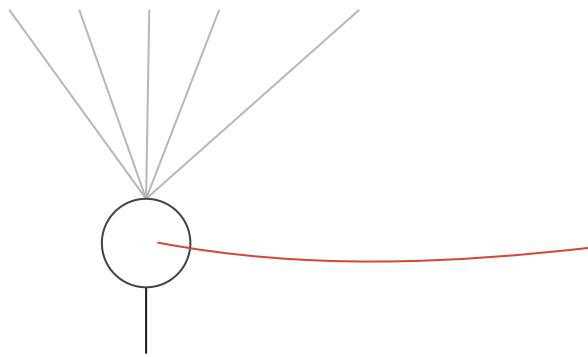


Relu !

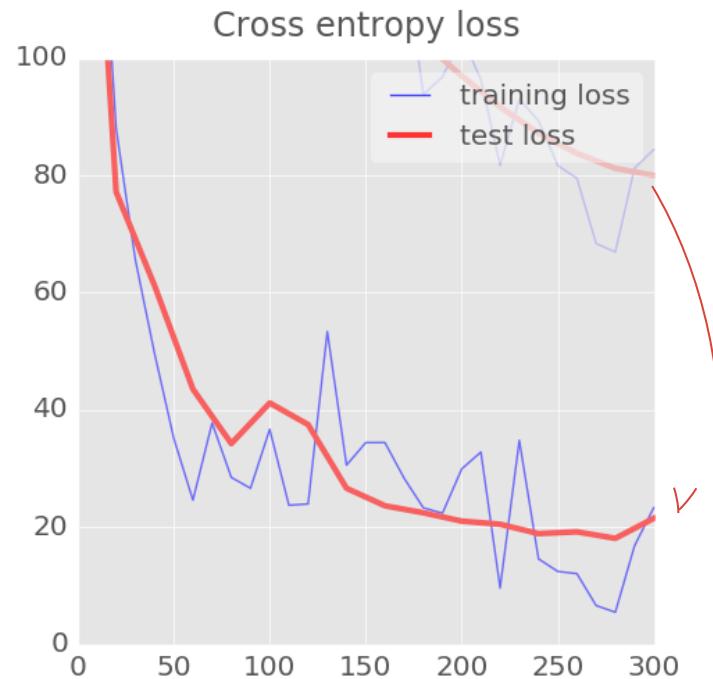


RELU

RELU = Rectified Linear Unit


$$Y = \text{tf.nn.relu}(\text{tf.matmul}(X, W) + b)$$

RELU

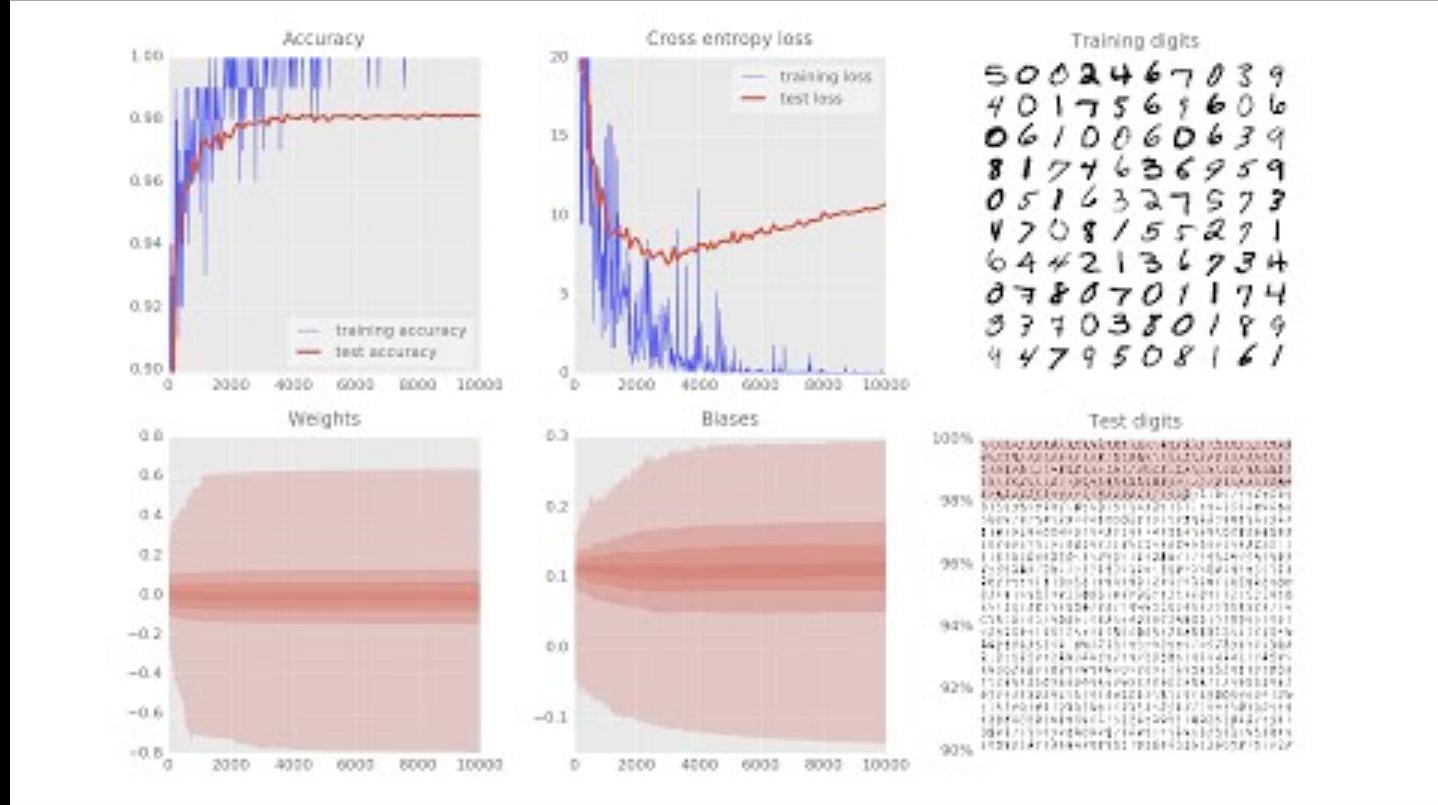


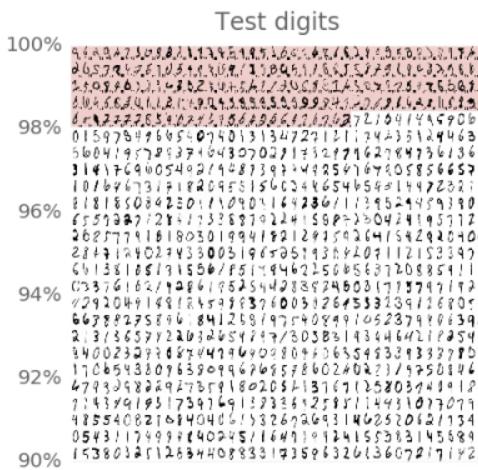
