CS 4700: Foundations of Artificial Intelligence

Prof. Bart Selman
selman@cs.cornell.edu

Machine Learning:
Neural Networks
R&N 18.7

Intro & perceptron learning

Rich history, starting in the early forties.

(McCulloch and Pitts 1943)

(including at least on suspicious death ...)

Two views:

- **Modeling the brain.**
- **"Just" representation of complex functions.**

(Continuous; contrast decision trees.)

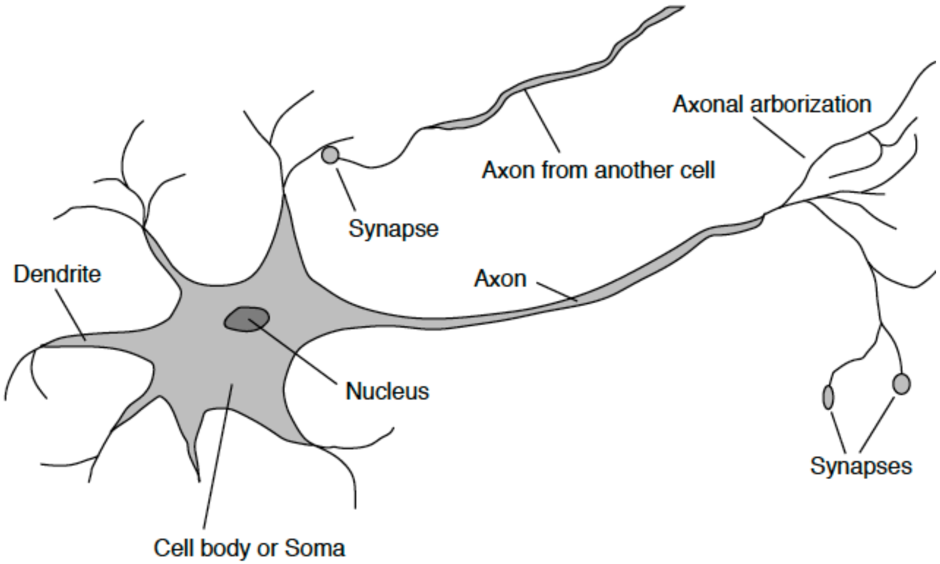
Much progress on both fronts.

Drawn interests from:

Neuro-science, Cognitive science, AI,

Physics, Statistics, and CS / EE.

Neuron: How the brain works



neurons ~ 100 Billion

Neurons / nerve cells

cell body or **soma**
branches: **dendrited**
single long fiber: **axom**
(100 or more times the diameter of cell body)
axon connects via **synapsis** to dendrites of other c
signals propagated via complicated electrochemical reaction
each cell has a certain electrical potential
when above **threshold**, pulse is sent down axon

synapses can increase (**excitatory**) / decrease (**inhibitory**) potential (signal)
but most importantly: have **plasticity** — can **learn / remember!**
In fact, learning can happen to single cell!
Note: current model gives neuron with little stucture. Complexity arises out of connectivity. Not clear this is "final" model.

Idea: collection of simple cells leads to complex behavior: *thought, action, and consciousness* ....
Challenged by e.g. Penrose.
Contrast with current computer design.

Massively Parallel

Neurons: highly parallel computation.

10 to 100 steps — given simple timing constraints, one can deduce that certain visual and other cognitive computations are carried out in about 10 to 100 layers of neurons.

Interesting experiments about how visual features we can detect in parallel.

Appears to need **massive parallelism.**

neurons ~ 100 Billion

Why not build a model like a network of neurons?

	Computer	Human Brain
Computational units	1 CPU, 10^5 gates	10^{11} neurons
Storage units	10^9 bits RAM, 10^{10} bits disk	10^{11} neurons, 10^{14} synapses
Cycle time	10^{-8} sec	10^{-3} sec
Bandwidth	10^9 bits/sec	10^{14} bits/sec
Neuron updates/sec	10^5	10^{14}

Tempting enterprise:

Design computer modeled after the brain.

Good company: Von Neumann (1958)

The Computer and the Brain

But the **connection machine** was not successful

(Hillis 1989 / Thinking Machines)

64K processors.

What was the problem?

R&N:

The exact way in which the brain enables thought is one of the great mysteries of science.

Much recent progress ....

Still, there are skeptics. Especially in CS.

The Skeptic's Position

Related to "levels of abstractions" common in CS.
(less so in EE / Cogn. Sci.)

Consider: Try to figure out how a computer program performing a heap sort works.

Q. How far would you get with a voltmeter? Wiring diagram?
Possibly the wrong level of abstraction!

Could be similar problem in understanding higher cognition using FMRI scans!

Still, let's see what neural net research has achieved.

New York Times: "Scientists See Promise in Deep-Learning Programs," Saturday, Nov. 24, front page.

http://www.nytimes.com/2012/11/24/science/scientists-see-advances-in-deep-learning-a-part-of-artificial-intelligence.html?hpw

Multi-layer neural networks, a resurgence!

a) **Winner one of the most recent learning competitions**
b) **Automatic (unsupervised) learning of "cat" and "human face" from 10 million of Google images; 16,000 cores 3 days; multi-layer neural network (Stanford & Google). ImageNet http://image-net.org/**
c) **Speech recognition and real-time translation (Microsoft Research, China).**

Aside: see web site for great survey article "A Few Useful Things to Know About Machine Learning" by Domingos, CACM, 2012.

Start at min. 3:00. Deep Neural Nets in speech recognition.

Artificial Neural Networks

Mathematical abstraction!

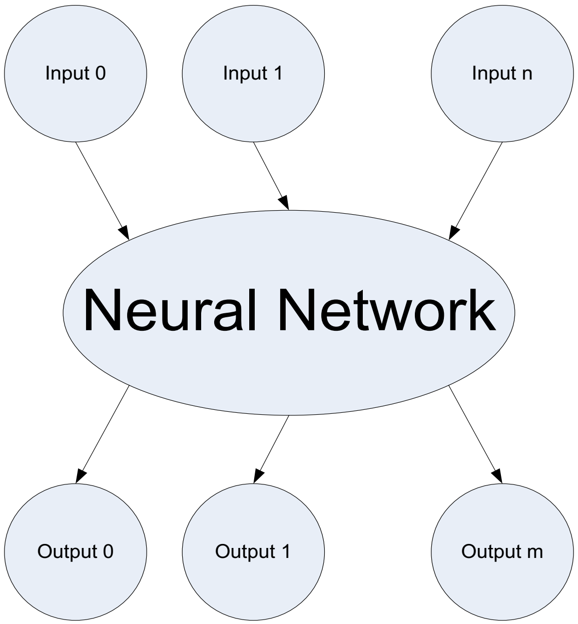
Basic Concepts

A Neural Network maps a set of inputs to a set of outputs

Number of inputs/outputs is variable

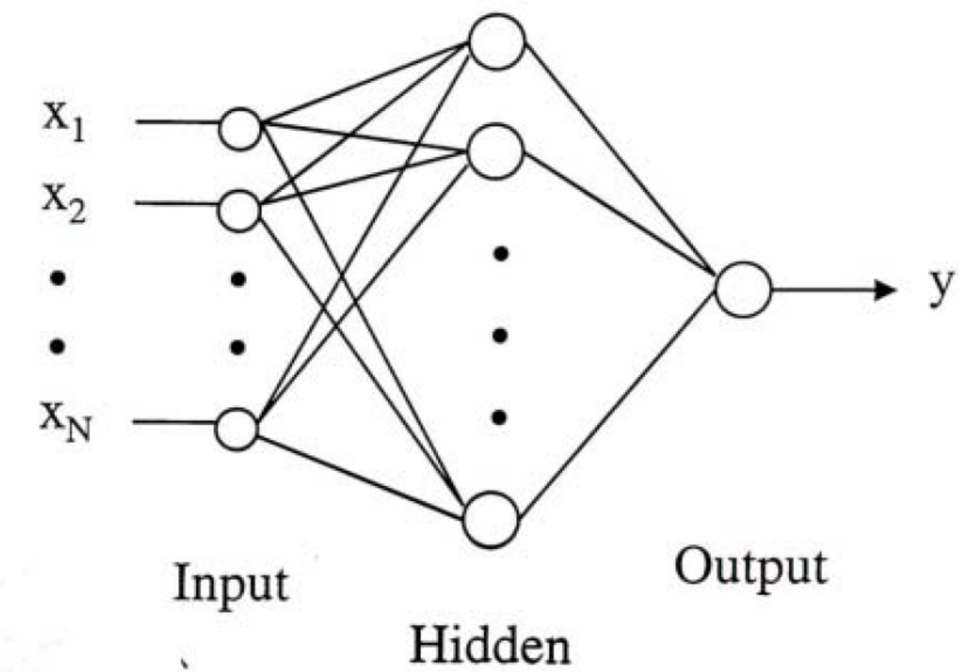
The Network itself is composed of an arbitrary number of nodes or units, connected by links, with an arbitrary topology.

A link from unit i to unit j serves to propagate the activation a_i to j, and it has a weight W_{ij}.



What can a neural networks do?

- Compute a known function / Approximate an unknown function
- Pattern Recognition / Signal Processing
- Learn to do any of the above

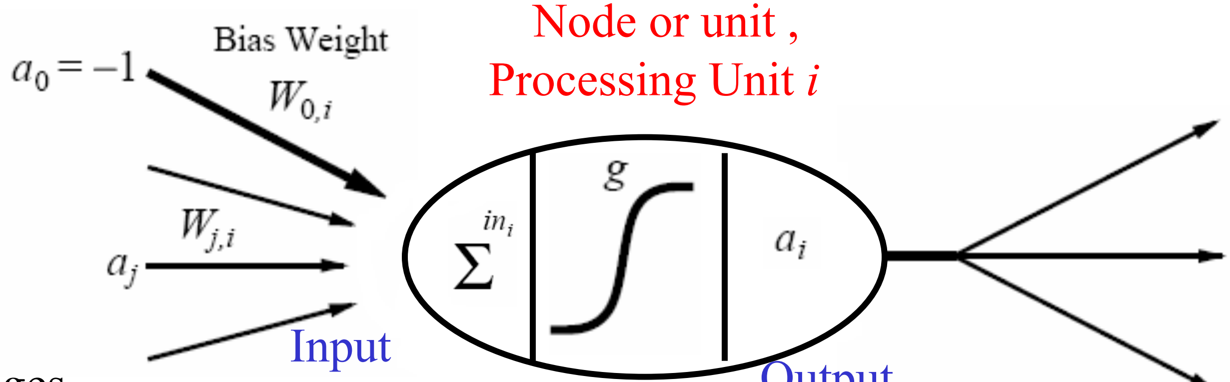


Different types of nodes

here

An Artificial Neuron Node or Unit: A Mathematical Abstraction

Artificial Neuron, Node or unit , Processing Unit *i*



Input edges, each with *weights* (positive, negative, and change over time, learning)

Input function(in_i): weighted sum of its inputs, including fixed input a_0.

$$in_i = \sum_{j=0}^{n} W_{j,i} a_j$$

Activation function (g) applied to input function (typically non-linear).

