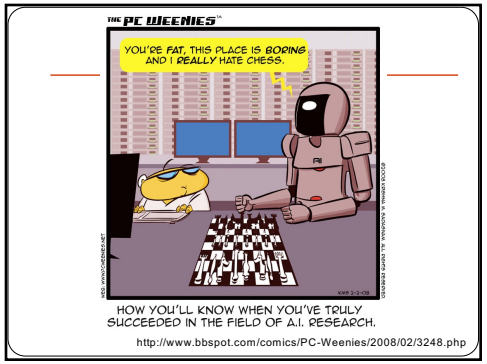

HOW YOU'LL KNOW WHEN YOU'VE TRULY SUCCEEDED IN THE FIELD OF A.I. RESEARCH.

http://www.bbspot.com/comics/PC-Weenies/2008/02/3248.php

1

Intro to AI

CS51A
David Kauchak
Fall 2025

Adapted from notes from:
Sara Owsley Sood

2

Admin

Assignment 6

Midterm

3

AI is a huge field

What is AI (artificial intelligence)…

4

AI is a huge field

What is AI…

One definition:

"*Building programs that enable computers to do what humans can do.*"

For example:
read, walk around, drive, play games, solve problems, learn, have conversations…

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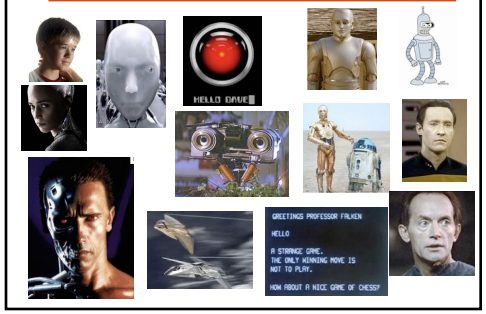
A broader definition

"Building programs that enable computers to do do *intelligent* things"

	human	vs.	rational
thinking	**Think like a human** Cognitive Modeling		**Think rationally** Logic-based Systems
vs.			
acting	**Act like a human** Turing Test		**Act rationally** Rational Agents

6

How is AI viewed in popular media?



7

What challenges are there?

8

What challenges are there?

Perception
- perceive the environment via sensors

Computer vision (perception via images/video)
- process visual information
- object identification, face recognition, motion tracking

Natural language processing and generation
- speech recognition, language understanding
- language translation, speech generation, summarization

9

What challenges are there?

Knowledge representation
- encode known information
- water is wet, the sun is hot, Dave is a person, …

Learning
- learn from environment
- What type of feedback? (supervised vs. unsupervised vs. reinforcement vs …)

Reasoning/problem solving
- achieve goals, solve problems
- planning
- How do you make an omelet? I'm carrying an umbrella and it's raining… will I get wet?

Robotics
- How can computers interact with the physical world?

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What can we currently do?

11

What can we currently do?

Understand spoken language?

speech recognition is really good, if:
- restricted vocabulary
- specific speaker with training

Gotten quite good in the last few years and shows up in lots of places:
- Mobile: Siri, Ok Google, etc.
- Home assistants: Alexa, Google Home

What does the spoken language actually mean (language understanding)?
- much harder problem!
- LLMs are getting better at this, though they don't explicit represent the "meaning"

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What can we currently do?

Speak?

Understandable, but most often wouldn't confuse it for a person (though this too is changing, particularly for pre-scripted)

Can do accents, intonations, etc.

Better with restricted vocabulary

Loquendo

- Dealing with facial expression is challenging

Kismet (MIT)

13

What can we currently do?

Drive a car?

14

What can we currently do?

Drive a car?

Freeway driving is relatively straightforward

Off-road a bit harder

- see DARPA grand challenges (2004, 2005)

And urban driving is even trickier

- Waymo
- Tesla
- Uber

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What can we currently do?

Drive a car?

Many driver assist technologies:

- Automatic breaking
- Automatic pedestrian detection
- Lane drift avoidance
- "smart" cruise control
- Blind spot warning
- …

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What can we currently do?

Identify emotion?

This is hard!

Some success in text

- movie reviews (assignment 7!)
- blogs
- twitter
- dealing with sarcasm is hard

Some success with faces

- strongly biased by training data
- works best when exaggerated

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What can we currently do?

Reasoning?

Success on small sub-problems

General purpose reasoning is harder

- Wolfram Alpha
- OpenCyc

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What can we currently do?

Walk?

Robots have had a variety of locomotion methods

Walking with legs, is challenging

- Differing terrains, stairs, running, ramps, etc.

