Bil 470 / YAP 470

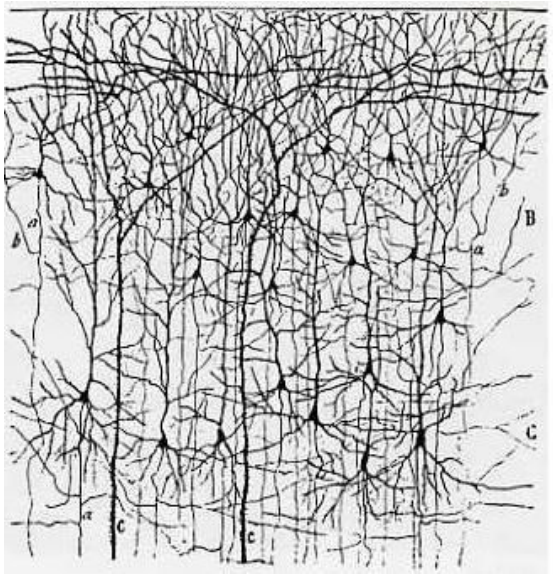
Introduction to Machine Learning (Yapay Öğrenme)

Batuhan Bardak

A Brief History of Neural Networks

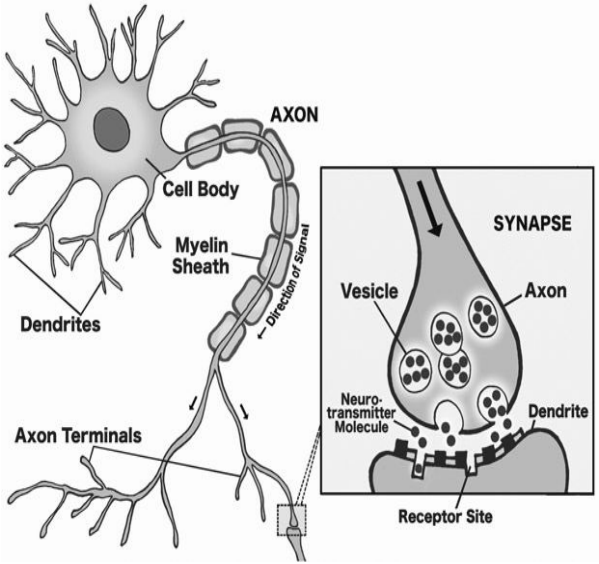
Date: 03.10.2022

Discovery of Neurons



Ramón y Cajal, 1900

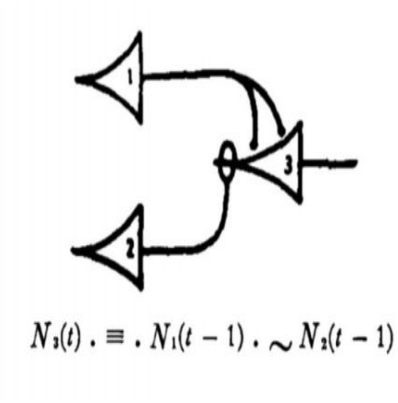
How the Human Brain Learns



Inputs arrive at dendrites, and axon serve as output channel

A Mathematical Model of Brain: McCulloch & Pitts Neuron

Artificial Neurons



MCP, 1943

BULLETIN OF
MATHEMATICAL BIOPHYSICS
VOLUME 5, 1943

A LOGICAL CALCULUS OF THE IDEAS IMMANENT IN NERVOUS ACTIVITY

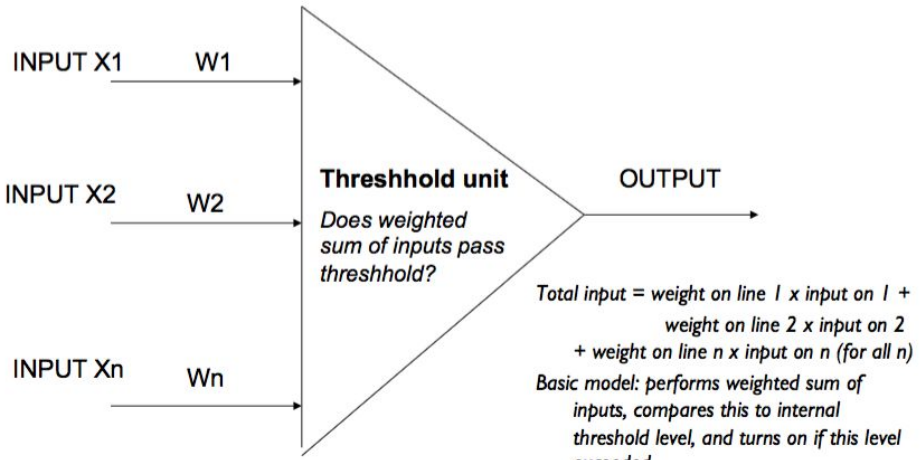
WARREN S. MCCULLOCH AND WALTER PITTS

FROM THE UNIVERSITY OF ILLINOIS, COLLEGE OF MEDICINE,
DEPARTMENT OF PSYCHIATRY AT THE ILLINOIS NEUROPSYCHIATRIC INSTITUTE,
AND THE UNIVERSITY OF CHICAGO

Because of the "all-or-none" character of nervous activity, neural events and the relations among them can be treated by means of propositional logic. It is found that the behavior of every net can be described in these terms, with the addition of more complicated logical means