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Neural Networks

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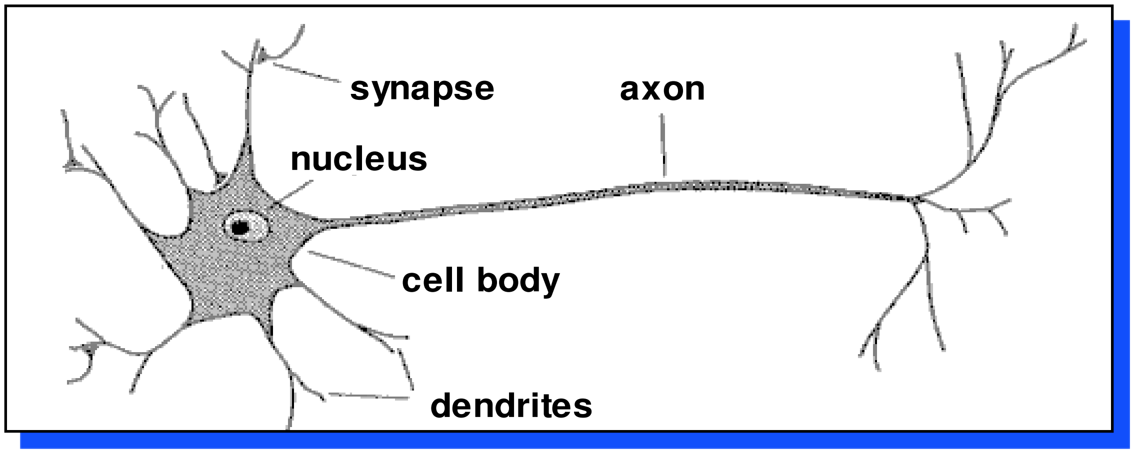
- Effective Calibration of Artificial Gene Regulatory Networks
- Large scale agent-based modeling of the humoral and cellular immune response
- A Memetic Immunological Algorithm for Resource Allocation Problem.

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

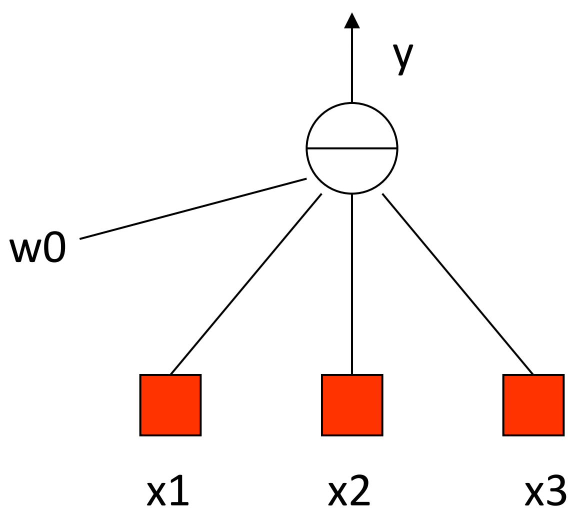
Biological neuron



- 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

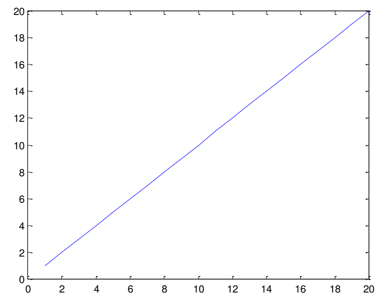
What is an artificial neuron ?

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



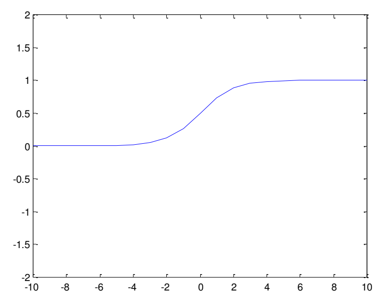
$$y = f\left(w_0 + \sum_{i=1}^{n-1} w_i x_i \right)$$