Getting better every year

- https://www.youtube.com/watch?v=8dFTc4W8wm0

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When will I have my robot helper?

What can we currently do?

21

What can we currently do?



22

What can we currently do?

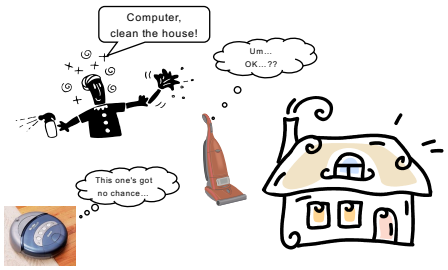
Fold a pile of towels?

UC Berkeley towel folding robot:

http://www.youtube.com/watch?v=gy5g33S0Gzo

23

How do we make computers "intelligent?"



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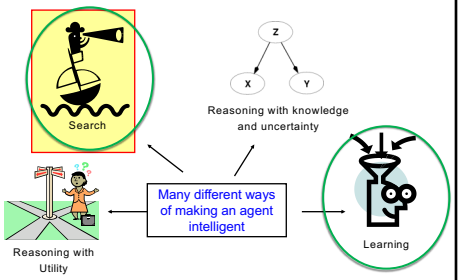
Fundamental problem of AI



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Machine Learning is...

Machine learning is about predicting the future based on the past.

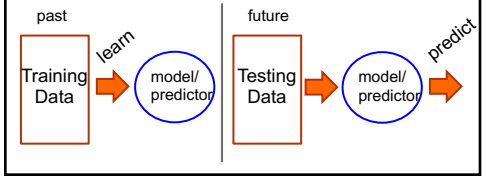
-- Hal Daume III

26

Machine Learning is...

Machine learning is about predicting the future based on the past.

-- Hal Daume III



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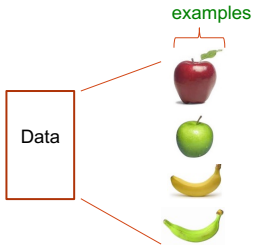
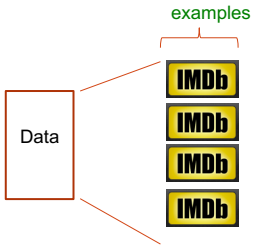
Data



28

Data



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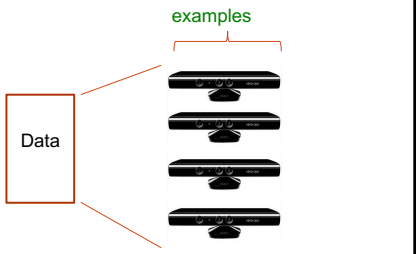
Data



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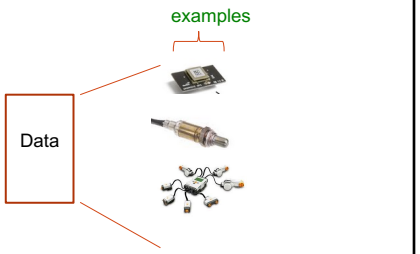
Data



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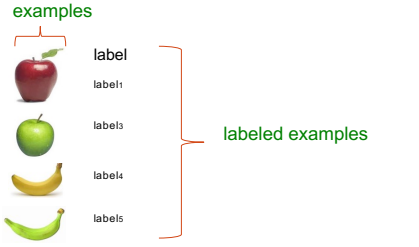
Supervised learning



Supervised learning: given labeled examples

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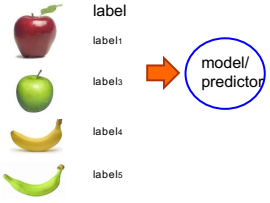
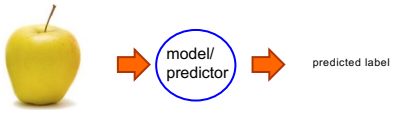
Supervised learning



Supervised learning: learn a model

33

Supervised learning



Supervised learning: learn to predict new example

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Neural Networks

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

People like biologically motivated approaches

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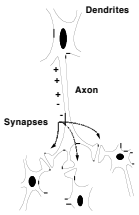
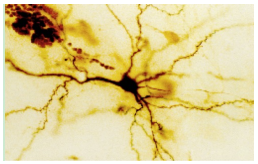
Our Nervous System



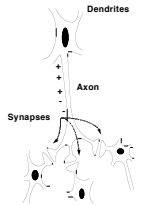


Neuron

What do you know?

