COMP 4752
Computational Intelligence

Lecture 20

Neural Networks

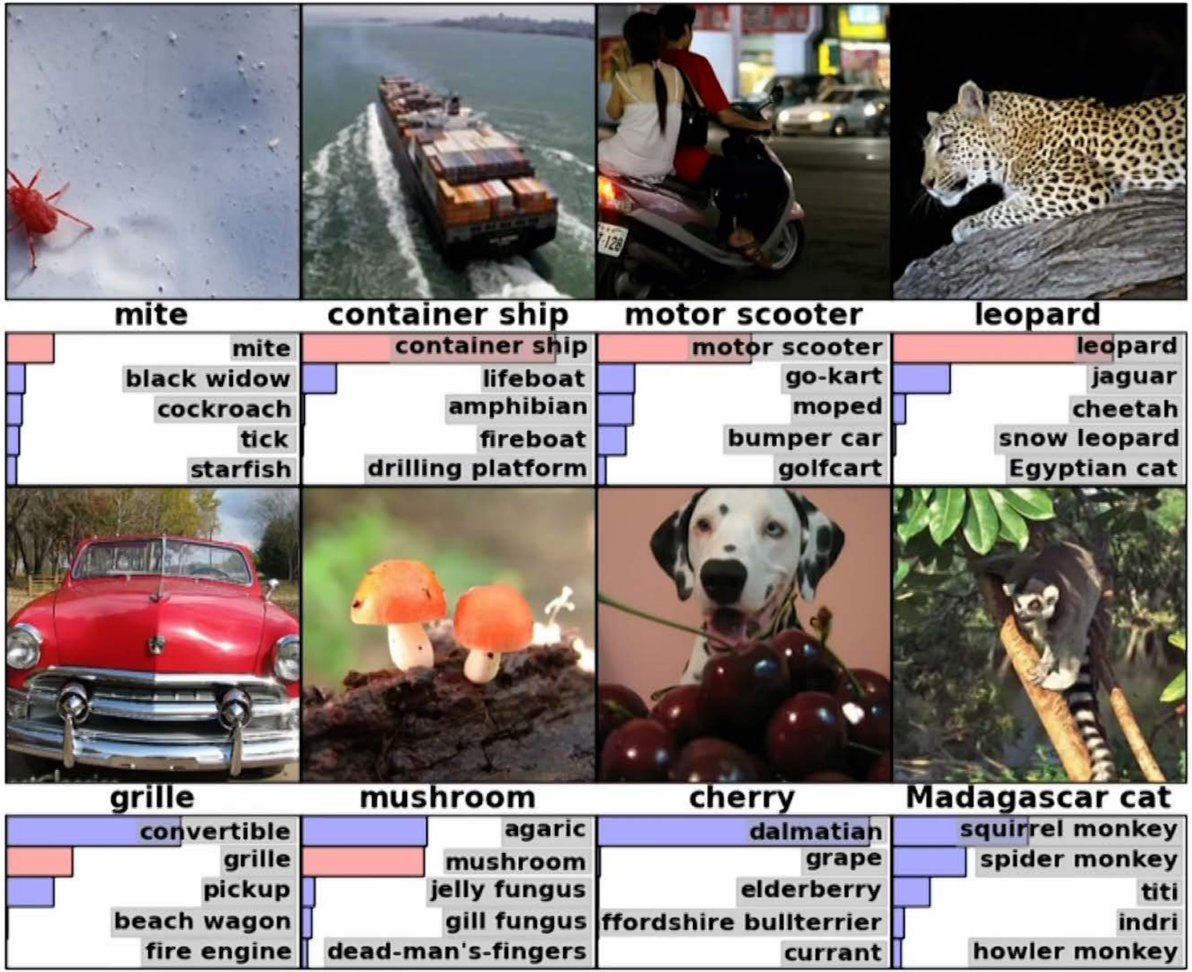
MEMORIAL
UNIVERSITY

Neural Networks

- In 2010, MIT was reviewing what topics it should drop from its AI course to make room for ‘more modern’ techniques
- Neural Networks were on the way out
- They decided to leave them in, just to show a possible model of the brain
- In almost 30 years of research, Neural Networks had failed to yield any significant results

Deep Neural Networks

- Geoffrey Hinton, 2012
  - ImageNet Classification with Deep Convolutional Neural Networks
- 60,000,000 parameters in the network
- Purpose: which of 1000 categories best characterized a given picture
- Blew away the competition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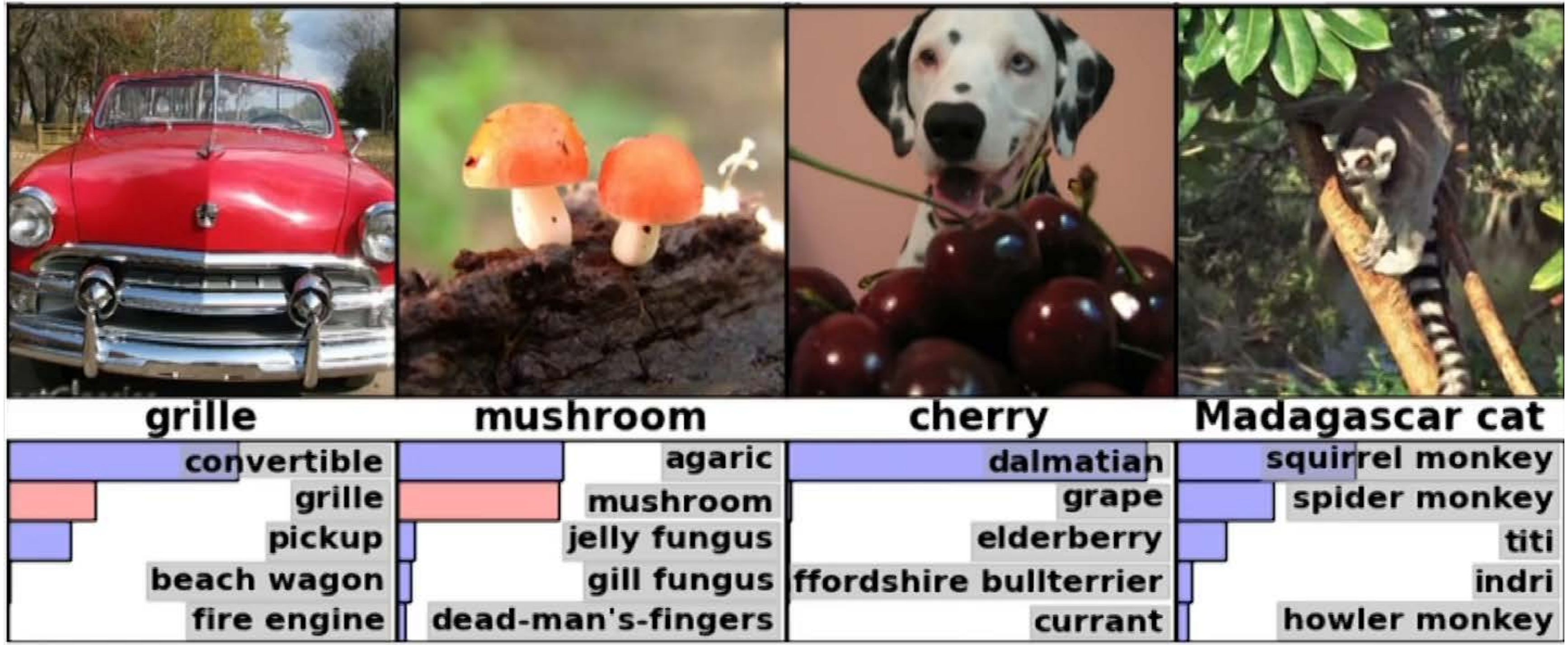
mite
black widow
cockroach
tick
starfish
container ship
container ship
lifeboat
amphibian
fireboat
drilling platform
motor scooter
motor scooter
go-kart
moped
bumper car
golfcart
leopard
leopard
jaguar
cheetah
snow leopard
Egyptian cat
grille
convertible
grille
pickup
beach wagon
fire engine
mushroom
agaric
mushroom
jelly fungus
gill fungus
dead-man's-fingers
cherry
dalmatian
grape
elderberry
ffordshire bullterrier
currant
Madagascar cat
squirrel monkey
spider monkey
titi
indri
howler monkey


