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Neural Networks

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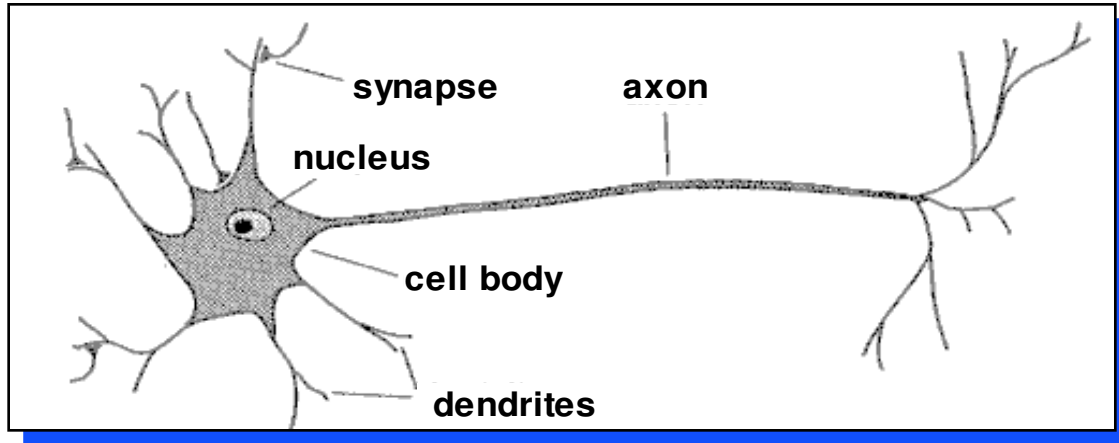
Recently published articles

- Wearable and Implantable Wireless Sensor Network Solutions for Healthcare Monitoring
- Managing Computing Infrastructure for IoT Data
- New Models for Monitoring and Clustering of the State of Plant Species based on Semantic Spaces
- A fuzzy Linear Regression Model for a Special Case of Interval Type-2 Fuzzy Sets
- Computer-aided Early Detection Diagnosis System of Breast Cancer with Fuzzy Clustering Means Approach

Biological inspirations

- Some numbers...
 - The human brain contains about 10 billion nerve cells (neurons)
 - Each neuron is connected to the others through 10000 synapses
- Properties of the brain
 - It can learn, reorganize itself from experience
 - It adapts to the environment
 - It is robust and fault tolerant

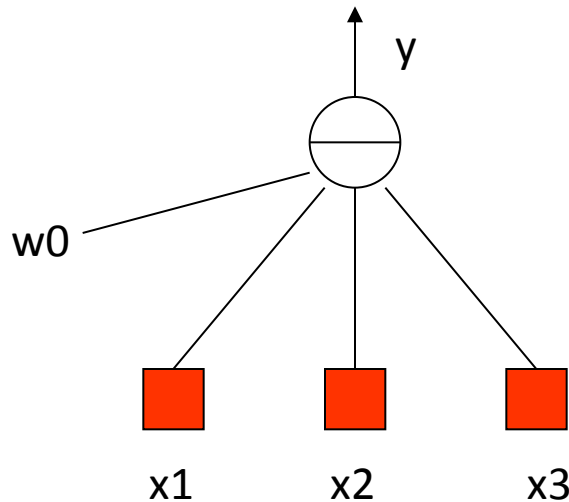
Biological neuron



- A neuron has
 - A branching input (dendrites)
 - A branching output (the axon)
- The information circulates from the dendrites to the axon via the cell body
- Axon connects to dendrites via synapses
 - Synapses vary in strength
 - Synapses may be excitatory or inhibitory

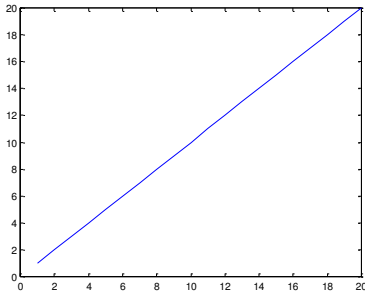
What is an artificial neuron ?

- Definition : Non linear, parameterized function with restricted output range



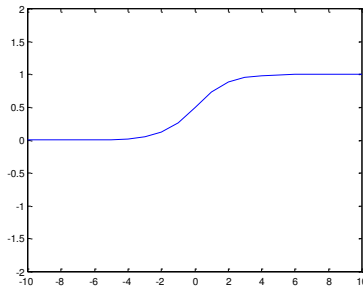
$$y = f \left(w_0 + \sum_{i=1}^{n-1} w_i x_i \right)$$