Activation functions



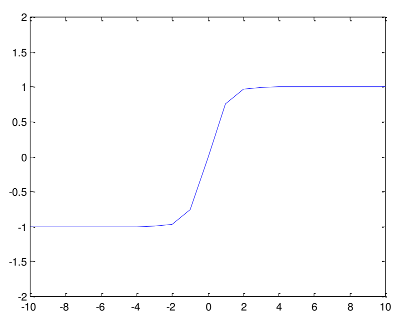
Linear

$$y = x$$



Logistic

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



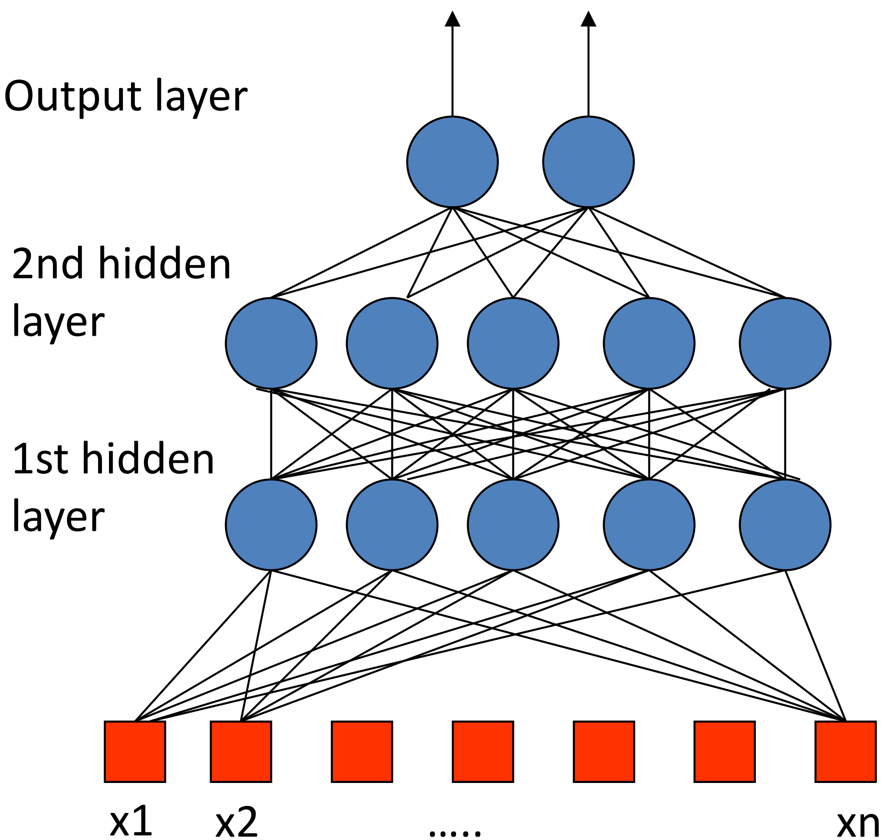
Hyperbolic tangent

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

Neural Networks

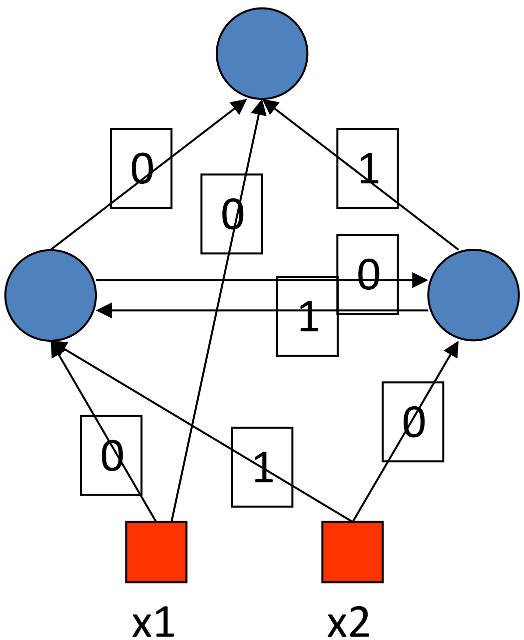
- A mathematical model to solve engineering problems
  - Group of highly connected neurons to realize compositions of non linear functions
- Tasks
  - Classification
  - Discrimination
  - Estimation
- 2 types of networks
  - Feed forward Neural Networks
  - Recurrent Neural Networks

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

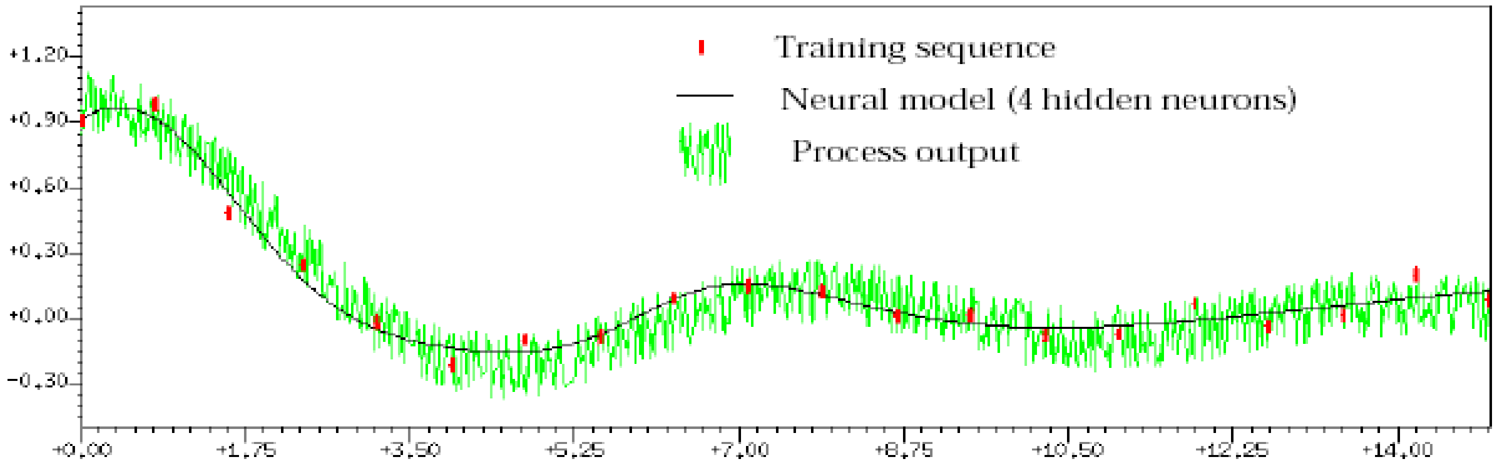
- Adaptivity
  - Adapt weights to environment and retrained easily
- Generalization ability
  - May provide against lack of data
- Fault tolerance
  - Graceful degradation of performances if damaged => The information is distributed within the entire net.

