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

Deep Learning

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Aprendizaje supervisado

- **Clasificación:**
  Para predecir el valor de un atributo categórico (discreto o nominal).

- **Regresión:**
  Para modelar funciones que toman valores continuos (esto es, predecir valores numéricos desconocidos).

Aplicaciones

Concesión de créditos, campañas de marketing dirigido, diagnóstico médico, detección de fraudes…

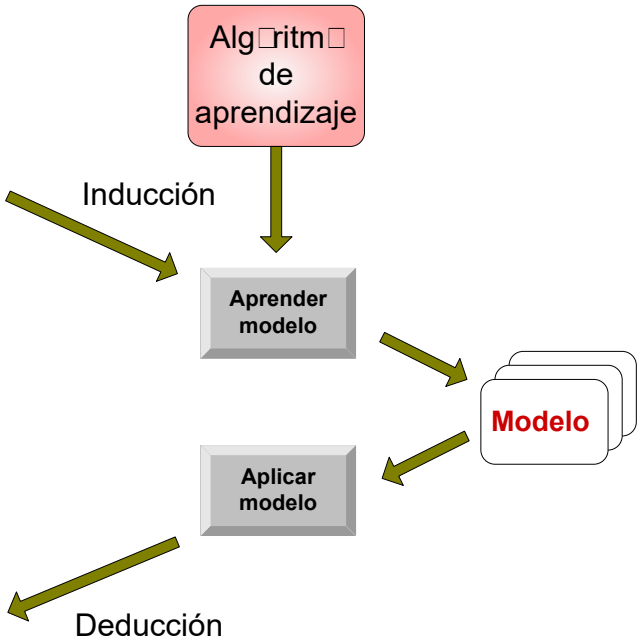
Aprendizaje supervisado

Tid	Attrib1	Attrib2	Attrib3	Class
1	Yes	Large	125K	No
2	N□	Medium	100K	No
3	N□	Small	70K	No
4	Yes	Medium	120K	No
5	N□	Large	95K	Yes
6	N□	Medium	60K	No
7	Yes	Large	220K	No
8	N□	Small	85K	Yes
9	N□	Medium	75K	No
10	N□	Small	90K	Yes

C□njunt□ de entrenamient□

Tid	Attrib1	Attrib2	Attrib3	Class
11	N□	Small	55K	?
12	Yes	Medium	80K	?
13	Yes	Large	110K	?
14	N□	Small	95K	?
15	N□	Large	67K	?

C□njunt□ de prueba



Aprendizaje supervisado

Construcción del modelo

- El conjunto de datos utilizado para construir el modelo de clasificación se denomina **conjunto de entrenamiento**.
- Cada caso/tupla/muestra corresponde a una clase predeterminada: los casos de entrenamiento vienen etiquetados por su atributo de clase.

Uso del modelo

- El modelo construido a partir del conjunto de entrenamiento se utiliza para clasificar nuevos datos.

Aprendizaje supervisado

Estimación de la precisión del modelo

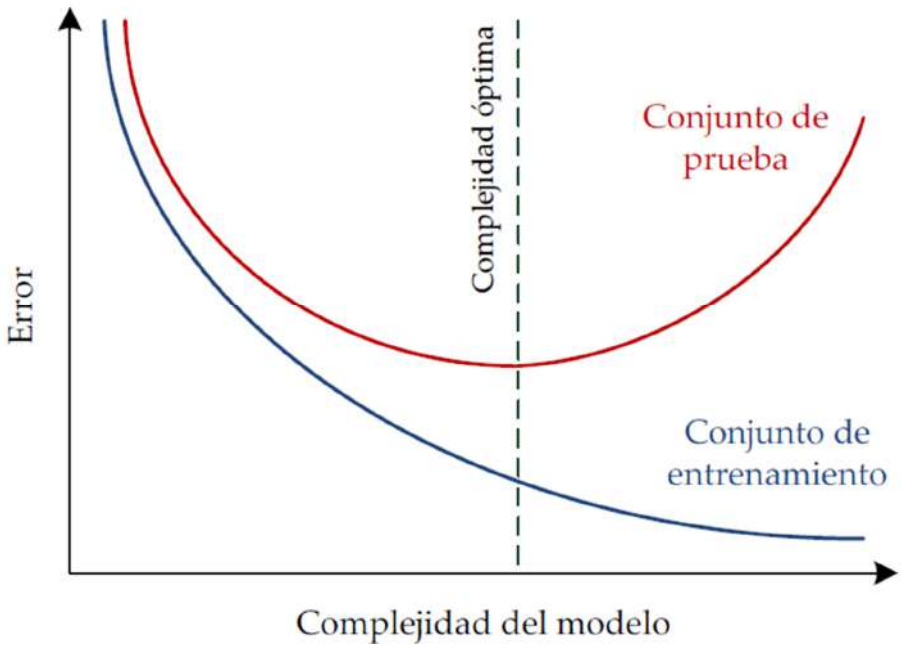
Antes de construir el modelo de clasificación, se divide el conjunto de datos disponible en

- un **conjunto de entrenamiento** (para construir el modelo) y
- un **conjunto de prueba** (para evaluar el modelo).

Aprendizaje supervisado

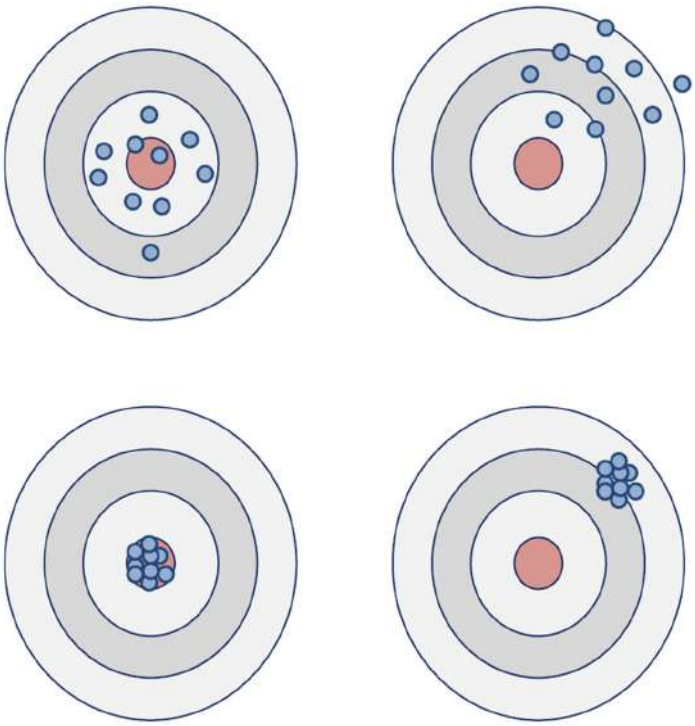
El problema del sobreaprendizaje

debido a la complejidad del modelo



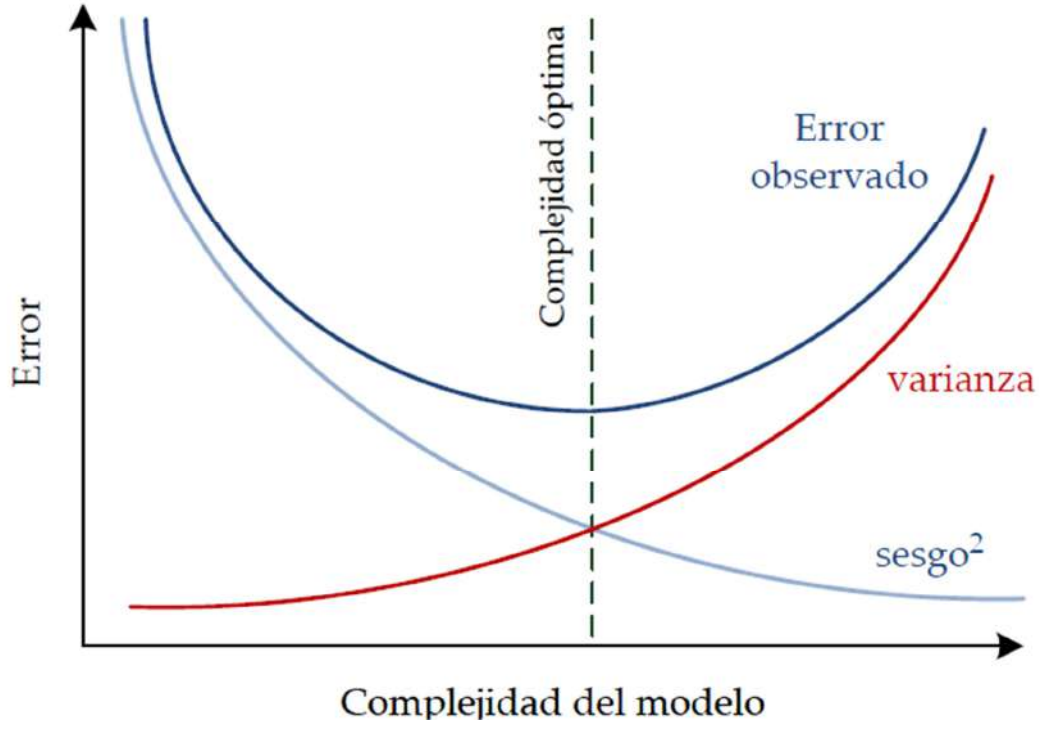
Aprendizaje supervisado

Descomposición del error en sesgo y varianza



Aprendizaje supervisado

Descomposición del error en sesgo y varianza



Aprendizaje supervisado

Criterios de evaluación

- **Precisión**
  (porcentaje de casos clasificados correctamente).
- **Eficiencia**
  (tiempo necesario para construir/usar el clasificador).
- **Robustez**
  (frente a ruido y valores nulos)
- **Escalabilidad**
  (utilidad en grandes bases de datos)
- **Interpretabilidad**
  (el clasificador, ¿es sólo una caja negra?)
- **Complejidad**
  (del modelo de clasificación) → Navaja de Occam.

Aprendizaje supervisado

Limitaciones de la precisión [accuracy]

Supongamos un problema con 2 clases no equilibradas:

- 99900 personas sanas
- 100 personas que padecen una enfermedad

Precisión engañosa: Si el modelo de clasificación siempre dice que los ejemplos son de la clase 1, su precisión es 99900/100000 = **99.9%**

Paradoja de los falsos positivos: Una prueba diagnóstica con el 99% de precisión identificará 99 de los 100 casos existentes, pero también 999 falsos positivos. Sólo un **9%** de los positivos lo son realmente!!!

Aprendizaje supervisado

Medidas sensibles a costes [cost-sensitive]

		Predicción	
		P	N
Real	P	TP	FN
	N	FP	TN

Accuracy

		Predicción	
		P	N
Real	P	TP	FN
	N	FP	TN

Recall

		Predicción	
		P	N
Real	P	TP	FN
	N	FP	TN

Precision

		Predicción	
		P	N
Real	P	TP	FN
	N	FP	TN

F-measure

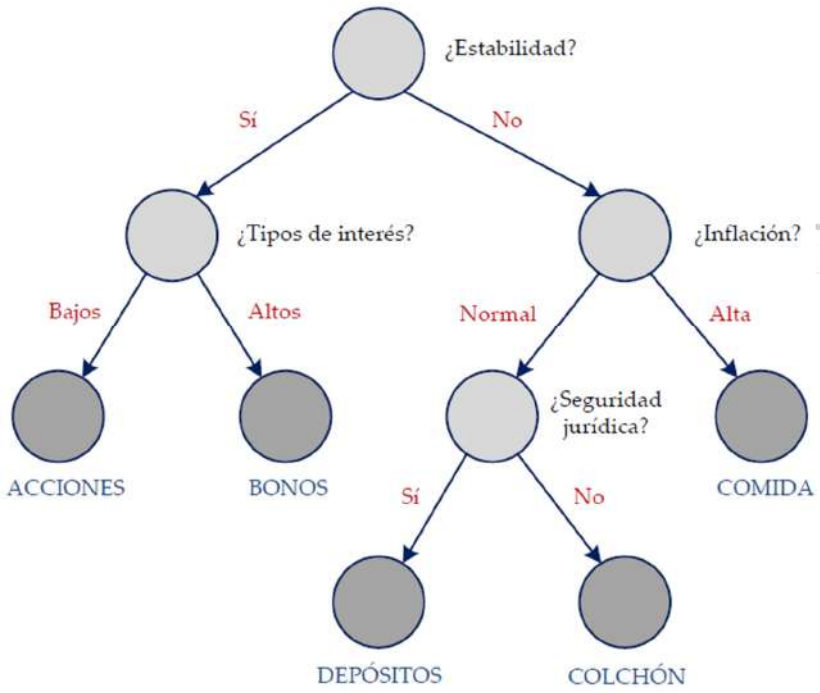
Aprendizaje supervisado

Algunos tipos de modelos de clasificación

- Modelos simbólicos
  - Árboles de decisión
  - Inducción de reglas (p.ej. listas de decisión)
- Modelos "estadísticos"
  - Clasificadores paramétricos
  - Modelos bayesianos, p.ej. redes bayesianas
- Modelos analógicos
  - Clasificadores basados en casos
  - SVMs (Support Vector Machines)
- Modelos conexionistas: Redes neuronales

Aprendizaje supervisado

Modelos simbólicos: Árboles de decisión



Aprendizaje supervisado

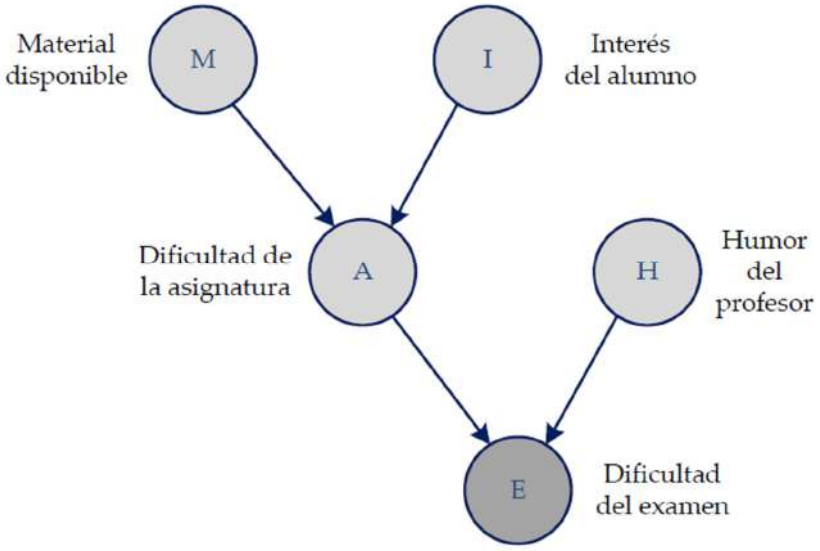
Clasificadores asociativos (reglas de asociación)

ART [Association Rule Trees]


```
P30 = A : TYPE = N (473|62)
P30 = C : TYPE = N (441|24)
P30 = T : TYPE = N (447|57)
else
  P28 = A and P32 = T : TYPE = EI (235|33)
  P28 = G and P32 = T : TYPE = EI (130|20)
  P28 = C and P32 = A : TYPE = IE (160|31)
  P28 = C and P32 = C : TYPE = IE (167|35)
  P28 = C and P32 = G : TYPE = IE (179|36)
  else
    P28 = A : TYPE = N (106|14)
    P28 = G : TYPE = N (94|4)
    else
      P29 = C and P31 = G : TYPE = EI (40|5)
      P29 = A and P31 = A : TYPE = IE (86|4)
      P29 = A and P31 = C : TYPE = IE (61|4)
      P29 = A and P31 = T : TYPE = IE (39|1)
      else
        P25 = A and P35 = G : TYPE = EI (54|5)
        P25 = G and P35 = G : TYPE = EI (63|7)
        else
          P23 = G and P35 = G : TYPE = EI (40|8)
          P23 = T and P35 = C : TYPE = IE (37|7)
          else
            P21 = G and P34 = A : TYPE = EI (41|5)
            else
              P28 = T and P29 = A : TYPE = IE (66|8)
              else
                P31 = G and P33 = A : TYPE = EI (62|9)
                else
                  P28 = T : TYPE = N (49|6)
                  else
                    P24 = C and P29 = A : TYPE = IE (39|8)
                    else
                      TYPE = IE (66|39)
```

Aprendizaje supervisado

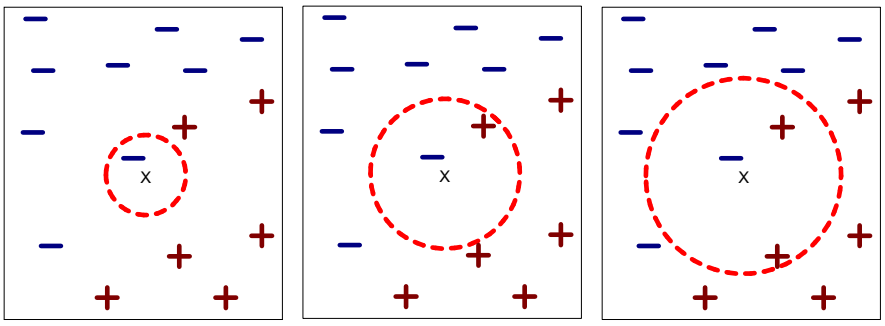
Redes bayesianas



Aprendizaje supervisado

Clasificadores basados en casos [lazy learners]

Almacenan el conjunto de entrenamiento (o parte de él) y lo utilizan directamente para clasificar nuevos datos.



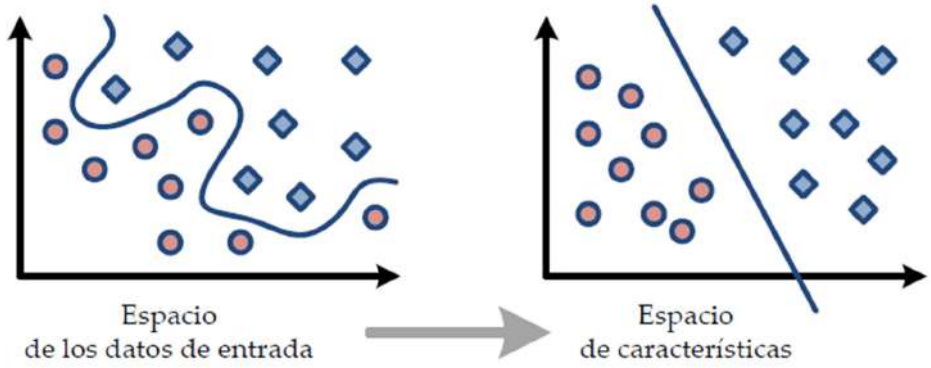
(a) 1-nearest neighb□r (b) 2-nearest neighb□r (c) 3-nearest neighb□r

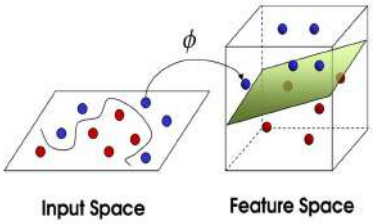
Ejemplos

- k-NN (k Nearest Neighbors)
- Razonamiento basado en casos (CBR)

Aprendizaje supervisado

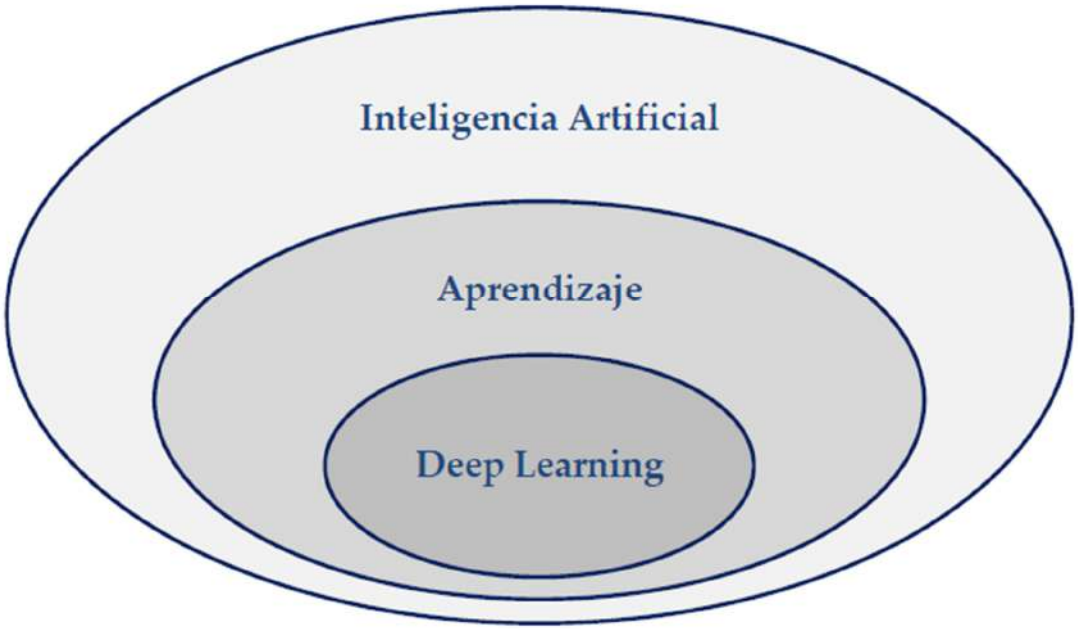
SVMs [Support Vector Machines]





De moda hasta la llegada del Deep Learning…

Deep Learning



Deep Learning

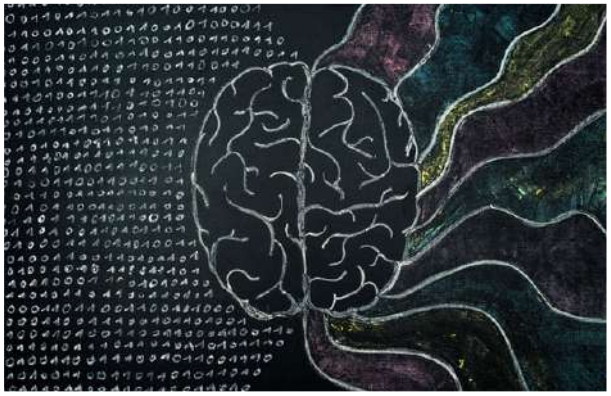
- Breve historia de las redes neuronales artificiales.
- Técnicas de deep learning:
  Entrenamiento de redes neuronales artificiales.
- En la práctica: Implementación de sistemas basados en redes neuronales artificiales.
- Limitaciones de las técnicas de deep learning.
- Aplicaciones de las técnicas de deep learning.

Redes neuronales artificiales

Redes neuronales artificiales

El cerebro humano

Inspiración de las redes neuronales artificiales



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

Redes neuronales artificiales

¿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.

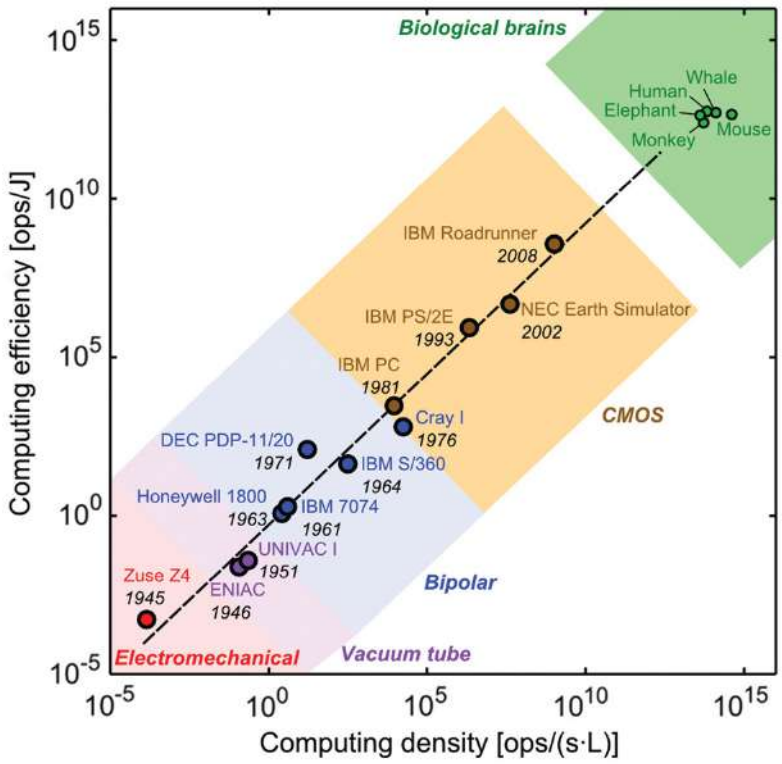
Redes neuronales artificiales

El cerebro humano

Diferencias entre un ordenador y el cerebro humano

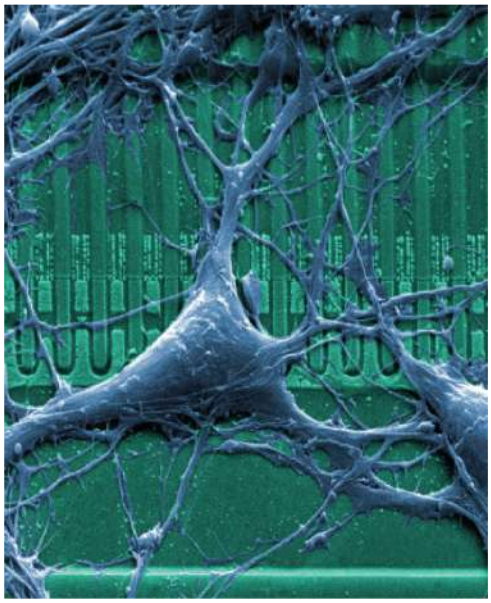
Ordenador	Cerebro humano
Computación en serie	Computación en paralelo
Poco robusto	Tolerancia a fallos
Programable	Aprendizaje autónomo
Digital	Analógico
10^9 transistores	**10^{11} neuronas** **$10^{14} \sim 10^{15}$ sinapsis**
Nanosegundos (3.6GHz)	Milisegundos (4~90Hz)
51.2 GB/s	10 spikes/s
210,000,000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

Redes neuronales artificiales



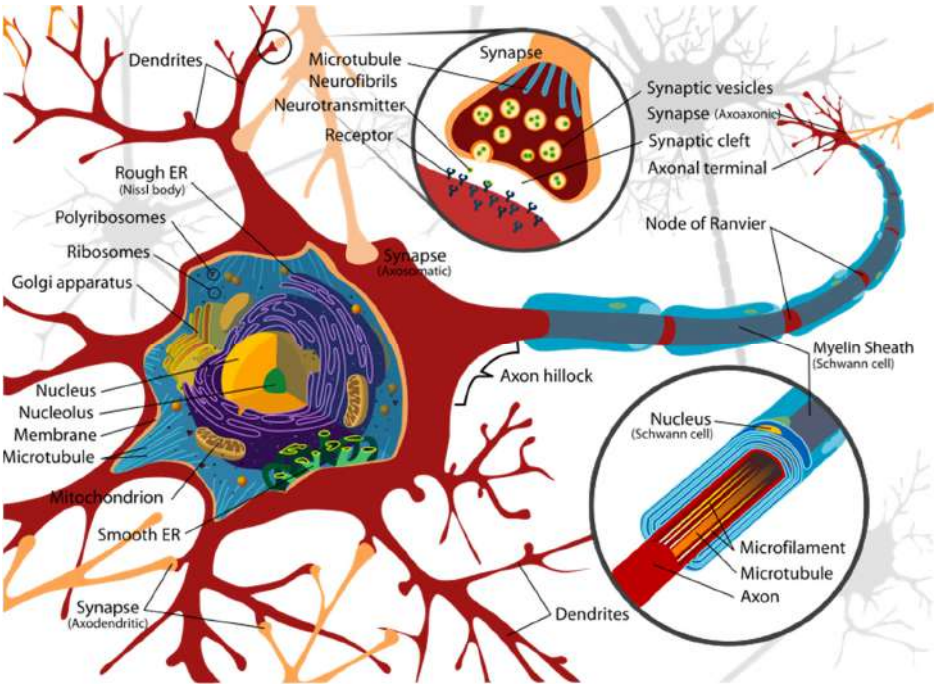
IBM Journal of Research and Development, 2011

Neuronas



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

Neuronas

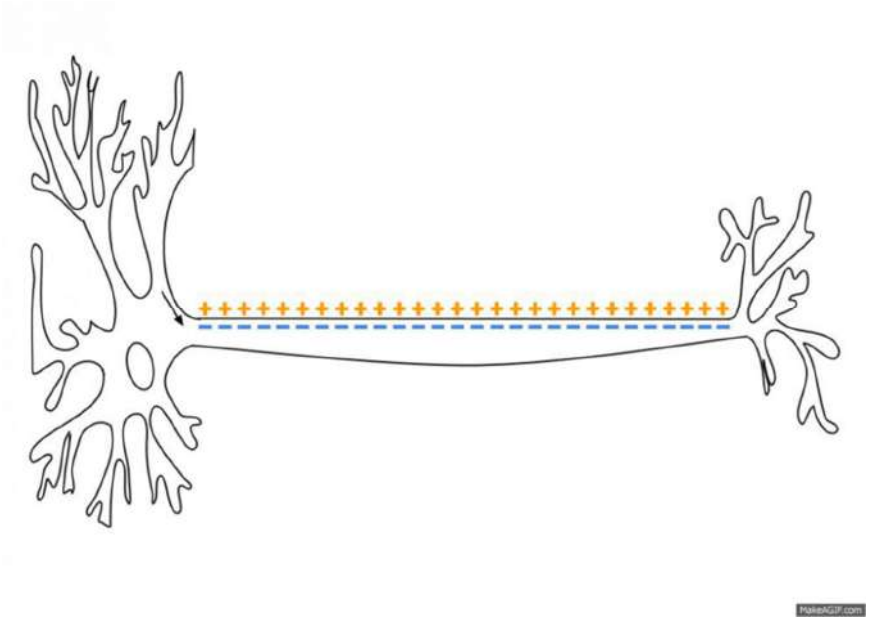


[Wikipedia]

Redes neuronales artificiales

Neuronas

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

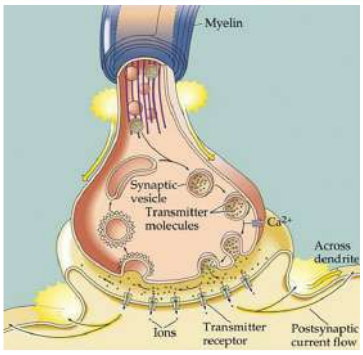


https://en.wikipedia.org/wiki/Action_potential

Redes neuronales artificiales

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.

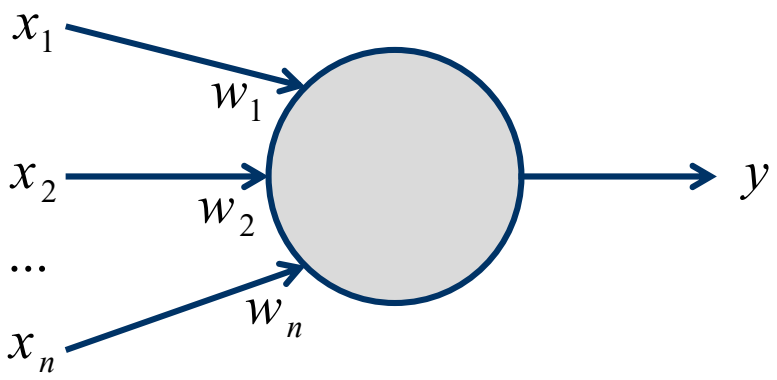
Como tenemos cerca de 10^{11} neuronas y de 10^{14} a 10^{15} sinapsis, muchas sinapsis pueden influir en un "cálculo" en un período de tiempo muy breve:

Ancho de banda muy superior al de un ordenador.

Redes neuronales artificiales

Neuronas

El modelo computacional más simple de una neurona



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

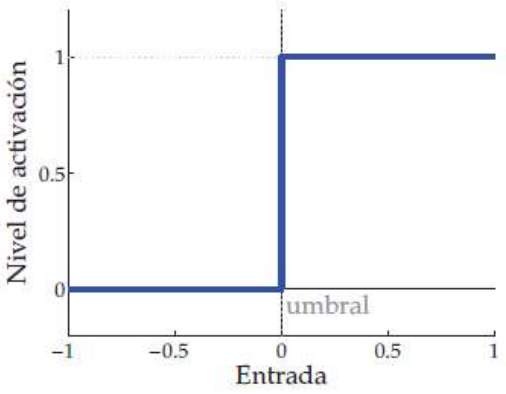
Redes neuronales artificiales

Modelo de neurona de McCulloch & Pitts

Neuronas binarias con umbral

$$z = \sum_i x_i w_i$$

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



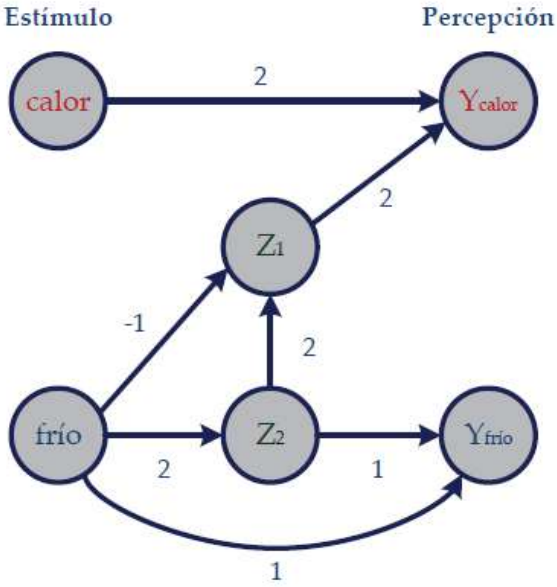
1943

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

Redes neuronales artificiales

Modelo de neurona de McCulloch & Pitts

Ejemplo: Percepción fisiológica del calor y del frío



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.

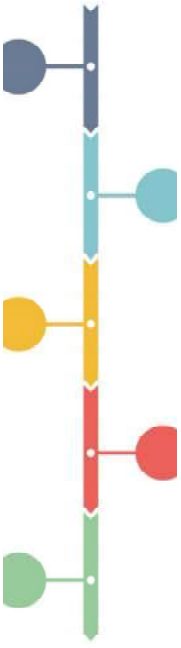
June 2012: Google uses deep learning to cut the error rate of its speech recognition software by 25 percent.

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."

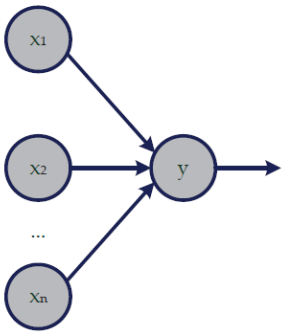


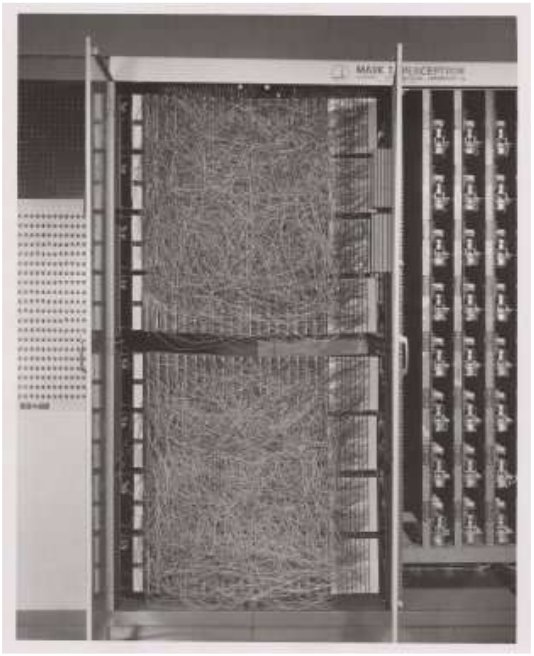
MIT Technology Review

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

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

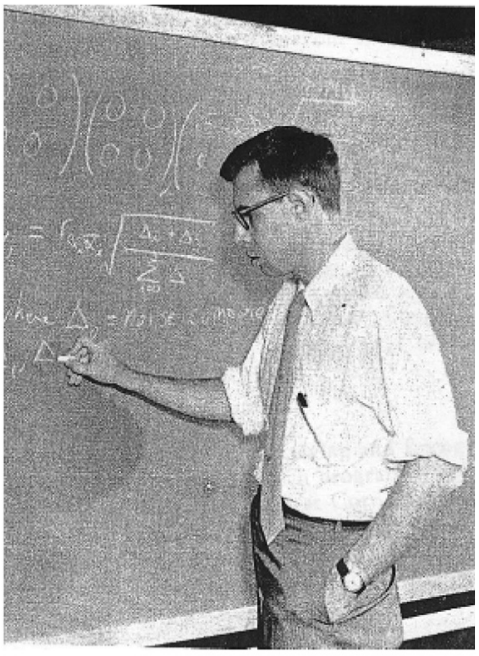
WASHINGTON, July 7 (UPI) —The Navy revealed the embryo of an electronic computer today that it expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence.

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.

