Deep Learning Workshop

"...what we want is a machine
that can learn from experience."

Alan Turing, 1947

Xenofon Karagiannis

AI vs ML vs DL vs Data Science

aaaaall hype buzzwords

AI - ANI and AGI (terminator/skynet)

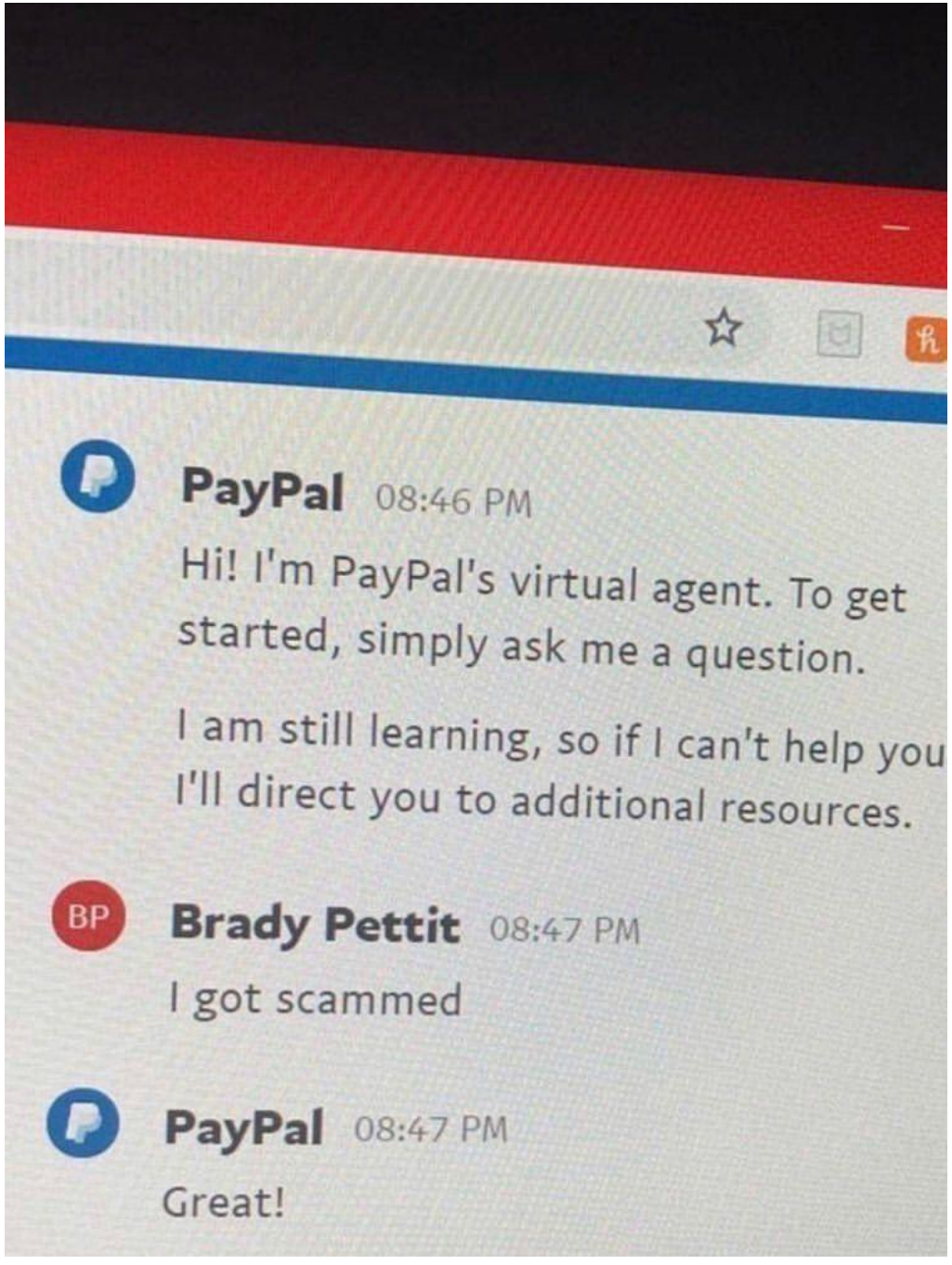
“AI is the new electricity”. Andrew NG
papers and articles!!!
news colaz Μερικές εφαρμογές
coursera: google cat,
edX: , speech reenactment, automatic handwriting gen
other: medical-images, smart-crops, sefl-driving cars
TensorFlow: an ML platform for solving impactful and challenging problems [link]

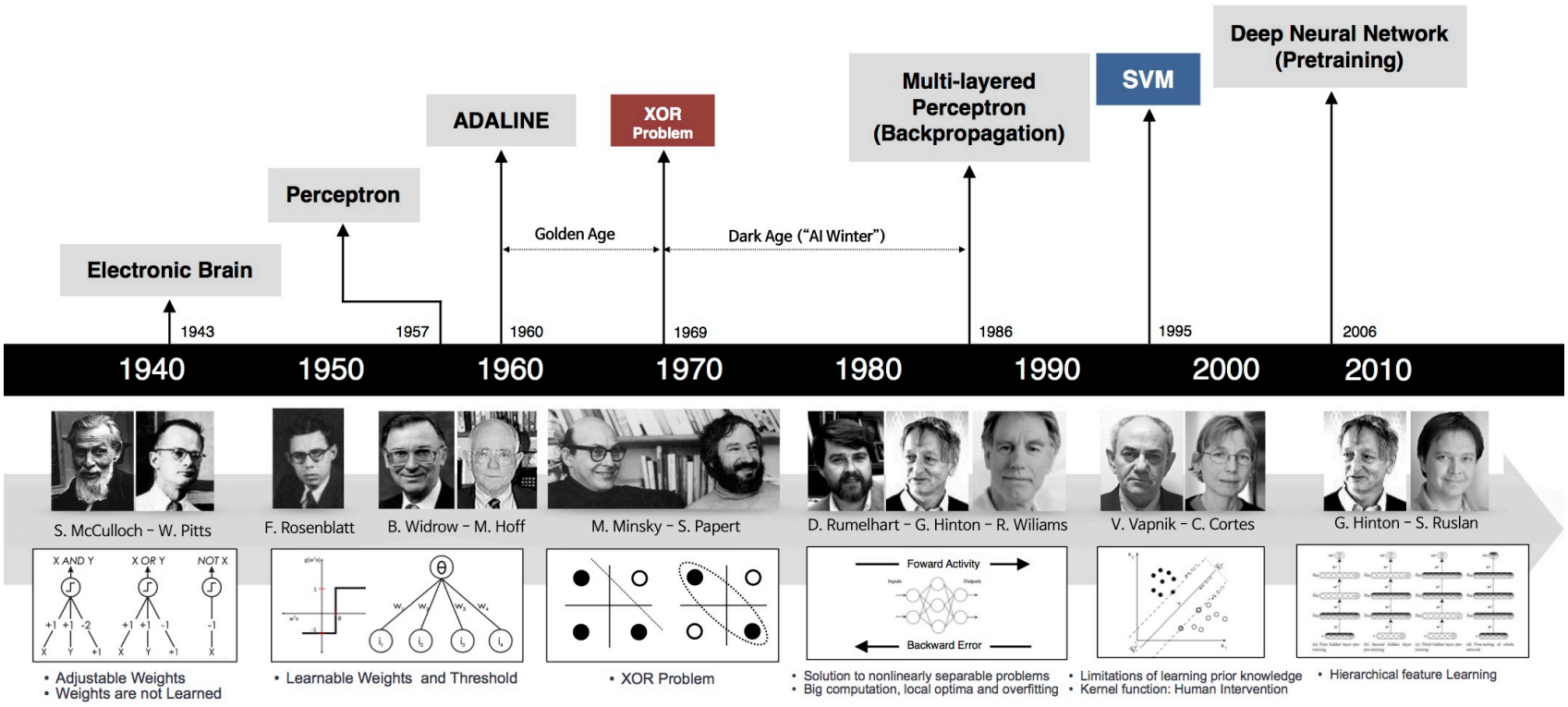
Color Restoration

Let there be Color! [link]
Let there be Color! [github]

AI failes!
#alexafails


Kaenbyou 01/13/2018
60+ hours on 16 GPU nvidia CUDA cluster.
dog


PayPal 08:46 PM
Hi! I'm PayPal's virtual agent. To get started, simply ask me a question.
I am still learning, so if I can't help you I'll direct you to additional resources.
BP
Brady Pettit 08:47 PM
I got scammed
PayPal 08:47 PM
Great!


