



NEURAL NETWORKS AND DISTRIBUTED INFORMATION PROCESSING



MOTIVATION: HOW INFORMATION IS PROCESSED IN THE BRAIN?

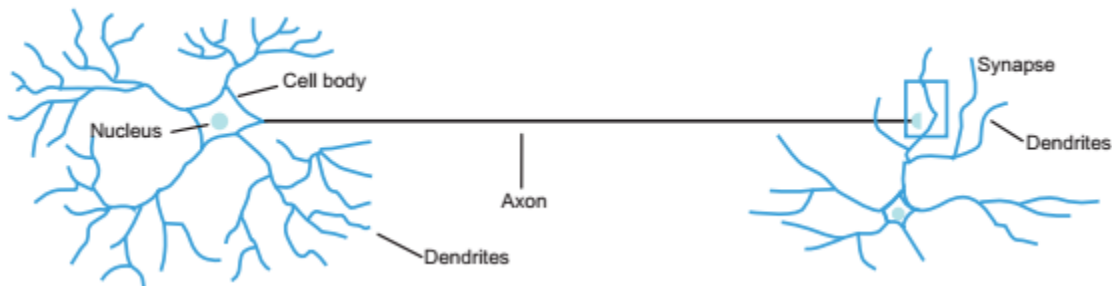
1. Single unit recording: too fine grained approach
2. PET, fMRI: too coarse grained approach
 - Identification of activated brain region for a certain task cannot tell us about how information is processed

MOTIVATION: HOW INFORMATION IS PROCESSED IN THE BRAIN?

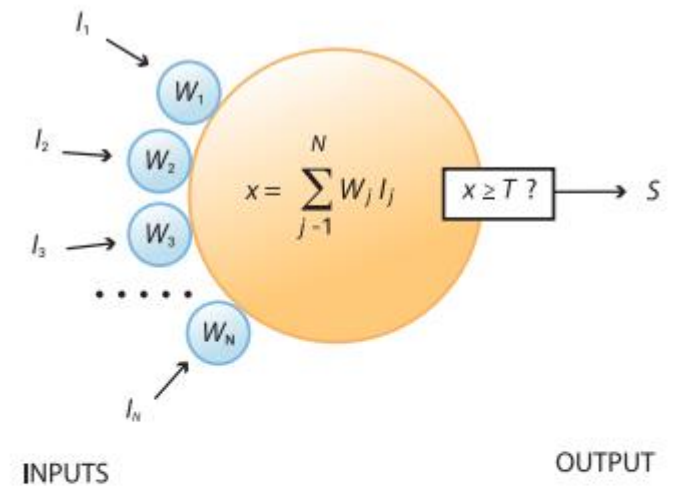
1. Fundamental feature of the brain is its *connectivity* and the crucial question in understanding the brain is how distributed patterns of activation across populations of neurons can give rise to perception, memory, sensori-motor control, and high-level cognition.
2. Indirect way of studying populations of neurons: neural network model
 - Modeling biological neurons and populations of neurons

NEURONS AND ARTIFICIAL NEURONS

Neurons



Artificial neurons

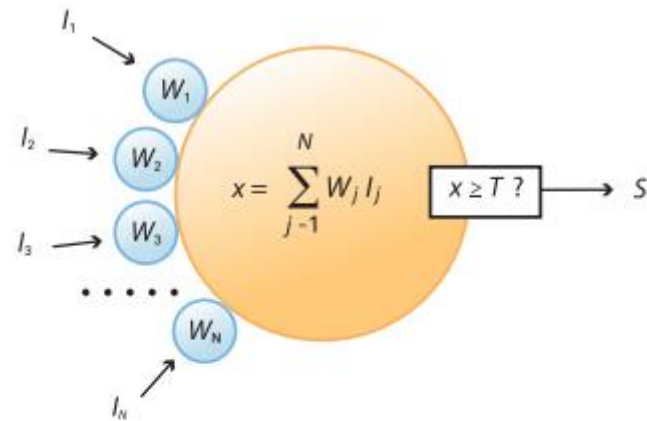


A typical neuron receives inputs from 10000 neurons

- I_j Input _{j}
- W_j The weight attached to input _{j}
- T The threshold of the neuron
- x The total input to the neuron
- S The output signal

