# Artificial Neural Networks
## Machine Learning and Pattern Recognition

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MC886/MO444, September 01, 2017

# Many inventions were inspired by Nature ...

Birds inspired us to fly

# Many inventions were inspired by Nature ...
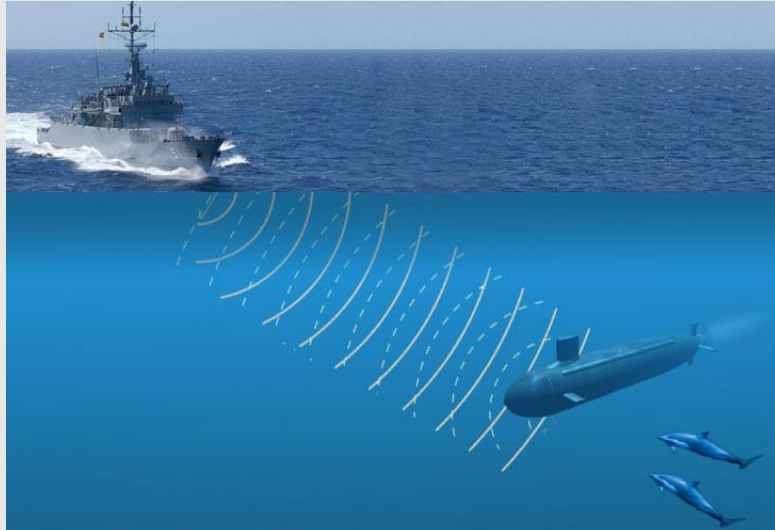
Burdock plants inspired velcro



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

# Many inventions were inspired by Nature ...

Dogs inspired ...

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

# Today's Agenda

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- 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

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- **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

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- **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

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- **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

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- **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

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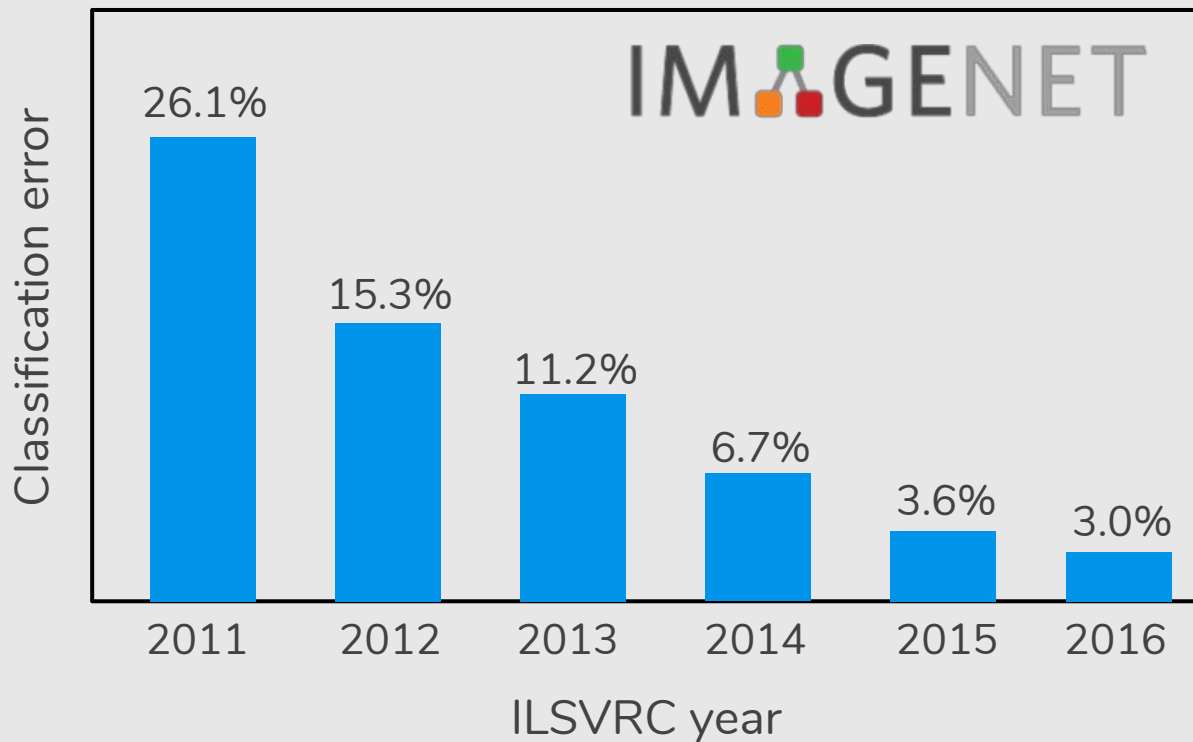- **2010s:** We are now witnessing yet another wave of interest in ANNs.