Output

$$a_i = g\left(\sum_{j=0}^{n} W_{j,i} a_j\right)$$

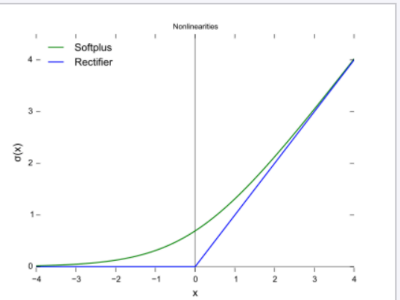
Output edges, each with *weights* (positive, negative, and change over time, learning)

→ a processing element producing an output based on a function of its inputs

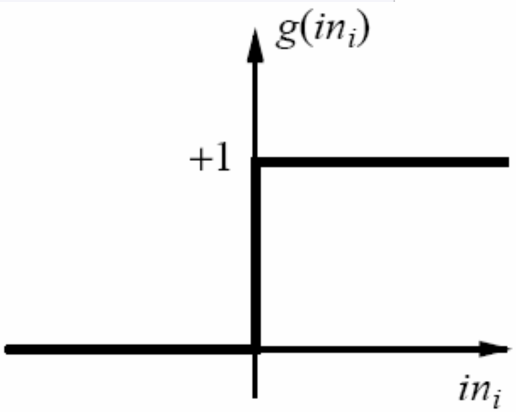
Note: the fixed input and bias weight are conventional; some authors instead, e.g., or a_0=1 and $-W_{0i}$

Activation Functions

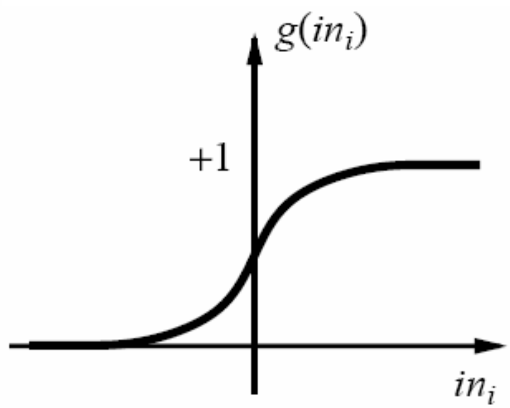
ReLU ---
Rectifier Linear Unit
(deep learning)



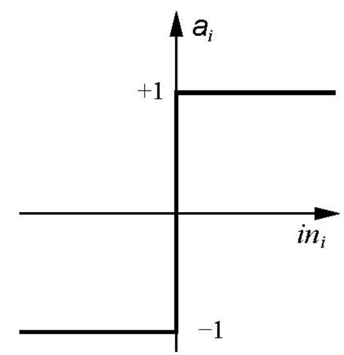
Plot of the rectifier (blue) and oftplus (green) functions near $x = 0$



(a)



(b)



(a) Threshold activation function → a step function or threshold function (outputs 1 when the input is positive; 0 otherwise).

(b) Sigmoid (or logistics function) activation function (key advantage: differentiable) $1/(1+e^{-x})$

(c) Sign function, +1 if input is positive, otherwise -1.

These functions have a threshold (either hard or soft) at zero.

→ Changing the bias weight $W_{0,i}$ moves the threshold location.

$$f(x) = \frac{1}{1+e^{-x}}$$

The derivative of $f(x)$ is:

$$f'(x) = f(x) \times (1 - f(x))$$

$$\frac{ds(x)}{dx} = \frac{1}{1+e^{-x}}$$

$$= \left(\frac{1}{1+e^{-x}}\right)^2 \frac{d}{dx}(1+e^{-x})$$

$$= \left(\frac{1}{1+e^{-x}}\right)^2 e^{-x}(-1)$$

$$= \left(\frac{1}{1+e^{-x}}\right)\left(\frac{1}{1+e^{-x}}\right)(-e^{-x})$$

$$= \left(\frac{1}{1+e^{-x}}\right)\left(\frac{-e^{-x}}{1+e^{-x}}\right)$$

$$= s(x)(1 - s(x))$$

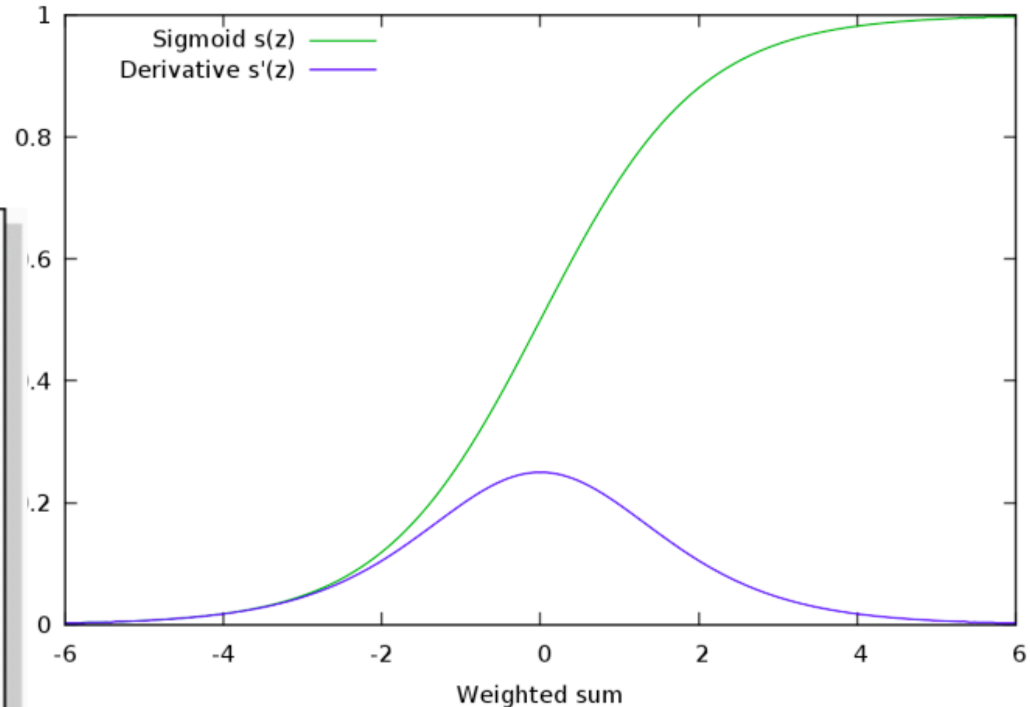


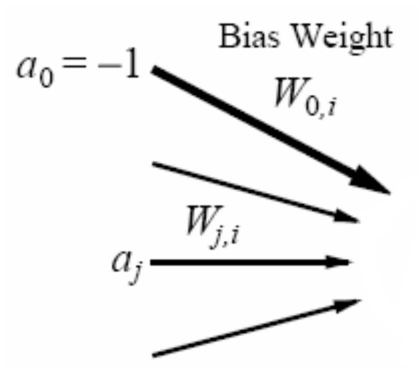
Figure of sigmoid and derivative.

Note: largest derivative at $x = 0$

That's where neuron is most sensitive to weight changes (effect of changes is well "controlled").

Threshold Activation Function

$g(in_i)$



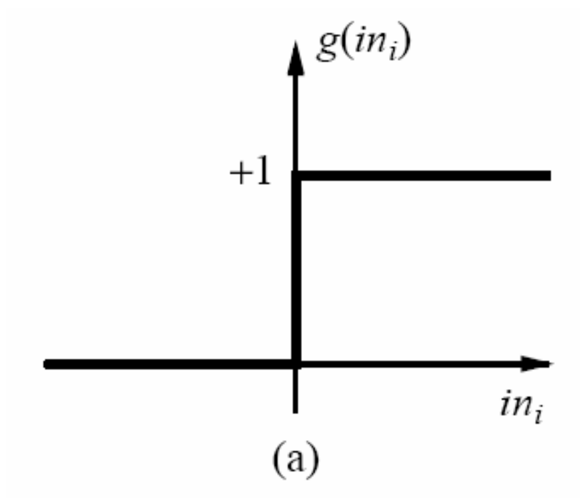
$$in_i = \sum_{j=0}^{n} W_{j,i} a_j > 0; \Leftrightarrow in_i = \sum_{j=1}^{n} w_{j,i} a_j + w_{0,i} a_0 > 0;$$

$$defining\ a_0 = -1\ we\ get \sum_{j=1}^{n} W_{j,i} a_j > w_{0,i},\ \theta_i = w_{0,i}$$

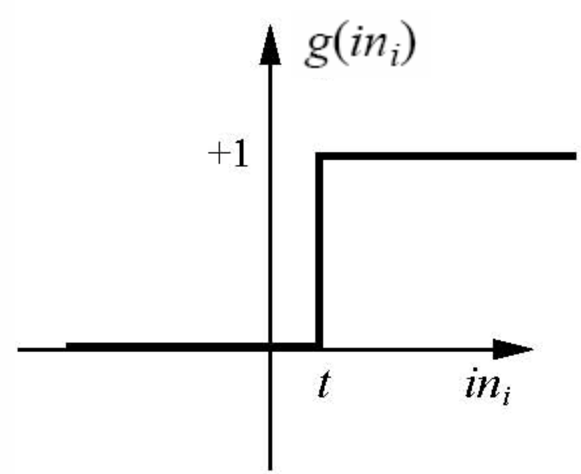
$$defining\ a_0 = 1\ we\ get \sum_{j=1}^{n} W_{j,i} a_j > -w_{0,i},\ \theta_i = -w_{0,i}$$

Input edges, each with *weights* (positive, negative, and change over time, learning)

