

Social Computing and Big Data Analytics

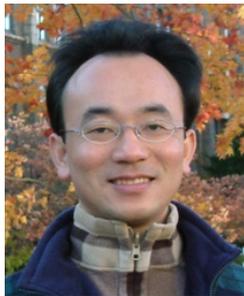
社群運算與大數據分析

Deep Learning with Theano and Keras in Python (Python Theano 和 Keras 深度學習)

1052SCBDA09

MIS MBA (M2226) (8606)

Wed, 8,9, (15:10-17:00) (L206)



Min-Yuh Day

戴敏育

Assistant Professor

專任助理教授

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淡江大學 資訊管理學系

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

2017-04-26



課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
1	2017/02/15	Course Orientation for Social Computing and Big Data Analytics (社群運算與大數據分析課程介紹)
2	2017/02/22	Data Science and Big Data Analytics: Discovering, Analyzing, Visualizing and Presenting Data (資料科學與大數據分析： 探索、分析、視覺化與呈現資料)
3	2017/03/01	Fundamental Big Data: MapReduce Paradigm, Hadoop and Spark Ecosystem (大數據基礎：MapReduce典範、 Hadoop與Spark生態系統)

課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
4	2017/03/08	Big Data Processing Platforms with SMACK: Spark, Mesos, Akka, Cassandra and Kafka (大數據處理平台SMACK： Spark, Mesos, Akka, Cassandra, Kafka)
5	2017/03/15	Big Data Analytics with Numpy in Python (Python Numpy 大數據分析)
6	2017/03/22	Finance Big Data Analytics with Pandas in Python (Python Pandas 財務大數據分析)
7	2017/03/29	Text Mining Techniques and Natural Language Processing (文字探勘分析技術與自然語言處理)
8	2017/04/05	Off-campus study (教學行政觀摩日)

課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
9	2017/04/12	Social Media Marketing Analytics (社群媒體行銷分析)
10	2017/04/19	期中報告 (Midterm Project Report)
11	2017/04/26	Deep Learning with Theano and Keras in Python (Python Theano 和 Keras 深度學習)
12	2017/05/03	Deep Learning with Google TensorFlow (Google TensorFlow 深度學習)
13	2017/05/10	Sentiment Analysis on Social Media with Deep Learning (深度學習社群媒體情感分析)

課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
14	2017/05/17	Social Network Analysis (社會網絡分析)
15	2017/05/24	Measurements of Social Network (社會網絡量測)
16	2017/05/31	Tools of Social Network Analysis (社會網絡分析工具)
17	2017/06/07	Final Project Presentation I (期末報告 I)
18	2017/06/14	Final Project Presentation II (期末報告 II)

Deep Learning

with

Theano

and

Keras

in

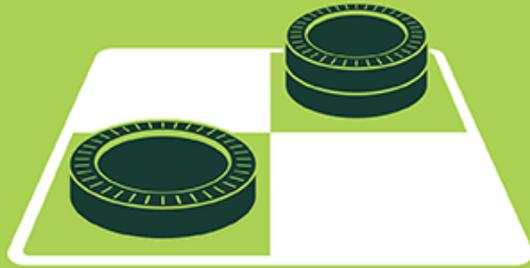
Python

Artificial Intelligence

Machine Learning & Deep Learning

ARTIFICIAL INTELLIGENCE

Early artificial intelligence stirs excitement.



MACHINE LEARNING

Machine learning begins to flourish.



DEEP LEARNING

Deep learning breakthroughs drive AI boom.



1950's

1960's

1970's

1980's

1990's

2000's

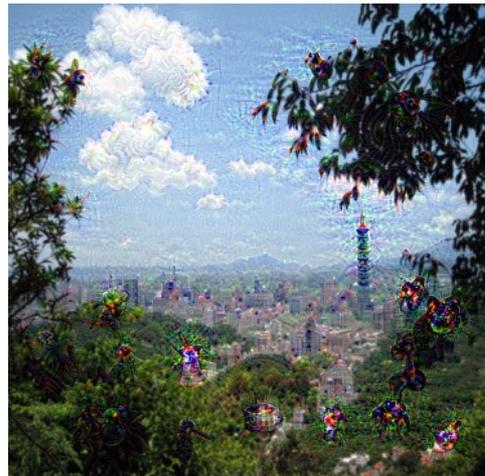
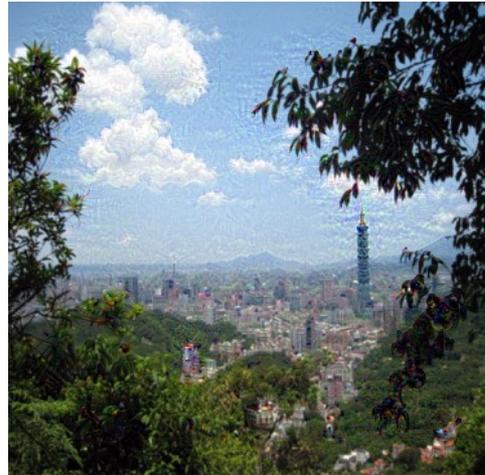
2010's

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

Deep Learning Evolution

Deep Learning

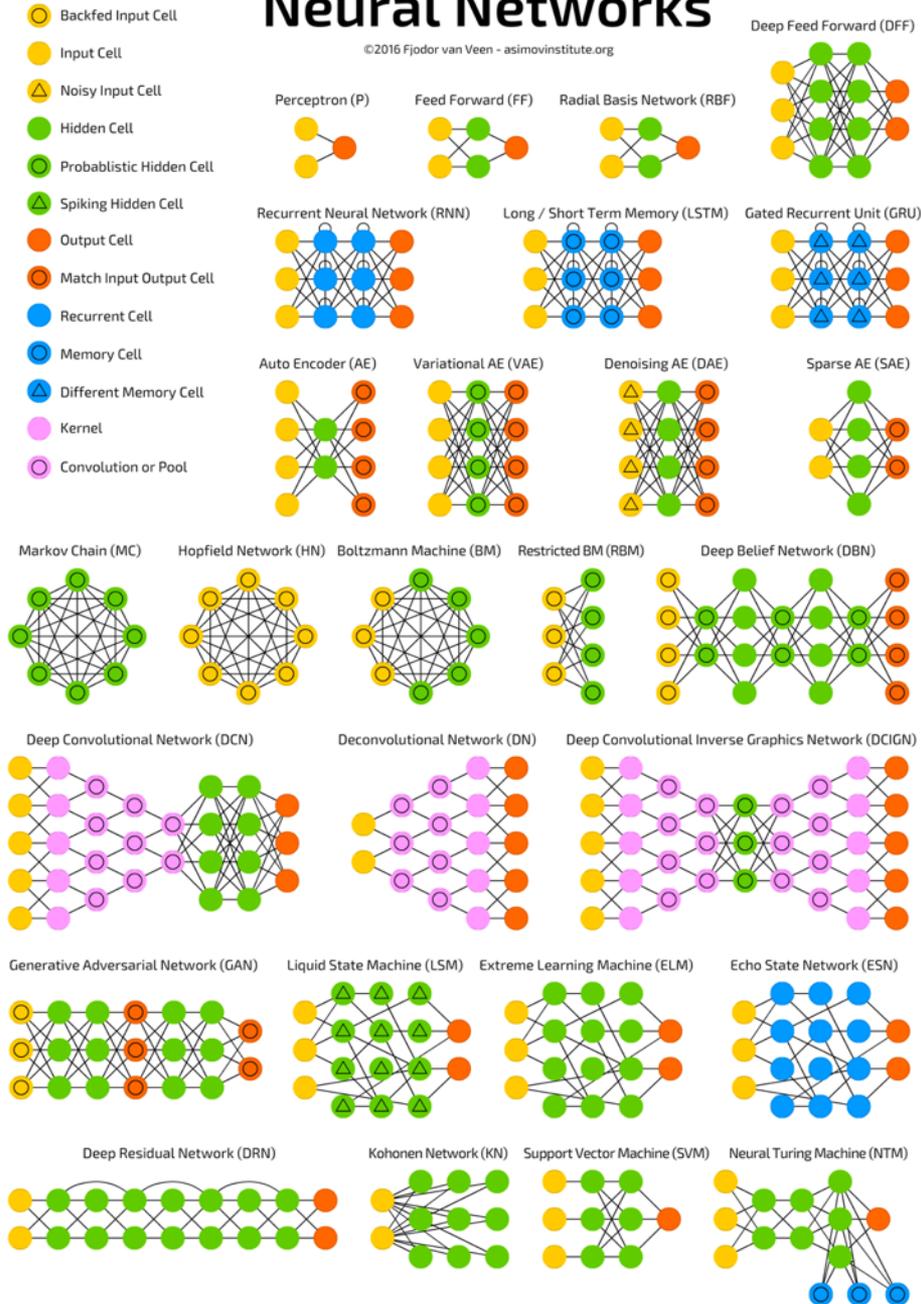
Deep Dream



Neural Networks (NN)

A mostly complete chart of Neural Networks

©2016 Fjodor van Veen - asimovinstitute.org

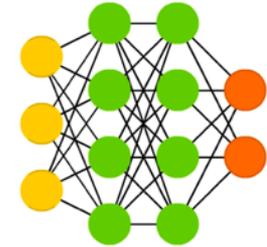


Neural Networks

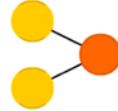
©2016 Fjodor van Veen - asimovinstitute.org

-  Backfed Input Cell
-  Input Cell
-  Noisy Input Cell
-  Hidden Cell
-  Probabilistic Hidden Cell
-  Spiking Hidden Cell
-  Output Cell
-  Match Input Output Cell
-  Recurrent Cell
-  Memory Cell
-  Different Memory Cell
-  Kernel
-  Convolution or Pool

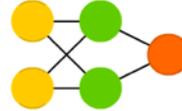
Deep Feed Forward (DFF)



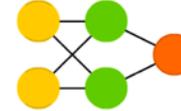
Perceptron (P)



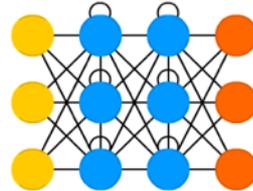
Feed Forward (FF)



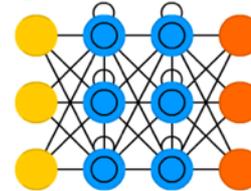
Radial Basis Network (RBF)



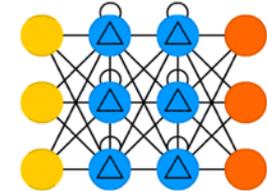
Recurrent Neural Network (RNN)



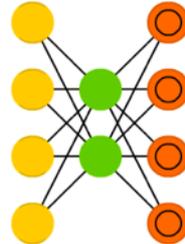
Long / Short Term Memory (LSTM)



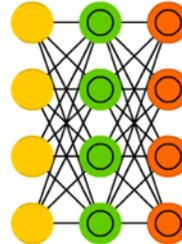
Gated Recurrent Unit (GRU)



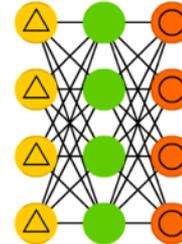
Auto Encoder (AE)



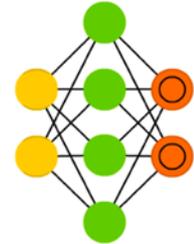
Variational AE (VAE)



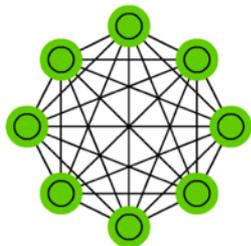
Denoising AE (DAE)



Sparse AE (SAE)



Markov Chain (MC)



Hopfield Network (HN)



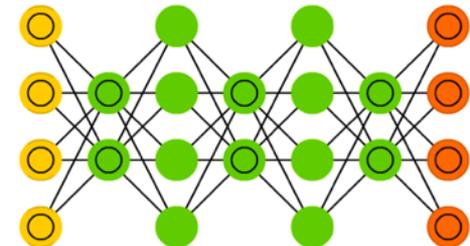
Boltzmann Machine (BM)



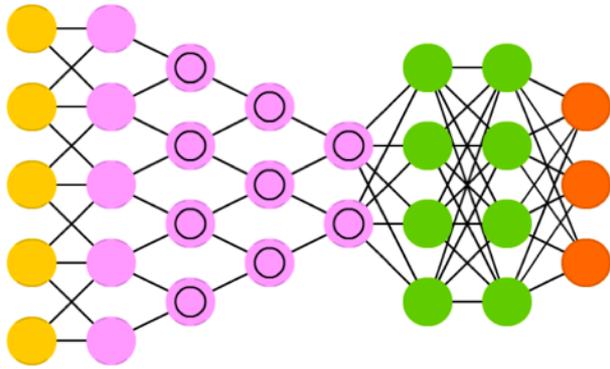
Restricted BM (RBM)



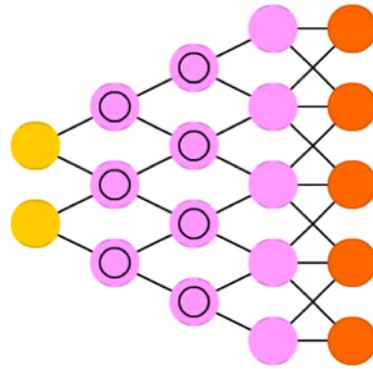
Deep Belief Network (DBN)



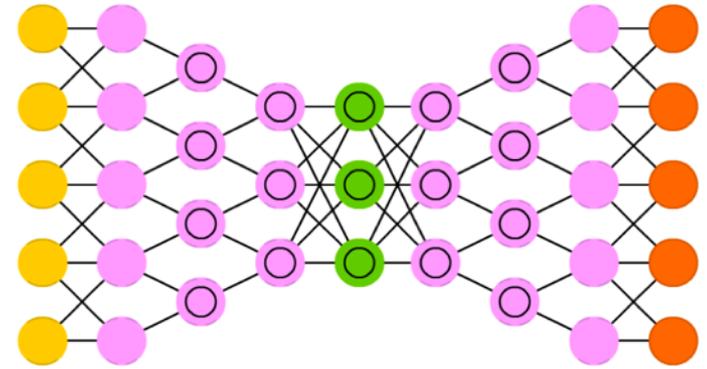
Deep Convolutional Network (DCN)



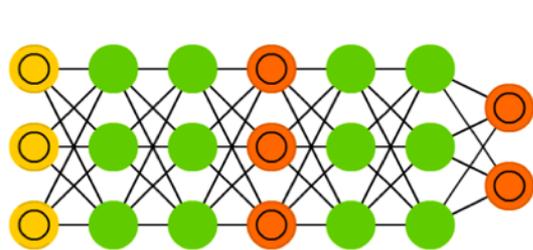
Deconvolutional Network (DN)



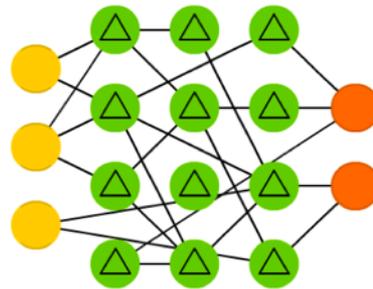
Deep Convolutional Inverse Graphics Network (DCIGN)



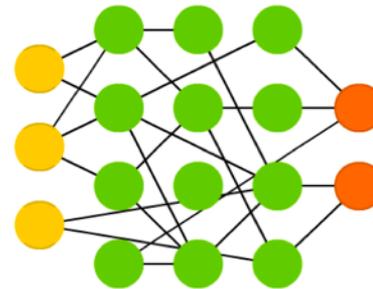
Generative Adversarial Network (GAN)



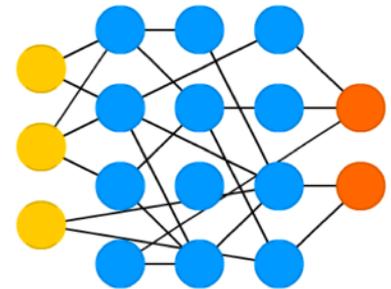
Liquid State Machine (LSM)



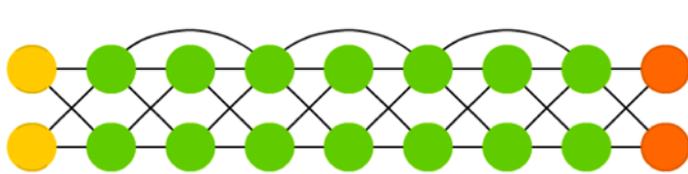
Extreme Learning Machine (ELM)



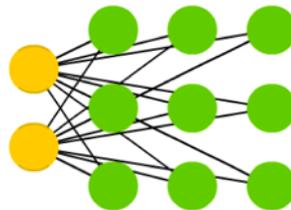
Echo State Network (ESN)



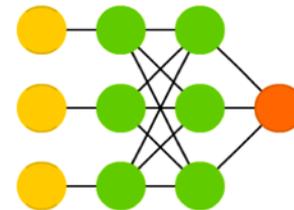
Deep Residual Network (DRN)



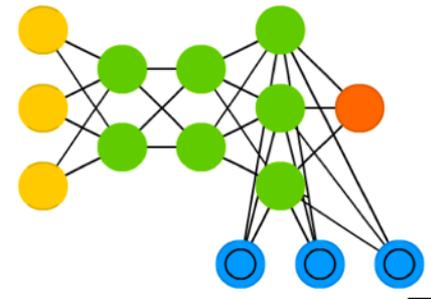
Kohonen Network (KN)



Support Vector Machine (SVM)

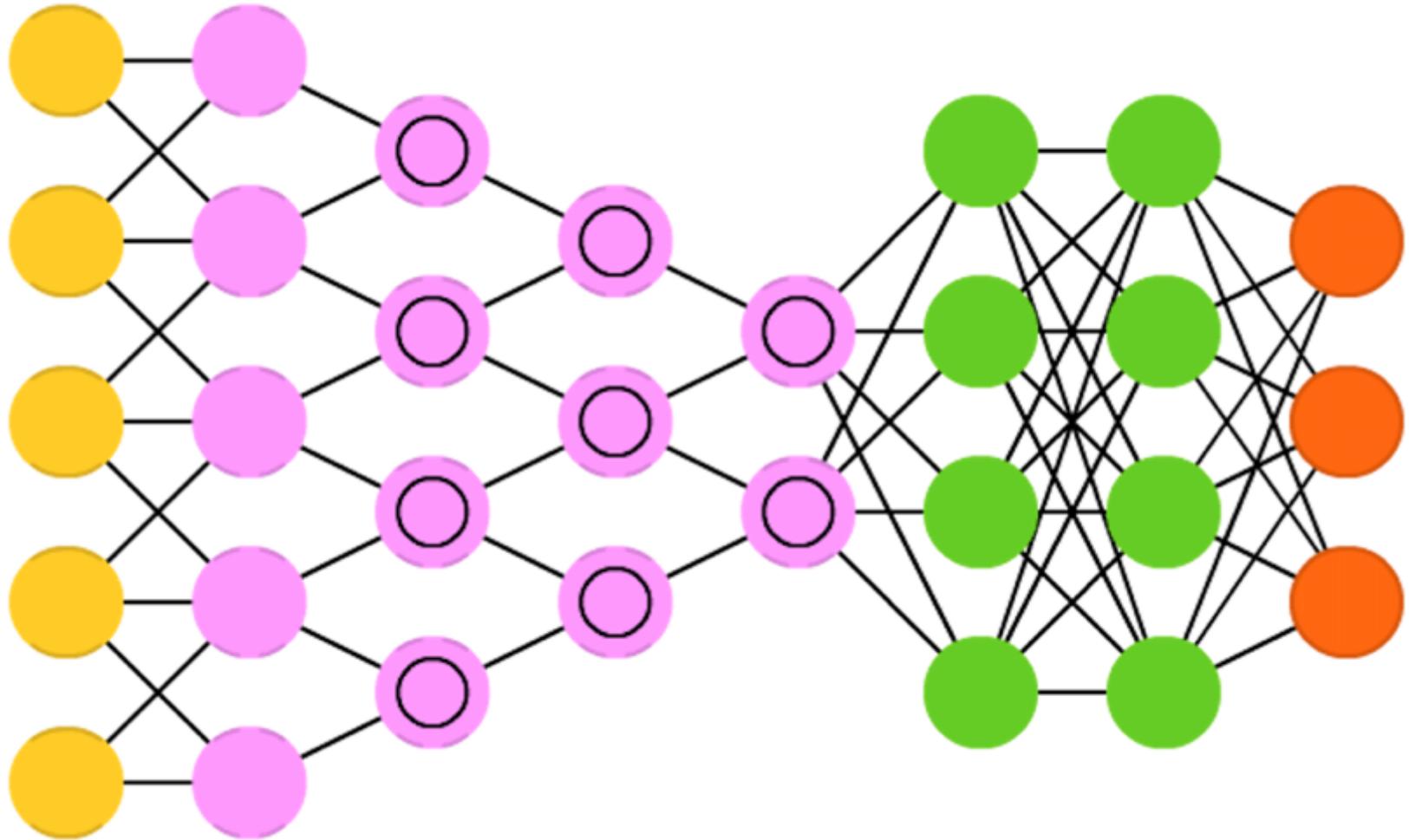


Neural Turing Machine (NTM)

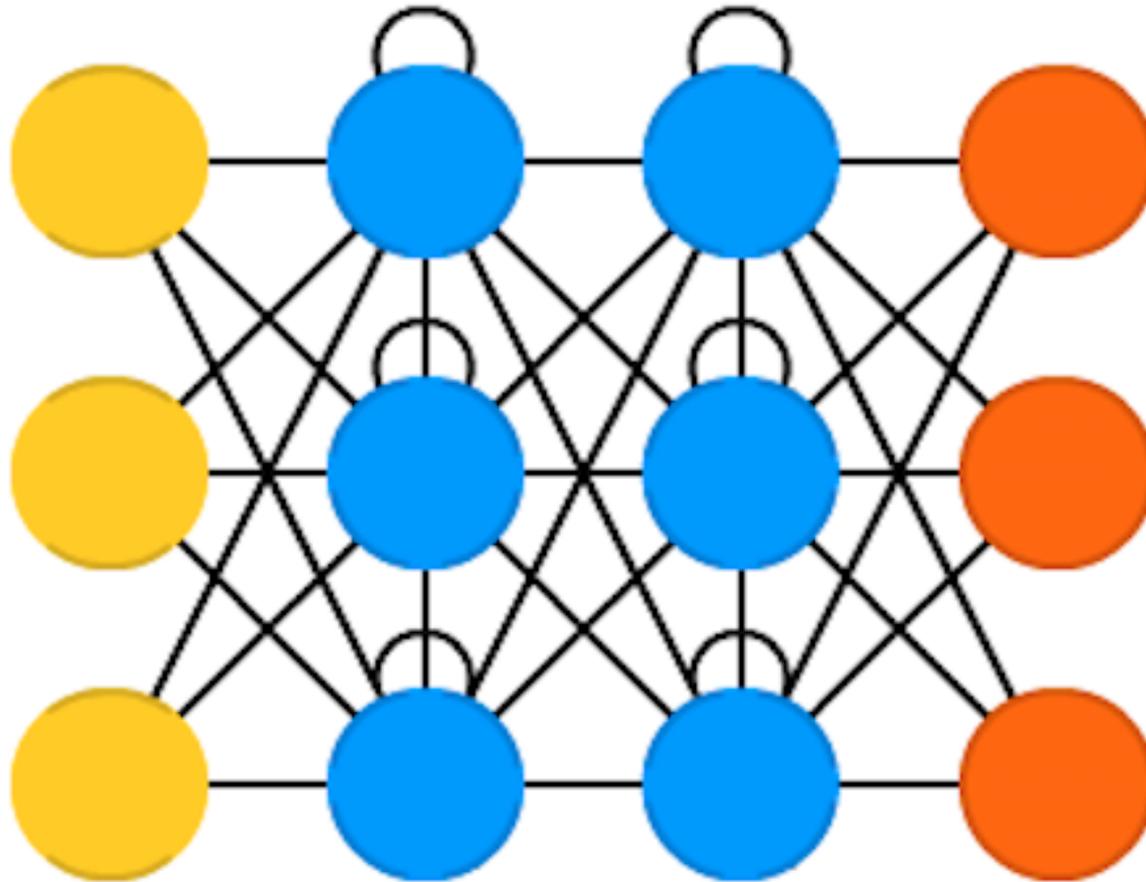


Convolutional Neural Networks

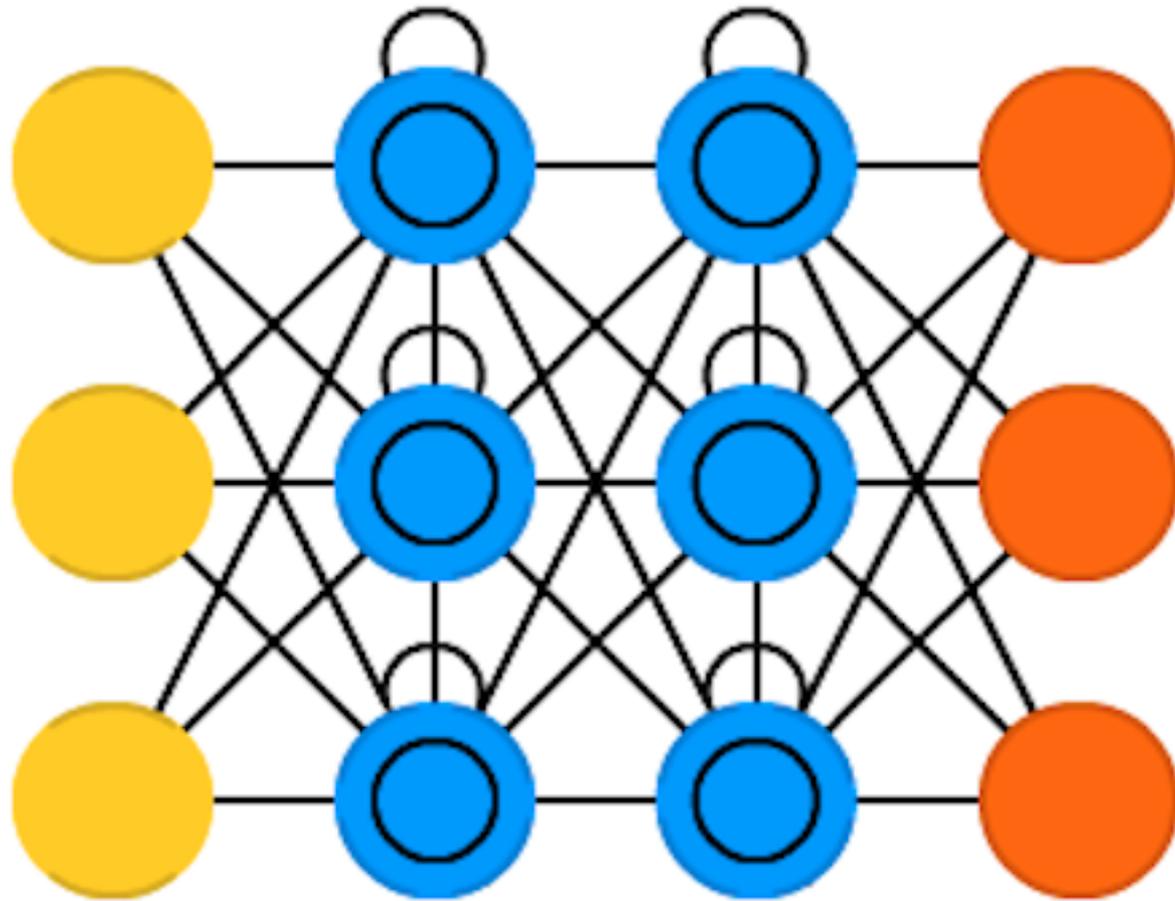
(CNN or Deep Convolutional Neural Networks, DCNN)



Recurrent Neural Networks (RNN)



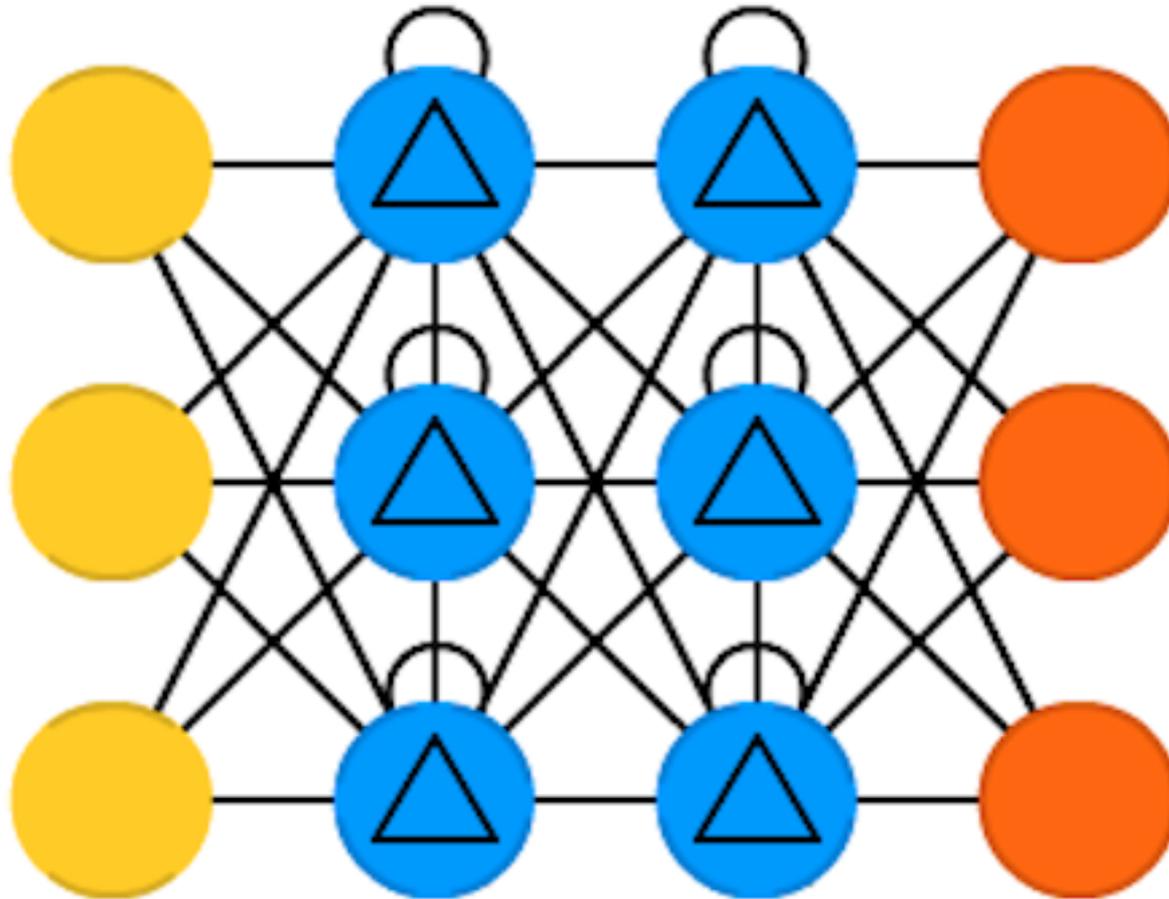
Long / Short Term Memory (LSTM)



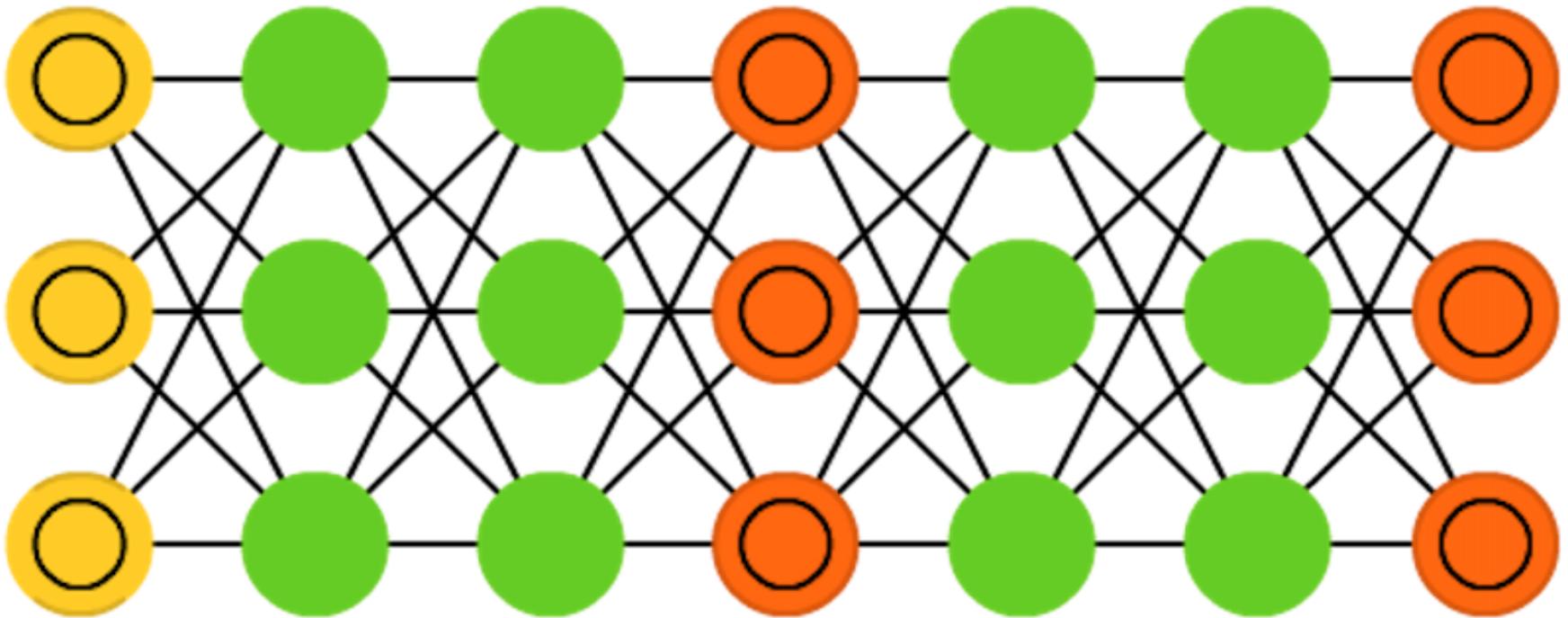
Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." *Neural computation* 9.8 (1997): 1735-1780.

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

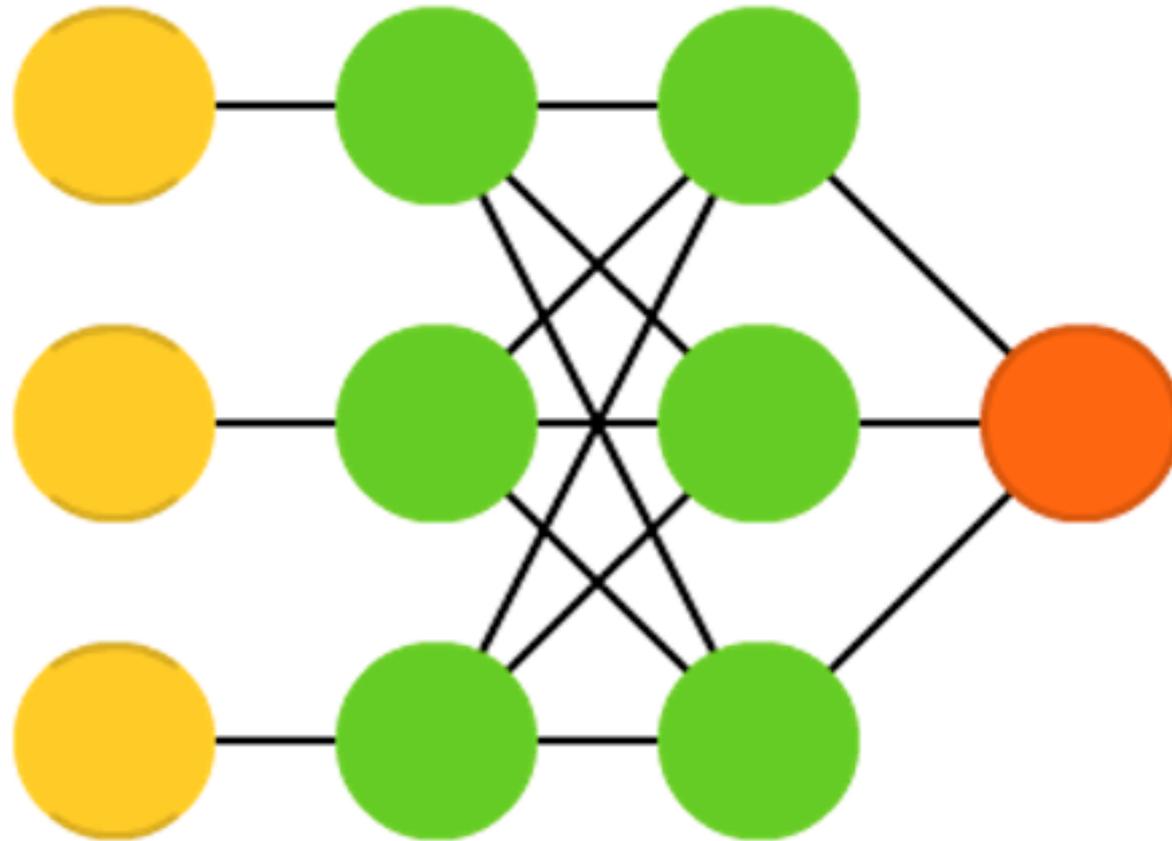
Gated Recurrent Units (GRU)



Generative Adversarial Networks (GAN)



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/>

**LeCun, Yann,
Yoshua Bengio,
and Geoffrey Hinton.**

"Deep learning."