# IMAGENET

## 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

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- **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

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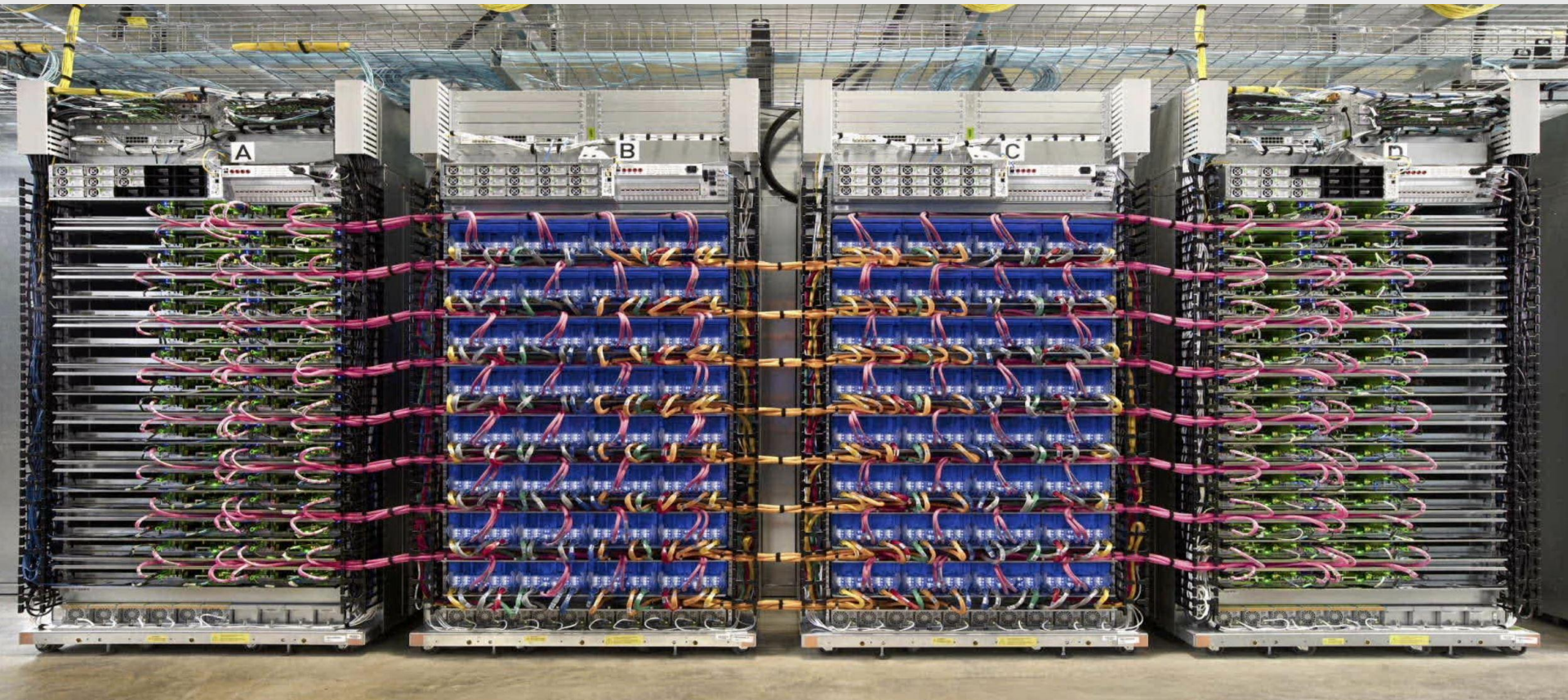
# IM▪GENET

**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

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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.

# From Biological to Artificial Neurons

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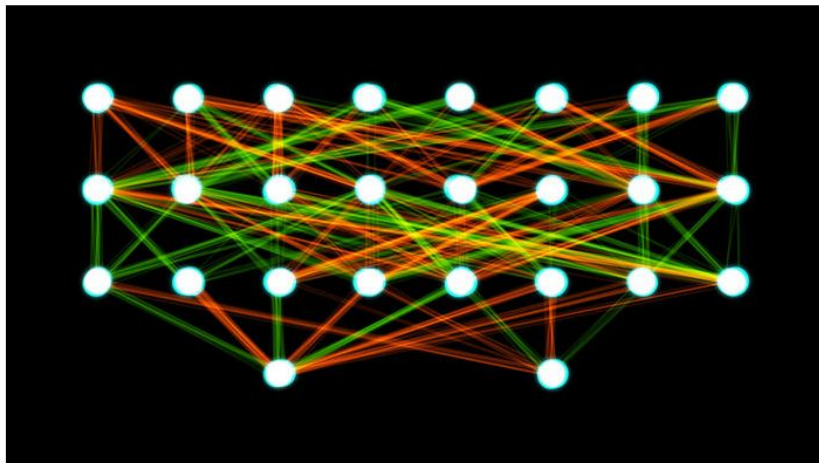
3. The **training algorithms** have been **improved**.

# Science

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A representation of a neural network.