Static modeling

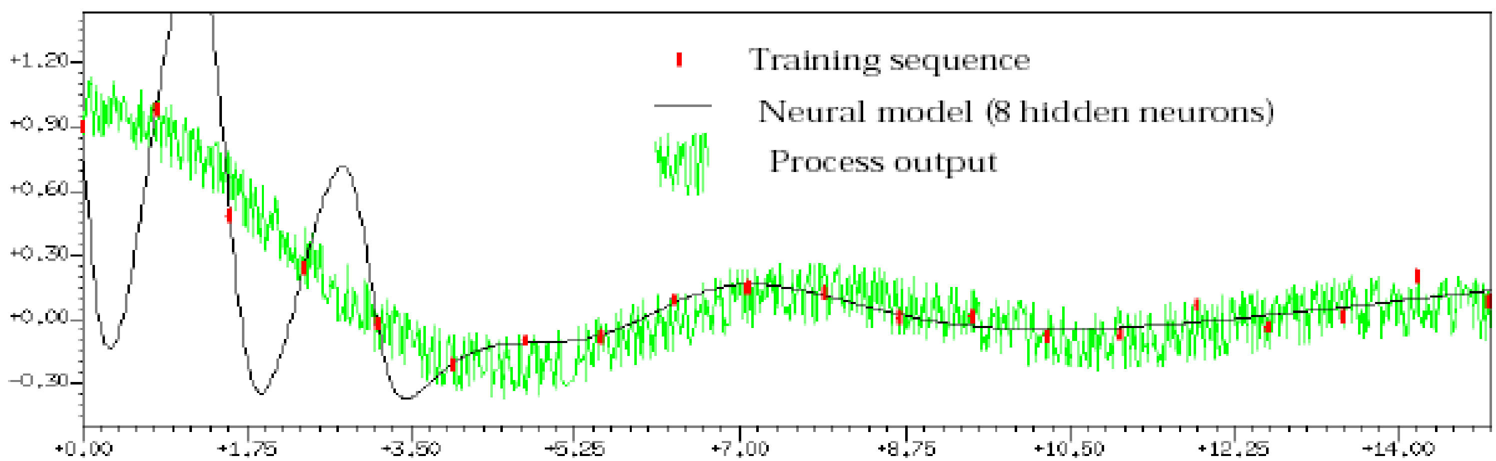
- In practice, it is rare to approximate a known function by a uniform function
- “black box” modeling : model of a process
- The y output variable depends on the input variable x with k=1 to N $\left\{x^k, y_p^k\right\}$
- Goal : Express this dependency by a function, for example a neural network

- 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 yp for a given input x
- Cost function: $$J(w) = \frac{1}{2}\sum_{k=1}^{N}\left[y_p(x^k) - g(x^k, w)\right]^2$$
- Goal: Minimize the cost function by determining the right function g

Example



Training sequence
Neural model (4 hidden neurons)
Process output
+1.20
+0.90
+0.60
+0.30
+0.00
-0.30
+0.00
+1.75
+3.50
+5.25
+7.00
+8.75
+10.50
+12.25
+14.00



Training sequence
Neural model (8 hidden neurons)
Process output
+1.20
+0.90
+0.60
+0.30
+0.00
-0.30
+0.00
+1.75
+3.50
+5.25
+7.00
+8.75
+10.50
+12.25
+14.00

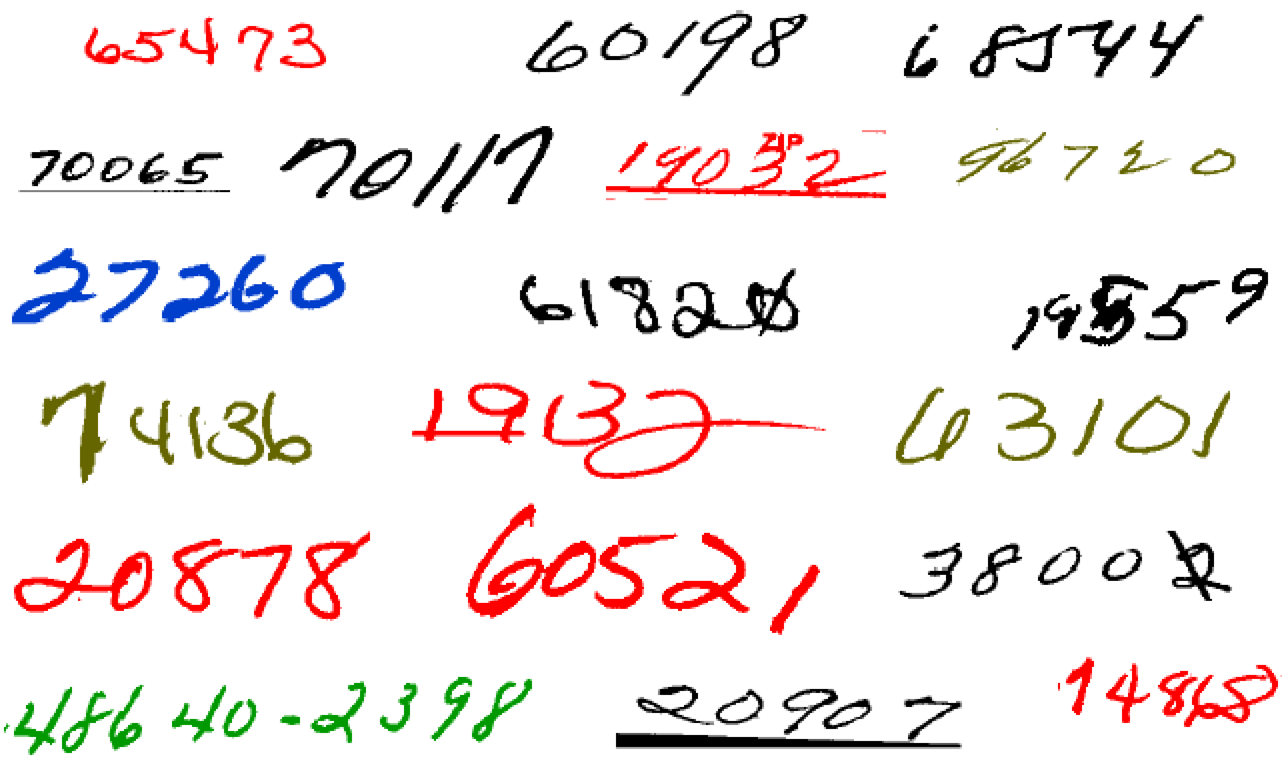
Classification (Discrimination)

- 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



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

What do we need to use NN ?

