

# Competitive Learning

Neural Networks

## Bibliography

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Kohonen, T., *Self-Organization and Associative Memory*, Springer-Verlag, 1984.

Carpenter, G. and S. Grossberg, A Massively Parallel Architecture for a Self-Organizing Neural Pattern Recognition machine, *Computer Vision, Graphics, and Image Processing*, 37, 54-115, 1987.

Carpenter, G. and S. Grossberg, ART2; Self-organization of stable category recognition codes for analog input patterns, *Applied Optics*, vol. 26, no. 23, 1987.

Carpenter, G. and S. Grossberg, The ART of adaptive Pattern recognition by a self-organizing neural network, *Computer*, March, 1988.

# Spontaneous Learning Unsupervised Learning

No Teacher

The system must come up with a  
spontaneous but reasonable scheme of  
categorizing patterns

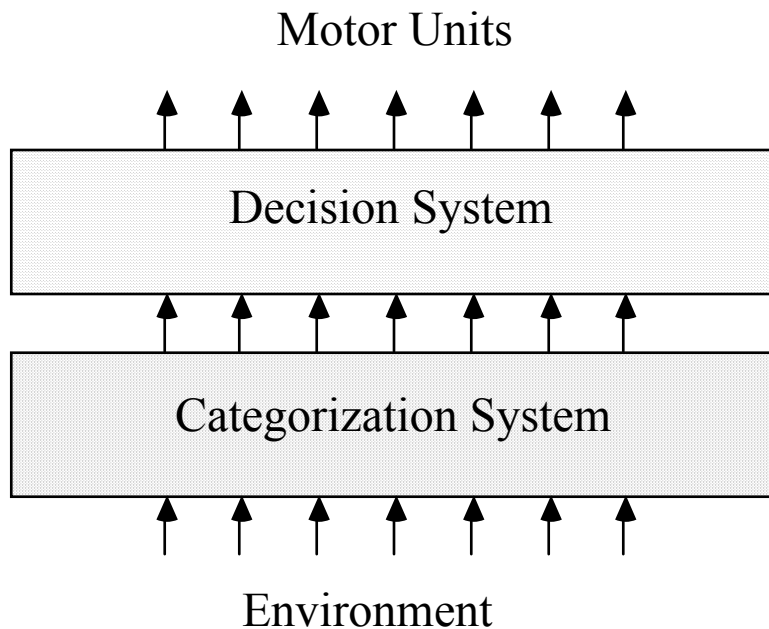
Like-to-Like

# Example ART II Classifications

Supervised and Unsupervised have very different goals

## Categorization vs Decision Systems

Different Target Applications

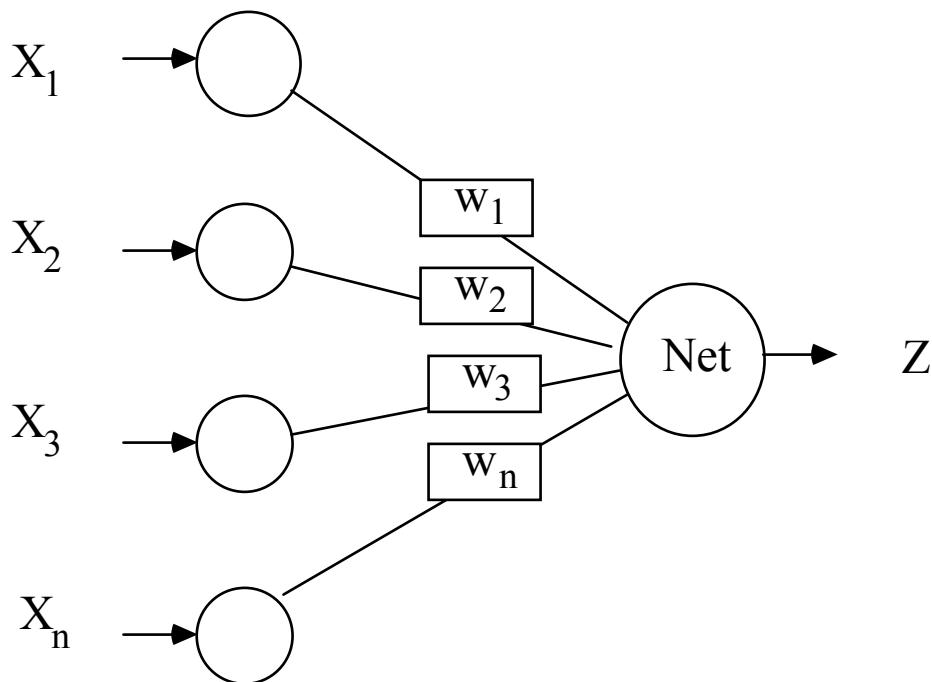


# Competitive Learning

Most common scheme for spontaneous learning

Relatively simple and intuitive

Weight vectors a *prototypes*  
assume real weights

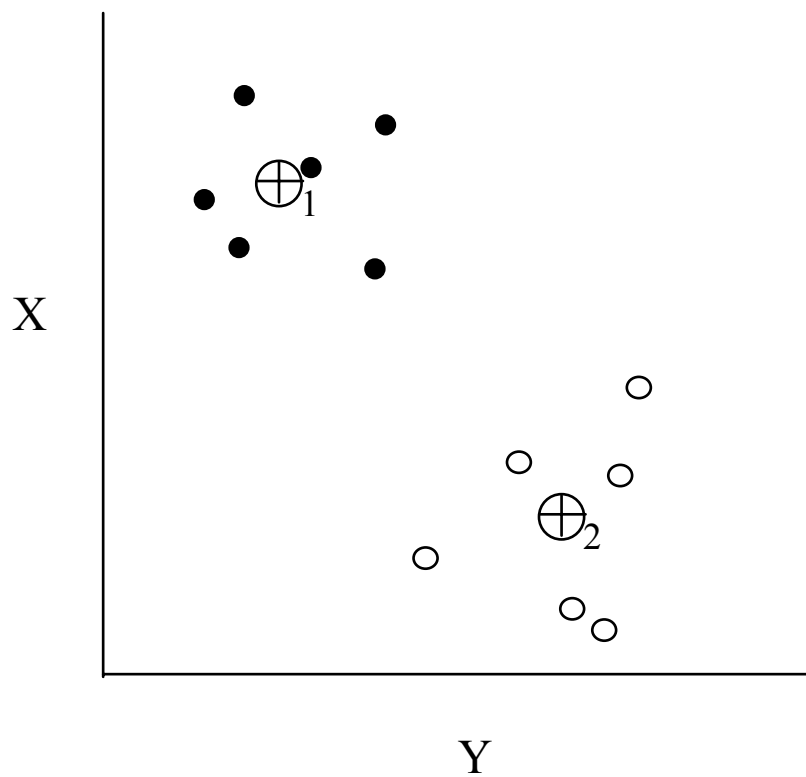
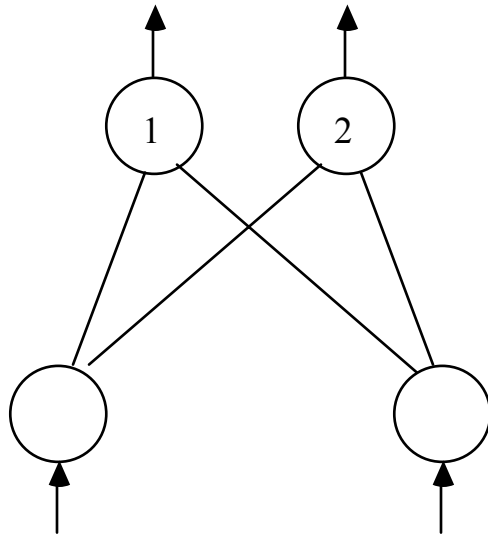