Akritasa/Wikimedia Commons

# Brainlike computers are a black box. Scientists are finally peering inside
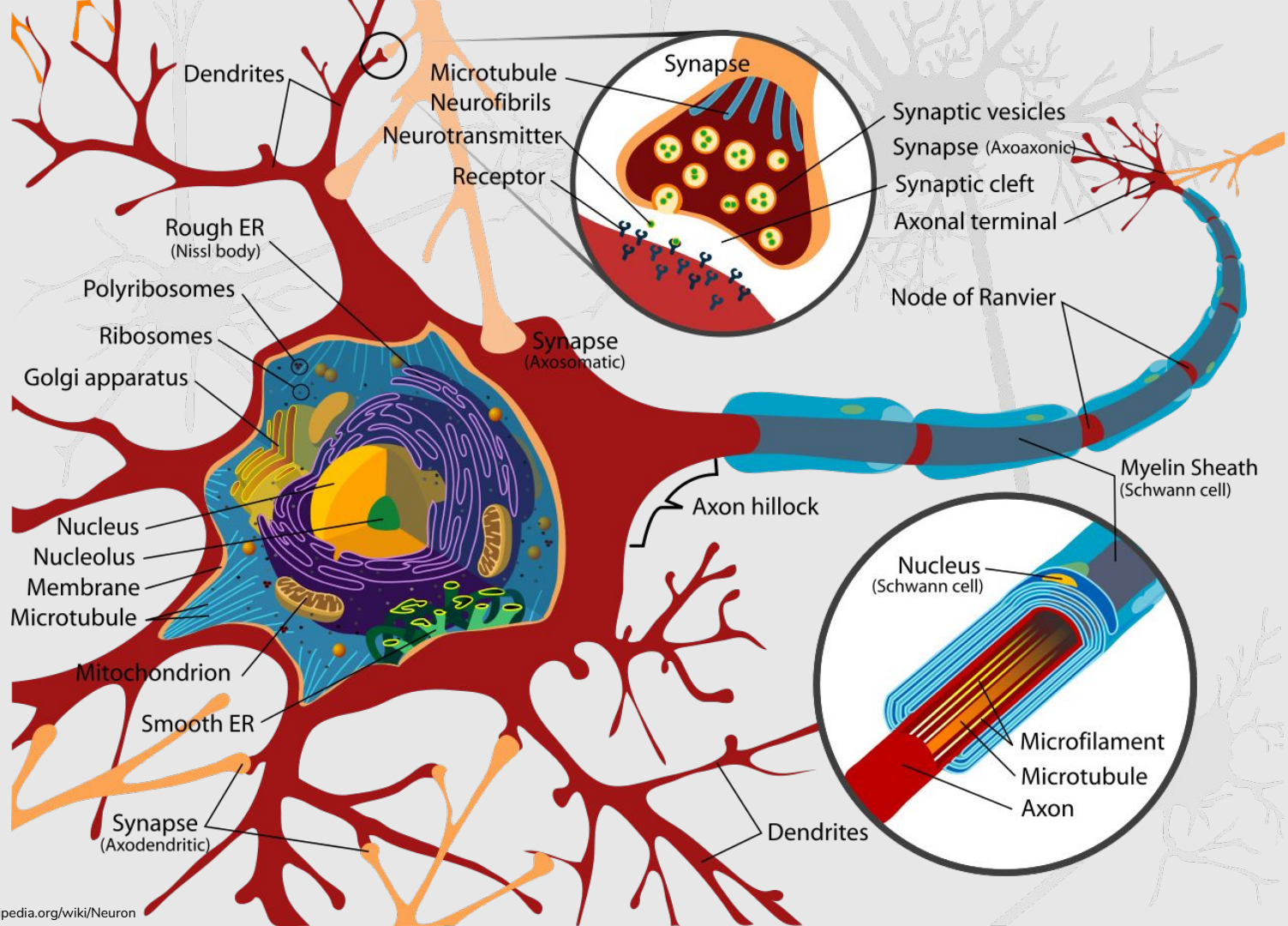
By Jackie Snow | Mar. 7, 2017 , 3:15 PM