Deep Neural Network (Pretraining)
SVM
Multi-layered Perceptron (Backpropagation)
XOR Problem
ADALINE
Perceptron
Electronic Brain
Golden Age
Dark Age ("AI Winter")
1943
1957
1960
1969
1986
1995
2006
1940
1950
1960
1970
1980
1990
2000
2010
S. McCulloch - W. Pitts
F. Rosenblatt
B. Widrow - M. Hoff
M. Minsky - S. Papert
D. Rumelhart - G. Hinton - R. Wiliams
V. Vapnik - C. Cortes
G. Hinton - S. Ruslan
X AND Y
X OR Y
NOT X
Foward Activity
Backward Error
• Adjustable Weights
• Weights are not Learned
• Learnable Weights and Threshold
• XOR Problem
• Solution to nonlinearly separable problems
• Big computation, local optima and overfitting
• Limitations of learning prior knowledge
• Kernel function: Human Intervention
• Hierarchical feature Learning

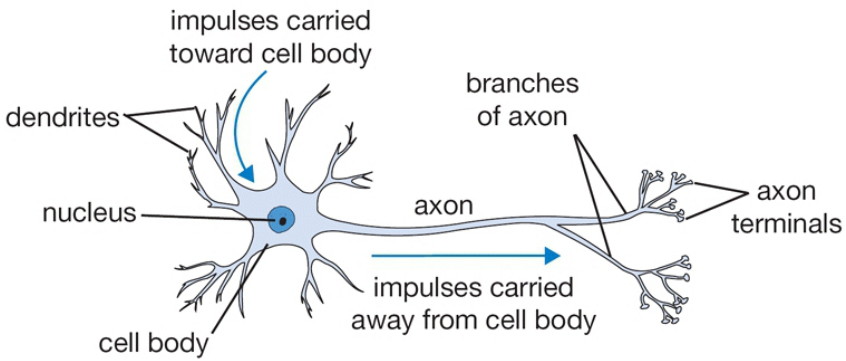
Neuron: The basic computational unit of the brain

Walter Pitts and Warren McCulloch [1943]:

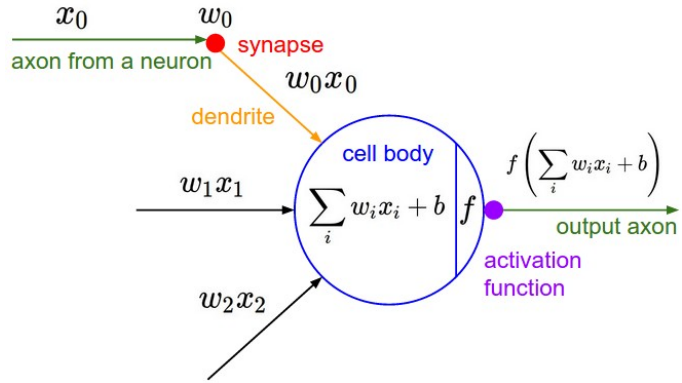
Thresholded logic unit (designed to mimic the way a neuron was thought to work)

adjustable but *not learned* weights

$$\text{output} = \begin{cases} 0 & \text{if } \sum_j w_j x_j \leq \text{ threshold} \\ 1 & \text{if } \sum_j w_j x_j > \text{ threshold} \end{cases}$$



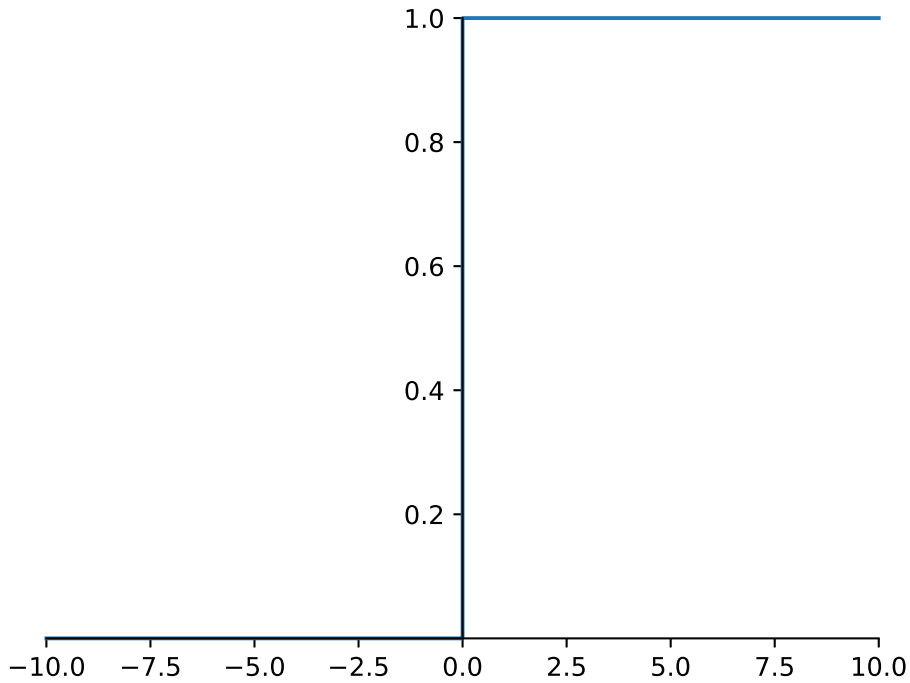
(i) Βιολογικός νευρώνας



(ii) Μαθηματικό μοντέλο - τεχνητός νευρώνας

Thresholded logic unit: Maps inputs to 1 or 0

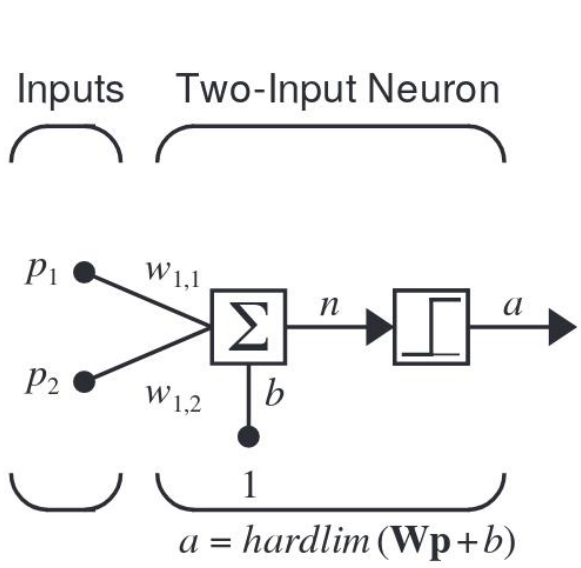
$$\text{output} = \begin{cases} 0 & \text{if } \sum_j w_j x_j \leq \text{ threshold} \\ 1 & \text{if } \sum_j w_j x_j > \text{ threshold} \end{cases}$$



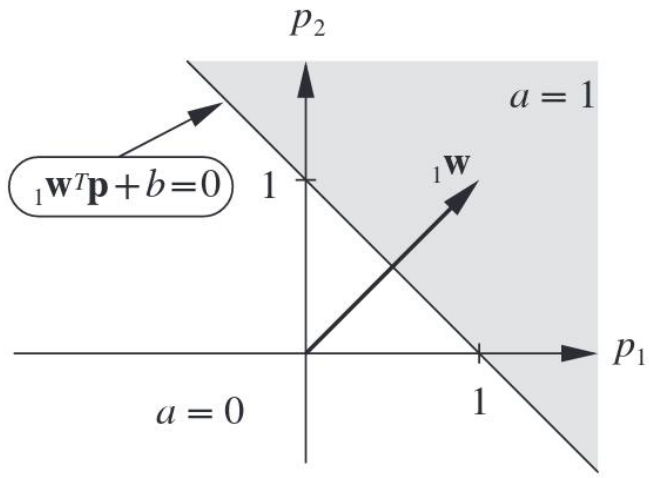
Frank Rosenblatt's "perceptron" [1957]:

First real precursor to modern neural networks

Developed **rule for learning weights**



$$w_{1,1} = 1 \qquad w_{1,2} = 1 \qquad b = -1$$



$$a = hardlim(_1\mathbf{w}^{\mathrm{T}}\mathbf{p} + b) = hardlim(w_{1,1}p_1 + w_{1,2}p_2 + b)$$