θ_i threshold value associated with unit i



θ_i=0



θ_i=t

Implementing Boolean Functions

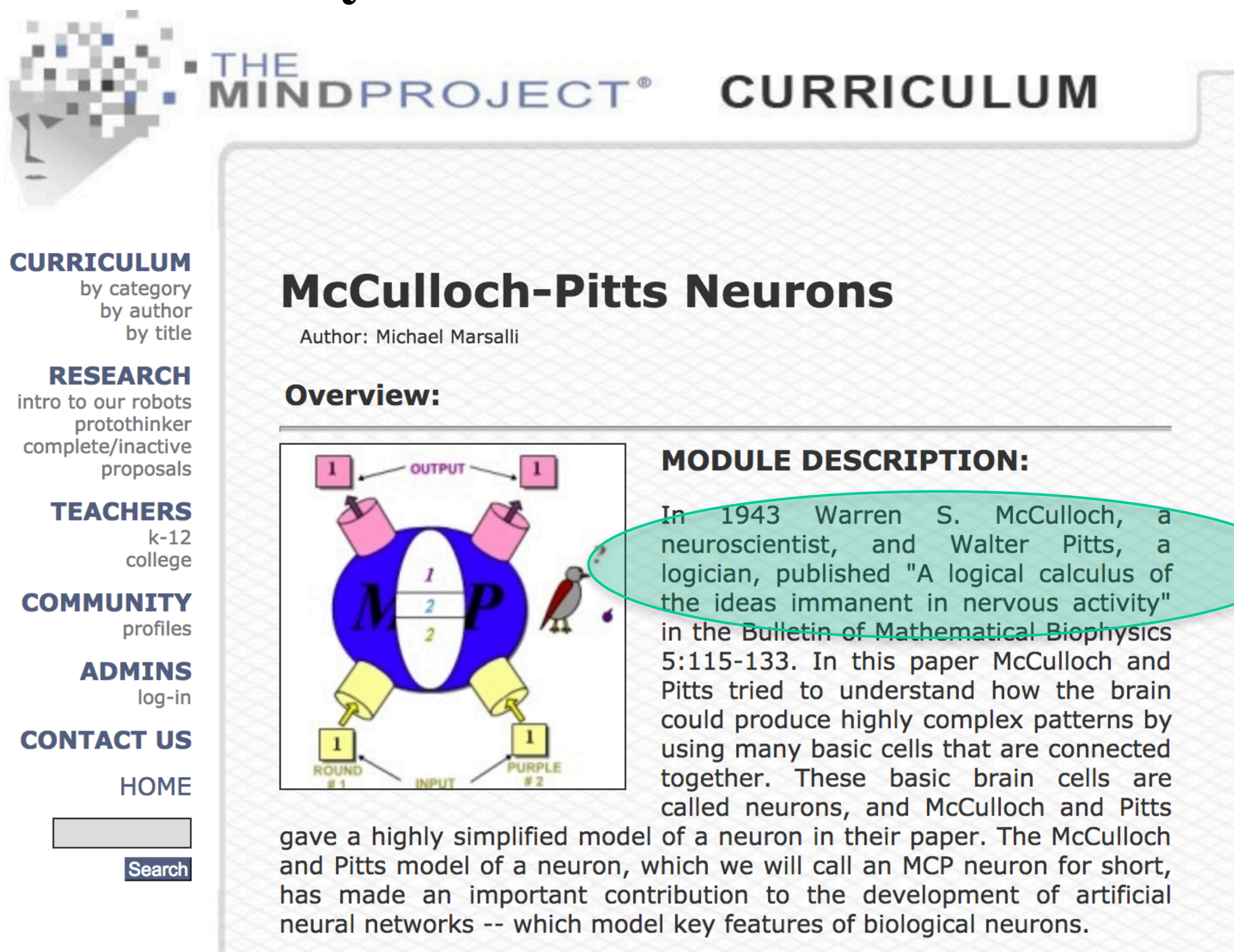
Units with a threshold activation function can act as logic gates; we can use these units to compute Boolean function of its inputs.

Activation of threshold units when:

$$\sum_{j=1}^{n} W_{j,i} a_j > W_{0,i}$$

Historical context: Modeling neurons in our brain as logical gates was a key event in viewing ”thinking as computation.”

The rest is history… ☺



THE MINDPROJECT® CURRICULUM

CURRICULUM
by category
by author
by title

RESEARCH
intro to our robots
protothinker
complete/inactive
proposals

TEACHERS
k-12
college

COMMUNITY
profiles

ADMINS
log-in

CONTACT US

HOME

Search

McCulloch-Pitts Neurons

Author: Michael Marsalli

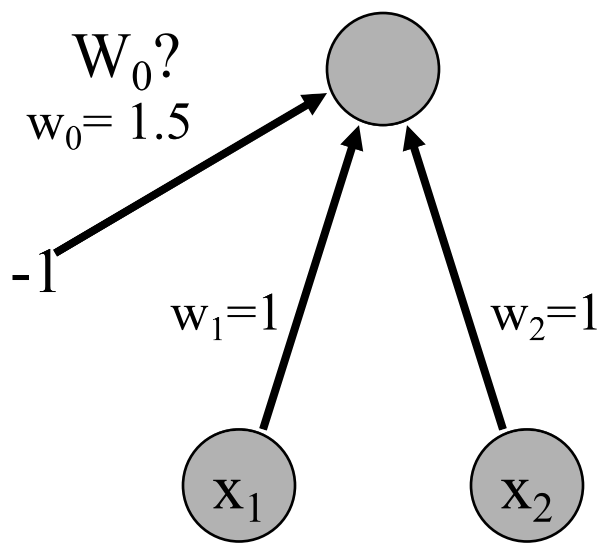
Overview:

MODULE DESCRIPTION:

In 1943 Warren S. McCulloch, a neuroscientist, and Walter Pitts, a logician, published "A logical calculus of the ideas immanent in nervous activity" in the Bulletin of Mathematical Biophysics 5:115-133. In this paper McCulloch and Pitts tried to understand how the brain could produce highly complex patterns by using many basic cells that are connected together. These basic brain cells are called neurons, and McCulloch and Pitts gave a highly simplified model of a neuron in their paper. The McCulloch and Pitts model of a neuron, which we will call an MCP neuron for short, has made an important contribution to the development of artificial neural networks -- which model key features of biological neurons.

Boolean AND

input x1	input x2	ouput
0	0	0
0	1	0
1	0	0
1	1	1



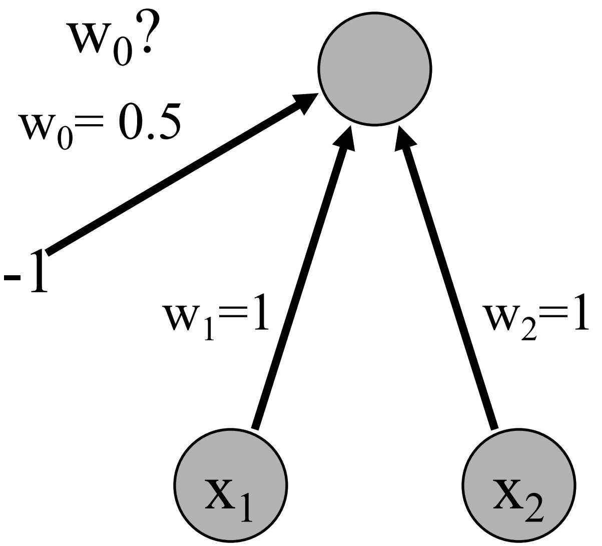
Activate threshold unit when:

$$\sum_{j=1}^{n} W_{j,i} a_j > W_{0,i}$$

What should W_0 be?

Boolean OR

input x1	input x2	ouput
0	0	0
0	1	1
1	0	1
1	1	1



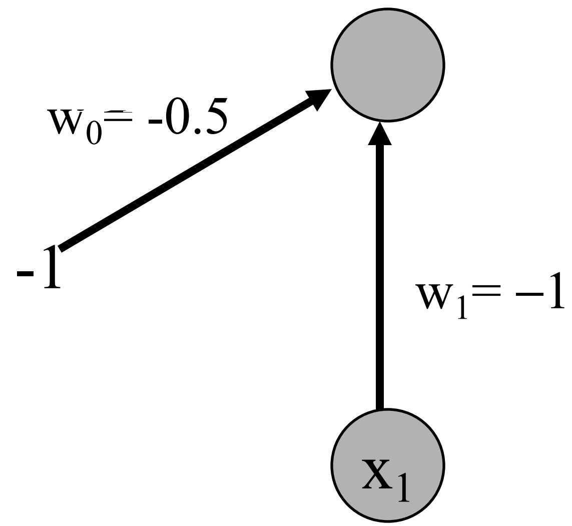
Activation of threshold units when:

$$\sum_{j=1}^{n} W_{j,i} a_j > W_{0,i}$$

What should W_0 be?

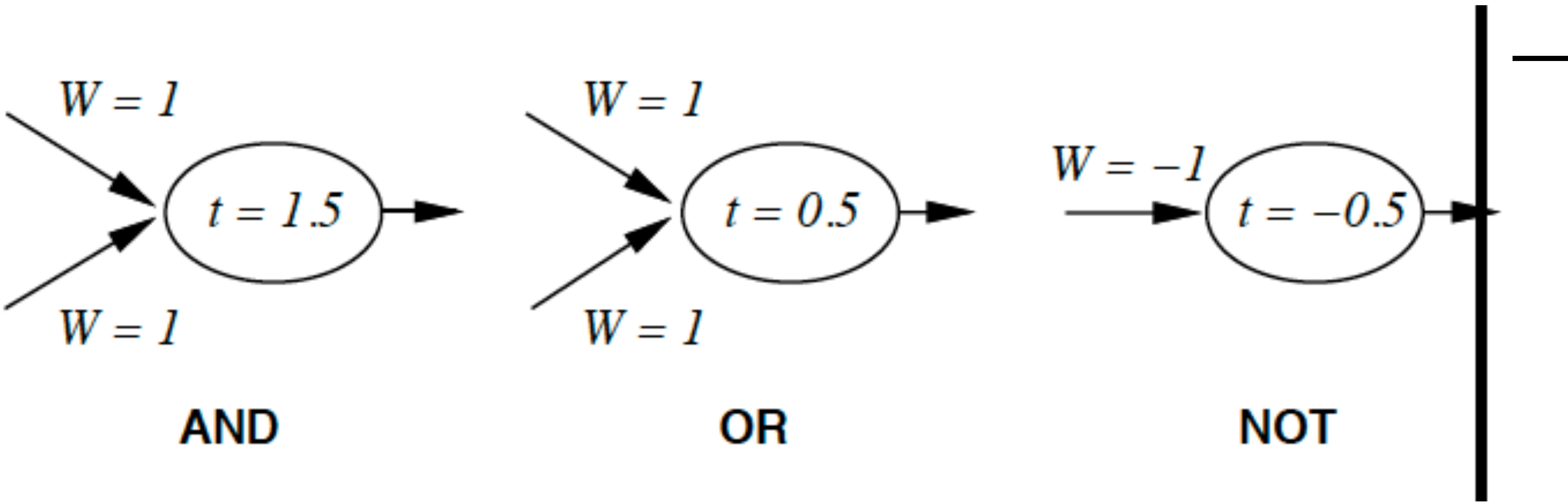
Inverter

input x1	output
0	1
1	0



Activation of threshold units when:

$$\sum_{j=1}^{n} W_{j,i} a_j > W_{0,i}$$



W = 1
t = 1.5
W = 1
AND
W = 1
t = 0.5
W = 1
OR
W = −1
t = −0.5
NOT

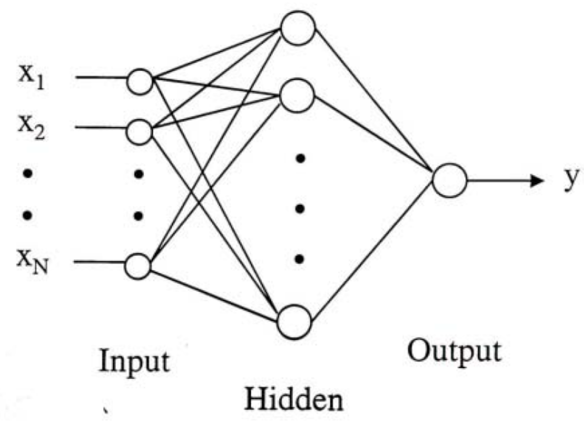
Network Structures

Acyclic or Feed-forward networks Our focus

Activation flows from input layer to output layer

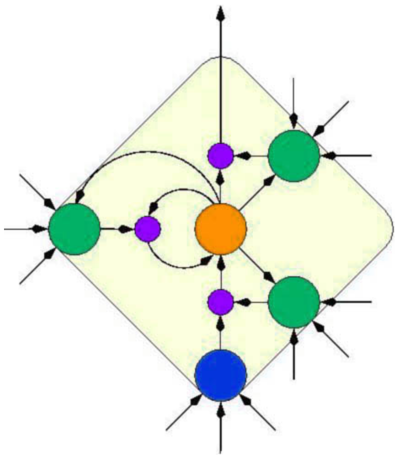
- single-layer perceptrons
- multi-layer perceptrons

Feed-forward networks implement functions, have no internal state (only weights).