grille
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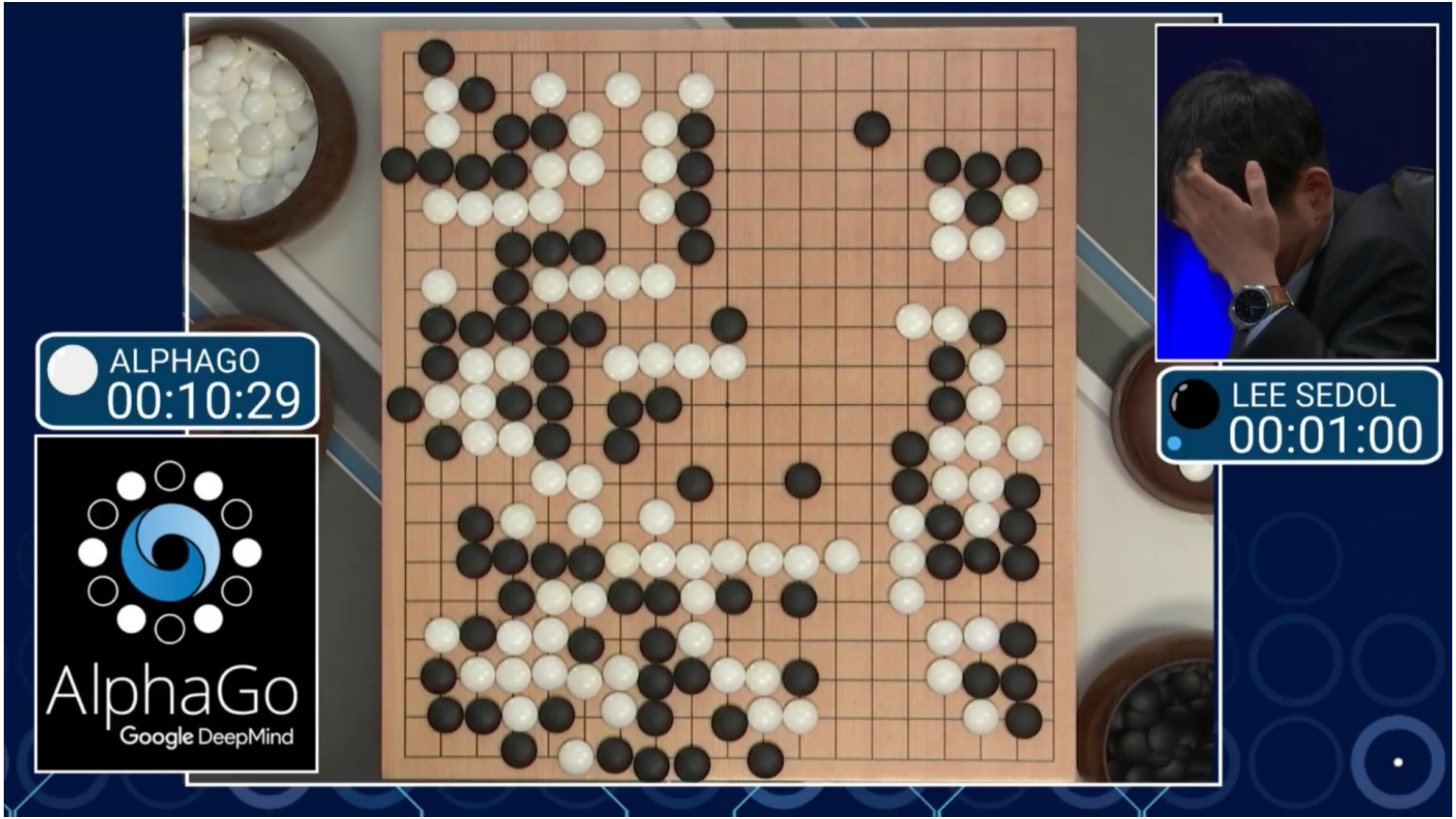
ALPHAGO
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LEE SEDOL
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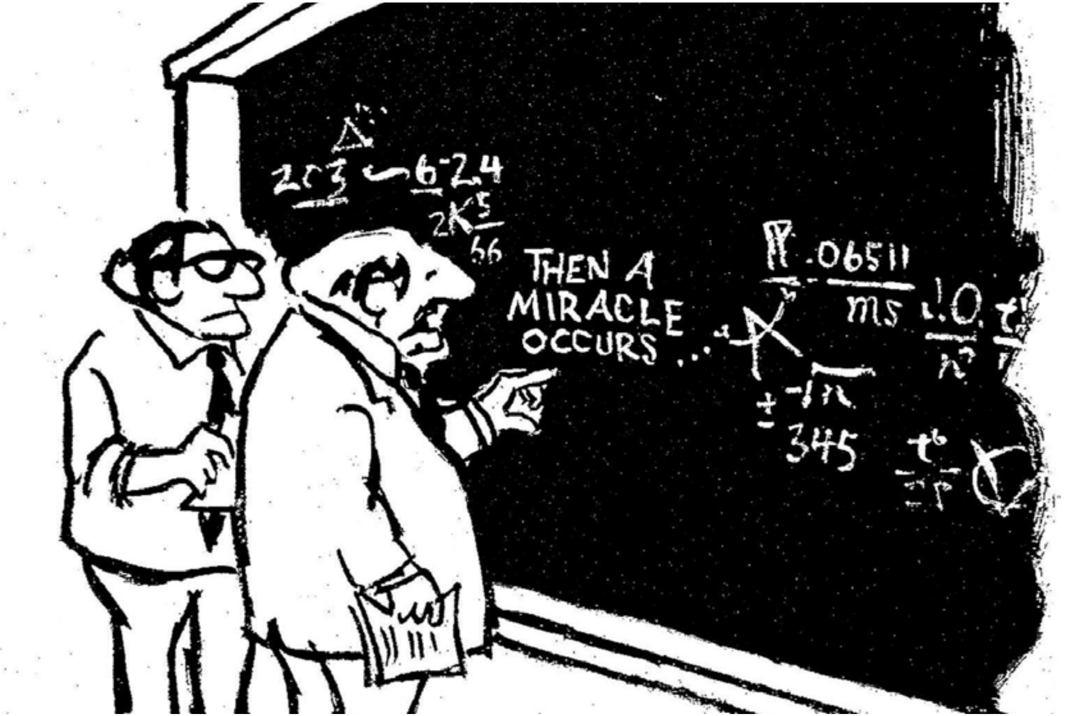
AlphaGo
Google DeepMind

