CPE 721 - Redes Neurais *Feedforward*

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Introdução

Redes Neurais Artificiais Feedforward

O que é isto ?

Para que serve ?

De onde veio ?

O que é isto ?

Inteligência Artificial / Computacional

Cognitiva, Simbólica

IA “tradicional”

Evolucionista

AG, Vida Artificial

Conexionista

Redes Neurais Artificiais

Redes Neurais Artificiais

Redes Feedforward (CPE 721)

Aproximadores e classificadores,

Redes “backpropagation”

Redes Não Supervisionadas

Classificadores

Redes Realimentadas

Otimizadores

Redes Neurais Naturais

Cursos em RNs no PEE da COPPE:

CPE 721 – Redes Neurais Feedforward
2011-2 – quartas e sextas, 10 às 12 h.

CPE xxx - Tópicos Especiais em Redes Neurais (?)
2011 - 3 - quartas e sextas, 10 às 12 h.

CPE 722 – Redes Neurais Não Supervisionadas e Agrupamento (?)
2010-3 – quartas e sextas, 10 às 12 h.

CPE 723 - Otimização Natural
2012-1 - quartas e sextas

Pré requisitos: apenas noções de álgebra linear

CPE 721 - Redes Neurais Feedforward

Programa:

Introdução, motivação ao uso.

Neurônios e redes neurais biológicas e artificiais. Estrutura feedforward.

O treinamento backpropagation.

Métodos mais eficientes; resilient BP e métodos de segunda ordem.

Pré-processamento: escolha das entradas, detecção de intrusos, escalamento, etc.
Dimensionamento da rede, escolha dos parâmetros iniciais.

Acompanhamento do treinamento: evolução do erro

Pós-processamento: análise e correção do erro, absorção do escalamento

Aproximadores e Classificadores, capacidade de mapeamento. Operação.

Poda. Redes Ótimas.

Redes de Base Radial.

Modelos híbridos neural-fenomenológicos.

Demonstrativos e exemplos de aplicações.

Referências bibliográficas:

Para iniciar:

*1 – Ivan Silva, I.; Spatti, D. e Flauzini, R. - "Redes Neurais Artificiais para engenharia e ciências aplicadas", Artliber, 2010, cap 1-6.

2 -Wasserman, P. – "Neural Computing", Van Nostrand Reinhold, 1989, Cap 1-3.

3 - Sarle, W.S. - ftp://ftp.sas.com/pub/neural/FAQ.html - uma página com muitas informações interessantes

Para aprofundar:

*4 - Haykin, S., "Neural Networks, A Comprehensive Foundation", Prentice Hall, 1999.

Ver também: Haykin, S., "Redes Neurais, Teoria e Prática", Bookman, 2001.

5 - Bishop, C. M. - "Pattern Recognition and Machine Learning", Springer, 2006.

Software:

Neuralworks, Neuroshell

* Toolboxes: Matlab, Statistica

Neunet www.cormactech.com/neunet

Freeware:

* WEKA www.cs.waikato.ac.nz/ml/weka/

SNNS (Stuttgart Neural Network Simulator) ftp.informatik.uni-stuttgart.de

NeuroLab, SIRENE (UFRJ e CEPEL) www.lps.ufrj.br/~caloba

Avaliação:

Listas de exercícios (+ aprendizado)

1 Teste

1 Projeto

Possíveis aulas extras

Para que serve ?

Emular sistemas neuronais biológicos visando obter as propriedades destes sistemas:

Redes Neurais Artificiais

Aprendizado ? **Generalização ?** **Robustez ?**

Aplicações:

Cálculo ? Não !!!

Simulação de Sistemas não Lineares
Reconhecimento de Padrões
Otimização

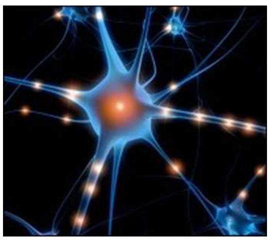
De onde veio ?

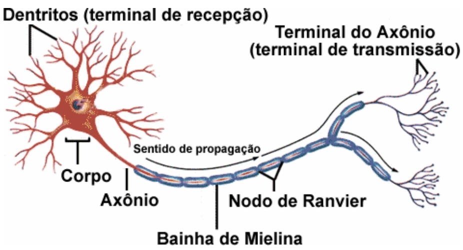
Breve Histórico

400 A.C. - Aristóteles

“De memória et reminiscentia”

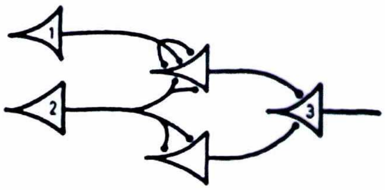
1900 - Biologia & Psicologia: Cajal, Skinner, etc.





1943 - McCulloch e Pitts

primeiro modelo matemático de neurônio



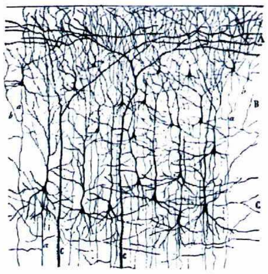


Figure 4a The following is the original caption. Kleine und mittelgrosse Pyramidenzellen der Sehrinde eines 20 tägigen Neugeborenen (Fissura calcarina). *A*, plexiforme Schicht; *B*, Schicht der kleinen Pyramiden; *C*, Schicht der mittelgrossen Pyramiden; *a*, absteigender Axencylinder; *b*, rückläufige Collateralen; *c*, Stiele von Riesenpyramiden.

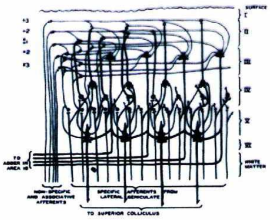
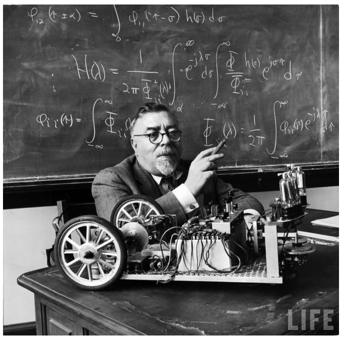


Figure 3 Impulses relayed by the lateral geniculate from the eyes ascend in specific afferents to layer IV where they branch laterally, exciting small cells singly and larger cells only by summation. Large cells thus represent larger visual areas. From layer IV impulses impinge on higher layers where summation is required from nonspecific thalamic afferents or associative fibers. From there they converge on large cells of the third layer which relay impulses to the parastriate area 18 for addition. On their way down they contribute to summation on the large pyramids of layer V which relays them to the superior colliculus.

