Intro to TensorFlow

Seattle, November 2016

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@random_forests

Agenda

10am - 10:30am

- Fibonacci sequence

10:30am - 11:15am

- Linear regression

11:15am - 12pm

- Deep Dream, Style Transfer, or TensorFlow for Poets

12pm - 12:30pm

- Lunch

12:30-1:30pm

- Basic and Deep MNIST

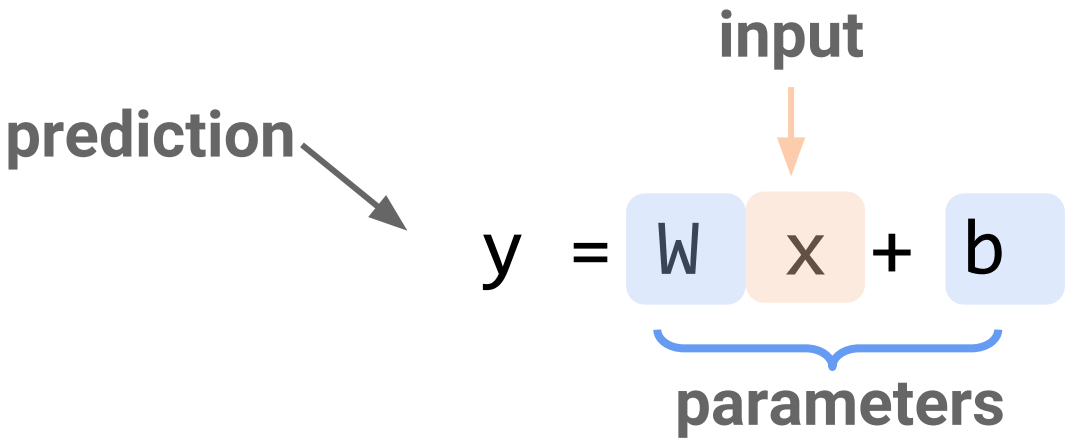
1:30pm - 2:30pm

- Networking

What’s Deep Learning?

Machine Learning ~= Programming + Data

“Learn” means a data-driven procedure to find useful values for parameters.



IS THIS A

CAT or DOG?

CAT DOG

OUTPUT LAYER

ACTIVATED NEURONS

INPUT LAYER

DEEP *neural* NETWORK

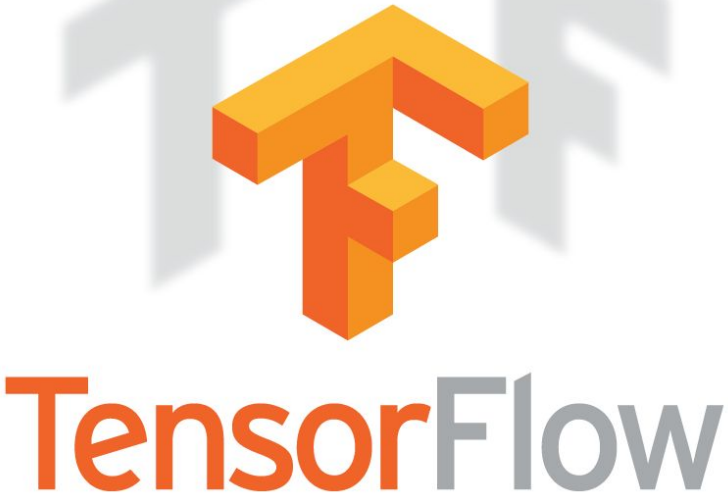
Demo: TensorFlow Playground

goo.gl/mXhncM

Deep Learning

Current state of the art in:

- **Image**: *classification, captioning*
- **Language**: *translation, parsing, summarization*
- **Speech**: *recognition, generation*
- **Games**: *AlphaGo, Atari*
- And much more.



- Fast, flexible, and scalable open-source machine learning library
- One system for research and production
- Runs on CPU, GPU, TPU, and Mobile
- Apache 2.0 license

A multidimensional array.

A graph of operations.

Open Source Models

github.com/tensorflow/models

Inception

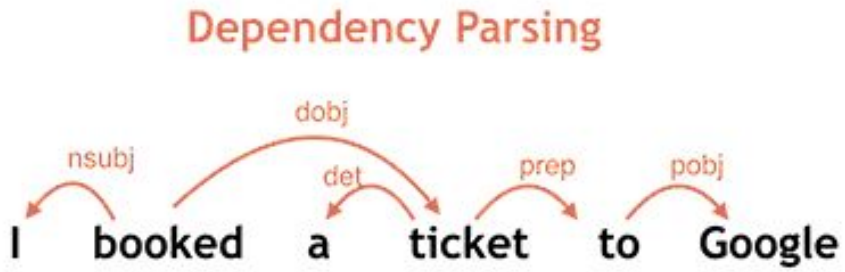
An Alaskan Malamute (left) and a Siberian Husky (right). Images from Wikipedia.

https://research.googleblog.com/2016/08/improving-inception-and-image.html

Show and Tell

https://research.googleblog.com/2016/09/show-and-tell-image-captioning-open.html

Parsey McParseface



https://research.googleblog.com/2016/05/announcing-syntaxnet-worlds-most.html

Text Summarization

Original text

- *Alice and Bob took the train to visit the zoo. They saw a **baby giraffe, a lion, and a flock of colorful tropical birds**.*

Abstractive summary

- *Alice and Bob visited the zoo and saw **animals and birds**.*

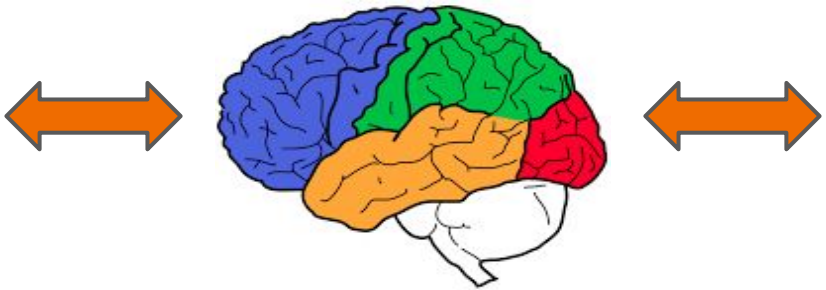
https://research.googleblog.com/2016/08/text-summarization-with-tensorflow.html

https://github.com/lengstrom/fast-style-transfer/

https://www.youtube.com/watch?v=DgPaCWJL7XI

“Universal” Machine Learning

Speech
Text
Search
Queries
Images
Videos
Labels
Entities
Words
Audio
Features



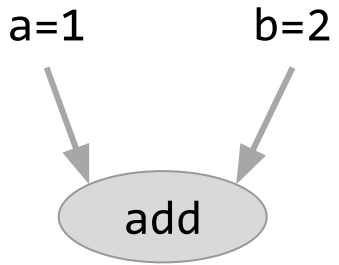
Speech
Text
Search
Queries
Images
Videos
Labels
Entities
Words
Audio
Features

Warm up

Graphs and Sessions

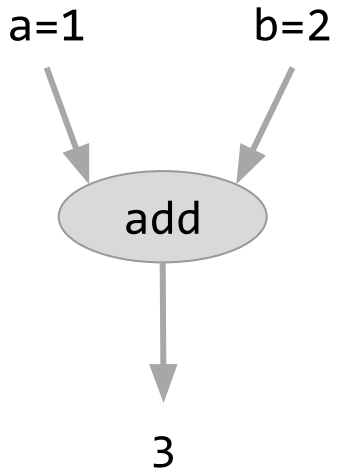
Build a graph...

```
import tensorflow as tf
a = tf.constant(1)
b = tf.constant(2)
c = tf.add(a, b)
```



… then run it

```
import tensorflow as tf
a = tf.constant(1)
b = tf.constant(2)
c = tf.add(a, b)

session = tf.Session()
value_of_c = session.run(c)
```



Building graphs looks *mostly* like numpy

With special operations for deep learning

Numpy	TensorFlow
add mul matmul … sum …	add mul matmul … reduce_sum … sigmoid relu …

What's the output?

```
import tensorflow as tf

my_var = tf.Variable(0)
add_op = tf.add(my_var,1)
assign_op = tf.assign(my_var, add_op)

session = tf.Session()
session.run(tf.initialize_all_variables())

for _ in range(3):
    print (session.run(assign_op))
```

These slides + code
goo.gl/nrdsxM

Install TensorFlow

```
$ git clone https://github.com/random-forests/tensorflow-workshop
$ cd tensorflow-workshop
$ jupyter notebook
```

goo.gl/nrdsxM

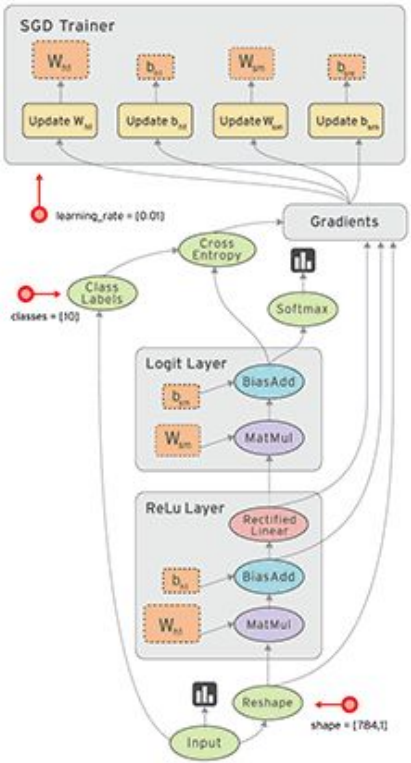
Exercise #1: Fibonacci Sequence
1_warm_up.ipynb

goo.gl/nrdsxM

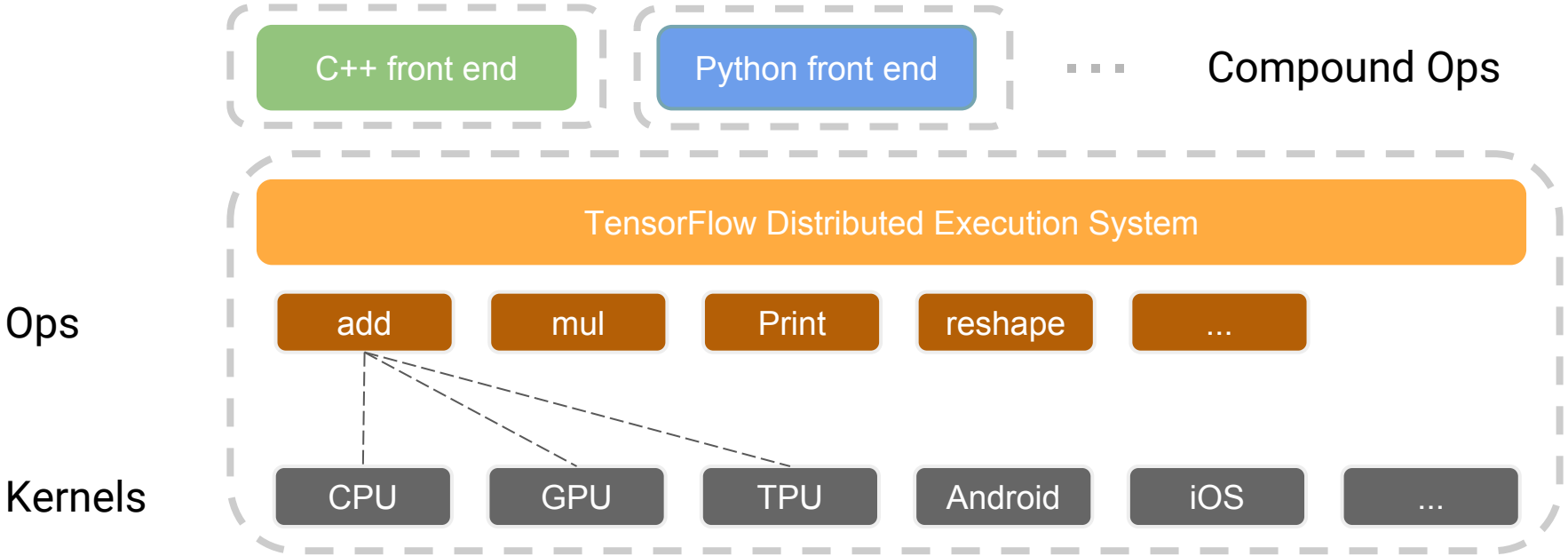
But why?

A graph is like a blueprint

- You define the graph in high-level language (Python)
- Graph is compiled and optimized
- Graph is executed (in parts or fully) on available devices (CPU, GPU, TPU)
- Nodes represent computations
- Data (tensors) flows between them



