

Introduction to Connectionism

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About neurons and networks

- We know a great deal what a neuron can do and what a brain can do
- But how do many neurons together become a functioning brain?
- How do we go from the structure of the brain to what a brain can do (i.e., behavior?)
- We will try to understand this with the aid of models

model



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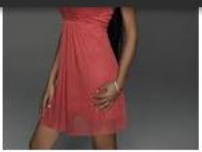
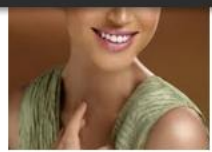
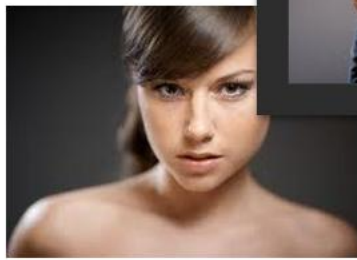
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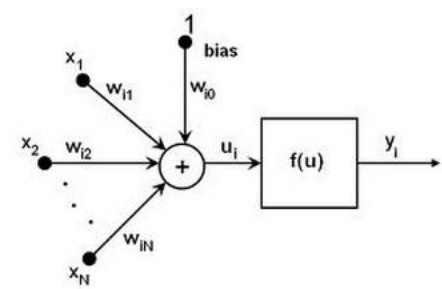
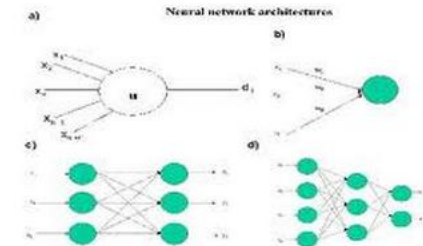
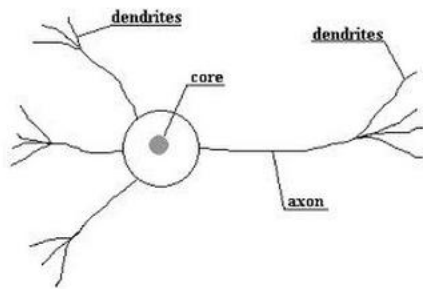
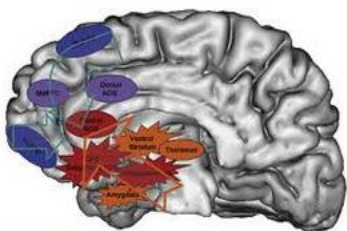
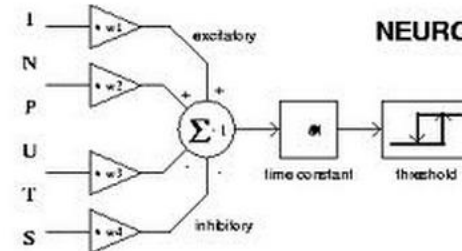
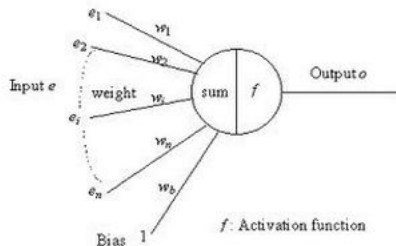
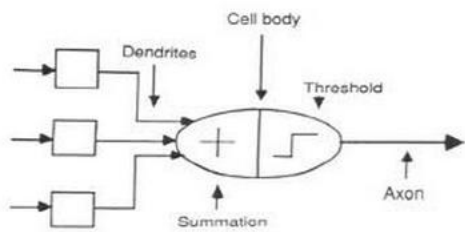
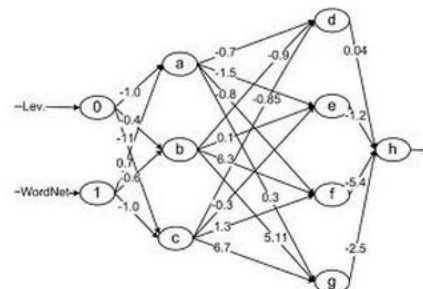
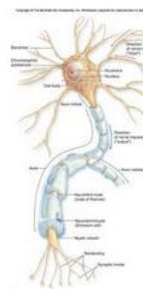
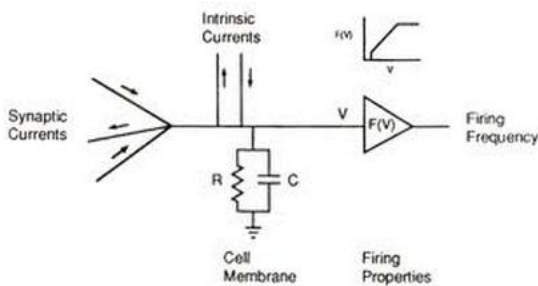
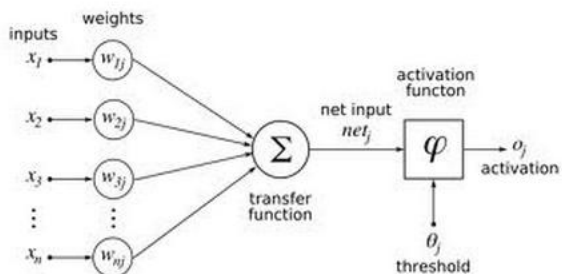


