



# Intro to TensorFlow

## Singapore, December 2016



**Josh Gordon**  
@random\_forests



**Wolff Dobson**  
@greenexecutive

# Agenda

**1pm - 1:30pm**

- Fibonacci sequence

**1:30pm - 2pm**

- Linear regression

**2:15pm to 3pm**

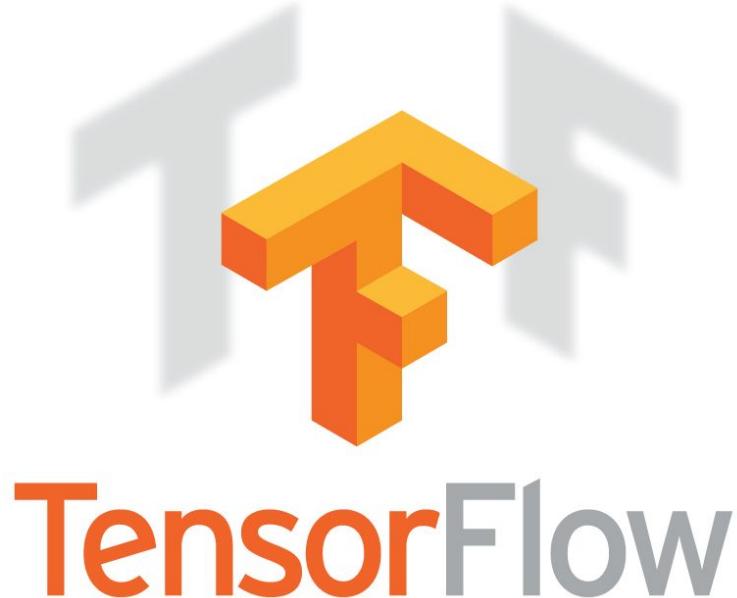
- Create your own artwork, or train your own image classifier

**3pm to 4pm**

- Basic and Deep MNIST, and tf.contrib.learn

**cd tensorflow-workshop; git pull**

# TensorFlow



- Fast, flexible, and scalable open-source machine learning library
- For research and production
- Runs on CPU, GPU, Android, iOS, Raspberry PI
- Apache 2.0 license

<https://research.googleblog.com/2016/11/celebrating-tensorflows-first-year.html>

# Cumulative GitHub Stars



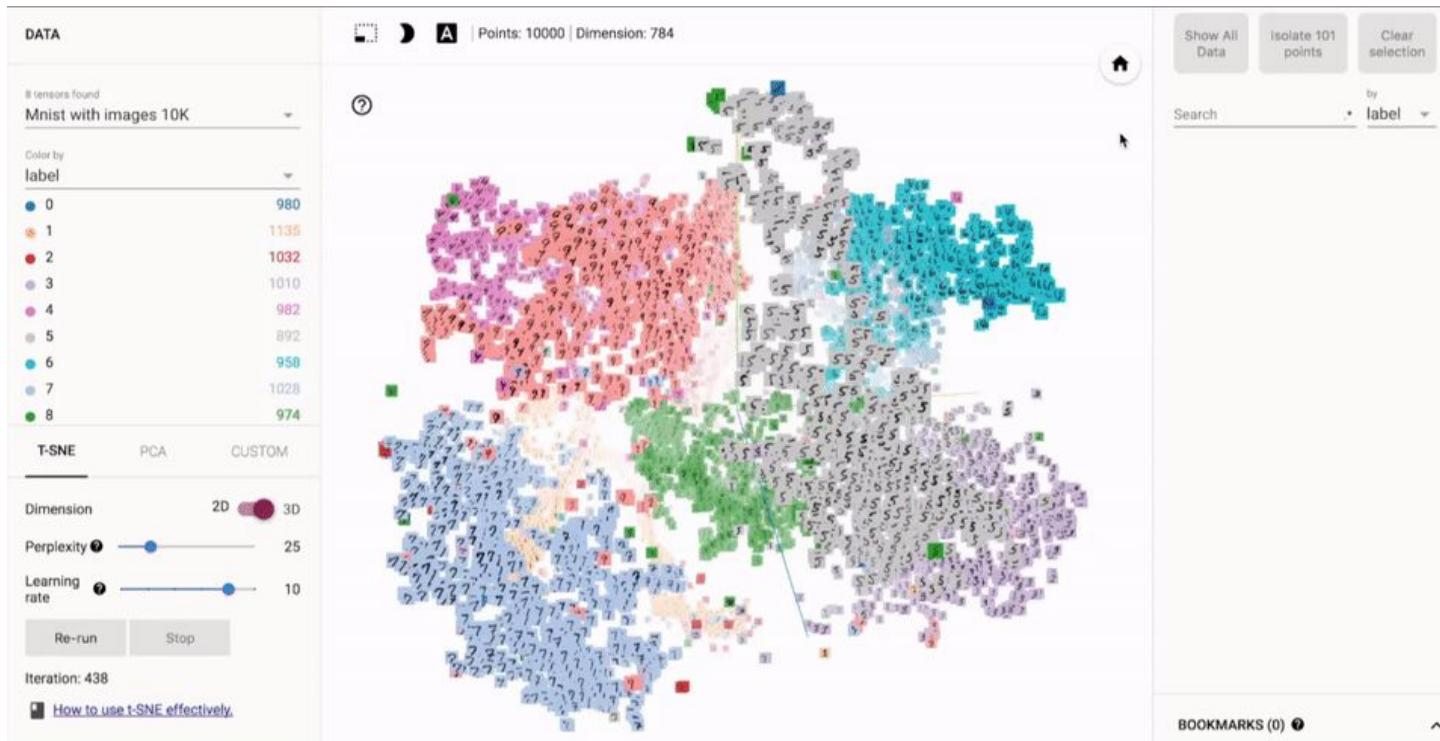
# Progress last year

| Release        | Milestone                   |
|----------------|-----------------------------|
| November 2015  | Initial release             |
| December (0.6) | Faster on GPUs; Python 3.3+ |
| February (0.7) | TensorFlow Serving          |
| April (0.8)    | Distributed TensorFlow      |
| June (0.9)     | iOS; Mac GPU                |
| August (0.10)  | Slim                        |
| October (0.11) | HDFS; CUDA 8, CuDNN 5       |

# Progress last year cont'd

| Release         | Milestone   |
|-----------------|---|
| November (0.12) | Windows 7, 10, and Server 2016;<br>TensorBoard Embedding Visualizer |

# TensorBoard Embedding Visualization: goo.gl/xfhi1H



# Why?



# Reproducible Research

Music <https://magenta.tensorflow.org/2016/11/09/tuning-recurrent-networks-with-reinforcement-learning/>

WaveNet <https://deepmind.com/blog/wavenet-generative-model-raw-audio/>

Translation <https://research.googleblog.com/2016/09/a-neural-network-for-machine.html>

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

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

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

Parsey McParseface <https://research.googleblog.com/2016/05/announcing-syntaxnet-worlds-most.html>

# Open Source Models: from Google and Many Others

Fast Style Transfer <https://github.com/lengstrom/fast-style-transfer/>

Colornet <https://github.com/pavelgonchar/colornet>

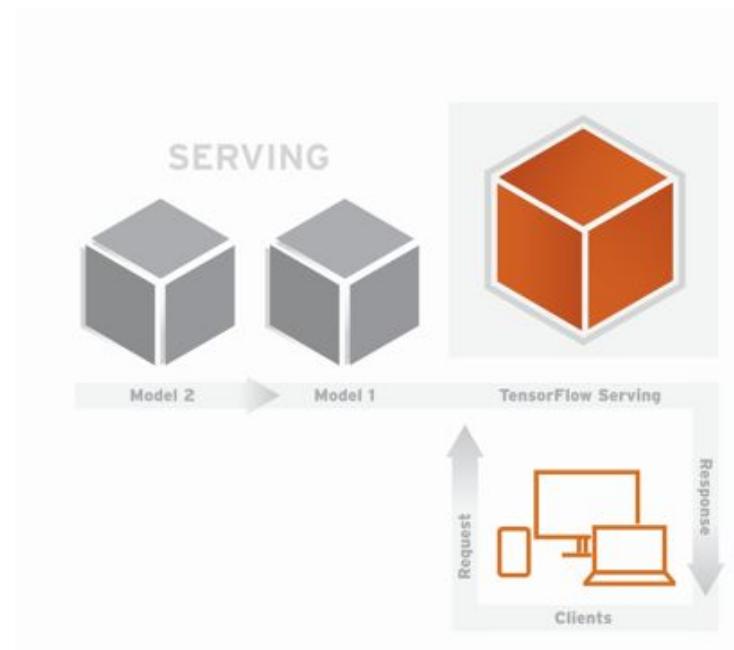
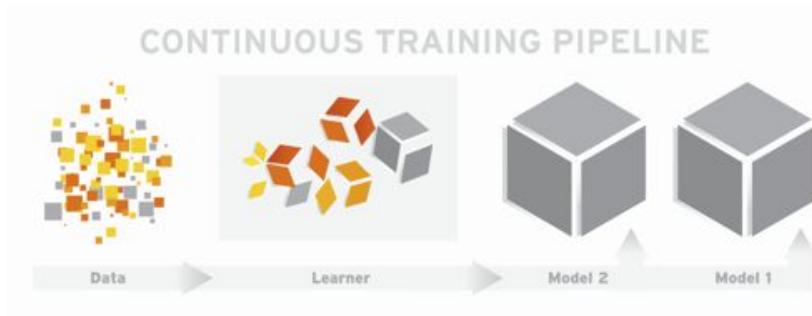
Super Resolution <https://github.com/david-gpu/srez>

TTS <https://github.com/ibab/tensorflow-wavenet>

Speech Recognition <https://github.com/buriburisuri/speech-to-text-wavenet>

Many more <https://github.com/jtoy/awesome-tensorflow>

# Research and Production



<https://research.googleblog.com/2016/02/running-your-models-in-production-with.html>

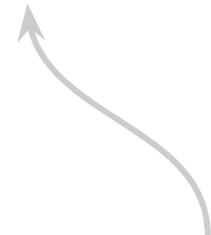
# Warm up

## Graphs and Sessions

A multidimensional array.



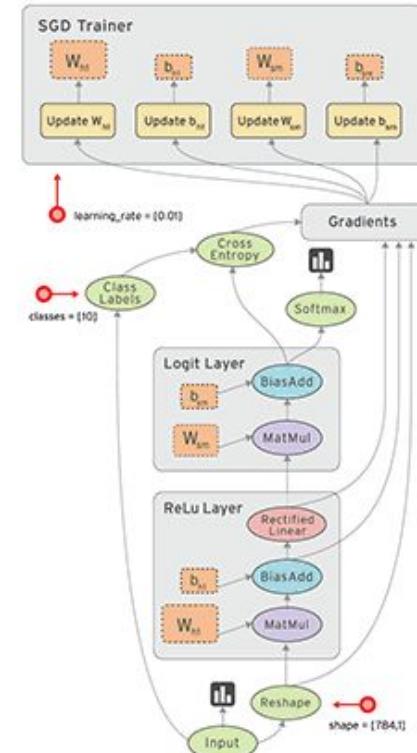
# TensorFlow



A graph of operations.

# A graph is like a blueprint

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

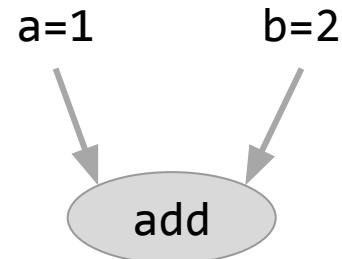


The background features a stylized landscape graphic composed of a grid of white lines on a yellow-orange gradient background. The grid forms rolling hills and mountains, creating a sense of depth and perspective.

But, why?

# Build a graph...

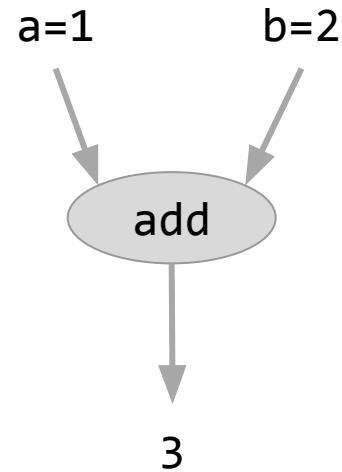
```
import tensorflow as tf  
a = tf.constant(1)  
b = tf.constant(2)  
c = tf.add(a, b)
```