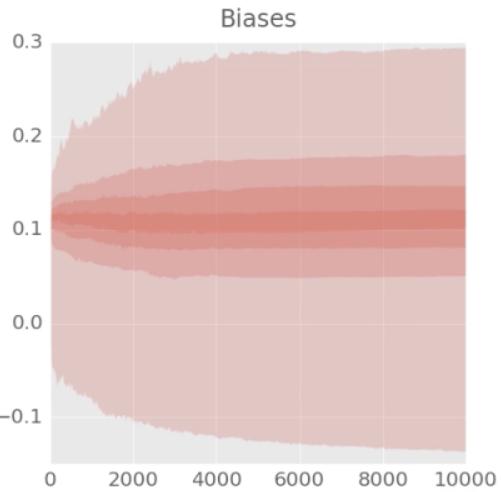
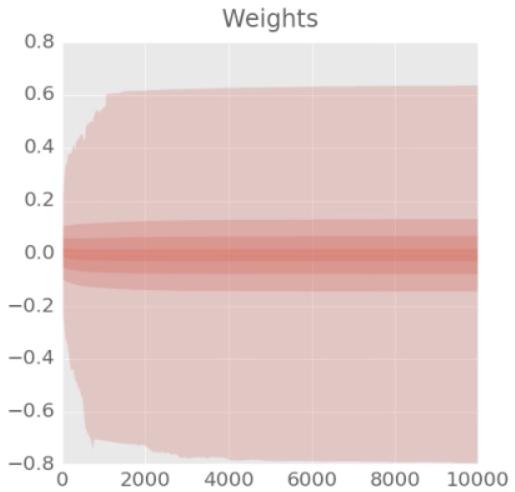
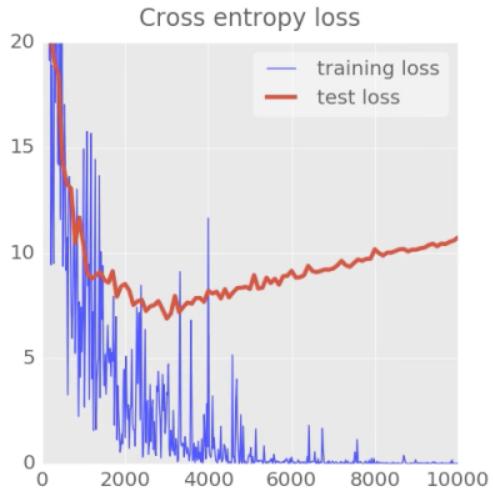
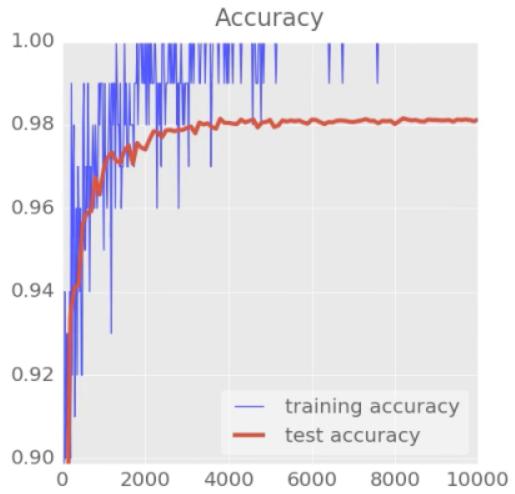
Slow down...

Learning rate
decay



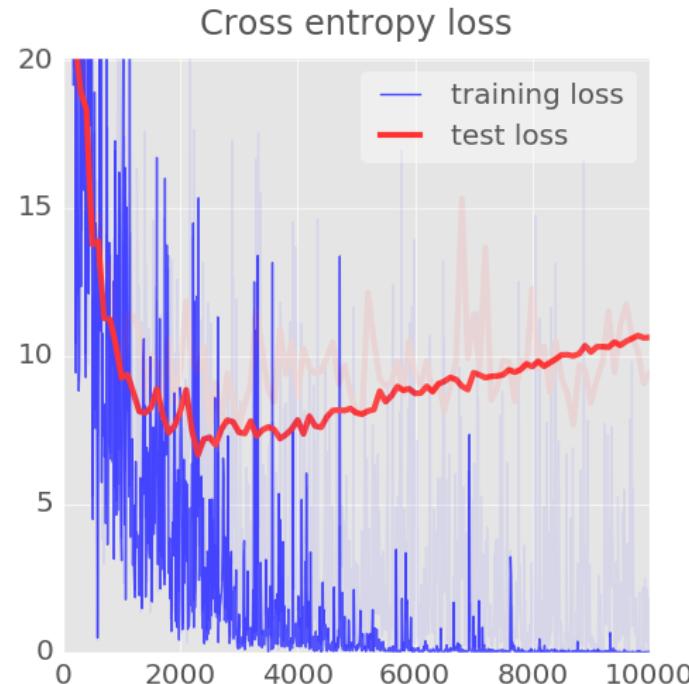
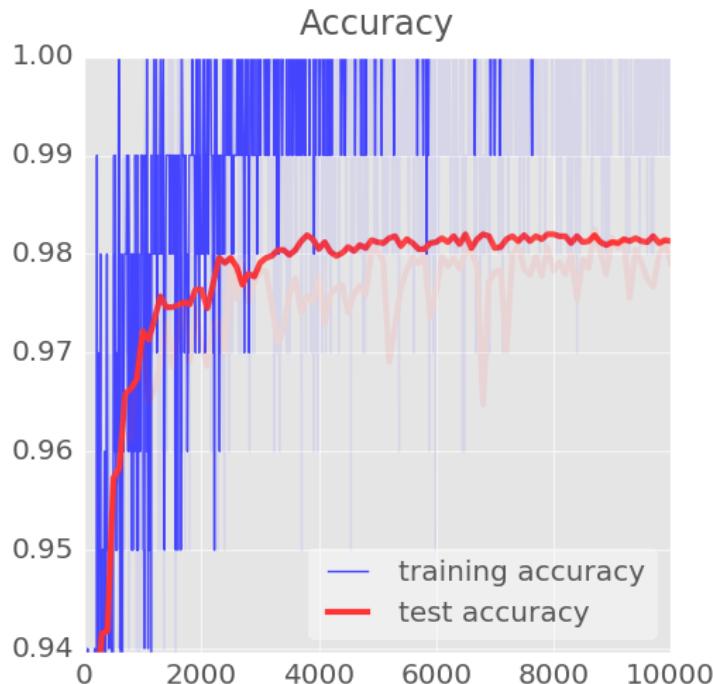
Demo





