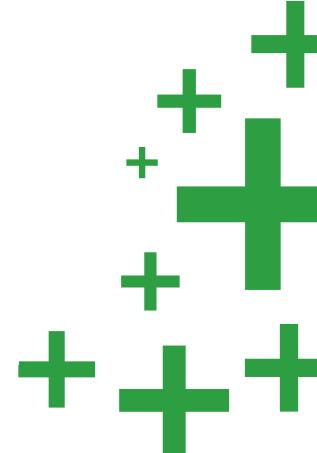
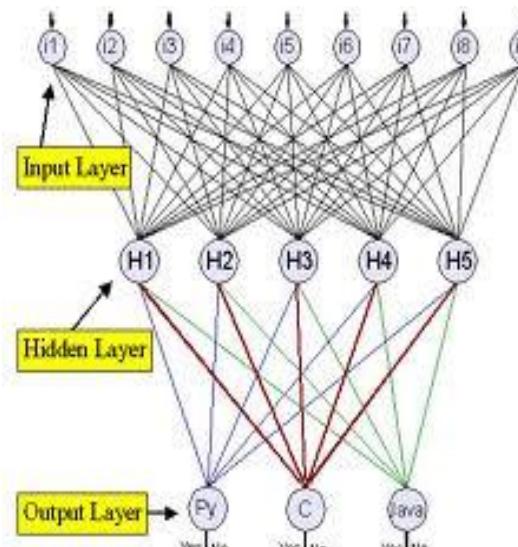
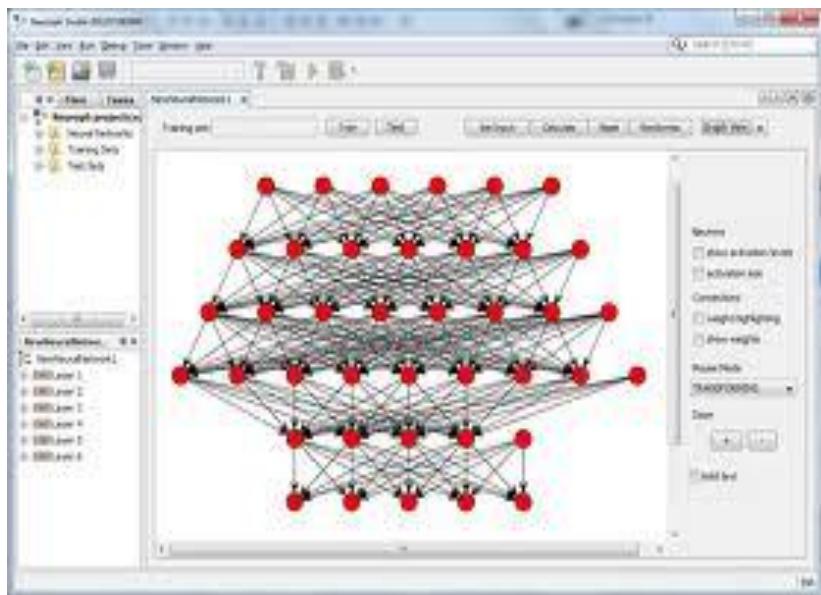


Sistemas de software basados en Redes Neuronales (Inteligencia Artificial Avanzada) y el Estado del Arte de la Tecnología Global



NEUROMORPHIC TECHNOLOGIES

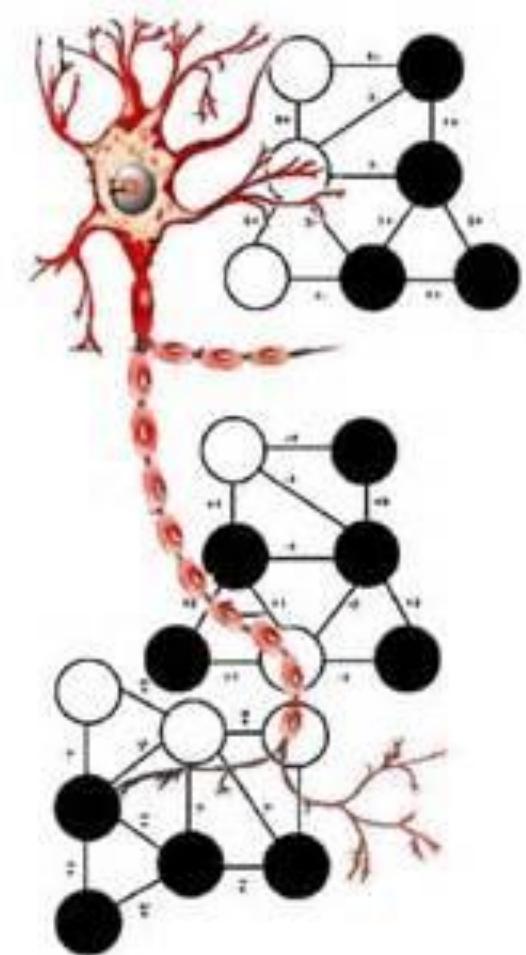
Fernando Jimenez Motte Ph.D.EE (c), M.S.E.E, B.S.E.E

Inteligencia Artificial Avanzada (Redes Neuronales con 3 ejes de visión)

1→ Arquitectura , Algoritmos y Aplicaciones.

2→ Hardware + Software.

3→ Neurocibernética y el advenimiento de la Biónica.





“The Gene is by far the most sophisticated program around.”

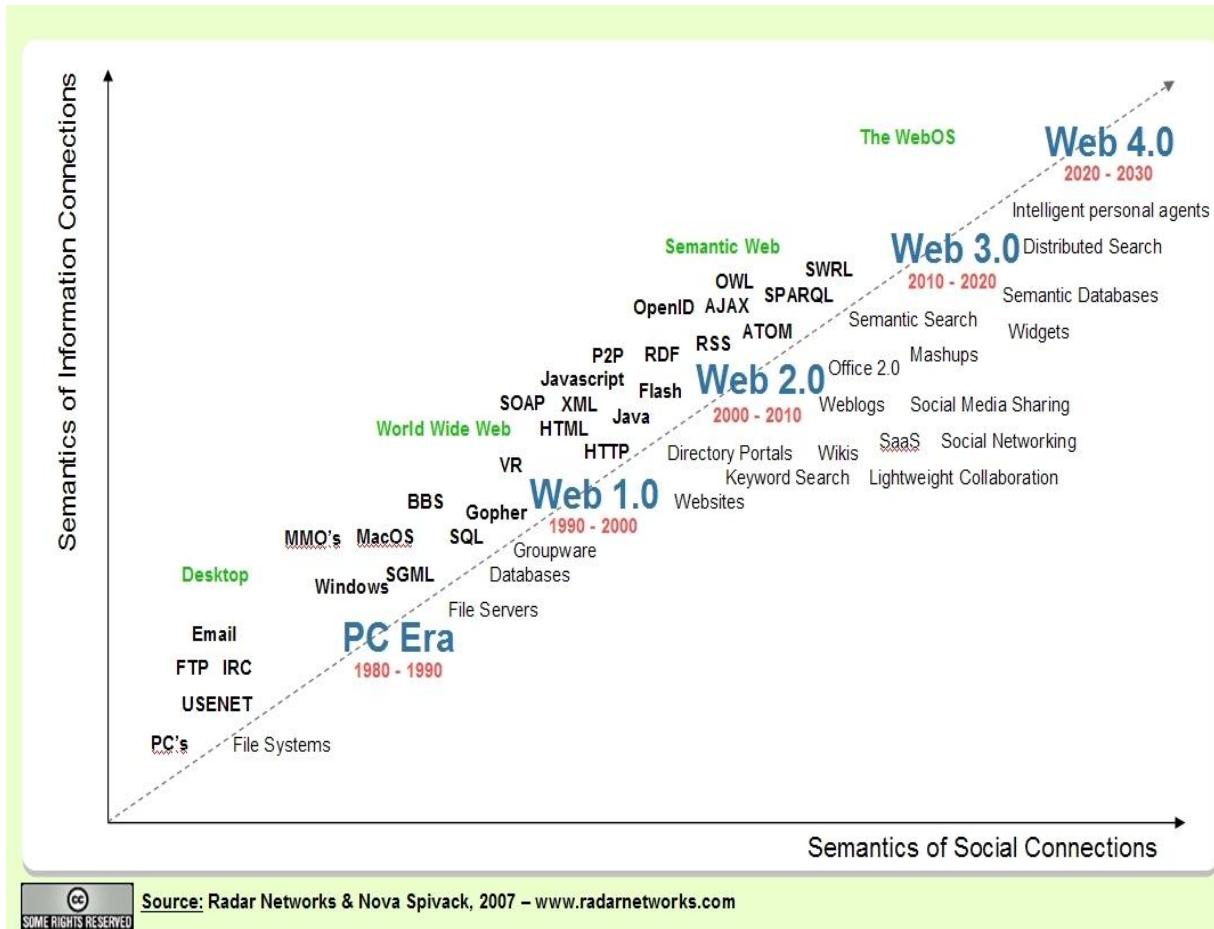
- Bill Gates, *Business Week*, June 27, 1994

Genes , Atoms , Cells and Neurons are the Building Blocks of the XXI Century

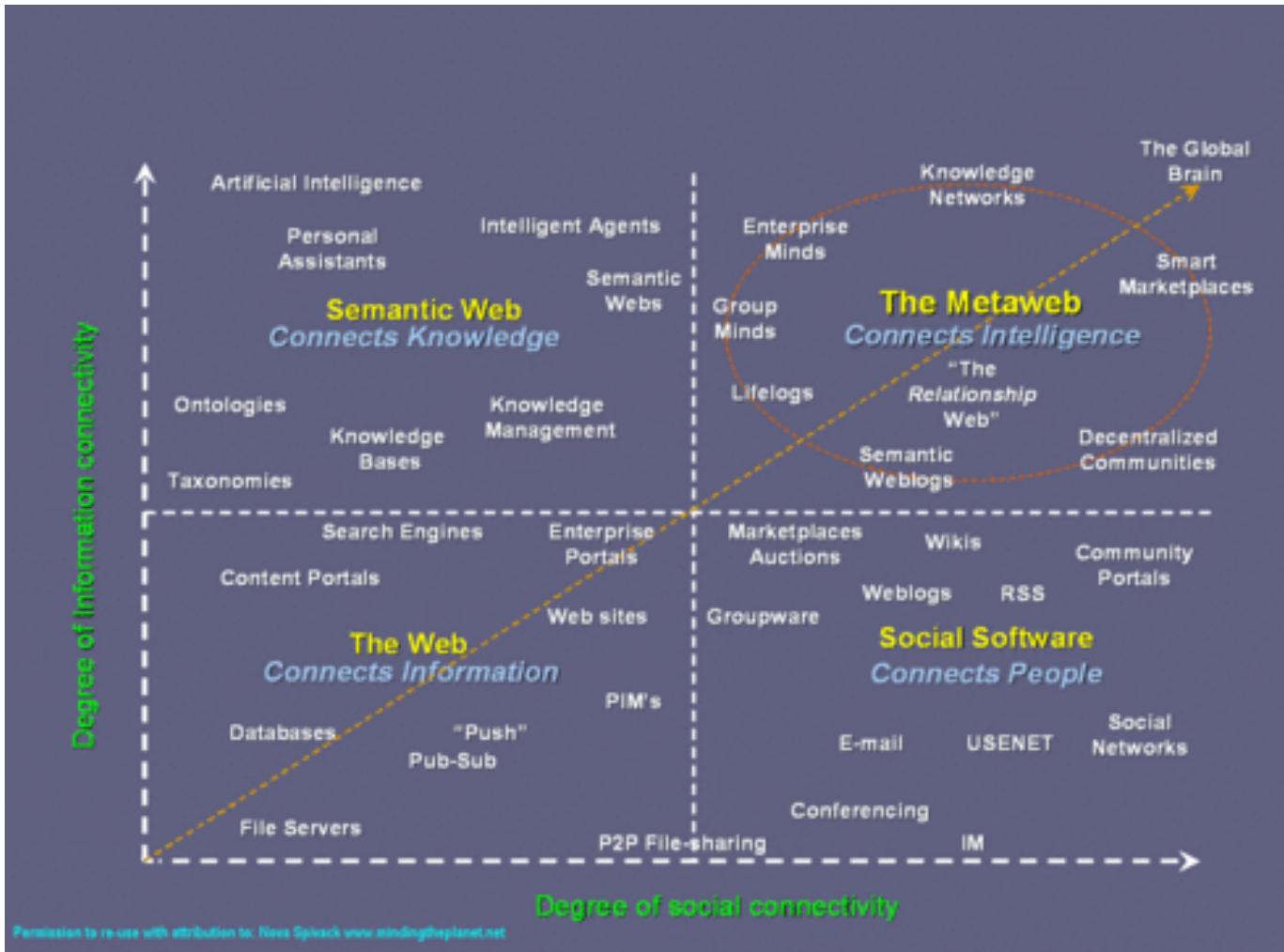
- Fernando Jiménez M, México 2011

Road Map de Tecnología y la evolución de la PC hasta la Web 4.0

Semántica de las conexiones sociales



The Semantic Web (AI)

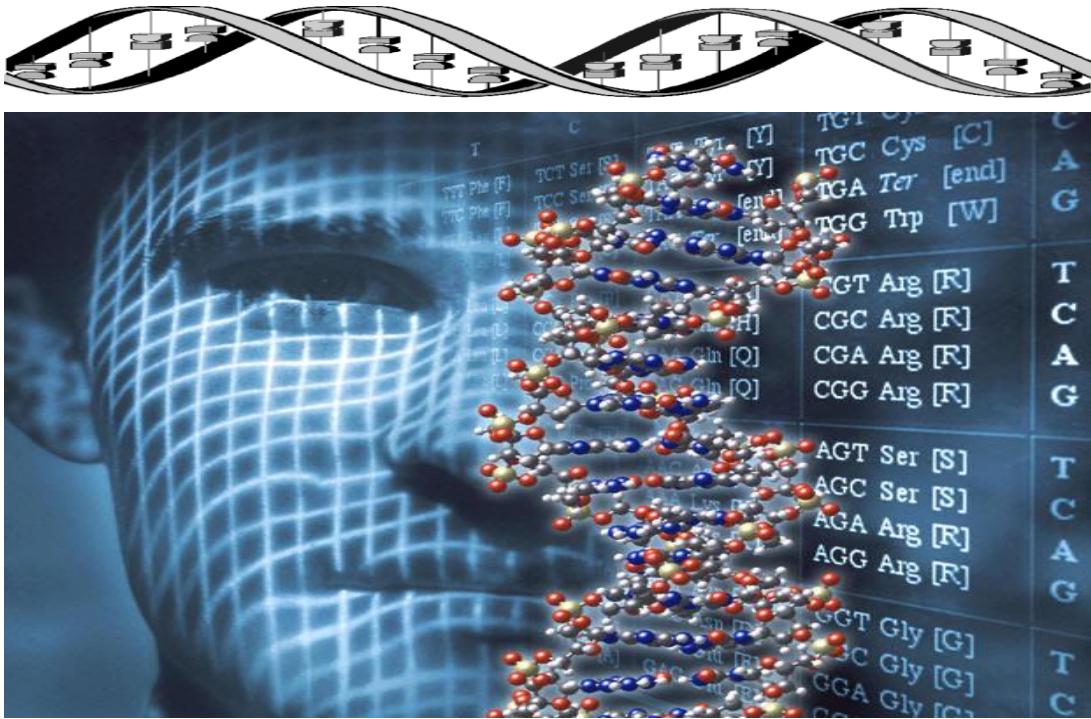
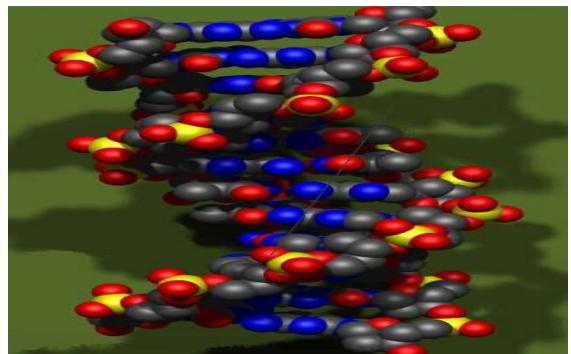
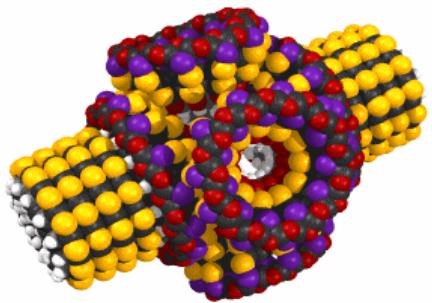


La evolución hacia la Inteligencia Artificial



EVOLUCION HACIA LA INTELIGENCIA ARTIFICIAL

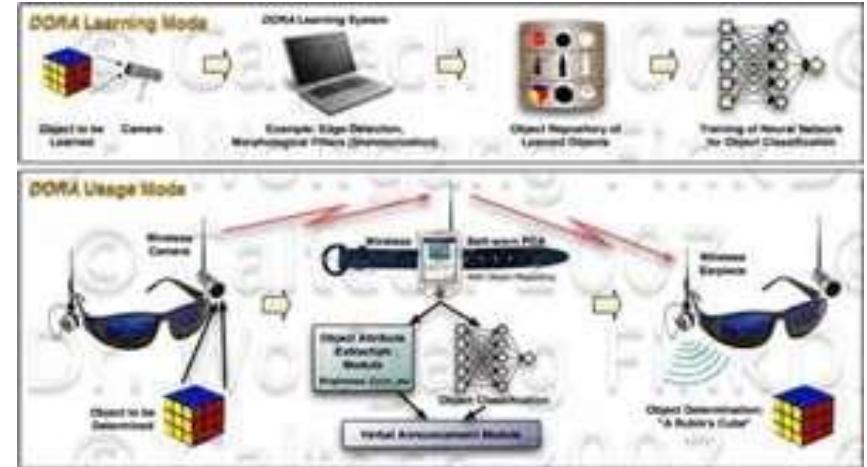
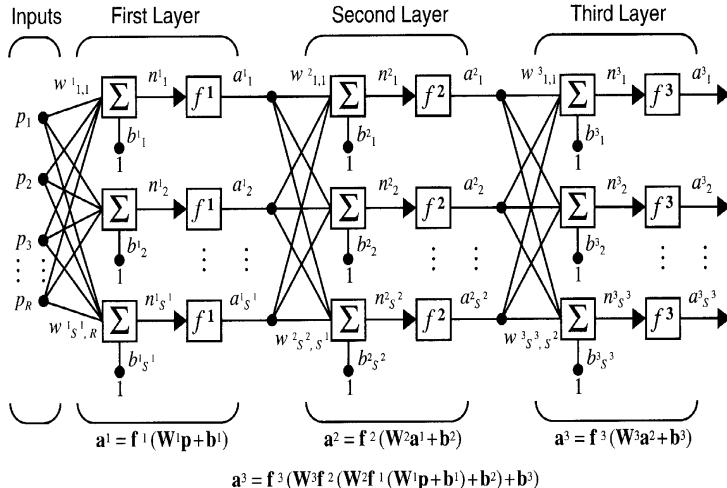
- Aumento exponencial de la capacidad computacional de las PC's.
- Capacidad de manejo computacional **masivo, paralelo y distribuído**.
- Escalamiento de la ciencia a la nube. (**Scaling Science to the Cloud**).
- Advenimiento de **Sistemas Neuro y biomiméticos**.
- Emergencia de la Neurocomputación o **Neurocomputing**.
- **Very large Scale Integrated Systems** VLSI.
- Convergencia de las **GRIN Technologies**.



"BACK TO THE FUTURE" 2010 - 2050
CONVERGENCIA DE LAS GRIN TECHNOLOGIES



ARQUITECTURAS ALGORITMOS Y APLICACIONES



Step 0. Initialize weights and biases

(0 or small random values).

Step 1. While stopping condition is false, do Steps 1–6.

Step 2. For each bipolar training pair $s : t$, do Steps 3–5.

Step 3. Set activation of each input unit, $i = 1, \dots, n$:

$$x_i = s_i.$$

Step 4. Compute activation of each output unit,

$j = 1, \dots, m$:

$$y_in_j = b_j + \sum_i x_i w_{ij}.$$

$$y_j = \begin{cases} 1 & \text{if } y_in_j > \theta \\ 0 & \text{if } -\theta \leq y_in_j \leq \theta \\ -1 & \text{if } y_in_j < -\theta \end{cases}$$

Qué es una Red Neuronal ?



Una Red Neuronal Artificial es un sistema de procesamiento de información o Processing Element (PE) en el caso de una neurona, el cual tiene características de performance en común con redes neuronales biológicas.

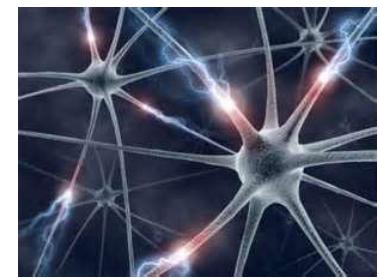
Han sido desarrolladas a través de generalizaciones de modelos matemáticos (Matemática Neurobiológica) basados en cognición humana o biología neuronal y basadas en asunciones como:

El procesamiento de información ocurre en muchos elementos simples llamados neuronas.

Las señales son enviadas entre neuronas a través de conexiones. (LINKS)

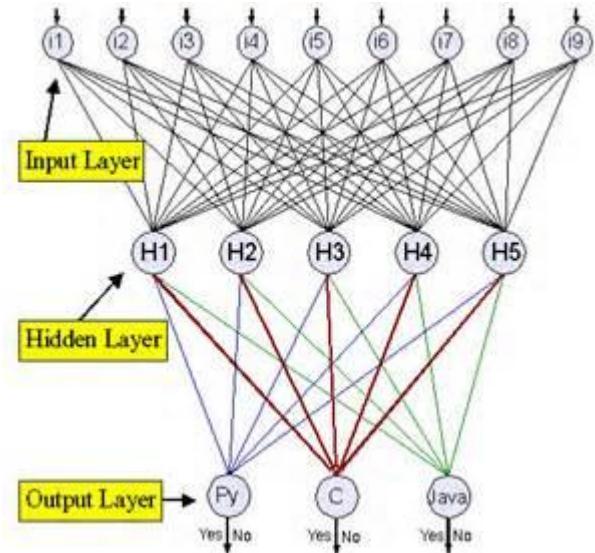
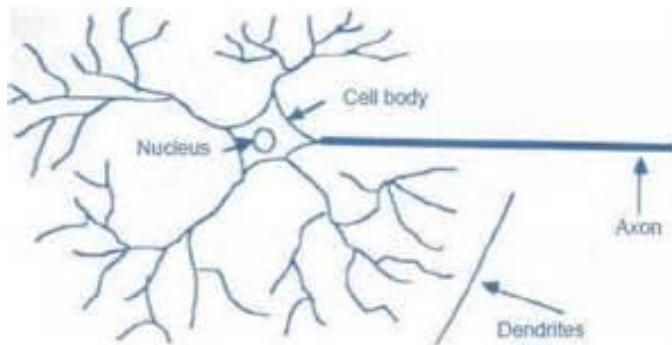


Qué es una Red Neuronal ?

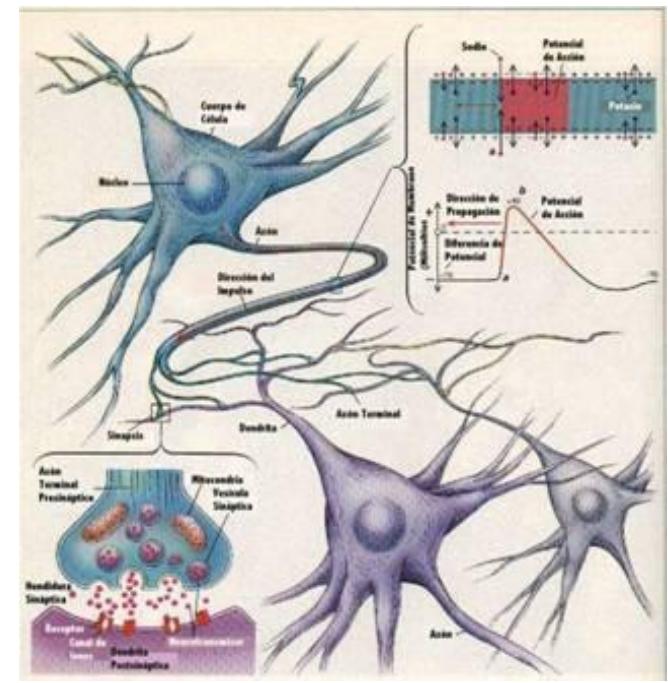
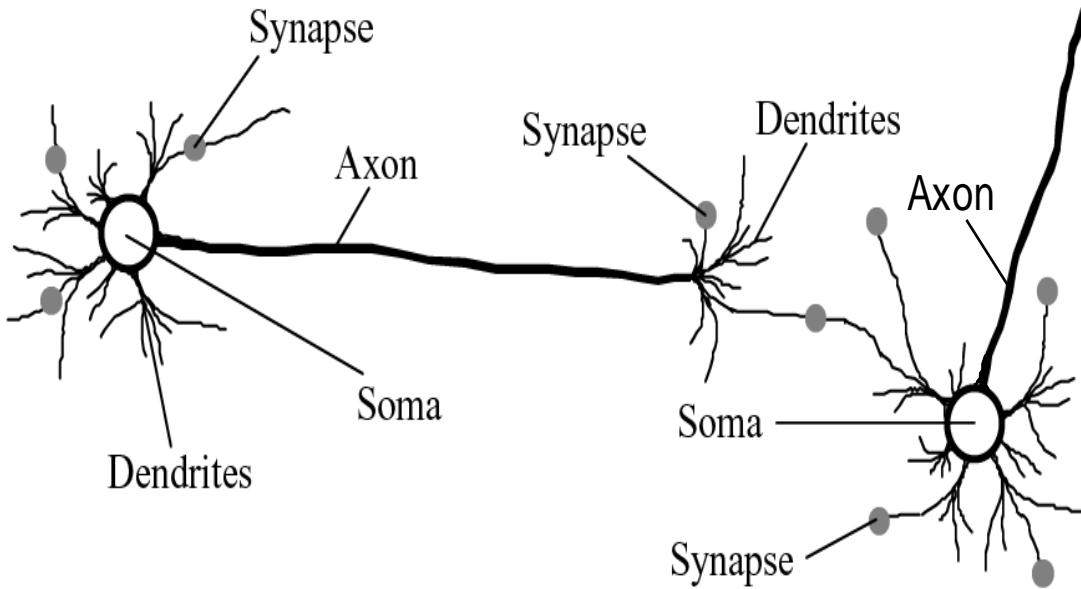


Cada conexión (LINK) tiene un peso asociado, el cual, en una red neuronal típica multiplica la señal transmitida.

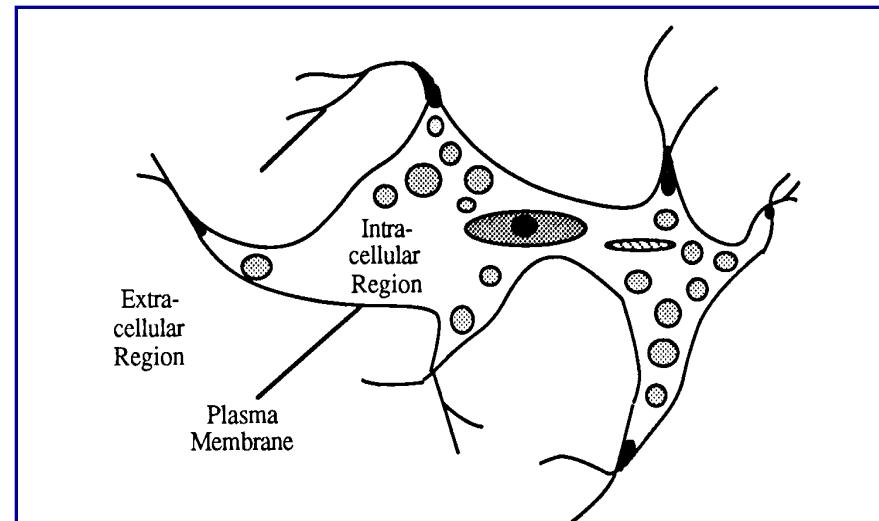
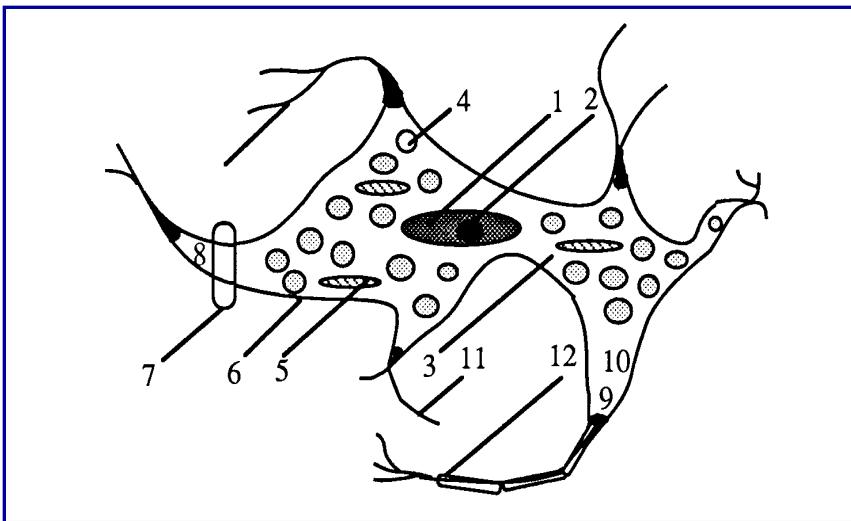
Cada neurona aplica una función de activación (usualmente no lineal) a su entrada neta (net_input) para determinar la señal de salida.



Red Neuronal Biológica



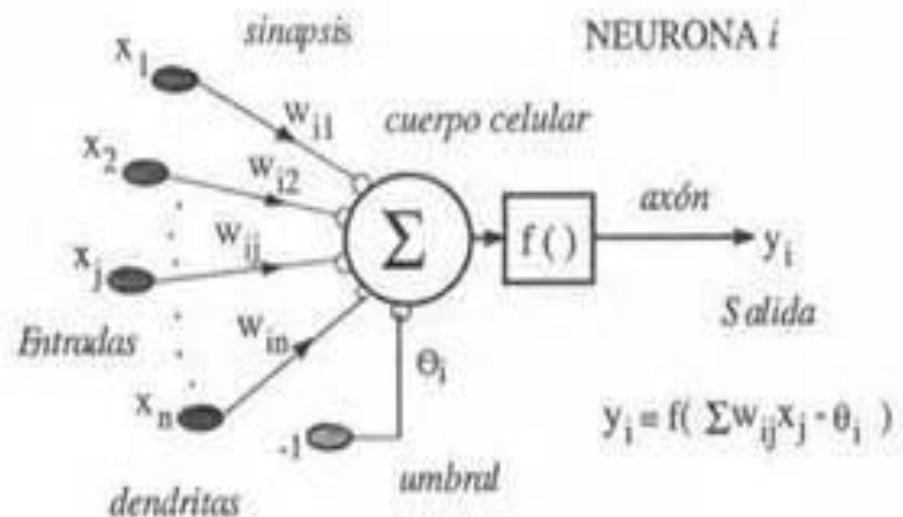
Estructura de una neurona biológica



1 Nucleo; 2 Nucleoide; 3 Soma; 6 Membrana Celular; 7 Región Sináptica , 8 Axon; 11 Dendritas



“Building block” de una Neurona Artificial



Analogía entre Redes Neuronales Biológicas y Redes Neuronales Artificiales

<i>Biological Neural Network</i>	<i>Artificial Neural Network</i>
Soma	Neuron
Dendrite	Input
Axon	Output
Synapse	Weight



Recursos disponibles en computadoras y cerebro humano

	Computer	Human Brain
Computational units	$1 \text{ CPU}, 10^5 \text{ gates}$	10^{11} neurons
Storage units	$10^9 \text{ bits RAM}, 10^{10} \text{ bits disk}$	$10^{11} \text{ neurons}, 10^{14} \text{ synapses}$
Cycle time	10^{-8} sec	10^{-3} sec
Bandwidth	10^9 bits/sec	10^{14} bits/sec
Neuron updates/sec	10^5	10^{14}

Tipos de Redes Neuronales

- **Aplicaciones**

- Clasificación (**Classification**)
- (**Clustering**)
- Aproximación de funciones (**Function approximation**)
- Predicción (**Prediction**)
- Toma de decisiones en situaciones con restricción (**constrained optimization**)

- **Tipo de conexión**

- Estática / **Static (feedforward)**
- Dinámica / Dynamic (**feedback**)

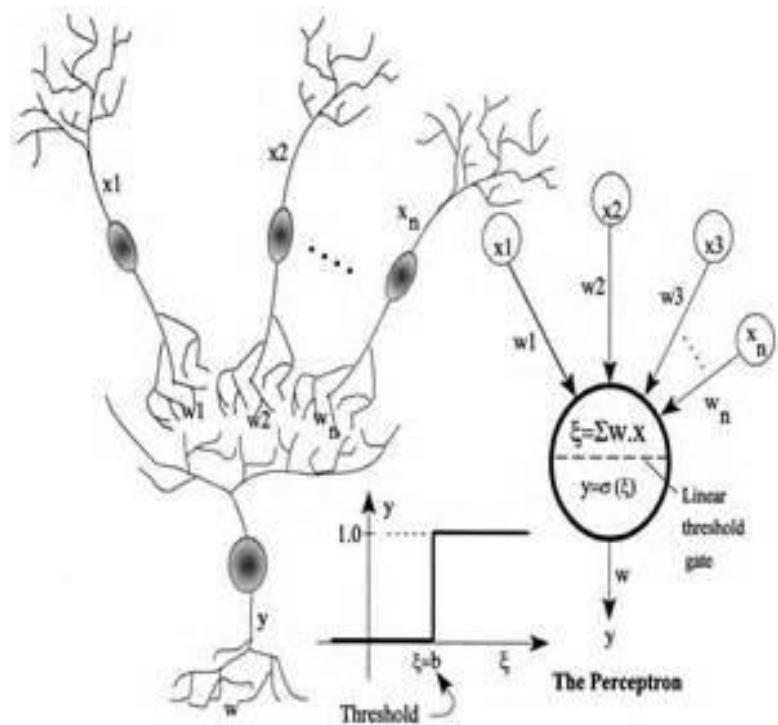
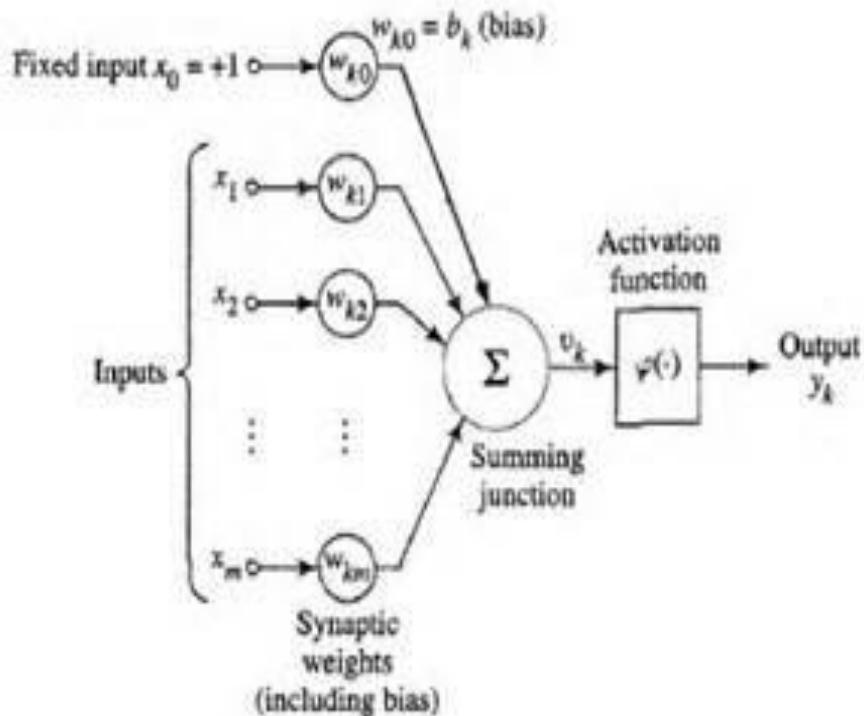
- **Topología**

- Una sola capa (**Single layer**)
- Multicapa (**Multilayer**)
- Recurrente (**Recurrent**)
- Auto Organizacional (**Self-organizing Neural Net**)

- **Método de aprendizaje**

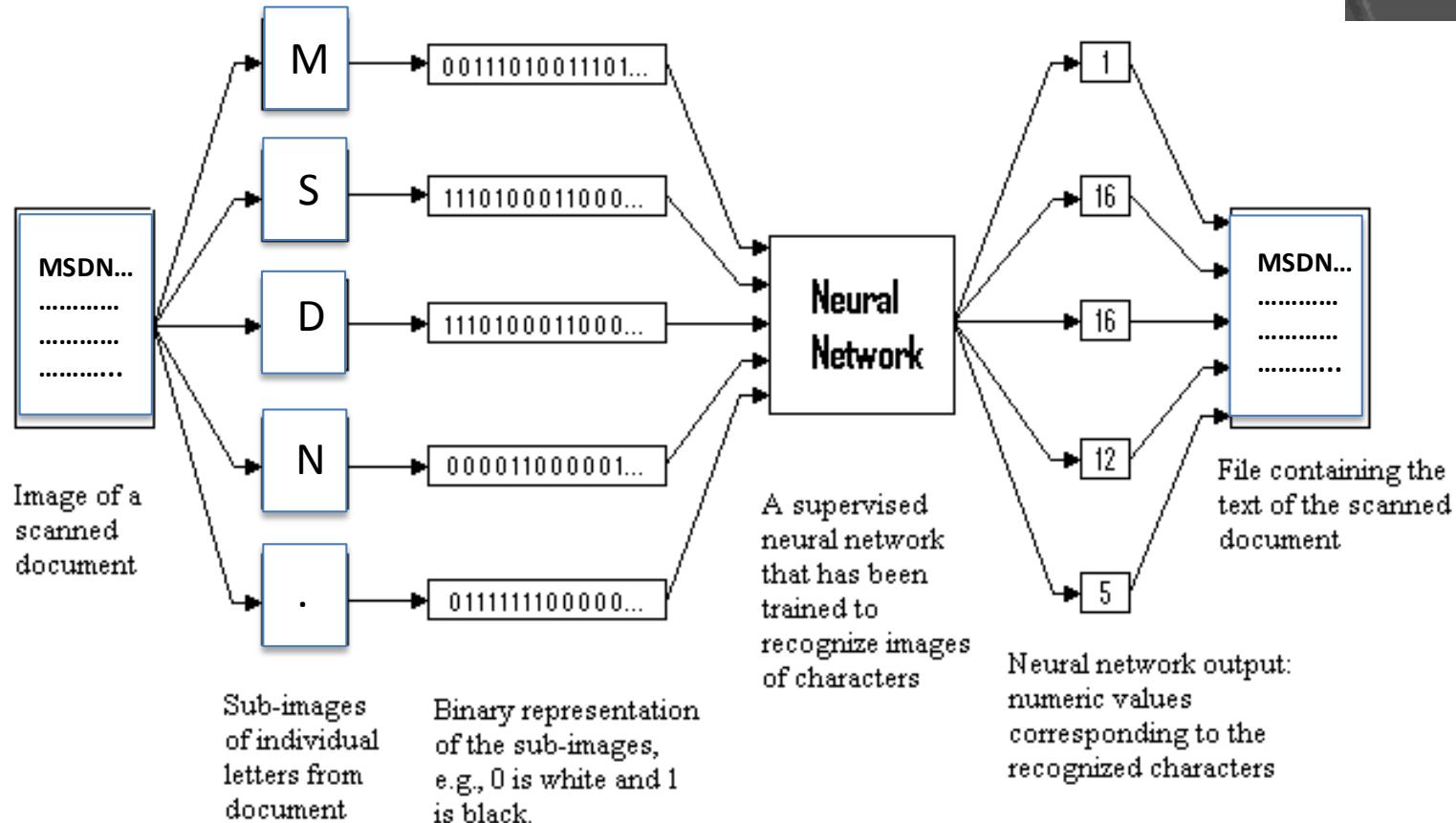
- Supervizada (**Supervised**)
- No Supervizada (**Unsupervised**)

Perceptron

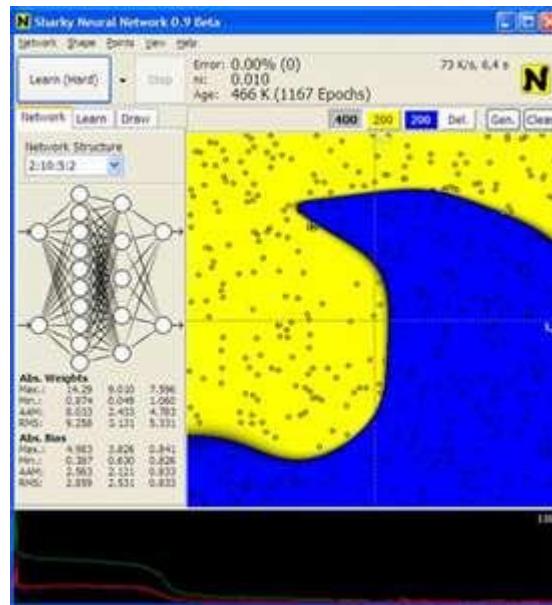
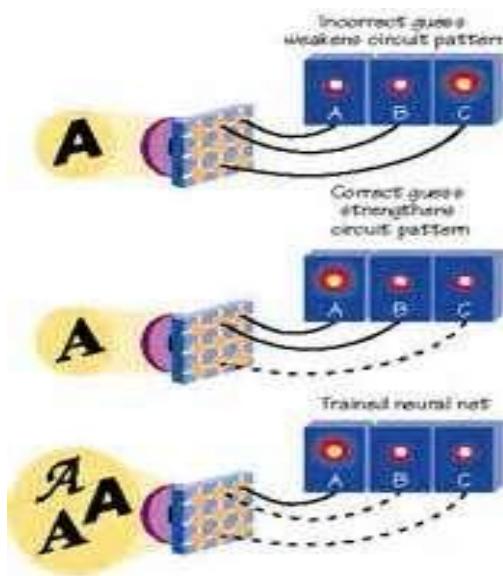
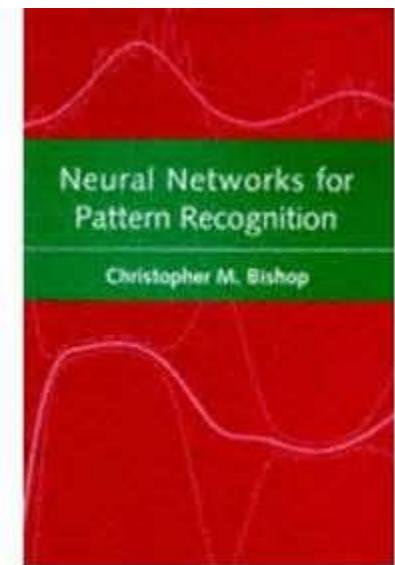
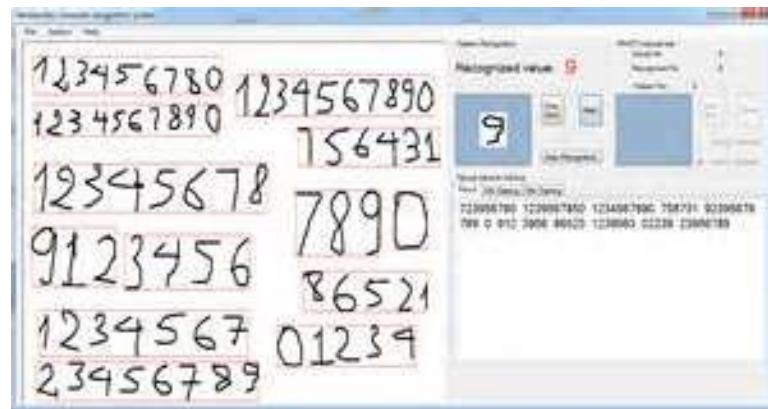
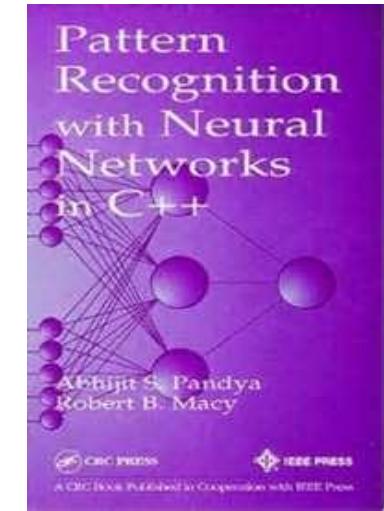


Perceptron

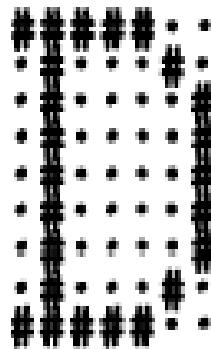
(Pattern Recognition/Pattern Classification)



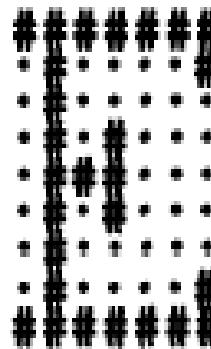
Redes Neuronales en Reconocimiento y Clasificación de Patrones (Pattern Recognition/Pattern Recognition)