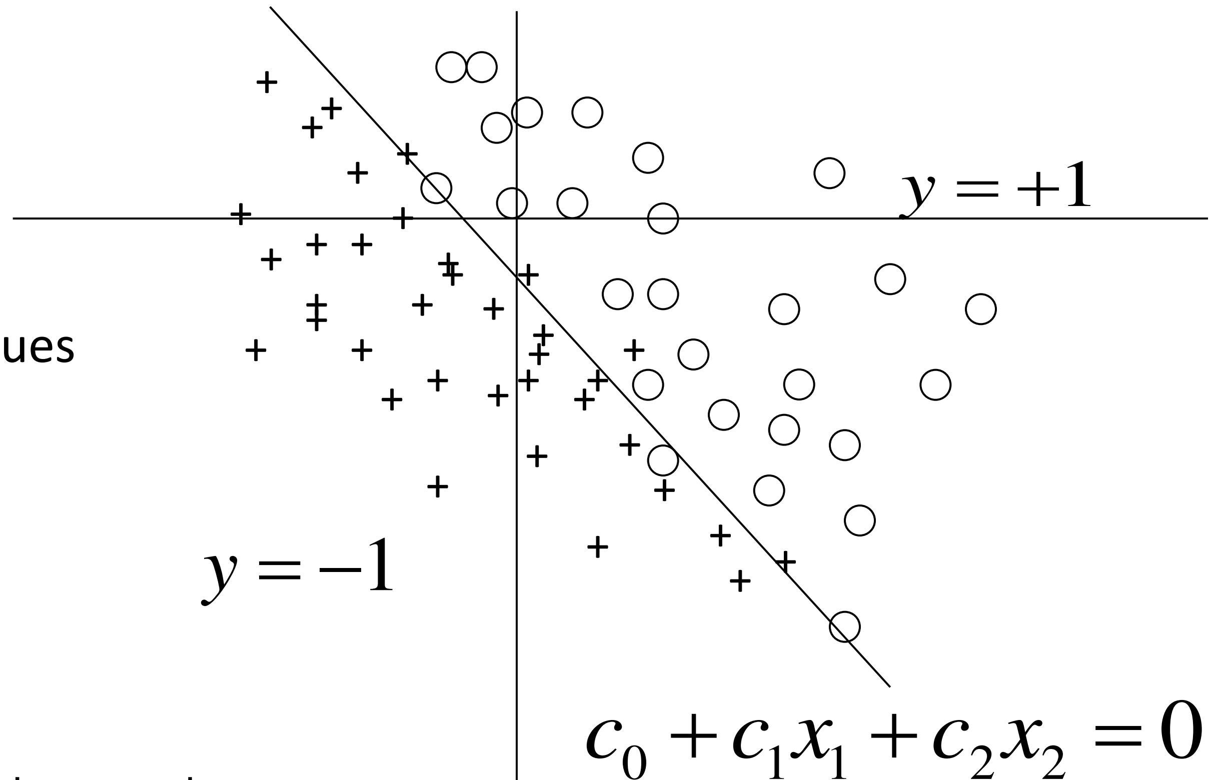
- Determination of pertinent inputs
- Collection of data for the learning and testing phase of the neural network
- Finding the optimum number of hidden nodes
- Estimate the parameters (Learning)
- Evaluate the performances of the network
- IF performances are not satisfactory then review all the precedent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

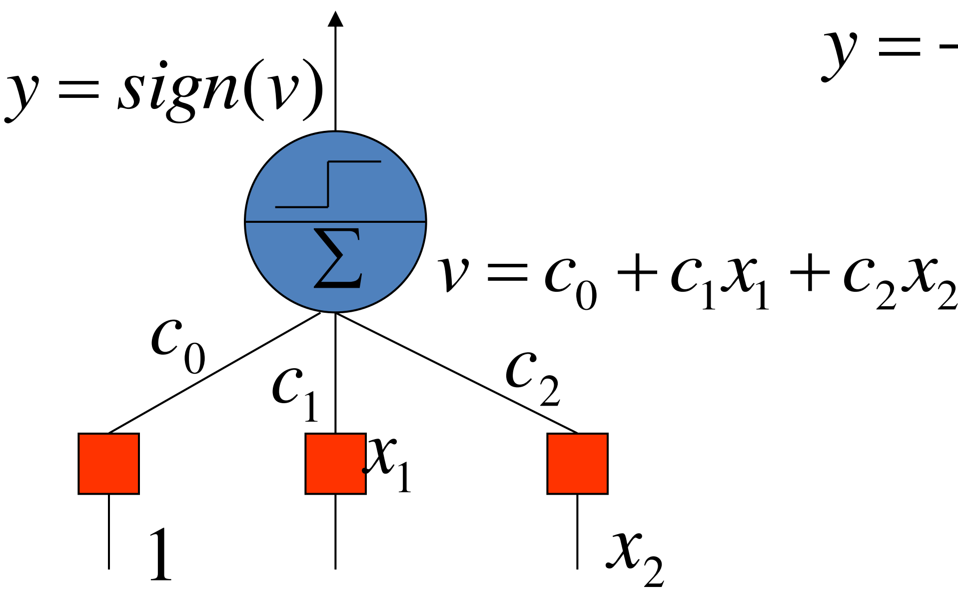
Classical neural architectures

- 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)