# ... 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)
```

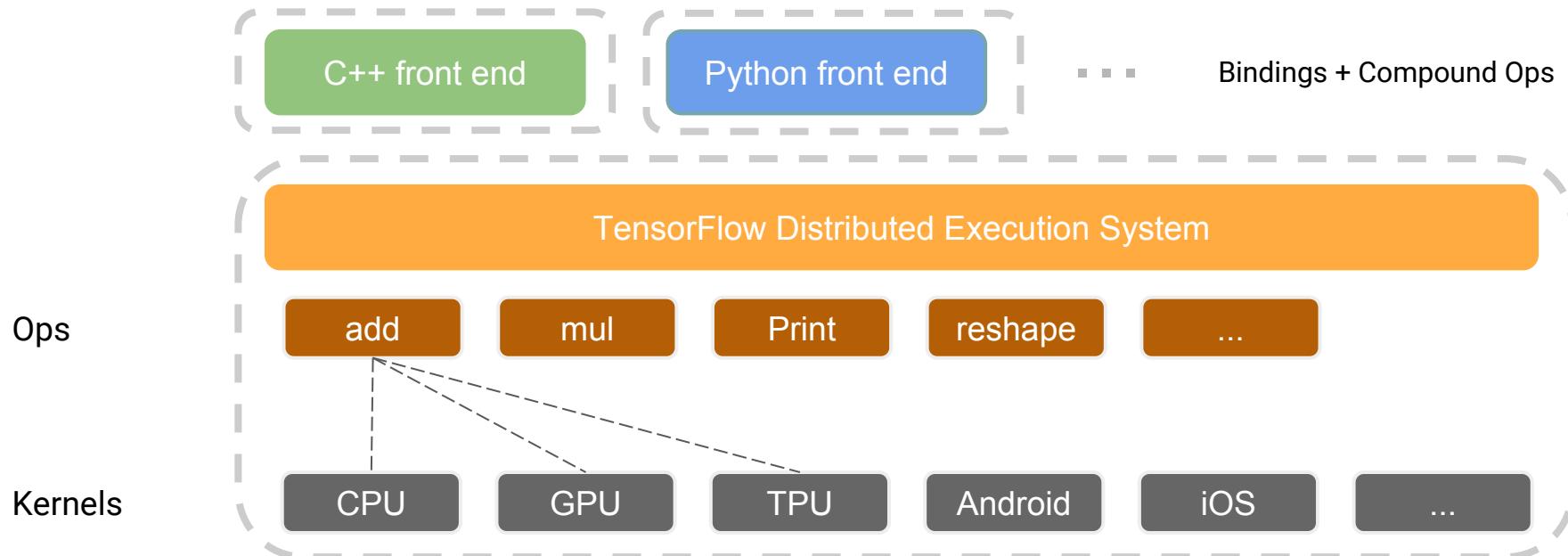


# Building graphs looks mostly like numpy

With special operations for deep learning

| Numpy  | TensorFlow |
|--------|------------|
| add    | add        |
| mul    | mul        |
| matmul | matmul     |
| ...    | ...        |
| sum    | reduce_sum |
| ...    | ...        |
|        | sigmoid    |
|        | relu       |
|        | ...        |

# Architecture



# 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.global_variables_initializer())

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

# Exercises

[goo.gl/nrdsxM](http://goo.gl/nrdsxM)

# Clone the repo and start a notebook

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

[goo.gl/nrdsxM](http://goo.gl/nrdsxM)

# Exercise #1: Fibonacci Sequence

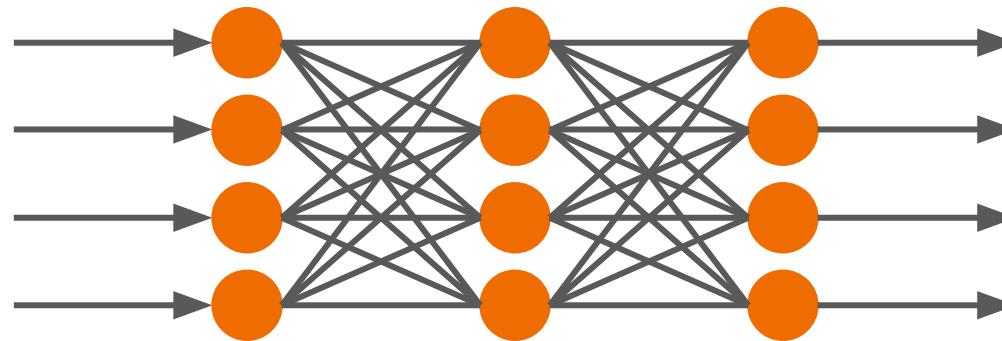
## 1\_warm\_up.ipynb

[goo.gl/nrdsxM](http://goo.gl/nrdsxM)

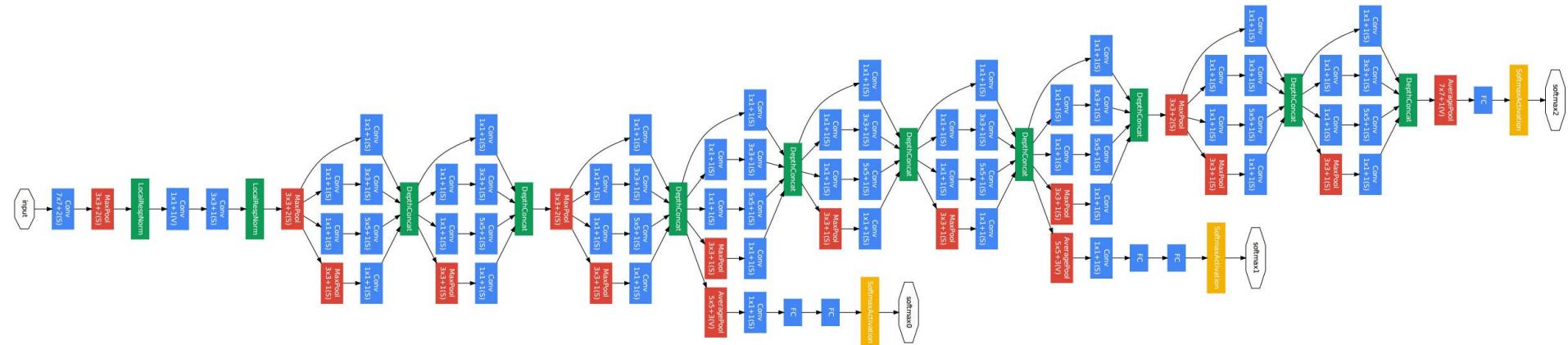


But why?

# Neural Networks, yesterday



# Remember Inception?



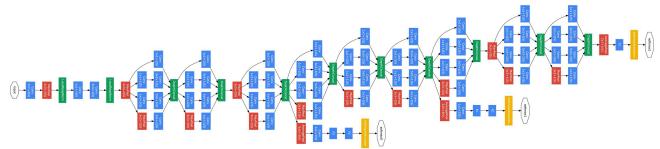
# Machine Learning gets complex quickly



Heterogenous  
systems



Distributed  
systems



Modeling complexity

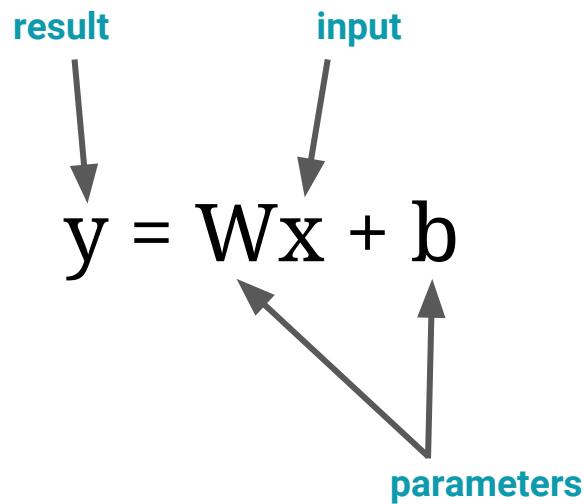
# Linear Regression

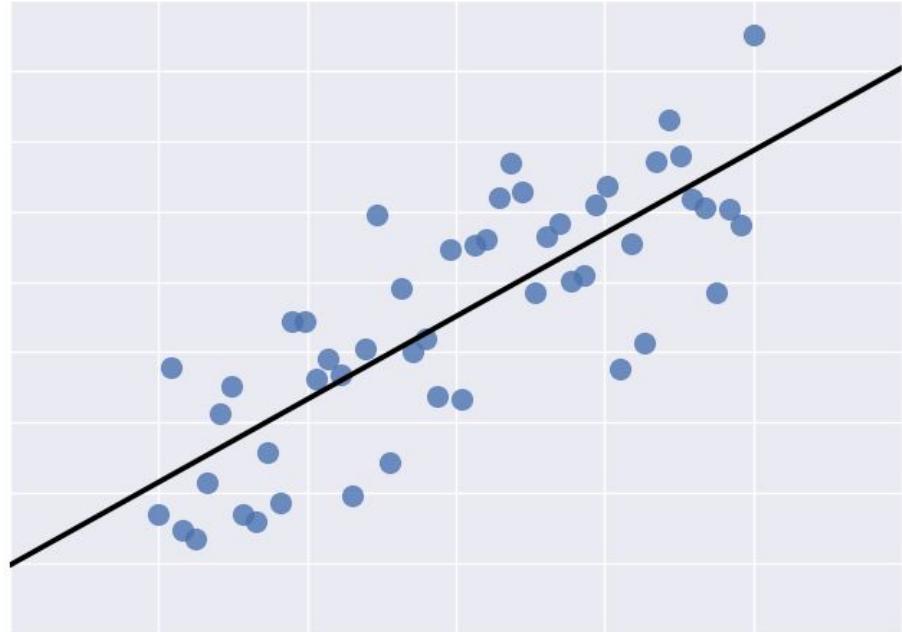
## Inference, Loss, Optimize

# Linear Regression

$$y = Wx + b$$

result      input  
parameters





# What are we trying to do?

**Mystery equation:**  $y = 0.1 * x + 0.3 + \text{noise}$

**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

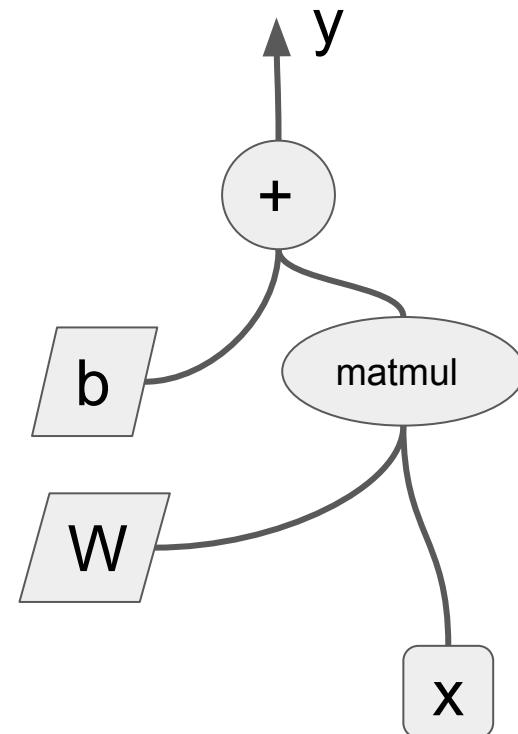
x = tf.placeholder(shape=[None],
                    dtype=tf.float32, name="x")

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

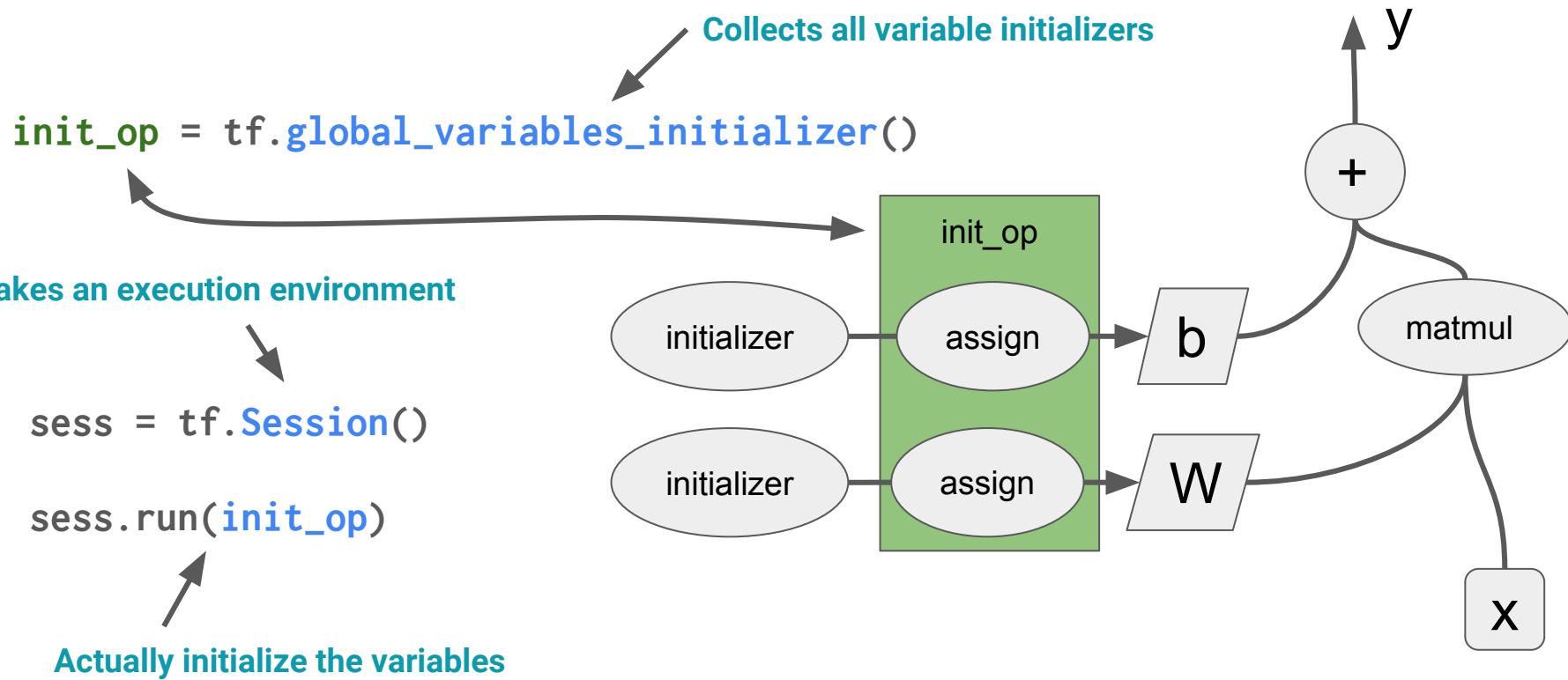
b = tf.Variable(tf.random_normal([1], name="b"))
```

# $y = Wx + b$ 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

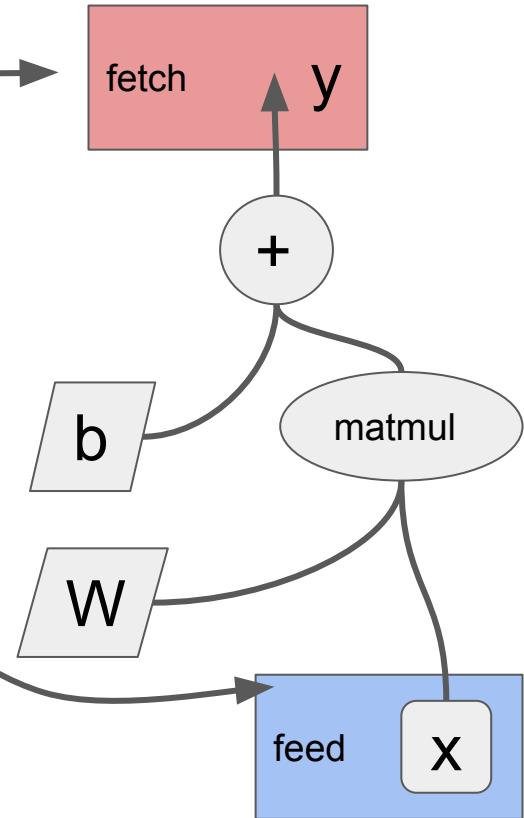


# Running the Computation

`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

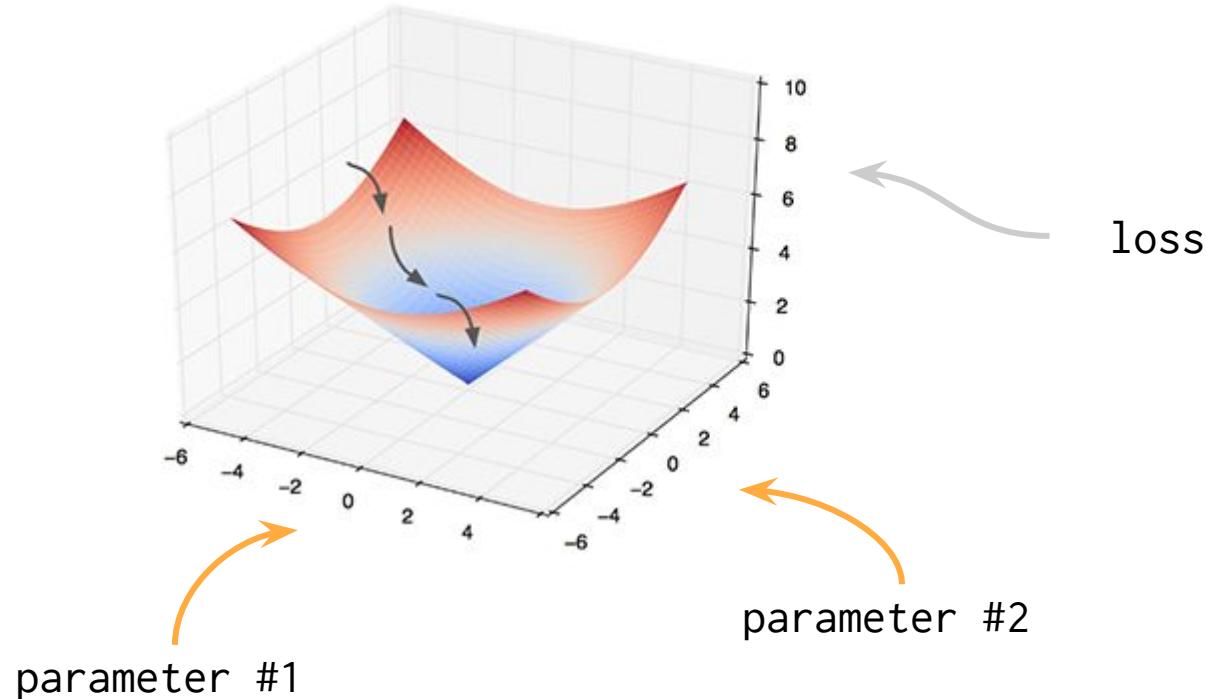
```
import tensorflow as tf
x = tf.placeholder(shape=[None],
                    dtype=tf.float32,
                    name='x')
W = tf.Variable(tf.random_normal([1], name="W"))
b = tf.Variable(tf.random_normal([1], name="b"))
y = W * x + b

with tf.Session() as sess:
    sess.run(tf.initialize_all_variables())
    print(sess.run(y, feed_dict={x: x_in}))
```

The diagram illustrates the execution flow of the provided TensorFlow script. It is divided into four main stages:

- Build the graph**: This stage includes the definition of tensors `x`, `W`, and `b`, and the construction of the computational graph via the expression `y = W * x + b`.
- Prepare execution env**: This stage includes the creation of a `Session` object.
- Initialize variables**: This stage includes the execution of the `tf.initialize_all_variables()` operation to initialize all variables.
- Run the computation**: This stage includes the execution of the `sess.run(y, feed_dict={x: x_in})` operation to run the computation and print the result.

# Concepts: Loss and Gradient Descent



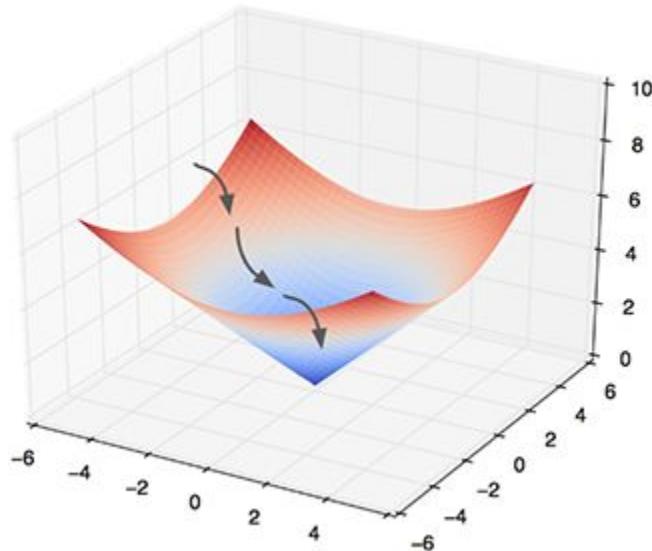
# Define a Loss

Given  $y$ ,  $y_{train}$  compute a loss, for instance:

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

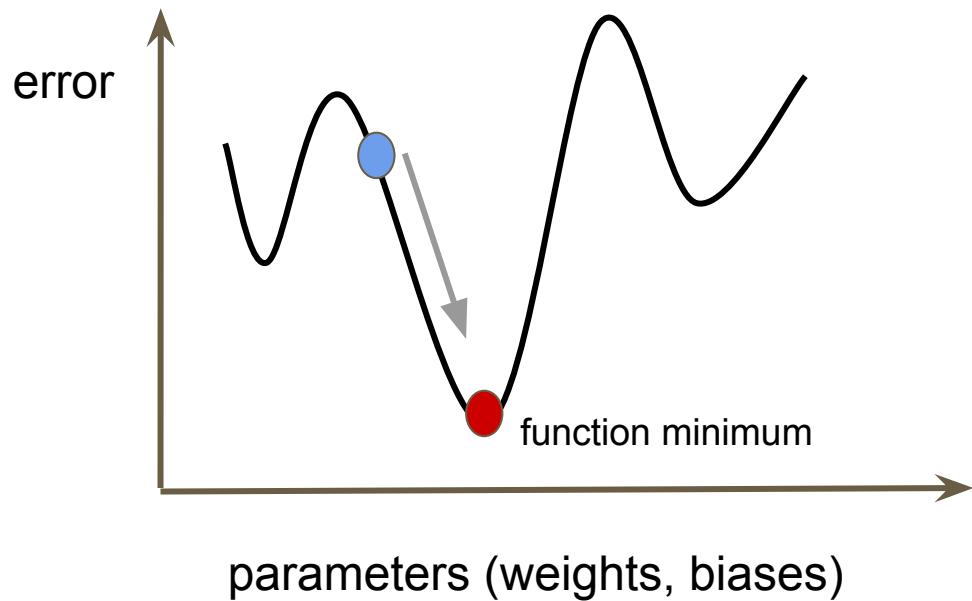
```
# create an operation that calculates loss  
loss = tf.reduce_mean(tf.square(y - y_train))
```

# Optimization



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

# Minimize loss using an optimizer



`tf.train.GradientDescentOptimizer`

Or, use one of:

`AdadeltaOptimizer`

`AdagradOptimizer`

`AdagradDAOptimizer`

`AdamOptimizer`

...