Recurrent networks

- Feed the outputs back into own inputs
  →Network is a dynamical system
  (stable state, oscillations, chaotic behavior)
  →Response of the network depends on initial state
- Can support short-term memory
- More difficult to understand



Recurrent Networks

Can capture internal state (activation keeps going around);

→ more complex agents.

Brain cannot be a just a feed-forward network!

Brain has many feed-back connections and cycles

→ brain is a recurrent network!

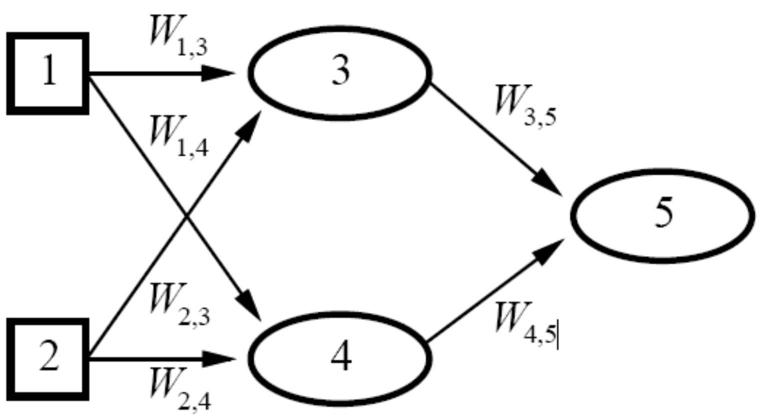
Two key examples:

Hopfield networks:

Boltzmann Machines .

Feed-forward Network: Represents a function of Its Input

Two input units **Two hidden units** **One Output**



(Bias unit omitted for simplicity)

Each unit receives input only from units in the immediately preceding layer.

Given an input vector x = (x_1,x_2), the activations of the input units are set to values of the input vector, i.e., $(a_1,a_2)=(x_1,x_2)$, and the network computes:

Weights are the parameters of the function

$$\begin{aligned} a_5 &= g(W_{3,5} \cdot a_3 + W_{4,5} \cdot a_4) \\ &= g(W_{3,5} \cdot g(W_{1,3} \cdot a_1 + W_{2,3} \cdot a_2) + W_{4,5} \cdot g(W_{1,4} \cdot a_1 + W_{2,4} \cdot a_2)) \end{aligned}$$

Feed-forward network computes a parameterized family of functions $\mathbf{h_W(x)}$

By adjusting the weights we get different functions: that is how learning is done in neural networks!

Note: the input layer in general does not include computing units.

Intermezzo

Home **The New York Times Magazine** Share 194

Can A.I. Be Taught to Explain Itself?

As machine learning becomes more powerful, the field's researchers increasingly find themselves unable to account for what their algorithms know — or how they know it.

By **CLIFF KUANG** NOV. 21, 2017

https://www.nytimes.com/2017/11/21/magazine/can-ai-be-taught-to-explain-itself.html

Hospital Emergency Admission Decision by Neural Net: Risk for pneumonia --- 10/11% fatal! (early 90s)

Rich Caruana, an academic who works at Microsoft Research, has spent almost his entire career in the shadow of this problem. When he was earning his Ph.D at Carnegie Mellon University in the 1990s, his thesis adviser asked him and a group of others to train a neural net — a forerunner of the deep neural net — to help evaluate risks for patients with pneumonia. Between 10 and 11 percent of cases would be fatal;

Decide quickly, which patients to treat right away and which ones can wait.

Neural net trained on case history. Prediction accuracy better than human! ☺

But, Caruana: Don't use it!

We don't know what it does! ☹

Specifically:

NN learned that "asthmatic patients tend to do well" …
I.e., can be send home! (low risk…)

Why? Discovered regularity is indeed part of the data set used for training.

Hmm. What's going on?

Analysis: Hospital staff immediately identify asthma as serious risk. Gave best care! Patient goes home quickly…

Need for Human Interpretable AI! But at what down-side?

Compare: Decision trees vs. Neural Nets

May hurt overall performance!

Perceptron

Cornell Aeronautical Laboratory

Rosenblatt &
Mark I Perceptron:
the first machine that could "learn" to recognize and identify optical patterns.

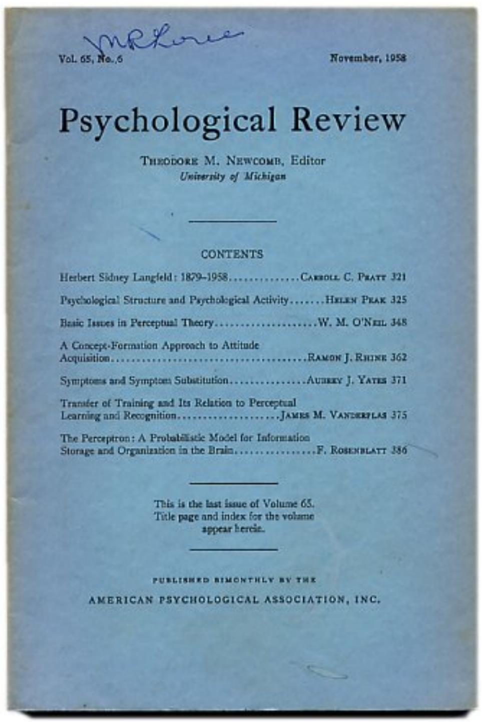
Perceptron

- Invented by Frank Rosenblatt in 1957 in an attempt to understand human memory, learning, and cognitive processes.
- The first neural network model by computation, with a remarkable learning algorithm:
  - If function can be represented by perceptron, the learning algorithm is guaranteed to quickly converge to the hidden function!
- Became the foundation of pattern recognition research

One of the earliest and most influential neural networks: An important milestone in AI.

here

Perceptron



ROSENBLATT, Frank.
(Cornell Aeronautical Laboratory at Cornell University)

The Perceptron: A Probabilistic Model for Information Storage and Organization in the Brain.

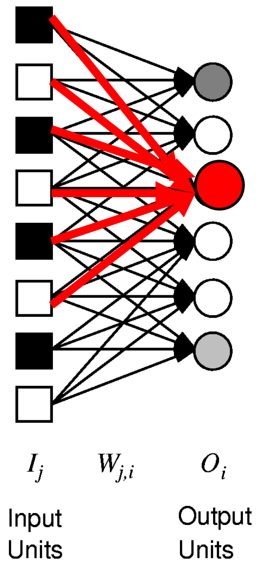
In, Psychological Review, Vol. 65, No. 6, pp. 386-408, November, 1958.

Single Layer Feed-forward Neural Networks
Perceptrons

Single-layer neural network (perceptron network)

A network with all the inputs connected directly to the outputs

–Output units all operate separately: no shared weights

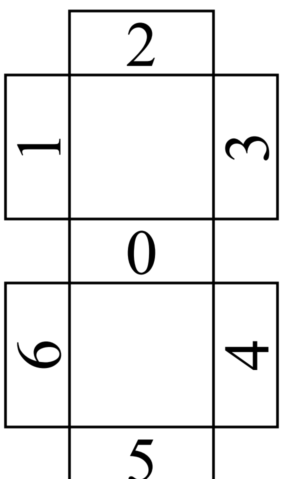


Perceptron Network

Since each output unit is independent of the others, we can limit our study to single output perceptrons.

Perceptron to Learn to Identify Digits
(From Pat. Winston, MIT)

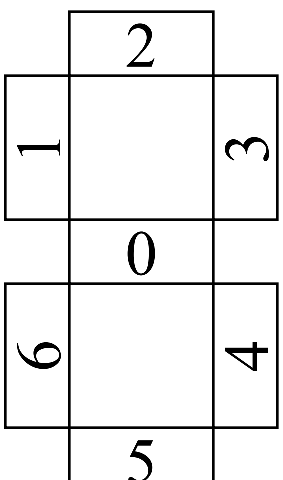
Seven line segments are enough to produce all 10 digits

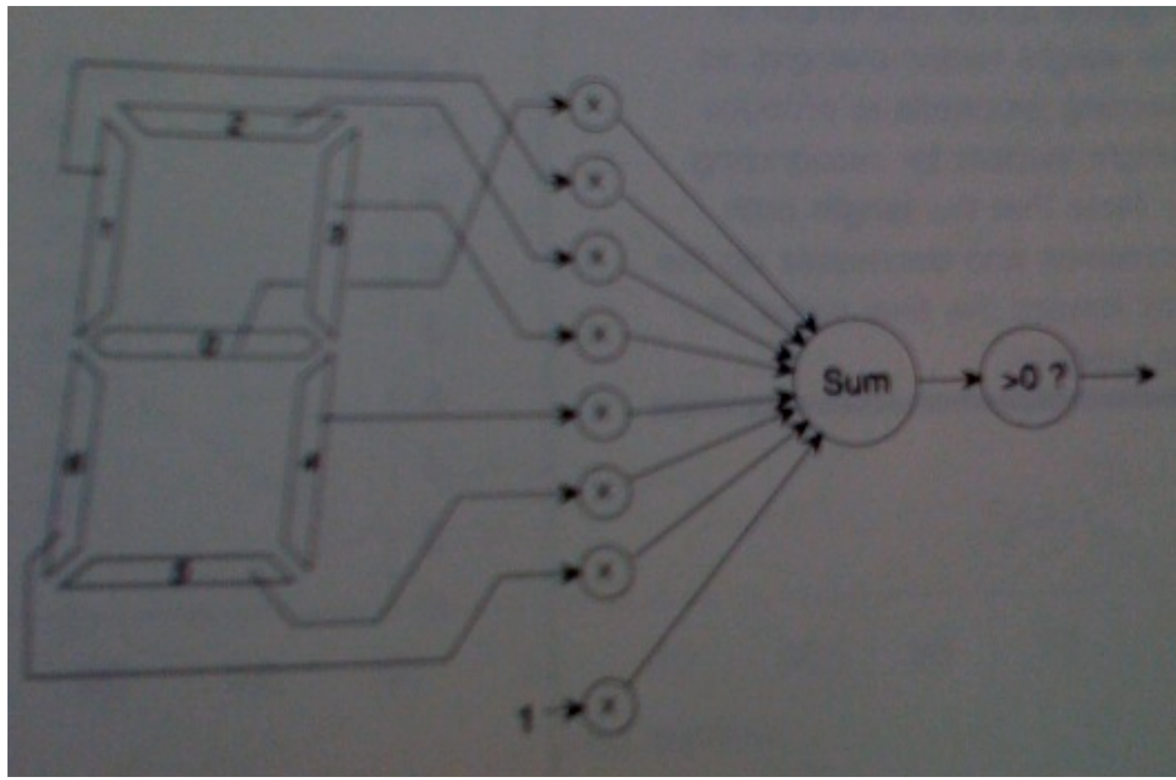


Digit	x_0	x_1	x_2	x_3	x_4	x_5	x_6
0	0	1	1	1	1	1	1
9	1	1	1	1	1	1	0
8	1	1	1	1	1	1	1
7	0	0	1	1	1	0	0
6	1	1	1	0	1	1	1
5	1	1	1	0	1	1	0
4	1	1	0	1	1	0	0
3	1	0	1	1	1	1	0
2	1	0	1	1	0	1	1
1	0	0	0	1	1	0	0

