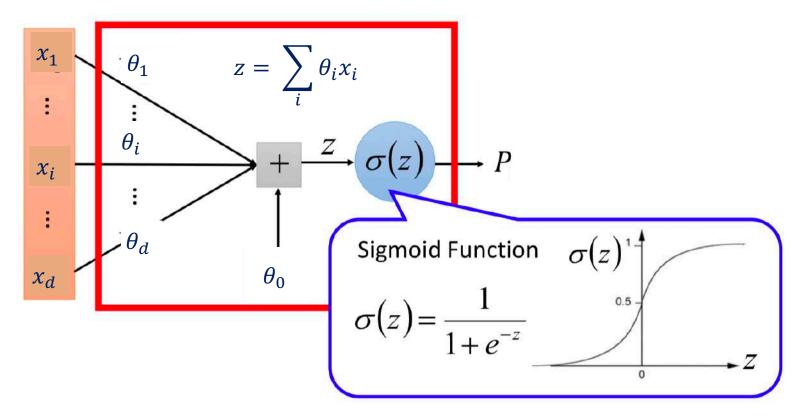


INTRODUCTION TO NEURAL NETWORK

Narges Norouzi

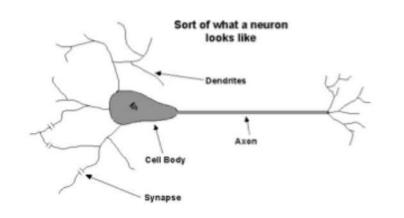
LOGISTIC FUNCTION

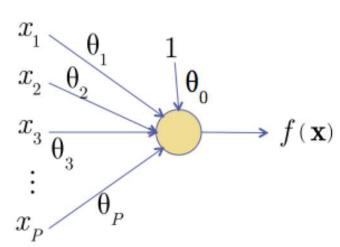


https://walkccc.github.io/CS/ML/5/

THE NEURON METAPHOR

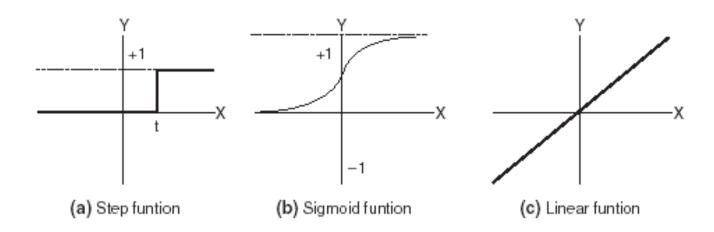
- Neurons
- Accept information from multiple inputs,
- Transmit information to other neurons.
- Multiply inputs by weights/parameters along edges
- Apply some function to the set of inputs at each node





ARTIFICIAL NEURONS

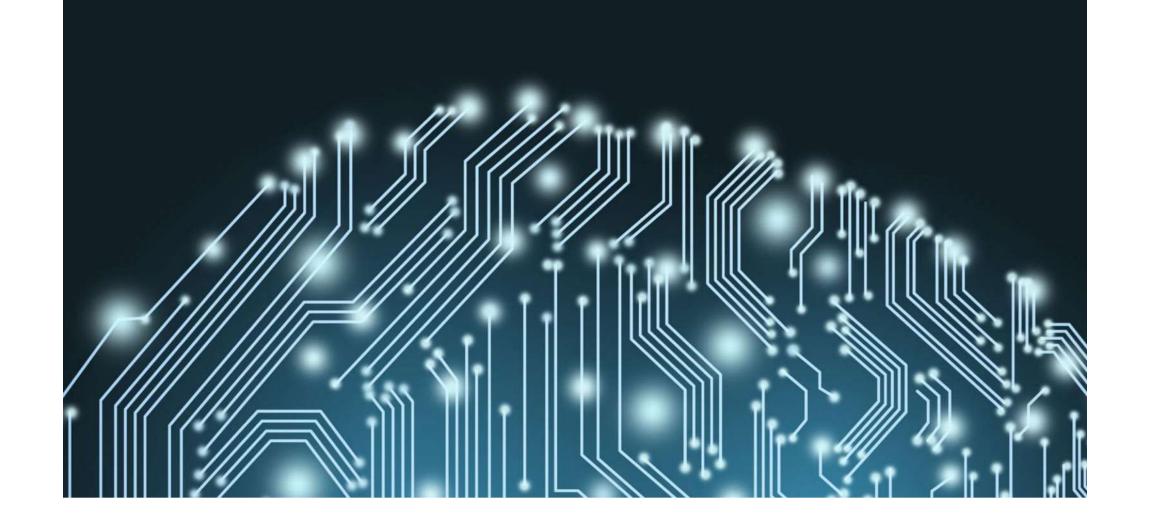
- Each neuron in the network receives one or more inputs.
- An activation function is applied to the inputs, which determines the output of the neuron the activation level.



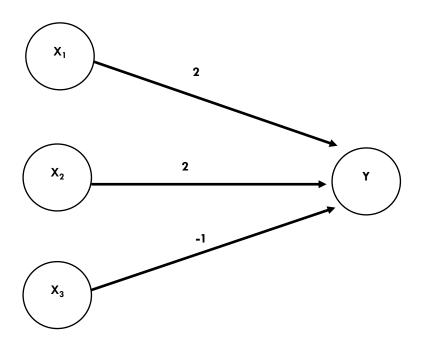
STANDARD ACTIVATION FUNCTIONS

- The hard-limiting threshold function
 - Corresponds to the biological paradigm
 - either fires or not
- Sigmoid function or the logistic function
 - The hyperbolic tangent (symmetrical)
 - Both functions have a simple differential