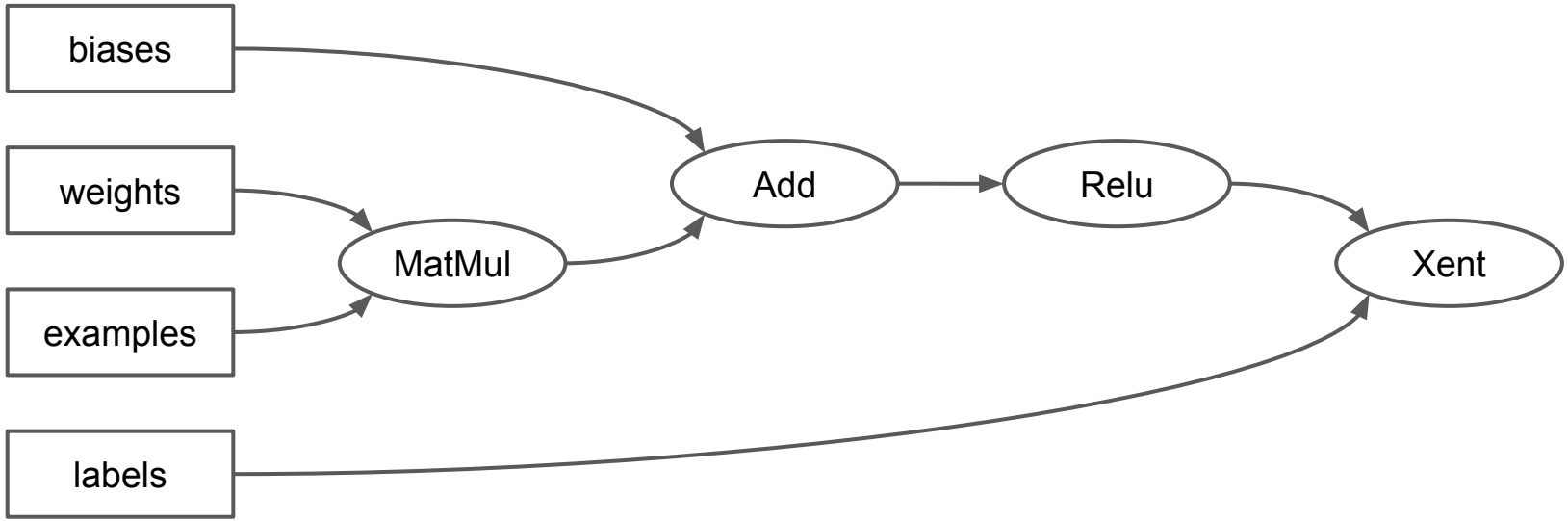
Architecture



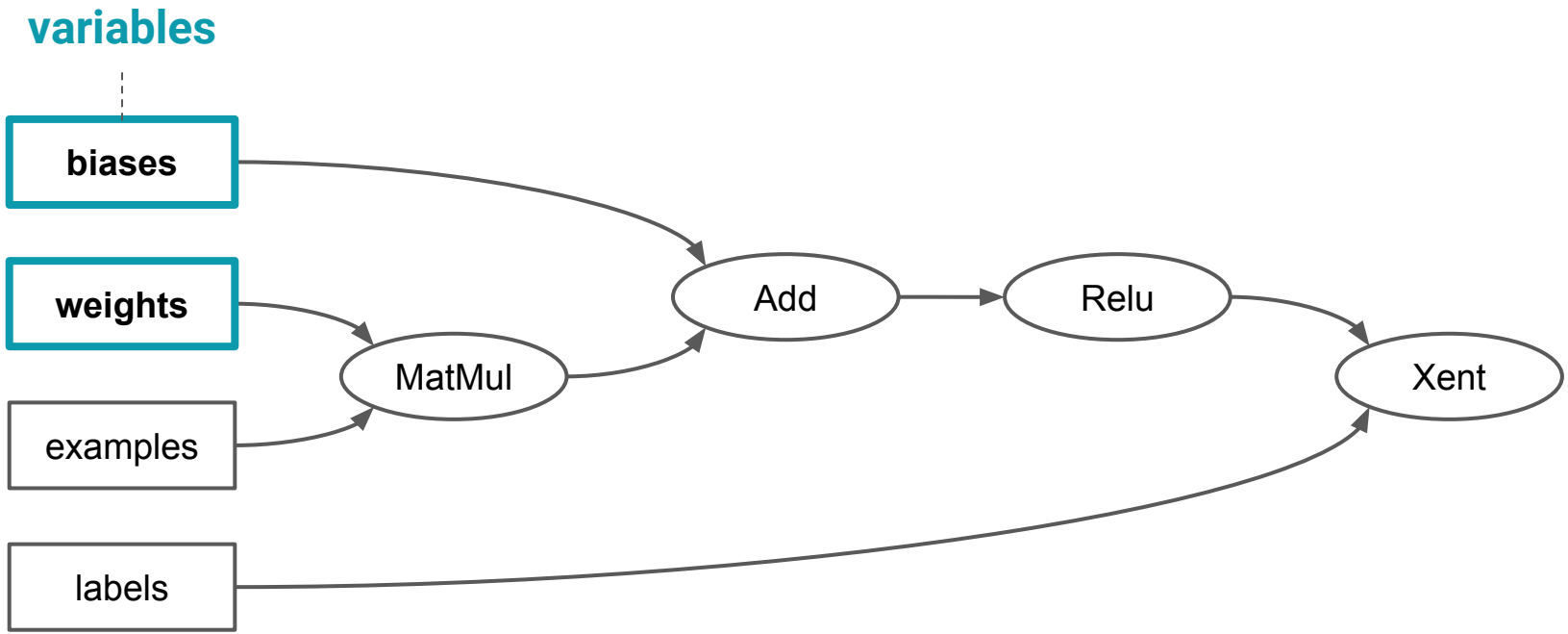
A Year of TensorFlow

- 0.6 Python 3.3; Faster on GPUs
- 0.7 TensorFlow Serving
- 0.8 Distributed TensorFLOW
- 0.9 iOS, Raspberry Pi
- 0.10 Slim
- 0.11 CuDNN v5

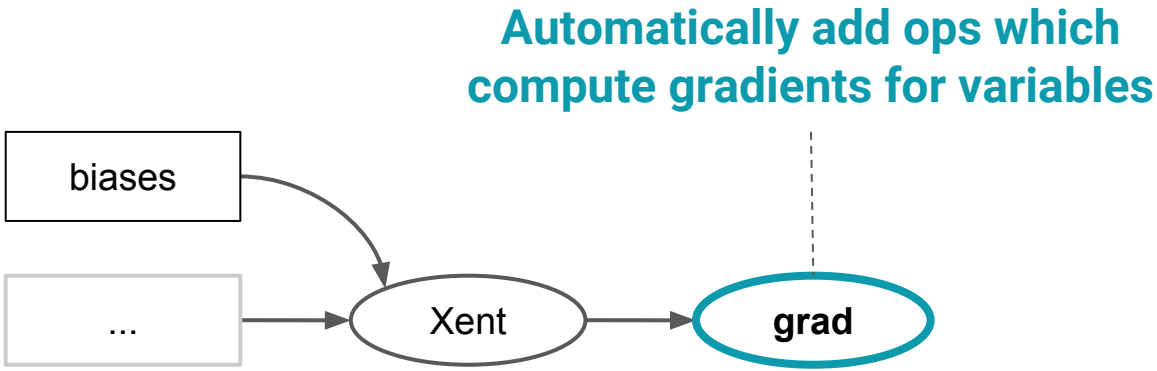
Graphs can be processed, compiled, remotely executed, assigned to devices.



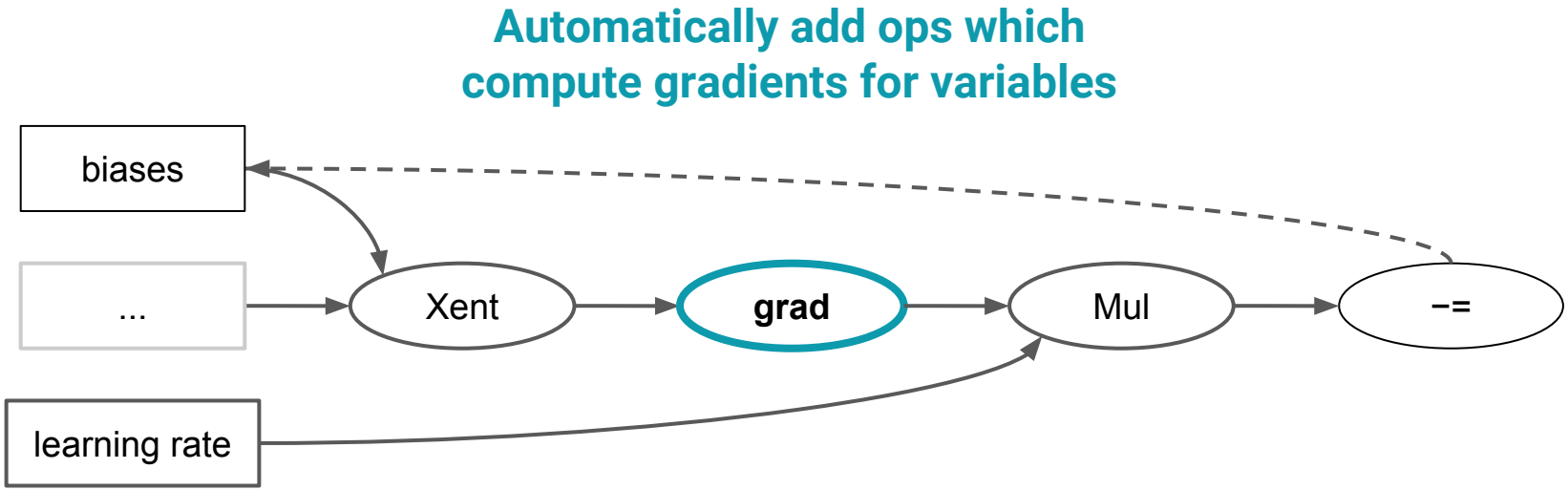
Data flow, with state



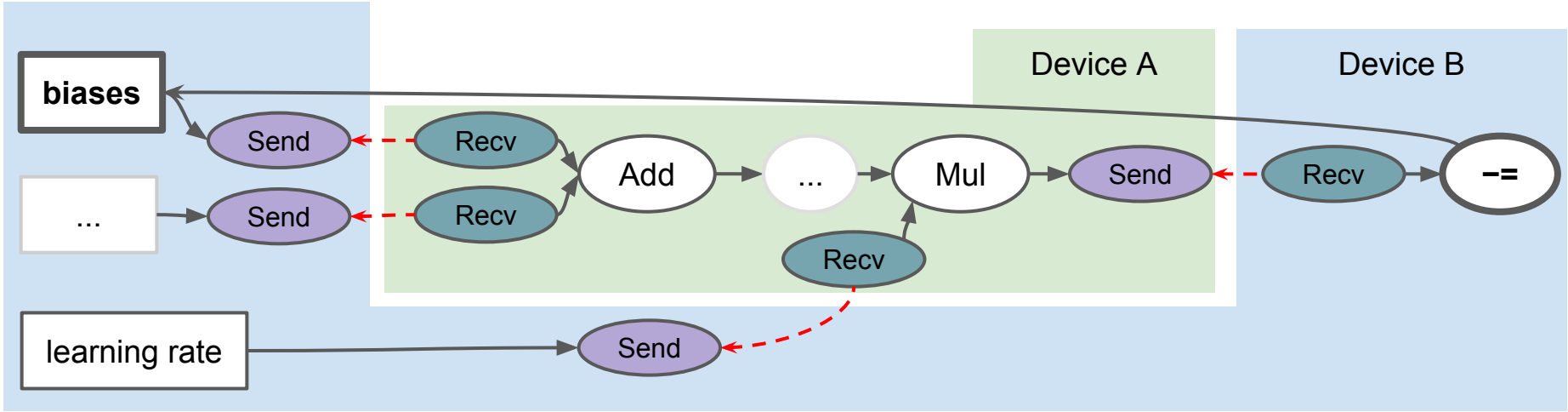
Automatic Differentiation



Automatic Differentiation



Distributed

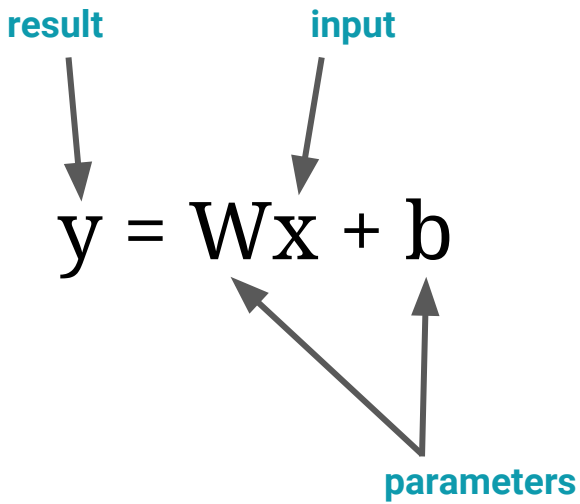


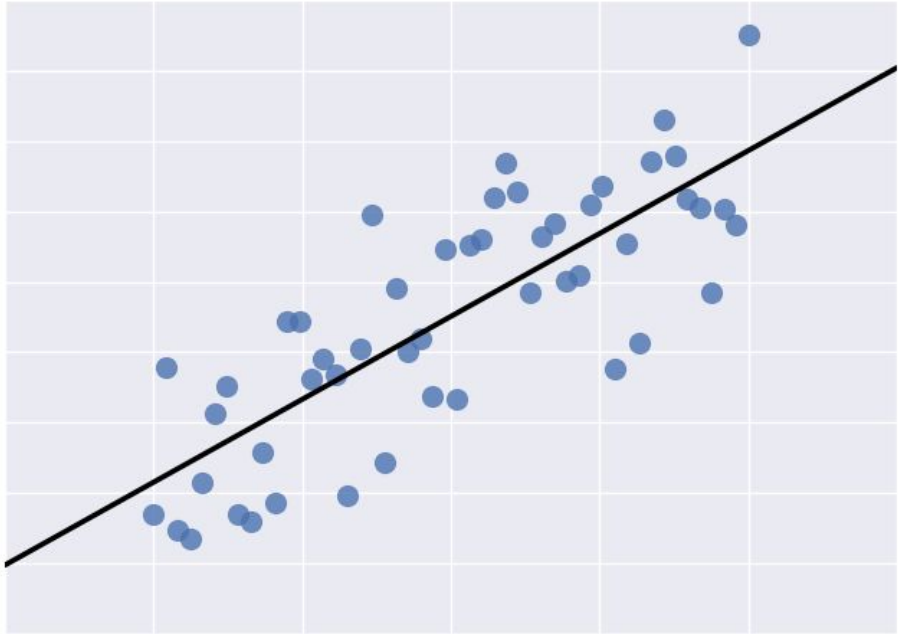
Send / receive nodes added automatically
Devices: Processes, Machines, CPUs, GPUs, TPUs, etc

Linear Regression

Inference, Loss, Training

Linear Regression





What are we trying to do?

Mystery equation: `y = 0.1 * x + 0.3 + noise`

Model: `y = W * x + b`

Objective: Given enough (*x*, *y*) samples, figure out the value of *W* and *b*.

Let's code this up

1. **Inference** (“given x, this is the code to predicts y”)

2. **Loss** (“quantify how bad our prediction was”)

3. **Optimize** (“update variables to improve the prediction”)

y = Wx + b in TensorFlow

```
import tensorflow as tf
```

y = Wx + b in TensorFlow

```
import tensorflow as tf

x = tf.placeholder(shape=[None],
                   dtype=tf.float32, name="x")
```

y = Wx + b in TensorFlow

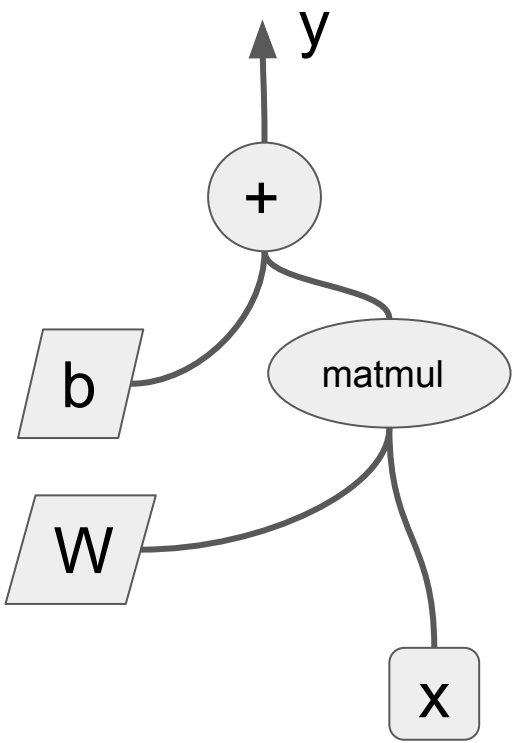
```
import tensorflow as tf

x = tf.placeholder(shape=[None],
                   dtype=tf.float32, name="x")

W = tf.Variable(tf.random_normal([1], name="W")
```

y = Wx + b in TensorFlow

```
import tensorflow as tf

x = tf.placeholder(shape=[None],
                   dtype=tf.float32, name="x")

W = tf.Variable(tf.random_normal([1], name="W")

b = tf.Variable(tf.random_normal([1], name="b")
```

y = Wx + b in TensorFlow

```
import tensorflow as tf

x = tf.placeholder(shape=[None],
                   dtype=tf.float32, name="x")

W = tf.Variable(tf.random_normal([1], name="W")

b = tf.Variable(tf.random_normal([1], name="b")

y = W * x + b
```



