NEURAL NETWORKS

David Kauchak
CS159 – Fall 2023

1

Admin

Assignment 5a

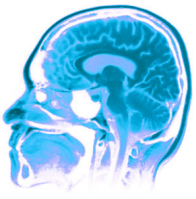
Quiz on Wednesday (and that's it for the day!)

2

Neural Networks

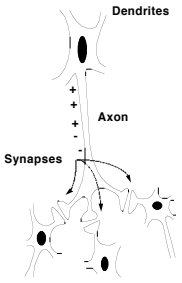
Neural Networks try to mimic the structure and function of our nervous system

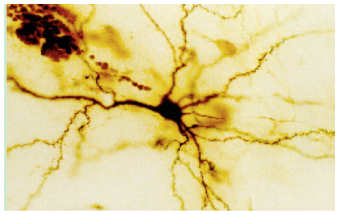
People like biologically motivated approaches



3

Our Nervous System



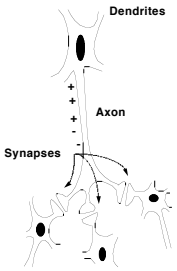


Neuron

What do you know?

4

Our nervous system: the computer science view



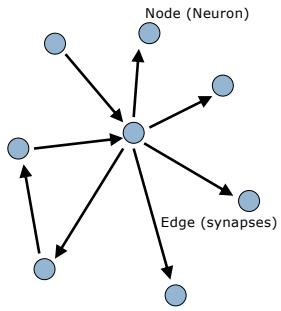
the human brain is a large collection of interconnected neurons

a NEURON is a brain cell

- they collect, process, and disseminate electrical signals
- they are connected via synapses
- they FIRE depending on the conditions of the neighboring neurons

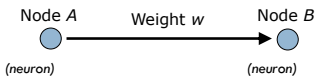
5

Artificial Neural Networks



our approximation

6

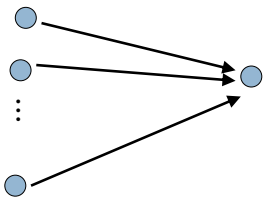


W is the strength of signal sent between A and B.

If *A* fires and *w* is **positive**, then *A* **stimulates** *B*.

If *A fires* and *w* is **negative**, then *A* **inhibits** *B*.

7



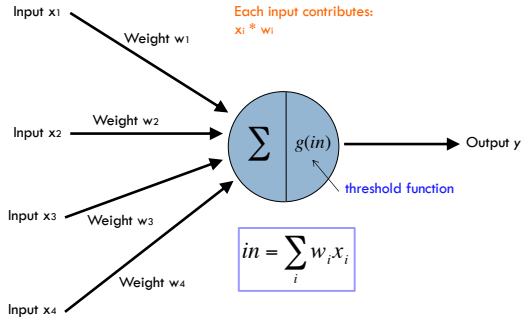
Neurons often have many, many connected input neurons

If a neuron is stimulated enough, then it also fires

How much stimulation is required is determined by its **threshold**

8

A Single Neuron/Perceptron



9

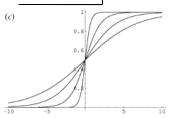
Activation functions

hard threshold:

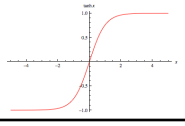
$$g(in) = \begin{cases} 1 & if\ in \geq T \\ 0 & otherwise \end{cases}$$

sigmoid

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



tanh x

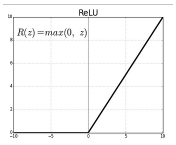


why other threshold functions?

10

Many other activation functions

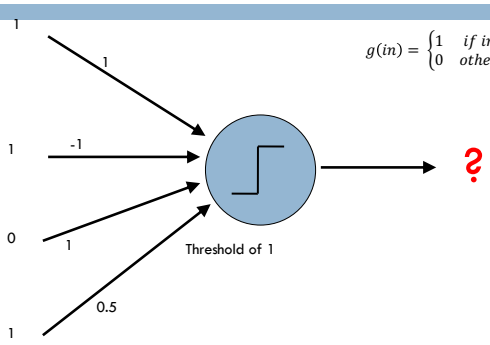
Rectified Linear Unit



Softmax (for probabilities)

