Tamkang Universit
淡江大學

人工智慧投資分析
Artificial Intelligence for Investment Analysis

TensorFlow 深度學習財務時間序列預測 (Deep Learning for Financial Time Series Forecasting with TensorFlow)

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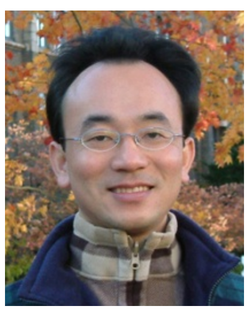
EMBA, IMTKU (M2399) (8540)
Thu 12,13,14 (19:20-22:10) (D503)



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淡江大學 資訊管理學系

http://mail. tku.edu.tw/myday/

2018-11-22; 2018-11-29; 2018-12-13

課程大綱 (Syllabus)

週次 (Week) 日期 (Date) 內容 (Subject/Topics)

1 2018/09/13 人工智慧投資分析課程介紹
(Course Orientation on Artificial Intelligence for Investment Analysis)

2 2018/09/20 AI 金融科技: 金融服務創新應用
(AI in FinTech: Financial Services Innovation and Application)

3 2018/09/27 機器人理財顧問與AI交談機器人
(Robo-Advisors and AI Chatbots)

4 2018/10/04 投資心理學與行為財務學
(Investing Psychology and Behavioral Finance)

5 2018/10/11 財務金融事件研究法 (Event Studies in Finance)

6 2018/10/18 人工智慧投資分析個案研究 I
(Case Study on Artificial Intelligence for Investment Analysis I)

課程大綱 (Syllabus)

週次 (Week) 日期 (Date) 內容 (Subject/Topics)

7 2018/10/25 Python AI投資分析基礎
(Foundations of AI Investment Analysis in Python)

8 2018/11/01 Python Pandas量化投資分析
(Quantitative Investing with Pandas in Python)

9 2018/11/08 Python Scikit-Learn 機器學習
(Machine Learning with Scikit-Learn in Python)

10 2018/11/15 期中報告 (Midterm Project Report)

11 2018/11/22 TensorFlow 深度學習財務時間序列預測 I
(Deep Learning for Financial Time Series Forecasting with TensorFlow I)

12 2018/11/29 TensorFlow 深度學習財務時間序列預測 II
(Deep Learning for Financial Time Series Forecasting with TensorFlow II)

課程大綱 (Syllabus)

週次 (Week) 日期 (Date) 內容 (Subject/Topics)

13 2018/12/06 人工智慧投資分析個案研究 II
(Case Study on Artificial Intelligence for Investment Analysis II)

14 2018/12/13 TensorFlow 深度學習財務時間序列預測 III
(Deep Learning for Financial Time Series Forecasting with TensorFlow III)

15 2018/12/20 投資組合最佳化與程式交易
(Portfolio Optimization and Algorithmic Trading)

16 2018/12/27 自然語言處理 (Natural Language Processing)

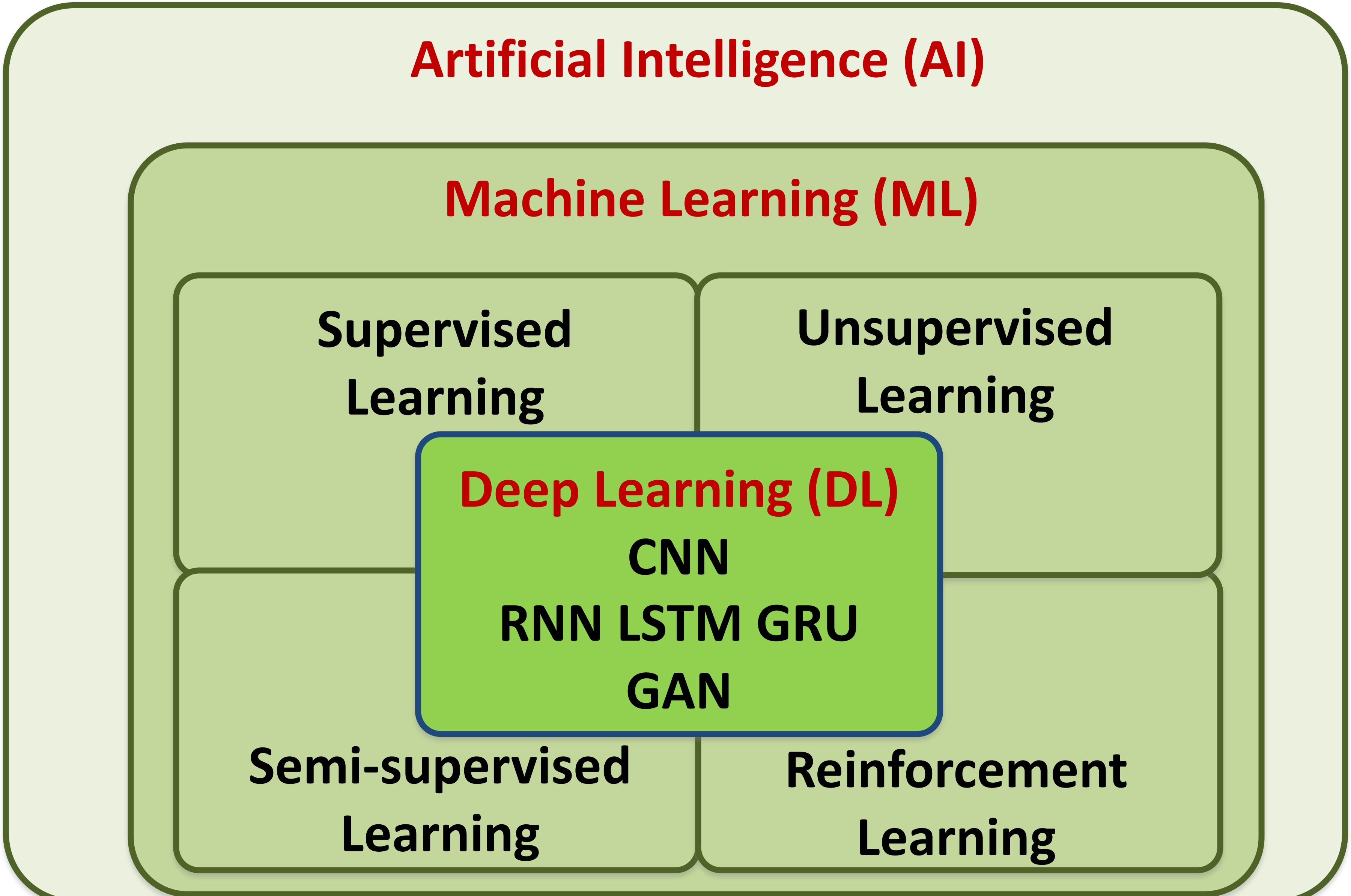
17 2019/01/03 期末報告 I (Final Project Presentation I)

18 2019/01/10 期末報告 II (Final Project Presentation II)

Outline

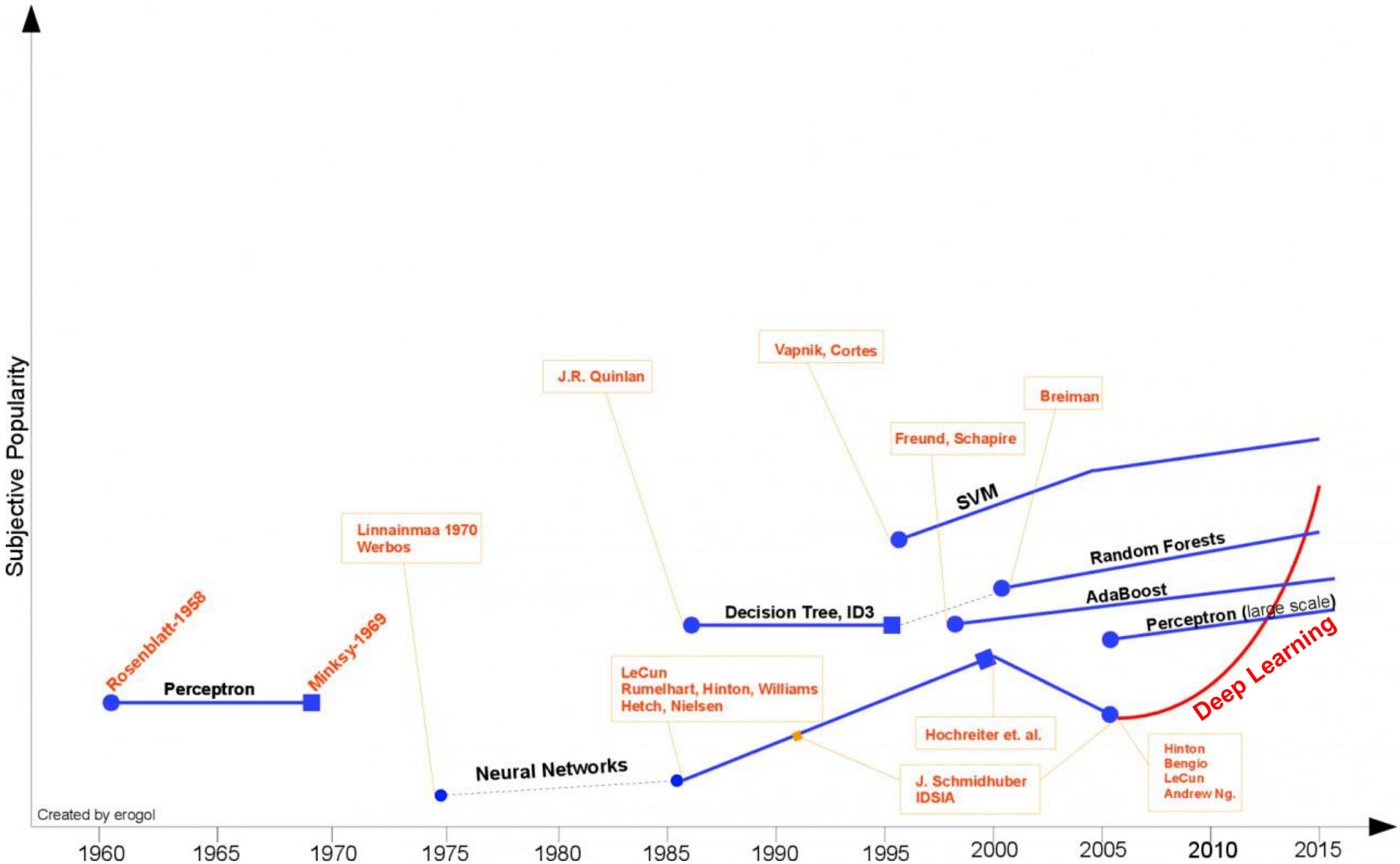
- Deep Learning for Financial Time Series Forecasting with TensorFlow
  - Deep Learning
  - Financial Time Series Forecasting
  - TensorFlow

AI, ML, DL



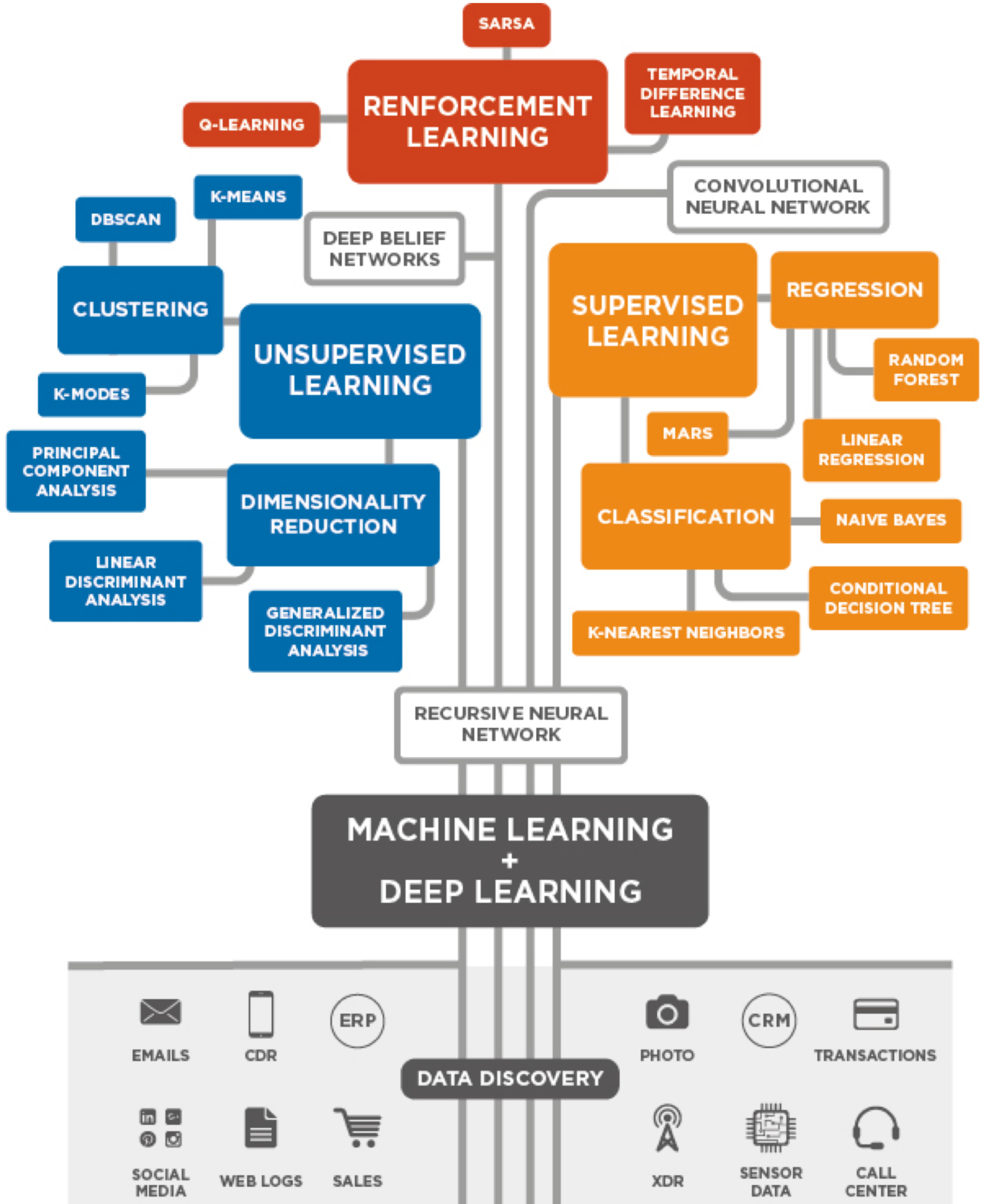
Source: https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/deep_learning.html

Deep Learning Evolution



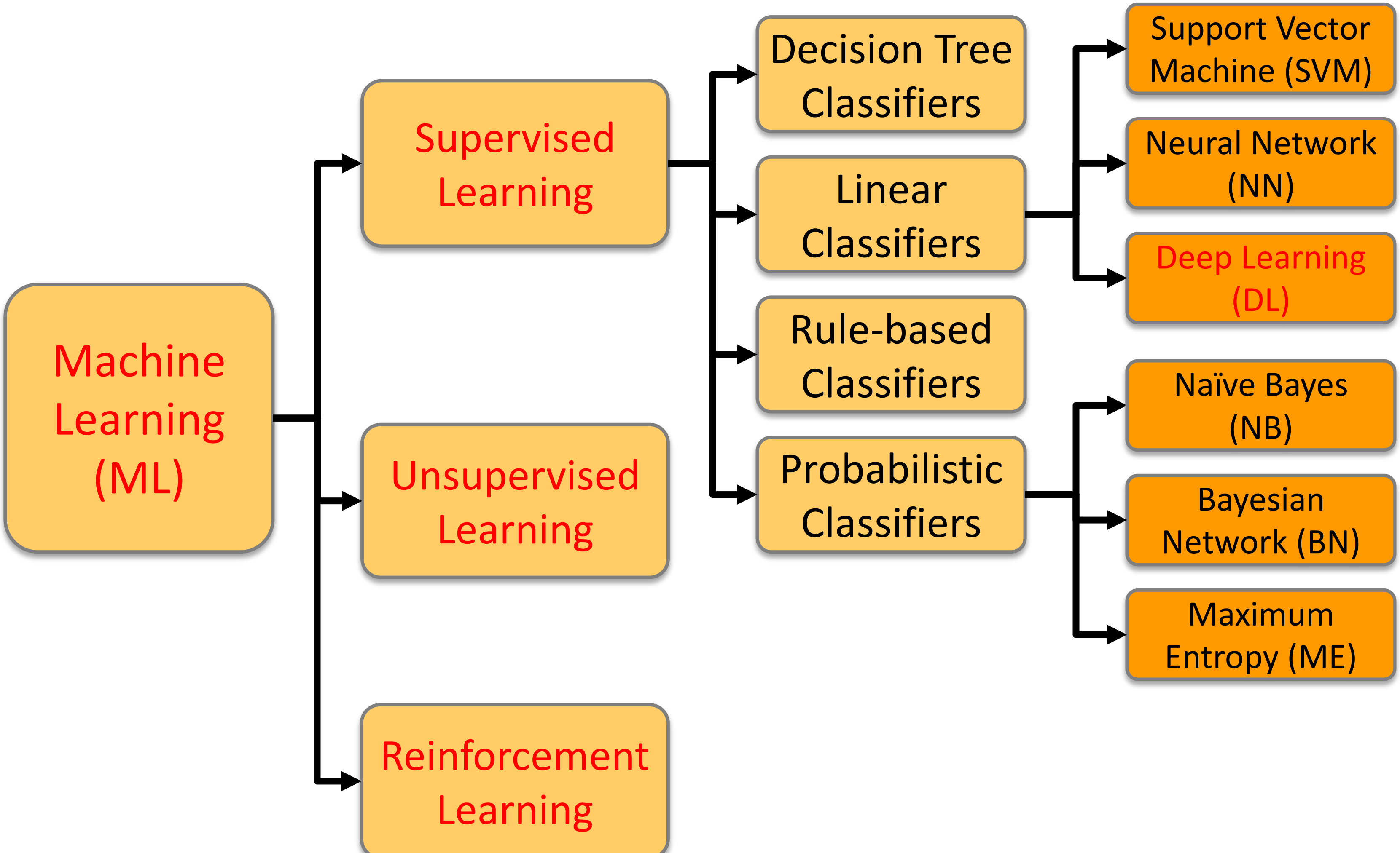
Source: http://www.erogol.com/brief-history-machine-learning/

3 Machine Learning Algorithms



Source: Enrico Galimberti, http://blogs.teradata.com/data-points/tree-machine-learning-algorithms/

Machine Learning (ML) / Deep Learning (DL)



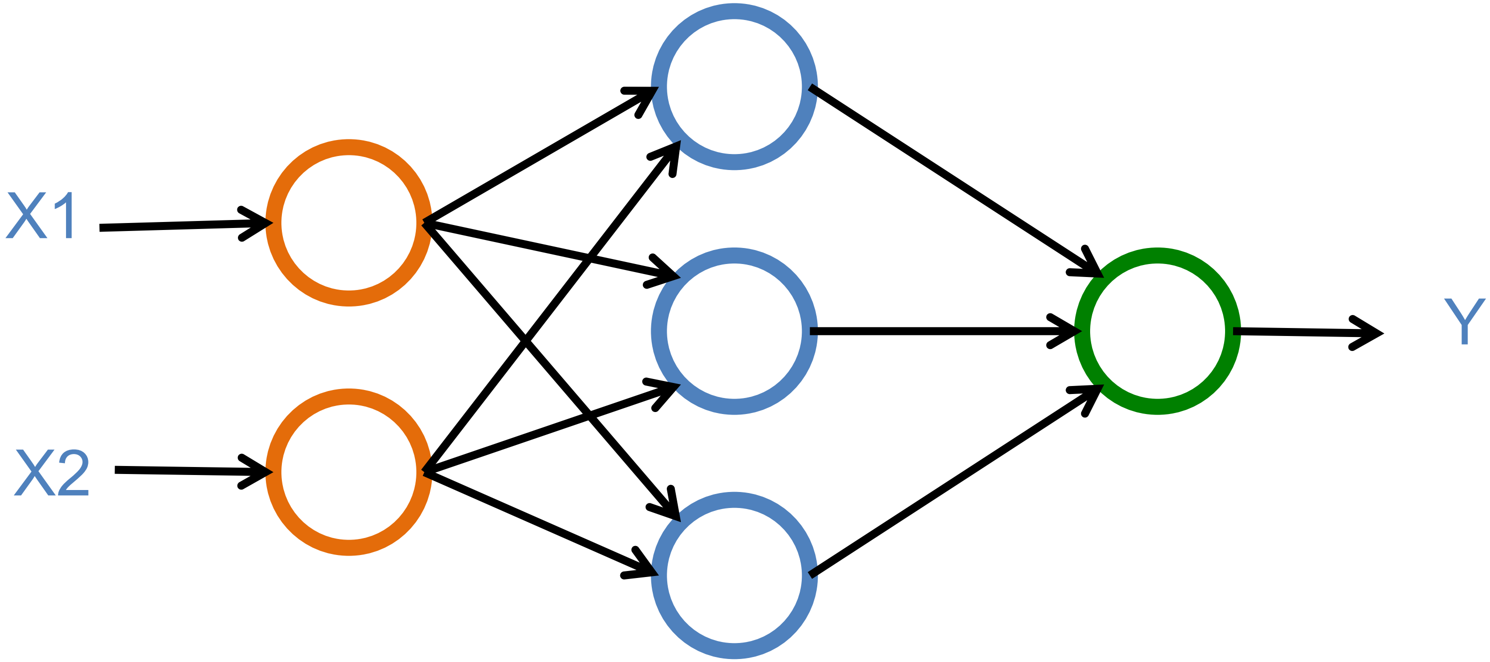
Source: Jesus Serrano-Guerrero, Jose A. Olivas, Francisco P. Romero, and Enrique Herrera-Viedma (2015), "Sentiment analysis: A review and comparative analysis of web services," Information Sciences, 311, pp. 18-38.

Deep Learning
and
Neural Networks

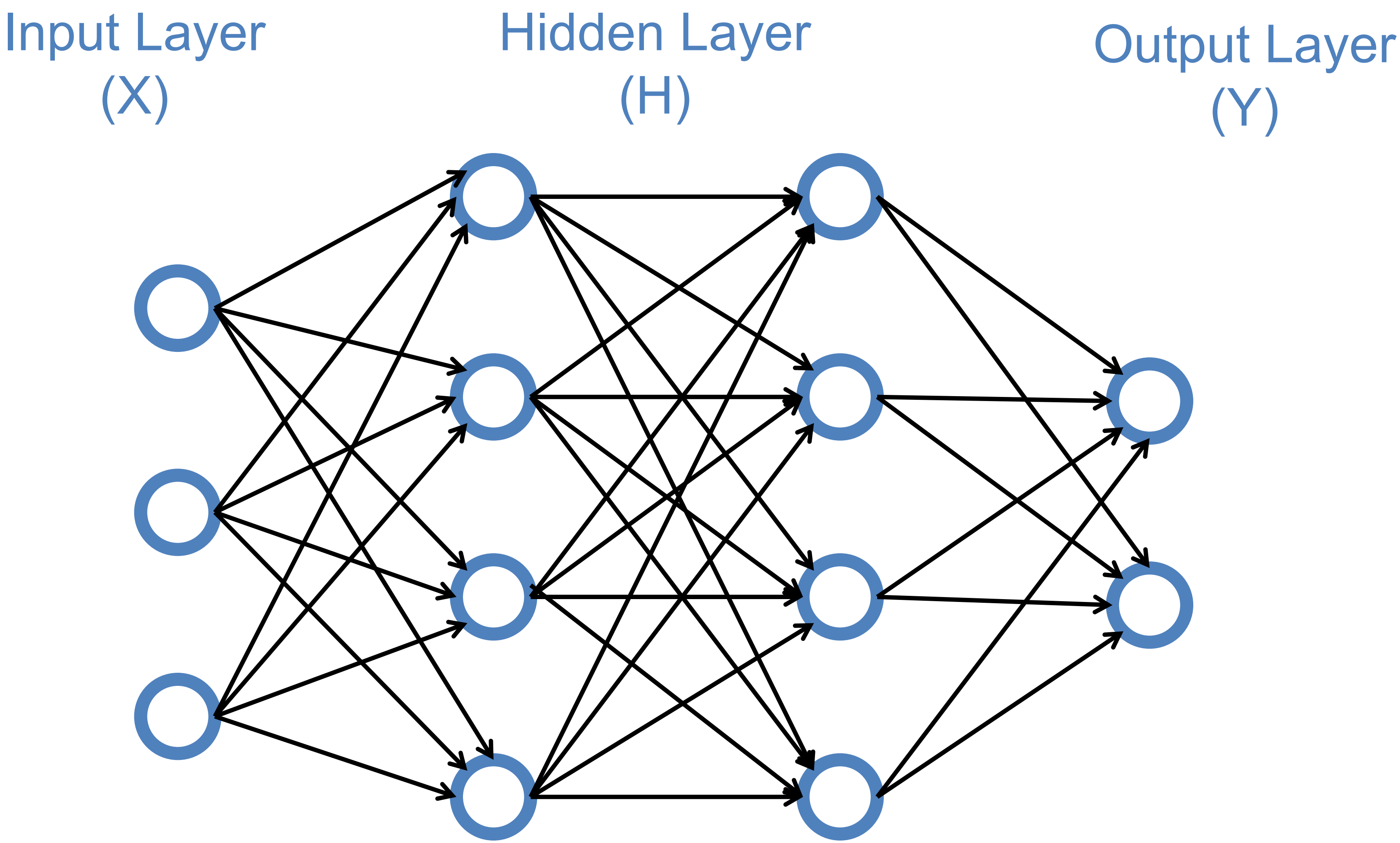
Deep Learning Foundations: Neural Networks

Deep Learning and Neural Networks

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



Deep Learning and Neural Networks



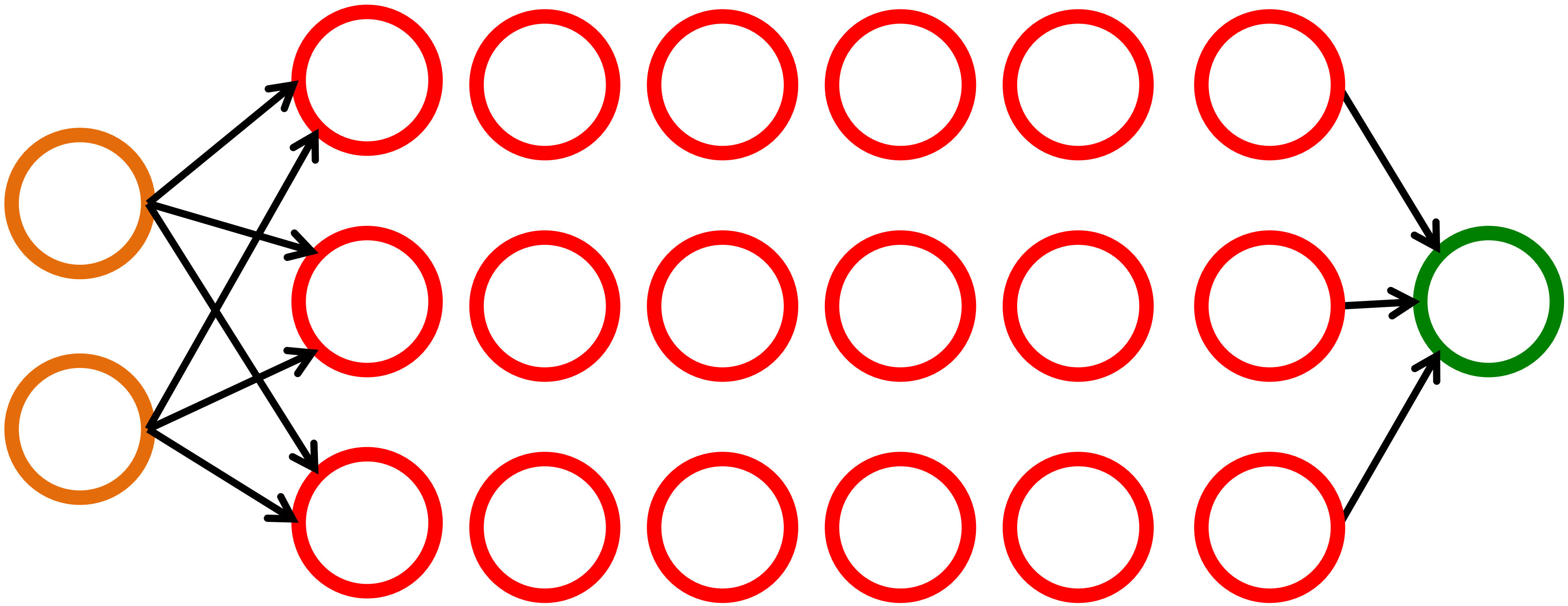
Deep Learning and Neural Networks

Input Layer (X)

Hidden Layers (H)

Output Layer (Y)

Deep Neural Networks
Deep Learning



Deep Learning
and
Deep Neural Networks

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.

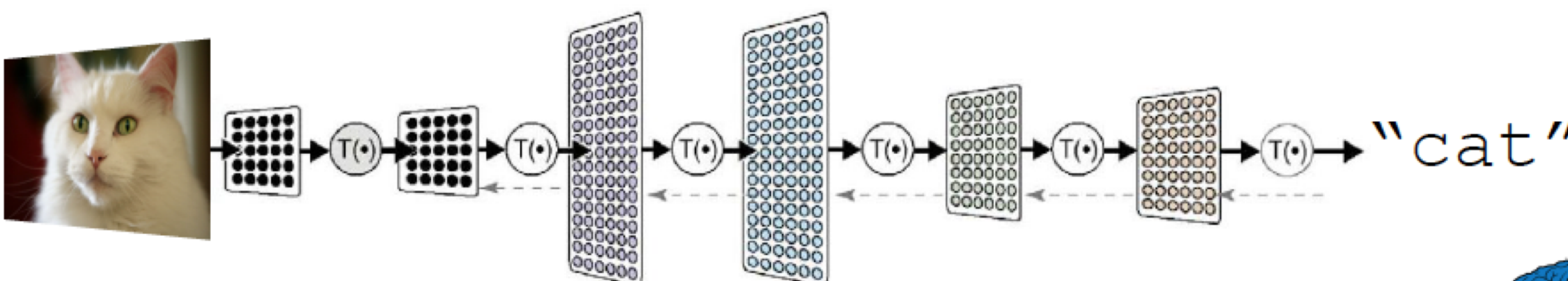
Machine-learning technology powers many aspects of modern society: from web searches to content filtering on social networks to recommendations on e-commerce websites, and it is increasingly present in consumer products such as cameras and smartphones. Machine-learning systems are used to identify objects 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, con- 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.

Deep Learning

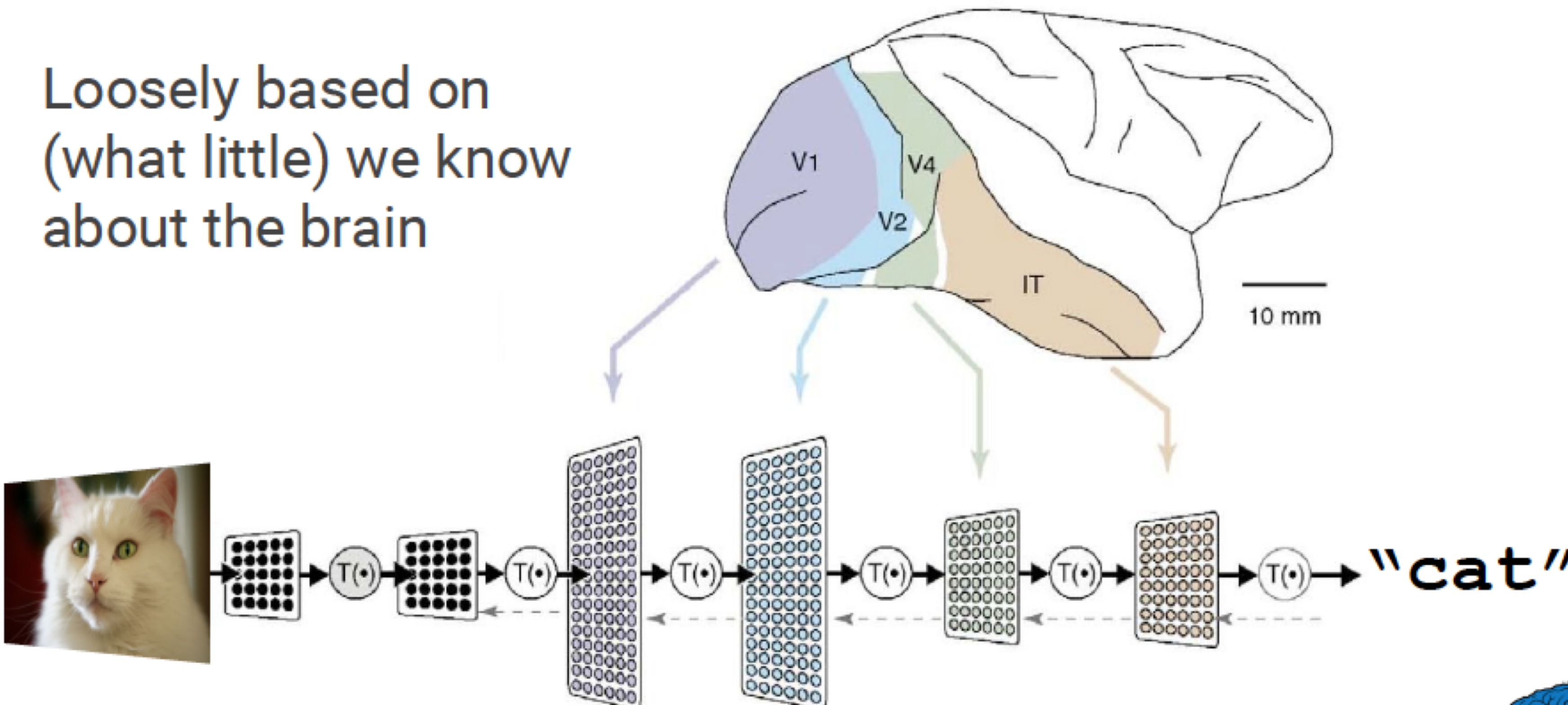
- A powerful class of machine learning model
- Modern reincarnation of artificial neural networks
- Collection of simple,
  trainable mathematical functions
- Compatible with many variants of machine learning



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

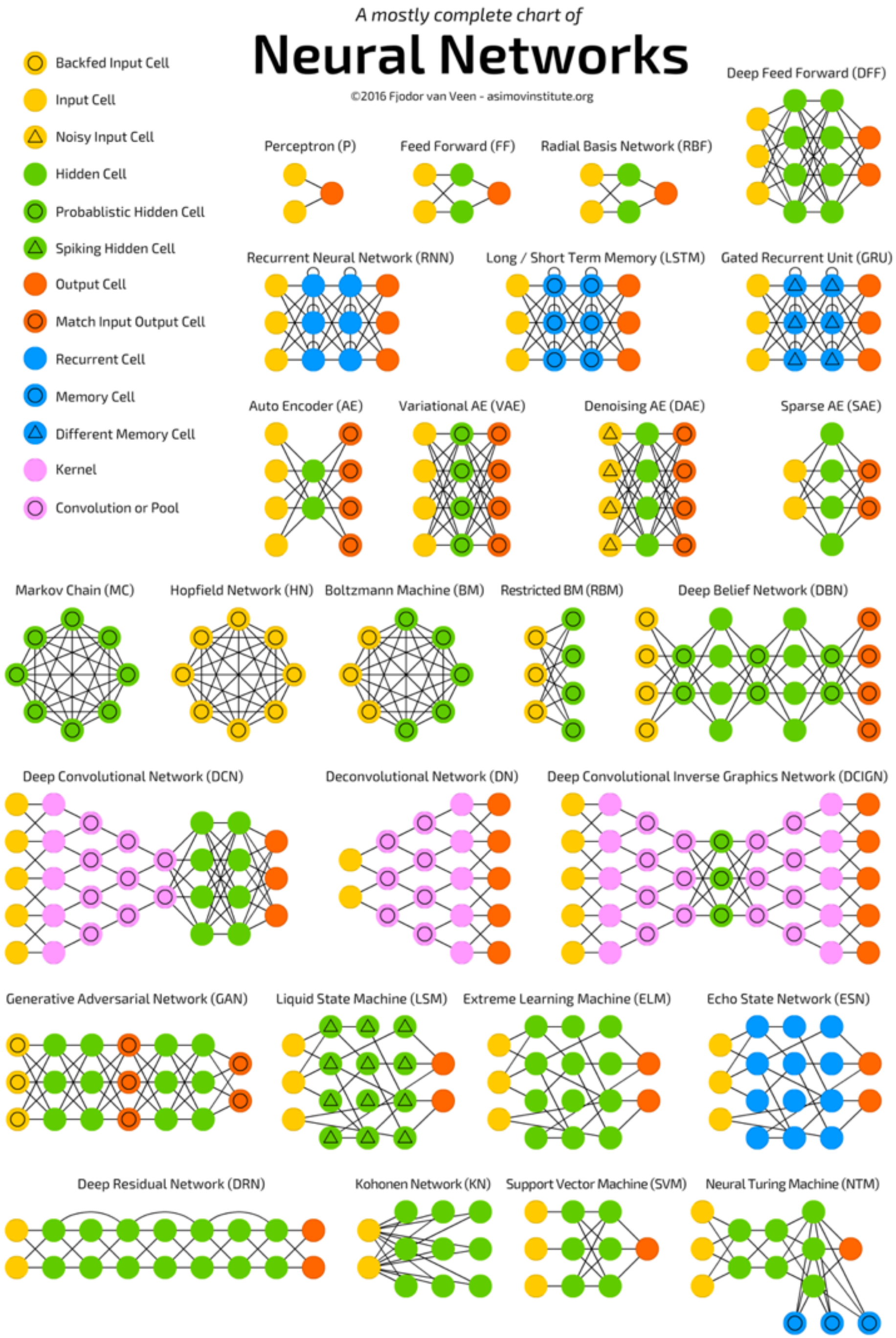
What is Deep Learning?

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

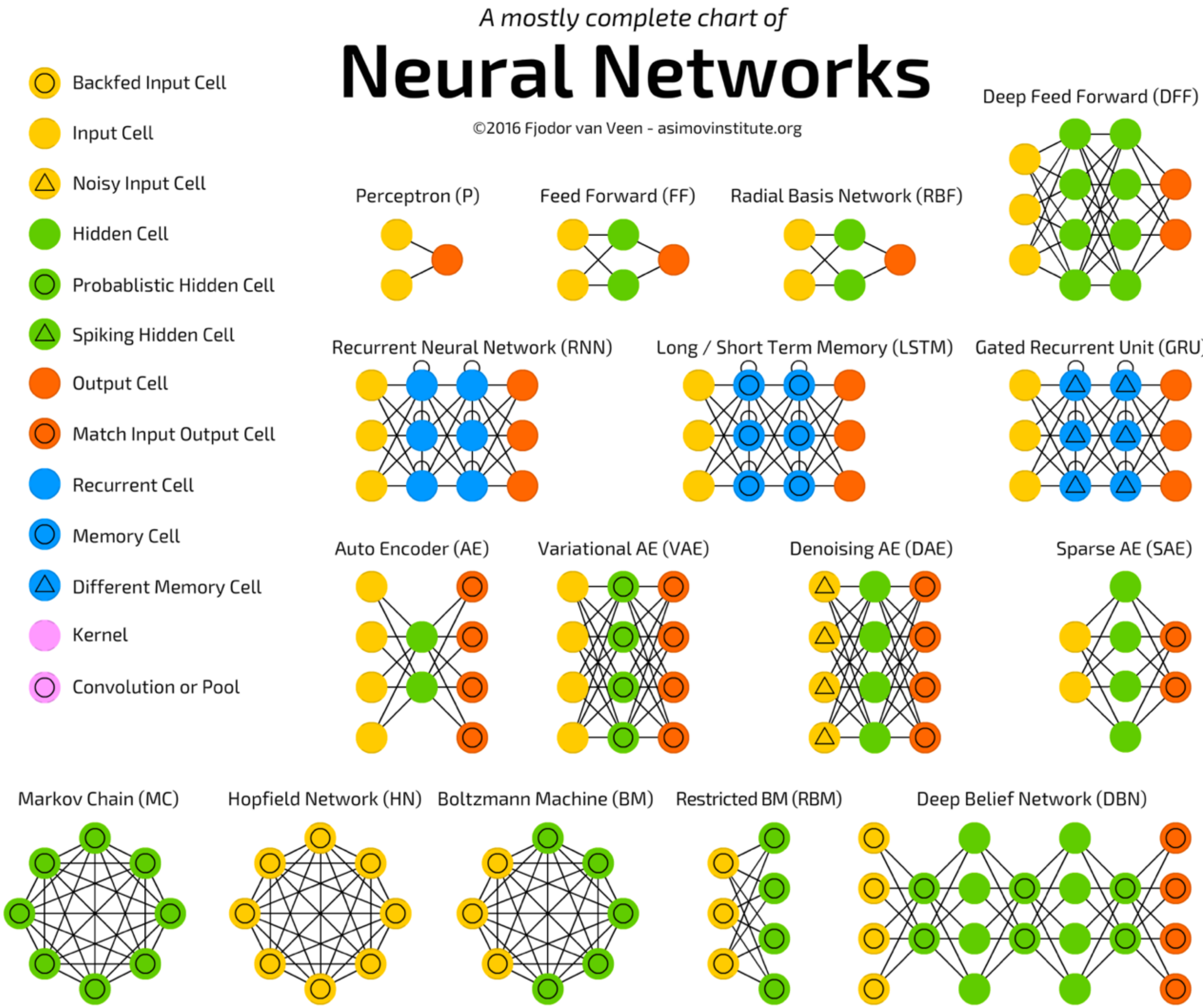


Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

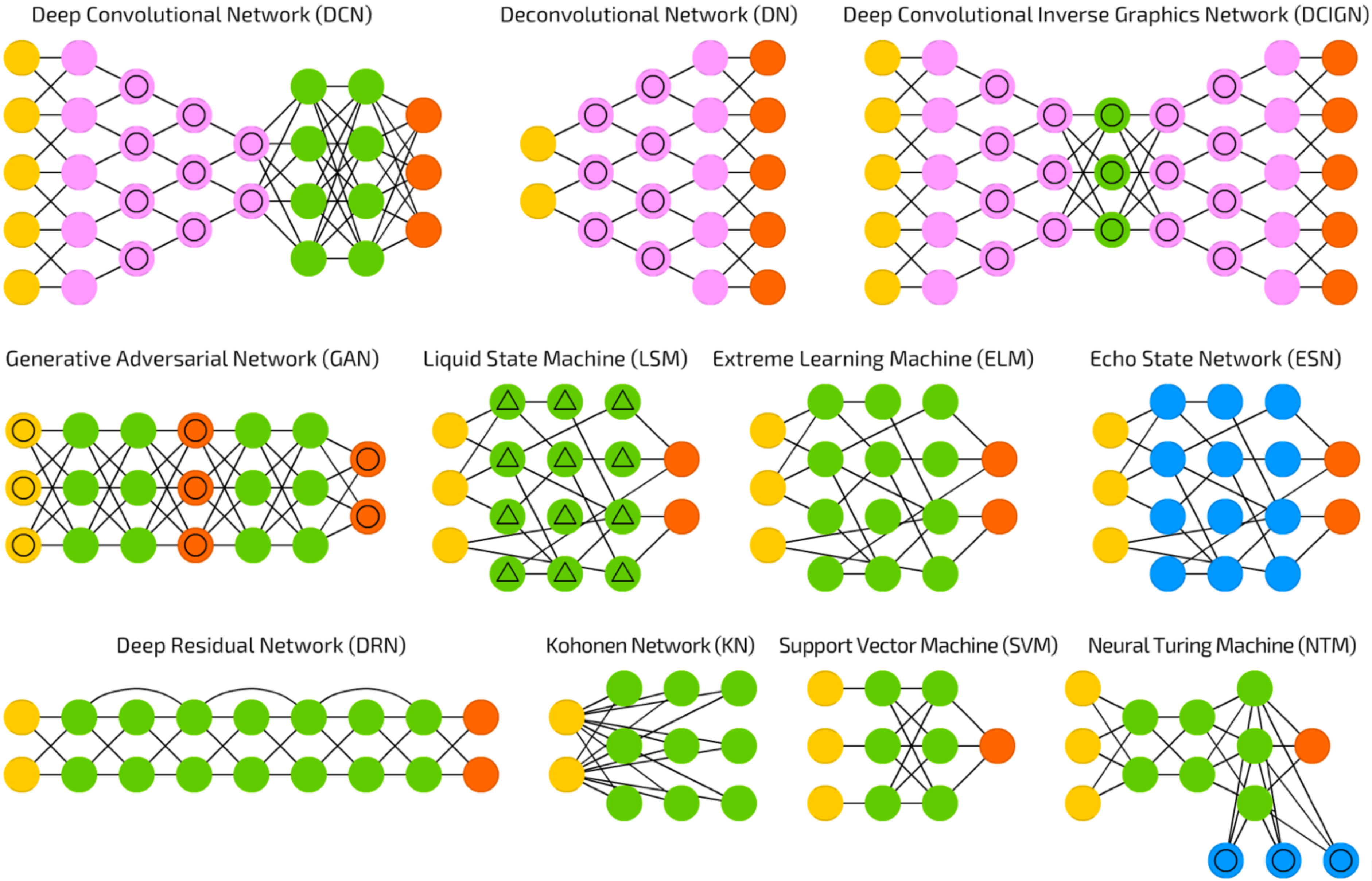
Neural Networks (NN)



Source: http://www.asimovinstitute.org/neural-network-zoo/



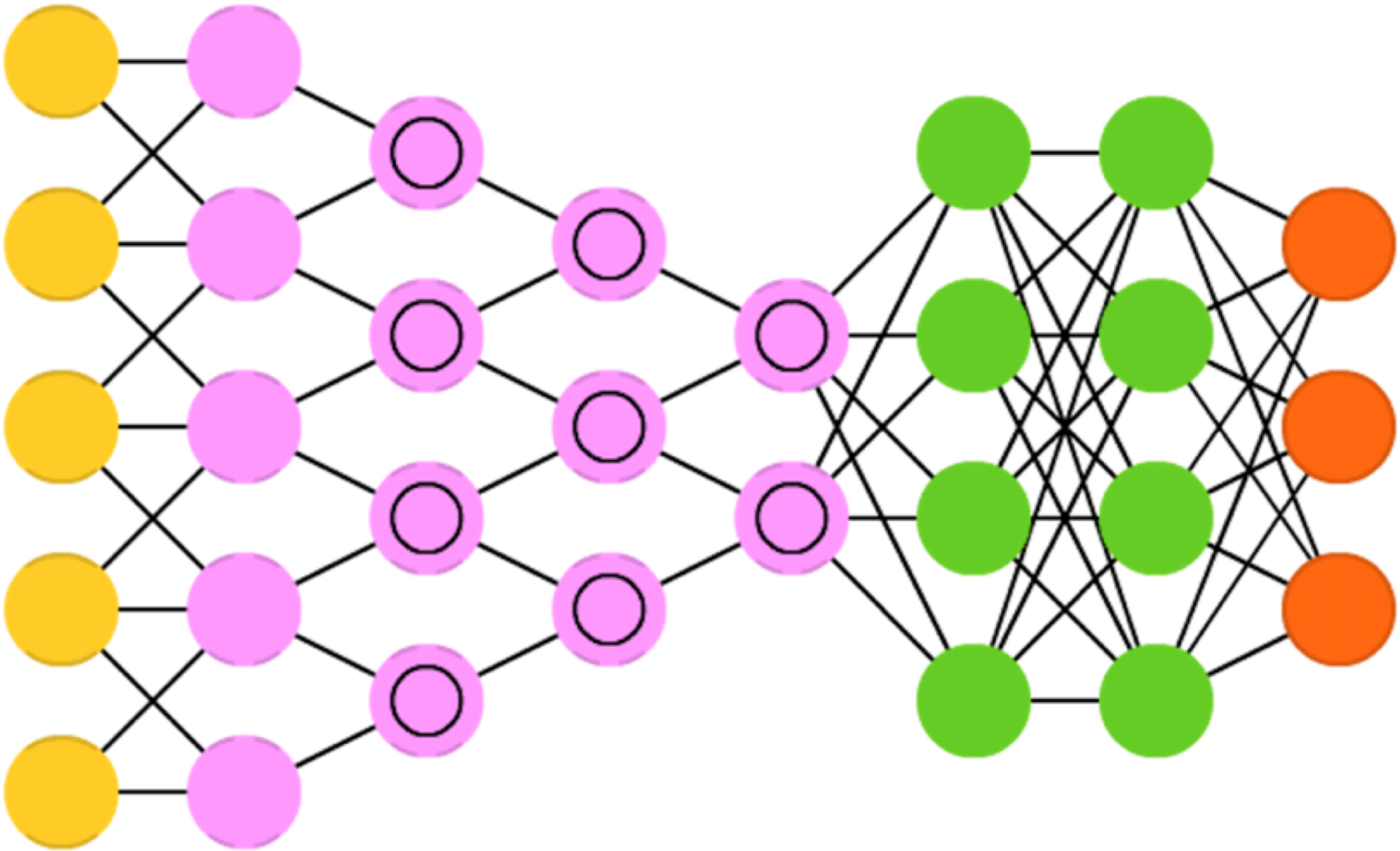
Source: http://www.asimovinstitute.org/neural-network-zoo/



Source: http://www.asimovinstitute.org/neural-network-zoo/

Convolutional Neural Networks

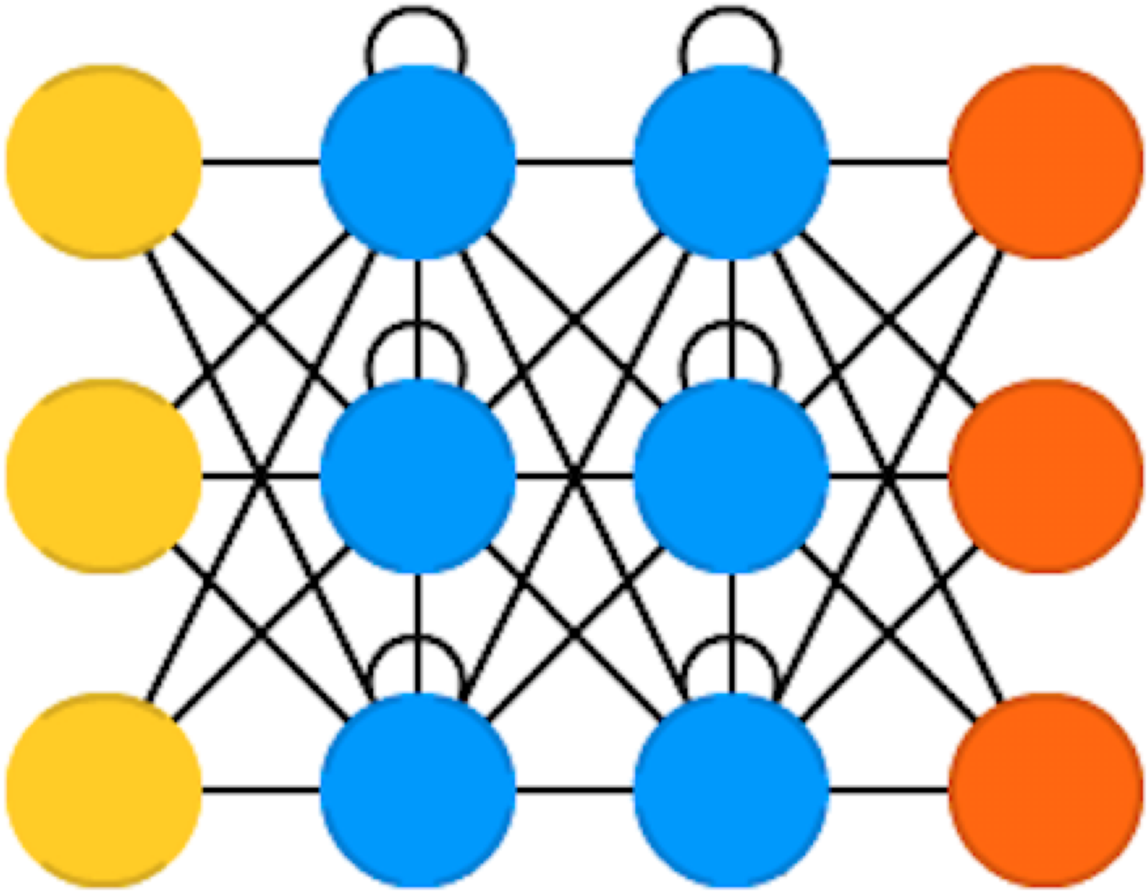
(CNN or Deep Convolutional Neural Networks, DCNN)



LeCun, Yann, et al. "Gradient-based learning applied to document recognition." Proceedings of the IEEE 86.11 (1998): 2278-2324.

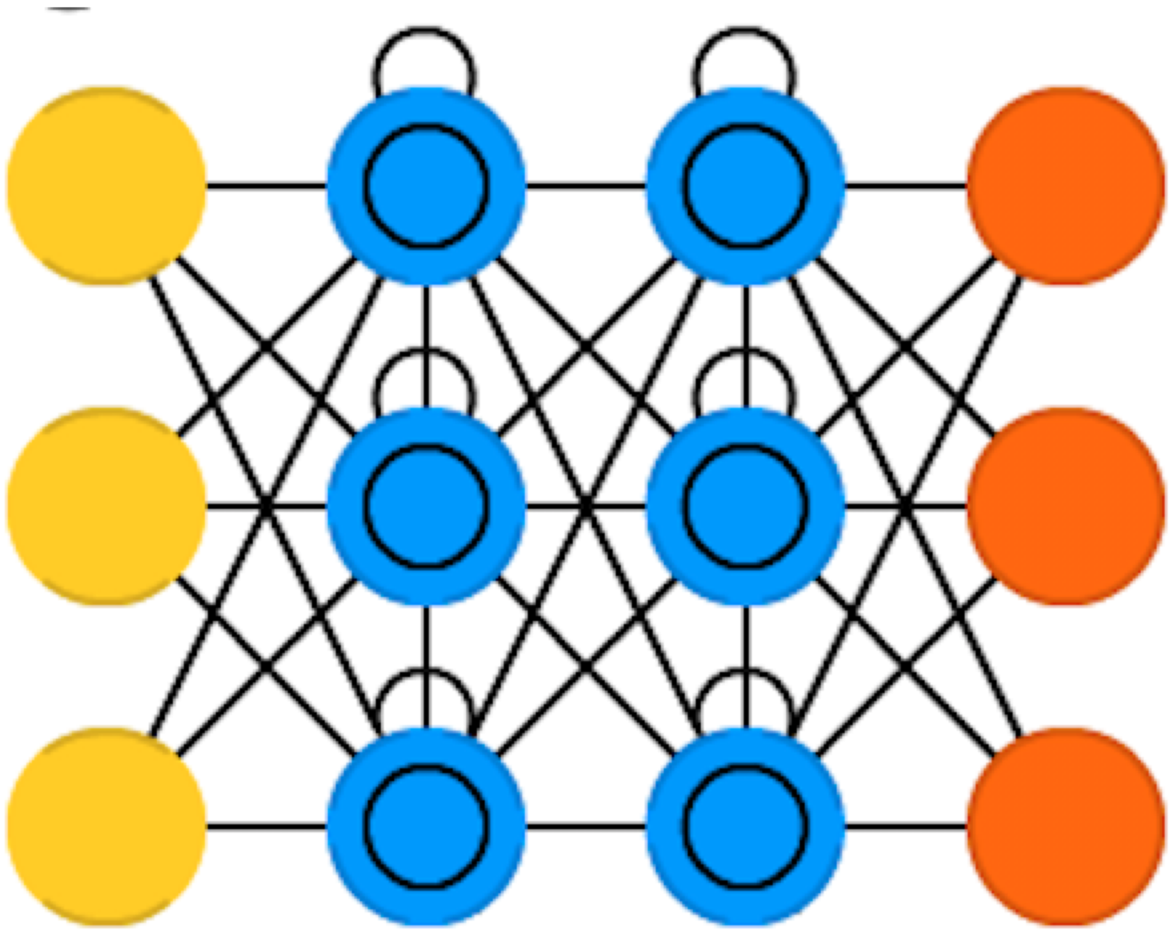
Source: http://www.asimovinstitute.org/neural-network-zoo/

Recurrent Neural Networks (RNN)



Elman, Jeffrey L. "Finding structure in time." Cognitive science 14.2 (1990): 179-211
Source: http://www.asimovinstitute.org/neural-network-zoo/

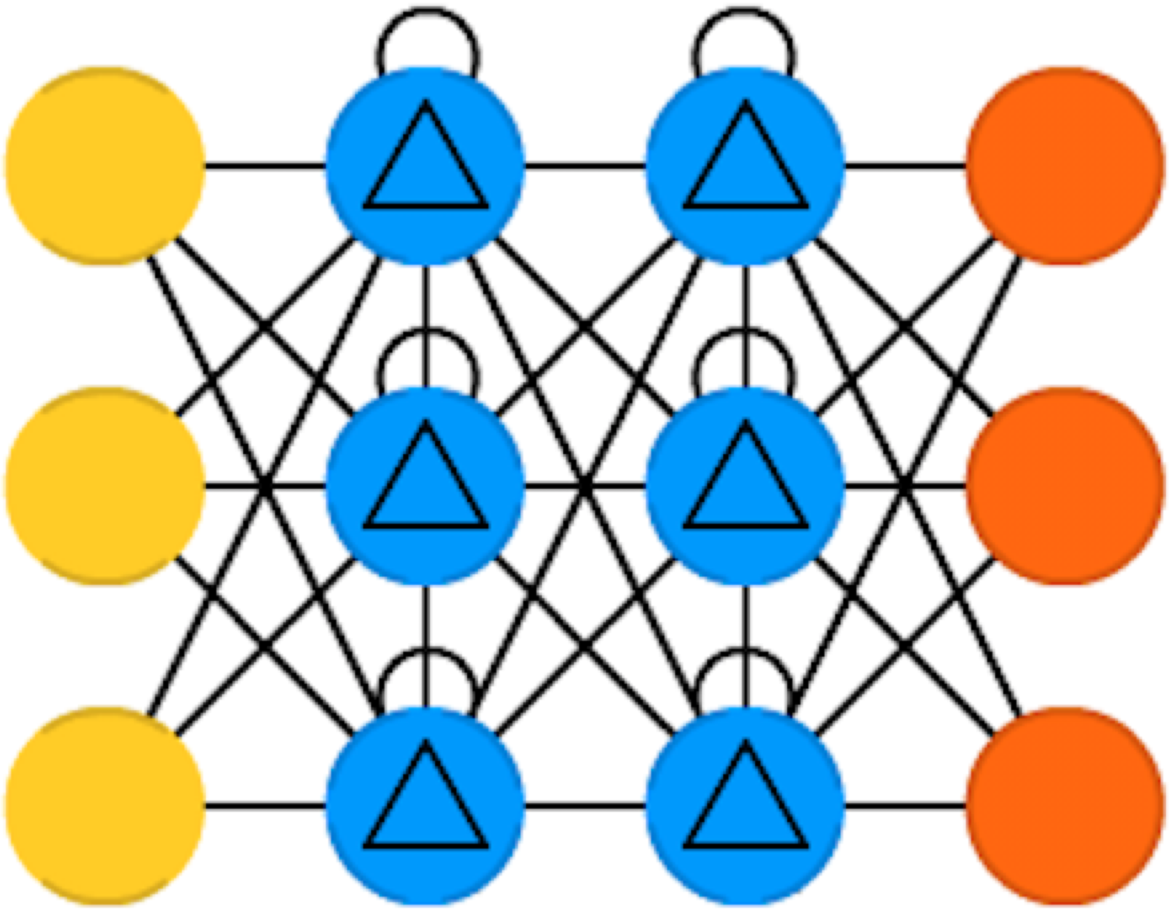
Long / Short Term Memory (LSTM)



Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." Neural computation 9.8 (1997): 1735-1780.

