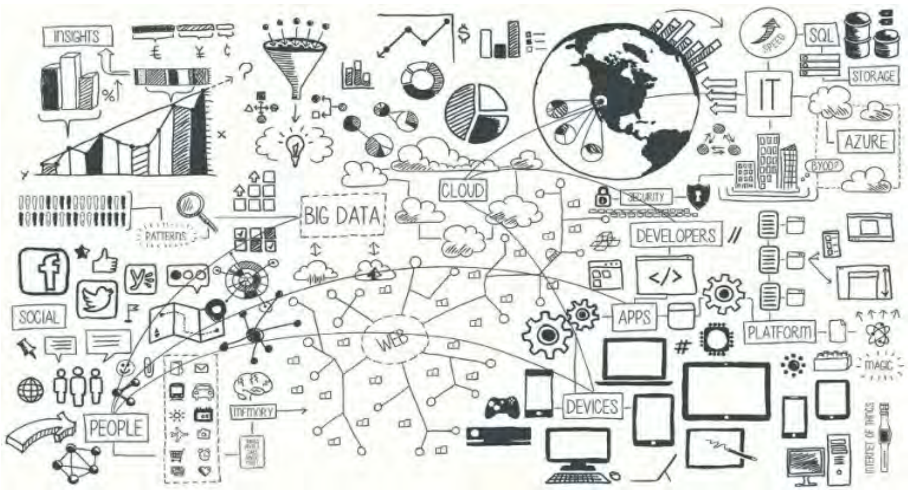
Machine Learning I
Neural Networks

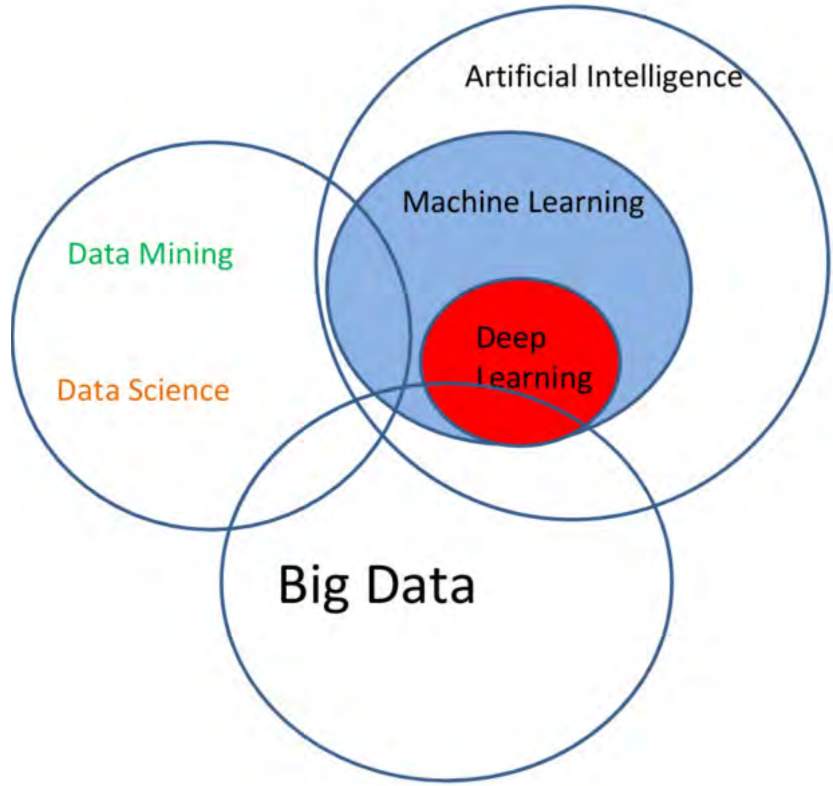
INTRODUCTION AND HISTORICAL PERSPECTIVE



José Manuel Gutiérrez
Jorge Baño
(IFCA)

Lara Lloret
Ignacio Heredia
(IFCA)