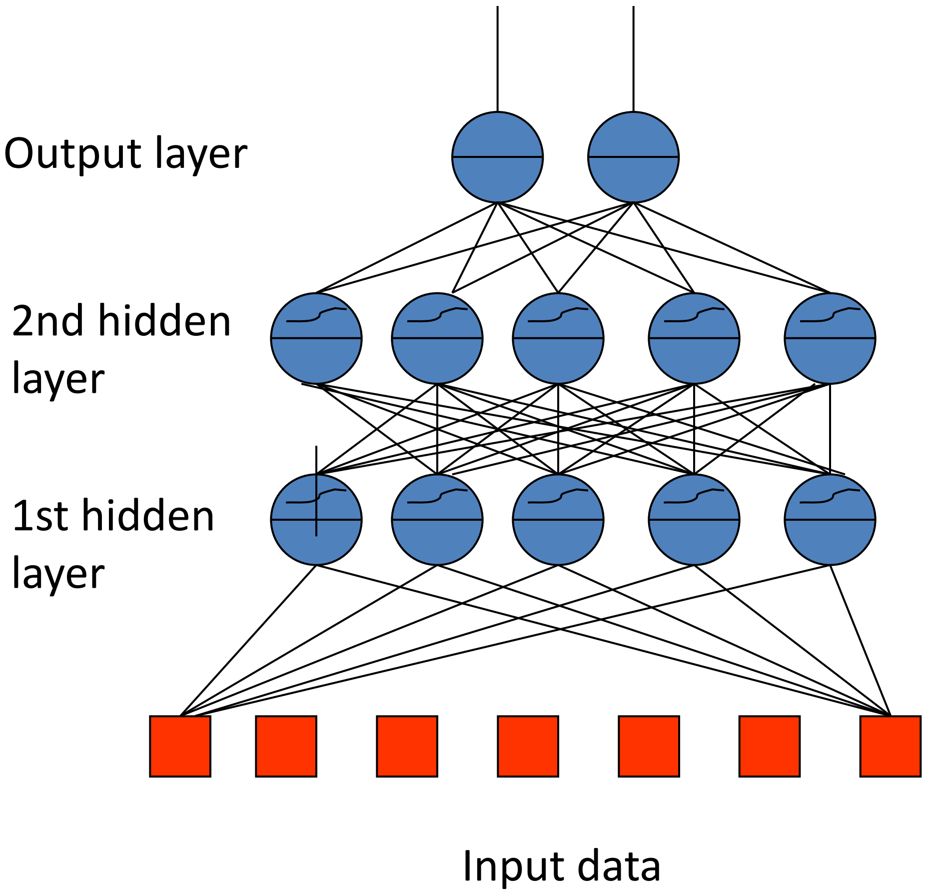
- Minimization of the cost function : $J(c) = \sum_{k \in M} -y_p^k v^k$
- J(c) is always >= 0 (M is the ensemble of bad classified examples)
- y_p^k is the target value
- Partial cost
  - If x^k is not well classified : $J^k(c) = -y_p^k v^k$
  - If x^k is well classified $J^k(c) = 0$
- Partial cost gradient $\longrightarrow$ $\boxed{\dfrac{\partial J^k(c)}{\partial c} = -y_p^k x^k}$
- Perceptron algorithm

$$\text{if } y_p^k v^k > 0 \ \ (\mathrm{x^k \text{ is well classified}}) : \mathrm{c(k) = c(k-1)}$$