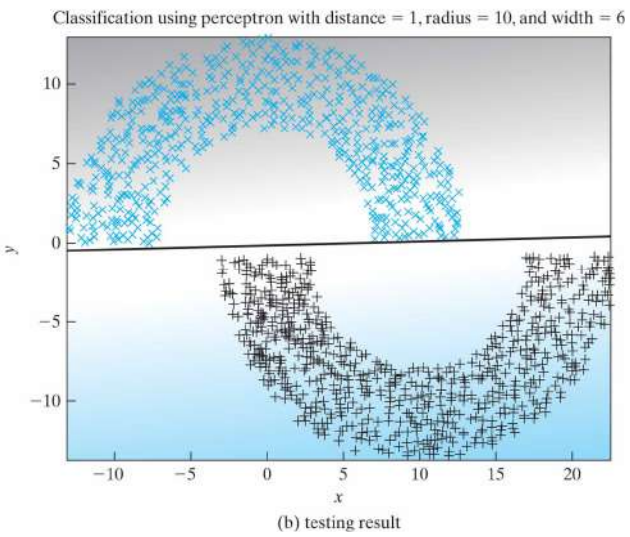


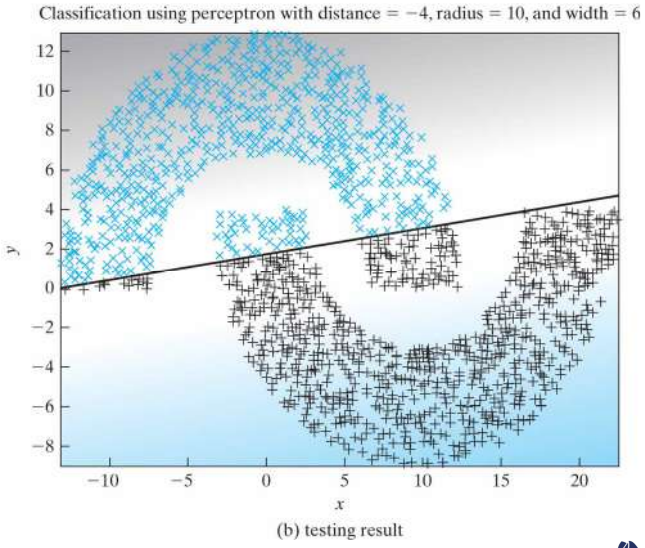
1958

El perceptrón

En realidad...

Un clasificador lineal





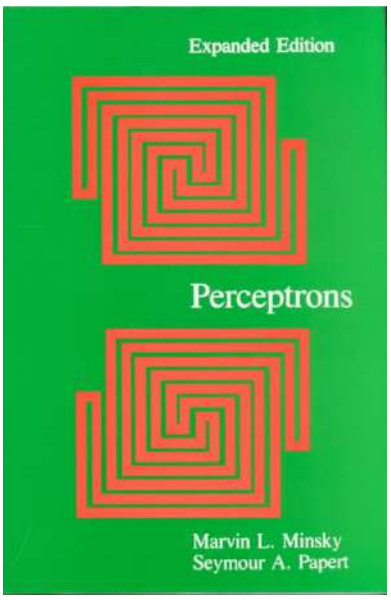
[Haykin: "Neural Networks and Learning Machines", 3rd edition]

Historia de las redes neuronales artificiales

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.

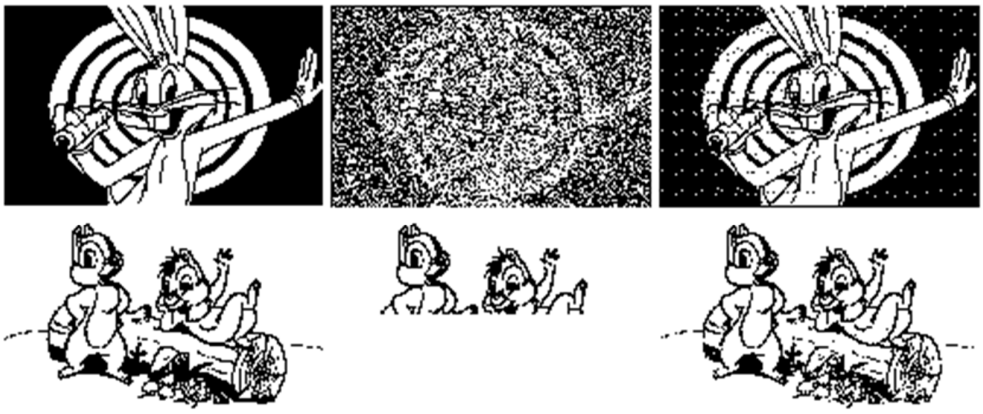


1969

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



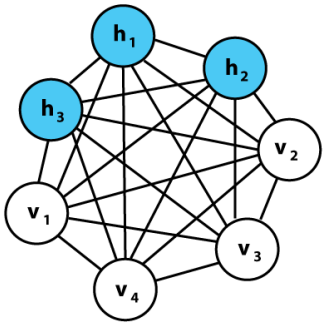
1982

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.

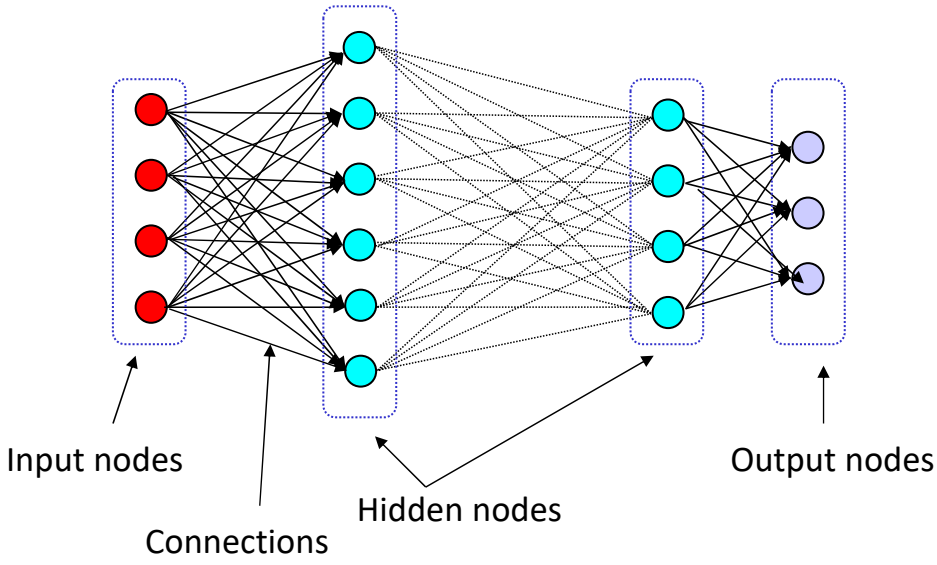


1985

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

Backpropagation

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

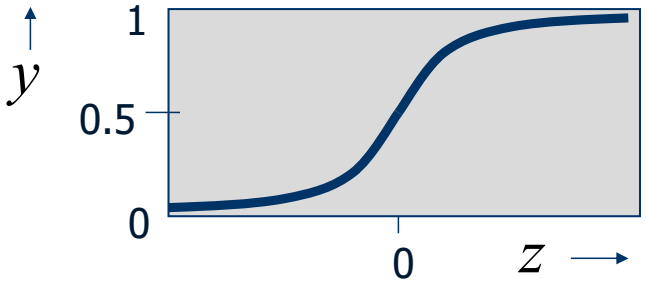
Historia de las redes neuronales artificiales

Backpropagation

Modelo de neurona sigmoidal

$$z = \sum_i x_i w_i$$

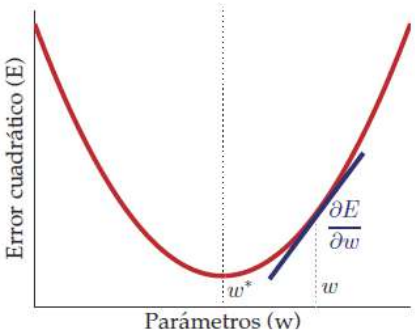
$$y = \frac{1}{1+e^{-z}}$$



1986

Backpropagation

Algoritmo de entrenamiento



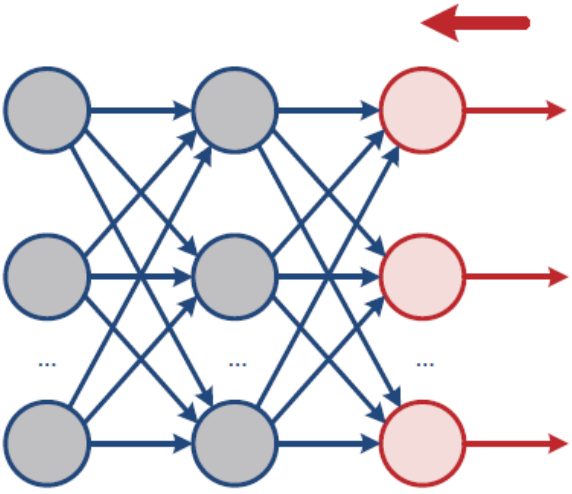
$$\Delta w_i = -\eta \frac{\partial E}{\partial w_i}$$

1986

Historia de las redes neuronales artificiales

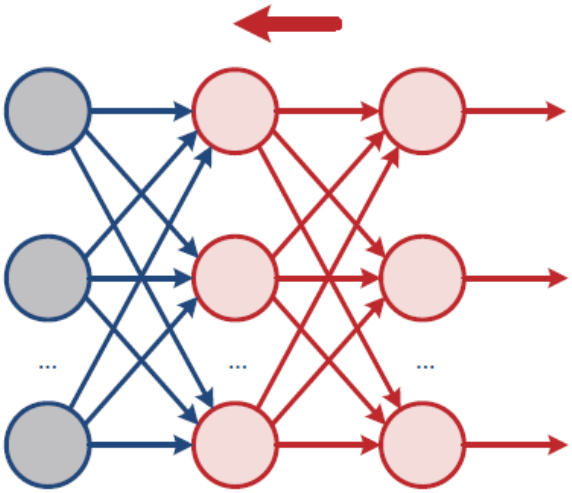
Backpropagation

Propagación de errores $\delta E/\delta y$



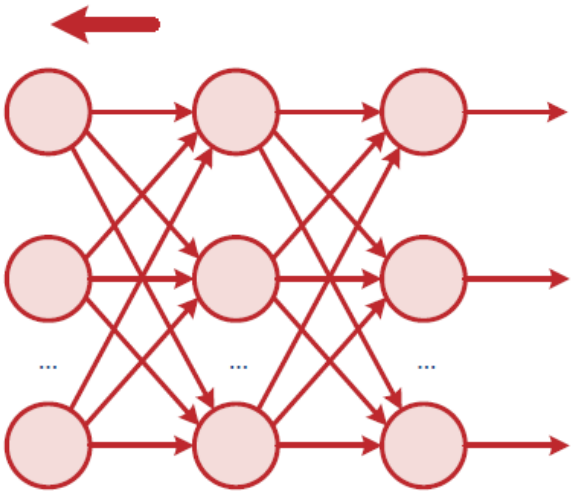
Backpropagation

Propagación de errores $\delta E/\delta y$



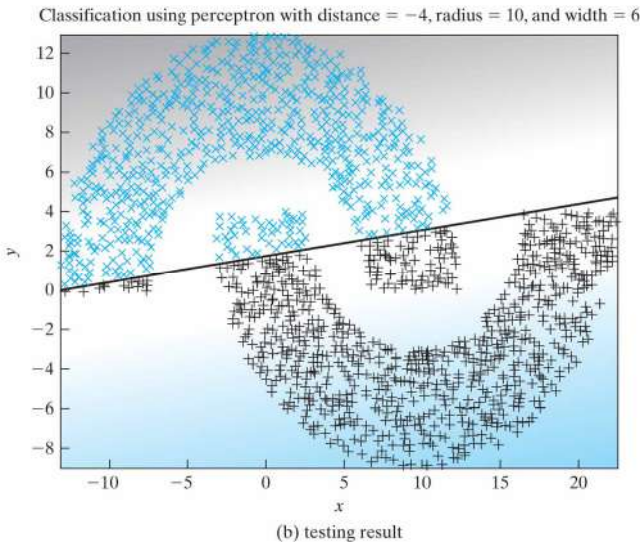
Backpropagation

Propagación de errores $\delta E/\delta y$

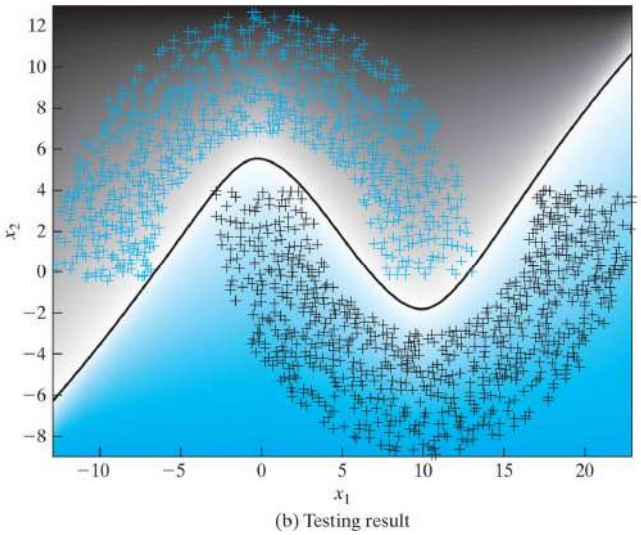


Backpropagation

El resultado…



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**.

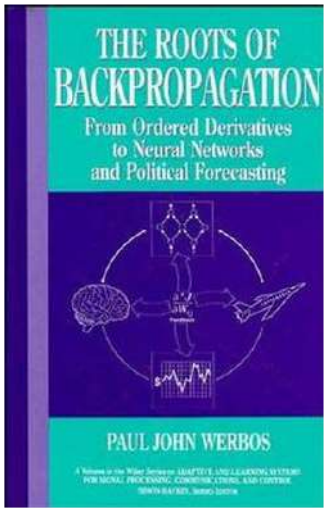
  Seppo Linnainmaa: "Taylor expansion of the accumulated rounding error". BIT Numerical Mathematics. 16(2):146–160, **1976**. DOI 10.1007/bf01931367.

1986???

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).

Política & Publicaciones

Geoffrey Hinton interview

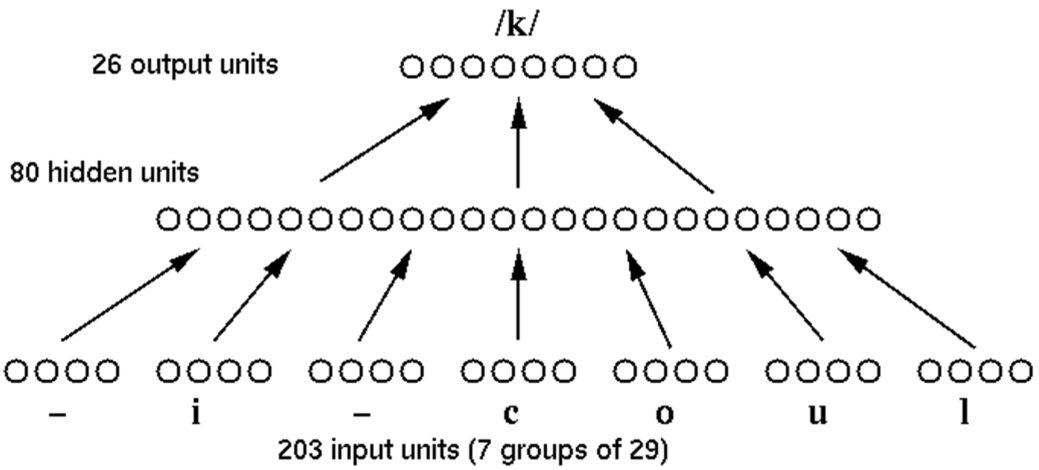
Neural Networks & Deep Learning

"… 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…"

Historia de las redes neuronales artificiales
Backpropagation

NETTalk

Síntesis de voz



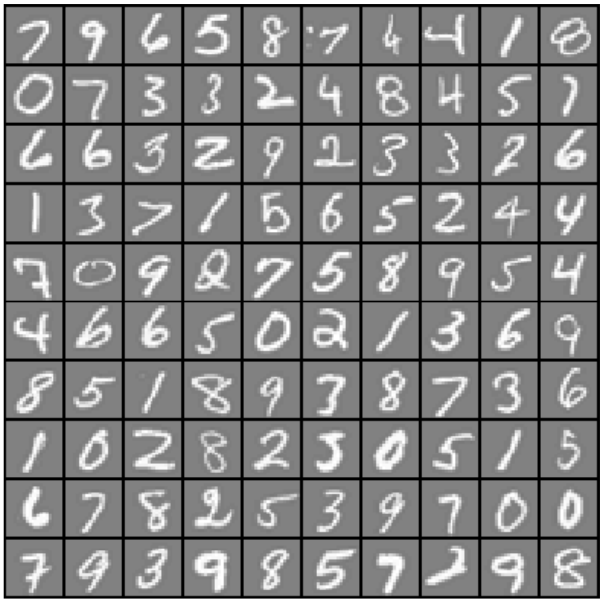
1986

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/

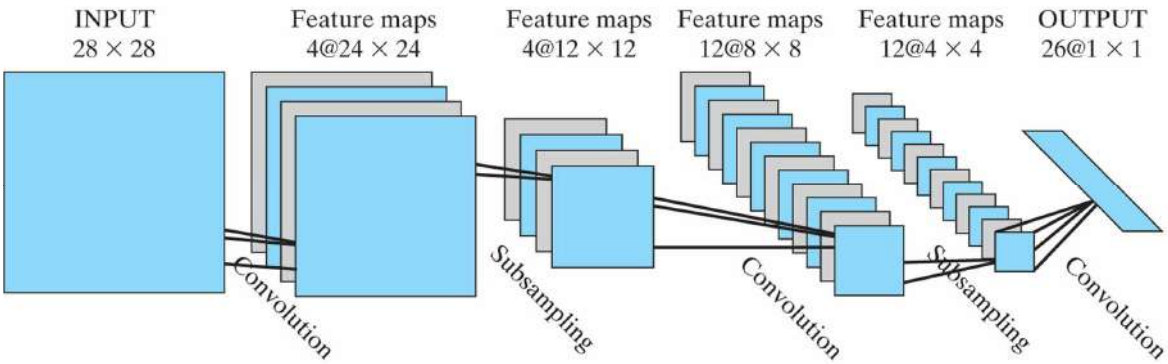


1990s

Redes convolutivas

LeNet

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

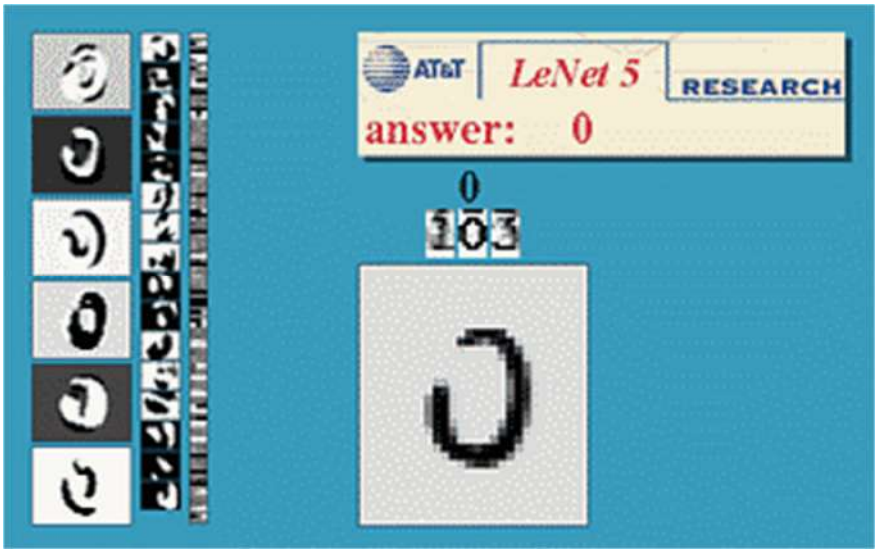


1990s

Redes convolutivas

LeNet

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



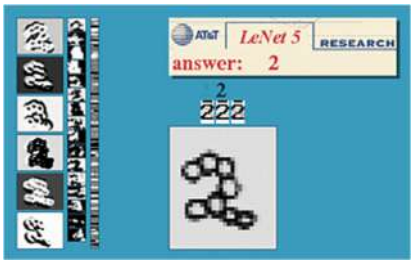
Historia de las redes neuronales artificiales

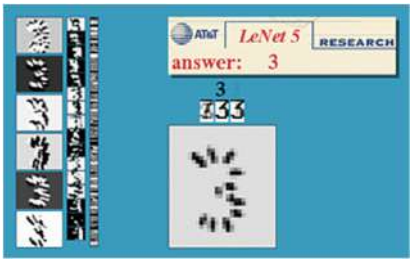
Redes convolutivas

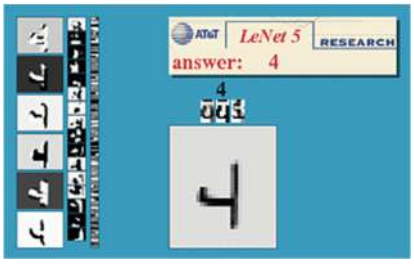
LeNet

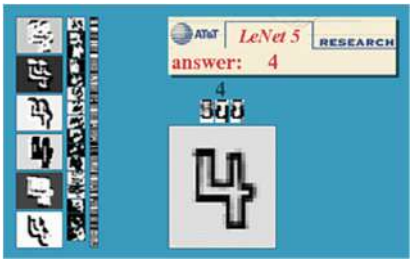
http://yann.lecun.com/exdb/lenet/

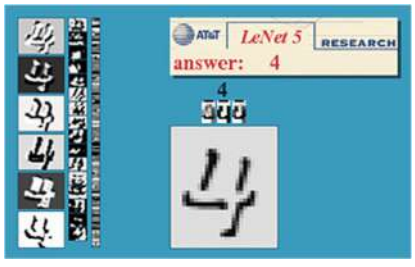
Ejemplos









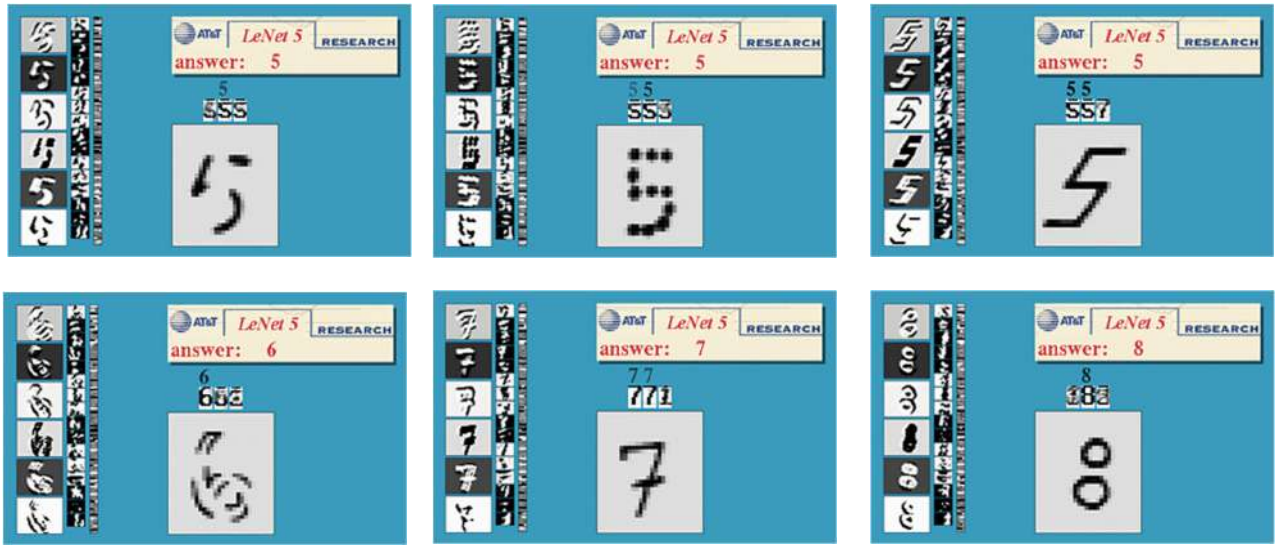


Redes convolutivas

LeNet

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

Ejemplos



Redes convolutivas

LeNet

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

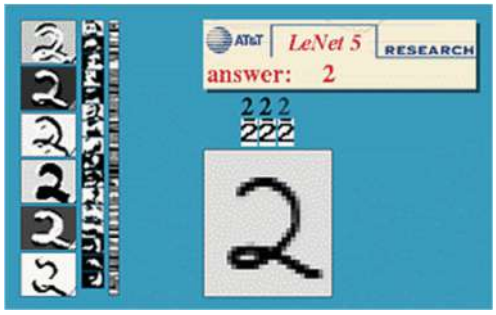
Variaciones en los datos de entrada

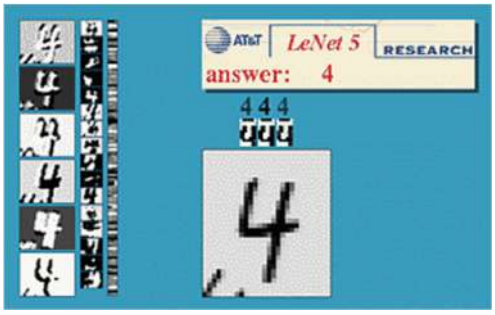
Redes convolutivas

LeNet

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

Robustez frente a la presencia de ruido en la imagen…



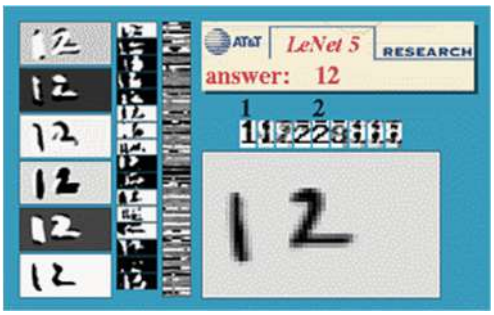


Redes convolutivas

LeNet

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

Casos curiosos



Redes convolutivas

Pooling operation used in convolutional neural networks is a big mistake, and the fact that it works so well is a disaster.

Geoffrey Hinton
Professor at University of Toronto
Google Brain Team Manager
Godfather of the MLP, Backpropagation and DNN

From Ask me anything on Reddit
https://www.reddit.com/r/MachineLearning/comments/2lmo0l/ama_geoffrey_hinton/

SVMs

Una apuesta...

AT&T Adaptive Systems Research Dept., Bell Labs

1. Jackel bets (one fancy dinner) that by March 14, 2000 people will understand
quantitatively why big neural nets working on large databases are not so bad.
(Understanding means that there will be clear conditions and bounds)

Vapnik bets (one fancy dinner) that Jackel is wrong.

But .. If Vapnik figures out the bounds and conditions, Vapnik still wins the bet.

****

2. Vapnik bets (one fancy dinner) that by March 14, 2005, no one in his right mind will use neural nets that are essentially like those used in 1995.

Jackel bets (one fancy dinner) that Vapnik is wrong

1995

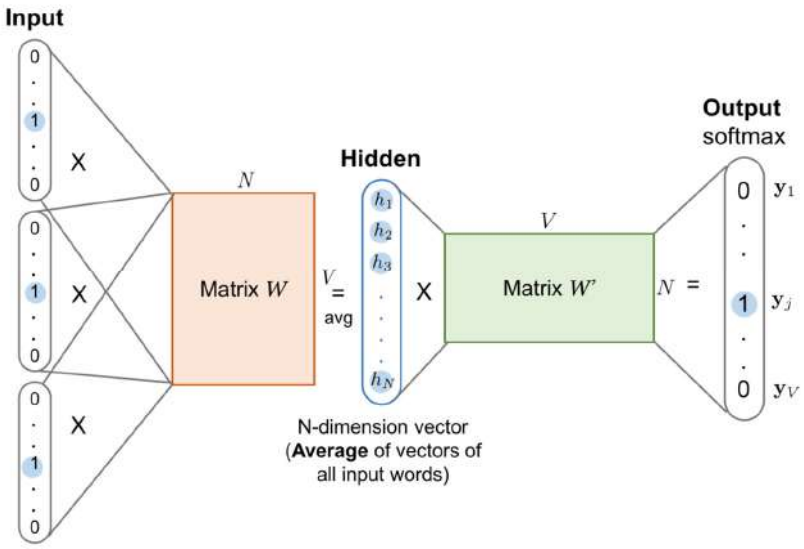
SVMs

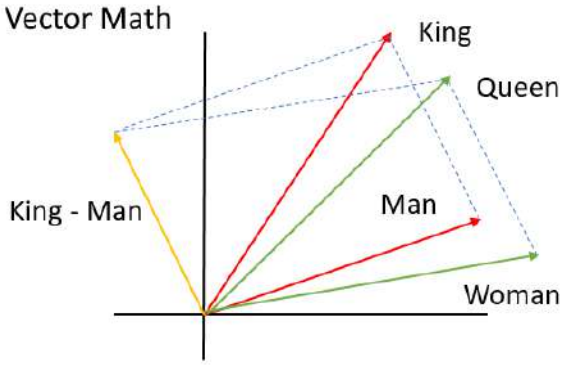
¿Por qué las SVMs nunca fueron una buena opción en IA?

Sólo son una reencarnación de los perceptrones…

- Expanden la entrada a una capa (enorme) de características **no adaptativas**.
- Sólo tienen una capa de pesos **adaptativos**.
- Disponen de un algoritmo eficiente para ajustar los pesos controlando el sobreaprendizaje (una forma inteligente de seleccionar características y encontrar los pesos adecuados).

Word embeddings



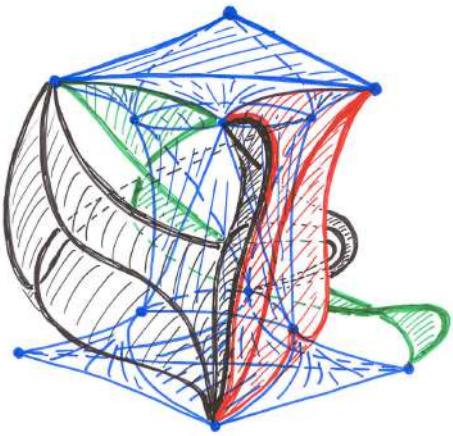


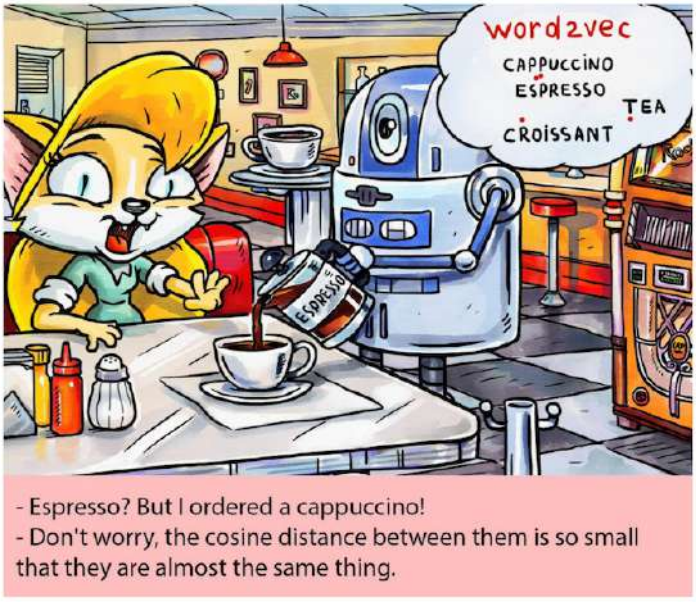
2000

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

Word embeddings

word2vec



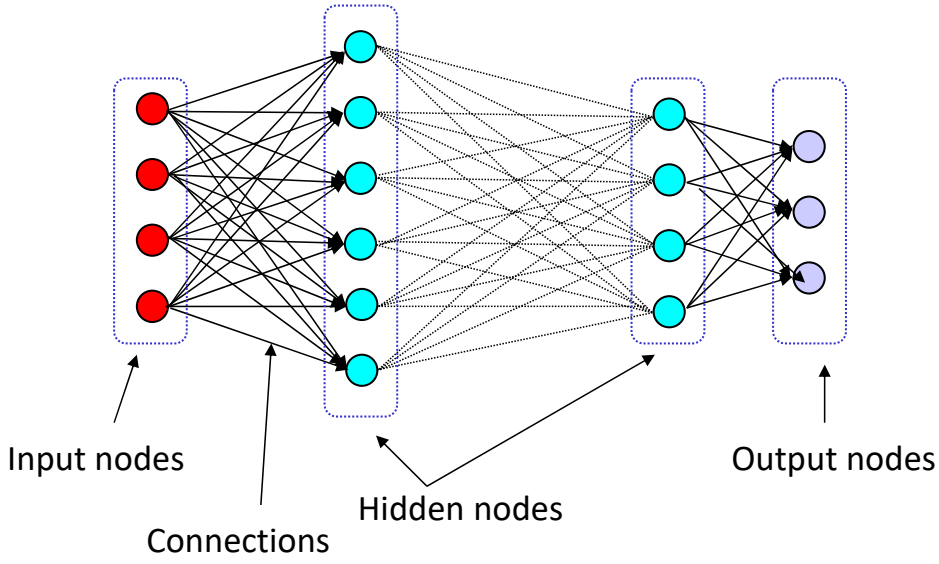


2000s

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)...



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).