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

Deep learning

Yann LeCun^{1,2}, Yoshua Bengio³ & Geoffrey Hinton^{4,5}

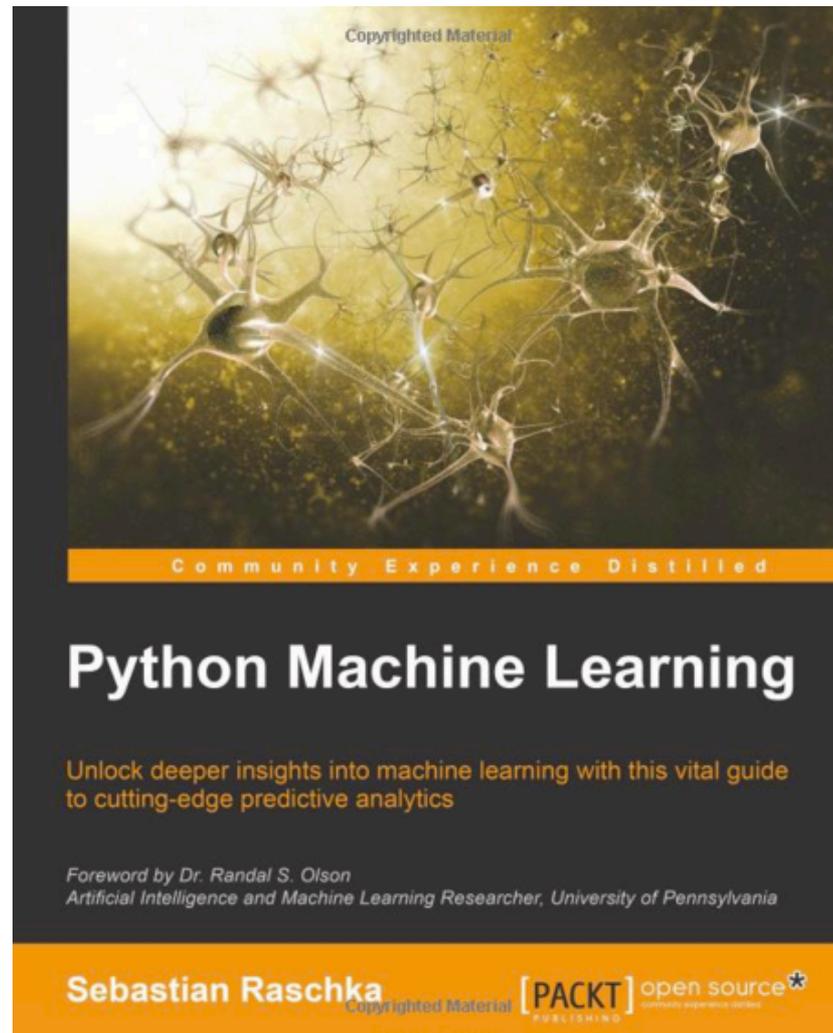
Deep learning allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction. These methods have dramatically improved the state-of-the-art in speech recognition, visual object recognition, object detection and many other 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.

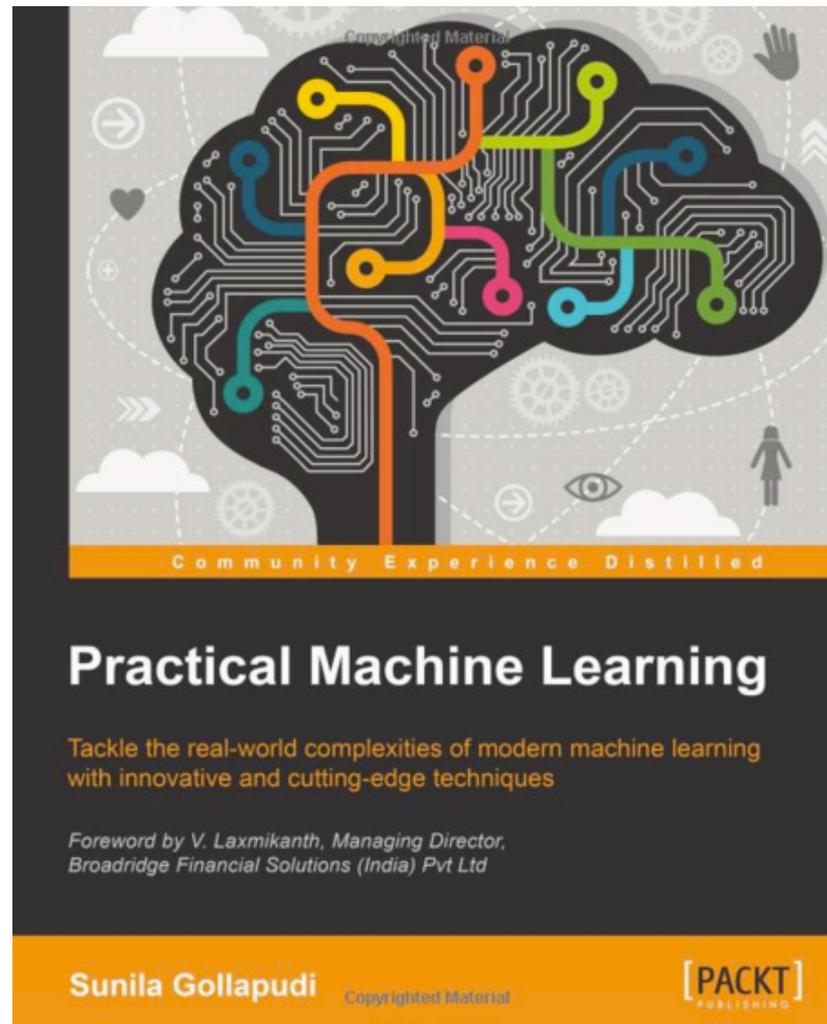
Conventional machine-learning techniques were limited in their ability to process natural data in their raw form. For decades, con-

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 recognition¹⁻⁴ and speech recognition⁵⁻⁷, it has beaten other machine-learning techniques at predicting the activity of potential drug molecules⁸, analysing particle accelerator data^{9,10}, reconstructing brain circuits¹¹, 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 understanding¹⁴, particularly topic classification, sentiment analysis, question answering¹⁵ and language translation^{16,17}.

Sebastian Raschka (2015),
Python Machine Learning,
Packt Publishing



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



Machine Learning Models

Deep Learning

Association rules

Decision tree

Clustering

Bayesian

Kernel

Ensemble

Dimensionality reduction

Regression Analysis

Instance based

Neural networks (NN) 1960

Multilayer Perceptrons (MLP) 1985

Restricted Boltzmann Machine (RBM) 1986

Support Vector Machine (SVM) 1995



Hinton presents the

Deep Belief Network (DBN)

**New interests in deep learning
and RBM**

State of the art MNIST

2005

Deep Recurrent Neural Network (RNN) 2009

Convolutional DBN 2010

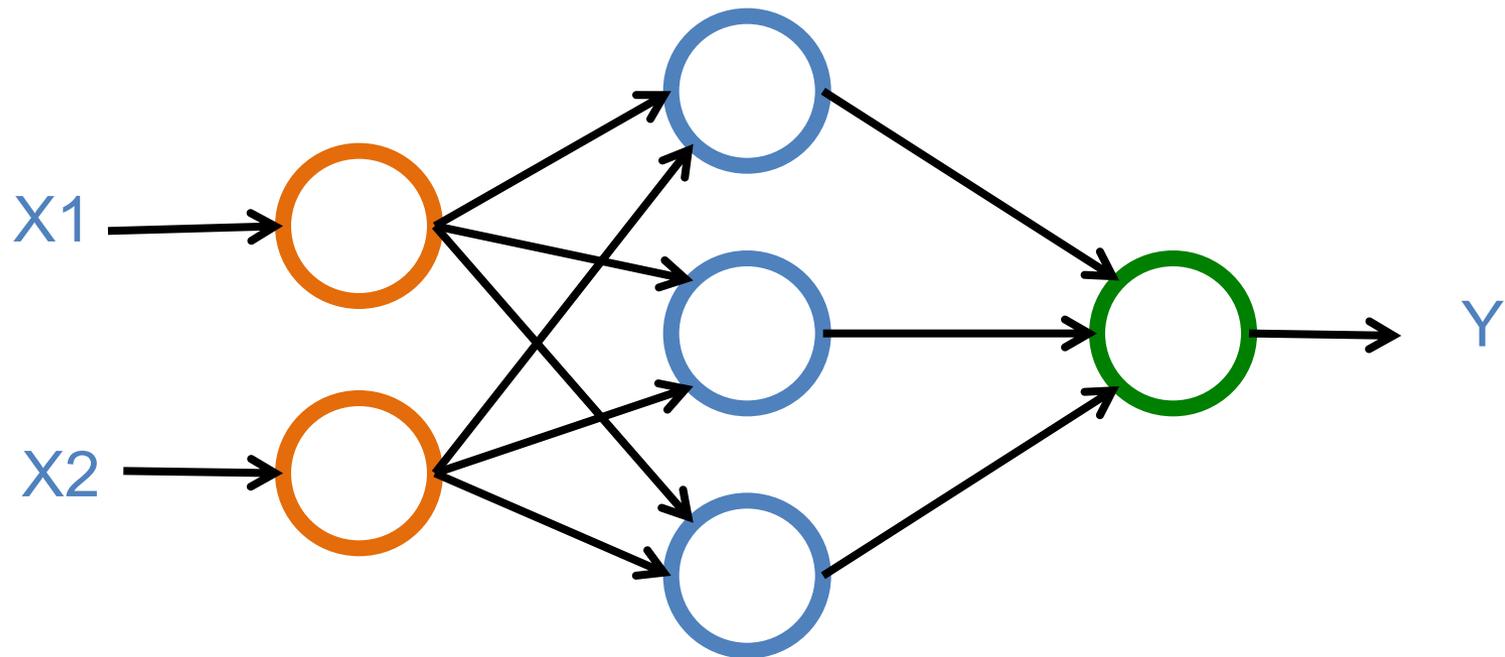
Max-Pooling CDBN 2011

Neural Networks

Input Layer
(X)

Hidden Layer
(H)

Output Layer
(Y)



Deep Learning

Geoffrey Hinton

Yann LeCun

Yoshua Bengio

Andrew Y. Ng



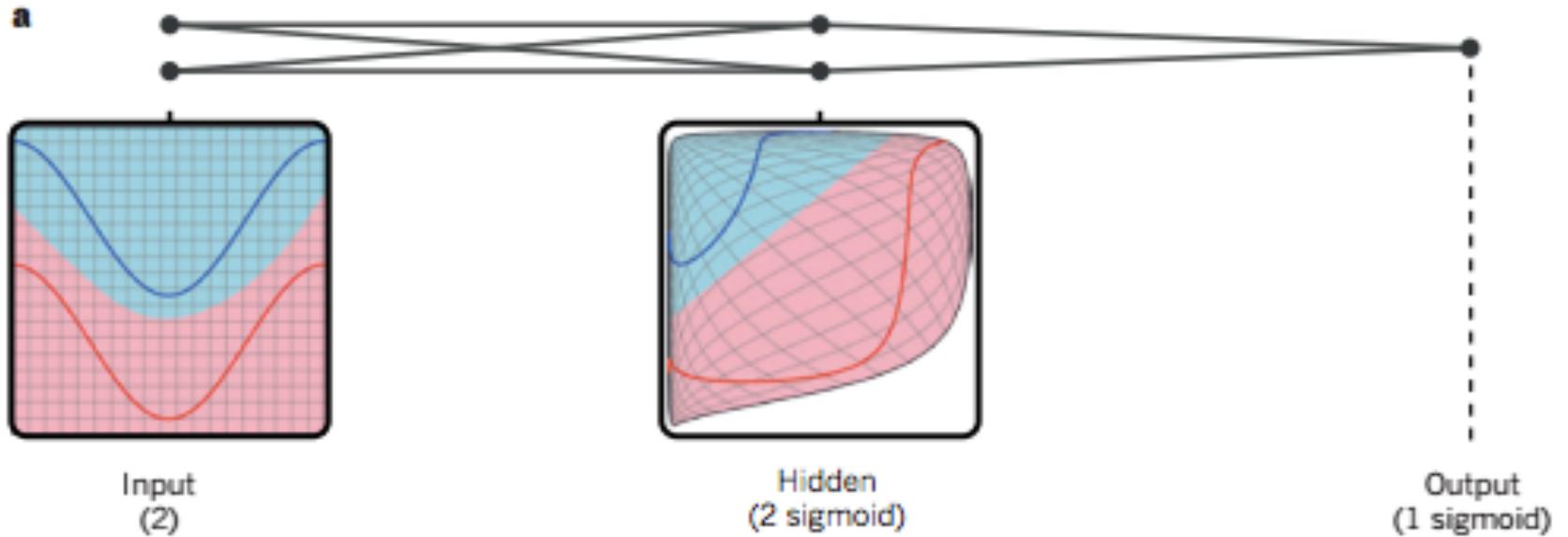
Geoffrey Hinton
Google
University of Toronto

**LeCun, Yann,
Yoshua Bengio,
and Geoffrey Hinton.**

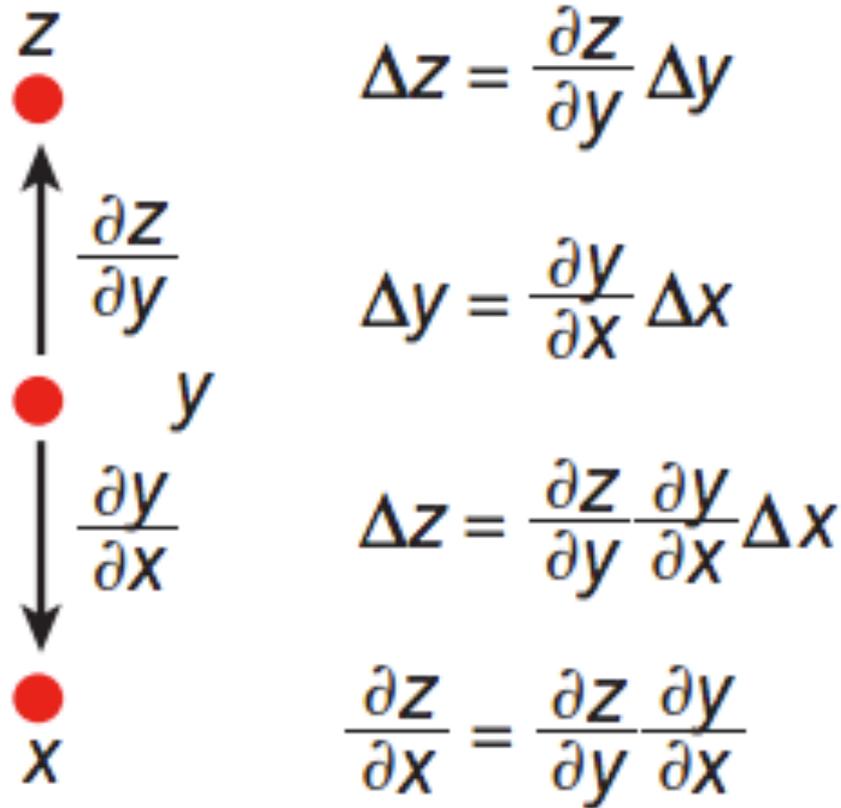
"Deep learning."

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

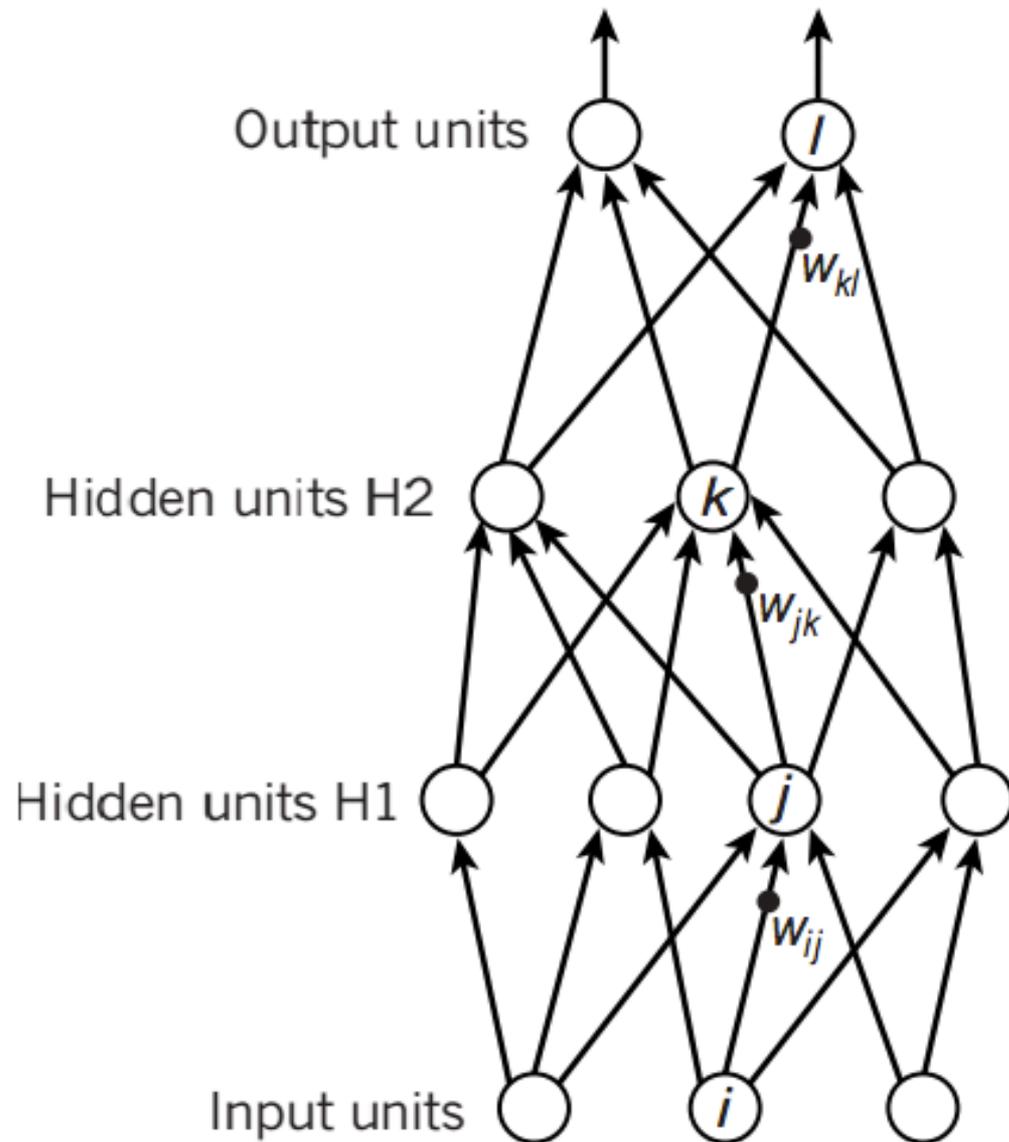
Deep Learning



Deep Learning



Deep Learning



$$y_l = f(z_l)$$

$$z_l = \sum_{k \in H2} w_{kl} y_k$$

$$y_k = f(z_k)$$

$$z_k = \sum_{j \in H1} w_{jk} y_j$$

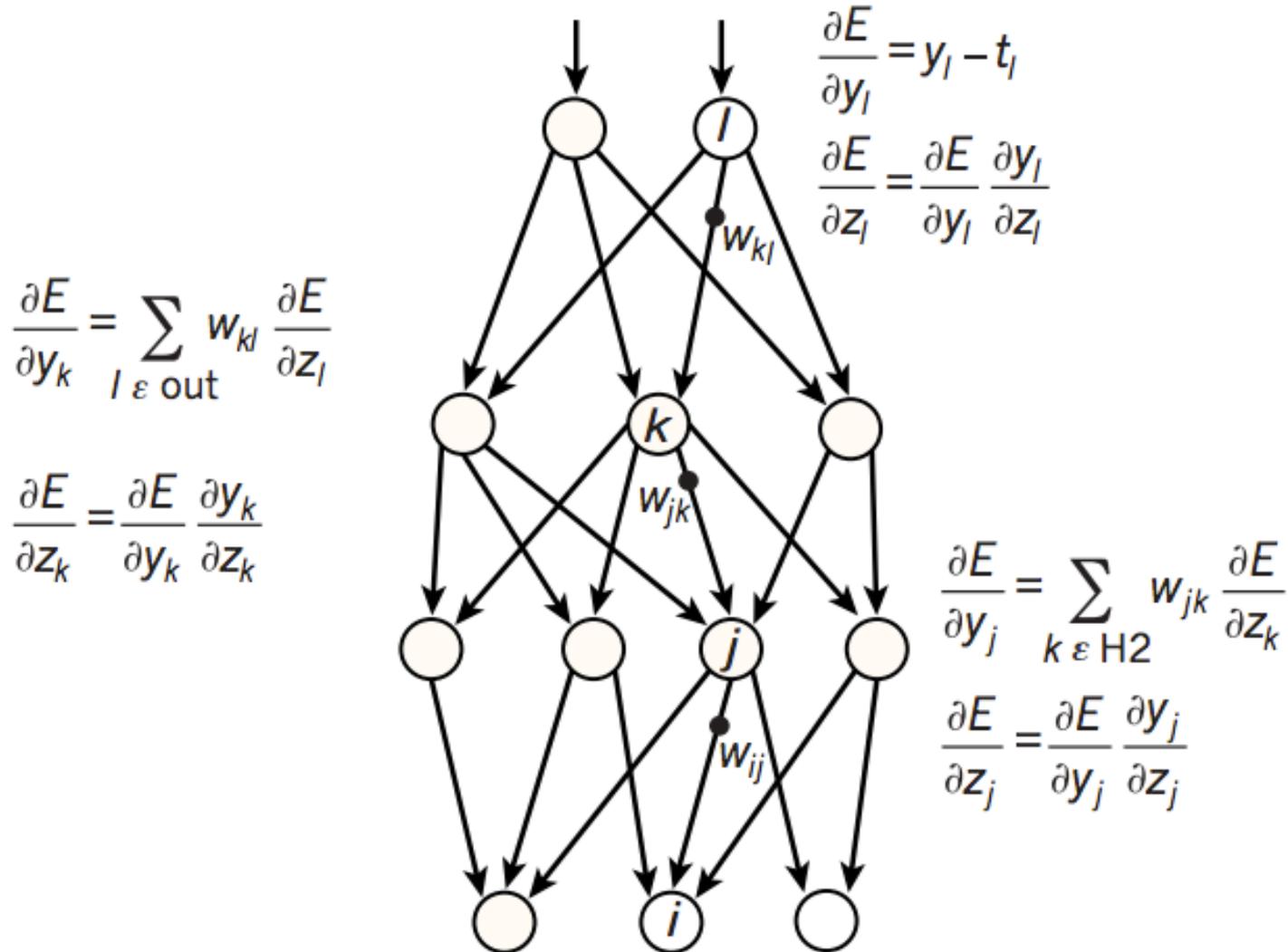
$$y_j = f(z_j)$$

$$z_j = \sum_{i \in \text{Input}} w_{ij} x_i$$

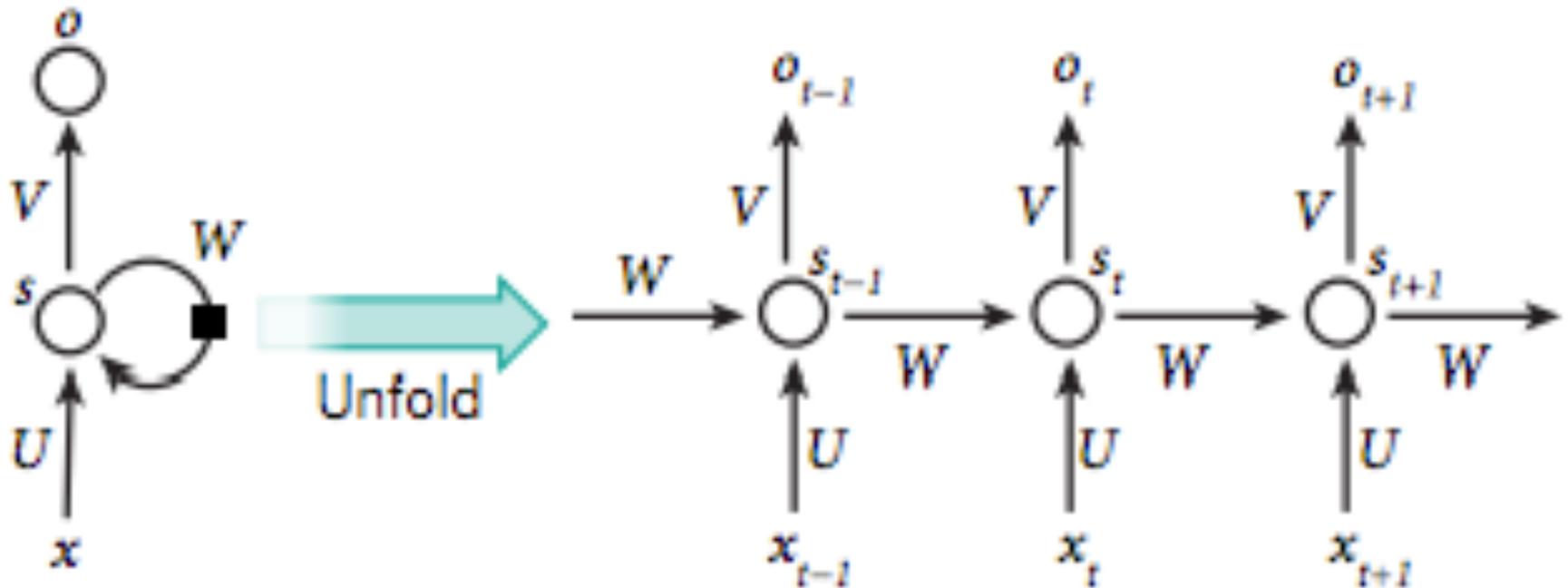
Deep Learning

d

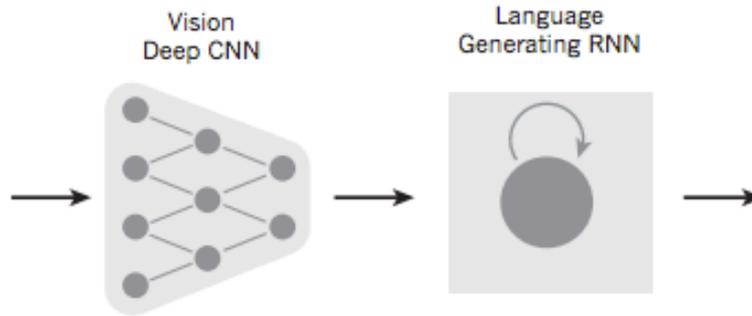
Compare outputs with correct answer to get error derivatives



Recurrent Neural Network (RNN)



From image to text



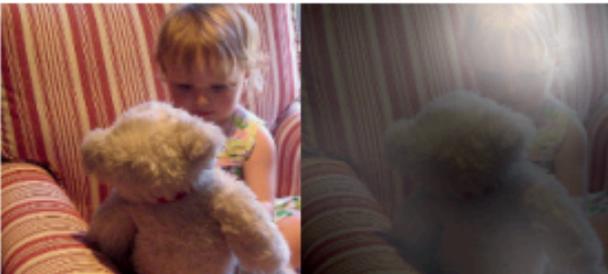
A woman is throwing a **frisbee** in a park.



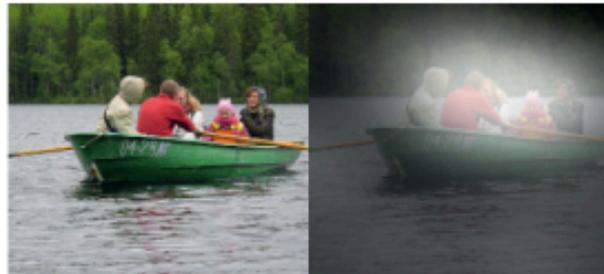
A **dog** is standing on a hardwood floor.



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.

From image to text

Image: deep convolution neural network (CNN)

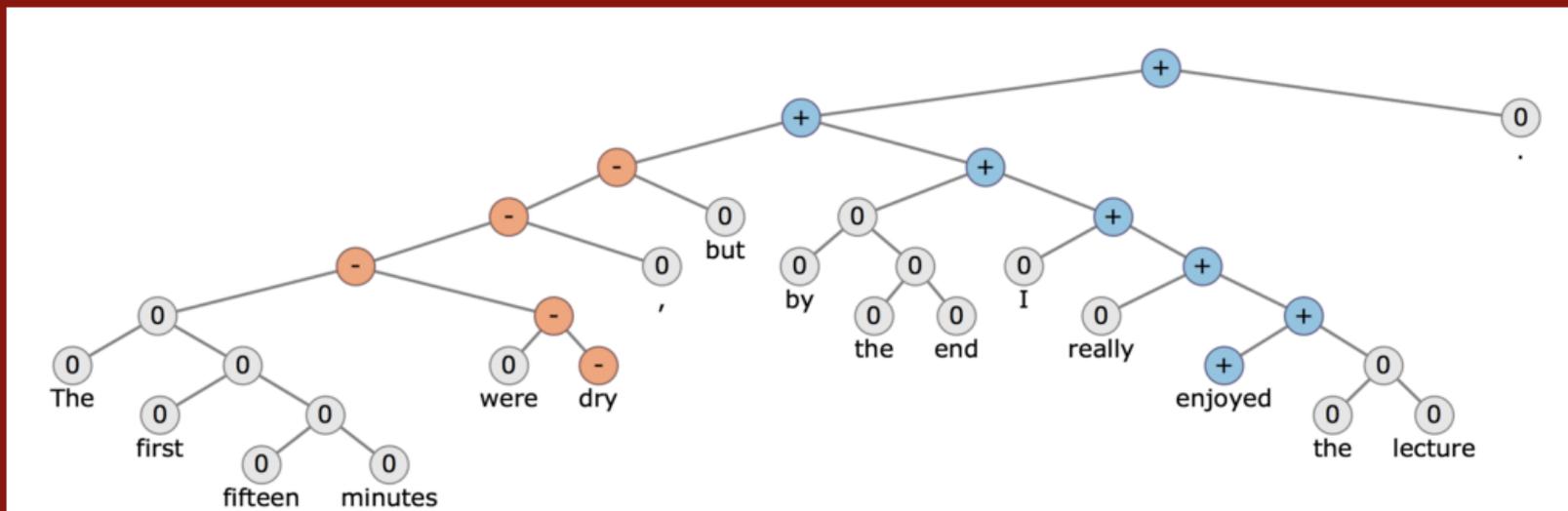
Text: recurrent neural network (RNN)



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

CS224d: Deep Learning for Natural Language Processing

CS224d: Deep Learning for Natural Language Processing

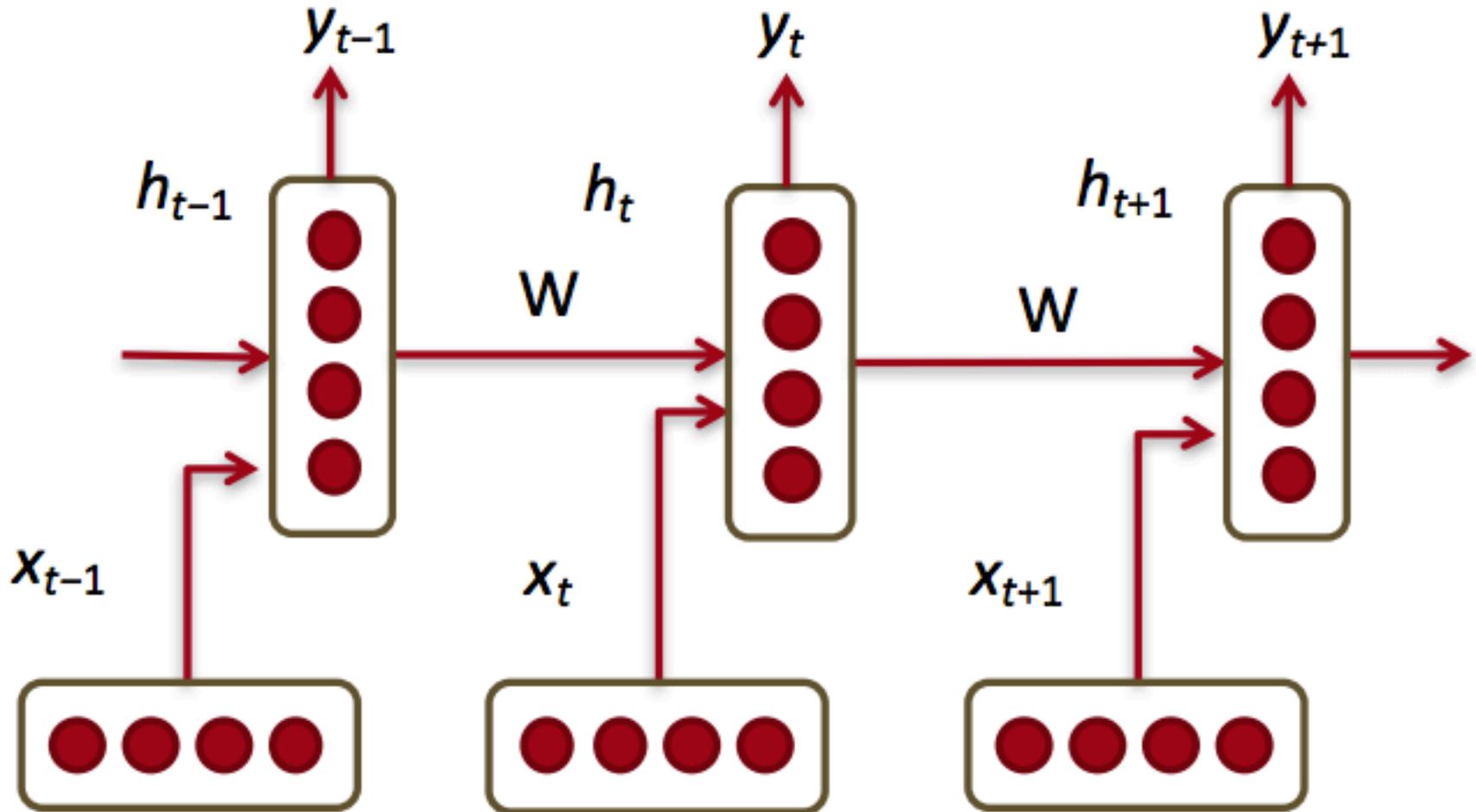


Course Description

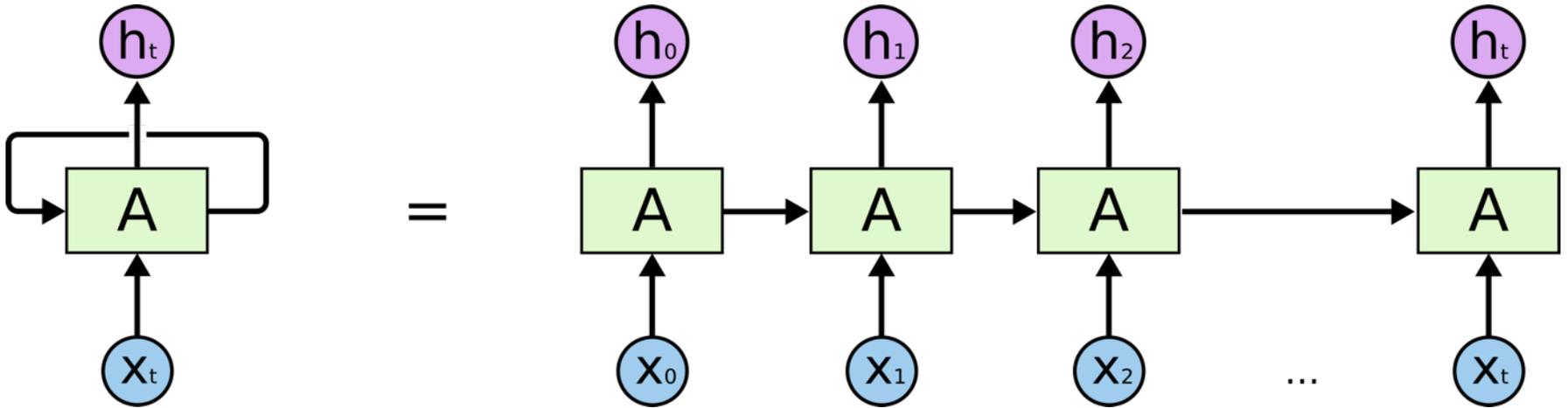
Natural language processing (NLP) is one of the most important technologies of the information age. Understanding complex language utterances is also a crucial part of artificial intelligence. Applications of NLP are everywhere because people communicate most everything in language: web search, advertisement, 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/>