for nets containing circles; and that for any logical expression satisfying certain conditions, one can find a net behaving in the fashion it describes. It is shown that many particular choices among possible neurophysiological assumptions are equivalent, in the sense that for every net behaving under one assumption, there exists another net which behaves under the other and gives the same results, although perhaps not in the same time. Various applications of the calculus are discussed.

McCulloch & Pitts Neuron

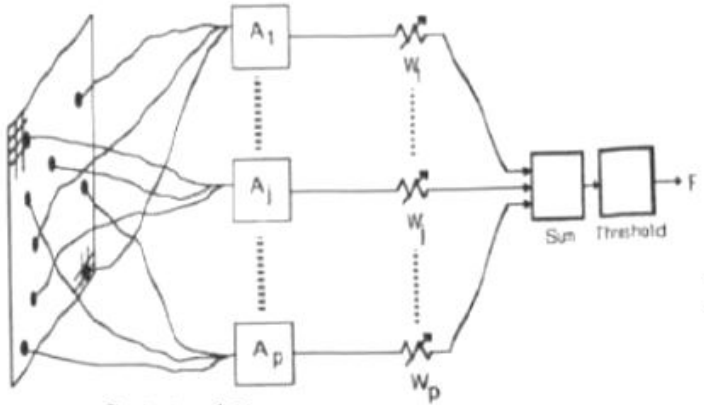
McCulloch Pitts Neuron



Total input = weight on line 1 x input on 1 + weight on line 2 x input on 2 + weight on line n x input on n (for all n)

Basic model: performs weighted sum of inputs, compares this to internal threshold level, and turns on if this level exceeded.

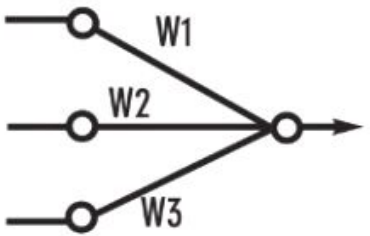
Perceptron



Original Perceptron

(From Perceptrons by M. L Minsky and S. Papert, 1969, Cambridge, MA: MIT Press. Copyright 1969 by MIT Press.

Frank Rosenblatt
(1928-1971)

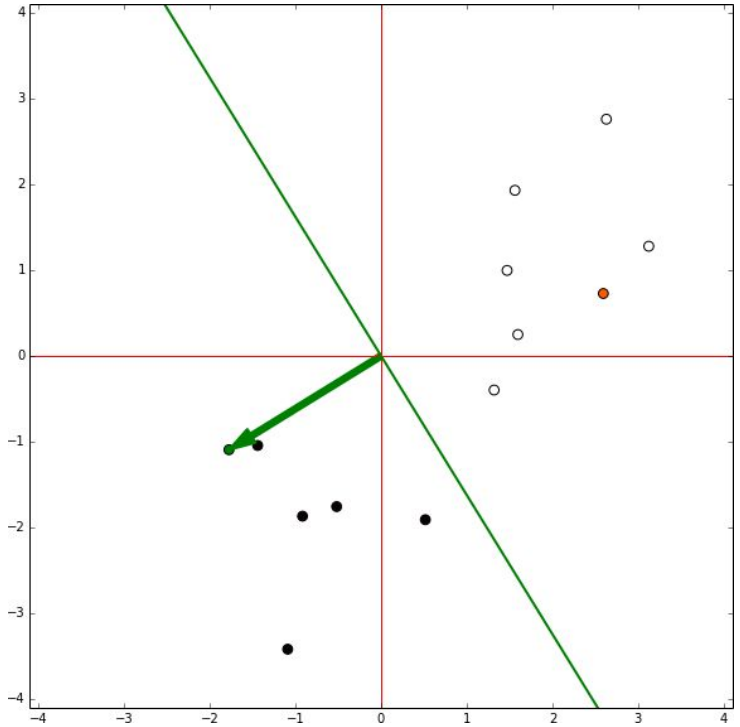


Simplified model:

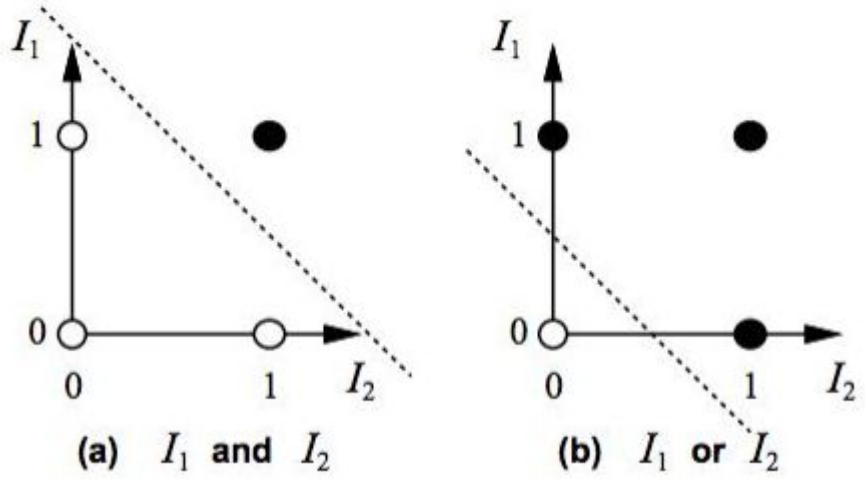
23

Frank Rosenblatt (1957)

Perceptron Learning Rule



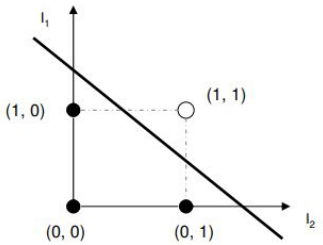
Linear Seperable Case



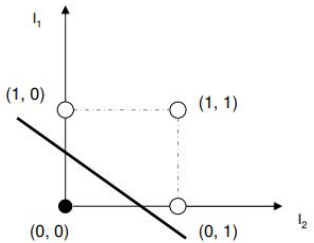
Xor Case

Use more than one neuron!

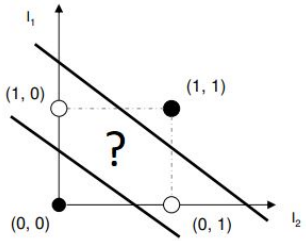
AND		
I_1	I_2	out
0	0	0
0	1	0
1	0	0
1	1	1



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



Backpropagation (1985)

A bit of history...

$$\frac{\partial E_p}{\partial w_{ji}} = \frac{\partial E_p}{\partial o_{pj}} \frac{\partial o_{pj}}{\partial w_{ji}}$$