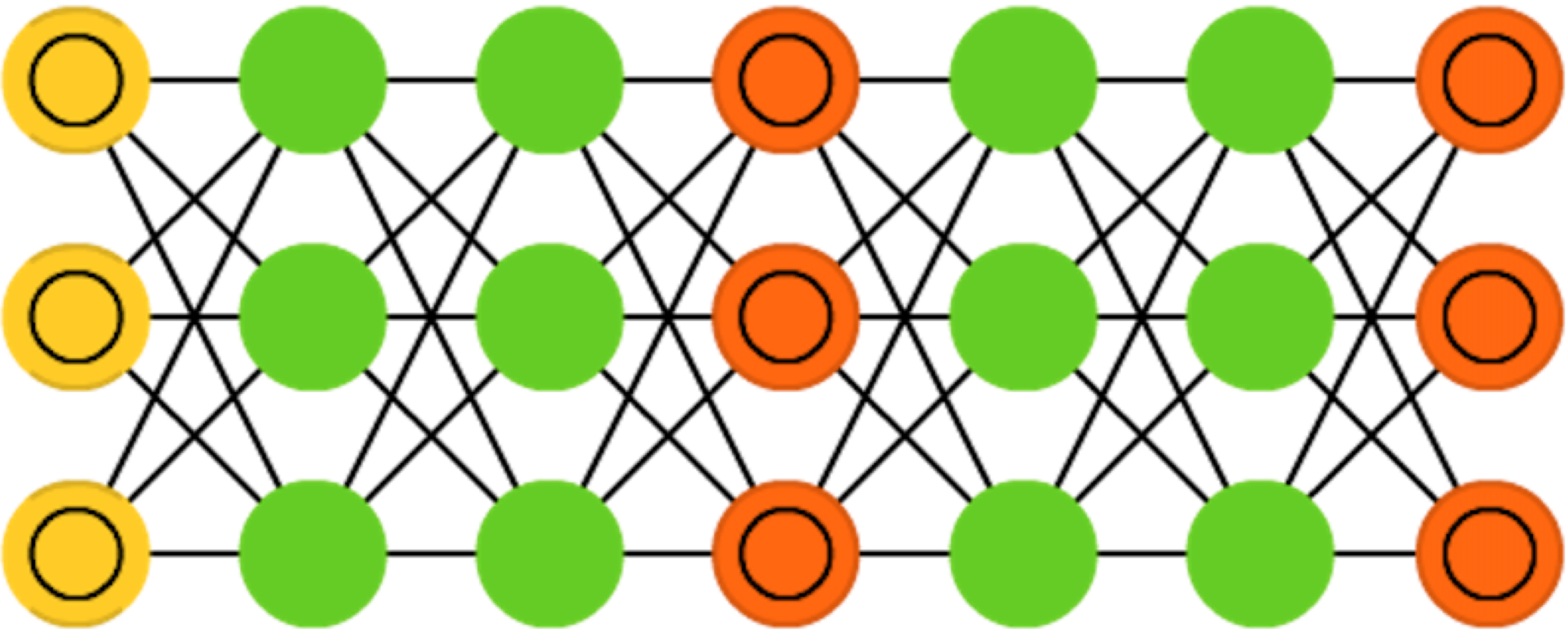
Source: http://www.asimovinstitute.org/neural-network-zoo/

Gated Recurrent Units (GRU)



Chung, Junyoung, et al. "Empirical evaluation of gated recurrent neural networks on sequence modeling." arXiv preprint arXiv:1412.3555 (2014).
Source: http://www.asimovinstitute.org/neural-network-zoo/

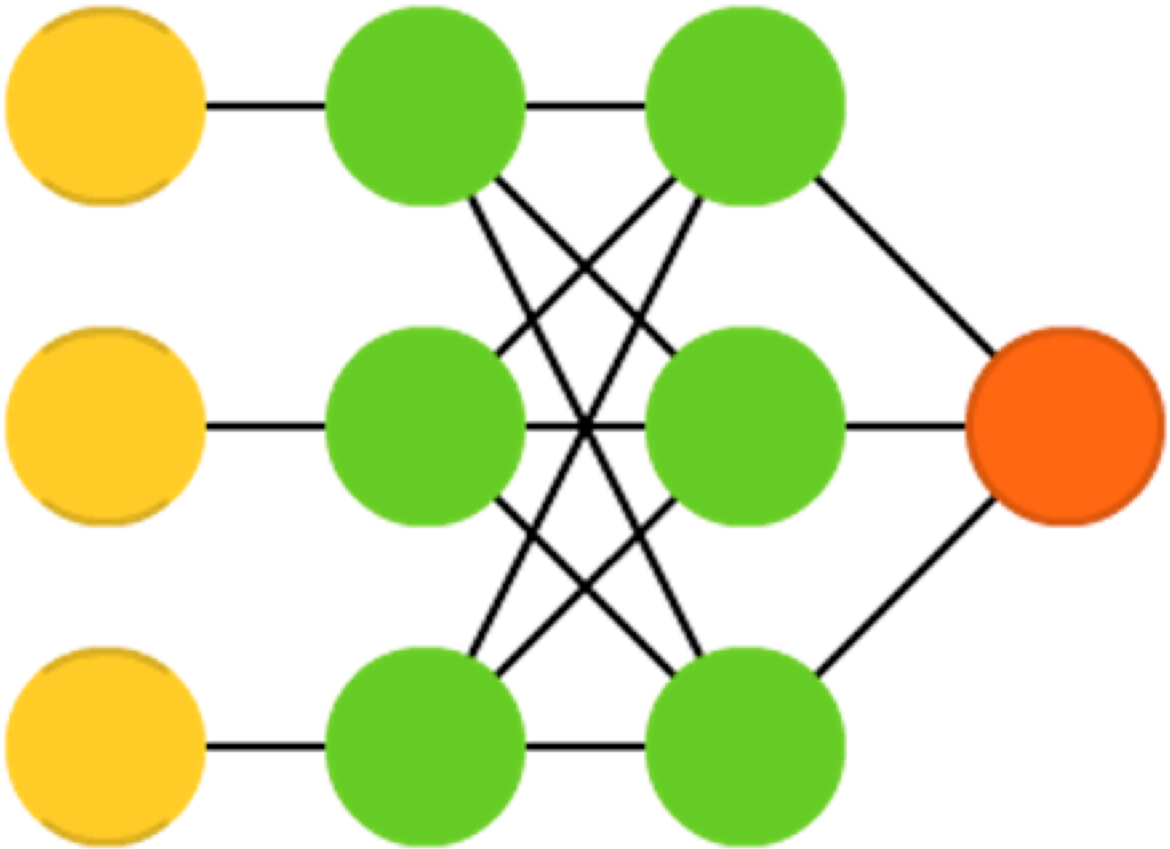
Generative Adversarial Networks (GAN)



Goodfellow, Ian, et al. "Generative adversarial nets." Advances in Neural Information Processing Systems. 2014.

Source: http://www.asimovinstitute.org/neural-network-zoo/

Support Vector Machines (SVM)

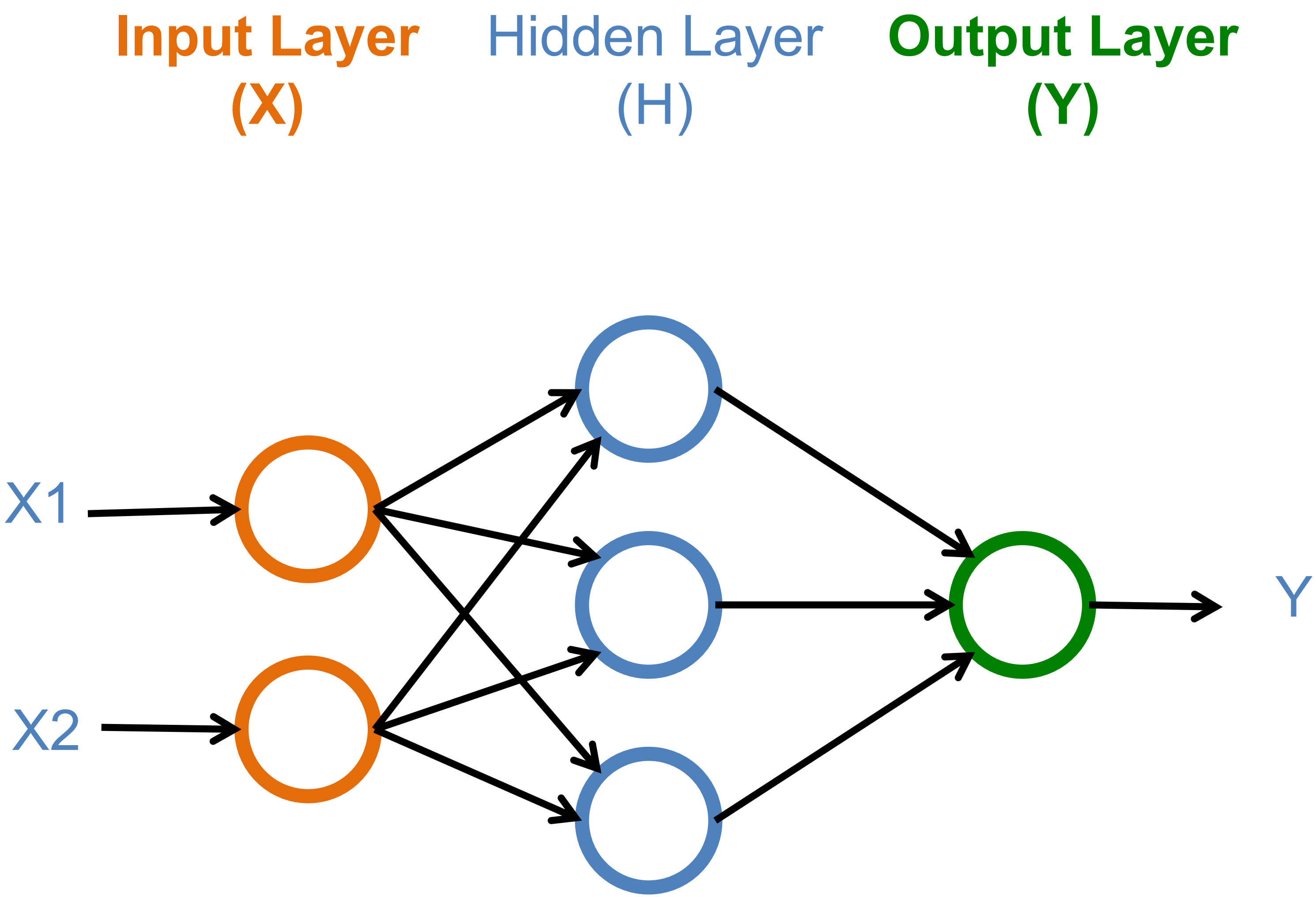


Cortes, Corinna, and Vladimir Vapnik. "Support-vector networks." Machine learning 20.3 (1995): 273-297.

Source: http://www.asimovinstitute.org/neural-network-zoo/

Neural networks (NN) 1960

Neural Networks



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

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

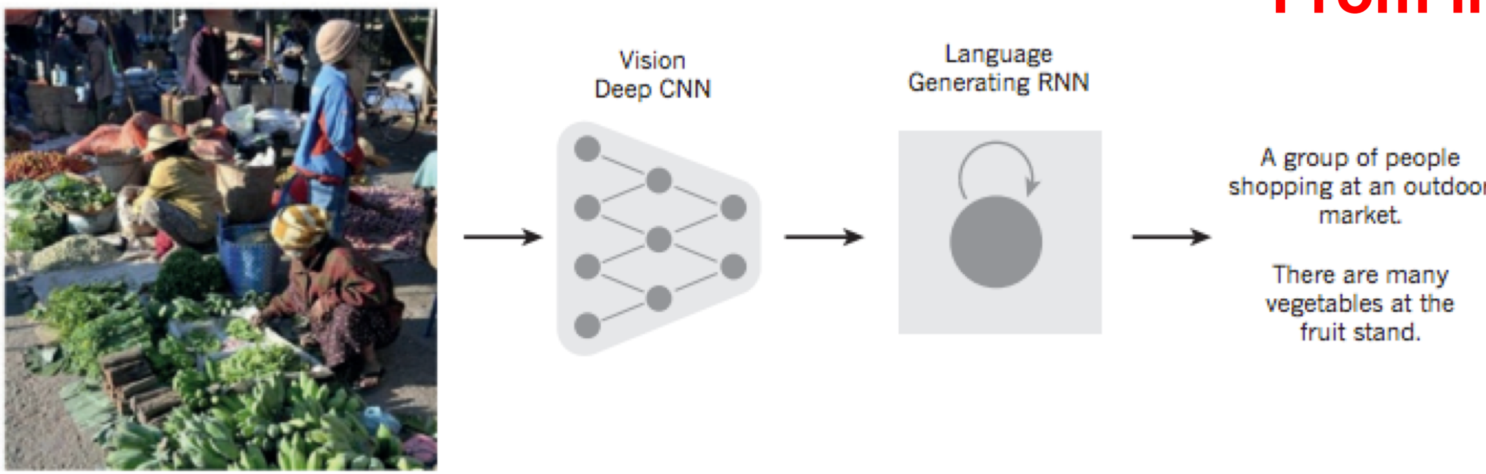
Convolutional DBN
2010

Max-Pooling CDBN 2011

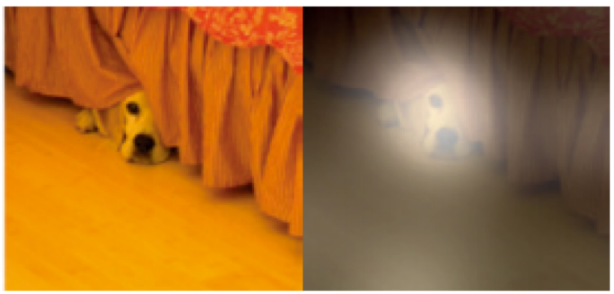
Deep Learning

Geoffrey Hinton
Yann LeCun
Yoshua Bengio
Andrew Y. Ng

From image to text

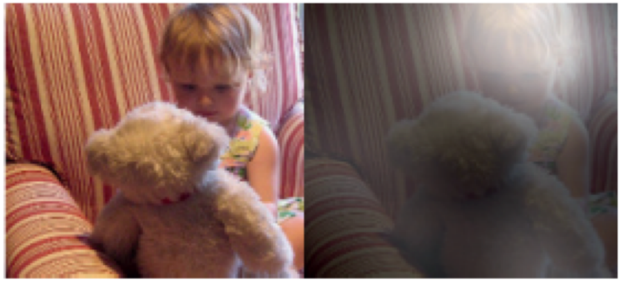


A woman is throwing a **frisbee** in a park.

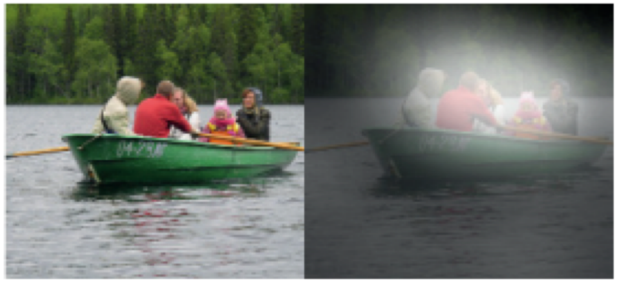


A **dog** is standing on a hardwood floor.

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

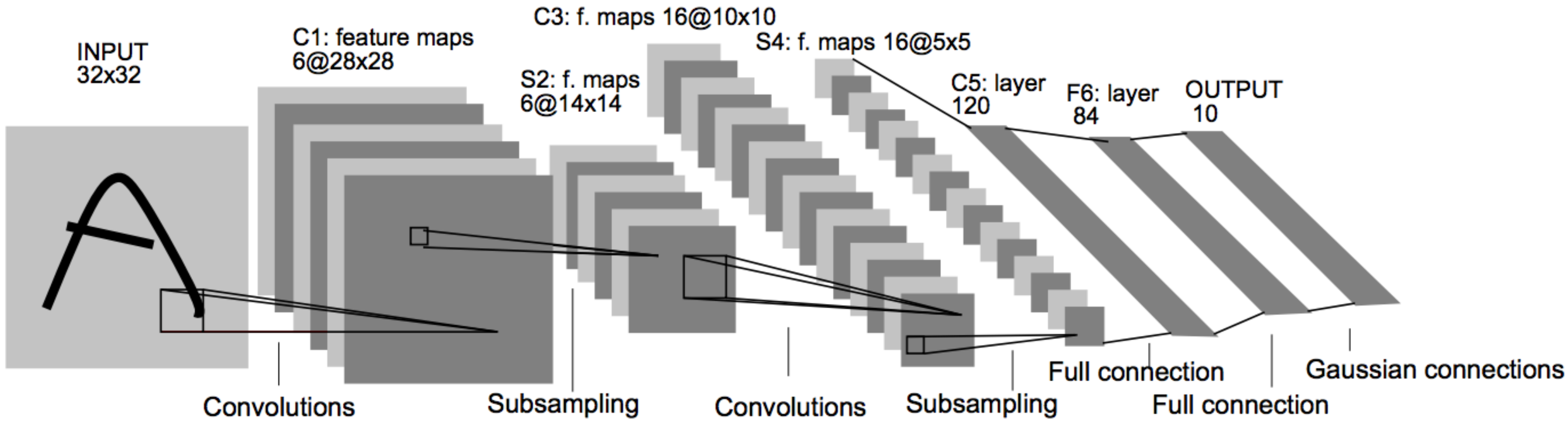
Image: deep convolution neural network (CNN)
Text: recurrent neural network (RNN)

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.

Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNN)



Architecture of LeNet-5 (7 Layers) (LeCun et al., 1998)

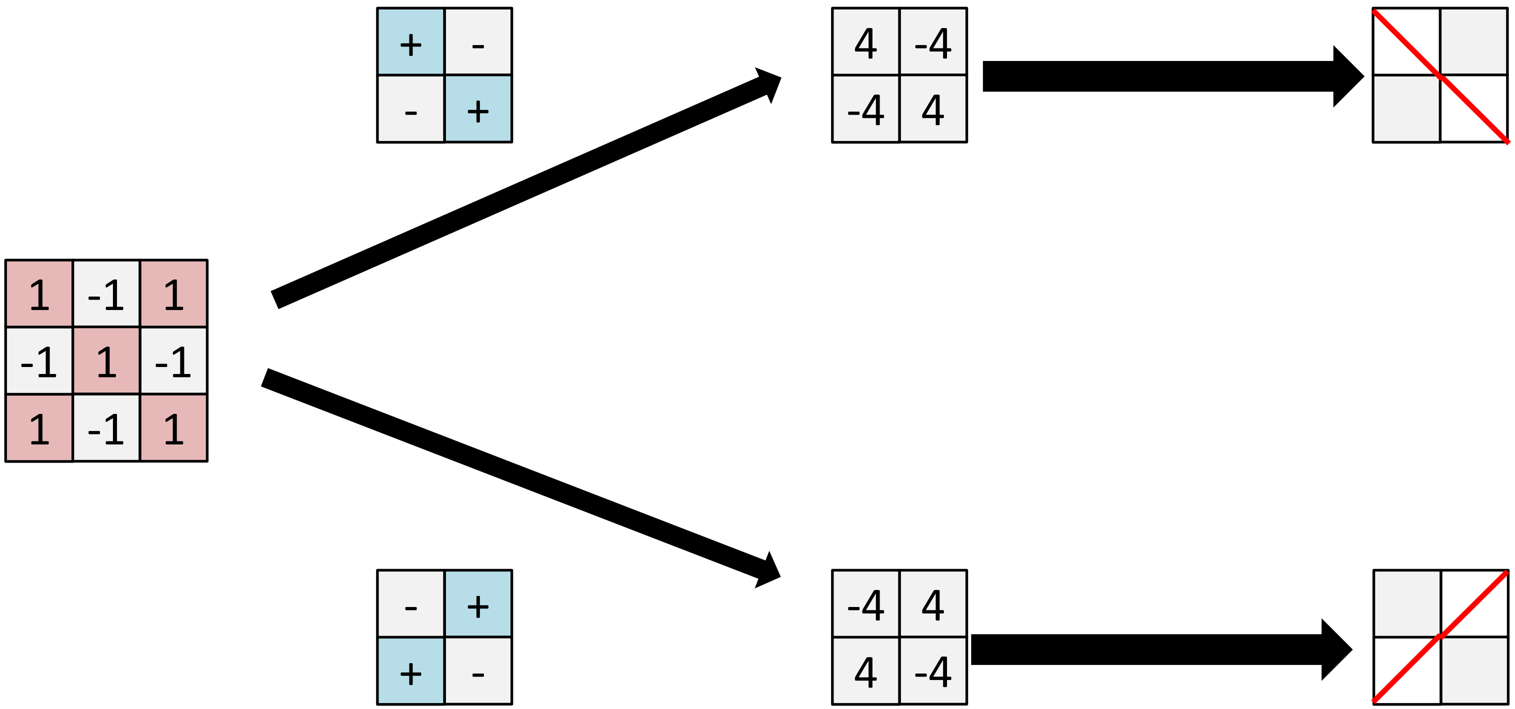
Source: http://yann.lecun.com/exdb/publis/pdf/lecun-01a.pdf

Source: LeCun, Yann, Léon Bottou, Yoshua Bengio, and Patrick Haffner. "Gradient-based learning applied to document recognition." *Proceedings of the IEEE* 86, no. 11 (1998): 2278-2324.

Convolutional Neural Networks (CNN)

- Convolution
- Pooling
- Fully Connection (FC) (Flattening)

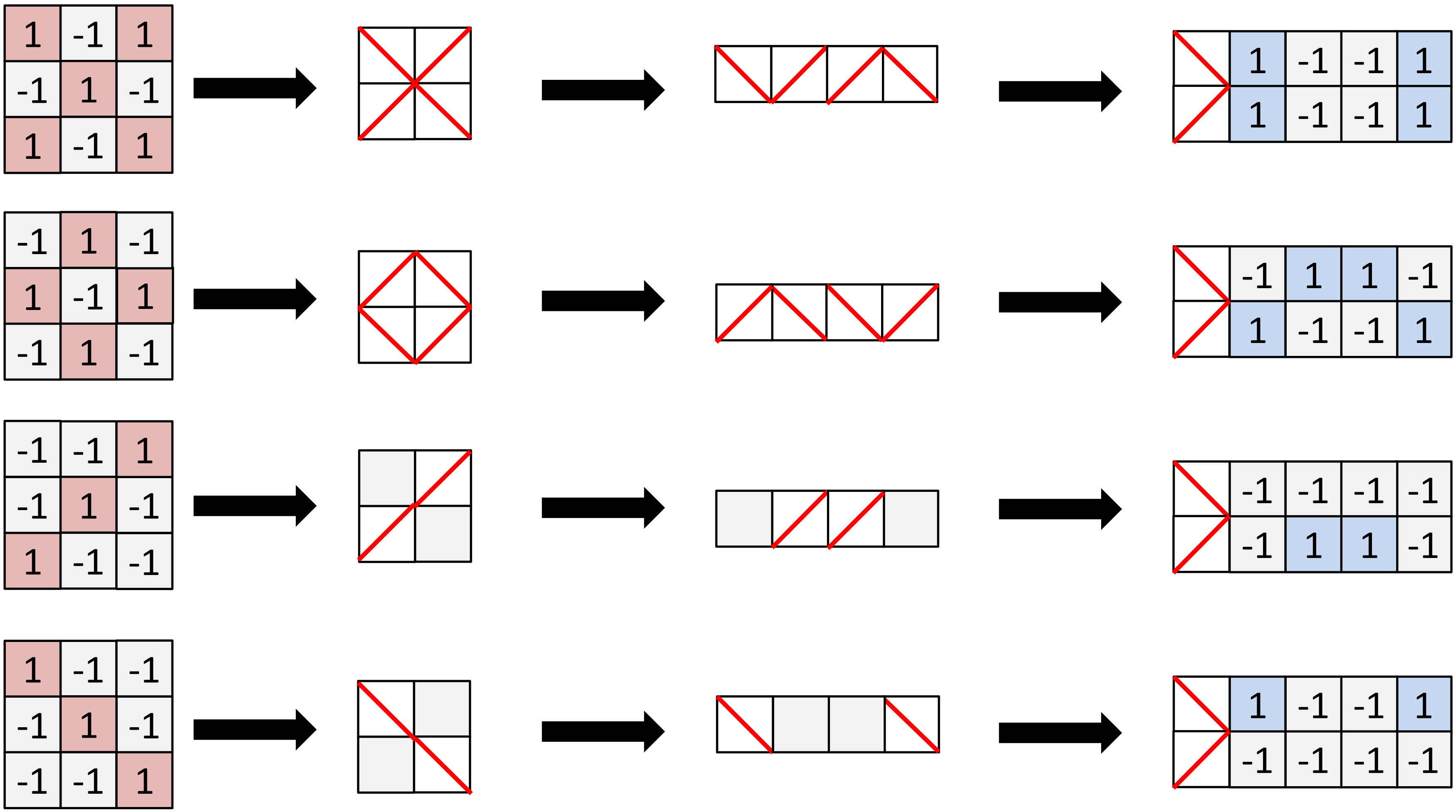
A friendly introduction to Convolutional Neural Networks and Image Recognition



Convolution Layer Pooling Layer

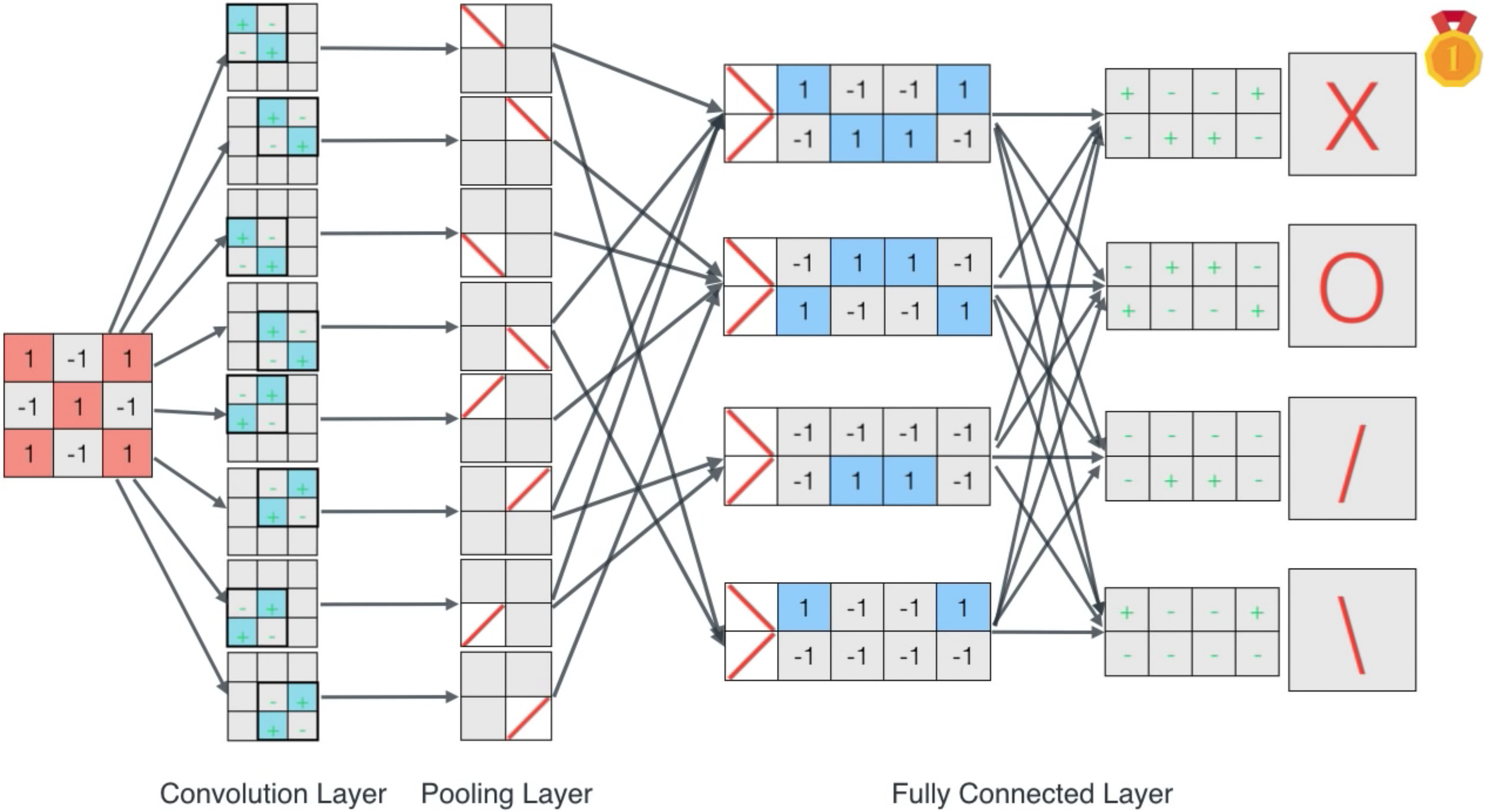
Source: Luis Serrano (2017), A friendly introduction to Convolutional Neural Networks and Image Recognition, https://www.youtube.com/watch?v=2-Ol7ZB0MmU

A friendly introduction to Convolutional Neural Networks and Image Recognition



Source: Luis Serrano (2017), A friendly introduction to Convolutional Neural Networks and Image Recognition, https://www.youtube.com/watch?v=2-Ol7ZB0MmU

A friendly introduction to Convolutional Neural Networks and Image Recognition



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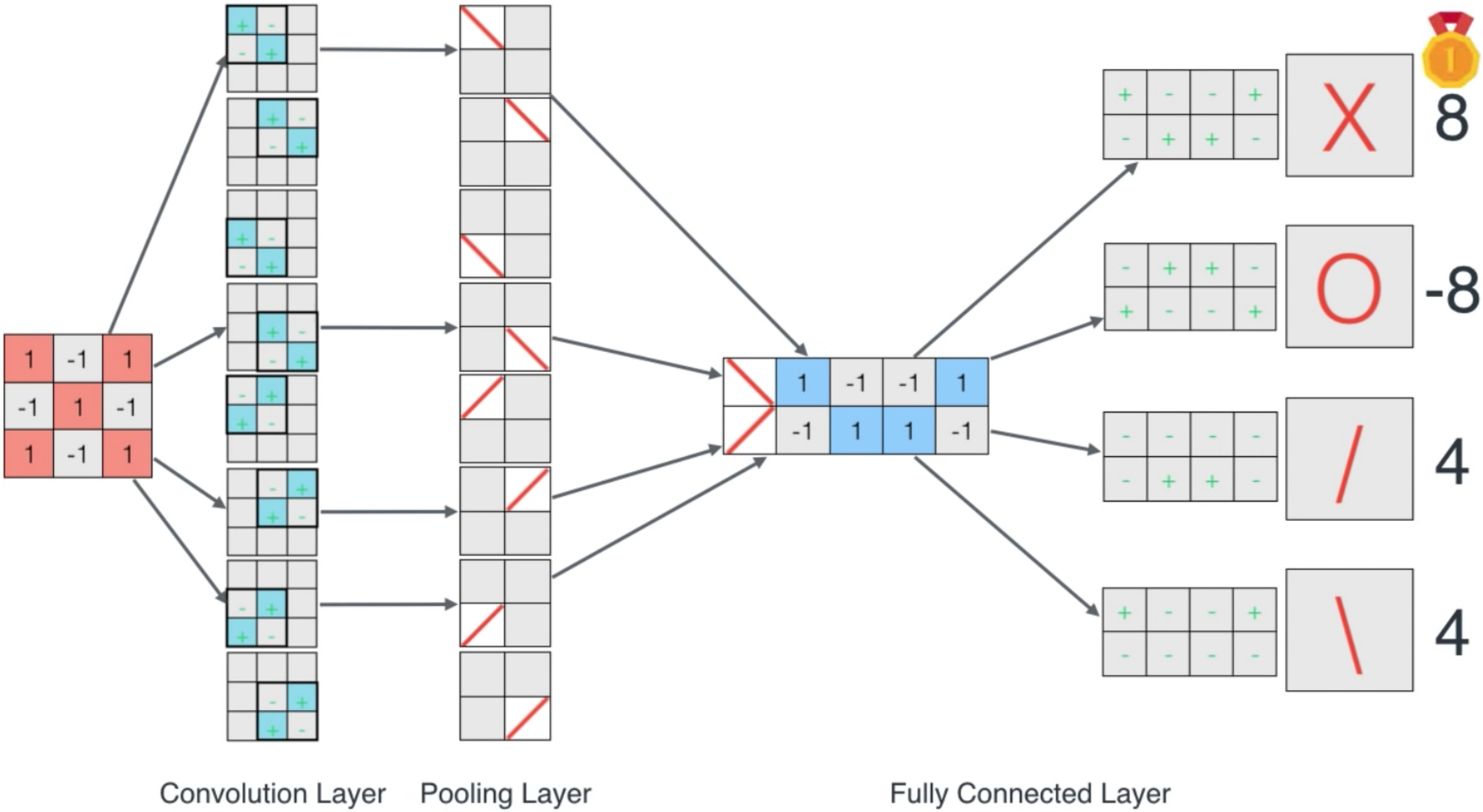
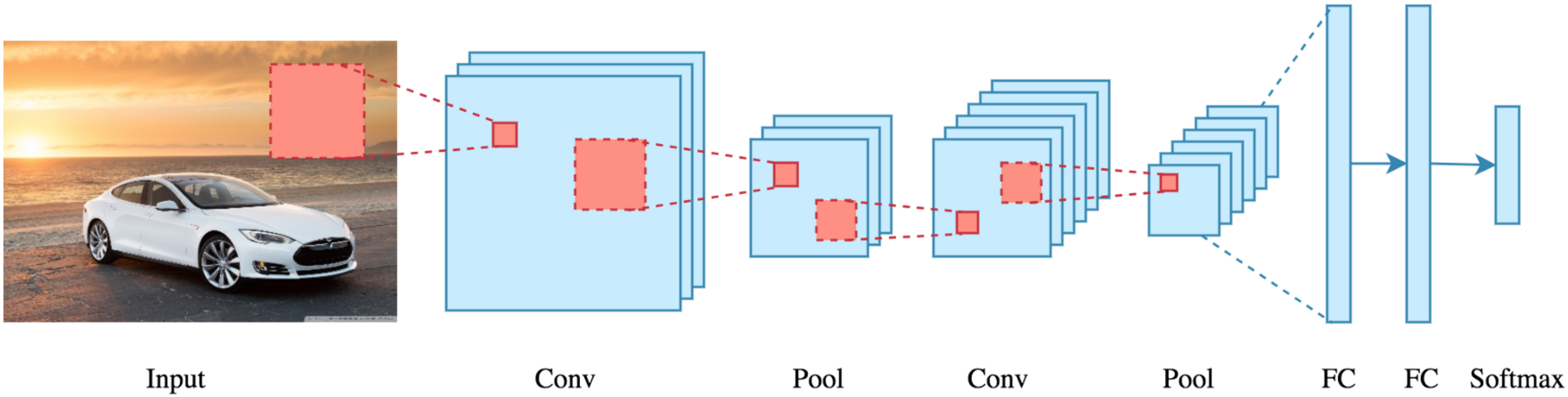
A friendly introduction to Convolutional Neural Networks and Image Recognition



Source: Luis Serrano (2017), A friendly introduction to Convolutional Neural Networks and Image Recognition, https://www.youtube.com/watch?v=2-Ol7ZB0MmU

CNN Architecture



Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks, https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Convolution Layer

Convolution is a **mathematical operation** to **merge two sets** of information

3x3 convolution

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

Input

1	0	1
0	1	0
1	0	1

Filter / Kernel

Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks, https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Convolution Layer
Input x Filter --> Feature Map

receptive field: 3x3

1x1	1x0	1x1	0	0
0x0	1x1	1x0	1	0
0x1	0x0	1x1	1	1
0	0	1	1	0
0	1	1	0	0

Input x Filter

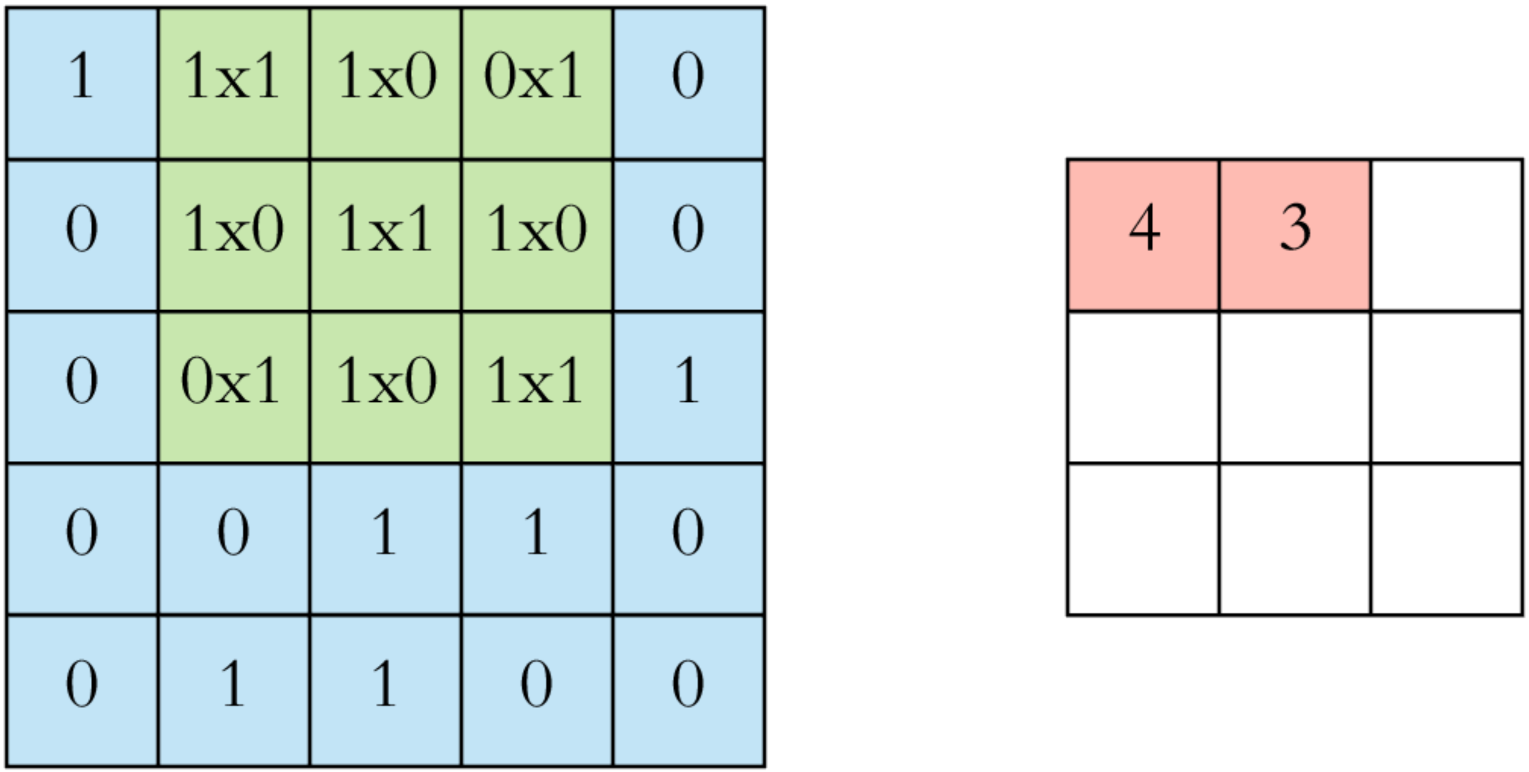
4		

Feature Map

Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks, https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Convolution Layer
Input x Filter --> Feature Map

receptive field: 3x3

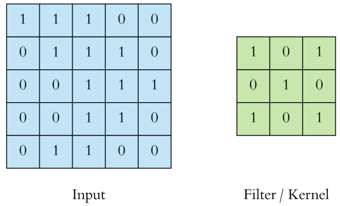


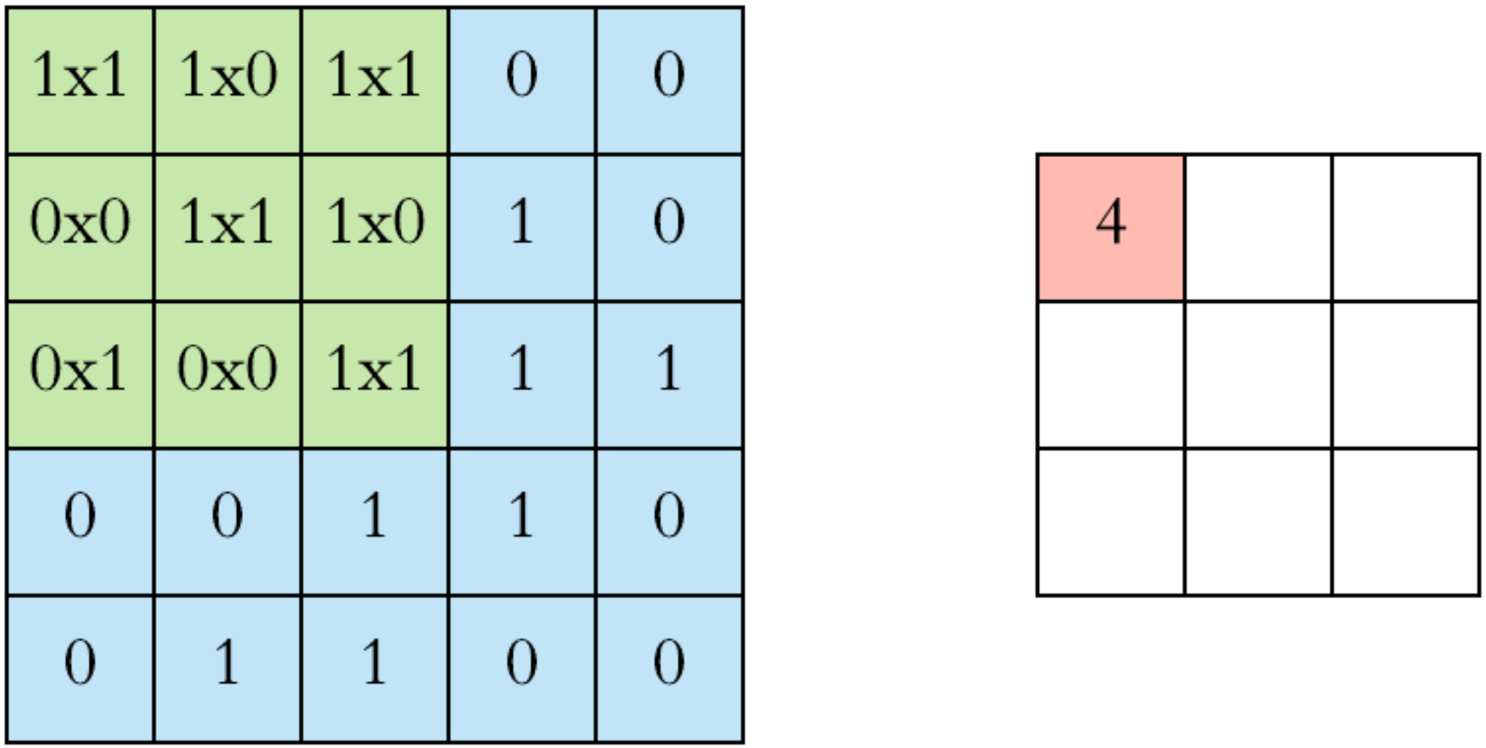
Input x Filter

Feature Map

Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks,
https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Convolution Layer



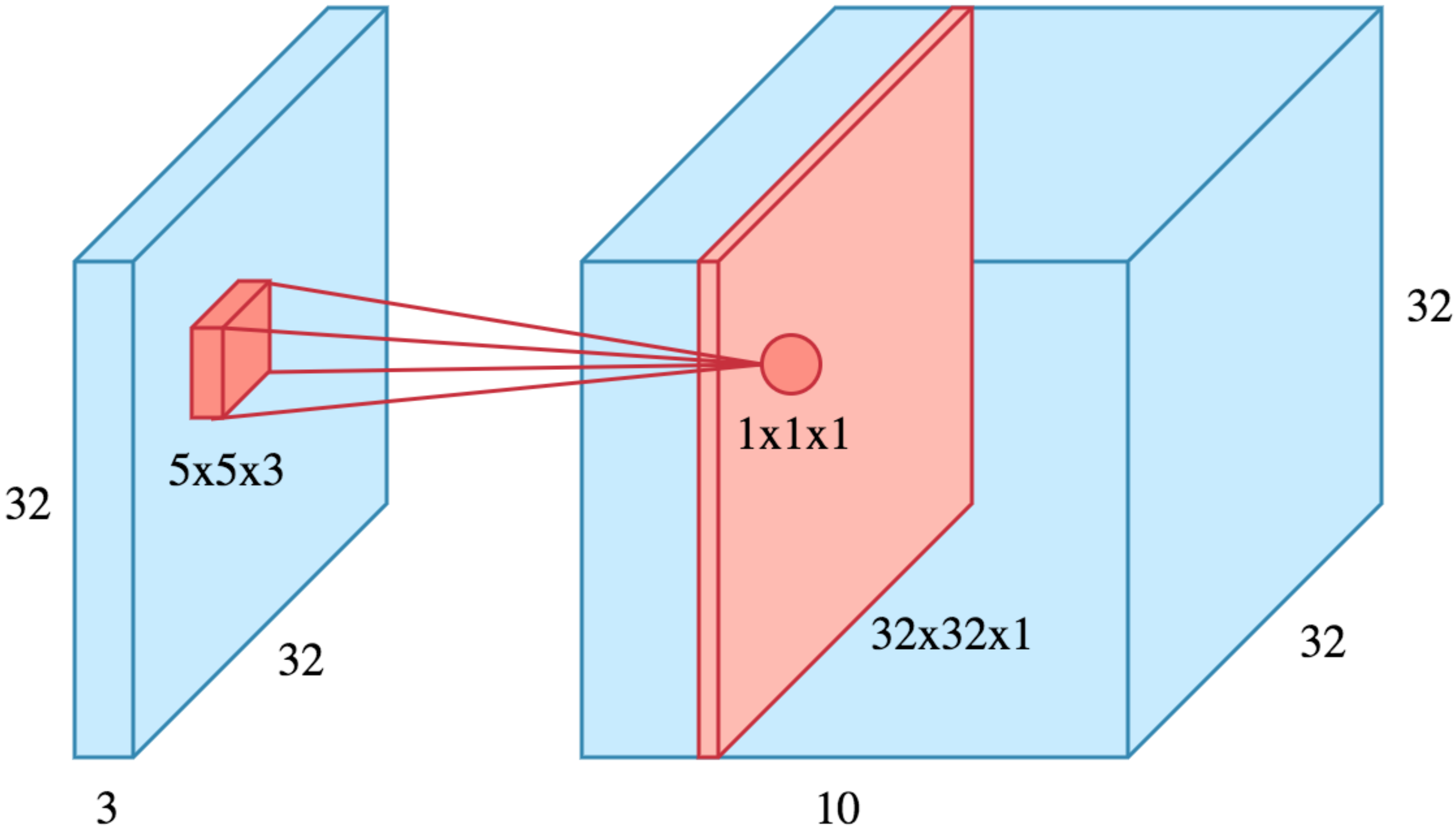


Example convolution operation shown in 2D using a 3x3 filter

Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks, https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Convolution Layer

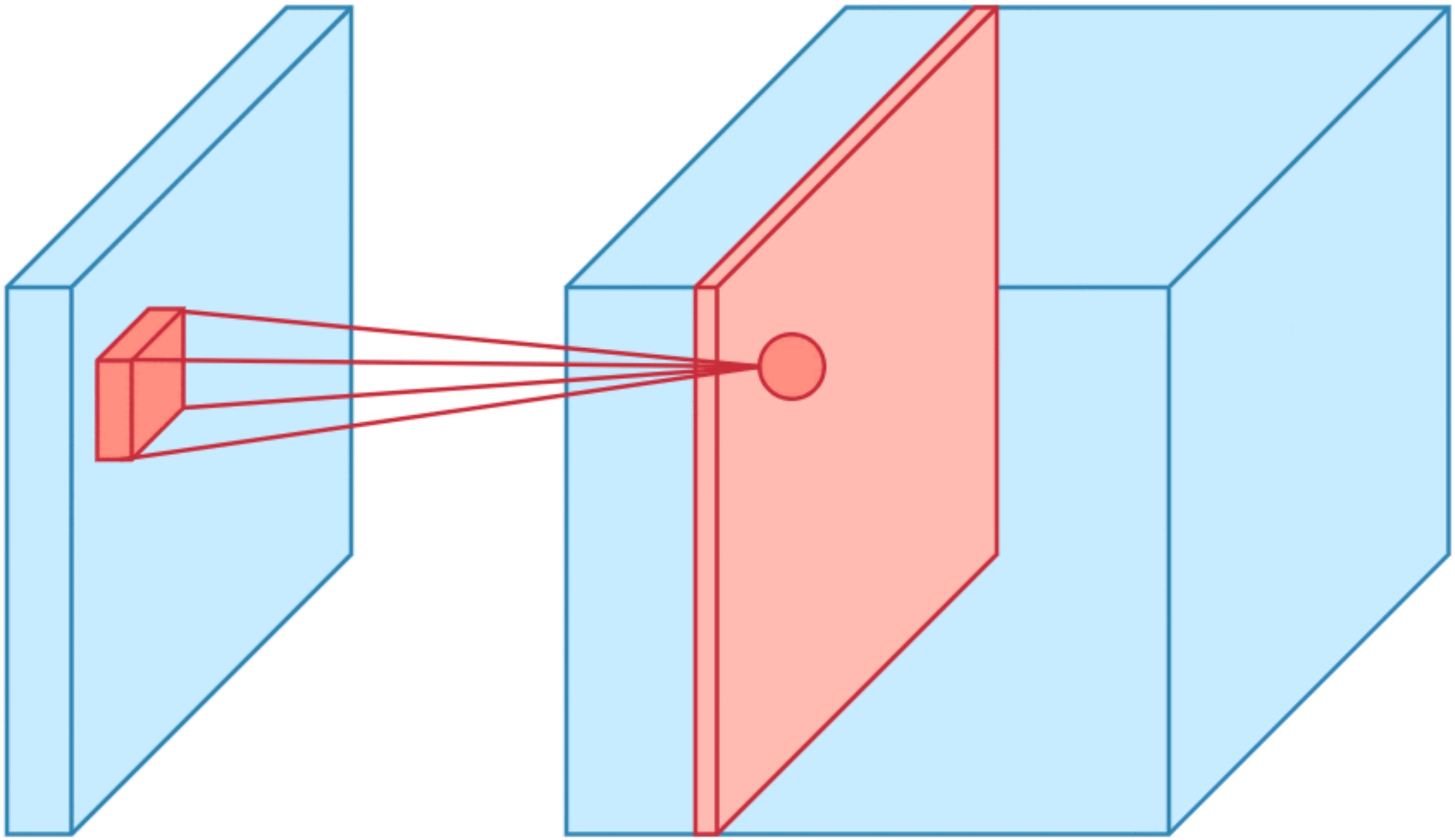
10 different filters 10 feature maps of size 32x32x1



final output of the convolution layer:
a volume of size 32x32x10

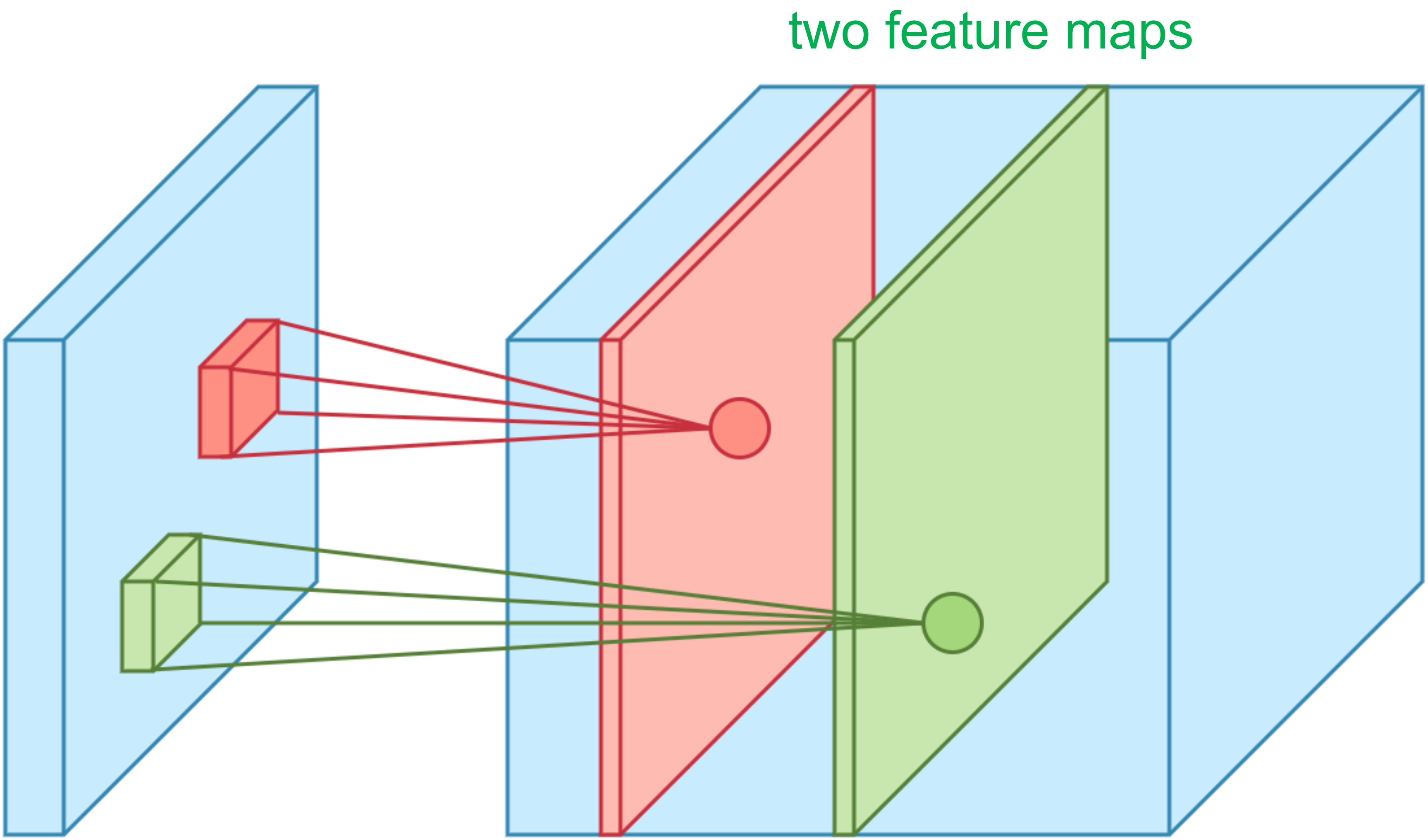
Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks,
https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Convolution Layer
Sliding operation at 4 locations



Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks, https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

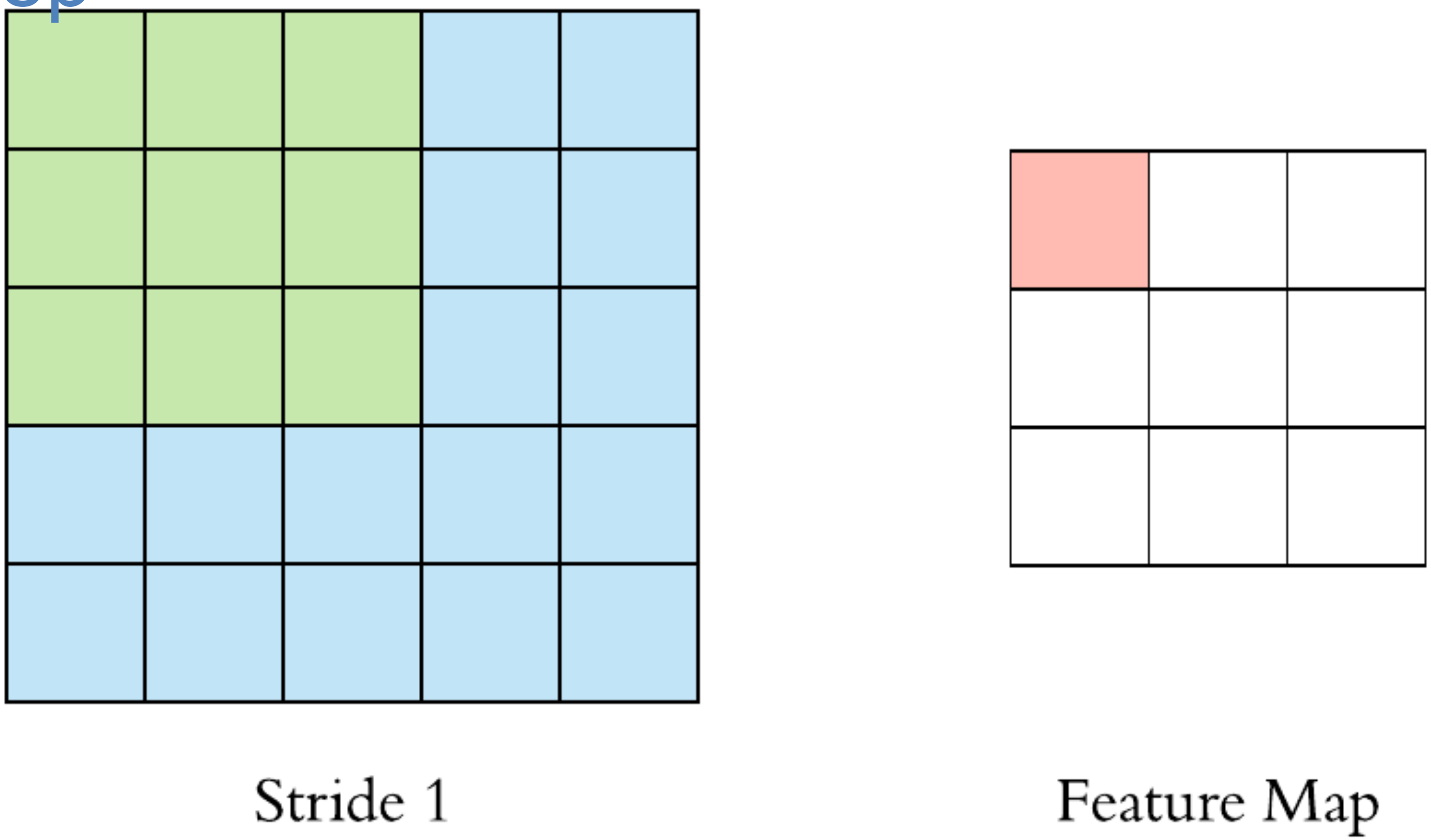
CNN Convolution Layer



Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks,
https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Convolution Layer

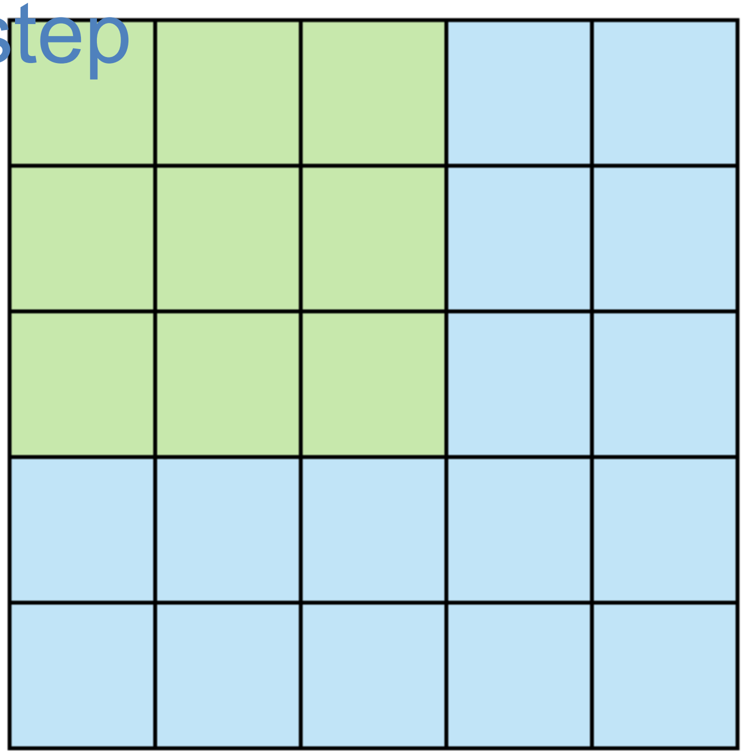
Stride specifies how much
we move the convolution filter at each
step



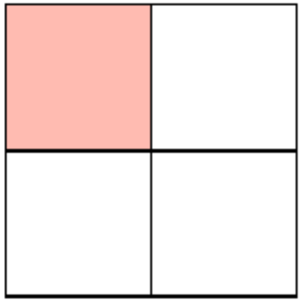
Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks,
https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Convolution Layer

