Tamkang University
淡江大學

Big Data Mining
巨量資料探勘

Tamkang University

Google TensorFlow 深度學習
(Deep Learning with Google TensorFlow)

1052DM10
MI4 (M2244) (3069)
Thu, 8, 9 (15:10-17:00) (B130)

Min-Yuh Day
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http://mail. tku.edu.tw/myday/

2017-05-11

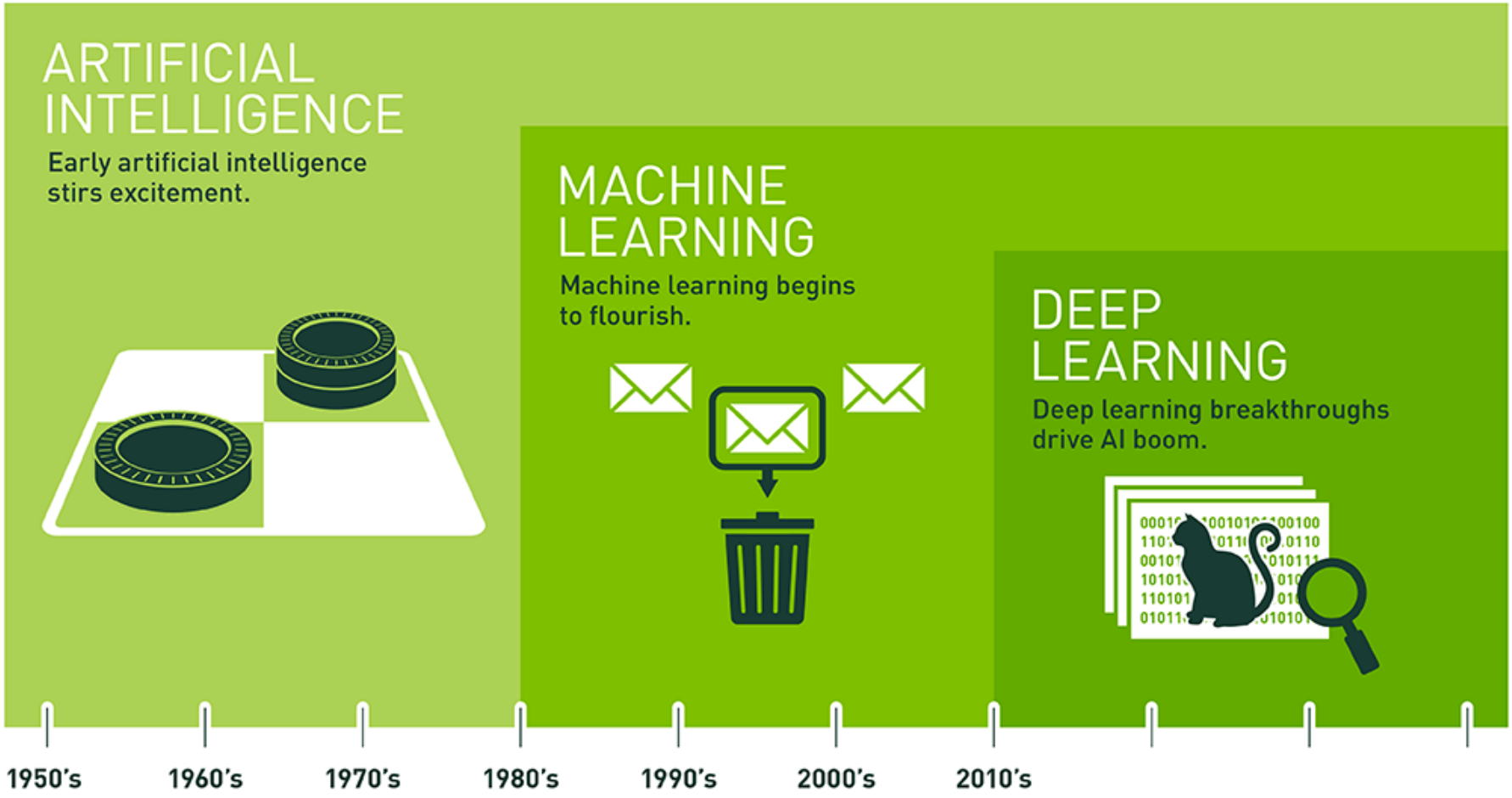
課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
1	2017/02/16	巨量資料探勘課程介紹 (Course Orientation for Big Data Mining)
2	2017/02/23	巨量資料基礎：MapReduce典範、Hadoop與Spark生態系統 (Fundamental Big Data: MapReduce Paradigm, Hadoop and Spark Ecosystem)
3	2017/03/02	關連分析 (Association Analysis)
4	2017/03/09	分類與預測 (Classification and Prediction)
5	2017/03/16	分群分析 (Cluster Analysis)
6	2017/03/23	個案分析與實作一 (SAS EM 分群分析)：Case Study 1 (Cluster Analysis – K-Means using SAS EM)
7	2017/03/30	個案分析與實作二 (SAS EM 關連分析)：Case Study 2 (Association Analysis using SAS EM)

課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
8	2017/04/06	教學行政觀摩日 (Off-campus study)
9	2017/04/13	期中報告 (Midterm Project Presentation)
10	2017/04/20	期中考試週 (Midterm Exam)
11	2017/04/27	個案分析與實作三 (SAS EM 決策樹、模型評估)：Case Study 3 (Decision Tree, Model Evaluation using SAS EM)
12	2017/05/04	個案分析與實作四 (SAS EM 迴歸分析、類神經網路)：Case Study 4 (Regression Analysis, Artificial Neural Network using SAS EM)
13	2017/05/11	Google TensorFlow 深度學習 (Deep Learning with Google TensorFlow)
14	2017/05/18	期末報告 (Final Project Presentation)
15	2017/05/25	畢業班考試 (Final Exam)

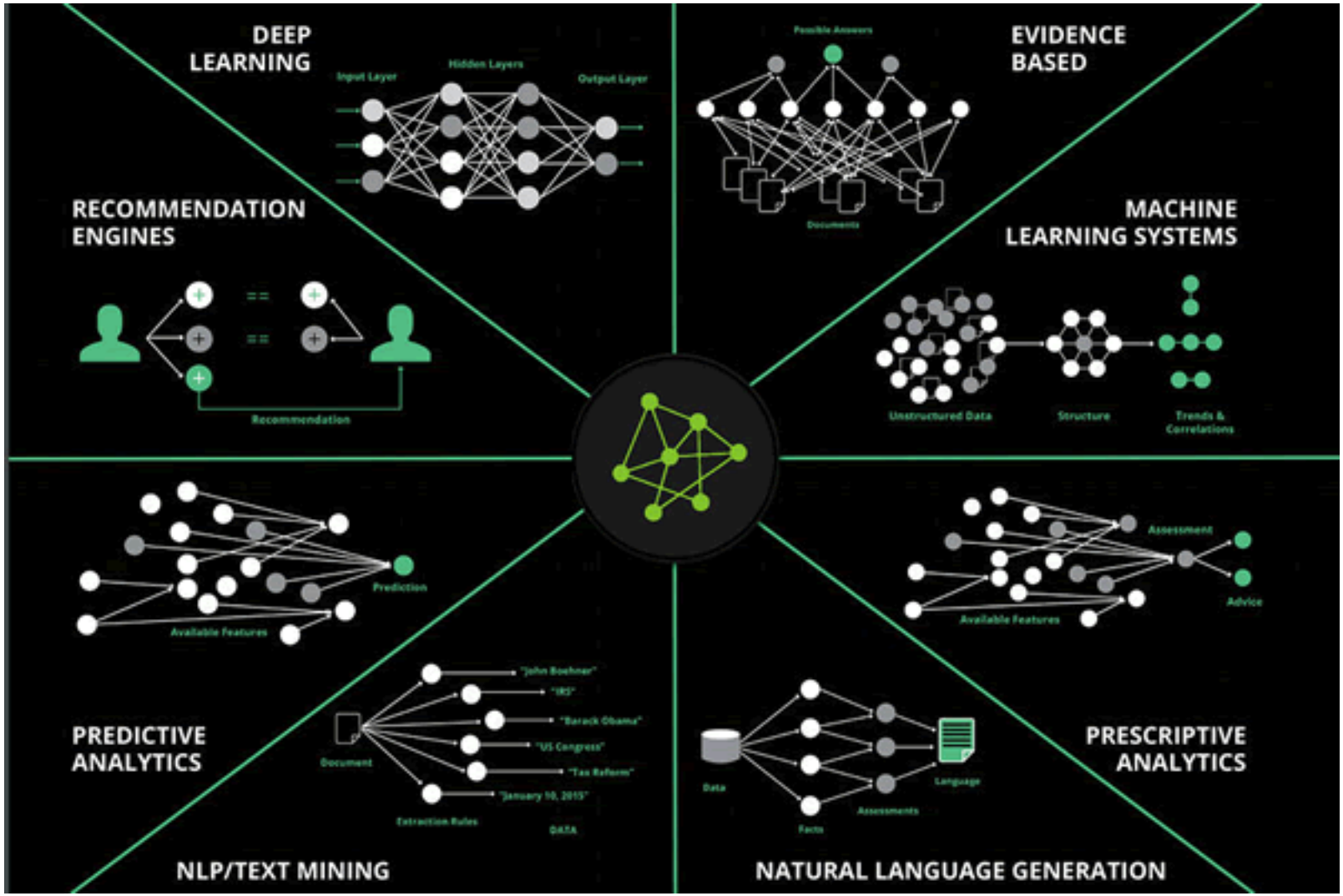
Artificial Intelligence
Machine Learning & Deep Learning



Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

Source: https://blogs.nvidia.com/blog/2016/07/29/whats-difference-artificial-intelligence-machine-learning-deep-learning-ai/

Artificial Intelligence (AI) is many things

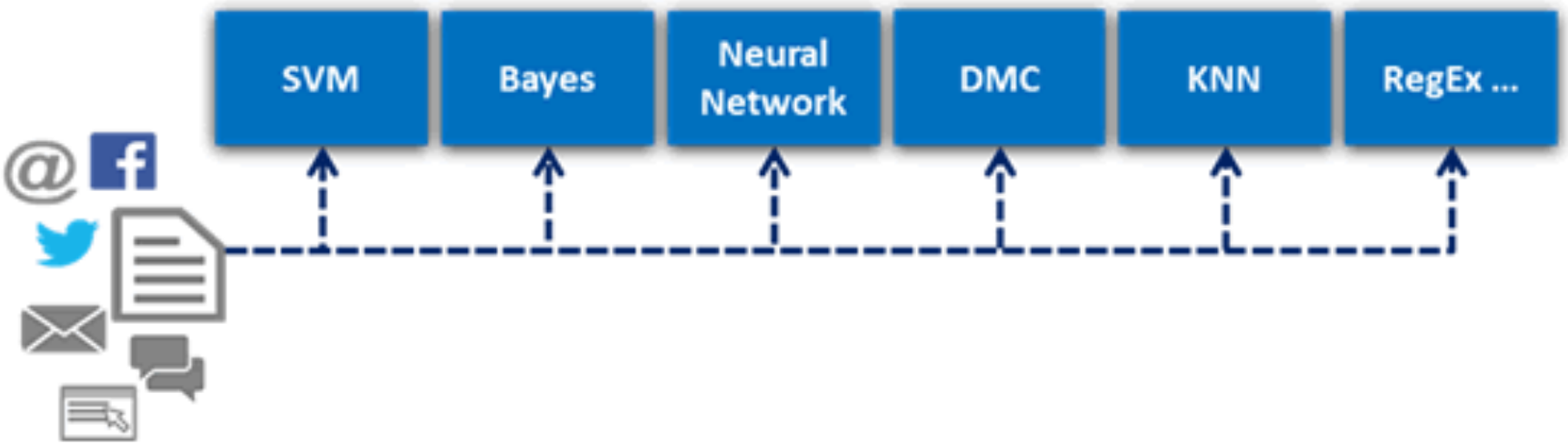


Ecosystem of AI

Source: https://www.i-scoop.eu/artificial-intelligence-cognitive-computing/

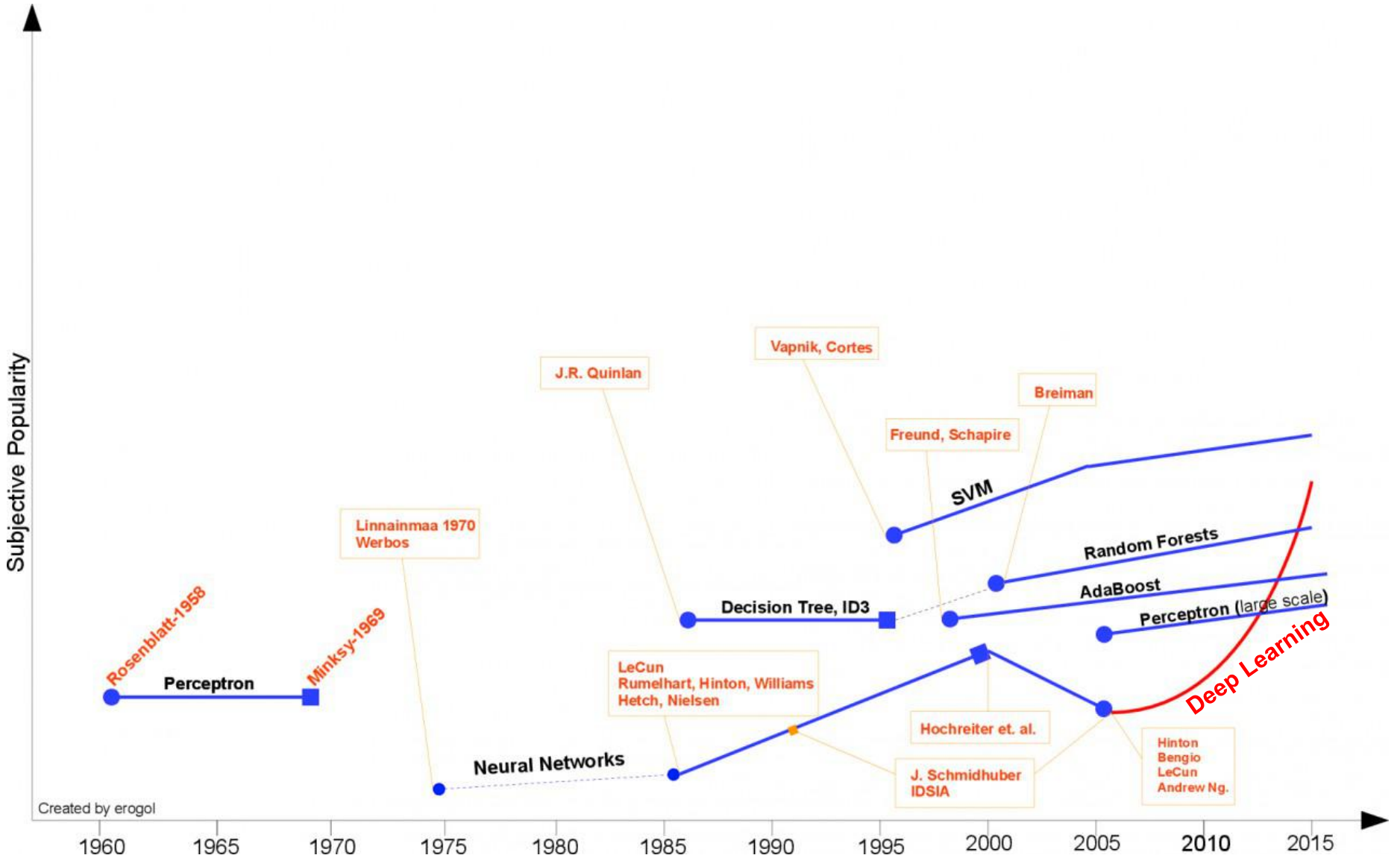
Artificial Intelligence (AI)

Intelligent Document Recognition algorithms



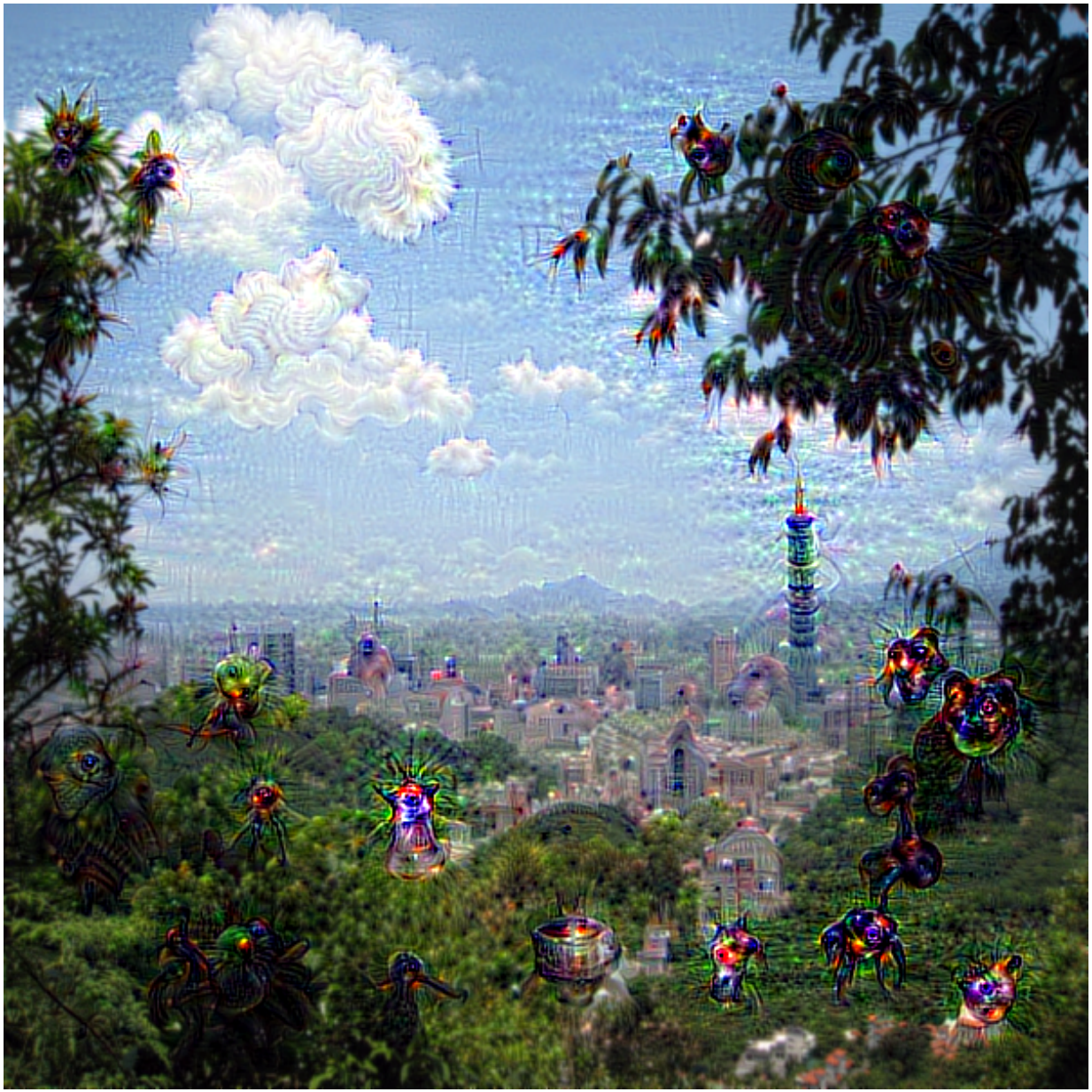
Source: https://www.i-scoop.eu/artificial-intelligence-cognitive-computing/

Deep Learning Evolution



Source: http://www.erogol.com/brief-history-machine-learning/

Deep Dream



https://github.com/fchollet/keras/blob/master/examples/deep_dream.py

LeCun, Yann,
Yoshua Bengio,
and Geoffrey Hinton.

"Deep learning."

Nature 521, no. 7553 (2015): 436-444.

REVIEW

doi:10.1038/nature14539

Deep learning

Yann LeCun[1,2], Yoshua Bengio[3] & Geoffrey Hinton[4,5]

Deep learning allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction. These methods have dramatically improved the state-of-the-art in speech recognition, visual object recognition, object detection and many other domains such as drug discovery and genomics. Deep learning discovers intricate structure in large data sets by using the backpropagation algorithm to indicate how a machine should change its internal parameters that are used to compute the representation in each layer from the representation in the previous layer. Deep convolutional nets have brought about breakthroughs in processing images, video, speech and audio, whereas recurrent nets have shone light on sequential data such as text and speech.

Machine-learning technology powers many aspects of modern society: from web searches to content filtering on social networks to recommendations on e-commerce websites, and it is increasingly present in consumer products such as cameras and smartphones. Machine-learning systems are used to identify objects in images, transcribe speech into text, match news items, posts or products with users' interests, and select relevant results of search. Increasingly, these applications make use of a class of techniques called deep learning.

Conventional machine-learning techniques were limited in their ability to process natural data in their raw form. For decades, constructing a pattern-recognition or machine-learning system required careful engineering and considerable domain expertise to design a feature extractor that transformed the raw data (such as the pixel values of an image) into a suitable internal representation or feature vector from which the learning subsystem, often a classifier, could detect or classify patterns in the input.

Representation learning is a set of methods that allows a machine to be fed with raw data and to automatically discover the representations needed for detection or classification. Deep-learning methods are representation-learning methods with multiple levels of representation, obtained by composing simple but non-linear modules that each transform the representation at one level (starting with the raw input) into a representation at a higher, slightly more abstract level. With the composition of enough such transformations, very complex functions can be learned. For classification tasks, higher layers of representation amplify aspects of the input that are important for discrimination and suppress irrelevant variations. An image, for example, comes in the form of an array of pixel values, and the learned features in the first layer of representation typically represent the presence or absence of edges at particular orientations and locations in the image. The second layer typically detects motifs by spotting particular arrangements of edges, regardless of small variations in the edge positions. The third layer may assemble motifs into larger combinations that correspond to parts of familiar objects, and subsequent layers would detect objects as combinations of these parts. The key aspect of deep learning is that these layers of features are not designed by human engineers: they are learned from data using a general-purpose learning procedure.

Deep learning is making major advances in solving problems that have resisted the best attempts of the artificial intelligence community for many years. It has turned out to be very good at discovering intricate structures in high-dimensional data and is therefore applicable to many domains of science, business and government. In addition to beating records in image recognition[1–4] and speech recognition[5–7], it has beaten other machine-learning techniques at predicting the activity of potential drug molecules[8], analysing particle accelerator data[9,10], reconstructing brain circuits[11], and predicting the effects of mutations in non-coding DNA on gene expression and disease[12,13]. Perhaps more surprisingly, deep learning has produced extremely promising results for various tasks in natural language understanding[14], particularly topic classification, sentiment analysis, question answering[15] and language translation[16,17].

Source: LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep learning." Nature 521, no. 7553 (2015): 436-444.

Machine Learning Models

- Deep Learning
- Association rules
- Decision tree
- Clustering
- Bayesian
- Kernel
- Ensemble
- Dimensionality reduction
- Regression Analysis
- Instance based

Source: Sunila Gollapudi (2016), Practical Machine Learning, Packt Publishing

Neural networks (NN) 1960

Source: Sunila Gollapudi (2016), Practical Machine Learning, Packt Publishing

Multilayer Perceptrons (MLP) 1985

Source: Sunila Gollapudi (2016), Practical Machine Learning, Packt Publishing

Support Vector Machine (SVM) 1995

Source: Sunila Gollapudi (2016), Practical Machine Learning, Packt Publishing

Hinton presents the

Deep Belief Network (DBN)

New interests in deep learning and RBM

State of the art MNIST

2005

Source: Sunila Gollapudi (2016), Practical Machine Learning, Packt Publishing

Deep Recurrent Neural Network (RNN) 2009

Source: Sunila Gollapudi (2016), Practical Machine Learning, Packt Publishing

Convolutional DBN 2010

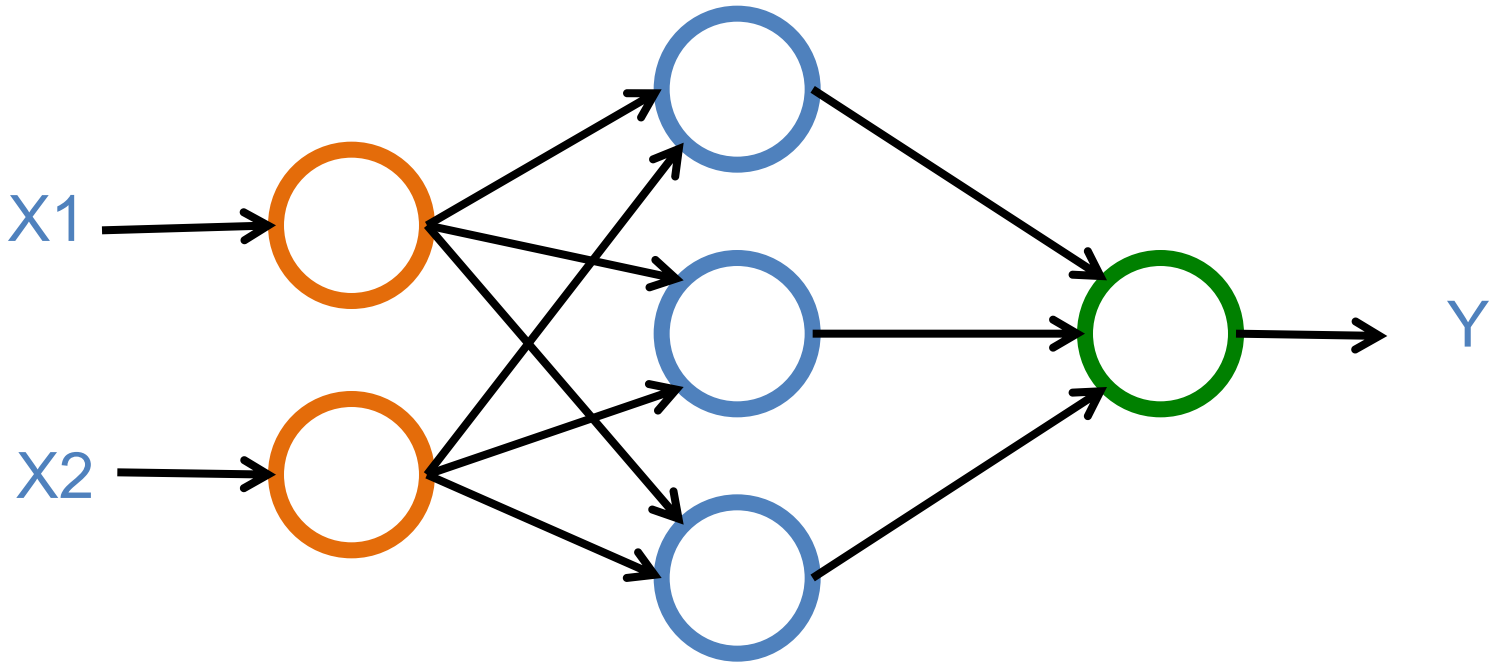
Source: Sunila Gollapudi (2016), Practical Machine Learning, Packt Publishing

Max-Pooling CDBN 2011

Source: Sunila Gollapudi (2016), Practical Machine Learning, Packt Publishing

Neural Networks

Input Layer (X) Hidden Layer (H) **Output Layer (Y)**



Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

Deep Learning

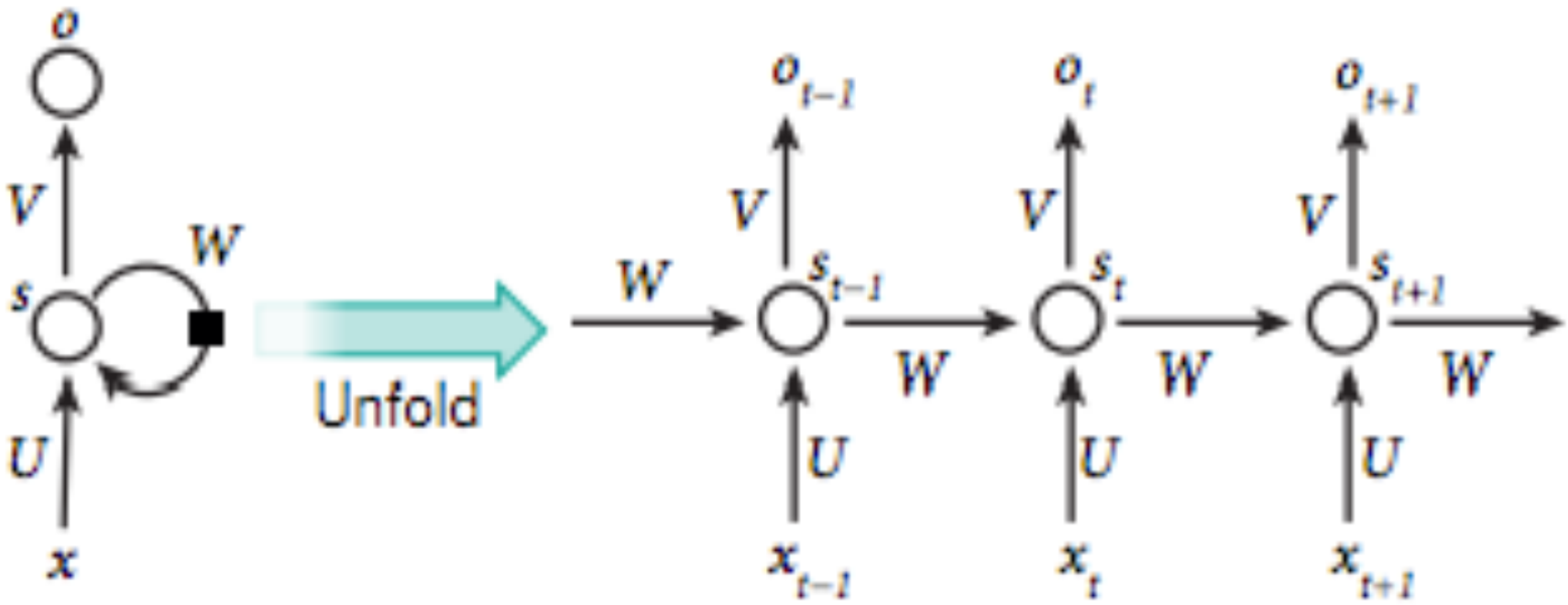
Geoffrey Hinton

Yann LeCun

Yoshua Bengio

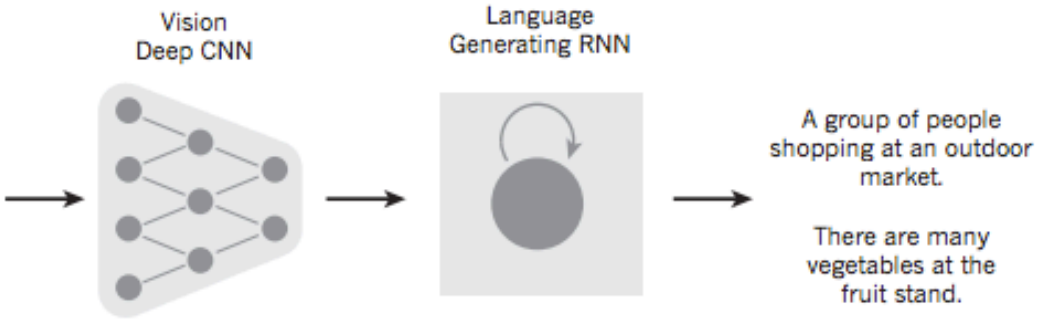
Andrew Y. Ng

Recurrent Neural Network (RNN)



Source: LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep learning." Nature 521, no. 7553 (2015): 436-444.

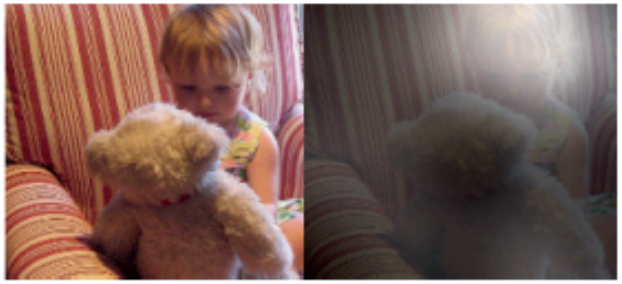
From image to text



A woman is throwing a **frisbee** in a park.

A **dog** is standing on a hardwood floor.

A **stop** sign is on a road with a mountain in the background



A little **girl** sitting on a bed with a teddy bear.

A group of **people** sitting on a boat in the water.

A giraffe standing in a forest with **trees** in the background.

Source: LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep learning." Nature 521, no. 7553 (2015): 436-444.

From image to text

Image: deep convolution neural network (CNN)

Text: recurrent neural network (RNN)

A group of **people** sitting on a boat in the water.

Source: LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep learning." Nature 521, no. 7553 (2015): 436-444.

CS224d: Deep Learning for Natural Language Processing

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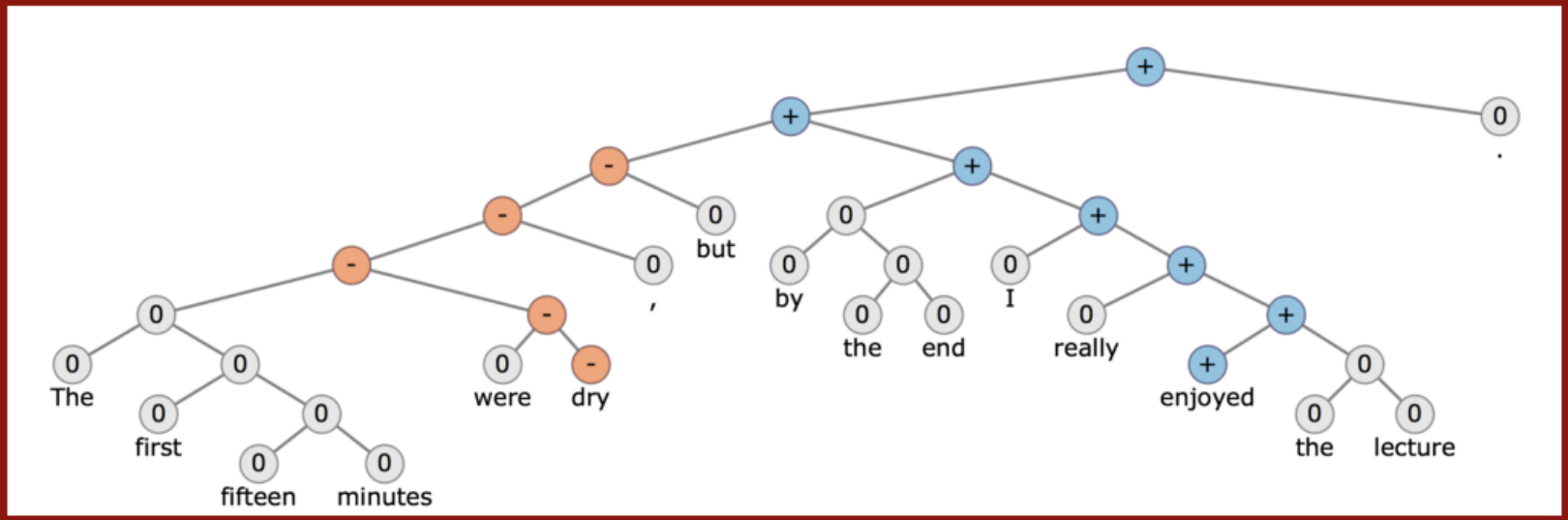
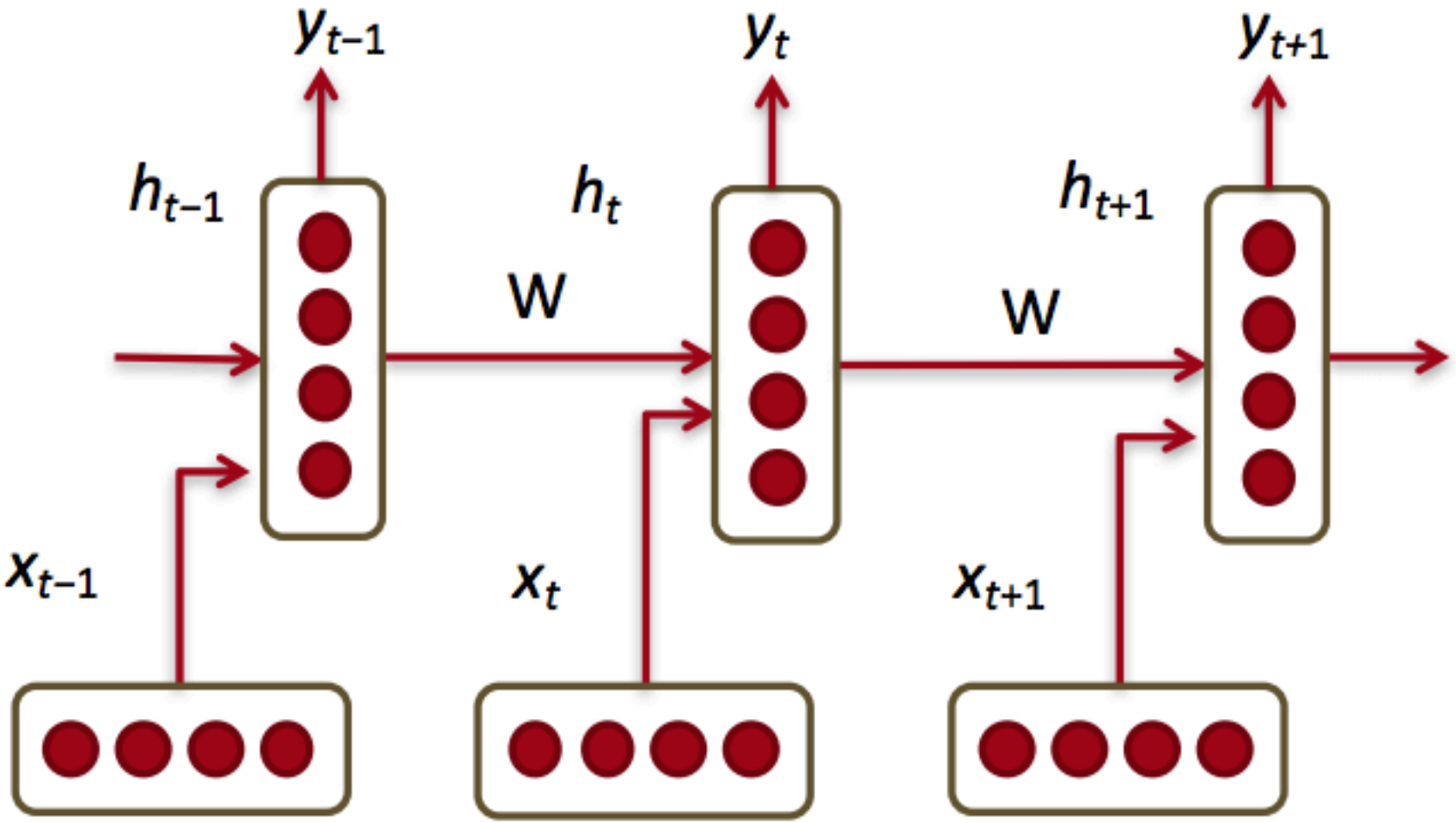


Course Description

Natural language processing (NLP) is one of the most important technologies of the information age. Understanding complex language utterances is also a crucial part of artificial intelligence. Applications of NLP are everywhere because people communicate most everything in language: web search, advertisement, emails, customer service, language translation, radiology reports, etc. There are a large variety of underlying tasks and machine learning models powering NLP applications. Recently, deep learning approaches have obtained very high performance across many different NLP tasks. These models can often be trained with a single end-to-end model and do not require traditional, task-specific feature engineering. In this spring quarter course students will learn to implement, train, debug, visualize and invent their own neural network models. The course provides a deep excursion into cutting-edge research in deep learning applied to NLP. The final project will involve training a complex recurrent neural network and applying it to a large scale NLP problem. On the model side we will cover word vector representations,

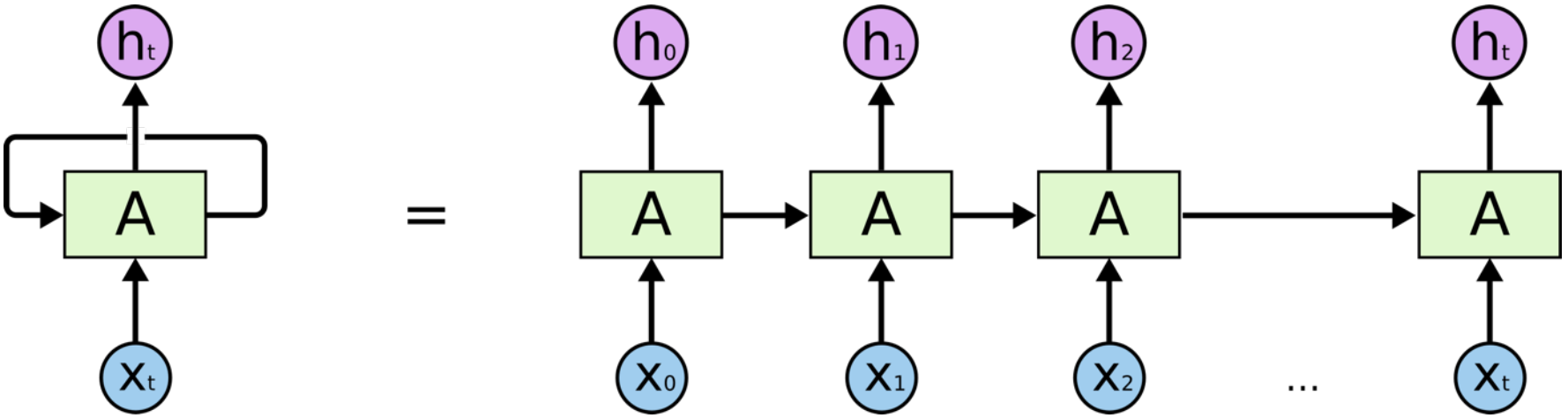
http://cs224d.stanford.edu/

Recurrent Neural Networks (RNNs)



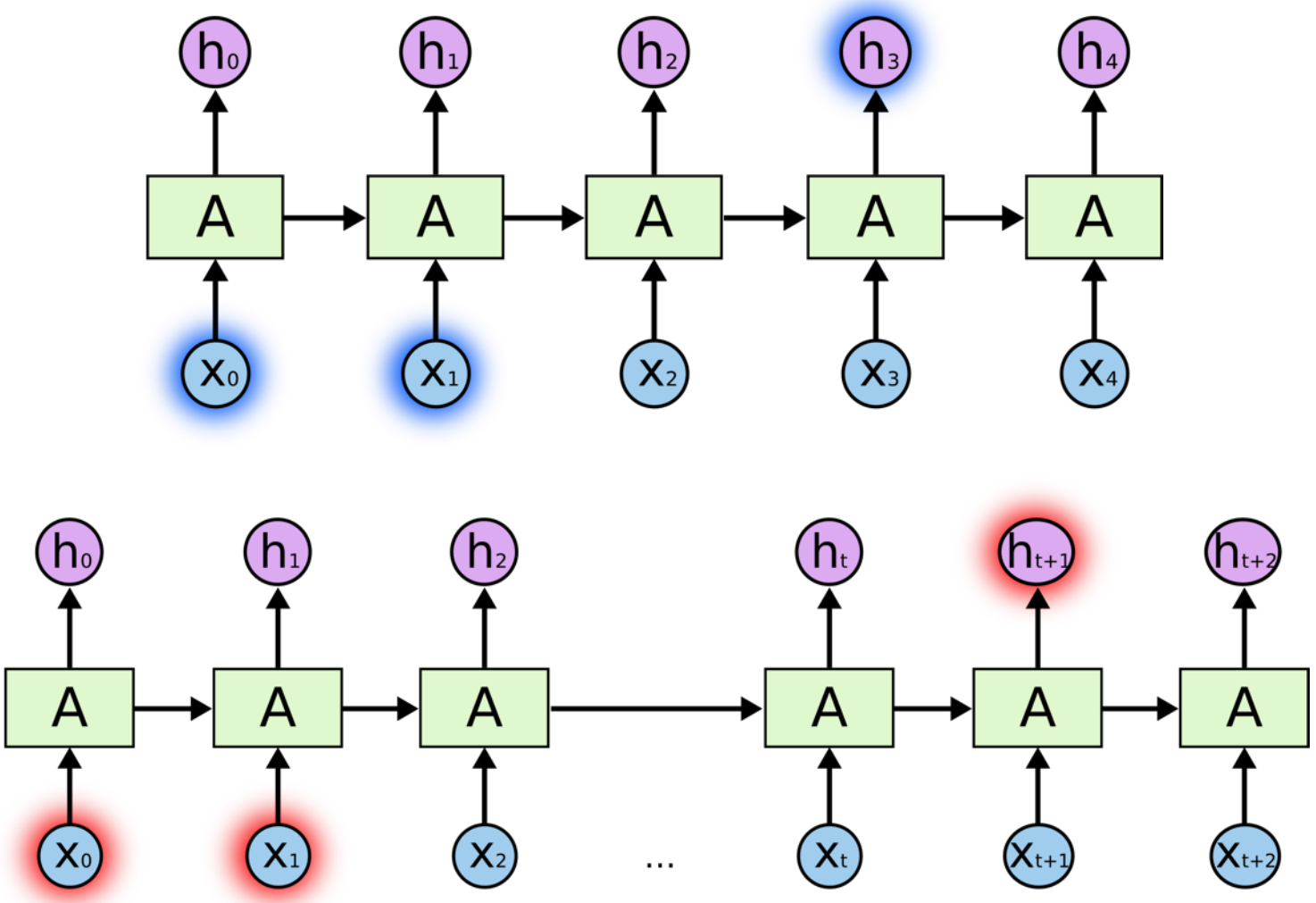
Source: http://cs224d.stanford.edu/lectures/CS224d-Lecture8.pdf

RNN



Source: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

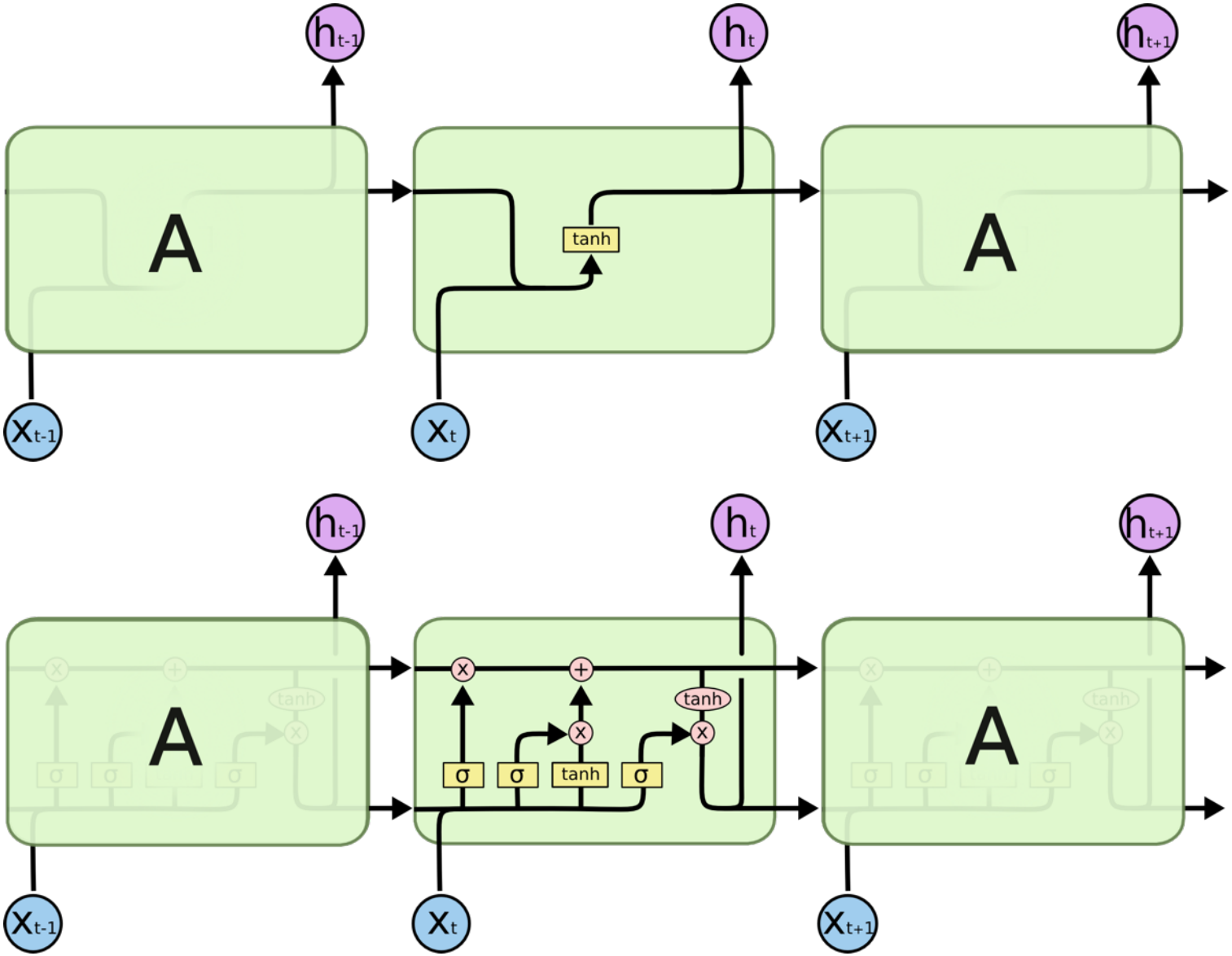
RNN long-term dependencies



I grew up in France… I speak fluent French.

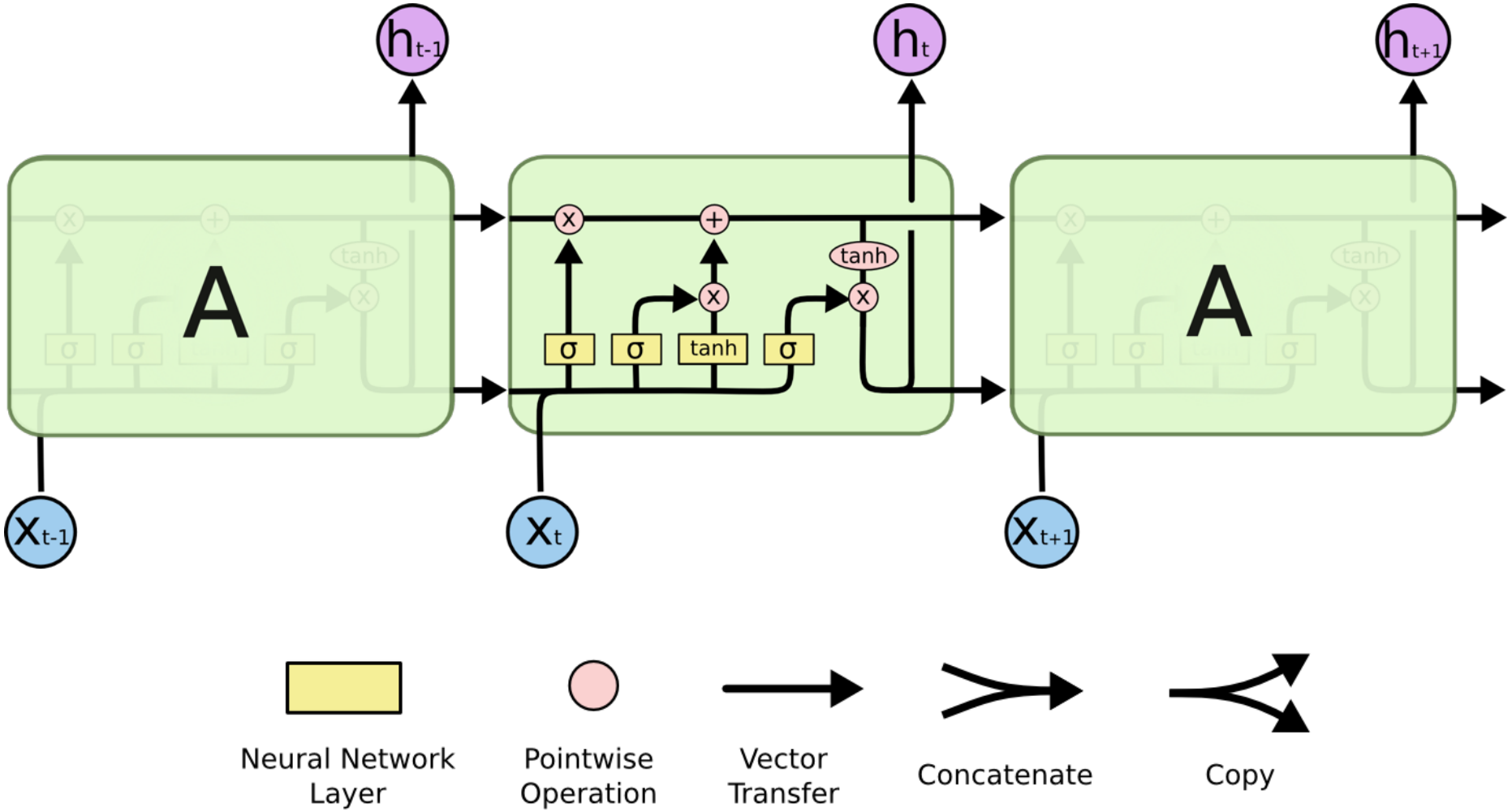
Source: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

RNN LSTM



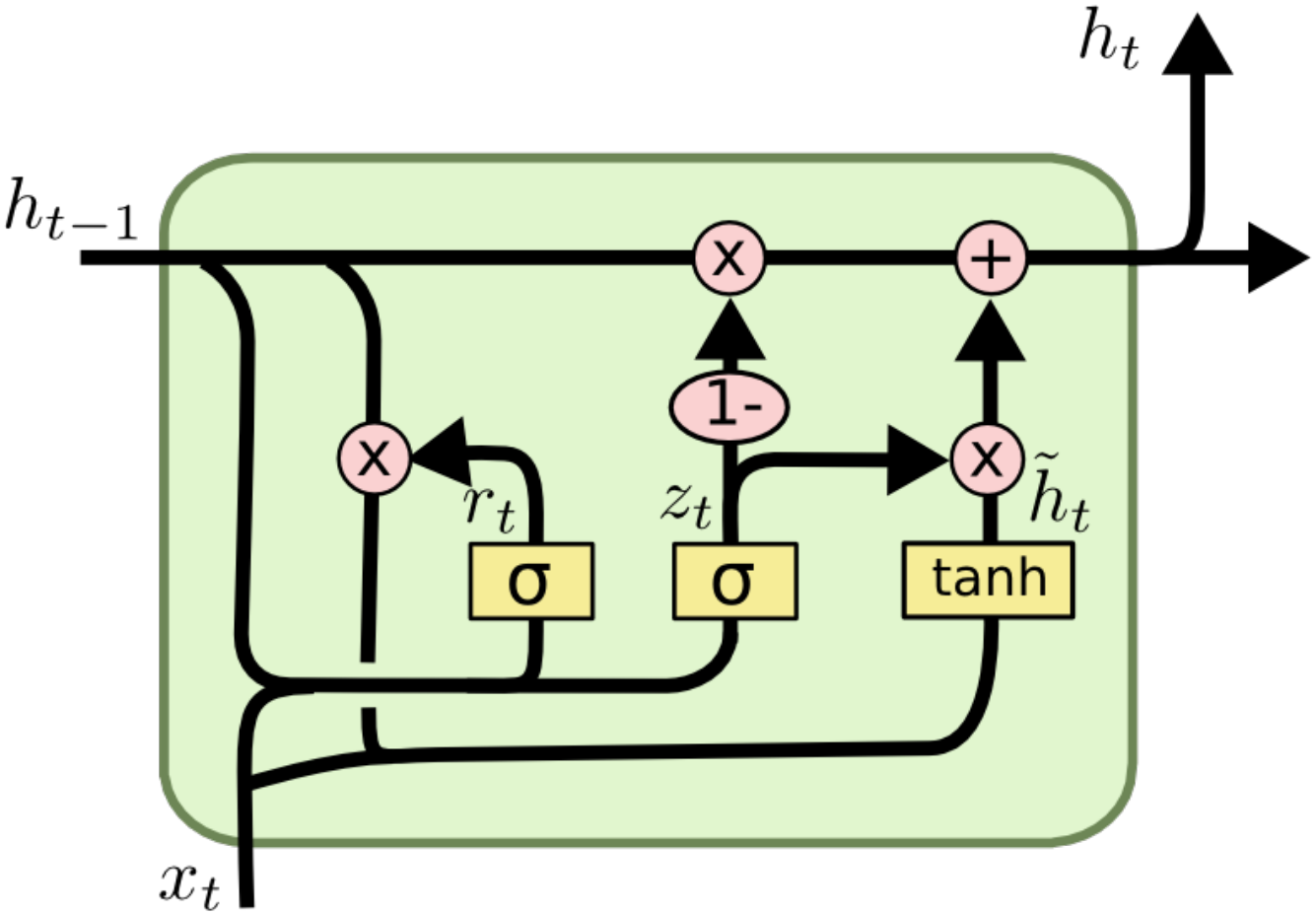
Source: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Long Short Term Memory (LSTM)



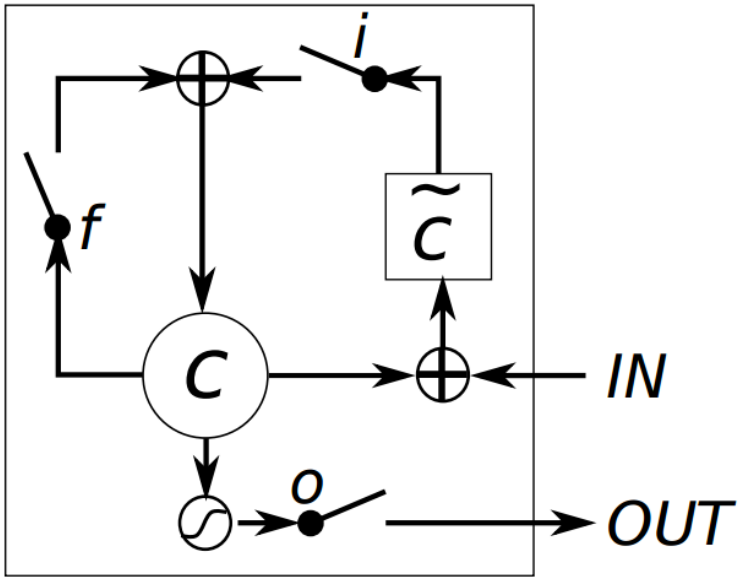
Source: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

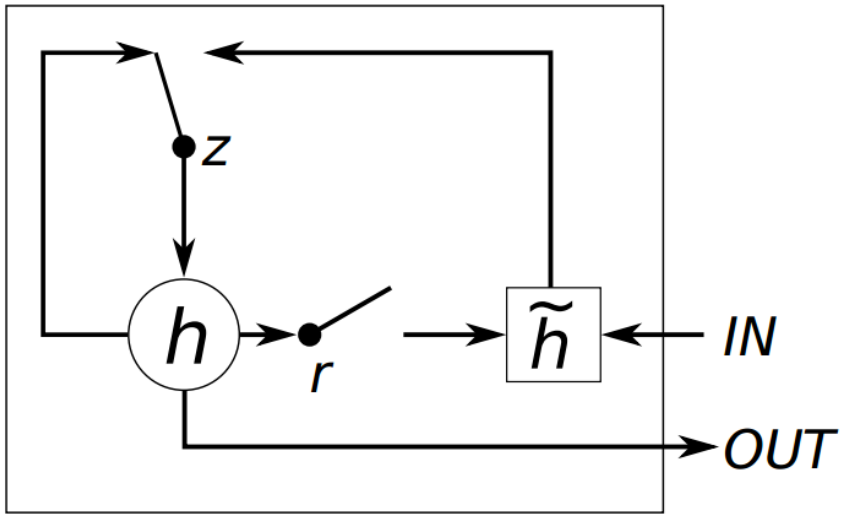
Gated Recurrent Unit (GRU)



Source: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM vs GRU





LSTM

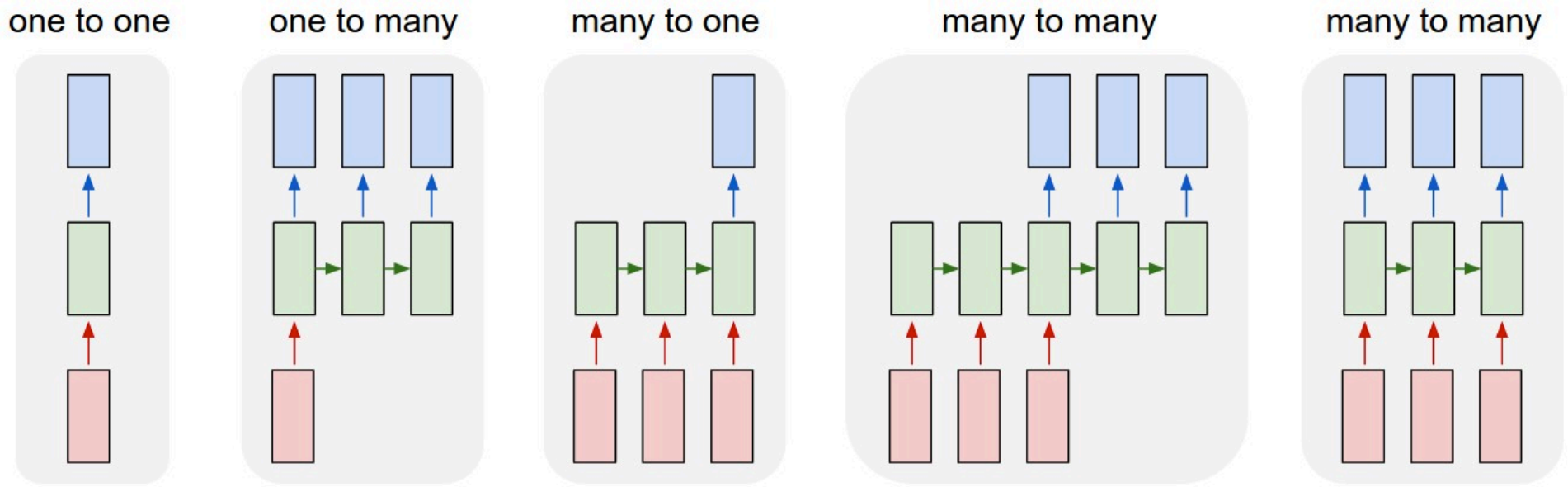
i, f and o are the input, forget and output gates, respectively.
c and c˜ denote the memory cell and the new memory cell content.

GRU

r and z are the reset and update gates, and h and h˜ are the activation and the candidate activation.

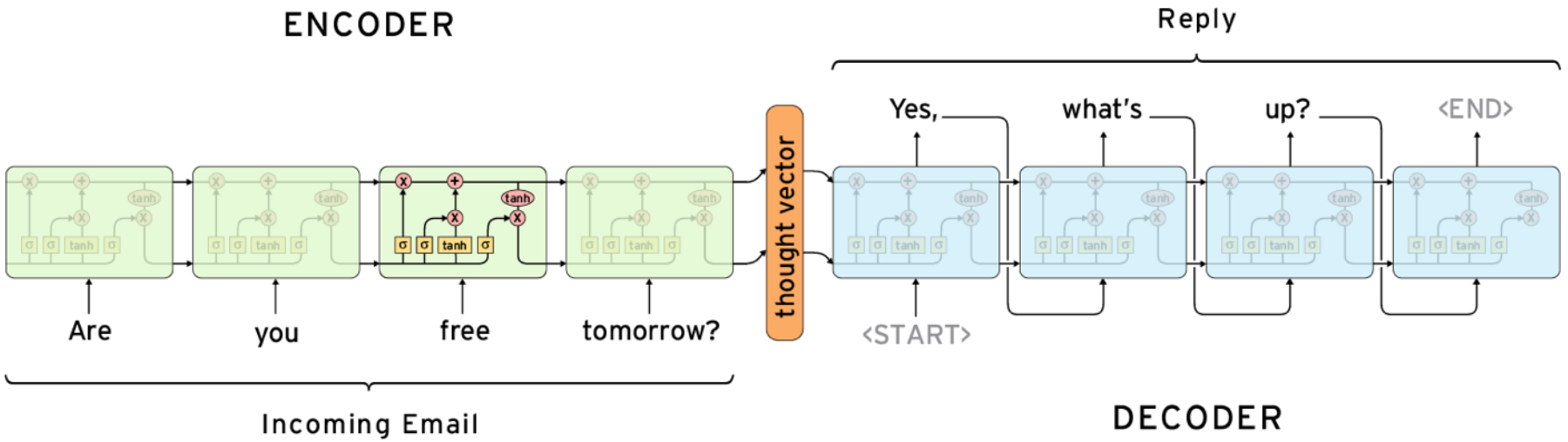
Source: Chung, Junyoung, Caglar Gulcehre, KyungHyun Cho, and Yoshua Bengio. "Empirical evaluation of gated recurrent neural networks on sequence modeling." *arXiv preprint arXiv:1412.3555* (2014).