Net most active for pattern similar to weights

# Standard Cluster Diagram

## Localist Model

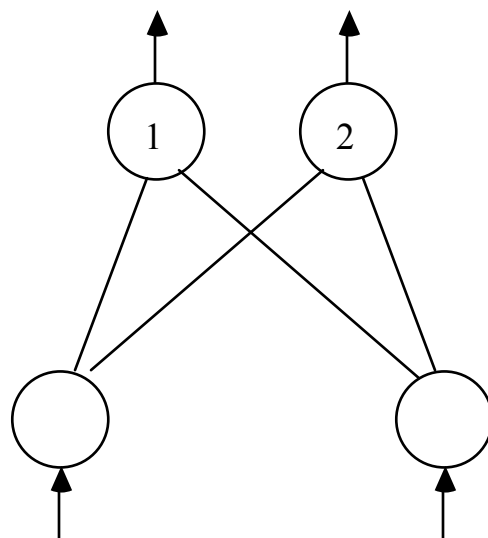
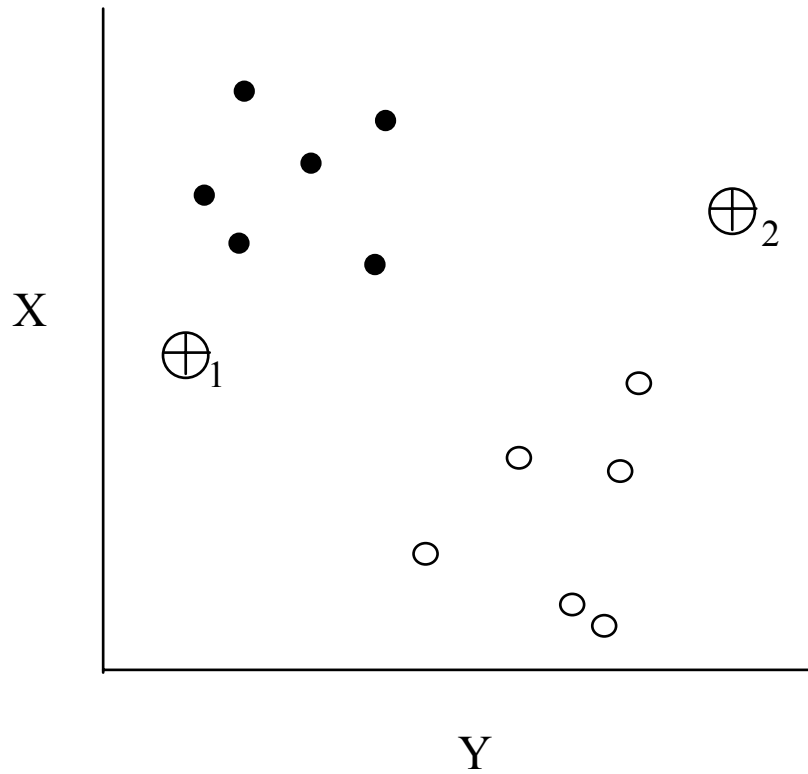
## 2 prototype example (Lateral Inhibition, Winner take all)



Desired Goal



How do we reach it from an initial state



# Simple Competitive Learning Algorithm

## Binary Inputs

Top nodes winner take all

Only winning unit has weights adjusted

Each unit as fixed weight  $\sum 1$ , weight is shifted during learning

$$\Delta w_{ij} = \begin{cases} 0 & \text{if unit } j \text{ loses else} \\ g\left(\frac{s_i}{n} - w_{ij}\right) & \end{cases}$$

where  $n$  is the number of active  $s_i$

Weight is shifted such that weight vector better matches the current winning input

## Extended models

Arbitrary inputs and weights

can use a distance metric rather than the *net*

# Simple Unsupervised Learning Model With Distance Metric

Initialize  $n$  nodes in the attribute dimension space (could be very small  $n$  and be constructive)

Until Convergence ( $\Delta d$  very small)

Input new  $\mathbf{x}$

Choose node  $i$  closest to  $\mathbf{x}$  ( $\text{Argmin}_i (D(n_i, \mathbf{x}))$ )

Optional: Add new node at  $\mathbf{x}$  (how to decide?)

