Intro to TensorFlow

NYC, November 2016

Welcome & Logistics

Thanks for coming!

- Format is a mix of talks and notebooks
- Content aimed at beginners

Goals for today

- Get started

Things you might want to know

- What's TensorFlow?
- What’s Deep Learning?
- How do I write some code?

Exercises

Fibonacci Sequence

- Graphs and sessions

Linear Regression

- Inference, loss, optimization

Neural Networks

- MNIST

Transfer Learning

- TensorFlow for Poets

Art

- Style Transfer
- Deep Dream

Agenda

10:15am - 10:30am

- Warm up

10:30am - 11am

- Linear Regression

11am - 12pm

- MNIST

12pm - 1pm

- Lunch

1pm - 2pm

- TensorFlow for Poets
- Style Transfer

2pm - 3pm

- Networking

What’s Deep Learning?

IS THIS A

CAT or DOG?

CAT DOG

OUTPUT LAYER

ACTIVATED NEURONS

INPUT LAYER

DEEP *neural* NETWORK

Deep Learning

Current state of the art in:

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

Open Source Models

github.com/tensorflow/models

Inception

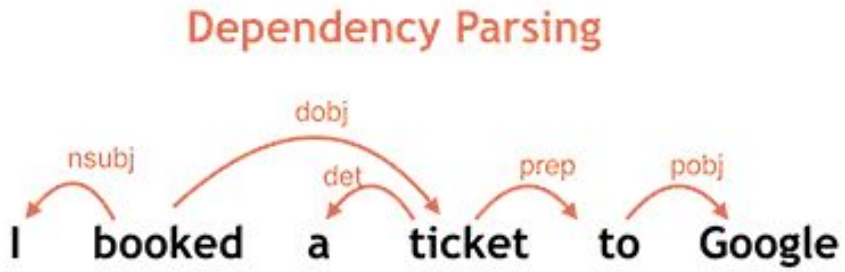
An Alaskan Malamute (left) and a Siberian Husky (right). Images from Wikipedia.

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

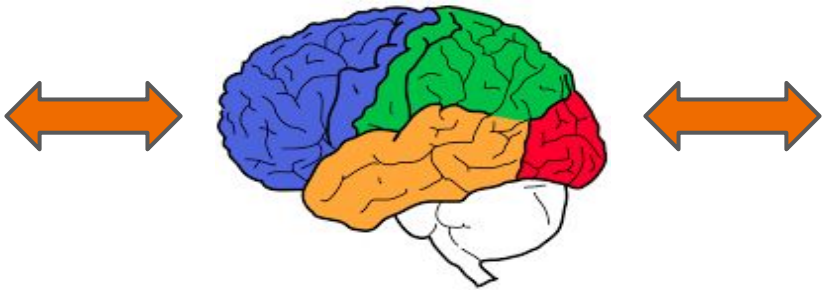
- *Alice and Bob visited the zoo and saw **animals and birds**.*

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

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

“Universal” Machine Learning

Speech
Text
Search
Queries
Images
Videos
Labels
Entities
Words
Audio
Features



Speech
Text
Search
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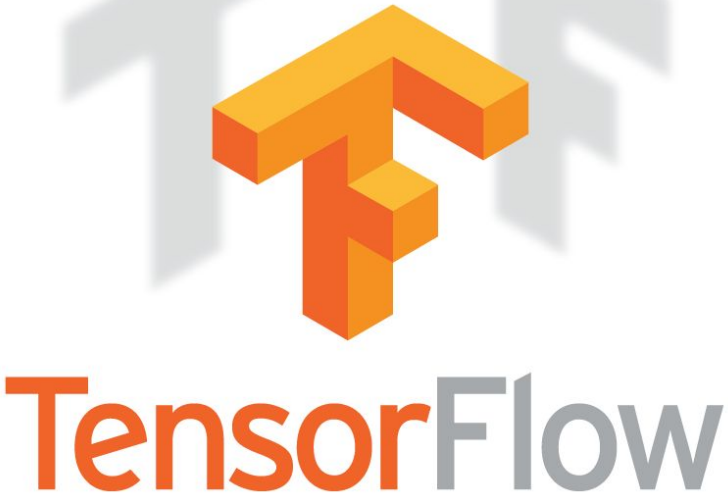
Images
Videos
Labels
Entities
Words
Audio
Features

What’s TensorFlow?



- 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

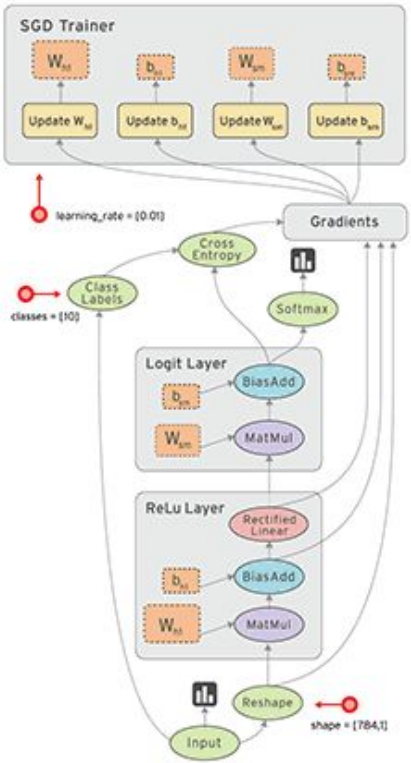
A multidimensional array.

A graph of operations.

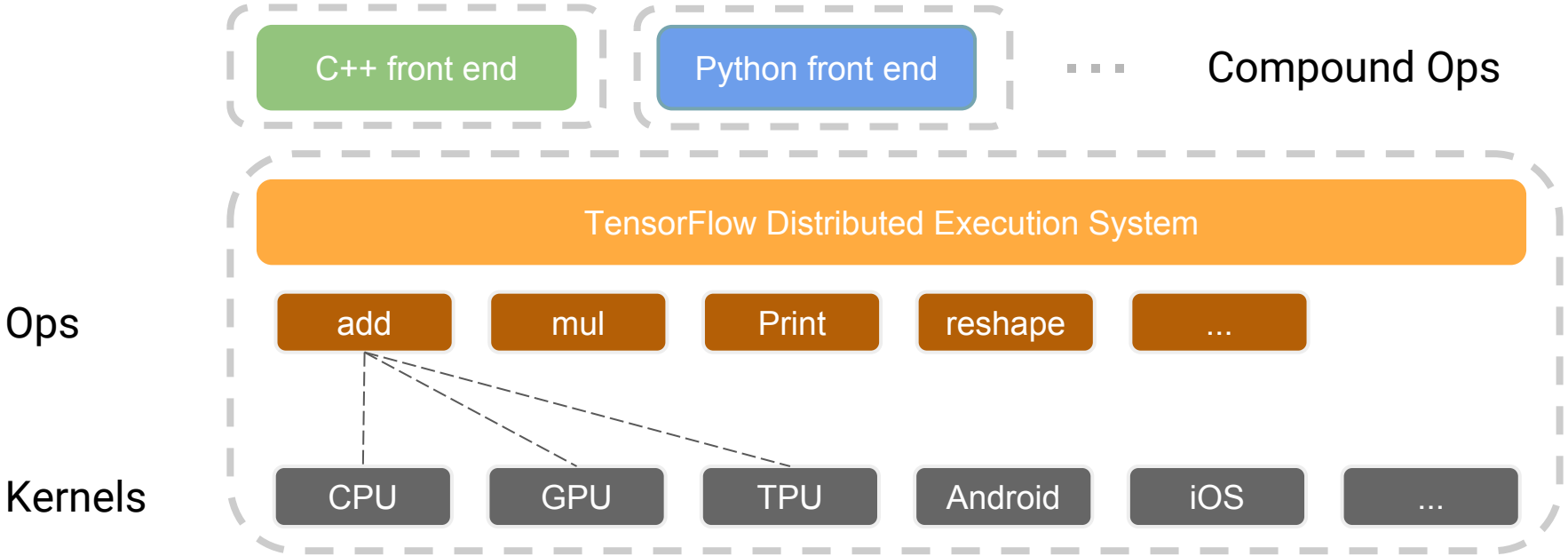
The TensorFlow Graph

Computation is defined as a graph

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



Architecture



A Year of TensorFlow

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

Working with Neural Networks

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

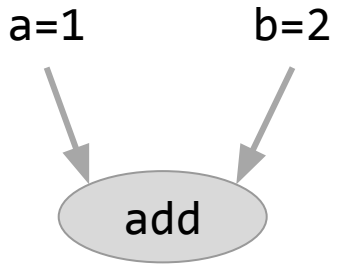
More control, more effort

Warm up

Graphs and Sessions

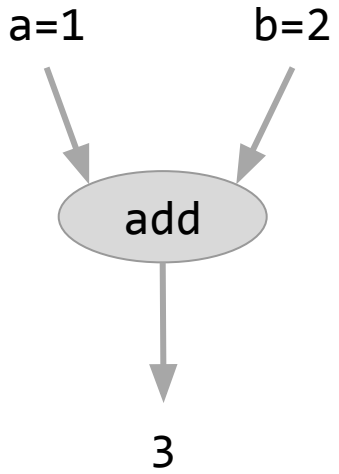
Build a graph...

```
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 functions for deep learning

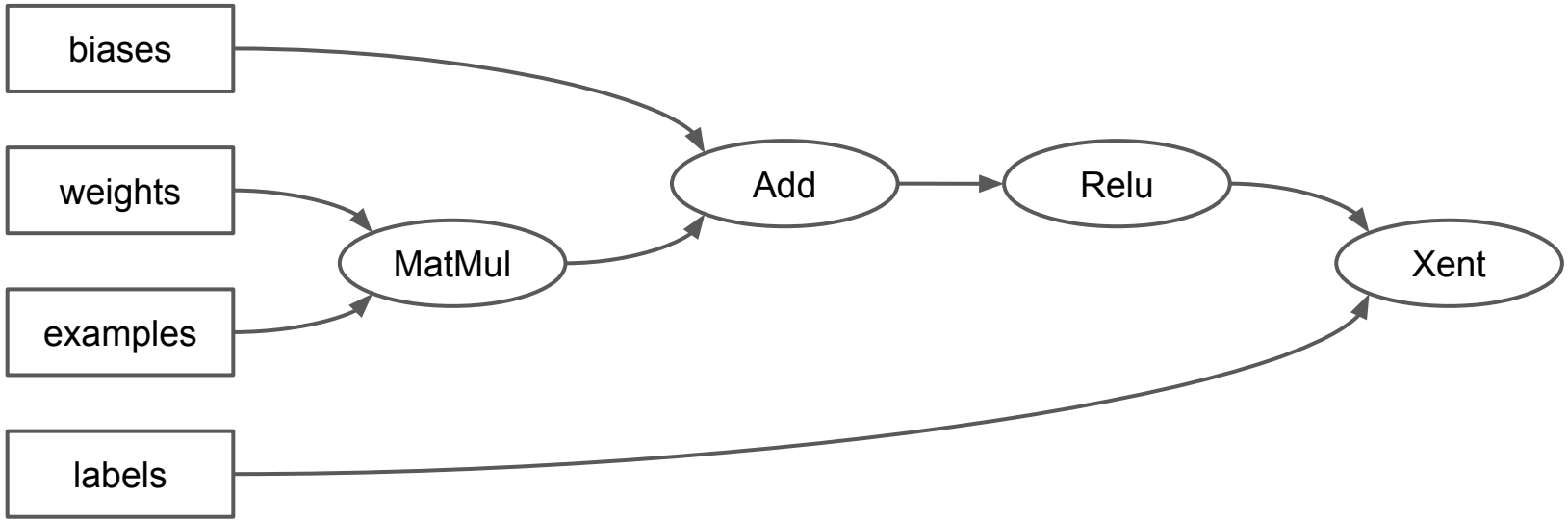
Numpy	TensorFlow
add mul matmul … sum …	add mul matmul … reduce_sum … sigmoid relu …

What's the output?

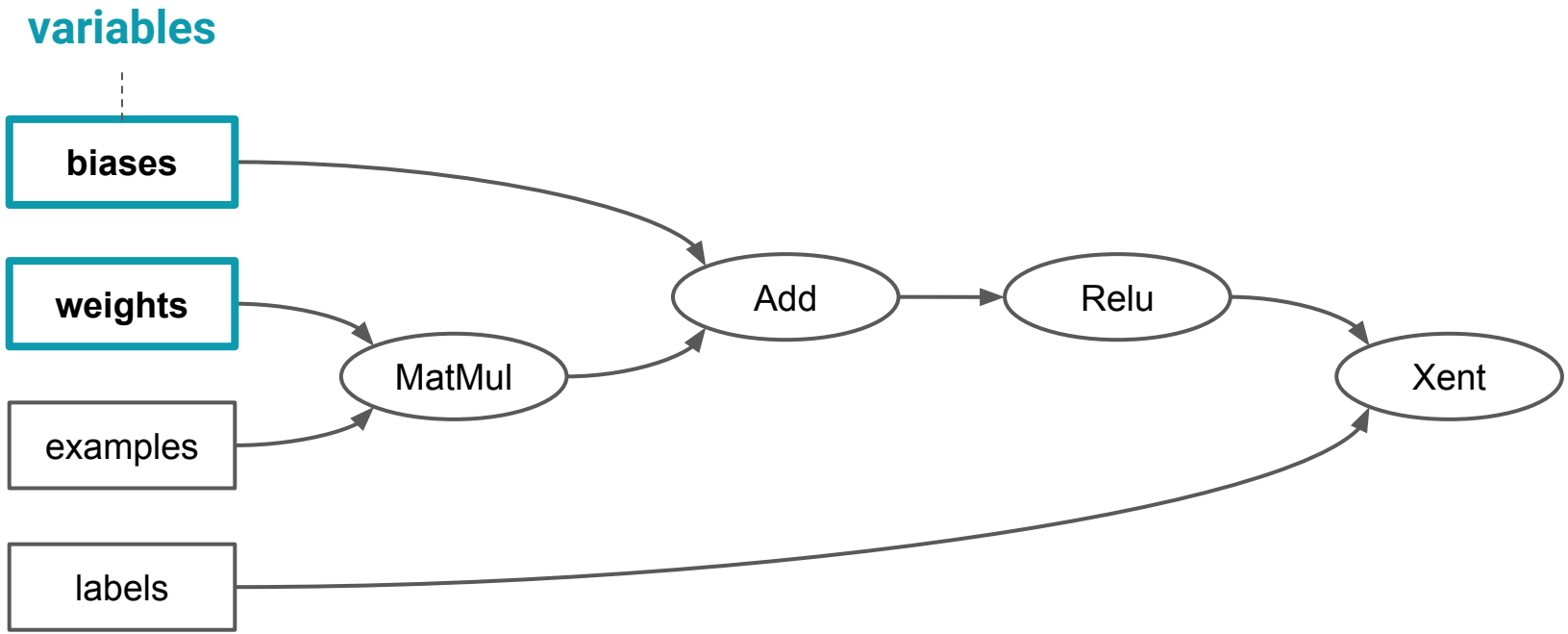
```
import tensorflow as tf