Activation functions



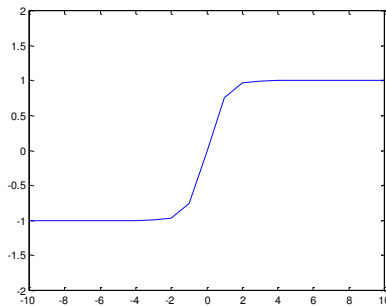
Linear

$$y = x$$



Logistic

$$y = \frac{1}{1 + \exp(-x)}$$



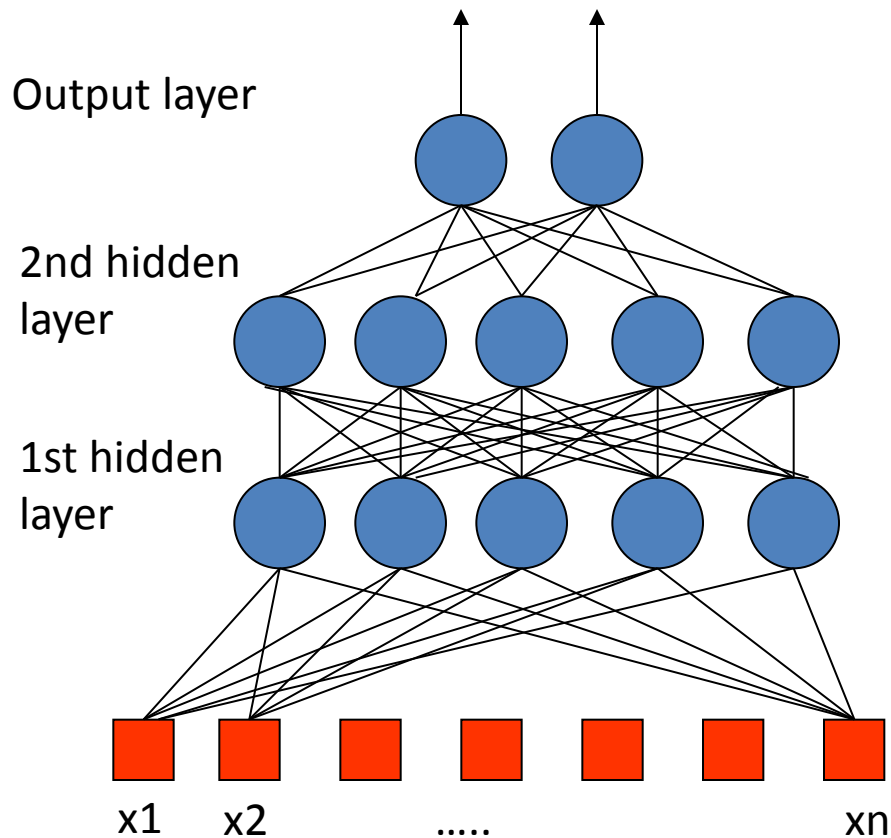
Hyperbolic tangent

$$y = \frac{\exp(x) - \exp(-x)}{\exp(x) + \exp(-x)}$$

Neural Networks

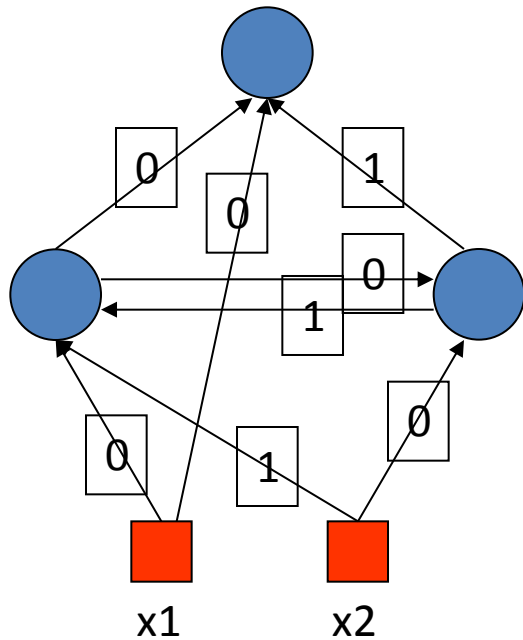
- A mathematical model to solve engineering problems
 - Group of highly connected neurons to realize compositions of non linear functions
- Tasks
 - Classification
 - Discrimination
 - Estimation
- 2 types of networks
 - Feed forward Neural Networks
 - Recurrent Neural Networks

Feed Forward Neural Networks



- The information is propagated from the inputs to the outputs
- Computations of **No** non linear functions from **n** input variables by compositions of **Nc** algebraic functions
- Time has no role (NO cycle between outputs and inputs)

Recurrent Neural Networks



- Can have arbitrary topologies
- Can model systems with internal states (dynamic ones)
- Delays are associated to a specific weight
- Training is more difficult
- Performance may be problematic
 - Stable Outputs may be more difficult to evaluate
 - Unexpected behavior (oscillation, chaos, ...)

Learning

- The procedure that consists in estimating the parameters of neurons so that the whole network can perform a specific task
- 2 types of learning
 - The supervised learning
 - The unsupervised learning
- The Learning process (supervised)
 - Present the network a number of inputs and their corresponding outputs
 - See how closely the actual outputs match the desired ones
 - Modify the parameters to better approximate the desired outputs

Supervised learning

- The desired response of the neural network in function of particular inputs is well known.
- A “Professor” may provide examples and teach the neural network how to fulfill a certain task

Unsupervised learning

- Idea : group typical input data in function of resemblance criteria un-known a priori
- Data clustering
- No need of a professor
 - The network finds itself the correlations between the data
 - Examples of such networks :
 - Kohonen feature maps

Properties of Neural Networks

- Supervised networks are universal approximators (Non recurrent networks)
- **Theorem : Any limited function can be approximated by a neural network with a finite number of hidden neurons to an arbitrary precision**
- Type of Approximators
 - Linear approximators : for a given precision, the number of parameters grows exponentially with the number of variables (polynomials)
 - Non-linear approximators (NN), the number of parameters grows linearly with the number of variables