36

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

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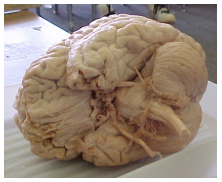
Our nervous system



The human brain

- contains ~10^{11} (100 billion) neurons
- each neuron is connected to ~10^{4} (10,000) other neurons
- Neurons can fire as fast as 10^{-3} seconds

How does this compare to a computer?

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Humans vs. Machines

10^{11} neurons
10^{11} neurons
10^{14} synapses
10^{-3} "cycle" time

10^{10} transistors
10^{11} bits of ram/memory
10^{13} bits on disk
10^{-9} cycle time

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Brains are still pretty fast

Who is this?

40

Brains are still pretty fast

If you were me, you'd be able to identify this person in 10^{-1} (1/10) s!

Given a neuron firing time of 10^{-3} s, how many neurons in sequence could fire in this time?

- A few hundred

What are possible explanations?

- either neurons are performing some very complicated computations
- brain is taking advantage of the **massive** parallelization (remember, neurons are connected ~10,000 other neurons)

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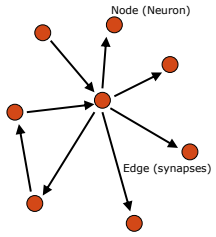
Artificial Neural Networks



our approximation

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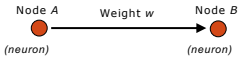
Neural networks



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*.

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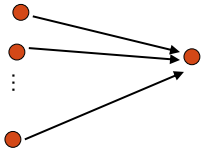
Neural networks



A given neuron has many, many connecting, input neurons

If a neuron is stimulated enough, then it also fires

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

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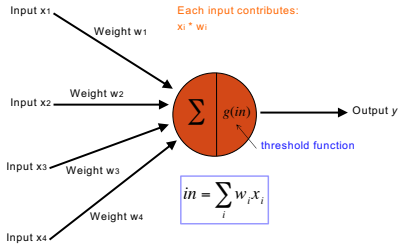
A Single Neuron/Perceptron



45

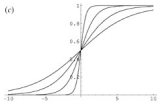
Possible threshold functions

hard threshold

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

sigmoid

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



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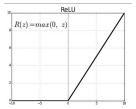
Many other activation functions

Rectified Linear Unit



Softmax (for probabilities)

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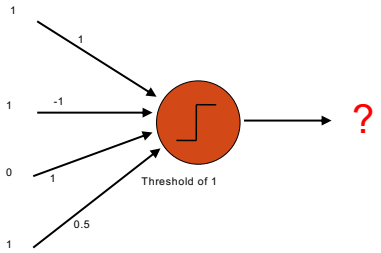
A Single Neuron/Perceptron



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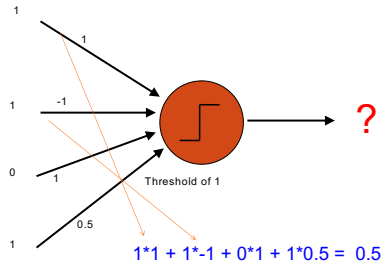
A Single Neuron/Perceptron



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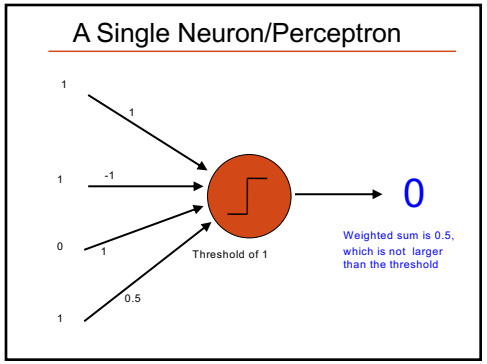
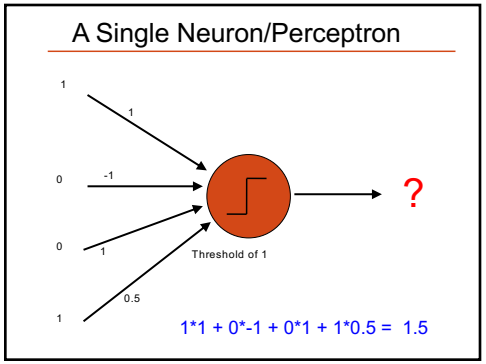
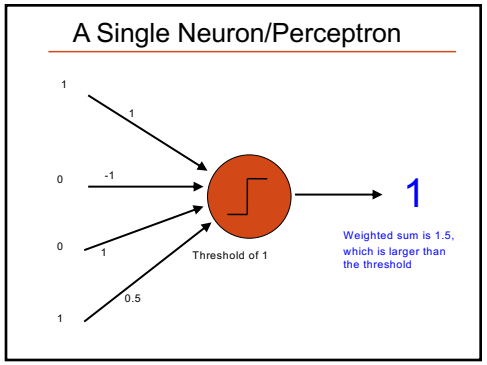