Historia de las redes neuronales artificiales
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)

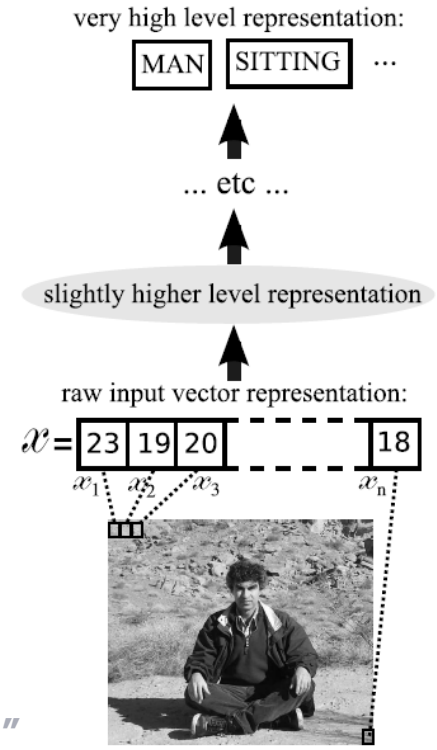
2018

acm A.M. TURING AWARD

Historia de las redes neuronales artificiales
Deep Learning

Estadística	Inteligencia Artificial
Dimensionalidad baja (<100)	Dimensionalidad alta (>>100)
Mucho ruido en los datos	El ruido no es el mayor problema
Sin demasiada estructura en los datos (puede capturarse usando modelos simples)	Mucha estructura en los datos (demasiado complicada para modelos simples)
PRINCIPAL PROBLEMA	PRINCIPAL PROBLEMA
Separar estructura de ruido	Descubrir una forma de representar la estructura que se pueda aprender
TÉCNICAS	TÉCNICAS
SVM [Support Vector Machines]	Backpropagation

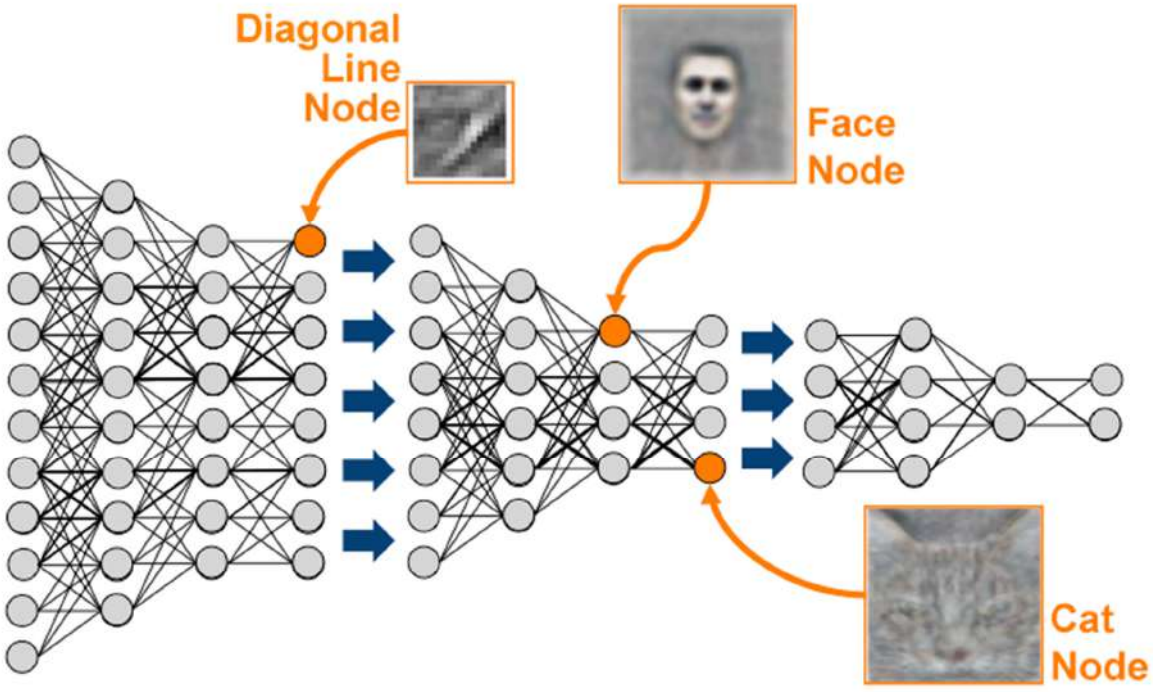
Motivación



Yoshua Bengio
"Learning Deep Architectures for AI"
2009

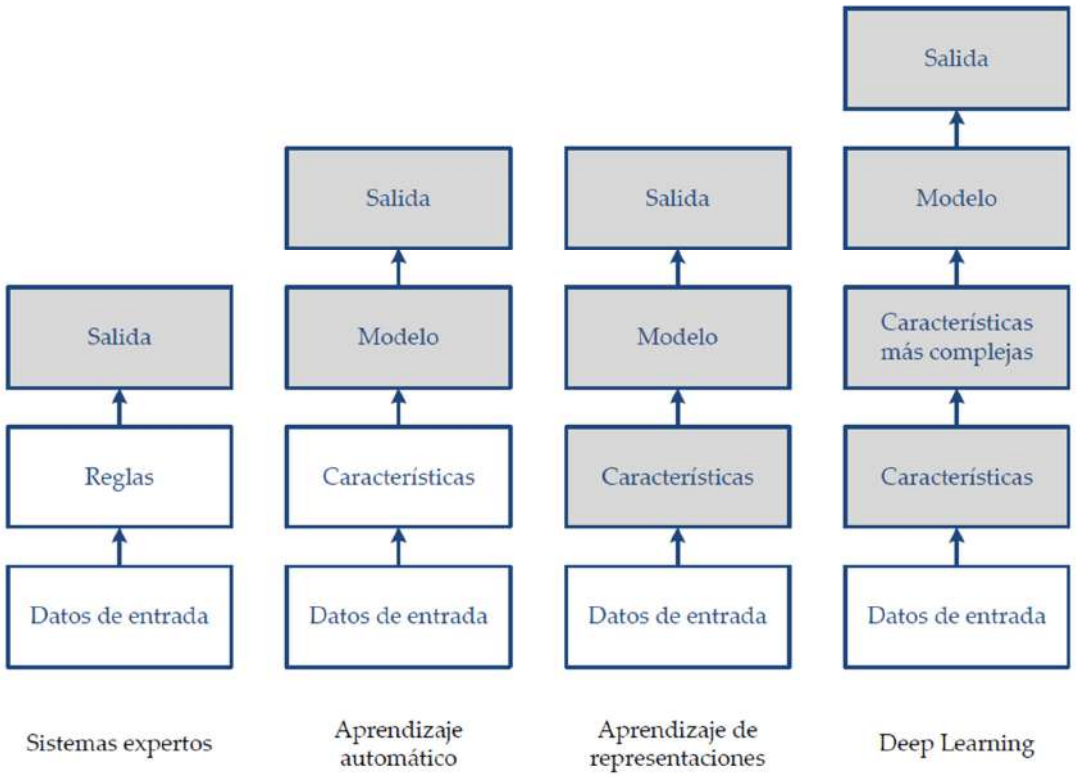
Historia de las redes neuronales artificiales
Deep Learning

Deep Learning as hierarchical feature representation



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

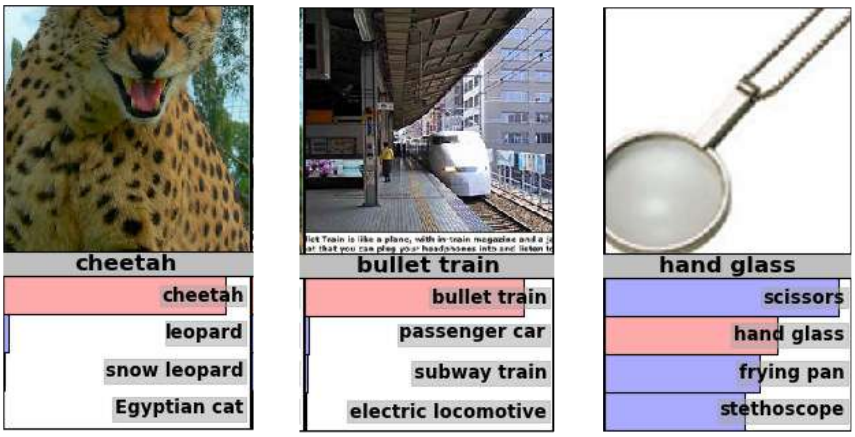
… the reviews [are] so ridiculous, that I don't know how to begin writing a rebuttal without insulting the reviewers … This time though, the reviewers were particularly clueless, or negatively biased, or both. I was very sure that this paper was going to get good reviews because: 1) it has two simple 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

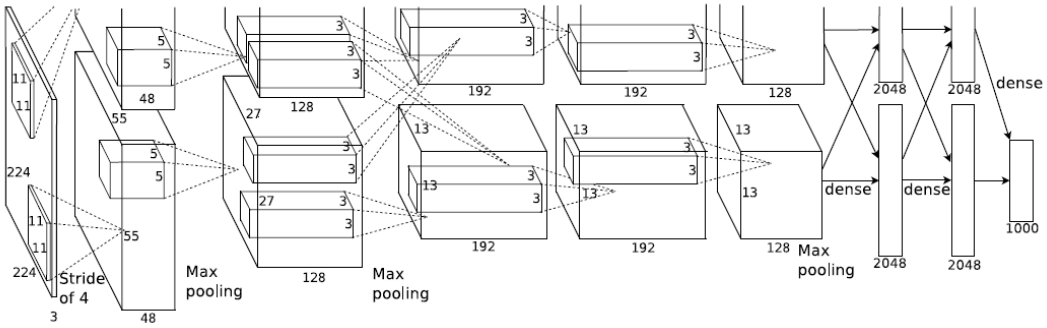


2012

IMAGENET

AlexNet

Red neuronal diseñada por Alex Krizhevsky (NIPS 2012)



2012

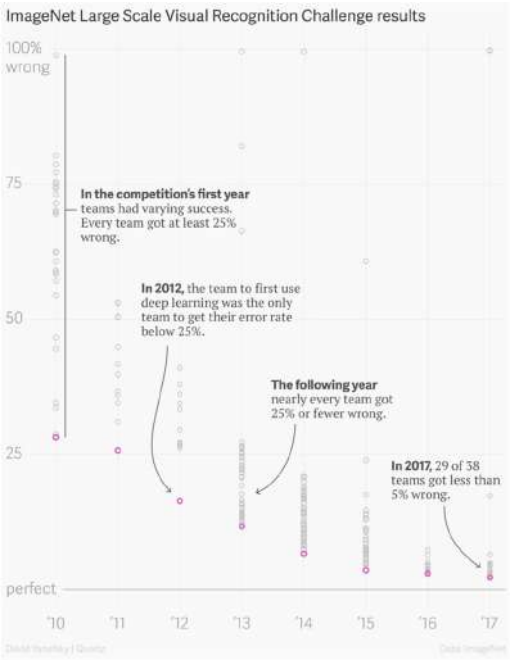
Tasa de error

Clasificación de imágenes

16.4% vs. 25% (2010)

IMAGENET

Large Scale Visual Recognition Challenge



Tasa de error

16.4% Alex Krizhevsky @ NIPS 2012

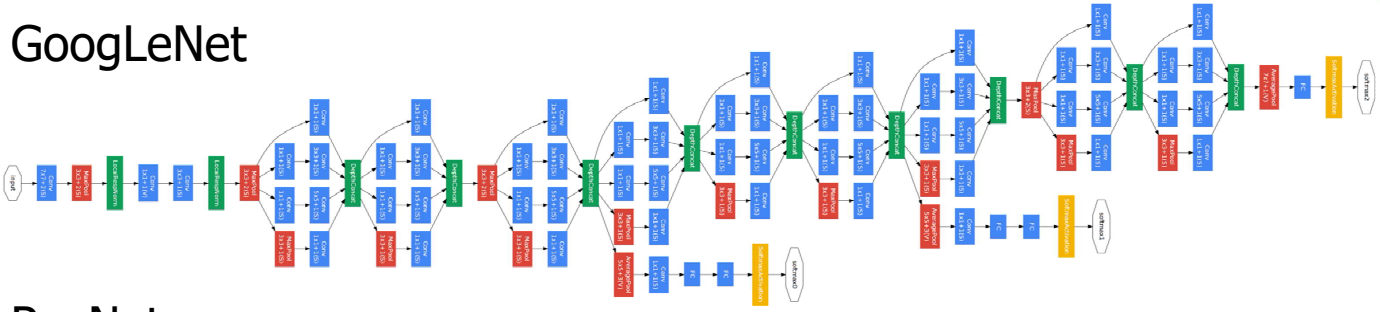
6.66% GoogLeNet @ ILSVRC'2014

4.94% PreLU-nets (MSR) @ 2015

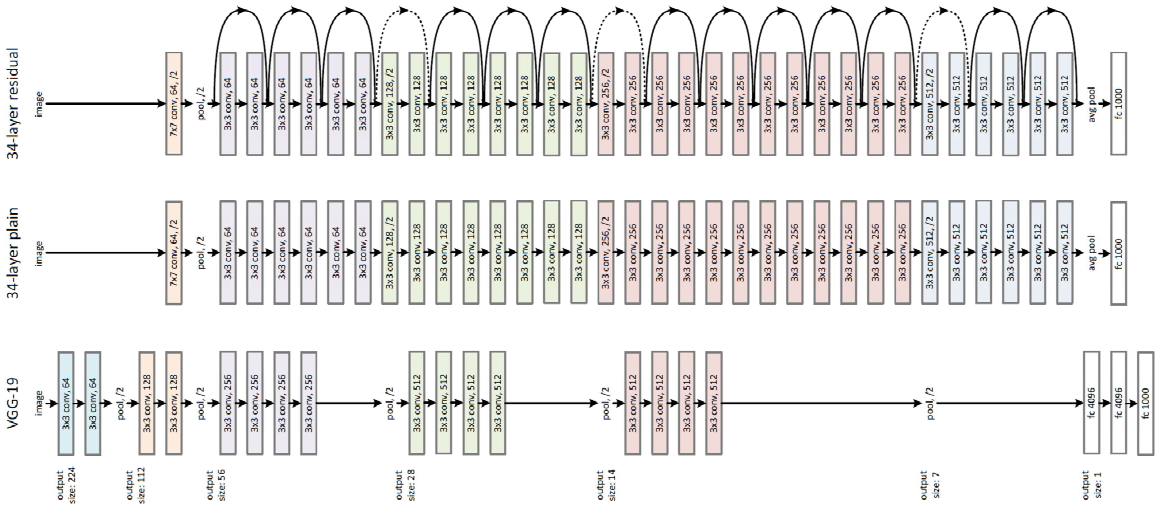
"Delving Deep into Rectifiers:
Surpassing Human-Level Performance
on ImageNet Classification"
arXiv, 2015, http://arxiv.org/pdf/1502.01852v1.pdf

Historia de las redes neuronales artificiales
Deep Learning

GoogLeNet



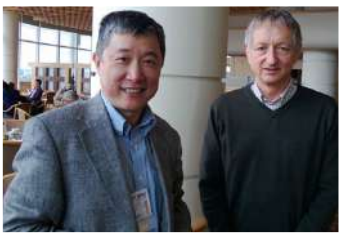
ResNets



Historia de las redes neuronales artificiales
Deep Learning

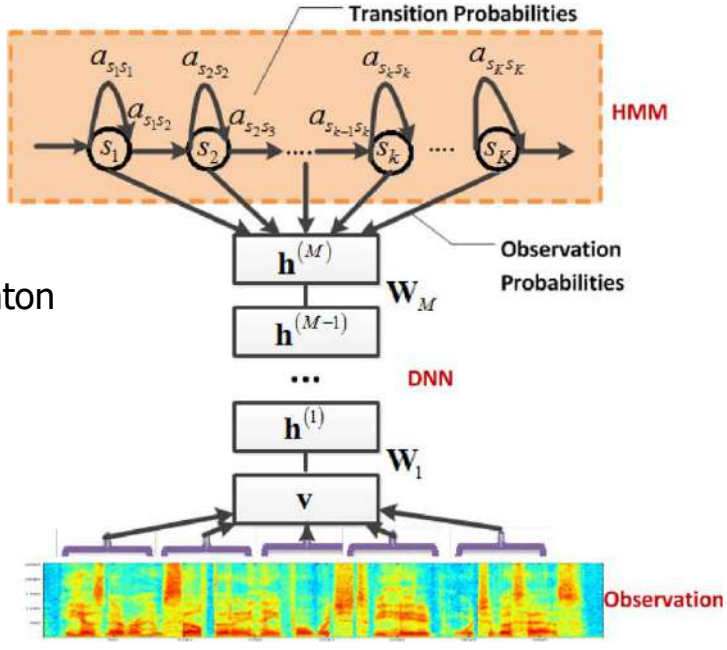
Reconocimiento de voz

Microsoft Research



Li Deng (MSR) & Geoff Hinton

Dong Yu (MSR)



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

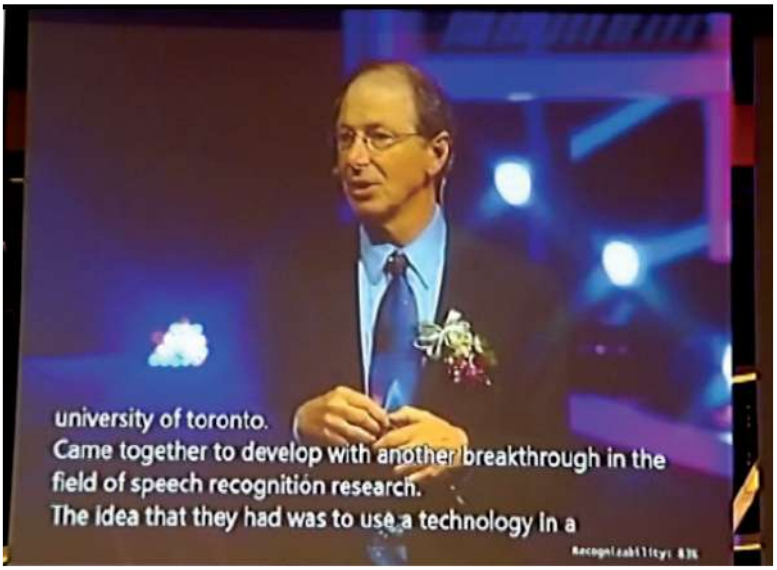
IBM

Google

2012

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

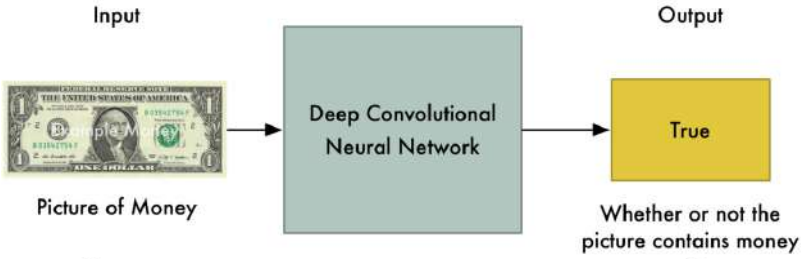
Traducción simultánea



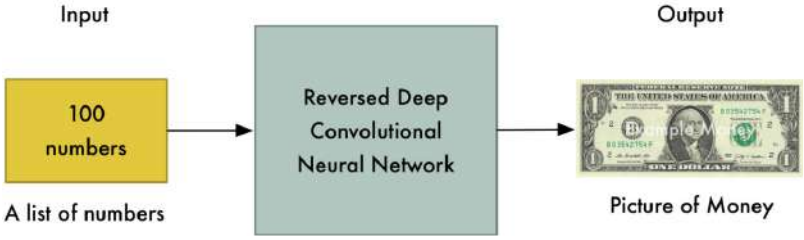
2012

GANs [Generative Adversarial Networks]

Discriminador



Generador



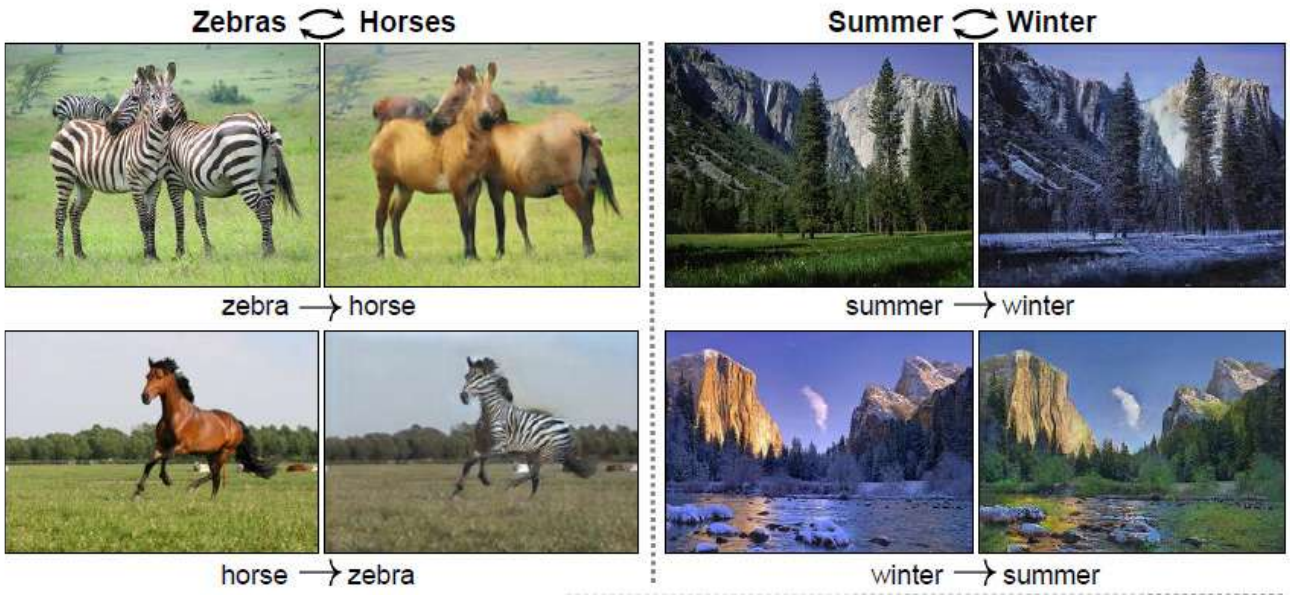
2014

Historia de las redes neuronales artificiales
Deep Learning

"Traducción de imágenes"

CycleGAN Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks, ICCV'2017

"Traducción de imágenes"



CycleGAN Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks, ICCV'2017

Historia de las redes neuronales artificiales
Deep Learning

"Traducción de imágenes"

CycleGAN Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks, ICCV'2017

Unsupervised Image-to-Image Translation Networks, NIPS'2017

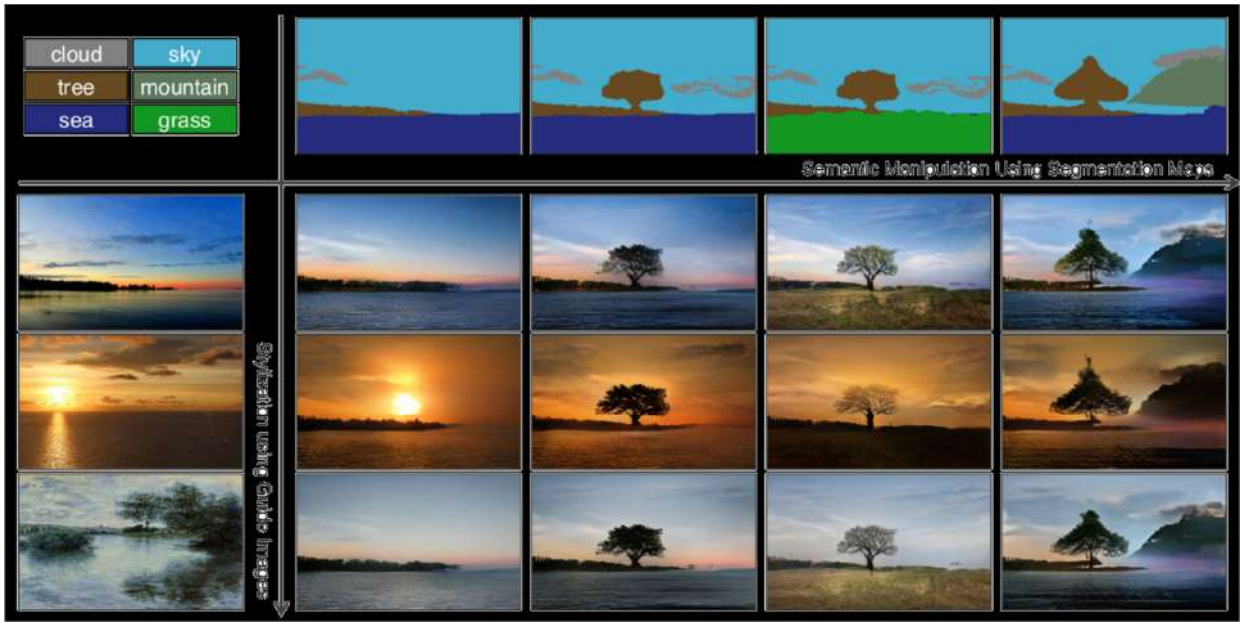
Historia de las redes neuronales artificiales
Deep Learning

Síntesis de imágenes

https://thispersondoesnotexist.com/

StyleGAN https://arxiv.org/abs/1812.04948 CVPR'2019

GauGAN



NVIDIA'2019

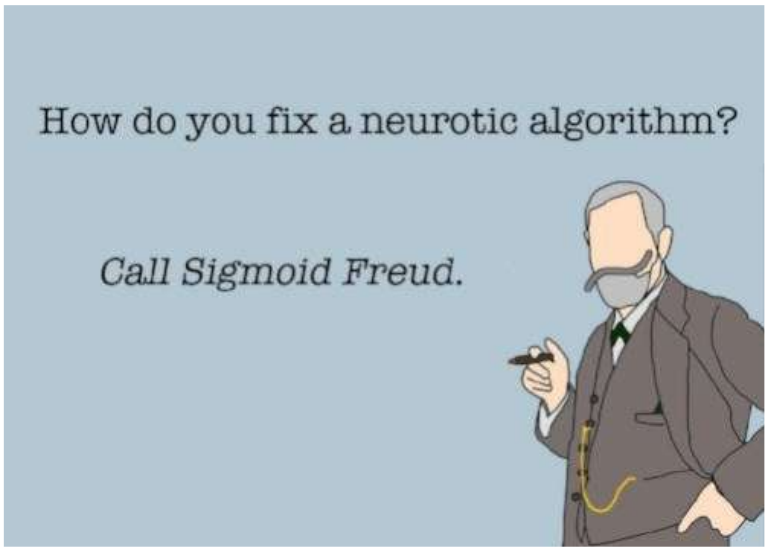
https://blogs.nvidia.com/blog/2019/03/18/gaugan-photorealistic-landscapes-nvidia-research/

Historia de las redes neuronales artificiales
Deep Learning

"You sketch, the AI paints"

GauGAN, NVIDIA, CVPR'2019

Técnicas de deep learning



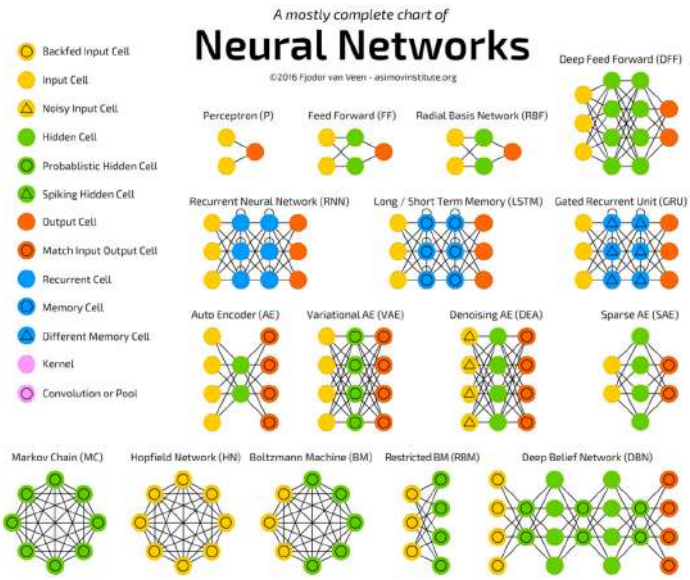
Técnicas de Deep Learning

Pero resulta que, después de todo,
la solución era muy simple:

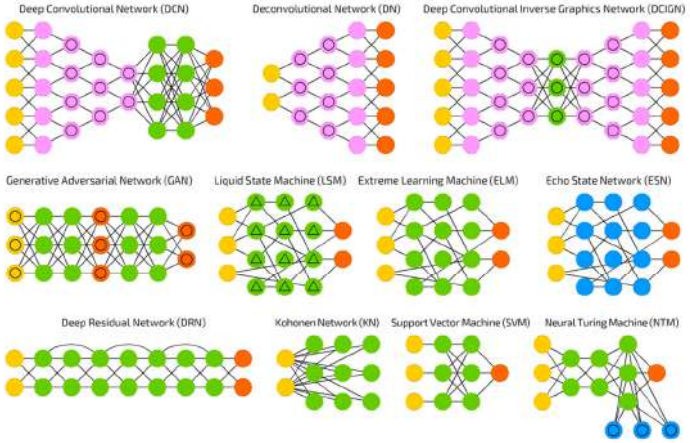
- Modelos paramétricos suficientemente grandes (redes neuronales con muchos pesos ajustables).
- Conjuntos de entrenamiento suficientemente grandes para entrenar las redes usando el gradiente descendente.

Richard Feynman, sobre el Universo:

It's not complicated, it's just a lot of it

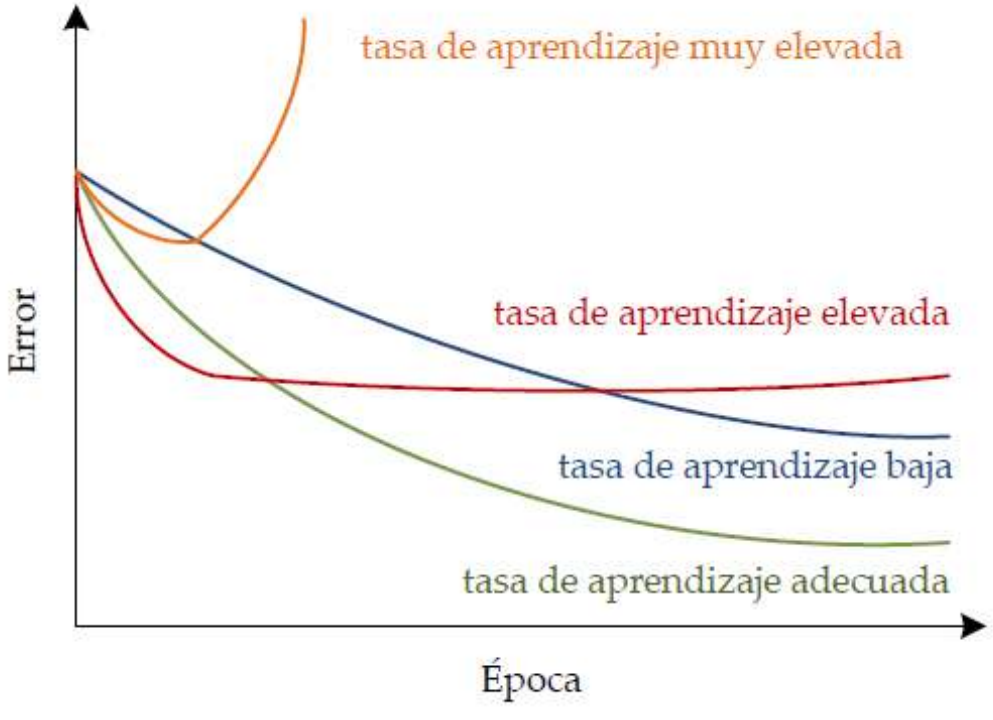


El zoo de las redes neuronales



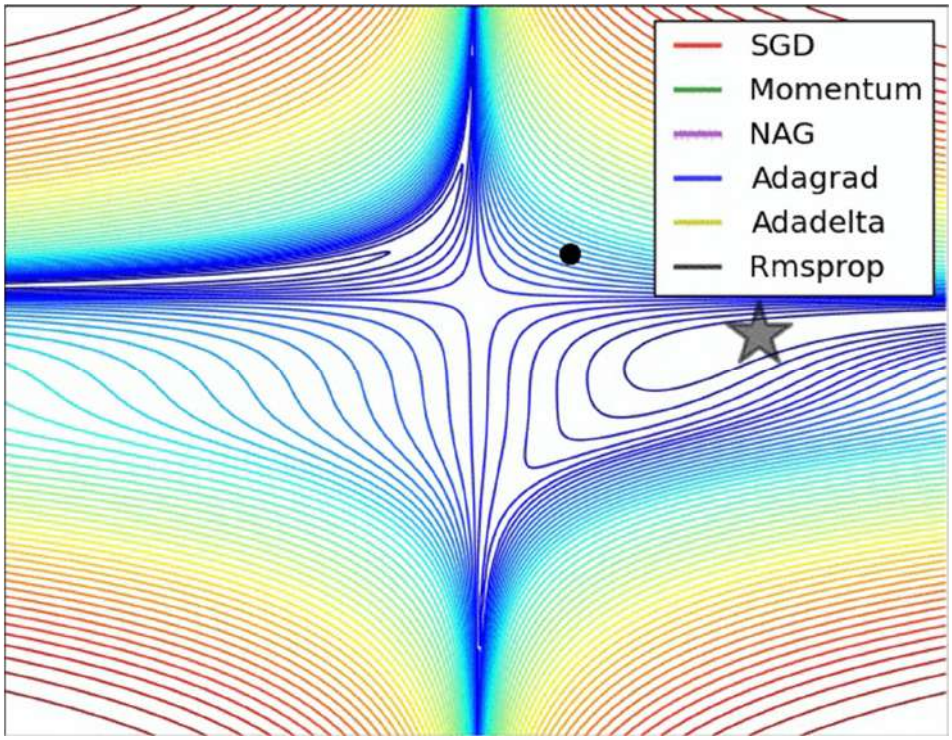
Algoritmos de optimización

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



Algoritmos de optimización

SGD [Stochastic Gradient Descent]

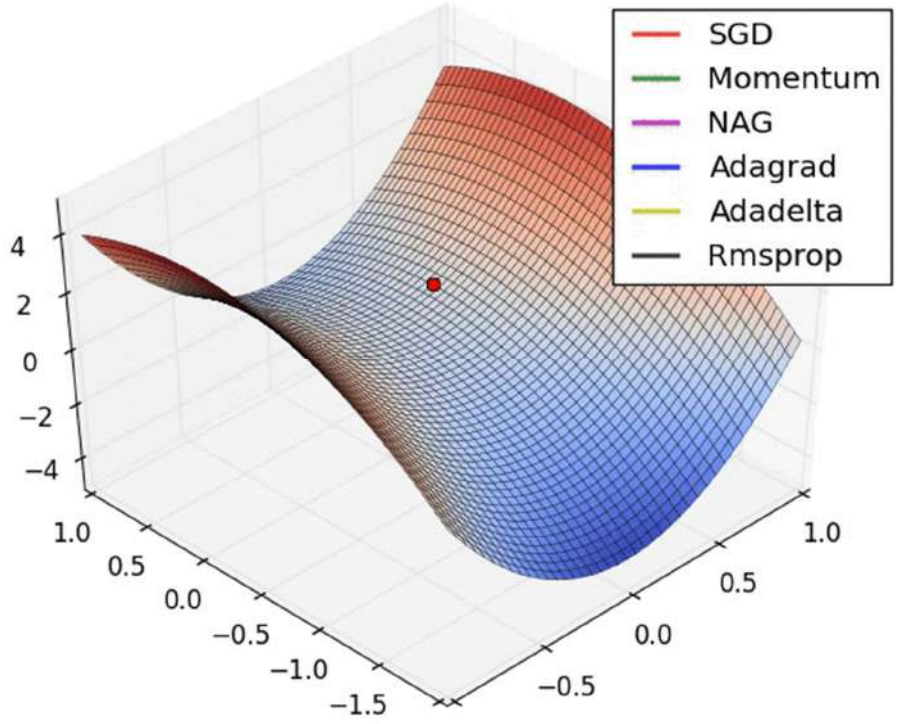


Alec Radford
https://twitter.com/alecrad

Técnicas de Deep Learning

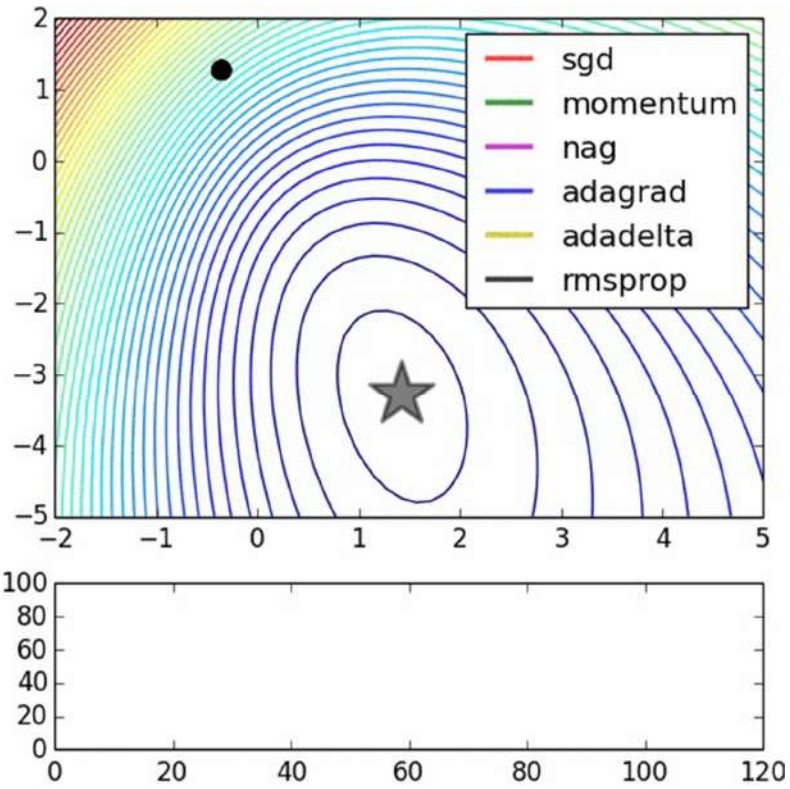
Algoritmos de optimización

SGD [Stochastic Gradient Descent] @ saddle point



Alec Radford
https://twitter.com/alecrad

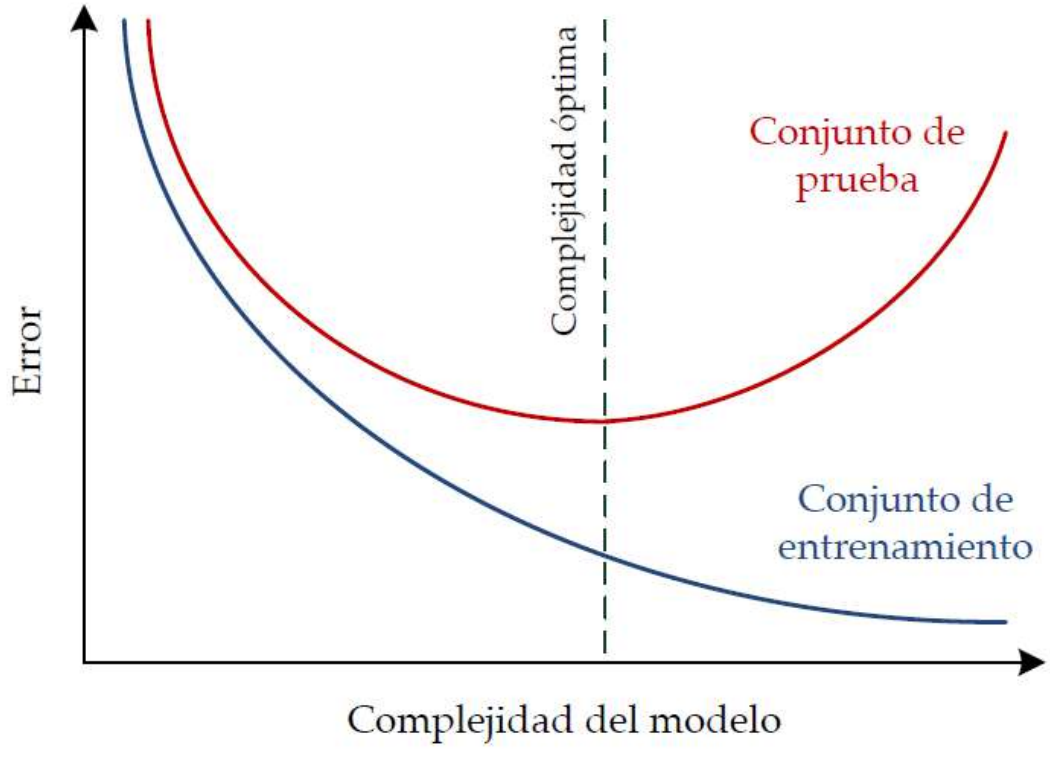
Algoritmos de optimización



Alec Radford
https://twitter.com/alecrad

Regularización

El problema del sobreaprendizaje



Regularización

Estrategias para evitar el sobreaprendizaje:

- Obtener más datos (la mejor opción si tenemos capacidad para entrenar la red usando más datos).

"You can't keep adjusting the data to prove that you would be the best Valentine's date for Scarlett Johansson."

- Ajustar los parámetros de la red para que tenga la capacidad adecuada (suficiente para identificar las regularidades en los datos, pero no demasiada para ajustarse a las espúreas, suponiendo que sean más débiles que las auténticas).

Regularización

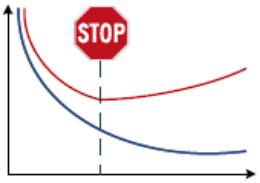
Capacidad de la red: Topología

Algunas formas de limitar la capacidad de la red actuando sobre su topología:

- **Arquitectura de la red**:
  Se limita el número de capas ocultas y/o el número de unidades por capa.

- **Weight sharing**:
  Se reduce el número de parámetros de la red haciendo que distintas neuronas compartan los mismos pesos (p.ej. redes convolutivas).

Capacidad de la red: Entrenamiento



Algunas formas de limitar la capacidad de la red actuando sobre su algoritmo de entrenamiento:

- **Early stopping**: Se comienza a entrenar la red con pesos pequeños y se para el entrenamiento antes de que sobreaprenda.
- **Weight decay**: Se penalizan los pesos grandes en función de sus valores al cuadrado (penalización L2) o absolutos (penalización L1).
- **Ruido**: Se añade ruido a los pesos o actividades de las neuronas de la red que se está entrenando.

Técnicas de Deep Learning
Regularización

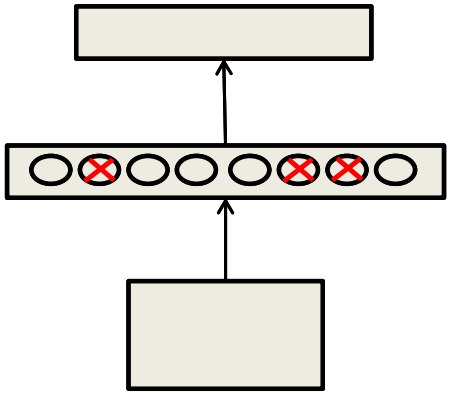
Una tercera estrategia: Combinar modelos

Model averaging" (a.k.a. "ensembles"):
Muchos modelos diferentes con distintos parámetros o el mismo tipo de modelo utilizando distintos subconjuntos del conjunto de entrenamiento [bagging].