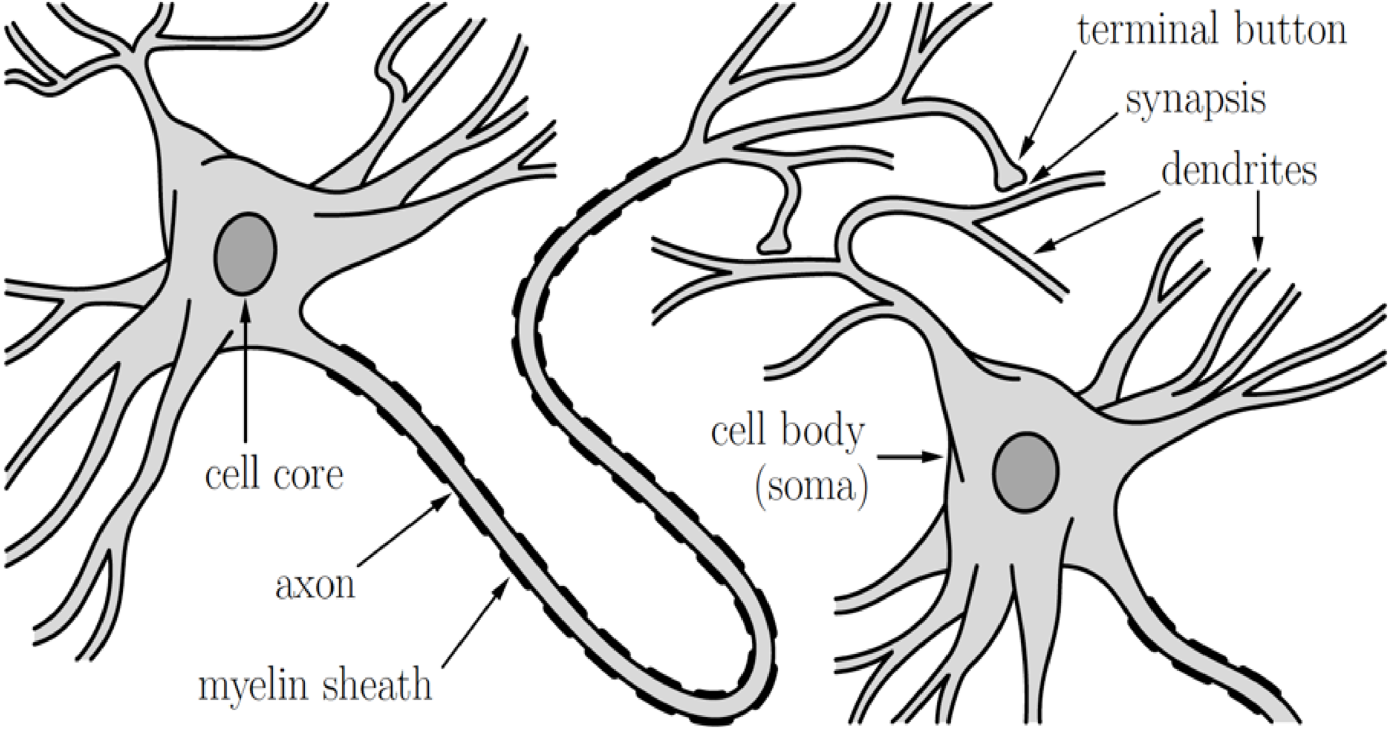

The Development of Campus Plans

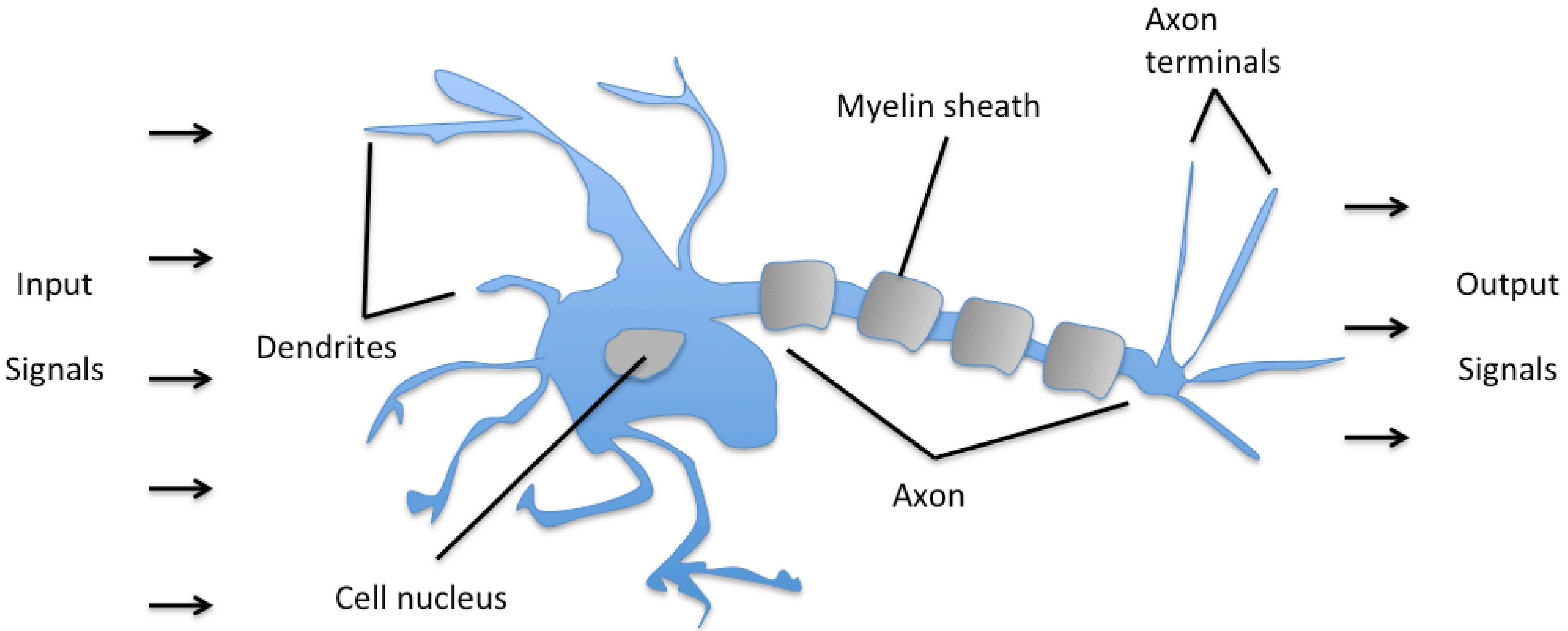
Neural Networks



	Computer	Brain
processing units	1 CPU, 10^9 transistors	10^{11} neurons
storage capacity	10^9 B RAM, 10^{12} B non-volatile memory	10^{11} neurons, 10^{14} synapses
processing speed	10^{-8} second	10^{-3} second
bandwidth	10^9 bits/sec.	10^{14} bits/sec.

The Neuron


terminal button
synapsis
dendrites
cell body
(soma)
cell core
axon
myelin sheath



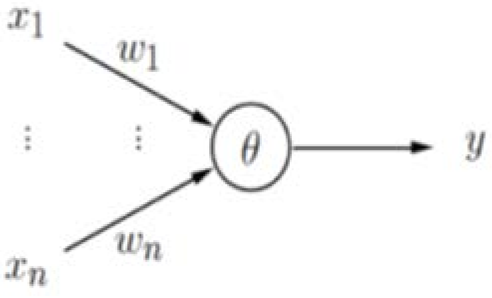
Schematic of a biological neuron.

