



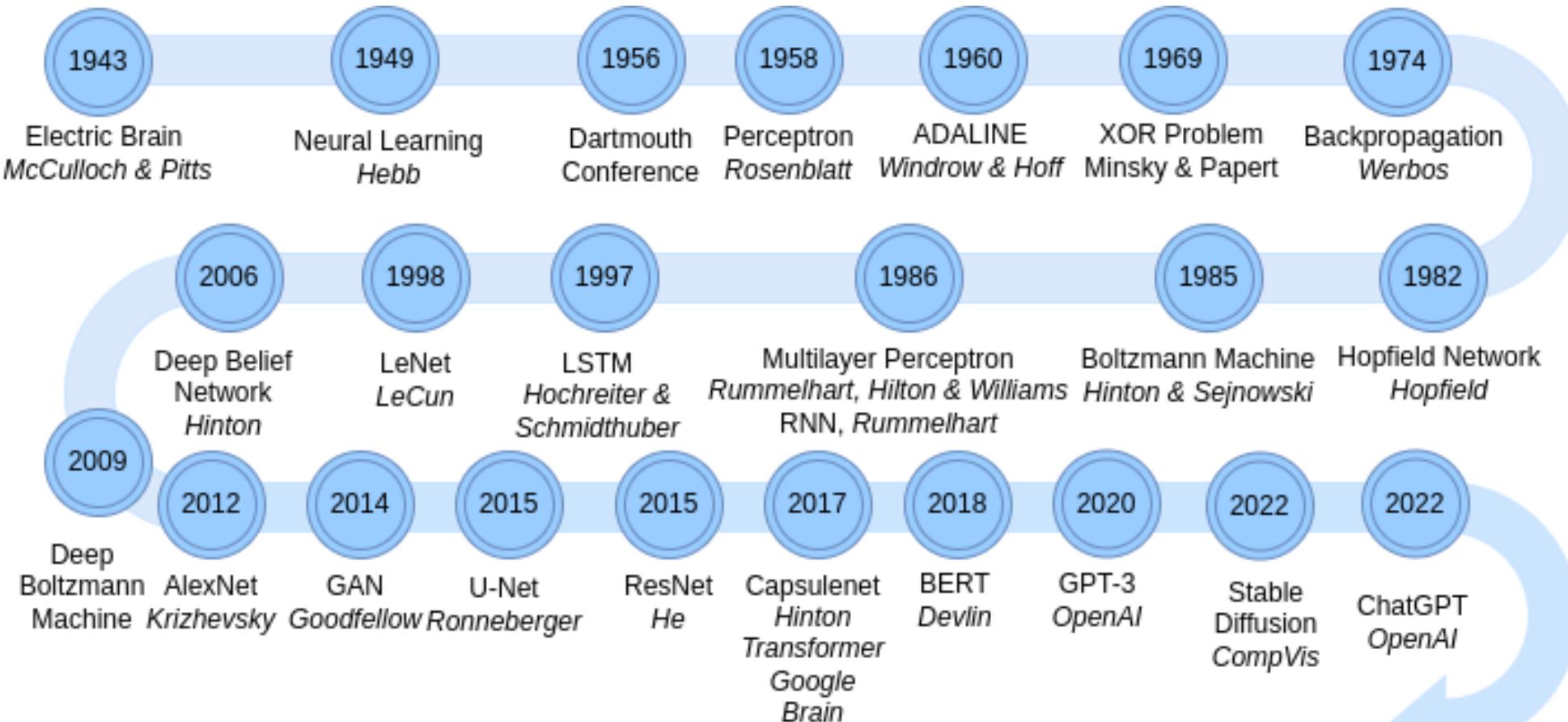
Deep Learning Aplicado al procesamiento de Imágenes

Día 1 – Introducción a Deep Learning

Dr. Rodrigo Salas Fuentes
rodrigo.salas@uv.cl



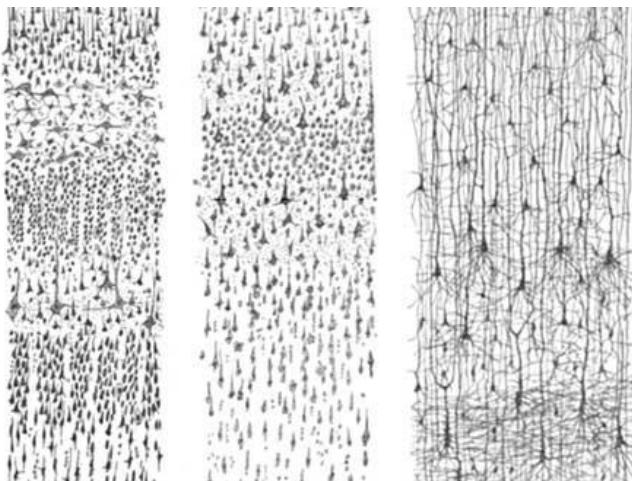
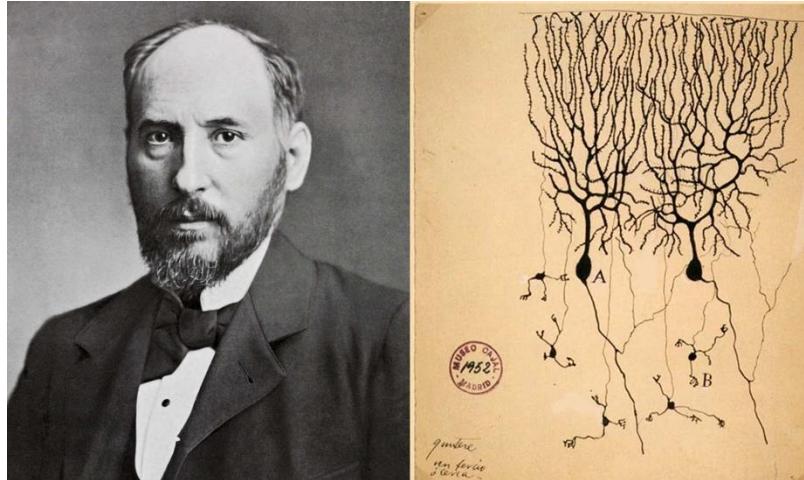
Breve historia de la Redes Neuronales Artificiales



<https://kritikalsolutions.com/different-types-of-neural-networks-in-deep-learning/>

El Sistema Nervioso y la Neurona Biológica

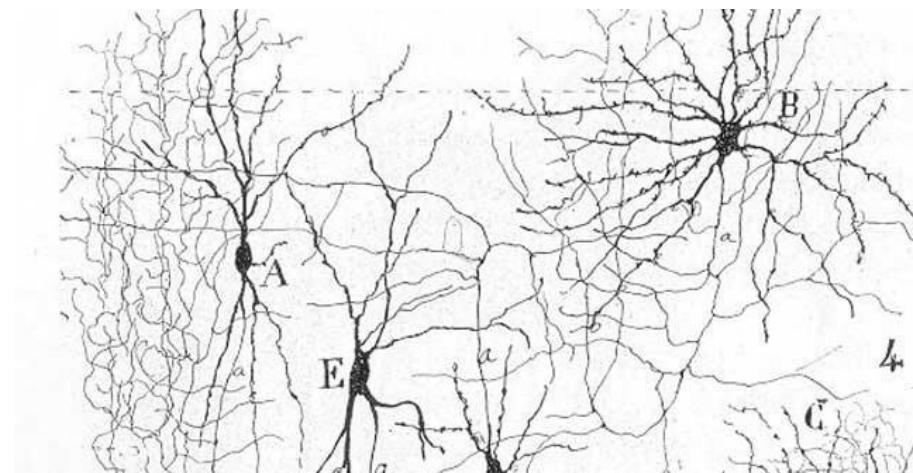
La Neurona Biológica



Estudio comparativo de las áreas
sensoriales del Cortex humano

Dr. Ing. Rodrigo Salas (UV-MEDING-iHealth)

Santiago Ramón y Cajal (1852-1934)
Médico Español
Premio Nobel de Medicina 1906 sobre
“estructura del sistema nervioso”
Desarrolló la doctrina de la “neurona”

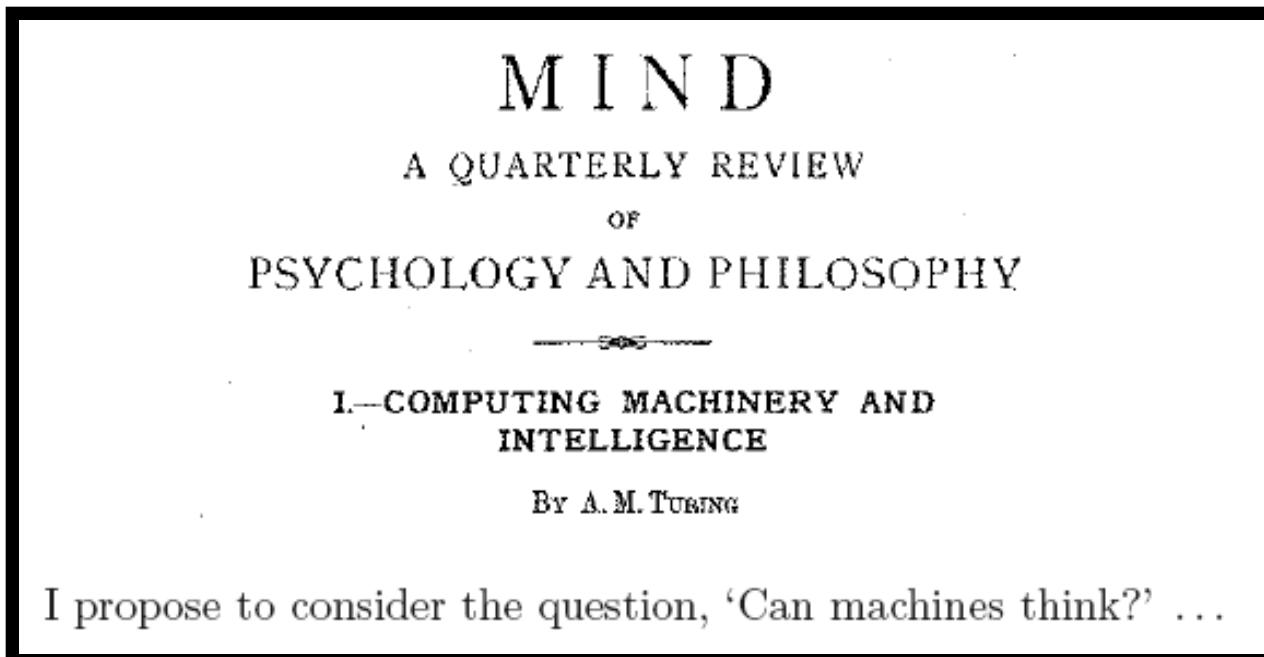


Morfología Neuronal del Cortex

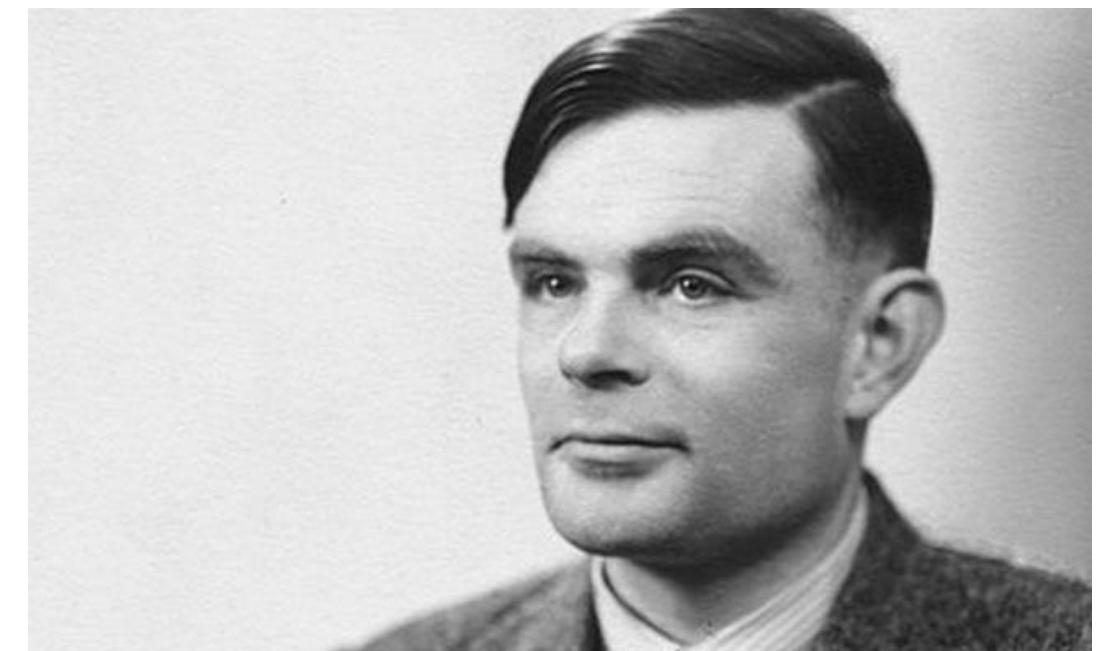
El nacimiento de la computación y la neurona artificial

¿Pueden las Máquinas Pensar?

- La historia de la IA comienza con el siguiente artículo:
 - Turing, A.M. (1950), Computing machinery and intelligence, *Mind*, Vol. 59, pp. 433-460.



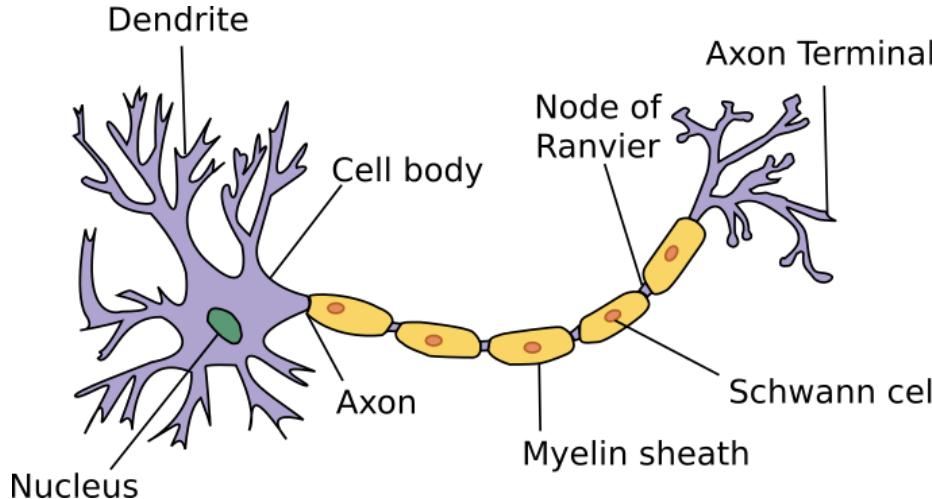
I propose to consider the question, 'Can machines think?' ...



La Neurona Artificial - 1943



Warren
McCulloch (1898
- 1972)

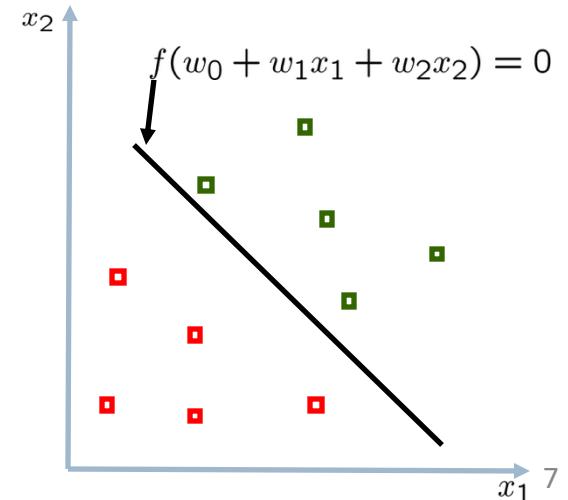
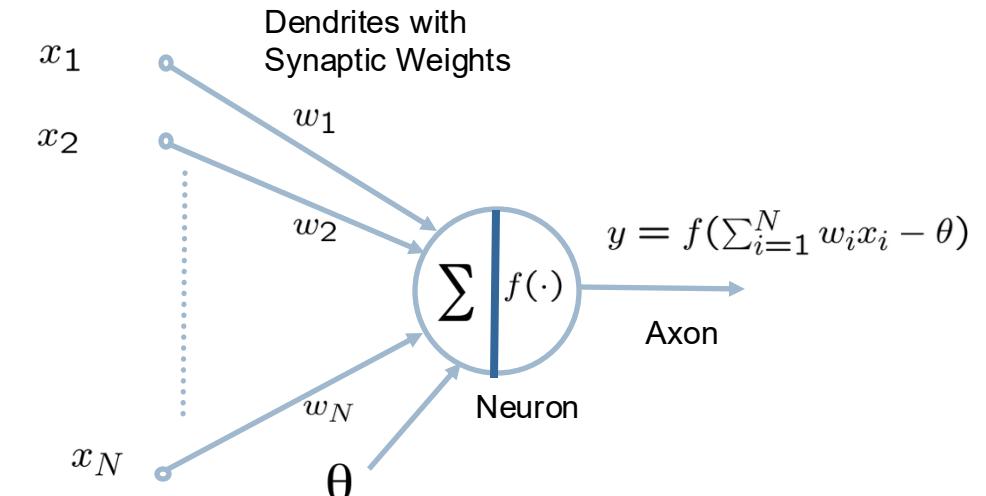


Walter Pitts
(1924 - 1969)

Warren McCulloch and Walter Pitts, A Logical Calculus of Ideas Immanent in Nervous Activity, 1943, Bulletin of Mathematical Biophysics 5:1 115-133.

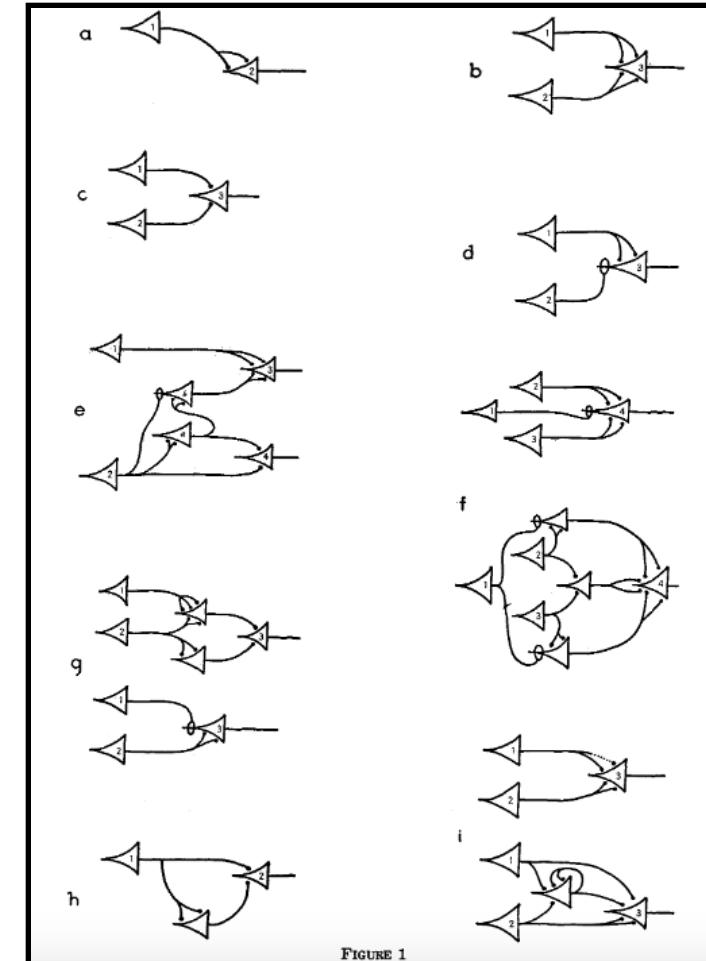
- McCulloch y Pitts (1943) demostraron que redes de neuronas artificiales pueden implementar funciones lógicas tales como AND, OR, XOR.
- Dispositivos de cómputo universales.

Dr. Ing. Rodrigo Salas (UV-MEDING-iHealth)

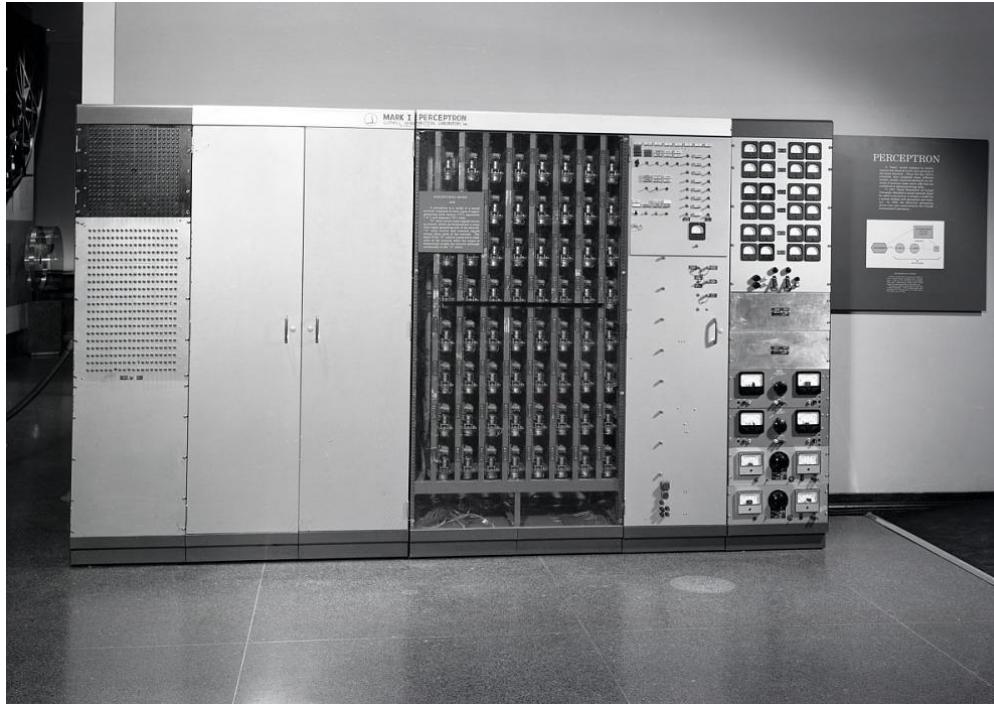


La Neurona Artificial es dispositivo cómputo universal

- McCulloch y Pitts (1943) demostraron que redes de neuronas artificiales pueden implementar funciones lógicas tales como AND, OR, XOR.
- Dispositivos de cómputo universales.



El Mark I - PERCEPTRON



https://americanhistory.si.edu/collections/search/object/nmah_334414

Rosenblatt, Frank (1957), The Perceptron--a perceiving and recognizing automaton. Report 85-460-1, Cornell Aeronautical Laboratory.

