DECSAI
Departamento de Ciencias de la Computación e I.A.
Universidad de Granada

Redes Neuronales

Fernando Berzal, berzal@acm.org

Redes Neuronales Artificiales

- Motivación
  - El cerebro humano
  - Computación neuromórfica
- Modelos de redes neuronales
  - Modelos de neuronas
  - Redes neuronales artificiales
- Historia de las redes neuronales artificiales
- Aplicaciones de las redes neuronales artificiales
- Herramientas

Redes Neuronales – Motivación

Fernando Berzal, berzal@acm.org

Introducción

El cerebro humano

Inspiración de las redes neuronales artificiales

Las RNA intentan modelar la estructura y funcionamiento de algunas partes del sistema nervioso animal.

Introducción

¿Por qué estudiar redes neuronales?

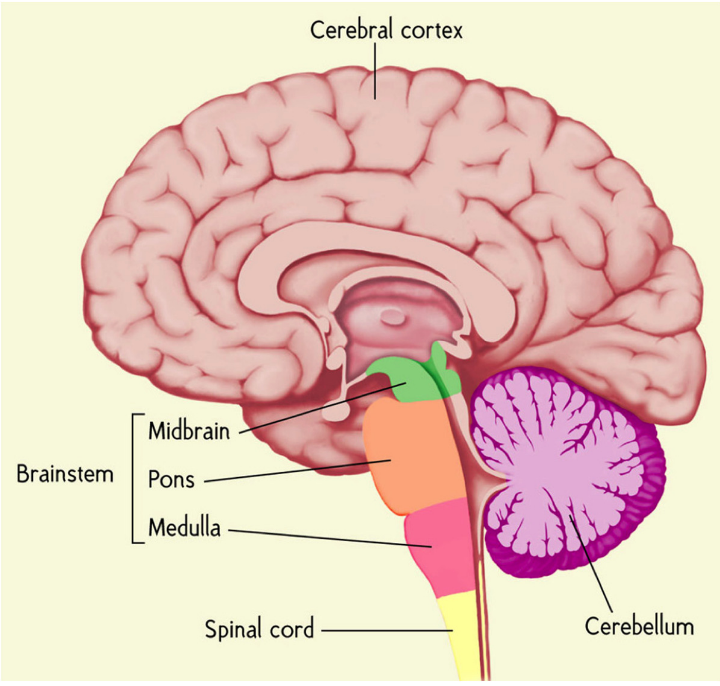
- Para comprender cómo funciona realmente el cerebro.
- Para diseñar un modelo de cómputo paralelo inspirado en las neuronas y sus sinapsis [conexiones] adaptativas.
- **Para resolver problemas prácticos utilizando algoritmos de aprendizaje inspirados en el cerebro.**

NOTA: Incluso aunque no sepamos realmente cómo funciona el cerebro, los algoritmos de aprendizaje nos serán muy útiles.

Introducción

El cerebro humano

Anatomía del cerebro

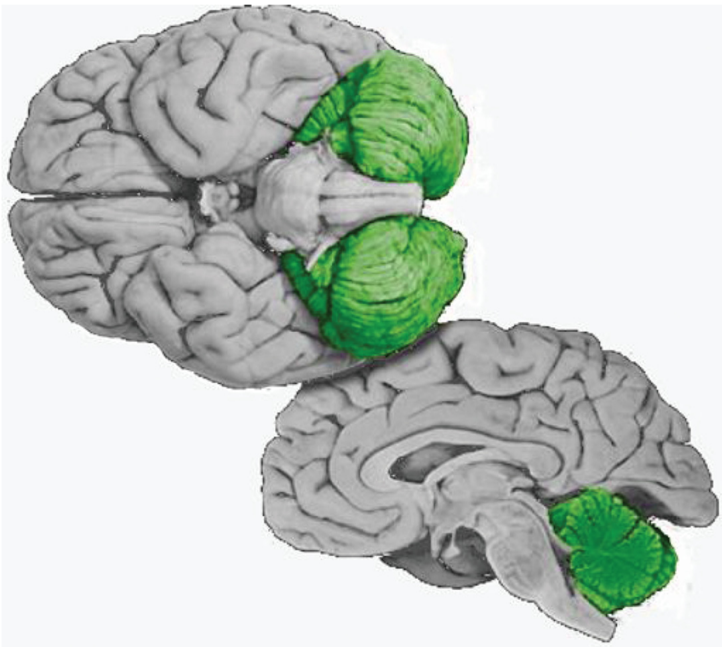


[Psychological Science, 2nd edition, W.W. Norton & Company]

Introducción

El cerebro humano

Anatomía del cerebro



El cerebelo

[Sylvius 4 Online, Sinauer Associates]

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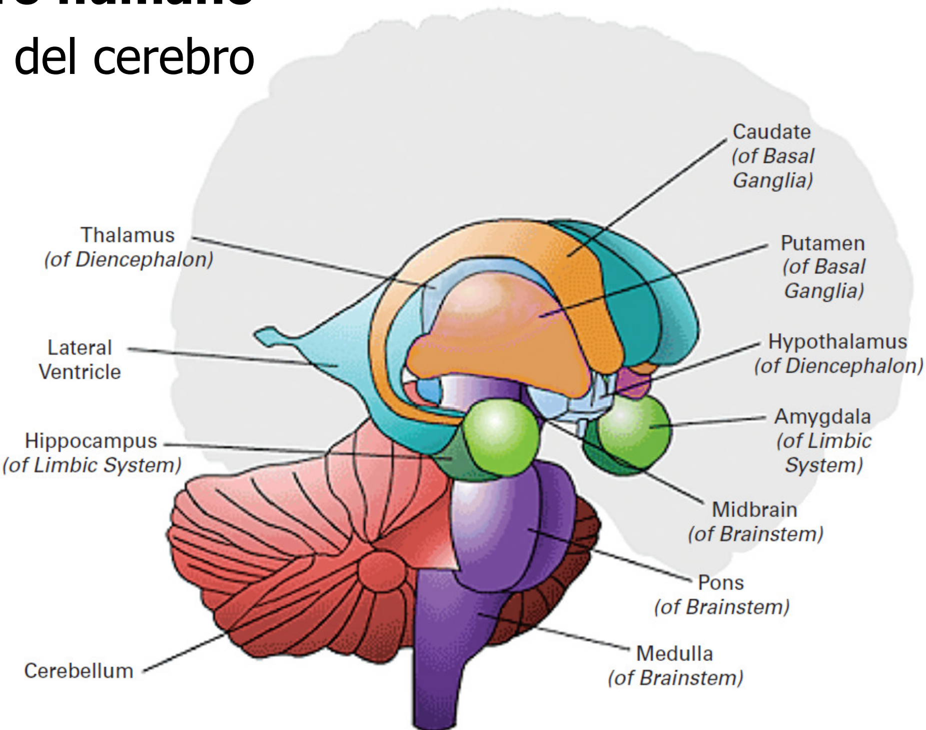
El cerebro humano

Anatomía del cerebro

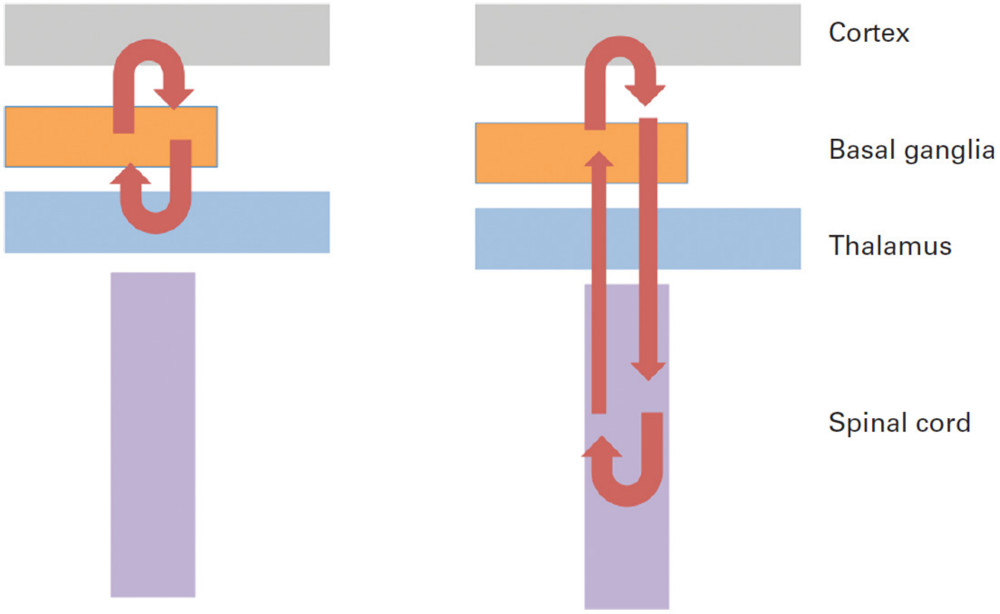


[Dana Ballard: Brain Computation as Hierarchical Abstraction, 2015]

Introducción

El cerebro humano

El ciclo de cálculo del cerebro

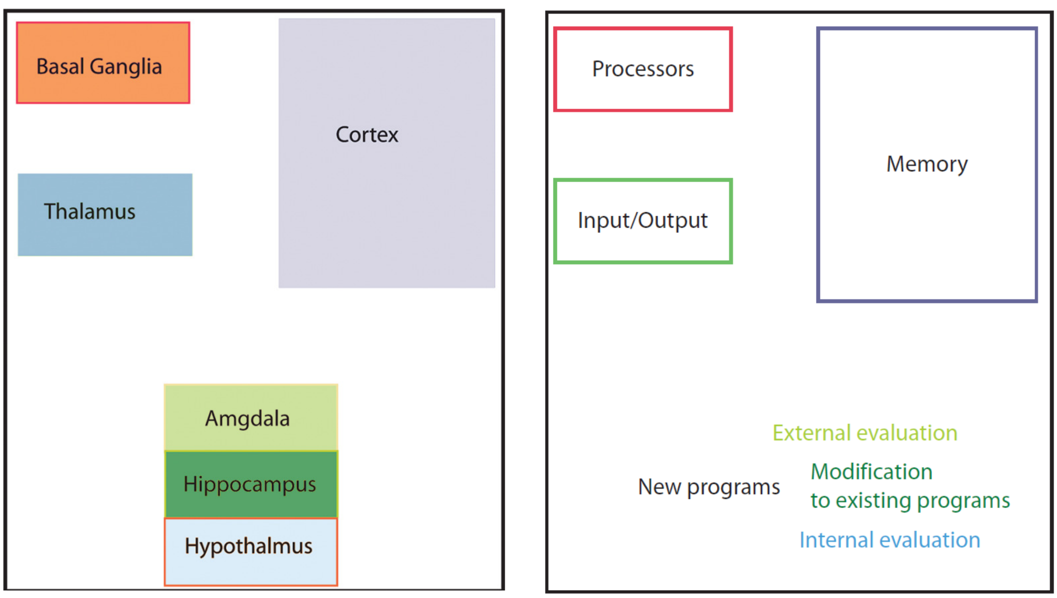


[Dana Ballard: Brain Computation as Hierarchical Abstraction, 2015]

Introducción

El cerebro humano

Analogía entre el cerebro humano y un ordenador



[Dana Ballard: Brain Computation as Hierarchical Abstraction, 2015]

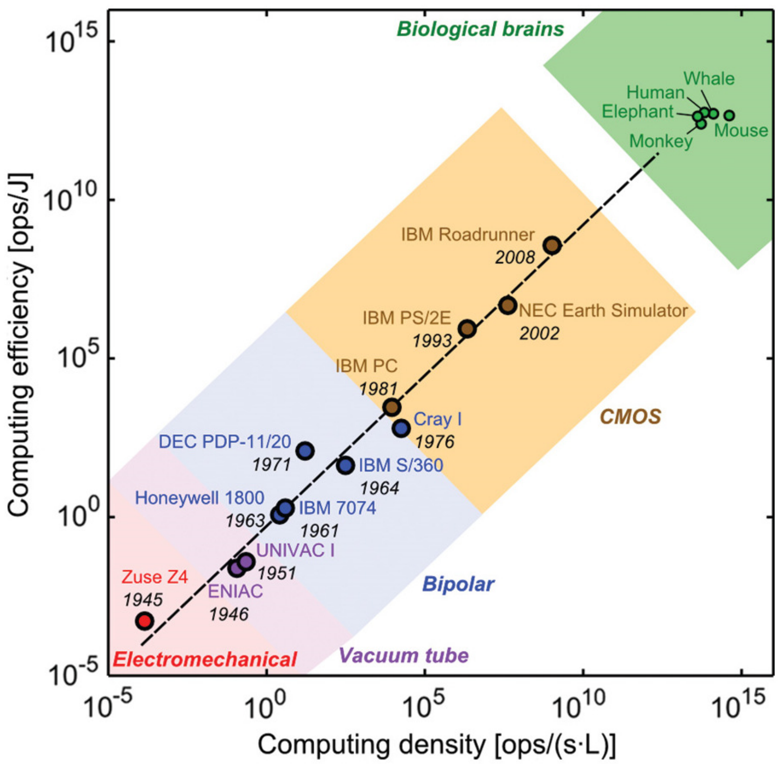
Introducción

El cerebro humano

Diferencias entre un ordenador y el cerebro humano

Ordenador	Cerebro humano
Computación en serie	Computación en paralelo
Poco robusto	Tolerancia a fallos
Programable	Aprendizaje autónomo
Digital	Analógico
10^9 transistores	**10^{11} neuronas** **$10^{14} \sim 10^{15}$ sinapsis**
Nanosegundos (3.6GHz)	Milisegundos (4~90Hz)
51.2 GB/s	10 spikes/s
210,000,000 m/s	1 ~ 100 m/s
2.3x10^{13} TEPS	**6.4x10^{14} TEPS**

Introducción

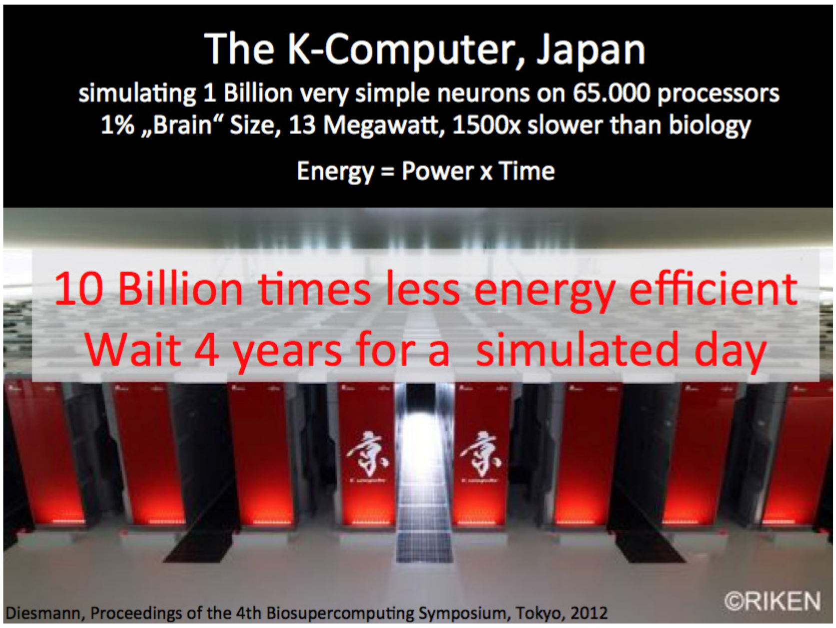


IBM Journal of Research and Development, 2011

Introducción

Arquitecturas basadas en el cerebro

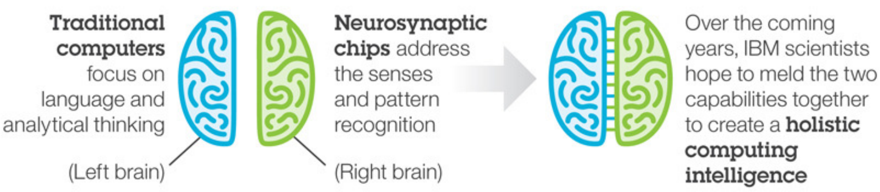
Simulación (muy ineficiente) ➔ "Neuromorphic Computing"

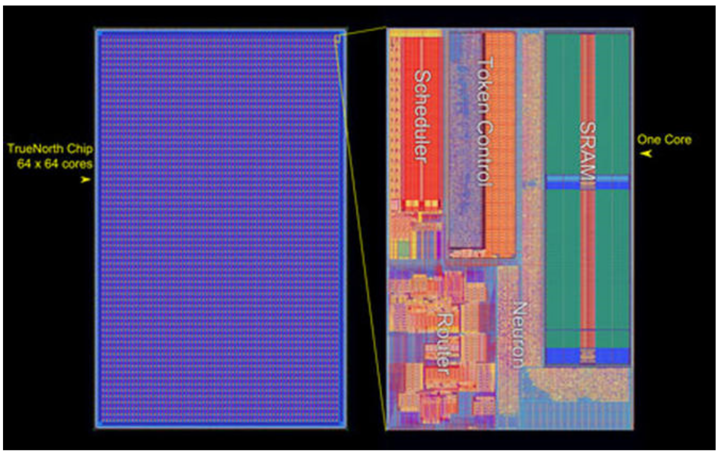


Introducción

Arquitecturas basadas en el cerebro

IBM TrueNorth Brain-inspired Computer



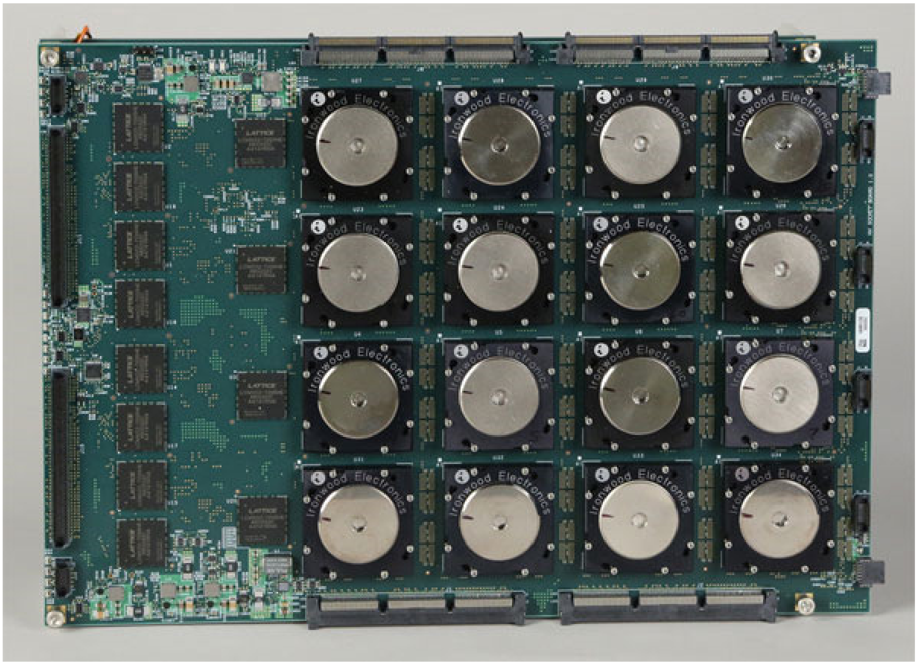


4096 cores
1M neurons
256M synapses
5.4B transistors
CMOS
70mW

Introducción

Arquitecturas basadas en el cerebro

IBM TrueNorth Brain-inspired Computer

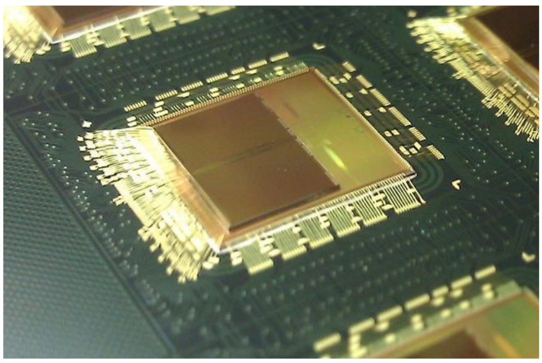


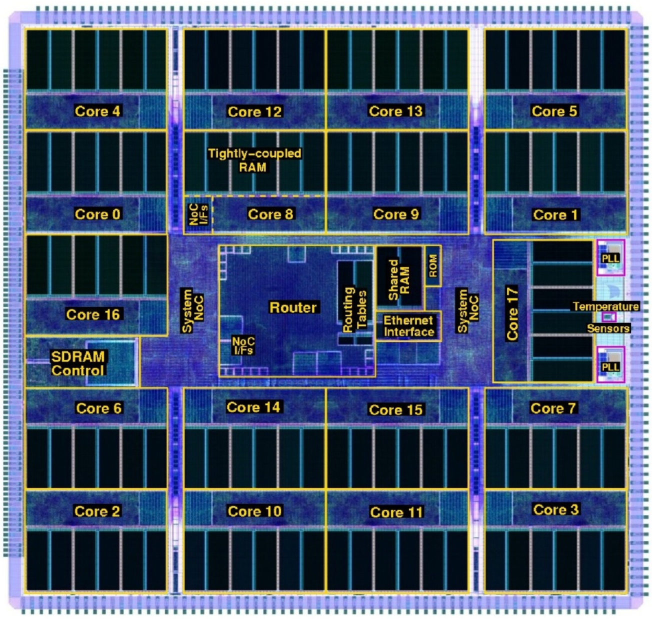
Synapse 16
16M neurons
4B synapses

Introducción

Arquitecturas basadas en el cerebro

SpiNNaker project (UK)