31	1	2	3
15:30h -17:30h	15:30h -17:30h	15:30h -17:30h	15:30h -17:30h
Machine Learning II	Machine Learning I	Machine Learning II	Machine Learning I
Aprendizaje estadístico. Métodos kernel para clasificación. SVM	**Fundamentos de Redes Neuronales**	**Práctica clasificación**	**Práctica de Aprendizaje con backpropagation**
Ignacio Santamaría	Jose Manuel Gutierrez	Steven Van Vaerenbergh	Jorge Baño Medina
	Herramientas en la	Sistemas de computación para	



8 Feb - Redes multicapa y el algoritmo de backpropagation
10 Feb - Prácticas de clasificación con redes multicapa
15 Feb - Prácticas de predicción con redes multicapa
17 Feb - Clustering y redes autoorganizativas
22 Feb - Reservoir computing

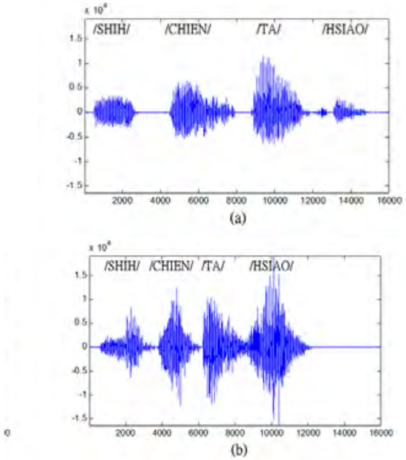
An Introduction to Functional Networks
E. Castillo, A. Cobo, J.M. Gutiérrez and E. Pruneda
Kluwer Academic Publishers **(1999).**

Paraninfo/International Thomson Publishing

LIBRO

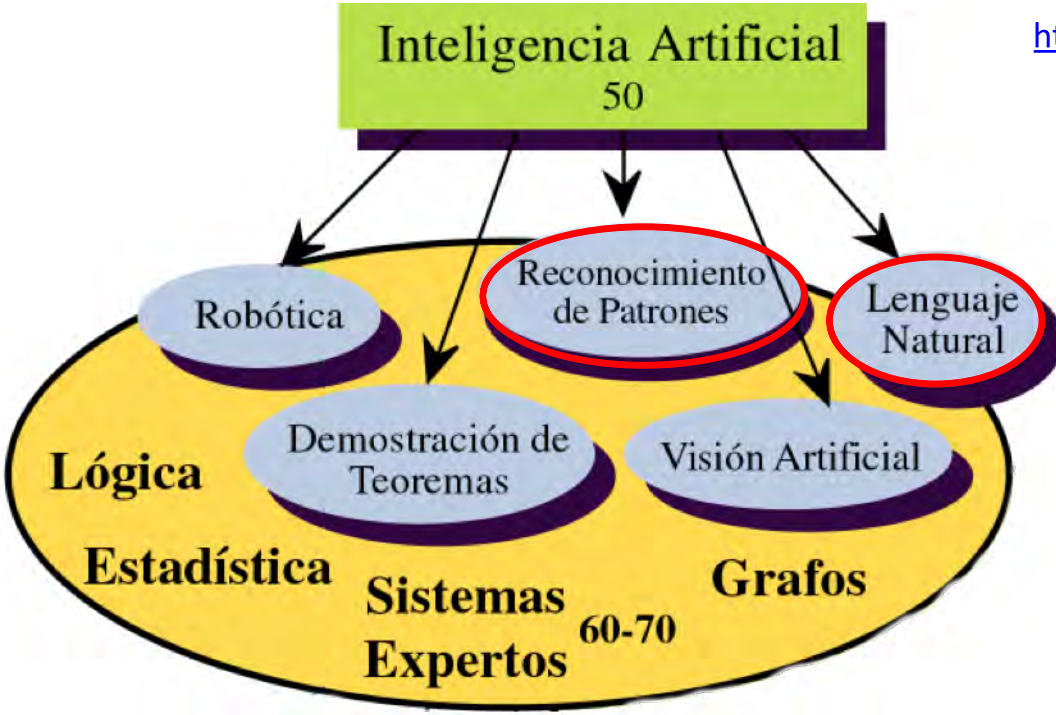
J.M. Gutiérrez, R. Cano, A.S. Cofiño, and C. Sordo
Redes Probabilísticas y Neuronales en las Ciencias Atmosféricas
Ministerio de Medio Ambiente (*Monografías del Instituto Nacional de Meteorología*), Madrid. 350 páginas, 2004