Stride specifies how much we move the convolution filter at each step



Stride 2

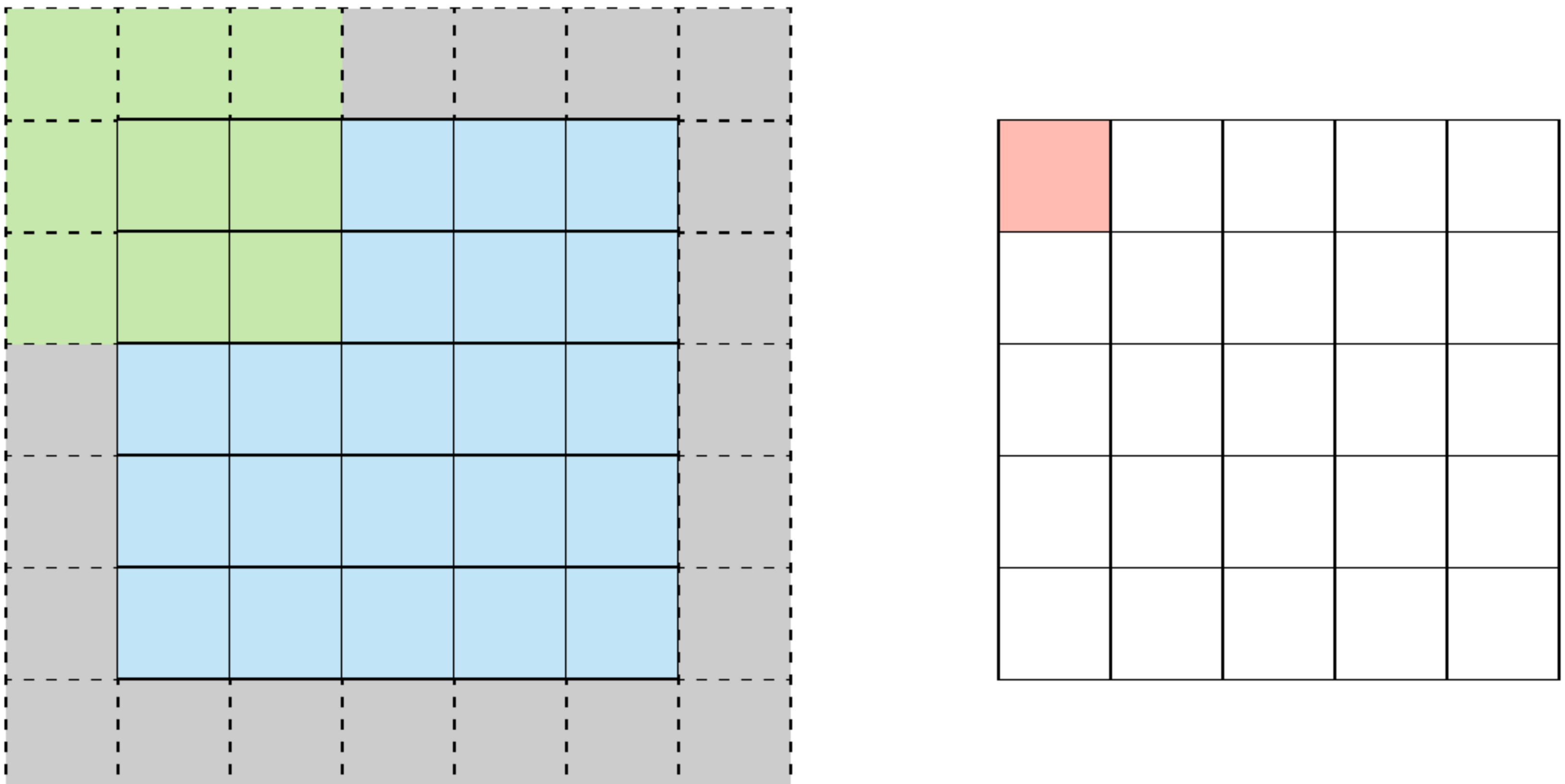


Feature Map

Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks, https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Convolution Layer

Stride 1 with Padding



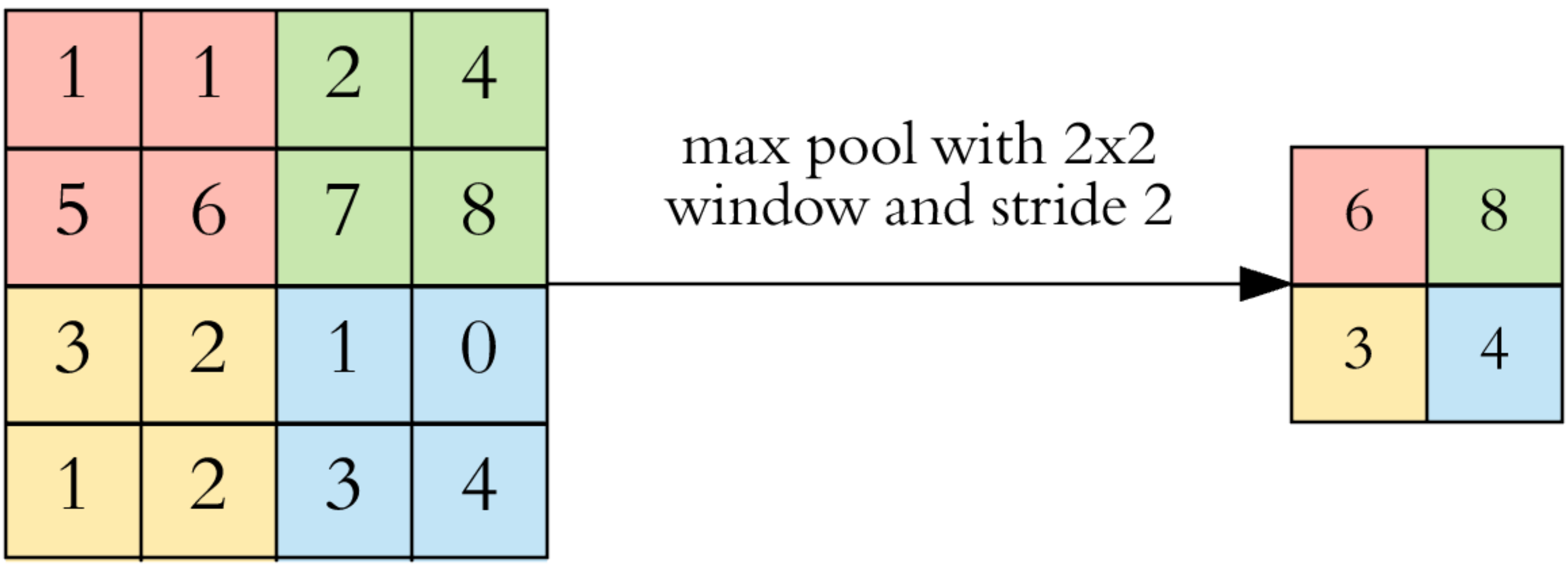
Stride 1 with Padding

Feature Map

Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks, https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

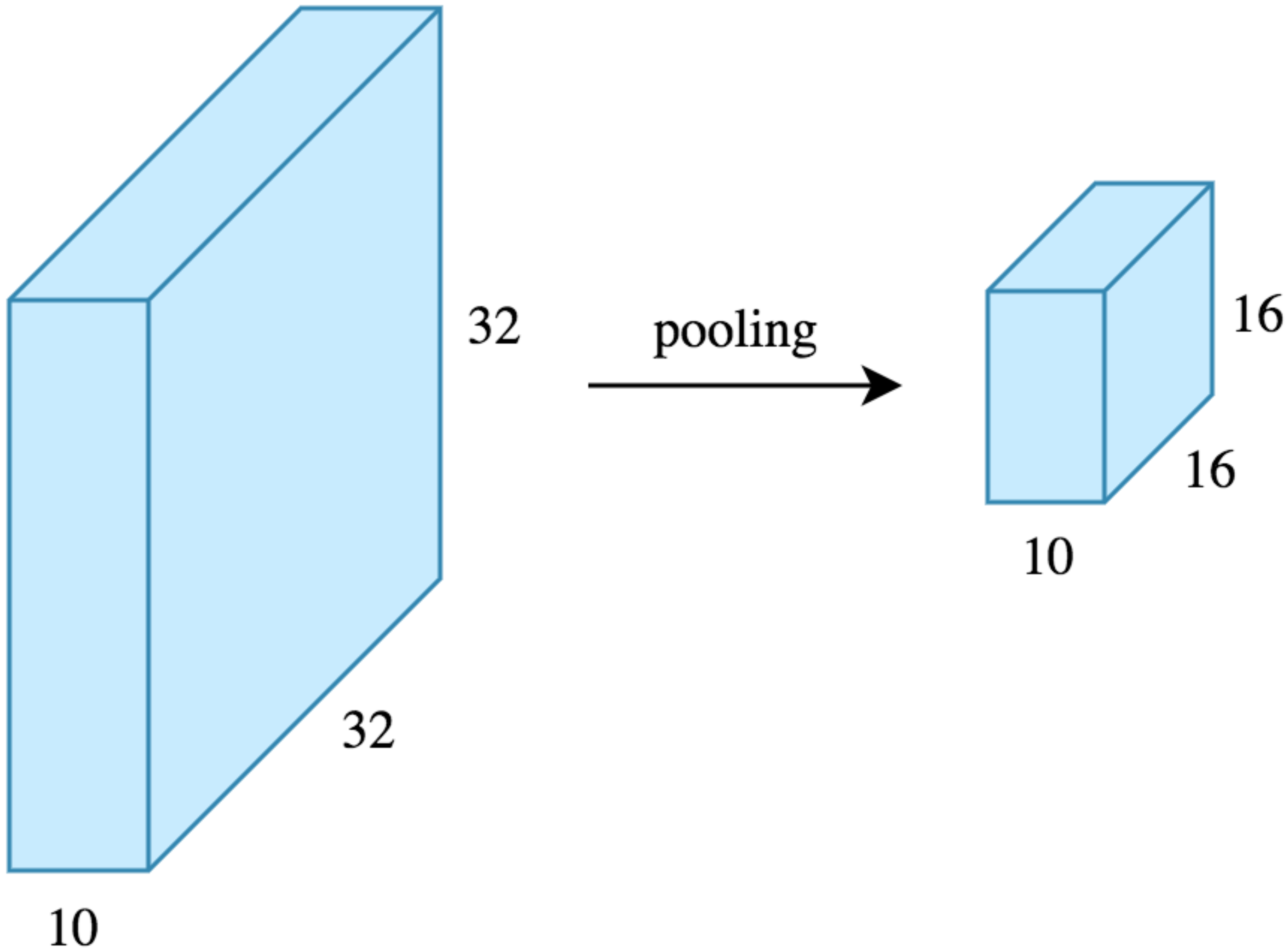
CNN Pooling Layer

Max Pooling



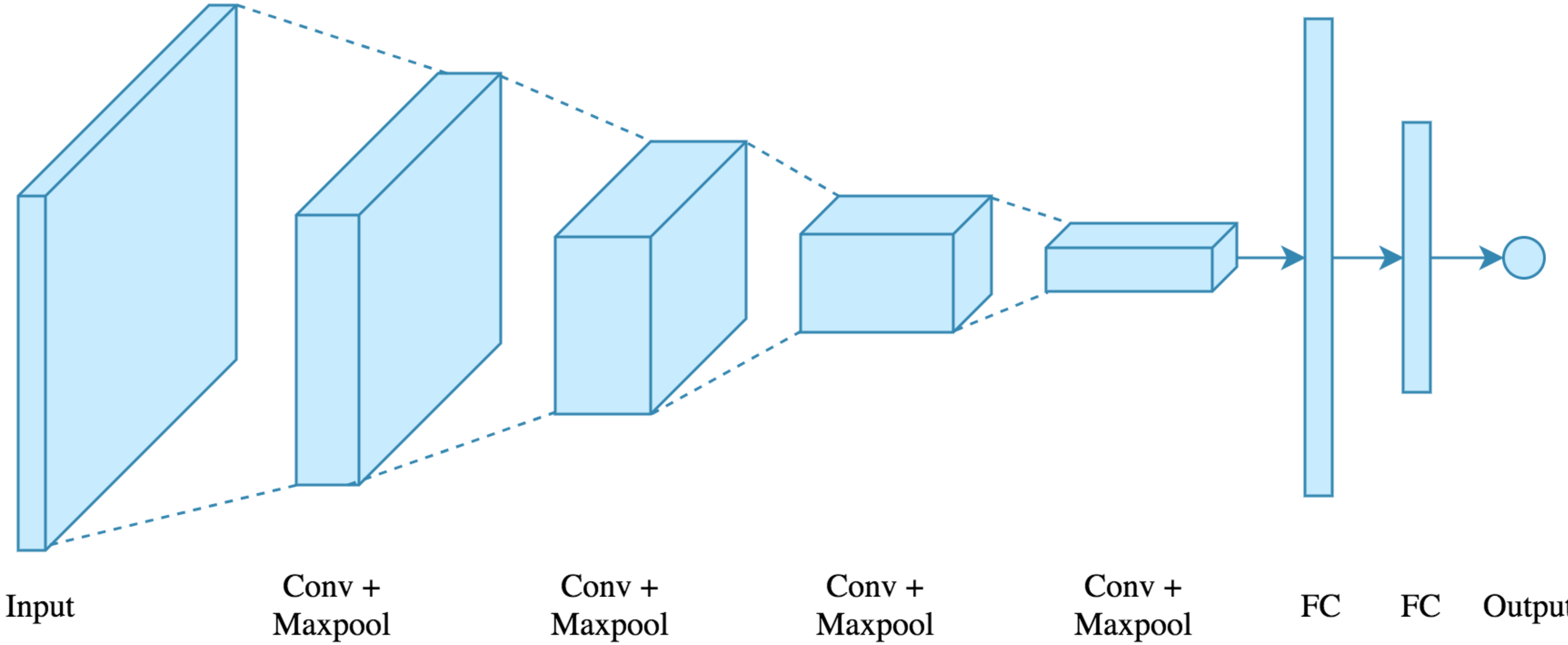
Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks,
https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Pooling Layer



Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks, https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Architecture
4 convolution + pooling layers, followed by 2 fully connected layers



Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks, https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

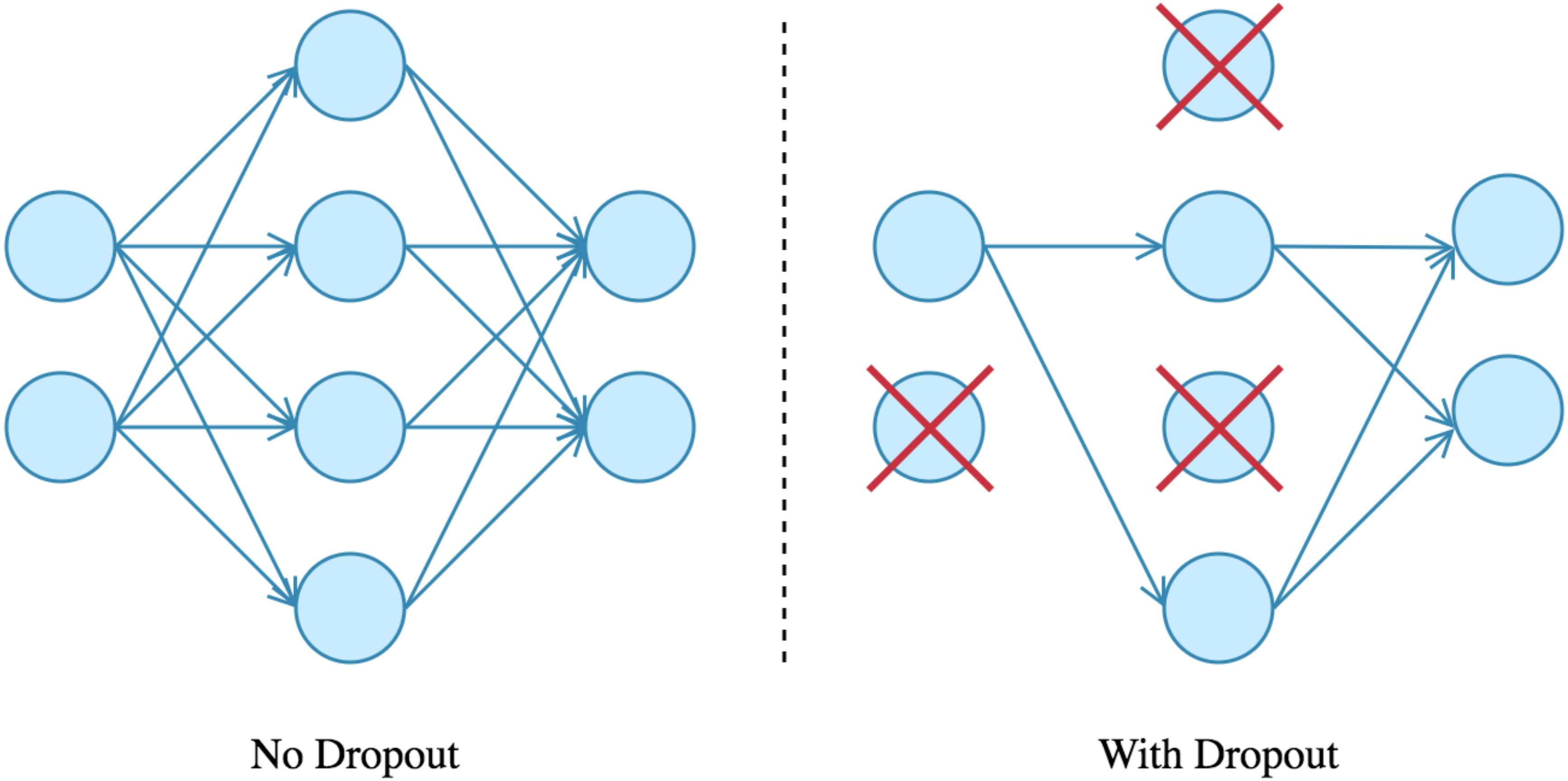
CNN Architecture
4 convolution + pooling layers, followed by 2 fully connected layers

https://gist.github.com/ardendertat/0fc5515057c47e7386fe04e9334504e3

```
model = Sequential()
model.add(Conv2D(32, (3, 3), activation='relu', padding='same', name='conv_1',
                 input_shape=(150, 150, 3)))
model.add(MaxPooling2D((2, 2), name='maxpool_1'))
model.add(Conv2D(64, (3, 3), activation='relu', padding='same', name='conv_2'))
model.add(MaxPooling2D((2, 2), name='maxpool_2'))
model.add(Conv2D(128, (3, 3), activation='relu', padding='same', name='conv_3'))
model.add(MaxPooling2D((2, 2), name='maxpool_3'))
model.add(Conv2D(128, (3, 3), activation='relu', padding='same', name='conv_4'))
model.add(MaxPooling2D((2, 2), name='maxpool_4'))
model.add(Flatten())
model.add(Dropout(0.5))
model.add(Dense(512, activation='relu', name='dense_1'))
model.add(Dense(128, activation='relu', name='dense_2'))
model.add(Dense(1, activation='sigmoid', name='output'))
```

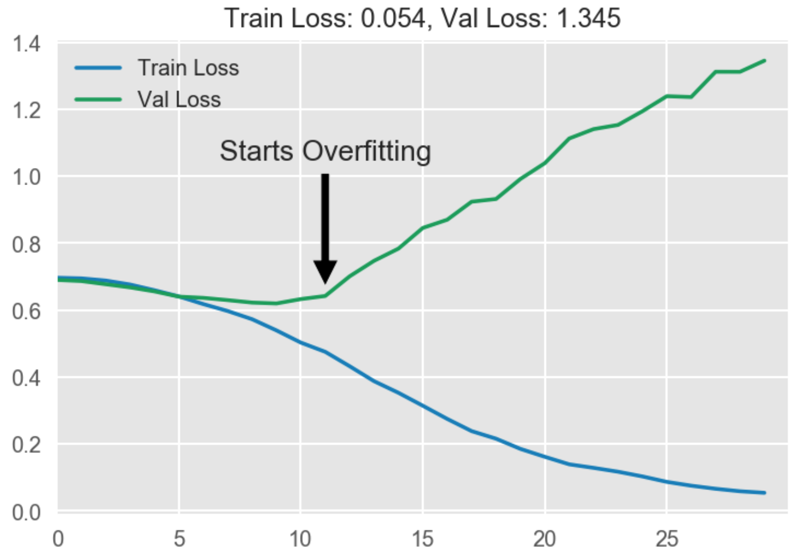
Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks,
https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

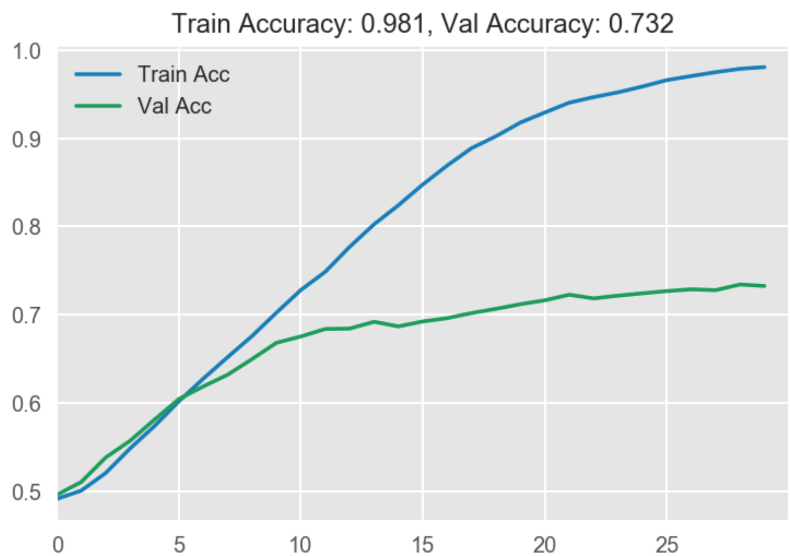
Dropout



Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks, https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

Model Performance

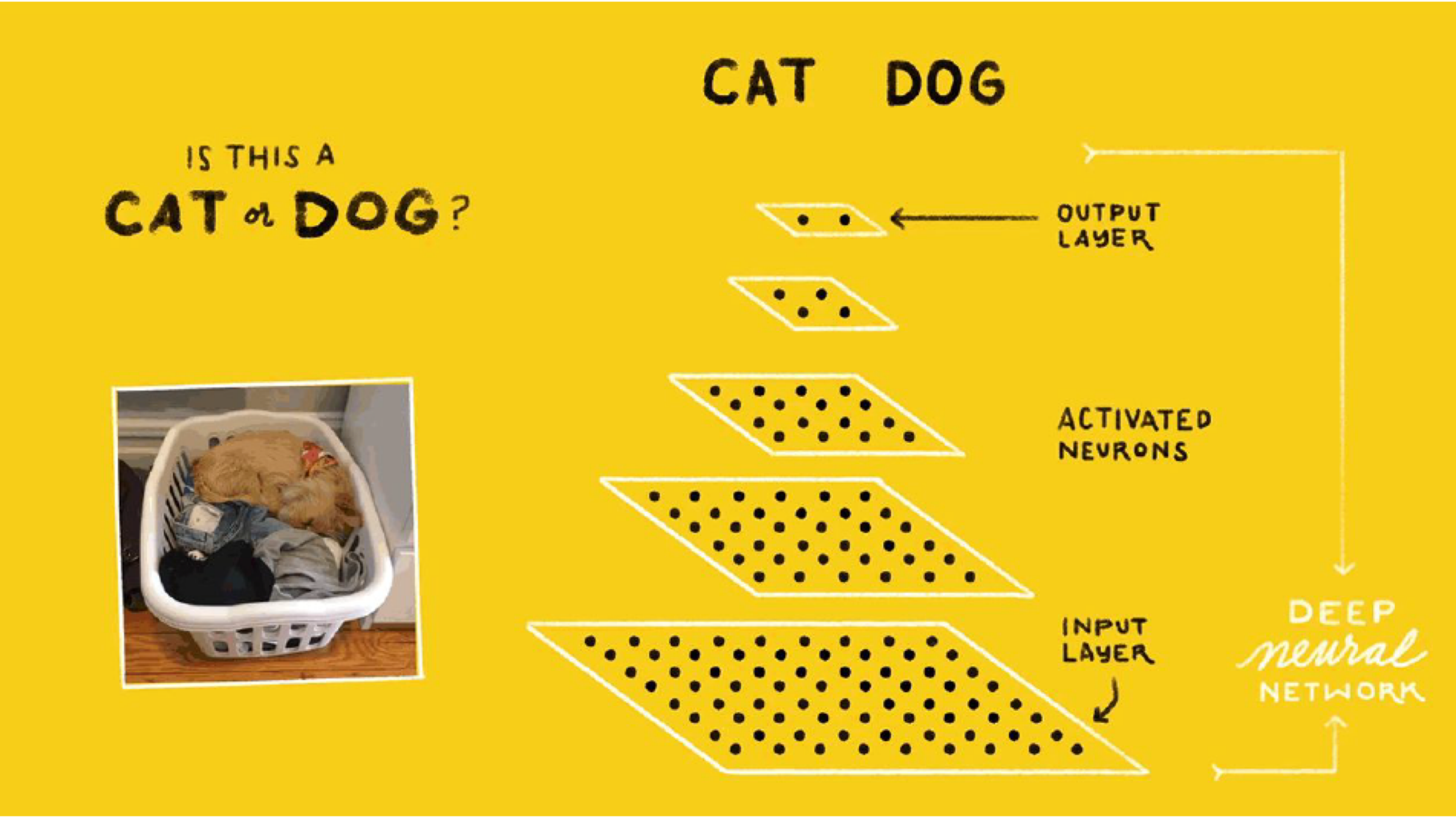




Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks, https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

Visual Recognition

Image Classification

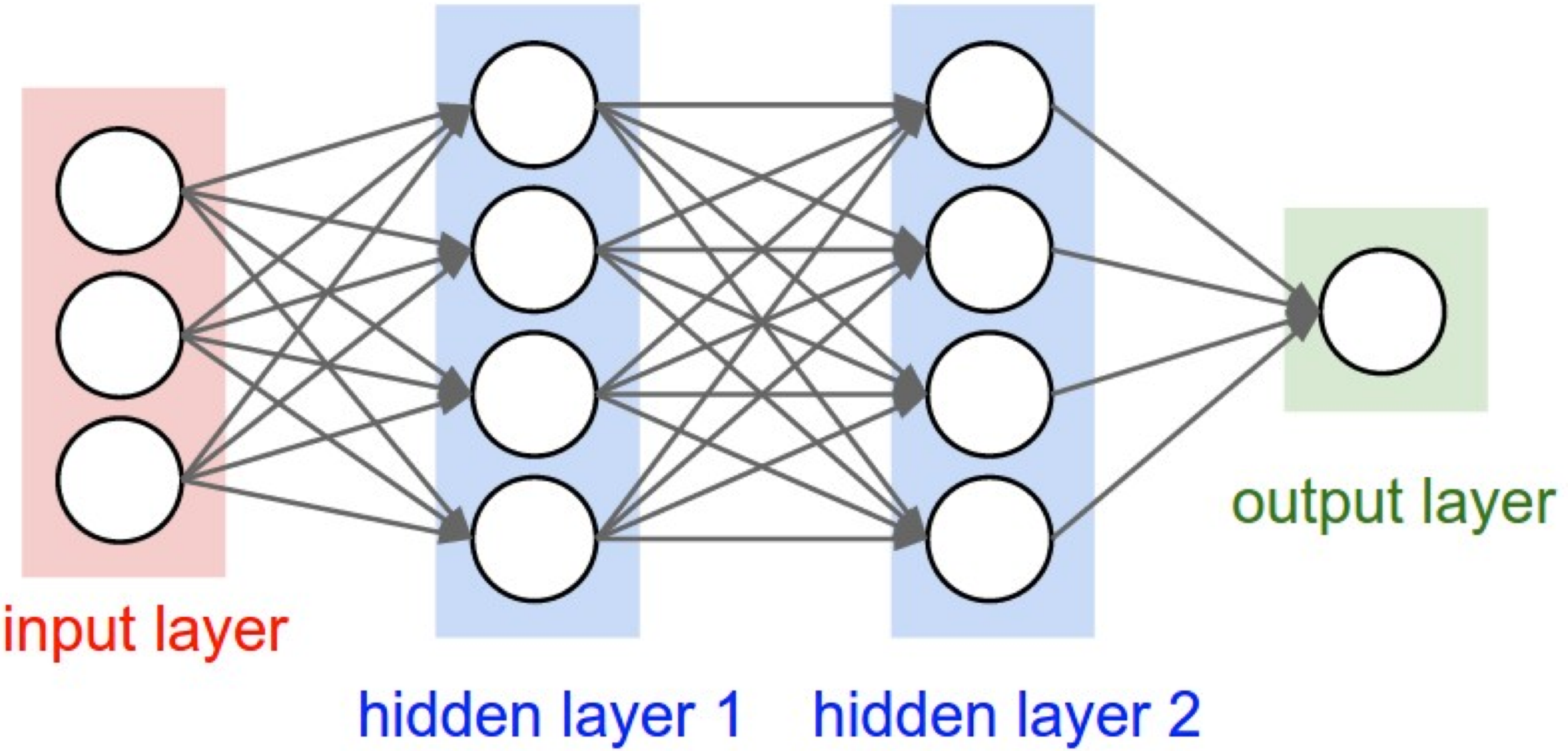


Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

Convolutional Neural Networks (CNNs / ConvNets)

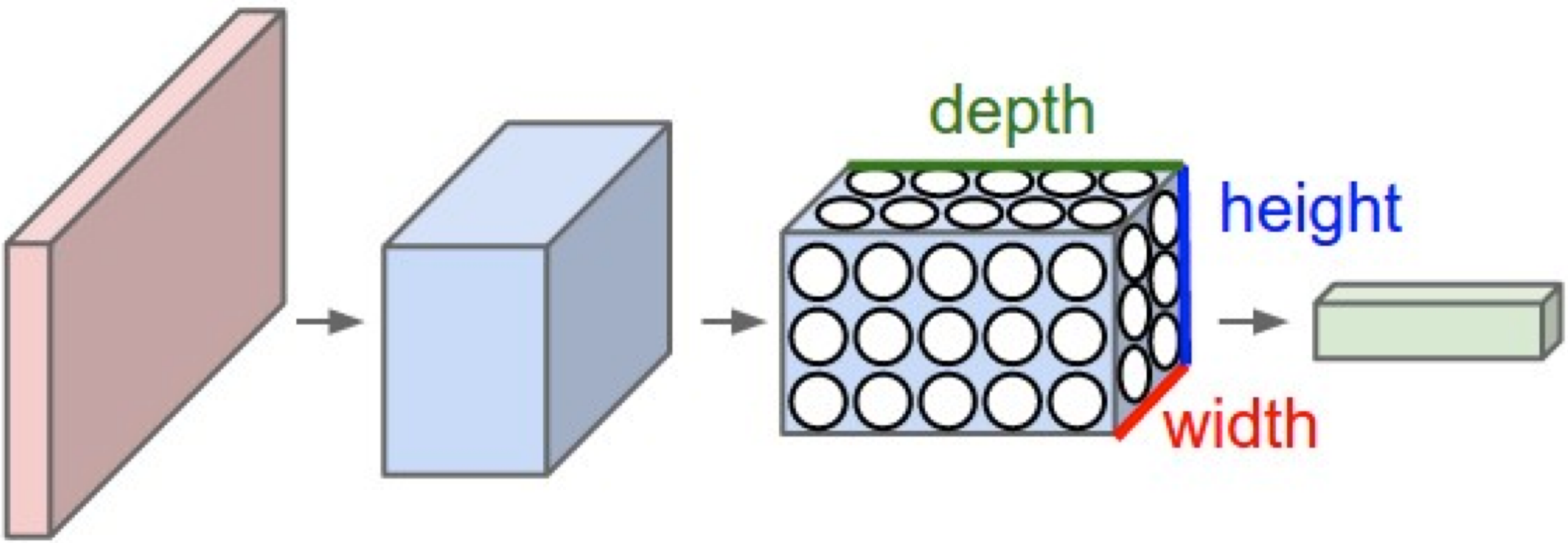
http://cs231n.github.io/convolutional-networks/

A regular 3-layer Neural Network



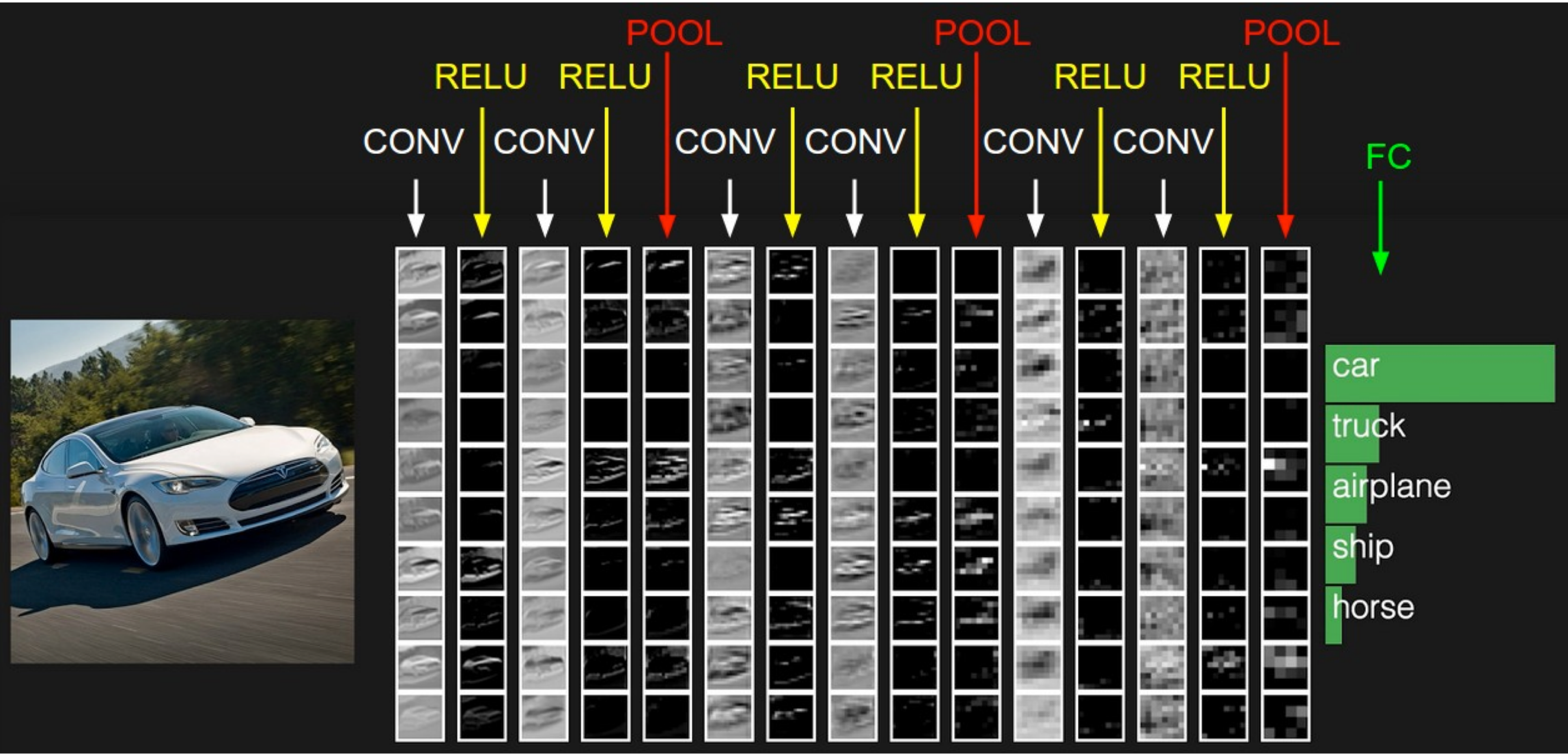
http://cs231n.github.io/convolutional-networks/

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



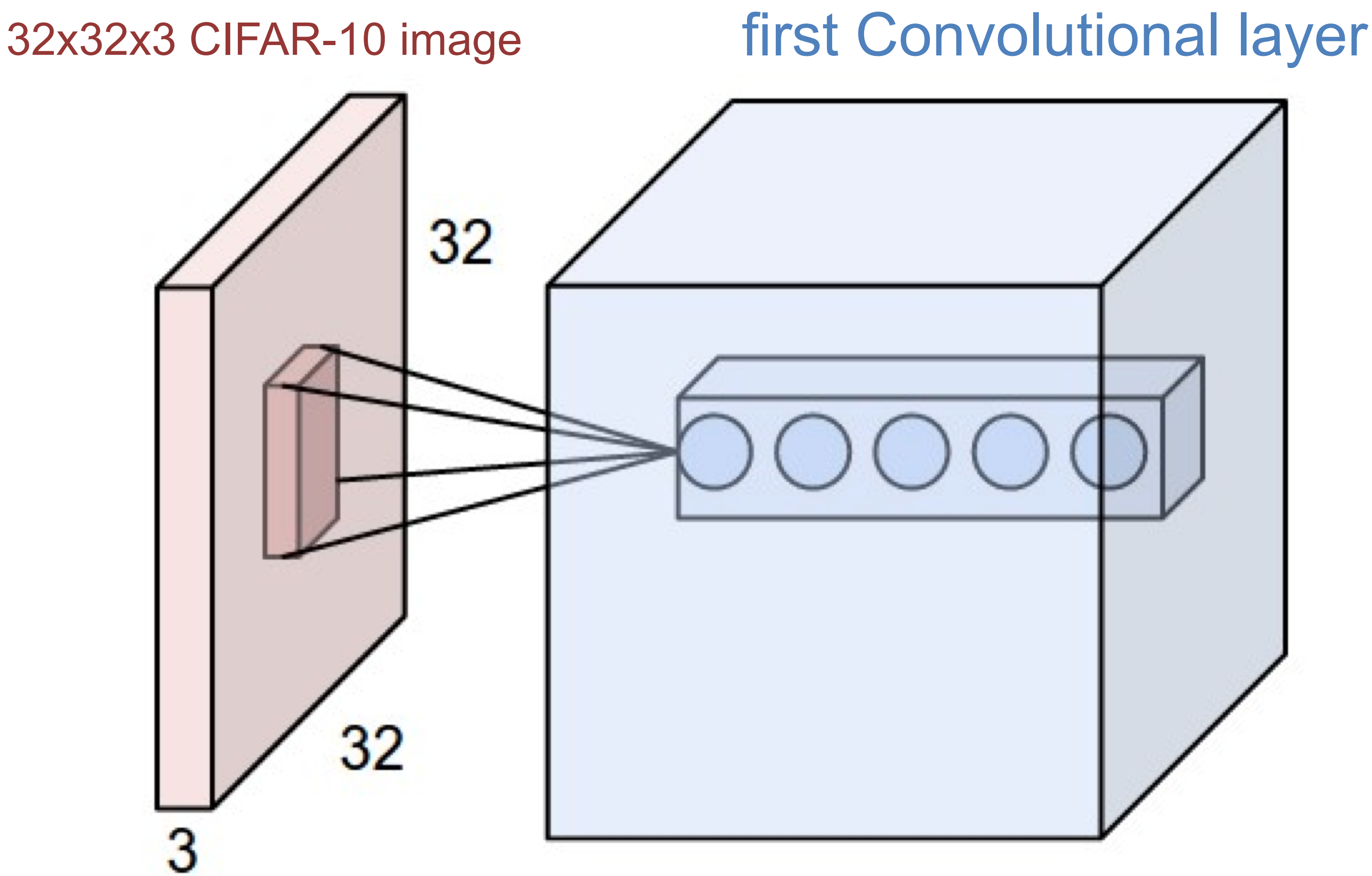
http://cs231n.github.io/convolutional-networks/

The activations of an example ConvNet architecture.



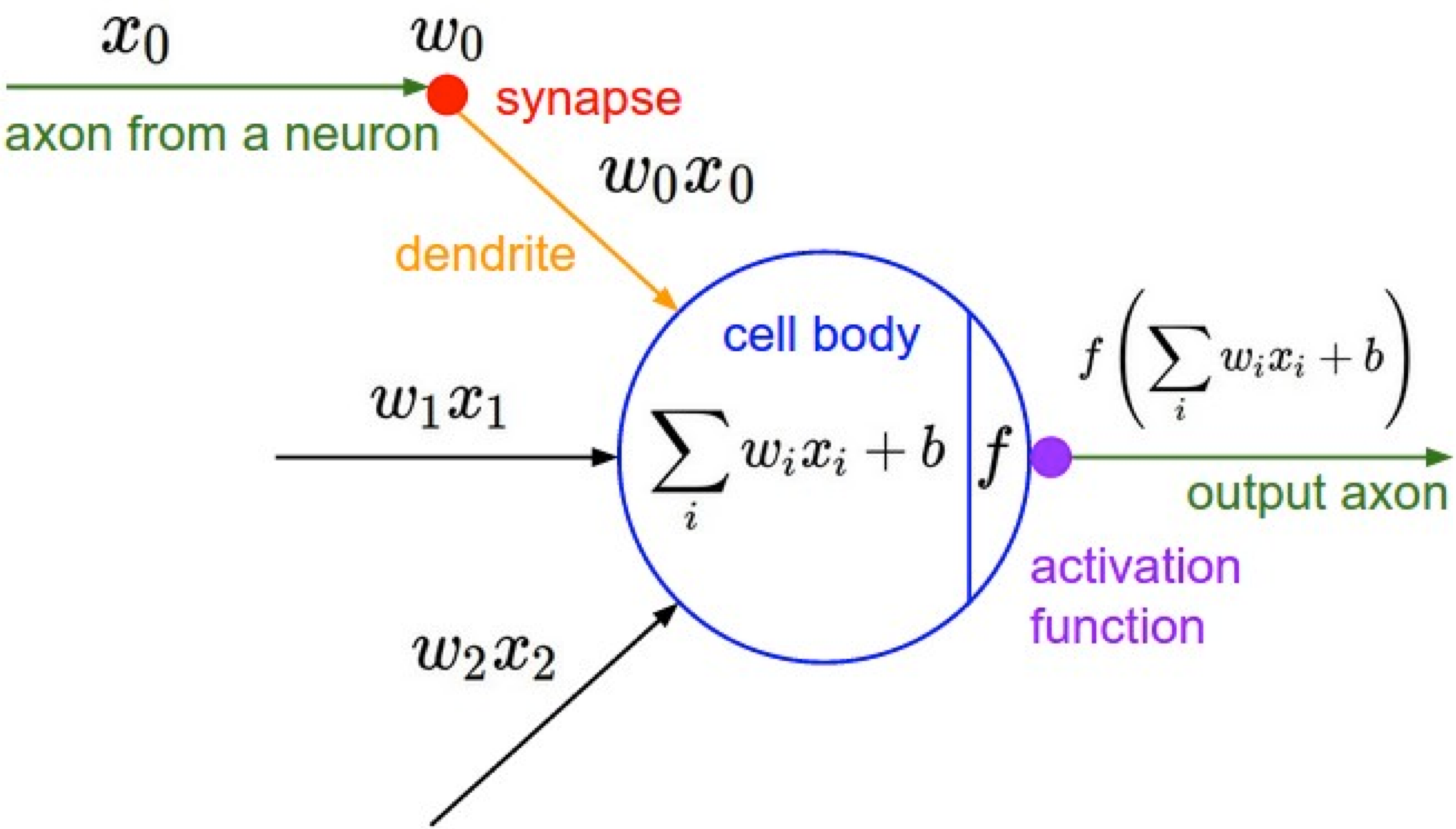
http://cs231n.github.io/convolutional-networks/

ConvNets



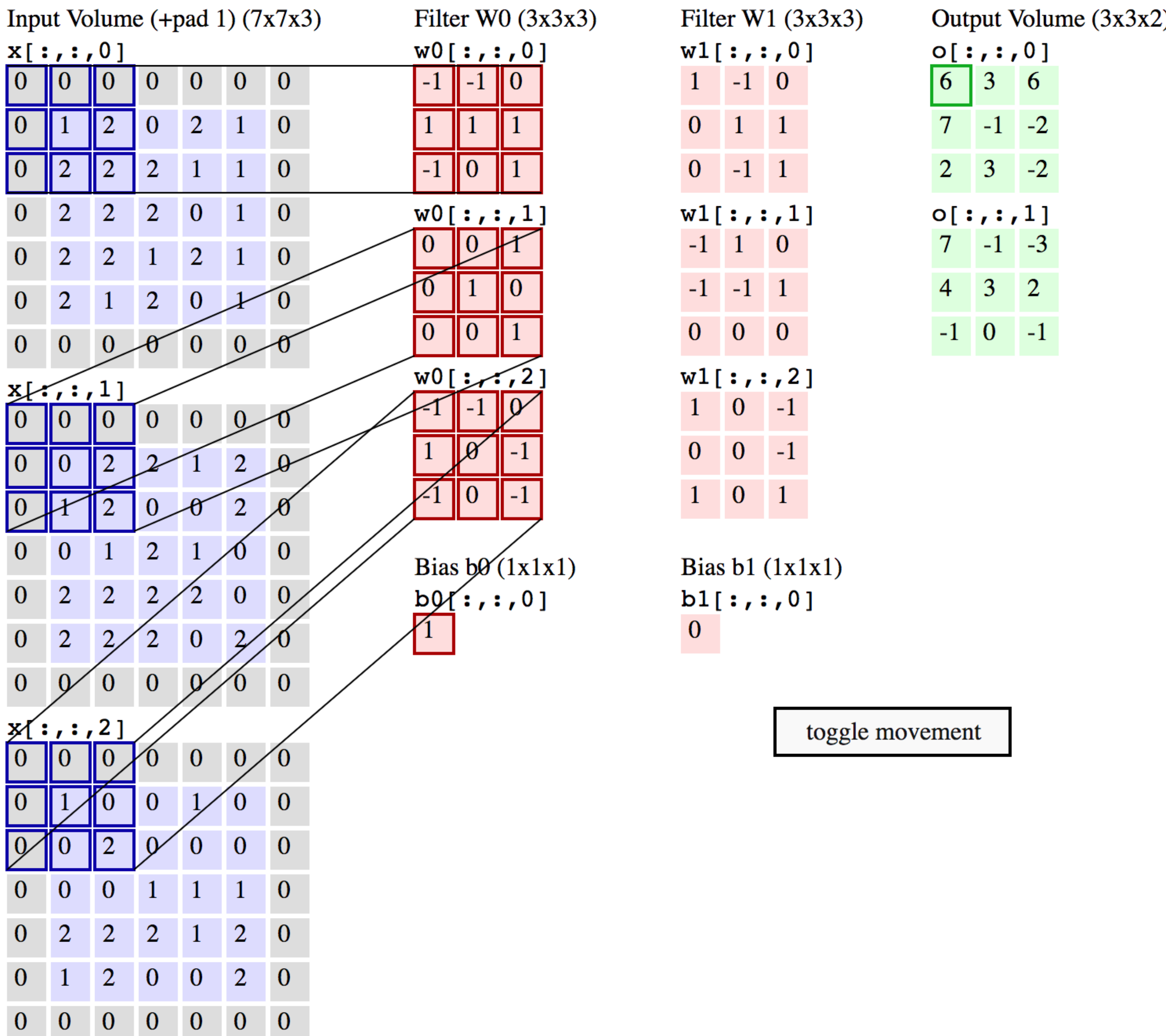
http://cs231n.github.io/convolutional-networks/

ConvNets



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

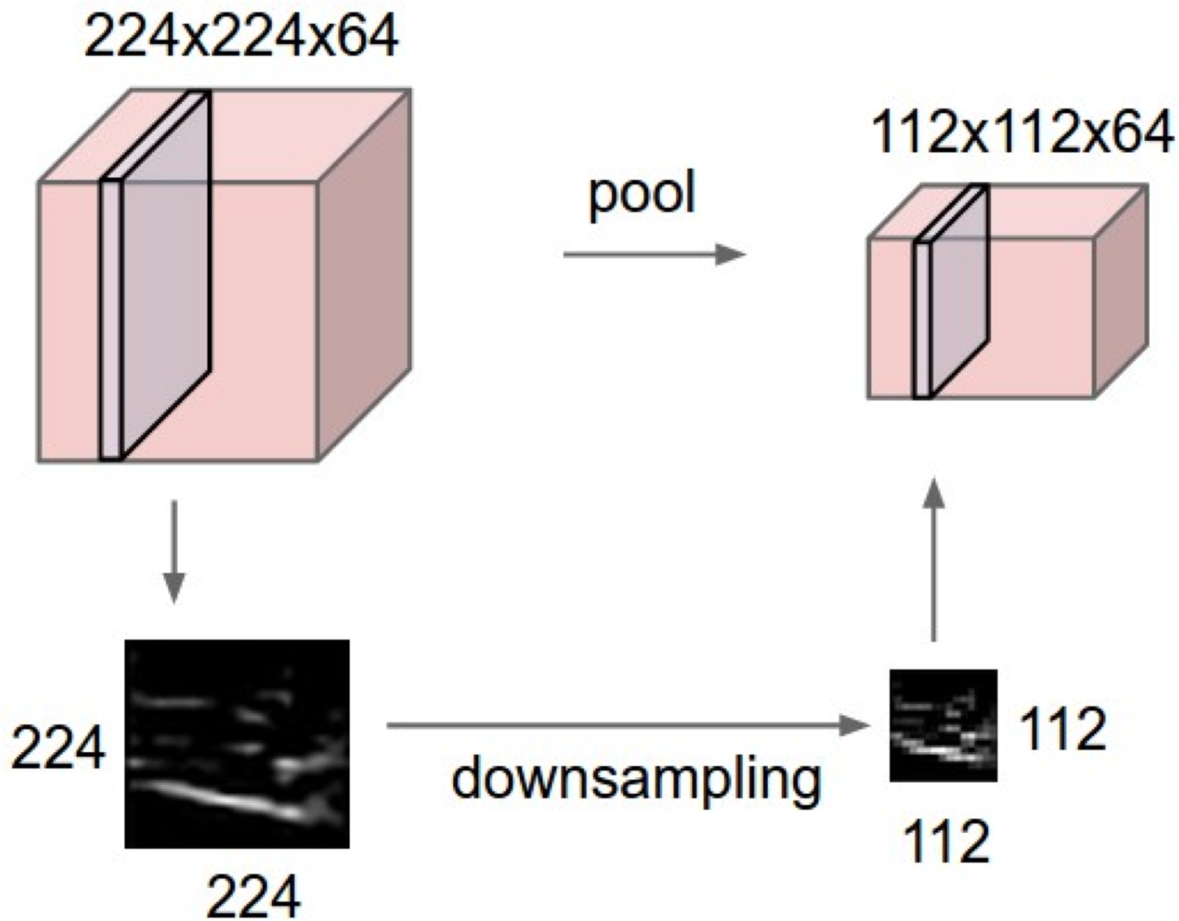
Convolution Demo



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

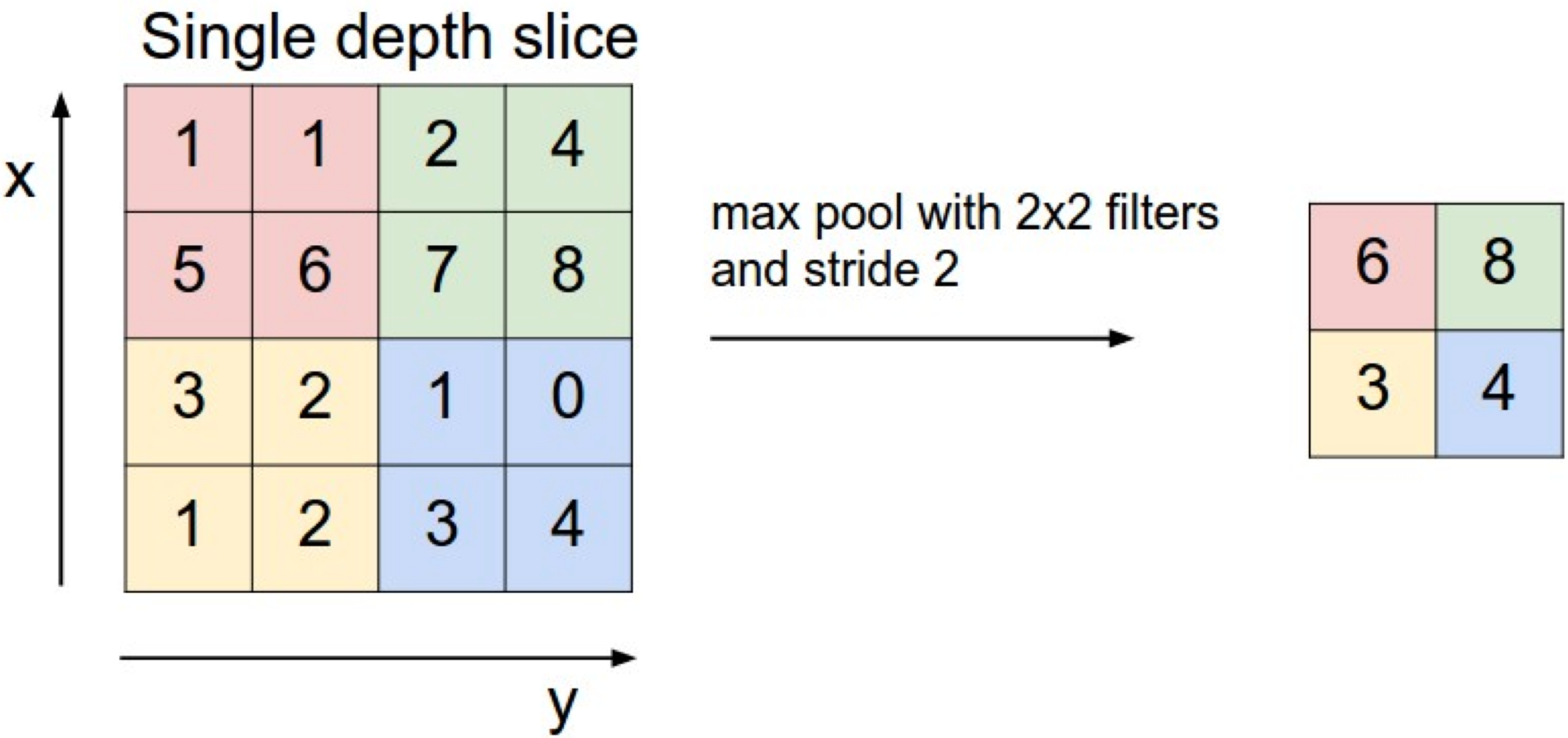
ConvNets

input volume of size [224x224x64]
is pooled with **filter** size 2, **stride** 2
into output volume of size [112x112x64]



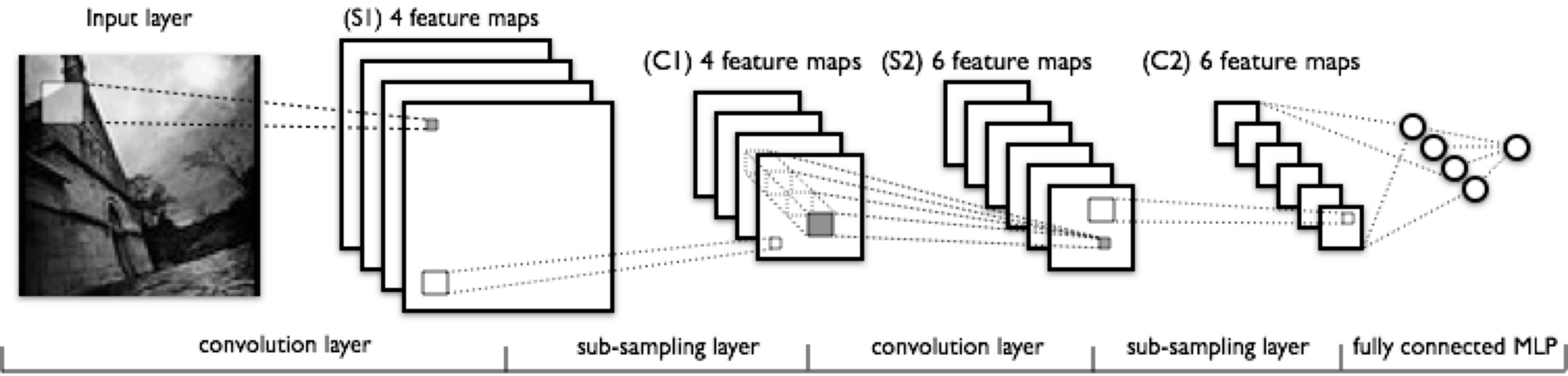
http://cs231n.github.io/convolutional-networks/

ConvNets
max pooling



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

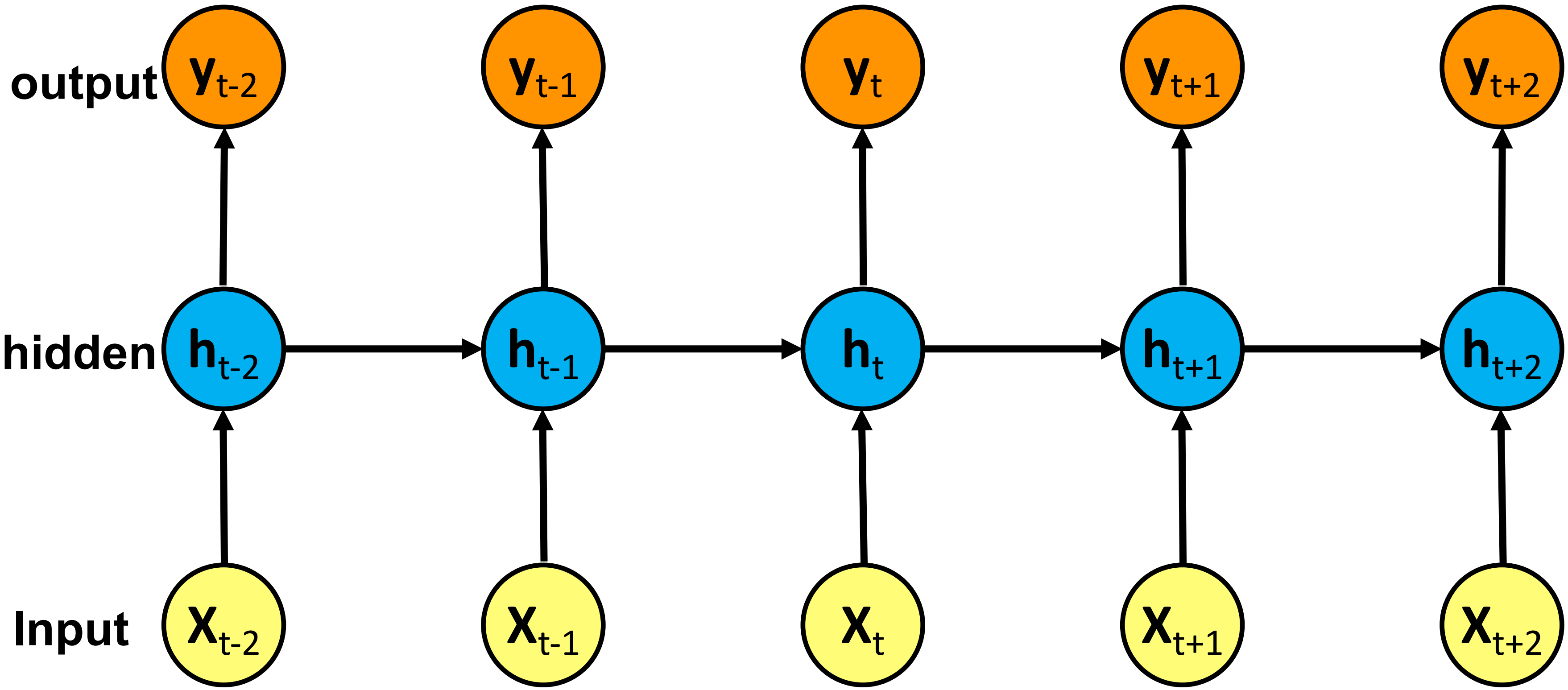
Convolutional Neural Networks (CNN) (LeNet)