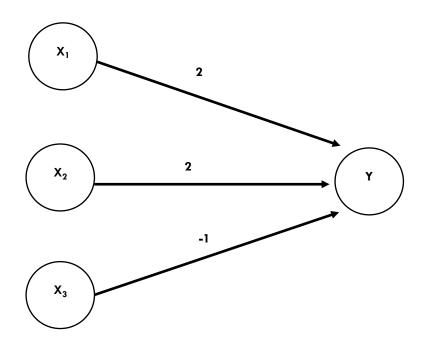
$$\phi(x) = \frac{1}{1 + e^{-ax}}$$



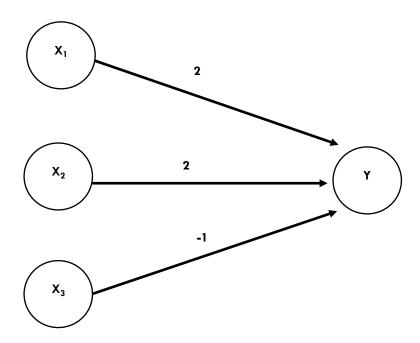
STEP FUNCTION ACTIVATION



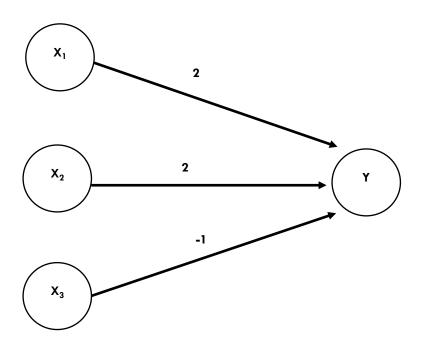
The activation of a neuron is binary. That is, the neuron either fires (activation of one) or does not fire (activation of zero).



If the weight on a path is positive the path is excitatory, otherwise it is inhibitory.

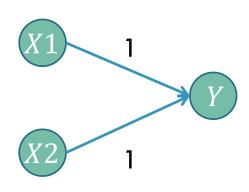


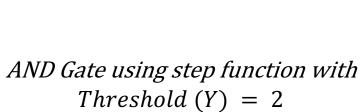
Each neuron has a fixed threshold. If the net input into the neuron is greater than the threshold, the neuron fires. The threshold is set such that any non-zero inhibitory input will prevent the neuron from firing.



It takes one time step for a signal to pass over one connection.

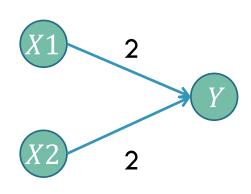
EXAMPLE - AND

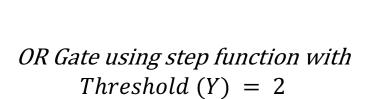




AND		
X1	X2	Y
- 1	- 1	1
1	0	0
0	-1	0
0	0	0

EXAMPLE - OR



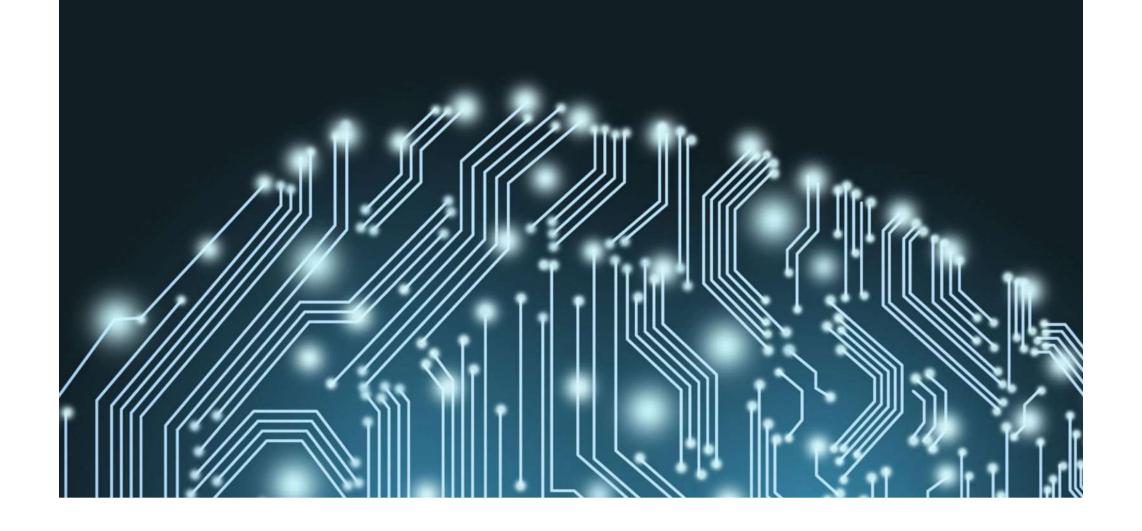


OR		
X1	X2	Y
1	1	1
1	0	1
0	1	1
0	0	0

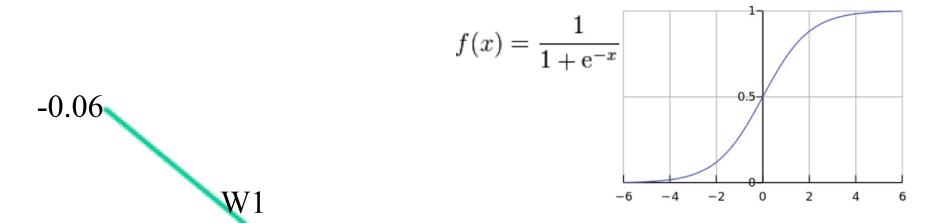
EXAMPLE - XOR

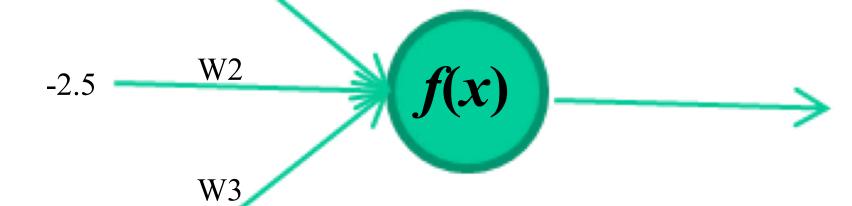
XOR		
X 1	X2	Υ
1	1	0
- 1	0	1
0	1	1
0	0	0