Variables Must be Initialized

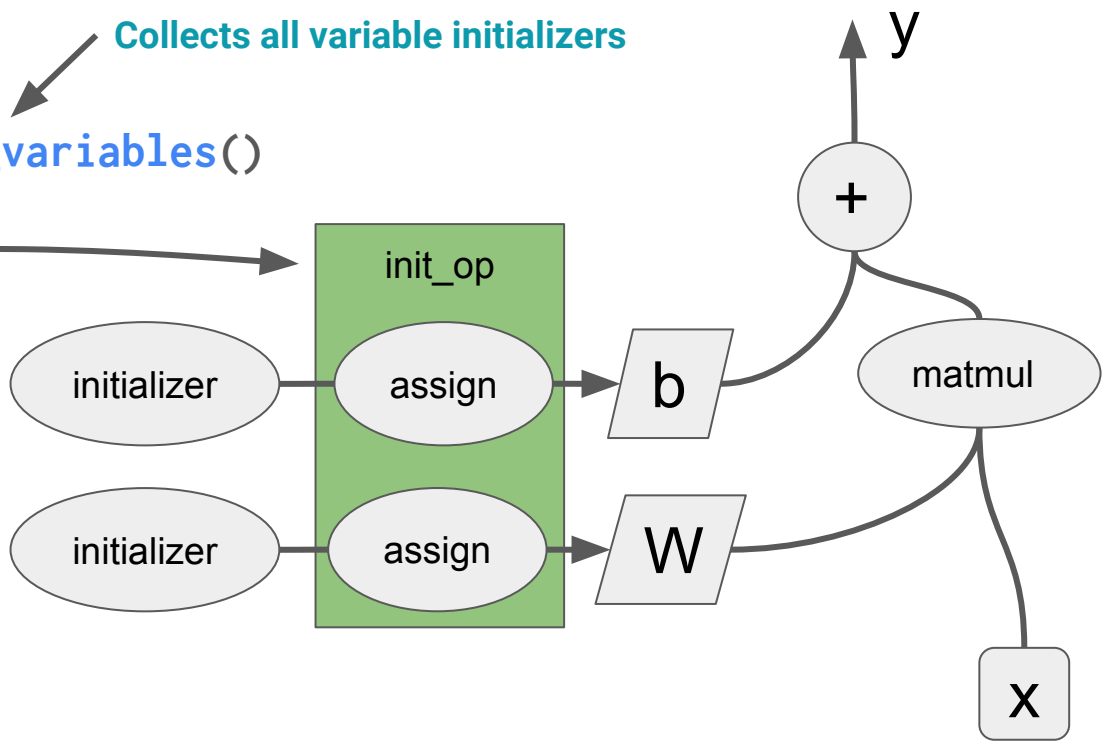
Collects all variable initializers

```
init_op = tf.initialize_all_variables()
```

Makes an execution environment

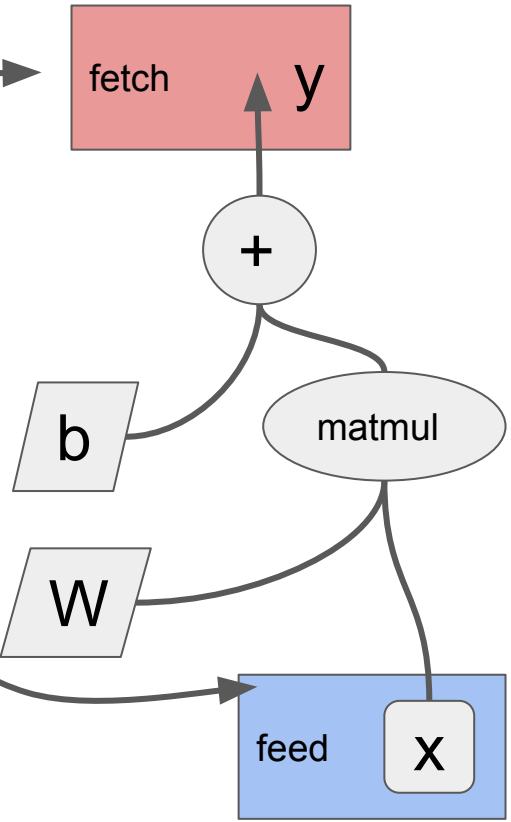
```
sess = tf.Session()

sess.run(init_op)
```

Actually initialize the variables



Running the Computation

```
x_in = 3

sess.run(y, feed_dict={x: x_in})
```



- Only what's used to compute a fetch will be evaluated
- All Tensors can be fed, but all placeholders must be fed

Inference: putting it all together

```
import tensorflow as tf
x = tf.placeholder(shape=[None],
                   dtype=tf.float32,
                   name='x')
W = tf.Variable(tf.random_normal([1], name="W")
b = tf.Variable(tf.random_normal([1], name="b")
y = W * x + b

with tf.Session() as sess:

  sess.run(tf.initialize_all_variables())

  print(sess.run(y, feed_dict={x: x_in}))
```

Build the graph

Prepare execution env

Initialize variables

Run the computation

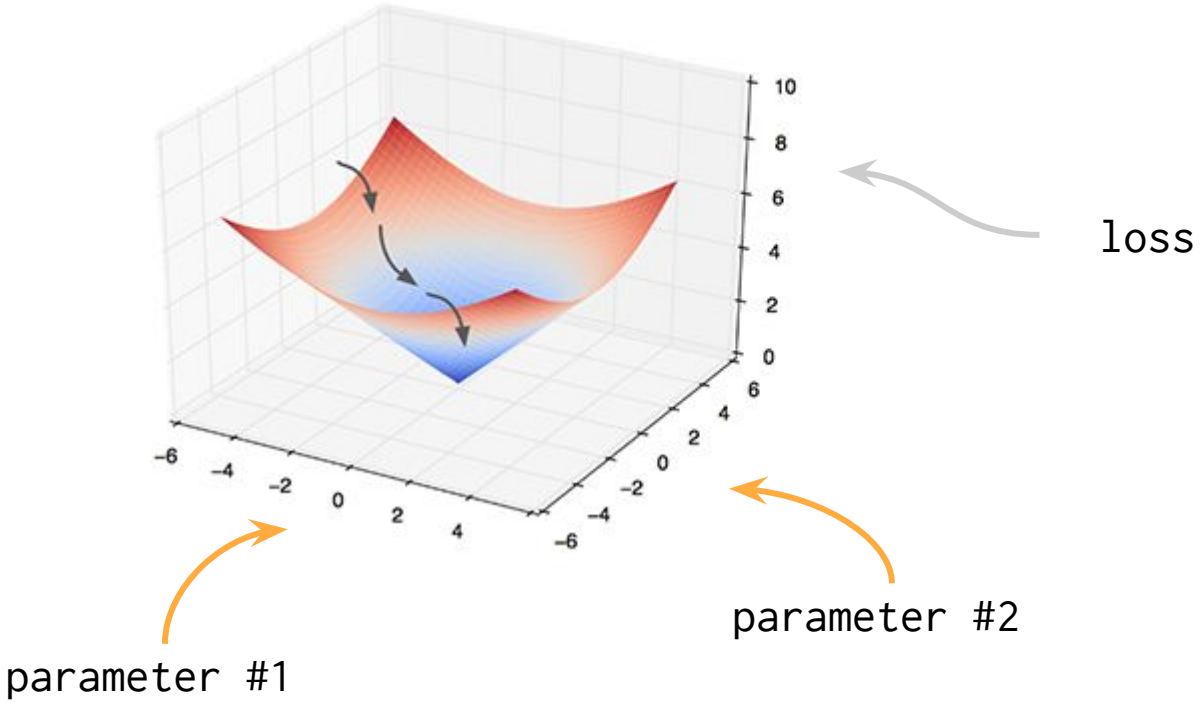
How do we find good parameter values?

Option 1: random guess

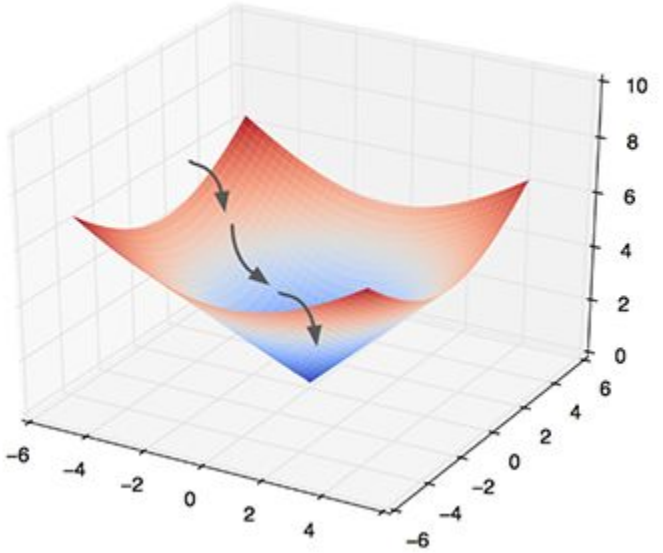
```
for _ in range(10,000)
   w,b = random(), random()
   acc = calculate_accuracy()
   if acc > best_acc:
     ...
```

What can go wrong?

Concepts: Loss and Gradient Descent



Optimization



	-5	-4	-3	-2	-1	0	1	2	3	4	5
5	50	41	34	29	26	25	26	29	34	41	50
4	41	32	25	20	17	16	17	20	25	32	41
3	34	25	18	13	10	9	10	13	18	25	34
2	29	20	13	8	5	4	5	8	13	20	29
1	26	17	10	5	2	1	2	5	10	17	26
0	25	16	9		1	0	1	4	9	16	25
-1	26	17	10	5	2	1	2	5	10	17	26
-2	29	20	13	8	5	4	5	8	13	20	29
-3	34	25	18	13	10	9	10	13	18	25	34
-4	41	32	25	20	17	16	17	20	25	32	41
-5	50	41	34	29	26	25	26	29	34	41	50

What can go wrong?

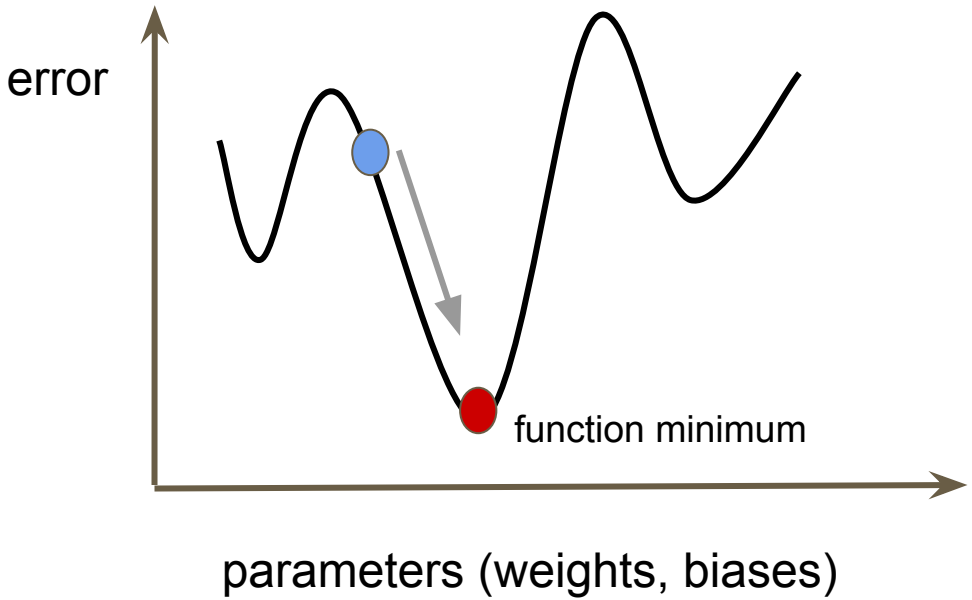
Define a Loss

Given y, y_train compute a loss, for instance:

$$loss = (y - y_{train})^2$$

```
# create an operation that calculates loss.
loss = tf.reduce_mean(tf.square(y - y_train))
```

Minimize loss using an optimizer



tf.train.GradientDescentOptimizer

Automatic Differentiation

Feed (x, y_{label}) pairs and adjust W and b to decrease the loss.

$$W \leftarrow W - \eta \, (dL/dW)$$

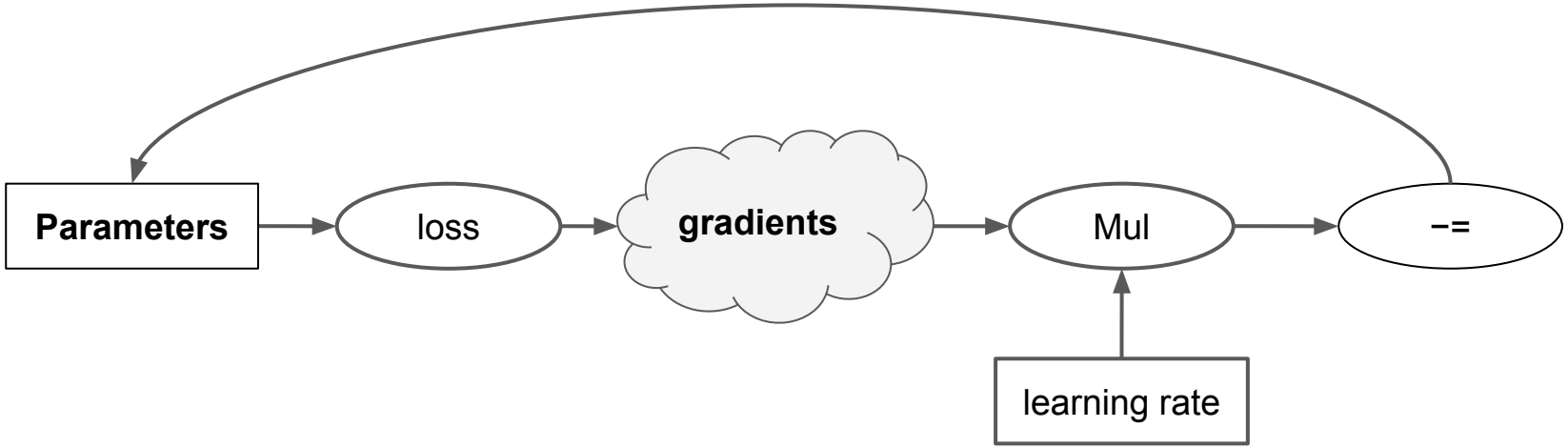
$$b \leftarrow b - \eta \, (dL/db)$$

TensorFlow computes gradients automatically

```
# Create an optimizer

optimizer = tf.train.GradientDescentOptimizer(0.5)

# Create an operation that minimizes loss.

train = optimizer.minimize(loss)
```

Learning rate

Behind the scenes



Putting it all together

```
loss = tf.reduce_mean(tf.square(y - y_train))
optimizer = tf.train.GradientDescentOptimizer(0.5)
train = optimizer.minimize(loss)
with tf.Session() as sess:
  sess.run(tf.initialize_all_variables())
  for i in range(1000):
    sess.run(train, feed_dict={x: x_data[i],
                               y_label: y_data[i]})
```