Other properties

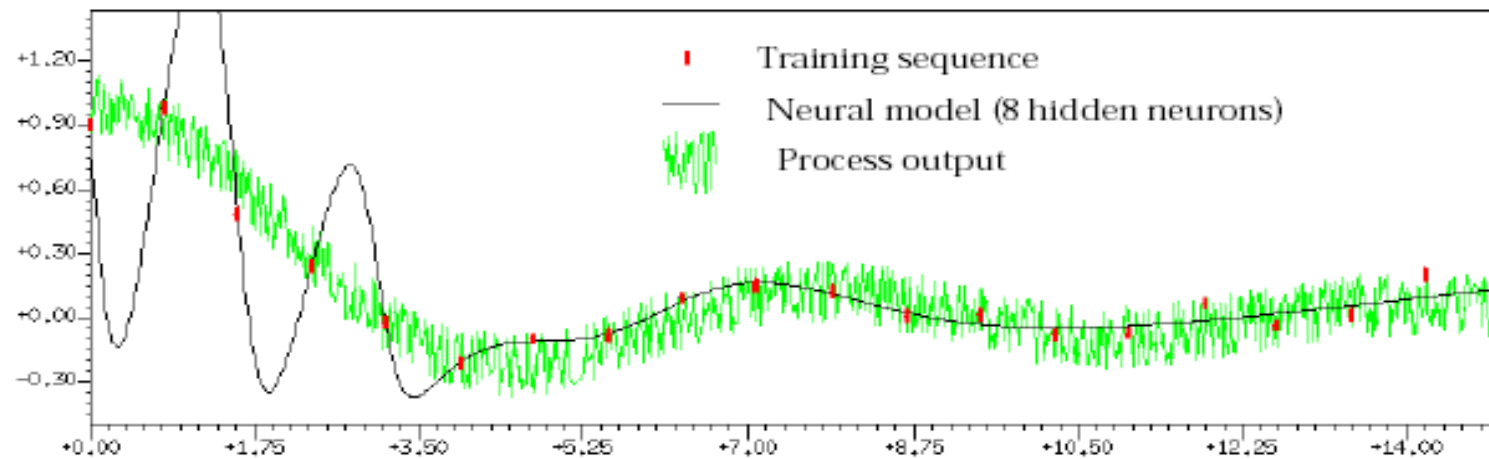
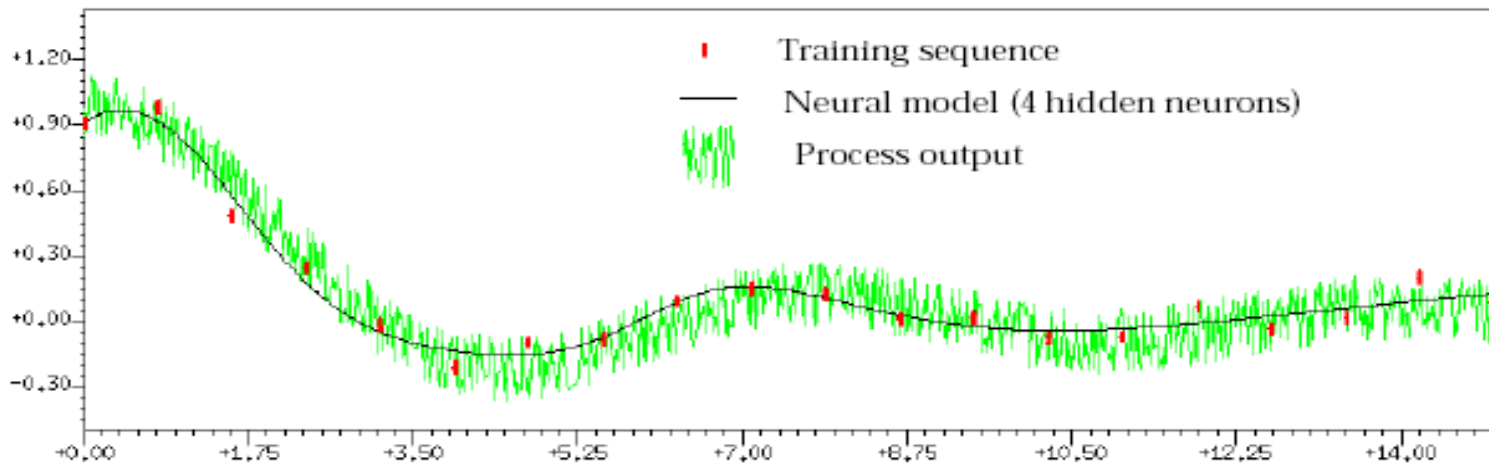
- **Adaptivity**
 - Adapt weights to environment and retrained easily
- **Generalization ability**
 - May provide against lack of data
- **Fault tolerance**
 - Graceful degradation of performances if damaged => The information is distributed within the entire net.

Static modeling

- In practice, it is rare to approximate a known function by a uniform function
- “black box” modeling : model of a process
- The y output variable depends on the input variable x with $k=1$ to N $\{x^k, y_p^k\}$
- Goal : Express this dependency by a function, for example a neural network

- If the learning ensemble results from measures, the noise intervenes
- Not an approximation but a fitting problem
- Regression function
- Approximation of the regression function : Estimate the more probable value of y_p for a given input x
- Cost function:
$$J(w) = \frac{1}{2} \sum_{k=1}^N [y_p(x^k) - g(x^k, w)]^2$$
- Goal: Minimize the cost function by determining the right function g

Example



Classification (Discrimination)

- Class objects in defined categories
- Rough decision OR
- Estimation of the probability for a certain object to belong to a specific class

Example : Data mining

- Applications : Economy, speech and patterns recognition, sociology, etc.

Example

65473 60198 68544
70065 70117 19032^{ZIP} 96720
27260 61820 19559
74136 ~~19137~~ 63101
20878 60521 38002
48640-2398 20907 14868

Examples of handwritten postal codes
drawn from a database available from the US Postal service

What do we need to use NN ?

