Machine Learning and Pattern Recognition
A High Level Overview

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(Main bulk of slides kindly provided by **Prof. Sandra Avila**)
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MC886/MO444

Many inventions were inspired by Nature ...

Birds inspired us to fly

https://i.pinimg.com/736x/18/4a/cc/184accf6b4d7980d2c2e8090ff295cd7--animal-tracks-friends.jpg

Many inventions were inspired by Nature ...

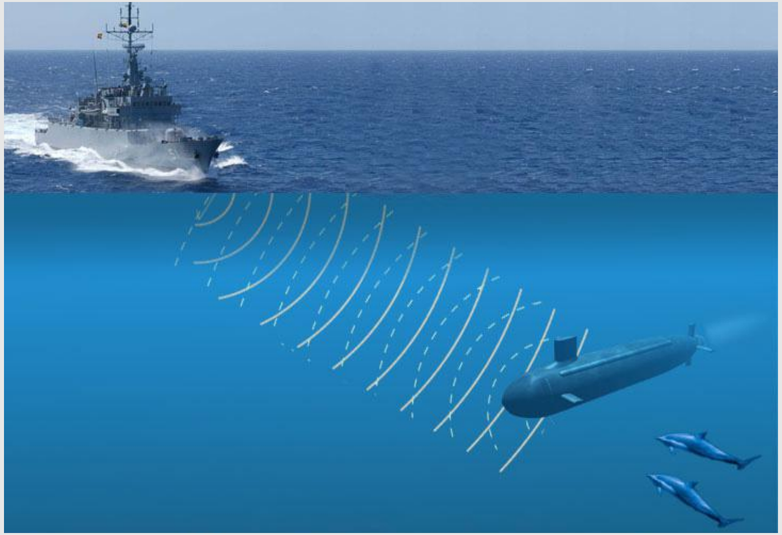
Burdock plants inspired velcro

http://www.youngworldclub.com/wp-content/uploads/2017/04/velcro.jpeg

https://c1.staticflickr.com/3/2887/12882961455_f2d6bee40c_b.jpg

Many inventions were inspired by Nature ...

Dolphins inspired sonar development



https://sites.google.com/site/echolocationkawproject/_/rsrc/1459209762464/sonars/image.jpeg

http://www.dolphinkind.com/images/dolphin_echolocation.jpg

Many inventions were inspired by Nature ...

Dogs inspired …

https://farm2.staticflickr.com/1586/24734777053_d1bdb8bba4_o.jpg

It seems logical to look at the brain's architecture for inspiration on how to build an intelligent machine.

Today’s Agenda

- Artificial Neural Networks
  - From Biological to Artificial Neurons
  - Biological Neurons
  - Logical Computations with Neurons
  - The Perceptron
  - Multi-Layer Perceptron and Backpropagation

From Biological to Artificial Neurons

From Biological to Artificial Neurons

- **1943:** Artificial Neural Networks (ANNs) were first introduced by the neurophysiologist Warren McCulloch and the mathematician Walter Pitts.

  “A Logical Calculus of Ideas Immanent in Nervous Activity”, Warren McCulloch and Walter Pitts. The bulletin of mathematical biophysics (1943).

From Biological to Artificial Neurons

- **Until the 1960s:** The early successes of ANNs led to the widespread belief that we would soon be conversing with truly intelligent machines.

- When it became clear that this promise would go unfulfilled funding flew elsewhere and ANNs entered a long dark era.

From Biological to Artificial Neurons

- **1980s:** There was a revival of interest in ANNs as new network architectures were invented and **better training techniques** were developed.

  "Learning representations by backpropagating errors". David E. Rumelhart, Geoffrey E. Hinton & Ronald J. Williams. Nature (1986).

From Biological to Artificial Neurons

- **1990s: Powerful alternative Machine Learning techniques** such as Support Vector Machines were favored by most researchers, as they seemed to offer better results and stronger theoretical foundations.

From Biological to Artificial Neurons

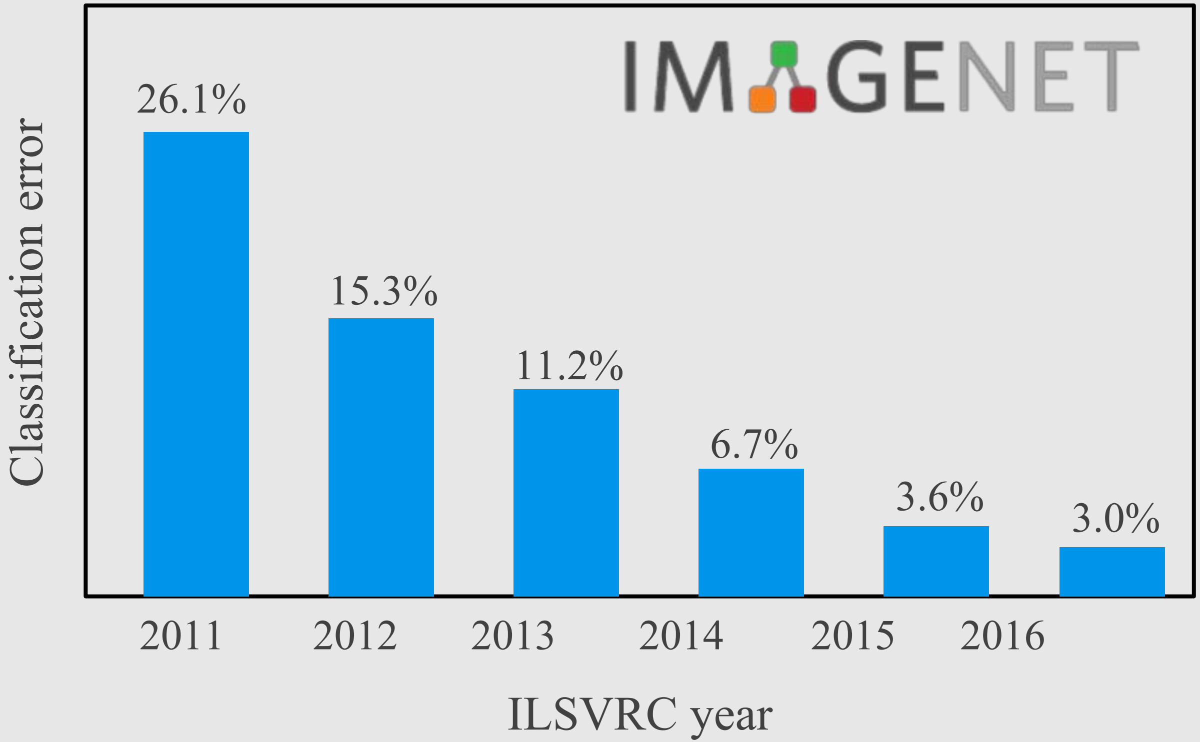
- **2010s:** We are now witnessing yet another wave of interest in ANNs.