Decision Boundary: $w_{1,1}p_1 + w_{1,2}p_2 + b = 0$

Linear equation: $ax + by + c = 0$

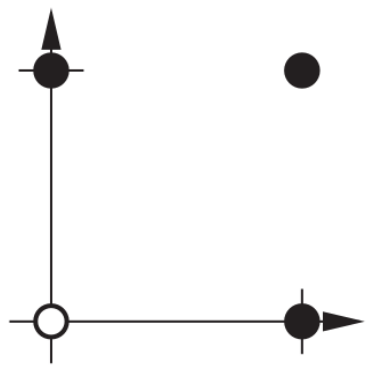
Supervised Learning

Network is provided with a set of examples of proper network behavior (inputs/targets)

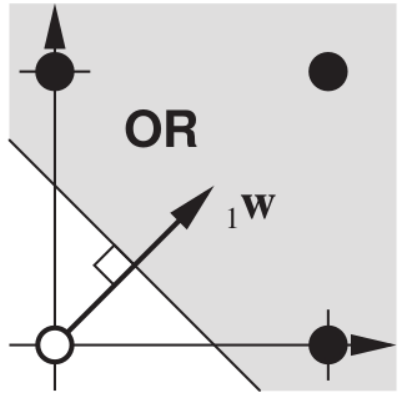
$$\{p_1, t_1\}, \{p_2, t_2\}, \ldots, \{p_Q, t_Q\}$$

Example - OR gate

$$\left\{\mathbf{p}_1 = \begin{bmatrix}0\\0\end{bmatrix}, t_1 = 0\right\} \quad \left\{\mathbf{p}_2 = \begin{bmatrix}0\\1\end{bmatrix}, t_2 = 1\right\} \quad \left\{\mathbf{p}_3 = \begin{bmatrix}1\\0\end{bmatrix}, t_3 = 1\right\} \quad \left\{\mathbf{p}_4 = \begin{bmatrix}1\\1\end{bmatrix}, t_4 = 1\right\}$$



Example - OR gate



Weight vector should be orthogonal to the decision boundary.

$$_1\mathbf{w} = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}$$

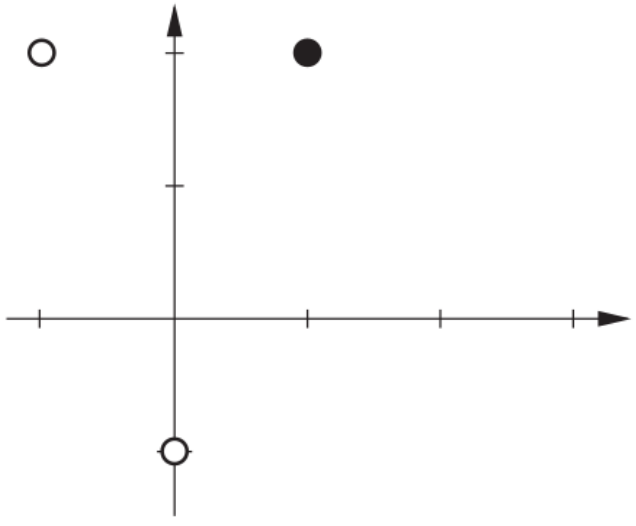
Pick a point on the decision boundary to find the bias.

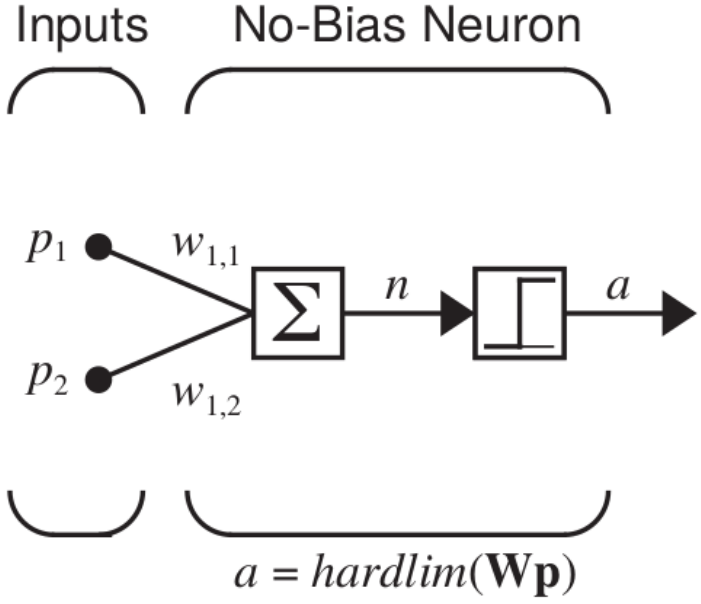
$$_1\mathbf{w}^T\mathbf{p} + b = \begin{bmatrix} 0.5 & 0.5 \end{bmatrix} \begin{bmatrix} 0 \\ 0.5 \end{bmatrix} + b = 0.25 + \mathrm{b} = 0 \quad \Rightarrow \quad b = -0.25$$

Learning Rule Test Problem

$$\{\mathbf{p}_1, \mathbf{t}_1\}, \{\mathbf{p}_2, \mathbf{t}_2\}, \ldots, \{\mathbf{p}_Q, \mathbf{t}_Q\}$$

$$\left\{\mathbf{p}_1 = \begin{bmatrix}1\\2\end{bmatrix}, t_1 = 1\right\} \quad \left\{\mathbf{p}_2 = \begin{bmatrix}-1\\2\end{bmatrix}, t_2 = 0\right\} \quad \left\{\mathbf{p}_3 = \begin{bmatrix}0\\-1\end{bmatrix}, t_3 = 0\right\}$$

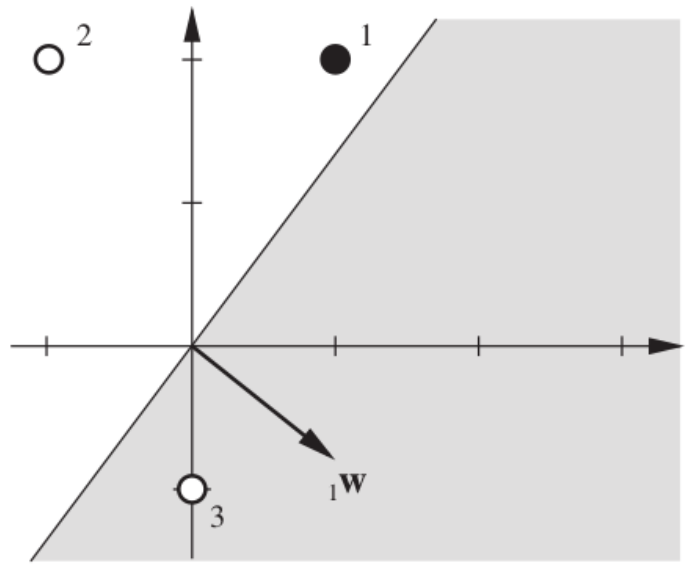




Starting Point

Random initial weight:

$$ {}_1\mathbf{w} = \begin{bmatrix} 1.0 \\ -0.8 \end{bmatrix} $$



Present $\mathbf{p}_1$ to the network:

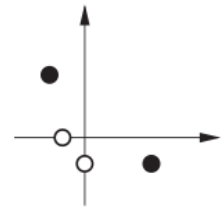
$$ a = hardlim({}_1\mathbf{w}^T \mathbf{p}_1) = hardlim\left(\begin{bmatrix} 1.0 & -0.8 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \end{bmatrix} \right) $$

$$ a = hardlim(-0.6) = 0 $$

Incorrect Classification.