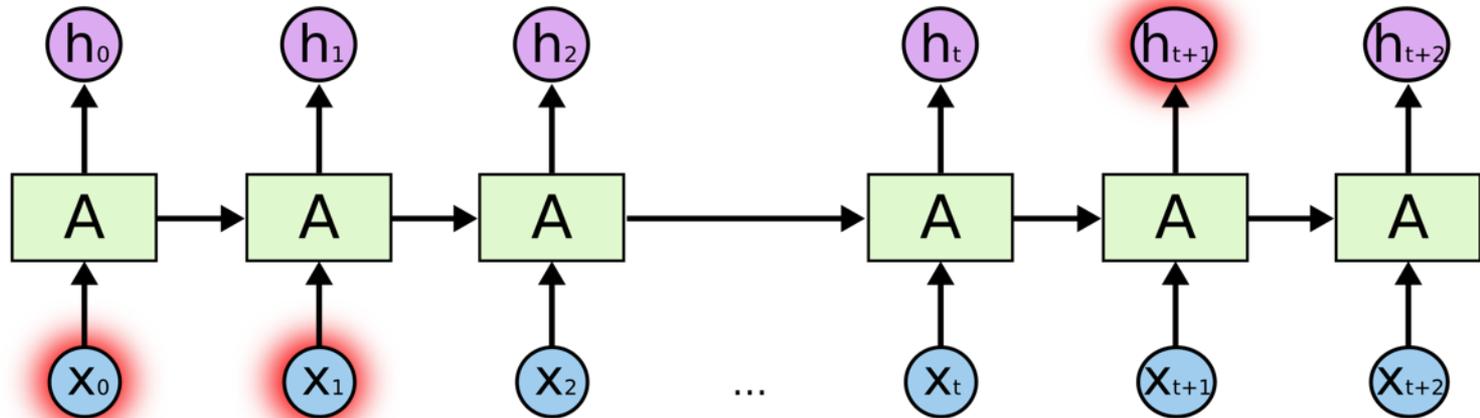
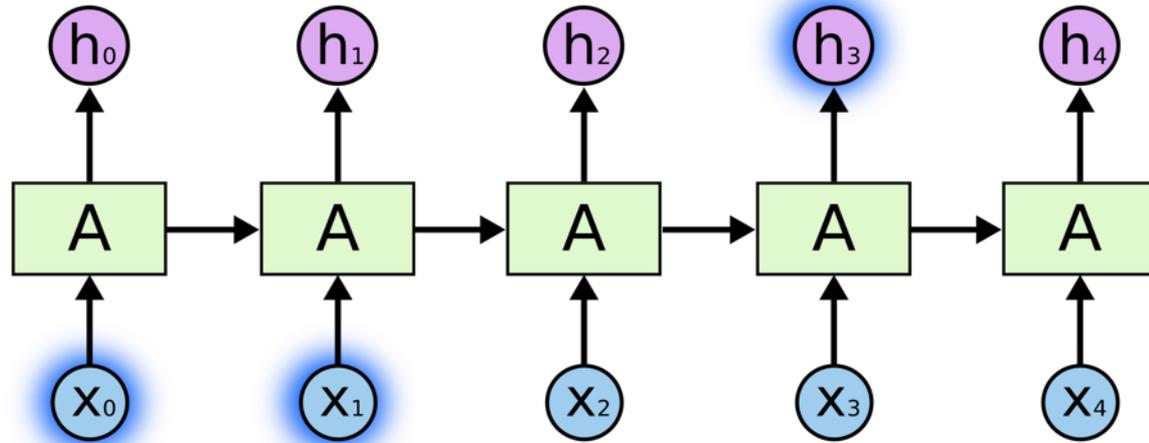
Recurrent Neural Networks (RNNs)



RNN

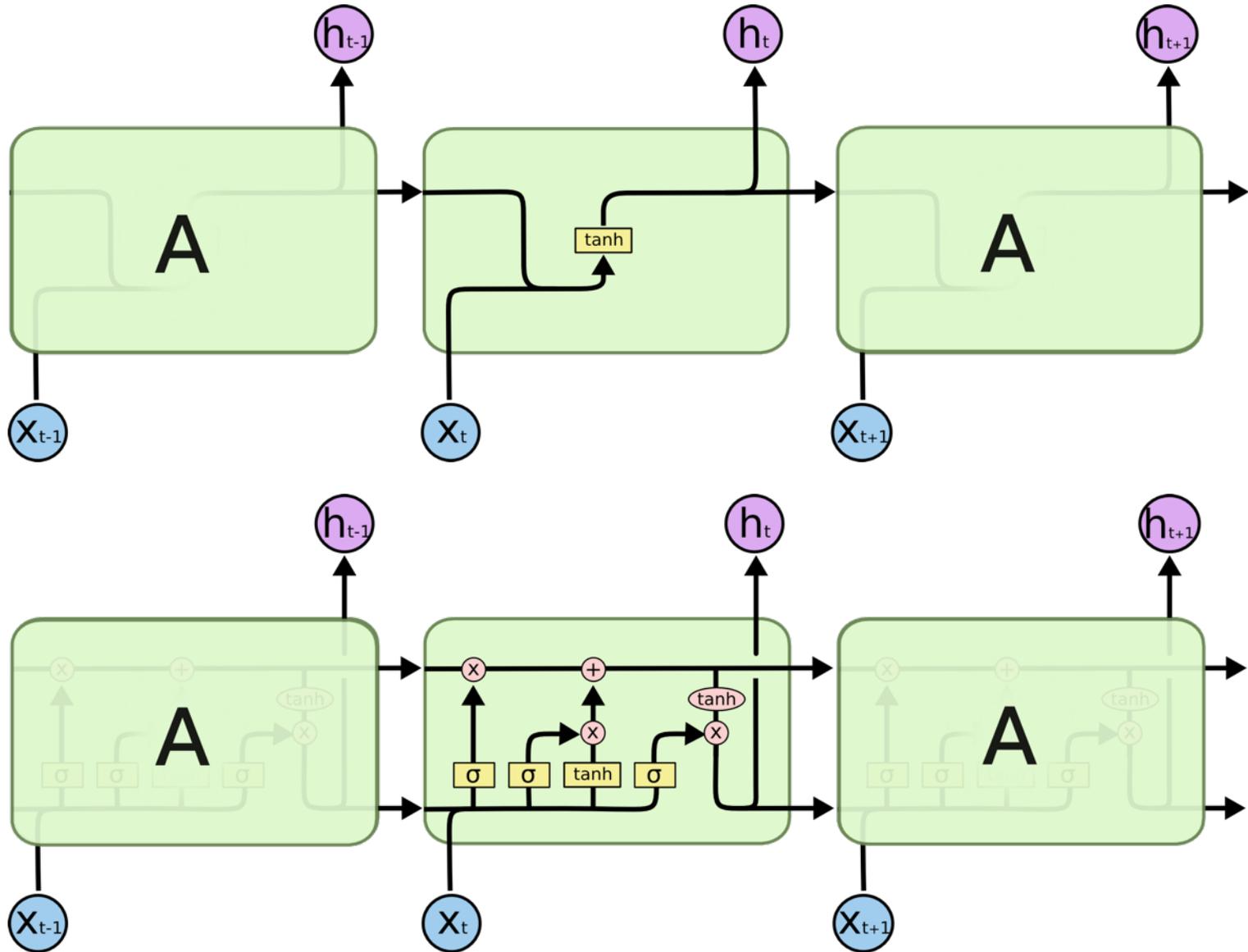


RNN long-term dependencies

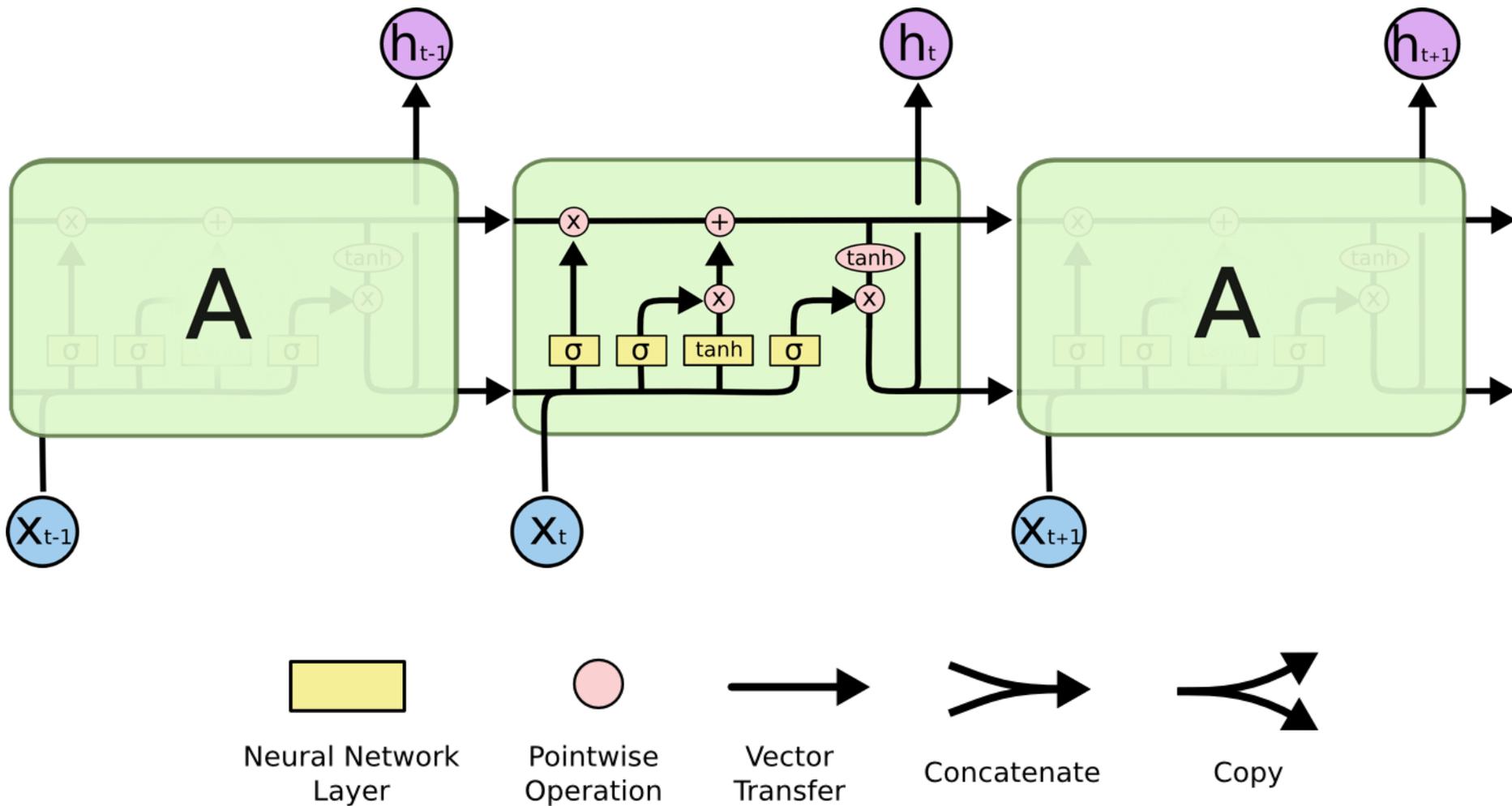


I grew up in France... I speak fluent French.

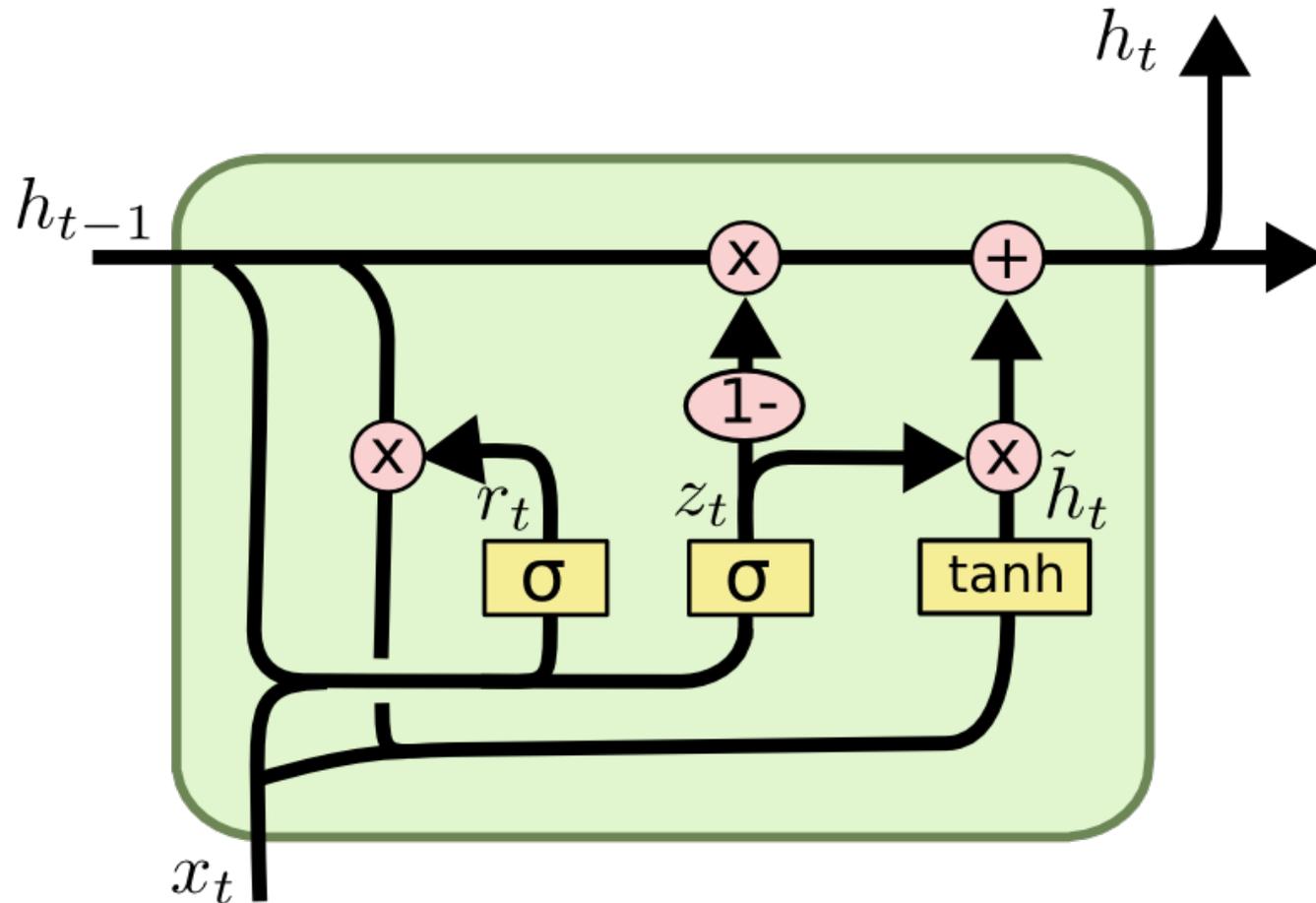
RNN LSTM



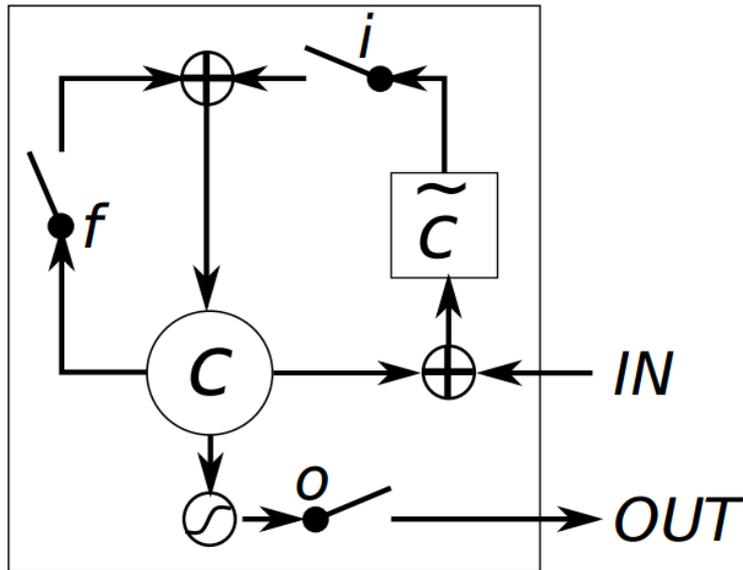
Long Short Term Memory (LSTM)



Gated Recurrent Unit (GRU)

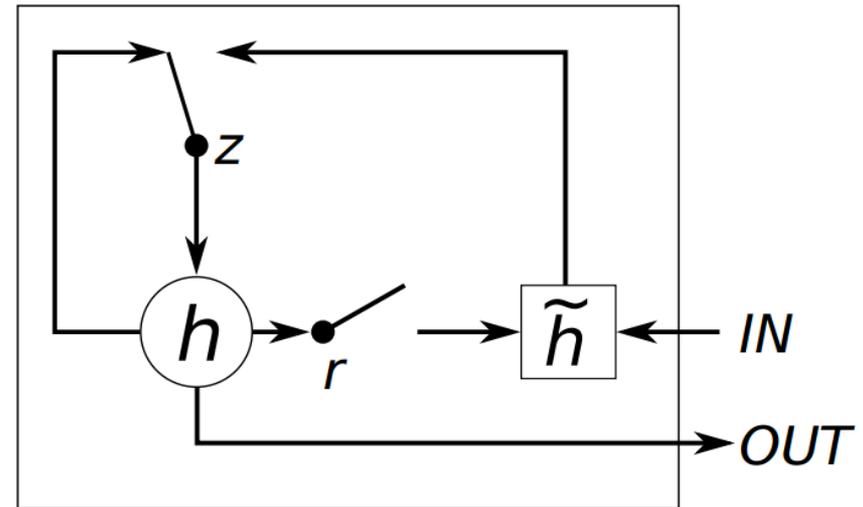


LSTM vs GRU



LSTM

i , f and o are the **input**, **forget** and **output** gates, respectively.
 c and \tilde{c} denote the memory cell and the new memory cell content.

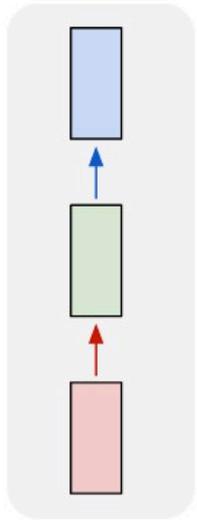


GRU

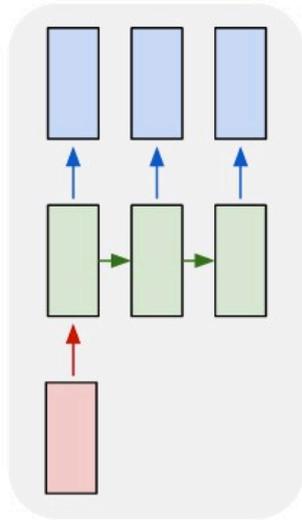
r and z are the **reset** and **update** gates, and h and \tilde{h} are the activation and the candidate activation.

LSTM Recurrent Neural Network

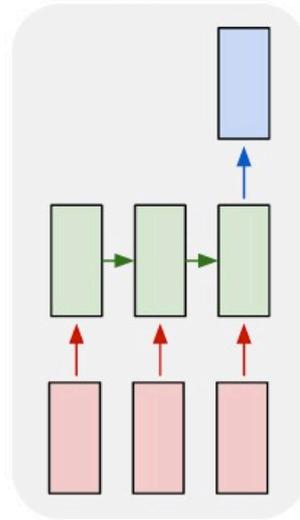
one to one



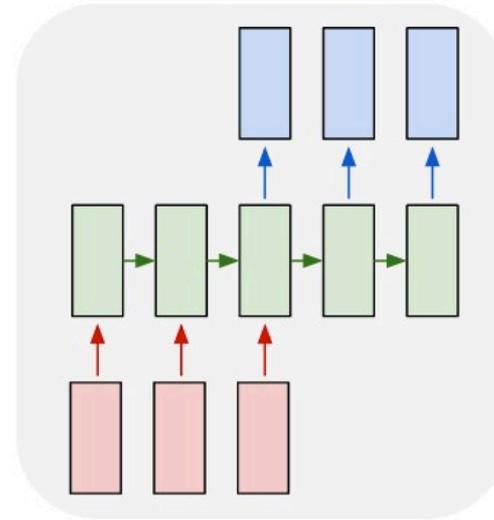
one to many



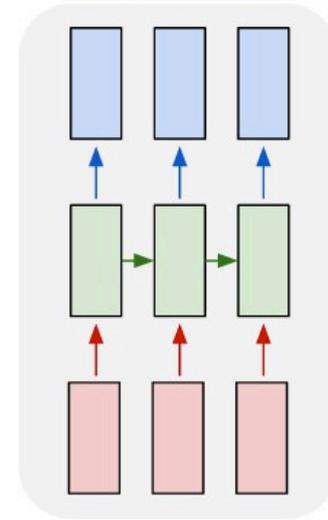
many to one



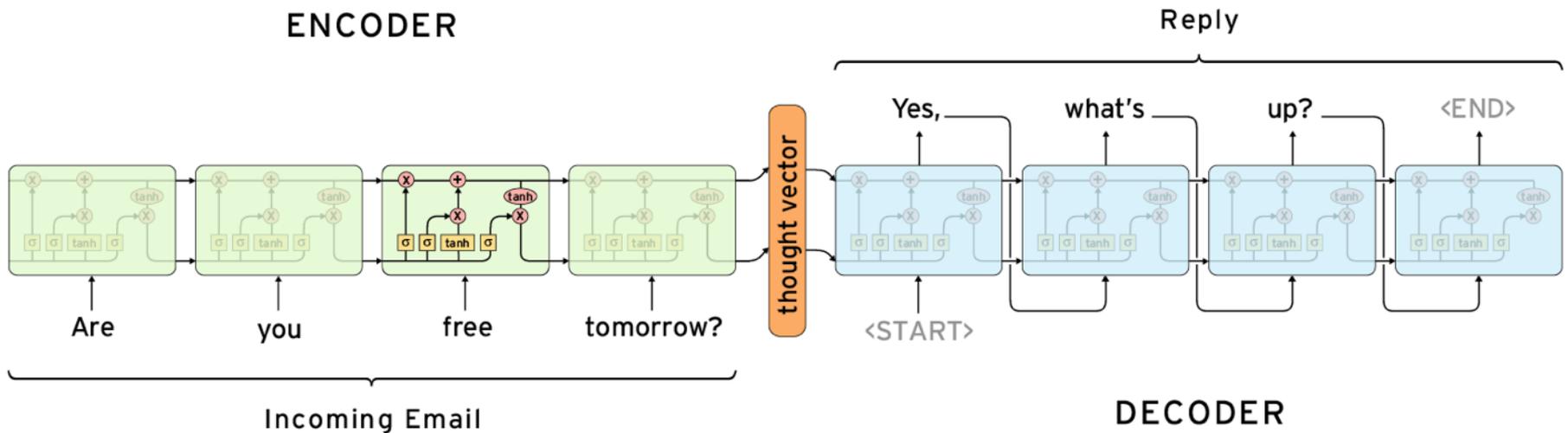
many to many



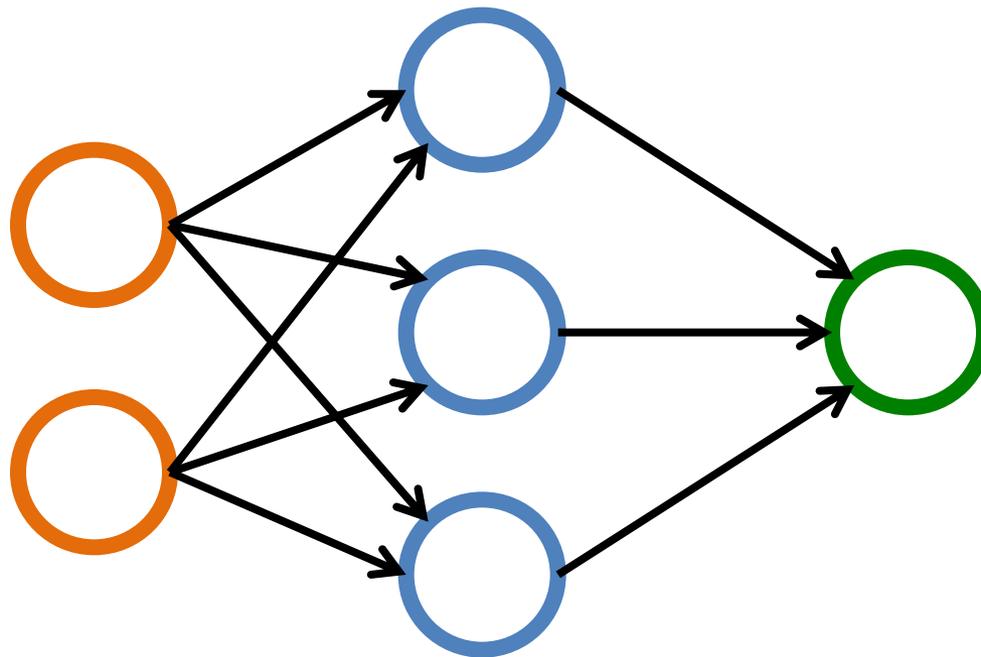
many to many



The Sequence to Sequence model (seq2seq)



Neural Networks

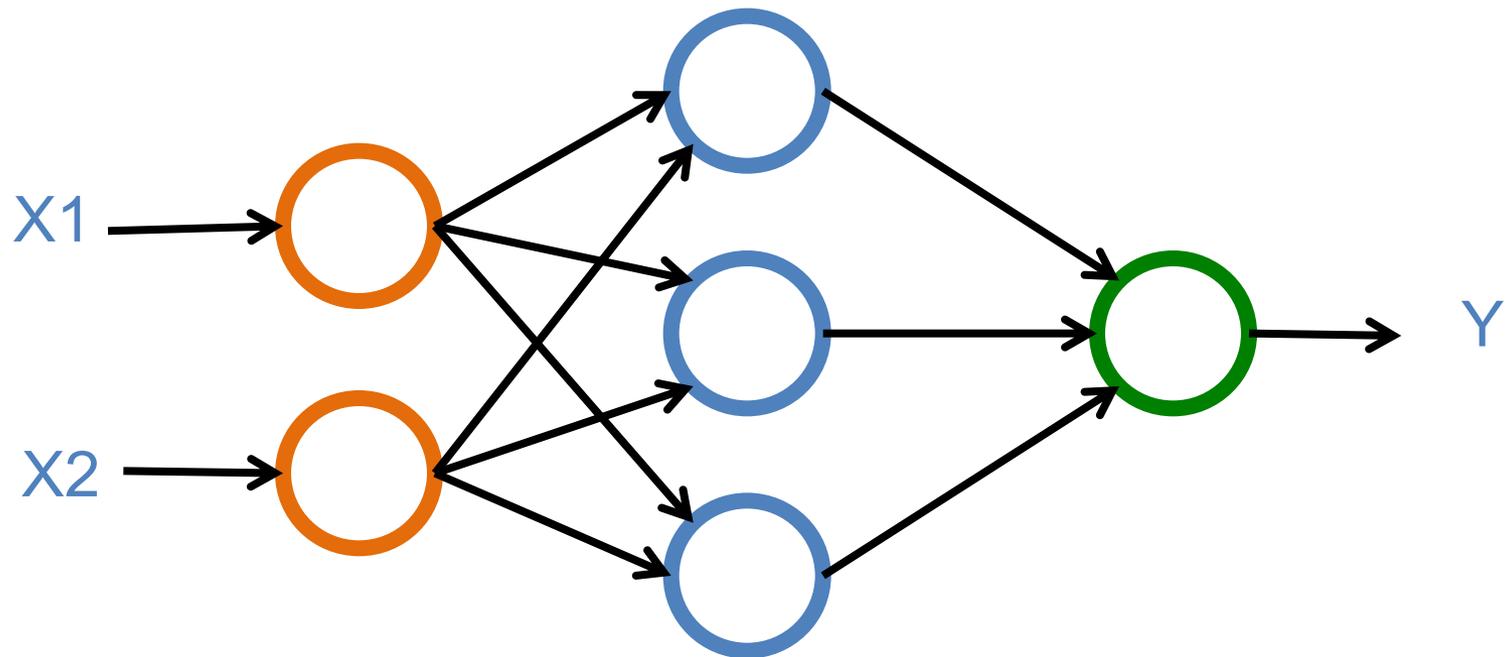


Neural Networks

Input Layer
(X)

Hidden Layer
(H)

Output Layer
(Y)



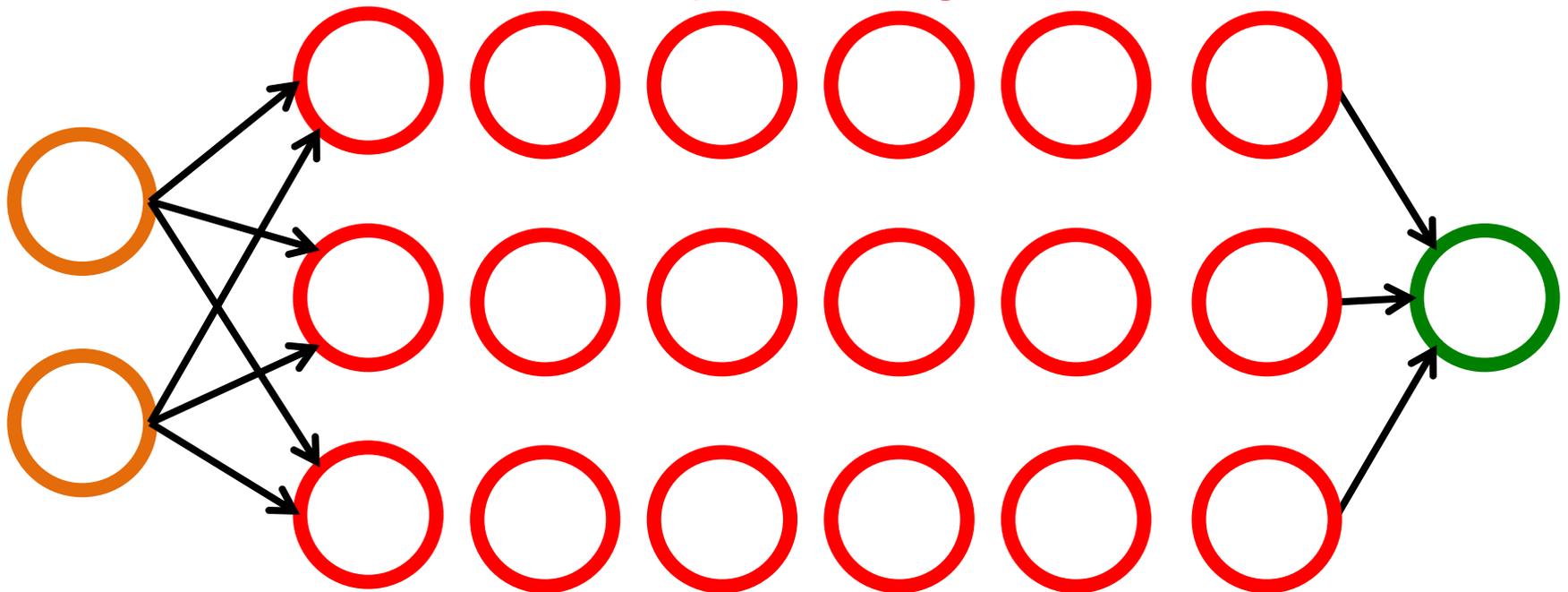
Neural Networks

Input Layer
(X)

Hidden Layers
(H)

Output Layer
(Y)

Deep Neural Networks
Deep Learning

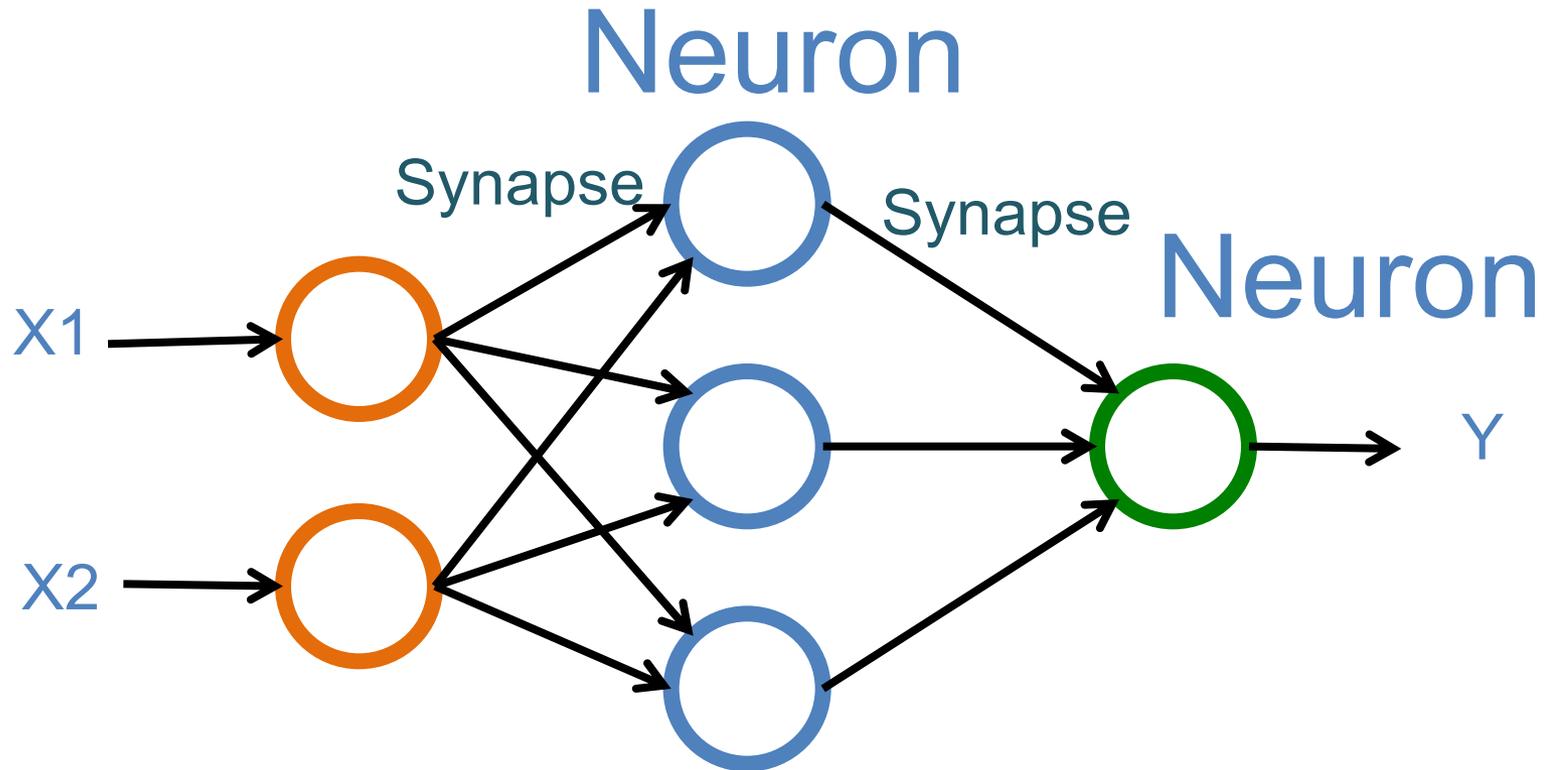


Neural Networks

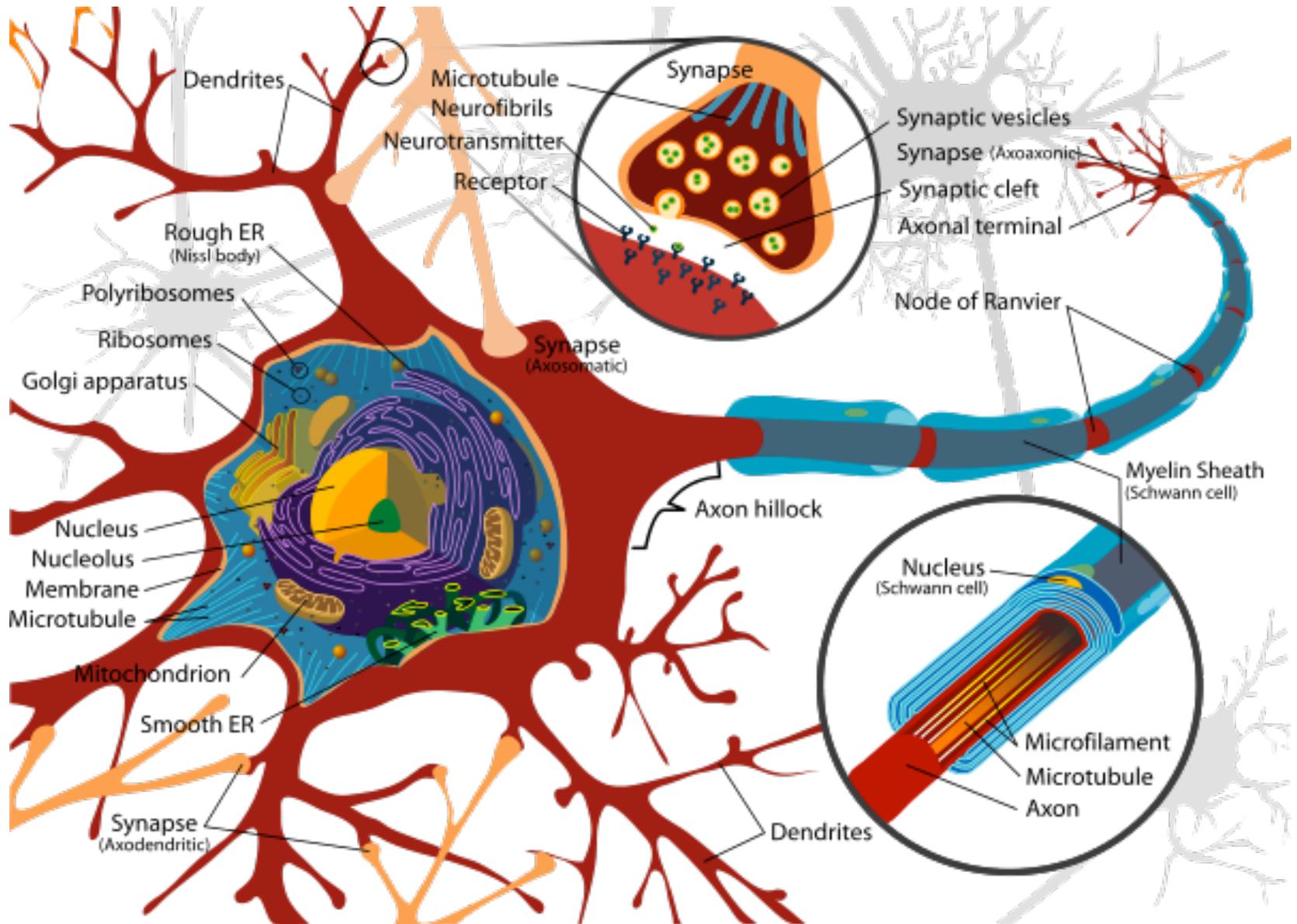
Input Layer
(X)