ILSVRC 2012 — Image Classification task

Rank	Name	Error Rate (%)	Description
1	University of Toronto	15.3	Deep Learning
2	University of Tokyo	26.2	Hand-crafted features and learning models
3	University of Oxford	26.9	
4	Xerox/INRIA	27.0	

Object recognition over 1,000,000 images and 1,000 categories (2 GPU)

“ImageNet classification with deep convolutional neural networks”. Alex Krizhevsky, Ilya Sutskever, Geoffrey Hinton. In: NIPS, 2012.



“ImageNet classification with deep convolutional neural networks”. Alex Krizhevsky, Ilya Sutskever, Geoffrey Hinton. In: NIPS, 2012.

From Biological to Artificial Neurons

- **2010s:** We are now witnessing yet another wave of interest in ANNs.

Will this wave die out like the previous ones did?

From Biological to Artificial Neurons

1. There is now a **huge quantity of data** available to train neural networks.

IMAGENET

www.image-net.org

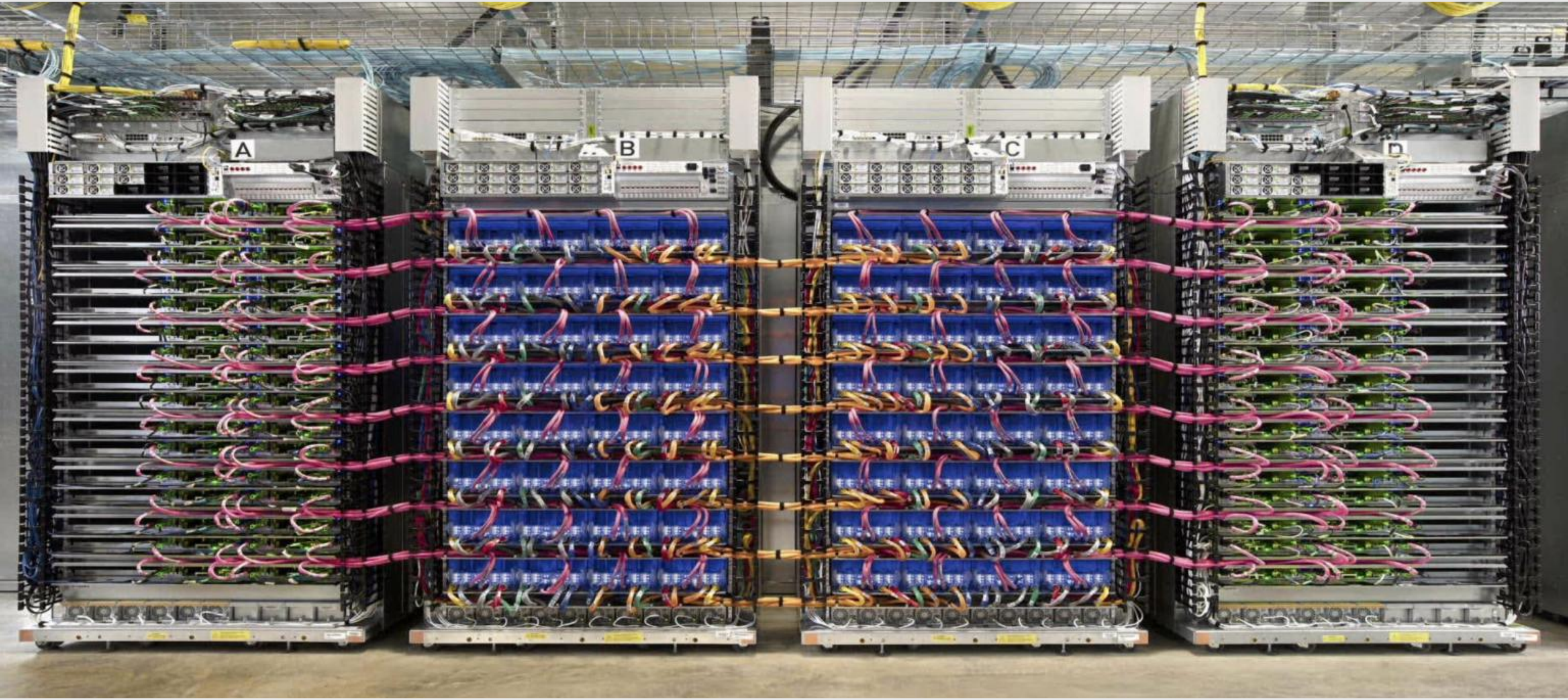
22K categories and **14M** images

- Animals
  - Bird
  - Fish
  - Mammal
  - Invertebrate
- Plants
  - Tree
  - Flower
- Food
- Materials
- Structures
- Artifact
  - Tools
  - Appliances
  - Structures
- Person
- Scenes
  - Indoor
  - Geological Formations
- Sport Activities

Deng, Dong, Socher, Li, Li, & Fei-Fei, 2009

From Biological to Artificial Neurons

1. There is now a **huge quantity of data** available to train neural networks.
2. **Computing power** now makes it possible to train large neural networks in a reasonable amount of time.