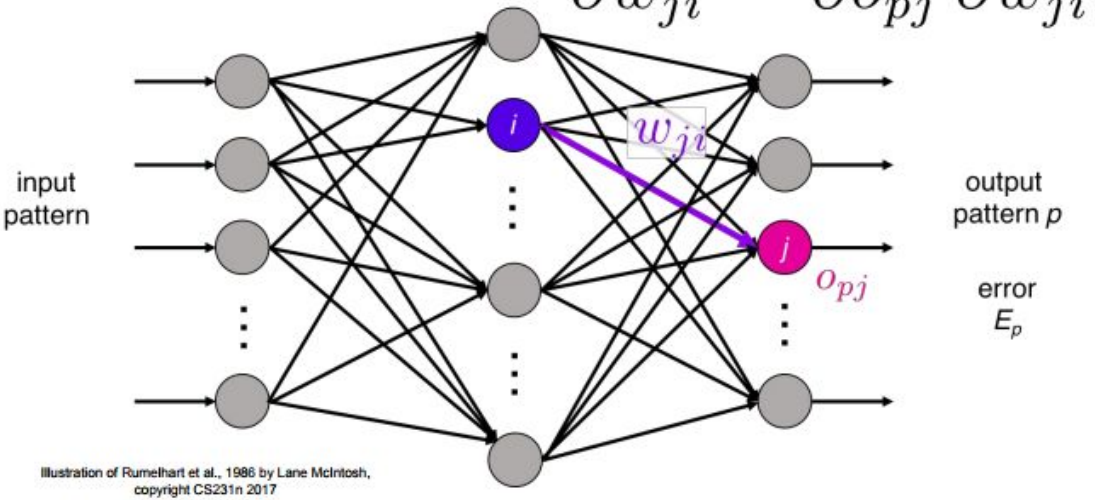


Illustration of Rumelhart et al., 1986 by Lane McIntosh, copyright CS231n 2017

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International journal of science

Letter | Published: 09 October 1986

Learning representations by back-propagating errors

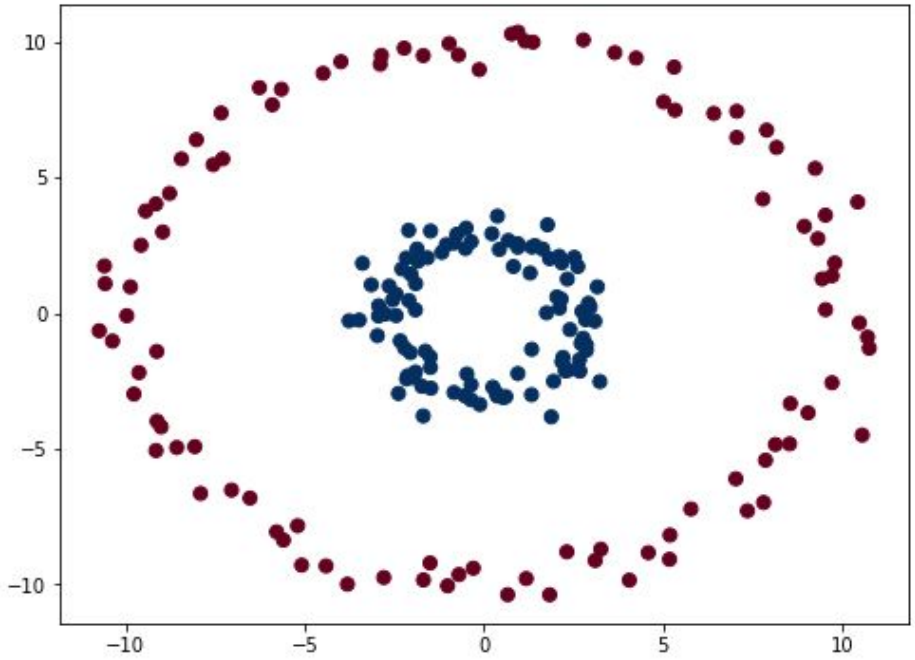
David E. Rumelhart, Geoffrey E. Hinton & Ronald J. Williams