Rosenblatt, Frank. Principles of Neurodynamics: Perceptrons and the Theory of Brain Mechanisms. Spartan Books, Washington DC, 1961

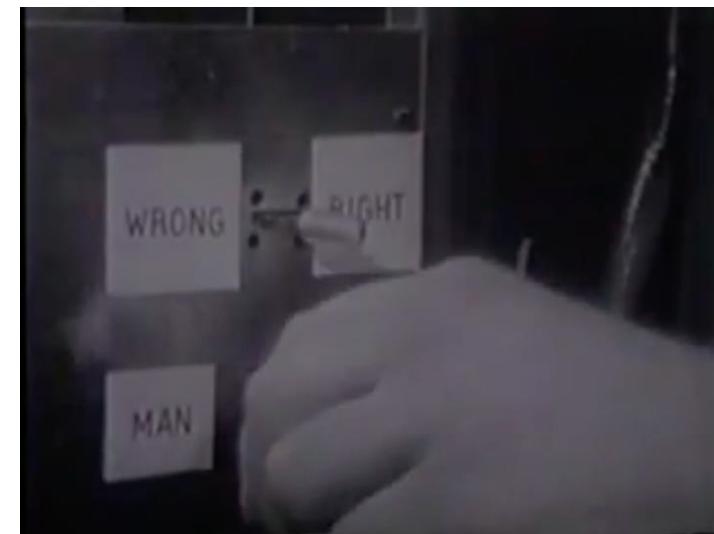
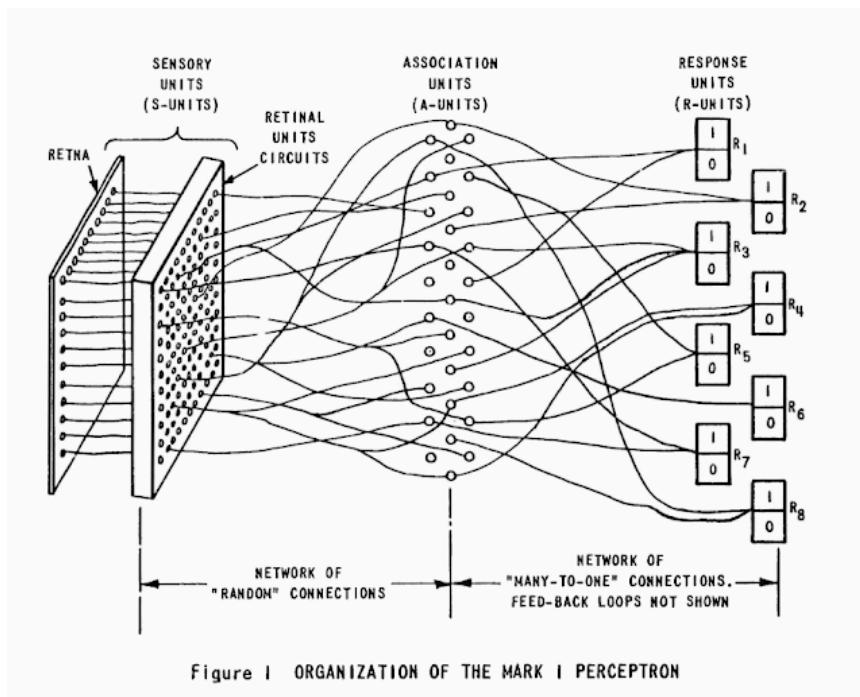


Frank Rosenblatt (11 de julio de 1928-11 de julio de 1971) fue un psicólogo estadounidense.

- El Mark I Perceptrón fue creado por el psicólogo Frank Rosenblatt para clasificar imágenes.
- El hardware del perceptrón estaba construido a medida y utilizaba potenciómetros para determinar los pesos de cada entrada .

El Mark I - PERCEPTRON

- A partir del input de 400 píxeles de la imagen obtenidas (20×20 puntos de resolución) el sistema era capaz, con relativa eficacia, de reconocer el género de la persona analizando una fotografía, a partir del desglose en partes (puntos) en la tarea de análisis.



El Perceptrón

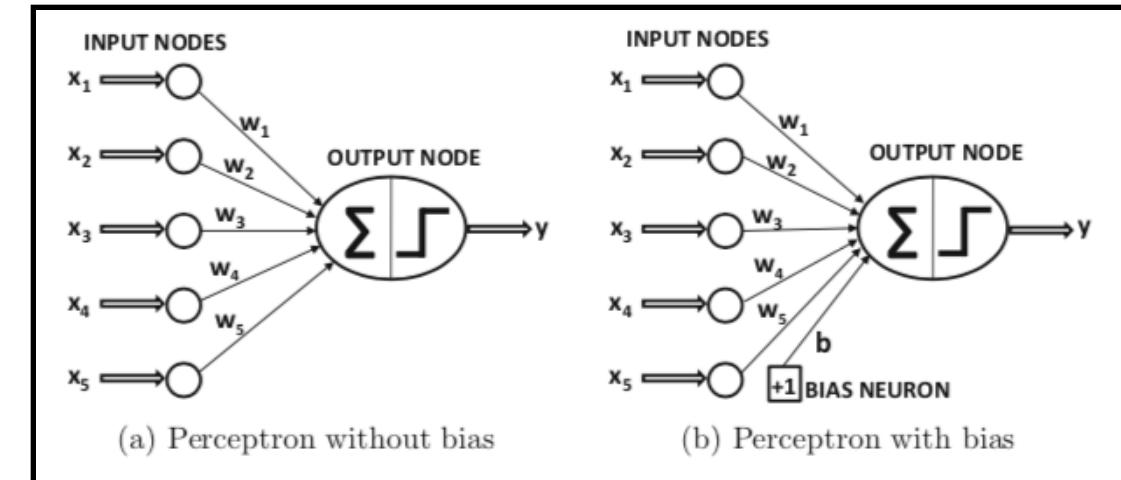
- El Perceptrón: Unidad de Cómputo simple

- Consiste en una única capa
 - Entrada: $\bar{X} = [x_1, \dots, x_d]$
 - Pesos: $\bar{W} = [w_1, \dots, w_d]$
 - Función de Agregación:

$$\bar{W} \cdot \bar{X} = \sum_{i=1}^d w_i x_i$$

- Función de Activación:

$$\hat{y} = sign\{\bar{W} \cdot \bar{X}\} = sign\{\sum_{j=1}^d w_j x_j\}$$



$$\hat{y} = sign\{\bar{W} \cdot \bar{X} + b\} = sign\{\sum_{j=1}^d w_j x_j + b\}$$

Hiperplano Separador

- Función de Activación

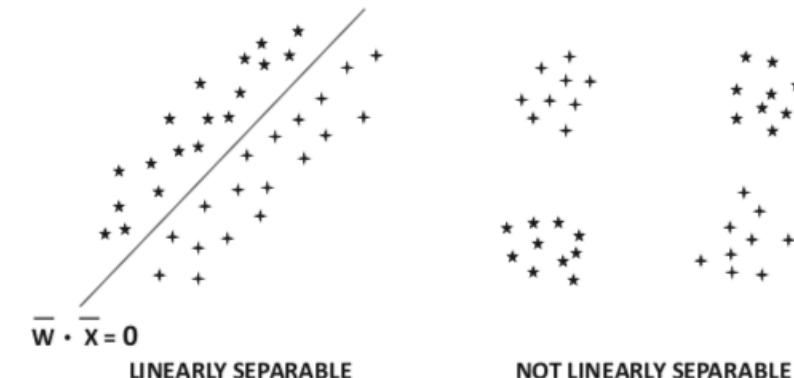
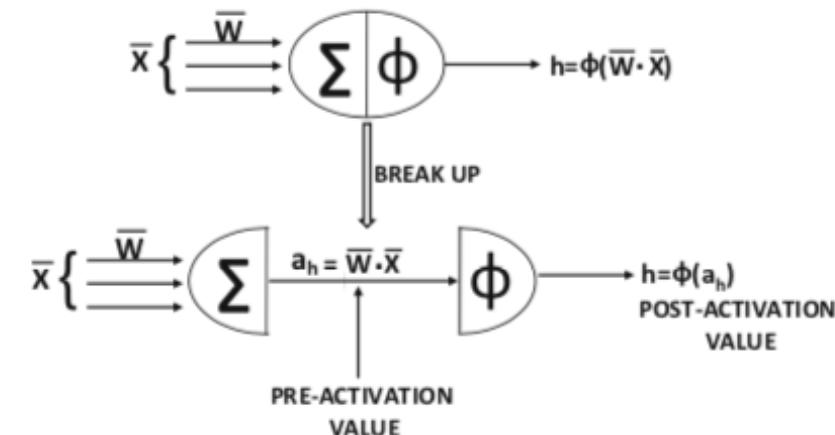
$$\hat{y} = \Phi(\overline{W} \cdot \overline{X})$$

- El hiperplano separador del perceptrón:

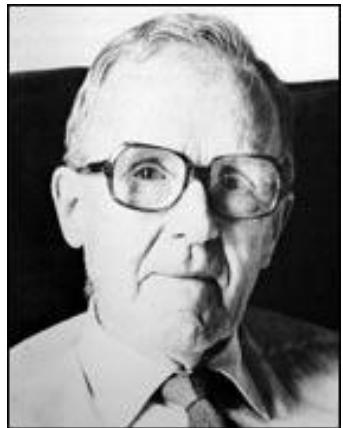
$$\overline{W} \cdot \overline{X} = 0$$

- Propiedad:

El algoritmo del perceptrón siempre converge a error cero en el conjunto de datos de entrenamiento cuando estos son linealmente separables.



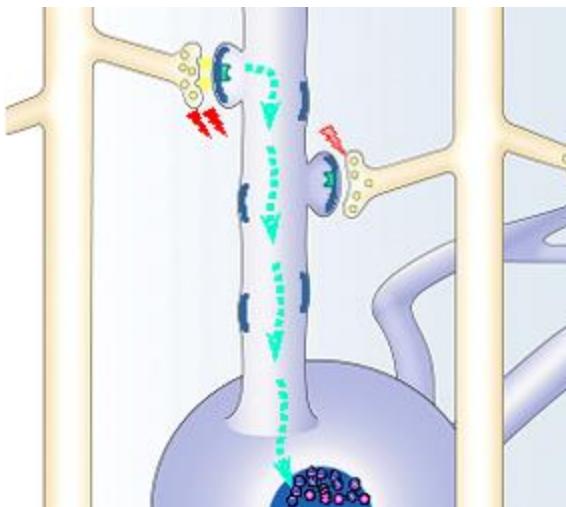
Regla de Aprendizaje de Hebb



Donald
Olding Hebb
(1904 –1985)

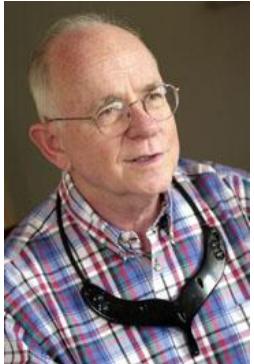
When an axon of cell A is near enough to excite cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased

The Organization of Behavior (1949)

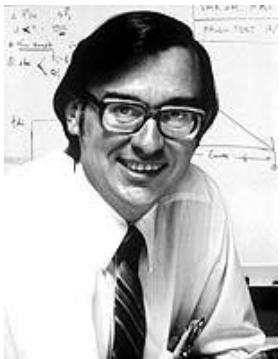


$$\Delta w_{ij} = \alpha y_i y_j$$

ADALINE: Adaptive Linear Neuron or later Adaptive Linear Element

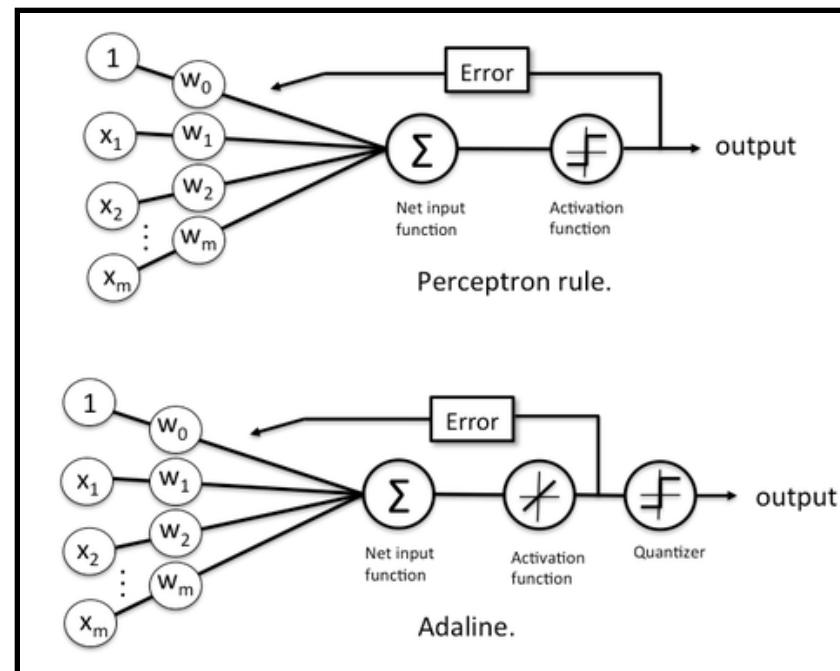


Bernard
Widrow
(1929--)



Dr. Marcian
Edward "Ted"
Hoff Jr. (1937 --)

- Propuesta por Widrow & Hoff 1960.
- Posee un algoritmo de aprendizaje que, basado en el error en la señal anterior a la salida y el valor deseado, actualiza los pesos.

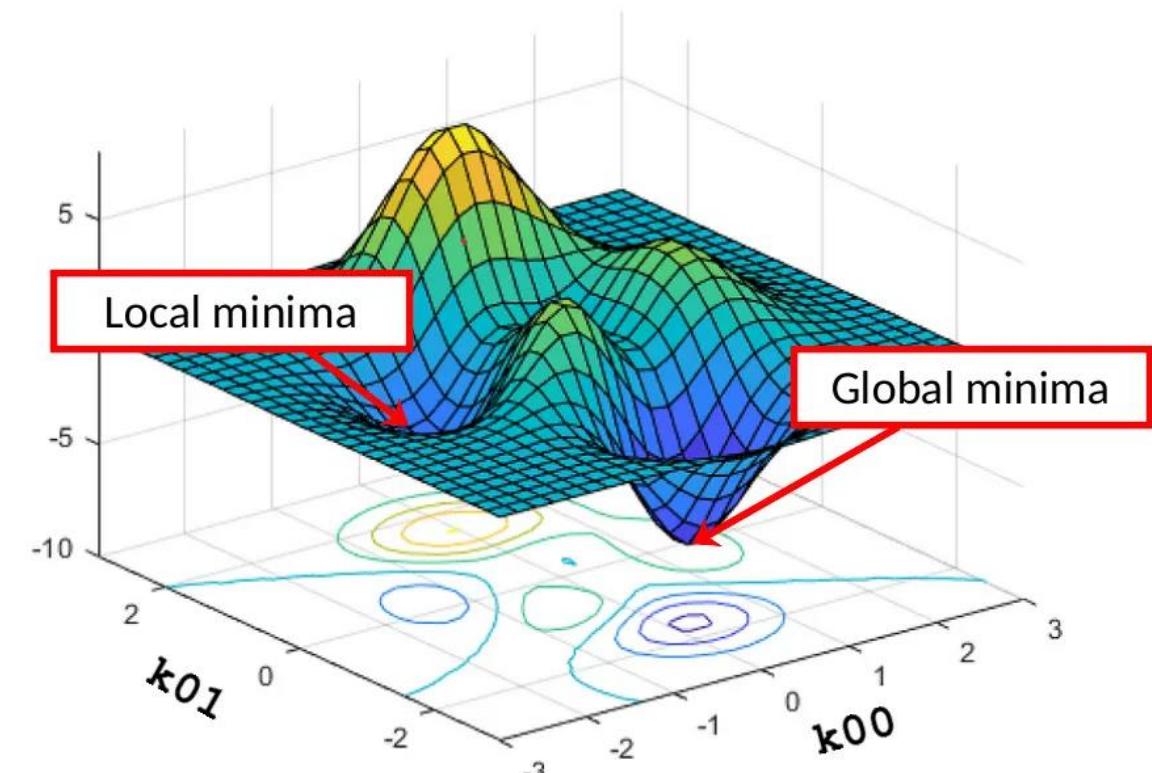
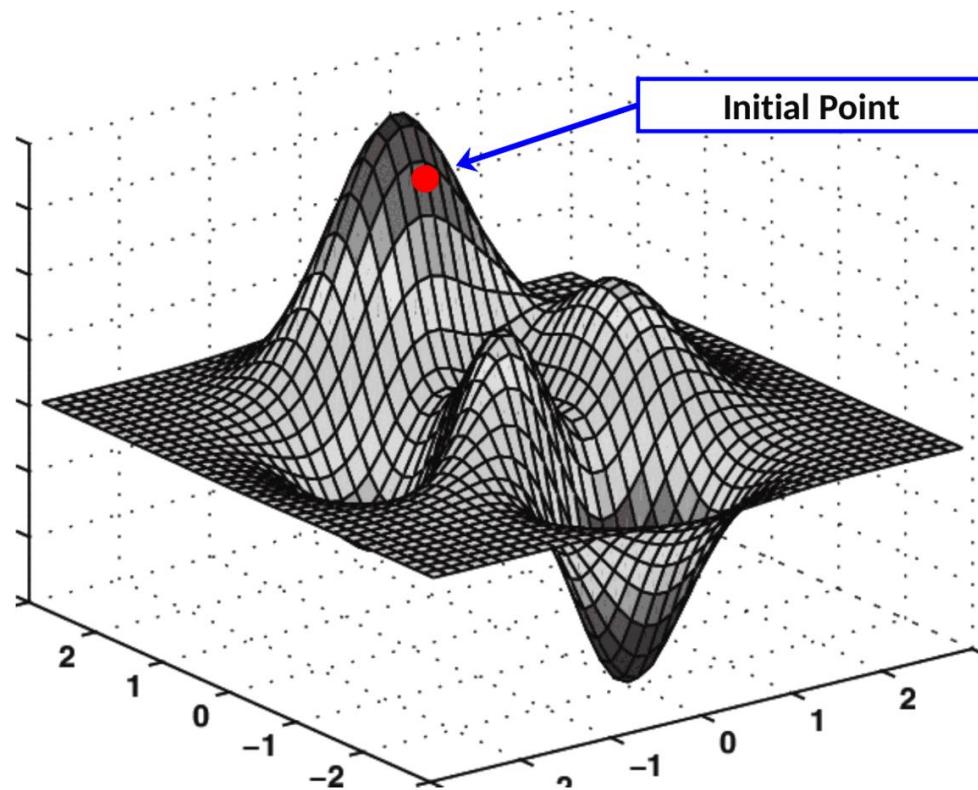


Regla Delta o Regla de Widrow and Hoff

$$w_j(t+1) = w_j(t) + \alpha(y - \hat{y})x_j$$

Regla Delta

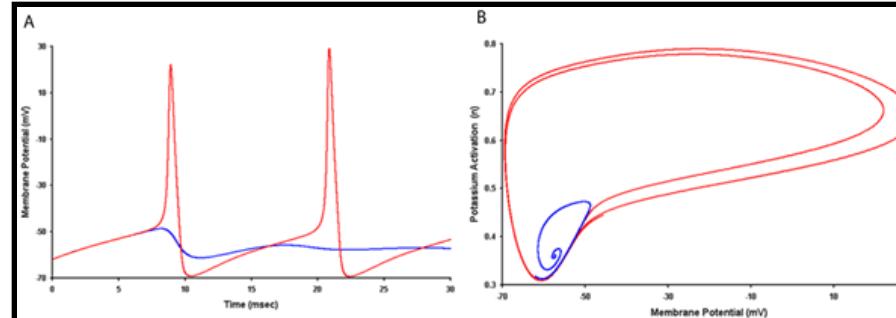
$$w_j(t+1) = w_j(t) + \alpha(y - \hat{y})x_j$$



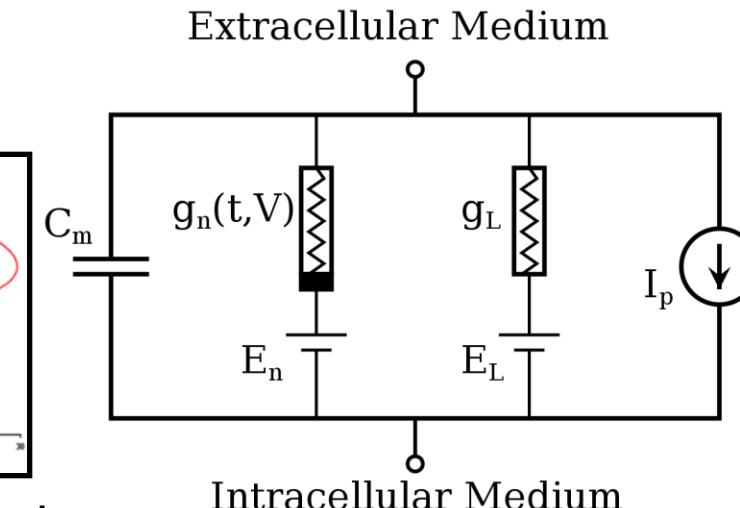
<https://pub.towardsai.net/deep-learning-from-scratch-in-modern-c-gradient-descent-670bc5889112>

Modelo de Hodgkin & Huxley

- Describe cómo se inician y transmiten los potenciales de acción en las neuronas



<http://people.maths.ox.ac.uk/krause/?action=hodgkinHuxley>



$$I = C_m \frac{dV_m}{dt} + \bar{g}_K n^4 (V_m - V_K) + \bar{g}_{Na} m^3 h (V_m - V_{Na}) + \bar{g}_l (V_m - V_l),$$

$$\frac{dn}{dt} = \alpha_n(V_m)(1 - n) - \beta_n(V_m)n$$

$$\frac{dm}{dt} = \alpha_m(V_m)(1 - m) - \beta_m(V_m)m$$

$$\frac{dh}{dt} = \alpha_h(V_m)(1 - h) - \beta_h(V_m)h$$

The Nobel Prize in
Physiology or Medicine
1963



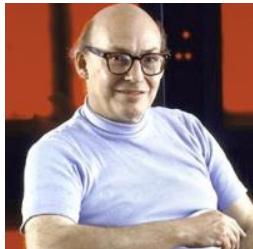
Sir John Carew
Eccles
Prize share: 1/3



Alan Lloyd Hodgkin
Prize share: 1/3
Andrew Fielding
Huxley
Prize share: 1/3

El invierno de las Redes Neuronales Artificiales

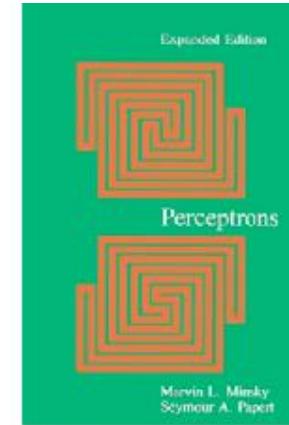
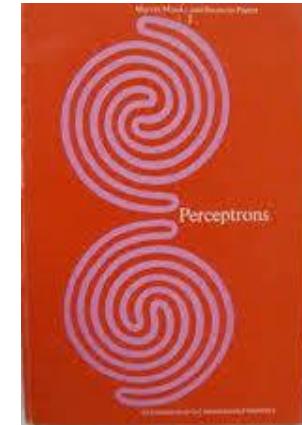
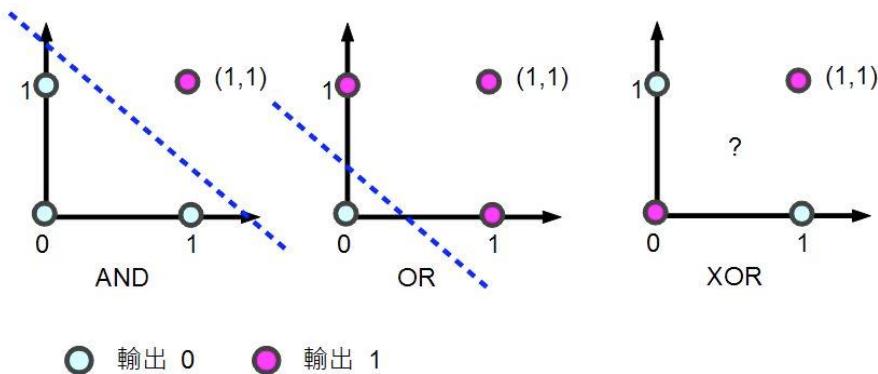
Perceptrones: Introducción a la Geometría Computacional



Marvin Minsky



Seymour Papert



- Marvin Minsky & Seymour Papert 1969: “Perceptrons: An Introduction to Computational Geometry”

Mainstream research into perceptrons came to an abrupt end in 1969, when Marvin Minsky and Seymour Papert published the book *Perceptrons*, which was perceived as outlining the limits of what perceptrons could do.