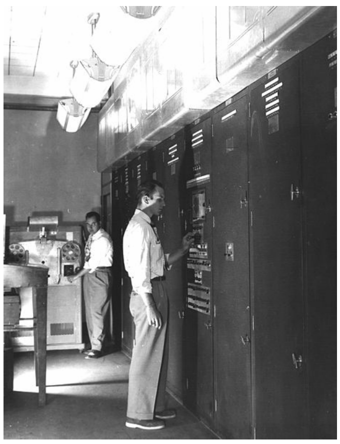
1947 - Norbert Wiener



"Cibernética"

1947 - 1951 - JohnVon Newman

EDVAC -
Electronic Discrete Variable Automatic Computer



6000 válvulas, 12.000 diodos,

56 kW, 45 m^2, 8 ton

1949 - Donald Hebb

primeiro modelo de aprendizado não supervisionado

1951 - Minsky e Edmonds

Snark - primeiro computador auto-adaptativo

1957 - Frank Rosenblatt

Perceptrons - aprendizado em sistemas não lineares

Mark I Perceptron Neurocomputer

imagens 20x20 pixels

Fig. 1.4. • Frank Rosenblatt (the inventor of the perceptron and designer of the I Perceptron neurocomputer) with the 400 pixel (20 × 20) Mark I Perceptron sensor. Photo courtesy of Arvin Calspan Advanced Technology Center.

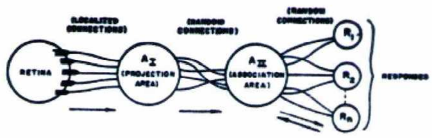
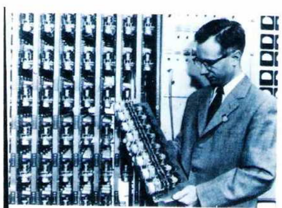


FIG. 1. Organization of a perceptron.



.5. • Charles Wightman holding a subrack of 8 motor/potentiometer pairs. Each /potentiometer pair functioned as a single adaptive weight value. The perceptron ng law was implemented in analog circuits that (when properly wired through the oard shown in Figure 1.6) would control the motor of each potentiometer (the nce of which functioned to implement one weight). Photo courtesy of Arvin Calspan d Technology Center

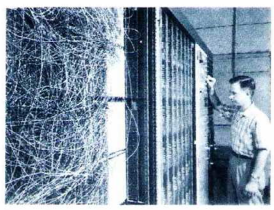
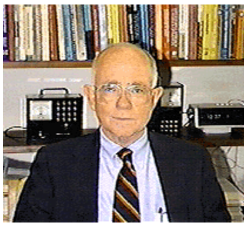
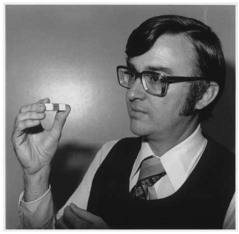


Fig. 1.6. • The Mark I Perceptron patchboard. The connection patterns were typically "random", so as to illustrate the ability of the perceptron to learn the desired pattern without need for precise wiring (in contrast to, unlike the precise wiring required in a programmed computer). Photo courtesy of Arvin Calspan Advanced Technology Center.

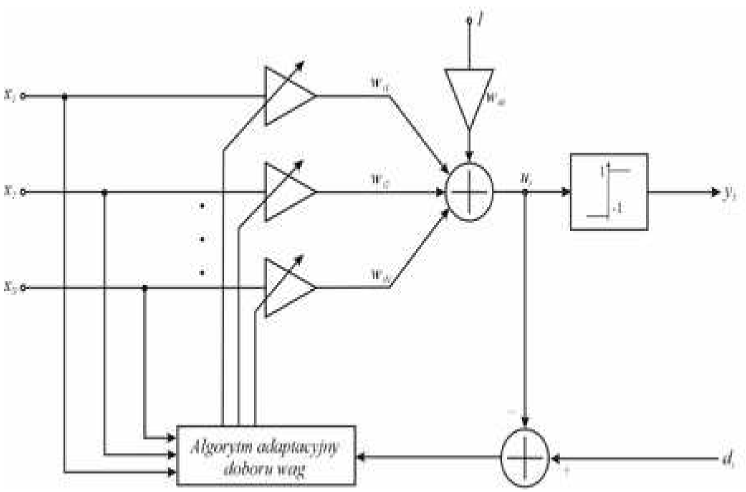
1960 - Widrow e Hoff





Adaline - adaptive linear neuron

LMS- *aprendizado em sistemas lineares*



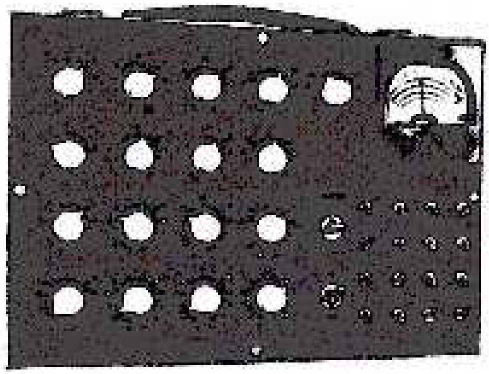
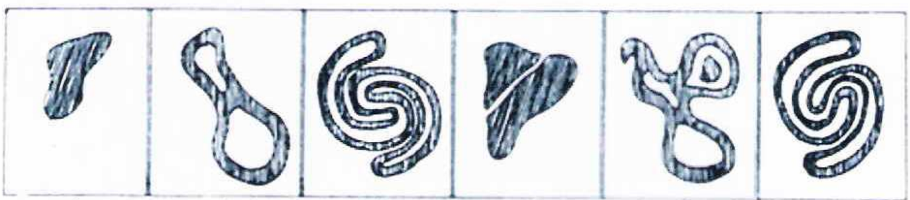


Figure 2 Adaline.