Nature **323**, 533–536 (09 October 1986) | Download Citation

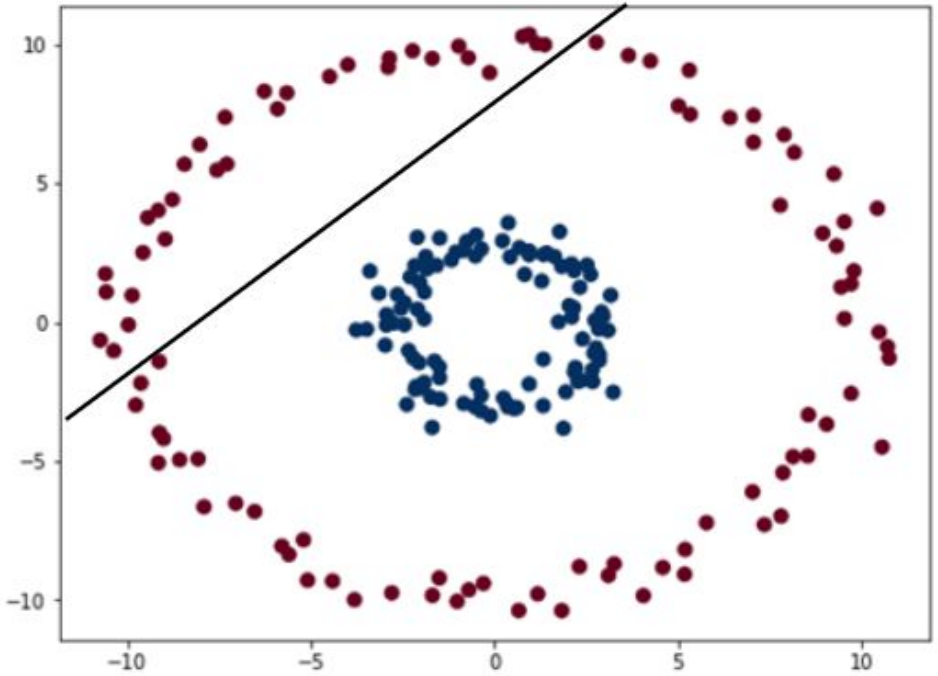
Abstract

We describe a new learning procedure, back-propagation, for networks of neurone-like units. The procedure repeatedly adjusts the weights of the connections in the network so as to minimize a measure of the difference between the actual output vector of the net and the desired output vector. As a result of the weight adjustments, internal 'hidden' units which are not part of the input or output come to represent important features of the task domain, and the regularities in the task are captured by the interactions of these units. The ability to create useful new features distinguishes back-propagation from earlier, simpler methods such as the perceptron-convergence procedure[1].

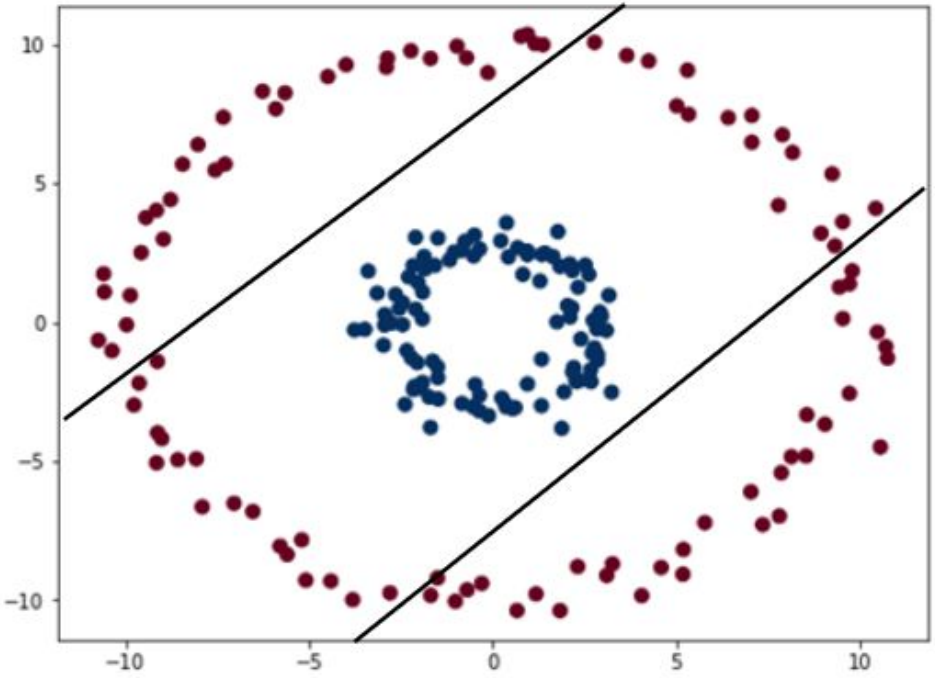
What to do in a More Complex Scenario?