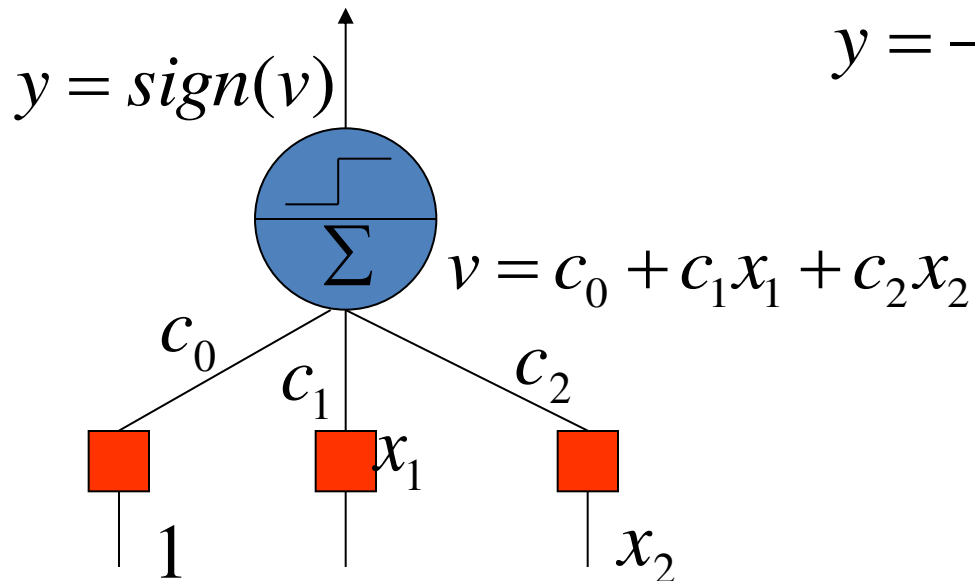
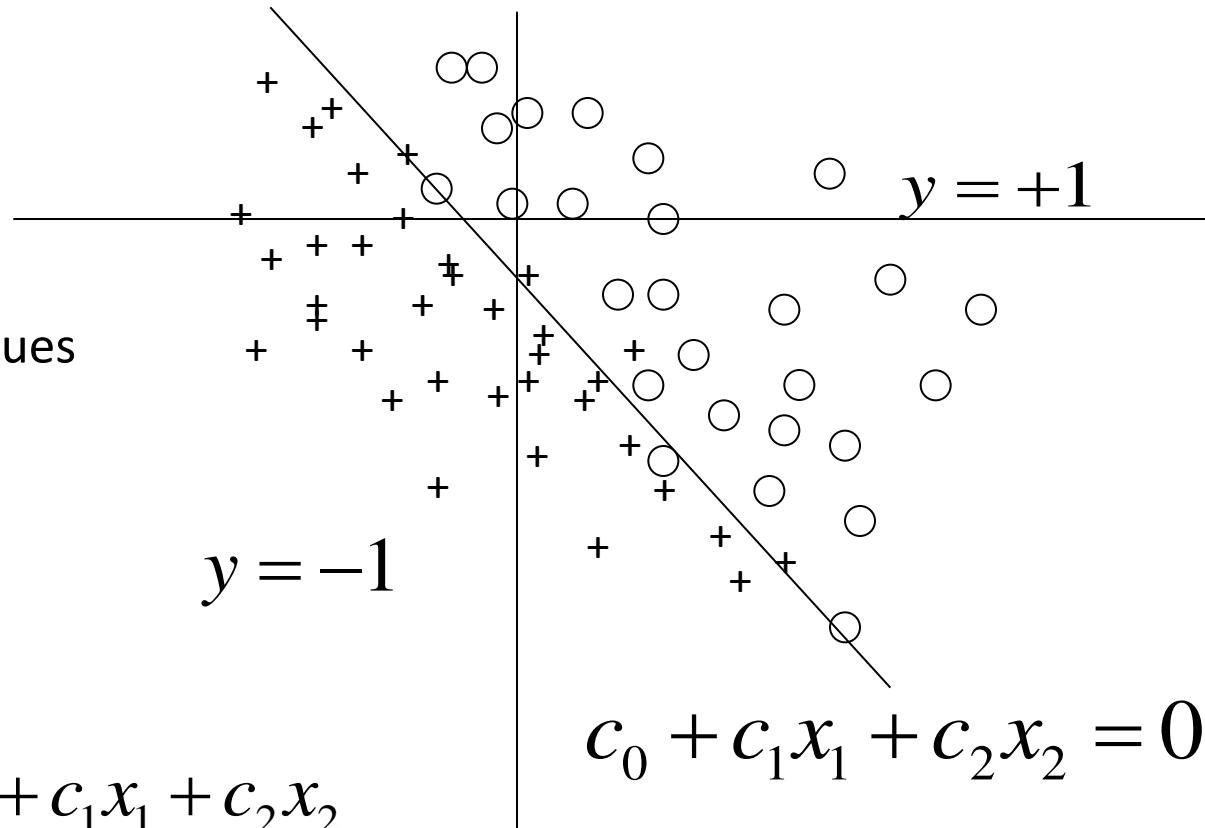
- Determination of pertinent inputs
- Collection of data for the learning and testing phase of the neural network
- Finding the optimum number of hidden nodes
- Estimate the parameters (Learning)
- Evaluate the performances of the network
- IF performances are not satisfactory then review all the precedent points

Classical neural architectures

- Perceptron
- Multi-Layer Perceptron
- Radial Basis Function (RBF)
- Kohonen Features maps
- Other architectures
 - An example : Shared weights neural networks

Perceptron

- Rosenblatt (1962)
- Linear separation
- Inputs : Vector of real values
- Outputs : 1 or -1



Learning (The perceptron rule)

- Minimization of the cost function : $J(c) = \sum_{k \in M} -y_p^k v^k$

- $J(c)$ is always ≥ 0 (M is the ensemble of bad classified examples)