Tentative Learning Rule

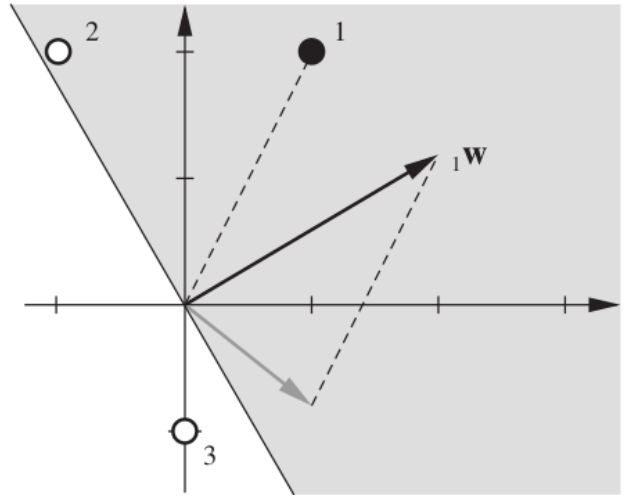
- Set ${}_1\mathbf{w}$ to $\mathbf{p}_1$
  - Not stable ×



- Add $\mathbf{p}_1$ to ${}_1\mathbf{w}$ ✓

Tentative Rule: If $t = 1$ and $a = 0$, then ${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old} + \mathbf{p}$

$${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old} + \mathbf{p}_1 = \begin{bmatrix} 1.0 \\ -0.8 \end{bmatrix} + \begin{bmatrix} 1 \\ 2 \end{bmatrix} = \begin{bmatrix} 2.0 \\ 1.2 \end{bmatrix}$$



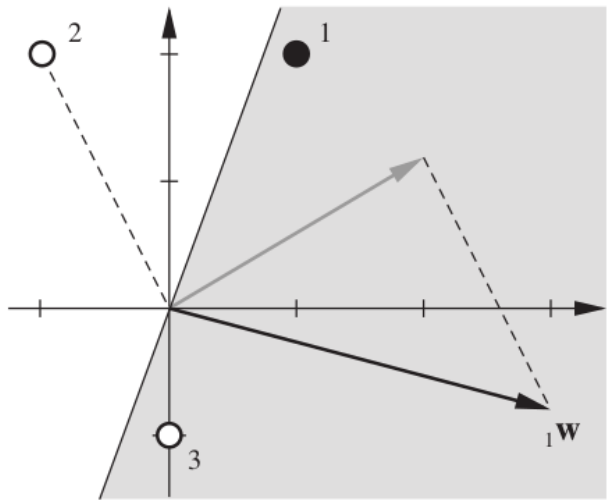
Second Input Vector

$$a = hardlim({}_1\mathbf{w}^T\mathbf{p}_2) = hardlim\left(\begin{bmatrix}2.0 & 1.2\end{bmatrix}\begin{bmatrix}-1\\2\end{bmatrix}\right)$$

$$a = hardlim(0.4) = 1 \quad \text{(Incorrect Classification)}$$

Modification to Rule: If $t = 0$ and $a = 1$, then ${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old} - \mathbf{p}$

$${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old} - \mathbf{p}_2 = \begin{bmatrix}2.0\\1.2\end{bmatrix} - \begin{bmatrix}-1\\2\end{bmatrix} = \begin{bmatrix}3.0\\-0.8\end{bmatrix}$$

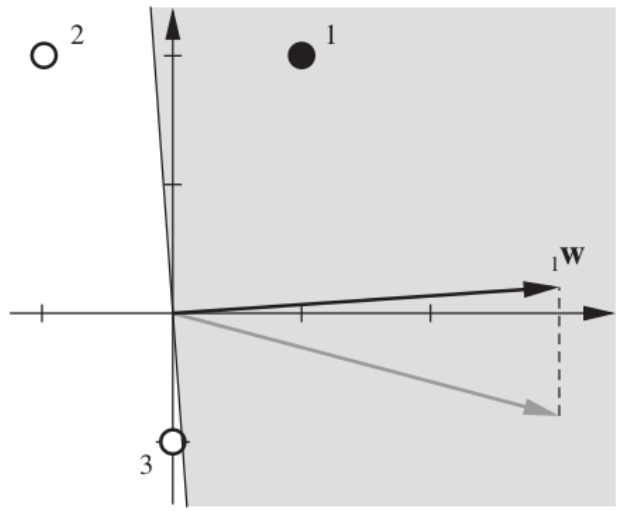


Third Input Vector

$$a = hardlim({}_1\mathbf{w}^T \mathbf{p}_3) = hardlim\left(\begin{bmatrix}3.0 & -0.8\end{bmatrix}\begin{bmatrix}0\\-1\end{bmatrix}\right)$$

$$a = \text{hardlim}(0.8) = 1 \qquad \text{(Incorrect Classification)}$$

$${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old} - \mathbf{p}_3 = \begin{bmatrix}3.0\\-0.8\end{bmatrix} - \begin{bmatrix}0\\-1\end{bmatrix} = \begin{bmatrix}3.0\\0.2\end{bmatrix}$$



Patterns are now correctly classified.

If $t = a$, then ${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old}$.

Unified Learning Rule

If $t = 1$ and $a = 0$, then ${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old} + \mathbf{p}$

If $t = 0$ and $a = 1$, then ${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old} - \mathbf{p}$

If $t = a$, then ${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old}$

$$e = t - a$$

If $e = 1$, then ${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old} + \mathbf{p}$

If $e = -1$, then ${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old} - \mathbf{p}$

If $e = 0$, then ${}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old}$

$$ {}_1\mathbf{w}^{new} = {}_1\mathbf{w}^{old} + e\mathbf{p} = {}_1\mathbf{w}^{old} + (t-a)\mathbf{p}$$

$$b^{new} = b^{old} + e$$

A bias is a weight with an input of 1.

Perceptron convergence theorem

The perceptron learning rule will converge to a weight vector (not necessarily unique) that gives the correct response for all training patterns, and it will do so in a finite number of steps.

Rosenblatt was so confident that the perceptron would lead to true AI, that in 1959 he remarked:

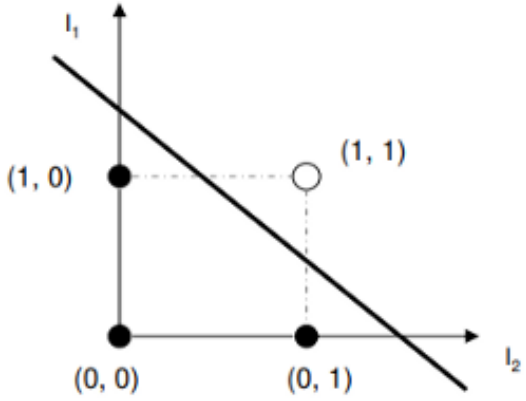
[The perceptron is] the embryo of an electronic computer that [the Navy] expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence.

Marvin Minsky and Seymor Papert - XOR problem [1969]

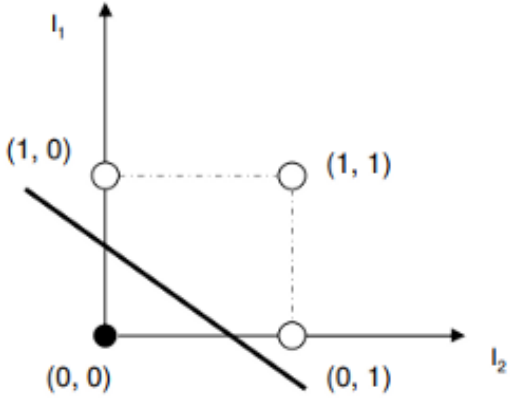
They showed that the perceptron was incapable of learning the simple exclusive-or (XOR) function.
They proved that it was theoretically impossible for it to learn such a function, no matter how long you let it train.
(this isn't surprising to us, as the model implied by the perceptron is a linear one and the XOR function is nonlinear)

At the time this was enough to kill all research on neural nets

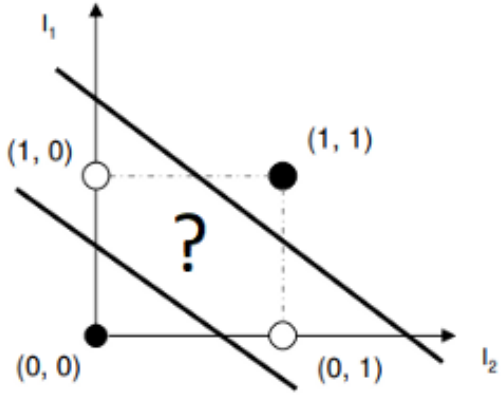
AND		
I_1	I_2	out
0	0	0
0	1	0
1	0	0
1	1	1