NEURONS AND ARTIFICIAL NEURONS

Artificial neurons



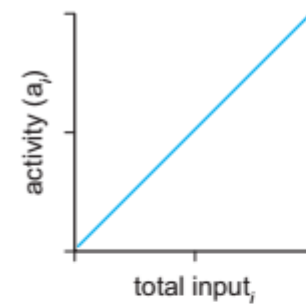
INPUTS

OUTPUT

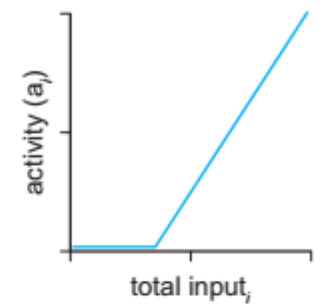
- I_j Input_j
- W_j The weight attached to input_j
- T The threshold of the neuron
- x The total input to the neuron
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Activation functions

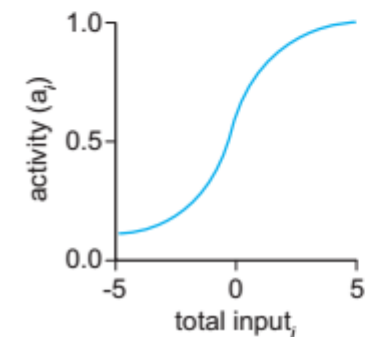
(a) Linear



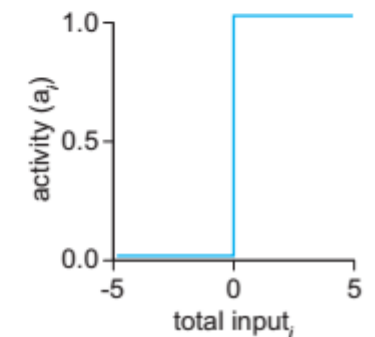
(b) Threshold linear



(c) Sigmoid



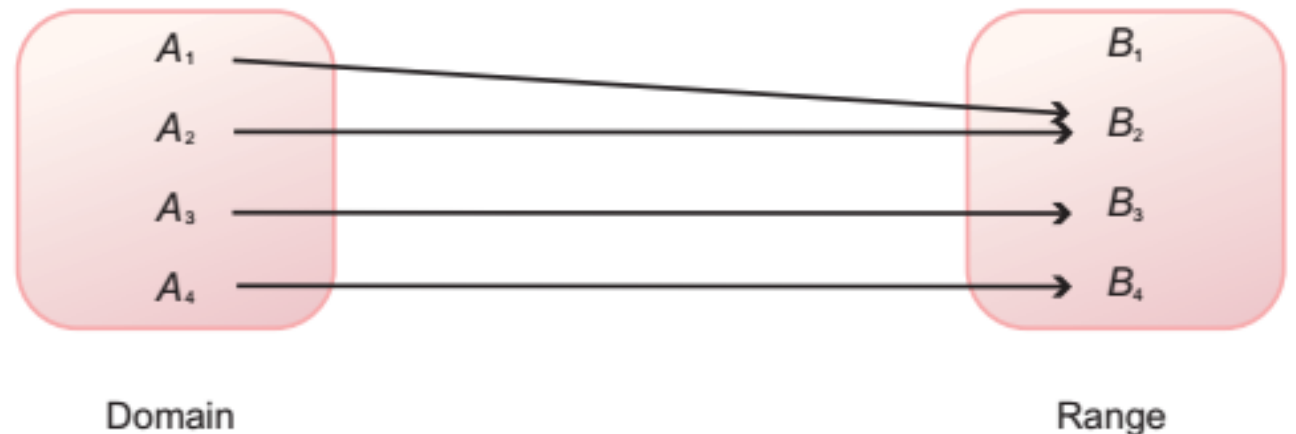
(d) Binary threshold



SINGLE-LAYER NETWORKS AND BOOLEAN FUNCTIONS

1. Mapping functions: Addition is a function, multiplication is a function, but taking square root is not a function (why?)
2. Domain, Range: A mapping function maps each item from the domain onto exactly one item from the range