neural model

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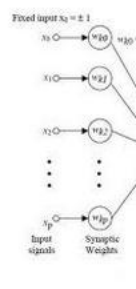
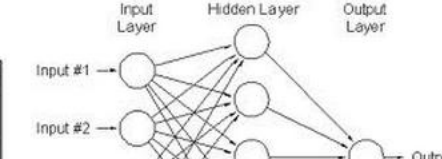
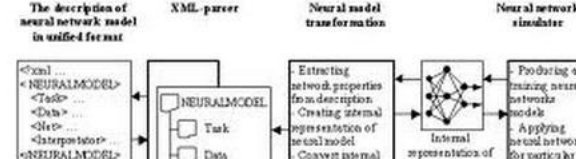
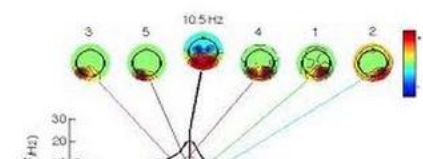
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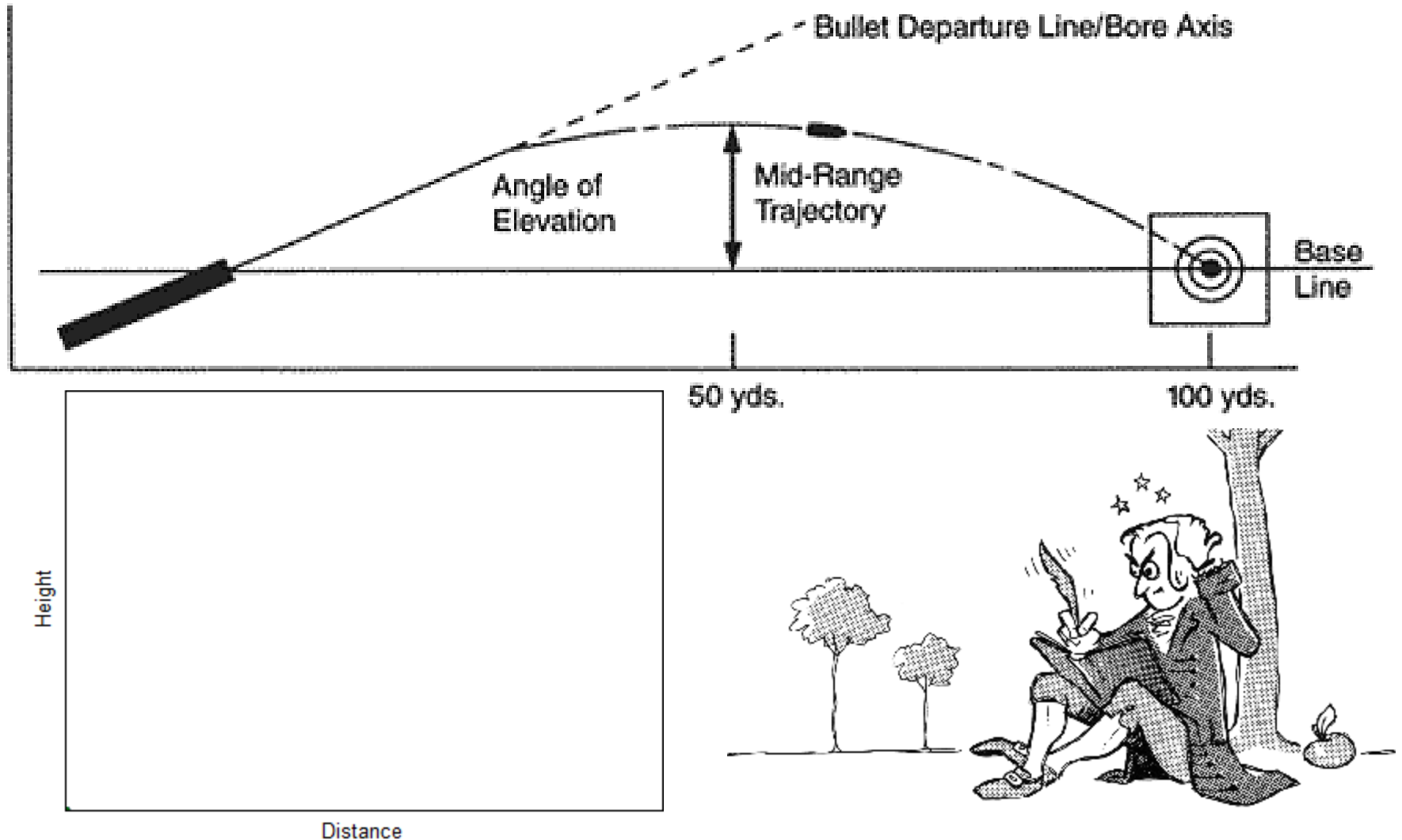


Overriding/Emotion Identification Automatic Emotion Regulation Voluntary Emotion Regulation Regions Implicated in Both Automatic and Voluntary Emotion Regulation

An improved neural network model for PMO forecasting



Model of how a bullet flies



This is an idealization



- A real bullet twists and turns
- There is air resistance
- There is wind and turbulence
- All of these are **ignored**

Models in science

- Modeling is about *ignoring details*
- Strictly speaking: Models are always wrong!
- because models always ignore certain details of reality (typically a lot of details)
- But models are also very helpful
- In science we do not always want details
- We want the essence

An image has a lot of detail but a road map can be much handier



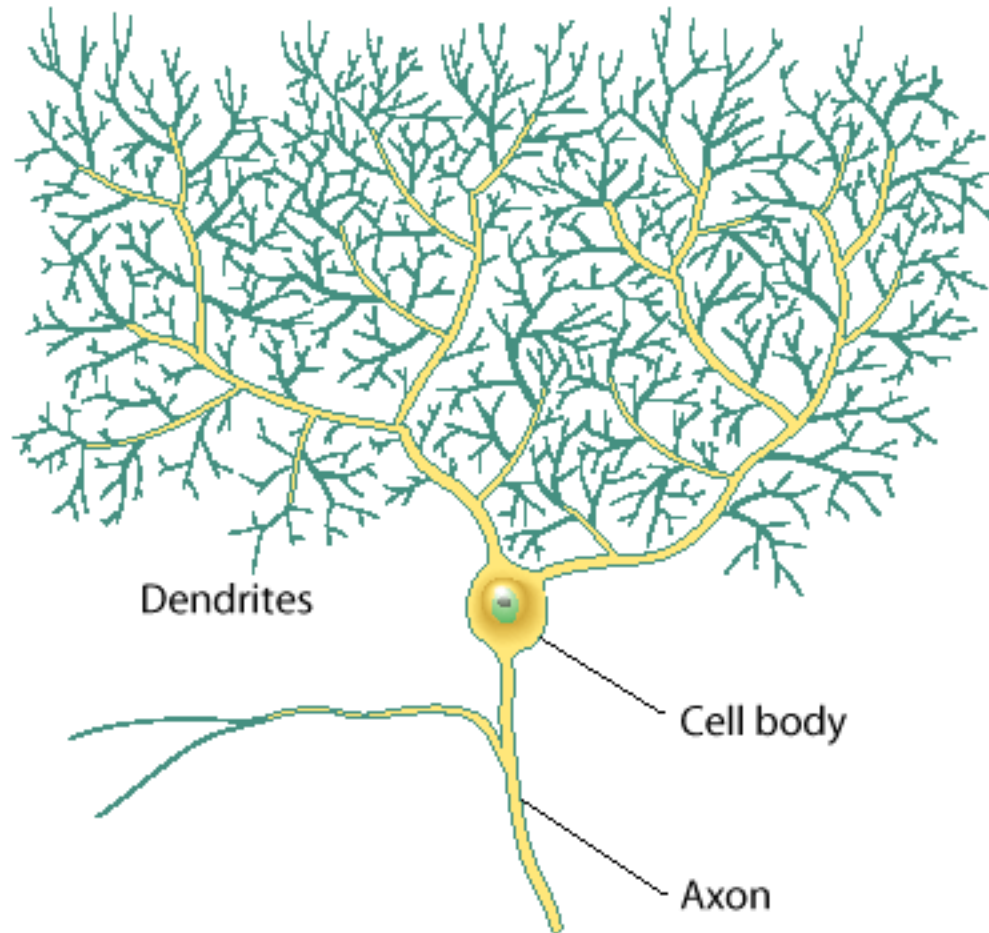
Neural Networks a.k.a. PDP or Parallel Distributed Processing a.k.a. Connectionism

- Based on an *abstract* view of the neuron
- Artificial neurons are connected to form large networks
- The connections determine the function of the network
- Connections can often be formed by learning and do not need to be ‘programmed’