- y_p^k is the target value

- Partial cost

– If x^k is not well classified : $J^k(c) = -y_p^k v^k$

– If x^k is well classified $J^k(c) = 0$

- Partial cost gradient



$$\frac{\partial J^k(c)}{\partial c} = -y_p^k x^k$$

- Perceptron algorithm

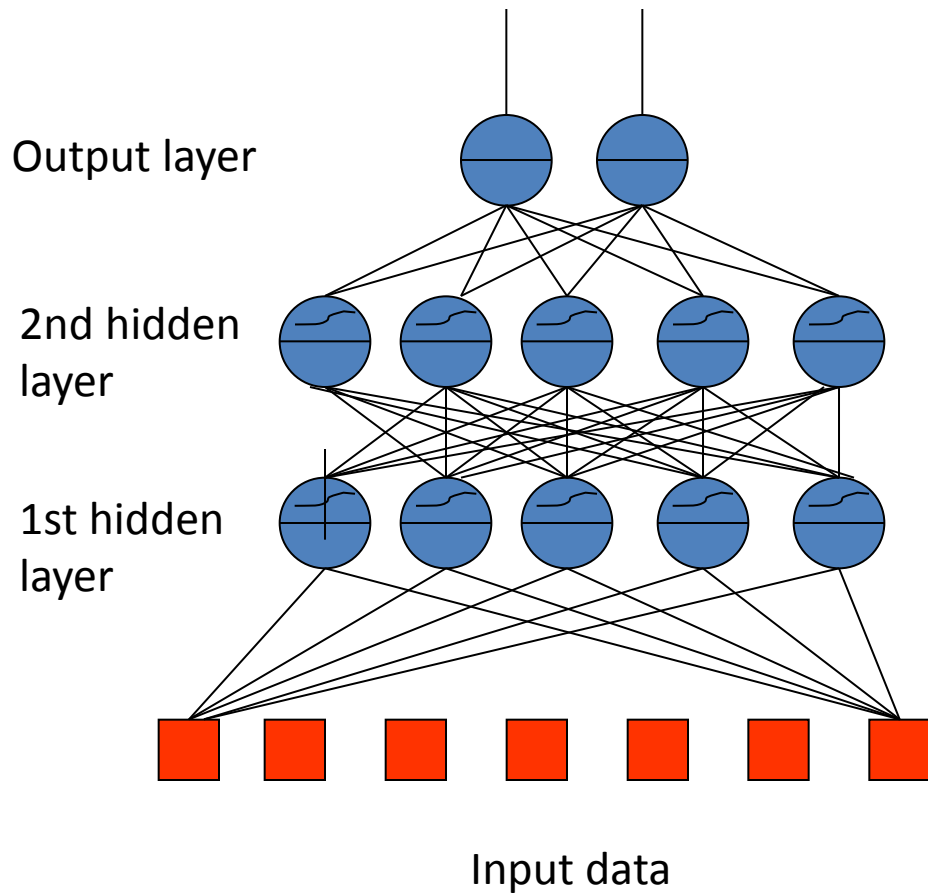
if $y_p^k v^k > 0$ (x^k is well classified) : $c(k) = c(k-1)$

if $y_p^k v^k < 0$ (x^k is not well classified) : $c(k) = c(k-1) + y_p^k x^k$

- The perceptron algorithm converges if examples are linearly separable

Multi-Layer Perceptron

- One or more hidden layers
- Sigmoid activation functions



Learning


- Back-propagation algorithm

$$net_j = w_{j0} + \sum_i^n w_{ji} o_i$$

$$o_j = f_j(net_j)$$

$$\Delta w_{ji} = -\alpha \frac{\partial E}{\partial w_{ji}} = -\alpha \frac{\partial E}{\partial net_j} \frac{\partial net_j}{\partial w_{ji}} = \alpha \delta_j o_i$$

Credit assignment

$$\delta_j = -\frac{\partial E}{\partial net_j}$$


$$\delta_j = -\frac{\partial E}{\partial o_j} \frac{\partial o_j}{\partial net_j} = -\frac{\partial E}{\partial o_j} f'(net_j)$$

$$E = \frac{1}{2} (t_j - o_j)^2 \Rightarrow \frac{\partial E}{\partial o_j} = -(t_j - o_j)$$

$$\delta_j = (t_j - o_j) f'(net_j)$$

If the jth node is an output unit

$$\frac{\partial E}{\partial o_j} = \sum_k^{\kappa} \frac{\partial E}{\partial net_k} \frac{\partial net_k}{\partial o_j} = - \sum_k^{\kappa} \delta_k w_{kj}$$

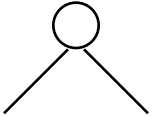
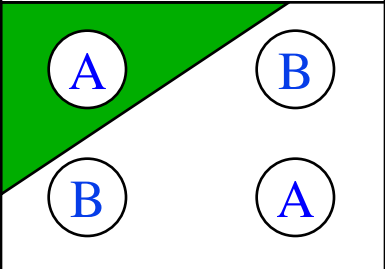
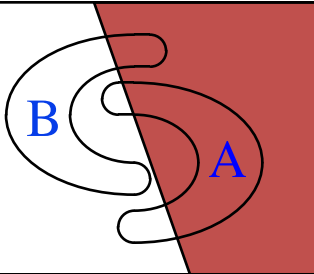
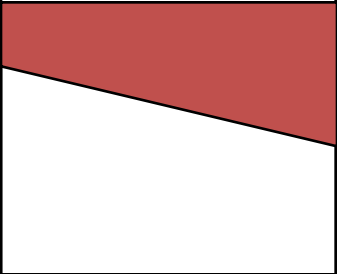
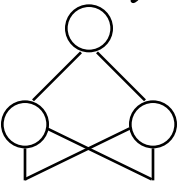
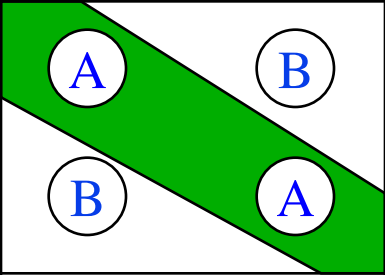
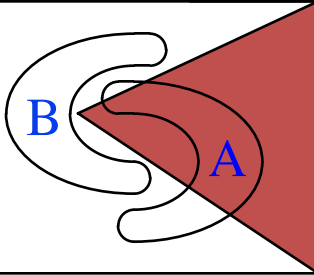
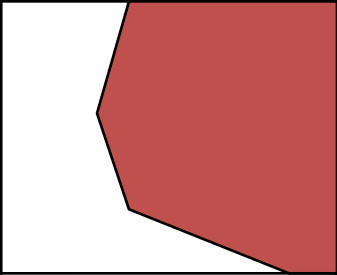
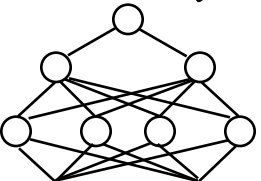
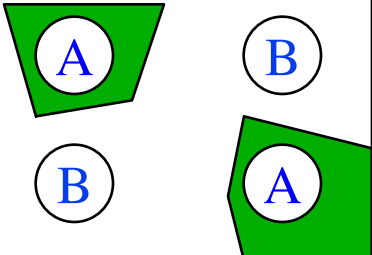
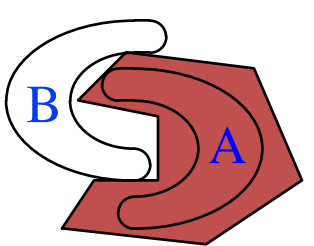
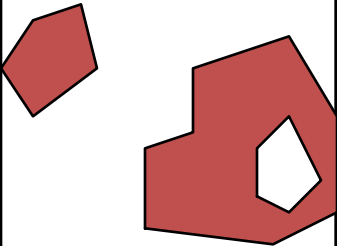
$$\delta_j = f'_j(net_j) \sum_k^{\kappa} \delta_k w_{kj}$$