http://www.meteo.unican.es/files/pdfs/LibroINM.pdf



R + openNLP

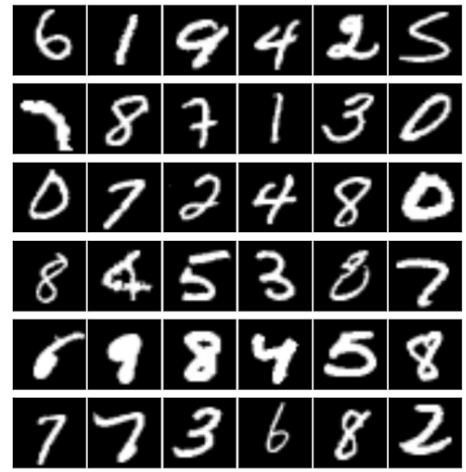
Overview of Natural Language Processing(NLP) with R and OpenNLP



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

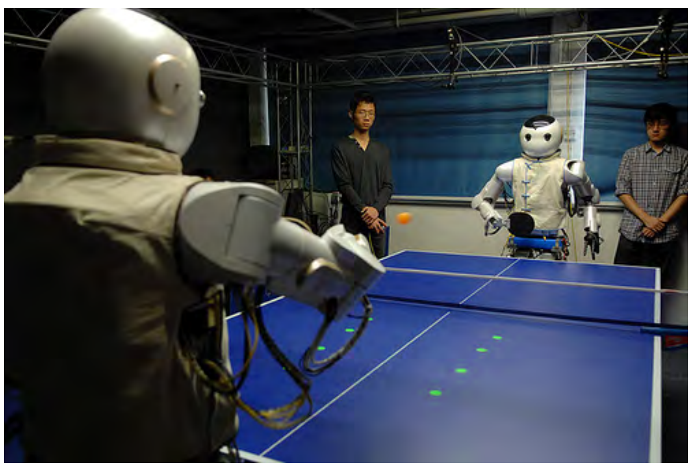
60000+10000 images 28x28

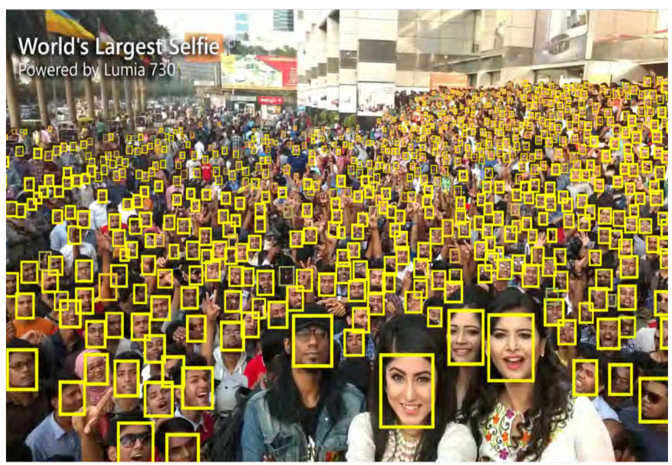
Labeled as {0,…,9}

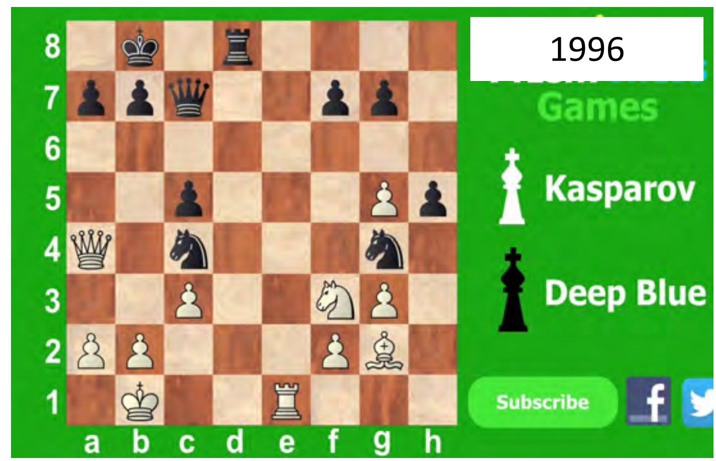


Lineal: 10%. k-NN: 3%. SVM: 1%.