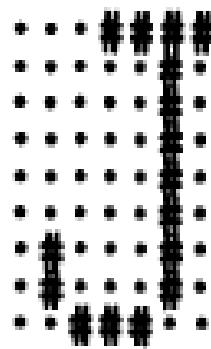
Reconocimiento de caracteres



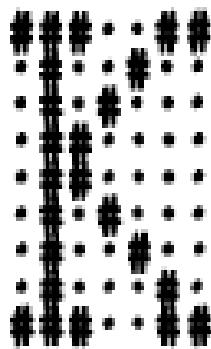
D1



E1

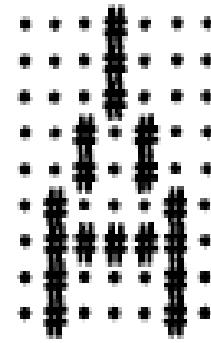


J1

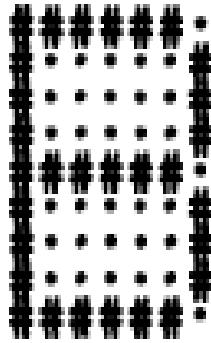


K1

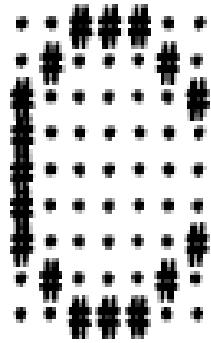
Input from
Font 2



A2



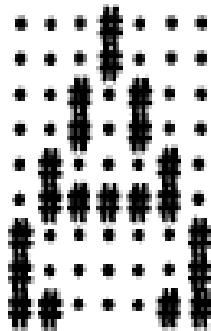
B2



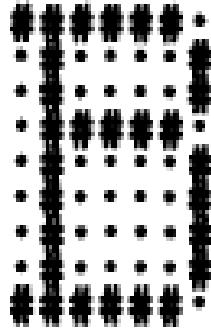
C2

Reconocimiento de caracteres

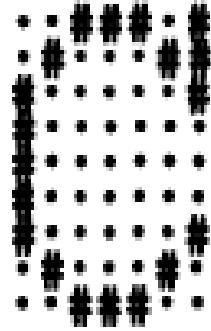
Input from
Font 3



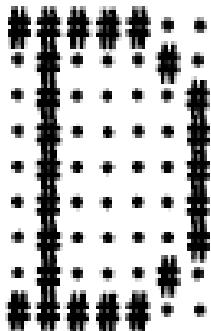
A3



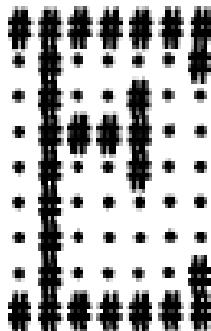
B3



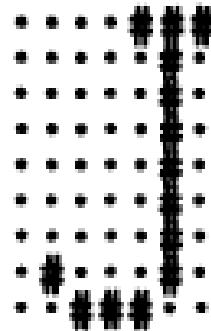
C3



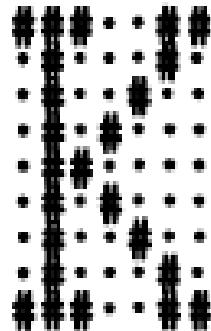
D3



E3

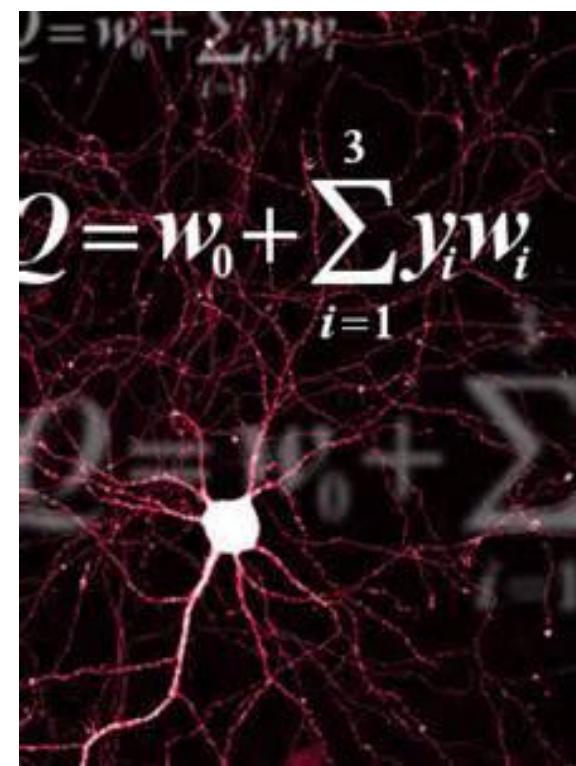
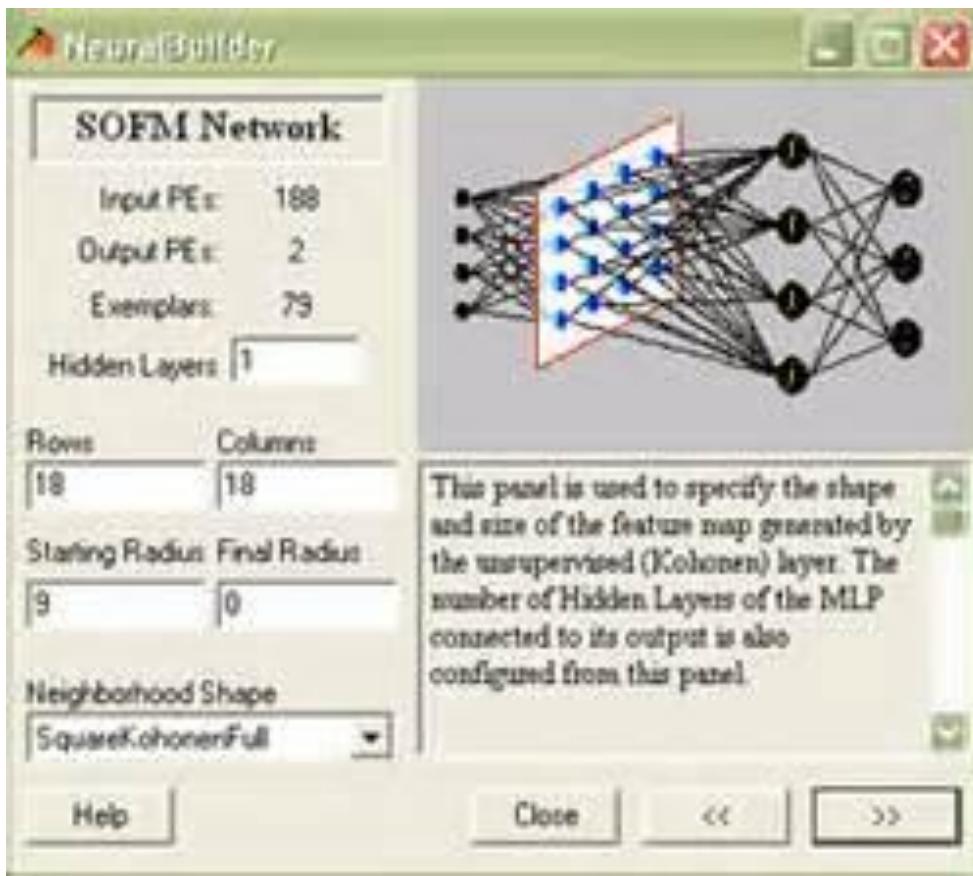


J3

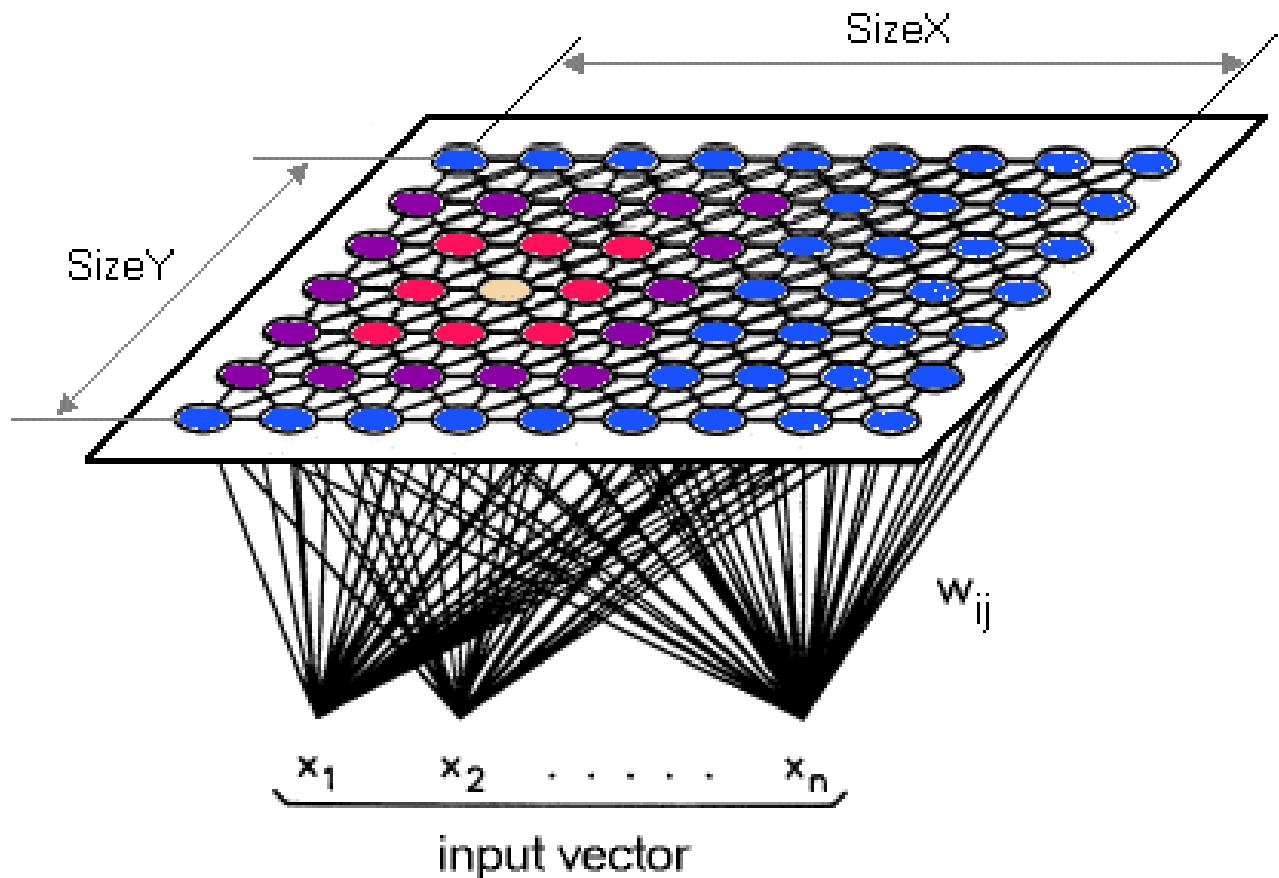


K3

REDES NEURONALES BASADAS EN COMPETICION (Neural Computation)

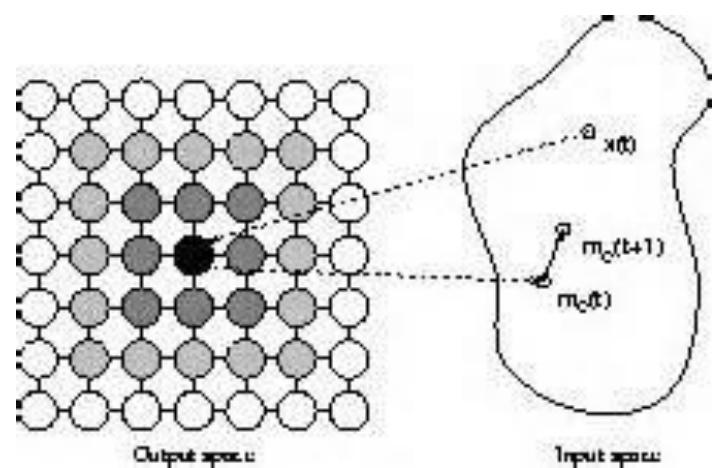
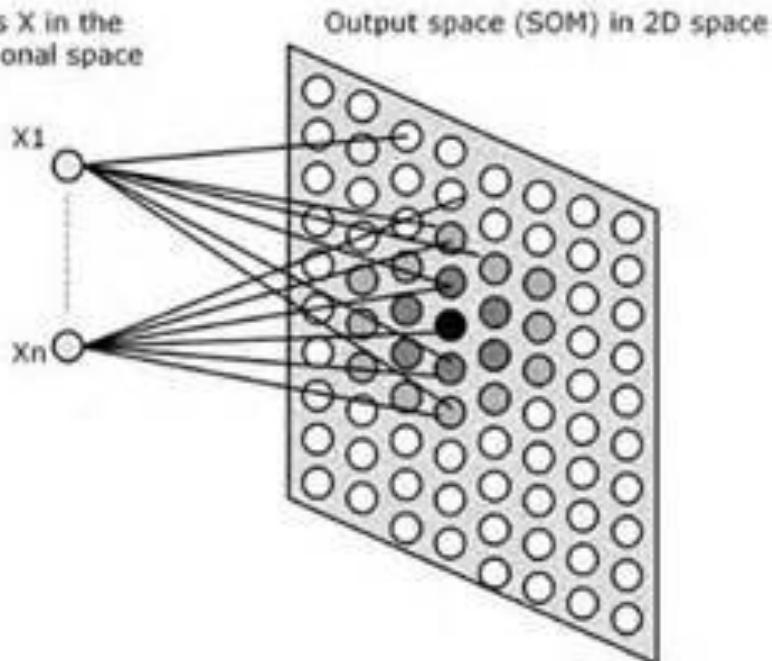


Self Organizing Map (SOM) Neural Network

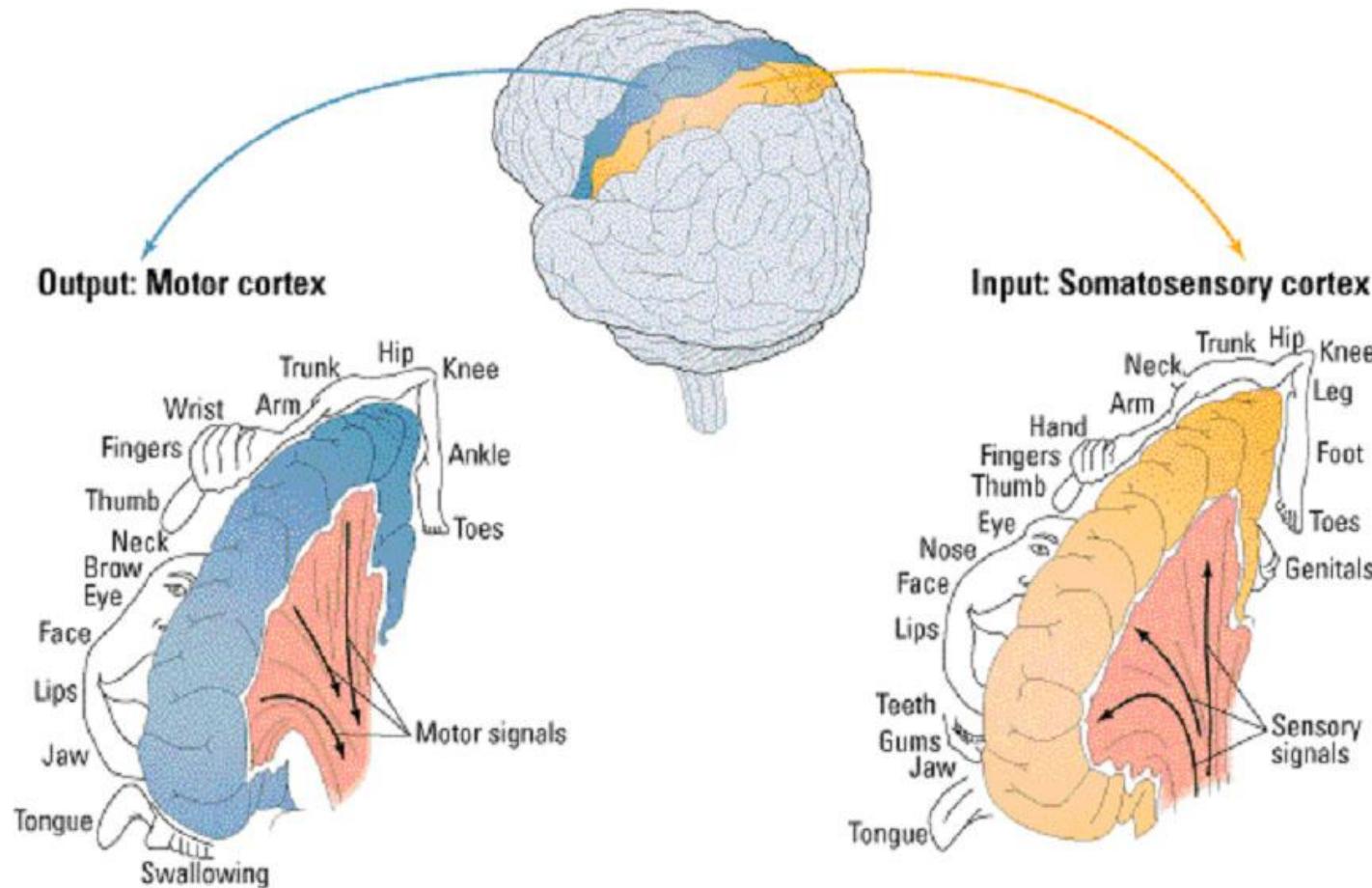


Self organizing maps

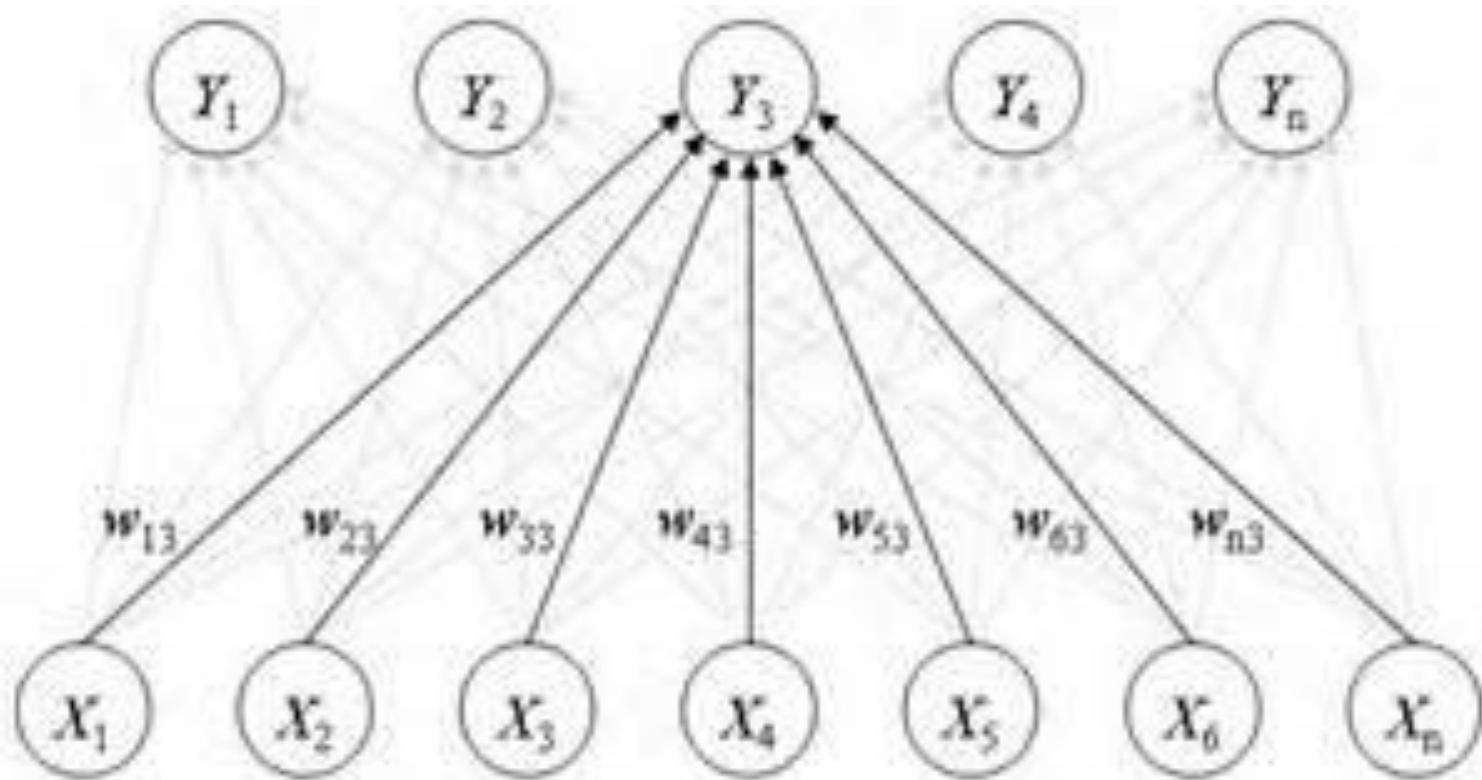
Input vectors X in the multidimensional space



Mapas auto organizantes del cuerpo humano (Somatosensory cortex)

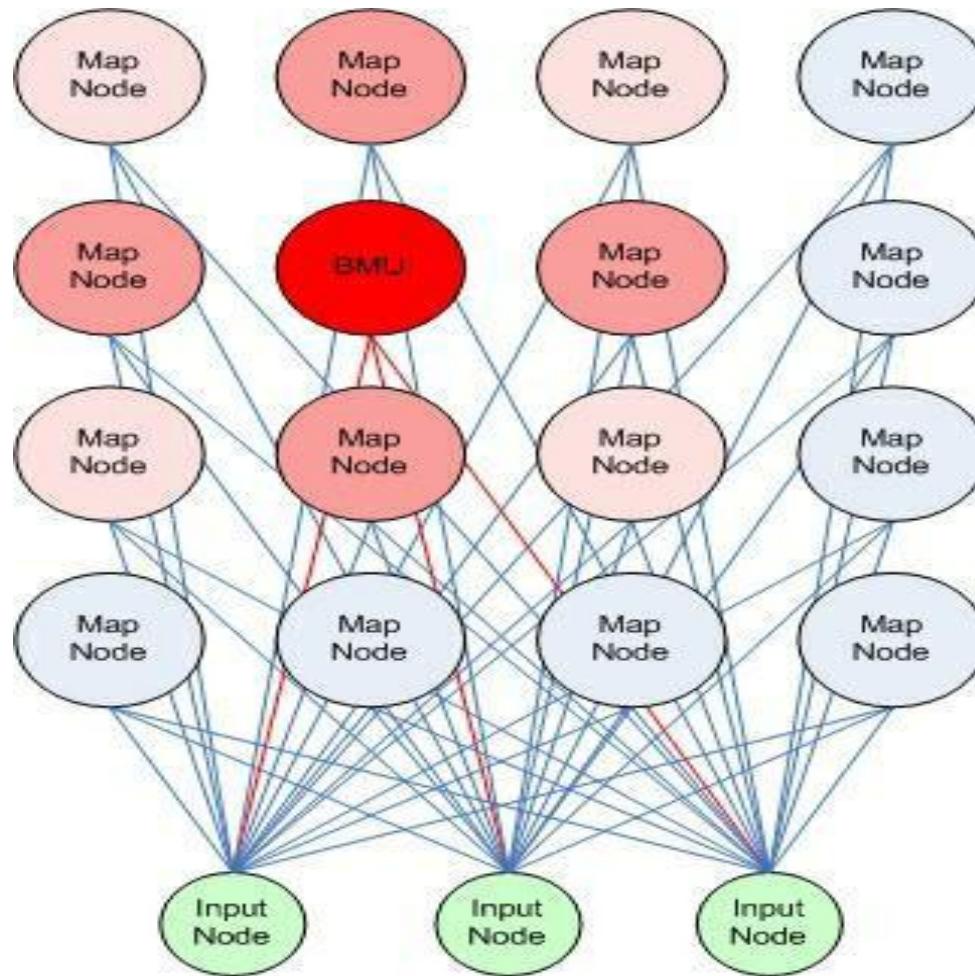


SELF ORGANIZING NEURAL NETWORK



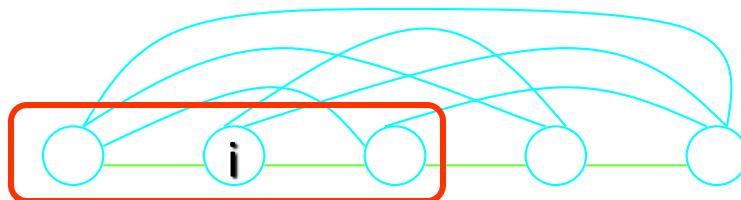
4x4 SOM Network

(4 nodes down, 4 nodes across)



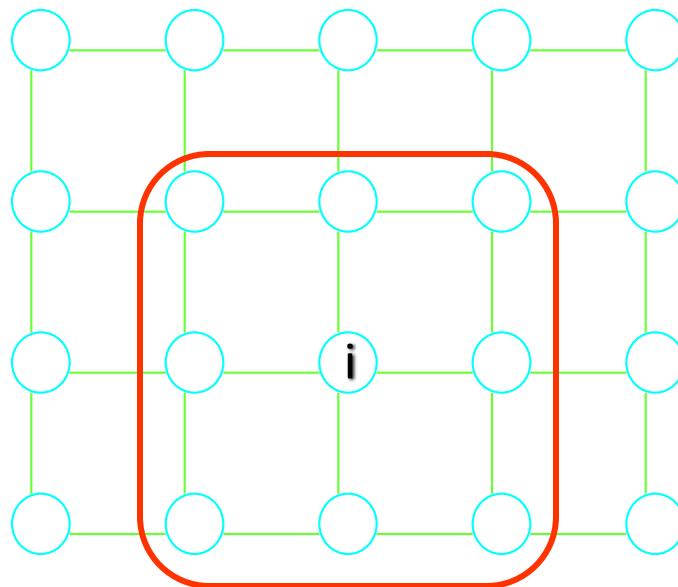
Self-Organizing Maps (Kohonen Maps)

Estructuras de salida típicas: (“Computational layer”)

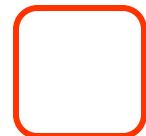


Uni-dimensional

(completamente interconectada para determinar la unidad ganadora. (“winner”))

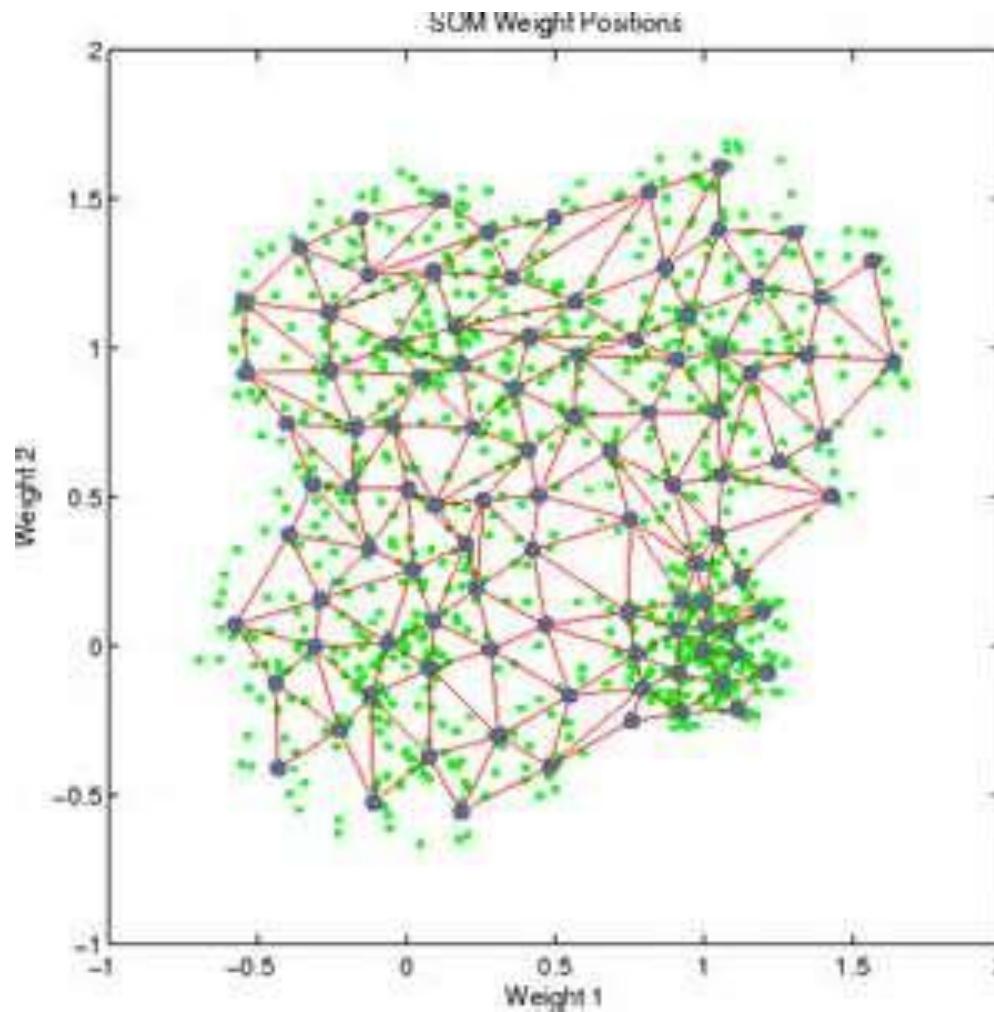


Bi-dimensional

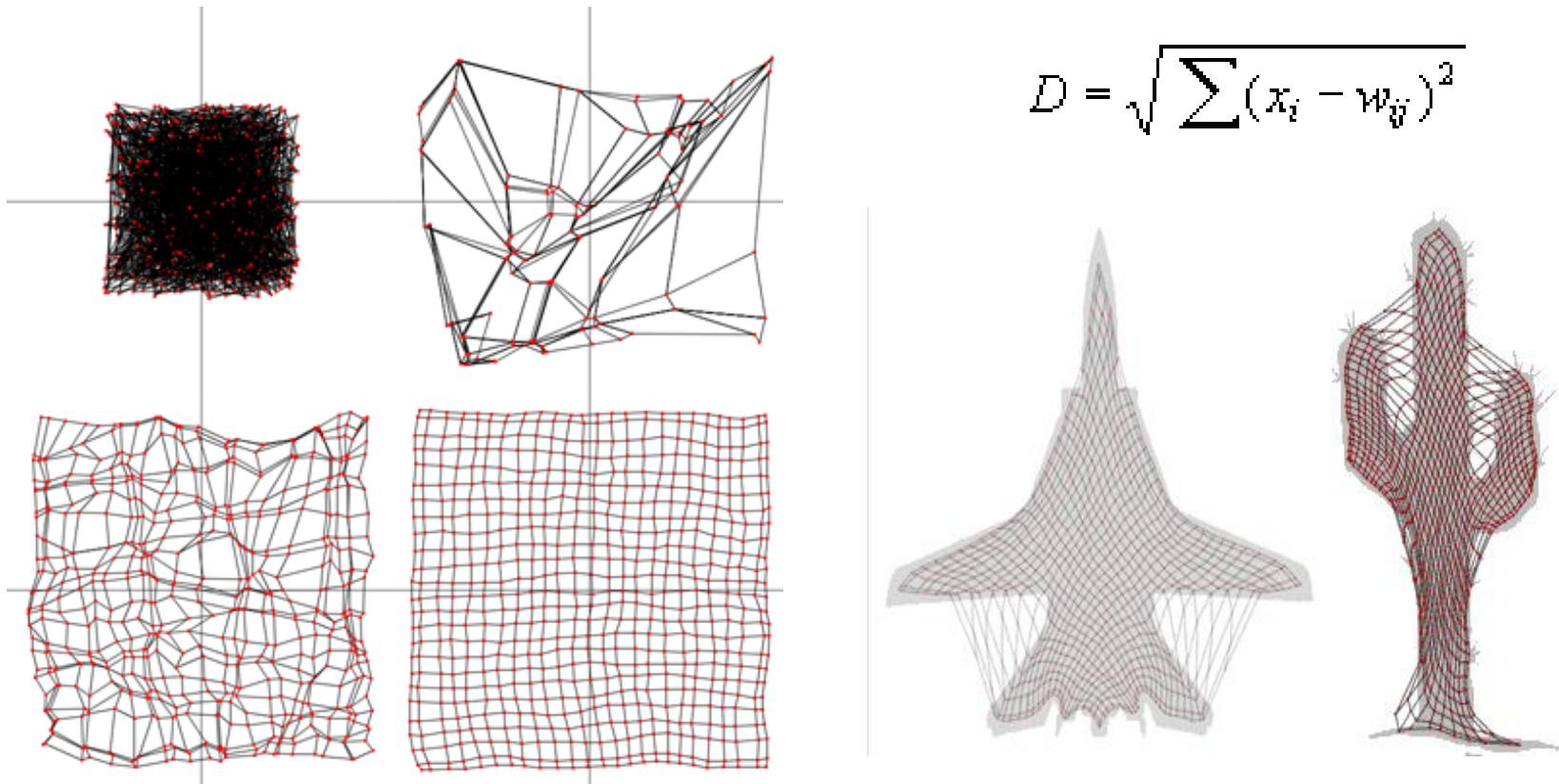


Vecindario de la neurona i

Mapas Auto Organizantes



Self Organizing Neural Network

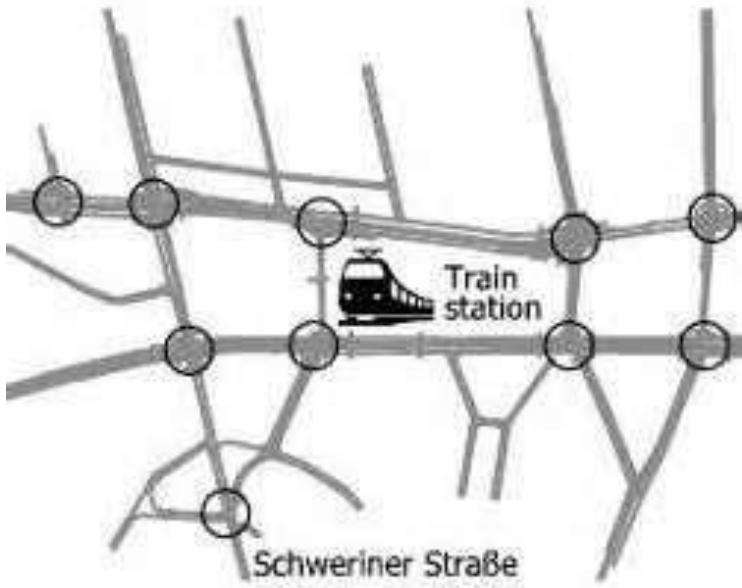


$$D = \sqrt{\sum (x_i - w_j)^2}$$

$$\Delta w_j = k(x_i - w_j)$$

Kohonen Learning

“Self Organizing Traffic Lights”



*La evolución de la inteligencia artificial la concepción moderna es que **la ciudad es la red neuronal**. Las diferentes vías, avenidas y autopistas de una ciudad **emulan a las dendritas y axones** de la estructura intracelular y extracelular de una neurona o red neuronal biológica. En la red vial de una ciudad, las intersecciones definen entonces neuronas y la red neuronal vial aprende del flujo de tráfico de vehículos.*

Arreglo lineal de “cluster” units

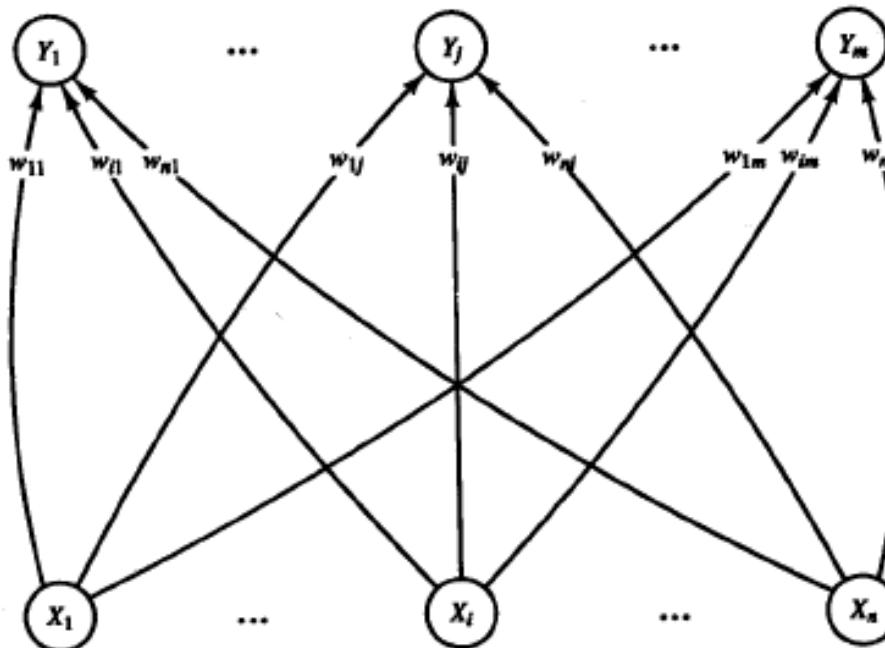


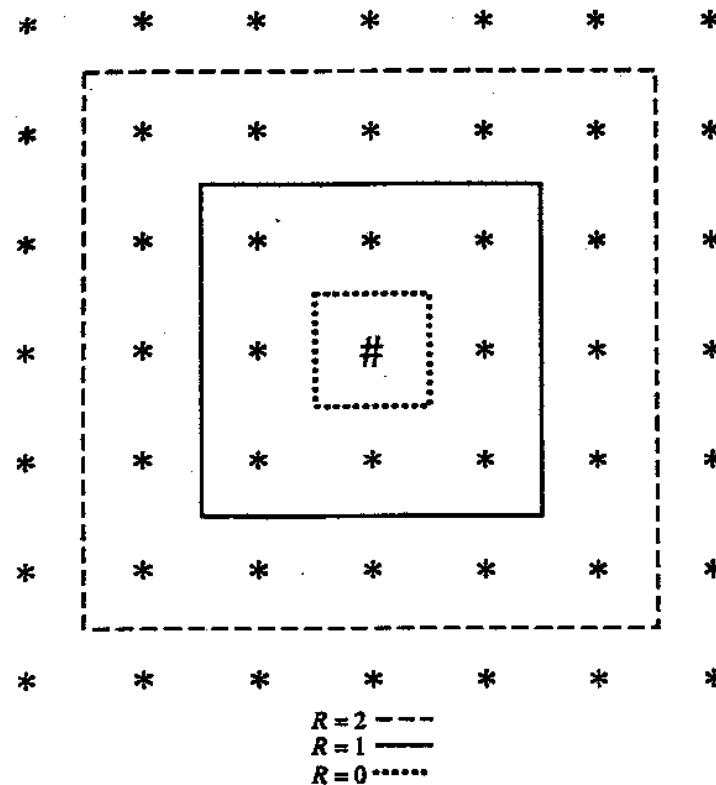
Figure 4.5 Kohonen self-organizing map.

* * * { * (* [#] *) * } * *

{ } R = 2 () R = 1 [] R = 0

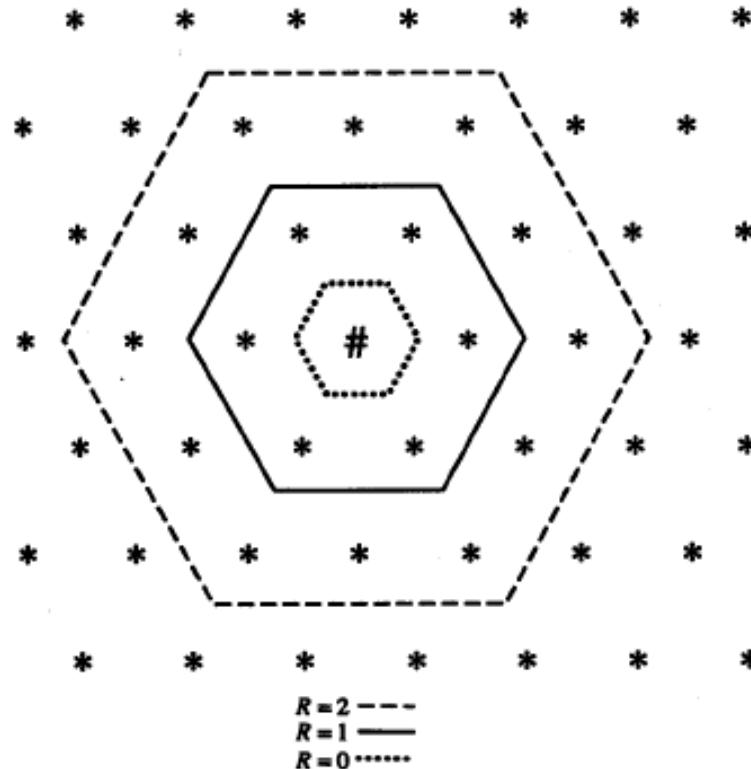
Arquitectura

- Grilla Rectangular



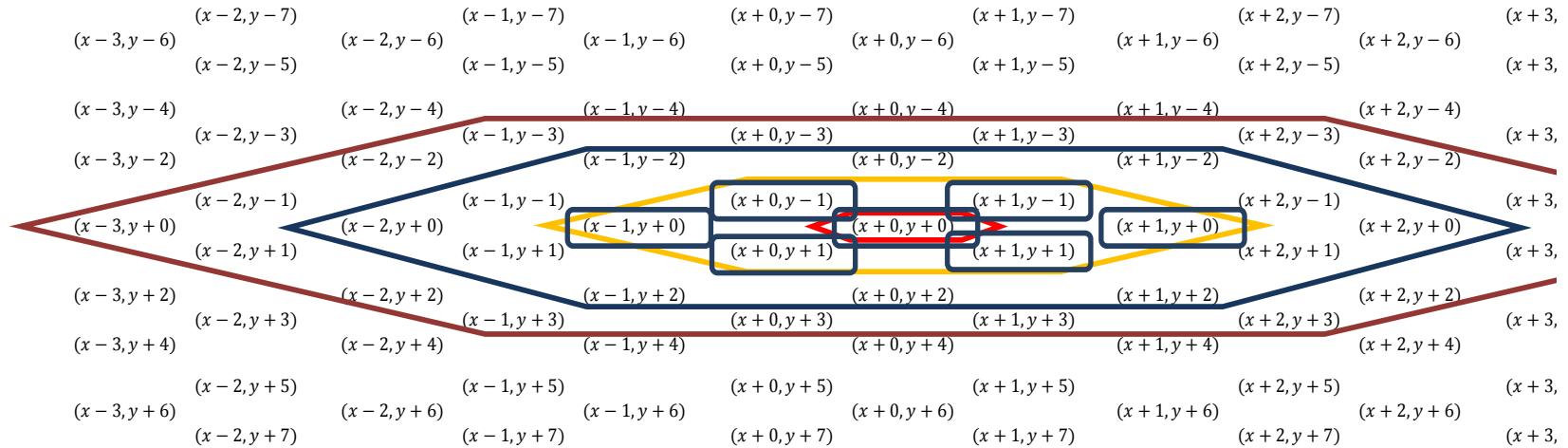
Arquitectura

- Grilla hexagonal



Computational hexagonal cluster

Análisis de los vecinos a un punto:



Winner

Dado $R = 1$, Se tienen los datos de la Matriz Pos:

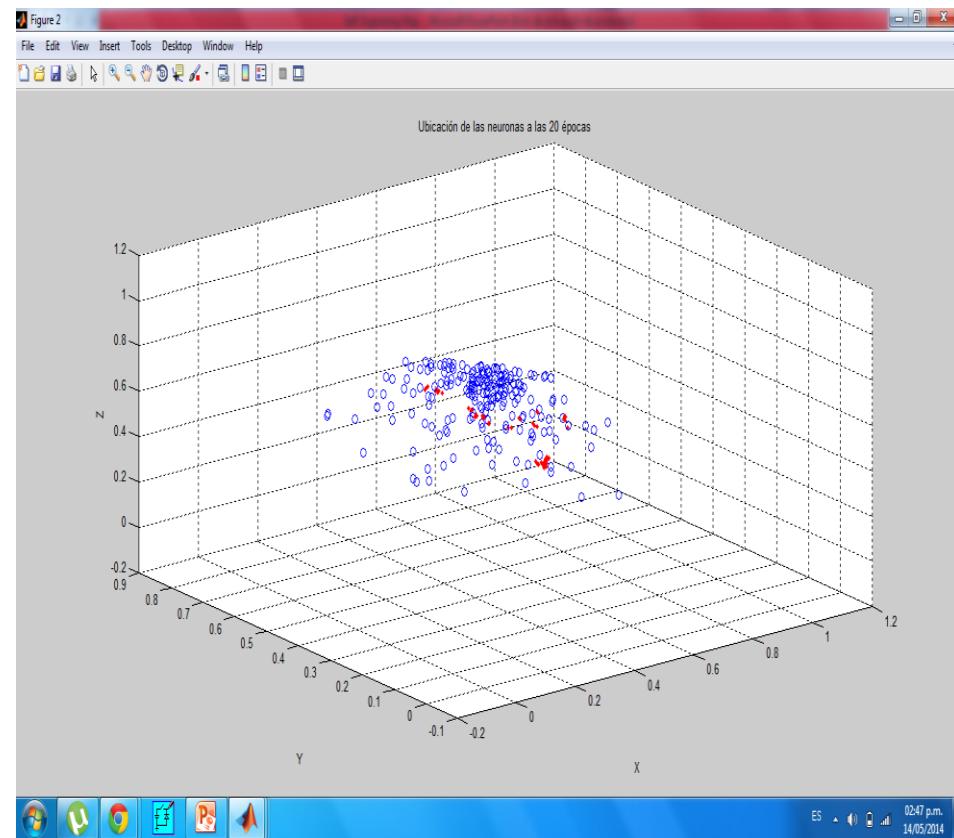
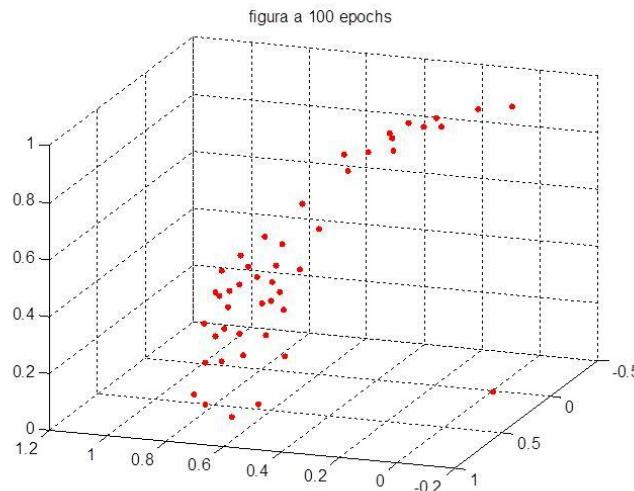
R

R

R

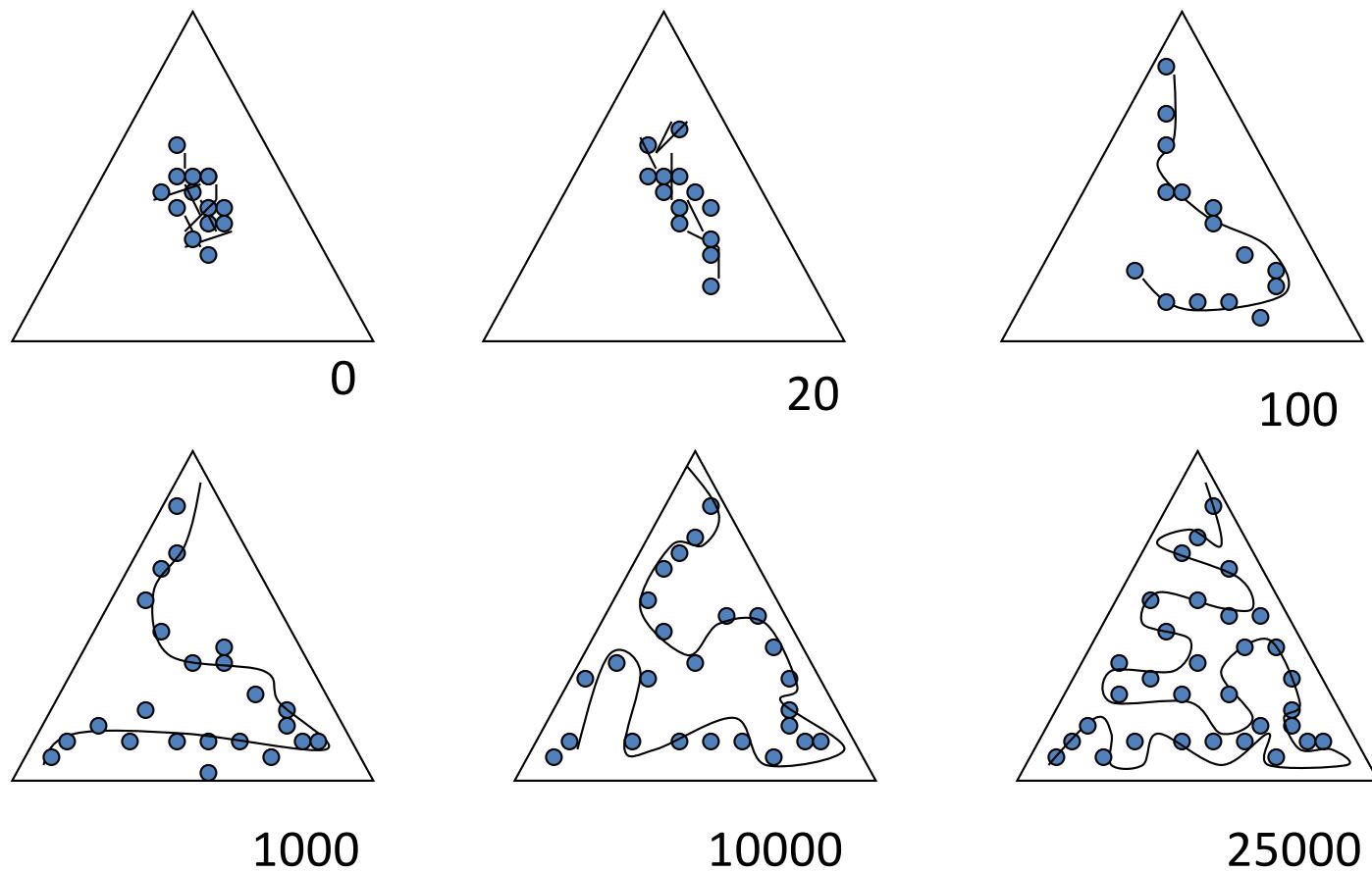
0	0	1	1	-1	0	1
-1	1	-1	1	0	0	0

Mapeo de Data Tridimensional 3D



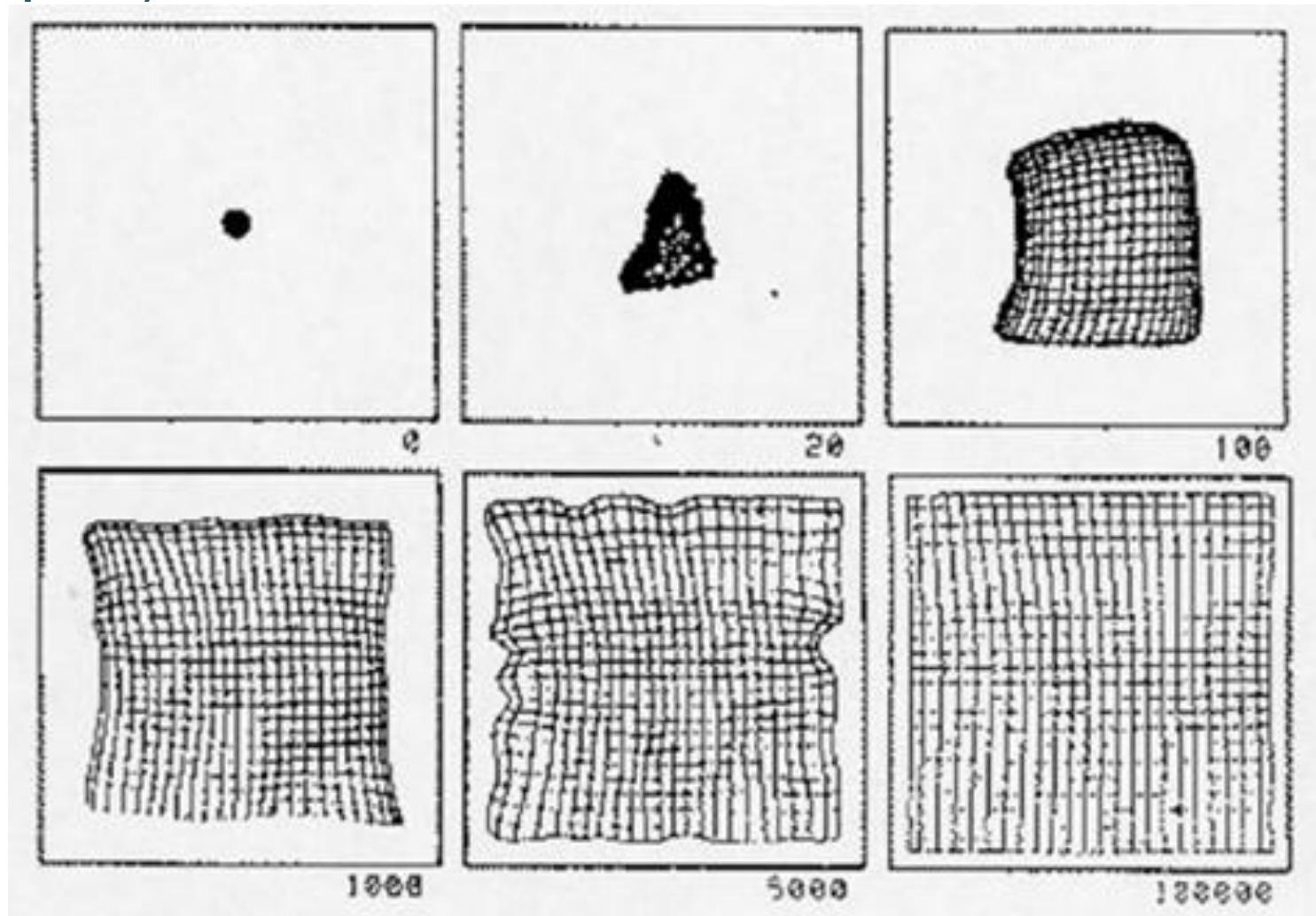
Entrenamiento no supervizado en SOMs

Ejemplo: Aprendiendo la representación unidimensional de un espacio de entrada (“**input space**”) bi dimensional.