Hidden Layer
(H)

Output Layer
(Y)

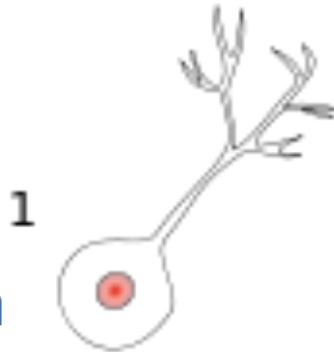


Neuron and Synapse



Neurons

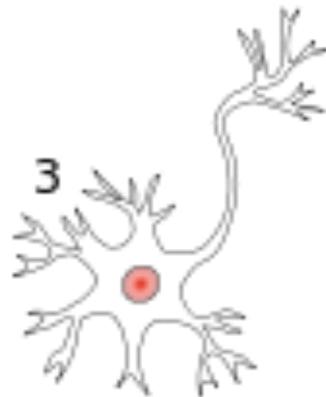
1 Unipolar neuron



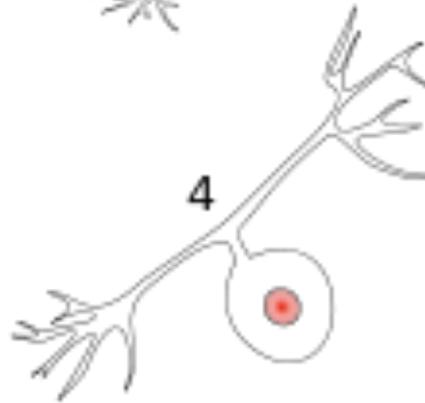
2 Bipolar neuron



3 Multipolar neuron



4 Pseudounipolar neuron

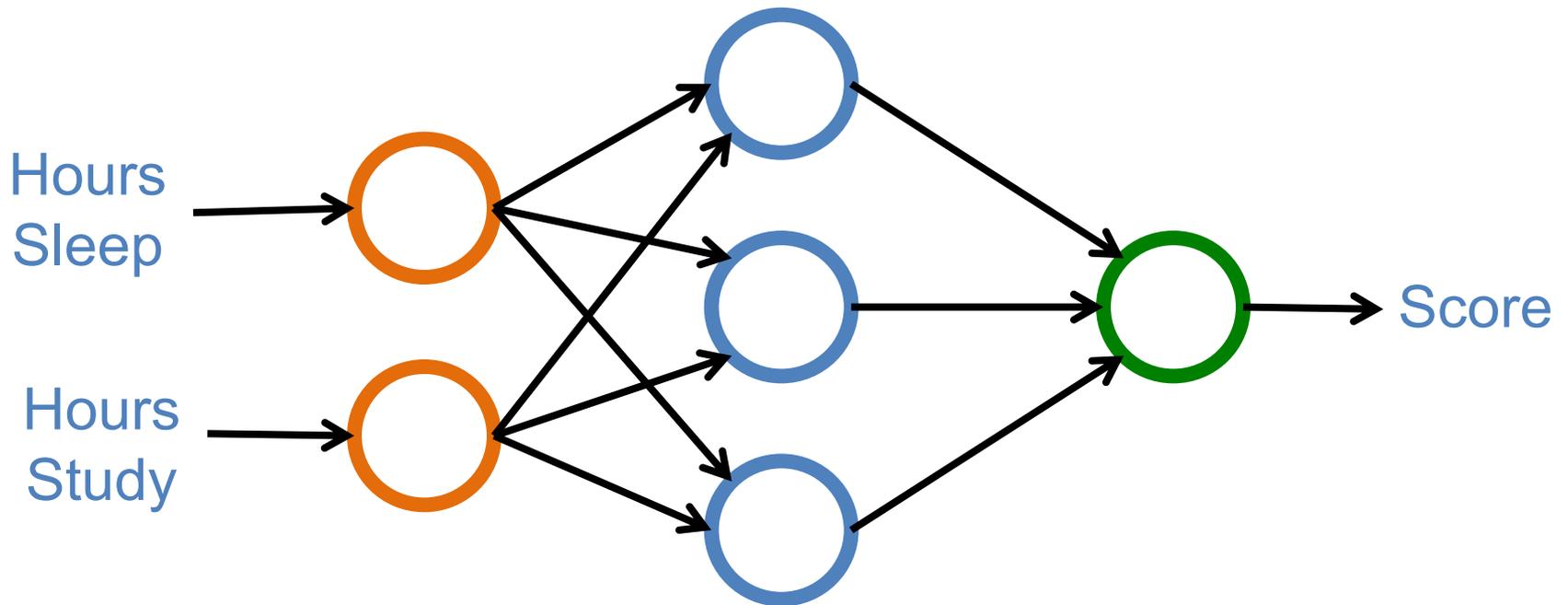


Neural Networks

Input Layer
(X)

Hidden Layer
(H)

Output Layer
(Y)

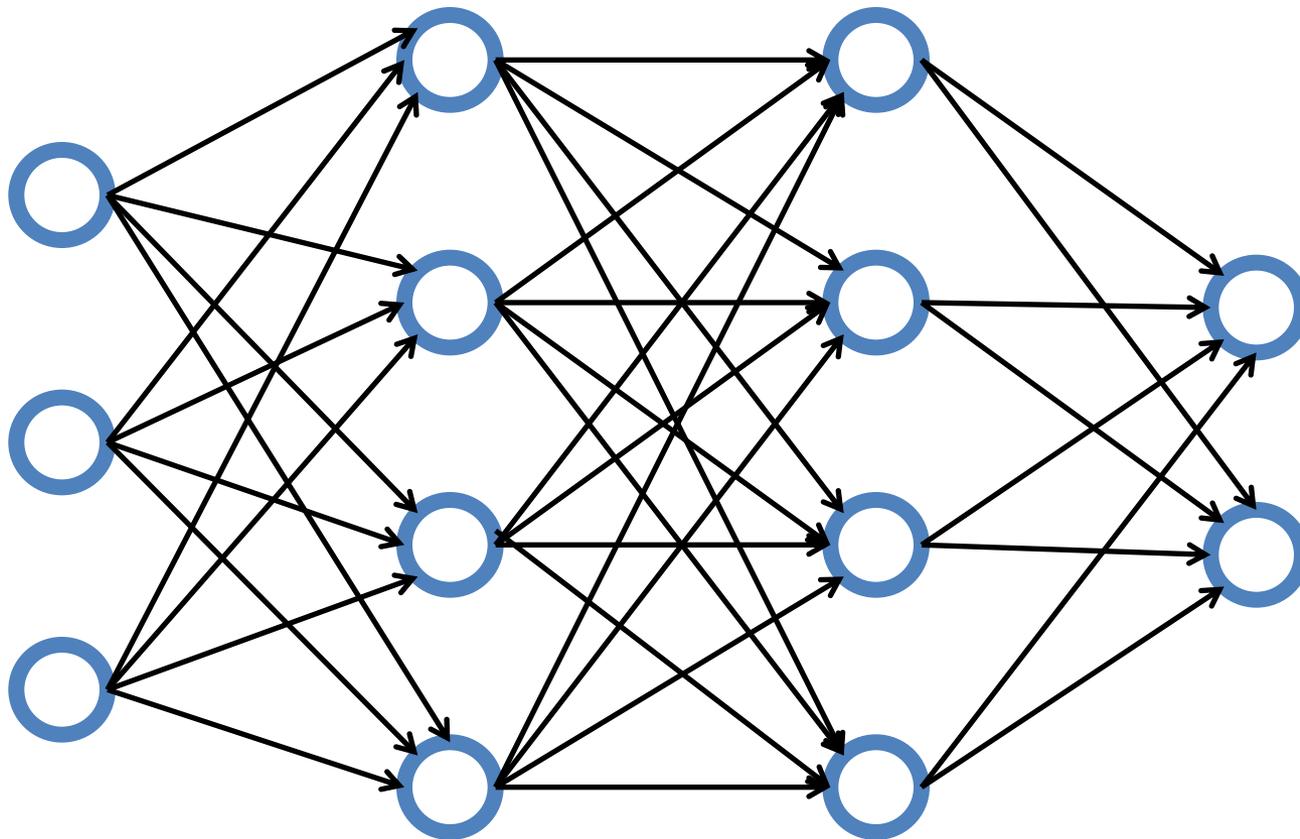


Neural Networks

Input Layer
(X)

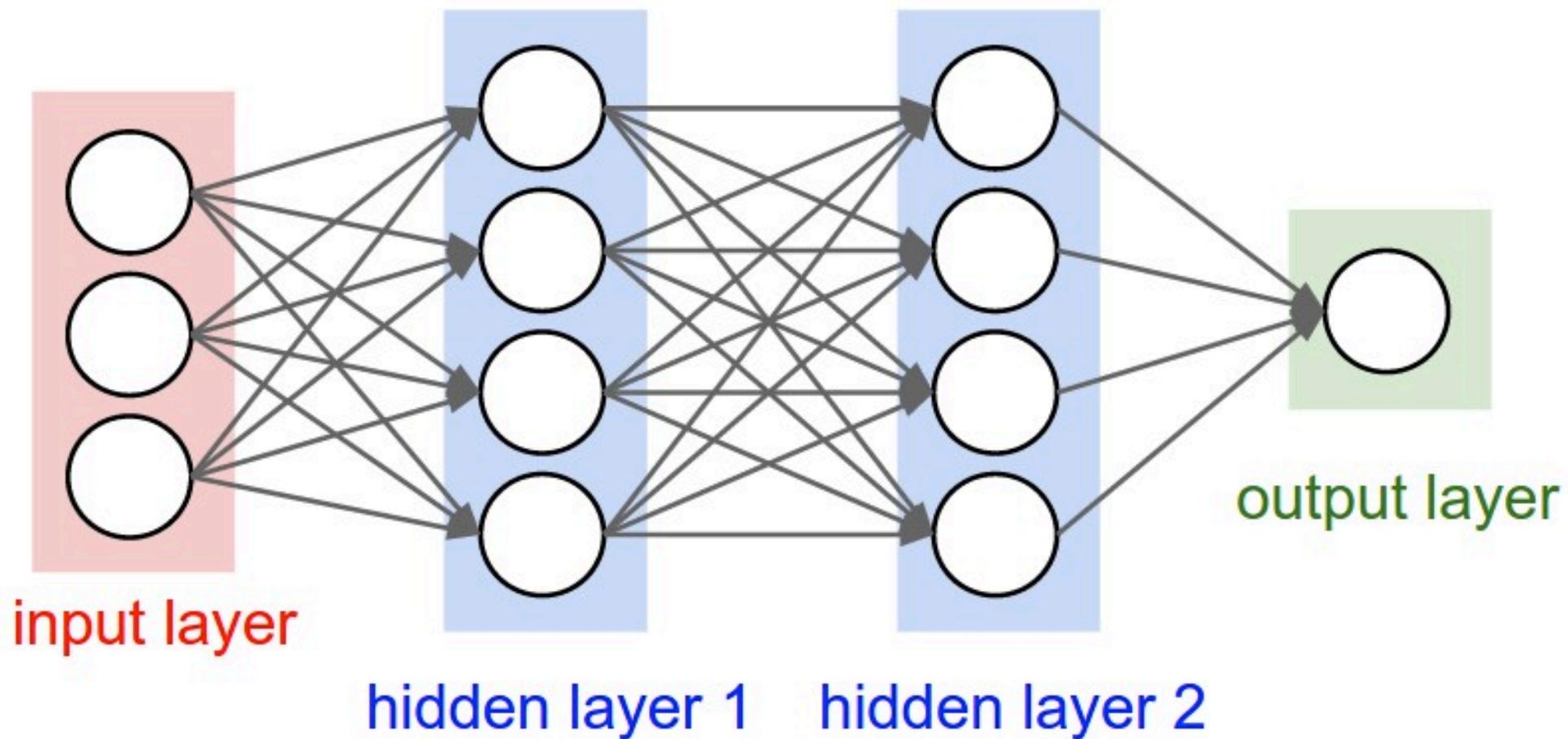
Hidden Layer
(H)

Output Layer
(Y)

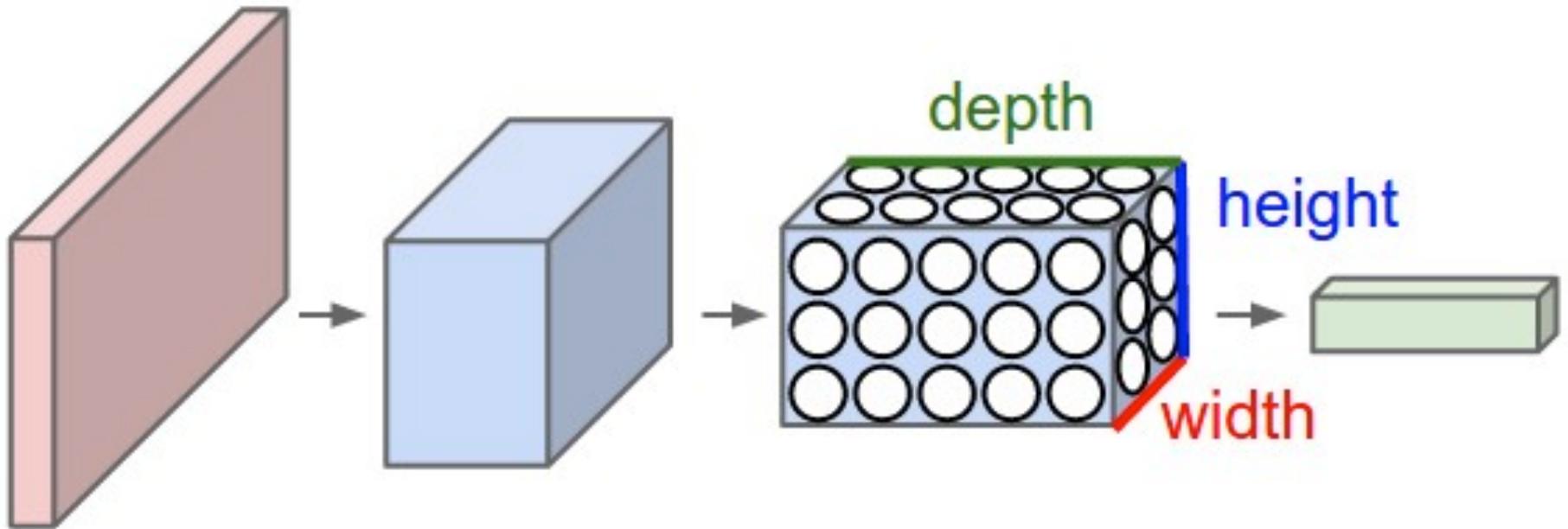


Convolutional Neural Networks (CNNs / ConvNets)

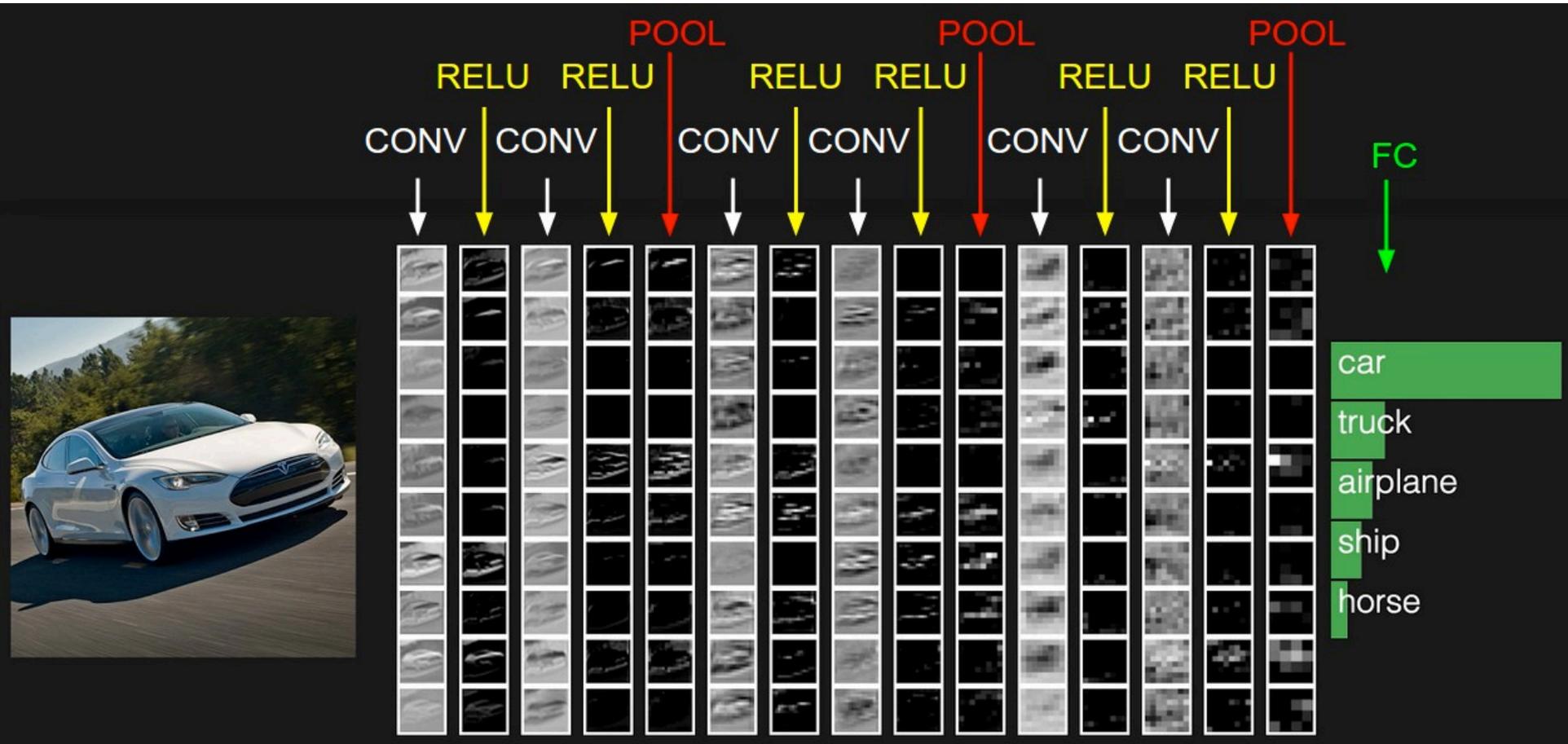
A regular 3-layer Neural Network



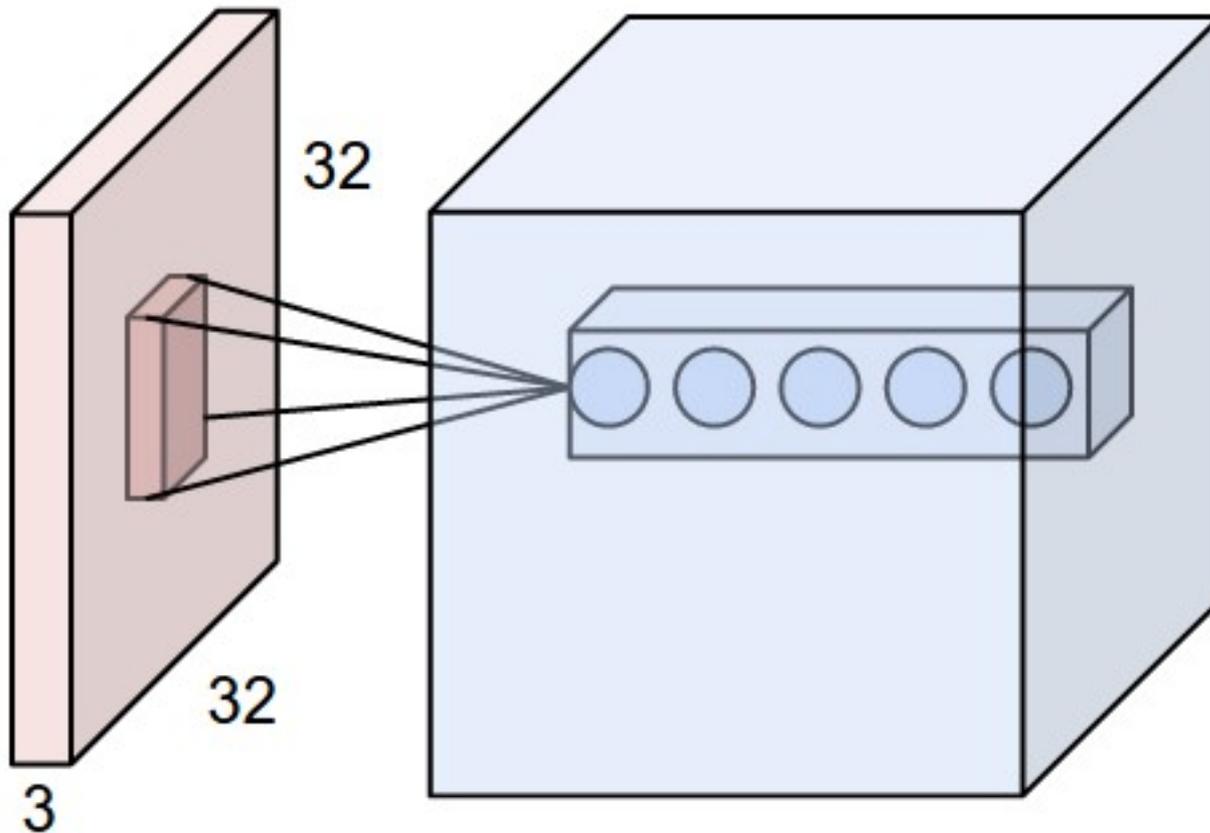
A ConvNet arranges its neurons in three dimensions (width, height, depth)



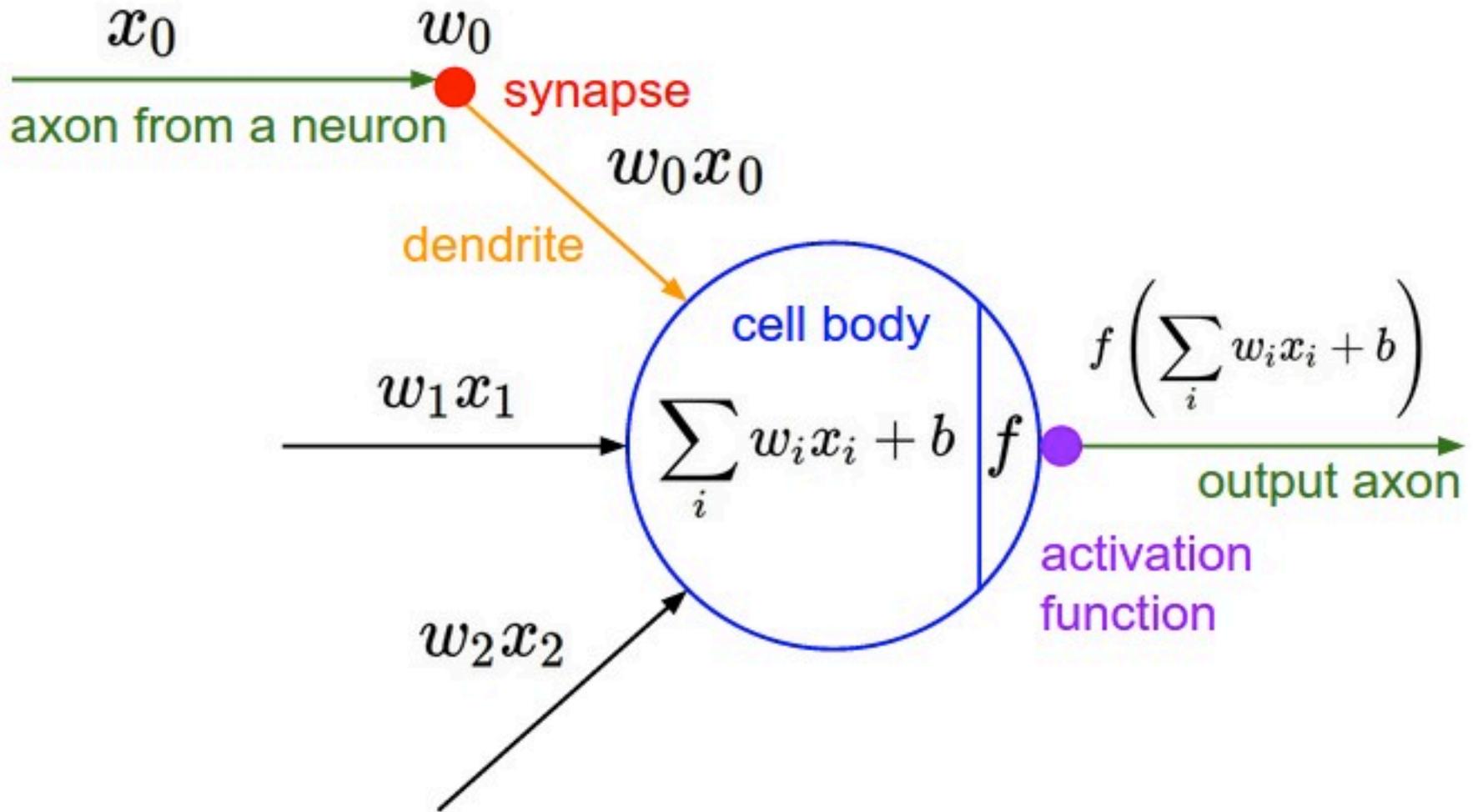
The activations of an example ConvNet architecture.



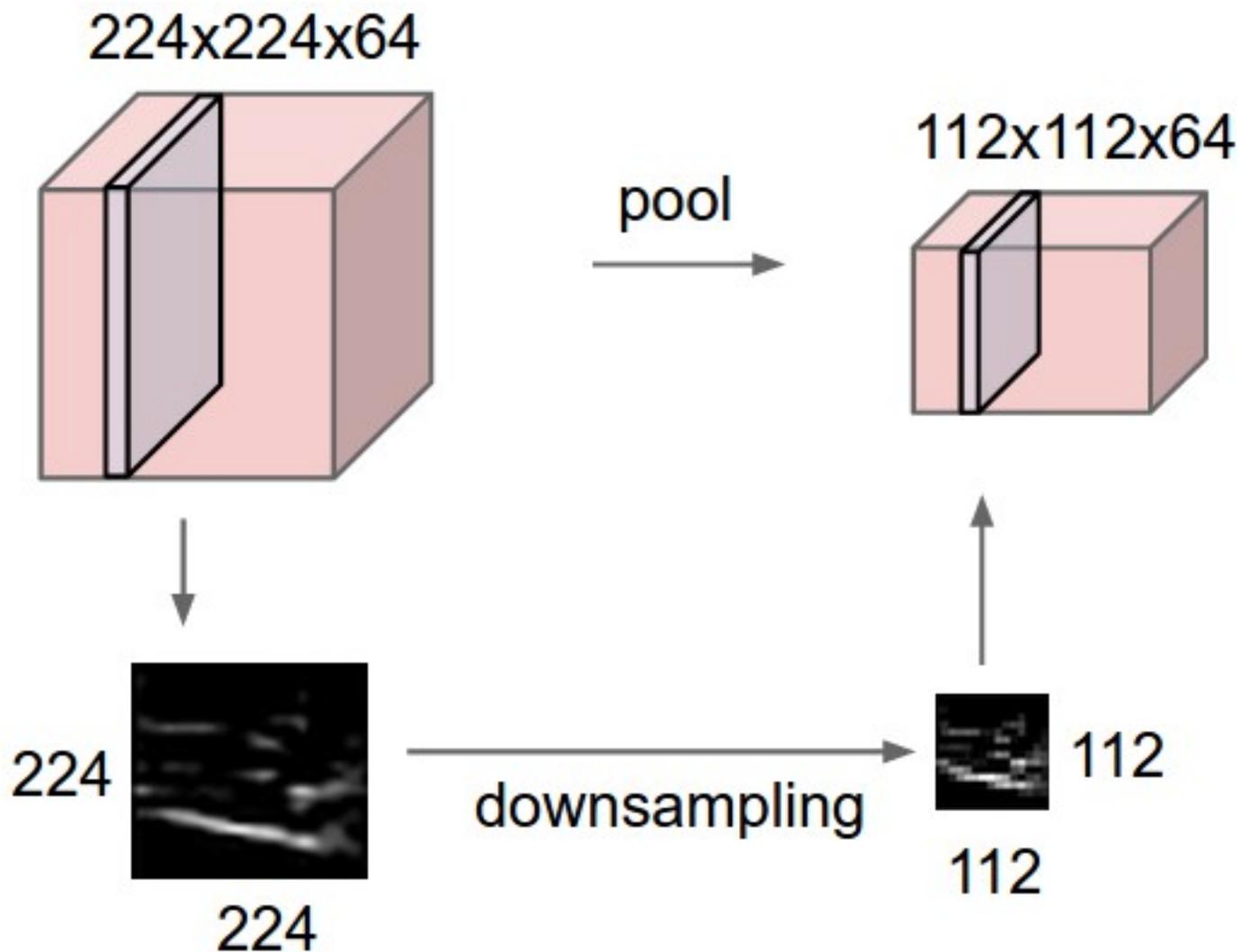
ConvNets



ConvNets



ConvNets



ConvNets

max pooling

Single depth slice

x

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

y

max pool with 2x2 filters
and stride 2



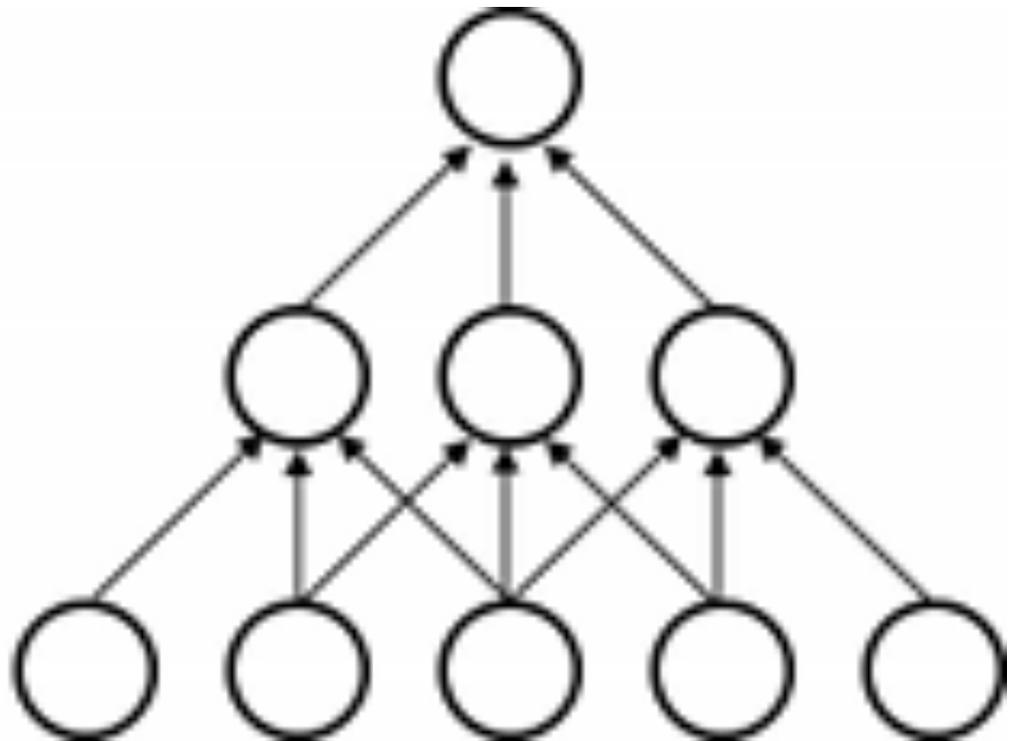
6	8
3	4

Convolutional Neural Networks (CNN) (LeNet) Sparse Connectivity

layer $m+1$

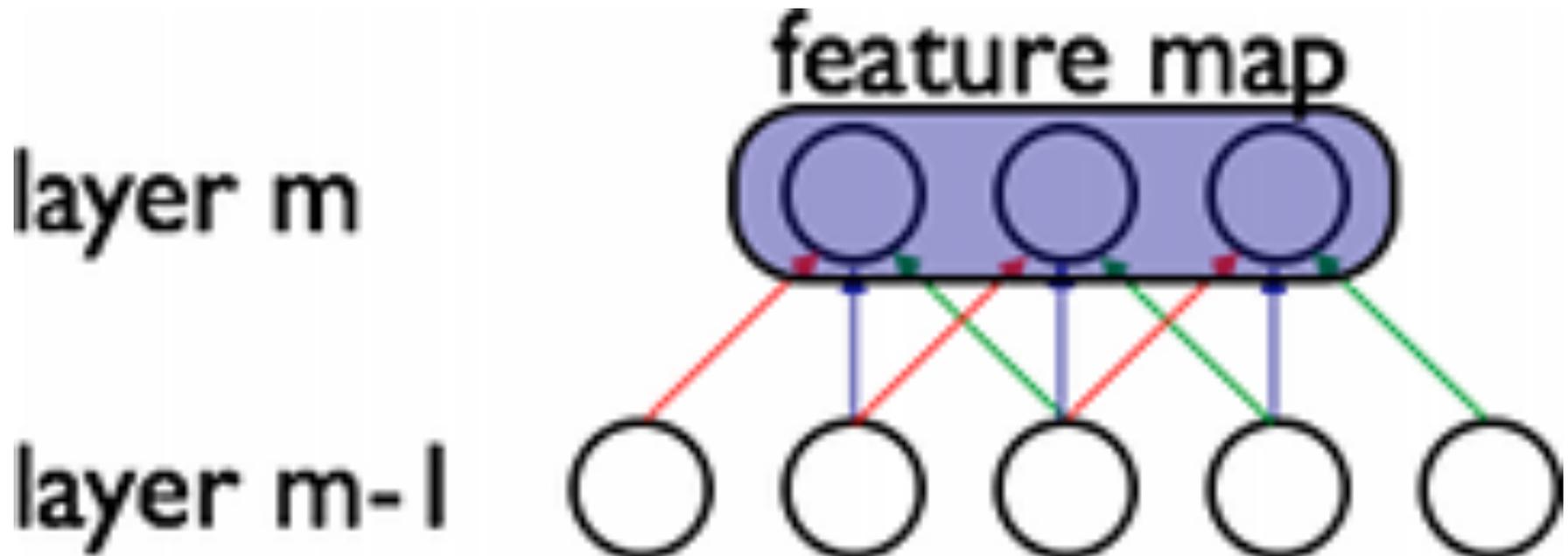
layer m

layer $m-1$



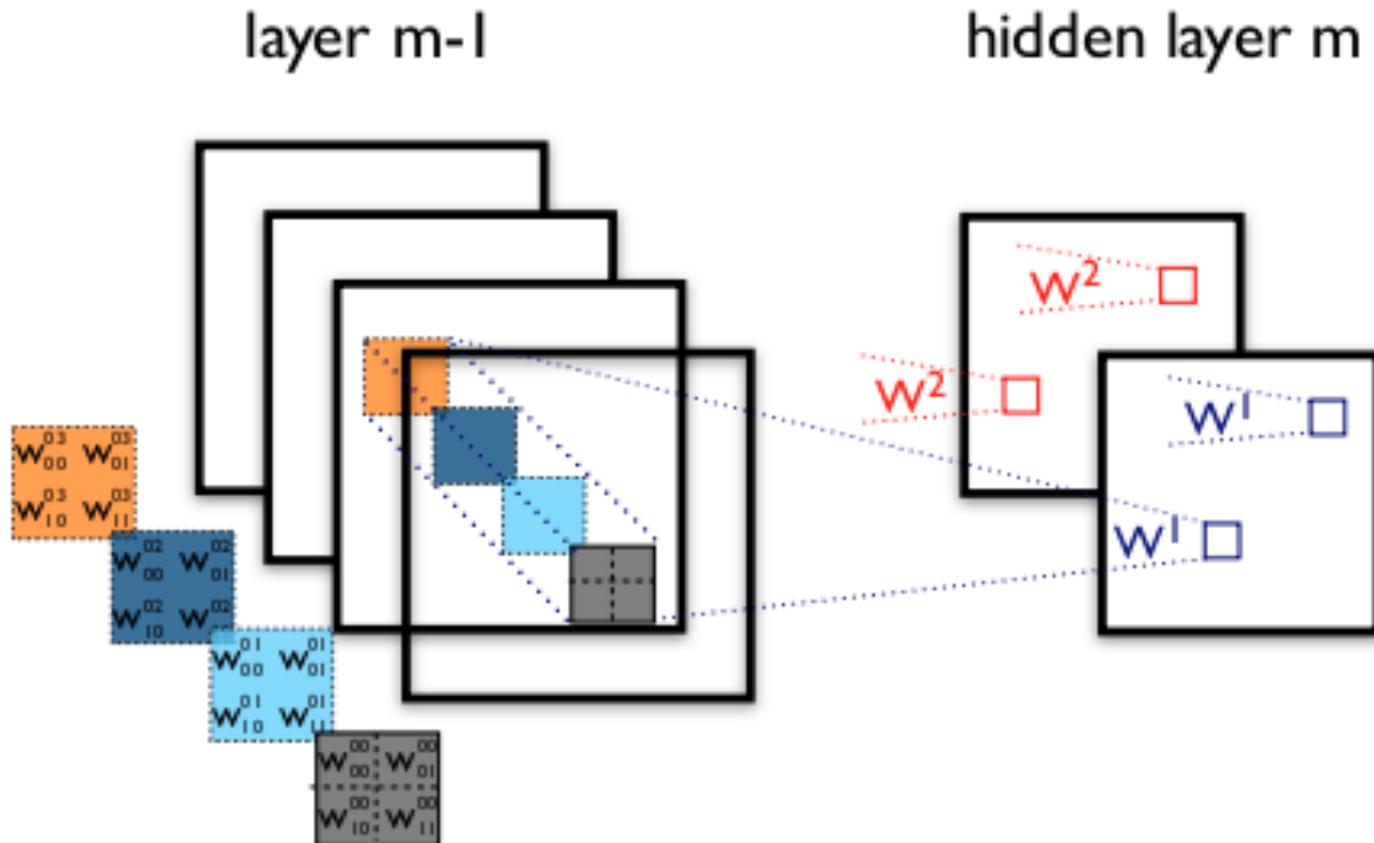
Convolutional Neural Networks (CNN) (LeNet)