$$\Delta w_{ji}(t) = \alpha \delta_j(t) o_i(t) + \gamma \Delta w_{ji}(t-1)$$

Momentum term to smooth
The weight changes over time

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

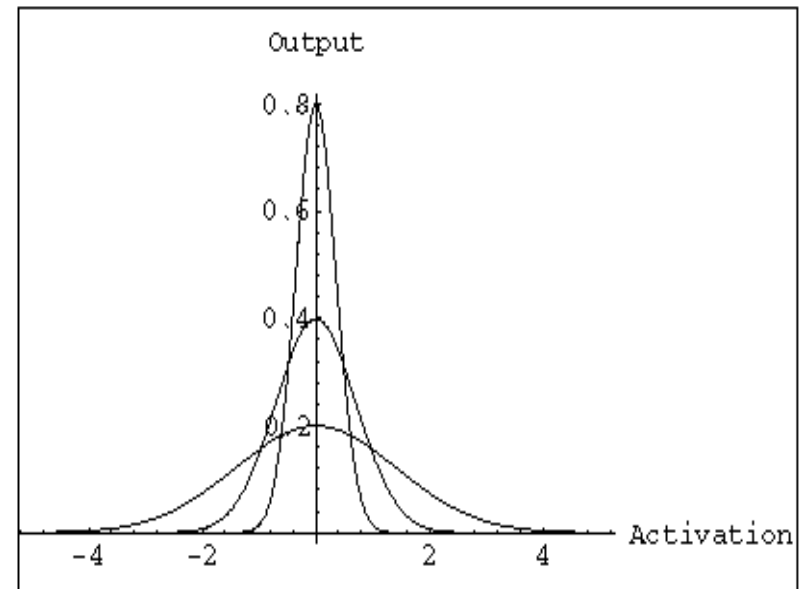
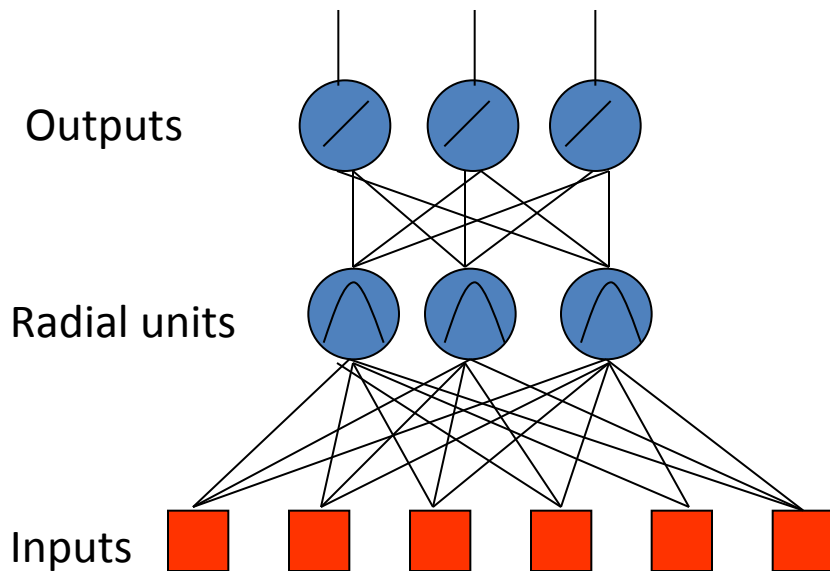
Different non linearly separable problems

<i>Structure</i>	<i>Types of Decision Regions</i>	<i>Exclusive-OR Problem</i>	<i>Classes with Meshed regions</i>	<i>Most General Region Shapes</i>
<p><i>Single-Layer</i></p> 	<p><i>Half Plane Bounded By Hyperplane</i></p>			
<p><i>Two-Layer</i></p> 	<p><i>Convex Open Or Closed Regions</i></p>			
<p><i>Three-Layer</i></p> 	<p><i>Arbitrary (Complexity Limited by No. of Nodes)</i></p>			

Radial Basis Functions (RBFs)

- Features

- One hidden layer
- The activation of a hidden unit is determined by the distance between the input vector and a prototype vector



- RBF hidden layer units have a receptive field which has a centre
- Generally, the hidden unit function is Gaussian
- The output Layer is linear
- Realized function

$$s(x) = \sum_{j=1}^K W_j \Phi(\|x - c_j\|)$$

$$\Phi(\|x - c_j\|) = \exp\left(-\left(\frac{\|x - c_j\|}{\sigma_j}\right)^2\right)$$

Learning

- The training is performed by deciding on
 - How many hidden nodes there should be
 - The centers and the sharpness of the Gaussians
- 2 steps
 - In the 1st stage, the input data set is used to determine the parameters of the basis functions
 - In the 2nd stage, functions are kept fixed while the second layer weights are estimated (Simple BP algorithm like for MLPs)