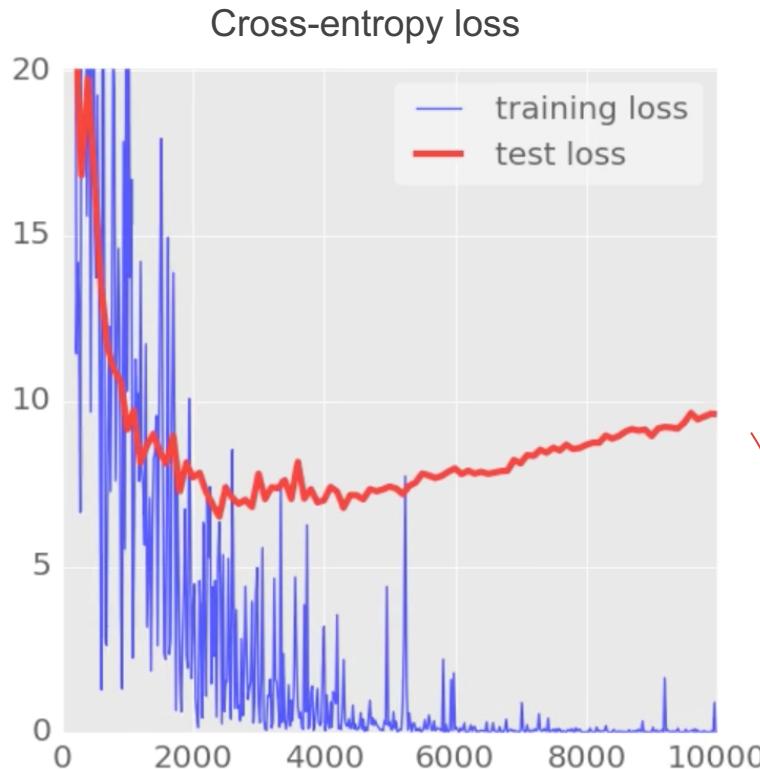
98
%

Learning rate decay



Learning rate 0.003 at start then dropping exponentially to 0.0001

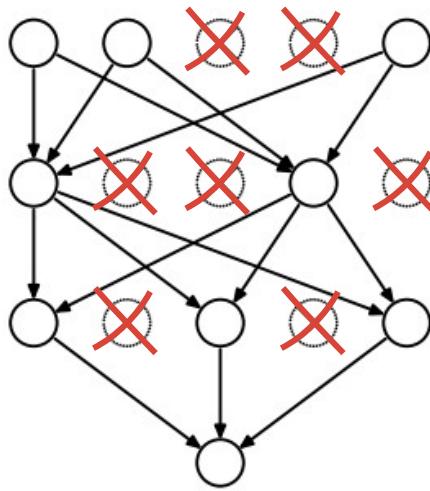
Overfitting



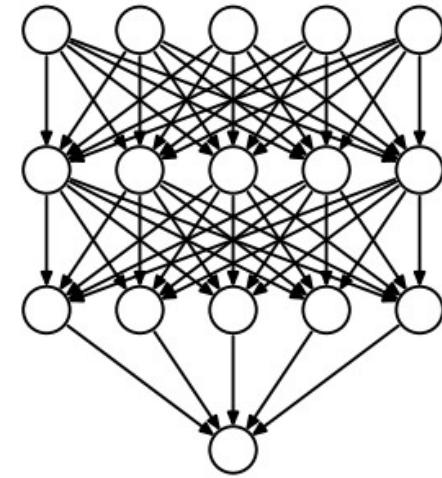
Dropout



Dropout



TRAINING
pkeep=0.75



EVALUATION
pkeep=1

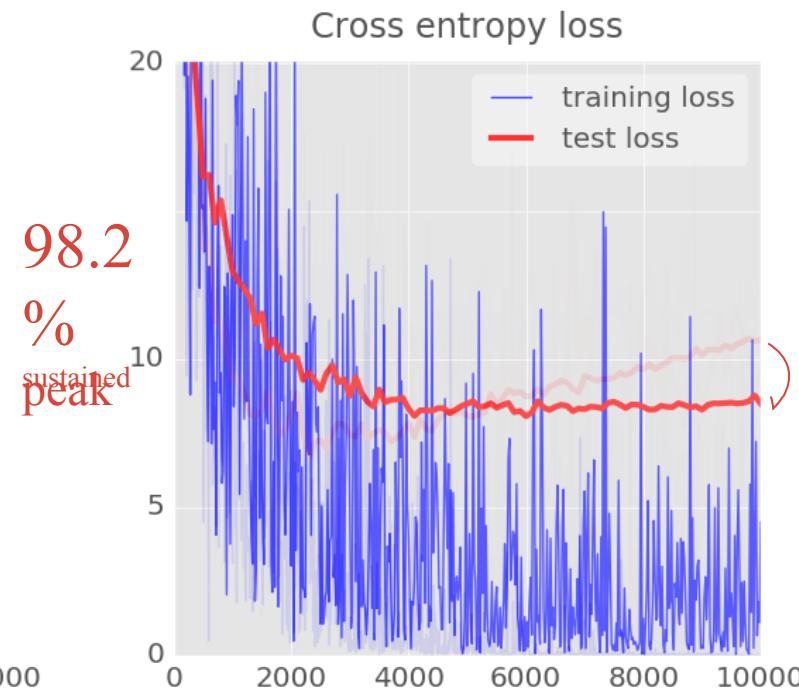
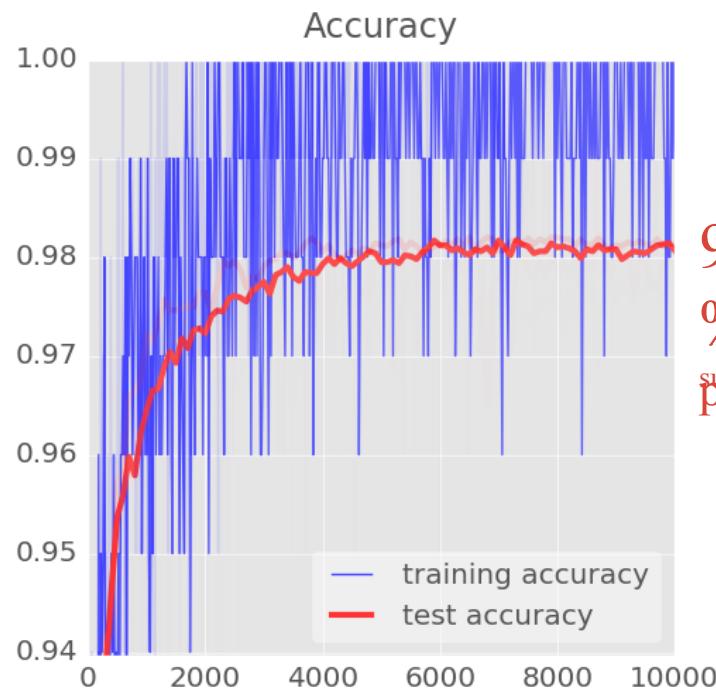
```
pkeep =  
tf.placeholder(tf.float32)
```

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

```
Y = tf.nn.dropout(Yf, pkeep)
```