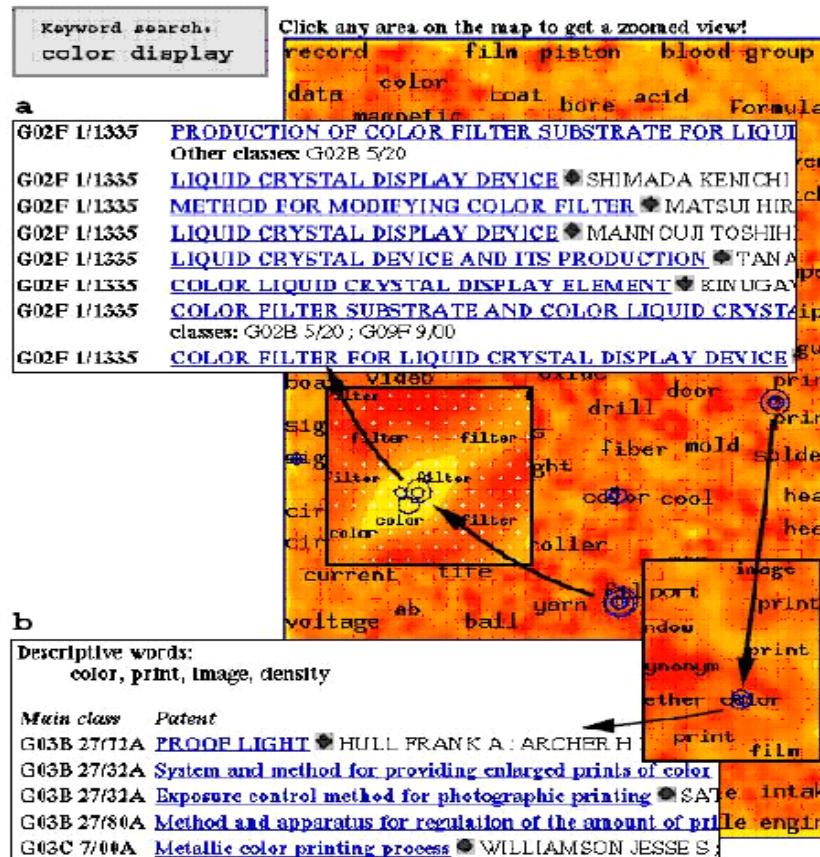
Entrenamiento no supervizado en SOMs

Ejemplo : Aprendiendo una representación bi-dimensional de un espacio de entrada (“**input space**”) bi dimensional.



Aplicaciones

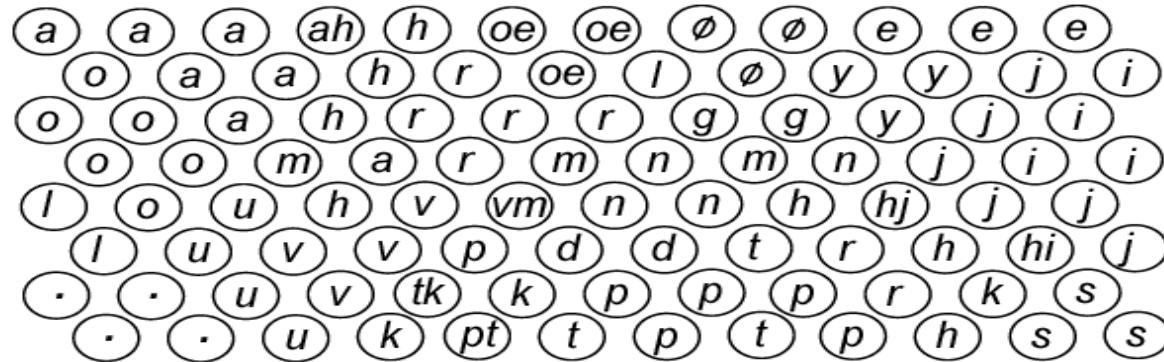
- **WEBSOM:** Organización de una colección masiva de documentos.



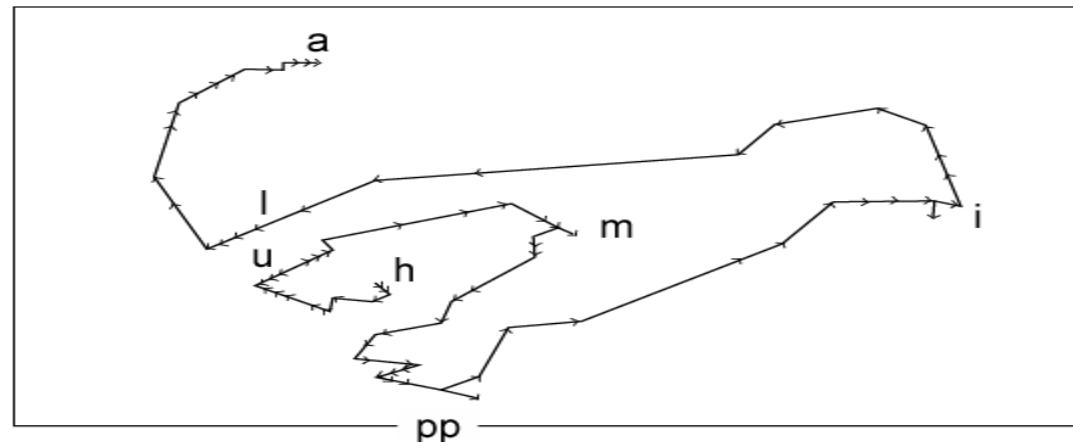
SOFM

“Phoneme Recognition”

- Phonotopic maps



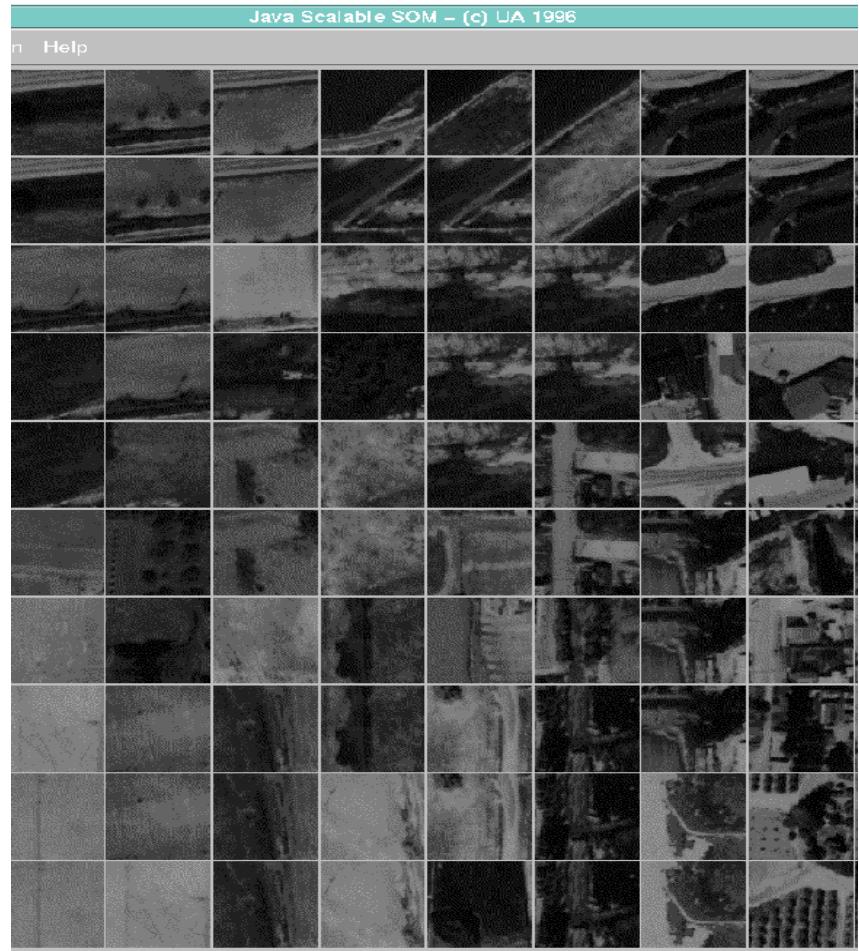
- Recognition result for “humppila”



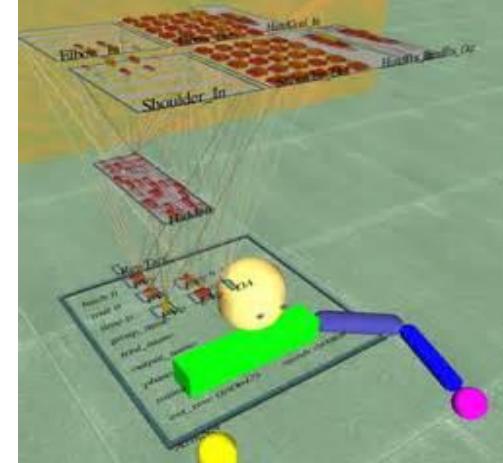
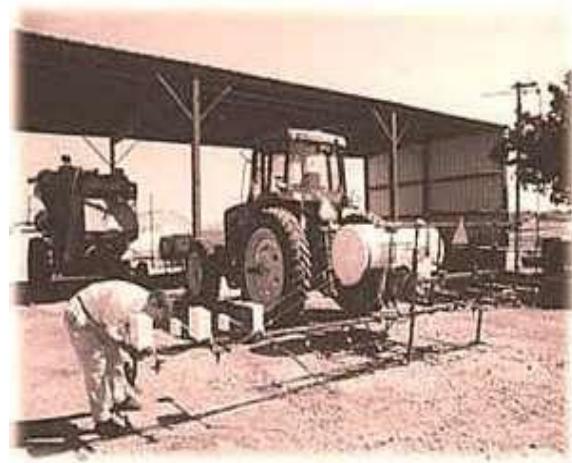
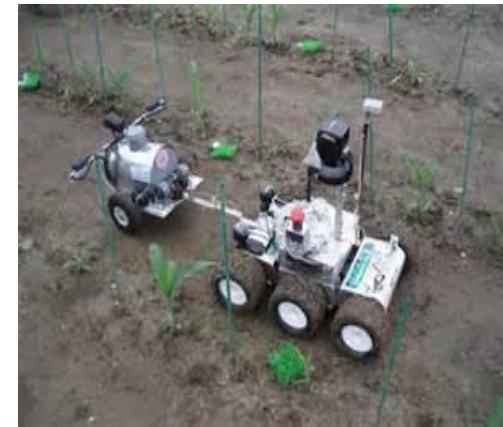
Entrenamiento no supervizado en SOMs

Ejemplo:

Aprendiendo el mapeo bi-dimensional de texturas de imágenes.

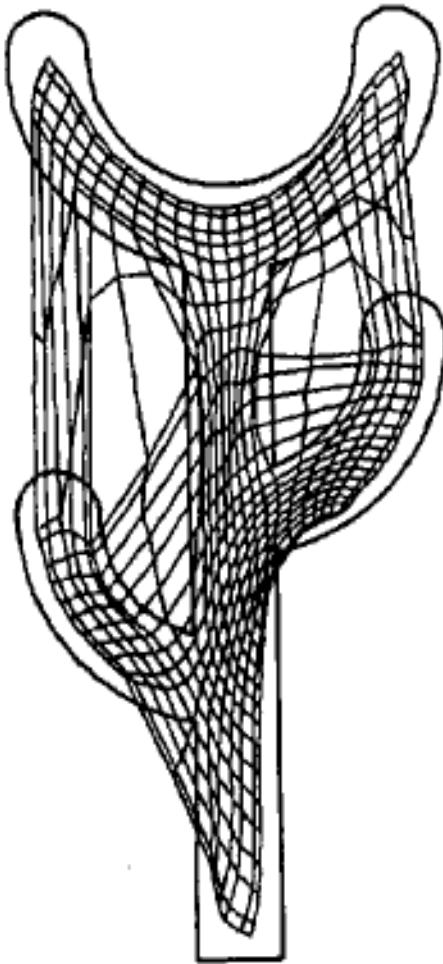


Neural Networks in Agriculture



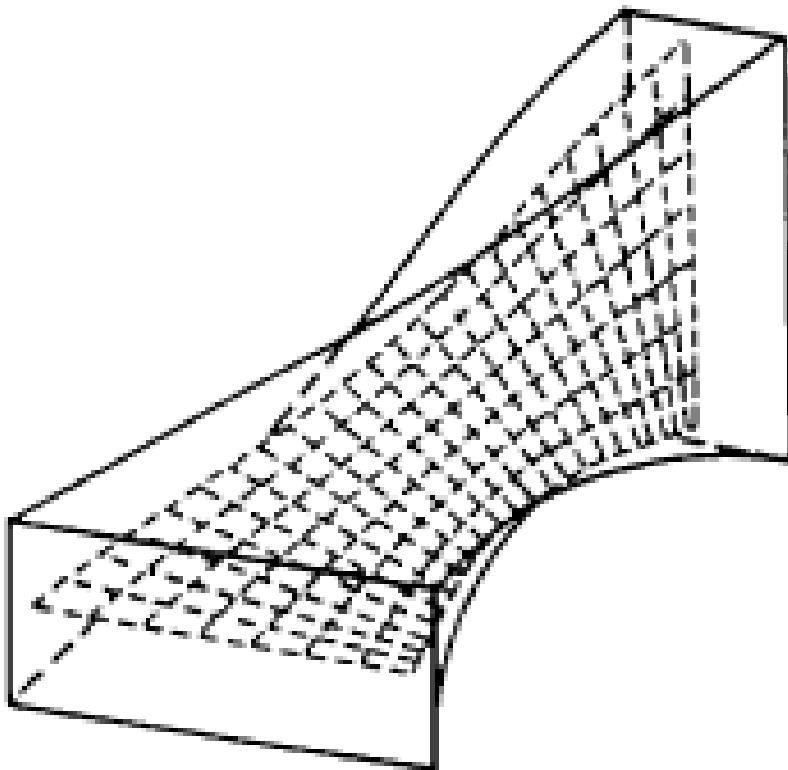
Self Organizing Map SOM

“Elastic virtual network”



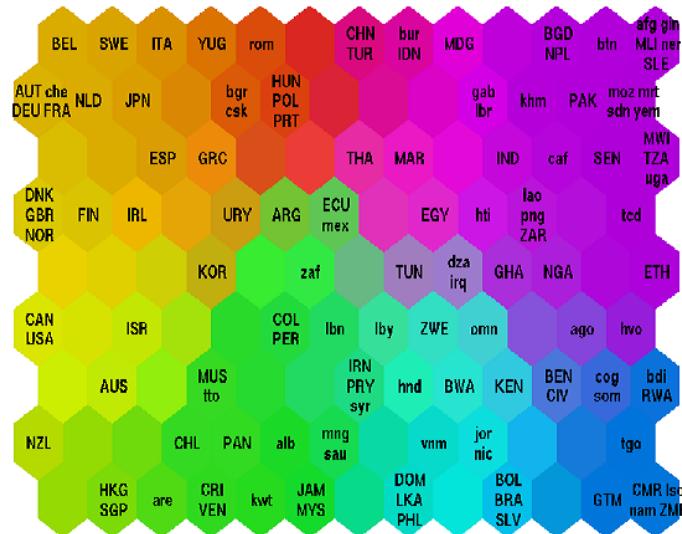
Self Organizing Map SOM

“Elastic virtual network”

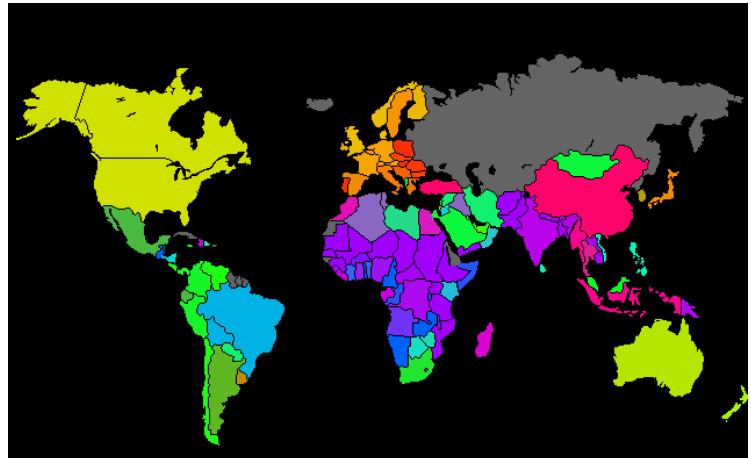


Aplicaciones

- ## • *Clasificando la pobreza mundial*

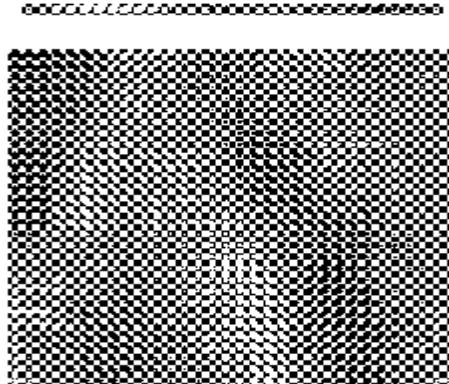
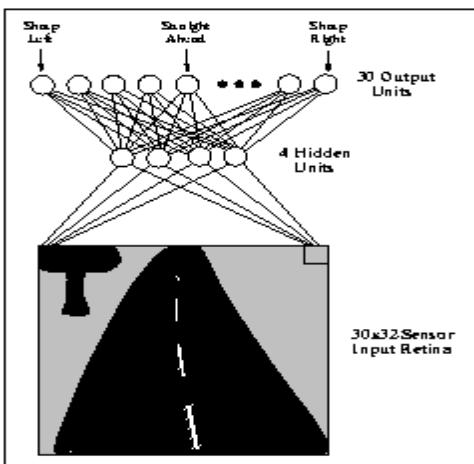
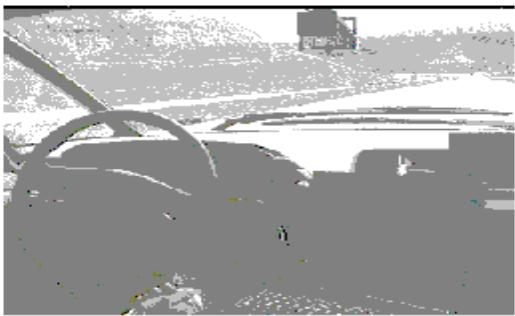


The Country Names



Autonomous Land Vehicle in a Neural Network

ALVINN system



- Input: 30 x 32 grid of pixel intensities (960 nodes)
- 4 hidden units
- Output: direction of steering (30 units)
- Training: 5 min. of human driving
- Test: up to 70 miles for distances of 90 miles on public highway. (driving in the left lane with other vehicles present)

Autonomous Land Vehicle in a Neural Network

ALVINN system

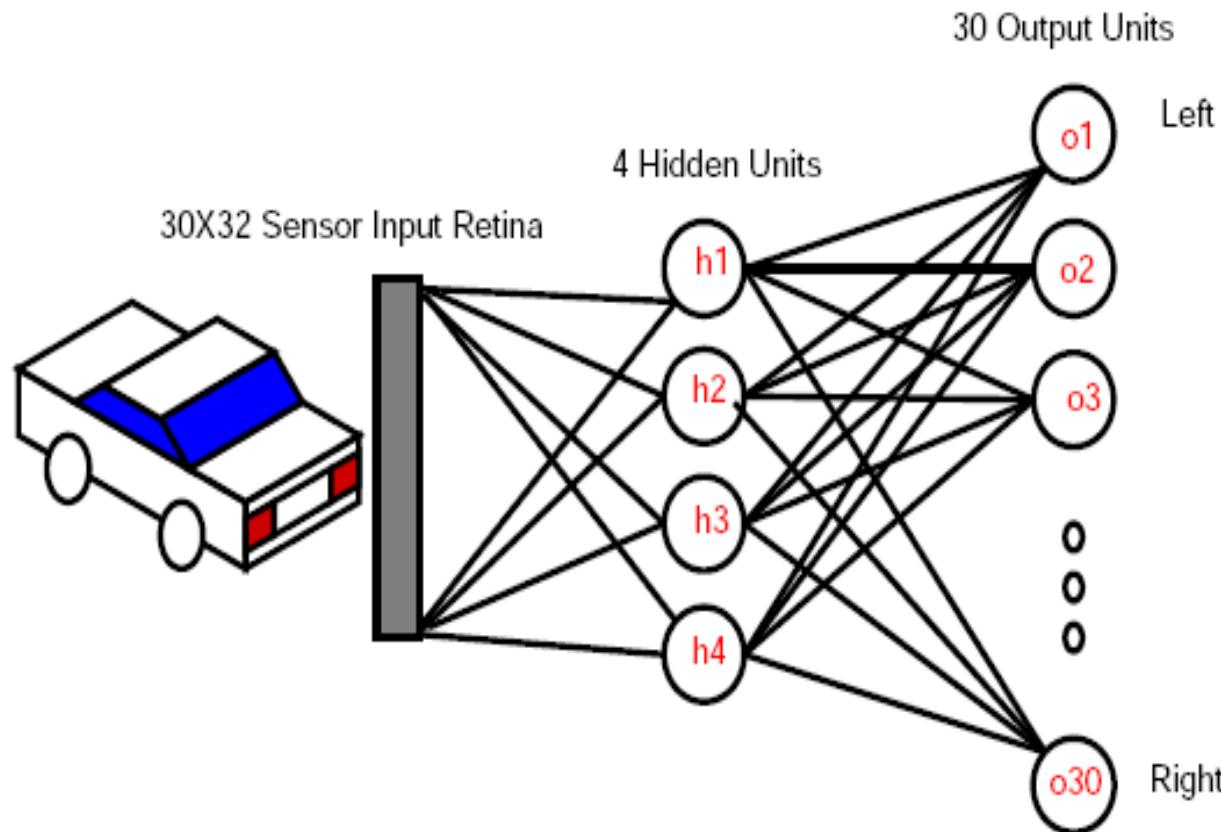
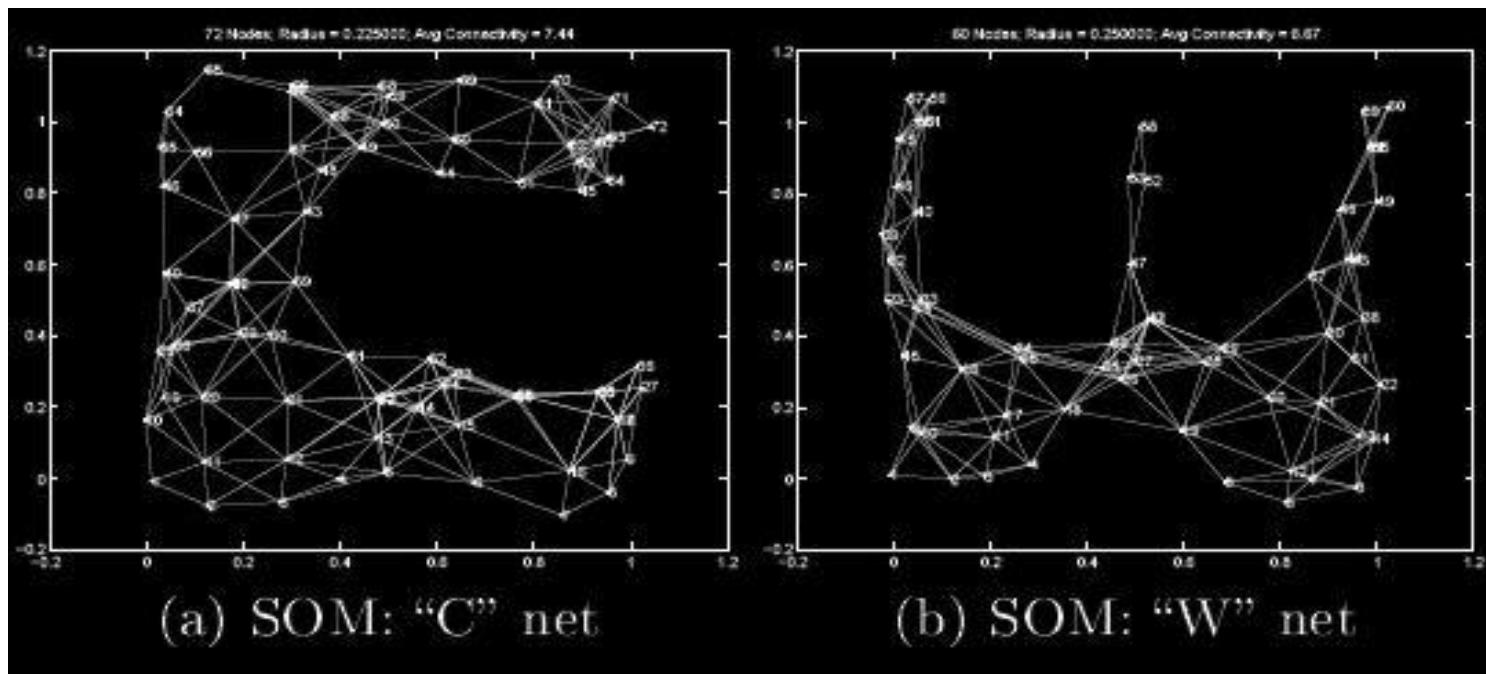


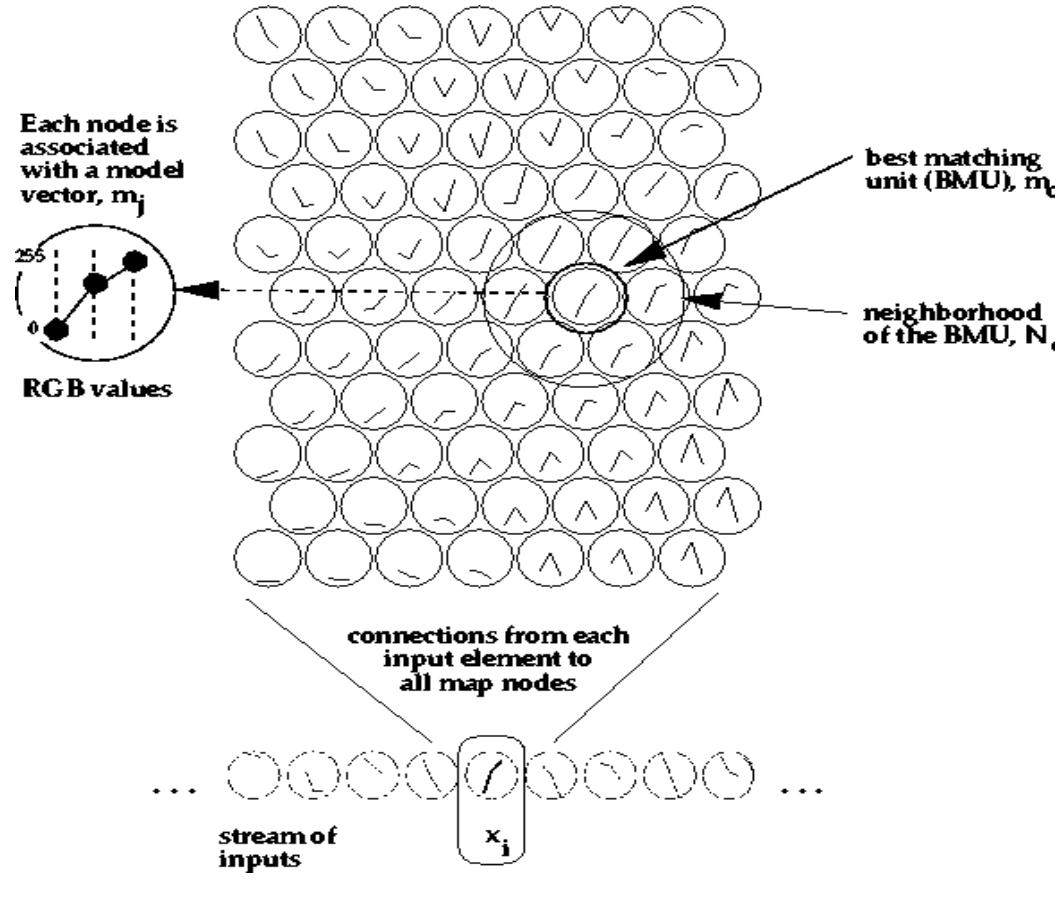
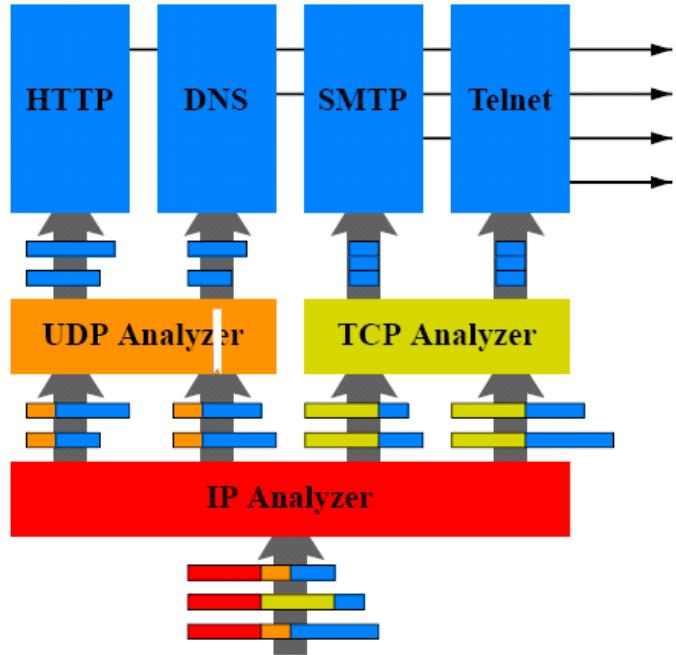
Figure 1: Main Structure

Wireless Localization Using Self-Organizing Maps

- Utiliza una Red Neuronal Auto Organizante para determinar las posiciones de los nodos de una red inalámbrica.



Multiple Self-Organizing Maps for Intruder Detection

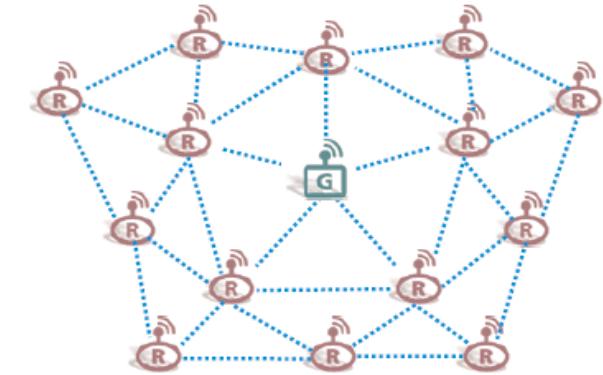


Euclidean Norm

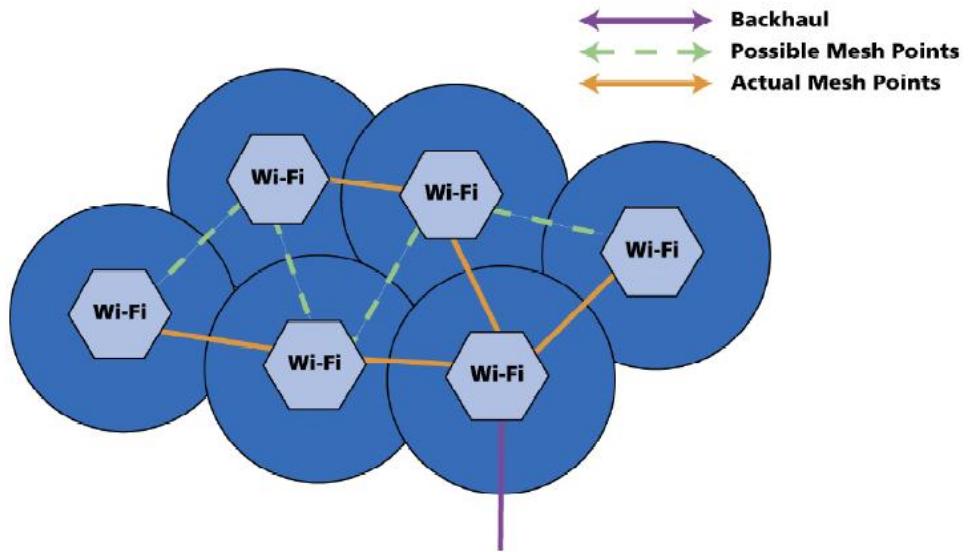
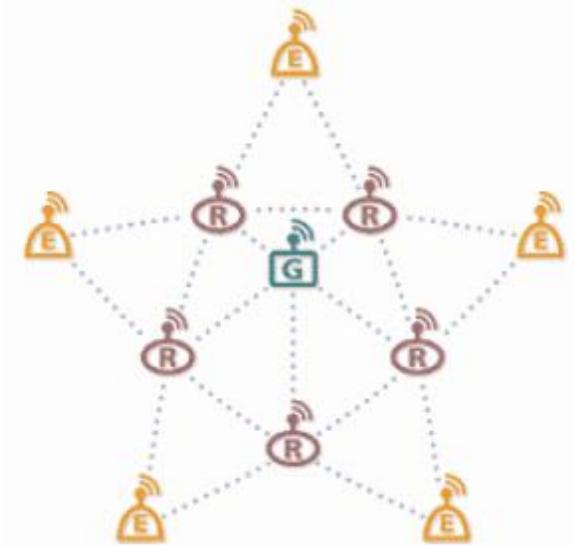
NEUROMORPHIC TECHNOLOGIES

Fernando Jimenez Motte Ph.D.EE (c), M.S.E.E, B.S.E.E

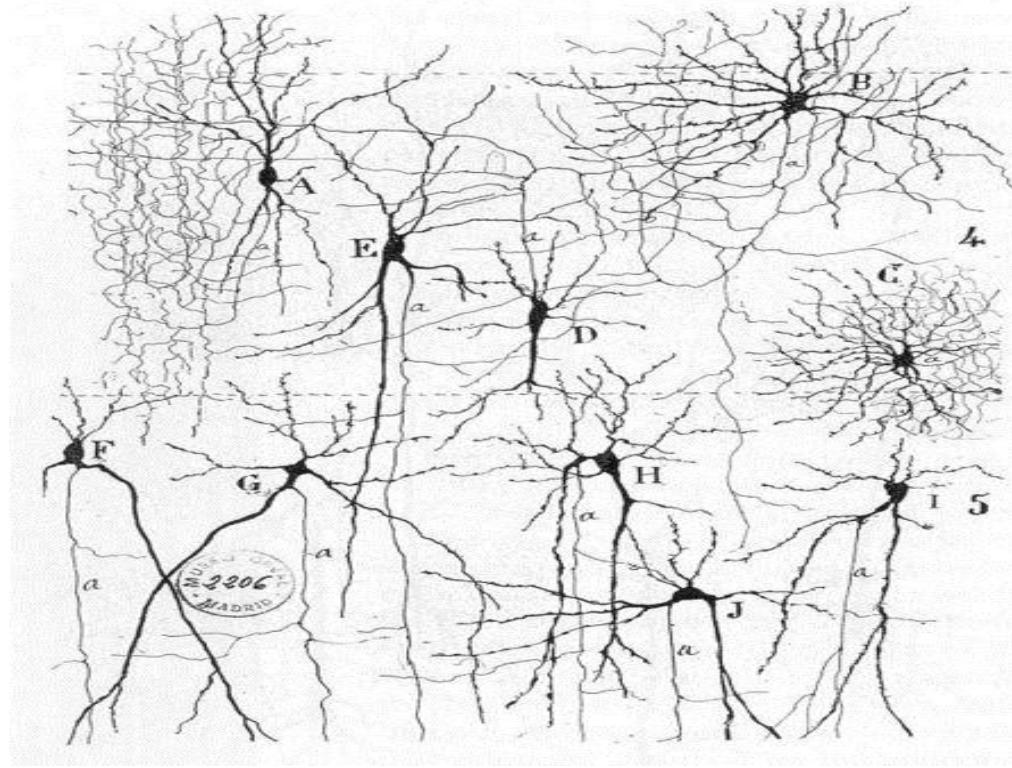
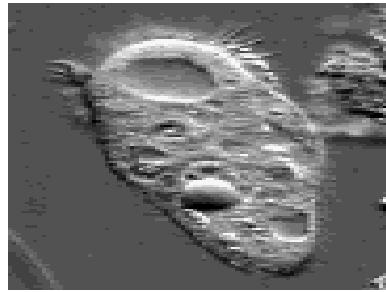
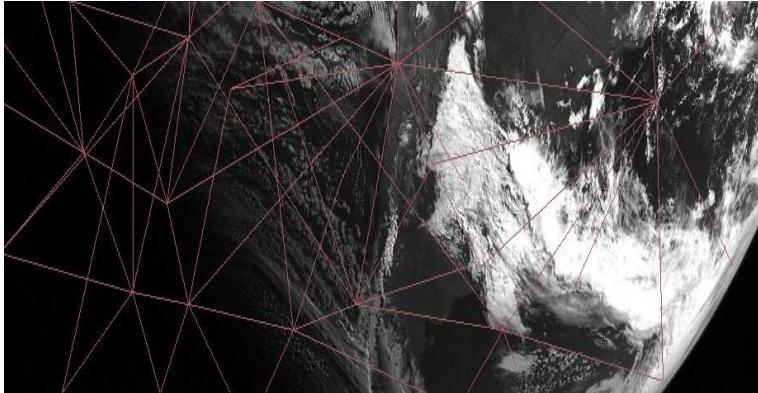
Self-Organizing Neighborhood Wireless Mesh Networks



A Self-Forming, Self-Healing Network



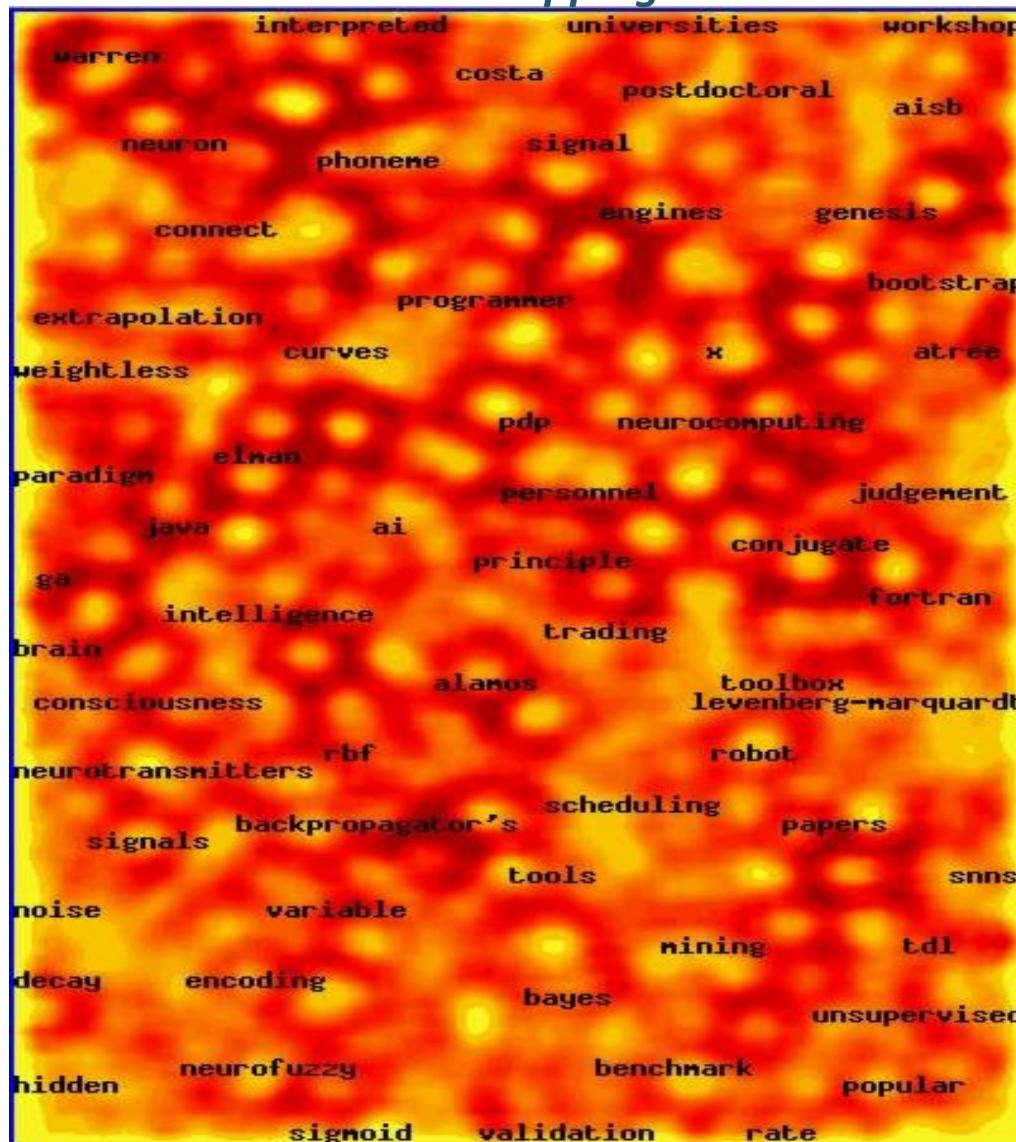
Millions of Neural Nets covering the world over the Internet



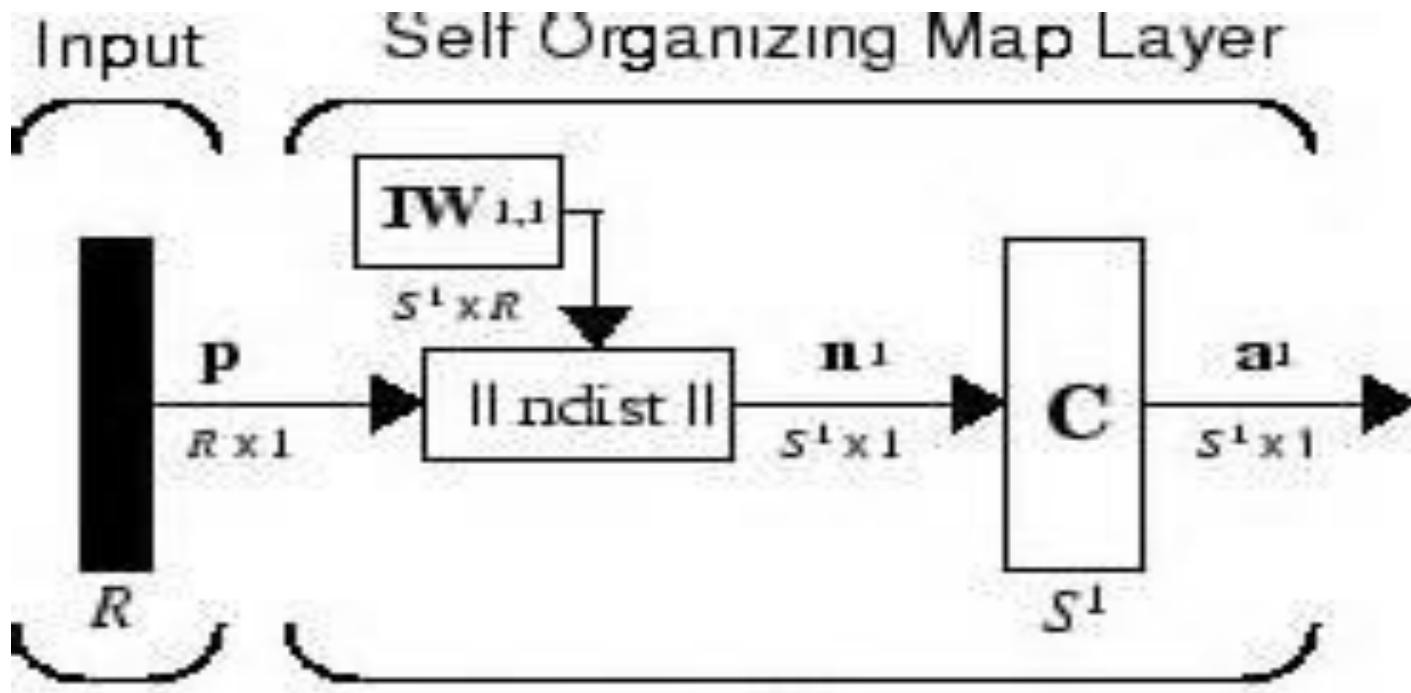
Each TCIP / Node becomes a Neuron so that a SuperNet is built over the Internet. The whole network will behave as a Synthetic Intellect,

Self Organizing Map SOM

"Semantic mapping"



SOM “building block” CAD/CAM



$$n_i^1 = - \| _i IW_{1,1} - p \|$$

$a^1 = \text{compet}(n^1)$

Self organized semantic map: Word categories

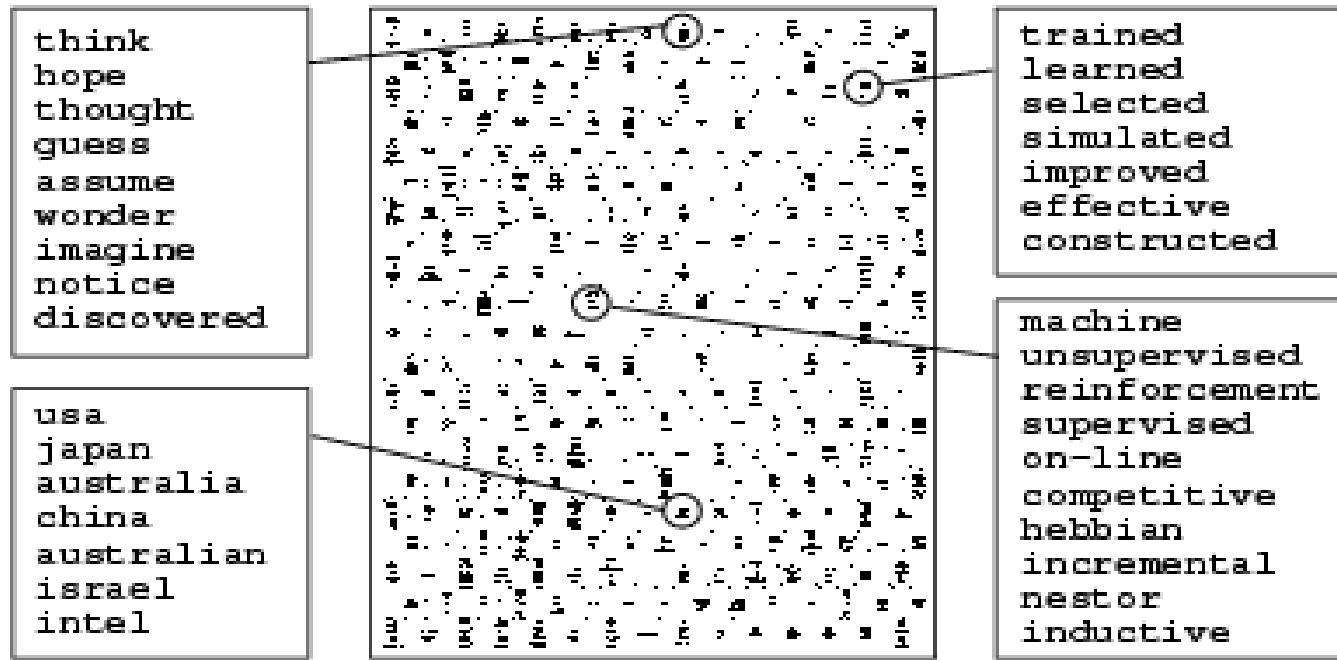


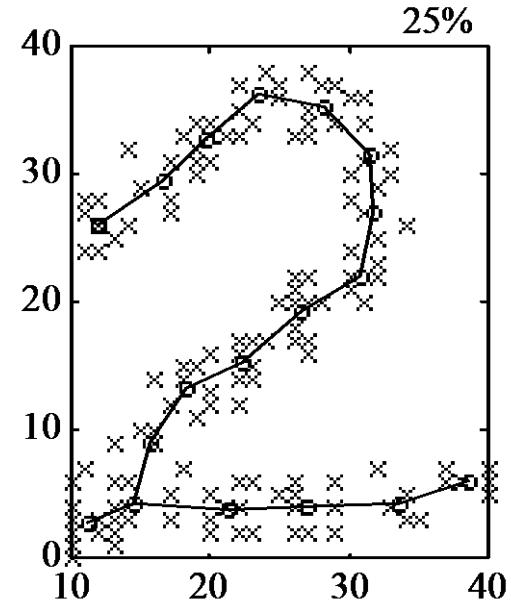
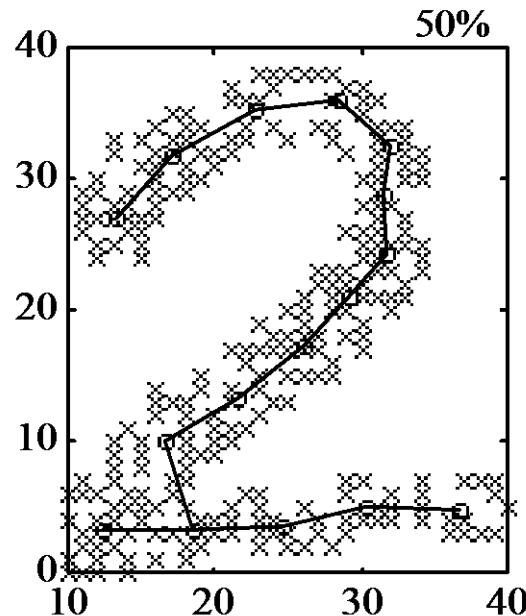
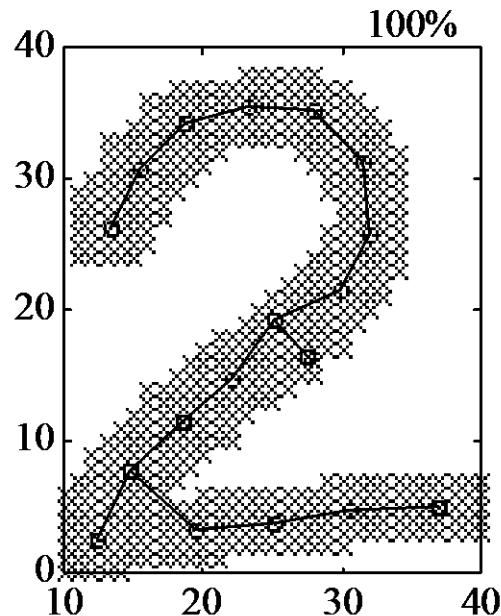
Figure 3: Sample word categories on a self-organized semantic map. Each inset shows the words that have been mapped into one word category. The text corpus consisted of articles from the Usenet newsgroup `comp.ai.neural-nets`.