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))
```

But, why?

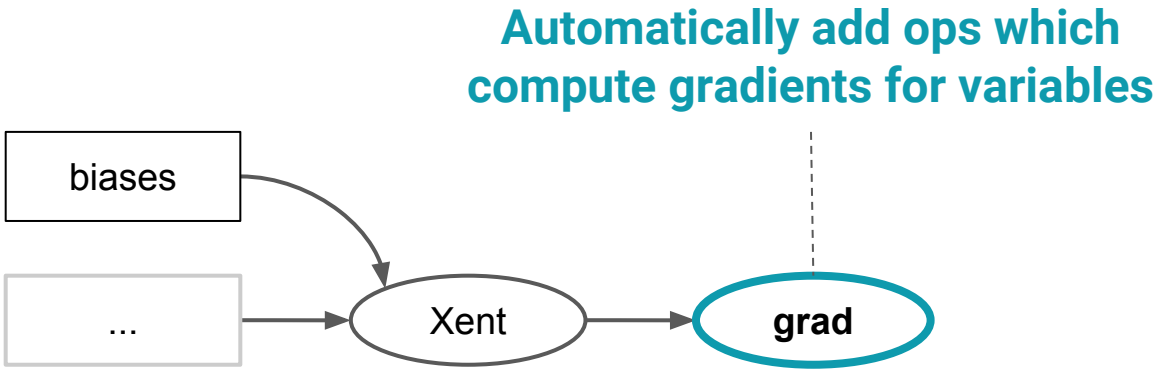
Graphs can be processed, compiled, remotely executed, assigned to devices.



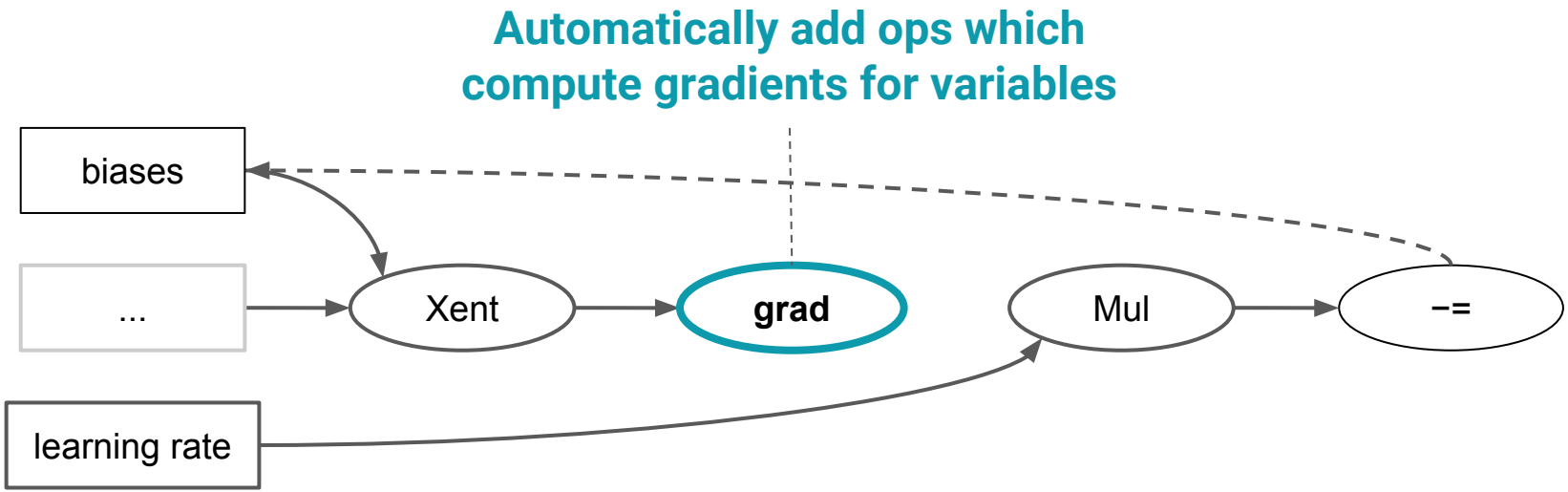
Graphs, with state



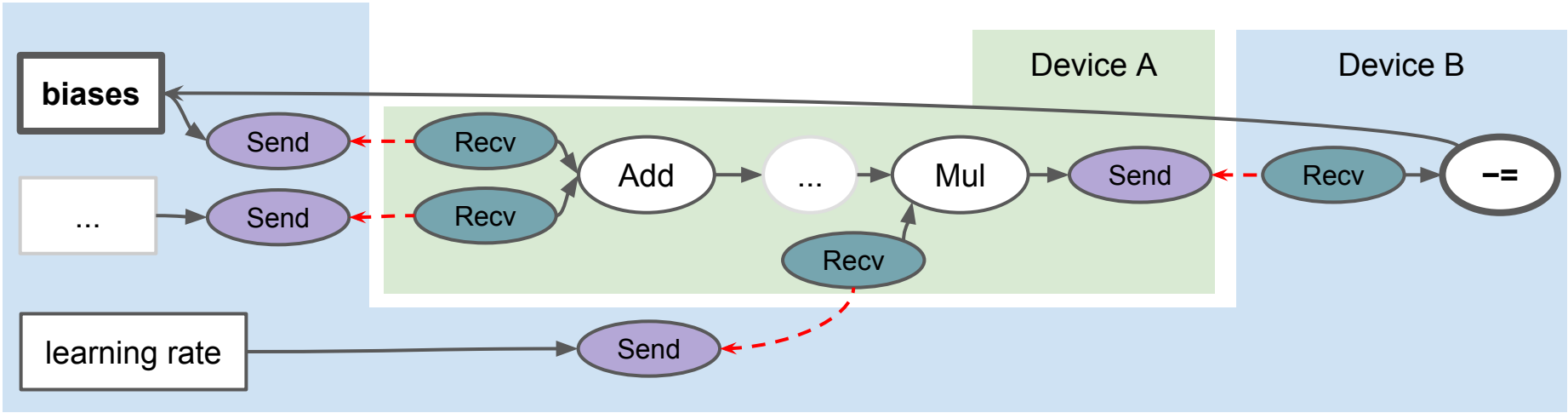
Automatic Differentiation



Automatic Differentiation



Graphs can be distributed and assigned to devices



Devices: Processes, Machines, CPUs, GPUs, TPUs, etc

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

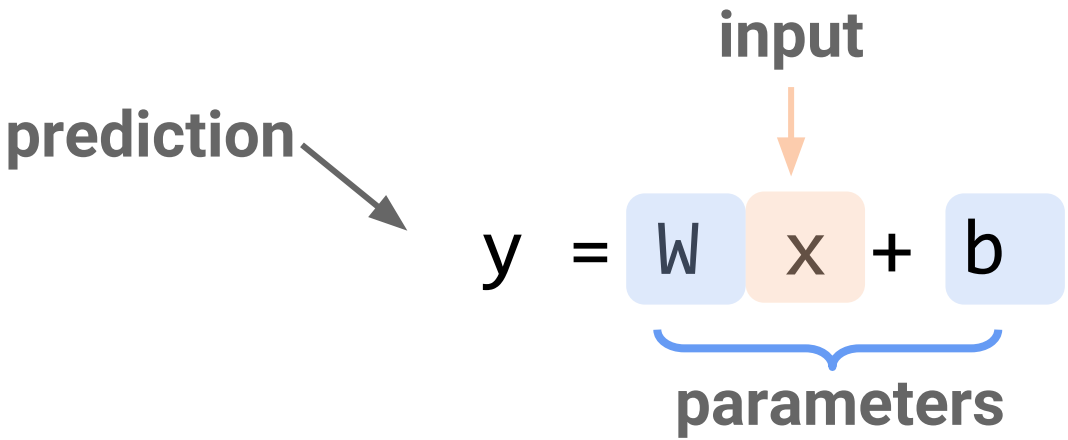
goo.gl/nrdsxM

Linear Regression

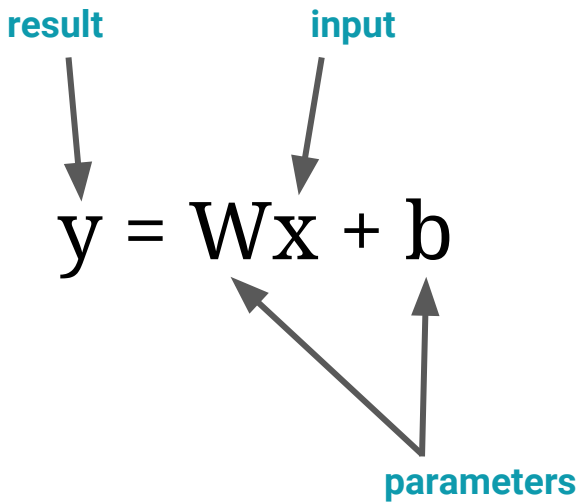
Inference, Loss, Training

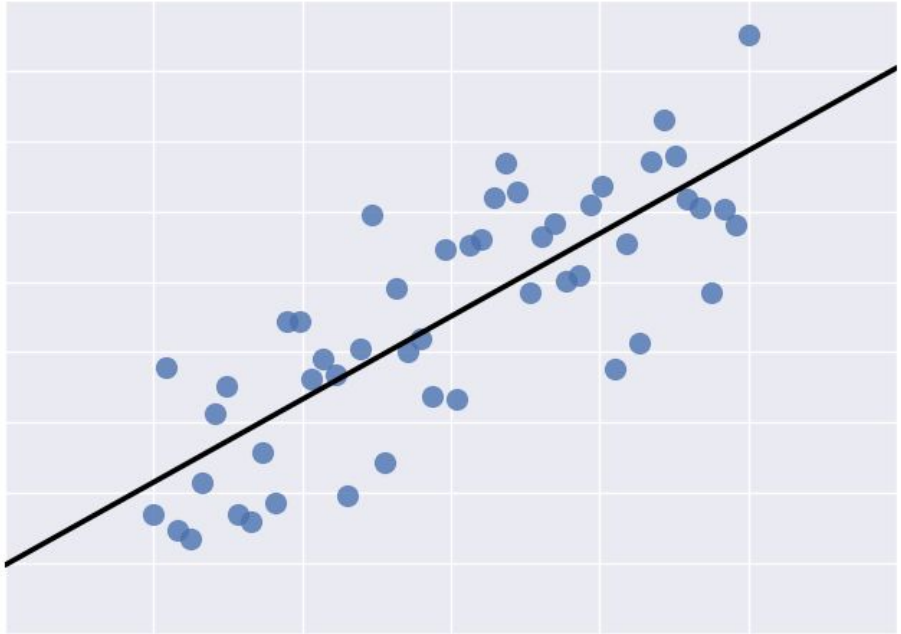
Machine Learning = Programming + Data

To “learn” means to find useful values for parameters.



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*.

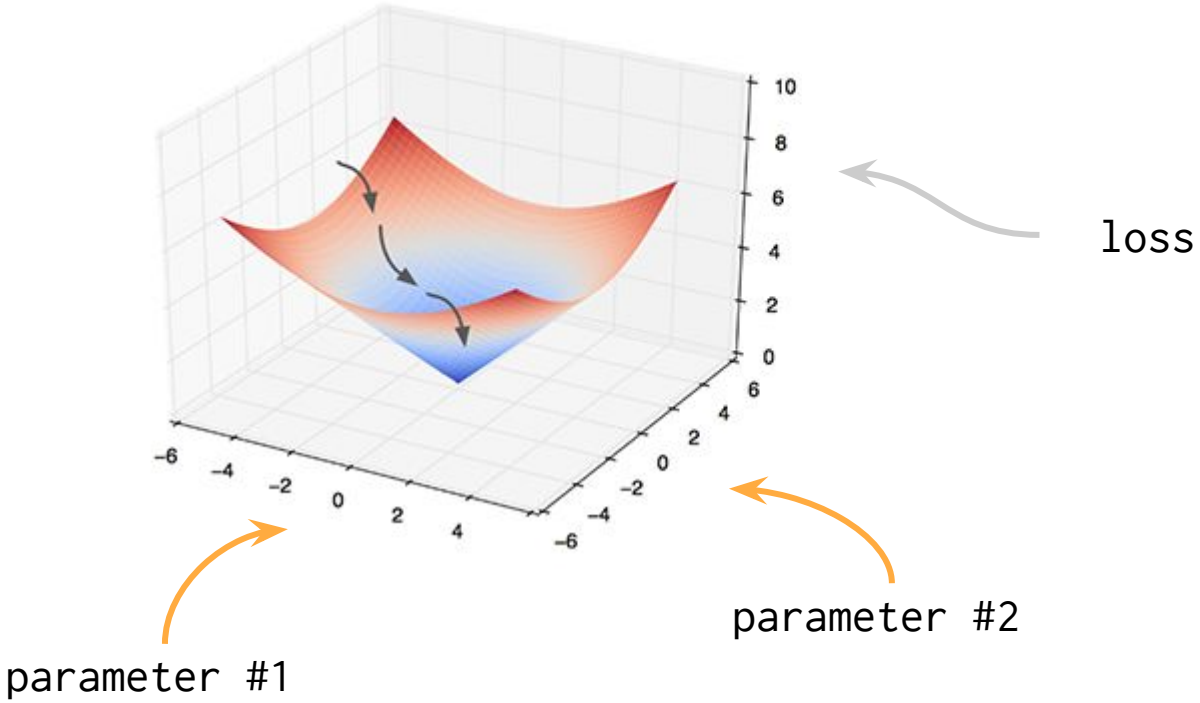
How do we find good parameter values?

Option 1: random guess

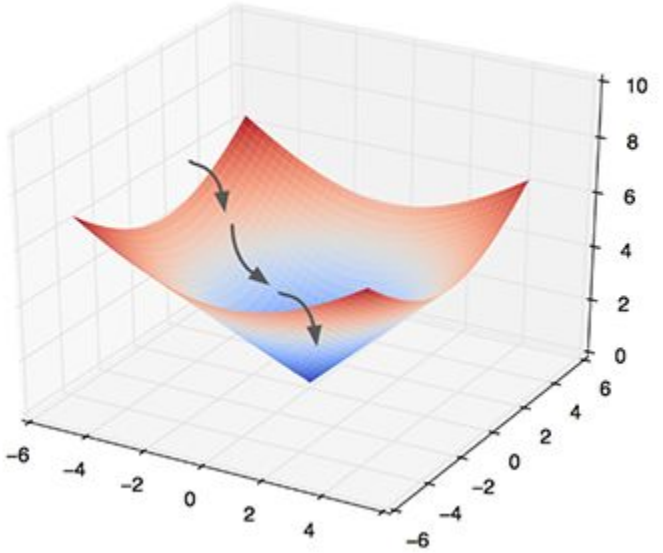
```
for _ in range(10,000)
   w,b = random(), random()
   acc = calculate_accuracy()
   if acc > best_acc:
     ...
```

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?

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

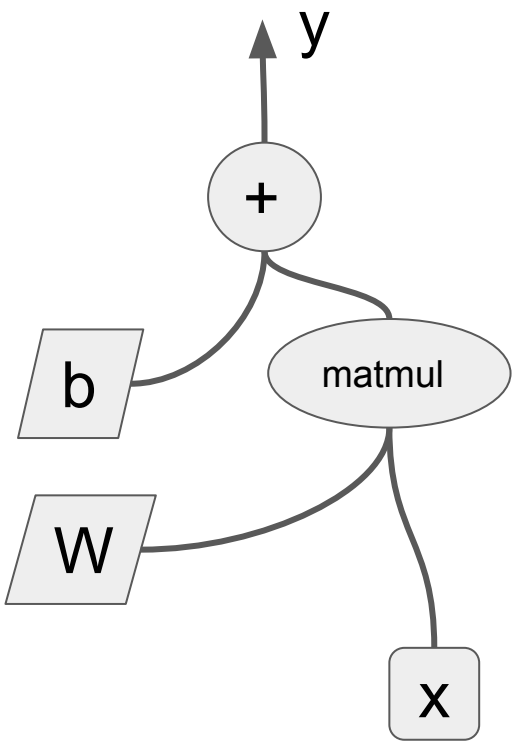
```
import tensorflow as tf