OR		
I_1	I_2	out
0	0	0
0	1	1
1	0	1
1	1	1



XOR		
I_1	I_2	out
0	0	0
0	1	1
1	0	1
1	1	0



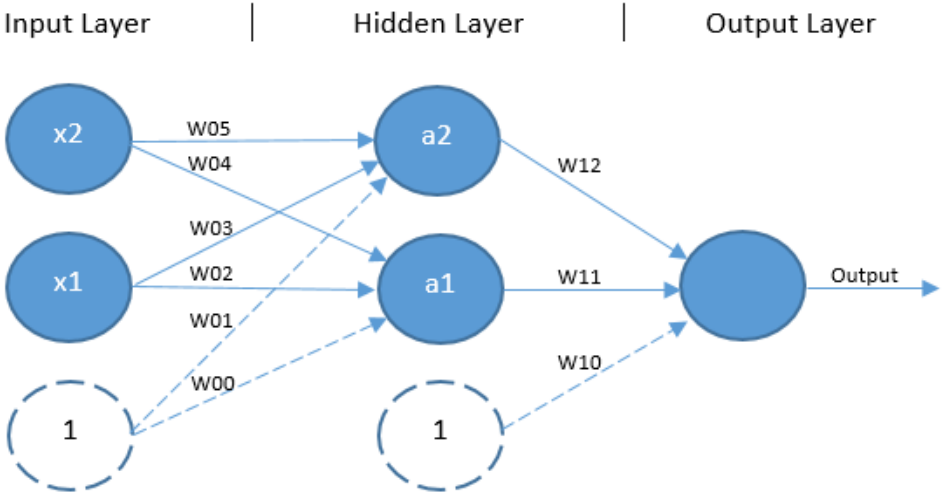

BRACE YOURSELVES
AI WINTER IS COMING
memegenerator.net

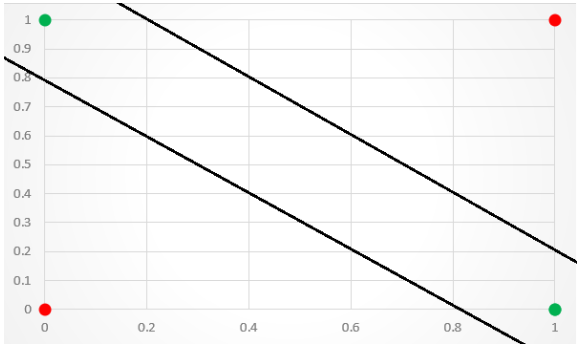
XOR Solution???

One single perceptron neuron: One decision boundary (hyperplane)

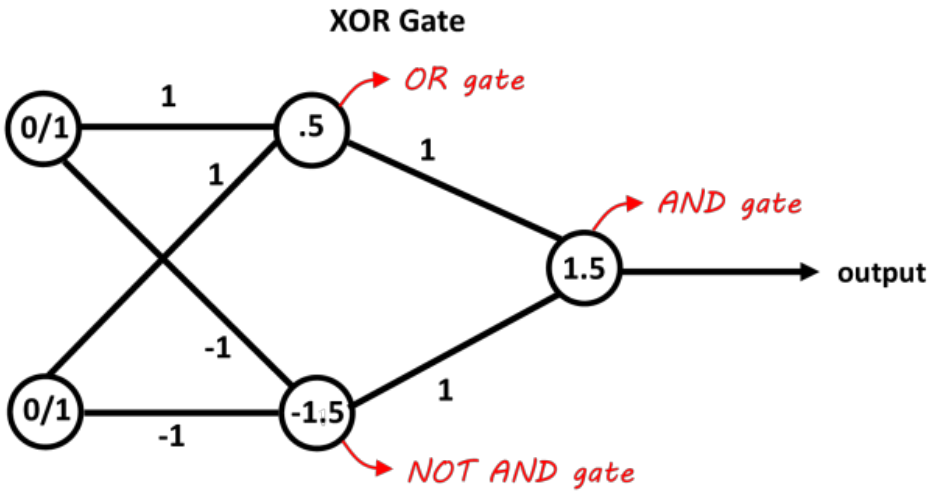
Two perceptron neurons: Two decision boundaries

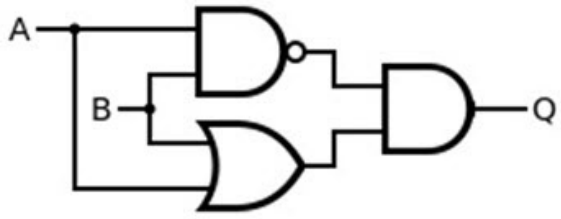
Multi Layer Perceptron (MLP)





As a logic gates





A network of perceptrons can be used to simulate a circuit containing many NAND gates. And because NAND gates are universal for computation, it follows that perceptrons are also universal for computation.

In the mathematical theory of artificial neural networks, the universal approximation theorem states that a feed-forward network with a single hidden layer containing a finite number of neurons can approximate continuous functions on compact subsets of R^n, under mild assumptions on the activation function. The theorem thus states that simple neural networks can represent a wide variety of interesting functions when given appropriate parameters

The problem: There was no equally powerfull rule (to the Perceptron's) for learning in networks with hidden units.

David. Rumelhard, Geoffrey. Hinton and Ronald. Williams - Learning Representations by back-propagating errors [1986]
(aka "Backpropagation")

Perceptron's delta rule: $\Delta_p w_{ji} = \eta(t_{pj} - o_{pj}) i_{pi} = \eta \delta_{pj} i_{pi}$

How was this rule derived?
For linear units, this rule minimizes the squares of the differences between the actual and the desired output values summed over the output units and all pairs of input/output vectors. $E = \sum E_p$

$$E_p = \frac{1}{2} \sum_j (t_{pj} - o_{pj})^2$$

We have: input and target data, network architecture
We want: an algorithm which lets us find weights and biases so that the output from the network approximates y(x) (target *t*) for all training inputs x. To quantify how well we're achieving this goal we define a cost function.

$$C(w,b) = \frac{1}{2n}\sum_x (t-\alpha)^2$$

w the collection of all weights in the network, *b* all the biases, *n* the total number of training inputs, α is the vector of outputs from the network when *x* is input, and the sum is over all training inputs, *x*.

The output α depends on x, w and b.
We'll call *C* the quadratic cost function (or mean squared error - MSE).

$C(w,b)$ is non-negative.
$C(w,b)$ becomes small i.e $C(w,b) \approx 0$ when $t \approx \alpha$.

$$C(w,b) = \frac{1}{2n}\sum_x (t-\alpha)^2$$

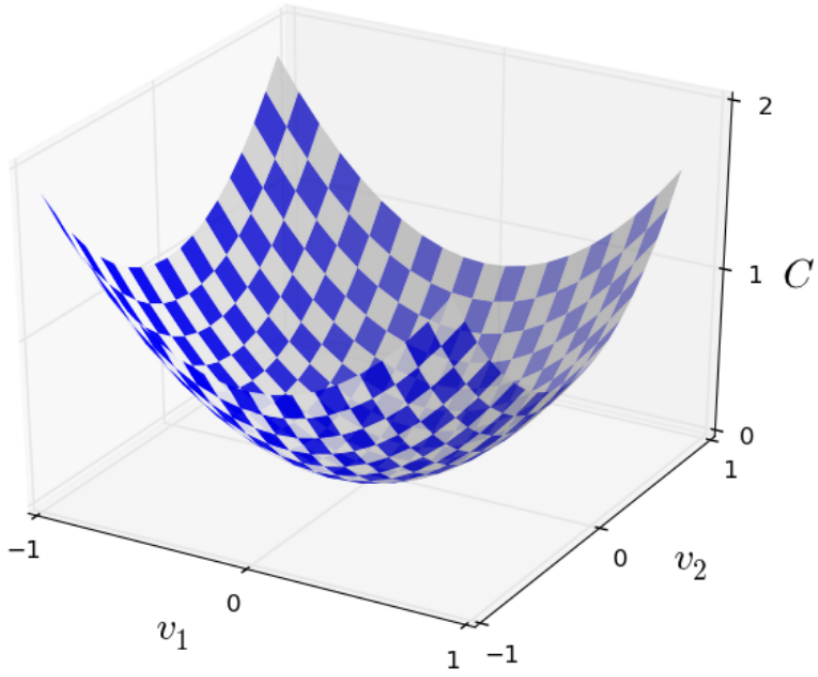
$y = 2x + 4$
$x = [1, 2, 3, 4, 5, 6, 7, 8]$
$t = [6, 8, 10, 12, 14, 16, 18, 20]$
For $w = 3, b = 2$.
$\alpha = [5, 8, 11, 14, 17, 20, 23, 26]$

$C(w,b) = \frac{(6-5)^2+(8-8)^2+(10-11)^2+\ldots+(20-26)^2}{16} = 5.75$

The aim of our training algorithm will be to minimize the cost C(w,b) as a function of the weights and biases. In other words, we want to find a set of weights and biases which make the cost as small as possible. We'll do that using an algorithm known as **gradient descent**.