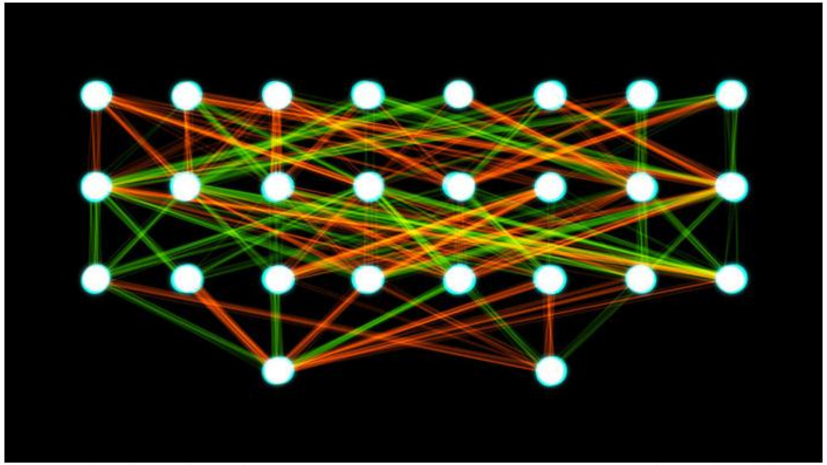


http://www.tomshardware.com/news/google-automl-aritifical-intelligence-ai,34533.html

From Biological to Artificial Neurons

1. There is now a **huge quantity of data** available to train neural networks.
2. **Computing power** now makes it possible to train large neural networks in a reasonable amount of time.
3. The **training algorithms** have been **improved**.

SHARE



A representation of a neural network. Akritasa/Wikimedia Commons

Brainlike computers are a black box. Scientists are finally peering inside

By Jackie Snow | Mar. 7, 2017 , 3:15 PM

Last month, Facebook announced software that could simply look at a photo and tell, for example, whether it was a picture of a cat or a dog. A related program identifies cancerous

http://www.sciencemag.org/news/2017/03/brainlike-computers-are-black-box-scientists-are-finally-peering-inside

From Biological to Artificial Neurons

1. There is now a **huge quantity of data** available to train neural networks.
2. **Computing power** now makes it possible to train large neural networks in a reasonable amount of time.
3. The **training algorithms** have been **improved**.
4. ANNs seem to have entered a virtuous circle of funding and progress.