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

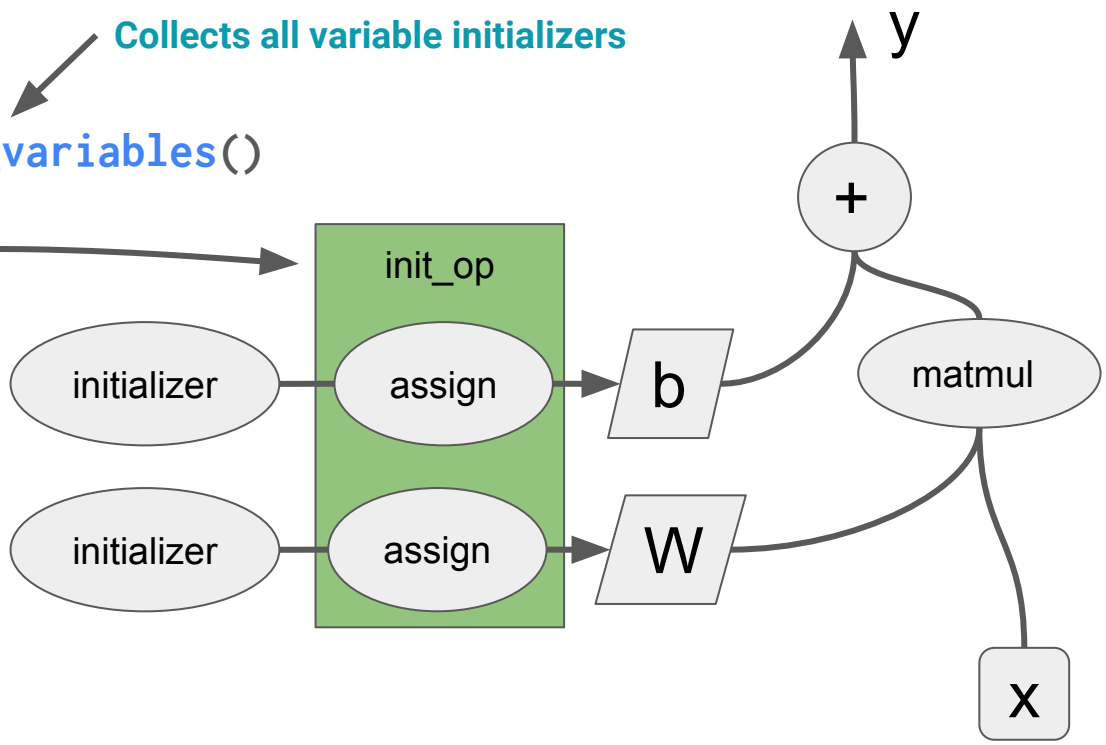
Collects all variable initializers

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

Makes an execution environment

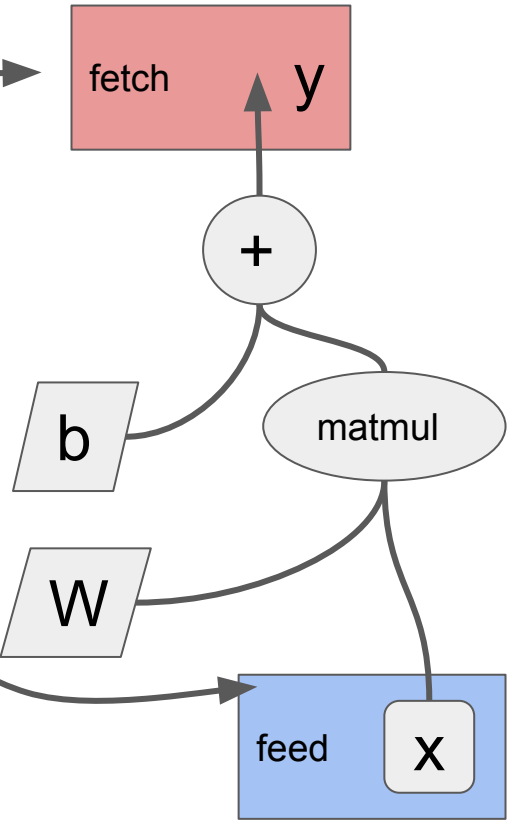
```
sess = tf.Session()

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

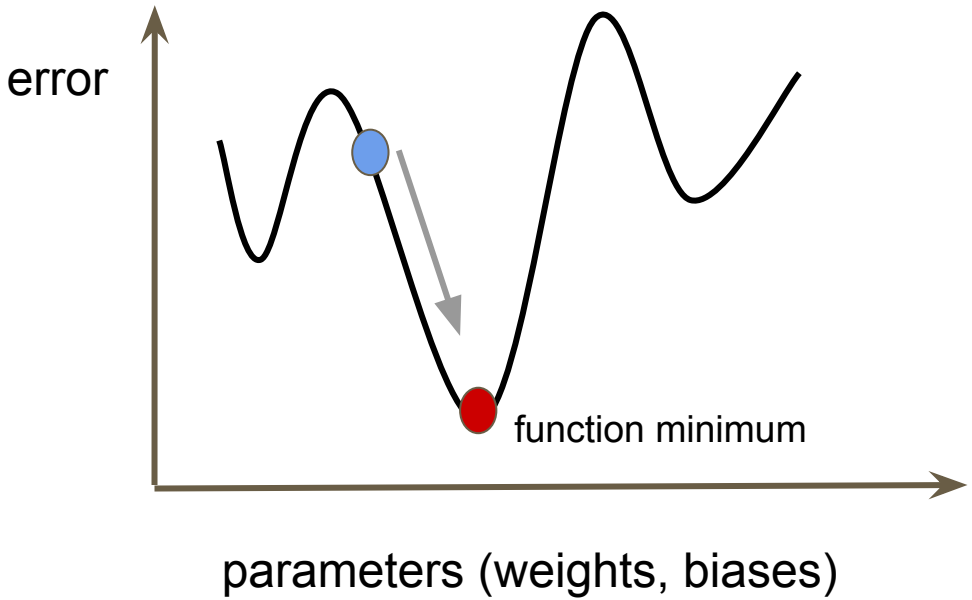
Define a Loss

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.

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

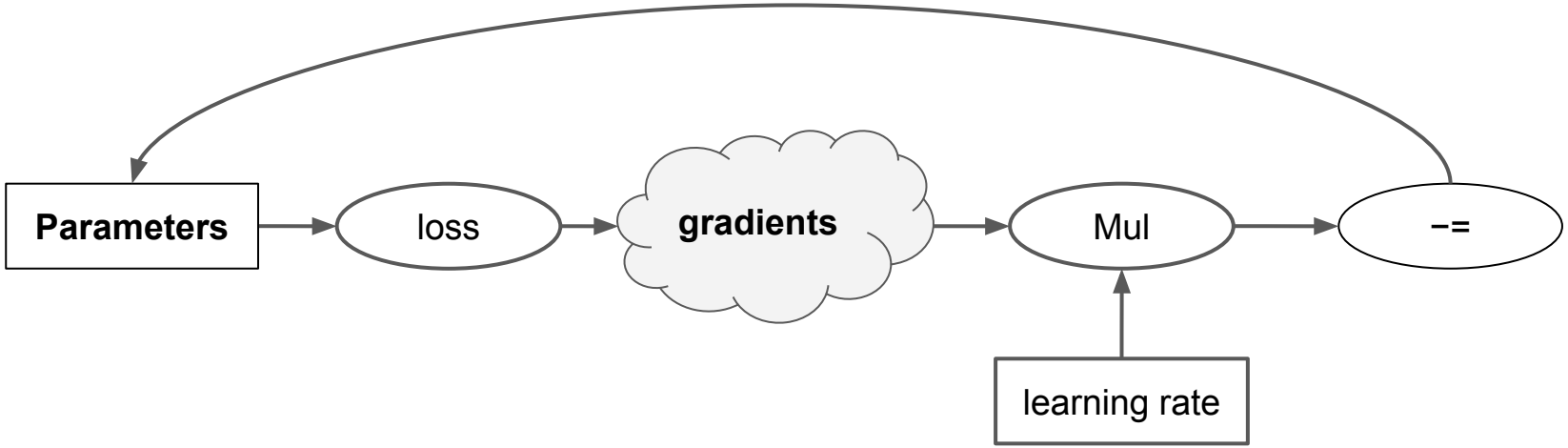
$$b \leftarrow b - \eta \, (dL/db)$$

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_in[i],
                               y_label: y_in[i]})
```