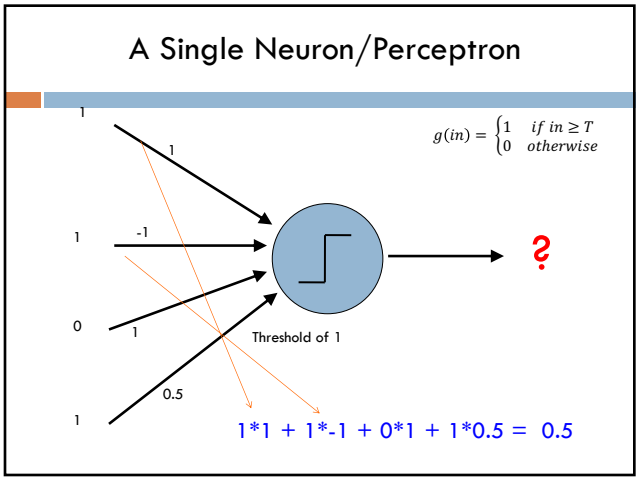
11

A Single Neuron/Perceptron

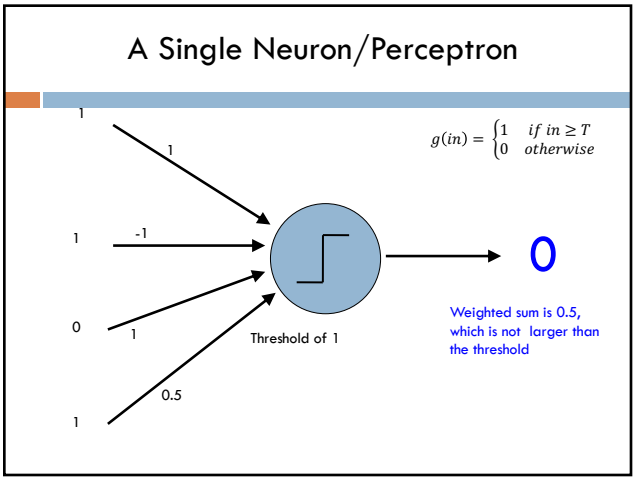


$$g(in) = \begin{cases} 1 & if\ in \geq T \\ 0 & otherwise \end{cases}$$

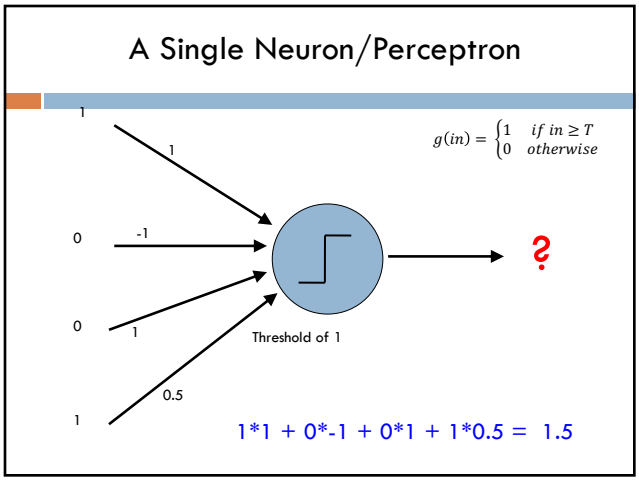
12


A Single Neuron/Perceptron
$g(in) = \begin{cases} 1 & if\ in \geq T \\ 0 & otherwise \end{cases}$
1
1
-1
0
1
0.5
1
Threshold of 1
?
1*1 + 1*-1 + 0*1 + 1*0.5 = 0.5

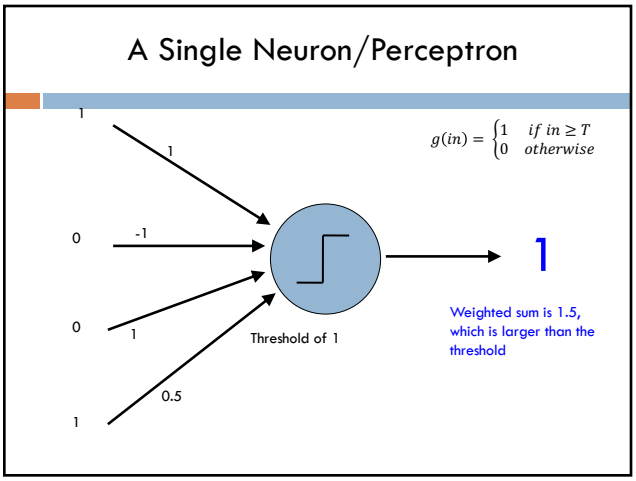
13


A Single Neuron/Perceptron
$g(in) = \begin{cases} 1 & if\ in \geq T \\ 0 & otherwise \end{cases}$
1
1
-1
0
1
0.5
1
Threshold of 1
0
Weighted sum is 0.5, which is not larger than the threshold

14

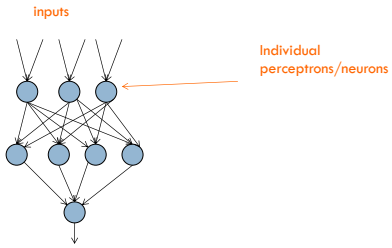

A Single Neuron/Perceptron
$g(in) = \begin{cases} 1 & if\ in \geq T \\ 0 & otherwise \end{cases}$
1
1
0
-1
0
1
0.5
1
Threshold of 1
?
1*1 + 0*-1 + 0*1 + 1*0.5 = 1.5