Biological Neurons

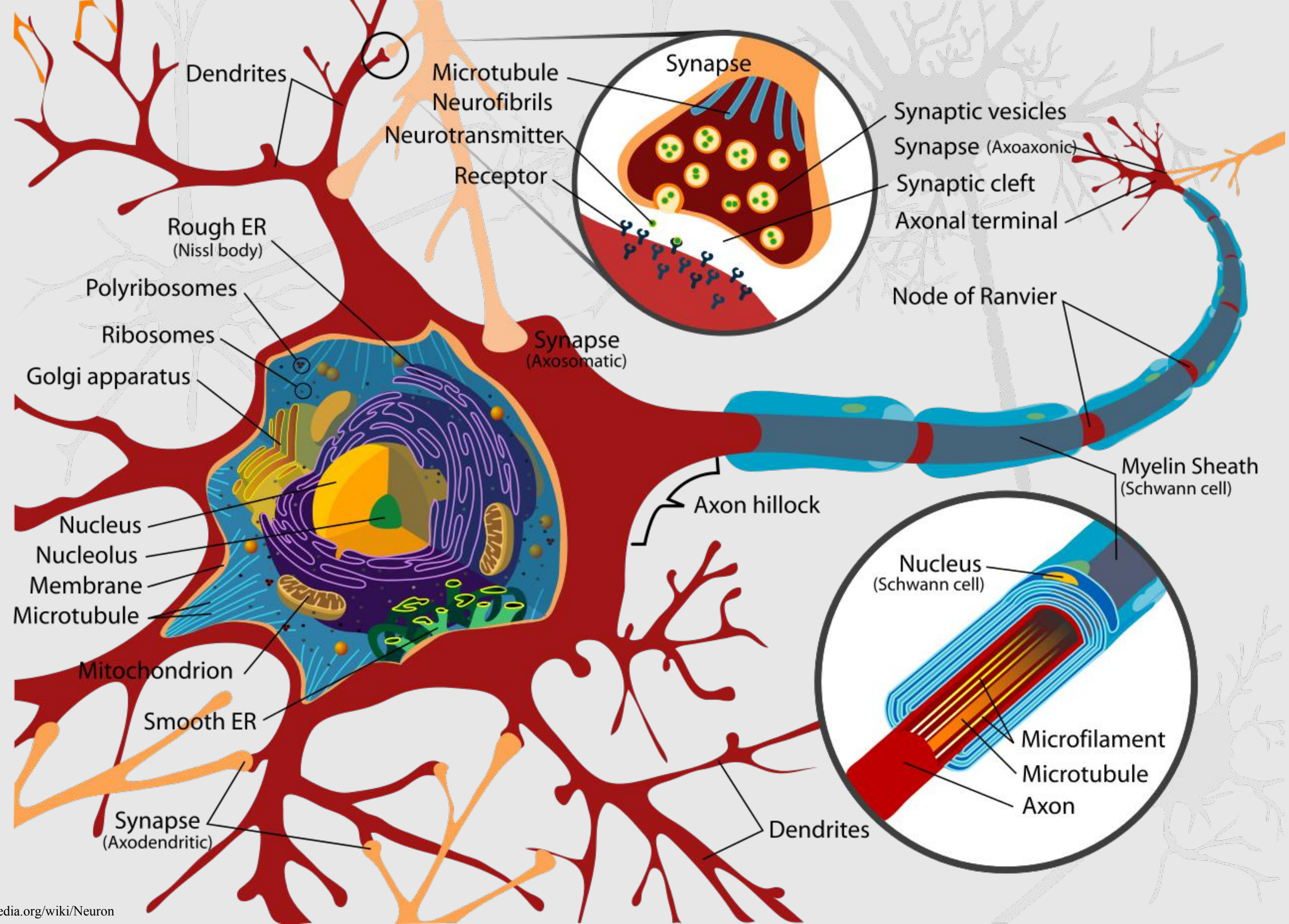
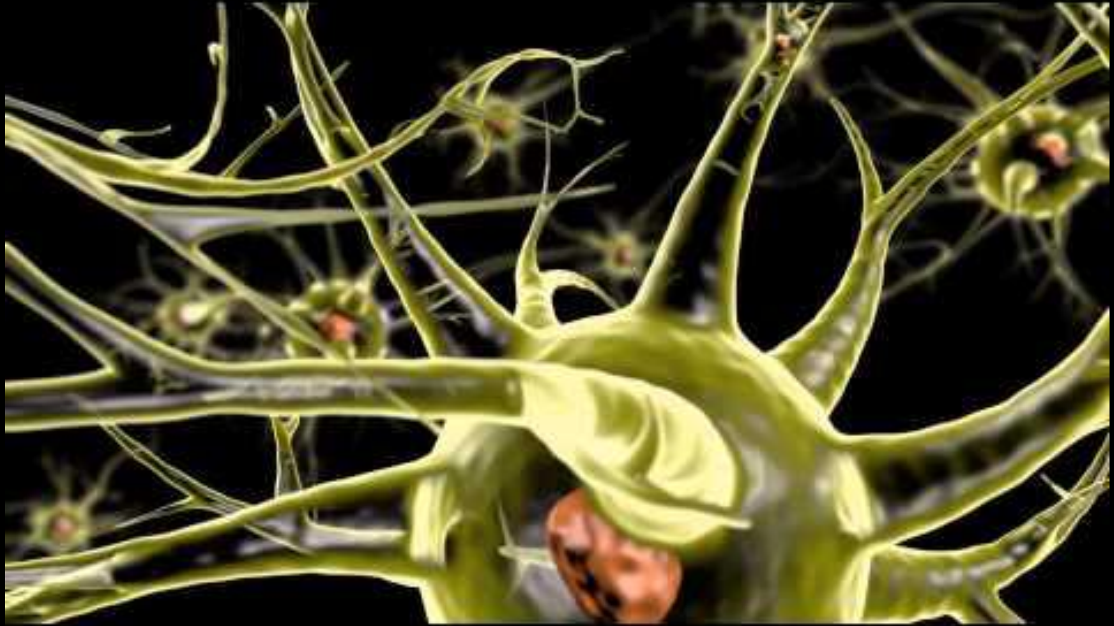
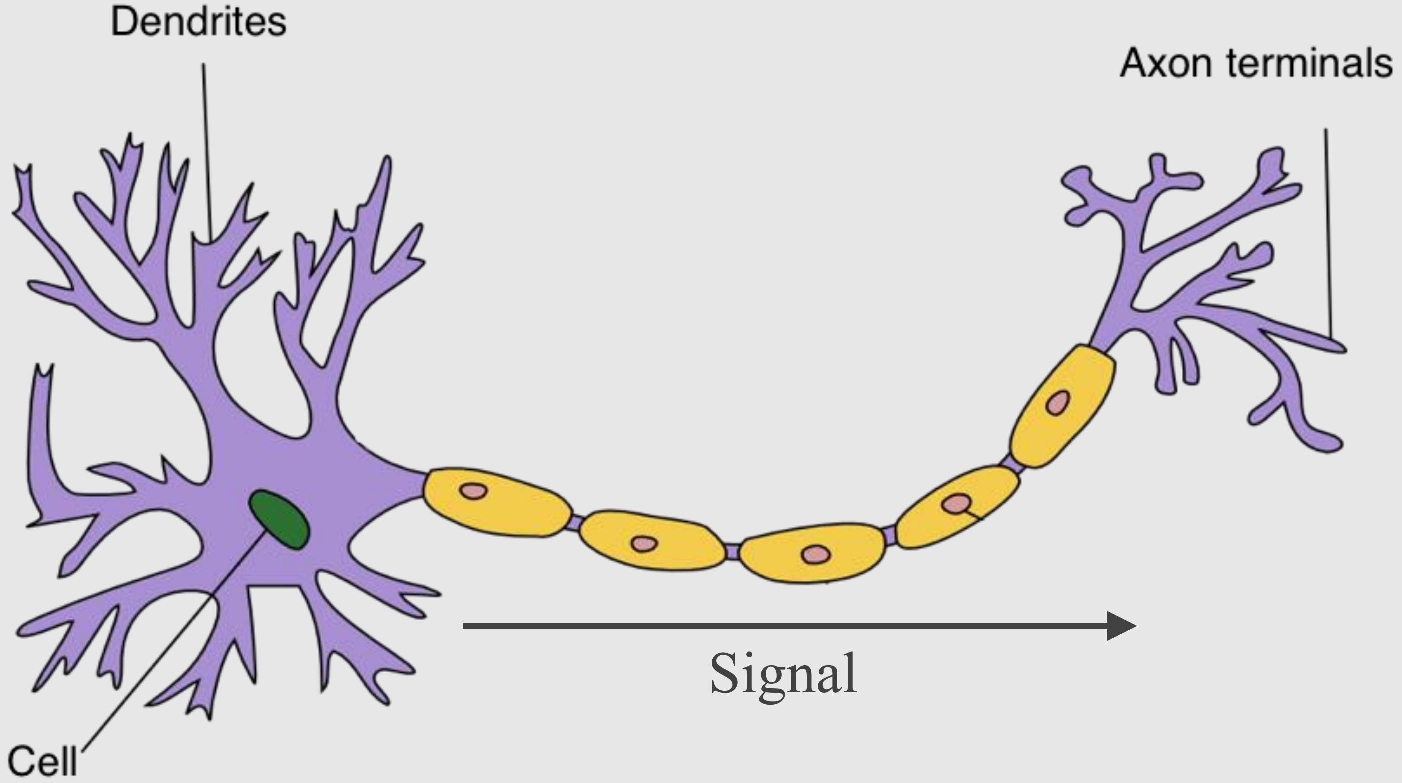