Shared Weights



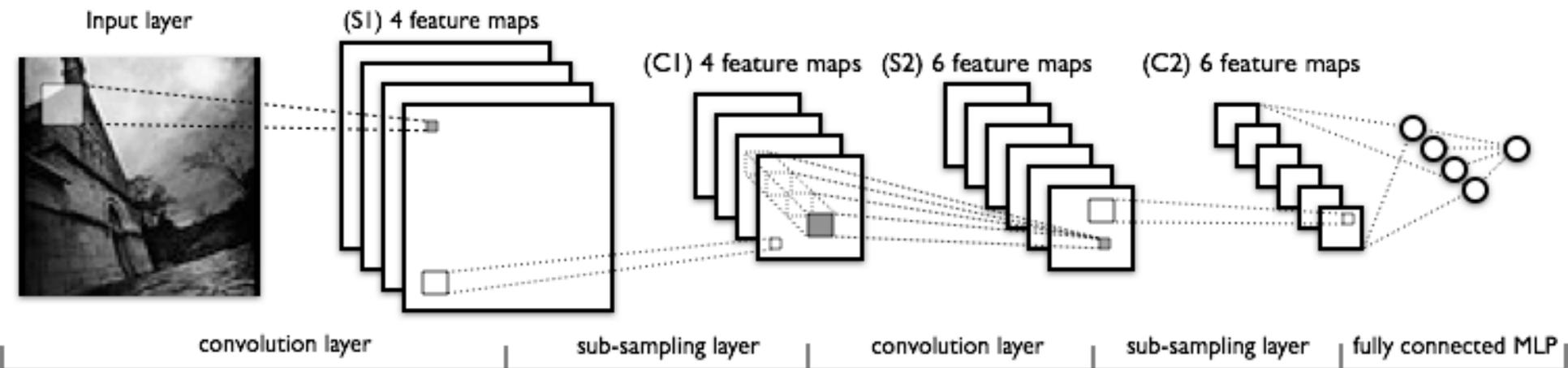
Convolutional Neural Networks (CNN) (LeNet)

example of a convolutional layer



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

Convolutional Neural Networks (CNN) (LeNet)



show flights from Boston to New York today

Recurrent Neural Networks with Word Embeddings

Semantic Parsing / Slot-Filling (Spoken Language Understanding)

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

show flights from Boston to New York today

show flights from Boston to New York today

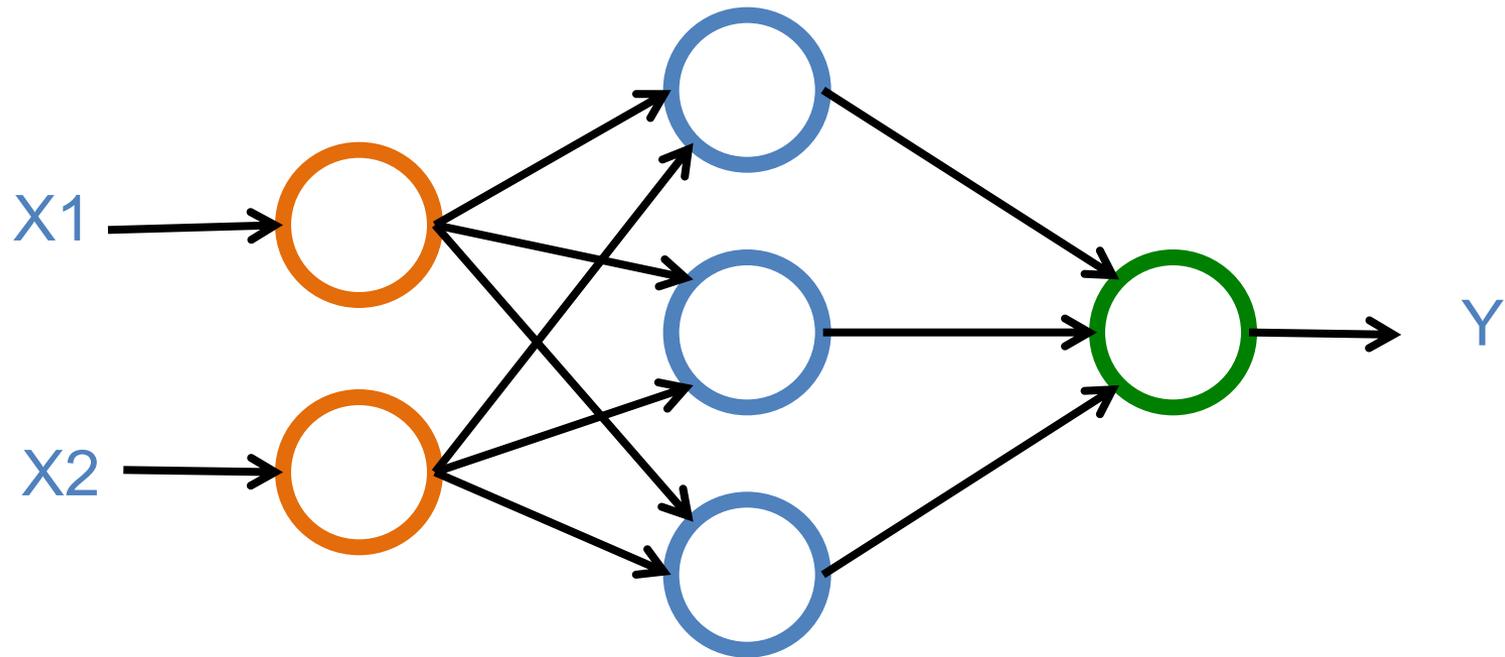
Input (words)	show	flights	from	Boston	to	New	York	today
Output (labels)	0	0	0	B-dept	0	B-arr	I-arr	B-date

Neural Networks

Input Layer
(X)

Hidden Layer
(H)

Output Layer
(Y)



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

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

Training a Network
=
Minimize the Cost Function

Training a Network

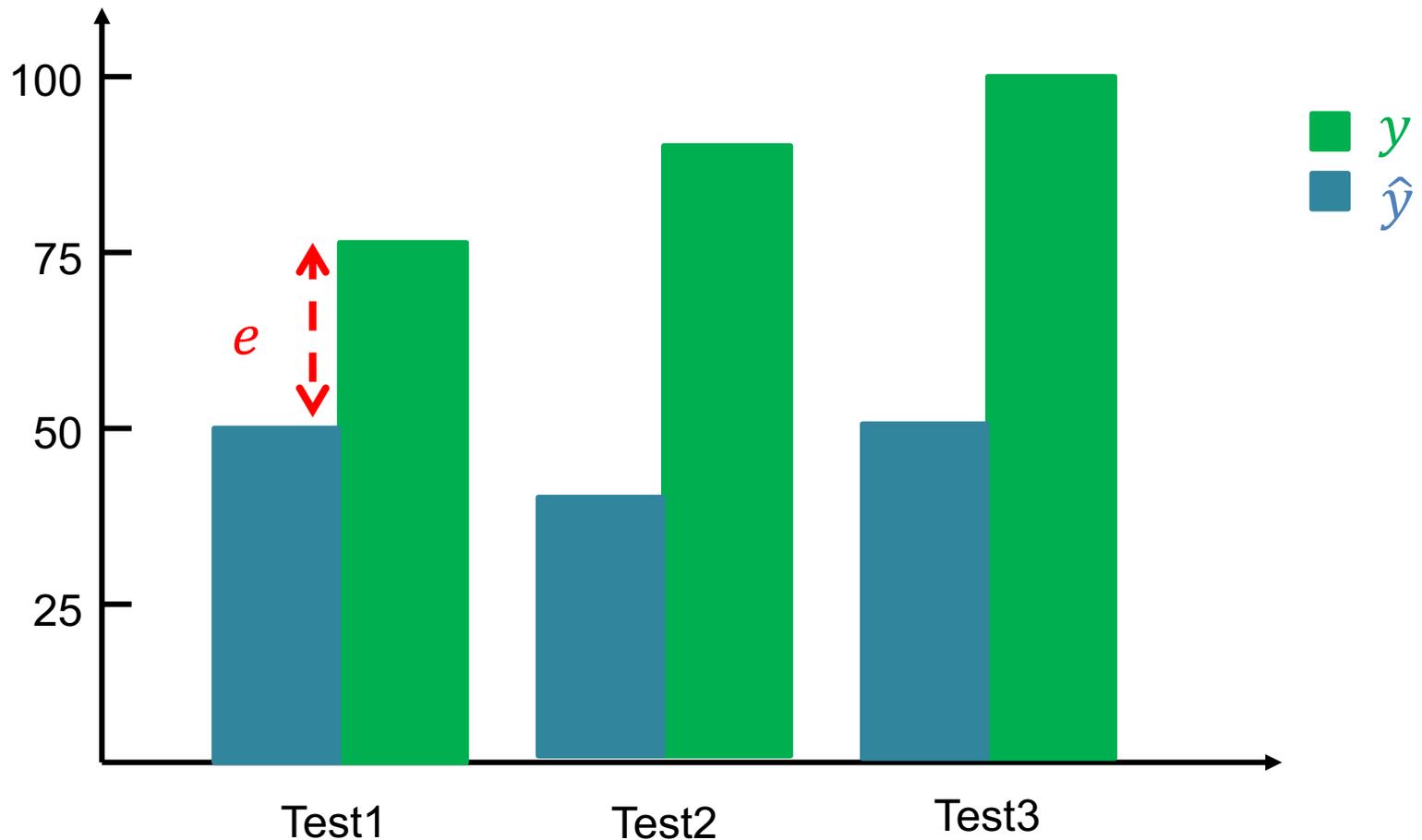
=

Minimize the **Cost** Function

Minimize the **Loss** Function

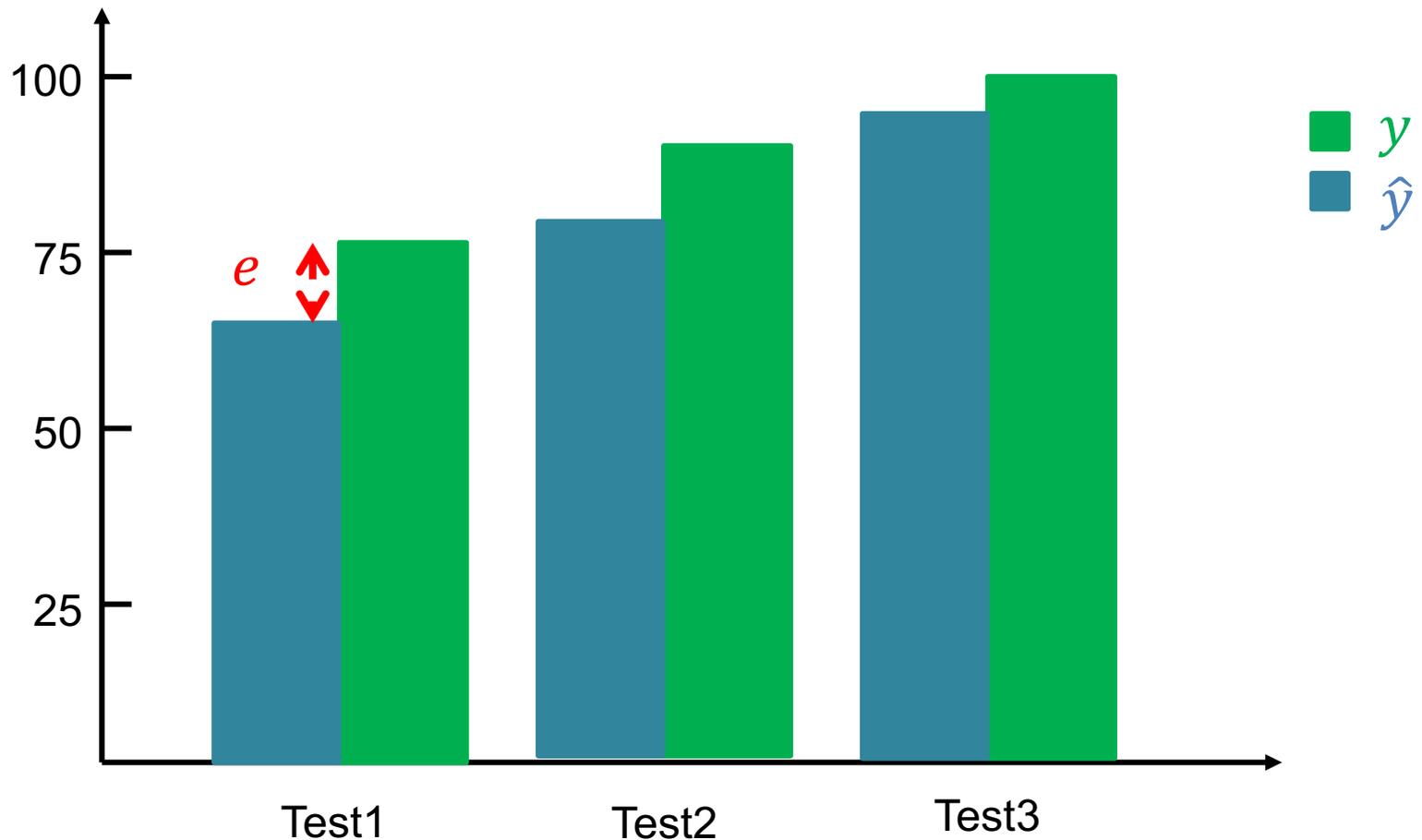
Error = Predict Y - Actual Y

Error : Cost : Loss



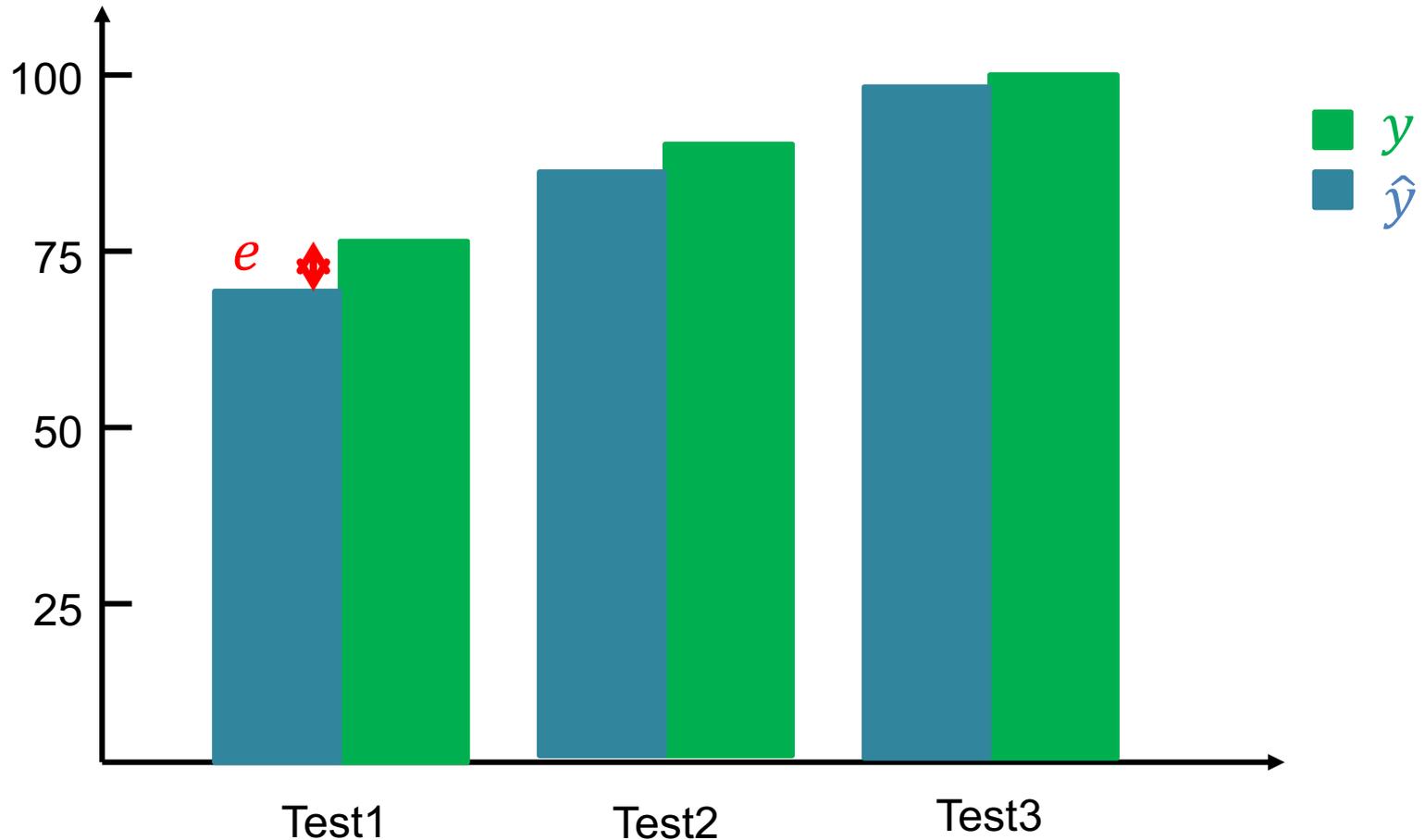
Error = Predict Y - Actual Y

Error : Cost : Loss



Error = Predict Y - Actual Y

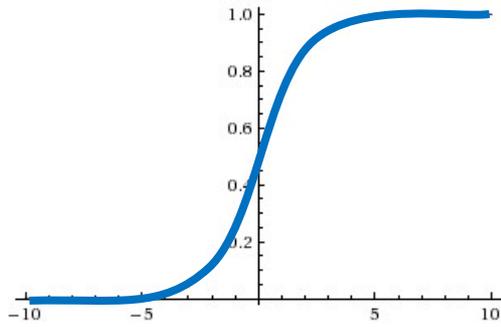
Error : Cost : Loss



Activation Functions

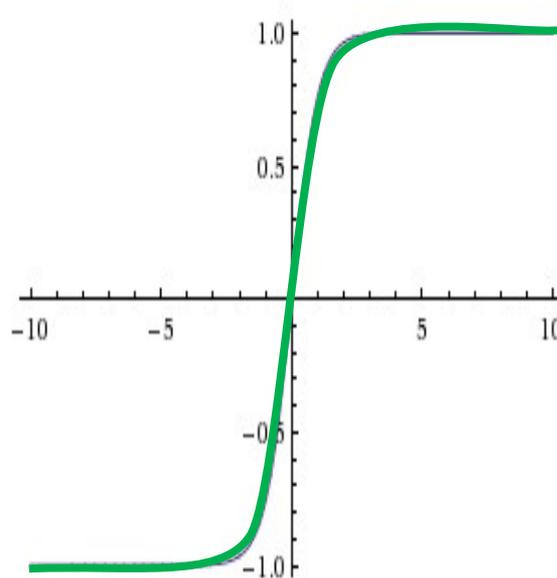
Activation Functions

Sigmoid



[0, 1]

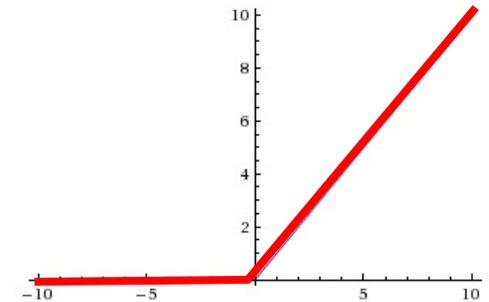
TanH



[-1, 1]

ReLU

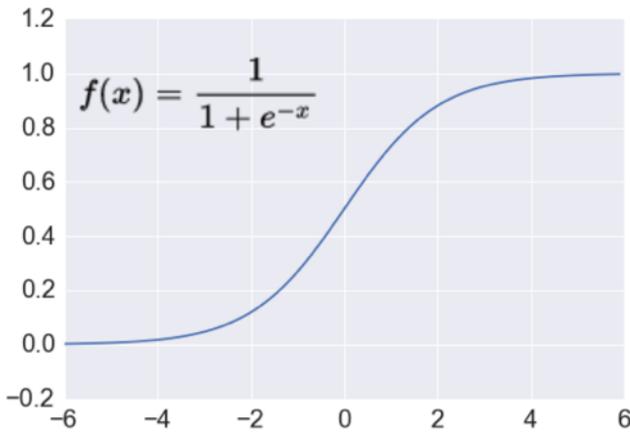
(Rectified Linear Unit)



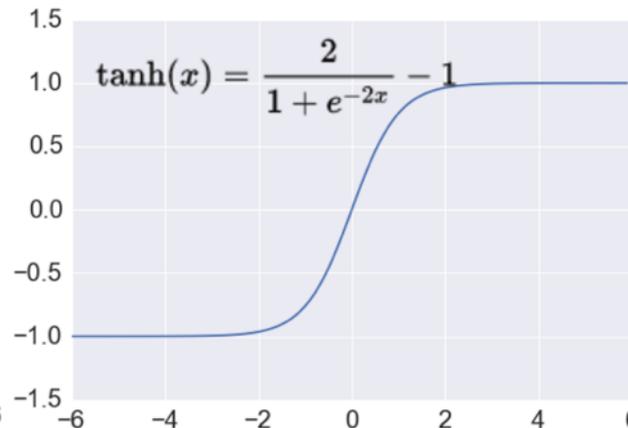
$f(x) = \max(0, x)$

Activation Functions

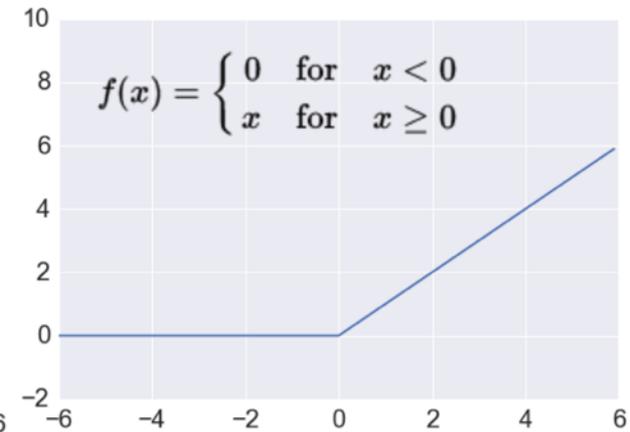
Sigmoid



TanH



ReLU



Loss Function

Binary Classification: 2 Class

**Activation Function:
Sigmoid**

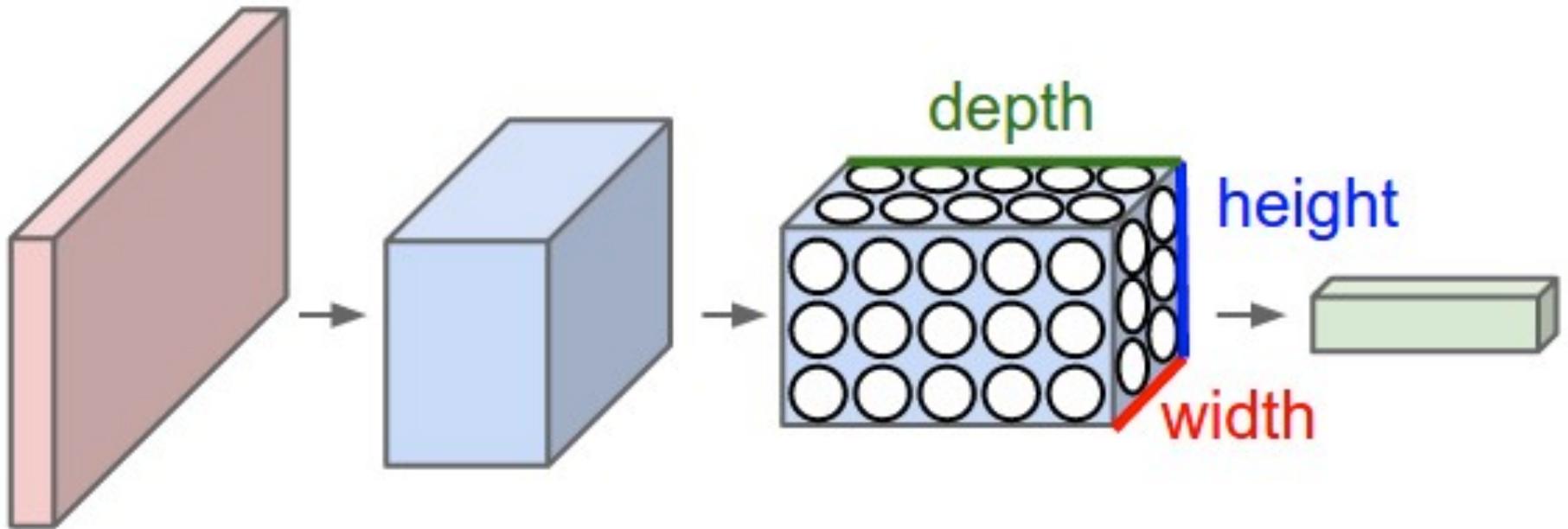
**Loss Function:
Binary Cross-Entropy**

Multiple Classification: 10 Class

**Activation Function:
SoftMAX**

**Loss Function:
Categorical Cross-Entropy**

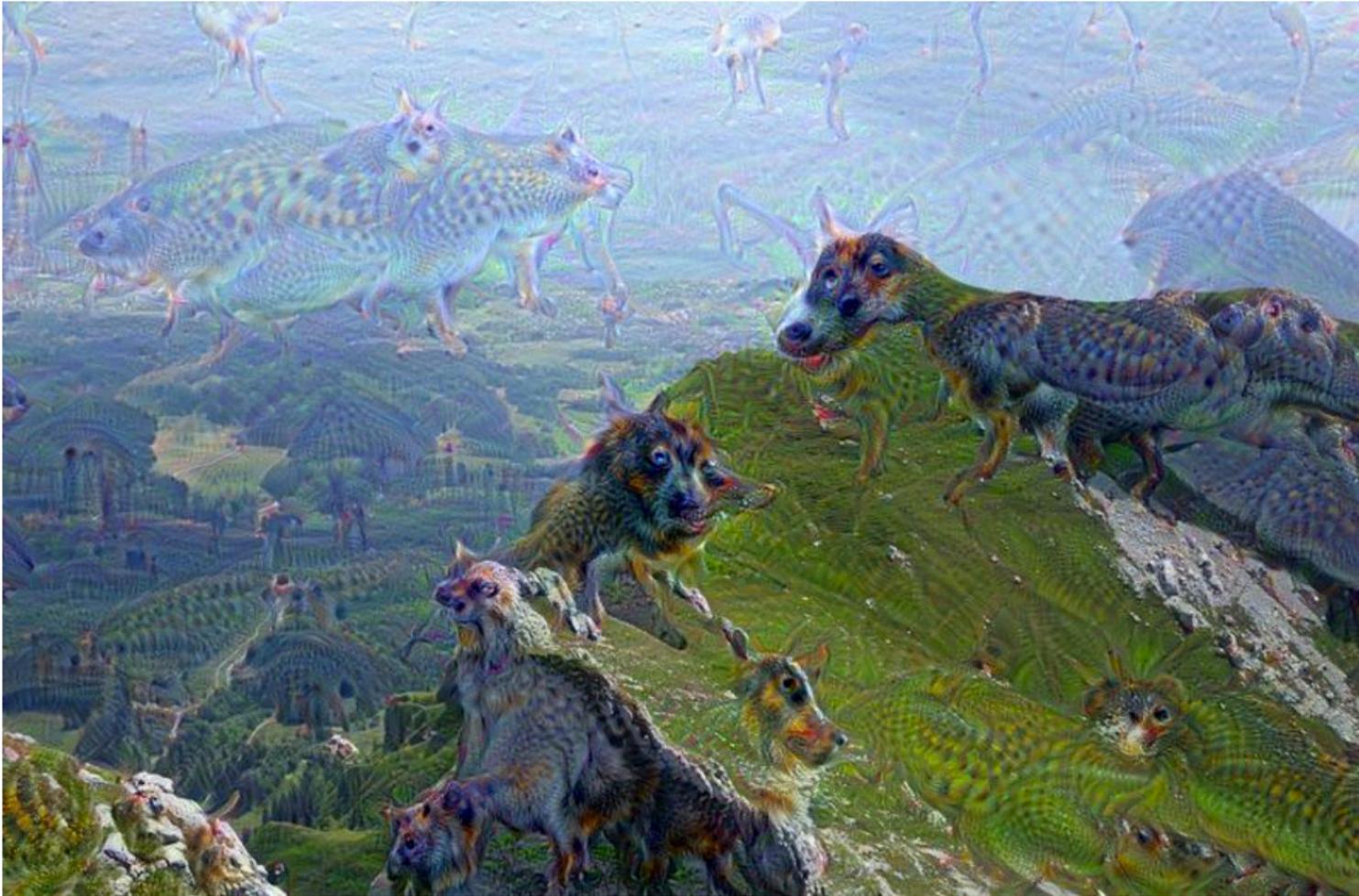
A ConvNet arranges its neurons in three dimensions (width, height, depth)



DeepDream

GitHub, Inc. [US] <https://github.com/tensorflow/tensorflow/blob/master/tensorflow/examples/tutorials/deepdream/deepdream.ipynb>

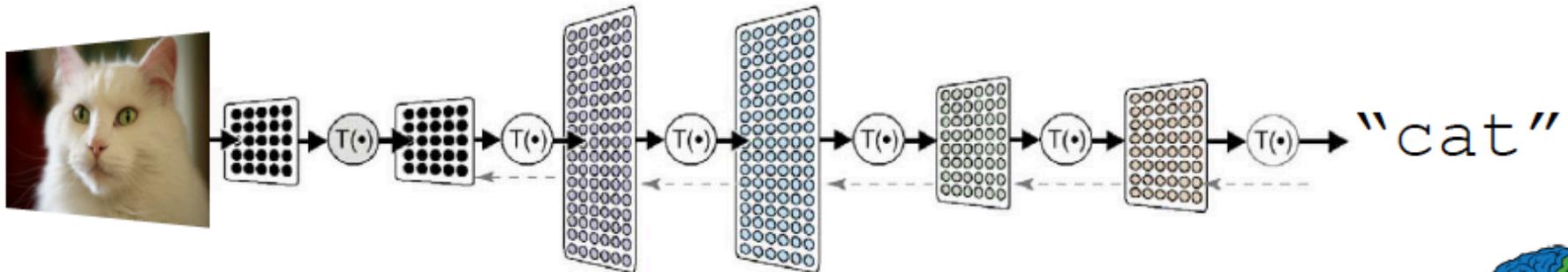
```
In [15]: render_deepdream(tf.square(T('mixed4c')), img0)
```



Note that results can differ from the [Caffe's](#) implementation, as we are using an independently trained network. Still, the network seems to like dogs and animal-like features due to the nature of the ImageNet dataset.

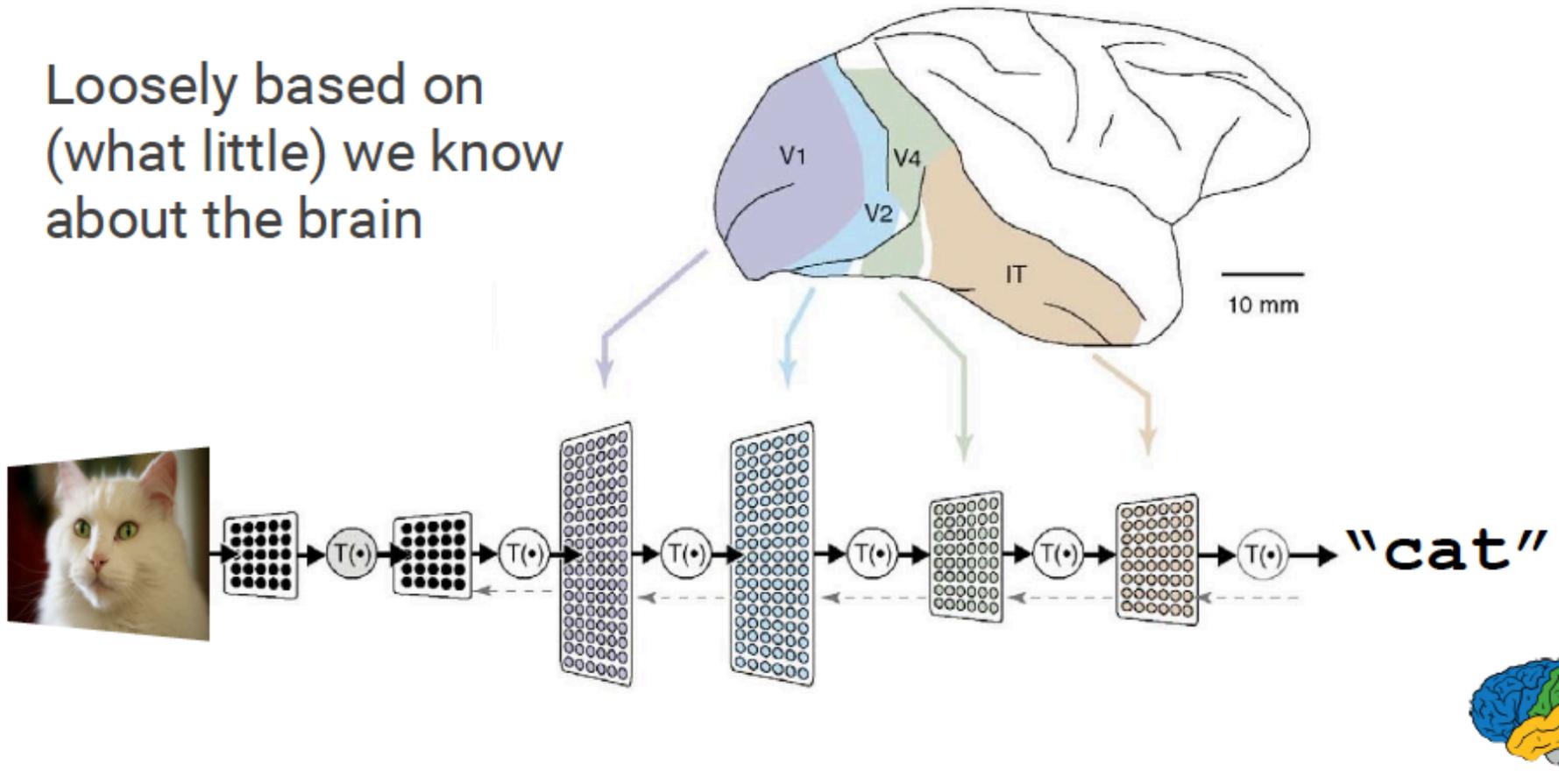
Deep Learning

- 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

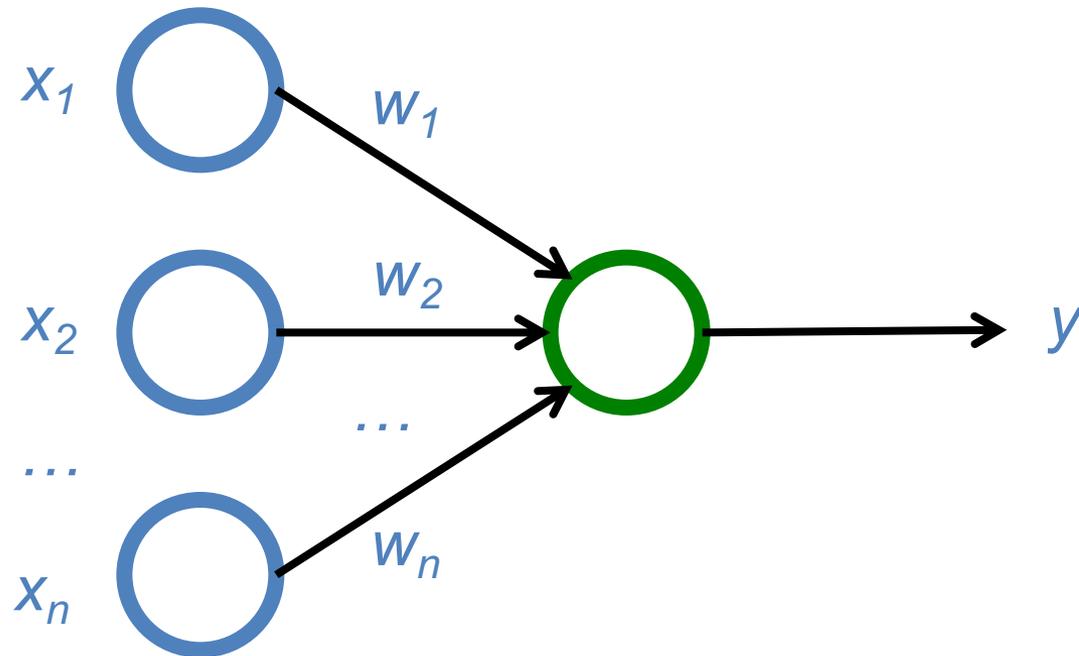


What is Deep Learning?