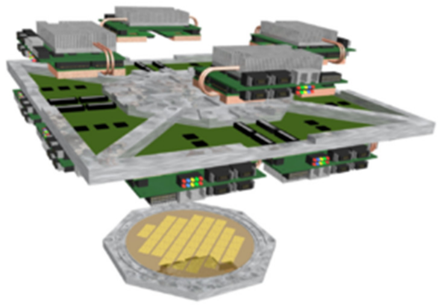


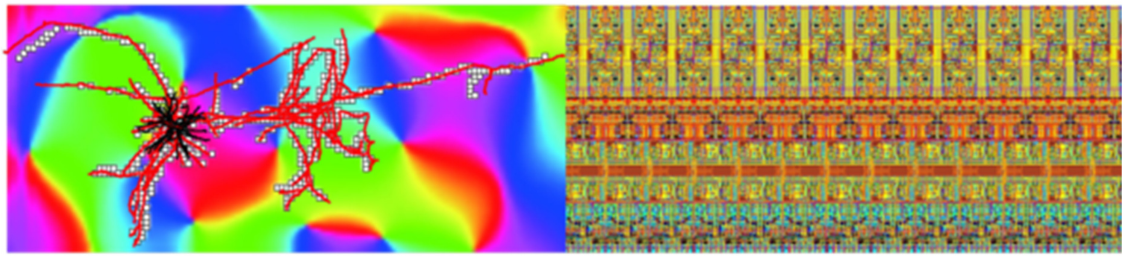
Globally Asynchronous Locally Synchronous (GALS) chip:
18 ARM968 processor nodes + 128MB Mobile DDR SDRAM
http://apt.cs.manchester.ac.uk/projects/SpiNNaker/project/

Introducción

Arquitecturas basadas en el cerebro

BrainScaleS (Germany)





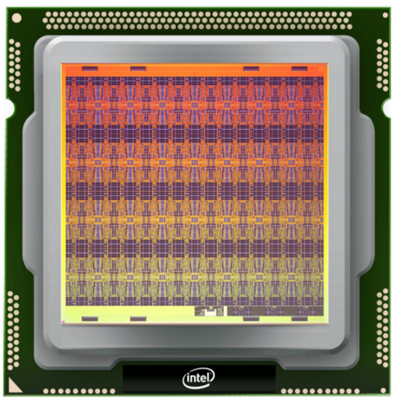
Mixed CMOS signals

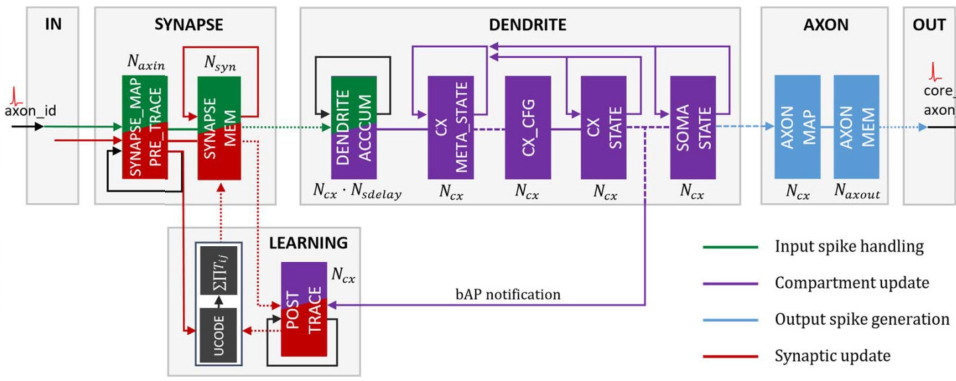
https://brainscales.kip.uni-heidelberg.de/

Introducción

Arquitecturas basadas en el cerebro

Intel Loihi (self-learning neuromorphic research chip)





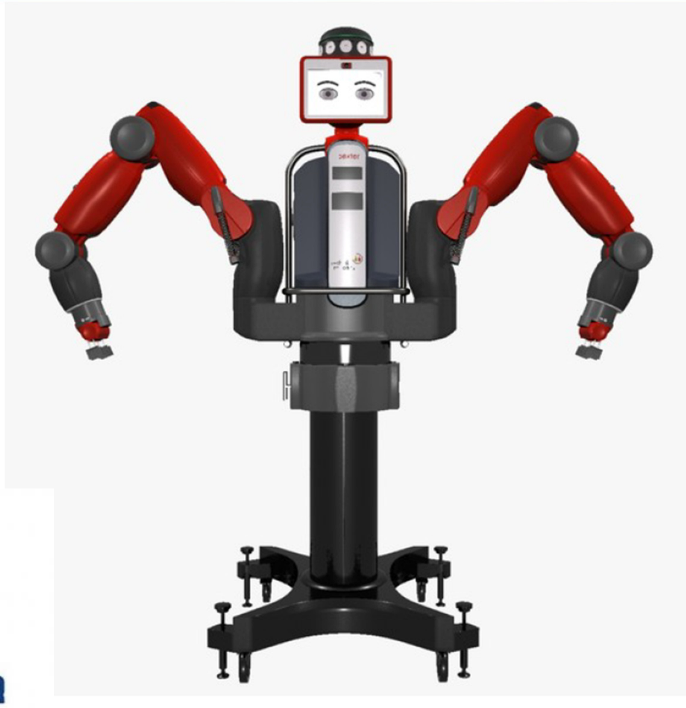
SNNs [Spiking Neural Networks]

130k neuronas / chip, 60mm^2, 14nm

https://www.intel.com/content/www/us/en/research/neuromorphic-computing.html/

https://ieeexplore.ieee.org/document/8259423/

Introducción



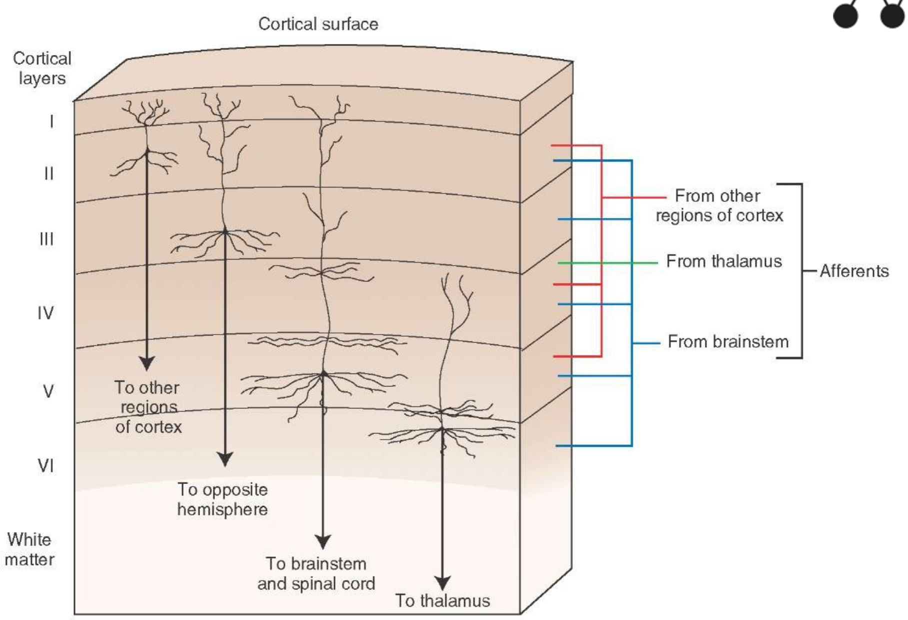
Laboratorio de Neuro-Robótica y Robots Colaborativos

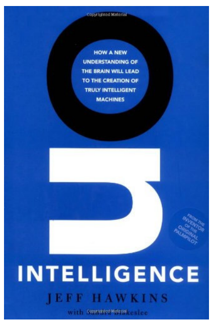
Introducción

Arquitecturas basadas en el cerebro

HTM [Hierarchical Temporal Memory]

Numenta





Introducción

Arquitecturas basadas en el cerebro

HTM [Hierarchical Temporal Memory]

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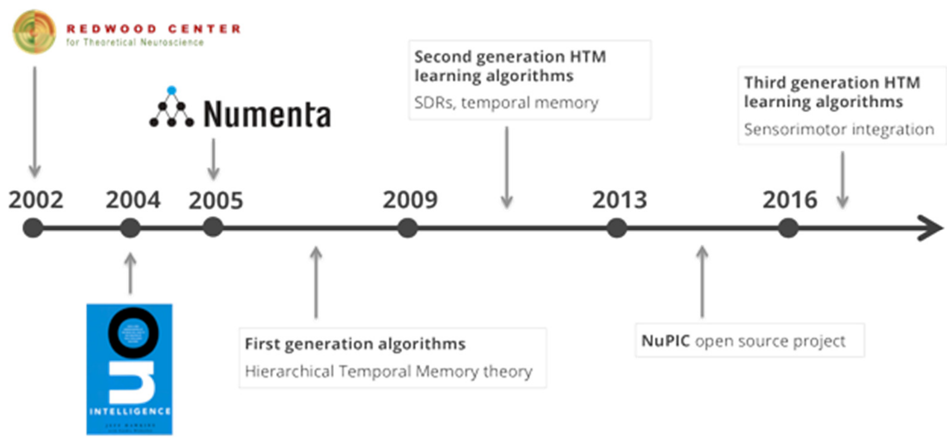

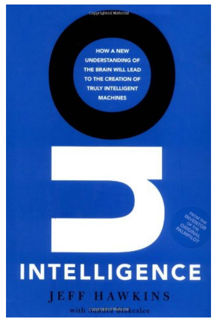

http://numenta.com/

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Arquitecturas basadas en el cerebro

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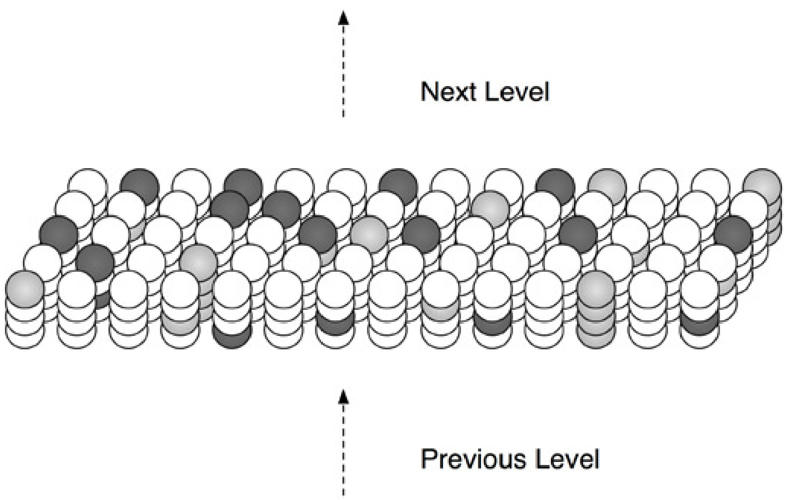

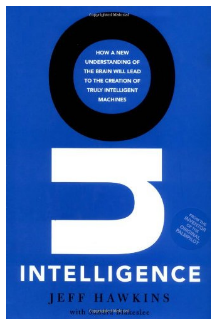

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Arquitecturas basadas en el cerebro

HTM [Hierarchical Temporal Memory]

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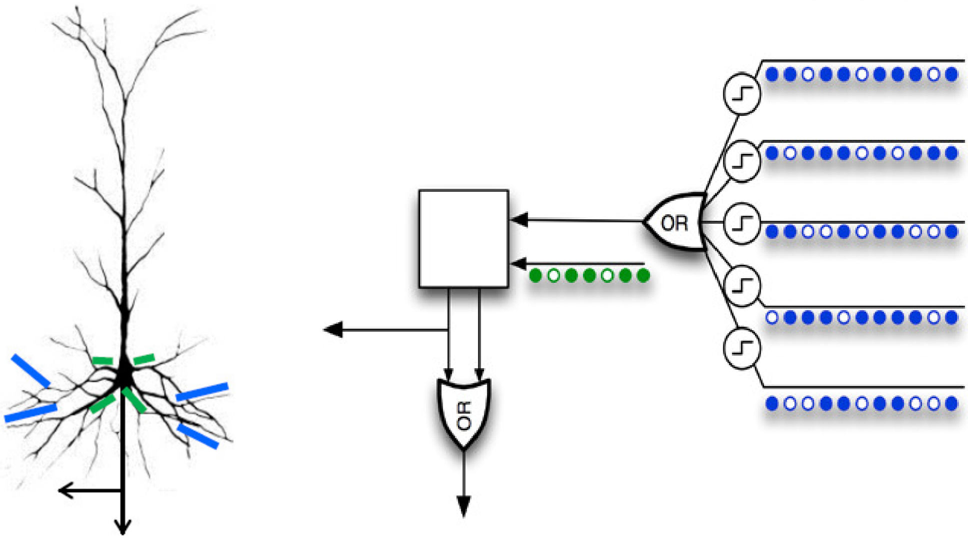
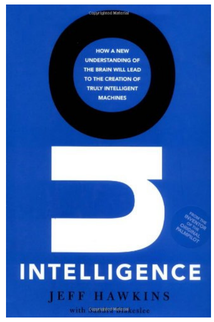
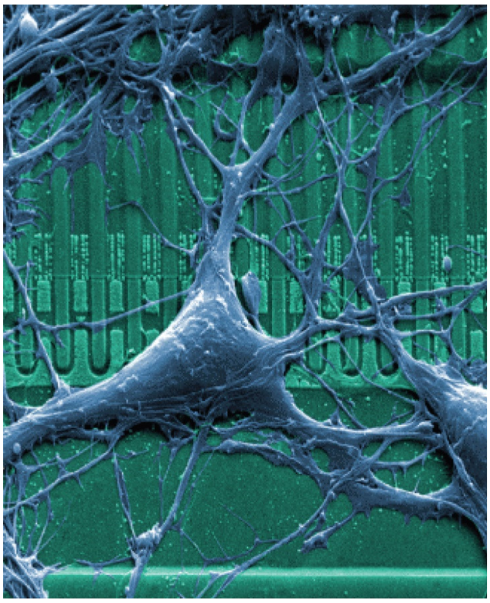




http://numenta.com/

Introducción

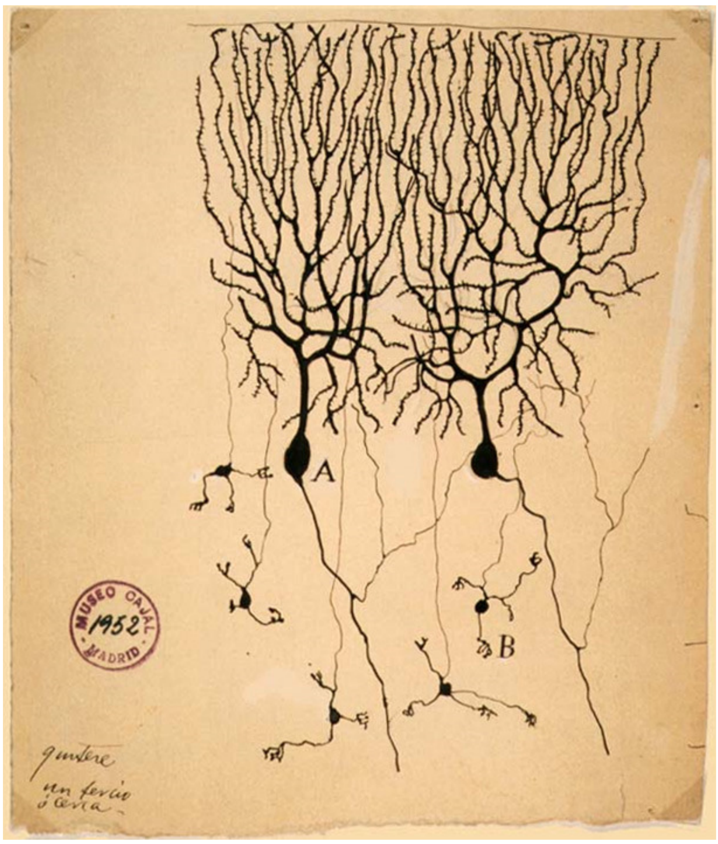
Neuronas



Microfotografía de una neurona "cultivada" sobre una oblea de silicio.
[Peter Fromherz, Max Planck Institute]

Introducción

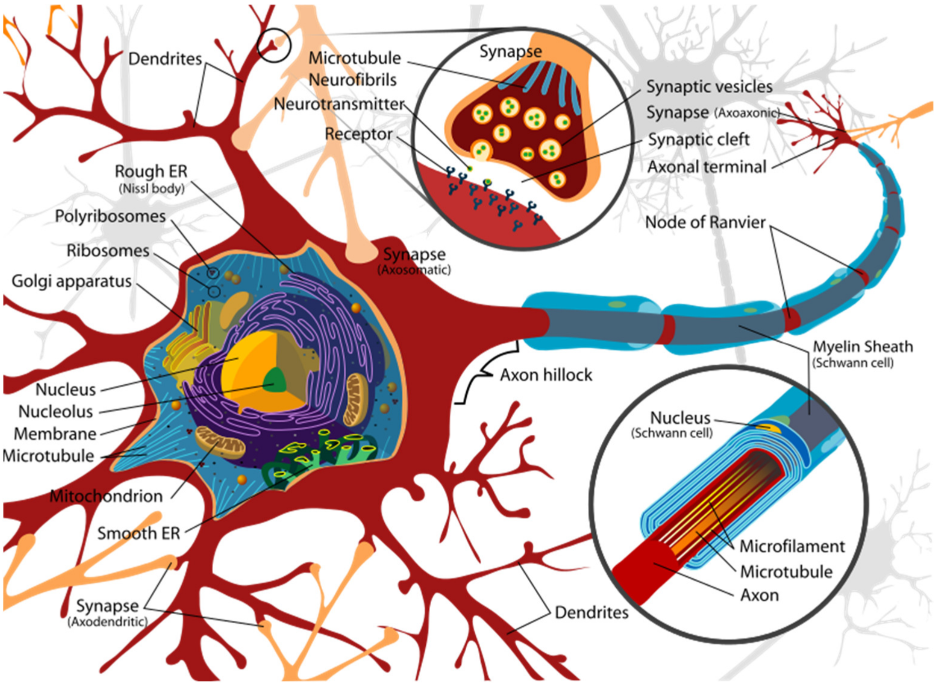
Neuronas



Neuronas del cerebelo
[Dibujo de Santiago Ramón y Cajal, 1899]

Introducción

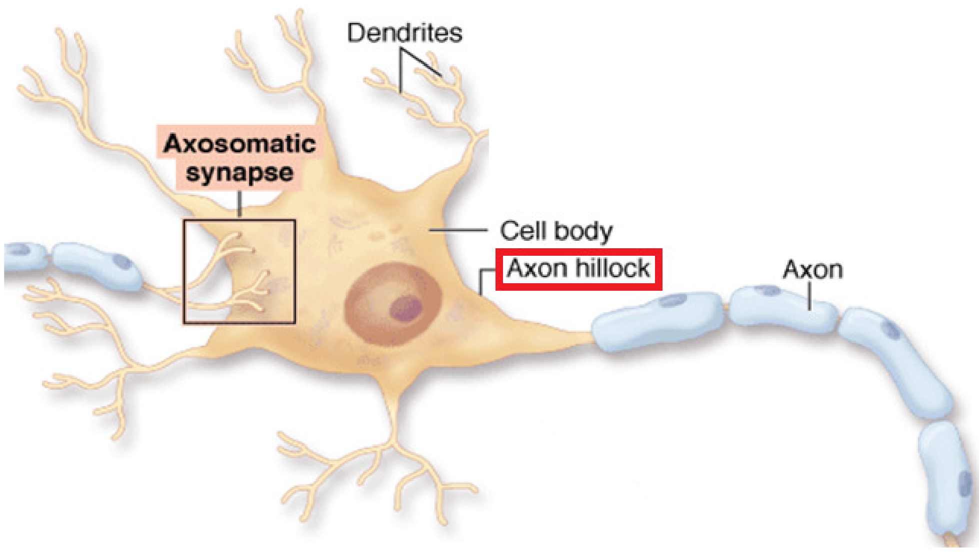
Neuronas



[Wikipedia]

Introducción

Neuronas

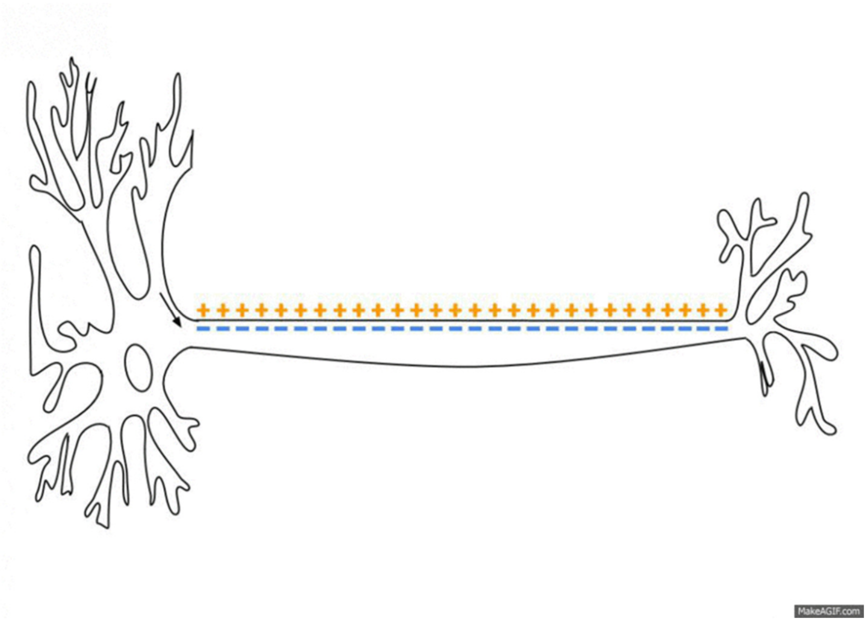


https://en.wikipedia.org/wiki/Axon_hillock

Introducción

Neuronas

Spike, a.k.a. action potential [potencial de acción]