Minimize some function, C(v)
it helps to imagine C as a function of just two variables, which we'll call v1 and v2

This our function as a kind of a valley!!!
and imagine a ball rolling down the slope of the valley.



$$\Delta C \approx \frac{\partial C}{\partial v_1}\Delta v_1 + \frac{\partial C}{\partial v_2}\Delta v_2$$

$$\Delta C \approx \nabla C \cdot \Delta v$$

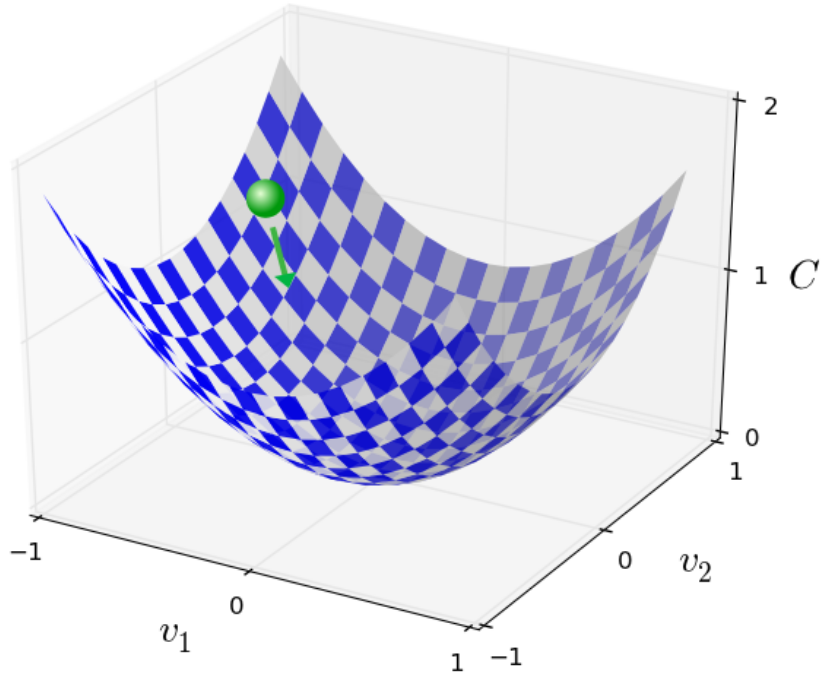
Choose Δv so as to make ΔC negative:

$\Delta v = -\eta \nabla C$

$\Delta C \approx -\eta \|\nabla C\|^2$

$\Delta C \leq 0$ i.e., C will always decrease,

$v \to v' = v - \eta \nabla C$



$$y = 2x + 4 = wx + b.$$

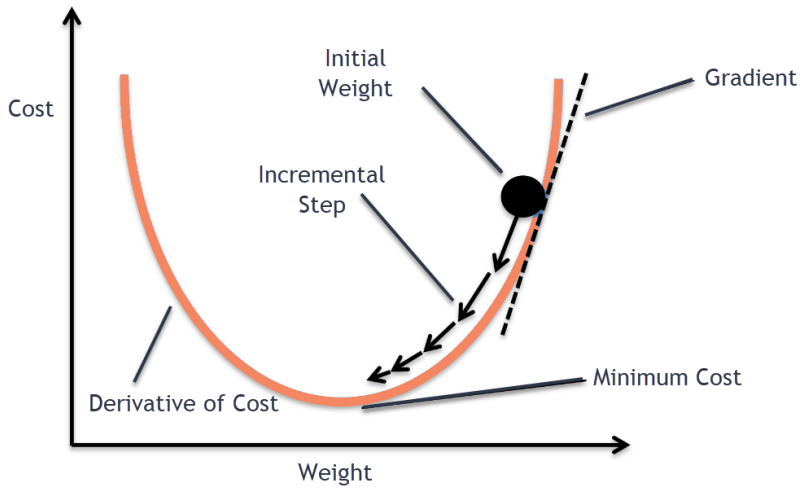
$$C(w,b) = \frac{1}{2n}\sum_x (t - \alpha)^2$$

$$\frac{\partial C(w,b)}{\partial b} = \frac{1}{n}\sum(t - (wx + b))$$

$$\frac{\partial C(w,b)}{\partial w} = \frac{1}{n}\sum(t - (wx + b)) \cdot x$$

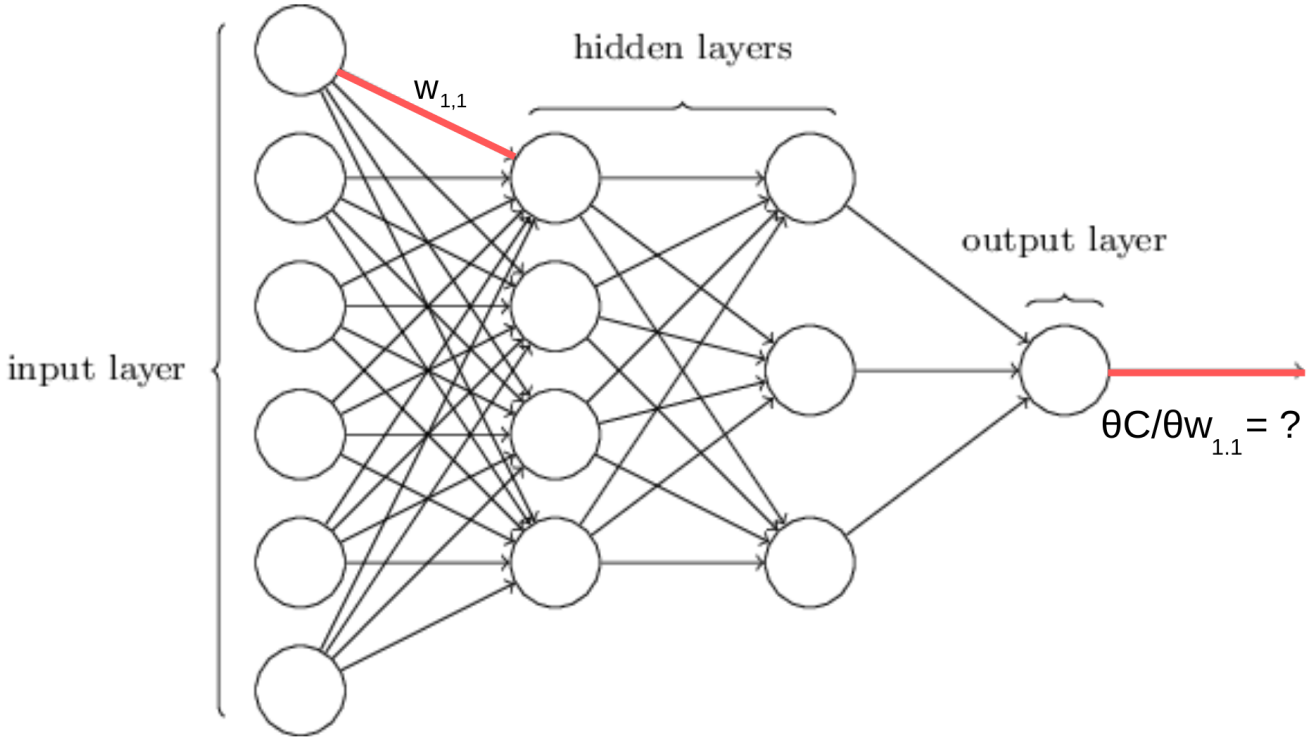
$$b' = b - \eta\frac{\partial C(w,b)}{\partial b}$$