15


A Single Neuron/Perceptron
$g(in) = \begin{cases} 1 & if\ in \geq T \\ 0 & otherwise \end{cases}$
1
1
0
-1
0
1
0.5
1
Threshold of 1
1
Weighted sum is 1.5, which is larger than the threshold

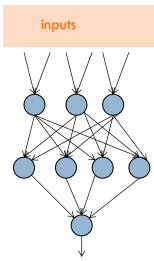
16

Neural network



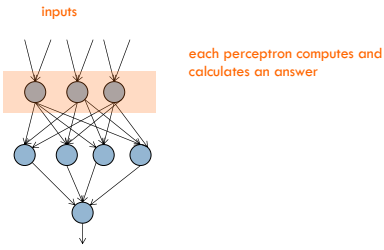
17

Neural network



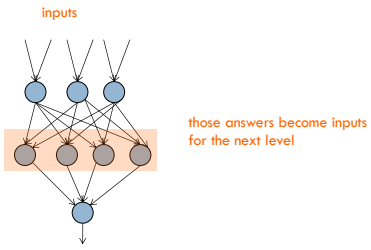
18

Neural network



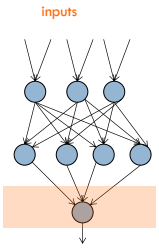
19

Neural network



20

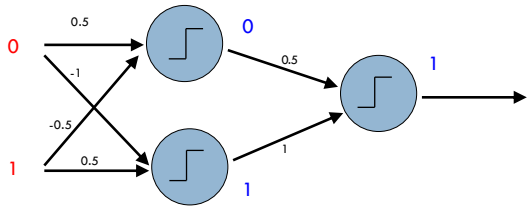
Neural network



finally get the answer after all levels compute

21

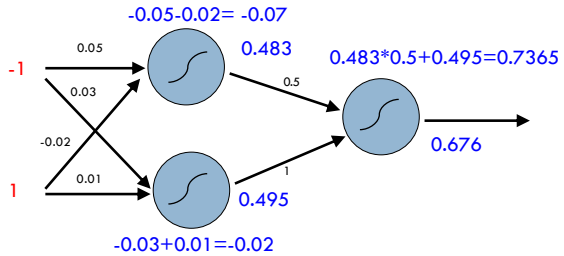
Computation (assume threshold 0)



$$g(in) = \begin{cases} 1 & if\ in \geq T \\ 0 & otherwise \end{cases}$$

22

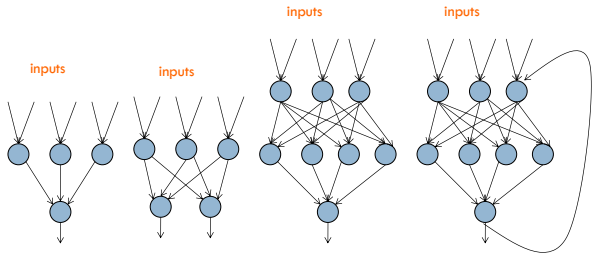
Computation



23

Neural networks

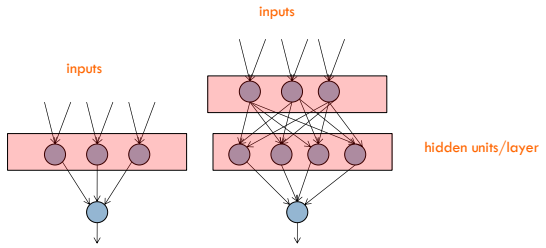
Different kinds/characteristics of networks



How are these different?

24

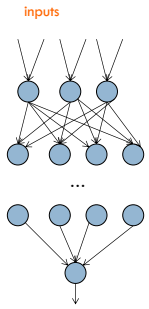
Hidden units/layers



Feed forward networks

25

Hidden units/layers

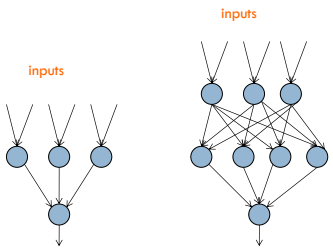


Can have many layers of hidden units of differing sizes

To count the number of layers, you count all but the inputs

26

Hidden units/layers



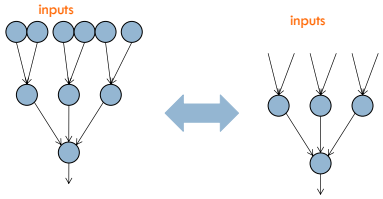
2-layer network

3-layer network

27

Alternate ways of visualizing

Sometimes the input layer will be drawn with nodes as well

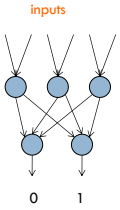


2-layer network

2-layer network

28

Multiple outputs



Can be used to model multiclass datasets or more interesting predictors, e.g. images

29

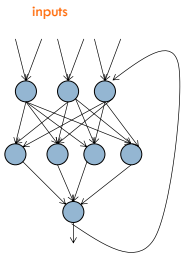
Multiple outputs

input

output
(edge detection)

30

Neural networks



Recurrent network

Output is fed back to input

Can support memory!