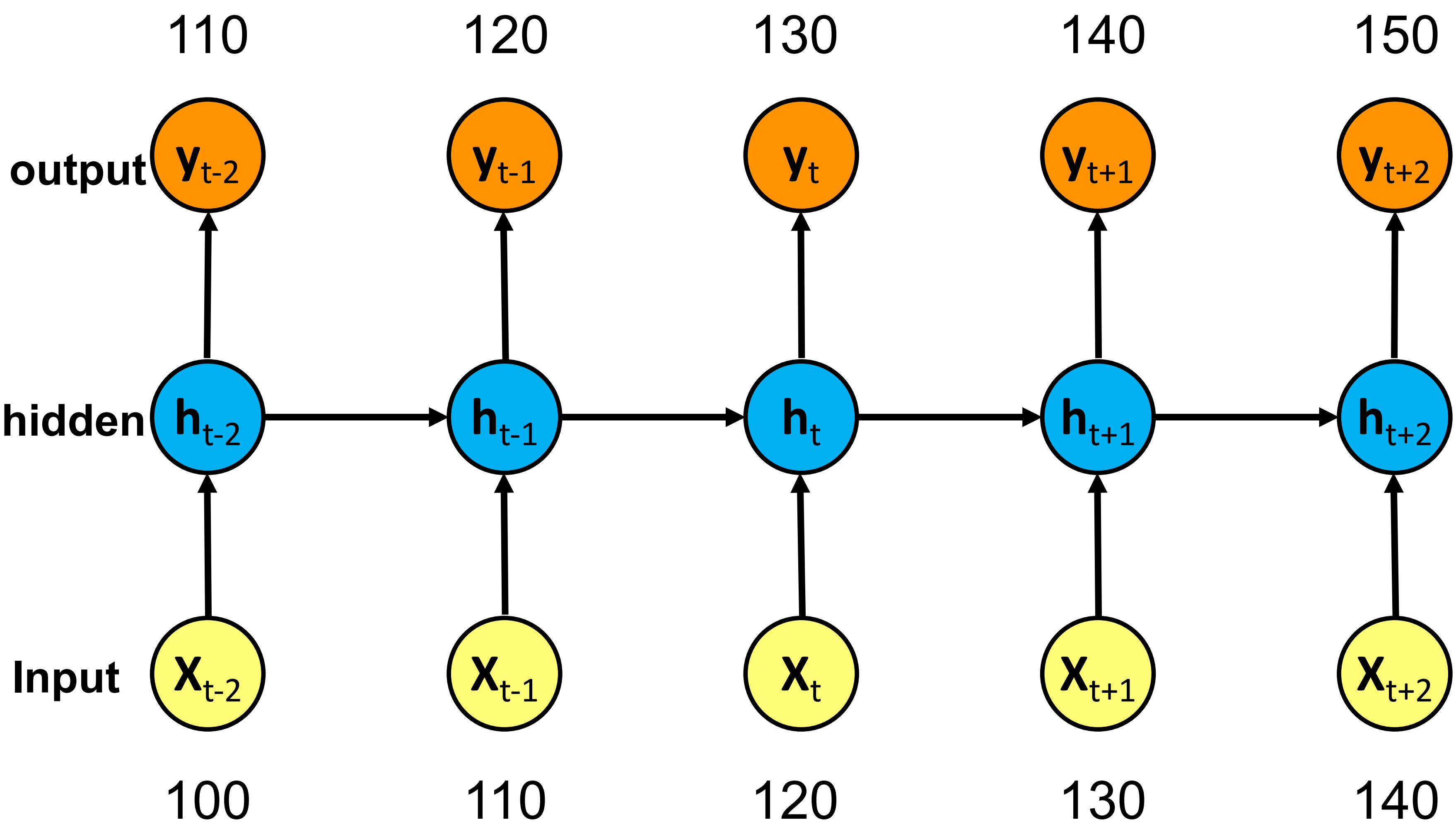
Source: http://deeplearning.net/tutorial/lenet.html

Recurrent Neural Networks (RNN)

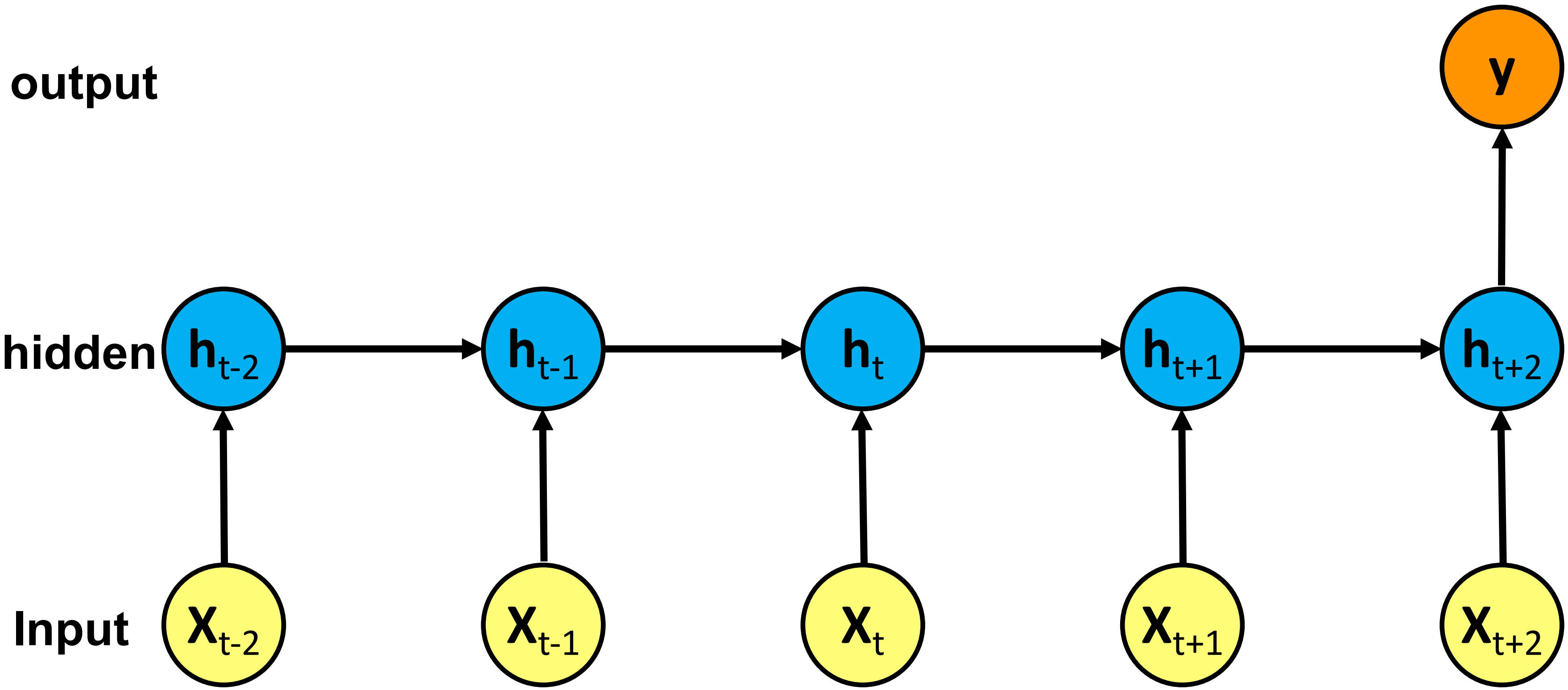
Recurrent Neural Networks (RNN)



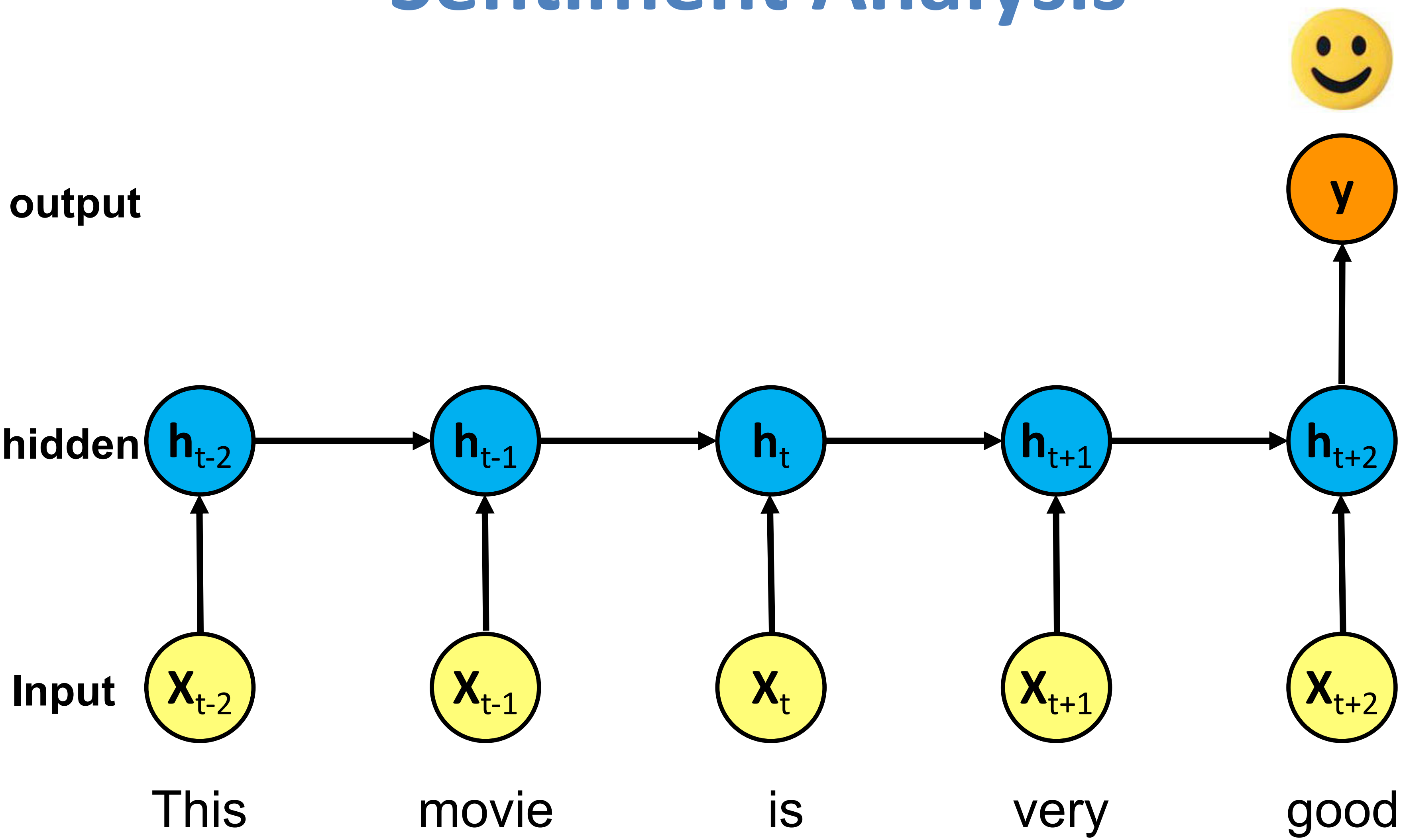
Recurrent Neural Networks (RNN) Time Series Forecasting



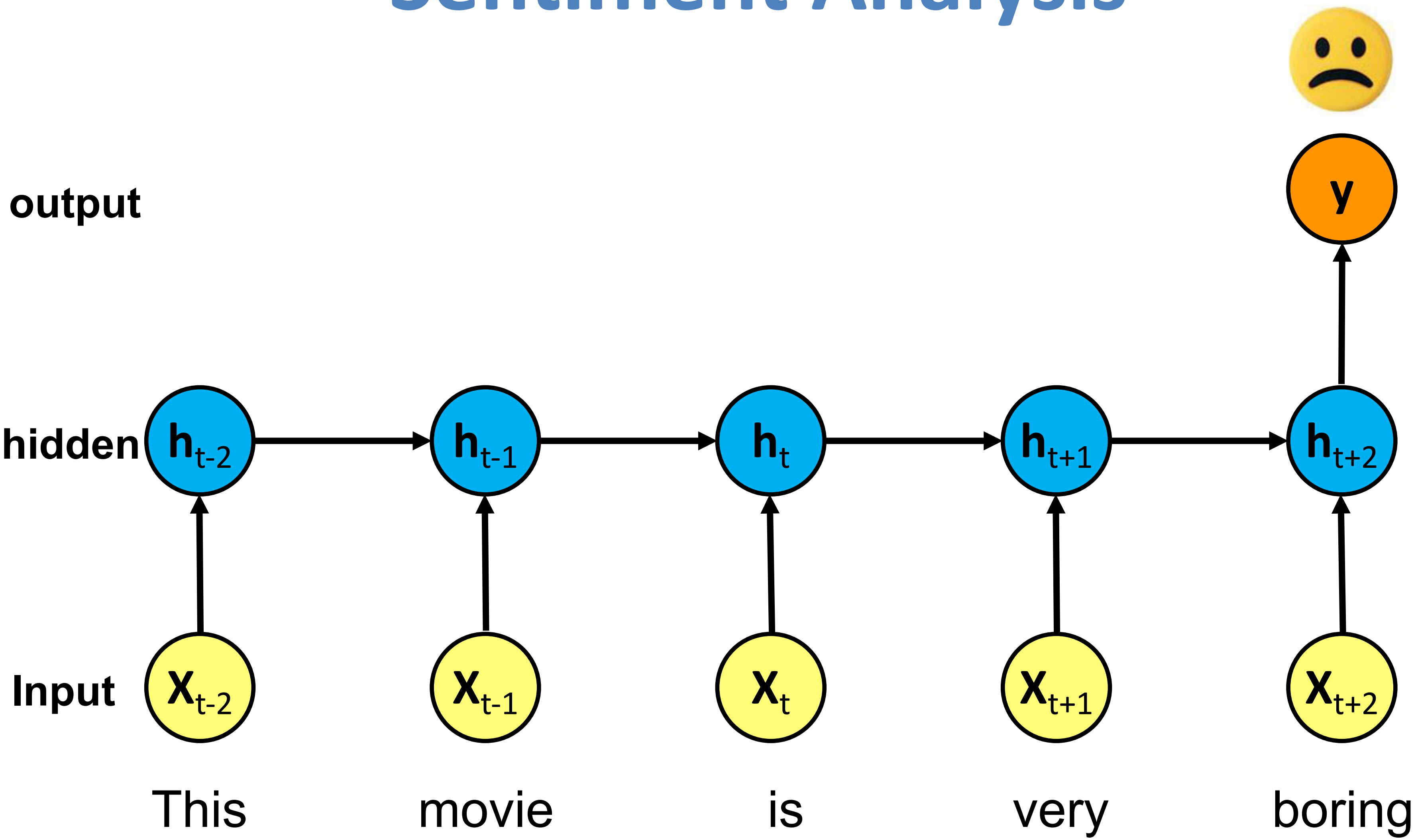
Recurrent Neural Networks (RNN)



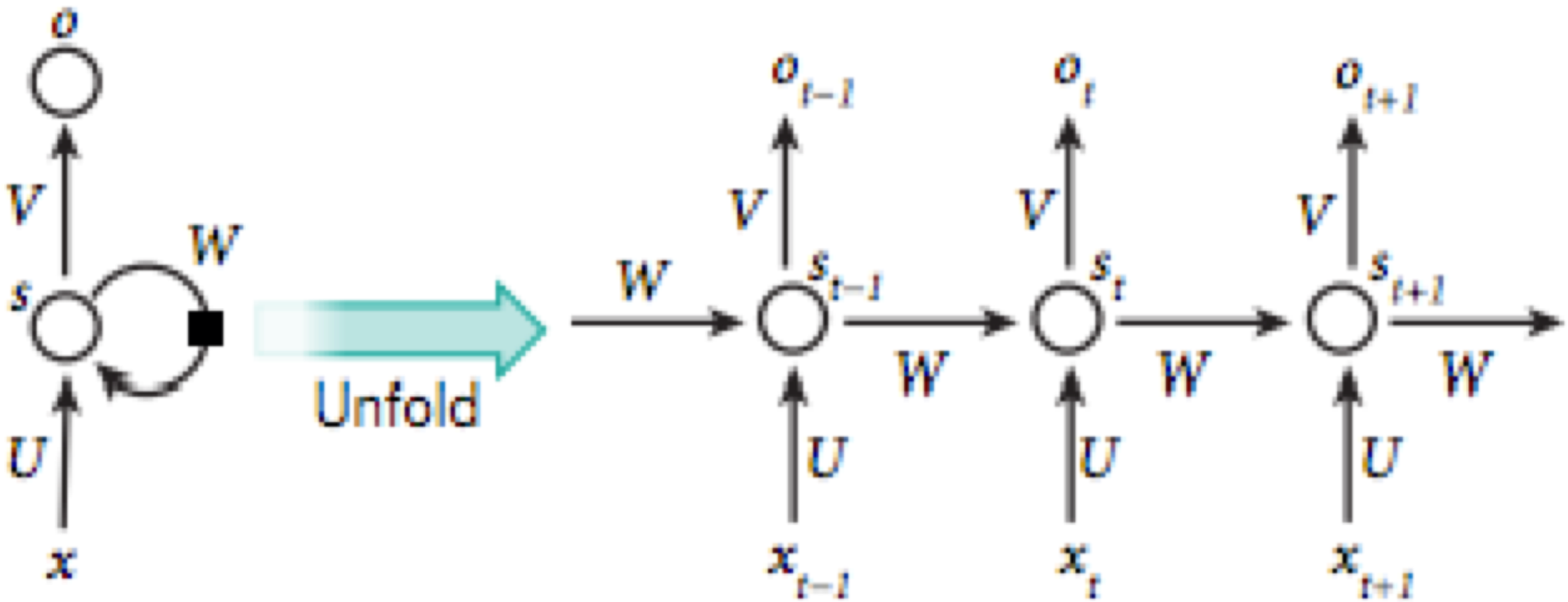
Recurrent Neural Networks (RNN) Sentiment Analysis



Recurrent Neural Networks (RNN)
Sentiment Analysis



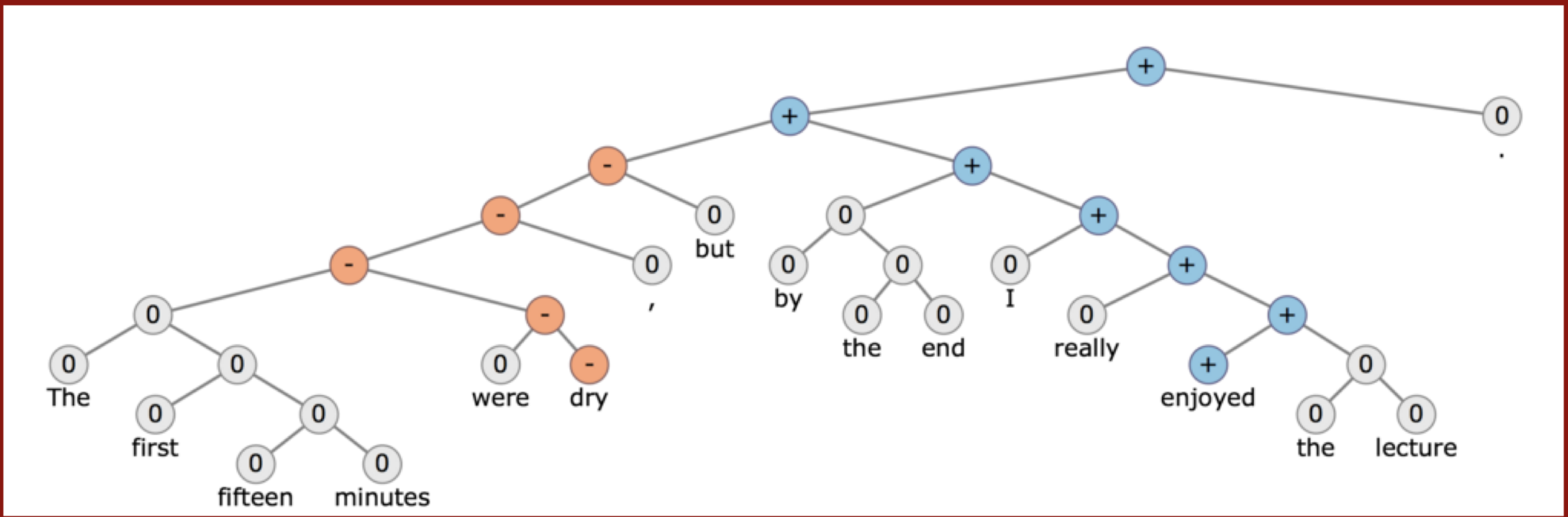
Recurrent Neural Network (RNN)



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

CS224d: Deep Learning for Natural Language Processing

CS224d: Deep Learning for Natural Language Processing

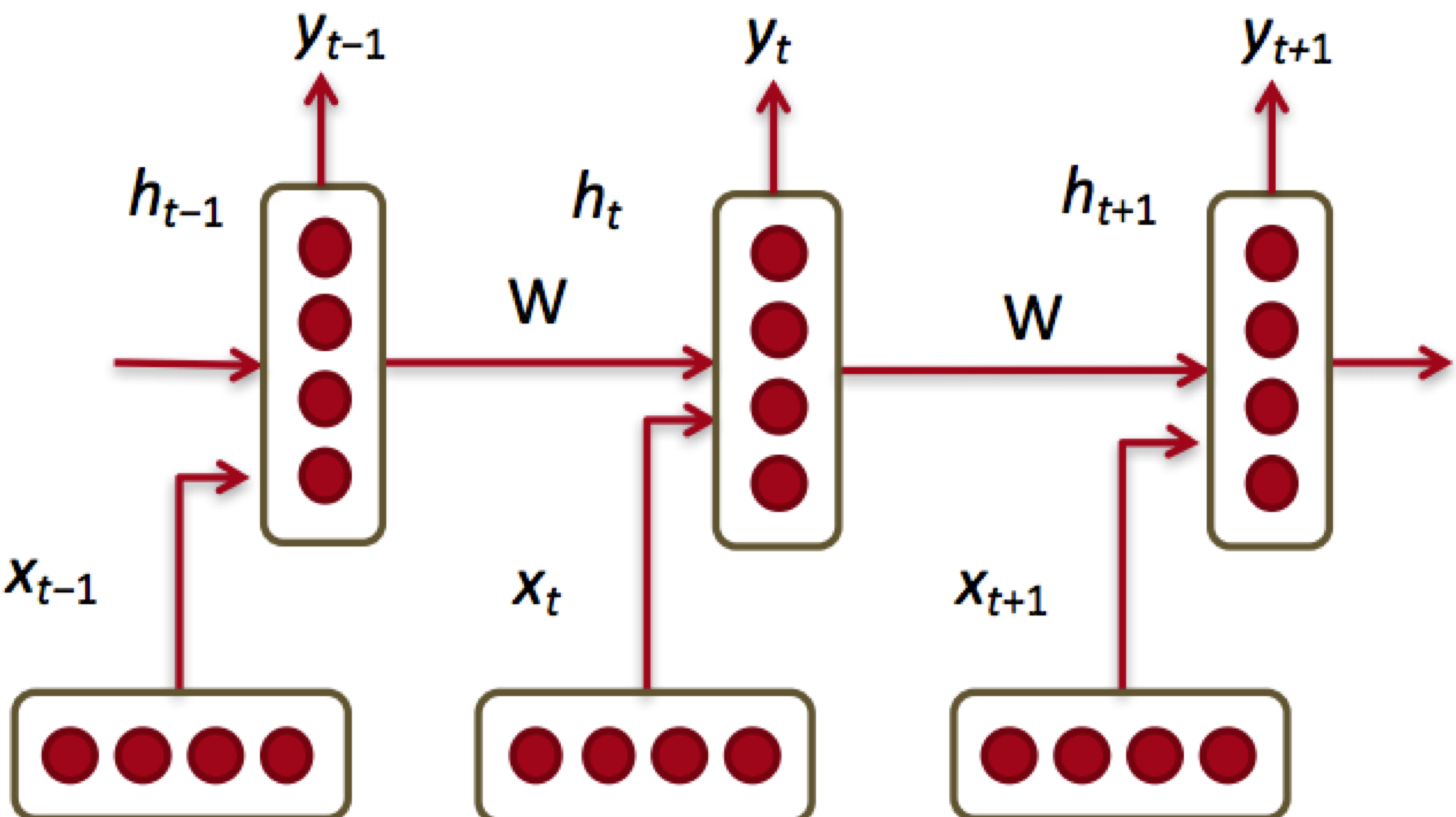


Course Description

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,

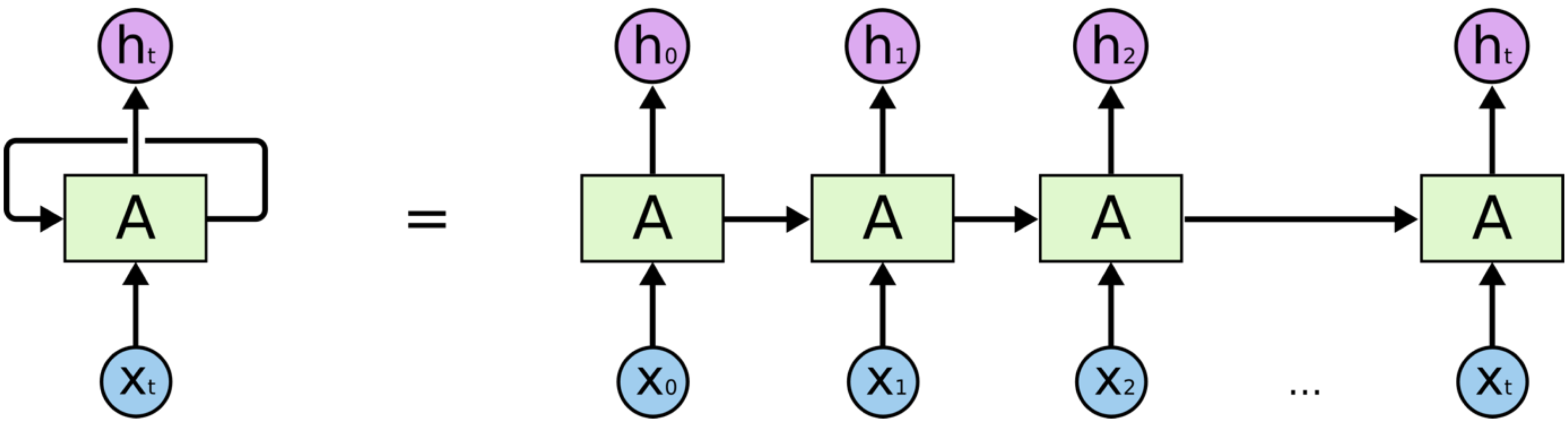
http://cs224d.stanford.edu/

Recurrent Neural Networks (RNNs)



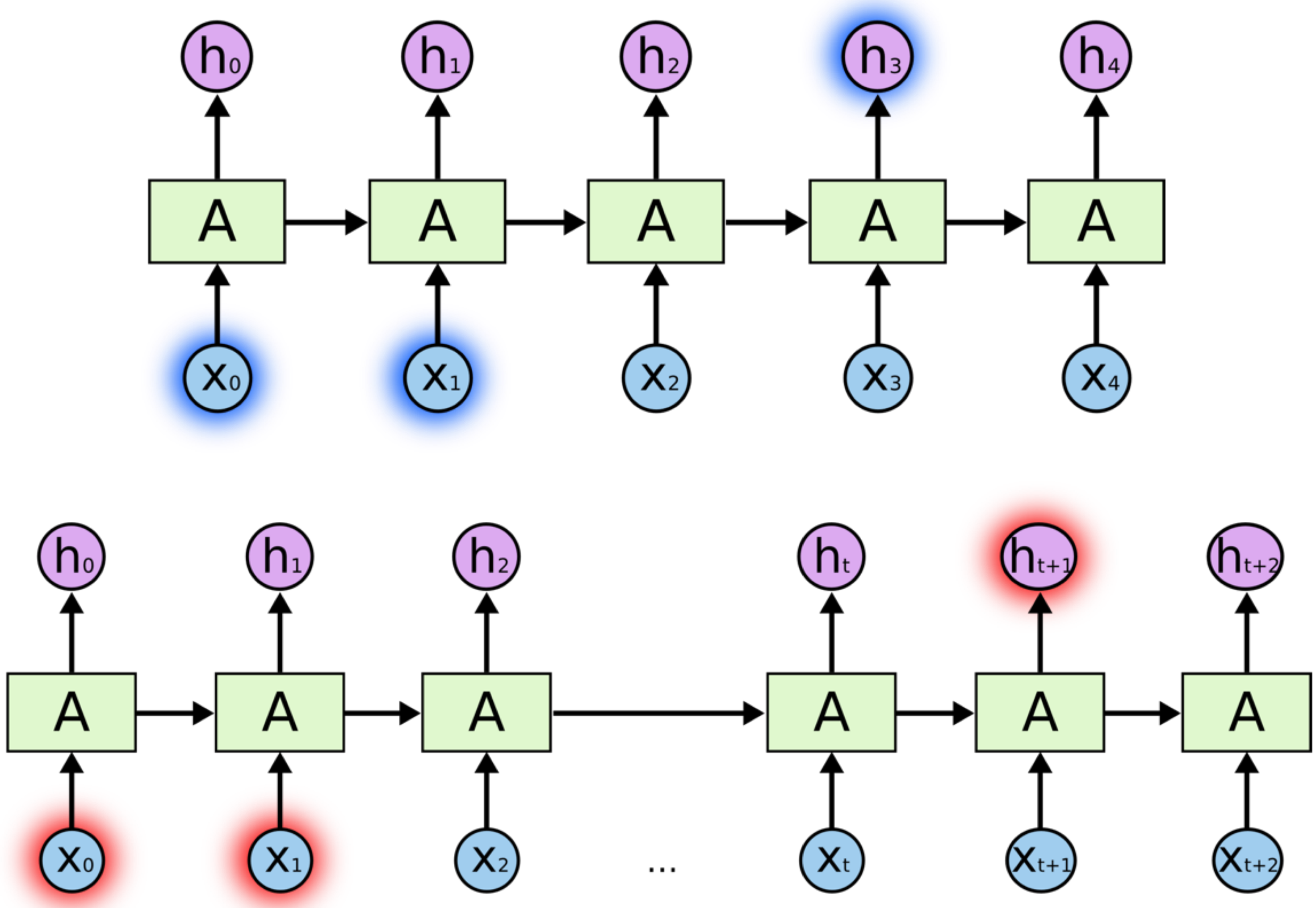
Source: http://cs224d.stanford.edu/lectures/CS224d-Lecture8.pdf

RNN



Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

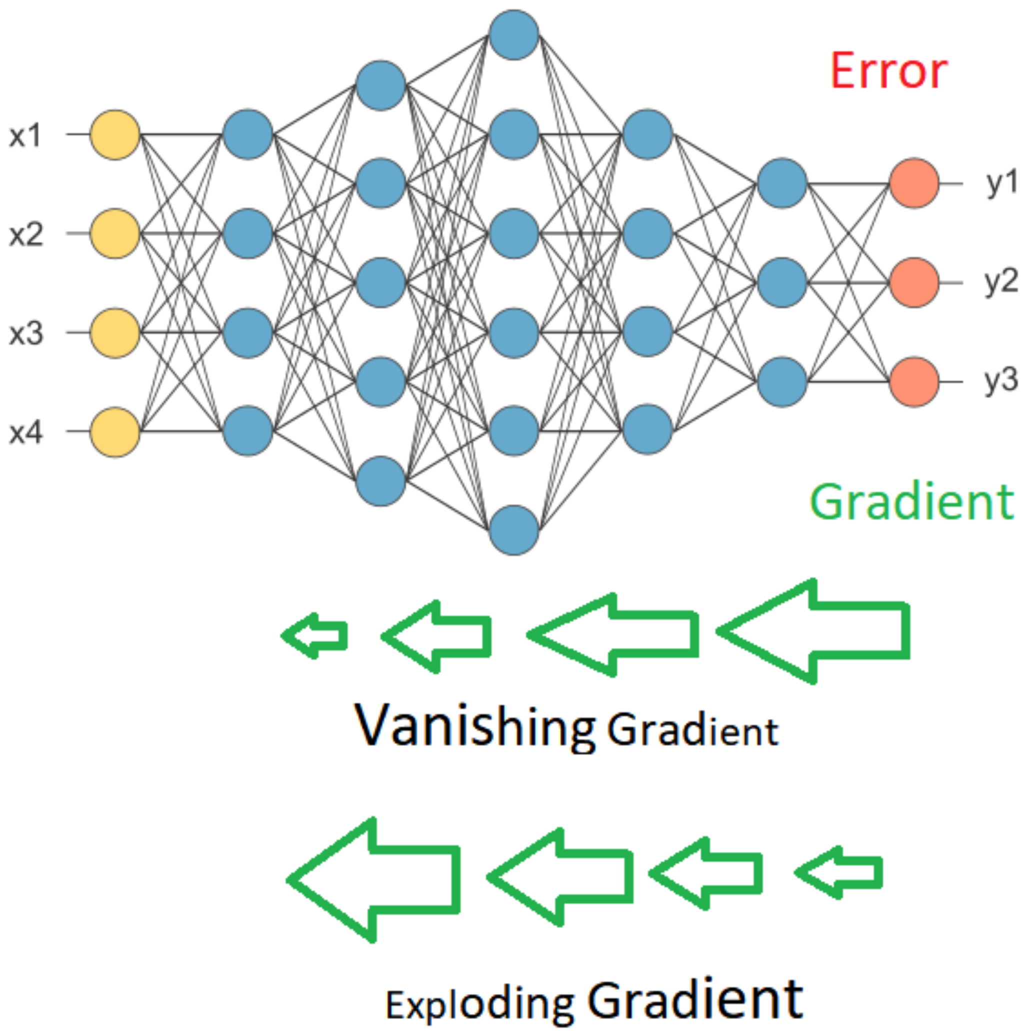
RNN long-term dependencies



I grew up in France… I speak fluent French.

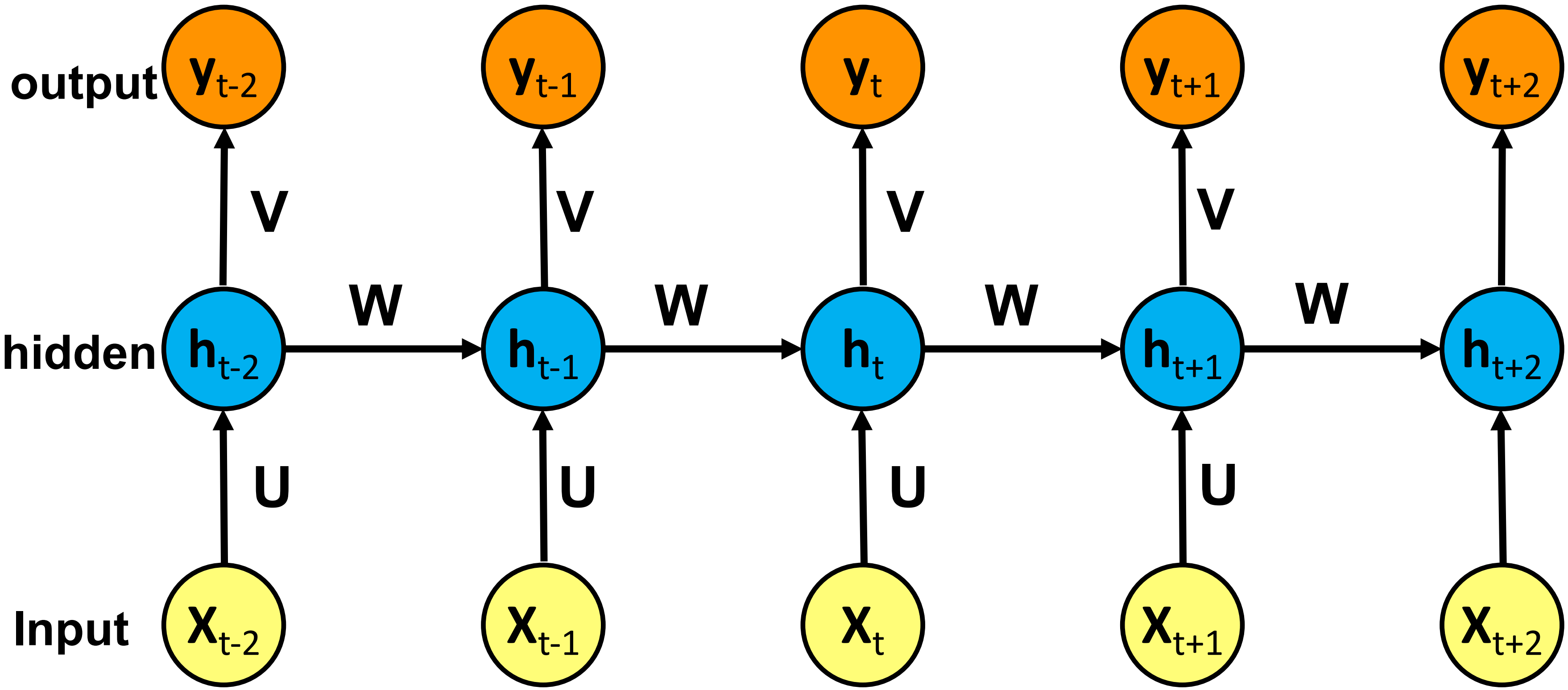
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Vanishing Gradient
Exploding Gradient

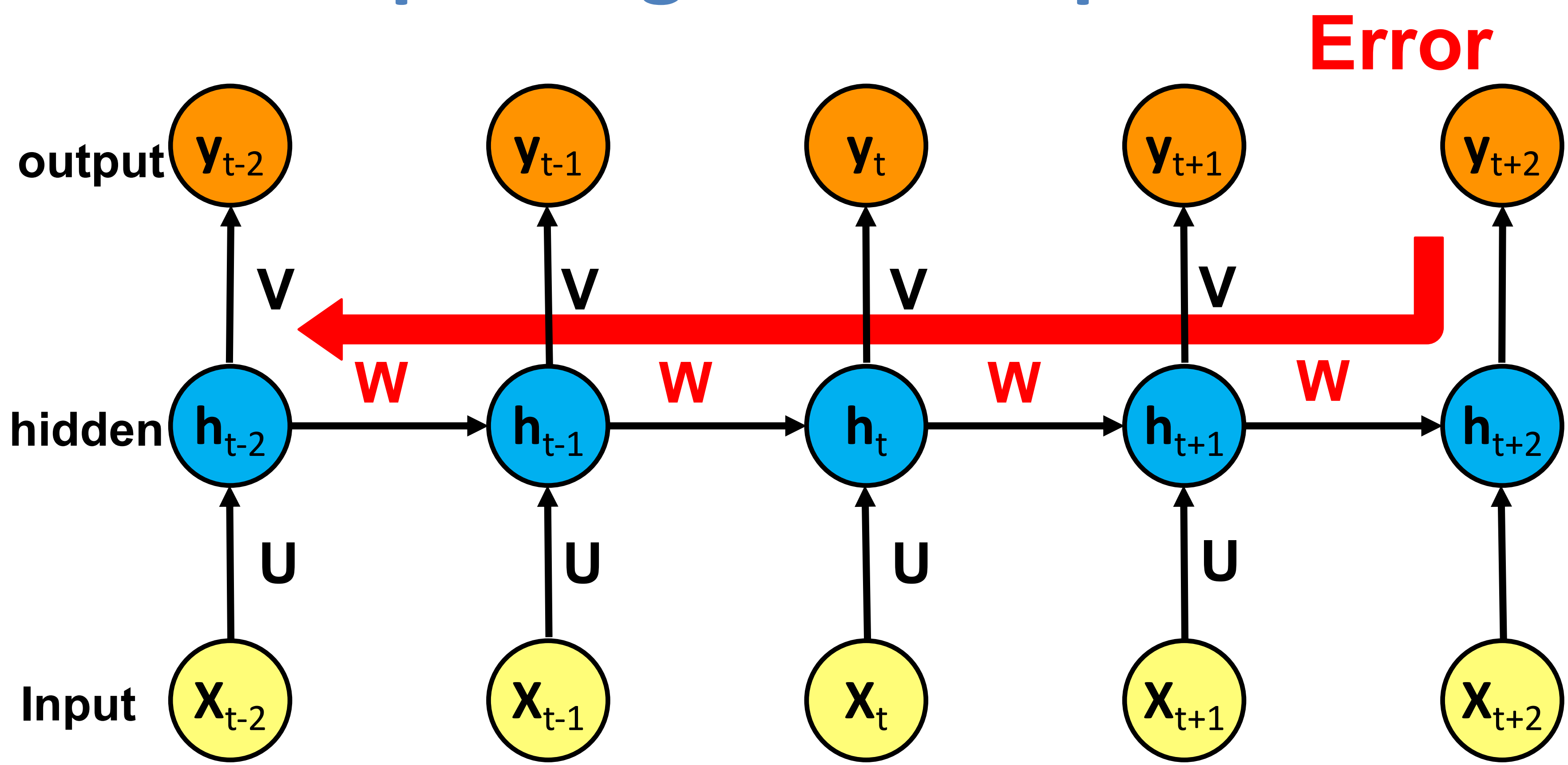


Source: https://medium.com/deep-math-machine-learning-ai/chapter-10-1-deepnlp-lstm-long-short-term-memory-networks-with-math-21477f8e4235

Recurrent Neural Networks (RNN)



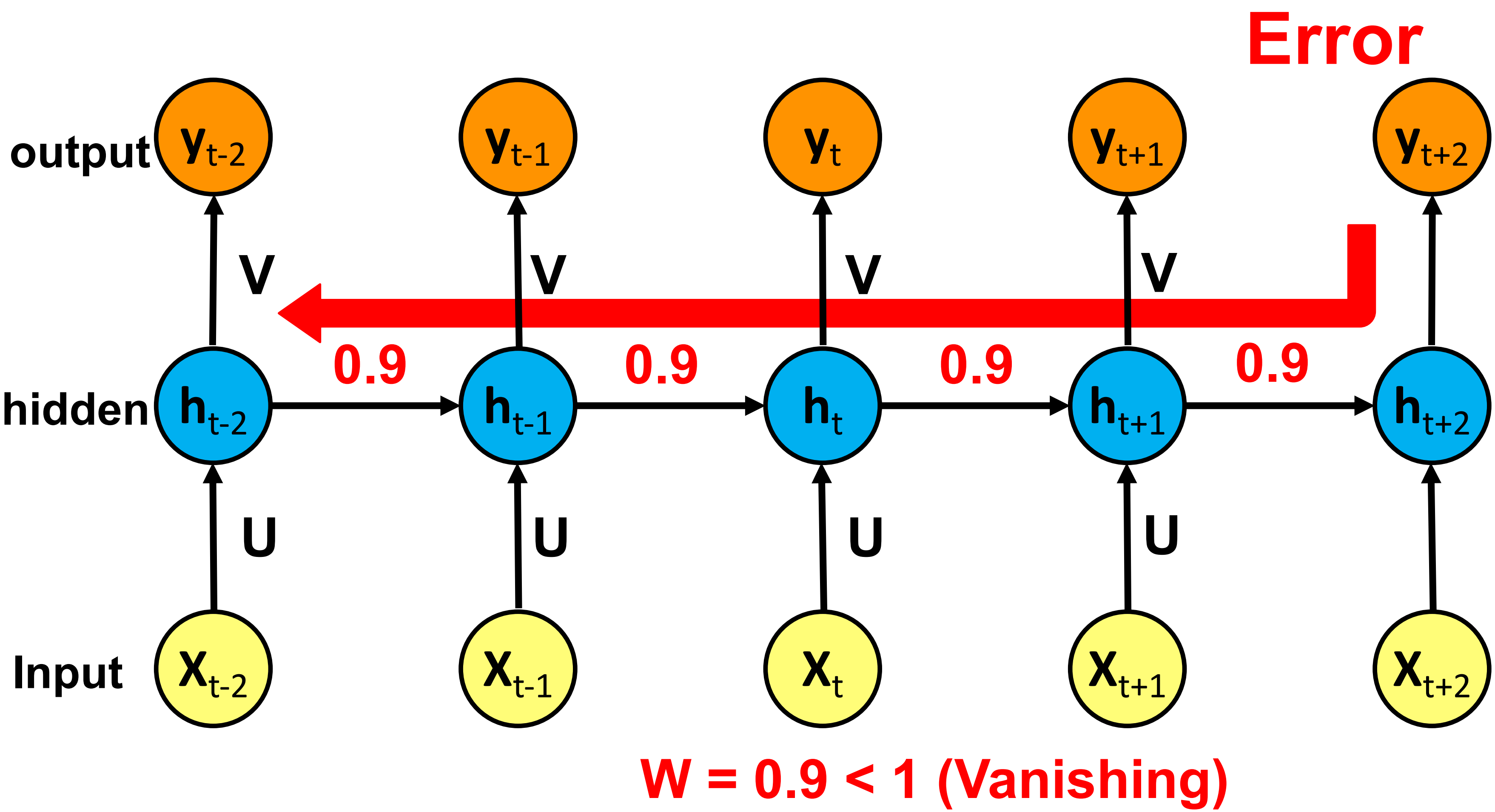
RNN
Vanishing Gradient problem
Exploding Gradient problem



if |W| < 1 (Vanishing)
if |W| > 1 (Exploding)

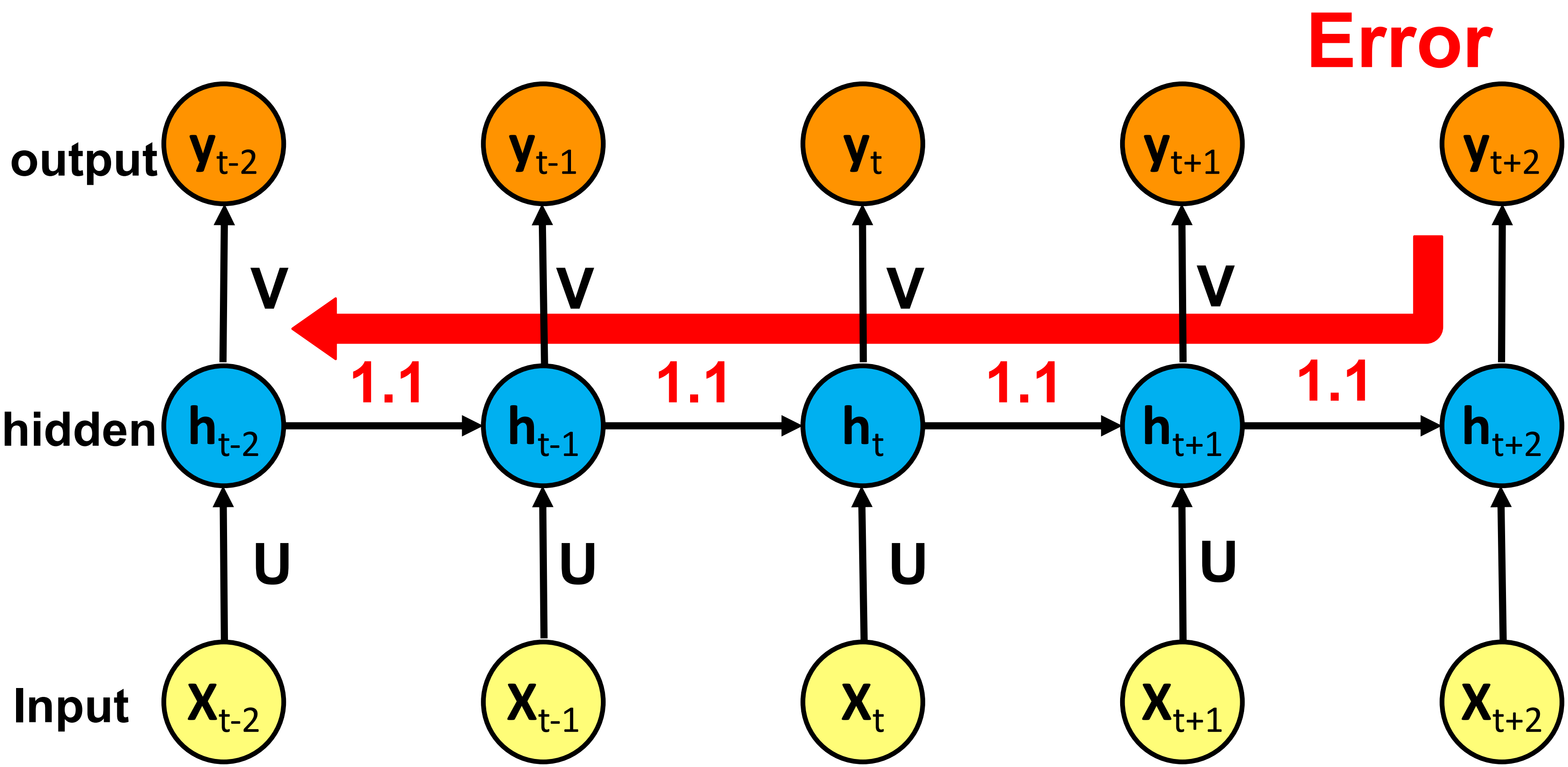
Source: https://medium.com/deep-math-machine-learning-ai/chapter-10-1-deepnlp-lstm-long-short-term-memory-networks-with-math-21477f8e4235

RNN
Vanishing Gradient problem



Source: https://medium.com/deep-math-machine-learning-ai/chapter-10-1-deepnlp-lstm-long-short-term-memory-networks-with-math-21477f8e4235

RNN
Exploding Gradient problem

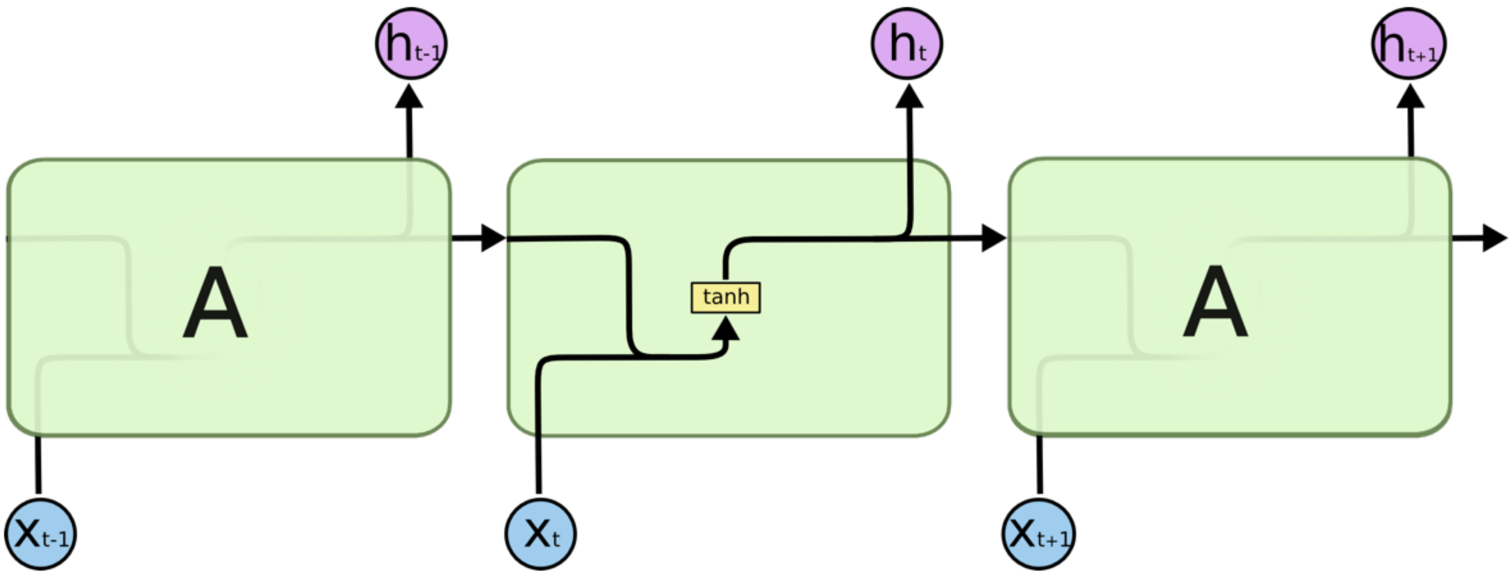


W = 1.1 > 1 (Exploding)

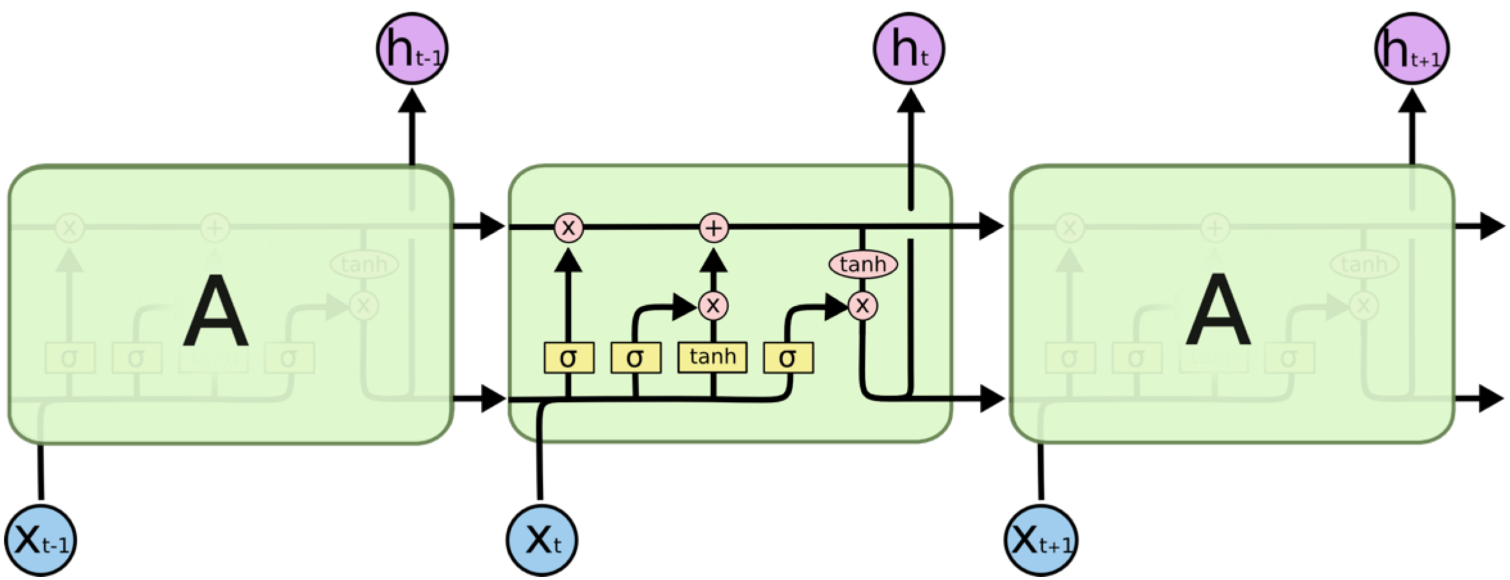
Source: https://medium.com/deep-math-machine-learning-ai/chapter-10-1-deepnlp-lstm-long-short-term-memory-networks-with-math-21477f8e4235

RNN LSTM

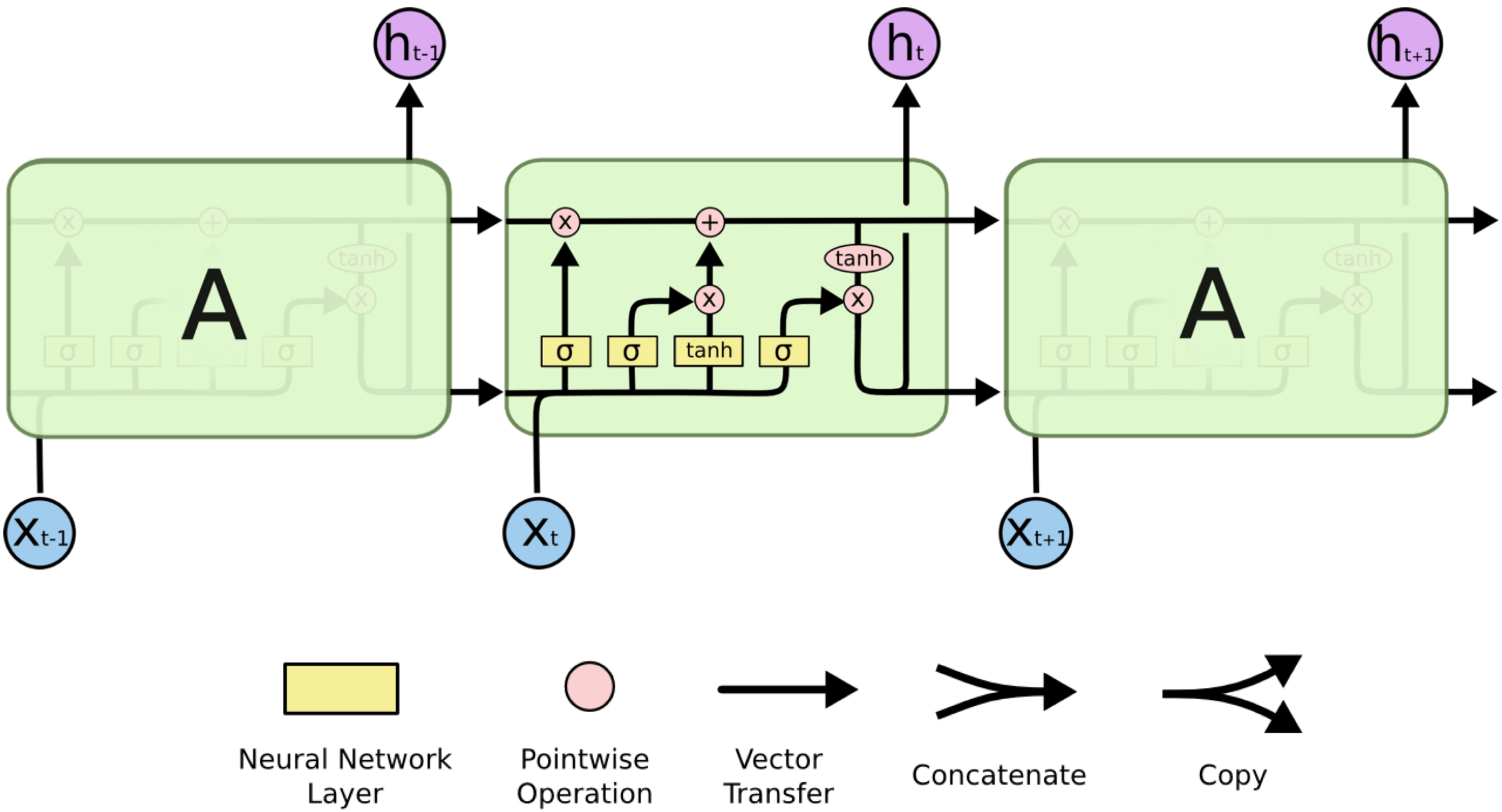
RNN



LSTM

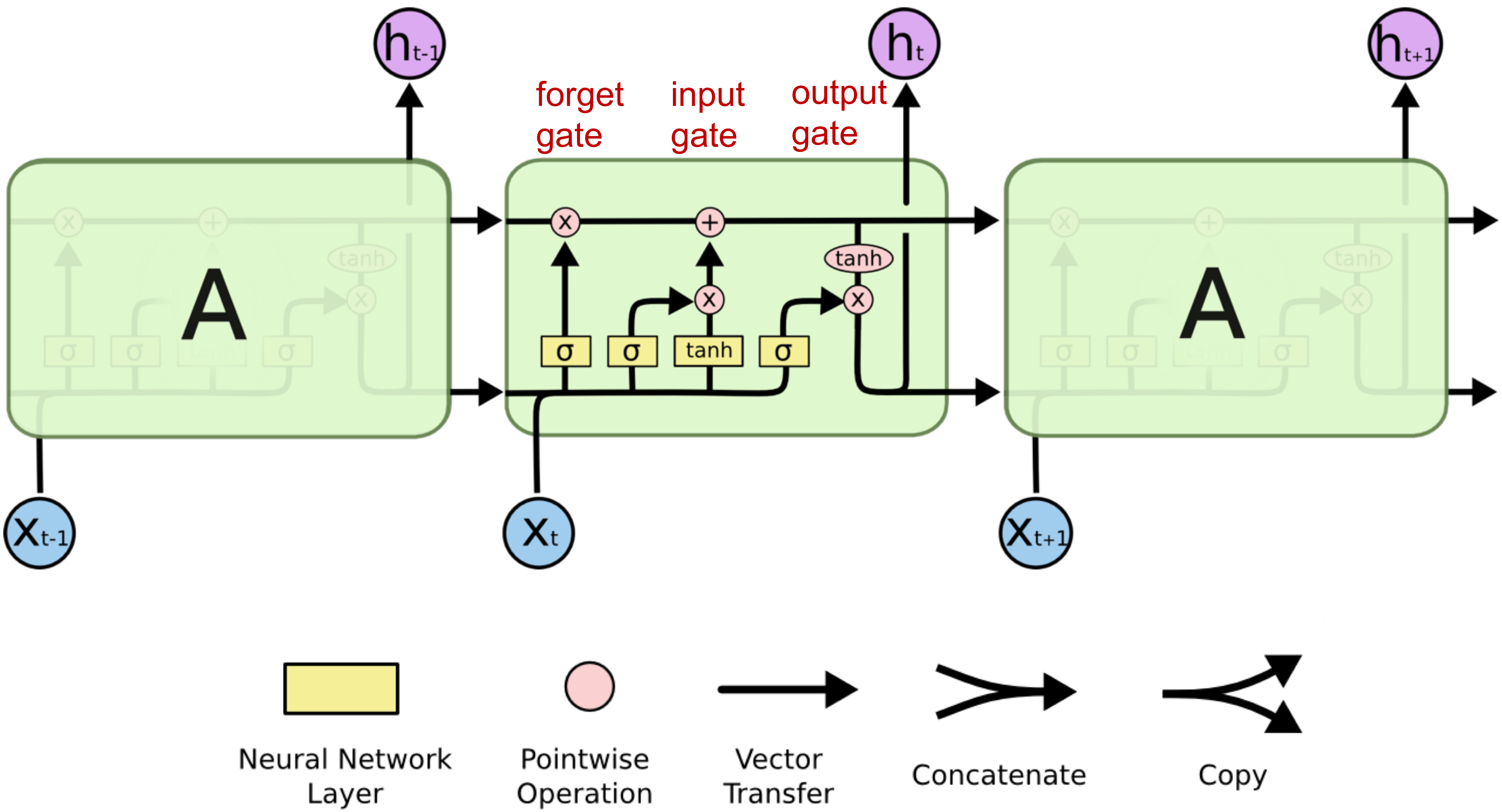


Long Short Term Memory (LSTM)