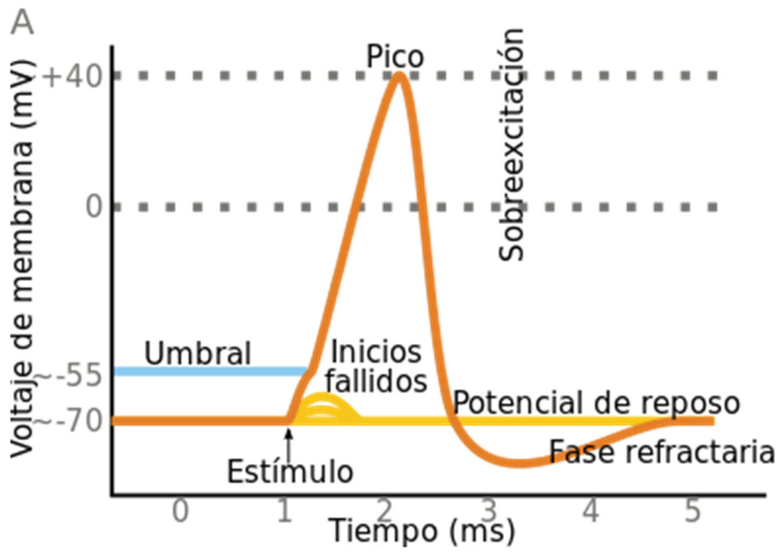


https://en.wikipedia.org/wiki/Action_potential

Introducción

Neuronas

Spike, a.k.a. action potential [potencial de acción]

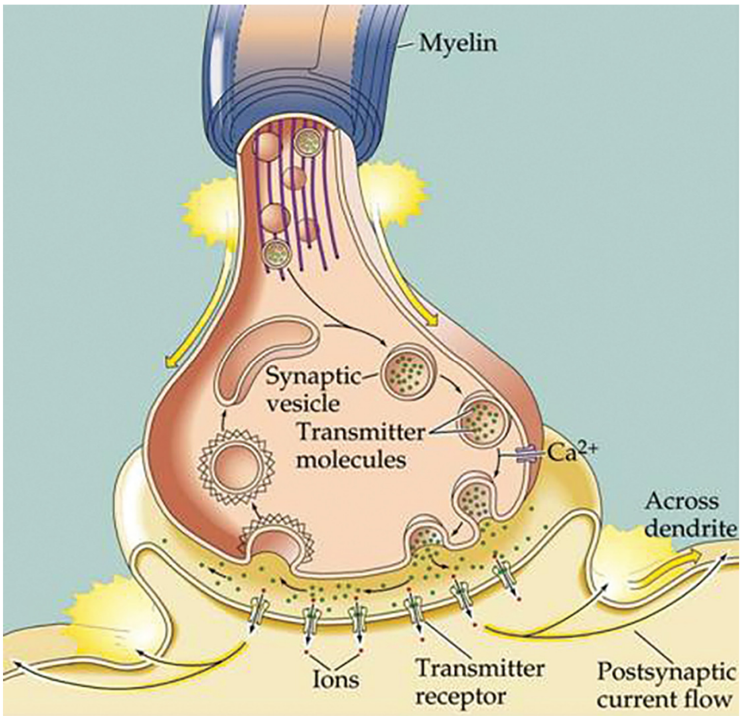


https://en.wikipedia.org/wiki/Action_potential

Introducción

Neuronas

Sinapsis



[Purves et al.: Neuroscience, 3rd edition, 2004]

Introducción

Neuronas

Sinapsis

Las sinapsis son lentas (en comparación con los transistores de un ordenador), pero…

- Son muy pequeñas y consumen muy poca energía.
- Se adaptan utilizando señales locales.

Como tenemos cerca de 10^{11} neuronas y de 10^{14} a 10^{15} sinapsis, muchas sinapsis pueden influir en un "cálculo" en un período de tiempo muy breve:

Ancho de banda muy superior al de un ordenador.

Introducción

Neuronas

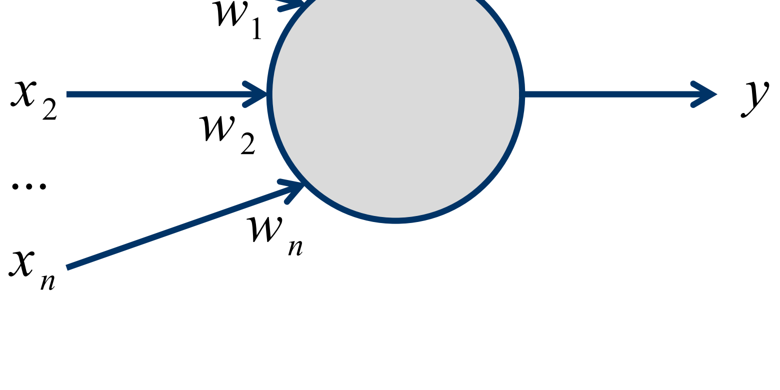
Sinapsis

- El efecto de cada entrada sobre una neurona depende de un peso sináptico (positivo o negativo)
- Los pesos sinápticos se adaptan [plasticidad]:
  La "efectividad" de una sinapsis puede cambiar.
  - Neurona pre-sináptica:
    Número de vesículas de neurotransmisores.
  - Neurona post-sináptica:
    Número de receptores de neurotransmisores.

Modelos de redes neuronales

Neuronas

El modelo computacional más simple de una neurona



$$y = \sum_i x_i w_i = x_1 w_1 + x_2 w_2 + \ldots + x_n w_n$$

Modelos de redes neuronales

Neuronas

- Diferentes partes del córtex se encargan de distintas tareas (daños locales tienen efectos específicos y la realización de tareas concretas aumenta el consumo de oxígeno en regiones determinadas).
- La estructura de todo el córtex es similar (6 capas de neuronas en una "servilleta arrugada" [Hawkins])

HIPÓTESIS

El córtex es un sistema de propósito general capaz de convertirse en hardware de propósito específico usando un algoritmo de aprendizaje (¿único?).

Modelos de redes neuronales

Redes neuronales artificiales

Modelos de neuronas

- Para modelar las neuronas tenemos que idealizarlas: Eliminar de detalles irrelevantes que no son esenciales para entender su funcionamiento.
- La idealización nos permitirá utilizar herramientas (p.ej. matemáticas) y establecer analogías.

Redes neuronales artificiales

Modelos de neuronas

- Una vez que tengamos un modelo básico,
  será más sencillo añadirle detalles y hacerlo más complejo para que sea más fiel a la realidad.

- Incluso modelos que son incorrectos de partida pueden resultarnos útiles.

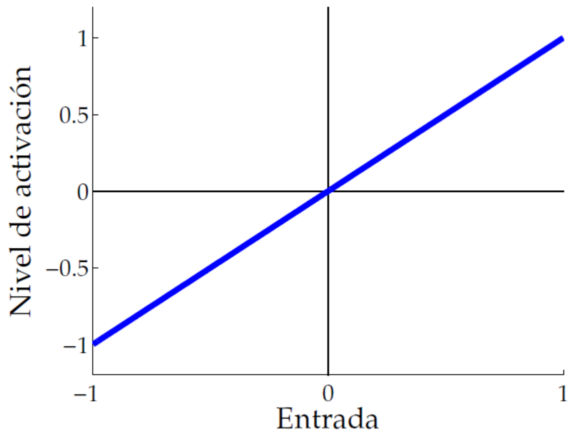
  p.ej. Asumir que las neuronas transmiten números reales en vez de potenciales de acción [spikes].

Redes neuronales artificiales

Modelos de neuronas: Neuronas lineales

$$y = b + \sum_i x_i w_i$$

y	Salida
x	Entradas
w	Pesos
b	Sesgo [bias]



- Sencillas, pero computacionalmente limitadas.

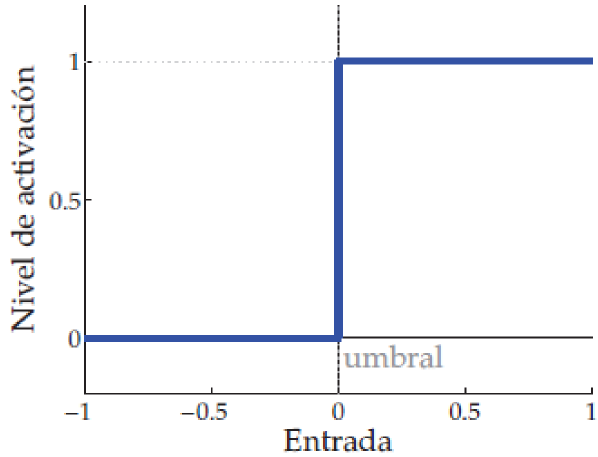
Modelos de redes neuronales

Redes neuronales artificiales

Modelos de neuronas: Neuronas binarias con umbral [McCulloch & Pitts, 1943]

$$z = b + \sum_i x_i w_i$$

$$y = \begin{cases} 1 & si\ z \geq 0 \\ 0 & en\ otro\ caso \end{cases}$$



Umbral θ=-b

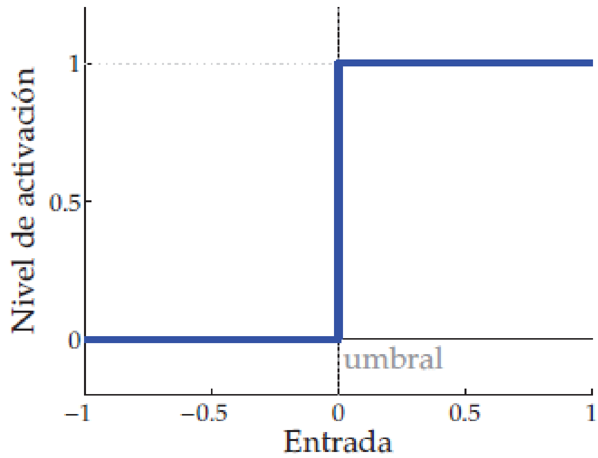
Modelos de redes neuronales

Redes neuronales artificiales

Modelos de neuronas: Neuronas binarias con umbral [McCulloch & Pitts, 1943]

$$z = \sum_i x_i w_i$$

$$y = \begin{cases} 1 & si\ z \geq 0 \\ 0 & en\ otro\ caso \end{cases}$$



Asumiendo $x_0=1$ y $w_0=b$ (umbral θ=-b)

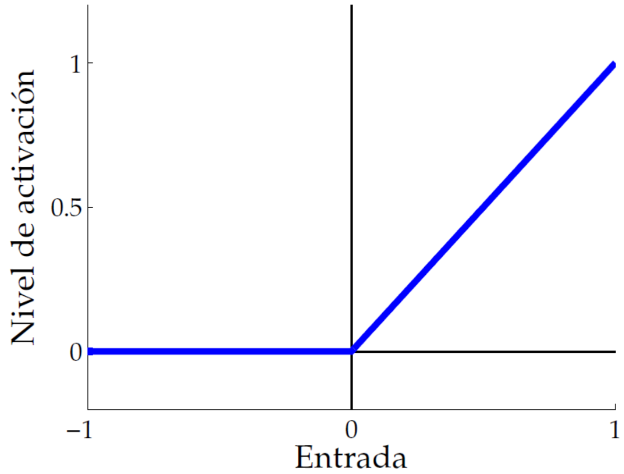
Modelos de redes neuronales

Redes neuronales artificiales

Modelos de neuronas: Neuronas lineales rectificadas

$$z = \sum_i x_i w_i$$

$$y = \begin{cases} z & si\ z \geq 0 \\ 0 & en\ otro\ caso \end{cases}$$



Asumiendo x_0=1 y w_0=b (umbral θ=-b)

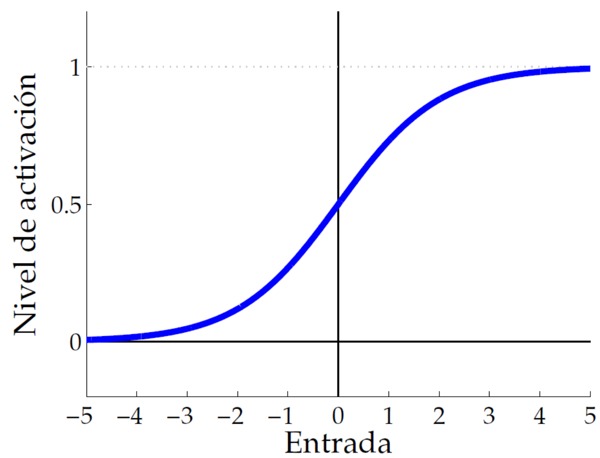
Modelos de redes neuronales

Redes neuronales artificiales

Modelos de neuronas: Neuronas sigmoidales

$$z = \sum_i x_i w_i$$

$$y = \frac{1}{1+e^{-z}}$$



- Función de activación suavizada y acotada.
  p.ej. Función logística, tangente hiperbólica…
- El uso de sus derivadas facilita el aprendizaje.

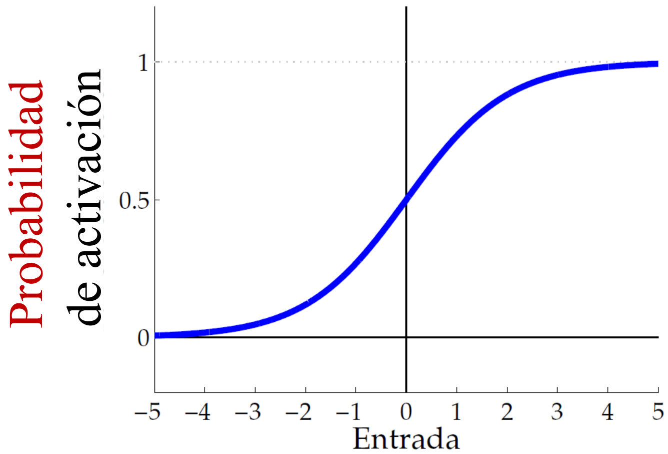
Modelos de redes neuronales

Redes neuronales artificiales

Modelos de neuronas: Neuronas binarias estocásticas

$$z = \sum_i x_i w_i$$

$$p = \frac{1}{1+e^{-z}}$$

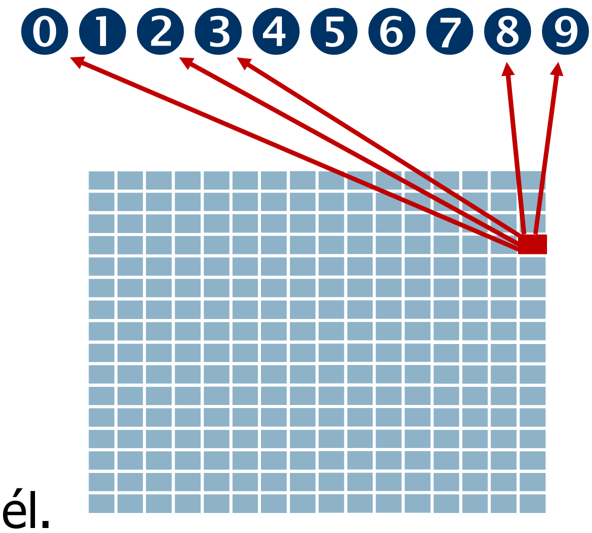


Las mismas ecuaciones que las neuronas sigmoidales, si bien su salida se interpreta como una probabilidad (de producir un spike en una pequeña ventana de tiempo)

Modelos de redes neuronales

Redes neuronales artificiales

Ejemplo de aprendizaje: Reconocimiento de dígitos (OCR)



Red neuronal con
2 capas de neuronas:

- Capa de salida:
  Símbolos reconocidos.
- Capa de entrada:
  Píxeles de la imagen

Cada píxel vota si tiene tinta en él.

Cada píxel puede votar a varios símbolos.

El símbolo con más votos gana.

Modelos de redes neuronales

Redes neuronales artificiales

Ejemplo de aprendizaje: Reconocimiento de dígitos (OCR)

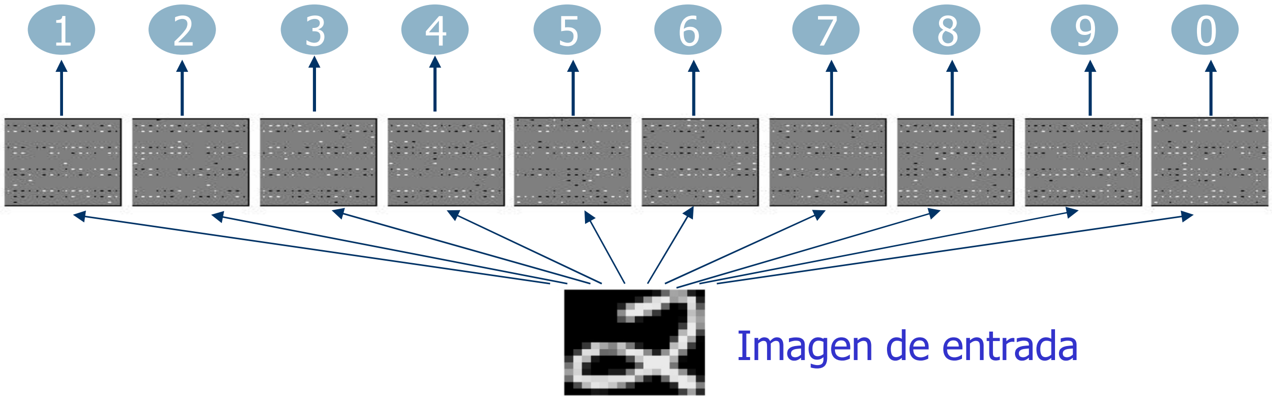


Imagen de entrada

Visualización: Cada unidad de salida tiene su propio "mapa" de la imagen de entrada que muestra el peso asociado a cada píxel de la imagen de entrada.

Modelos de redes neuronales

Redes neuronales artificiales

Ejemplo de aprendizaje: Reconocimiento de dígitos (OCR)

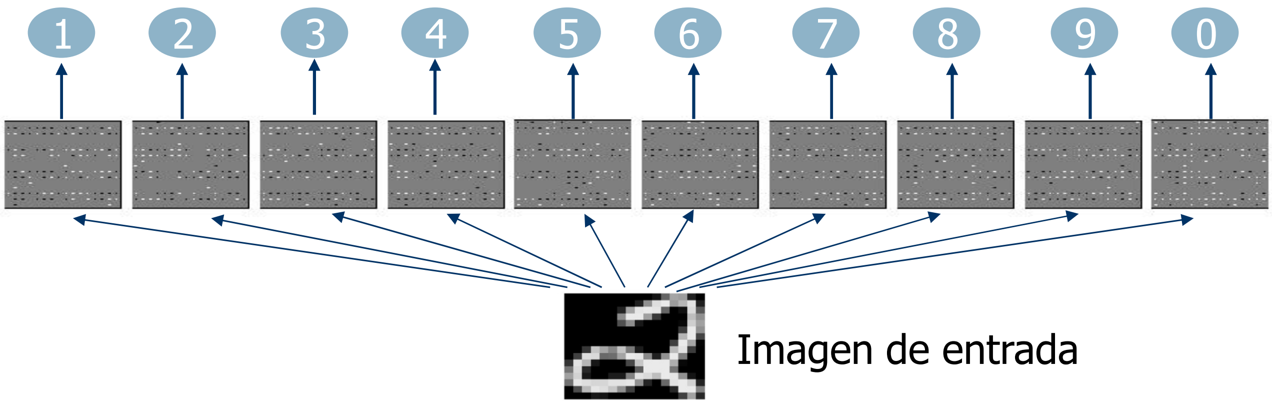


Imagen de entrada

Entrenamiento: Se le enseña una imagen a la red…

- Se incrementan los pesos asociados a los píxeles activos para el símbolo de la imagen (clase correcta).
- Se decrementan los pesos de los píxeles activos de la imagen si la red se equivoca y predice un símbolo equivocado (error).