XOR Gate using step function with Threshold(Y) = 2

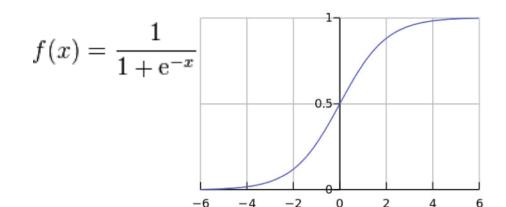


SIGMOID ACTIVATION





1.4



-0.06

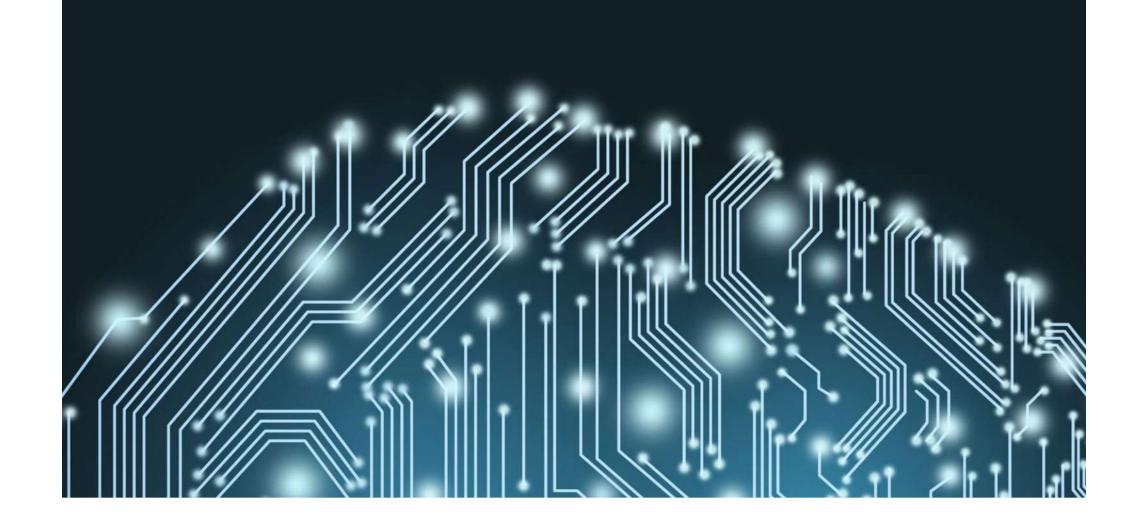
2.7

-2.5 -8.6 f(x)

0.002 $x = -0.06 \times 2$

 $x = -0.06 \times 2.7 + 2.5 \times 8.6 + 1.4 \times 0.002 = 21.34$

1.4



COMBINING ARTIFICIAL NEURONS

DEEP LEARNING OUTLINE

Introduction of Deep Learning

"Hello World" for Deep Learning

Tips for Deep Learning

MACHINE LEARNING ≈ LOOKING FOR A FUNCTION

Speech Recognition

)= "How are you"

Image Recognition



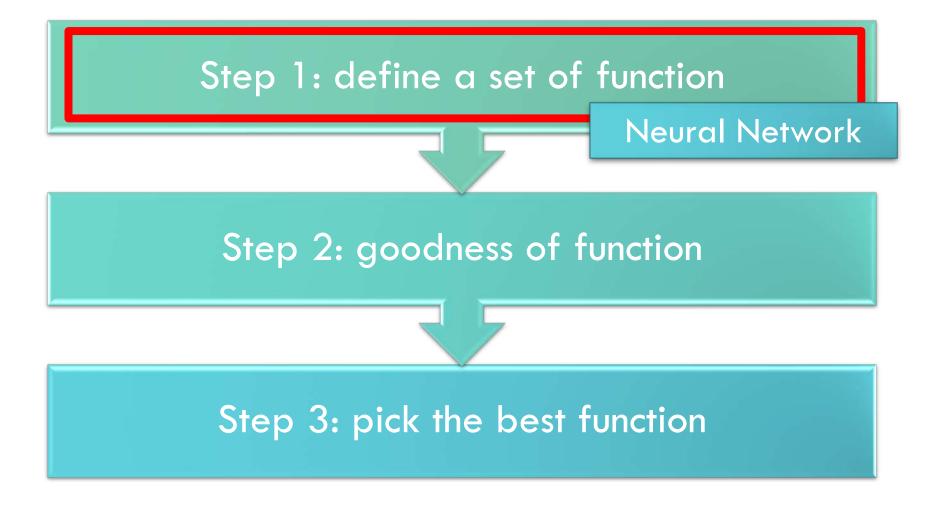
Playing Go



Dialogue System

$$f($$
 "Hi" $)=$ "Hello" (what the user said) (system response)