Cronología de SOM's

- Kohonen (1984). **Speech recognition** - a map of phonemes in the Finish language
- **Optical character recognition** - clustering of letters of different fonts
- Angeliol *et al* (1988) – travelling salesman problem (an **optimization problem**)
- Kohonen (1990) – learning vector quantization (**pattern classification problem**)
- Ritter & Kohonen (1989) – **semantic maps**

“Skeletonization of images”

- Esqueletización de imágenes ruidosas.
- Aplicación del MST SOM: robustez con respecto al ruido.



CELLULAR NEURAL NETWORK CNN ARCHITECTURE WITH 3X3 NEIGHBORHOOD CONNECTIVITY

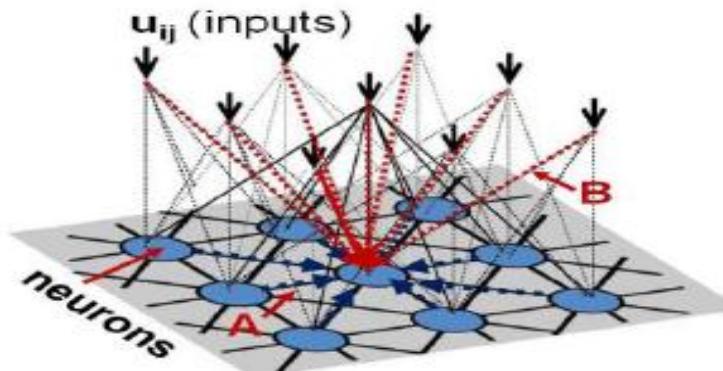
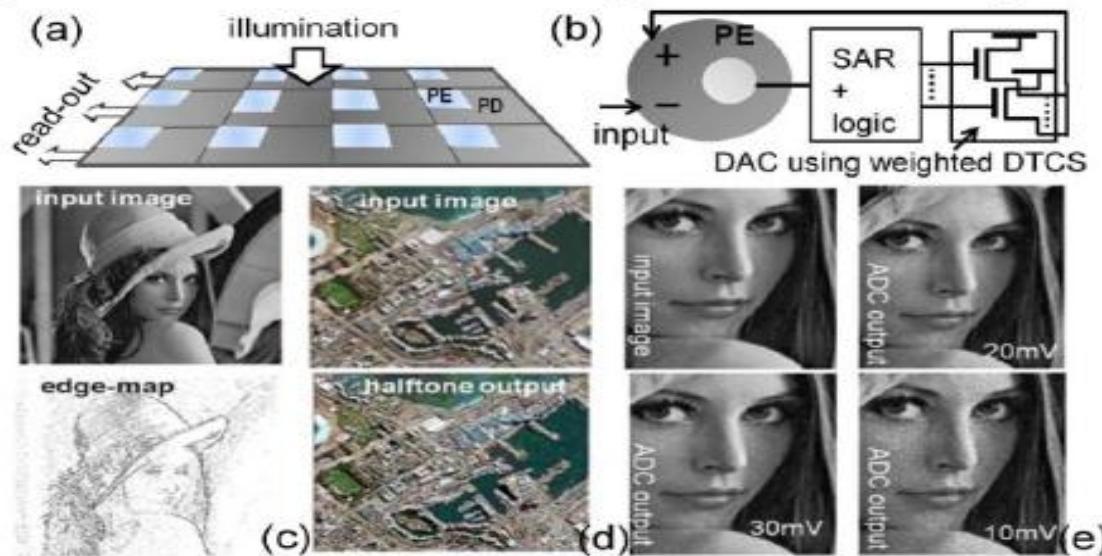
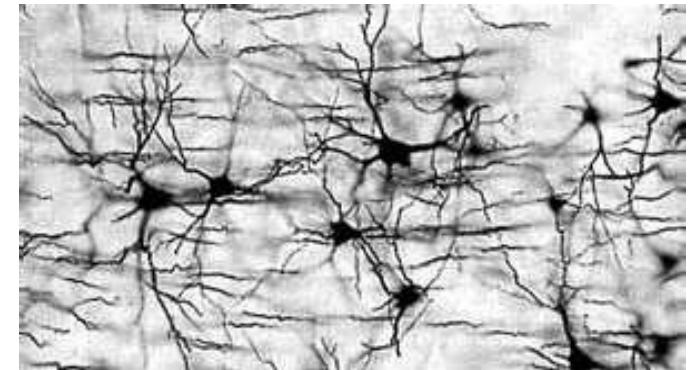
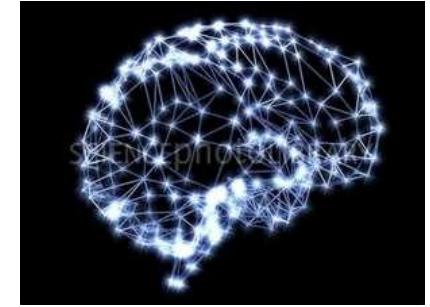
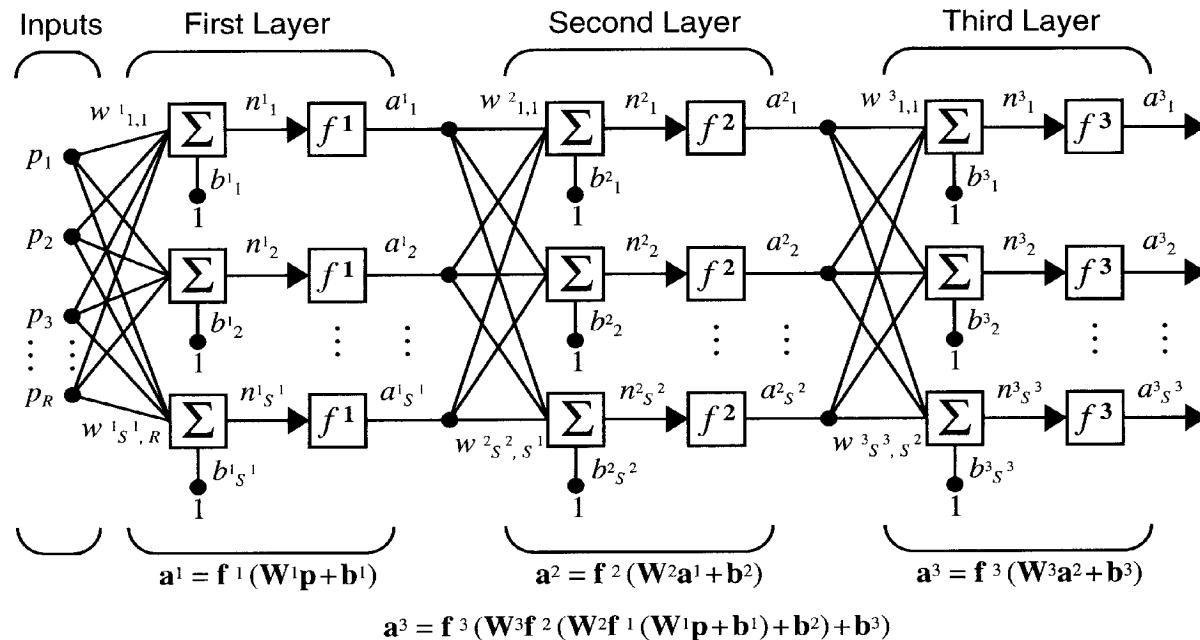


Fig. 9. CNN architecture with 3x3 neighbourhood connectivity

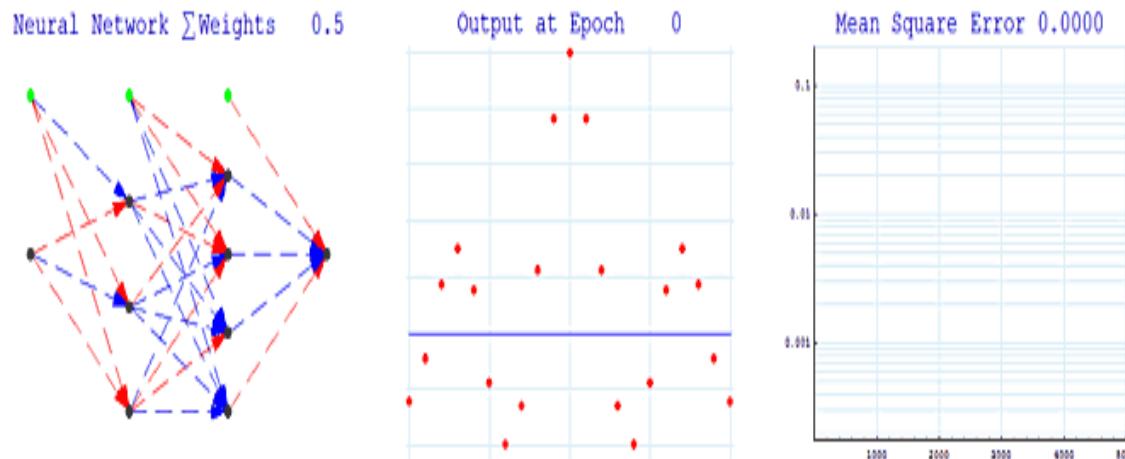


RED NEURONAL DE MULTIPLES CAPAS

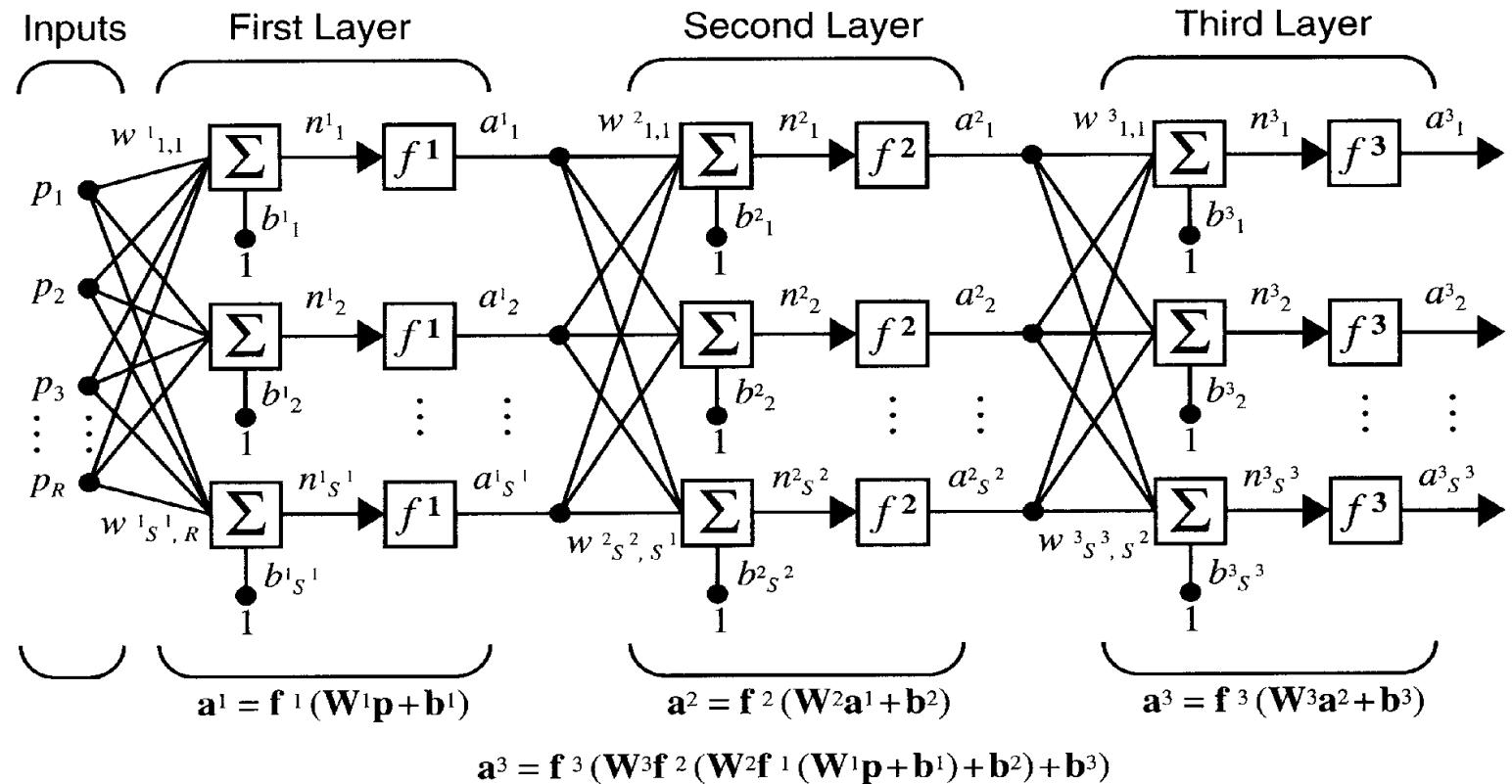


Backpropagation Neural Network

(Red Neuronal de Retropropagación)



Three-Layer Network



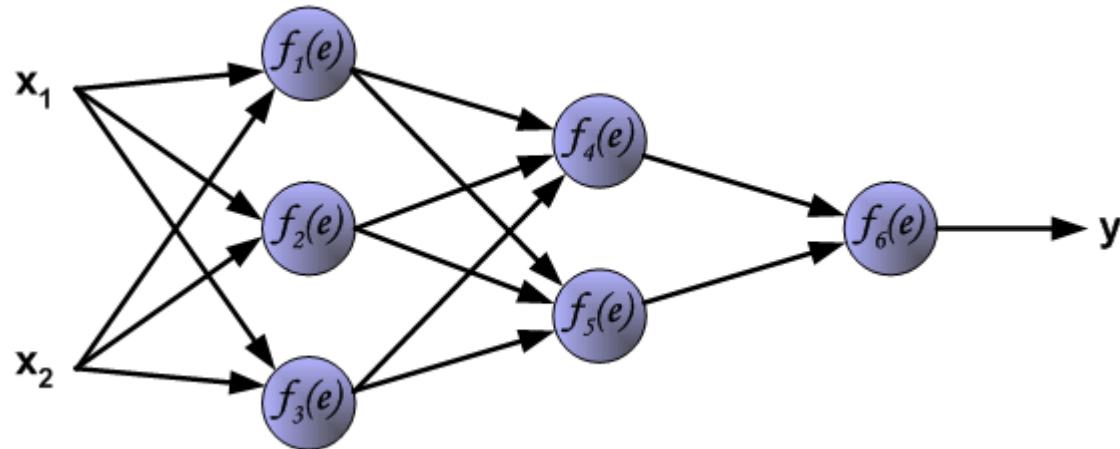
Number of neurons in each layer: $R - S^1 - S^2 - S^3$

Algoritmo de aprendizaje

Backpropagation

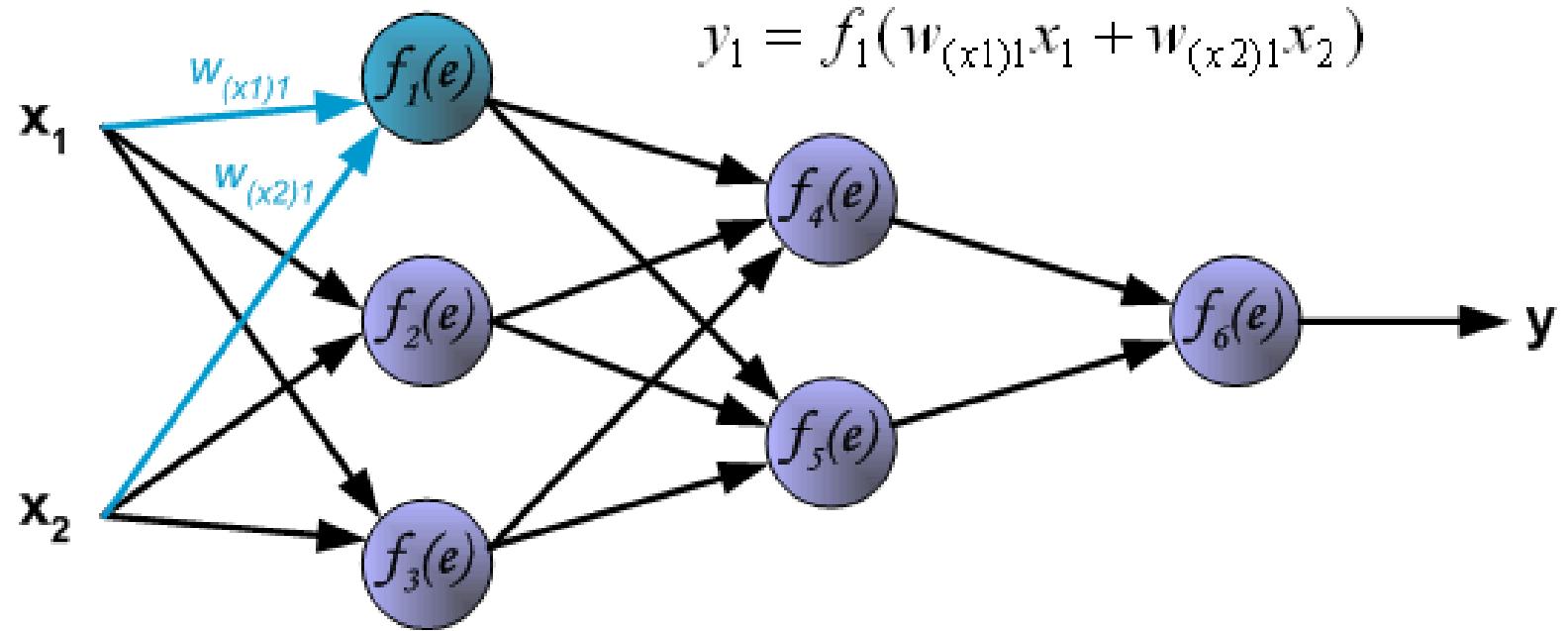
Las siguientes diapositivas describen el proceso de enseñanza del algoritmo de aprendizaje para redes neuronales de retropropagación de múltiples capas.

Para ilustrar este proceso, la red neural que utilizaremos consiste de tres capas con dos entradas y una salida como se muestra en la siguiente arquitectura:



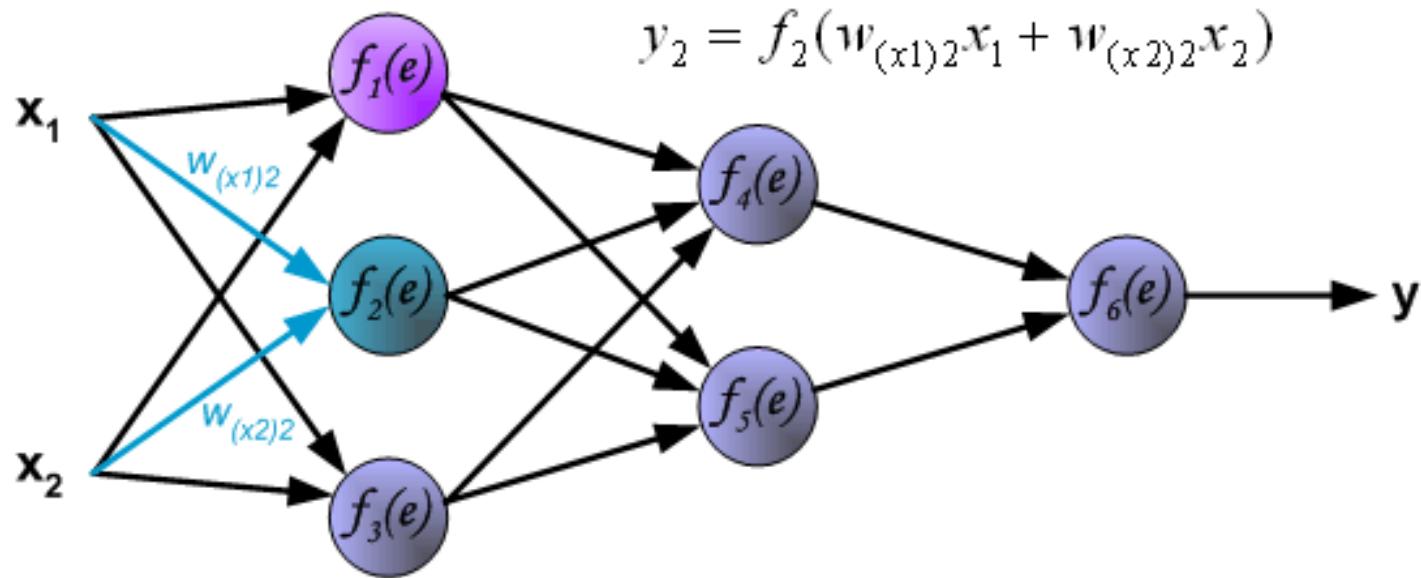
Algoritmo de aprendizaje

Backpropagation



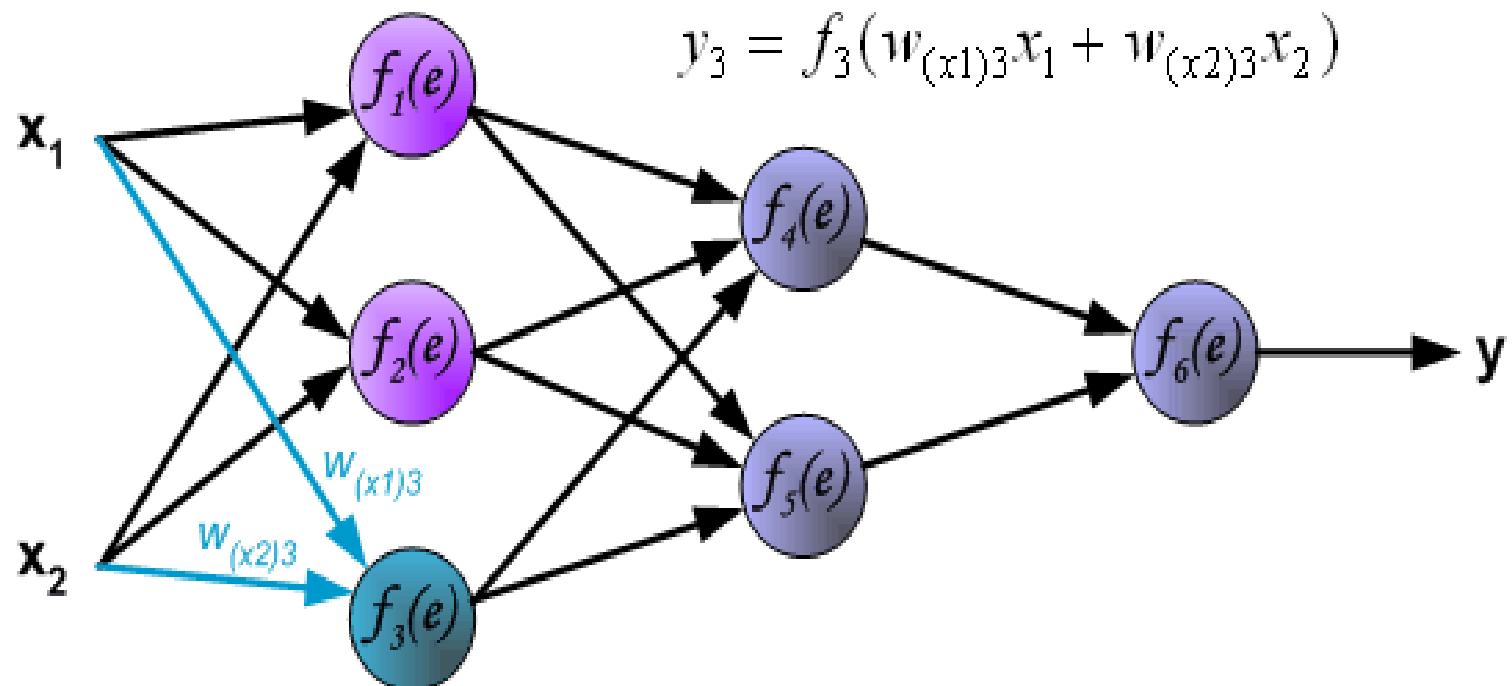
Algoritmo de aprendizaje

Backpropagation



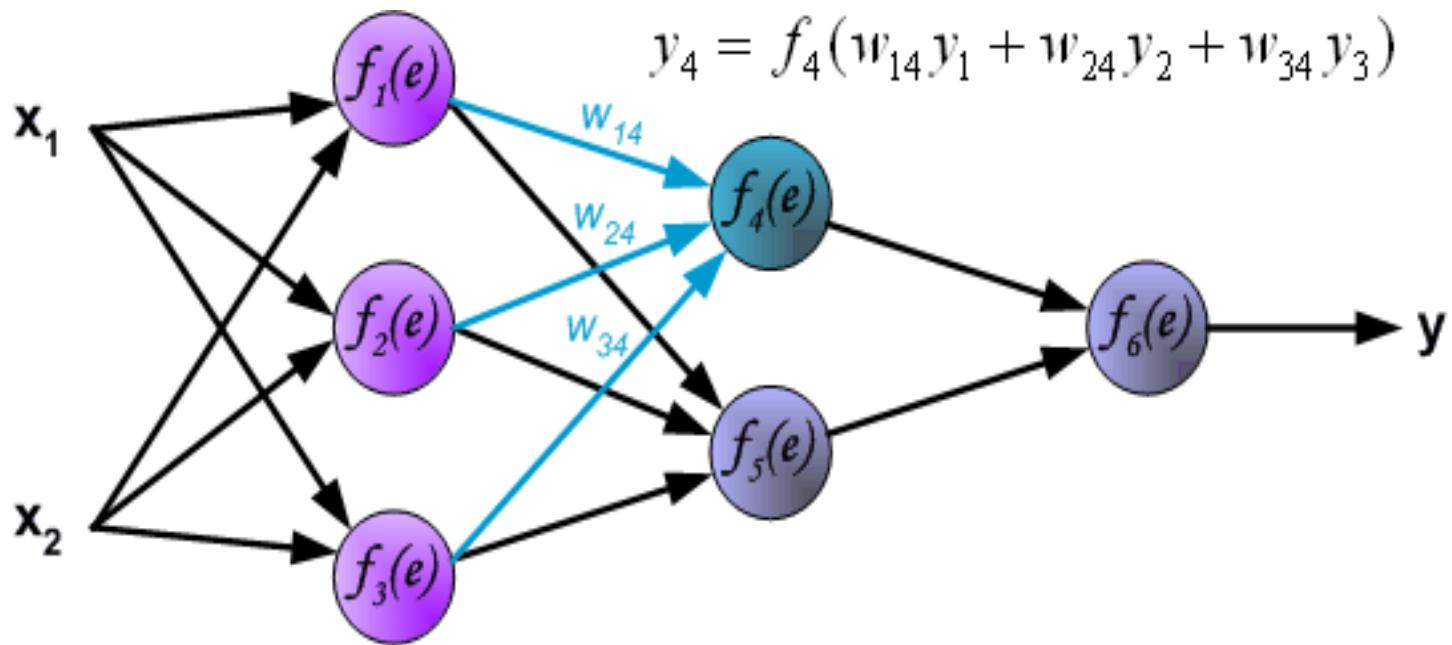
Algoritmo de aprendizaje

Backpropagation



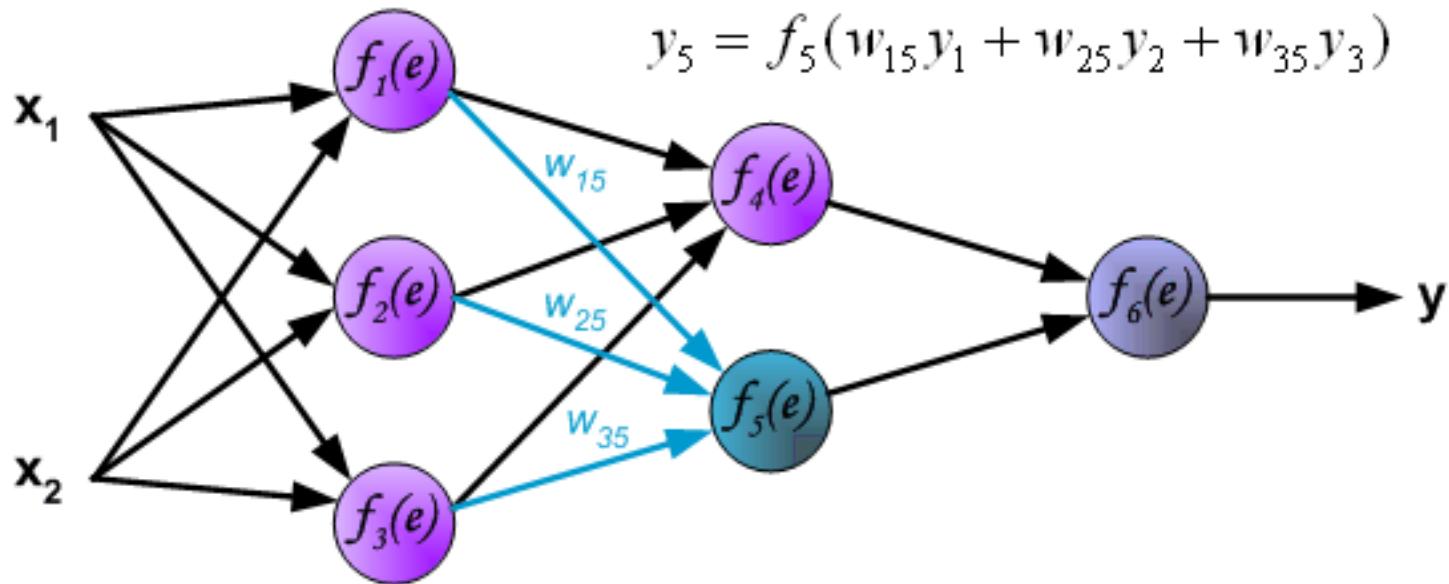
Algoritmo de aprendizaje

Backpropagation



Algoritmo de aprendizaje

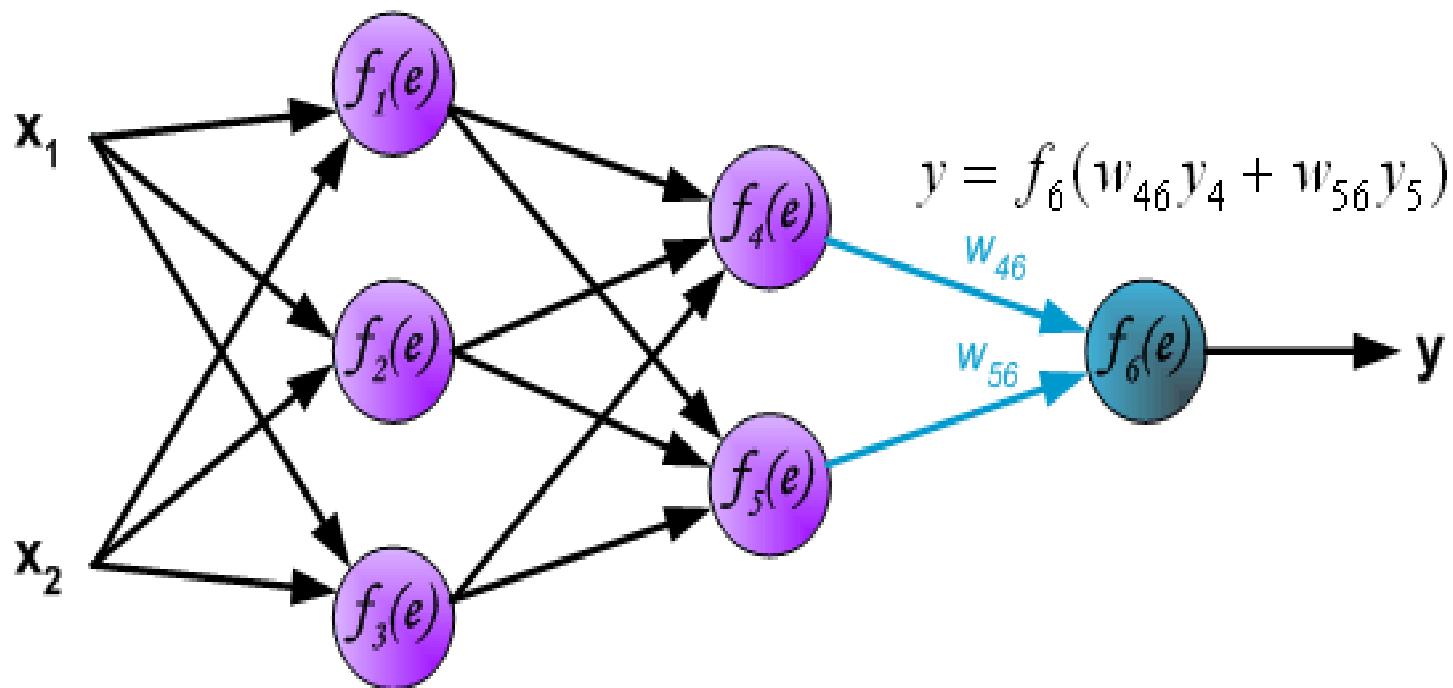
Backpropagation



Algoritmo de aprendizaje

Backpropagation

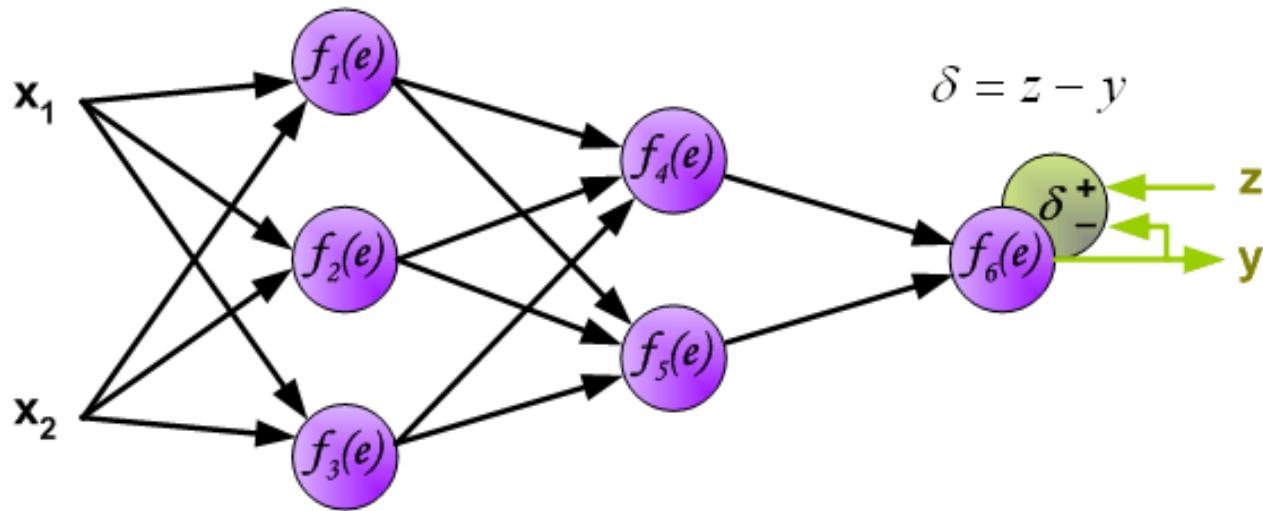
Propagación de las señales a través del “output layer”



Algoritmo de aprendizaje

Backpropagation

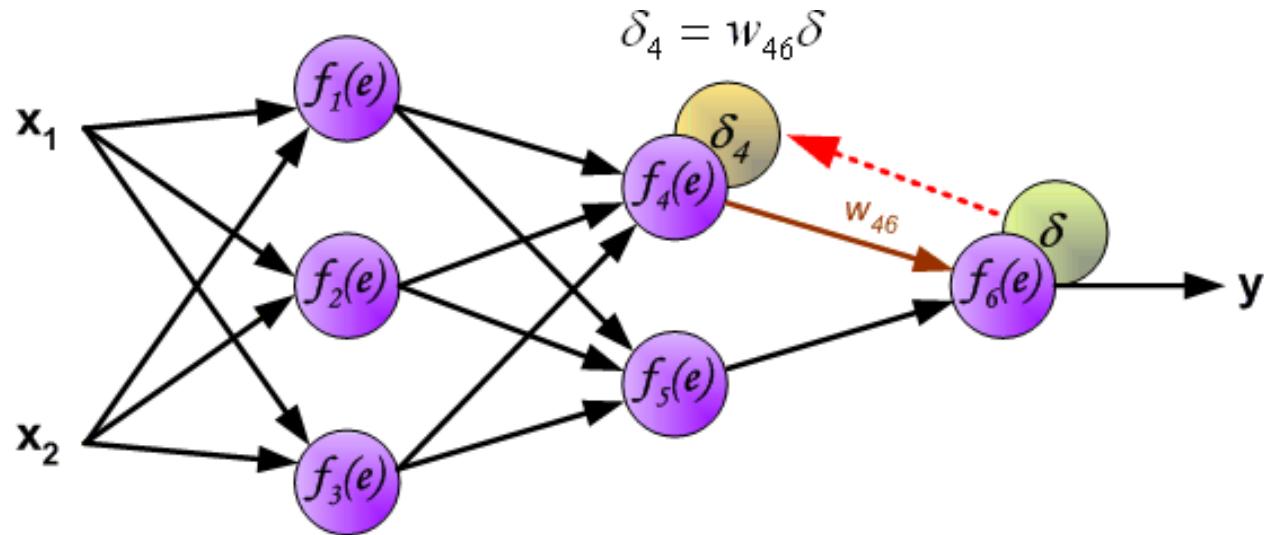
En el paso siguiente del algoritmo se obtiene la señal de salida de la red y se compara con el valor de salida deseado (valor objetivo o “target”). La diferencia se llama **error de la señal d** de la capa de salida de la red neuronal.



Algoritmo de aprendizaje

Backpropagation

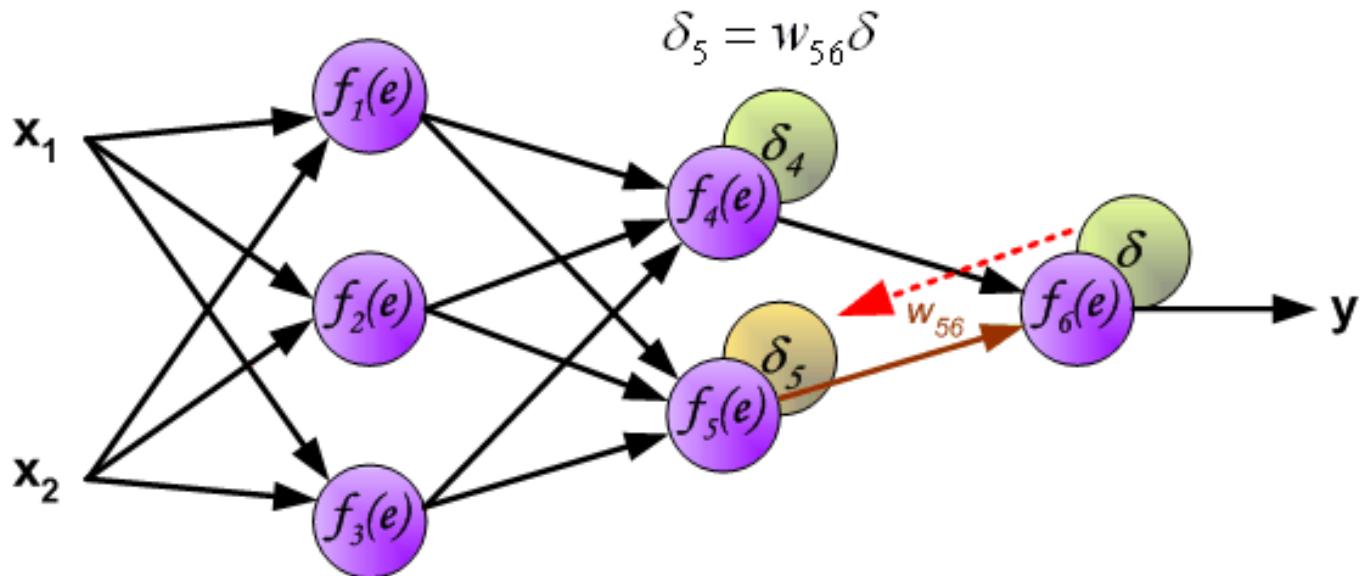
La idea es la de propagar la **señal de error δ** (*calculado en la etapa de enseñanza*) de nuevo a todas las neuronas, cuyas señales de salida fueron entrada para dicha neurona.



Algoritmo de aprendizaje

Backpropagation

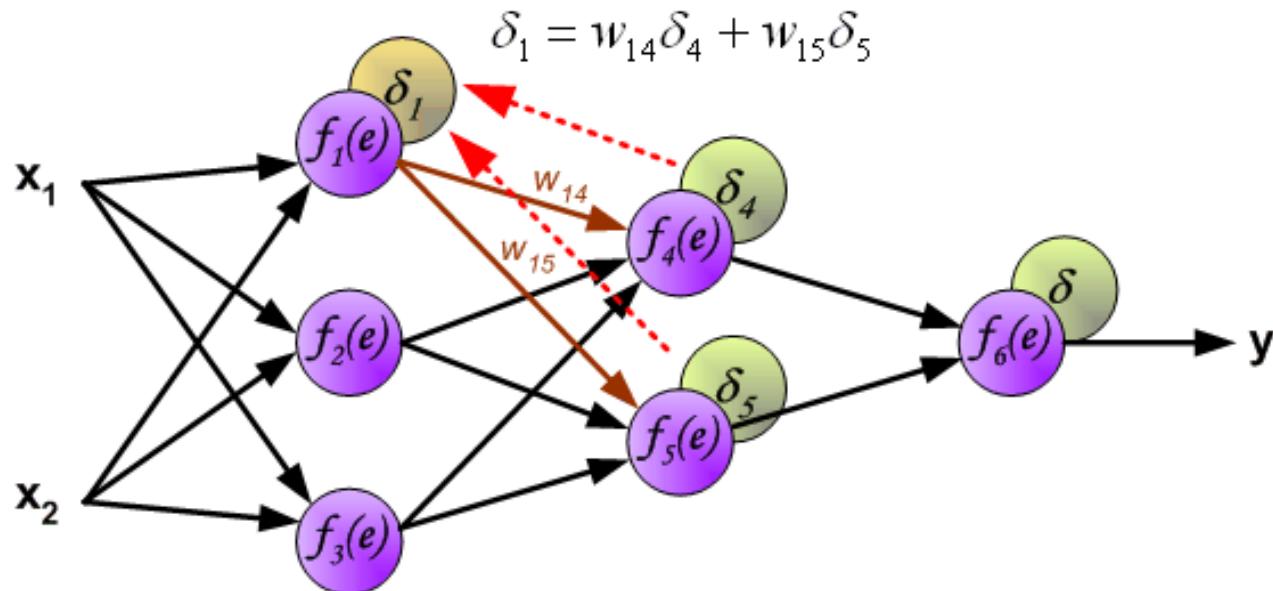
La idea es la de propagar la **señal de error \mathbf{d}** (*calculado en la etapa de enseñanza*) de nuevo a todas las neuronas, cuyas señales de salida fueron entrada para dicha neurona.