LSTM Recurrent Neural Network



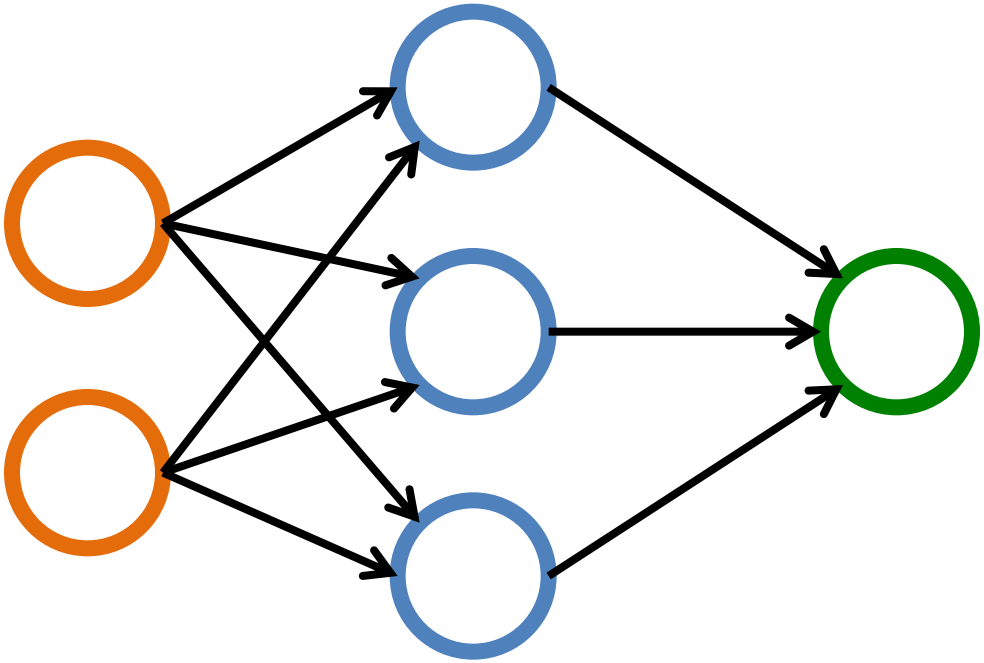
Source: https://github.com/Vict0rSch/deep_learning/tree/master/keras/recurrent

The Sequence to Sequence model (seq2seq)



Source: http://suriyadeepan.github.io/2016-12-31-practical-seq2seq/

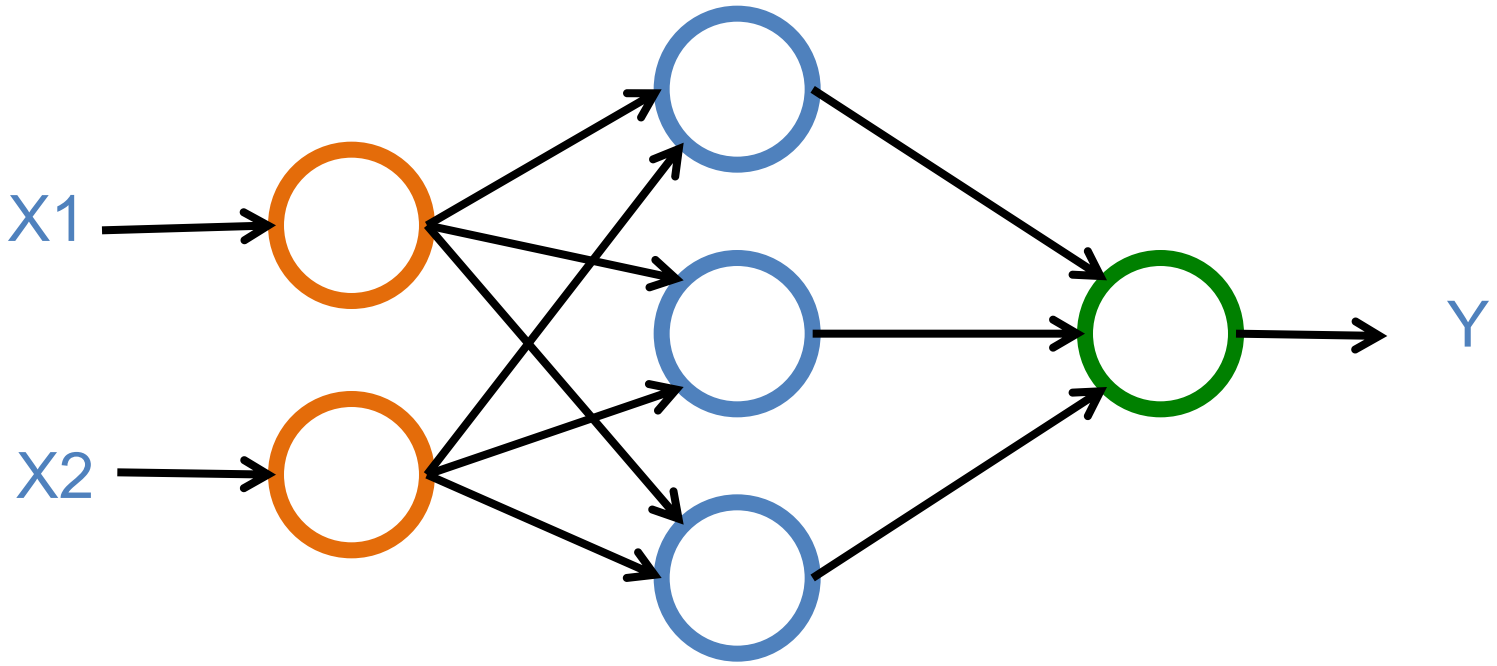
Neural Networks



Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

Neural Networks

Input Layer (X) Hidden Layer (H) **Output Layer (Y)**



Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

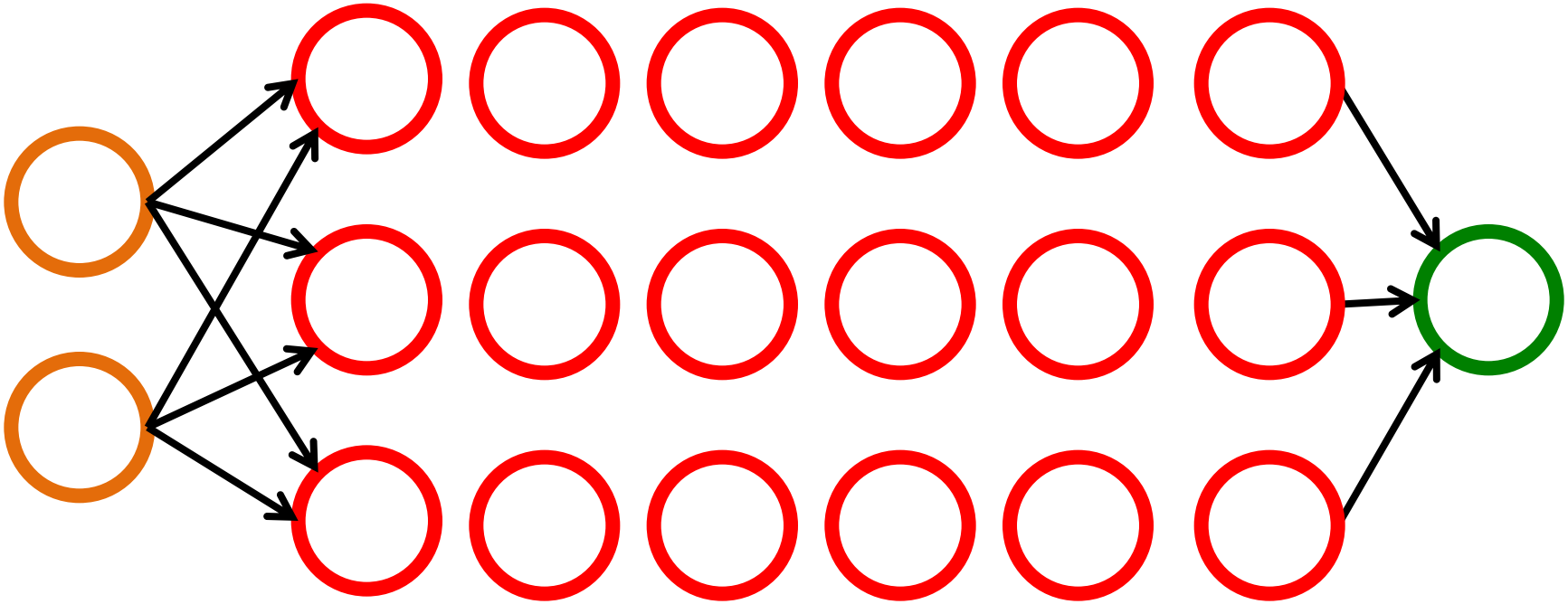
Neural Networks

Input Layer (X)

Hidden Layers (H)

Output Layer (Y)

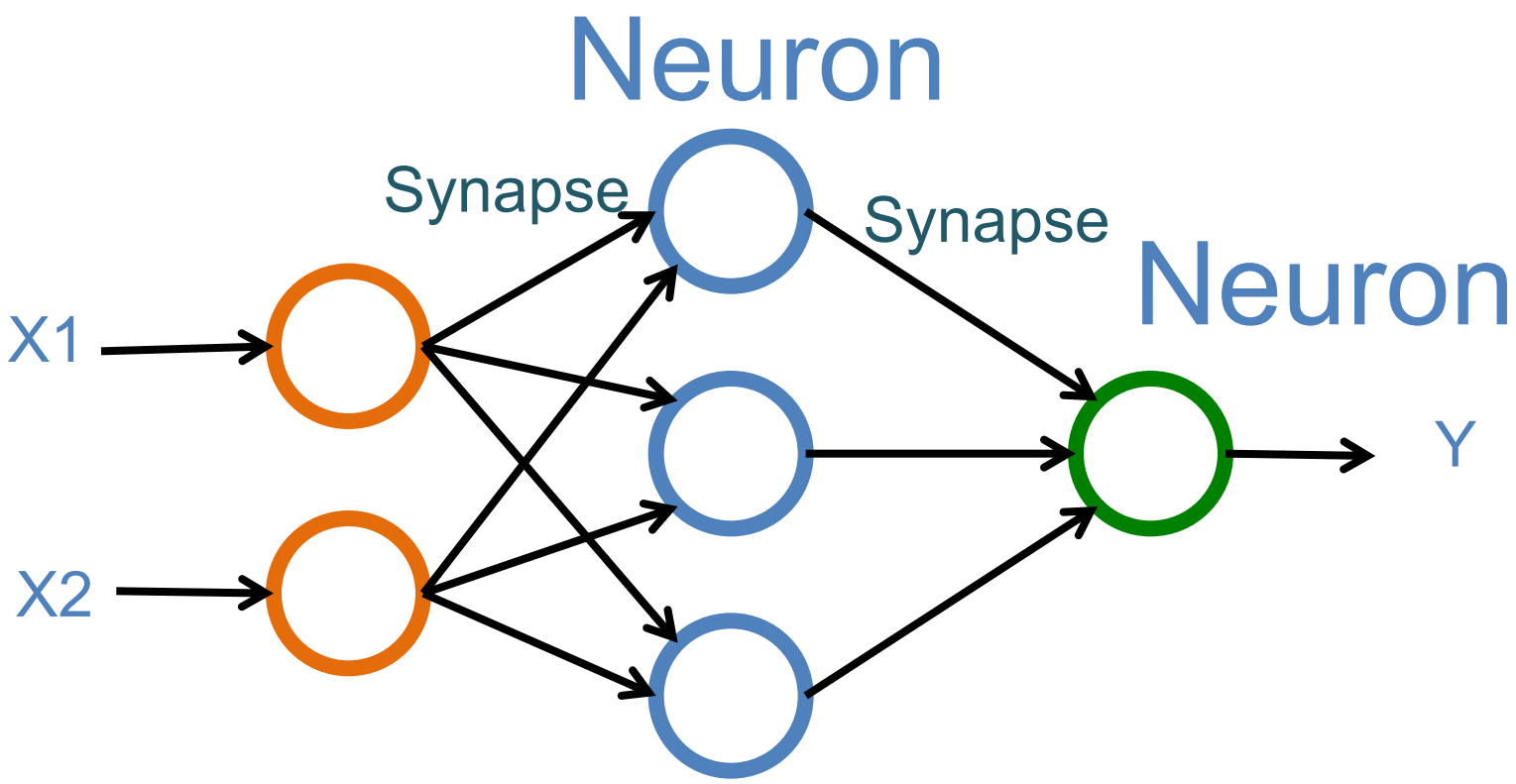
Deep Neural Networks
Deep Learning



Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

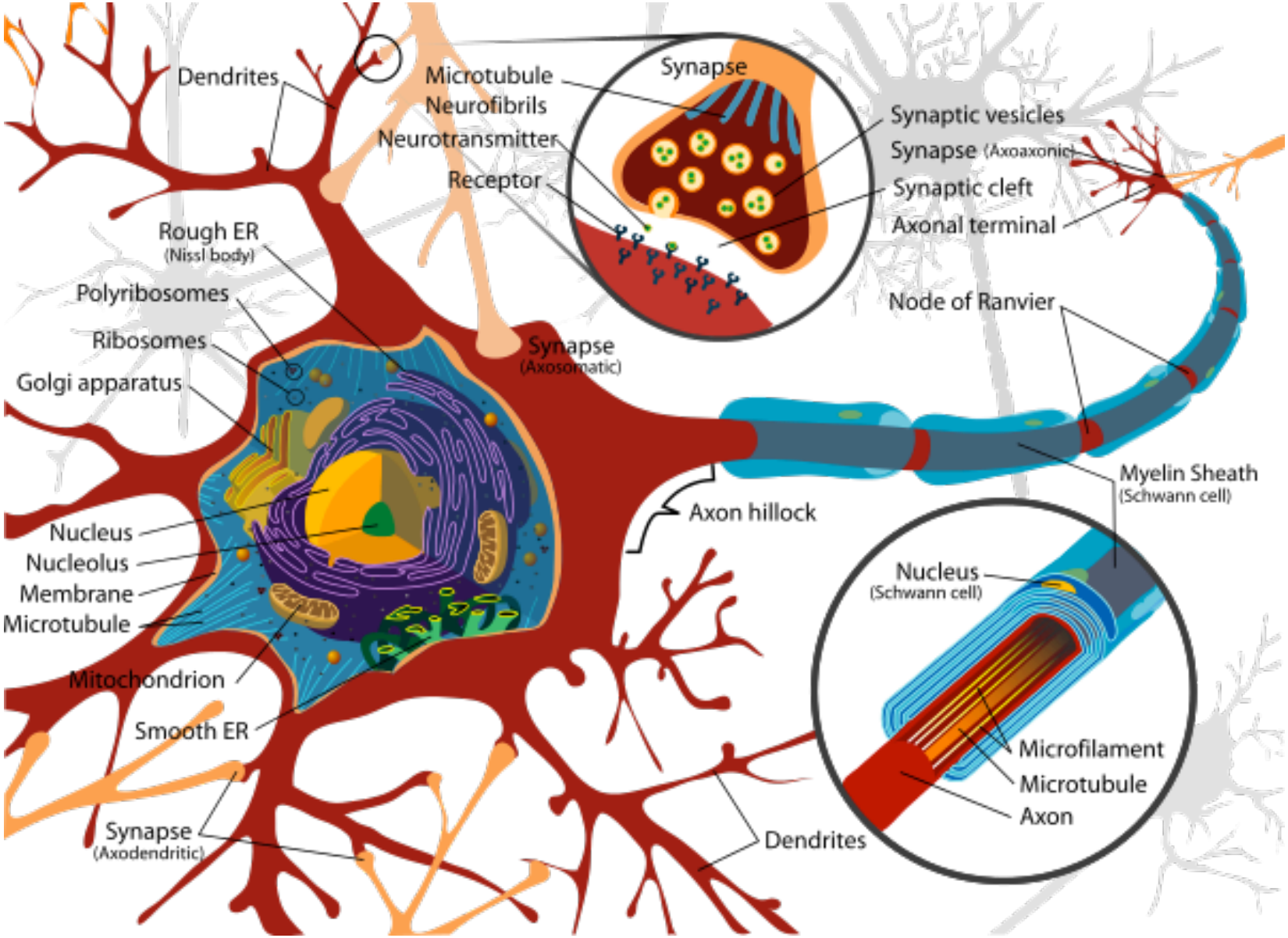
Neural Networks

Input Layer (X) Hidden Layer (H) **Output Layer (Y)**



Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

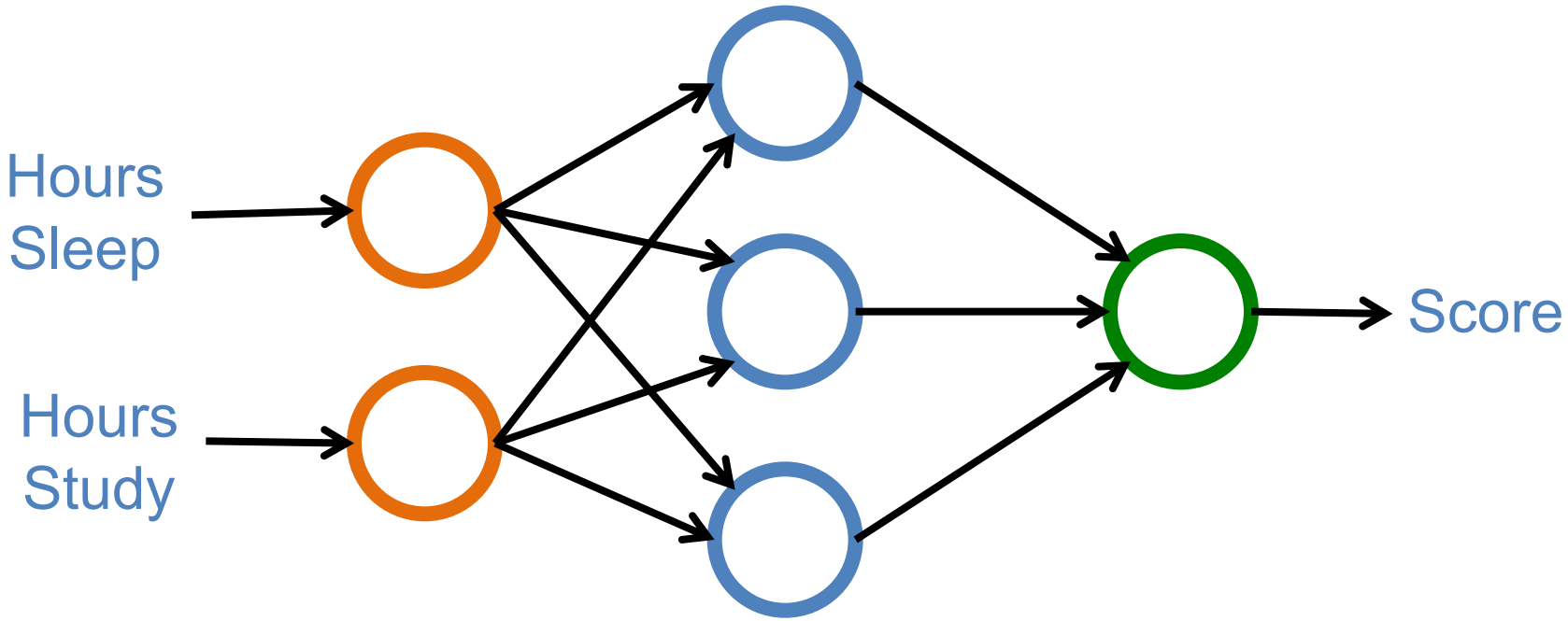
Neuron and Synapse



Source: https://en.wikipedia.org/wiki/Neuron

Neural Networks

Input Layer (X) Hidden Layer (H) **Output Layer (Y)**



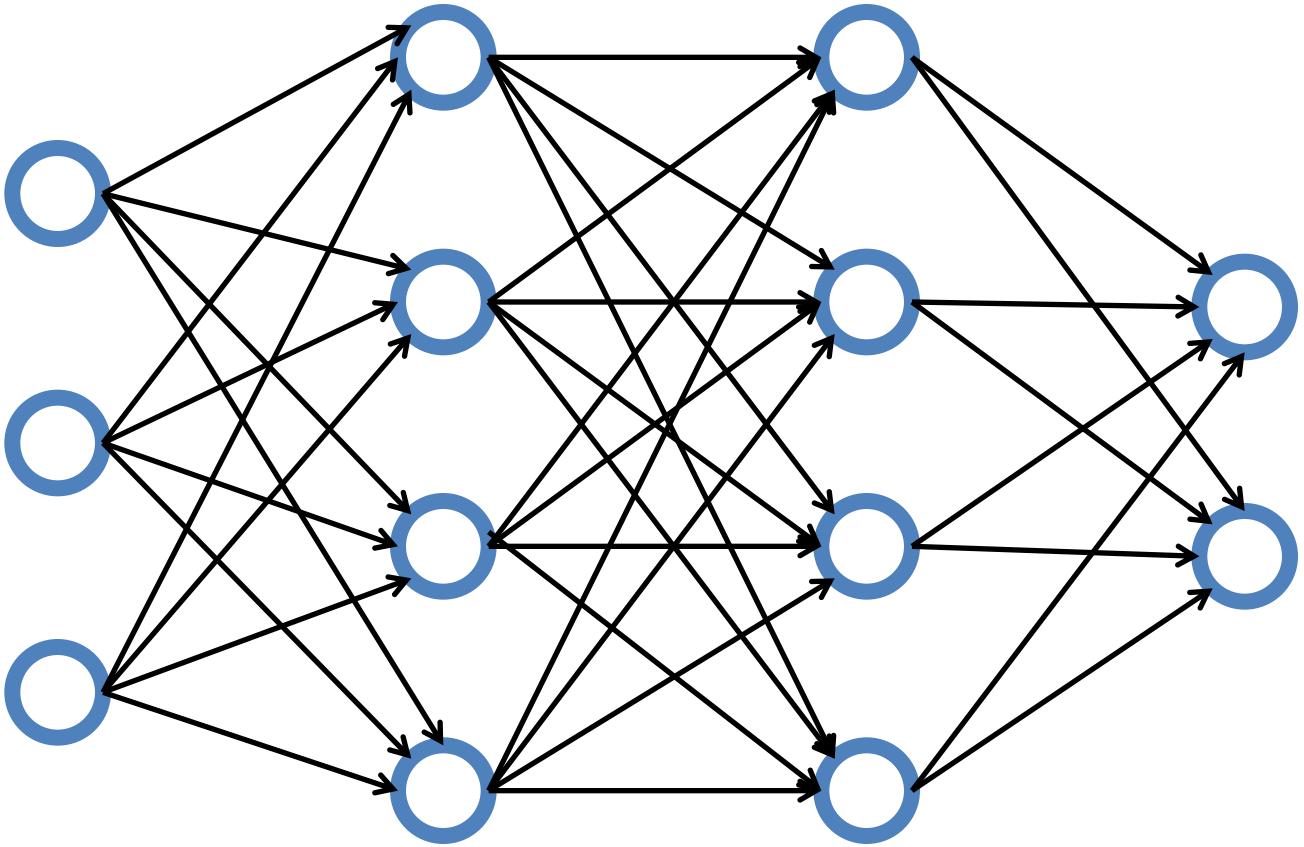
Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

Neural Networks

Input Layer (X)

Hidden Layer (H)

Output Layer (Y)

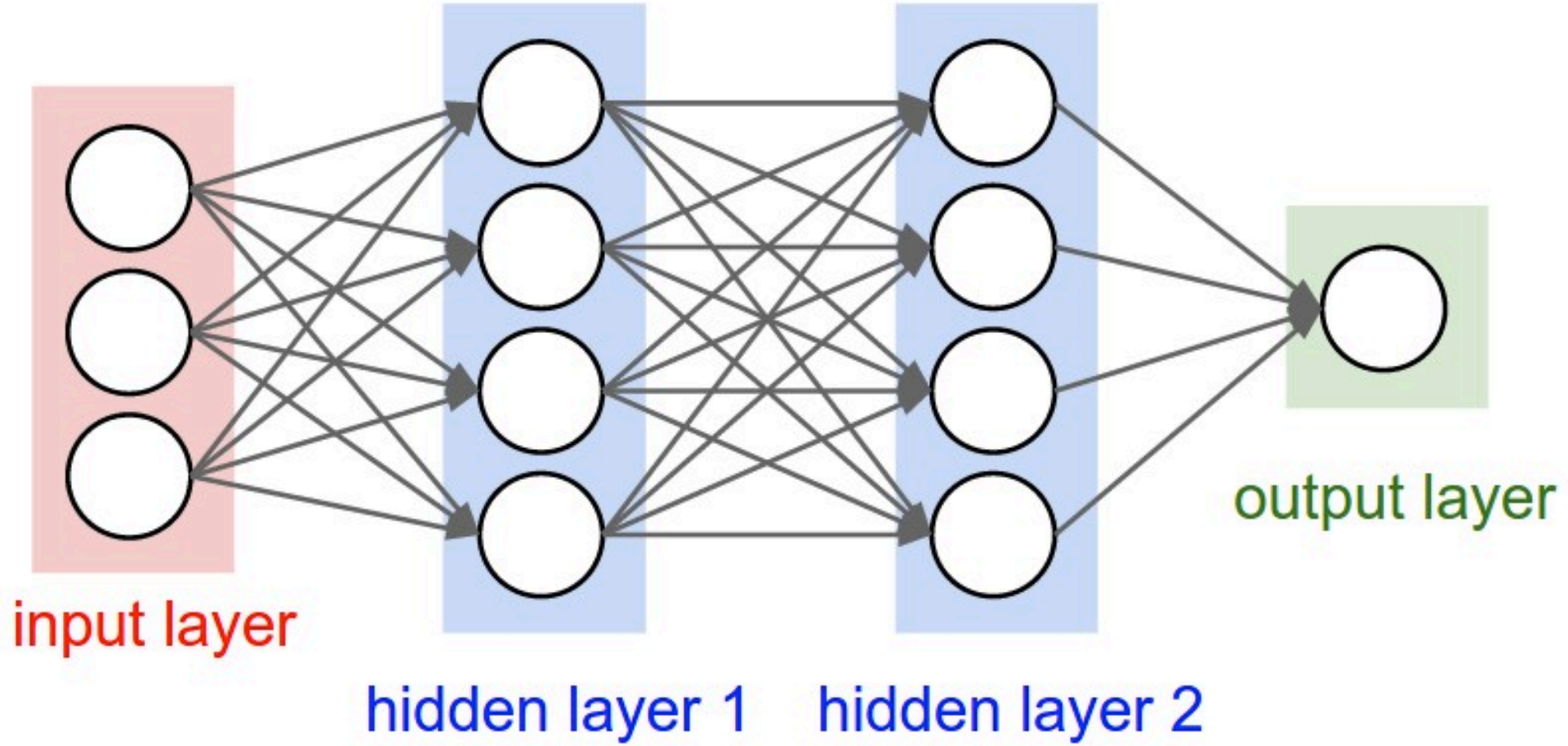


Source: https://www.youtube.com/watch?v=P2HPcj8lRJE&list=PLjJh1vlSEYgvGod9wWiydumYl8hOXixNu&index=2

Convolutional Neural Networks (CNNs / ConvNets)

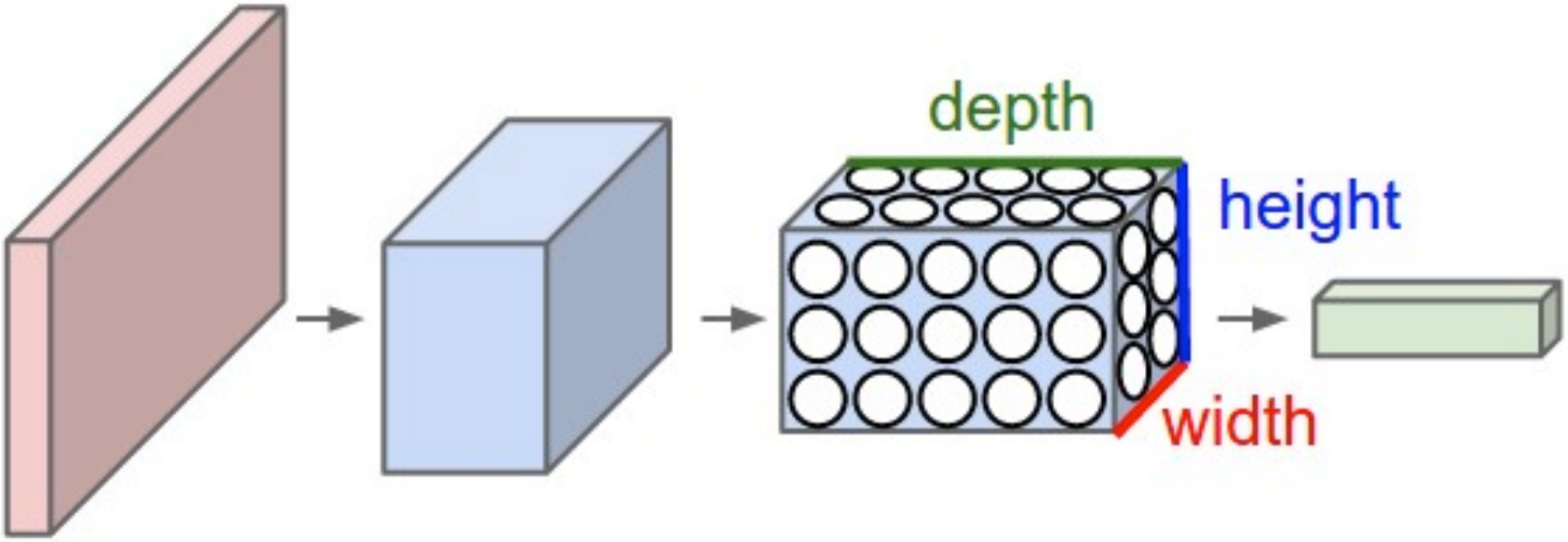
http://cs231n.github.io/convolutional-networks/

A regular 3-layer Neural Network



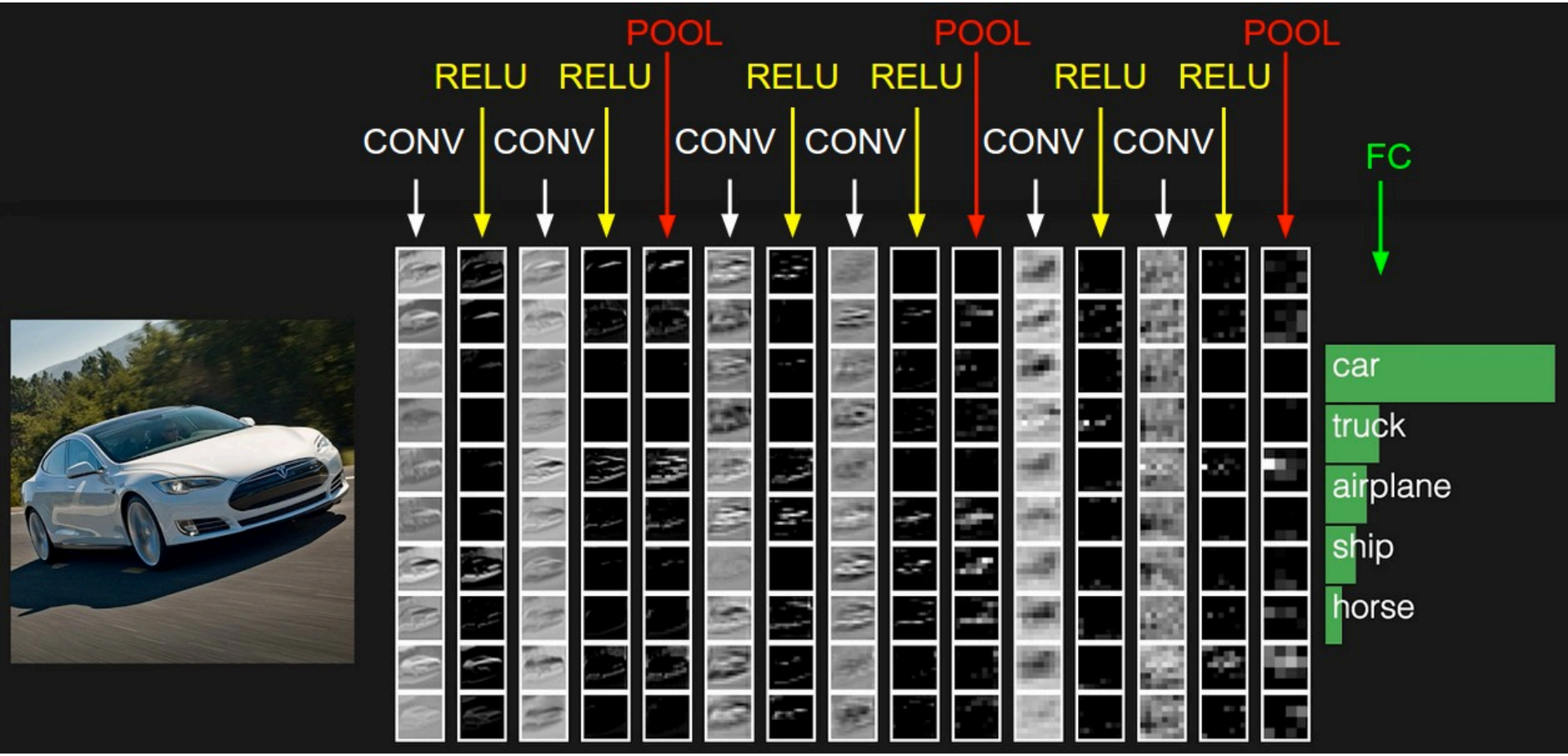
http://cs231n.github.io/convolutional-networks/

A ConvNet arranges its neurons in three dimensions (width, height, depth)



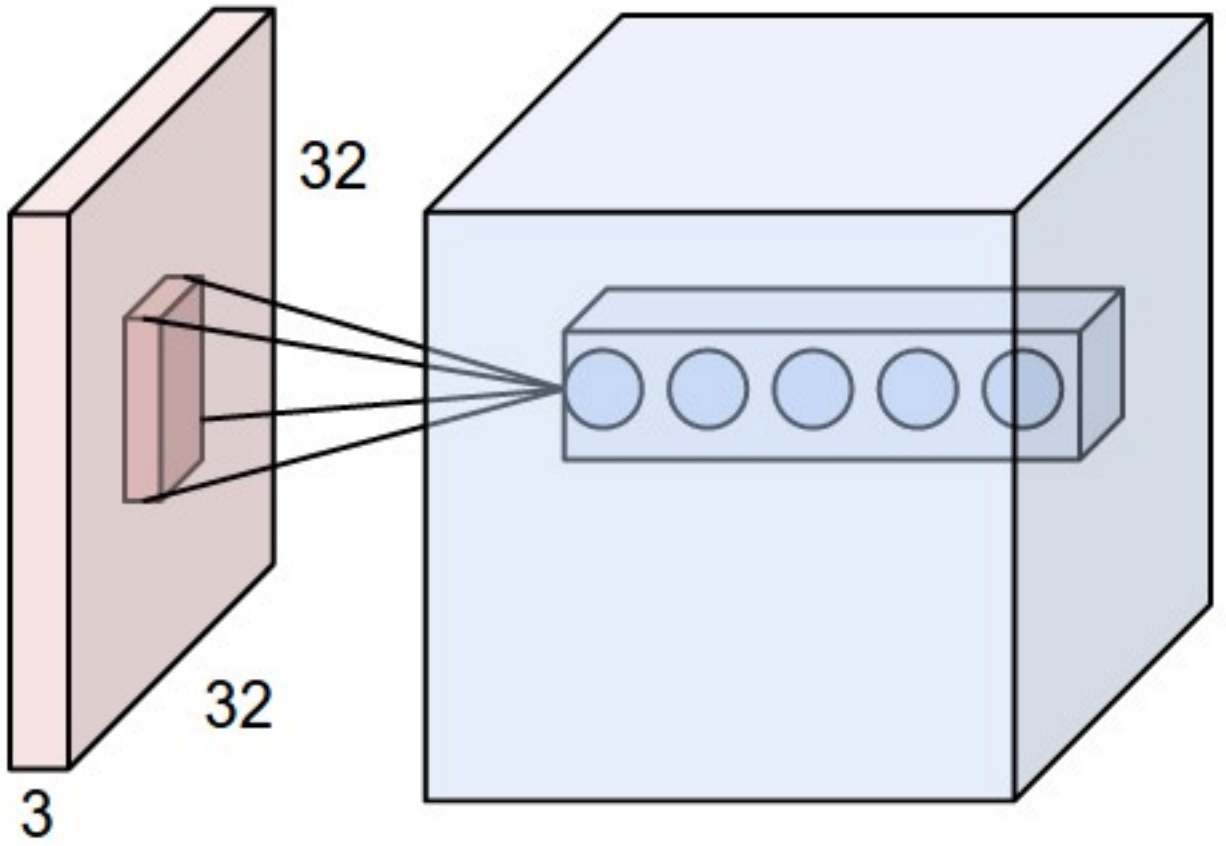
http://cs231n.github.io/convolutional-networks/

The activations of an example ConvNet architecture.



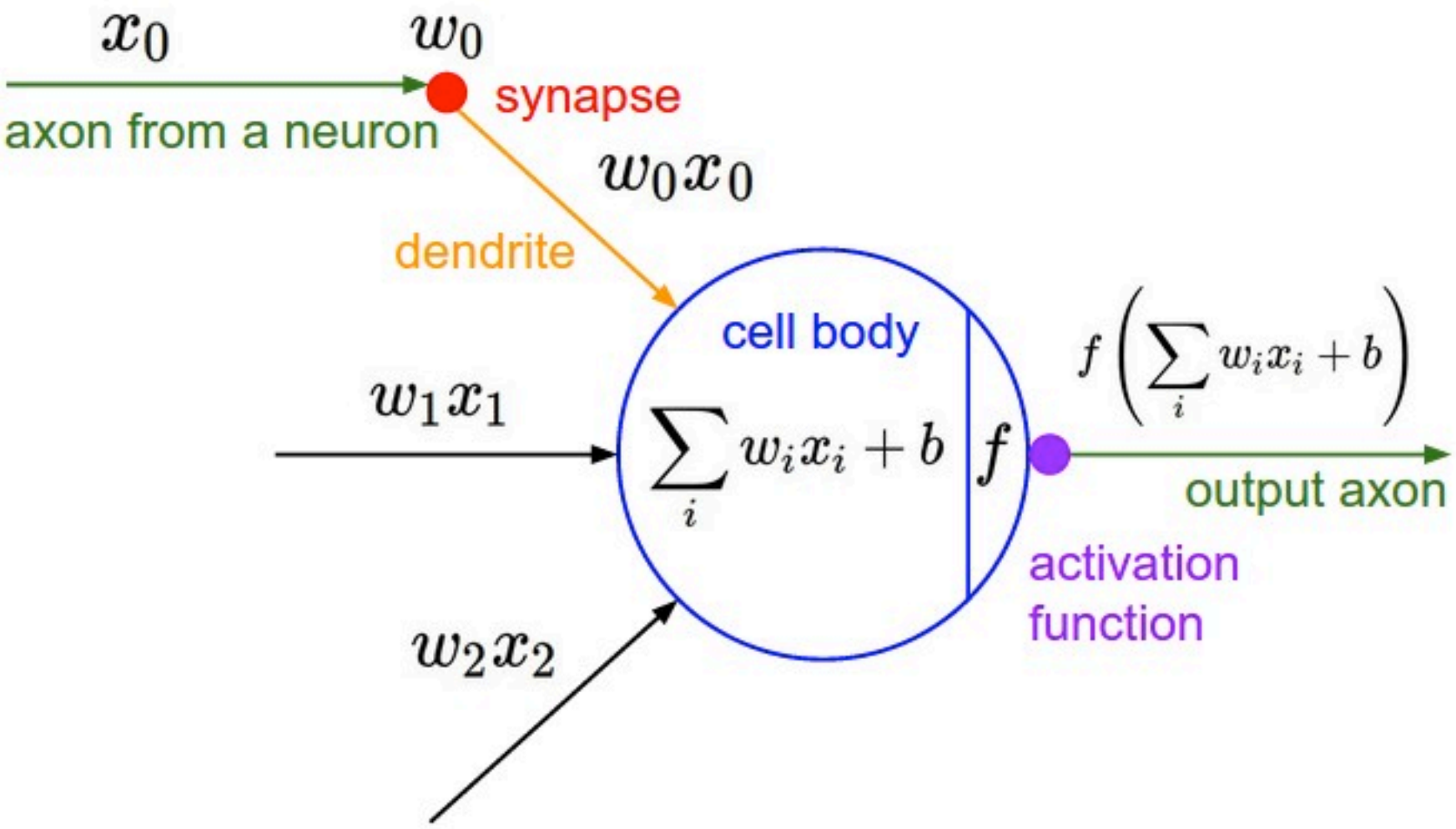
http://cs231n.github.io/convolutional-networks/

ConvNets



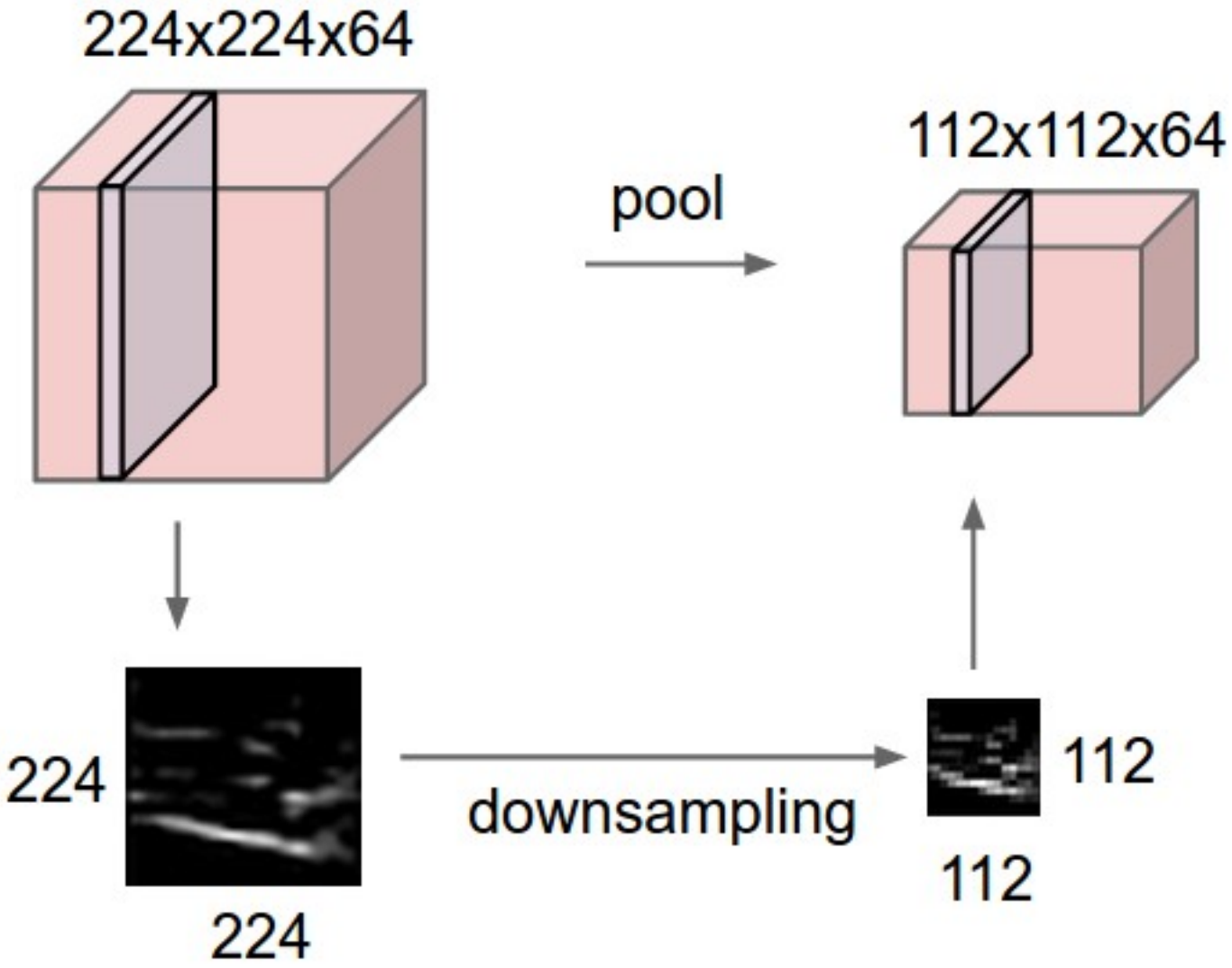
http://cs231n.github.io/convolutional-networks/

ConvNets



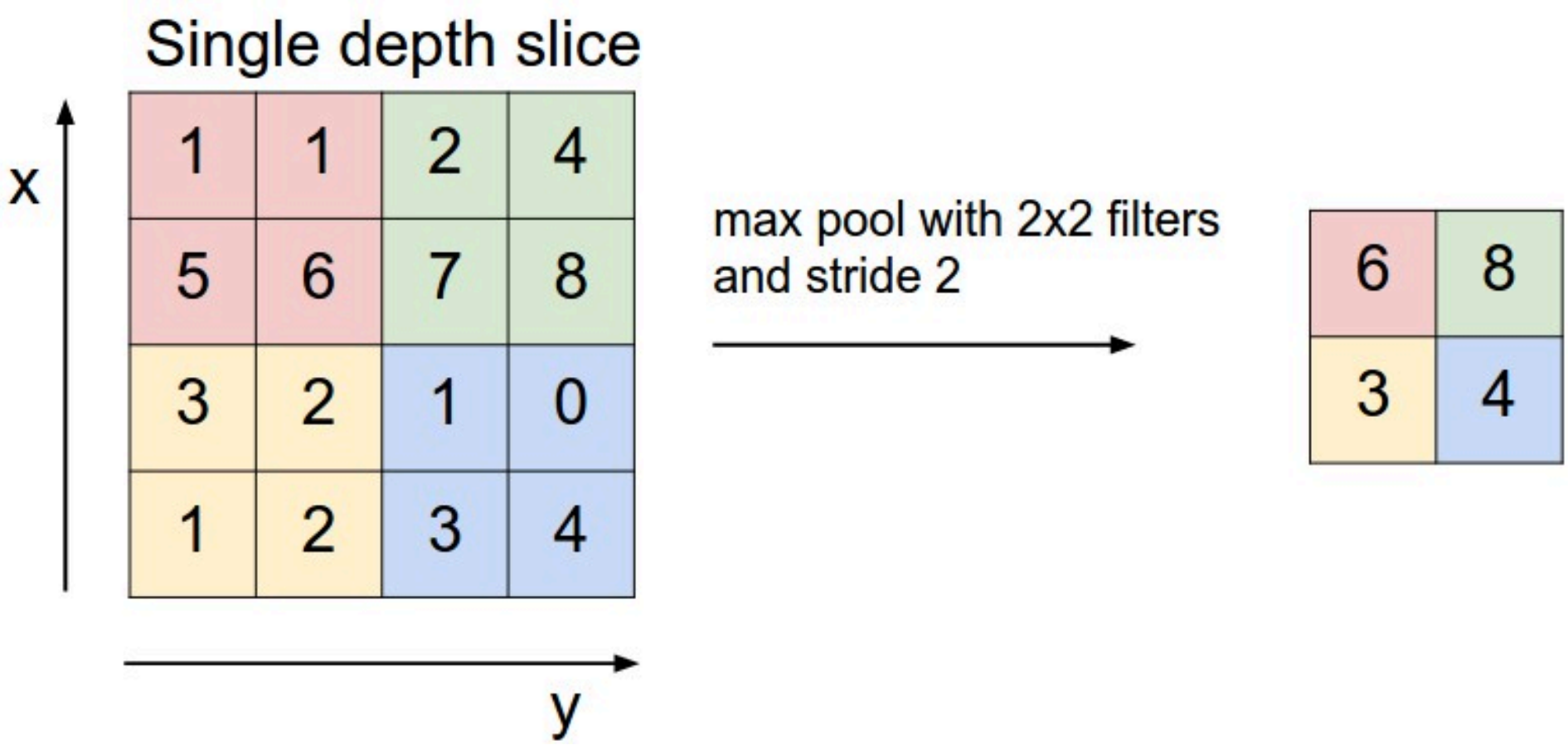
http://cs231n.github.io/convolutional-networks/

ConvNets



http://cs231n.github.io/convolutional-networks/

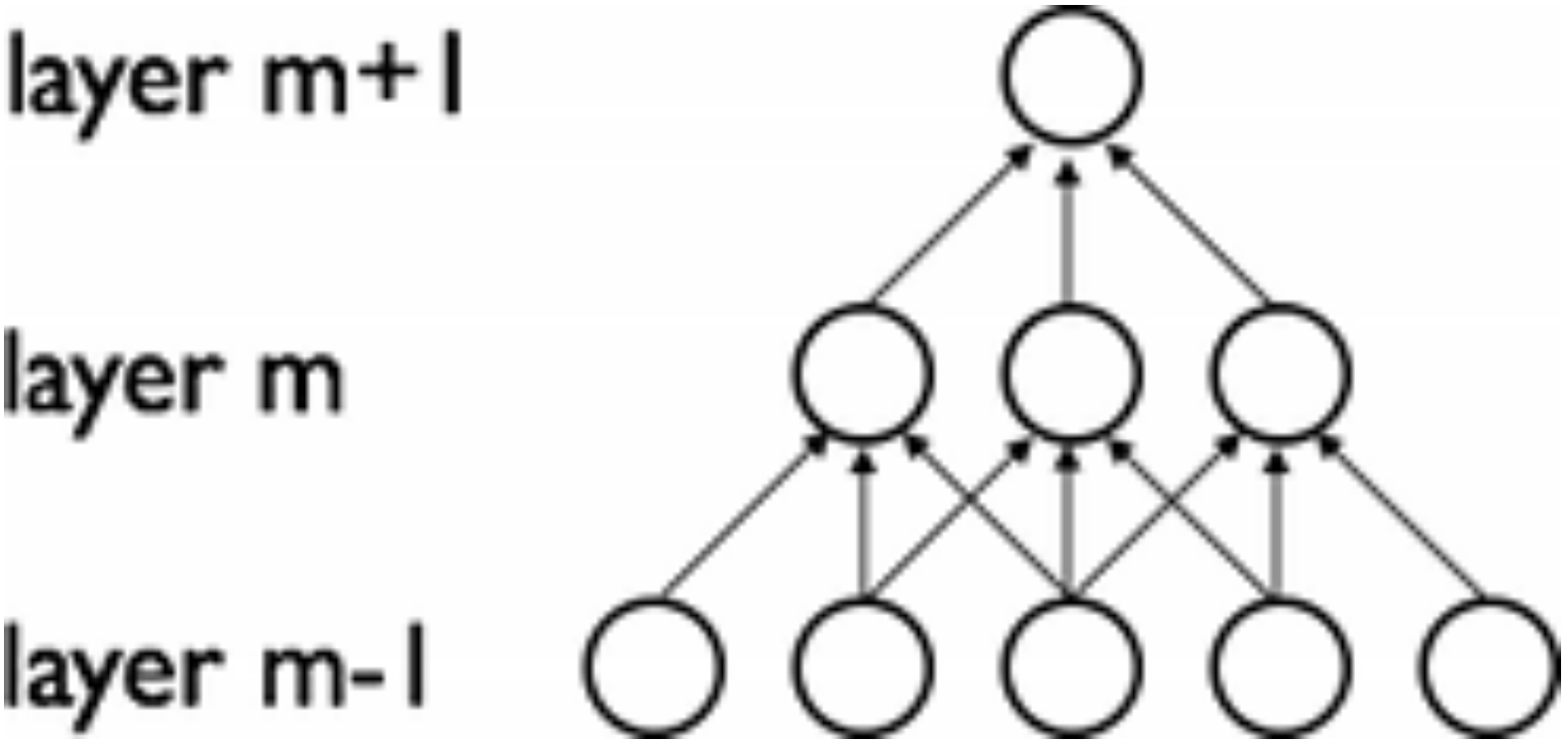
ConvNets
max pooling



http://cs231n.github.io/convolutional-networks/

Convolutional Neural Networks (CNN) (LeNet)

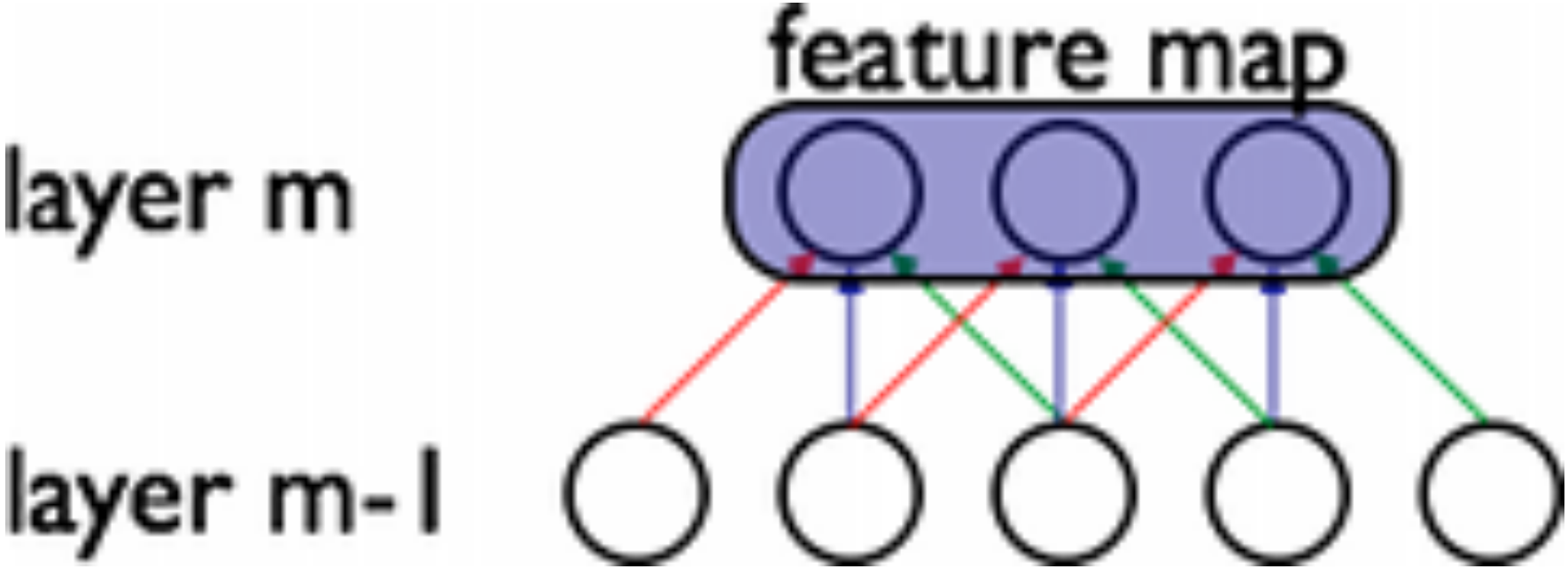
Sparse Connectivity



Source: http://deeplearning.net/tutorial/lenet.html

Convolutional Neural Networks (CNN) (LeNet)

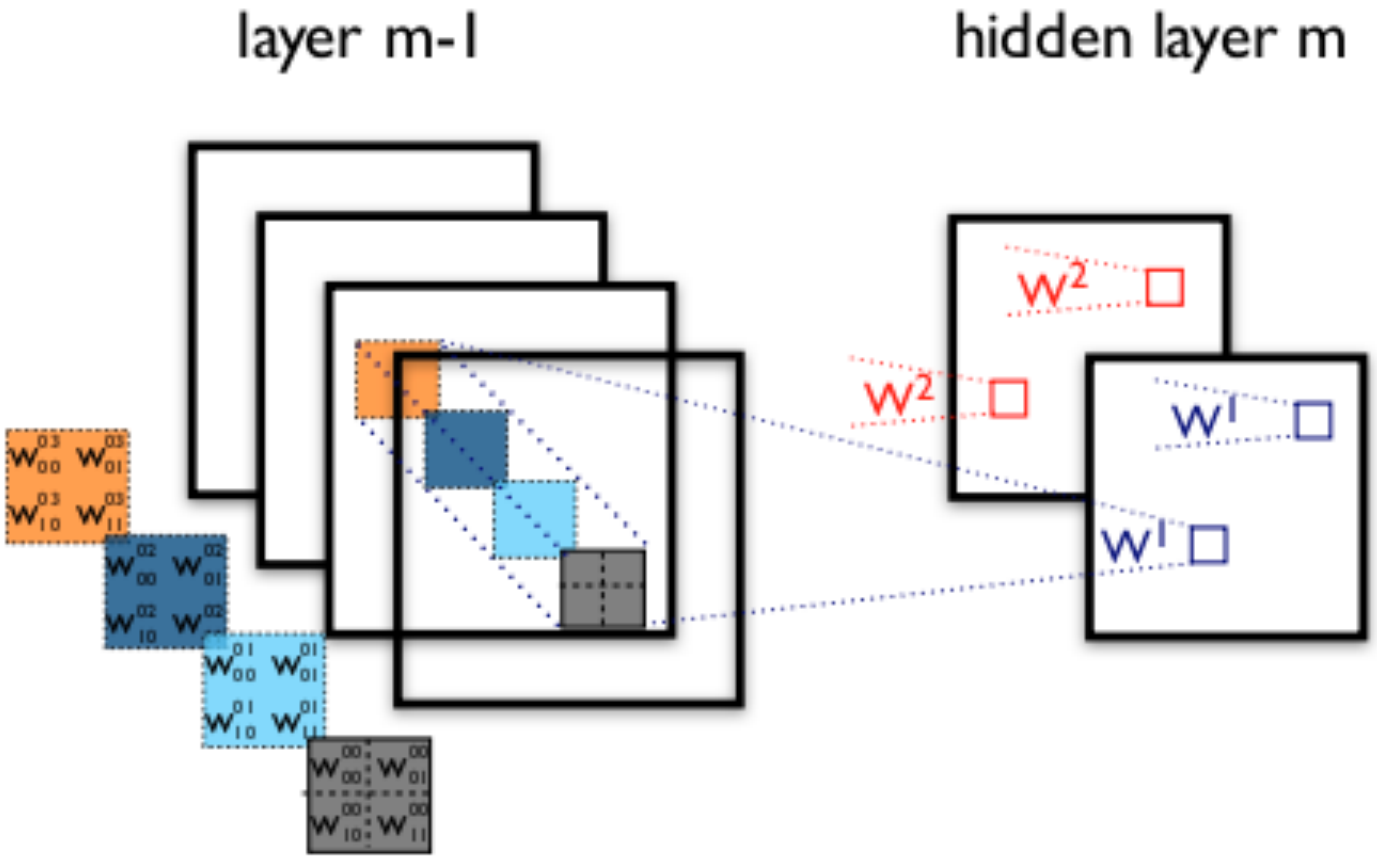
Shared Weights



Source: http://deeplearning.net/tutorial/lenet.html

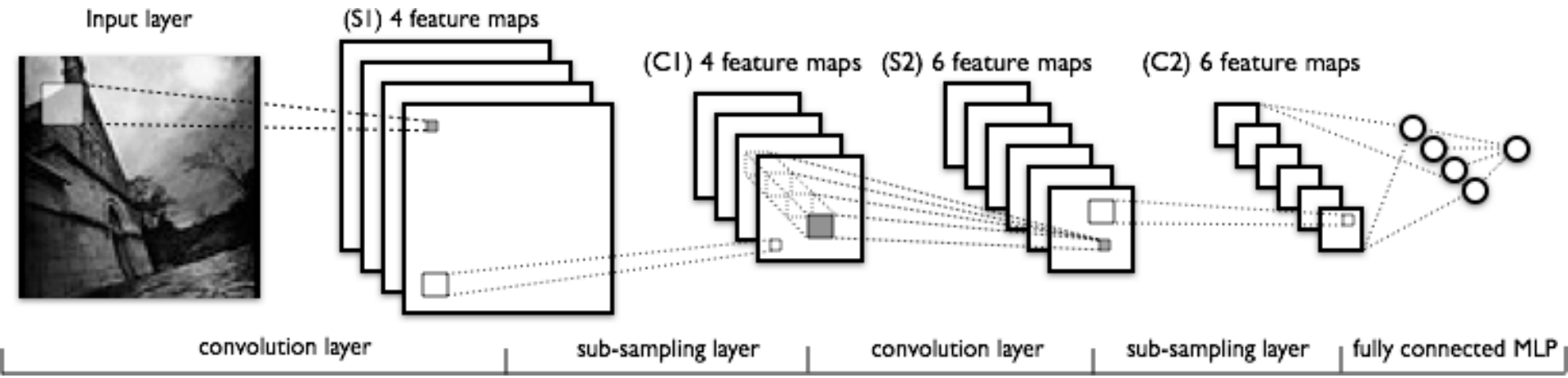
Convolutional Neural Networks (CNN) (LeNet)

example of a convolutional layer



Source: http://deeplearning.net/tutorial/lenet.html

Convolutional Neural Networks (CNN) (LeNet)



Source: http://deeplearning.net/tutorial/lenet.html

show flights from Boston to New York today

Source: http://deeplearning.net/tutorial/rnnslu.html

Recurrent Neural Networks with Word Embeddings
Semantic Parsing / Slot-Filling (Spoken Language Understanding)

Input (words)	show	flights	from	Boston	to	New	York	today
Output (labels)	O	O	O	B-dept	O	B-arr	I-arr	B-date

Source: http://deeplearning.net/tutorial/rnnslu.html

show flights from Boston to New York today

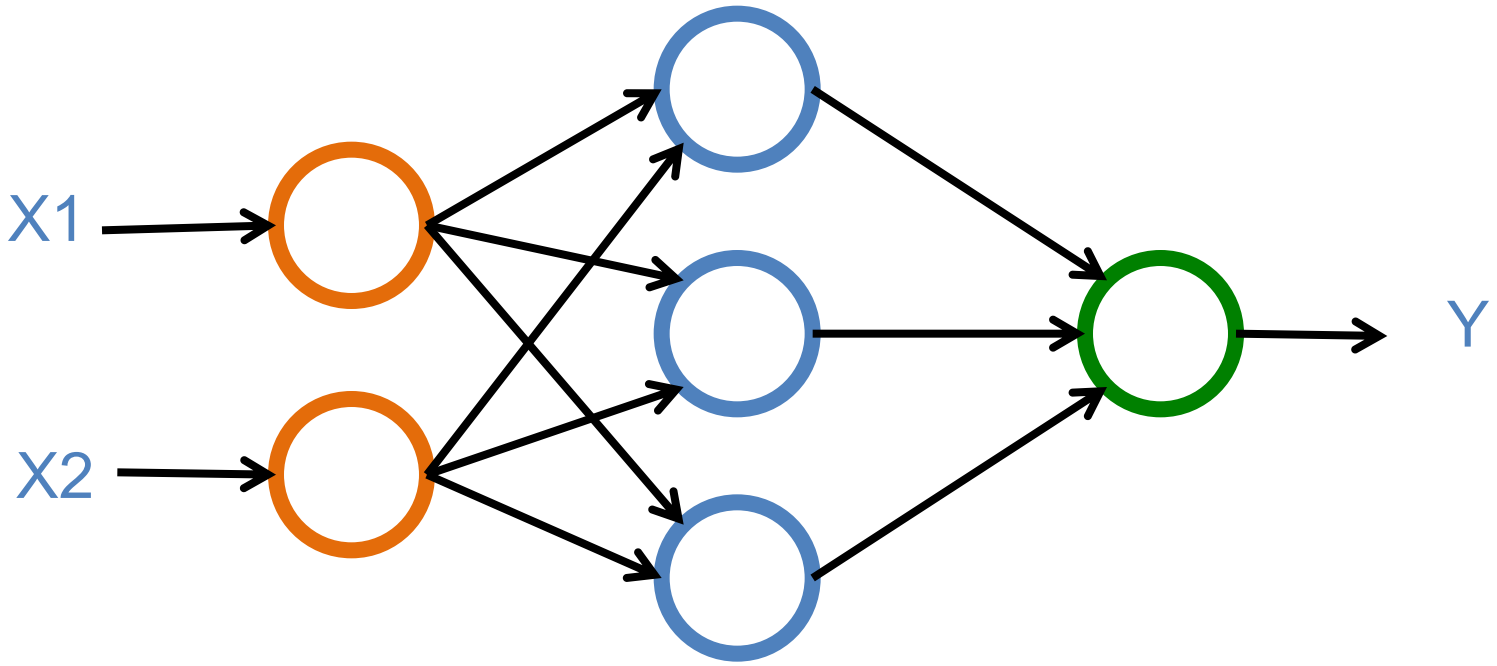
show flights from Boston to New York today

Input (words)	show	flights	from	Boston	to	New	York	today
Output (labels)	O	O	O	B-dept	O	B-arr	I-arr	B-date

Source: http://deeplearning.net/tutorial/rnnslu.html

Neural Networks

Input Layer (X) Hidden Layer (H) **Output Layer (Y)**



Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

X		Y
Hours Sleep	Hours Study	Score
3	5	75
5	1	82
10	2	93
8	3	?

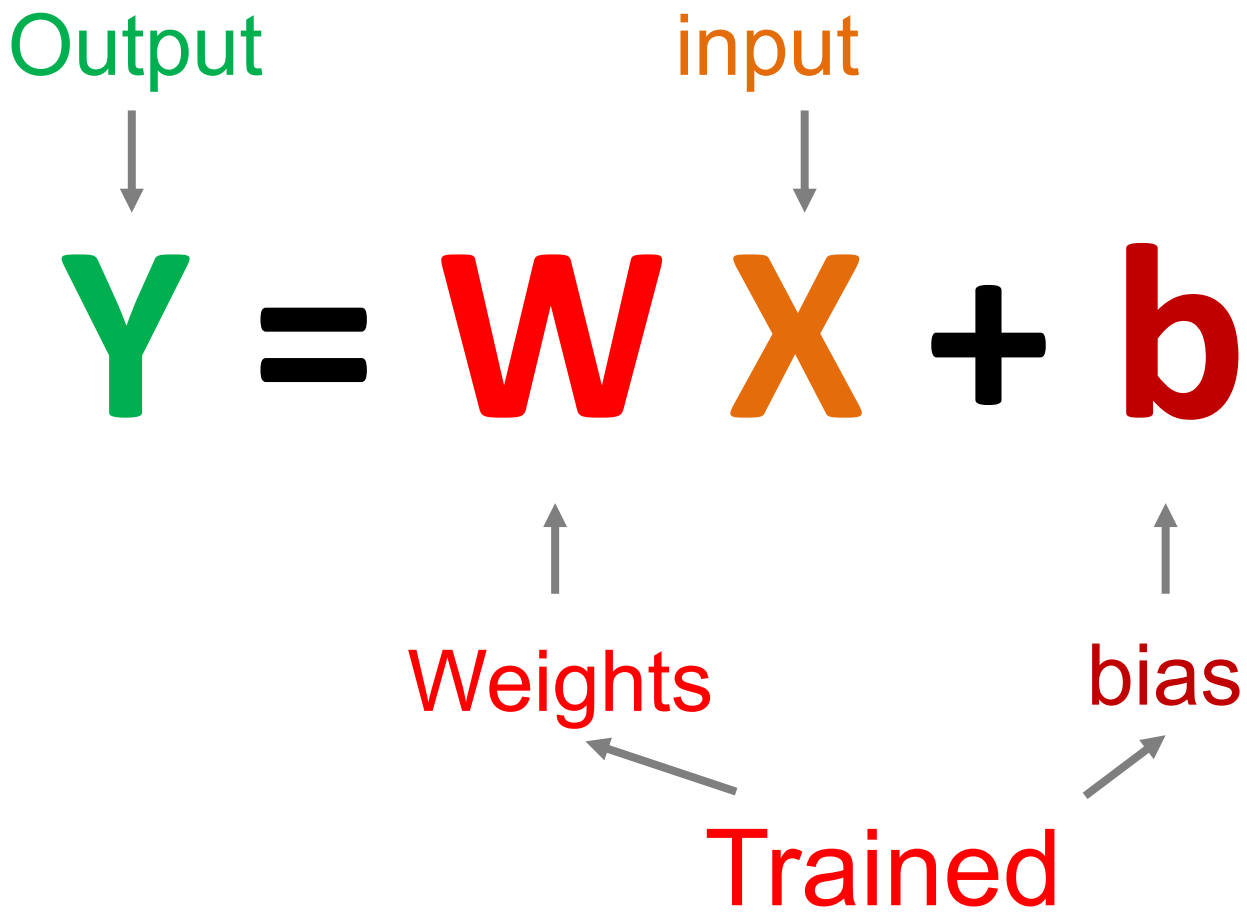
Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

	X		Y
	Hours Sleep	Hours Study	Score
Training	3	5	75
	5	1	82
	10	2	93
Testing	8	3	?

Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

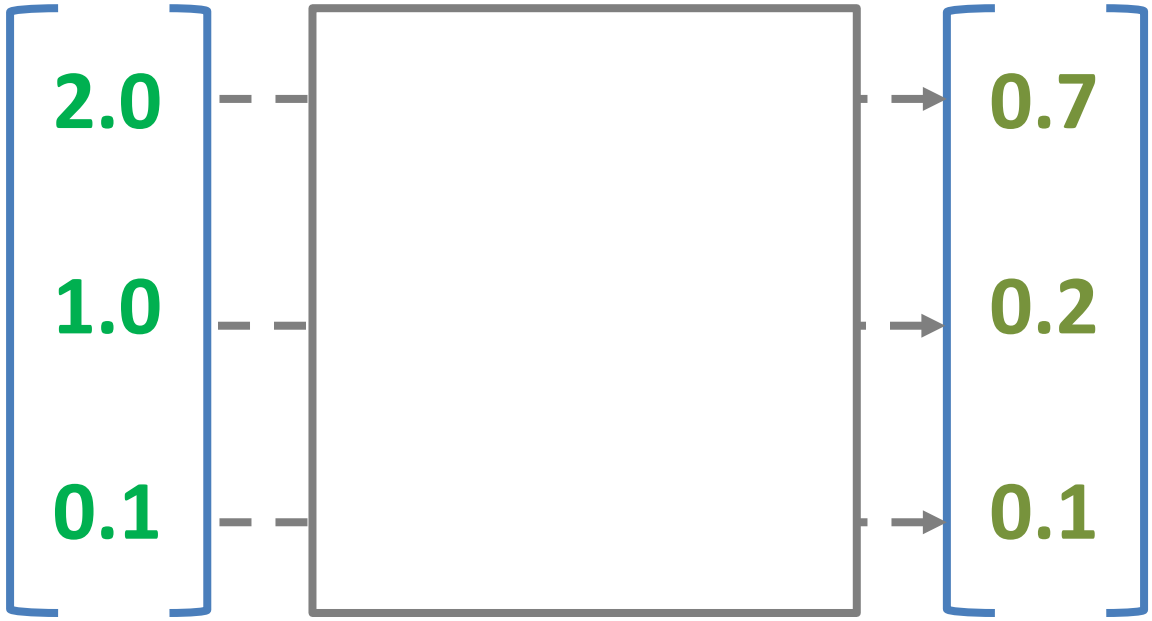
$$Y = W X + b$$

Source: https://www.youtube.com/watch?v=G8eNWzxOgqE



Source: https://www.youtube.com/watch?v=G8eNWzxOgqE

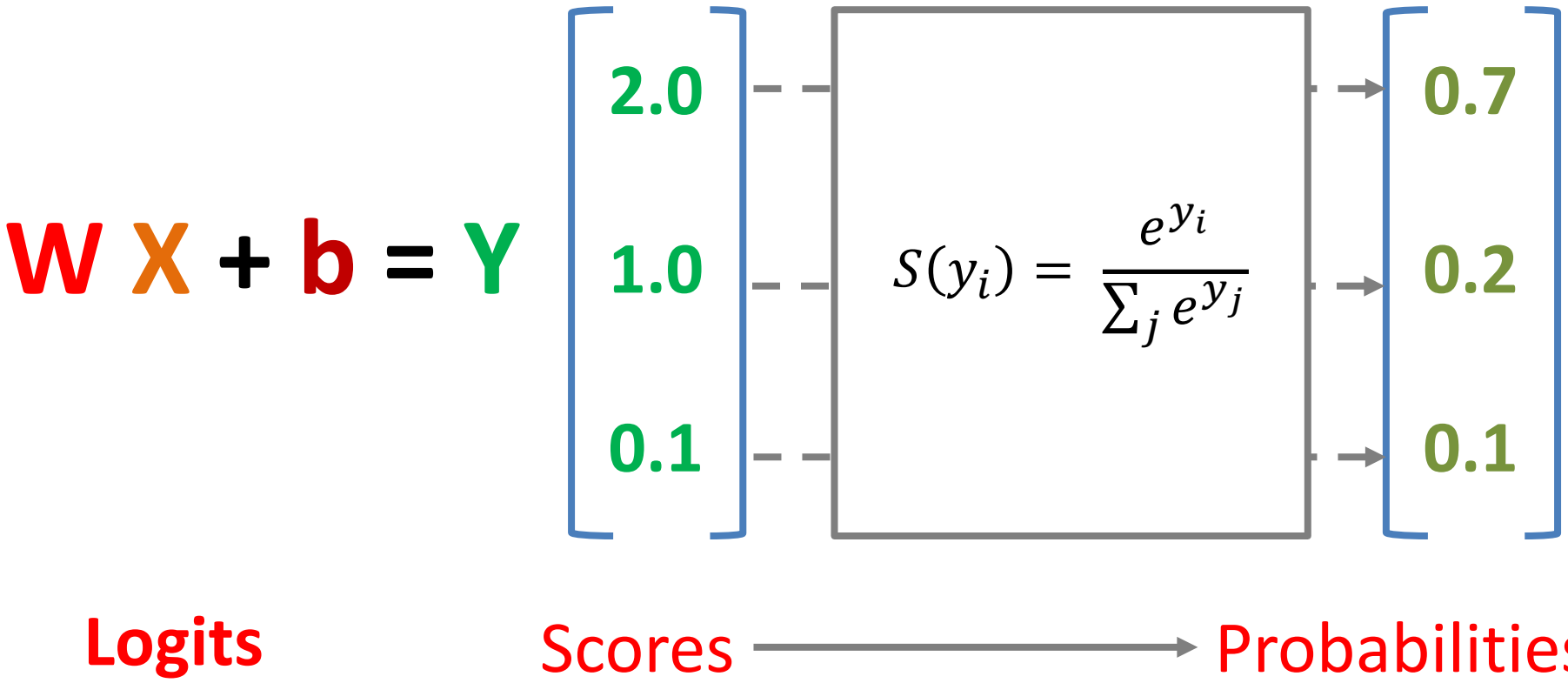
$$W\,X + b = Y$$



Scores → Probabilities

Source: https://www.youtube.com/watch?v=G8eNWzxOgqE

SoftMAX



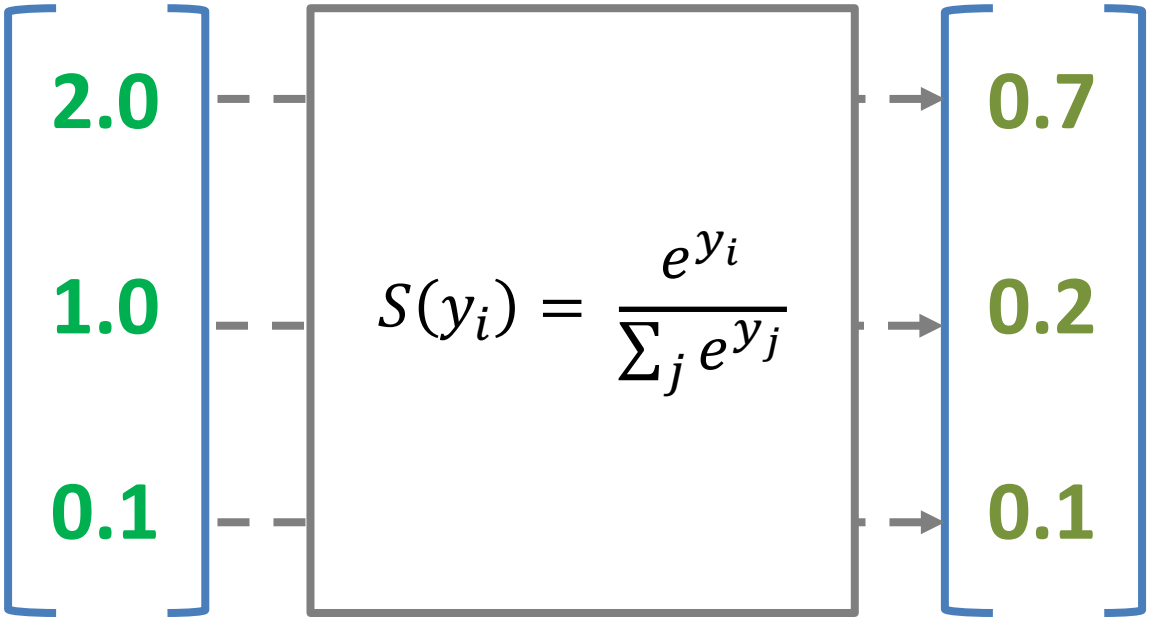
Source: https://www.youtube.com/watch?v=G8eNWzxOgqE

$$S(y_i) = \frac{e^{y_i}}{\sum_j e^{y_i}} = \frac{e^{2.0}}{e^{2.0}+e^{1.0}+e^{0.1}} = \frac{2.7182^{2.0}}{2.7182^{2.0}+2.7182^{1.0}+2.7182^{0.1}} = 0.7$$

$$S(y_i) = \frac{e^{y_i}}{\sum_j e^{y_j}} = \frac{e^{1.0}}{e^{2.0}+e^{1.0}+e^{0.1}} = \frac{2.7182^{1.0}}{2.7182^{2.0}+2.7182^{1.0}+2.7182^{0.1}} = 0.2$$

$$S(y_i) = \frac{e^{y_i}}{\sum_j e^{y_j}} = \frac{e^{0.1}}{e^{2.0}+e^{1.0}+e^{0.1}} = \frac{2.7182^{0.1}}{2.7182^{2.0}+2.7182^{1.0}+2.7182^{0.1}} = 0.1$$

W X + b = Y



Logits Scores → Probabilities

Source: https://www.youtube.com/watch?v=G8eNWzxOgqE

Training a Network
=
Minimize the Cost Function

Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

Training a Network

=

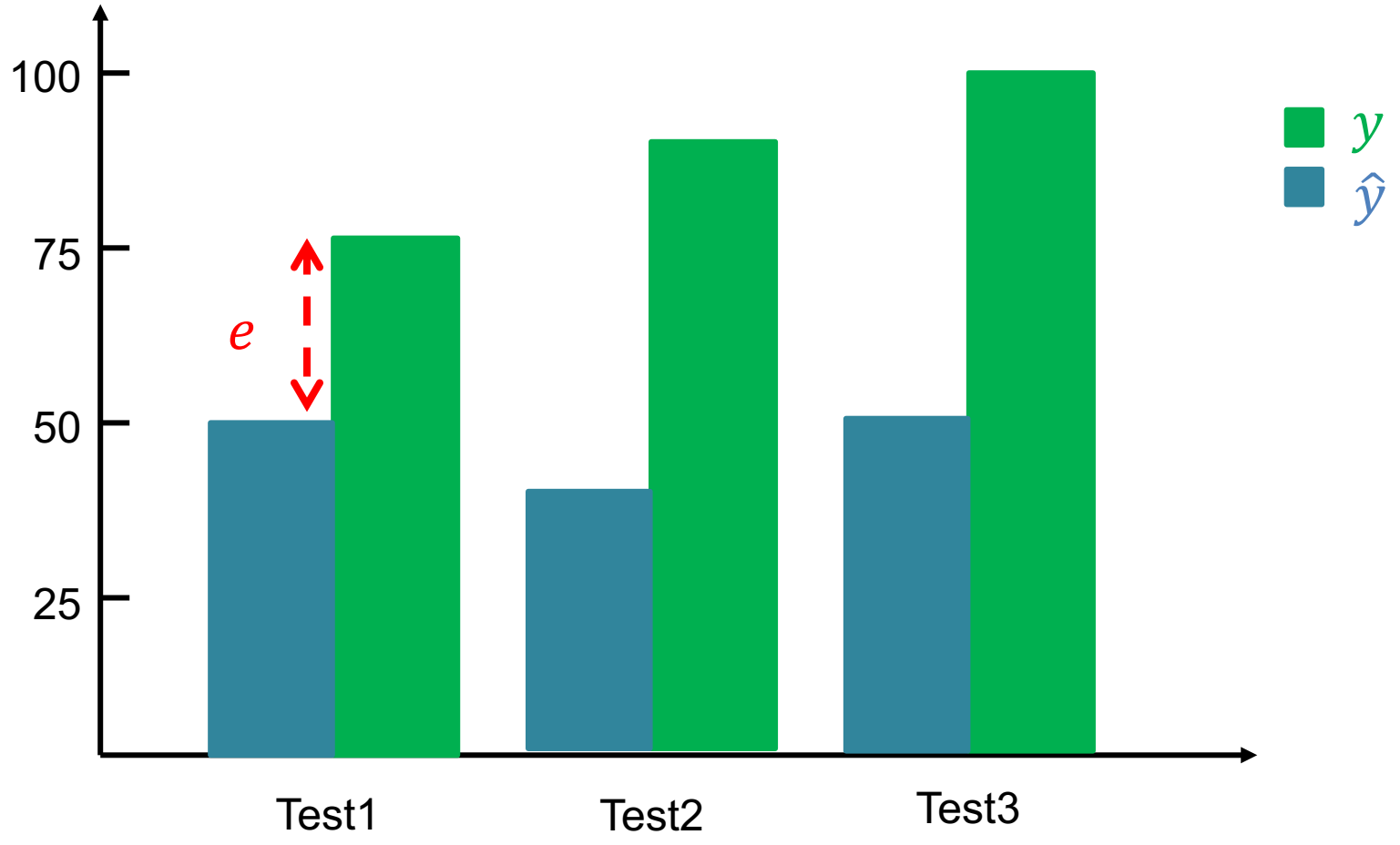
Minimize the Cost Function

Minimize the Loss Function

Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

Error = Predict Y - Actual Y

Error : Cost : Loss



Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

Error = Predict Y - Actual Y

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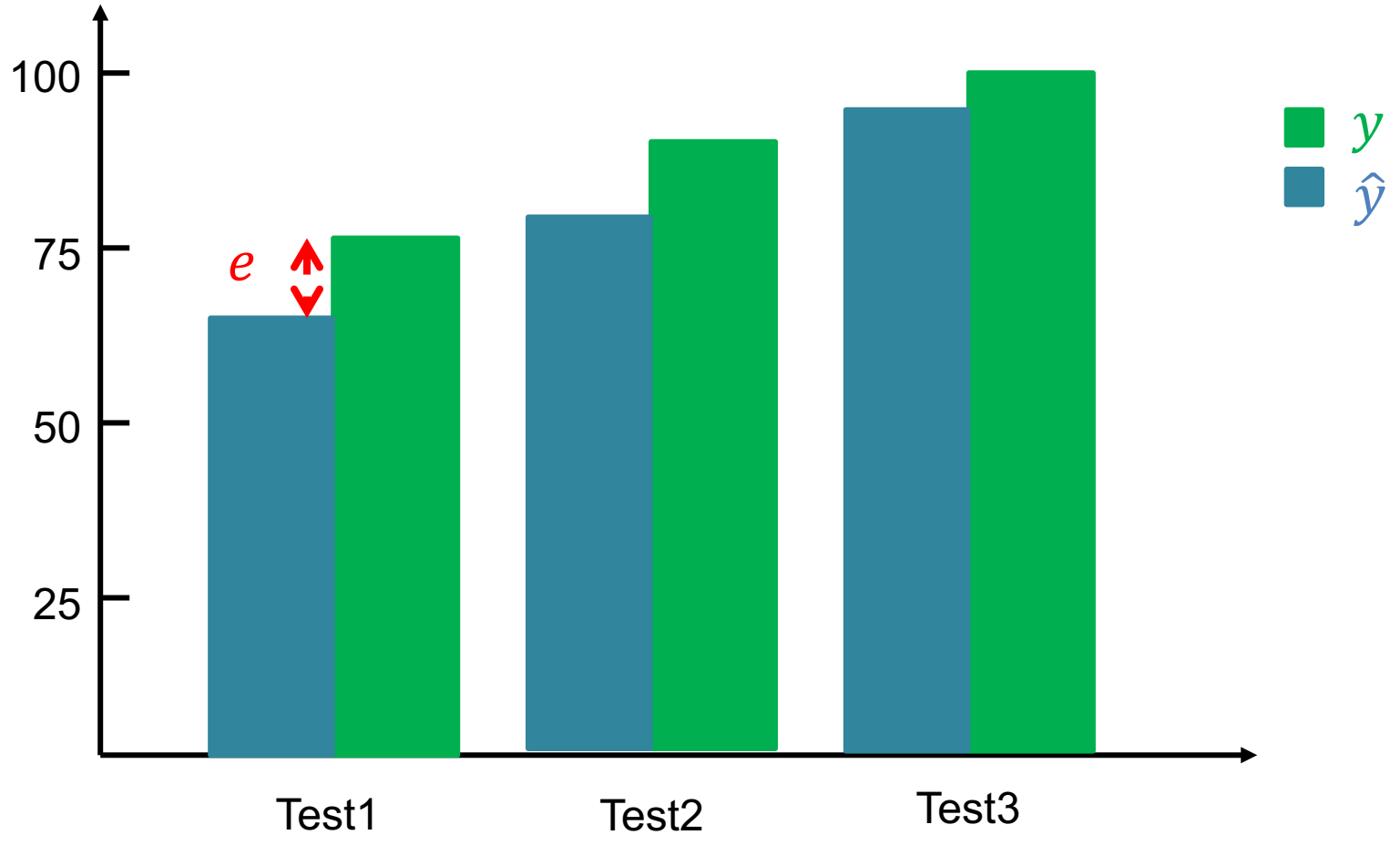

Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

Error = Predict Y - Actual Y

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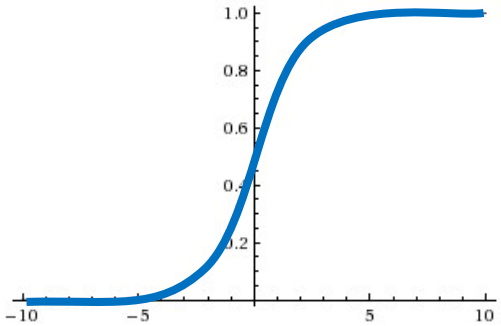
Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

Activation Functions

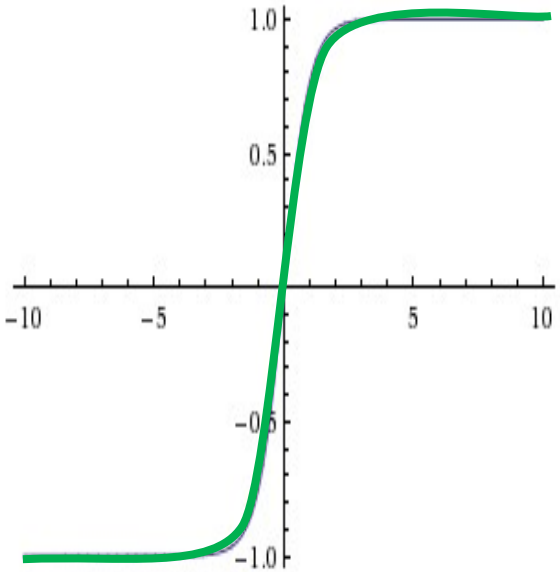
Activation Functions

Sigmoid



[0, 1]

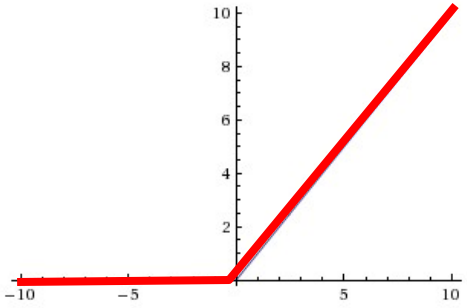
TanH



[-1, 1]

ReLU

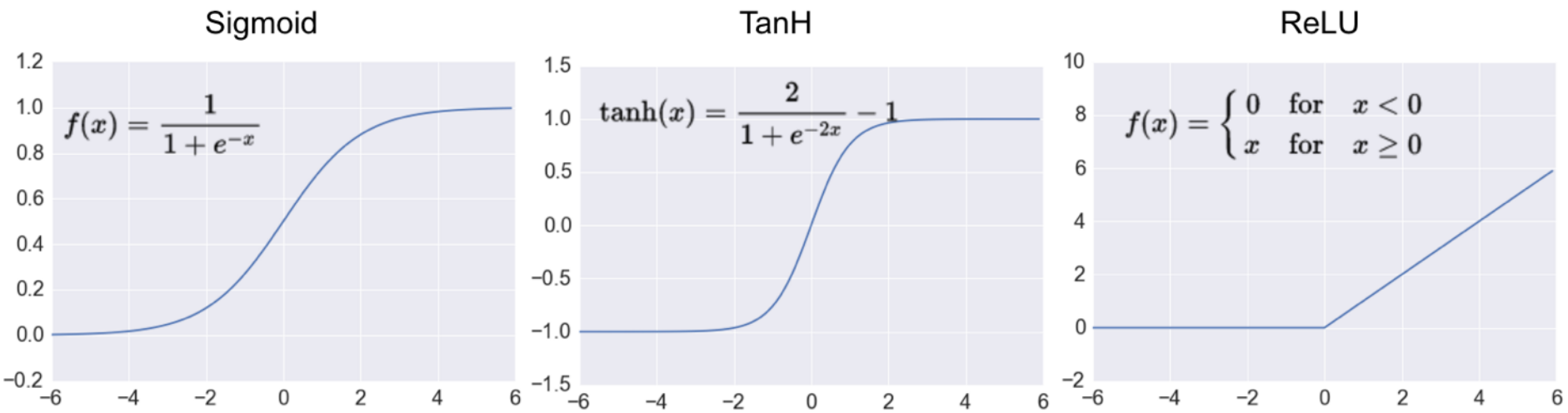
(Rectified Linear Unit)



$f(x) = max(0, x)$

Source: http://cs231n.github.io/neural-networks-1/

Activation Functions



Source: http://adilmoujahid.com/posts/2016/06/introduction-deep-learning-python-caffe/

Loss Function

Binary Classification: 2 Class

Activation Function: Sigmoid

Loss Function: Binary Cross-Entropy

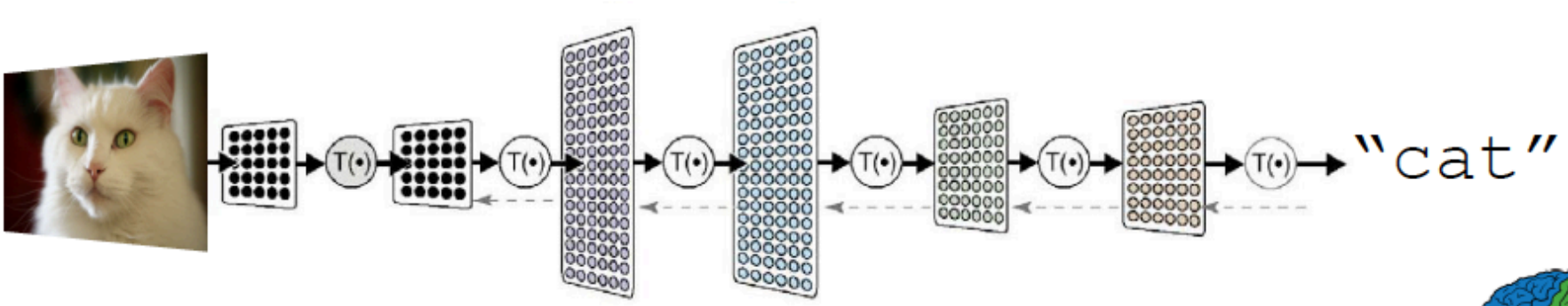
Multiple Classification: 10 Class

Activation Function:
SoftMAX

Loss Function:
Categorical Cross-Entropy

Deep Learning

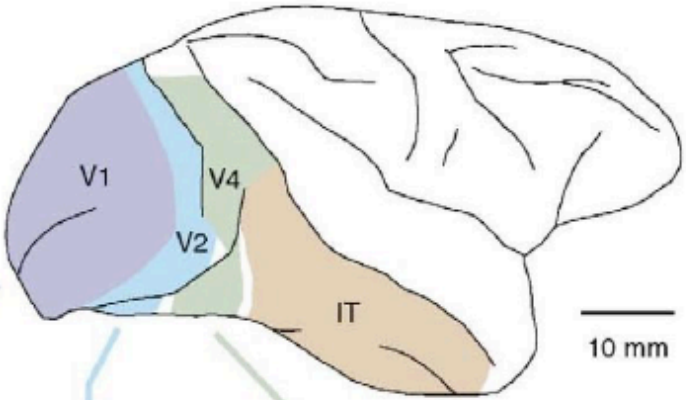
- A powerful class of machine learning model
- Modern reincarnation of artificial neural networks
- Collection of simple,
  trainable mathematical functions
- Compatible with many variants of machine learning

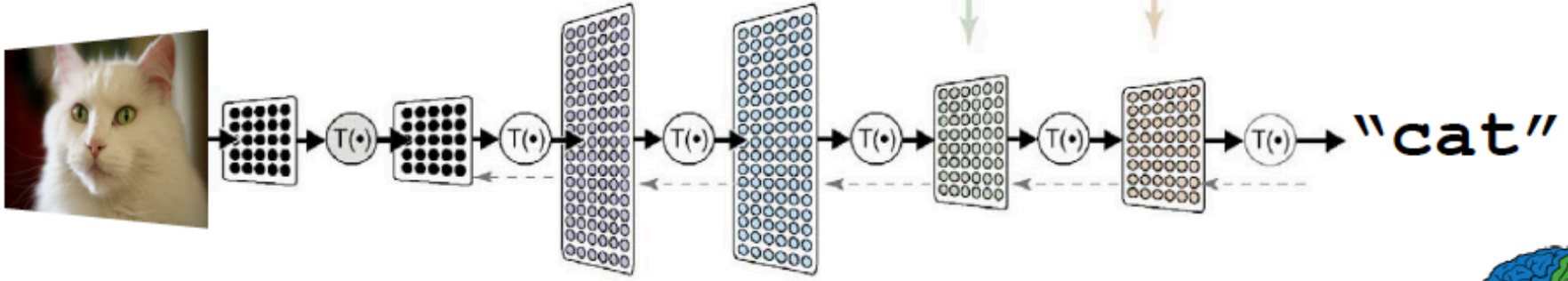


Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

What is Deep Learning?