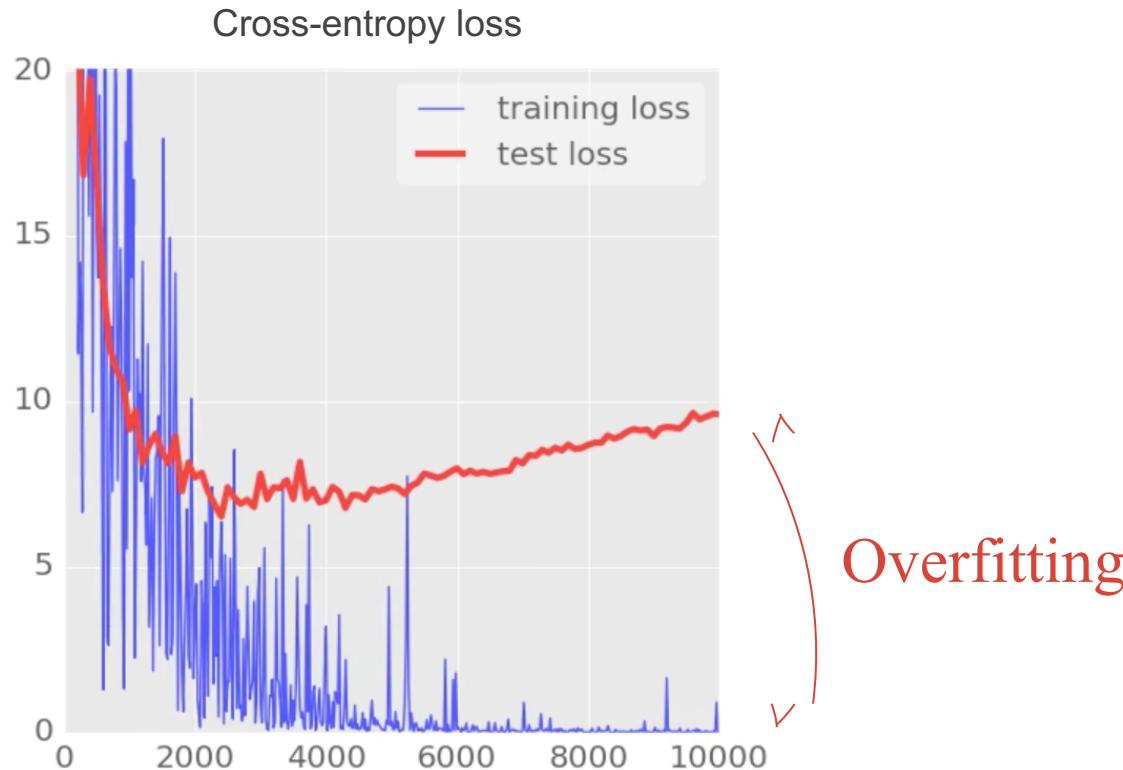
Google Cloud

All the party tricks



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

Overfitting

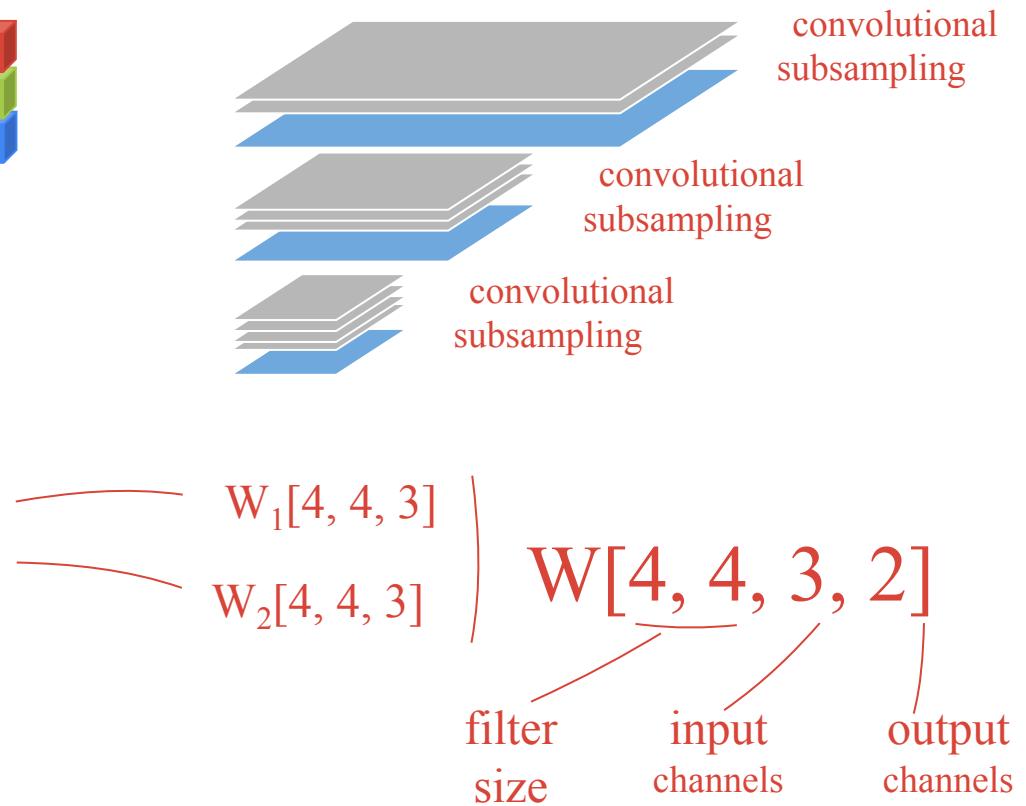
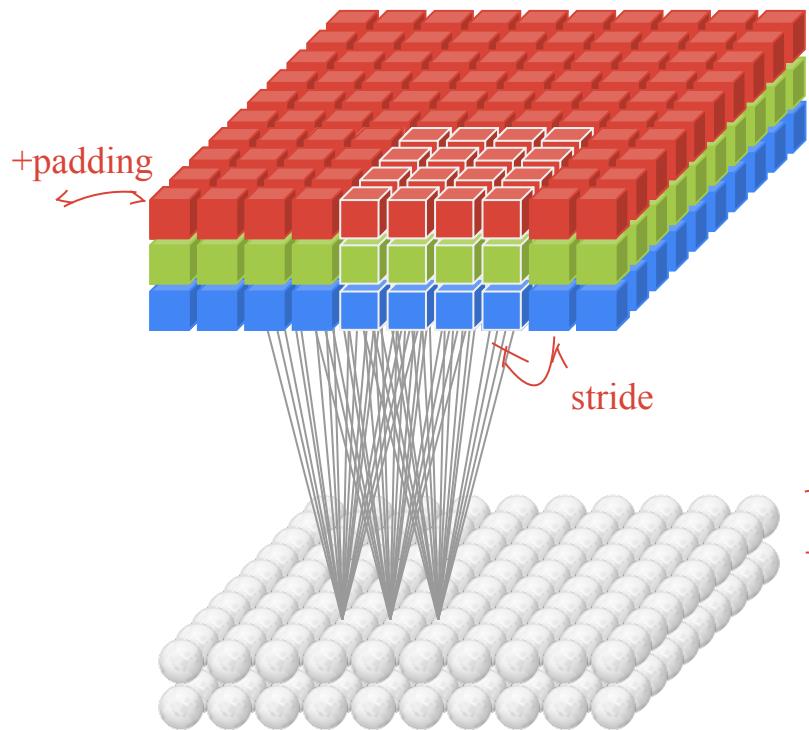




Overfitting
?!?