The Neuron

- Axons from one neuron extend to the dendrites of another neuron
- Stimulation of the dendritic tree of a neuron may cause the axon to ‘spike’, like a transmission line
- After firing, the neuron will go ‘quiet’ for a while (refractory period)
- Firing can affect surrounding / connected neurons, cause a chain reaction

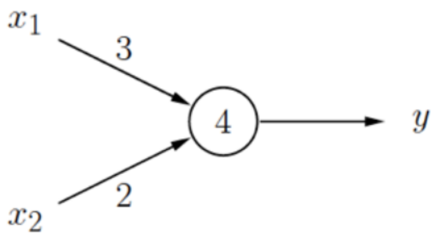
Threshold Logic Units (TLU)

- Inputs x_1, x_2, ... x_n, binary (fire or don't fire)
- Weights w_1, w_2, ..., w_n (real values)
- Inputs multiplied by weights, and summed
- Output spike if result sum meets threshold

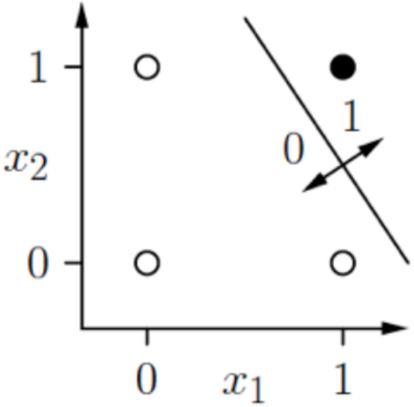


$$y = \begin{cases} 1, & \text{if} \quad \vec{x}\vec{w} = \sum_{i=1}^{n} w_i x_i \geq \theta, \\ 0, & \text{otherwise.} \end{cases}$$

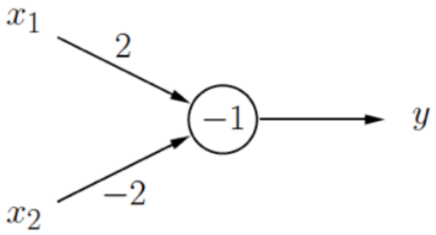
TLU for the conjunction $x_1 \wedge x_2$



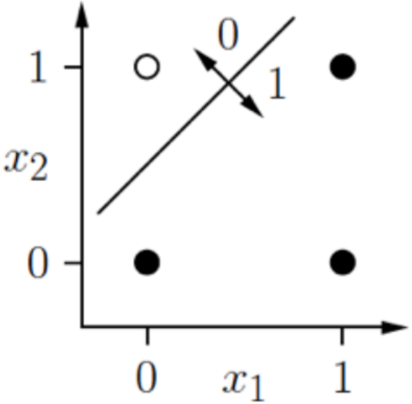
x_1	x_2	$3x_1 + 2x_2$	y
0	0	0	0
1	0	3	0
0	1	2	0
1	1	5	1



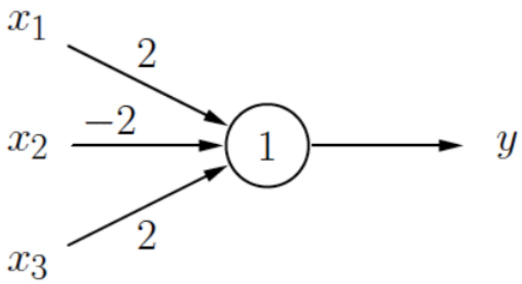
TLU for the implication $x_2 \rightarrow x_1$



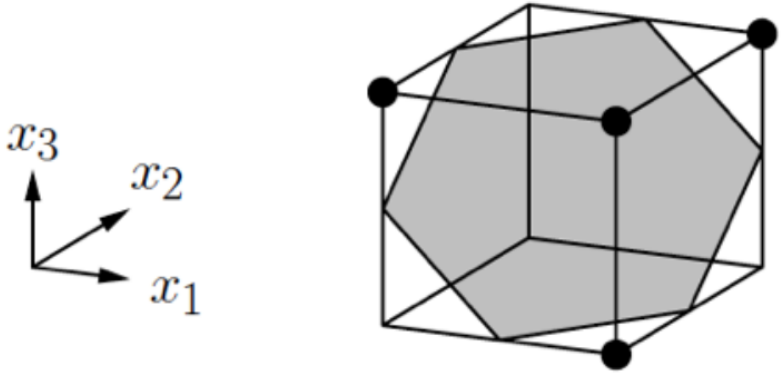
x_1	x_2	$2x_1 - 2x_2$	y
0	0	0	1
1	0	2	1
0	1	–2	0
1	1	0	1



TLU for $(x_1 \wedge \overline{x_2}) \vee (x_1 \wedge x_3) \vee (\overline{x_2} \wedge x_3)$



x_1	x_2	x_3	$\sum_i w_i x_i$	y
0	0	0	0	0
1	0	0	2	1
0	1	0	−2	0
1	1	0	0	0
0	0	1	2	1
1	0	1	4	1
0	1	1	0	0
1	1	1	2	1



TLU Linear Separability

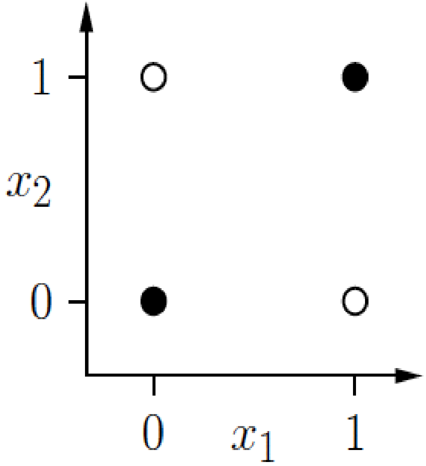
- We call two points in an n-dimensional space linear separable if they can be separated by an (n-1)-dimensional hyperplane. One of these sets may contain points on the hyperplane
- A Boolean function is called linearly separable if the set of points of 0 and the set of points of 1 are linearly separable