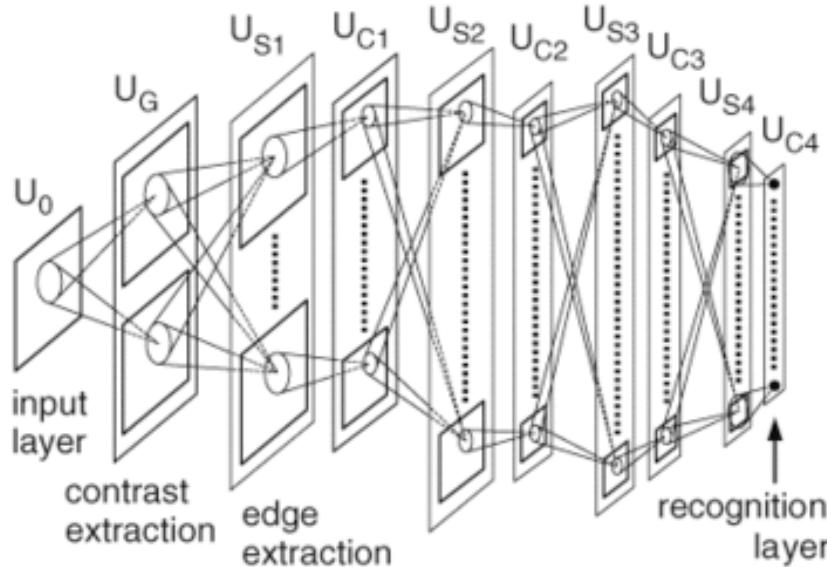
<https://rjlipton.wordpress.com/2016/01/27/minsky-the-theorist/>

El renacer de las Redes Neuronales Artificiales

Neocognitron

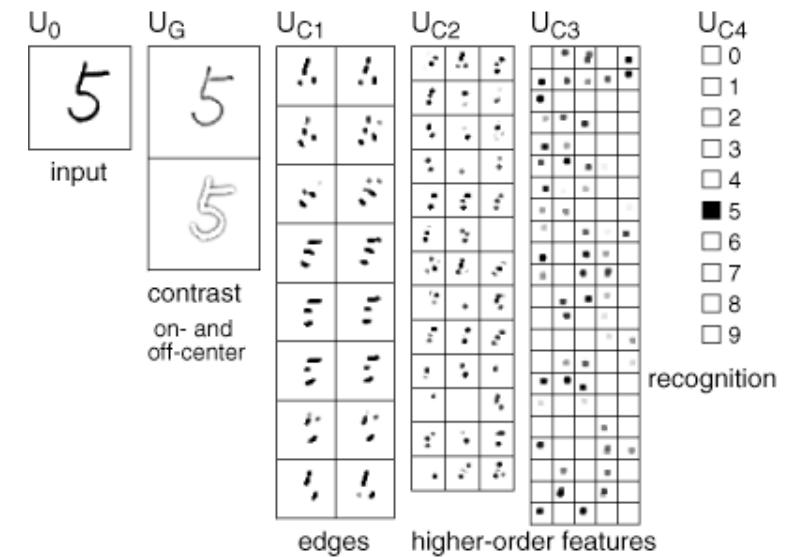


**Dr. Kunihiko Fukushima,
Kansai University,
Japan.**



K. Fukushima: "Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position", *Biological Cybernetics*, 36[4], pp. 193-202 (April 1980).

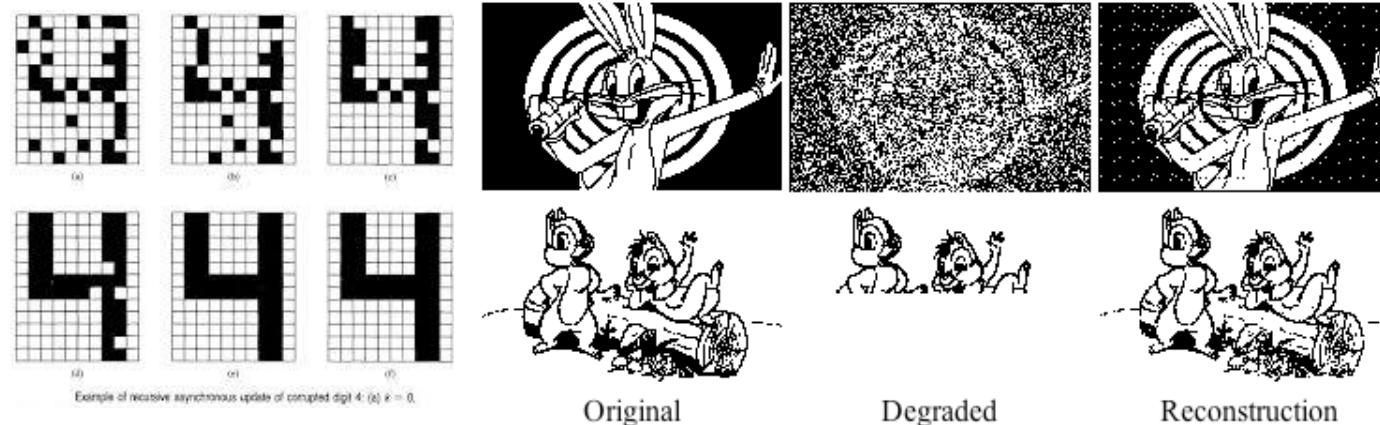
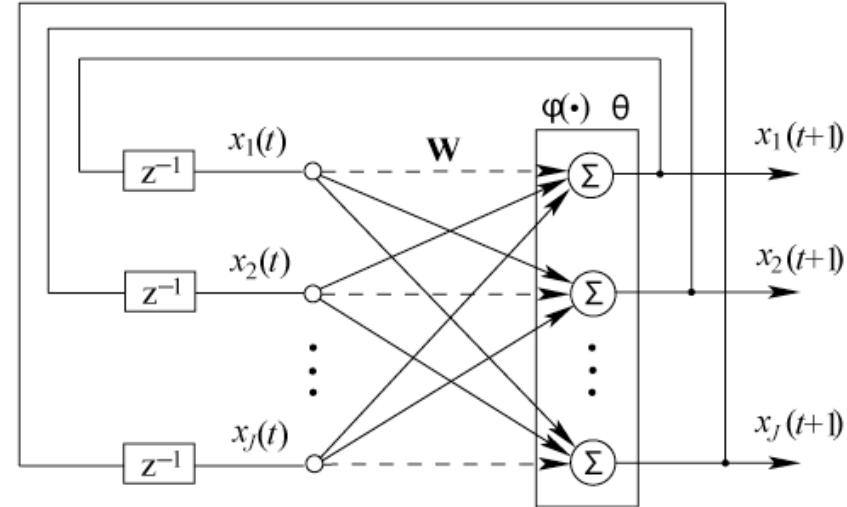
The neocognitron, proposed by Fukushima (1980), is a hierarchical multilayered neural network capable of robust visual pattern recognition through learning



Memoria asociativa - Redes de Hopfield



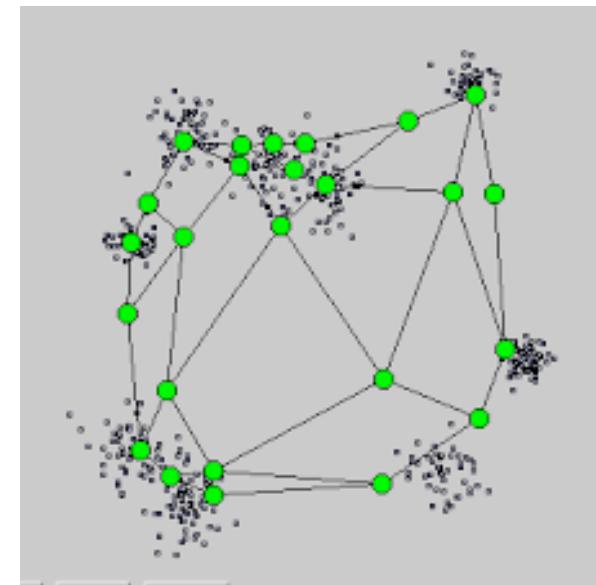
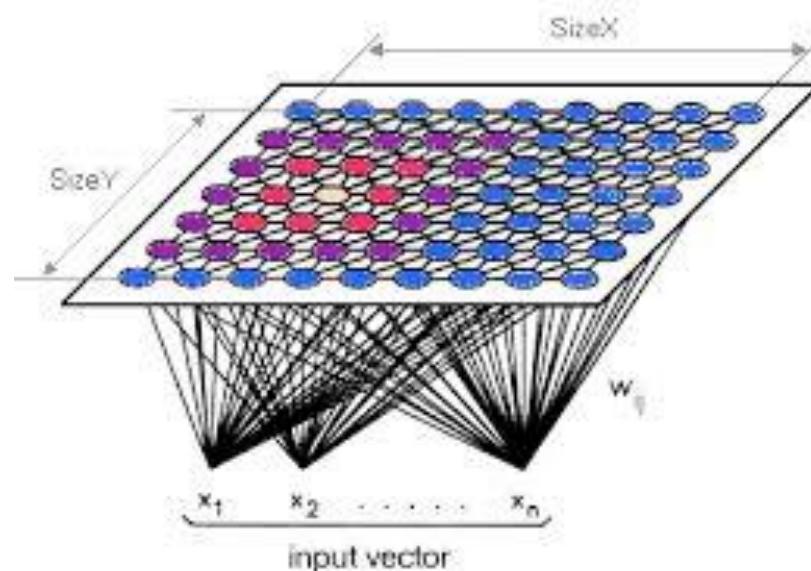
John Joseph Hopfield (born July 15, 1933) is an American scientist most widely known for his invention of an associative neural network in 1982. It is now more commonly known as the Hopfield Network.



Mapas auto-organizativos de Kohonen



Teuvo Kohonen
Teuvo Kohonen (born July 11, 1934) has made many contributions to the field of artificial neural networks, including the Learning Vector Quantization algorithm, and SOM

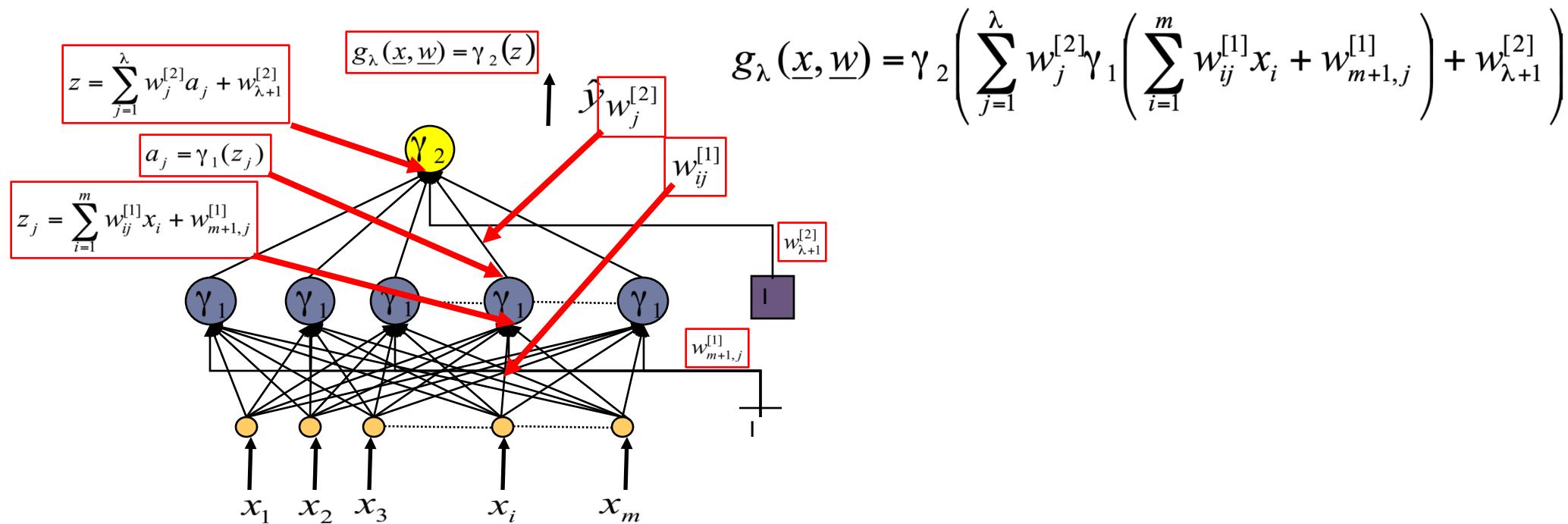
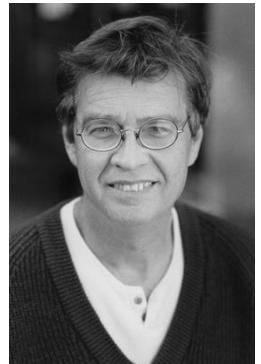


El Perceptrón Multicapa (MLP)

Output Layer

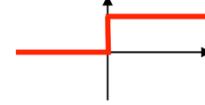
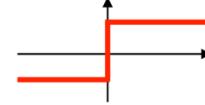
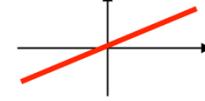
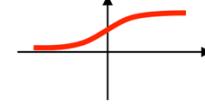
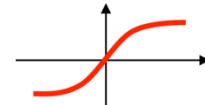
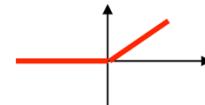
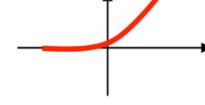
Hidden Layer

Input Layer



Rumelhart, David E., Geoffrey E. Hinton, and R. J. Williams. "Learning Internal Representations by Error Propagation", Parallel distributed processing: Explorations in the microstructure of cognition, Volume 1: Foundations. MIT Press, 1986

Funciones de Activación

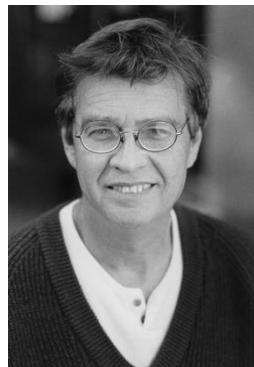
Activation function	Equation	Example	1D Graph
Unit step (Heaviside)	$\phi(z) = \begin{cases} 0, & z < 0, \\ 0.5, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Sign (Signum)	$\phi(z) = \begin{cases} -1, & z < 0, \\ 0, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Linear	$\phi(z) = z$	Adaline, linear regression	
Piece-wise linear	$\phi(z) = \begin{cases} 1, & z \geq \frac{1}{2}, \\ z + \frac{1}{2}, & -\frac{1}{2} < z < \frac{1}{2}, \\ 0, & z \leq -\frac{1}{2}, \end{cases}$	Support vector machine	
Logistic (sigmoid)	$\phi(z) = \frac{1}{1 + e^{-z}}$	Logistic regression, Multi-layer NN	
Hyperbolic tangent	$\phi(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$	Multi-layer Neural Networks	
Rectifier, ReLU (Rectified Linear Unit)	$\phi(z) = \max(0, z)$	Multi-layer Neural Networks	
Rectifier, softplus	$\phi(z) = \ln(1 + e^z)$	Multi-layer Neural Networks	

Retropropagación del Error (Backpropagation)

$$\mathbf{w}(t + 1) = \mathbf{w}(t) - \alpha(t) \nabla_{\mathbf{w}} l(h(\cdot, \mathbf{w}); z_t)$$

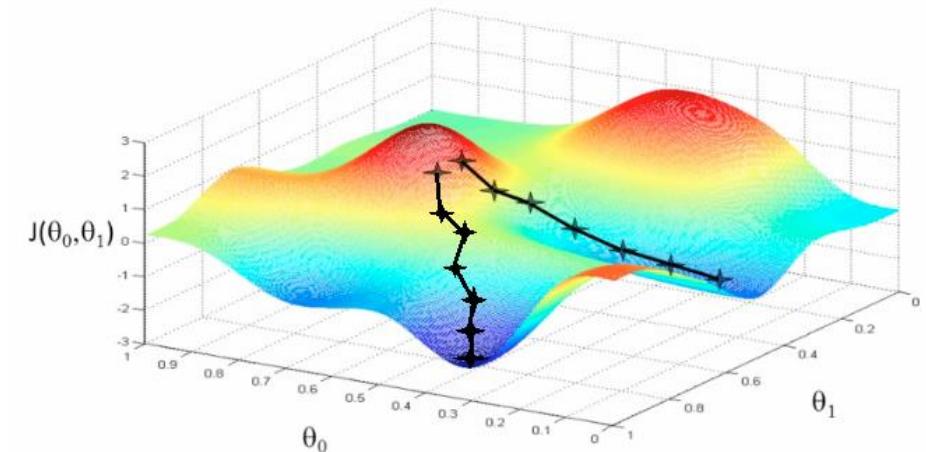


Paul Werbos.
1974 | In his Harvard PhD thesis, Paul Werbos describes training neural networks through backpropagation.



Rumelhart, David E., Geoffrey E. Hinton, and R. J. Williams. "Learning Internal Representations by Error Propagation", Parallel distributed processing: Explorations in the microstructure of cognition, Volume I: Foundations. MIT Press, 1986

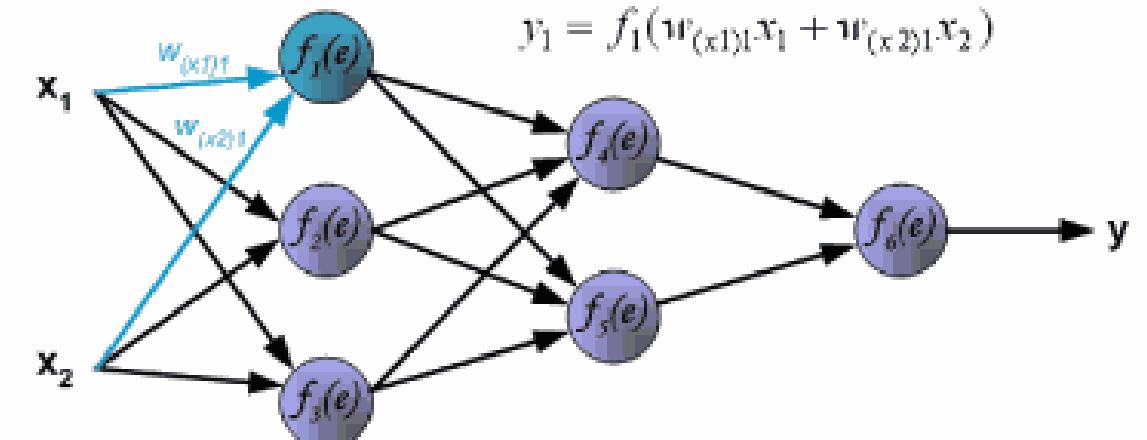
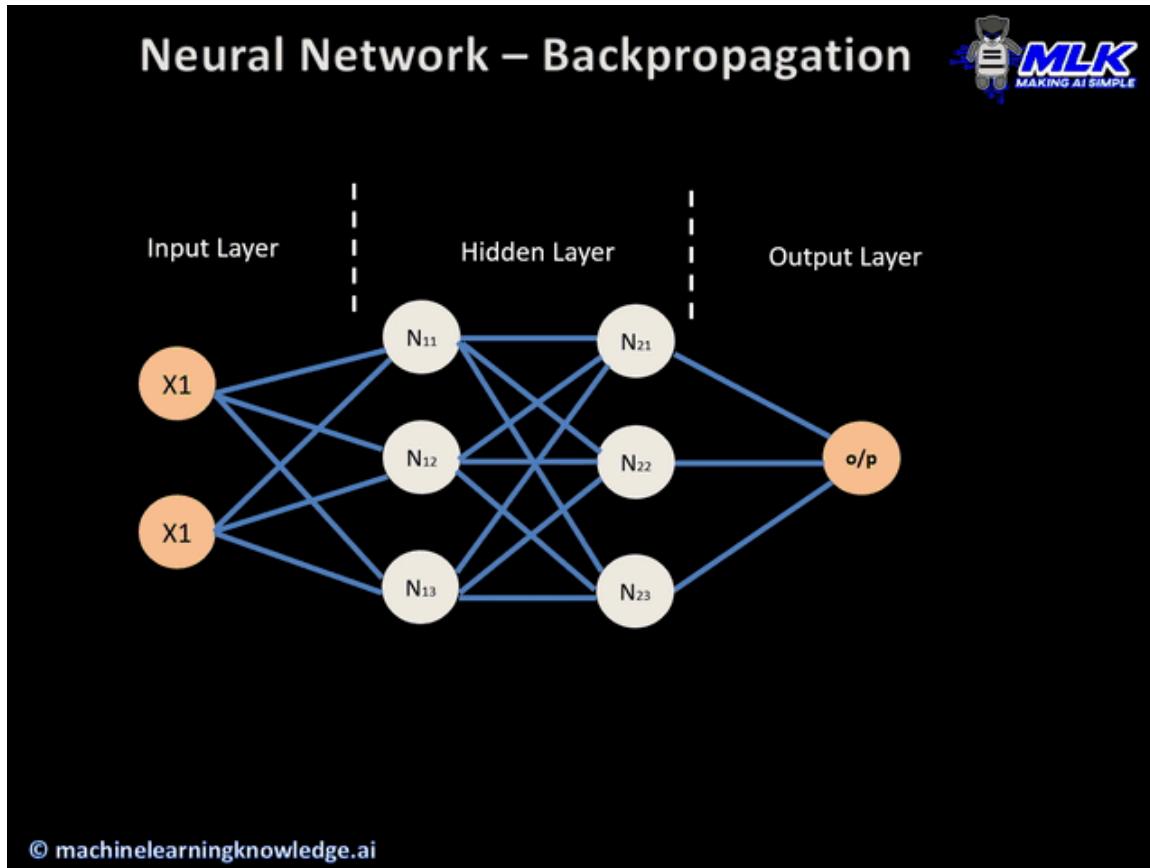
http://www.holehouse.org/mlclass/01_02_Introduction_regression_analysis_and_gr.html



Algoritmo de Aprendizaje: Backpropagation

- El algoritmo de **retropropagación o backpropagation** aprovecha la regla de la cadena del cálculo diferencial, que calcula los gradientes de error en términos de sumas de productos de gradiente local en las diversas rutas desde un nodo hasta la salida.
- Tiene 2 fases:
 - **Fase de avance o inferencia:**
 - Se ejecuta el perceptrón multicapa para una entrada dada y se computan todos los resultados de salidas de cada nodo y sus derivadas hasta el nodo de salida.
 - **Fase de retropropagación o retroceso:**
 - El objetivo principal de la fase hacia atrás es aprender el gradiente de la función de pérdida con respecto a los diferentes pesos mediante el uso de la regla de la cadena del cálculo diferencial.
 - Estos gradientes se utilizan para actualizar los pesos. Los gradientes se aprenden en la dirección hacia atrás, comenzando desde el nodo de salida.