A Single Neuron/Perceptron
1
1
1
-1
0
1
1
0.5
Threshold of 1
0
Weighted sum is 0.5, which is not larger than the threshold

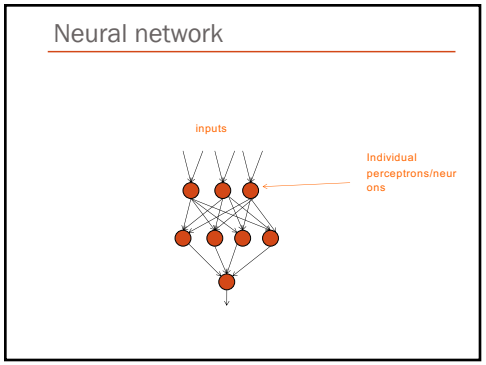
50


A Single Neuron/Perceptron
1
1
0
-1
0
1
1
0.5
Threshold of 1
?
1*1 + 0*-1 + 0*1 + 1*0.5 = 1.5

51


A Single Neuron/Perceptron
1
1
0
-1
0
1
1
0.5
Threshold of 1
1
Weighted sum is 1.5, which is larger than the threshold

52


Neural network
inputs
Individual perceptrons/neurons

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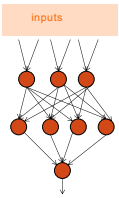
Neural network



some inputs are provided/entered

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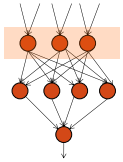
Neural network



each perceptron computes and calculates an answer

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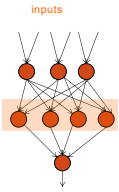
Neural network



those answers become inputs for the next level

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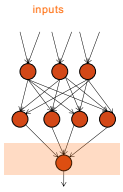
Neural network



finally get the answer after all levels compute

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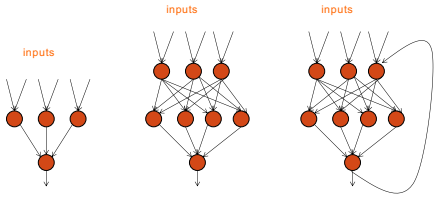
Neural network

Different kinds/characteristics of networks



How are these different?

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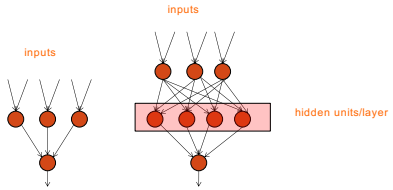
Neural network



Feed forward networks

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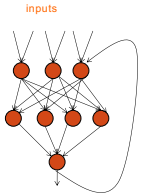
Neural network



Recurrent network

Output is fed back to input

Can support memory!

How?

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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

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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

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Examples - boolean 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

63

AND

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

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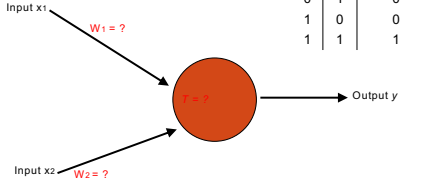
AND

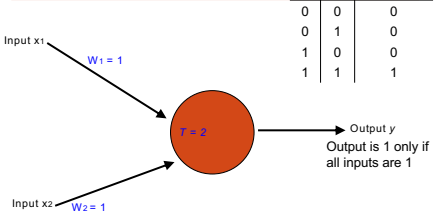
x_1	x_2	x_1 **and** x_2
0	0	0
0	1	0
1	0	0
1	1	1



65

AND

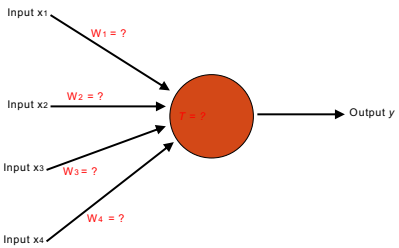
x_1	x_2	x_1 **and** x_2
0	0	0
0	1	0
1	0	0
1	1	1