Linear Separability

- Consider the bi-implication problem, in which there is no separation line

$$x_1 \leftrightarrow x_2$$

x_1	x_2	y
0	0	1
1	0	0
0	1	0
1	1	1

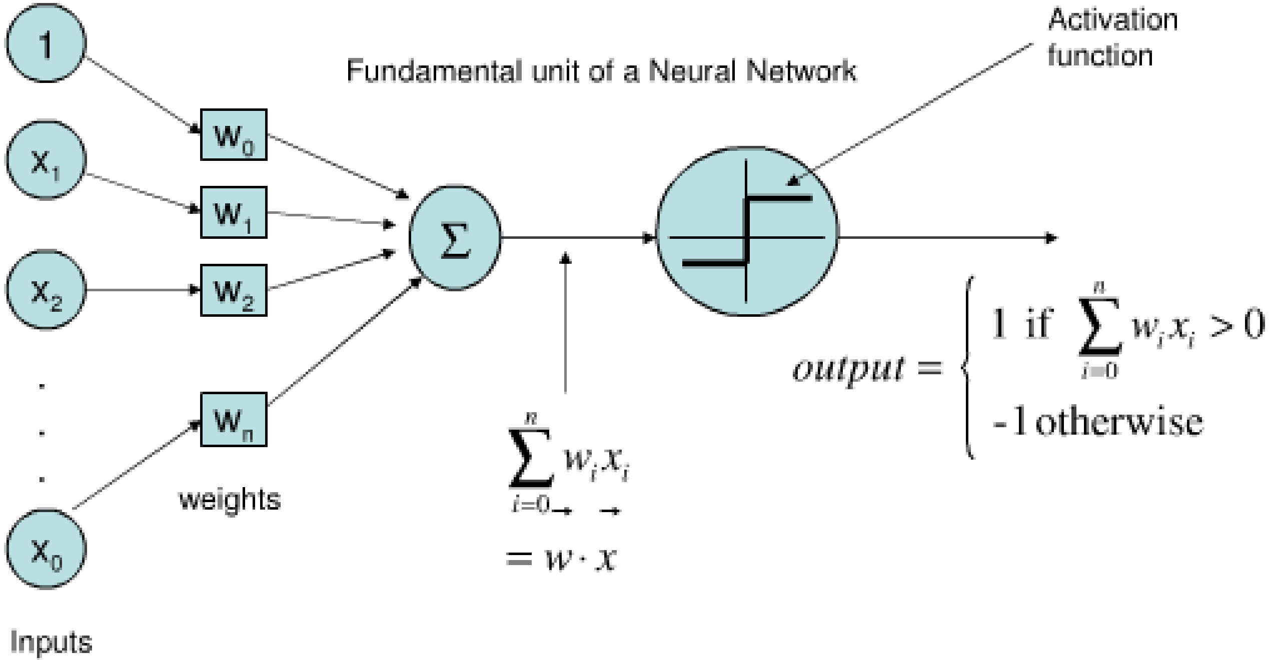


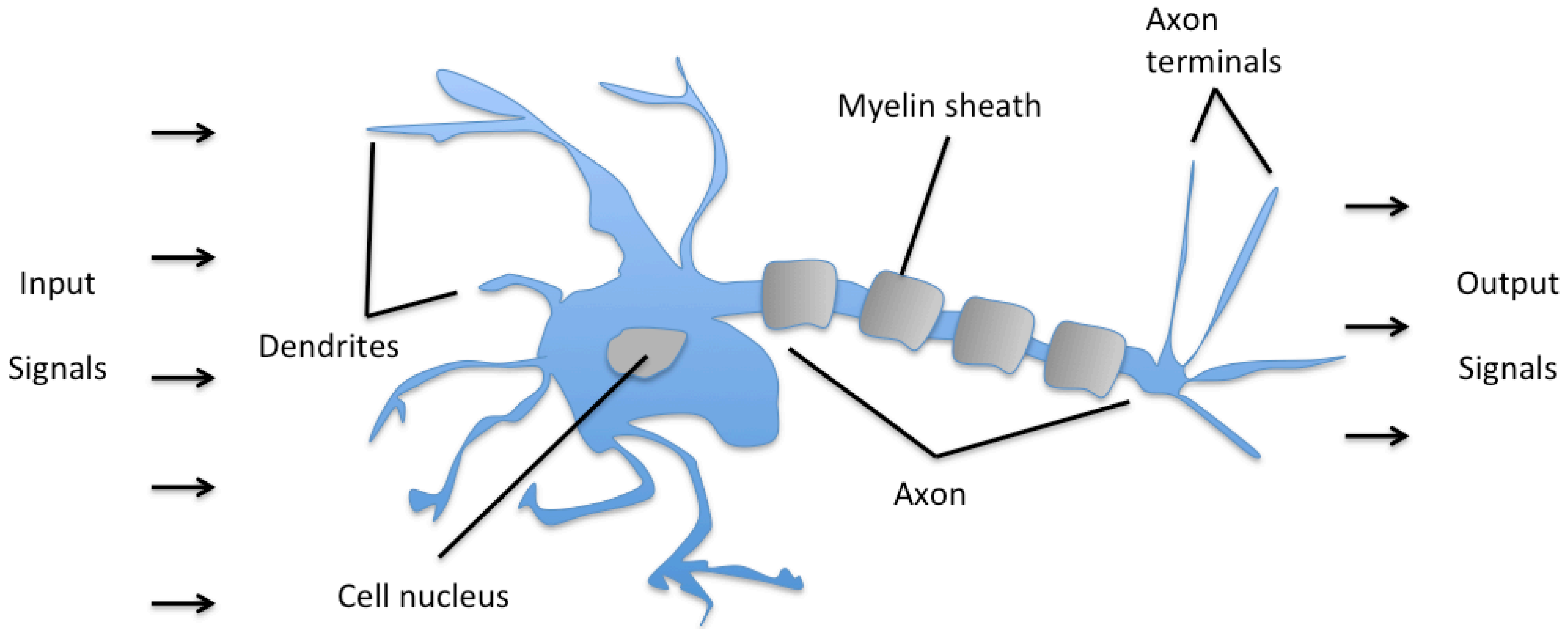
Linear Separable Boolean Functions

inputs	Boolean functions	linearly separable functions
1	4	4
2	16	14
3	256	104
4	65536	1774
5	$4.3 \cdot 10^9$	94572
6	$1.8 \cdot 10^{19}$	$5.0 \cdot 10^6$

- For many inputs, TLU can't compute functions
- Networks of TLUs are needed to overcome this

Perceptron (Simple Neuron)





Schematic of a biological neuron.

A Simplified Brain Model

Input

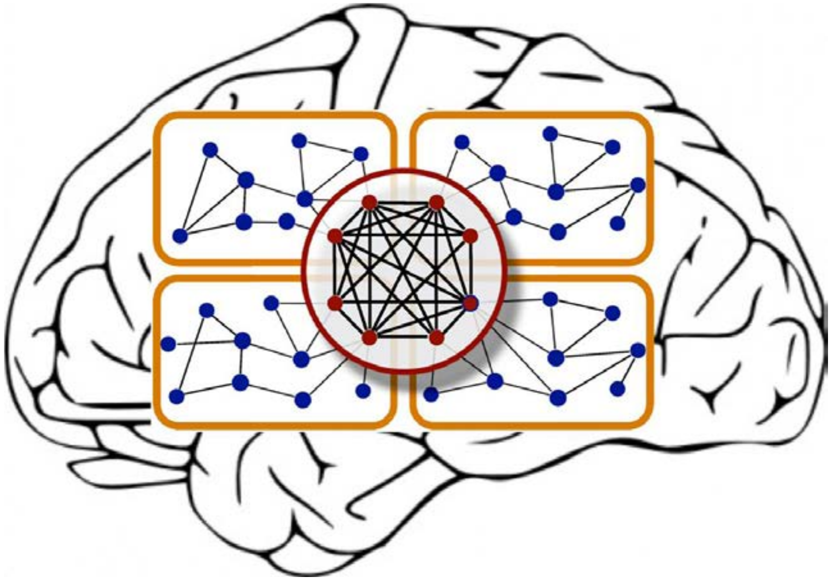
x_1

x_2

.

.

x_n



Output

y_1

y_2

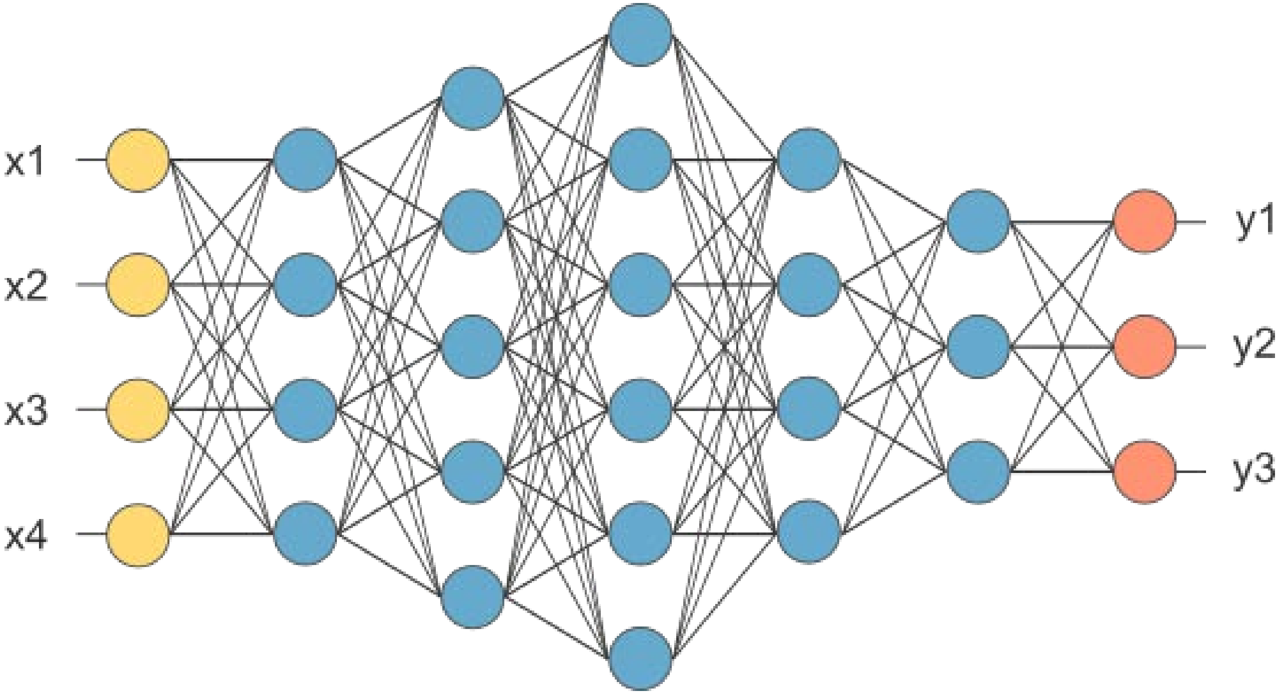
.