Dropout

¡las conspiraciones complejas no son robustas!

-- Geoff Hinton.



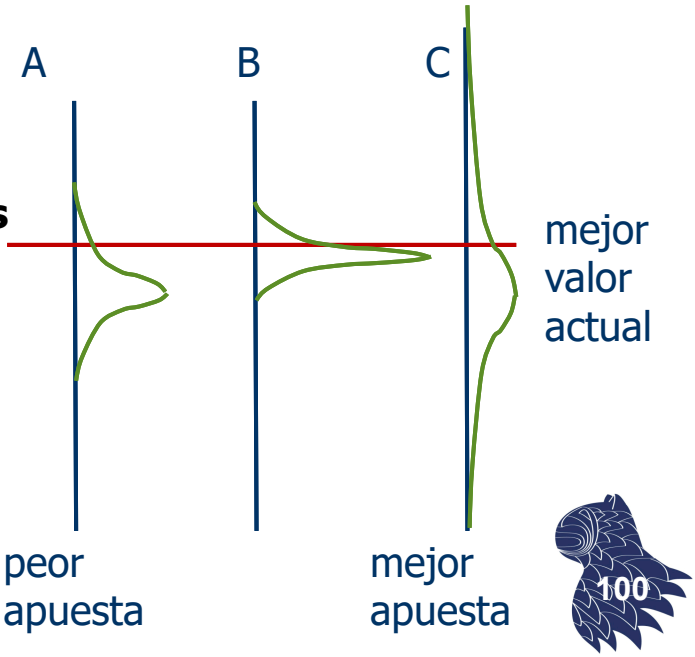
Ajuste de hiperparámetros

Una de las principales dificultades prácticas del uso de redes neuronales es la destreza que requiere establecer todos sus parámetros ("arte" más que ciencia)

p.ej.

Modelo de procesos gaussianos
A partir de la mejor configuración conocida, se elige una combinación de hiperparámetros tal que la mejora esperada sea grande (sin preocuparse por la posibilidad de empeorar).

Snoek, Larochelle & Adams
NIPS 2012



Técnicas de Deep Learning

Ajuste de hiperparámetros

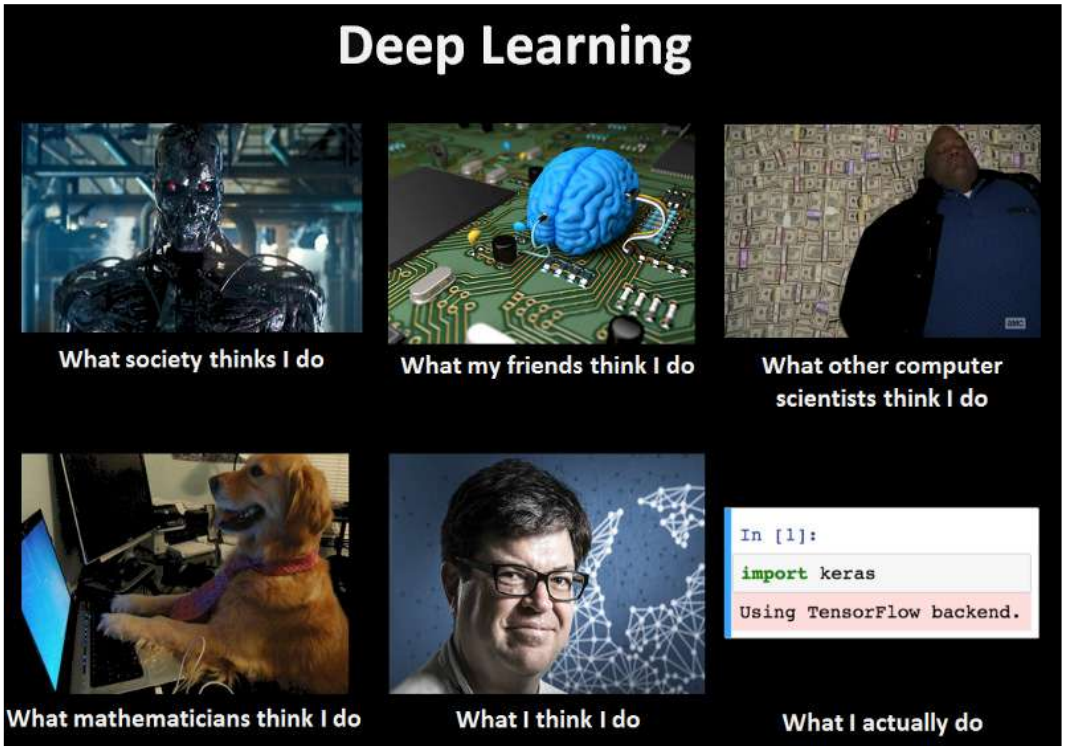
AutoML

Aprendizaje automático [Machine Learning]

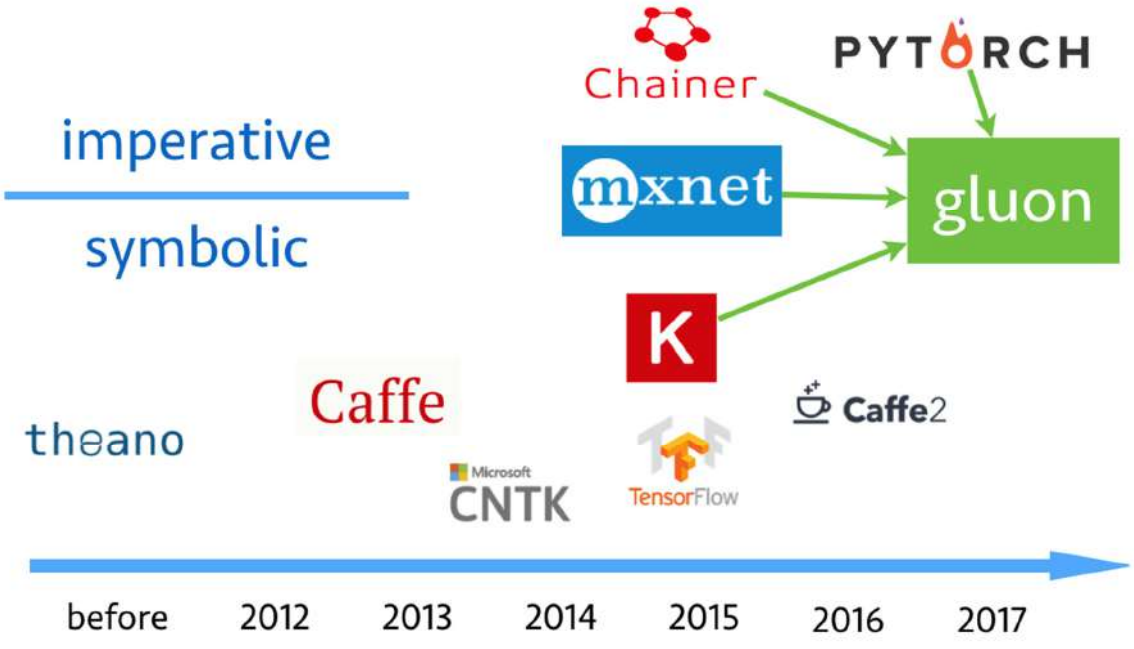
- Mucho mejor que ir haciendo pruebas manualmente (no es el tipo de tarea que los humanos hacemos bien).

- Evita sesgos psicológicos no deseados: método menos propenso a funcionar mejor con el método que nos gusta y peor con el que no (las personas no podemos evitarlo ;-)

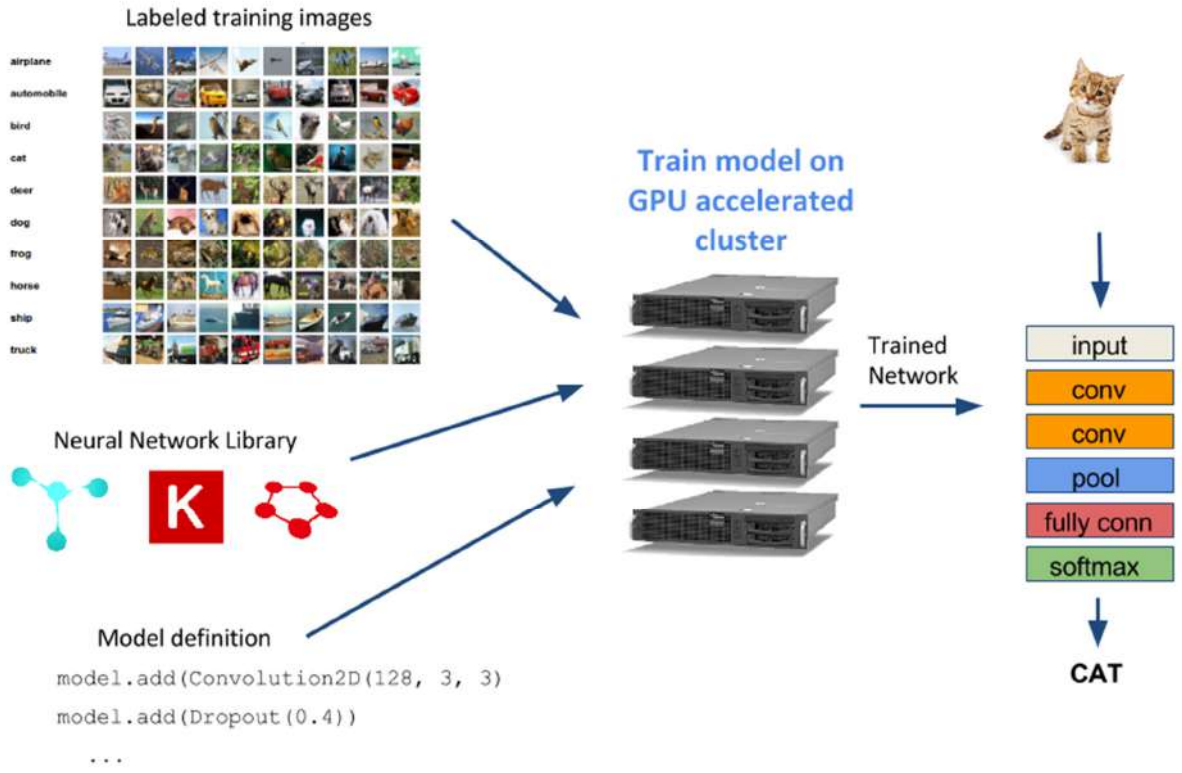
En la práctica



En la práctica
Software para deep learning



En la práctica
Software para deep learning

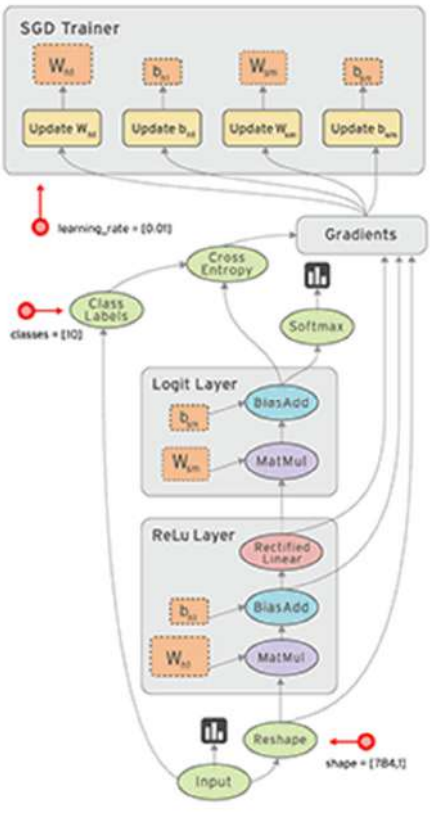


En la práctica
Software para deep learning

Google TensorFlow

https://www.tensorflow.org/

Licencia Apache 2.0



Data flow graph

En la práctica
Software para deep learning

Keras

fast.ai

GLUON

TensorFlow

Caffe

PyTorch

Caffe2

APACHE mxnet

Chainer

Microsoft CNTK

DL4J

dy/net

theano

En la práctica

They are neither neural nor networks!

They are chains of differentiable, parameterized geometric functions, trained with gradient descent (obtained via chain rule)

A small set of high school level ideas put together

Francois Chollet
Creator of Keras
Google AI Researcher

https://twitter.com/fchollet/status/951906139632840704

En la práctica

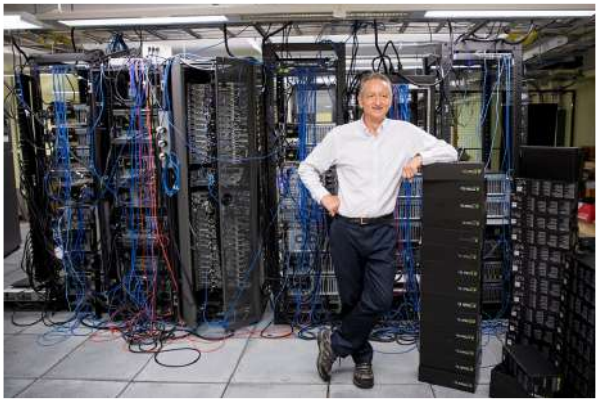
My favorite definition of Deep Learning is matrix multiplication, a lot of matrix multiplication...

Barbara Fusinska
Machine Learning Programmer at Microsoft

From Keynote Networks are like onions: Practical Deep Learning with TensorFlow
https://www.youtube.com/watch?v=95IV8DoWRwI

En la práctica

En deep learning, todo son vectores…



The Vector Institute for AI
University of Toronto
http://vectorinstitute.ai/

En la práctica

With all due respect
to the brilliant Geoff Hinton,
thought is not a vector,
and AI is not a problem in statistics.

-- Oren Etzioni

Shortcomings of Deep Learning
https://www.kdnuggets.com/2016/11/shortcomings-deep-learning.html

Aplicaciones del Deep Learning

Existen problemas para los que es extremadamente difícil desarrollar manualmente un programa de ordenador que los resuelva.

Ejemplo: Visión artificial

[Terminator, 1984]

Aplicaciones del Deep Learning

De hecho, el reconocimiento de objetos…

- Ni siquiera sabemos cómo se hace realmente en nuestro cerebro (por lo que difícilmente podremos diseñar un algoritmo que haga exactamente lo mismo).

- Incluso aunque tuviésemos una idea más precisa de cómo se hace en nuestro cerebro, el programa necesario podría ser tremendamente complicado :-(

Aplicaciones del Deep Learning

Aprendizaje automático
/ Inteligencia Computacional
/ Redes neuronales artificiales [deep learning]

- En vez de diseñar un algoritmo que resuelva el problema, recopilamos un montón de datos (ejemplos).

- Diseñamos un algoritmo que aprenda de esos datos y cree el programa necesario para resolver el problema.

Aplicaciones del Deep Learning

La solución basada en deep learning

- El programa generado automáticamente no tiene por qué parecerse a un programa implementado manualmente (en el caso de las redes neuronales, puede contener millones de números reales).
- Si tenemos éxito, el programa funcionará bien para nuevos ejemplos, aunque sean diferentes a los que utilizamos para su entrenamiento.
- Si los datos cambian, el programa puede cambiar entrenándolo de nuevo.

Limitaciones del Deep Learning

Limitaciones

Cualquier cosa que requiera razonar, planificar a largo plazo o manipular datos de forma algorítmica está fuera del alcance de las técnicas actuales de deep learning.

p.ej. Ordenar un conjunto de datos puede ser extremadamente difícil usando una red neuronal.

Limitaciones del Deep Learning

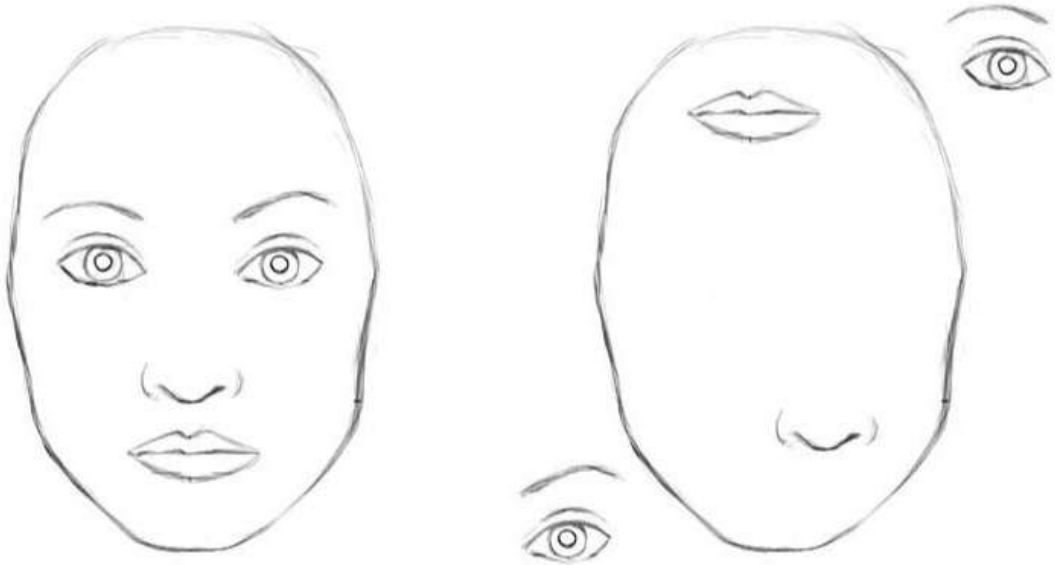
Limitaciones

Falta de compresión (en sentido humano) …

The boy is holding a baseball bat.

Limitaciones del Deep Learning

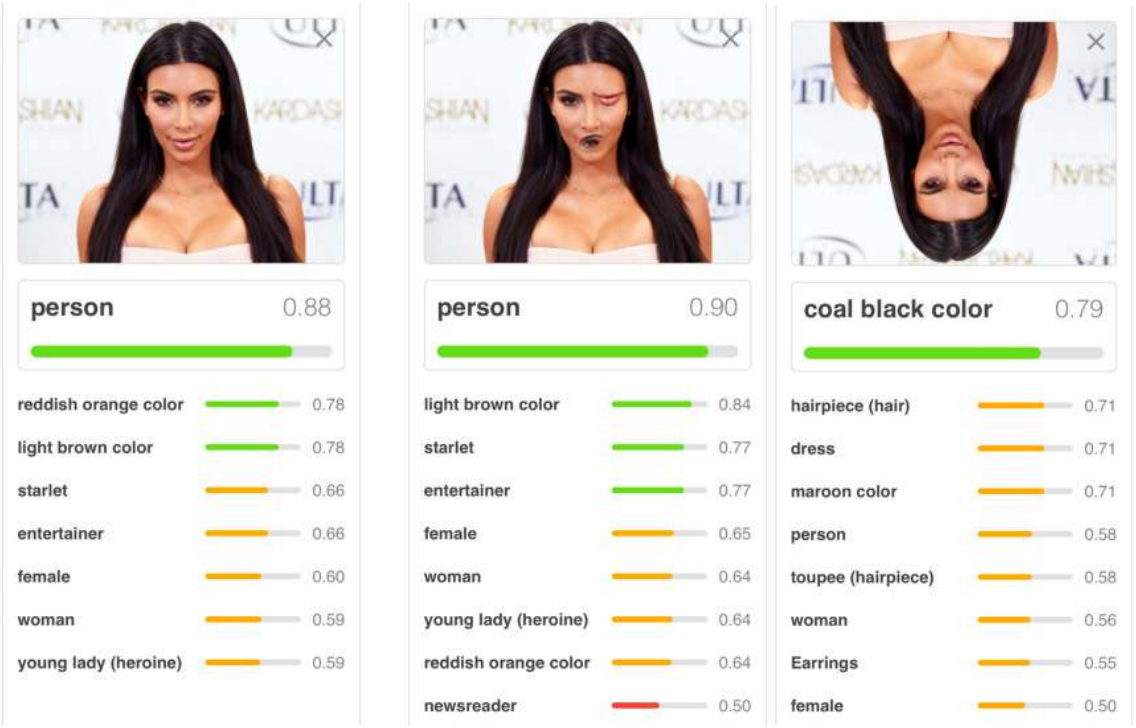
Las redes convolutivas [CNNs] funcionan muy bien en la práctica, pero…



… para una CNN, ambas imágenes son similares ☹

Limitaciones del Deep Learning

"Convolutional neural networks are doomed"
—Geoffrey Hinton



Limitaciones del Deep Learning

- Las redes convolutivas detectan características, pero no su colocación relativa (traslación & rotación).

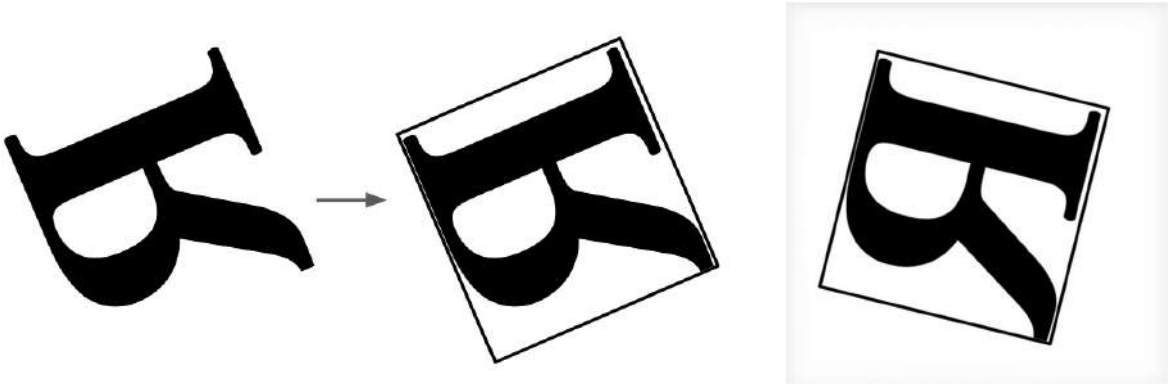
- Las redes convolutivas ignoran las posiciones relativas utilizando "pooling", un apaño que funciona sorprendentemente bien en la práctica:

"The pooling operation used in convolutional neural networks is a big mistake and the fact that it works so well is a disaster." – Geoffrey Hinton

Limitaciones del Deep Learning

Problema clave de las redes convolutivas

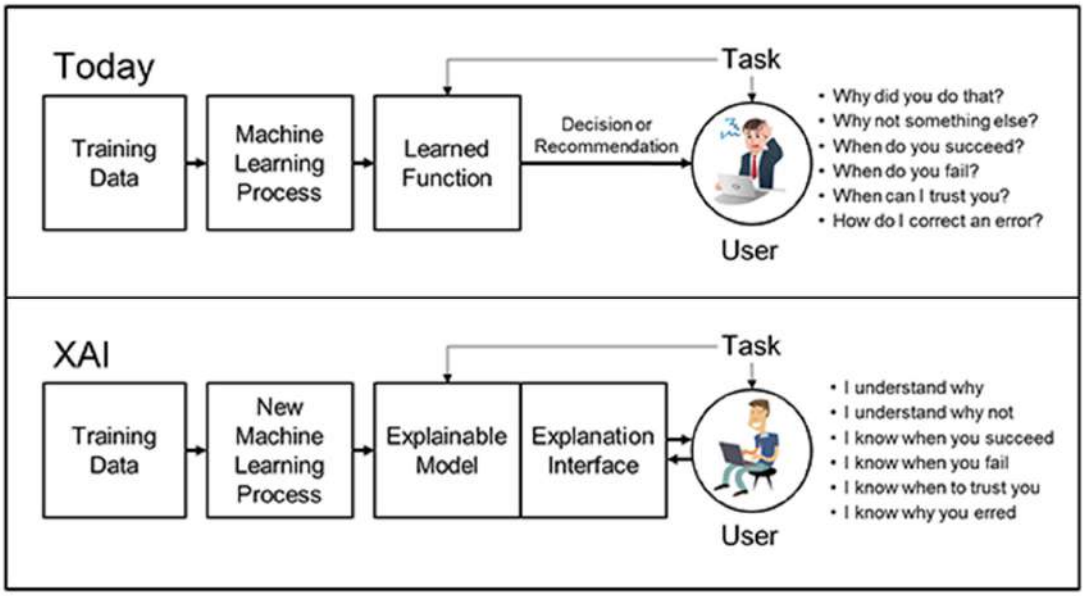
La representación interna de una red convolutiva no tiene en cuenta las relaciones espaciales entre objetos, ni la jerarquía existente entre objetos simples y los objetos compuestos de los que forman parte.



Limitaciones del Deep Learning

Limitaciones

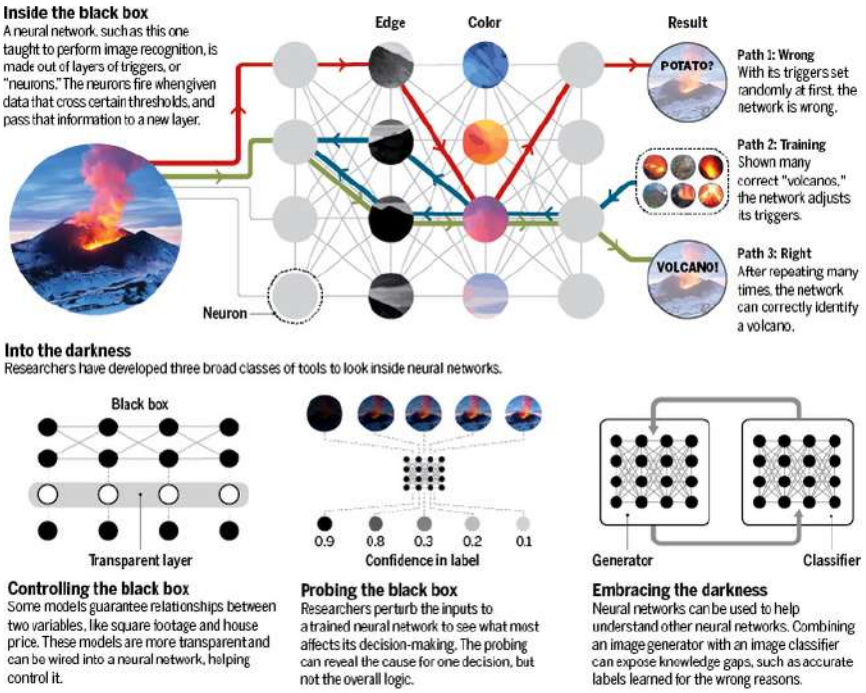
Falta de interpretabilidad:
Redes neuronales como cajas negras



Limitaciones del Deep Learning

Limitaciones

Falta de interpretabilidad



Mecanismos de atención

Limitaciones

A woman is throwing a frisbee in a park.

A dog is standing on a hardwood floor.

A stop sign is on a road with a mountain in the background.

A little girl sitting on a bed with a teddy bear.

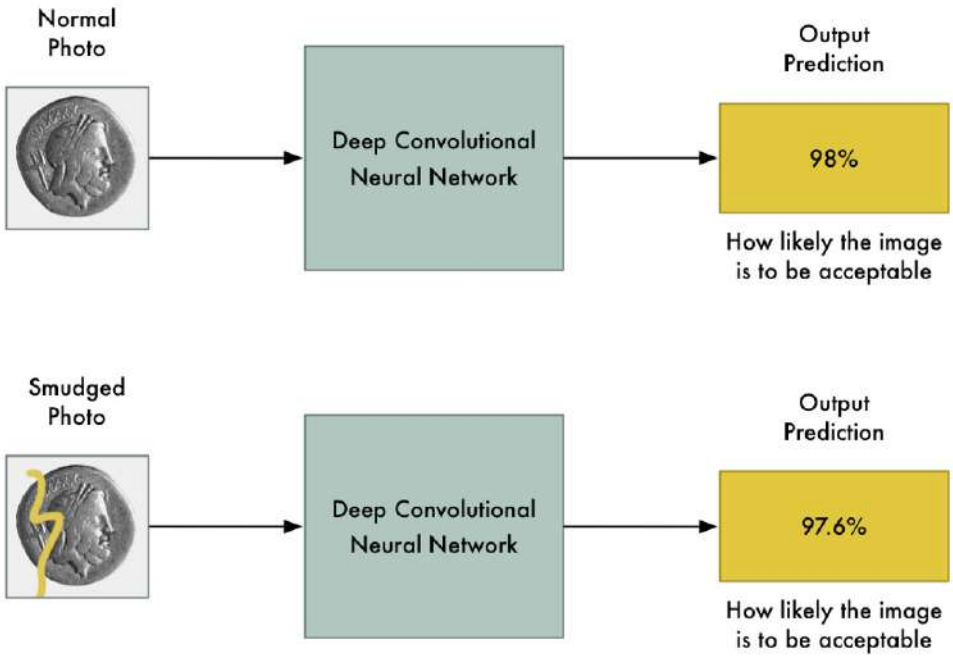
A group of people sitting on a boat in the water.

A giraffe standing in a forest with trees in the background.

Mecanismos de atención en la descripción textual de imágenes [image captioning]

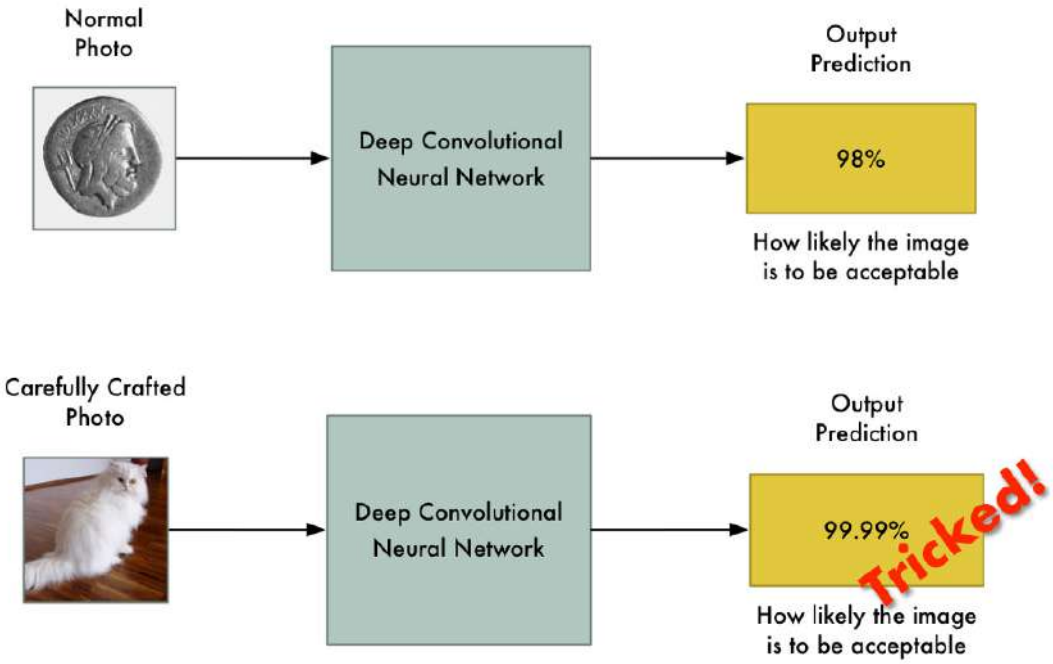
Limitaciones del Deep Learning

Lo deseable…



Limitaciones del Deep Learning

Lo que puede pasar…

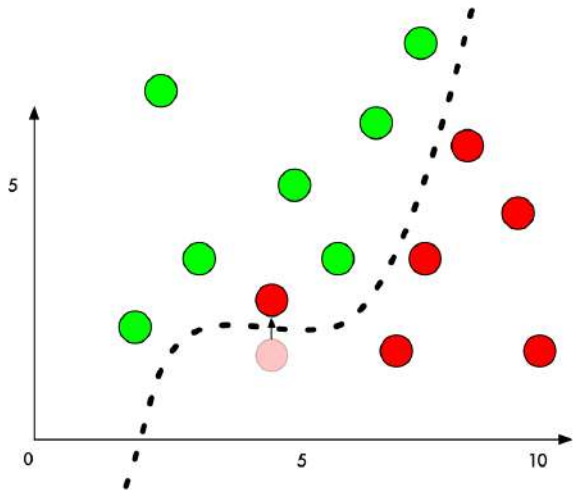


Limitaciones del Deep Learning

Ejemplos diseñados por un adversario
(o cómo engañar fácilmente a una red neuronal)

Si conocemos la red, podemos saber exactamente cómo modificar mínimamente la entrada para confundir a la red neuronal…

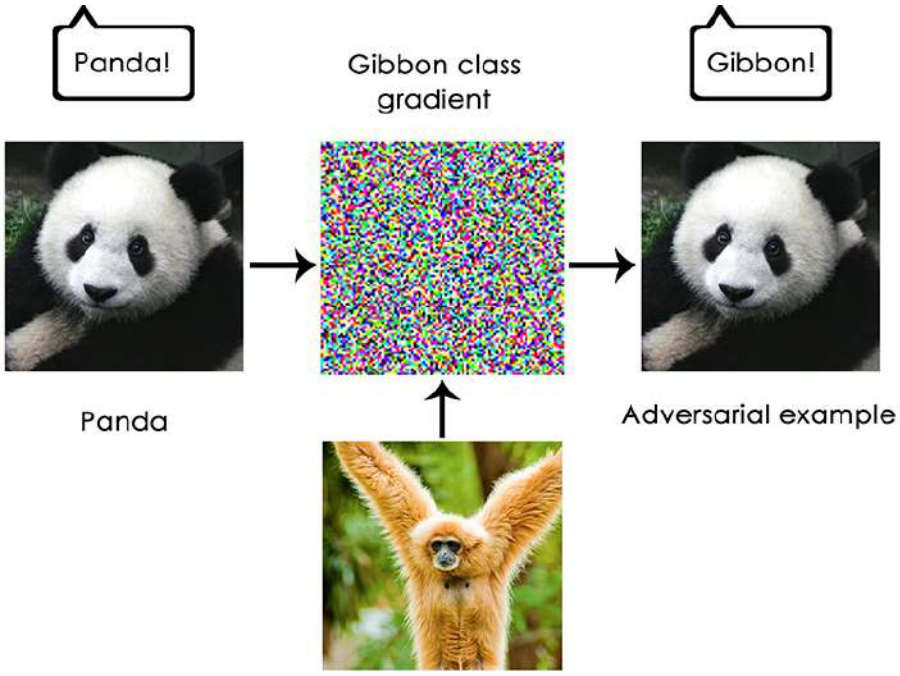
… en la dirección del gradiente !!!