Retropropagación del Error (Backpropagation)



<https://medium.com/deeper-deep-learning-tr/adim-adim-forward-and-back-propagation-cf4cd18276ee>

Algoritmo de Aprendizaje: Backpropagation

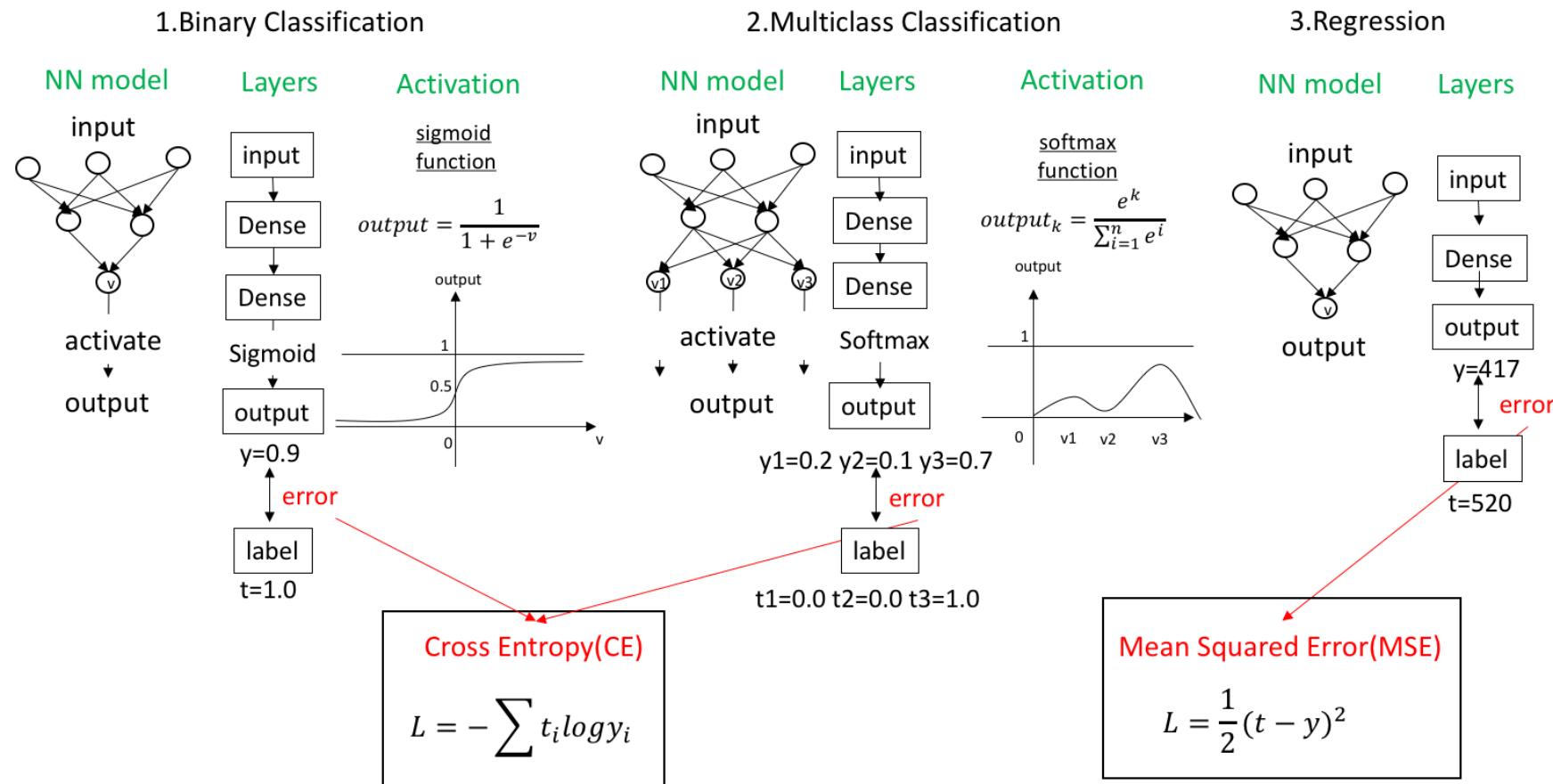
$$\delta(o, o) = \frac{\partial L}{\partial a_o} = \Phi'(a_o) \cdot \frac{\partial L}{\partial o}$$

$$\frac{\partial L}{\partial w_{(h_{r-1}, h_r)}} = \delta(h_r, o) \cdot h_{r-1}$$

$$\frac{\partial L}{\partial w_{(h_{r-1}, h_r)}} = \underbrace{\frac{\partial L}{\partial o} \cdot \Phi'(a_o)}_{\text{Backpropagation computes } \delta(h_r, o) = \frac{\partial L}{\partial a_{h_r}}} \cdot \underbrace{\left[\sum_{[h_r, h_{r+1}, \dots, h_k, o] \in \mathcal{P}} \frac{\partial a_o}{\partial a_{h_k}} \prod_{i=r}^{k-1} \frac{\partial a_{h_{i+1}}}{\partial a_{h_i}} \right]}_{h_{r-1}}$$

$$\delta(h_r, o) = \frac{\partial L}{\partial a_{h_r}} = \sum_{h: h_r \Rightarrow h} \underbrace{\frac{\partial L}{\partial a_h}}_{\Phi'(a_{h_r})w_{(h_r, h)}} \underbrace{\frac{\partial a_h}{\partial a_{h_r}}}_{\delta(h, o)} = \Phi'(a_{h_r}) \sum_{h: h_r \Rightarrow h} w_{(h_r, h)} \cdot \delta(h, o)$$

Funciones de Pérdida



https://www.renom.jp/notebooks/tutorial/basic_algorithm/lossfunction/notebook.html

Aproximadores Universales

Theorem of Universal Approximation:

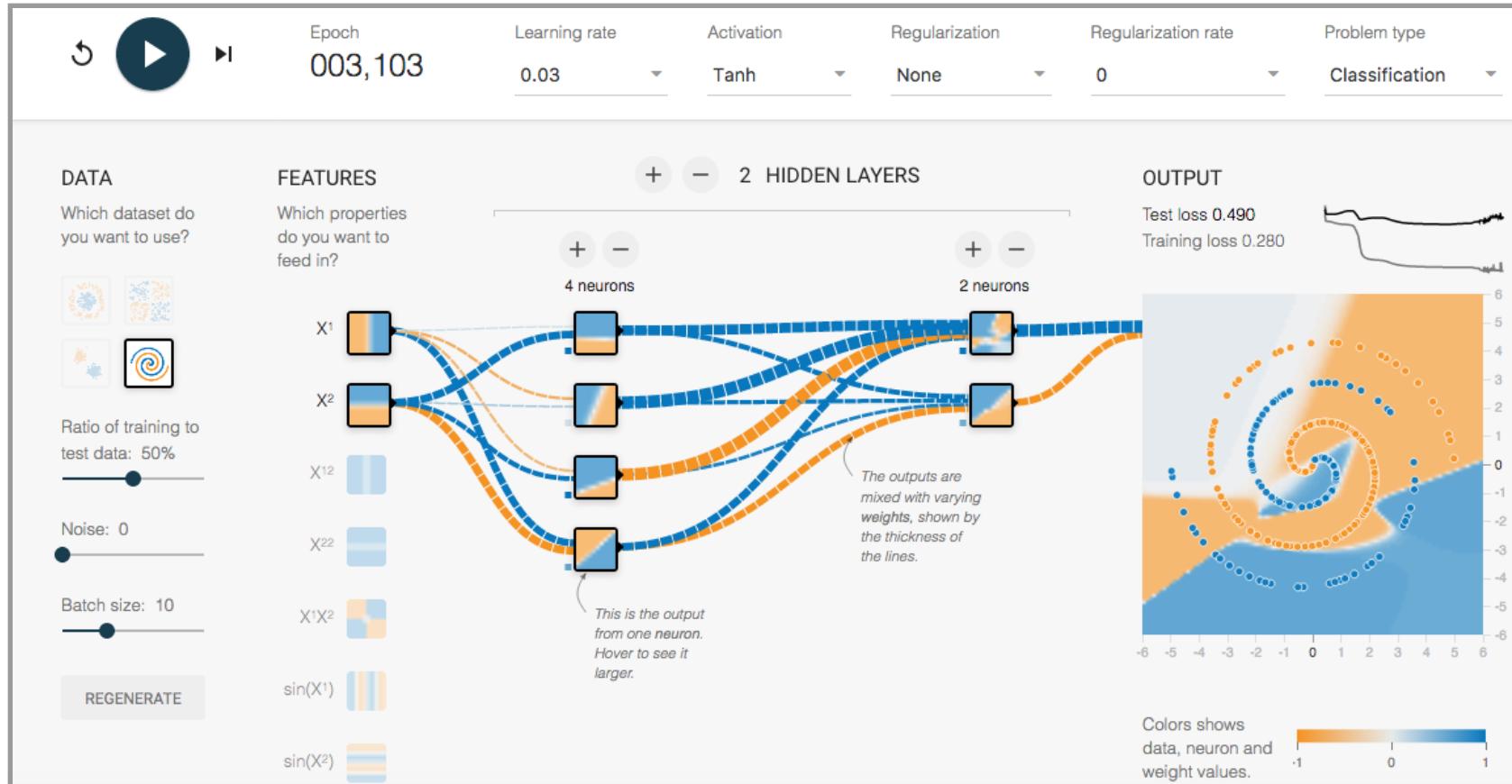
“Every bounded continuous function with bounded support can be approximated arbitrarily closely by a multi-layer perceptron by selecting enough but a finite number of hidden neurons with appropriate transfer function”



**Cybenko., G. (1989) "Approximations by superpositions of sigmoidal functions",
Mathematics of Control, Signals, and Systems, 2 (4), 303-314**

Kurt Hornik, Maxwell Stinchcombe, and Halbert White. Multilayer feedforward networks are universal approximators. Neural Networks, 2:359--366, 1989

Jugando con Redes Neuronales Artificiales

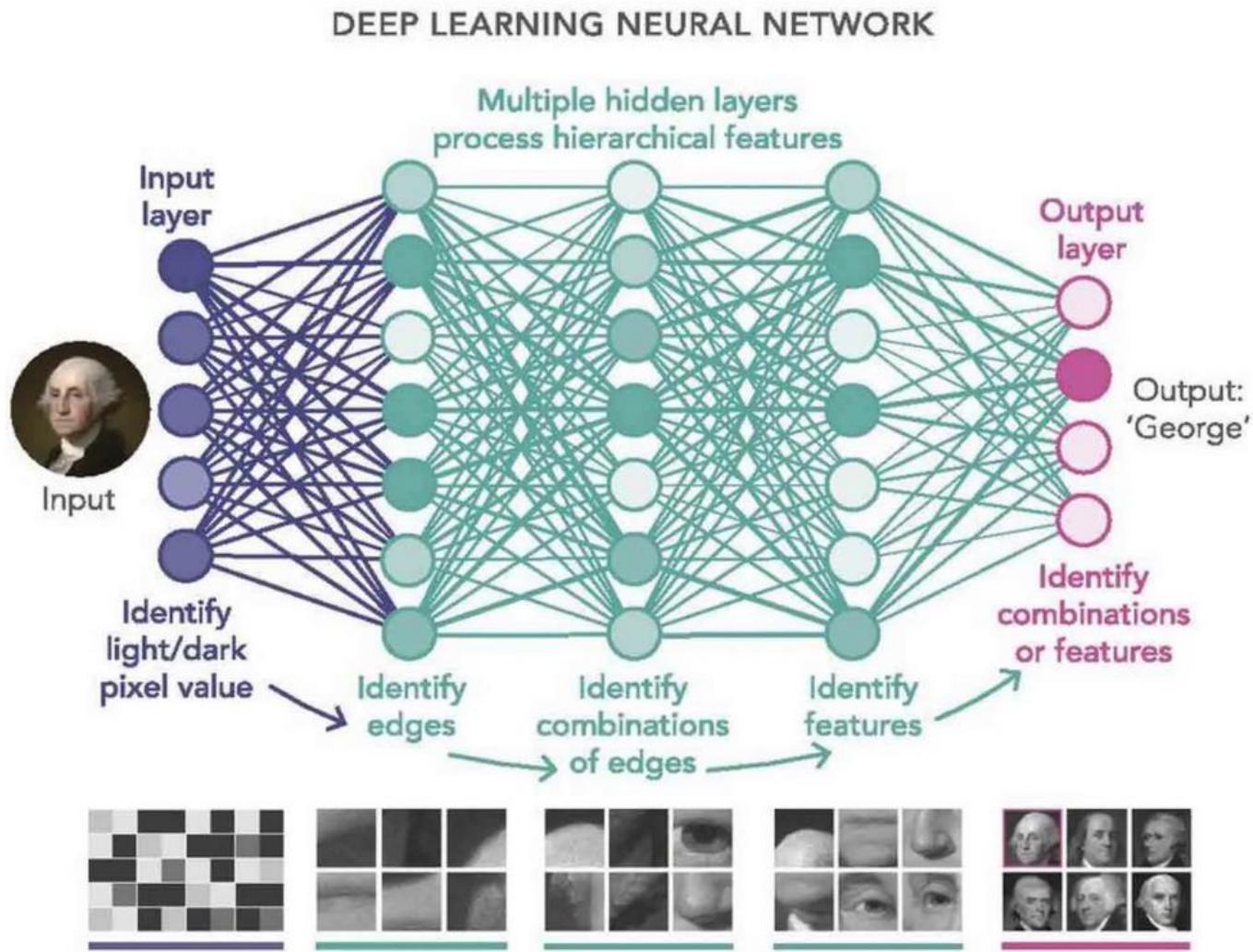


<http://playground.tensorflow.org/>

El Aprendizaje Profundo en la era de la Inteligencia Artificial

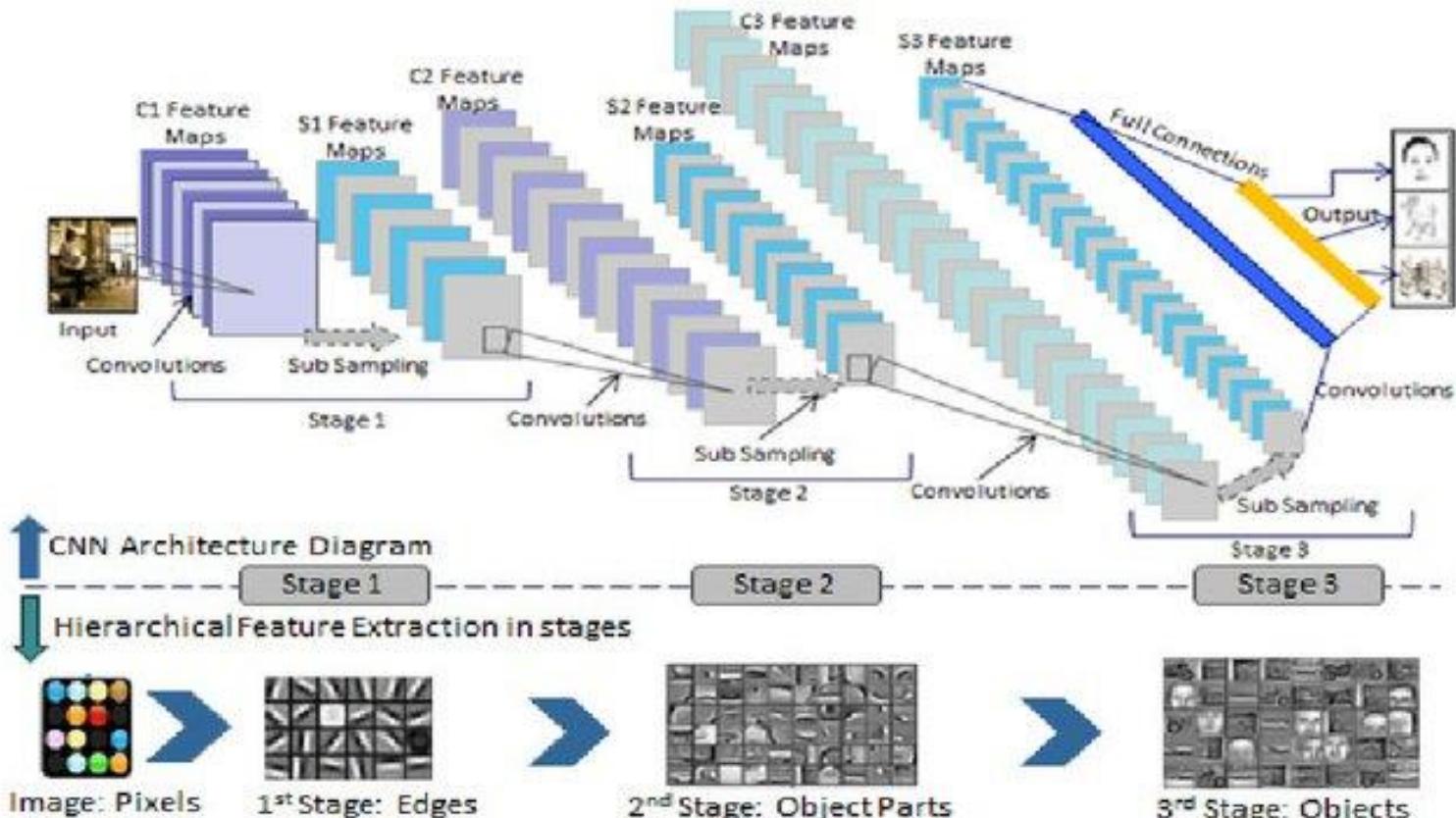
¿Qué es el deep learning?

- **Deep Learning (DL)** es un método basado en redes neuronales profundas que aprenden automáticamente estructuras y patrones complejos en los datos mediante representaciones jerarquicas no lineales
- Se inspira en la estructura neuronal del cerebro humano
- El modelo se compone por multiples capas intermedias
- Permite modelar relaciones no lineales en grandes volúmenes de datos



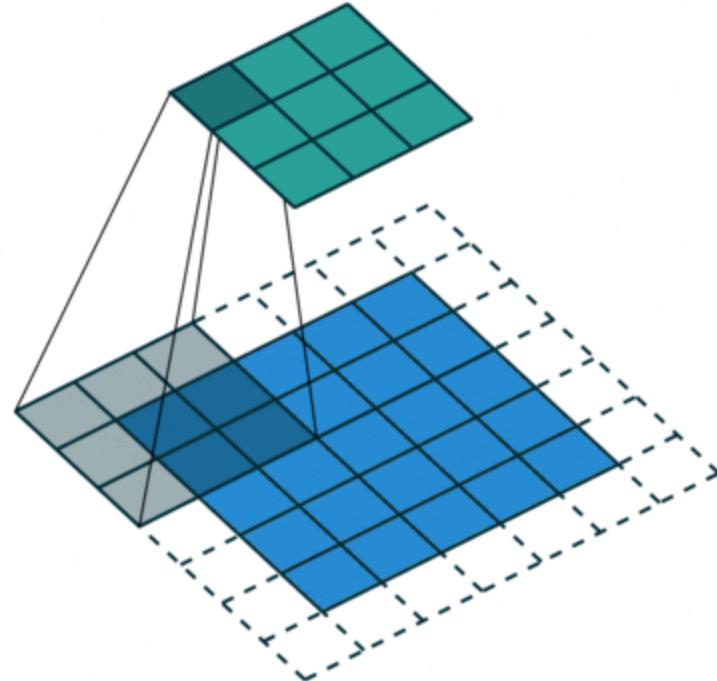
M. Mitchell Warldrop, Artificial Neural Network; from <https://www.pnas.org>

Red Neuronal Convolucional



Katole et al. Hierarchical Deep Learning Architecture For 10K Objects Classification. Doi: 10.5121/csit.2015.51408

Operaciones convolucionales



Kernel: Pequeño filtro que recorre la imagen y extrae características locales como bordes, texturas o patrones.

1 <small>$\times 1$</small>	1 <small>$\times 0$</small>	1 <small>$\times 1$</small>	0	0
0 <small>$\times 0$</small>	1 <small>$\times 1$</small>	1 <small>$\times 0$</small>	1	0
0 <small>$\times 1$</small>	0 <small>$\times 0$</small>	1 <small>$\times 1$</small>	1	1
0	0	1	1	0
0	1	1	0	0

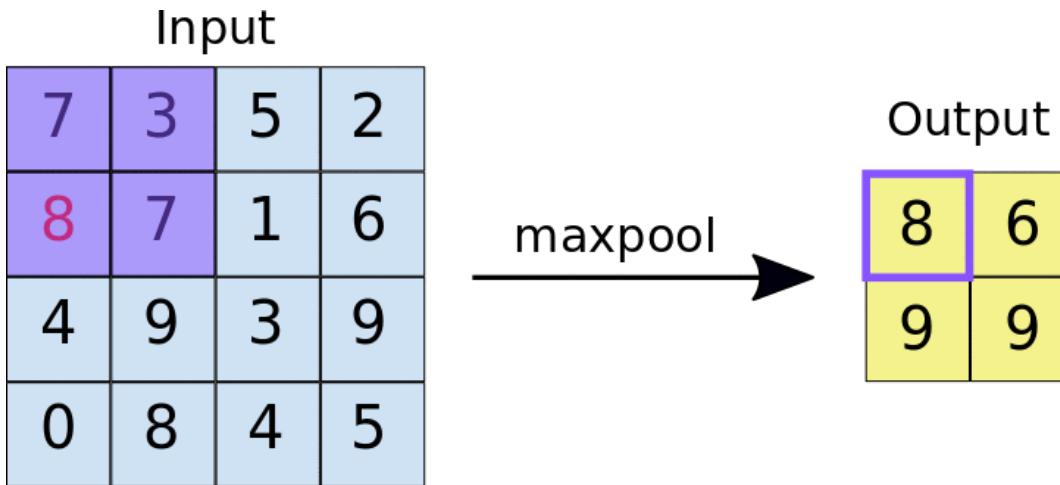
Image

4		

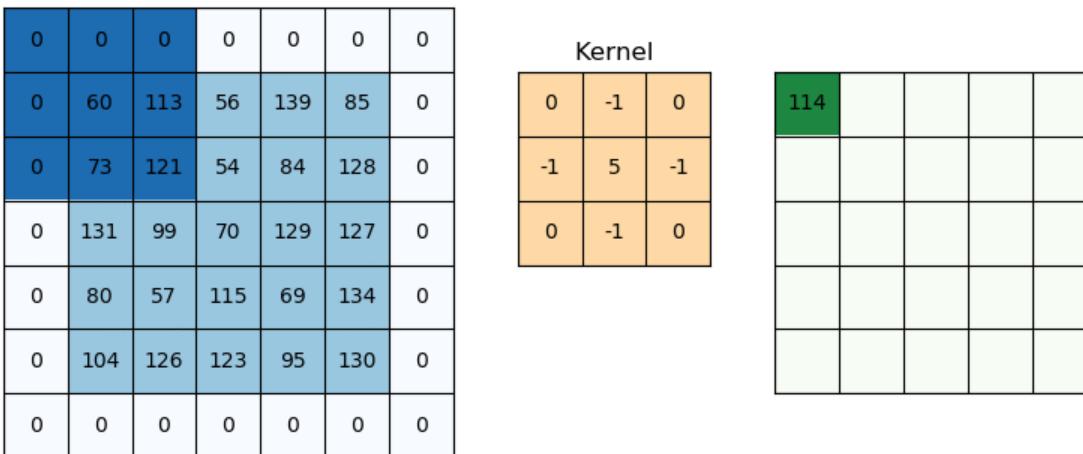
Convolved
Feature

Convolución: Operación que multiplica y suma los valores del kernel con regiones locales de la imagen para generar un mapa de características.