Algoritmo de aprendizaje

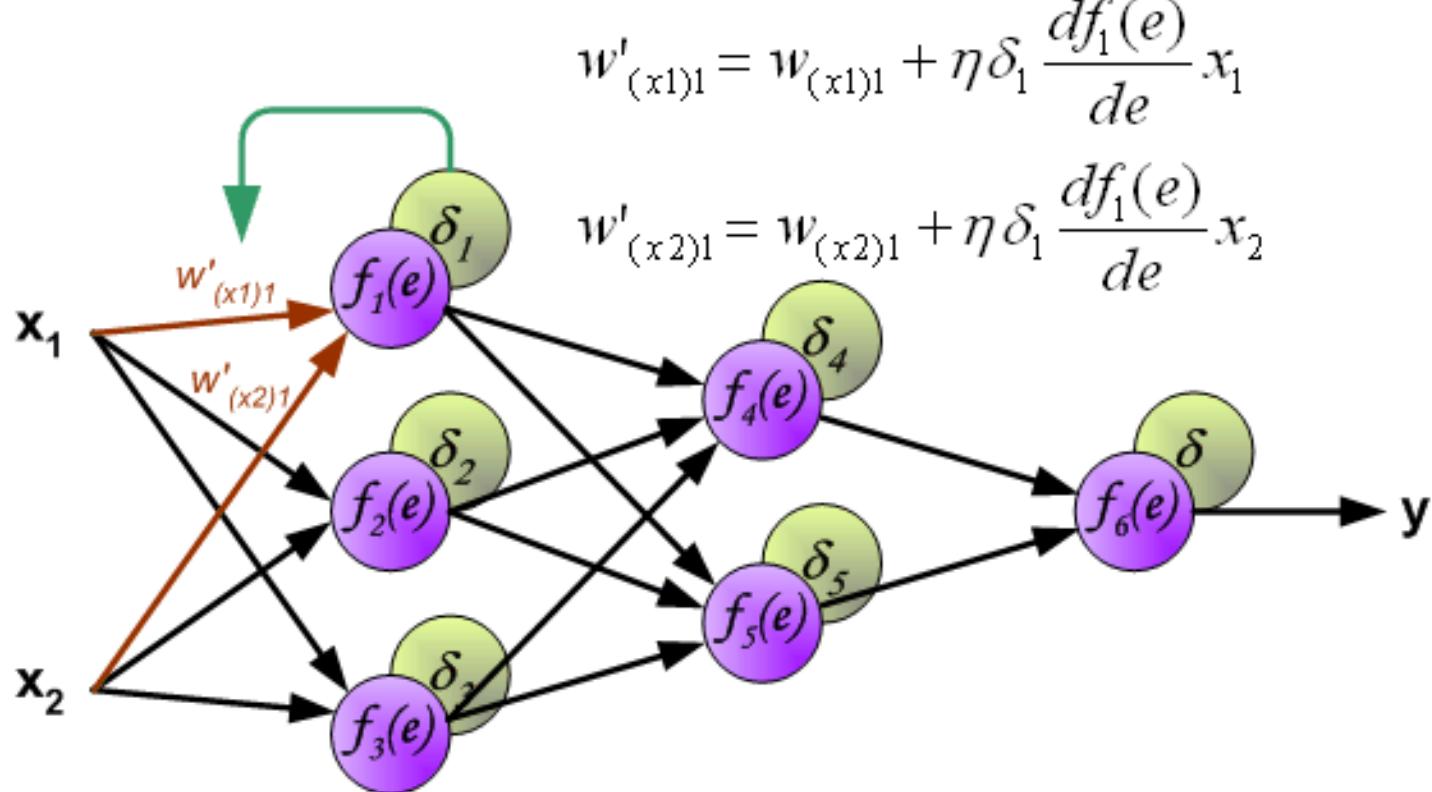
Backpropagation

Los pesos wmn «coeficientes utilizados para propagar errores hacia atrás son iguales a utilizar, a los que fueron utilizados para calcular el valor de salida. La dirección del flujo de datos cambia (*se propagan las señales de salida a entradas de una después de la otra*). Esta técnica se utiliza para todas las capas de red.



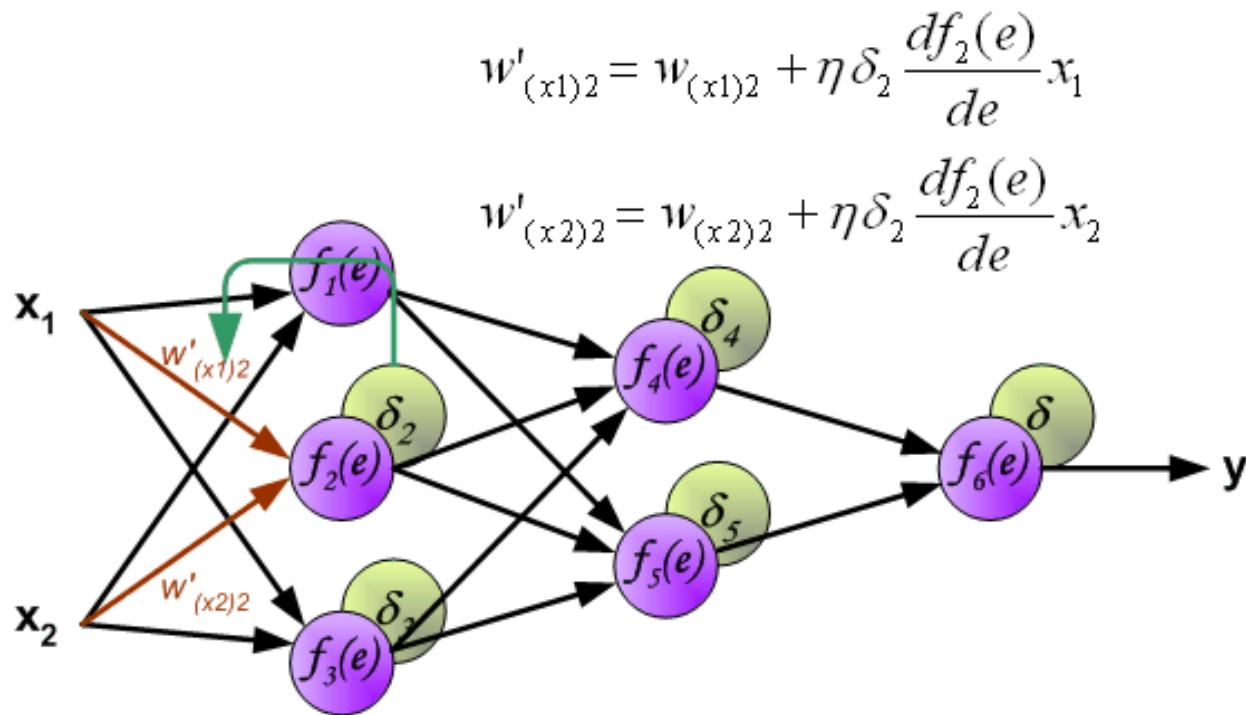
Algoritmo de aprendizaje

Backpropagation



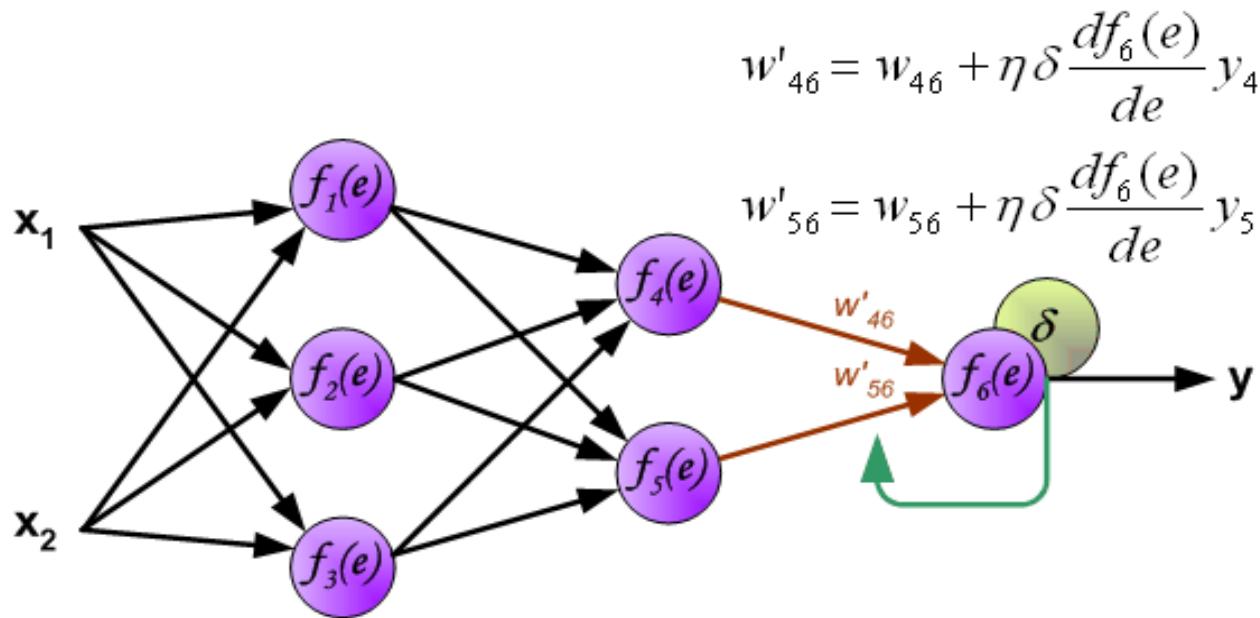
Algoritmo de aprendizaje

Backpropagation



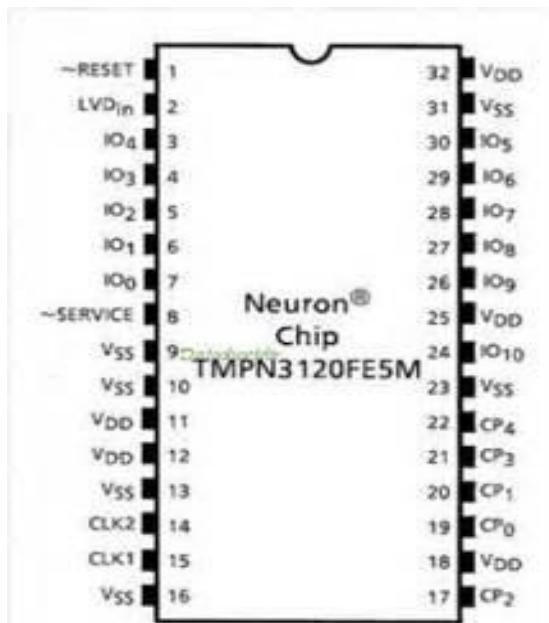
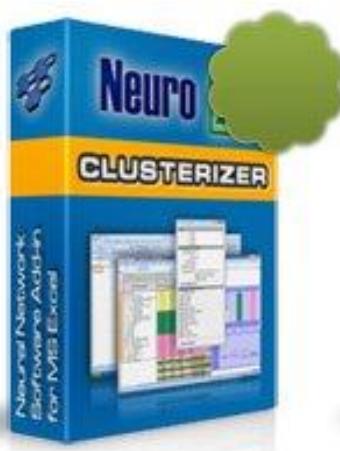
Algoritmo de aprendizaje

Backpropagation

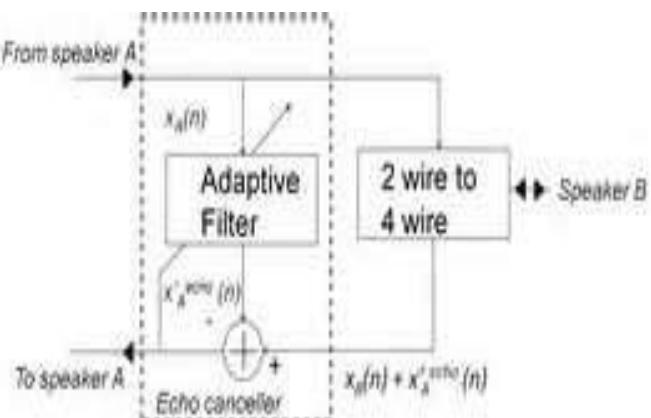
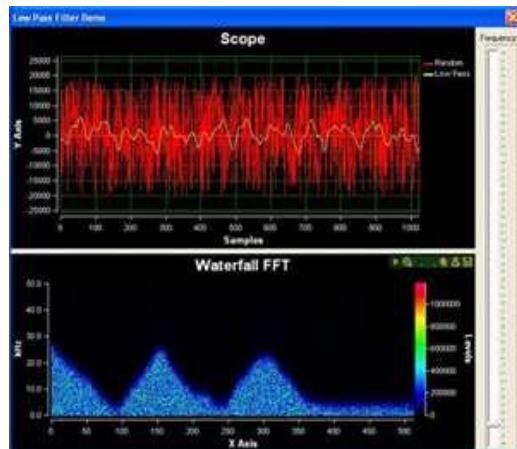
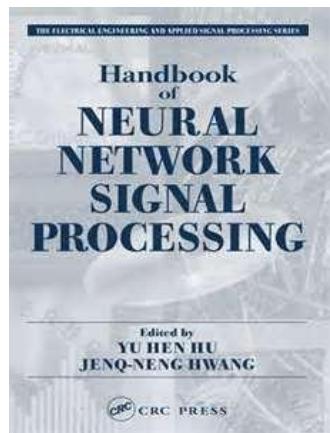
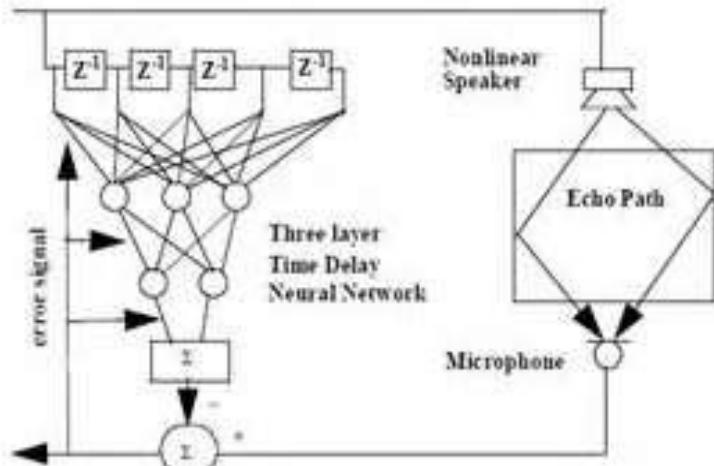
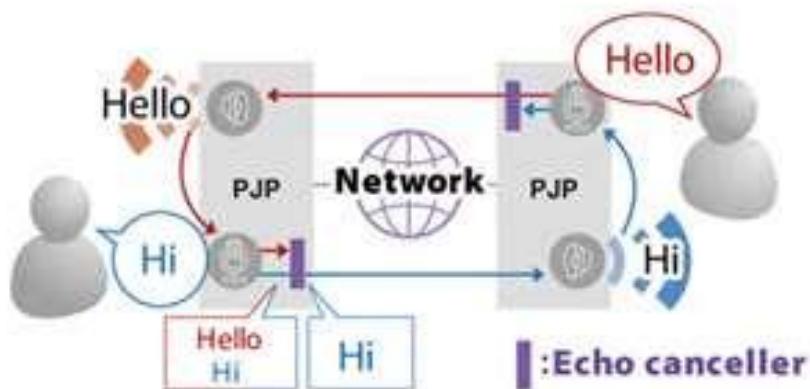


REDES NEURONALES

HARDWARE - SOFTWARE



Redes Neuronales en Procesamiento Digital de Señales DSP



Redes Neuronales en Ingeniería de Control (Neural Network Adaptive Control Systems)

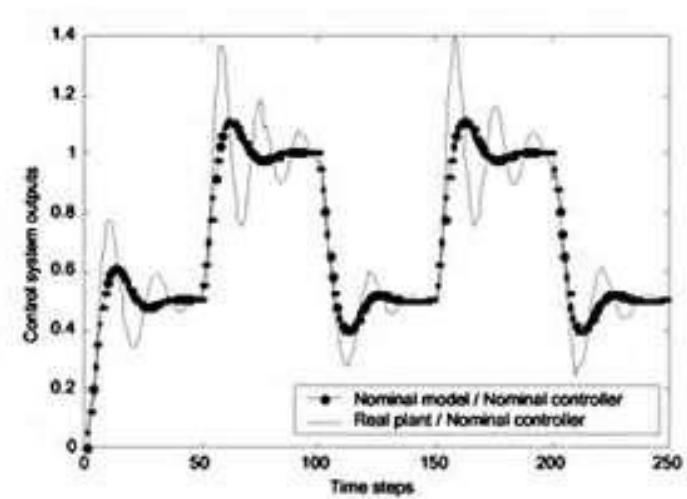
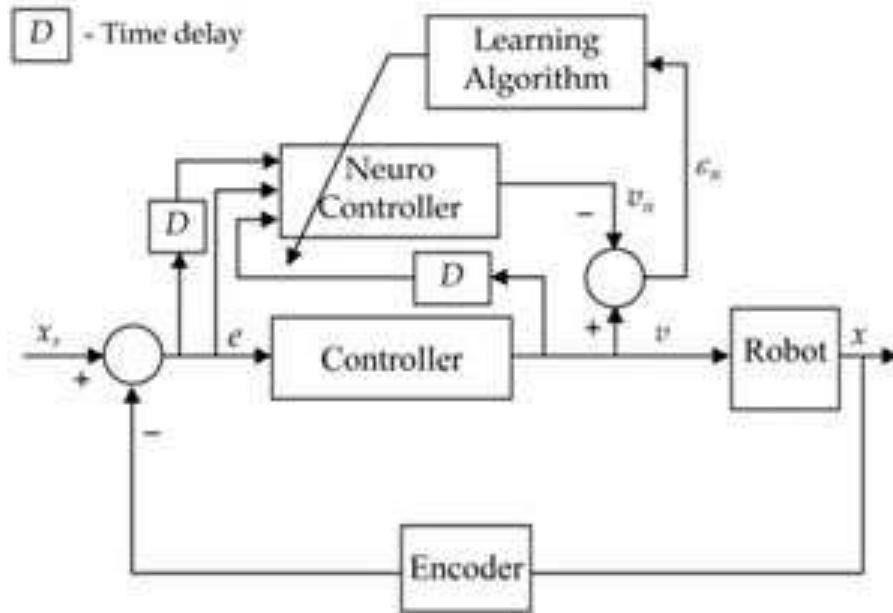


Figura 8: Control system performance using the nominal controller.

Redes Neuronales en Ingeniería de Control (Modelamiento Inverso)

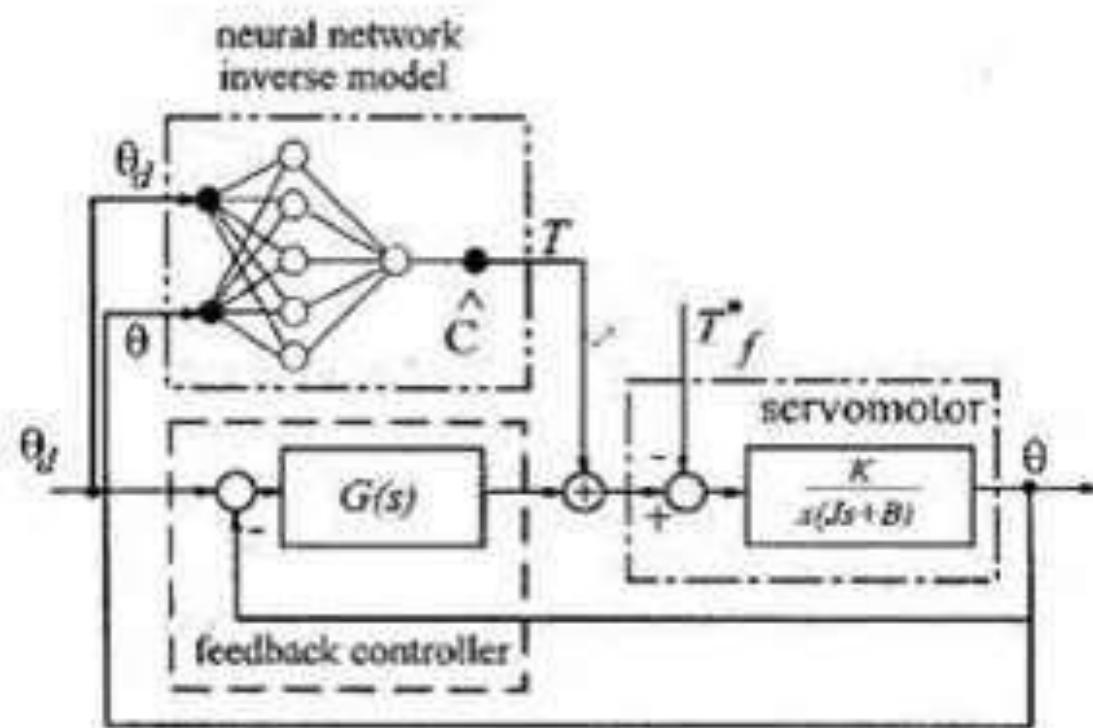
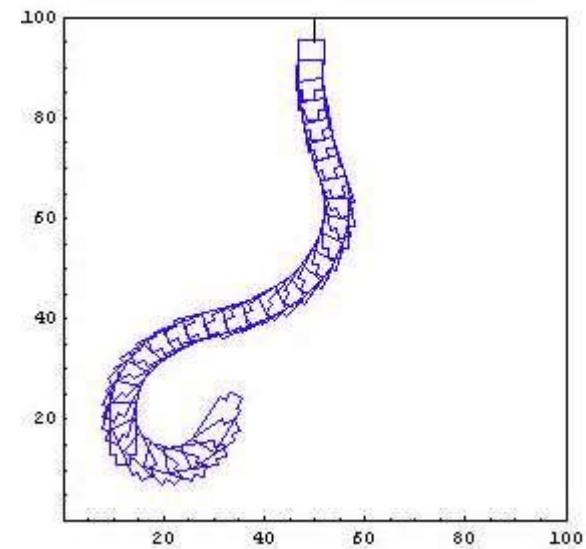
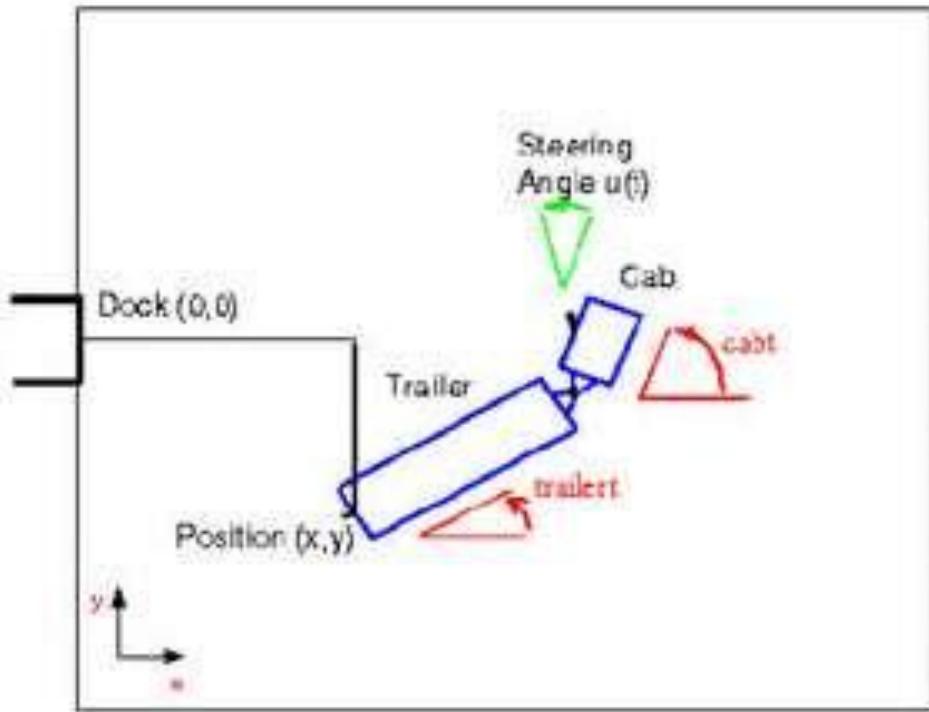
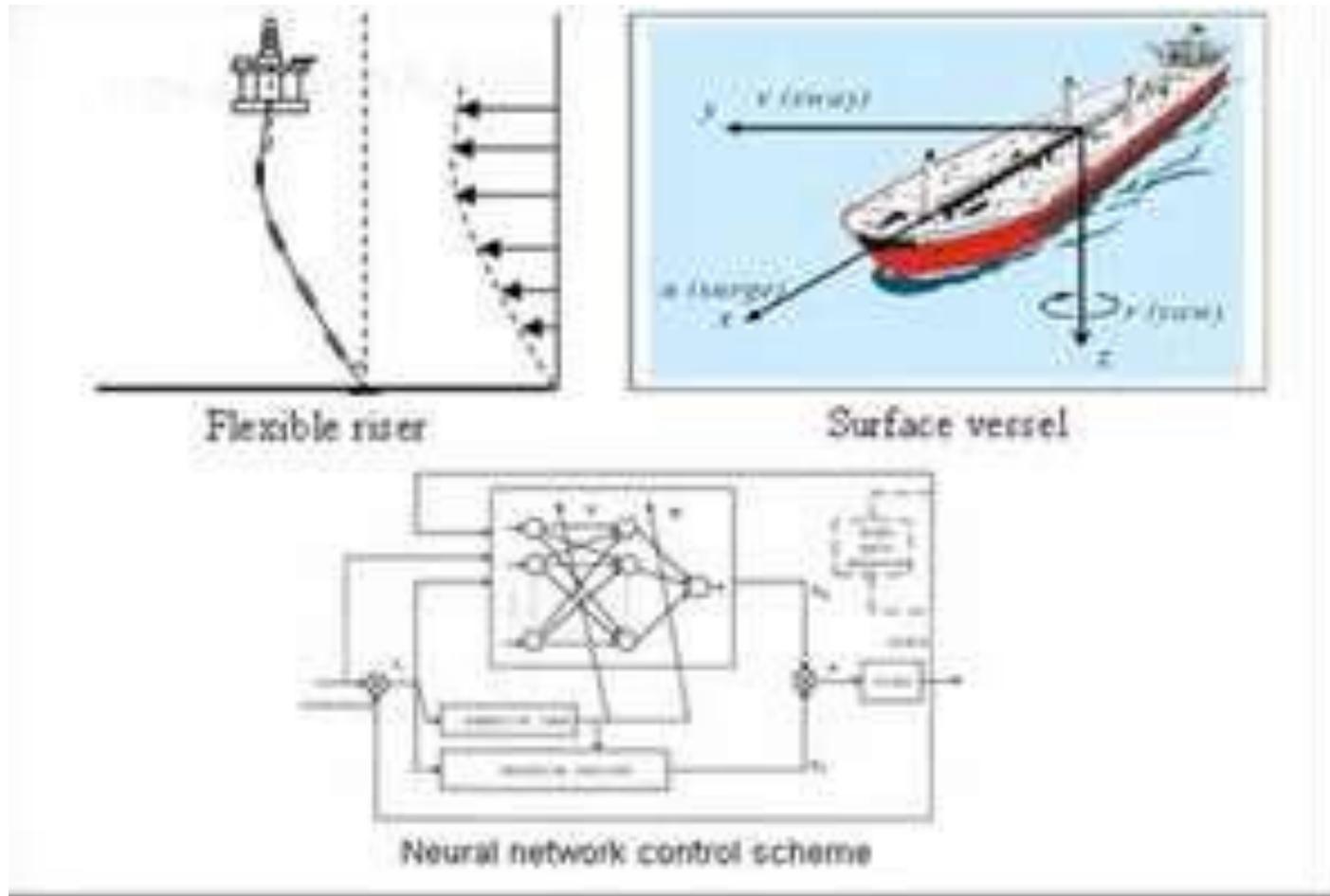


Fig. 7. Structure of the complete control system

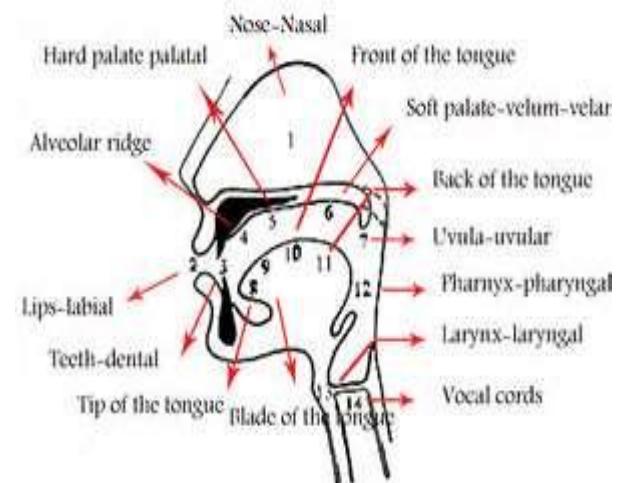
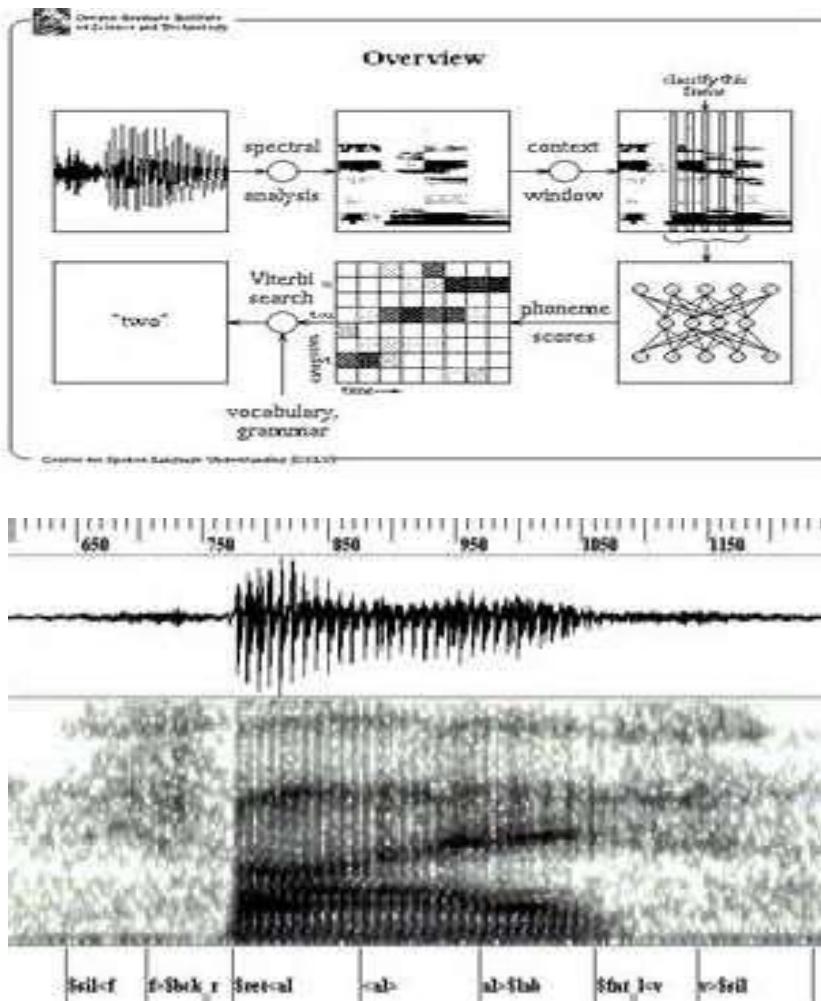
Redes Neuronales en Ingeniería de Control Inteligente ("Upper backer Track Neural Network")



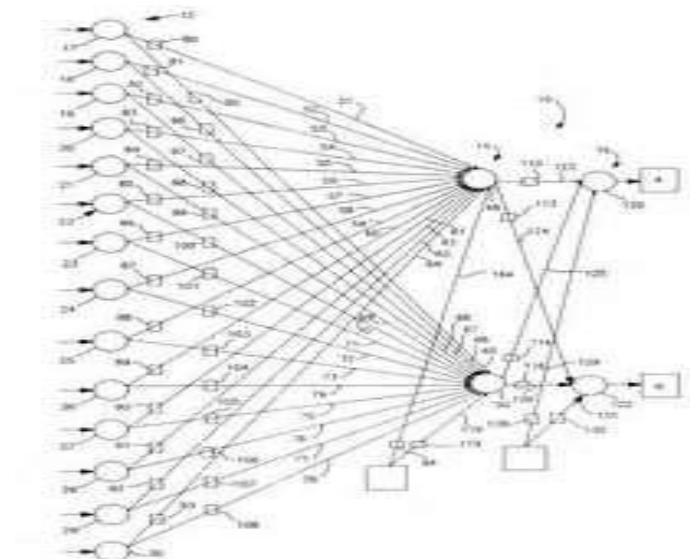
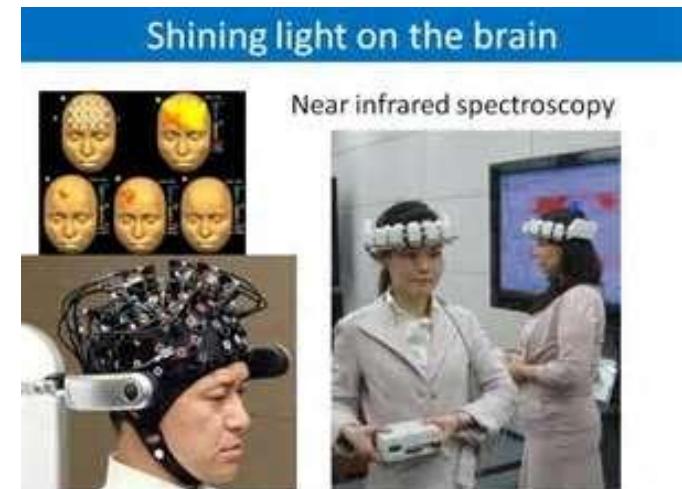
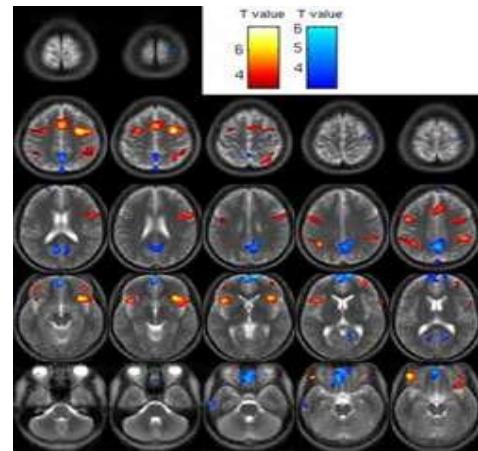
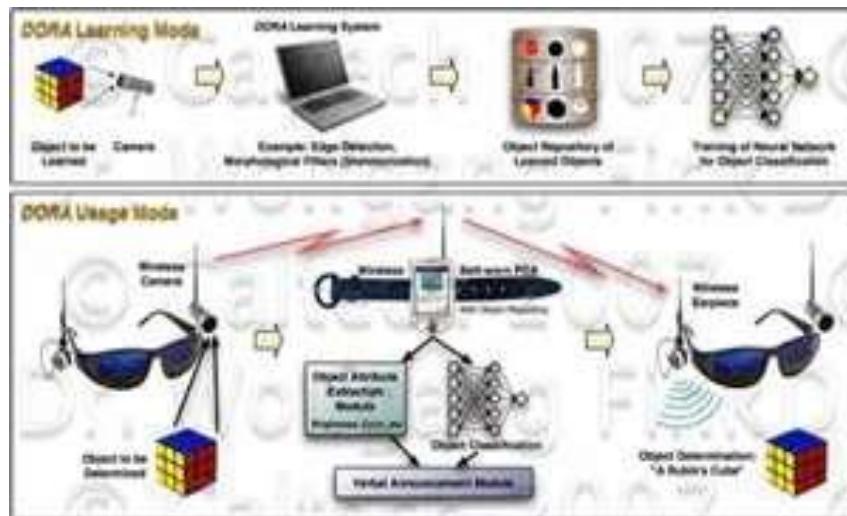
Redes Neuronales en Ingeniería de Control (Navigation & Collision Avoidance)



Redes Neuronales en Reconocimiento de lenguaje y voz



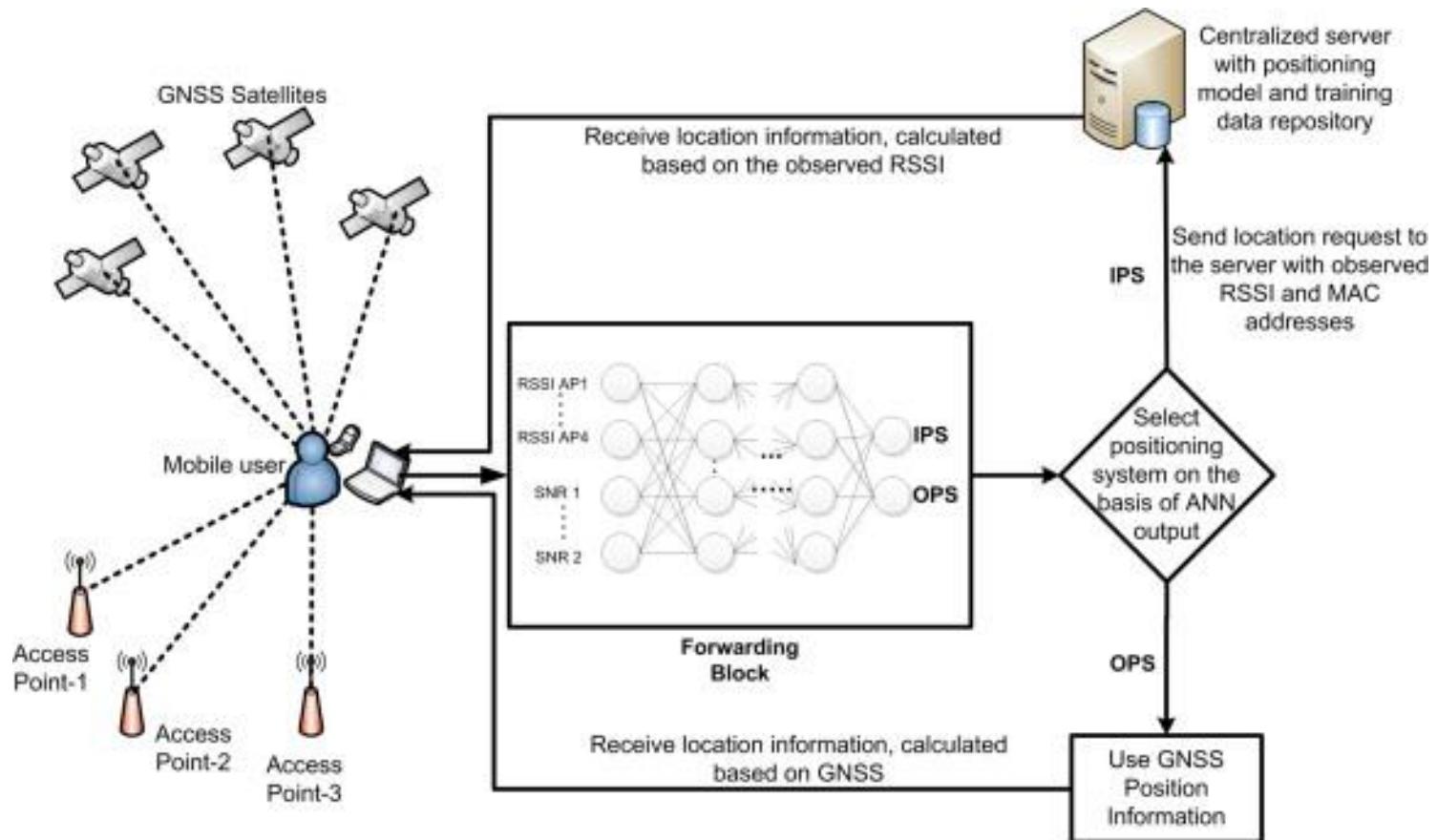
Redes Neuronales en Medicina y Bio Ingeniería



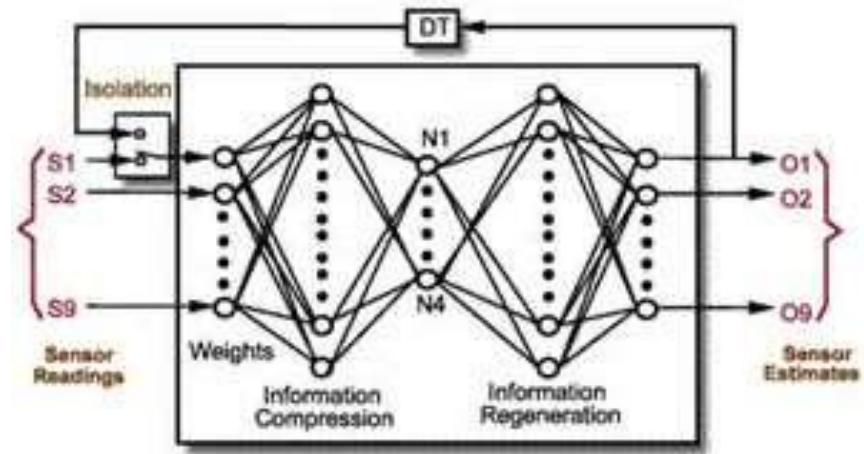
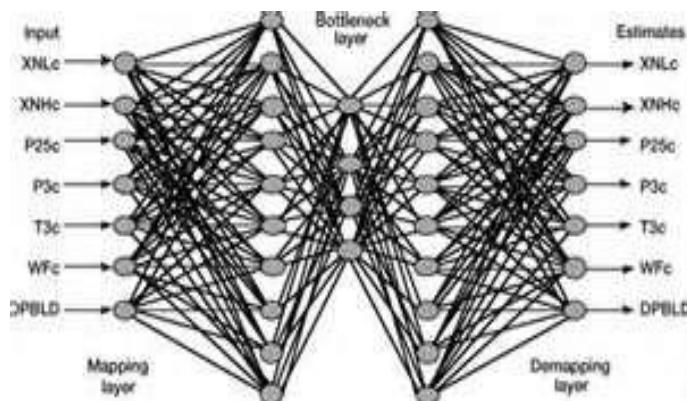
NEUROMORPHIC TECHNOLOGIES

Fernando Jimenez Motte Ph.D.EE (c), M.S.E.E, B.S.E.E

GLOBAL NAVIGATIONAL SATELLITE SYSTEM GNSS



Redes Neuronales en Ingeniería de Control (Pathfinder + Sojourner en Marte)



Redes Neuronales en Ingeniería de Control (Control No Lineal de Manipuladores de Robot)

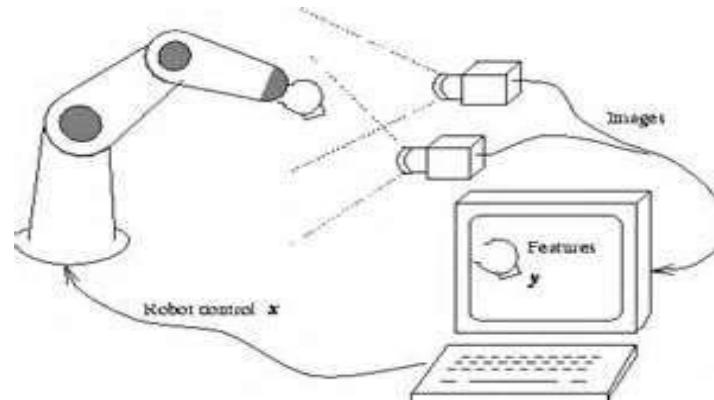
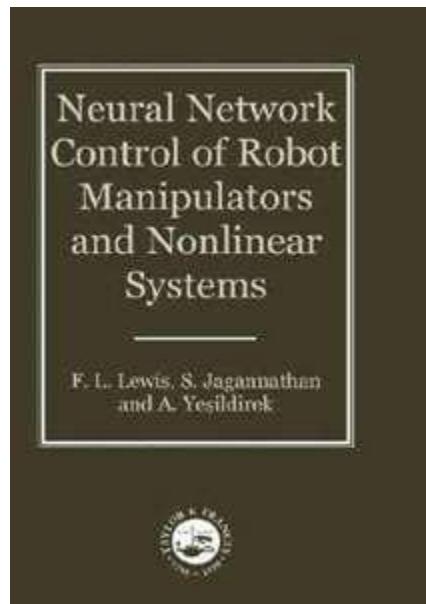
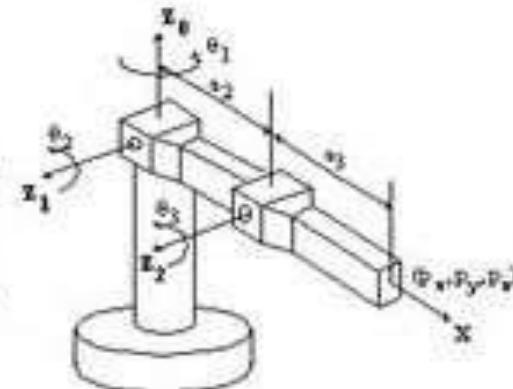


Table 2 Link parameter table

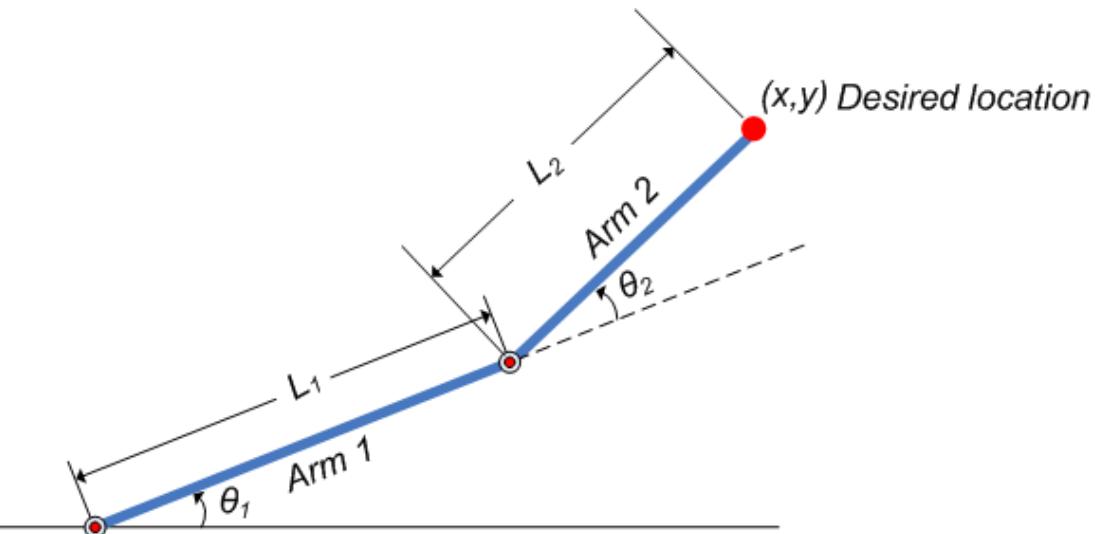
link	variable	α	s	d
1	θ_1	90°	0	0
2	θ_2	0°	s_2	0
3	θ_3	0°	s_3	0

Denavit-Hartenberg
Transformations

$$x_3 = A_2 A_1 A_0 = \begin{bmatrix} c_1 c_{23} & -c_1 s_{23} & r_1 & c_2(s_3 c_{23} + s_2 c_2) \\ c_1 s_{23} & c_1 c_{23} & 0 & c_2(s_3 c_{23} + s_2 c_2) \\ s_{23} & -s_{23} & 0 & s_3 c_{23} + s_2 c_2 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$



Neuro Fuzzy Robot Inverse Kinematics Modelling



$$x = L_1 \cos \theta_1 + L_2 \cos(\theta_1 + \theta_2)$$

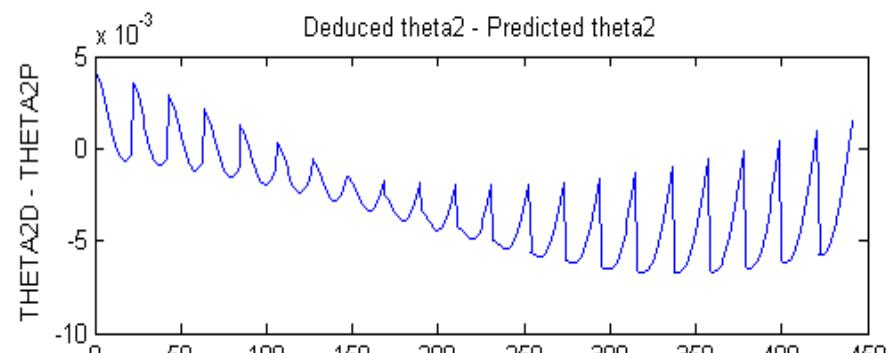
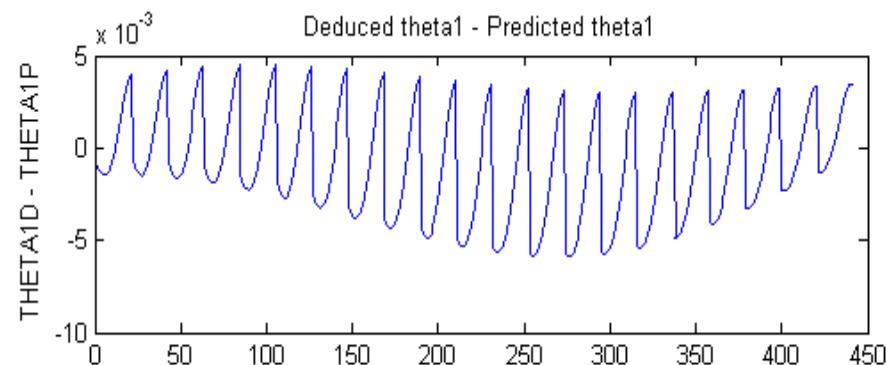
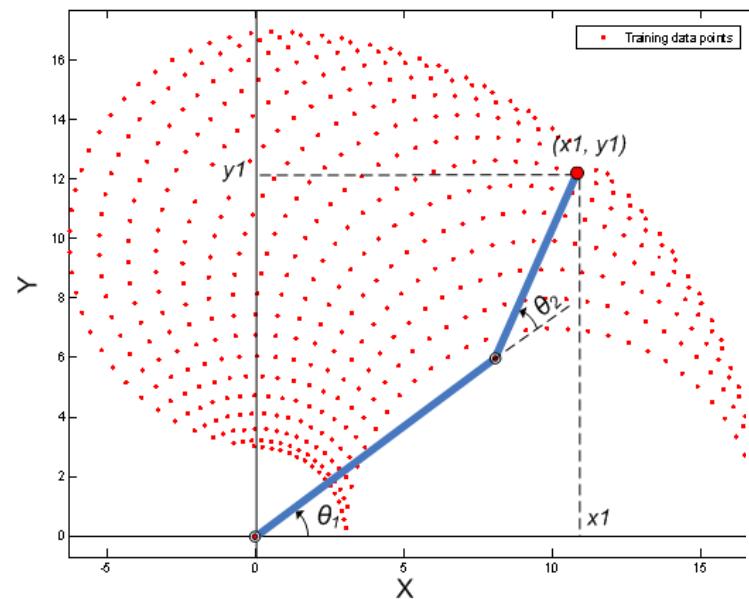
$$y = L_1 \sin \theta_1 + L_2 \sin(\theta_1 + \theta_2)$$

$$x^2 + y^2 = (L_1)^2 + (L_2)^2 + 2L_1L_2[\cos \theta_1 \cos(\theta_1 + \theta_2) + \sin \theta_1 \sin(\theta_1 + \theta_2)]$$

$$x^2 + y^2 = (L_1)^2 + (L_2)^2 + 2L_1L_2 \cos(\theta_2)$$

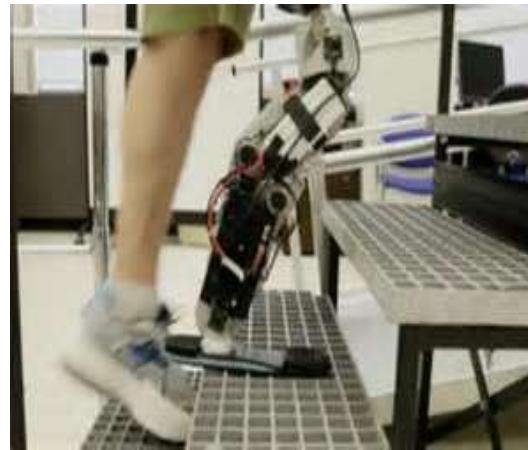
$$\theta_2 = \cos^{-1}[(x^2 + y^2 - (L_1)^2 - (L_2)^2)/(2L_1L_2)]$$

X-Y co-ordinates generated for all theta1 and theta2 combinations
using forward kinematics formulae



Redes Neuronales en Interfase Hombre Máquina

“Human Machine Interfase/Bionics”





Neural Network-Based Face Detection. (Face Pattern Recognition).