Modelos de redes neuronales

Redes neuronales artificiales

Ejemplo de aprendizaje: Reconocimiento de dígitos (OCR)

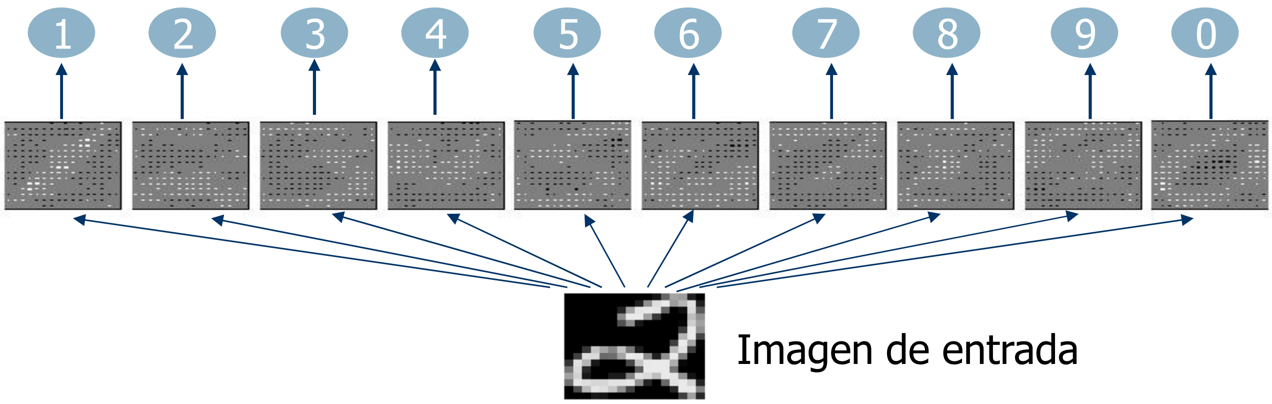


Imagen de entrada

Aprendizaje…

Modelos de redes neuronales

Redes neuronales artificiales

Ejemplo de aprendizaje: Reconocimiento de dígitos (OCR)

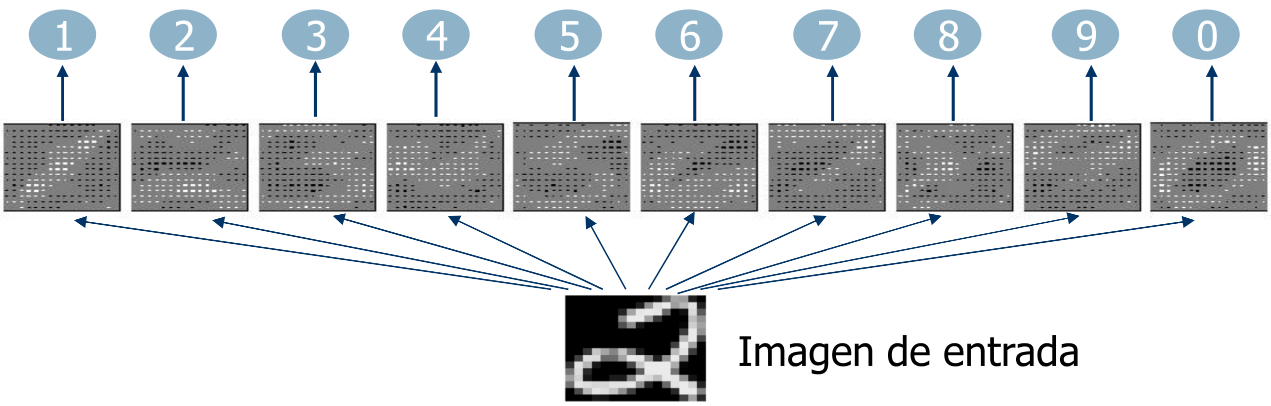


Imagen de entrada

Aprendizaje…

Modelos de redes neuronales

Redes neuronales artificiales

Ejemplo de aprendizaje: Reconocimiento de dígitos (OCR)

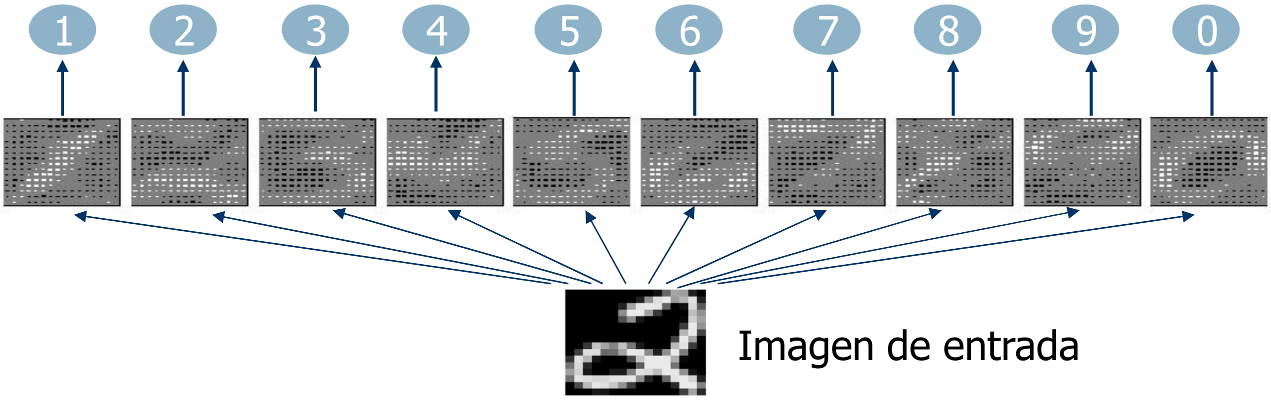


Imagen de entrada

Aprendizaje…

Modelos de redes neuronales

Redes neuronales artificiales

Ejemplo de aprendizaje: Reconocimiento de dígitos (OCR)

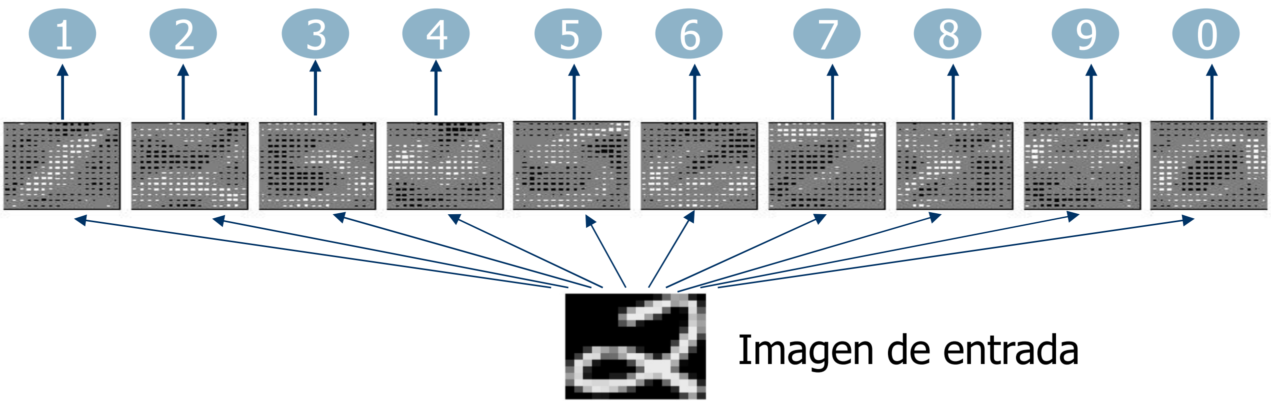


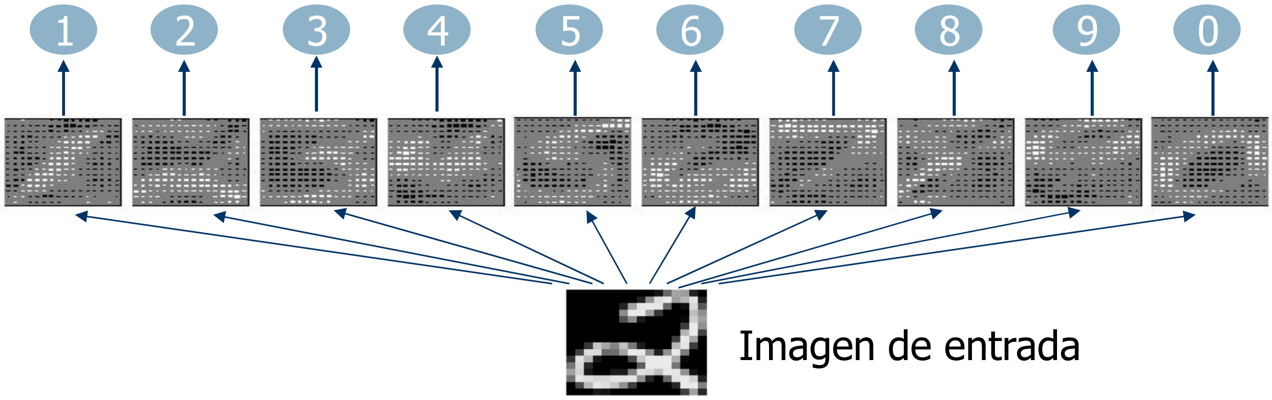
Imagen de entrada

Aprendizaje…

Modelos de redes neuronales

Redes neuronales artificiales

Ejemplo de aprendizaje: Reconocimiento de dígitos (OCR)

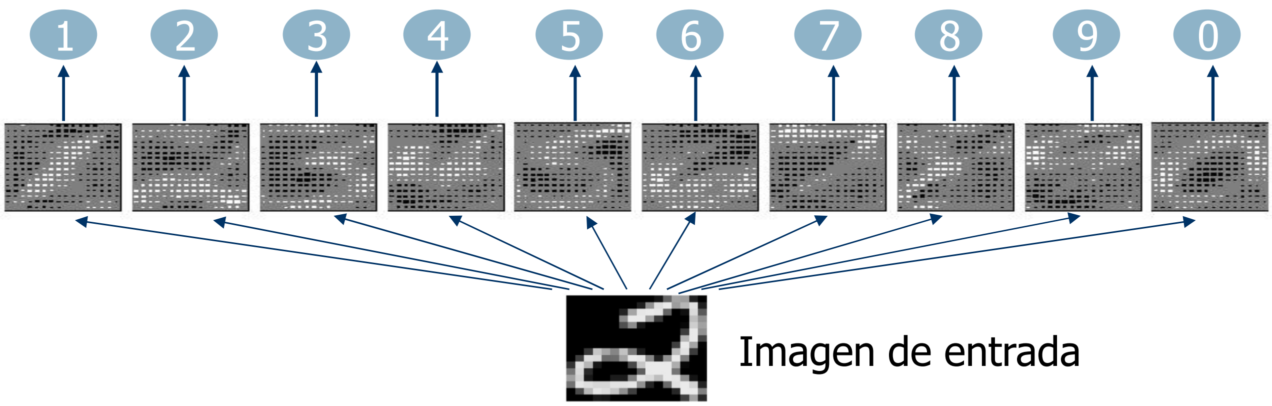


Aprendizaje…

Modelos de redes neuronales

Redes neuronales artificiales

Ejemplo de aprendizaje: Reconocimiento de dígitos (OCR)



Aprendizaje…

Redes neuronales artificiales

Ejemplo de aprendizaje: Reconocimiento de dígitos (OCR)

- Una red neuronal tan simple, con una capa de entrada y una de salida, es equivalente a tener una plantilla rígida para cada símbolo (se elige el símbolo cuya plantilla se solapa más con la imagen de entrada).
- Las distintas formas en que pueden variar los dígitos manuscritos son demasiado complicadas para que se puedan capturar con plantillas tan simples.

Redes neuronales artificiales

Ejemplo de aprendizaje: Reconocimiento de dígitos (OCR)

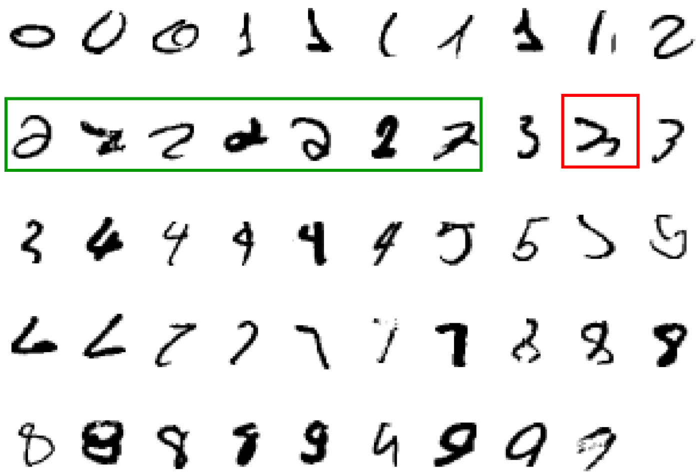
- Aprenderemos formas de capturar las variaciones de los símbolos aprendiendo sus características: capas intermedias de neuronas, a.k.a. capas ocultas.
- Podremos incluso hacerlo utilizando técnicas no supervisadas, creando una representación interna de la entrada que luego sea útil en otras tareas (p.ej. aprendizaje supervisado para clasificar símbolos).

Modelos de redes neuronales

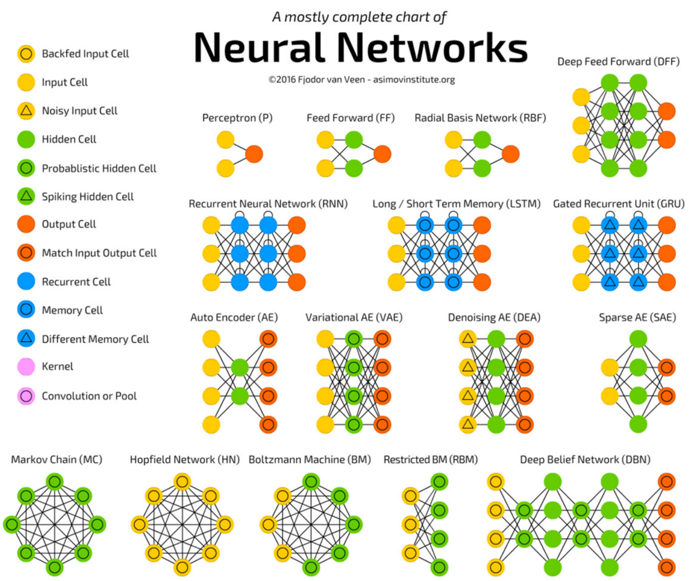
Redes neuronales artificiales

Ejemplo de aprendizaje: Reconocimiento de dígitos (OCR)

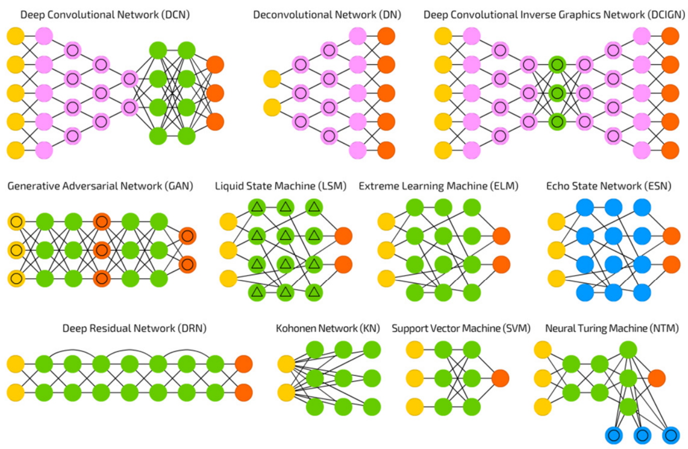
- Seremos capaces de clasificar correctamente símbolos como los siguientes la primera vez que los veamos:



Modelos de redes neuronales



El zoo de las redes neuronales



DECSAI
Departamento de Ciencias de la Computación e I.A.
Universidad de Granada

Historia de las Redes Neuronales

Fernando Berzal, berzal@acm.org

Historia

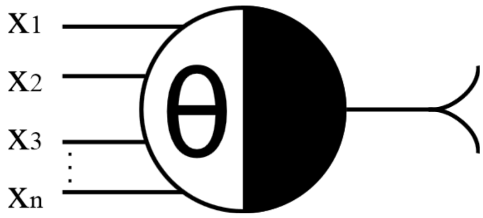
1943	Neurona de McCulloch-Pitts
1957	Perceptrón
1960	ADALINE
1969	Minsky & Papert: "Perceptrons"
1974-1986	Backpropagation
1982	Redes de Hopfield
1985	Máquinas de Boltzmann
1986	Harmonium [Restricted Boltzmann Machines]
2006	Deep Learning

Neurona de McCullock & Pitts

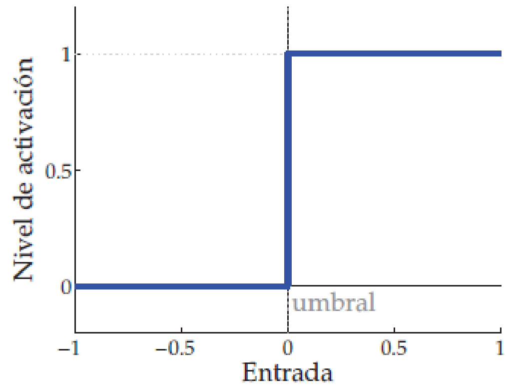
Modelo de neurona de McCulloch & Pitts

Nacimiento de las redes neuronales artificiales:

Circuitos booleanos como modelos del cerebro



Threshold Logic Unit (TLU):
Primer modelo de neurona artificial



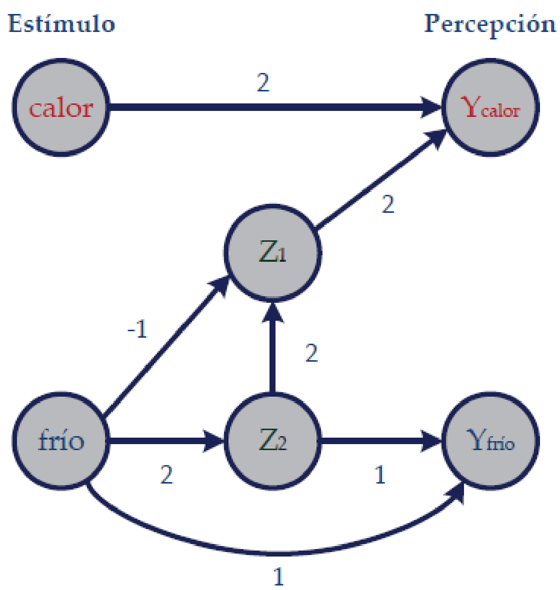
1943

Warren McCulloch & Walter Pitts:
"A logical calculus of the ideas immanent in nervous activity."
Bulletin of Mathematical Biophysics, 5:115-133.

Neurona de McCullock & Pitts

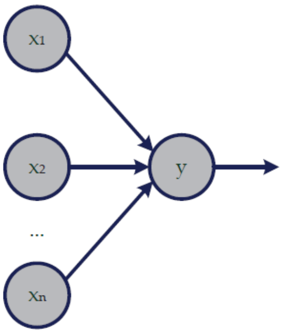
Modelo de neurona de McCulloch & Pitts

Ejemplo: Percepción fisiológica del calor y del frío

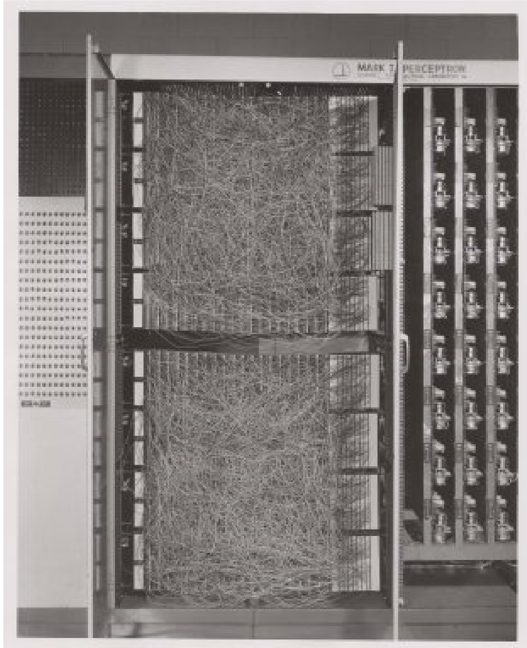


El perceptrón

Primer algoritmo
de aprendizaje supervisado



Mark I Perceptron Machine
Primera implementación…



1957

Frank Rosenblatt:
"The Perceptron - A perceiving and recognizing automaton". Report 85-460-1,
Cornell Aeronautical Laboratory, 1957.

El perceptrón

En la prensa…

New York Times

NEW NAVY DEVICE LEARNS BY DOING

Psychologist Shows Embryo of Computer Designed to Read and Grow Wiser

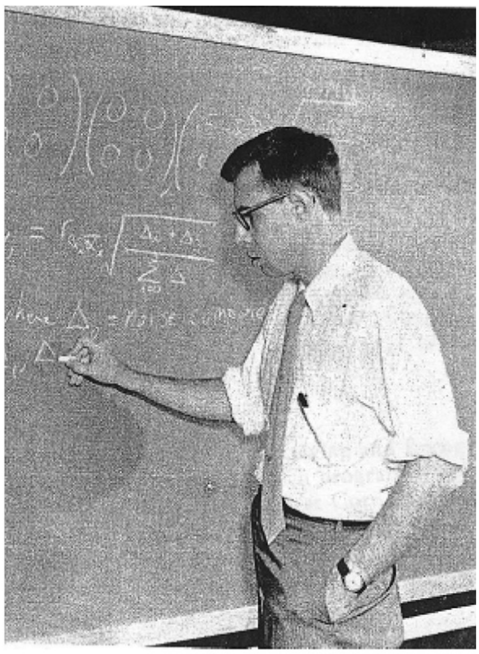
WASHINGTON, July 7 (UPI)—The Navy revealed the embryo of an electronic computer today that it expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence.

The embryo—the Weather Bureau's $2,000,000 "704" computer—learned to differentiate between right and left after fifty attempts in the Navy's demonstration for newsmen.

The service said it would use this principle to build the first of its Perceptron thinking machines that will be able to read and write. It is expected to be finished in about a year at a cost of $100,000.

Dr. Frank Rosenblatt, designer of the Perceptron, conducted the demonstration. He said the machine would be the first device to think as the human brain. As do human beings, Perceptron will make mistakes at first, but will grow wiser as it gains experience, he said.

Dr. Rosenblatt, a research psychologist at the Cornell Aeronautical Laboratory, Buffalo, said Perceptrons might be fired to the planets as mechanical space explorers.

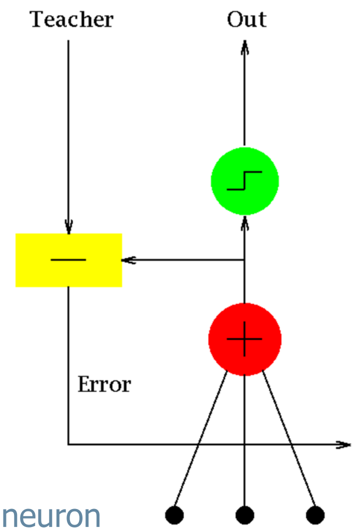


1958

El ADALINE

ADALINE [Adaptive Linear Element/Neuron]

Red neuronal de una sola capa
y dispositivo físico construido con memristores.