$$w' = w - \eta\frac{\partial C(w,b)}{\partial w}$$

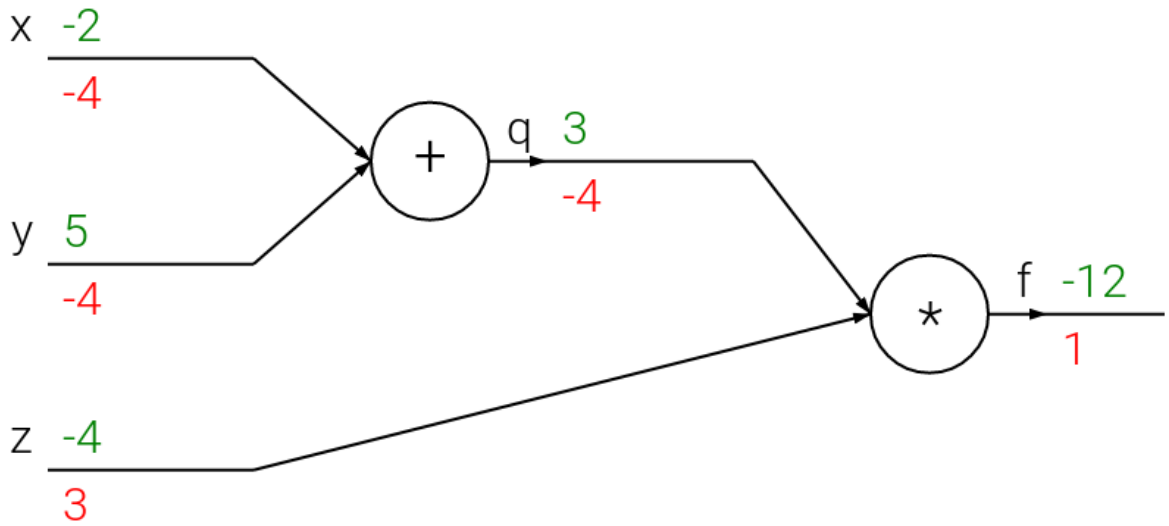


So, how do we train a Multi Layer Perceptron?

$$w_{1.1}^{new} = w_{1.1}^{old} - \eta \frac{\partial C}{\partial w_{1.1}}$$



Back Propagation: PROPAGATE the errors BACK to the input weights!



Chain rule to the rescue!

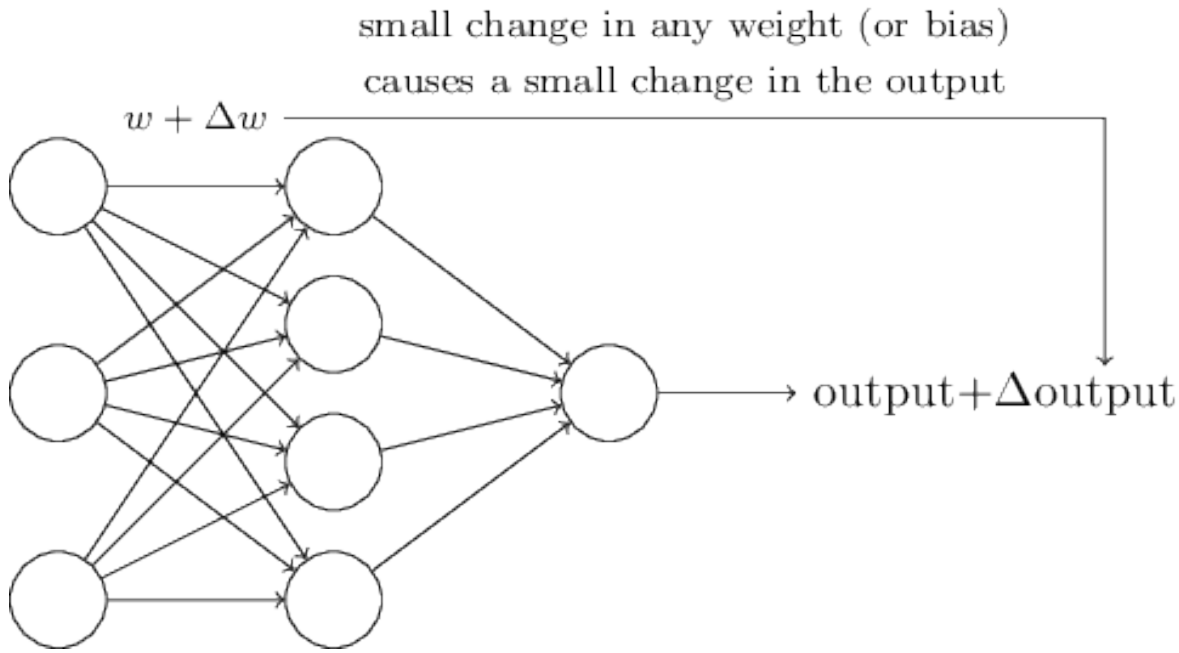
$$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial q}\frac{\partial q}{\partial x} = \frac{\partial (q \cdot z)}{\partial q}\frac{\partial (x + y)}{\partial x} = z \cdot 1 = z = -4$$

$$\frac{\partial f}{\partial z} = \frac{\partial (q \cdot z)}{\partial z} = q = 3$$

Sigmoid neurons - Sigmoid activation function

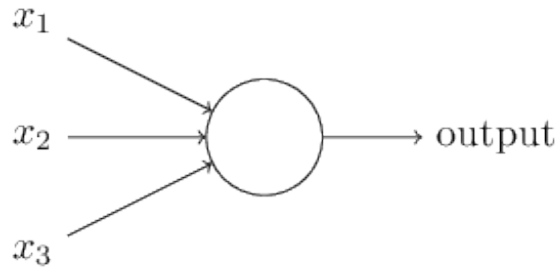
We want a small change in weight to cause only a small corresponding change in the output from the network.

Not possible with perceptrons! - a small change in the weights or bias of any single perceptron in the network can sometimes cause the output of that perceptron to completely flip, say from 0 to 1

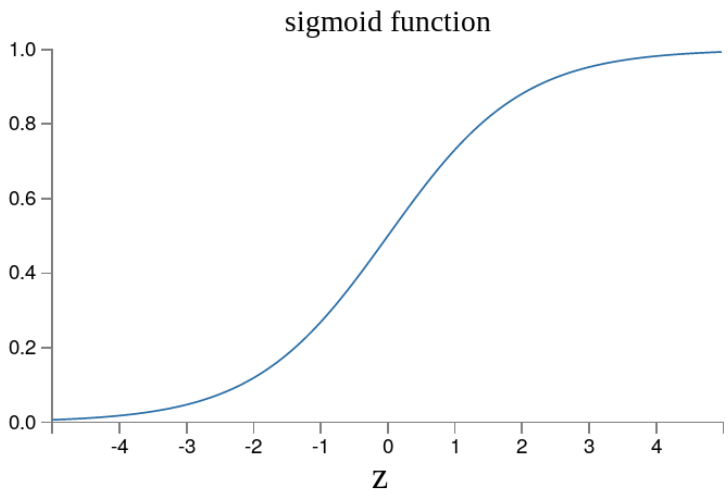


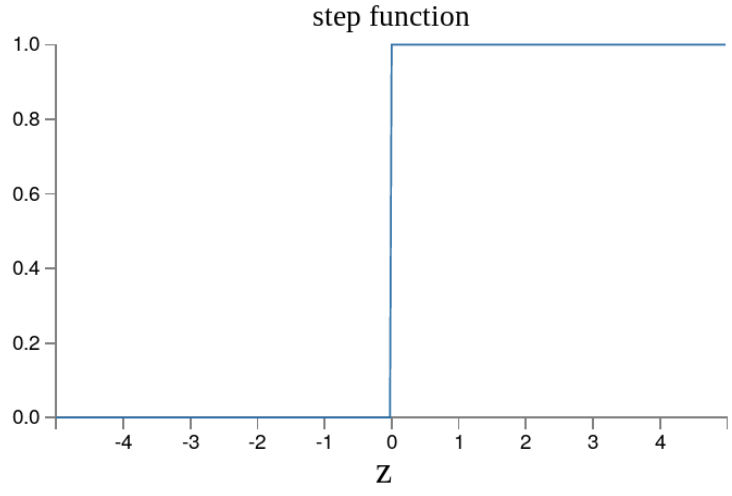
The ouputs of the sigmoid neuron is NOT 0 or 1.