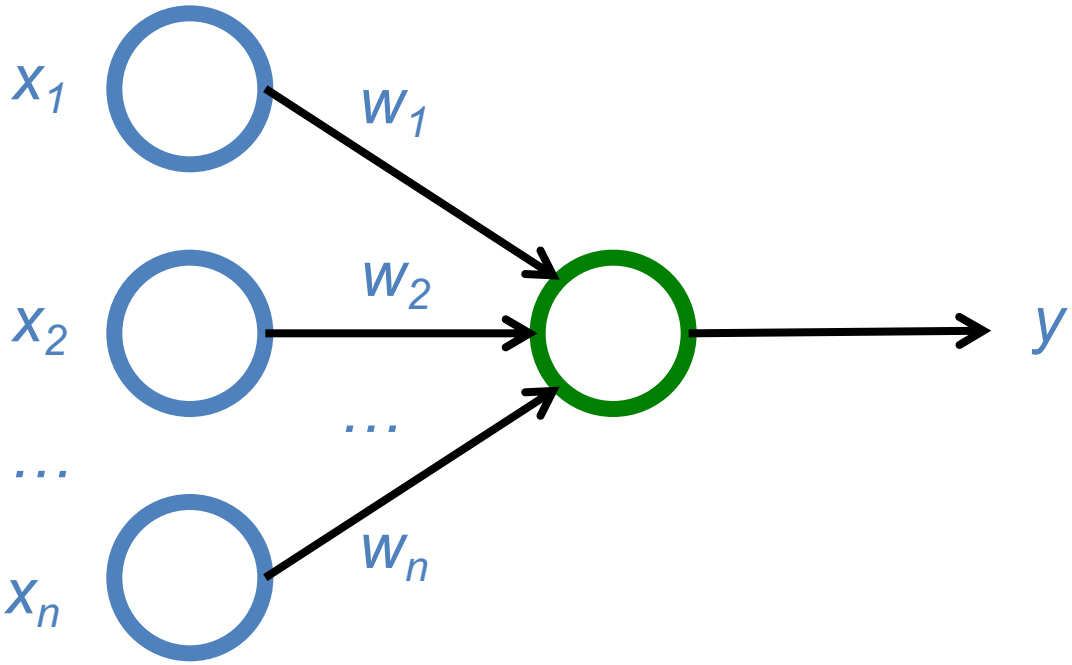
- Loosely based on (what little) we know about the brain





Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

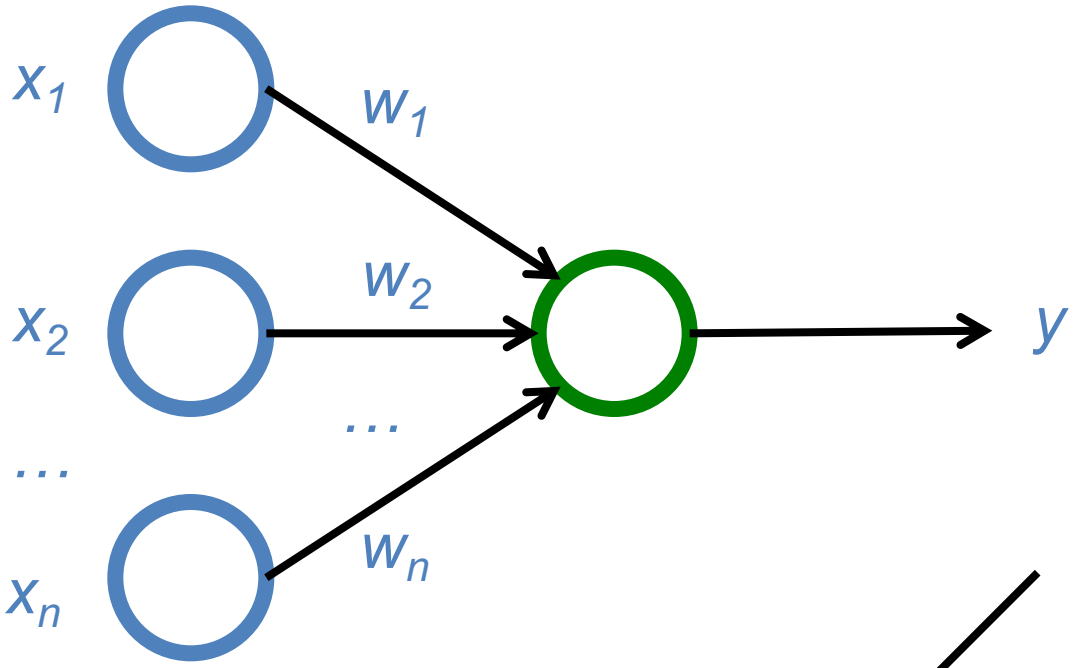
The Neuron



Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

The Neuron

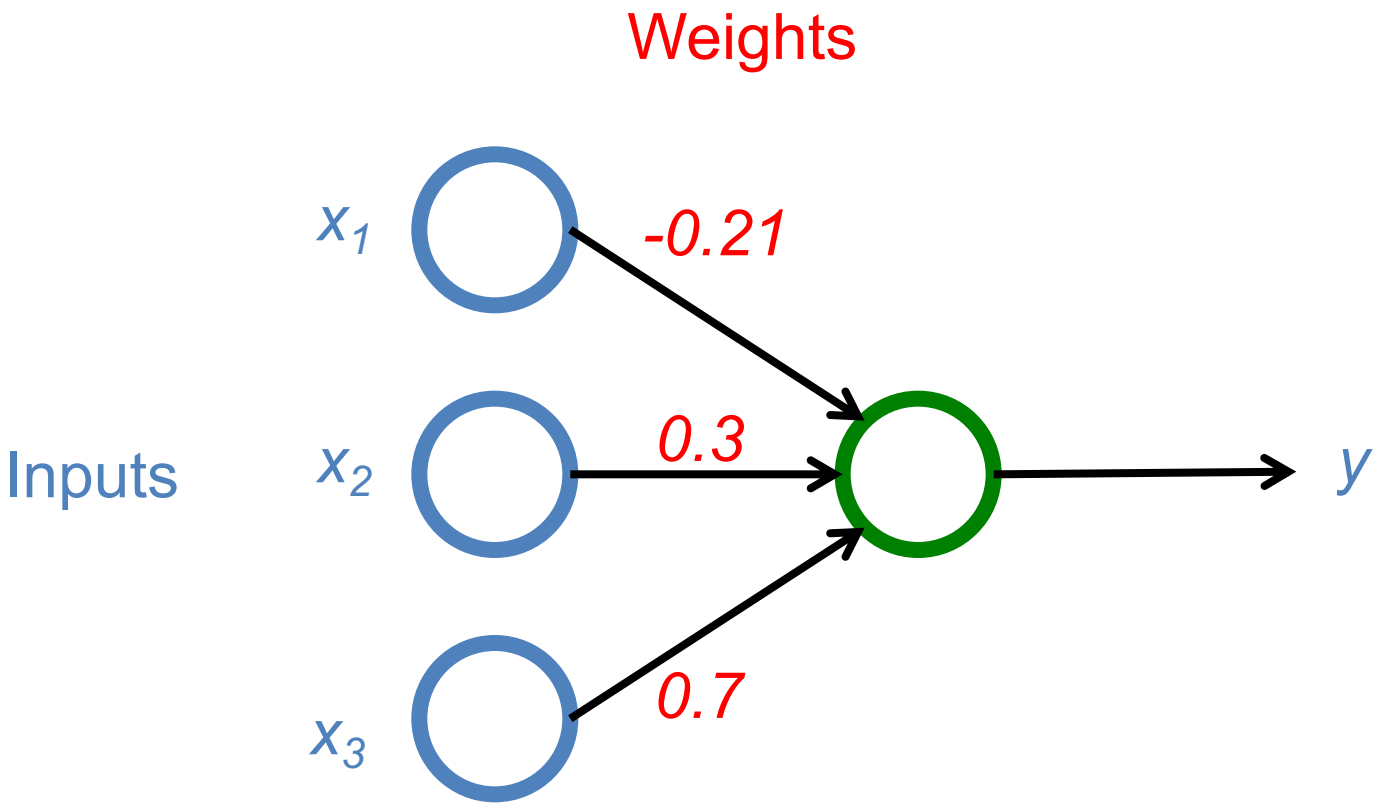
$$y = F\left(\sum_i w_i x_i\right)$$



$$F(x) = \max(0, x)$$

Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

$$y = max\,(\,0,\, -0.21 * x_1 + 0.3 * x_2 + 0.7 * x_3\,)$$



IS THIS A
CAT or DOG?

CAT DOG

OUTPUT LAYER

ACTIVATED NEURONS

INPUT LAYER

DEEP neural NETWORK

Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

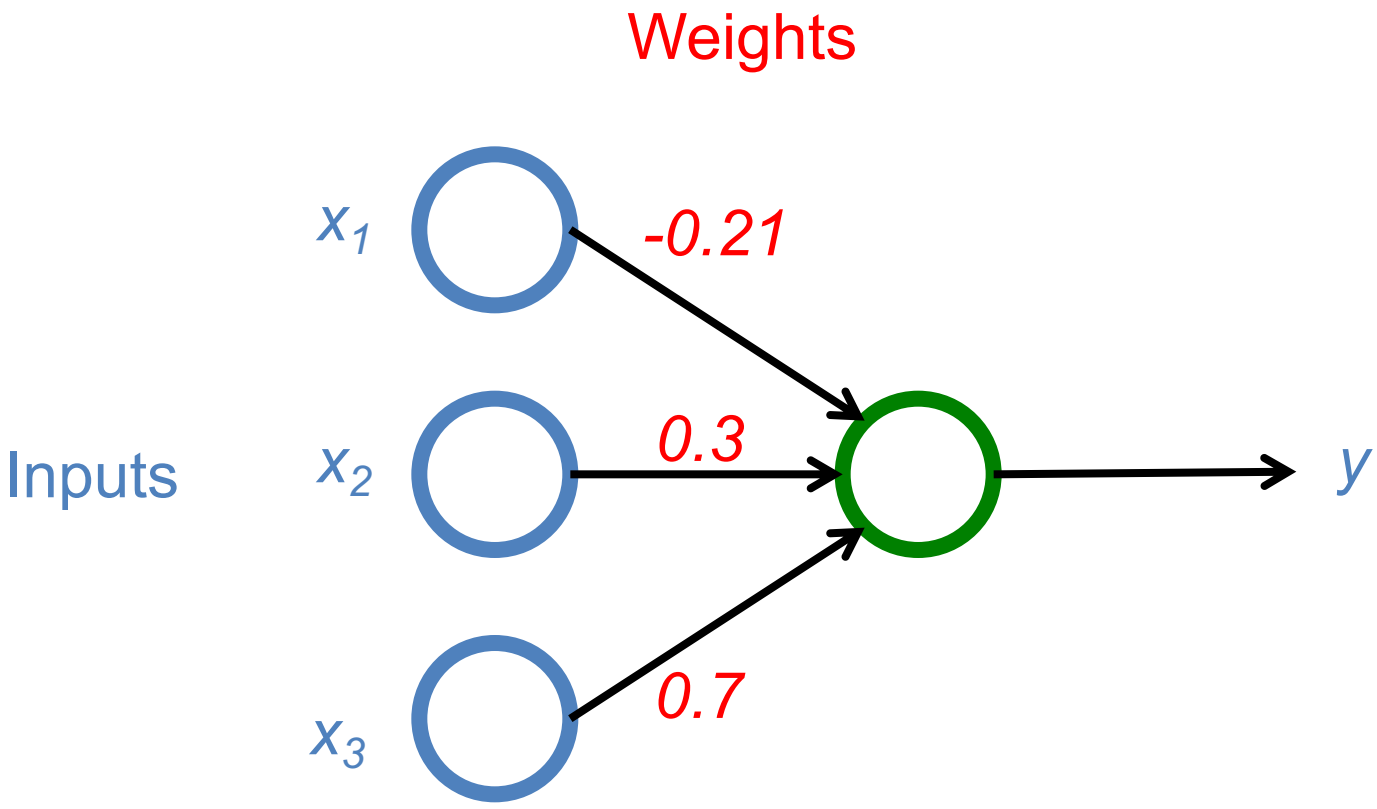
Learning Algorithm

While not done:

- Pick a random training example “(input, label)”
- Run neural network on “input”
- Adjust weights on edges to make output closer to “label”

Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

$$y = max\,(\,0,\ -0.21 * x_1 + 0.3 * x_2 + 0.7 * x_3\,)$$



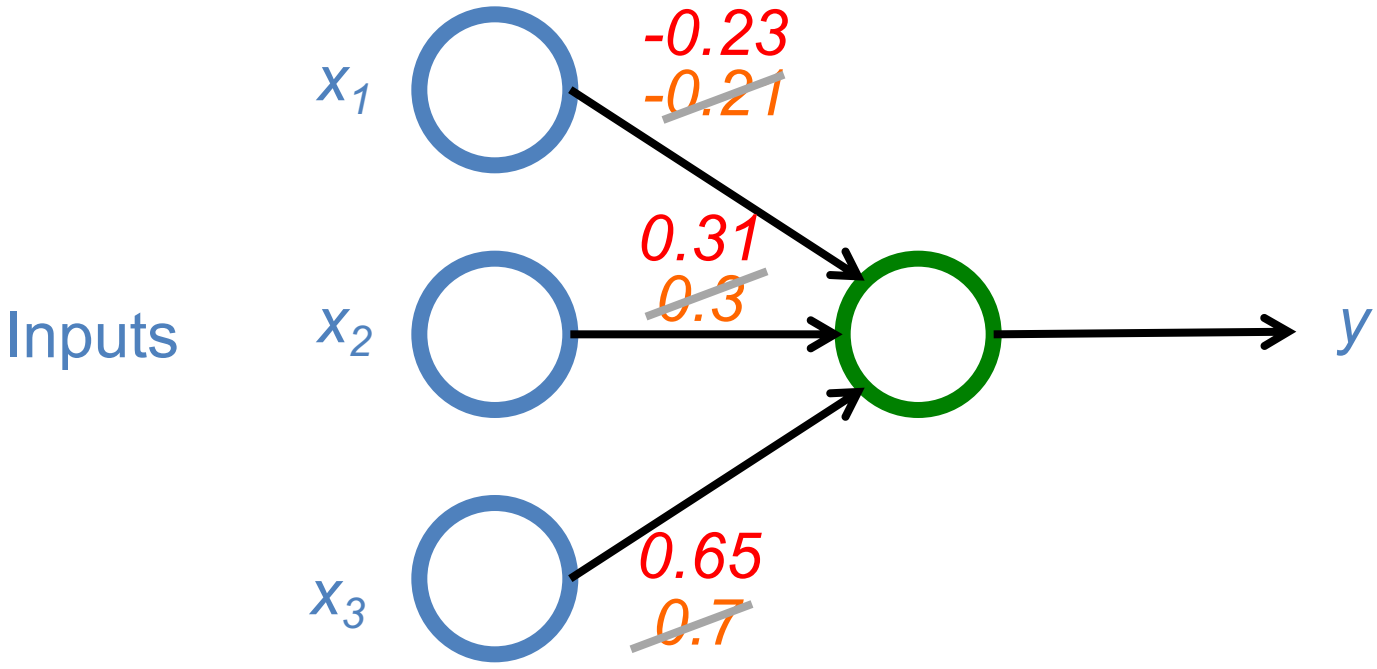
Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

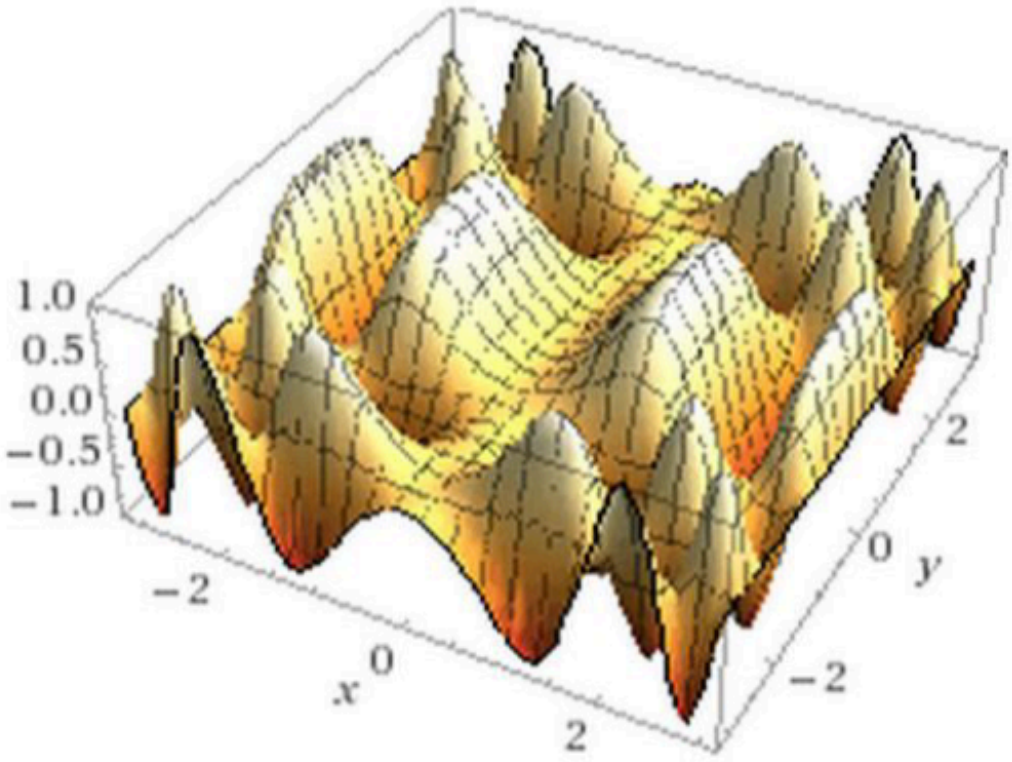
Next time:

$$y = max\,(\,0,\ -0.23 * x_1 + 0.31 * x_2 + 0.65 * x_3\,)$$

~~$$y = max\,(\,0,\ -0.21 * x_1 + 0.3 * x_2 + 0.7 * x_3\,)$$~~

Weights





This shows a function of 2 variables: real neural nets are functions of hundreds of millions of variables!

Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

Important Property of Neural Networks

Results get better with

More data +

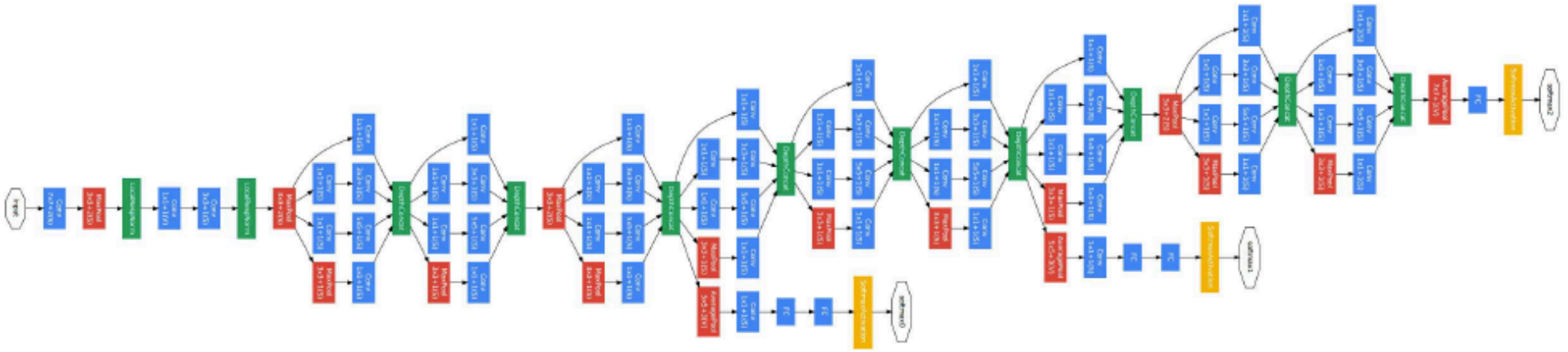
Bigger models +

More computation

(Better algorithms, new insights
and improved techniques always help, too!)

Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

The Inception Architecture (GoogLeNet, 2014)



Going Deeper with Convolutions

Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, Andrew Rabinovich

ArXiv 2014, CVPR 2015

Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

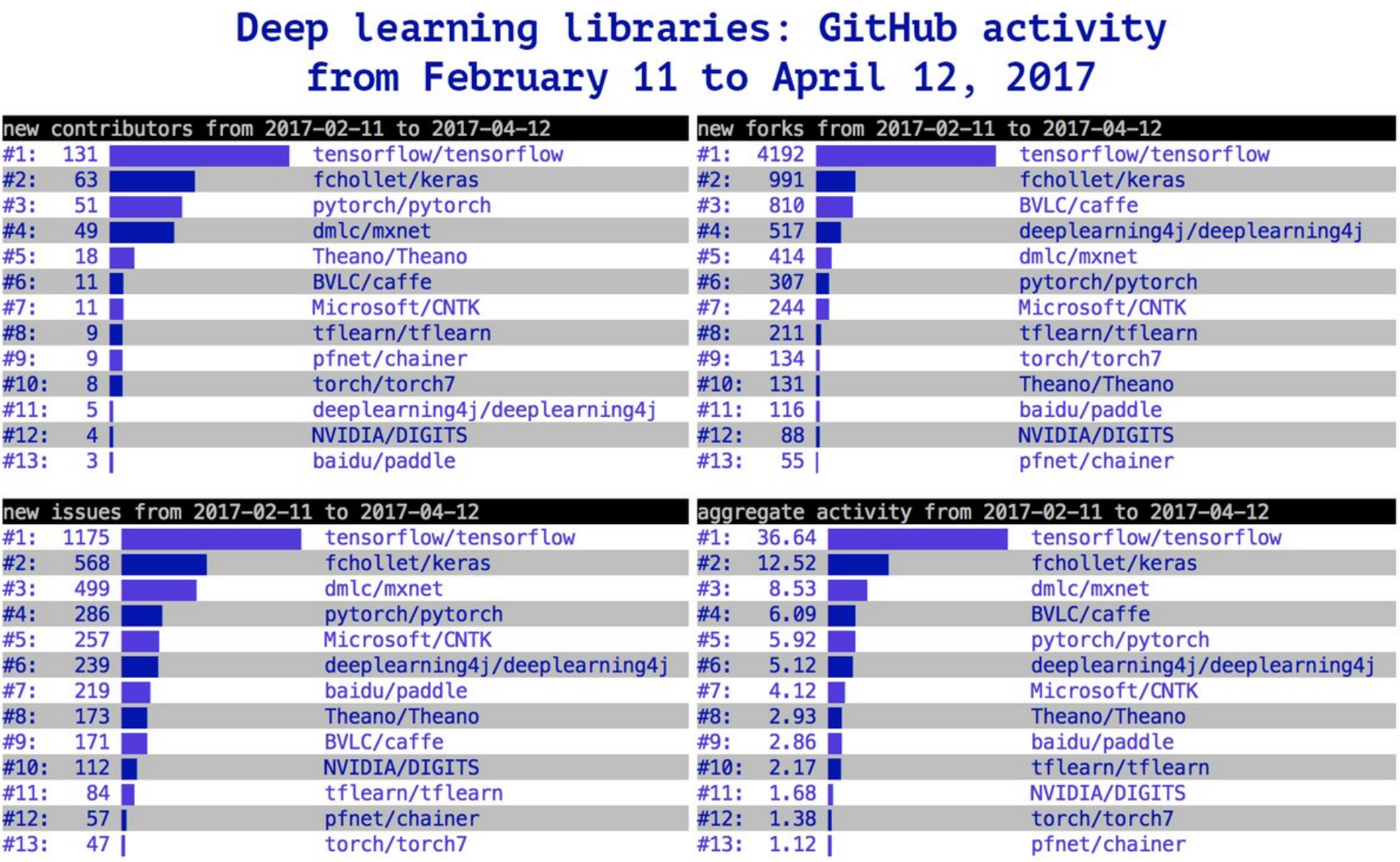
Deep Learning Software

- Keras
  - Deep Learning library for Theano and TensorFlow
- Tensorflow
  - TensorFlow™ is an open source software library for numerical computation using data flow graphs.
- Theano
  - CPU/GPU symbolic expression compiler in python (from MILA lab at University of Montreal)

Source: http://deeplearning.net/software_links/

Deep Learning with Google TensorFlow

Deep Learning Libraries: Tensorflow and Keras

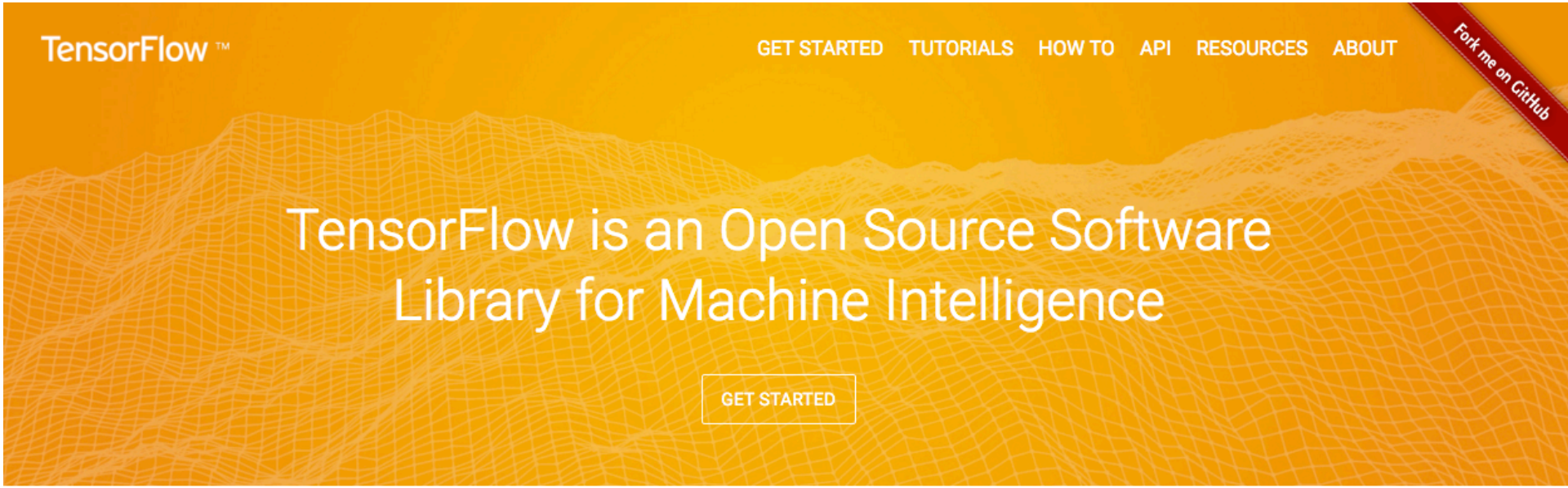


Source: https://twitter.com/fchollet/status/852194634470223873

TensorFlow

Source: https://github.com/tensorflow/tensorflow

Google TensorFlow



About TensorFlow

TensorFlow™ is an open source software library for numerical computation using data flow graphs. Nodes in the graph represent mathematical operations, while the graph edges represent the multidimensional data arrays (tensors) communicated between them. The flexible architecture allows you to deploy computation to one or more CPUs or GPUs in a desktop, server, or mobile device with a single API.

https://www.tensorflow.org/

TensorFlow

TensorFlow

is an

Open Source Software Library

for

Machine Intelligence

https://www.tensorflow.org/

TensorFlow

numerical computation using data flow graphs

https://www.tensorflow.org/

TensorFlow

Tensor

- **3**
  - # a rank 0 tensor; this is a **scalar** with shape []
- **[1. ,2., 3.]**
  - # a rank 1 tensor; this is a **vector** with shape [3]
- **[[1., 2., 3.], [4., 5., 6.]]**
  - # a rank 2 tensor; a **matrix** with shape [2, 3]
- **[[[1., 2., 3.]], [[7., 8., 9.]]]**
  - # a rank 3 **tensor** with shape [2, 1, 3]

https://www.tensorflow.org/

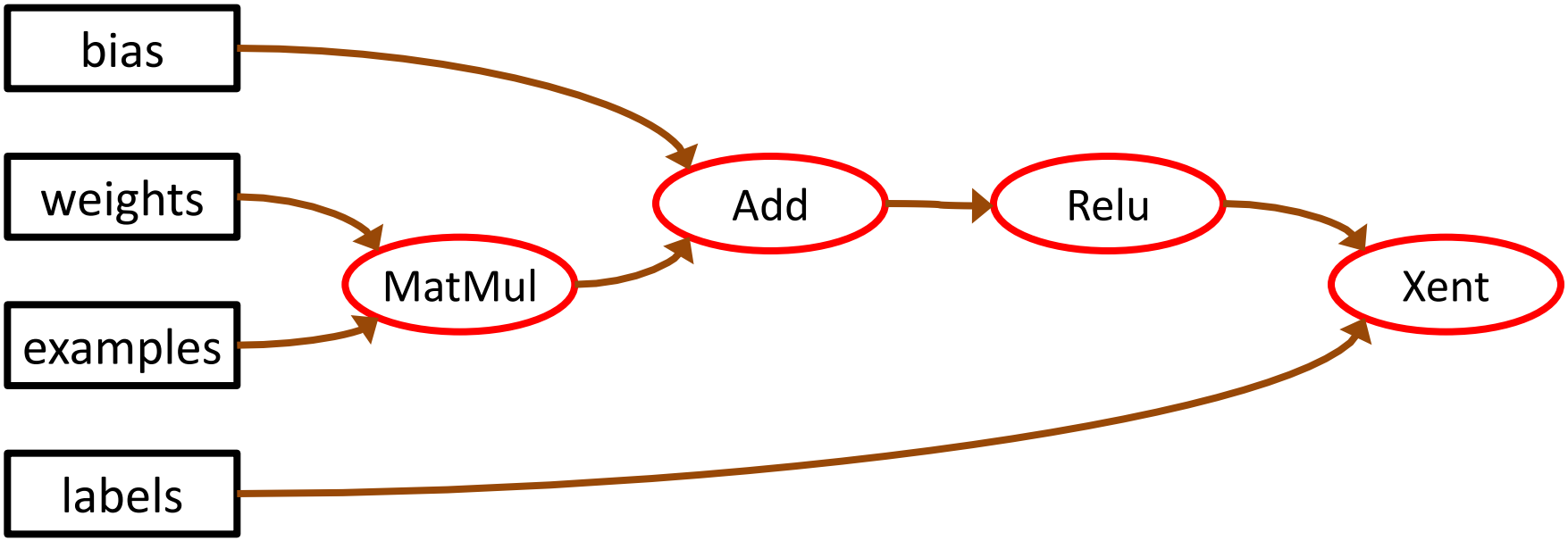
TensorFlow

Nodes:
mathematical operations

edges:
multidimensional data arrays (tensors)
communicated between nodes

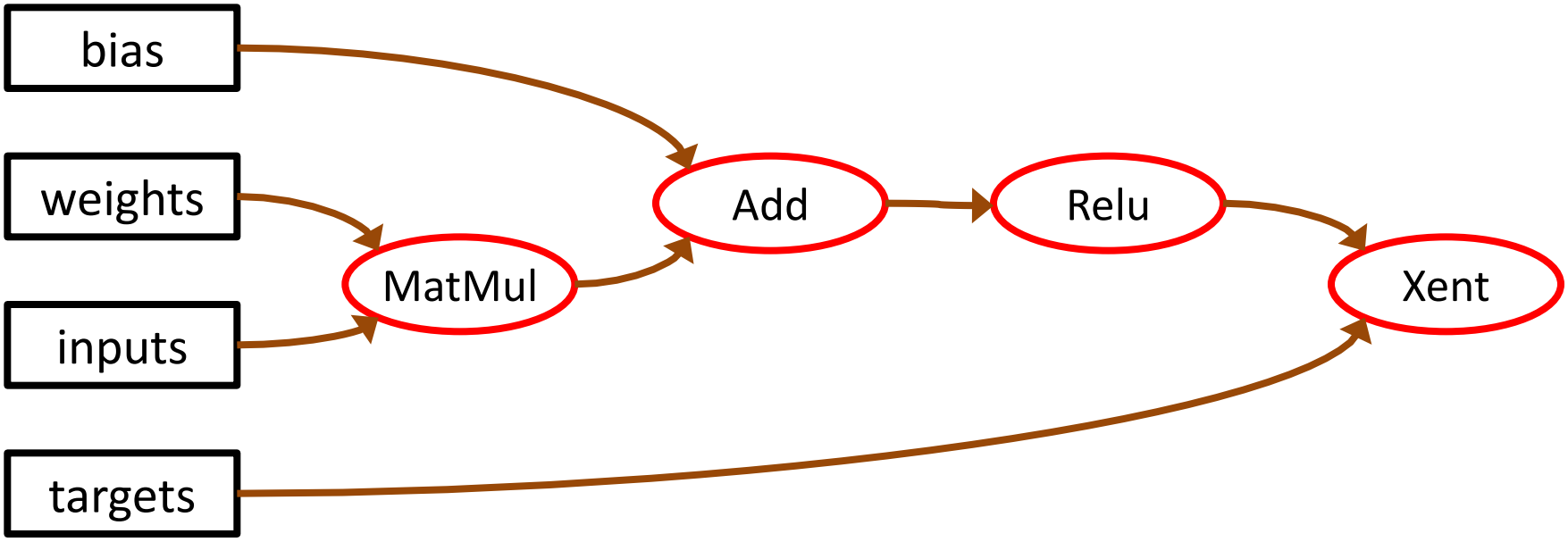
Computation is a Dataflow Graph

Graph of Nodes,
also called Operations or ops.



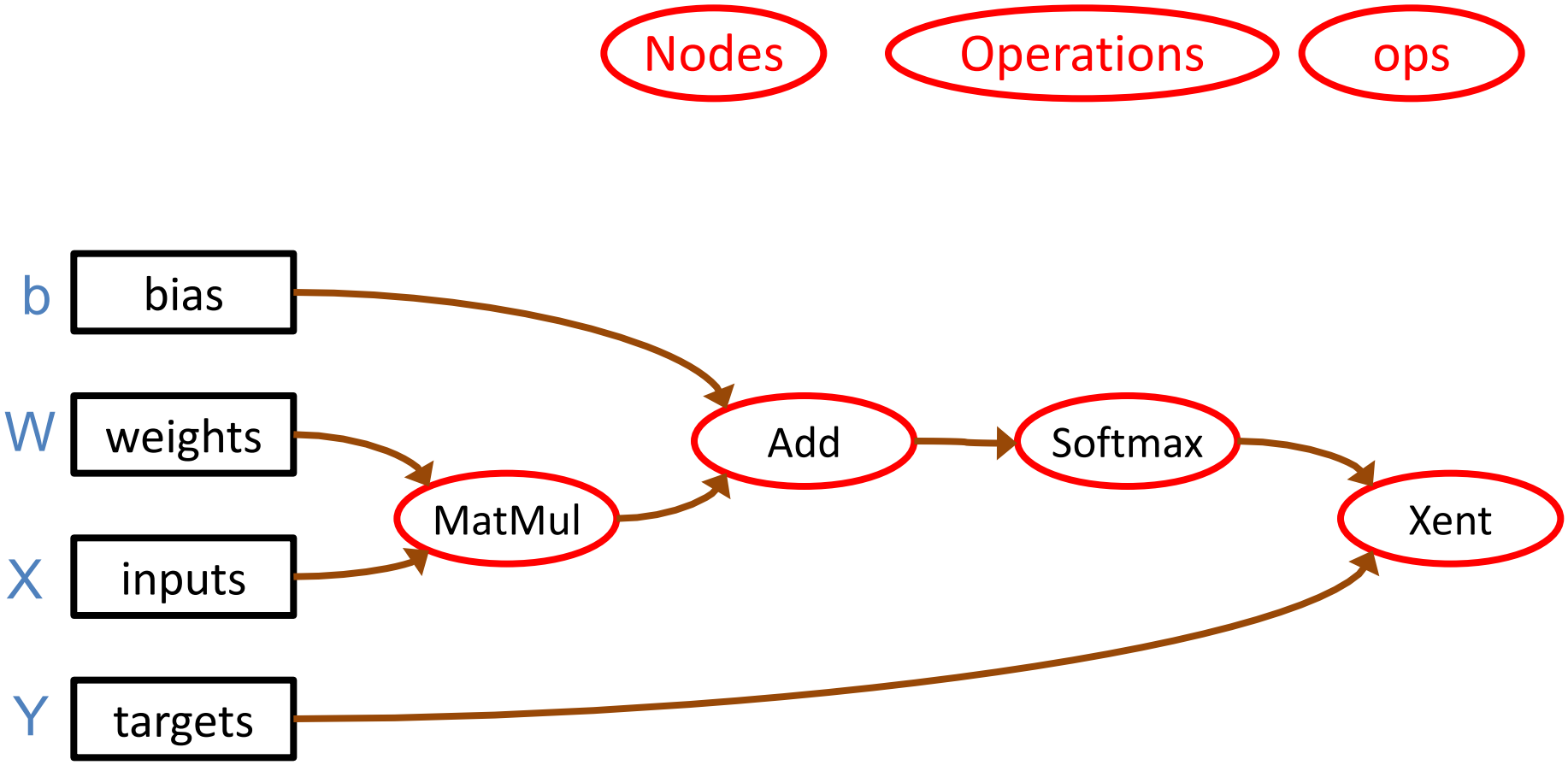
Computation is a Dataflow Graph

Edges are N-dimensional arrays: **Tensors**



Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

Logistic Regression as Dataflow Graph

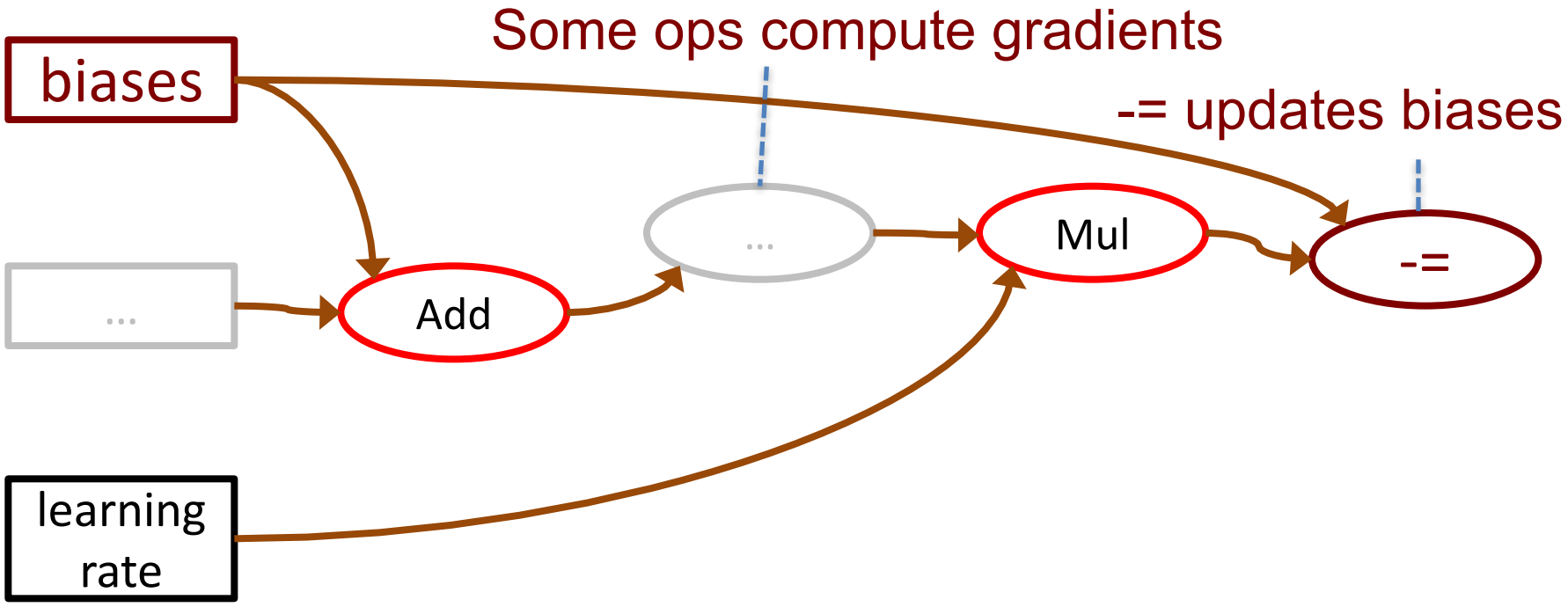


Edges are N-dimensional arrays: **Tensors**

Computation is a Dataflow Graph

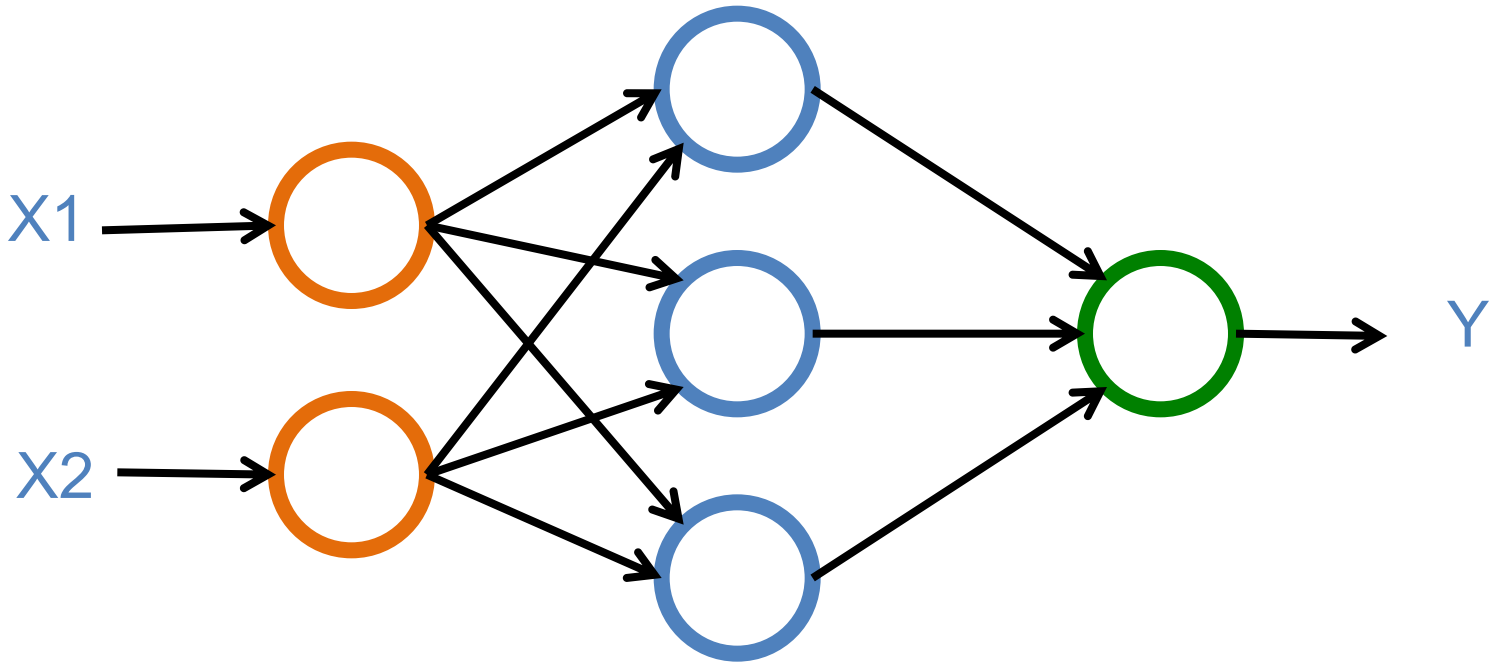
with state

‘Biases’ is a variable



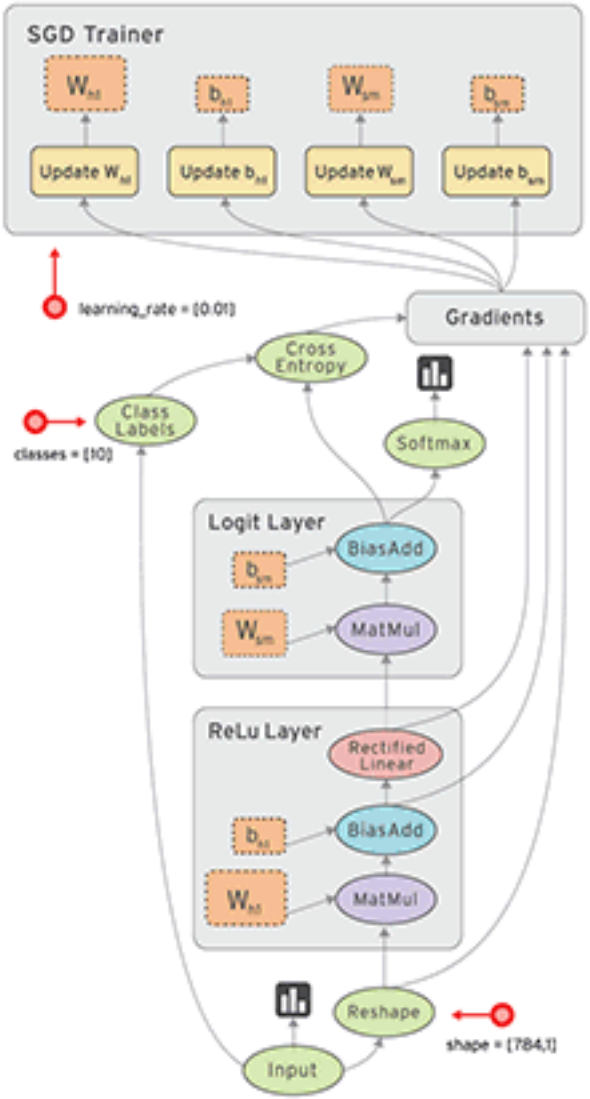
Neural Networks

Input Layer (X) Hidden Layer (H) **Output Layer (Y)**



Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

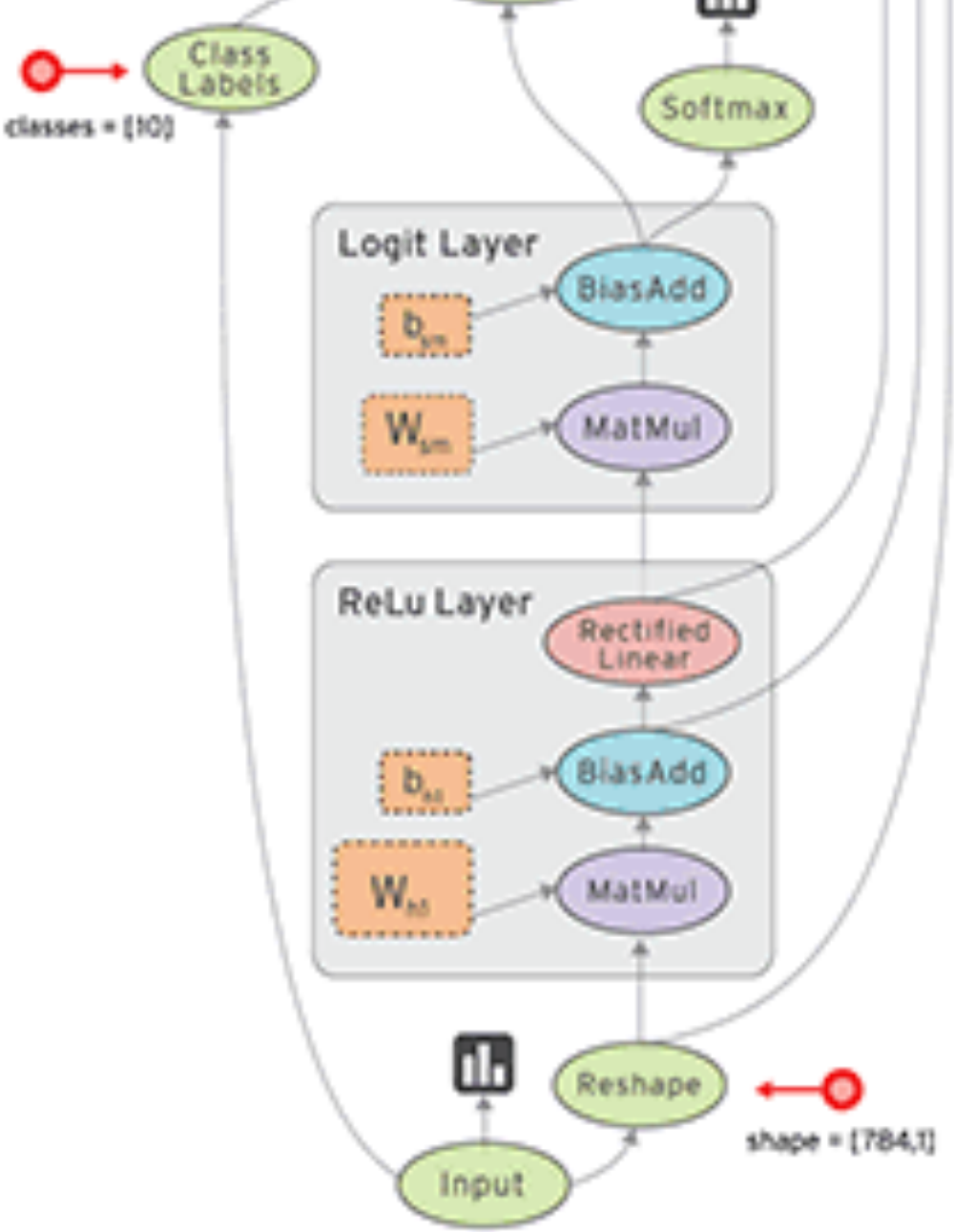
Data Flow Graph



Source: https://www.tensorflow.org/

TensorFlow

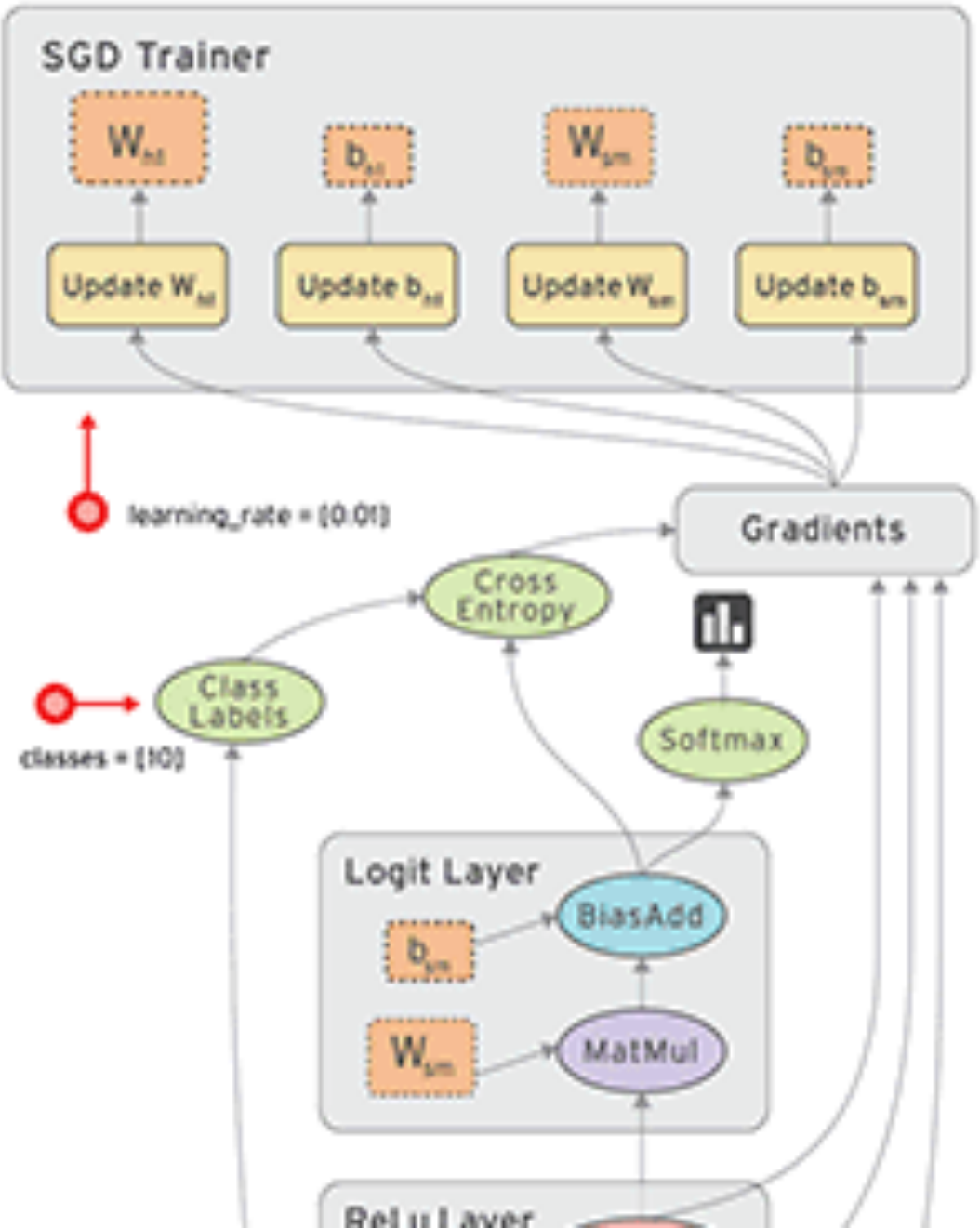
Data Flow Graph



Source: https://www.tensorflow.org/

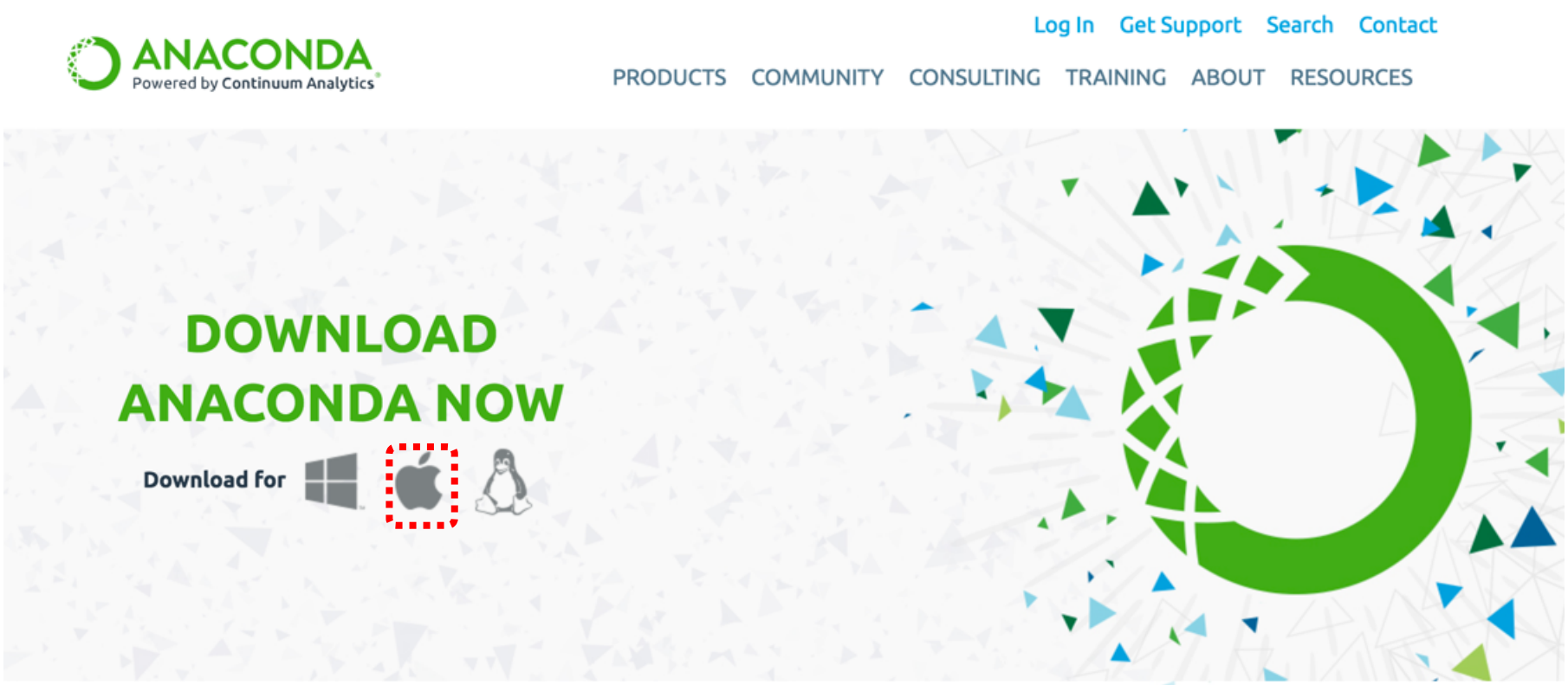
TensorFlow

Data Flow Graph



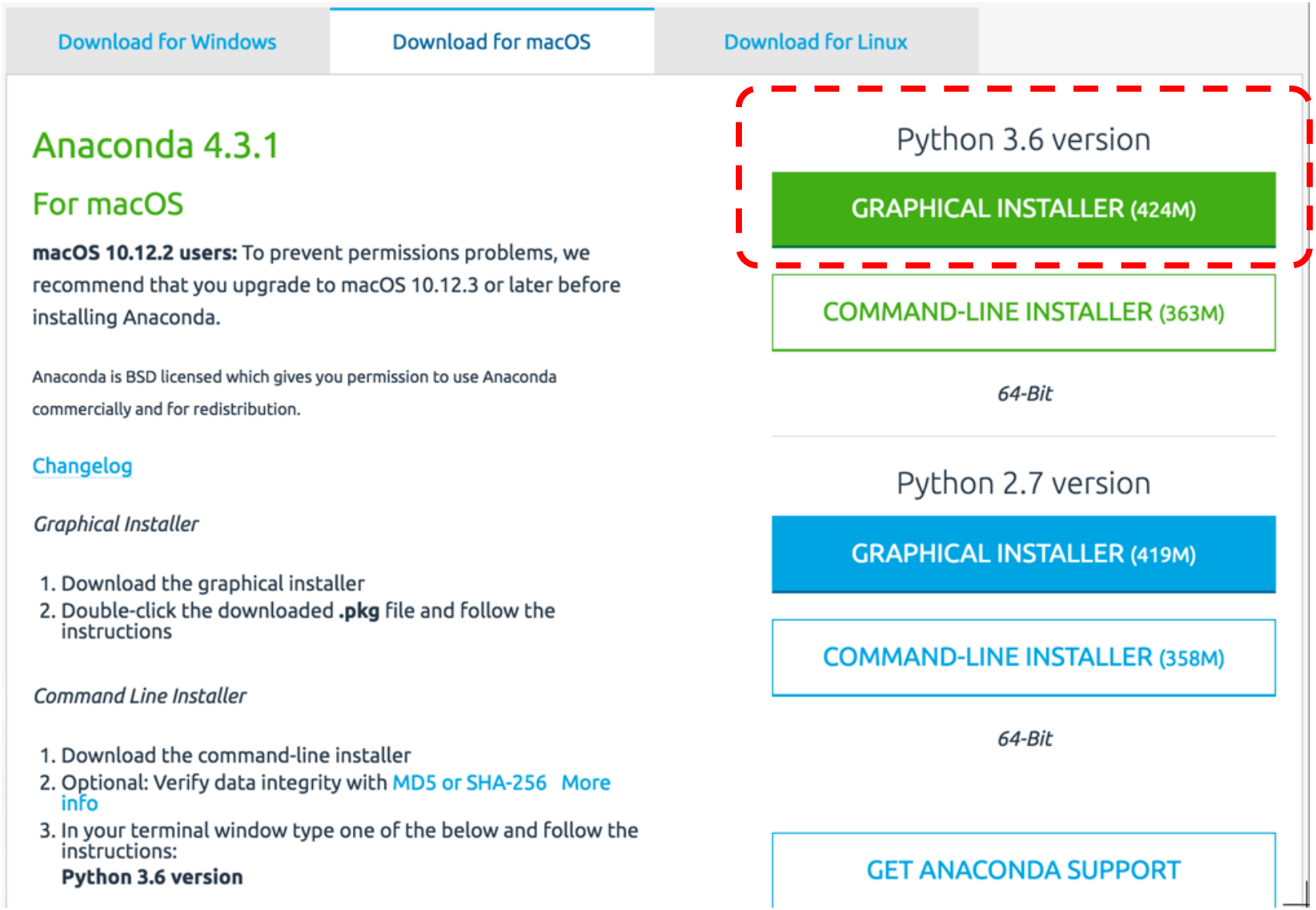
Python

Download Anaconda



https://www.continuum.io/downloads

Download Anaconda Python 3.6



https://www.continuum.io/downloads

OS X Anaconda Python 3.6 Installation

Command Line Installer

Download the command-line installer

In your terminal window type one of the below and follow the instructions:

Python 3.6 version

```
bash Anaconda3-4.3.1-MacOSX-x86_64.sh
```

Python 2.7 version

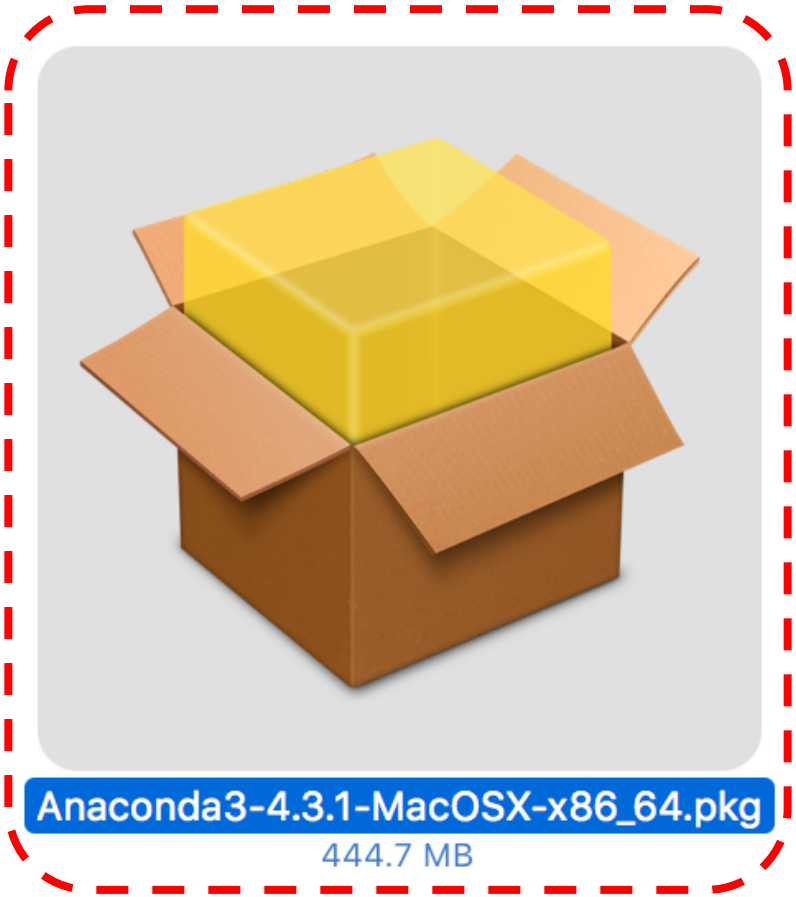
```
bash Anaconda2-4.3.1-MacOSX-x86_64.sh
```

https://www.continuum.io/downloads

OS X Anaconda 3 - 4.3.1

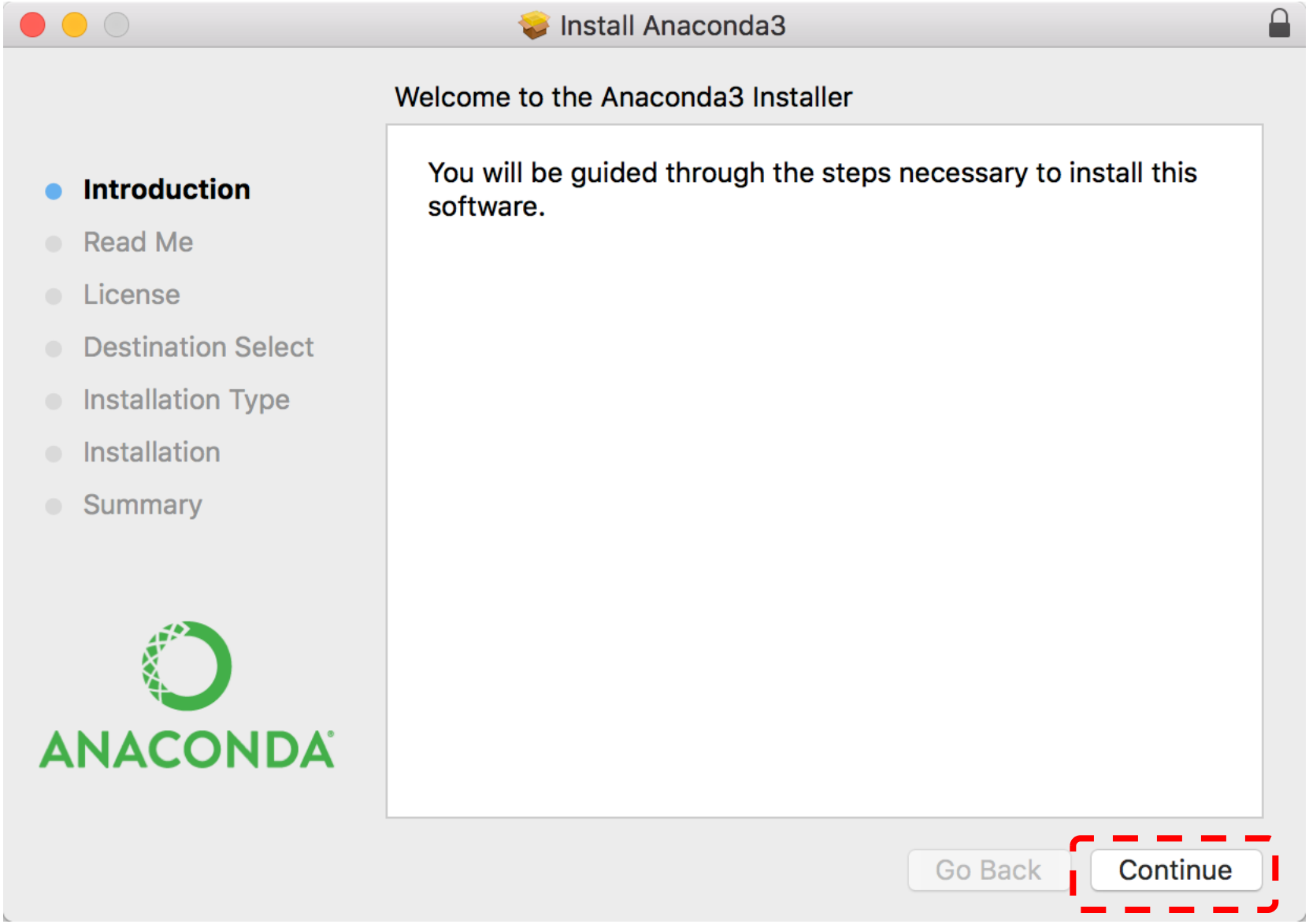
Python 3.6 Installation

Anaconda3-4.3.1-MacOSX-x86_64.pkg

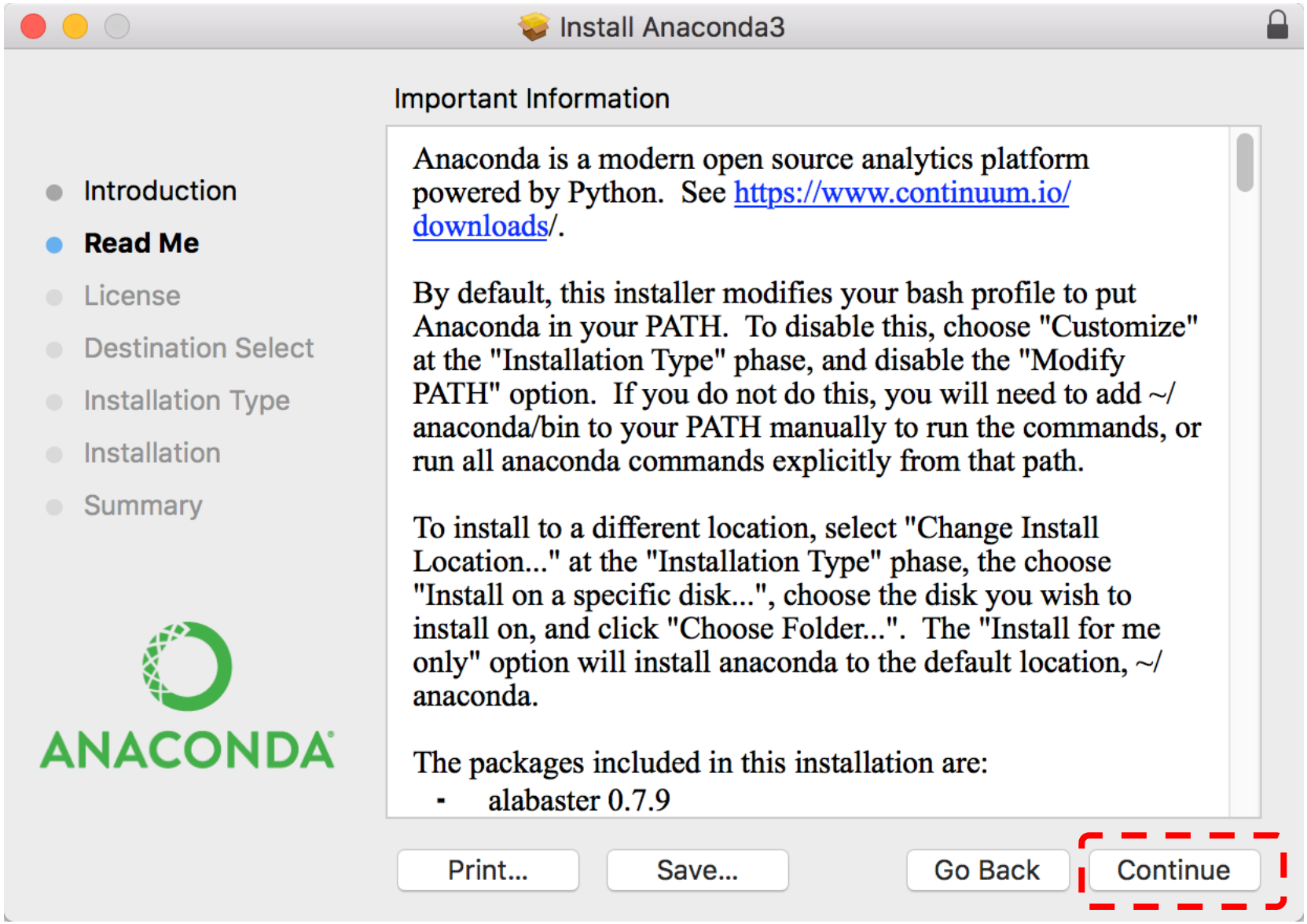


Installer package

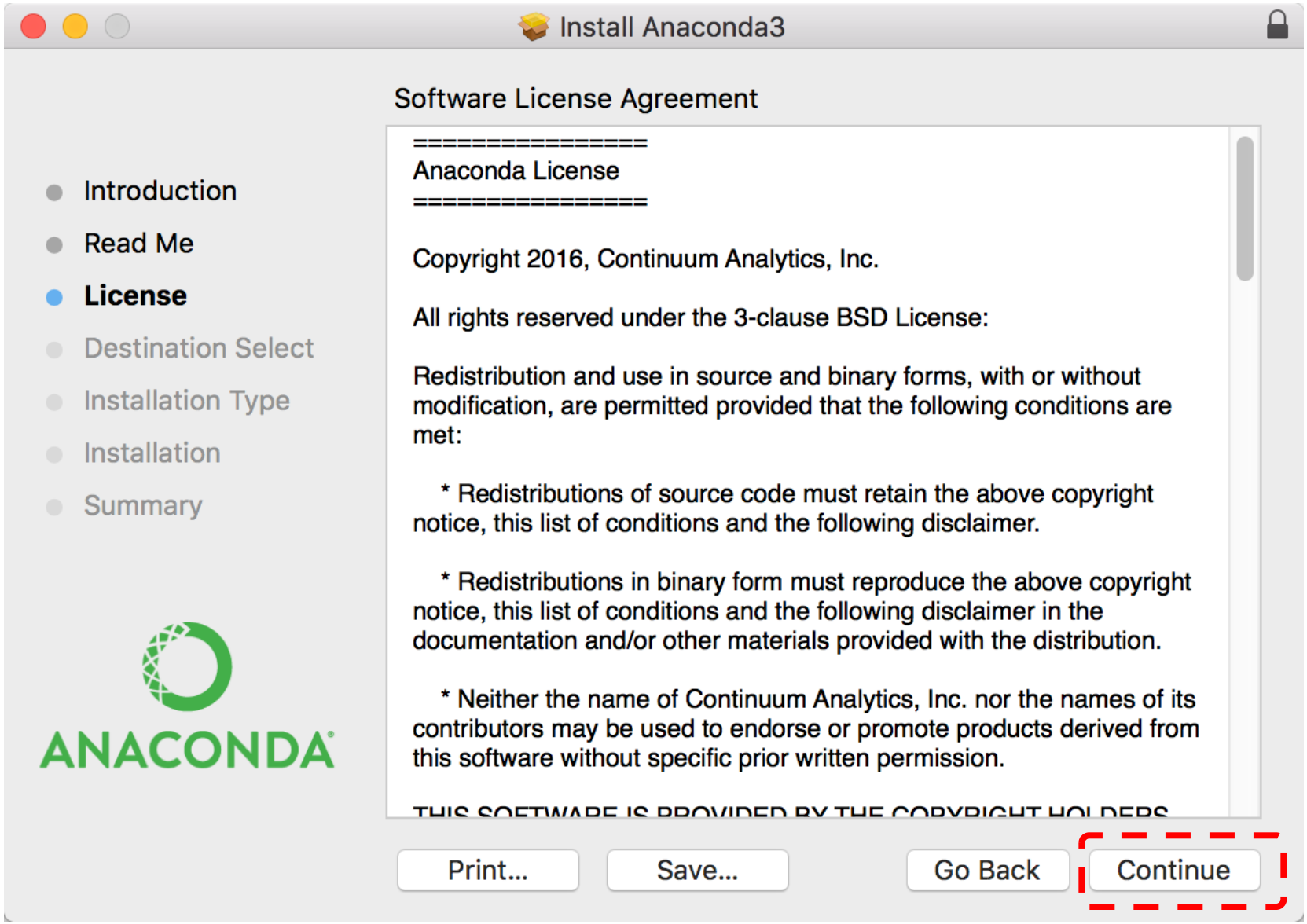
Install Anaconda 3



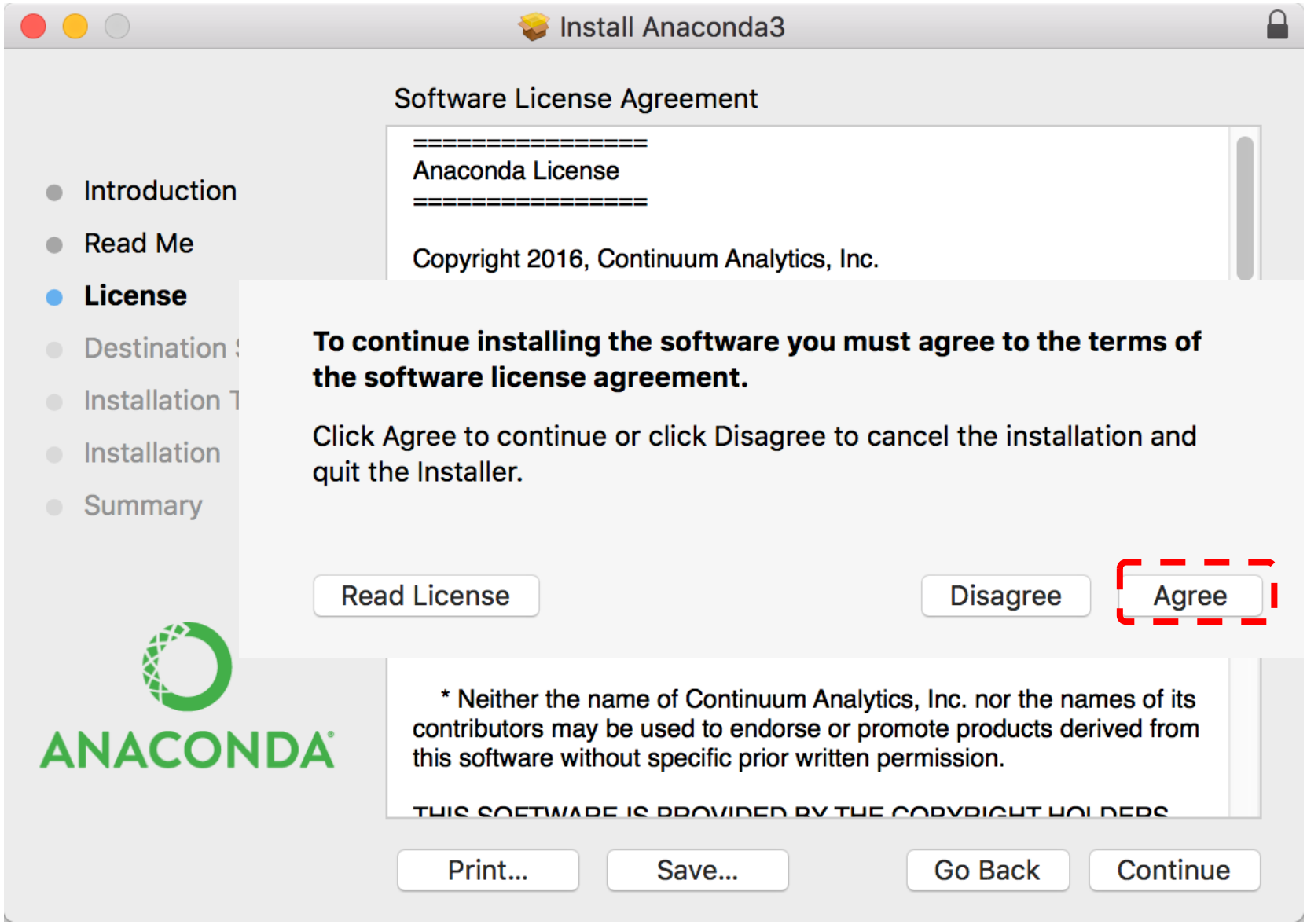
Install Anaconda 3



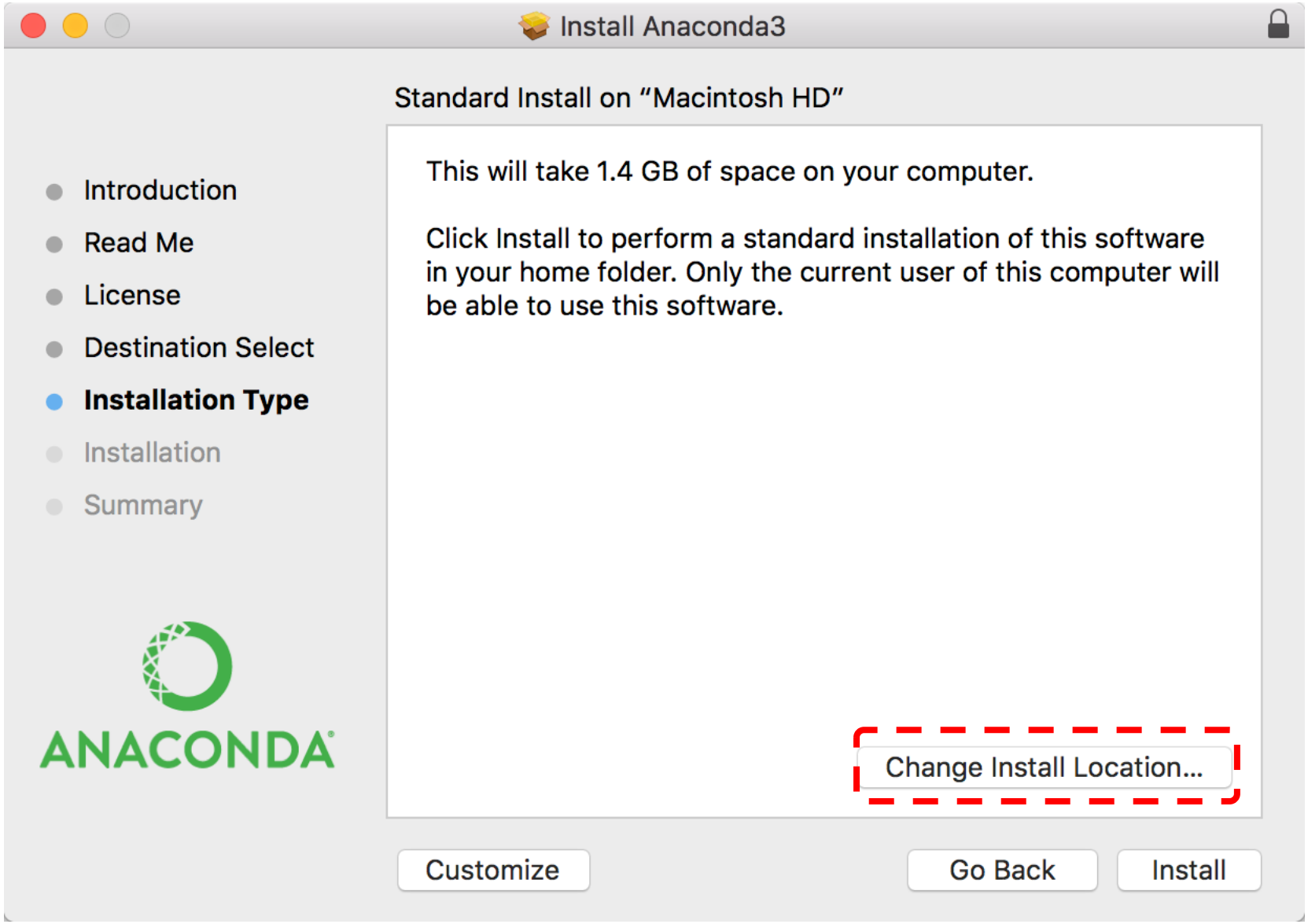
Install Anaconda 3



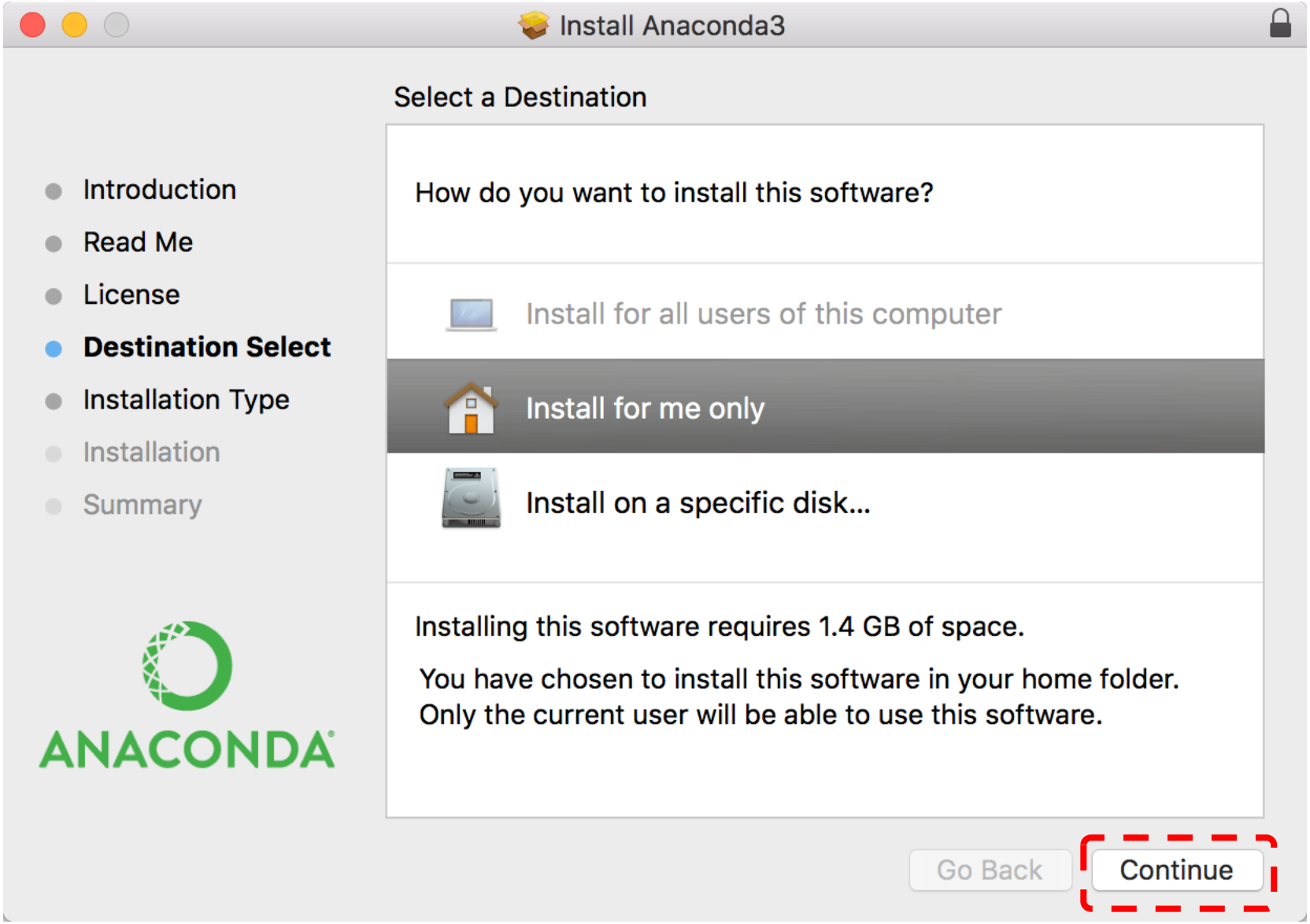
Install Anaconda 3



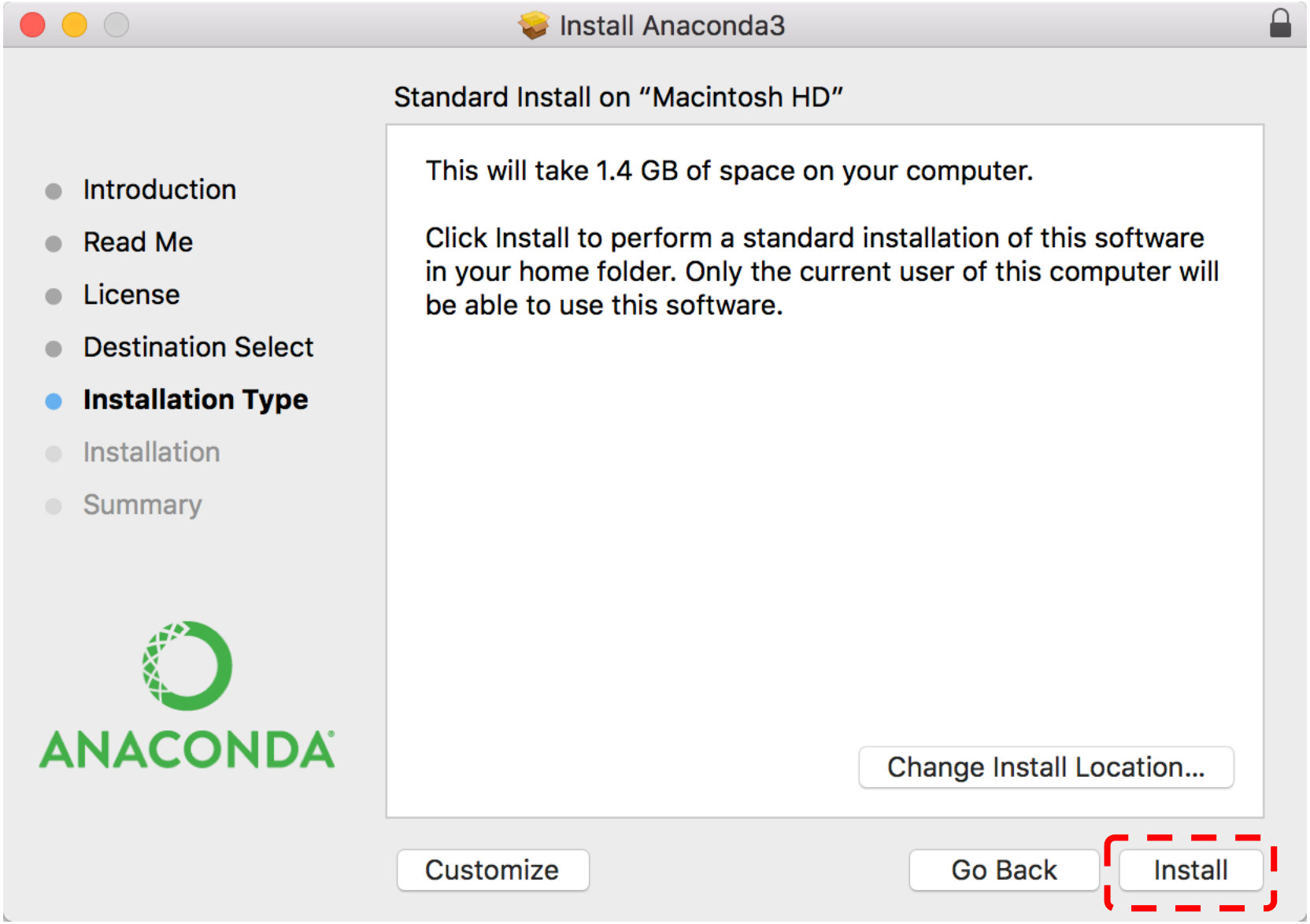
Install Anaconda 3



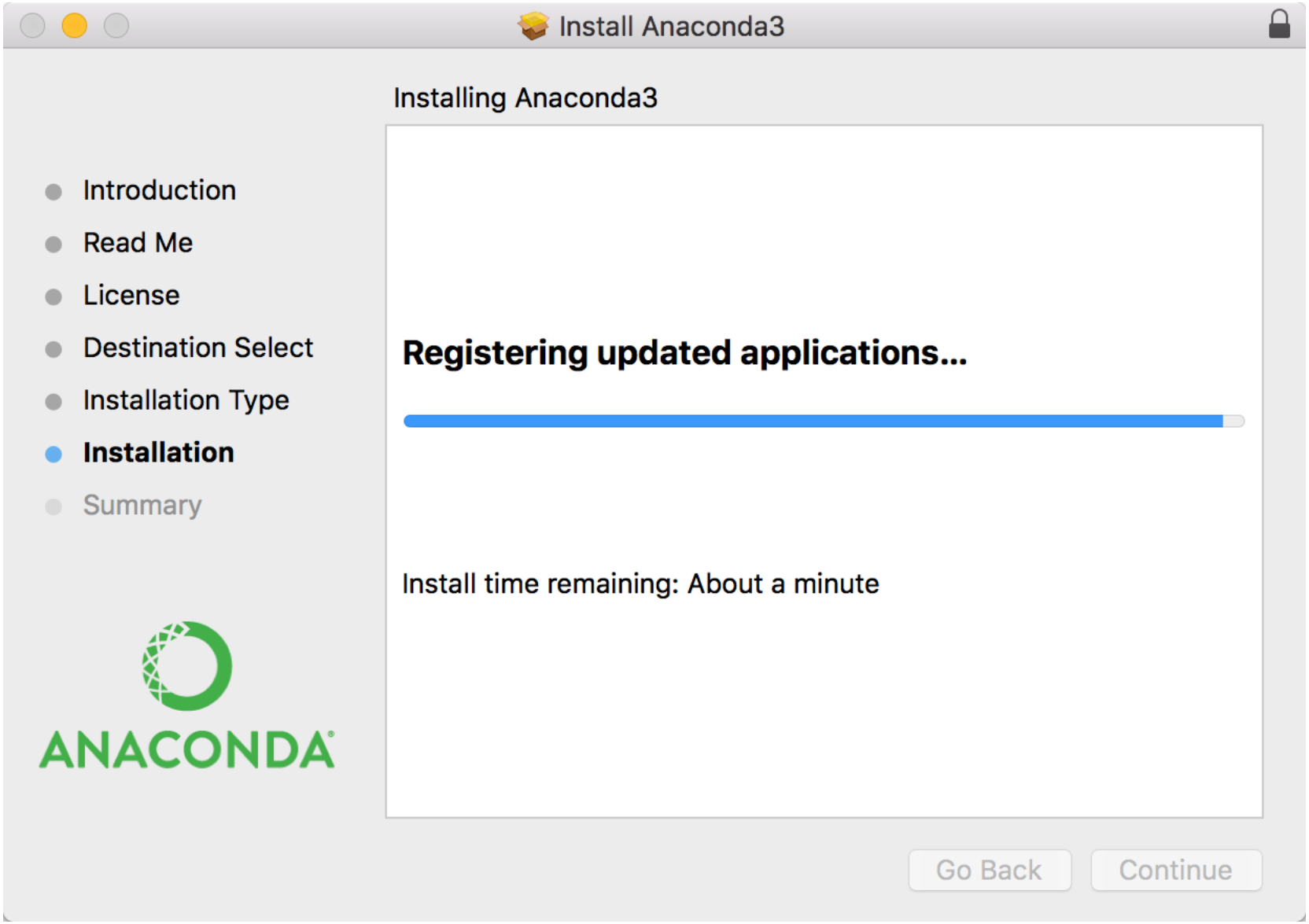
Install Anaconda 3



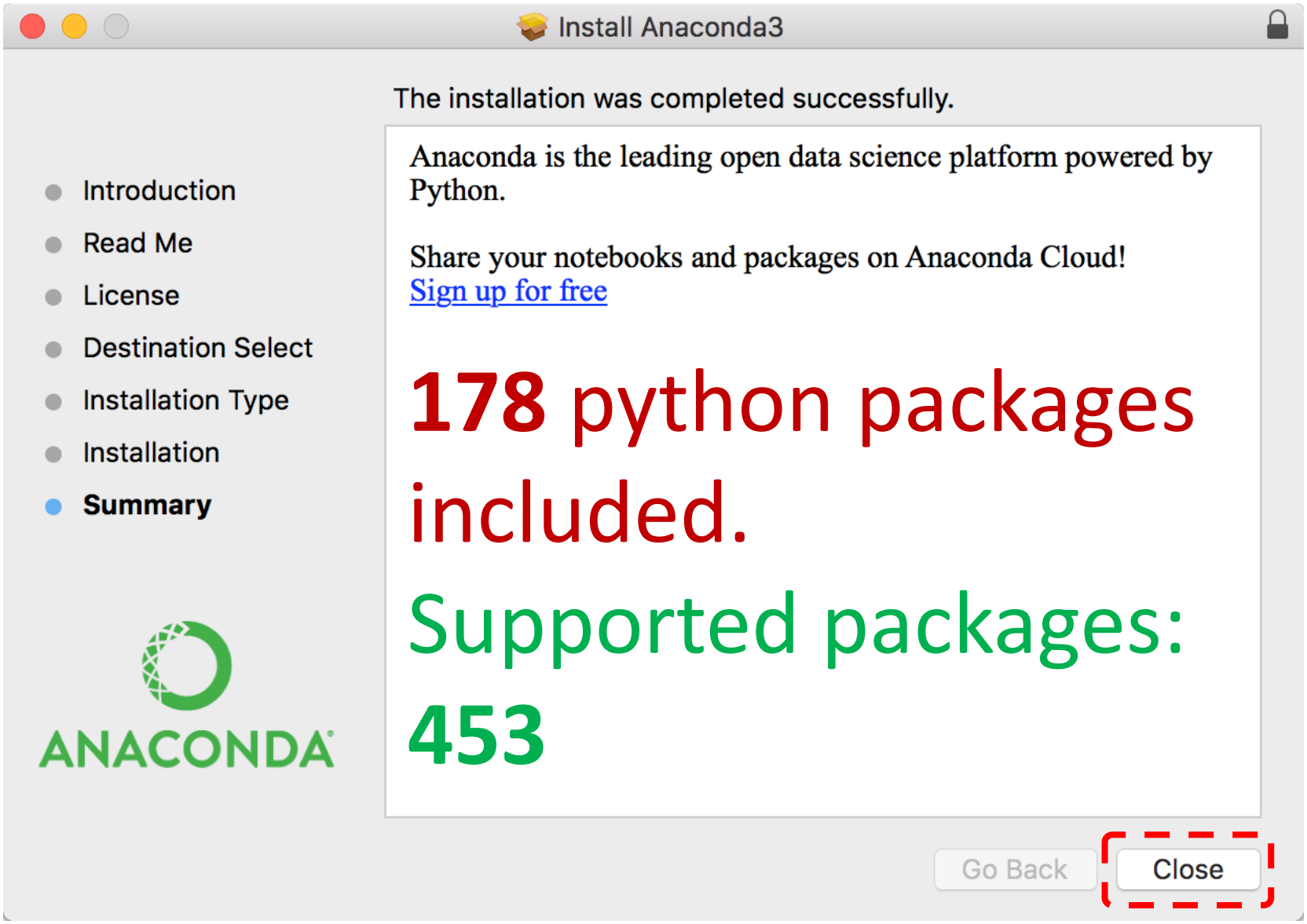
Install Anaconda 3



Install Anaconda 3



Install Anaconda 3



Source: https://docs.continuum.io/anaconda/pkg-docs

Install Anaconda 3

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2	alabaster	0.7.9
3	anaconda	4.3.1
4	anaconda-client	1.6.0
5	anaconda-navigator	1.5.0
6	anaconda-project	0.4.1
7	appnope	0.1.0
8	appscript	1.0.1
9	astroid	1.4.9
10	astropy	1.3
11	babel	2.3.4
12	backports	1.0
13	beautifulsoup4	4.5.3
14	bitarray	0.8.1
15	blaze	0.10.1
16	bokeh	0.12.4
17	boto	2.45.0
18	bottleneck	1.2.0
19	cffi	1.9.1
20	chardet	2.3.0
21	chest	0.2.3
22	click	6.7
23	cloudpickle	0.2.2
24	clyent	1.2.2
25	colorama	0.3.7
26	conda	4.3.14
27	conda-env	2.6.0
28	configobj	5.0.6
29	contextlib2	0.5.4
30	cryptography	1.7.1
31	curl	7.52.1
32	cycler	0.10.0
33	cython	0.25.2
34	cytoolz	0.8.2
35	dask	0.13.0
36	datashape	0.5.4
37	decorator	4.0.11
38	dill	0.2.5
39	docutils	0.13.1
40	entrypoints	0.2.2
41	et_xmlfile	1.0.1
42	fastcache	1.0.2
43	flask	0.12
44	flask-cors	3.0.2
45	freetype	2.5.5
46	get_terminal_size	1.0.0
47	gevent	1.2.1
48	greenlet	0.4.11
49	h5py	2.6.0
50	hdf5	1.8.17
51	heapdict	1.0.0
52	icu	54.1
53	idna	2.2
54	imagesize	0.7.1
55	ipykernel	4.5.2
56	ipython	5.1.0
57	ipython_genutils	0.1.0
58	ipywidgets	5.2.2
59	isort	4.2.5
60	itsdangerous	0.24
61	jbig	2.1
62	jdcal	1.3
63	jedi	0.9.0
64	jinja2	2.9.4
65	jpeg	9b
66	jsonschema	2.5.1
67	jupyter	1.0.0
68	jupyter_client	4.4.0
69	jupyter_console	5.0.0
70	jupyter_core	4.2.1
71	lazy-object-proxy	1.2.2
72	libiconv	1.14
73	libpng	1.6.27
74	libtiff	4.0.6
75	libxml2	2.9.4
76	libxslt	1.1.29
77	llvmlite	0.15.0
78	locket	0.2.0
79	lxml	3.7.2
80	markupsafe	0.23
81	matplotlib	2.0.0
82	mistune	0.7.3
83	mkl	2017.0.1
84	mkl-service	1.1.2
85	mpmath	0.19
86	multipledispatch	0.4.9
87	nbconvert	4.2.0
88	nbformat	4.2.0
89	networkx	1.11
90	nltk	3.2.2
91	nose	1.3.7
92	notebook	4.3.1
93	numba	0.30.1
94	numexpr	2.6.1
95	numpy	1.11.3
96	numpydoc	0.6.0
97	odo	0.5.0
98	openpyxl	2.4.1
99	openssl	1.0.2k
100	pandas	0.19.2
101	partd	0.3.7
102	path.py	10.0
103	pathlib2	2.2.0
104	patsy	0.4.1
105	pep8	1.7.0
106	pexpect	4.2.1
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109	pip	9.0.1
110	ply	3.9
111	prompt_toolkit	1.0.9
112	psutil	5.0.1
113	ptyprocess	0.5.1
114	py	1.4.32
115	pyasn1	0.1.9
116	pycosat	0.6.1
117	pycparser	2.17
118	pycrypto	2.6.1
119	pycurl	7.43.0
120	pyflakes	1.5.0
121	pygments	2.1.3
122	pylint	1.6.4
123	pyopenssl	16.2.0
124	pyparsing	2.1.4
125	pyqt	5.6.0
126	pytables	3.3.0
127	pytest	3.0.5
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129	python-dateutil	2.6.0
130	python.app	1.2
131	pytz	2016.10
132	pyyaml	3.12
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136	qtconsole	4.2.1
137	qtpy	1.2.1
138	readline	6.2
139	redis	3.2.0
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141	requests	2.12.4
142	rope	0.9.4
143	ruamel_yaml	0.11.14
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152	six	1.10.0
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154	sockjs-tornado	1.0.3
155	sphinx	1.5.1
156	spyder	3.1.2
157	sqlalchemy	1.1.5
158	sqlite	3.13.0
159	statsmodels	0.6.1
160	sympy	1.0
161	terminado	0.6
162	tk	8.5.18
163	toolz	0.8.2
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165	traitlets	4.3.1
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175	xlwt	1.2.0
176	xz	5.2.2
177	yaml	0.1.6
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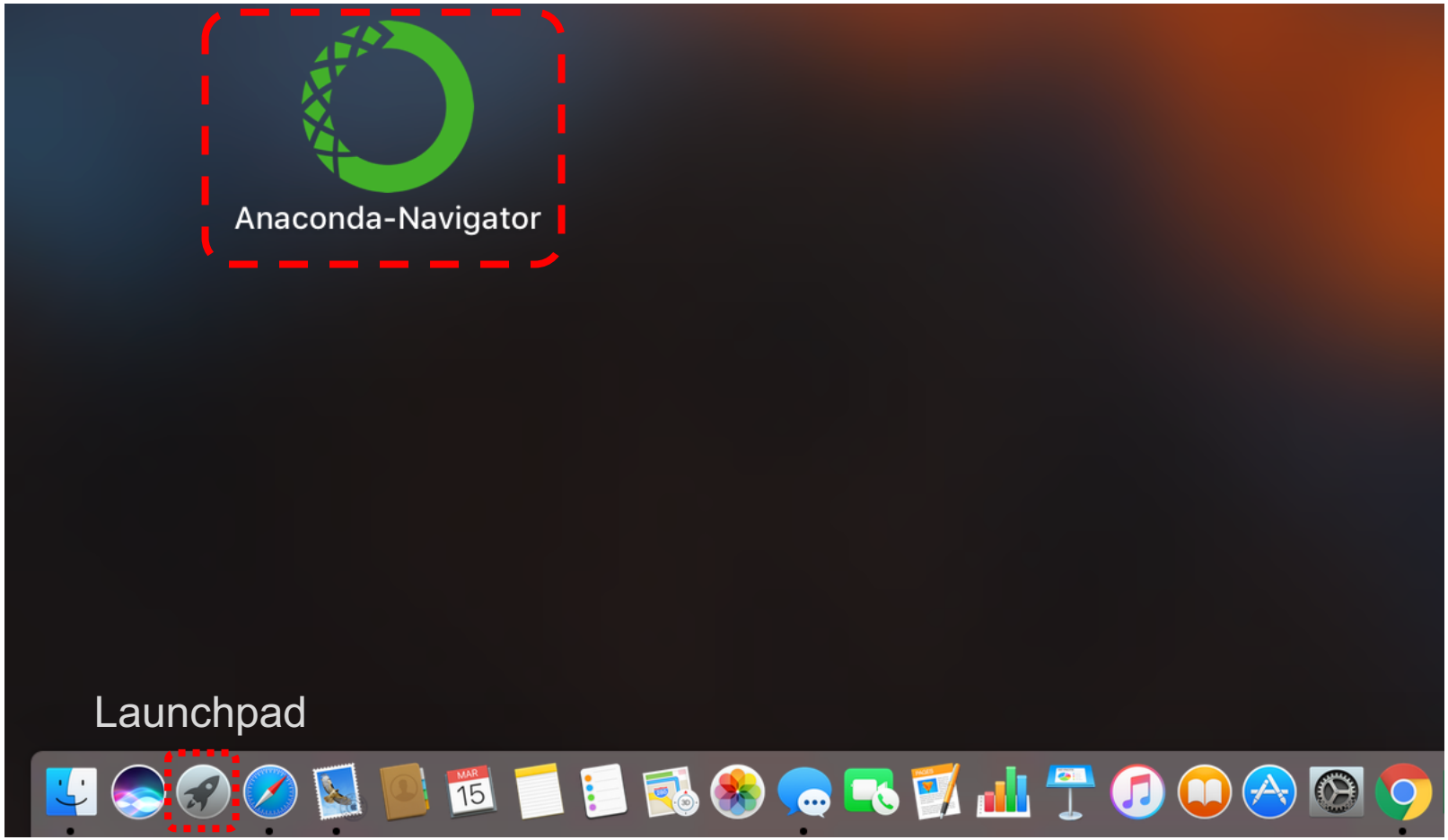
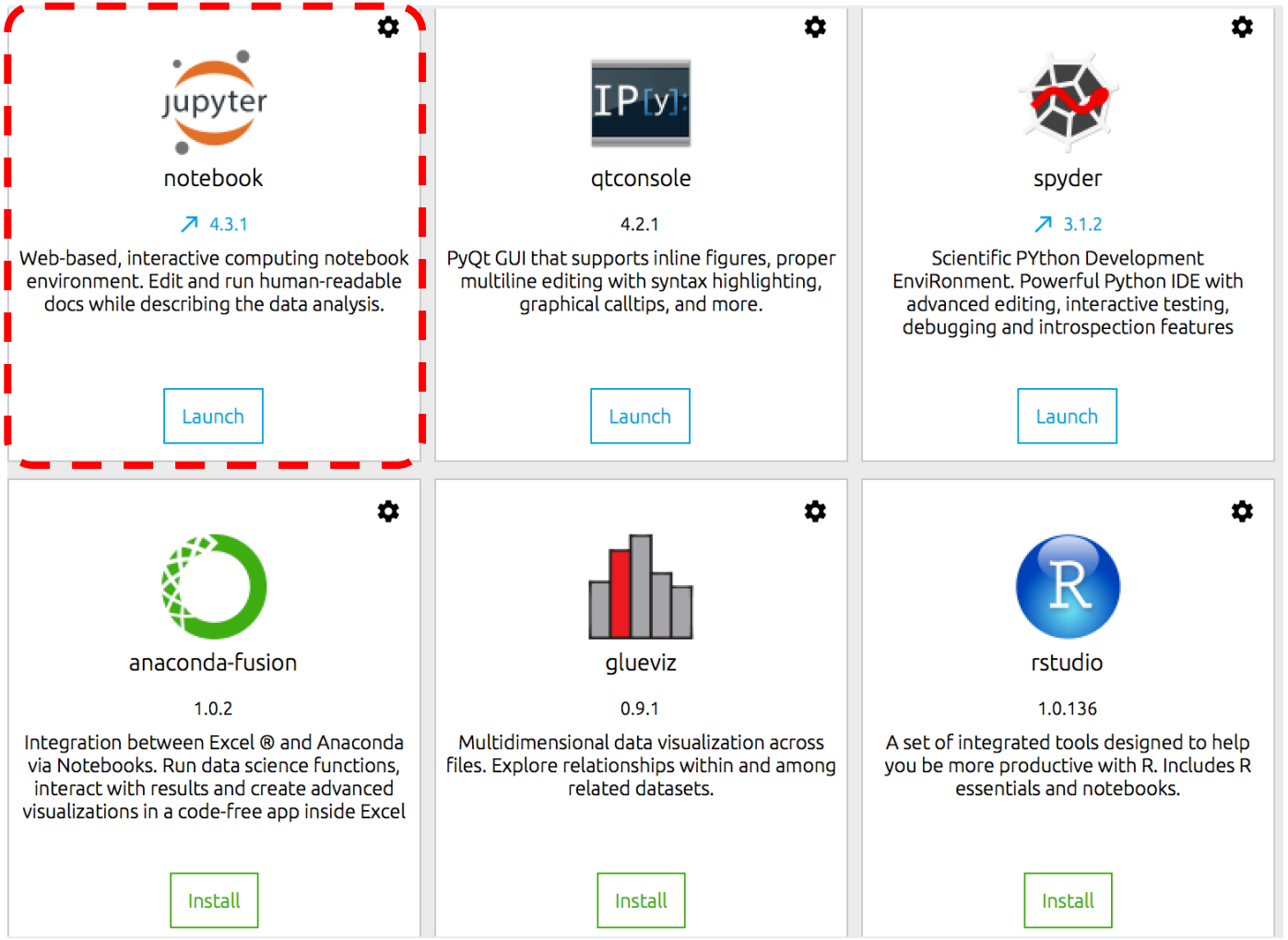
178 python packages included.

Anaconda-Navigator

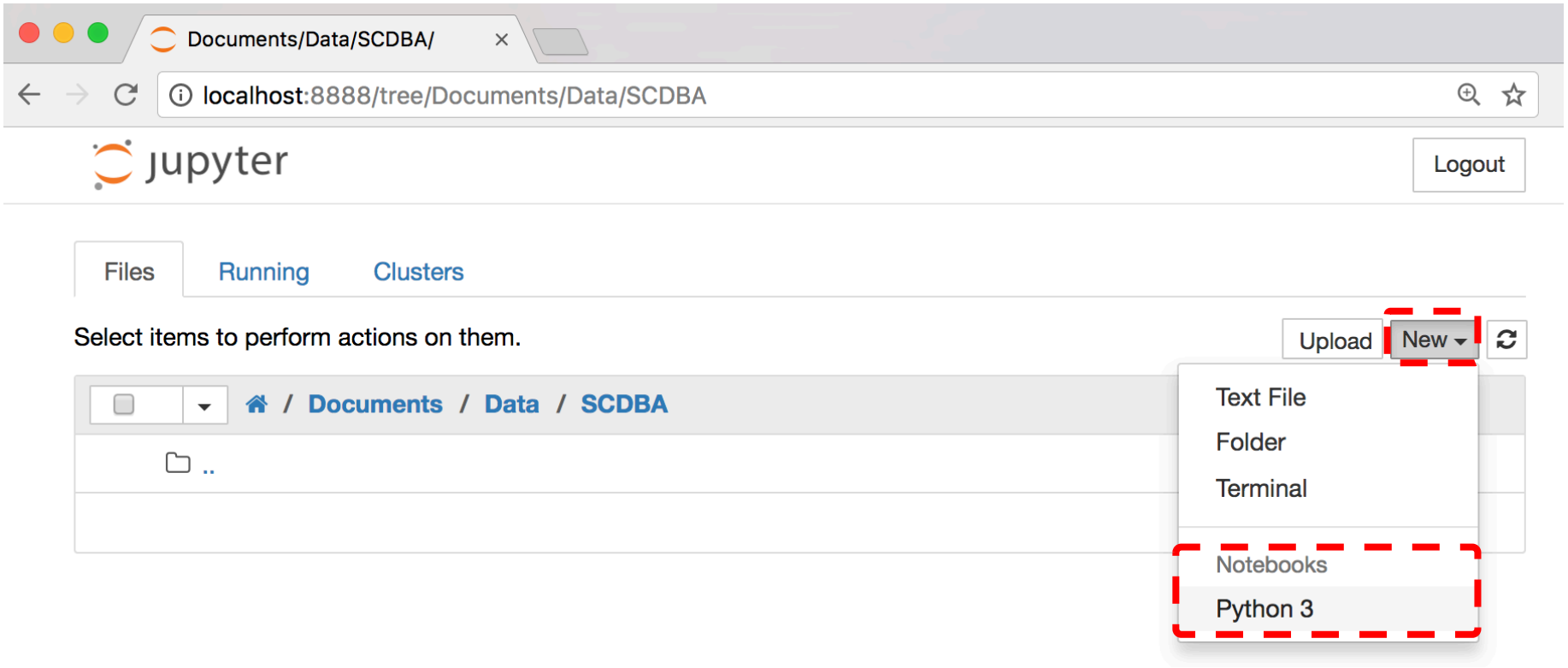


Anaconda-Navigator

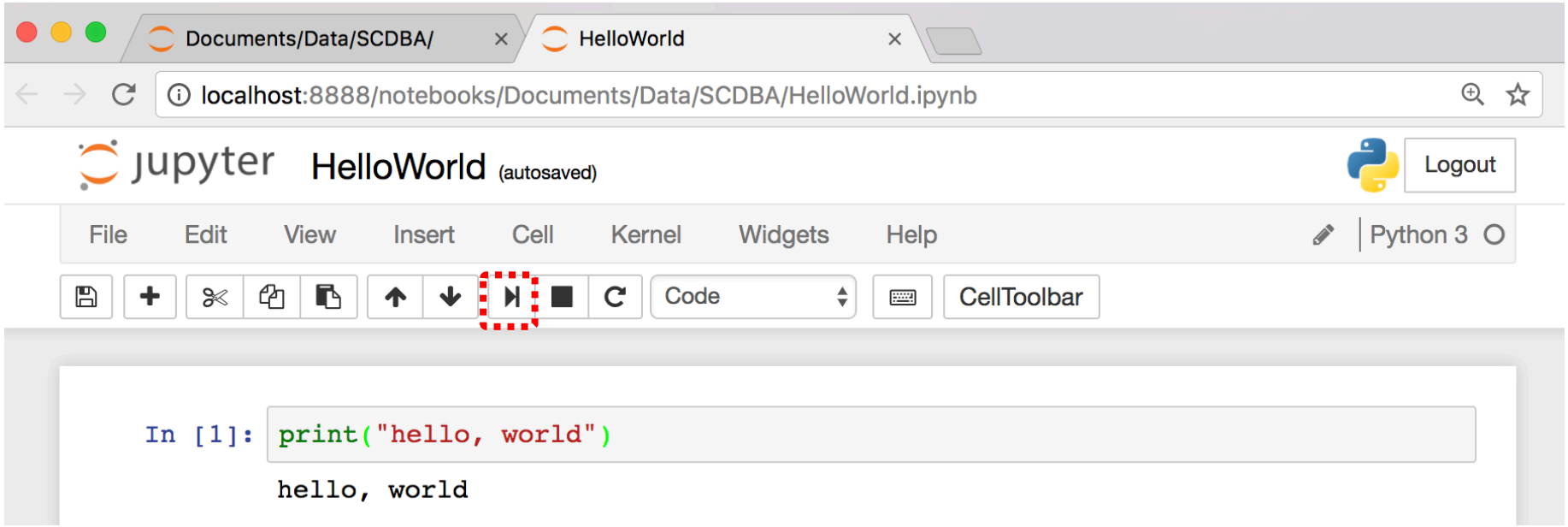
Jupyter Notebook



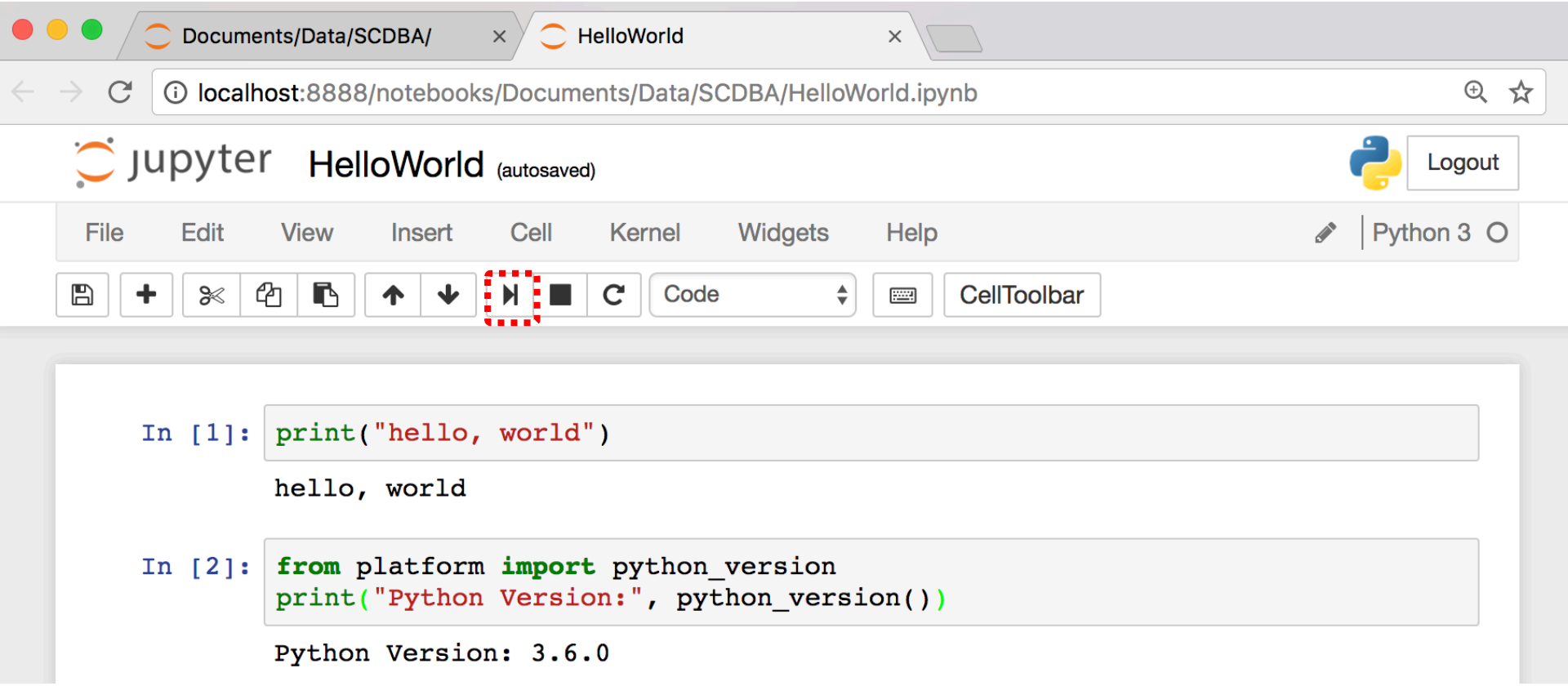
Jupyter Notebook
New Python 3



print("hello, world")



```
from platform import python_version
print("Python Version:", python_version())
```

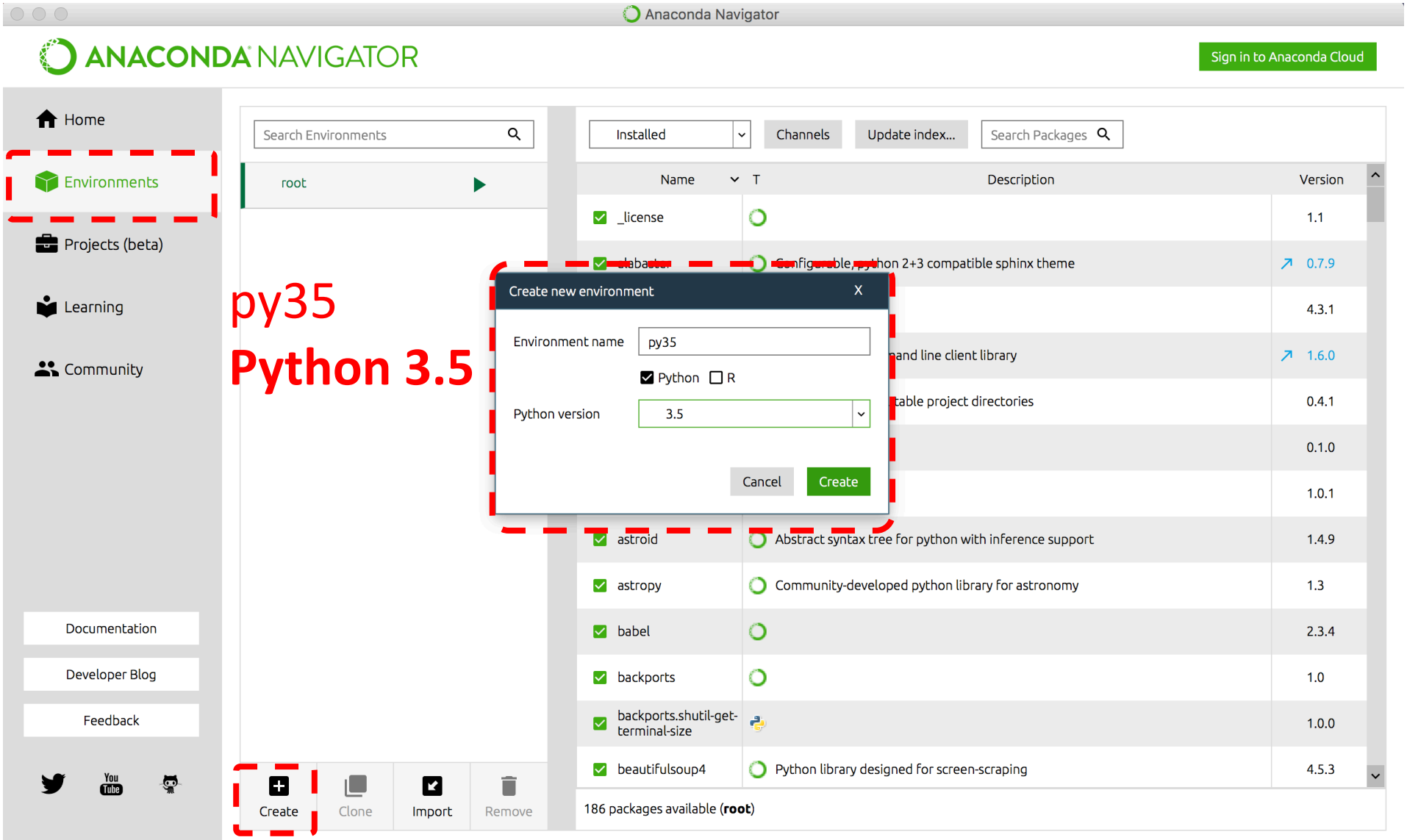


Create Python Environments with Anaconda

- Python 3.6
- Python 3.5
  - Python 3.5.3
  - Python 3.5.2
- Python 2.7

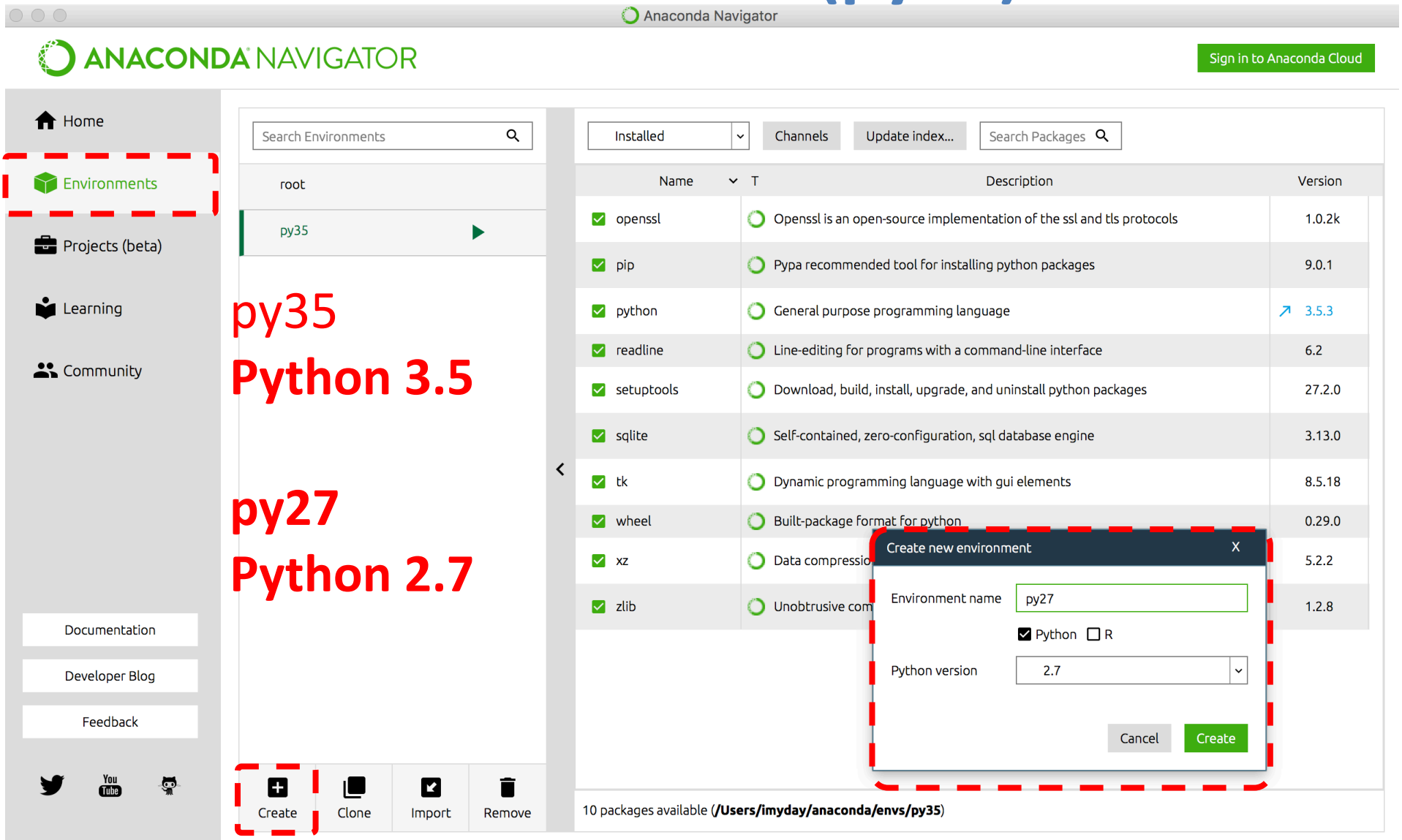
https://conda.io/docs/py2or3.html

Anaconda Create New Python 3.5 Environment (py35)



Source: http://conda.pydata.org/docs/py2or3.html

Anaconda Create New Python 2.7 Environment (py27)



Source: http://conda.pydata.org/docs/py2or3.html

Verify that conda is installed, check current conda version

- **`conda --version`**

- Update conda to the current version
  - **`conda update conda`**

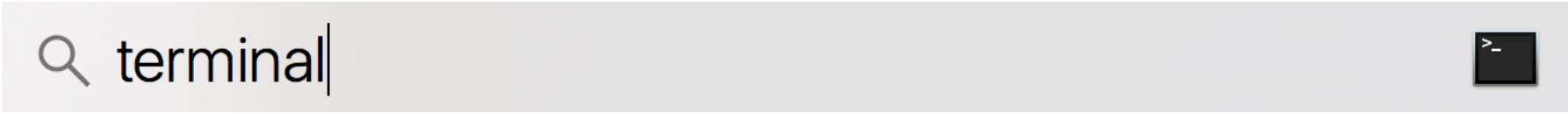
http://conda.pydata.org/docs/using/using.html#verify-that-conda-is-installed-check-current-conda-version

Check current conda version
Check current python version
Check conda environments

- `conda --version`
- `python --version`
- `conda info --envs`

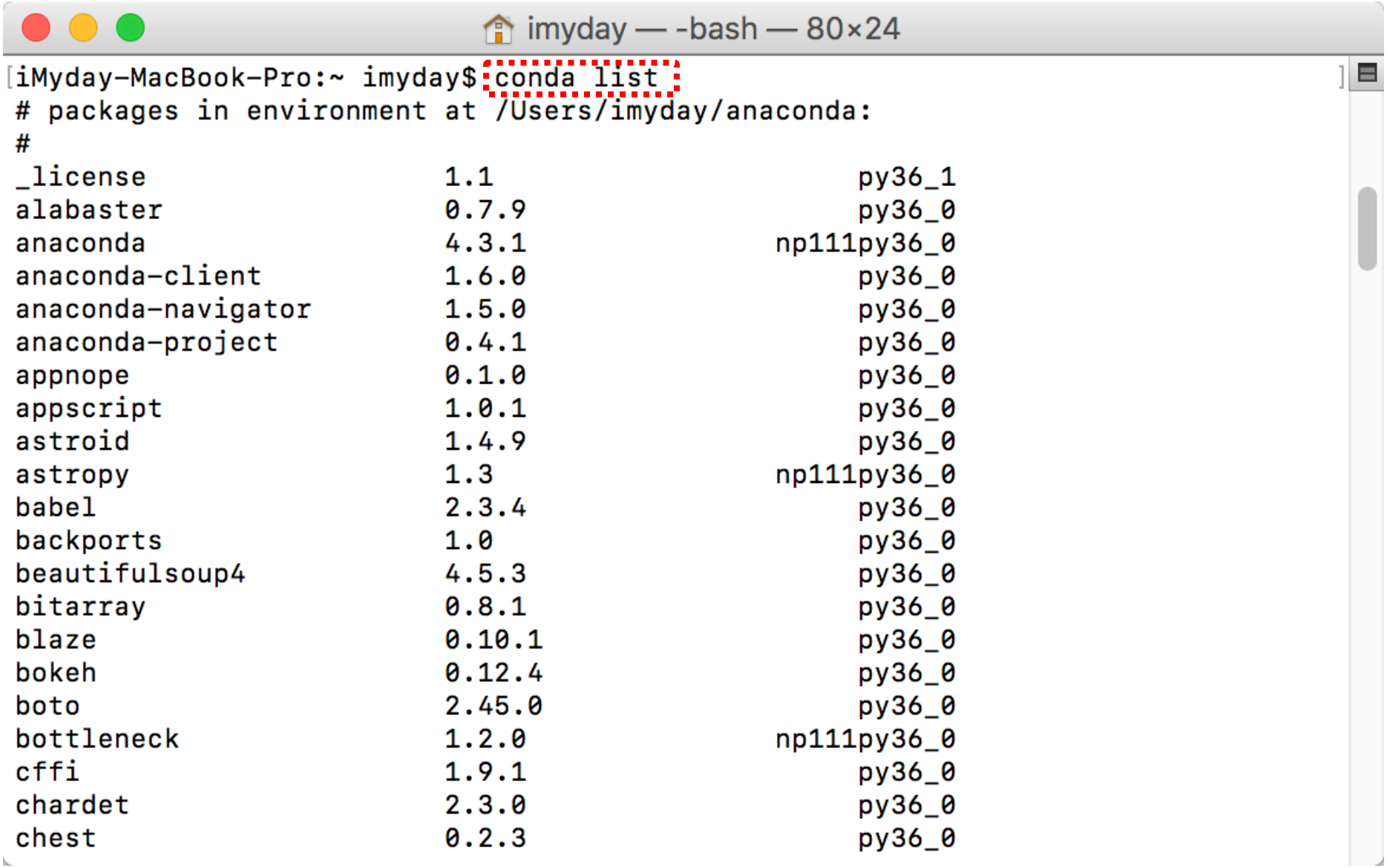
http://conda.pydata.org/docs/using/using.html#verify-that-conda-is-installed-check-current-conda-version

Terminal



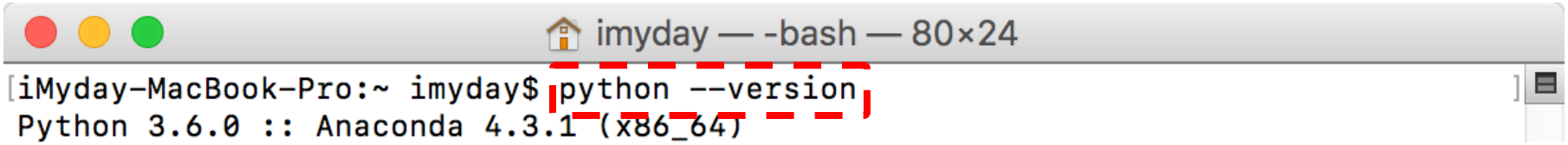

```
terminal
```

conda list

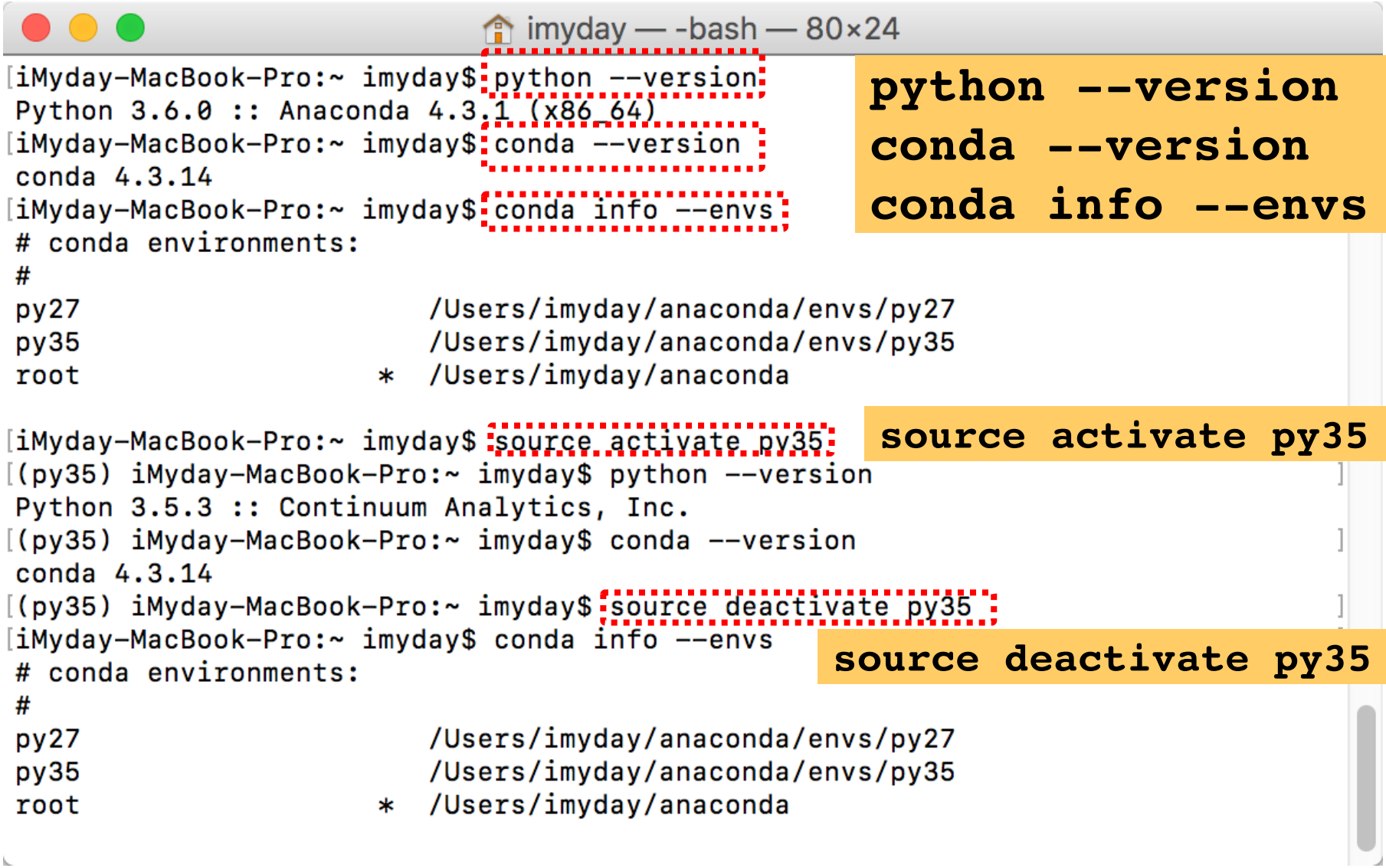


http://conda.pydata.org/docs/using/using.html#verify-that-conda-is-installed-check-current-conda-version

python --version



conda --version

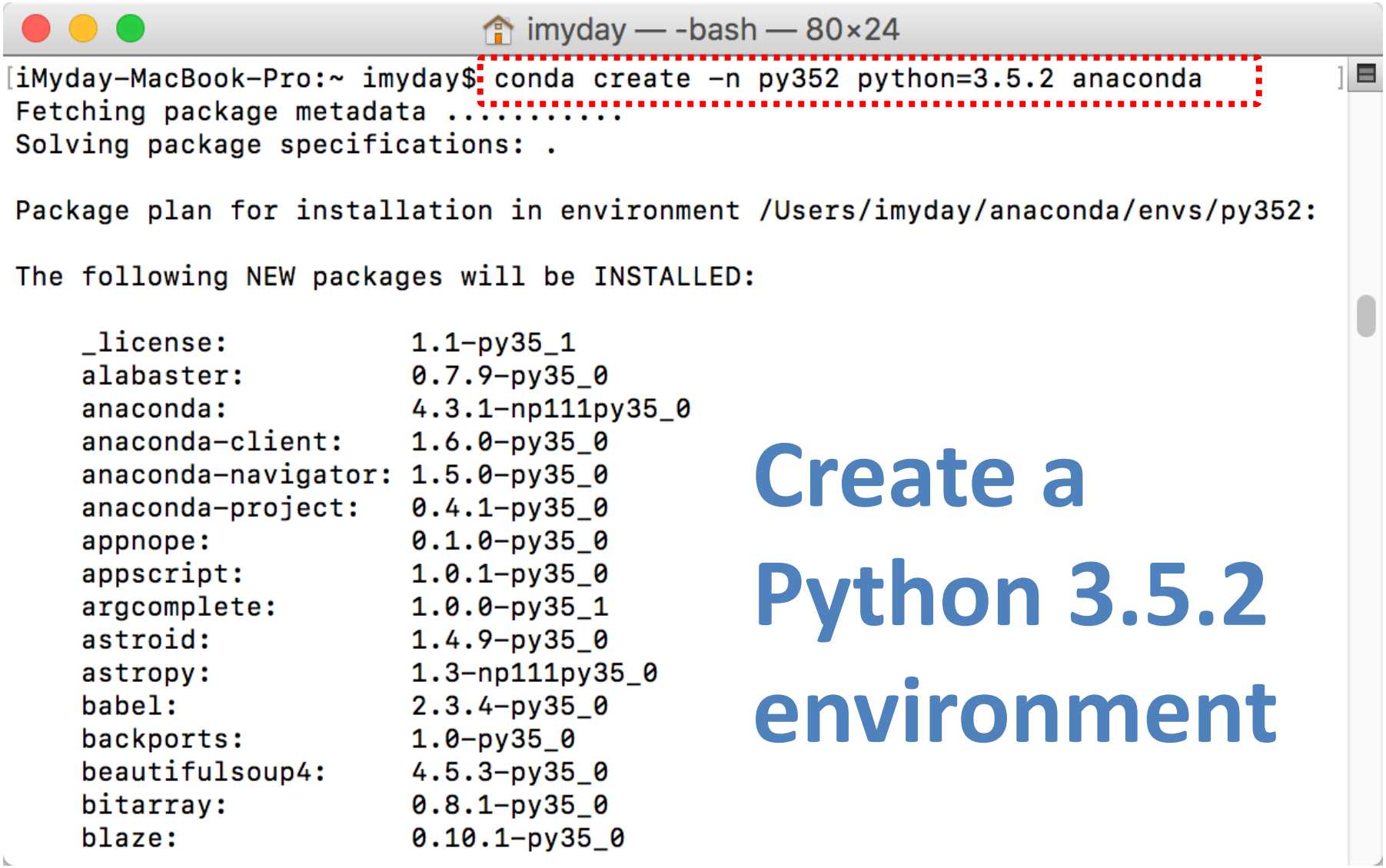


python --version
conda --version
conda info --envs

source activate py35

source deactivate py35

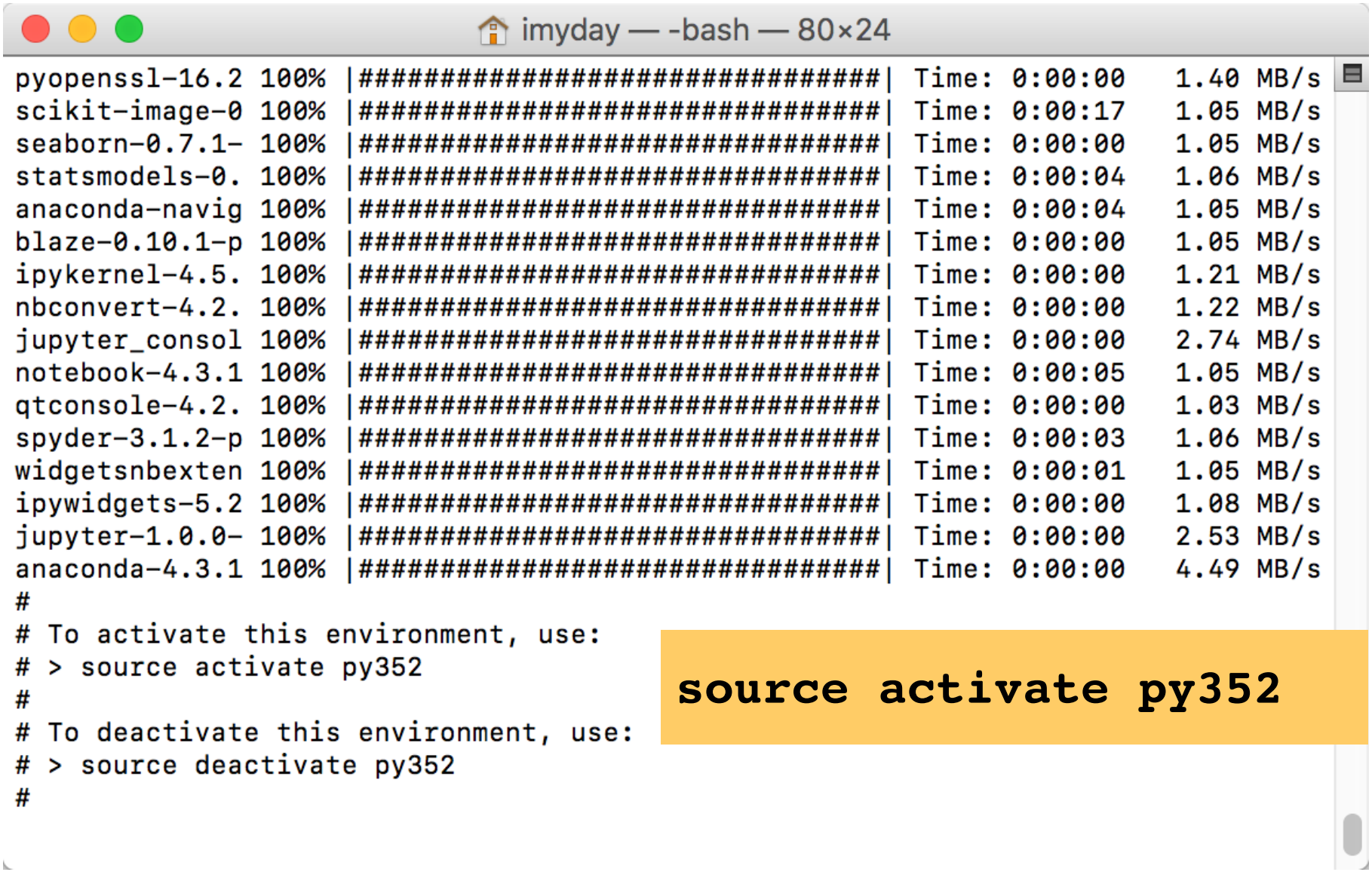
conda create -n py352 python=3.5.2 anaconda