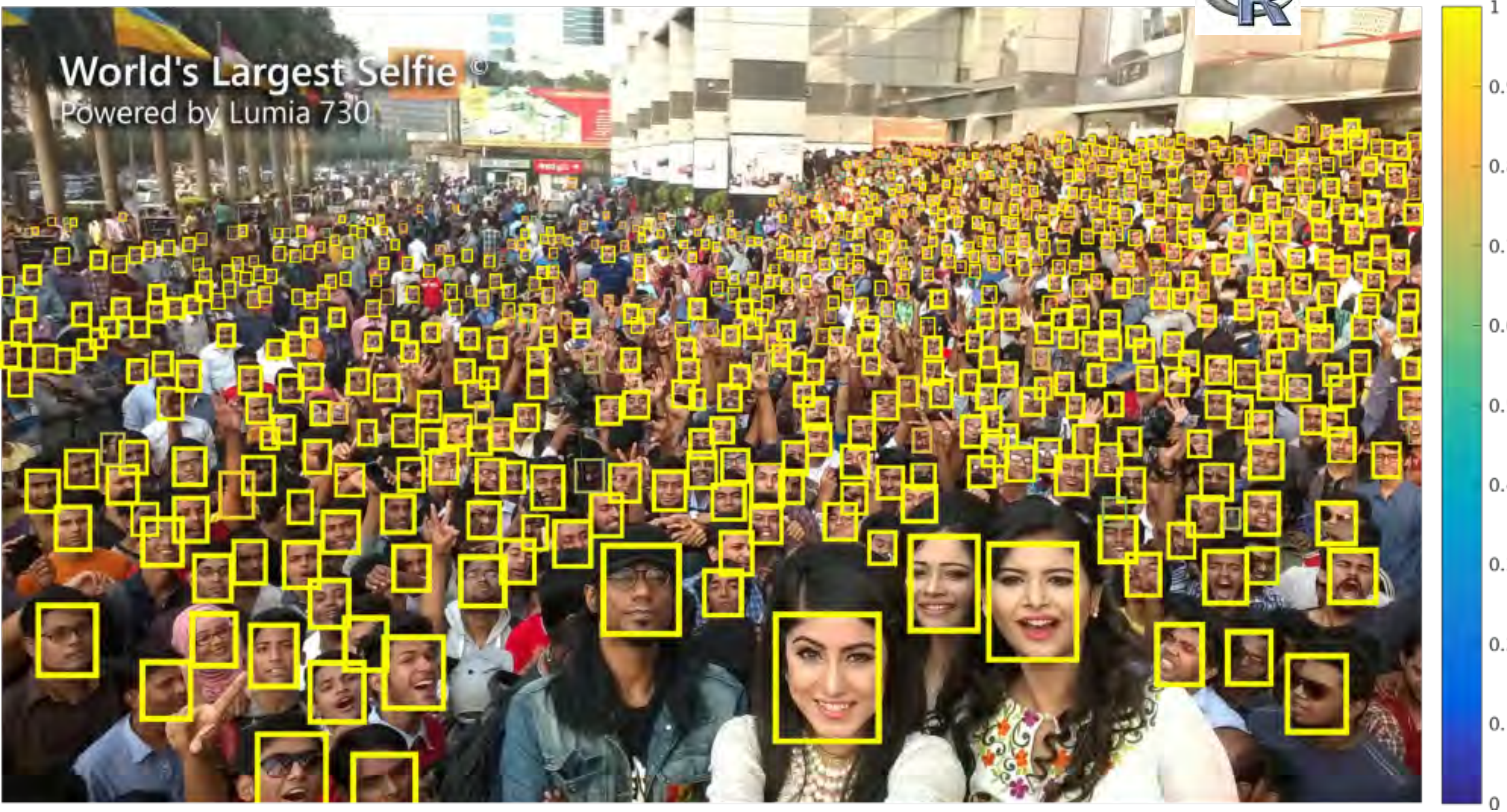
Deep: 0.3%







https://github.com/peiyunh/tiny

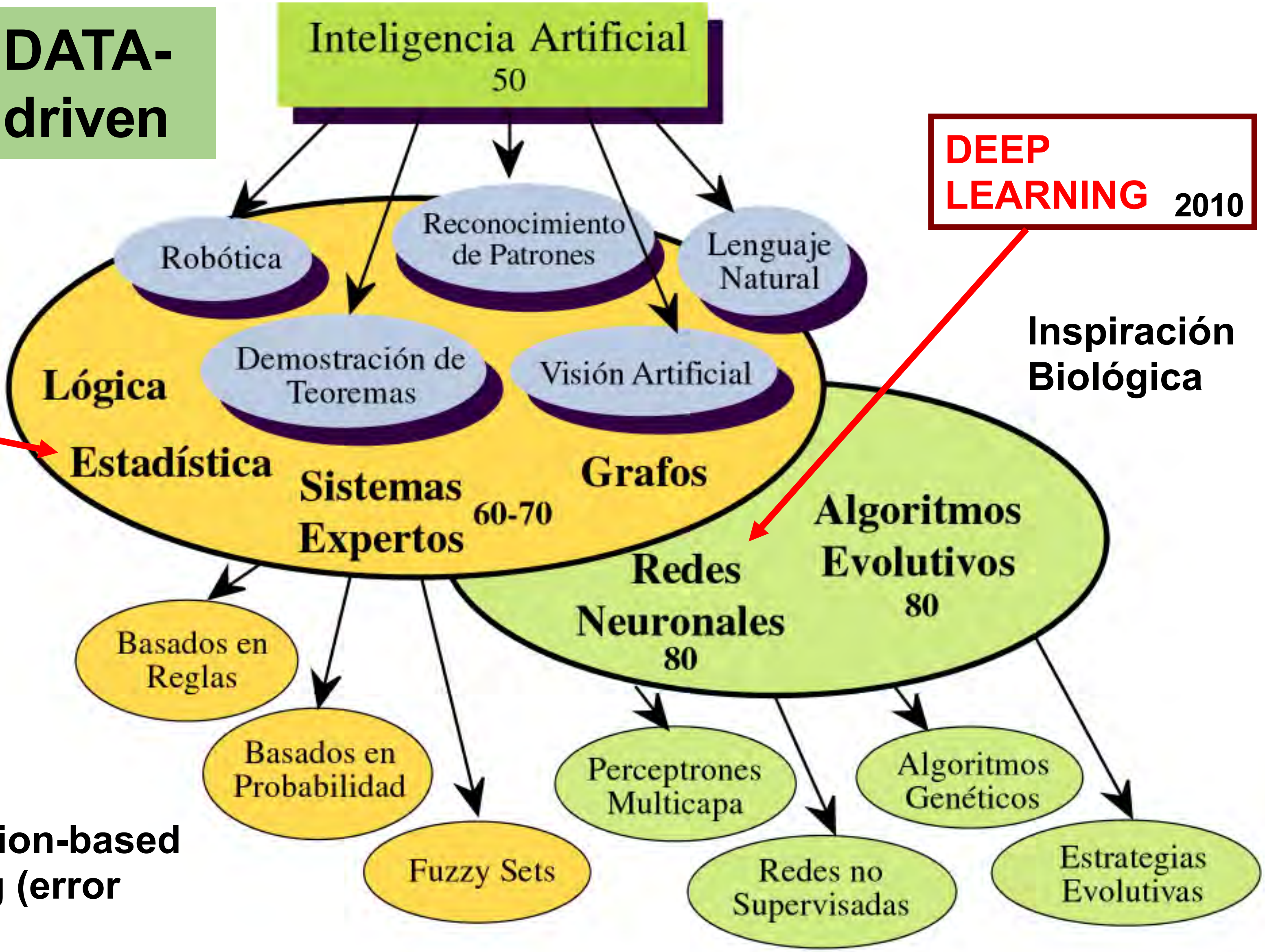


We develop a face detector (Tiny Face Detector) that can find ~800 faces out of ~1000 reportedly present, by