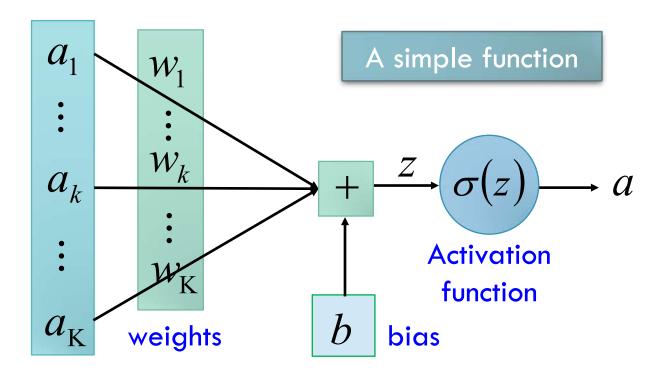
THREE STEPS FOR DEEP LEARNING



NEURAL NETWORK

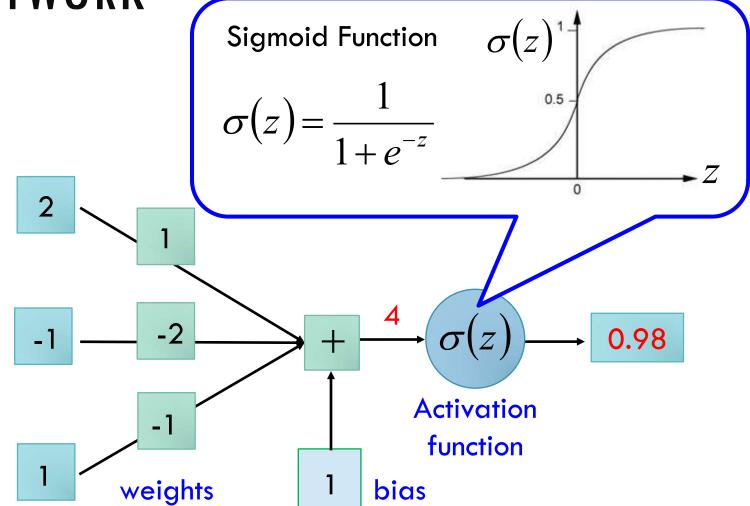
Neuron

$$z = a_1 w_1 + \dots + a_k w_k + \dots + a_K w_K + b$$



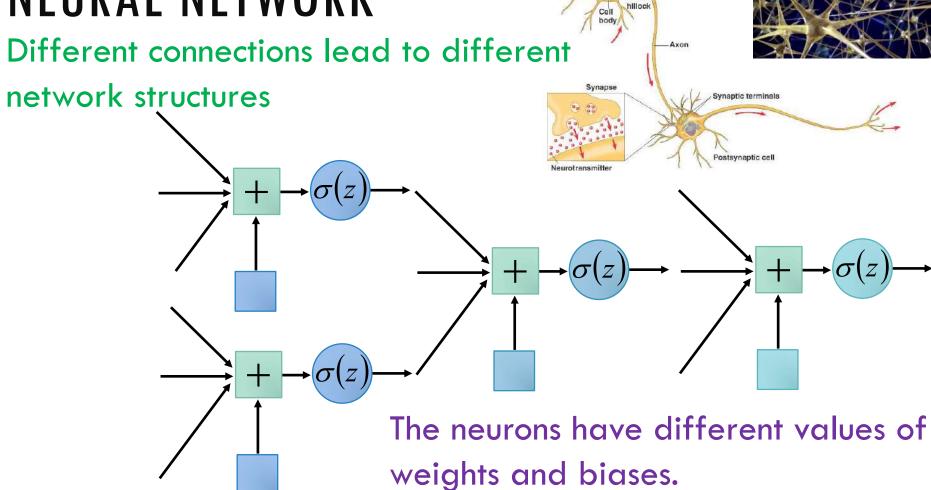
NEURAL NETWORK

Neuron

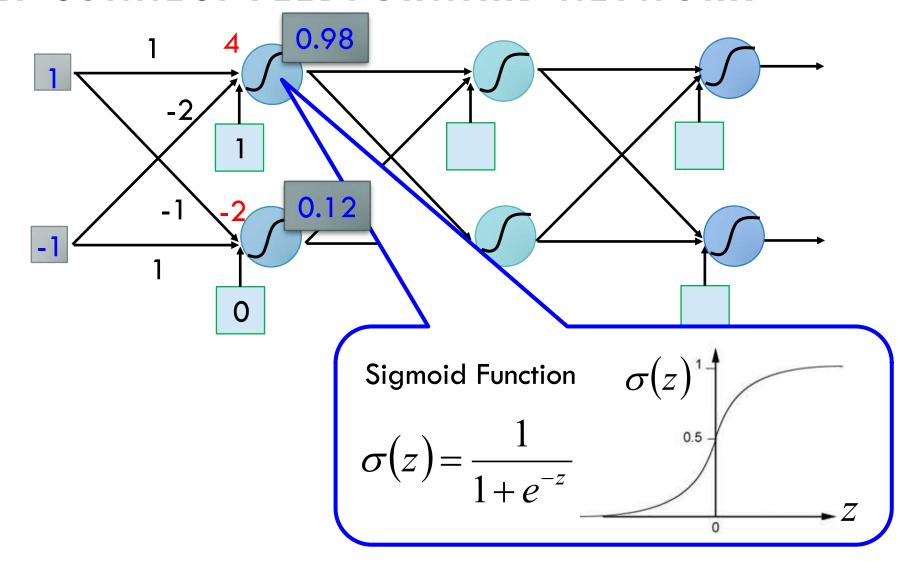


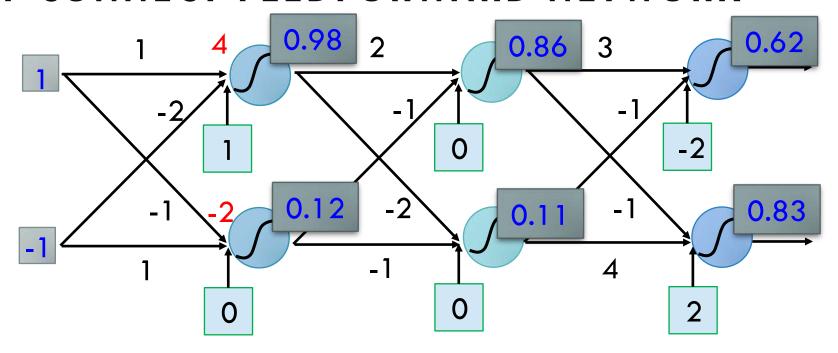
NEURAL NETWORK

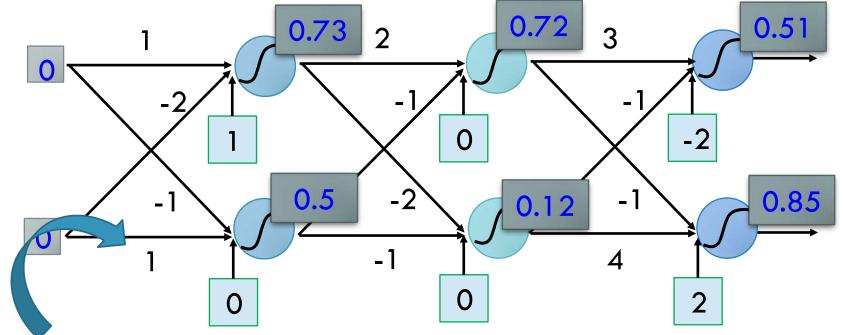
Different connections lead to different



Weights and biases are network parameters heta







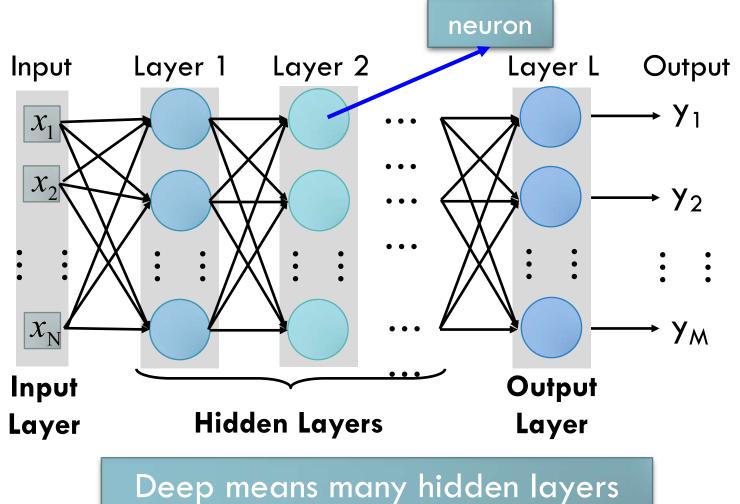