A Convolutional Neural Network Hand Tracker. (Gesture Recognition).

Neural Networks for speech and image processing.

Speech recognition with Neural Networks.

Conversational Speech Transcription Using Context-Dependent Deep Neural Networks.

**Speech recognition breakthrough via machine translation that converted spoken English words into computer-generated Chinese language.
(Human/natural machine interface HMI).**

Microsoft Neural Network Algorithm

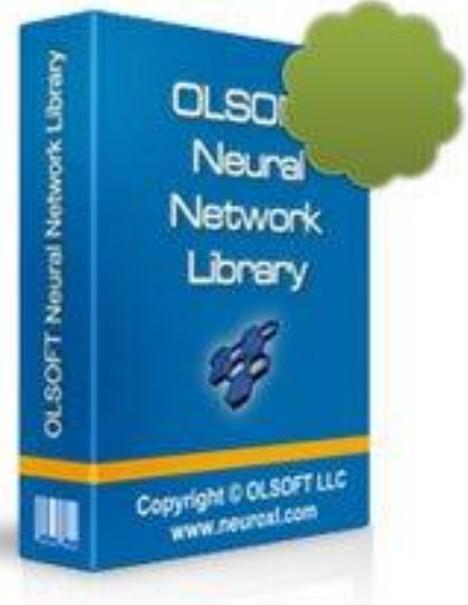
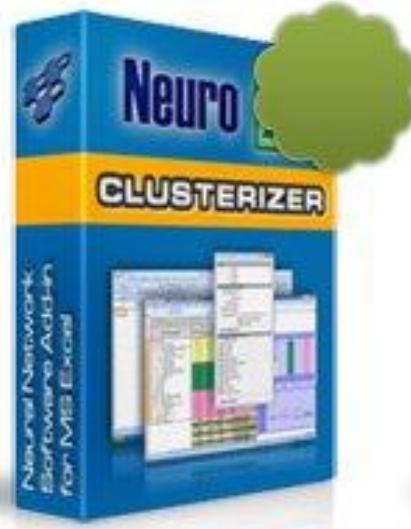
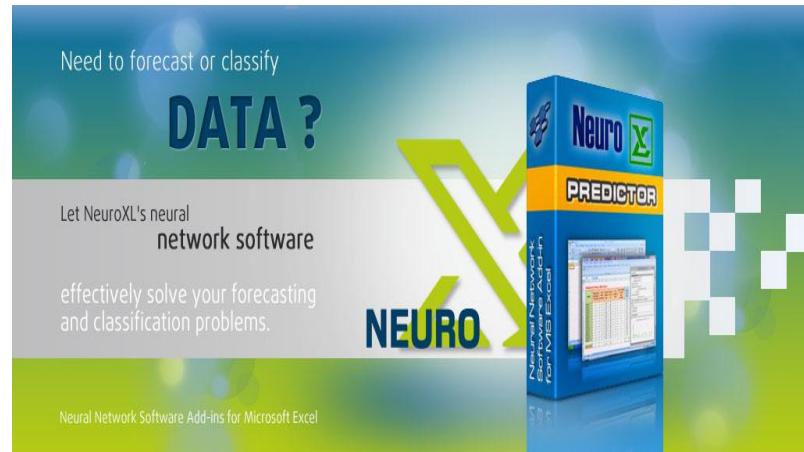
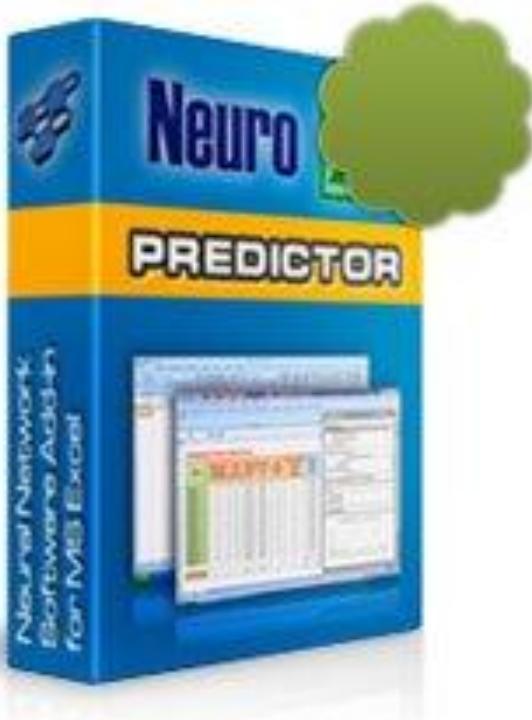
SQL Server

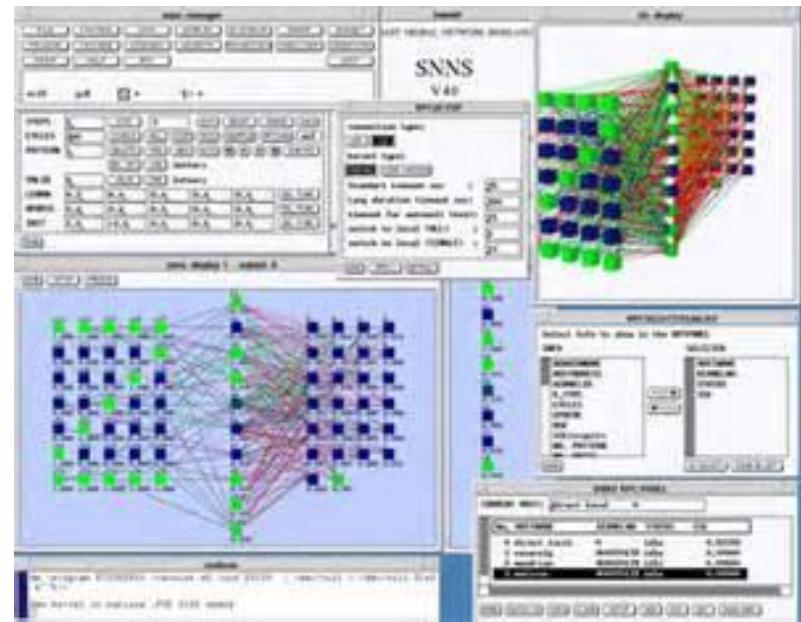
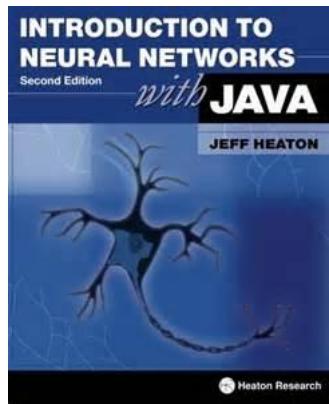
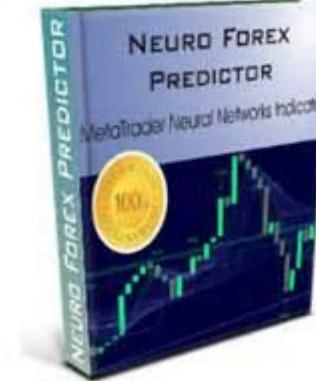
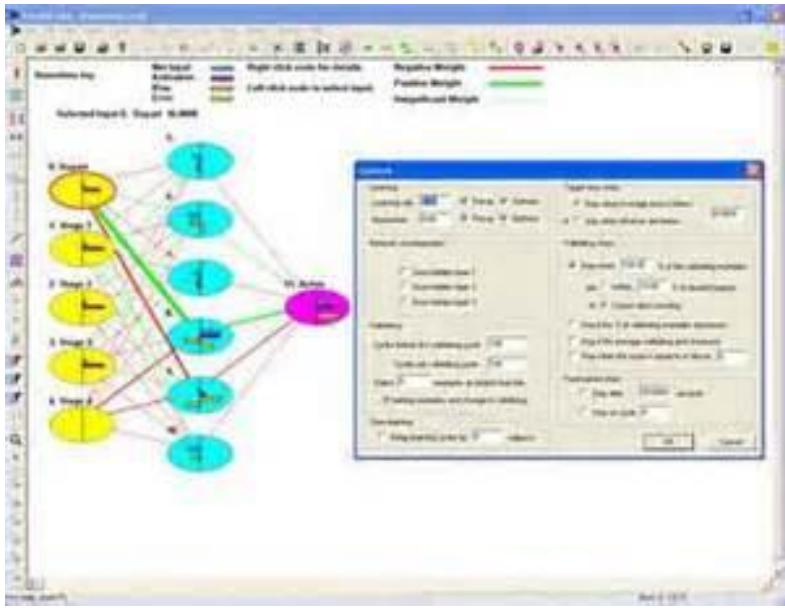
In SQL Server Analysis Services, the Microsoft Neural Network algorithm **combines each possible state of the input attribute with each possible state of the predictable attribute**, and uses the **training data to calculate probabilities**. You can later use these probabilities for classification or regression, and to predict an outcome of the predicted attribute, based on the input attributes.

A **mining model** that is constructed with the **Microsoft Neural Network algorithm** **can contain multiple networks**, depending on the number of columns that are used for both input and prediction, or that are used only for prediction. The number of networks that a single mining model contains depends on the number of states that are contained by the input columns and predictable columns that the mining model uses.



NEURO SOLUTIONS FOR EXCEL

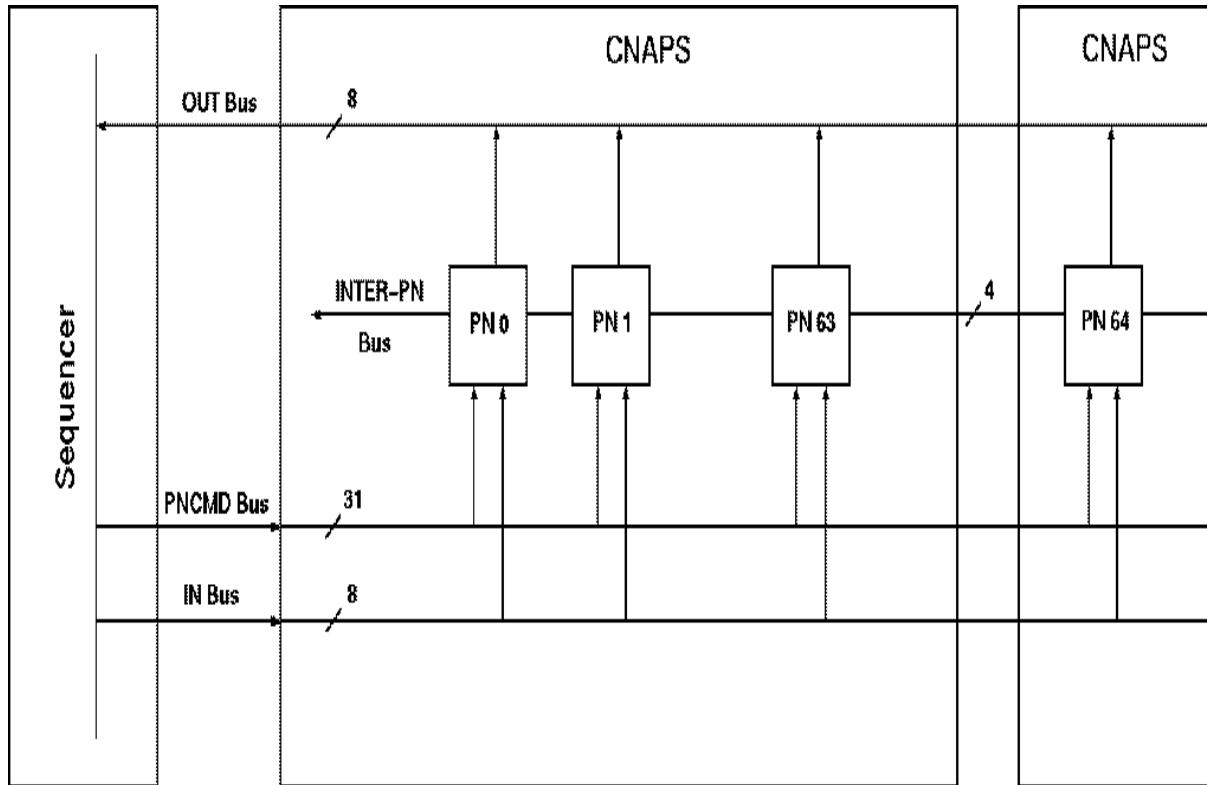




NEUROMORPHIC TECHNOLOGIES
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CNAPS Chip

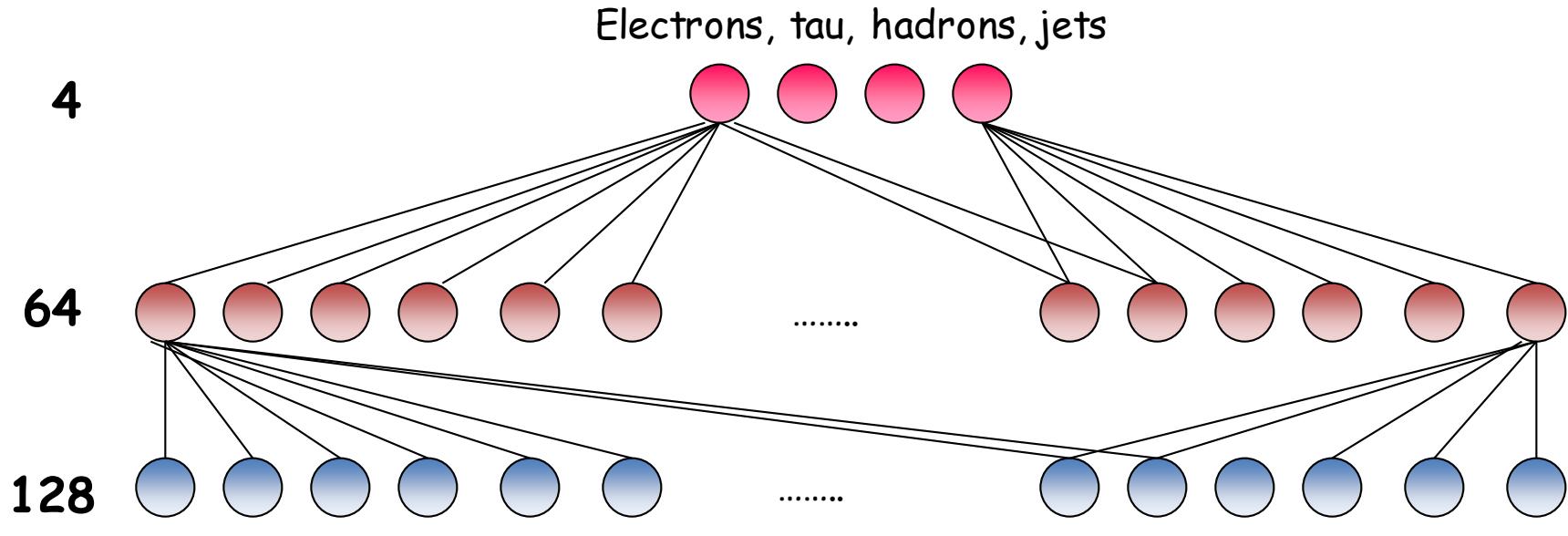
(Parallel processor for Pattern Recognition, Image Processing and Neural networks)



**CNAPS 1064 chip
Adaptive Solutions,
Oregon**

**64 x 64 x 1 in 8 µs
(8 bit inputs, 16 bit weights,**

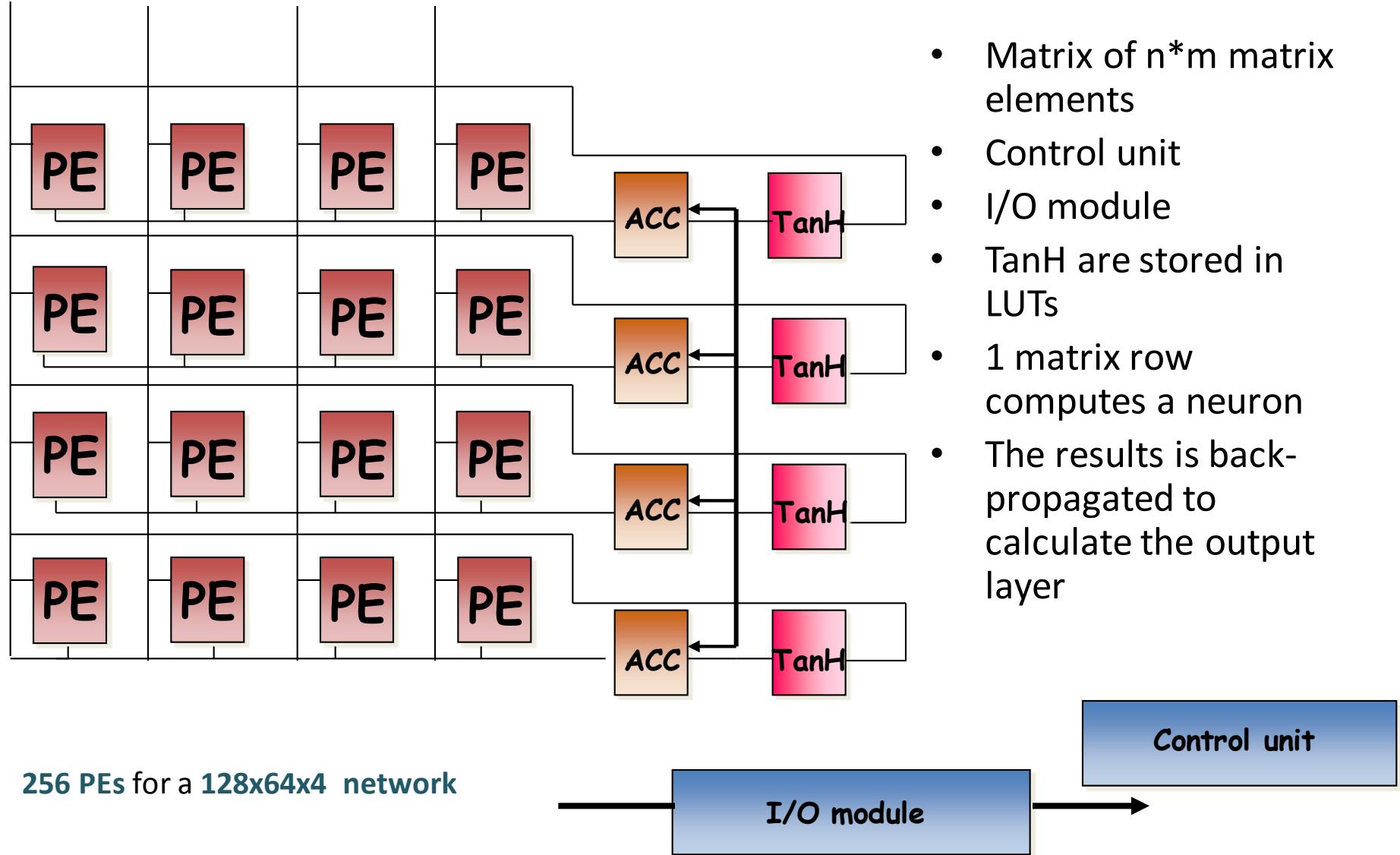
Neural Network architecture



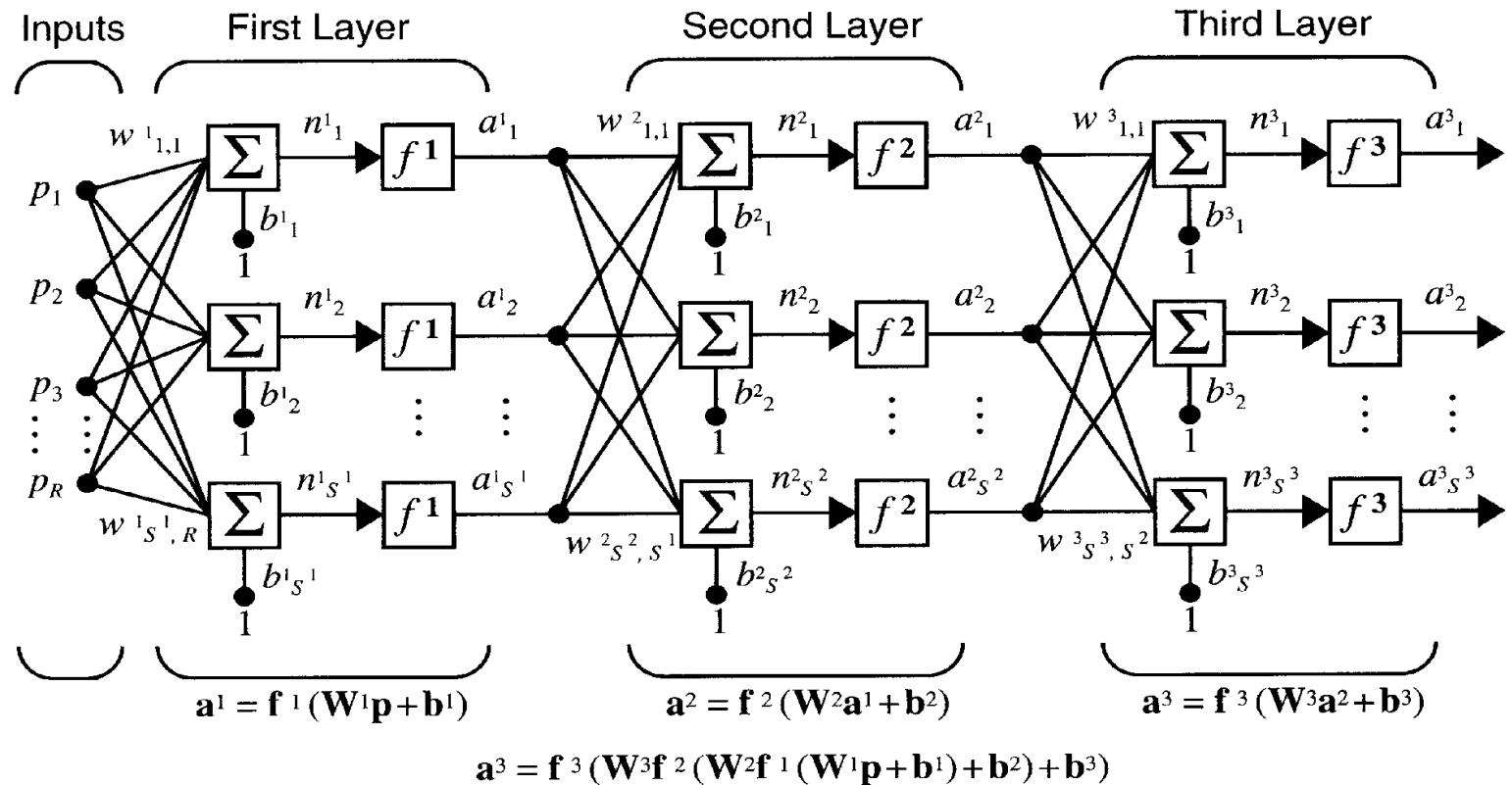
Execution time : ~500 ns with data arriving every BC=25ns

Weights coded in 16 bits
States coded in 8 bits

Very fast architecture



Three-Layer Network



Number of neurons in each layer: $R - S^1 - S^2 - S^3$

CELULAR NEURAL NETWORK CNN ARCHITECTURE WITH 3X3 NEIGHBORHOOD CONNECTIVITY

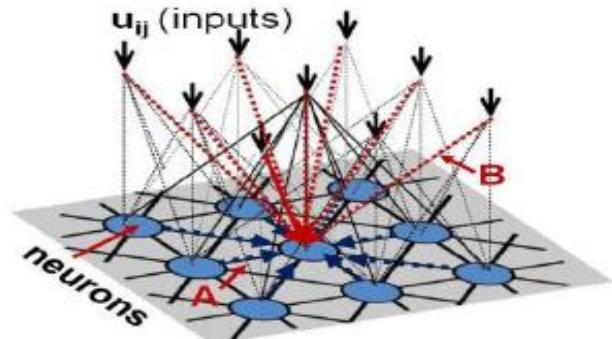
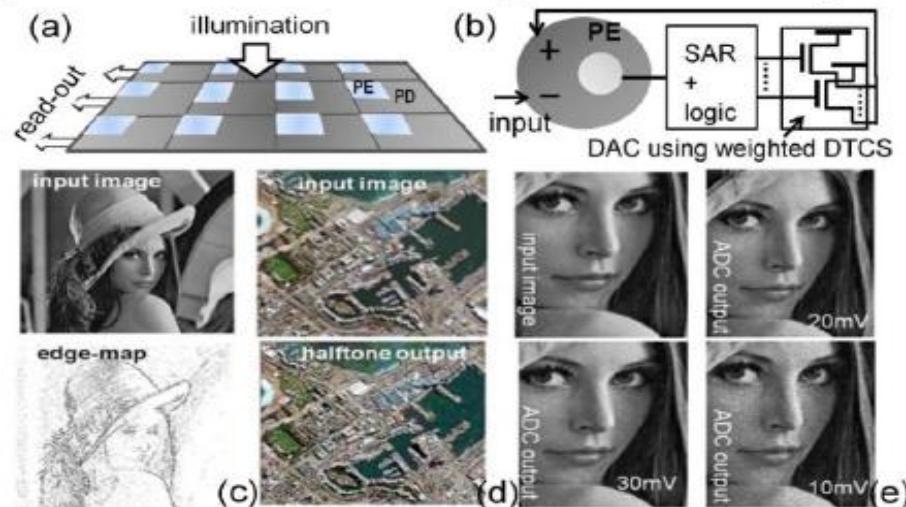
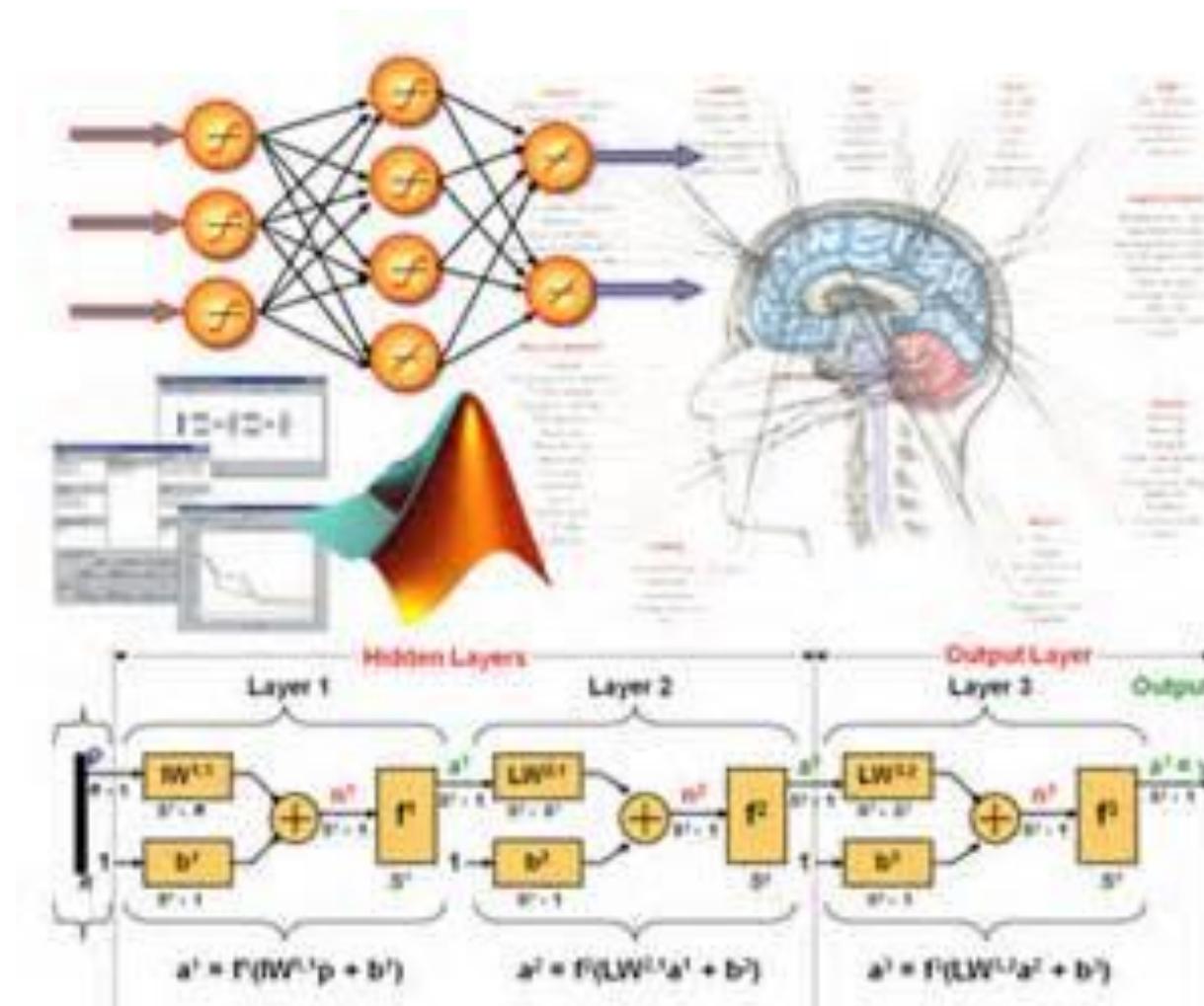


Fig. 9. CNN architecture with 3x3 neighbourhood connectivity



Matlab + Simulink Neural Network Toolbox

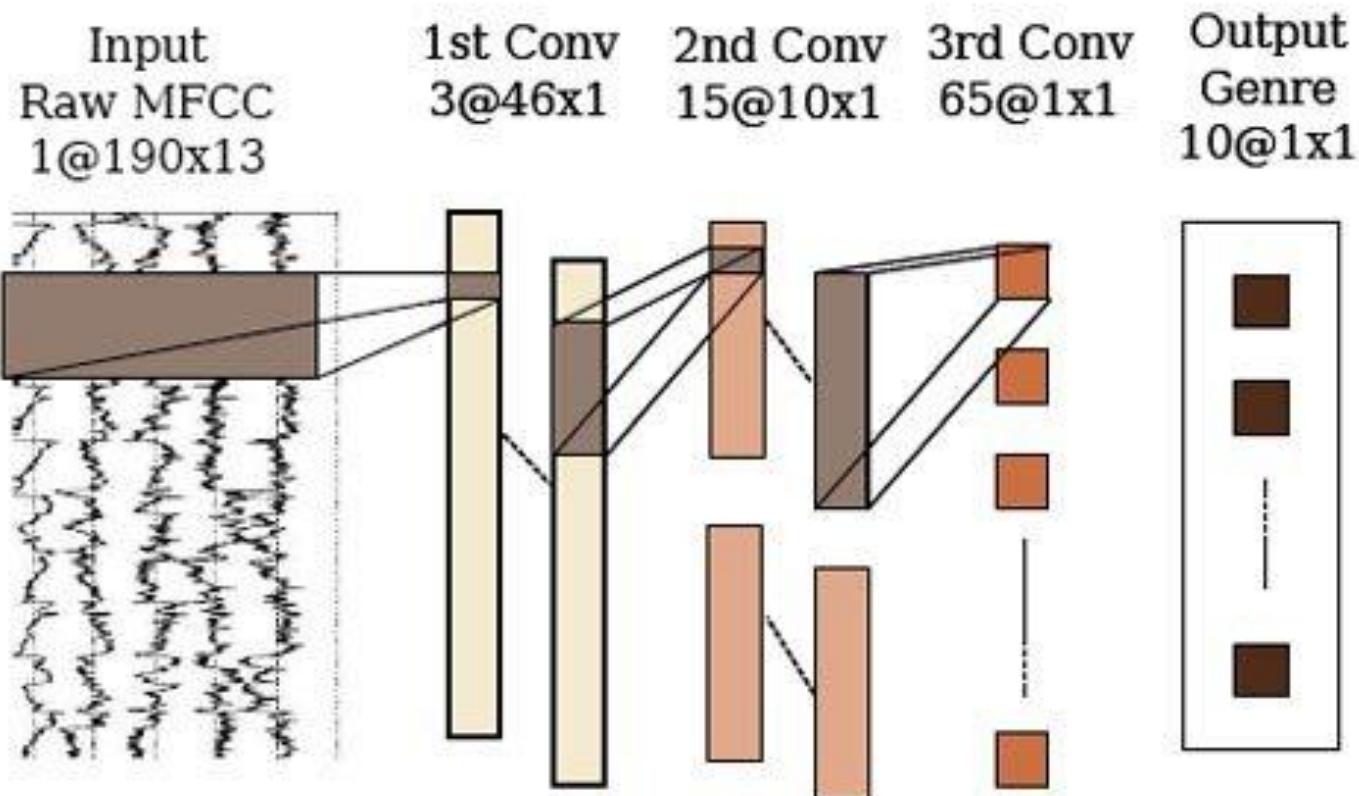


NEUROMORPHIC TECHNOLOGIES

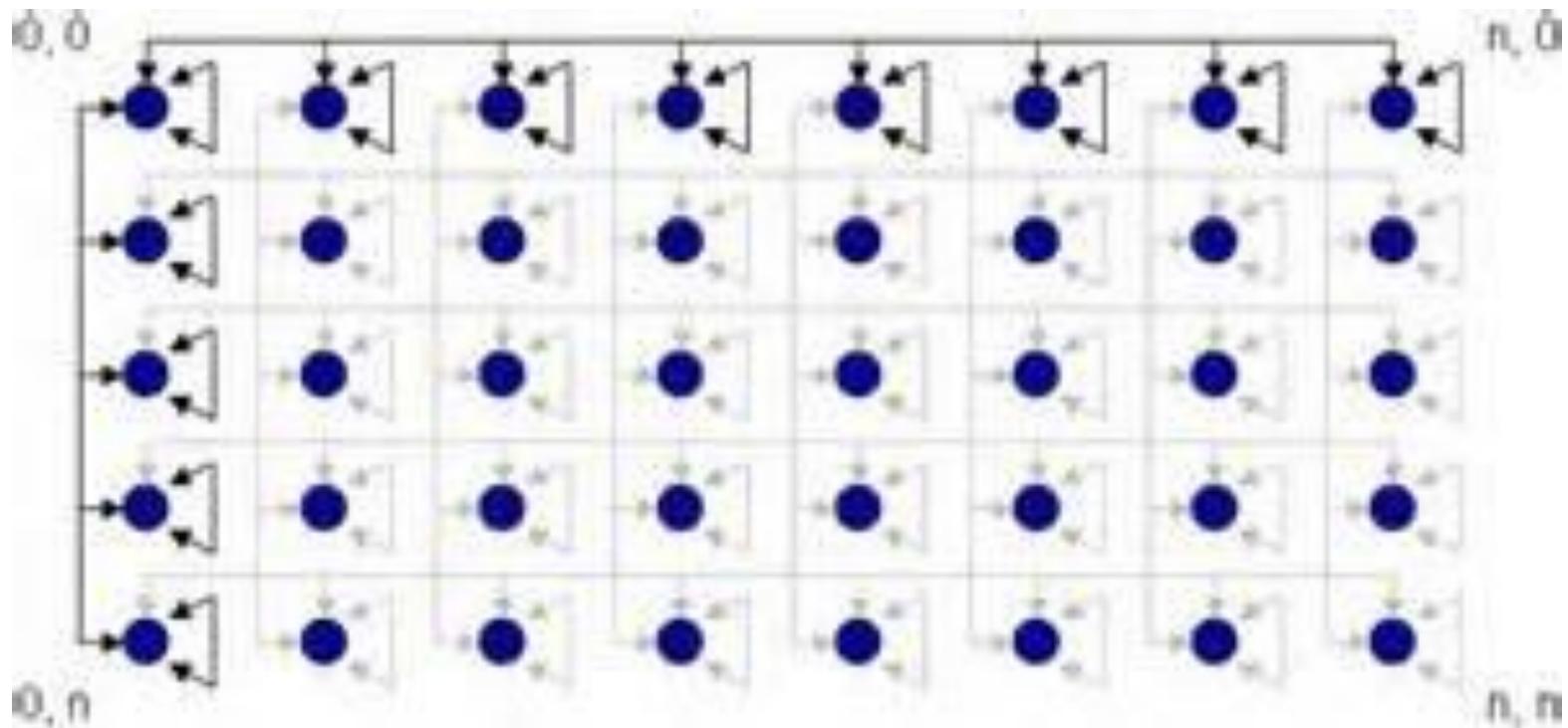
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Celullar Neural Network

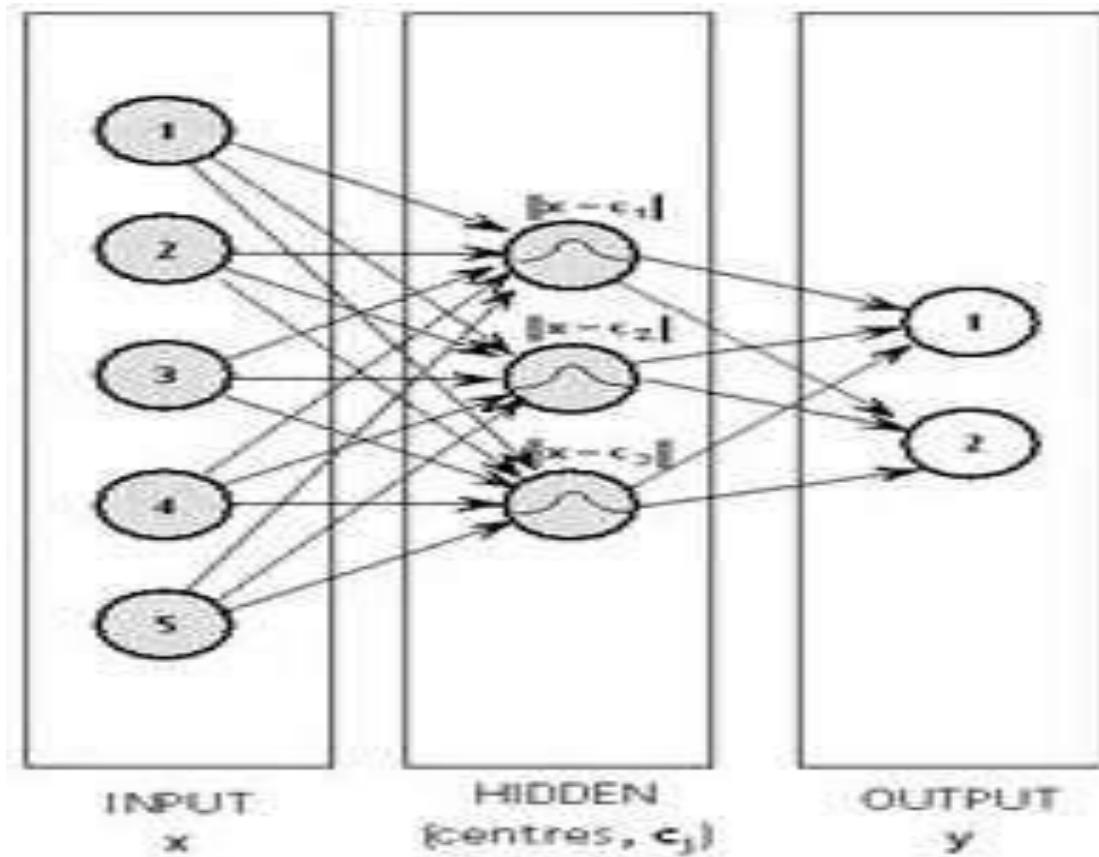
CNN Architecture for Audio



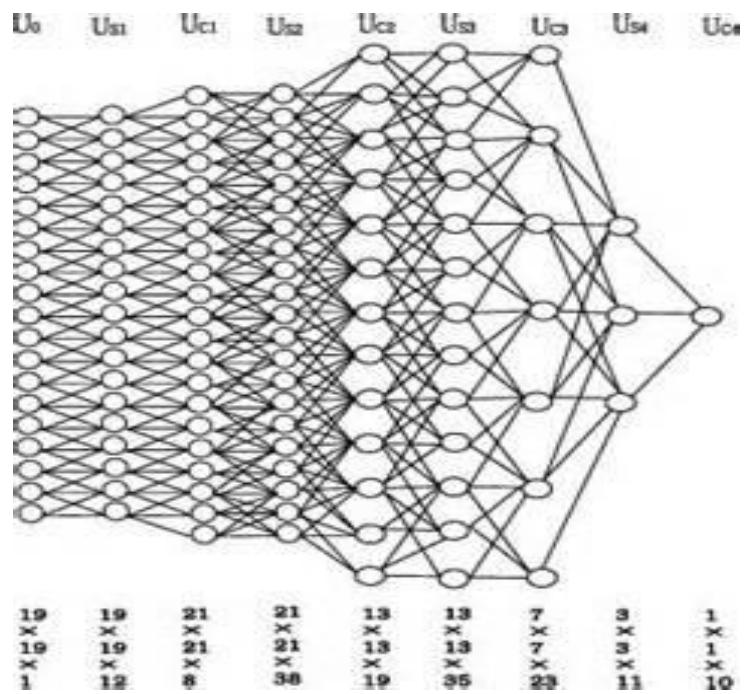
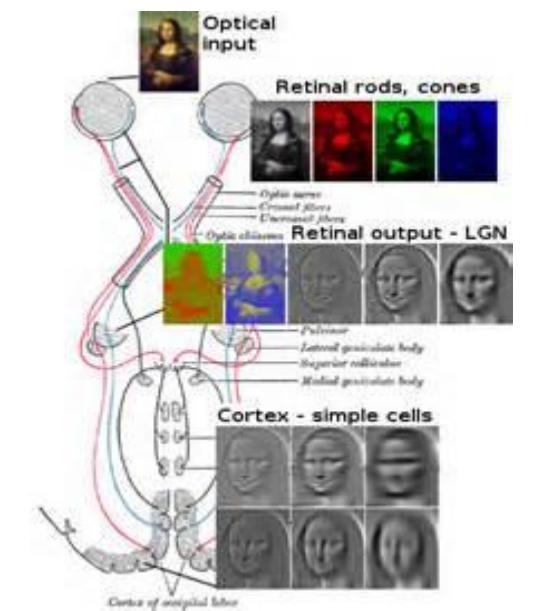
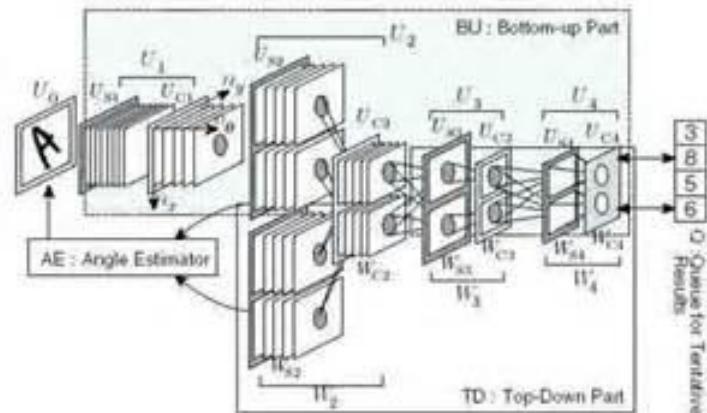
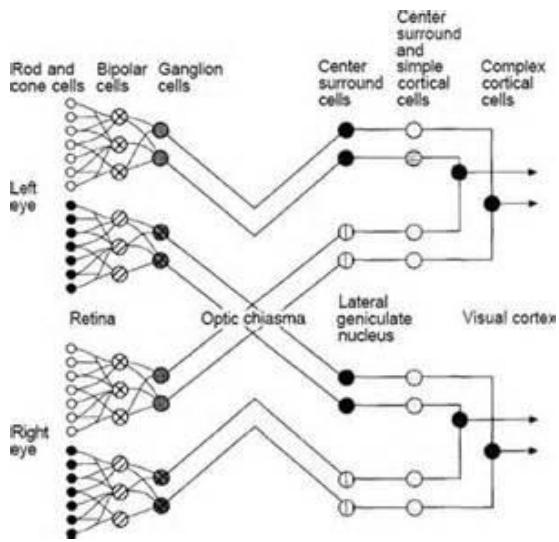
Boltzmann Machine Neural Network



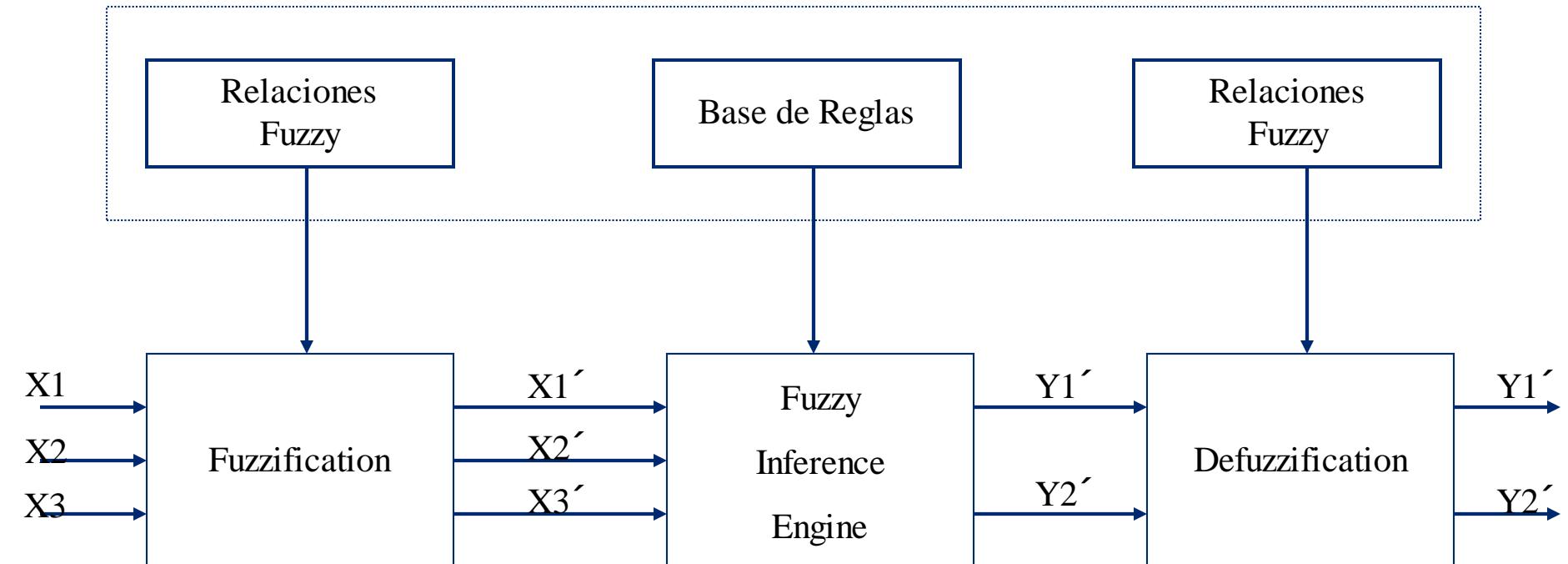
Radial Basis Function RBF



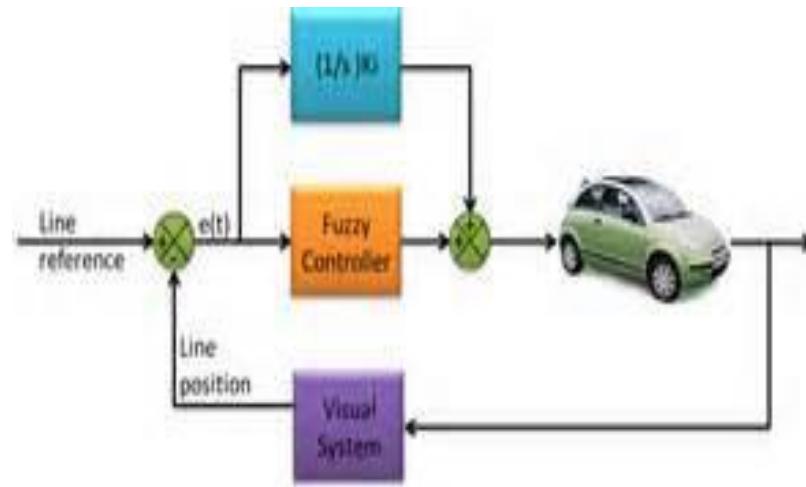
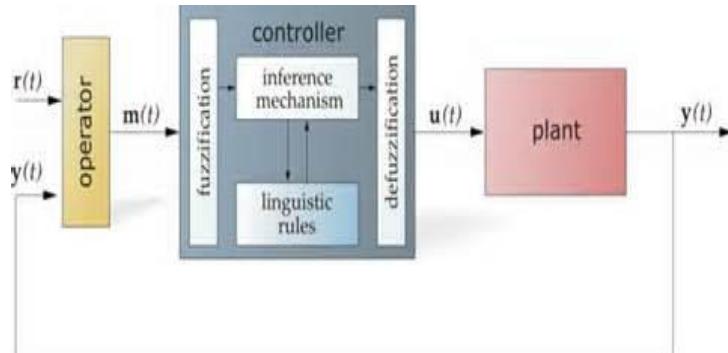
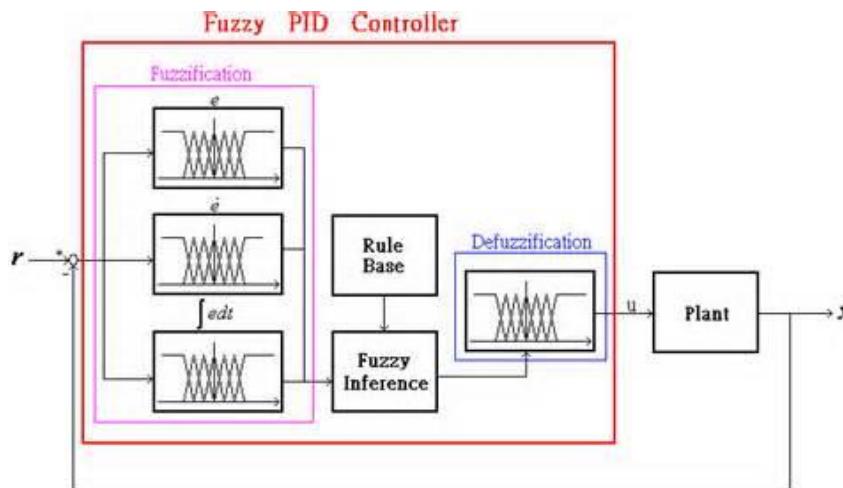
Neocognitron



Inferencia difusa – razonamiento aproximado



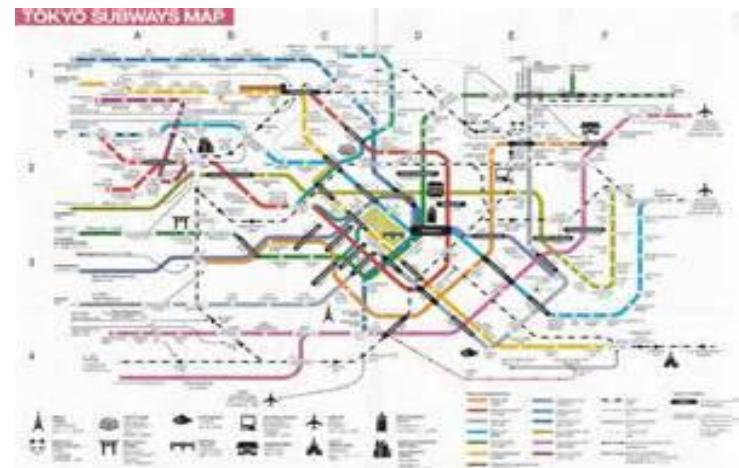
Fuzzy logic control



Fuzzy Engineering Applications

In the city of Sendai in Japan, a 16-station subway system is controlled by a fuzzy computer (Seiji Yasunobu and Soji Miyamoto of Hitachi) – the ride is so smooth, riders do not need to hold straps.