Operaciones convolucionales



Max-Pooling: Técnica de reducción de dimensionalidad que conserva solo el valor máximo de regiones locales, manteniendo las características más importantes.

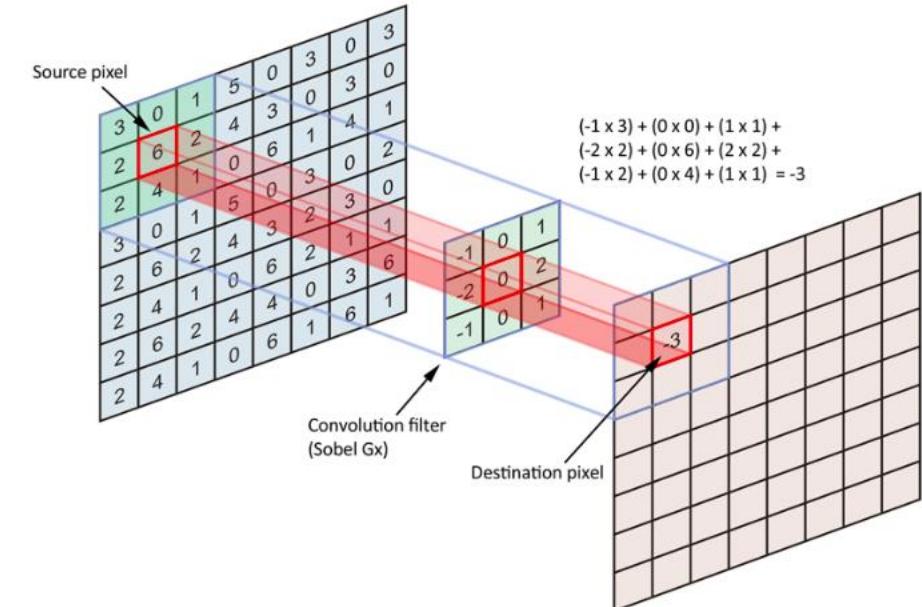


Padding: Adición de bordes (normalmente ceros) alrededor de la imagen para mantener el tamaño de salida o evitar pérdida de información en los bordes.

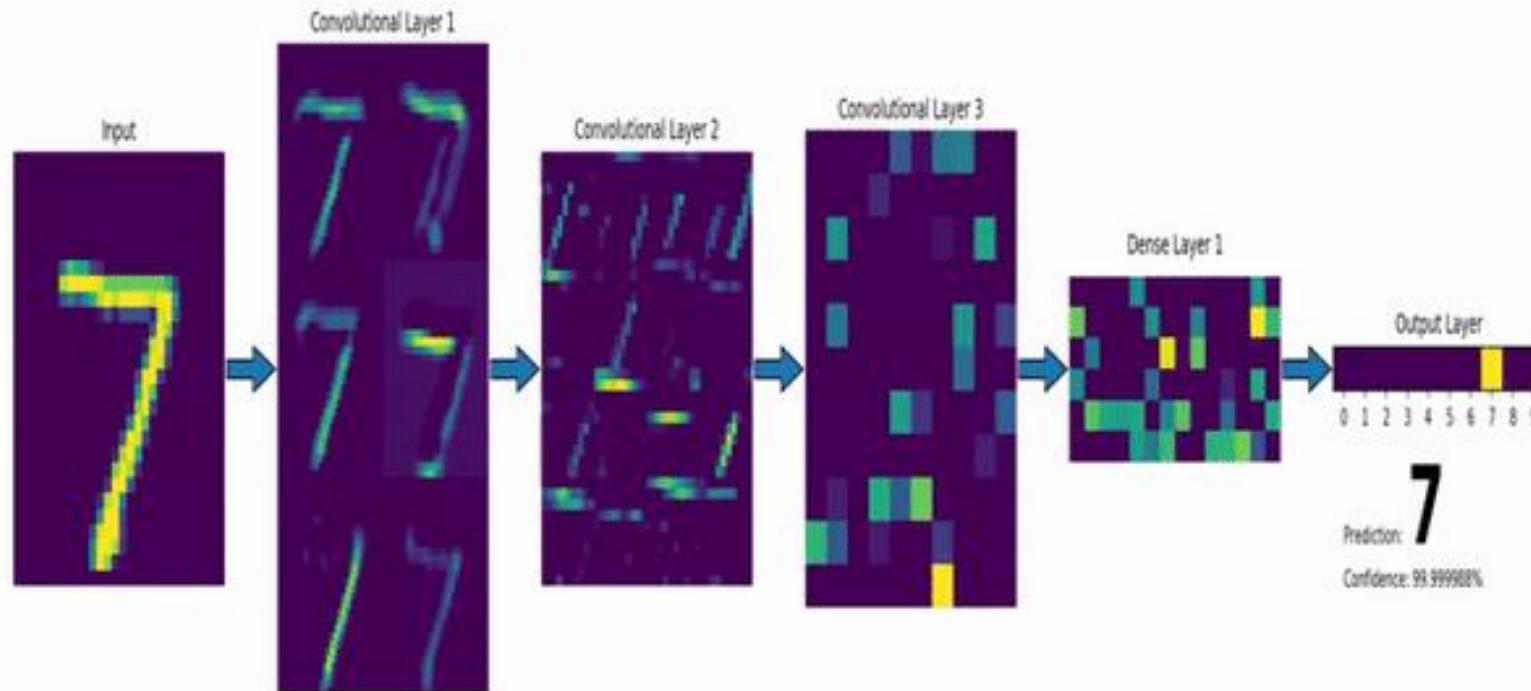
Capa Convolucional – Extracción de Características

Input Volume (+pad 1) (7x7x3)	Filter W0 (3x3x3)	Output Volume (3x3x2)
x[:, :, 0]	w0[:, :, 0]	$\sigma[:, :, 0]$
0 0 0 0 0 0 0	-1 0 1	2 3 3
0 0 0 1 0 2 0	0 0 1	3 7 3
0 1 0 2 0 1 0	1 -1 1	8 10 -3
0 1 0 2 2 0 0	w0[:, :, 1]	$\sigma[:, :, 1]$
0 2 0 0 2 0 0	-1 0 1	-8 -8 -3
0 2 1 2 2 0 0	1 -1 1	1 -1 0
0 0 0 0 0 0 0	0 1 0	-3 1 0
x[:, :, 1]	w0[:, :, 2]	$\sigma[:, :, 2]$
0 0 0 0 0 0 0	-1 1 1	-3 -8 -5
0 2 1 2 1 1 0	1 1 0	
0 2 1 2 0 1 0	0 -1 0	
0 0 2 1 0 1 0	1 0 0	
0 1 2 2 2 2 0	Bias b0 (1x1x1)	
0 0 1 2 0 1 0	b0[:, :, 0]	0
0 0 0 0 0 0 0		
x[:, :, 2]		
0 0 0 0 0 0 0		
0 2 1 1 2 0 0		
0 1 0 0 1 0 0		
0 0 1 0 0 0 0		
0 1 0 2 1 0 0		
0 2 2 1 1 1 0		
0 0 0 0 0 0 0		

toggle movement

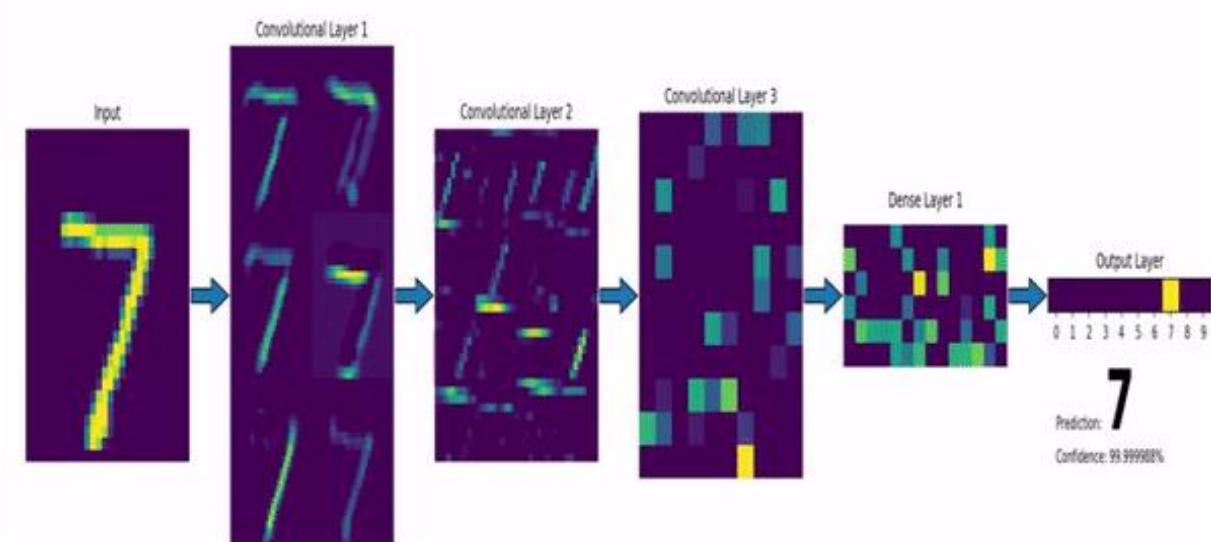
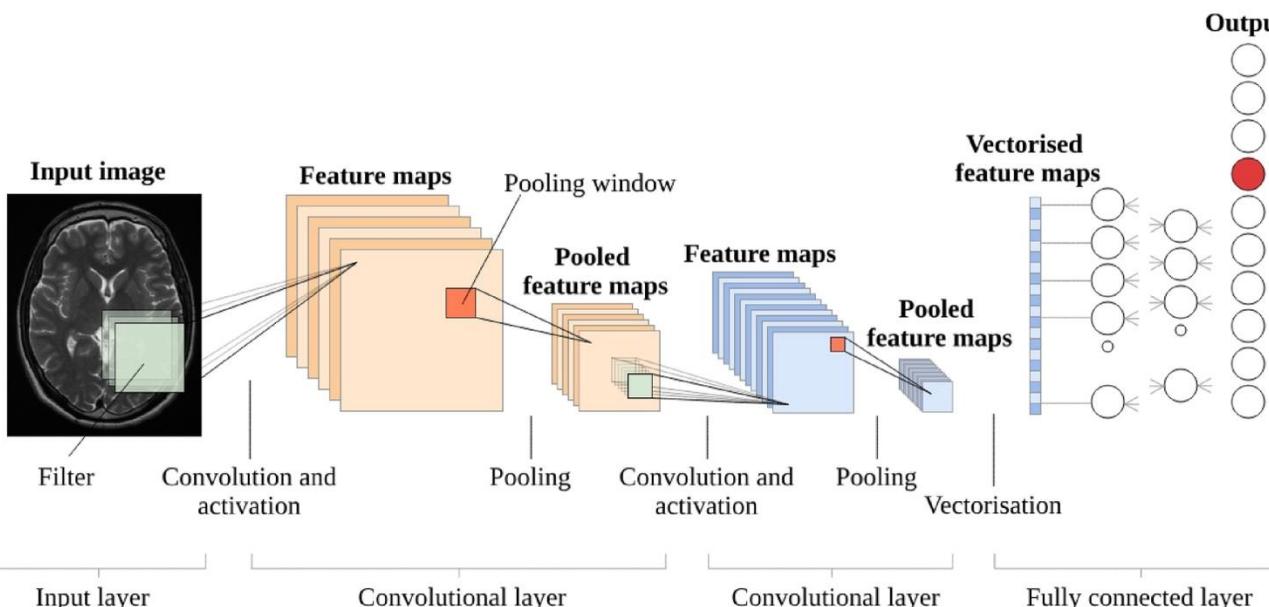


Visualización de aprendizaje de filtros



<https://www.louisbouchard.ai/densenet-explained/> of semantic segmentation, classification and localization, object detection and instance segmentation (Li, Johnson and Yeung, 2017)

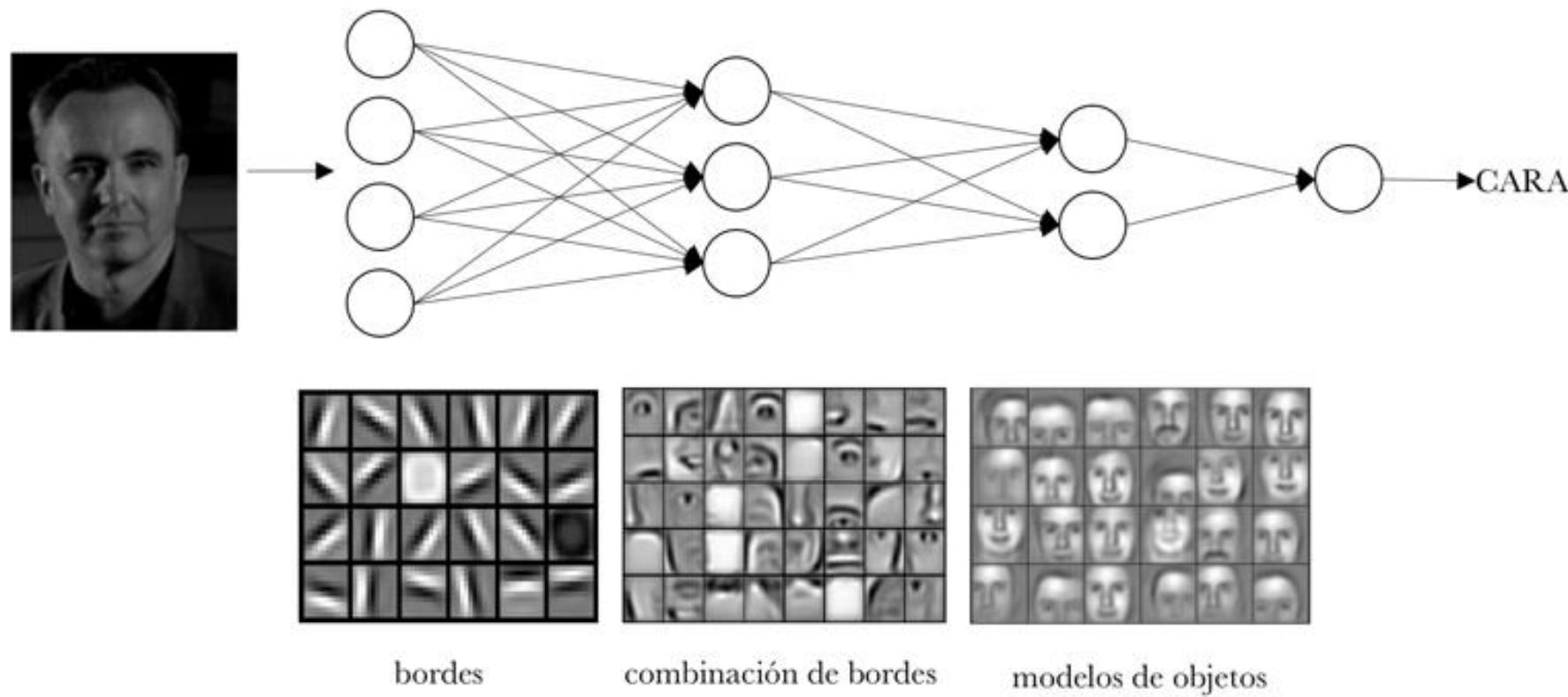
Red Neuronal Convolucional



<https://doi.org/10.1016/j.zemedi.2018.11.002>

<https://www.louisbouchard.ai/densenet-explained/>

Aprendizaje de Características jerárquicas



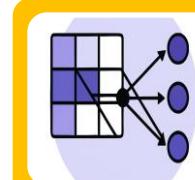
viewnext.com/transfer-learning-y-redes-convolucionales/

Red neuronal convolucional

La red convolucional (CNN) es un tipo de red neuronal especializada en procesar datos con estructura espacial. Su diseño permite detectar patrones visuales directamente desde los píxeles, sin necesidad de definir manualmente las características.



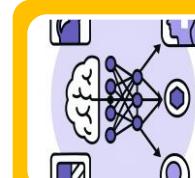
Cada neurona se conecta solo a una **región local** del input (campo receptivo), capturando patrones como bordes o texturas.



Apila capas jerárquicamente, aprendiendo desde detalles simples hasta representaciones complejas.

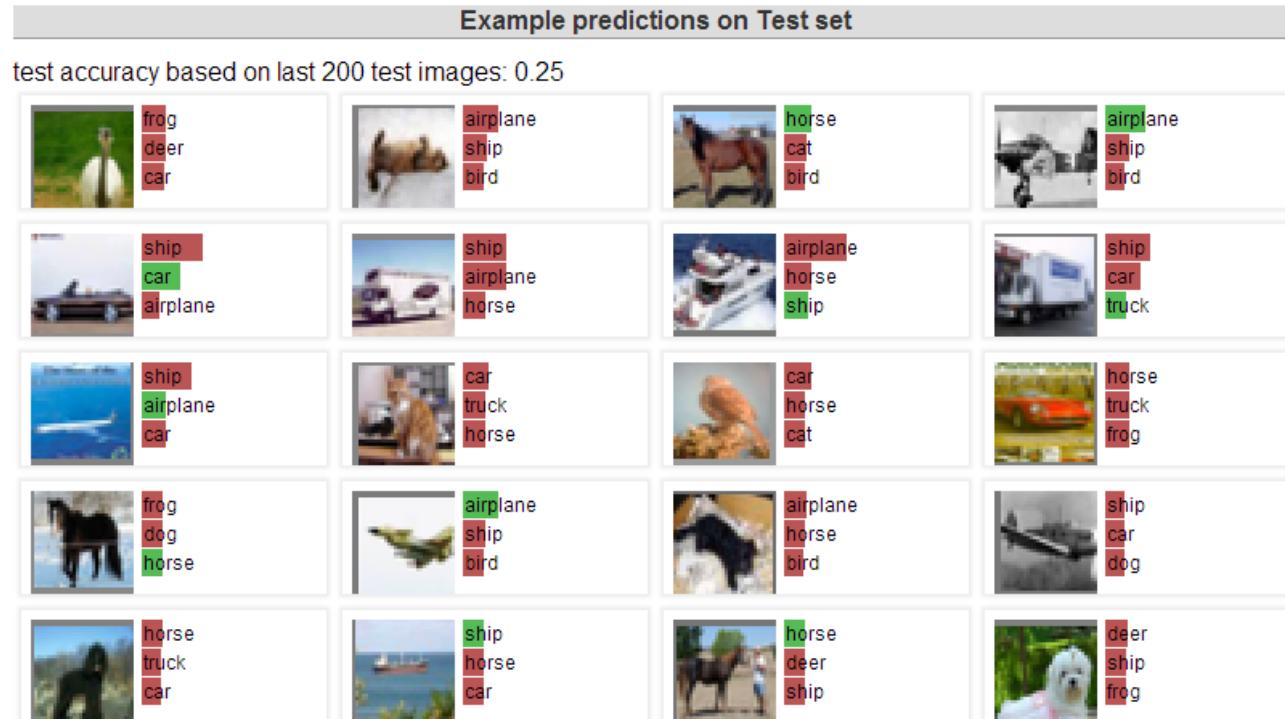
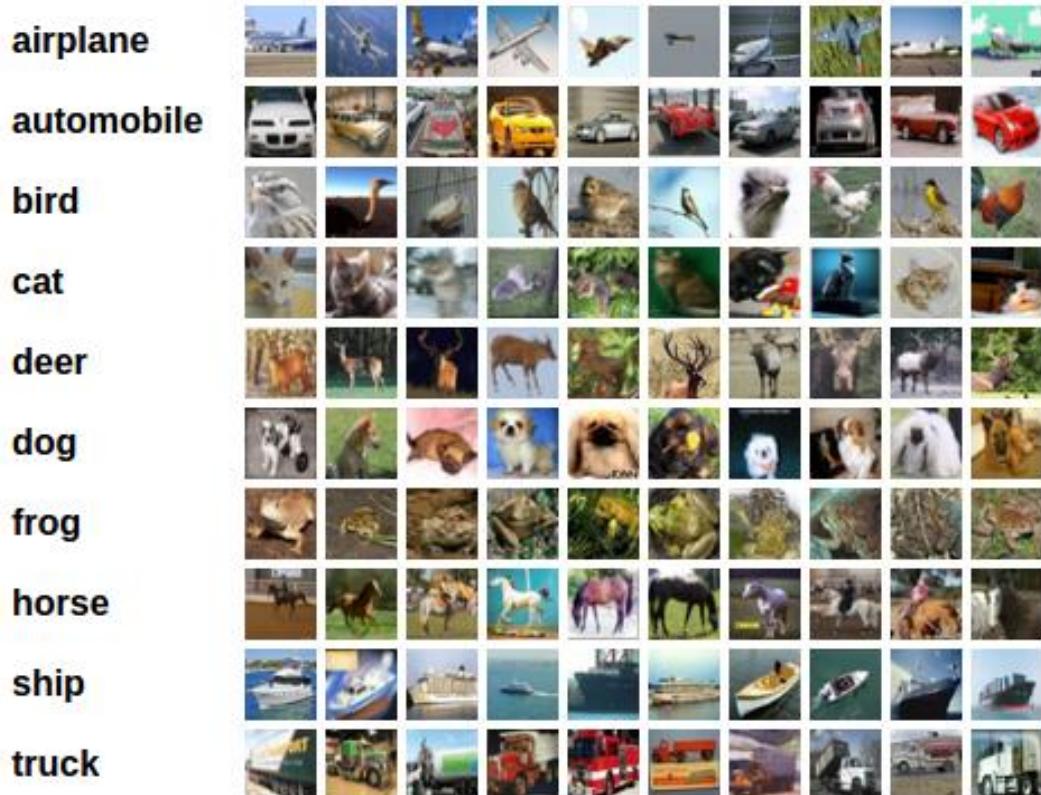


Usa **pesos compartidos** y **filtros** que recorren la imagen, reduciendo drásticamente la cantidad de parámetros.