Good for temporal data

31

History of Neural Networks

McCulloch and Pitts (1943) – introduced model of artificial neurons and suggested they could learn

Hebb (1949) – Simple updating rule for learning

Rosenblatt (1962) - the *perceptron* model

Minsky and Papert (1969) – wrote *Perceptrons*

Bryson and Ho (1969, but largely ignored until 1980s--Rosenblatt) – invented back-propagation learning for multilayer networks

32

Training the perceptron

First wave in neural networks in the 1960's

Single neuron

Trainable: its threshold and input weights can be modified

If the neuron doesn't give the desired output, then it has made a mistake

Input weights and threshold can be changed according to a learning algorithm

33

Examples - Logical operators

AND – if all inputs are 1, return 1, otherwise return 0

OR – if at least one input is 1, return 1, otherwise return 0

NOT – return the opposite of the input

XOR – if exactly one input is 1, then return 1, otherwise return 0

34

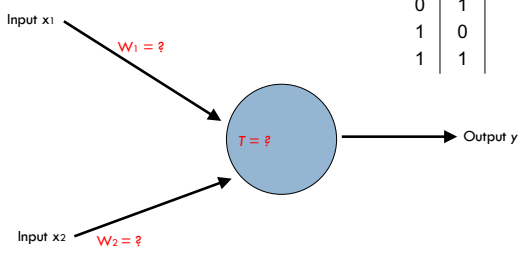