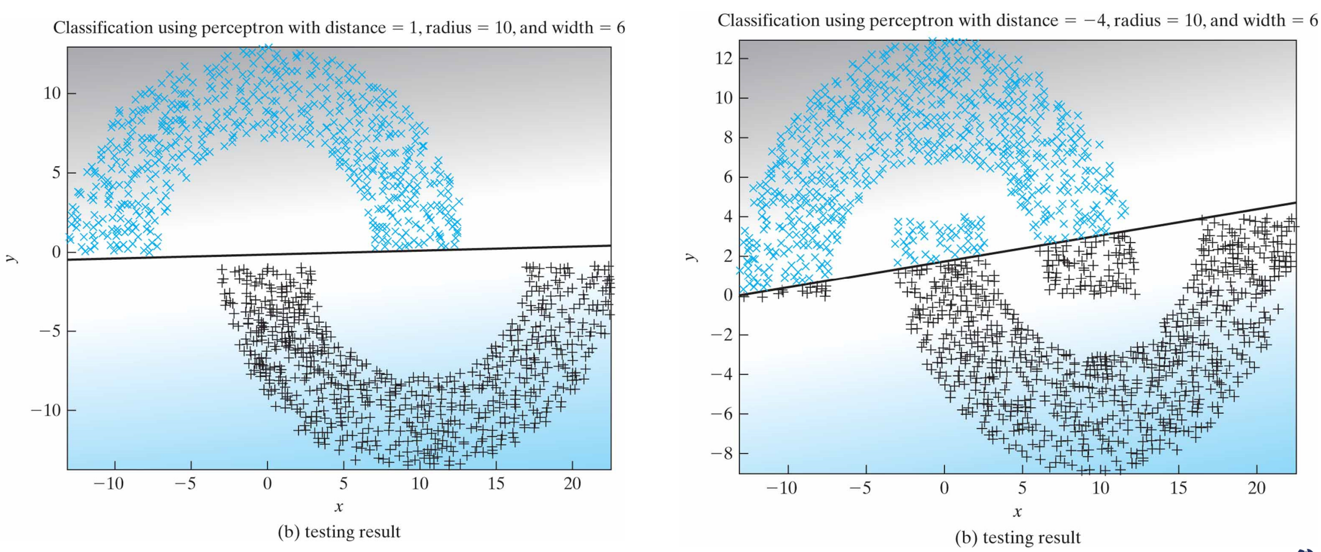
1960

Bernard Widrow:
An adaptive "ADALINE" neuron
using chemical "memristors"
Technical Report 1553-2
Stanford University, 1960

El perceptrón

En realidad…

Un clasificador lineal

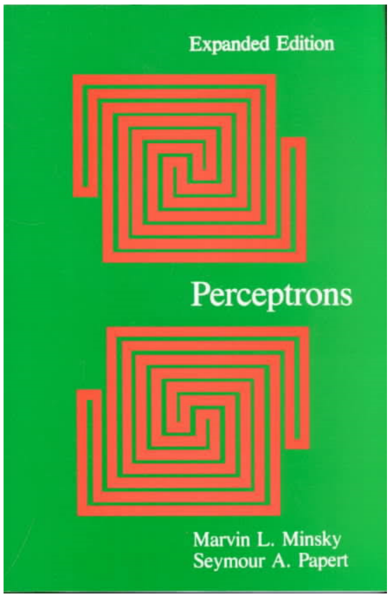


[Haykin: "Neural Networks and Learning Machines", 3rd edition]

El perceptrón

Análisis de las capacidades
y limitaciones del perceptrón:

- Muchos pensaron que esas limitaciones se extendían a todos los modelos de redes neuronales, aunque no es así.
- Abandono de los modelos conexionistas.
- La investigación en redes neuronales casi desaparece.

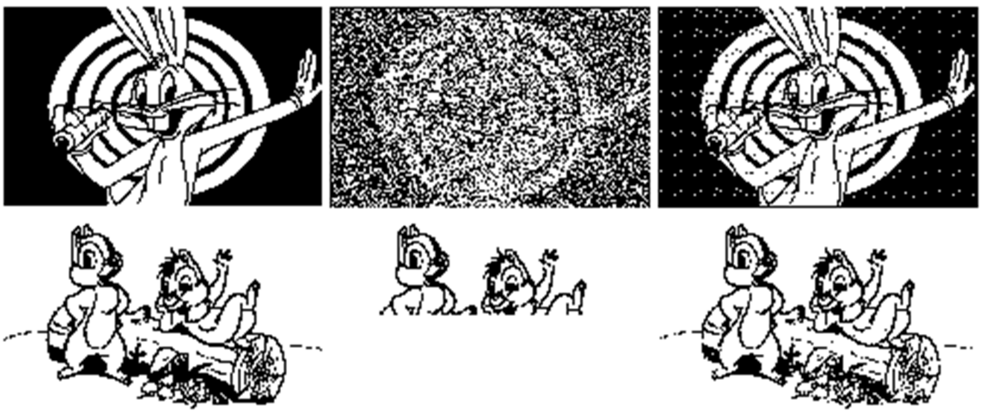


1969

Marvin Minsky & Seymour Papert:
"Perceptrons: An Introduction to Computational Geometry". MIT Press, expanded edition, 1987
ISBN 0262631113

Redes de Hopfield

Redes recurrentes
que funcionan como memorias asociativas



Original · Degraded · Reconstruction

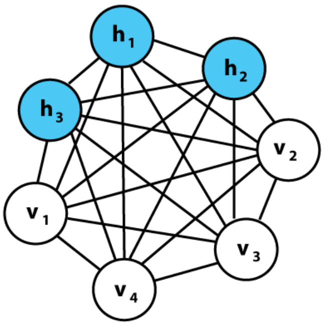
1982

John J. Hopfield:
"Neural networks and physical systems with emergent collective computational abilities"
Proceedings of the National Academy of Sciences
PNAS 79(8):2554–2558, 1982

Máquinas de Boltzmann

Un contraejemplo:

Sí que se pueden entrenar redes con múltiples capas de neuronas.



1985

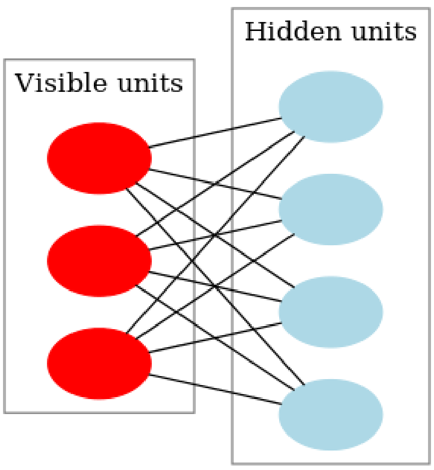
David H. Ackley, Geoffrey E. Hinton & Terrence J. Sejnowski: "A Learning Algorithm for Boltzmann Machines", Cognitive Science 9(1):147–169, 1985. DOI 10.1207/s15516709cog0901_7

Máquinas de Boltzmann

Máquinas de Boltzmann restringidas

Harmonium = Restricted Boltzmann Machines

(máquinas de Boltzmann con estructura fija: grafos bipartidos con una capa de neuronas ocultas y una capa de neuronas "visibles", sin conexiones entre las neuronas de la misma capa)



1986

Paul Smolensky: "Information Processing in Dynamical Systems: Foundations of Harmony Theory", incluido en David E. Rumelhart & James L. McLelland, "Parallel Distributed Processing: Explorations in the Microstructure of Cognition", Volume 1: Foundations, chapter 6, pp. 194-281. MIT Press, 1986. ISBN 0-262-68053-X.

Modelos alternativos

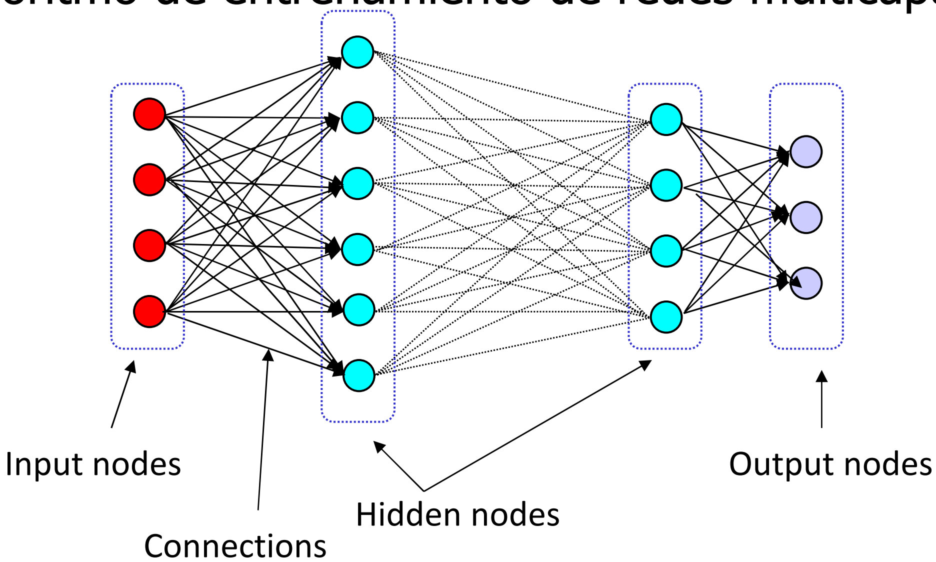
Otros modelos clásicos de redes neuronales artificiales

- Neocognitron
  Kunihiko Fukushima, 1980
- Self-Organizing Map [SOM]
  Teuvo Kohonen, 1982
- Counter-Propagation
  Robert Hecht-Nielsen, 1986
- Adaptive Resonance Theory [ART]
  Stephen Grossberg & Gail Carpenter, 1987
- Bidirectional Associative Memory [BAM]
  Bart Kosko, 1988

Backpropagation

Renacimiento de las redes neuronales artificiales

Algoritmo de entrenamiento de redes multicapa

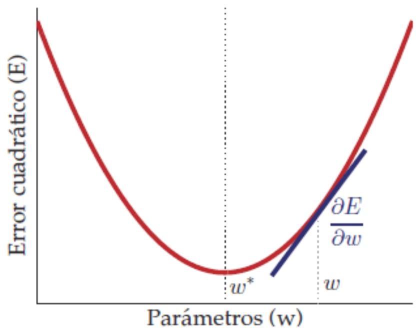


1986

David E. Rumelhart, Geoffrey E. Hinton & Ronald J. Williams: "Learning representations by back-propagating errors" Nature 323(6088):533–536, 1986. DOI 10.1038/323533a0

Historia de las redes neuronales artificiales
Backpropagation

Algoritmo de entrenamiento

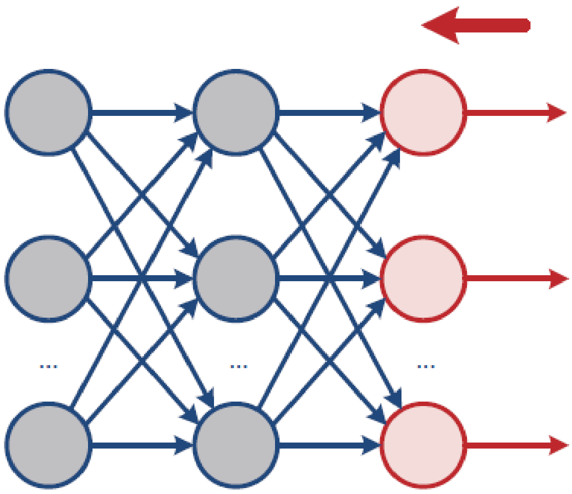


$$\Delta w_i = -\eta \frac{\partial E}{\partial w_i}$$

1986

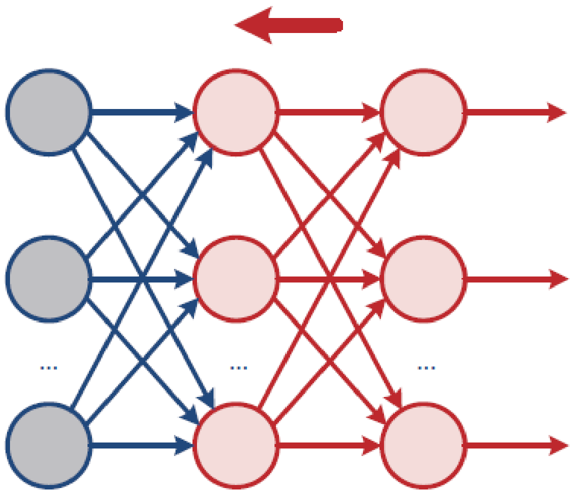
Historia de las redes neuronales artificiales
Backpropagation

Propagación de errores δE/δy



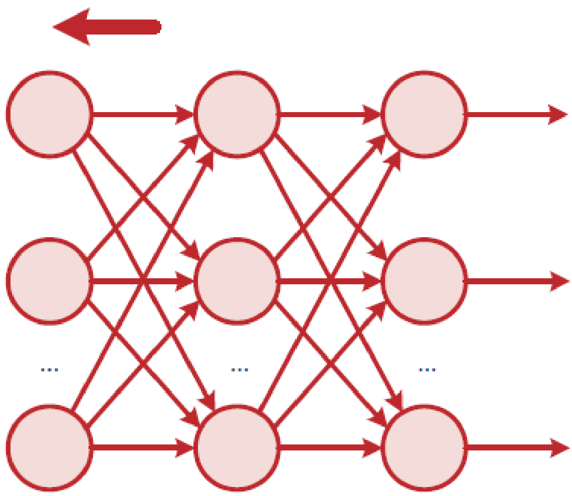
Backpropagation

Propagación de errores δE/δy



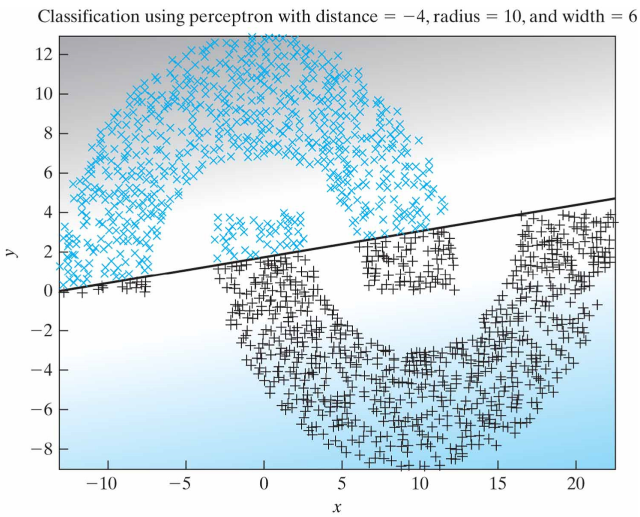
Backpropagation

Propagación de errores δE/δy

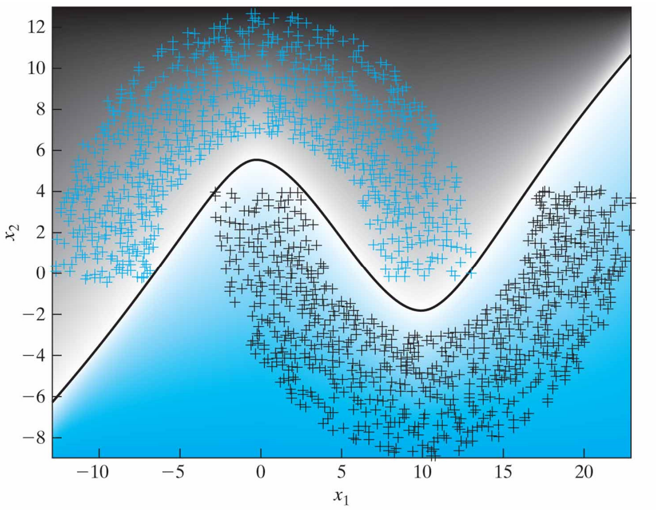


Backpropagation

El resultado…



(b) testing result



(b) Testing result

Perceptrón

Red multicapa

Backpropagation

Algoritmo redescubierto en múltiples ocasiones…

- Sistemas de control (años 60)

  Arthur E. Bryson, W.F. Denham & S.E. Dreyfus: "Optimal programming problems with inequality constraints. I: Necessary conditions for extremal solutions." AIAA J. 1(11):2544-2550, **1963**.

  Arthur E, Bryson & Yu-Chi Ho: "Applied optimal control: optimization, estimation, and control." Blaisdell Publishing Company / Xerox College Publishing, p. 481, **1969**.

- Diferenciación automática (años 70)

  Seppo Linnainmaa: The representation of the cumulative rounding error of an algorithm as a Taylor expansion of the local rounding errors. Master's Thesis (in Finnish), University of Helsinki, 6–7, **1970**.

  Seppo Linnainmaa: "Taylor expansion of the accumulated rounding error". BIT Numerical Mathematics. 16(2):146–160, **1976**. DOI 10.1007/bf01931367.

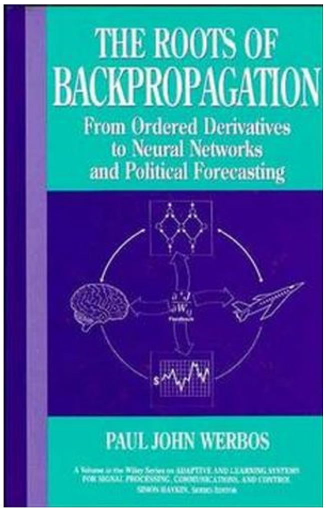
1986???

Backpropagation

Algoritmo redescubierto en múltiples ocasiones…

- Redes neuronales (1974!!!)
  Paul John Werbos: "Beyond Regression: New Tools for Prediction and Analysis in the Behavioral Sciences." PhD thesis, Harvard University, **1974**.

Paul John Werbos:
"The Roots of Backpropagation:
From Ordered Derivatives
to Neural Networks and Political Forecasting."
John Wiley & Sons, Inc., 1994.
ISBN 0471598976



1986???

Historia de las redes neuronales artificiales

Backpropagation

Política & Publicaciones

Referencias bibliográficas del artículo de Nature

Learning representations by back-propagating errors

David E. Rumelhart*, Geoffrey E. Hinton† & Ronald J. Williams*

Received 1 May; accepted 31 July 1986.

1. Rosenblatt, F. *Principles of Neurodynamics* (Spartan, Washington, DC, 1961).
2. Minsky, M. L. & Papert, S. *Perceptrons* (MIT, Cambridge, 1969).
3. Le Cun, Y. *Proc. Cognitiva* **85**, 599–604 (1985).
4. Rumelhart, D. E., Hinton, G. E. & Williams, R. J. in *Parallel Distributed Processing: Explorations in the Microstructure of Cognition.* Vol. 1: *Foundations* (eds Rumelhart, D. E. & McClelland, J. L.) 318–362 (MIT, Cambridge, 1986).

Backpropagation

Política & Publicaciones

Geoffrey Hinton interview

Neural Networks & Deep Learning

coursera

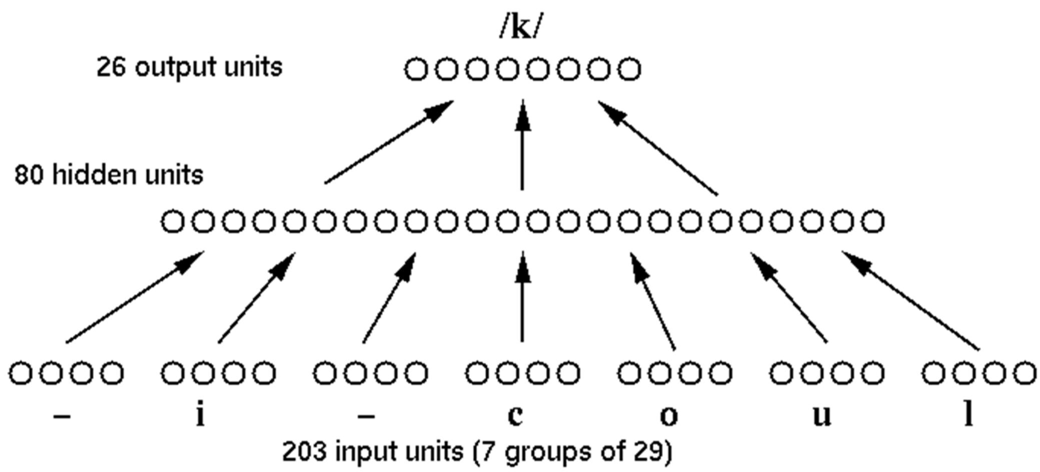
deeplearning.ai

"... we managed to get a paper into Nature in 1986. And **I did quite a lot of political work to get the paper accepted**. I figured out that one of the referees was probably going to be Stuart Sutherland, who was a well known psychologist in Britain. And I went to talk to him for a long time, and explained to him exactly what was going on. And he was very impressed by the fact that we showed that backprop could learn representations for words..."

Backpropagation

NETTalk

Síntesis de voz



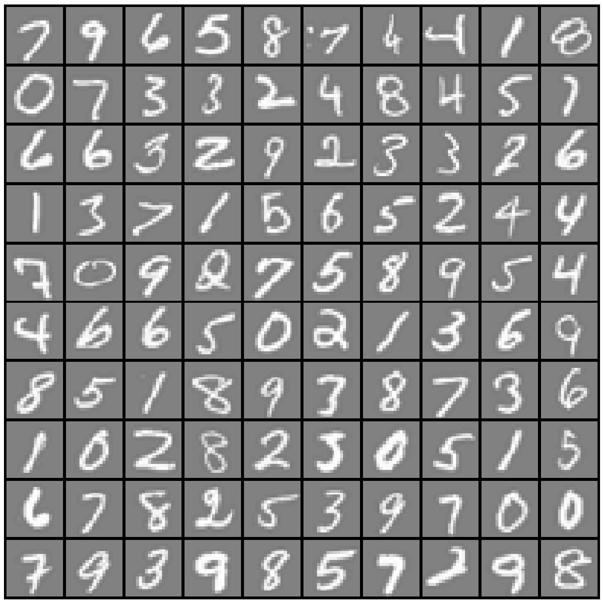
1986

Terrence J. Sejnowski & Charles Rosenberg: "NETtalk: a parallel network that learns to read aloud," Cognitive Science, 14, 179-211, 1986.