1969 - Minsky e Papert

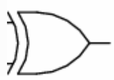
"Perceptrons"

$$\psi_{\text{CONNECTED}}(X) = \begin{cases} 1 & \text{if } X \text{ is a connected figure,} \\ 0 & \text{otherwise.} \end{cases}$$



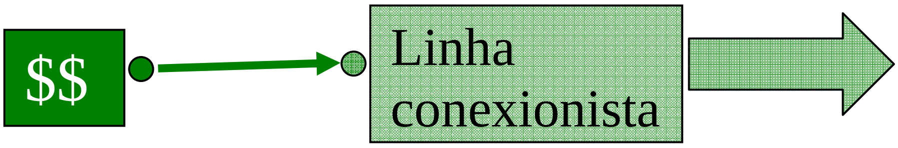
1 1 1 0 0 0

sive-OR gate

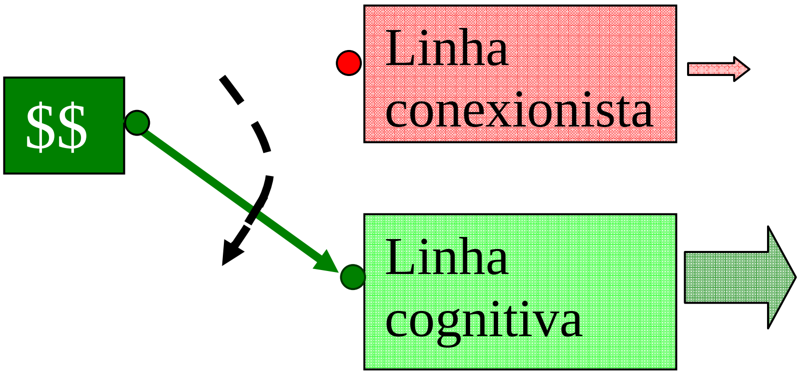


Output
0
1
1
0

ANTES do “Perceptrons”:



DEPOIS do “Perceptrons”:



”no ching, no ming”

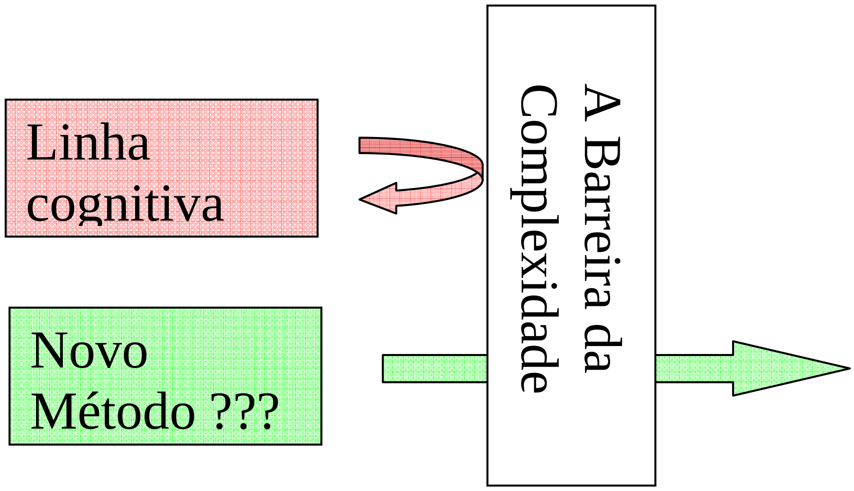
1969 - 1982 A época das trevas

Aprendizado não supervisionado, auto-organização

Amari, Anderson, Fukushima, Grossberg, Kohonen

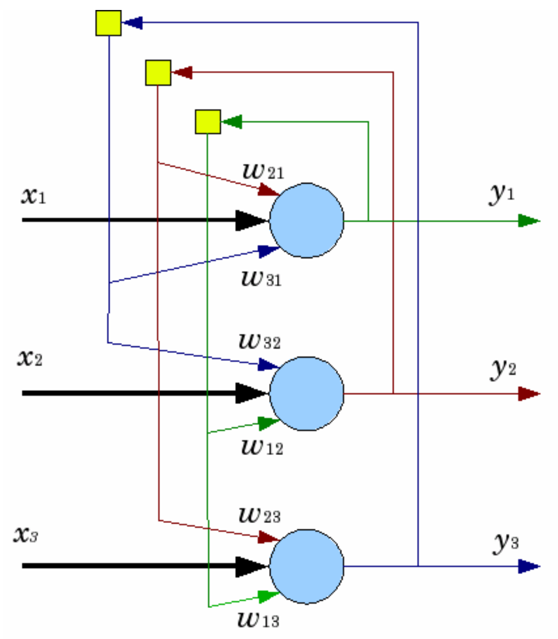
1974 - Paul Werbos

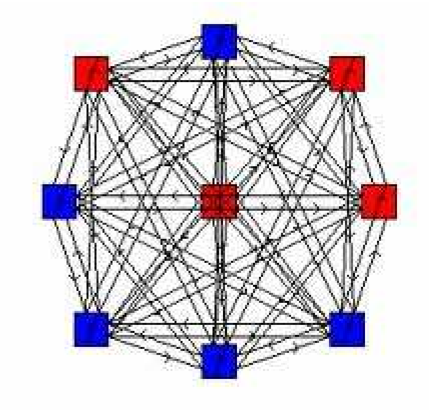
“Beyound Regression”



1982 John Hopfield

Redes conexionistas em otimização

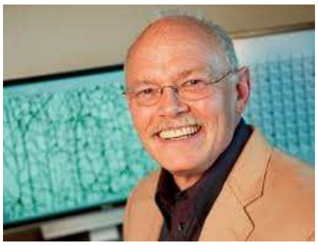


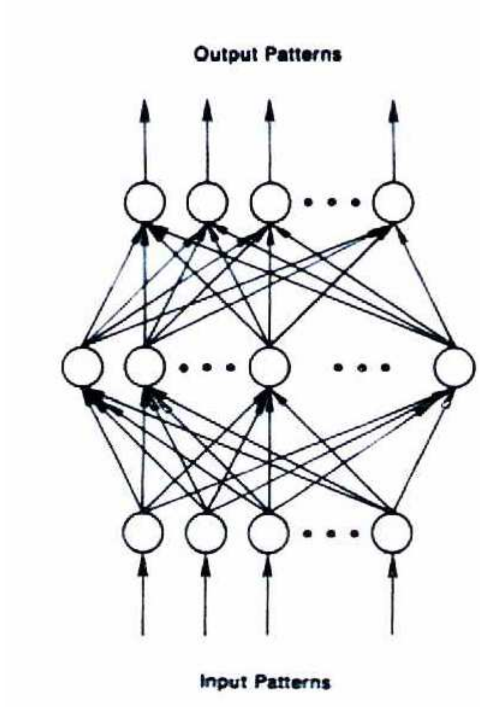


1986 - Rumelhart, Williams e Hinton

"PDP (Parallel Distributed Processing) I e II"

a ***re-****descoberta da Backpropagation.*





1987 - *1º Congresso em Redes Neurais*

(IEEE Int. Conf. on Neural Networks - 1700 participantes)