Define a loss

Create an optimizer

Op to minimize the loss

Initialize variables

Iteratively run the training op

Linear Regression
2_linear_regression.ipynb

goo.gl/nrdsxM

Demo: TensorBoard

goo.gl/nrdsxM

MNIST

Classification vs. Regression

Regression

- Predict a number (a price, or the probability it'll rain)

Classification

- Predict a category ("apple", "orange")

MNIST “the only benchmark that matters”

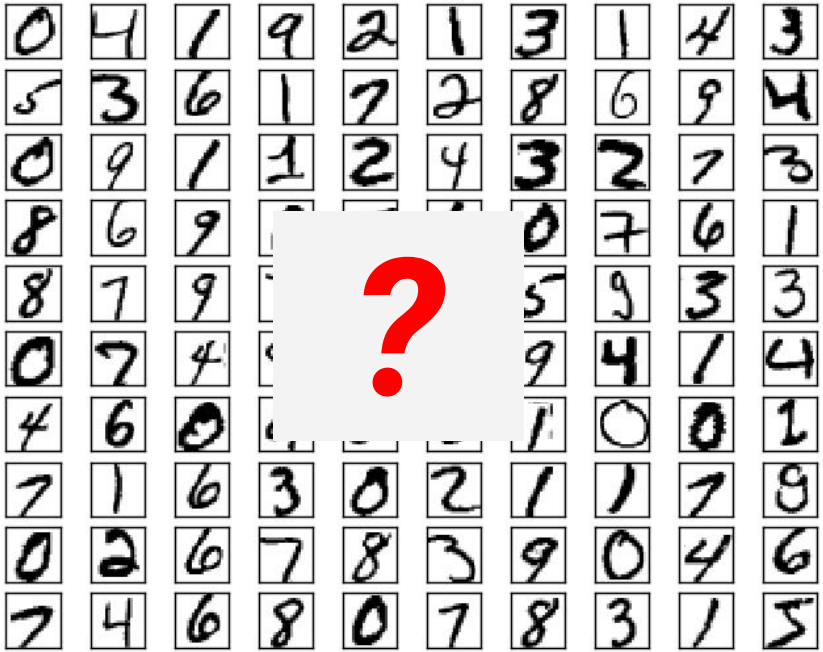
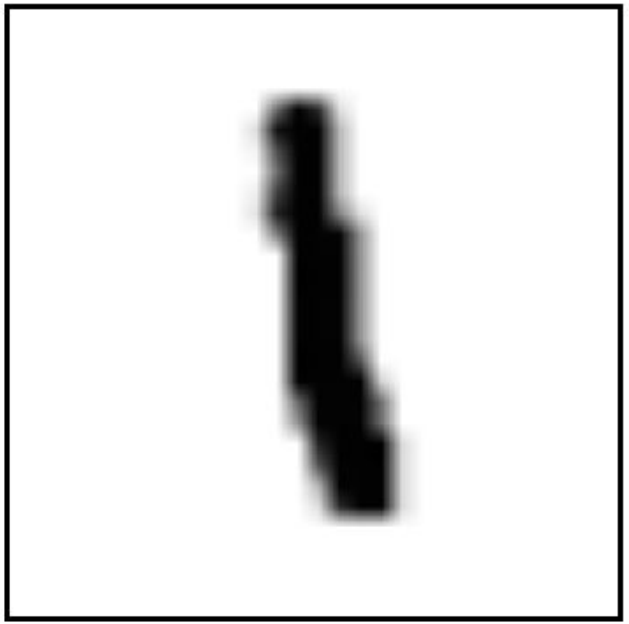


Image from https://github.com/mnielsen/neural-networks-and-deep-learning

We see



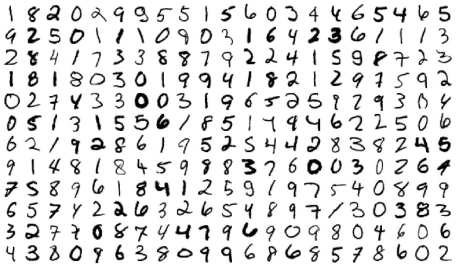
Computer “sees”

$$\approx$$

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

Train / test split

Original: 65,000



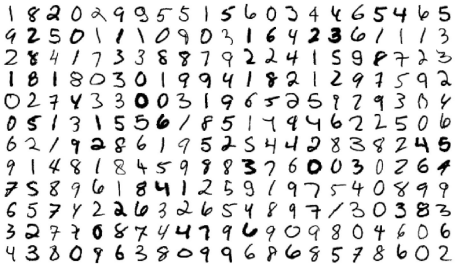
Images

Labels

5 0 4 1 9 2

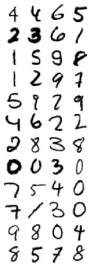
Train / test split

Original: 65,000



Train: 55,000

Test: 10,000



Now we just need...

An image of a handwritten digit

```
def classify (pixels):
  # ...
  # ...
  # ...
  return 8
```

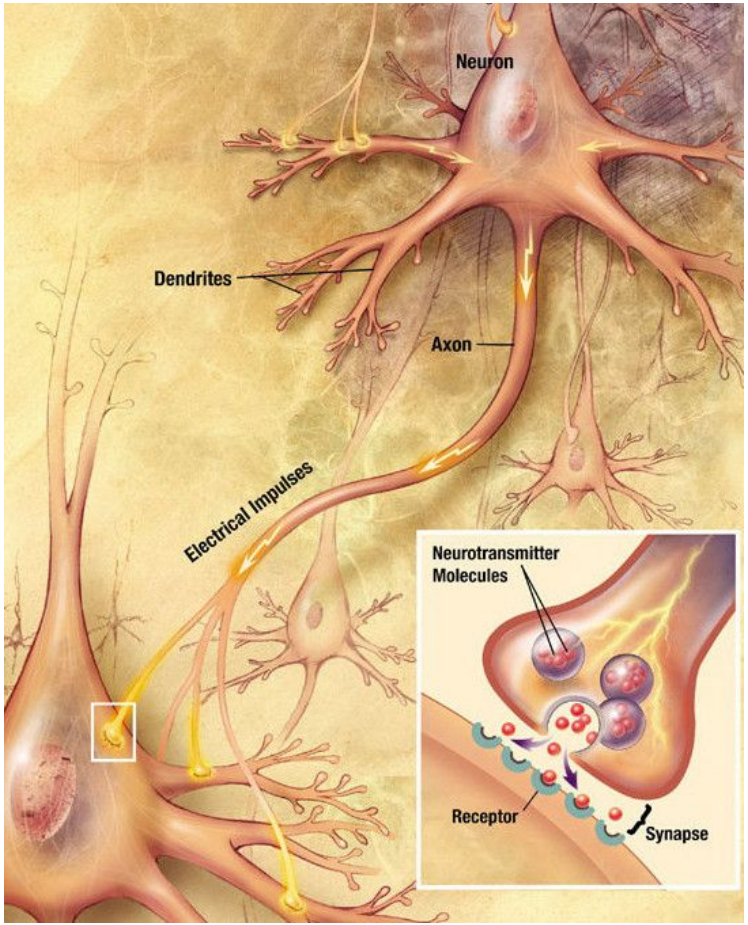
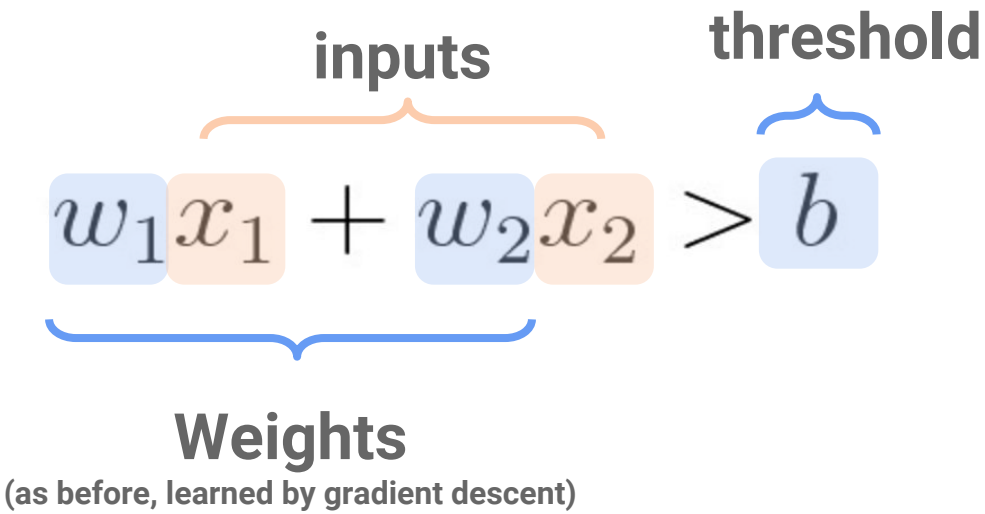
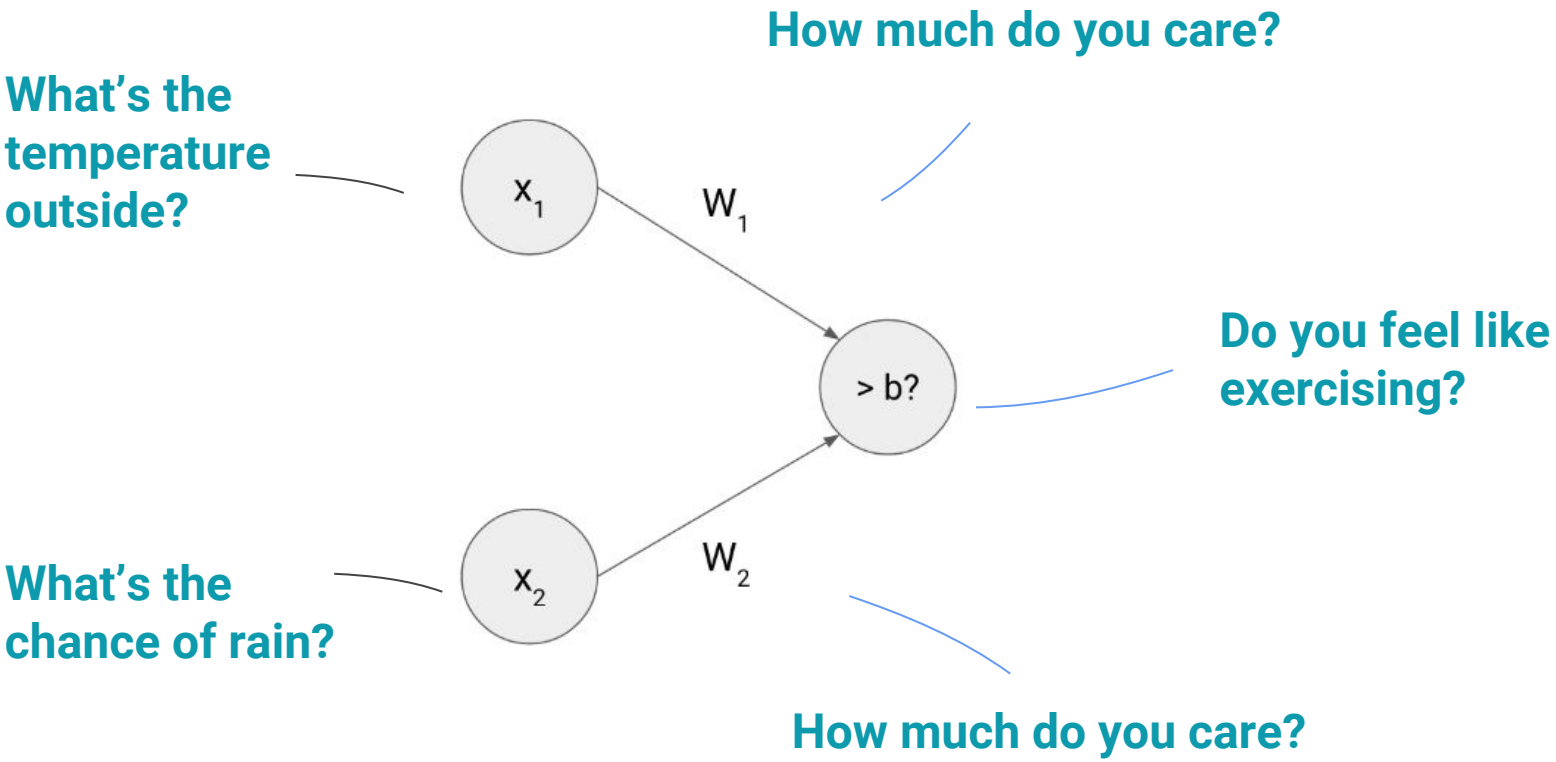


Image from [Wikipedia]