Redes convolutivas

The MNIST database of handwritten digits

http://yann.lecun.com/exdb/mnist/

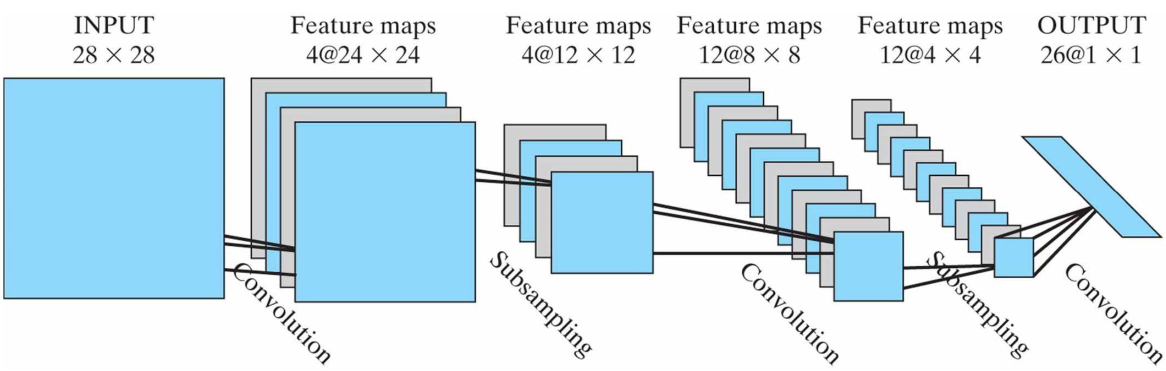


1990s

Redes convolutivas

LeNet

http://yann.lecun.com/exdb/lenet/

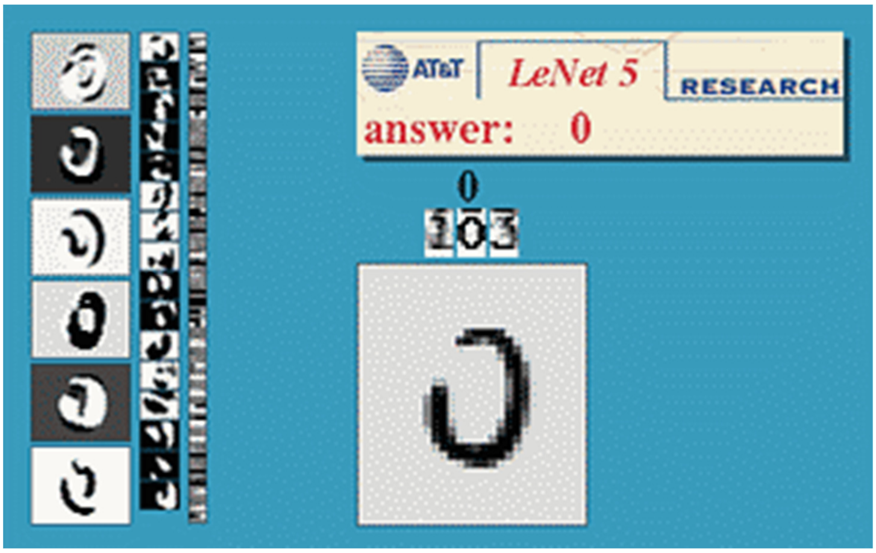


1990s

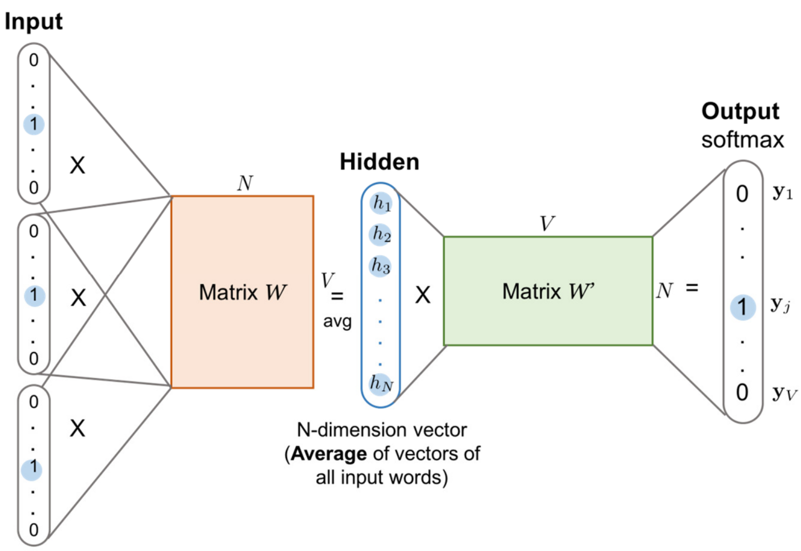
Redes convolutivas

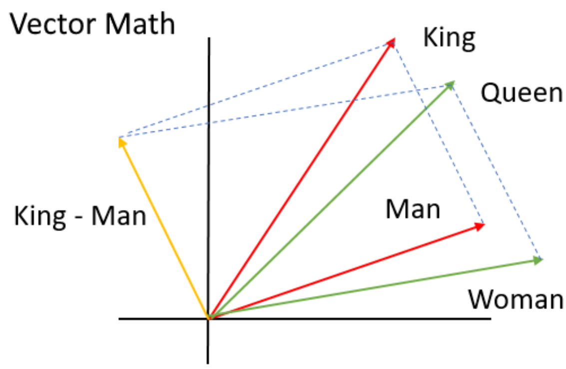
LeNet

http://yann.lecun.com/exdb/lenet/



Word embeddings



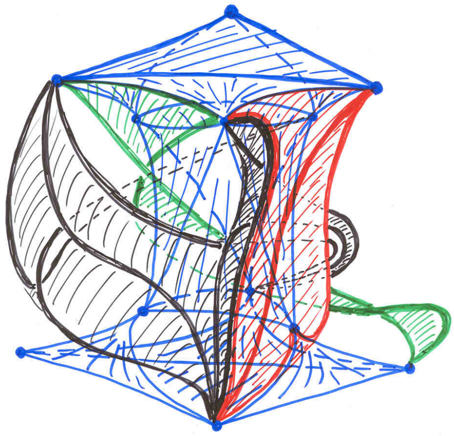


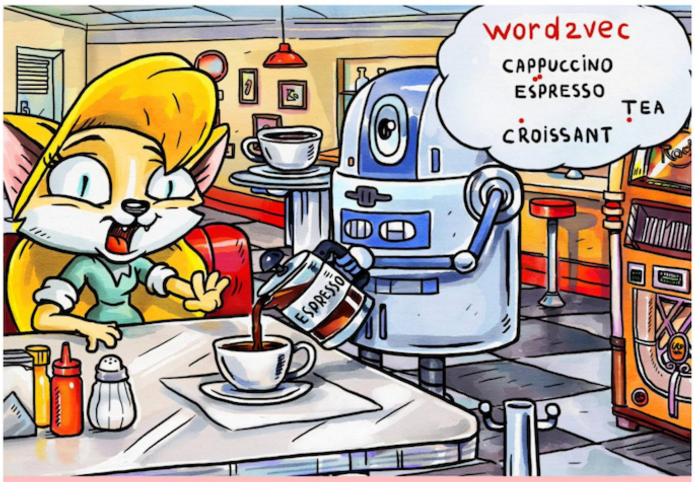
2000

Yoshua Bengio, Réjean Ducharme, Pascal Vincent
"A neural probabilistic language model."
NIPS 2000: 932-938
JMLR 3:1137-1155, 2003

Word embeddings

word2vec





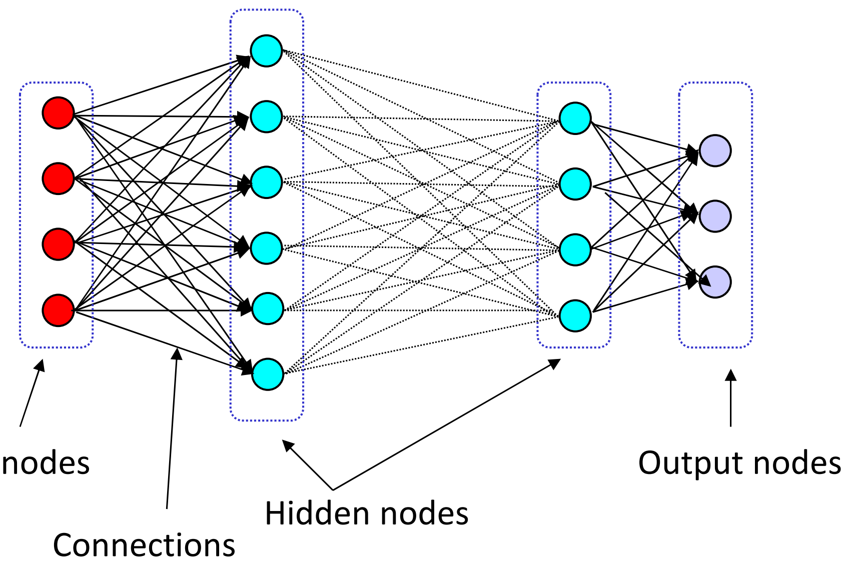
- Espresso? But I ordered a cappuccino!
- Don't worry, the cosine distance between them is so small that they are almost the same thing.

2000s

Tomas Mikolov et al.: "Efficient Estimation of Word Representations in Vector Space" arXiv:1301.3781, 2013

Deep Learning

Backpropagation no funcionaba bien con redes que tengan varias capas ocultas (salvo en el caso de las redes convolutivas)…



Deep Learning

Algunos hechos hicieron que backpropagation no tuviera éxito en tareas en las que luego se ha demostrado útil:

- Capacidad de cálculo limitada.
- Disponibilidad de conjuntos de datos etiquetados.
- "Deep networks" demasiado pequeñas (e inicializadas de forma poco razonable).

Deep Learning

2006: The Deep Breakthrough

- Hinton, Osindero & Teh « A Fast Learning Algorithm for Deep Belief Nets », *Neural Computation*, 2006
- Bengio, Lamblin, Popovici, Larochelle « Greedy Layer-Wise Training of Deep Networks », *NIPS'2006*
- Ranzato, Poultney, Chopra, LeCun « Efficient Learning of Sparse Representations with an Energy-Based Model », *NIPS'2006*

2006

[Yoshua Bengio]

Geoffrey Hinton
(University of Toronto & Google)

Yann LeCun
(AT&T Labs → NYU → Facebook)

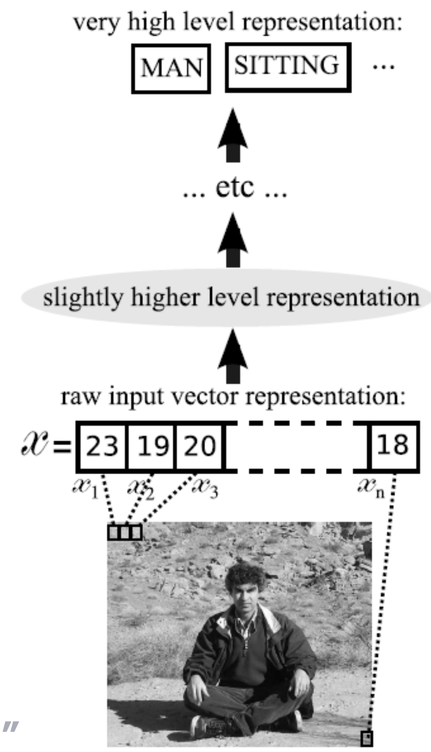
Joshua Bengio
(University of Montréal & IBM Watson)

2018

acm

A.M. TURING AWARD

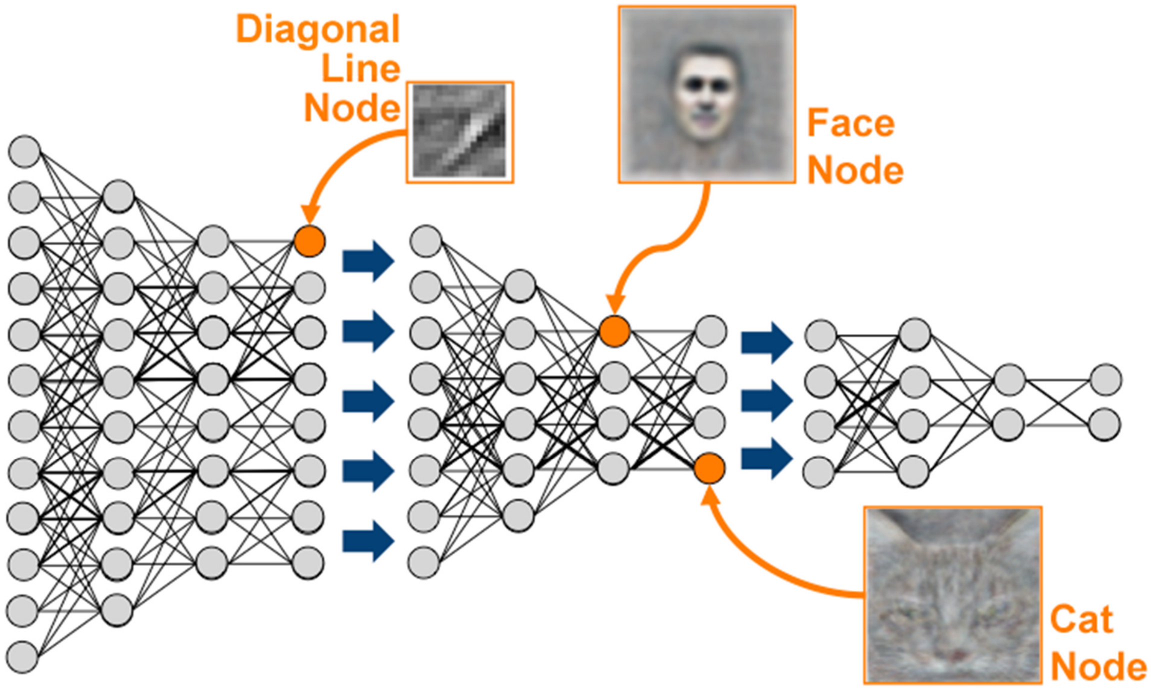
Motivación



Yoshua Bengio
"Learning Deep Architectures for AI"
2009

Deep Learning

Deep Learning as hierarchical feature representation



Deep Learning

¿Cuál era el problema de backpropagation?

- Requiere datos etiquetados,
  pero casi todos los datos disponibles no lo están.
- No resulta demasiado escalable:
  Demasiado lento en redes con múltiples capas ocultas.
- Se puede quedar atascado en óptimos locales
  (¿lejos de ser óptimos en "deep networks"?).

Política & Publicaciones

Yann LeCun @ CVPR'2012

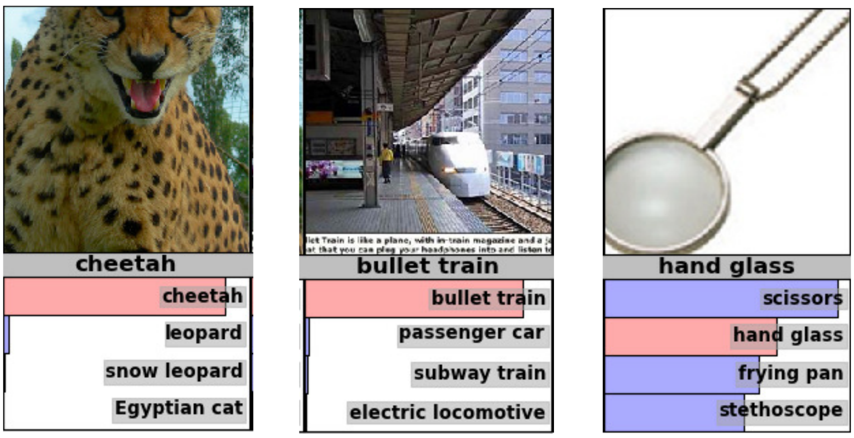
… the reviews [are] so ridiculous, that I don't know how to begin writing a rebuttal without insulting the reviewers … This time though, the reviewers were particularly clueless, or negatively biased, or both. I was very sure that this paper was going to get good reviews because: 1) it has two simple and generally applicable ideas for segmentation… 2) it uses no hand-crafted features… 3) it beats all published results on 3 standard datasets for scene parsing; 4) it's an order of magnitude faster than the competing methods.
If that is not enough to get good reviews, I just don't know what is."

Historia de las redes neuronales artificiales
Deep Learning

IMAGENET

Large Scale Visual Recognition Challenge

Reconocimiento de objetos reales en imágenes



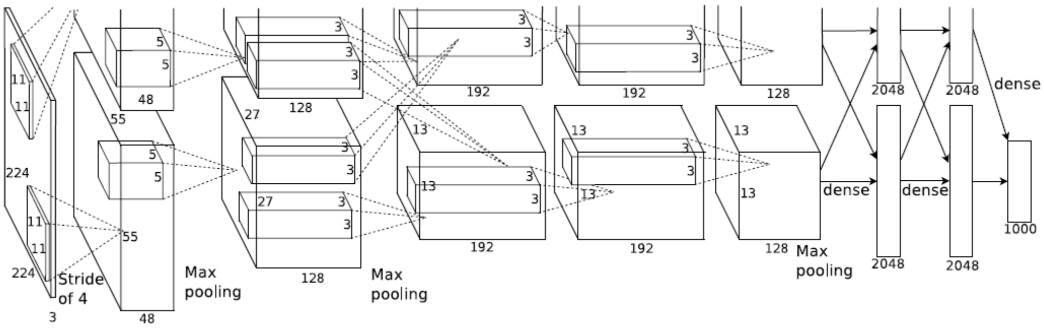
2012

Deep Learning

IMAGENET

AlexNet

Red neuronal diseñada por Alex Krizhevsky (NIPS 2012)



2012

Tasa de error

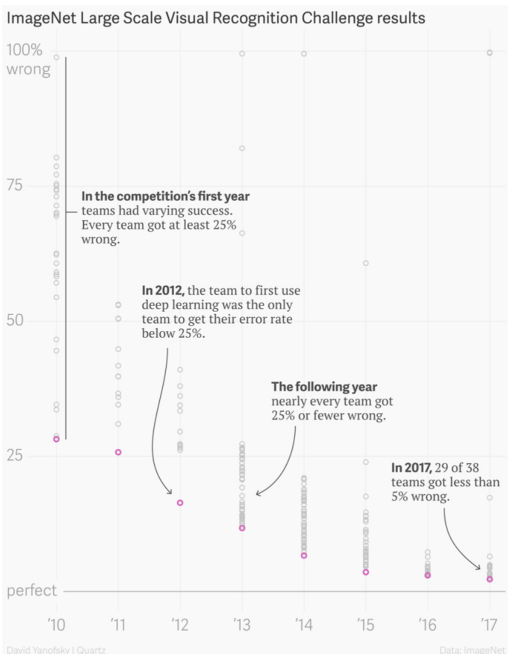
Clasificación de imágenes

16.4% vs. 25% (2010)

Deep Learning

IMAGENET

Large Scale Visual Recognition Challenge



Tasa de error

16.4% Alex Krizhevsky @ NIPS 2012

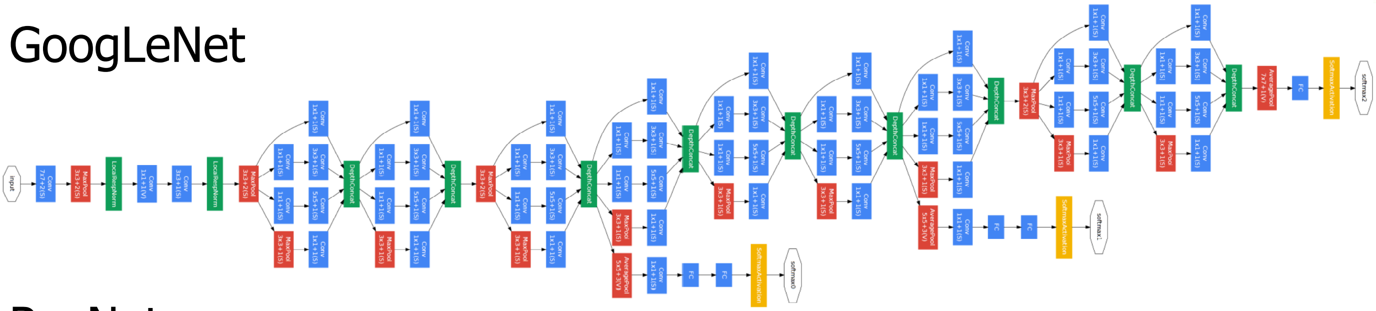
6.66% GoogLeNet @ ILSVRC'2014

4.94% PreLU-nets (MSR) @ 2015

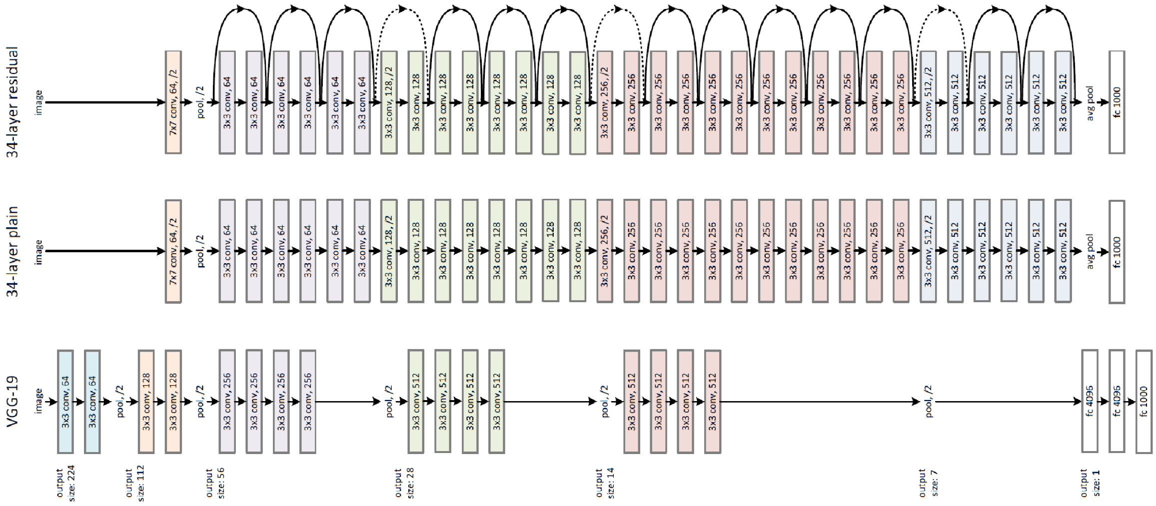
"Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification"
arXiv, 2015, http://arxiv.org/pdf/1502.01852v1.pdf