- Functions are single-valued



BINARY BOOLEAN FUNCTION: AND GATE

Truth table for binary Boolean function

| DOMAIN | RANGE |
|--------------|-------|
| FALSE, FALSE | |
| FALSE, TRUE | FALSE |
| TRUE, FALSE | TRUE |
| TRUE, TRUE | |

Truth table for the Boolean function AND

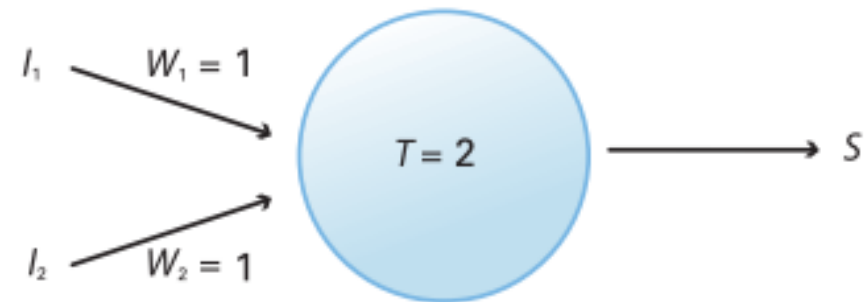
| A | B | A AND B |
|-------|-------|---------|
| FALSE | FALSE | FALSE |
| FALSE | TRUE | FALSE |
| TRUE | FALSE | FALSE |
| TRUE | TRUE | TRUE |

BINARY BOOLEAN FUNCTION: AND GATE

Truth table for the Boolean function AND

| A | B | A AND B |
|-------|-------|---------|
| FALSE | FALSE | FALSE |
| FALSE | TRUE | FALSE |
| TRUE | FALSE | FALSE |
| TRUE | TRUE | TRUE |

Single-layer network representing AND

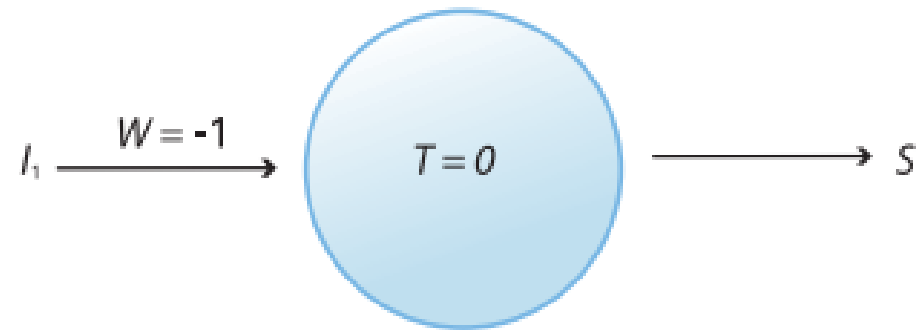


BINARY BOOLEAN FUNCTION: OR GATE

Truth table for the Boolean function OR

Single-layer network representing OR

UNARY FUNCTION: NOT GATE



LEARNING IN SINGLE-LAYER NETWORKS: THE PERCEPTRON CONVERGENCE RULE

- The key to getting single unit to represent Boolean functions such as NOT and OR lies in setting the weights and the threshold.
- How do the weights get set? How does the threshold get set?