AND

x_1	x_2	x_1 **and** x_2
0	0	0
0	1	0
1	0	0
1	1	1

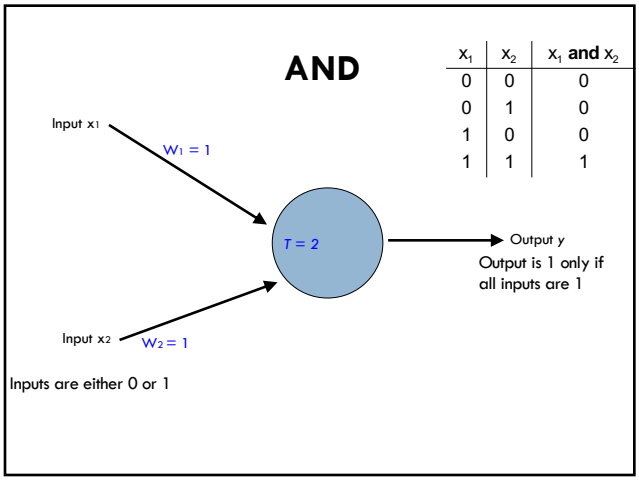
35

AND

x_1	x_2	x_1 **and** x_2
0	0	0
0	1	0
1	0	0
1	1	1

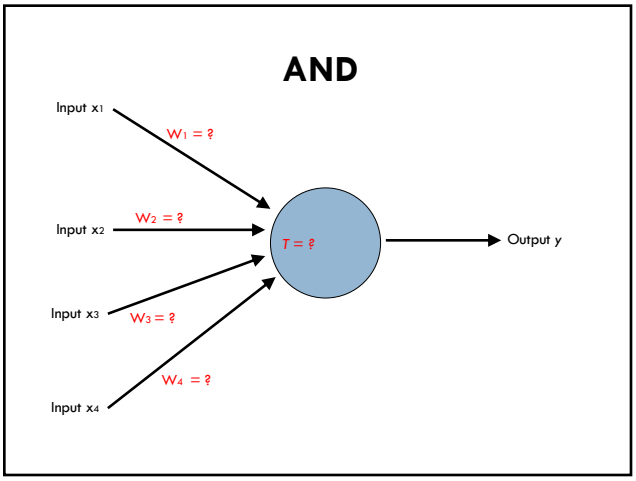


36

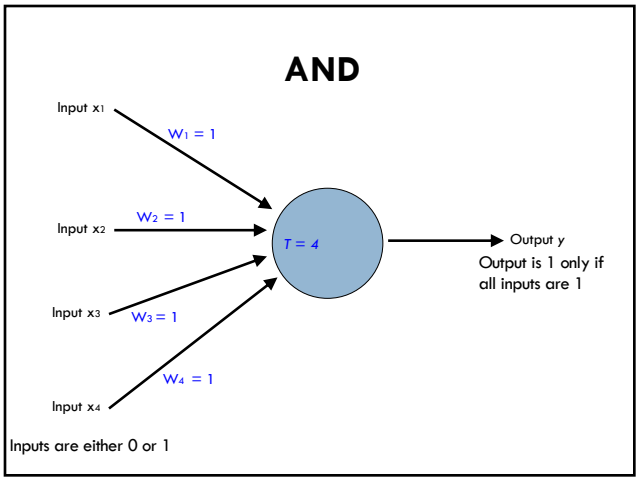


x_1	x_2	x_1 and x_2
0	0	0
0	1	0
1	0	0
1	1	1

37



38

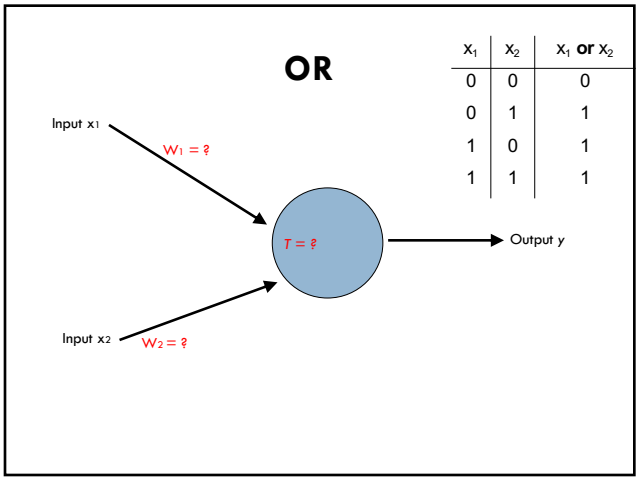


39

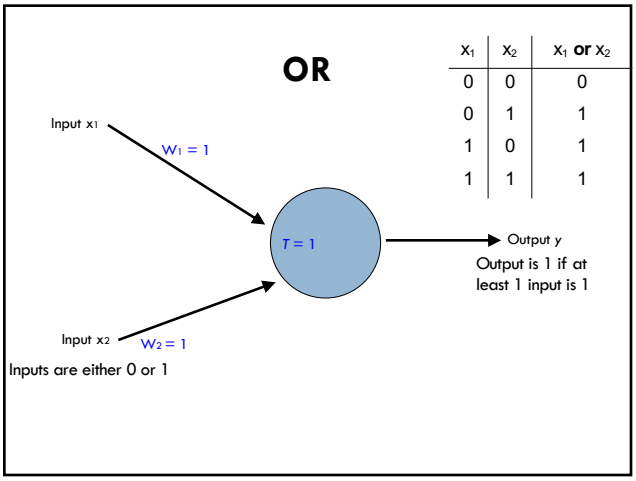
OR

x_1	x_2	x_1 **or** x_2
0	0	0
0	1	1
1	0	1
1	1	1

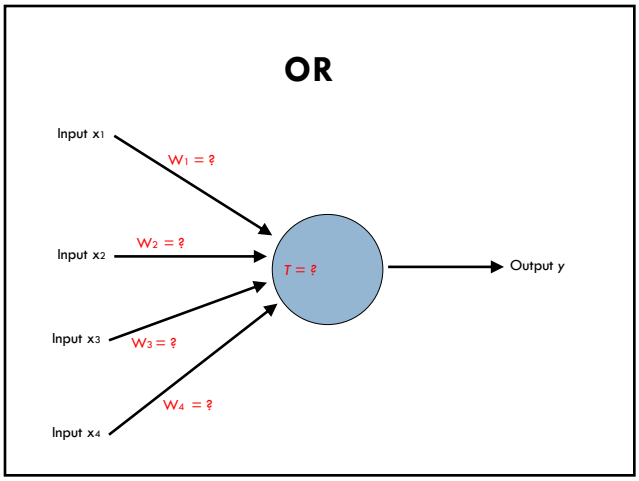
40



41



42



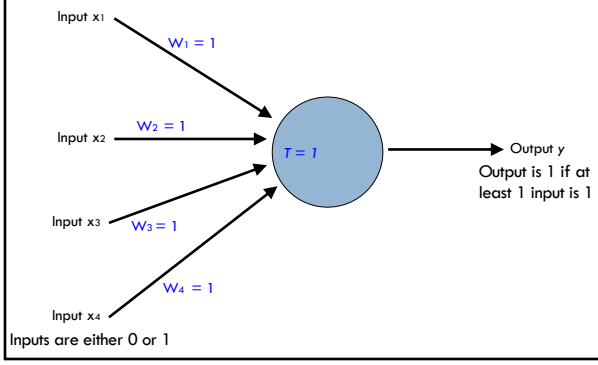
43

NOT

x_1	**not** x_1
0	1
1	0

44

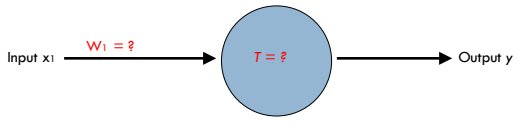
OR



45

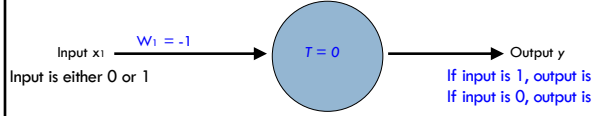
NOT

x_1	not x_1
0	1
1	0



46

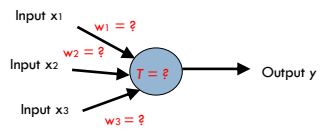
NOT



47

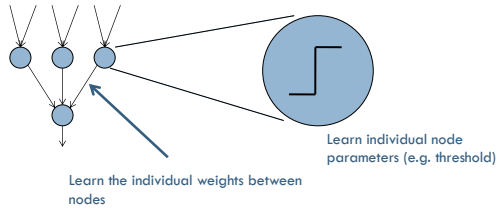
How about…

x_1	x_2	x_3	x_1 and x_2
0	0	0	1
0	1	0	0
1	0	0	1
1	1	0	0
0	0	1	1
0	1	1	1
1	0	1	1
1	1	1	0



48

Training neural networks



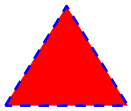
49

Positive or negative?

NEGATIVE