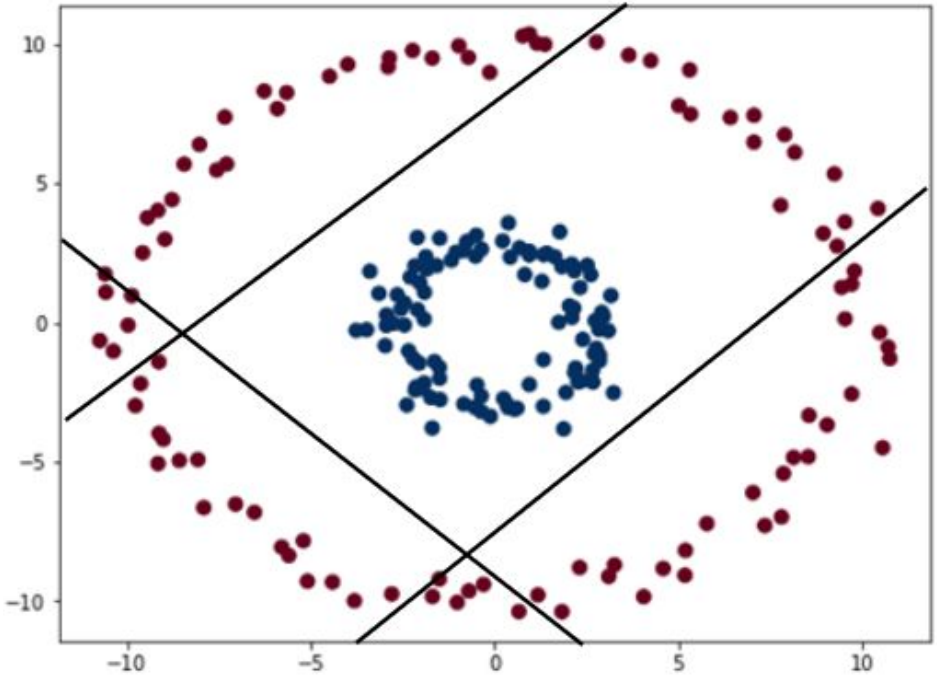
First Neuron



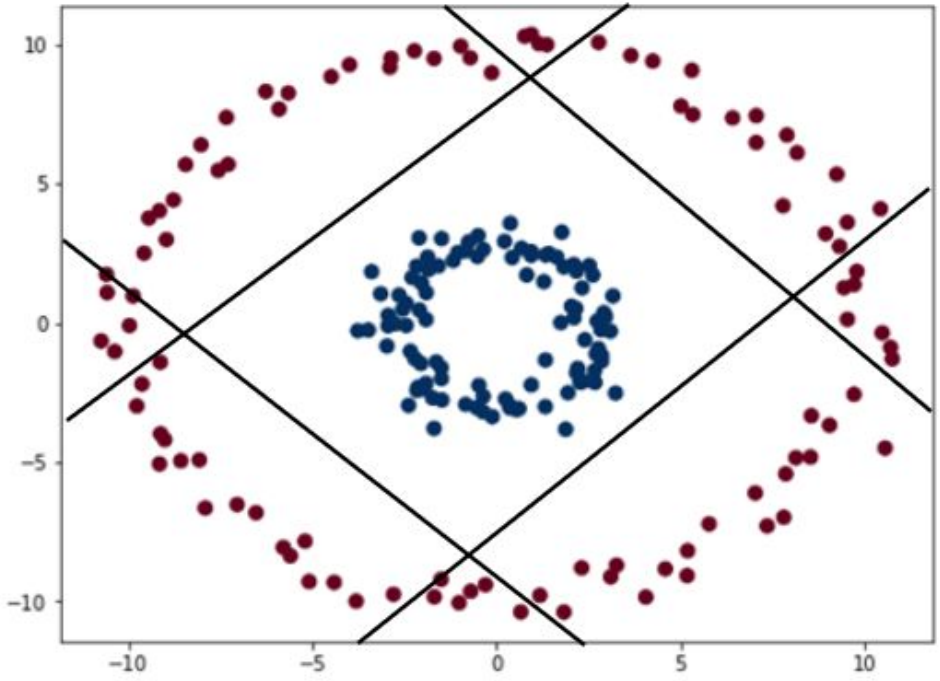
Second Neuron



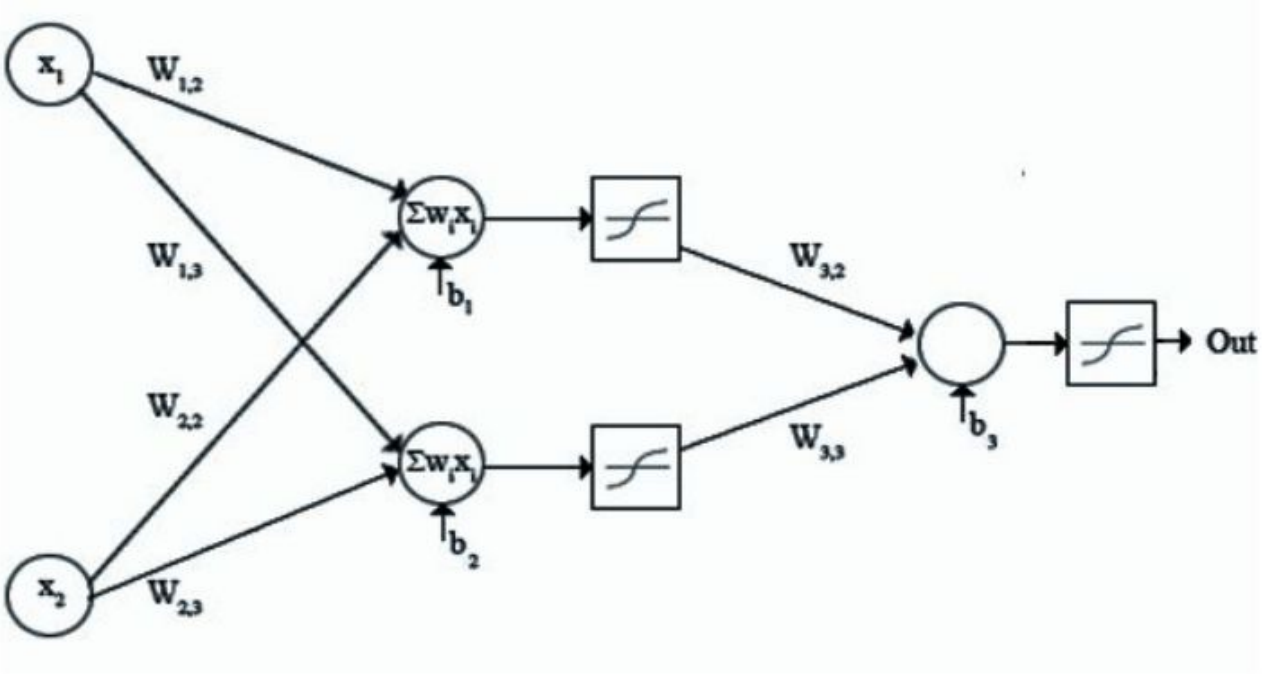