Convolutional layer



Hacker's tip

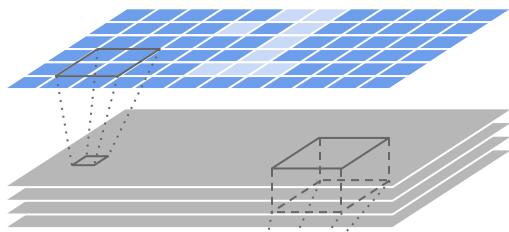


ALL
Convolu-
tional

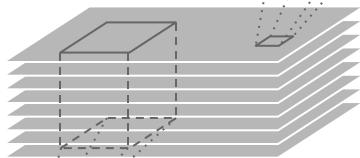
Convolutional neural network

+ biases on all layers

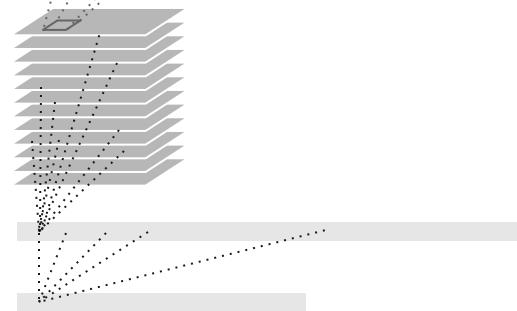
28x28x1



28x28x4



14x14x8



7x7x12

200
10

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 $W4[7 \times 7 \times 12, 200]$

softmax readout layer $W5[200, 10]$

Tensorflow - initialisation

K=4

L=8

M=12

filter
size

input
channels

output
channels

```
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

weights initialised with
random values

```
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)
```

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)
```

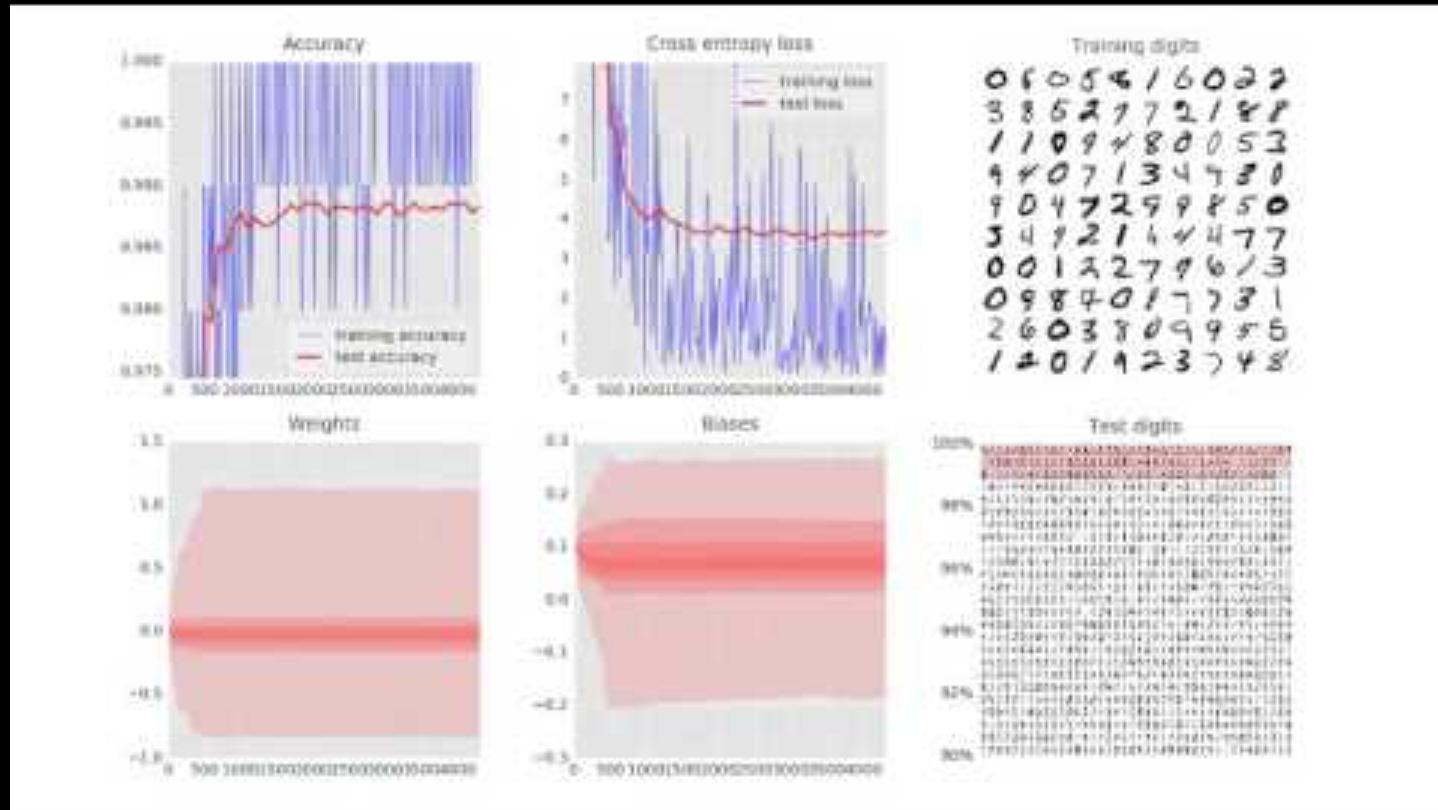
```
Y = tf.nn.softmax(tf.matmul(Y4, W5) + B5)
```