HEBBIAN LEARNING (HEBBIAN SYNAPSE)

- “The Organization of Behavior” (1949, Donald Hebb)
- Fire together, wire together – Hebbian learning (unsupervised learning)
- Frank Rosenblatt: Modification of Hebbian learning rule
 - Perceptron!!!
 - Supervised learning – adjust weight and threshold by the error between desired output and actual output of the neural population (perceptron convergence rule)

THE PERCEPTRON CONVERGENCE RULE

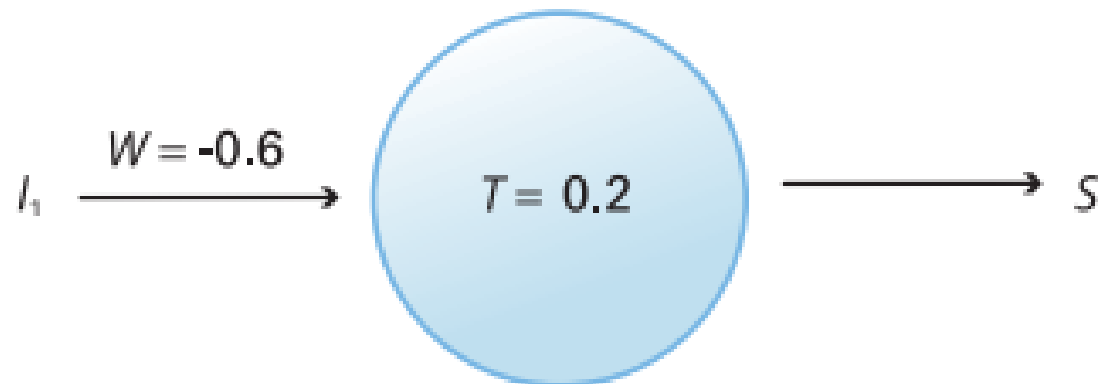
$\delta = \text{Intended output} - \text{Actual output}$

ε : learning rate ($0 < \varepsilon < 1$)

$\Delta T = -\varepsilon \times \delta$ (ΔT : threshold adjustment)

$\Delta W_i = \varepsilon \times \delta \times I_i$ (ΔW_i : weight adjustment for input i)

NOT gate



THE PERCEPTRON CONVERGENCE RULE

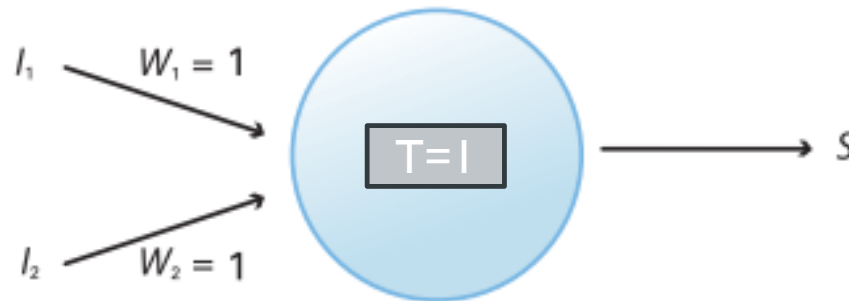
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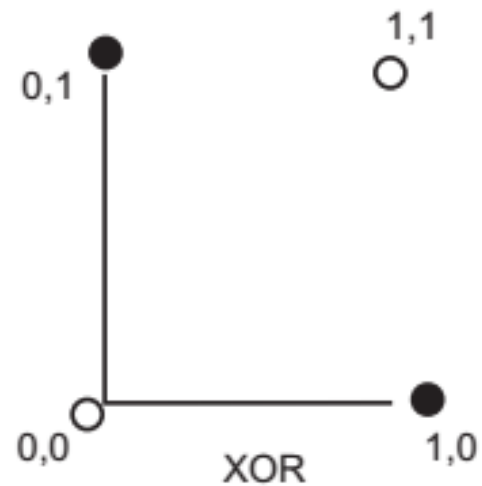
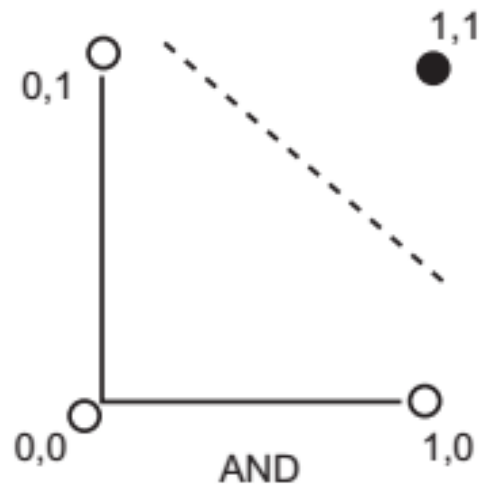
$\Delta W_i = \varepsilon \times \delta \times I_i$ (ΔW_i : weight adjustment for input i)