# Automatic Differentiation

Feed  $(x, y_{\text{label}})$  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
```

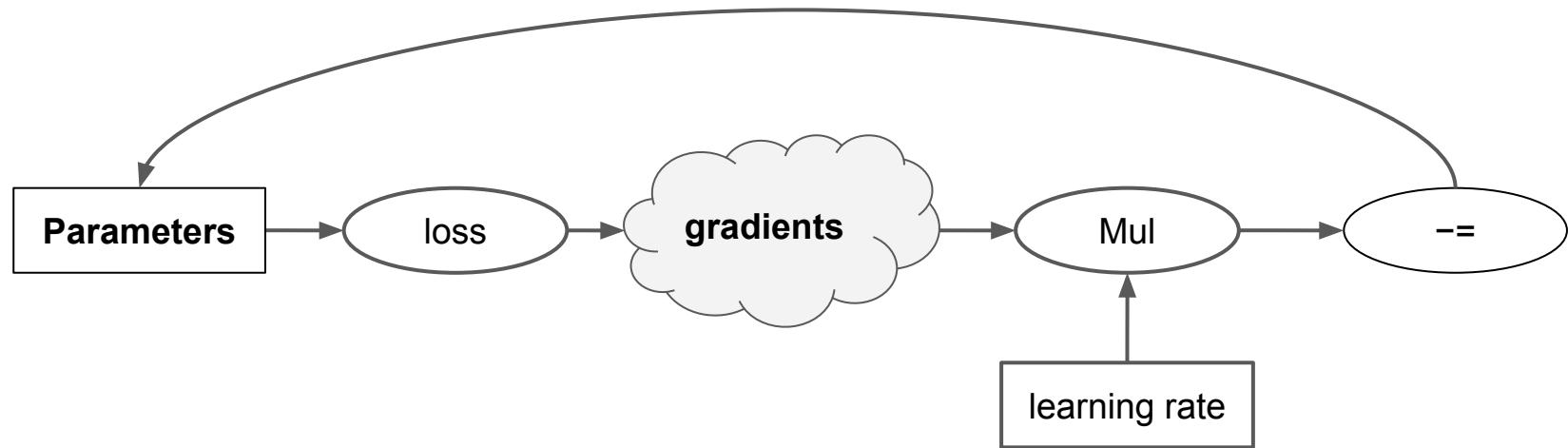
```
optimizer = tf.train.GradientDescentOptimizer(0.5)
```