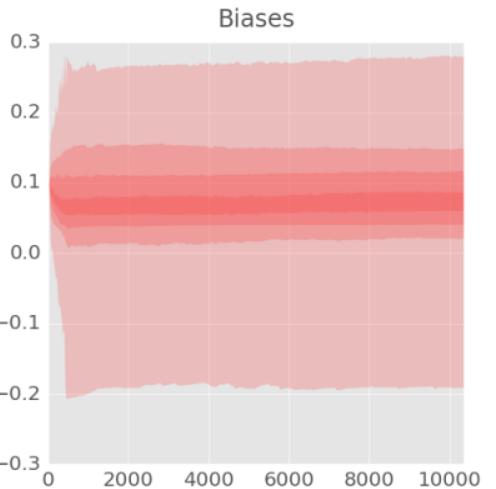
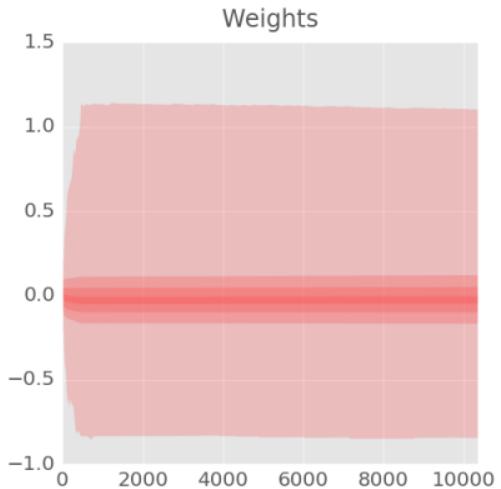
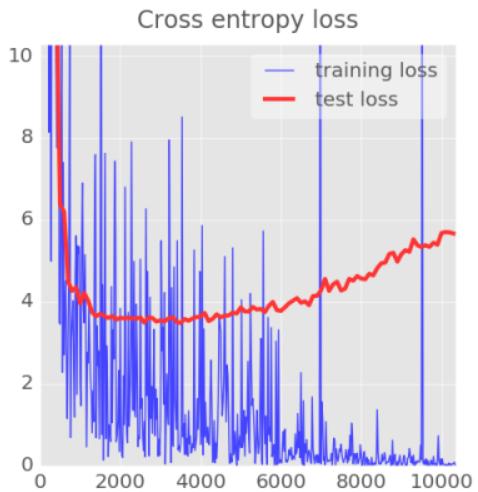
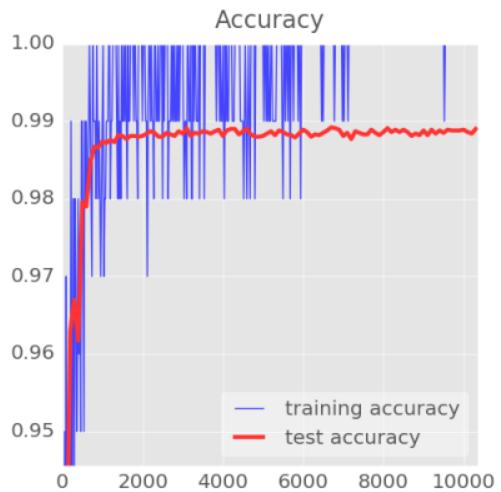
flatten all values for fully
connected layer

$Y3 [100, 7, 7, 12]$

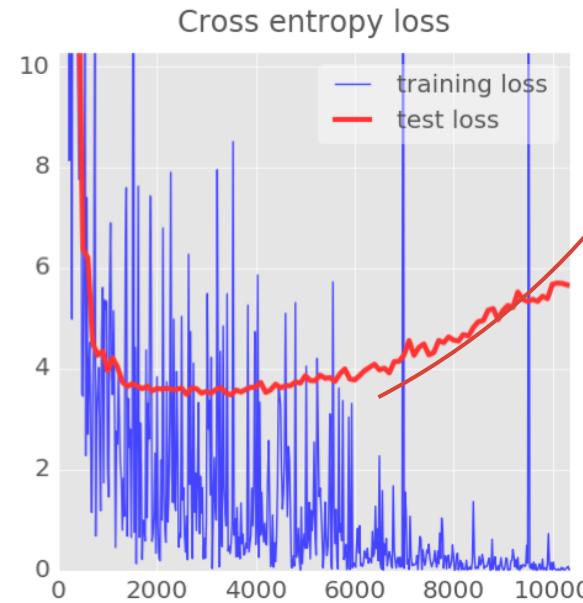
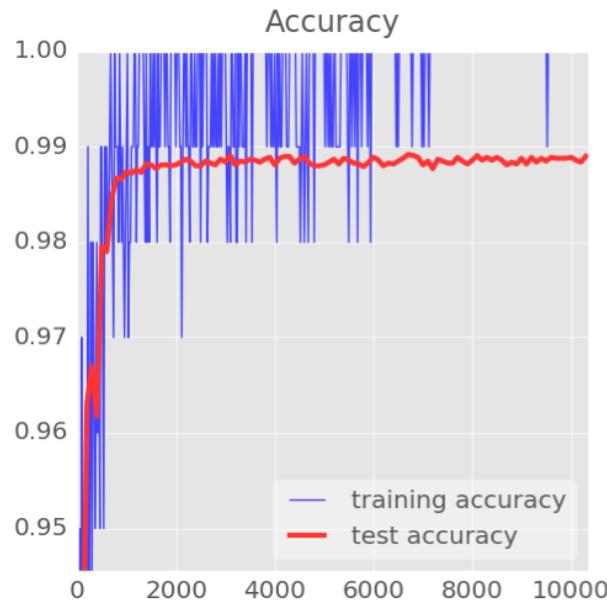
$YY [100, 7 \times 7 \times 12]$

Demo





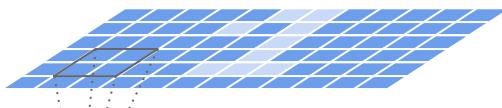
WTFH ???