AND gate



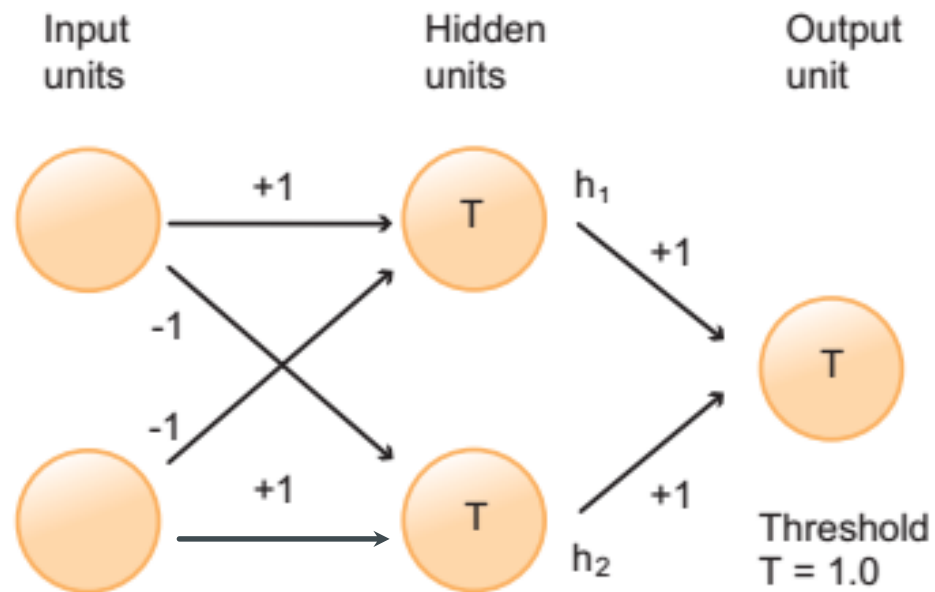
THE LIMITS OF PERCEPTRON CONVERGENCE

- Linear separability : XOR gate



| I_1 | I_2 | OUTPUT |
|-------|-------|--------|
| 0 | 0 | 0 |
| 0 | 1 | 1 |
| 1 | 0 | 1 |