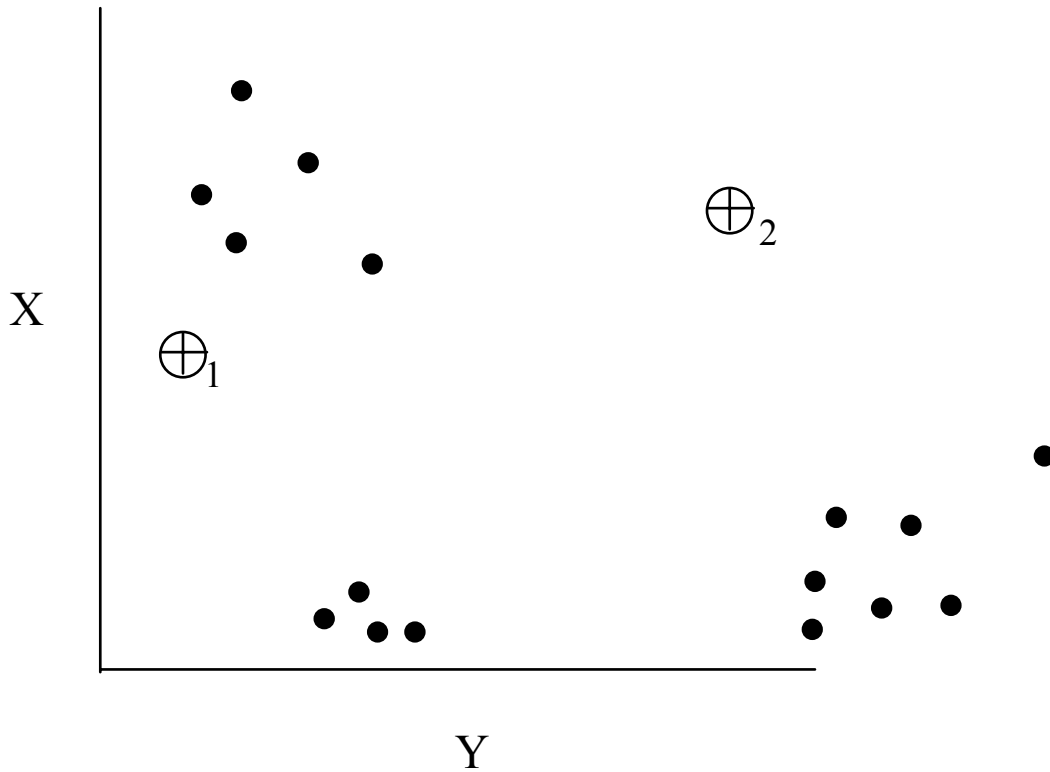
Move  $n_i$  slightly closer to  $\mathbf{x}$  ( $\Delta d_i = d_i + cx_i$ )

( $d$  is a node dimension and  $c$  is a learning rate)

Optional: Prune nodes (how to decide?)