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
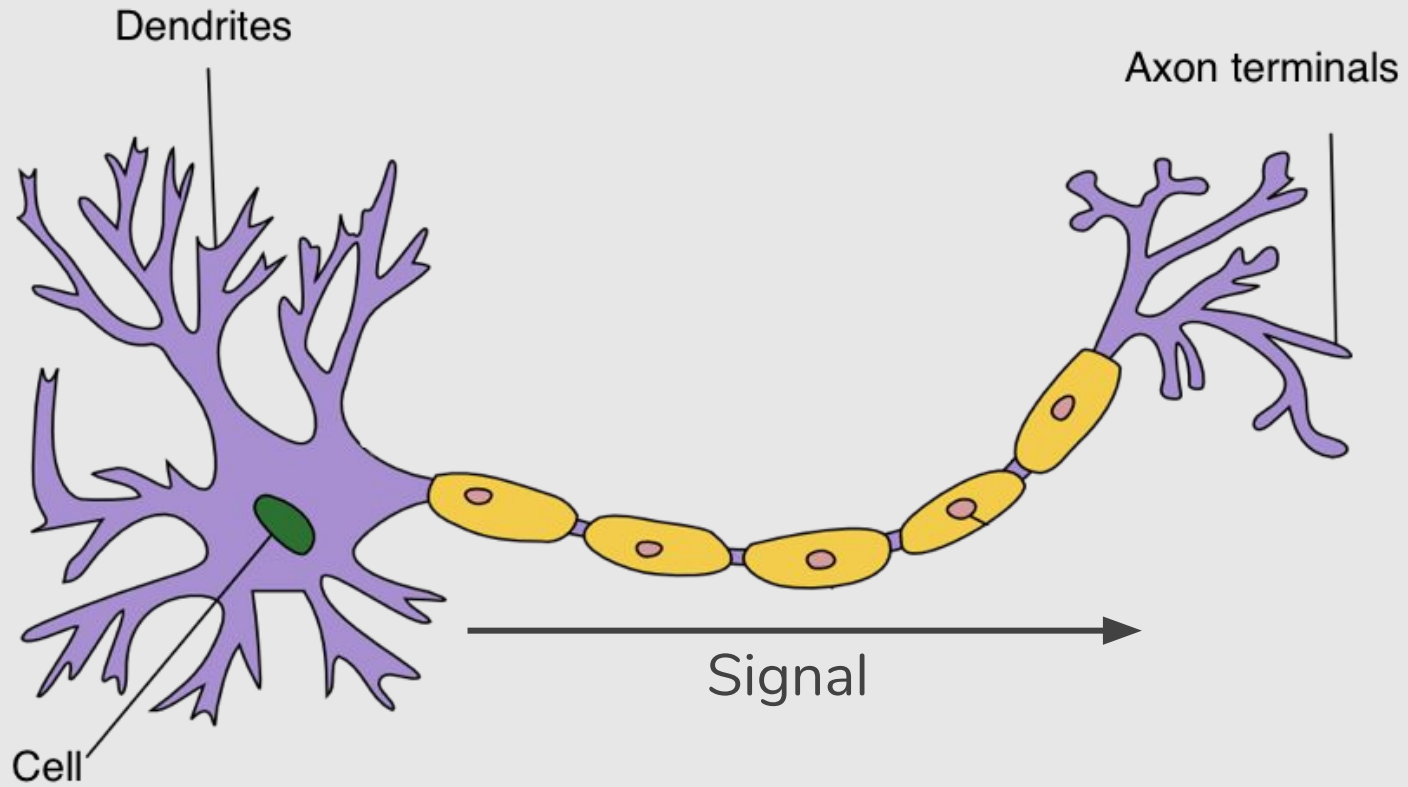
# From Biological to Artificial Neurons

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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**.

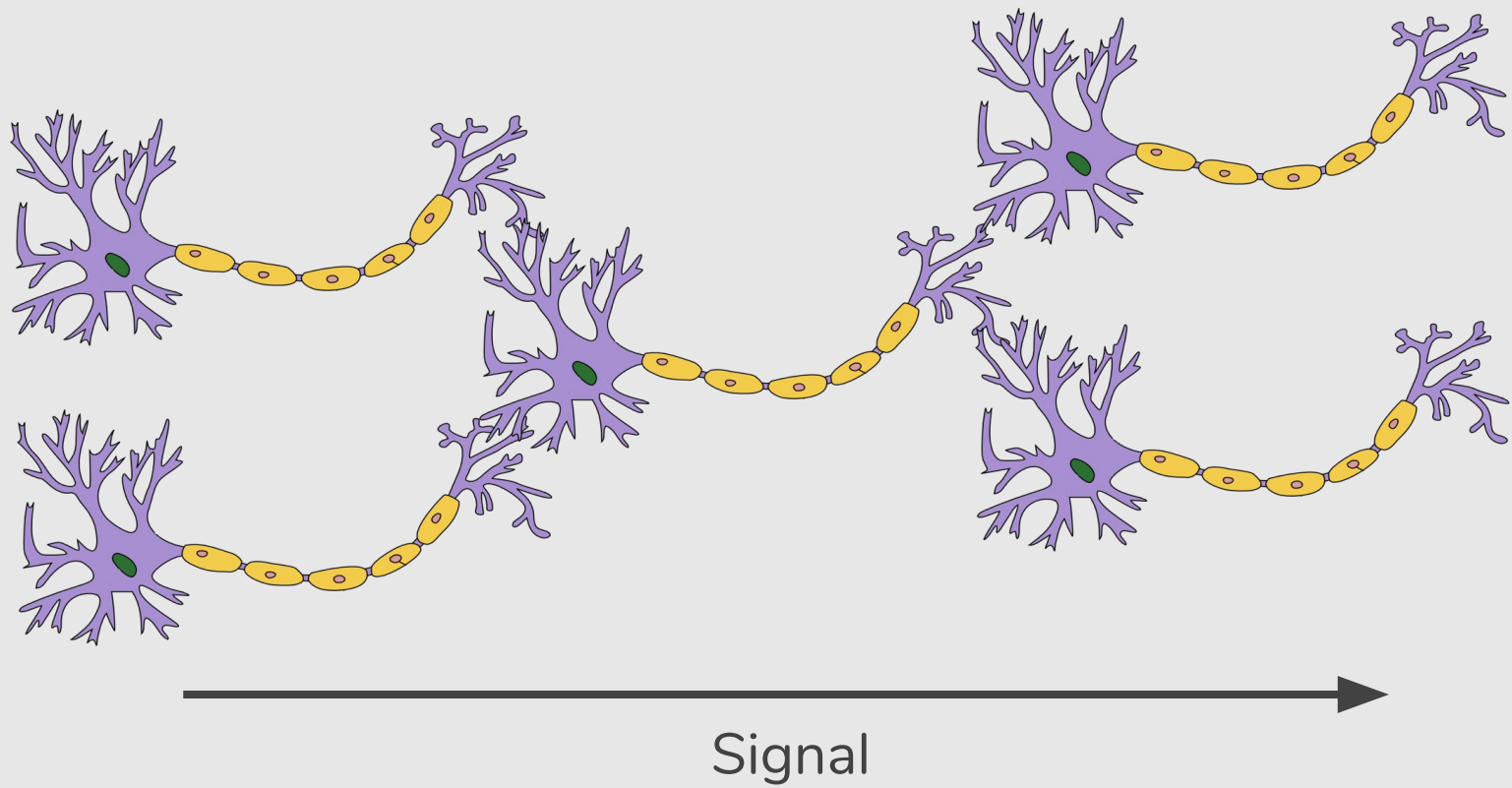4. ANNs seem to have entered a virtuous circle of funding and progress.