```
# 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]})
```

The diagram illustrates the components of the provided TensorFlow code. It uses curly braces to group related code snippets and map them to their corresponding TensorFlow operations:

- The first three lines of code (defining loss, creating an optimizer, and minimizing the loss) are grouped by a brace on the right, labeled "Define a loss", "Create an optimizer", and "Op to minimize the loss" respectively.
- The line "sess.run(tf.initialize\_all\_variables())" is grouped by a brace on the right, labeled "Initialize variables".
- The loop starting with "for i in range(1000)" and its body are grouped by a brace on the right, labeled "Iteratively run the training op".

# Exercise #2: Linear Regression

## 2\_linear\_regression.ipynb

[goo.gl/nrdsxM](http://goo.gl/nrdsxM)

# Demo: TensorBoard

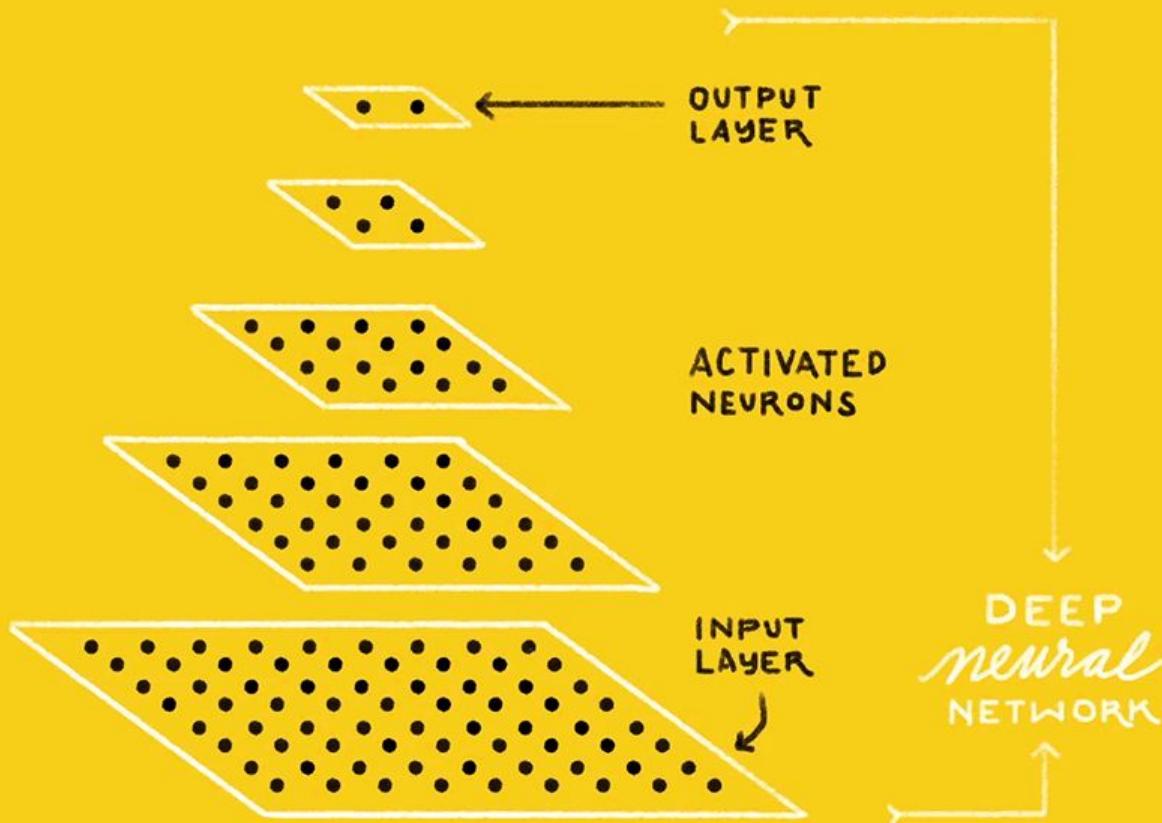
[goo.gl/nrdsxM](http://goo.gl/nrdsxM)

# Neural Networks

IS THIS A  
**CAT or DOG?**



CAT   DOG



# Deep Learning

Current state of the art in:

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

# Neural Networks in TensorFlow

## Options:

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

# Open Source Models

# Understanding Images

# Inception



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

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

# Demo

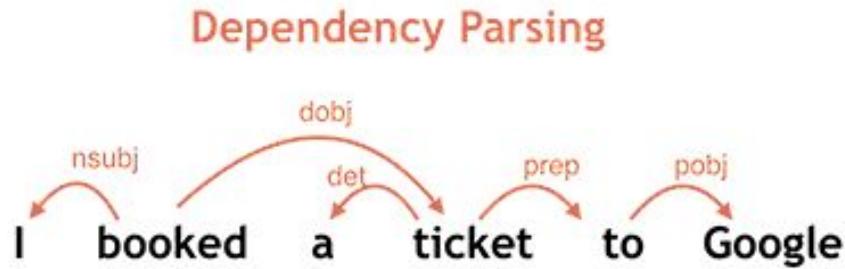
# Show and Tell



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

# Understanding Text

# Parsey McParseface



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

# Text Summarization

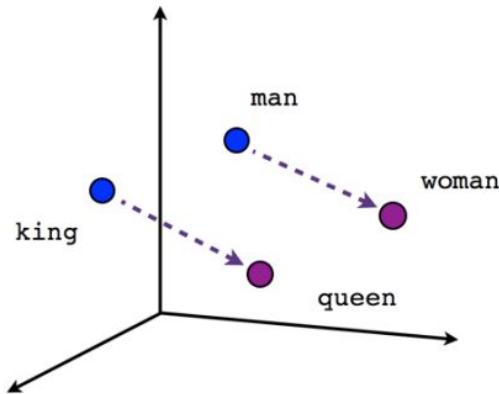
## Original text

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

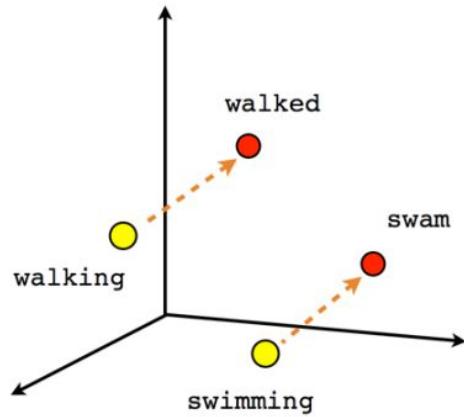
## Abstractive summary

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

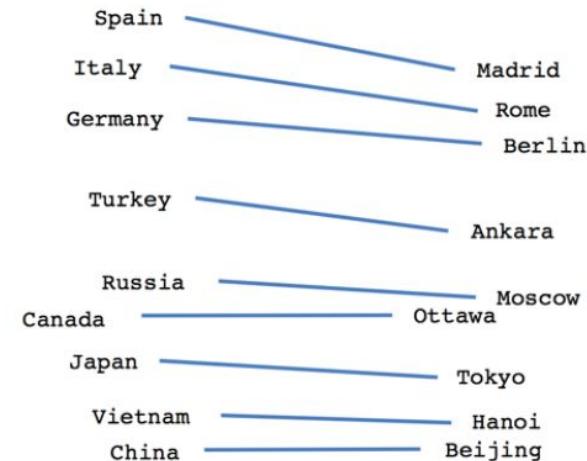
# Word Embeddings



Male-Female

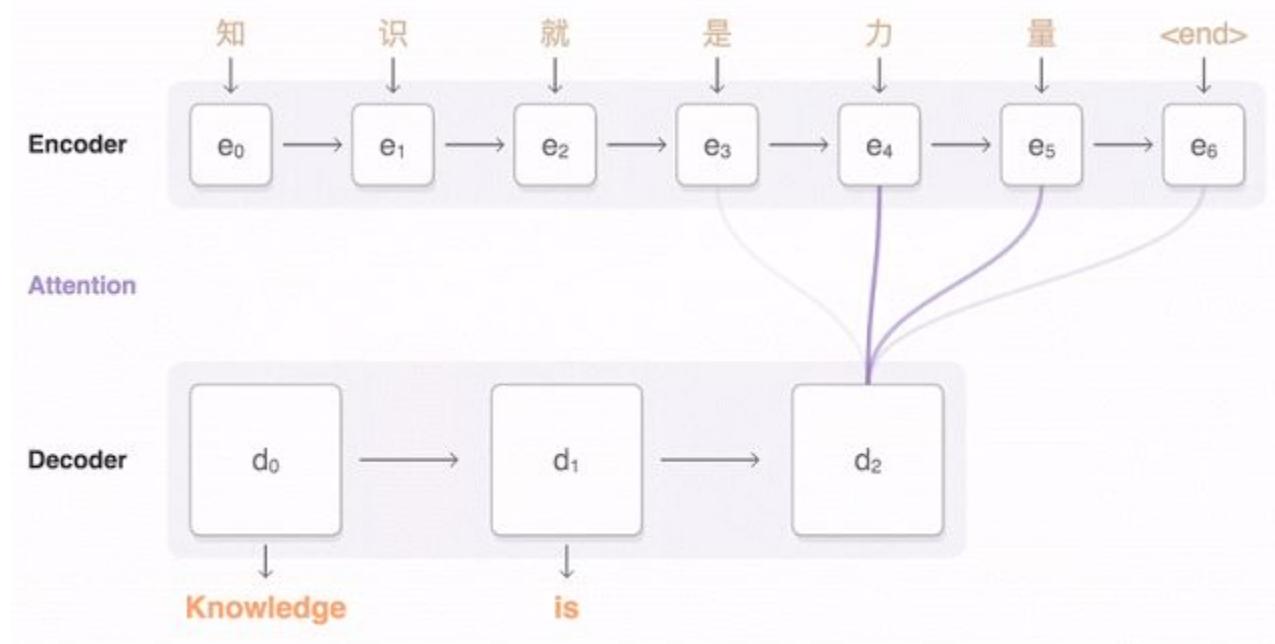


Verb tense

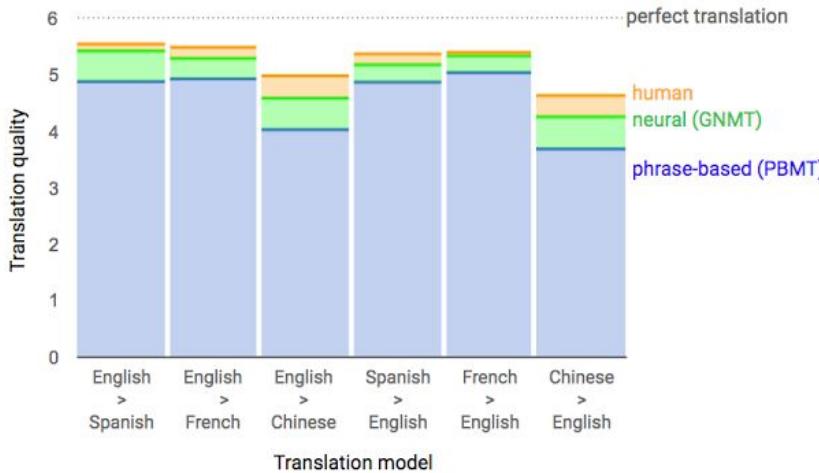


Country-Capital

# Translation



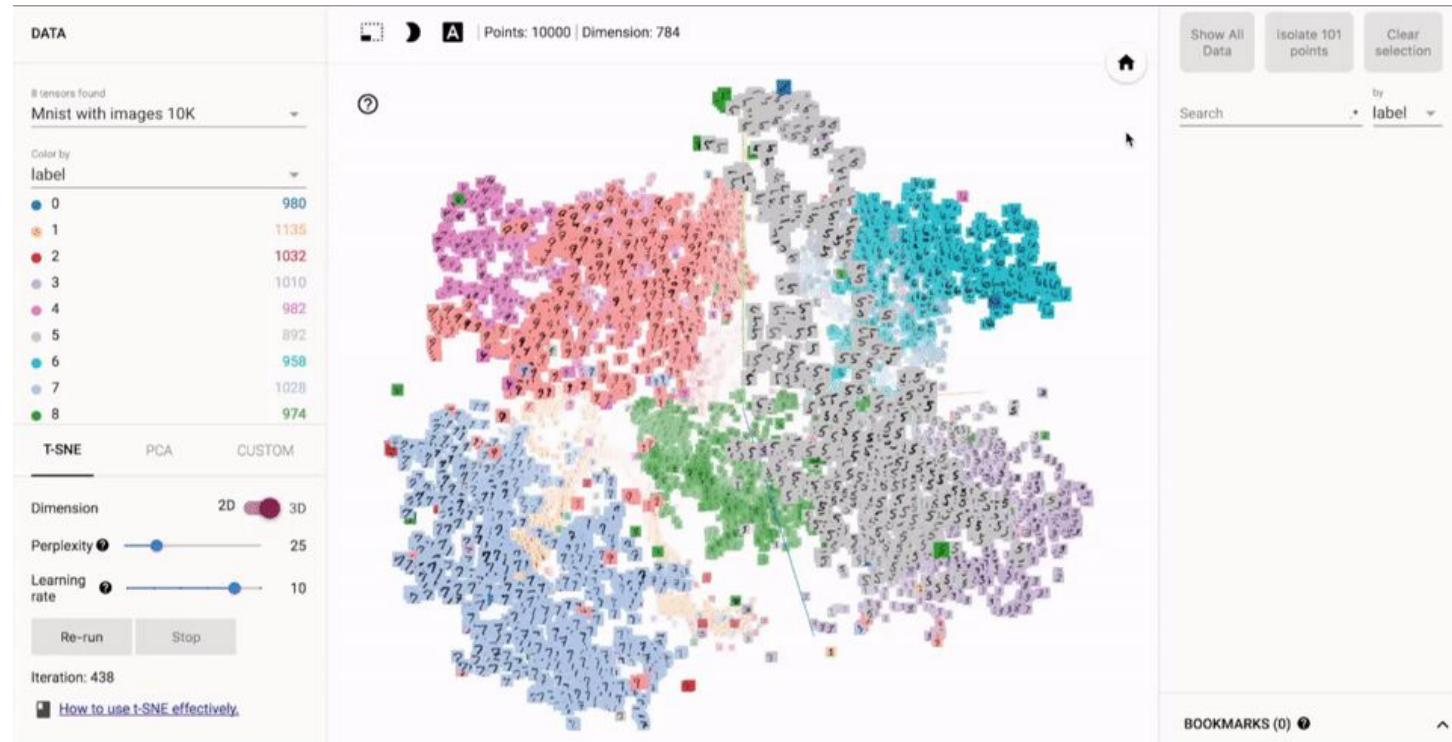
<https://research.googleblog.com/2016/09/a-neural-network-for-machine.html>