Fundação da International Neural Networks Society

1988 - Broomhead e Low

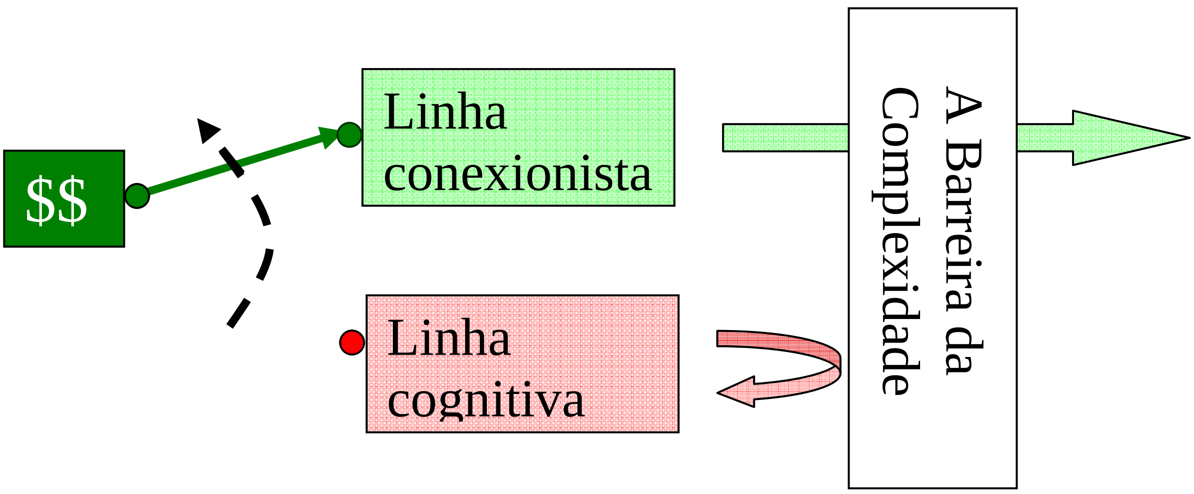
Redes de Base Radial

1988 - *Revista "Neural Networks"*

1989 - *IEEE Transactions on Neural Networks*

1992 - 98 - Vapnik

Máquinas de Vetor Suporte



Sociedades científicas:

International Neural Networks Society, INNS,

IEEE Computational Intelligence Society
(antiga IEEE Neural Networks Society)

Sociedade Brasileira de Inteligência Computacional, SBIC,
(antiga Sociedade Brasileira de Redes Neurais, SBRN), www.sbrn.org.br

Revistas

Neural Networks, INNS

IEEE Trans. on Neural networks, IEEE

Learning and non-linear models, SBRN, www.sbrn.org.br

Congressos:

International Joint Conference on Neural Networks.
anual, da INNS e IEEE-NNS. Próximos: San Jose, CA, Julho de 2011;
Brisbane, AU, 2012

Congresso Brasileiro de Redes Neurais,
bi-anual, da SBRN. Próximo: Fortaleza, Novembro de 2011

Simpósio Brasileiro de Redes Neurais,
bi-anual, da SBC. Próximo: 2012

Quando usar ?

Existe um algoritmo (modelo fenomenológico) satisfatório ?

SIM - então use o algoritmo

NÃO - então pense em usar redes neurais

Redes Neurais

não são a panacéia universal !!

Como implementar as Redes Neurais Artificiais ?

Emulando os sistemas biológicos !

Neurônio biológico

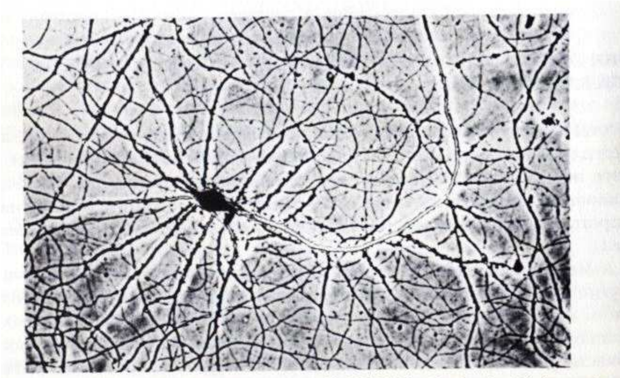
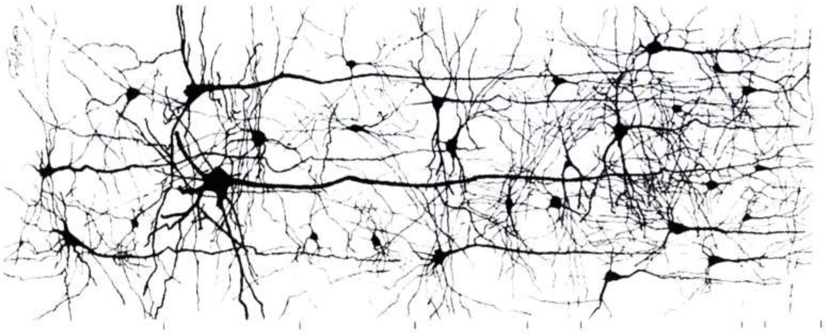
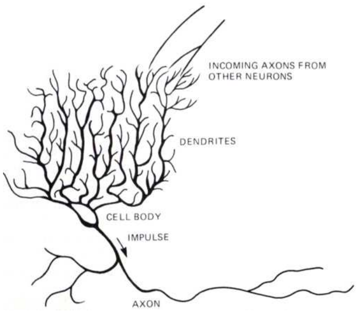
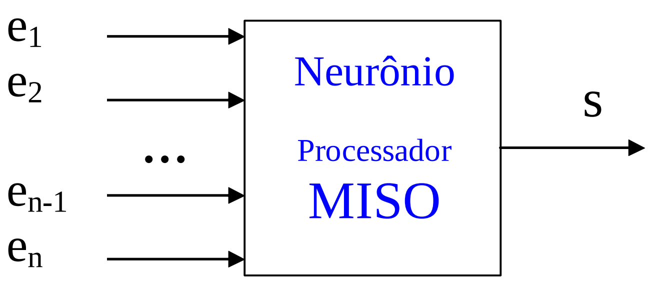


Figure 1-2a. A biological neuron magnified 400× with the dendritic tree in the foreground (courtesy of Gary Banker and Aaron Waxman, Univ. of Virginia).