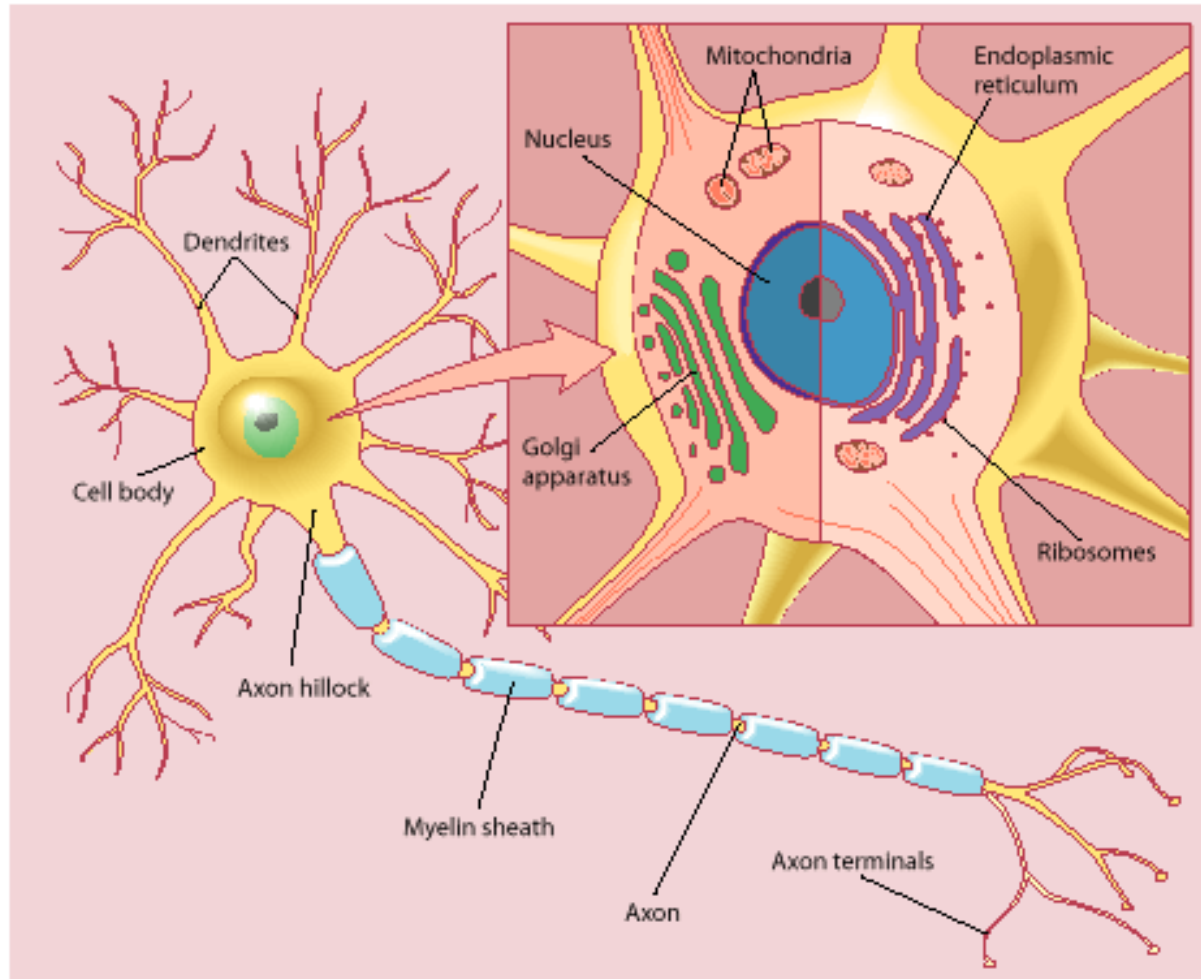
Overview

- Biological and connectionist neurons
 - McCulloch and Pitts
- Hebbian learning
 - The Hebb rule
 - Competitive learning
 - Willshaw networks
- Illustration of key characteristics
 - Pattern completion
 - Graceful degradation

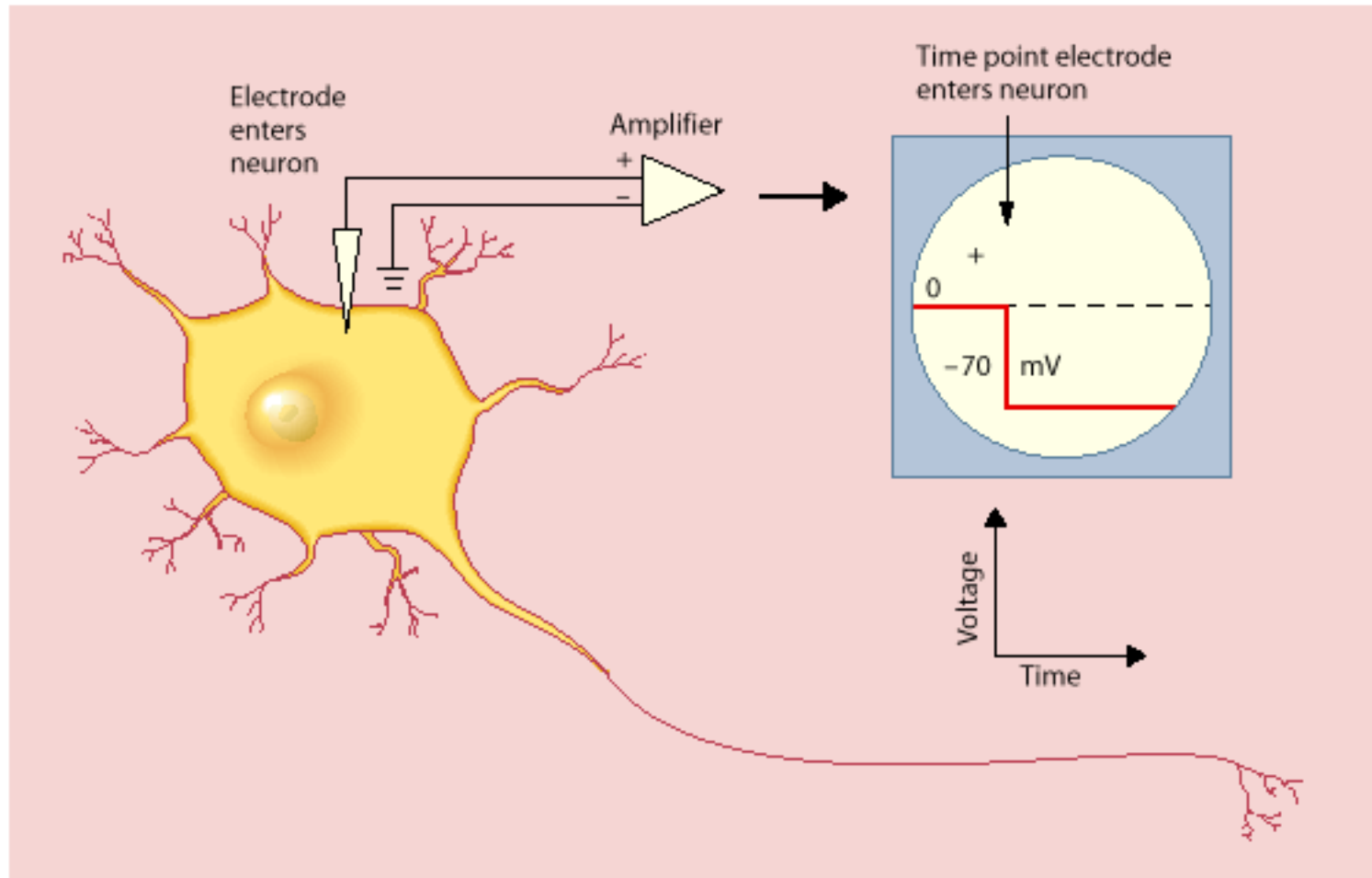
Many neurons have elaborate arborizations



The axon is covered with myelin sheaths for faster conductivity



With single-cell recordings, action potentials (spikes) can be recorded



McCulloch-Pitts (1943) Neuron.