| <i>Input sentence:</i>                    | <i>Translation (PBMT):</i>  | <i>Translation (GNMT):</i>   | <i>Translation (human):</i>   |
|---|---|--|---|
| 李克強此行將啟動中加總理年度對話機制，與加拿大總理杜魯多舉行兩國總理首次年度對話。 | Li Keqiang premier added this line to start the annual dialogue mechanism with the Canadian Prime Minister Trudeau two prime ministers held its first annual session. | Li Keqiang will start the annual dialogue mechanism with Prime Minister Trudeau of Canada and hold the first annual dialogue between the two premiers. | Li Keqiang will initiate the annual dialogue mechanism between premiers of China and Canada during this visit, and hold the first annual dialogue with Premier Trudeau of Canada. |

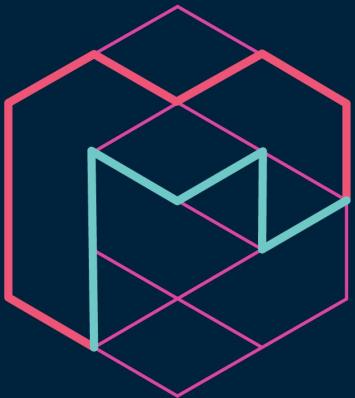
<https://research.googleblog.com/2016/09/a-neural-network-for-machine.html>

# TensorBoard

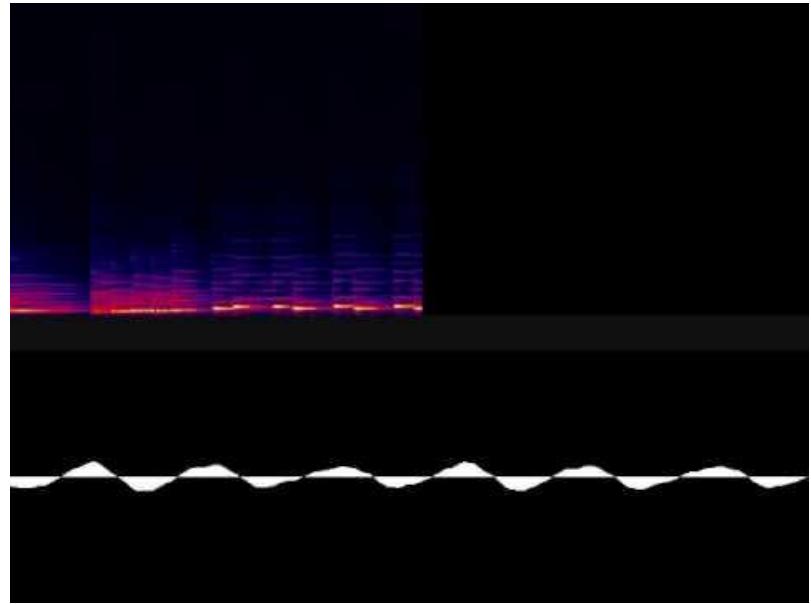
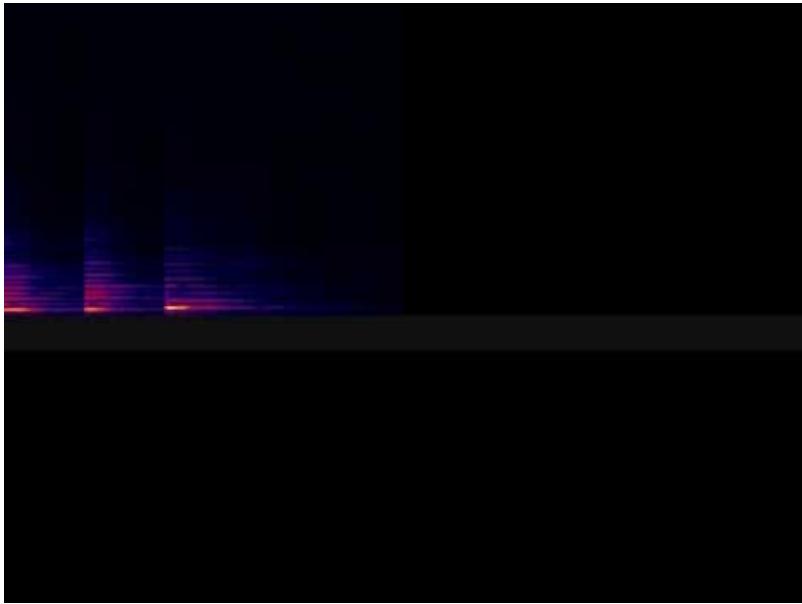


[https://www.tensorflow.org/versions/r0.12/how\\_tos/embedding\\_viz/index.html](https://www.tensorflow.org/versions/r0.12/how_tos/embedding_viz/index.html)

# Speech and Music



MAGENTA



<https://magenta.tensorflow.org/2016/11/09/tuning-recurrent-networks-with-reinforcement-learning/>

# TTS

[English - Parametric](#)

[English - Concatenative](#)

[English - WaveNet](#)

[Mandarin - Parametric](#)

[Mandarin - Concatenative](#)

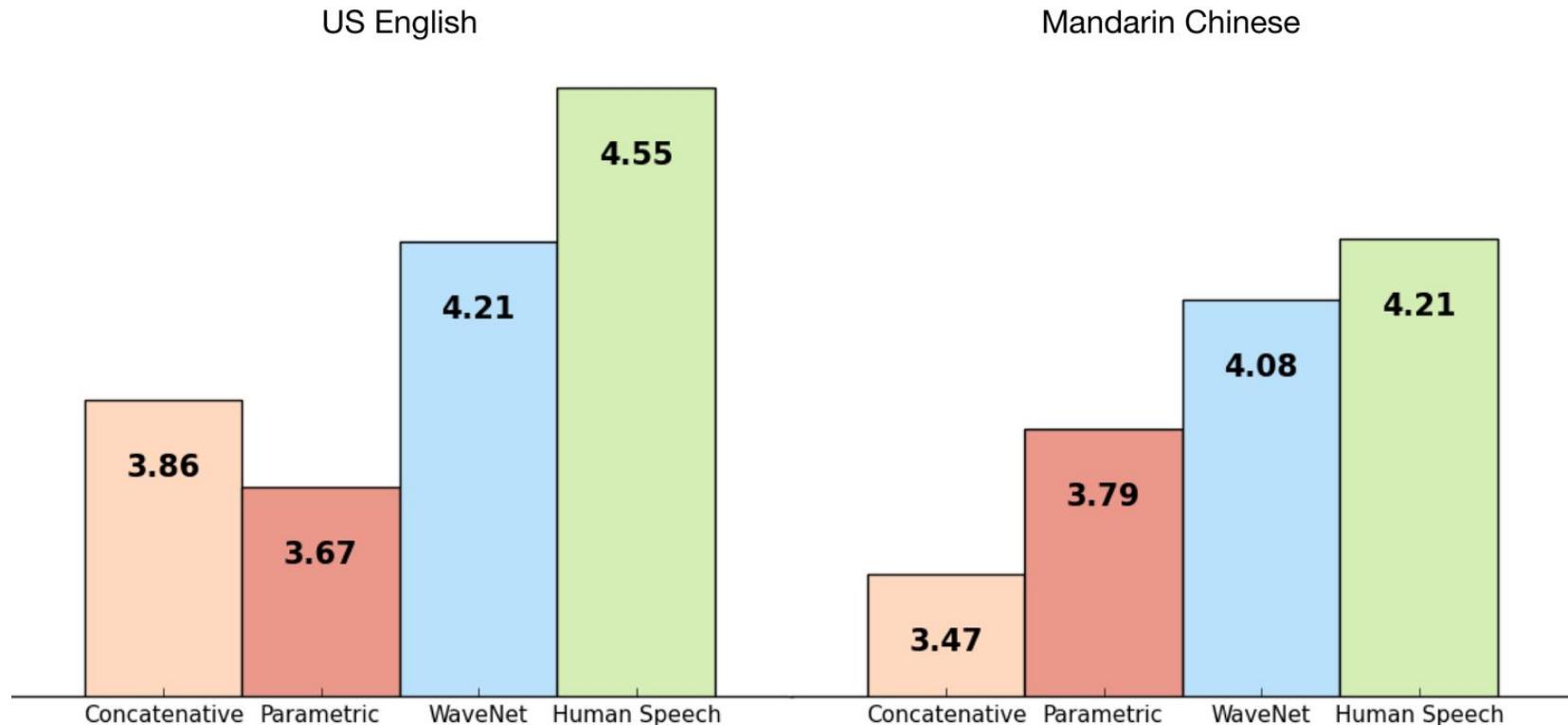
[Mandarin - WaveNet](#)

[Bonus - on hold](#)

<https://deepmind.com/blog/wavenet-generative-model-raw-audio/>

<https://magenta.tensorflow.org/2016/11/09/tuning-recurrent-networks-with-reinforcement-learning/>

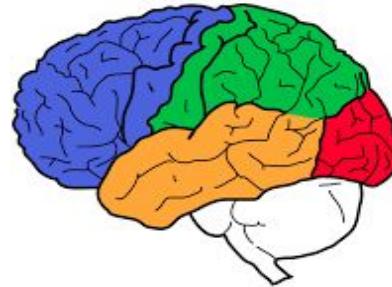
# WaveNet



<https://deepmind.com/blog/wavenet-generative-model-raw-audio/>

# “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*

# Deep Learning and Art

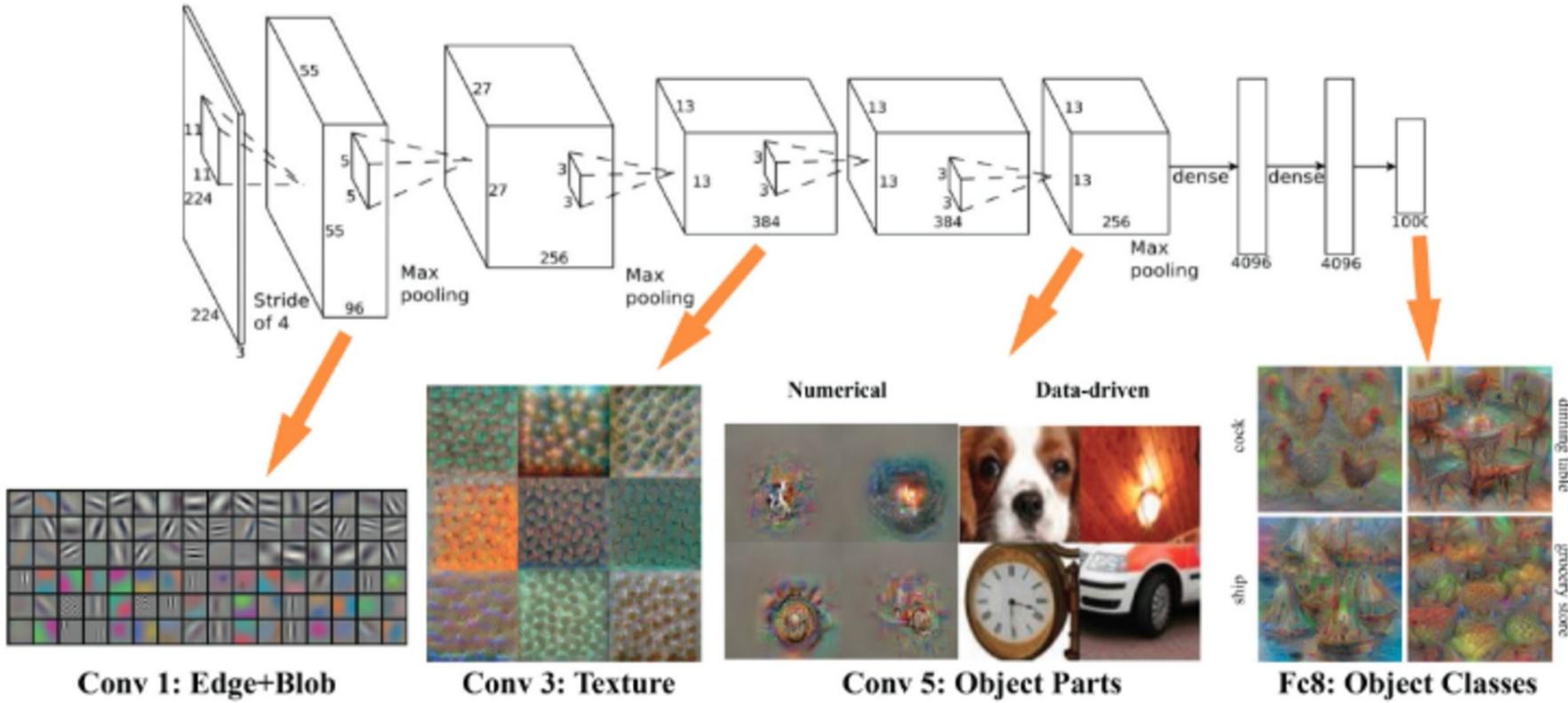


Image source - [Wikipedia](#)

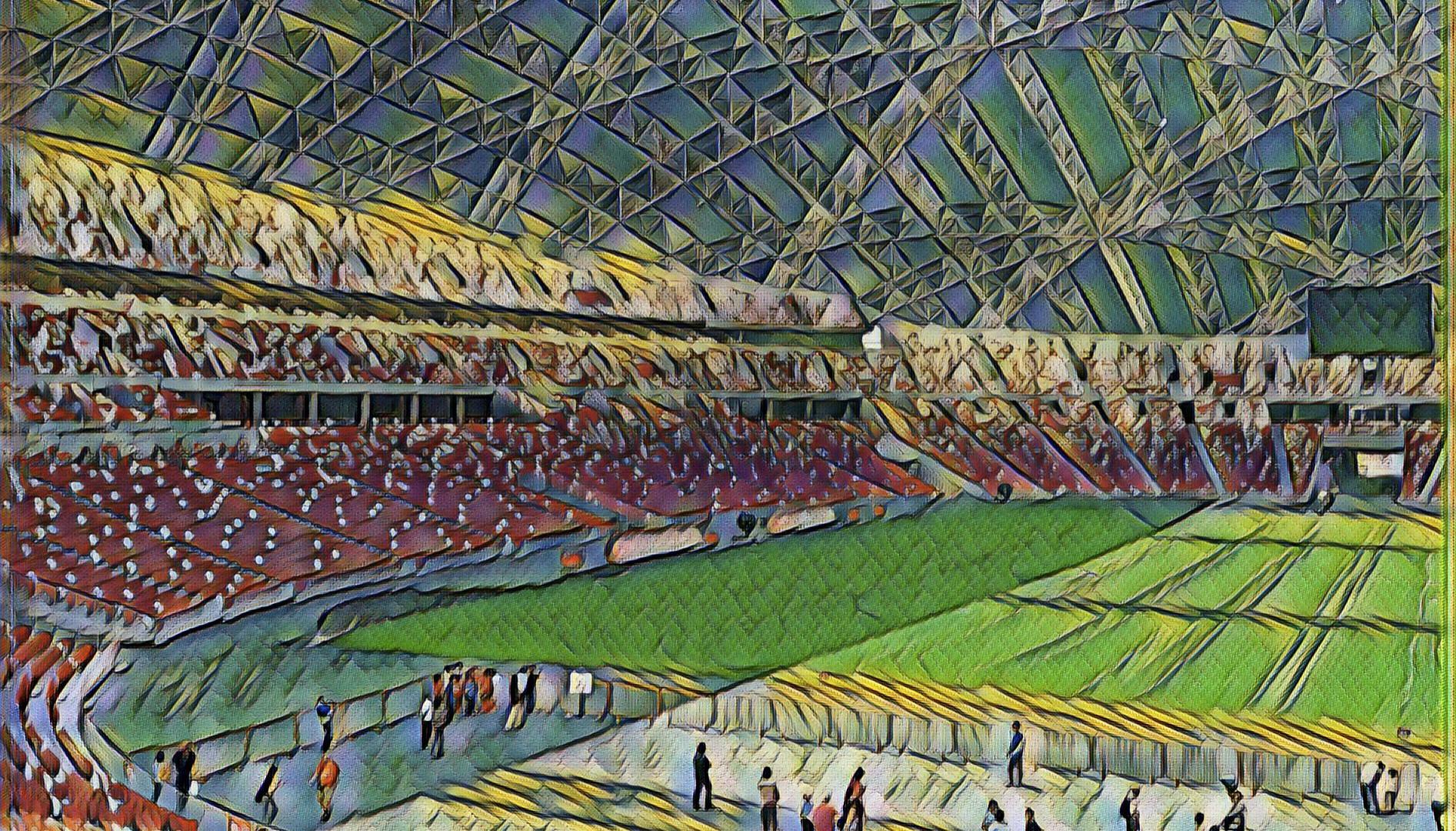




Image source - [Wikipedia](#)



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







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

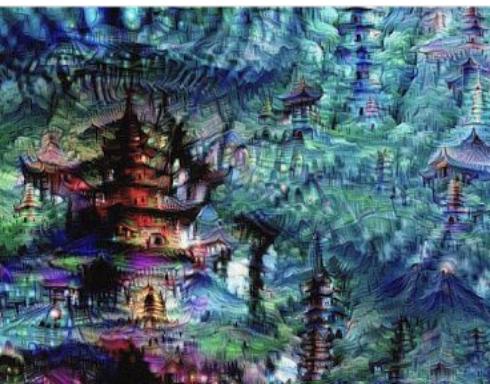
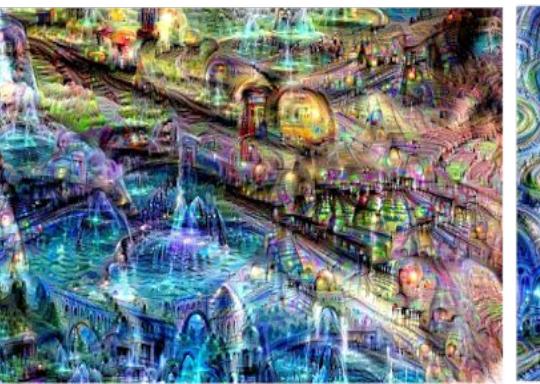


From <https://github.com/cysmith/neural-style-tf>



Fast Style Transfer  
[goo.gl/owF2z9](http://goo.gl/owF2z9)

Style Transfer  