Neurônio biológico

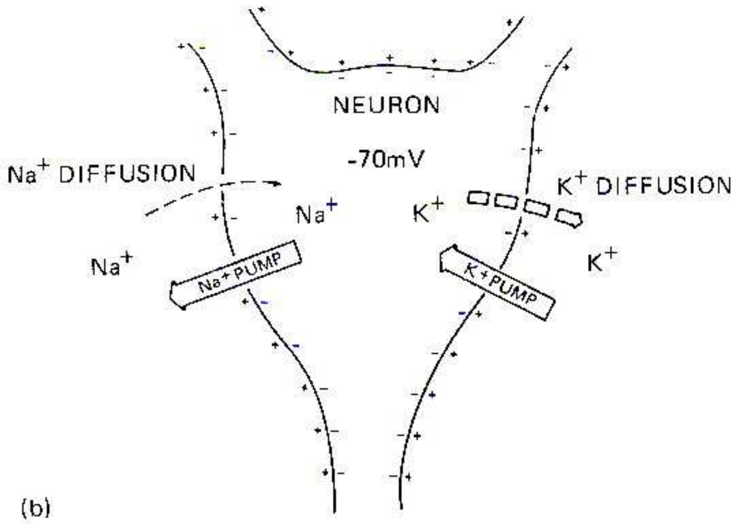




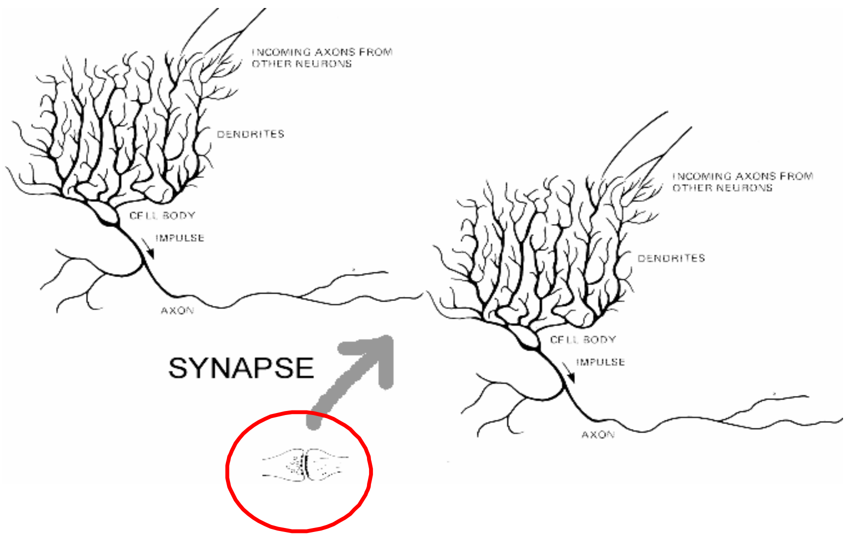
- 70 mV < saída < + 50 mV

$$\text{estado} \begin{cases} \text{ativo, excitado} & \text{saída} > s_0 \\ \text{inativo, inativo} & \text{saída} < s_0 \end{cases}$$

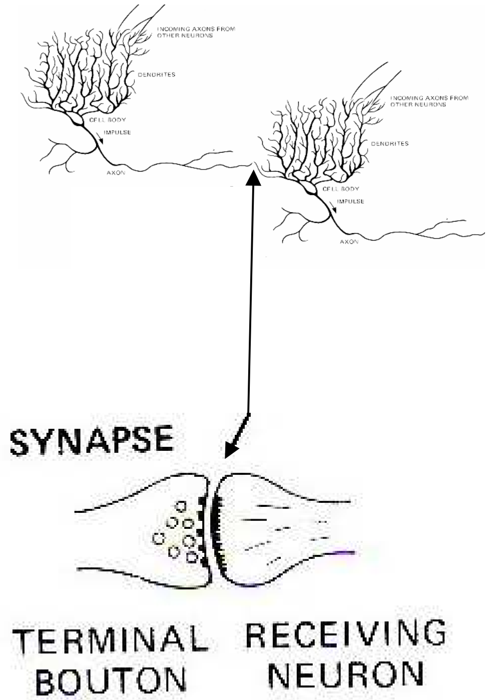
Polarização dos Neurônios - Bombas de Íons



Comunicação entre neurônios:



Sinapse



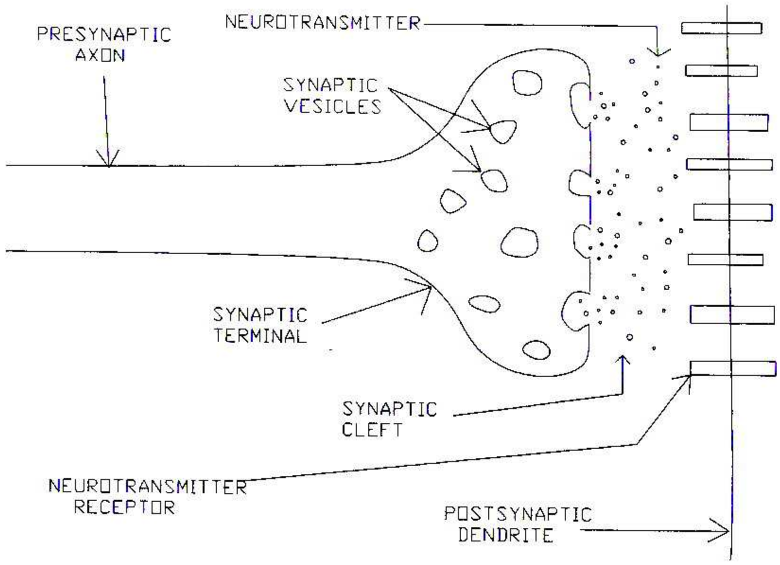
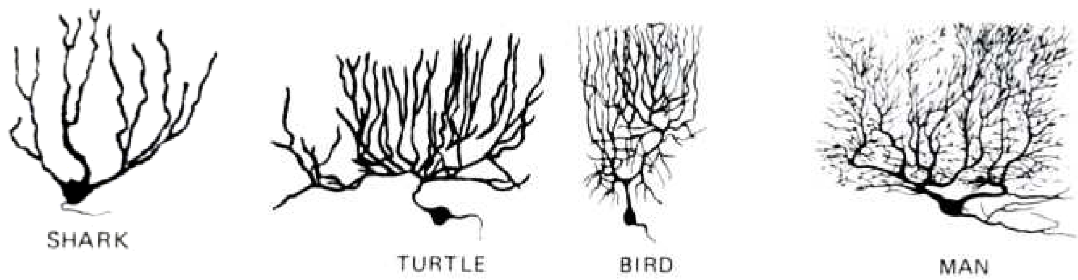