Limitaciones del Deep Learning

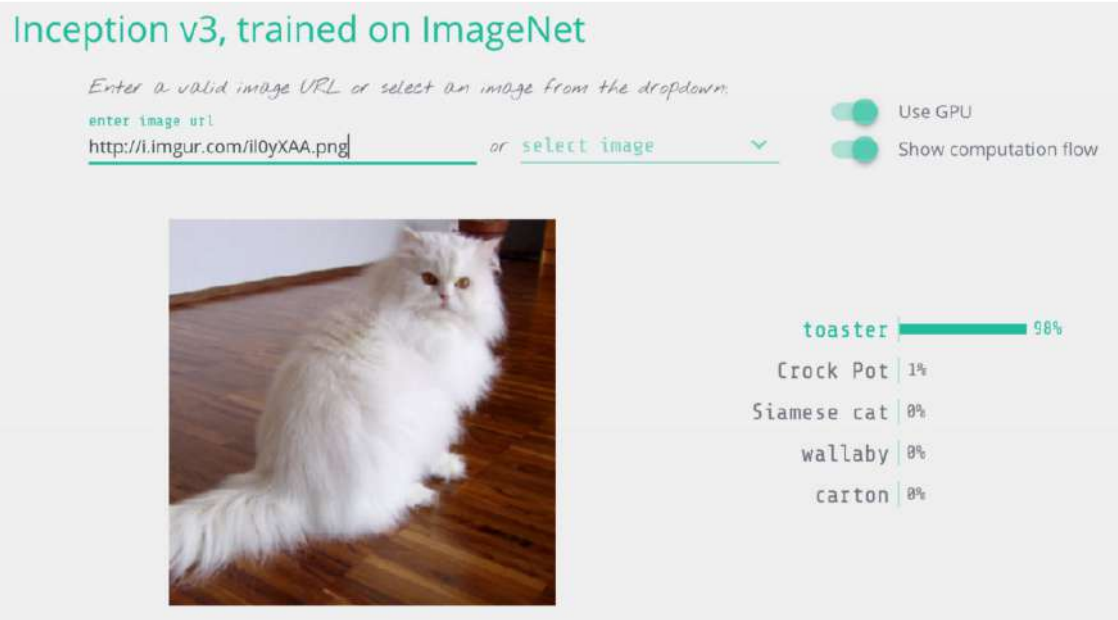
Limitaciones

Situaciones con adversario [adversarial examples]



Limitaciones del Deep Learning

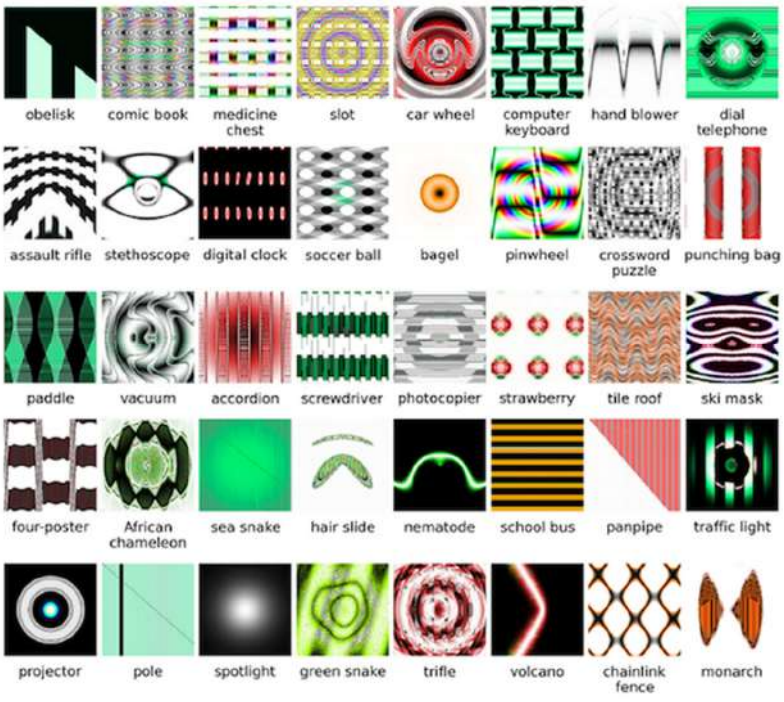
Ejemplos diseñados por un adversario
(o cómo engañar fácilmente a una red neuronal)



Limitaciones del Deep Learning

Limitaciones

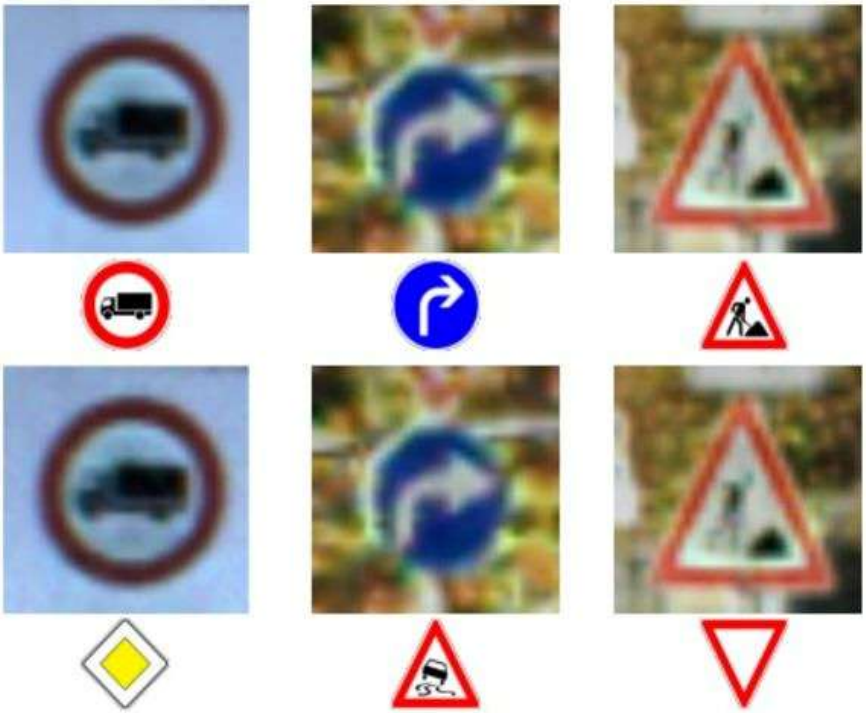
Situaciones con adversario [adversarial examples]



Limitaciones del Deep Learning

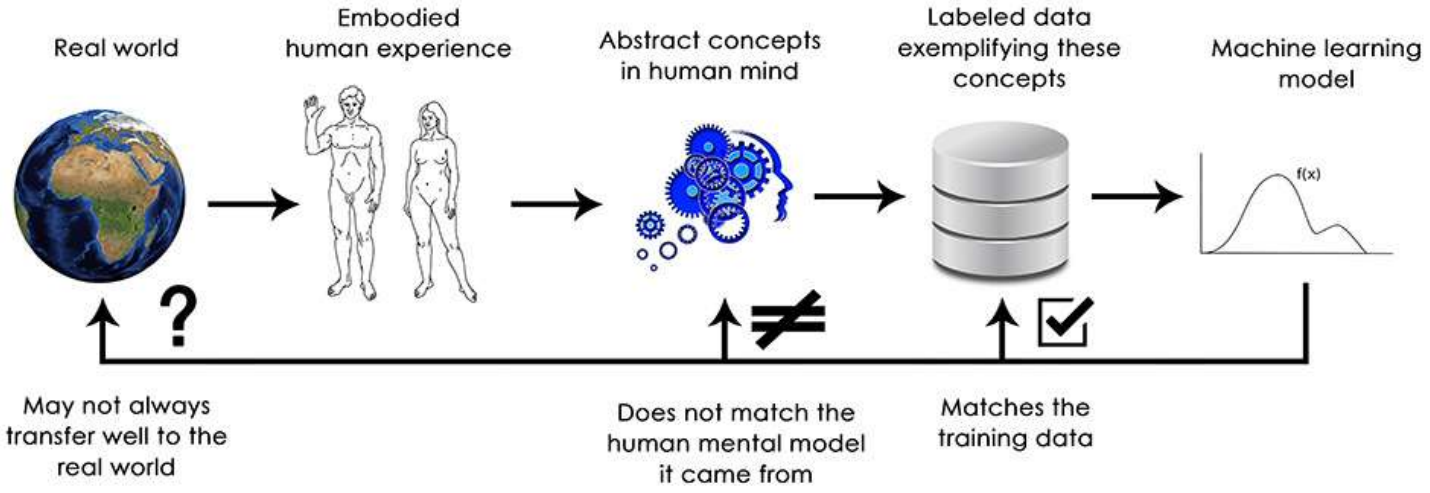
Limitaciones

Situaciones con adversario [adversarial examples]



Limitaciones del Deep Learning

Limitaciones

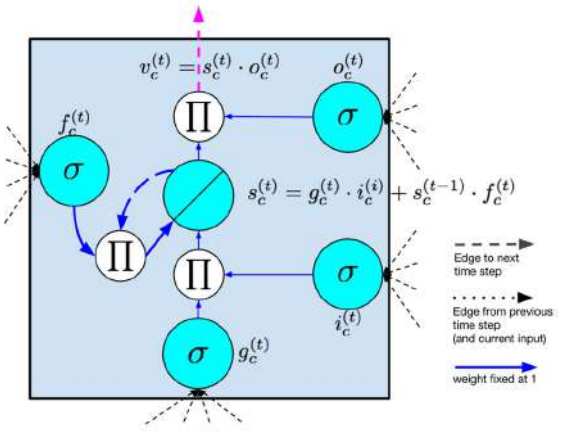


"Never fall into the trap of believing that neural networks understand the task they perform"

https://blog.keras.io/the-limitations-of-deep-learning.html

Deep Learning

Para algunos investigadores, que intentan obtener garantías teóricas basadas en resultados matemáticos: "[deep learning] might seem to be a regression" ;-)



LSTM (red recurrente)

En la práctica, los algoritmos con las mejores propiedades teóricas no son siempre los que mejor funcionan (sin restar importancia al estudio de las propiedades de los algoritmos de aprendizaje).

Deep Learning

Las técnicas heurísticas tienen éxito gracias a la disponibilidad de grandes conjuntos de datos (en los que el riesgo de sobreaprendizaje es menor) y la capacidad de cálculo de los sistemas actuales.

La validación con conjuntos de datos de prueba independientes ofrece una estimación de su comportamiento esperado en situaciones reales (los análisis teóricos se centran en el peor caso).

Deep Learning

Few Things Are Guaranteed

When attainable, theoretical guarantees are beautiful. They reflect clear thinking and provide deep insight to the structure of a problem. Given a working algorithm, a theory which explains its performance deepens understanding and provides a basis for further intuition. Given the absence of a working algorithm, theory offers a path of attack.

However, there is also beauty in the idea that well-founded intuitions paired with rigorous empirical study can yield consistently functioning systems that outperform better-understood models, and sometimes even humans at many important tasks. Empiricism offers a path forward for applications where formal analysis is stifled, and potentially opens new directions that might eventually admit deeper theoretical understanding in the future.

Zachary Lipton:
"Deep Learning and the Triumph of Empiricism"
KDnuggets, July 2015

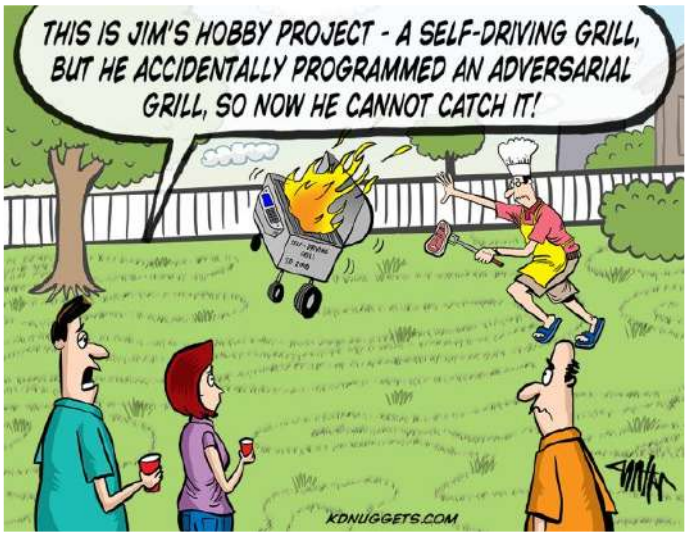
Deep Learning

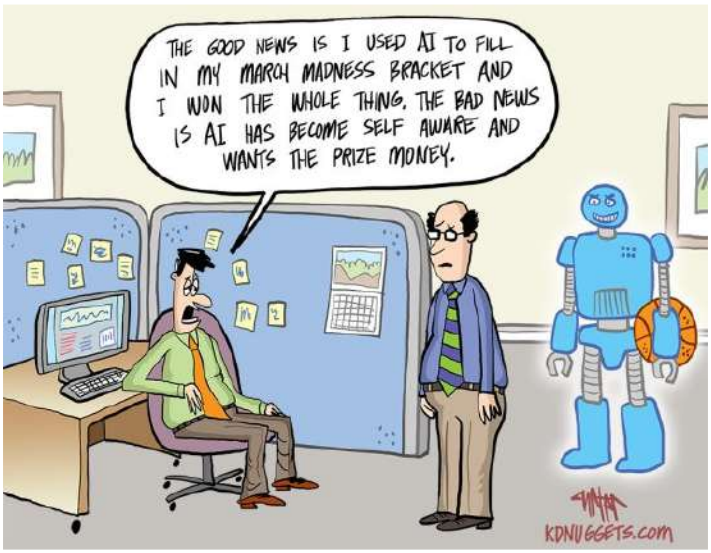
The only real success of deep learning so far has been the ability to map space X to space Y using a continuous geometric transform, given large amounts of human-annotated data. Doing this well is a game-changer for essentially every industry, but it is still a very long way from human-level AI.

… machine learning models could be defined as "learnable programs"; currently we can only learn programs that belong to a very narrow and specific subset of all possible programs. But what if we could learn *any* program, in a modular and reusable way?

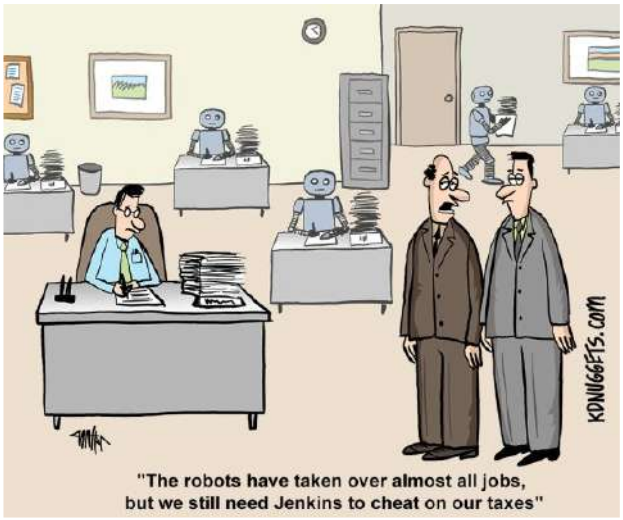
-- François Chollet: "The limitations of deep learning"
https://blog.keras.io/the-limitations-of-deep-learning.html

Deep Learning

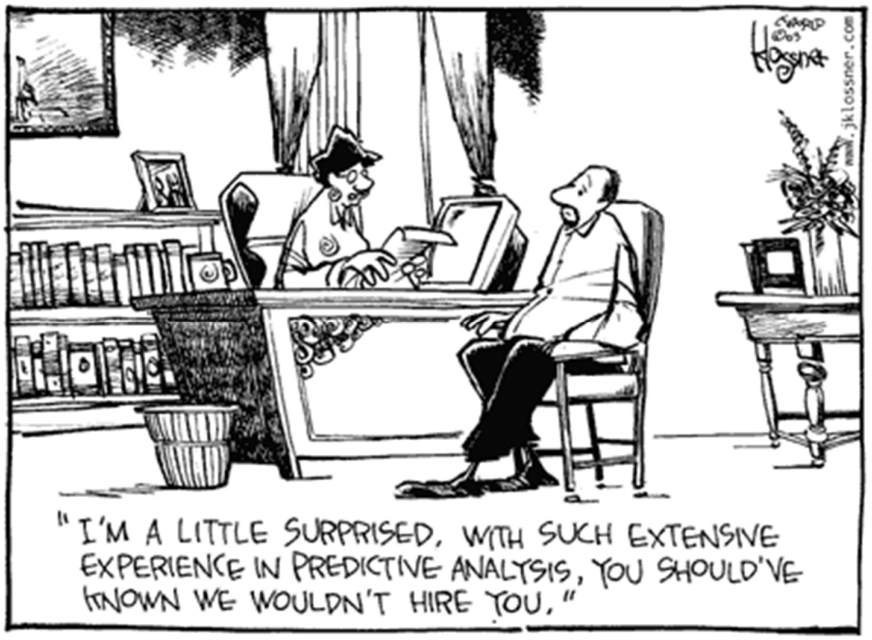




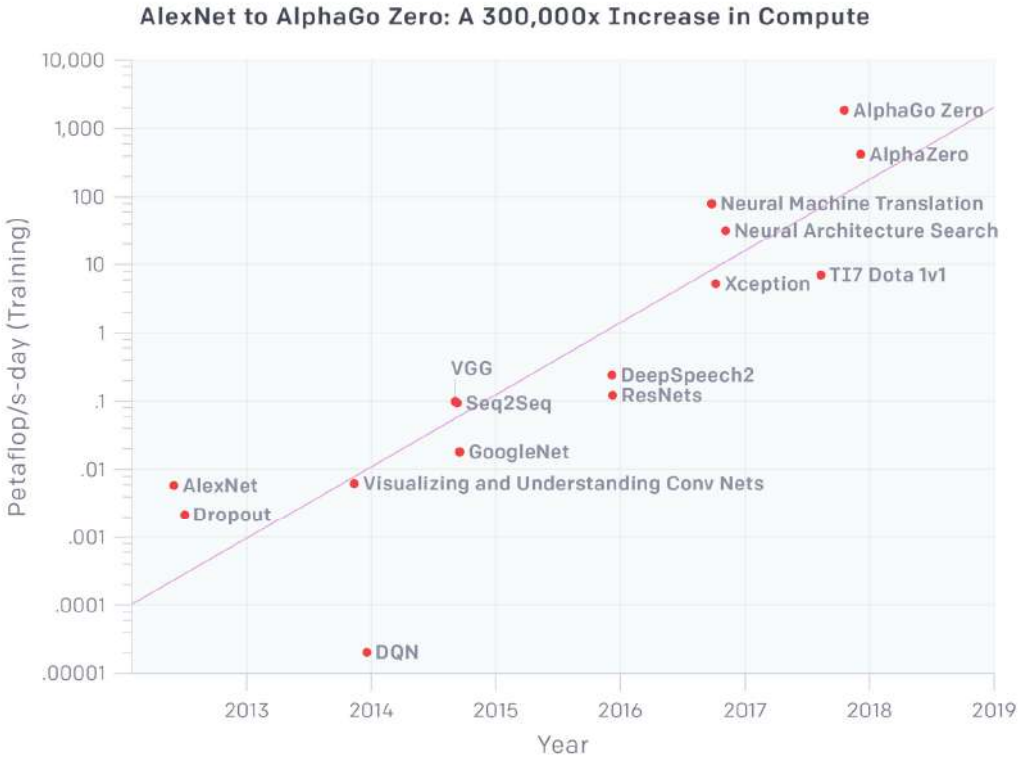
Deep Learning



Deep Learning

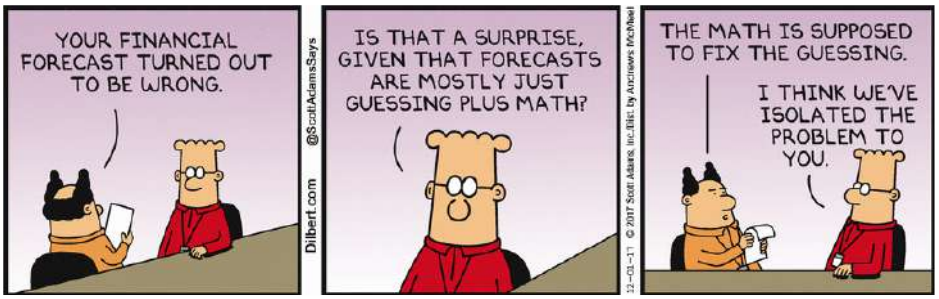


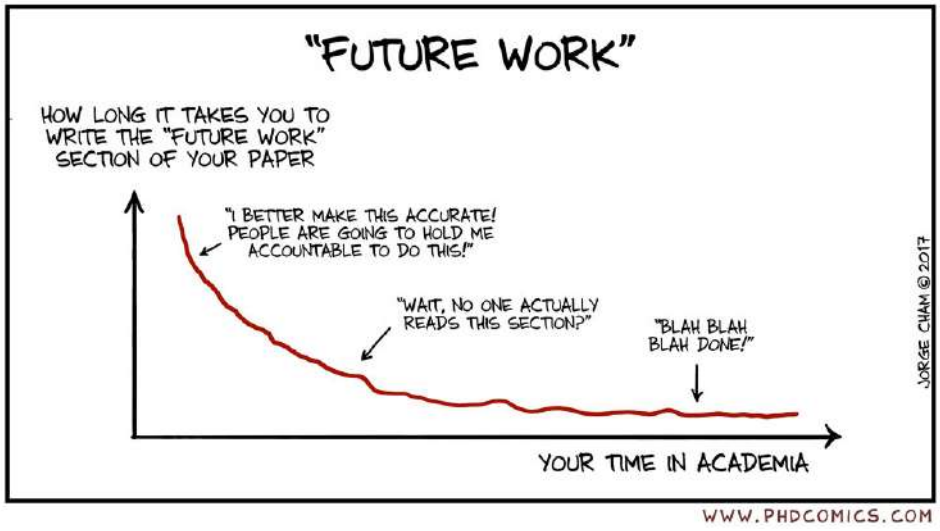
El futuro...



https://openai.com/blog/ai-and-compute/

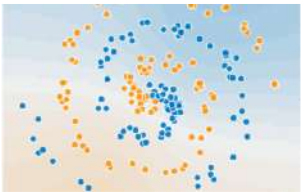
El futuro...





Demos

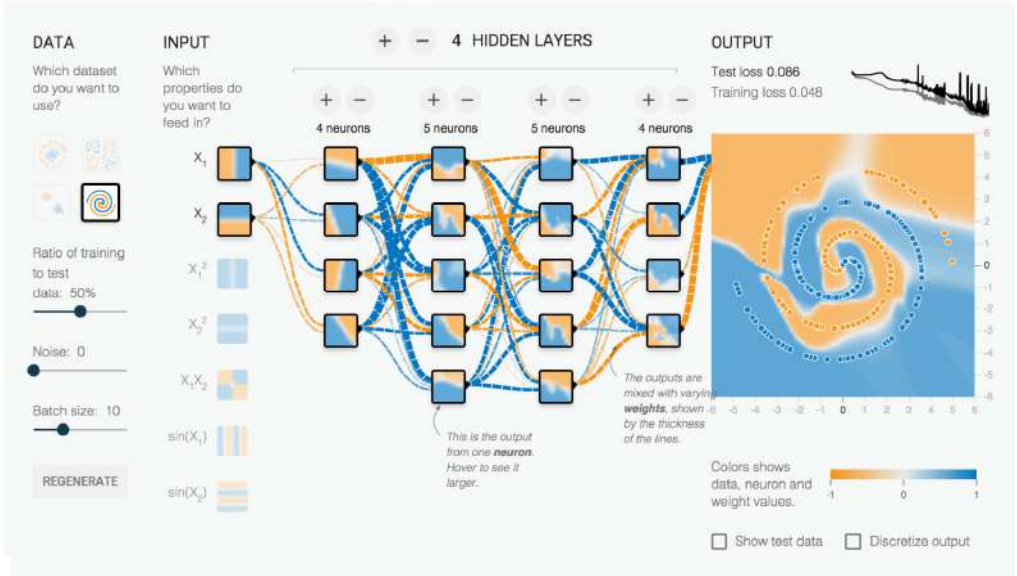
Para jugar un poco...



http://playground.tensorflow.org/

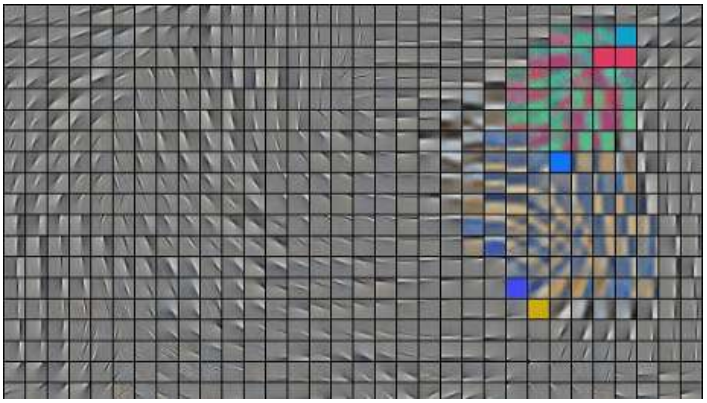
http://ml4a.github.io/demos/

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



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

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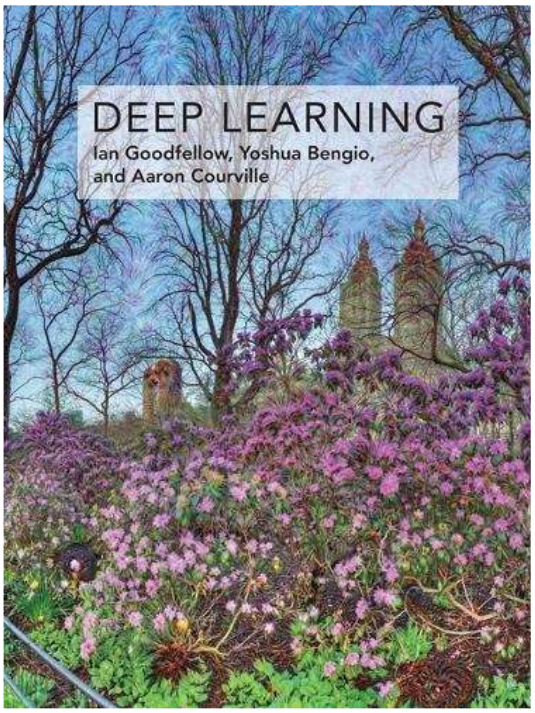
Ian Goodfellow,
Yoshua Bengio
& Aaron Courville:
Deep Learning
MIT Press, 2016
ISBN 0262035618

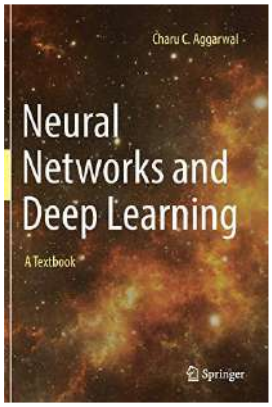


http://www.deeplearningbook.org

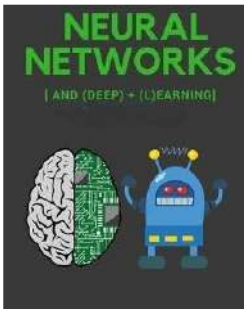
Bibliografía

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



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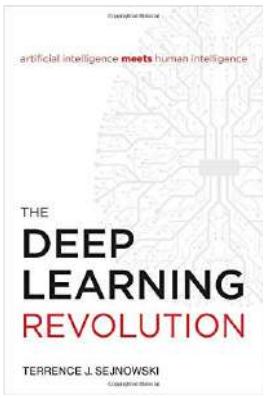
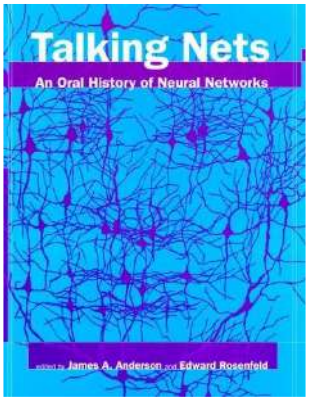
Evolución histórica





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  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

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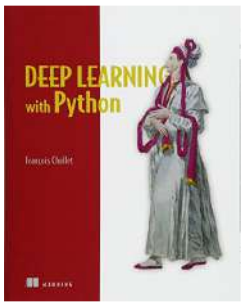
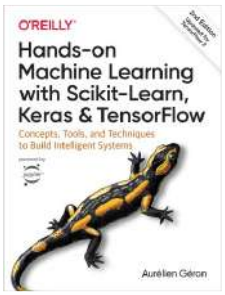
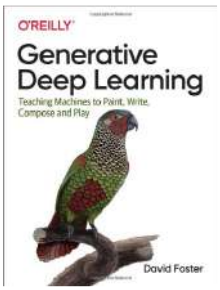
Lecturas complementarias

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

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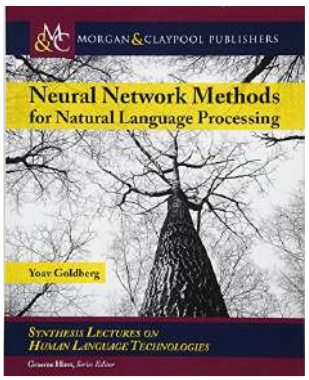
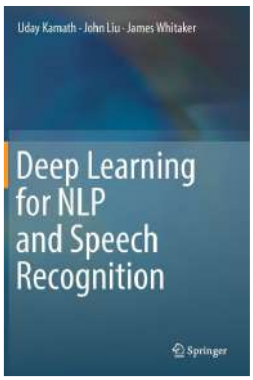
Lecturas complementarias

Áreas de aplicación, p.ej. NLP





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  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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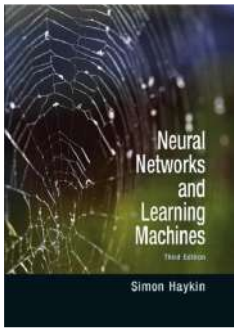

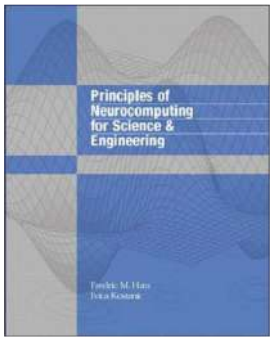

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  Principles of Neurocomputing for Science and Engineering
  McGraw-Hill Higher Education, 2000
  ISBN 0070259666

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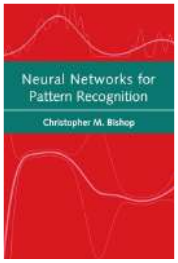

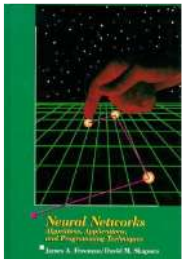

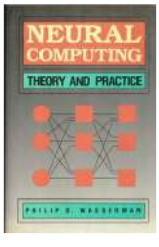

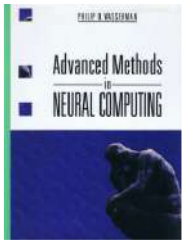

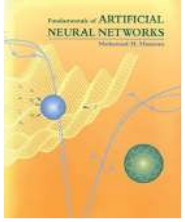

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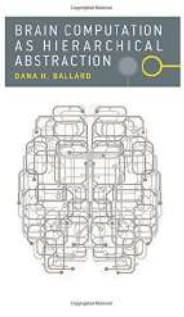

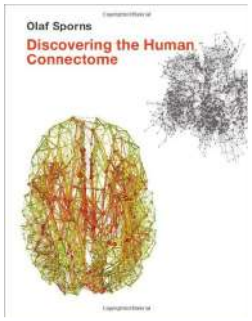

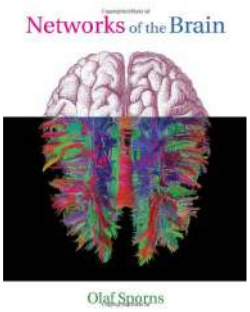

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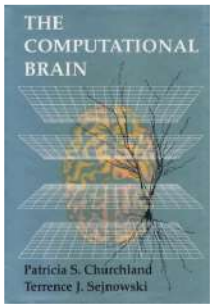

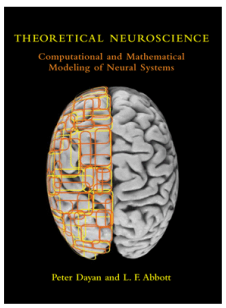

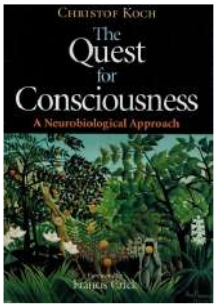

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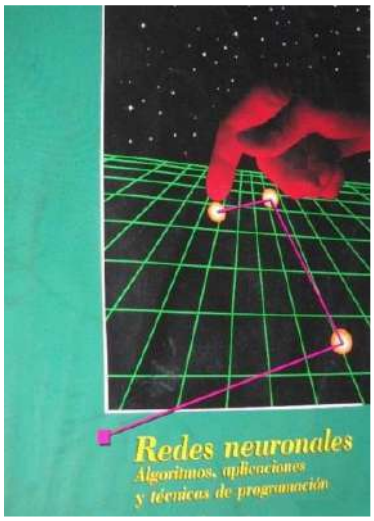

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  … con un disco de 3½”

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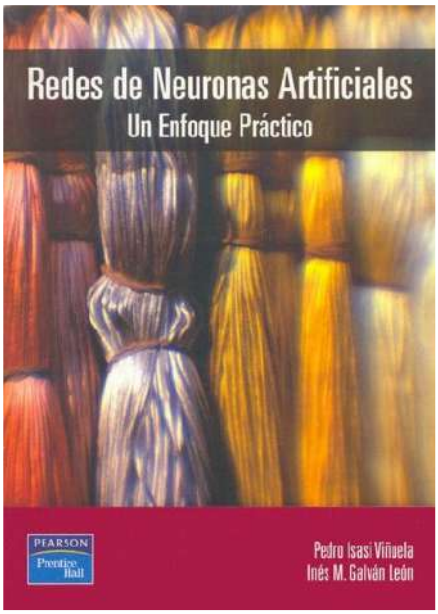

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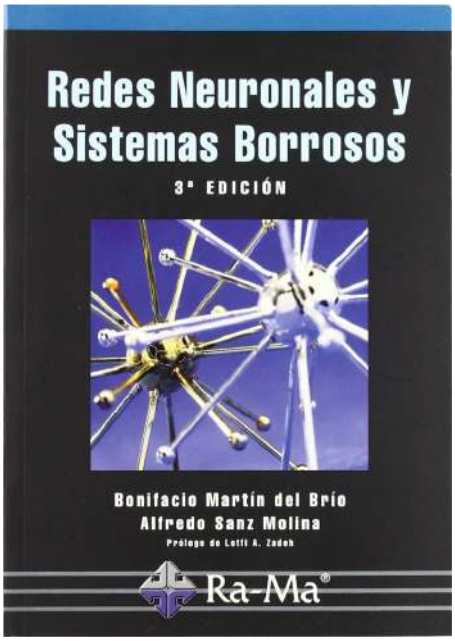

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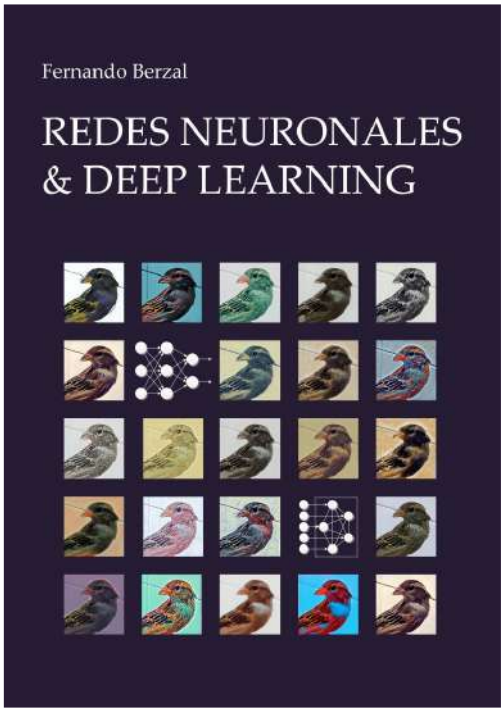

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Edición en dos volúmenes, 2019
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ISBN 1-0903-2030-2
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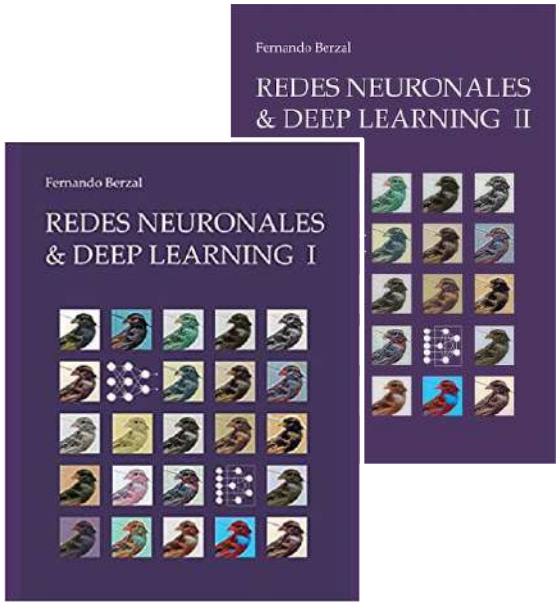
ISBN 1-0903-3688-8

https://deep-learning.ikor.org

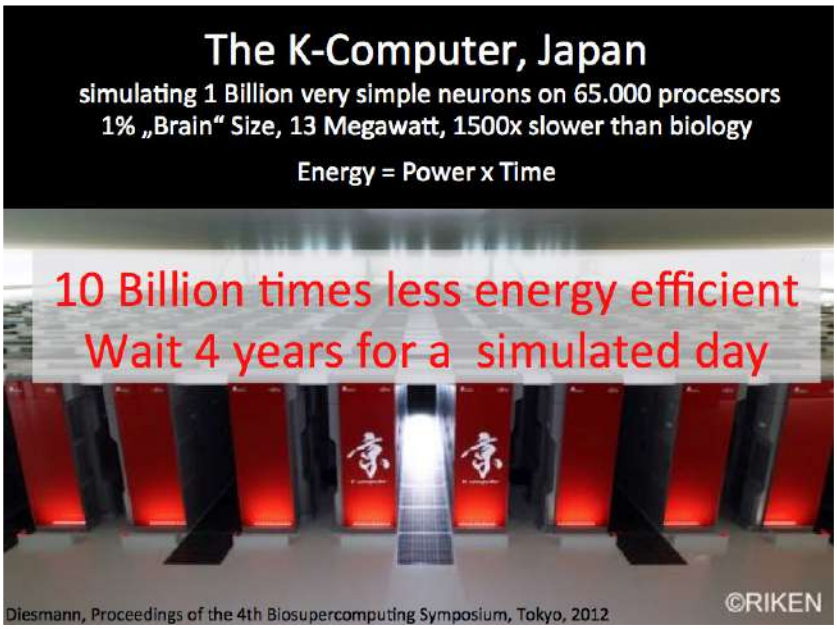


Extras

Otros modelos de redes

Arquitecturas basadas en el cerebro

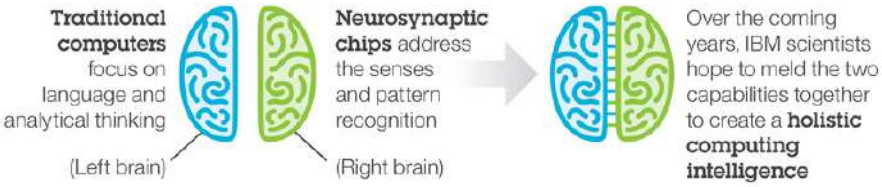
Simulación (muy ineficiente) ➔ "Neuromorphic Computing"