# Biological Neurons

Dendrites

Microtubule
Neurofibrils
Neurotransmitter
Receptor

Synapse

Synaptic vesicles
Synapse (Axoaxonic)
Synaptic cleft
Axonal terminal

Rough ER
(Nissl body)

Polyribosomes

Ribosomes

Golgi apparatus

Synapse
(Axosomatic)

Node of Ranvier

Nucleus
Nucleolus
Membrane
Microtubule

Axon hillock

Myelin Sheath
(Schwann cell)

Mitochondrion

Smooth ER

Nucleus
(Schwann cell)

Synapse
(Axodendritic)

Dendrites

Microfilament
Microtubule
Axon

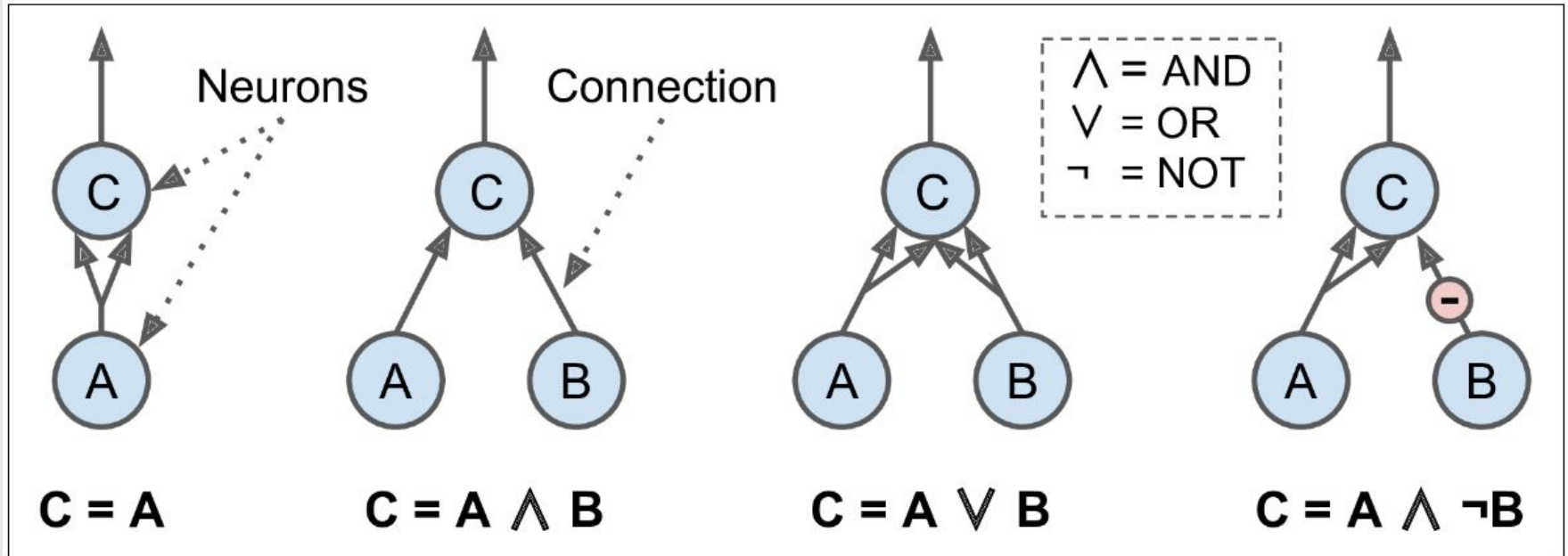https://www.youtube.com/watch?v=A9Xru1ReRwc

Signal

# Logical Computations with Neurons

# Logical Computations with Neurons

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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.