Deep Learning

GoogLeNet



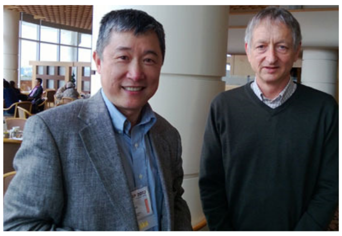
ResNets



Deep Learning

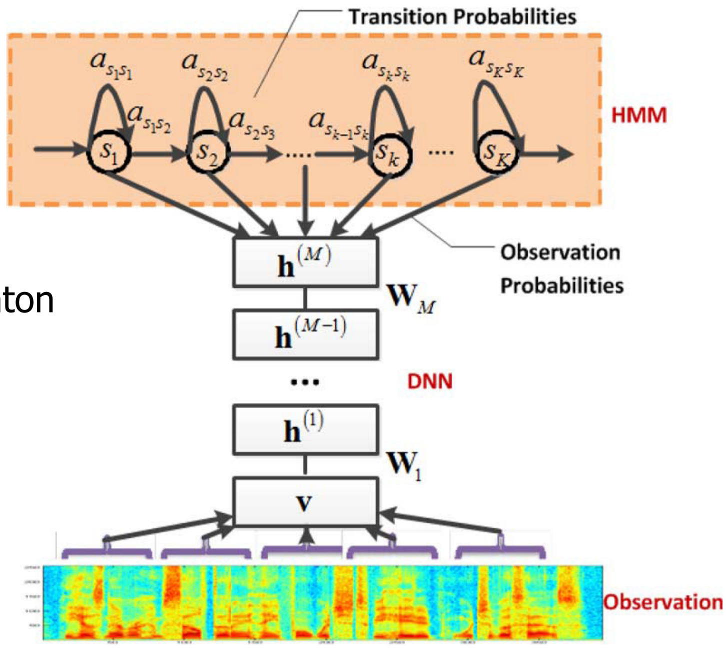
Reconocimiento de voz

Microsoft Research



Li Deng (MSR) & Geoff Hinton

Dong Yu (MSR)



Deep Learning

Reconocimiento de voz

Task	Hours of training data	Deep Neural Network	Gaussian Mixture Model	GMM with more data
Switchboard (Microsoft Research)	309	18.5%	27.4%	18.6% (2000 hrs)
English broadcast news (IBM)	50	17.5%	18.8%	
Google Voice Search (Android 4.1)	5,870	12.3% (and falling)		16.0% (>>5,870 hrs)

Microsoft Research

IBM

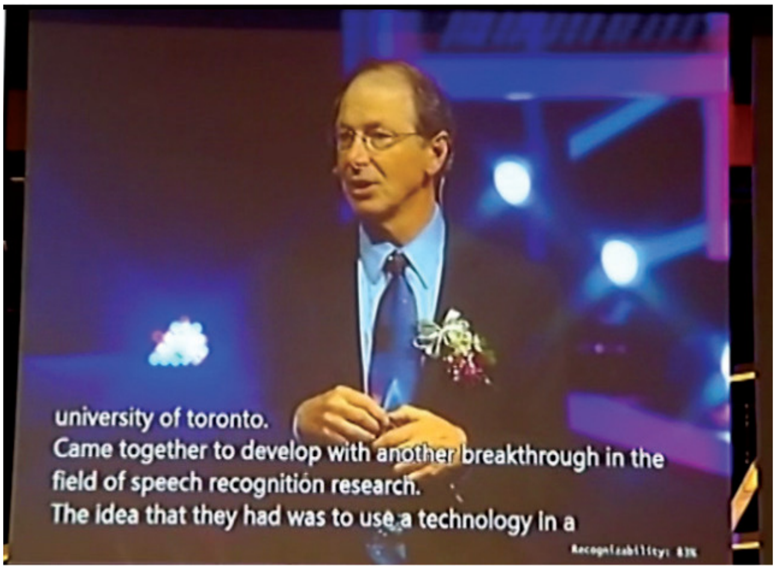
Google

2012

Geoffrey Hinton, Li Deng, Dong Yu et al.:
"Deep Neural Networks
for Acoustic Modeling in Speech Recognition"
IEEE Signal Processing Magazine, 2012

Deep Learning

Traducción simultánea



2012

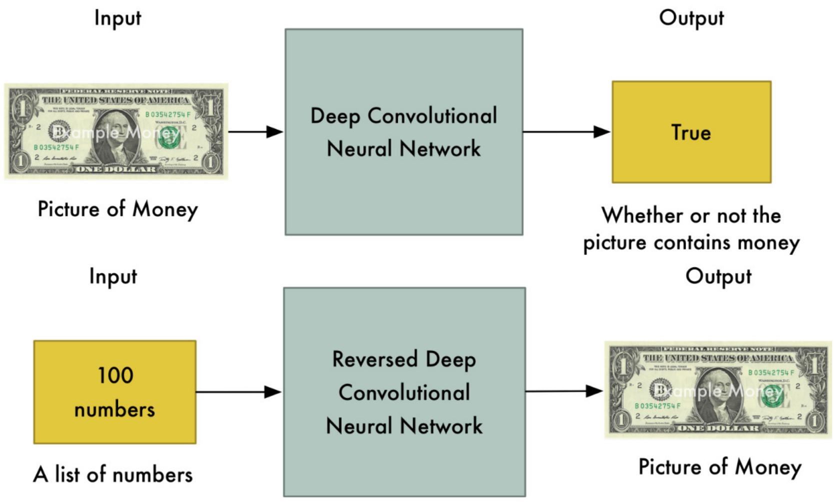
Historia de las redes neuronales artificiales

Deep Learning

GANs [Generative Adversarial Networks]

Discriminador

Generador

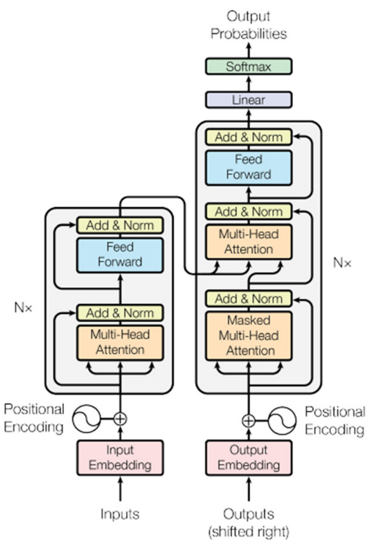


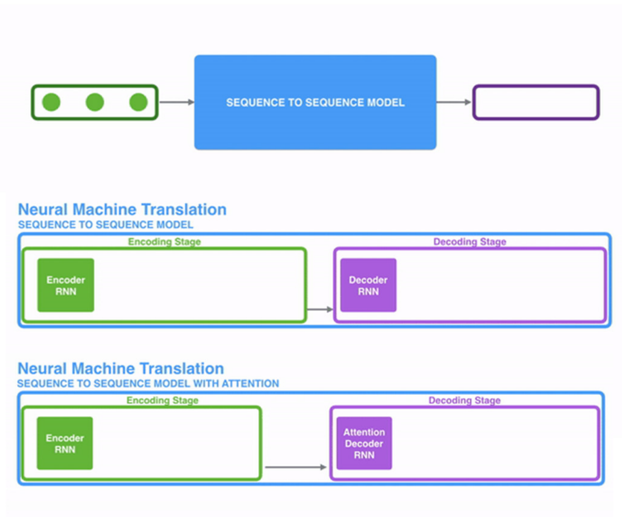
2014

Historia de las redes neuronales artificiales

Deep Learning

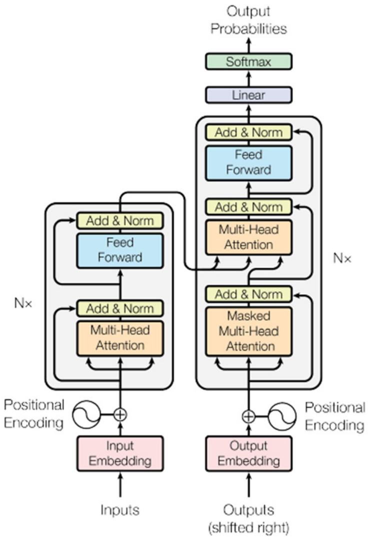
Transformers: “Attention is All You Need”

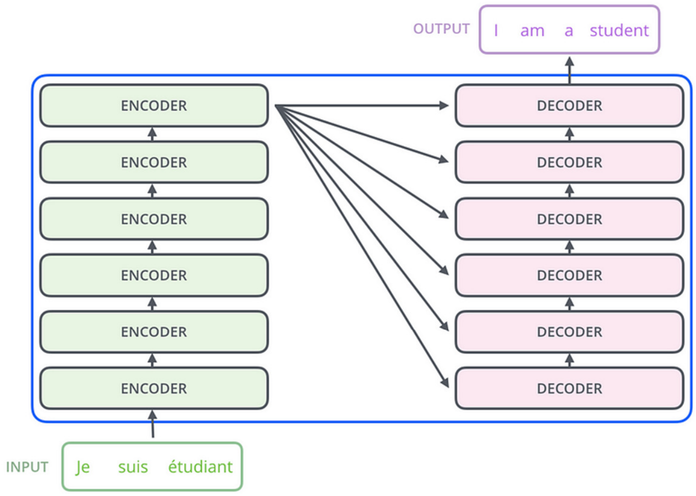




2017

Transformers: "Attention is All You Need"





2017

Historia de las redes neuronales artificiales
Deep Learning

DALL-E

Versión modificada de GPT-3
para generar imágenes de 256x256
a partir de descripciones textuales
[12B parámetros]

DALL-E 2 (2022) 1024x1024
@ Bing Creator
https://www.bing.com/create

vibrant portrait painting of Salvador Dalí with a robotic half face

a dolphin in an astronaut suit on saturn, artstation

2021

Midjourney

https://www.midjourney.com/

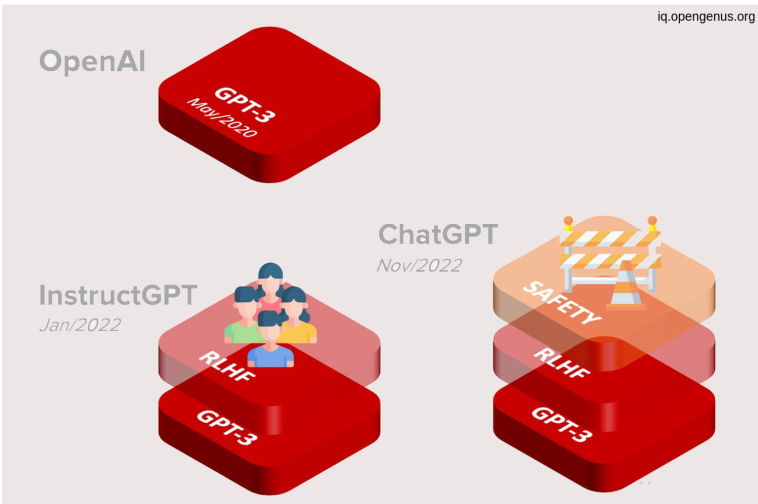
2022

Discord

Historia de las redes neuronales artificiales
Deep Learning

ChatGPT

GPT-3.5
175B parámetros
+
RLHF
Reinforcement Learning
from Human Feedback
+
Safety features



2022

Deep Learning

GPT-4

GPT-4 Technical Report

OpenAI*

2 Scope and Limitations of this Technical Report

This report focuses on the capabilities, limitations, and safety properties of GPT-4. GPT-4 is a Transformer-style model [39] pre-trained to predict the next token in a document, using both publicly available data (such as internet data) and data licensed from third-party providers. The model was then fine-tuned using Reinforcement Learning from Human Feedback (RLHF) [40]. Given both the competitive landscape and the safety implications of large-scale models like GPT-4, this report contains no further details about the architecture (including model size), hardware, training compute, dataset construction, training method, or similar.

2023

Historia

1956: Psychologist Frank Rosenblatt uses theories about how brain cells work to design the perceptron, an artificial neural network that can be trained to categorize simple shapes.

1969: AI pioneers Marvin Minsky and Seymour Papert write a book critical of perceptrons that quashes interest in neural networks for decades.

1986: Yann LeCun and Geoff Hinton perfect backpropagation to train neural networks that pass data through successive layers of artificial neurons, allowing them to learn more complex skills.

1987: Terry Sejnowski at Johns Hopkins University creates a system called NETtalk that can be trained to pronounce text, going from random babbling to recognizable speech.

1990: At Bell Labs, LeCun uses backpropagation to train a network that can read handwritten text. AT&T later uses it in machines that can read checks.

1995: Bell Labs mathematician Vladimir Vapnik publishes an alternative method for training software to categorize data such as images. This sidelines neural networks again.

2006: Hinton's research group at the University of Toronto develops ways to train much larger networks with tens of layers of artificial neurons.

June 2012: Google uses deep learning to cut the error rate of its speech recognition software by 25 percent.

October 2012: Hinton and two colleagues from the University of Toronto win the largest challenge for software that recognizes objects in photos, almost halving the previous error rate.

March 2013: Google buys DNN Research, the company founded by the Toronto team to develop their ideas. Hinton starts working at Google.

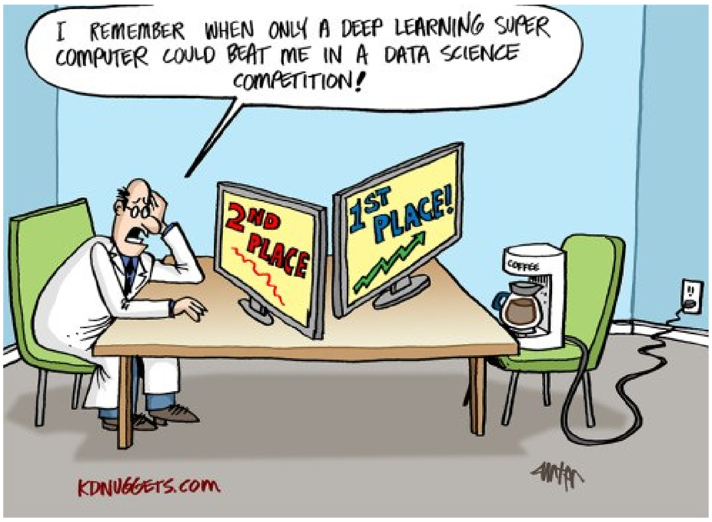
March 2014: Facebook starts using deep learning to power its facial recognition Vfeature, which identifies people in uploaded photos.

May 2015: Google Photos launches. The service uses deep learning to group photos of the same people and let you search your snapshots using terms like "beach" or "dog."

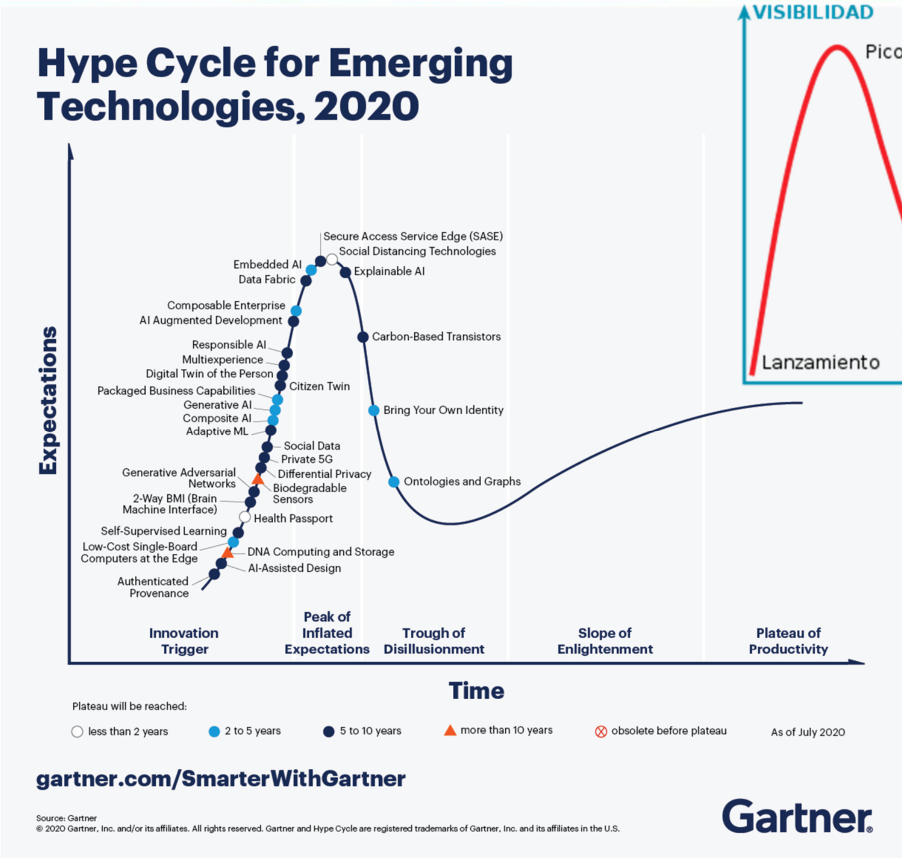
MIT Technology Review

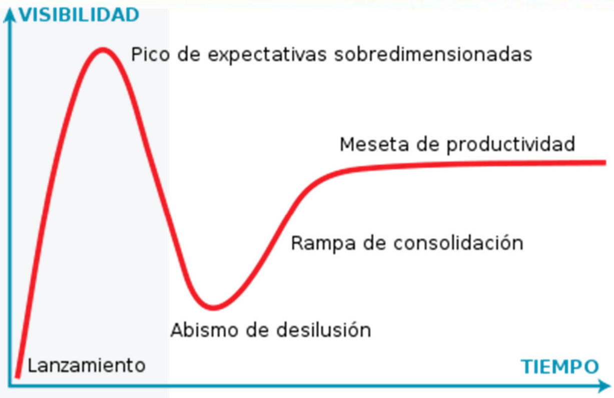
MIT Technology Review: "Teaching Machines to Understand Us", August 2015