| 1 | 1 | 0 |

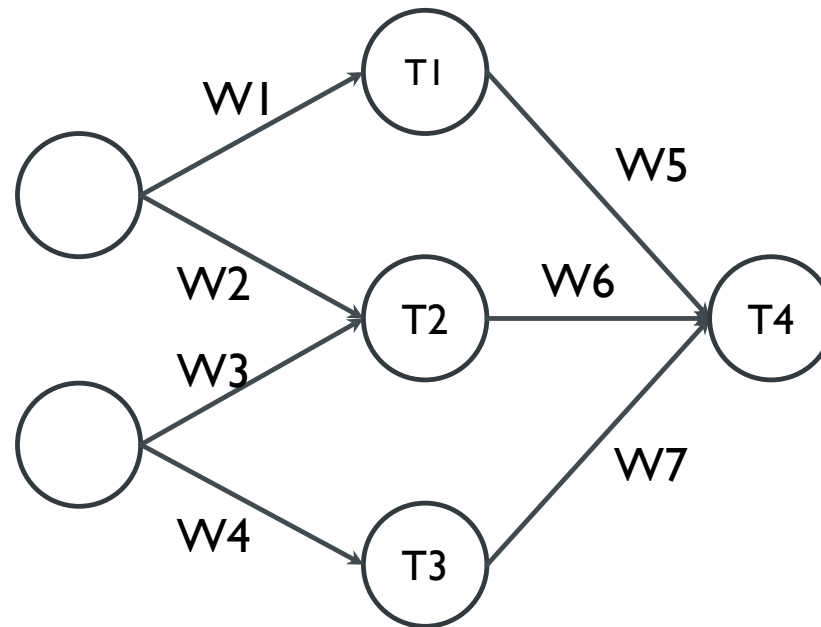
A MULTILAYER NETWORK



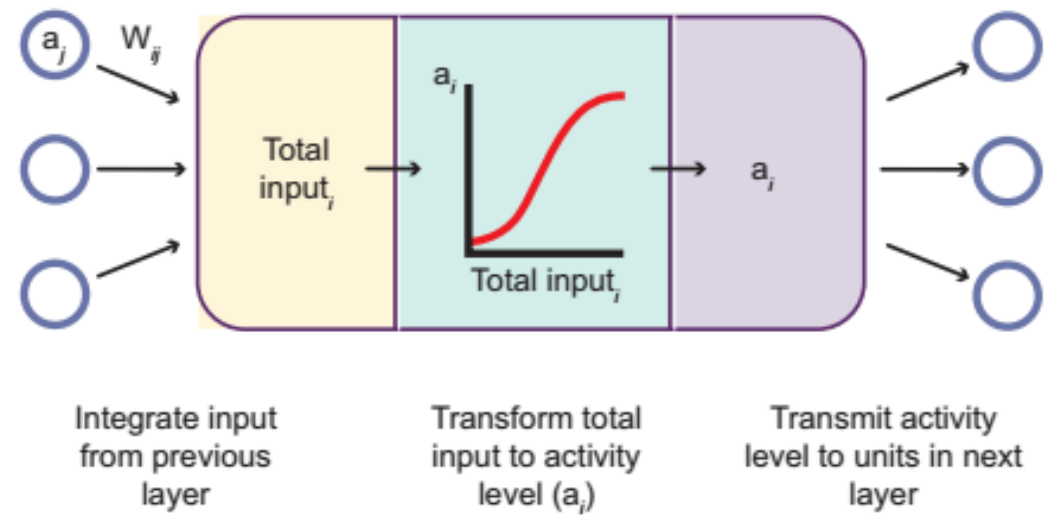
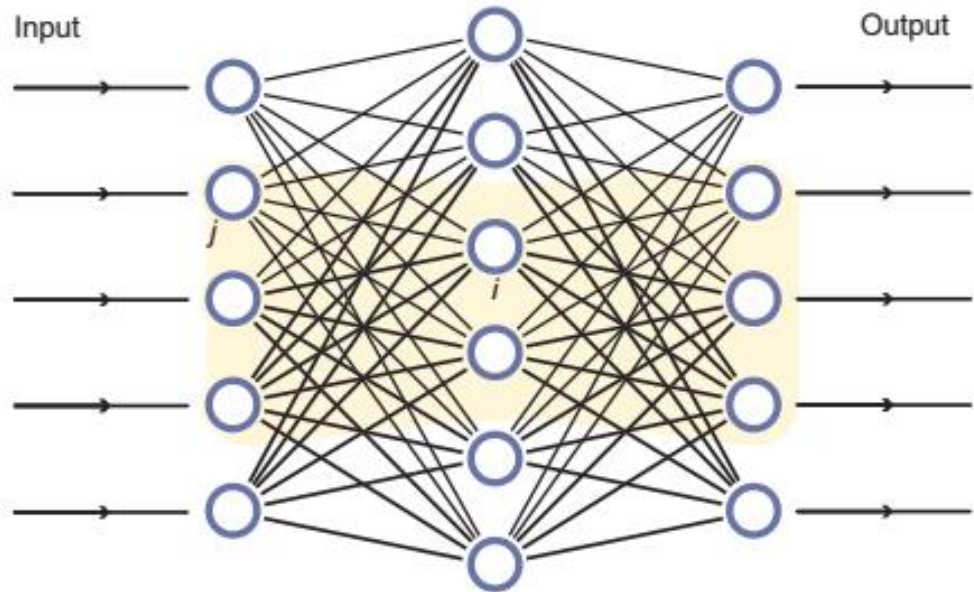
Training rule? What is the required output of the hidden units?