Figure A-3. Synapse

sinapses são ponderadores

Memória:



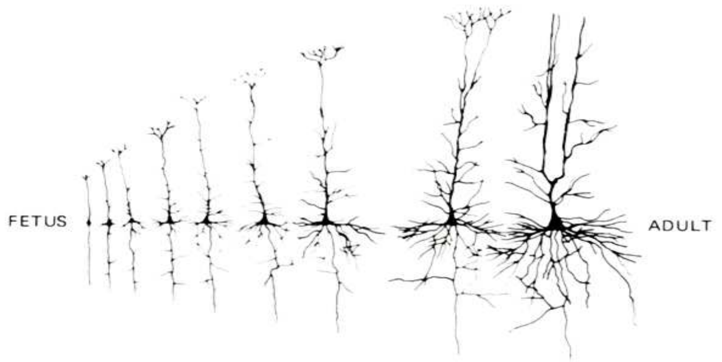
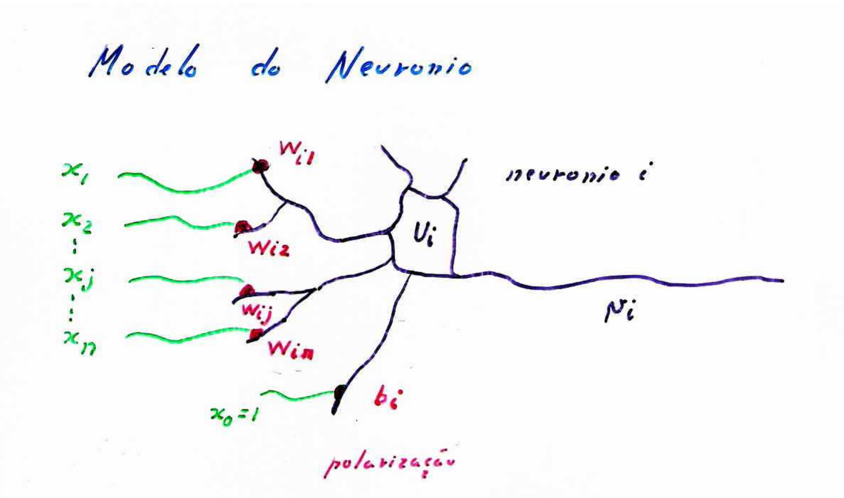


Figure 7-13. Growth of the dendritic trees and axon branches of cortical pyramidal cells in the human, from fetus to adult. (Courtesy of Sidman and Rakic 1982, and Poliakov in Sarkisov and Preobrazenskaya 1959.)

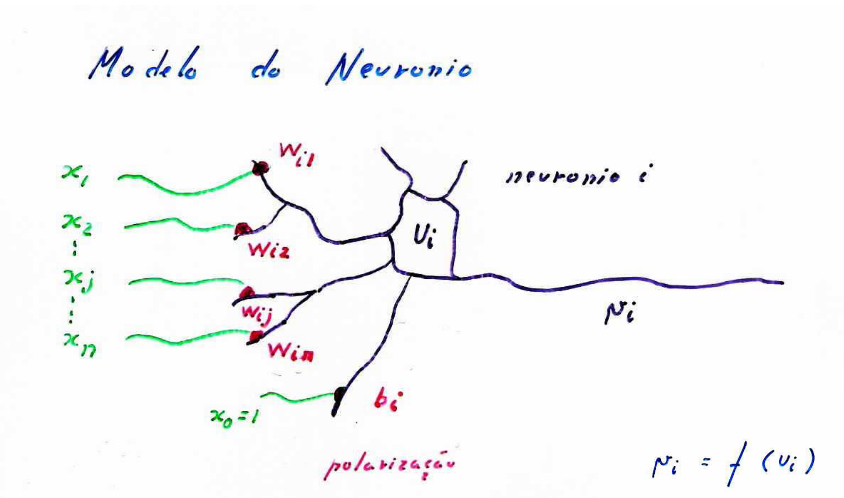
Neurônio - elemento de processamento



$$u_i = \sum_{j=1}^{n} w_{ij}\, x_j + b_i = \underline{w}_i^t\, \underline{x} + b_i$$

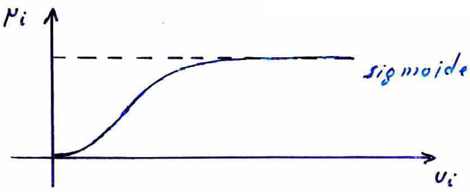
$$\underline{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \qquad \underline{w}_i = \begin{bmatrix} w_{i1} \\ w_{i2} \\ \vdots \\ w_{in} \end{bmatrix}$$