A direct quote:

1. The activity of the neuron is an “all-or-none” process
2. A certain fixed number of synapses must be excited within the period of latent addition in order to excite a neuron at any time, and this number is independent of previous activity and position of the neuron

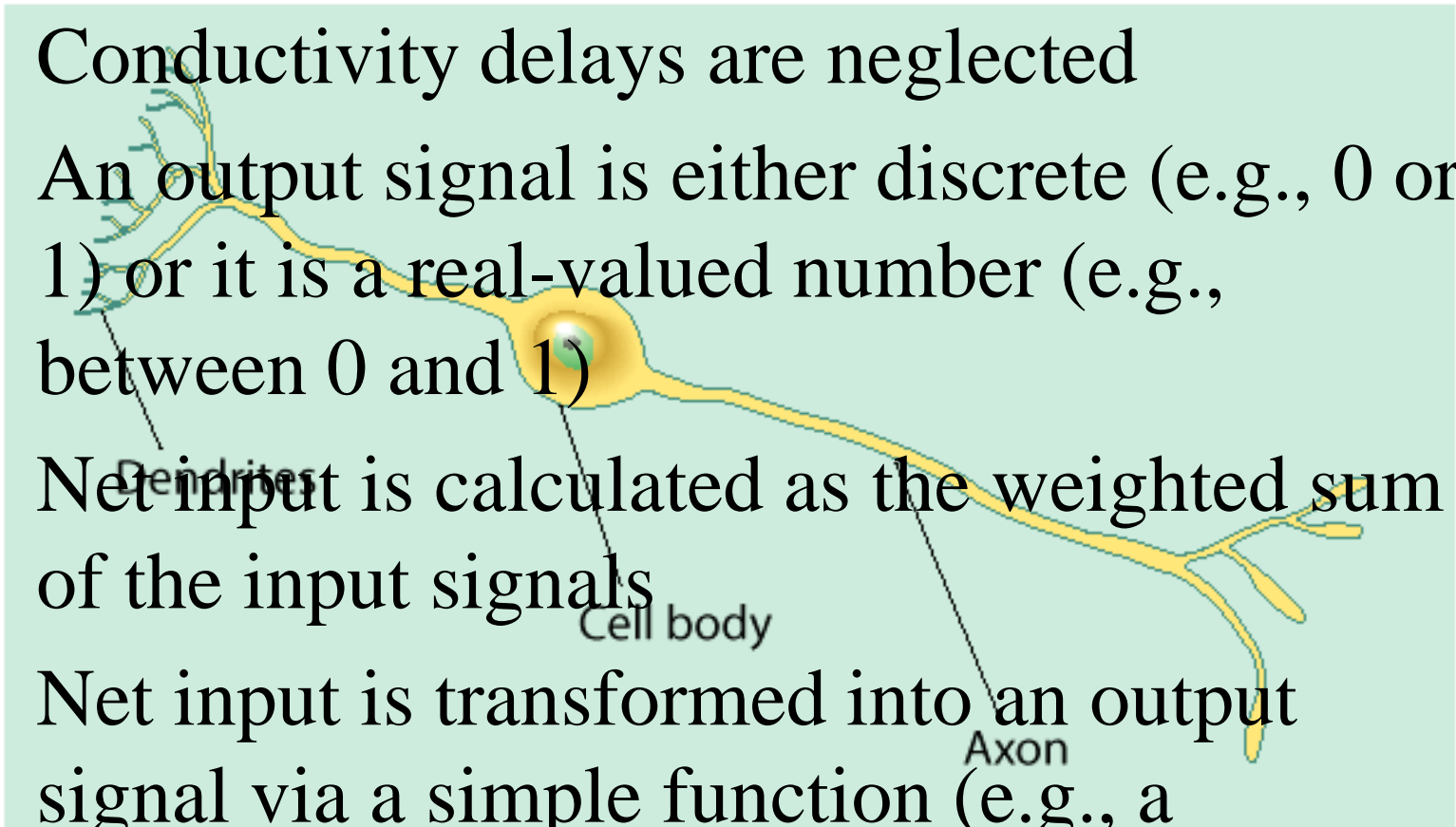
McCulloch-Pitts (1943) Neuron

3. The only significant delay within the nervous system is synaptic delay
4. The activity of any inhibitory synapse absolutely prevents excitation of the neuron at that time
5. The structure of the net does not change with time

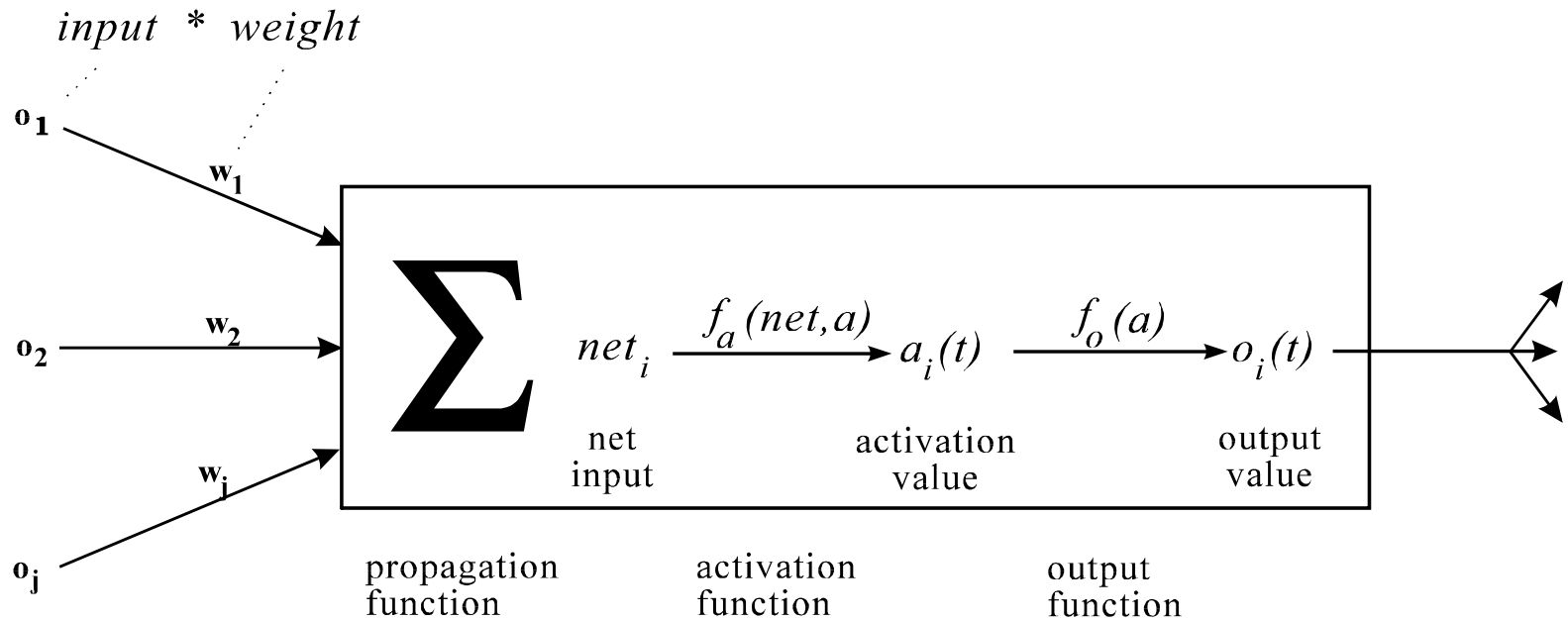
From: A logical calculus of the ideas immanent in nervous activity. *Bulletin of Mathematical Biophysics*, 5, 115-133.