Create a Python 3.5.2 environment

Source: http://conda.pydata.org/docs/py2or3.html

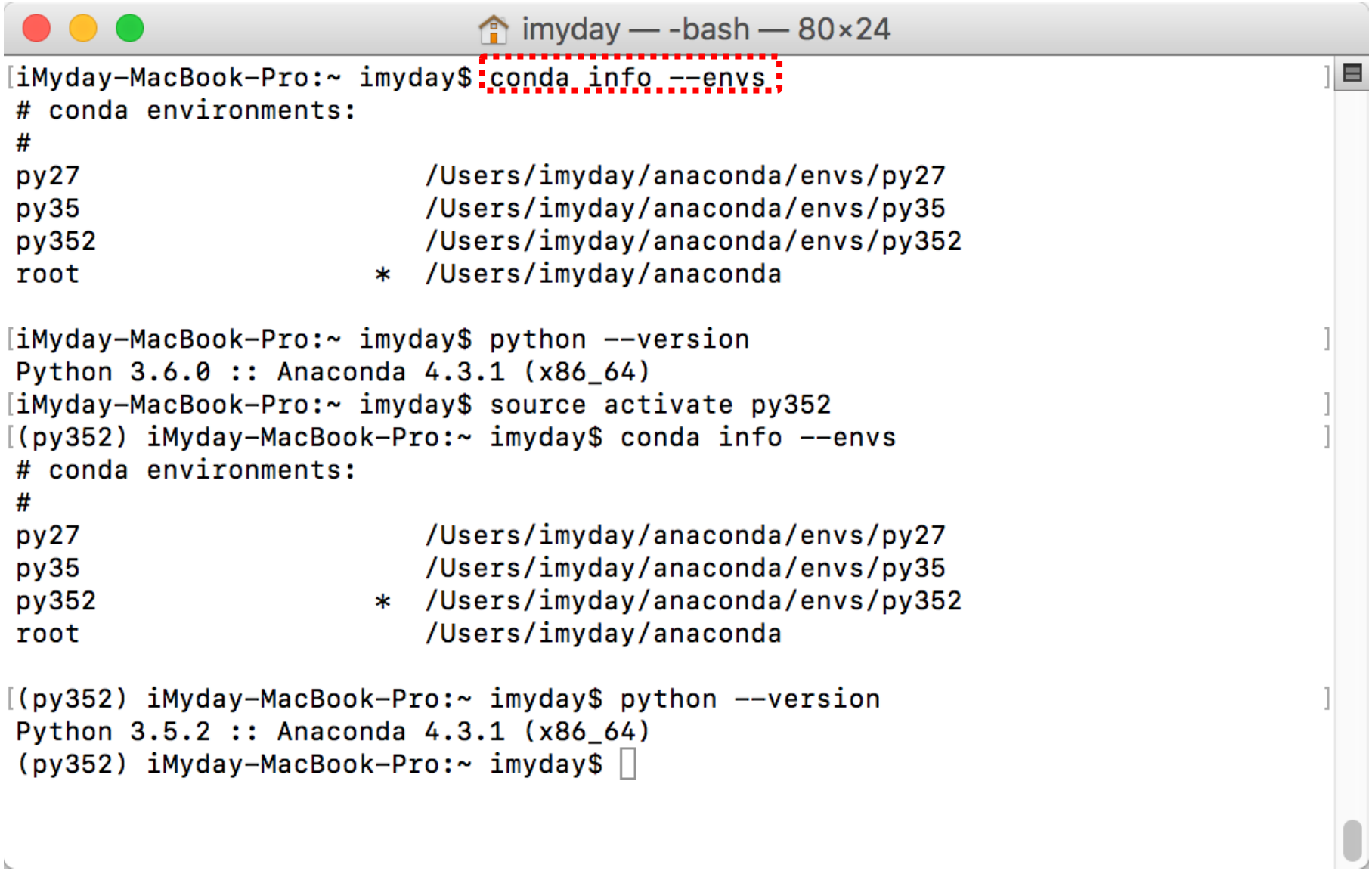
conda create -n py352 python=3.5.2 anaconda



source activate py352

Source: http://conda.pydata.org/docs/py2or3.html

conda info --envs



TensorFlow

```
conda info --envs
```

```
conda --version
python --version
```

```
conda list
```

```
conda create -n tensorflow python=3.5
```

```
source activate tensorflow
```

```
activate tensorflow
```

Source: http://deeplearning.net/software/theano/install.html#anaconda

```
sudo pip install keras
```

```
pip install keras
```

```
pip install tensorflow
```

```
pip install ipython[all]
```

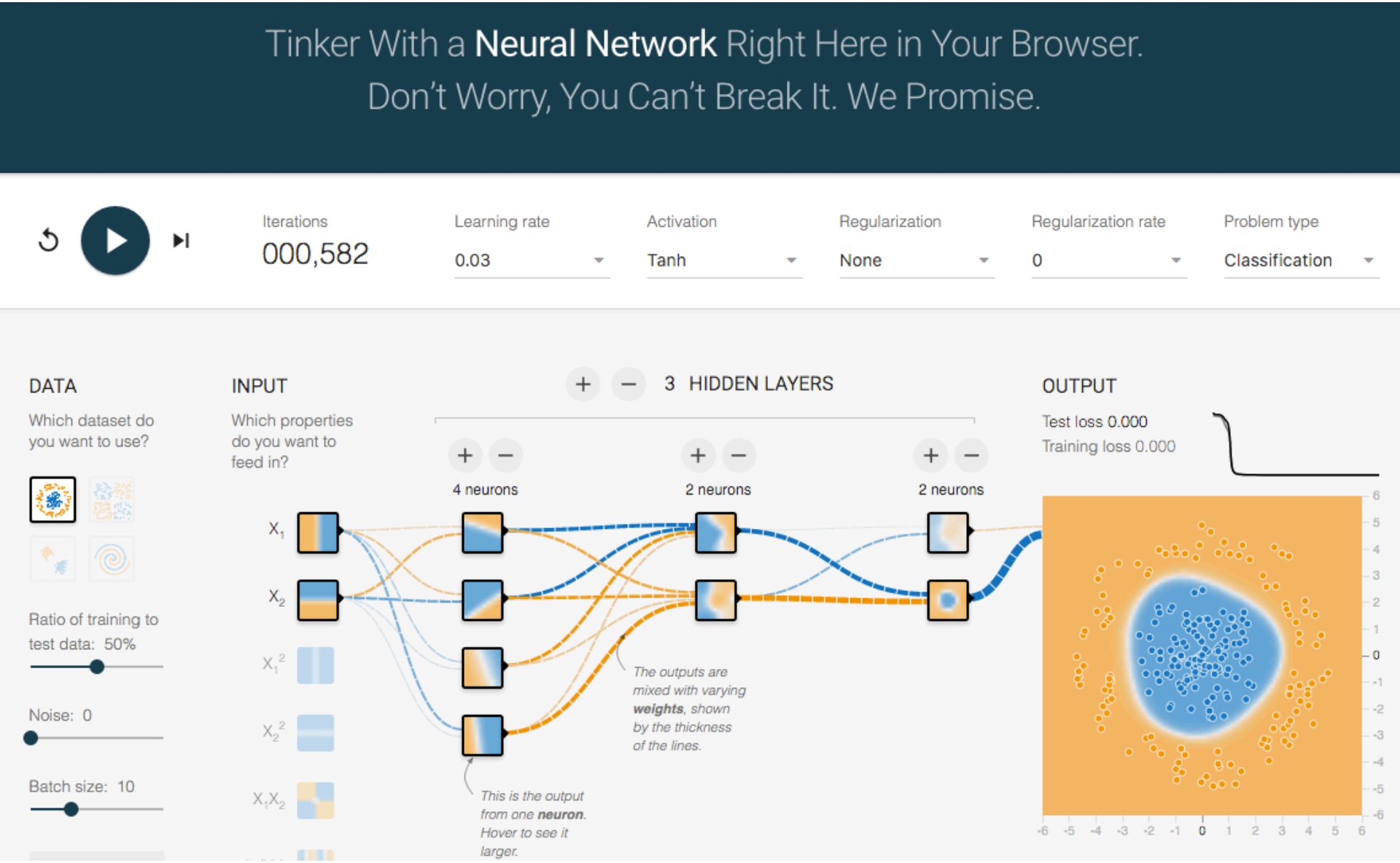
Source: https://github.com/martin-gorner/tensorflow-mnist-tutorial/blob/master/INSTALL.txt

Source: http://deeplearning.net/software/theano/install.html#anaconda

pip install tensorflow

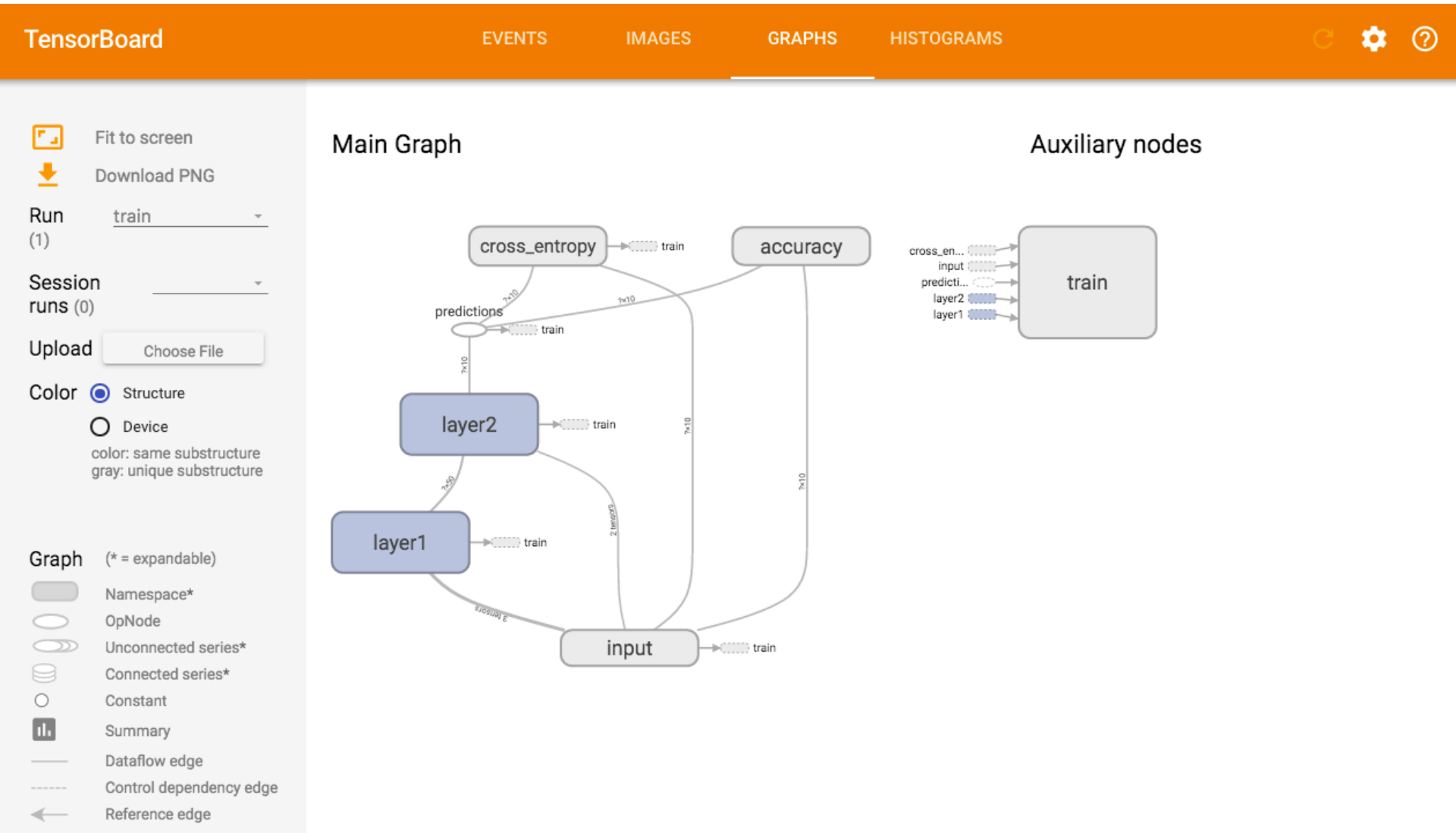
```
bash-3.2$ pip install tensorflow
Collecting tensorflow
  Downloading tensorflow-1.1.0-cp36-cp36m-macosx_10_11_x86_64.whl (31.3MB)
    100% |████████████████████████████████| 31.3MB 23kB/s
Requirement already satisfied: wheel>=0.26 in ./anaconda/lib/python3.6/site-packages (from tensorflow)
Requirement already satisfied: six>=1.10.0 in ./anaconda/lib/python3.6/site-packages (from tensorflow)
Collecting protobuf>=3.2.0 (from tensorflow)
  Downloading protobuf-3.2.0-py2.py3-none-any.whl (360kB)
    100% |████████████████████████████████| 368kB 453kB/s
Requirement already satisfied: werkzeug>=0.11.10 in ./anaconda/lib/python3.6/site-packages (from tensorflow)
Requirement already satisfied: numpy>=1.11.0 in ./anaconda/lib/python3.6/site-packages (from tensorflow)
Requirement already satisfied: setuptools in ./anaconda/lib/python3.6/site-packages/setuptools-27.2.0-py3.6.
egg (from protobuf>=3.2.0->tensorflow)
Installing collected packages: protobuf, tensorflow
Successfully installed protobuf-3.2.0 tensorflow-1.1.0
bash-3.2$
```

TensorFlow Playground



http://playground.tensorflow.org/

TensorBoard



https://www.tensorflow.org/tensorboard/index.html#graphs

Try your first TensorFlow

```
$ python

>>> import tensorflow as tf
>>> hello = tf.constant('Hello, TensorFlow!')
>>> sess = tf.Session()
>>> sess.run(hello)
Hello, TensorFlow!
>>> a = tf.constant(10)
>>> b = tf.constant(32)
>>> sess.run(a+b)
42
>>>
```

https://github.com/tensorflow/tensorflow

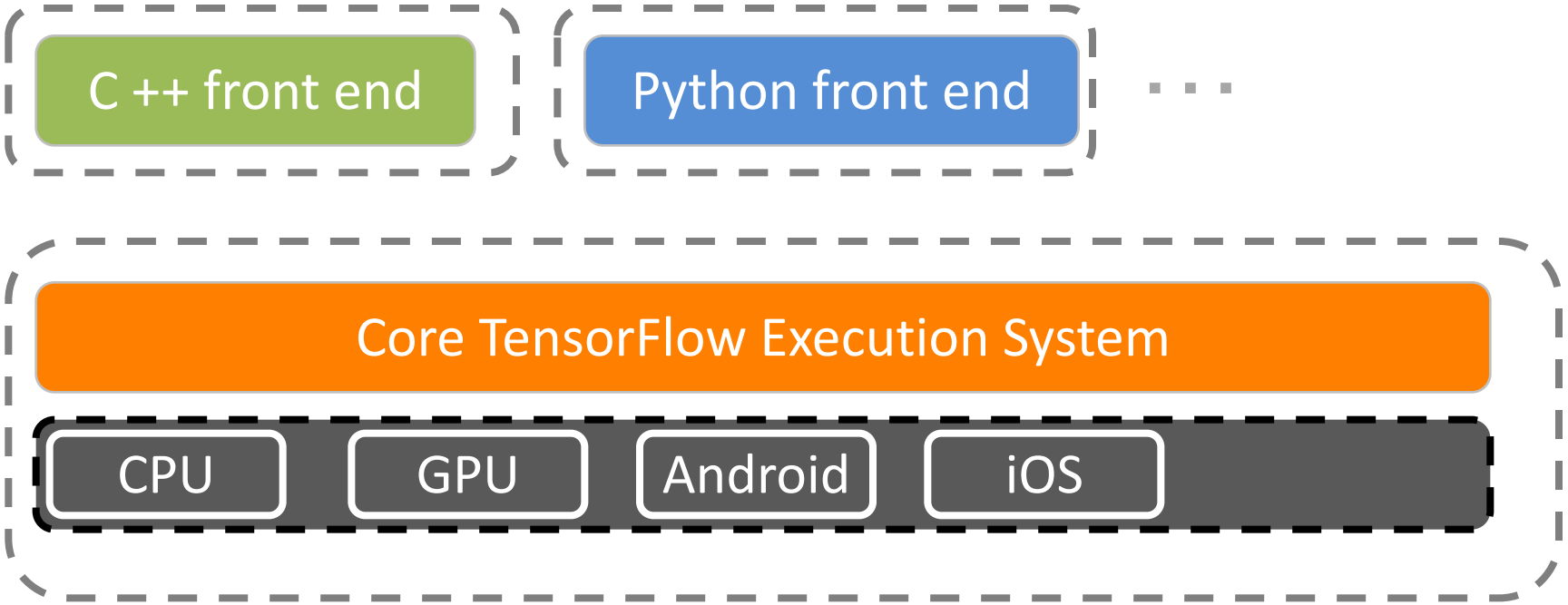
Try your first TensorFlow

```
$ python

>>> import tensorflow as tf
>>> hello = tf.constant('Hello, TensorFlow!')
>>> sess = tf.Session()
>>> sess.run(hello)
'Hello, TensorFlow!'
>>> a = tf.constant(10)
>>> b = tf.constant(32)
>>> sess.run(a+b)
 42
>>>
```

https://github.com/tensorflow/tensorflow

Architecture of TensorFlow



Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

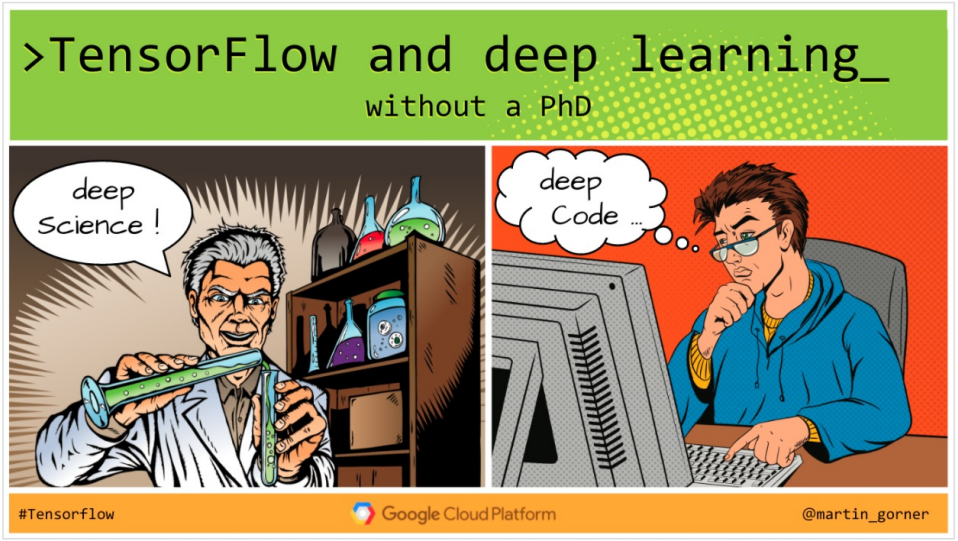
TensorFlow and Deep Learning

TensorFlow and Deep Learning

Did you find a mistake? Please file a bug.

TensorFlow and deep learning, without a PhD — 149 min remaining

1. Overview



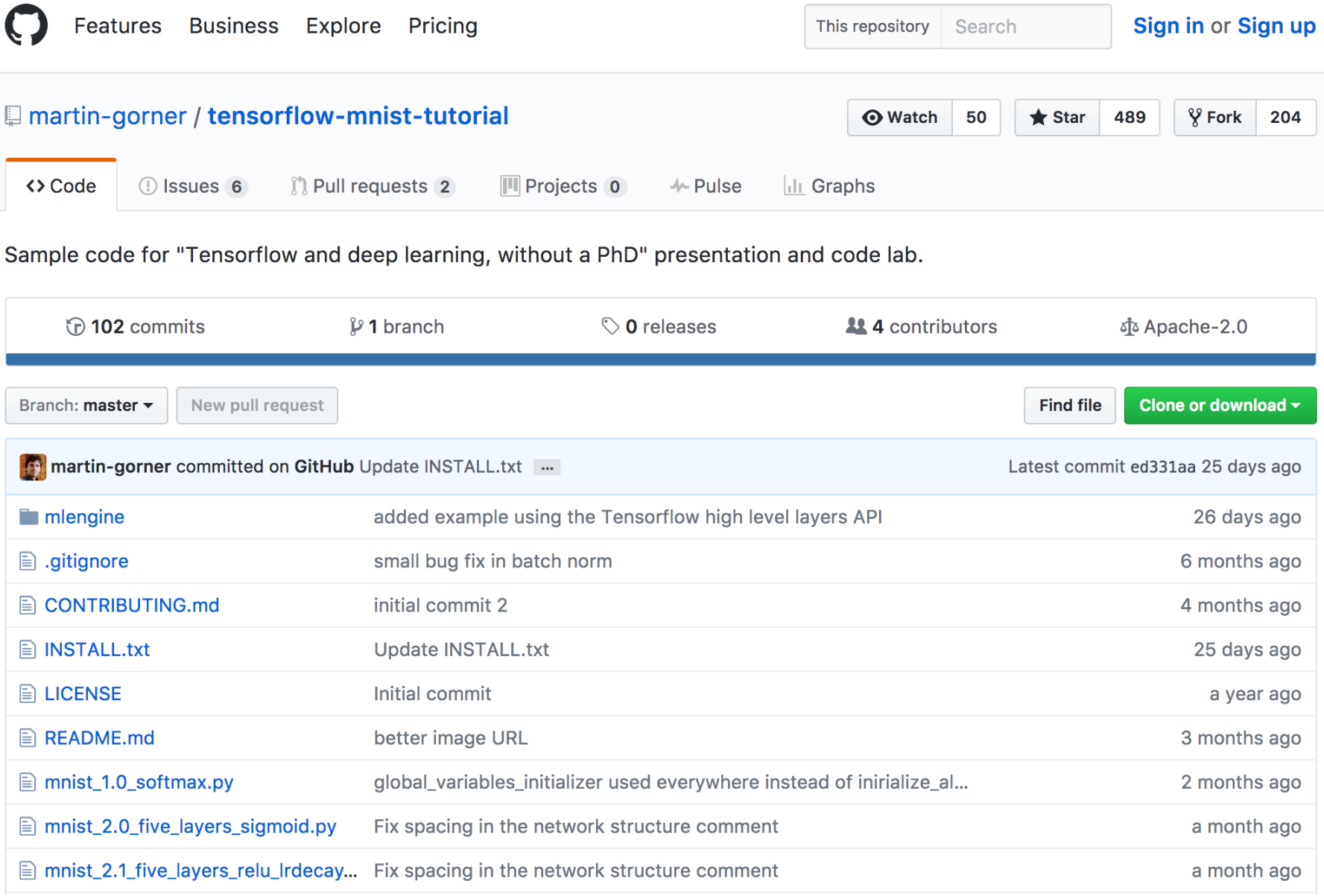
In this codelab, you will learn how to build and train a neural network that recognises handwritten digits. Along the way, as you enhance your neural network to achieve 99% accuracy, you will also discover the tools of the trade that deep learning professionals use to train their models efficiently.

This codelab uses the MNIST dataset, a collection of 60,000 labeled digits that has kept generations of PhDs busy for almost two decades. You will solve the problem with less than 100 lines of Python / TensorFlow code.

What you'll learn

Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/#0

TensorFlow MNIST Tutorial



https://github.com/martin-gorner/tensorflow-mnist-tutorial/

TensorFlow and Deep Learning

- What is a neural network and how to train it
- How to build a basic 1-layer neural network using TensorFlow
- How to add more layers
- Training tips and tricks: overfitting, dropout, learning rate decay ...
- How to troubleshoot deep neural networks
- How to build convolutional networks

Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/#0

TensorFlow MNIST Tutorial

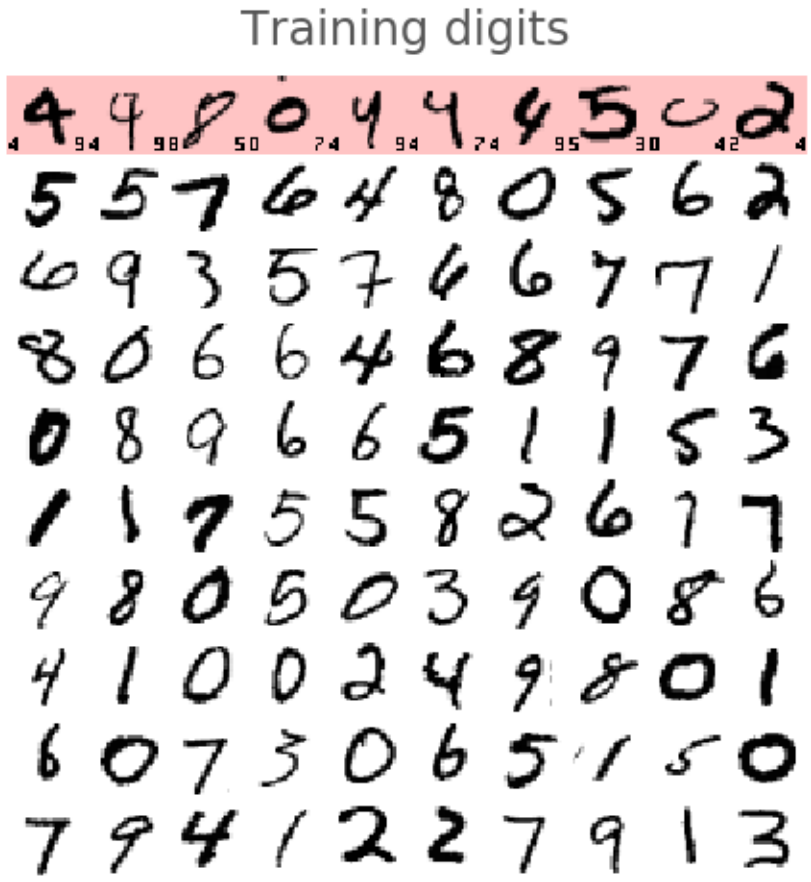
```
git clone https://github.com/martin-gorner/tensorflow-mnist-tutorial.git
```

```
cd tensorflow-mnist-tutorial
```

```
python3 mnist_1.0_softmax.py
```

Source: https://github.com/martin-gorner/tensorflow-mnist-tutorial/blob/master/INSTALL.txt

MNIST dataset: 60,000 labeled digits



Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/#0

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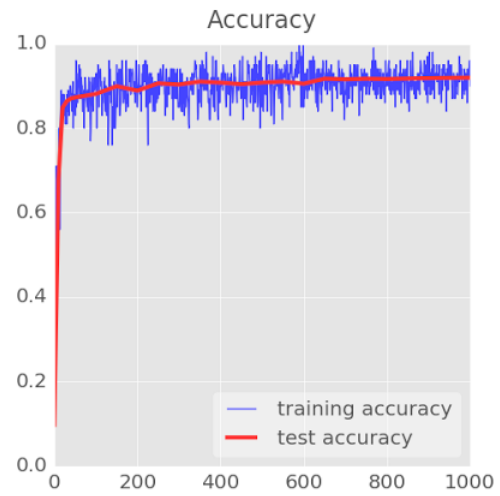
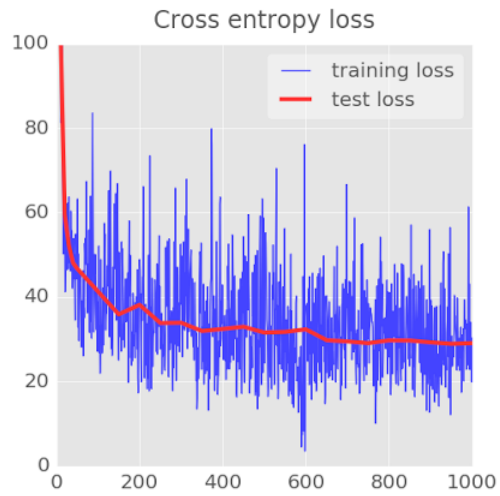
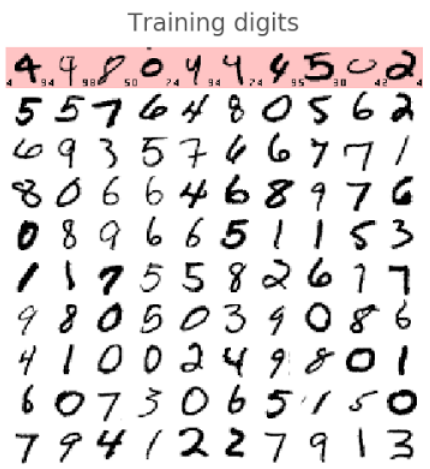
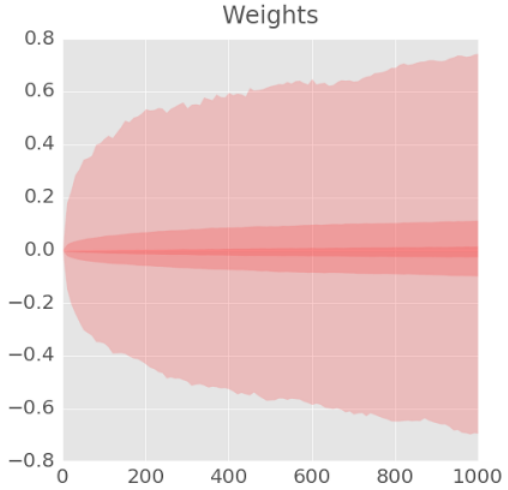
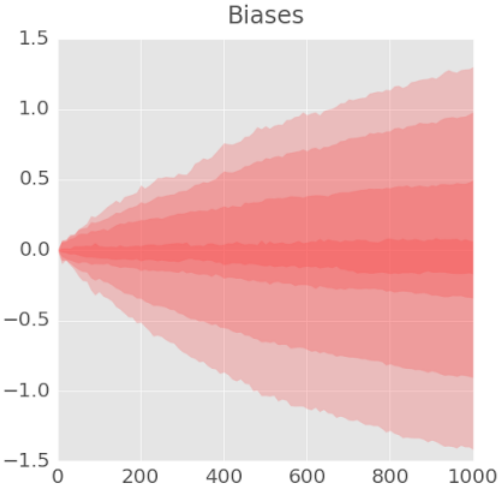
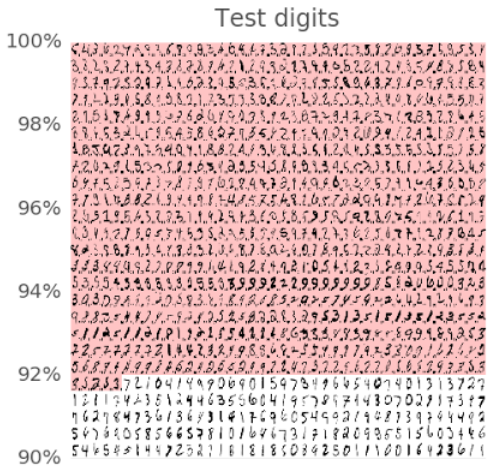












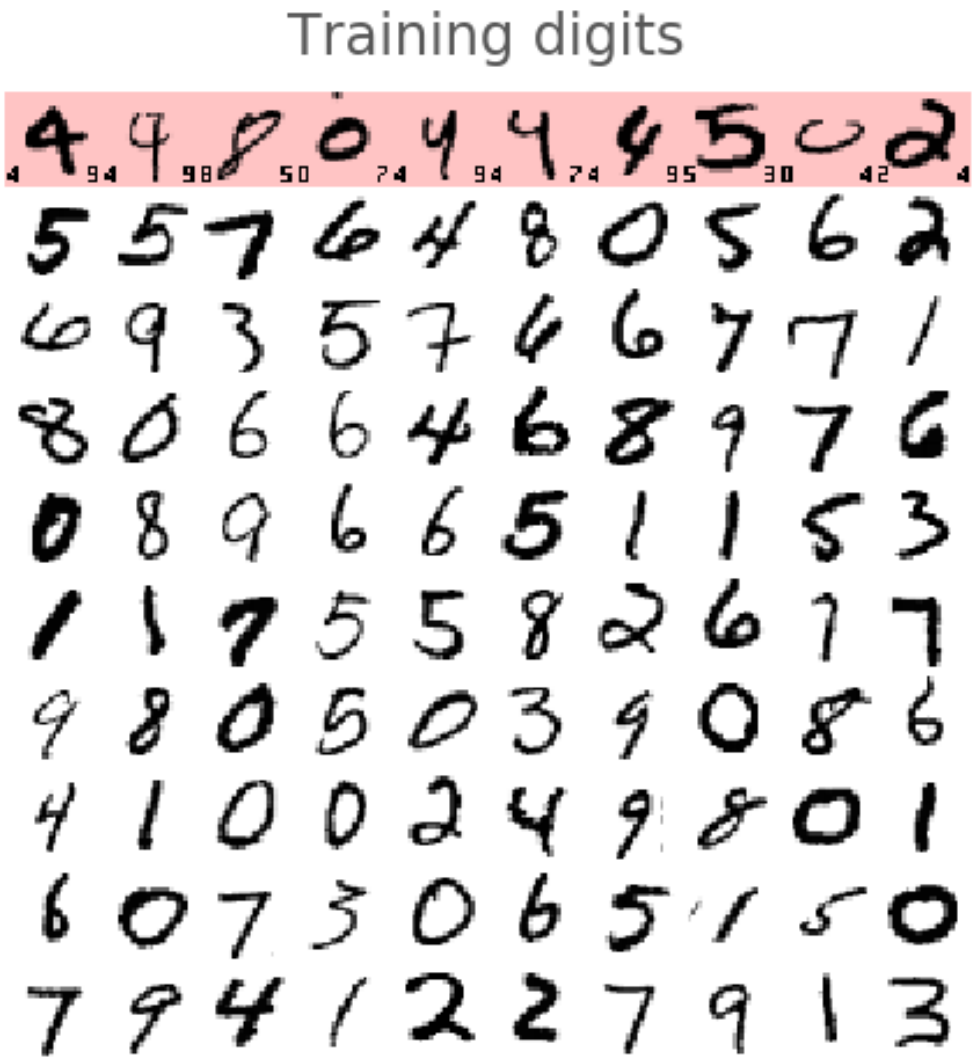
Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/#1

Train a Neural Network

Training digits
updates to weights and biases =>
better recognition (loop)

Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/#2

Training digits



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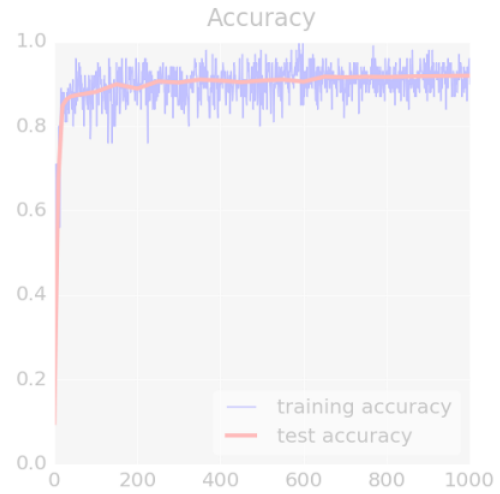
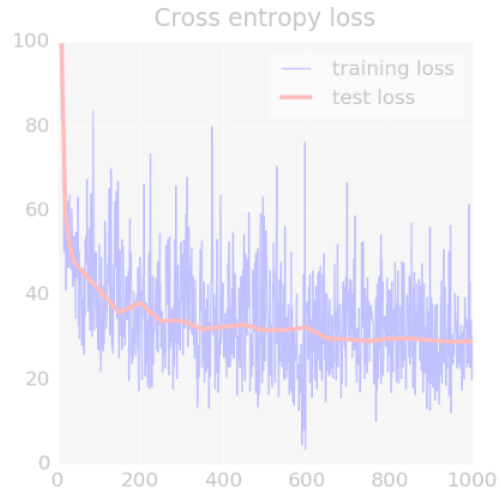
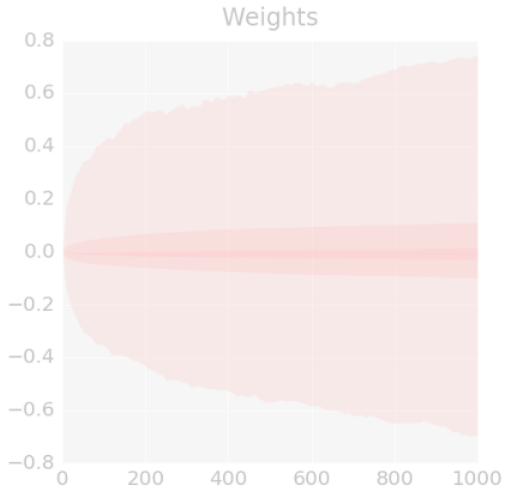
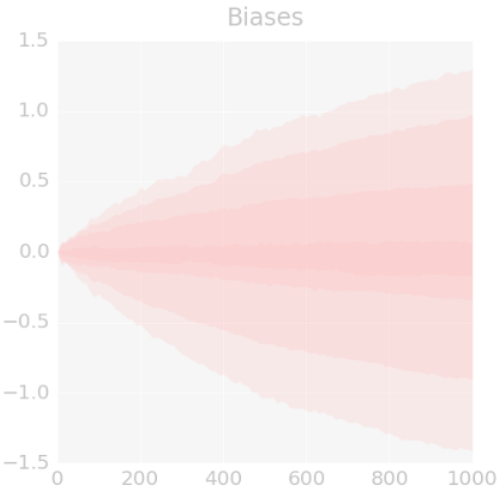
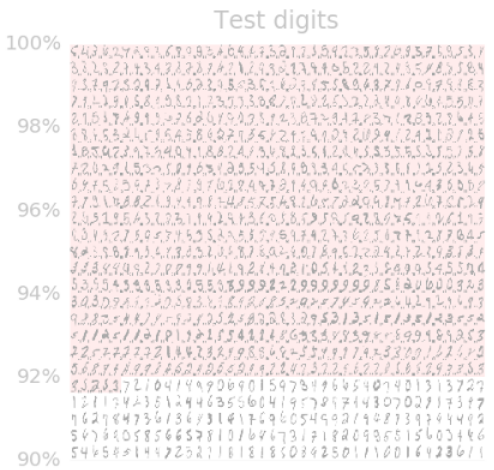
Training digits











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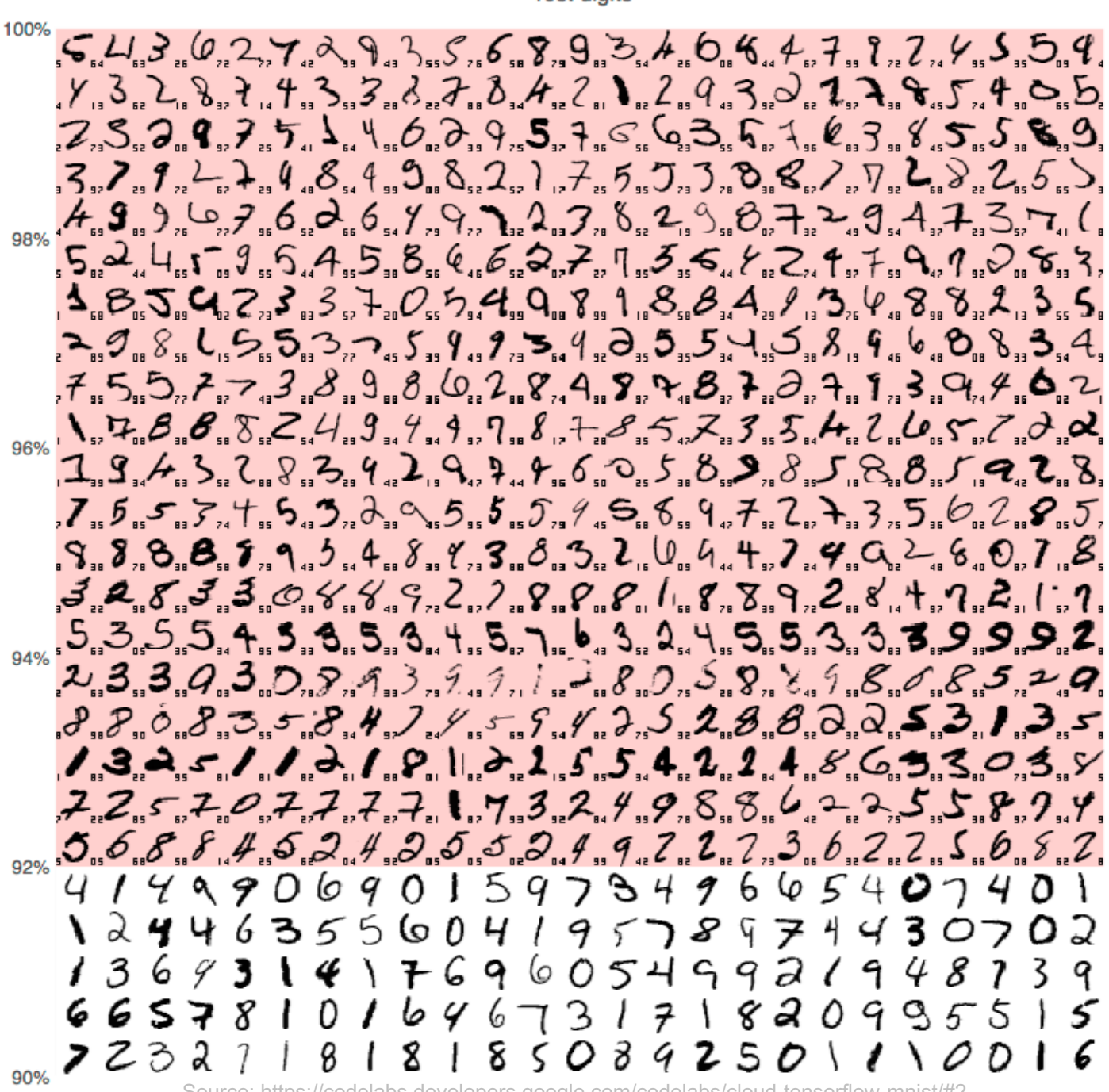
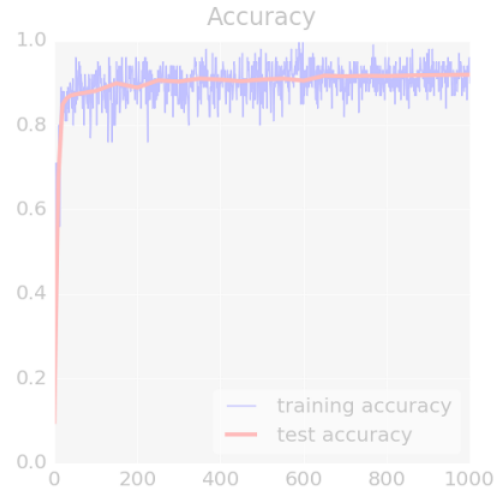
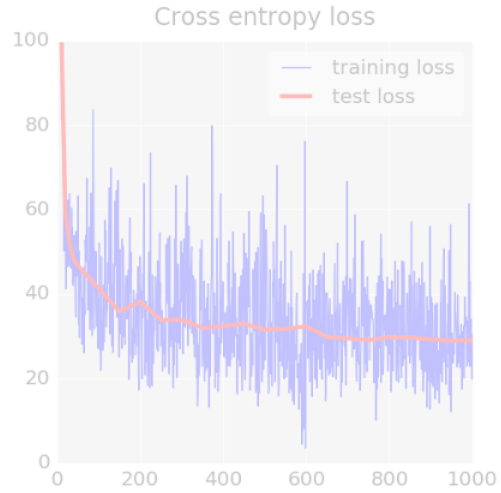
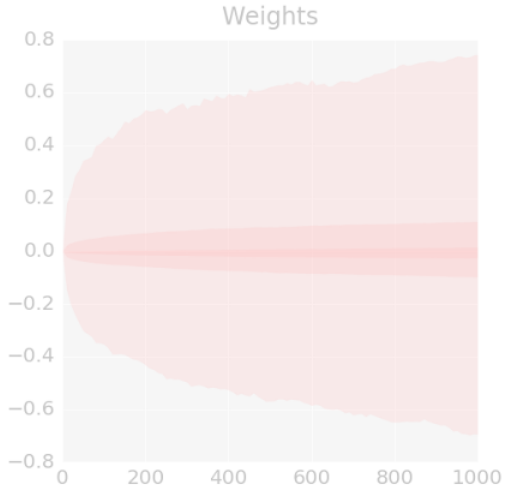


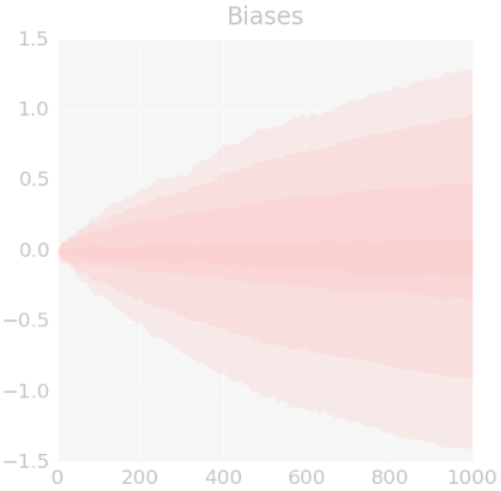
Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/#2

Test digits









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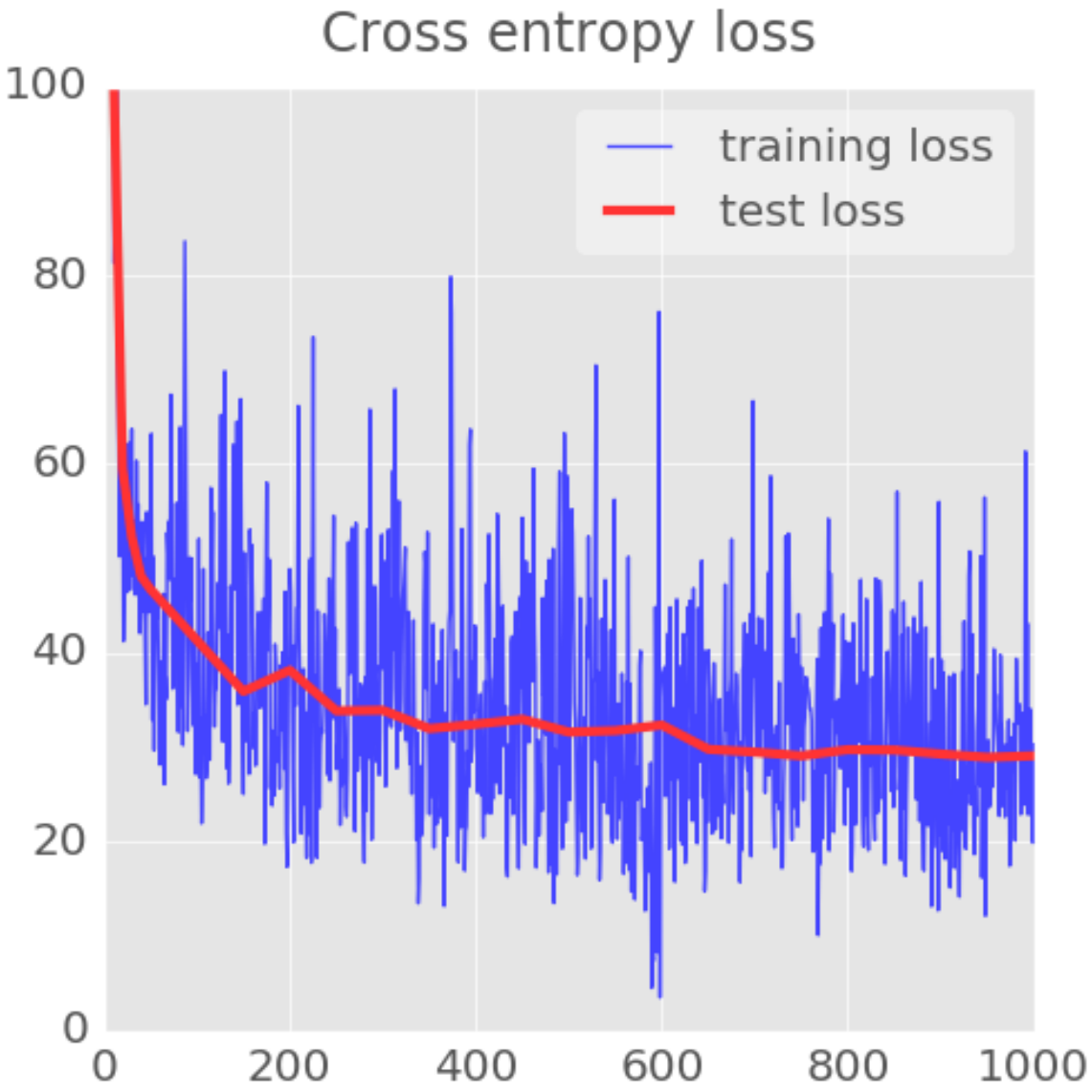
Cross entropy loss



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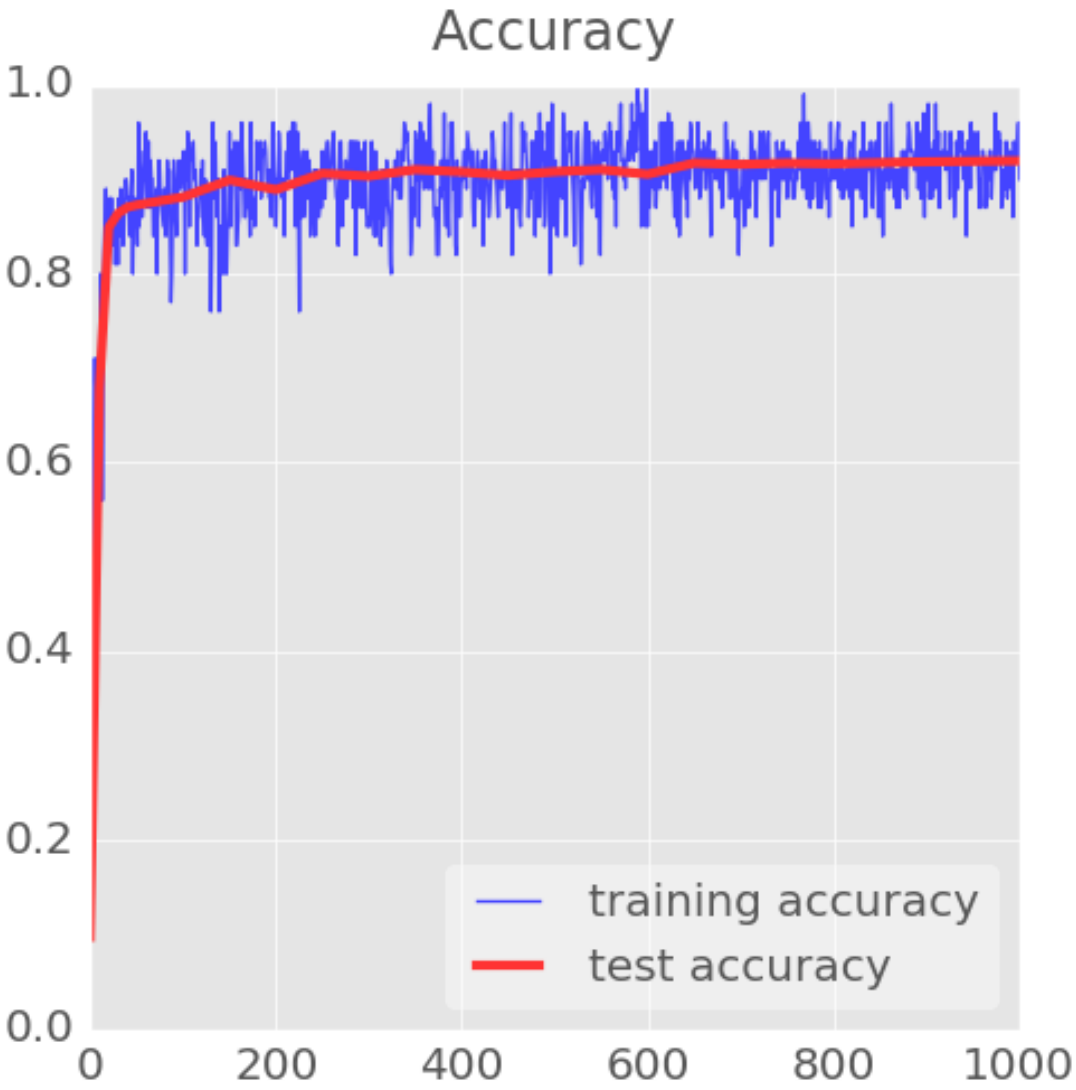
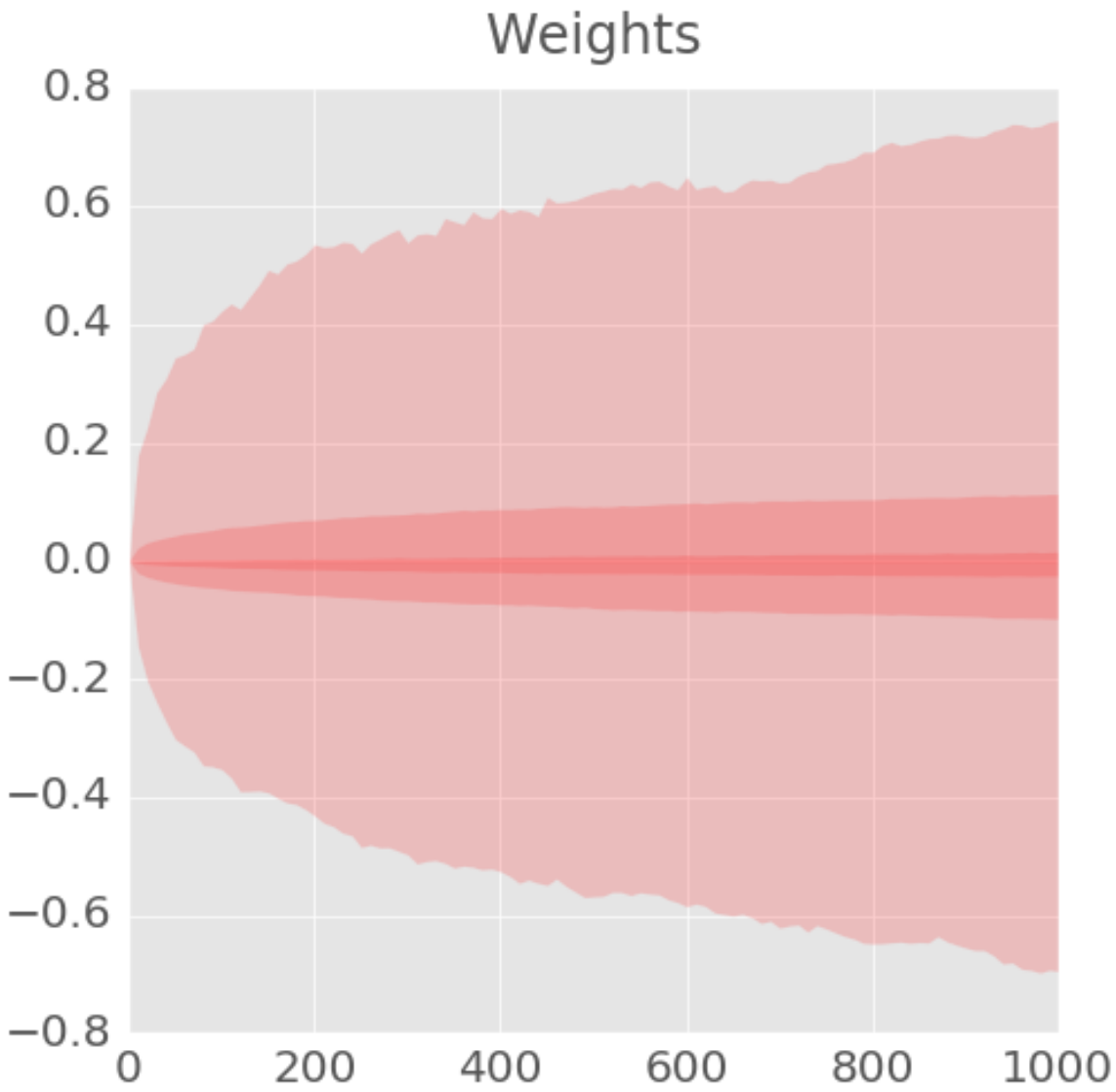
Accuracy



Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/#2

Weights



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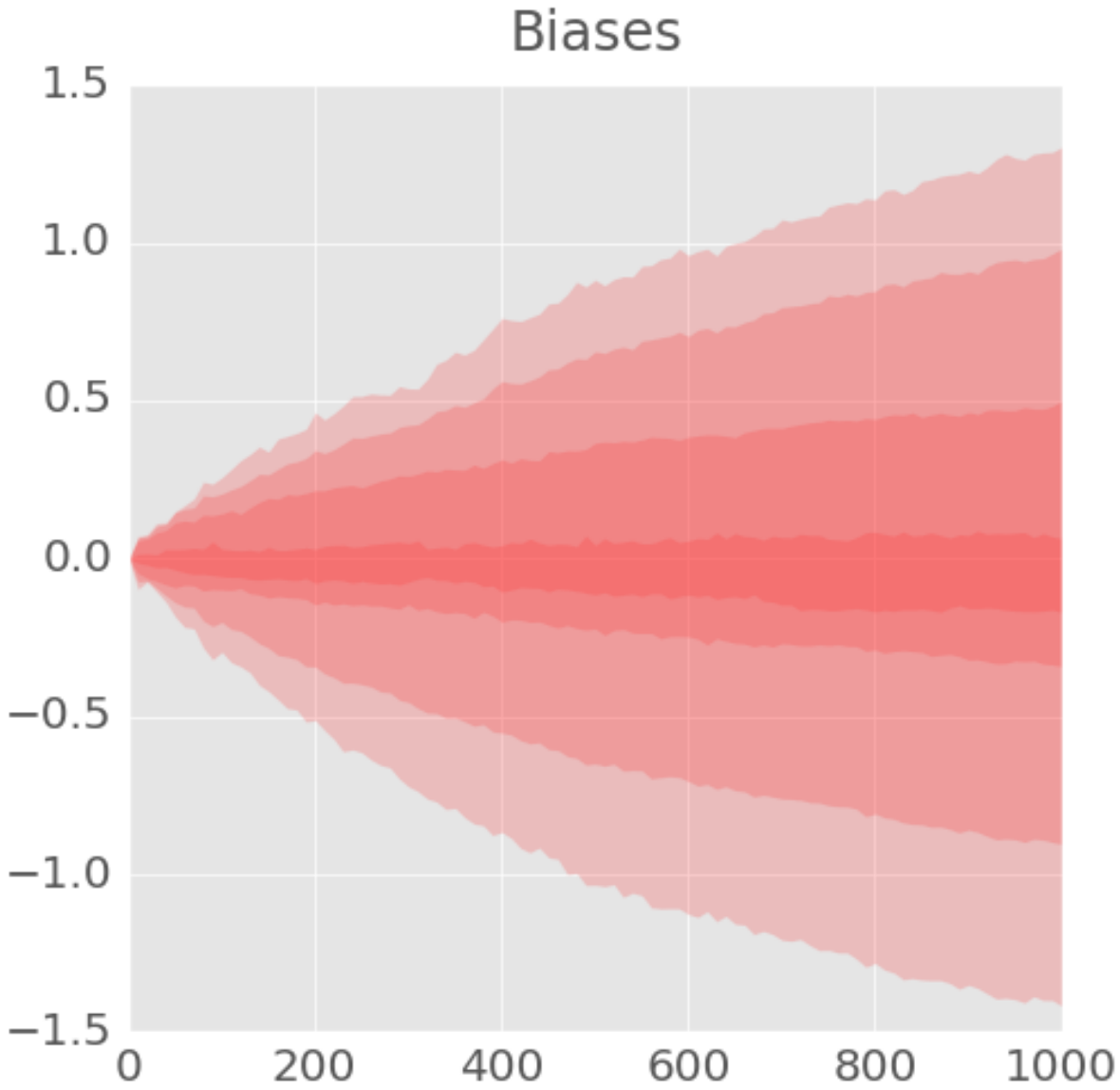
Biases



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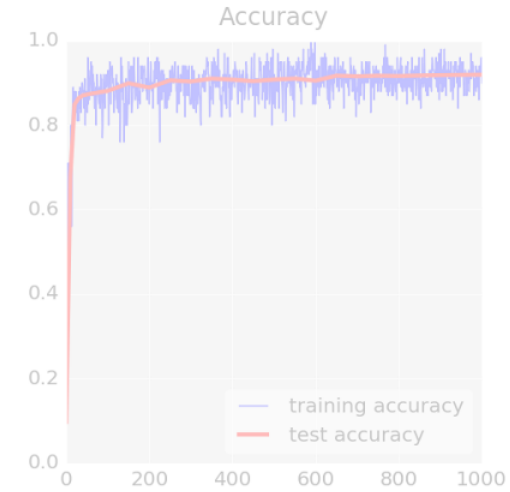
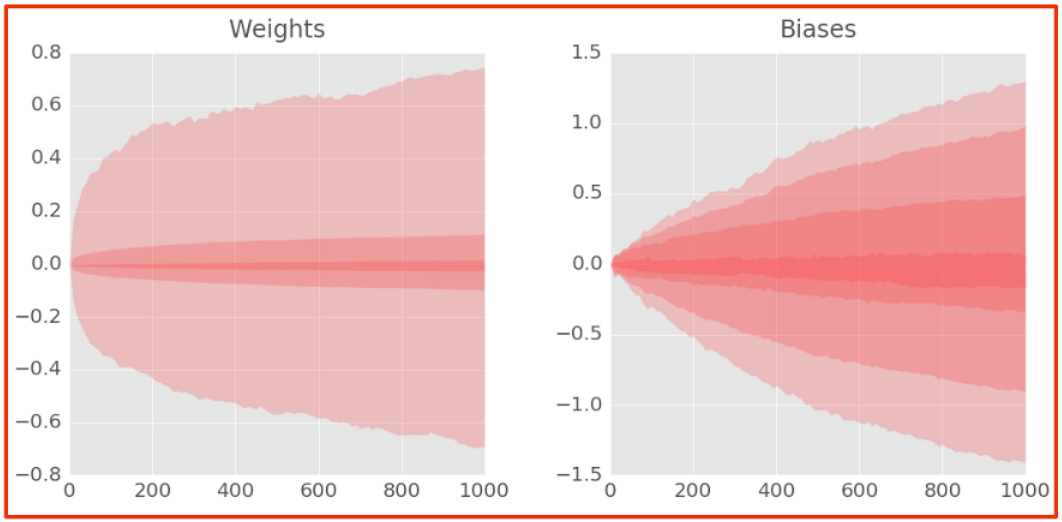
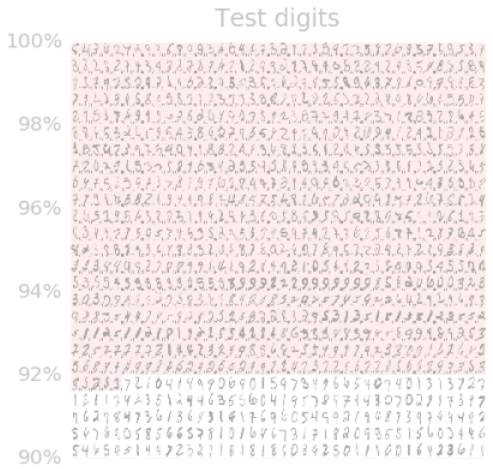
Weights and Biases





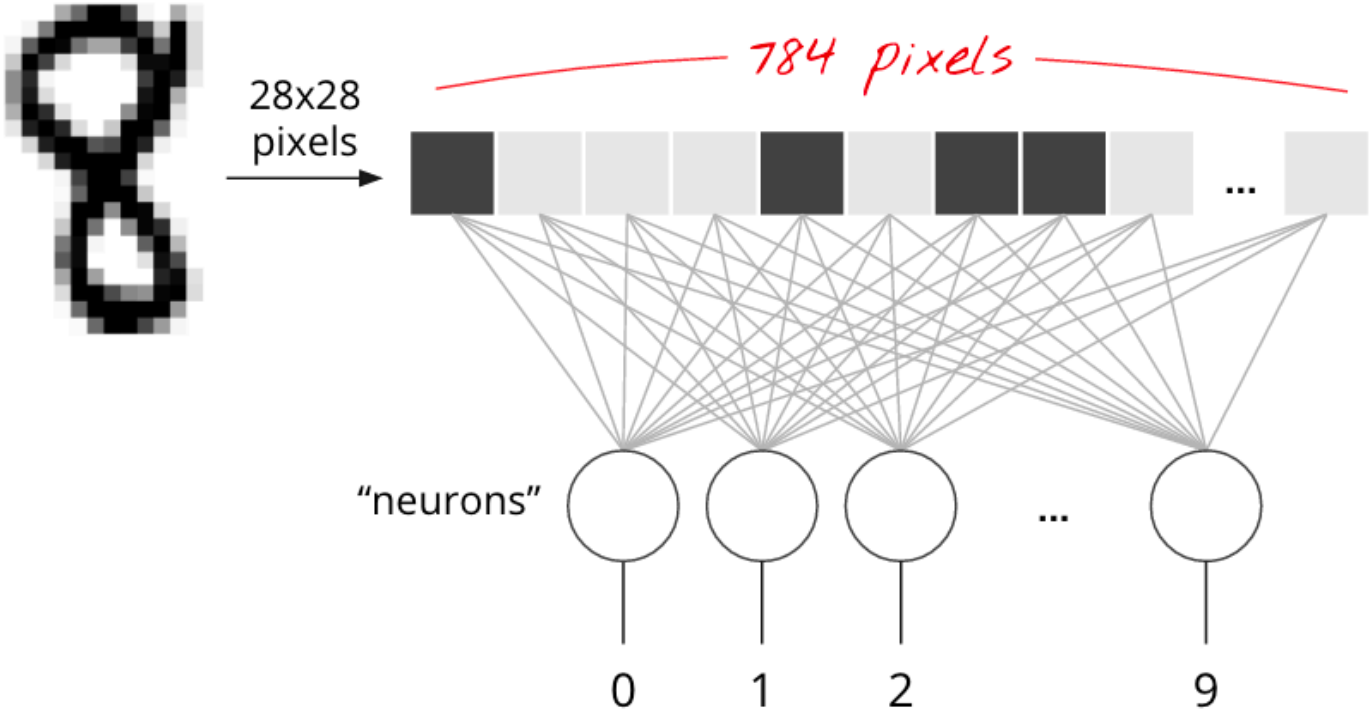


Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/#2

Cookbook

Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

Very Simple Model: Softmax Classification

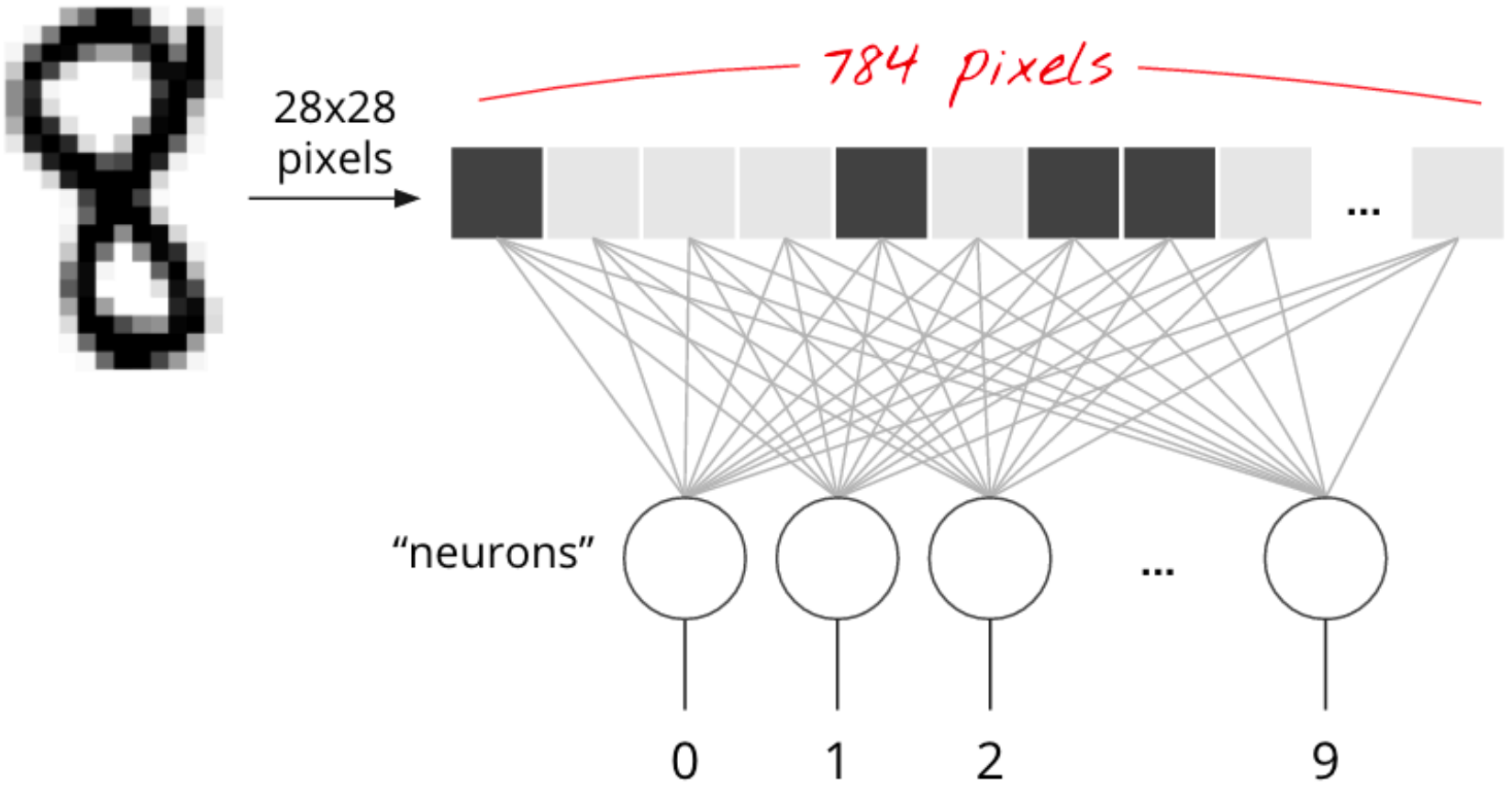


weighted sum of all pixels + bias

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

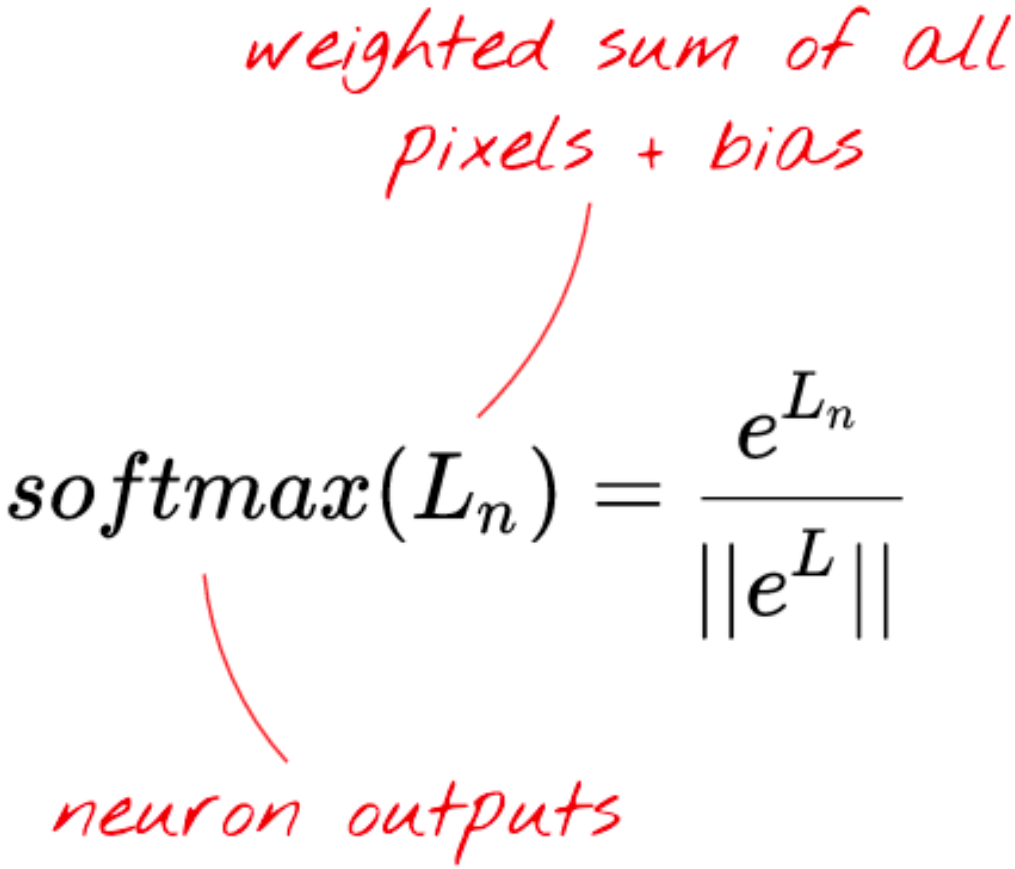
neuron outputs

Very Simple Model: Softmax Classification



Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

Very Simple Model: Softmax Classification



Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

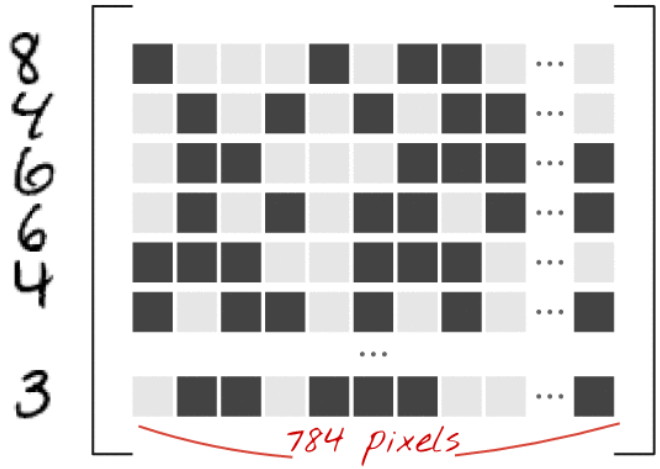
In Matrix notation, 100 images at a time

$$\begin{bmatrix} W_{0,0} & W_{0,1} & W_{0,2} & W_{0,3} & \dots & W_{0,9} \\ W_{1,0} & W_{1,1} & W_{1,2} & W_{1,3} & \dots & W_{1,9} \\ W_{2,0} & W_{2,1} & W_{2,2} & W_{2,3} & \dots & W_{2,9} \\ W_{3,0} & W_{3,1} & W_{3,2} & W_{3,3} & \dots & W_{3,9} \\ W_{4,0} & W_{4,1} & W_{4,2} & W_{4,3} & \dots & W_{4,9} \\ W_{5,0} & W_{5,1} & W_{5,2} & W_{5,3} & \dots & W_{5,9} \\ W_{6,0} & W_{6,1} & W_{6,2} & W_{6,3} & \dots & W_{6,9} \\ W_{7,0} & W_{7,1} & W_{7,2} & W_{7,3} & \dots & W_{7,9} \\ W_{8,0} & W_{8,1} & W_{8,2} & W_{8,3} & \dots & W_{8,9} \\ & & \dots & & & \\ W_{783,0} & W_{783,1} & W_{783,2} & \dots & & W_{783,9} \end{bmatrix}$$