Neurônio - elemento de processamento



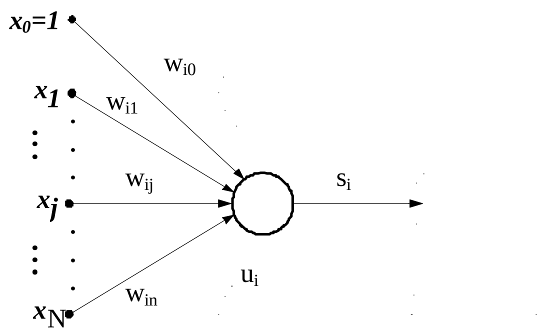
$$y_i = f(u_i)$$

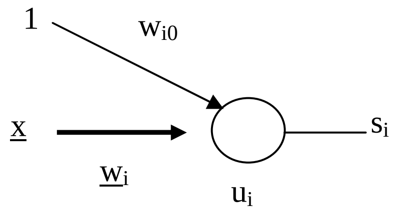
função de ativação



$$\frac{dy_i}{du_i} \geq 0$$

Neurônio - elemento de processamento

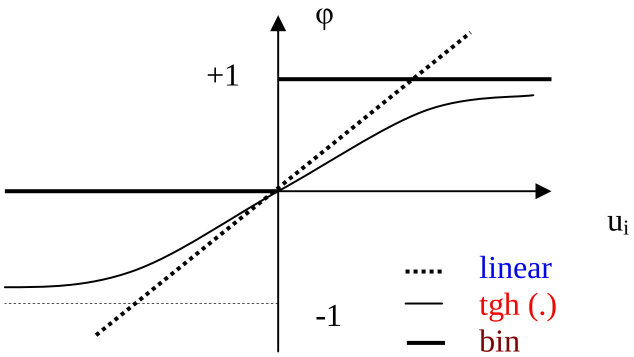




$$u_i = \sum_{j=1}^{N} w_{ij}\, x_j + w_{i0} = \underline{w}_i^t\, \underline{x} + w_{i0}$$

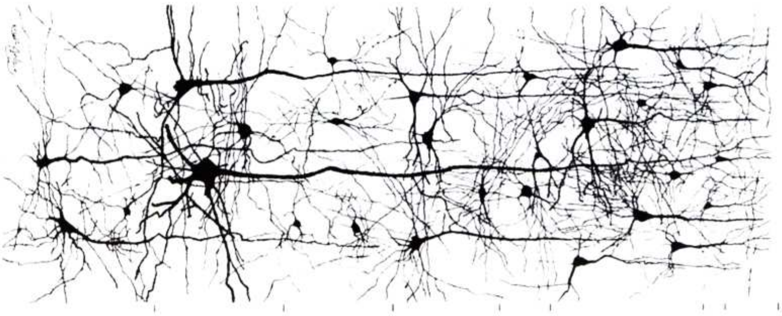
$$s_i = s(u_i)$$

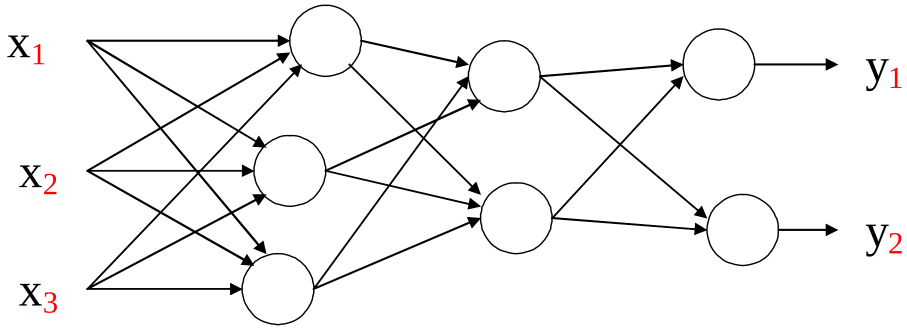
Função de Ativação s(u)



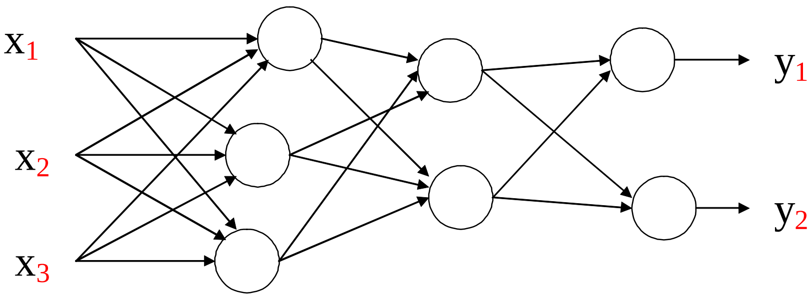
Neurônio	**Função de ativação $s_i(u_i)$**	**Ganho linearizado $g_i(s_i) = ds_i / du_i$**
linear	u_i	**1**
Não linear, tipo tgh	$tgh(u_i) = \dfrac{1 - e^{-2u_i}}{1 + e^{-2u_i}}$	$1 - s_i^2$
Não linear, tipo binário	$deg(u_i) = \begin{cases} 0 & se\ u_i < 0 \\ 1 & se\ u_i \geq 0 \end{cases}$	-

Arquitetura da Rede





Arquitetura da Rede

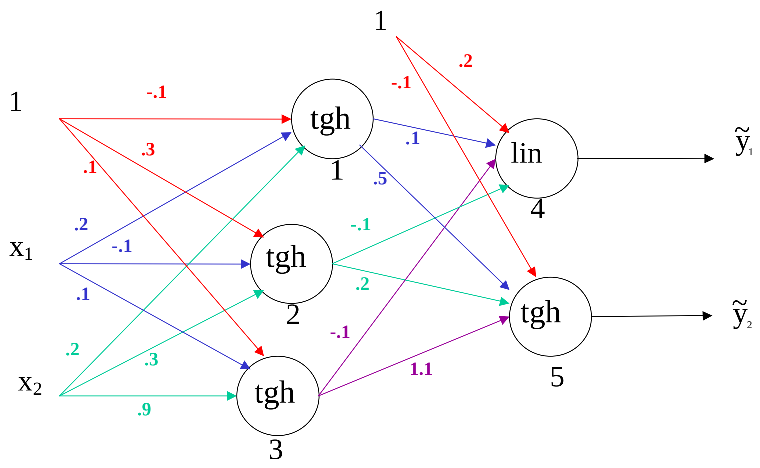


Rede feedforward

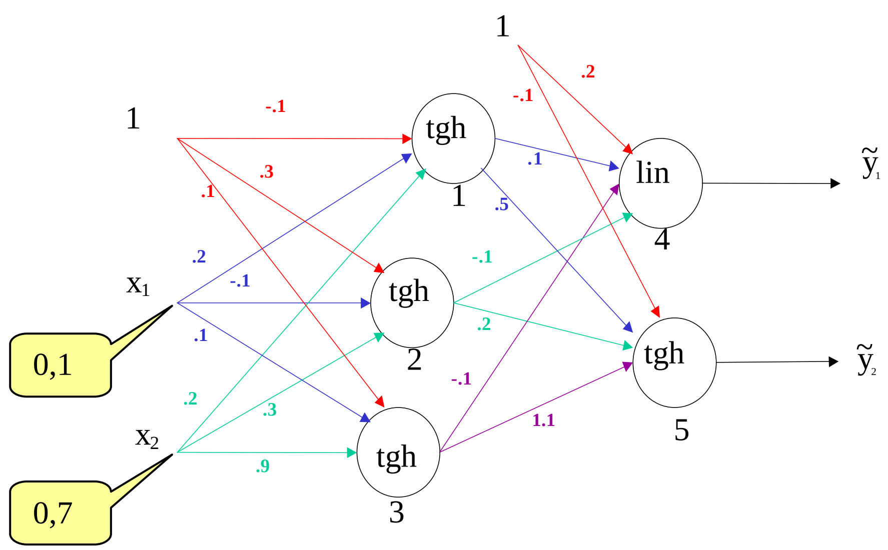
(sem realimentação)