Neural networks abstract from the details of real neurons

- Conductivity delays are neglected
- An output signal is either discrete (e.g., 0 or 1) or it is a real-valued number (e.g., between 0 and 1)
- Net input is calculated as the weighted sum of the input signals
- Net input is transformed into an output signal via a simple function (e.g., a threshold function)



Artificial 'neuron'



How to ‘program’ neural networks?

- The learning problem
- Selfridge (1958): evolutionary or ‘shake-and-check’ (hill climbing)
- Other approaches
 - Unsupervised or regularity detection
 - Supervised learning
 - Reinforcement learning has ‘some’ supervision

Neural networks and David Marr's model (1969)

- Marr's ideas are based on the learning rule by Donald Hebb (1949)
- Hebb-Marr networks can be auto-associative or hetero-associative
- The work by Marr and Hebb has been extremely influential in neural network theory

Hebb (1949)

“When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A’s efficiency, as one of the cells firing B, is increased”

From: The organization of behavior.

Hebb (1949)

Also introduces the word *connectionism* in its current meaning

“The theory is evidently a form of **connectionism**, one of the switchboard variety, though it does not deal in direct connections between afferent and efferent pathways: not an ‘S-R’ psychology, if R means a muscular response. The connections serve rather to establish autonomous central activities, which then are the basis of further learning” (p.xix)

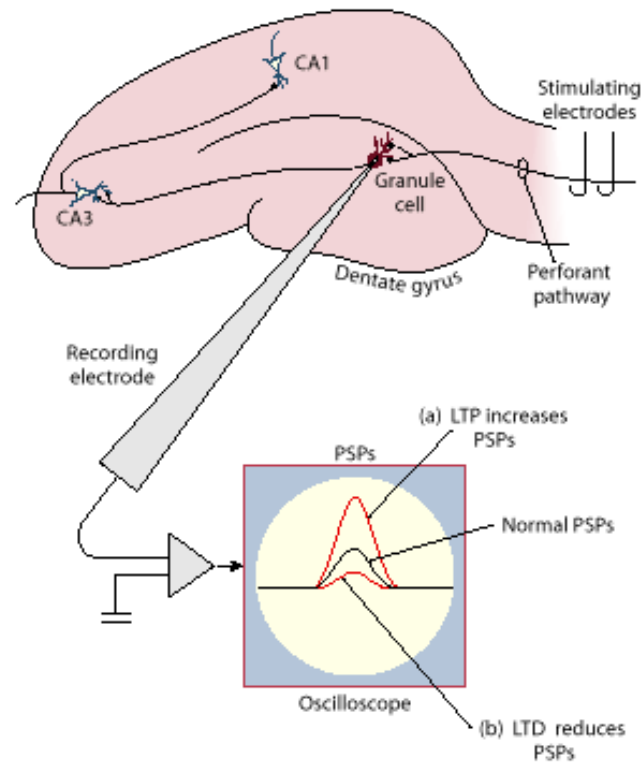
Hebb-rule sound-bite:

Neurons that fire together,
wire together

William James (1890)

- Let us assume as the basis of all our subsequent reasoning this law:
- *When two elementary brain-processes have been active together or in immediate succession, one of them, on re-occurring, tends to propagate its excitement into the other.*
- *From: Psychology (Briefer Course).*

The Hebb rule is found with long term potentiation (LTP) in the hippocampus

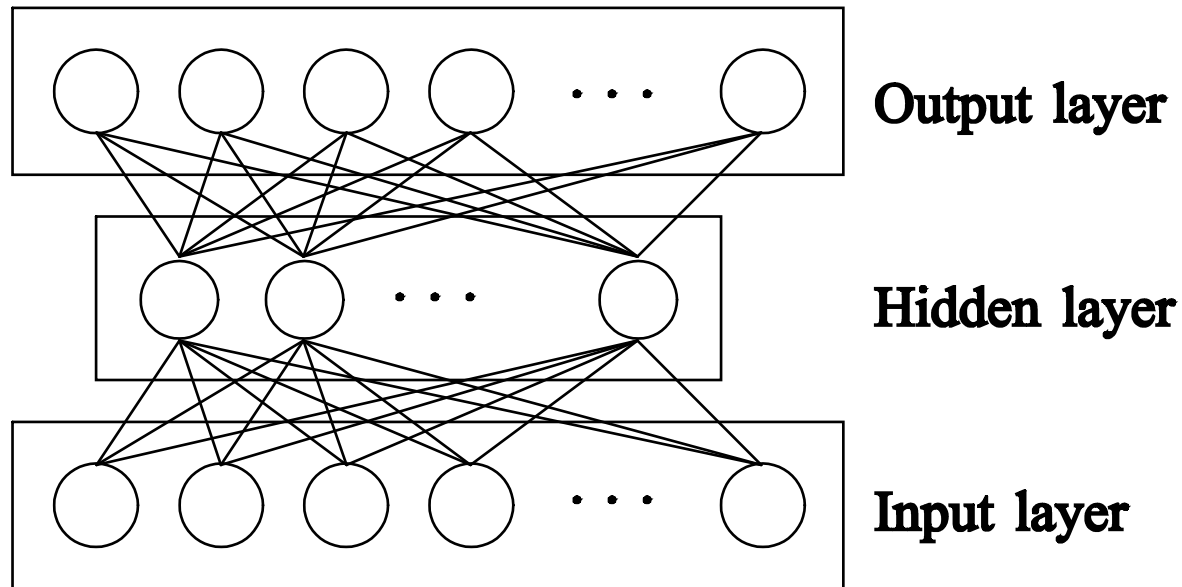


With Hebbian learning, two learning methods are possible

- With *unsupervised learning* there is no teacher: the network tries to discern regularities in the input patterns
- With *supervised learning* an input is associated with an output
 - If the input and output are the same, we speak of *auto-associative* learning
 - If they are different it is called *hetero-associative* learning

Another type of network is based on error-correcting learning

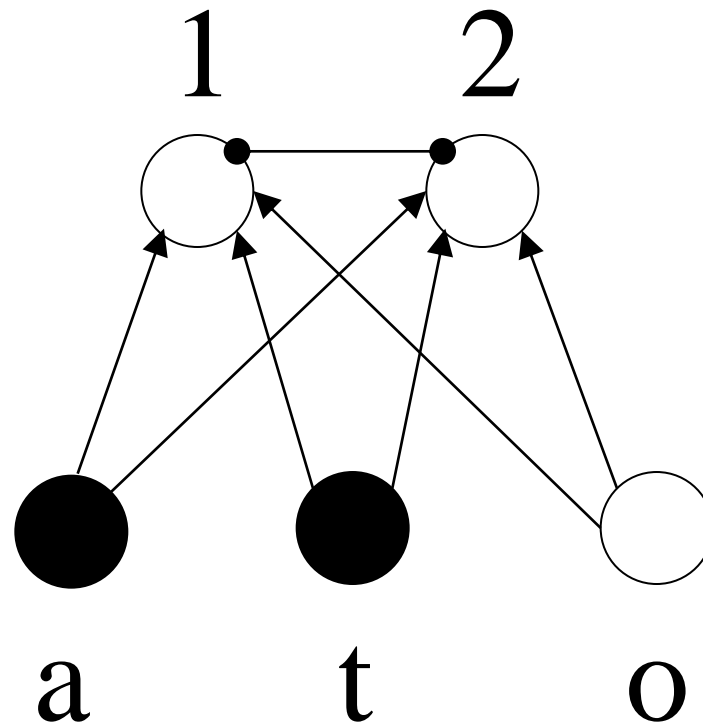
The most popular algorithm is called backpropagation