Performance criteria: *safety, riding comfort, traceability to target speed, and accuracy of stopping gap.*



*For safety; IF the speed of train is approaching the limit speed,
THEN select the maximum brake notch.*

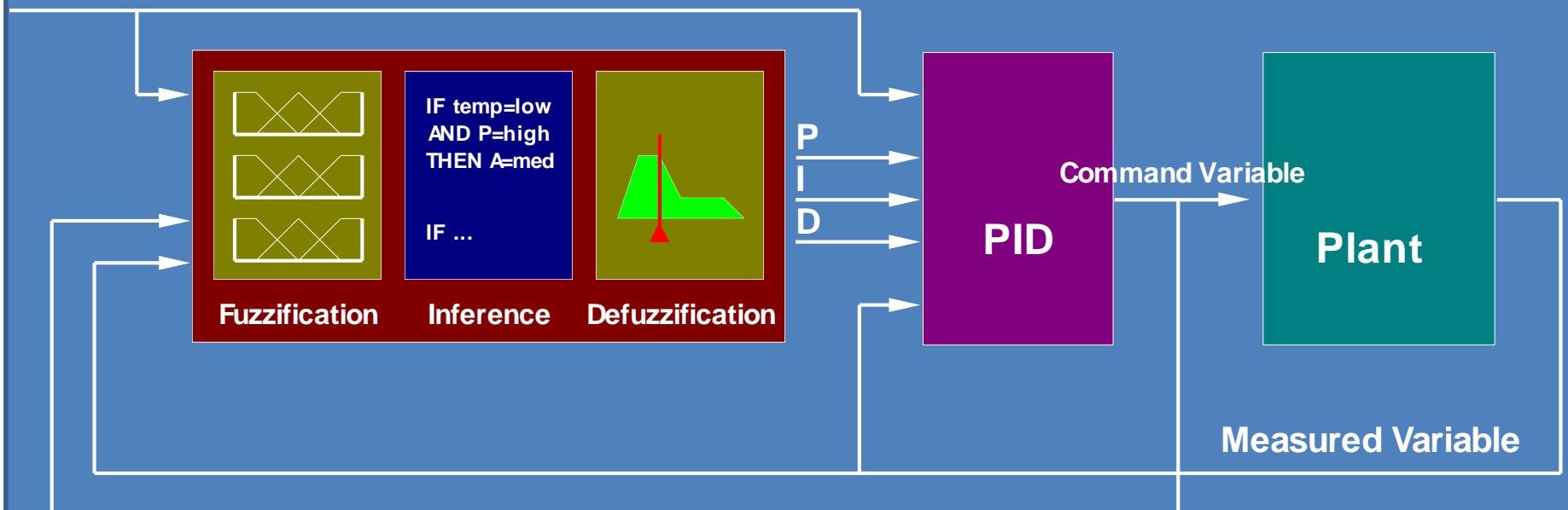
*For riding comfort; IF the speed is in the allowed range,
THEN do not change the control notch*

Types of Fuzzy Controllers:

- PID Adaptation -

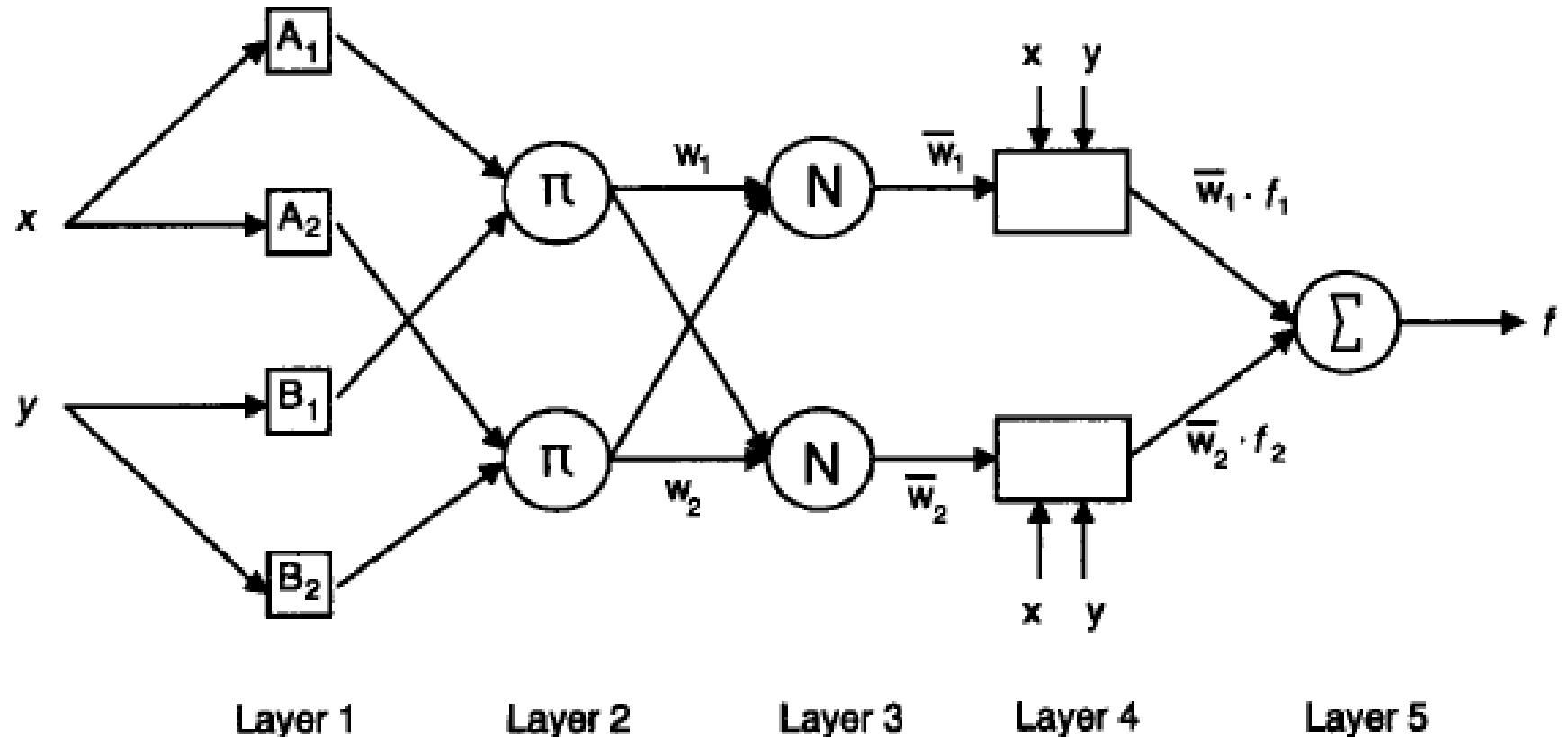
Fuzzy Logic Controller Adapts the P, I, and D Parameter of a Conventional PID Controller:

Set Point Variable



The Fuzzy Logic System Analyzes the Performance of the PID Controller and Optimizes It !

“Adaptive Network Fuzzy Inference System (ANFIS)



Layer 1

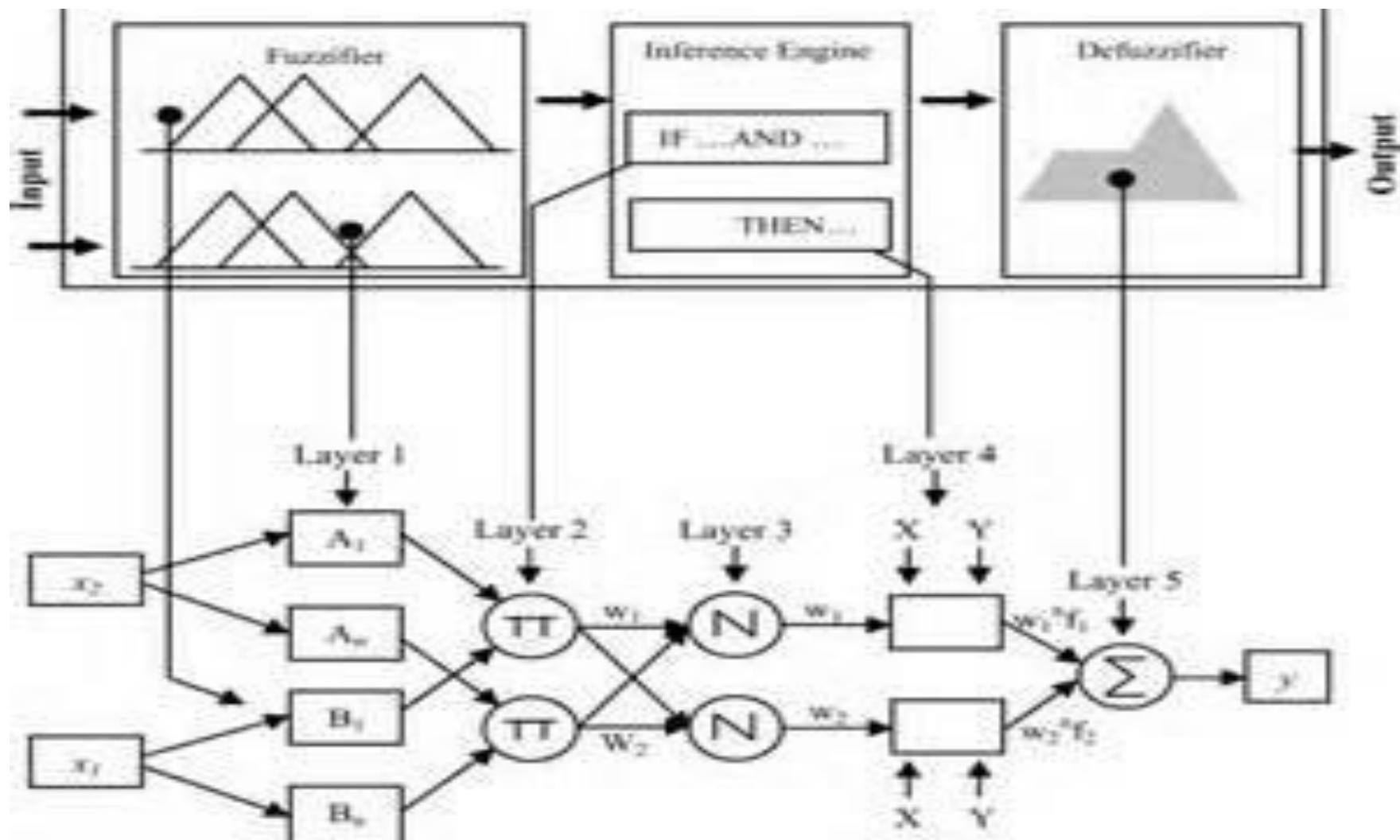
Layer 2

Layer 3

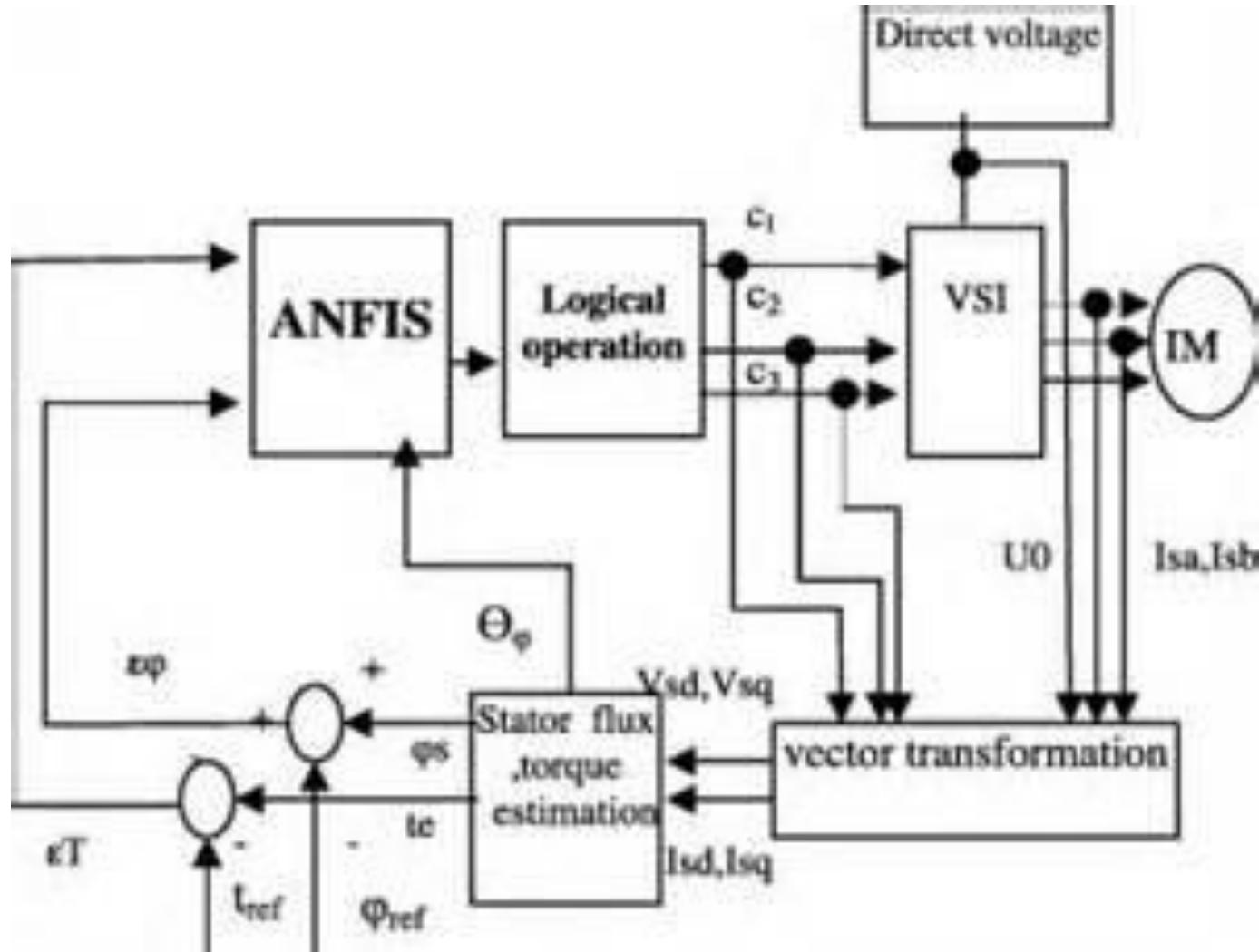
Layer 4

Layer 5

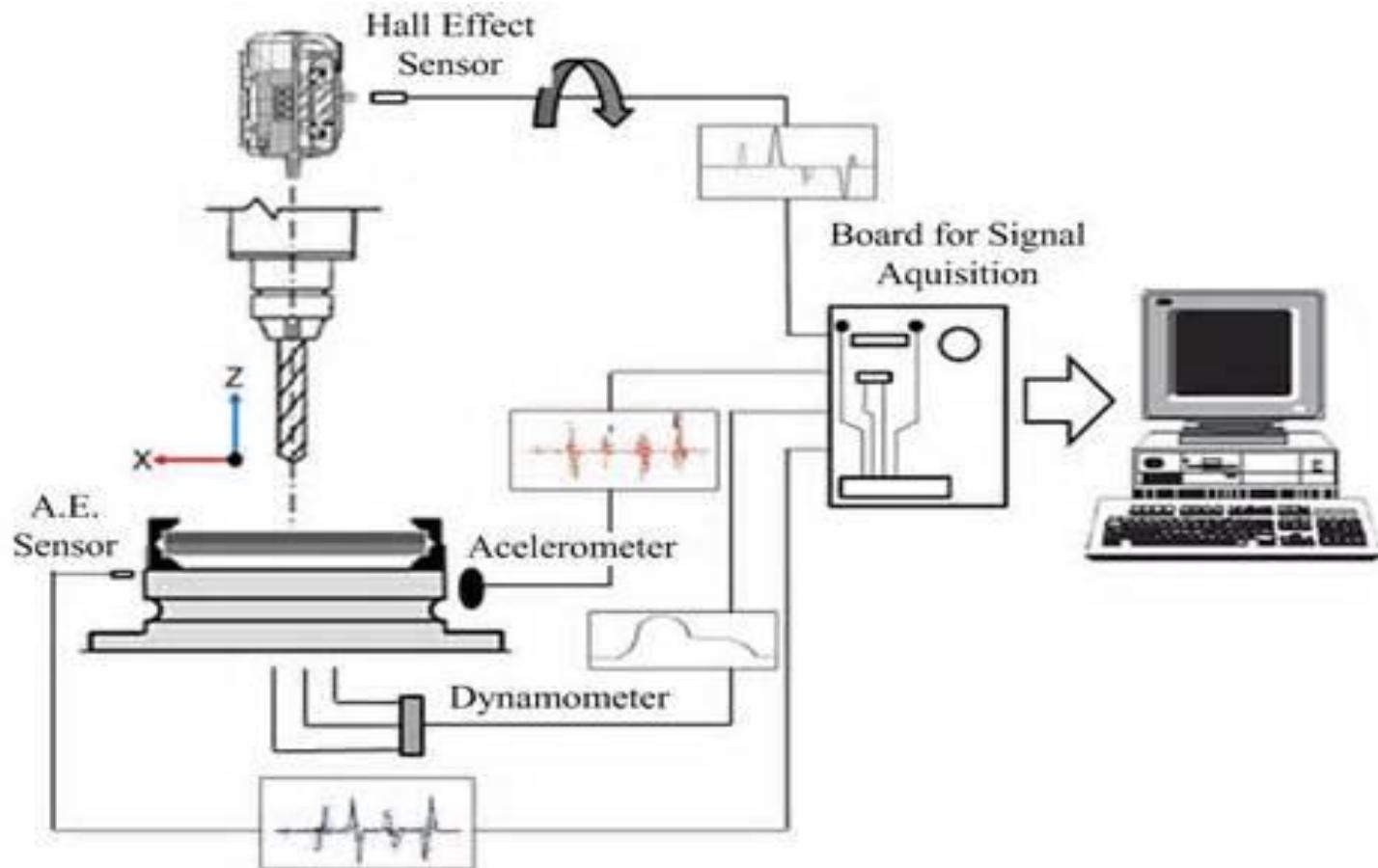
Neuro Fuzzy System



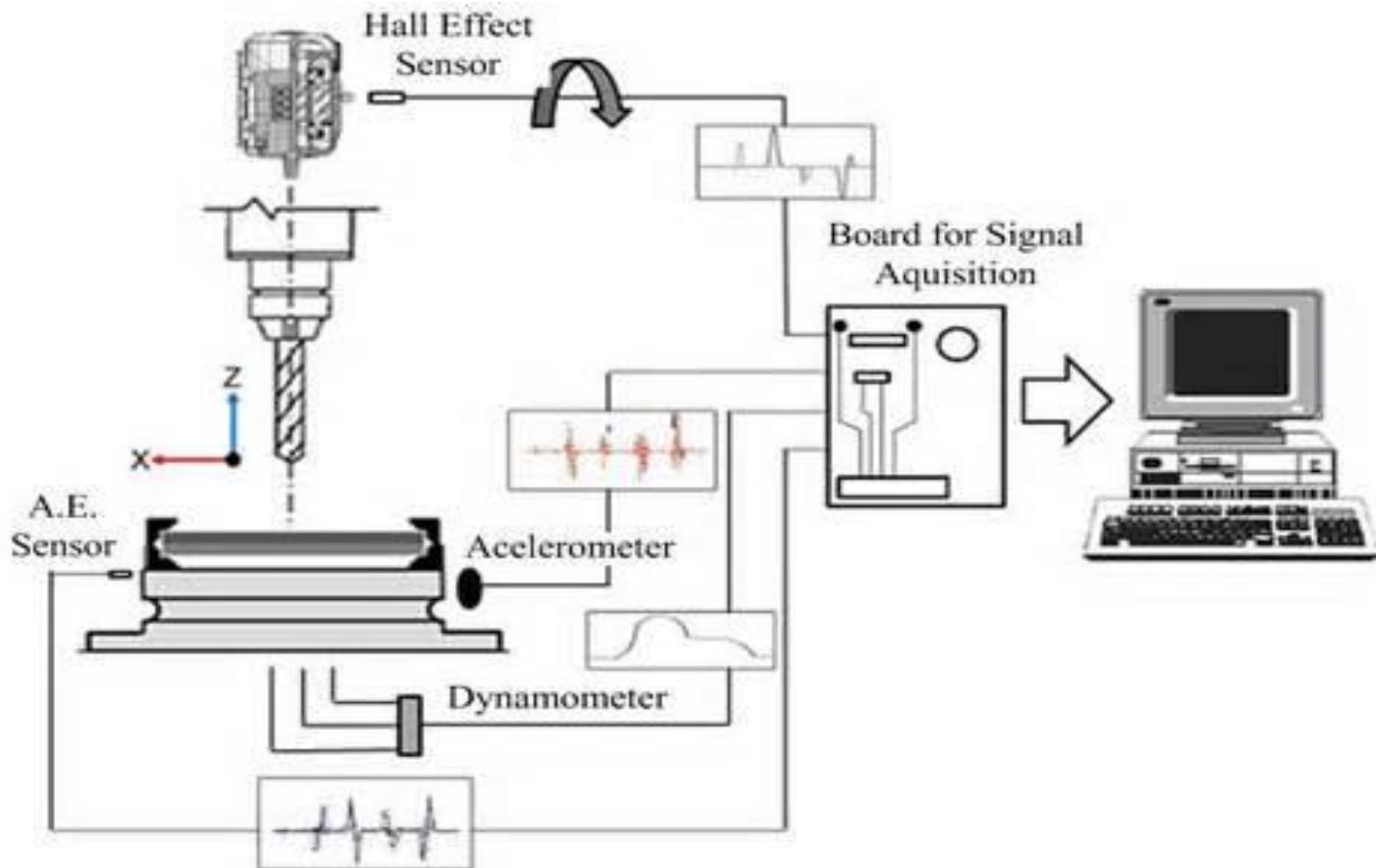
Adaptive Neuro Fuzzy Induction Motor



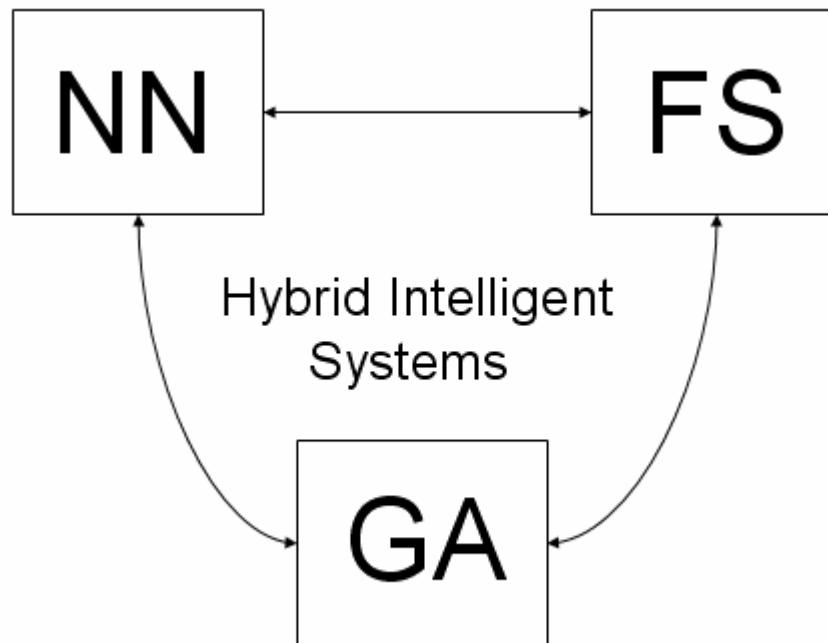
MLP / ANFIS predicción de corte para taladros

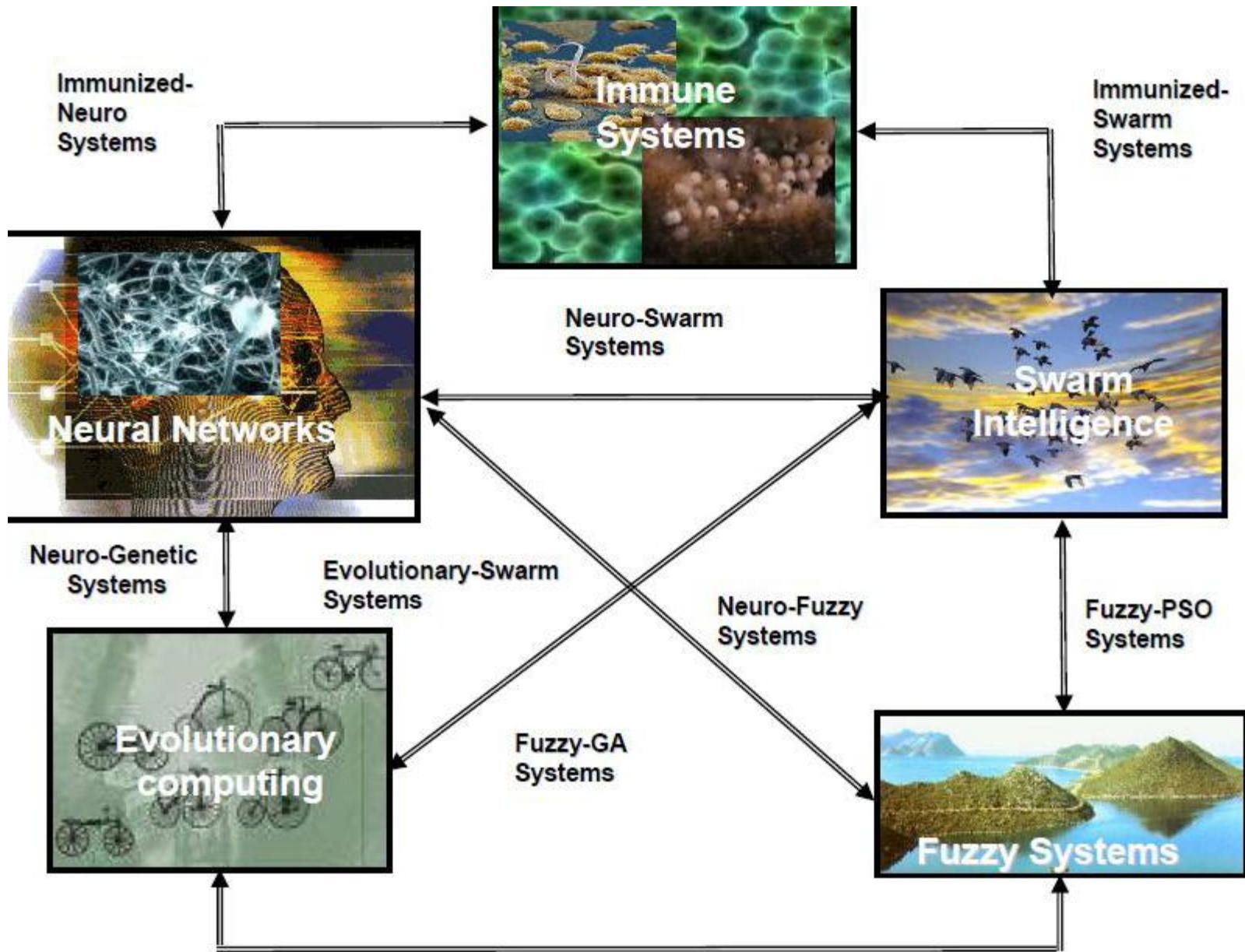


MLP / ANFIS predicción de corte para taladros



Neuro Fuzzy Genetic System

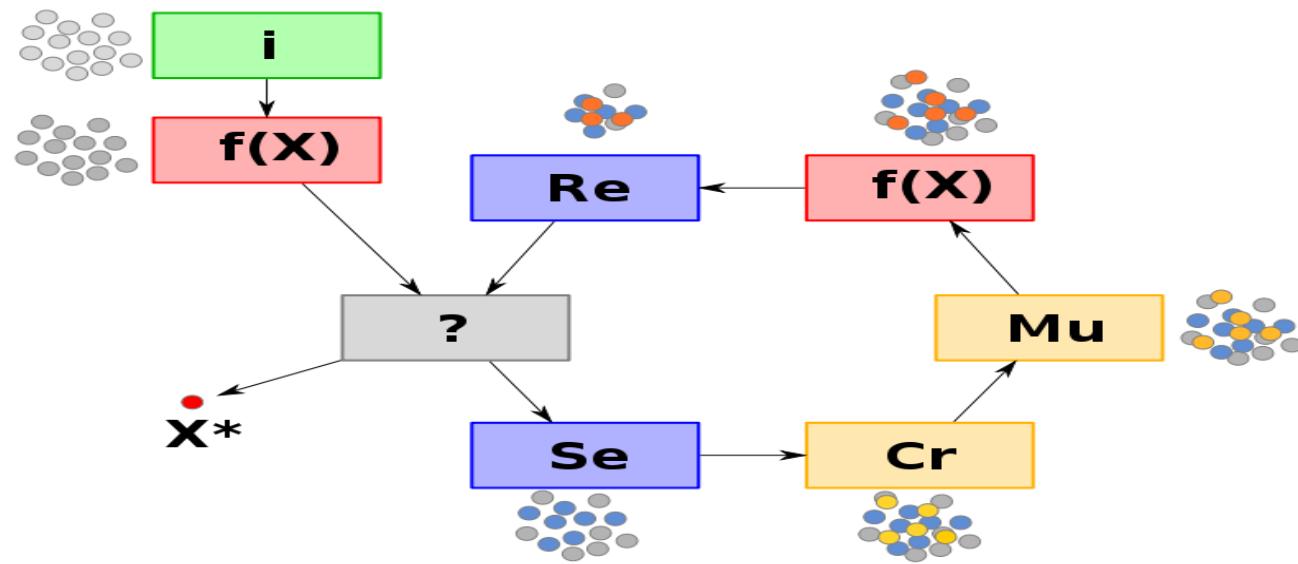




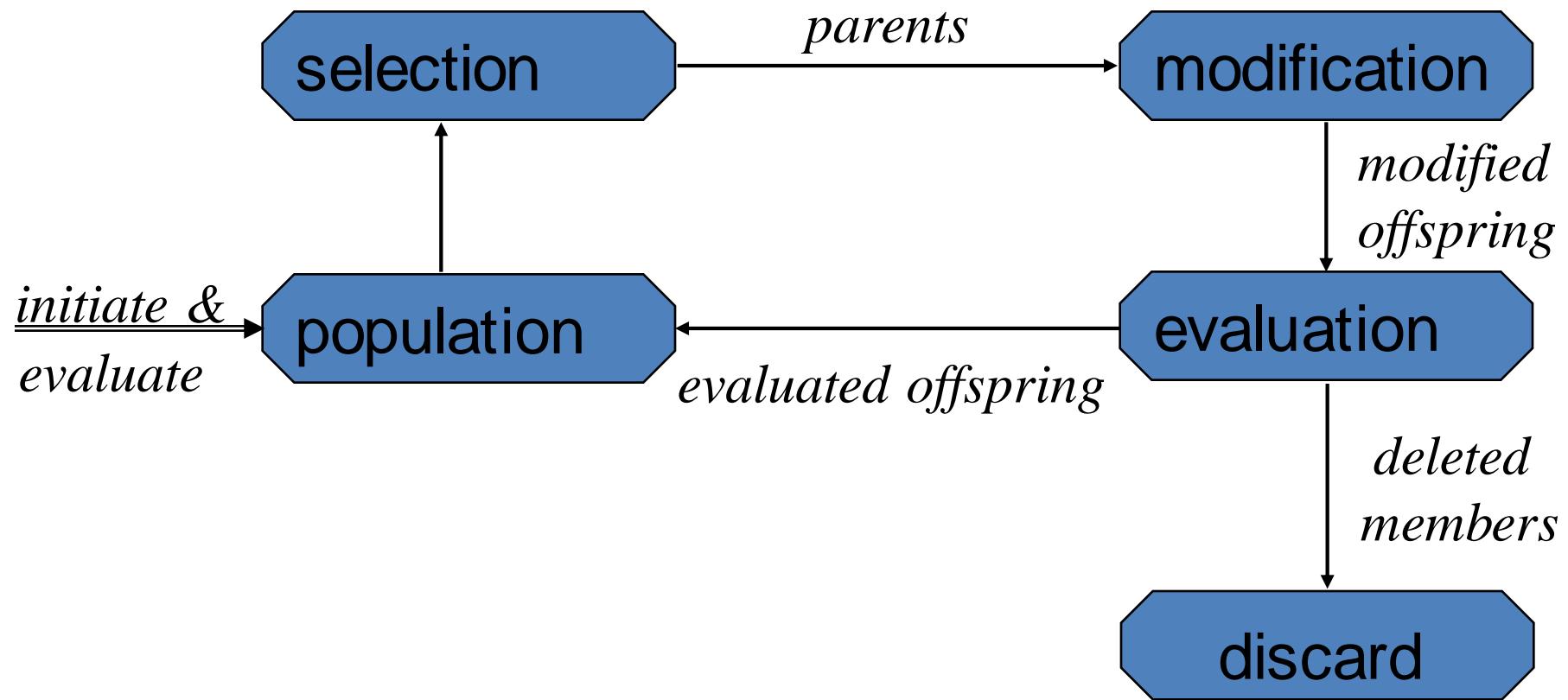
Componentes de un Algoritmo Genético

Definición de un problema a través de :

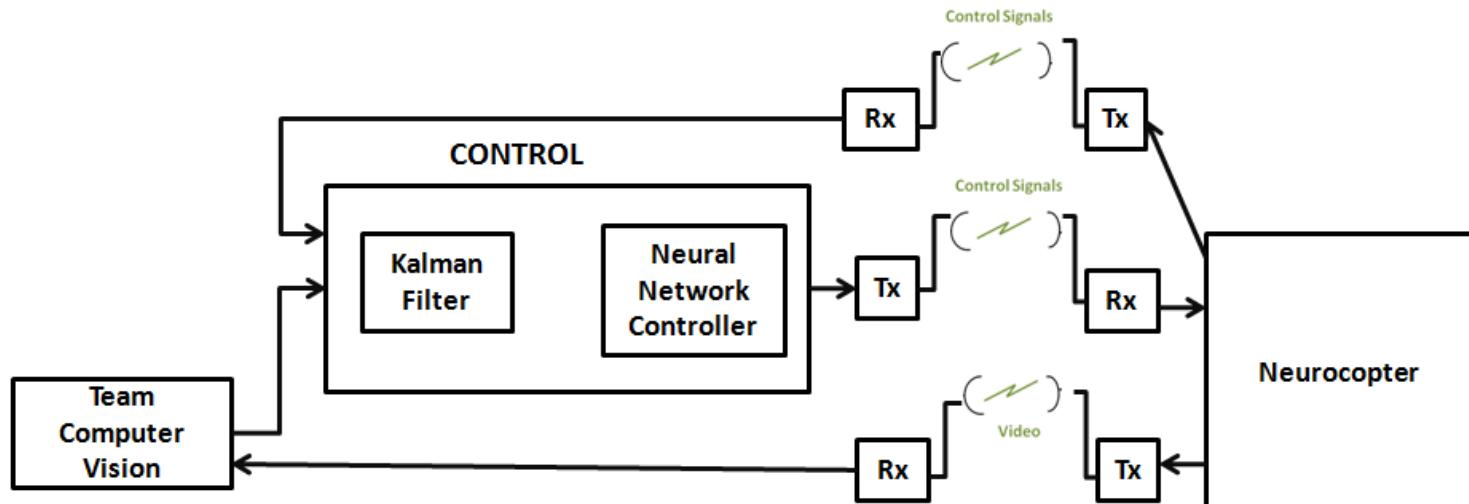
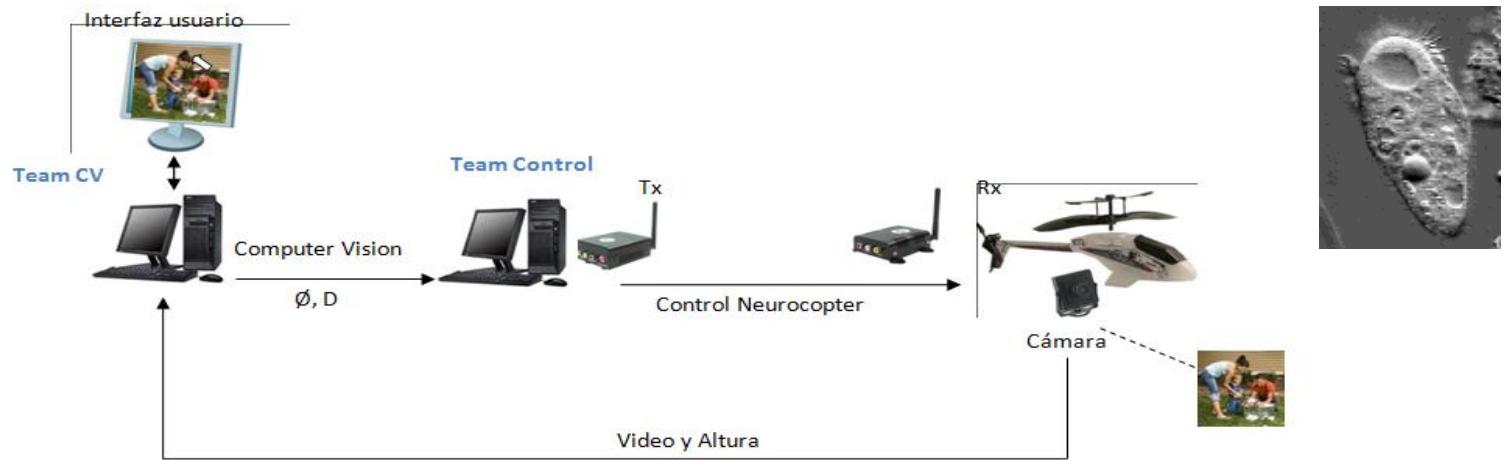
Principios de Codificación	<i>(gene, chromosome)</i>
Procedimientos de Inicialización	<i>(creation)</i>
Selección de Padres	<i>(reproduction)</i>
Operadores Genéticos	<i>(mutation, recombination)</i>
Función de evaluación	<i>(environment)</i>
Condición de Término	

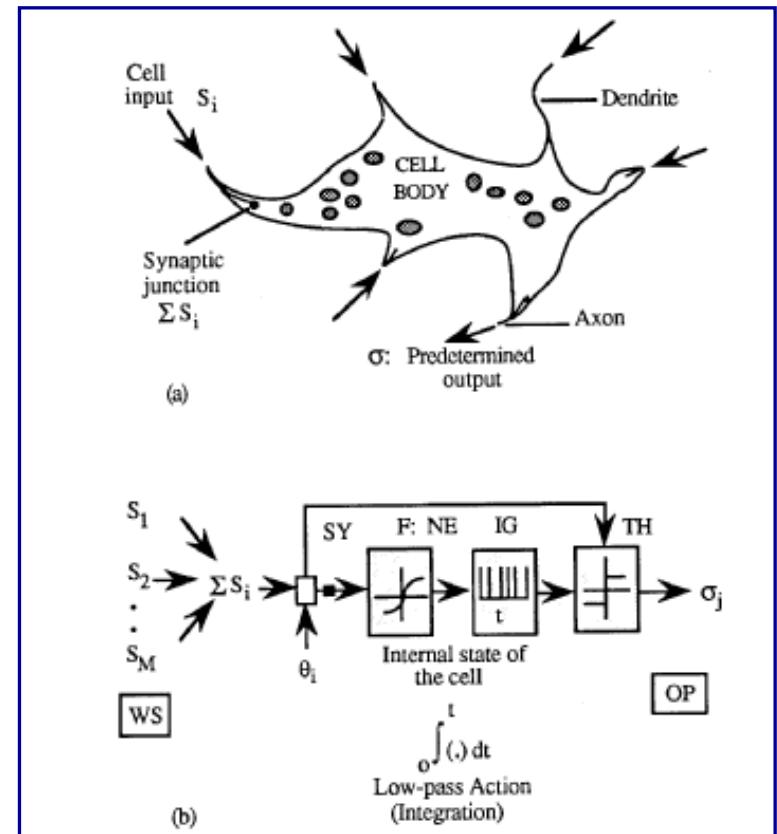
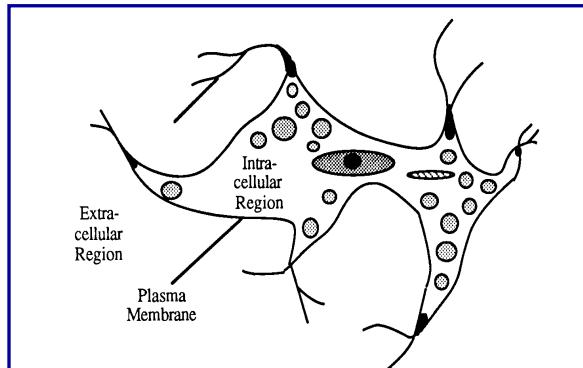
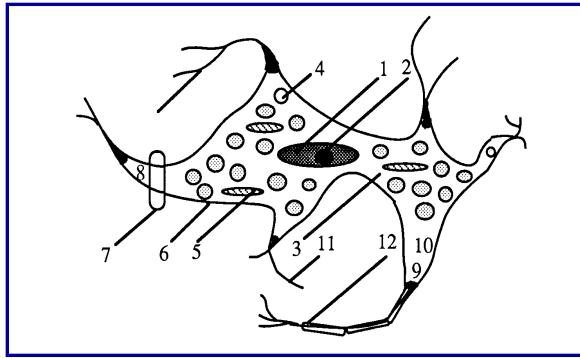
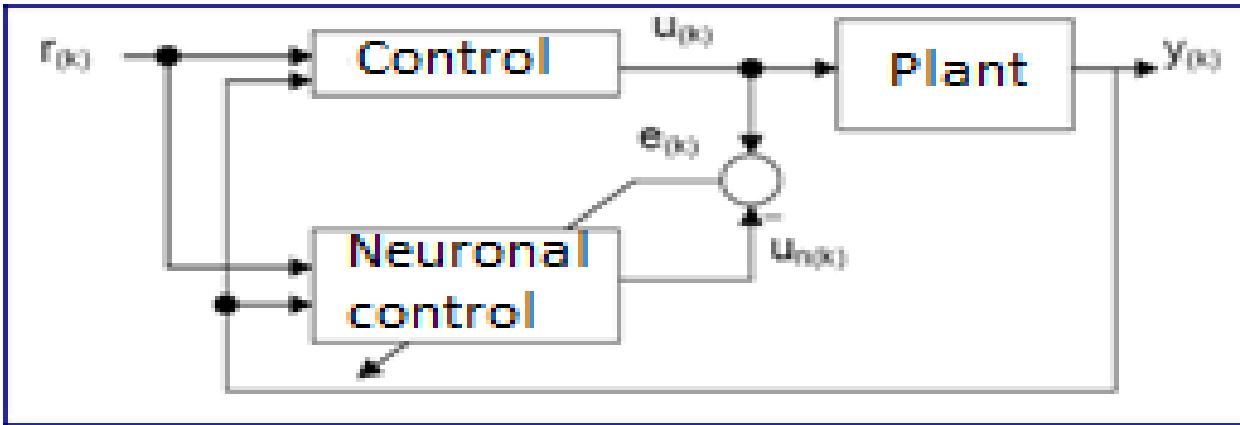