10 columns

784 lines

X: 100 images, one per line, flattened



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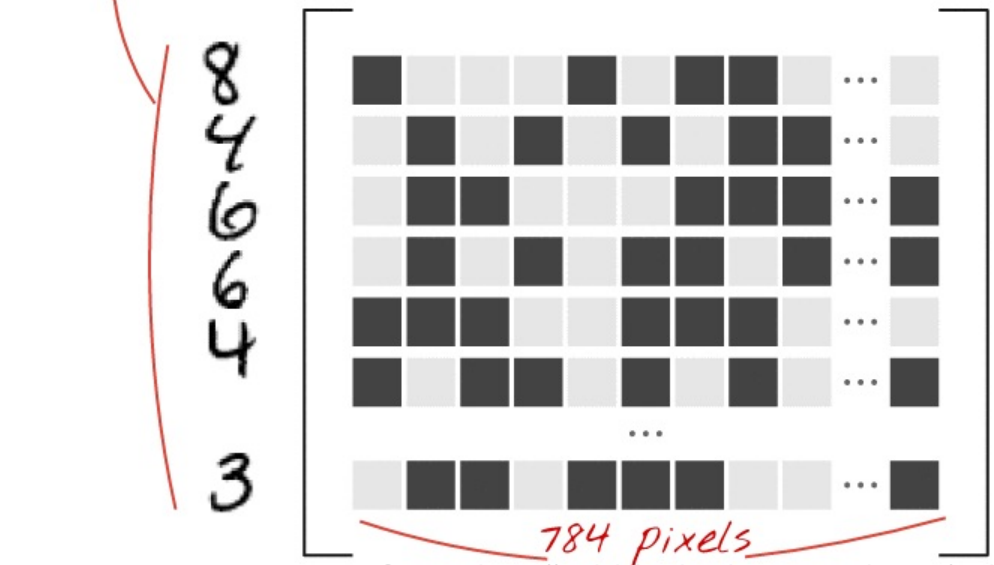
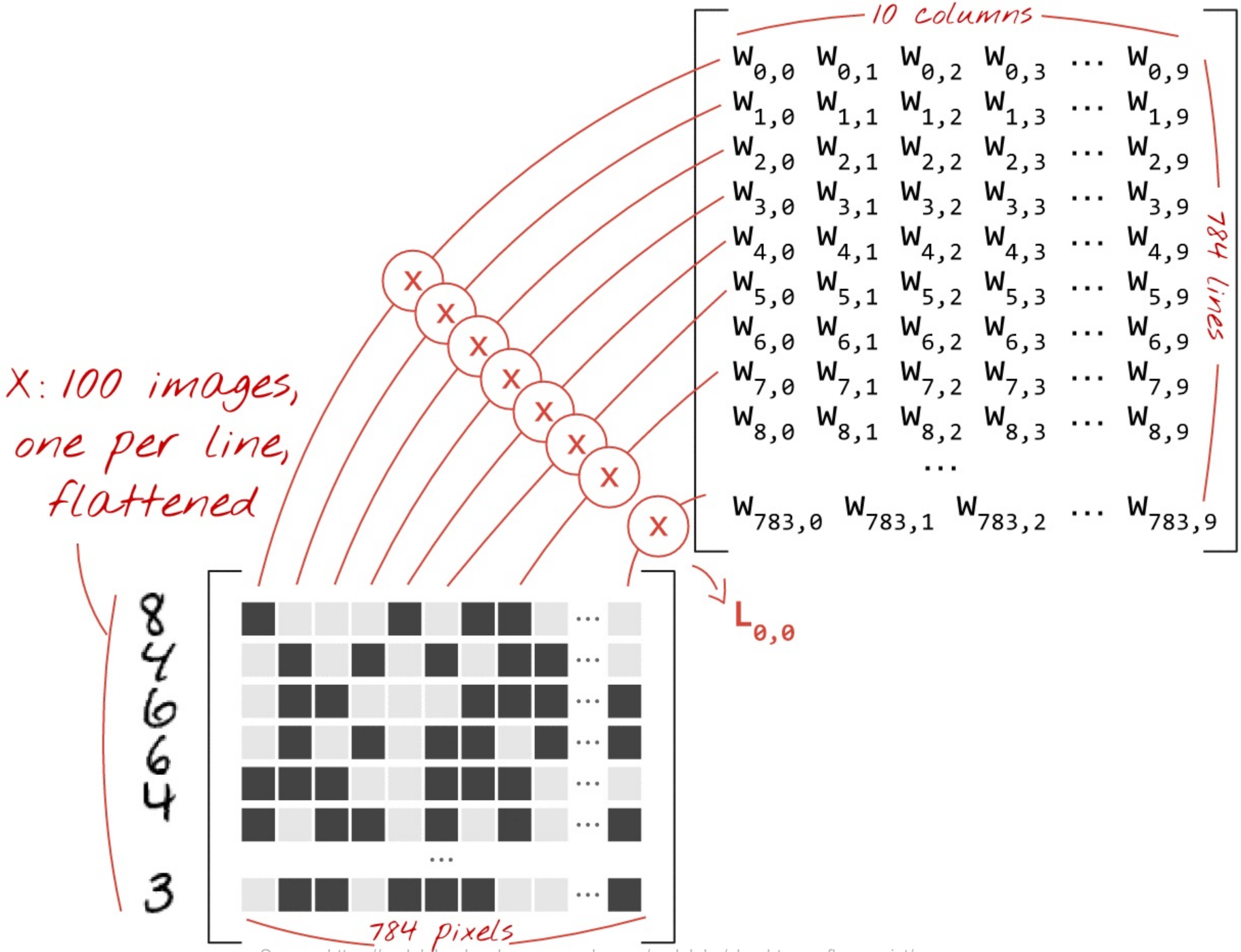
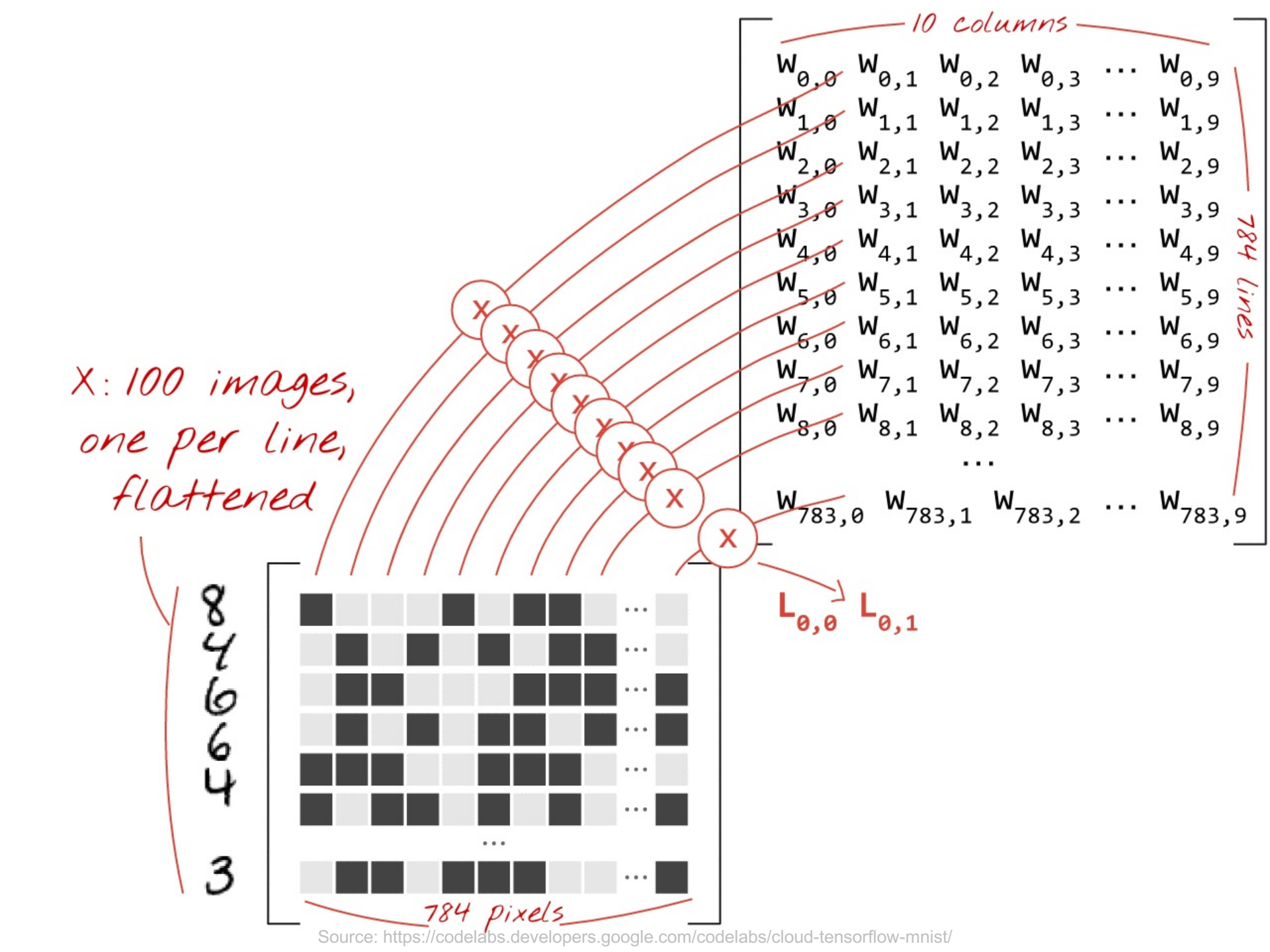


$$\begin{bmatrix} w_{0,0} & w_{0,1} & w_{0,2} & w_{0,3} & \dots & w_{0,9} \\ w_{1,0} & w_{1,1} & w_{1,2} & w_{1,3} & \dots & w_{1,9} \\ w_{2,0} & w_{2,1} & w_{2,2} & w_{2,3} & \dots & w_{2,9} \\ w_{3,0} & w_{3,1} & w_{3,2} & w_{3,3} & \dots & w_{3,9} \\ w_{4,0} & w_{4,1} & w_{4,2} & w_{4,3} & \dots & w_{4,9} \\ w_{5,0} & w_{5,1} & w_{5,2} & w_{5,3} & \dots & w_{5,9} \\ w_{6,0} & w_{6,1} & w_{6,2} & w_{6,3} & \dots & w_{6,9} \\ w_{7,0} & w_{7,1} & w_{7,2} & w_{7,3} & \dots & w_{7,9} \\ w_{8,0} & w_{8,1} & w_{8,2} & w_{8,3} & \dots & w_{8,9} \\ & & \dots & & & \\ w_{783,0} & w_{783,1} & w_{783,2} & & \dots & w_{783,9} \end{bmatrix}$$

10 columns

784 lines


10 columns
784 lines
X: 100 images, one per line, flattened
784 pixels
$L_{0,0}$
Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/



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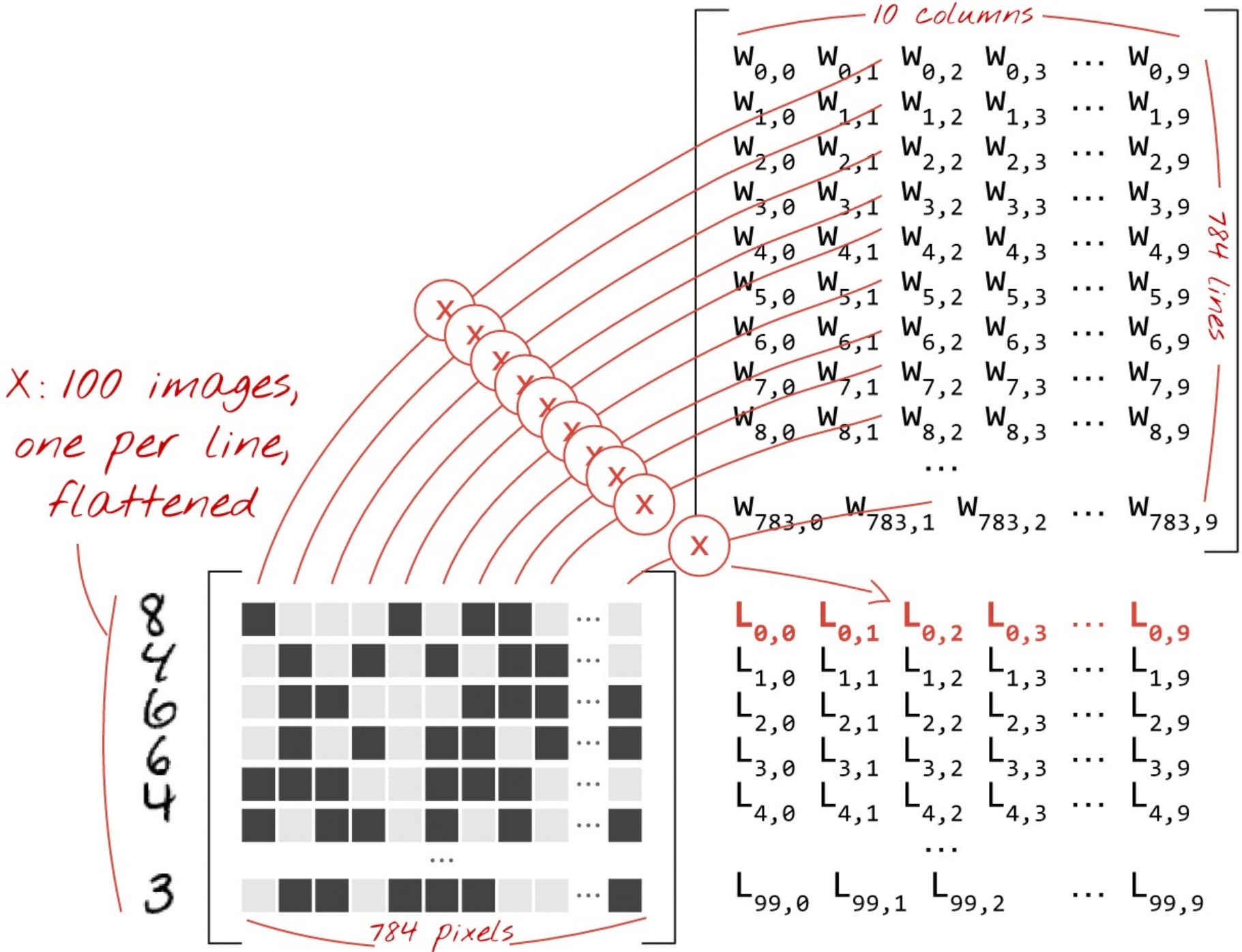

10 columns
784 lines
X: 100 images, one per line, flattened
784 pixels
Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

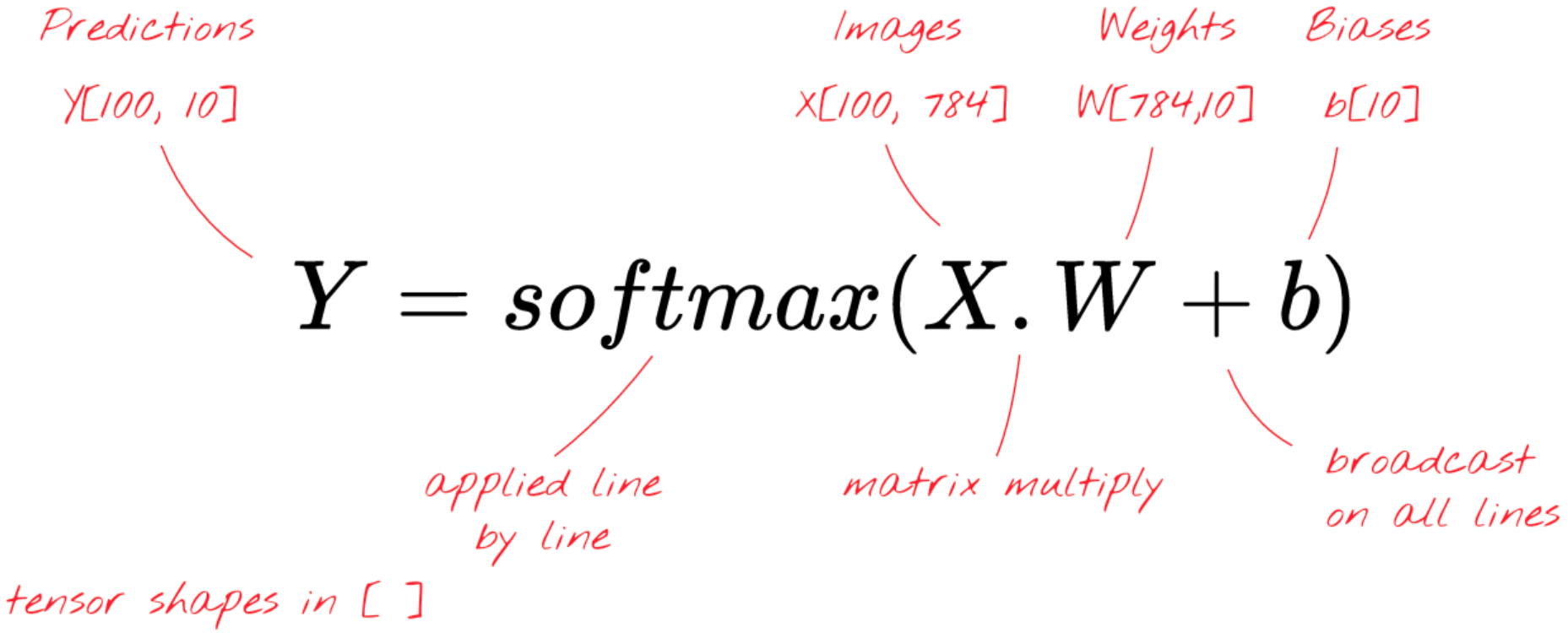
What are "weights" and "biases" ?

How is the "cross-entropy" computed ?

How exactly does the training algorithm work ?

Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

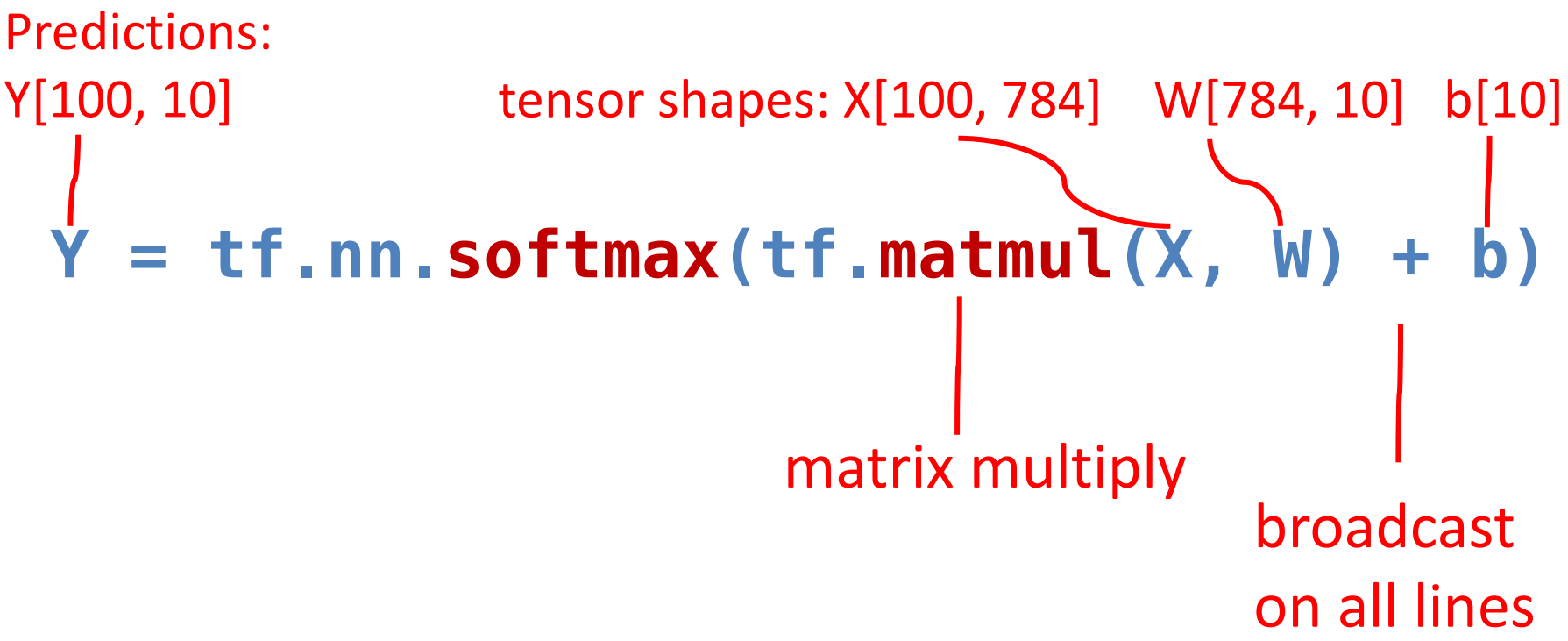
Y = f(X)




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

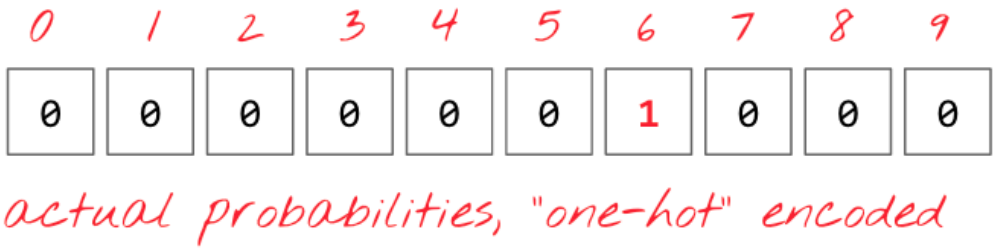
Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

TensorFlow (Python) Softmax

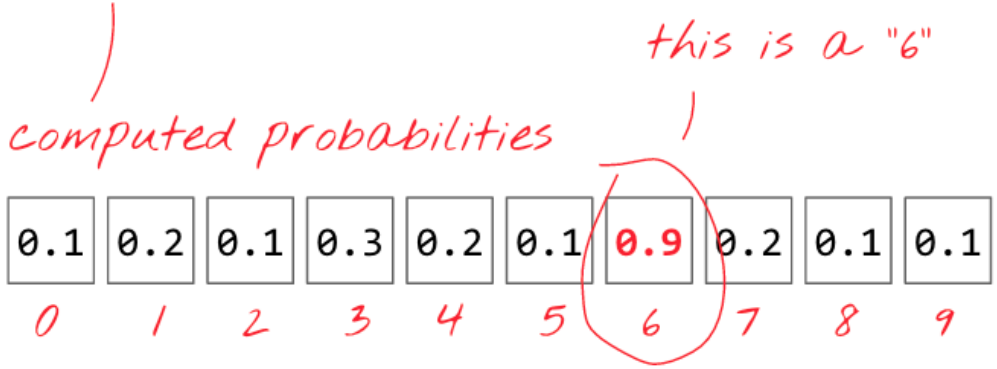


Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

Cross Entropy

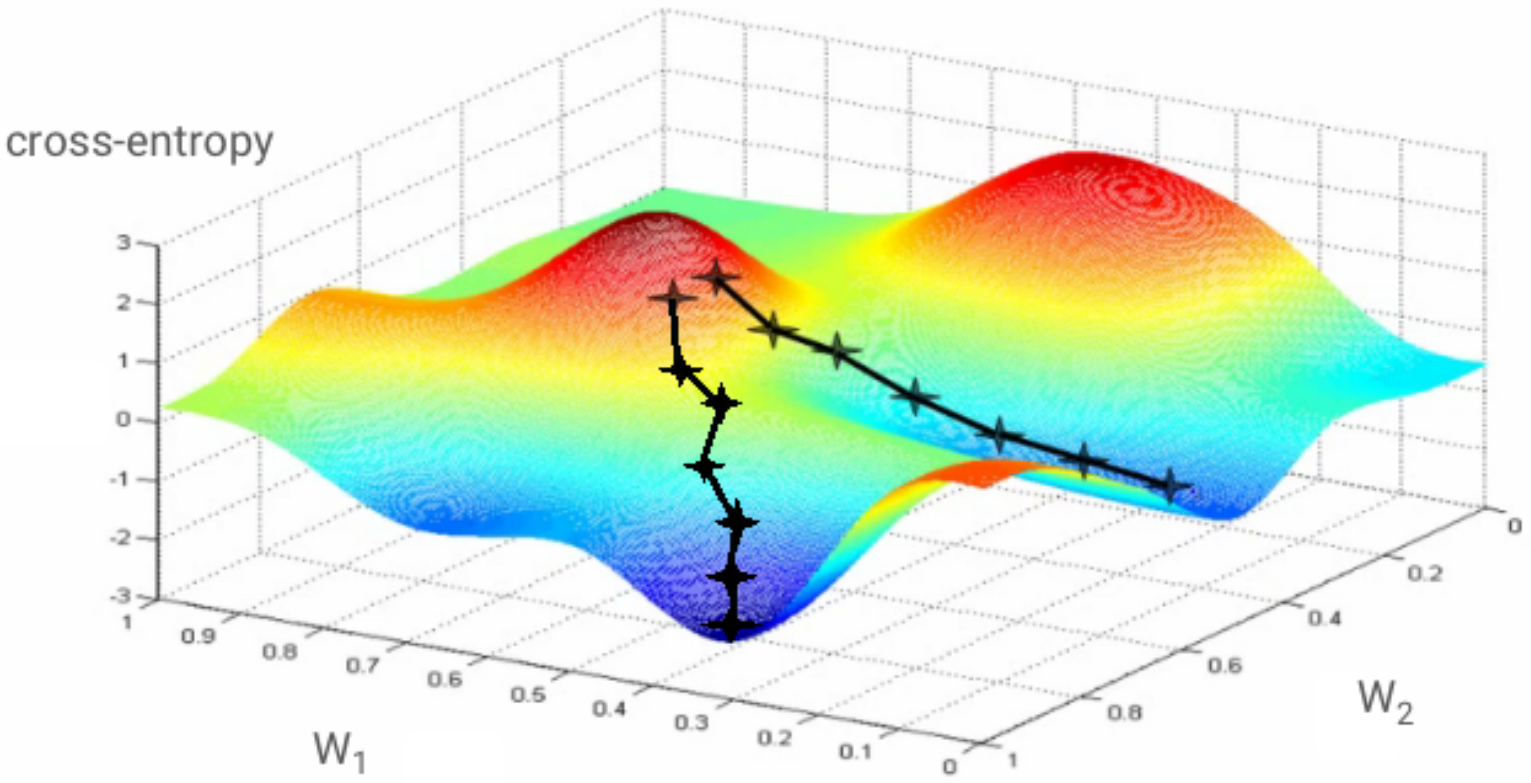


Cross entropy: $-\sum Y_i' . log(Y_i)$



Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

Minimizing Cross Entropy (Minimizing Loss)



Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

Training Loop

Training digits and labels

=> loss function

=> gradient (partial derivatives)

=> steepest descent

=> update weights and biases

=> repeat with next mini-batch of training images and labels

Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

"mini-batches":
100 images and labels

Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

```
import tensorflow as tf
```

Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/#5

mnist_1.0_softmax.py

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

init = tf.initialize_all_variables()
```

Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/#5

mnist_1.0_softmax.py

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

# loss function
cross_entropy = -tf.reduce_sum(Y_ * tf.log(Y))
# % of correct answers found in batch
is_correct = tf.equal(tf.argmax(Y,1), tf.argmax(Y_,1))
accuracy = tf.reduce_mean(tf.cast(is_correct, tf.float32))
```

Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/#5

mnist_1.0_softmax.py

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

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

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

Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/#5

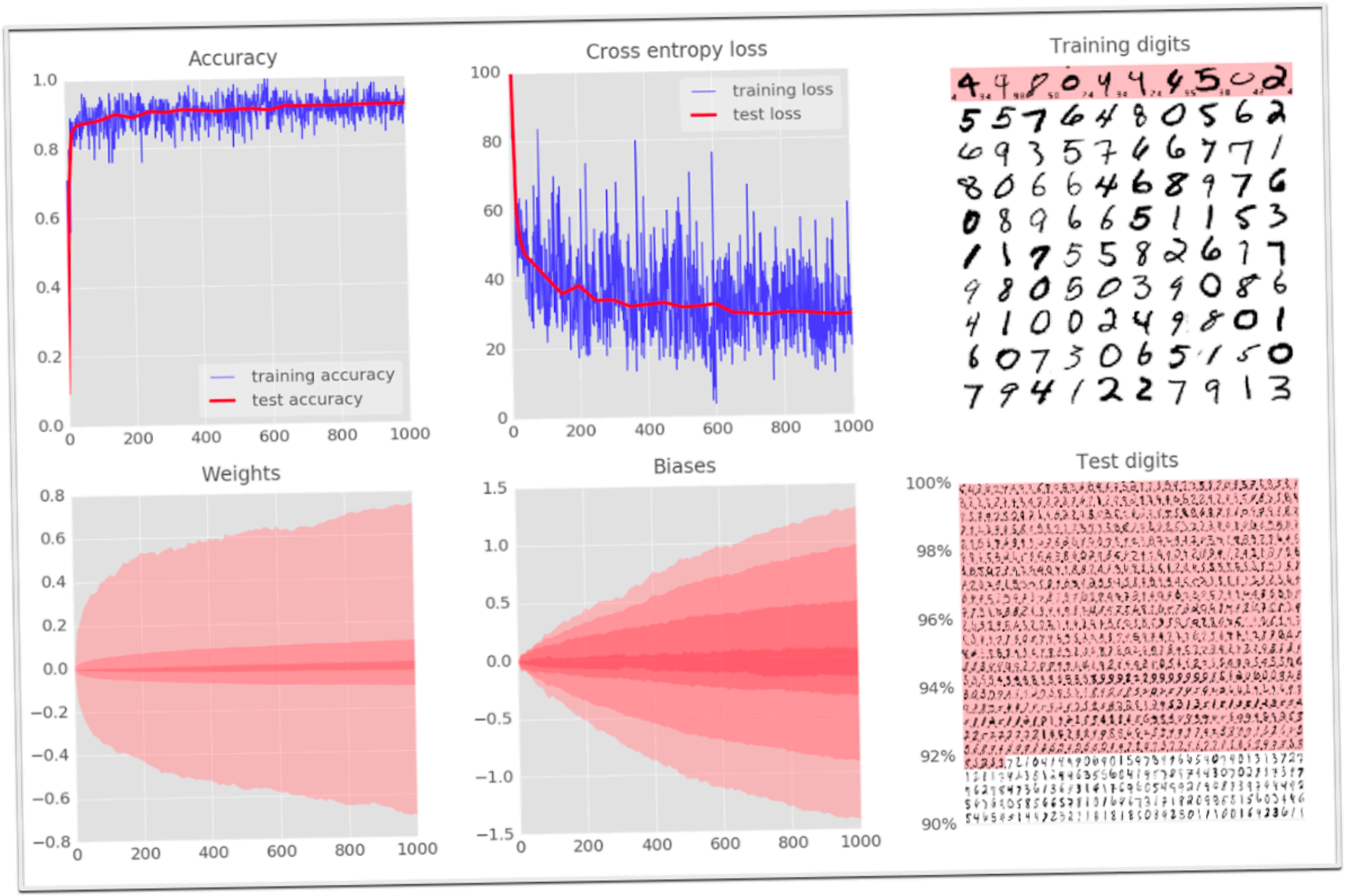
mnist_1.0_softmax.py

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


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

Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/#5

mnist_1.0_softmax.py



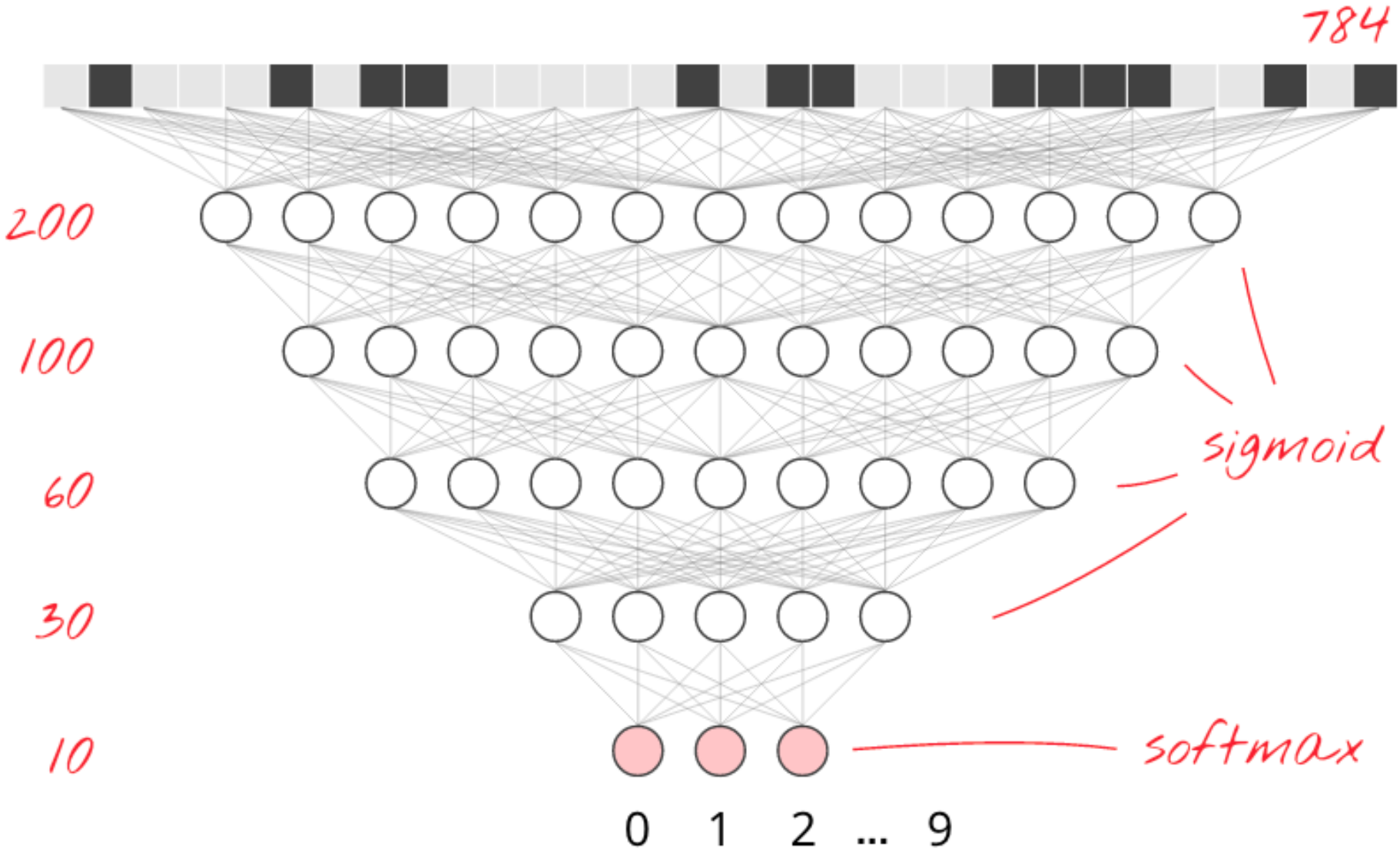
92%

Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/#5

Deep Learning

Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

5 fully-connected layers



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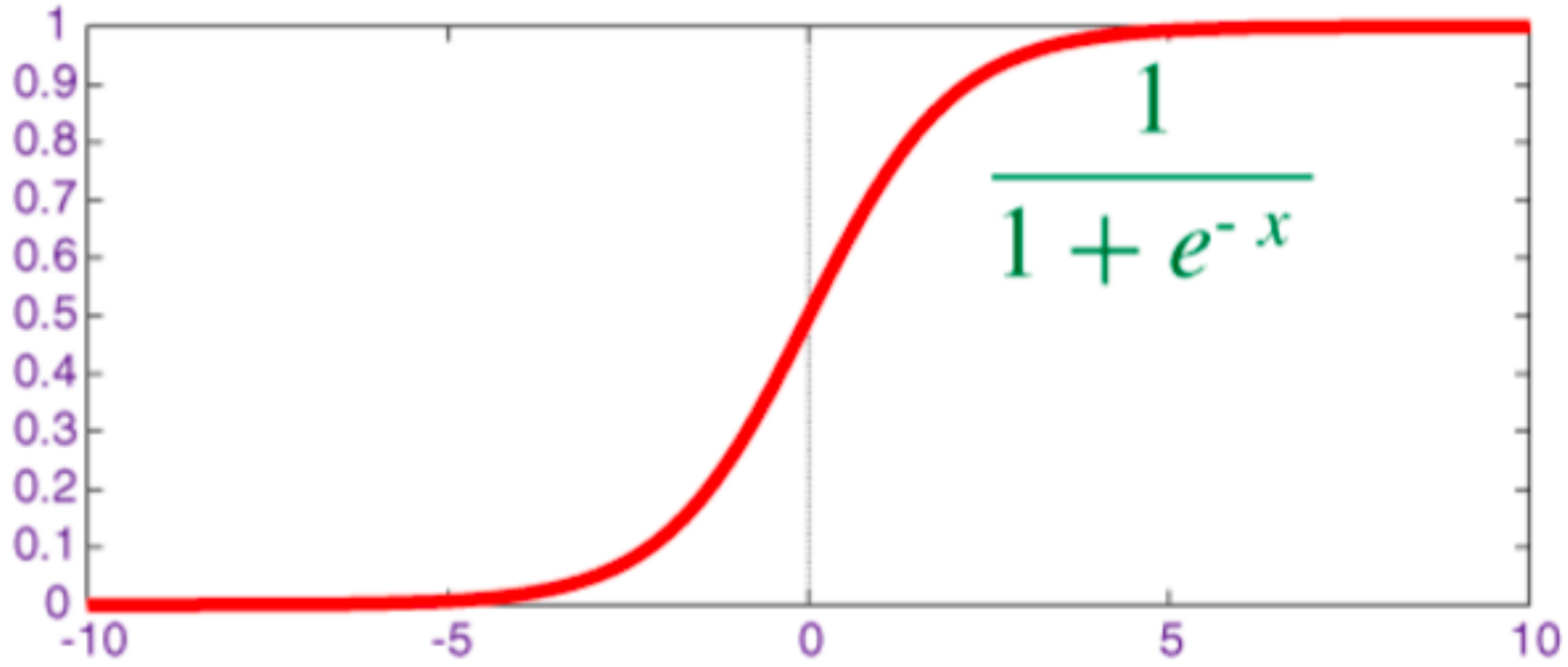
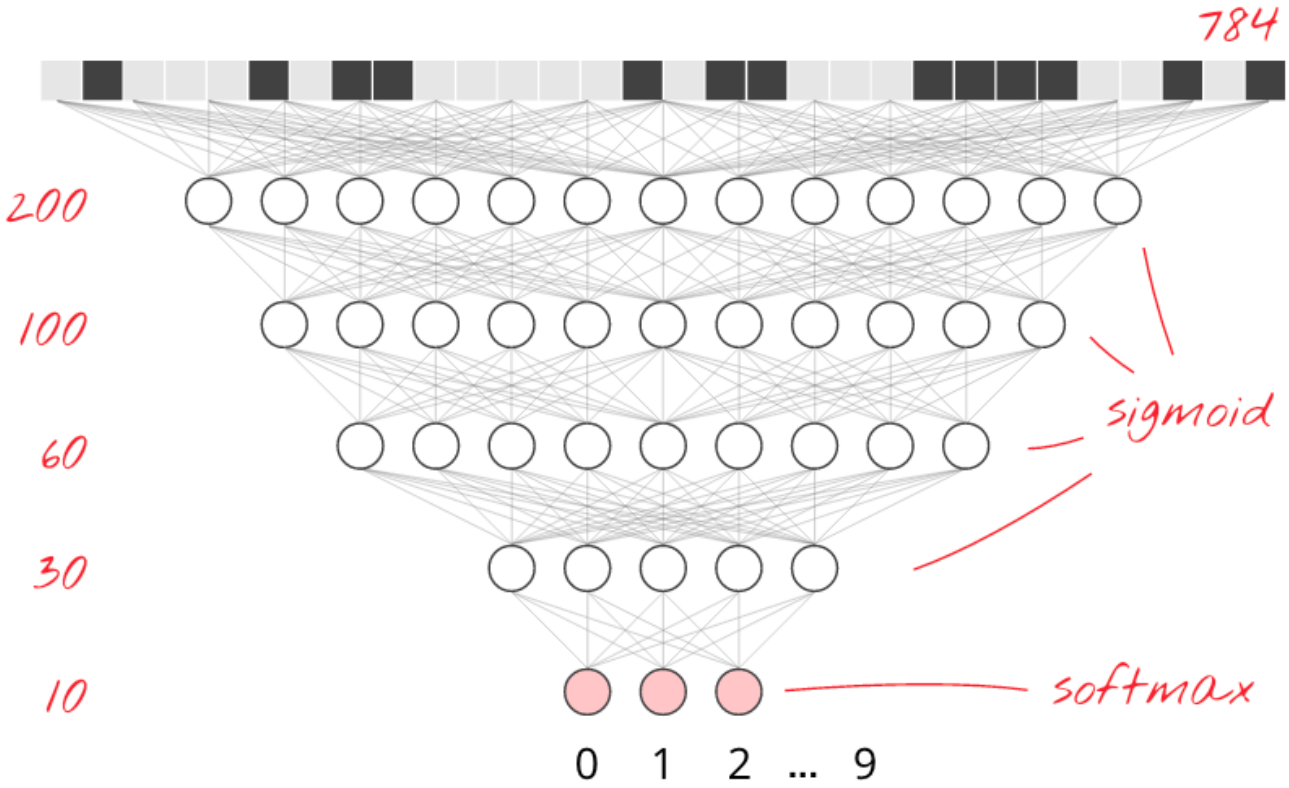
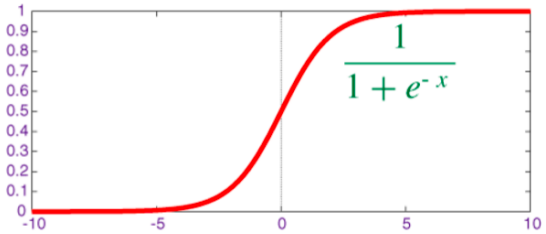
Sigmoid



Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

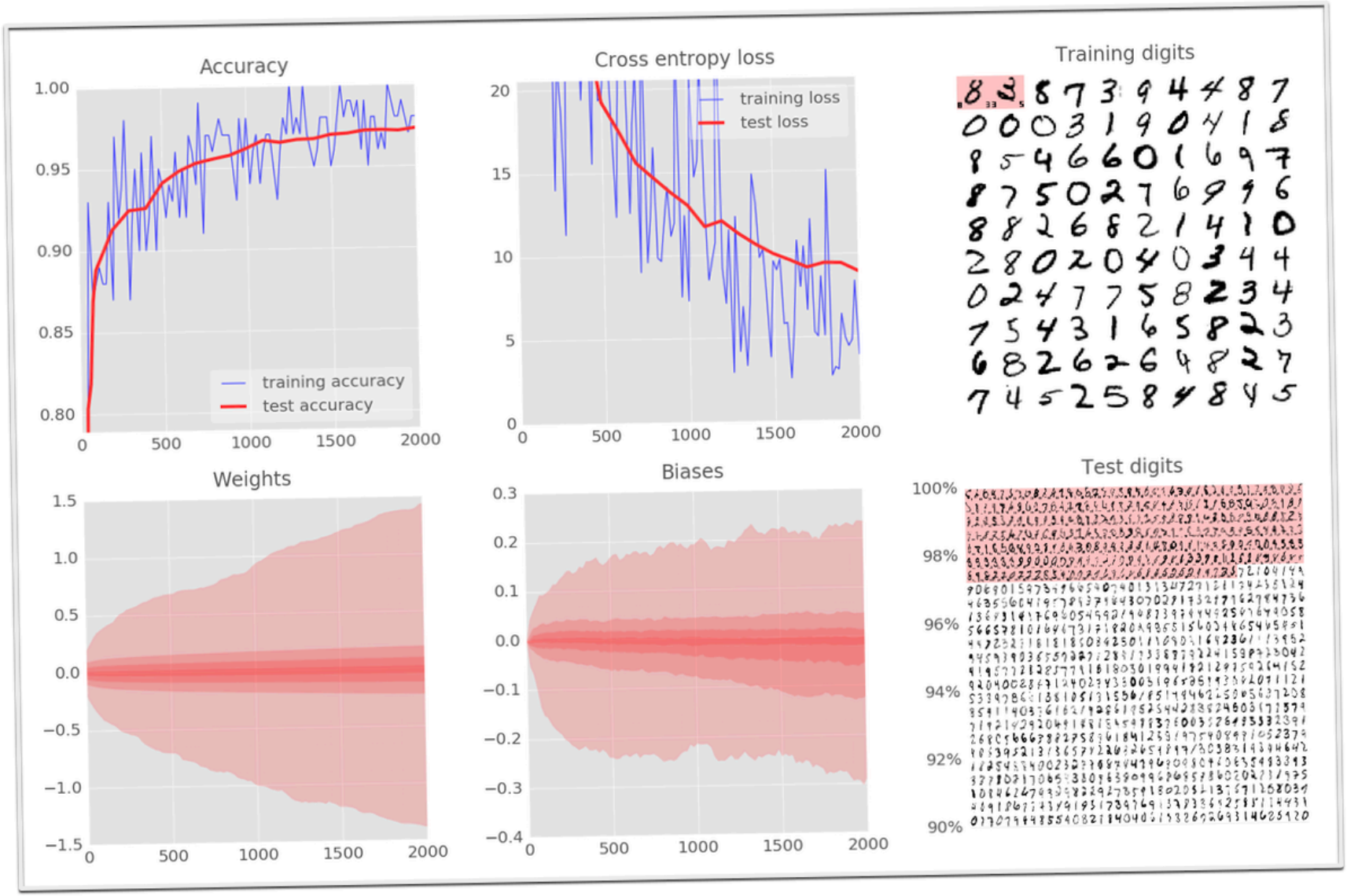
5 fully-connected layers





Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

TensorFlow MNIST Tutorial

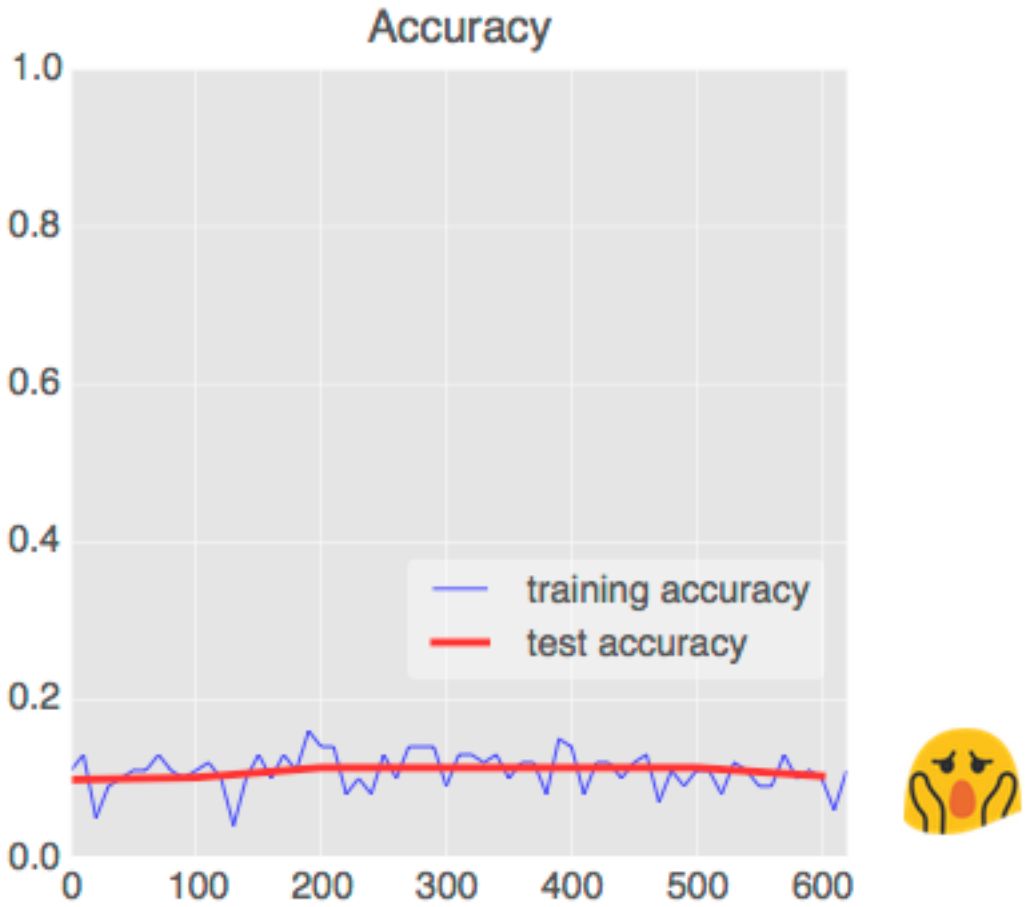


97%

ReLU

Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

TensorFlow MNIST Tutorial



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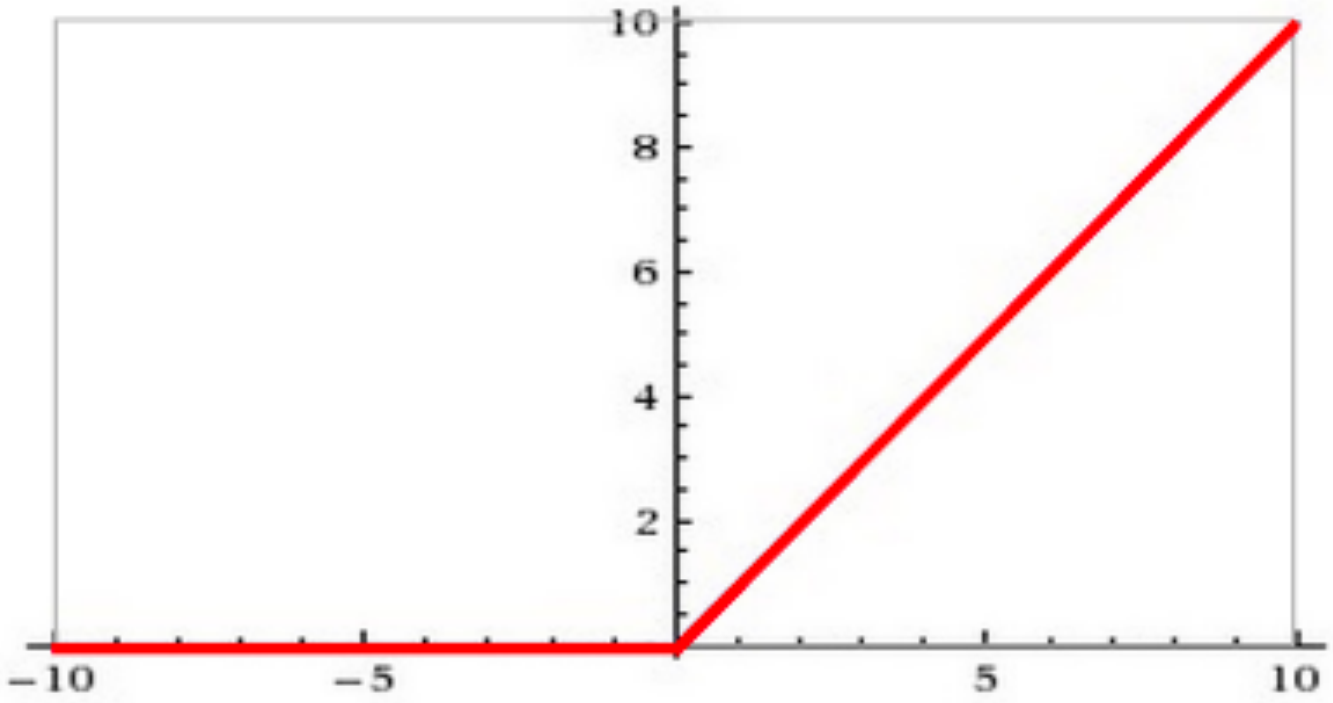
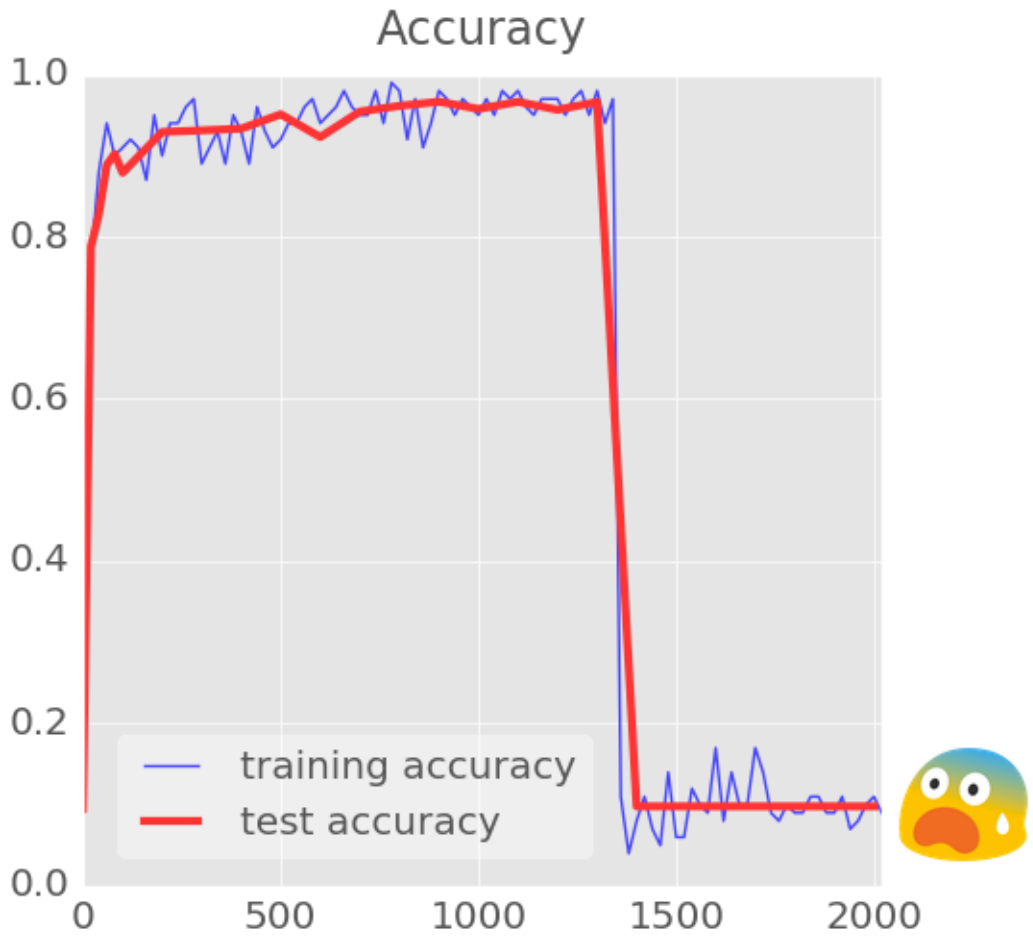
ReLU



Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

TensorFlow MNIST Tutorial



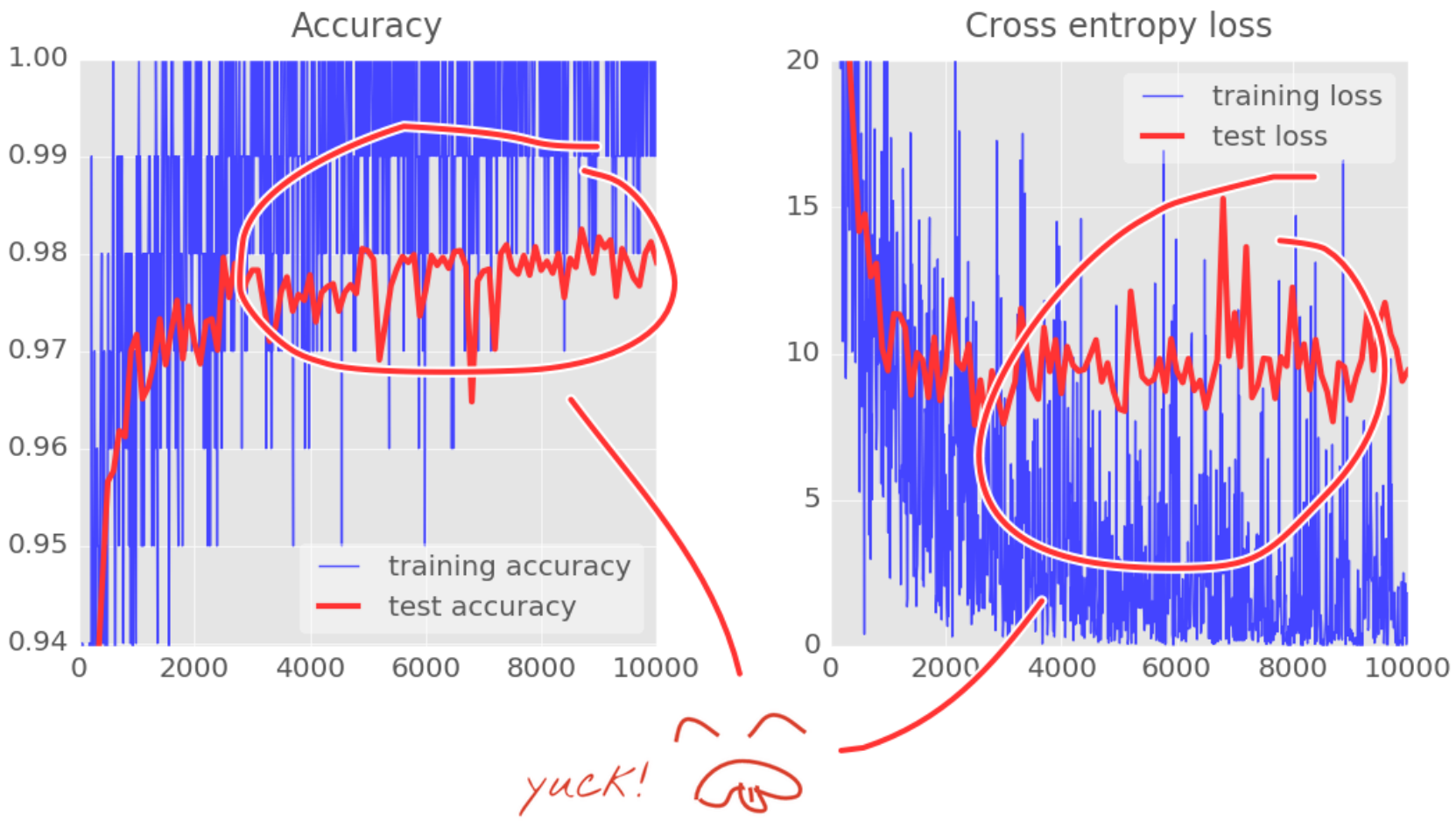
Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

Learning Rate

Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

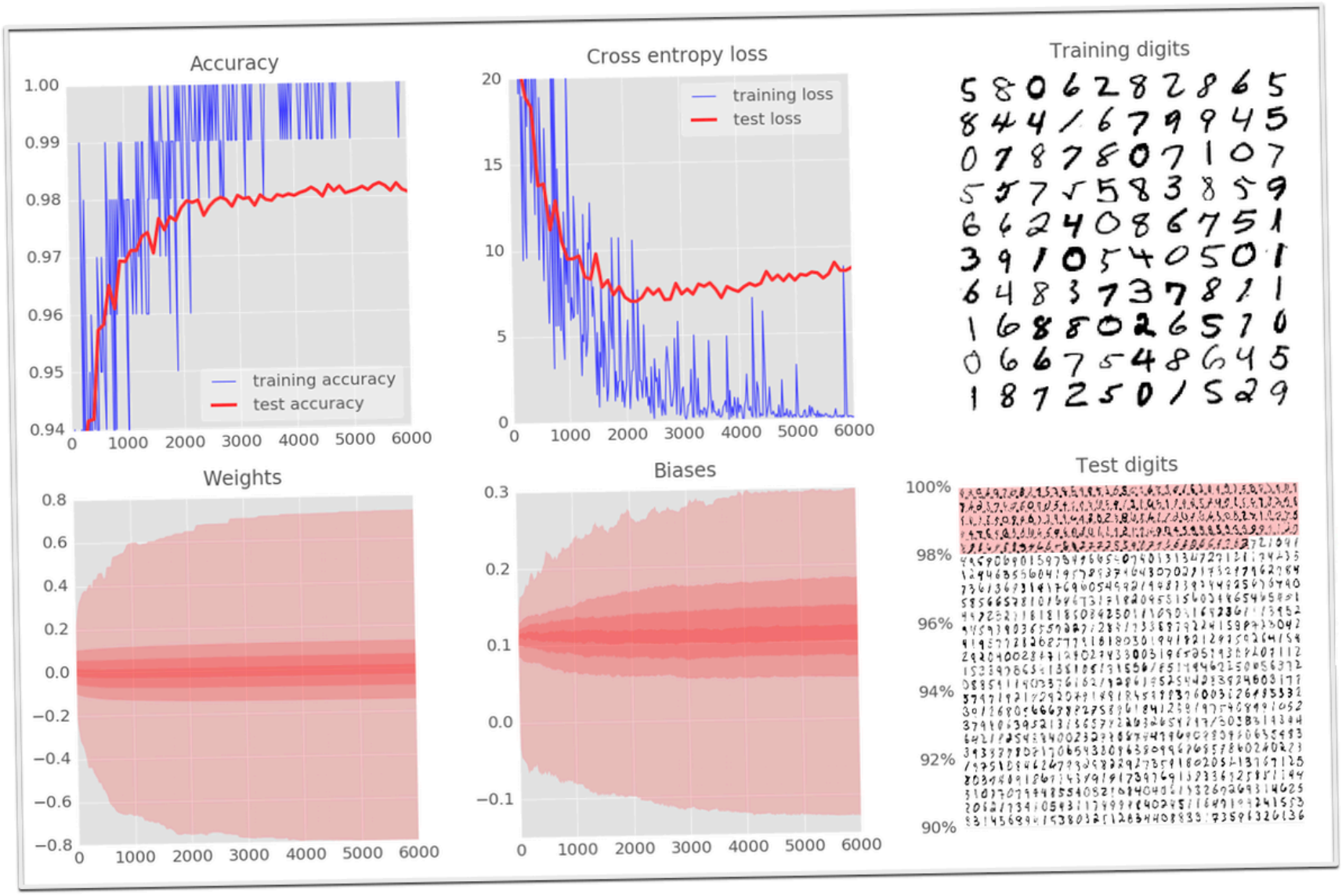
TensorFlow MNIST Tutorial

LR = 0.003



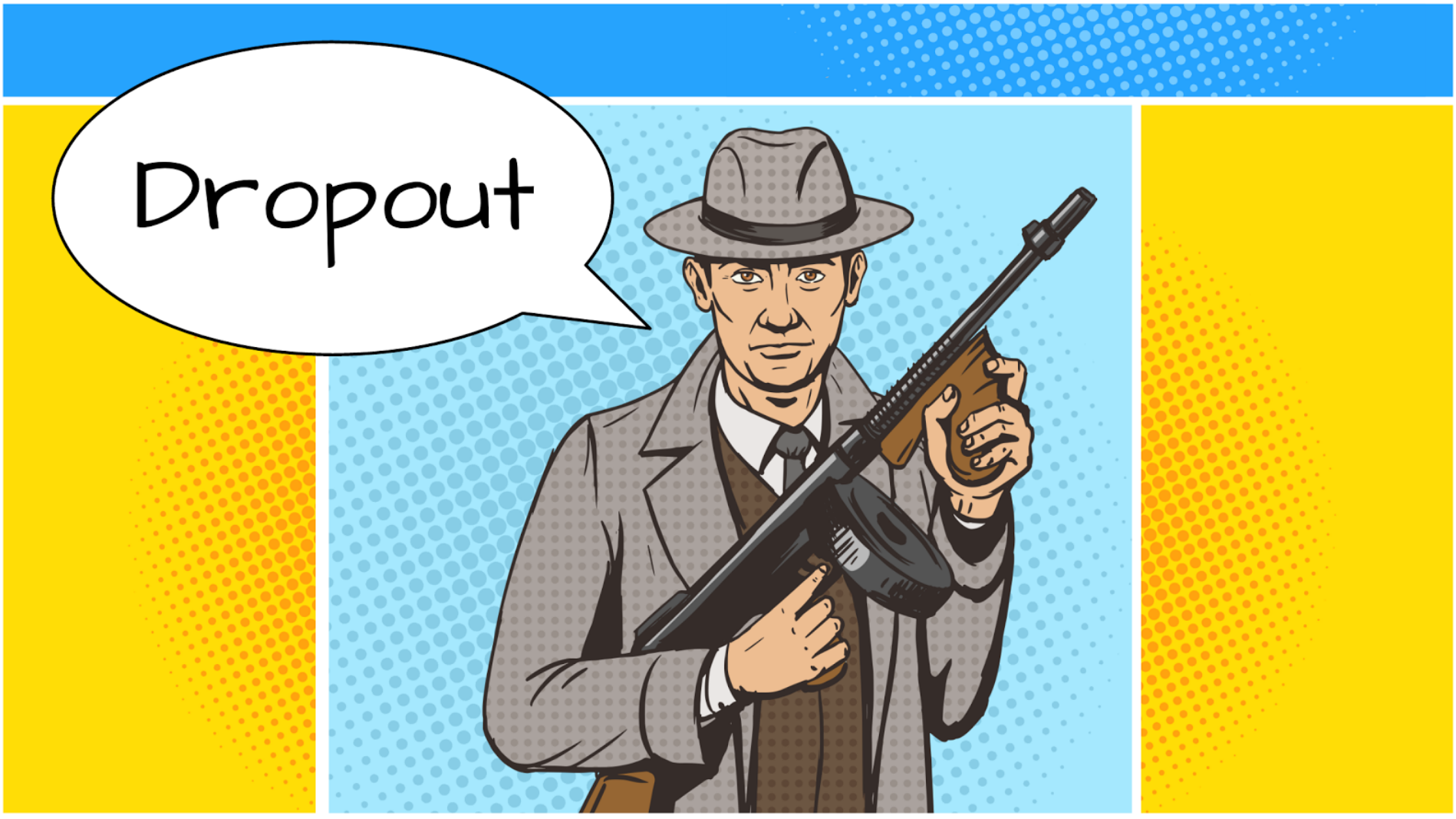
Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