[goo.gl/M5hiYY](http://goo.gl/M5hiYY)





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



goo.gl/1kBXyO

# References

## Supercharging Style Transfer

<https://research.googleblog.com/2016/10/supercharging-style-transfer.html>

## Inceptionism: Going Deeper into Neural Networks

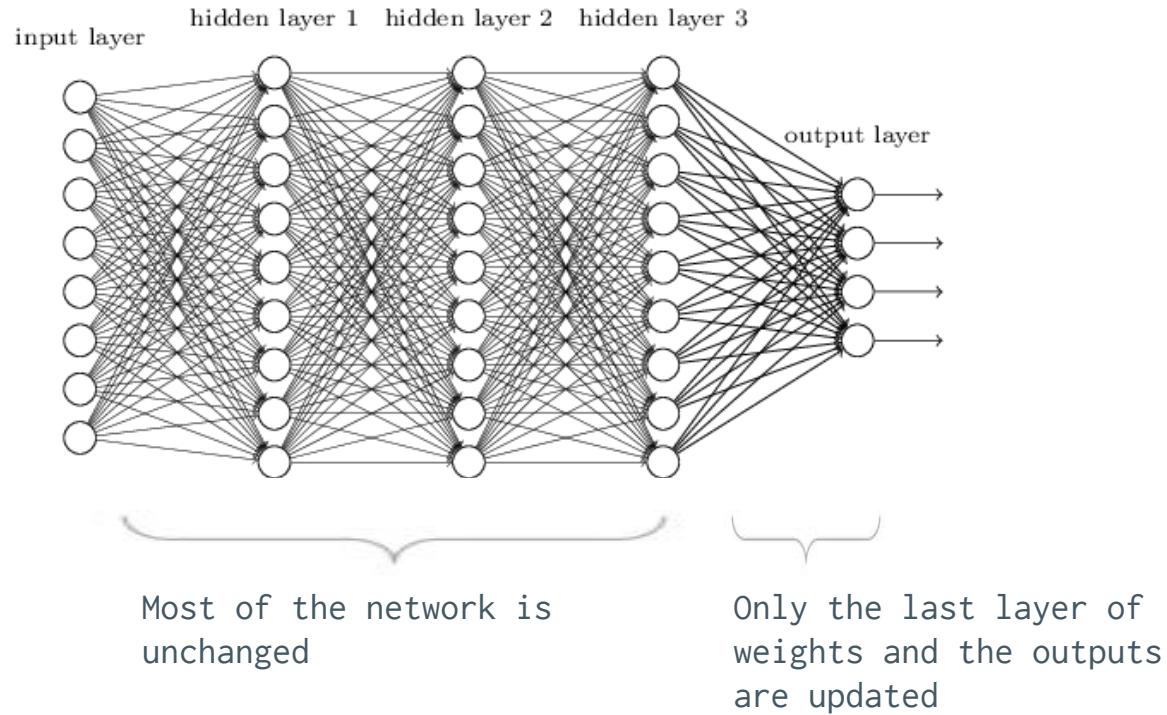
<https://research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html>

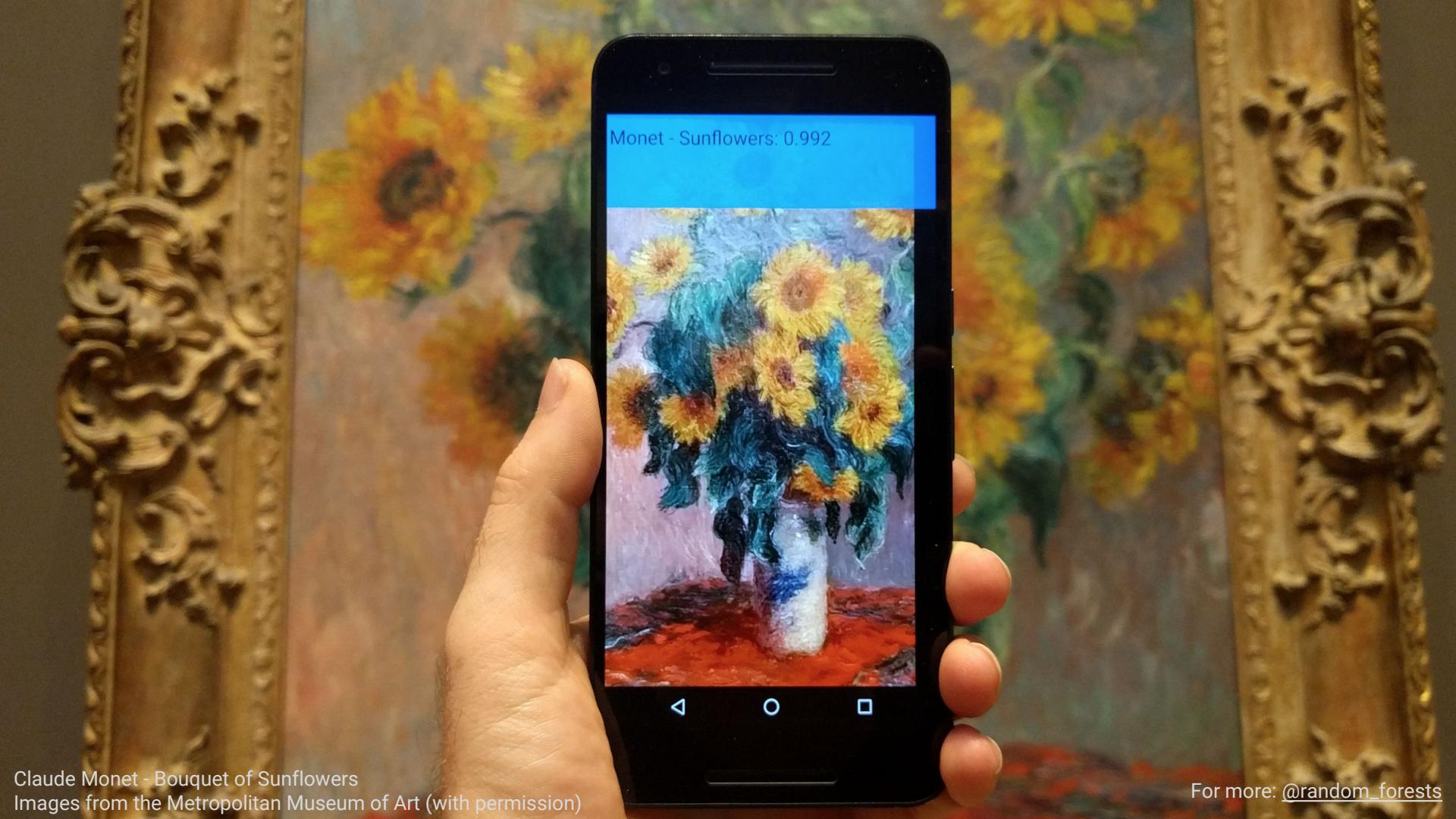


# Create your own image classifier

[goo.gl/xGsB9d](http://goo.gl/xGsB9d)

# Transfer Learning





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

For more: [@random\\_forests](https://github.com/Random-Forests)

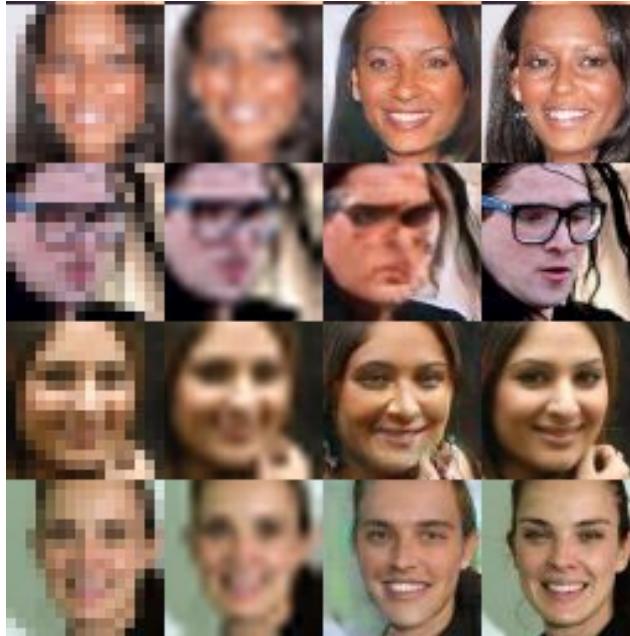
## Exercise #3

Fast Style Transfer  
[goo.gl/owF2z9](http://goo.gl/owF2z9)

TensorFlow for Poets  
[goo.gl/xGsB9d](http://goo.gl/xGsB9d)

Deep Dream  
[goo.gl/1kBXyO](http://goo.gl/1kBXyO)

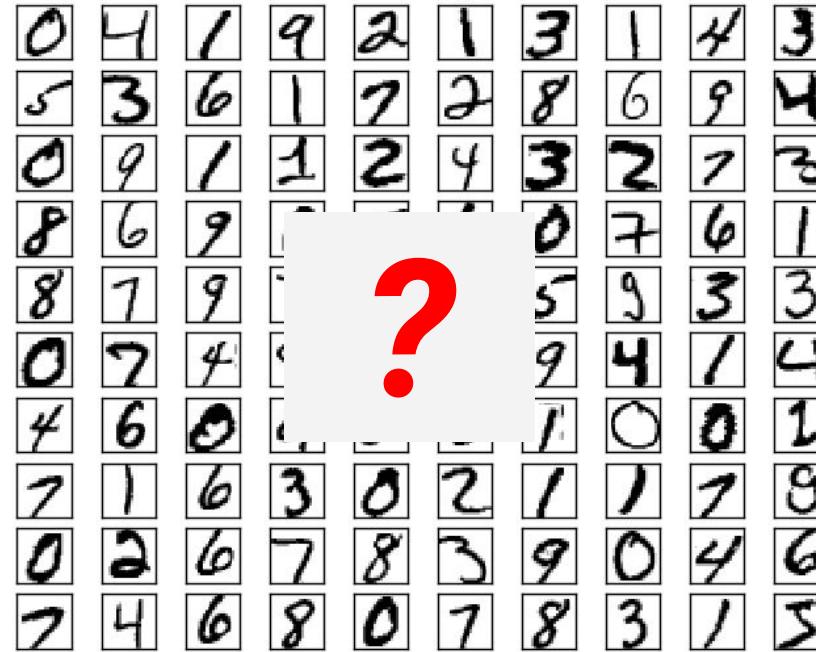
# Also: Super-resolution



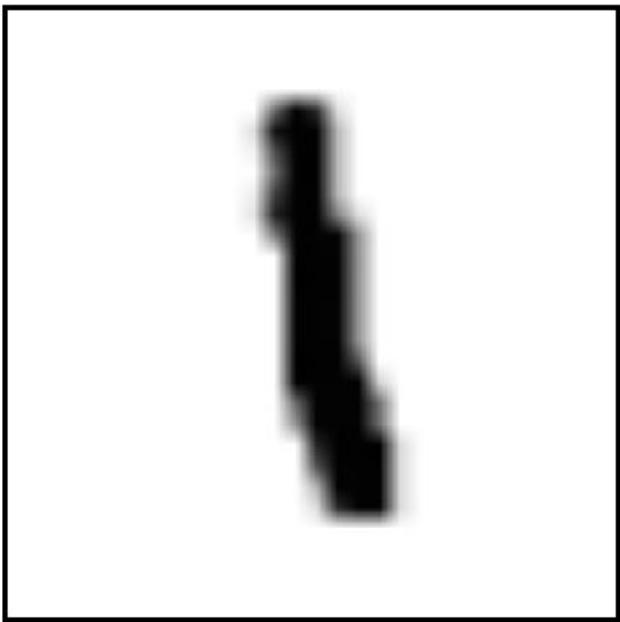
<https://github.com/david-gpu/srez>

# Basic and Deep MNIST

# Hello “computer vision” world



# We see



# Computer “sees”

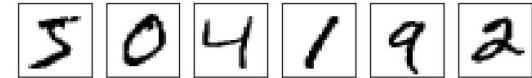
2

# Dataset

Original: 65,000

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

Images



Labels

5 0 4 1 9 2

# Train / test split

Original: 65,000

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

Train: 55,000

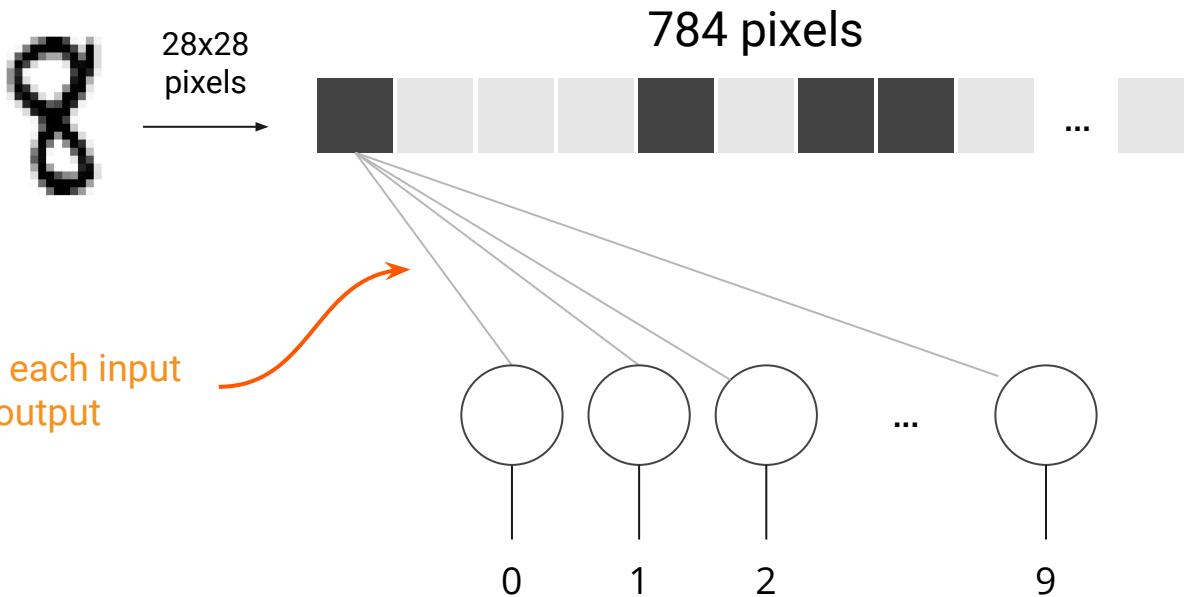
1 8 2 0 2 9 9 5 5 1 5 6 0 3 4 4  
9 2 5 0 1 1 1 0 9 0 3 1 6 4 **2 3**  
2 8 4 1 7 3 3 8 8 7 9 2 2 4 1 5  
1 8 1 8 0 3 0 1 9 9 4 1 8 2 1 2  
0 2 7 4 3 3 0 0 3 1 9 6 5 3 6 1  
0 5 1 3 1 5 5 6 1 8 5 1 1 9 4 6  
6 2 1 9 2 8 6 1 9 5 2 5 4 4 2 8  
9 1 4 8 1 8 4 5 9 9 8 3 7 6 0 0  
7 5 8 9 6 1 8 4 1 2 5 9 1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

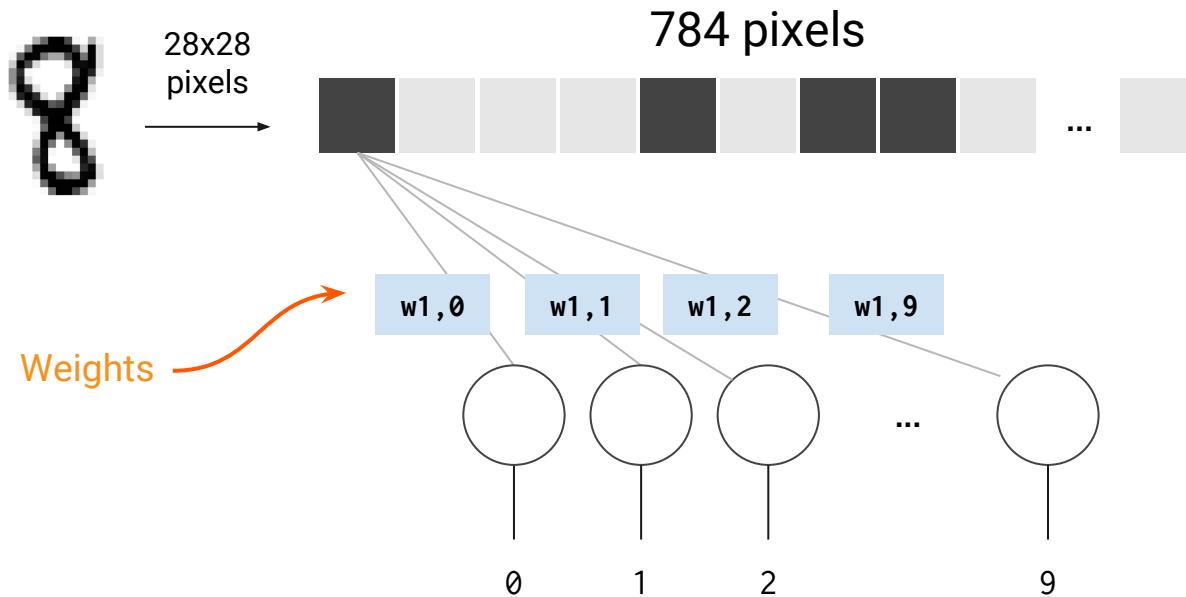
Test: 10,000

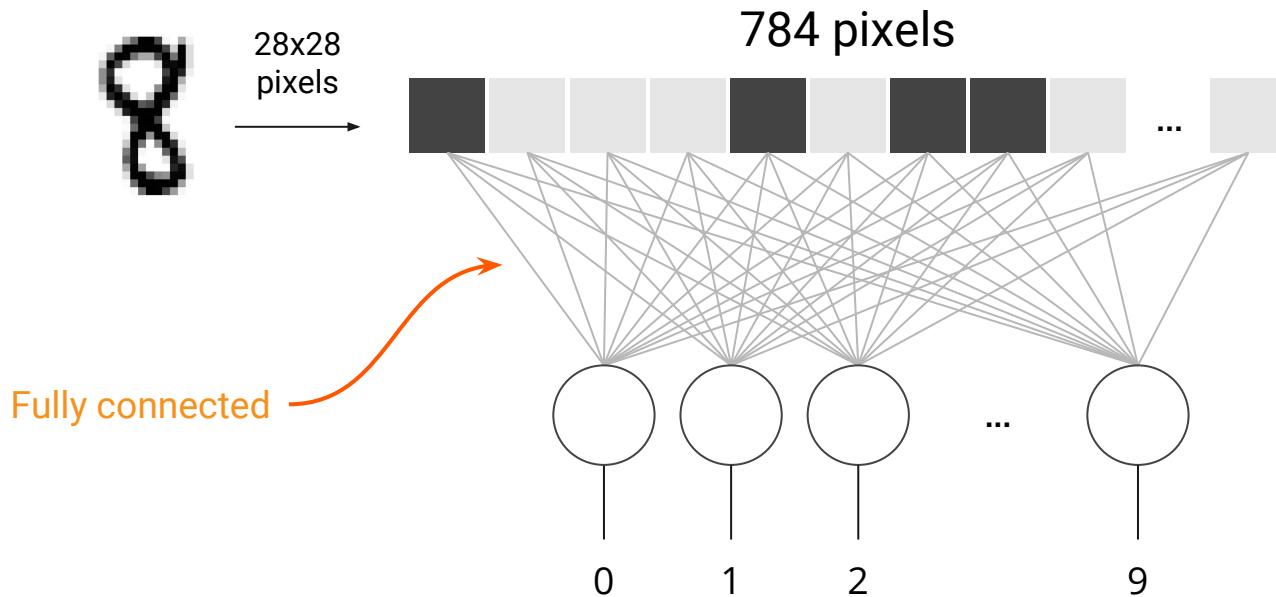
4 4 6 5  
**2 3** 6 1  
1 5 9 8  
1 2 9 7  
5 1 7 9  
4 6 2 2  
2 8 3 8  
**0 0 3 0**  
7 5 4 0  
7 1 3 0  
9 8 0 4  
8 5 7 8

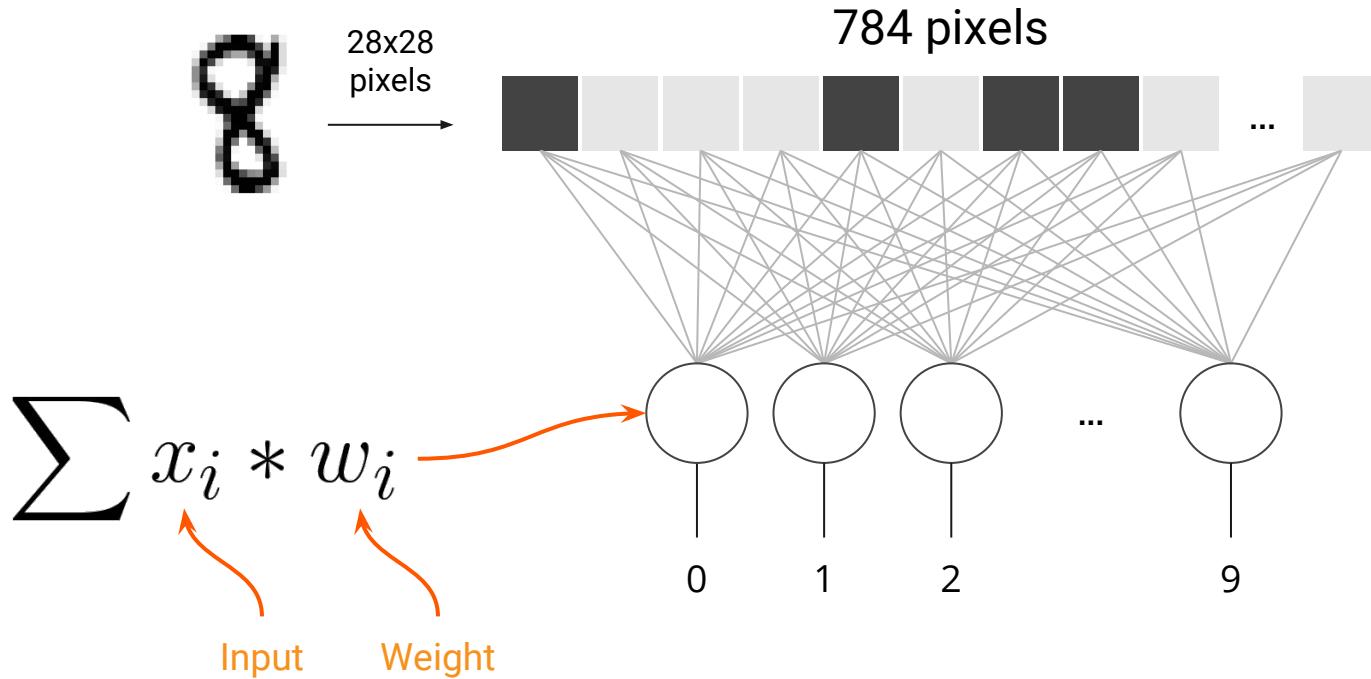
# Placeholders

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









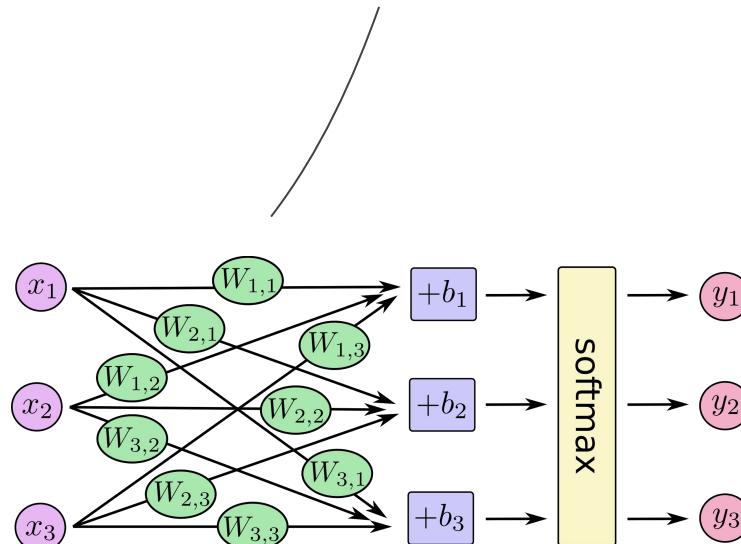
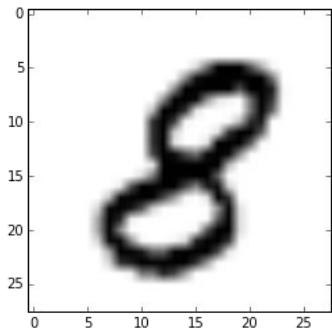
# Inference...