This is a function.

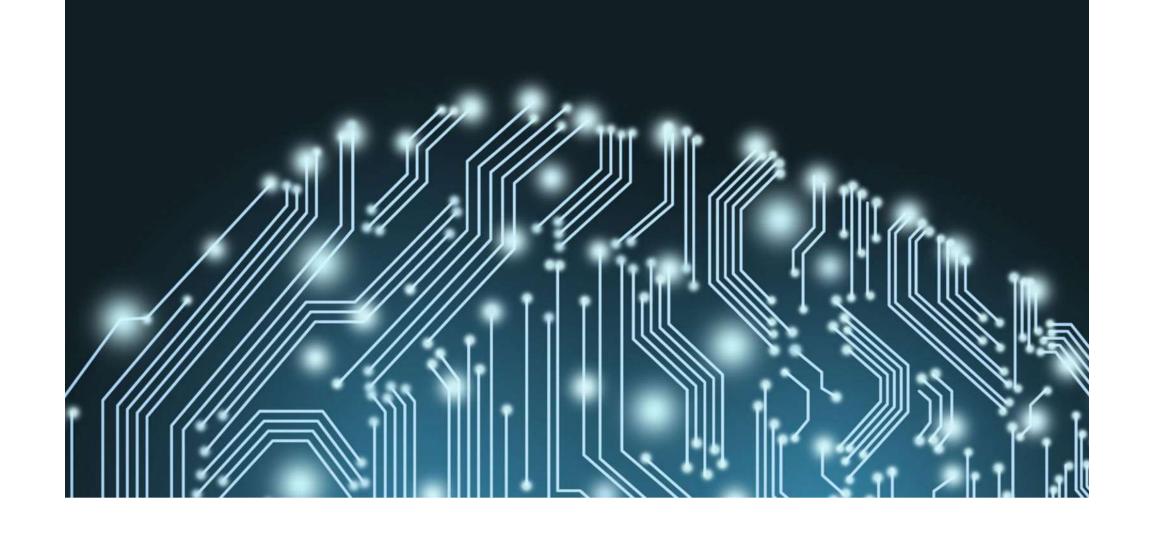
Input vector, output vector

$$f\left(\begin{bmatrix}1\\-1\end{bmatrix}\right) = \begin{bmatrix}0.62\\0.83\end{bmatrix} \quad f\left(\begin{bmatrix}0\\0\end{bmatrix}\right) = \begin{bmatrix}0.51\\0.85\end{bmatrix}$$

Given parameters θ , define a function

Given network structure, define a function set

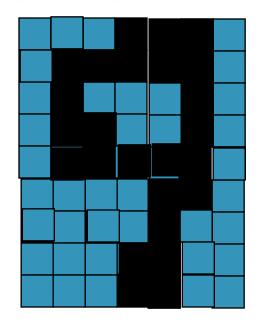




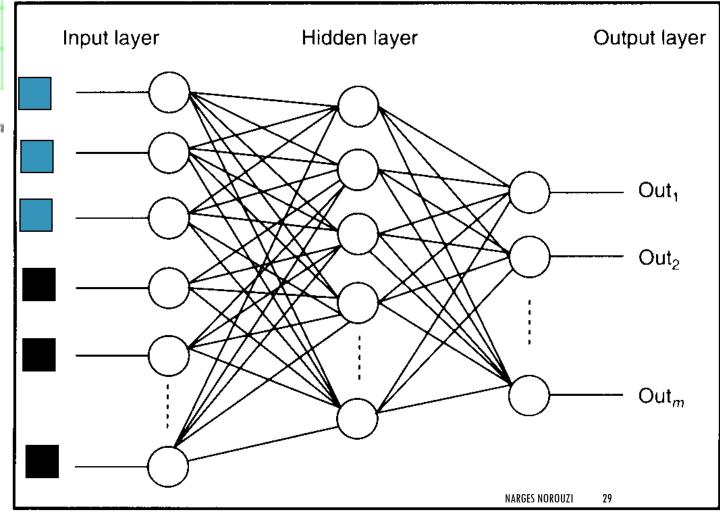
EXAMPLE: DIGIT CLASSIFICATION

0123456789

Figure 1.2: Examples of handwritten digits from postal envelopes.