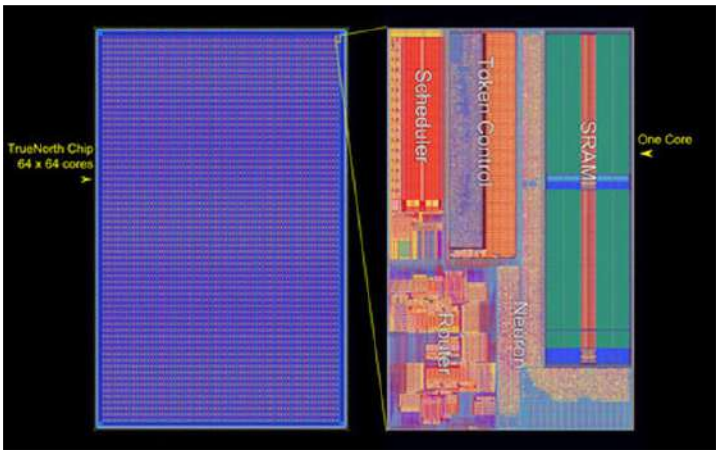


Otros modelos de redes

Arquitecturas basadas en el cerebro

IBM TrueNorth Brain-inspired Computer



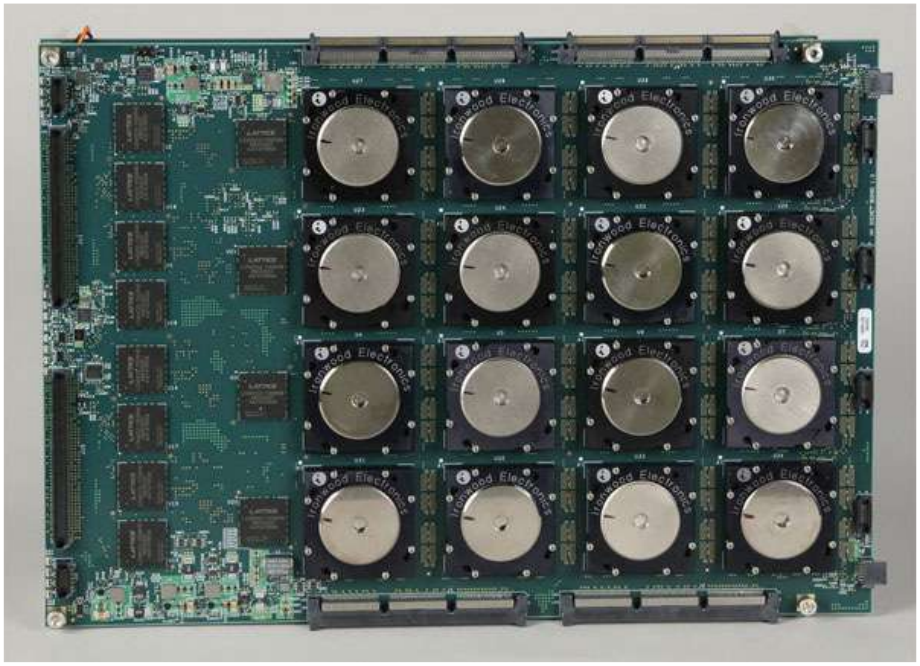


4096 cores
1M neurons
256M synapses
5.4B transistors
CMOS
70mW

Otros modelos de redes

Arquitecturas basadas en el cerebro

IBM TrueNorth Brain-inspired Computer

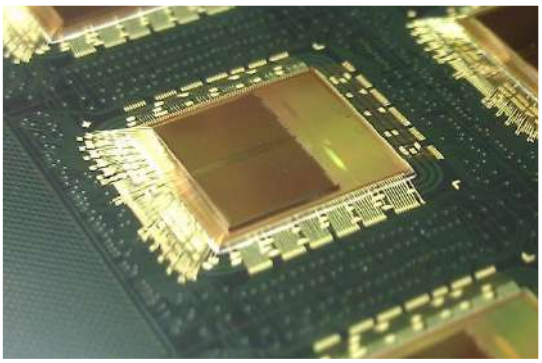


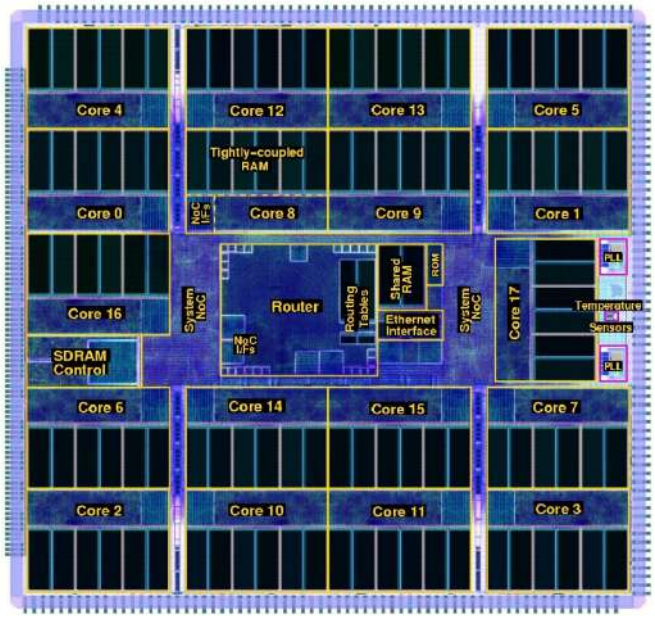
Synapse 16
16M neurons
4B synapses

Otros modelos de redes

Arquitecturas basadas en el cerebro

SpiNNaker project (UK)



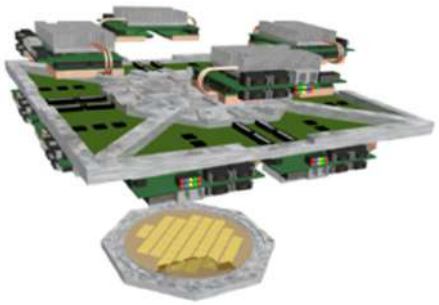


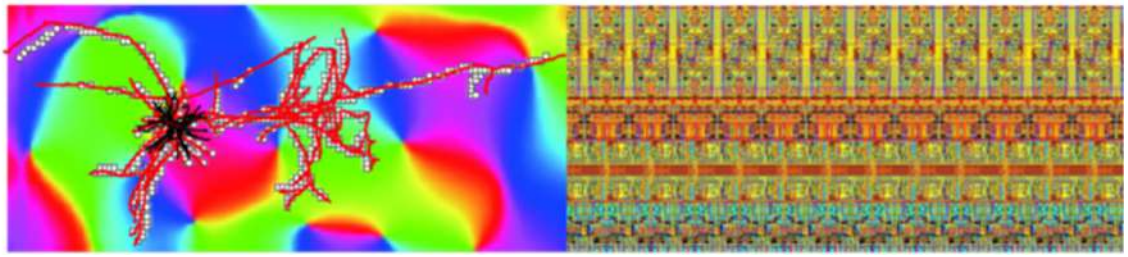
Globally Asynchronous Locally Synchronous (GALS) chip:
18 ARM968 processor nodes + 128MB Mobile DDR SDRAM
http://apt.cs.manchester.ac.uk/projects/SpiNNaker/project/

Otros modelos de redes

Arquitecturas basadas en el cerebro

BrainScaleS (Germany)



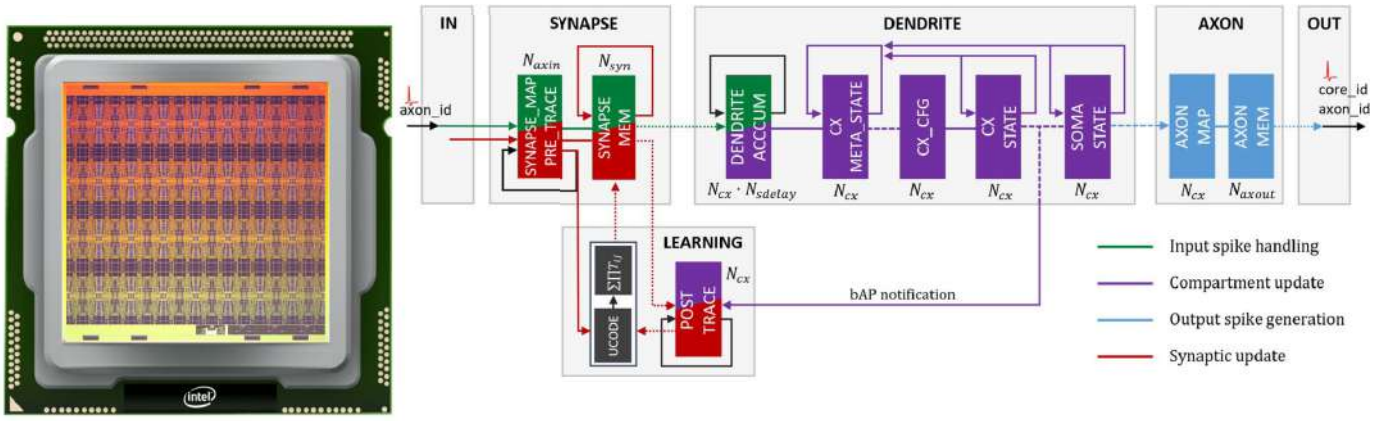


Mixed CMOS signals
https://brainscales.kip.uni-heidelberg.de/

Otros modelos de redes

Arquitecturas basadas en el cerebro

Intel Loihi (self-learning neuromorphic research chip)



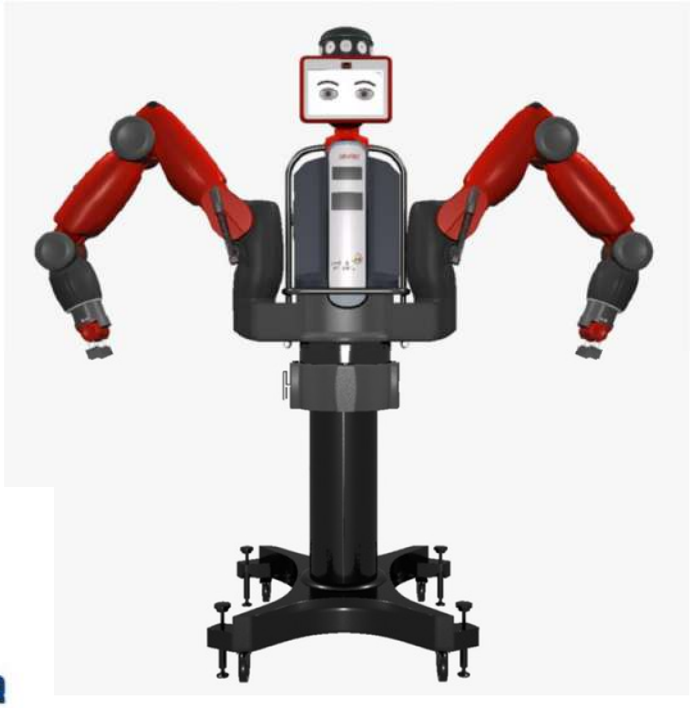
SNNs [Spiking Neural Networks]

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

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

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

Otros modelos de redes



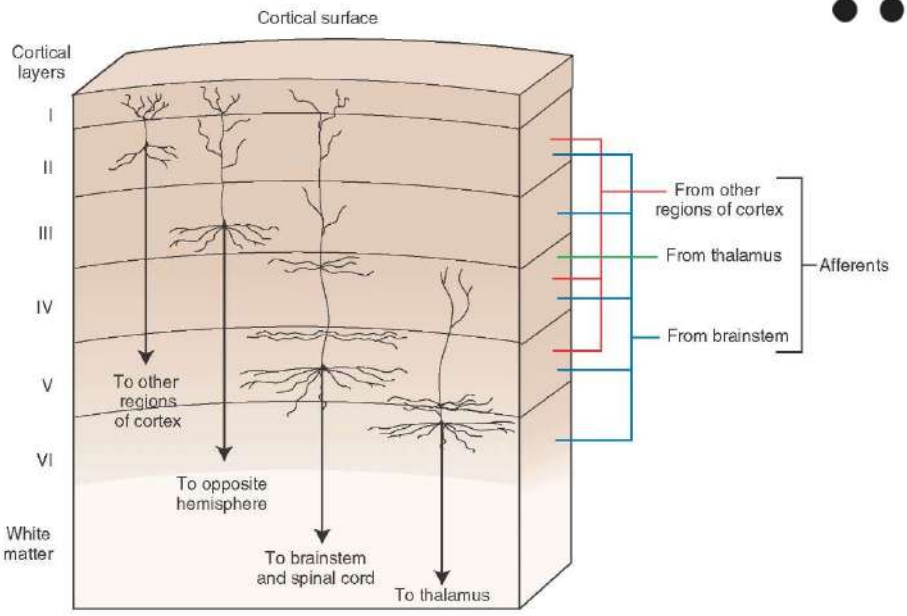
CITIC-UGR

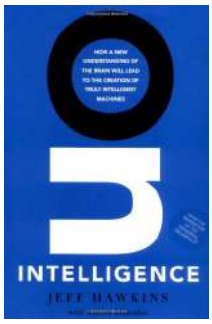
Otros modelos de redes

Arquitecturas basadas en el cerebro

HTM [Hierarchical Temporal Memory]

Numenta



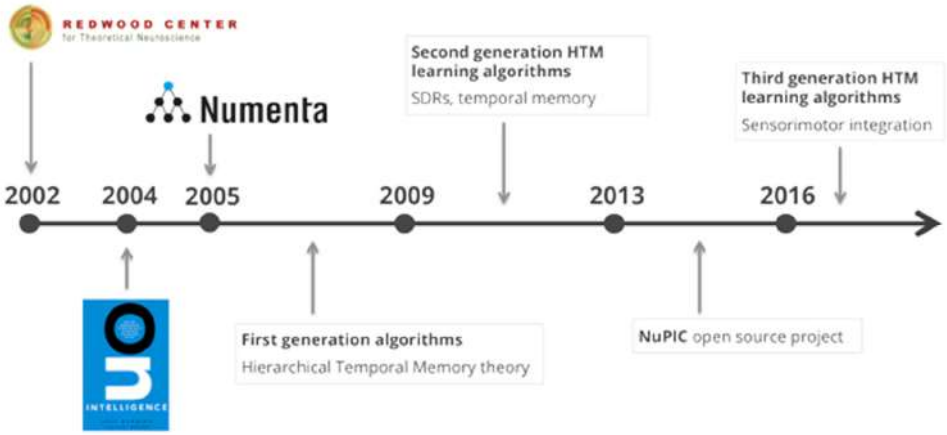


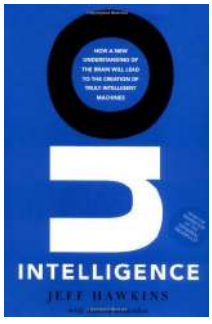
Otros modelos de redes

Arquitecturas basadas en el cerebro

HTM [Hierarchical Temporal Memory]

Numenta





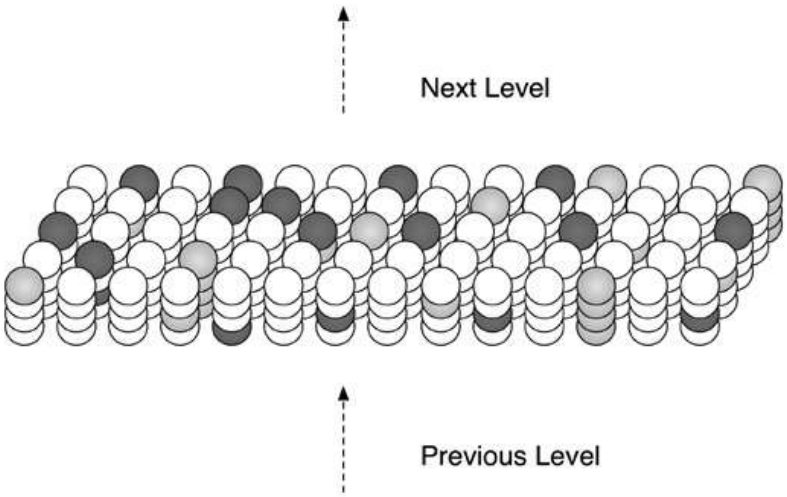
http://numenta.com/

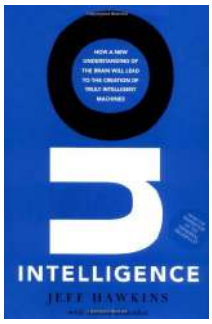
Otros modelos de redes

Arquitecturas basadas en el cerebro

HTM [Hierarchical Temporal Memory]

Numenta





http://numenta.com/

Otros modelos de redes

Arquitecturas basadas en el cerebro

HTM [Hierarchical Temporal Memory]

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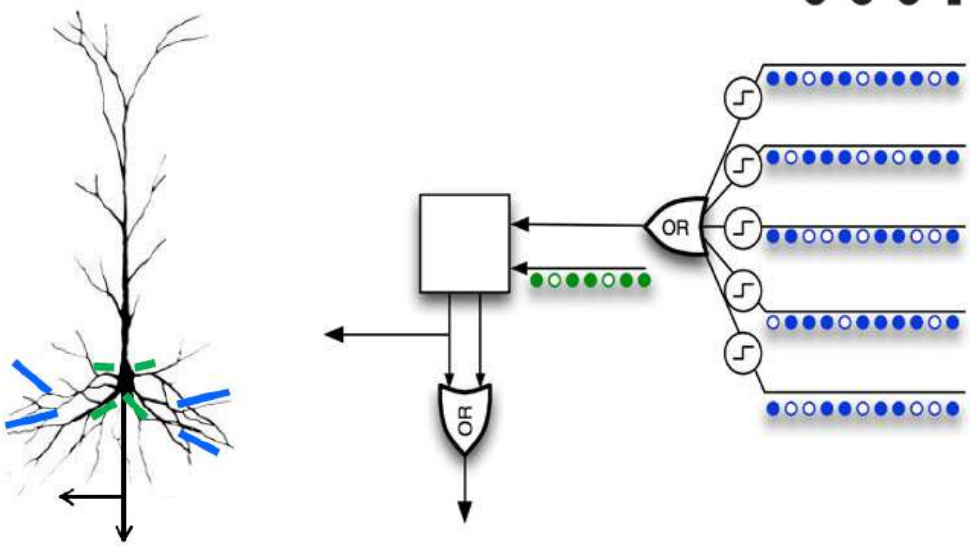
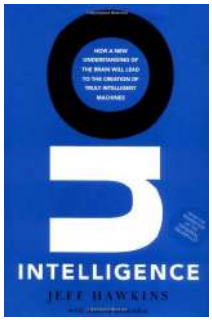




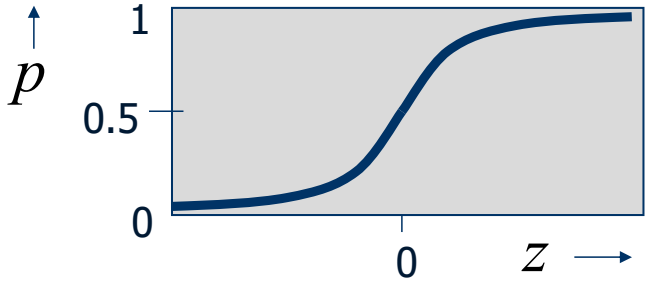
http://numenta.com/

Otros modelos de redes

Neuronas binarias estocásticas

$$z = \sum_i x_i w_i$$

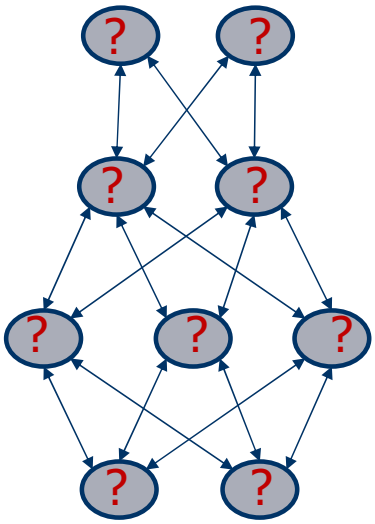
$$p = \frac{1}{1+e^{-z}}$$



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).

Otros modelos de redes

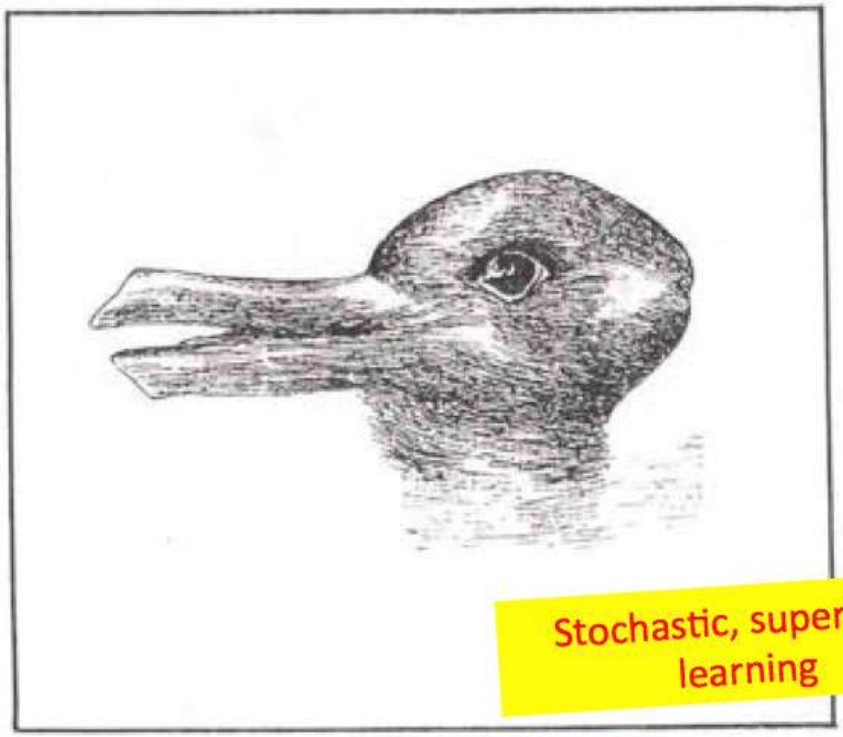
Máquinas de Boltzmann



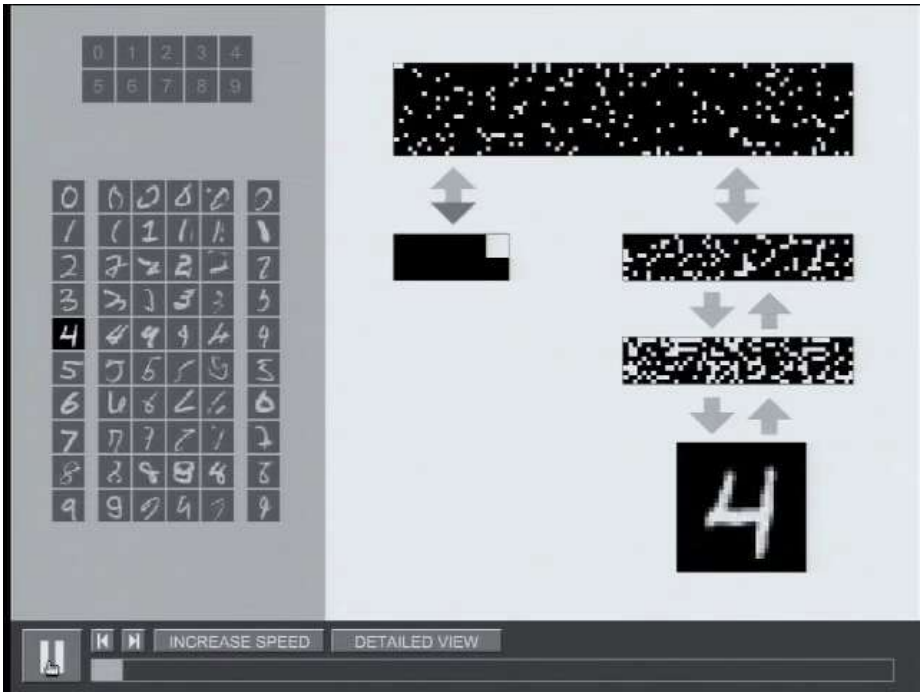
- En una máquina de Boltzmann, las actualizaciones estocásticas de las distintas unidades deben ser secuenciales.
- Existe una arquitectura que admite actualizaciones paralelas alternas mucho más eficientes: **DBM [Deep Boltzmann Machine]**
  - Sin conexiones entre unidades de una misma capa.
  - Sin conexiones entre capas no adyacentes.

Otros modelos de redes

Máquinas de Boltzmann



Otros modelos de redes



Geoffrey Hinton: "The Next Generation of Neural Networks"
Google Tech Talks, 2007
https://www.youtube.com/watch?v=AyzOUbkUf3M

Otros modelos de redes

Geoff Hinton doesn't need to make hidden units.
They hide by themselves when he approaches.

Geoff Hinton doesn't disagree with you,
he contrastively diverges

Deep Belief Nets actually
believe deeply in Geoff Hinton.

Yann LeCun: "Geoff Hinton facts"
http://yann.lecun.com/ex/fun/index.html

En la práctica

Hardware para deep learning

GPU [procesador SIMD]: Data-level parallelism

NVIDIA Pascal SIMD Processor

NVIDIA Pascal P100 GPU

Facebook Big Sur

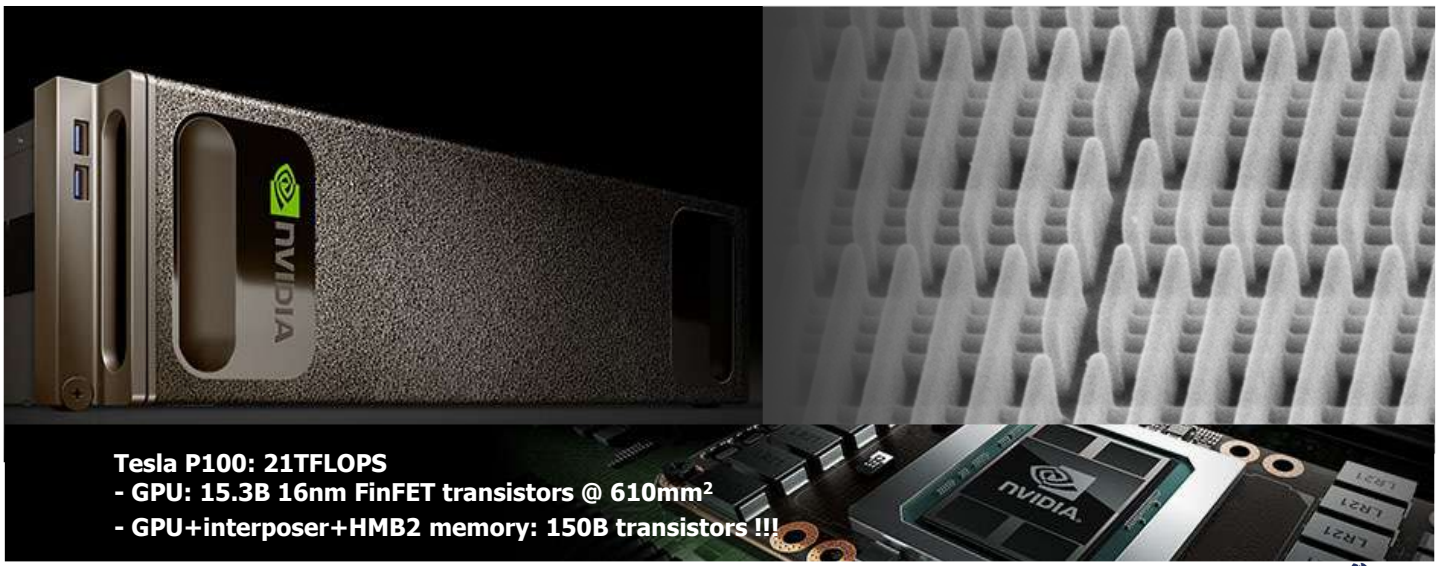
Servidor con 8 GPUs NVIDIA Tesla para deep learning

Facebook Engineering Blog, December 2015
https://code.facebook.com/posts/1687861518126048/facebook-to-open-source-ai-hardware-design/

En la práctica
Hardware para deep learning

NVIDIA DGX-1 deep learning supercomputer $ 129 000

8x GPUs NVIDIA Tesla P100, 28672 CUDA cores

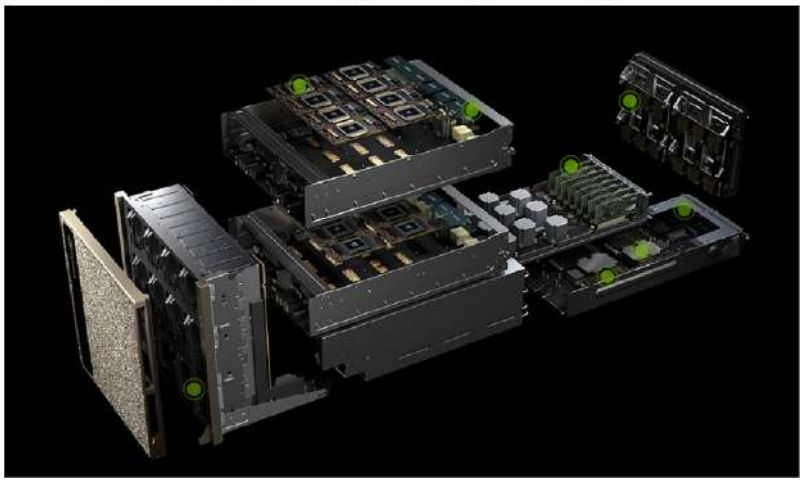


DGX-1: 8xP100, 512 GB DDR4, 4x1.92TB SSD, 170 TFLOPS, 60kg, 3200W
A $2 Billion Chip to Accelerate Artificial Intelligence, MIT Technology Review, April 2016
https://www.technologyreview.com/s/601195/a-2-billion-chip-to-accelerate-artificial-intelligence/
http://www.nvidia.com/object/deep-learning-system.html

En la práctica
Hardware para deep learning

NVIDIA DGX-2 deep learning supercomputer $ 399 000

16x GPUs NVIDIA Tesla V100, 81920 CUDA cores, 2 petaFLOPS



DGX-2: 16x V100, 96MB SRAM, 512 GB DDR, 30TB SSD, 2 petaFLOPS, 10kW, 163kg

https://www.nvidia.com/en-us/data-center/dgx-2/

En la práctica
Hardware para deep learning

NVIDIA DGX A100 $ 199 000

8x NVIDIA Ampere A100 Tensor Core GPUs, 5 petaFLOPS

A100 accelerator (May 2020): TSMC 7nm N7, 54.2B transistors, 6912 CUDA cores, 400W

DGX A100: 8x A100, 320GB GPU memory, 1TB system, 15TB SSD, 5 petaFLOPS, 6.5kW, 123kg

https://www.nvidia.com/en-us/data-center/dgx-a100/

En la práctica

Hardware para deep learning

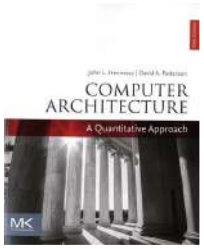
DSAs [Domain-Specific Architectures]

- **ASICs** [Application-Specific Integrated Circuits]
  - Mayor coste NRE [Non recurrent engineeering]
  - Mayor rendimiento
- Circuitos reconfigurables,
  p.ej. **FPGAs** [Field-Programmable Gate Arrays]
  - Menor coste NRE
  - Menor rendimiento

En la práctica

Hardware para deep learning

DSAs [Domain-Specific Architectures]

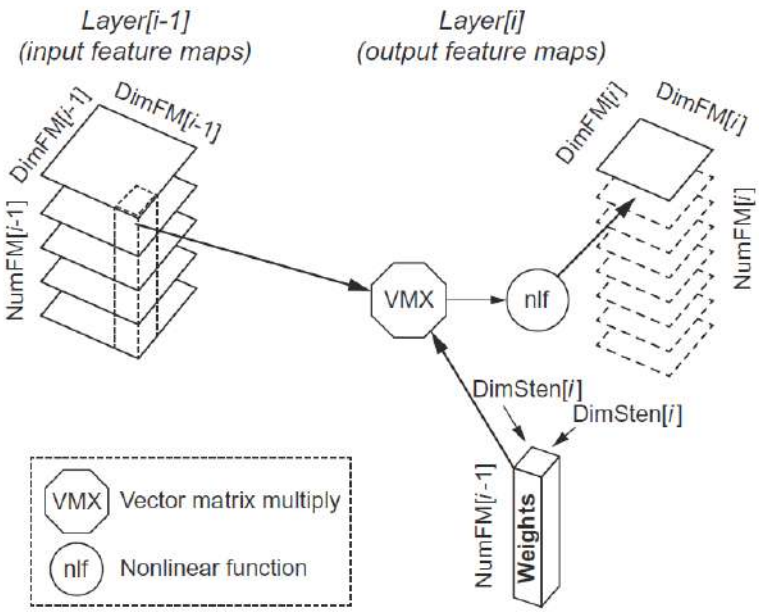


Diseño energéticamente eficiente

- Memorias dedicadas [scratchpad] gestionadas por el programador en lugar de memorias caché.
- Recursos ahorrados en la microarquitectura dedicados a más unidades funcionales o más memoria.
- Paralelismo ajustado al dominio de aplicación (SIMD).
- Reducción de la precisión (8-, 16-bit), para aprovechar mejor el ancho de banda de memoria.
- DSL [domain-specific language] para portar código a la DSA, p.ej. Halide (visión) o TensorFlow (DNNs).

DSAs [Domain-Specific Architectures]

Ejemplo: CNN



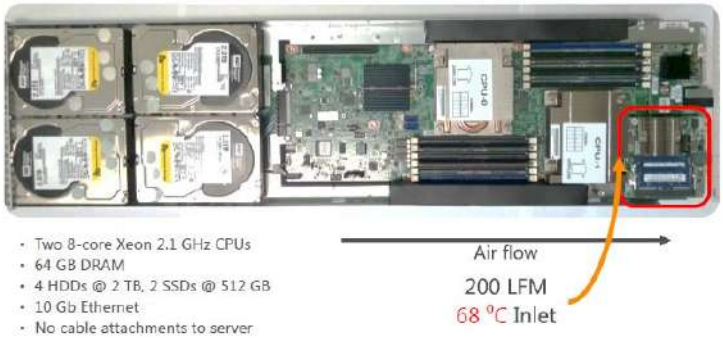
Intensidad aritmética:

operations/weight = 2 x DimFM[i]²

Microsoft Research Catapult

FPGAs [Field Programmable Gate Arrays]

- Menor consumo de energía: 25W
- Menor ancho de banda: 11GB/s
  (datos en la memoria DDR3 de la propia FPGA para evitar PCIe)



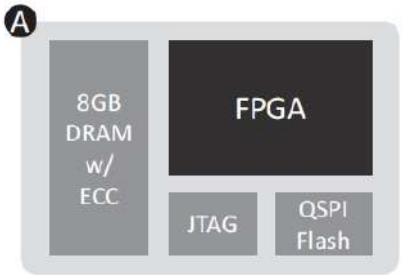
CPU-FPGA minimalista:
FPGA Altera Stratix V @ Open CloudServer

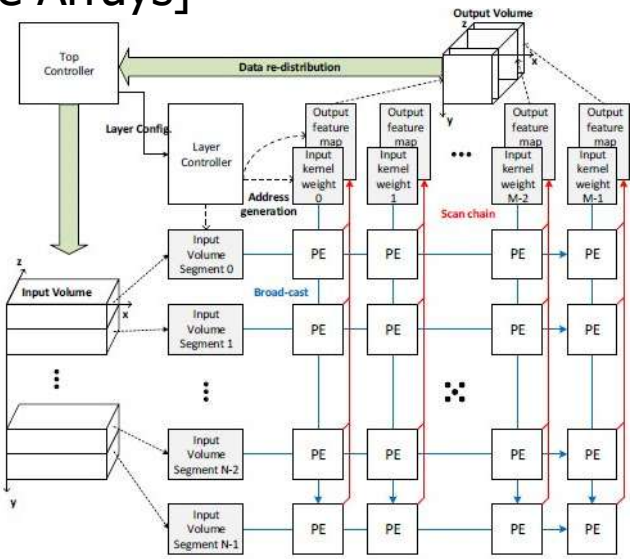
Toward Accelerating Deep Learning at Scale Using Specialized Logic
HOTCHIPS'2015: A Symposium on High Performance Chips, August 2015

Microsoft Catapult v1

FPGAs [Field Programmable Gate Arrays]

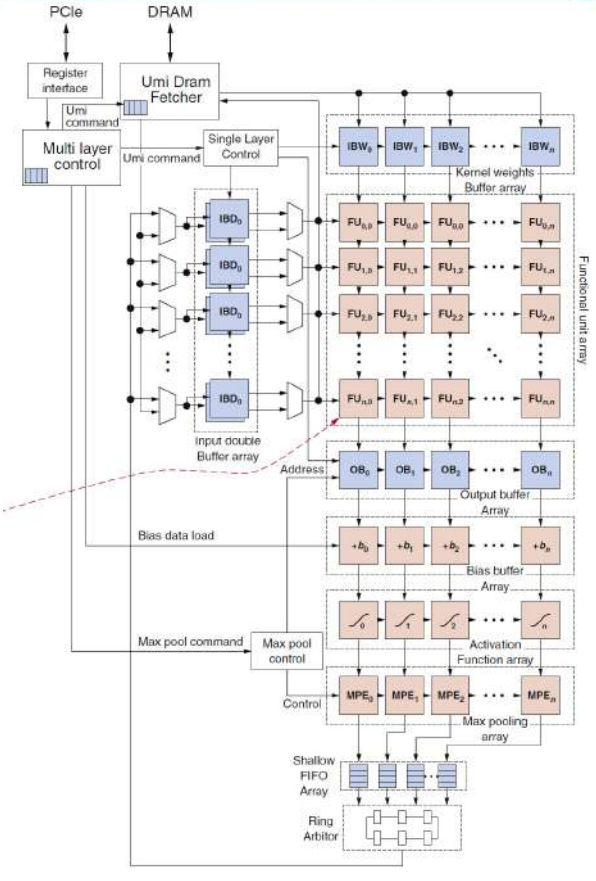
- 3926 18-bit ALUs
- 2D array of PEs
- Red 20Gbps entre 48 FPGAs (topología de toro 6x8)