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

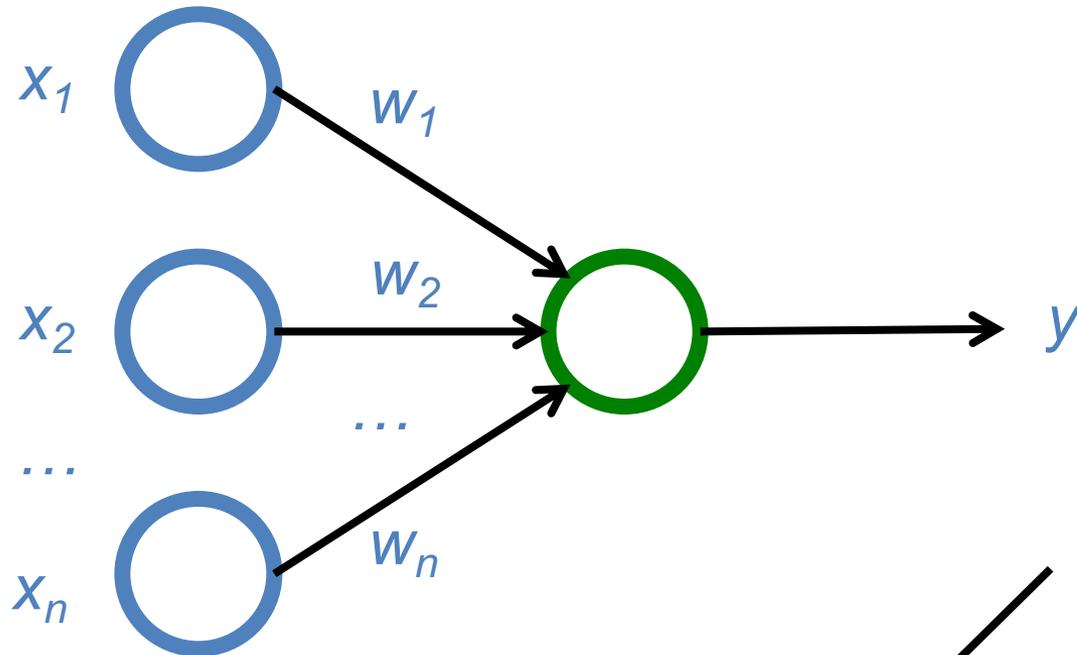


The Neuron



The Neuron

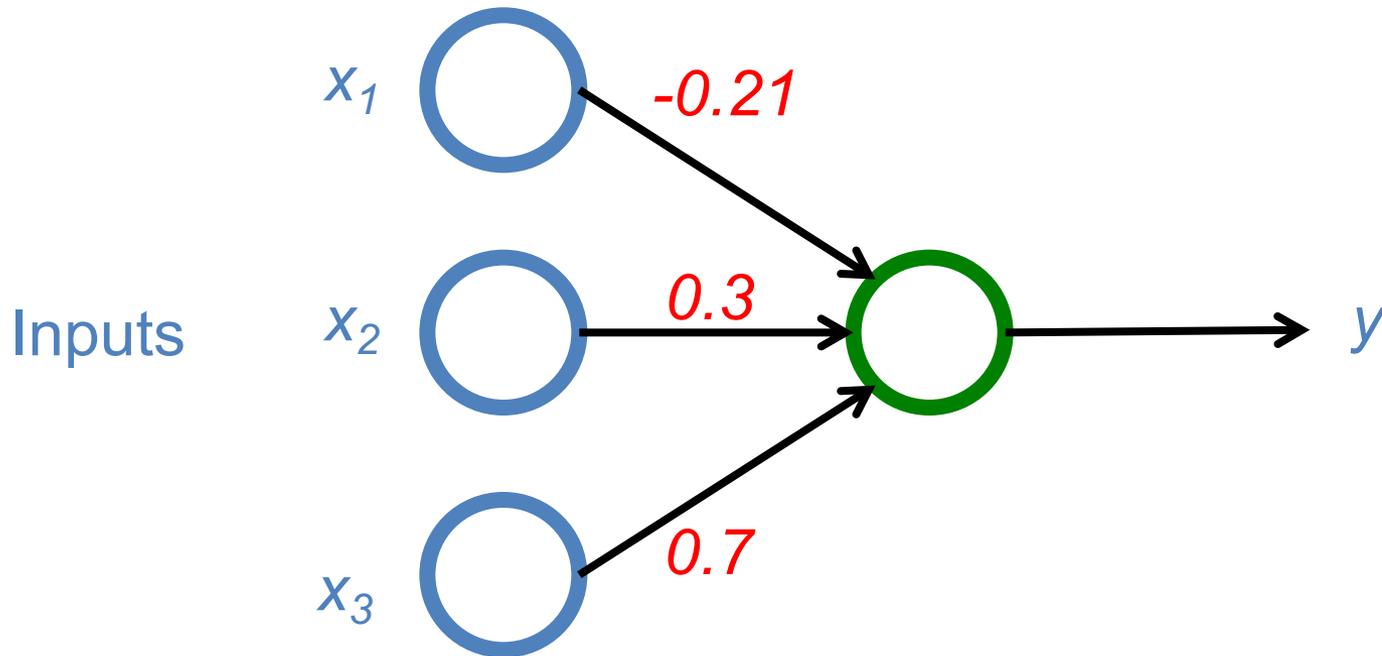
$$y = F\left(\sum_i w_i x_i\right)$$



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

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

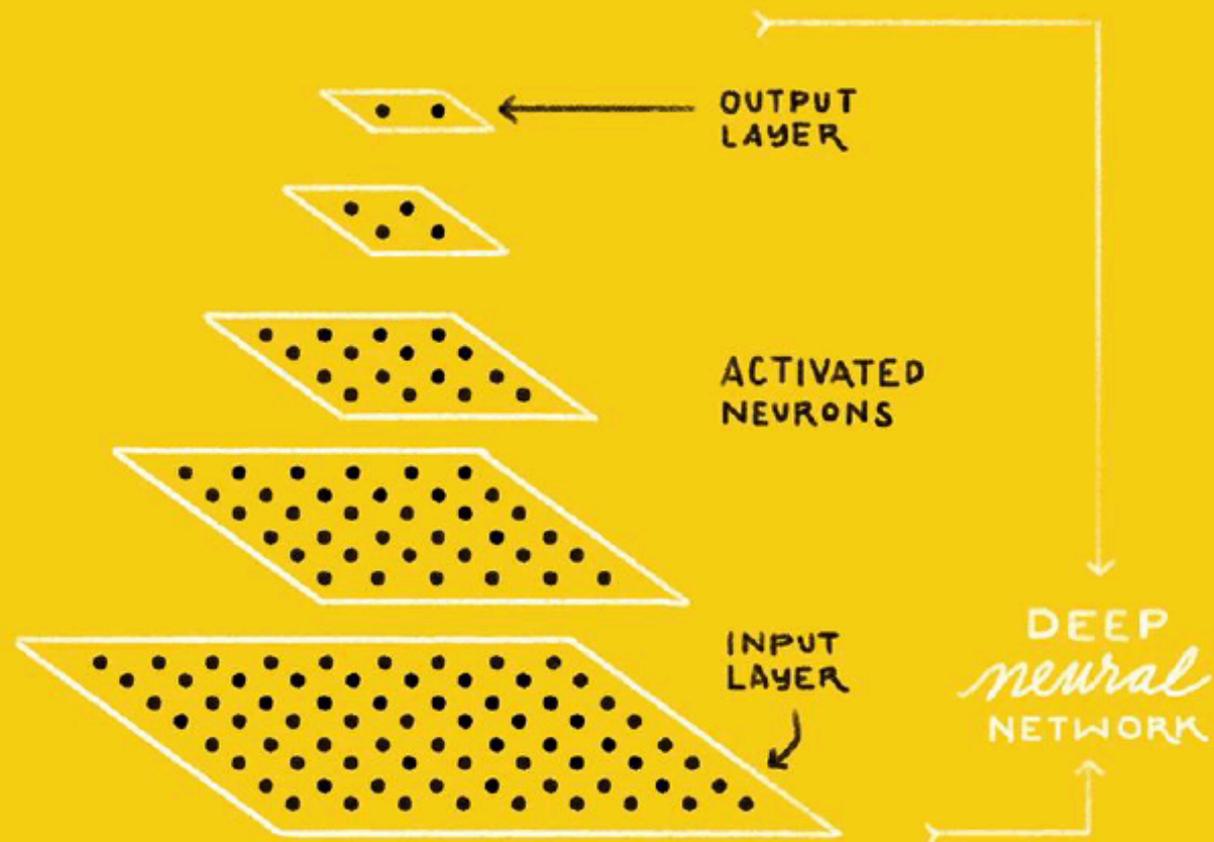
Weights



IS THIS A
CAT or **DOG**?



CAT **DOG**



Learning Algorithm

While not done:

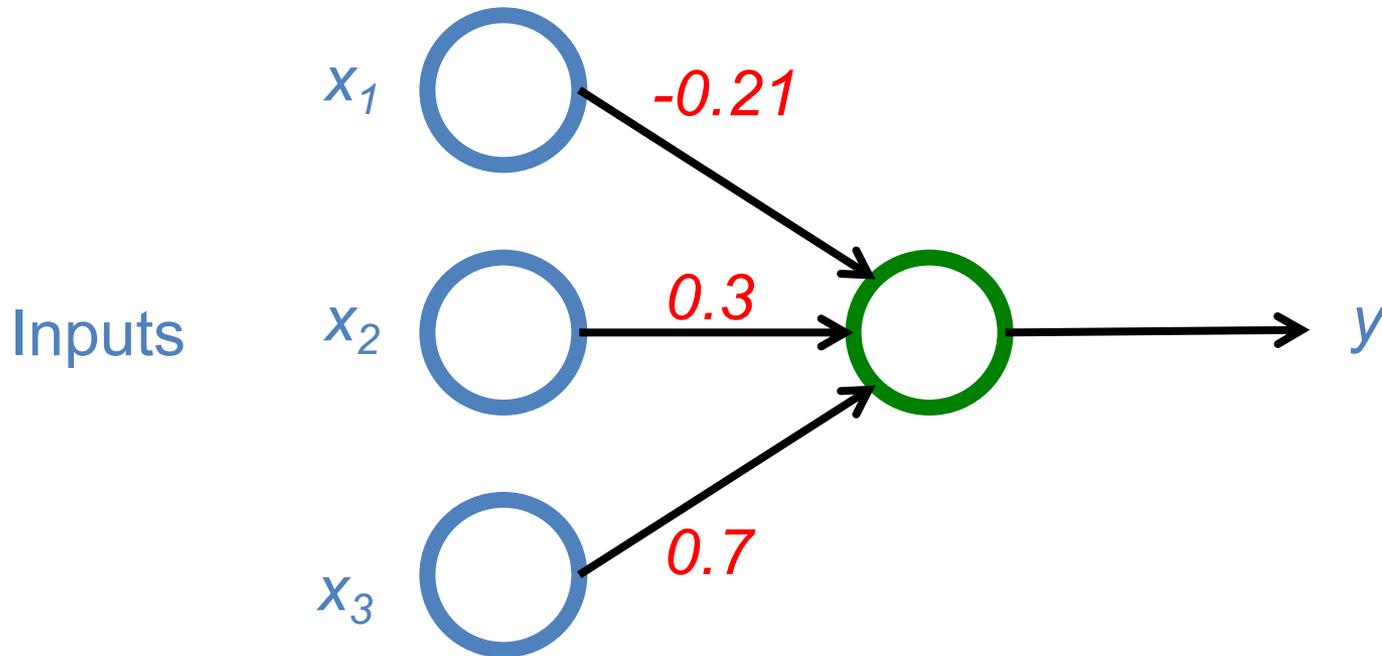
Pick a random training example “(input, label)”

Run neural network on “input”

Adjust weights on edges to make output closer to “label”

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

Weights

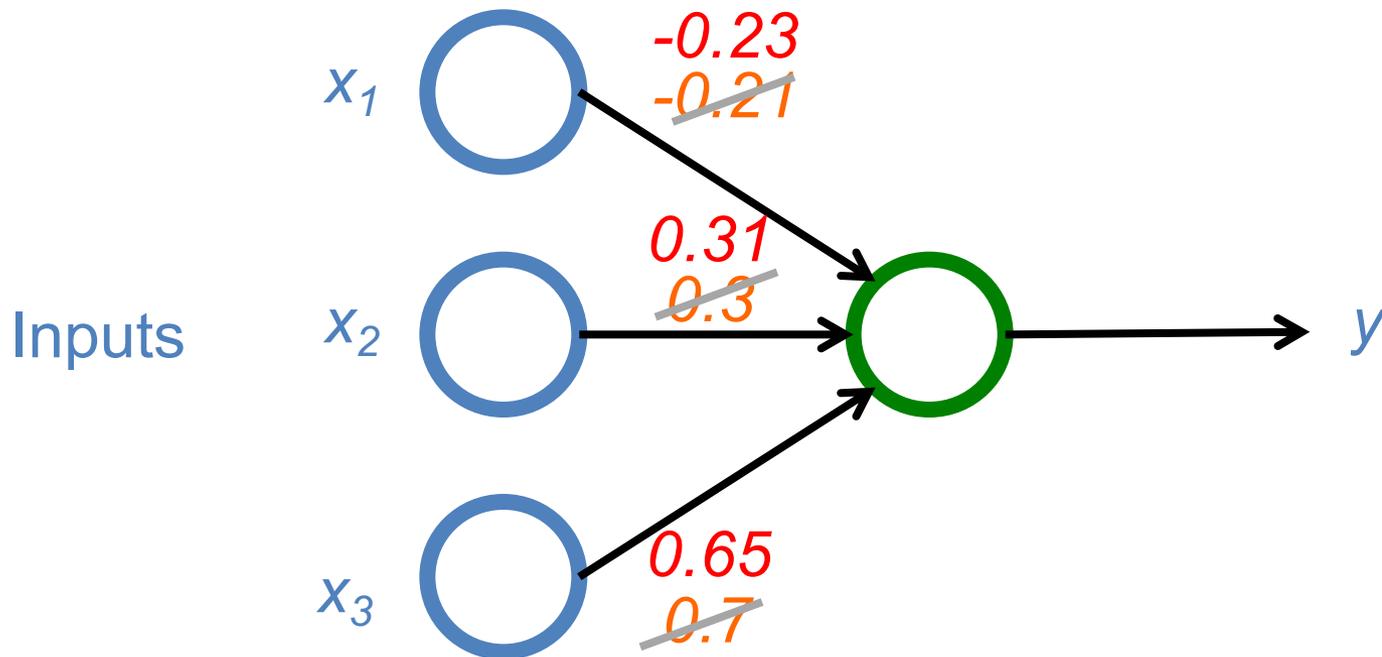


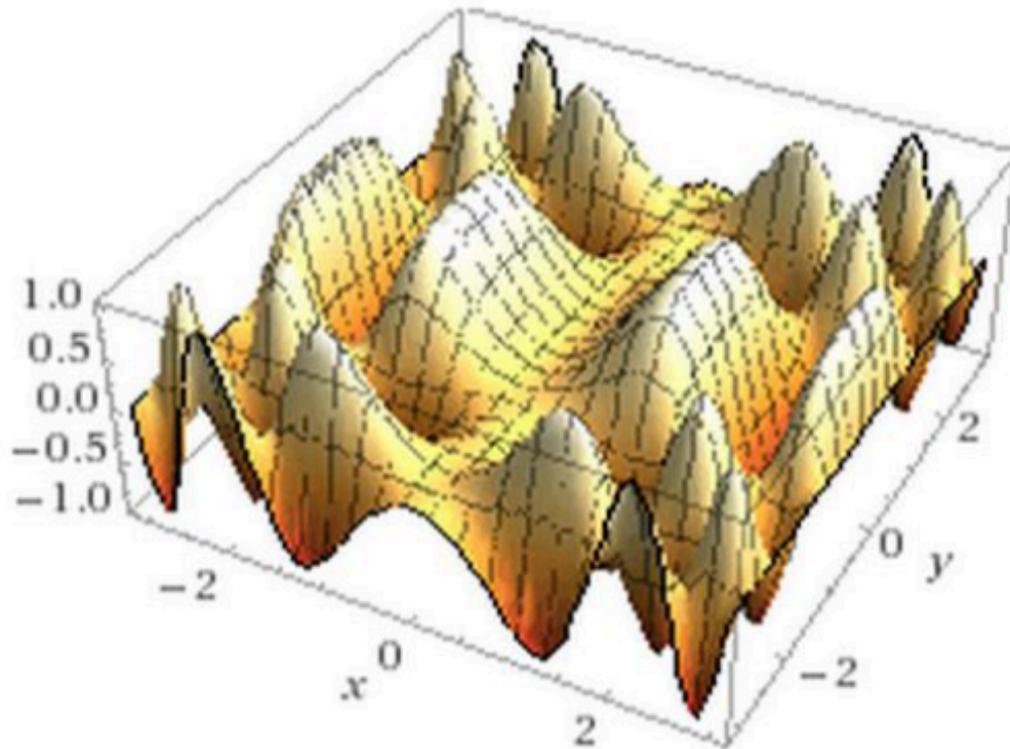
Next time:

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

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

Weights





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

Important Property of Neural Networks

Results get better with

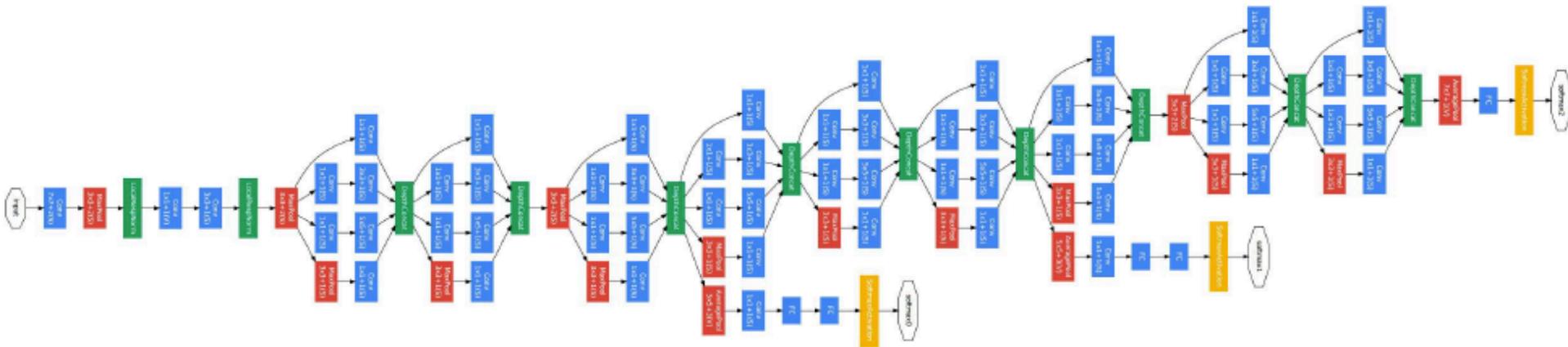
More data +

Bigger models +

More computation

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

The Inception Architecture (GoogLeNet, 2014)



Going Deeper with Convolutions

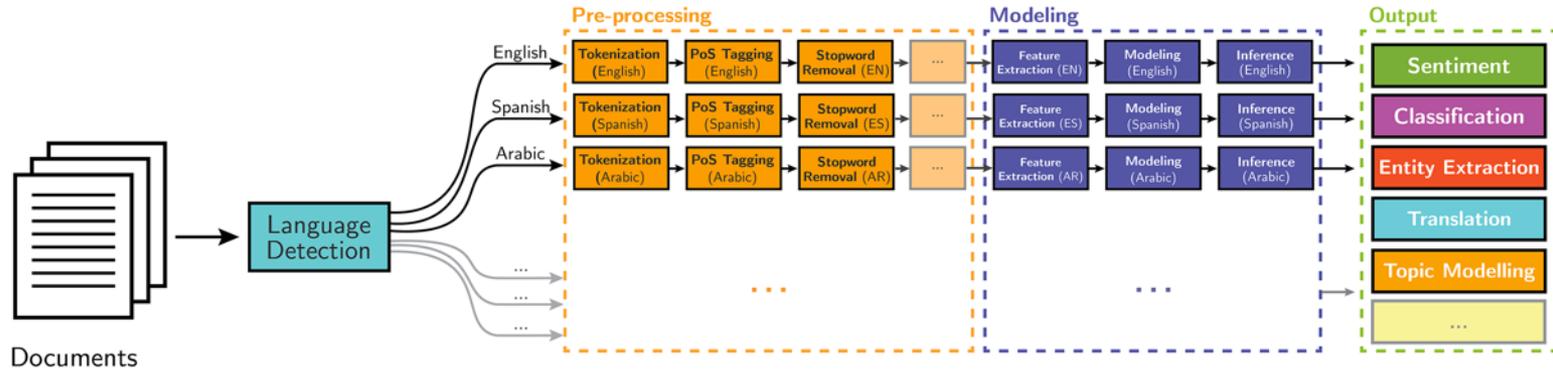
Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, Andrew Rabinovich

ArXiv 2014, CVPR 2015

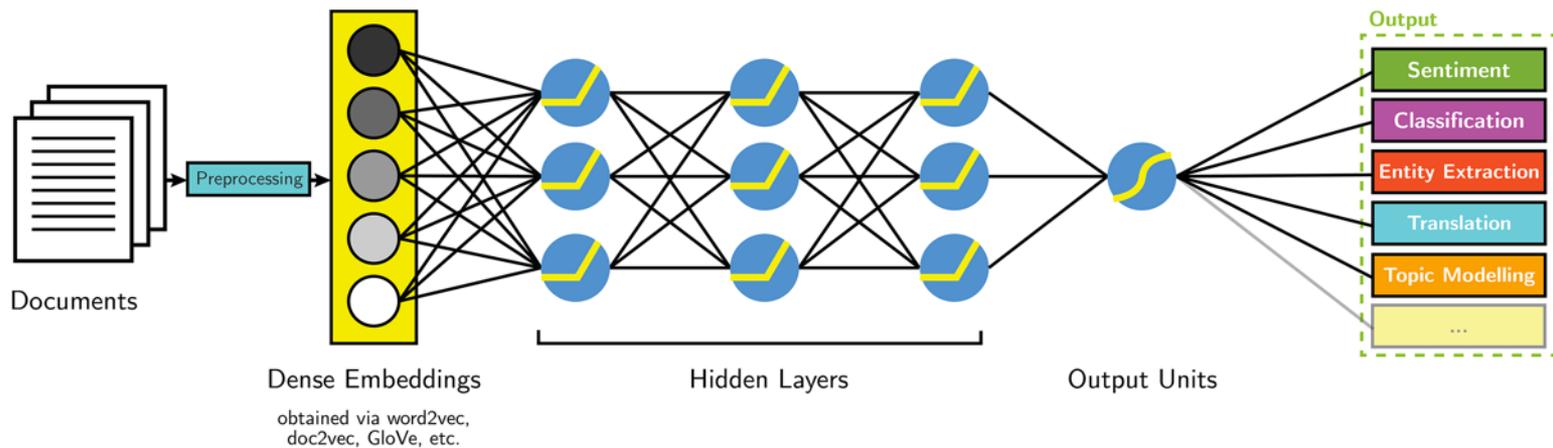


NLP

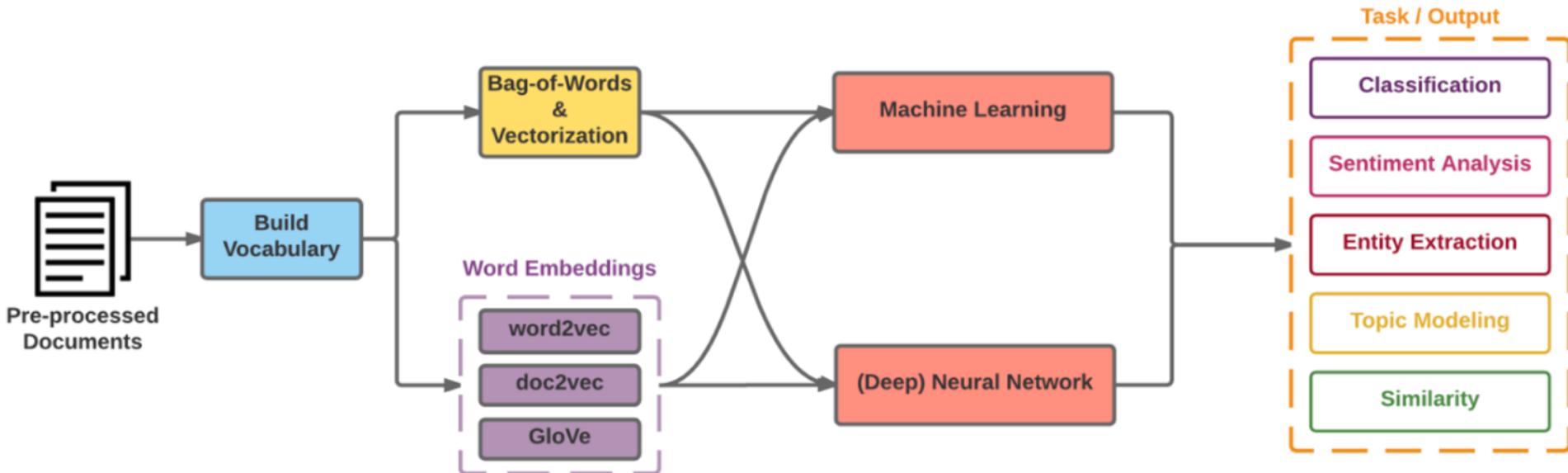
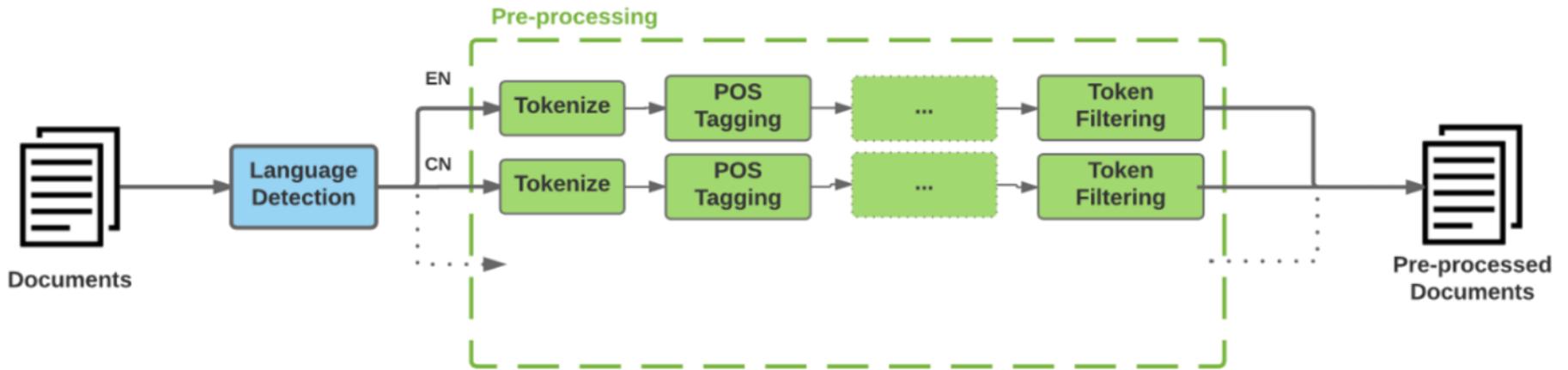
Classical NLP



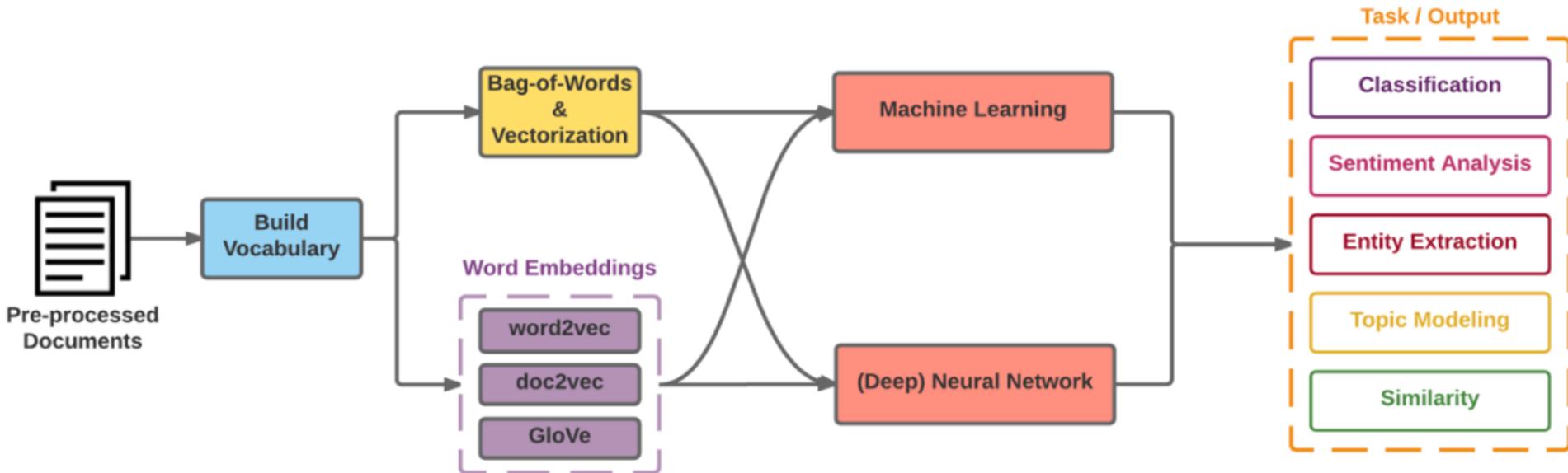
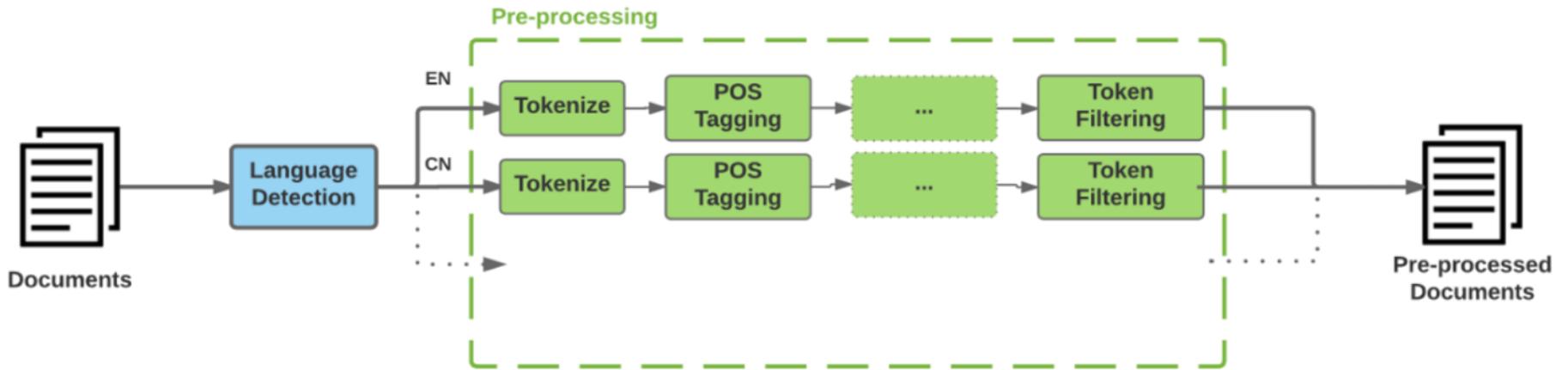
Deep Learning-based NLP



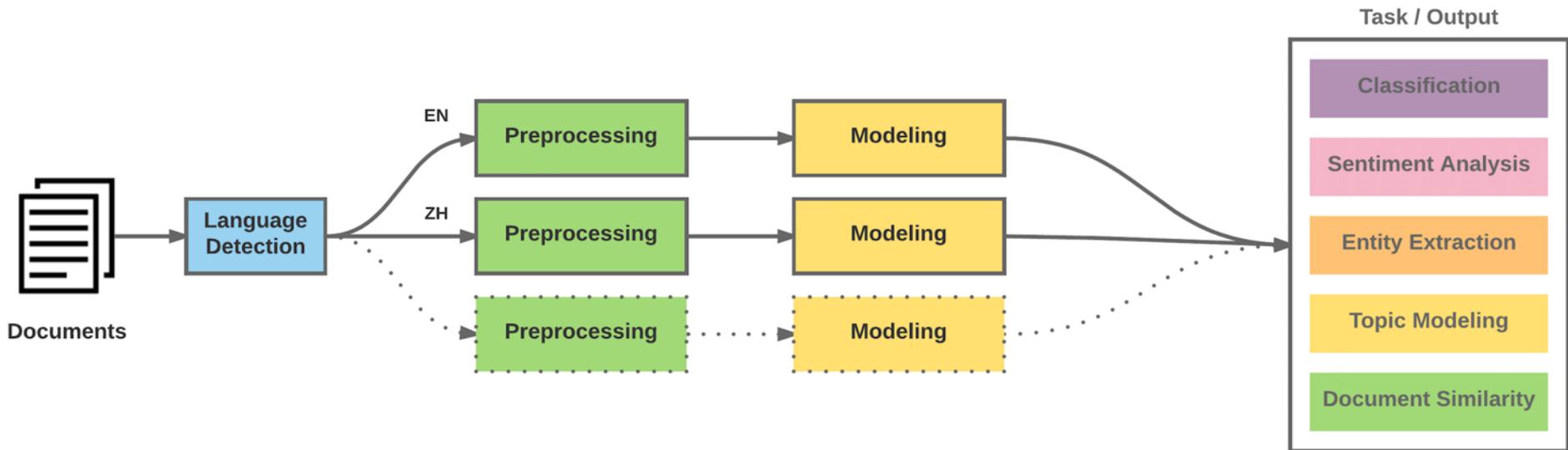
Modern NLP Pipeline



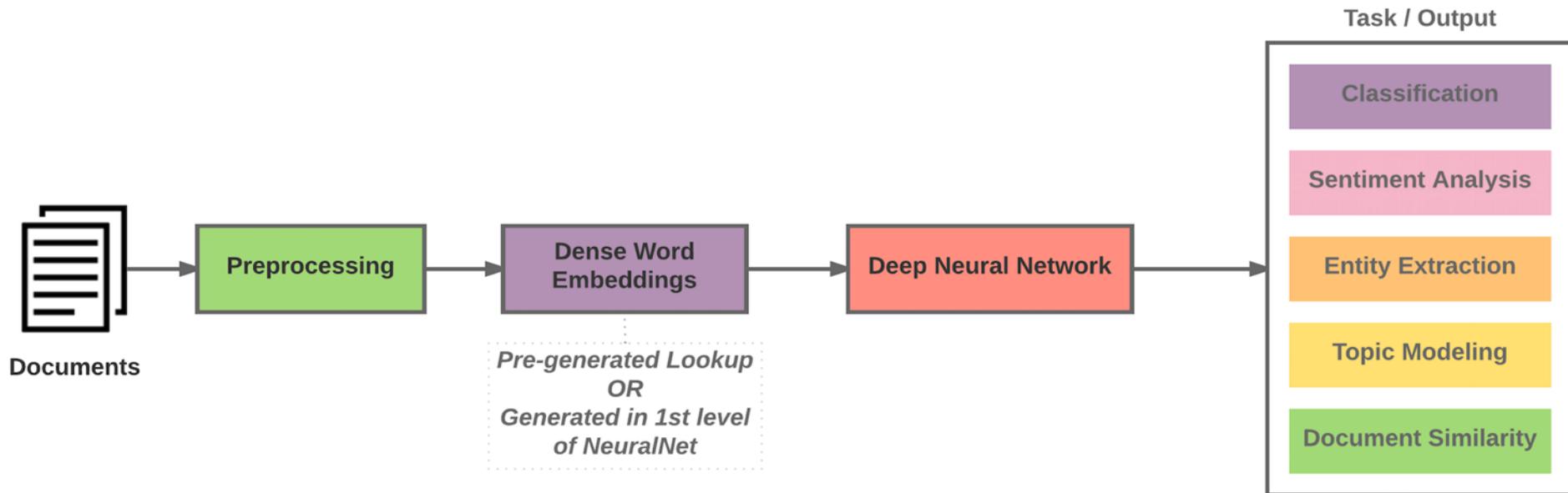
Modern NLP Pipeline



Modern NLP Pipeline



Deep Learning NLP



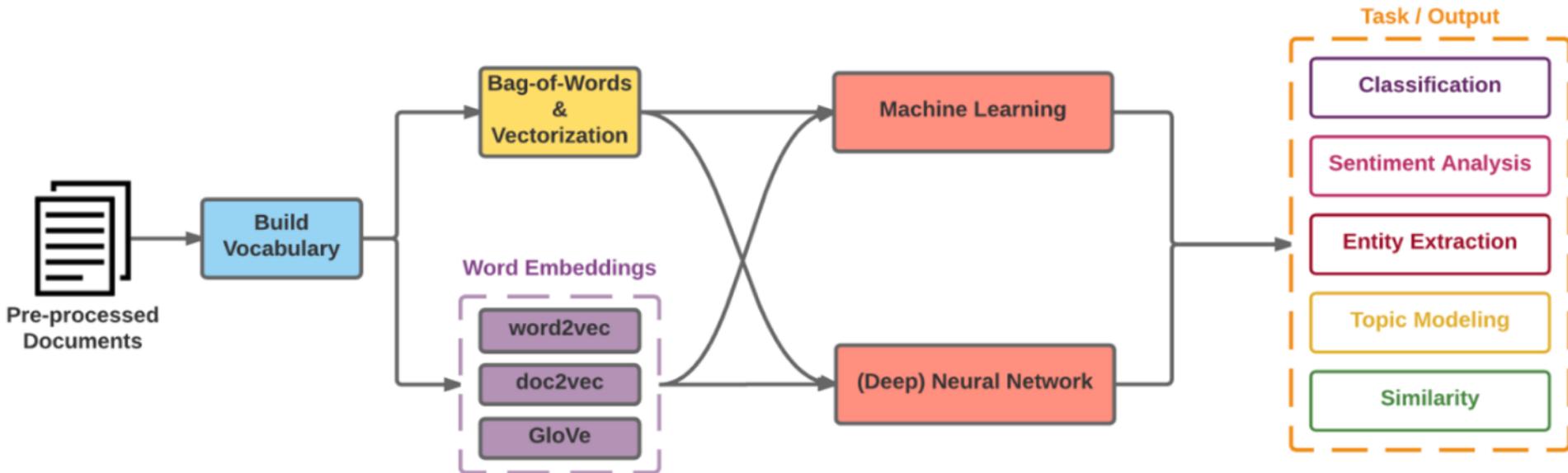
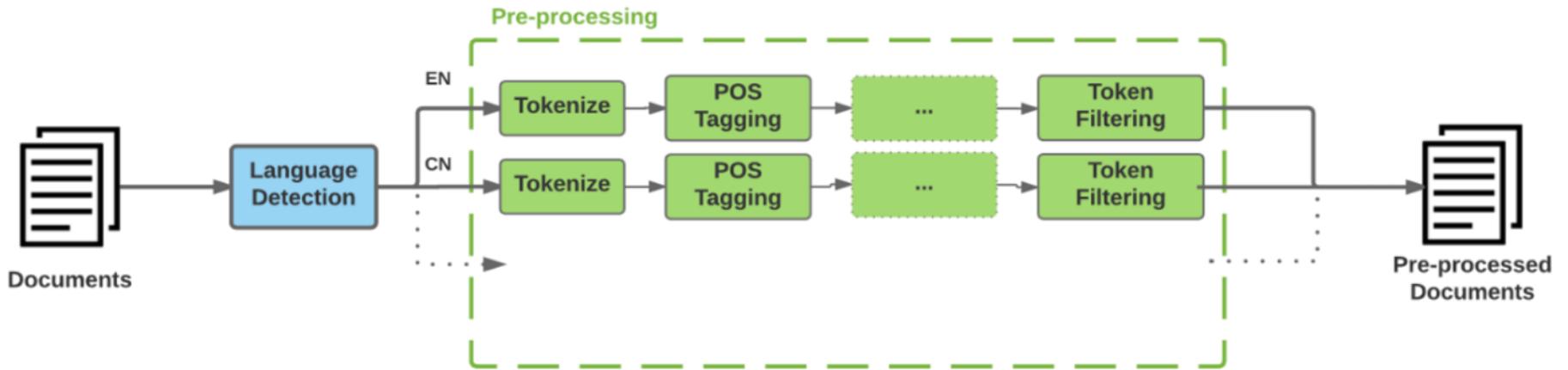
Vector Representations of Words

Word Embeddings

Word2Vec

GloVe

Modern NLP Pipeline



Facebook Research FastText

Pre-trained word vectors

Word2Vec

wiki.zh.vec (861MB)

332647 word

300 vec

Pre-trained word vectors for 90 languages,
trained on Wikipedia using fastText.