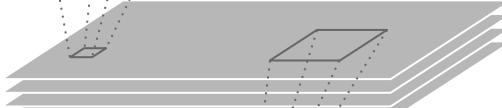
Bigger convolutional network + dropout

+ biases on all layers

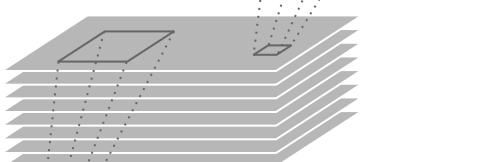
28x28x1



28x28x6



14x14x12



7x7x24



200
10

+DROPOUT
 $p=0.75$

convolutional layer, **6 channels**

$W1[6, 6, 1, 6]$ stride 1

convolutional layer, **12 channels**

$W2[5, 5, 6, 12]$ stride 2

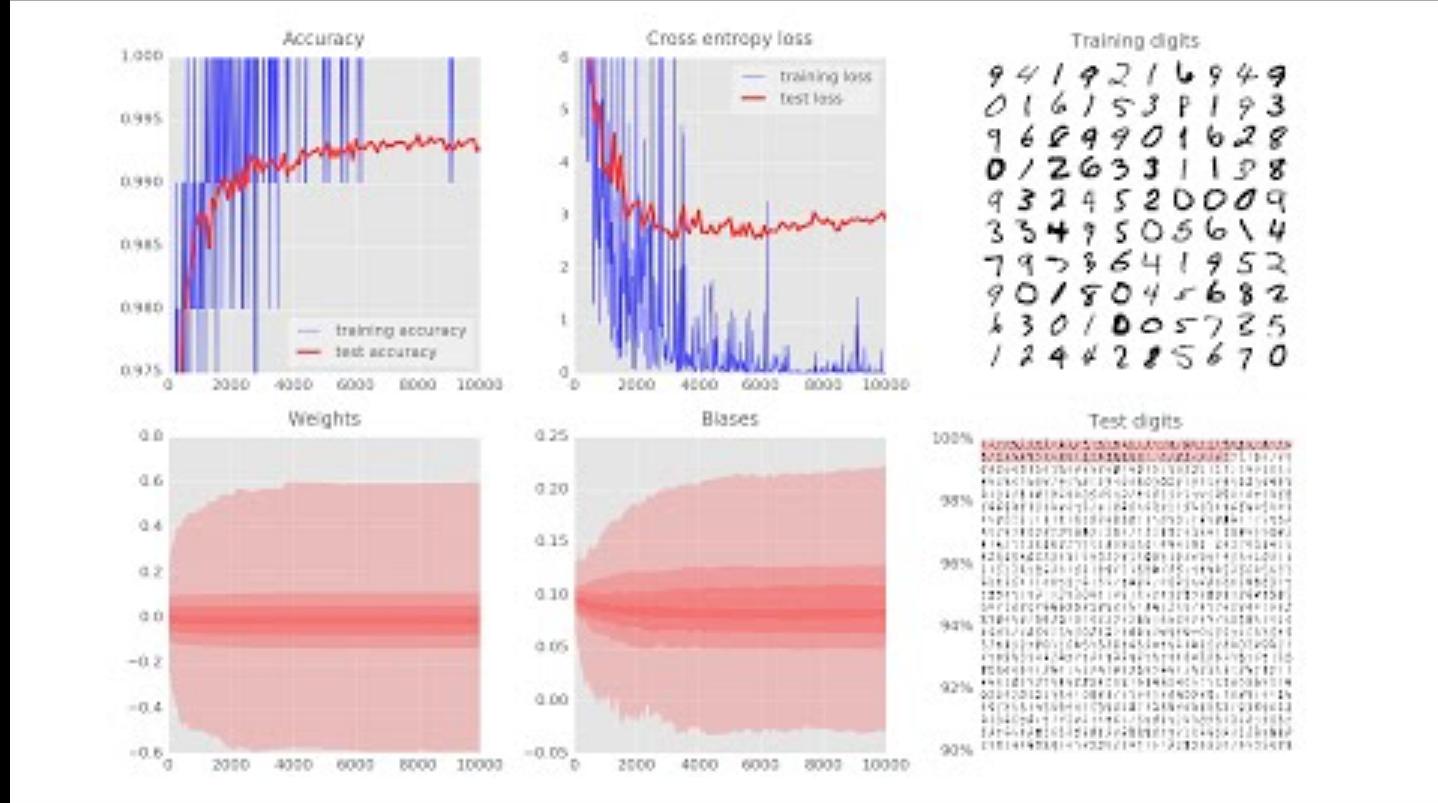
convolutional layer, **24 channels**

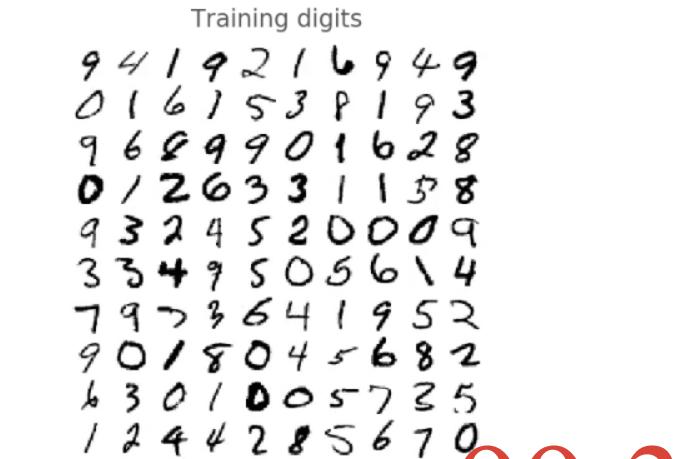
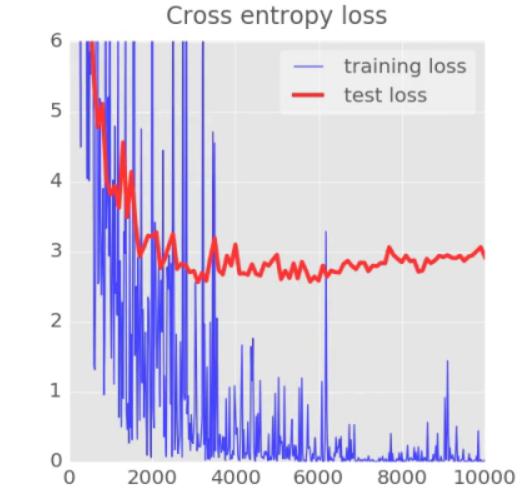
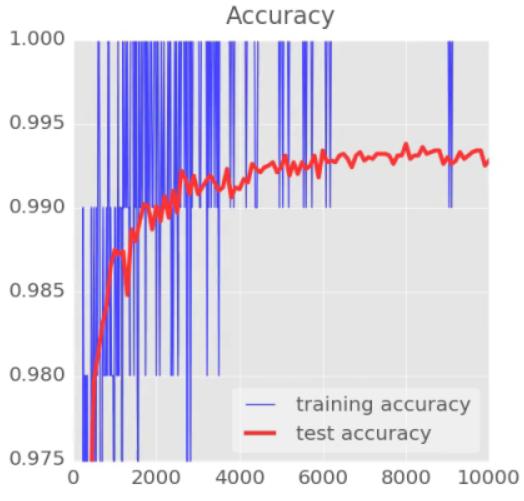
$W3[4, 4, 12, 24]$ stride 2

fully connected layer $W4[7x7x24, 200]$

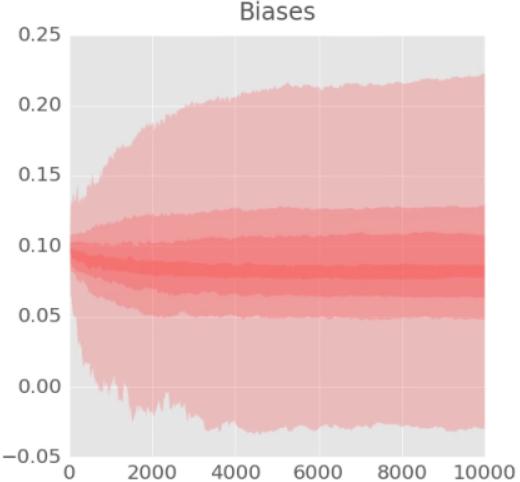
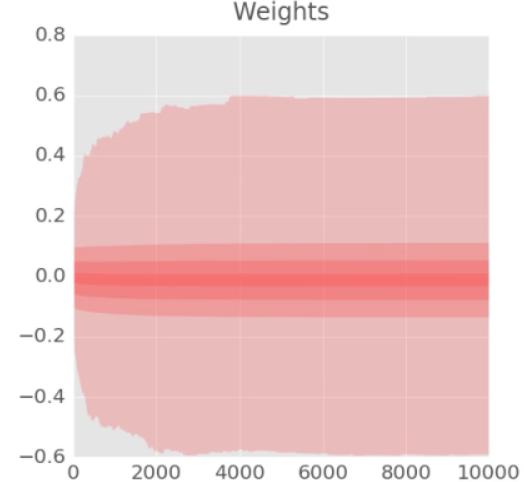
softmax readout layer $W5[200, 10]$