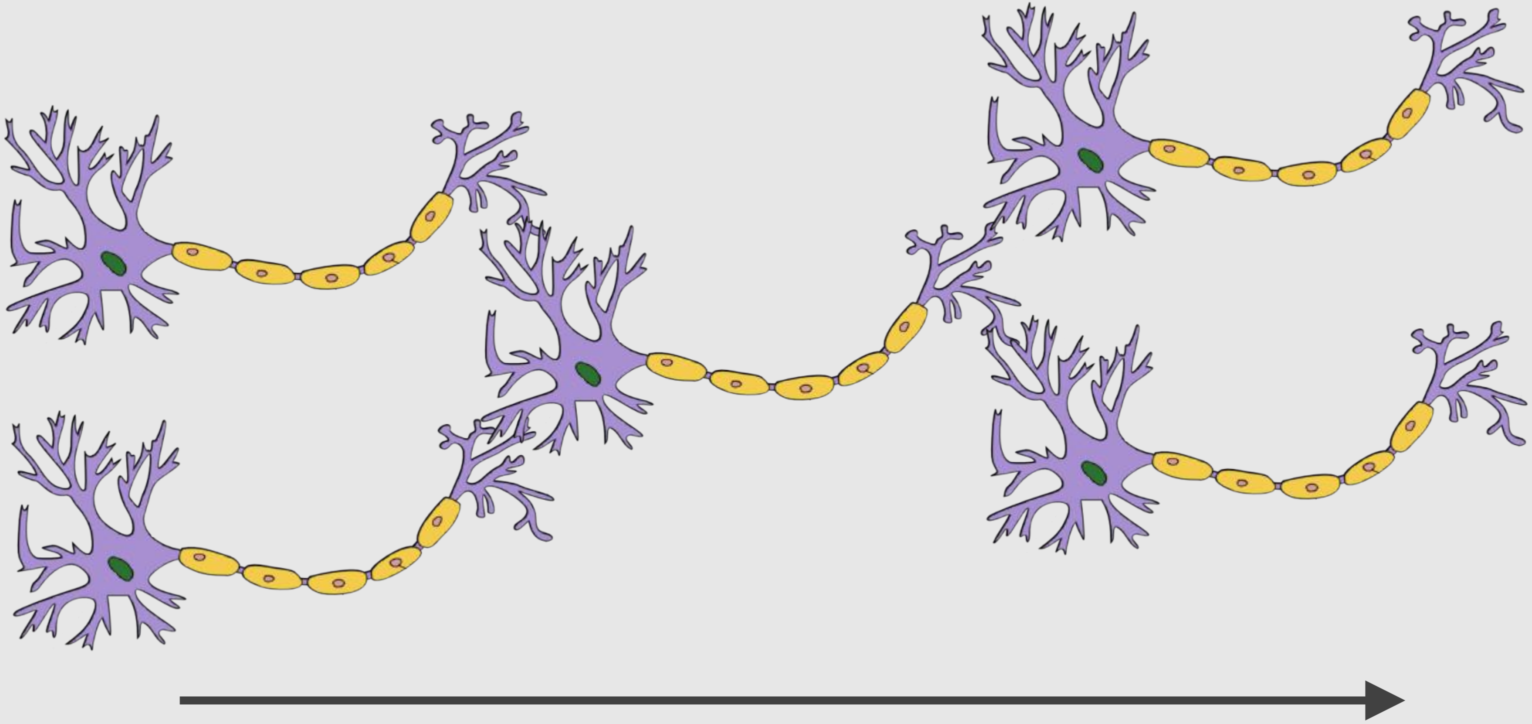
Image Credit: https://en.wikipedia.org/wiki/Neuron



https://www.youtube.com/watch?v=A9Xru1ReRwc



http://www.jeremyjordan.me/content/images/2017/06/Neuron_Hand-tuned.png



Signal

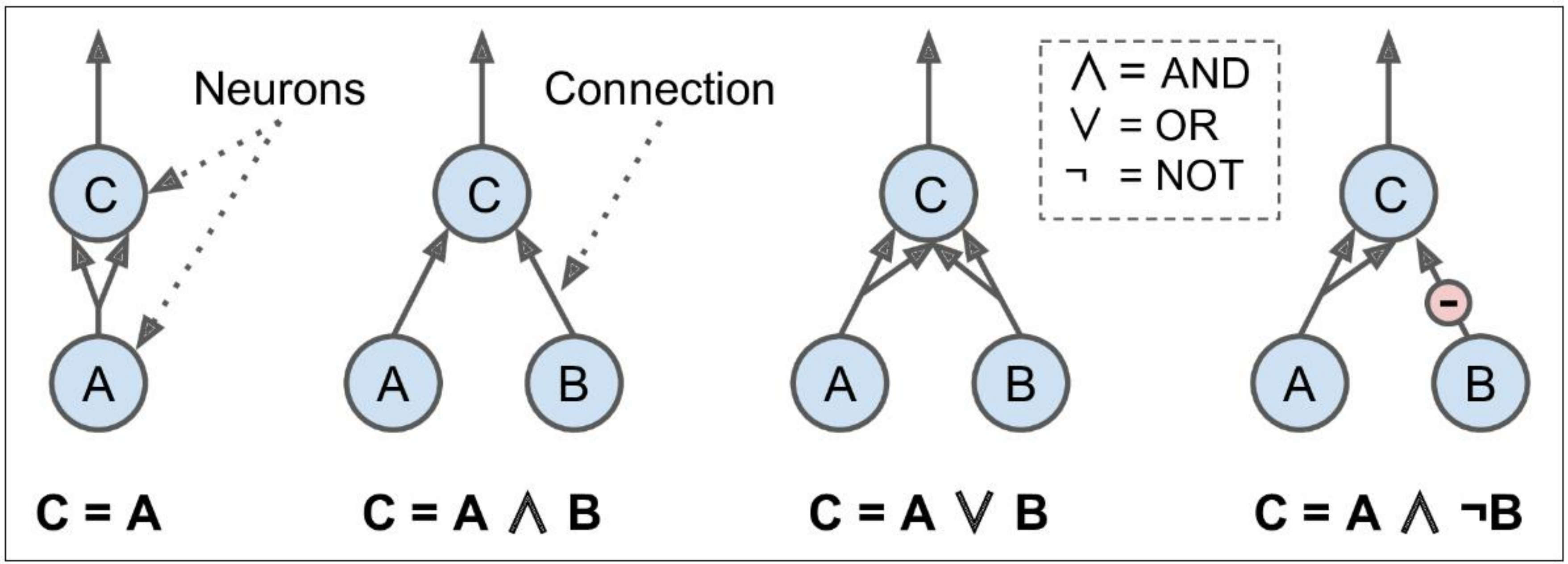
http://www.jeremyjordan.me/content/images/2017/06/Neuron_Hand-tuned.png