Microsoft Catapult v1

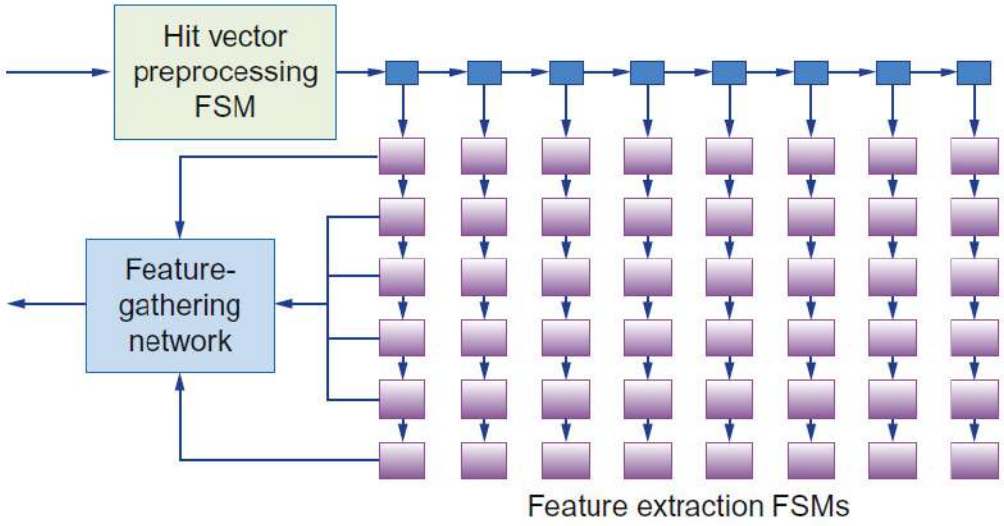
CNN Accelerator



FU [Functional Unit]
= ALU + Registers

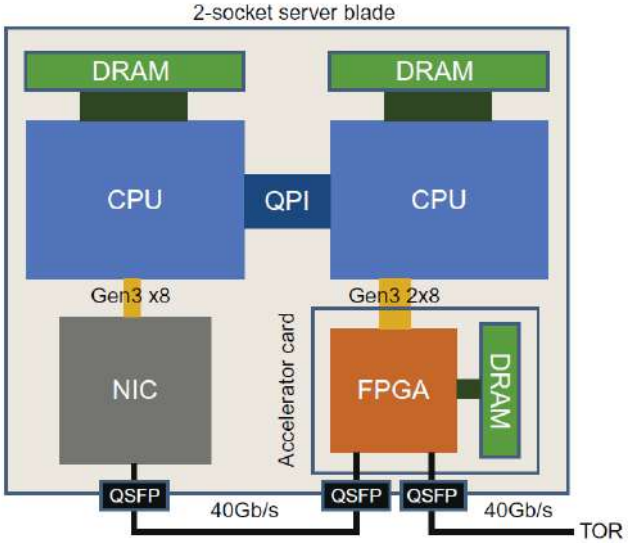
Microsoft Catapult v1

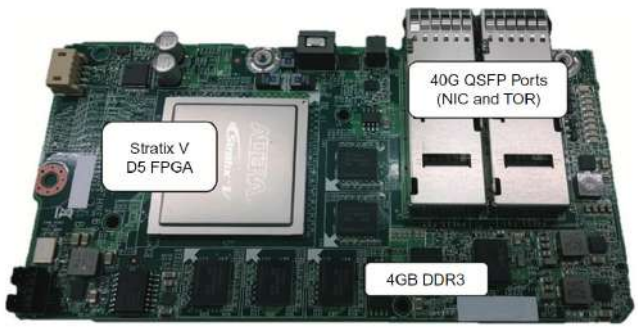
Search engine ranking @ Bing



Microsoft Catapult v2

Cambio en la posición de la FPGA en el centro de datos (entre la CPU y el NIC de cada servidor, 32W)





Usos: CNN, Bing & Azure Networking

A cloud-scale acceleration architecture. MICRO Conference, 2016

Microsoft Research Project BrainWave

FPGAs [Field Programmable Gate Arrays]

- DNNs as "hardware microservices"

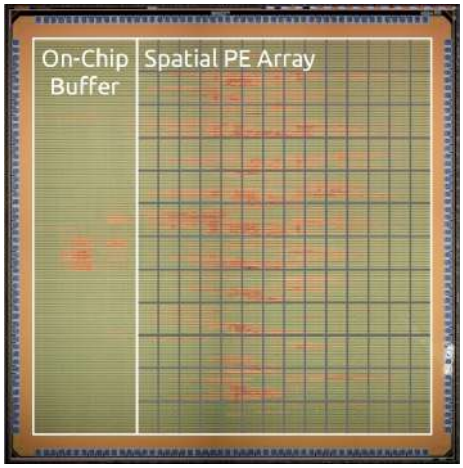
FPGA Intel Stratix 10 (e.g. GRU @ 39.5TFLOPS)

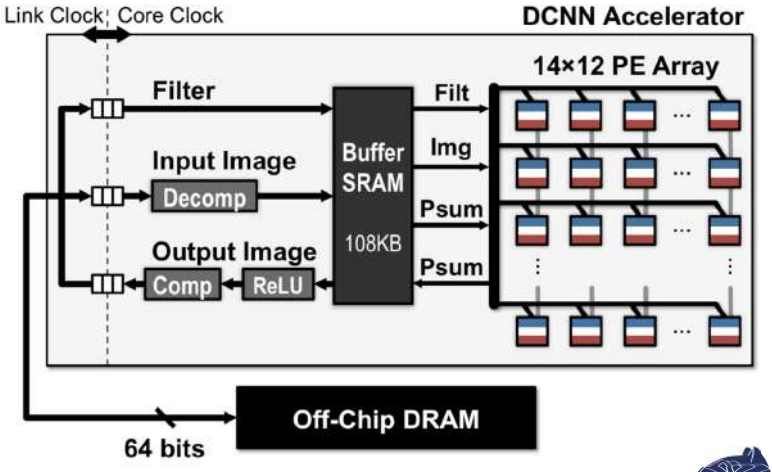
Accelerating Persistent Neural Networks at Datacenter Scale
HOTCHIPS'2017 & NIPS'2017

MIT Eyeriss

168 PE [Processing Elements], 0.3W (<10% mobile GPU)

http://www.mit.edu/~sze/eyeriss.html





A Deep Learning AI Chip for Your Phone, IEEE Spectrum, February 2016
http://spectrum.ieee.org/tech-talk/semiconductors/processors/a-deep-learning-ai-chip-for-your-phone

TPU [Tensor Processing Unit]

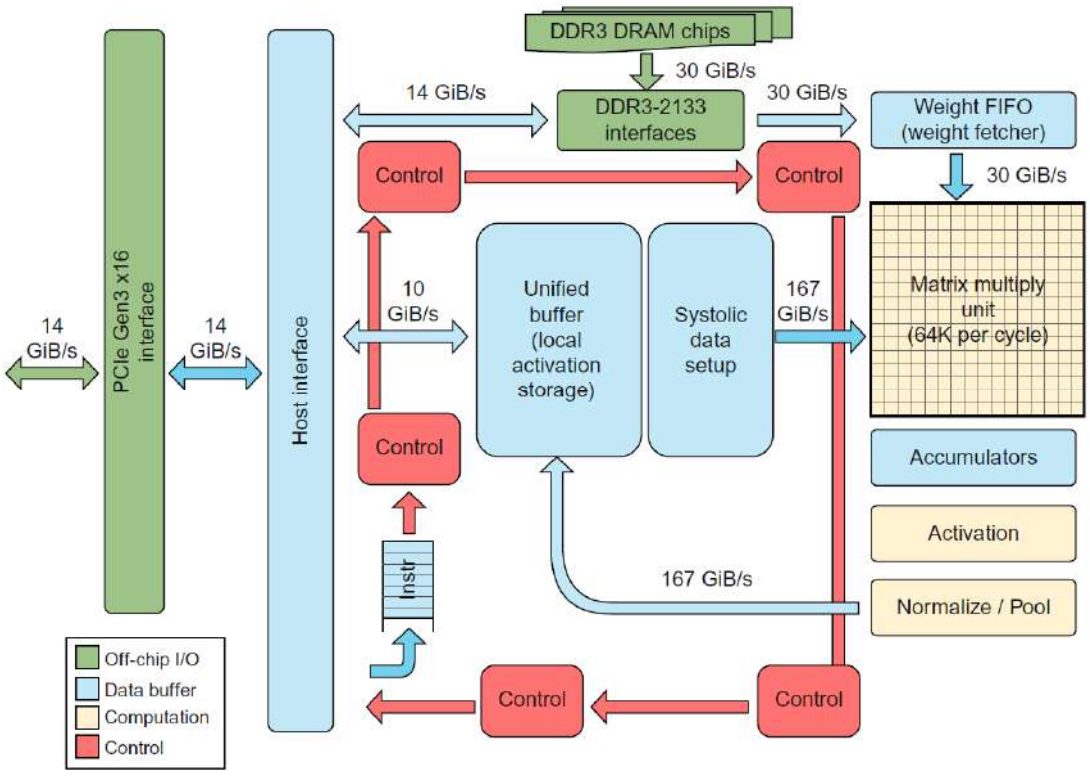
Google, 2015-

Características

- 65,536 (256x256) 8-bit ALU Matrix Multiply Unit
- Large software-managed on-chip memory
- Single-threaded, deterministic execution model
- Coprocessor on the PCIe I/O bus
- The host server sends instructions over the PCIe bus directly to the TPU for it to execute, rather than having the TPU fetch the instructions (closer to FPUs than to GPUs).

En la práctica
Hardware para deep learning

TPU [Tensor Processing Unit]



TPU [Tensor Processing Unit]

CISC ISA (due to slow PCIe bus)

- `Read_Host_Memory`
  (CPU Host Memory -> Unified Buffer)
- `Read_Weights`
  (Weight Memory -> Weight Buffer)
- `MatrixMultiply / Convolve`
  (Unified Buffer -> Accumulators)
- `Activate`
  (Accumulators -> Outout Buffer)
- `Write_Host_Memory`
  (Unified Buffer -> CPU Host Memory)

Clock cycles per instruction (CPI) ~ 10-20

TPU Microarchitecture

- Goal:

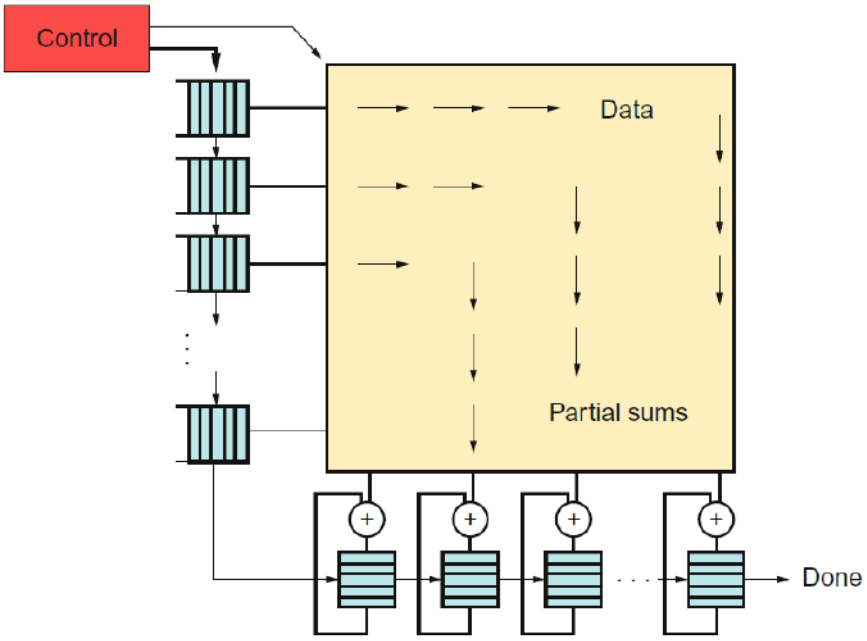
  Keep the Matrix Multiply Unit busy.

- Plan:

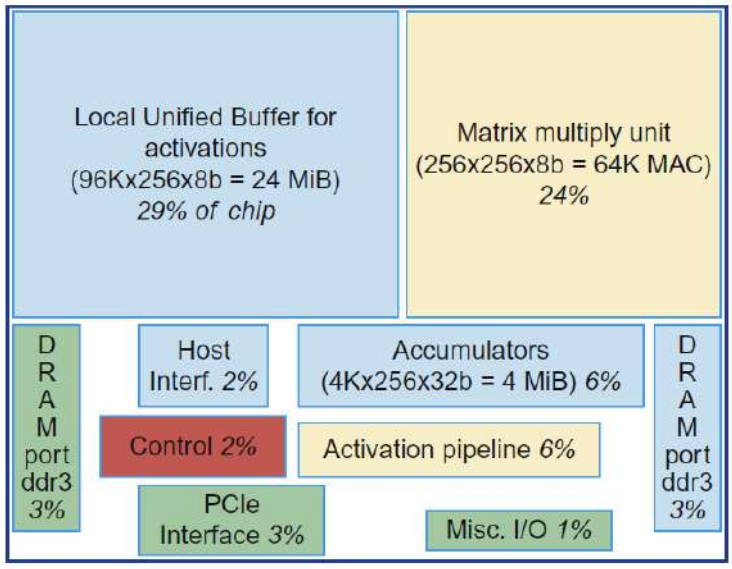
  Hide the execution of the other instructions by overlapping their execution with the MatrixMultiply instruction

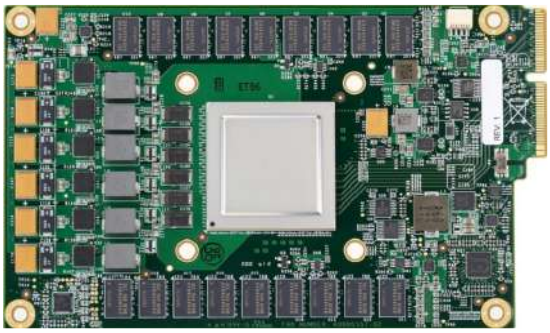
TPU Microarchitecture

The Matrix Multiply Unit uses systolic execution to save energy by reducing reads and writes of the Unified Buffer



TPU Implementation





TPU die floor plan

TPU Programming

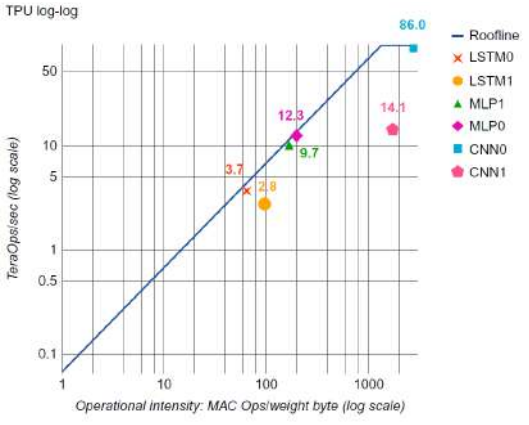
- The portion of the application run on the TPU is typically written using TensorFlow and is compiled into an API that can run on GPUs or TPUs.

TPU Software

- Lightweight kernel driver:
  Memory management and interrupts.
- User space driver:
  Sets up and controls TPU execution, reformats data into TPU order, and translates API calls into TPU instructions and turns them into an application binary.

TPU Applications

		DNN layers							
Name	LOC	FC	Conv	Element	Pool	Total	Weights	TPU Ops/Weight	% deployed TPUs 2016
MLP0	100	5				5	20M	200	61%
MLP1	1000	4				4	5M	168	
LSTM0	1000	24		34		58	52M	64	29%
LSTM1	1500	37		19		56	34M	96	
CNN0	1000		16			16	8M	2888	5%
CNN1	1000	4	72		13	89	100M	1750	



6 applications, 95% workload @ Google

- MLP: RankBrain
- LSTM: Google Neural Translator
- CNN: DeepMind AlphaGo

TPU Terminology

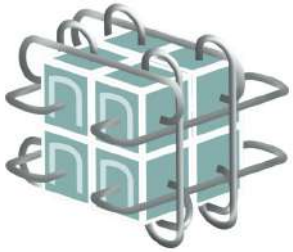
Accumulators	—	The 4096 256 × 32-bit registers (4 MiB) that collect the output of the MMU and are input to the Activation Unit
Activation unit	—	Performs the nonlinear functions (ReLU, sigmoid, hyperbolic tangent, max pool, and average pool). Its input comes from the Accumulators and its output goes to the Unified Buffer
Matrix multiply unit	MMU	A systolic array of 256 × 256 8-bit arithmetic units that perform multiply-add. Its inputs are the Weight Memory and the Unified Buffer, and its output is the Accumulators
Systolic array	—	An array of processing units that in lockstep input data from upstream neighbors, compute partial results, and pass some inputs and results to downstream neighbors
Unified buffer	UB	A 24 MiB on-chip memory that holds the activations. It was sized to try to avoid spilling activations to DRAM when running a DNN
Weight memory	—	An 8 MiB external DRAM chip containing the weights for the MMU. Weights are transferred to a *Weight FIFO* before entering the MMU

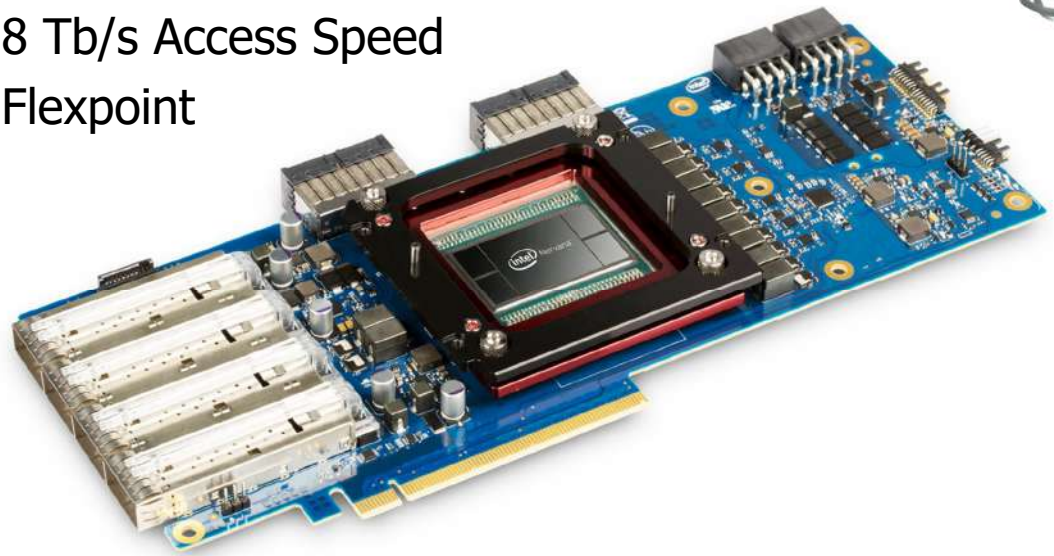
En la práctica
Hardware para deep learning

CPU **Intel i7**	**GPU** **NVIDIA**	**FPGA** **Catapult**	**ASIC** **TPU**
SIMD extensions (MMX, SSE, AVX)	Streaming multiprocessors	3926 18-bit PEs (reconfigurable)	256x256 Matrix Multiply Unit
1D SIMD		2D SIMD	
Multithreading		Pipelined systolic array	
Out-of-order execution	Multiprocessing	Programmable controller	Simple execution of instructions
32 & 64-bit FP	32 & 64-bit FP	18-bit integers	8-bit integers
x86 ISA (C, Java, Python…)	**PTX** (CUDA, OpenCL)	**RTL** (Verilog, VHDL)	**Reduced CISC** ISA (API via DSLs: Halide, TensorFlow)

Intel Nervana Neural Network Processor (NNP)

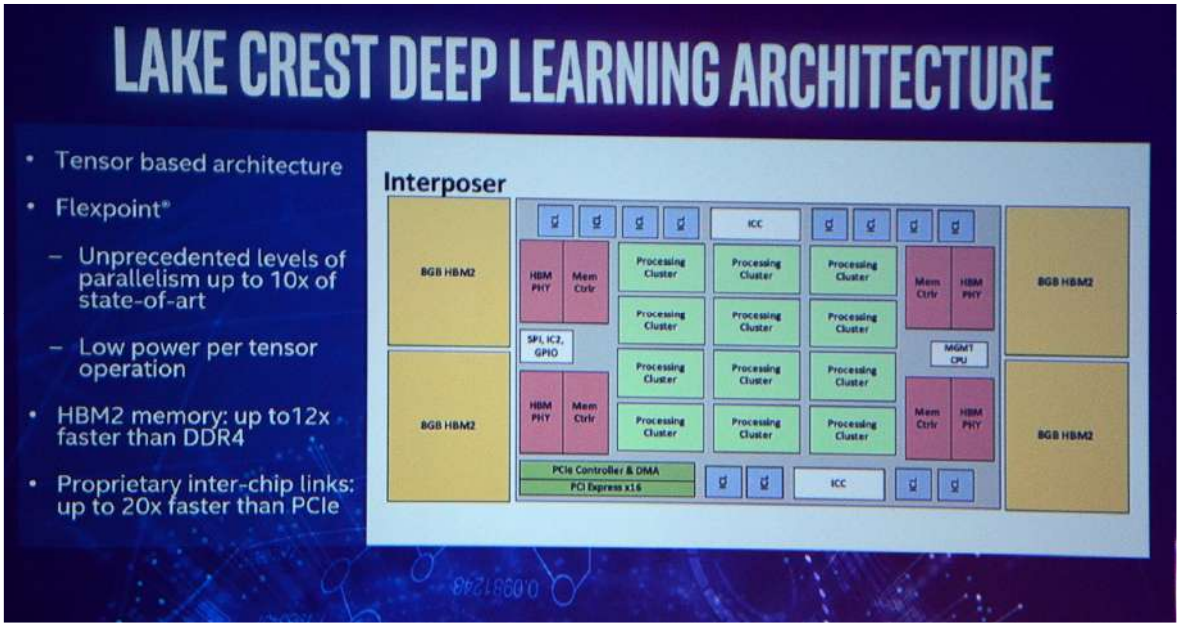
"Lake Crest"
32 GB HBM2,
1 TB/s Bandwidth
8 Tb/s Access Speed
Flexpoint





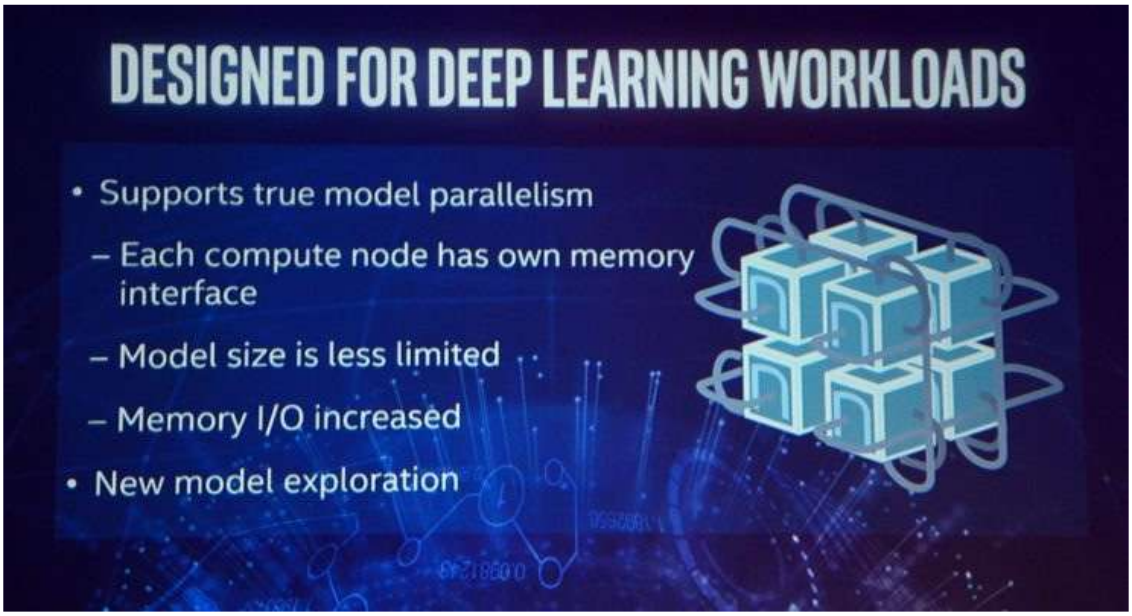
Intel Nervana Neural Network Processor (NNP)

"Lake Crest"



Intel Nervana Neural Network Processor (NNP)

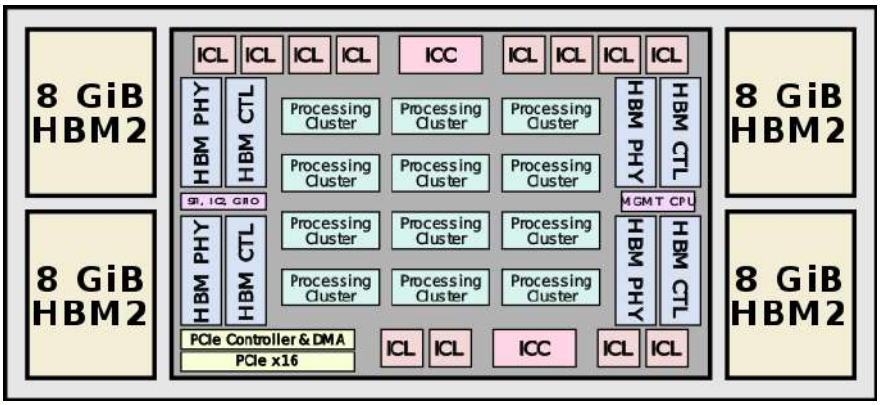
"Lake Crest"

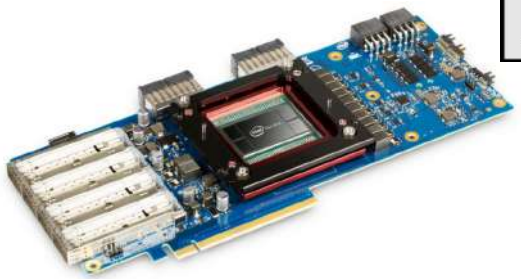


Intel Nervana Neural Network Processor (NNP)

"Lake Crest", 1st generation NNP, 2016

nervana SYSTEMS



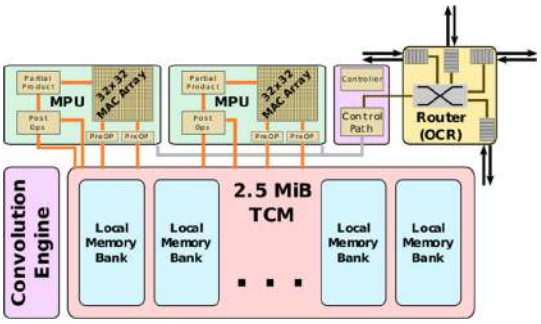


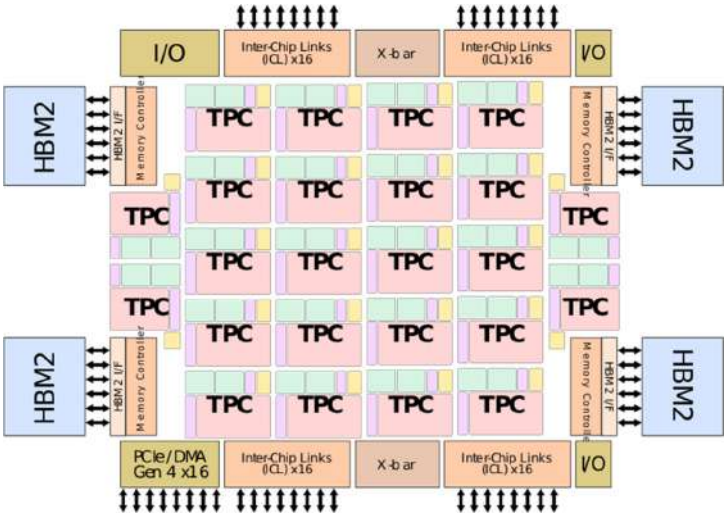
Lake Crest Accelerator PCIe card

Hardware para deep learning

Intel Nervana Neural Network Processor (NNP)

"Spring Crest", 2nd generation NNP, 2019





NNP T-1400, 375W, 108TFLOPS

Hardware especializado

Intel Nervana Neural Network Processor (NNP)

Febrero 2020:

"Intel Axes Nervana Just Two Months After Launch"

Habana HLS-1 (8x HL-205)

Intel + Habana Labs

$2bn

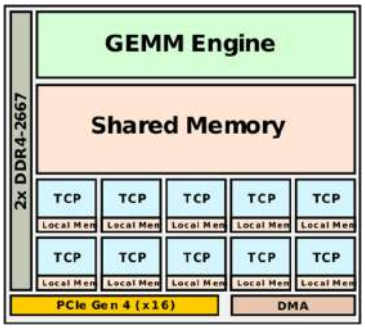
News Release
December 16, 2019
Contact Intel PR

Intel Acquires Artificial Intelligence Chipmaker Habana Labs

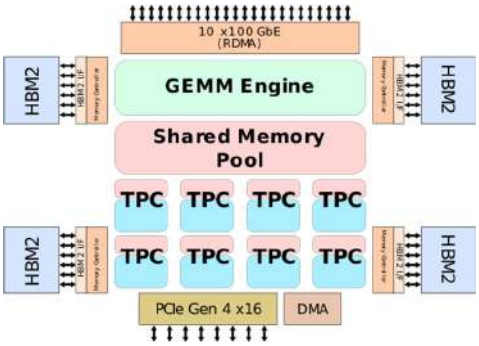
Combination Advances Intel's AI Strategy, Strengthens Portfolio of AI Accelerators for the Data Center

SANTA CLARA Calif., Dec. 16, 2019 – Intel Corporation today announced that it has acquired Habana Labs, an Israel-based developer of programmable deep learning accelerators for the data center for approximately $2 billion. The combination strengthens Intel's artificial intelligence (AI) portfolio and accelerates its efforts in the nascent, fast-growing AI silicon market, which Intel expects to be greater than $25 billion by 2024[1].

habana GOYA



habana GAUDI



En la práctica
Hardware para deep learning

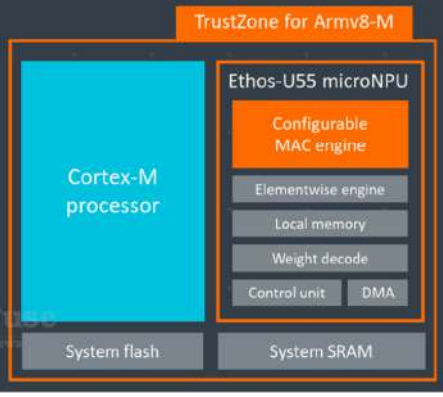
ARM Ethos microNPU

Cortex M55 CPU + Ethos U55 NPU (2020)

arm ETHOS

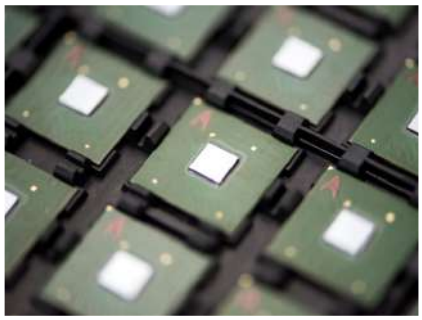
Ethos-U55: The First microNPU for Cortex-M

- ✓ Highest efficiency and small memory footprint
- ✓ 32, 64, 128, or 256 unit multiply-accumulate (MAC) engine
- ✓ Weight decoder and DMA for on-the-fly weight decompression
- ✓ Tooling available for offline optimization
- ✓ Works with a range of Cortex-M processors:
  - Cortex-M55
  - Cortex-M7
  - Cortex-M33
  - Cortex-M4



Implementaciones analógicas

… para reducir el consumo energético



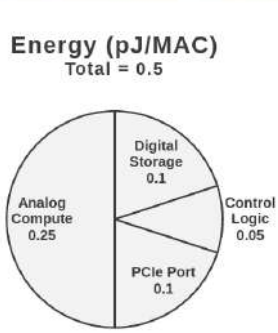
Trillion operations per watt (TOPS/W)

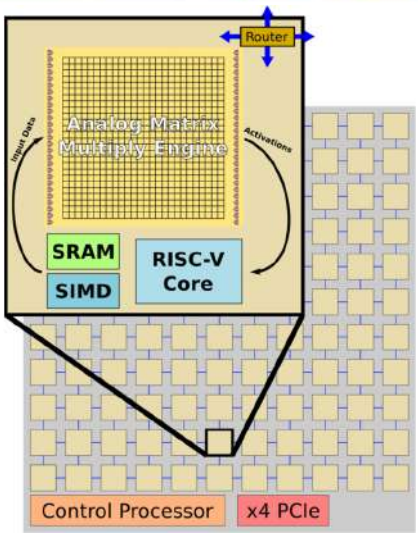
- 0.4 TOPS/W: NVIDIA Volta V100 GPU
- 4 TOPS/W: **Mythic AI** analog in-memory computing, (analog flash array + programmable digital circuit) https://www.mythic-ai.com/
- 20 TOPS/W: **Syntiant** Neural Decision Processor (NDP), (entire analog network) https://www.syntiant.com/

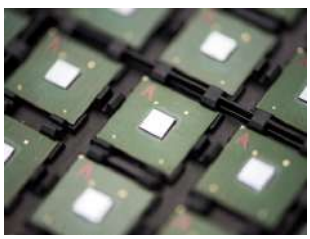
Two Startups Use Processing in Flash Memory for AI at the Edge, IEEE Spectrum, August 2018
https://spectrum.ieee.org/tech-talk/computing/embedded-systems/two-startups-use-processing-in-flash-memory-for-ai-at-the-edge

En la práctica
Hardware para deep learning

Mythic AI IPU



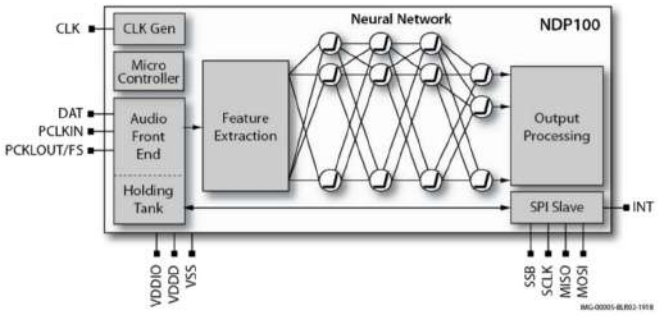


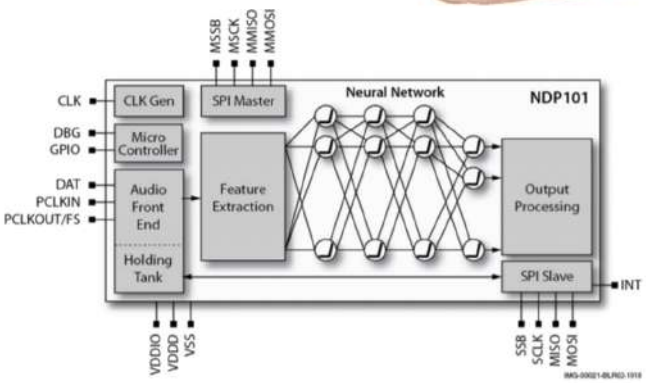


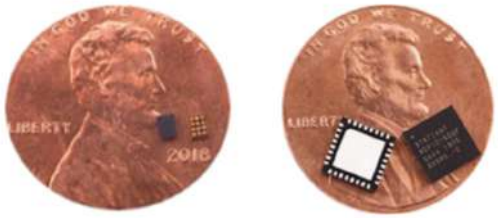
Hardware para deep learning

Syntiant NDP [Neural Decision Processor]

<140μW



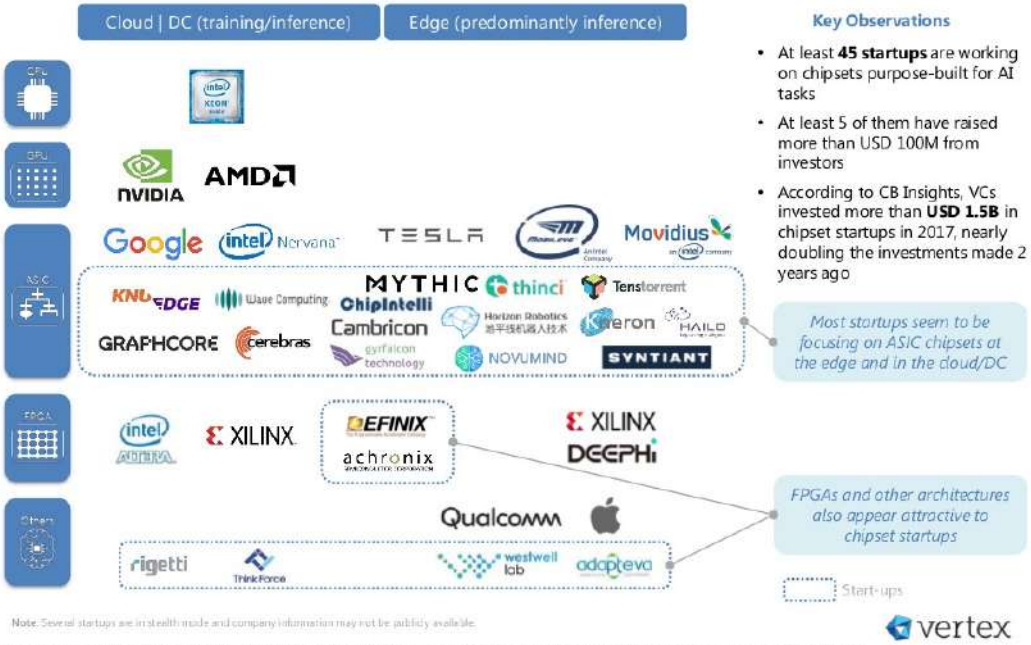




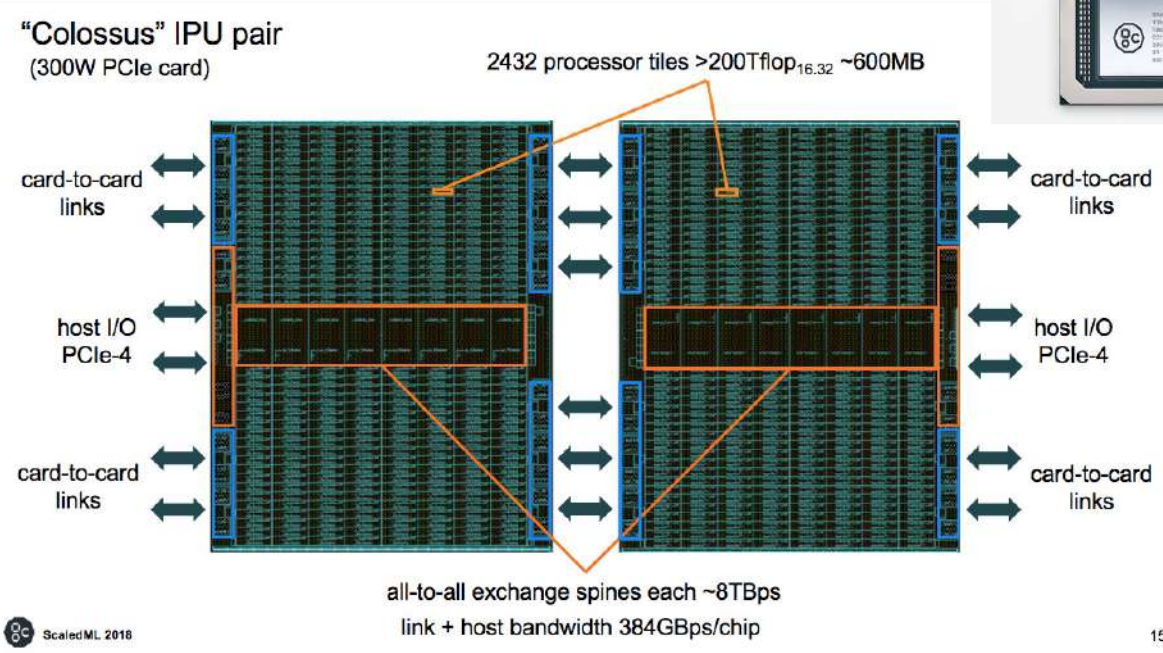
Syntiant NDP100 & NDP101

Hardware para deep learning

Docenas de empresas desarrollan chips para IA…

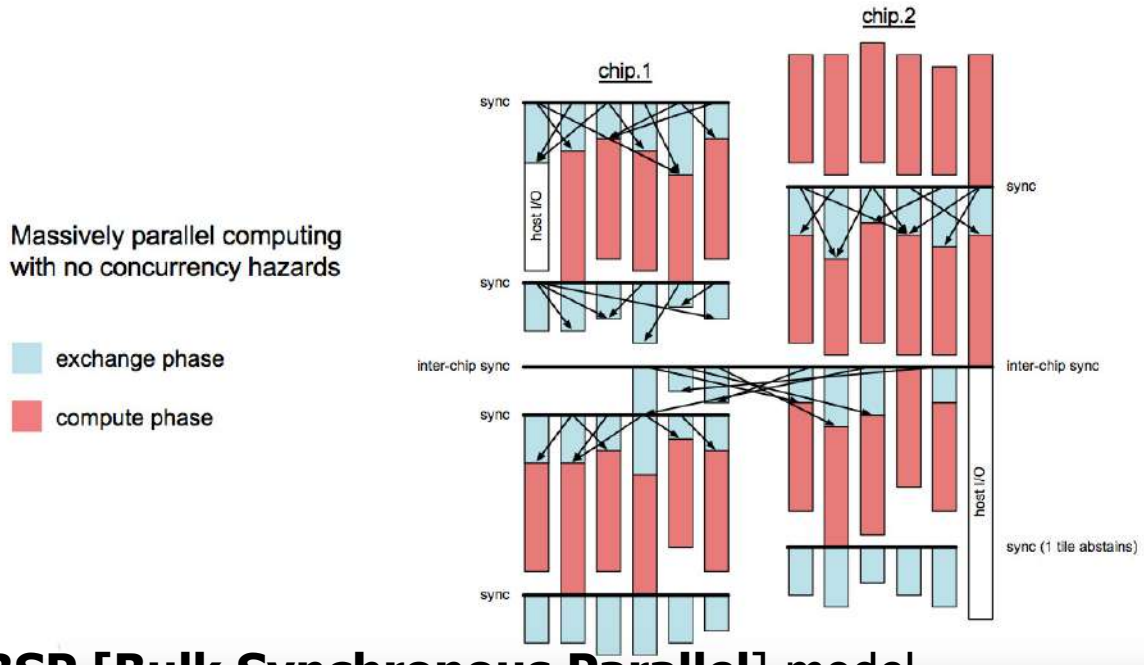


Graphcore Colossus IPU, UK



IPU [Intelligent Processing Unit] pair

Graphcore Colossus IPU, UK



BSP [Bulk Synchronous Parallel] model
https://en.wikipedia.org/wiki/Bulk_synchronous_parallel