TensorFlow MNIST Tutorial



Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

Dropout



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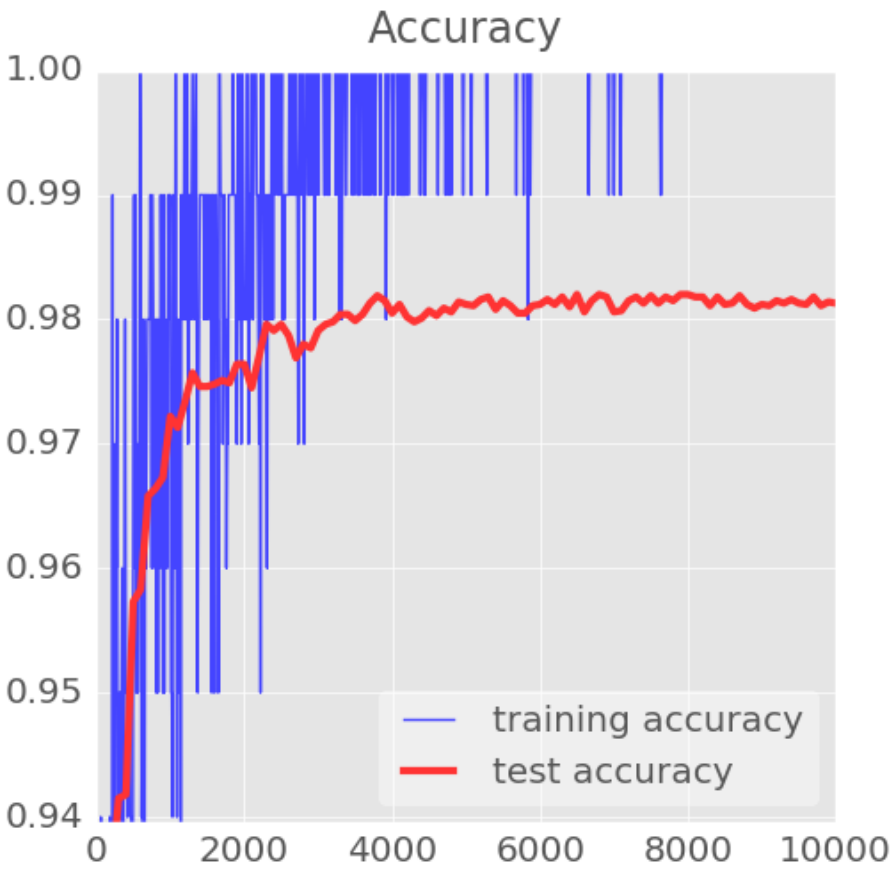
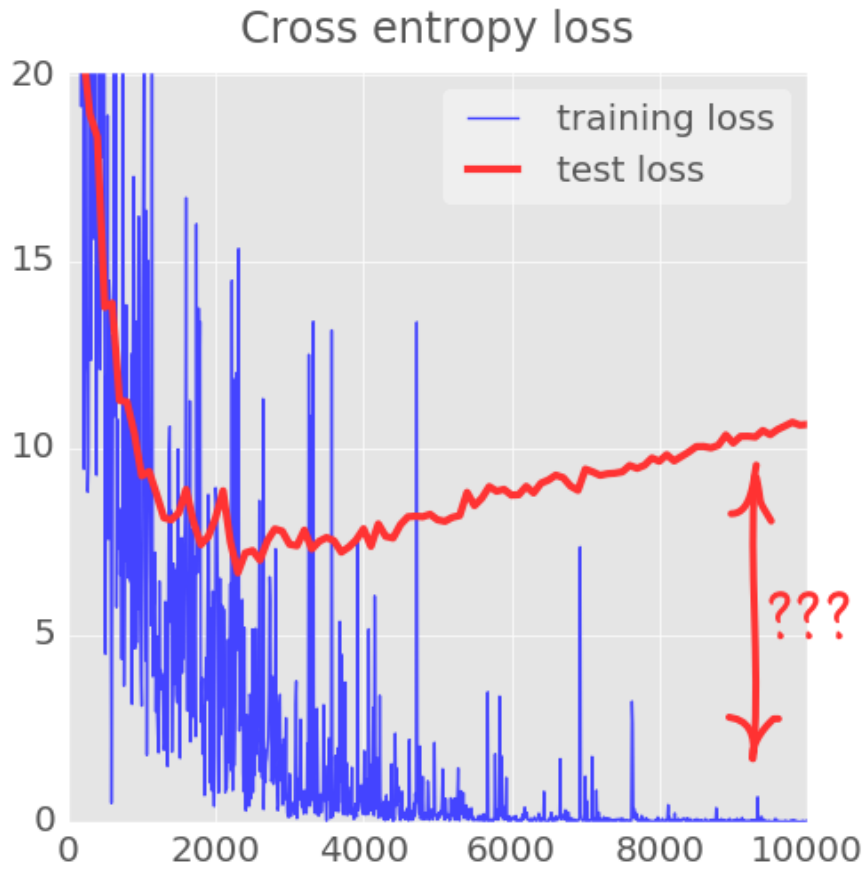
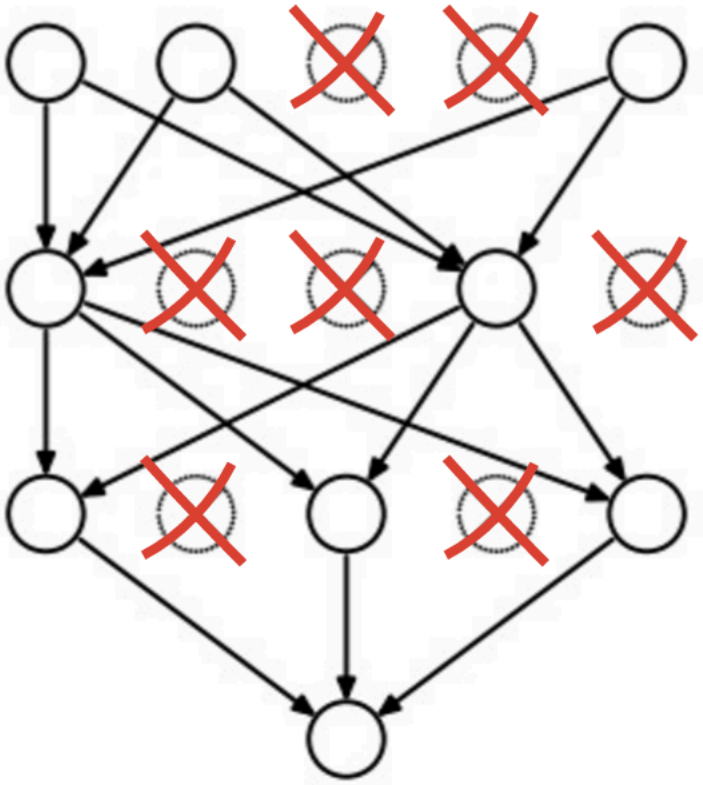
Overfitting



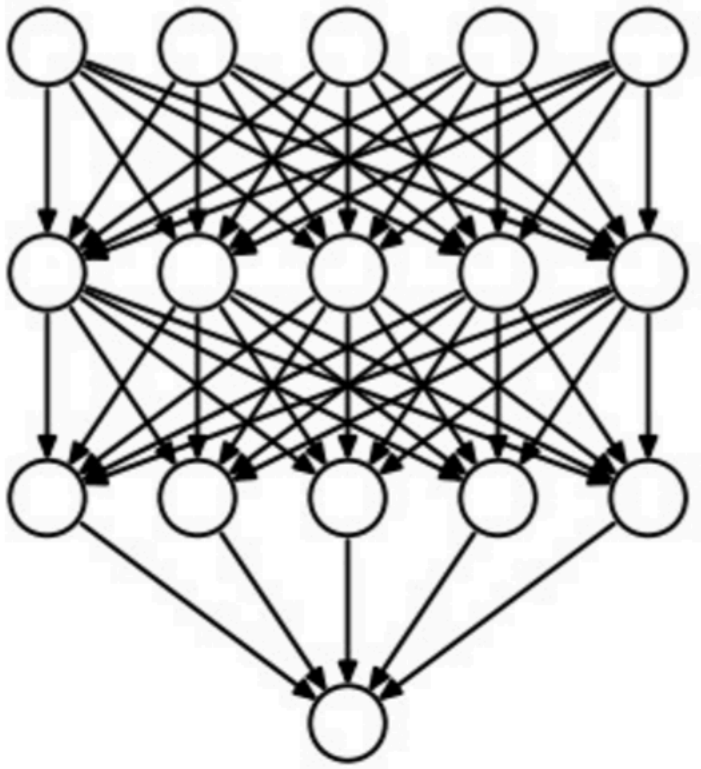


Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

Dropout



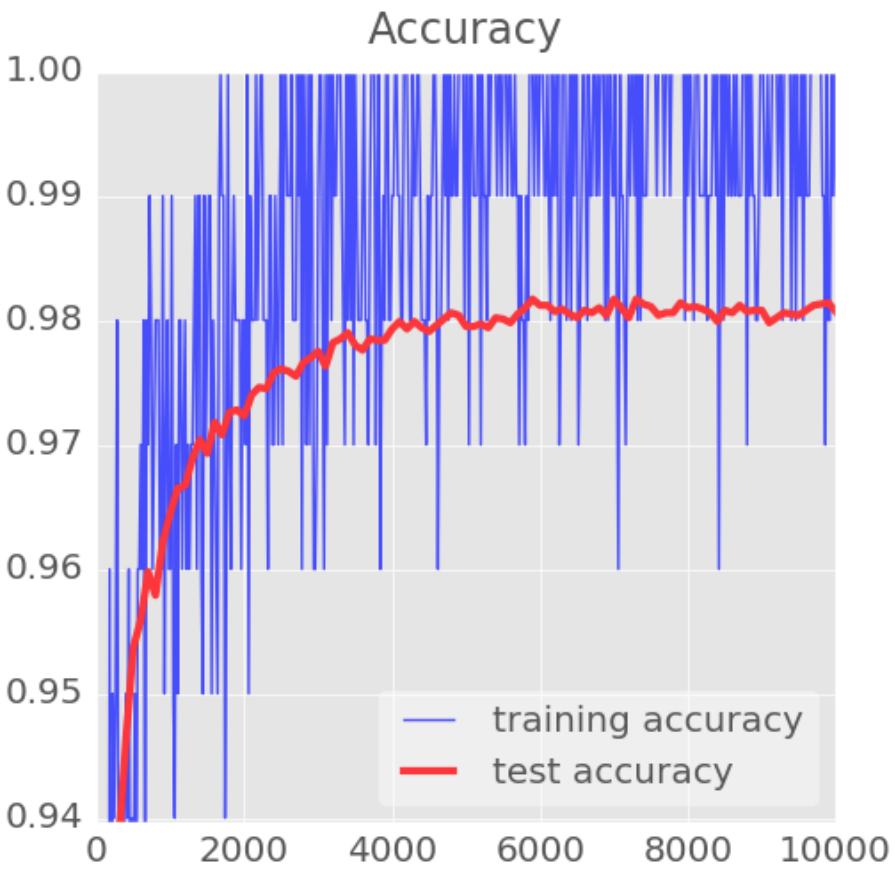
Training
pkeep = 0.75

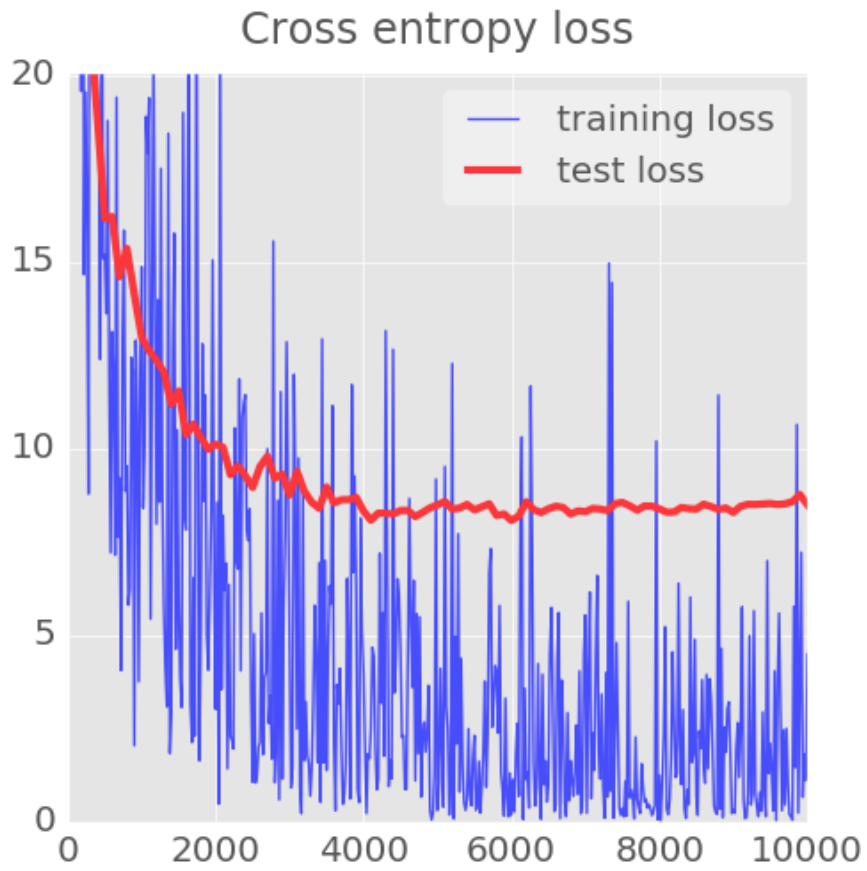


Test
pkeep = 1.0

Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

TensorFlow MNIST Tutorial

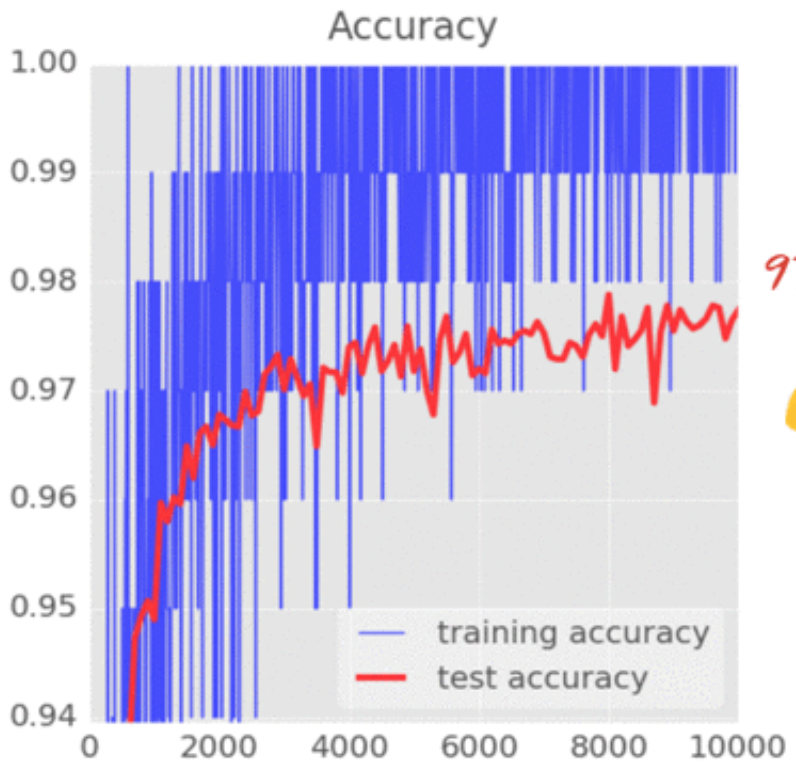




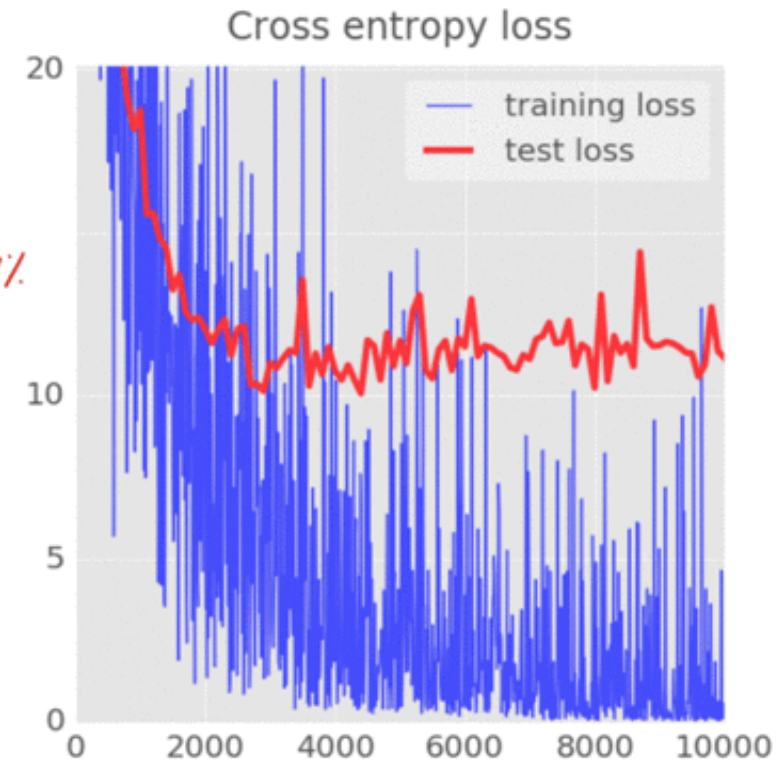
Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

TensorFlow MNIST Tutorial

5 layers
sigmoid



97.9%

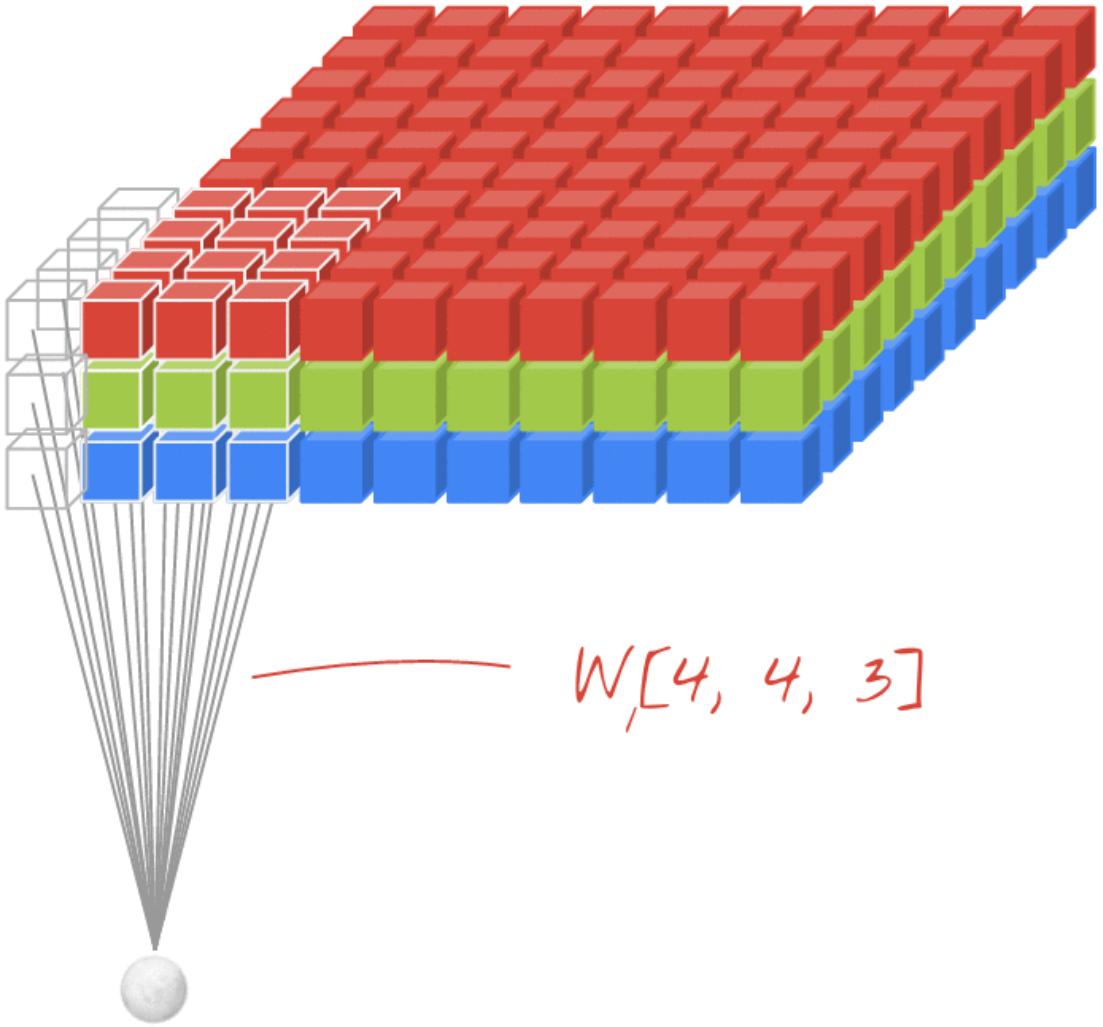


Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

Overfitting

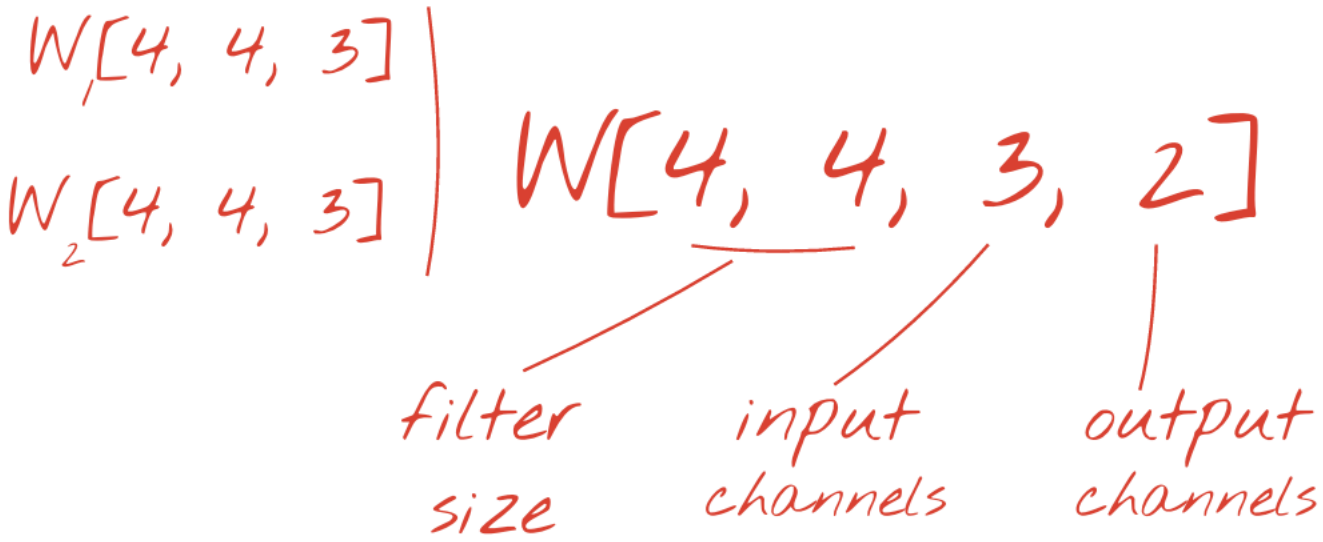
Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

Convolutional Layer



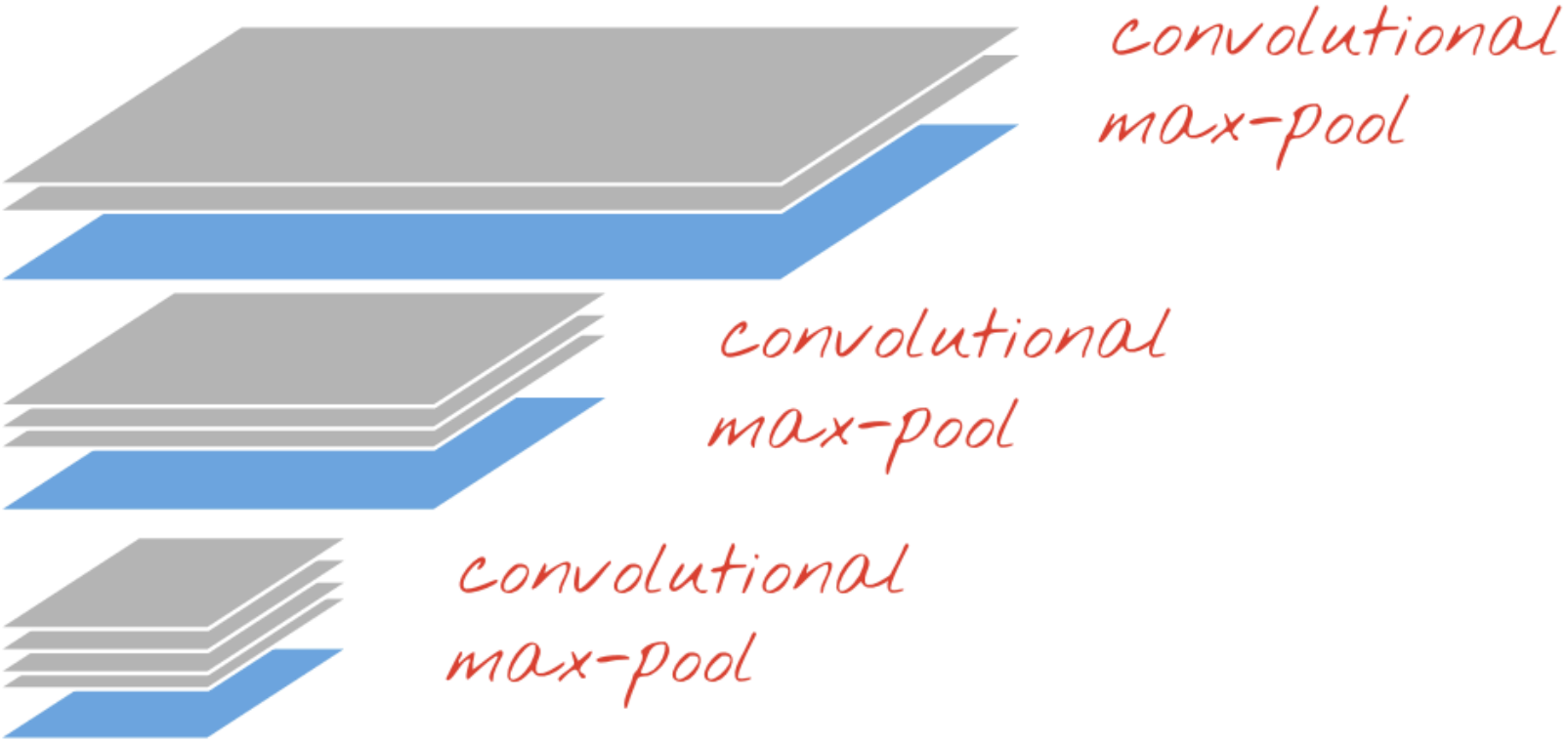
Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

Convolutional Layer



Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

Convolutional Max-Pool



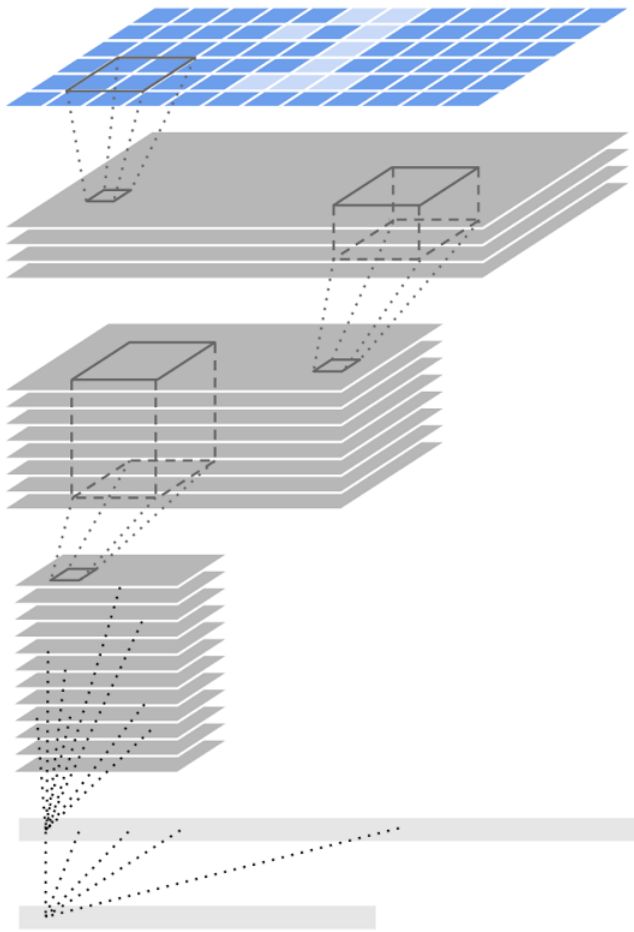
Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

All Convolutional

Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

Bigger Convolutional Neural Network

+ biases on all layers



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

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

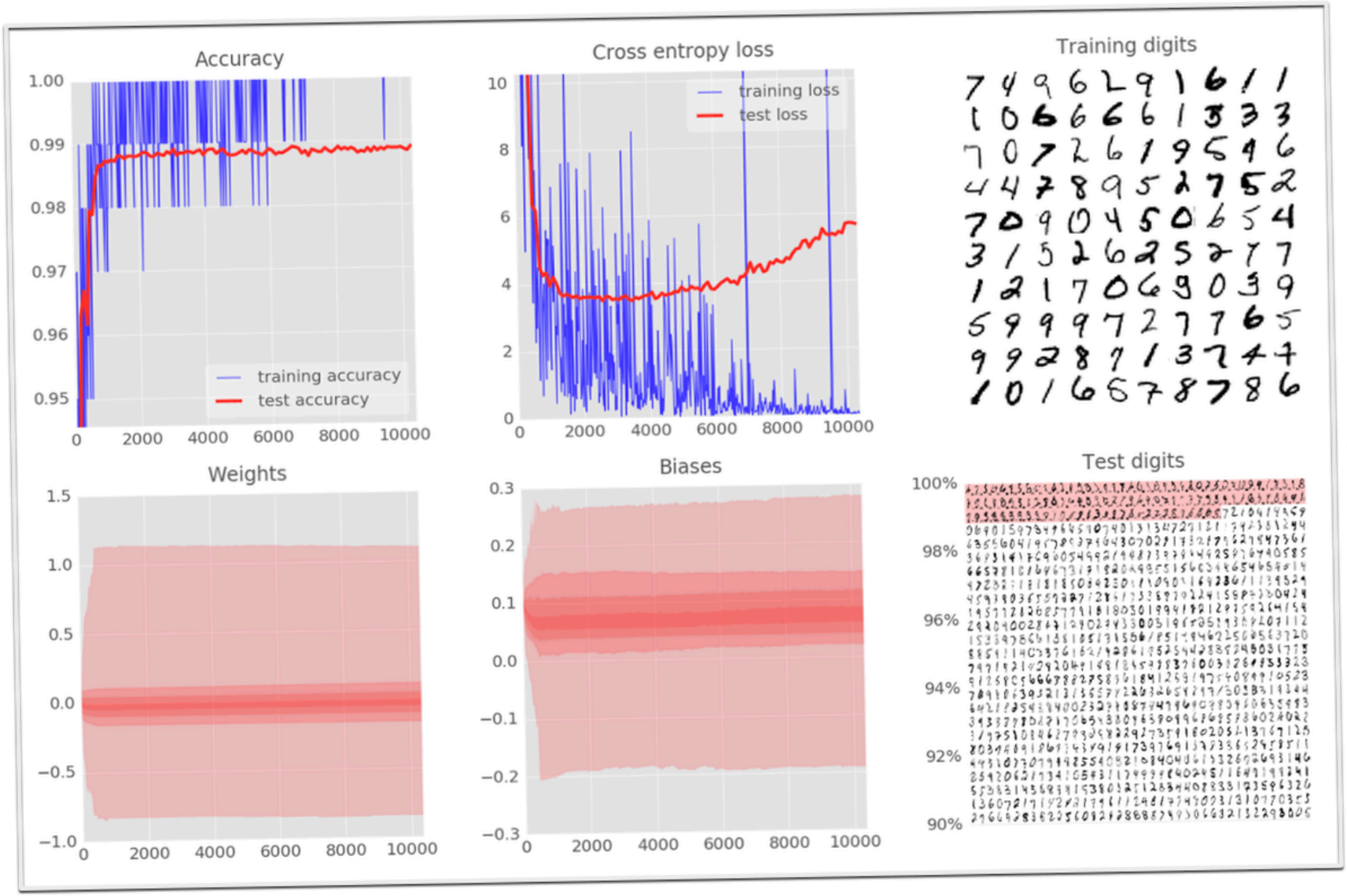
convolutional layer, 12 channels
W3[4, 4, 8, 12] stride 2

fully connected layer
W4[7x7x12, 200]

softmax readout layer
W5[200, 10]

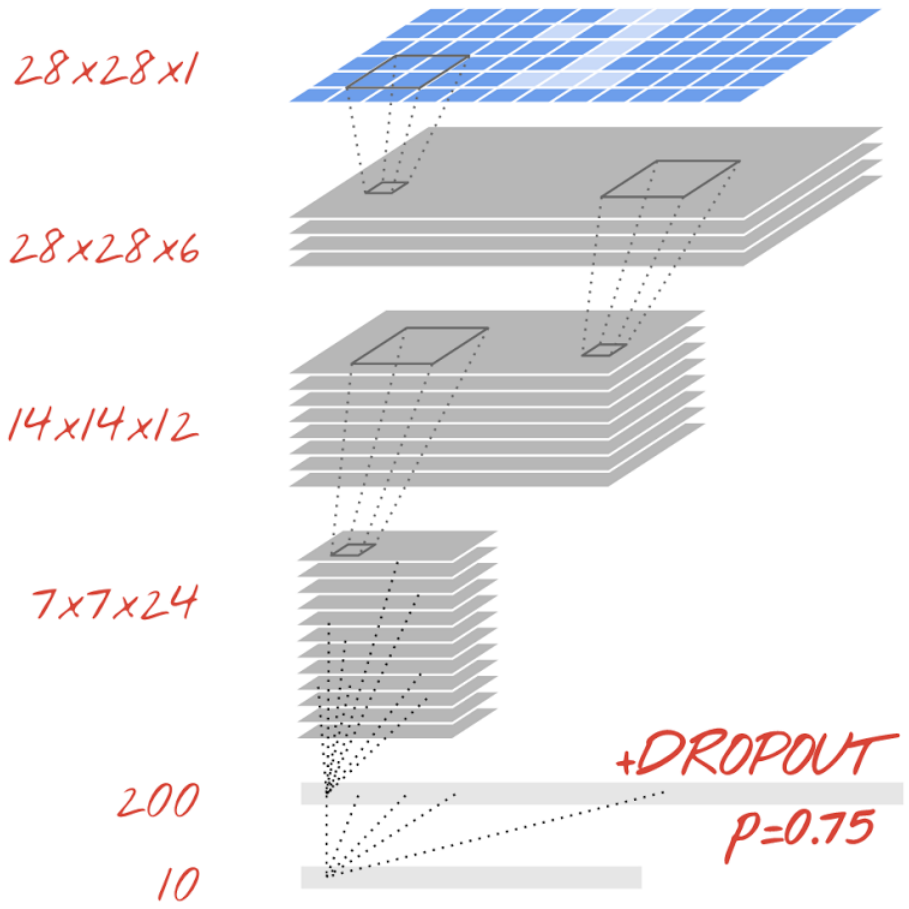
Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

Bigger Convolutional Neural Network



98.9%

Bigger Convolutional Neural Network + Dropout



+ biases on all layers

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

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

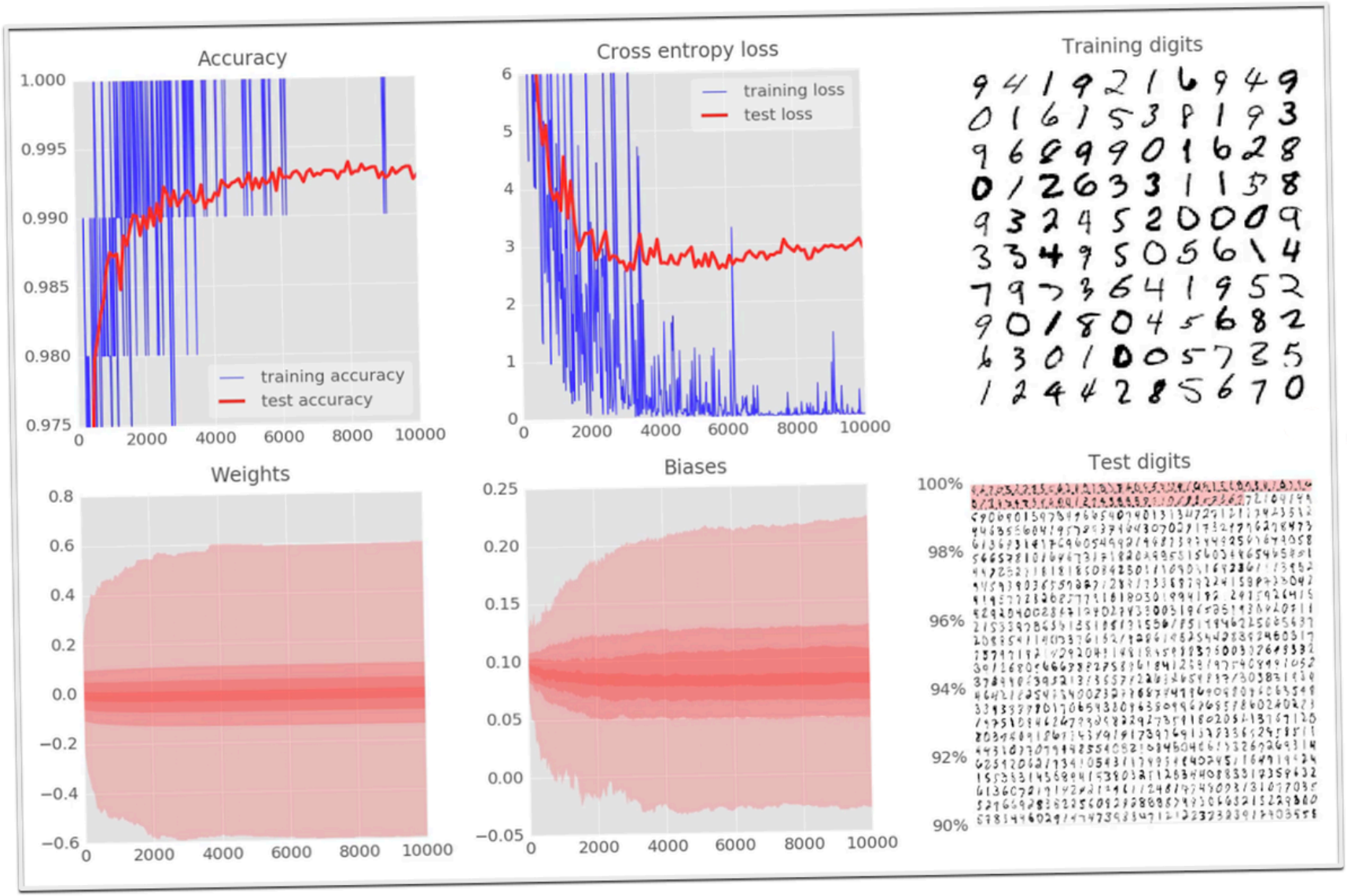
convolutional layer, **24** channels
W3[**4**, **4**, 12, 24] stride 2

fully connected layer
W4[7x7x24, 200]

softmax readout layer
W5[200, 10]

Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

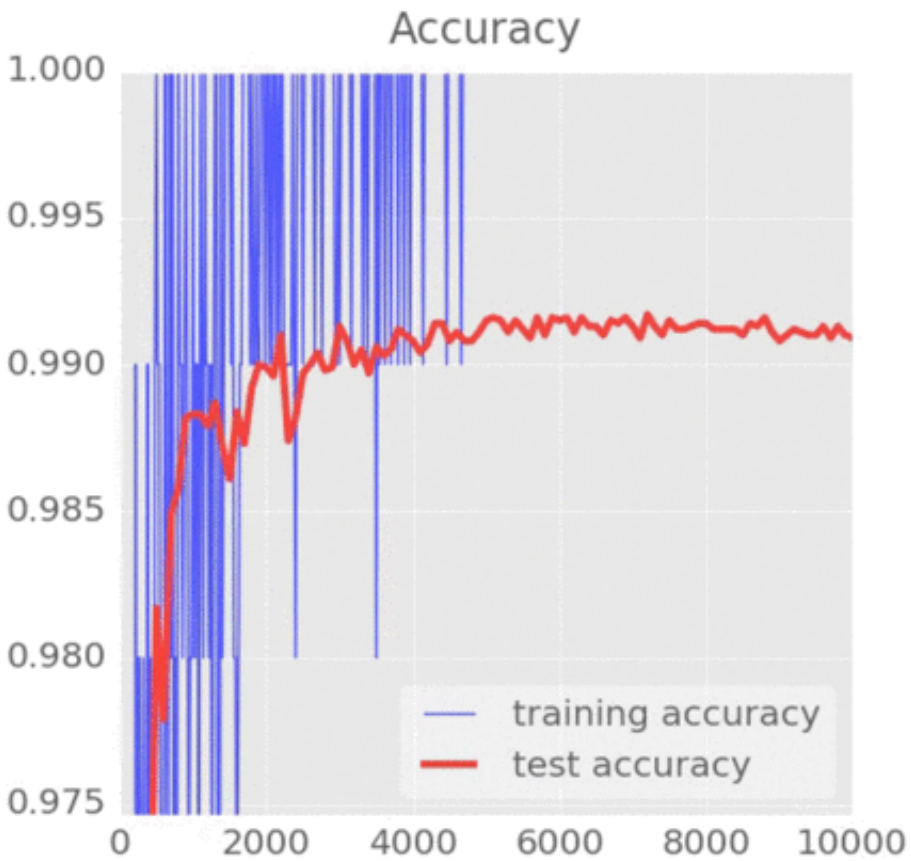
TensorFlow MNIST Tutorial

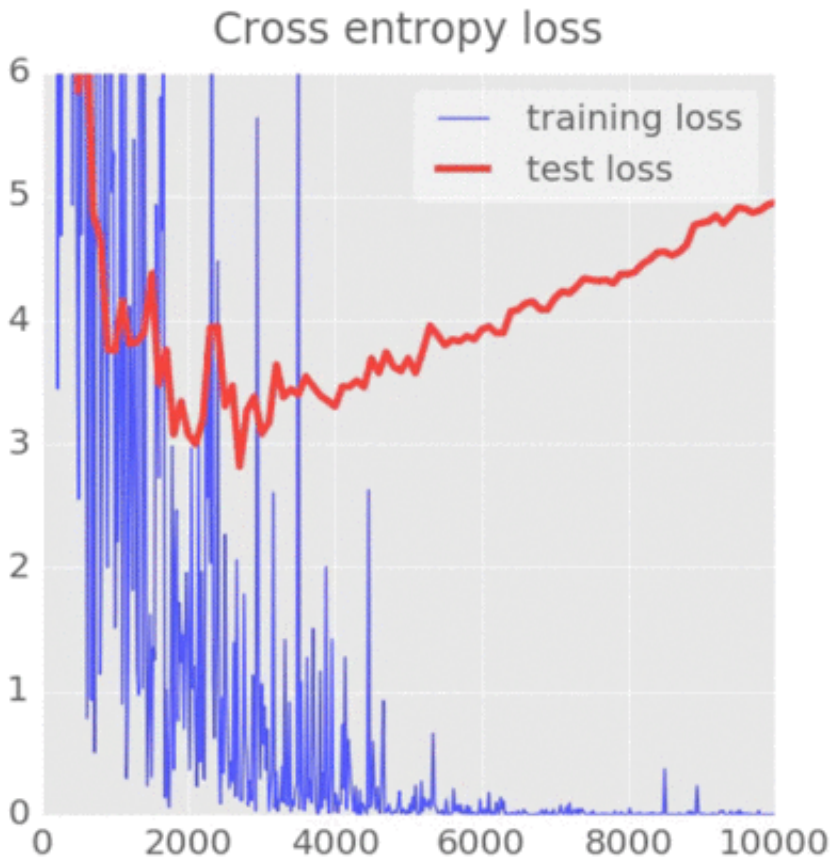


99.3%

Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

TensorFlow MNIST Tutorial

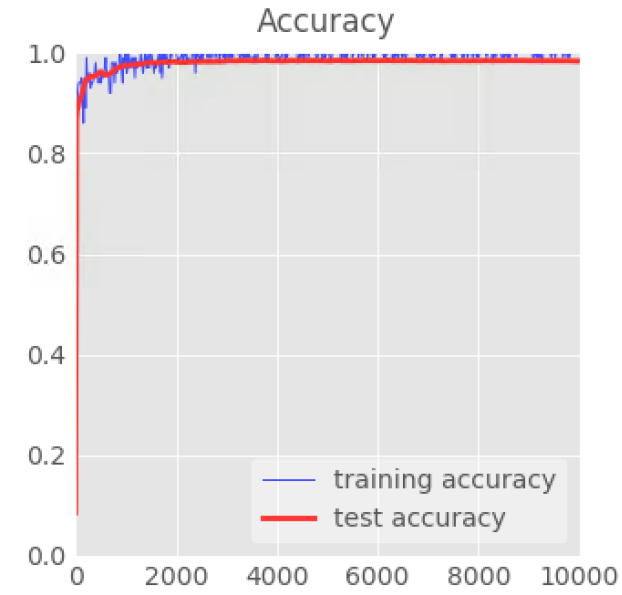


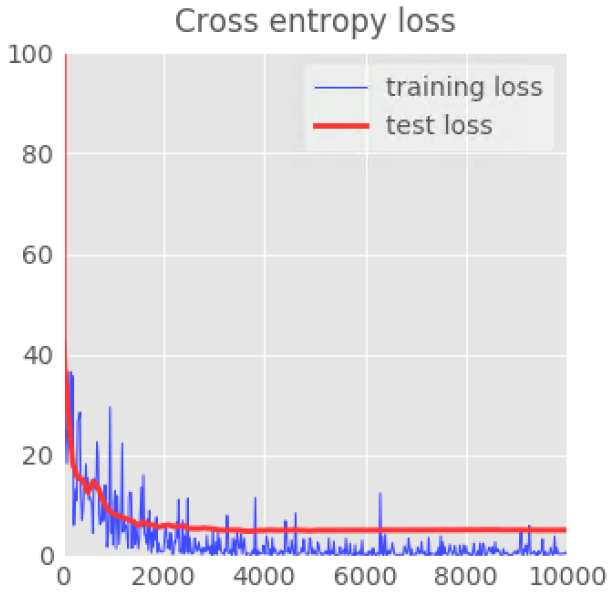


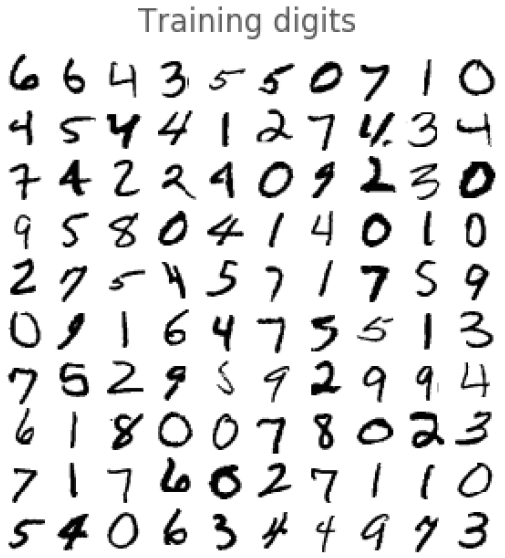
larger convolutional network

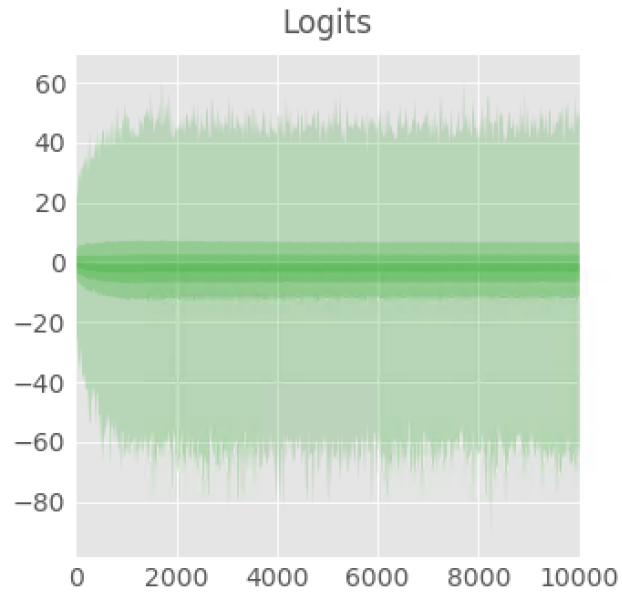
Source: https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/

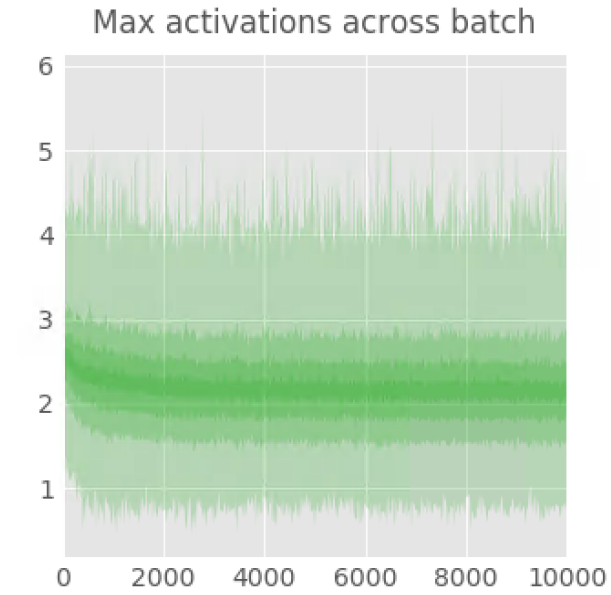
TensorFlow MNIST Tutorial

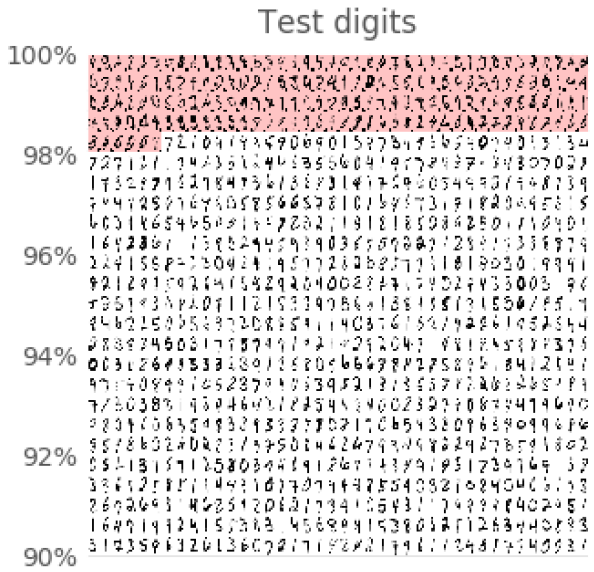












Source: https://github.com/martin-gorner/tensorflow-mnist-tutorial/

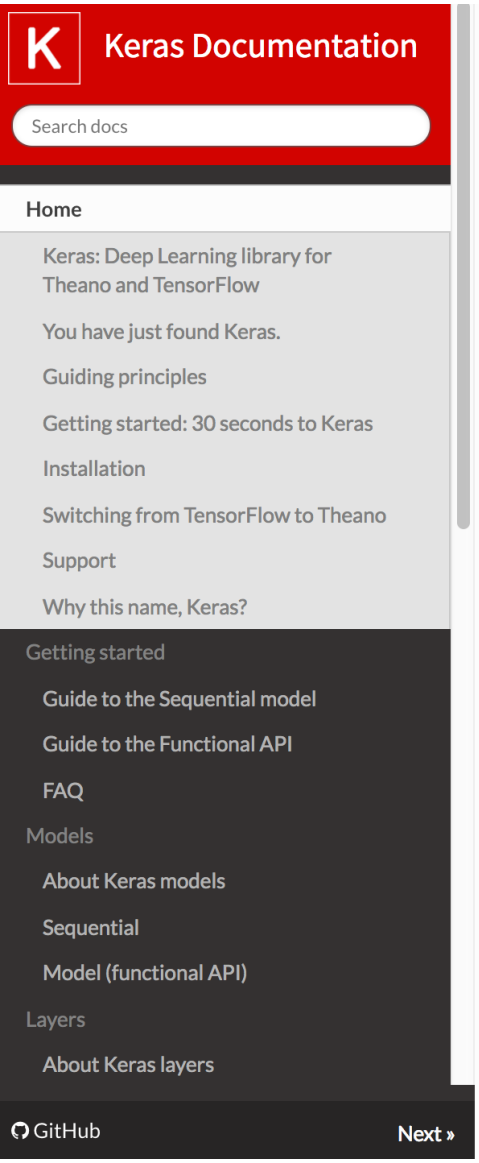
Keras

Keras

- Keras is a high-level neural networks API
- Written in Python and capable of running on top of either TensorFlow or Theano.
- It was developed with a focus on enabling fast experimentation.
- Being able to go from idea to result with the least possible delay is key to doing good research.

Source: https://keras.io/

Keras



Docs » Home

Edit on GitHub

Keras: Deep Learning library for Theano and TensorFlow

You have just found Keras.

Keras is a high-level neural networks API, written in Python and capable of running on top of either TensorFlow or Theano. It was developed with a focus on enabling fast experimentation. *Being able to go from idea to result with the least possible delay is key to doing good research.*

Use Keras if you need a deep learning library that:

- Allows for easy and fast prototyping (through user friendliness, modularity, and extensibility).
- Supports both convolutional networks and recurrent networks, as well as combinations of the two.
- Runs seamlessly on CPU and GPU.

Read the documentation at Keras.io.

Keras is compatible with: **Python 2.7-3.5**.

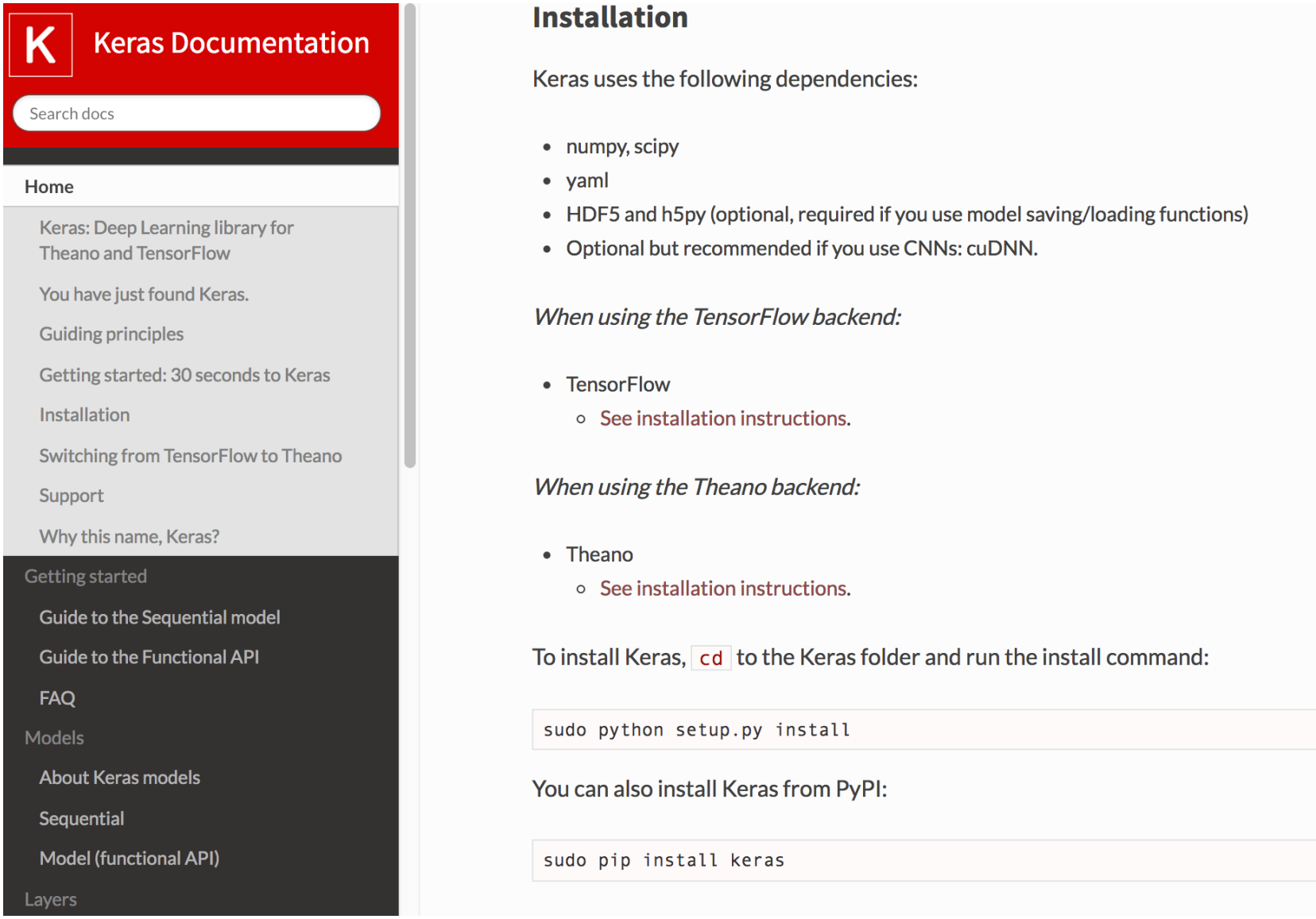
Guiding principles

- **User friendliness.** Keras is an API designed for human beings, not machines. It puts user experience front and center. Keras follows best practices for reducing cognitive load: it offers consistent & simple APIs, it minimizes the number of user actions required for common use cases, and it provides clear and actionable feedback upon user error.
- **Modularity.** A model is understood as a sequence or a graph of standalone, fully-configurable modules that can

http://keras.io/

Deep Learning with Keras

Keras Installation



https://keras.io/#installation

```
conda info --envs
```

```
conda --version
python --version
```

```
conda list
```

```
conda create -n tensorflow python=3.5
```

```
source activate tensorflow
```

```
activate tensorflow
```

Source: http://deeplearning.net/software/theano/install.html#anaconda

```
pip install Theano
```

```
conda install pydot
```

```
sudo pip install keras
```

```
pip install keras
```

```
pip install tensorflow
```

```
pip install ipython[all]
```

Source: http://deeplearning.net/software/theano/install.html#anaconda

Gensim

pip install -U gensim

```
bash-3.2$ pip install -U gensim
Collecting gensim
  Downloading gensim-2.0.0-cp36-cp36m-macosx_10_6_intel.macosx_10_9_intel.macosx_10_9_x8
6_64.macosx_10_10_intel.macosx_10_10_x86_64.whl (5.6MB)
    100% |████████████████████████████████| 5.6MB 126kB/s
Requirement already up-to-date: six>=1.5.0 in ./anaconda/lib/python3.6/site-packages (fr
om gensim)
Collecting scipy>=0.7.0 (from gensim)
  Downloading scipy-0.19.0-cp36-cp36m-macosx_10_6_intel.macosx_10_9_intel.macosx_10_9_x8
6_64.macosx_10_10_intel.macosx_10_10_x86_64.whl (16.2MB)
    100% |████████████████████████████████| 16.2MB 43kB/s
Collecting smart-open>=1.2.1 (from gensim)
  Downloading smart_open-1.5.2.tar.gz
Collecting numpy>=1.3 (from gensim)
  Downloading numpy-1.12.1-cp36-cp36m-macosx_10_6_intel.macosx_10_9_intel.macosx_10_9_x8
6_64.macosx_10_10_intel.macosx_10_10_x86_64.whl (4.4MB)
    100% |████████████████████████████████| 4.4MB 148kB/s
Collecting boto>=2.32 (from smart-open>=1.2.1->gensim)
  Downloading boto-2.46.1-py2.py3-none-any.whl (1.4MB)
    100% |████████████████████████████████| 1.4MB 372kB/s
Requirement already up-to-date: bz2file in ./anaconda/lib/python3.6/site-packages (from
smart-open>=1.2.1->gensim)
Collecting requests (from smart-open>=1.2.1->gensim)
  Downloading requests-2.13.0-py2.py3-none-any.whl (584kB)
    100% |████████████████████████████████| 593kB 632kB/s
Building wheels for collected packages: smart-open
  Running setup.py bdist_wheel for smart-open ... done
  Stored in directory: /Users/imyday/Library/Caches/pip/wheels/02/44/43/68e963ce2b45baef
a913a4e558bcd787403458afddffcf45ca
Successfully built smart-open
Installing collected packages: numpy, scipy, boto, requests, smart-open, gensim
  Found existing installation: numpy 1.11.3
    Uninstalling numpy-1.11.3:
      Successfully uninstalled numpy-1.11.3
  Found existing installation: scipy 0.18.1
    Uninstalling scipy-0.18.1:
      Successfully uninstalled scipy-0.18.1
  Found existing installation: boto 2.45.0
    DEPRECATION: Uninstalling a distutils installed project (boto) has been deprecated a
nd will be removed in a future version. This is due to the fact that uninstalling a dist
utils project will only partially uninstall the project.
    Uninstalling boto-2.45.0:
      Successfully uninstalled boto-2.45.0
  Found existing installation: requests 2.12.4
    Uninstalling requests-2.12.4:
      Successfully uninstalled requests-2.12.4
  Found existing installation: smart-open 1.4.0
    Uninstalling smart-open-1.4.0:
      Successfully uninstalled smart-open-1.4.0
  Found existing installation: gensim 1.0.1
    Uninstalling gensim-1.0.1:
      Successfully uninstalled gensim-1.0.1
Successfully installed boto-2.46.1 gensim-2.0.0 numpy-1.12.1 requests-2.13.0 scipy-0.19.
0 smart-open-1.5.2
bash-3.2$
```

Keras

sudo pip install keras

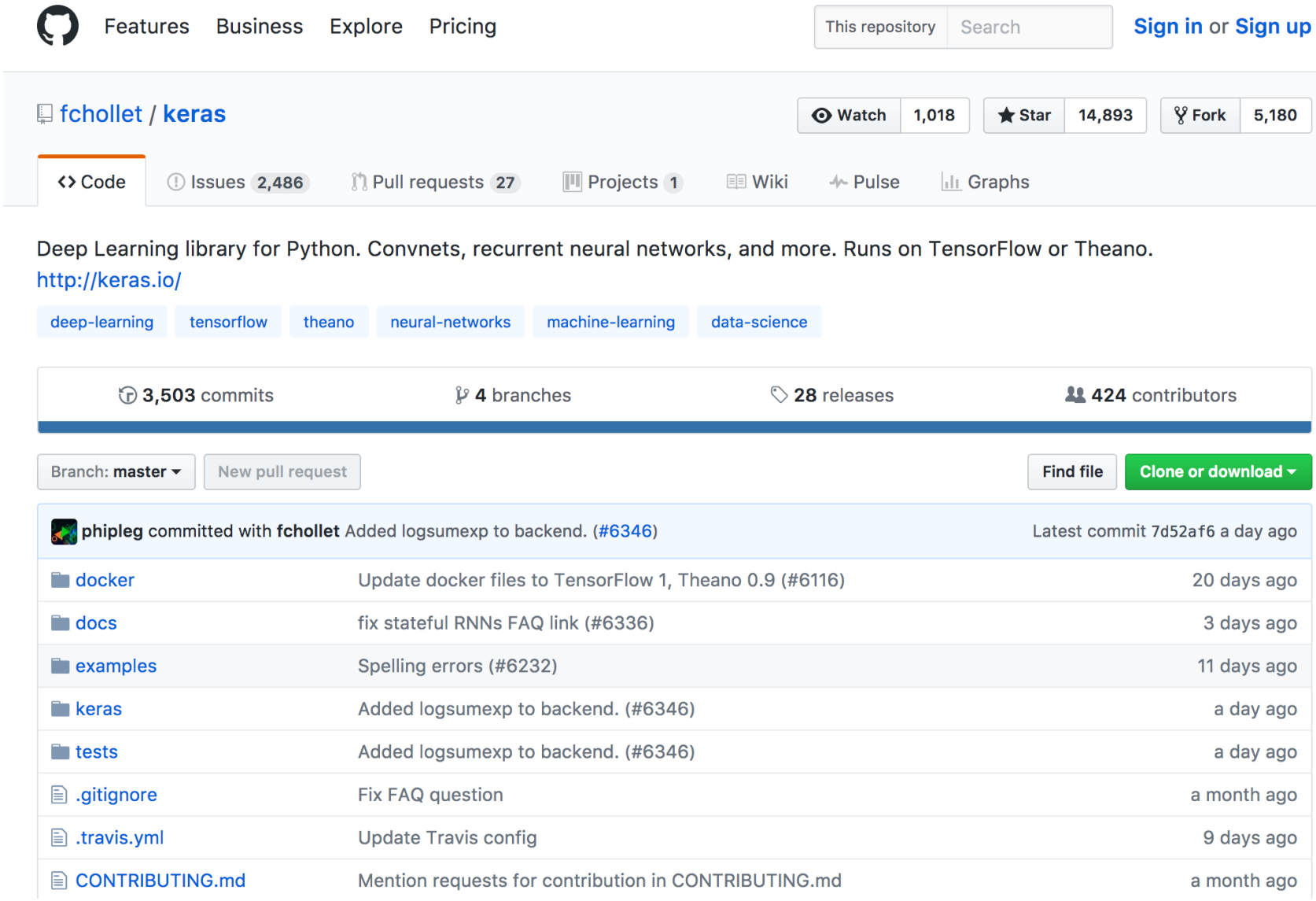
```
bash-3.2$ sudo pip install keras
Password:
The directory '/Users/imyday/Library/Caches/pip/http' or its parent directory is not owned by the current us
er and the cache has been disabled. Please check the permissions and owner of that directory. If executing p
ip with sudo, you may want sudo's -H flag.
The directory '/Users/imyday/Library/Caches/pip' or its parent directory is not owned by the current user an
d caching wheels has been disabled. check the permissions and owner of that directory. If executing pip with
 sudo, you may want sudo's -H flag.
Collecting keras
  Downloading Keras-2.0.3.tar.gz (196kB)
    100% |████████████████████████████████| 204kB 365kB/s
Collecting theano (from keras)
  Downloading Theano-0.9.0.tar.gz (3.1MB)
    100% |████████████████████████████████| 3.1MB 148kB/s
Requirement already satisfied: pyyaml in ./anaconda/lib/python3.6/site-packages (from keras)
Requirement already satisfied: six in ./anaconda/lib/python3.6/site-packages (from keras)
Requirement already satisfied: numpy>=1.9.1 in ./anaconda/lib/python3.6/site-packages (from theano->keras)
Requirement already satisfied: scipy>=0.14 in ./anaconda/lib/python3.6/site-packages (from theano->keras)
Installing collected packages: theano, keras
  Running setup.py install for theano ... done
  Running setup.py install for keras ... done
Successfully installed keras-2.0.3 theano-0.9.0
bash-3.2$
```

TensorFlow

pip install tensorflow

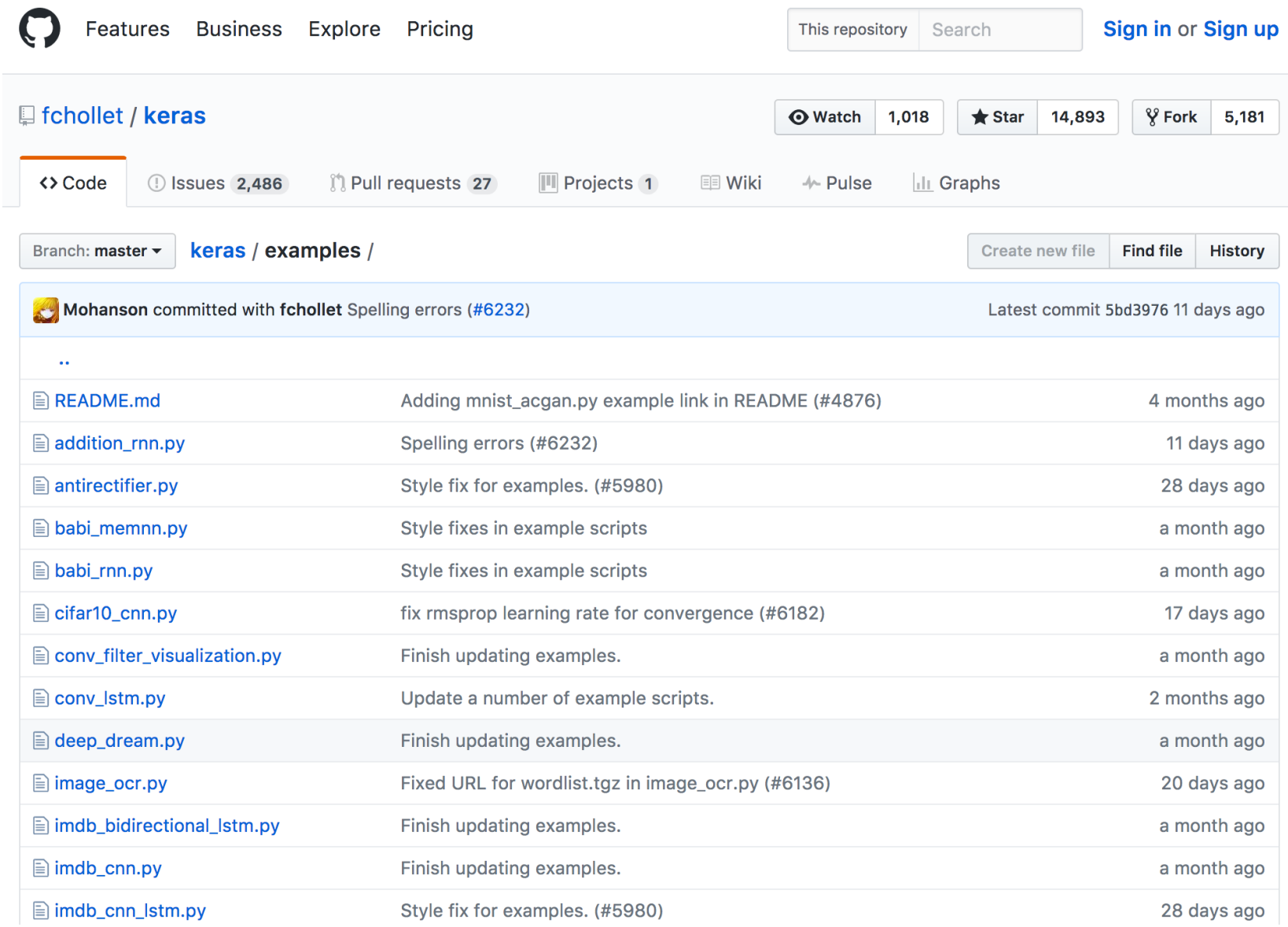
```
bash-3.2$ pip install tensorflow
Collecting tensorflow
  Downloading tensorflow-1.1.0-cp36-cp36m-macosx_10_11_x86_64.whl (31.3MB)
    100% |████████████████████████████████| 31.3MB 23kB/s
Requirement already satisfied: wheel>=0.26 in ./anaconda/lib/python3.6/site-packages (from tensorflow)
Requirement already satisfied: six>=1.10.0 in ./anaconda/lib/python3.6/site-packages (from tensorflow)
Collecting protobuf>=3.2.0 (from tensorflow)
  Downloading protobuf-3.2.0-py2.py3-none-any.whl (360kB)
    100% |████████████████████████████████| 368kB 453kB/s
Requirement already satisfied: werkzeug>=0.11.10 in ./anaconda/lib/python3.6/site-packages (from tensorflow)
Requirement already satisfied: numpy>=1.11.0 in ./anaconda/lib/python3.6/site-packages (from tensorflow)
Requirement already satisfied: setuptools in ./anaconda/lib/python3.6/site-packages/setuptools-27.2.0-py3.6.
egg (from protobuf>=3.2.0->tensorflow)
Installing collected packages: protobuf, tensorflow
Successfully installed protobuf-3.2.0 tensorflow-1.1.0
bash-3.2$
```

Keras Github



https://github.com/fchollet/keras

Keras Examples



https://github.com/fchollet/keras/tree/master/examples

Keras MINST CNN

localhost:8888/notebooks/Documents/SCDBA/DL/Keras_mnist_cnn.ipynb

jupyter Keras_mnist_cnn Last Checkpoint: an hour ago (autosaved) Logout

File Edit View Insert Cell Kernel Widgets Help Python 3

Code CellToolbar

```
from __future__ import print_function
import keras
from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D
from keras import backend as K

batch_size = 128
num_classes = 10
epochs = 12

# input image dimensions
img_rows, img_cols = 28, 28

# the data, shuffled and split between train and test sets
(x_train, y_train), (x_test, y_test) = mnist.load_data()

if K.image_data_format() == 'channels_first':
    x_train = x_train.reshape(x_train.shape[0], 1, img_rows, img_cols)
    x_test = x_test.reshape(x_test.shape[0], 1, img_rows, img_cols)
    input_shape = (1, img_rows, img_cols)
else:
    x_train = x_train.reshape(x_train.shape[0], img_rows, img_cols, 1)
    x_test = x_test.reshape(x_test.shape[0], img_rows, img_cols, 1)
    input_shape = (img_rows, img_cols, 1)

x_train = x_train.astype('float32')
x_test = x_test.astype('float32')
x_train /= 255
x_test /= 255
print('x_train shape:', x_train.shape)
print(x_train.shape[0], 'train samples')
print(x_test.shape[0], 'test samples')
```

Source: https://github.com/fchollet/keras/blob/master/examples/mnist_cnn.py

Keras MINST CNN

localhost:8888/notebooks/Documents/SCDBA/DL/Keras_mnist_cnn.ipynb

jupyter Keras_mnist_cnn Last Checkpoint: an hour ago (autosaved) Logout

File Edit View Insert Cell Kernel Widgets Help Python 3

Code CellToolbar

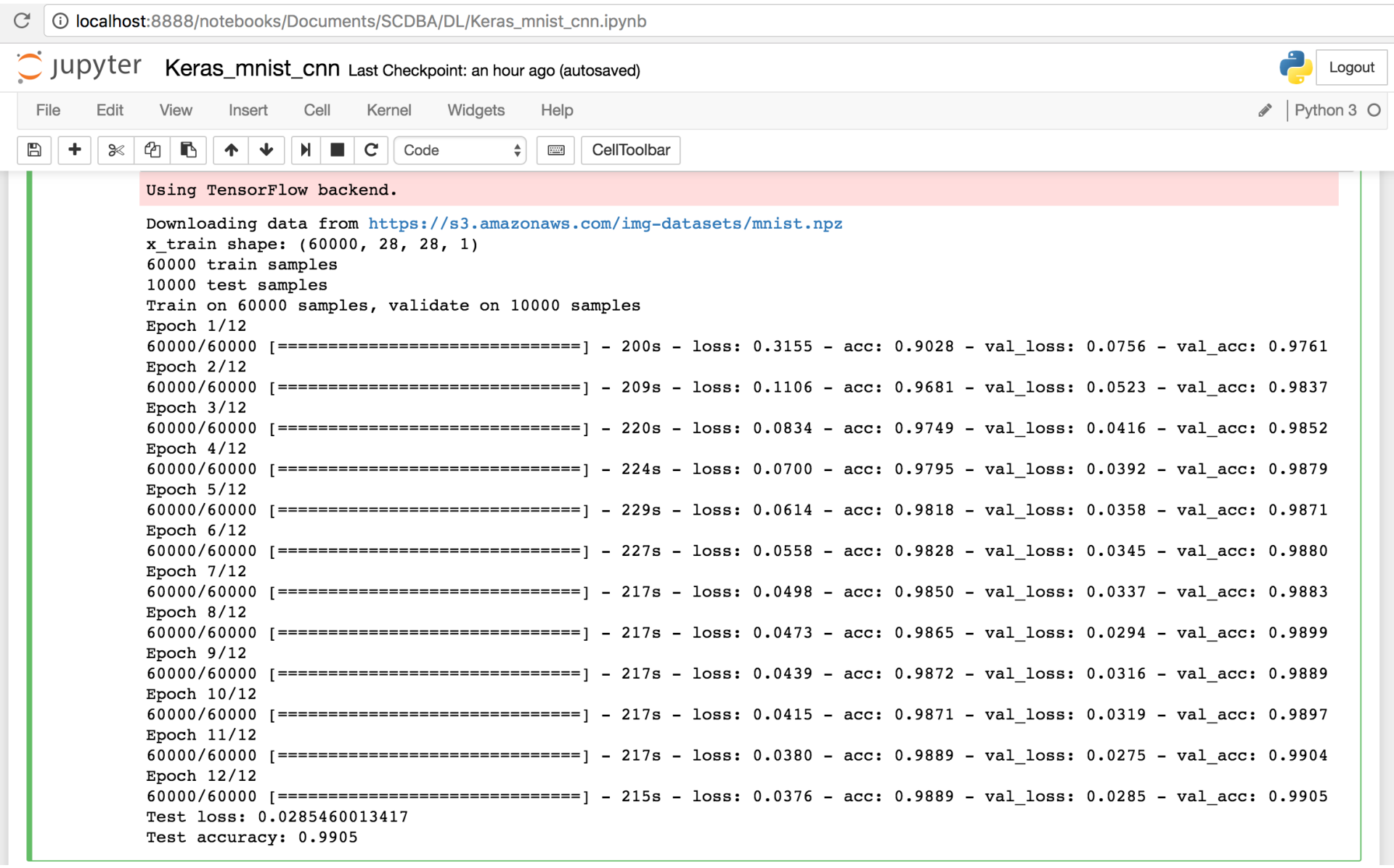
```
# convert class vectors to binary class matrices
y_train = keras.utils.to_categorical(y_train, num_classes)
y_test = keras.utils.to_categorical(y_test, num_classes)

model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3),
                 activation='relu',
                 input_shape=input_shape))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes, activation='softmax'))

model.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adadelta(),
              metrics=['accuracy'])

model.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=epochs,
          verbose=1,
          validation_data=(x_test, y_test))
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Using TensorFlow backend.
```

```
Downloading data from https://s3.amazonaws.com/img-datasets/mnist.npz
x_train shape: (60000, 28, 28, 1)
60000 train samples
10000 test samples
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
```