50

Positive or negative?



NEGATIVE

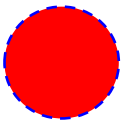
51

Positive or negative?

POSITIVE

52

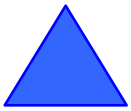
Positive or negative?



NEGATIVE

53

Positive or negative?



POSITIVE

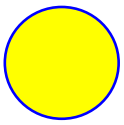
54

Positive or negative?

POSITIVE

55

Positive or negative?



NEGATIVE

56

Positive or negative?

POSITIVE

57

A method to the madness

blue = positive

yellow triangles = positive

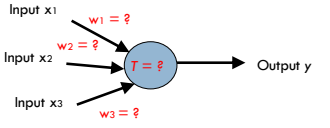
all others negative

How did you figure this out (or some of it)?

58

Training a neuron (perceptron)

x_1	x_2	x_3	x_1 and x_2
0	0	0	1
0	1	0	0
1	0	0	1
1	1	0	0
0	0	1	1
0	1	1	1
1	0	1	1
1	1	1	0



1. start with some initial weights and thresholds
2. show examples repeatedly to NN
3. update weights/thresholds by comparing NN output to actual output

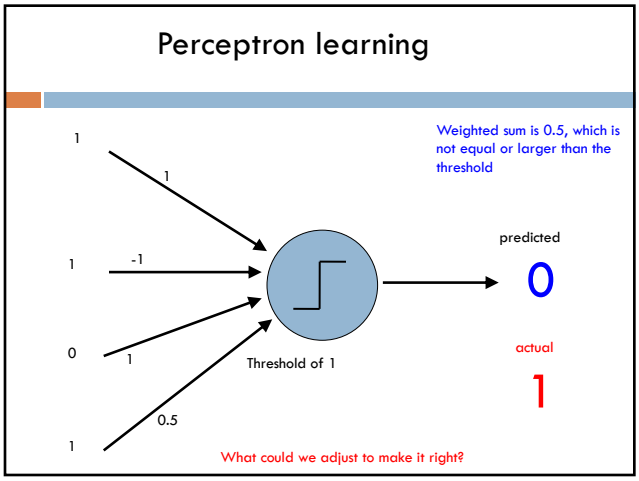
59

Perceptron learning algorithm

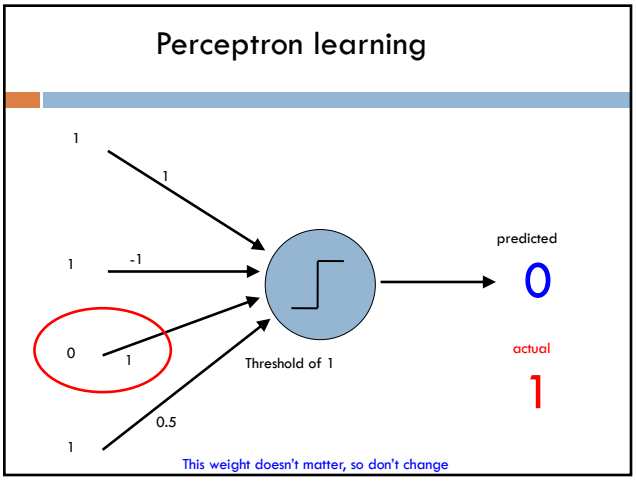
repeat until you get all examples right:

- for each "training" example:
  - calculate current prediction on example
  - if *wrong*:
    - update weights and threshold towards getting this example correct

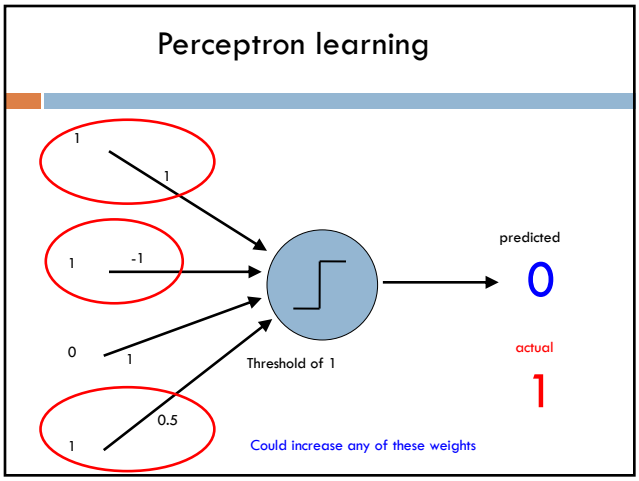
60


Perceptron learning
Weighted sum is 0.5, which is not equal or larger than the threshold
1
1
1
-1
0
1
1
0.5
Threshold of 1
predicted
0
actual
1
What could we adjust to make it right?

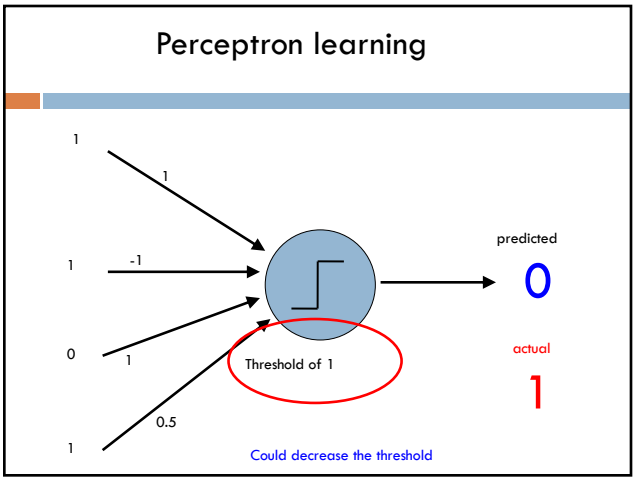
61


Perceptron learning
1
1
1
-1
0
1
1
0.5
Threshold of 1
predicted
0
actual
1
This weight doesn't matter, so don't change

62


Perceptron learning
1
1
1
-1
0
1
1
0.5
Threshold of 1
predicted
0
actual
1
Could increase any of these weights

63


Perceptron learning
1
1
1
-1
0
1
1
0.5
Threshold of 1
predicted
0
actual
1
Could decrease the threshold

64

Perceptron learning

A few missing details, but not much more than this

Keeps adjusting weights as long as it makes mistakes

Run through the training data multiple times until convergence, some number of iterations, or until weights don't change (much)

65

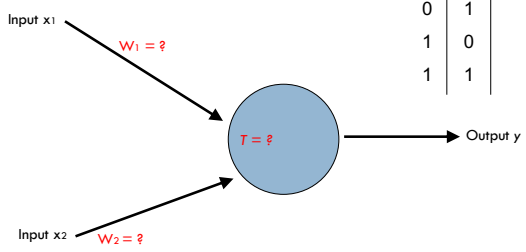
XOR

x_1	x_2	x_1 **or** x_2
0	0	0
0	1	1
1	0	1
1	1	0

66

XOR

x_1	x_2	x_1 **xor** x_2
0	0	0
0	1	1
1	0	1
1	1	0



67

Perceptron learning

A few missing details, but not much more than this

Keeps adjusting weights as long as it makes mistakes

Run through the training data multiple times until convergence, some number of iterations, or until weights don't change (much)

If the training data is linearly separable the perceptron learning algorithm is guaranteed to converge to the "correct" solution (where it gets all examples right)

68

Linearly Separable

x_1	x_2	x_1 and x_2
0	0	0
0	1	0
1	0	0
1	1	1

x_1	x_2	x_1 or x_2
0	0	0
0	1	1
1	0	1
1	1	1

x_1	x_2	x_1 xor x_2
0	0	0
0	1	1
1	0	1
1	1	0

A data set is linearly separable if you can separate one example type from the other with a line (plane)

Which of these are linearly separable?