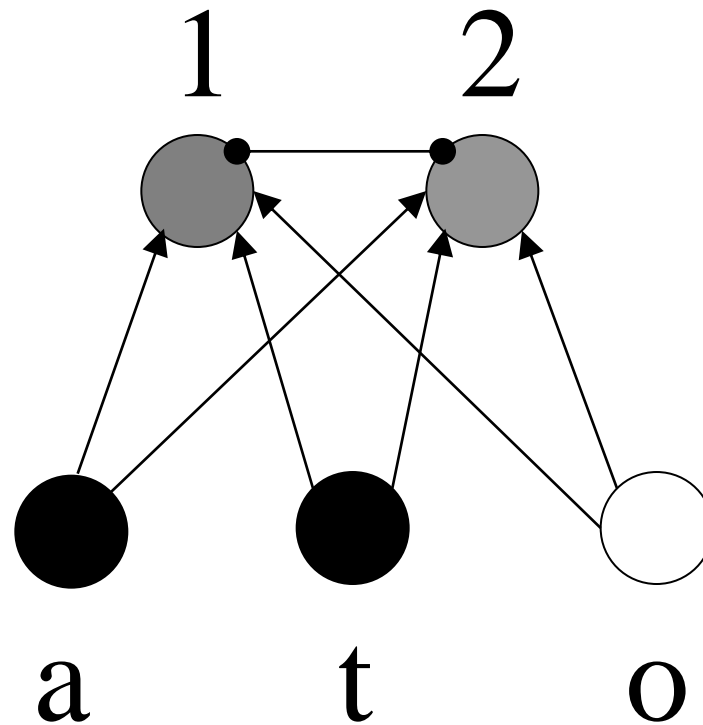
We will look at an example of each type of Hebbian learning

- *Competitive learning* is a form of unsupervised learning
- Hetero-associative learning in *Willshaw networks* is an example of supervised learning

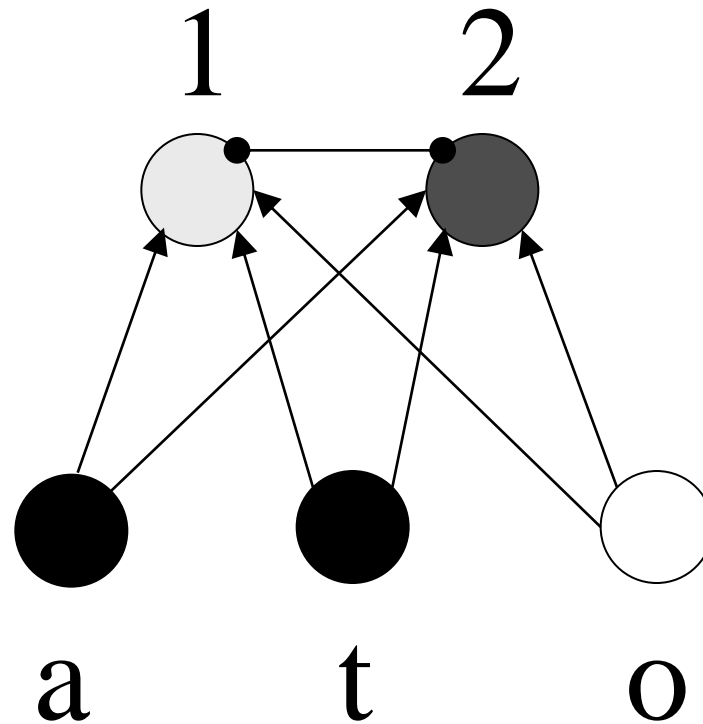
Example of competitive learning:
Stimulus 'at' is presented



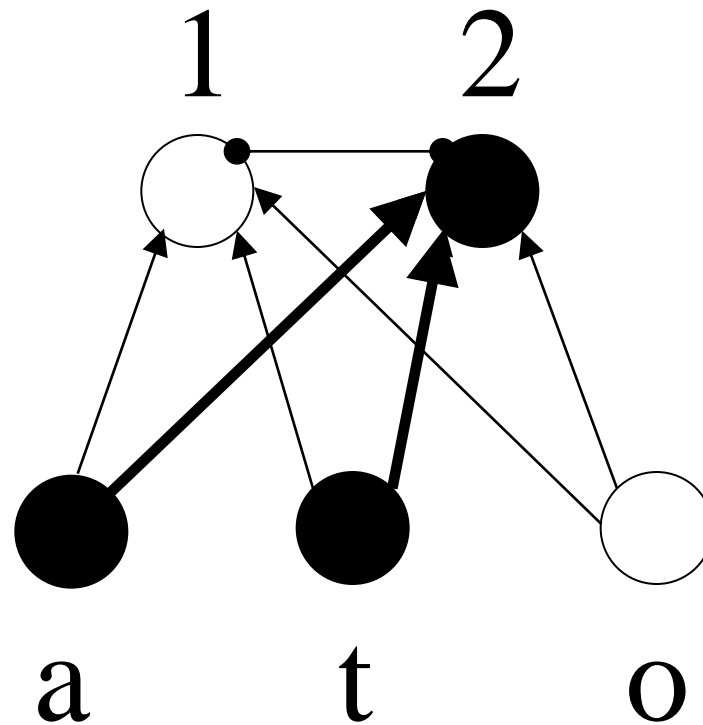
Example of competitive learning:
Competition starts at category level