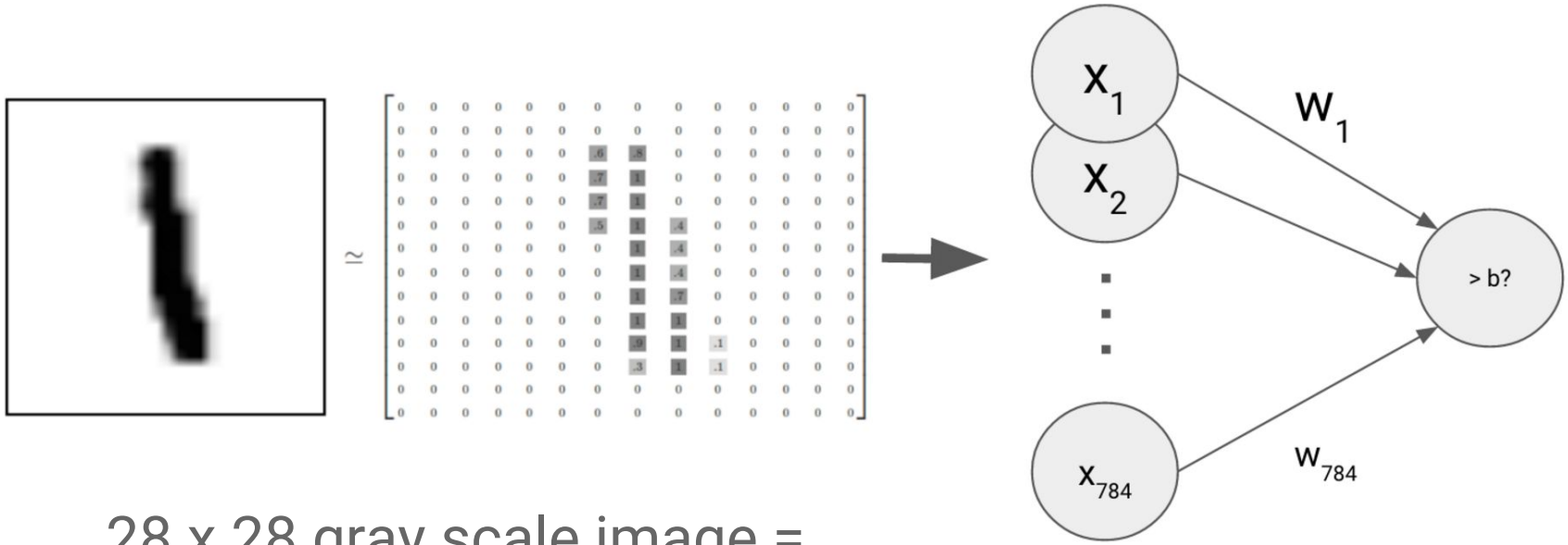
A “neuron” classifies input into two types



Should you play soccer today?



A classifier for a single digit



28 x 28 gray scale image =

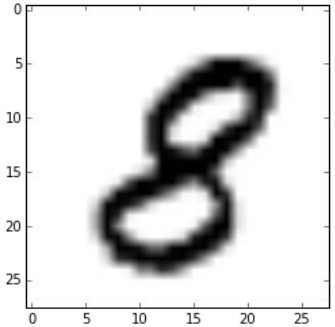
784 inputs = 784 weights

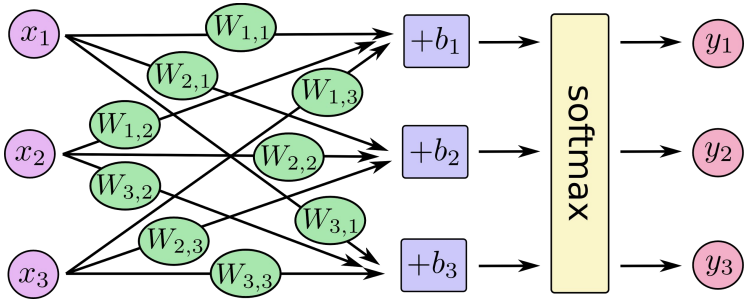
$$\sum_{i=0}^{n} X_i W_i > b$$

A classifier for each digit

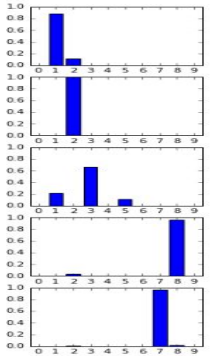
784 weights for each digit, so 784 x 10 total

input vector
(pixel data)

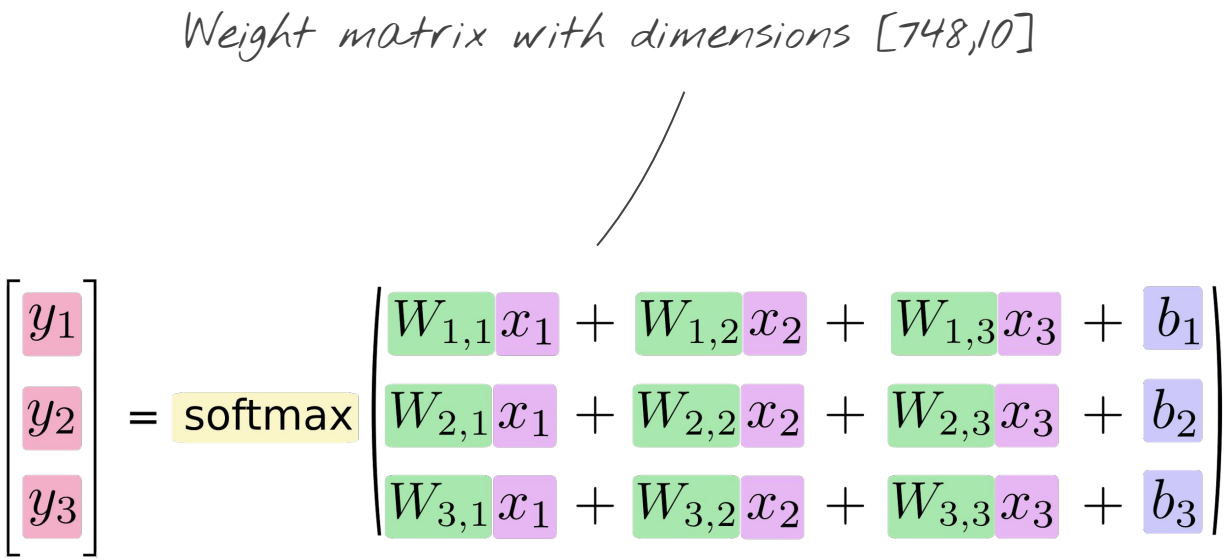




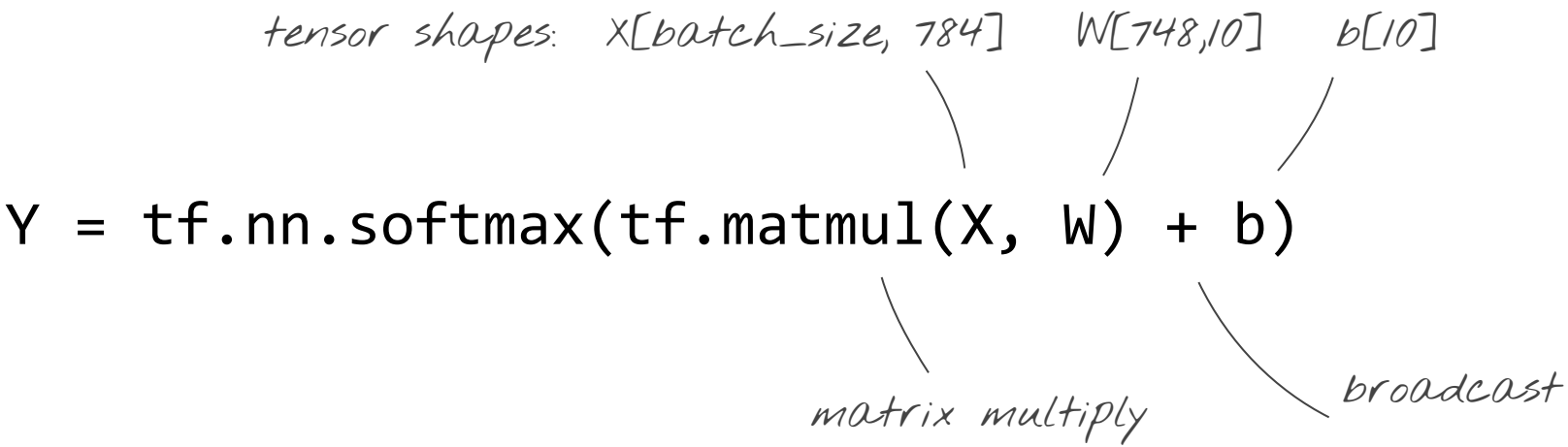
output vector
(probability of
each digit))



Written as a matrix multiply



In TensorFlow



```
# define placeholders
x = tf.placeholder(tf.float32, [None, NUM_PIXELS], name="pixels")
y_ = tf.placeholder(tf.float32, [None, NUM_CLASSES], name="labels")
```

```
# Define the model
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
```

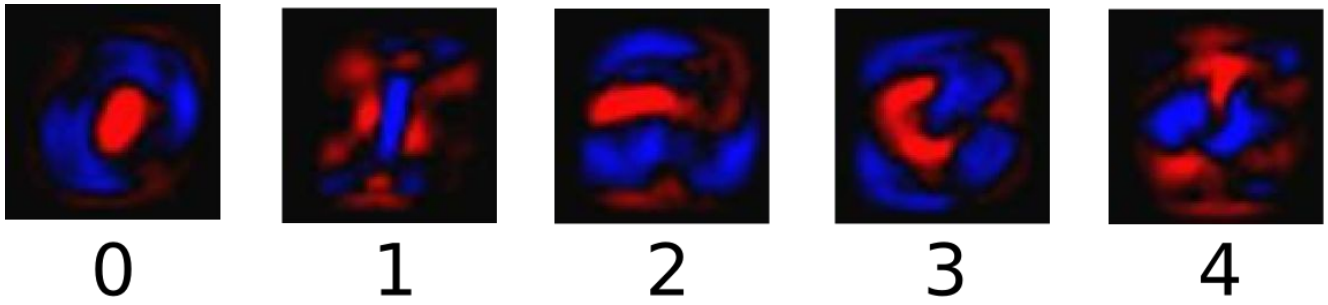
```
# Define loss and optimizer
loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(y, y_))
train_step =
   tf.train.GradientDescentOptimizer(LEARNING_RATE).minimize(loss)
```

```
# Initialize variables after the model is defined
sess.run(tf.initialize_all_variables())

# 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})
```

```
# 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}))
```

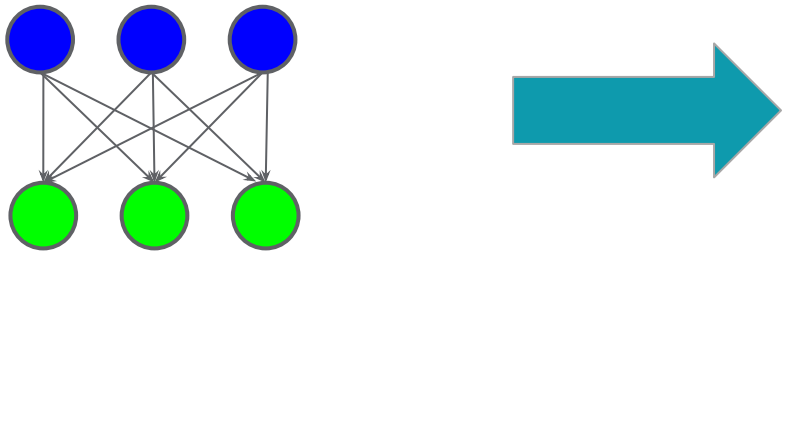
3_basic_mnist.ipynb

goo.gl/nrdsxM

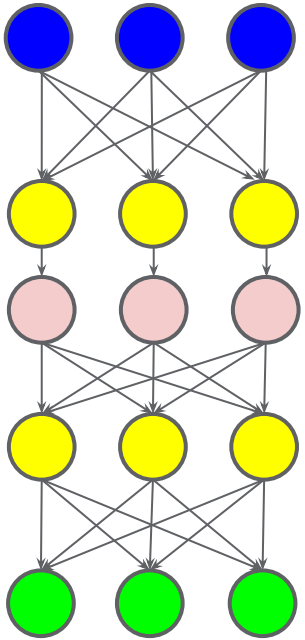

0
1
2
3
4
5
6
7
8
9

Going Deeper

Hidden layers



Hidden layers



Input (pixels)

Weights and biases 1

Hidden Layer 1

Activation Function

Weights and biases 2

Hidden Layer 2

Output

```
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
```

Learning 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

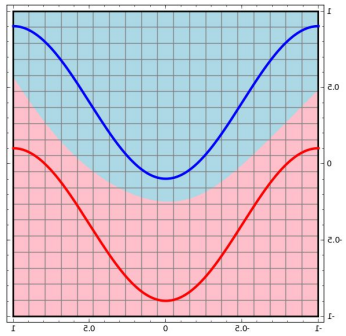
Module 1: Neural Networks

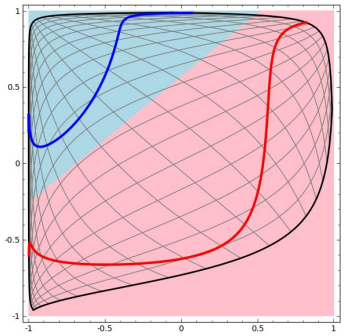
Image Classification: Data-driven Approach, k-Nearest Neighbor, train/val/test splits