Inputs are either 0 or 1

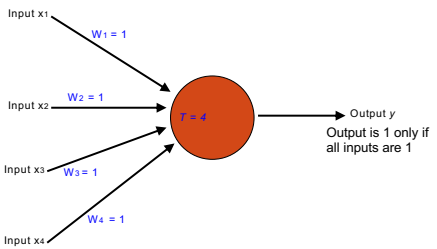
66

AND



67

AND



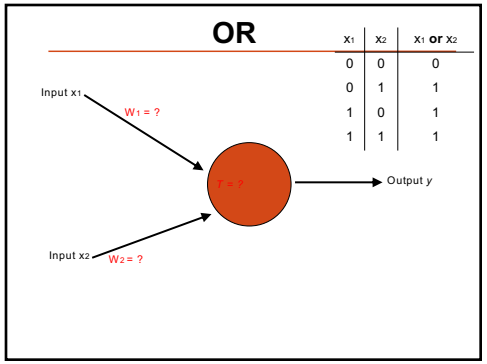
Inputs are either 0 or 1

68

OR

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

69


OR
x1 x2 x1 or x2
0 0 0
0 1 1
1 0 1
1 1 1
Input x1
W1 = ?
T = ?
Output y
Input x2
W2 = ?

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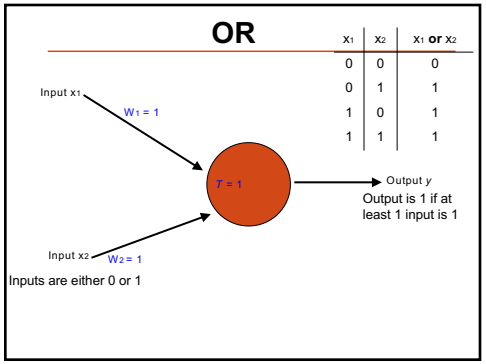
OR
x1 x2 x1 or x2
0 0 0
0 1 1
1 0 1
1 1 1
Input x1
W1 = 1
T = 1
Output y
Output is 1 if at least 1 input is 1
Input x2
W2 = 1
Inputs are either 0 or 1

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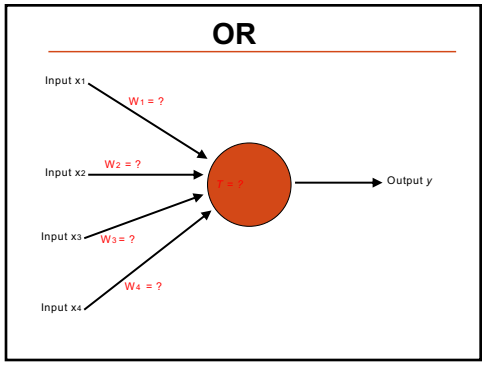
OR
Input x1
W1 = ?
Input x2
W2 = ?
T = ?
Output y
Input x3
W3 = ?
Input x4
W4 = ?

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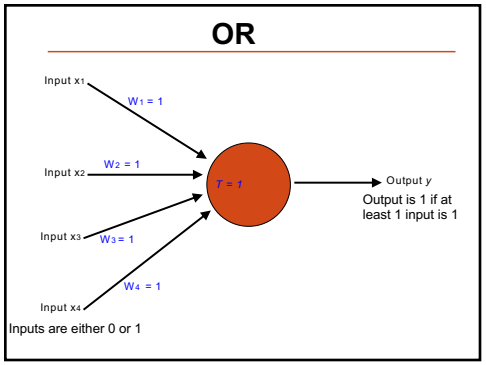
OR
Input x1
W1 = 1
Input x2
W2 = 1
T = 1
Output y
Output is 1 if at least 1 input is 1
Input x3
W3 = 1
Input x4
W4 = 1
Inputs are either 0 or 1

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NOT

x_1	**not** x_1
0	1
1	0

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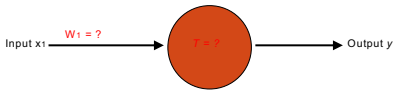
NOT

x_1	**not** x_1
0	1
1	0



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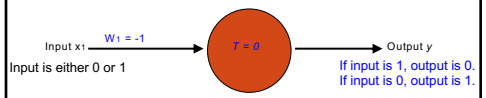
NOT



Input is either 0 or 1

If input is 1, output is 0.
If input is 0, output is 1.

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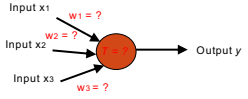
How about...

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



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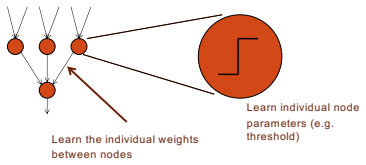
Training neural networks



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