MLPs versus RBFs

- **Classification**

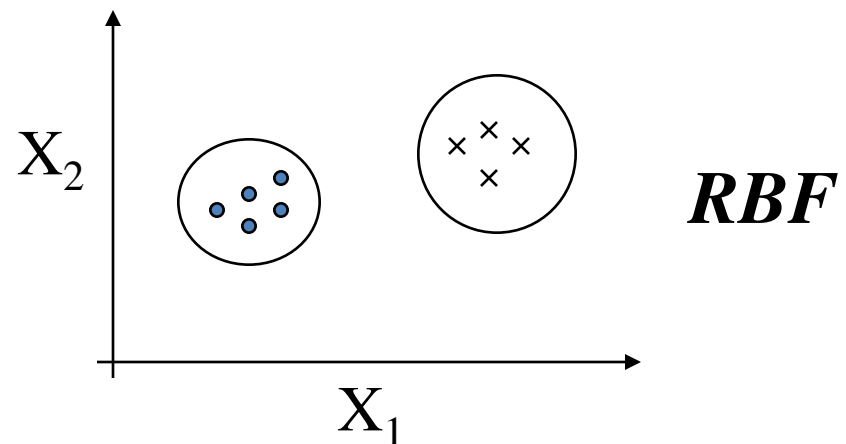
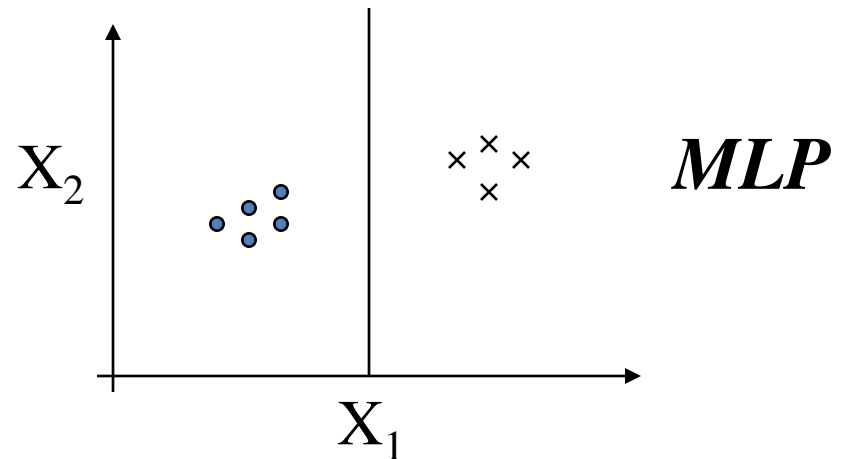
- MLPs separate classes via hyperplanes
- RBFs separate classes via hyperspheres

- **Learning**

- MLPs use distributed learning
- RBFs use localized learning
- RBFs train faster

- **Structure**

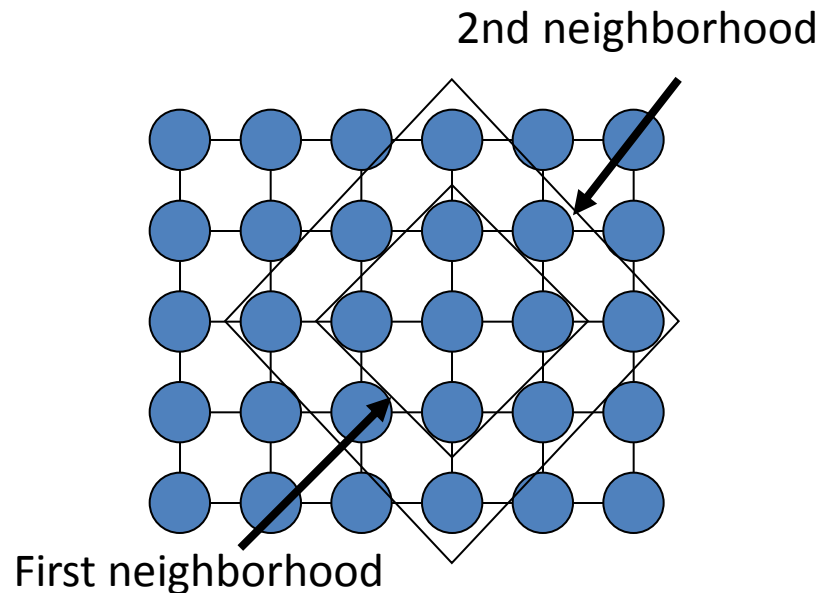
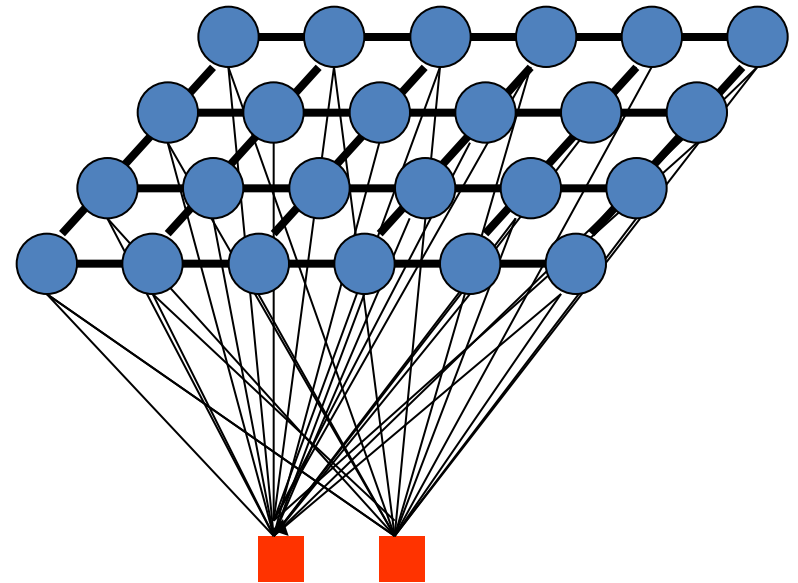
- MLPs have one or more hidden layers
- RBFs have only one layer
- RBFs require more hidden neurons => curse of dimensionality