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

- The perceptron algorithm converges if examples are linearly separable

Multi-Layer Perceptron



- One or more hidden layers
- Sigmoid activations functions

Learning

- Back-propagation algorithm

Credit assignment

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

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

$$o_j = f_j\left(net_j\right)$$

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

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

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

If the jth node is an output unit

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

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

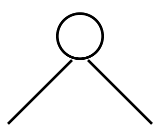
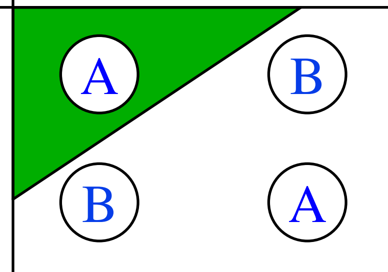
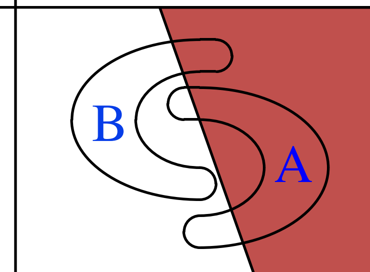
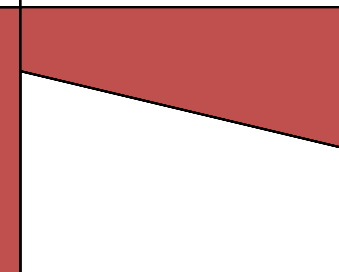
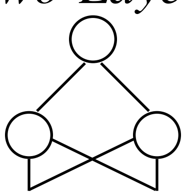
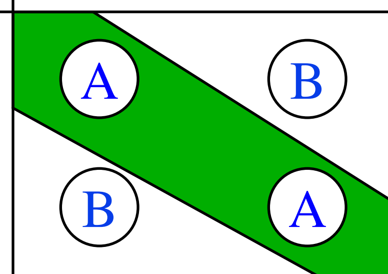
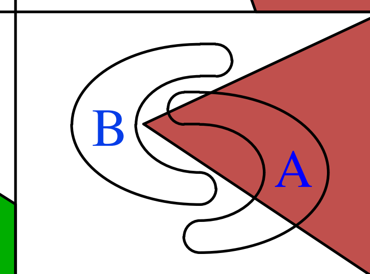
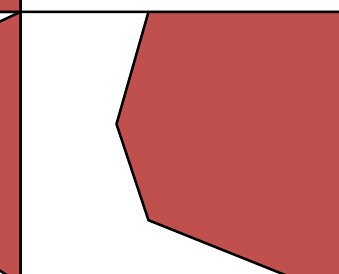
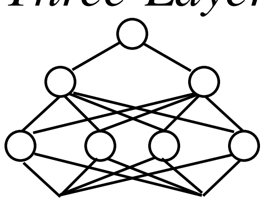
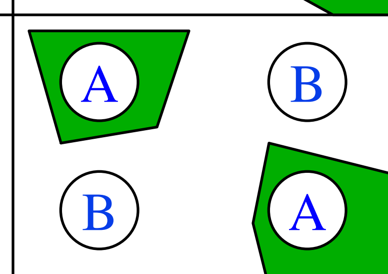
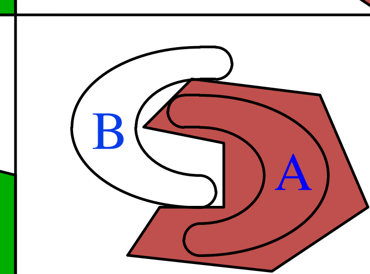
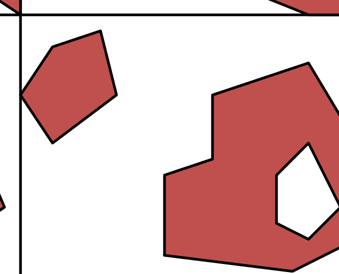
$$\delta_j = f'_j(net_j) \sum_k^{\kappa} \delta_k w_{kj}$$

Momentum term to smooth
The weight changes over time

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

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

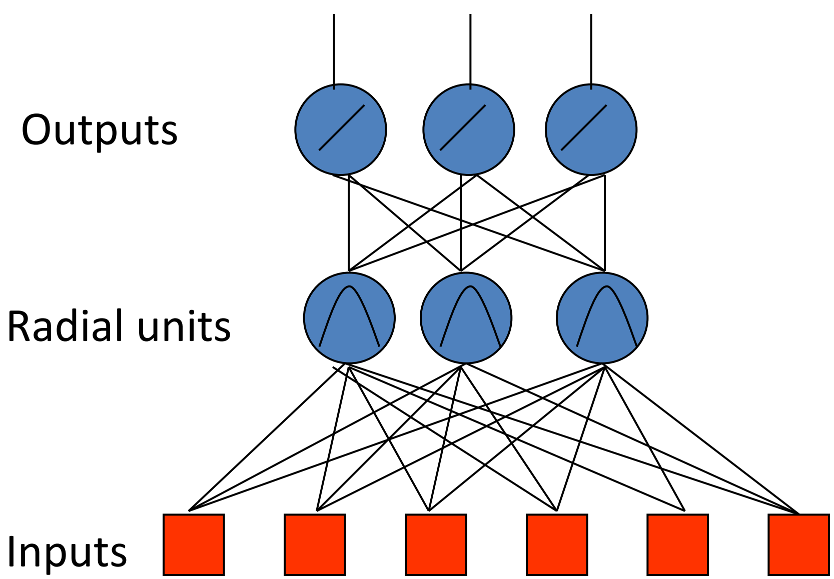
Different non linearly separable problems

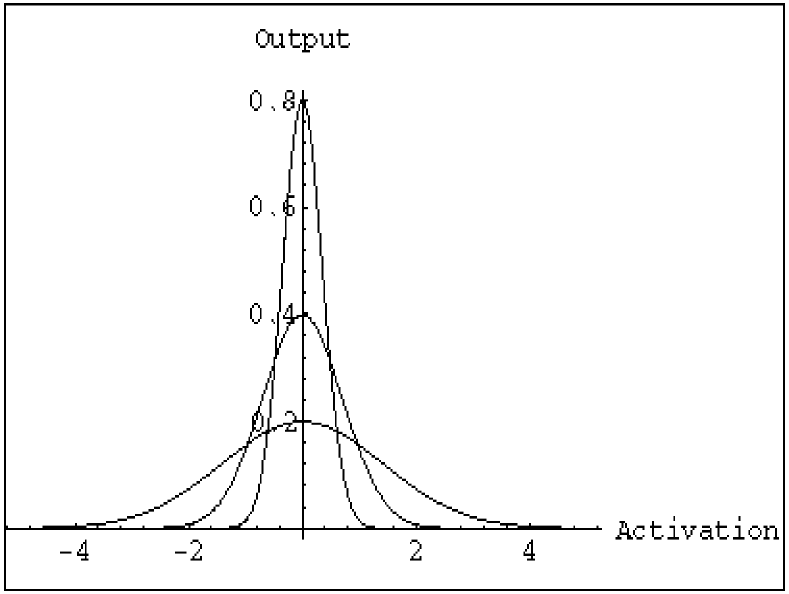
Structure	*Types of Decision Regions*	*Exclusive-OR Problem*	*Classes with Meshed regions*	*Most General Region Shapes*
Single-Layer 	*Half Plane Bounded By Hyperplane*			
Two-Layer 	*Convex Open Or Closed Regions*			
Three-Layer 	Abitrary (Complexity Limited by No. of Nodes)			