Demo

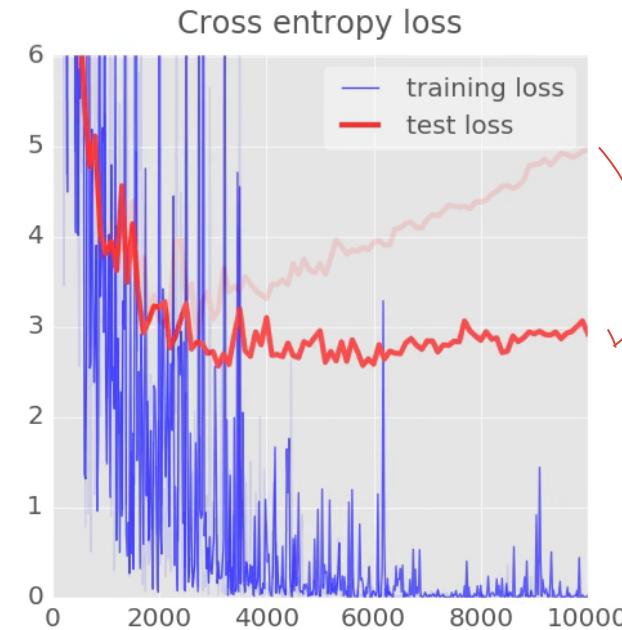
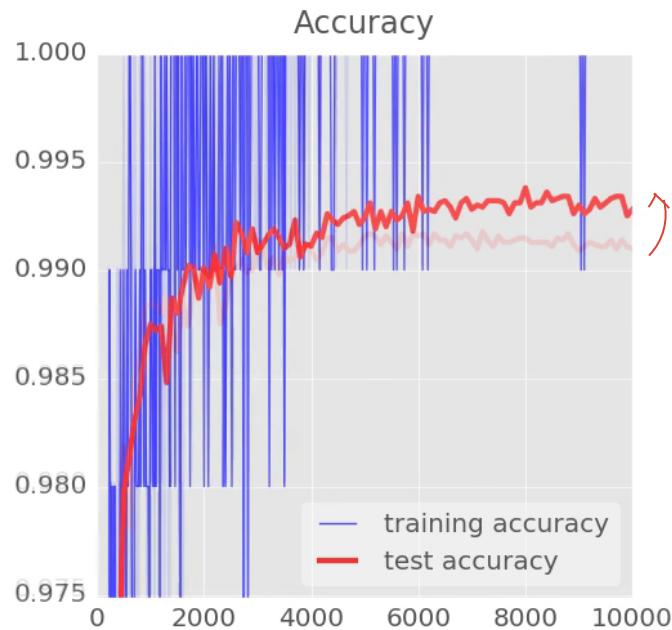




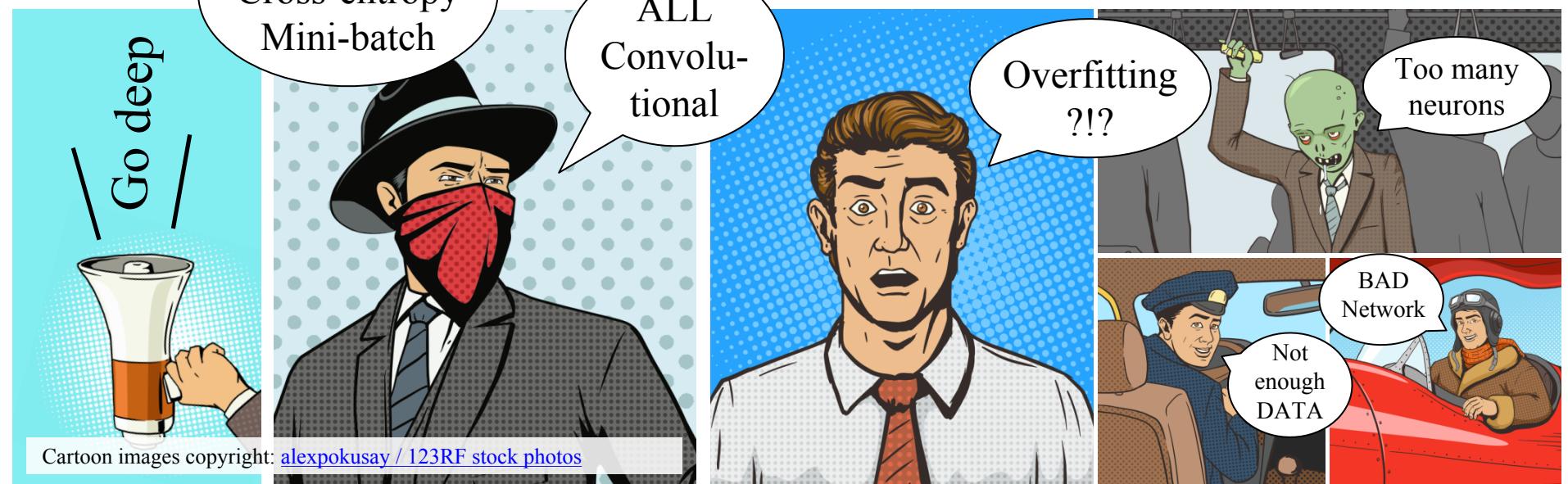
99.3



YEAH !



with dropout



THIS IS YOUR MACHINE LEARNING SYSTEM?

YUP! YOU POUR THE DATA INTO THIS BIG
PILE OF LINEAR ALGEBRA, THEN COLLECT
THE ANSWERS ON THE OTHER SIDE.

WHAT IF THE ANSWERS ARE WRONG?

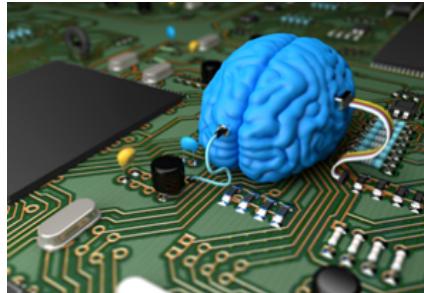
JUST STIR THE PILE UNTIL
THEY START LOOKING RIGHT.



THANKS!



What society thinks I do

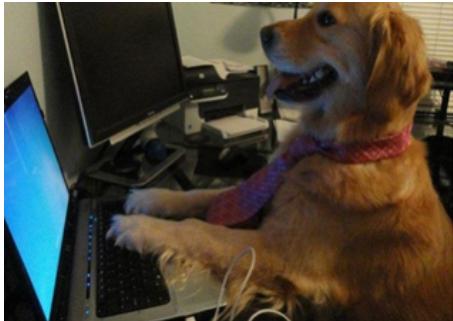


What my friends think I do



What other computer
scientists think I do

```
from tensorflow import *
```



What mathematicians think I do



What I think I do

ML6

What I actually do

Where to start?

<http://bit.ly/2yg1nD0>



Tensorflow
tensorflow.org



ML6
ml6.eu



Developer codelabs
codelabs.developers.google.com



Find Examples
github.com/tensorflow