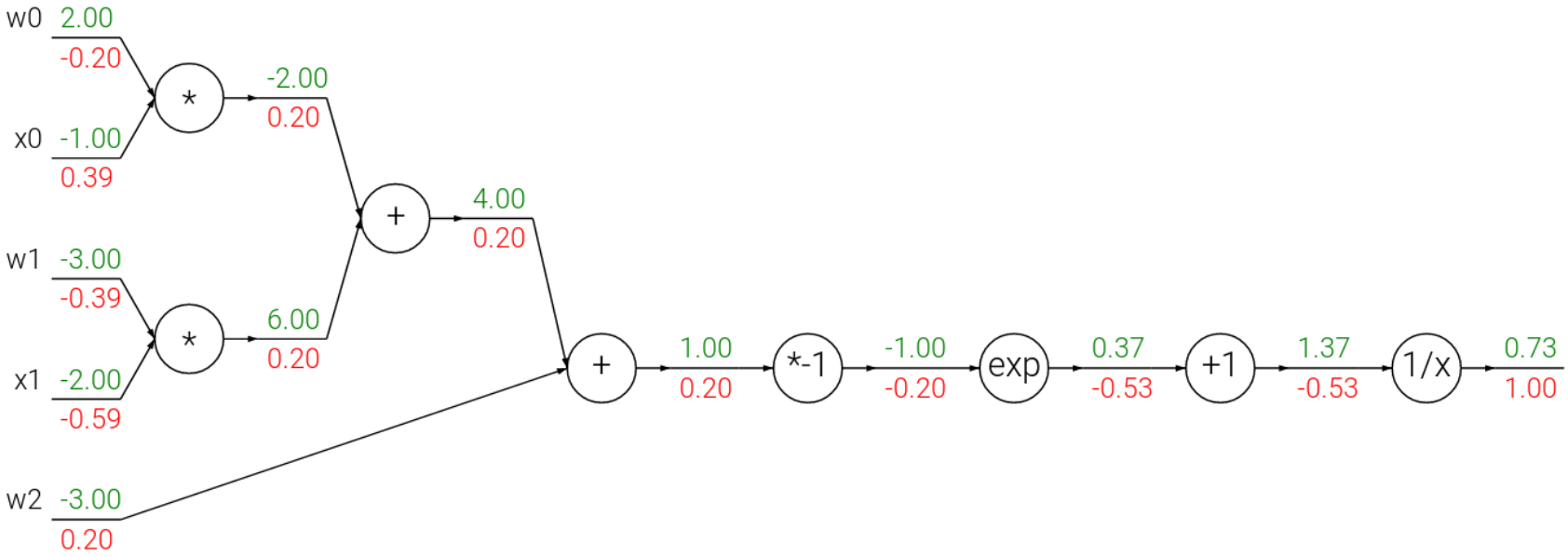
$output = \sigma(w \cdot x + b)$, where σ is the sigmoid function.



$$\sigma(z) = \frac{1}{1+e^{-z}} = \frac{1}{1+exp(-\sum_j w_j x_j - b)}$$

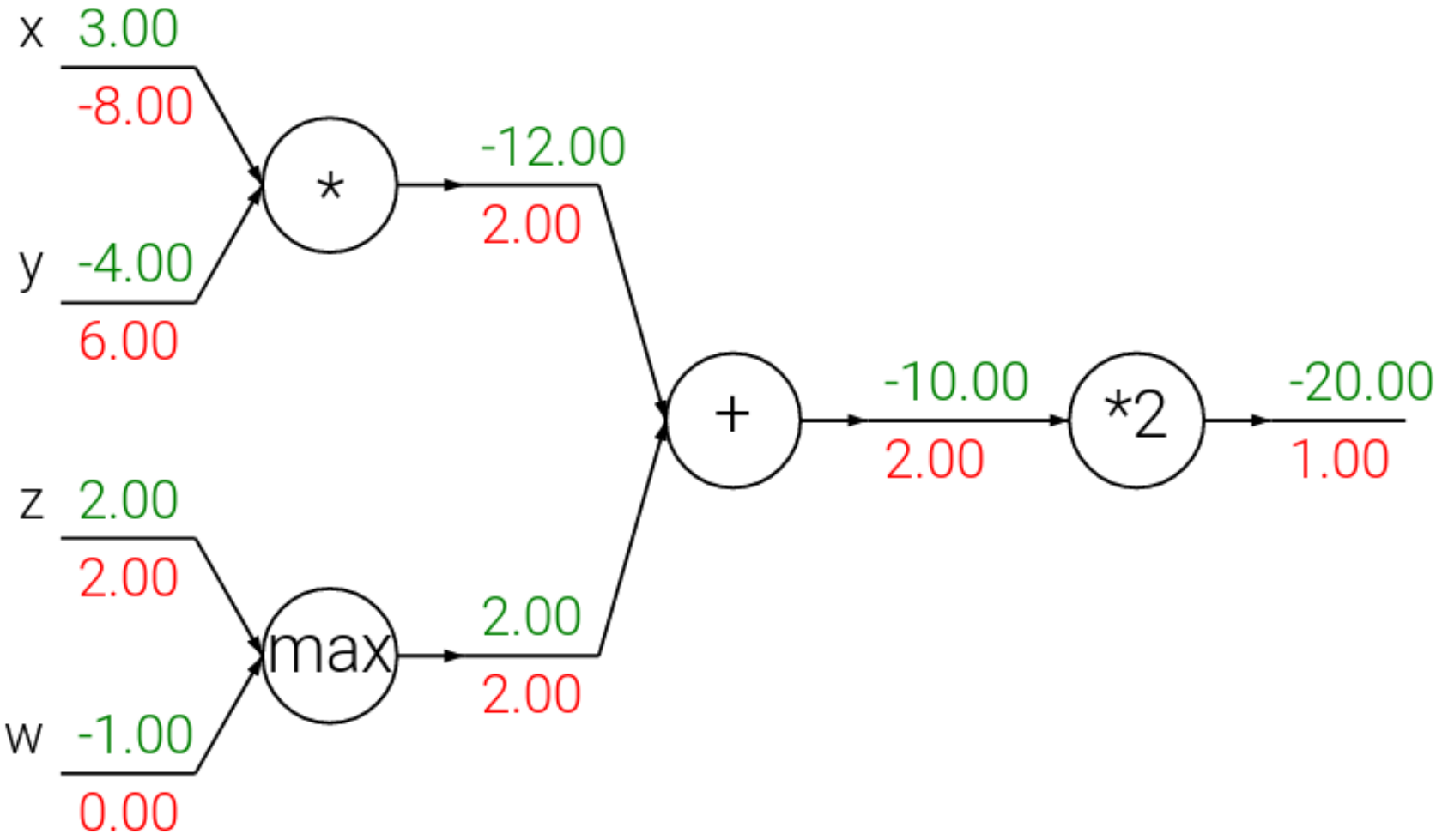






$q = w_0 \cdot x_0, \quad p = w_1 \cdot x_1, \quad s = q + p, \quad t = w_2 + s, \quad r = -t, \quad u = e^r,$
$v = u + 1$ and $z = \frac{1}{v}$

$$\frac{\partial z}{\partial w_0} = \frac{\partial z}{\partial v}\frac{\partial v}{\partial u}\frac{\partial u}{\partial r}\frac{\partial r}{\partial t}\frac{\partial t}{\partial s}\frac{\partial s}{\partial q}\frac{\partial q}{\partial w_0} =$$
$$-0.53 \cdot 1 \cdot 0.37 \cdot (-1) \cdot 1 \cdot 1 \cdot x_0 = -0.1961 \approx -0.20$$


x
3.00
-8.00
y
-4.00
6.00
*
-12.00
2.00
z
2.00
2.00
w
-1.00
0.00
max
2.00
2.00
+
-10.00
2.00
*2
-20.00
1.00

softmax,
NN as matrices,
MNIST example keras (dense)
overfitting / underfitting

Python script - draw/update boundaries while learning!!!
https://cs.stanford.edu/people/karpathy/convnetjs/demo/classify2d.html
1 neuron demo - gates, function approximation (y = 2x), house prices, etc
(gradient descent) python demo - XOR problem (boundaries cant converge)
Linear model!!! meaning a straight line or a linear hyperplane

Linera regression learn the rules

machine learning is all about a computer learning the patterns that distinguish things
map x to y example (y = x-1)

Laurence Moroney
traditional programming vs ML (rules + data = ans VS ans + data = rules)
the computer will figure out the rules
+ examples slides

CNNs