.

y_m

$$\overline{y} = f(\overline{x}, \overline{w}, \overline{t})$$

Neural Network



'Training' a Neural Network

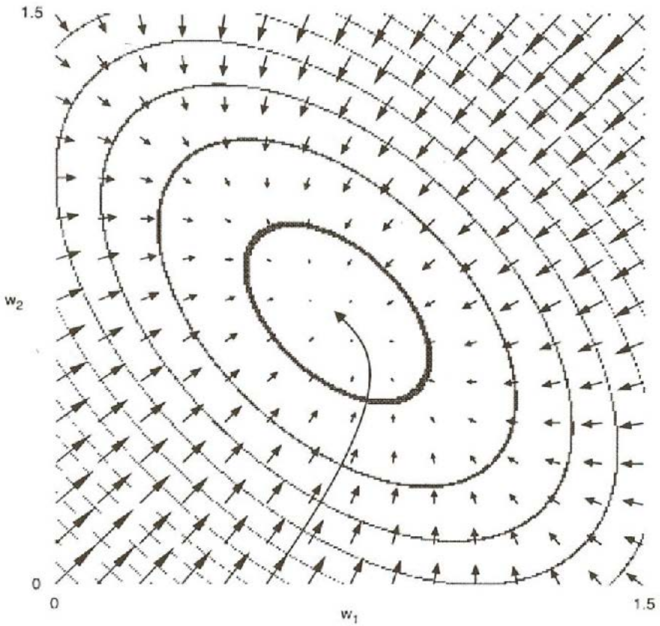
- Given input data and known outputs
- Running inputs through the network gives us a calculated value $\overline{y} = f(\overline{x}, \overline{w}, \overline{t})$ (feed forward)
- Training a neural network involves tuning the weights/thresholds until the values we get out of the network match our training data
- A neural network is a function approximator

Training Progress

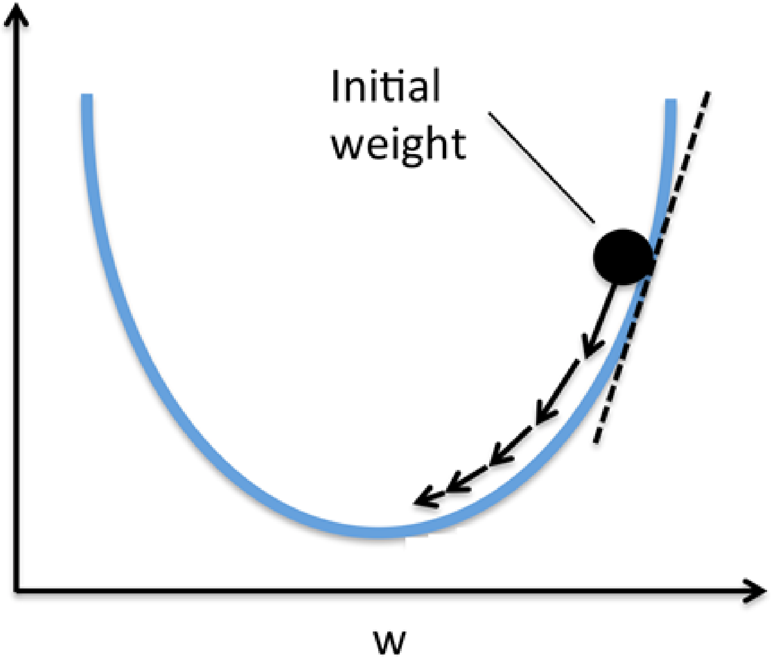
- Desired function: $\overline{d} = g(\overline{x})$
- NN function: $\overline{y} = f(\overline{x}, \overline{w}, \overline{t})$
- Performance should be a function of the desired $\overline{d}$ and the calculated $\overline{y}$
- How about vector distance? $P = \left|\overline{d} - \overline{y}\right|^2$
- Best performance is P = 0, but minimizing

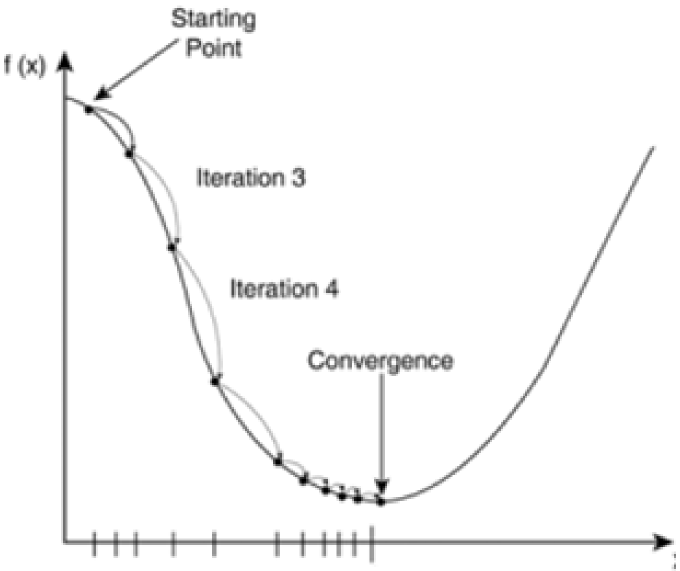
Adjusting the Weights

- Weights w_1, w_2
- Performance contour
- At any given time we are at a given (w_1, w_2)
- Find the action that brings us toward P_{max}
- Hill climbing? Intractible



Gradient Descent





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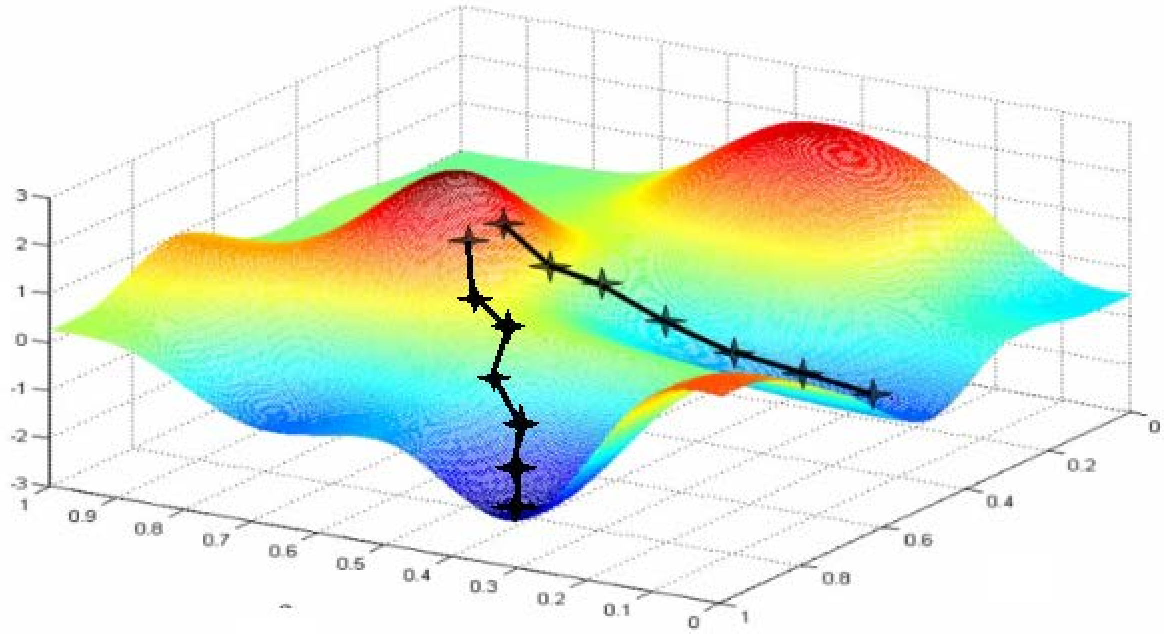