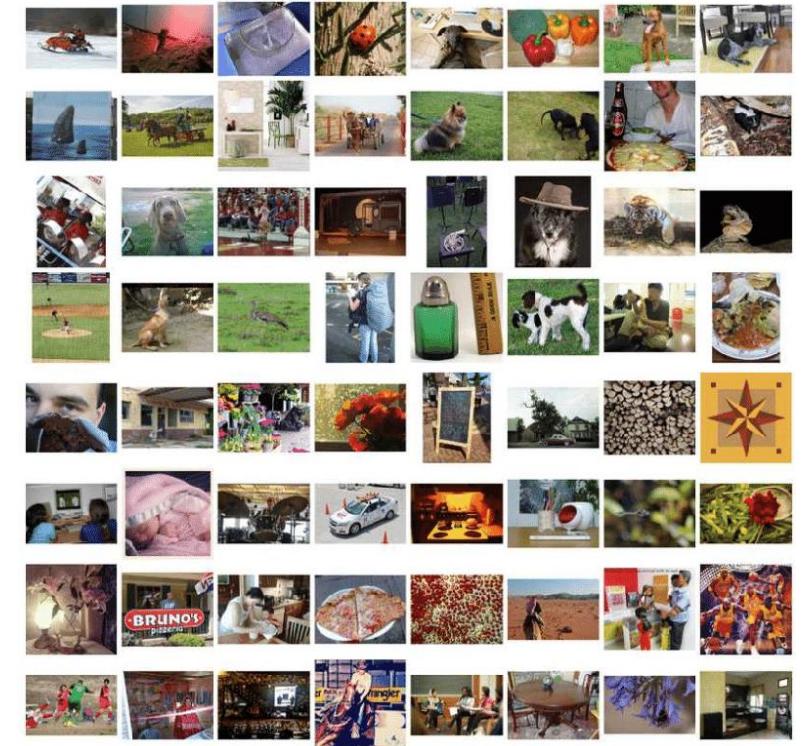
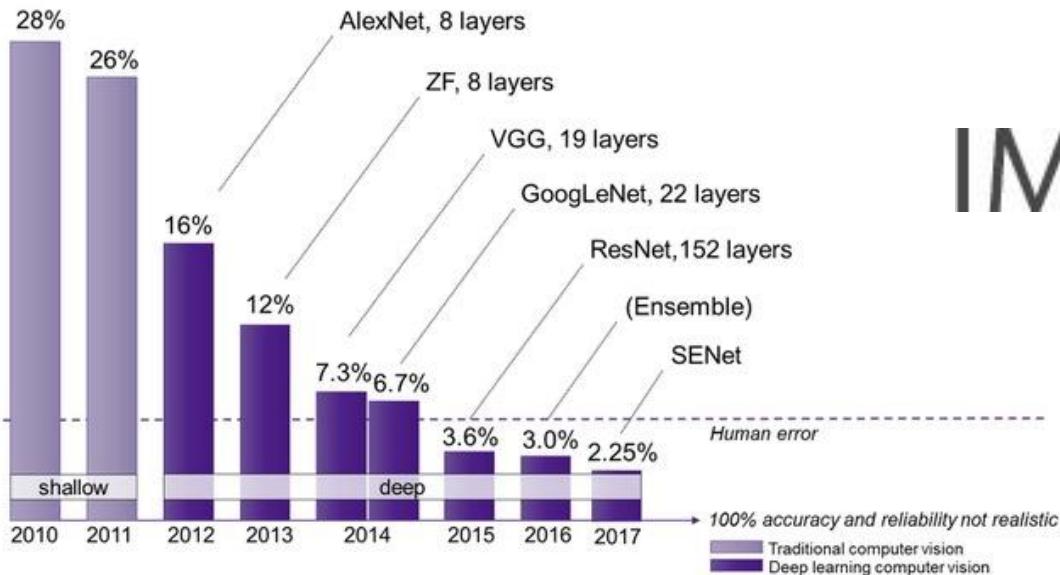
Es altamente efectiva en tareas como **clasificación, segmentación y detección de objetos**.

ConvNetJS CIFAR-10 demo



<http://cs.stanford.edu/people/karpathy/convnetjs/demo/cifar10.html>

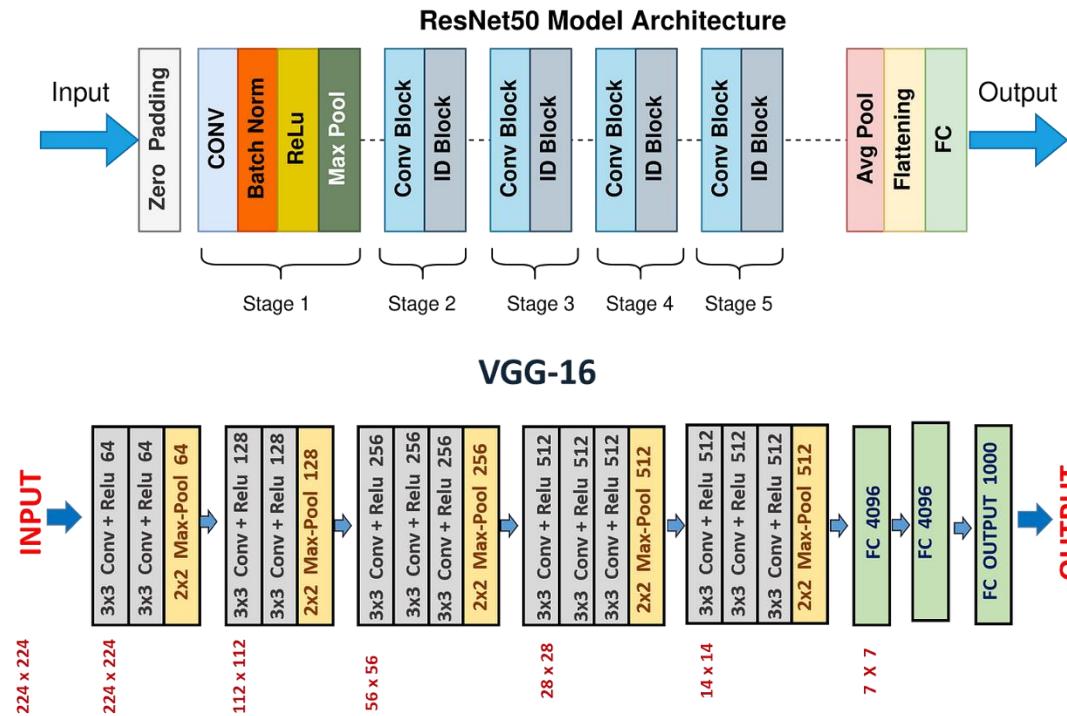
Large Scale Visual Recognition Challenge (ILSVRC)



<http://www.image-net.org/challenges/LSVRC/>

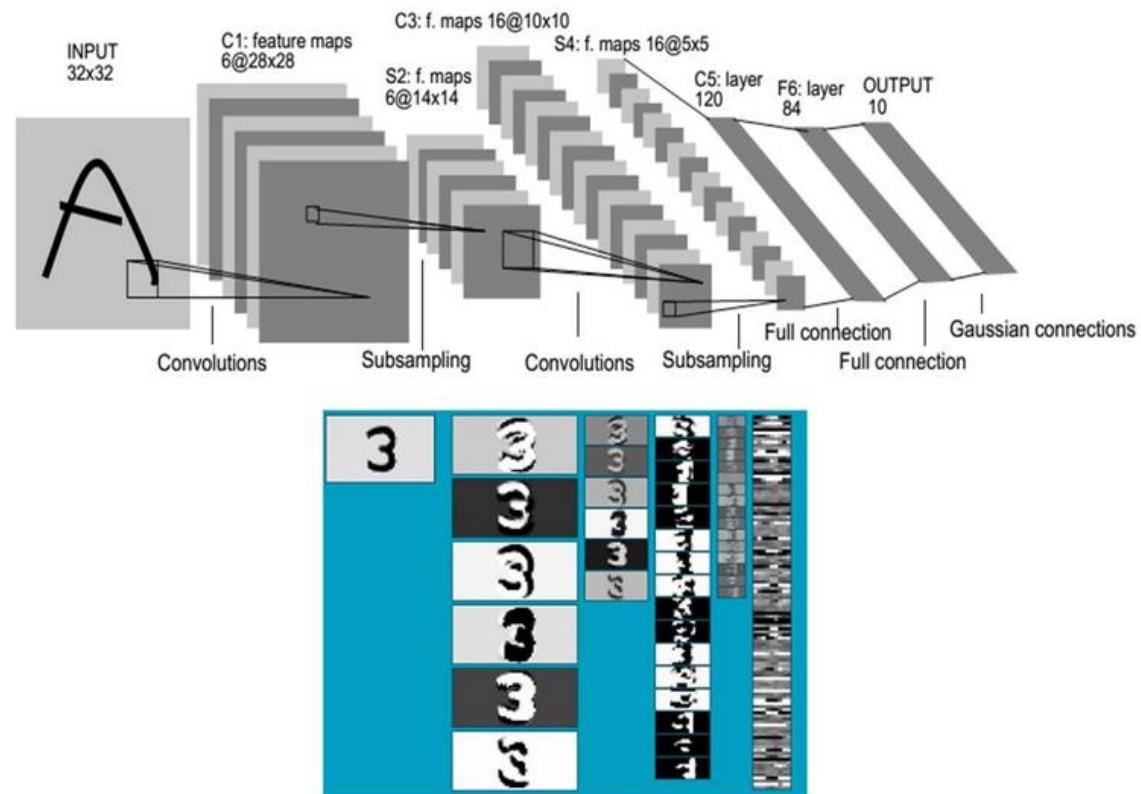
<https://gigaom.com/2014/08/22/with-enlitic-a-veteran-data-scientist-plans-to-fight-disease-using-deep-learning/>

Arquitecturas basadas en CNN

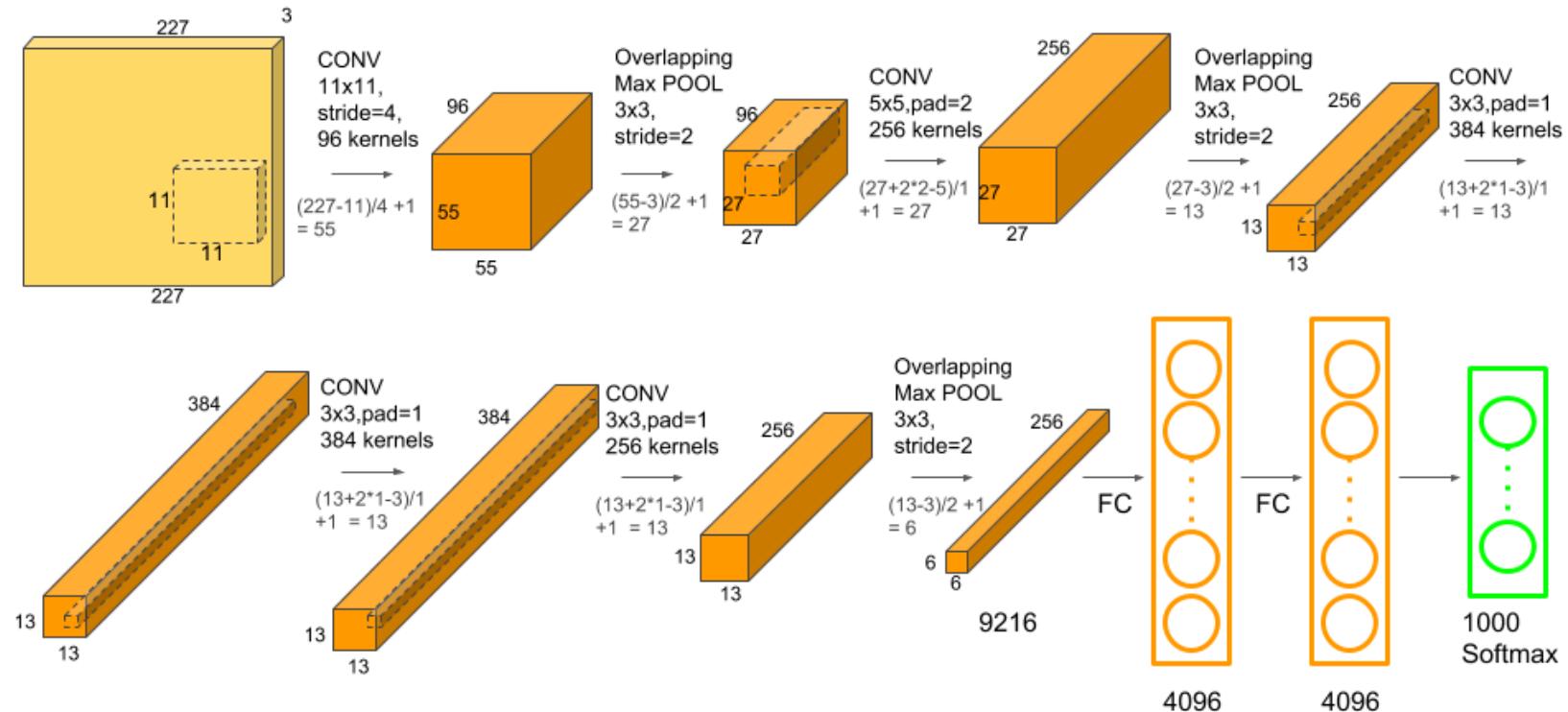


Estas arquitecturas CNN (VGG, ResNet, U-Net) aprenden representaciones visuales jerárquicas y se adaptan a tareas como clasificación y segmentación pixel a pixel.

LeNet

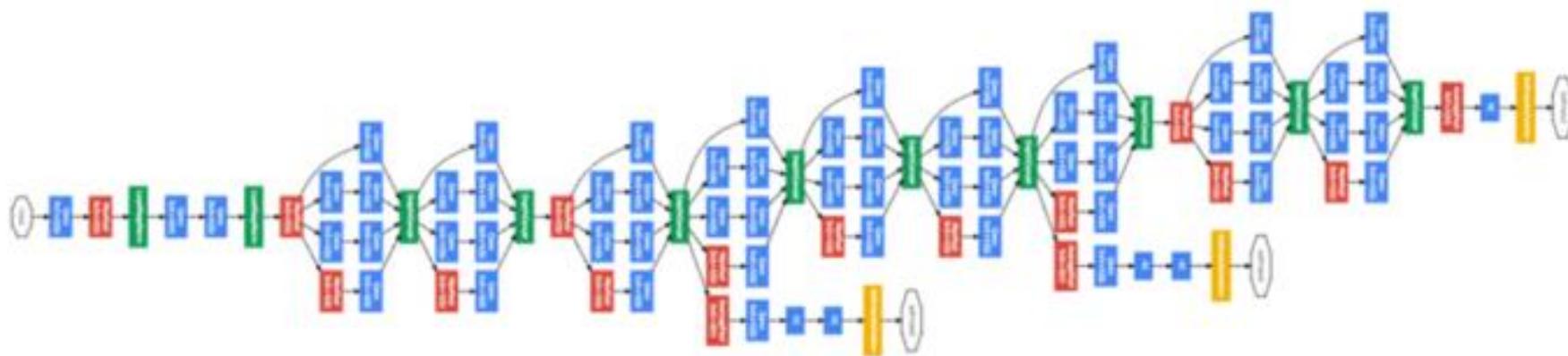


AlexNet

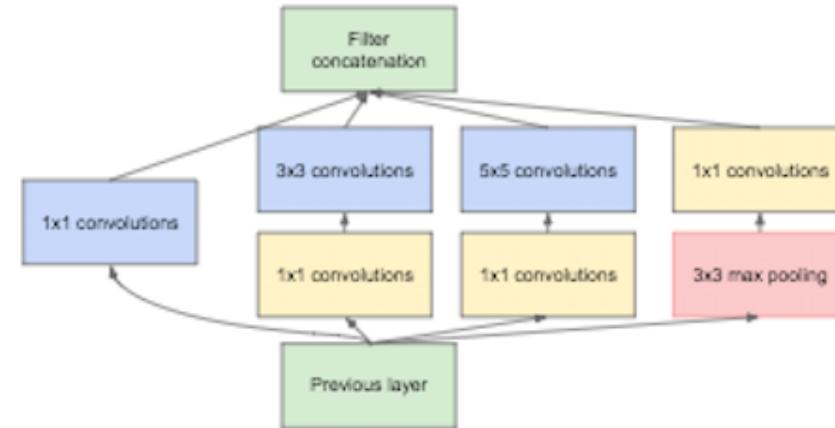


<https://medium.com/@smallfishbigsea/a-walk-through-of-alexnet-6cbd137a5637>

GoogLeNet



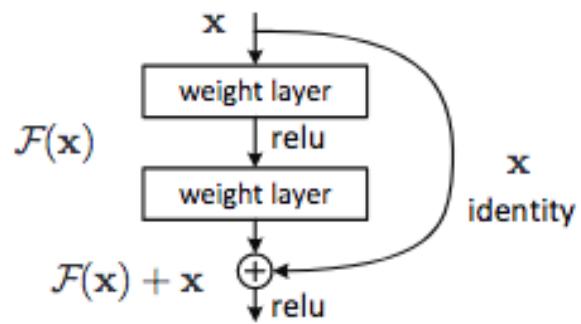
- **GoogLeNet:** desarrollado por C. Szegedy et al. from Google. (2014).
- Introdujo el módulo de Inception, el cual redujo el número de parámetros en la red (Sparsity)



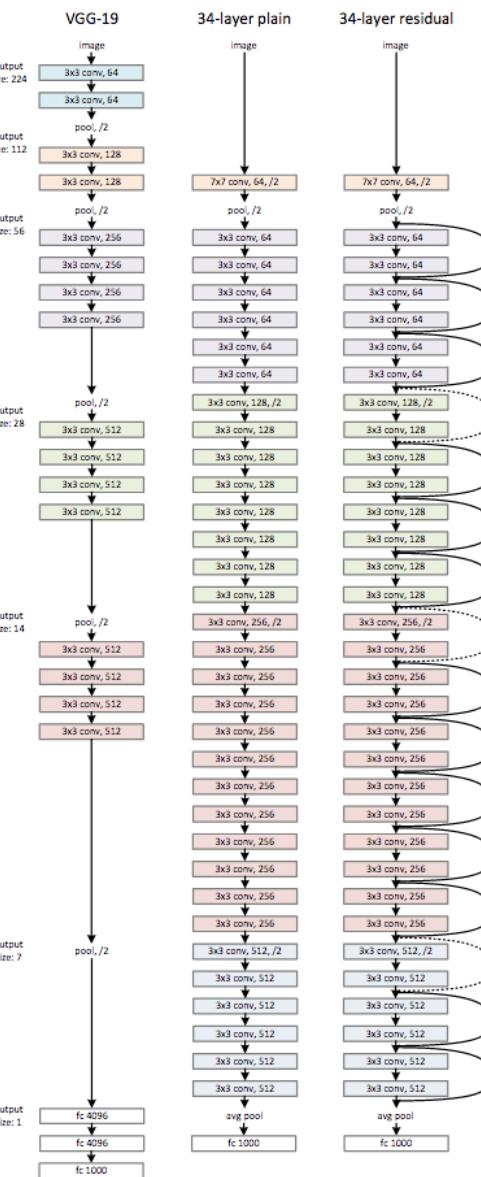
Módulo de Inception con reducción de la dimensionalidad

Residual Learning

- El aprendizaje residual (ResNet) fue propuesto por **K. He et al. (2015)**
 - Se utiliza para aprender con mayor profundidad

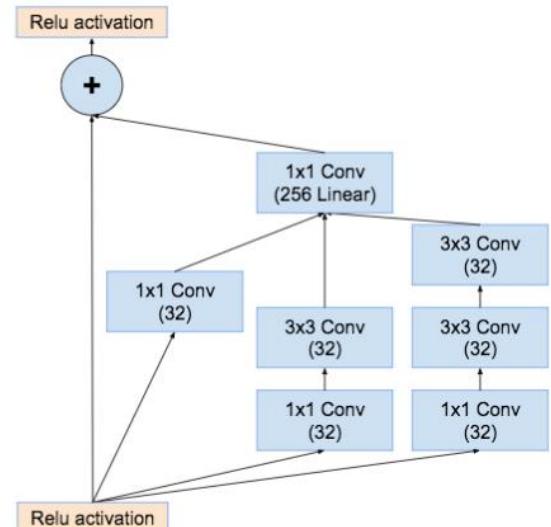


Bloque de aprendizaje residual

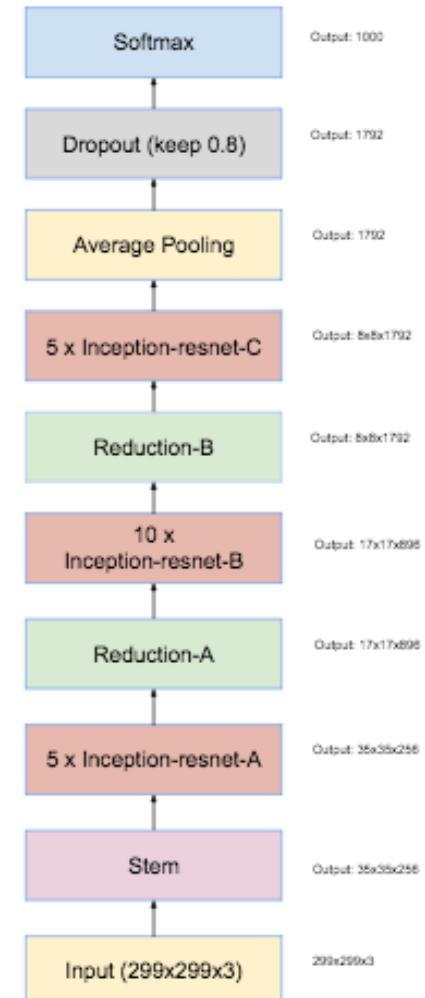


Inception-Resnet

- Propuesto por C. Szegedy 2016
- Combina el módulo de Inception (Sparsity) con el módulo ResNet (Deep)