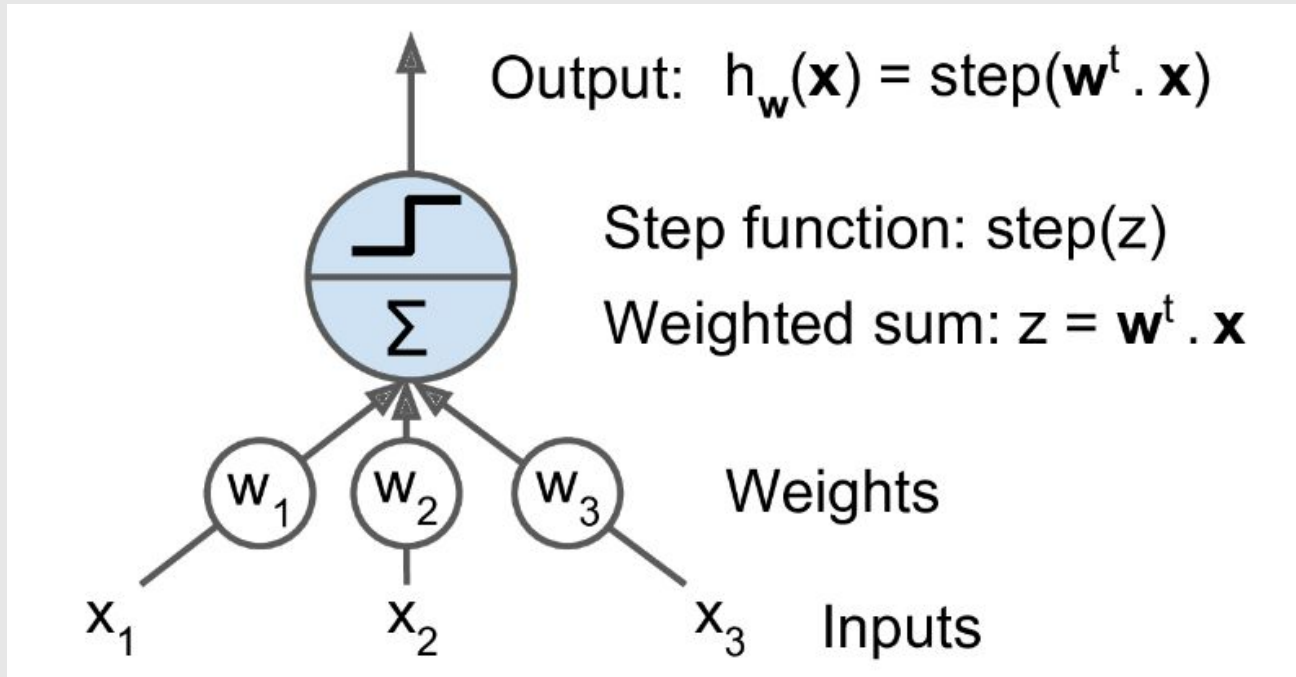Artificial Neural Networks performing simple logical computations

# The Perceptron

# The Perceptron

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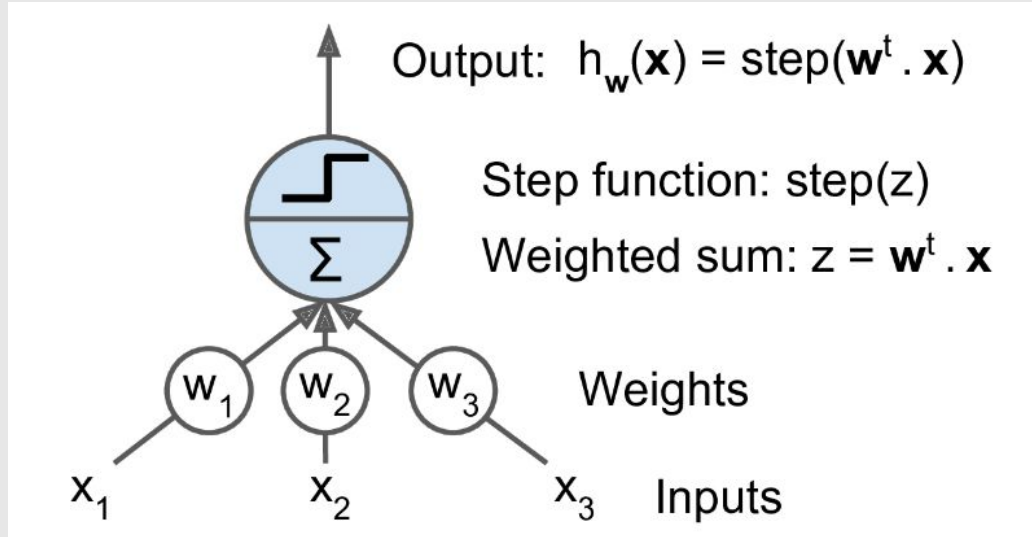
Invented in 1957 by Frank Rosenblatt.