Perceptron to Learn to Identify Digits
(From Pat. Winston, MIT)

Seven line segments are enough to produce all 10 digits



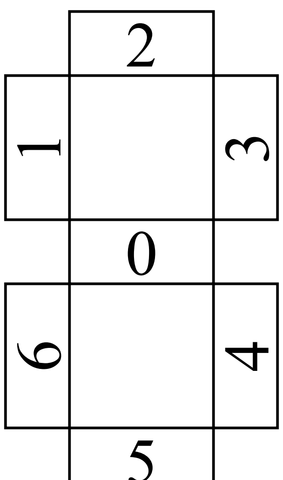


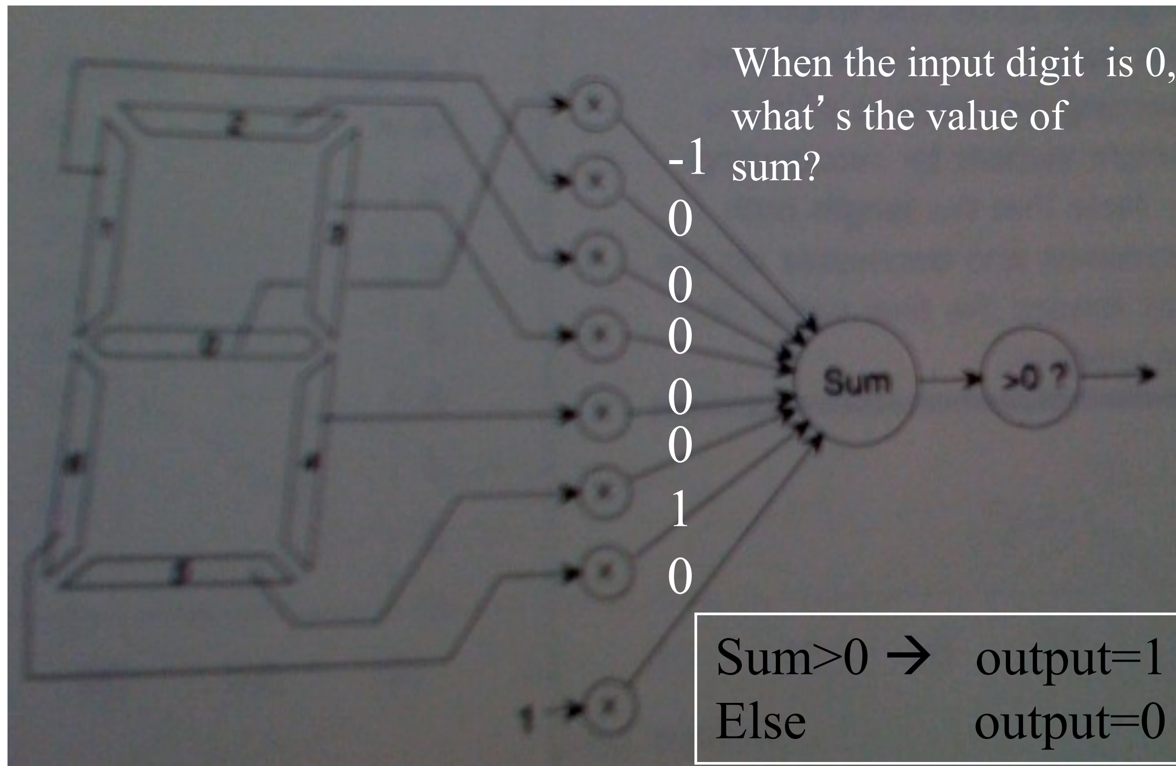
A vision system reports which of the seven segments in the display are on, therefore producing the inputs for the perceptron.

Perceptron to Learn to Identify Digit 0

Digit	x_0	x_1	x_2	x_3	x_4	x_5	x_6	X_7 (fixed input)
0	0	1	1	1	1	1	1	1

Seven line segments are enough to produce all 10 digits





A vision system reports which of the seven segments in the display are on, therefore producing the inputs for the perceptron.

Perceptrons

Remarkable learning algorithm: (Rosenblatt 1960)

if function can be represented by perceptron,

then learning algorithm is guaranteed to quickly converge

to the hidden function!

enormous popularity, early / mid 60's

But analysis by Minsky and Papert (1969)

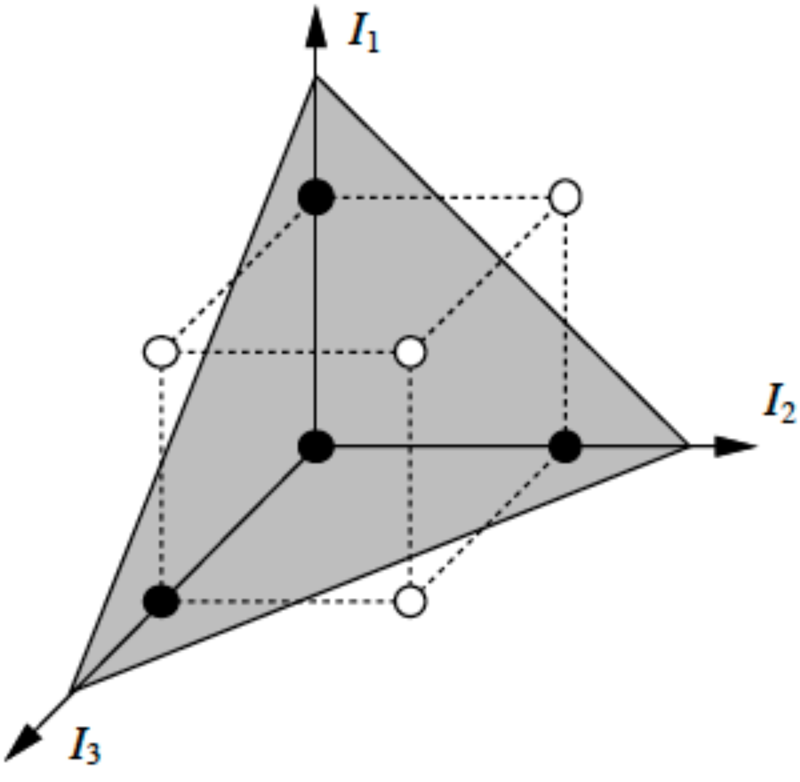
showed certain simple functions cannot be represented

(Boolean XOR)

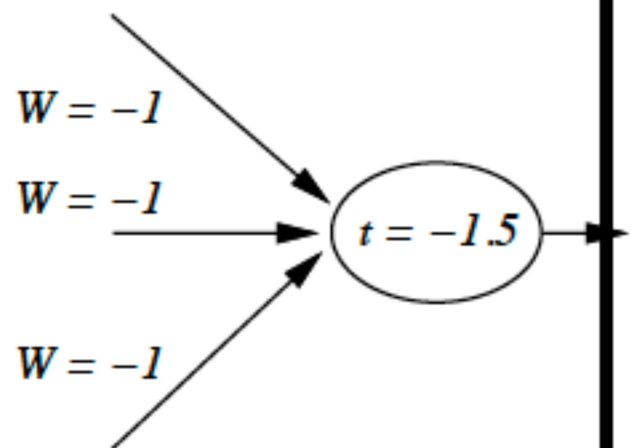
Killed the field! (and possibly Rosenblatt (rumored)).

But Minsky used a simplified model. Single layer.

Linearly separable functions only

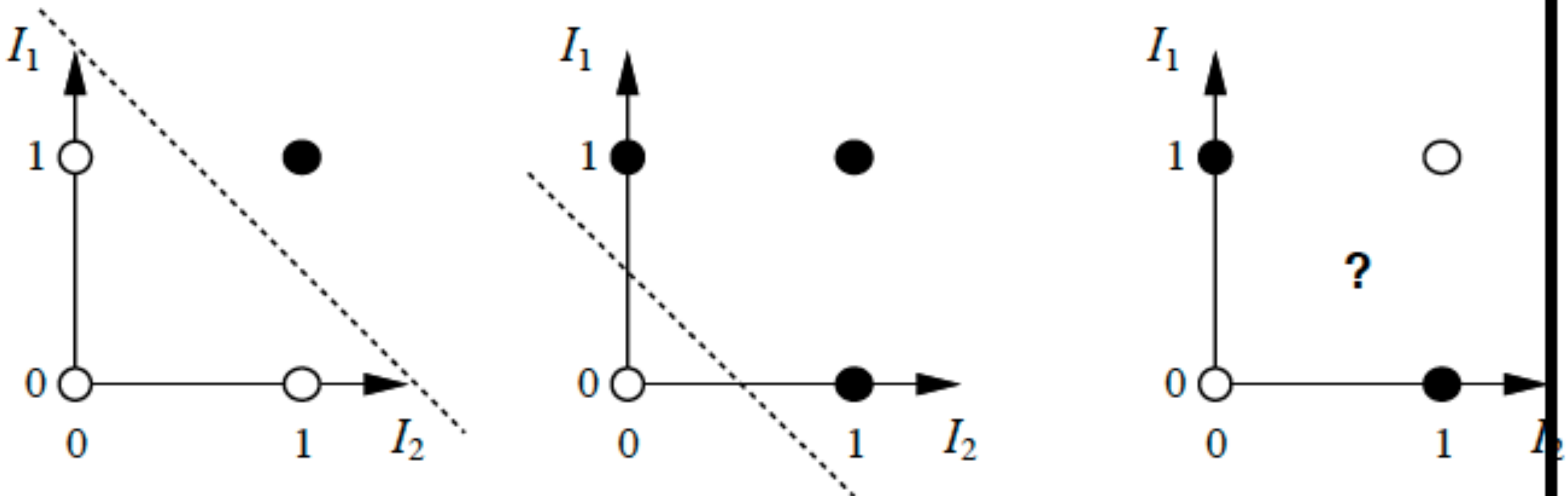


(a) Separating plane



(b) Weights and threshold

Assume: 0/1 signals. Open circles: “off” or “0”. Closed “on” or “1”.



(a) I_1 **and** I_2 **(b)** I_1 **or** I_2 **(c)** I_1 **xor** I_2

XOR: Try solving equations for weights! (with threshold). Show unsolvable.