These vectors in dimension 300 were obtained using
the skip-gram model with default parameters.

<https://github.com/facebookresearch/fastText/blob/master/pretrained-vectors.md>

Facebook Research FastText

Word2Vec: wiki.zh.vec

(861MB) (332647 word 300 vec)

wiki.zh.vec

31845 yg -0.3978 0.49084 -0.54621 0.078991 0.8584 -0.26163 -0.45787 0.060828 0.36513 -0.03771 0.80791 0.16613 1.4828 -0.89862 0.085965
31846 迴圈 -0.034834 0.71651 -0.4377 0.48344 0.31117 -0.51783 -0.40156 -0.057097 0.31535 -0.088301 0.23436 0.30884 1.2932 -0.6704 0.215
31847 ぶっ -0.23267 0.39349 -0.90806 -0.53805 0.59308 -0.31819 -0.64229 0.16871 0.10086 0.09342 1.0914 -0.16019 1.6954 -0.70604 -0.218
31848 三公 0.54129 0.55641 -0.4348 0.25094 0.1631 -0.10326 -0.54099 0.064742 0.13175 0.10217 0.84938 -0.10287 1.312 -0.74969 0.24025 -0
31849 水貨 -0.14451 0.80455 -0.6145 0.55905 0.58307 -0.02559 -0.41088 -0.19056 -0.09178 0.33935 1.1927
31850 刚才 0.19347 0.553 -0.64736 0.26358 0.83816 -0.24098 -0.83997 -0.16232 -0.024786 -0.2483 0.69732
31851 無知 -0.0089777 0.90866 -0.25306 0.72983 0.67791 -0.3285 -0.63835 0.075295 0.4774 -0.04134 0.7210
31852 好轉 -0.026068 0.92676 -0.47469 0.50129 0.67343 -0.32509 -0.32917 0.066499 0.3875 0.0011722 0.66
31853 紀事 0.40541 0.67654 -0.5351 0.30329 0.43042 -0.24675 -0.19287 0.34207 0.35516 -0.076331 0.85916
31854 變回 -0.089933 0.88136 -0.43524 0.59963 0.6403 -0.70981 -0.56788 -0.074018 0.16905 -0.086594 0.6
31855 牟尼 -0.26578 0.6434 0.028982 -0.044001 0.88297 -0.17646 -0.64672 0.040483 0.43653 0.084908 0.74
31856 埋藏 -0.0985 0.85082 -0.33363 0.24784 0.71518 -0.59054 -0.73731 0.050949 0.36726 -0.076886 0.817
31857 正大 0.21069 0.27605 -0.83862 -0.099698 0.47894 -0.32196 -0.38288 -0.01892 0.40548 -0.029619 0.7
31858 kis -0.30595 0.18482 -0.71287 -0.314 0.44776 -0.44245 -0.36447 -0.23723 0.00098801 -0.2528 0.60
31859 合奏 0.1841 0.60874 -0.51376 -0.48002 0.21506 -0.55515 -0.71746 0.030735 0.39508 -0.40856 0.6226
31860 精兵 0.25619 0.77186 -0.48847 0.23118 0.27254 0.21305 -0.3517 0.47305 0.24882 -0.34756 1.025 0.1
31861 疲勞 -0.072521 1.0381 -0.51933 0.19421 0.67573 -0.45204 -0.20126 0.22704 0.44196 0.018401 0.3473
31862 襪 -0.11771 1.4272 -1.0849 0.77532 0.87026 -0.6892 -0.3521 0.036517 0.42727 -0.1871 0.82789 -0.0
31863 小貓 -0.21554 0.73988 -0.39628 0.044656 1.0602 -0.67047 -0.54102 0.11888 0.1693 0.19343 1.0841 0.
31864 lai -0.25451 0.31596 -0.29228 -0.19144 0.99059 -0.24459 -0.66342 0.063093 -0.061142 -0.22749 0.6
31865 偏東 -0.50835 1.0943 0.043918 0.29173 1.0161 -0.32493 -0.27305 0.026946 0.46811 -0.3874 1.4049 0.
31866 大约是 -0.35726 -0.03476 -0.28672 0.075447 0.18175 -0.39421 -0.32088 0.025225 0.34808 0.074744 0.
31867 franch -0.6046 -0.3235 0.024041 -0.2756 0.74761 -0.14654 0.0082566 -0.10071 0.53593 -0.17374 0.2
31868 brazilian -0.54029 -0.63905 -0.094006 -0.68768 0.33263 -0.1583 -0.060424 0.20644 0.46234 -0.0764
31869 夹竹桃 -0.4361 0.011429 -0.078896 -0.078186 0.37747 -0.052101 -0.096683 0.10769 0.62661 -0.37252
31870 continent -0.37761 -0.72151 -0.42248 -0.81768 0.5016 -0.48569 0.13464 0.12644 0.32292 0.18099 0.
31871 我还是 0.097443 0.28929 -0.14202 0.034027 0.50621 -0.1647 -0.45849 -0.16198 0.13965 -0.33451 0.61
31872 vienna -0.25827 -0.050966 0.050502 -0.63466 0.4949 -0.17448 -0.59978 0.20269 0.37532 0.059419 0.
31873 固态 -0.12678 0.4556 -0.27108 0.12506 0.52106 -0.058477 -0.69296 0.12162 0.26508 -0.089028 0.752
31874 吉普 -0.33693 0.48335 -0.58455 0.13722 0.74856 -0.24529 -0.41125 -0.13832 0.33871 -0.12051 0.864
31875 實物 0.030096 0.65756 -0.67982 0.2203 0.38492 -0.19001 -0.53136 -0.10322 0.24523 0.15287 0.92591
31876 教职 0.11559 0.67087 -0.5111 0.14955 0.61417 -0.51571 -0.47901 0.29445 0.37629 -0.24232 0.4608 -0
31877 惕 0.50469 1.5357 -0.64393 0.48668 0.69479 -0.23443 -0.47863 0.16288 0.3347 -0.51673 0.86777 0.0
31878 岸上 0.088323 0.85815 -0.485 0.30383 0.75965 -0.25031 -0.76678 0.12805 0.37641 -0.088752 0.65012
31879 议和 0.26835 0.94854 -0.27972 0.097623 0.43305 -0.031361 -0.57406 0.21608 0.3324 -0.36823 0.6987
31880 aka -0.21332 0.11216 -0.48872 -0.18531 0.79093 -0.34221 -0.51122 0.10067 0.29963 -0.075253 0.642
31881 滑鐵盧 -0.28726 0.88014 -0.39751 -0.056992 0.37408 -0.16967 -0.20673 -0.048533 -0.1978 -0.13107 0

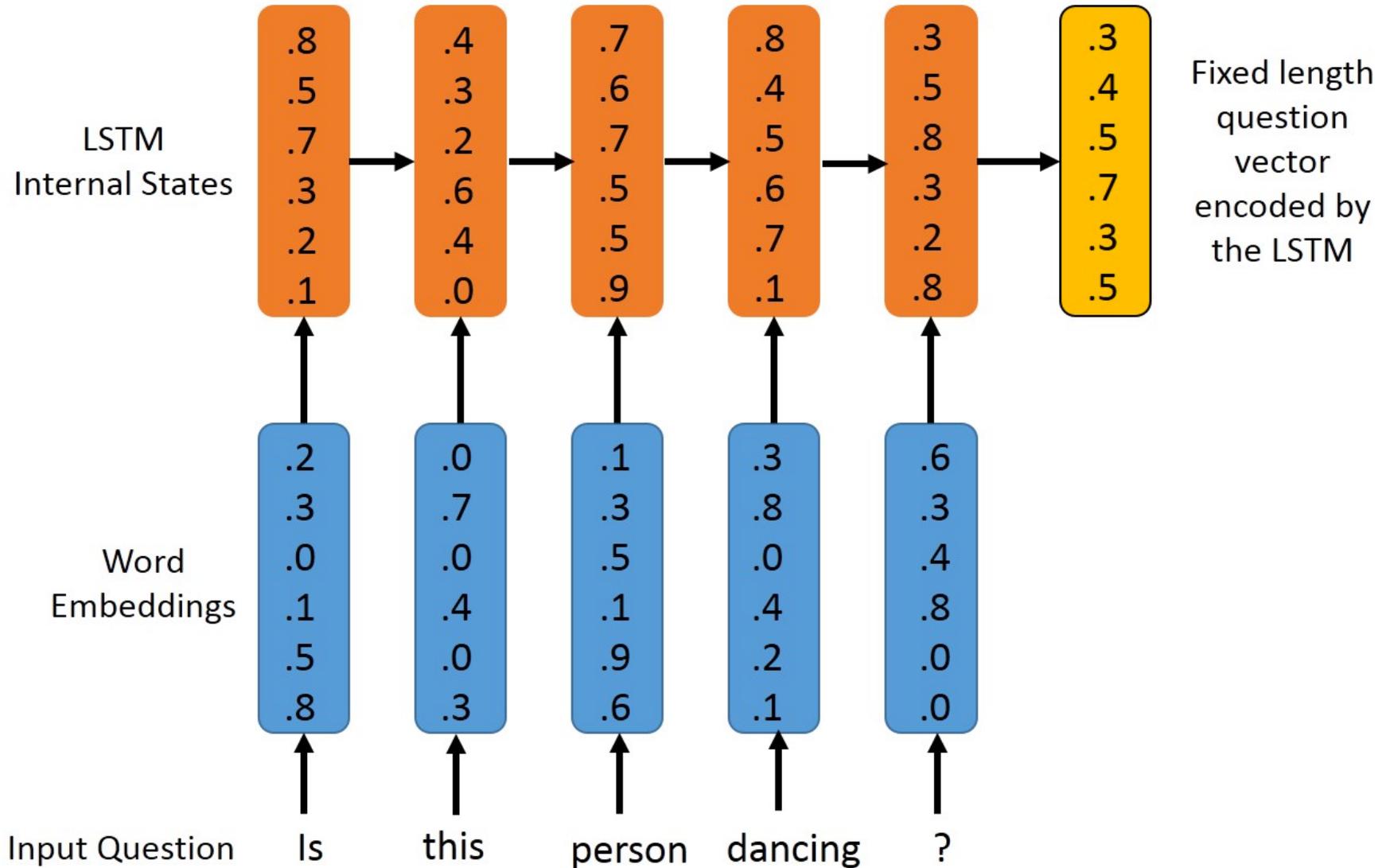
Models

The models can be downloaded from:

- Afrikaans: [bin+text](#), [text](#)
- Albanian: [bin+text](#), [text](#)
- Arabic: [bin+text](#), [text](#)
- Armenian: [bin+text](#), [text](#)
- Asturian: [bin+text](#), [text](#)
- Azerbaijani: [bin+text](#), [text](#)
- Bashkir: [bin+text](#), [text](#)
- Basque: [bin+text](#), [text](#)
- Belarusian: [bin+text](#), [text](#)
- Bengali: [bin+text](#), [text](#)
- Bosnian: [bin+text](#), [text](#)
- Breton: [bin+text](#), [text](#)
- Bulgarian: [bin+text](#), [text](#)
- Burmese: [bin+text](#), [text](#)
- Catalan: [bin+text](#), [text](#)
- Cebuano: [bin+text](#), [text](#)
- Chechen: [bin+text](#), [text](#)
- Chinese: [bin+text](#), [text](#)
- Chuvash: [bin+text](#), [text](#)
- Croatian: [bin+text](#), [text](#)
- Czech: [bin+text](#), [text](#)

Word Embeddings in LSTM RNN

Time Expanded LSTM Network



Deep Learning Software

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

🏠 Theano

theano

0.9 release ▾

- Release Notes
- Theano at a Glance
- Requirements
- Installing Theano
- Updating Theano
- Tutorial
- Extending Theano
- Developer Start Guide
- Optimizations
- API Documentation
- Troubleshooting
- Glossary
- Links
- Internal Documentation

📄
v: release ▾

[Docs](#) » [Welcome](#)

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Welcome

Theano is a Python library that allows you to define, optimize, and evaluate mathematical expressions involving multi-dimensional arrays efficiently. Theano features:

- **tight integration with NumPy** – Use `numpy.ndarray` in Theano-compiled functions.
- **transparent use of a GPU** – Perform data-intensive computations much faster than on a CPU.
- **efficient symbolic differentiation** – Theano does your derivatives for functions with one or many inputs.
- **speed and stability optimizations** – Get the right answer for `log(1+x)` even when `x` is really tiny.
- **dynamic C code generation** – Evaluate expressions faster.
- **extensive unit-testing and self-verification** – Detect and diagnose many types of errors.

Theano has been powering large-scale computationally intensive scientific investigations since 2007. But it is also approachable enough to be used in the classroom (University of Montreal's [deep learning/machine learning](#) classes).

News

- 2017/03/20: Release of Theano 0.9.0. Everybody is encouraged to update.
- 2017/03/13: Release of Theano 0.9.0rc4, with crash fixes and bug fixes.



HOME

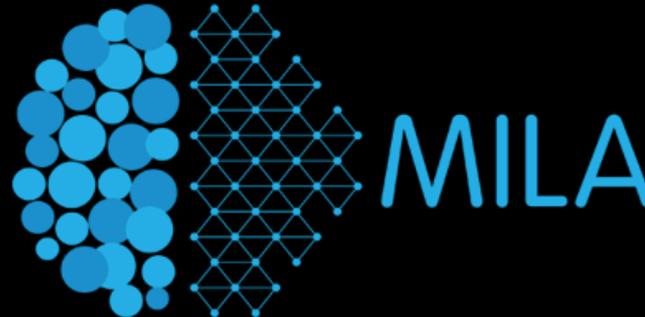
MILA

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TRAINING

FRANÇAIS

Montreal
Institute for
Learning
Algorithms



Dedicated to understanding the fundamentals of learning and intelligence

FACULTY



Yoshua Bengio



Pascal Vincent



Christopher Pal



Aaron Courville

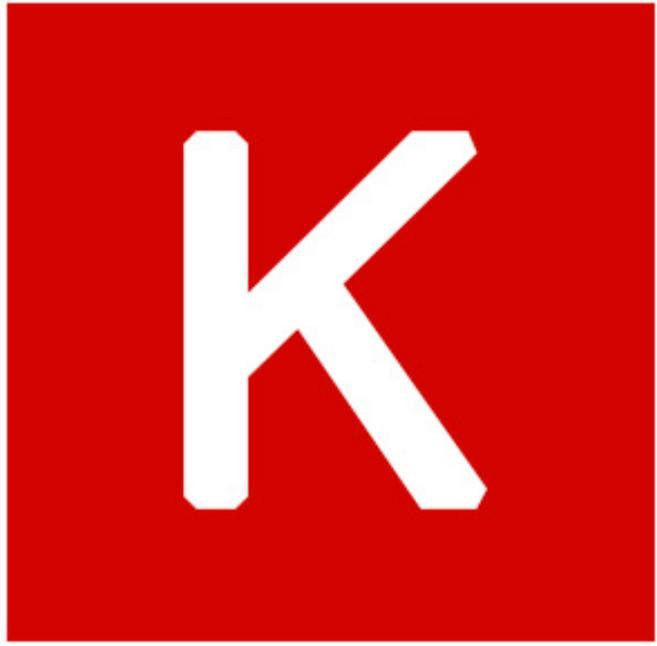


Roland Memisevic



Laurent Charlin

<https://mila.umontreal.ca/en/>



K



Keras



Keras

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

Keras

K Keras Documentation

Home

- Keras: Deep Learning library for Theano and TensorFlow
- You have just found Keras.
- Guiding principles
- Getting started: 30 seconds to Keras
- Installation
- Switching from TensorFlow to Theano
- Support
- Why this name, Keras?

Getting started

- Guide to the Sequential model
- Guide to the Functional API
- FAQ

Models

- About Keras models
- Sequential
- Model (functional API)

Layers

- About Keras layers

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[Edit on GitHub](#)

Keras: Deep Learning library for Theano and TensorFlow

You have just found Keras.

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

Use Keras if you need a deep learning library that:

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

Read the documentation at [Keras.io](#).

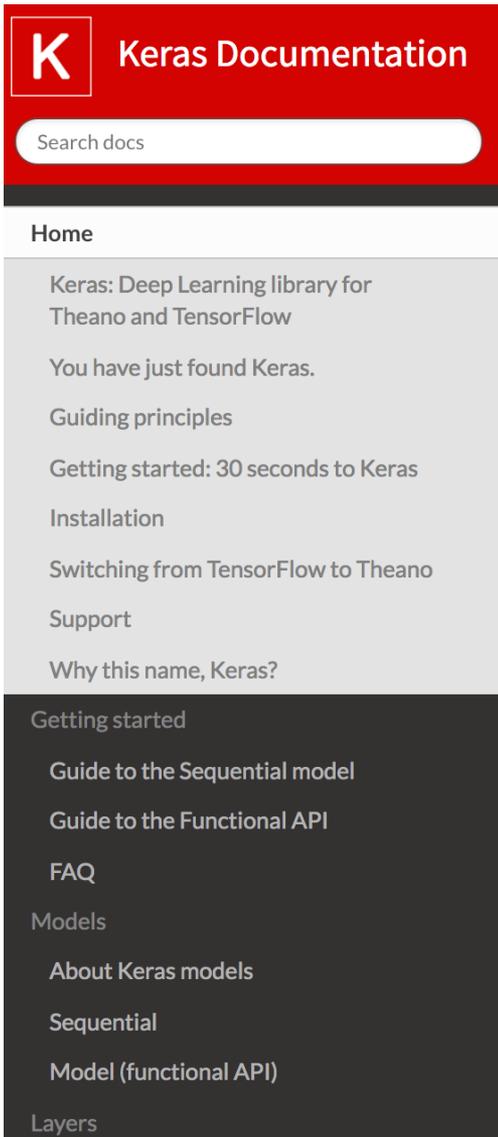
Keras is compatible with: **Python 2.7-3.5**.

Guiding principles

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

Deep Learning with Keras

Keras Installation



The image shows a sidebar from the Keras Documentation website. At the top is a red header with a white 'K' logo and the text 'Keras Documentation'. Below this is a search bar labeled 'Search docs'. The sidebar is divided into two sections: a light gray section for 'Home' and a dark gray section for 'Getting started'. The 'Home' section includes links for 'Keras: Deep Learning library for Theano and TensorFlow', 'You have just found Keras.', 'Guiding principles', 'Getting started: 30 seconds to Keras', 'Installation', 'Switching from TensorFlow to Theano', 'Support', and 'Why this name, Keras?'. The 'Getting started' section includes links for 'Guide to the Sequential model', 'Guide to the Functional API', 'FAQ', 'Models', 'About Keras models', 'Sequential', 'Model (functional API)', and 'Layers'.

Installation

Keras uses the following dependencies:

- numpy, scipy
- yaml
- HDF5 and h5py (optional, required if you use model saving/loading functions)
- Optional but recommended if you use CNNs: cuDNN.

When using the TensorFlow backend:

- TensorFlow
 - See installation instructions.

When using the Theano backend:

- Theano
 - See installation instructions.

To install Keras, `cd` to the Keras folder and run the install command:

```
sudo python setup.py install
```

You can also install Keras from PyPI:

```
sudo pip install keras
```

```
conda info --envs
```

```
conda --version
```

```
python --version
```

```
conda list
```

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

```
source activate tensorflow
```

```
activate tensorflow
```

```
pip install Theano
```

```
conda install pydot
```

```
sudo pip install keras
```

```
pip install keras
```

```
pip install tensorflow
```

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

Gensim

pip install -U gensim

```
bash-3.2$ pip install -U gensim
Collecting gensim
  Downloading gensim-2.0.0-cp36-cp36m-macosx_10_6_intel.macosx_10_9_intel.macosx_10_9_x86_64.macosx_10_10_intel.macosx_10_10_x86_64.whl (5.6MB)
    100% |#####| 5.6MB 126kB/s
Requirement already up-to-date: six>=1.5.0 in ./anaconda/lib/python3.6/site-packages (from gensim)
Collecting scipy>=0.7.0 (from gensim)
  Downloading scipy-0.19.0-cp36-cp36m-macosx_10_6_intel.macosx_10_9_intel.macosx_10_9_x86_64.macosx_10_10_intel.macosx_10_10_x86_64.whl (16.2MB)
    100% |#####| 16.2MB 43kB/s
Collecting smart-open>=1.2.1 (from gensim)
  Downloading smart_open-1.5.2.tar.gz
Collecting numpy>=1.3 (from gensim)
  Downloading numpy-1.12.1-cp36-cp36m-macosx_10_6_intel.macosx_10_9_intel.macosx_10_9_x86_64.macosx_10_10_intel.macosx_10_10_x86_64.whl (4.4MB)
    100% |#####| 4.4MB 148kB/s
Collecting boto>=2.32 (from smart-open>=1.2.1->gensim)
  Downloading boto-2.46.1-py2.py3-none-any.whl (1.4MB)
    100% |#####| 1.4MB 372kB/s
Requirement already up-to-date: bz2file in ./anaconda/lib/python3.6/site-packages (from smart-open>=1.2.1->gensim)
Collecting requests (from smart-open>=1.2.1->gensim)
  Downloading requests-2.13.0-py2.py3-none-any.whl (584kB)
    100% |#####| 593kB 632kB/s
Building wheels for collected packages: smart-open
Running setup.py bdist_wheel for smart-open ... done
Stored in directory: /Users/imyday/Library/Caches/pip/wheels/02/44/43/68e963ce2b45baefa913a4e558bcd787403458afddffcf45ca
Successfully built smart-open
Installing collected packages: numpy, scipy, boto, requests, smart-open, gensim
Found existing installation: numpy 1.11.3
  Uninstalling numpy-1.11.3:
    Successfully uninstalled numpy-1.11.3
Found existing installation: scipy 0.18.1
  Uninstalling scipy-0.18.1:
    Successfully uninstalled scipy-0.18.1
Found existing installation: boto 2.45.0
  DEPRECATION: Uninstalling a distutils installed project (boto) has been deprecated and will be removed in a future version. This is due to the fact that uninstalling a distutils project will only partially uninstall the project.
  Uninstalling boto-2.45.0:
    Successfully uninstalled boto-2.45.0
Found existing installation: requests 2.12.4
  Uninstalling requests-2.12.4:
    Successfully uninstalled requests-2.12.4
Found existing installation: smart-open 1.4.0
  Uninstalling smart-open-1.4.0:
    Successfully uninstalled smart-open-1.4.0
Found existing installation: gensim 1.0.1
  Uninstalling gensim-1.0.1:
    Successfully uninstalled gensim-1.0.1
Successfully installed boto-2.46.1 gensim-2.0.0 numpy-1.12.1 requests-2.13.0 scipy-0.19.0 smart-open-1.5.2
bash-3.2$
```

Keras

sudo pip install keras

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

TensorFlow

pip install tensorflow

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

Theano Example

```
import theano
from theano import tensor as T

a = T.scalar()
b = T.scalar()

y = a * b

multiply = theano.function(inputs=[a, b], outputs=y)

print(multiply(2, 3)) #6
print(multiply(4, 5)) #20
```

Theano Example

```
In [1]: #https://github.com/Newmu/Theano-Tutorials
import theano
from theano import tensor as T

a = T.scalar()
b = T.scalar()

y = a * b

multiply = theano.function(inputs=[a, b], outputs=y)

print(multiply(2, 3)) #6
print(multiply(4, 5)) #20
```

```
WARNING (theano.configdefaults): g++ not detected ! Theano will be unable to execute optimized C-implementations (for both CPU and GPU) and will default to Python implementations. Performance will be severely degraded. To remove this warning, set Theano flags cxx to an empty string.
```

```
WARNING:theano.configdefaults:g++ not detected ! Theano will be unable to execute optimized C-implementations (for both CPU and GPU) and will default to Python implementations. Performance will be severely degraded. To remove this warning, set Theano flags cxx to an empty string.
```

```
6.0
20.0
```

Keras Github



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Wiki

Pulse

Graphs

Deep Learning library for Python. Convnets, recurrent neural networks, and more. Runs on TensorFlow or Theano.

<http://keras.io/>

deep-learning

tensorflow

theano

neural-networks

machine-learning

data-science

3,503 commits

4 branches

28 releases

424 contributors

Branch: master

New pull request

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 phiple committed with fchollet	Added logsumexp to backend. (#6346)	Latest commit 7d52af6 a day ago
 docker	Update docker files to TensorFlow 1, Theano 0.9 (#6116)	20 days ago
 docs	fix stateful RNNs FAQ link (#6336)	3 days ago
 examples	Spelling errors (#6232)	11 days ago
 keras	Added logsumexp to backend. (#6346)	a day ago
 tests	Added logsumexp to backend. (#6346)	a day ago
 .gitignore	Fix FAQ question	a month ago
 .travis.yml	Update Travis config	9 days ago
 CONTRIBUTING.md	Mention requests for contribution in CONTRIBUTING.md	a month ago

<https://github.com/fchollet/keras>

Keras Examples



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History



Mohanson committed with fchollet Spelling errors (#6232)

Latest commit 5bd3976 11 days ago

..

README.md	Adding mnist_acgan.py example link in README (#4876)	4 months ago
addition_rnn.py	Spelling errors (#6232)	11 days ago
antirectifier.py	Style fix for examples. (#5980)	28 days ago
babi_memnn.py	Style fixes in example scripts	a month ago
babi_rnn.py	Style fixes in example scripts	a month ago
cifar10_cnn.py	fix rmsprop learning rate for convergence (#6182)	17 days ago
conv_filter_visualization.py	Finish updating examples.	a month ago
conv_lstm.py	Update a number of example scripts.	2 months ago
deep_dream.py	Finish updating examples.	a month ago
image_ocr.py	Fixed URL for wordlist.tgz in image_ocr.py (#6136)	20 days ago
imdb_bidirectional_lstm.py	Finish updating examples.	a month ago
imdb_cnn.py	Finish updating examples.	a month ago
imdb_cnn_lstm.py	Style fix for examples. (#5980)	28 days ago

Keras MNIST CNN

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

Jupyter Keras_mnist_cnn Last Checkpoint: an hour ago (autosaved)

Python 3 Logout

File Edit View Insert Cell Kernel Widgets Help

Python 3

Code CellToolbar

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

batch_size = 128
num_classes = 10
epochs = 12

# input image dimensions
img_rows, img_cols = 28, 28

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

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

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

Keras MNIST CNN

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

Jupyter Keras_mnist_cnn Last Checkpoint: an hour ago (autosaved)

Logout

File Edit View Insert Cell Kernel Widgets Help

Python 3

Code CellToolbar

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

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

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

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

Using TensorFlow backend.

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

Keras MNIST CNN

```
localhost:8888/notebooks/Documents/SCDBA/DL/Keras_mnist_cnn.ipynb
jupyter Keras_mnist_cnn Last Checkpoint: an hour ago (autosaved)
File Edit View Insert Cell Kernel Widgets Help Python 3
Using TensorFlow backend.
Downloading data from https://s3.amazonaws.com/img-datasets/mnist.npz
x_train shape: (60000, 28, 28, 1)
60000 train samples
10000 test samples
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
60000/60000 [=====] - 200s - loss: 0.3155 - acc: 0.9028 - val_loss: 0.0756 - val_acc: 0.9761
Epoch 2/12
60000/60000 [=====] - 209s - loss: 0.1106 - acc: 0.9681 - val_loss: 0.0523 - val_acc: 0.9837
Epoch 3/12
60000/60000 [=====] - 220s - loss: 0.0834 - acc: 0.9749 - val_loss: 0.0416 - val_acc: 0.9852
Epoch 4/12
60000/60000 [=====] - 224s - loss: 0.0700 - acc: 0.9795 - val_loss: 0.0392 - val_acc: 0.9879
Epoch 5/12
60000/60000 [=====] - 229s - loss: 0.0614 - acc: 0.9818 - val_loss: 0.0358 - val_acc: 0.9871
Epoch 6/12
60000/60000 [=====] - 227s - loss: 0.0558 - acc: 0.9828 - val_loss: 0.0345 - val_acc: 0.9880
Epoch 7/12
60000/60000 [=====] - 217s - loss: 0.0498 - acc: 0.9850 - val_loss: 0.0337 - val_acc: 0.9883
Epoch 8/12
60000/60000 [=====] - 217s - loss: 0.0473 - acc: 0.9865 - val_loss: 0.0294 - val_acc: 0.9899
Epoch 9/12
60000/60000 [=====] - 217s - loss: 0.0439 - acc: 0.9872 - val_loss: 0.0316 - val_acc: 0.9889
Epoch 10/12
60000/60000 [=====] - 217s - loss: 0.0415 - acc: 0.9871 - val_loss: 0.0319 - val_acc: 0.9897
Epoch 11/12
60000/60000 [=====] - 217s - loss: 0.0380 - acc: 0.9889 - val_loss: 0.0275 - val_acc: 0.9904
Epoch 12/12
60000/60000 [=====] - 215s - loss: 0.0376 - acc: 0.9889 - val_loss: 0.0285 - val_acc: 0.9905
Test loss: 0.0285460013417
Test accuracy: 0.9905
```

Keras MINST CNN

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

batch_size = 128
num_classes = 10
epochs = 12

# input image dimensions
img_rows, img_cols = 28, 28

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

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

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

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

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

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

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

Keras MNIST CNN

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

Keras MNIST CNN

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

# input image dimensions
img_rows, img_cols = 28, 28

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

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

Keras MNIST CNN

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

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

Keras MNIST CNN

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

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

Keras MNIST CNN

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

Keras MNIST CNN

python mnist_cnn.py

Using TensorFlow backend.

Downloading data from <https://s3.amazonaws.com/img-datasets/mnist.npz>

x_train shape: (60000, 28, 28, 1)

60000 train samples

10000 test samples

Train on 60000 samples, validate on 10000 samples

Epoch 1/12

60000/60000 [=====] - 108s - loss: 0.3510 - acc: 0.8921 - val_loss: 0.0880 - val_acc: 0.9738

Epoch 2/12

60000/60000 [=====] - 106s - loss: 0.1200 - acc: 0.9649 - val_loss: 0.0567 - val_acc: 0.9820

Epoch 3/12

60000/60000 [=====] - 104s - loss: 0.0889 - acc: 0.9735 - val_loss: 0.0438 - val_acc: 0.9856

Epoch 4/12

60000/60000 [=====] - 106s - loss: 0.0744 - acc: 0.9783 - val_loss: 0.0392 - val_acc: 0.9862

Epoch 5/12

60000/60000 [=====] - 106s - loss: 0.0648 - acc: 0.9807 - val_loss: 0.0363 - val_acc: 0.9873

Epoch 6/12

60000/60000 [=====] - 109s - loss: 0.0574 - acc: 0.9840 - val_loss: 0.0348 - val_acc: 0.9884

Epoch 7/12

60000/60000 [=====] - 104s - loss: 0.0522 - acc: 0.9842 - val_loss: 0.0324 - val_acc: 0.9890

Epoch 8/12

60000/60000 [=====] - 104s - loss: 0.0484 - acc: 0.9856 - val_loss: 0.0315 - val_acc: 0.9894

Epoch 9/12

60000/60000 [=====] - 104s - loss: 0.0447 - acc: 0.9870 - val_loss: 0.0296 - val_acc: 0.9902

Epoch 10/12

60000/60000 [=====] - 109s - loss: 0.0419 - acc: 0.9877 - val_loss: 0.0338 - val_acc: 0.9894

Epoch 11/12

60000/60000 [=====] - 104s - loss: 0.0405 - acc: 0.9879 - val_loss: 0.0301 - val_acc: 0.9896

Epoch 12/12

60000/60000 [=====] - 127s - loss: 0.0391 - acc: 0.9883 - val_loss: 0.0304 - val_acc: 0.9899

Test loss: 0.030424870987

Test accuracy: 0.9899

Keras IMDB CNN

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

Jupyter Keras_imdb_cnn Last Checkpoint: 15 minutes ago (unsaved changes)



File Edit View Insert Cell Kernel Widgets Help

Python 3

Code CellToolbar

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

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

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

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

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

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

Keras IMDB CNN

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

jupyter Keras_imdb_cnn Last Checkpoint: 19 minutes ago (autosaved)



File Edit View Insert Cell Kernel Widgets Help

Python 3

Code CellToolbar

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

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

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

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

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

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

Using TensorFlow backend.

Loading data...

Downloading data from <https://s3.amazonaws.com/text-datasets/imdb.npz>

25000 train sequences

Keras IMDB CNN

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

jupyter Keras_imdb_cnn Last Checkpoint: 13 minutes ago (autosaved)

Logout

File Edit View Insert Cell Kernel Widgets Help

Python 3

Code CellToolbar

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

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

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

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

Using TensorFlow backend.

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

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

Keras IMDB CNN

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

Keras IMDB LSTM

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

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

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

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

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

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

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

Keras IMDB LSTM

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

Keras IMDB LSTM

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

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

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

Keras IMDB LSTM

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

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

Keras IMDB LSTM

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

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

Keras IMDB LSTM

python imdb_lstm.py
Using TensorFlow backend.

Loading data...

25000 train sequences

25000 test sequences

Pad sequences (samples x time)

x_train shape: (25000, 80)

x_test shape: (25000, 80)

Build model...

Train...