- 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



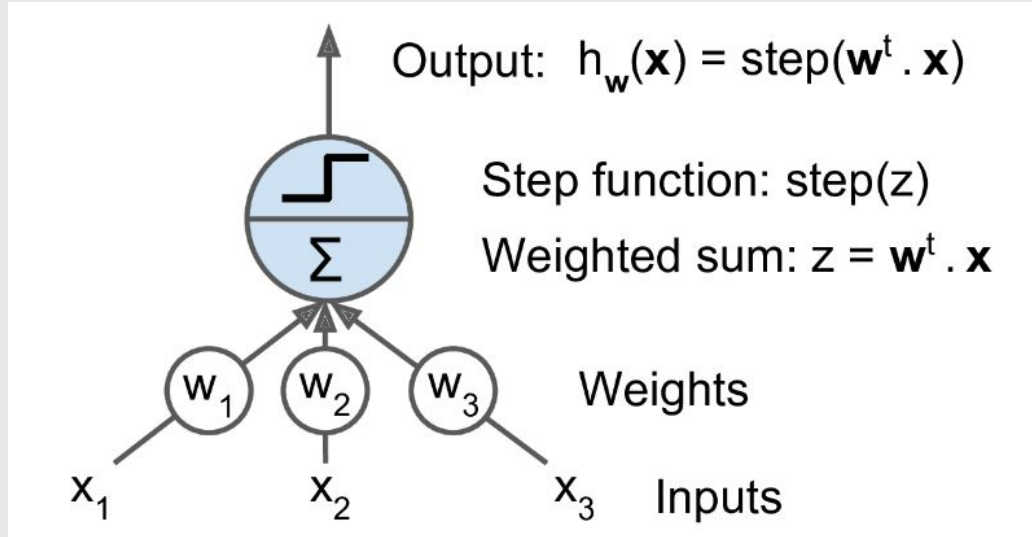Output:  $h_{\mathbf{w}}(\mathbf{x}) = \text{step}(\mathbf{w}^t \cdot \mathbf{x})$

Step function: $\text{step}(z)$

Weighted sum: $z = \mathbf{w}^t \cdot \mathbf{x}$

Weights

Inputs

$x_1$  $x_2$  $x_3$

$w_1$  $w_2$  $w_3$

Linear Threshold Unit

# The Perceptron

Output:  $h_w(\mathbf{x}) = \text{step}(\mathbf{w}^t . \mathbf{x})$

Step function: step(z)

Weighted sum: $z = \mathbf{w}^t . \mathbf{x}$

Weights

$x_1$  $x_2$  $x_3$   Inputs

Linear Threshold Unit

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

# The Perceptron

Output: $h_w(\mathbf{x}) = \text{step}(\mathbf{w}^t \cdot \mathbf{x})$

Step function: step(z)

Weighted sum: $z = \mathbf{w}^t \cdot \mathbf{x}$

Weights

$w_1$  $w_2$  $w_3$

$x_1$  $x_2$  $x_3$   Inputs
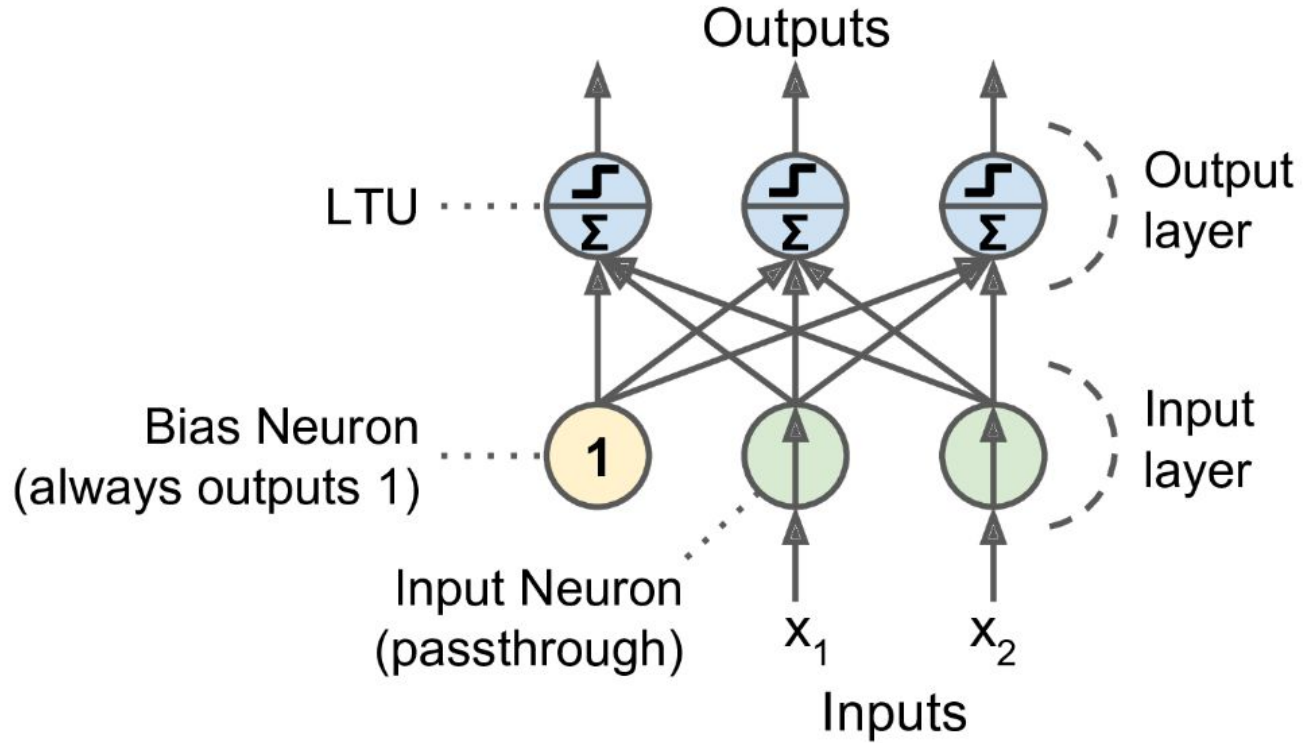
Linear Threshold Unit