```
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
```

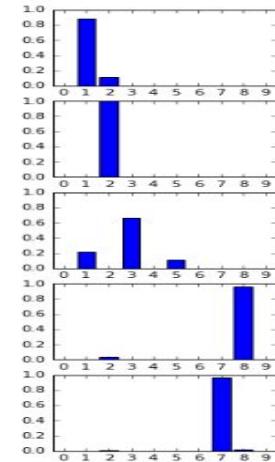
# Softmax

784 weights for each digit, so  $784 \times 10$  total connections

input vector  
(pixel data)



output vector  
(probability of  
each digit)



# Written as a matrix multiply

Weight matrix with dimensions [748,10]


$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \text{softmax} \begin{pmatrix} W_{1,1}x_1 + W_{1,2}x_2 + W_{1,3}x_3 + b_1 \\ W_{2,1}x_1 + W_{2,2}x_2 + W_{2,3}x_3 + b_2 \\ W_{3,1}x_1 + W_{3,2}x_2 + W_{3,3}x_3 + b_3 \end{pmatrix}$$

# In TensorFlow

tensor shapes:  $X[batch\_size, 784]$      $W[784, 10]$      $b[10]$

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

matrix multiply

broadcast

# Loss

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

# Optimization

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

# Training with batches

```
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

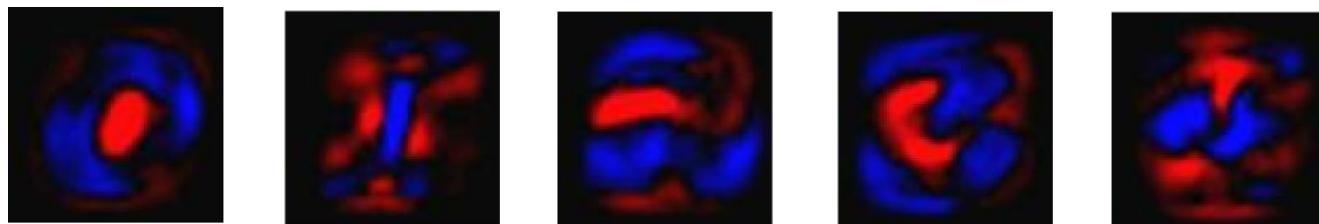
```
correct_prediction = tf.equal(tf.argmax(y, 1), tf.argmax(y_, 1))
accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))

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

**3\_basic\_mnist.ipynb**

**[goo.gl/nrdsxM](http://goo.gl/nrdsxM)**

# Visualizing the learned weights



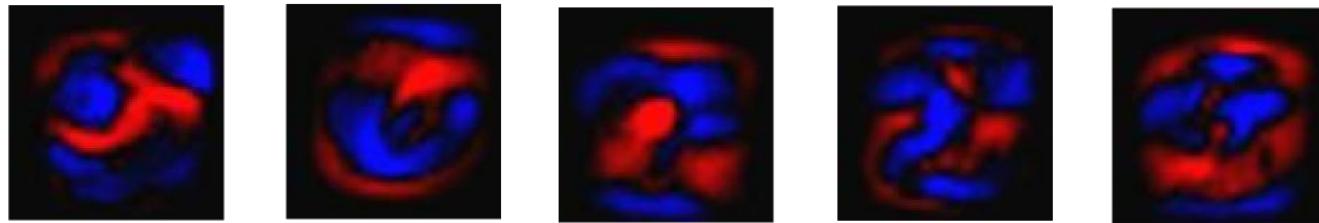
0

1

2

3

4



5

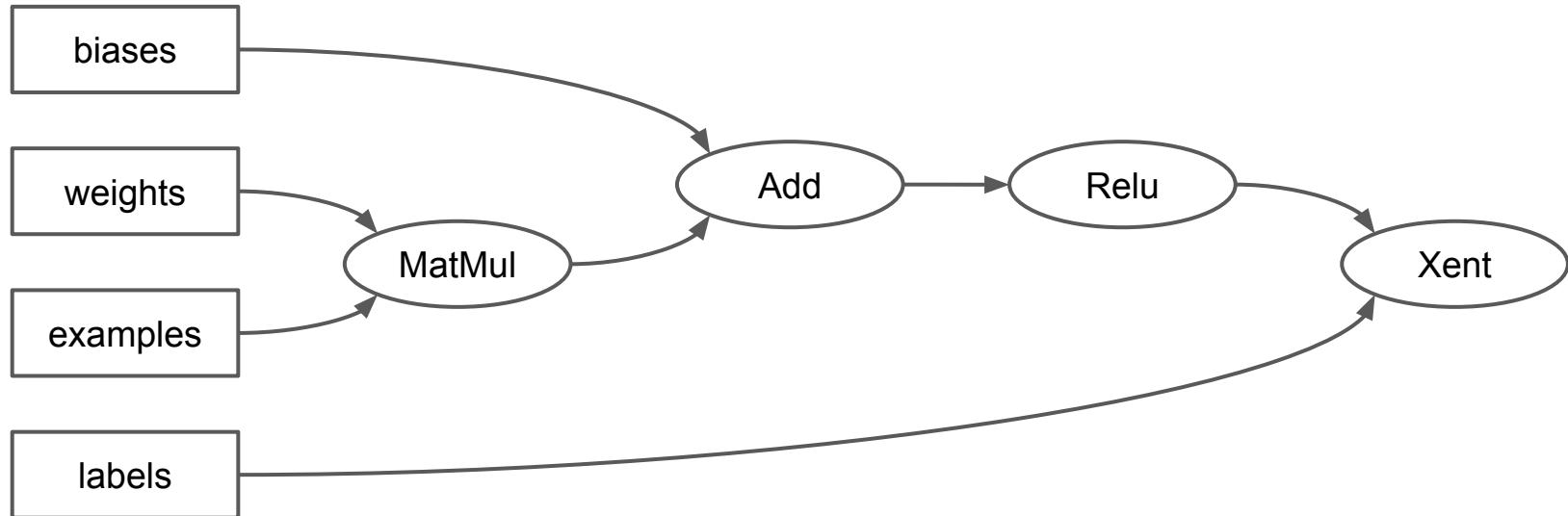
6

7

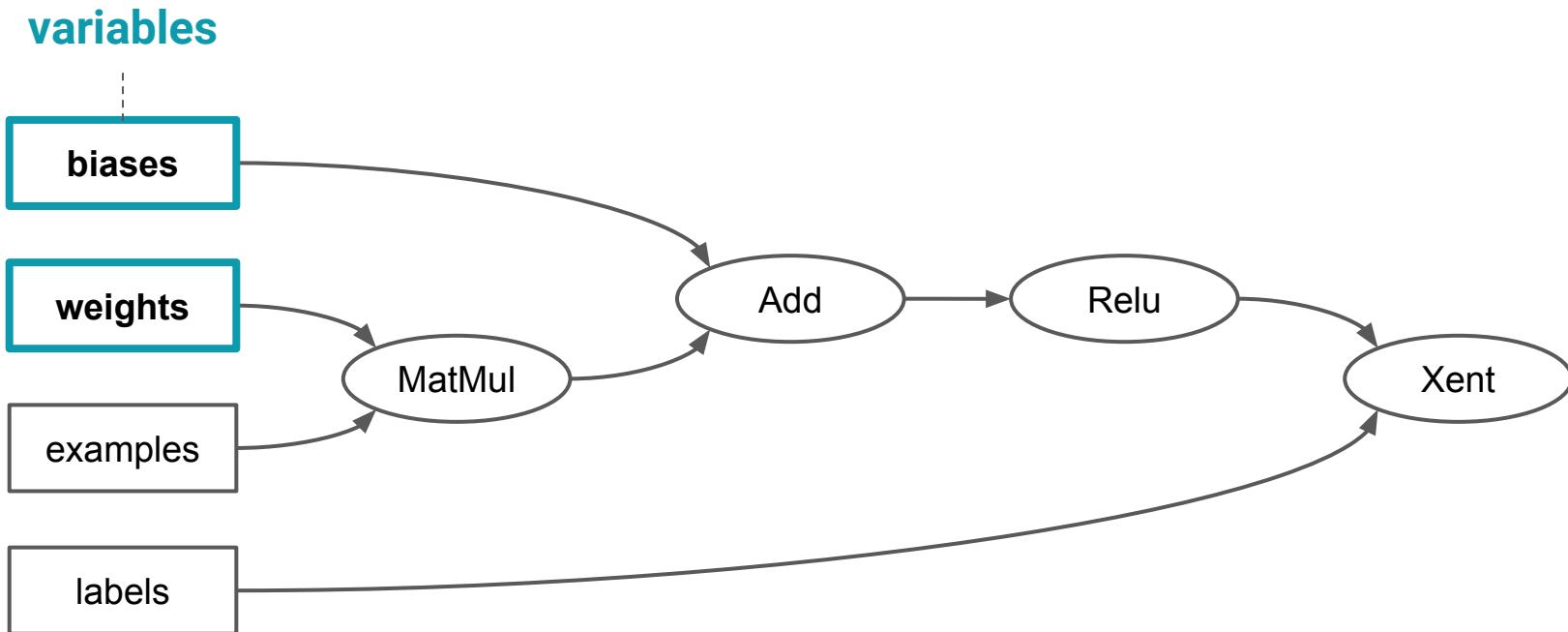
8

9

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

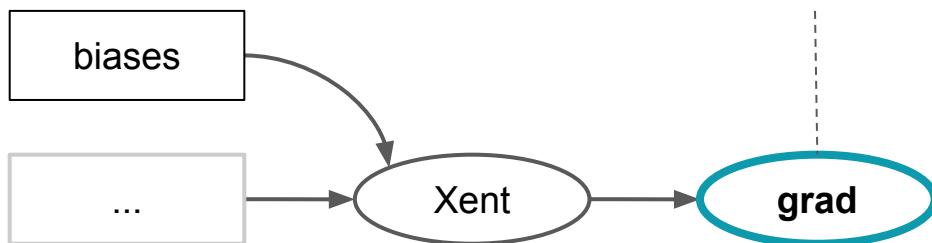


# Data flow, with state



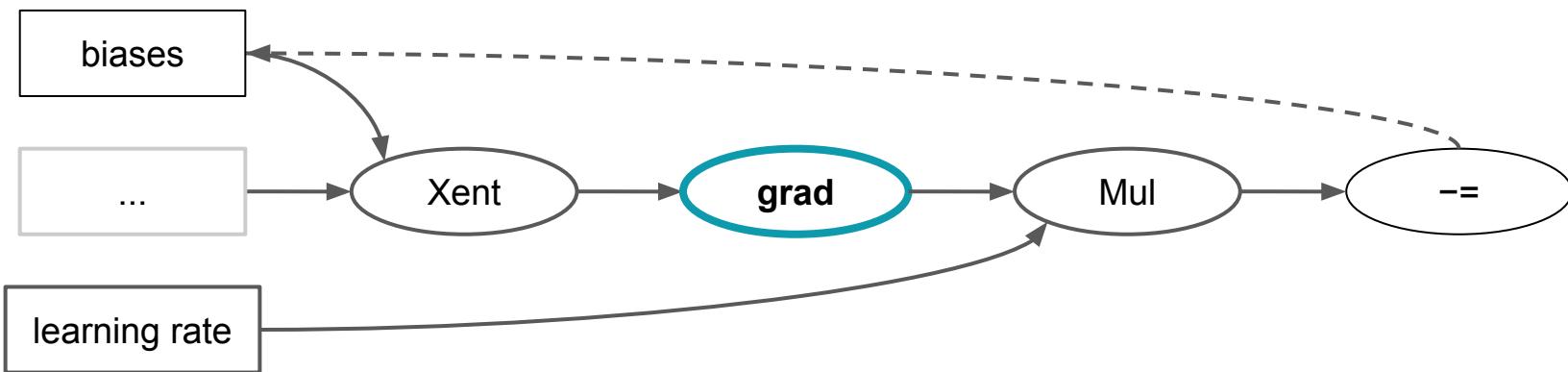
# Automatic Differentiation

Automatically add ops which  
compute gradients for variables

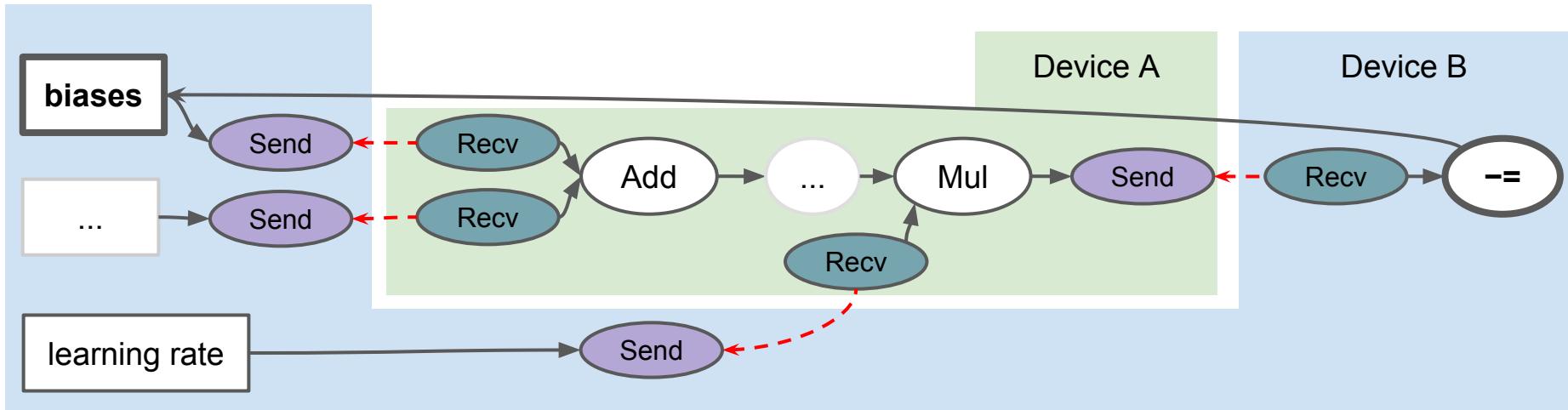


# Automatic Differentiation

Automatically add ops which compute gradients for variables



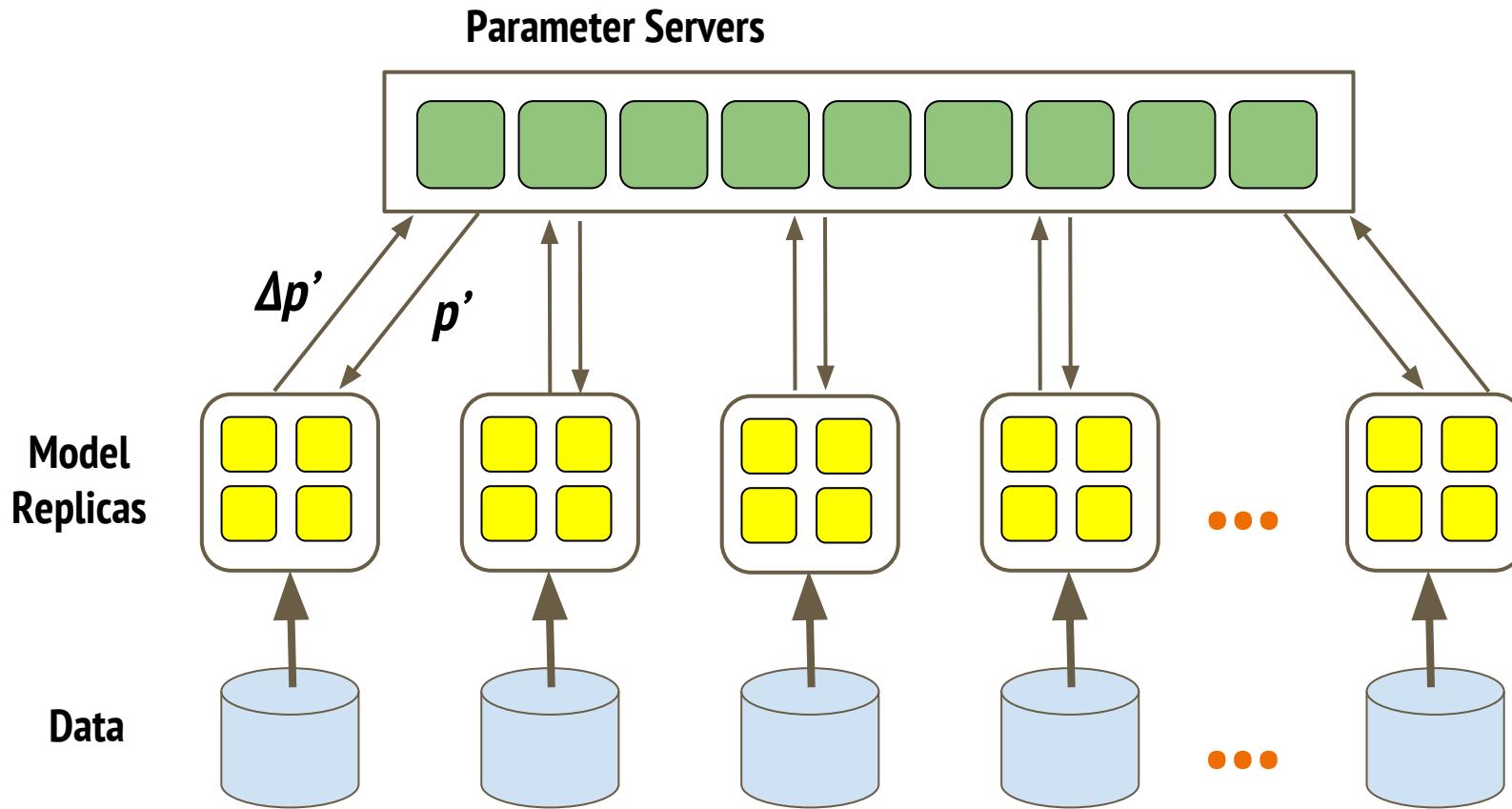
# Distributed



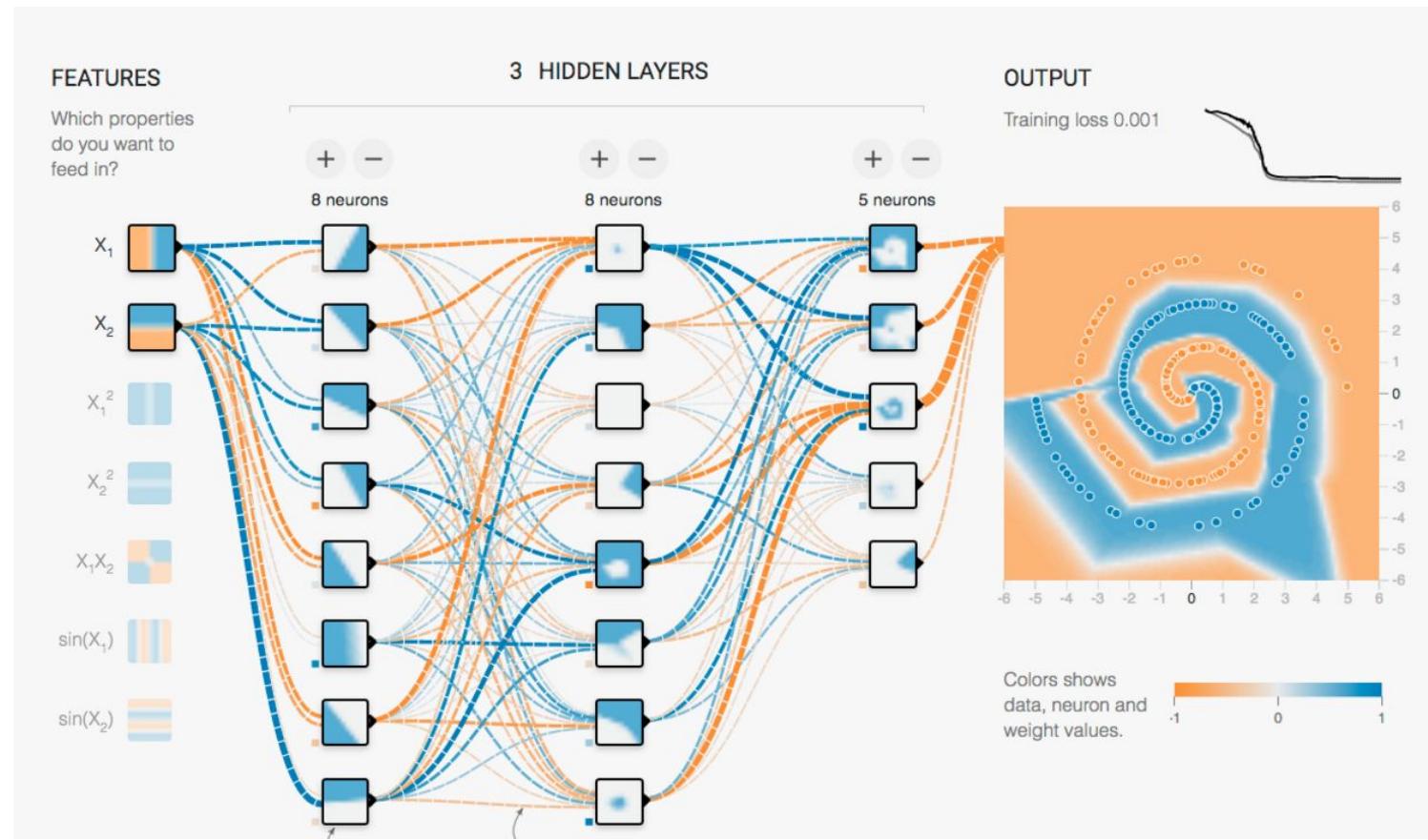
Send / receive nodes added automatically

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

# Data Parallelism



# Going Deeper

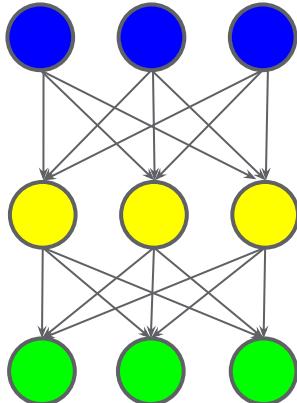


Hidden layers = Hierarchies of features

# Demo: TensorFlow Playground

[goo.gl/mXhncM](http://goo.gl/mXhncM)

# 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](http://goo.gl/nrdsxM)

# Higher level APIs

# Higher level APIs

## **tf.contrib.learn**

<https://www.tensorflow.org/versions/r0.12/tutorials/tflearn/index.html>

## **tf.slim**

<https://research.googleblog.com/2016/08/tf-slim-high-level-library-to-define.html>

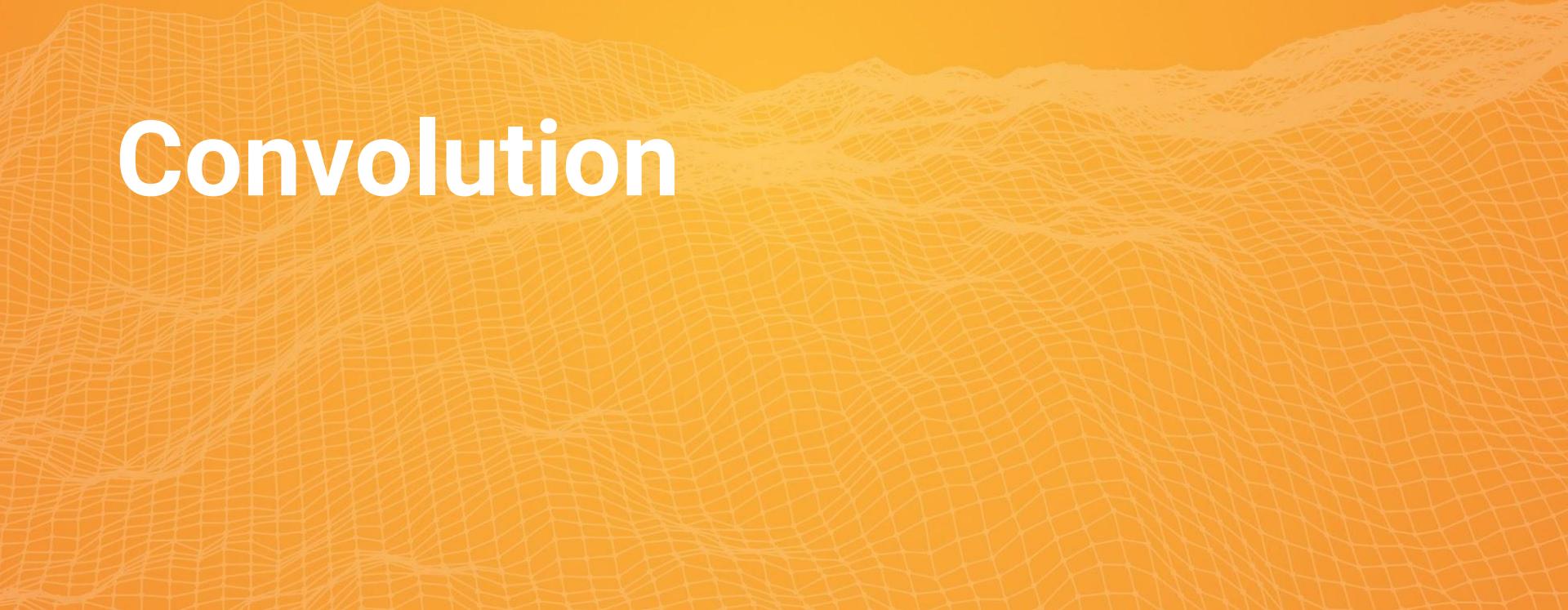
## **Keras**

<https://keras.io/>

# 5\_mnist\_tf\_contrib\_learn.ipynb

[goo.gl/nrdsxM](http://goo.gl/nrdsxM)

# Convolution



|   |   |   |   |   |
|---|---|---|---|---|
| 1<br><small><math>\times 1</math></small> | 1<br><small><math>\times 0</math></small> | 1<br><small><math>\times 1</math></small> | 0 | 0 |
| 0<br><small><math>\times 0</math></small> | 1<br><small><math>\times 1</math></small> | 1<br><small><math>\times 0</math></small> | 1 | 0 |
| 0<br><small><math>\times 1</math></small> | 0<br><small><math>\times 0</math></small> | 1<br><small><math>\times 1</math></small> | 1 | 1 |
| 0   | 0   | 1   | 1 | 0 |
| 0   | 1   | 1   | 0 | 0 |

Image

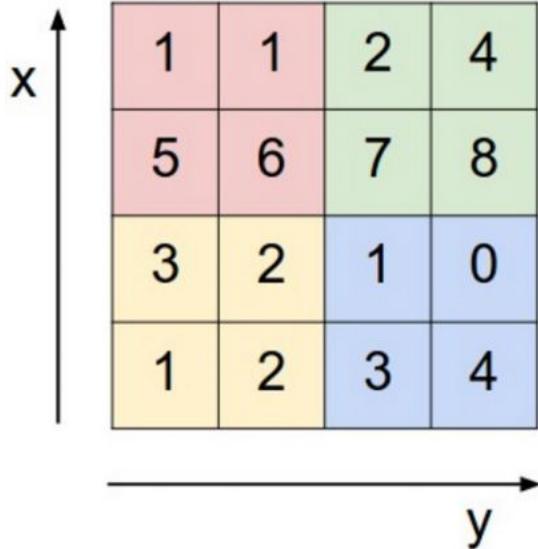