Define a loss

Create an optimizer

Op to minimize the loss

Initialize variables

Iteratively run the training op

Demo: TensorBoard

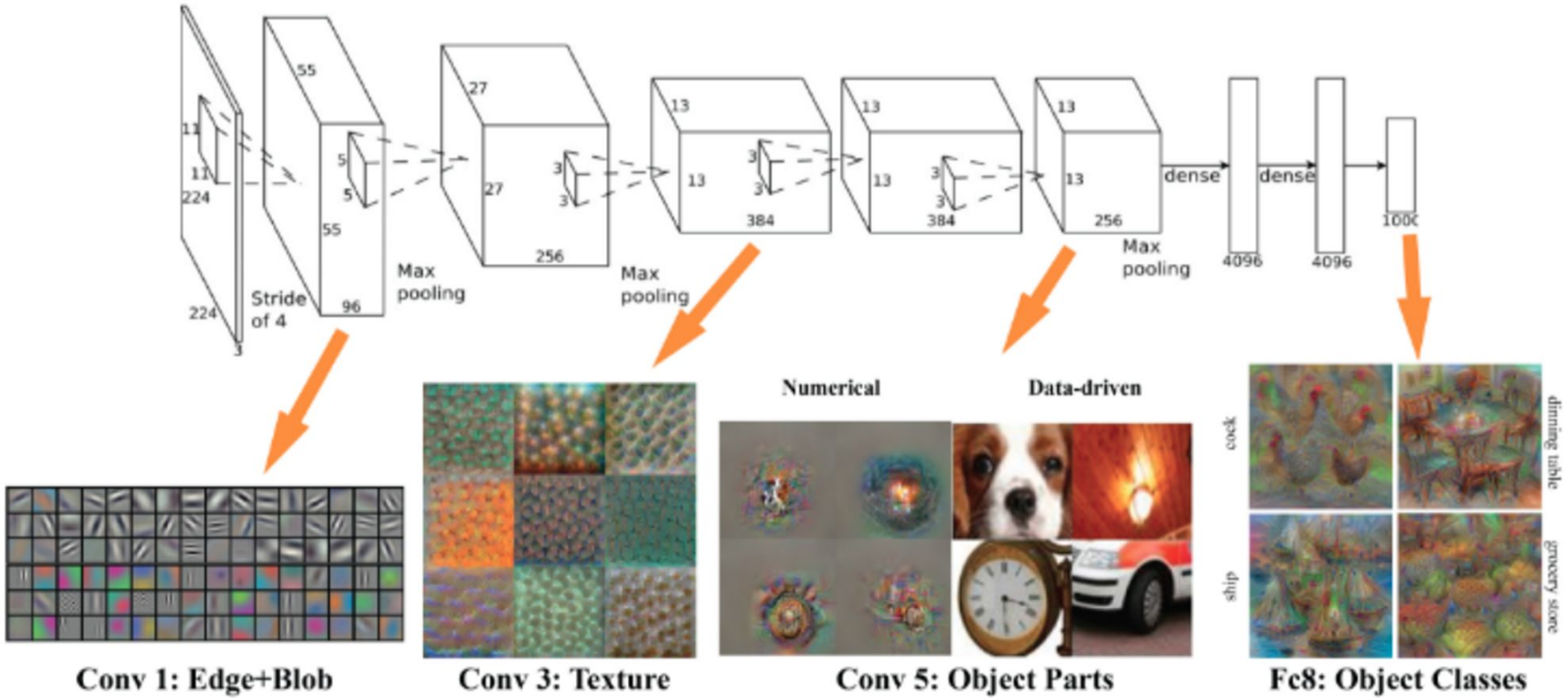
goo.gl/nrdsxM

Exercise #2: Linear Regression
2_linear_regression.ipynb

goo.gl/nrdsxM

Create your own artwork

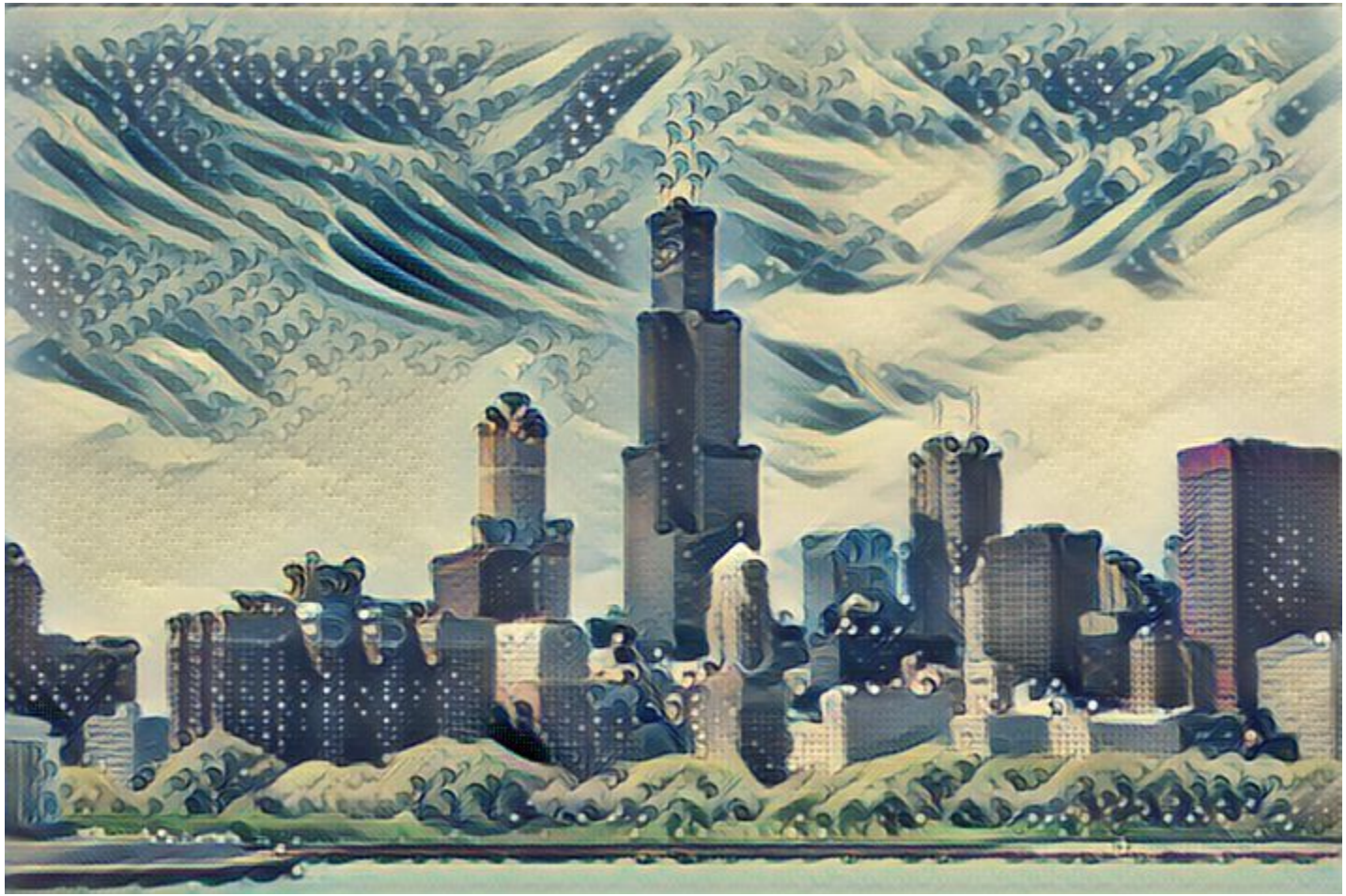
Style Transfer and Deep Dream



From: A Matlab Plugin to Visualize Neurons from Deep Models, Donglai Wei et. al.

Style Transfer

Images from https://github.com/lengstrom/fast-style-transfer/



Images from https://github.com/lengstrom/fast-style-transfer/

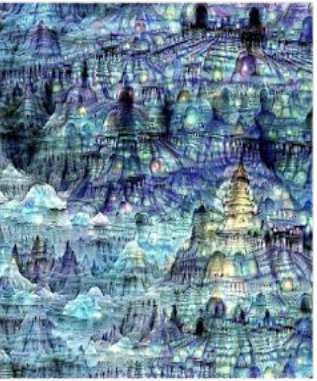
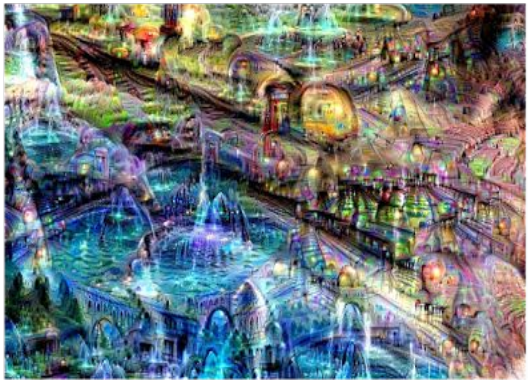
https://github.com/lengstrom/fast-style-transfer/

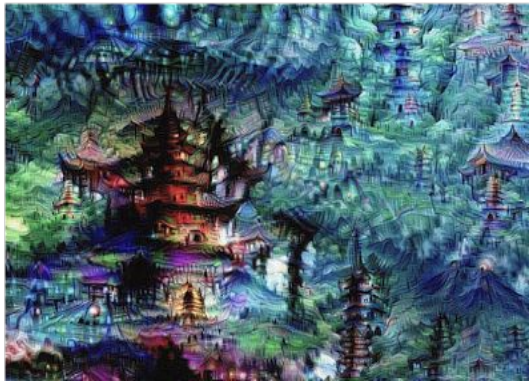
From https://github.com/cysmith/neural-style-tf

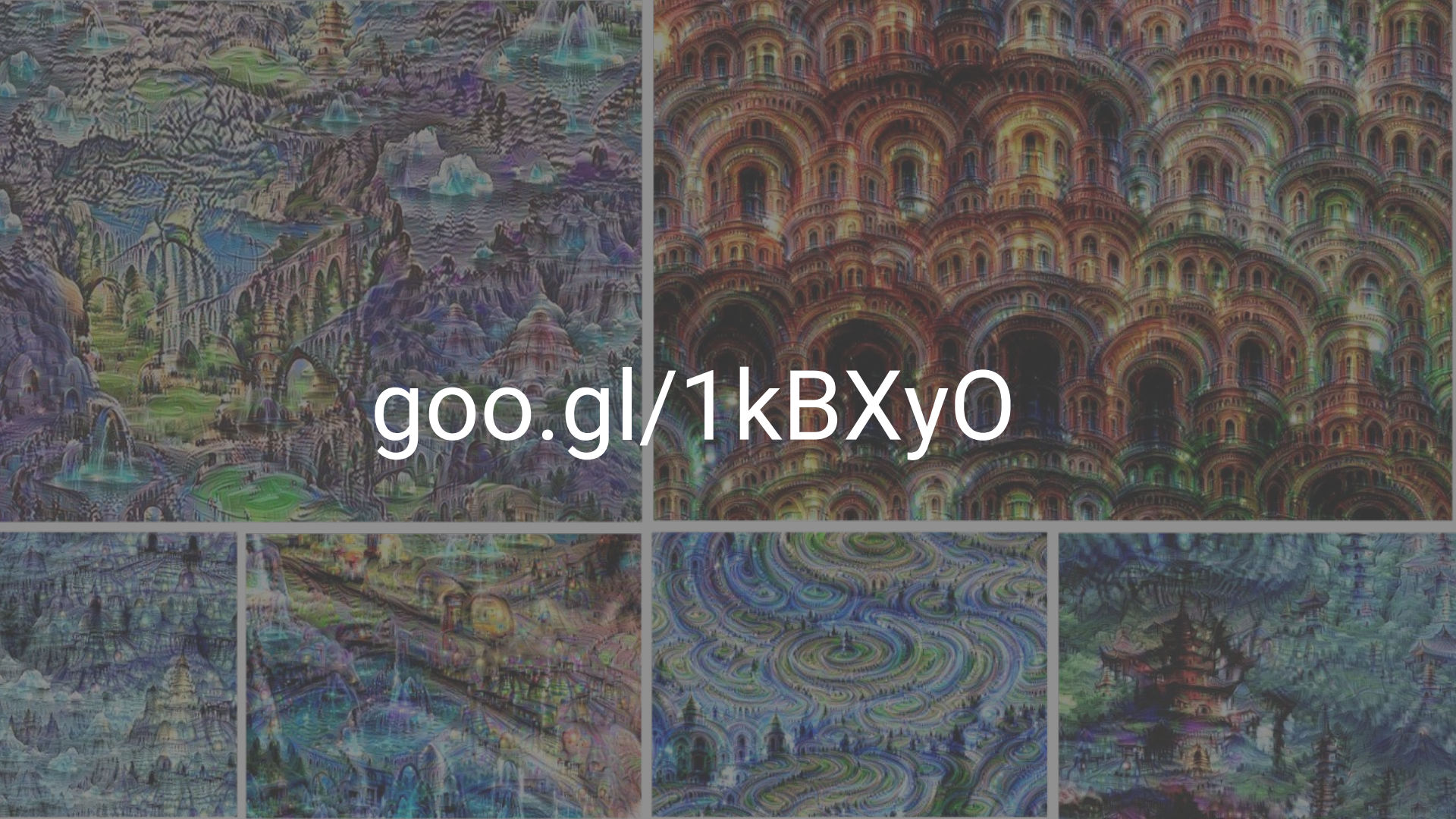
Style Transfer
goo.gl/M5hiYY

Fast Style Transfer
goo.gl/owF2z9






goo.gl/1kBXyO

References

Supercharging Style Transfer
https://research.googleblog.com/2016/10/supercharging-style-transfer.html

Inceptionism: Going Deeper into Neural Networks
https://research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html

TensorFlow for Poets

Train your own image classifier

goo.gl/xGsB9d

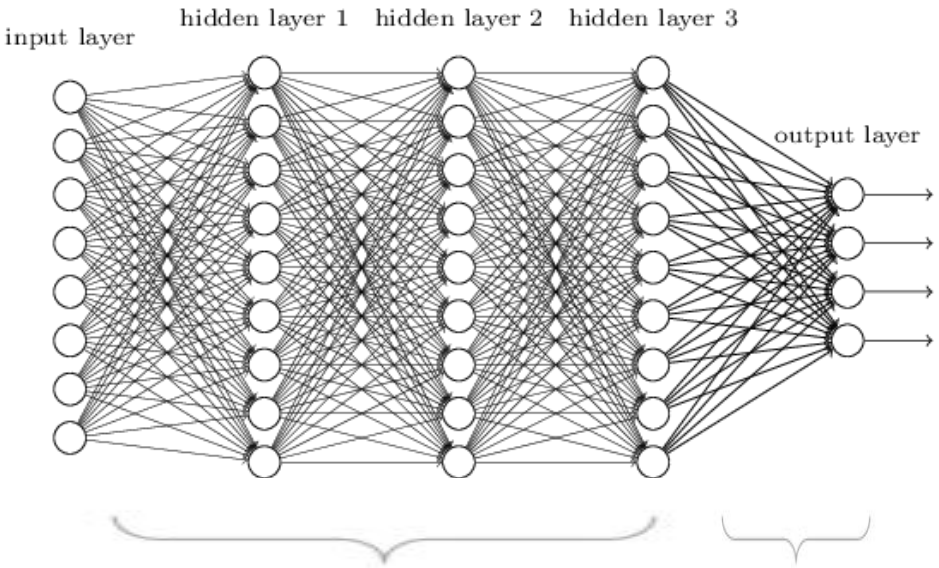
Remember Inception?

- Load the graph and learned weights; use the model
- 1,000 categories: pandas, cats, bears
- Performs “about” as well as people on this task

Images via Wikipedia

www.tensorflow.org/tutorials/image_recognition/index.html

Transfer Learning



Most of the network is unchanged

Only the last layer of weights and the outputs are updated

Image: neuralnetworksanddeeplearning.com

Advantages

- Minutes vs weeks
- Handful of new training data
- Reuse learned “features”
- Two ways to do this
  a. Directly in TensorFlow
  b. TensorFlow for Poets

Claude Monet - Bouquet of Sunflowers
Images from the Metropolitan Museum of Art (with permission)

For more: @random_forests

Ex #3: Divide into groups, try your favorite.