Neural Networks – An Introduction Dr. Andrew Hunter

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

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

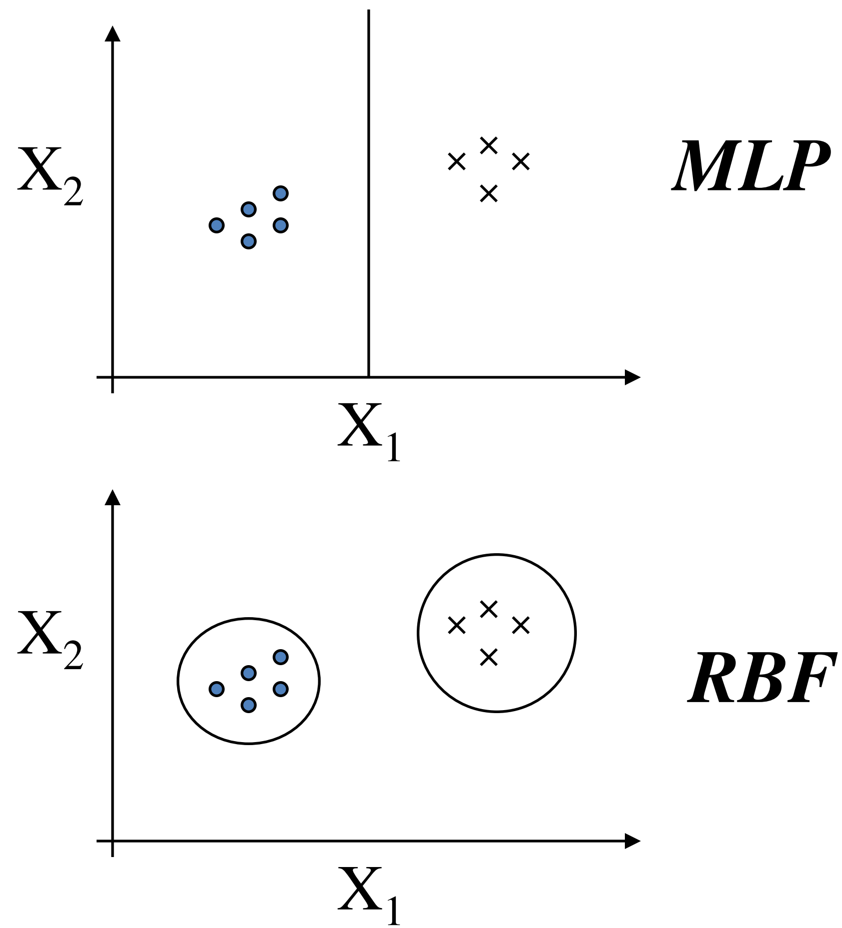
$$\Phi\left(\left\| x - c_j \right\|\right) = \exp - \left(\frac{\left\| x - c_j \right\|}{\sigma_j} \right)^2$$

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

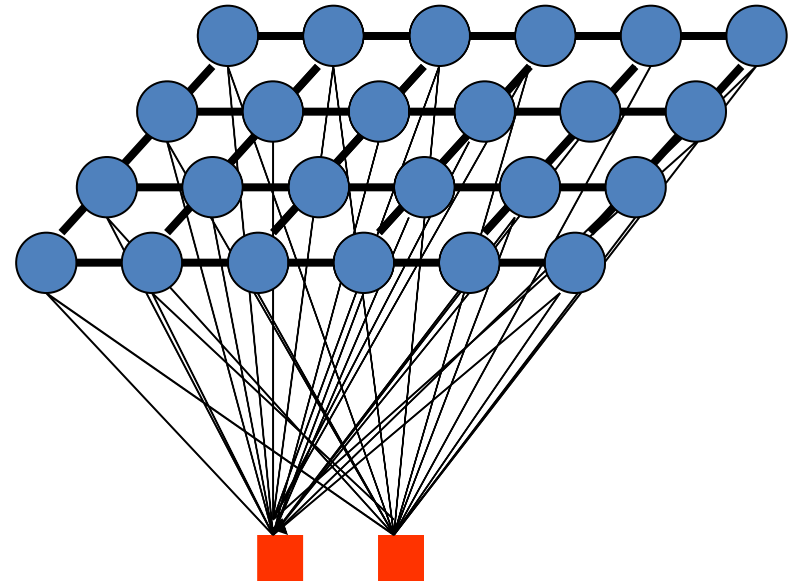
- **Classification**
  - MLPs separate classes via hyperplanes
  - RBFs separate classes via hyperspheres
- **Learning**
  - MLPs use distributed learning
  - RBFs use localized learning
  - RBFs train faster
- **Structure**
  - MLPs have one or more hidden layers
  - RBFs have only one layer
  - RBFs require more hidden neurons => curse of dimensionality