A MULTILAYER NETWORK

Other solution for XOR gate?



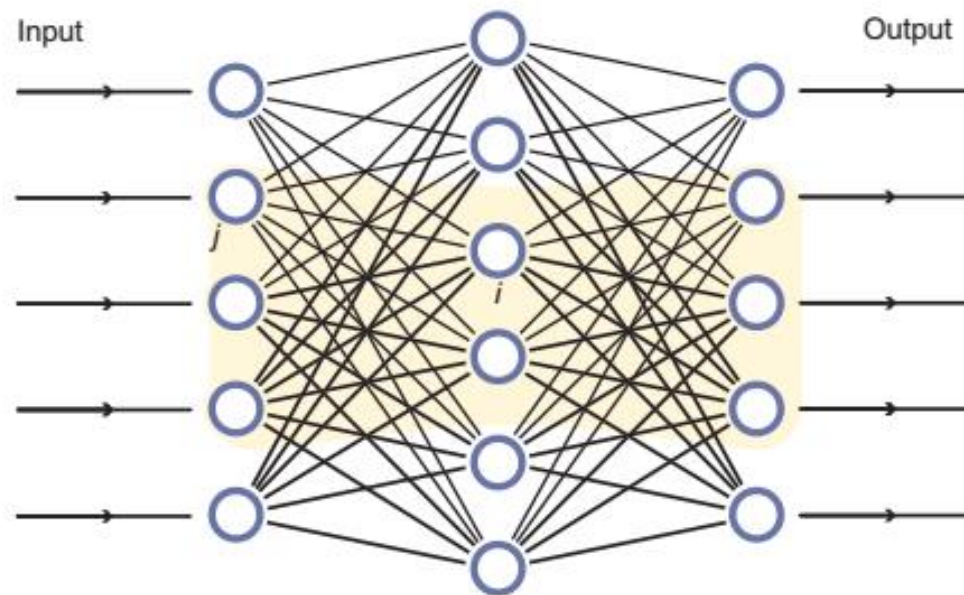
A MULTILAYER NETWORK



$$\text{Total input} = \sum_{j=1}^N w_{ij} a_j$$

A MULTILAYER NETWORK

Training rule? What is the required output of the hidden units?



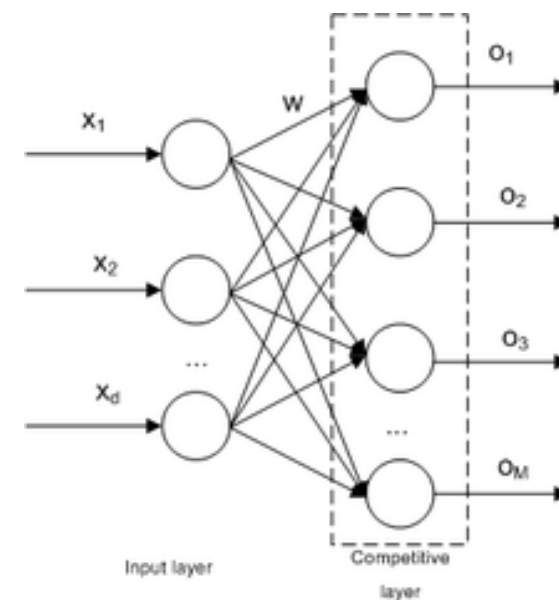
The Backpropagation algorithm

THE BACKPROPAGATION ALGORITHM



HOW BIOLOGICALLY PLAUSIBLE ARE NEURAL NETWORKS?

- A single cortical column: 200000 neurons, vs. complicated artificial neural network: 5000 units
- Random assignments of weights vs. well organized structure
- Backpropagation algorithm is not biologically plausible
- Supervised learning vs. diffuse, relatively unfocused feedback
- Alternative learning algorithm – *local algorithms*
 - *Competitive networks*



INFORMATION PROCESSING IN NEURAL NETWORKS: KEY FEATURES

1. Distributed representations
2. No clear distinction between information storage and information processing
3. The ability to learn from “experience”