Ciclo Evolucionario

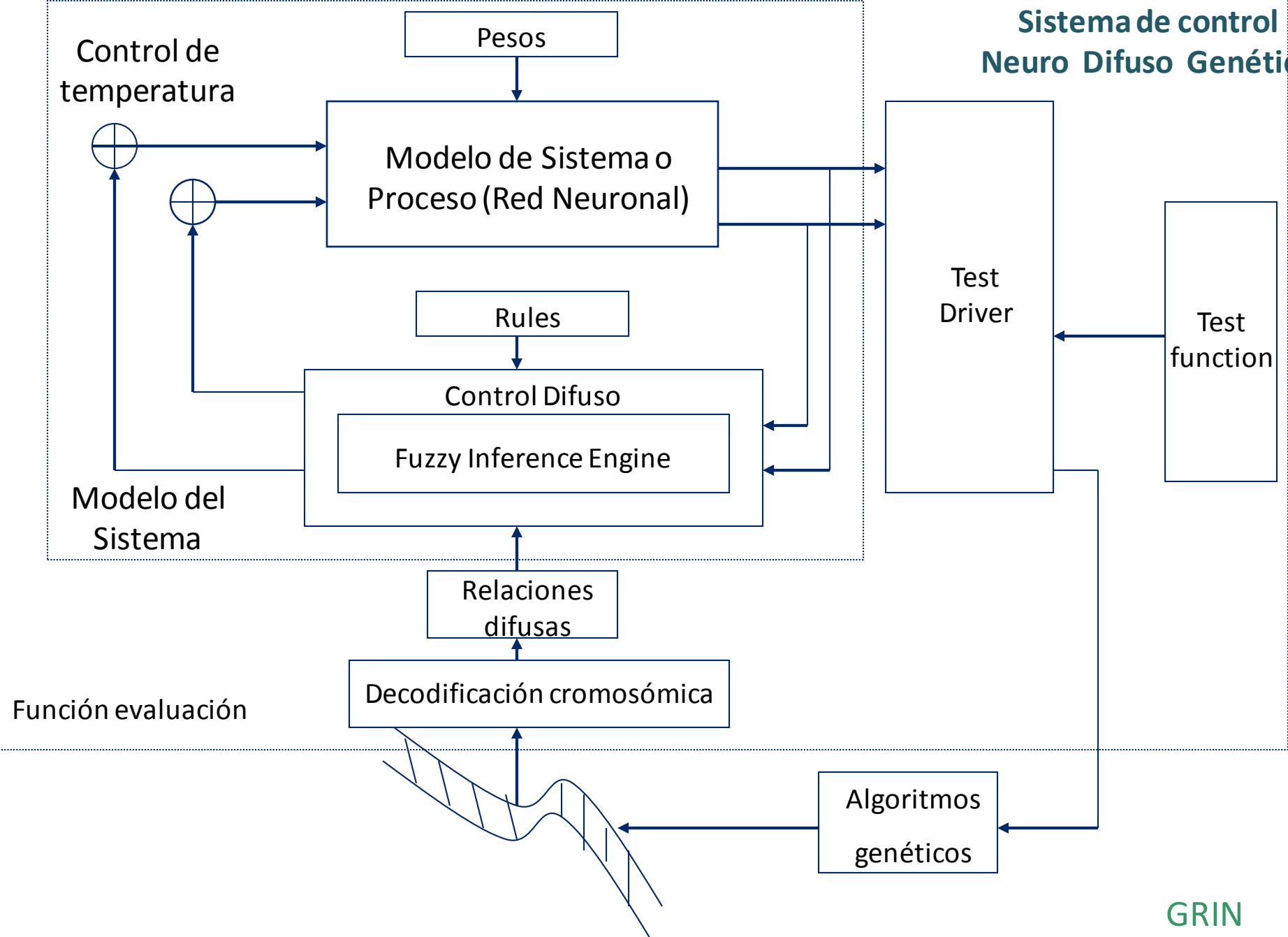


NEURO COPTER 1.0 DESIGN



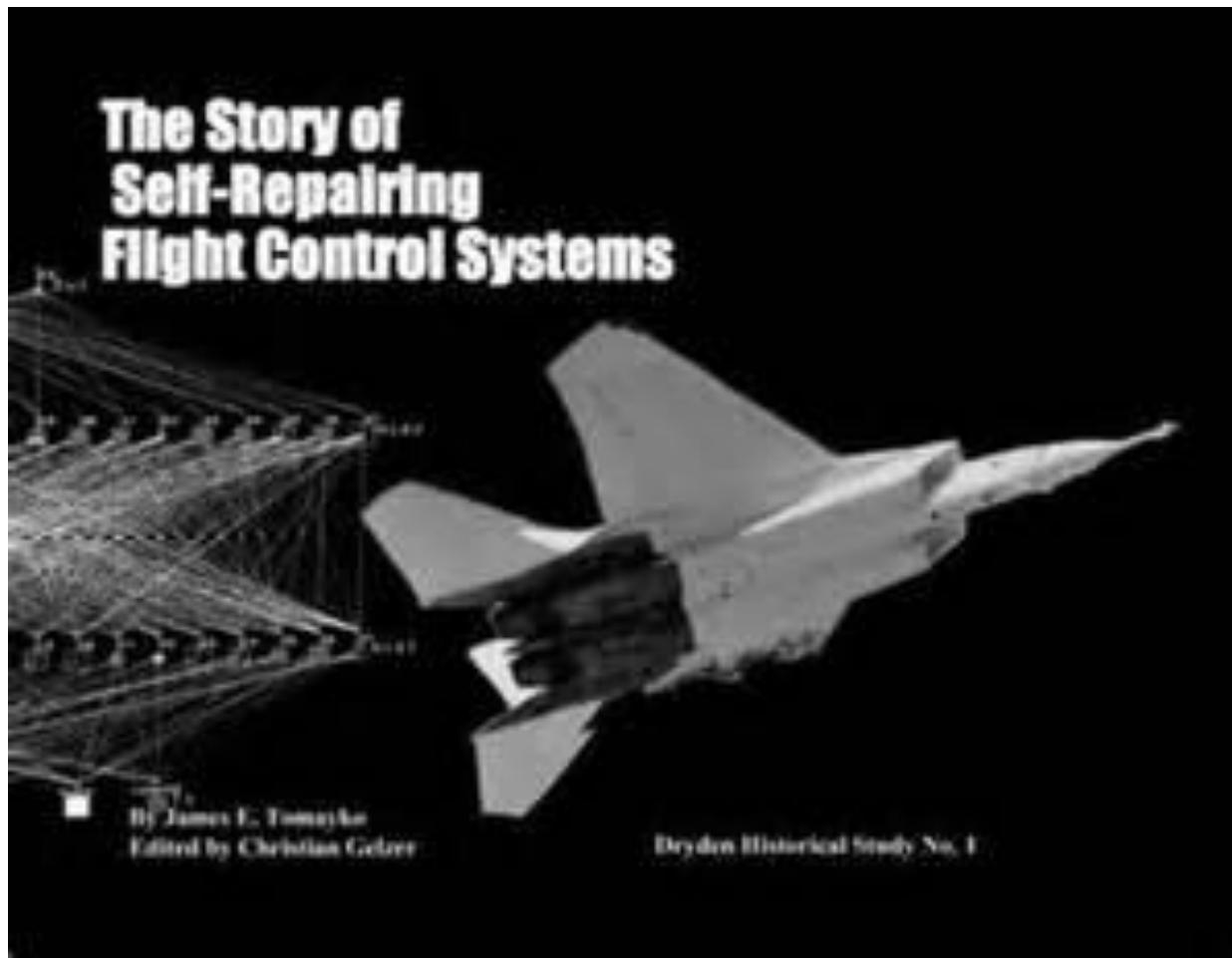


Sistema de control Neuro Difuso Genético

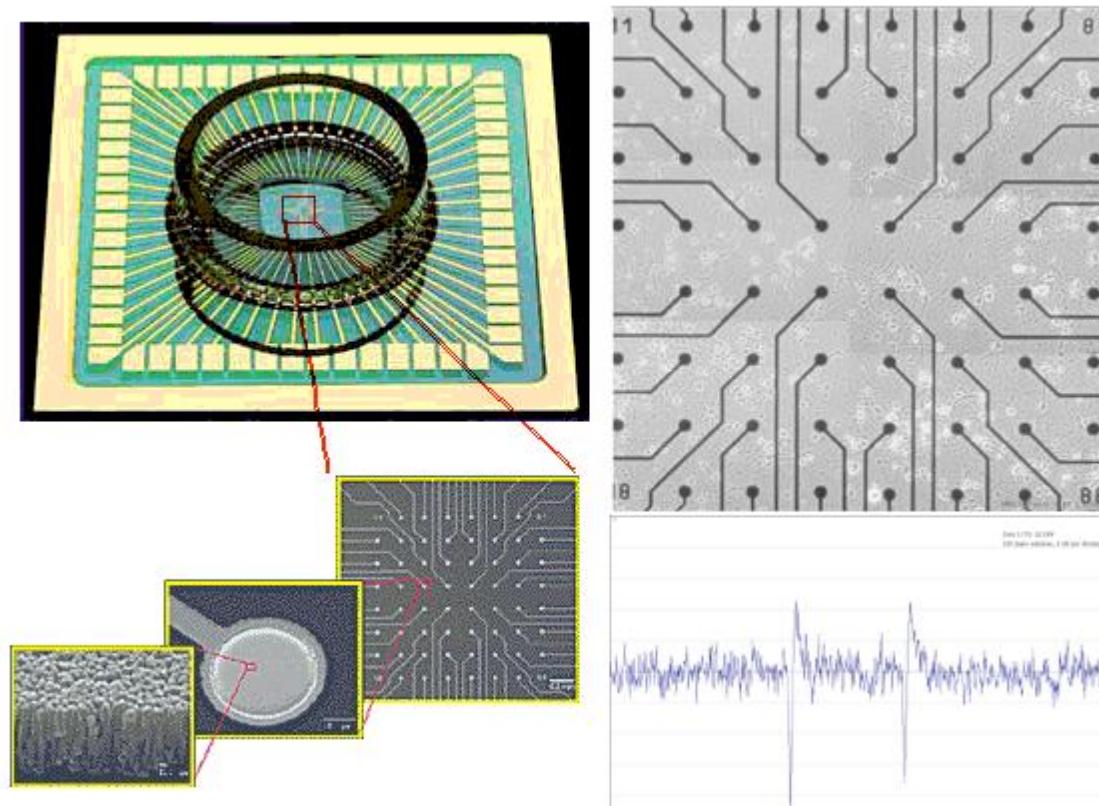


GRIN

Self Repairing Flight Control Systems



Neural Flight Control System using living rat cortical neurons for pitch and roll control

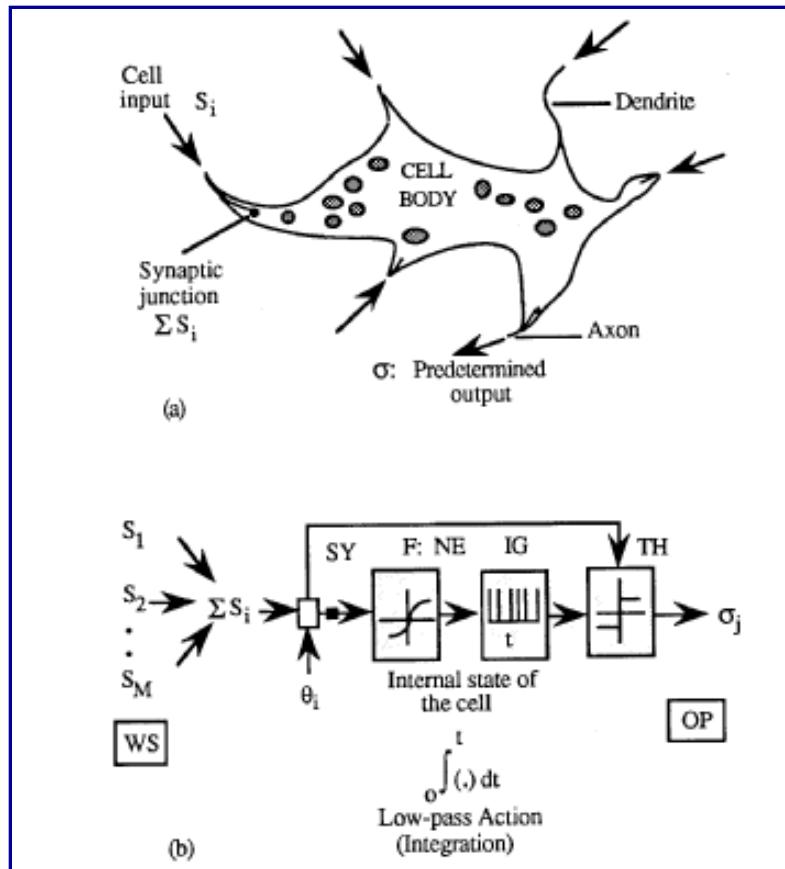


INTELIGENCIA ARTIFICIAL /NEURO CIBERNETICA

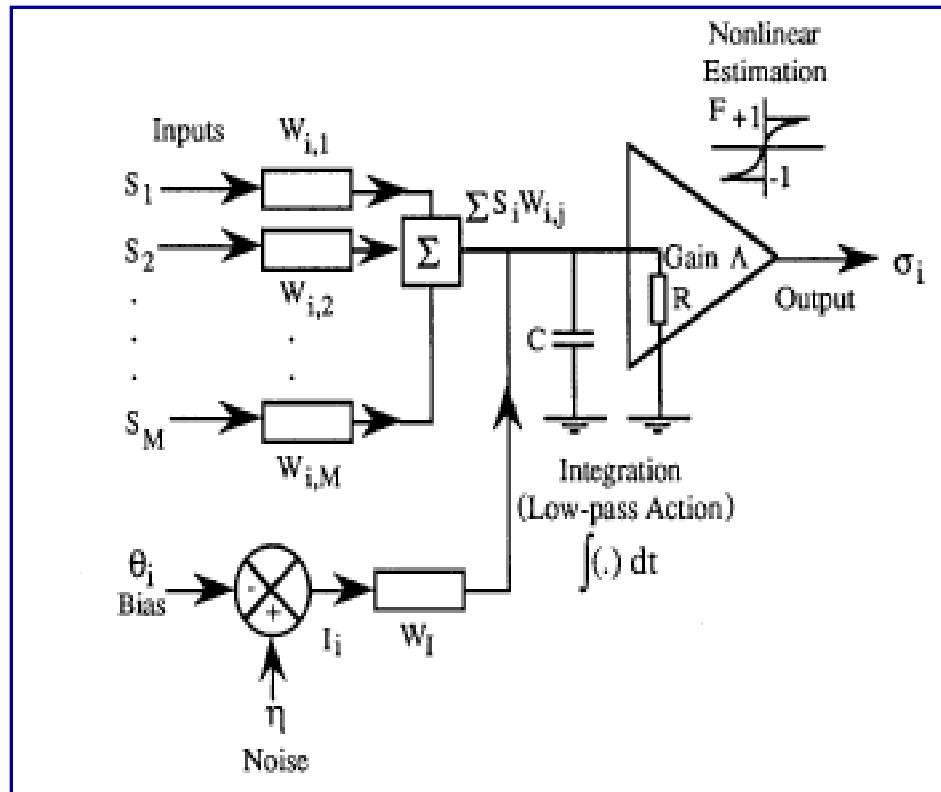
La emergencia de la Biónica



“Dinámica Estocástica del Complejo Neuronal”

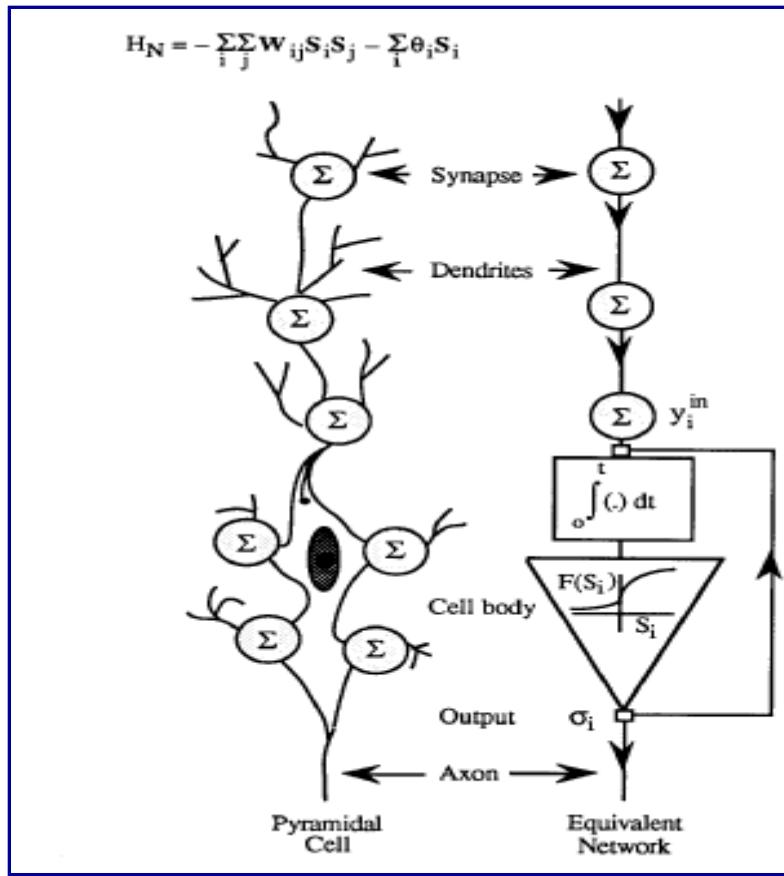


Representación de Red de la actividad Neurocelular



Aspectos estocásticos de un complejo neuronal infectado por ruido.

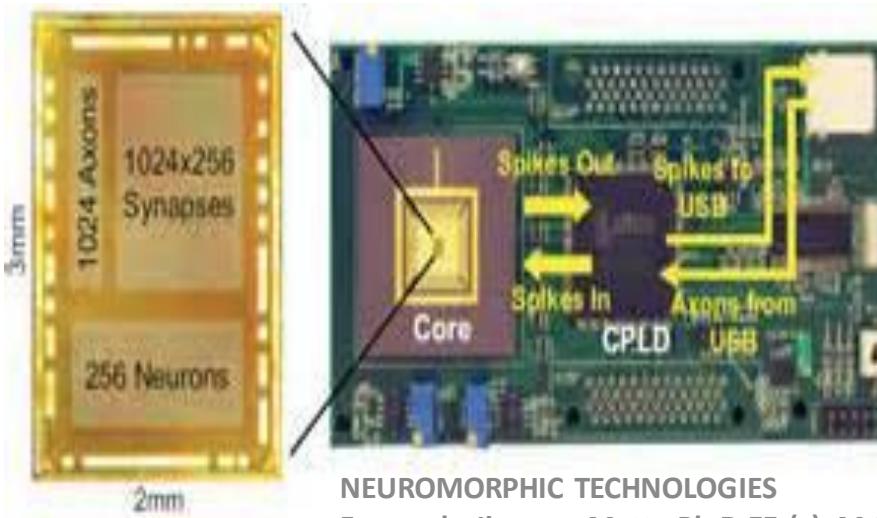
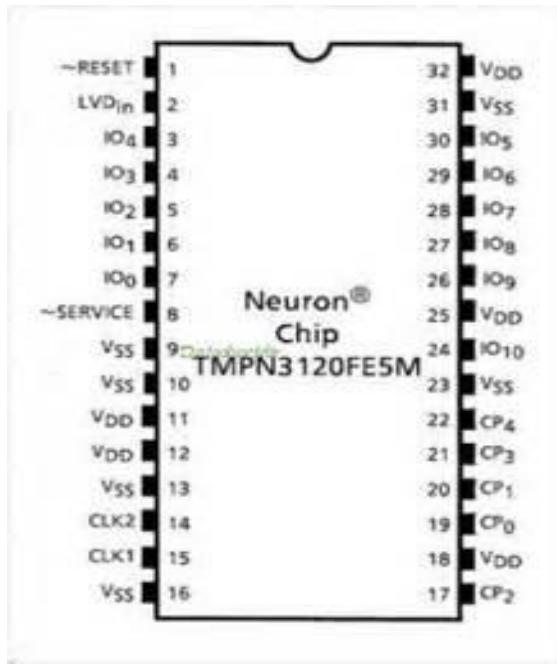
Teoría de Campo Neuronal



Control del complejo organizativo (minimización de entropía)



NEUROMORPHIC ENGINEERING



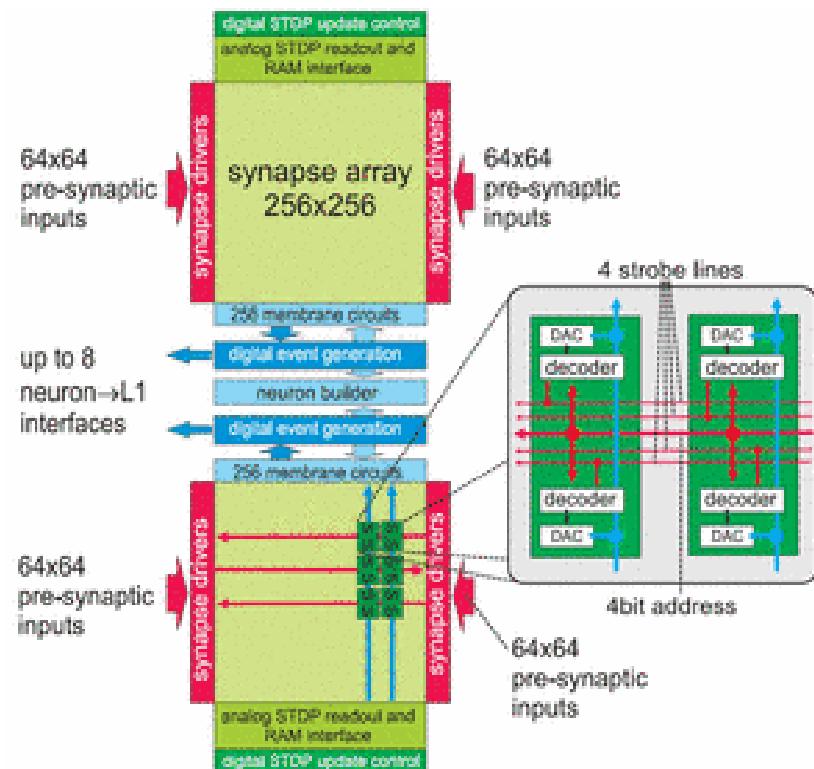
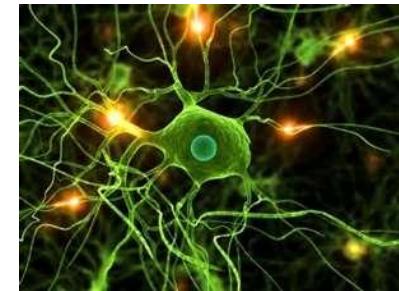
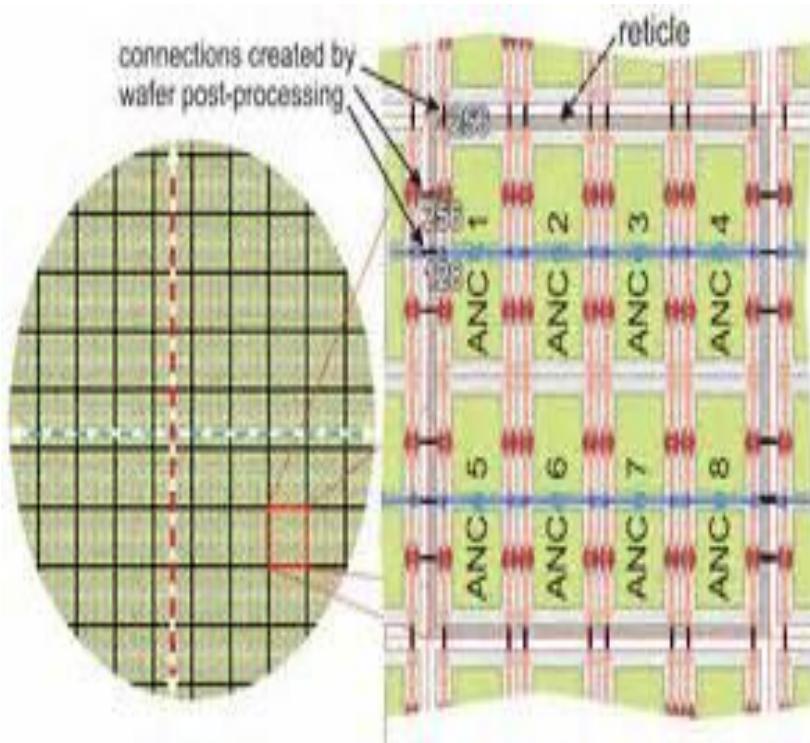
NEUROMORPHIC TECHNOLOGIES

Fernando Jimenez Motte Ph.D.EE (c), M.S.E.E, B.S.E.E



Analog Neural Network Core (ANNCORE)

containing 128k synapses and 512 membrane circuits which can be grouped together to form neurons with up to 16k synapses.



Próximos Chips Neuromórficos a ser lanzados por IBM e INTEL

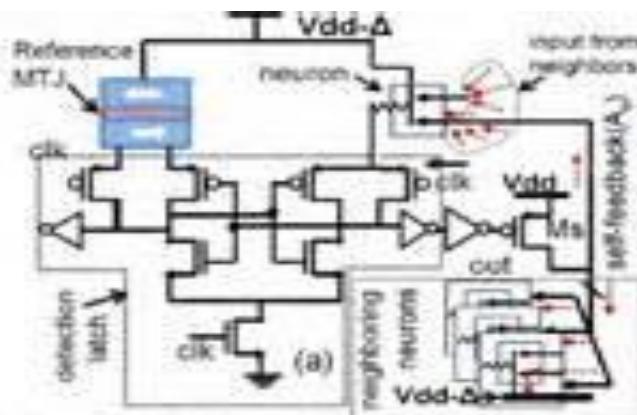


Fig. 7 Differential MTJ latch for inter-crossed current-mode signaling using deep mode current source (DTCS) transistor M_f.

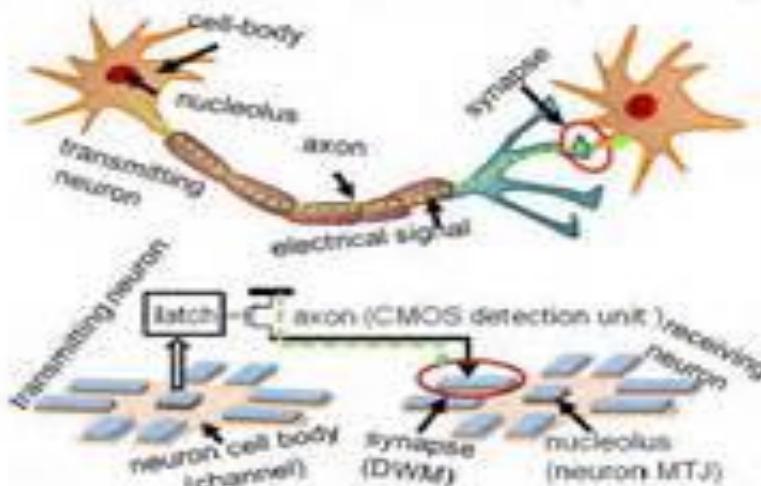
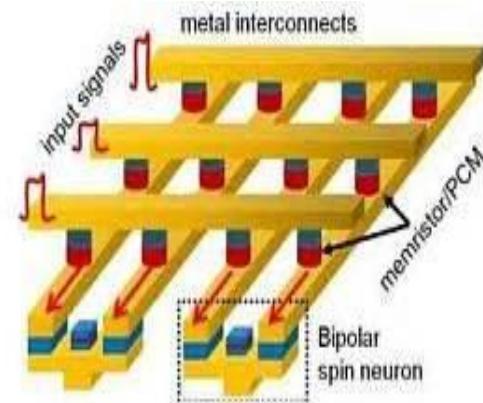
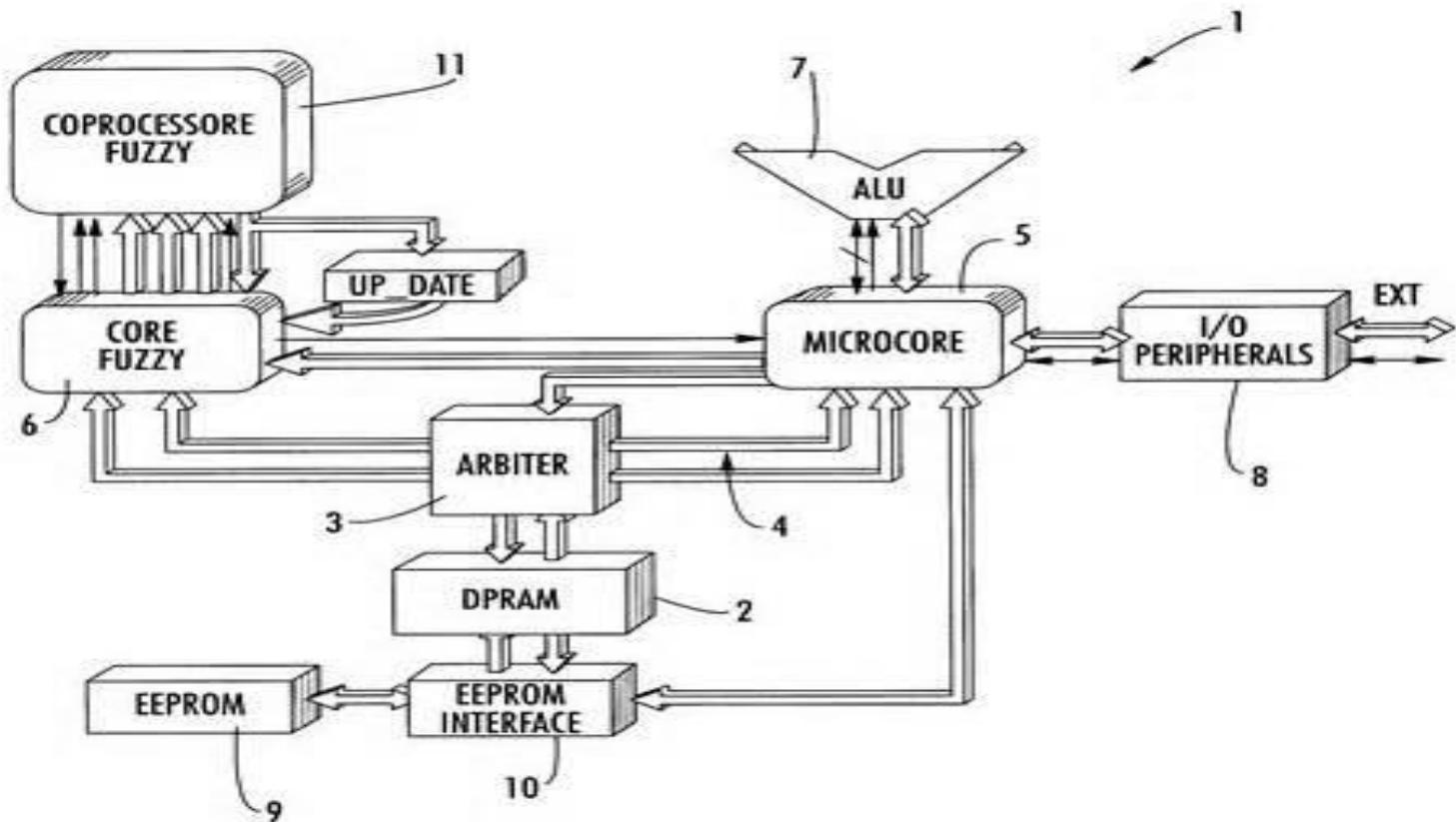


Fig. 8 Correspondence of the spin-CMOS Hybrid NN to biological neural network

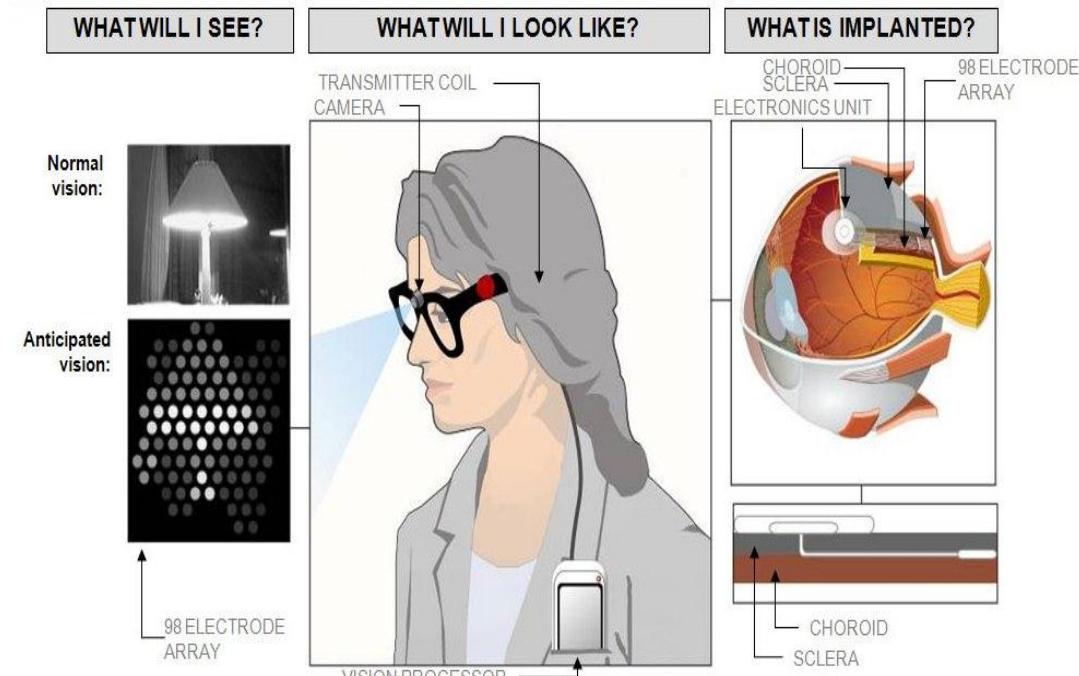
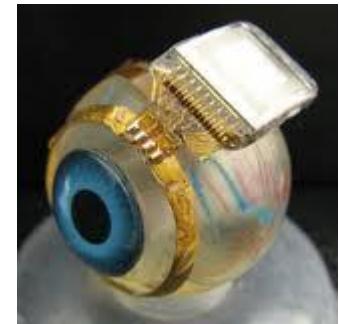


Neuro Fuzzy Processors

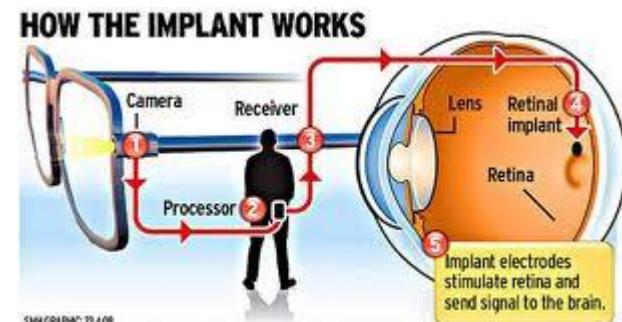
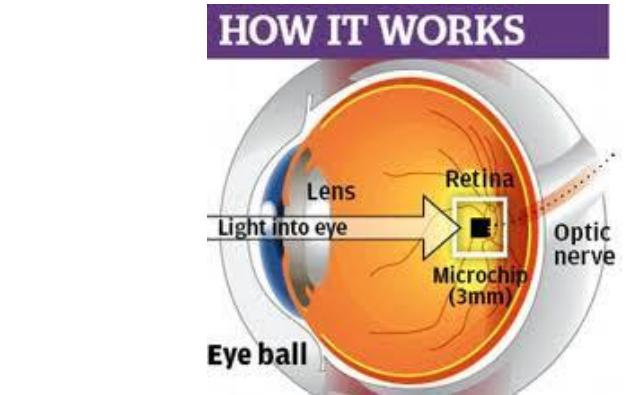


Bionic Eye

Wide-view neurostimulator



A wide-view neurostimulator provides mobility through navigation and avoidance of obstacles



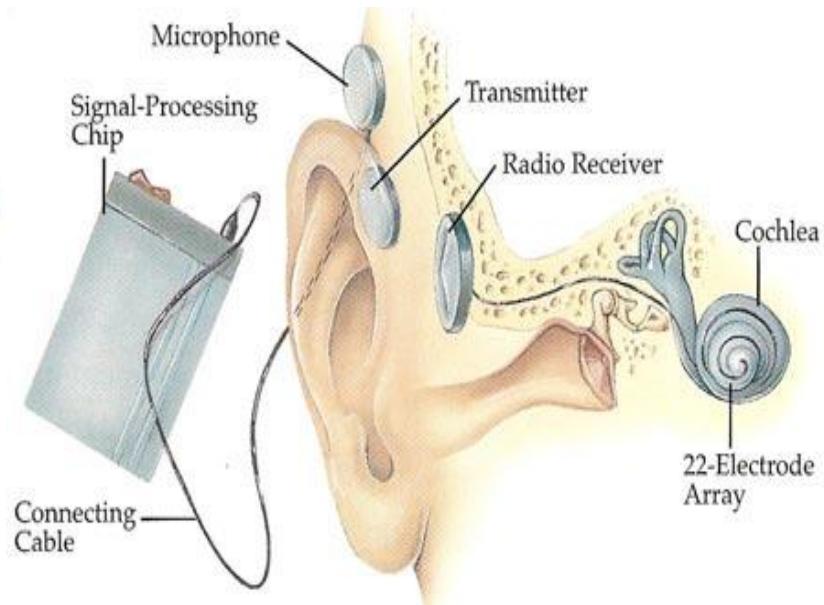
Bionic ear

How a bionic ear works

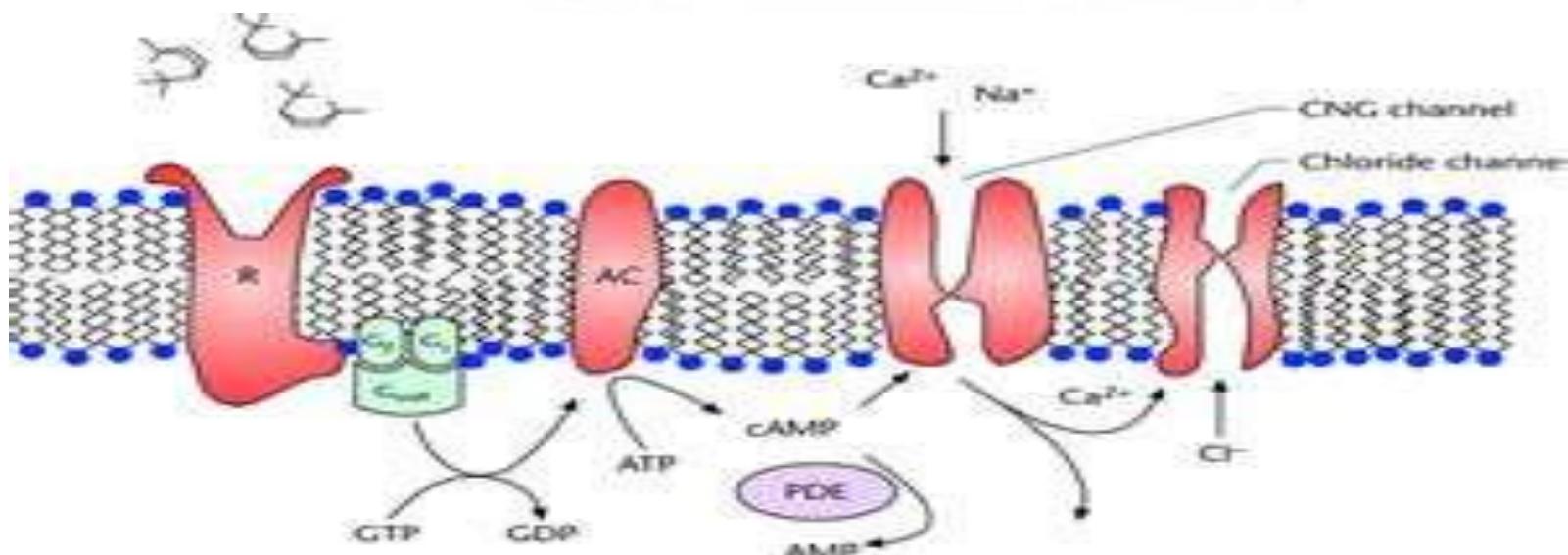
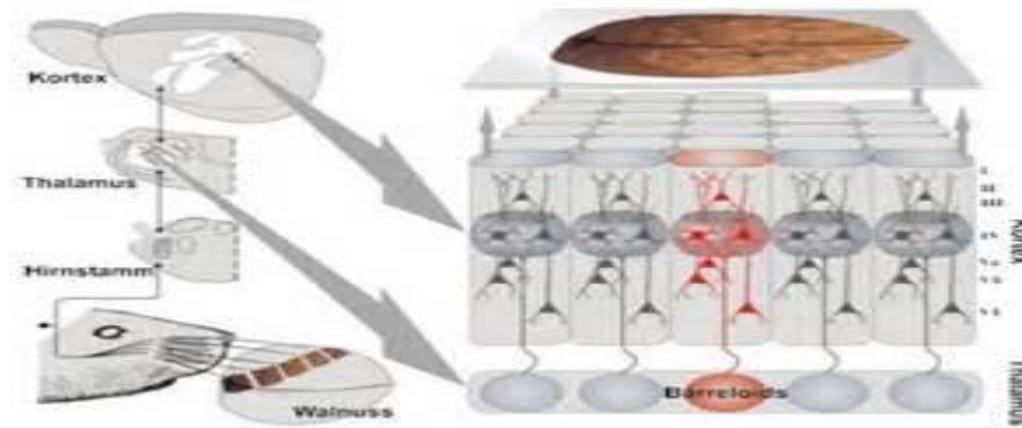
- ① The sound processor captures sounds and converts them into digital code.
- ② The sound processor transmits the digitally coded sound through the coil to the implant just under the skin.
- ③ The implant converts the digitally coded sound to electrical impulses and sends them along the electrode array, which is positioned in the cochlea.
- ④ The implant's electrodes stimulate the cochlea's hearing nerve which sends the impulses to the brain where they are interpreted as sound.



Image courtesy of **Cochlear**



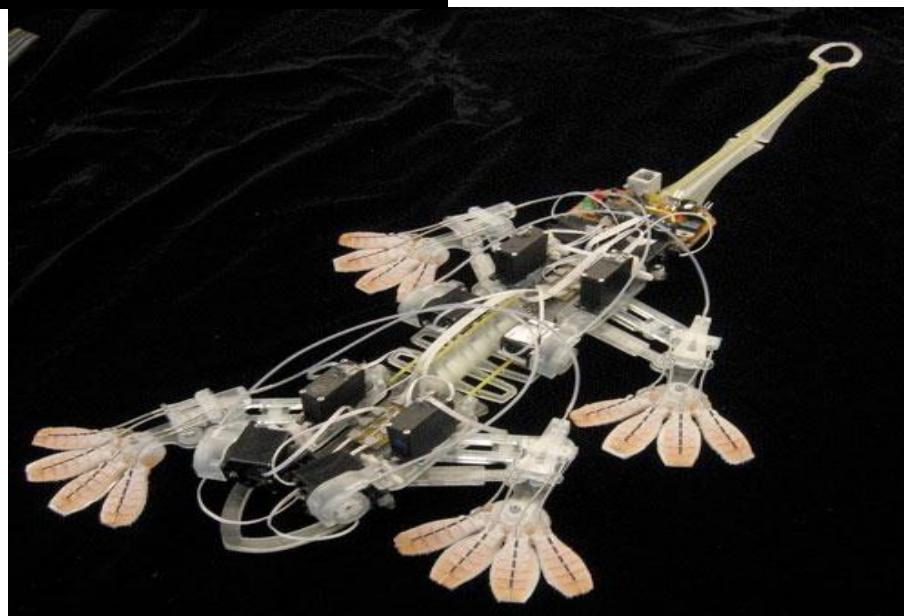
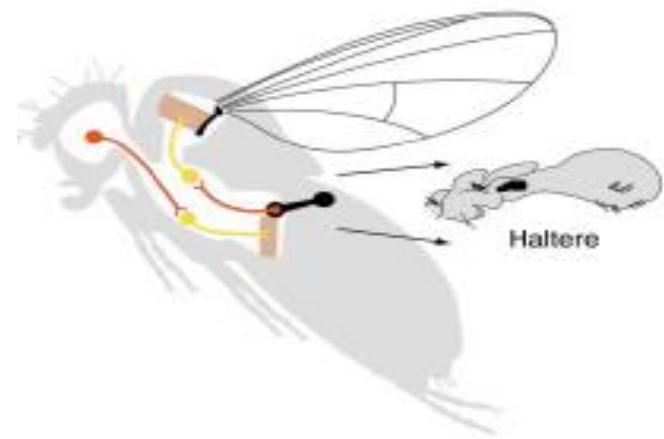
THE MESSENGER (Neural Network Somatosensory maps)



NEUROMORPHIC TECHNOLOGIES

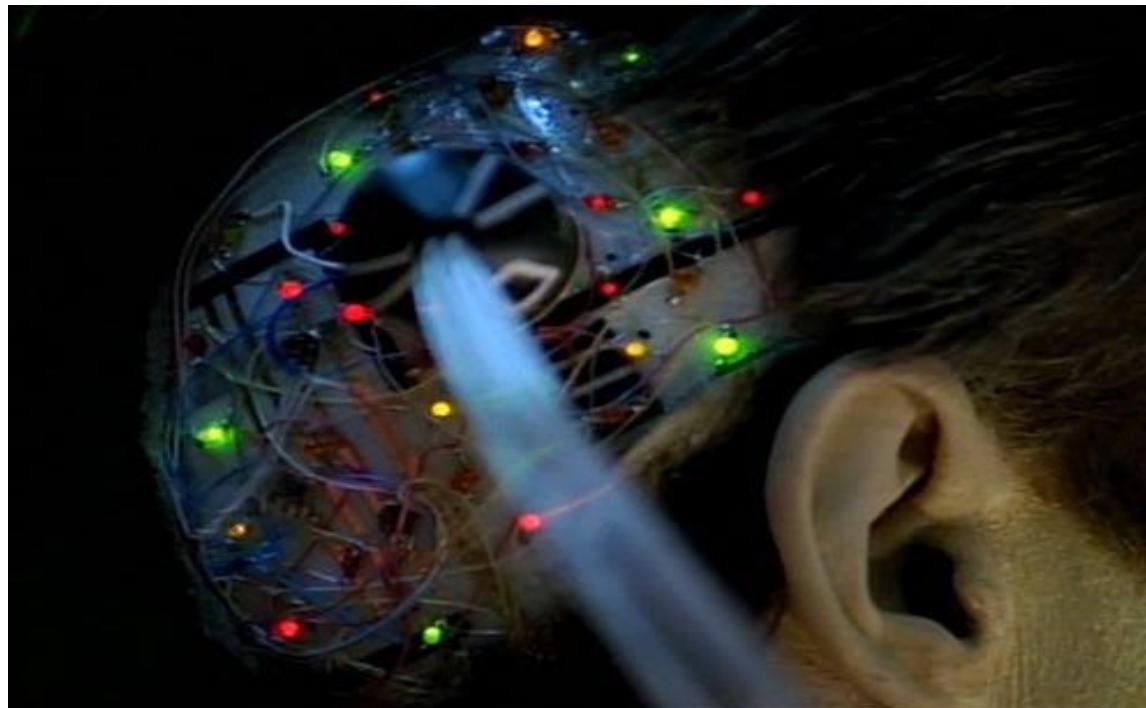
Fernando Jimenez Motte Ph.D.EE (c), M.S.E.E, B.S.E.E

Era de los Sistemas Neuromiméticos



Año 2030-2050

El cerebro Artificial: Positronic Brain



Red Neuronal Artificial para emular un Cerebro Humanoide

El Humanoide Data (“Star Trek”) tiene 100,000 terabytes de memoria (equiv a 100,000,000 de 1-GB hard drives). Tiene una capacidad de almacenamiento de 800 quadrillones de bits (100 quadrillion bytes). Data procesa 60 trillones de operaciones x segundo . Si uno compara su capacidad de almacenamiento de 100,000 terabytes con la los ordenadores actuales, podría decirse que la del ser humano es equivalente a unos 3 Terabytes, es decir Data contendría 260,000 Cerebros humanos



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NEUROMORPHIC TECHNOLOGIES

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