Third Neuron



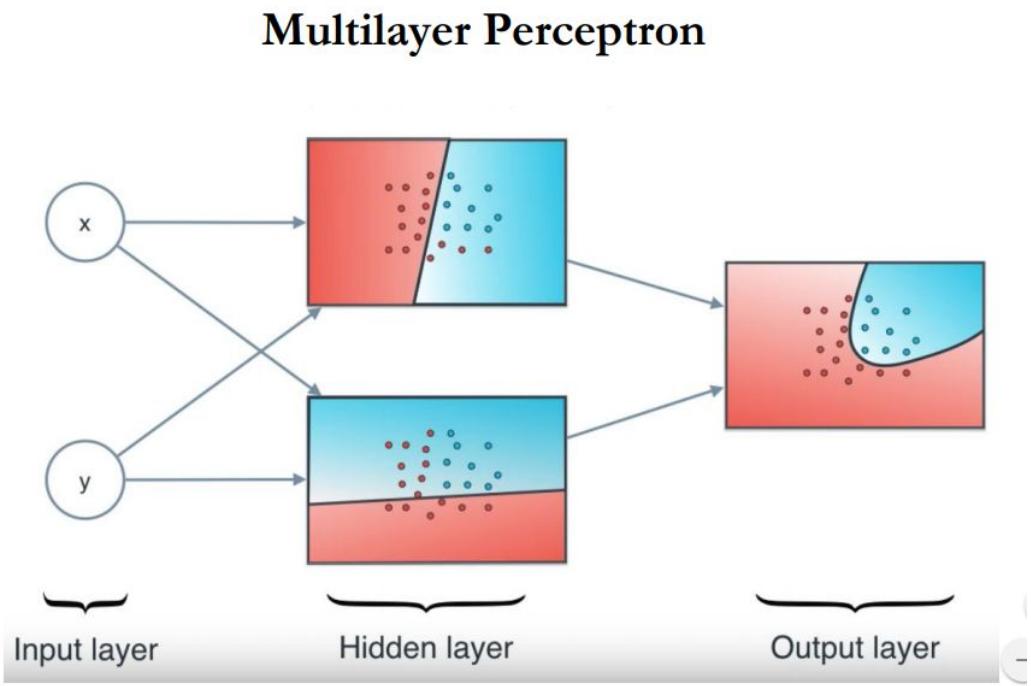
Fourth Neuron



Multilayer Perceptron



Multilayer Perceptron



Next Class:

Neural Networks