|   |  |  |
|---|--|--|
| 4 |  |  |
|   |  |  |
|   |  |  |
|   |  |  |

Convolved Feature

Convolution with  $3 \times 3$  Filter. Source:

[http://deeplearning.stanford.edu/wiki/index.php/Feature\\_extraction\\_using\\_convolution](http://deeplearning.stanford.edu/wiki/index.php/Feature_extraction_using_convolution)

### Single depth slice



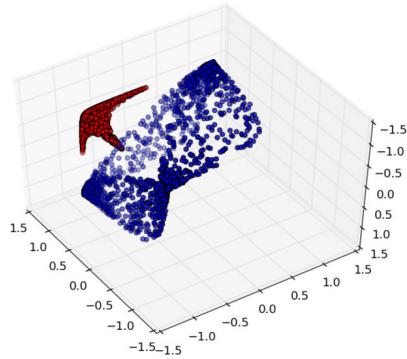
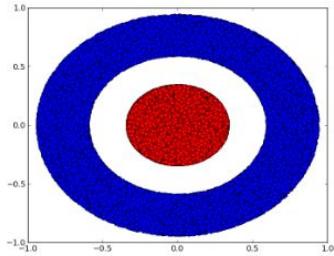
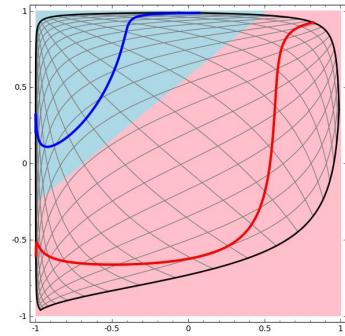
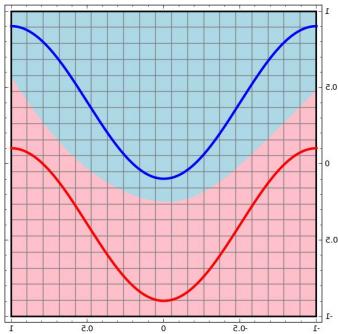
max pool with 2x2 filters  
and stride 2

A 2x2 grid representing the output of max pooling. The values are:

|   |   |
|---|---|
| 6 | 8 |
| 3 | 4 |

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

Learn more: [colah.github.io](https://colah.github.io)



From: [Neural Networks, Manifolds, and Topology](https://colah.github.io), 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](#)

# 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 when learning ML?**

- Nope. What matters is designing a proper experiment.

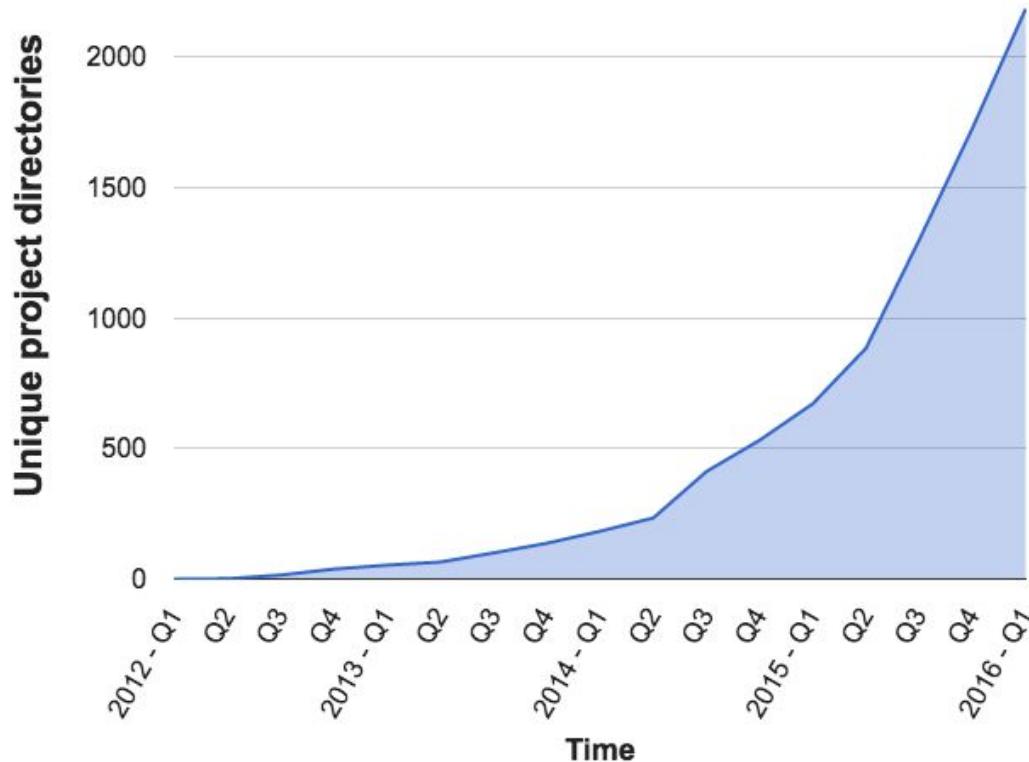
**6\_conv\_mnist.ipynb**

[goo.gl/nrdsxM](http://goo.gl/nrdsxM)

# Deep Learning at Google

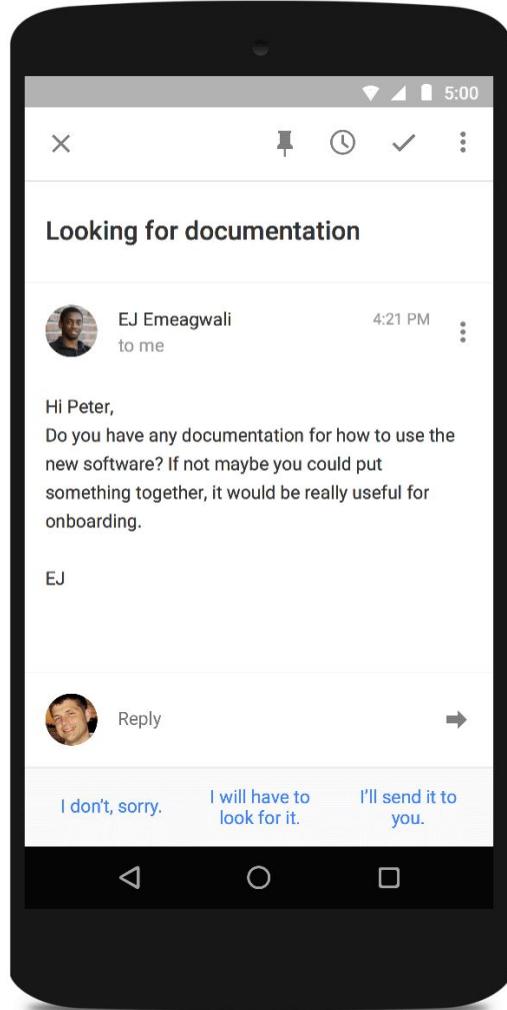
# Growing Use of Deep Learning at Google

# of directories containing model description files





EXIT

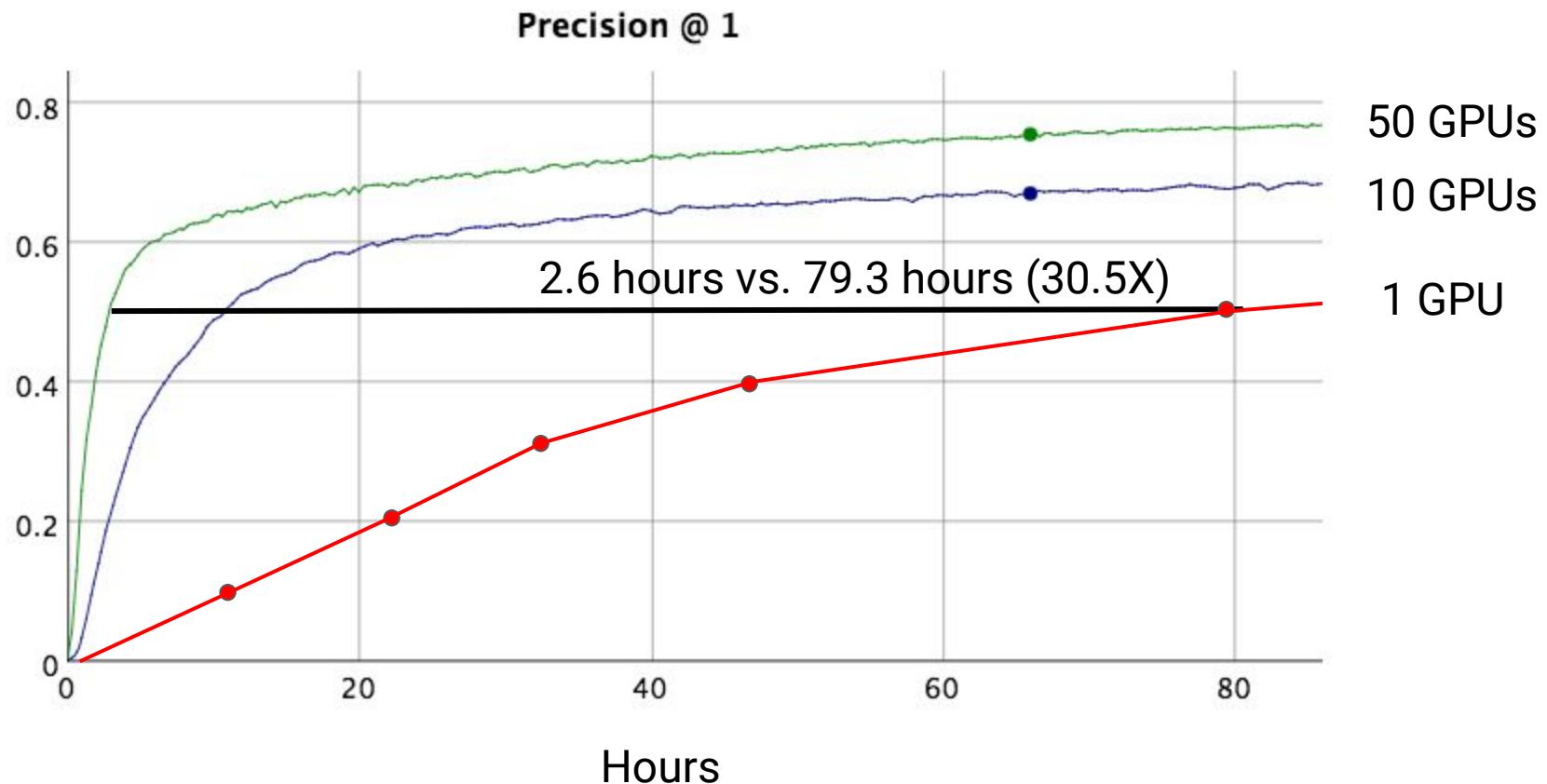


## Smart reply in Inbox by Gmail

10%

of all responses  
sent on mobile

# Image Model (Inception) Synchronous Training



# AlphaGo

BBC News Sport Weather iPlayer TV Radio More Search

## 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

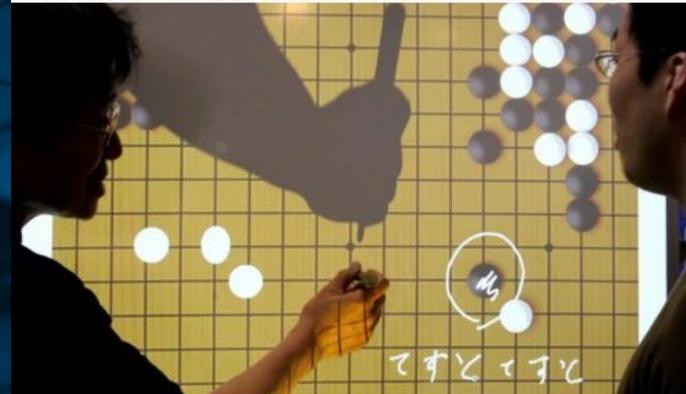
- How did they do it?
- What is the game Go?

Facebook trains AI to beat humans at Go



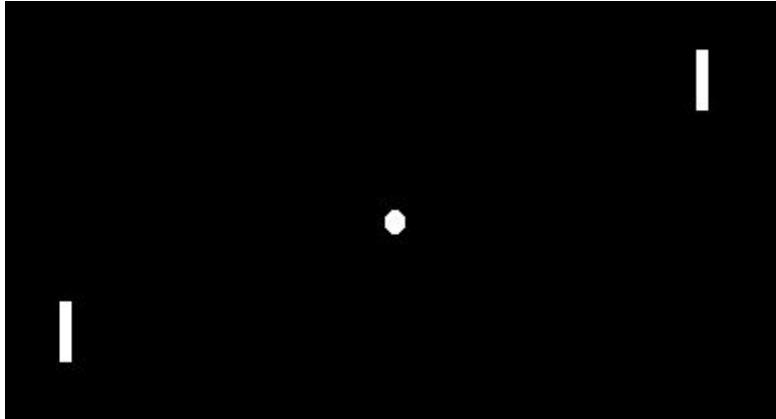
## Google's AI just cracked the game that supposedly no computer could beat

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.



<https://deepmind.com/research/dqn/>

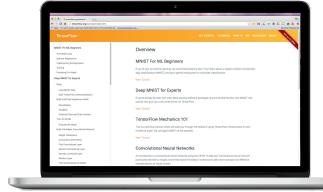
# Detection of Diabetic Eye Disease



<https://research.googleblog.com/2016/11/deep-learning-for-detection-of-diabetic.html>

# Next steps

Tutorials and code  
[tensorflow.org](http://tensorflow.org)



Totally new to ML?  
Recipes [goo.gl/KewA03](http://goo.gl/KewA03)

Intro to Deep Learning with TensorFlow  
Udacity class [goo.gl/iHssl](http://goo.gl/iHssl)

Stanford's CS231n  
[cs231n.github.io](http://cs231n.github.io)

Udacity's Machine Learning Nanodegree  
[goo.gl/ODpXj4](http://goo.gl/ODpXj4)

These slides + exercises  
[goo.gl/nrdsxM](http://goo.gl/nrdsxM)

TensorFlow Playground  
[goo.gl/mXhncM](http://goo.gl/mXhncM)

Chris Olah's blog  
[Colah.github.io](http://Colah.github.io)

Michael Nielsen's book  
[neuralnetworksanddeeplearning.com](http://neuralnetworksanddeeplearning.com)

# Thank you and have fun!



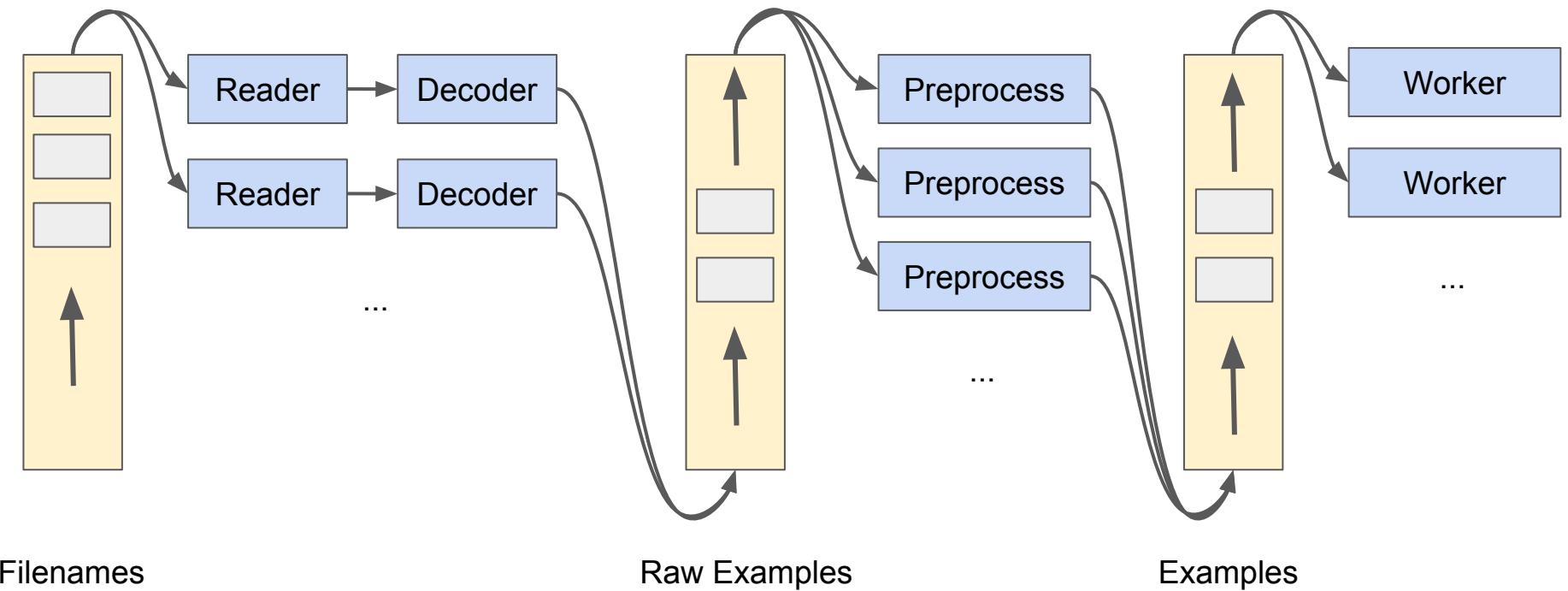
Josh Gordon  
[@random\\_forests](https://twitter.com/random_forests)



Wolff Dobson  
[@greenexec](https://twitter.com/greenexec)



# Input Pipelines with Queues





<https://cloud.google.com/blog/big-data/2016/08/how-a-japanese-cucumber-farmer-is-using-deep-learning-and-tensorflow>

# TensorFlow powered Cucumber Sorter



From: <http://workpiles.com/2016/02/tensorflow-cnn-cucumber/>

# Questions?