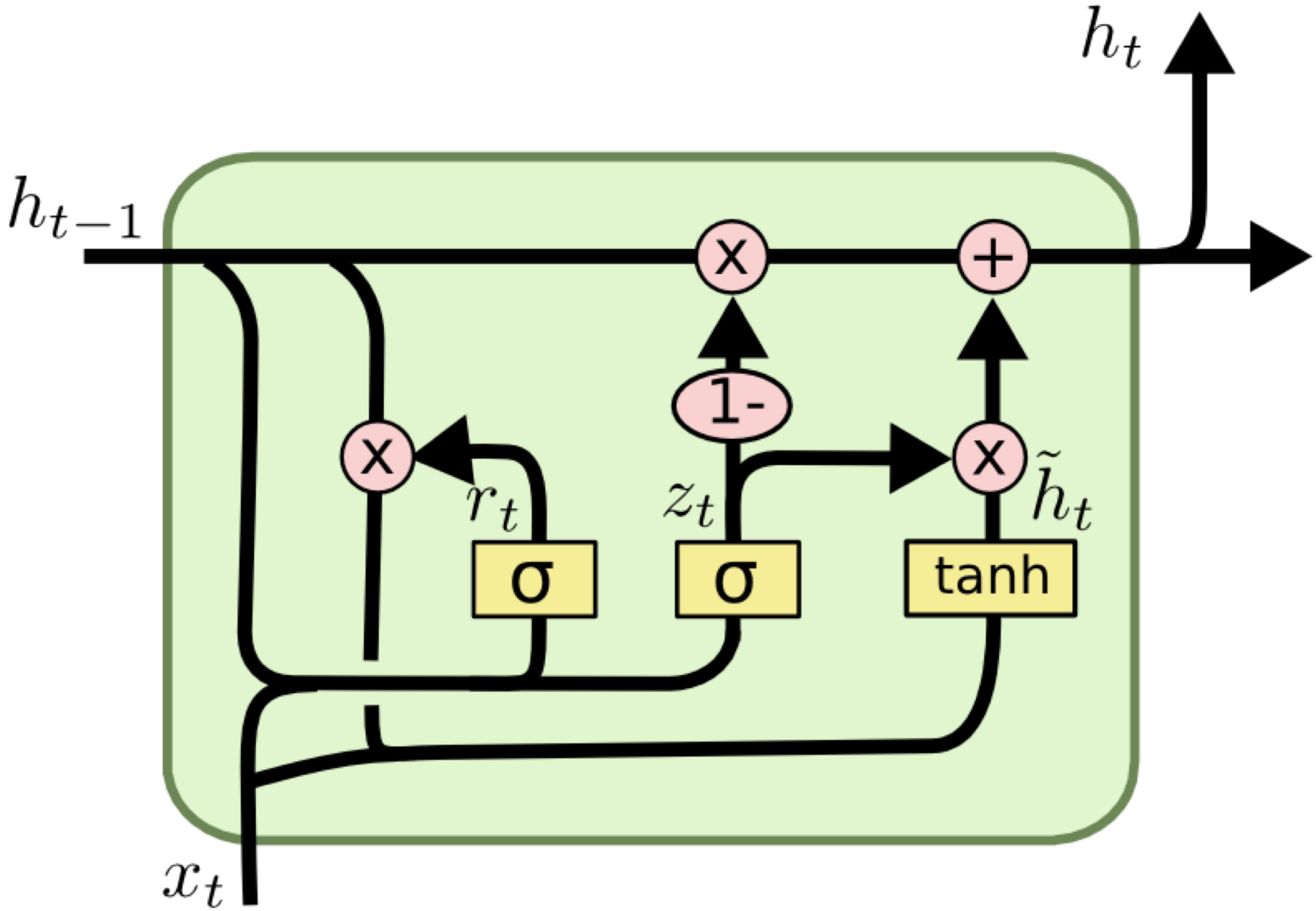
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Long Short Term Memory (LSTM)



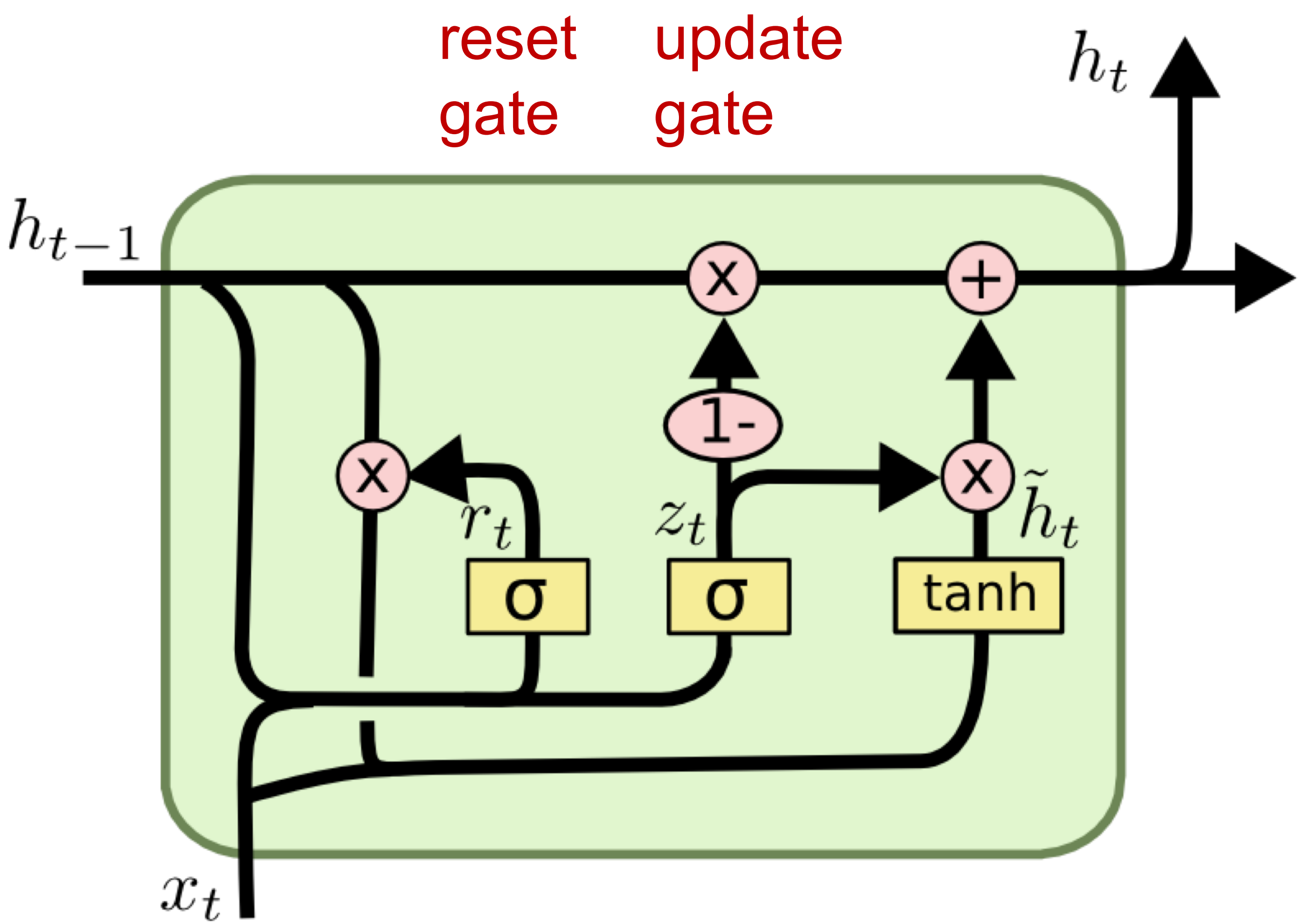
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Gated Recurrent Unit (GRU)



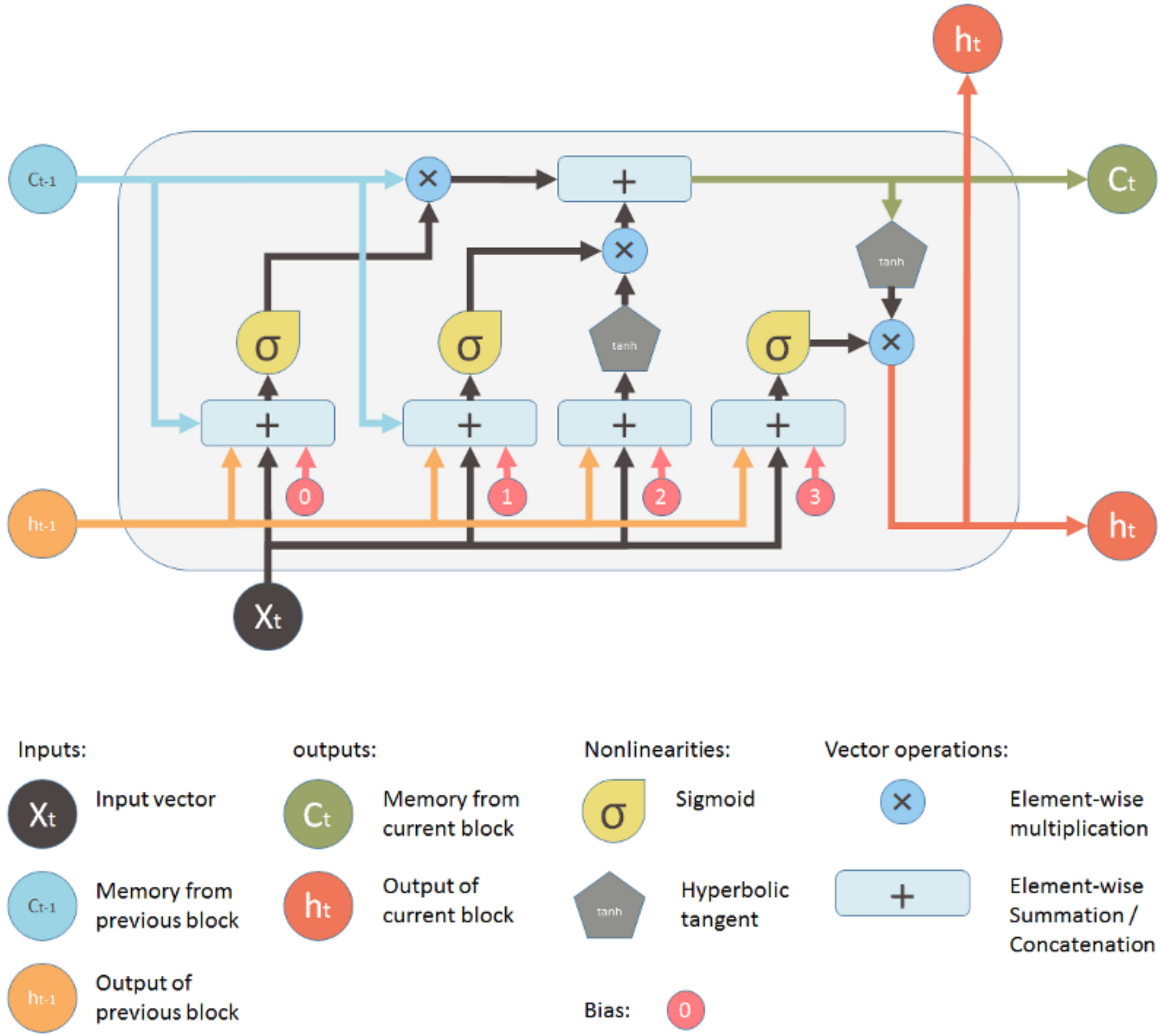
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Gated Recurrent Unit (GRU)



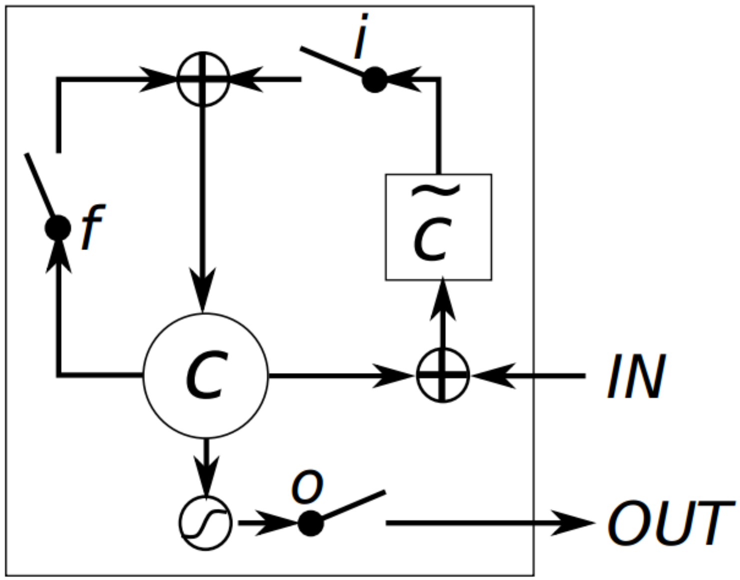
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

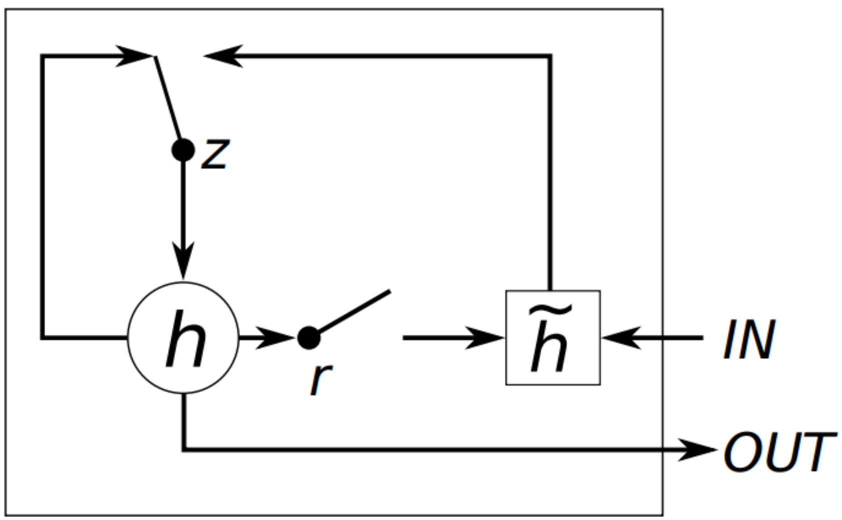
LSTM



Source: Shi Yan (2016), Understanding LSTM and its diagrams, https://medium.com/mlreview/understanding-lstm-and-its-diagrams-37e2f46f1714

LSTM vs GRU





LSTM

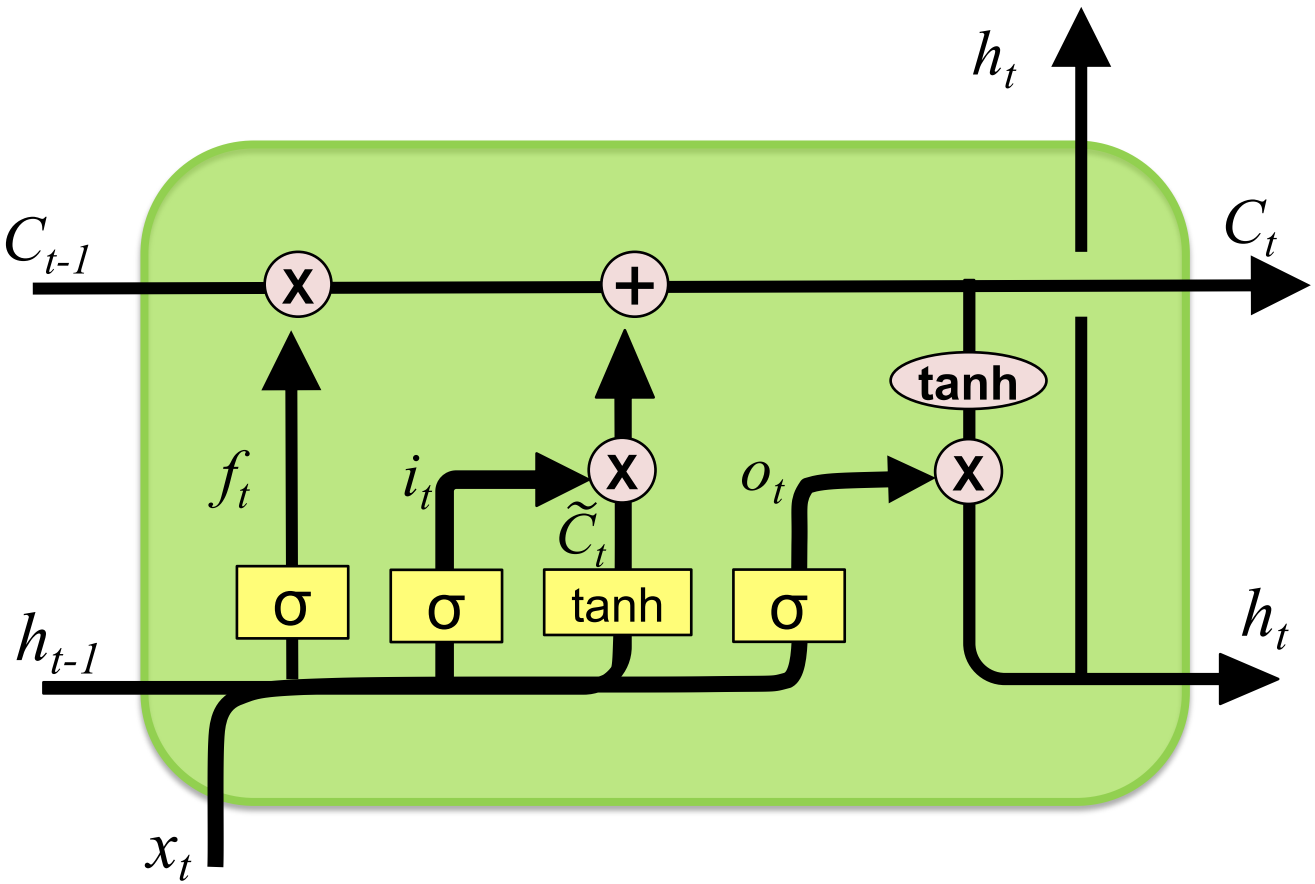
i, f and o are the input, forget and output gates, respectively.
c and c˜ denote the memory cell and the new memory cell content.

GRU

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

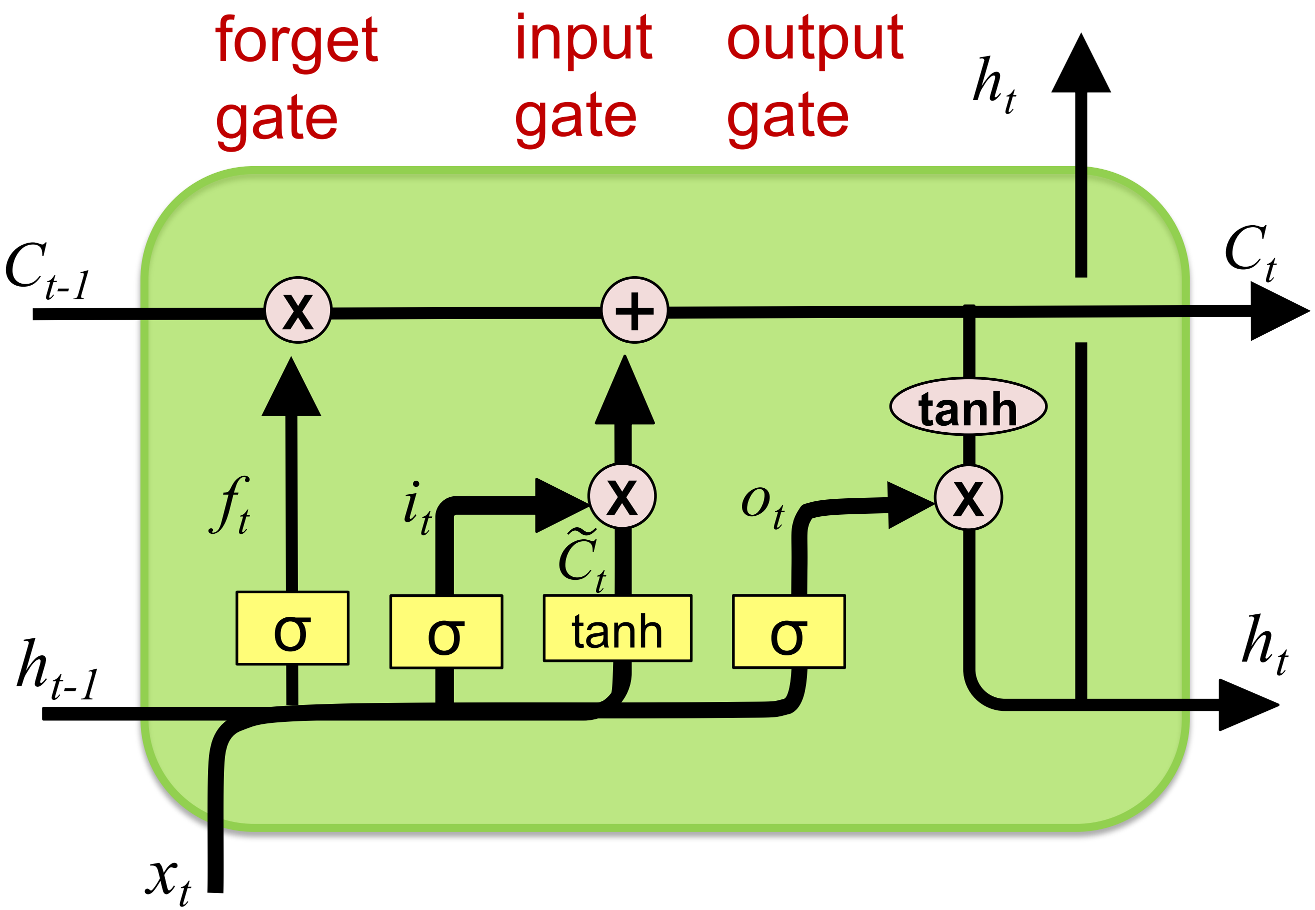
Source: Chung, Junyoung, Caglar Gulcehre, KyungHyun Cho, and Yoshua Bengio. "Empirical evaluation of gated recurrent neural networks on sequence modeling." *arXiv preprint arXiv:1412.3555* (2014).

Long Short Term Memory (LSTM)



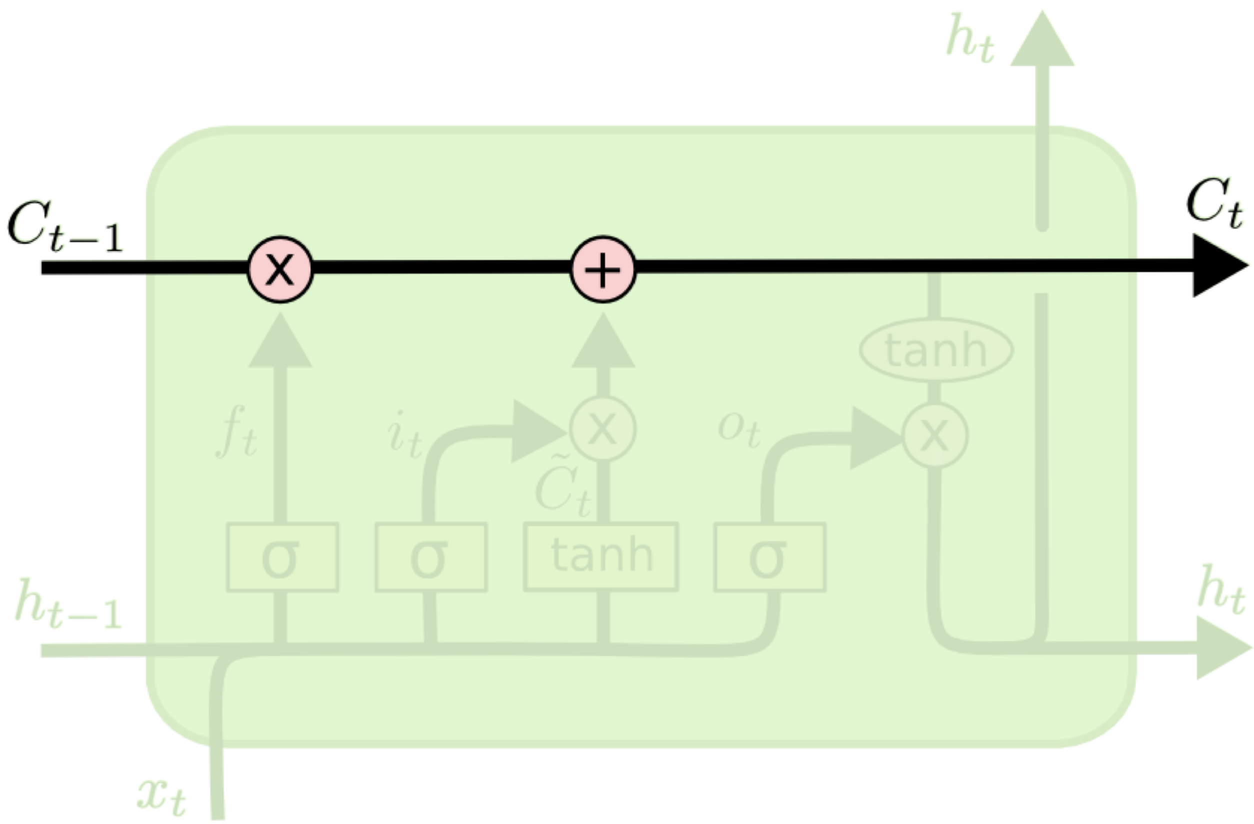
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Long Short Term Memory (LSTM)



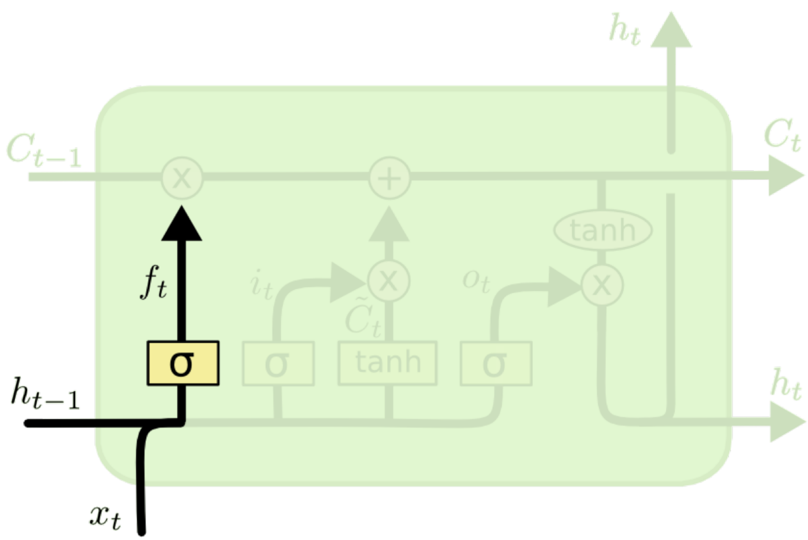
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM
Memory state (C)



Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

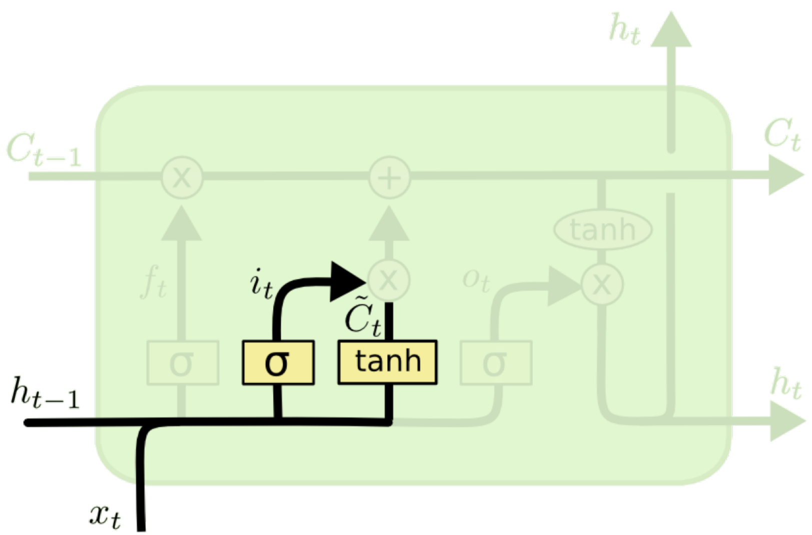
LSTM
forget gate (f)



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$

Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM
input gate (i)

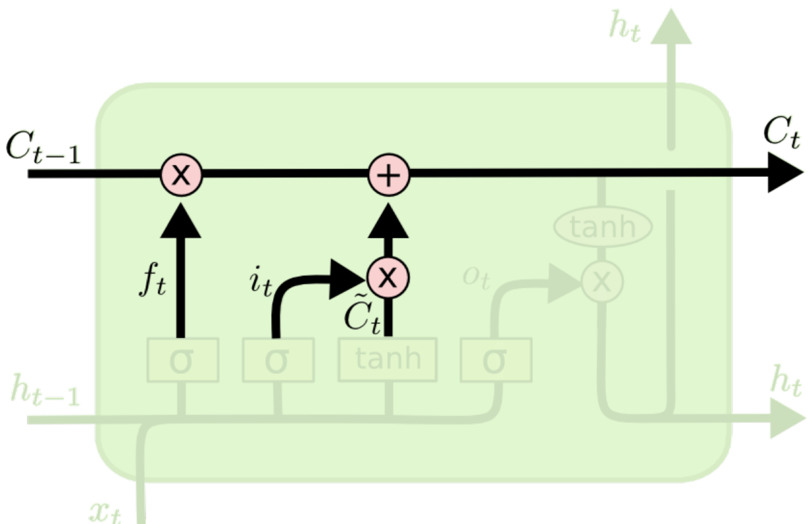


$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

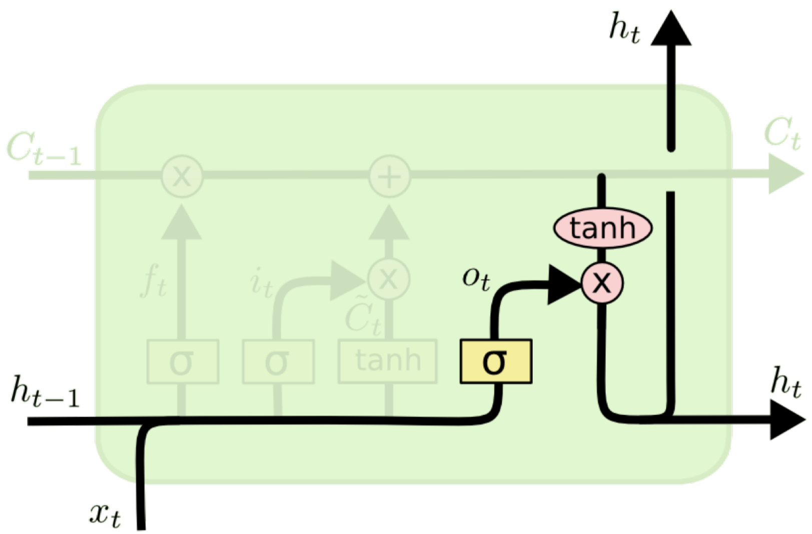
LSTM
Memory state (C)



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM
output gate (o)

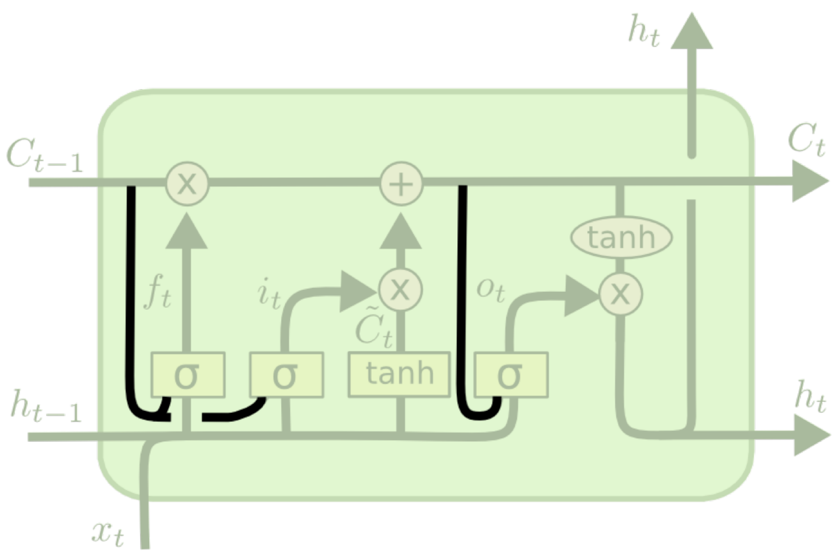


$$o_t = \sigma\left(W_o \; [\,h_{t-1}, x_t] \; + \; b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

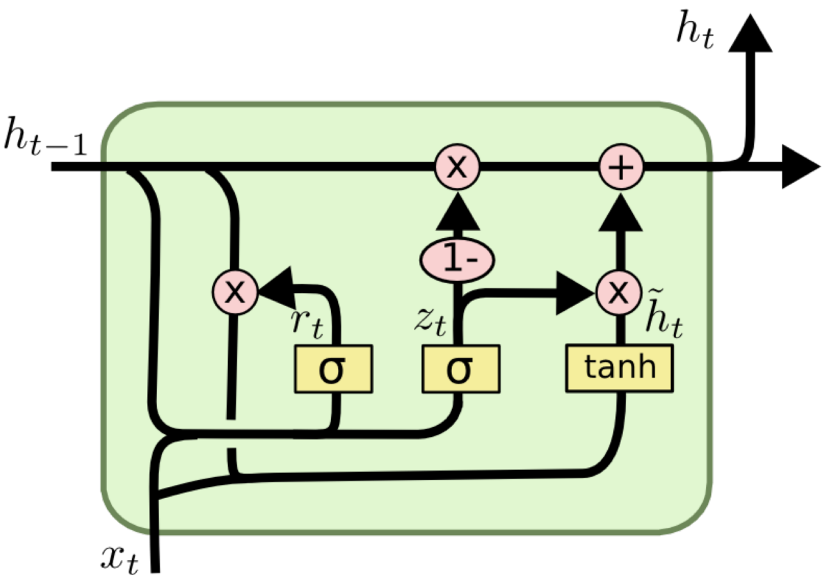
LSTM
forget (f), input (i), output (o) gates



$$f_t = \sigma\left(W_f \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \; + \; b_f\right)$$
$$i_t = \sigma\left(W_i \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \; + \; b_i\right)$$
$$o_t = \sigma\left(W_o \cdot [\boldsymbol{C_t}, h_{t-1}, x_t] \; + \; b_o\right)$$

Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Gated Recurrent Unit (GRU)
update (z), reset (r) gates



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

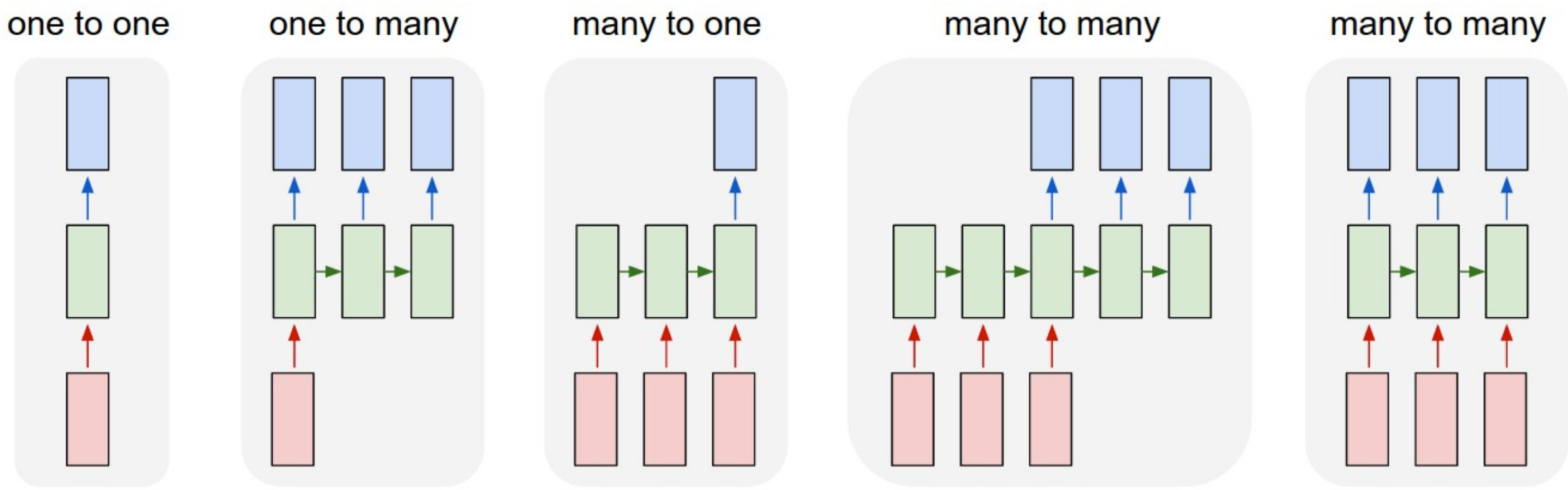
$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM Recurrent Neural Network



Traditional Neural Network

Music Generation

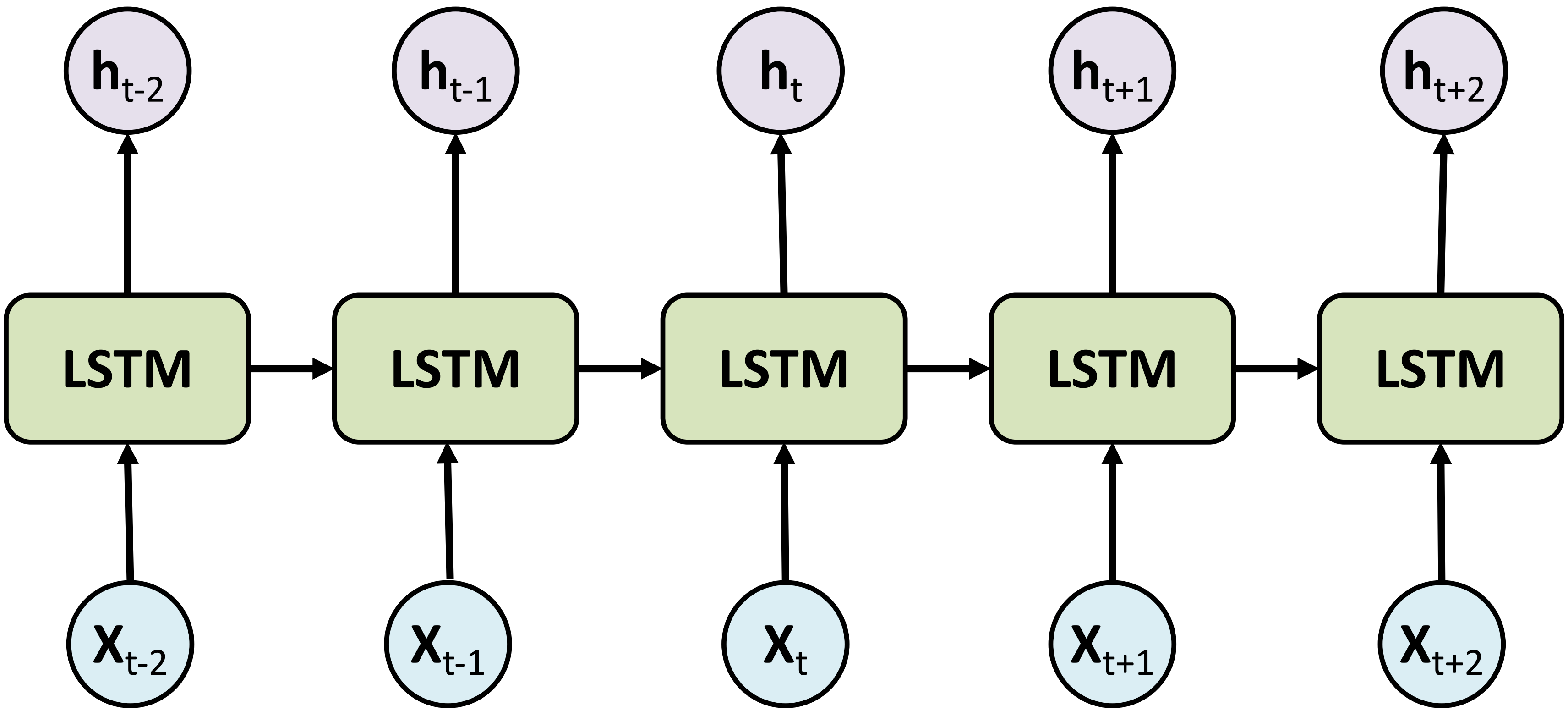
Sentiment Classification

Name Entity Recognition

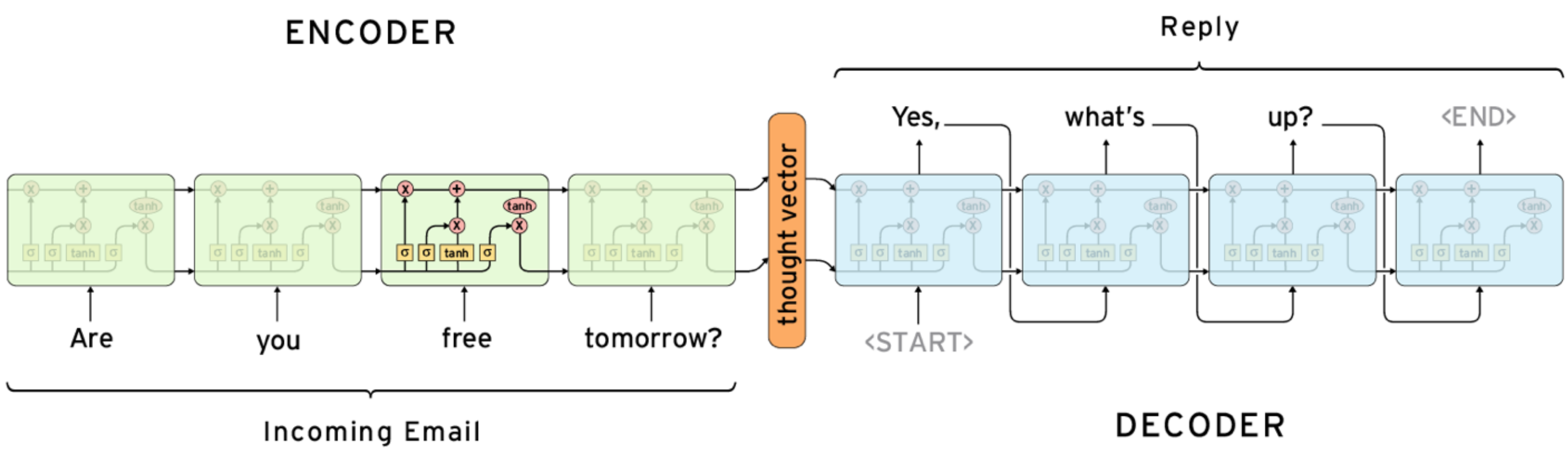
Machine Translation

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

Long Short Term Memory (LSTM) for Time Series Forecasting

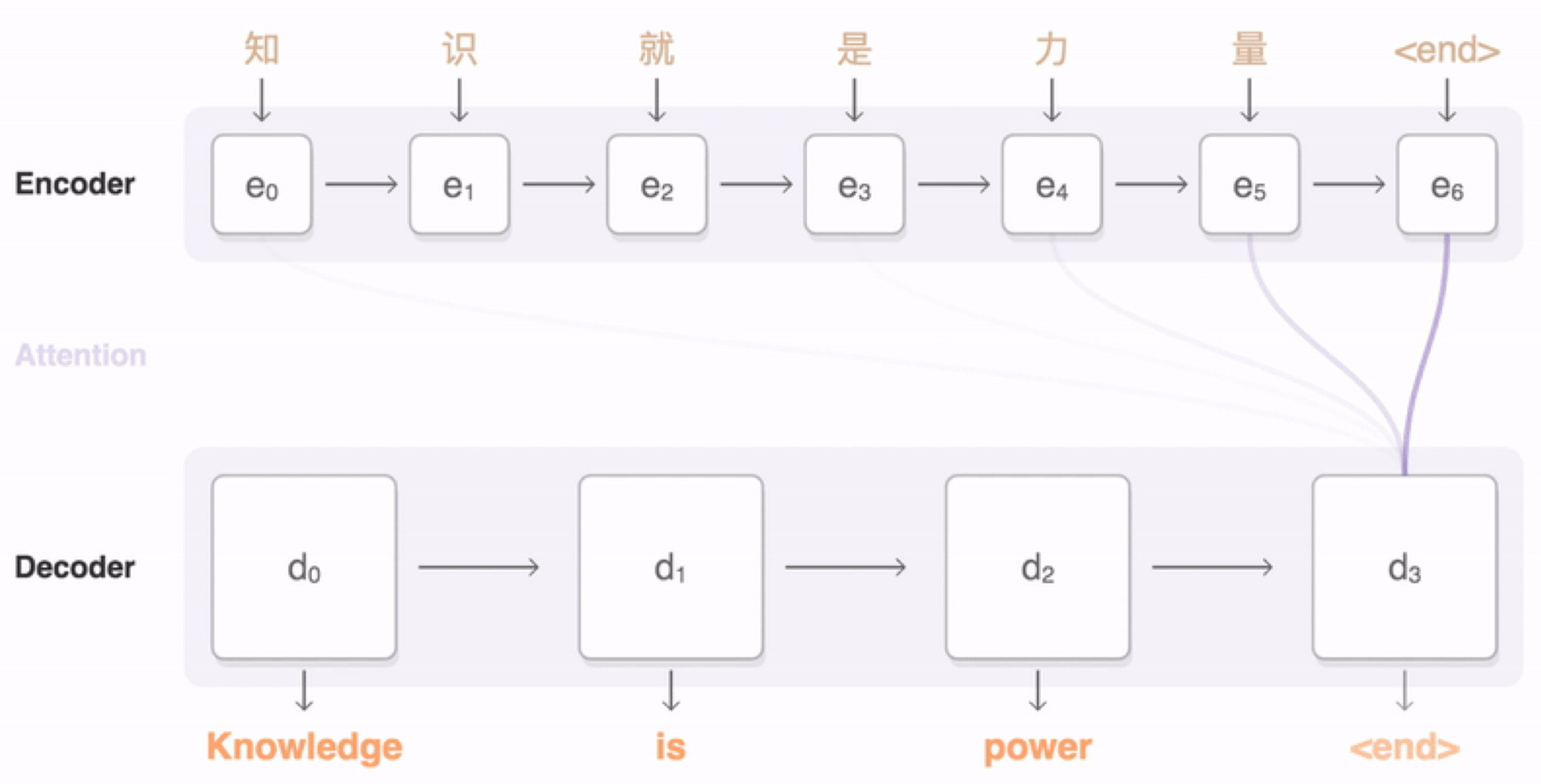


The Sequence to Sequence model (seq2seq)



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

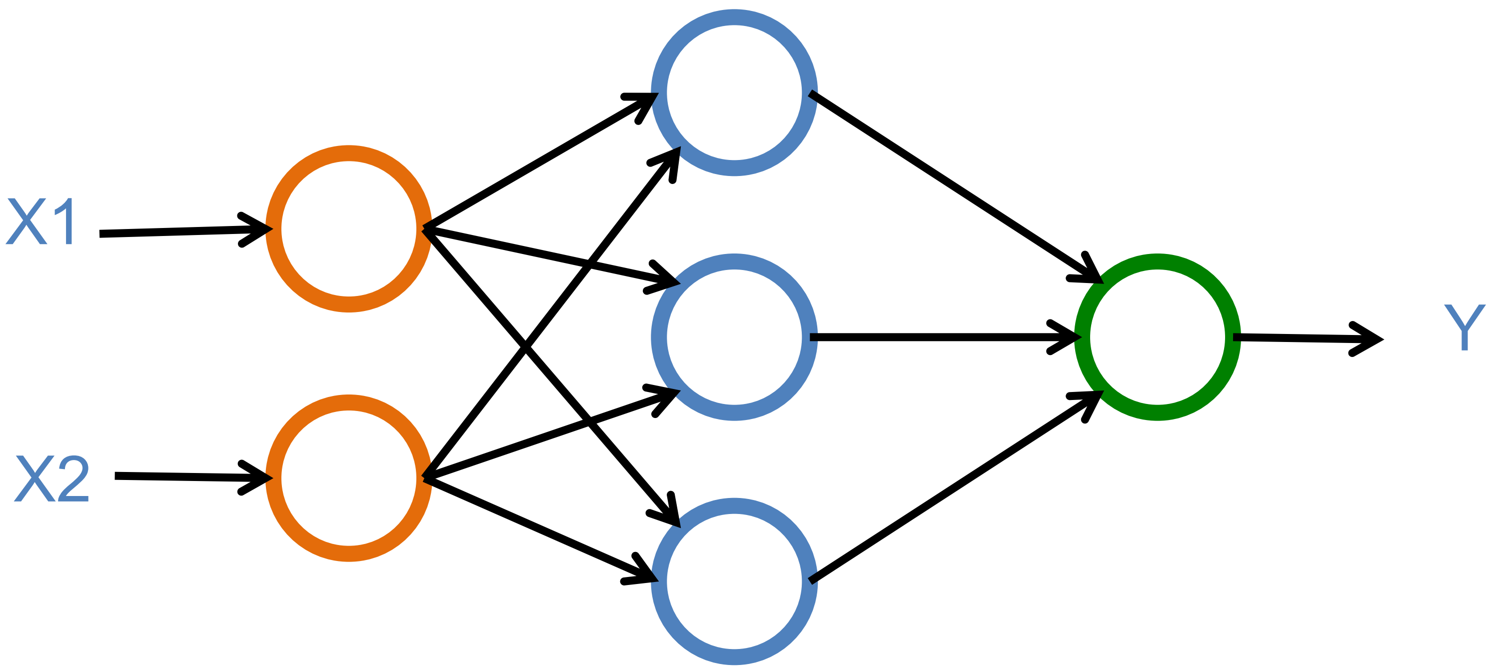
Sequence to Sequence (Seq2Seq)



Source: https://google.github.io/seq2seq/

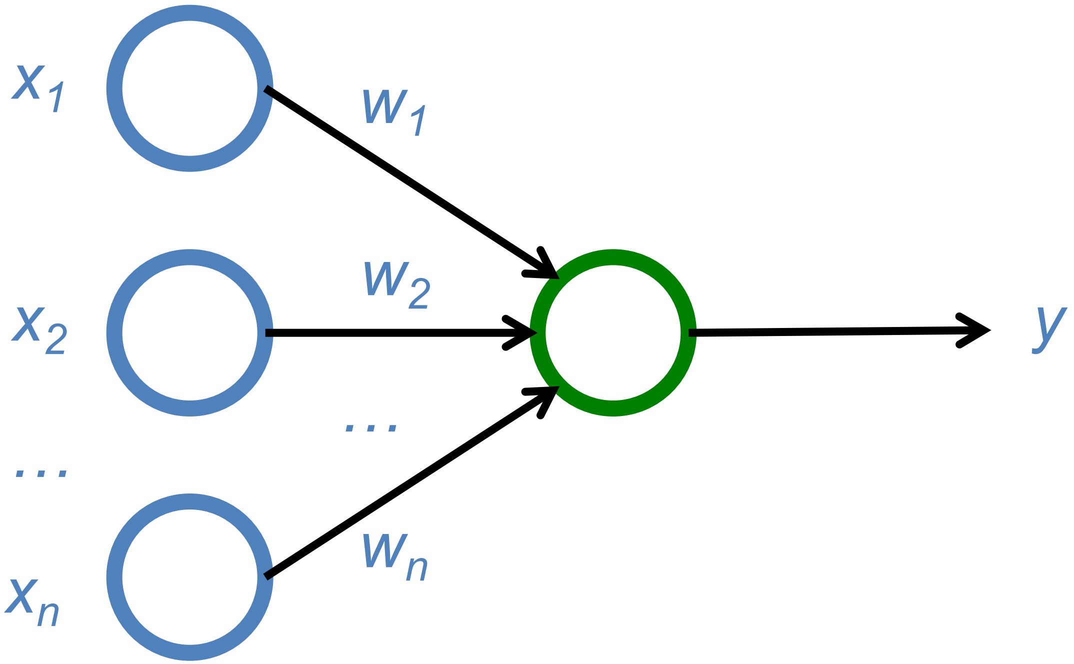
Neural Networks

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



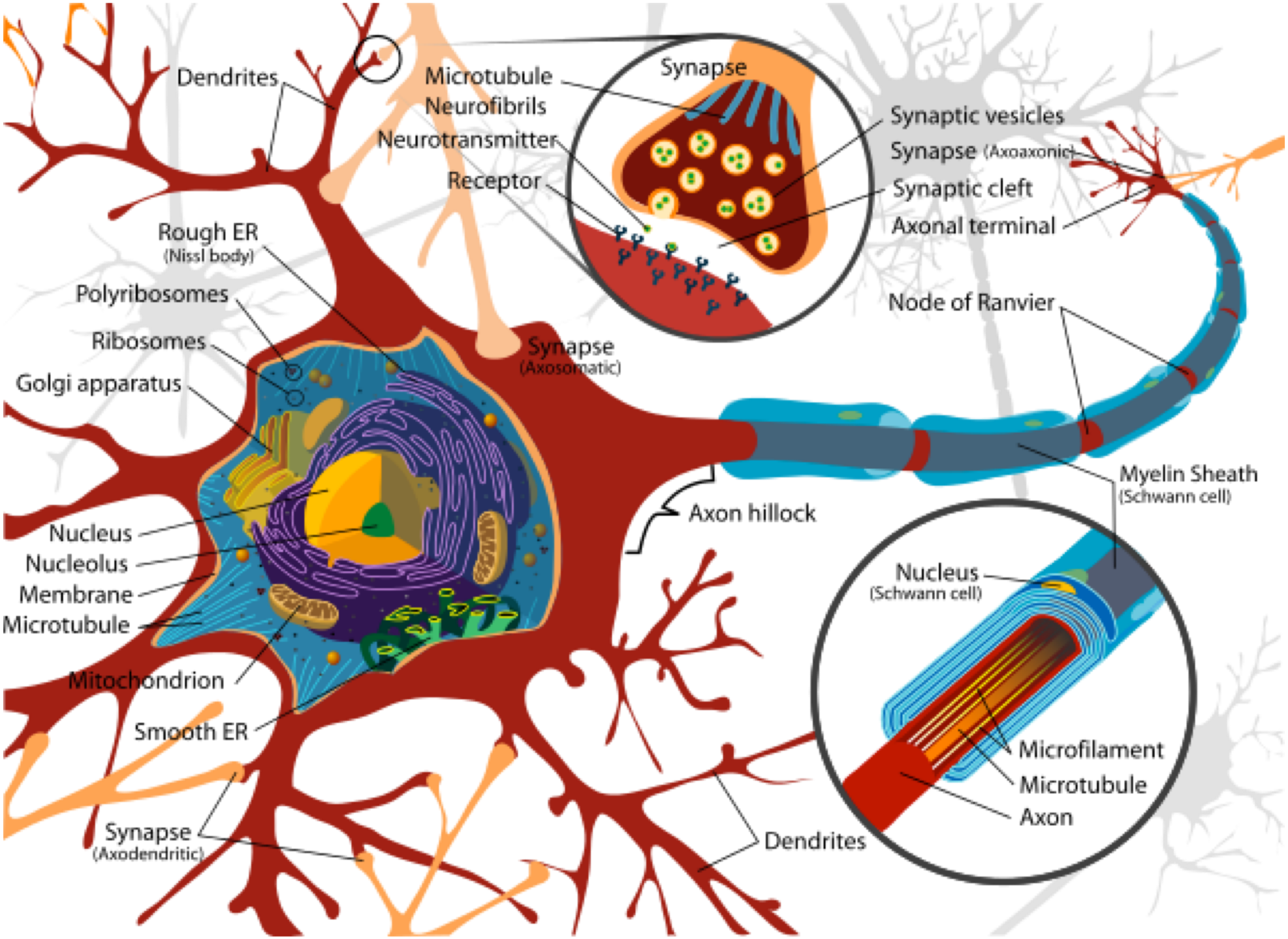
Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