# Dynamic Node Growth

Y



What will happen here

vigilance metric for node growth

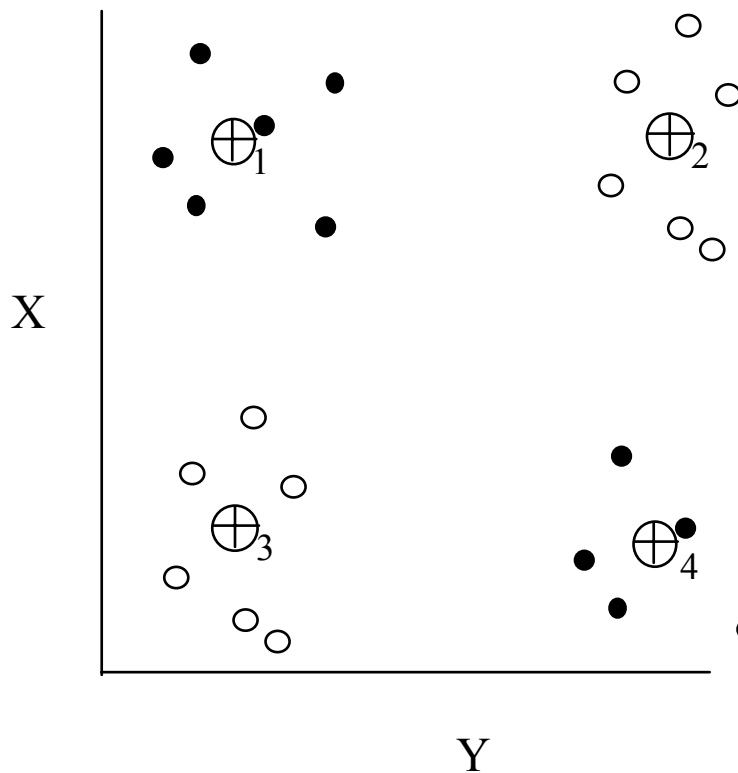
non-global vigilance

noisy patterns

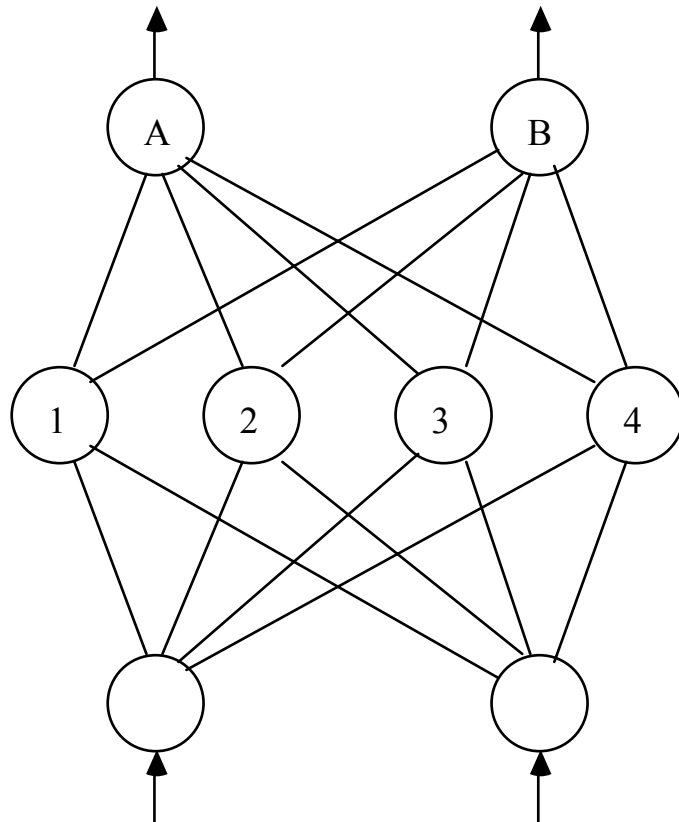
# Supervised learning with competitive scheme

Simply assign output value to each prototype

Basically, multiple prototypes can have the same value



# Multi-layer net using competitive learning



# RCE Learning

(Restricted Coulomb Energy)



ART (Adaptive Resonance Theory)

Spontaneous Competitive Learner

Dynamic Node Growth

Global Vigilance

# Competitive Learning

## Powerful Intuitive Model

Focused applications (Categorizing)

Easily extended to supervised models

## Potential Integration