Módulo de Inception-ResNet-A

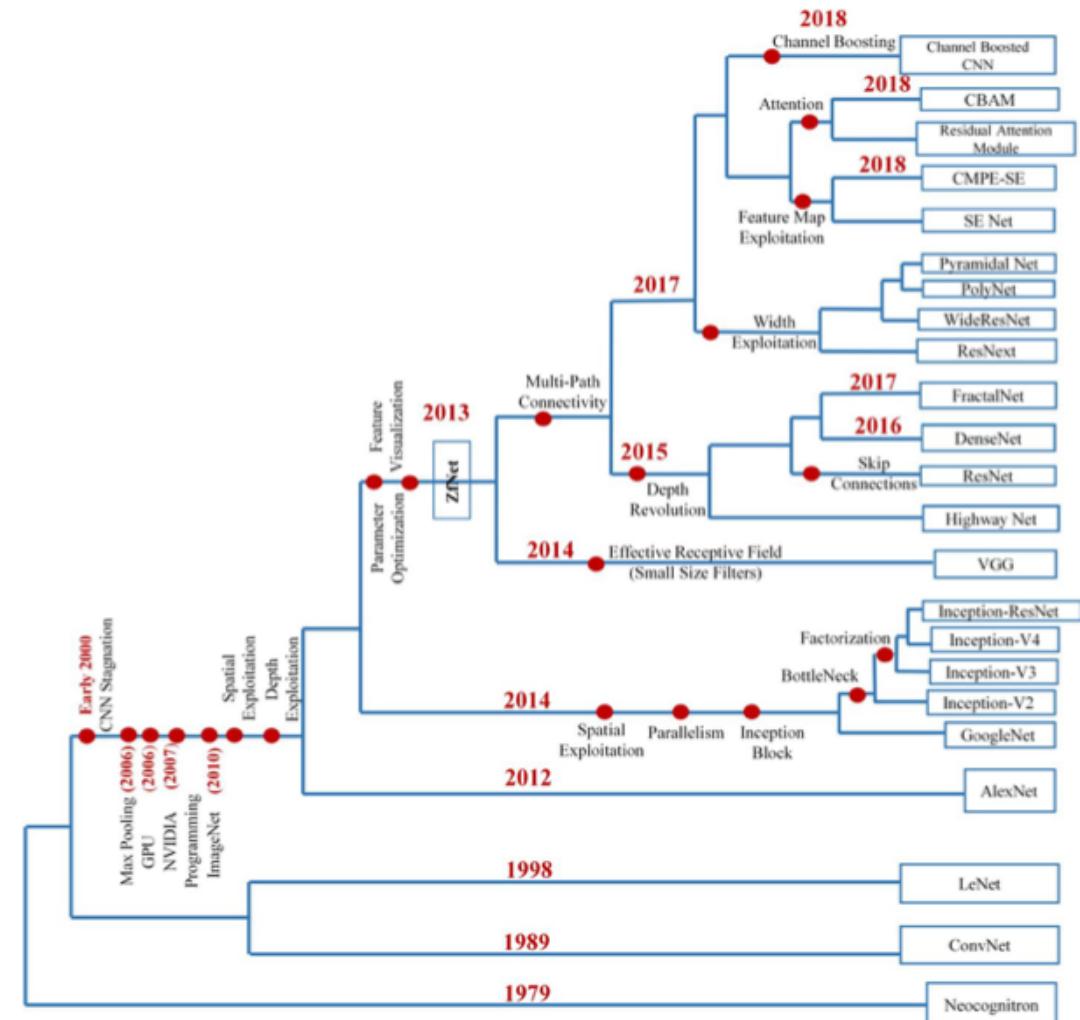
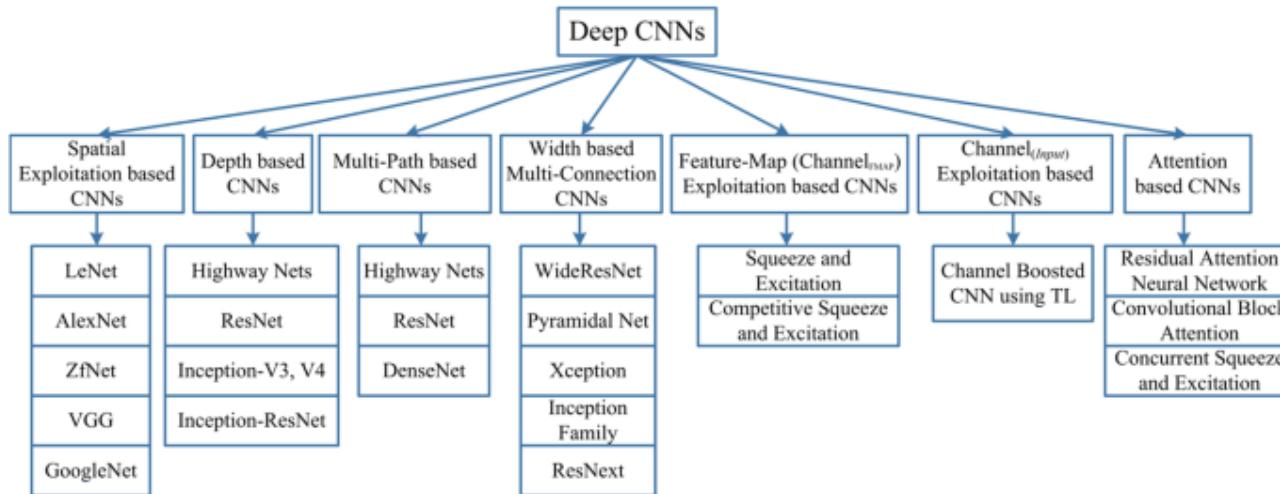


Arquitecturas de Deep Learning

Artificial Intelligence Review (2020) 53:5455–5516
<https://doi.org/10.1007/s10462-020-09825-6>

A survey of the recent architectures of deep convolutional neural networks

Asifullah Khan^{1,2} · Anabia Sohail^{1,2} · Umme Zahoor¹ · Aqsa Saeed Qureshi¹



Benchmark Analysis of Deep Learning

IEEE Access

Multidisciplinary | Rapid Review | Open Access Journal

Received October 1, 2018, accepted October 17, 2018, date of publication October 24, 2018, date of current version November 19, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2877890

Benchmark Analysis of Representative Deep Neural Network Architectures

SIMONE BIANCO^{ID¹}, REMI CADENE², LUIGI CELONA^{ID¹}, AND PAOLO NAPOLETANO^{ID¹}

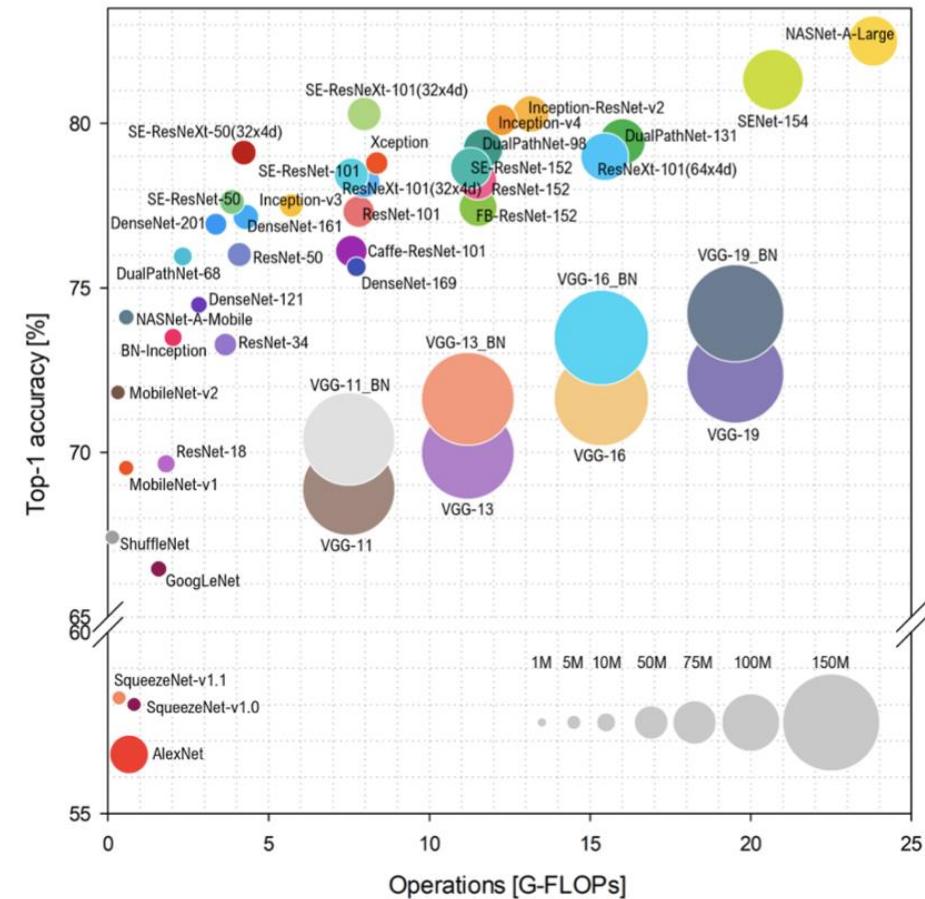
¹Department of Informatics, Systems and Communication, University of Milano-Bicocca, 20126 Milan, Italy

²LIP6, CNRS, Sorbonne Université, 75005 Paris, France

Corresponding author: Luigi Celona (luigi.celona@disco.unimib.it)

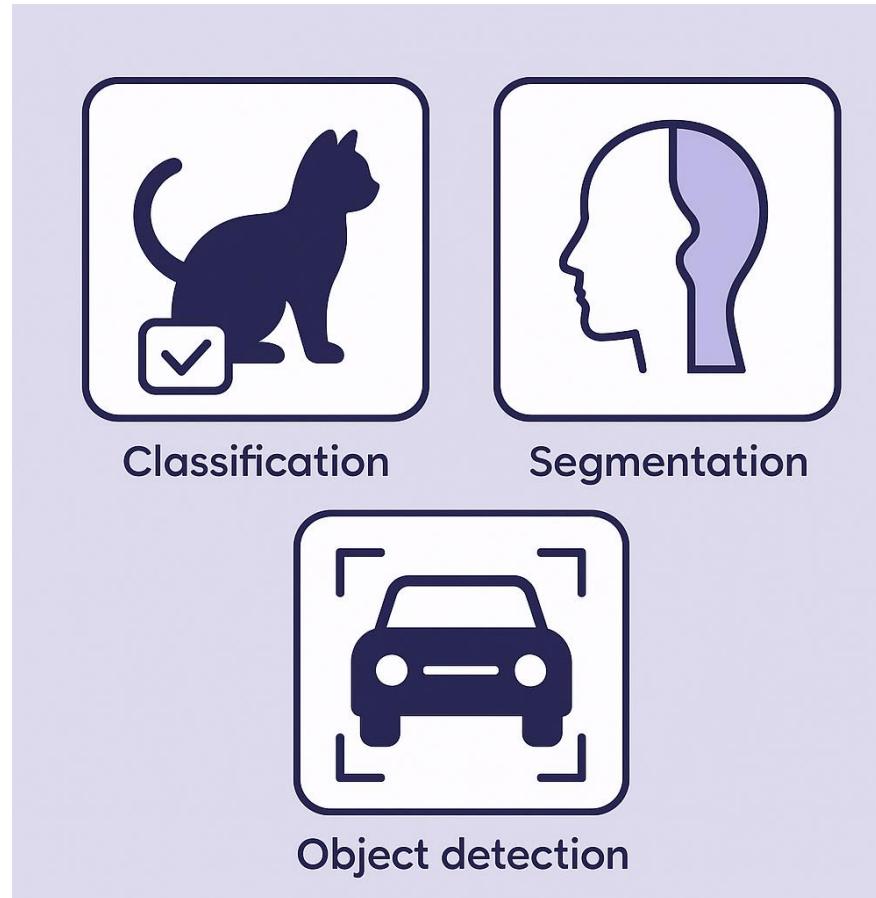
This paper presents an in-depth analysis of the majority of the deep neural networks (DNNs) proposed in the state of the art for image recognition.

For each DNN, multiple performance indices are observed, such as recognition accuracy, model complexity, computational complexity, memory usage, and inference time.

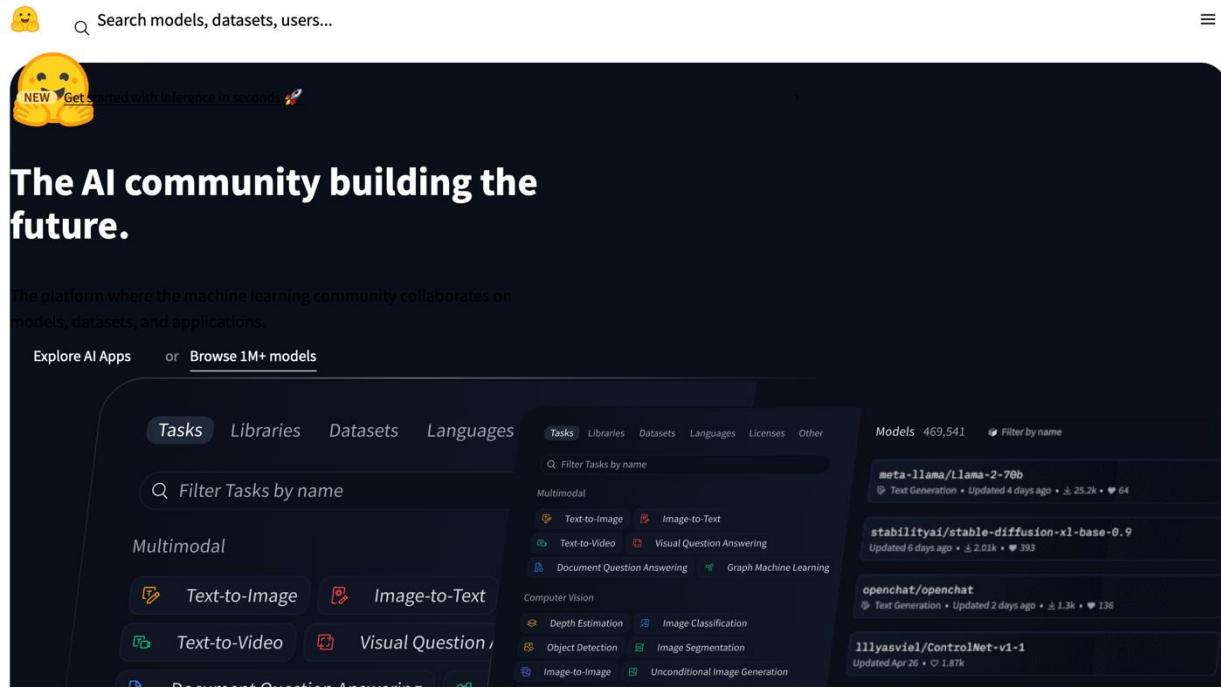


Deep Learning aplicado al procesamiento de Imágenes

Aplicaciones de Deep Learning en imágenes



Hugging Face



The AI community building the future.

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Explore AI Apps or Browse 1M+ models

- Tasks: Multimodal (Text-to-Image, Image-to-Text, Text-to-Video, Visual Question Answering), Computer Vision (Depth Estimation, Object Detection, Image Segmentation, Image-to-Image, Unconditional Image Generation)
- Libraries: Multimodal (Text-to-Image, Image-to-Text, Text-to-Video, Visual Question Answering), Computer Vision (Depth Estimation, Object Detection, Image Segmentation, Image-to-Image, Unconditional Image Generation)
- Datasets: Multimodal (Text-to-Image, Image-to-Text, Text-to-Video, Visual Question Answering), Computer Vision (Depth Estimation, Object Detection, Image Segmentation, Image-to-Image, Unconditional Image Generation)
- Languages: Multimodal (Text-to-Image, Image-to-Text, Text-to-Video, Visual Question Answering), Computer Vision (Depth Estimation, Object Detection, Image Segmentation, Image-to-Image, Unconditional Image Generation)

Models: 469,541

Model Name	Description	Last Updated	Downloads
meta-llama/llama-2-70b	Text Generation • Updated 4 days ago • 25.2k • 64	Updated 4 days ago	25.2k
stabilityai/stable-diffusion-xl-base-0.9	Updated 6 days ago • 2.01k • 393	Updated 6 days ago	2.01k
openchat/openchat	Text Generation • Updated 2 days ago • 1.3k • 136	Updated 2 days ago	1.3k
1illyasviel/ControlNet-v1-1	Updated Apr 26 • 1.87k	Updated Apr 26	1.87k

💡 mawady/demo-catsvsdogs-gradio 🚧 like 2 • Running :

CatsVsDogs Classifier

Playground: Infererence of Object Classification (Binary) using ResNet18 model and CatsVsDogs dataset. Libraries: PyTorch, Gradio.

img
 Coloque la imagen aquí
 - O -
 Haga click para cargar

output


Limpiar
Enviar

Examples




[By Dr. Mohamed Elawady](#)

<https://huggingface.co/spaces/mawady/demo-catsvsdogs-gradio>

Tareas de deep learning con visión por computadora

Semantic
Segmentation



GRASS, CAT,
TREE, SKY

No objects, just pixels

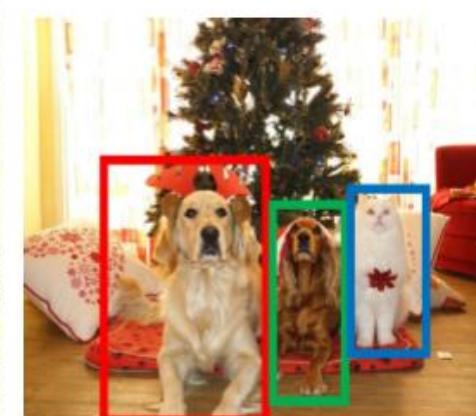
Classification
+ Localization



CAT

Single Object

Object
Detection



DOG, DOG, CAT

Multiple Object

Instance
Segmentation

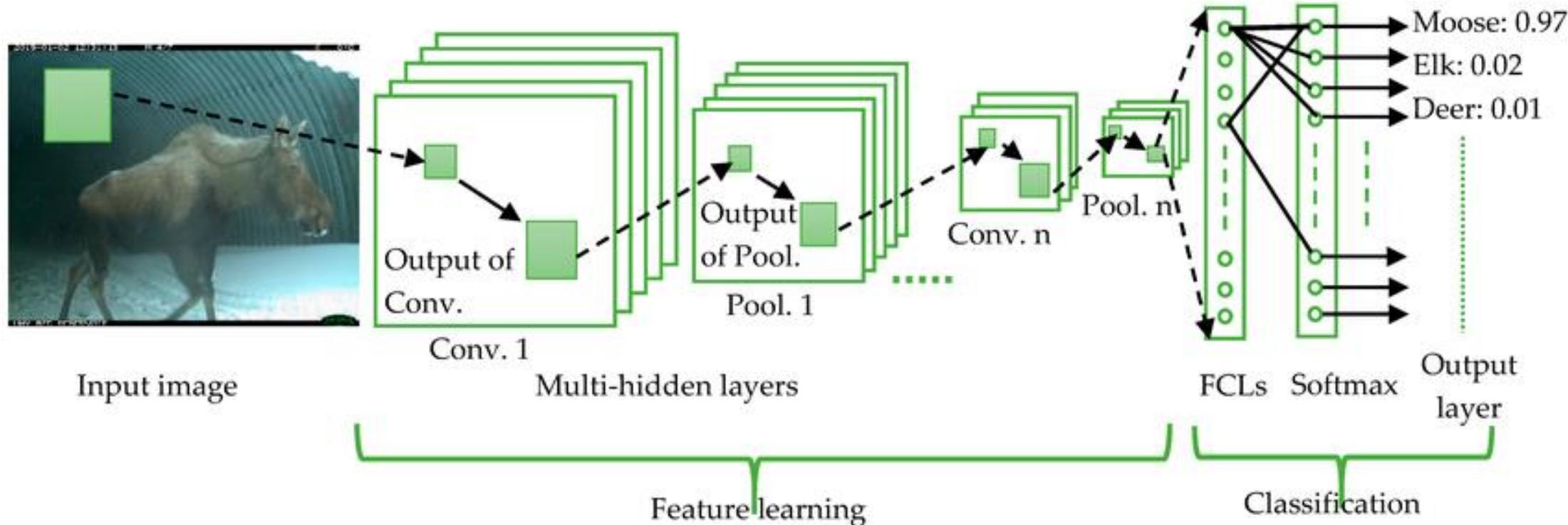


DOG, DOG, CAT

This image is CC0 public domain

Comparison of semantic segmentation, classification and localization, object detection and instance segmentation (Li, Johnson and Yeung, 2017)

Clasificación de imágenes

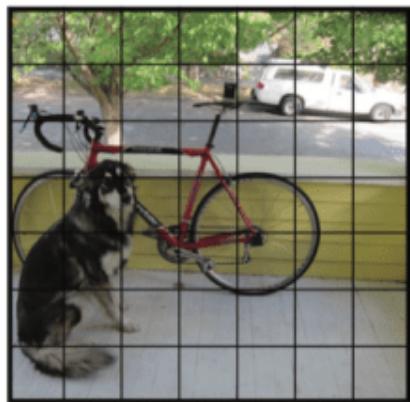


La red extrae características visuales de la imagen a través de capas de convolución y pooling. Luego, estas representaciones se procesan en capas totalmente conectadas para asignar probabilidades a cada clase. El modelo aprende a identificar patrones que permiten clasificar automáticamente lo que hay en la imagen.

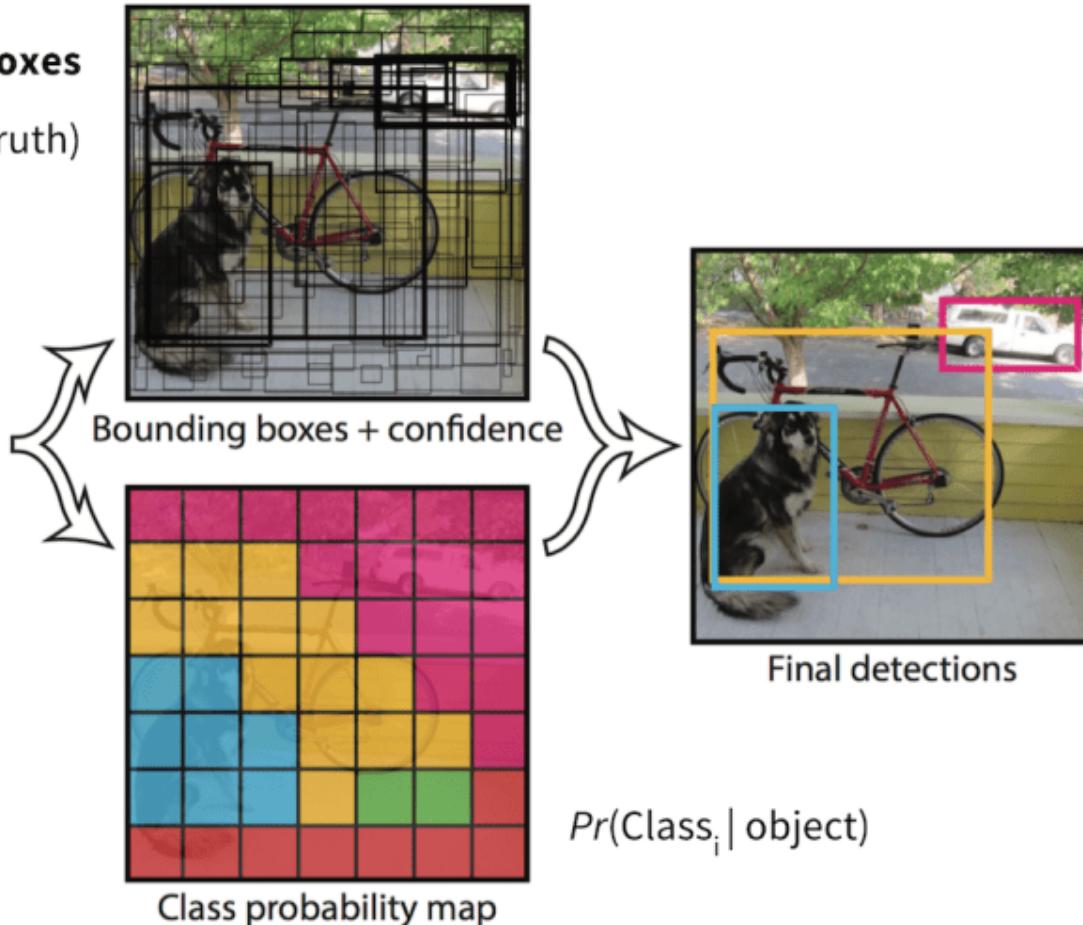
Detección de objetos

$S \times S \times B$ bounding boxes

confidence = $Pr(\text{object}) \times \text{IoU}(\text{pred, truth})$



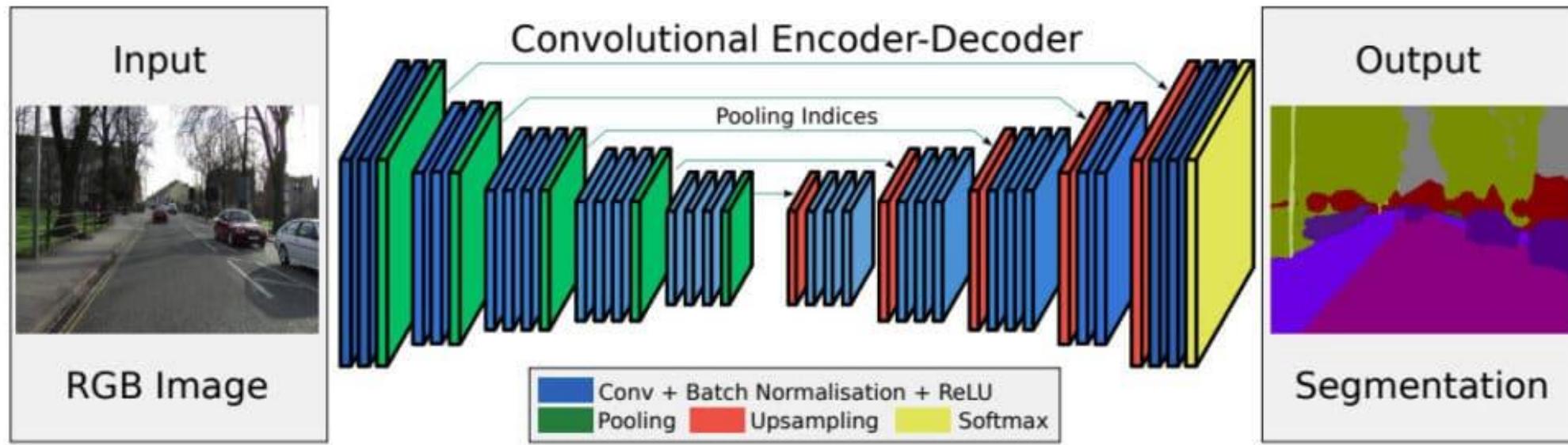
$S \times S$ grid on input



Dr. Ing. Rodrigo Salas (UV-MEDING-iHealth)

La detección de objetos combina localización y clasificación: el modelo divide la imagen en una grilla, predice cajas delimitadoras (bounding boxes) y asigna a cada una probabilidad de clase. A través de medidas como IoU y confidence scores, se identifican y ubican múltiples objetos en una sola imagen.