Deep Learning

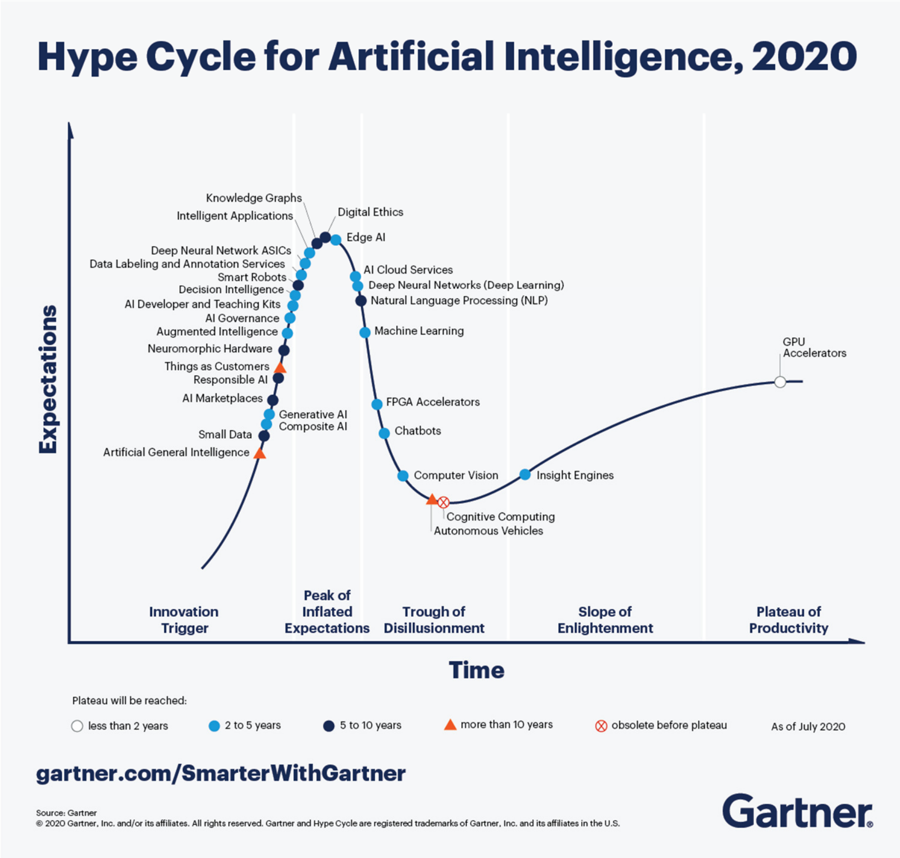


Deep Learning

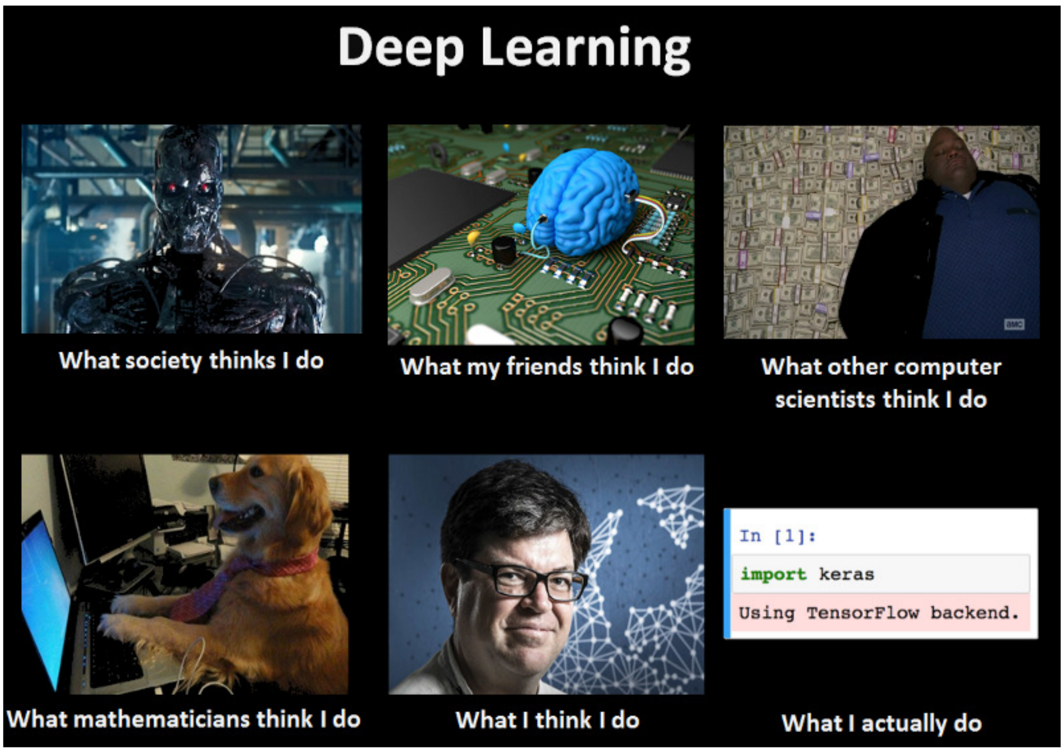




Deep Learning



En la práctica…



DECSAI
Departamento de Ciencias de la Computación e I.A.
Universidad de Granada

RN&DL – Información adicional

Fernando Berzal, berzal@acm.org

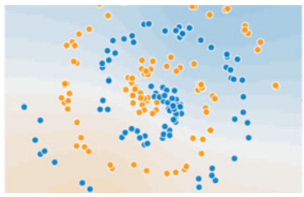
Demos

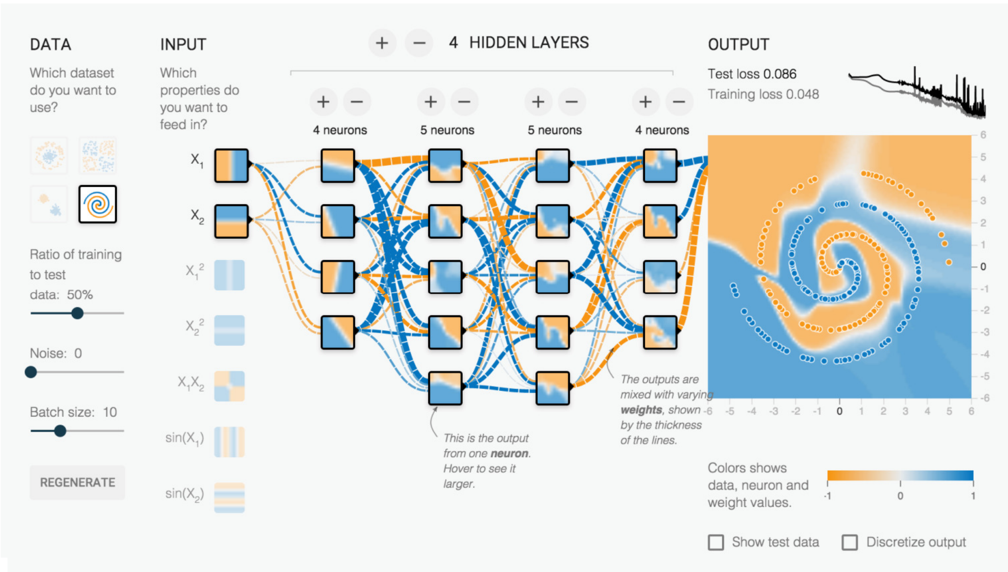
Para jugar un poco…

http://playground.tensorflow.org/

http://ml4a.github.io/demos/

http://demos.algorithmia.com/classify-places/

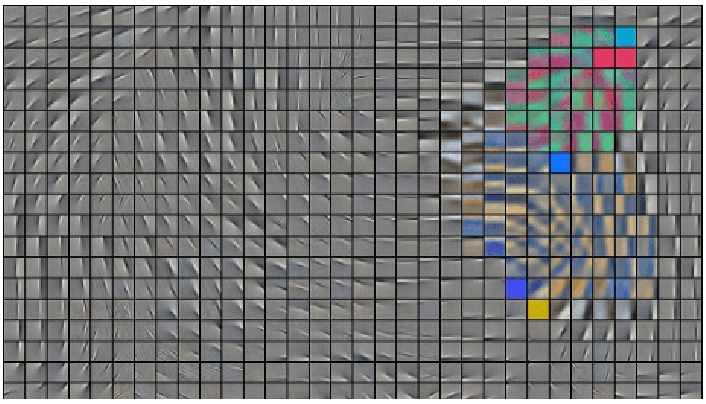




Cursos

Neural Networks for Machine Learning
by Geoffrey Hinton
(University of Toronto & Google)
https://www.coursera.org/course/neuralnets

coursera



UNIVERSITY OF TORONTO

Cursos

Deep Learning Specialization
by Andrew Ng, 2017

- Neural Networks and Deep Learning
- Improving Deep Neural Networks: Hyperparameter tuning, Regularization and Optimization
- Structuring Machine Learning Projects
- Convolutional Neural Networks
- Sequence Models

coursera

deeplearning.ai

https://www.coursera.org/specializations/deep-learning

Cursos & Tutoriales

- **Deep Learning Tutorial**
  Andrew Ng et al. (Stanford University)
  http://ufldl.stanford.edu/tutorial/

- **Deep Learning: Methods and Applications**
  Li Deng & Dong Yu (Microsoft Research)
  http://research.microsoft.com/apps/pubs/default.aspx?id=209355

- **Deep Learning for Natural Language Processing**
  Richard Socher et al. (Stanford University CS224d)
  http://cs224d.stanford.edu/

- **Convolutional Neural Networks for Visual Recognition**
  Andrej Karpathy (Stanford University CS231n)
  http://cs231n.github.io/

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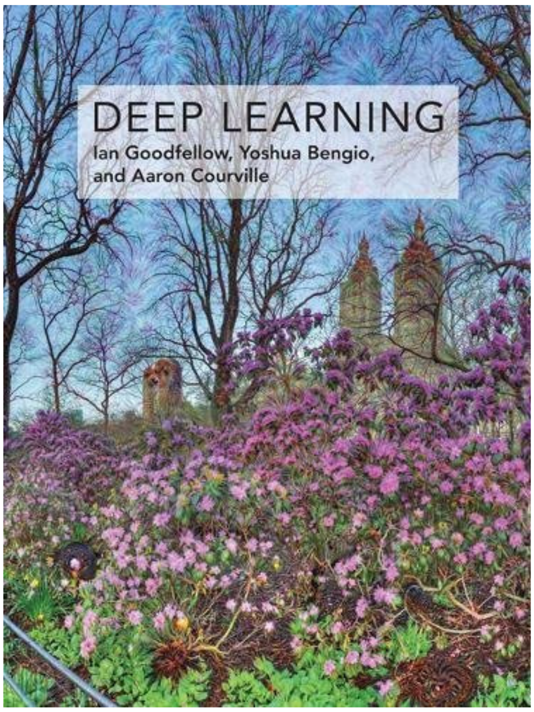
Lecturas recomendadas

Ian Goodfellow,
Yoshua Bengio
& Aaron Courville:
Deep Learning
MIT Press, 2016
ISBN 0262035618

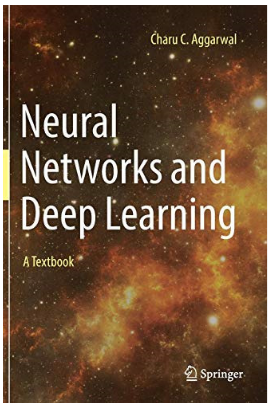


http://www.deeplearningbook.org

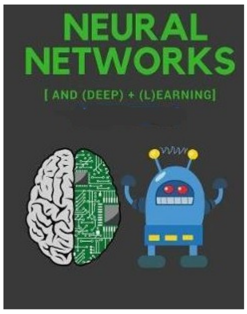
Bibliografía

Lecturas complementarias

Fundamentos



- Charu C. Aggarwal:
  Neural Networks and Deep Learning:
  A Textbook.
  Springer, 2018
  ISBN 3319944622
  http://link.springer.com/978-3-319-94463-0



- Michael Nielsen:
  Neural Networks and Deep Learning:
  Determination Press, 2015
  http://neuralnetworksanddeeplearning.com/

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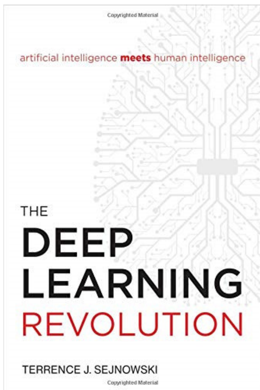
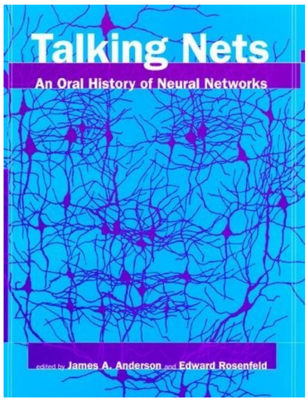
Lecturas complementarias

Evolución histórica





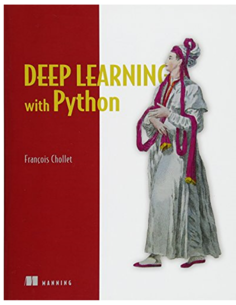
- Terrence J. Sejnowski:
  The Deep Learning Revolution
  MIT Press, 2018
  ISBN 026203803X
  https://mitpress.mit.edu/books/deep-learning-revolution

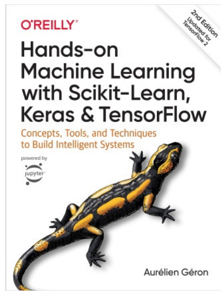
- James A. Anderson & Edward Rosenfeld (editores):
  Talking Nets: An Oral History of Neural Networks
  The MIT Press, 1998
  ISBN 0262011670
  https://mitpress.mit.edu/books/talking-nets

Bibliografía

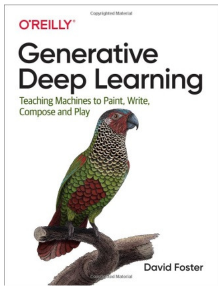
Lecturas complementarias

Con una orientación práctica





- François Chollet:
  Deep Learning with Python
  Manning Publications, 2018
  ISBN 1617294438
  https://github.com/fchollet/deep-learning-with-python-notebooks

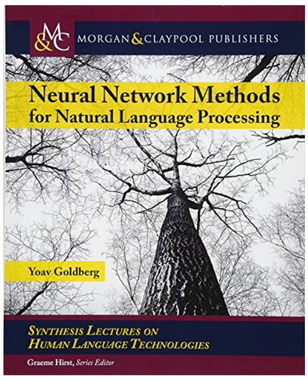


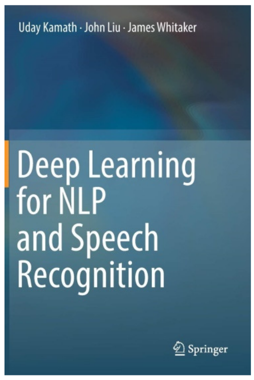
- Aurélien Géron: **Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems**
  O'Reilly, 2nd edition, 2019, ISBN 1627052984
  https://github.com/ageron/handson-ml2
- David Foster: **Generative Deep Learning: Teaching Machines to Paint, Write, Compose, and Play**
  O'Reilly, 2019, ISBN 1492041947
  https://github.com/davidADSP/GDL_code

Bibliografía

Lecturas complementarias

Áreas de aplicación, p.ej. NLP





- Yoav Goldberg:
  Neural Network Methods in Natural Language Processing
  Morgan & Claypool Publishers, 2017
  ISBN 1627052984
  https://doi.org/10.2200/S00762ED1V01Y201703HLT037
- Uday Kamath, John Liu & James Whitaker:
  Deep Learning for NLP and Speech Recognition
  Springer, 2019
  ISBN 3030145956
  http://link.springer.com/978-3-030-14595-8

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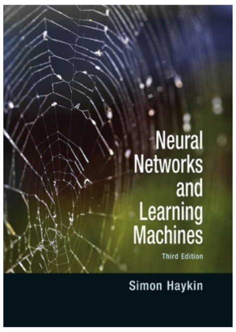
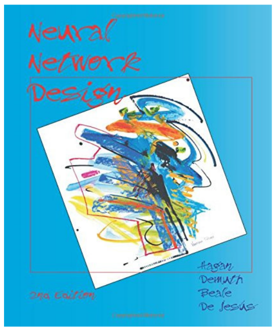
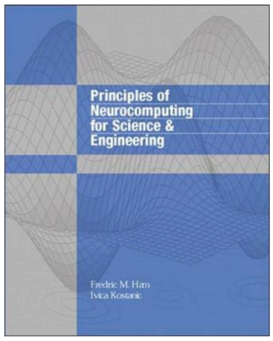
Redes neuronales artificiales







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  and Learning Machines
  Prentice Hall, 3rd edition, 2008
  ISBN 0131471392
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  Mark H. Beale & Orlando de Jesús:
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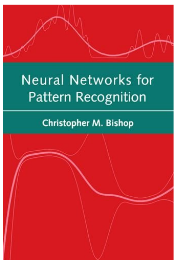
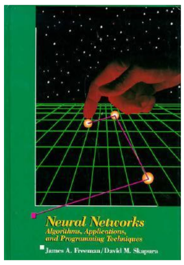
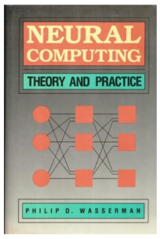
  Martin Hagan, 2nd edition, 2014
  ISBN 0971732116
  http://hagan.okstate.edu/NNDesign.pdf
- Fredric M. Ham & Ivica Kostanic:
  Principles of Neurocomputing
  for Science and Engineering
  McGraw-Hill Higher Education, 2000
  ISBN 0070259666

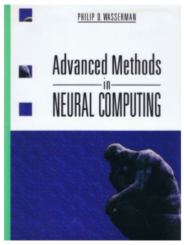
Bibliografía complementaria

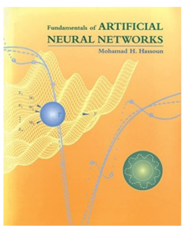
Redes neuronales artificiales











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  MIT Press, 2003. ISBN 0262514672
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"wetware"

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- Olaf Sporns: **Discovering the Human Connectome.** MIT Press, 2012. ISBN 0262017903
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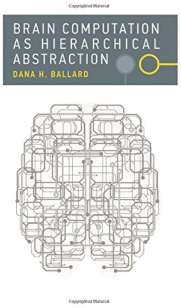

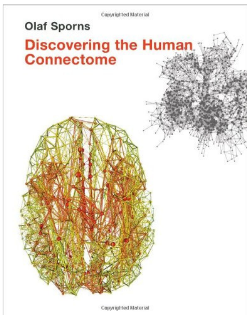

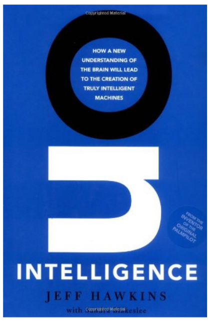

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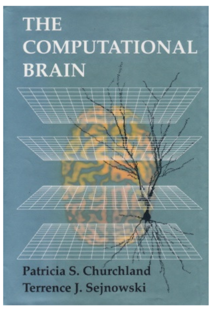
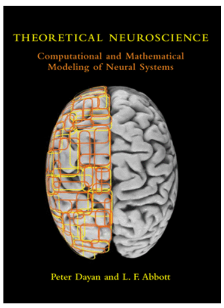
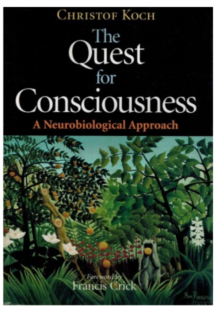
Computational Neuroscience

- Patricia S. Churchland & Terrence J. Sejnowski: **The Computational Brain**. MIT Press, 1992. ISBN 0262031884
- Peter Dayan & L.F. Abbott: **Theoretical Neuroscience: Computational and Mathematical Modeling of Neural Systems.** MIT Press, 2001. ISBN 0262041995.
- Christof Koch: **The Quest for Consciousness: A Neurobiological Approach.** Roberts & Company Publishers, 2004. ISBN 0974707708

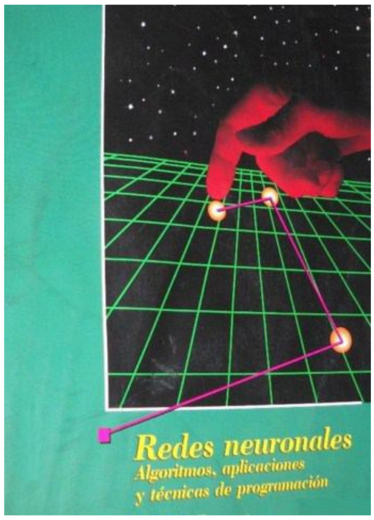






Bibliografía

Bibliografía en castellano



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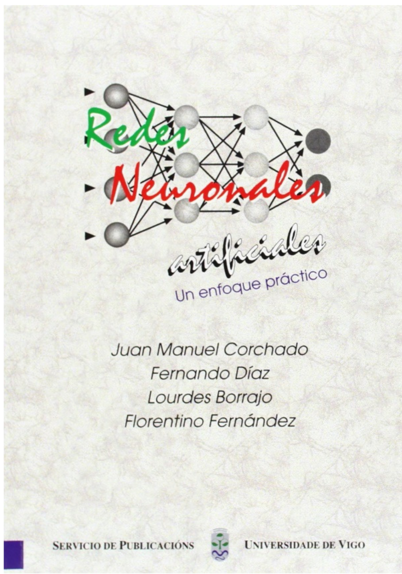
  & David M. Skapura:
  Redes Neuronales:
  Algoritmos, aplicaciones
  y técnicas de programación
  Addison-Wesley / Díaz de Santos, 1993.
  ISBN 020160115X

… con ejemplos de código en Pascal

Bibliografía

Bibliografía en castellano



- Juan Manuel Corchado,
  Fernando Díaz,
  Lourdes Borrajo
  & Florentino Fernández:
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  ISBN 8481581453

… con un disco de 3½”

Bibliografía

Bibliografía en castellano

- Pedro Isasi Viñuela
  & Inés M. Galván León
  Las redes neuronales artificiales: Un enfoque práctico
  Prentice Hall, 2004
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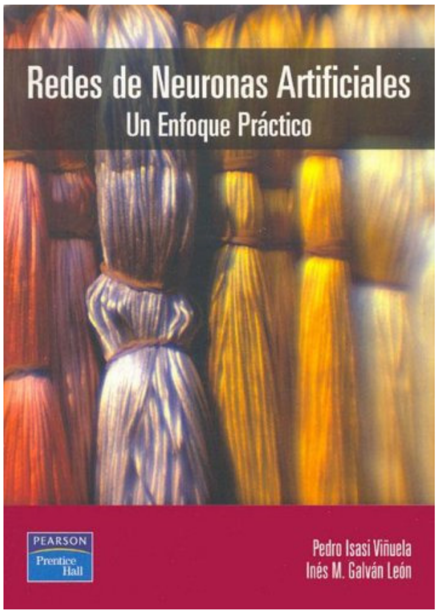
  Descatalogado :-(



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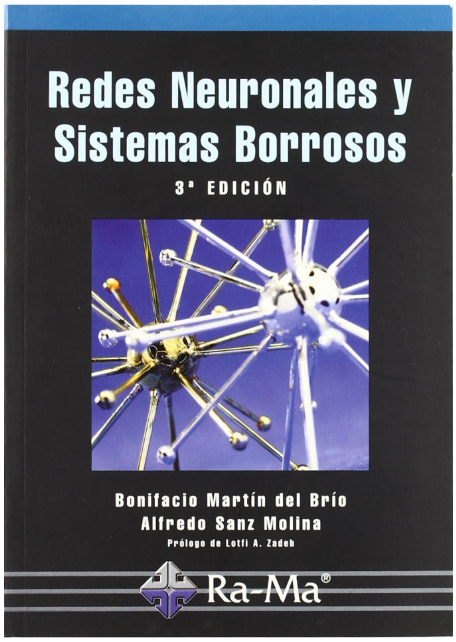

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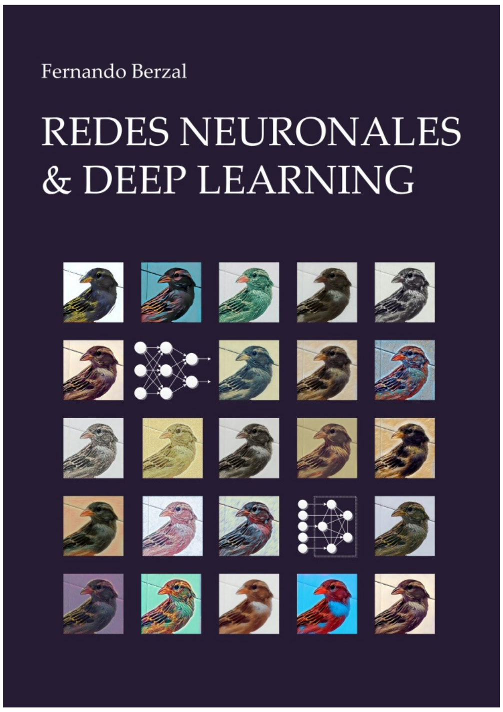

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