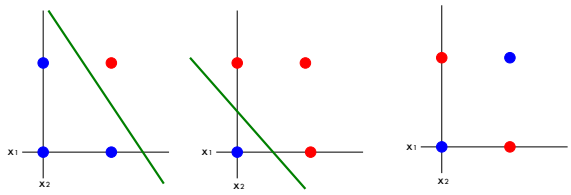
69

Which of these are linearly separable?

x_1	x_2	x_1 and x_2
0	0	0
0	1	0
1	0	0
1	1	1

x_1	x_2	x_1 or x_2
0	0	0
0	1	1
1	0	1
1	1	1

x_1	x_2	x_1 xor x_2
0	0	0
0	1	1
1	0	1
1	1	0



70

Perceptrons

1969 book by Marvin Minsky and Seymour Papert

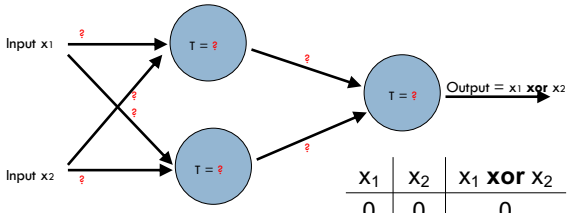
The problem is that they can only work for classification problems that are linearly separable

Insufficiently expressive

"Important research problem" to investigate multilayer networks although they were pessimistic about their value

71

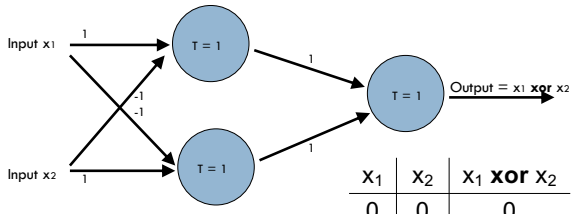
XOR



x_1	x_2	x_1 **xor** x_2
0	0	0
0	1	1
1	0	1
1	1	0

72

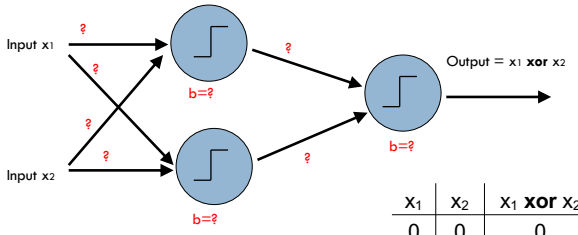
XOR



x_1	x_2	x_1 **xor** x_2
0	0	0
0	1	1
1	0	1
1	1	0

73

Training



How do we learn the weights?

x_1	x_2	x_1 **xor** x_2
0	0	0
0	1	1
1	0	1
1	1	0

74

Training multilayer networks

perceptron learning: if the perceptron's output is different than the expected output, update the weights

gradient descent: compare output to label and adjust based on loss function

Any other problem with these for general NNs?

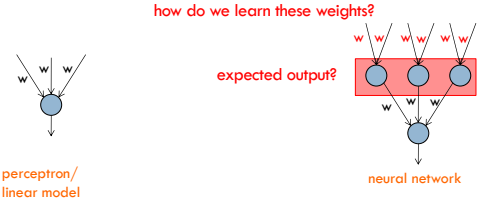
75

Learning in multilayer networks

Challenge: for multilayer networks, we don't know what the expected output/error is for the internal nodes!

how do we learn these weights?

expected output?



76

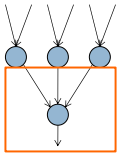
Backpropagation: intuition

Gradient descent method for learning weights by optimizing a loss function

1. calculate output of all nodes
2. calculate the weights for the output layer based on the error
3. "backpropagate" errors through hidden layers

77

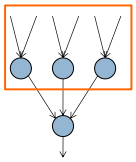
Backpropagation: intuition



We can calculate the actual error here

78

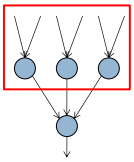
Backpropagation: intuition



Key idea: propagate the error back to this layer

79

Backpropagation: intuition



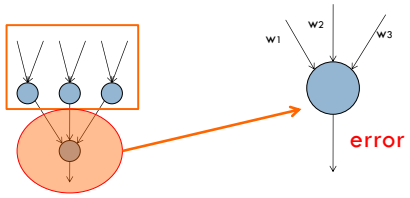
"backpropagate" the error:

Assume all of these nodes were responsible for some of the error

How can we figure out how much they were responsible for?

80

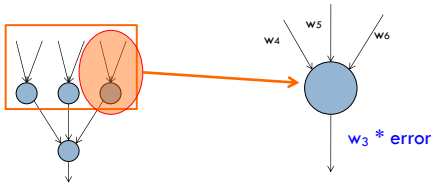
Backpropagation: intuition



error for node is ~ w_i * error

81

Backpropagation: intuition



Calculate as normal using this as the error

82

Mind reader game

https://web.media.mit.edu/~guysatat/MindReader/index.html

83