1) TensorFlow for Poets
2) Deep Dream
3) Style Transfer

goo.gl/nrdsxM

Also: Super-resolution

https://github.com/david-gpu/srez

Basic and Deep MNIST

Working with Neural Networks

1. Use a pre-trained model
2. Use a higher-level API
3. Define and train your network directly in TensorFlow

More control, more effort

Hello “computer vision” world

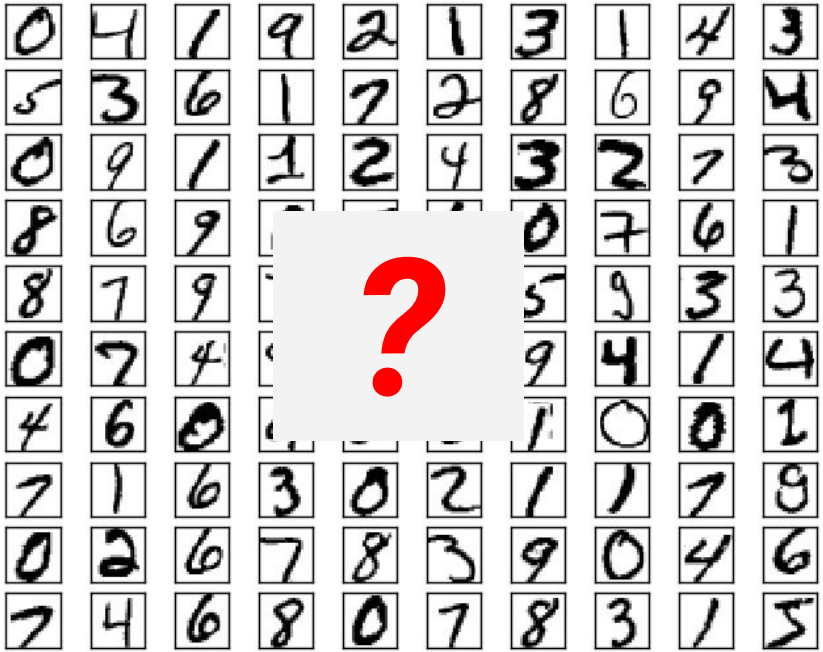
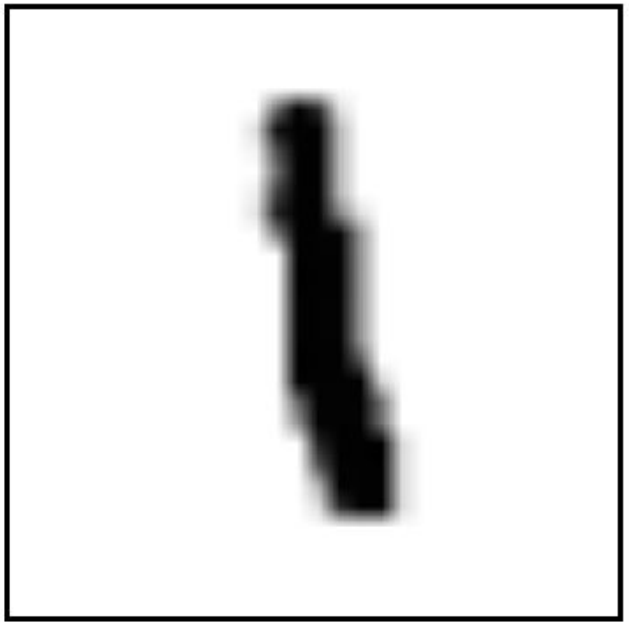


Image from https://github.com/mnielsen/neural-networks-and-deep-learning

We see



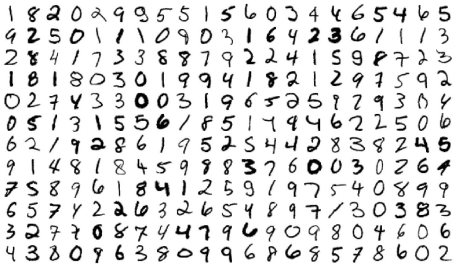
Computer “sees”

$$\approx$$

$$\begin{bmatrix}
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & .6 & .8 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & .7 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & .7 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & .5 & 1 & .4 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & .4 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & .4 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & .7 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & .9 & 1 & .1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & .3 & 1 & .1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}$$

Dataset

Original: 65,000



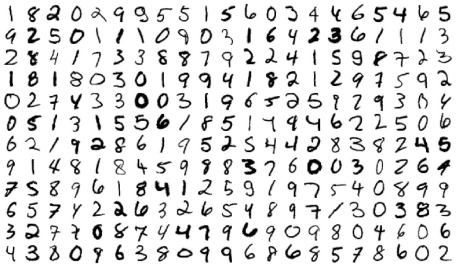
Images

Labels

5 0 4 1 9 2

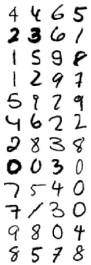
Train / test split

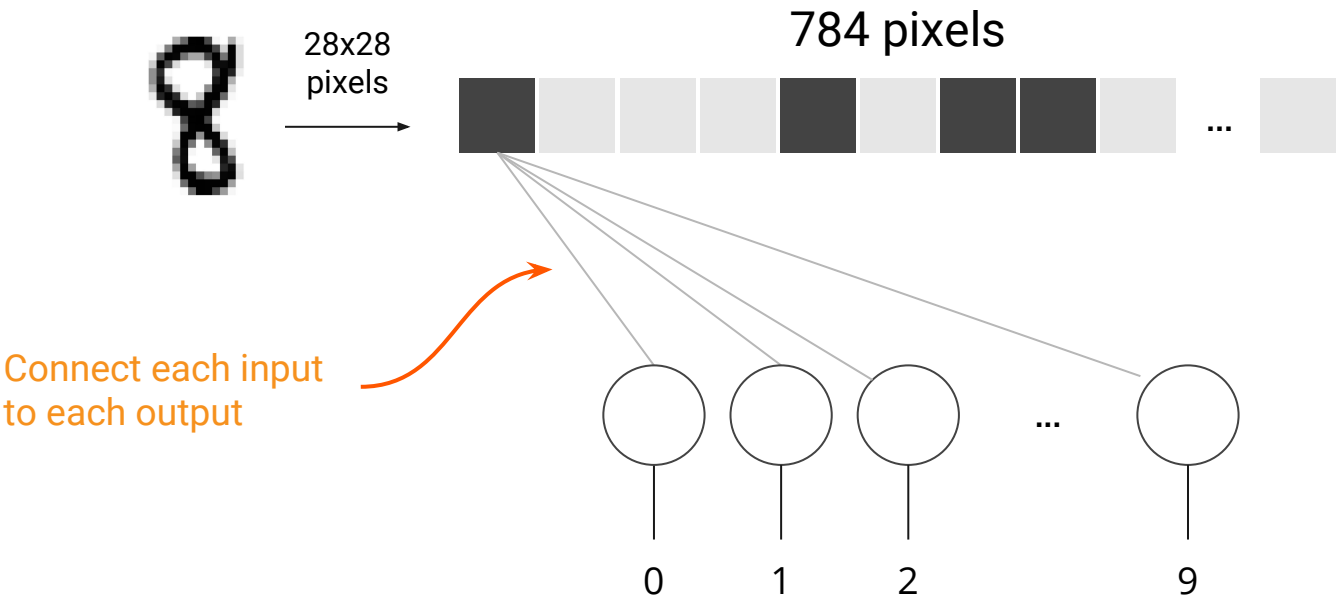
Original: 65,000

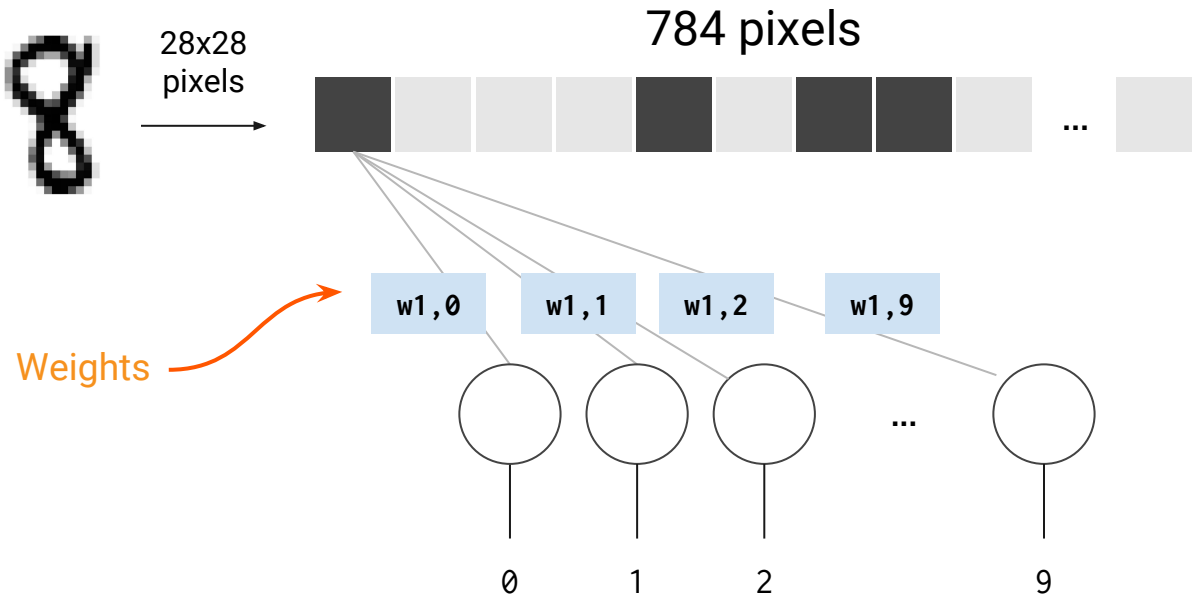


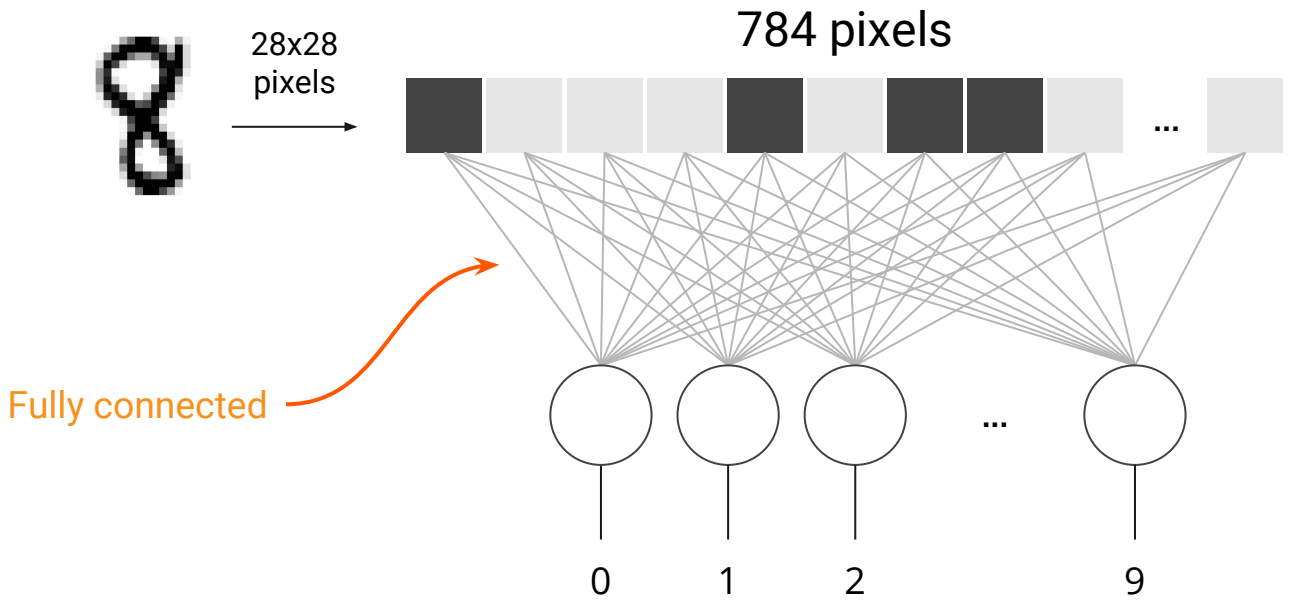
Train: 55,000

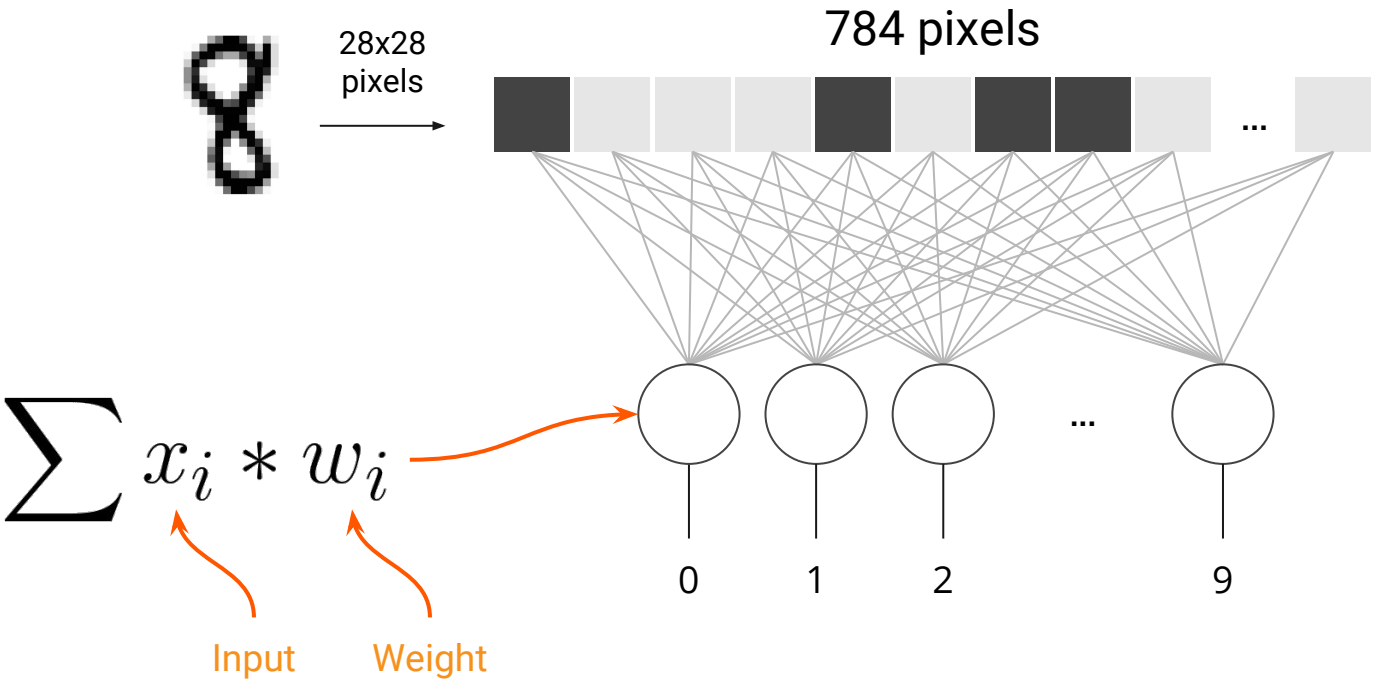
Test: 10,000




28x28
pixels
784 pixels
...
Connect each input
to each output
...
0
1
2
9


28x28
pixels
784 pixels
...
w1,0
w1,1
w1,2
w1,9
Weights
...
0
1
2
9

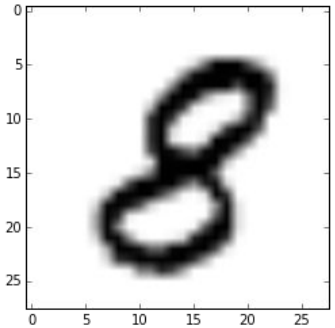

28x28
pixels
784 pixels
...
Fully connected
...
0
1
2
9

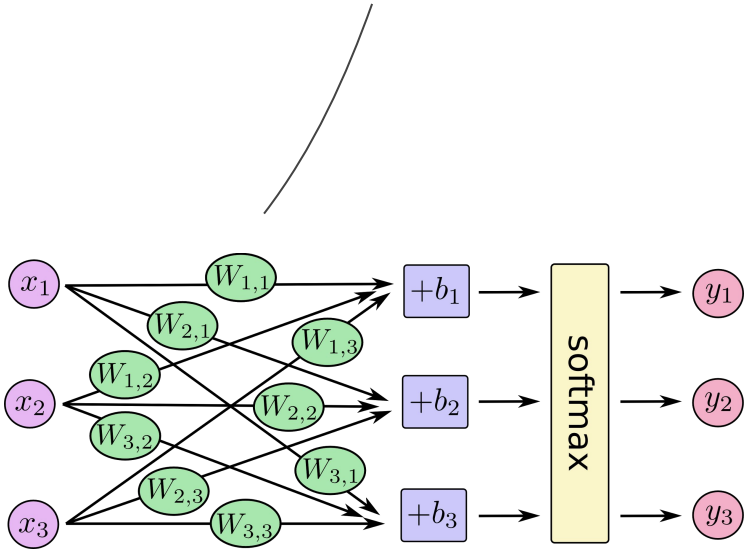

28x28
pixels
784 pixels
...
$\sum x_i * w_i$
Input
Weight
0
1
2
...
9

Softmax

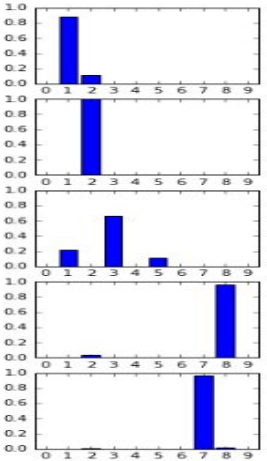
784 weights for each digit, so 784 x 10 total connections

input vector
(pixel data)