Example of competitive learning: Competition resolves

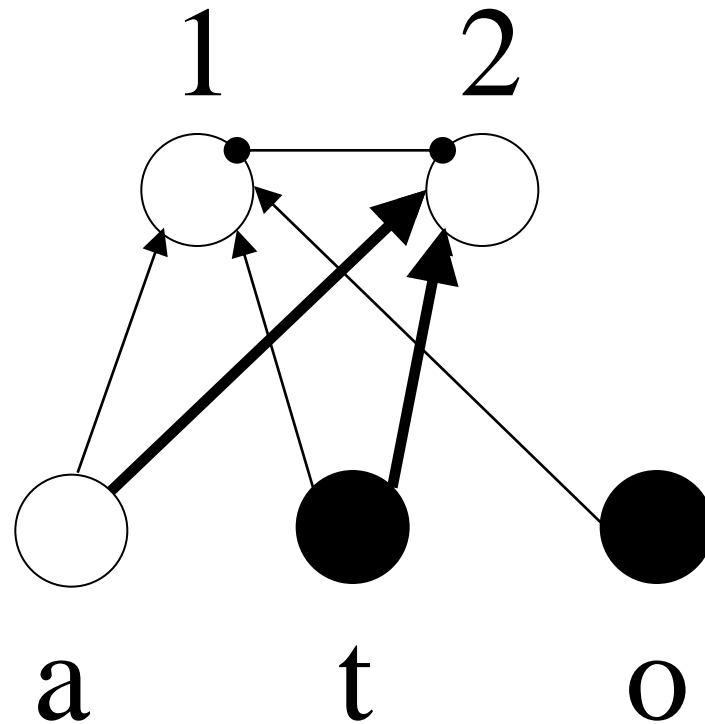


Example of competitive learning: Hebbian learning takes place

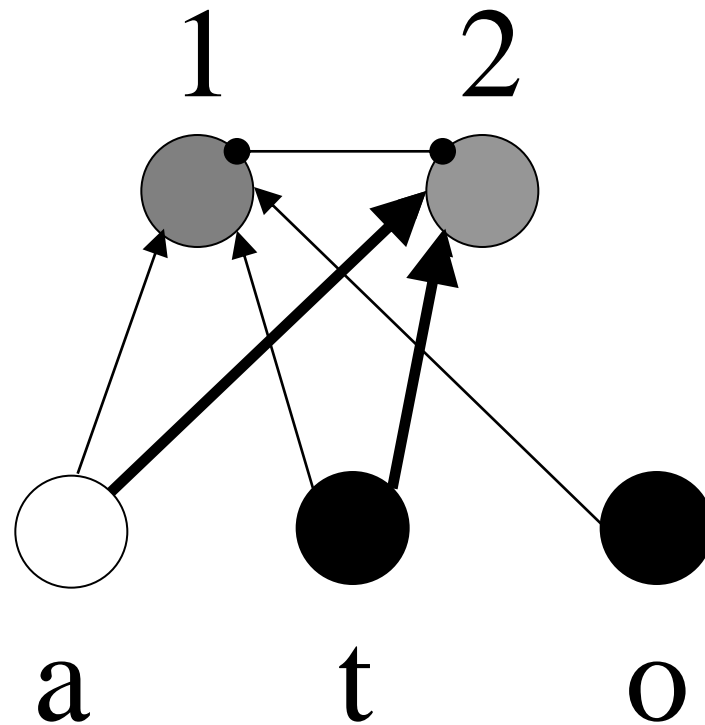


Category node 2 now represents 'at'

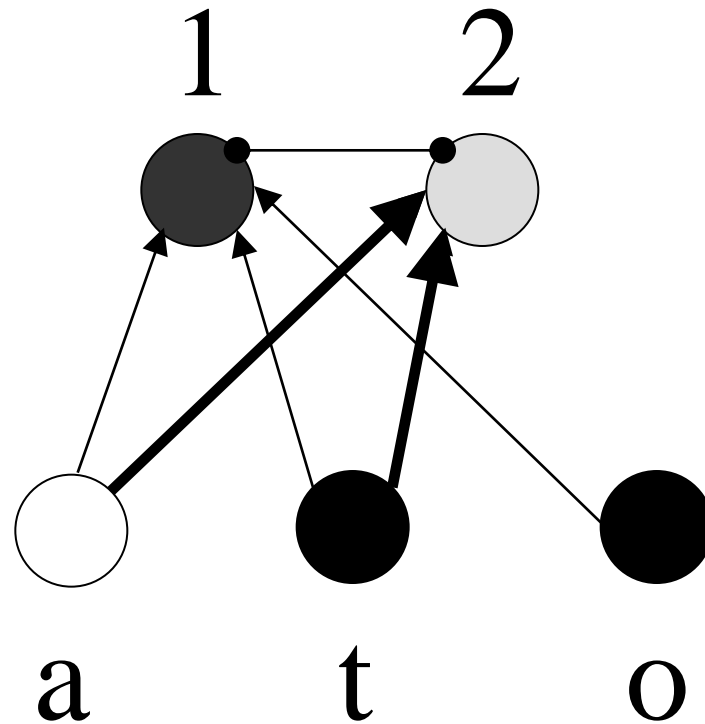
Presenting 'to' leads to activation of category node 1



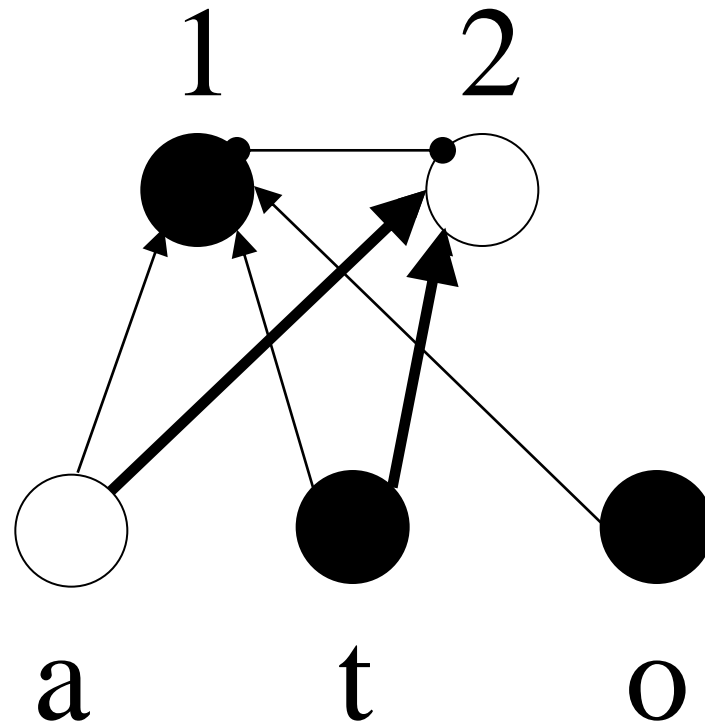
Presenting 'to' leads to activation of category node 1



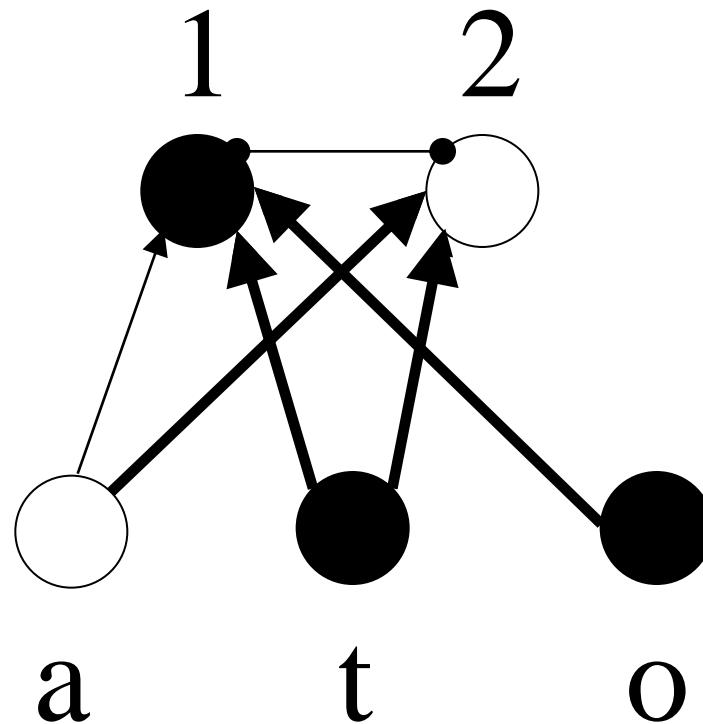
Presenting 'to' leads to activation of category node 1



Presenting 'to' leads to activation of category node 1



Category 1 is established through
Hebbian learning as well



Category node 1 now represents 'to'

Willshaw networks

- A weight either has the value 0 or 1
- A weight is set to 1 if input and output are 1
- At retrieval the net input is divided by the total number of active nodes in the input pattern