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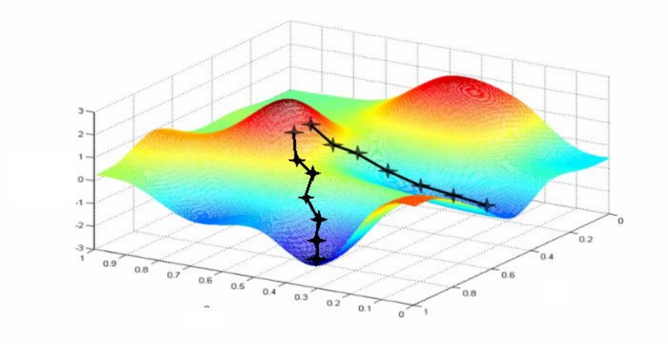
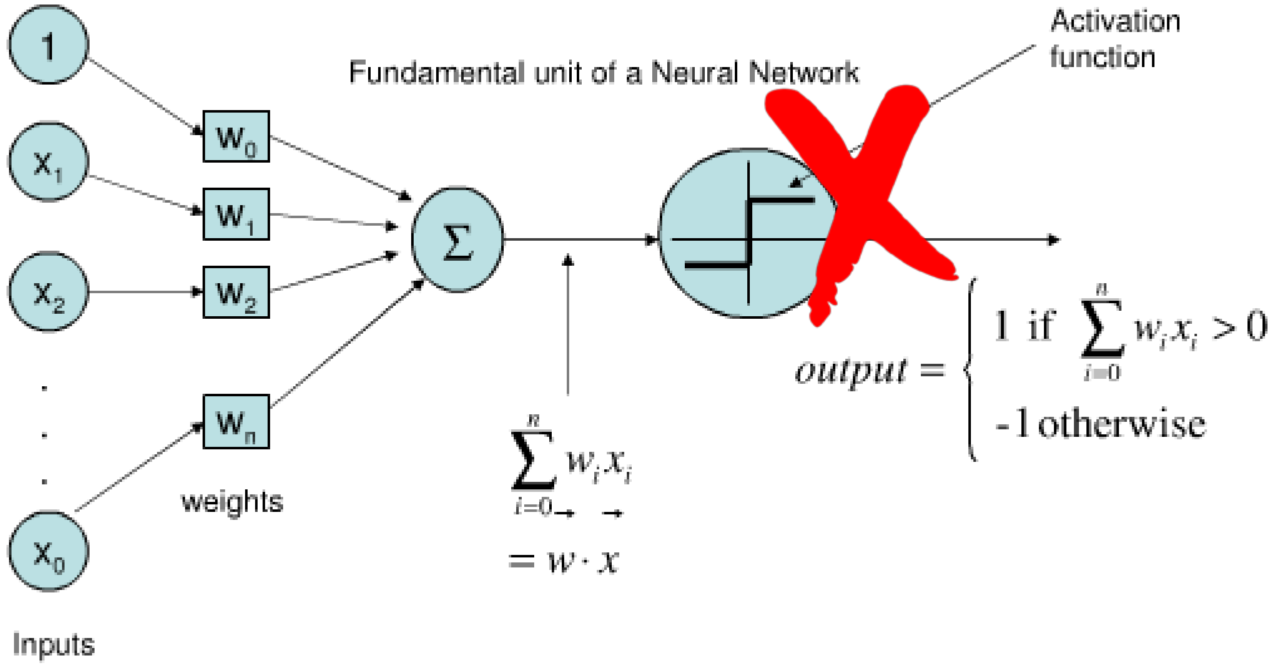


- Derivative $\frac{\partial P}{\partial w}$
- Update $\Delta w = r\,\frac{\partial P}{\partial w}$
- Weight(s) $\Delta \overline{w} = r\,(\frac{\partial P}{\partial w_1} i + \frac{\partial P}{\partial w_2}\,\mathrm{j})$

- Obstacle: When does this work?
  - Only when P is differentiable

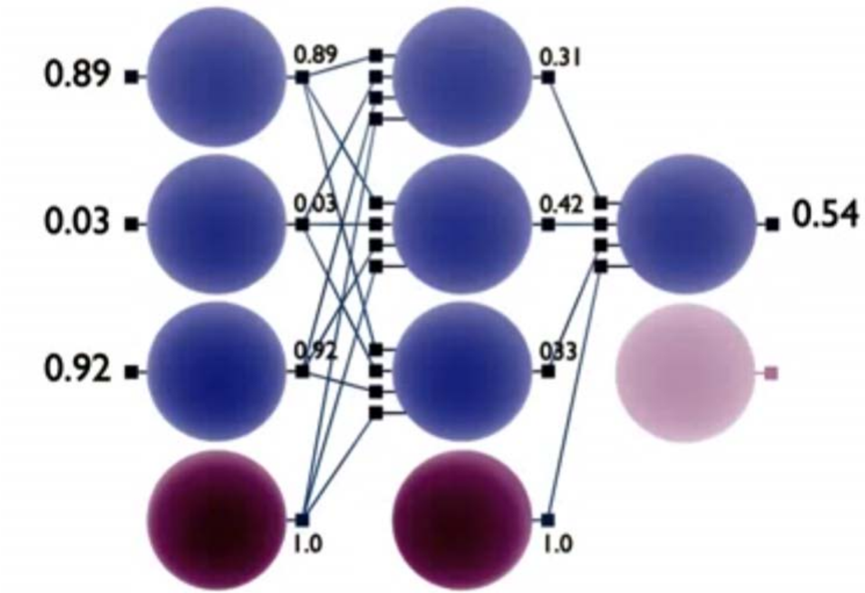

Fundamental unit of a Neural Network
Activation function
1
x1
x2
x0
w0
w1
w2
wn
weights
Inputs
Σ
$\sum_{i=0}^{n} w_i x_i = \vec{w} \cdot \vec{x}$
$output = \begin{cases} 1 \text{ if } \sum_{i=0}^{n} w_i x_i > 0 \\ -1 \text{ otherwise} \end{cases}$

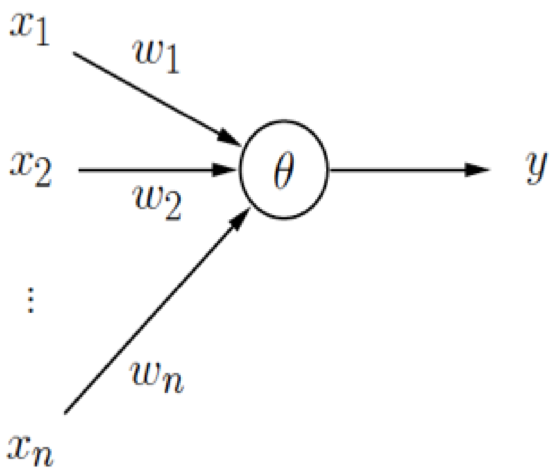
Step 1: Removing Threshold

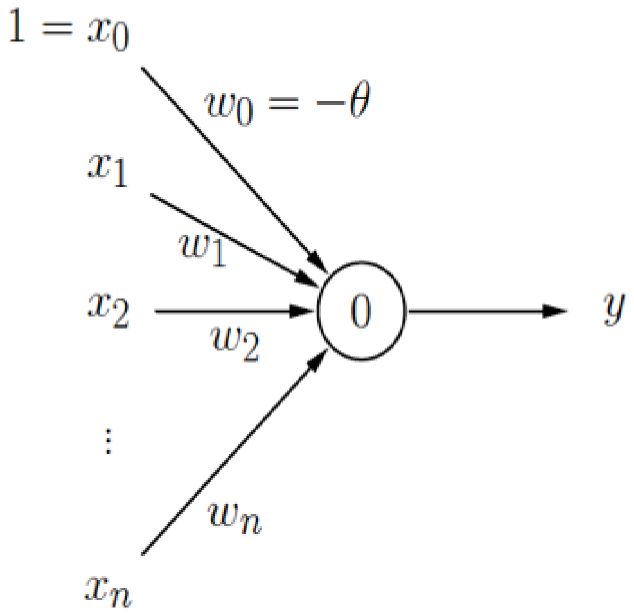
- Thresholding makes our function non-differentiable, also annoying to compute
- Ideally, we want $\overline{y} = f(\overline{x}, \overline{w})$
- Took 25 years to figure out a good way to accomplish this
- Enter the Bias Neuron