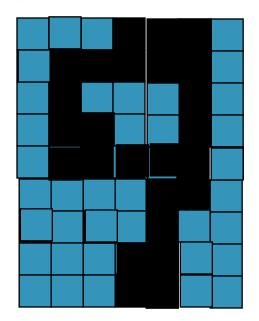


FEATURE DETECTORS

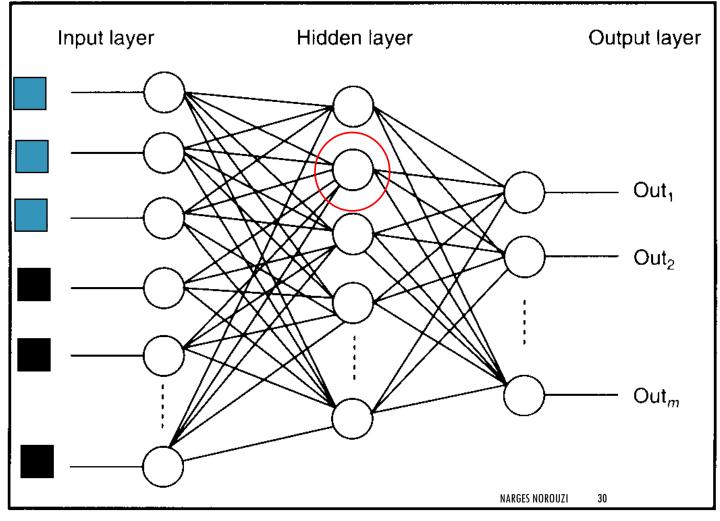


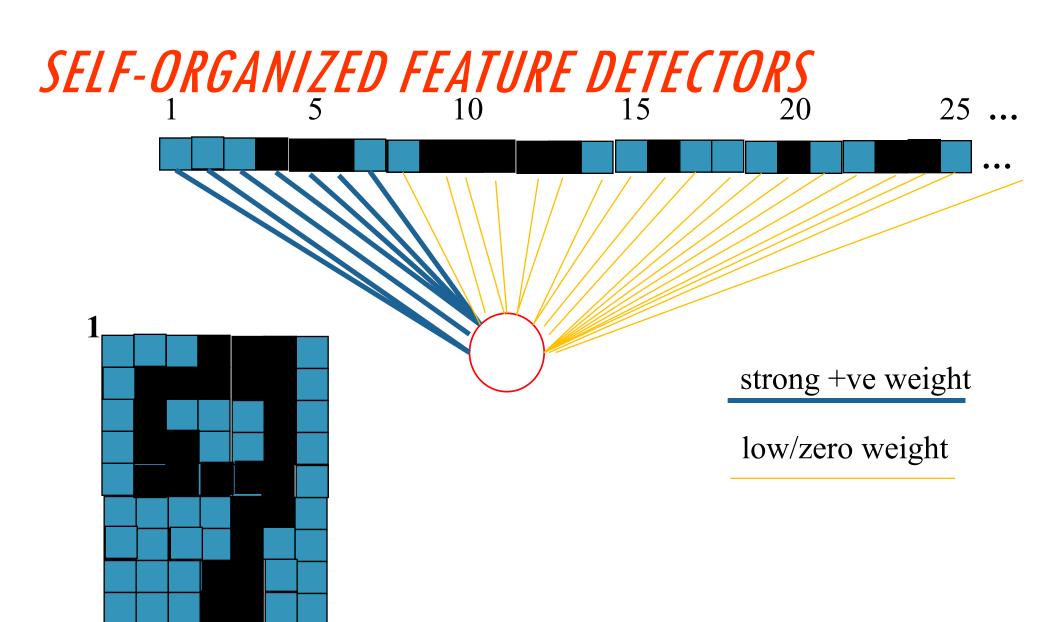
0123456789 0123456789 0123456789 012345678

Figure 1.2: Examples of handwritten digits from postal envelopes.



WHAT IS THIS UNIT DOING?



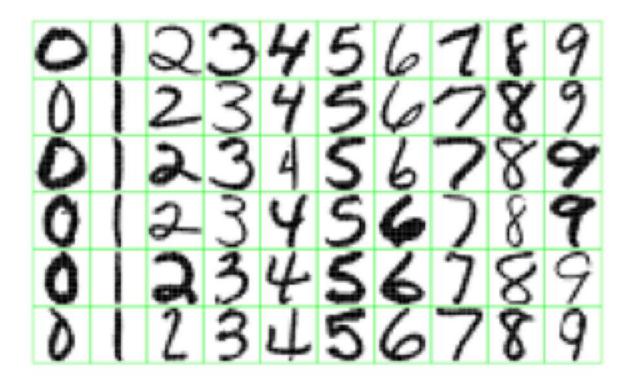


WHAT DOES THIS UNIT DETECT? 1 5 10 15 20 strong +ve weight low/zero weight it will send strong signal for a horizontal line in the top row, ignoring everywhere else