Self organizing maps

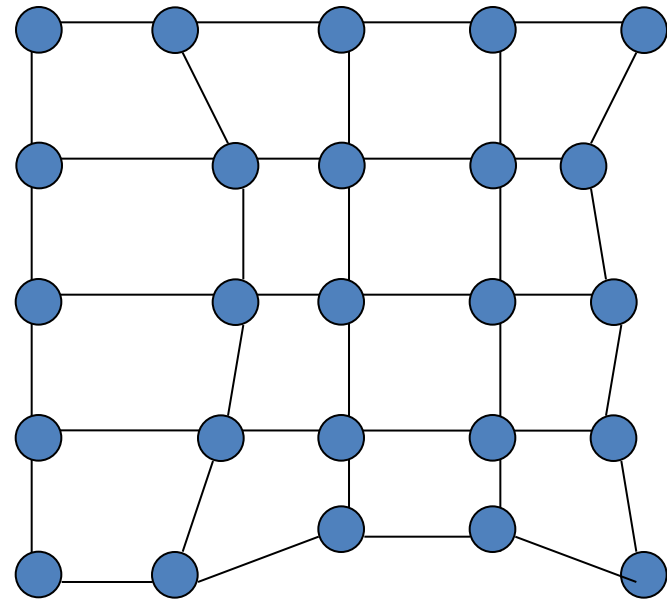
- The purpose of SOM is to map a multidimensional input space onto a topology preserving map of neurons
 - Preserve a topological so that neighboring neurons respond to « similar »input patterns
 - The topological structure is often a 2 or 3 dimensional space
- Each neuron is assigned a weight vector with the same dimensionality of the input space
- Input patterns are compared to each weight vector and the closest wins (Euclidean Distance)

- The activation of the neuron is spread in its direct neighborhood => neighbors become sensitive to the same input patterns
- Block distance
- The size of the neighborhood is initially large but reduce over time => Specialization of the network



Adaptation

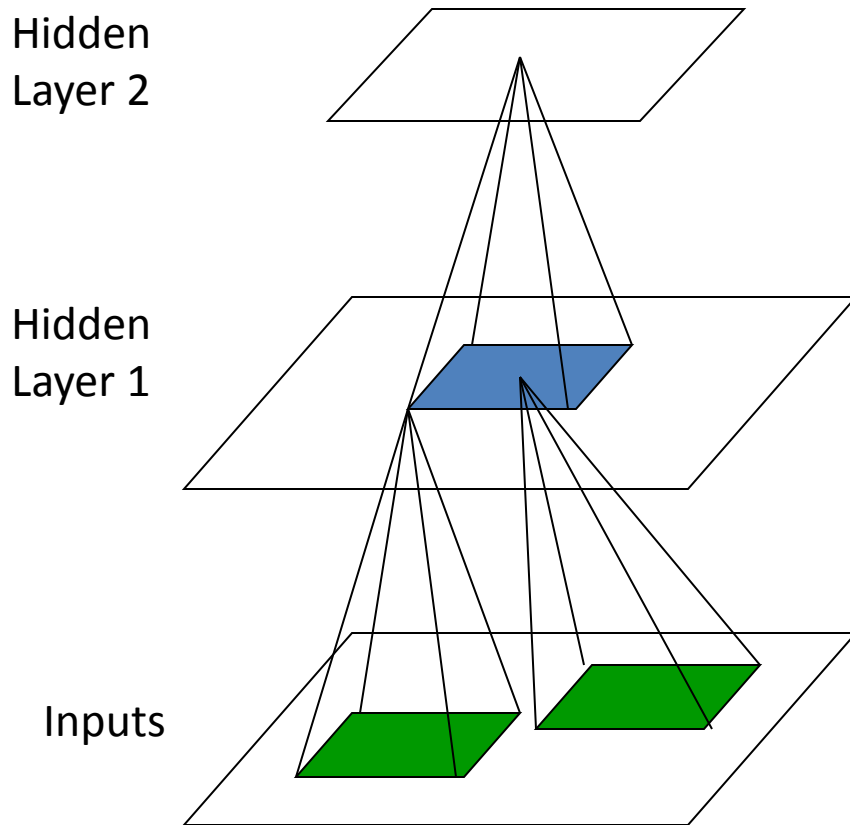
- During training, the “winner” neuron and its neighborhood adapts to make their weight vector more similar to the input pattern that caused the activation
- The neurons are moved closer to the input pattern
- The magnitude of the adaptation is controlled via a learning parameter which decays over time



Shared weights neural networks: Time Delay Neural Networks (TDNNs)

- Introduced by Waibel in 1989
- Properties
 - Local, shift invariant feature extraction
 - Notion of receptive fields combining local information into more abstract patterns at a higher level
 - Weight sharing concept (All neurons in a feature share the same weights)
 - All neurons detect the same feature but in different position
- Principal Applications
 - Speech recognition
 - Image analysis

TDNNs (cont'd)



- Objects recognition in an image
- Each hidden unit receive inputs only from a small region of the input space : receptive field
- Shared weights for all receptive fields => translation invariance in the response of the network

- Advantages

- Reduced number of weights

- Require fewer examples in the training set

- Faster learning

- Invariance under time or space translation

- Faster execution of the net (in comparison of full connected MLP)

Neural Networks (Applications)

- Face recognition
- Time series prediction
- Process identification
- Process control
- Optical character recognition
- Adaptative filtering
- Etc...

Conclusion on Neural Networks

- Neural networks are utilized as statistical tools
 - Adjust non linear functions to fulfill a task
 - Need of multiple and representative examples but fewer than in other methods
- Neural networks enable to model complex static phenomena (FF) as well as dynamic ones (RNN)
- NN are good classifiers BUT
 - Good representations of data have to be formulated
 - Training vectors must be statistically representative of the entire input space
 - Unsupervised techniques can help
- The use of NN needs a good comprehension of the problem

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