The Neuron



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

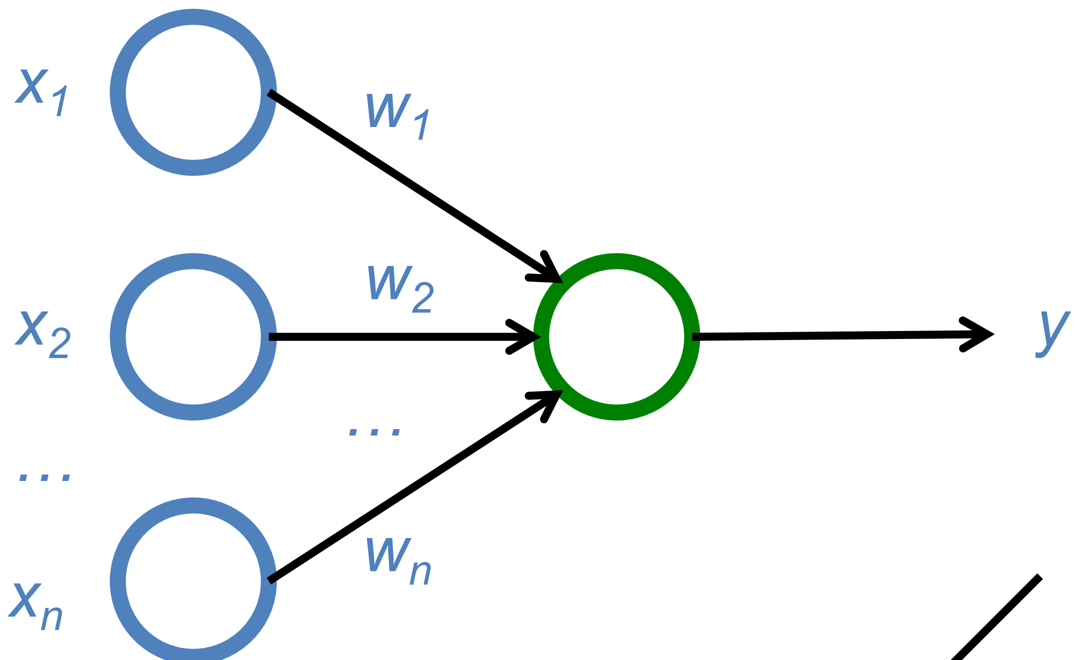
Neuron and Synapse

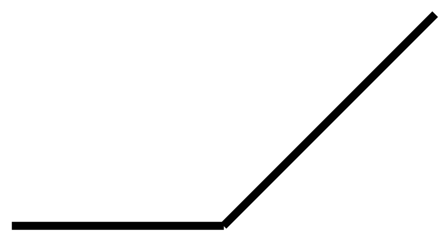


Source: https://en.wikipedia.org/wiki/Neuron

The Neuron

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

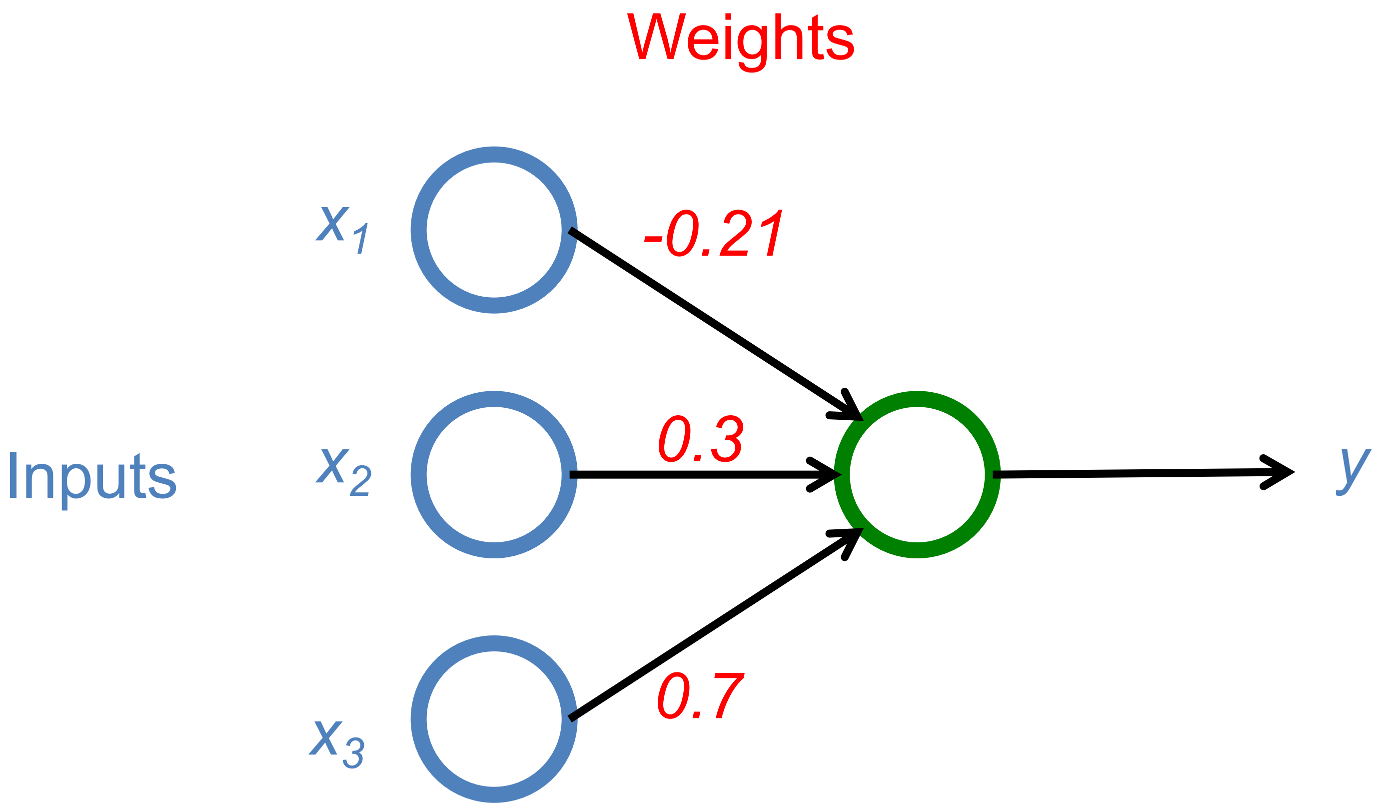




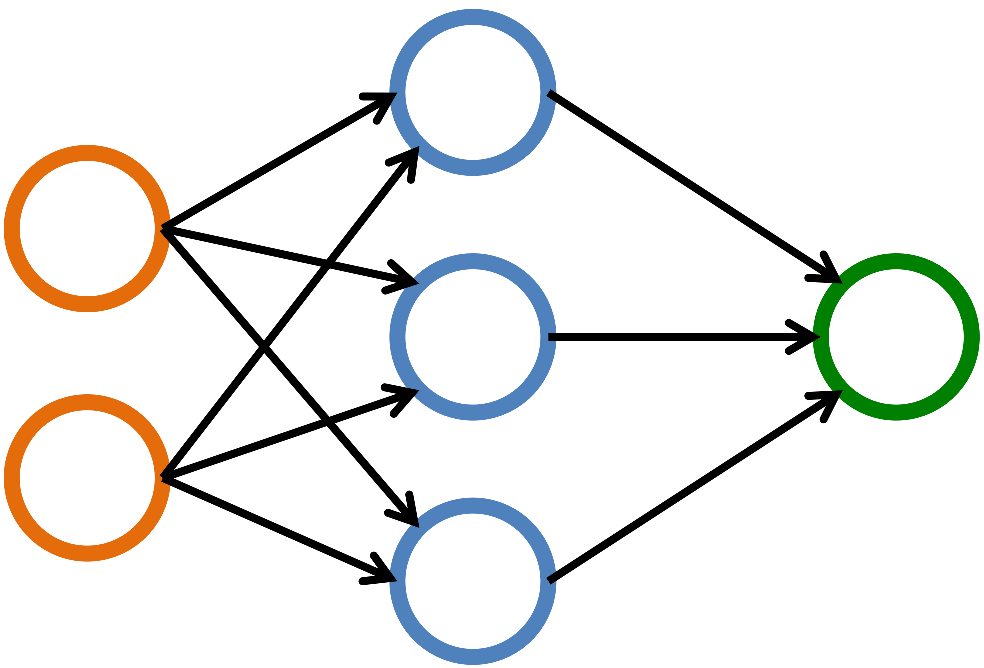
$$F(x) = \max(0, x)$$

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

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

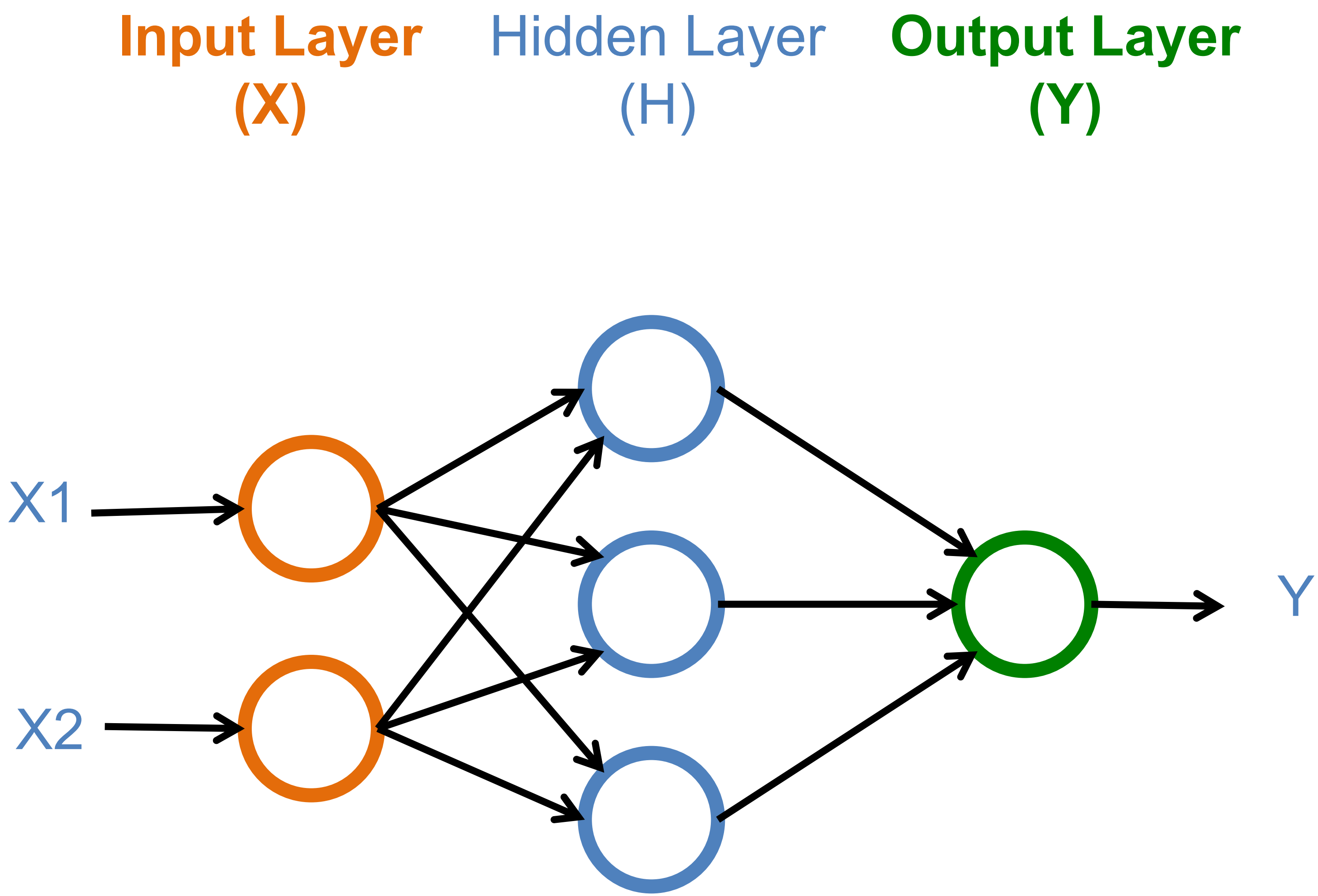


Neural Networks



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

Neural Networks



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

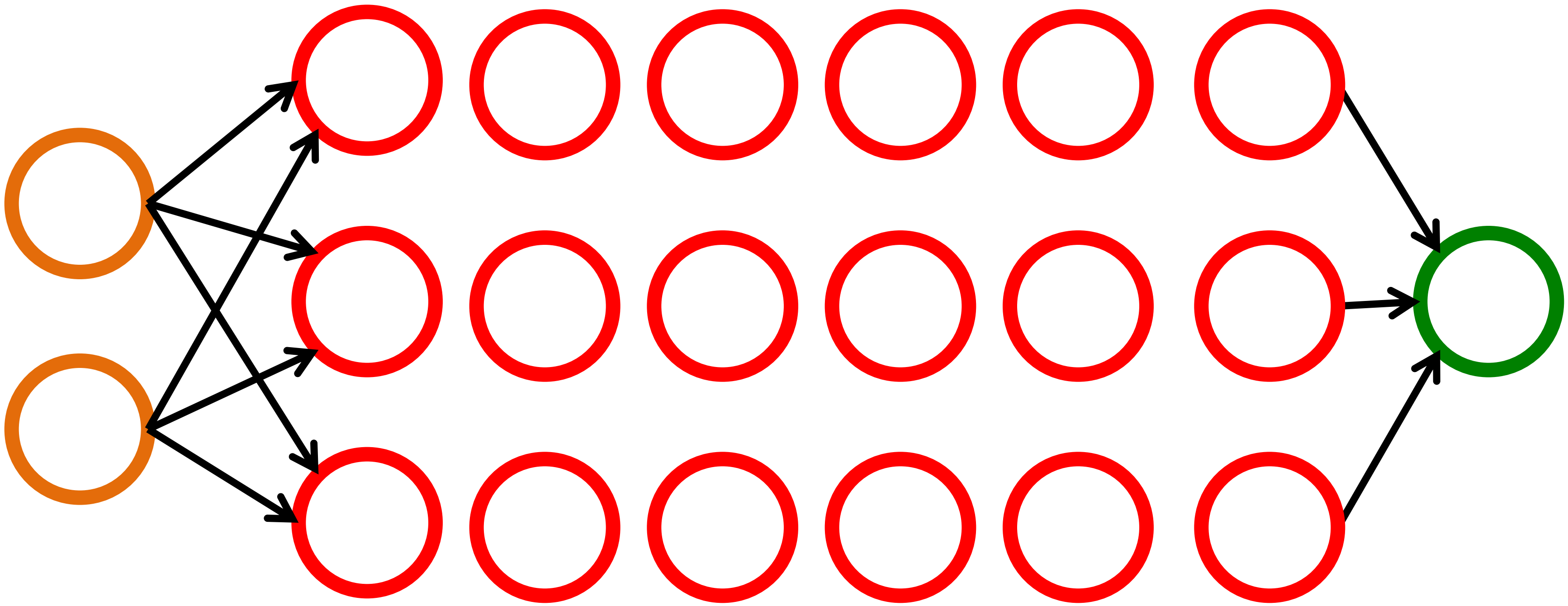
Neural Networks

Input Layer
(X)

Hidden Layers
(H)

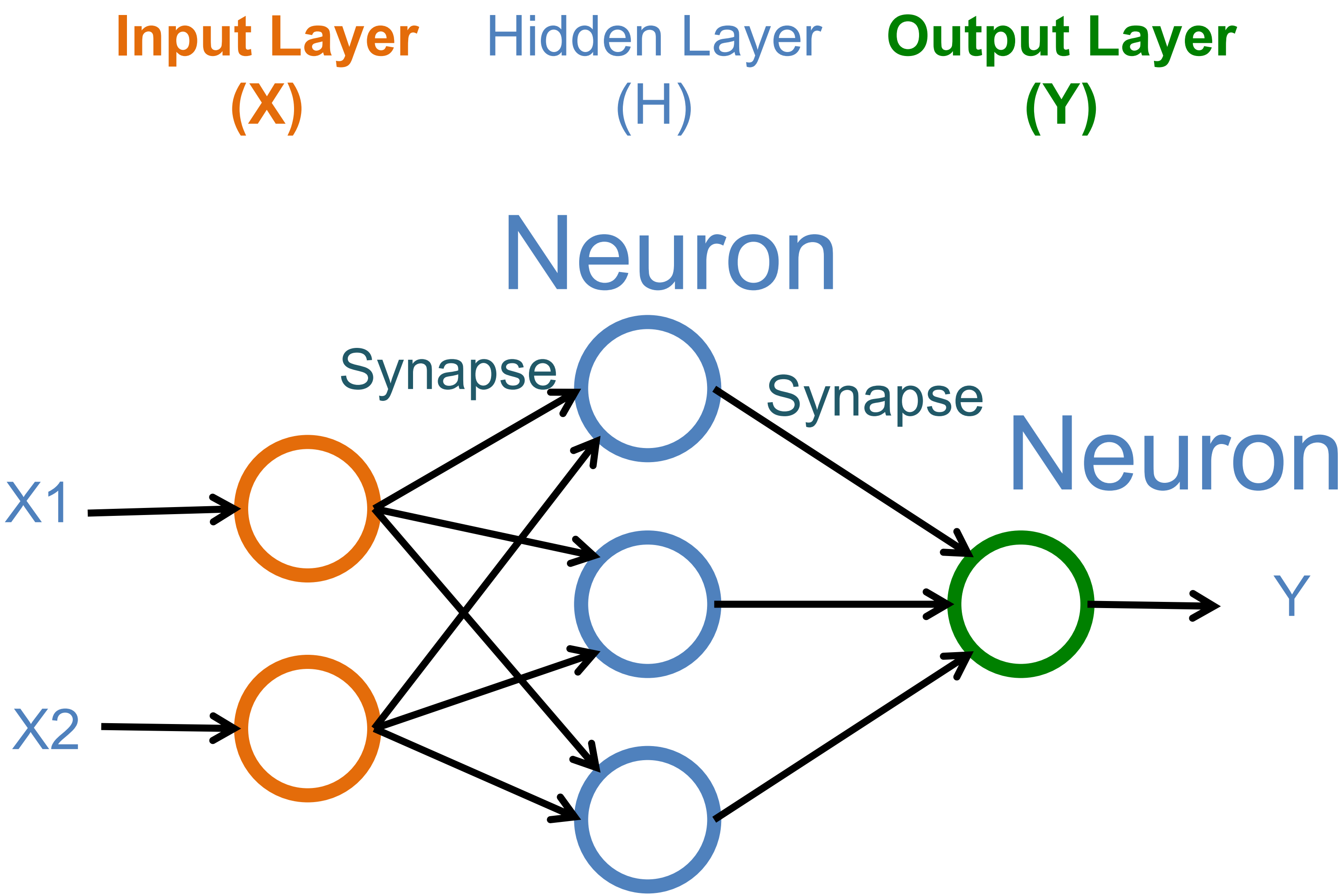
Output Layer
(Y)

Deep Neural Networks
Deep Learning



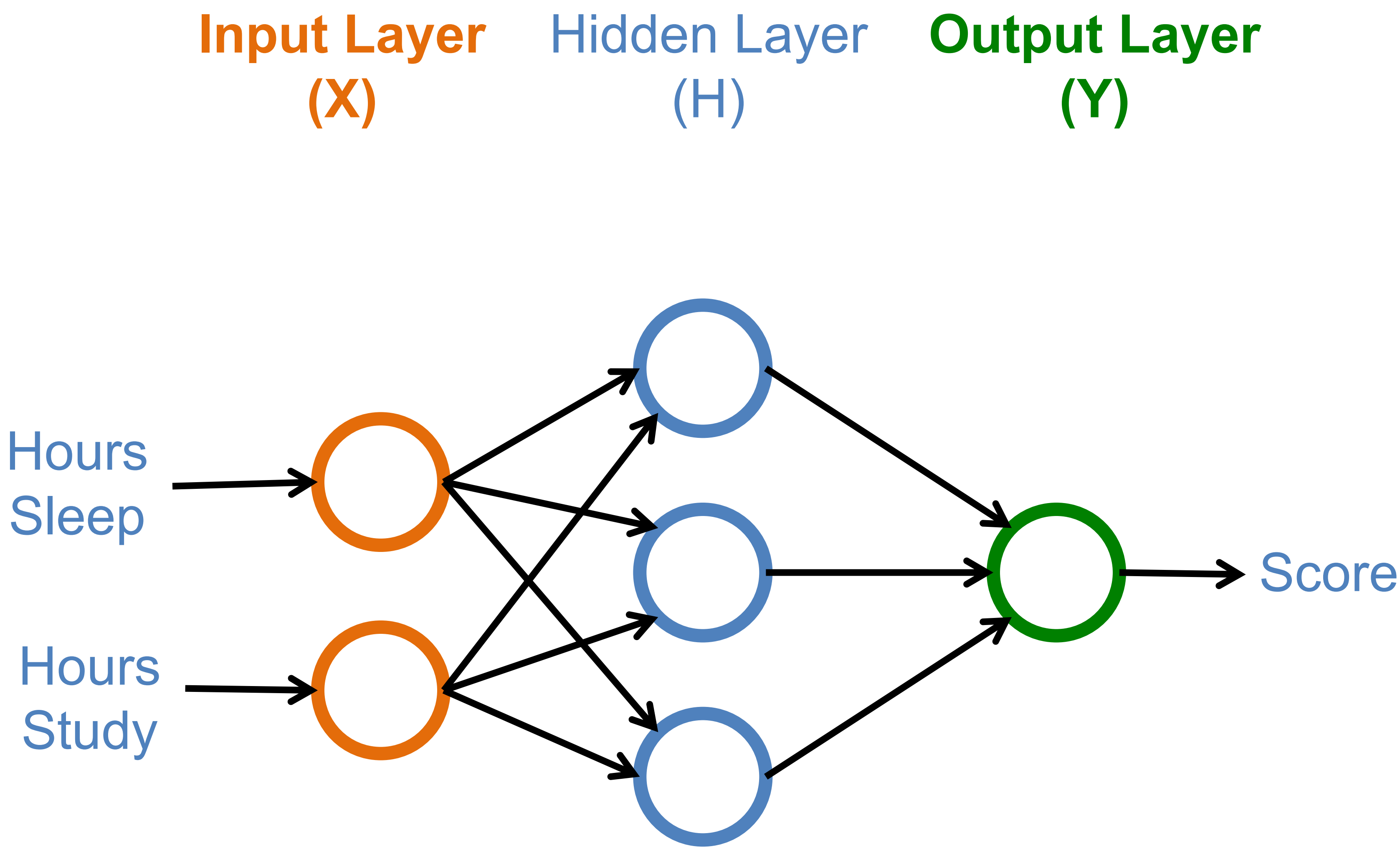
Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

Neural Networks



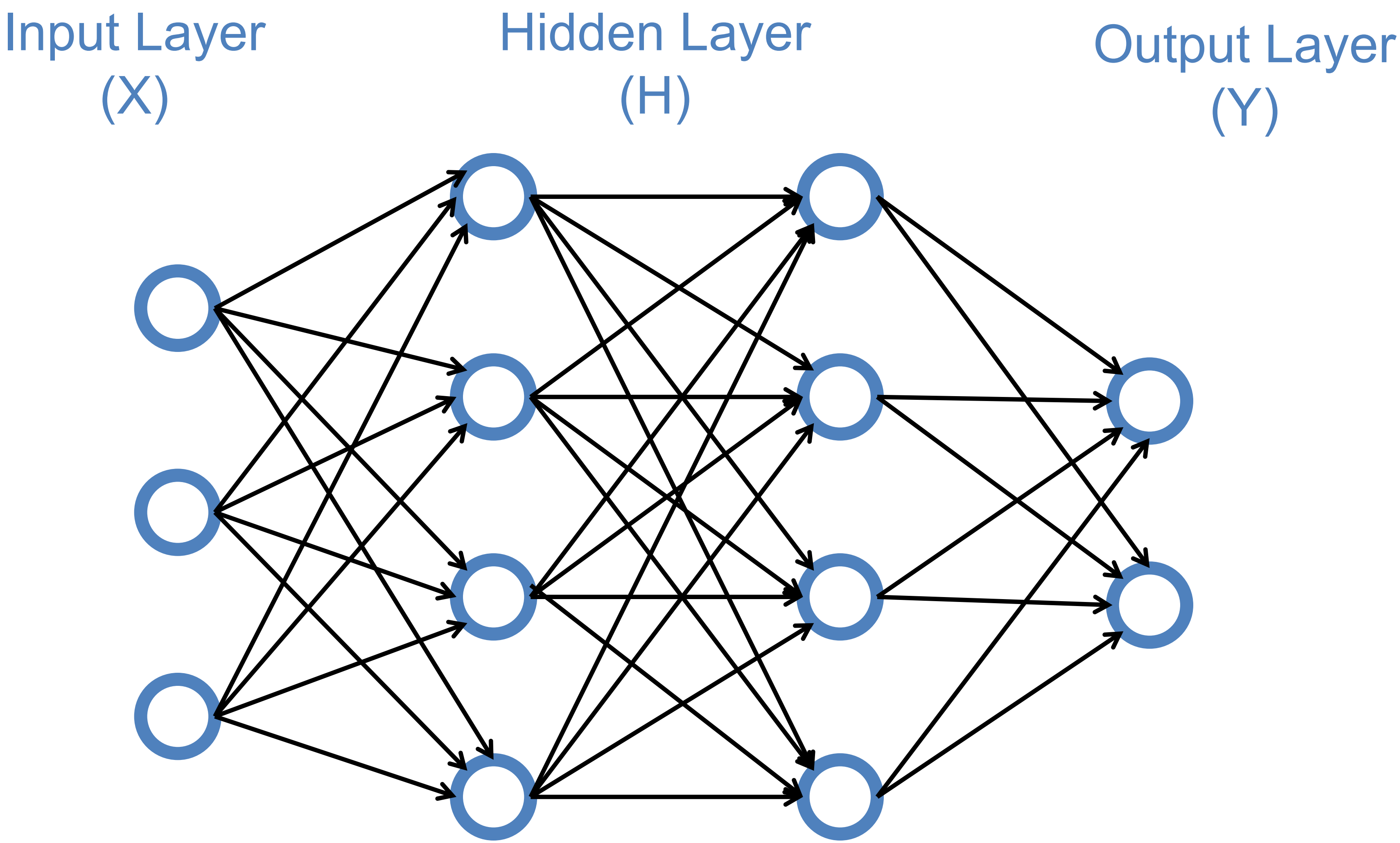
Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

Neural Networks



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

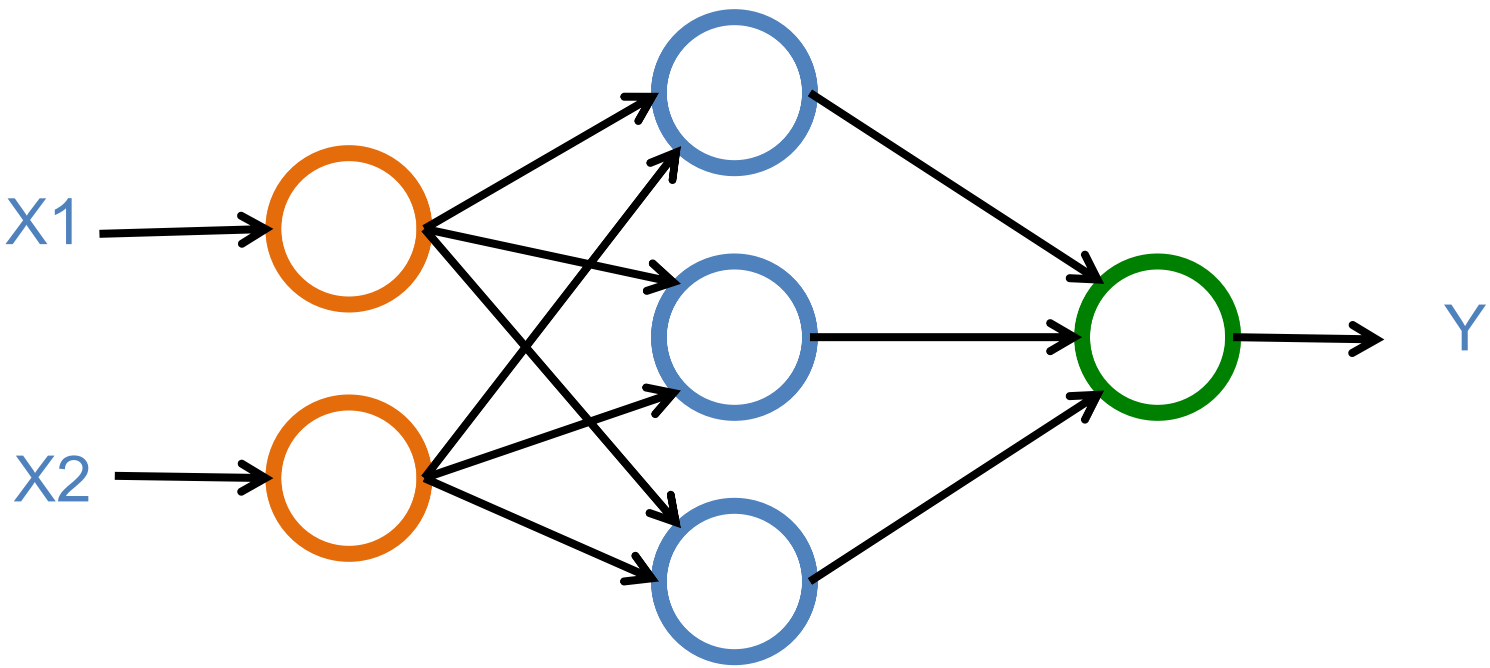
Neural Networks



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

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

Output

input

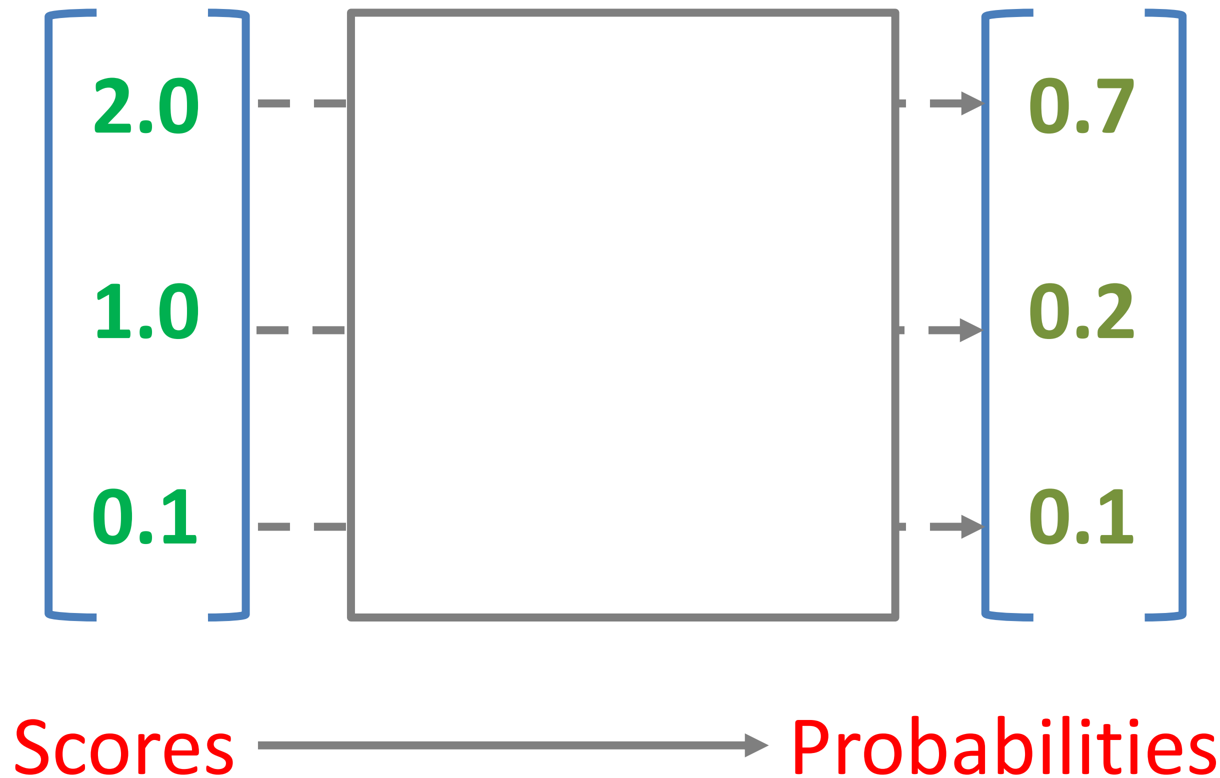
$$Y = W X + b$$

Weights

bias

Trained

$$W X + b = Y$$



SoftMAX

$$\mathbf{W}\,\mathbf{X} + \mathbf{b} = \mathbf{Y} \qquad \begin{bmatrix} 2.0 \\ 1.0 \\ 0.1 \end{bmatrix} \longrightarrow S(y_i) = \frac{e^{y_i}}{\sum_j e^{y_j}} \longrightarrow \begin{bmatrix} 0.7 \\ 0.2 \\ 0.1 \end{bmatrix}$$

Logits

Scores $\longrightarrow$ Probabilities

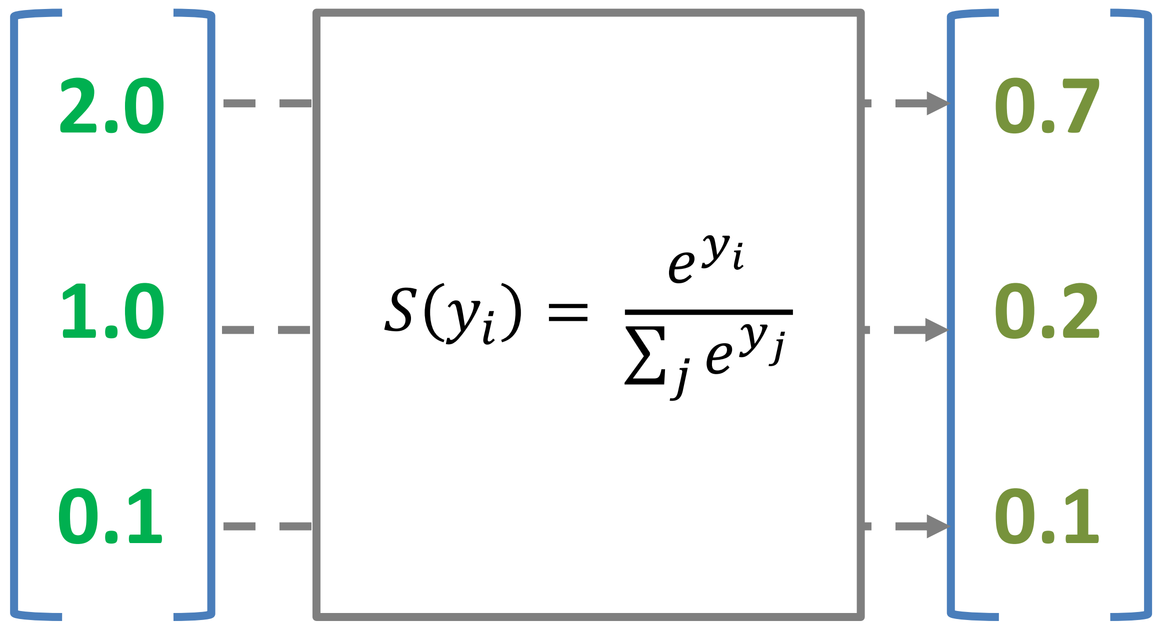
Source: https://www.youtube.com/watch?v=G8eNWzxOgqE

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

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

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

W X + b = Y



Logits

Scores → Probabilities

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

Training a Network

=

Minimize the Cost Function

Training a Network

=

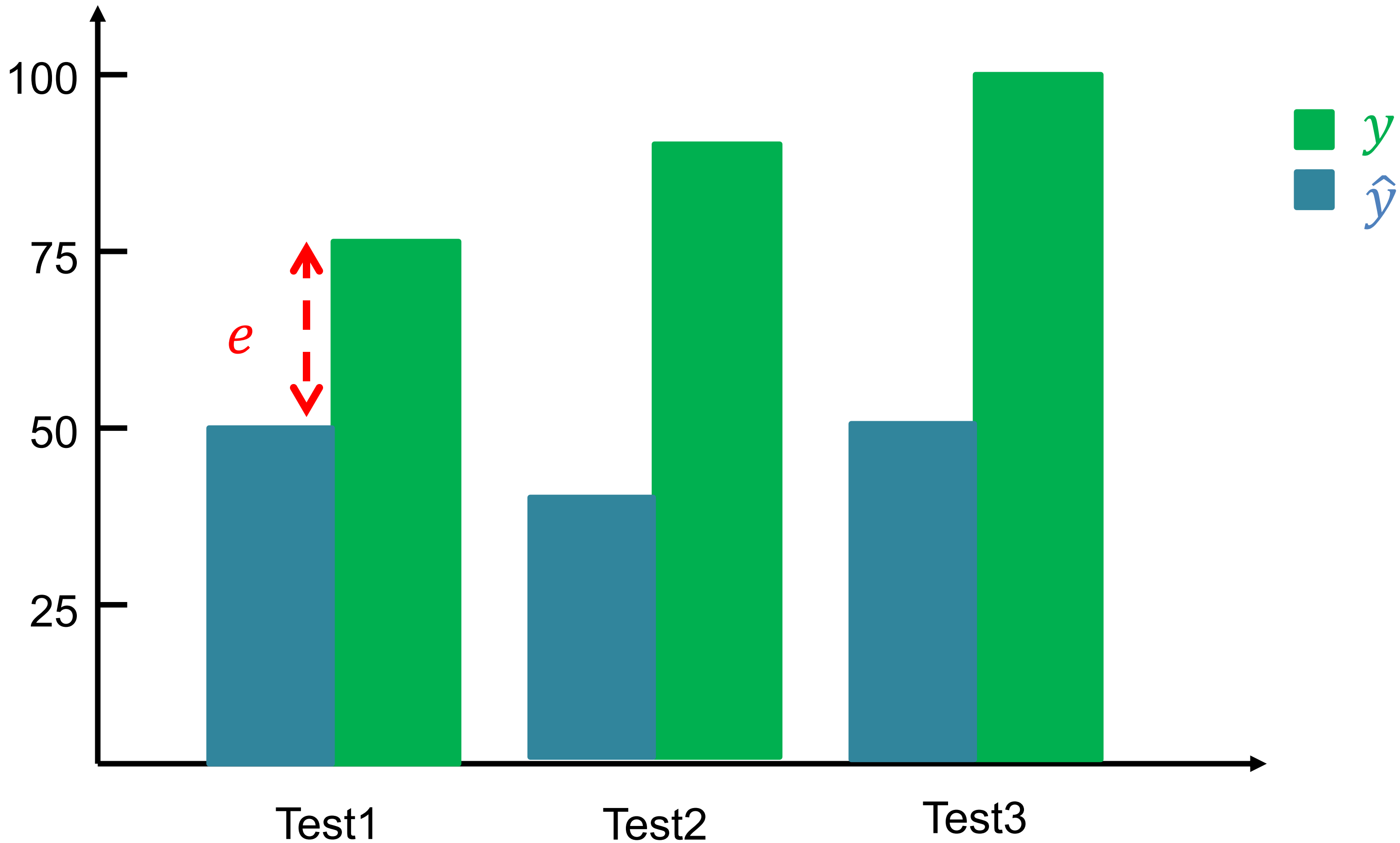
Minimize the Cost Function

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

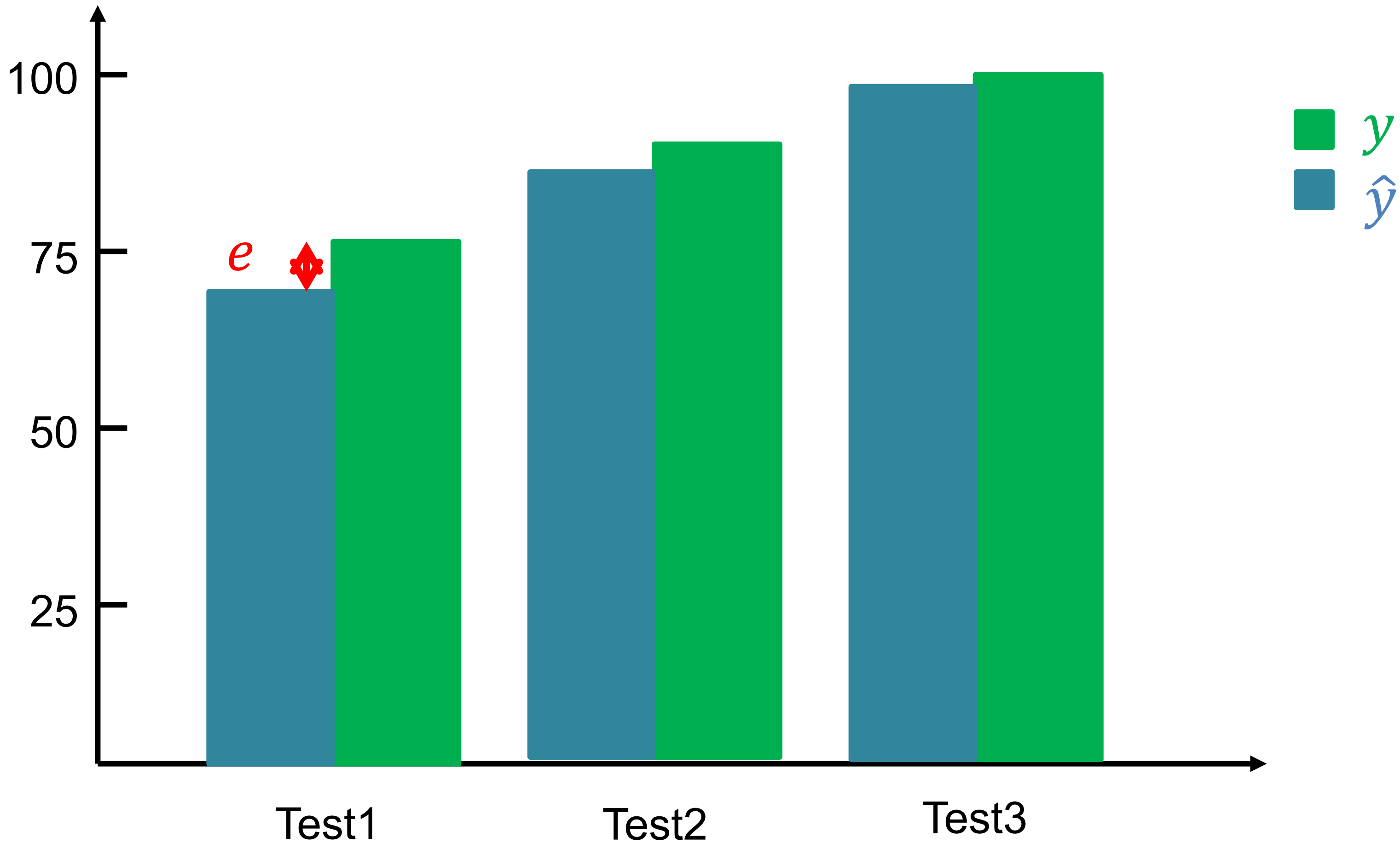
Error = Predict Y - Actual Y

Error : Cost : Loss

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

Error = Predict Y - Actual Y

Error : Cost : Loss

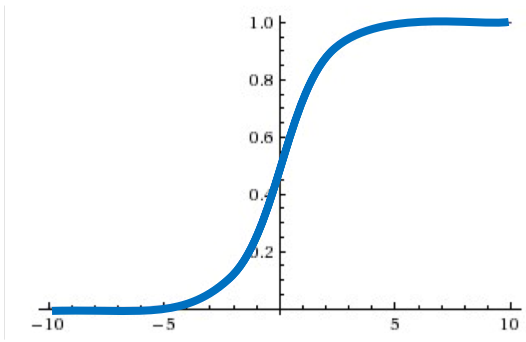


Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

Activation Functions

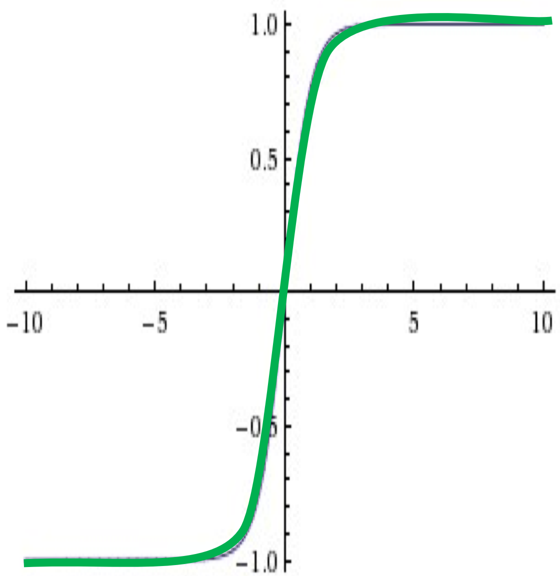
Activation Functions

Sigmoid



[0, 1]

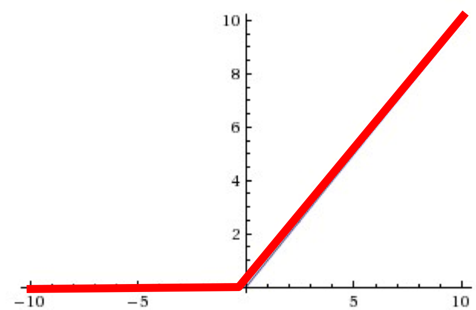
TanH



[-1, 1]

ReLU

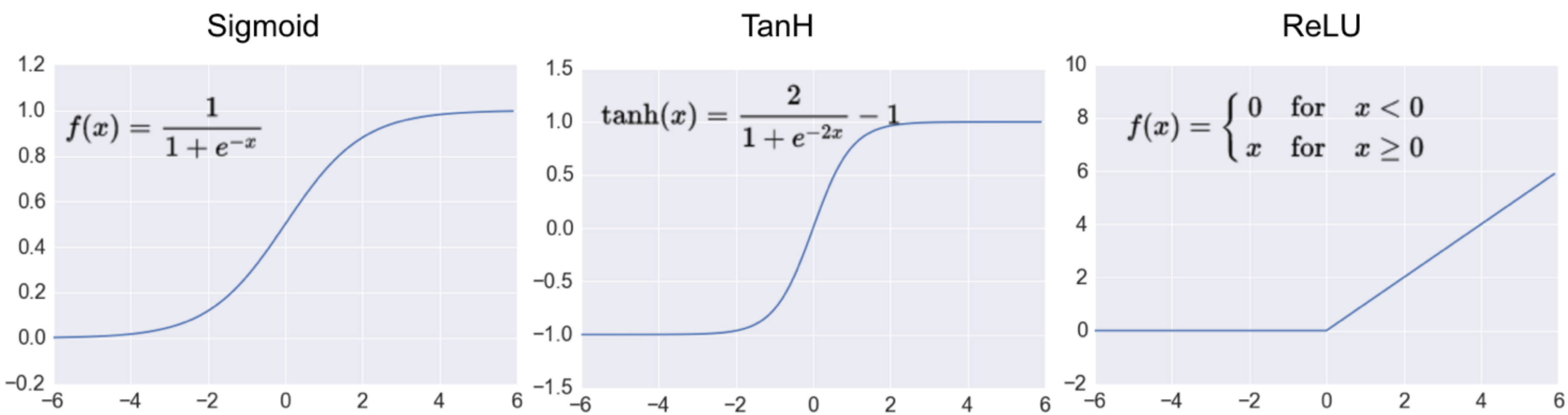
(Rectified Linear Unit)



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

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

Activation Functions



Loss Function

Binary Classification: 2 Class

Activation Function:
Sigmoid

Loss Function:
Binary Cross-Entropy

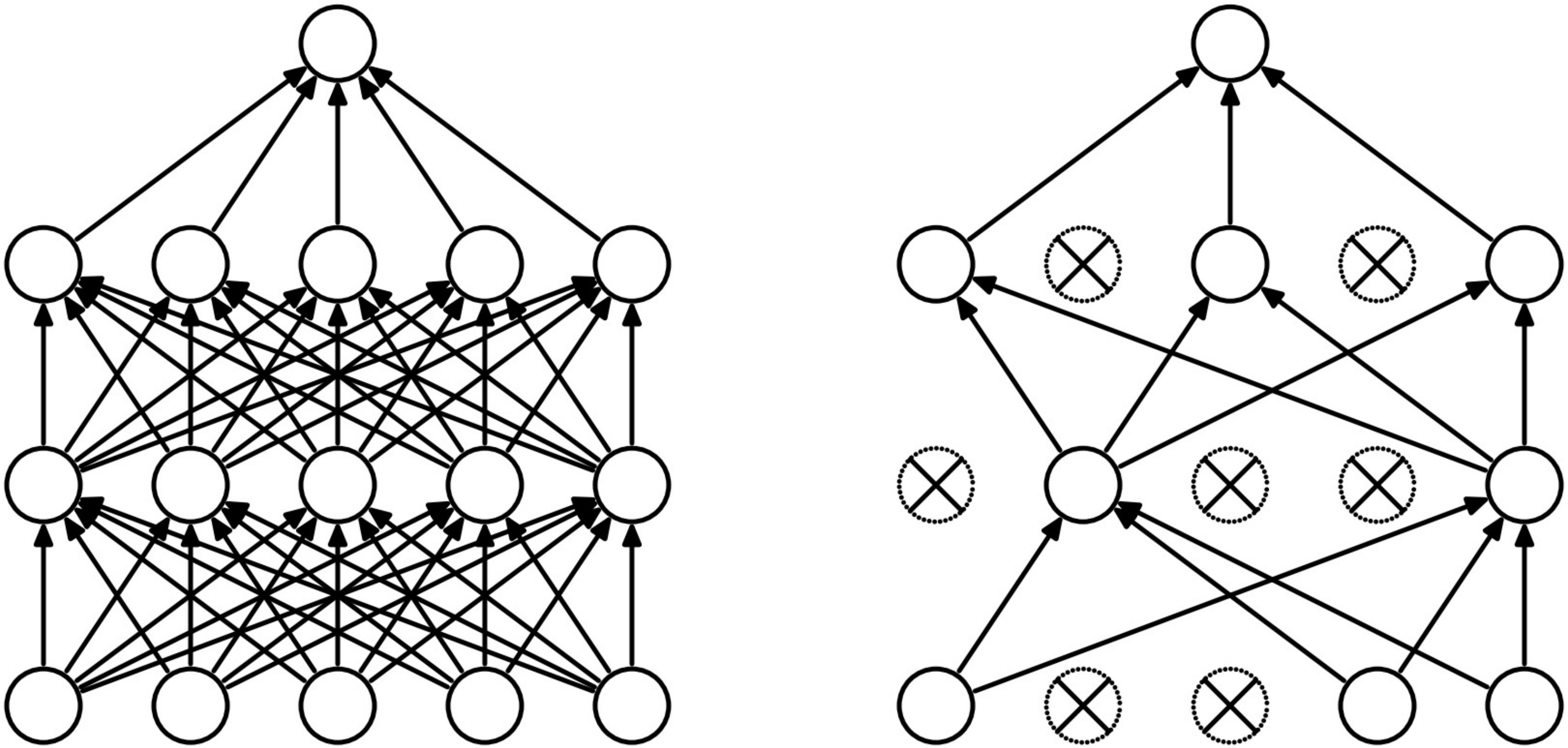
Multiple Classification: 10 Class

Activation Function:
SoftMAX

Loss Function:
Categorical Cross-Entropy

Dropout

Dropout: a simple way to prevent neural networks from overfitting



(a) Standard Neural Net (b) After applying dropout.

Source: Srivastava, Nitish, Geoffrey E. Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. "Dropout: a simple way to prevent neural networks from overfitting." *Journal of machine learning research* 15, no. 1 (2014): 1929-1958.

Learning Algorithm

While not done:

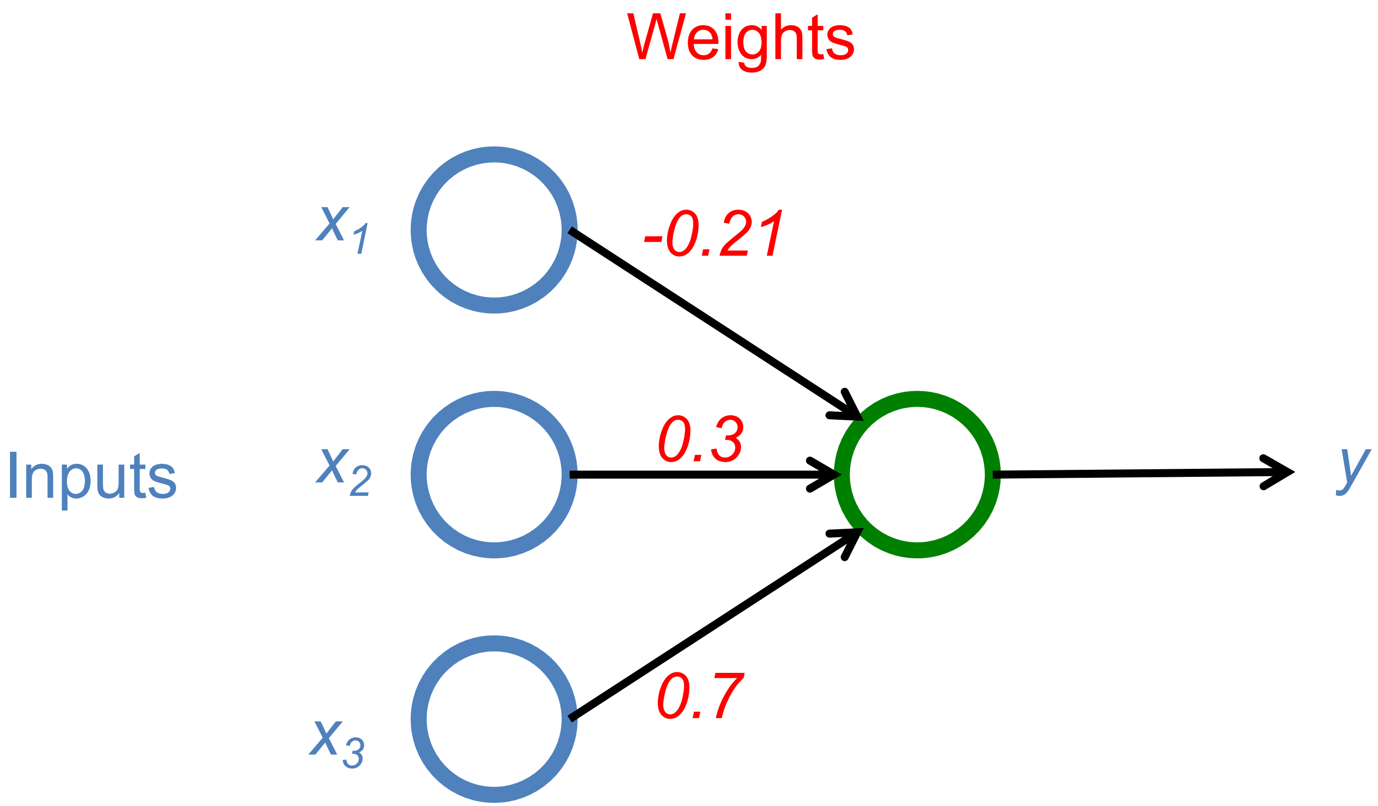
Pick a random training example "(input, label)"

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

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

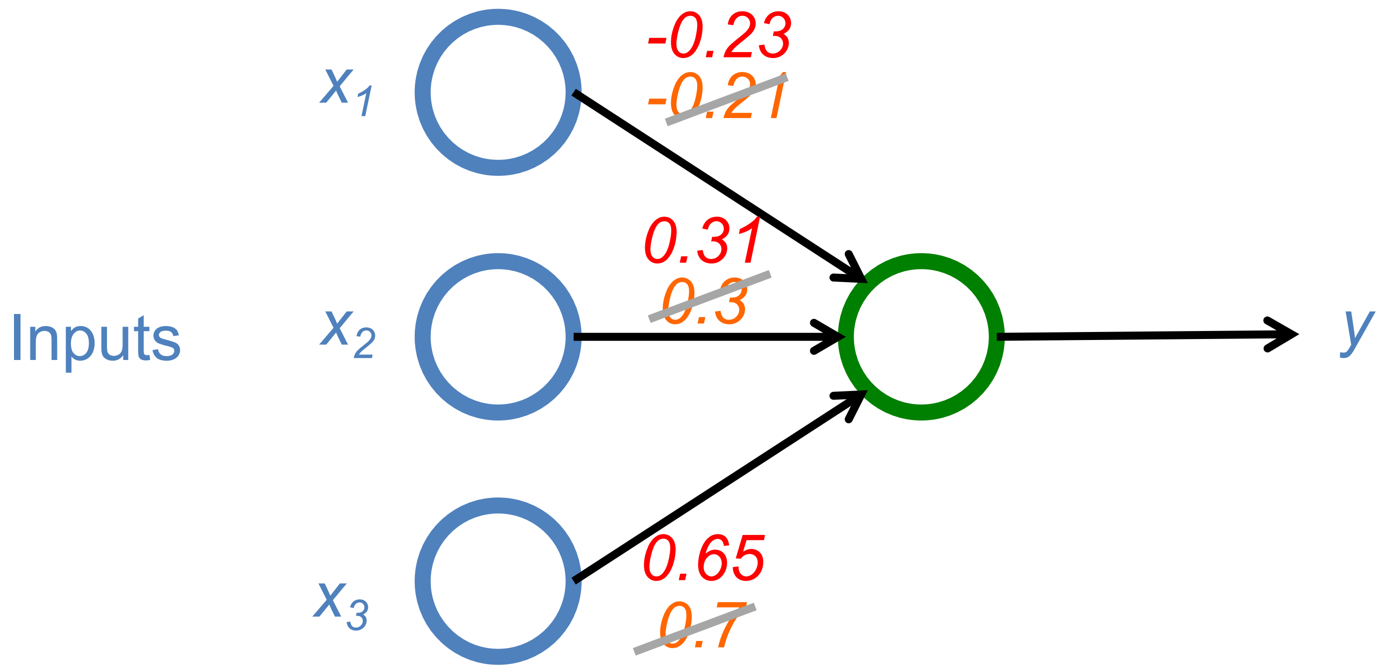


Next time:

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

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

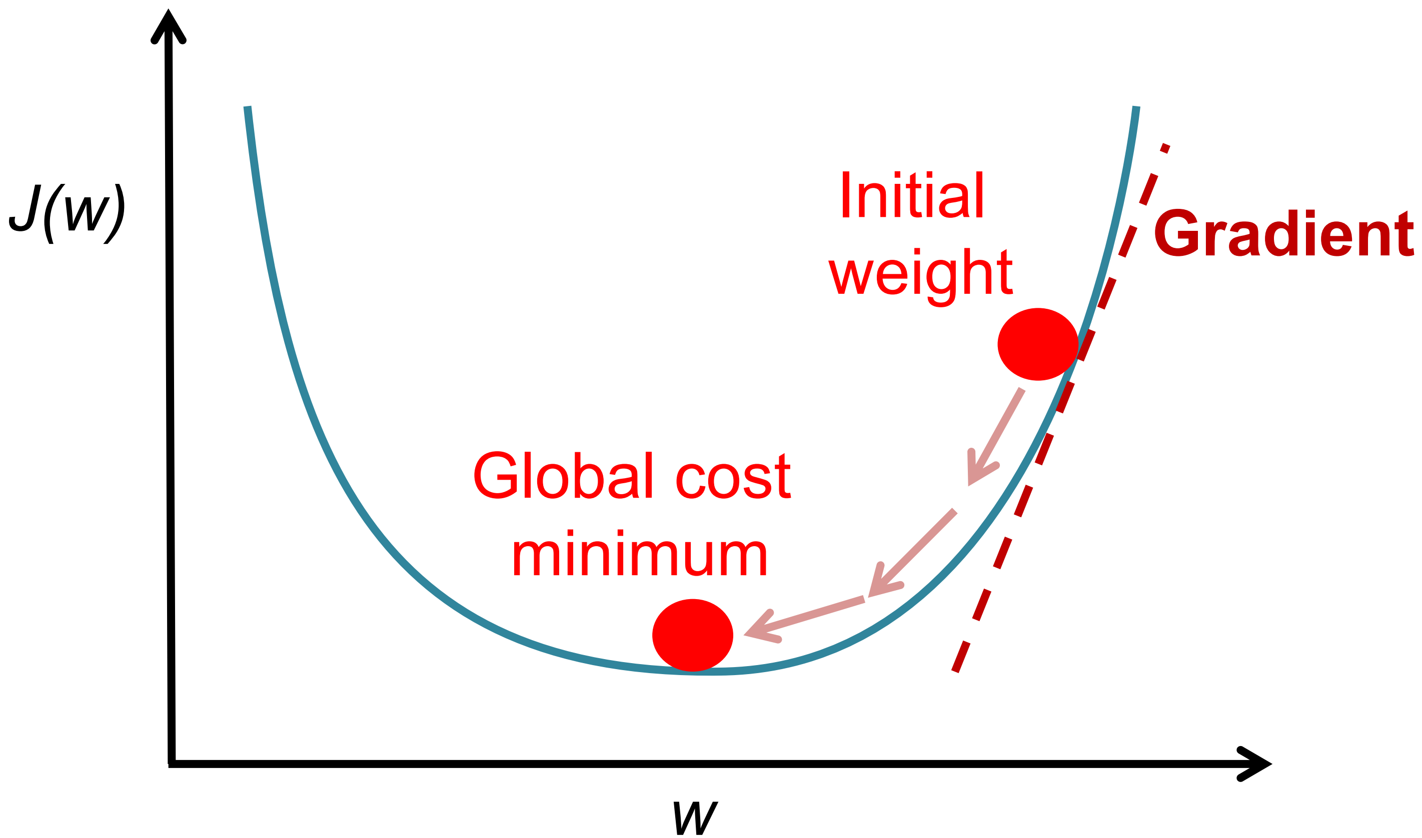
Weights

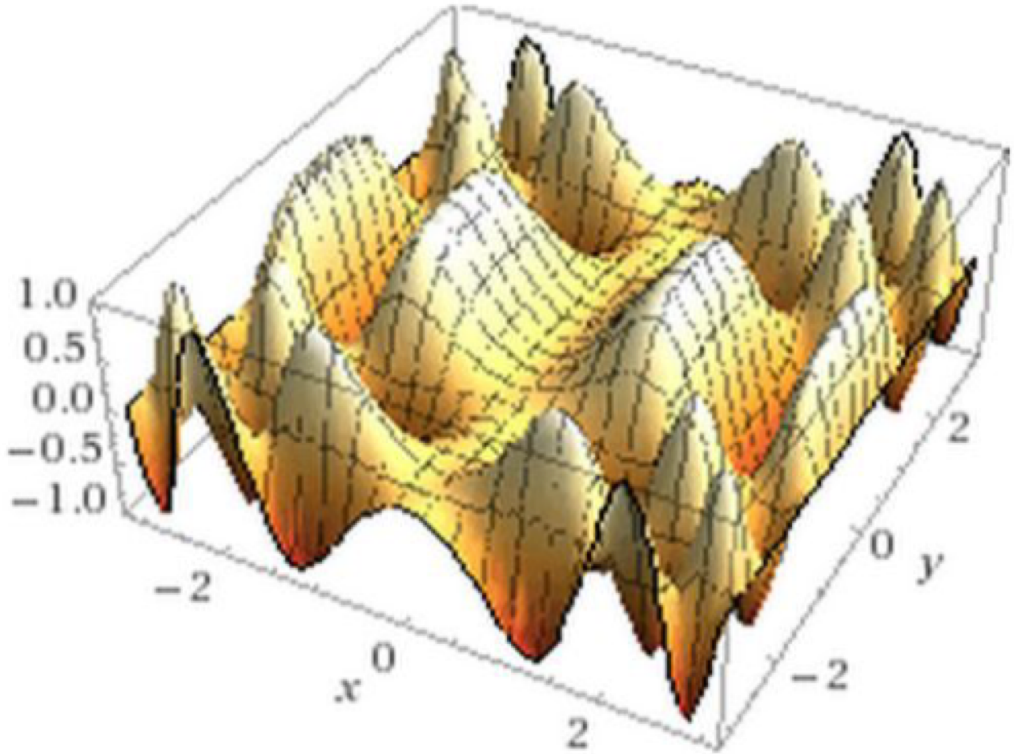


Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

Optimizer:

Stochastic Gradient Descent (SGD)

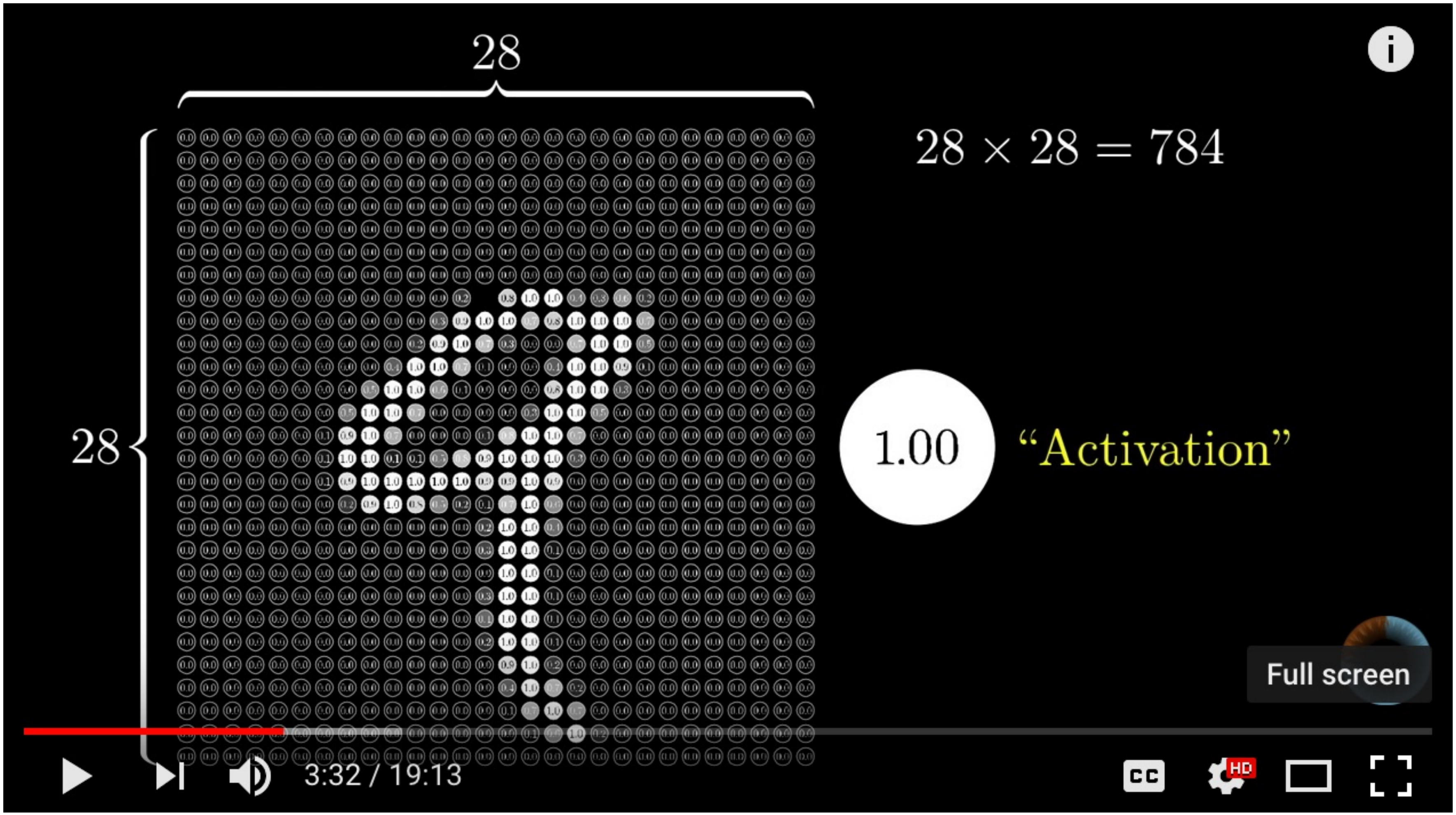




This shows a function of 2 variables: real neural nets are functions of hundreds of millions of variables!