Segmentación semántica



La segmentación semántica asigna una etiqueta a cada píxel de la imagen, identificando qué clase pertenece a cada región (por ejemplo: calle, auto, persona).

Este proceso se realiza con redes tipo **encoder–decoder**, donde el encoder extrae características y el decoder reconstruye un mapa de clases con la misma resolución que la imagen original.

La época de la Inteligencia Artificial recién comienza

Deep-Learning



Yann LeCun



Yoshua Bengio



Geoffrey Hinton



The screenshot shows the header of a Nature journal article. The title 'nature' is in large white letters, followed by 'International weekly journal of science'. Below the title is a navigation bar with links: Home, News & Comment, Research, Careers & Jobs, Current Issue, Archive, Audio & Video, and For Authors. A breadcrumb trail below the navigation bar shows the article's path: Archive > Volume 521 > Issue 7553 > Insights > Reviews > Article. The main section is titled 'ARTICLE PREVIEW' with a link to 'view full access options'. The article title 'Deep learning' is displayed prominently.

NATURE | INSIGHT | REVIEW



Deep learning

Yann LeCun, Yoshua Bengio & Geoffrey Hinton

Affiliations | Corresponding author

Nature 521, 436–444 (28 May 2015) doi:10.1038/nature14539

Received 25 February 2015 | Accepted 01 May 2015 | Published online 27 May 2015



Citation



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Article metrics

Traducir representaciones de alto nivel



Vision
Deep-CNN

Language
Generating
RNN

Un grupo de personas comprando en un mercado exterior
Existen muchas frutas en los stands de frutas



Una mujer está lanzando un disco en el parque



Un perro en un piso de madera



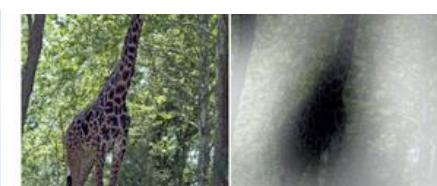
Un signo pare en el camino con unas montañas en el fondo



Una pequeña niña sentada en el sofa con un osito.



Un grupo de personas en un bote en el agua



Una jirafa en el bosque con árboles en el fondo

Turing Awards 2019

SCIENCE \ TECH \ ARTIFICIAL INTELLIGENCE

'Godfathers of AI' honored with Turing Award, the Nobel Prize of computing

Yoshua Bengio, Geoffrey Hinton, and Yann LeCun laid the foundations for modern AI

By James Vincent | Mar 27, 2019, 6:02am EDT



Turing Award Won by 3 Pioneers in Artificial Intelligence



From left, Yann LeCun, Geoffrey Hinton and Yoshua Bengio. The researchers worked on key developments for neural networks, which are reshaping how computer systems are built.

AlphaGo Algorithm

- Algoritmo basado en Deep-Learning vence a un jugador profesional.



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Archive > Volume 529 > Issue 7587 > News > Article

NATURE | NEWS

عربي

Google AI algorithm masters ancient game of Go

Deep-learning software defeats human professional for first time.

Elizabeth Gibney

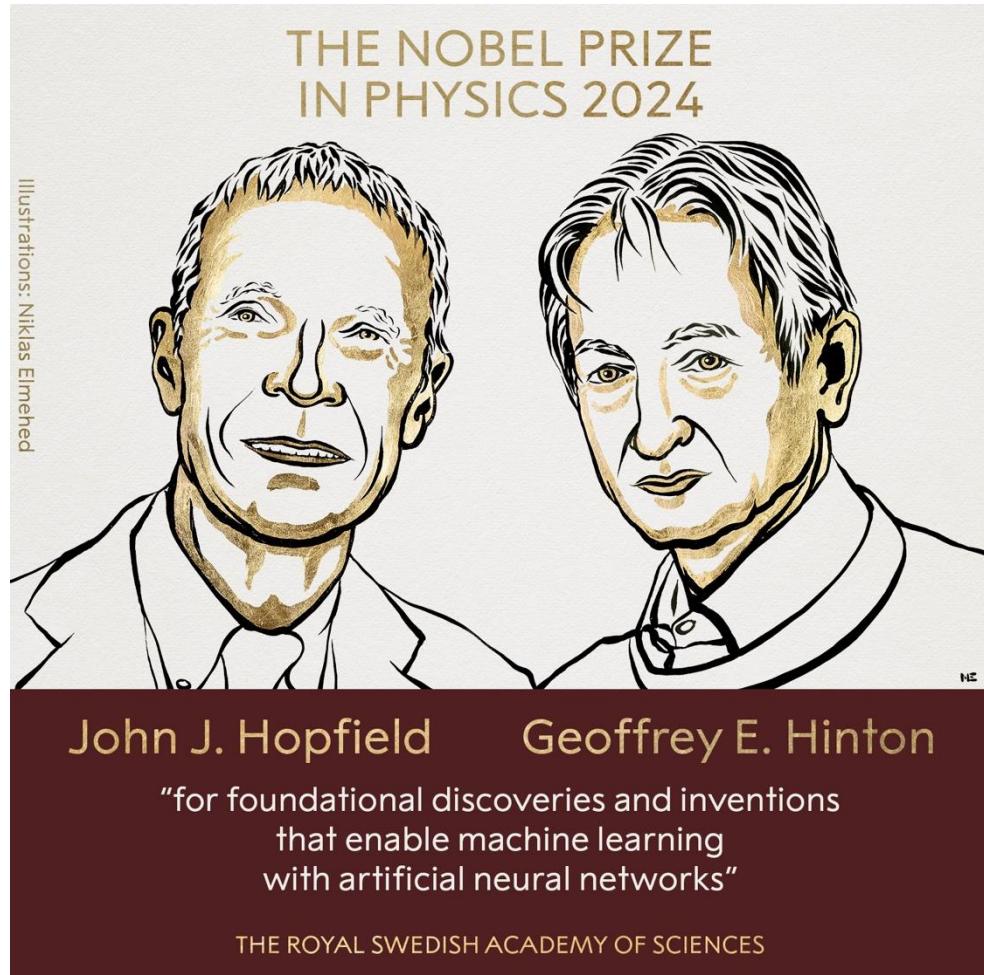
27 January 2016

 PDF

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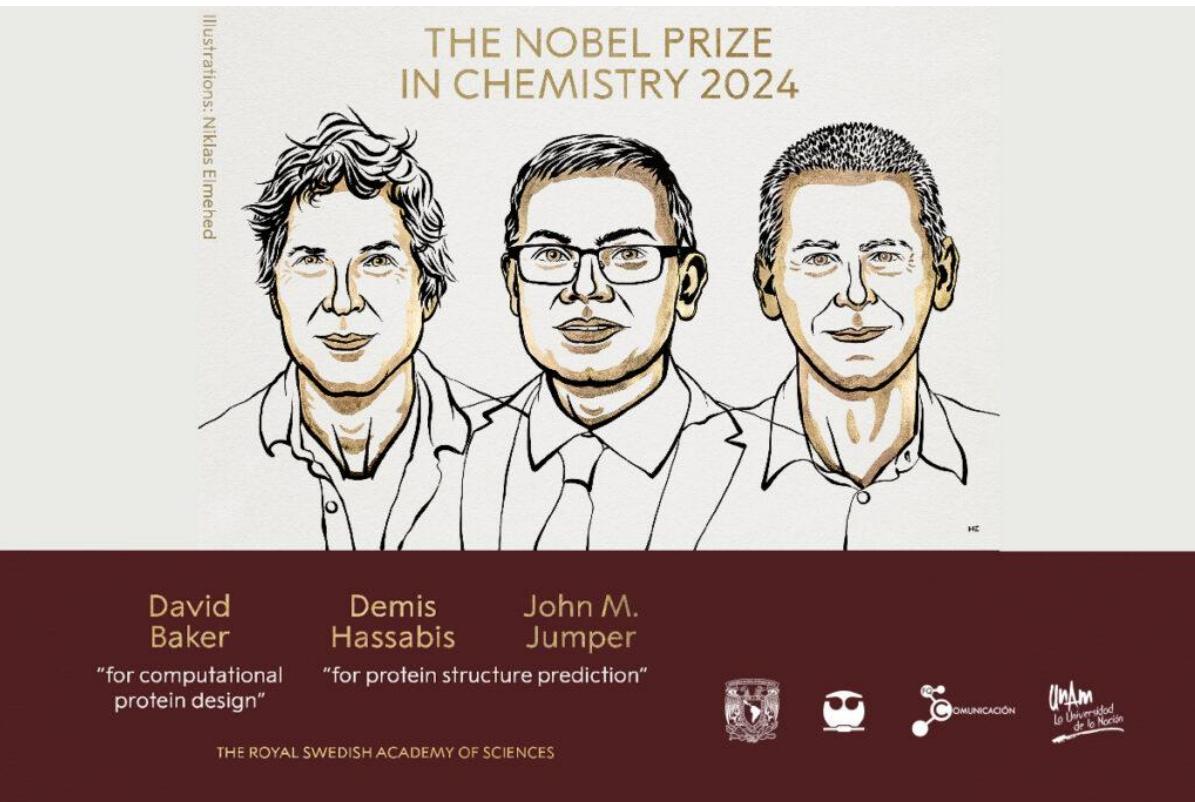
Premio Nobel de Física 2024



This year's Nobel Prize in Physics has been awarded to John J. Hopfield (Princeton University, NJ, USA) and Geoffrey E. Hinton (University of Toronto, Canada) "for foundational discoveries and inventions that enable machine learning with artificial neural networks."

<https://www.ift.uam-csic.es/en/news/nobel-prize-physics-2024-goes-innovations-machine-learning>

Premio Nobel de Química 2024



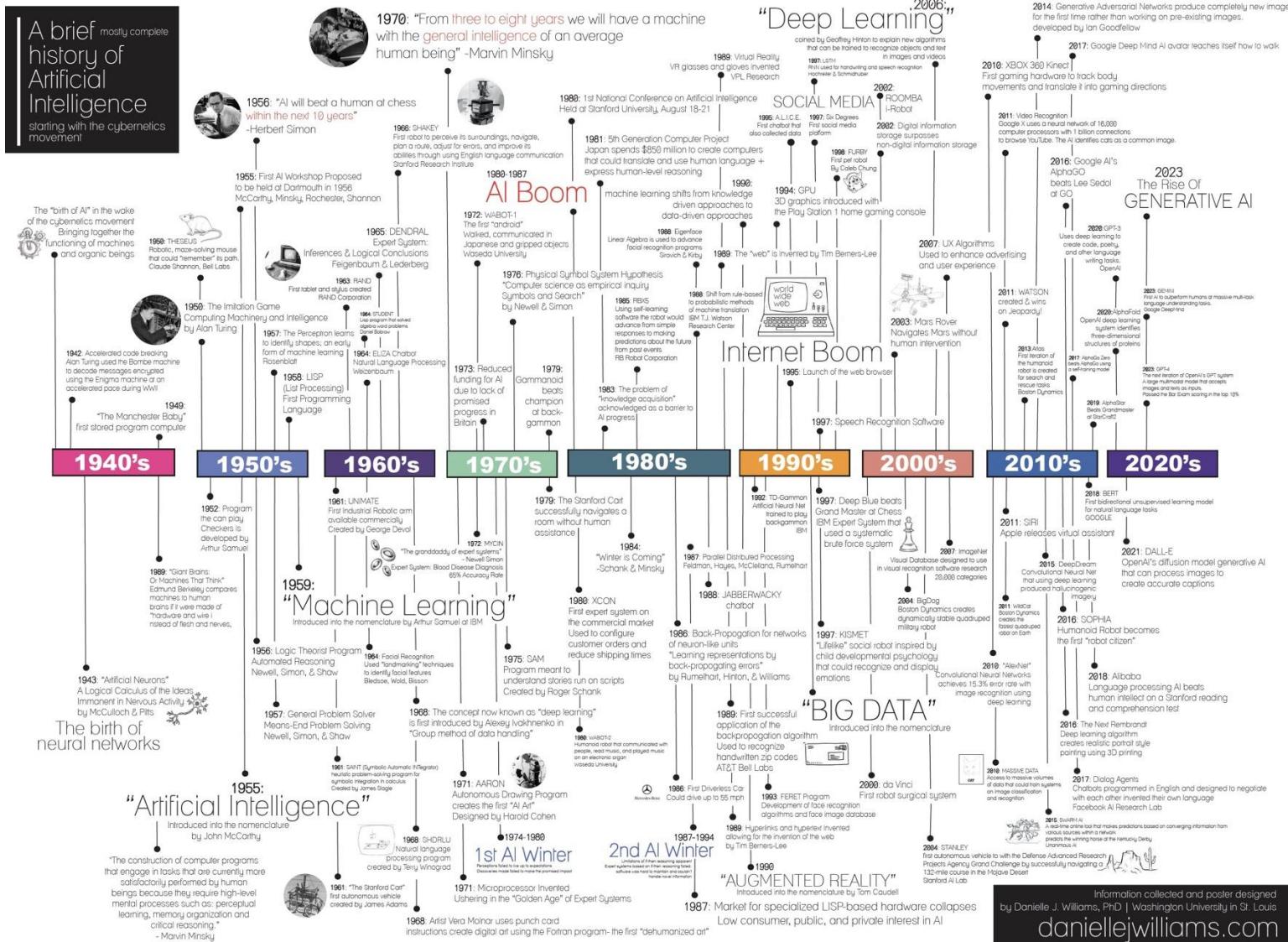
Por su trabajo de investigación que permite predecir estructuras de proteínas y diseñar nuevas moléculas de este tipo, los científicos David Baker, Demis Hassabis y John M. Jumper obtuvieron el Premio Nobel de Química 2024 que otorga la Real Academia Sueca de Ciencias.

Baker fue reconocido por construir tipos completamente nuevos de proteínas, mientras que Hassabis y Jumper desarrollaron un modelo de inteligencia artificial (IA) que permite predecir las complejas estructuras de las proteínas.

<https://www.ift.uam-csic.es/en/news/nobel-prize-physics-2024-goes-innovations-machine-learning>



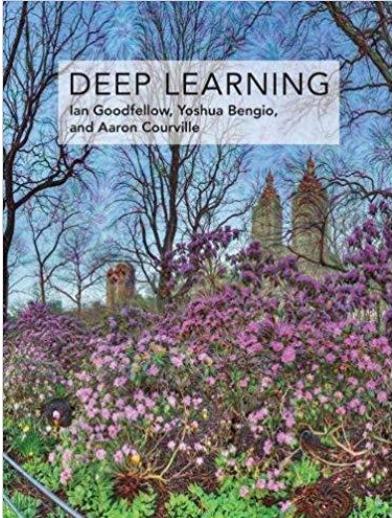
La Historia continua



Danielle J. Williams, PhD

<https://www.daniellejwilliams.com/posters>

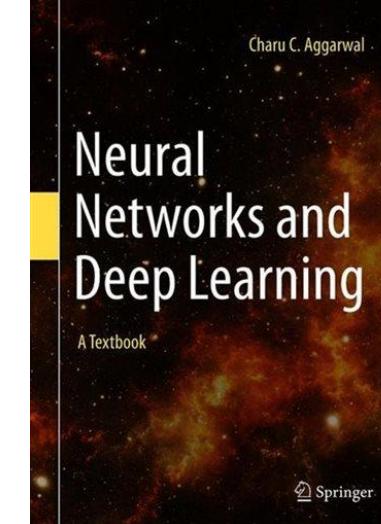
Libros sobre Redes Neuronales Artificiales



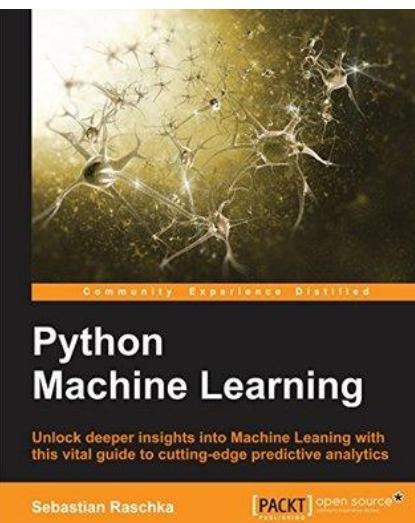
Ian Goodfellow



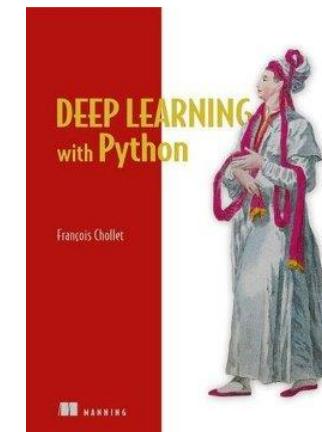
Yoshua Bengio **Aaron Courville**



Charu Aggarwal



Sebastian Raschka



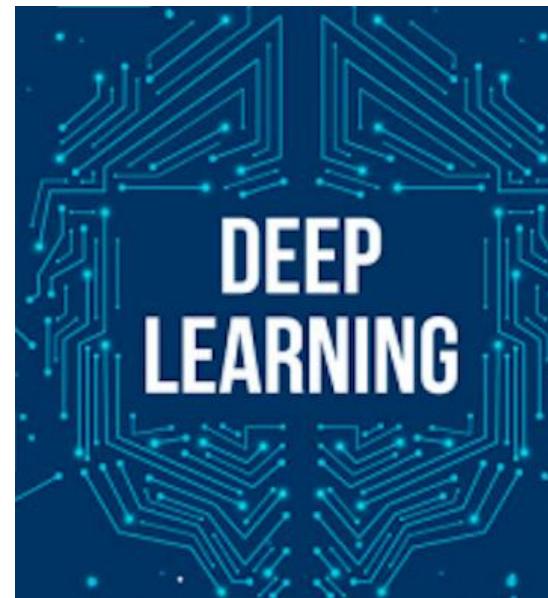
Francois Chollet

Dr. Ing. Rodrigo Salas (UV-MEDING-iHealth)

Toolbox de Deep Learning



PYTORCH
Deep Learning with PyTorch



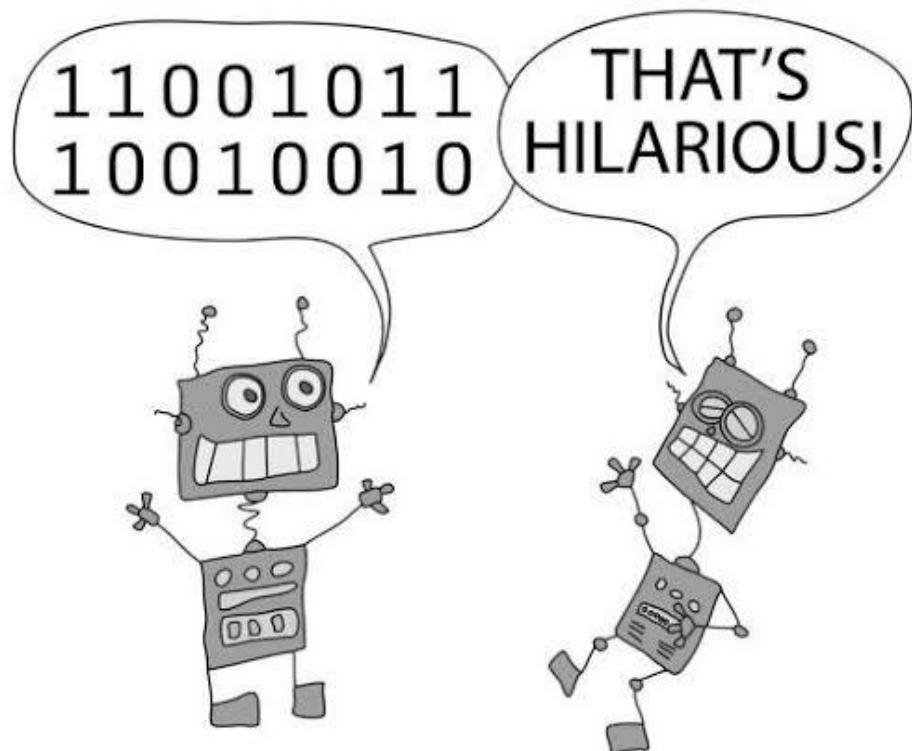
Caffe



theano



dmlc
mxnet

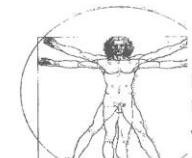


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Thanks for your Attention

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