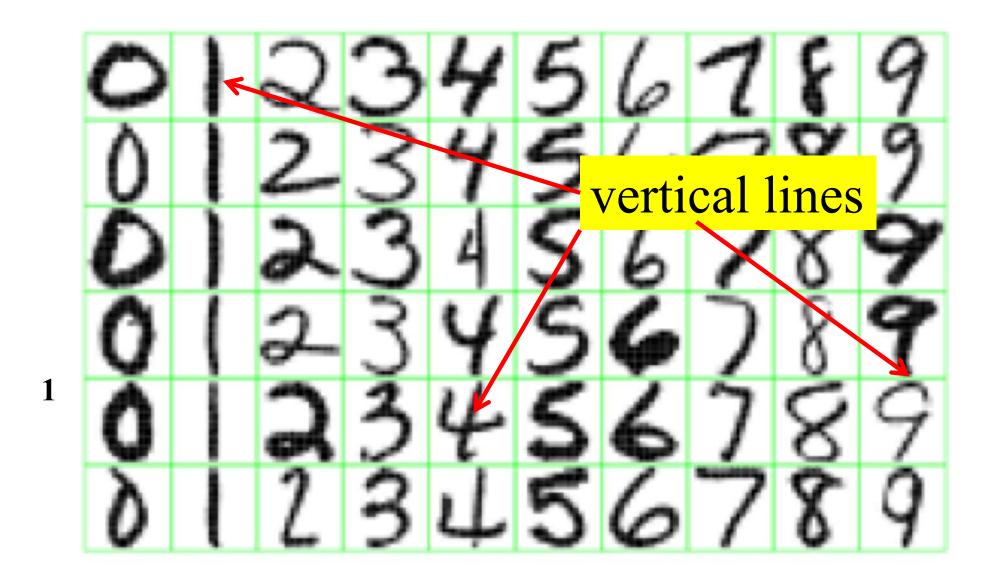
63

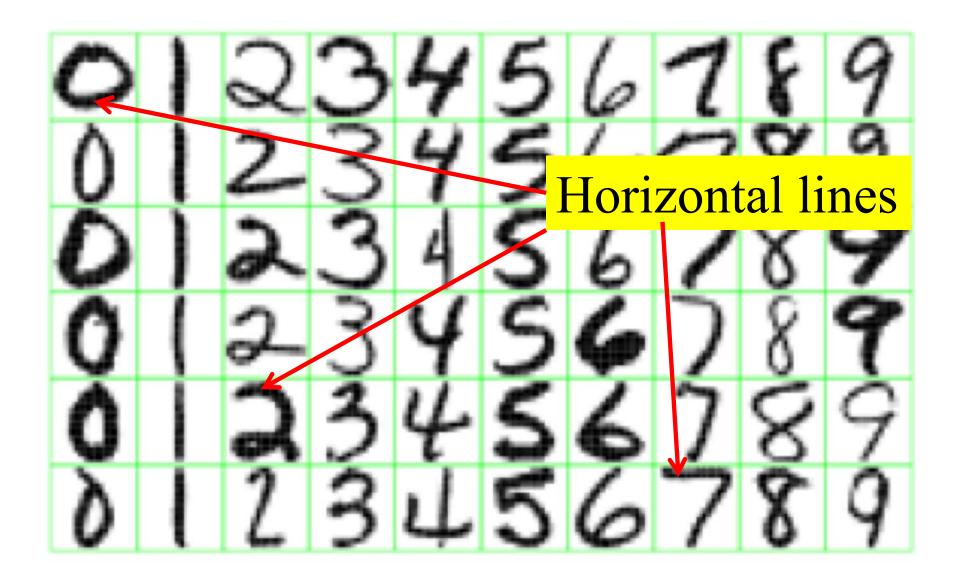
WHAT DOES THIS UNIT DETECT? 1 5 10 15 20 strong +ve weight low/zero weight Strong signal for a dark area in the top left corner

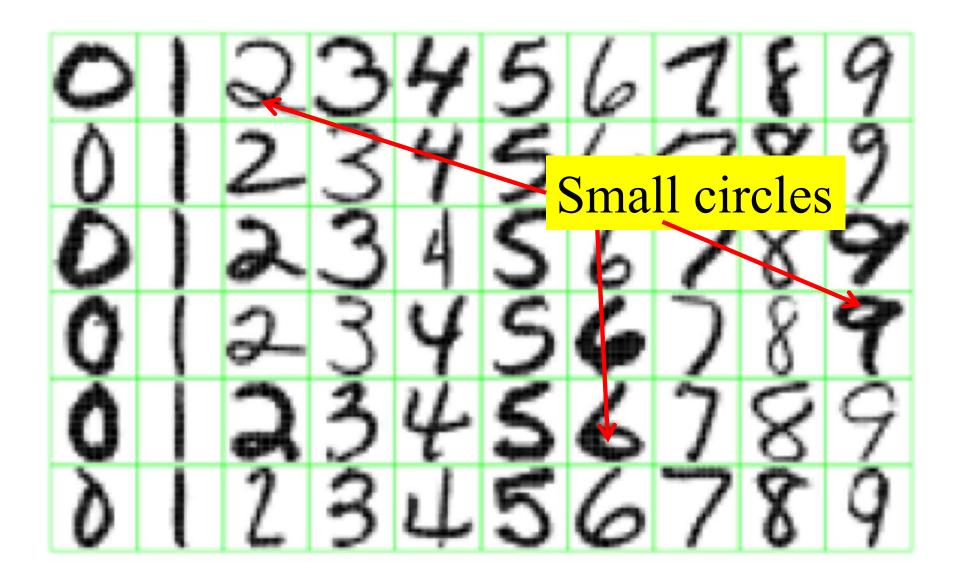
63

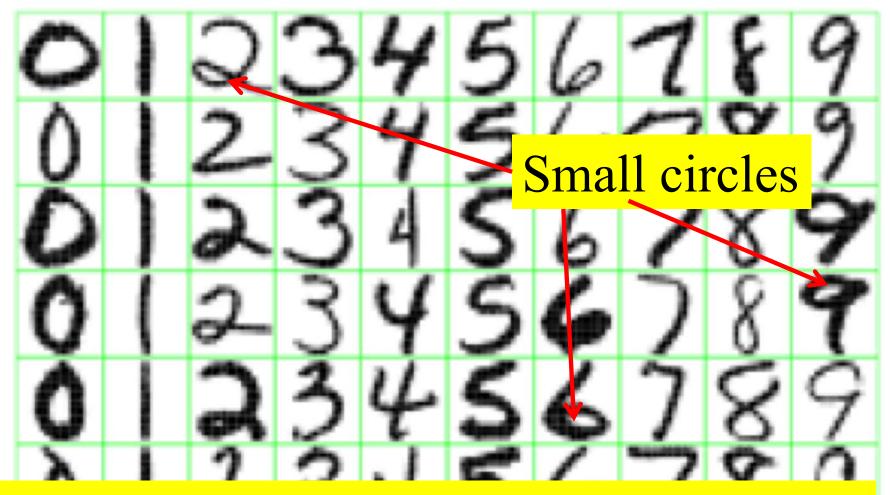


What features might you expect a good NN to learn, when trained with data like this?