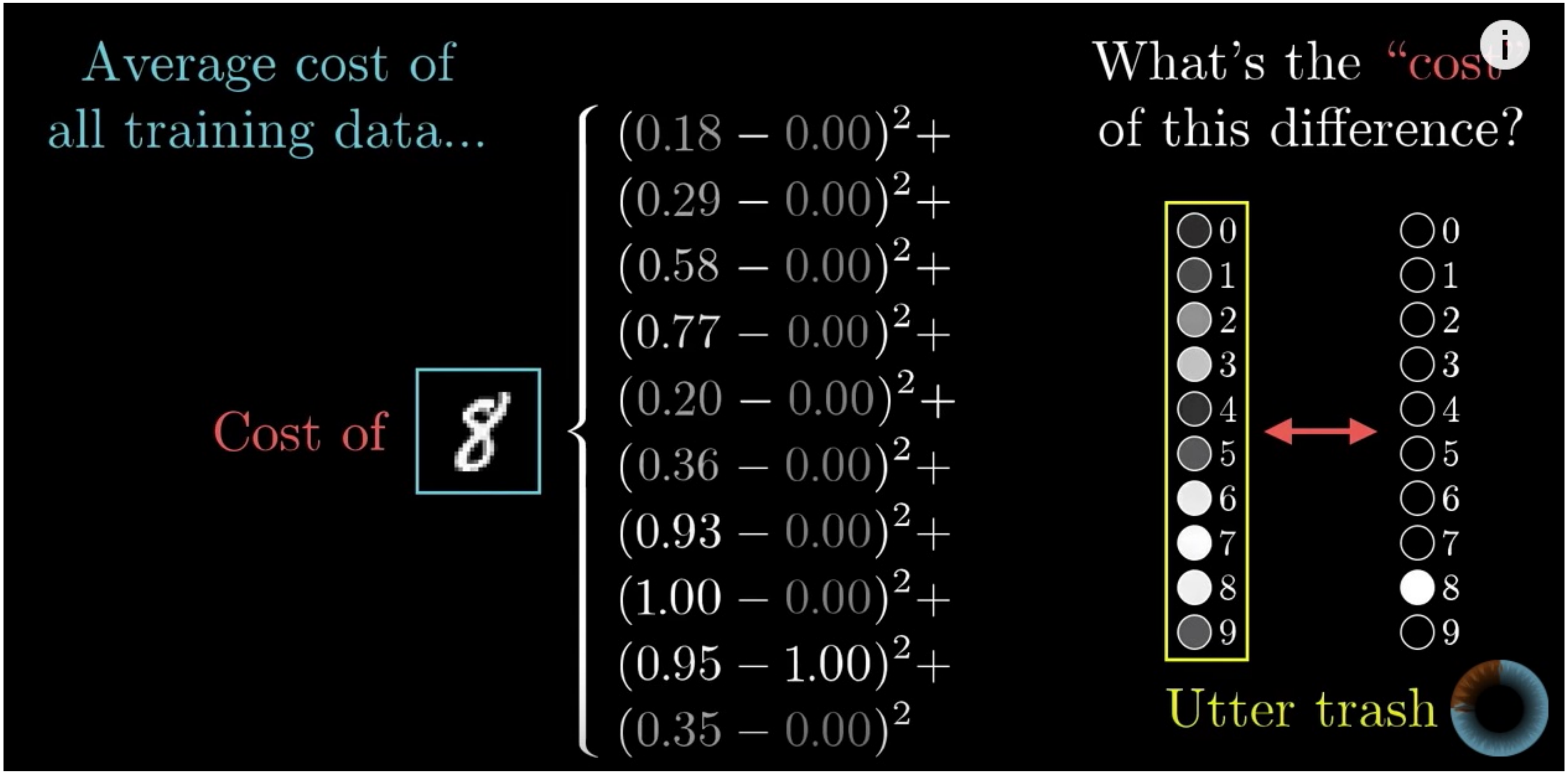
Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

Neural Network and Deep Learning



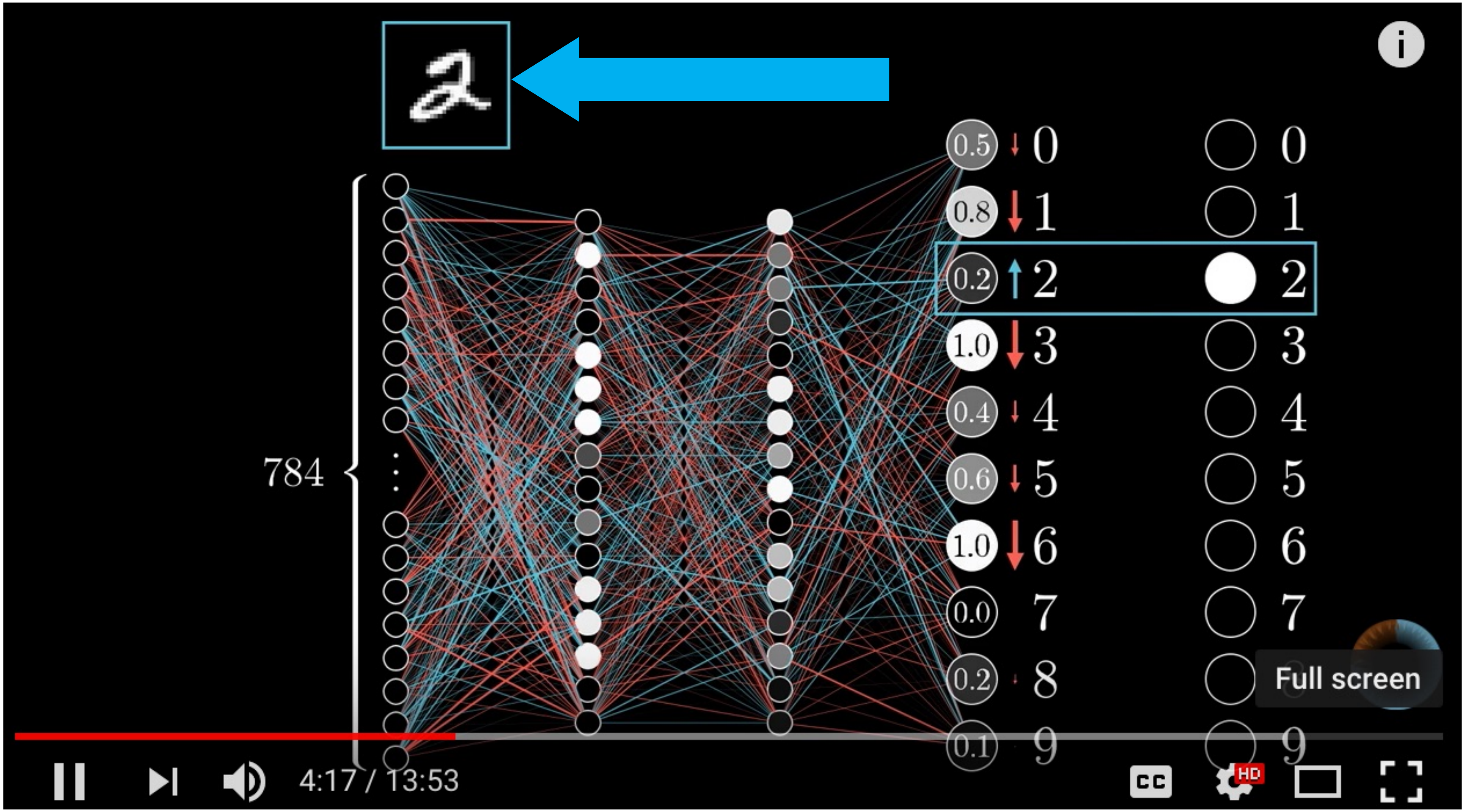
Source: 3Blue1Brown (2017), But what *is* a Neural Network? | Chapter 1, deep learning,
https://www.youtube.com/watch?v=aircAruvnKk

Gradient Descent
how neural networks learn



Source: 3Blue1Brown (2017), Gradient descent, how neural networks learn | Chapter 2, deep learning, https://www.youtube.com/watch?v=IHZwWFHWa-w

Backpropagation



Source: 3Blue1Brown (2017), What is backpropagation really doing? | Chapter 3, deep learning, https://www.youtube.com/watch?v=Ilg3gGewQ5U

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”

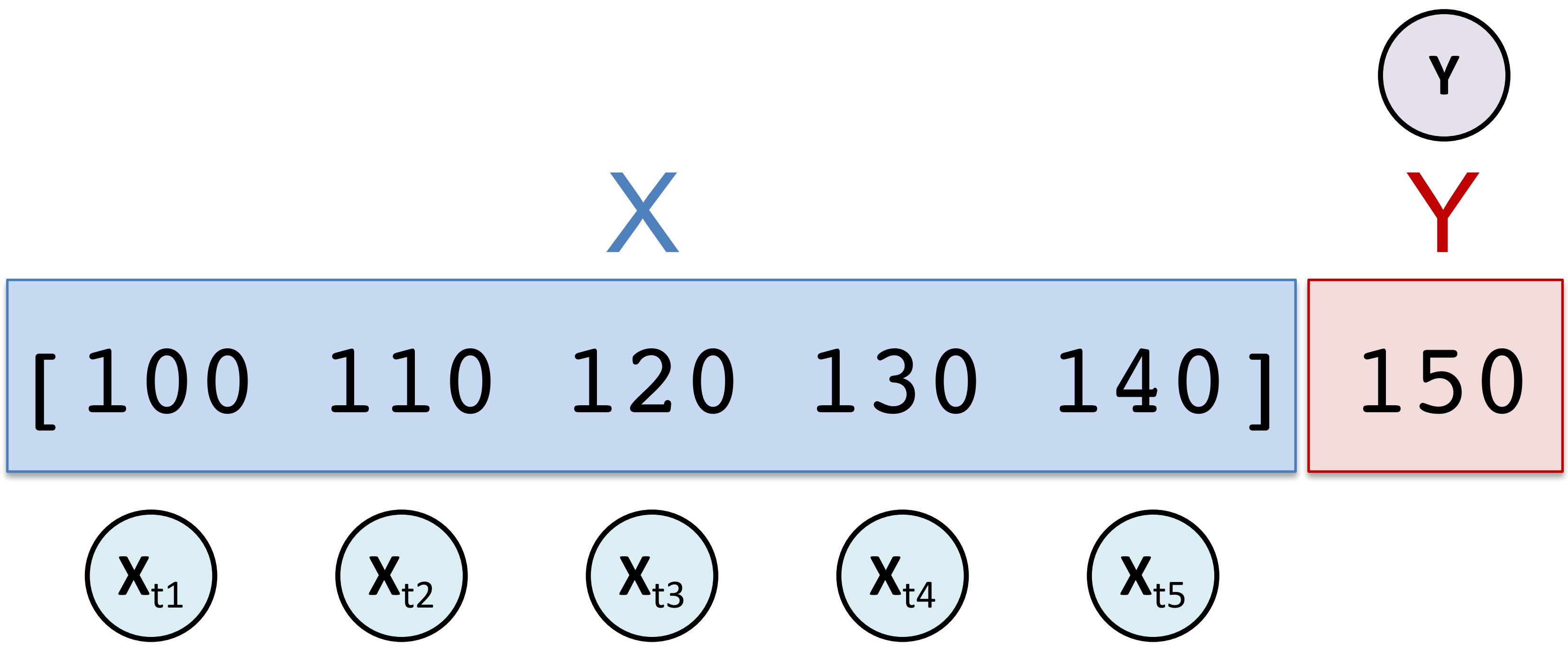
Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

Financial Time Series Forecasting

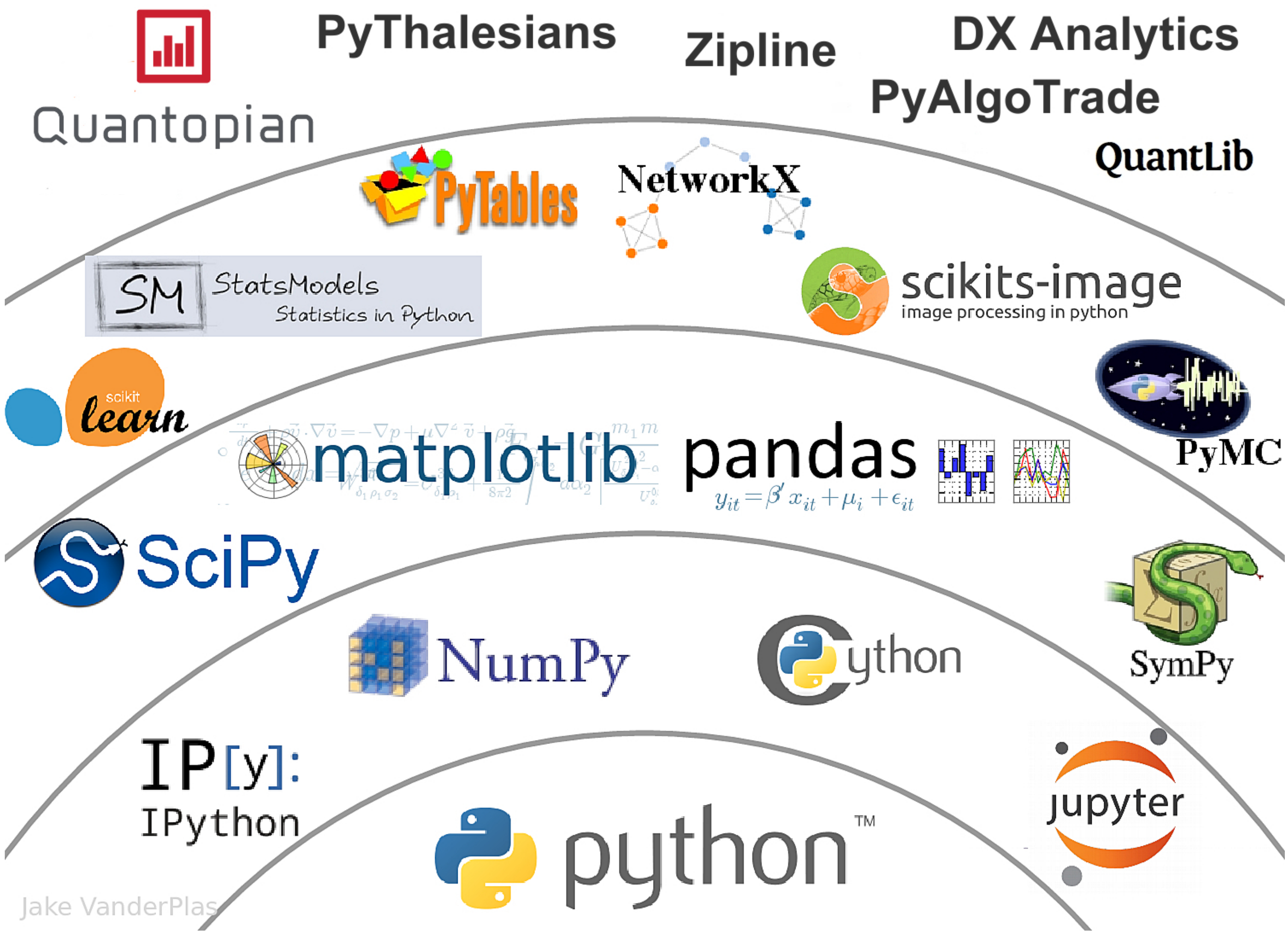
Time Series Data

Time Series Data

[100, 110, 120, 130, 140, 150]



The Quant Finance PyData Stack



Source: http://nbviewer.jupyter.org/format/slides/github/quantopian/pyfolio/blob/master/pyfolio/examples/overview_slides.ipynb#/5

Python in Google Colab

https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT

CO python101.ipynb

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CODE TEXT CELL CELL CONNECTED EDITING

```python
# !pip install pandas_datareader
import pandas as pd
import pandas_datareader.data as web
import matplotlib.pyplot as plt
import seaborn as sns
import datetime as dt
%matplotlib inline

#Read Stock Data from Yahoo Finance
end = dt.datetime.now()
#start = dt.datetime(end.year-2, end.month, end.day)
start = dt.datetime(2016, 1, 1)
df = web.DataReader("AAPL", 'yahoo', start, end)
df.to_csv('AAPL.csv')
df.from_csv('AAPL.csv')
df.tail()

df['Adj Close'].plot(legend=True, figsize=(12, 8), title='AAPL', label='Adj Close')
plt.figure(figsize=(12,9))
top = plt.subplot2grid((12,9), (0, 0), rowspan=10, colspan=9)
bottom = plt.subplot2grid((12,9), (10,0), rowspan=2, colspan=9)
top.plot(df.index, df['Adj Close'], color='blue') #df.index gives the dates
bottom.bar(df.index, df['Volume'])

# set the labels
top.axes.get_xaxis().set_visible(False)
top.set_title('AAPL')
top.set_ylabel('Adj Close')
bottom.set_ylabel('Volume')

plt.figure(figsize=(12,9))
sns.distplot(df['Adj Close'].dropna(), bins=50, color='purple')

# simple moving averages
df['MA05'] = df['Adj Close'].rolling(5).mean() #5 days
df['MA20'] = df['Adj Close'].rolling(20).mean() #20 days
df['MA60'] = df['Adj Close'].rolling(60).mean() #60 days
df2 = pd.DataFrame({'Adj Close': df['Adj Close'],'MA05': df['MA05'],'MA20': df['MA20'], 'MA60': df['MA60']})
df2.plot(figsize=(12, 9), legend=True, title='AAPL')
df2.to_csv('AAPL_MA.csv')
fig = plt.gcf()
fig.set_size_inches(12, 9)
fig.savefig('AAPL_plot.png', dpi=300)
```

pandas

Python Data Analysis Library

providing high-performance, easy-to-use
data structures and data analysis tools
for the Python programming language.

Source: http://pandas.pydata.org/

pandas Ecosystem

- Statistics and Machine Learning
  - Statsmodels
  - sklearn-pandas
- Visualization
  - Bokeh
  - yhat/ggplot
  - Seaborn
  - Vincent
  - IPython Vega
  - Plotly
  - Pandas-Qt
- IDE
  - IPython
  - quantopian/qgrid
  - Spyder
- API
  - pandas-datareader
  - quandl/Python
  - pydatastream
  - pandaSDMX
  - fredapi
- Domain Specific
  - Geopandas
  - xarray
- Out-of-core
  - Dask
  - Blaze
  - Odo

Source: http://pandas.pydata.org/pandas-docs/stable/index.html

pandas-datareader

pandas-datareader

latest

Search docs

- What's New
- Remote Data Access
- Caching queries
- Other Data Sources
- Data Readers

Read the Docs v: latest

pandas-datareader

Up to date remote data access for pandas, works for multiple versions of pandas.

pypi v0.7.0 | build failing | coverage 79% | docs passing | health 95%

Warning

As of v0.6.0 Yahoo!, Google Options, Google Quotes and EDGAR have been immediately deprecated due to large changes in their API and no stable replacement.

Note

As of v0.6.0 Google finance is still functioning for historical price data, although there are frequent reports of failures. Failure is frequently encountered when bulk downloading historical price data.

Usage

Starting in 0.19.0, pandas no longer supports `pandas.io.data` or `pandas.io.wb`, so you must replace your imports from `pandas.io` with those from `pandas_datareader`:

```
from pandas.io import data, wb # becomes
from pandas_datareader import data, wb
```

Many functions from the data module have been included in the top level API.

https://pandas-datareader.readthedocs.io/en/latest/

Quandl

https://www.quandl.com/tools/python

PyDatastream

Search projects

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PyDatastream 0.5.1

```
pip install PyDatastream
```

Latest version

Last released: Nov 17, 2017

Python interface to the Thomson Reuters Dataworks Enterprise (Datastream) API

Navigation

- Project description
- Release history
- Download files

Project description

PyDatastream is a Python interface to the **Thomson Dataworks Enterprise (DWE)** SOAP API (non free), with some convenience functions for retrieving Datastream data specifically. This package requires valid credentials for this API.

For the documentation please refer to README.md inside the package or on the GitHub (https://github.com/vfilimonov/pydatastream/blob/master/README.md).

https://pypi.org/project/PyDatastream/

pandasSDMX

Table Of Contents

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pandaSDMX: Statistical Data and Metadata eXchange in Python

pandaSDMX is an Apache 2.0-licensed Python client to retrieve and acquire statistical data and metadata disseminated in SDMX 2.1, an ISO-standard widely used by institutions such as statistics offices, central banks, and international organisations. pandaSDMX exposes datasets and related structural metadata including dataflows, codelists, and datastructure definitions as pandas Series or multi-indexed DataFrames. Many other output formats and storage backends are available thanks to Odo.

Supported data providers

pandaSDMX ships with built-in support for the following agencies (others may be configured by the user):

- Australian Bureau of Statistics (ABS)
- European Central Bank (ECB)
- Eurostat
- French National Institute for Statistics (INSEE)
- Instituto Nacional de la Estadìstica y Geografia - INEGI (Mexico)
- International Monetary Fund (IMF) - SDMX Central only
- International Labour Organization (ILO)
- Italian statistics Office (ISTAT)
- Norges Bank (Norway)
- Organisation for Economic Cooperation and Development (OECD)
- United Nations Statistics Division (UNSD)
- UNESCO (free registration required)
- World Bank - World Integrated Trade Solution (WITS)

https://pandasdmx.readthedocs.io/en/latest/

Fred API

ECONOMIC RESEARCH
FEDERAL RESERVE BANK of ST. LOUIS

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Home > Developer API > FRED API

API Keys | Terms of Use

FRED® API

General Documentation | API | Toolkits

The FRED® API is a web service that allows developers to write programs and build applications that retrieve economic data from the FRED® and ALFRED® websites hosted by the Economic Research Division of the Federal Reserve Bank of St. Louis. Requests can be customized according to data source, release, category, series, and other preferences.

General Documentation

- Overview
- What is FRED®?
- What is ALFRED®?
- FRED® versus ALFRED®
- Real-Time Periods
- Errors

API

Categories

- fred/category – Get a category.
- fred/category/children – Get the child categories for a specified parent category.
- fred/category/related – Get the related categories for a category.
- fred/category/series – Get the series in a category.
- fred/category/tags – Get the tags for a category.
- fred/category/related_tags – Get the related tags for a category.

https://research.stlouisfed.org/docs/api/fred/

Python Pandas for Finance

Source: https://mapattack.wordpress.com/2017/02/12/using-python-for-stocks-1/

! pip install pandas_datareader

```
1 ! pip install pandas_datareader
```

```
Collecting pandas_datareader
  Downloading https://files.pythonhosted.org/packages/cc/5c/ea5b6dcfd0f55c5fb1e37fb45335ec01cceca199b8a79339137f5ed269e0/pandas_datarea
    100% |████████████████████████████████| 112kB 2.7MB/s
Collecting lxml (from pandas_datareader)
  Downloading https://files.pythonhosted.org/packages/03/a4/9eea8035fc7c7670e5eab97f34ff2ef0ddd78a491bf96df5accedb0e63f5/lxml-4.2.5-cp3
    100% |████████████████████████████████| 5.8MB 7.5MB/s
Requirement already satisfied: pandas>=0.19.2 in /usr/local/lib/python3.6/dist-packages (from pandas_datareader) (0.22.0)
Requirement already satisfied: requests>=2.3.0 in /usr/local/lib/python3.6/dist-packages (from pandas_datareader) (2.18.4)
Requirement already satisfied: wrapt in /usr/local/lib/python3.6/dist-packages (from pandas_datareader) (1.10.11)
Requirement already satisfied: python-dateutil>=2 in /usr/local/lib/python3.6/dist-packages (from pandas>=0.19.2->pandas_datareader) (2
Requirement already satisfied: numpy>=1.9.0 in /usr/local/lib/python3.6/dist-packages (from pandas>=0.19.2->pandas_datareader) (1.14.6)
Requirement already satisfied: pytz>=2011k in /usr/local/lib/python3.6/dist-packages (from pandas>=0.19.2->pandas_datareader) (2018.5)
Requirement already satisfied: idna<2.7,>=2.5 in /usr/local/lib/python3.6/dist-packages (from requests>=2.3.0->pandas_datareader) (2.6)
Requirement already satisfied: chardet<3.1.0,>=3.0.2 in /usr/local/lib/python3.6/dist-packages (from requests>=2.3.0->pandas_datareader
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.6/dist-packages (from requests>=2.3.0->pandas_datareader) (
Requirement already satisfied: urllib3<1.23,>=1.21.1 in /usr/local/lib/python3.6/dist-packages (from requests>=2.3.0->pandas_datareader
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.6/dist-packages (from python-dateutil>=2->pandas>=0.19.2->pandas_data
Installing collected packages: lxml, pandas-datareader
Successfully installed lxml-4.2.5 pandas-datareader-0.7.0
```

conda install pandas-datareader

```
imyday — -bash — 80×24
iMyday-MacBook-Pro:~ imyday$ conda install pandas-datareader
Fetching package metadata ...........
Solving package specifications: .

Package plan for installation in environment /Users/imyday/anaconda:

The following NEW packages will be INSTALLED:

    pandas-datareader: 0.2.1-py36_0
    requests-file:     1.4.1-py36_0

Proceed ([y]/n)? y

requests-file- 100% |################################| Time: 0:00:00   1.55 MB/s
pandas-datarea 100% |################################| Time: 0:00:00 409.66 kB/s
iMyday-MacBook-Pro:~ imyday$ conda list
# packages in environment at /Users/imyday/anaconda:
#
_license                  1.1                      py36_1
alabaster                 0.7.9                    py36_0
anaconda                  4.3.1               np111py36_0
anaconda-client           1.6.0                    py36_0
anaconda-navigator        1.5.0                    py36_0
anaconda-project          0.4.1                    py36_0
```


AAPL
Adj Close
MA05
MA20
MA60
220
200
180
160
140
120
100
80
2016-02
2016-06
2016-10
2017-02
2017-06
2017-10
2018-02
2018-06
2018-10
Date

Finance Data from Yahoo Finance

```
# !pip install pandas_datareader
import pandas_datareader.data as web
import datetime as dt
#Read Stock Data from Yahoo Finance
end = dt.datetime(2017, 12, 31)
start = dt.datetime(2016, 1, 1)
df = web.DataReader("AAPL", 'yahoo', start, end)
df.to_csv('AAPL.csv')
df.from_csv('AAPL.csv')
df.tail()
```

```
# !pip install pandas_datareader
import pandas as pd
import pandas_datareader.data as web
import matplotlib.pyplot as plt
import seaborn as sns
import datetime as dt
%matplotlib inline

#Read Stock Data from Yahoo Finance
end = dt.datetime.now()
#start = dt.datetime(end.year-2, end.month,
end.day)
start = dt.datetime(2016, 1, 1)
df = web.DataReader("AAPL", 'yahoo', start, end)
df.to_csv('AAPL.csv')
df.from_csv('AAPL.csv')
df.tail()
```

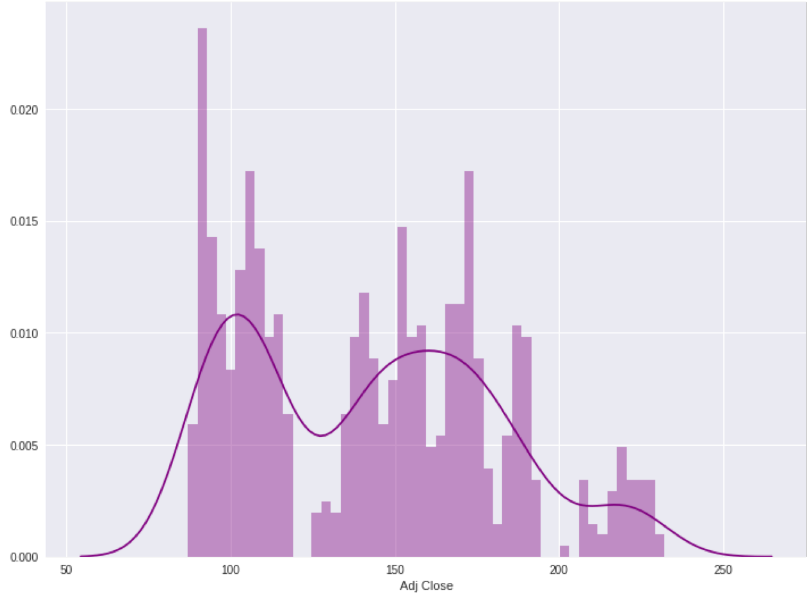
```python
df['Adj Close'].plot(legend=True, figsize=(12, 8), title='AAPL’, label='Adj Close')
```

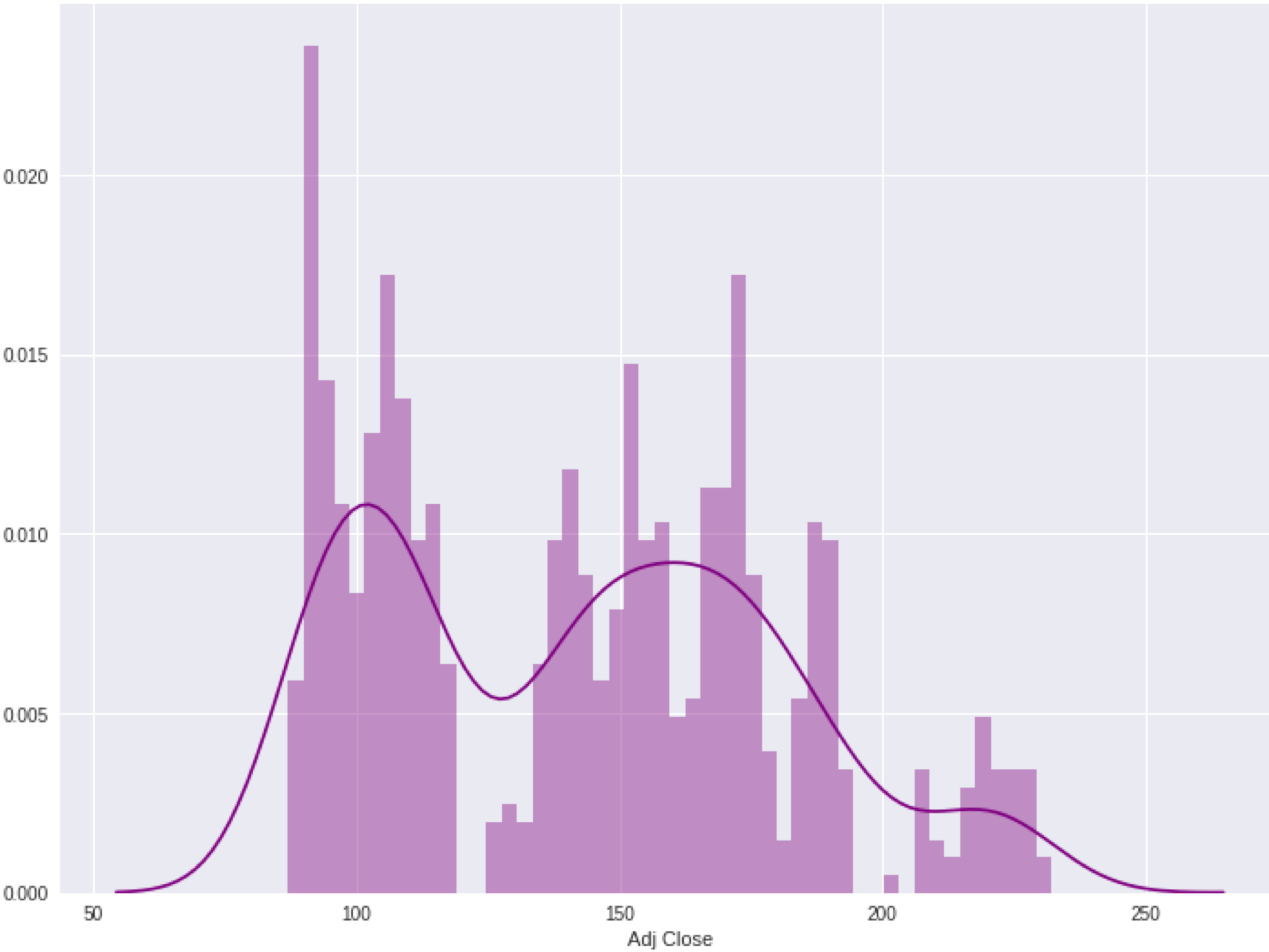
```
plt.figure(figsize=(12,9))
top = plt.subplot2grid((12,9), (0, 0),
rowspan=10, colspan=9)
bottom = plt.subplot2grid((12,9), (10,0),
rowspan=2, colspan=9)
top.plot(df.index, df['Adj Close'],
color='blue') #df.index gives the dates
bottom.bar(df.index, df['Volume'])
```

AAPL
Adj Close
220
200
180
160
140
120
100
80
1e8
Volume
1.0
0.5
0.0
2016-02
2016-06
2016-10
2017-02
2017-06
2017-10
2018-02
2018-06
2018-10

```
 # set the labels
top.axes.get_xaxis().set_visible(False)
top.set_title('AAPL')
top.set_ylabel('Adj Close')
bottom.set_ylabel('Volume')

plt.figure(figsize=(12,9))
sns.distplot(df['Adj Close'].dropna(),
bins=50, color='purple')
```




0.020
0.015
0.010
0.005
0.000
50
100
150
200
250
Adj Close

```
# simple moving averages
df['MA05'] = df['Adj Close'].rolling(5).mean()
#5 days
df['MA20'] = df['Adj
Close'].rolling(20).mean() #20 days
df['MA60'] = df['Adj
Close'].rolling(60).mean() #60 days
df2 = pd.DataFrame({'Adj Close': df['Adj
Close'],'MA05': df['MA05'],'MA20': df['MA20'],
'MA60': df['MA60']})
df2.plot(figsize=(12, 9), legend=True,
title='AAPL')
df2.to_csv('AAPL_MA.csv')
fig = plt.gcf()
fig.set_size_inches(12, 9)
fig.savefig('AAPL_plot.png', dpi=300)
plt.show()
```


AAPL
Adj Close
MA05
MA20
MA60
220
200
180
160
140
120
100
80
2016-02
2016-06
2016-10
2017-02
2017-06
2017-10
2018-02
2018-06
2018-10
Date

```python
# !pip install pandas_datareader
import pandas as pd
import pandas_datareader.data as web
import matplotlib.pyplot as plt
import seaborn as sns
import datetime as dt
%matplotlib inline

#Read Stock Data from Yahoo Finance
end = dt.datetime.now()
#start = dt.datetime(end.year-2, end.month, end.day)
start = dt.datetime(2016, 1, 1)
df = web.DataReader("AAPL", 'yahoo', start, end)
df.to_csv('AAPL.csv')
df.from_csv('AAPL.csv')
df.tail()

df['Adj Close'].plot(legend=True, figsize=(12, 8), title='AAPL', label='Adj Close')
plt.figure(figsize=(12,9))
top = plt.subplot2grid((12,9), (0, 0), rowspan=10, colspan=9)
bottom = plt.subplot2grid((12,9), (10,0), rowspan=2, colspan=9)
top.plot(df.index, df['Adj Close'], color='blue') #df.index gives the dates
bottom.bar(df.index, df['Volume'])

# set the labels
top.axes.get_xaxis().set_visible(False)
top.set_title('AAPL')
top.set_ylabel('Adj Close')
bottom.set_ylabel('Volume')

plt.figure(figsize=(12,9))
sns.distplot(df['Adj Close'].dropna(), bins=50, color='purple')

# simple moving averages
df['MA05'] = df['Adj Close'].rolling(5).mean() #5 days
df['MA20'] = df['Adj Close'].rolling(20).mean() #20 days
df['MA60'] = df['Adj Close'].rolling(60).mean() #60 days
df2 = pd.DataFrame({'Adj Close': df['Adj Close'],'MA05': df['MA05'],'MA20': df['MA20'], 'MA60': df['MA60']})
df2.plot(figsize=(12, 9), legend=True, title='AAPL')
df2.to_csv('AAPL_MA.csv')
fig = plt.gcf()
fig.set_size_inches(12, 9)
fig.savefig('AAPL_plot.png', dpi=300)
plt.show()
```

```python
# !pip install pandas_datareader
import pandas as pd
import pandas_datareader.data as web
import matplotlib.pyplot as plt
import seaborn as sns
import datetime as dt
%matplotlib inline

#Read Stock Data from Yahoo Finance
end = dt.datetime.now()
#start = dt.datetime(end.year-2, end.month, end.day)
start = dt.datetime(2016, 1, 1)
df = web.DataReader("AAPL", 'yahoo', start, end)
df.to_csv('AAPL.csv')
df.from_csv('AAPL.csv')
df.tail()

df['Adj Close'].plot(legend=True, figsize=(12, 8), title='AAPL', label='Adj Close')
plt.figure(figsize=(12,9))
top = plt.subplot2grid((12,9), (0, 0), rowspan=10, colspan=9)
bottom = plt.subplot2grid((12,9), (10,0), rowspan=2, colspan=9)
top.plot(df.index, df['Adj Close'], color='blue') #df.index gives the dates
bottom.bar(df.index, df['Volume'])

# set the labels
top.axes.get_xaxis().set_visible(False)
top.set_title('AAPL')
top.set_ylabel('Adj Close')
bottom.set_ylabel('Volume')

plt.figure(figsize=(12,9))
sns.distplot(df['Adj Close'].dropna(), bins=50, color='purple')

# simple moving averages
df['MA05'] = df['Adj Close'].rolling(5).mean() #5 days
df['MA20'] = df['Adj Close'].rolling(20).mean() #20 days
df['MA60'] = df['Adj Close'].rolling(60).mean() #60 days
df2 = pd.DataFrame({'Adj Close': df['Adj Close'],'MA05': df['MA05'],'MA20': df['MA20'], 'MA60': df['MA60']})
df2.plot(figsize=(12, 9), legend=True, title='AAPL')
df2.to_csv('AAPL_MA.csv')
fig = plt.gcf()
fig.set_size_inches(12, 9)
fig.savefig('AAPL_plot.png', dpi=300)
plt.show()
```

Finance Data from Quandl

```
# ! pip install quandl
import quandl
# quandl.ApiConfig.api_key = "YOURAPIKEY"
df = quandl.get("WIKI/AAPL", start_date="2016-01-01", end_date="2017-12-31")
df.to_csv('AAPL.csv')
df.from_csv('AAPL.csv')
df.tail()
```

```
# ! pip install quandl
import quandl
# quandl.ApiConfig.api_key = "YOURAPIKEY"
df = quandl.get("WIKI/AAPL", start_date="2016-01-01", end_date="2017-12-31")
df.to_csv('AAPL.csv')
df.from_csv('AAPL.csv')
df.tail()
```

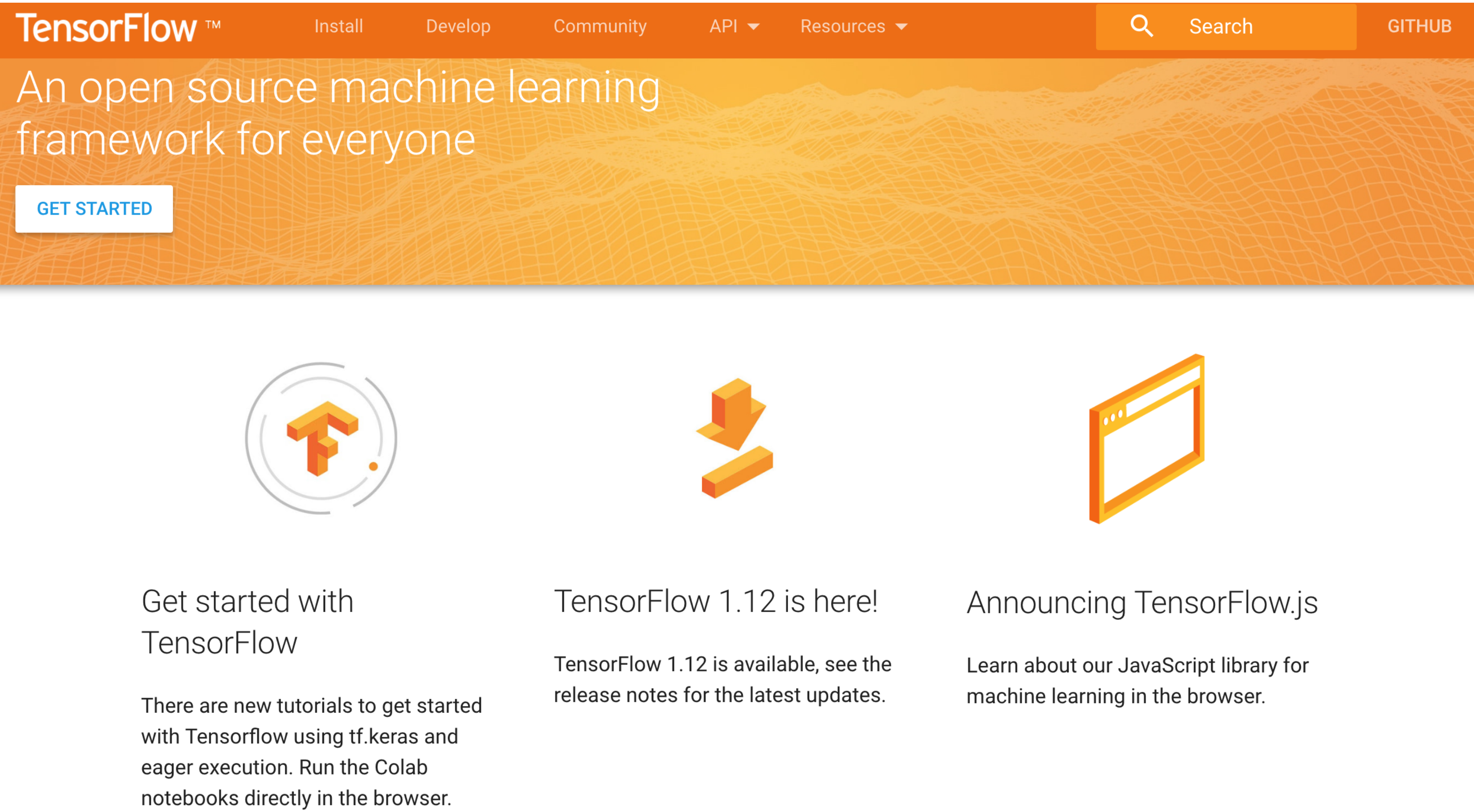
```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:5: FutureWarning: from_csv is deprecated. Please use read_csv(...) instead
  """
```

Date	Open	High	Low	Close	Volume	Ex-Dividend	Split Ratio	Adj. Open	Adj. High	Adj. Low	Adj. Close	Adj. Volume
2017-12-22	174.68	175.424	174.500	175.01	16052615.0	0.0	1.0	174.68	175.424	174.500	175.01	16052615.0
2017-12-26	170.80	171.470	169.679	170.57	32968167.0	0.0	1.0	170.80	171.470	169.679	170.57	32968167.0
2017-12-27	170.10	170.780	169.710	170.60	21672062.0	0.0	1.0	170.10	170.780	169.710	170.60	21672062.0
2017-12-28	171.00	171.850	170.480	171.08	15997739.0	0.0	1.0	171.00	171.850	170.480	171.08	15997739.0
2017-12-29	170.52	170.590	169.220	169.23	25643711.0	0.0	1.0	170.52	170.590	169.220	169.23	25643711.0

Source: https://www.quandl.com/tools/python

Deep Learning with TensorFlow

TensorFlow



https://www.tensorflow.org/

Deep Learning Software

- TensorFlow
  - TensorFlow™ is an open source software library for high performance numerical computation.
- Keras
  - Deep Learning library for TensorFlow, CNTK
- PyTorch
  - An open source deep learning platform that provides a seamless path from research prototyping to production deployment.
- CNTK
  - Computational Network Toolkit by Microsoft Research

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

tf.keras

Keras:

High-level API for TensorFlow

Keras

Keras Documentation

Search docs

GitHub Next »

Docs » Home

Edit on GitHub

Keras: The Python Deep Learning library

Keras

You have just found Keras.

Keras is a high-level neural networks API, written in Python and capable of running on top of TensorFlow, CNTK, 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:

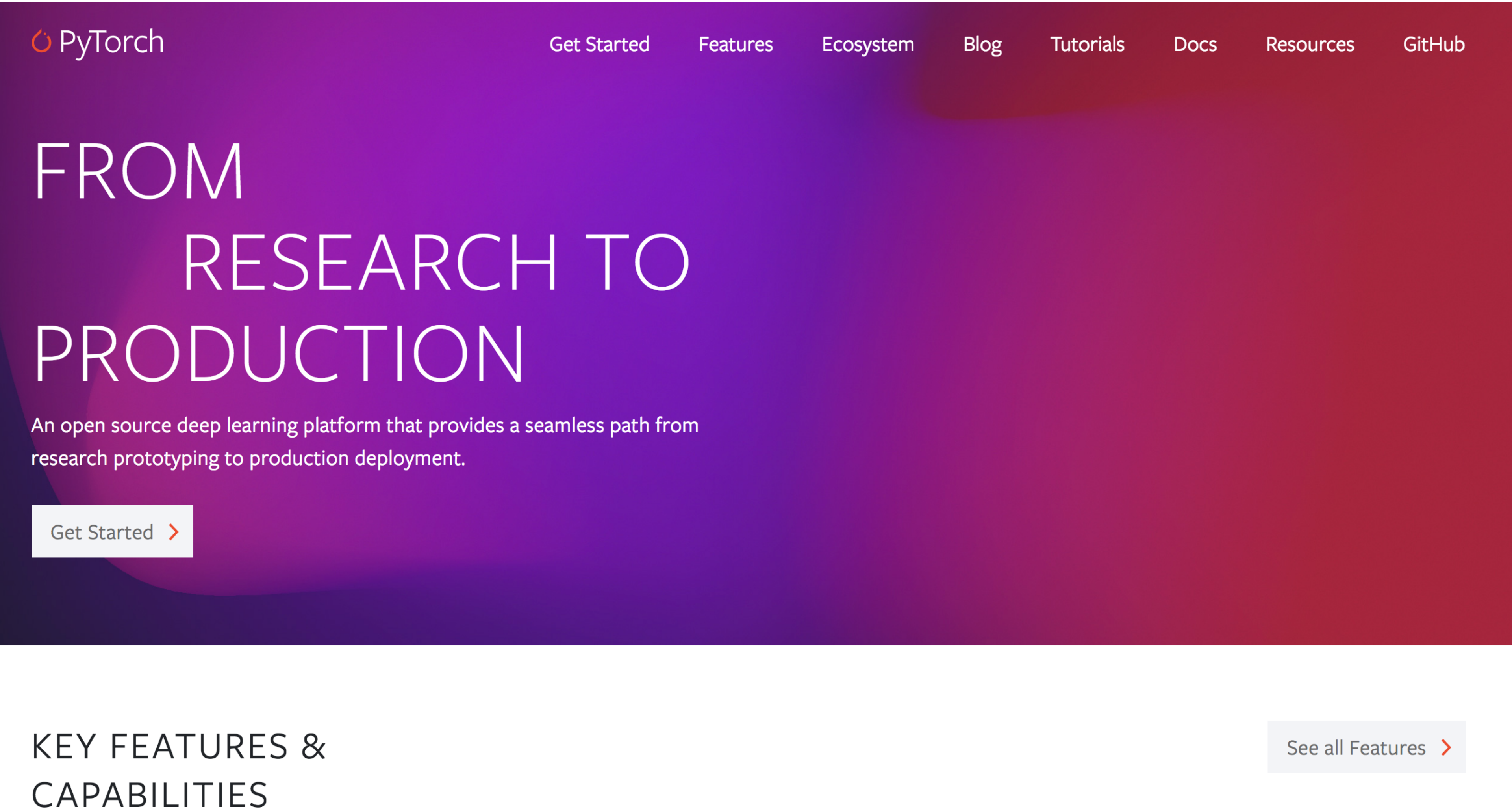
- Allows for easy and fast prototyping (through user friendliness, modularity, and extensibility).
- Supports both convolutional networks and recurrent networks, as well as combinations of the two.
- Runs seamlessly on CPU and GPU.

Read the documentation at Keras.io.

Keras is compatible with: **Python 2.7-3.6**.

http://keras.io/

PyTorch



http://pytorch.org/

Keras

Keras

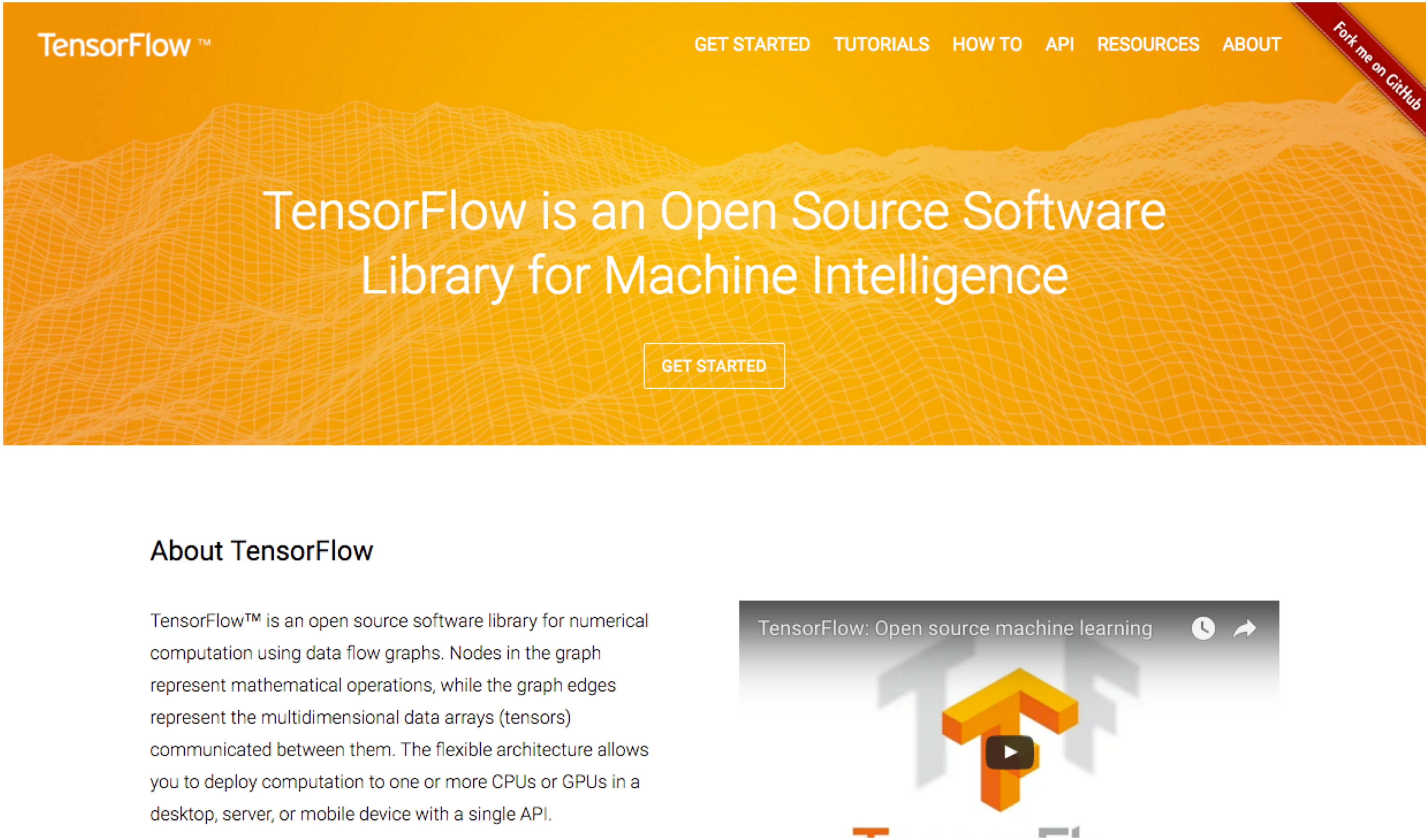
- Keras is a high-level neural networks API
- Written in Python and capable of running on top of TensorFlow, CNTK, or Theano.
- It was developed with a focus on enabling fast experimentation.
- Being able to go from idea to result with the least possible delay is key to doing good research.

Source: https://keras.io/

TensorFlow

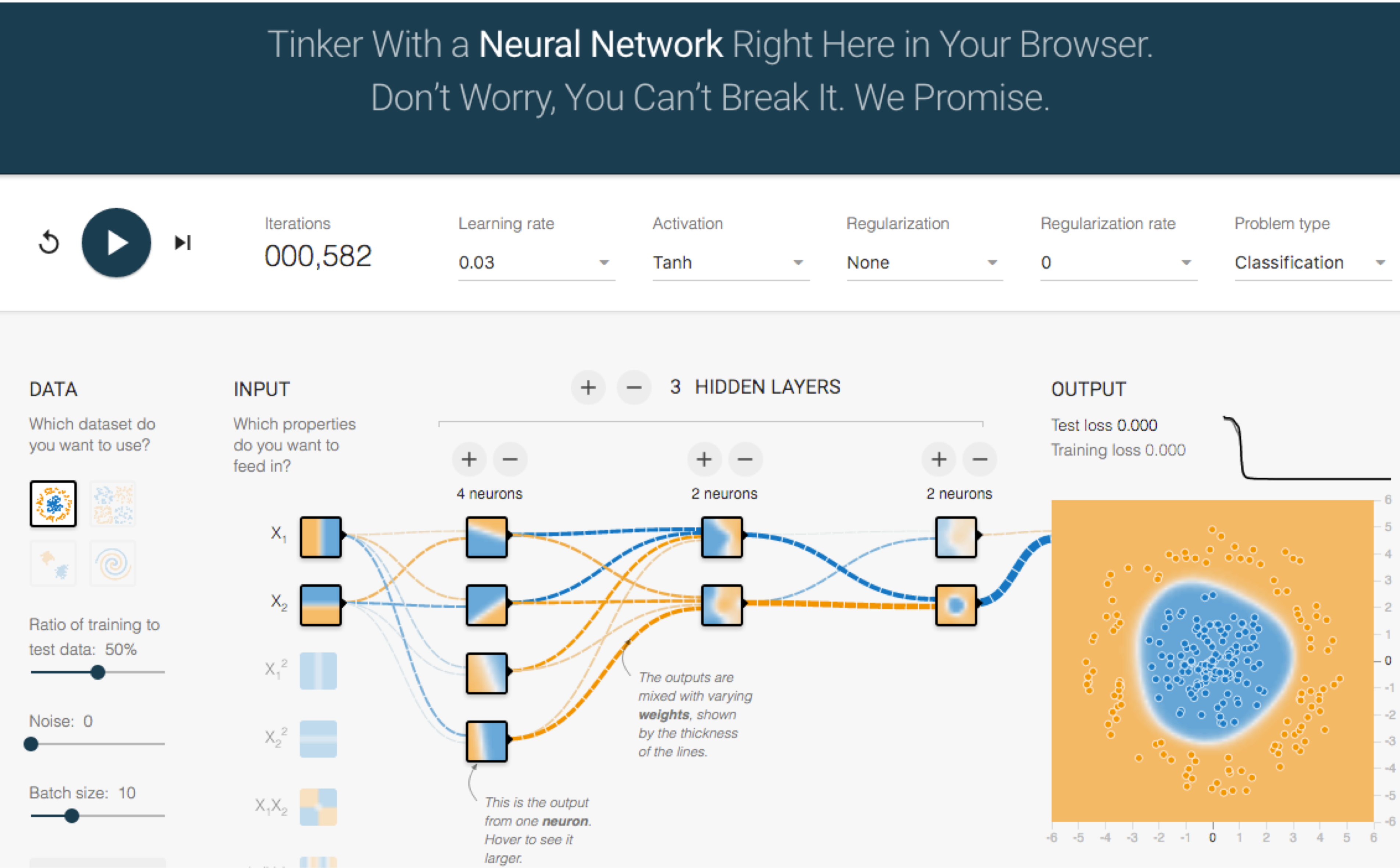
Source: https://github.com/tensorflow/tensorflow

Google TensorFlow



https://www.tensorflow.org/

TensorFlow Playground



http://playground.tensorflow.org/

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/

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/

Scalar 80

Vector $[50 \;\; 60 \;\; 70]$

Matrix
$$\begin{bmatrix} 50 & 60 & 70 \\ 55 & 65 & 75 \end{bmatrix}$$

Tensor
$$\begin{bmatrix} [50 \;\; 60 \;\; 70] & [70 \;\; 80 \;\; 90] \\ [55 \;\; 65 \;\; 75] & [75 \;\; 85 \;\; 95] \end{bmatrix}$$

Nodes:

mathematical operations

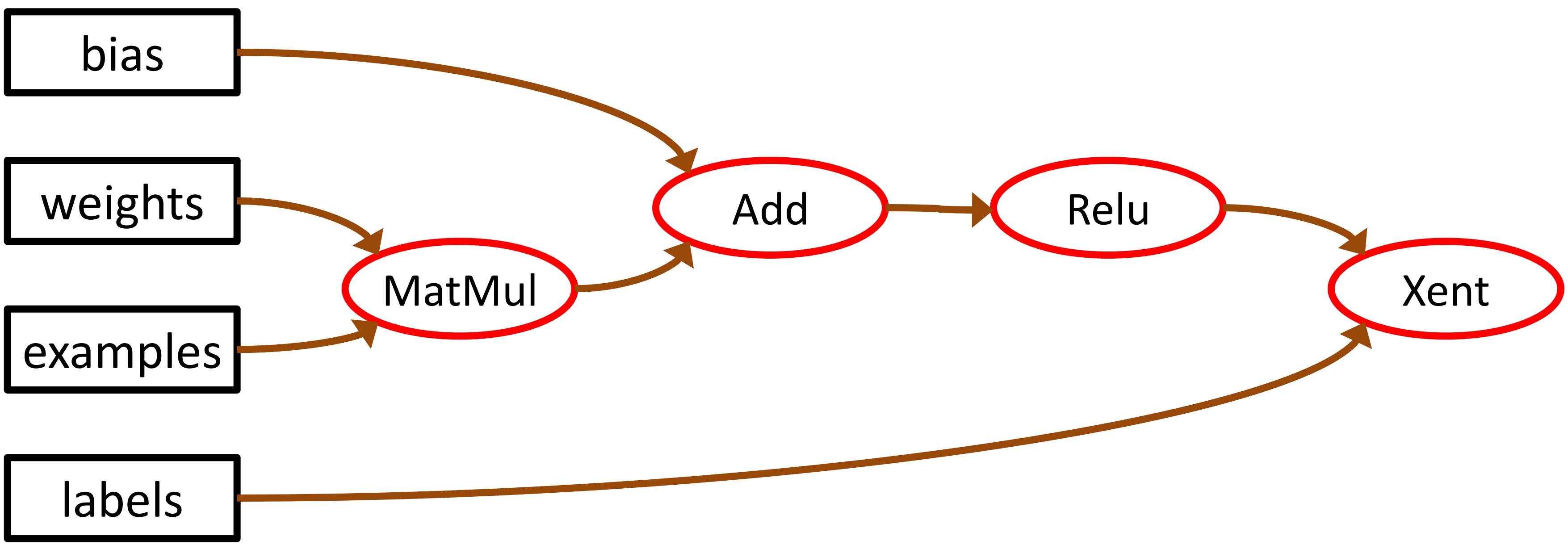
edges:

multidimensional data arrays (tensors)

communicated between nodes

Computation is a Dataflow Graph

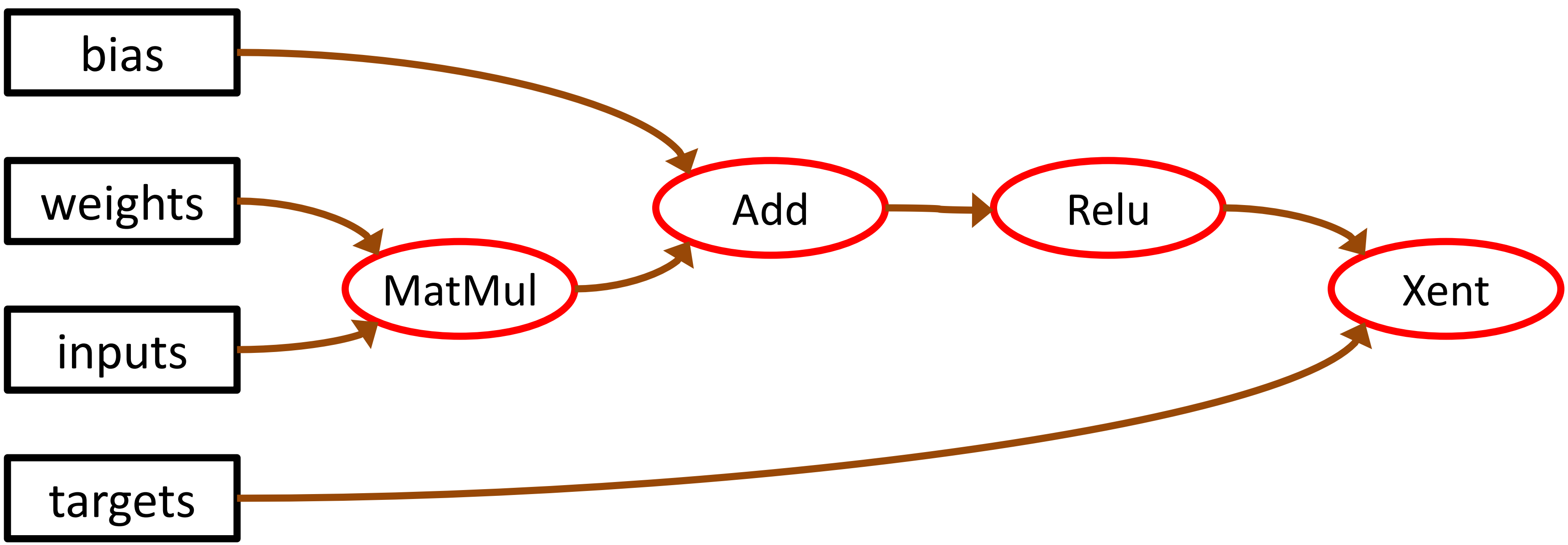
Graph of Nodes,
also called Operations or ops.