Mid eighties: comeback — multilayed networks

(Turing machine compatible)

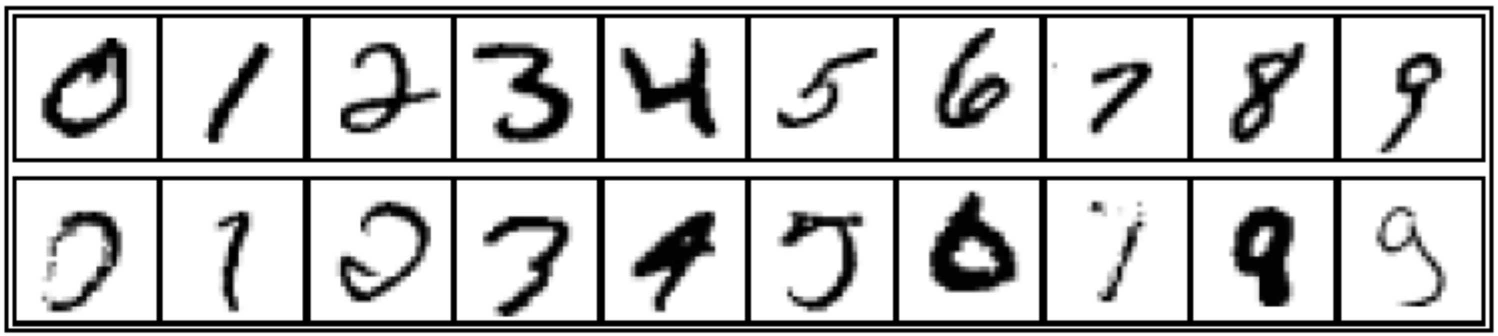
learning procedures: **backpropagation**

Possibly one of the most popular / widely used learning methods today.

John Denker: *"neural nets are the second best thing for learning anything!"* **Update: or perhaps the best! ☺**

backprop and perceptron learning

Handwritten digit recognition



3-nearest-neighbor = 2.4% error
400–300–10 unit MLP = 1.6% error
LeNet: 768–192–30–10 unit MLP = 0.9% error

Current best (kernel machines, vision algorithms) ≈ 0.6% error (more specialized)

But, deep neural nets even better!

Representations

How are concepts represented in the brain / neural net?

local representations / grandmother cell

distributed representations

Pros / Cons?

distributed appeared to have won **but**

UCLA researchers showed (1997)

single cell can learn a concept! (concept: facial expressions / a cell responding to “angry face”!)

Note: can discover hidden features (“regularities”) unsupervised with multi-layer networks.

- Neural Net Learning

Perceptron Learning: Intuition

Weight Update

→ Input I_j (j=1,2,…,n)

→ Single output O: target output, T.

Consider some initial weights

Define example error: $Err = T - O$

Now just move weights in right direction!

If the error is positive, then we need to increase O.

Err >0 → need to increase O;

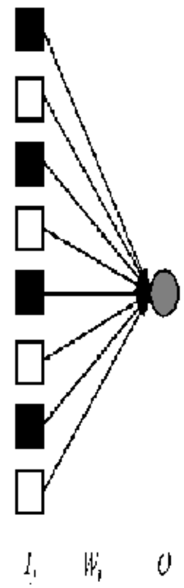
Err <0 → need to decrease O;

Each input unit j, contributes $W_j I_j$ to total input.

So, use:

$$W_j \leftarrow W_j + \alpha \times I_j \times Err$$

Perceptron Learning Rule (Rosenblatt 1960)



α is the learning rate (for now assume 1).

Perceptron Learning: Simple Example

Let's consider an example (adapted from Patrick Wintson book, MIT)

Framework and notation:

0/1 signals

Input vector: $\vec{X} =< x_0, x_1, x_2 \cdots, x_n >$

Weight vector: $\vec{W} =< w_0, w_1, w_2 \cdots, w_n >$

$x_0 = 1$ and $\theta_0 = -w_0$, simulate the threshold.

O is output (0 or 1) (single output).

Learning rate = 1.

Threshold function: $S = \sum_{k=0}^{k=n} w_k x_k \quad S > 0 \; then \; O = 1 \quad else \quad O = 0$

$$Err = T - O$$

$$W_j \leftarrow W_j + \alpha \times I_j \times Err$$

Perceptron Learning: Simple Example

Set of examples, each example is a pair $(\vec{x}_i, y_i)$ i.e., an input vector and a label y (0 or 1).

This procedure provably converges (polynomial number of steps) if the function is represented by a perceptron (i.e., linearly separable)

Learning procedure, called the "*error correcting method*"

- Start with all zero weight vector.
- Cycle (repeatedly) through examples and for each example do:
  - **If perceptron is 0 while it should be 1, add the input vector to the weight vector**
  - **If perceptron is 1 while it should be 0, subtract the input vector to the weight vector**
  - **Otherwise do nothing.**

Intuitively correct, (e.g., if output is 0 but it should be 1, the weights are increased) !

Perceptron Learning: Simple Example

Consider learning the logical OR function.

Our examples are:

Sample	x0	x1	x2	label
1	1	0	0	0
2	1	0	1	1
3	1	1	0	1
4	1	1	1	1

Activation Function

$$S = \sum_{k=0}^{k=n} w_k x_k \quad S > 0 \; then \; O = 1 \quad else \quad O = 0$$

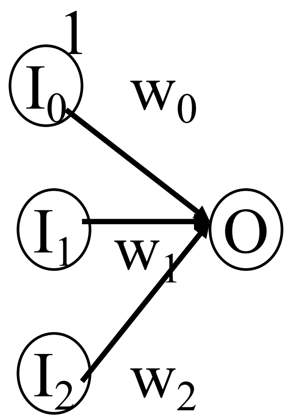
$$S = \sum_{k=0}^{k=n} w_k x_k \quad S > 0 \; then \; O = 1 \quad else \quad O = 0$$

Perceptron Learning: Simple Example

Error correcting method

If perceptron is 0 while it should be 1,
add the input vector to the weight vector
If perceptron is 1 while it should be 0,
subtract the input vector to the weight vector
Otherwise do nothing.

We'll use a single perceptron with three inputs.
We'll start with all weights 0 W= <0,0,0>



Example 1 I= < 1 0 0> label=0 W= <0,0,0>
Perceptron (1×0+ 0×0+ 0×0 =0, S=0) output → 0
→it classifies it as 0, so correct, do nothing

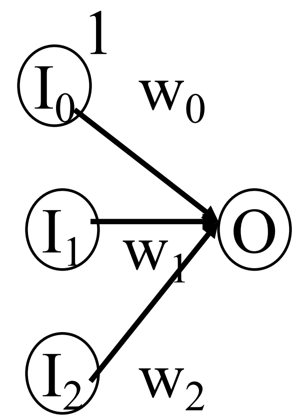
Example 2 I=<1 0 1> label=1 W= <0,0,0>
Perceptron (1×0+ 0×0+ 1×0 = 0) output →0
→it classifies it as 0, while it should be 1, so we add input to weights
W = <0,0,0> + <1,0,1>= <1,0,1>

Example 3 I=<1 1 0> label=1 W= <1,0,1>

Perceptron $(1\times 0+ 1\times 0+ 0\times 0 > 0)$ output = 1

→it classifies it as 1, correct, do nothing

W = <1,0,1>



Example 4 I=<1 1 1> label=1 W= <1,0,1>

Perceptron $(1\times 0+ 1\times 0+ 1\times 0 > 0)$ output = 1

→it classifies it as 1, correct, do nothing

W = <1,0,1>

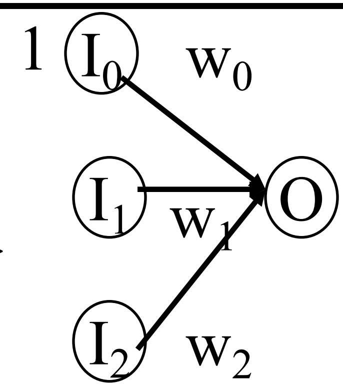
Error correcting method

If perceptron is 0 while it should be 1,
add the input vector to the weight vector

If perceptron is 1 while it should be 0,
subtract the input vector from the weight vector

Otherwise do nothing.

Perceptron Learning: Simple Example



Epoch 2, through the examples, W = <1,0,1> .

Example 1 I = <1,0,0> label=0 W = <1,0,1>

Perceptron ($1\times1+ 0\times0+ 0\times1 >0$) output → 1

→it classifies it as 1, while it should be 0, so subtract input from weights

W = <1,0,1> - <1,0,0> = <0, 0, 1>

Example 2 I=<1 0 1> label=1 W= <0,0,1>

Perceptron ($1\times0+ 0\times0+ 1\times1 > 0$) output →1

→it classifies it as 1, so correct, do nothing

Example 3 I=<1 1 0> label=1 W= <0,0,1>

Perceptron ($1\times0+ 1\times0+ 0\times1 > 0$) output = 0

→it classifies it as 0, while it should be 1, so add input to weights

W = <0,0,1> + W = <1,1,0> = <1, 1, 1>

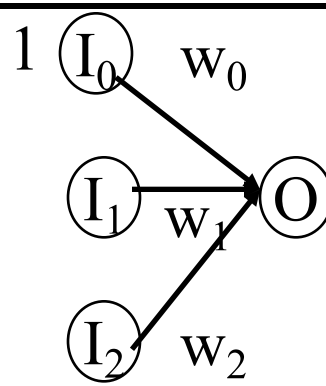
Example 4 I=<1 1 1> label=1 W= <1,1,1>

Perceptron ($1\times1+ 1\times1+ 1\times1 > 0$) output = 1

→it classifies it as 1, correct, do nothing

W = <1,1,1>

Perceptron Learning: Simple Example



Epoch 3, through the examples, W = <1,1,1> .

Example 1 I=<1,0,0> label=0 W = <1,1,1>

Perceptron ($1\times1+ 0\times1+ 0\times1 >0$) output → 1

→it classifies it as 1, while it should be 0, so subtract input from weights

W = <1,1,1> - W = <1,0,0> = <0, 1, 1>

Example 2 I=<1 0 1> label=1 W= <0, 1, 1>

Perceptron ($1\times0+ 0\times1+ 1\times1 > 0$) output →1

→it classifies it as 1, so correct, do nothing

Example 3 $I=<1\ 1\ 0>$ label=1 $W= <0, 1, 1>$

Perceptron $(1\times0+ 1\times1+ 0\times1 > 0)$ output = 1

→it classifies it as 1, correct, do nothing

Example 4 $I=<1\ 1\ 1>$ label=1 $W= <0, 1, 1>$

Perceptron $(1\times0+ 1\times1+ 1\times1 > 0)$ output = 1

→it classifies it as 1, correct, do nothing

$W = <1,1,1>$

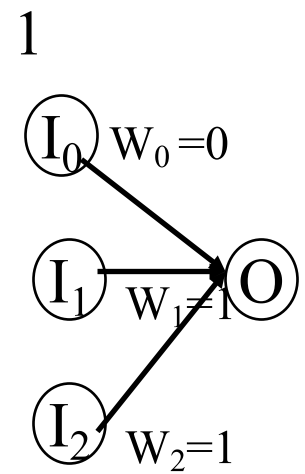
Perceptron Learning: Simple Example

Epoch 4, through the examples, W= <0, 1, 1>.

Example 1 I= <1,0,0> label=0 W = <0,1,1>

Perceptron ($1 \times 0 + 0 \times 1 + 0 \times 1 = 0$) output → 0

→it classifies it as 0, so correct, do nothing



OR

So the final weight vector W= <0, 1, 1> classifies all examples correctly, and the perceptron has learned the function!