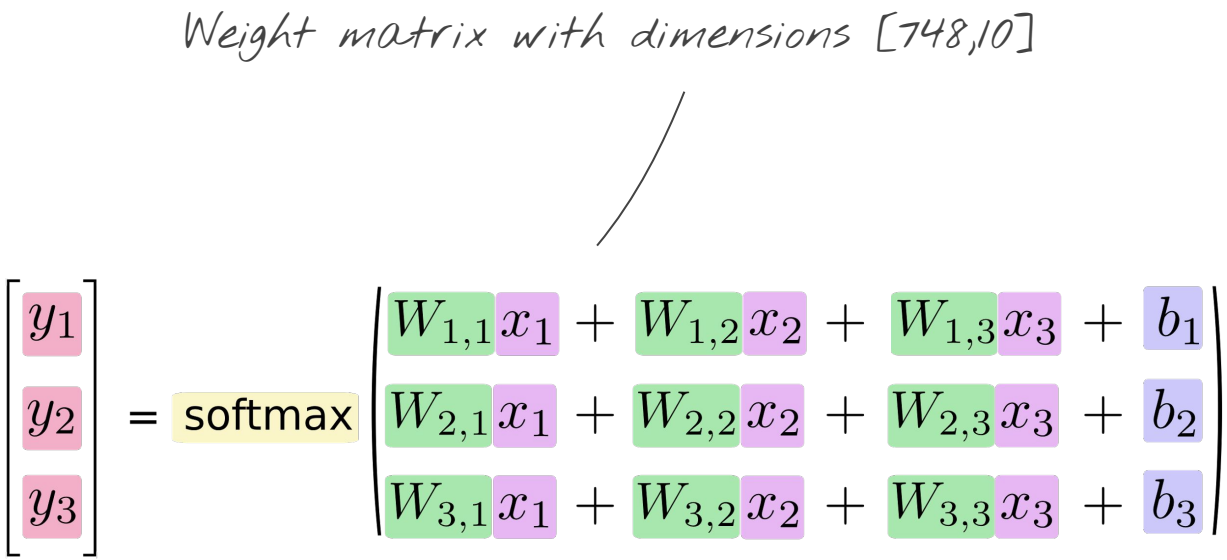




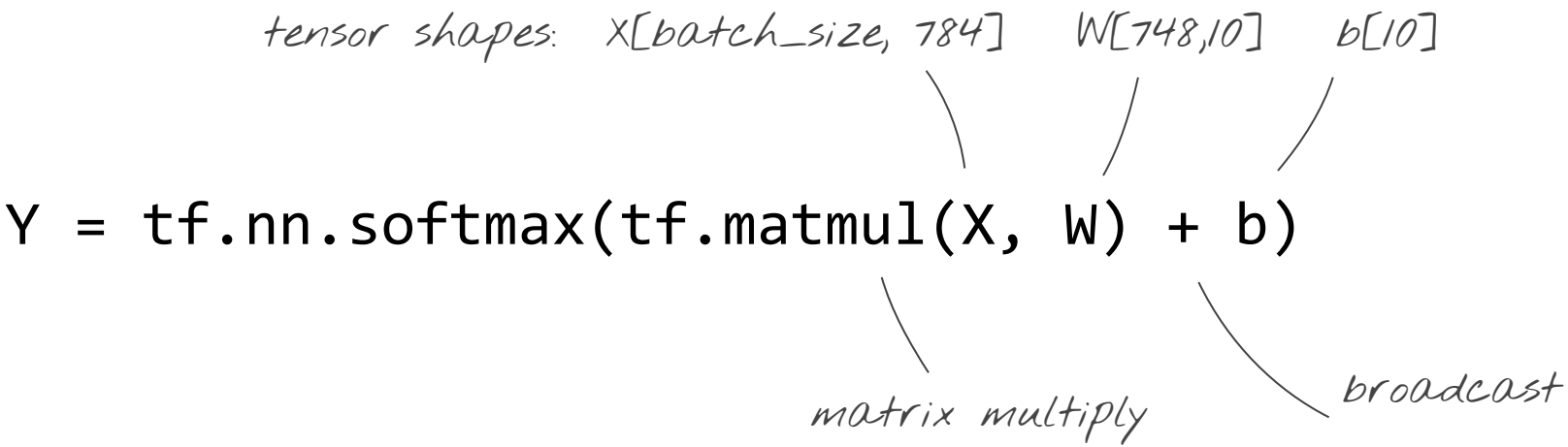
output vector
(probability of
each digit)



Written as a matrix multiply



In TensorFlow



Placeholders

```
x = tf.placeholder(tf.float32, [None, NUM_PIXELS], name="pixels")

y_ = tf.placeholder(tf.float32, [None, NUM_CLASSES], name="labels")
```

Inference

```
W = tf.Variable(tf.zeros([NUM_PIXELS, NUM_CLASSES]), name="weights")

b = tf.Variable(tf.zeros([NUM_CLASSES]), name="biases")

y = tf.matmul(x, W) + b
```

Loss and optimization

```
loss =
   tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(y, y_))

train_step =
   tf.train.GradientDescentOptimizer(LEARNING_RATE).minimize(loss)
```

Training

```
# Train the model
for i in range(TRAIN_STEPS):
    batch_xs, batch_ys = mnist.train.next_batch(BATCH_SIZE)
    sess.run(train_step, feed_dict={x: batch_xs, y_: batch_ys})
```

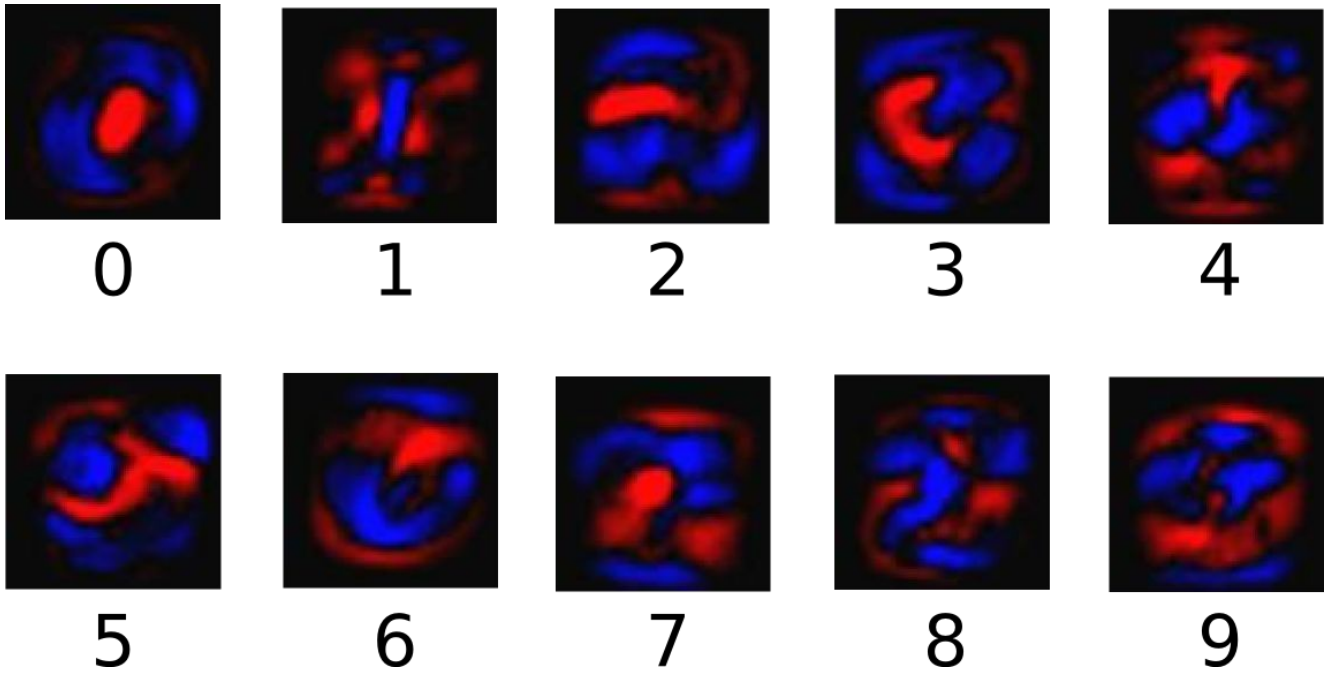
Evaluation

```
# Evaluate the trained model
correct_prediction = tf.equal(tf.argmax(y, 1), tf.argmax(y_, 1))
accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))

print("Accuracy %f" % sess.run(accuracy, feed_dict={x:
mnist.test.images, y_: mnist.test.labels}))
```

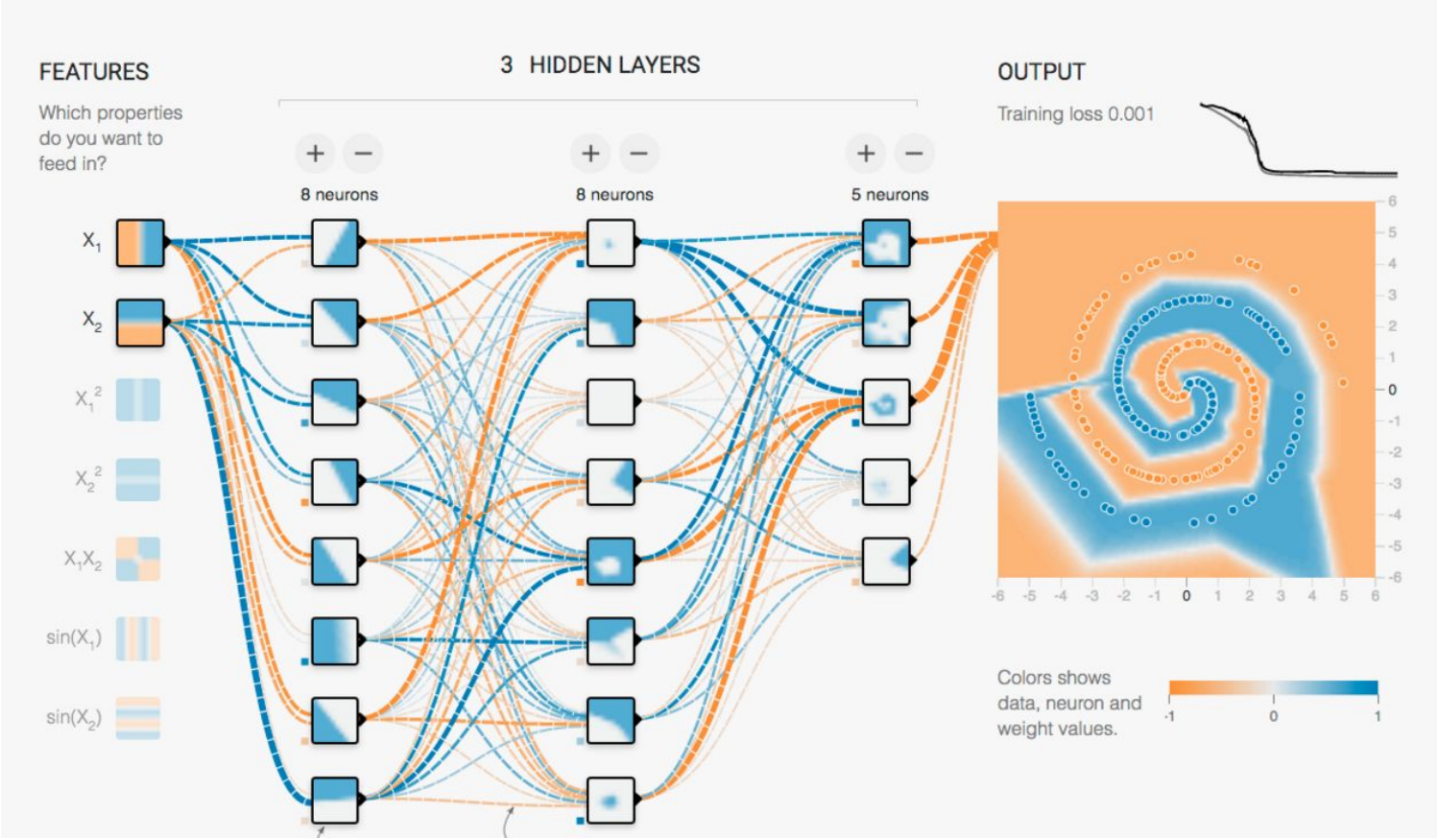
3_basic_mnist.ipynb

goo.gl/nrdsxM

Visualizing the learned weights

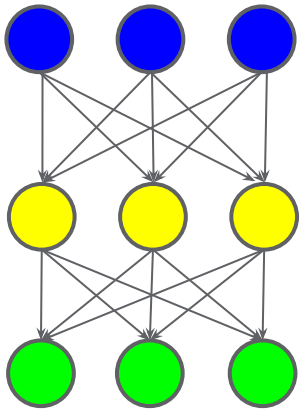


Going Deeper



More **hidden layers** = More **hierarchies** of features

Hidden layers



```
weights1 = weight_variable(NUM_PIXELS, HIDDEN1_UNITS)

biases1 = bias_variable(HIDDEN1_UNITS)

hidden1 = tf.nn.relu(tf.matmul(x, weights1) + biases1)

weights2 = weight_variable(HIDDEN1_UNITS, NUM_CLASSES)

biases2 = bias_variable(NUM_CLASSES, "biases2")

y = tf.matmul(hidden1, weights2) + biases2
```