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

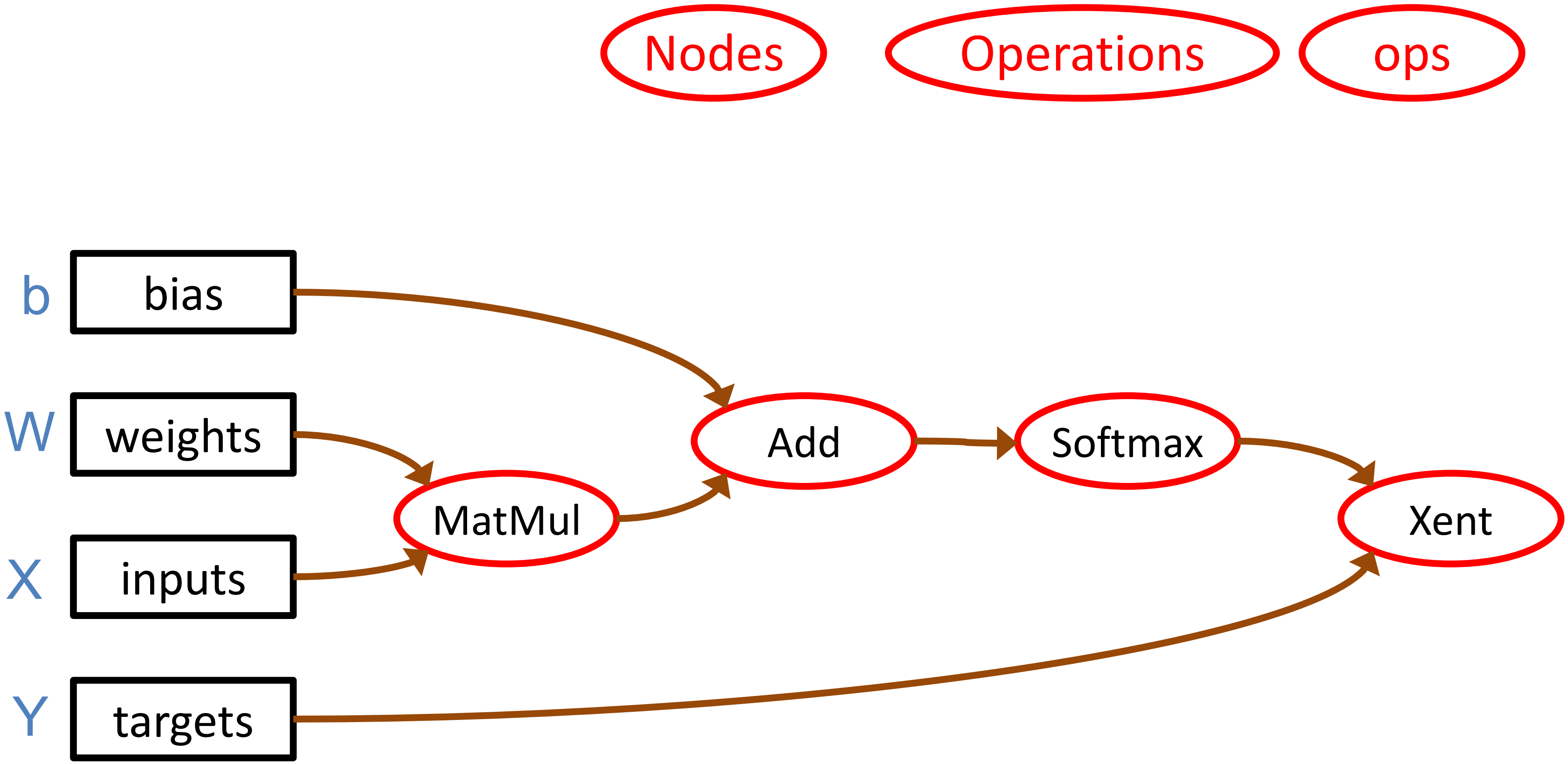
Computation is a Dataflow Graph

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**

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

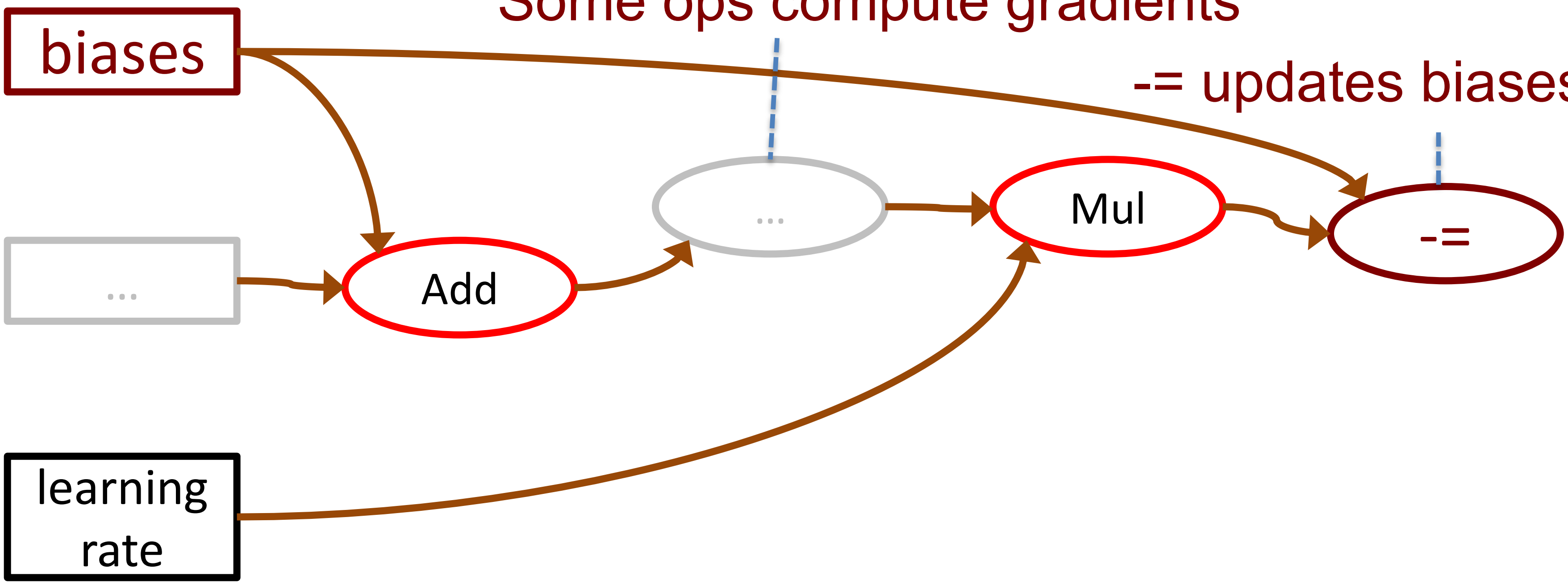
Computation is a Dataflow Graph

with state

‘Biases’ is a variable

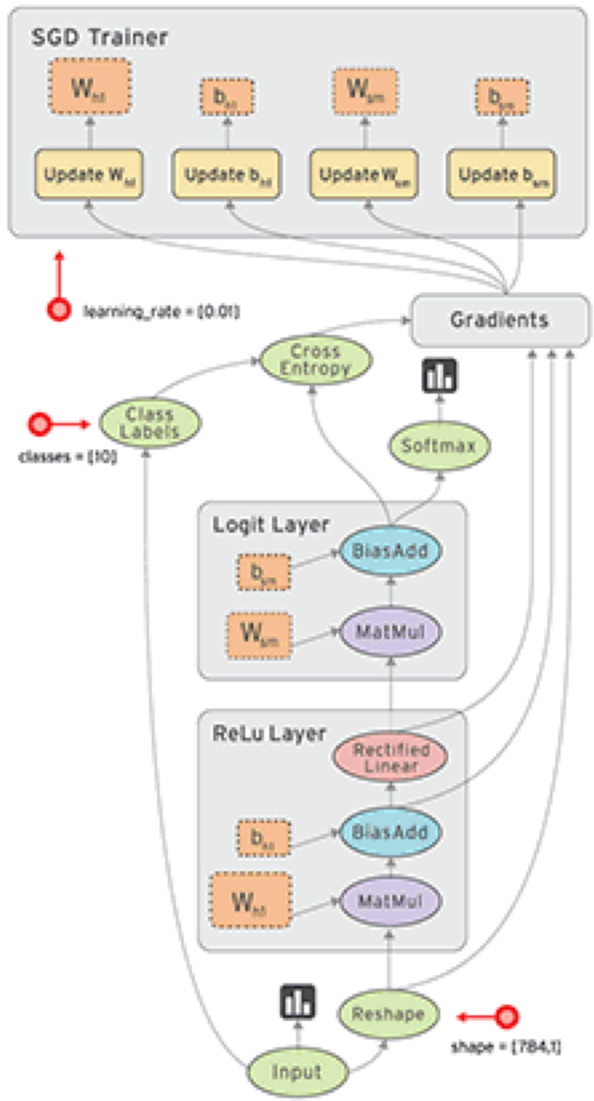
Some ops compute gradients

-= updates biases



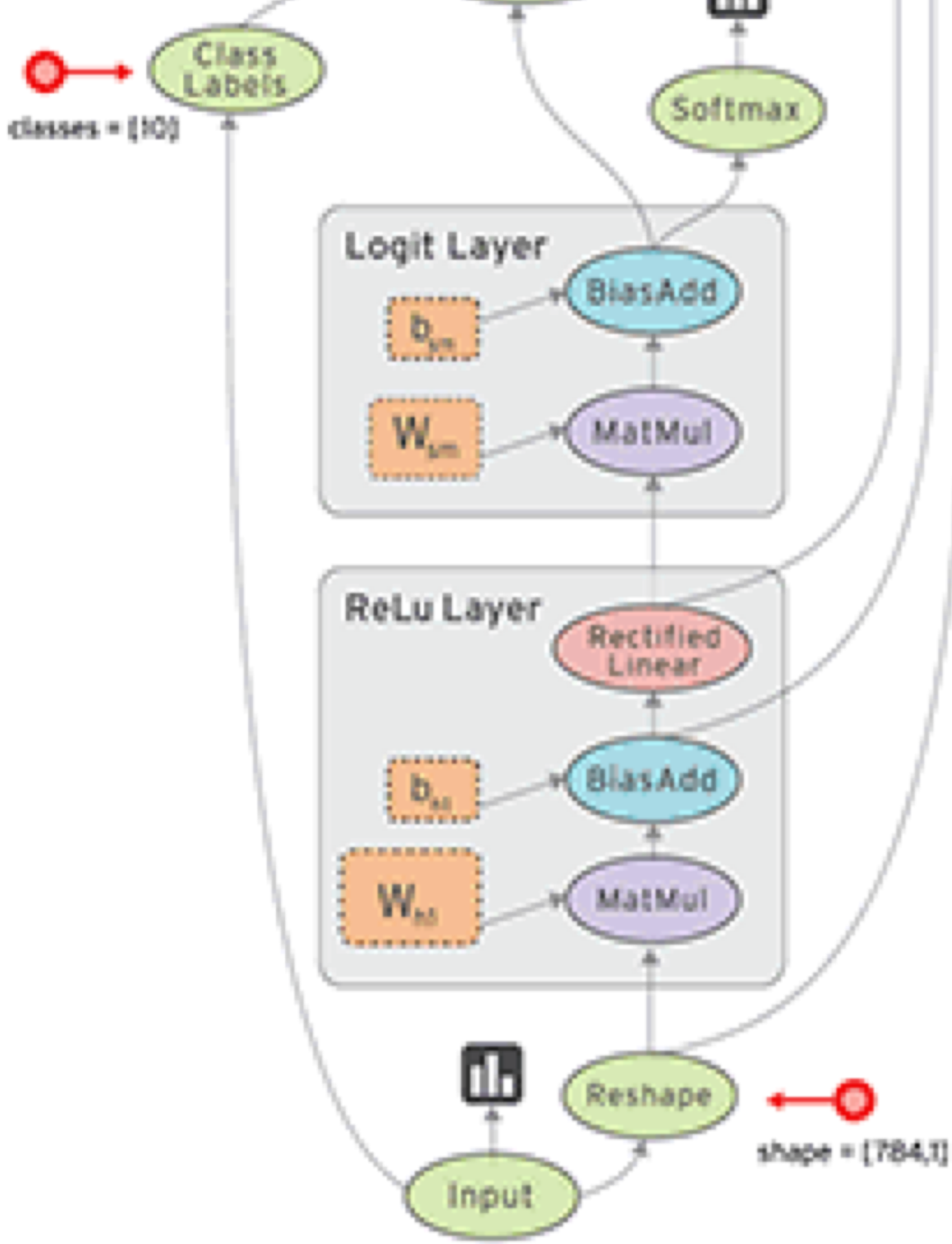
Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

Data Flow Graph



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

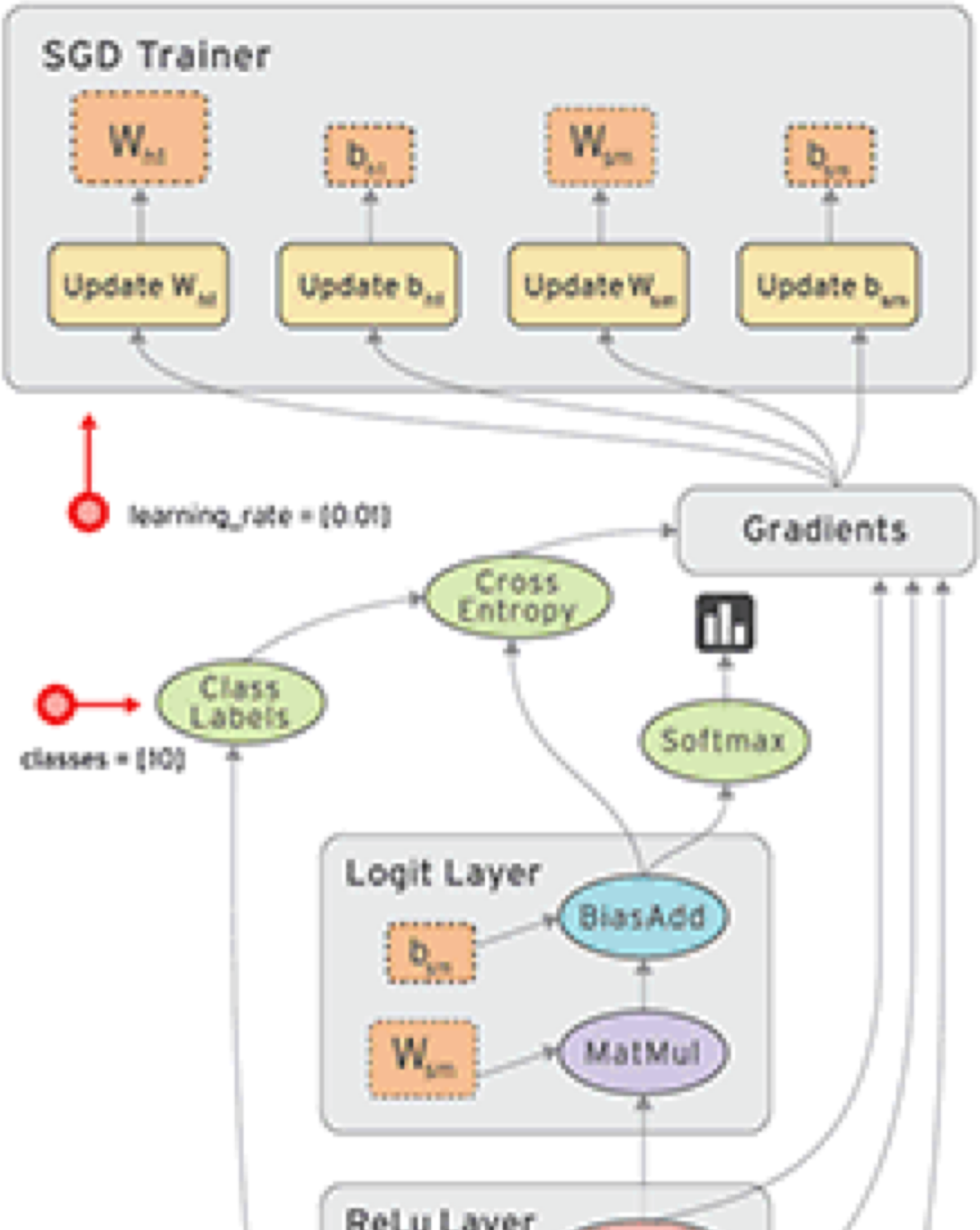
Data Flow Graph



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

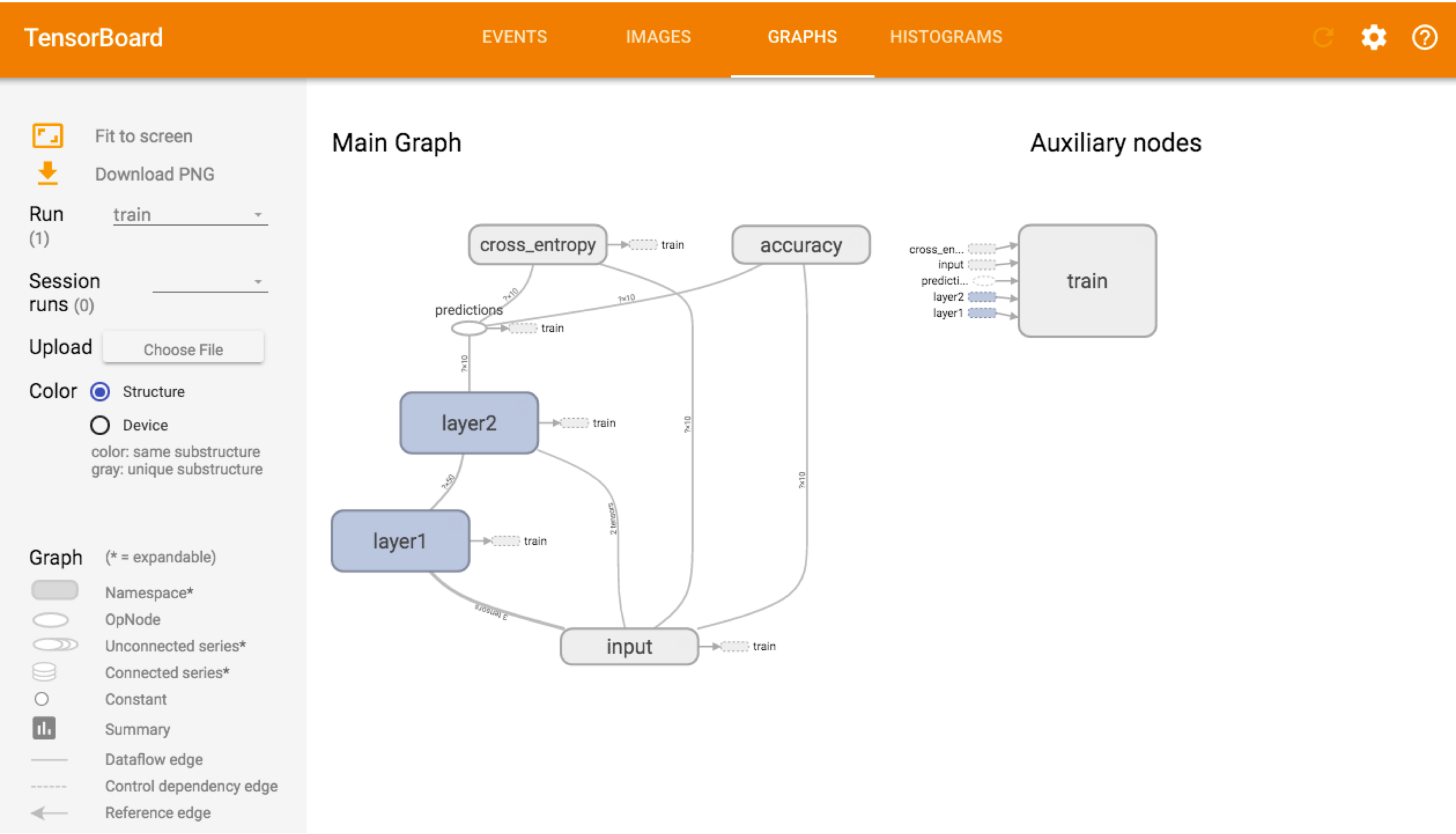
TensorFlow

Data Flow Graph



TensorFlow

TensorBoard



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

Getting Started with TensorFlow

TensorFlow ™ | Install | Develop | API r1.4 | Deploy | Extend | Community | Versions | Search | GITHUB

Develop

GET STARTED | PROGRAMMER'S GUIDE | TUTORIALS | PERFORMANCE | MOBILE

Getting Started With TensorFlow

This guide gets you started programming in TensorFlow. Before using this guide, install TensorFlow. To get the most out of this guide, you should know the following:

- How to program in Python.
- At least a little bit about arrays.
- Ideally, something about machine learning. However, if you know little or nothing about machine learning, then this is still the first guide you should read.

TensorFlow provides multiple APIs. The lowest level API--TensorFlow Core-- provides you with complete programming control. We recommend TensorFlow Core for machine learning researchers and others who require fine levels of control over their models. The higher level APIs are built on top of TensorFlow Core. These higher level APIs are typically easier to learn and use than TensorFlow Core. In addition, the higher level APIs make repetitive tasks easier and more consistent between different users. A high-level API like tf.estimator helps you manage data sets, estimators, training and inference.

This guide begins with a tutorial on TensorFlow Core. Later, we demonstrate how to implement the same model in tf.estimator. Knowing TensorFlow Core principles will give you a great mental model of how things are working internally when you use the more compact higher level API.

Contents

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

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

Hello TensorFlow

```python
import tensorflow as tf
hello = tf.constant('Hello, TensorFlow!')
sess = tf.Session()
sess.run(hello)
```

```
b'Hello, TensorFlow!'
```

https://github.com/tensorflow/tensorflow

tf.Session()
sess.run()

```
import tensorflow as tf
sess = tf.Session()
a = tf.constant(10)
b = tf.constant(32)
sess.run(a+b)
```

```
42
```

https://github.com/tensorflow/tensorflow

Linear Regression Model

```
import tensorflow as tf

# Model parameters
W = tf.Variable([.3], dtype=tf.float32)
b = tf.Variable([-.3], dtype=tf.float32)
# Model input and output
x = tf.placeholder(tf.float32)
linear_model = W*x + b
y = tf.placeholder(tf.float32)

# loss
loss = tf.reduce_sum(tf.square(linear_model - y)) # sum of the squares
# optimizer
optimizer = tf.train.GradientDescentOptimizer(0.01)
train = optimizer.minimize(loss)

# training data
x_train = [1, 2, 3, 4]
y_train = [0, -1, -2, -3]
# training loop
init = tf.global_variables_initializer()
sess = tf.Session()
sess.run(init) # reset values to wrong
for i in range(1000):
  sess.run(train, {x: x_train, y: y_train})

# evaluate training accuracy
curr_W, curr_b, curr_loss = sess.run([W, b, loss], {x: x_train, y: y_train})
print("W: %s b: %s loss: %s"%(curr_W, curr_b, curr_loss))
```

```
W: [-0.9999969] b: [ 0.99999082] loss: 5.69997e-11
```

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

tf.estimator

```
import numpy as np
import tensorflow as tf

feature_columns = [tf.feature_column.numeric_column("x", shape=[1])]

estimator = tf.estimator.LinearRegressor(feature_columns=feature_columns)

x_train = np.array([1., 2., 3., 4.])
y_train = np.array([0., -1., -2., -3.])
x_eval = np.array([2., 5., 8., 1.])
y_eval = np.array([-1.01, -4.1, -7, 0.])
input_fn = tf.estimator.inputs.numpy_input_fn(
    {"x": x_train}, y_train, batch_size=4, num_epochs=None, shuffle=True)
train_input_fn = tf.estimator.inputs.numpy_input_fn(
    {"x": x_train}, y_train, batch_size=4, num_epochs=1000, shuffle=False)
eval_input_fn = tf.estimator.inputs.numpy_input_fn(
    {"x": x_eval}, y_eval, batch_size=4, num_epochs=1000, shuffle=False)

estimator.train(input_fn=input_fn, steps=1000)

train_metrics = estimator.evaluate(input_fn=train_input_fn)
eval_metrics = estimator.evaluate(input_fn=eval_input_fn)
print("train metrics: %r"% train_metrics)
print("eval metrics: %r"% eval_metrics)
```

```
train metrics: {'average_loss': 2.7210228e-07, 'loss': 1.0884091e-06, 'global_step': 1000}
eval metrics: {'average_loss': 0.0025725411, 'loss': 0.010290165, 'global_step': 1000}
```

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

Deep Learning for Financial Time Series Forecasting

Deep Learning
for
Financial Market Prediction
Stock Market Prediction
Stock Price Prediction
Time Series Prediction

Time Series Data

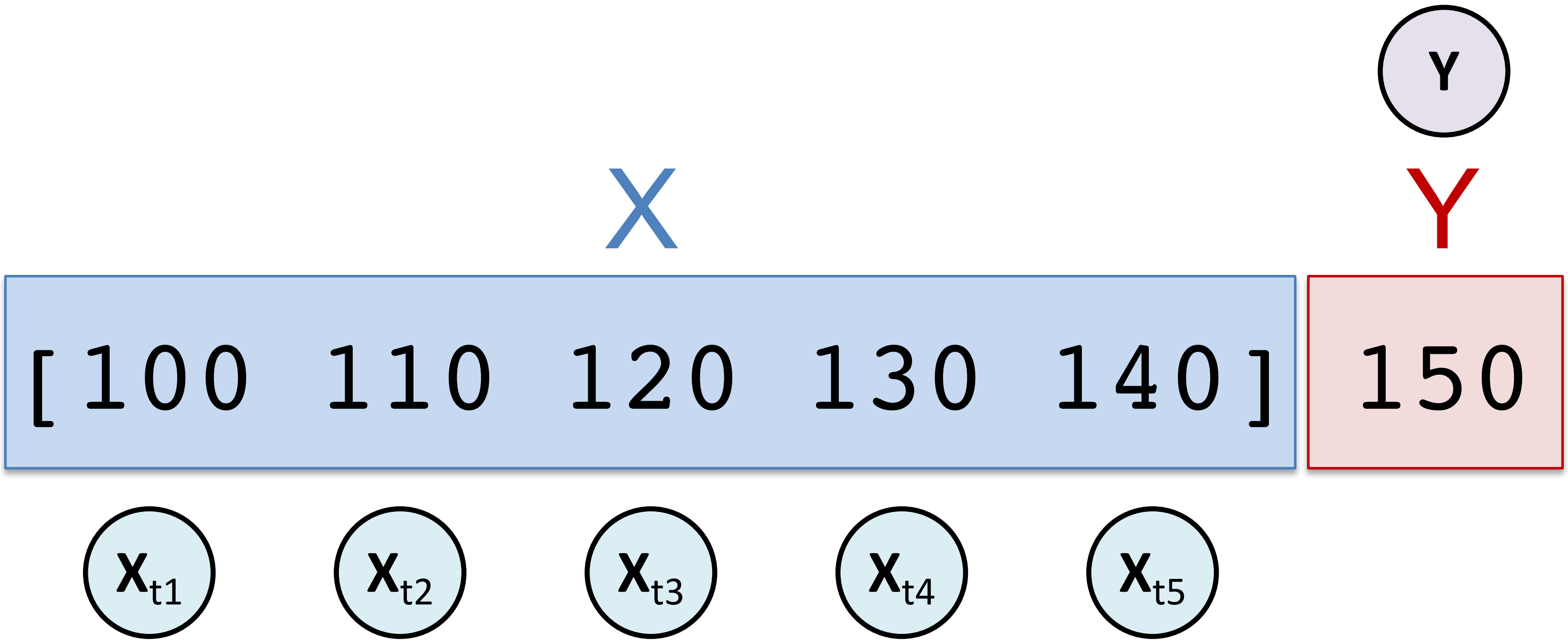
```
df['Adj Close'].plot(legend=True, figsize=(12, 8), title='AAPL', label='Adj Close')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1150bac88>
```

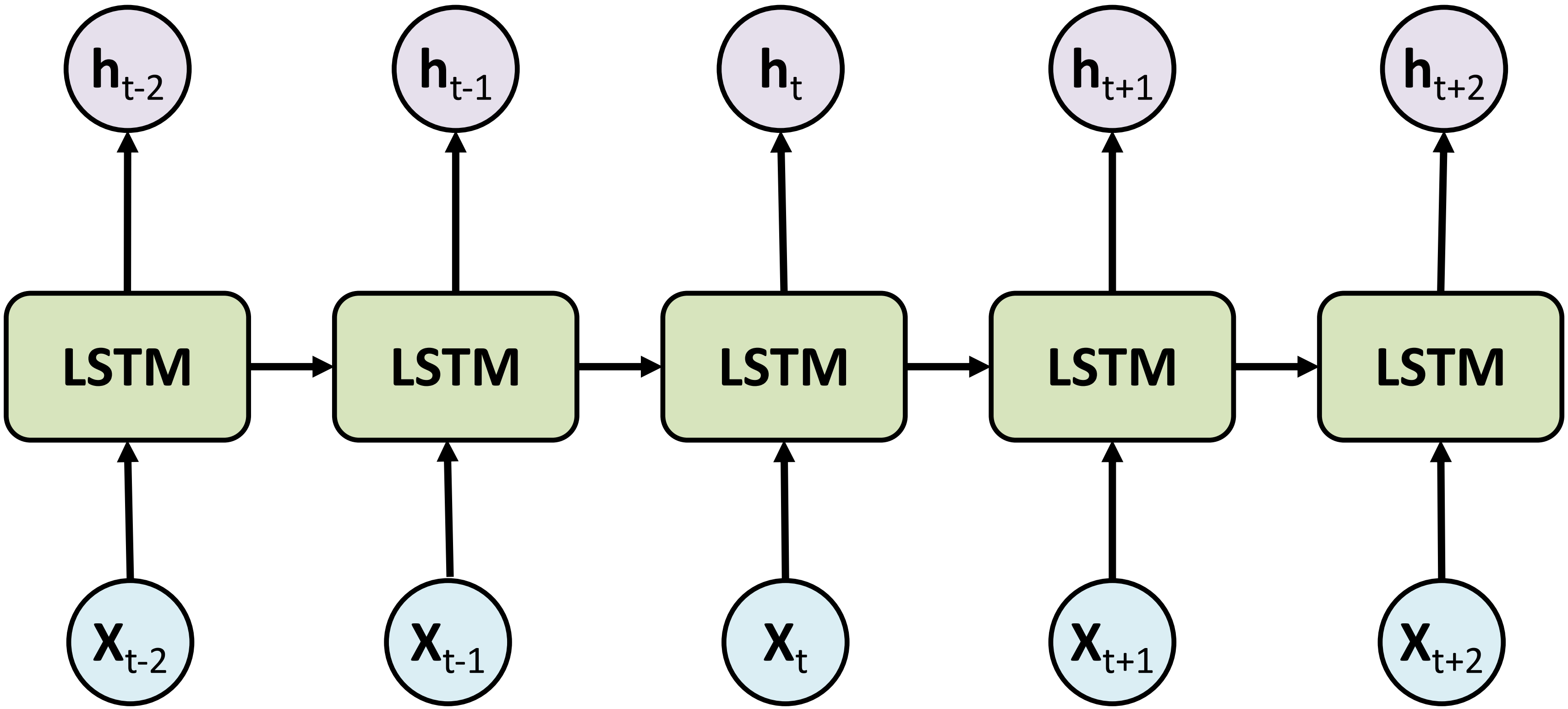
Source: https://mapattack.wordpress.com/2017/02/12/using-python-for-stocks-1/

Time Series Data

[100, 110, 120, 130, 140, 150]



Long Short Term Memory (LSTM) for Time Series Forecasting



Time Series Data

[10, 20, 30, 40, 50, 60, 70, 80, 90]

X	Y
[10 20 30]	40
[20 30 40]	50
[30 40 50]	60
[40 50 60]	70
[50 60 70]	80
[60 70 80]	90

Deep Learning for Financial Time Series Forecasting

https://colab.research.google.com/drive/1aEK0eSev8Q-Y0nNY32geFk7CB8pVgSQM

Deep_Learning_for_Financial_Time_Series_Forecasting.ipynb

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```python
# univariate data preparation
from numpy import array
# split a univariate sequence into samples
def split_sequence(sequence, n_steps):
    X, y = list(), list()
    for i in range(len(sequence)):
        # find the end of this pattern
        end_ix = i + n_steps
        # check if we are beyond the sequence
        if end_ix > len(sequence)-1:
            break
        # gather input and output parts of the pattern
        seq_x, seq_y = sequence[i:end_ix], sequence[end_ix]
        X.append(seq_x)
        y.append(seq_y)
    return array(X), array(y)
# define input sequence
raw_seq = [10, 20, 30, 40, 50, 60, 70, 80, 90]
# choose a number of time steps
n_steps = 3
# split into samples
X, y = split_sequence(raw_seq, n_steps)
# summarize the data
for i in range(len(X)):
    print(X[i], y[i])
```

```
[10 20 30] 40
[20 30 40] 50
[30 40 50] 60
[40 50 60] 70
[50 60 70] 80
[60 70 80] 90
```

Source: https://machinelearningmastery.com/how-to-develop-lstm-models-for-time-series-forecasting/

Deep Learning for Financial Time Series Forecasting

https://colab.research.google.com/drive/1aEK0eSev8Q-Y0nNY32geFk7CB8pVgSQM

Deep_Learning_for_Financial_Time_Series_Forecasting.ipynb

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LSTM for Time Series Forecasting

```python
# univariate lstm example
from numpy import array
from keras.models import Sequential
from keras.layers import LSTM
from keras.layers import Dense
import matplotlib.pyplot as plt
%matplotlib inline

# define dataset
X = array([[100, 110, 120], [110, 120, 130], [120, 130, 140], [130, 140, 150], [140, 150, 160]])
y = array([130, 140, 150, 160, 170])
# reshape from [samples, timesteps] into [samples, timesteps, features]
X = X.reshape((X.shape[0], X.shape[1], 1))
# define model
model = Sequential()
model.add(LSTM(50, activation='relu', input_shape=(3, 1)))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse')
# fit model
history = model.fit(X, y, epochs=2000, verbose=0)
# demonstrate prediction
x_input = array([150, 160, 170])
x_input = x_input.reshape((1, 3, 1))
yhat = model.predict(x_input, verbose=0)
print('yhat', yhat)
print(model.summary())
# list all data in history
print(history.history.keys())
# summarize history for loss
print('loss:', '%f'%history.history['loss'][-1])
print('loss:', history.history['loss'][-1])
plt.plot(history.history['loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.show()
```

```
yhat [[181.34615]]
```

Source: https://machinelearningmastery.com/how-to-develop-lstm-models-for-time-series-forecasting/

Deep Learning for Financial Time Series Forecasting

https://colab.research.google.com/drive/1aEK0eSev8Q-Y0nNY32geFk7CB8pVgSQM

Deep_Learning_for_Financial_Time_Series_Forecasting.ipynb

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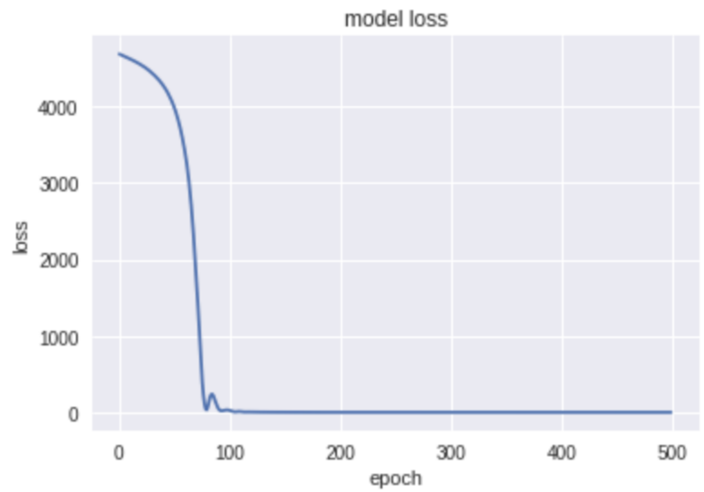
```
# univariate lstm example
from numpy import array
from keras.models import Sequential
from keras.layers import LSTM
from keras.layers import Dense
import matplotlib.pyplot as plt
%matplotlib inline
# split a univariate sequence into samples
def split_sequence(sequence, n_steps):
    X, y = list(), list()
    for i in range(len(sequence)):
        # find the end of this pattern
        end_ix = i + n_steps
        # check if we are beyond the sequence
        if end_ix > len(sequence)-1:
            break
        # gather input and output parts of the pattern
        seq_x, seq_y = sequence[i:end_ix], sequence[end_ix]
        X.append(seq_x)
        y.append(seq_y)
    return array(X), array(y)
# define input sequence
raw_seq = [10, 20, 30, 40, 50, 60, 70, 80, 90]
# choose a number of time steps
n_steps = 3
# split into samples
X, y = split_sequence(raw_seq, n_steps)
# reshape from [samples, timesteps] into [samples, timesteps, features]
n_features = 1
X = X.reshape((X.shape[0], X.shape[1], n_features))
# define model
model = Sequential()
model.add(LSTM(50, activation='relu', input_shape=(n_steps, n_features)))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse')
# fit model
history = model.fit(X, y, epochs=500, verbose=0)
# demonstrate prediction
x_input = array([70, 80, 90])
x_input = x_input.reshape((1, n_steps, n_features))
yhat = model.predict(x_input, verbose=0)
print(yhat)
print('yhat', yhat)
print(model.summary())
```

Source: https://machinelearningmastery.com/how-to-develop-lstm-models-for-time-series-forecasting/

Deep Learning for Financial Time Series Forecasting

https://colab.research.google.com/drive/1aEK0eSev8Q-Y0nNY32geFk7CB8pVgSQM

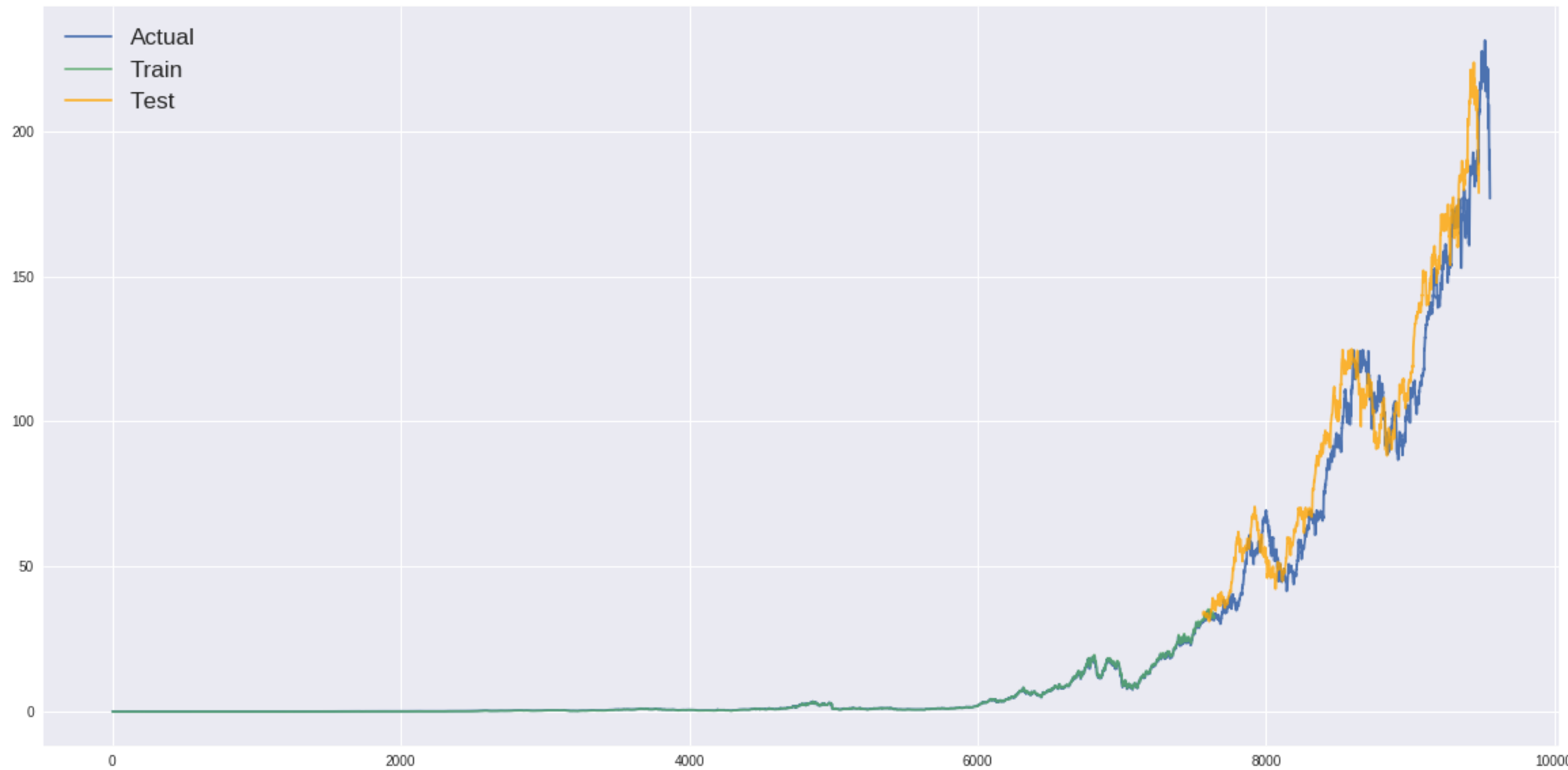
```
Using TensorFlow backend.
[[102.31296]]
yhat [[102.31296]]
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_1 (LSTM)                (None, 50)                10400     
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 51        
=================================================================
Total params: 10,451
Trainable params: 10,451
Non-trainable params: 0
_________________________________________________________________
None
dict_keys(['loss'])
loss: 0.000000
loss: 1.2578432517784677e-07
```



Source: https://machinelearningmastery.com/how-to-develop-lstm-models-for-time-series-forecasting/

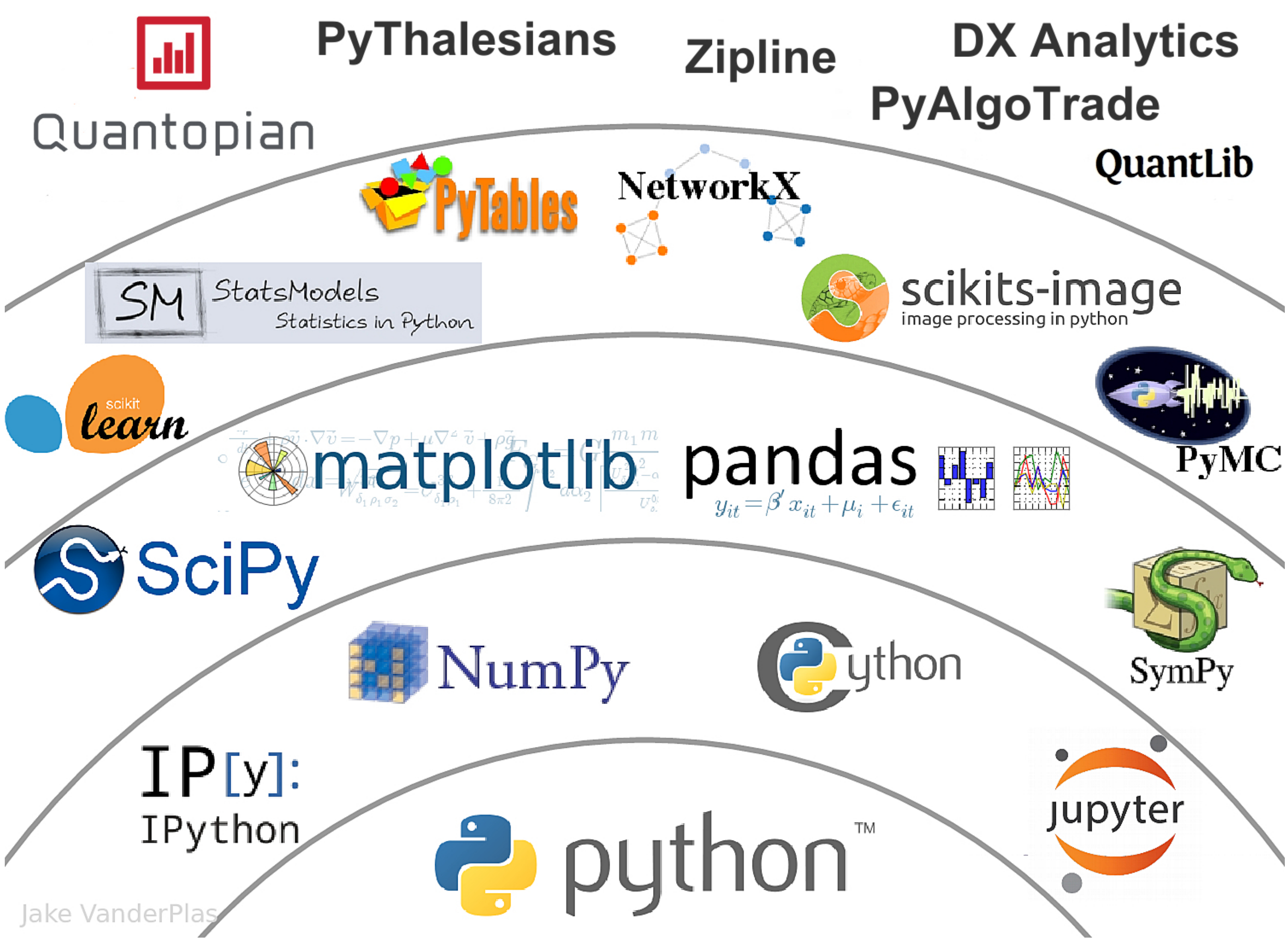
Deep Learning for Financial Time Series Forecasting

https://colab.research.google.com/drive/1aEK0eSev8Q-Y0nNY32geFk7CB8pVgSQM



Source: https://github.com/yash-1337/AAPL_LSTM_Stock_Predictor/blob/master/AAPL_daily_LSTM_stock_predictor.ipynb

The Quant Finance PyData Stack



Source: http://nbviewer.jupyter.org/format/slides/github/quantopian/pyfolio/blob/master/pyfolio/examples/overview_slides.ipynb#/5

AI + VDI POC

AI + VDI POS
TensorFlow Models

- M1: Basic Classification (Image Classification) (65 Seconds)
  - https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/keras/basic_classification.ipynb
- M2: Basic Text Classification (Text Classification) (46 Seconds)
  - https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/keras/basic_text_classification.ipynb
- M3: Basic Regression (Predict House Prices) (43 Seconds)
  - https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/keras/basic_regression.ipynb
- M4: Pix2Pix Eager (Option) (7-8 Hours)
  - https://colab.research.google.com/github/tensorflow/tensorflow/blob/master/tensorflow/contrib/eager/python/examples/pix2pix/pix2pix_eager.ipynb
- M5. NMT with Attention (Option) (20-30 minutes)
  - https://colab.research.google.com/github/tensorflow/tensorflow/blob/master/tensorflow/contrib/eager/python/examples/nmt_with_attention/nmt_with_attention.ipynb

Basic Classification

Fashion MNIST Image Classification

https://colab.research.google.com/drive/19PJOJi1vn1kjcutlzNHjRSLbeVl4kd5z

tf01_basic_classification.ipynb

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SECTION

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Train your first neural network: basic classification

View on TensorFlow.org | Run in Google Colab | View source on GitHub

This guide trains a neural network model to classify images of clothing, like sneakers and shirts. It's okay if you don't understand all the details, this is a fast-paced overview of a complete TensorFlow program with the details explained as we go.

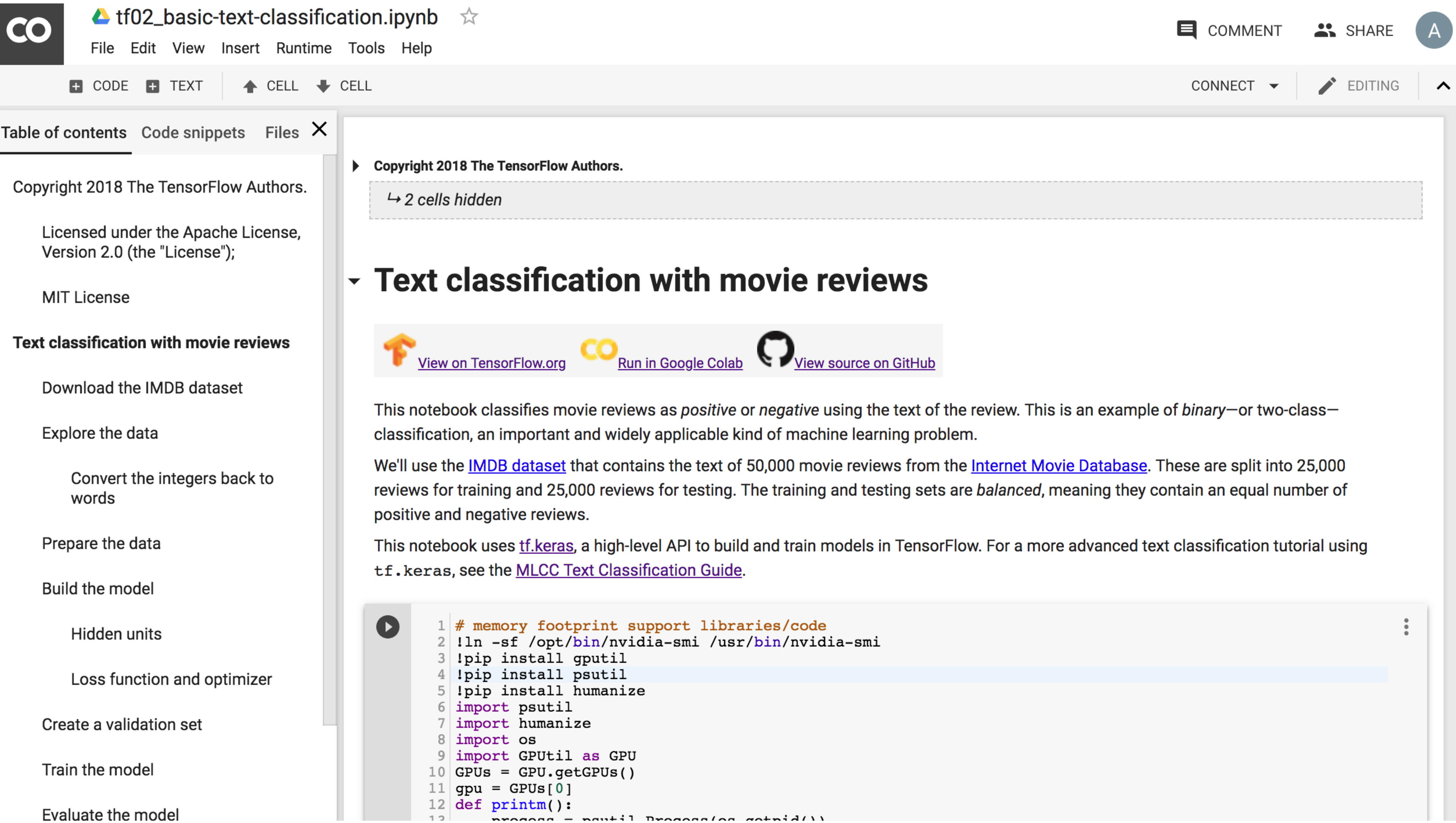
This guide uses tf.keras, a high-level API to build and train models in TensorFlow.

```
# memory footprint support libraries/code
!ln -sf /opt/bin/nvidia-smi /usr/bin/nvidia-smi
!pip install gputil
!pip install psutil
!pip install humanize
import psutil
import humanize
import os
import GPUtil as GPU
GPUs = GPU.getGPUs()
gpu = GPUs[0]
def printm():
    process = psutil.Process(os.getpid())
    print("Gen RAM Free: " + humanize.naturalsize( psutil.virtual_memory().available ), " | Pro
    print("GPU RAM Free: {0:.0f}MB | Used: {1:.0f}MB | Util {2:3.0f}% | Total {3:.0f}MB".format
printm()
```

Source: https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/keras/basic_classification.ipynb

Text Classification
IMDB Movie Reviews

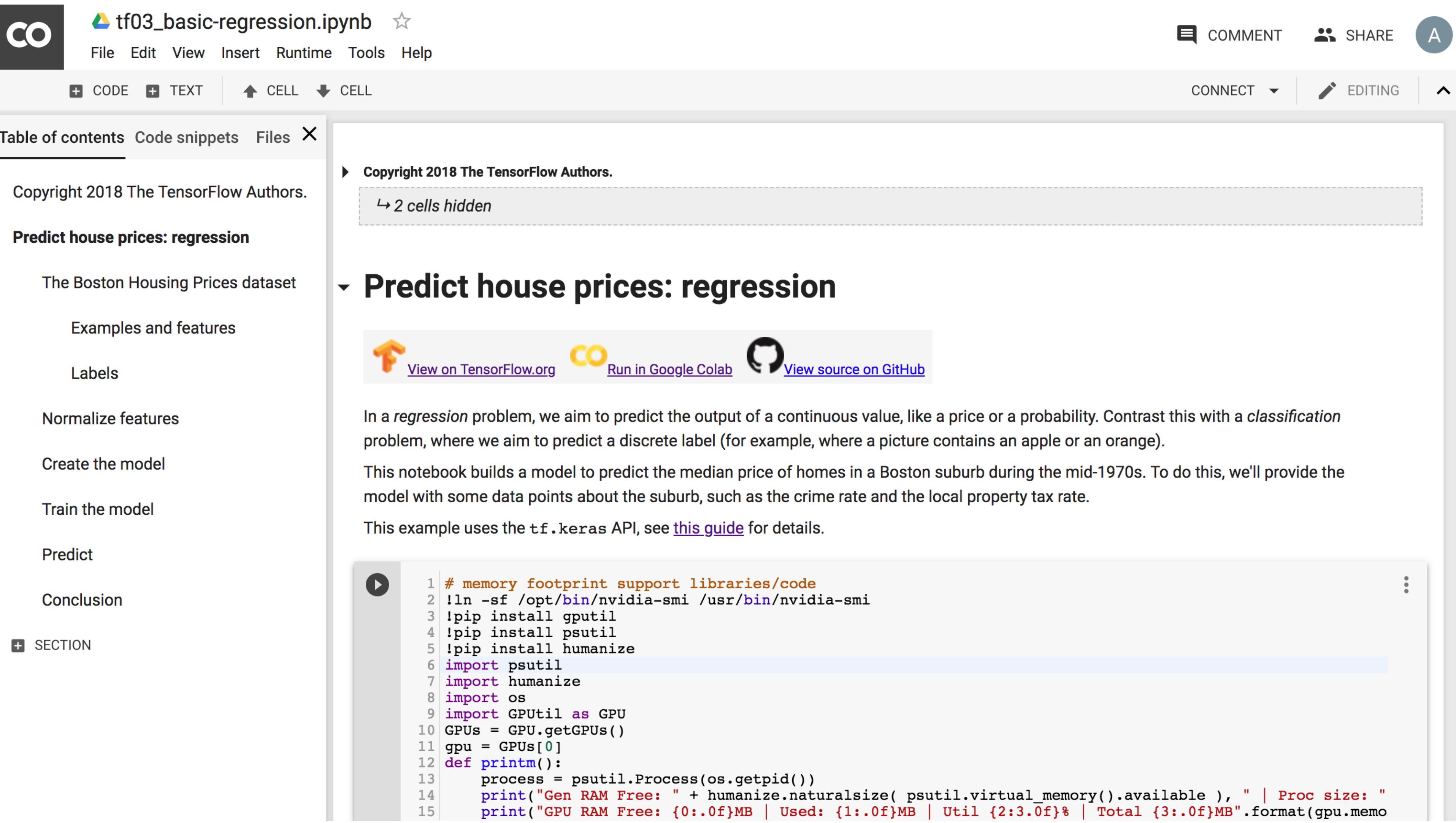
https://colab.research.google.com/drive/1x16h1GhHsLIrLYtPCvCHaoO1W-i_gror



Source: https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/keras/basic_text_classification.ipynb

Basic Regression
Predict House Prices

https://colab.research.google.com/drive/1v4c8ZHTnRtgd2_25K_AURjR6SCVBRdlj



Source: https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/keras/basic_regression.ipynb

AI+VDI POC
ISAC+TKU Test

- AI+VDI POC Folder (3+1 ipynb) (v3.0.20181120)
  - https://drive.google.com/open?id=1qHOemktbEmUz-ot8eFxIKbGwJvXlrjtc
- run3models.ipynb
  - https://colab.research.google.com/drive/1HQ1GrIqQUUPCct7_AVgoMwMrh0UqMm0f

Summary

- **Deep Learning for Financial Time Series Forecasting with TensorFlow**
  - **Deep Learning**
  - **Financial Time Series Forecasting**
  - **TensorFlow**

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- https://github.com/leriomaggio/deep-learning-keras-tensorflow