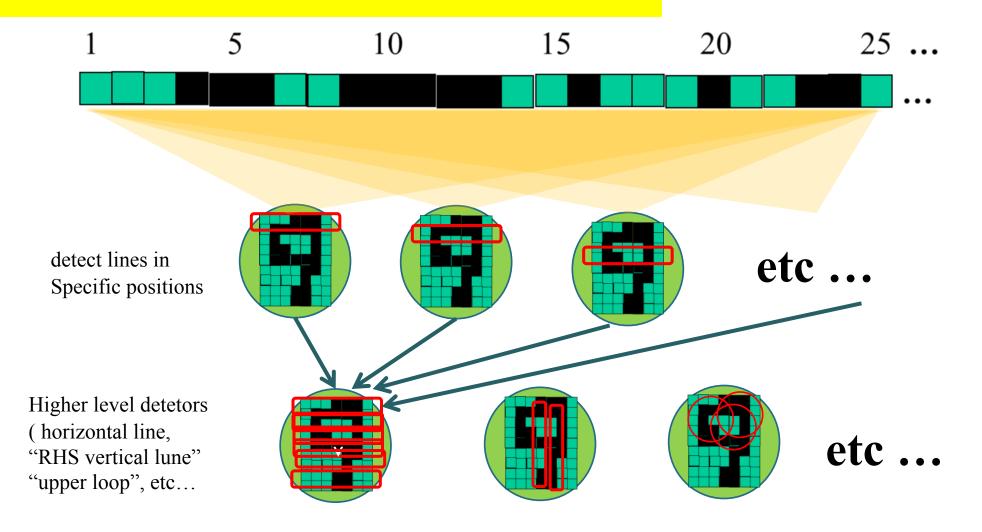




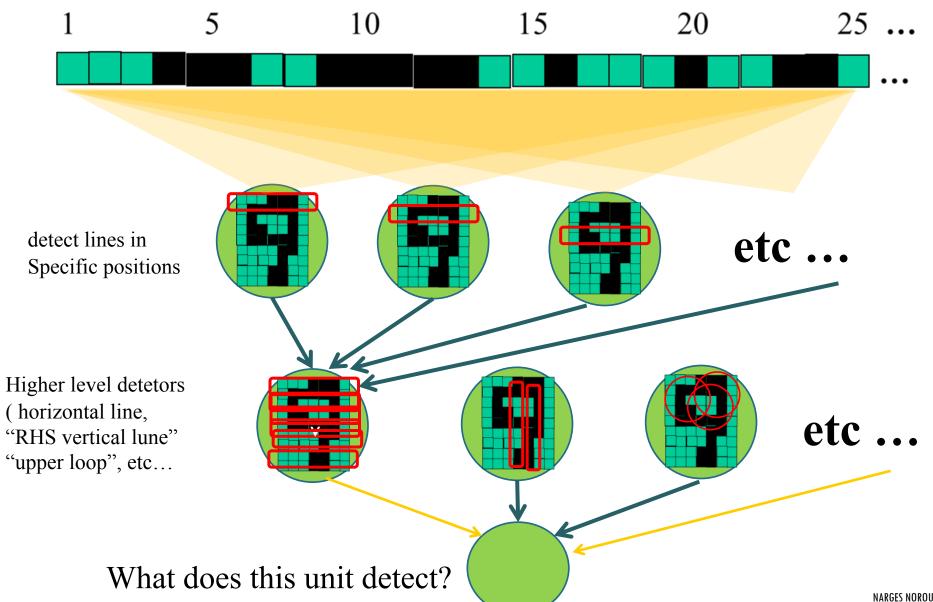


But what about position invariance ??? our example unit detectors were tied to specific parts of the image

SUCCESSIVE LAYERS CAN LEARN HIGHER-LEVEL FEATURES ...

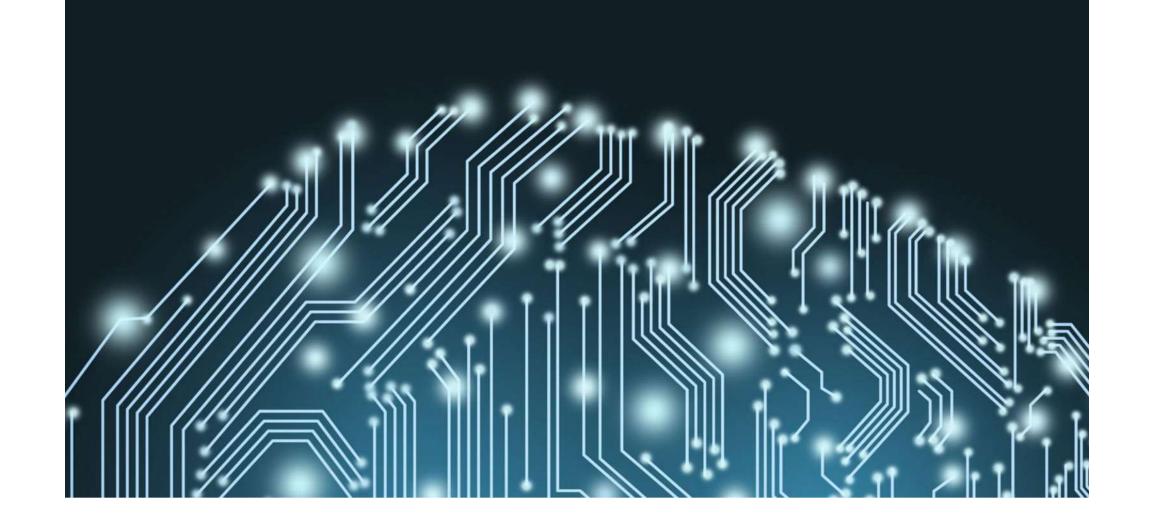


SUCCESSIVE LAYERS CAN LEARN HIGHER-LEVEL FEATURES ...



CLASS EXERCISE

bit.ly/ce-10



MORE ABOUT NN LATER...