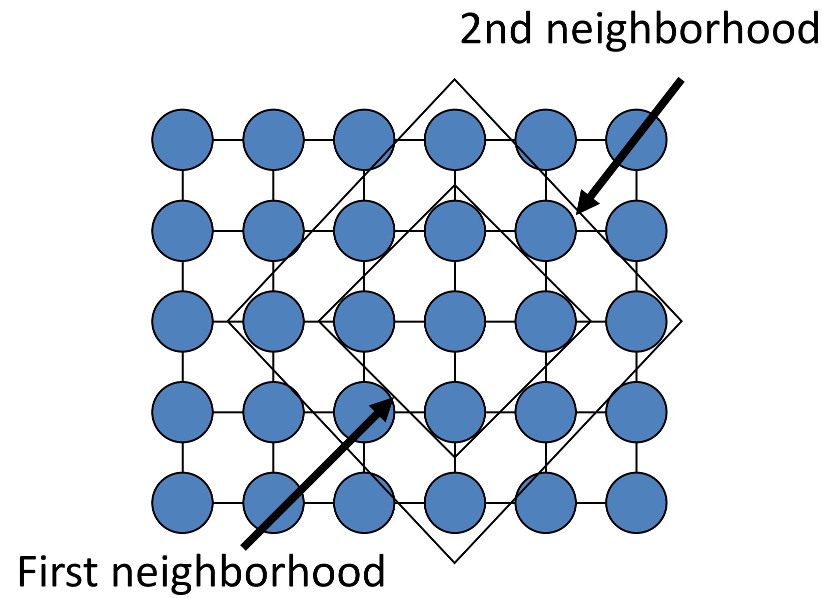


Self organizing maps

- 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)

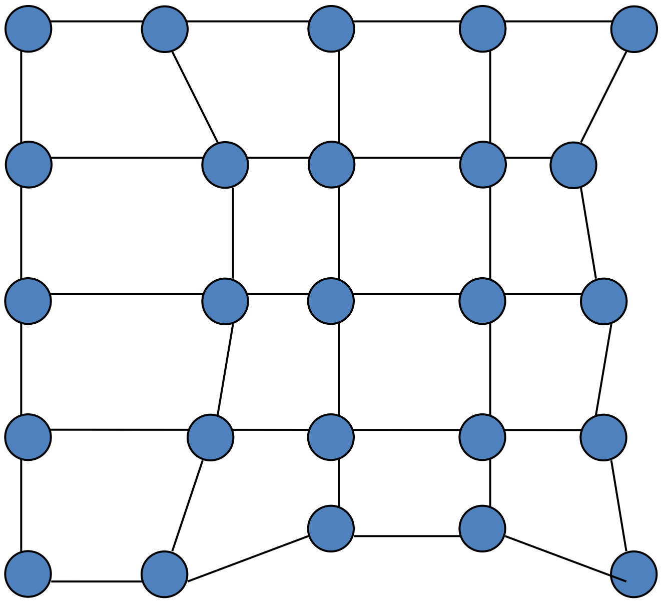
- The activation of the neuron is spread in its direct neighborhood =>neighbors become sensitive to the same input patterns
- Block distance
- The size of the neighborhood is initially large but reduce over time => Specialization of the network





Adaptation

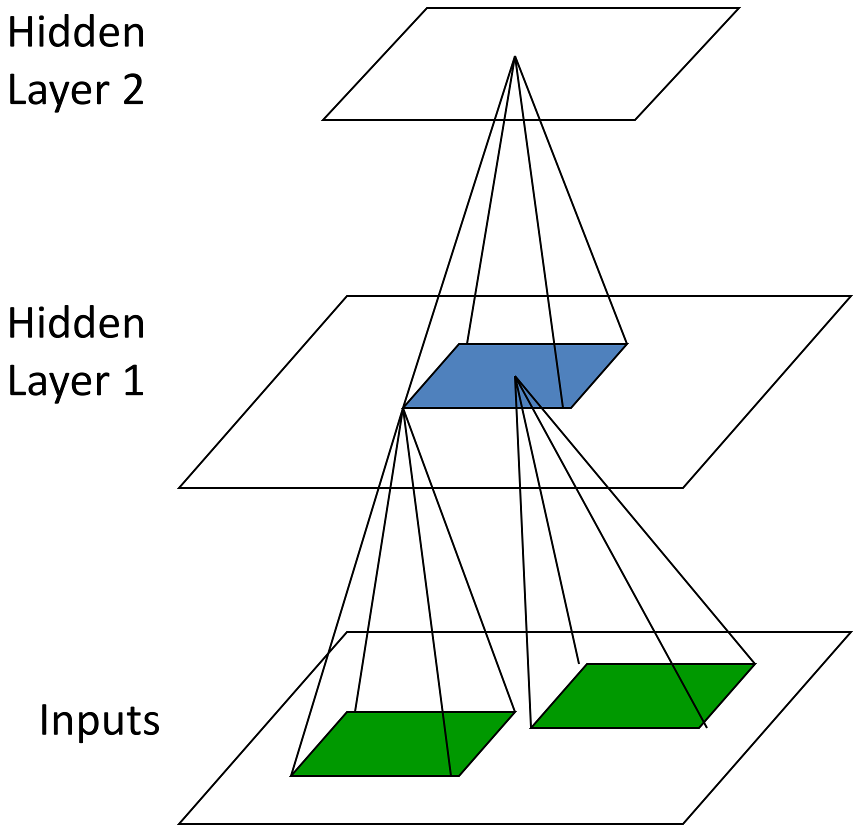
- During training, the “winner” neuron and its neighborhood adapts to make their weight vector more similar to the input pattern that caused the activation
- The neurons are moved closer to the input pattern
- The magnitude of the adaptation is controlled via a learning parameter which decays over time



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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