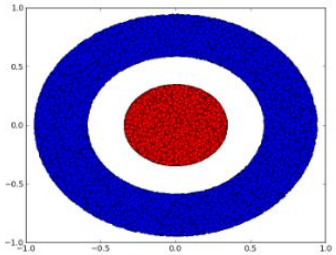
L1/L2 distances, hyperparameter search, cross-validation

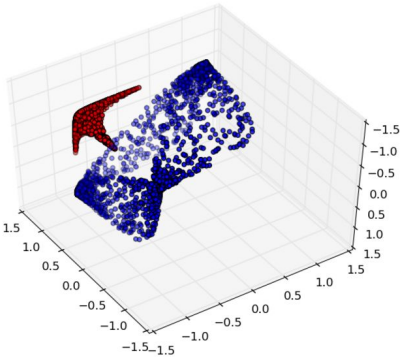
Linear classification: Support Vector Machine, Softmax

Learning more: colah.github.io









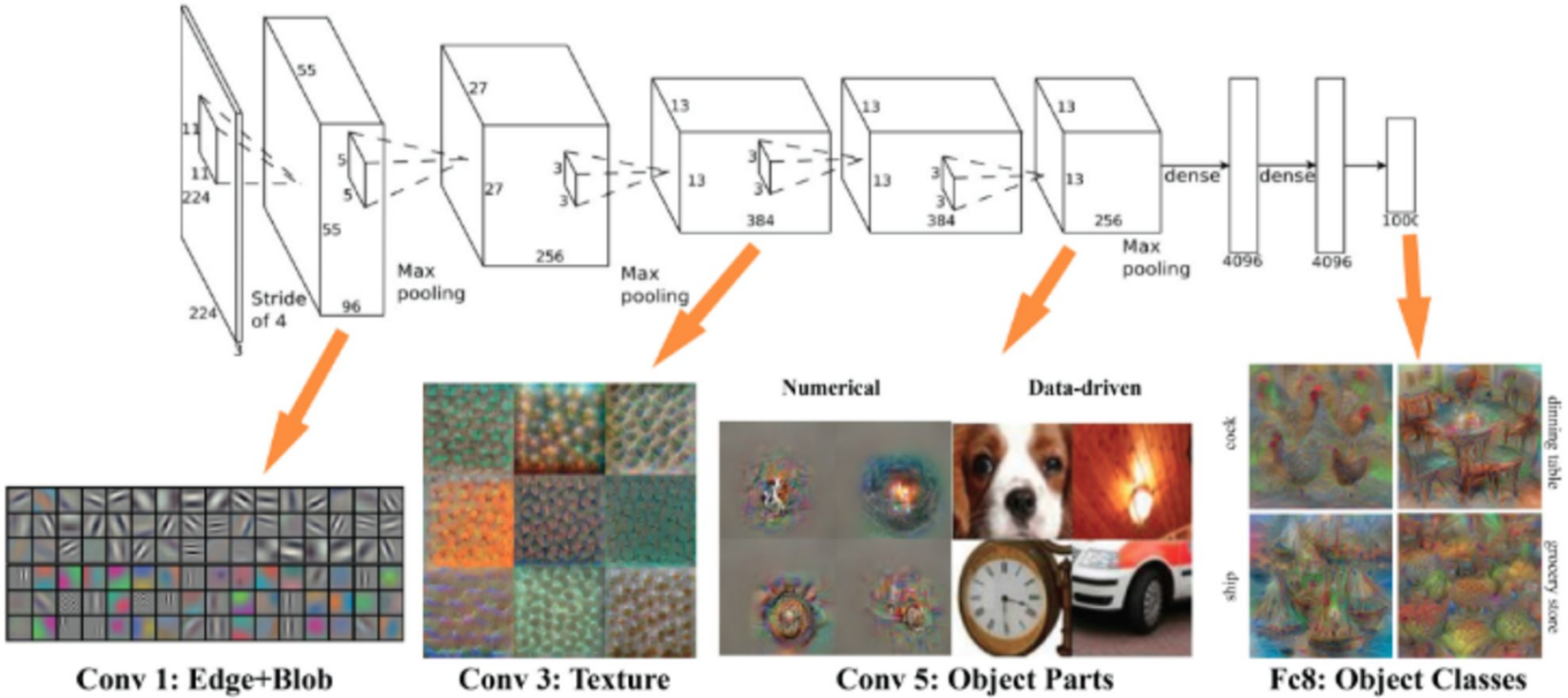
From: Neural Networks, Manifolds, and Topology, colah's blog

Progression and caveats

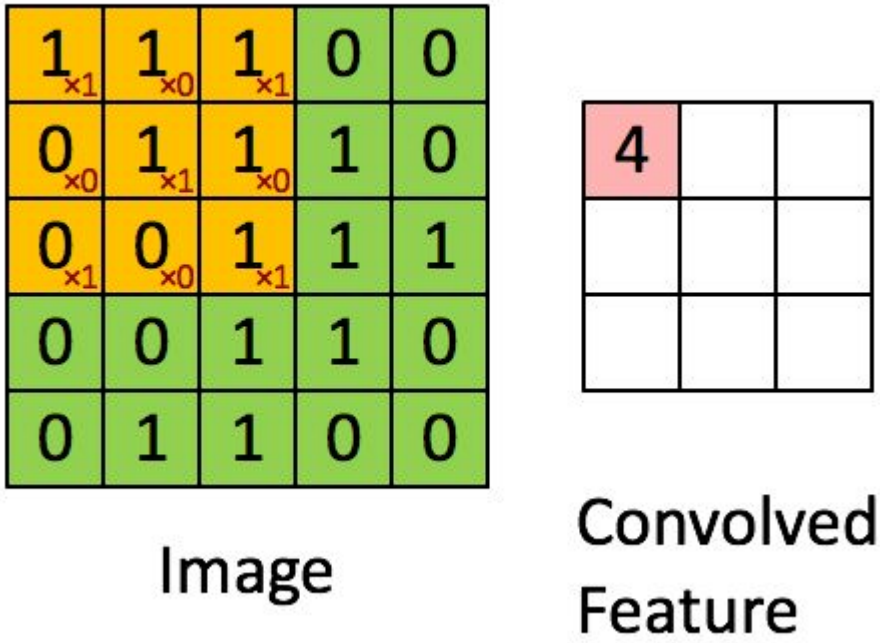
- Linear ~90%
- Two-layer DNN ~96%
- ConvNet ~99% (close to the state of the art on this toy problem)

Should you focus on accuracy?

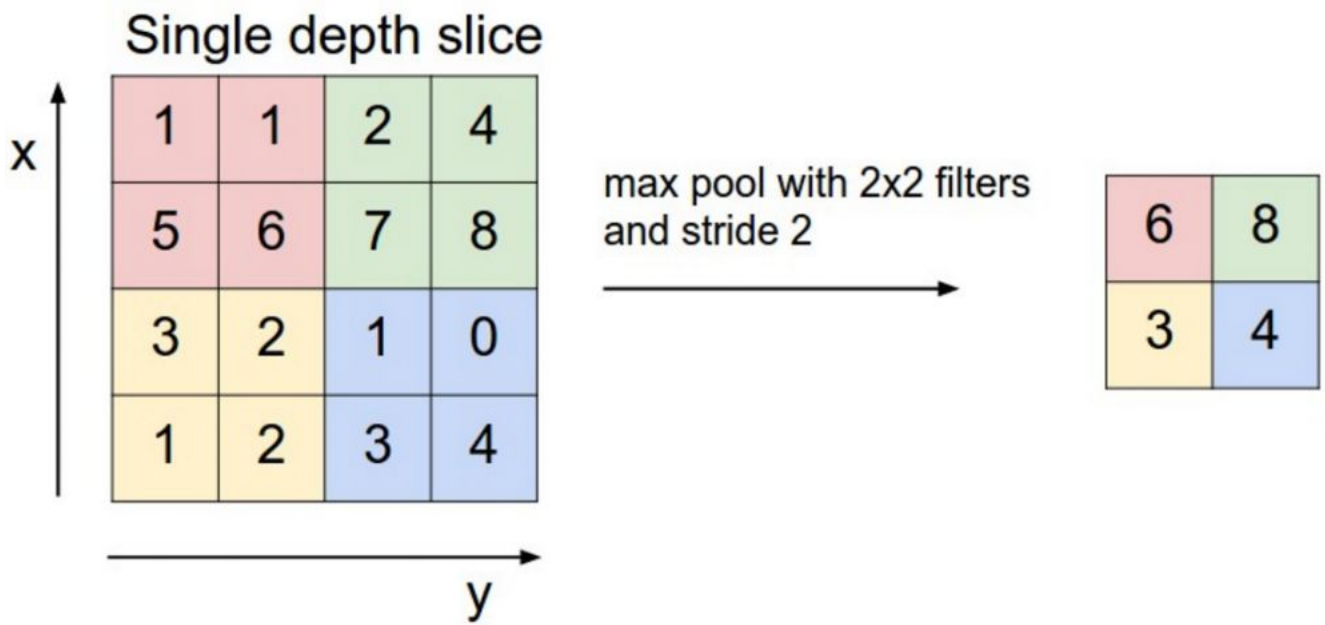
- What matters is designing a proper experiment.



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



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

4_deep_mnist.ipynb

goo.gl/nrdsxM

Art

Image: Leonid Afremov – Rain Princess

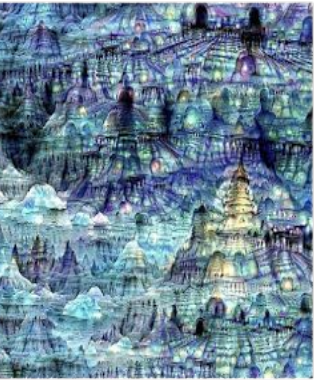
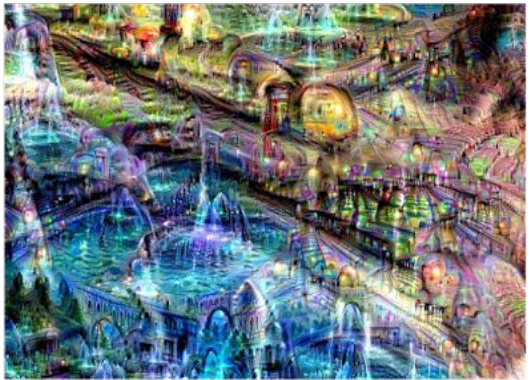
Image: Stephen Wilkes, National Geographic

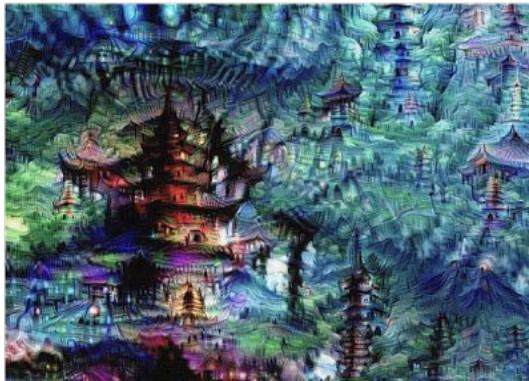

goo.gl/M5hiYY
goo.gl/owF2z9

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

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





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


goo.gl/OCYseb

Try Style Transfer or Deep Dream

goo.gl/M5hiYY
goo.gl/owF2z9
goo.gl/OCYseb

Using Pretrained Models

Remember Inception?