Logical Computations with Neurons

Logical Computations with Neurons

McCulloch and Pitts (1943) proposed a very simple model:

- It has one or more binary (on/off) inputs and one binary output.
- The artificial neuron **simply** activates its output when more than a certain number of its inputs are active.



Artificial Neural Networks performing simple logical computations

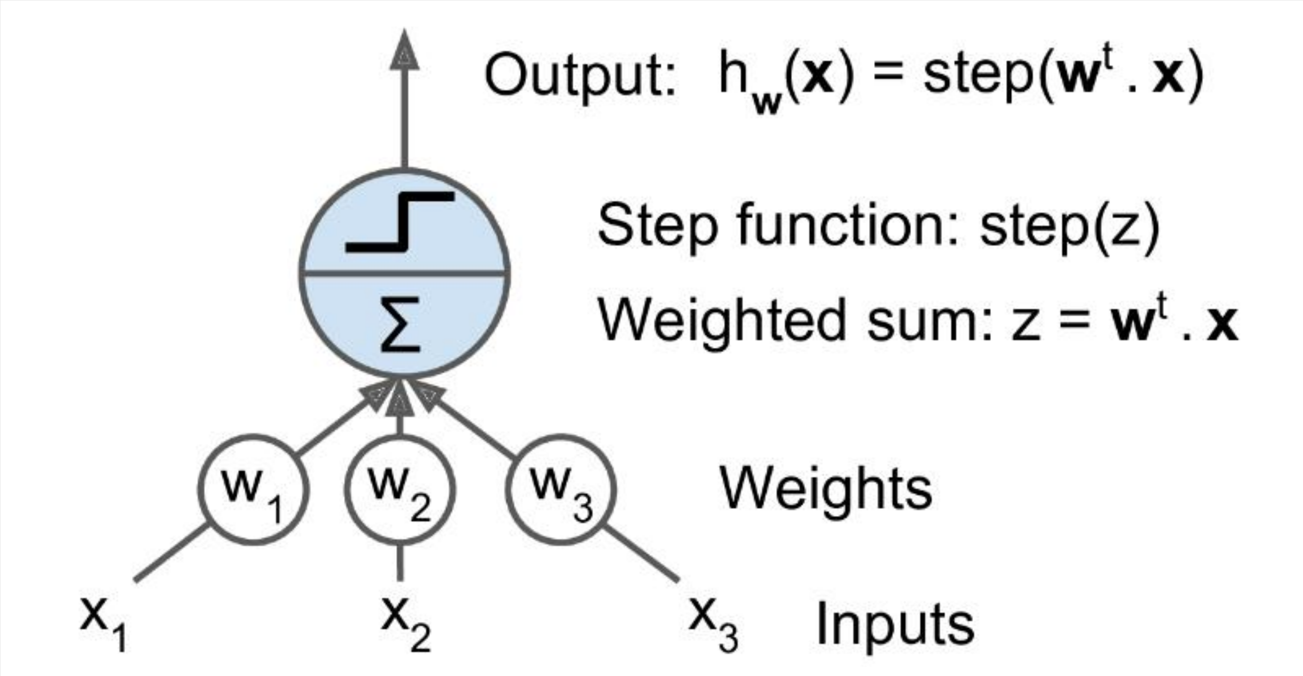
The Perceptron

The Perceptron

Invented in 1957 by Frank Rosenblatt.

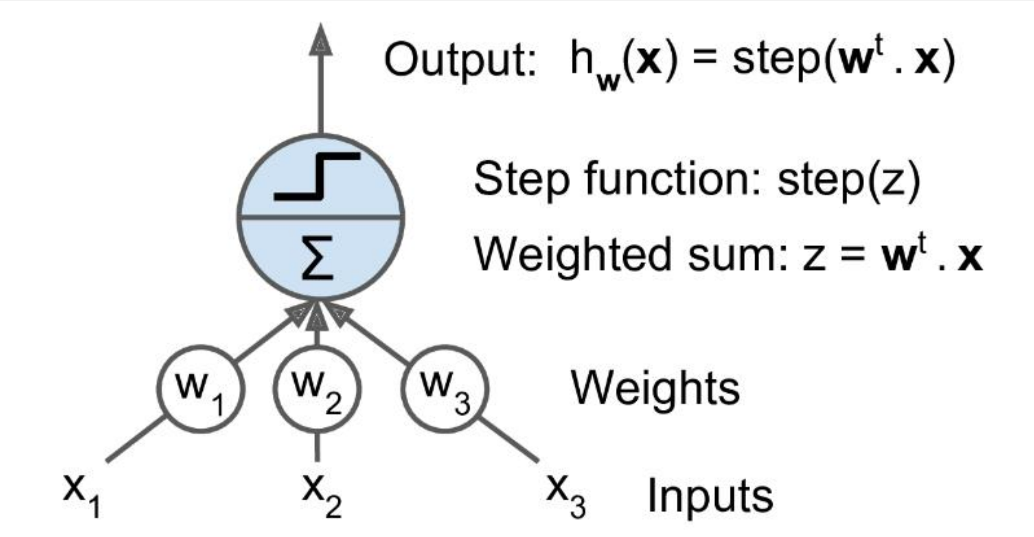
- It is based on a Linear Threshold Unit (LTU):
  - The inputs and output are now **numbers** (instead of binary on/off values) and each input connection is associated with a **weight**.
- The LTU computes a weighted sum of its inputs then it applies a step function to that sum and outputs the result.