Train on 25000 samples, validate on 25000 samples

Epoch 1/15

25000/25000 [=====] - 111s - loss: 0.4561 - acc: 0.7837 - val_loss: 0.3892 - val_acc: 0.8275

Epoch 2/15

25000/25000 [=====] - 112s - loss: 0.2947 - acc: 0.8792 - val_loss: 0.4266 - val_acc: 0.8353

Epoch 3/15

25000/25000 [=====] - 111s - loss: 0.2122 - acc: 0.9178 - val_loss: 0.4133 - val_acc: 0.8284

Epoch 4/15

25000/25000 [=====] - 112s - loss: 0.1461 - acc: 0.9450 - val_loss: 0.4670 - val_acc: 0.8260

Epoch 5/15

25000/25000 [=====] - 113s - loss: 0.1038 - acc: 0.9633 - val_loss: 0.5580 - val_acc: 0.8203

Epoch 6/15

25000/25000 [=====] - 113s - loss: 0.0739 - acc: 0.9749 - val_loss: 0.6738 - val_acc: 0.8174

Epoch 7/15

25000/25000 [=====] - 113s - loss: 0.0542 - acc: 0.9810 - val_loss: 0.7463 - val_acc: 0.8154

Epoch 8/15

25000/25000 [=====] - 113s - loss: 0.0428 - acc: 0.9856 - val_loss: 0.8131 - val_acc: 0.8157

Epoch 9/15

25000/25000 [=====] - 115s - loss: 0.0334 - acc: 0.9889 - val_loss: 0.8566 - val_acc: 0.8165

Epoch 10/15

25000/25000 [=====] - 114s - loss: 0.0248 - acc: 0.9920 - val_loss: 0.9186 - val_acc: 0.8165

Epoch 11/15

25000/25000 [=====] - 116s - loss: 0.0156 - acc: 0.9955 - val_loss: 0.9016 - val_acc: 0.8082

Epoch 12/15

25000/25000 [=====] - 117s - loss: 0.0196 - acc: 0.9942 - val_loss: 0.9720 - val_acc: 0.8124

Epoch 13/15

25000/25000 [=====] - 120s - loss: 0.0152 - acc: 0.9957 - val_loss: 1.0064 - val_acc: 0.8148

Epoch 14/15

25000/25000 [=====] - 121s - loss: 0.0128 - acc: 0.9961 - val_loss: 1.1103 - val_acc: 0.8121

Epoch 15/15

25000/25000 [=====] - 114s - loss: 0.0110 - acc: 0.9970 - val_loss: 1.0173 - val_acc: 0.8132

25000/25000 [=====] - 23s

Test score: 1.01734088922

Test accuracy: 0.8132

Keras IMDB FastText

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

Keras IMDB CNN LSTM

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

imdb_lstm_2.py

```
from __future__ import print_function

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

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

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

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

imdb_lstm_2.py

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

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

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

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

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

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

imdb_lstm_2.py

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

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

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

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

imdb_lstm_2.py

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

score, acc = model.evaluate(x_test, y_test,
                            batch_size=batch_size)

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

imdb_lstm_2.py

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

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

imdb_lstm_2.py

Deep Learning Training Visualization

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

imdb_lstm_2.py

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

python filename.py

```
python imdb_fasttext_2.py
```

```
python imdb_cnn_2.py
```

```
python imdb_lstm_2.py
```

```
python imdb_cnn_lstm_2.py
```

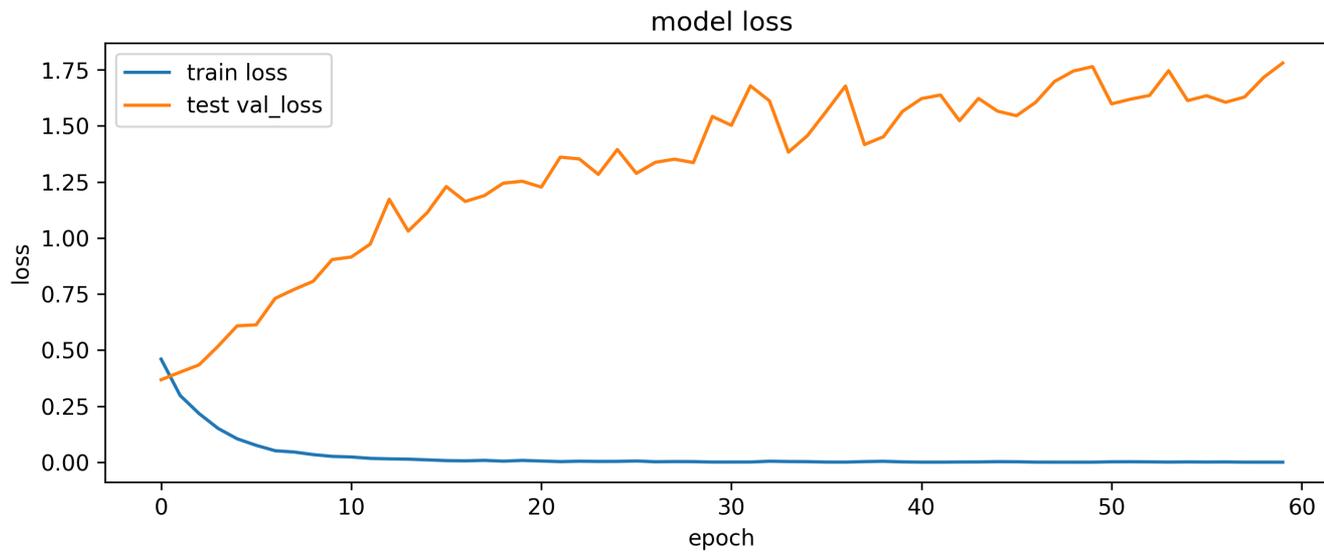
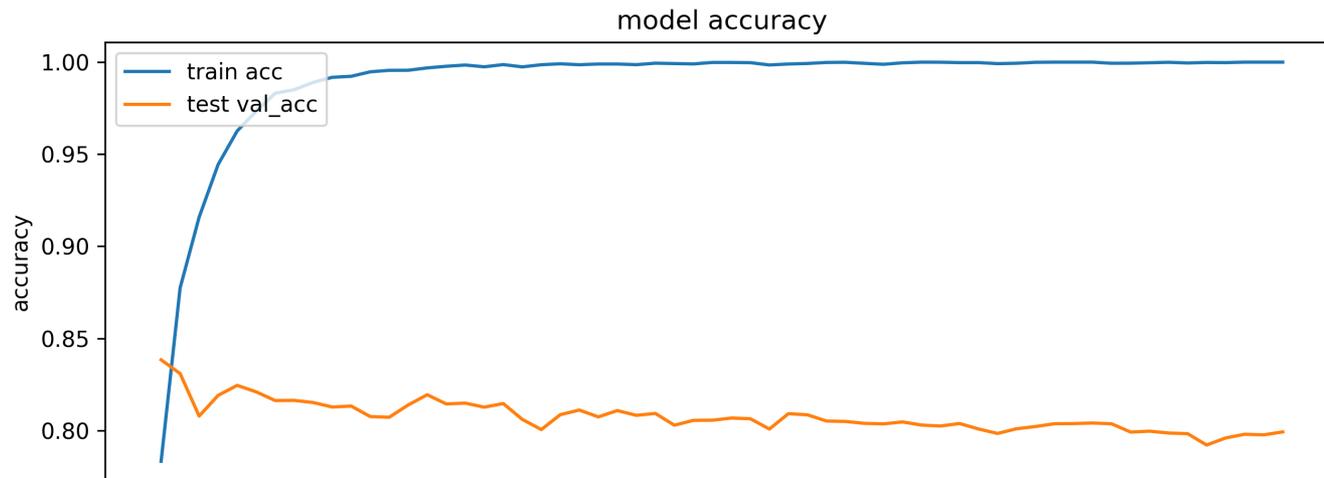
```
python imdb_bidirectional_lstm_2.py
```

Deep Learning Summary

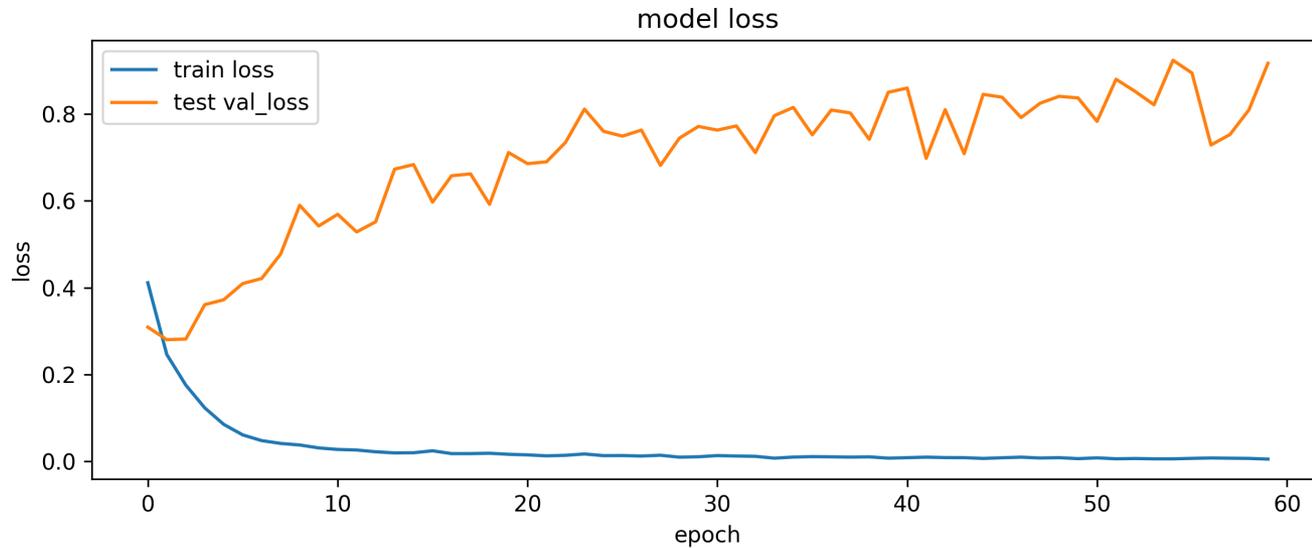
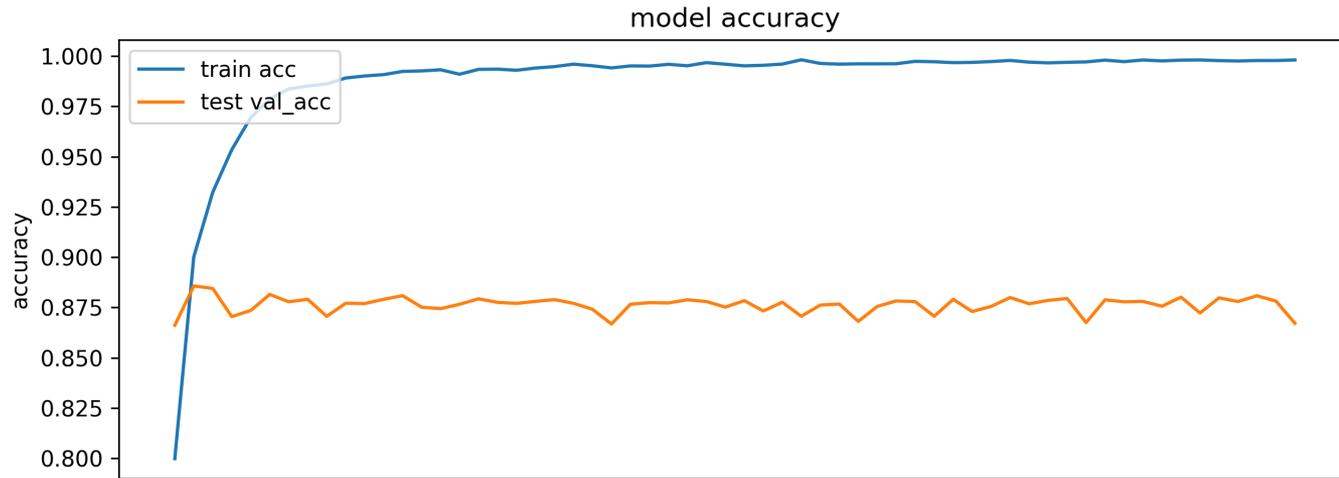
```
#Log File for Deep Learning Summary Analysis
log_file_utf8("logfile.txt", 'DL_Summary:\t' + py_filename +
'\tepochs\t' + str(epochs) +
'\tscore\t' + str(score) +
'\taccuracy\t' + str(acc) +
'\tTimer\t' + str(round(timer_end - timer_start, 2)) +
'\thistory\t' + str(history.history))
```

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

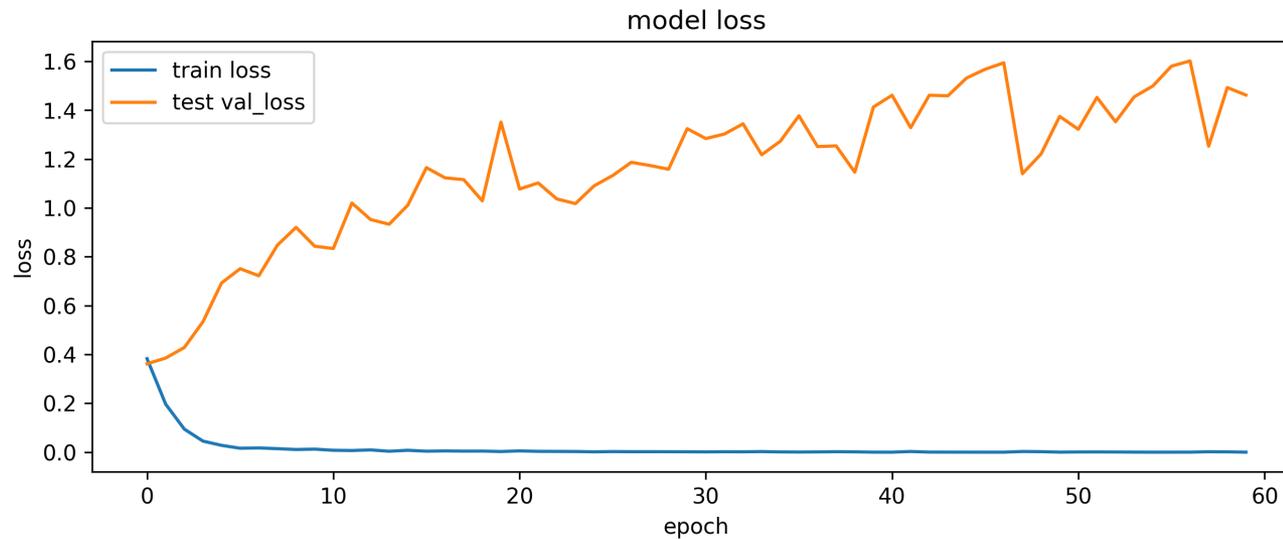
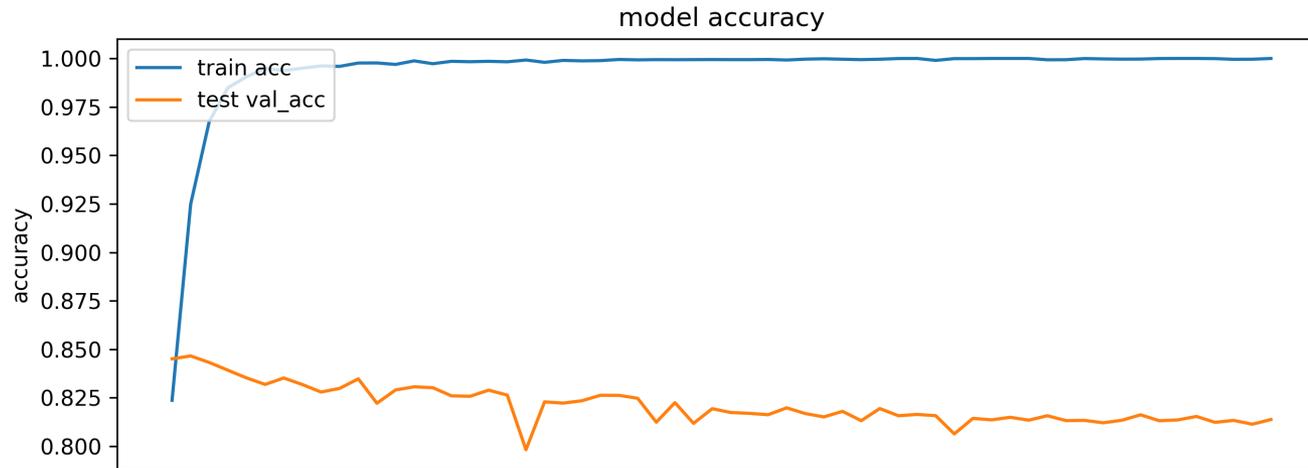
imdb_lstm_2.py



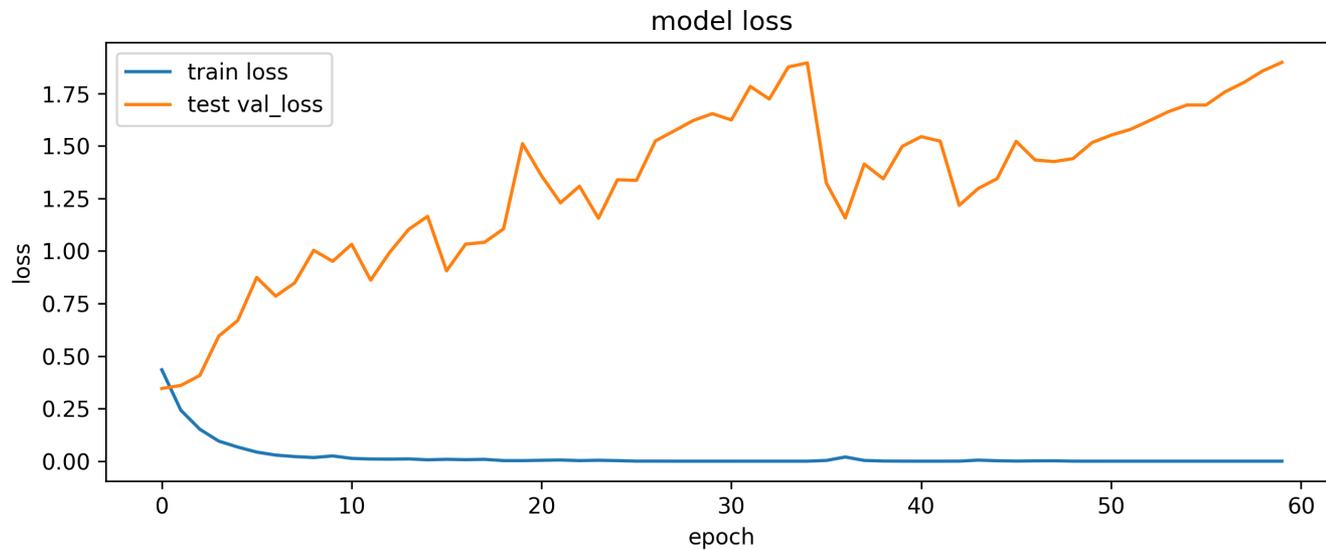
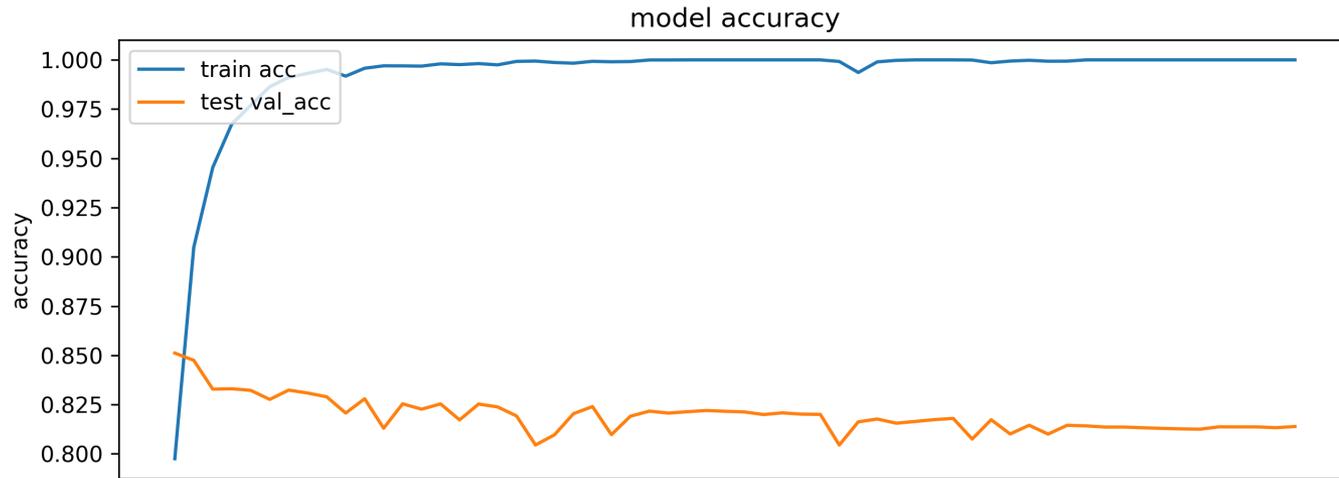
imdb_cnn_2.py



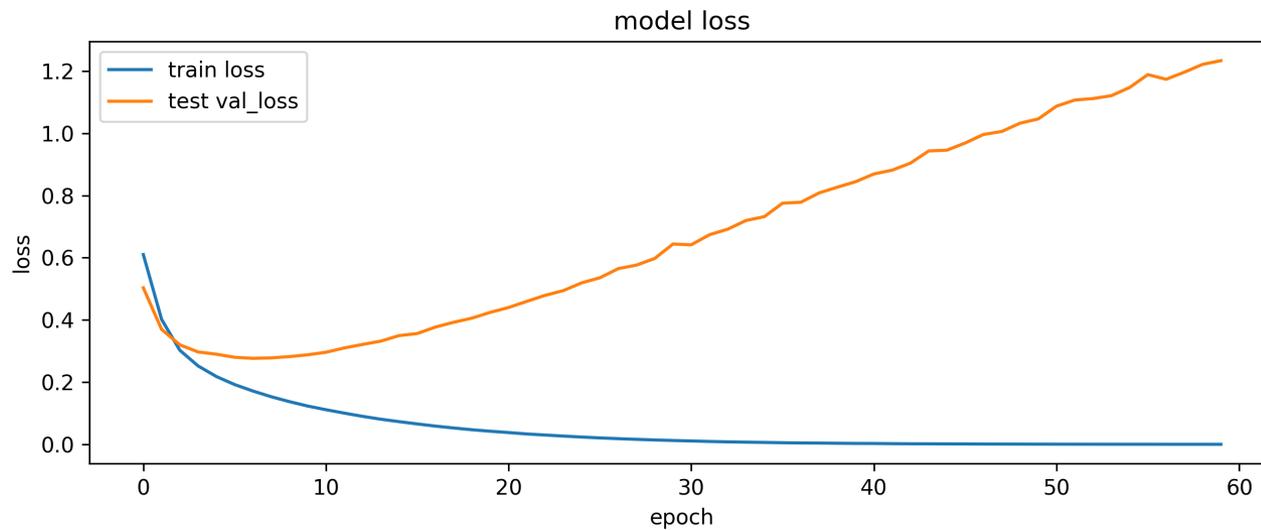
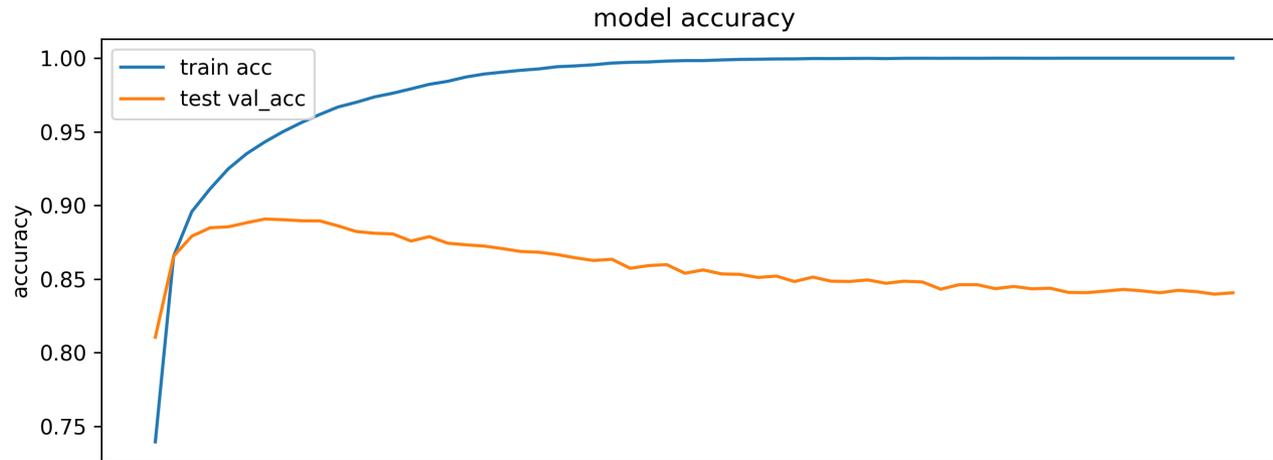
imdb_cnn_lstm_2.py



imdb_bidirectional_lstm_2.py



imdb_fasttext_2.py



Deep Learning with CPU vs. GPU

Timings:

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

TensorFlow MNIST Tutorial



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Pulse

Graphs

Sample code for "Tensorflow and deep learning, without a PhD" presentation and code lab.

102 commits

1 branch

0 releases

4 contributors

Apache-2.0

Branch: master

New pull request

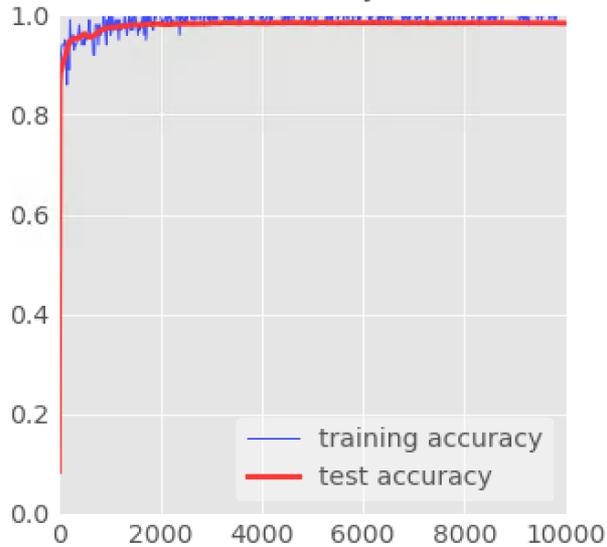
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Clone or download

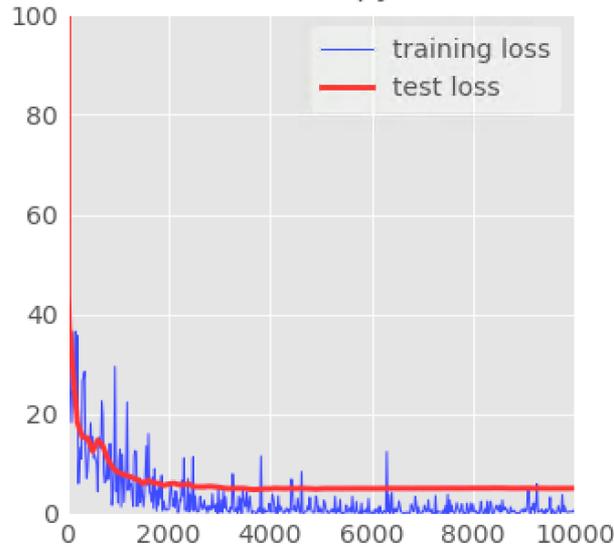
martin-gorner committed on GitHub Update INSTALL.txt ...	Latest commit ed331aa 25 days ago
mlengine	added example using the Tensorflow high level layers API 26 days ago
.gitignore	small bug fix in batch norm 6 months ago
CONTRIBUTING.md	initial commit 2 4 months ago
INSTALL.txt	Update INSTALL.txt 25 days ago
LICENSE	Initial commit a year ago
README.md	better image URL 3 months ago
mnist_1.0_softmax.py	global_variables_initializer used everywhere instead of initalize_al... 2 months ago
mnist_2.0_five_layers_sigmoid.py	Fix spacing in the network structure comment a month ago
mnist_2.1_five_layers_relu_lrdecay...	Fix spacing in the network structure comment a month ago

TensorFlow MNIST Tutorial

Accuracy



Cross entropy loss

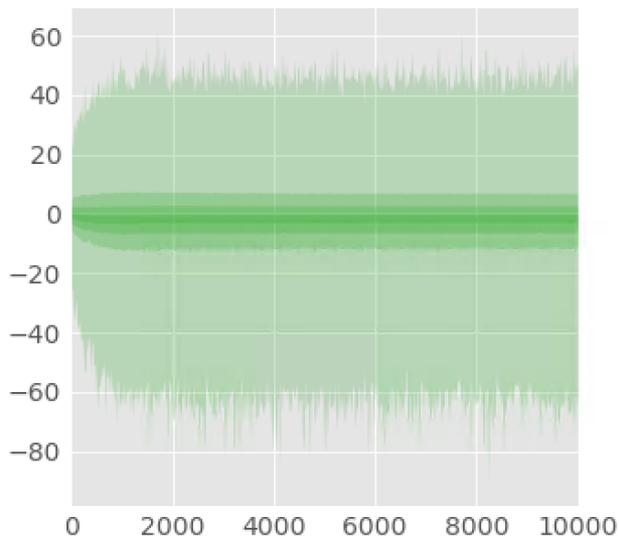


Training digits

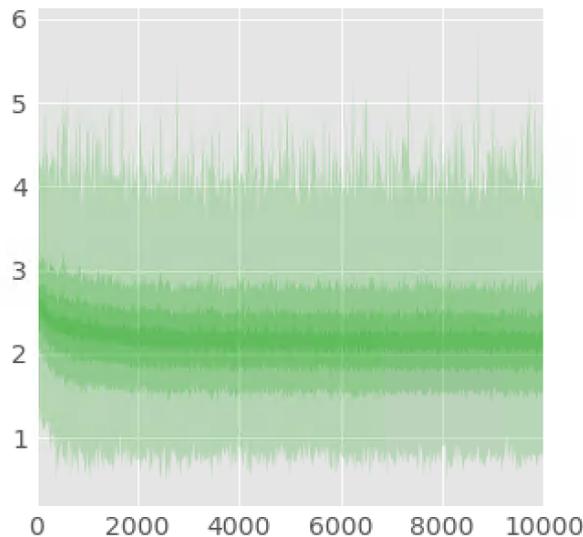
```

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

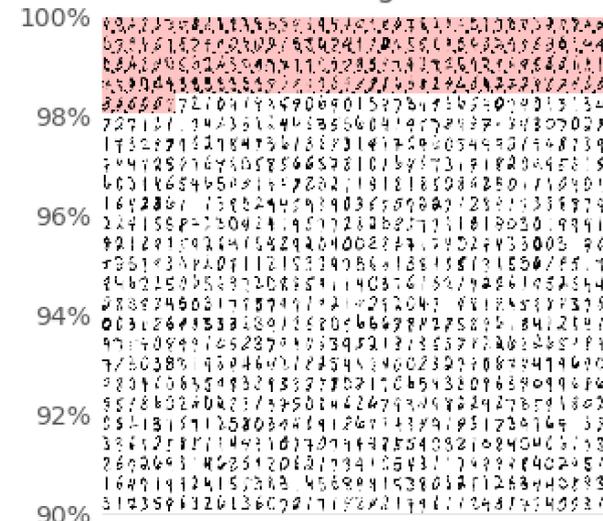
Logits



Max activations across batch



Test digits



TensorFlow Playground

Tinker With a **Neural Network** Right Here in Your Browser.
Don't Worry, You Can't Break It. We Promise.



Iterations
000,582

Learning rate
0.03

Activation
Tanh

Regularization
None

Regularization rate
0

Problem type
Classification

DATA

Which dataset do you want to use?



Ratio of training to test data: 50%

Noise: 0

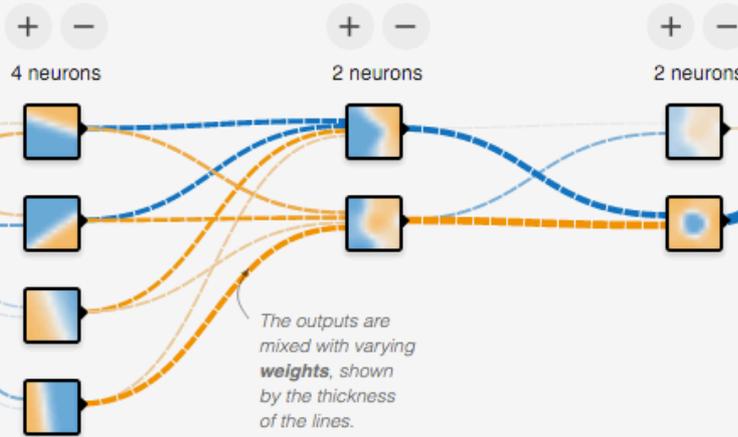
Batch size: 10

INPUT

Which properties do you want to feed in?



+ - 3 HIDDEN LAYERS

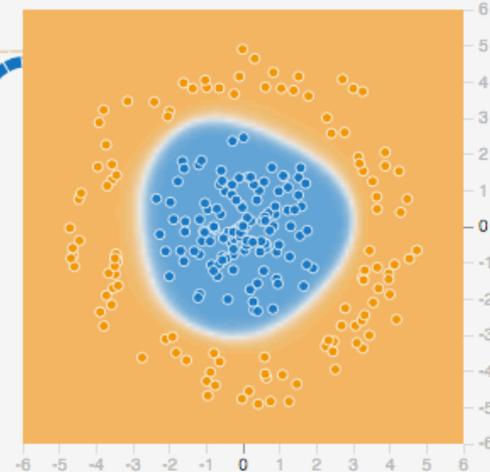


The outputs are mixed with varying **weights**, shown by the thickness of the lines.

This is the output from one **neuron**. Hover to see it larger.

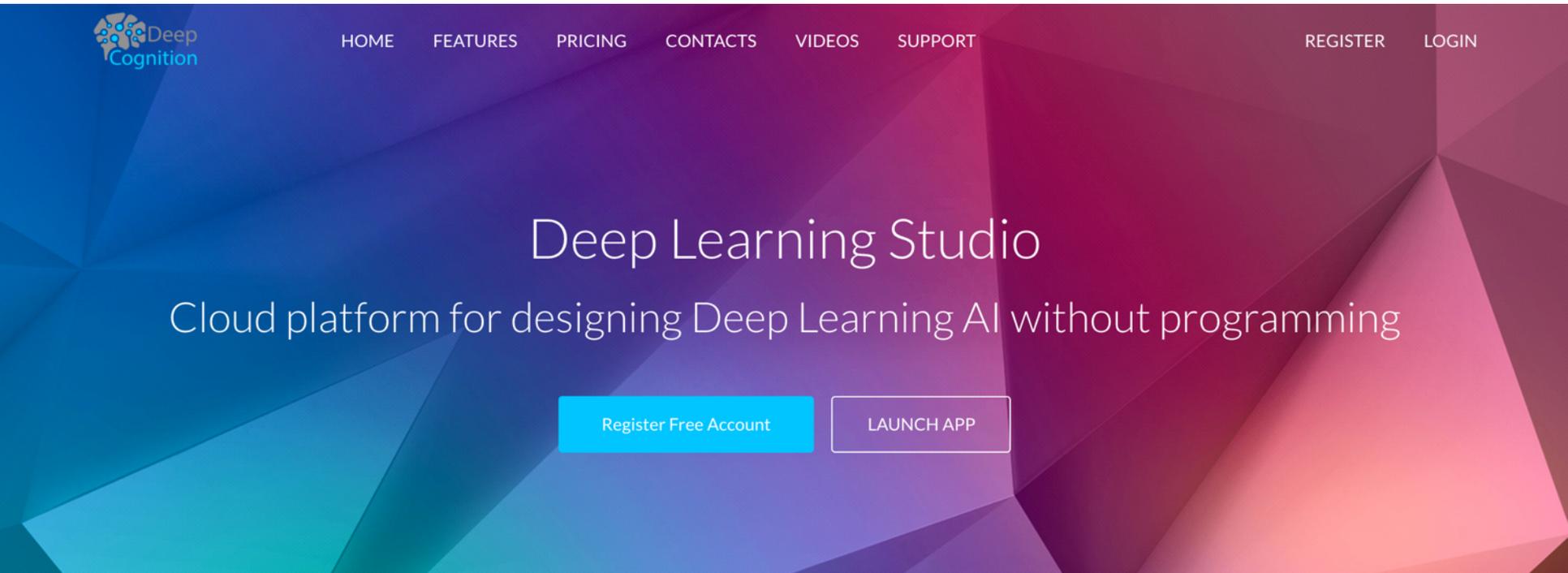
OUTPUT

Test loss 0.000
Training loss 0.000



Deep Learning Studio

Cloud platform for designing Deep Learning AI without programming



The screenshot shows the Deep Learning Studio interface for a CIFAR-10 project. The top bar includes the logo, "Deep Learning Studio beta - beta", the project name "CIFAR-10 - Object Recognition in Images", and a user profile "mandeep2". The interface is divided into several tabs: Data, Model, HyperParameters, Training, Results, and Inference. The "Model" tab is active, showing a diagram of a neural network layer labeled "Input_2" with a bidirectional arrow and the parameters "(None, 3, 32, 32)". On the left, a sidebar lists "Pre-Trained Models" with "InceptionV3" and "VGG19" options. On the right, the "Results" tab shows a green checkmark and text: "Instantiate the vgg19 architecture, more...", "Include Top Fully Connect...", "false", "trainable", and "10".

Deep Learning Studio

Cloud platform for designing Deep Learning AI without programming

The screenshot displays the Deep Learning Studio interface for building a neural network. The main workspace shows a flowchart of the model architecture with the following layers:

- Input_2**: (None, 3, 32, 32)
- VGG19_1**: (None, 512, 1, 1)
- Flatten_2**: (None, 512)
- Dense_5**: (None, 100)
- Dropout_1**: (None, 100)
- Dense_3**: (None, 10)
- Output_2**: (None, 10)

The left sidebar contains a menu with categories: Pre-Trained Models (listing InceptionV3, VGG19, VGG16, ResNet50), Special Functions, Convolutional Layers, Core Layers, Pooling Layers, Recurrent Layers, Advanced Activations Layers, Convolutional Recurrent Layers, and Noise Layers. The right sidebar shows configuration options for the VGG19 architecture, including a 'trainable' dropdown set to '10' and a 'Show Advance Options' toggle.



Deep Learning Studio

Cloud platform for designing Deep Learning AI without programming

eta

MNIST Handwritten Digits Classifier

Model HyperParameters Training Results

Dataset Source: Testing ▾

Training Run: Run0 ▾ Start Inference or Download Trained Model

Digit Label	Image	predictions
• 9		• 9
• 1		• 1
• 1		• 1
• 5		• 3
• 0		• 0
• 5		• 5
• 1		• 1
• 2		• 6
• 2		• 2
• 3		• 3

« Previous 1 2 3 4 5 ... 351 Next »

Download Results

References

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- Sebastian Raschka (2015), Python Machine Learning, Packt Publishing
- Martin Gorner (2017), TensorFlow and Deep Learning without a PhD, Part 1 (Google Cloud Next '17), <https://www.youtube.com/watch?v=u4alGiomYP4>
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- Deep Learning SIMPLIFIED, <https://www.youtube.com/playlist?list=PLjJh1vISEYgvGod9wWiydumYl8hOXixNu>
- TensorFlow: <https://www.tensorflow.org/>
- Theano: <http://deeplearning.net/software/theano/>
- Keras: <http://keras.io/>
- Deep Learning Studio: Cloud platform for designing Deep Learning AI without programming, <http://deepcognition.ai/>