Aside: in more realistic cases the bias (W0) will not be 0.
(This was just a toy example!)
Also, in general, many more inputs (100 to 1000)

Epoch	x0	x1	x2	Desired Target	w0	w1	w2	Output	Error	New w0	New w1	New w2
1 example 1	1	0	0	0	0	0	0	0	0	0	0	0

Epoch	x0	x1	x2	Desired Target	w0	w1	w2	Output	Error	New w0	New w1	New w2
1 example 1	1	0	0	0	0	0	0	0	0	0	0	0
example 2	1	0	1	1	0	0	0	0	1	1	0	1

Epoch	x0	x1	x2	Desired Target	w0	w1	w2	Output	Error	New w0	New w1	New w2
1 example 1	1	0	0	0	0	0	0	0	0	0	0	0
example 2	1	0	1	1	0	0	0	0	1	1	0	1
example 3	1	1	0	1	1	0	1	1	0	1	0	1

Epoch	x0	x1	x2	Desired Target	w0	w1	w2	Output	Error	New w0	New w1	New w2
1 example 1	1	0	0	0	0	0	0	0	0	0	0	0
example 2	1	0	1	1	0	0	0	0	1	1	0	1
example 3	1	1	0	1	1	0	1	1	0	1	0	1
example 4	1	1	1	1	1	0	1	1	0	1	0	1

Epoch	x0	x1	x2	Desired Target	w0	w1	w2	Output	Error	New w0	New w1	New w2
1 example 1	1	0	0	0	0	0	0	0	0	0	0	0
example 2	1	0	1	1	0	0	0	0	1	1	0	1
example 3	1	1	0	1	1	0	1	1	0	1	0	1
example 4	1	1	1	1	1	0	1	1	0	1	0	1
2 example 1	1	0	0	0	1	0	1	1	-1	0	0	1

Epoch	x0	x1	x2	Desired Target	w0	w1	w2	Output	Error	New w0	New w1	New w2
1 example 1	1	0	0	0	0	0	0	0	0	0	0	0
example 2	1	0	1	1	0	0	0	0	1	1	0	1
example 3	1	1	0	1	1	0	1	1	0	1	0	1
example 4	1	1	1	1	1	0	1	1	0	1	0	1
2 example 1	1	0	0	0	1	0	1	1	-1	0	0	1
example 2	1	0	1	1	0	0	1	1	0	0	0	1

Epoch	x0	x1	x2	Desired Target	w0	w1	w2	Output	Error	New w0	New w1	New w2
1 example 1	1	0	0	0	0	0	0	0	0	0	0	0
example 2	1	0	1	1	0	0	0	0	1	1	0	1
example 3	1	1	0	1	1	0	1	1	0	1	0	1
example 4	1	1	1	1	1	0	1	1	0	1	0	1
2 example 1	1	0	0	0	1	0	1	1	-1	0	0	1
example 2	1	0	1	1	0	0	1	1	0	0	0	1
example 3	1	1	0	1	0	0	1	0	1	1	1	1

Epoch	x0	x1	x2	Desired Target	w0	w1	w2	Output	Error	New w0	New w1	New w2
1 example 1	1	0	0	0	0	0	0	0	0	0	0	0
example 2	1	0	1	1	0	0	0	0	1	1	0	1
example 3	1	1	0	1	1	0	1	1	0	1	0	1
example 4	1	1	1	1	1	0	1	1	0	1	0	1
2 example 1	1	0	0	0	1	0	1	1	-1	0	0	1
example 2	1	0	1	1	0	0	1	1	0	0	0	1
example 3	1	1	0	1	0	0	1	0	1	1	1	1
example 4	1	1	1	1	1	1	1	1	0	1	1	1

Epoch	x0	x1	x2	Desired Target	w0	w1	w2	Output	Error	New w0	New w1	New w2
1 example 1	1	0	0	0	0	0	0	0	0	0	0	0
example 2	1	0	1	1	0	0	0	0	1	1	0	1
example 3	1	1	0	1	1	0	1	1	0	1	0	1
example 4	1	1	1	1	1	0	1	1	0	1	0	1
2 example 1	1	0	0	0	1	0	1	1	-1	0	0	1
example 2	1	0	1	1	0	0	1	1	0	0	0	1
example 3	1	1	0	1	0	0	1	0	1	1	1	1
example 4	1	1	1	1	1	1	1	1	0	1	1	1
3 example 1	1	0	0	0	1	1	1	1	-1	0	1	1

Epoch	x0	x1	x2	Desired Target	w0	w1	w2	Output	Error	New w0	New w1	New w2
1 example 1	1	0	0	0	0	0	0	0	0	0	0	0
example 2	1	0	1	1	0	0	0	0	1	1	0	1
example 3	1	1	0	1	1	0	1	1	0	1	0	1
example 4	1	1	1	1	1	0	1	1	0	1	0	1
2 example 1	1	0	0	0	1	0	1	1	-1	0	0	1
example 2	1	0	1	1	0	0	1	1	0	0	0	1
example 3	1	1	0	1	0	0	1	0	1	1	1	1
example 4	1	1	1	1	1	1	1	1	0	1	1	1
3 example 1	1	0	0	0	1	1	1	1	-1	0	1	1
example 2	1	0	1	1	0	1	1	1	0	0	1	1

Epoch	x0	x1	x2	Desired Target	w0	w1	w2	Output	Error	New w0	New w1	New w2
1 example 1	1	0	0	0	0	0	0	0	0	0	0	0
example 2	1	0	1	1	0	0	0	0	1	1	0	1
example 3	1	1	0	1	1	0	1	1	0	1	0	1
example 4	1	1	1	1	1	0	1	1	0	1	0	1
2 example 1	1	0	0	0	1	0	1	1	-1	0	0	1
example 2	1	0	1	1	0	0	1	1	0	0	0	1
example 3	1	1	0	1	0	0	1	0	1	1	1	1
example 4	1	1	1	1	1	1	1	1	0	1	1	1
3 example 1	1	0	0	0	1	1	1	1	-1	0	1	1
example 2	1	0	1	1	0	1	1	1	0	0	1	1
example 3	1	1	0	1	0	1	1	1	0	0	1	1

Epoch	x0	x1	x2	Desired Target	w0	w1	w2	Output	Error	New w0	New w1	New w2
1 example 1	1	0	0	0	0	0	0	0	0	0	0	0
example 2	1	0	1	1	0	0	0	0	1	1	0	1
example 3	1	1	0	1	1	0	1	1	0	1	0	1
example 4	1	1	1	1	1	0	1	1	0	1	0	1
2 example 1	1	0	0	0	1	0	1	1	-1	0	0	1
example 2	1	0	1	1	0	0	1	1	0	0	0	1
example 3	1	1	0	1	0	0	1	0	1	1	1	1
example 4	1	1	1	1	1	1	1	1	0	1	1	1
3 example 1	1	0	0	0	1	1	1	1	-1	0	1	1
example 2	1	0	1	1	0	1	1	1	0	0	1	1
example 3	1	1	0	1	0	1	1	1	0	0	1	1
example 4	1	1	1	1	0	1	1	1	0	0	1	1

Epoch	x0	x1	x2	Desired Target	w0	w1	w2	Output	Error	New w0	New w1	New w2
1 example 1	1	0	0	0	0	0	0	0	0	0	0	0
example 2	1	0	1	1	0	0	0	0	1	1	0	1
example 3	1	1	0	1	1	0	1	1	0	1	0	1
example 4	1	1	1	1	1	0	1	1	0	1	0	1
2 example 1	1	0	0	0	1	0	1	1	-1	0	0	1
example 2	1	0	1	1	0	0	1	1	0	0	0	1
example 3	1	1	0	1	0	0	1	0	1	1	1	1
example 4	1	1	1	1	1	1	1	1	0	1	1	1
3 example 1	1	0	0	0	1	1	1	1	-1	0	1	1
example 2	1	0	1	1	0	1	1	1	0	0	1	1
example 3	1	1	0	1	0	1	1	1	0	0	1	1
example 4	1	1	1	1	0	1	1	1	0	0	1	1
4 example 1	1	0	0	0	0	1	1	0	0	0	1	1

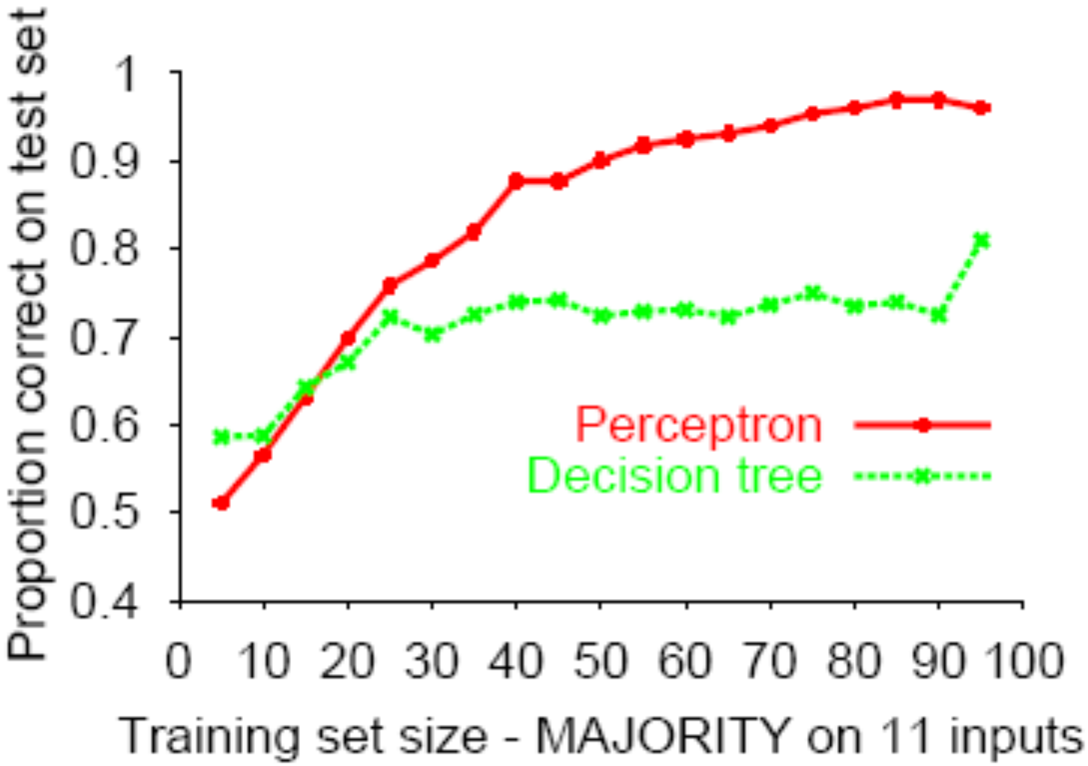
Convergence of Perceptron Learning Algorithm