- Estática
- Estruturalmente estável

Exemplo de operação da rede:



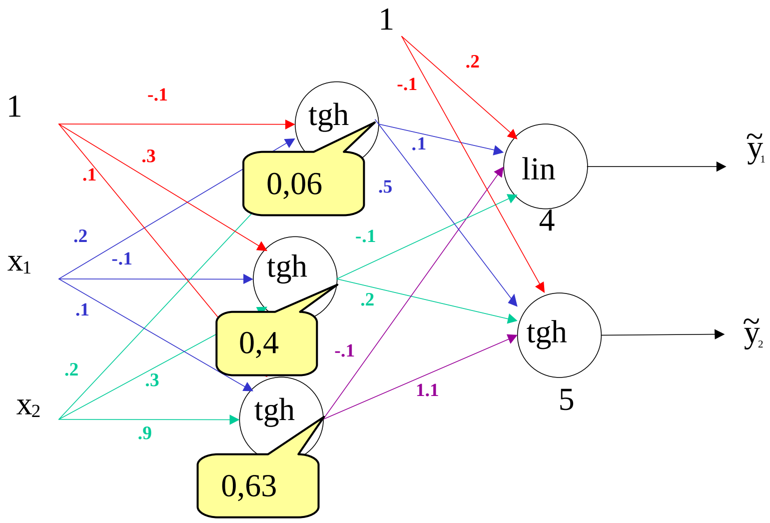
$$\underline{\mathbf{x}} = \begin{bmatrix} 0,1 \\ 0,7 \end{bmatrix} \qquad \tilde{\mathbf{y}} = ?$$



$$u_1 = -0{,}1 + (0{,}2)(0{,}1) + (0{,}2)(0{,}7) = 0{,}06$$

$$v_1 = \text{tgh}(\,0{,}06\,) = 0{,}06$$

$v_2 = 0{,}46 \qquad v_3 = 0{,}63$

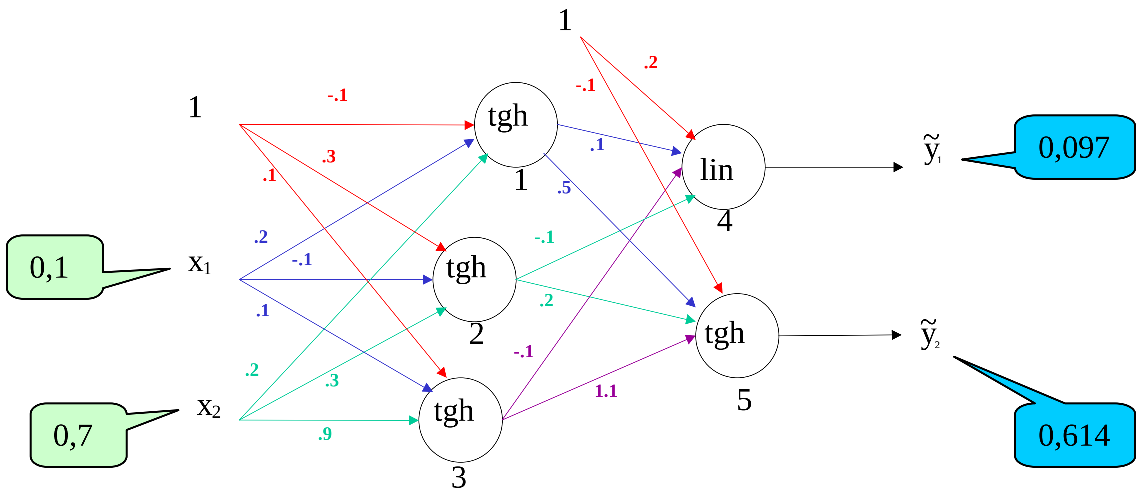


$$u_4 = 0{,}2 + (0{,}1)(0{,}06) + (-0{,}1)(0{,}46) + (-0{,}1)(0{,}63) = 0{,}097$$

$$v_4 = 0{,}097 \quad \text{(linear!)}$$

$$u_5 = -0{,}1 + (0{,}5)(0{,}06) + (0{,}2)(0{,}46) + (1{,}1)(0{,}63) = 0{,}715$$

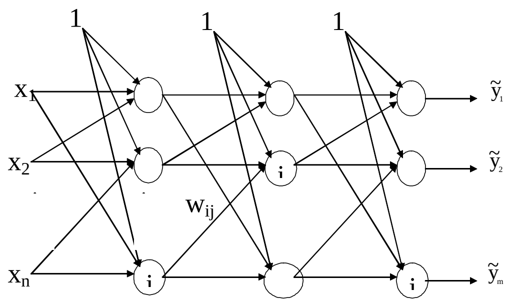
$$v_5 = \text{tgh}(0{,}715) = 0{,}614$$

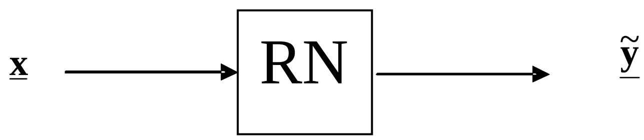


$$\underline{\mathbf{x}} = \begin{bmatrix} 0{,}1 \\ 0{,}7 \end{bmatrix} \qquad \tilde{\mathbf{y}} = \begin{bmatrix} 0{,}097 \\ 0{,}614 \end{bmatrix}$$

Redes Neurais *FeedForward*

Mapeador Não Linear





$$\underline{\tilde{y}} = \varphi(\underline{x})$$

Aproximador Universal !