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

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

The Perceptron

# So how is a Perceptron trained?

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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?

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

# Multi-Layer Perceptron and Backpropagation

Output layer

Hidden layer

Input layer

$x_1$     $x_2$
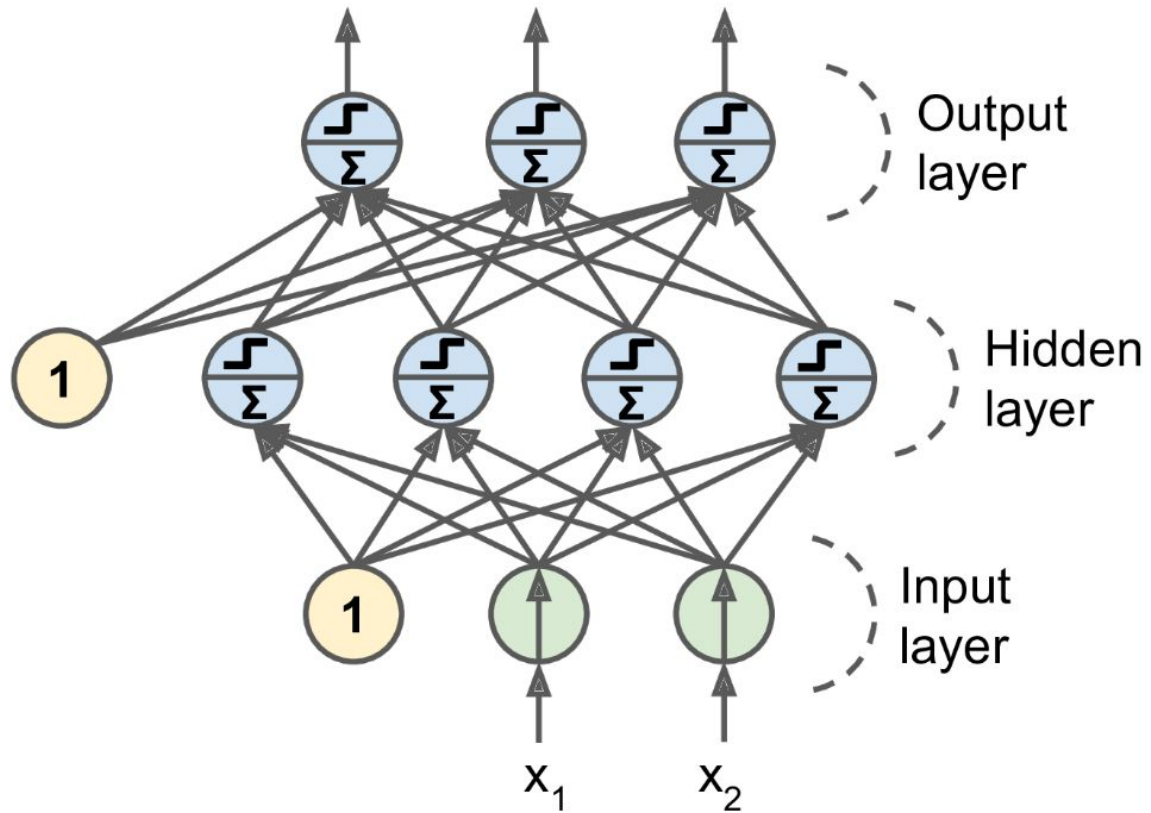
To be continued …

# References

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**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