The Perceptron



Linear Threshold Unit

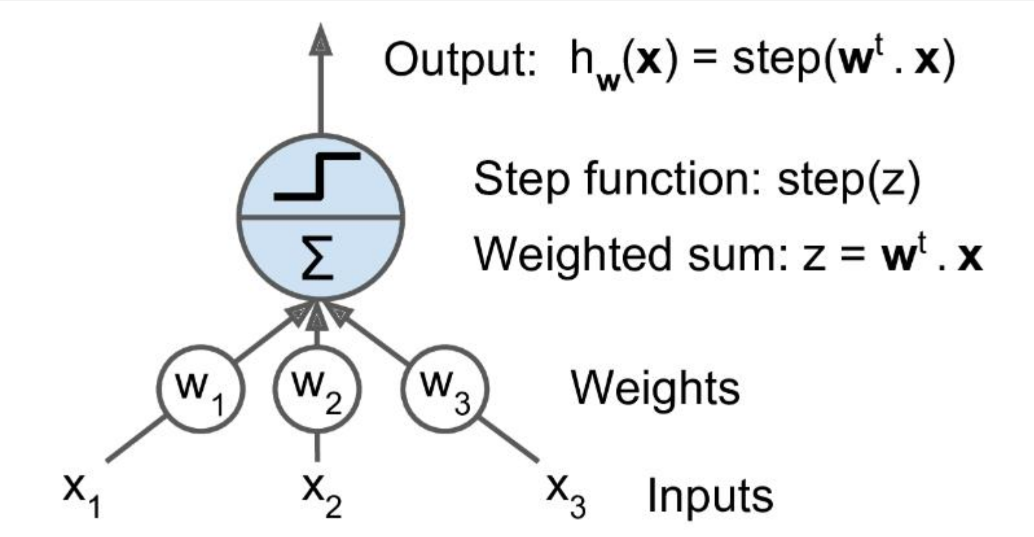
The Perceptron



Linear Threshold Unit

$$\text{heaviside}(z) = \begin{cases} 0 & \text{if } z < 0 \\ 1 & \text{if } z \geq 0 \end{cases}$$