Source: https://github.com/fchollet/keras/blob/master/examples/mnist_cnn.py

Keras MINST CNN



Source: https://github.com/fchollet/keras/blob/master/examples/mnist_cnn.py

Keras MINST CNN

```
from __future__ import print_function
import keras
from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D
from keras import backend as K

batch_size = 128
num_classes = 10
epochs = 12

# input image dimensions
img_rows, img_cols = 28, 28

# the data, shuffled and split between train and test sets
(x_train, y_train), (x_test, y_test) = mnist.load_data()

if K.image_data_format() == 'channels_first':
    x_train = x_train.reshape(x_train.shape[0], 1, img_rows, img_cols)
    x_test = x_test.reshape(x_test.shape[0], 1, img_rows, img_cols)
    input_shape = (1, img_rows, img_cols)
else:
    x_train = x_train.reshape(x_train.shape[0], img_rows, img_cols, 1)
    x_test = x_test.reshape(x_test.shape[0], img_rows, img_cols, 1)
    input_shape = (img_rows, img_cols, 1)

x_train = x_train.astype('float32')
x_test = x_test.astype('float32')
x_train /= 255
x_test /= 255
print('x_train shape:', x_train.shape)
print(x_train.shape[0], 'train samples')
print(x_test.shape[0], 'test samples')

# convert class vectors to binary class matrices
y_train = keras.utils.to_categorical(y_train, num_classes)
y_test = keras.utils.to_categorical(y_test, num_classes)

model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3),
                 activation='relu',
                 input_shape=input_shape))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes, activation='softmax'))

model.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adadelta(),
              metrics=['accuracy'])

model.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=epochs,
          verbose=1,
          validation_data=(x_test, y_test))
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

Source: https://github.com/fchollet/keras/blob/master/examples/mnist_cnn.py

Keras MINST CNN

```
from __future__ import print_function
import keras
from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D
from keras import backend as K
```

Source: https://github.com/fchollet/keras/blob/master/examples/mnist_cnn.py

Keras MINST CNN

```
batch_size = 128
num_classes = 10
epochs = 12

# input image dimensions
img_rows, img_cols = 28, 28

# the data, shuffled and split between train and test sets
(x_train, y_train), (x_test, y_test) = mnist.load_data()

if K.image_data_format() == 'channels_first':
    x_train = x_train.reshape(x_train.shape[0], 1, img_rows, img_cols)
    x_test = x_test.reshape(x_test.shape[0], 1, img_rows, img_cols)
    input_shape = (1, img_rows, img_cols)
else:
    x_train = x_train.reshape(x_train.shape[0], img_rows, img_cols, 1)
    x_test = x_test.reshape(x_test.shape[0], img_rows, img_cols, 1)
    input_shape = (img_rows, img_cols, 1)
```

Source: https://github.com/fchollet/keras/blob/master/examples/mnist_cnn.py

Keras MINST CNN

```
x_train = x_train.astype('float32')
x_test = x_test.astype('float32')
x_train /= 255
x_test /= 255
print('x_train shape:', x_train.shape)
print(x_train.shape[0], 'train samples')
print(x_test.shape[0], 'test samples')

# convert class vectors to binary class matrices
y_train = keras.utils.to_categorical(y_train, num_classes)
y_test = keras.utils.to_categorical(y_test, num_classes)
```

Source: https://github.com/fchollet/keras/blob/master/examples/mnist_cnn.py

Keras MINST CNN

```
model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3),
                 activation='relu',
                 input_shape=input_shape))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes, activation='softmax'))

model.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adadelta(),
              metrics=['accuracy'])
```

Source: https://github.com/fchollet/keras/blob/master/examples/mnist_cnn.py

Keras MINST CNN

```
model.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=epochs,
          verbose=1,
          validation_data=(x_test, y_test))
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

Source: https://github.com/fchollet/keras/blob/master/examples/mnist_cnn.py

Keras MINST CNN

```
python mnist_cnn.py
Using TensorFlow backend.
Downloading data from https://s3.amazonaws.com/img-datasets/mnist.npz
x_train shape: (60000, 28, 28, 1)
60000 train samples
10000 test samples
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [==============================] - 108s - loss: 0.3510 - acc: 0.8921 - val_loss: 0.0880 - val_acc: 0.9738
Epoch 2/12
60000/60000 [==============================] - 106s - loss: 0.1200 - acc: 0.9649 - val_loss: 0.0567 - val_acc: 0.9820
Epoch 3/12
60000/60000 [==============================] - 104s - loss: 0.0889 - acc: 0.9735 - val_loss: 0.0438 - val_acc: 0.9856
Epoch 4/12
60000/60000 [==============================] - 106s - loss: 0.0744 - acc: 0.9783 - val_loss: 0.0392 - val_acc: 0.9862
Epoch 5/12
60000/60000 [==============================] - 106s - loss: 0.0648 - acc: 0.9807 - val_loss: 0.0363 - val_acc: 0.9873
Epoch 6/12
60000/60000 [==============================] - 109s - loss: 0.0574 - acc: 0.9840 - val_loss: 0.0348 - val_acc: 0.9884
Epoch 7/12
60000/60000 [==============================] - 104s - loss: 0.0522 - acc: 0.9842 - val_loss: 0.0324 - val_acc: 0.9890
Epoch 8/12
60000/60000 [==============================] - 104s - loss: 0.0484 - acc: 0.9856 - val_loss: 0.0315 - val_acc: 0.9894
Epoch 9/12
60000/60000 [==============================] - 104s - loss: 0.0447 - acc: 0.9870 - val_loss: 0.0296 - val_acc: 0.9902
Epoch 10/12
60000/60000 [==============================] - 109s - loss: 0.0419 - acc: 0.9877 - val_loss: 0.0338 - val_acc: 0.9894
Epoch 11/12
60000/60000 [==============================] - 104s - loss: 0.0405 - acc: 0.9879 - val_loss: 0.0301 - val_acc: 0.9896
Epoch 12/12
60000/60000 [==============================] - 127s - loss: 0.0391 - acc: 0.9883 - val_loss: 0.0304 - val_acc: 0.9899
Test loss: 0.030424870987
Test accuracy: 0.9899
```

IMDB
Large Movie Review Dataset

- This is a dataset for binary sentiment classification containing substantially more data than previous benchmark datasets.
- We provide a set of 25,000 highly polar movie reviews for training, and 25,000 for testing.
- There is additional unlabeled data for use as well.
- Raw text and already processed bag of words formats are provided.
- Large Movie Review Dataset v1.0
  - http://ai.stanford.edu/~amaas/data/sentiment/aclImdb_v1.tar.gz

Source: http://ai.stanford.edu/~amaas/data/sentiment/

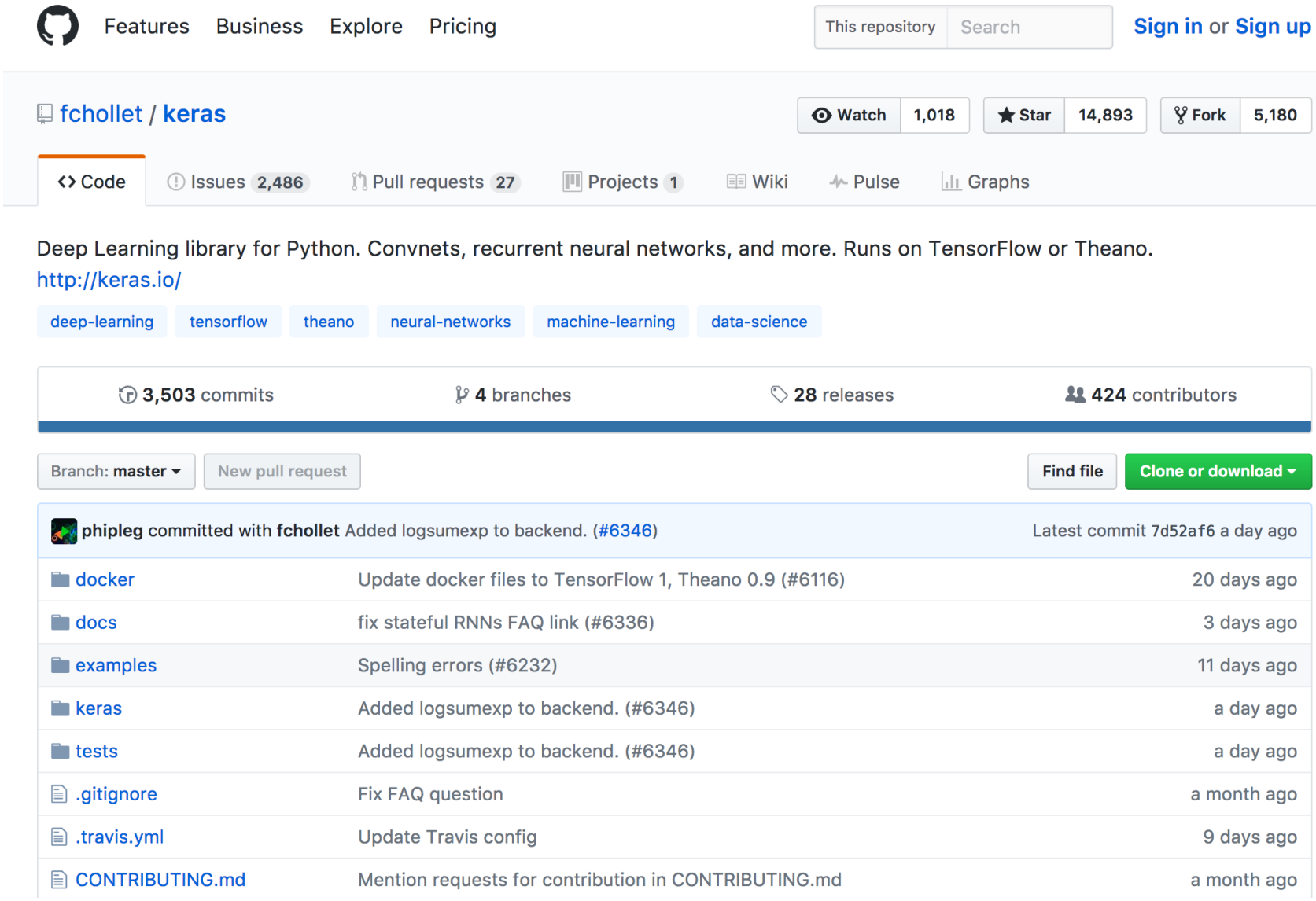
IMDB Dataset (Mass et al., 2011)

Features	PL04	Our Dataset	Subjectivity
Bag of Words (bnc)	85.45	87.80	87.77
Bag of Words (bΔt'c)	85.80	88.23	85.65
LDA	66.70	67.42	66.65
LSA	84.55	83.96	82.82
Our Semantic Only	87.10	87.30	86.65
Our Full	84.65	87.44	86.19
Our Full, Additional Unlabeled	87.05	87.99	87.22
Our Semantic + Bag of Words (bnc)	88.30	88.28	88.58
Our Full + Bag of Words (bnc)	87.85	88.33	88.45
Our Full, Add'l Unlabeled + Bag of Words (bnc)	88.90	88.89	88.13
Bag of Words SVM (Pang and Lee, 2004)	87.15	N/A	90.00
Contextual Valence Shifters (Kennedy and Inkpen, 2006)	86.20	N/A	N/A
tf.Δidf Weighting (Martineau and Finin, 2009)	88.10	N/A	N/A
Appraisal Taxonomy (Whitelaw et al., 2005)	90.20	N/A	N/A

Table 2: Classification accuracy on three tasks. From left to right the datasets are: A collection of 2,000 movie reviews often used as a benchmark of sentiment classification (Pang and Lee, 2004), 50,000 reviews we gathered from IMDB, and the sentence subjectivity dataset also released by (Pang and Lee, 2004). All tasks are balanced two-class problems.

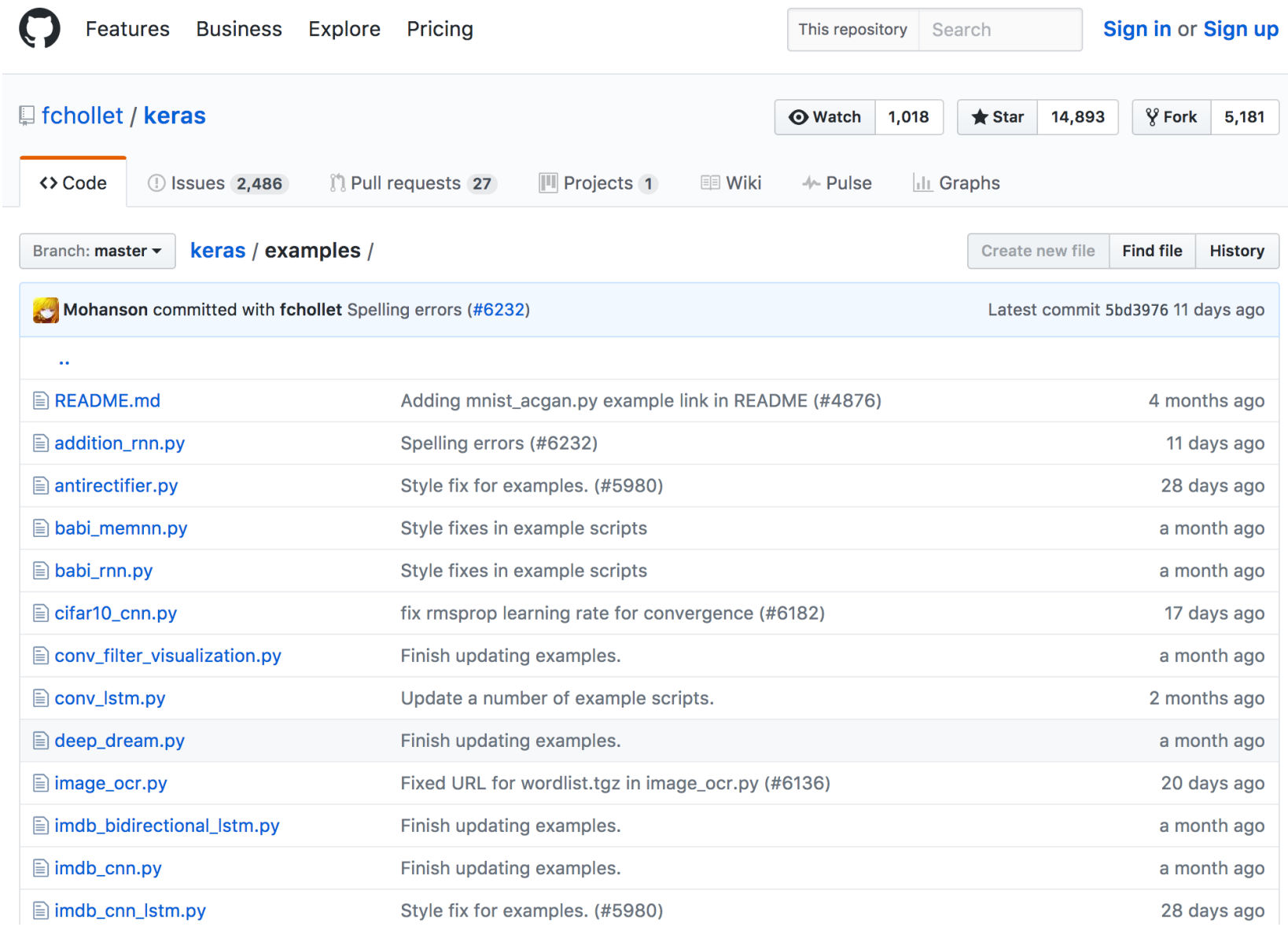
Source: Andrew L. Maas, Raymond E. Daly, Peter T. Pham, Dan Huang, Andrew Y. Ng, and Christopher Potts. (2011). Learning Word Vectors for Sentiment Analysis. *The 49th Annual Meeting of the Association for Computational Linguistics (ACL 2011)*

Keras Github



https://github.com/fchollet/keras

Keras Examples



https://github.com/fchollet/keras/tree/master/examples

Keras Examples

- imdb_bidirectional_lstm.py Trains a Bidirectional LSTM on the IMDB sentiment classification task.
- imdb_cnn.py Demonstrates the use of Convolution1D for text classification.
- imdb_cnn_lstm.py Trains a convolutional stack followed by a recurrent stack network on the IMDB sentiment classification task.
- imdb_fasttext.py Trains a FastText model on the IMDB sentiment classification task.
- imdb_lstm.py Trains a LSTM on the IMDB sentiment classification task.
- lstm_benchmark.py Compares different LSTM implementations on the IMDB sentiment classification task.
- lstm_text_generation.py Generates text from Nietzsche's writings.

Source: https://github.com/fchollet/keras/tree/master/examples

Keras IMDB Movie reviews sentiment classification

- Dataset of 25,000 movies reviews from IMDB, labeled by sentiment (positive/negative).
- Reviews have been preprocessed, and each review is encoded as a sequence of word indexes (integers).
- For convenience, words are indexed by overall frequency in the dataset, so that for instance the integer "3" encodes the 3rd most frequent word in the data.
- This allows for quick filtering operations such as: "only consider the top 10,000 most common words, but eliminate the top 20 most common words".
- As a convention, "0" does not stand for a specific word, but instead is used to encode any unknown word.

Source: https://keras.io/datasets/

Keras IMDB load_data

```
def load_data(path='imdb.npz',
              num_words=None,
              skip_top=0,
              maxlen=None,
              seed=113,
              start_char=1,
              oov_char=2,
              index_from=3):
  path = get_file(
      path, origin='https://s3.amazonaws.com/text-datasets/imdb.npz')
  f = np.load(path)
  x_train = f['x_train']
  labels_train = f['y_train']
  x_test = f['x_test']
  labels_test = f['y_test']
  f.close()
```

Source: keras/datasets/imdb.py

Keras IMDB get_word_index

```
def get_word_index(path='imdb_word_index.json'):
  path = get_file(
      path,
      origin='https://s3.amazonaws.com/text-datasets/imdb_word_index.json')
  f = open(path)
  data = json.load(f)
  f.close()
  return data
```

Source: keras/datasets/imdb.py

Keras IMDB CNN

localhost:8888/notebooks/Documents/SCDBA/DL/Keras_imdb_cnn.ipynb

jupyter Keras_imdb_cnn Last Checkpoint: 15 minutes ago (unsaved changes) Logout

File Edit View Insert Cell Kernel Widgets Help Python 3

Code CellToolbar

```
from __future__ import print_function
from keras.preprocessing import sequence
from keras.models import Sequential
from keras.layers import Dense, Dropout, Activation
from keras.layers import Embedding
from keras.layers import Conv1D, GlobalMaxPooling1D
from keras.datasets import imdb

# set parameters:
max_features = 5000
maxlen = 400
batch_size = 32
embedding_dims = 50
filters = 250
kernel_size = 3
hidden_dims = 250
epochs = 2

print('Loading data...')
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=max_features)
print(len(x_train), 'train sequences')
print(len(x_test), 'test sequences')

print('Pad sequences (samples x time)')
x_train = sequence.pad_sequences(x_train, maxlen=maxlen)
x_test = sequence.pad_sequences(x_test, maxlen=maxlen)
print('x_train shape:', x_train.shape)
print('x_test shape:', x_test.shape)

print('Build model...')
model = Sequential()

# we start off with an efficient embedding layer which maps
# our vocab indices into embedding_dims dimensions
model.add(Embedding(max_features,
                    embedding_dims,
```

Source: https://github.com/fchollet/keras/blob/master/examples/imdb_cnn.py

Keras IMDB CNN

localhost:8888/notebooks/Documents/SCDBA/DL/Keras_imdb_cnn.ipynb

jupyter Keras_imdb_cnn Last Checkpoint: 19 minutes ago (autosaved) Logout

File Edit View Insert Cell Kernel Widgets Help Python 3

Code CellToolbar

```
model.add(Embedding(max_features,
                    embedding_dims,
                    input_length=maxlen))
model.add(Dropout(0.2))

# we add a Convolution1D, which will learn filters
# word group filters of size filter_length:
model.add(Conv1D(filters,
                 kernel_size,
                 padding='valid',
                 activation='relu',
                 strides=1))
# we use max pooling:
model.add(GlobalMaxPooling1D())

# We add a vanilla hidden layer:
model.add(Dense(hidden_dims))
model.add(Dropout(0.2))
model.add(Activation('relu'))

# We project onto a single unit output layer, and squash it with a sigmoid:
model.add(Dense(1))
model.add(Activation('sigmoid'))

model.compile(loss='binary_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
model.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=epochs,
          validation_data=(x_test, y_test))
```

```
Using TensorFlow backend.
```

```
Loading data...
Downloading data from https://s3.amazonaws.com/text-datasets/imdb.npz
25000 train sequences
```

Source: https://github.com/fchollet/keras/blob/master/examples/imdb_cnn.py

Keras IMDB CNN

localhost:8888/notebooks/Documents/SCDBA/DL/Keras_imdb_cnn.ipynb

jupyter Keras_imdb_cnn Last Checkpoint: 13 minutes ago (autosaved) Logout

File Edit View Insert Cell Kernel Widgets Help Python 3

Code CellToolbar

```
# we use max pooling:
model.add(GlobalMaxPooling1D())

# We add a vanilla hidden layer:
model.add(Dense(hidden_dims))
model.add(Dropout(0.2))
model.add(Activation('relu'))

# We project onto a single unit output layer, and squash it with a sigmoid:
model.add(Dense(1))
model.add(Activation('sigmoid'))

model.compile(loss='binary_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
model.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=epochs,
          validation_data=(x_test, y_test))
```

```
Using TensorFlow backend.
```

```
Loading data...
Downloading data from https://s3.amazonaws.com/text-datasets/imdb.npz
25000 train sequences
25000 test sequences
Pad sequences (samples x time)
x_train shape: (25000, 400)
x_test shape: (25000, 400)
Build model...
Train on 25000 samples, validate on 25000 samples
Epoch 1/2
25000/25000 [==============================] - 266s - loss: 0.4110 - acc: 0.8012 - val_loss: 0.2965 - val_acc: 0.8739
Epoch 2/2
25000/25000 [==============================] - 286s - loss: 0.2429 - acc: 0.9020 - val_loss: 0.2726 - val_acc: 0.8862
```

Out[1]: <keras.callbacks.History at 0x11dc37b00>

Source: https://github.com/fchollet/keras/blob/master/examples/imdb_cnn.py

Keras IMDB CNN

```
python imdb_cnn.py
Using TensorFlow backend.
Loading data...
Downloading data from https://s3.amazonaws.com/text-datasets/imdb.npz
25000 train sequences
25000 test sequences
Pad sequences (samples x time)
x_train shape: (25000, 400)
x_test shape: (25000, 400)
Build model...
Train on 25000 samples, validate on 25000 samples
Epoch 1/2
25000/25000 [==============================] - 157s - loss: 0.4050 - acc: 0.8065 - val_loss: 0.2924 - val_acc: 0.8750
Epoch 2/2
25000/25000 [==============================] - 128s - loss: 0.2433 - acc: 0.9040 - val_loss: 0.2701 - val_acc: 0.8865
Exception ignored in: <bound method BaseSession.__del__ of <tensorflow.python.client.session.Session object at 0x0000019F153C2A20>>
Traceback (most recent call last):
  File "C:\Program Files\Anaconda3\lib\site-packages\tensorflow\python\client\session.py", line 587, in __del__
AttributeError: 'NoneType' object has no attribute 'TF_NewStatus'
```

Source: https://github.com/fchollet/keras/blob/master/examples/imdb_cnn.py

Keras IMDB LSTM

```
from __future__ import print_function
from keras.preprocessing import sequence
from keras.models import Sequential
from keras.layers import Dense, Embedding
from keras.layers import LSTM
from keras.datasets import imdb

max_features = 20000
maxlen = 80  # cut texts after this number of words (among top max_features most common words)
batch_size = 32

print('Loading data...')
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=max_features)
print(len(x_train), 'train sequences')
print(len(x_test), 'test sequences')

print('Pad sequences (samples x time)')
x_train = sequence.pad_sequences(x_train, maxlen=maxlen)
x_test = sequence.pad_sequences(x_test, maxlen=maxlen)
print('x_train shape:', x_train.shape)
print('x_test shape:', x_test.shape)

print('Build model...')
model = Sequential()
model.add(Embedding(max_features, 128))
model.add(LSTM(128, dropout=0.2, recurrent_dropout=0.2))
model.add(Dense(1, activation='sigmoid'))

# try using different optimizers and different optimizer configs
model.compile(loss='binary_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])

print('Train...')
model.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=15,
          validation_data=(x_test, y_test))
score, acc = model.evaluate(x_test, y_test,
                            batch_size=batch_size)
print('Test score:', score)
print('Test accuracy:', acc)
```

Source: https://github.com/fchollet/keras/blob/master/examples/imdb_lstm.py

Keras IMDB LSTM

```
from __future__ import print_function
from keras.preprocessing import sequence
from keras.models import Sequential
from keras.layers import Dense, Embedding
from keras.layers import LSTM
from keras.datasets import imdb
```

Source: https://github.com/fchollet/keras/blob/master/examples/imdb_lstm.py

Keras IMDB LSTM

```
max_features = 20000
maxlen = 80  # cut texts after this number of words (among top
max_features most common words)
batch_size = 32

print('Loading data...')
(x_train, y_train), (x_test, y_test) =
imdb.load_data(num_words=max_features)
print(len(x_train), 'train sequences')
print(len(x_test), 'test sequences')

print('Pad sequences (samples x time)')
x_train = sequence.pad_sequences(x_train, maxlen=maxlen)
x_test = sequence.pad_sequences(x_test, maxlen=maxlen)
print('x_train shape:', x_train.shape)
print('x_test shape:', x_test.shape)
```

Source: https://github.com/fchollet/keras/blob/master/examples/imdb_lstm.py

Keras IMDB LSTM

```
print('Build model...')
model = Sequential()
model.add(Embedding(max_features, 128))
model.add(LSTM(128, dropout=0.2, recurrent_dropout=0.2))
model.add(Dense(1, activation='sigmoid'))

# try using different optimizers and different optimizer configs
model.compile(loss='binary_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```

Source: https://github.com/fchollet/keras/blob/master/examples/imdb_lstm.py

Keras IMDB LSTM

```
print('Train...')
model.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=15,
          validation_data=(x_test, y_test))
score, acc = model.evaluate(x_test, y_test,

batch_size=batch_size)
print('Test score:', score)
print('Test accuracy:', acc)
```

Source: https://github.com/fchollet/keras/blob/master/examples/imdb_lstm.py

Keras IMDB LSTM

```
python imdb_lstm.py
Using TensorFlow backend.
Loading data...
25000 train sequences
25000 test sequences
Pad sequences (samples x time)
x_train shape: (25000, 80)
x_test shape: (25000, 80)
Build model...
Train...
Train on 25000 samples, validate on 25000 samples
Epoch 1/15
25000/25000 [==============================] - 111s - loss: 0.4561 - acc: 0.7837 - val_loss: 0.3892 - val_acc: 0.8275
Epoch 2/15
25000/25000 [==============================] - 112s - loss: 0.2947 - acc: 0.8792 - val_loss: 0.4266 - val_acc: 0.8353
Epoch 3/15
25000/25000 [==============================] - 111s - loss: 0.2122 - acc: 0.9178 - val_loss: 0.4133 - val_acc: 0.8284
Epoch 4/15
25000/25000 [==============================] - 112s - loss: 0.1461 - acc: 0.9450 - val_loss: 0.4670 - val_acc: 0.8260
Epoch 5/15
25000/25000 [==============================] - 113s - loss: 0.1038 - acc: 0.9633 - val_loss: 0.5580 - val_acc: 0.8203
Epoch 6/15
25000/25000 [==============================] - 113s - loss: 0.0739 - acc: 0.9749 - val_loss: 0.6738 - val_acc: 0.8174
Epoch 7/15
25000/25000 [==============================] - 113s - loss: 0.0542 - acc: 0.9810 - val_loss: 0.7463 - val_acc: 0.8154
Epoch 8/15
25000/25000 [==============================] - 113s - loss: 0.0428 - acc: 0.9856 - val_loss: 0.8131 - val_acc: 0.8157
Epoch 9/15
25000/25000 [==============================] - 115s - loss: 0.0334 - acc: 0.9889 - val_loss: 0.8566 - val_acc: 0.8165
Epoch 10/15
25000/25000 [==============================] - 114s - loss: 0.0248 - acc: 0.9920 - val_loss: 0.9186 - val_acc: 0.8165
Epoch 11/15
25000/25000 [==============================] - 116s - loss: 0.0156 - acc: 0.9955 - val_loss: 0.9016 - val_acc: 0.8082
Epoch 12/15
25000/25000 [==============================] - 117s - loss: 0.0196 - acc: 0.9942 - val_loss: 0.9720 - val_acc: 0.8124
Epoch 13/15
25000/25000 [==============================] - 120s - loss: 0.0152 - acc: 0.9957 - val_loss: 1.0064 - val_acc: 0.8148
Epoch 14/15
25000/25000 [==============================] - 121s - loss: 0.0128 - acc: 0.9961 - val_loss: 1.1103 - val_acc: 0.8121
Epoch 15/15
25000/25000 [==============================] - 114s - loss: 0.0110 - acc: 0.9970 - val_loss: 1.0173 - val_acc: 0.8132
25000/25000 [==============================] - 23s
Test score: 1.01734088922
Test accuracy: 0.8132
```

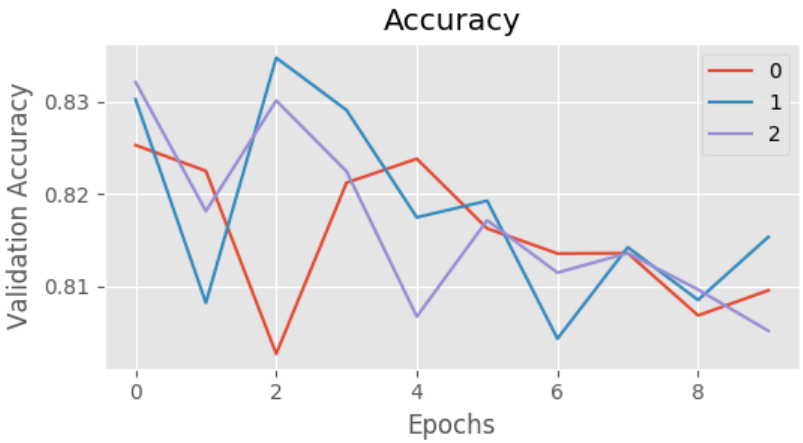
Keras IMDB FastText

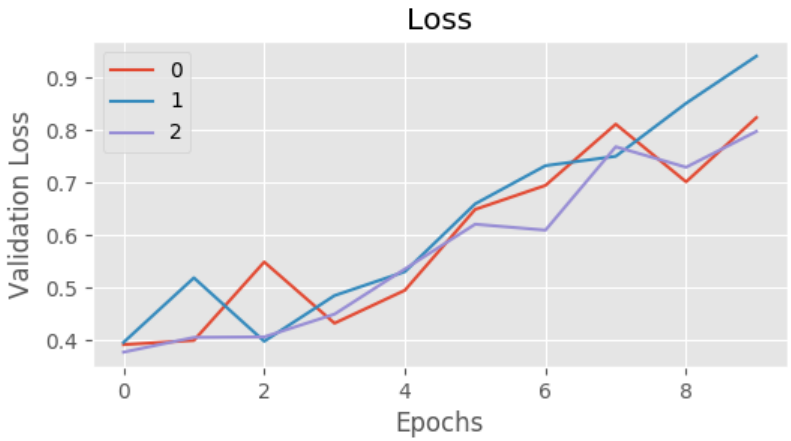
```
python imdb_fasttext.py
Using TensorFlow backend.
Loading data...
25000 train sequences
25000 test sequences
Average train sequence length: 238
Average test sequence length: 230
Pad sequences (samples x time)
x_train shape: (25000, 400)
x_test shape: (25000, 400)
Build model...
Train on 25000 samples, validate on 25000 samples
Epoch 1/5
25000/25000 [==============================] - 14s - loss: 0.6102 - acc: 0.7397 - val_loss: 0.5034 - val_acc: 0.8105
Epoch 2/5
25000/25000 [==============================] - 14s - loss: 0.4019 - acc: 0.8656 - val_loss: 0.3697 - val_acc: 0.8654
Epoch 3/5
25000/25000 [==============================] - 14s - loss: 0.3025 - acc: 0.8959 - val_loss: 0.3199 - val_acc: 0.8791
Epoch 4/5
25000/25000 [==============================] - 14s - loss: 0.2521 - acc: 0.9113 - val_loss: 0.2971 - val_acc: 0.8848
Epoch 5/5
25000/25000 [==============================] - 14s - loss: 0.2181 - acc: 0.9249 - val_loss: 0.2899 - val_acc: 0.8855
Exception ignored in: <bound method BaseSession.__del__ of <tensorflow.python.client.session.Session object at
0x000001E3257DB438>>
Traceback (most recent call last):
  File "C:\Program Files\Anaconda3\lib\site-packages\tensorflow\python\client\session.py", line 587, in __del__
AttributeError: 'NoneType' object has no attribute 'TF_NewStatus'
```

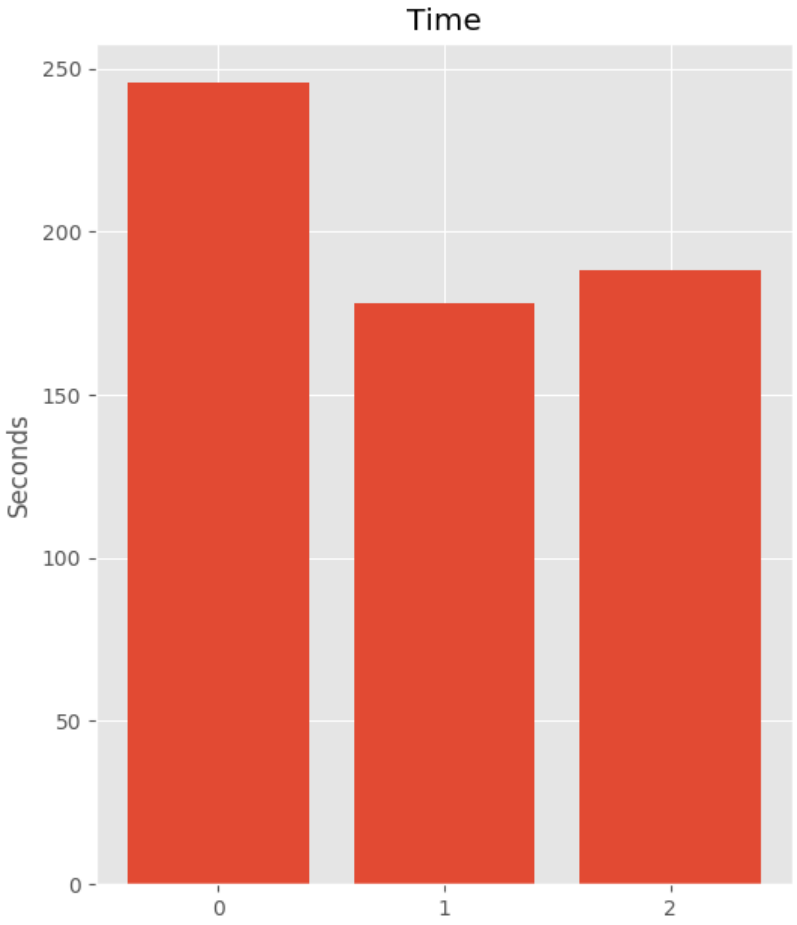
Keras IMDB CNN LSTM

```
python imdb_cnn_lstm_2.py
Using TensorFlow backend.
Loading data...
25000 train sequences
25000 test sequences
Pad sequences (samples x time)
x_train shape: (25000, 100)
x_test shape: (25000, 100)
Build model...
Train...
Train on 25000 samples, validate on 25000 samples
Epoch 1/2
25000/25000 [==============================] - 64s - loss: 0.3824 - acc: 0.8238 - val_loss: 0.3591 - val_acc: 0.8467
Epoch 2/2
25000/25000 [==============================] - 63s - loss: 0.1953 - acc: 0.9261 - val_loss: 0.3827 - val_acc: 0.8488
24990/25000 [============================>.] - ETA: 0s
Test score: 0.382728585386
Test accuracy: 0.848799994493
```

Keras LSTM Benchmark







Source: https://github.com/fchollet/keras/blob/master/examples/lstm_benchmark.py

imdb_lstm_2.py

```
from __future__ import print_function

from keras.preprocessing import sequence
from keras.models import Sequential
from keras.layers import Dense, Embedding
from keras.layers import LSTM
from keras.datasets import imdb

py_filename = 'imdb_lstm_2.py'
max_features = 20000
maxlen = 80  # cut texts after this number of words (among top max_features
most common words)
batch_size = 32
epochs = 20 #60

#%matplotlib inline
import matplotlib
import matplotlib.pyplot as plt
import numpy as np

import codecs
import datetime
import timeit
timer_start = timeit.default_timer()
#timer_end = timeit.default_timer()
#print('timer_end - timer_start', timer_end - timer_start)
```

imdb_lstm_2.py

```
def getDateTimeNow():
    strnow = datetime.datetime.now().strftime("%Y%m%d_%H%M%S")
    return strnow

def read_file_utf8(filename):
    with codecs.open(filename,'r',encoding='utf-8') as f:
        text = f.read()
    return text

def write_file_utf8(filename,text):
    with codecs.open(filename, 'w', encoding='utf-8') as f:
        f.write(text)
        f.close()

def log_file_utf8(filename, text):
    with codecs.open(filename, 'a', encoding='utf-8') as f:
        #append file
        f.write(text + '\n')
        f.close()

log_file_utf8("logfile.txt", '***** ' + py_filename + ' *****')
log_file_utf8("logfile.txt", '***** Start DateTime: ' + getDateTimeNow())

print('Start: ', datetime.datetime.now().strftime("%Y%m%d_%H%M%S"))
```

imdb_lstm_2.py

```
print('Loading data...')
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=max_features)
print(len(x_train), 'train sequences')
print(len(x_test), 'test sequences')

print('Pad sequences (samples x time)')
x_train = sequence.pad_sequences(x_train, maxlen=maxlen)
x_test = sequence.pad_sequences(x_test, maxlen=maxlen)
print('x_train shape:', x_train.shape)
print('x_test shape:', x_test.shape)

print('Build model...')
model = Sequential()
model.add(Embedding(max_features, 128))
model.add(LSTM(128, dropout=0.2, recurrent_dropout=0.2))
model.add(Dense(1, activation='sigmoid'))

# try using different optimizers and different optimizer configs
model.compile(loss='binary_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```

imdb_lstm_2.py

```
print('Train...')
print('model.fit: ', datetime.datetime.now().strftime("%Y%m%d_%H%M%S"))
history = model.fit(x_train, y_train,
          batch_size = batch_size,
          epochs = epochs,
          validation_data = (x_test, y_test))

score, acc = model.evaluate(x_test, y_test,
                            batch_size=batch_size)
print('Test score:', score)
print('Test accuracy:', acc)
```

imdb_lstm_2.py

```
timer_end = timeit.default_timer()
print('Timer: ', str(round(timer_end - timer_start, 2)), 's')
print('DateTime: ', datetime.datetime.now().strftime("%Y%m%d_%H%M%S"))
log_file_utf8("logfile.txt", 'Timer: ' + str(round(timer_end - timer_start, 2))
+ ' s')
log_file_utf8("logfile.txt", '***** End Datetime: ' +
datetime.datetime.now().strftime("%Y%m%d_%H%M%S"))

# summarize history for accuracy
#http://machinelearningmastery.com/display-deep-learning-model-training-history-in-keras/
print('history.history.keys():', history.history.keys())
print('history.history:', history.history)
log_file_utf8("logfile.txt", 'history.history:' + str(history.history))
```

imdb_lstm_2.py

```
# Deep Learning Training Visualization
plt.figure(figsize=(10, 8))  # make separate figure
ax1 = plt.subplot(2, 1, 1)
plt.plot(history.history['acc'])
plt.plot(history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
ax1.xaxis.set_major_locator(plt.NullLocator())
#plt.xlabel('epoch')
plt.legend(['train acc', 'test val_acc'], loc='upper left')
#plt.show()
ax2 = plt.subplot(2, 1, 2)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train loss', 'test val_loss'], loc='upper left')
plt.savefig("training_accuacy_loss_" + py_filename + "_" + str(epochs) +
".png", dpi= 300)
```

imdb_lstm_2.py

```
#Log File for Deep Learning Summary Analysis
log_file_utf8("logfile.txt", 'DL_Summary:\tpy_filename\t'  + py_filename +
    '\tepochs\t' + str(epochs) +
    '\tscore\t' + str(score) +
    '\taccuracy\t' + str(acc) +
    '\tTimer\t ' + str(round(timer_end - timer_start, 2)) +
    '\thistory\t' + str(history.history))
#plt.show()
```

python filename.py

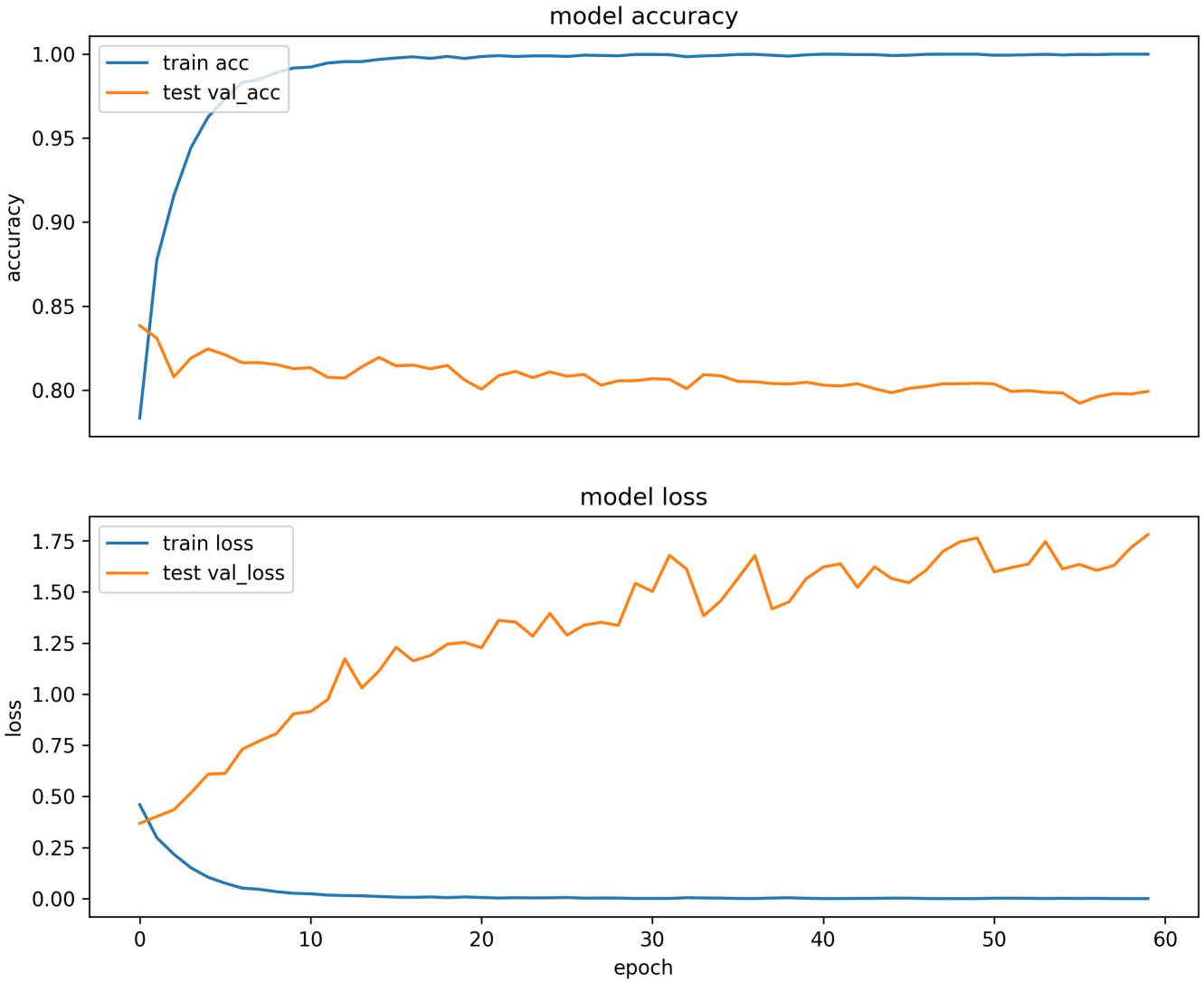
```
python imdb_fasttext_2.py
python imdb_cnn_2.py
python imdb_lstm_2.py
python imdb_cnn_lstm_2.py
python imdb_bidirectional_lstm_2.py
```

Deep Learning Summary

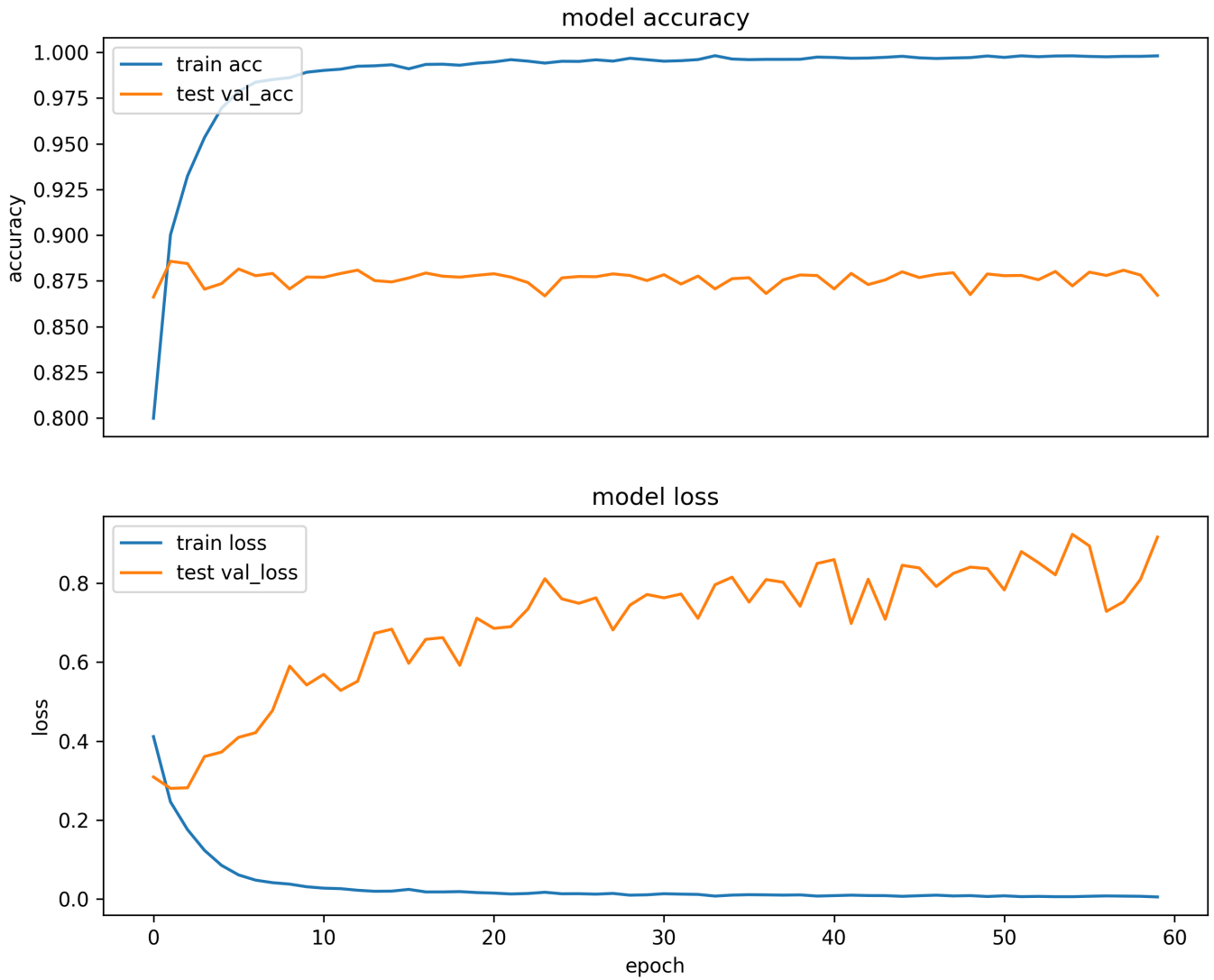
```
 #Log File for Deep Learning Summary Analysis
log_file_utf8("logfile.txt", 'DL_Summary:\tpy_filename\t'  + py_filename +
    '\tepochs\t' + str(epochs) +
    '\tscore\t' + str(score) +
    '\taccuracy\t' + str(acc) +
    '\tTimer\t ' + str(round(timer_end - timer_start, 2)) +
    '\thistory\t' + str(history.history))
```

Model	epochs	Score	Accuracy	Timer (s)
imdb_lstm_2.py	30	0.6440	0.8540	**682.57**
imdb_cnn_2.py	30	0.7186	**0.8775**	4320.38
imdb_lstm_2.py	30	1.5716	0.8052	3958.93
imdb_cnn_lstm_2.py	30	1.3105	0.8240	2471.65
imdb_bidirectional_lstm_2.py	30	1.4083	0.8255	4344.36
imdb_fasttext_2.py	30	**0.6439**	0.8540	1117.78
imdb_fasttext_2.py	60	1.2335	0.8407	1297.02
imdb_cnn_2.py	60	0.9170	0.8672	8507.48
imdb_lstm_2.py	60	1.7803	0.7992	8039.67
imdb_cnn_lstm_2.py	60	1.4623	0.8137	4912.25
imdb_bidirectional_lstm_2.py	60	1.8975	0.8138	8589.17

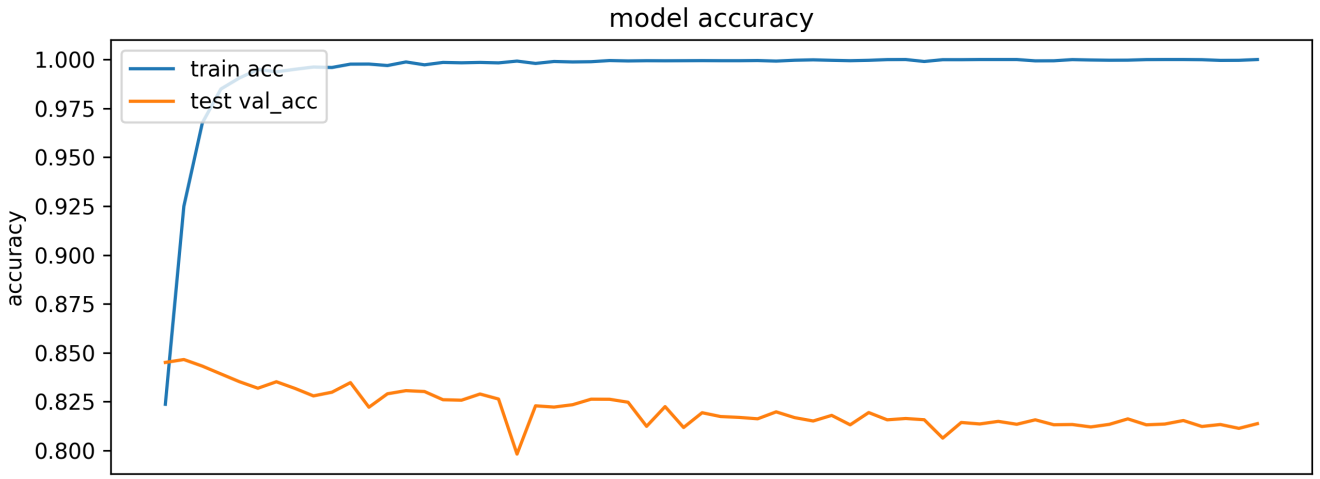
imdb_lstm_2.py

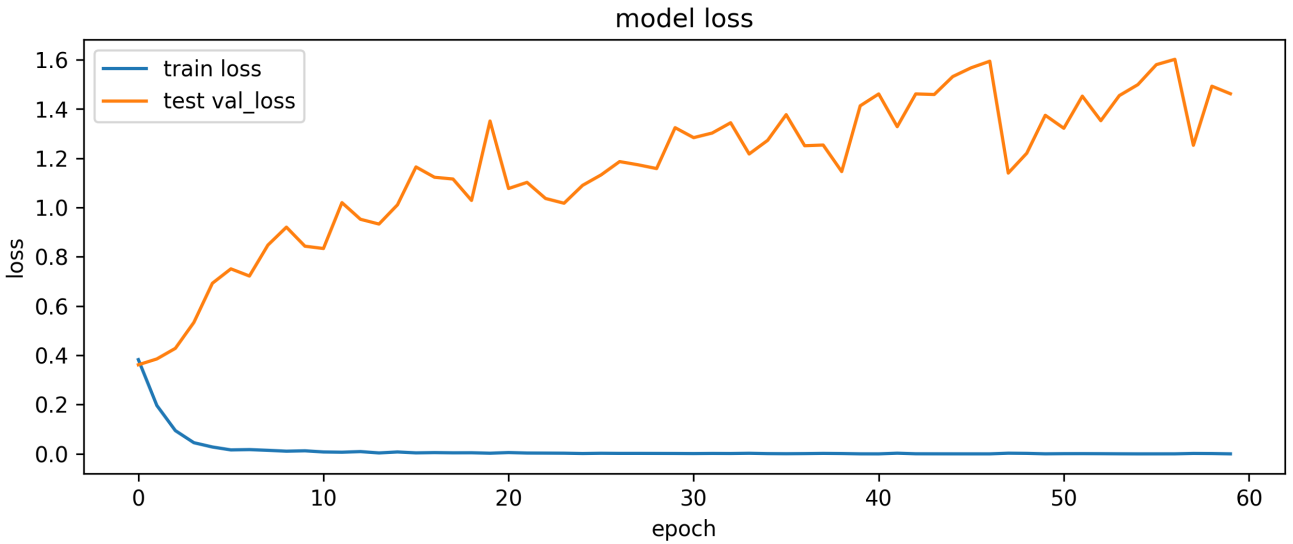


imdb_cnn_2.py

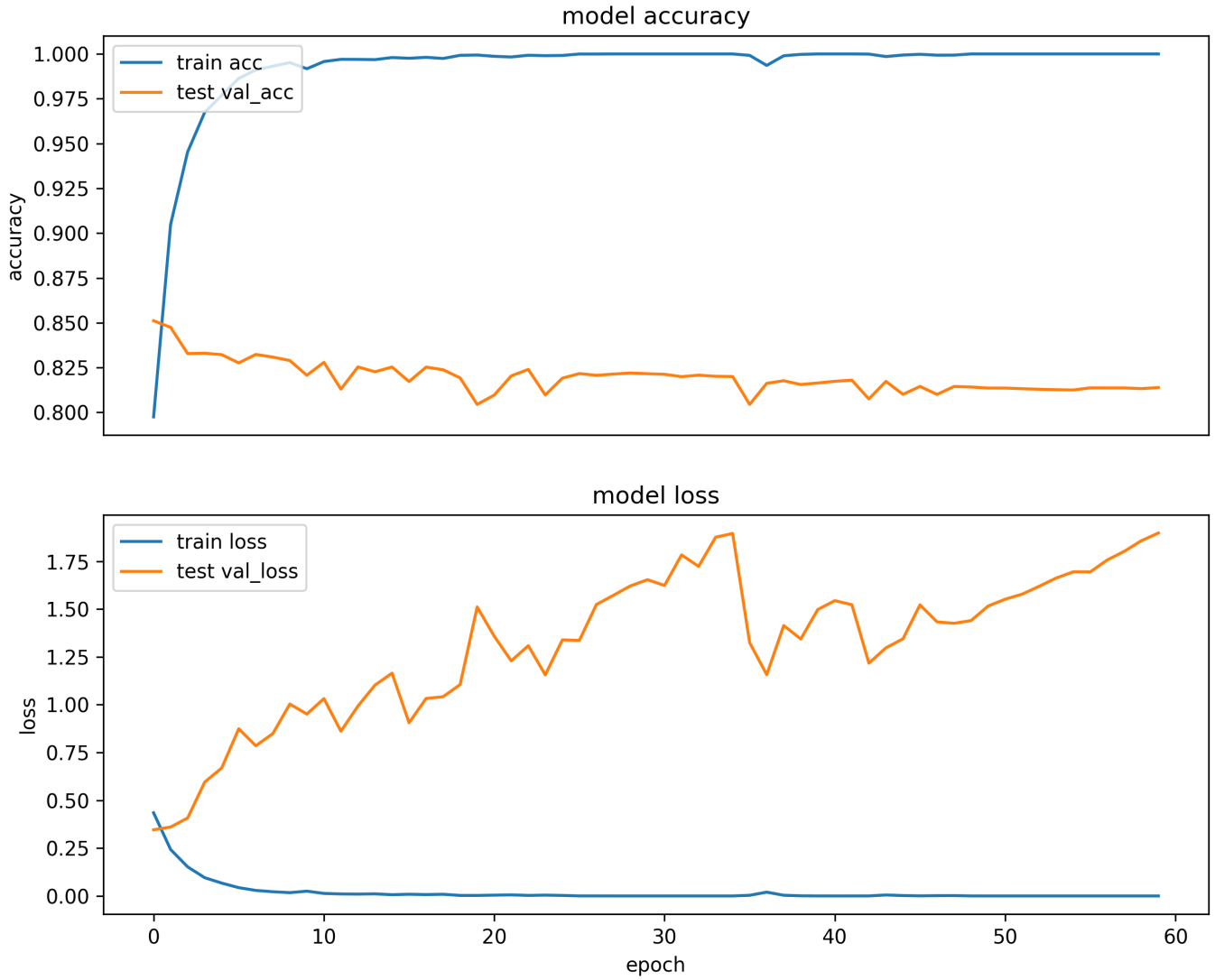

model accuracy
train acc
test val_acc
accuracy
1.000
0.975
0.950
0.925
0.900
0.875
0.850
0.825
0.800
model loss
train loss
test val_loss
loss
0.8
0.6
0.4
0.2
0.0
0
10
20
30
40
50
60
epoch

imdb_cnn_lstm_2.py

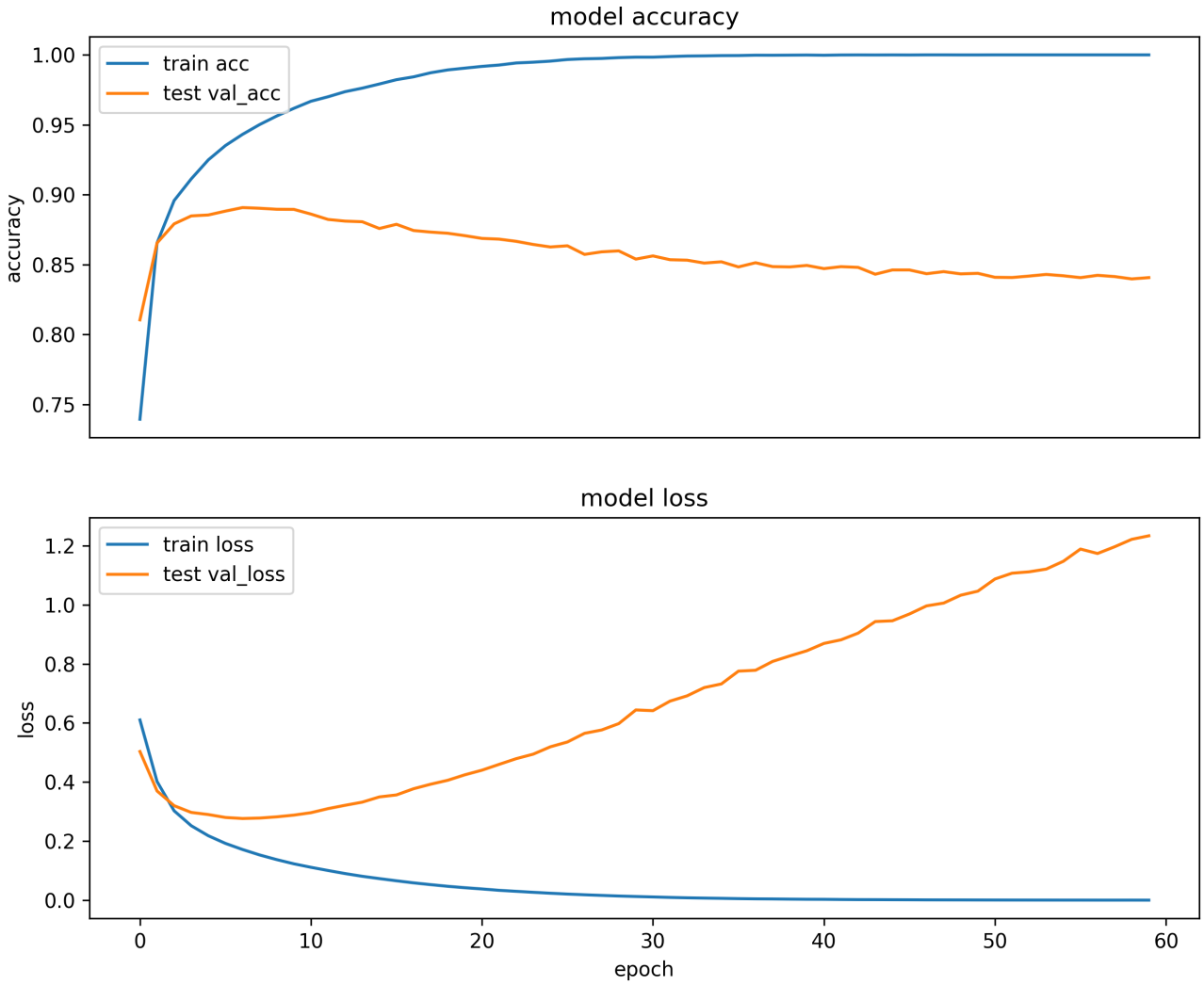




imdb_bidirectional_lstm_2.py



imdb_fasttext_2.py



Deep Learning with CPU vs. GPU

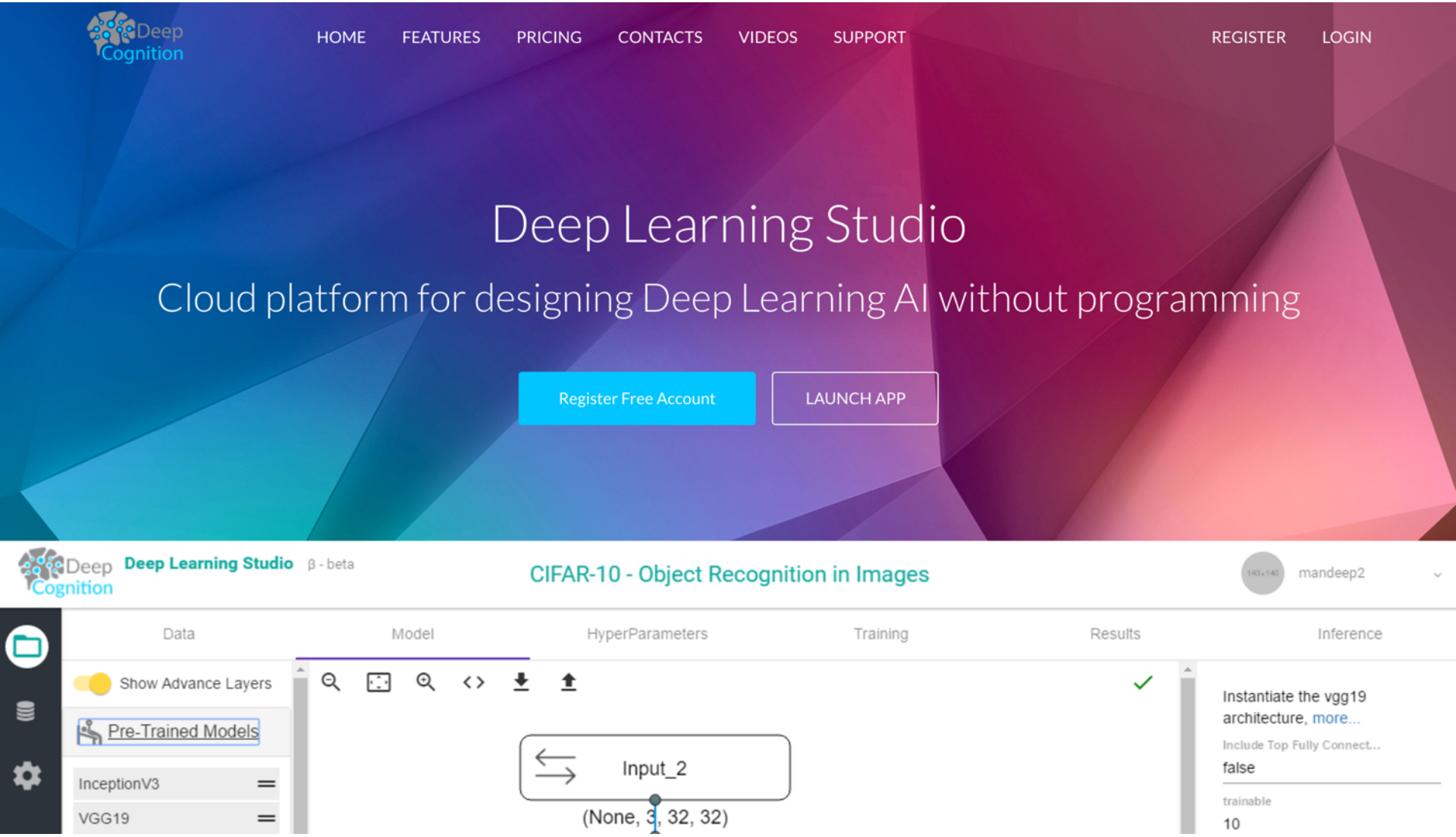
Timings:

Hardware	Backend	Time / Epoch
CPU	TF	3 hrs
Titan X (maxwell)	TF	4 min
Titan X (maxwell)	TH	7 min

Source: https://github.com/fchollet/keras/blob/master/examples/mnist_acgan.py

Deep Learning Studio

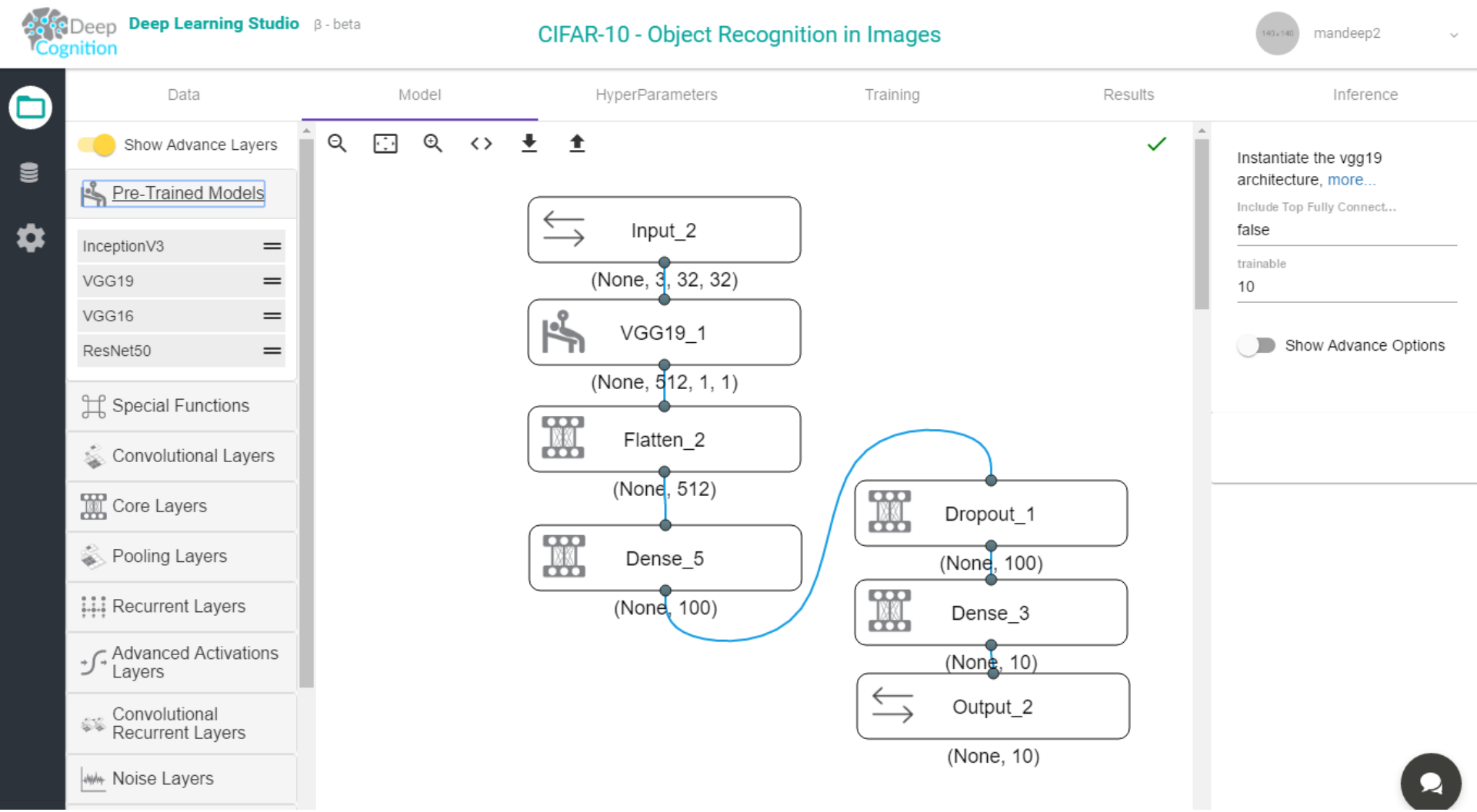
Cloud platform for designing Deep Learning AI without programming



http://deepcognition.ai/

Deep Learning Studio

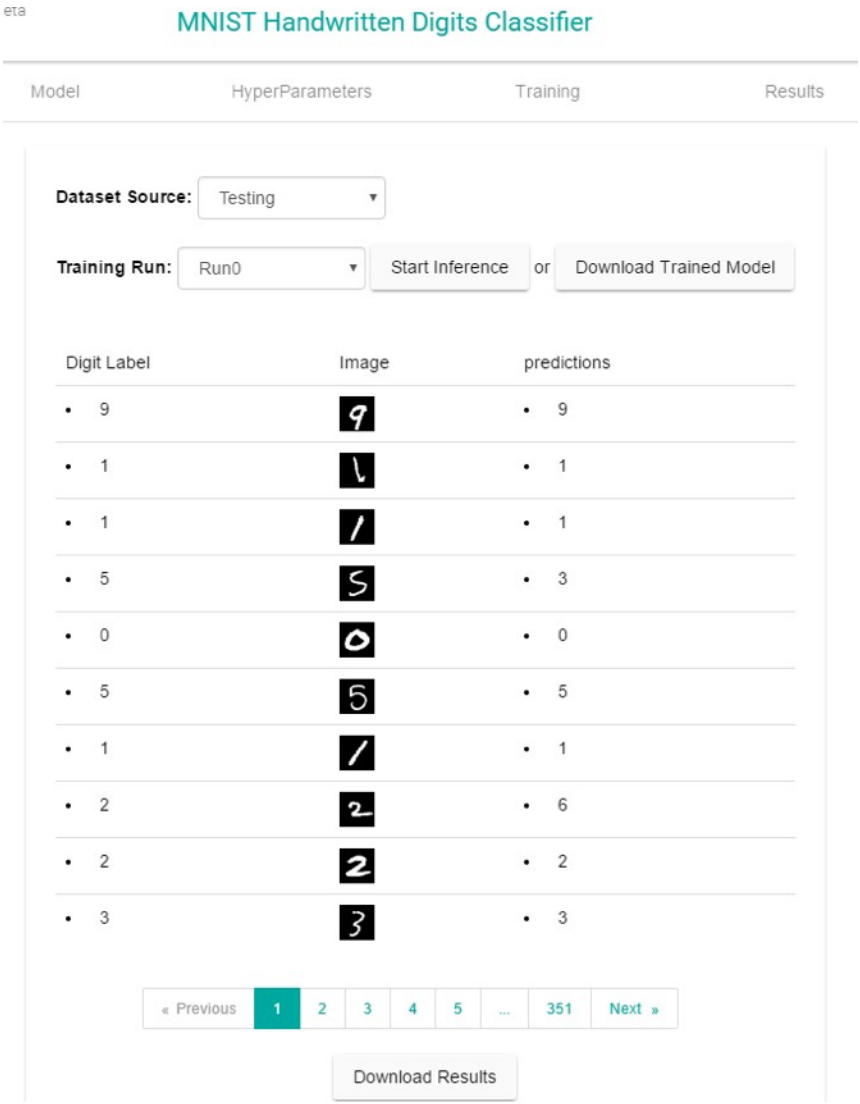
Cloud platform for designing Deep Learning AI without programming



http://deepcognition.ai/

Deep Learning Studio

Cloud platform for designing Deep Learning AI without programming



http://deepcognition.ai/

References

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- Martin Gorner (2017), TensorFlow and Deep Learning without a PhD, Part 2 (Google Cloud Next '17), https://www.youtube.com/watch?v=fTUwdXUFfI8
- Martin Gorner (2017), TensorFlow and Deep Learning without a PhD, https://goo.gl/pHeXe7, https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist
- Deep Learning Basics: Neural Networks Demystified, https://www.youtube.com/playlist?list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU
- Deep Learning SIMPLIFIED, https://www.youtube.com/playlist?list=PLjJh1vlSEYgvGod9wWiydumYl8hOXixNu
- TensorFlow: https://www.tensorflow.org/
- Theano: http://deeplearning.net/software/theano/
- Keras: http://keras.io/
- Deep Learning Studio: Cloud platform for designing Deep Learning AI without programming, http://deepcognition.ai/
- Natural Language Processing with Deep Learning (Winter 2017), https://www.youtube.com/playlist?list=PL3FW7Lu3i5Jsnh1rnUwq_TcylNr7EkRe6
- Udacity, Deep Learning, https://www.youtube.com/playlist?list=PLAwxTw4SYaPn_OWPFT9ulXLuQrImzHfOV
- http://p.migdal.pl/2017/04/30/teaching-deep-learning.html
- https://github.com/leriomaggio/deep-learning-keras-tensorflow