Università Parthenope
DiST
Dipartimento di Scienze e Tecnologie

# Machine Learning (part II)

## Hebbian Learning

Angelo Ciaramella

# Introduction

- McCulloch-Pitts Neuron
  - fixed weights
- Learning
  - weights adaption
  - learning approach

# Learning

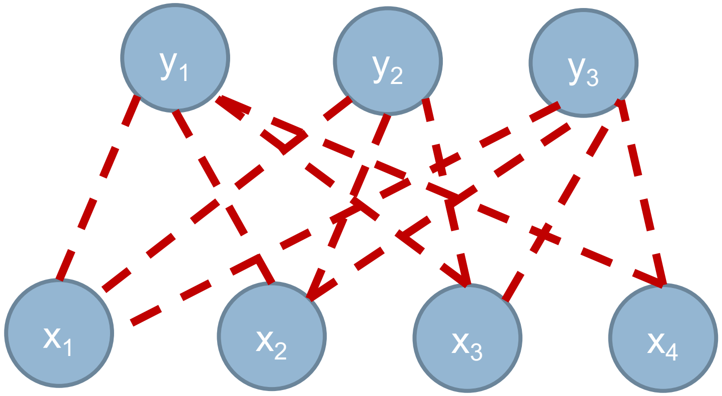
- First learning hypotheses
  - Donald O. Hebb
  - 1949 – Book titled: *The organization of behavior*
  - *neurophysiological evidence*

- *Principle*

  *If two connected neurons are simultaneously active, the synaptic efficacy of the connection is reinforced*

# Hebb's rule

Synapses




$\mu$ learning rate

$\Delta w_{ij} = \eta y_i x_j$

Learning rule

| x | y |
|---|---|
| 1 0 0 1 | 1 0 0 |
| 0 1 0 0 | 0 1 0 |
| 0 0 10 | 0 0 1 |

Learning example

# Hebb's algorithm

- Initialize the synaptic weights

$$w_{ij}=0$$

- Calculate synaptic changes

$$\Delta w_{ij}=\eta y_i x_j$$

- Update the synaptic weights

$$w_{ij}(t) = w_{ij}(\mathrm{t}-1) + \Delta w_{ij}$$

# Considerations

- Limitations
  - The Hebb rule allows to learn only orthogonal patterns
  - Mixed responses are called interferences

- Some improvements
  - Postsynaptic rule
  - Presynaptic rule

# Postsynaptic rule

- Postsynaptic rule
  - Stent-Singer
    - neurophysiologicals that highlighted the mechanism in biological circuits
  - rule
    - increased when the postsynaptic and presynaptic units are active
    - decreased when the postsynaptic unit is active but the presynaptic unit is inactive
  - reduction of the interference phenomenon
  - too many inhibitory synapses
    - it is not found in biological systems but in all the artifcial neural networks

# Presynaptic rule

- Presynaptic rule
  - increased when the postsynaptic and presynaptic units are active
  - decreased when the presynaptic unit is active but the postynaptic unit is inactive
  - It works well when many different and partially overlapping patterns need to be associated with the same pattern

# Postsynaptic rule

$$\Delta w_{ij} = \eta\left(y_i x_j + \left(x_j - 1\right) y_i\right)$$

postsynaptic rule

$$\Delta w_{ij} = \eta\left(y_i x_j + (y_i - 1) x_j\right)$$

presynaptic rule

# Hebbian learning and NNs

- NNs based on the Hebb's rule
  - Hopfield network
    - recurrent artificial NN described by Little in 1974
    - popularized by John Hopfield in 1982
    - content-addressable («associative») memory systems with binary threshold nodes
    - They are guaranteed to converge to a local minimum
      - converge to a false pattern (wrong local minimum) rather than the stored pattern (expected local minimum
    - provide a model for understanding human memory

# Hebbian learning and NNs

- NNs based on the Hebb's rule
  - Oja's rule
    - Finnish computer scientist Erkki Oja
    - Is a model of how neurons in the brain or in artificial neural networks change connection strength
    - solves stability problems of Hebbian learning
    - generates an algorithm for
      - Principal Component Analysis (PCA)
      - non-linear PCA
      - Independent Component Analaysis (ICA)