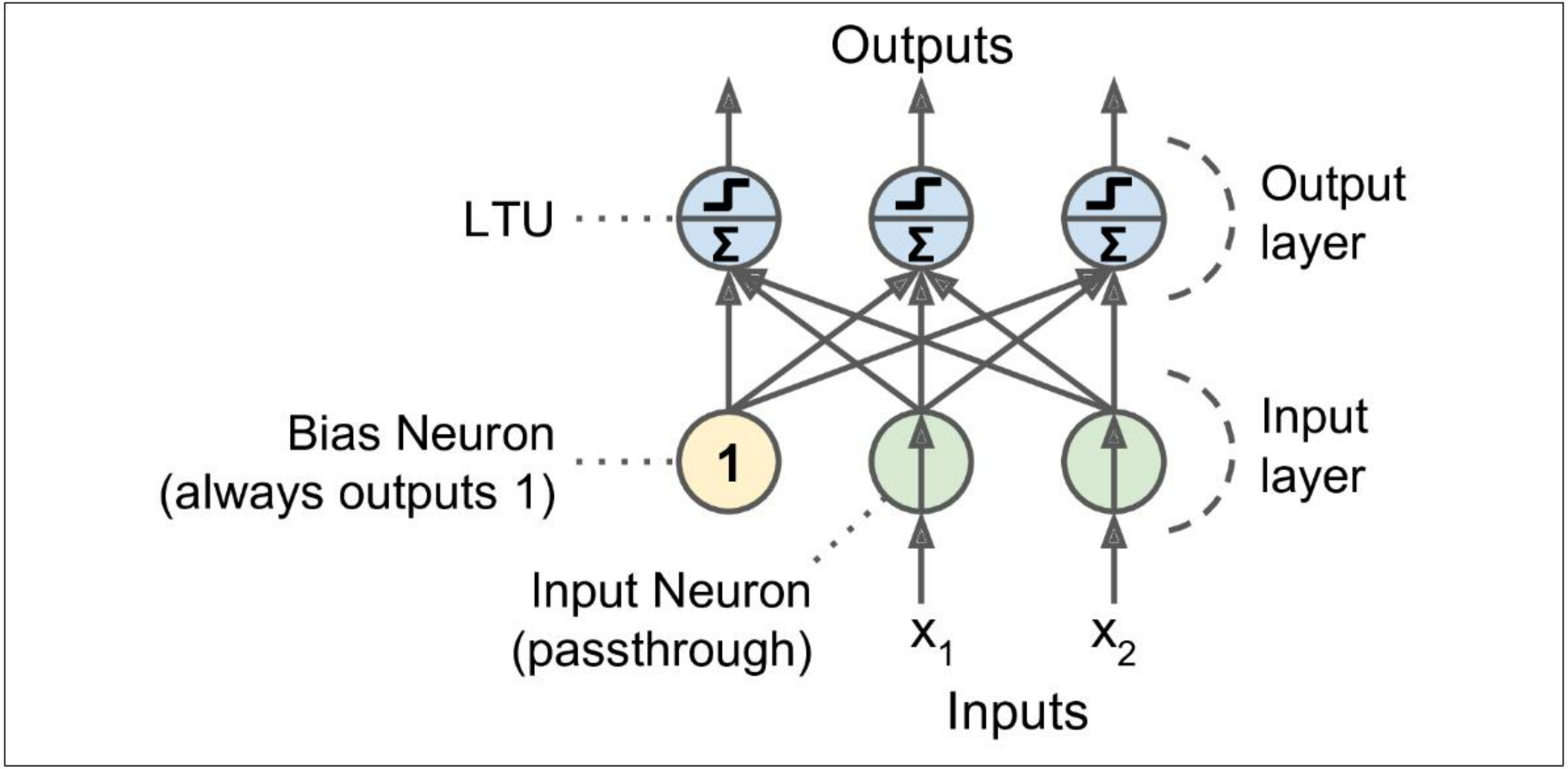
The Perceptron



Linear Threshold Unit

$$\text{heaviside}(z) = \begin{cases} 0 & \text{if } z < 0 \\ 1 & \text{if } z \geq 0 \end{cases}$$

$$\text{sign}(z) = \begin{cases} -1 & \text{if } z < 0 \\ 0 & \text{if } z = 0 \\ +1 & \text{if } z > 0 \end{cases}$$



The Perceptron

So how is a Perceptron trained?

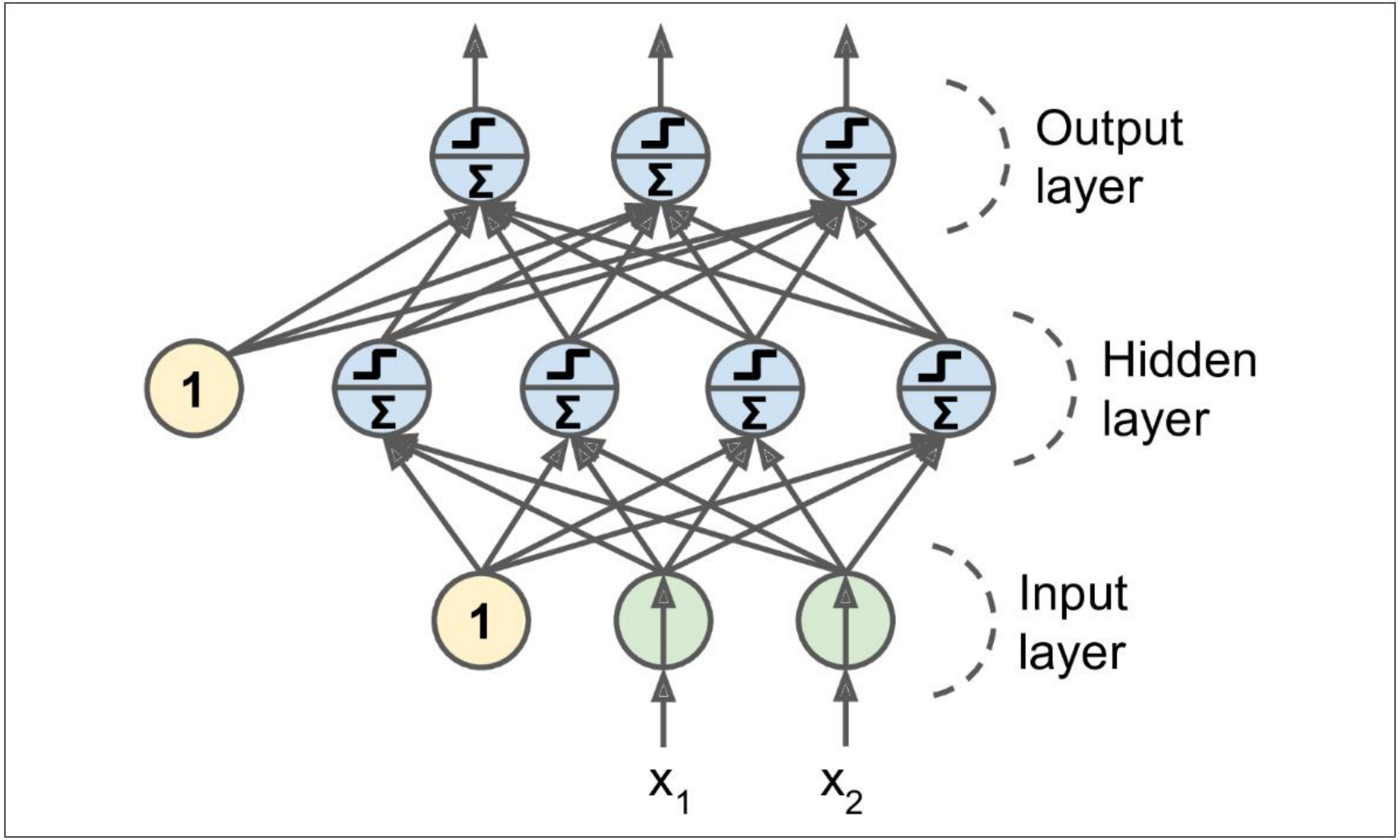
Hebb’s rule (1949): the connection weight between two neurons is increased whenever they have the same output.

- The Perceptron is fed one training instance at a time, and for each instance it makes its predictions.
- For every output neuron that produced a wrong prediction, it reinforces the connection weights from the inputs that would have contributed to the correct prediction.

So how is a Perceptron trained?

$$w_{i,j}^{(\text{next step})} = w_{i,j} + \alpha(\hat{y}_j - y_j)x_i$$

Multi-Layer Perceptron and Backpropagation


Output
layer
Hidden
layer
Input
layer
1
1
x1
x2

To be continued ...

References

Machine Learning Books

- Hands-On Machine Learning with Scikit-Learn and TensorFlow, Chap. 10
- Pattern Recognition and Machine Learning, Chap. 5
- Pattern Classification, Chap. 6

Machine Learning Courses

- https://www.coursera.org/learn/machine-learning, Week 4 & 5
- https://www.coursera.org/learn/neural-networks