4_deep_mnist.ipynb

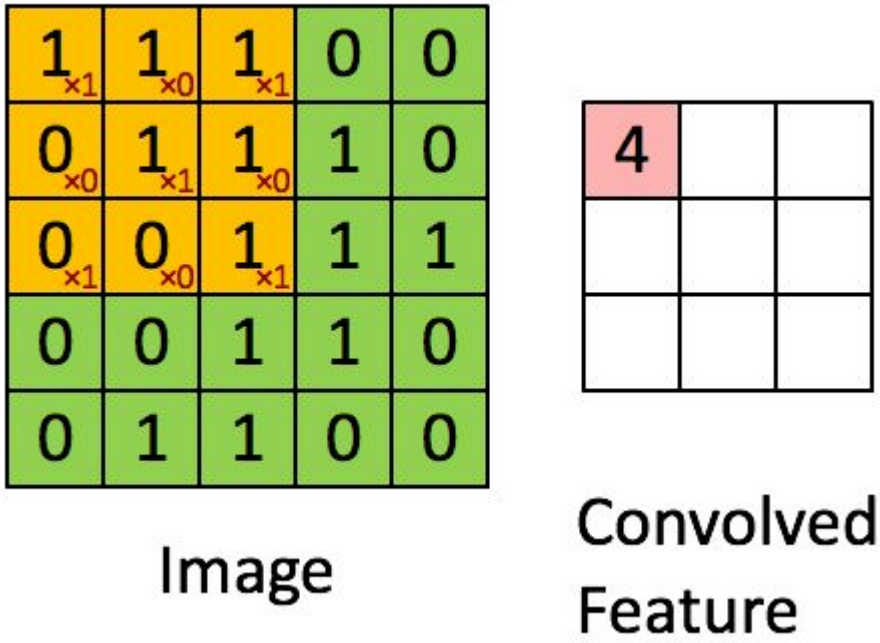
goo.gl/nrdsxM

Progression and caveats

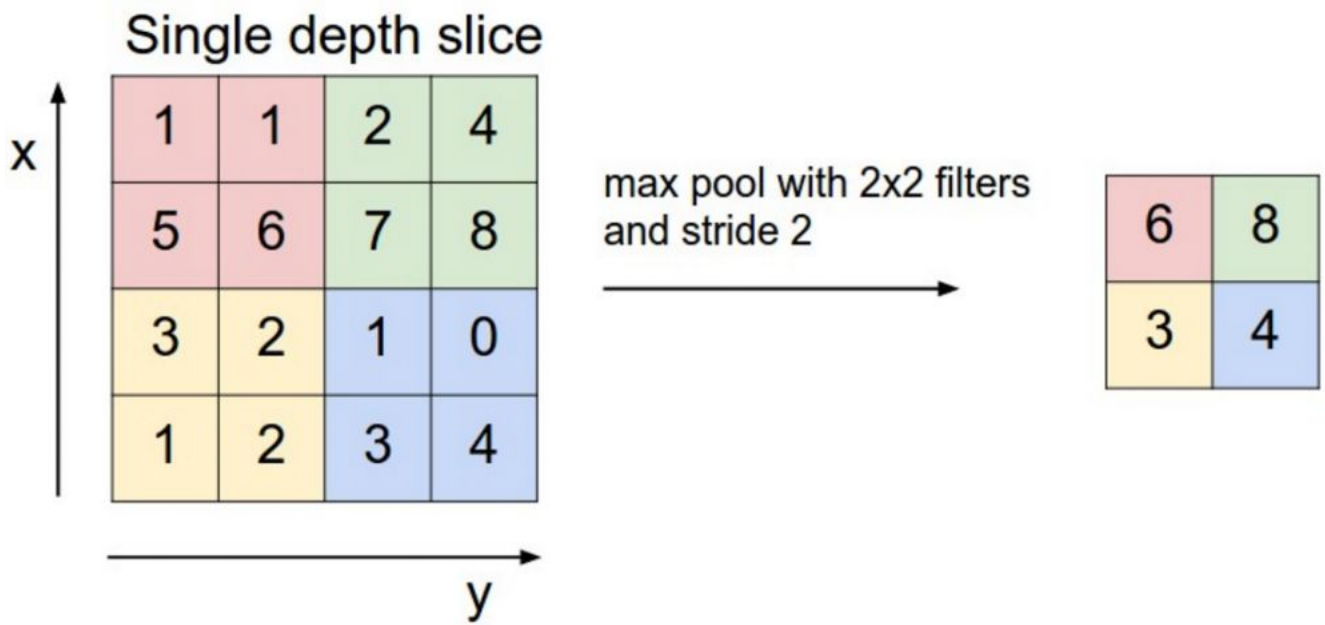
- Linear ~90%
- Two-layer DNN ~96%
- ConvNet ~99% (close to the state of the art on this toy problem)

Should you focus on accuracy?

- What matters is designing a proper experiment.

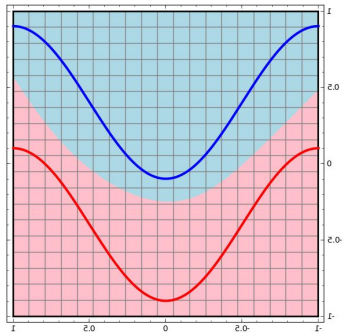


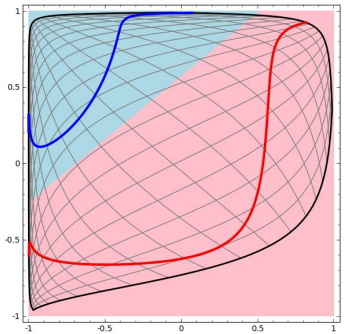
Convolution with 3×3 Filter. Source:
http://deeplearning.stanford.edu/wiki/index.php/Feature_extraction_using_convolution

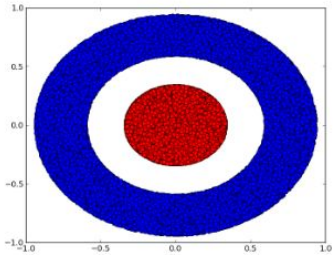


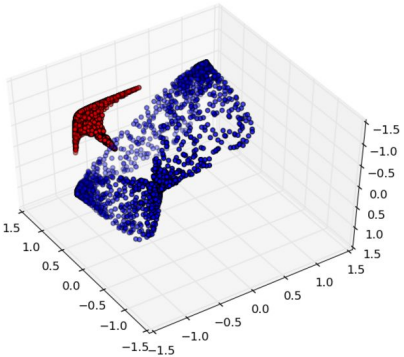
Max pooling in CNN. Source: http://cs231n.github.io/convolutional-networks/#pool

Learn more: colah.github.io









From: Neural Networks, Manifolds, and Topology, colah's blog

Learn more: Stanford's cs231n

CS231n Convolutional Neural Networks for Visual Recognition

These notes accompany the Stanford CS class CS231n: Convolutional Neural Networks for Visual Recognition.
For questions/concerns/bug reports regarding contact Justin Johnson regarding the assignments, or contact Andrej Karpathy regarding the course notes. You can also submit a pull request directly to our git repo.
We encourage the use of the hypothes.is extension to annotate comments and discuss these notes inline.

Winter 2016 Assignments

Assignment #1: Image Classification, kNN, SVM, Softmax, Neural Network

Assignment #2: Fully-Connected Nets, Batch Normalization, Dropout, Convolutional Nets

Assignment #3: Recurrent Neural Networks, Image Captioning, Image Gradients, DeepDream

Module 0: Preparation

Python / Numpy Tutorial

IPython Notebook Tutorial

Terminal.com Tutorial

AWS Tutorial

Module 1: Neural Networks

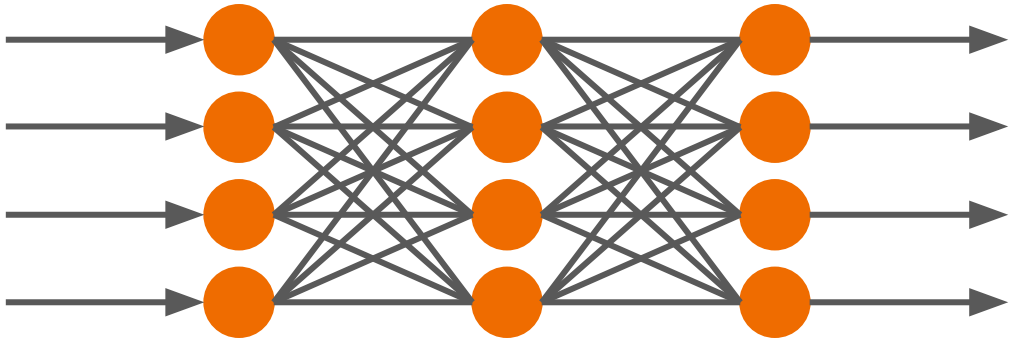
Image Classification: Data-driven Approach, k-Nearest Neighbor, train/val/test splits

L1/L2 distances, hyperparameter search, cross-validation

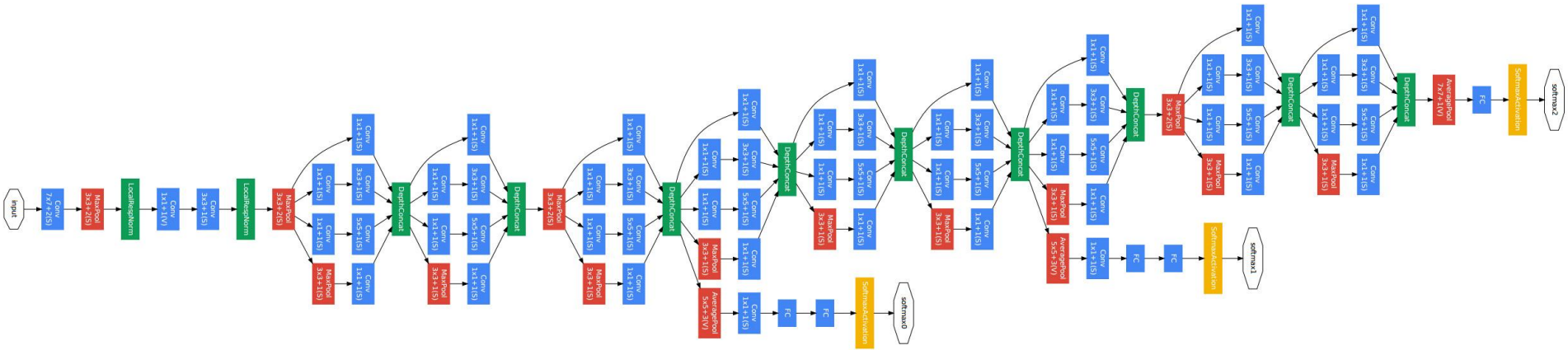
Linear classification: Support Vector Machine, Softmax

But why?

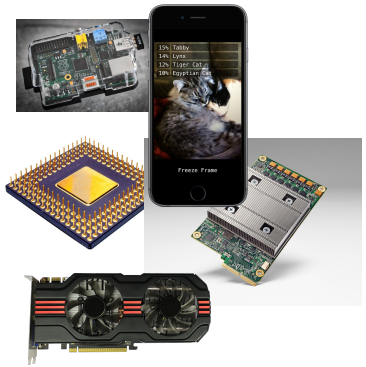
Neural Networks, yesterday



Remember Inception?