Perceptron converges to a consistent function, if…

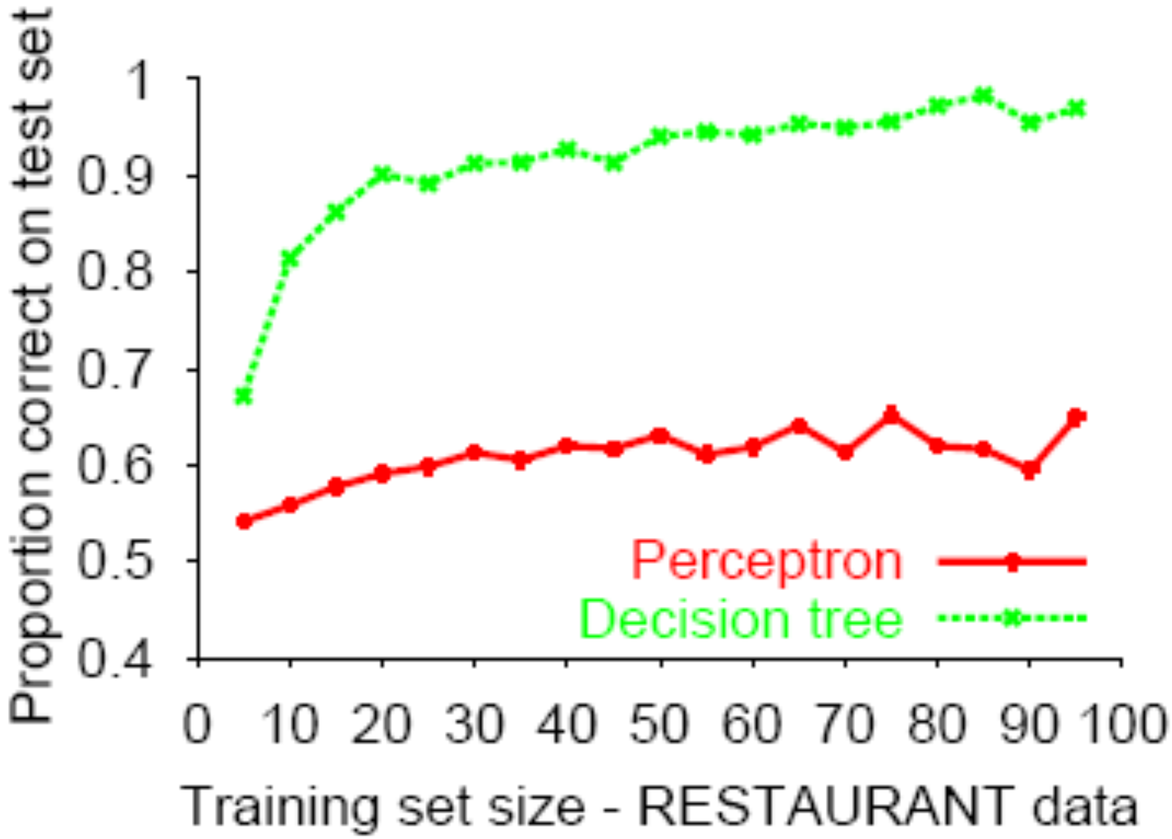
… training data linearly separable

… step size α sufficiently small

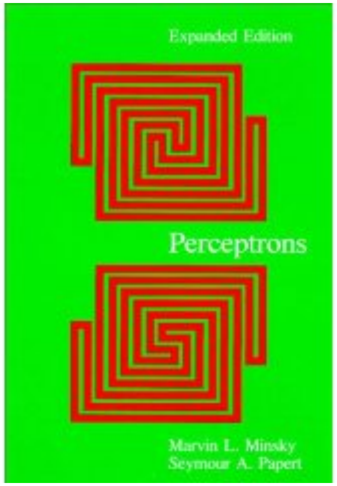
… no “hidden” units



Perceptron learns majority function easily, DTL is hopeless



DTL learns restaurant function easily, perceptron cannot represent it



Good news: Adding hidden layer allows more target functions to be represented.

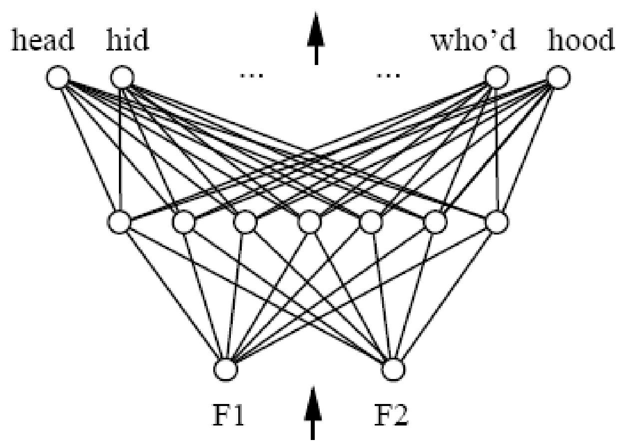
Minsky & Papert (1969)

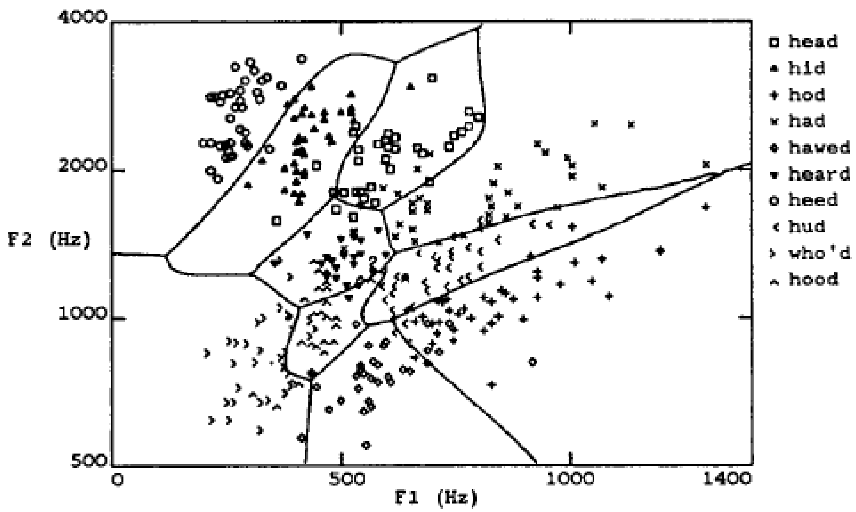
Multi-layer Perceptrons (MLPs)

Single-layer perceptrons can only represent linear decision surfaces.

Multi-layer perceptrons can represent non-linear decision surfaces.

Hidden Layer





Output units

The choice of how to represent the output then determines the form of the cross-entropy function

1. Linear output $z = W^T h + b$. Often used as mean of Gaussian distribution.

$$p(\boldsymbol{y} \mid \boldsymbol{x}) = \mathcal{N}(\boldsymbol{y}; \hat{\boldsymbol{y}}, \boldsymbol{I}).$$

2. Sigmoid function for Bernoulli distribution. Output P(y=1 | x)

Output units

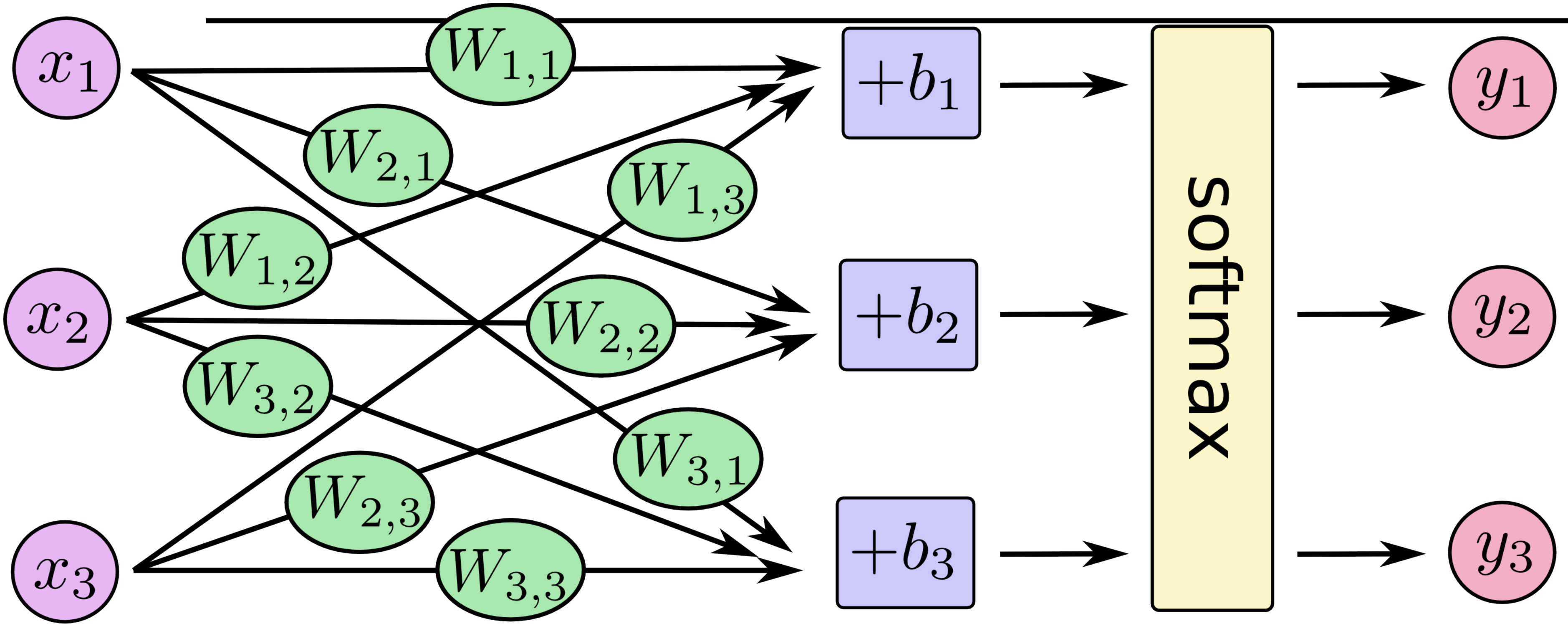
3. Softmax for Multinoulli output distributions. Predict a vector, each element being P(y = i| x)

A linear layer

$$\boldsymbol{z} = \boldsymbol{W}^\top \boldsymbol{h} + \boldsymbol{b},$$

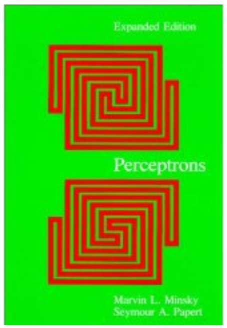
Softmax function

$$\text{softmax}(\boldsymbol{z})_i = \frac{\exp(z_i)}{\sum_j \exp(z_j)}.$$



Hidden Layer

Output Layer



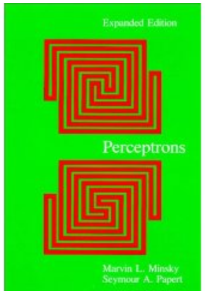
Bad news: No algorithm for learning in multi-layered networks, and no convergence theorem was known in 1969!

Minsky & Papert (1969) *"[The perceptron] has many features to attract attention: its linearity; its intriguing learning theorem; its clear paradigmatic simplicity as a kind of parallel computation. There is no reason to suppose that any of these virtues carry over to the many-layered version. Nevertheless, we consider it to be an important research problem to elucidate (or reject) our intuitive judgment that the extension is sterile."*

Minsky & Papert (1969) pricked the neural network balloon …they almost killed the field.

Rumors say these results may have killed Rosenblatt….

Winter of Neural Networks 69-86.



Two major problems they saw were

1. How can the learning algorithm apportion credit (or blame) to individual weights for incorrect classifications depending on a (sometimes) large number of weights?

2. How can such a network learn useful higher-order features?

Back Propagation - Next

Good news: Successful credit-apportionment learning algorithms developed soon afterwards (e.g., back-propagation). Still successful, in spite of lack of convergence theorem.