Example of a simple heteroassociative memory of the Willshaw type

			1	0	0	1	1	0	
			0	0	1	0	1	1	
			1	1	0	1	0	0	
0	1	0				1		1	1
0	0	0							
1	1	0	1			1	1	1	1
0	0	1	1	1			1		
1	1	1	1	1	1	1	1	1	1
1	0	1	1	1			1	1	

Example of pattern retrieval

(1 0 0 1 1 0)

0
0
1
0
1
1

			1		1	1
	1		1	1	1	1
		1	1		1	
	1	1	1	1	1	1
	1	1		1	1	

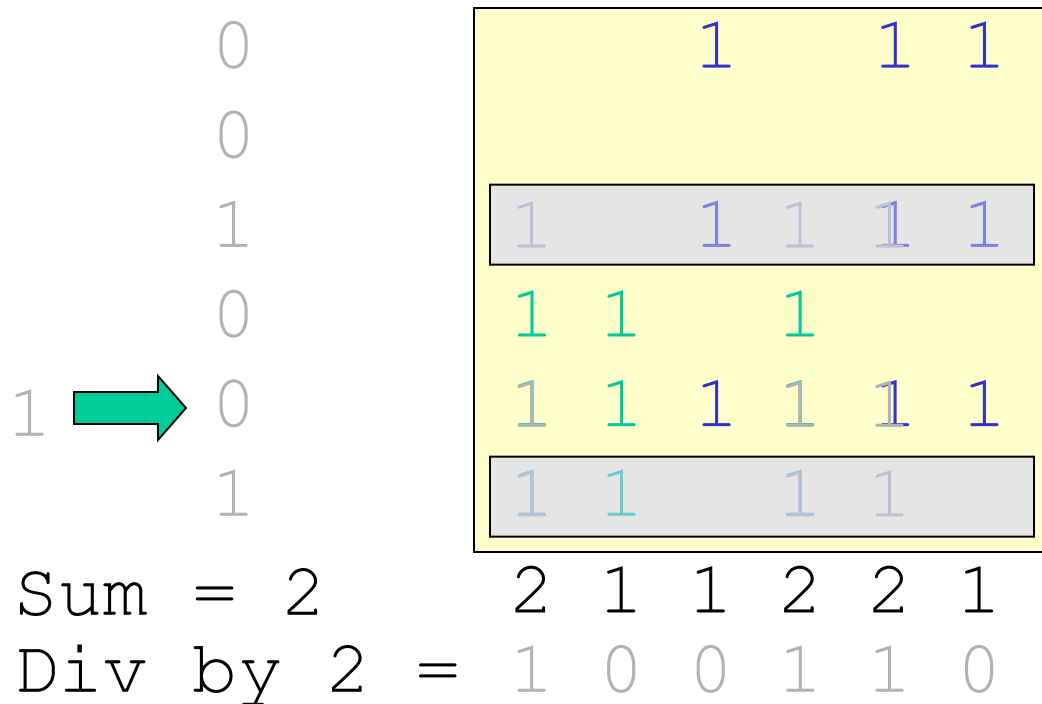
Sum = 3

Div by 3 =

3 2 2 3 3 2
1 0 0 1 1 0

Example of successful pattern completion using a subpattern

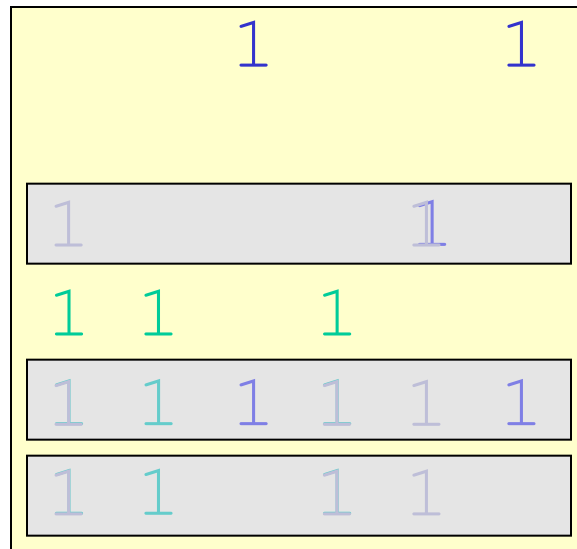
(1 0 0 1 1 0)



Example graceful degradation: small lesions have small effects

(1 0 0 1 1 0)

0
0
1
0
1
1



Sum = 3

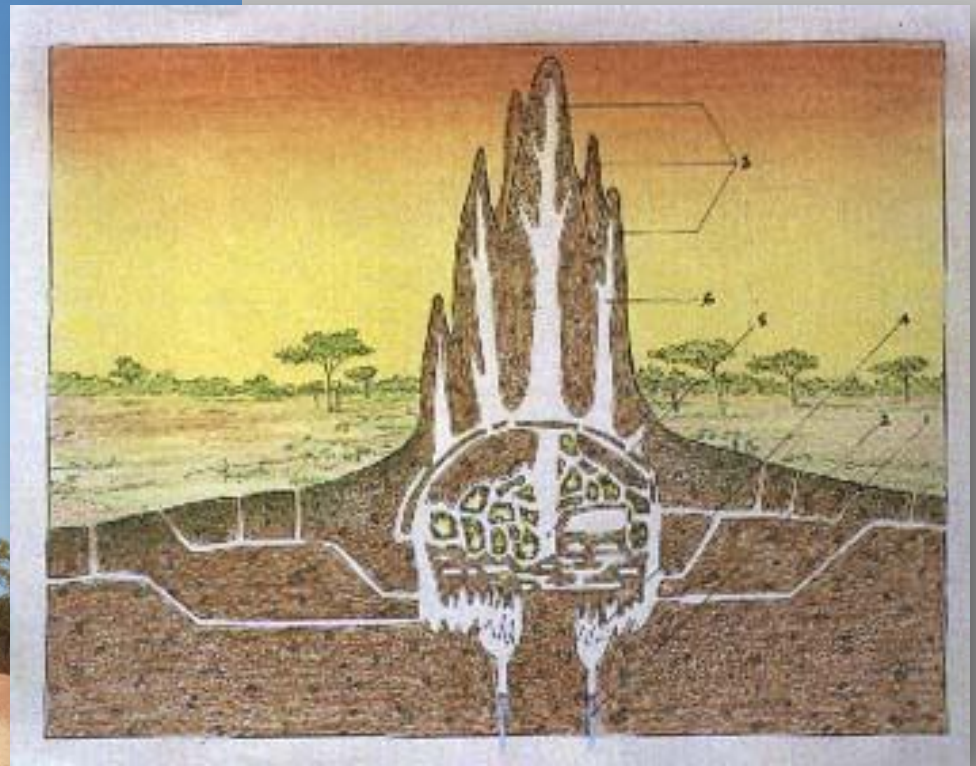
Div by 3 =

3 2 1 2 3 1
1 0 0 0 1 0

The connections determine the
function of the network

Modeling recognition of simple patterns: The
structure of the network determines *what it
can recognize*

Massive parallelism leads to completely new, 'emergent' phenomena



**Birds follow simple rules, yet
end up flying in synchrony**



**Birds follow simple rules, yet
end up flying in synchrony**



Summing up

- Neural networks can learn input-output associations
- They are able to retrieve an output on the basis of incomplete input cues
- They show graceful degradation
- Eventually the network will become overloaded with too many patterns
- New behavior *emerges* from the interplay of many neurons in a network