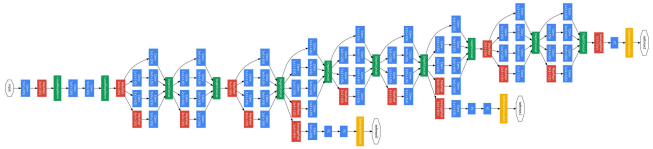


Machine Learning gets complex quickly



Heterogenous systems

Distributed systems

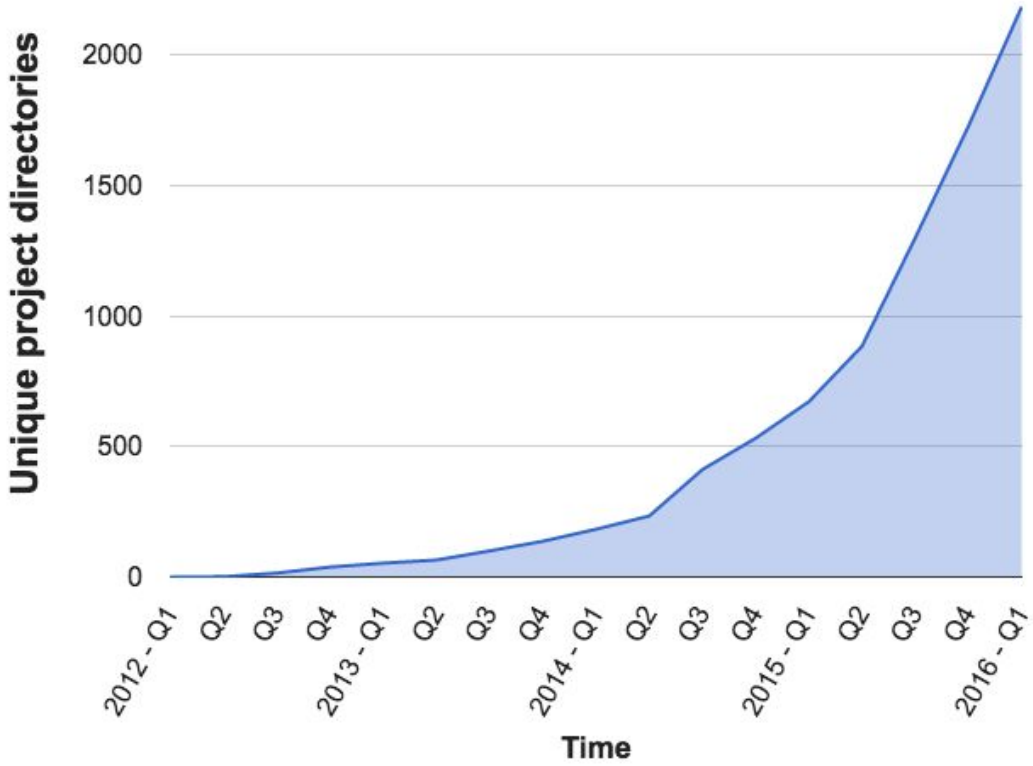


Modeling complexity

Deep Learning at Google

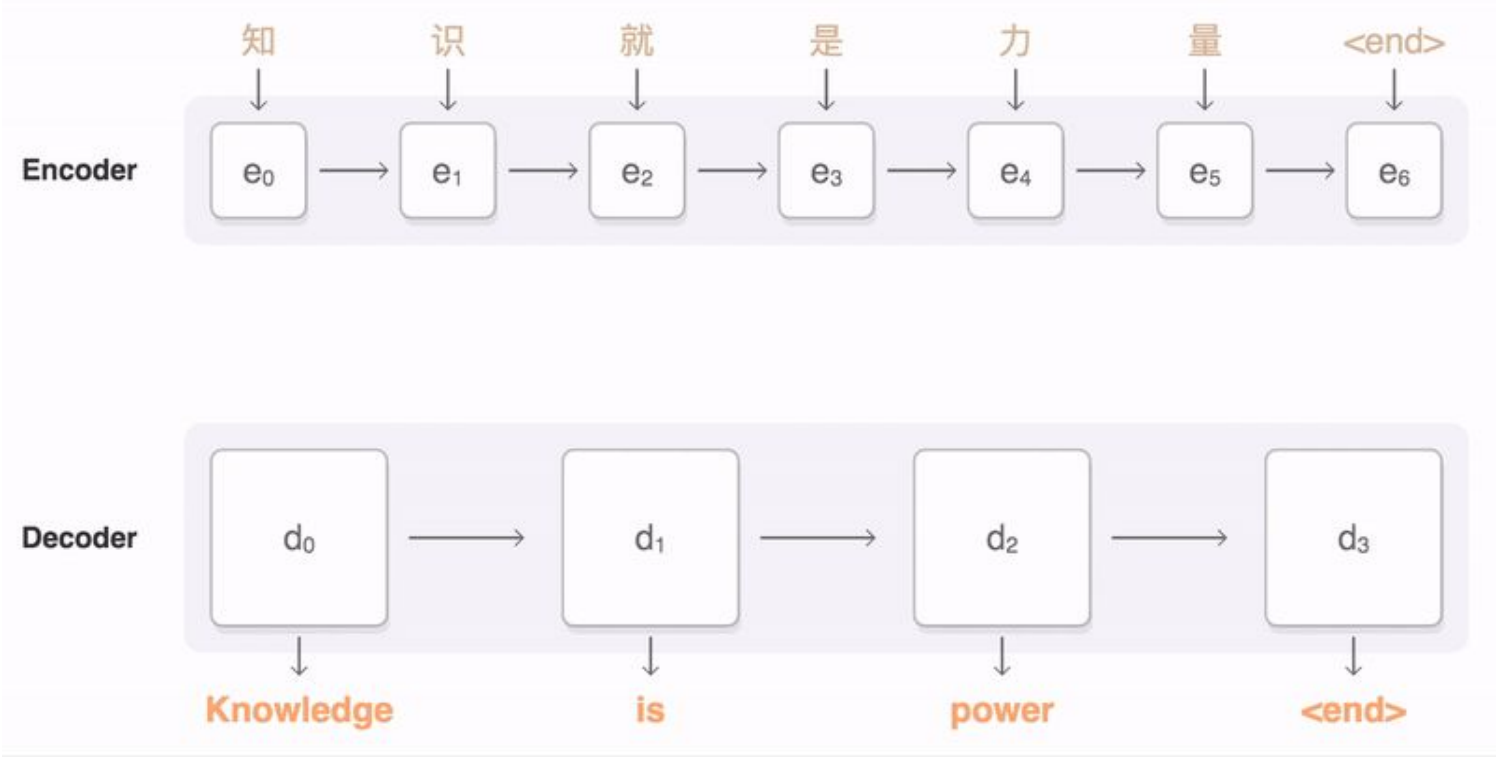
Growing Use of Deep Learning at Google

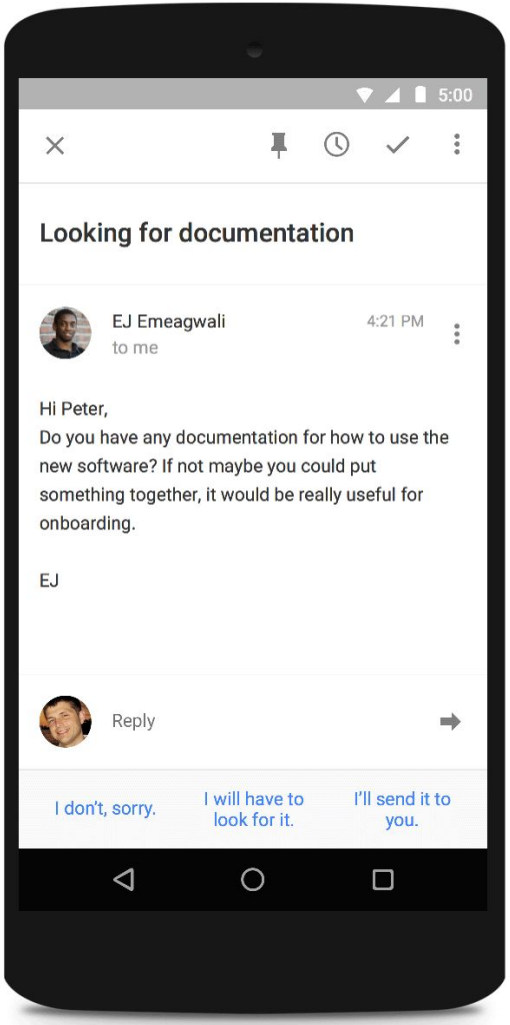
of directories containing model description files




EXIT

Google Neural Machine Translation



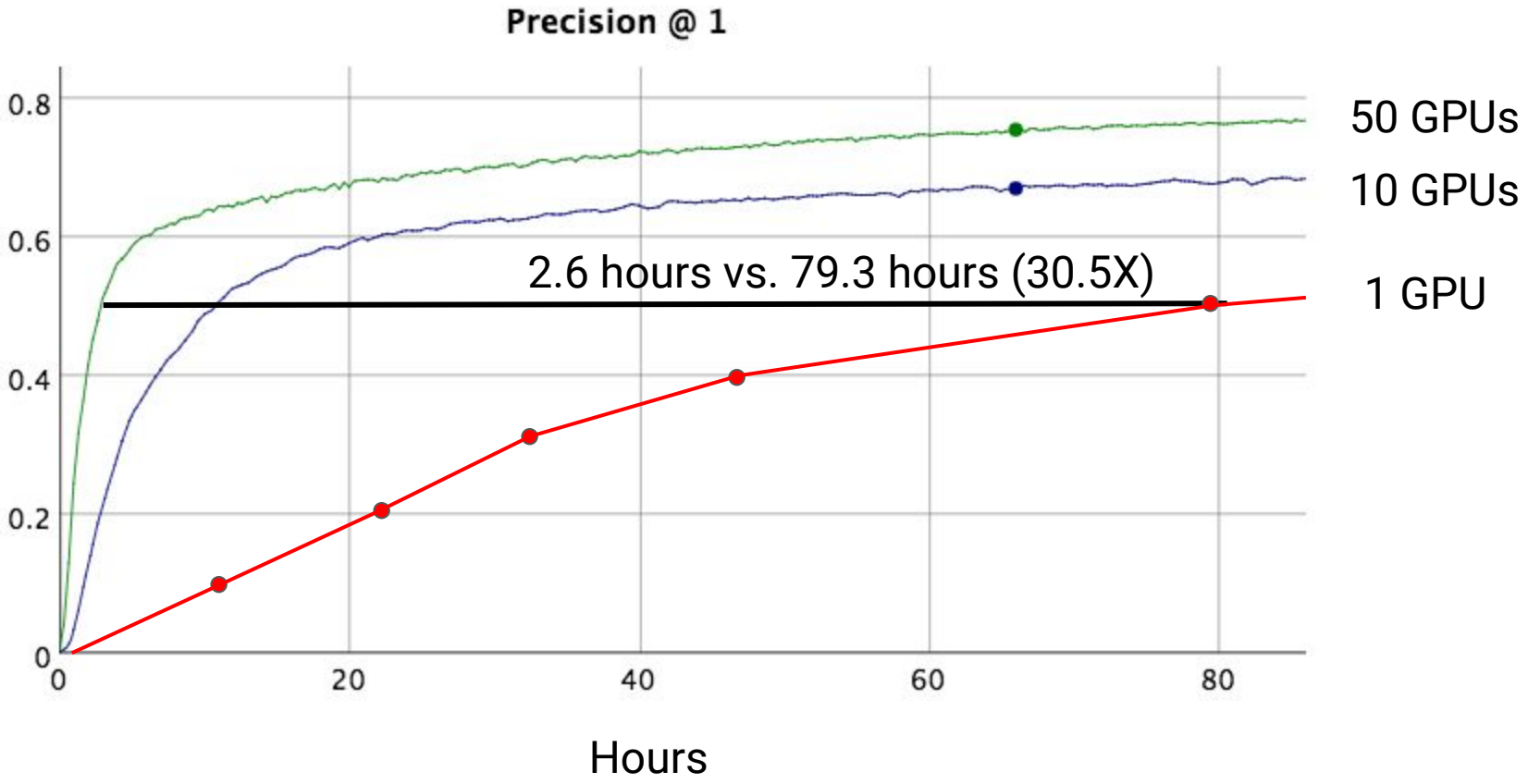


Smart reply in Inbox by Gmail

10%

of all responses sent on mobile

Image Model (Inception) Synchronous Training



AlphaGo

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NEWS Find local news

Home UK World Business Politics Tech Science Health Education Entertainment & Arts More

Technology

Google achieves AI 'breakthrough' at Go

An artificial intelligence program developed by Google beats Europe's top player at the ancient Chinese game of Go, about a decade earlier than expected.

27 January 2016 | Technology

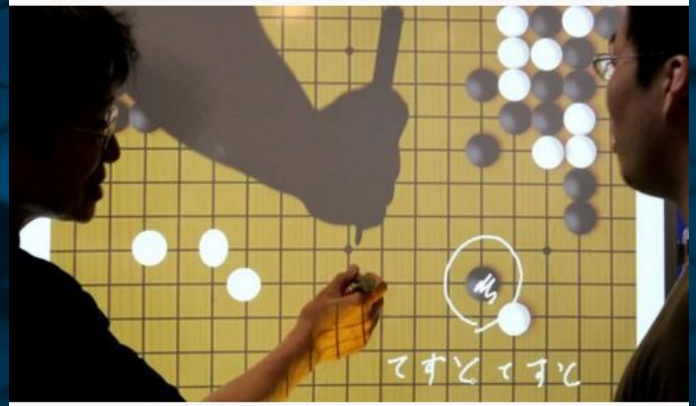
How did they do it?

What is the game Go?

Facebook trains AI to beat humans at Go

Google's AI just cracked the game that supposedly no computer could beat

By Mike Murphy | January 27, 2016



Going up. (Reuters/Kiyoshi Ota)

Computers have slowly started to encroach on activities we previously believed only the brilliantly sophisticated human brain could handle. IBM's Deep Blue supercomputer beat Grand Master Garry Kasparov at chess in 1997, and in 2011 IBM's Watson beat former human winners at the quiz game *Jeopardy*. But the ancient board game Go has long been one of the major goals of artificial intelligence research. It's understood to be one of the most difficult games for computers to handle due to the sheer number of possible moves a player can make at any given point. Until now, that is.

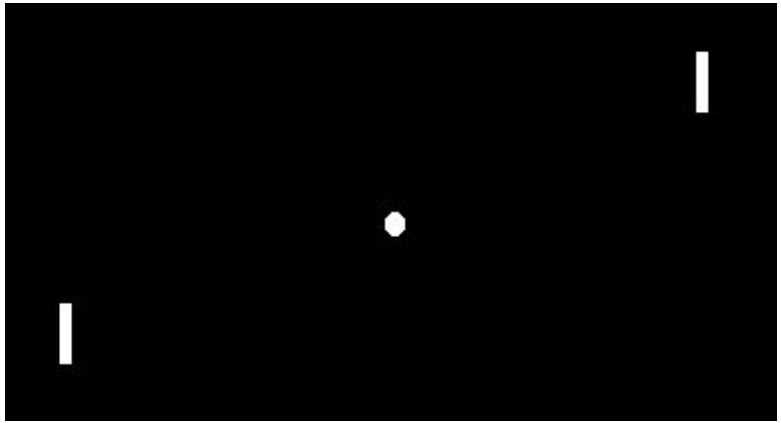



image.display
000 5 1

Next steps

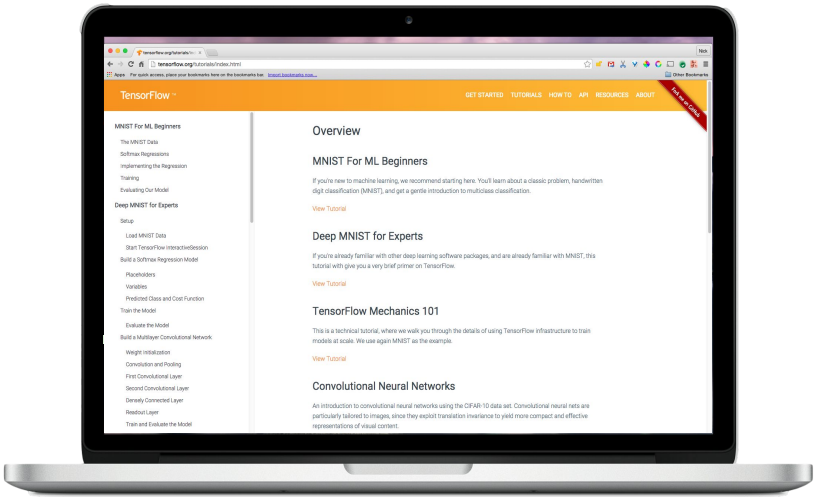
Tutorials and code
tensorflow.org

Intro to Deep Learning with TensorFlow
Udacity class goo.gl/iHssII

Stanford's CS231n
cs231n.github.io

Udacity's Machine Learning Nanodegree
goo.gl/ODpXj4

Totally new to ML?
Recipes goo.gl/KewA03

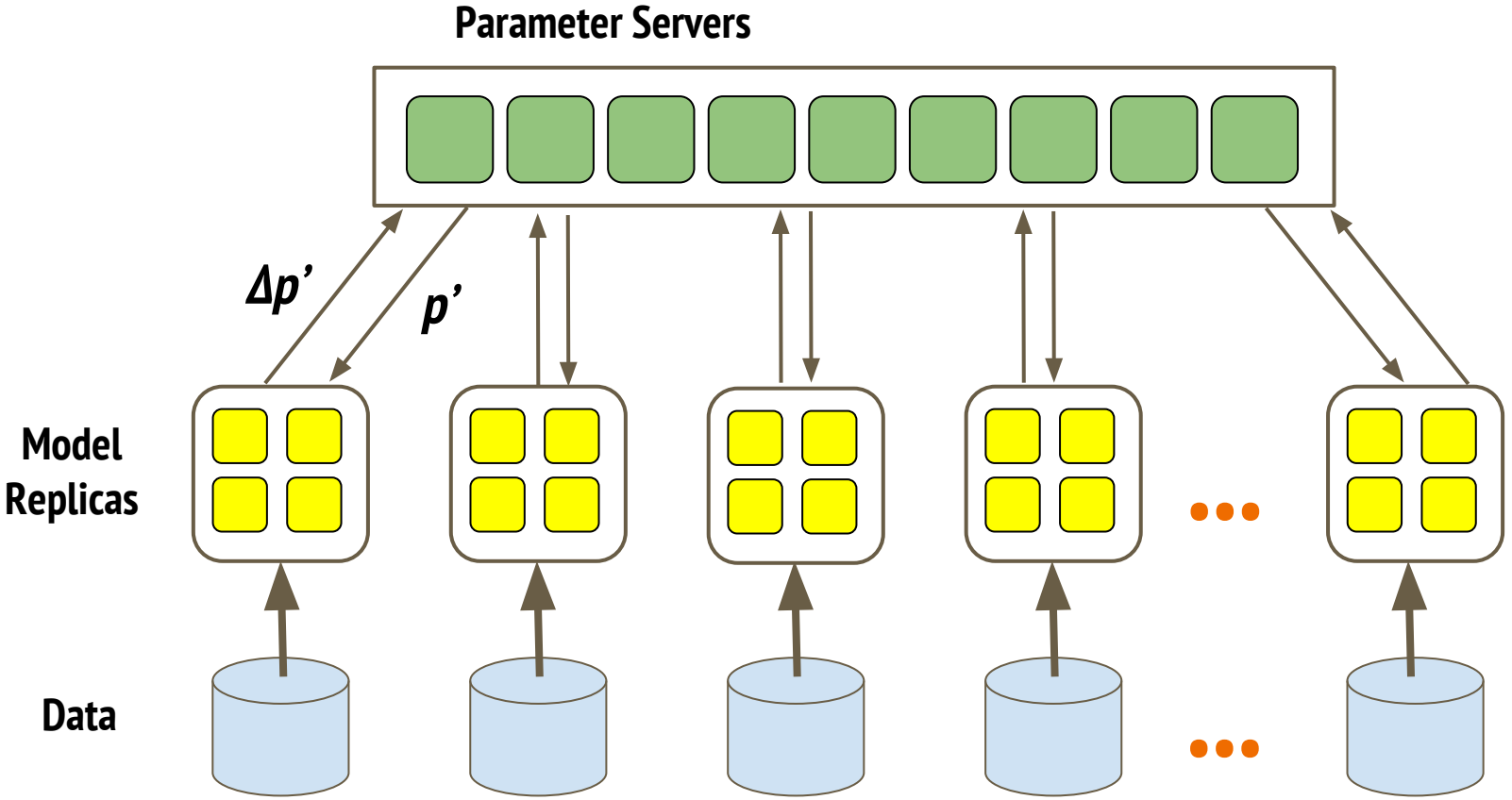


Thank you and have fun!

Josh Gordon
@random_forests

Extras

Data Parallelism



Input Pipelines with Queues