Bias Neuron

- An extra neuron added to each layer
- Has fixed output value of 1.0
- Has effect similar to that of thresholding with easier compute





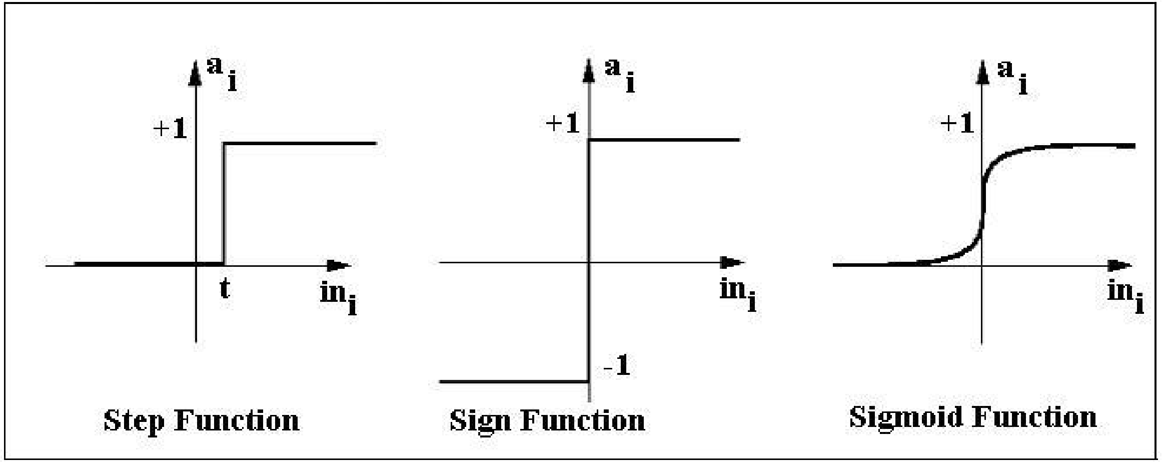


$$\sum_{i=1}^{n} w_i x_i \geq \theta$$

$$\sum_{i=1}^{n} w_i x_i - \theta \geq 0$$

Step 2: Smoothing the Activation

- Step function non-differentiable
- Apply a sigmoid function to smooth it out



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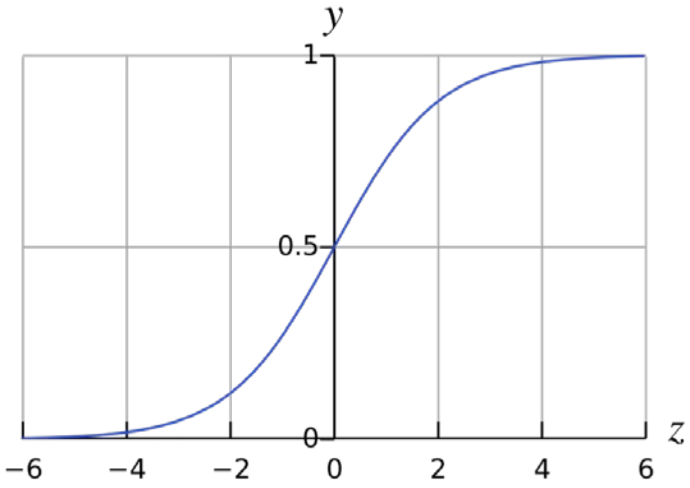
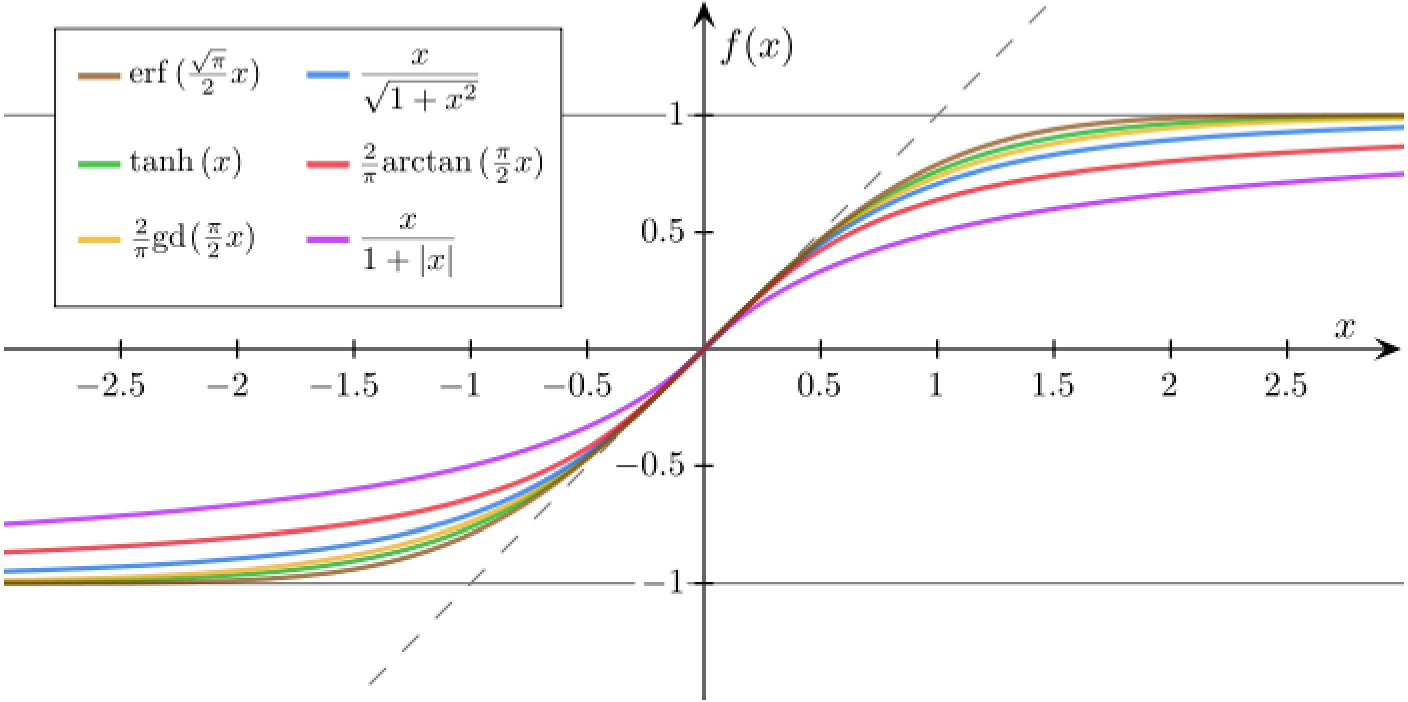


$$z = w_1 x_1 + w_2 x_2 + \ldots + w_n x_n$$

$$y = \frac{1}{1 + e^{-z}}$$

Sigmoid Functions



The Improved Neuron