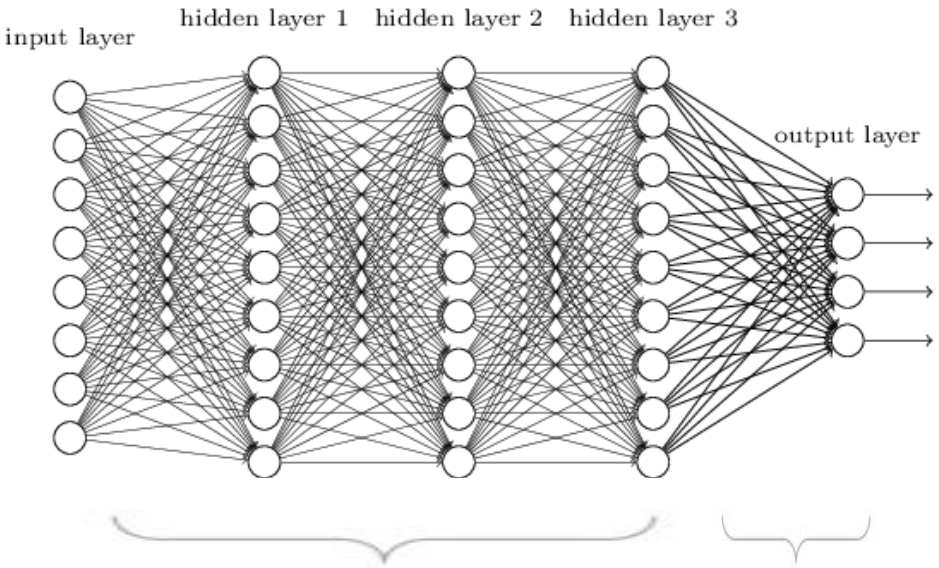
- Load the graph and learned weights; use the model
- 1,000 categories: pandas, cats, bears
- Performs “about” as well as people on this task

Images via Wikipedia

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

Demo: classifying images with Inception

Transfer Learning



Most of the network is unchanged

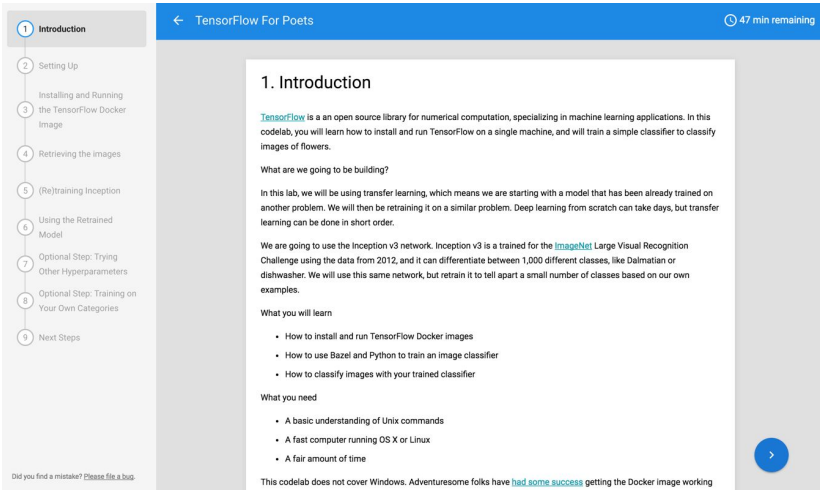
Only the last layer of weights and the outputs are updated

Image: neuralnetworksanddeeplearning.com

Advantages

- Train in minutes vs weeks
- Only need a handful of new training data
- Reuse learned “features”
- Two ways to do this
  a. Directly in TensorFlow (tutorial)
  b. TensorFlow for Poets

TensorFlow for Poets



Codelab - goo.gl/xGsB9d

Thanks, Pete Warden!

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

TensorFlow for Poets

goo.gl/xGsB9d

Using Higher-level APIs

tf.contrib.learn

- Implements a scikit-learn inspired API
- Creates the graph for you behind the scenes

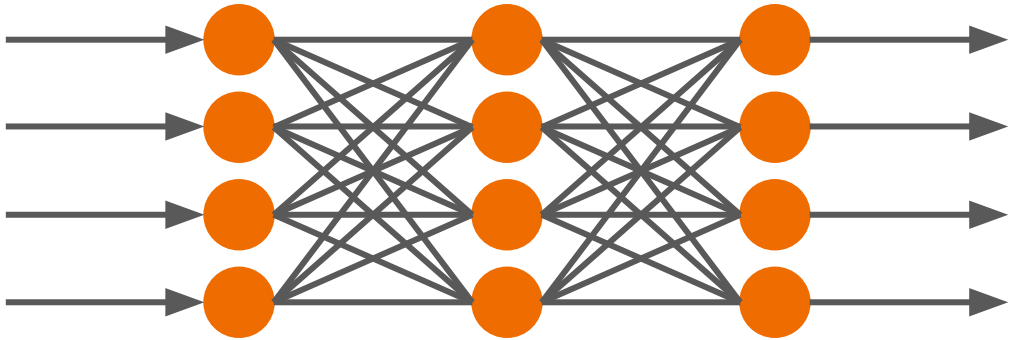
- https://www.tensorflow.org/versions/master/tutorials/tflearn/index.html#tf-contrib-learn-quickstart

5_mnist_tf_contrib_learn.ipynb

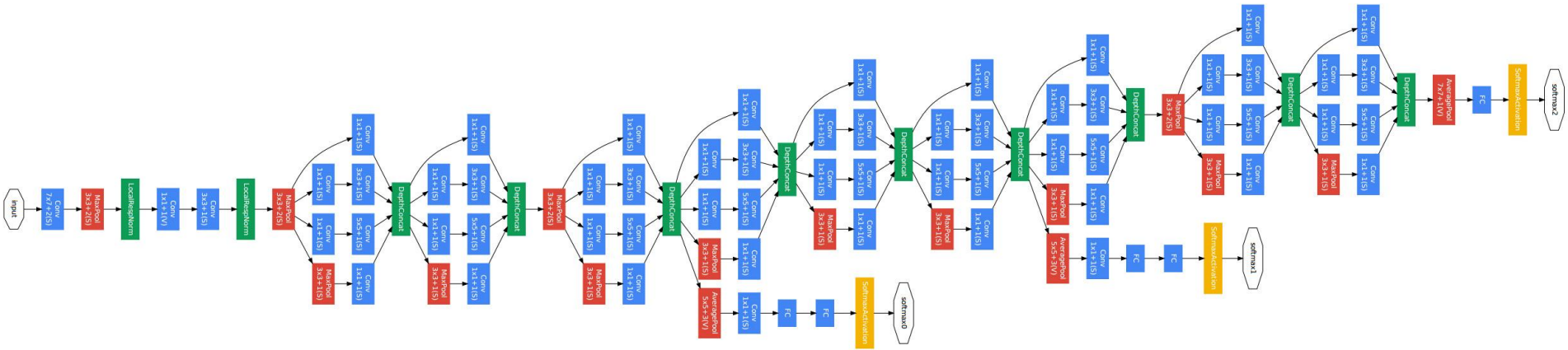
goo.gl/nrdsxM

But why?

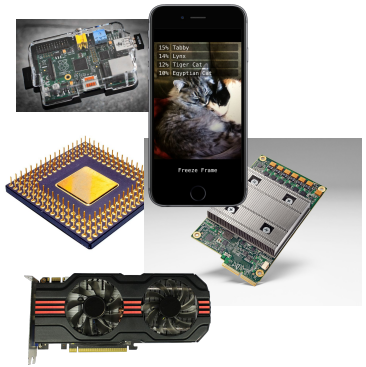
Neural Networks, yesterday



Remember Inception?

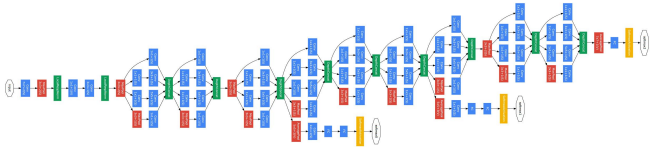


Machine Learning gets complex quickly



Heterogenous systems

Distributed systems



Modeling complexity

Next steps

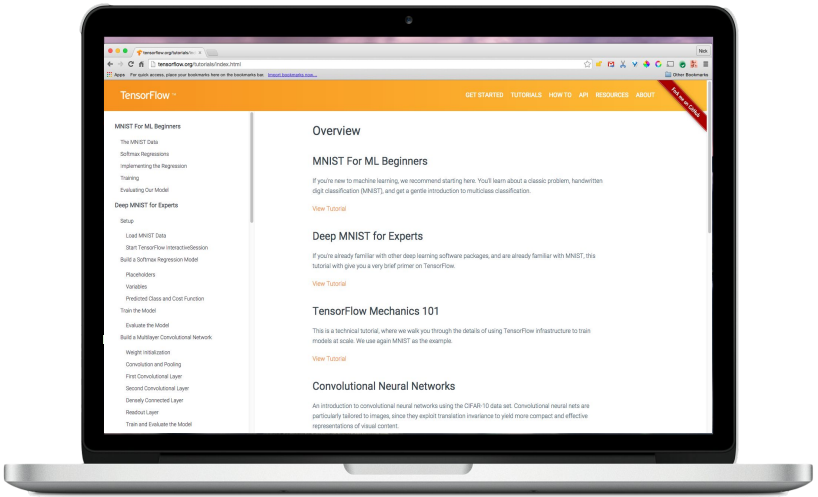
Tutorials and code
tensorflow.org

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!