Hardware para deep learning

Graphcore Colossus IPU, UK

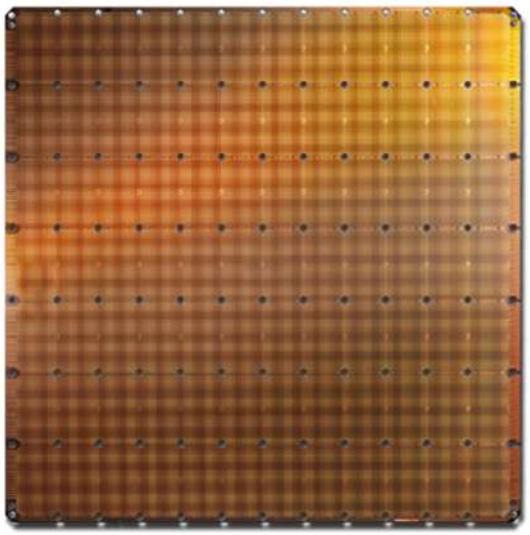
1 petaFLOP
IPU M2000 machine

Dell DSS8440

Hardware para deep learning

Cerebras WSE [Wafer-Scale Engine]

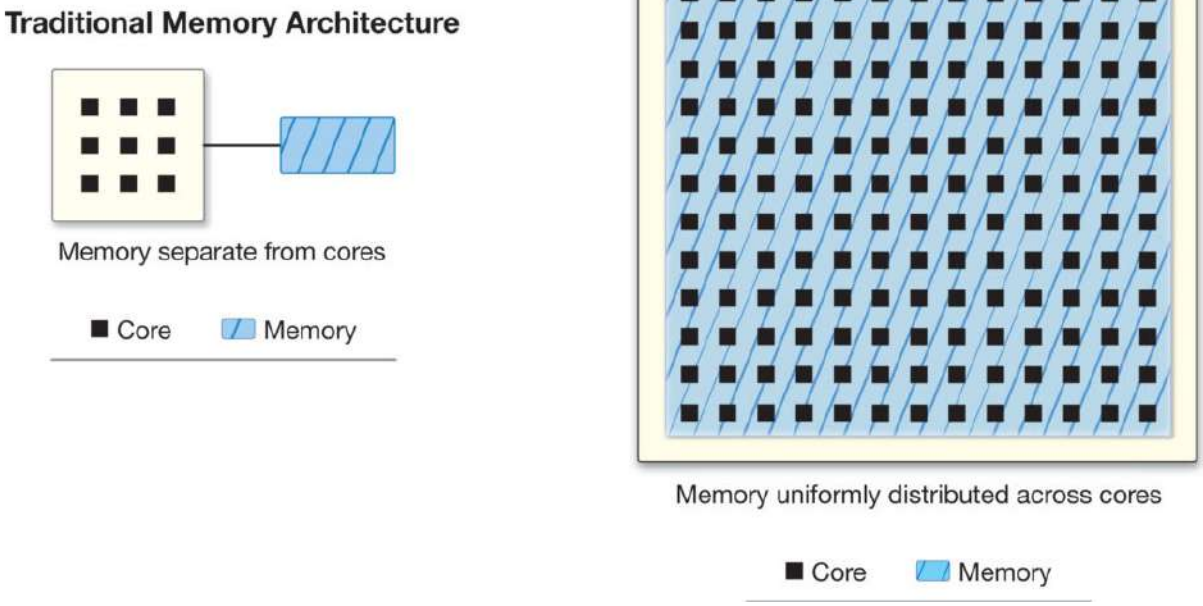
>400000 AI cores, 18GB SRAM, 17.5kW



Cerebras WSE
1.2 Trillion transistors
46,225 mm² silicon

Largest GPU
21.1 Billion transistors
815 mm² silicon

Cerebras WSE [Wafer-Scale Engine]



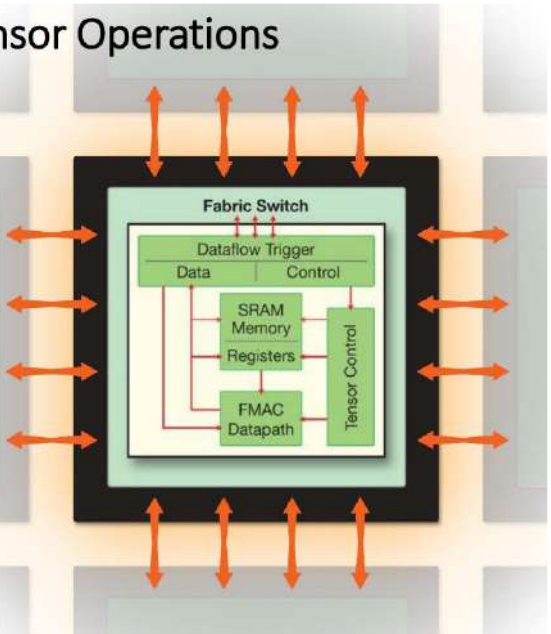
En la práctica
Hardware para deep learning

Cerebras WSE [Wafer-Scale Engine]

Flexible Cores Optimized for Tensor Operations

Key to supporting rapidly evolving NN architectures

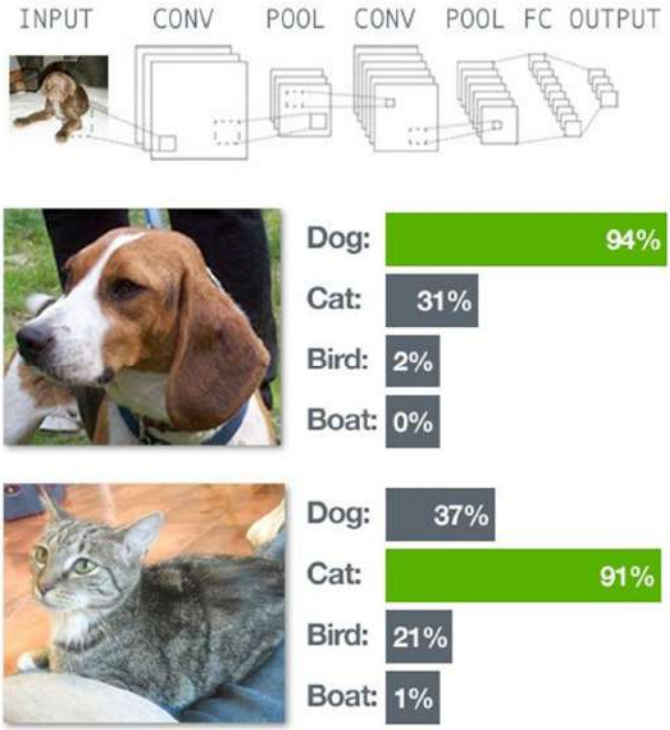
- Fully programmable compute core
- Full array of general instructions with ML extensions
- Flexible general ops for control processing
  - e.g. arithmetic, logical, load/store, branch
- Optimized tensor ops for data processing
  - Tensors as first class operands
  - e.g. `fmac [z] = [z], [w], a`
    `3D 3D 2D scalar`



cerebras

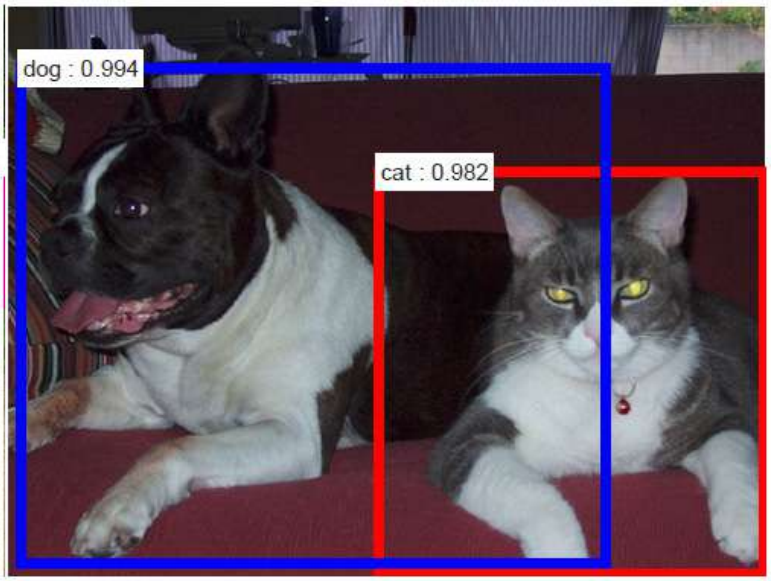
Aplicaciones del Deep Learning

Clasificación de imágenes



Aplicaciones del Deep Learning

Detección de objetos



Detección de objetos usando redes convolutivas, 2017

Aplicaciones del Deep Learning

Detección de objetos

CVPR'2018

Aplicaciones del Deep Learning

Segmentación de imágenes

Input Image

Aplicaciones del Deep Learning

Vehículos autónomos

Aplicaciones del Deep Learning

Vehículos autónomos

2005 DARPA Grand Challenge

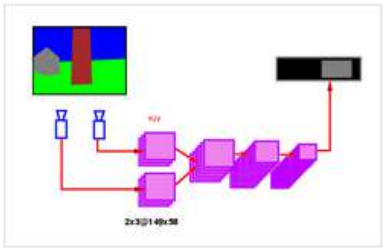
Aplicaciones del Deep Learning

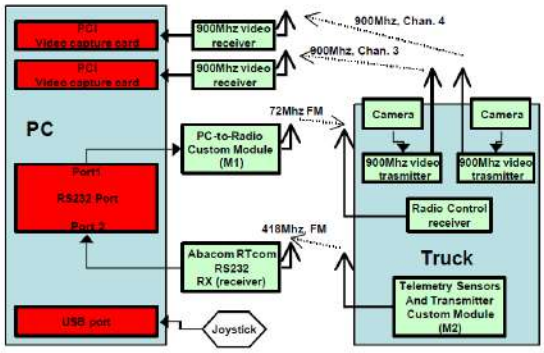
Vehículos autónomos

Autonomous Land Vehicle In a Neural Network (ALVINN)
NAVigational LABoratory II (NAVLAB II)
Control de dirección de un vehículo, CMU Ph.D. thesis, 1992

Aplicaciones del Deep Learning

Vehículos autónomos

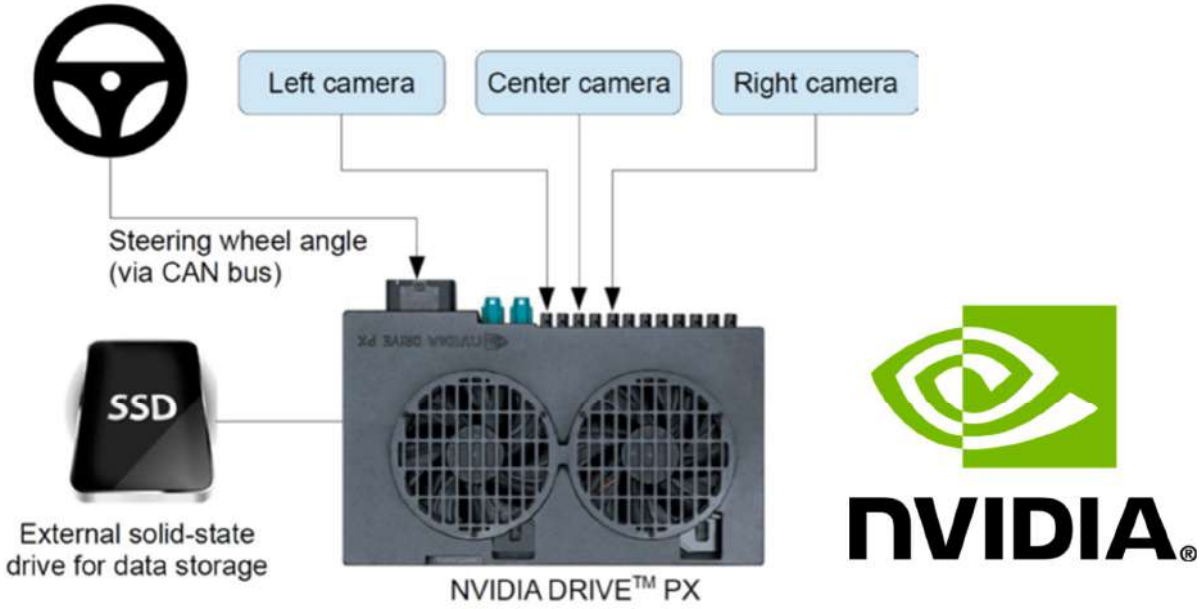




DAVE, 2004
Autonomous Off-Road Vehicle Control using End-to-End Learning
NYU Courant Institute / CBLL [Computational & Biological Learning Lab]
http://www.cs.nyu.edu/~yann/research/dave/

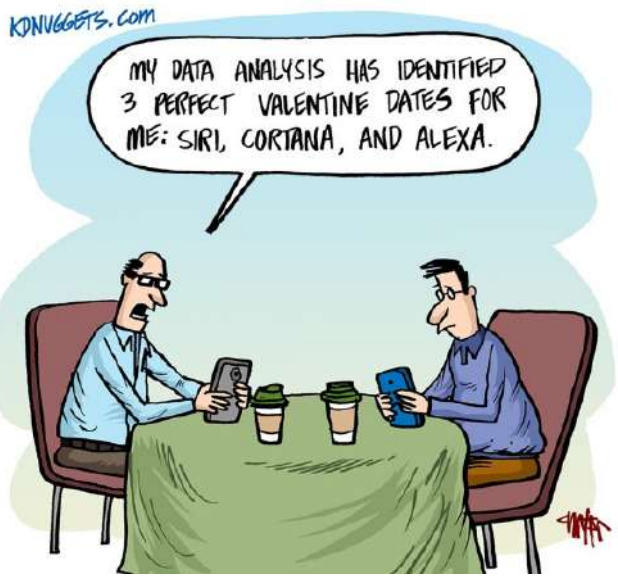
Aplicaciones del Deep Learning

Vehículos autónomos



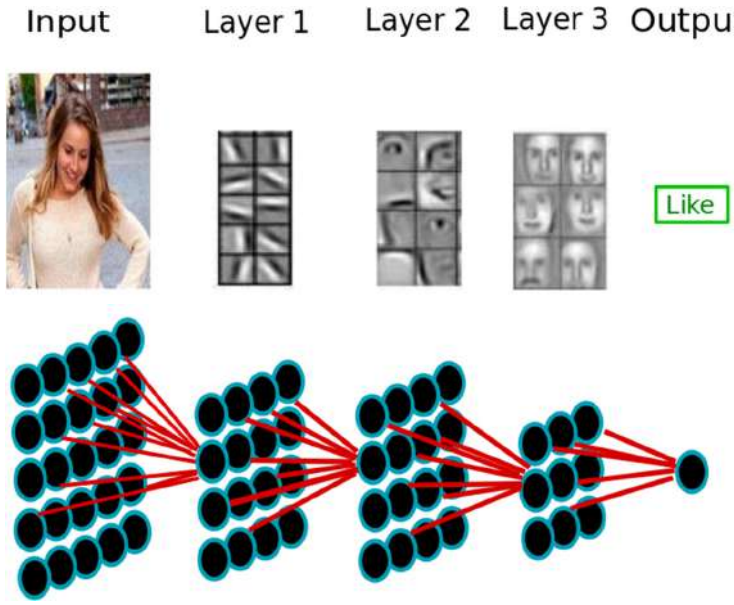
DAVE2, after DARPA Autonomous Vehicle (DAVE) project
NVIDIA, 2016. http://arxiv.org/abs/1604.07316
Completamente autónomo con sólo 100 horas de entrenamiento!!!

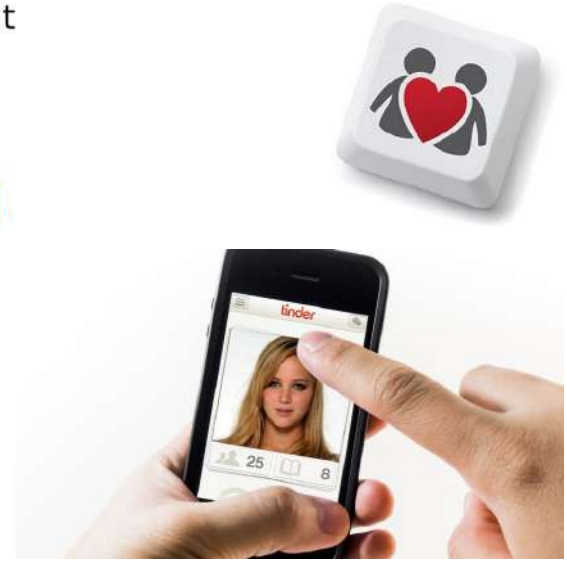
Aplicaciones del Deep Learning



Aplicaciones del Deep Learning

Citas por Internet, e.g. Tinder & OKCupid.com





Harm De Vries & Jason Yosinski:
Can deep learning help you find the perfect match?
ICML'2015 Deep Learning Workshop

Aplicaciones del Deep Learning

Detección de tiburones

SharkSpotter, Australia, 2017

Aplicaciones del Deep Learning

Traducción automática de señales

Google app

Otavio Good (Google Translate):

How Google Translate squeezes deep learning onto a phone

http://googleresearch.blogspot.com.es/2015/07/how-google-translate-squeezes-deep.html

Aplicaciones del Deep Learning

Descripción textual de imágenes [image captioning]

Aplicaciones del Deep Learning

Descripción textual de imágenes

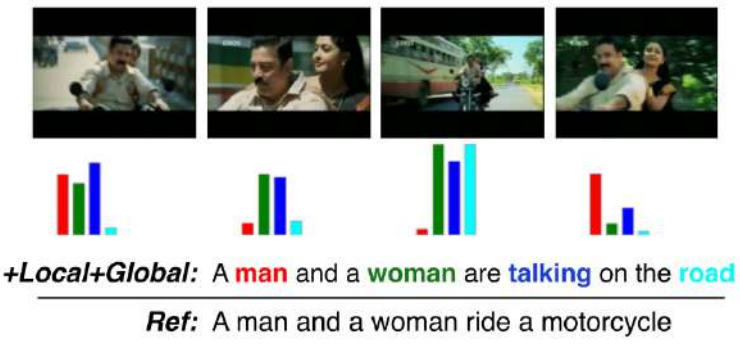
"La inteligencia visual de un niño de 3 años…"
-- Fei-Fei Li (Stanford)

a young boy is holding a baseball bat.

"The search for a thinking machine"
BBC News, 17 September 2015
http://www.bbc.com/news/technology-32334573

Aplicaciones del Deep Learning

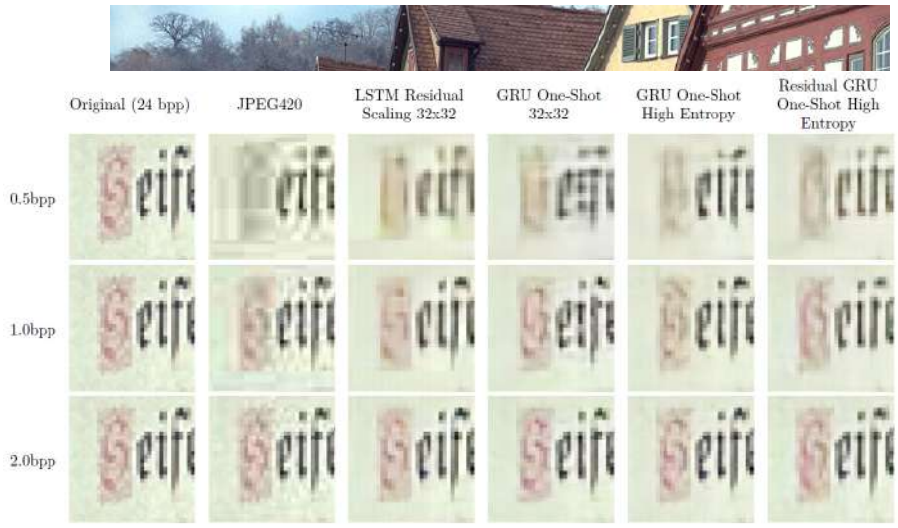
Descripción textual de vídeos [video clip description]



Youtube2Text

Aplicaciones del Deep Learning

Compresión de imágenes



http://www.piedpiper.com/

Full Resolution Image Compression with Recurrent Neural Networks arXiv, August 2016, http://arxiv.org/abs/1608.05148

Aplicaciones del Deep Learning

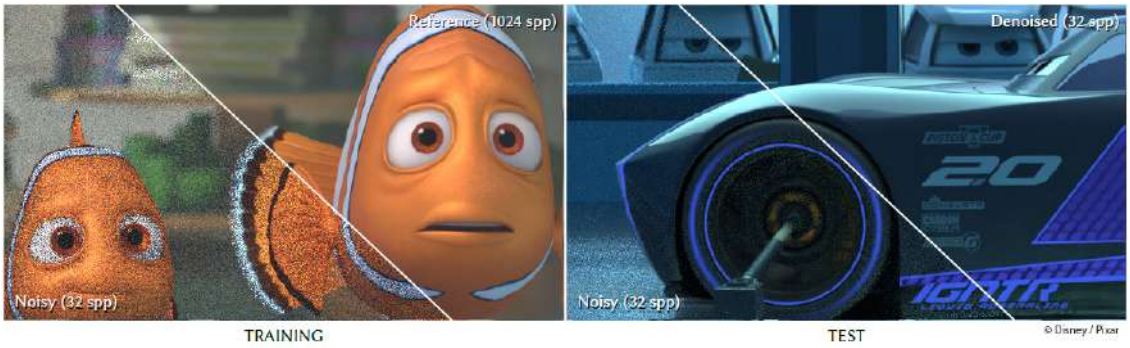
Retoque fotográfico

Figure 6: Original (top) vs. enhanced (bottom) images for iPhone 6, HTC One M9 and Huawei P9 cameras.

WESPE: Weakly Supervised Photo Enhancer for Digital Cameras. CVPR 2018. https://arxiv.org/abs/1709.01118

Aplicaciones del Deep Learning

Síntesis de imágenes
Eliminación de ruido
@ UCSB, Disney & Pixar



SIGGRAPH 2017
http://cvc.ucsb.edu/graphics/Papers/SIGGRAPH2017_KPCN/

Aplicaciones del Deep Learning

Síntesis de imágenes
Coloreado de fotografías

ECCV 2016 http://richzhang.github.io/colorization/

Aplicaciones del Deep Learning

Síntesis de imágenes

Coloreado de fotografías interactivo

SIGGRAPH 2017

https://richzhang.github.io/ideepcolor/

Aplicaciones del Deep Learning

Síntesis de imágenes: "Inceptionism"

Usando una red ya entrenada para reconocer objetos…

"El grito"

Edvard Munch

… visto por una red neuronal

http://deepdreamgenerator.com

https://github.com/google/deepdream

Aplicaciones del Deep Learning

Síntesis de imágenes

Transferencia de estilos

Leon A. Gatys, Alexander S. Ecker & Matthias Bethge:
A Neural Algorithm of Artistic Style
arXiv, 2015. http://arxiv.org/abs/1508.06576

Aplicaciones del Deep Learning

Síntesis de imágenes

Transferencia de estilos

Aplicaciones del Deep Learning

Transferencia de estilos

Aplicaciones del Deep Learning

Videojuegos (Atari 2600)

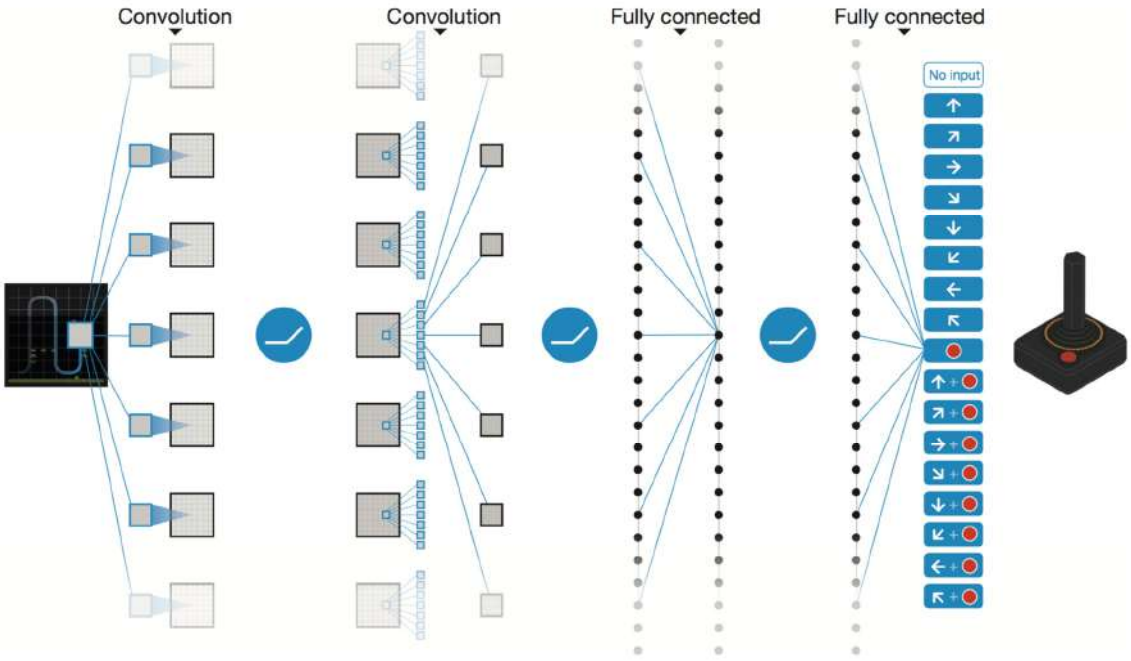
Google DeepMind

"Google AI beats humans at more classic arcade games than ever before"
http://arxiv.org/pdf/1509.06461v1.pdf (September 2015)

Aplicaciones del Deep Learning

Videojuegos

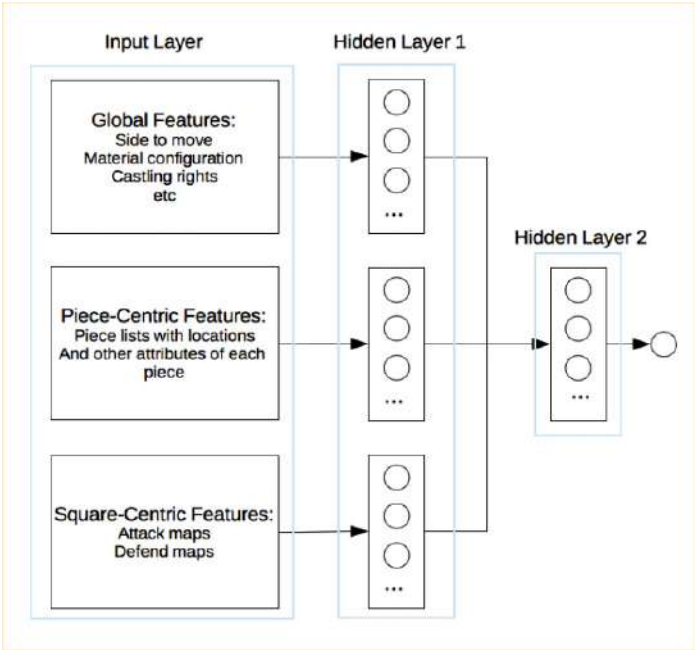
Deep Q Learning (Nature, 2015)



Aplicaciones del Deep Learning

Juegos

Ajedrez



Matthew Lai (Imperial College London):
"Giraffe: Using Deep Reinforcement Learning to Play Chess"
http://arxiv.org/abs/1509.01549 (September 2015)

Aplicaciones del Deep Learning

Juegos: Poker

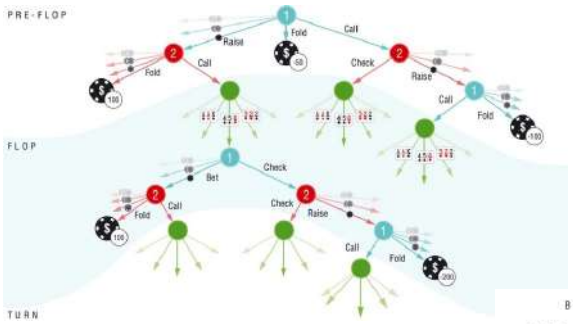
DeepStack

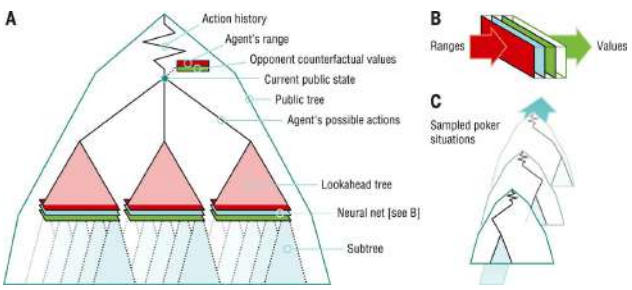
https://www.deepstack.ai/

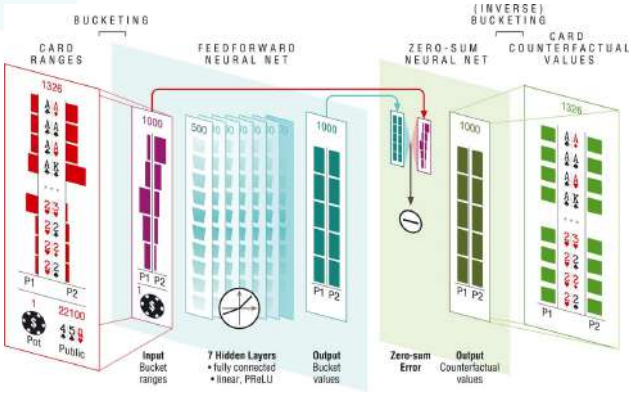
Aplicaciones

Juegos

Poker





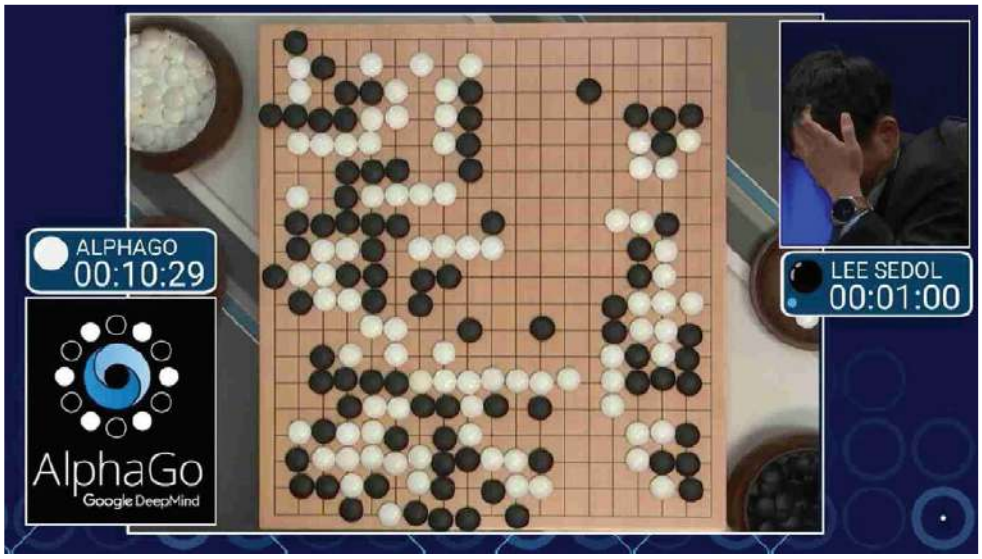


DeepStack: Expert-level artificial intelligence in heads-up no-limit poker
Science, Vol. 356, Issue 6337, pp. 508-513, 5 May 2017
DOI: 10.1126/science.aam6960

Aplicaciones del Deep Learning

Juegos: Go

AlphaGo



https://deepmind.com/research/alphago/

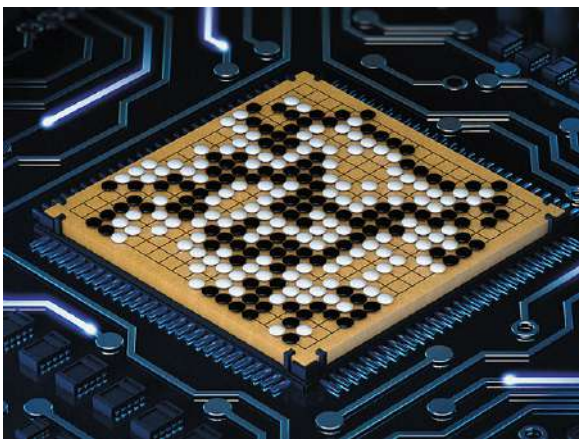
Aplicaciones

Juegos

Go: Los campeones humanos se negaban a jugar contra ordenadores porque eran demasiado malos (b>300)…

Octubre 2015, Londres:
AlphaGo (Google DeepMind) vence al campeón europeo Fan Hui [2-dan], 5-0.

Marzo de 2016, Seúl: $1M
AlphaGo (Google DeepMind) vence a Lee Sedol [9-dan], 4-1.



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

Aplicaciones del Deep Learning

Juegos

AlphaGo Zero

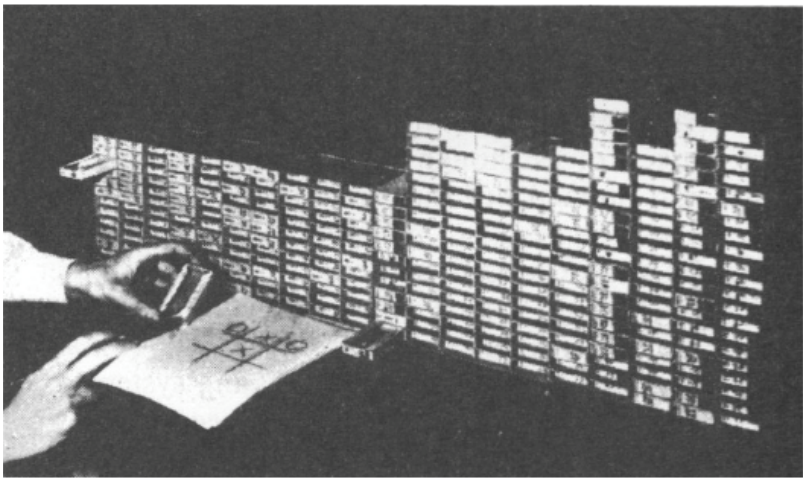
https://elpais.com/elpais/2018/12/05/ciencia/1544007034_265553.html

Aplicaciones del Deep Learning

Juegos: Go

Really???

The Matchbox Machine



1961

MENACE
Matchbox Educable Noughts And Crosses Engine

Donald Michie:
"Experiments on the mechanization of game-learning
Part I. Characterization of the model and its parameters"
The Computer Journal, 6(3):232–236, November 1963,
The British Computer Society, https://doi.org/10.1093/comjnl/6.3.232