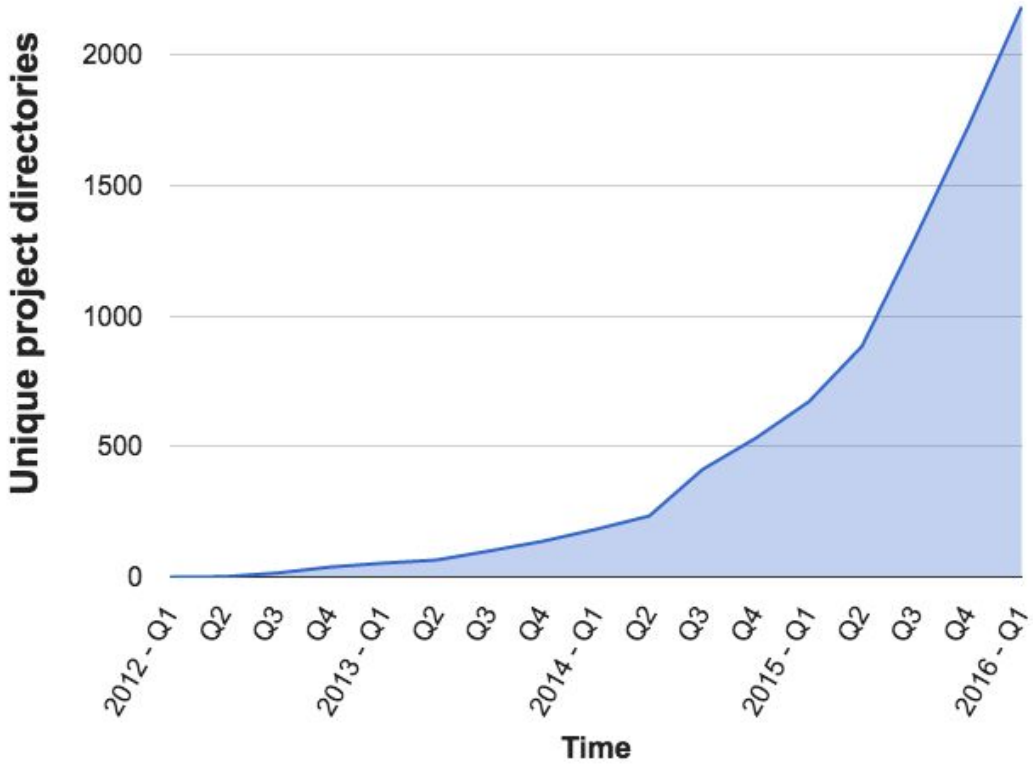
Josh Gordon
@random_forests

Extras

Deep Learning at Google

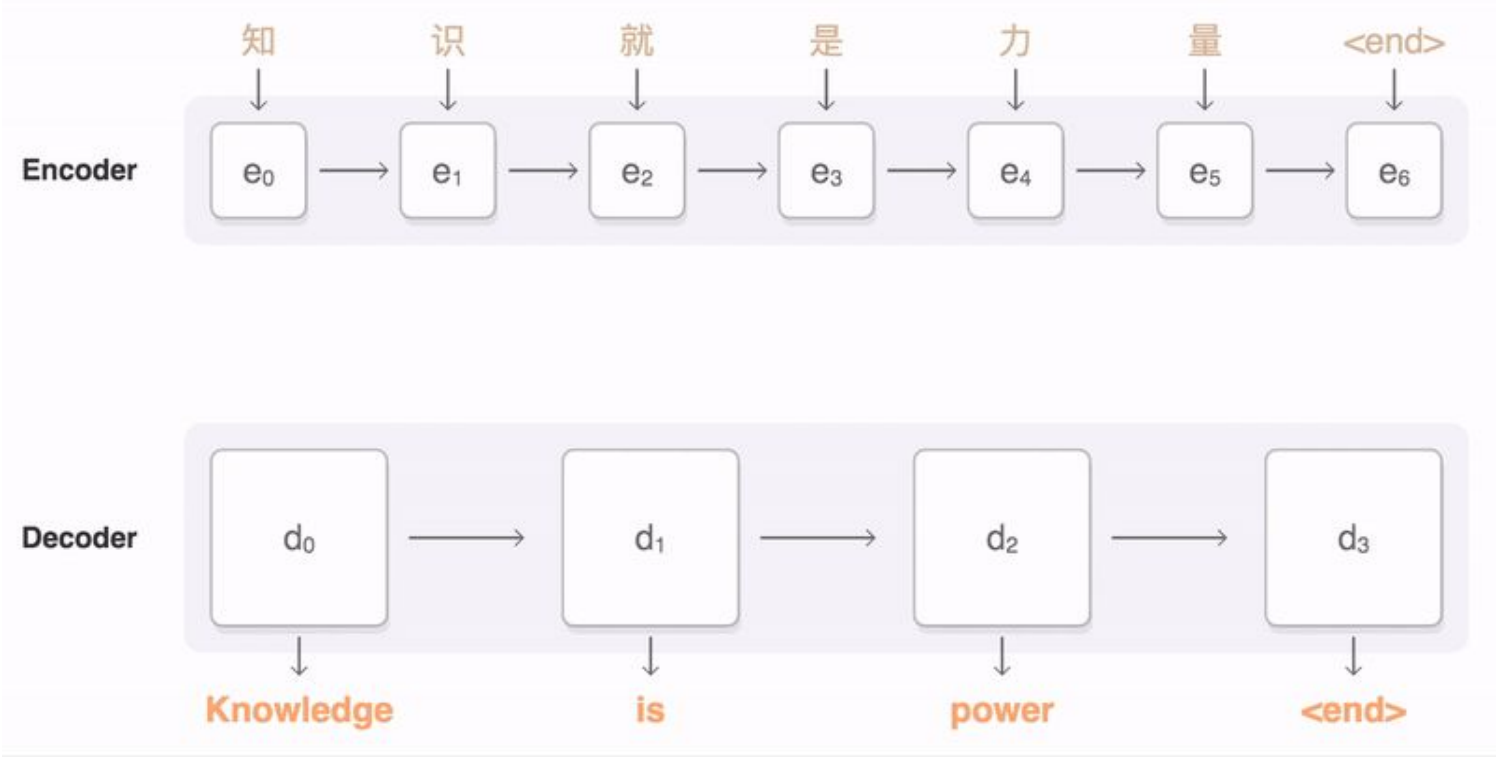
Growing Use of Deep Learning at Google

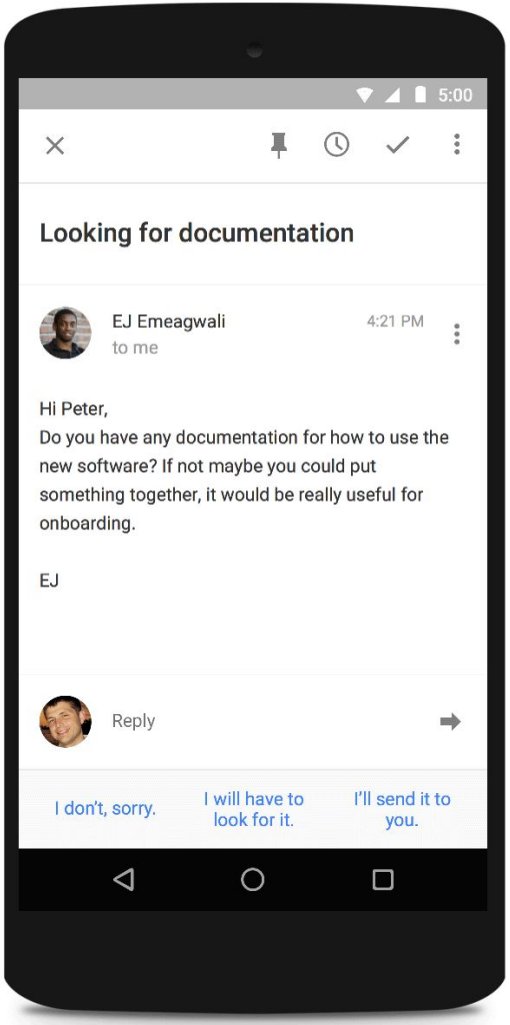
of directories containing model description files




EXIT

Google Neural Machine Translation



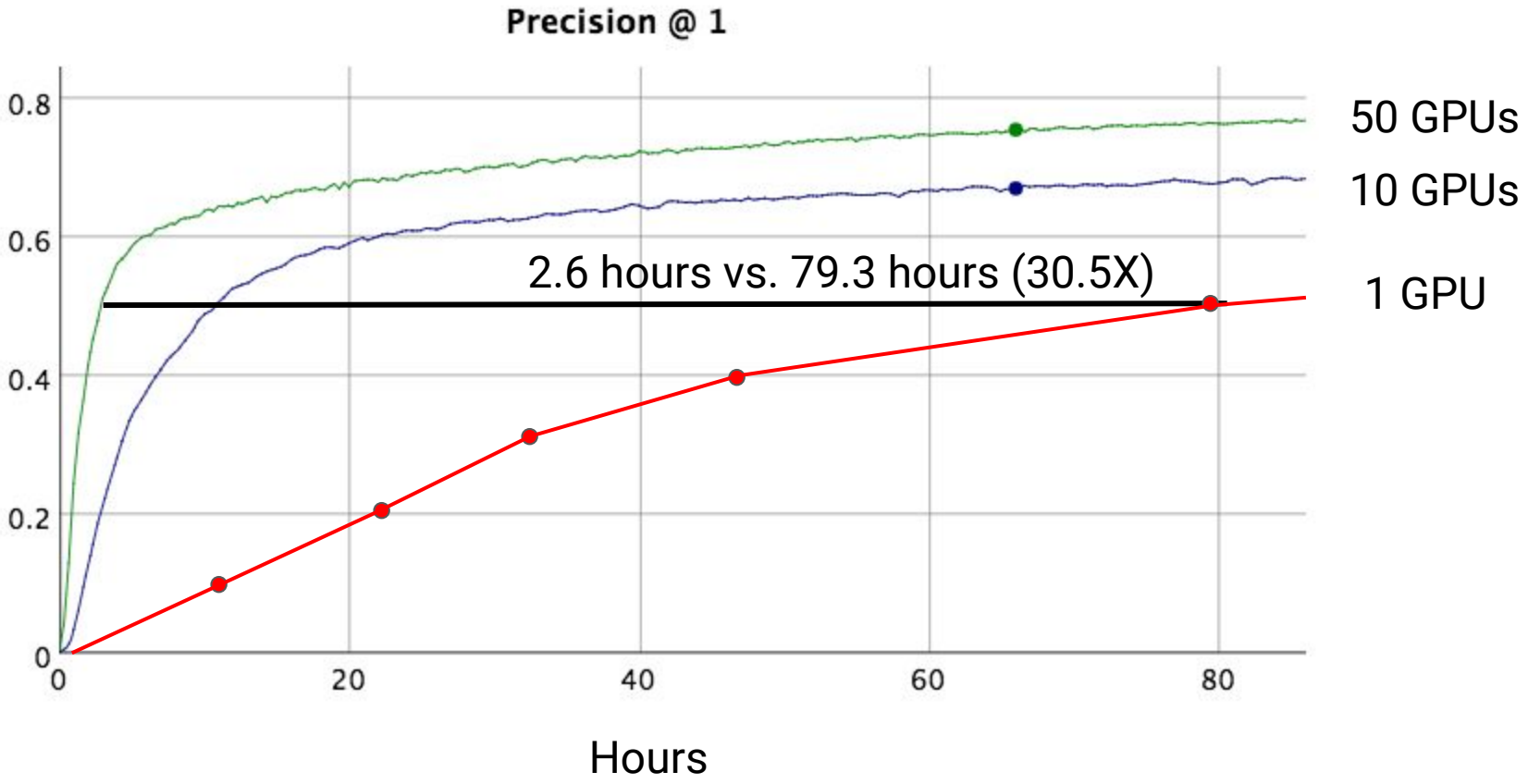


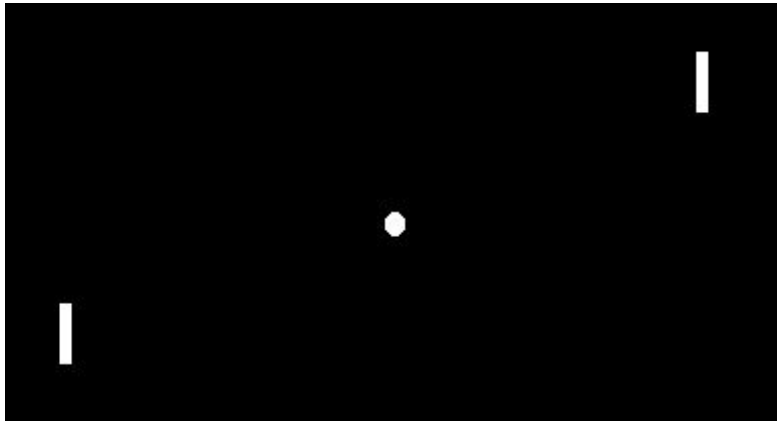
Smart reply in Inbox by Gmail

10%

of all responses sent on mobile

Image Model (Inception) Synchronous Training



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AlphaGo

BBC News Sport Weather iPlayer TV Radio More Search

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

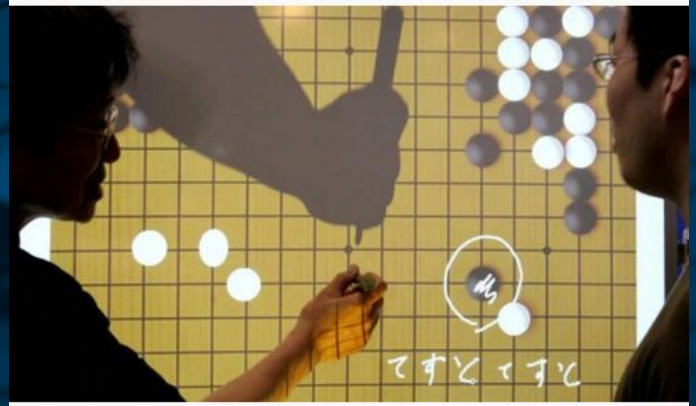
How did they do it?

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

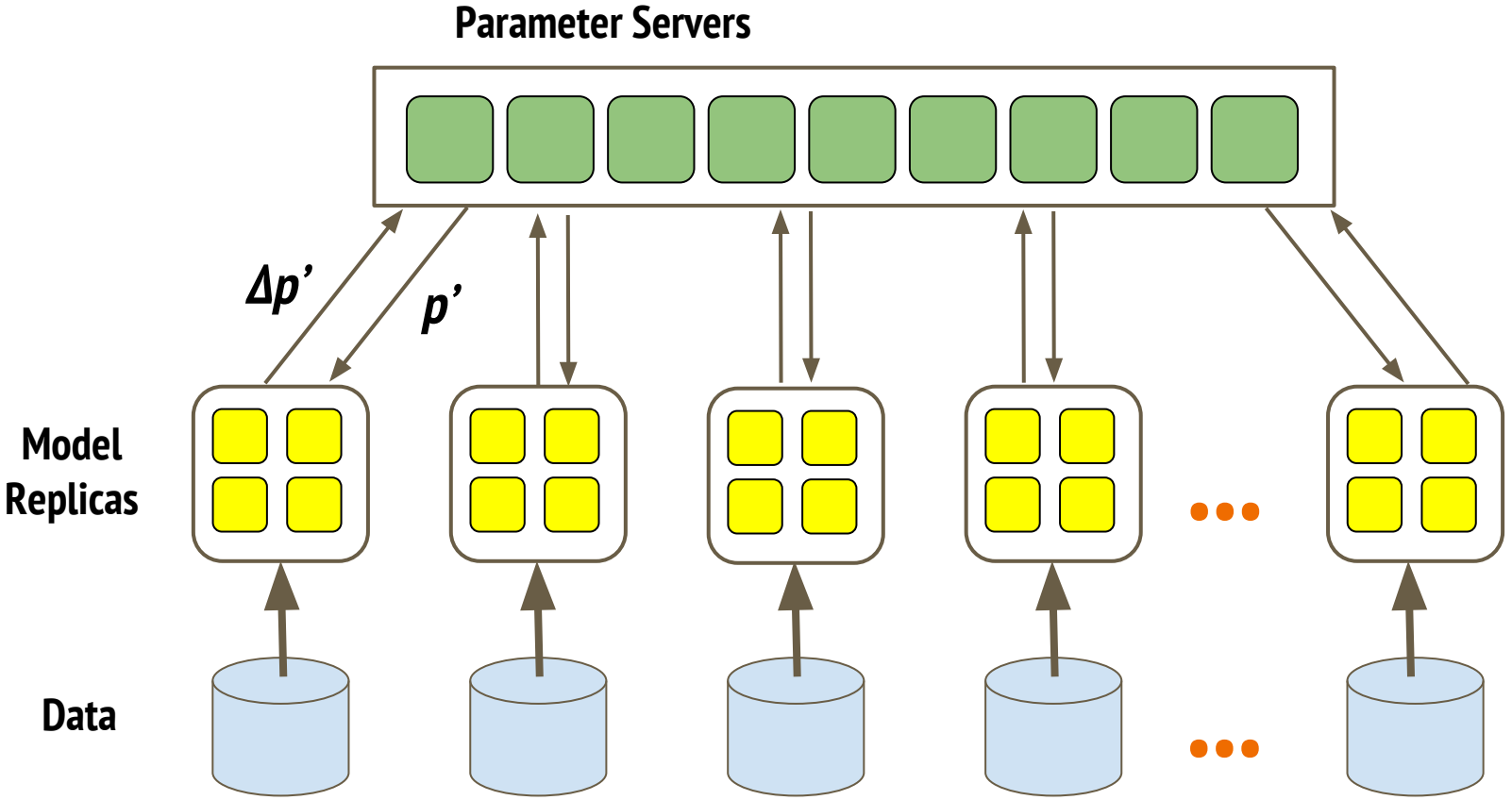
By Mike Murphy | January 27, 2016



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.

Data Parallelism



Input Pipelines with Queues