making use of novel characterization of scale, resolution, and context to find small objects.

Nuevos Paradigmas **DATA-driven**

Inspiración estadística

STATISTICAL LEARNING **2000**



DEEP LEARNING **2010**

Inspiración Biológica

Data driven using abstract representations

Kernels, neural network, etc.

Optimization-based reasoning (error function).

Empirical risk, gradient descend, etc.

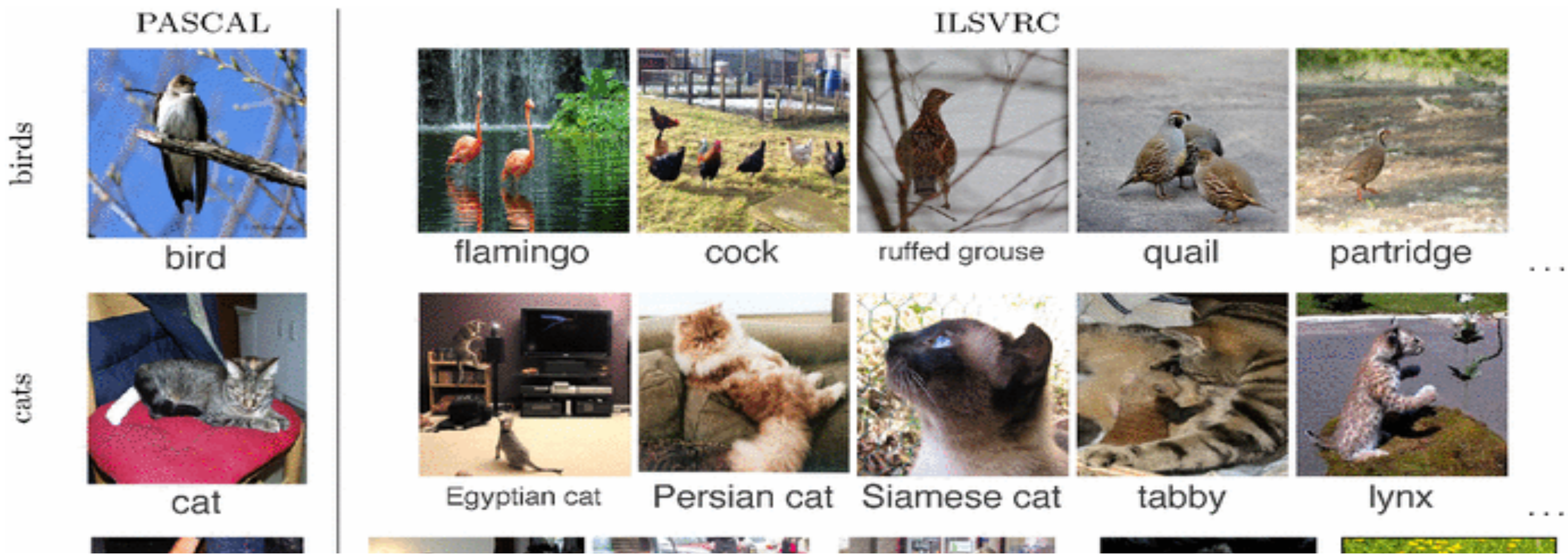
Parallel processing

HPC, GPUs, cloud, etc.

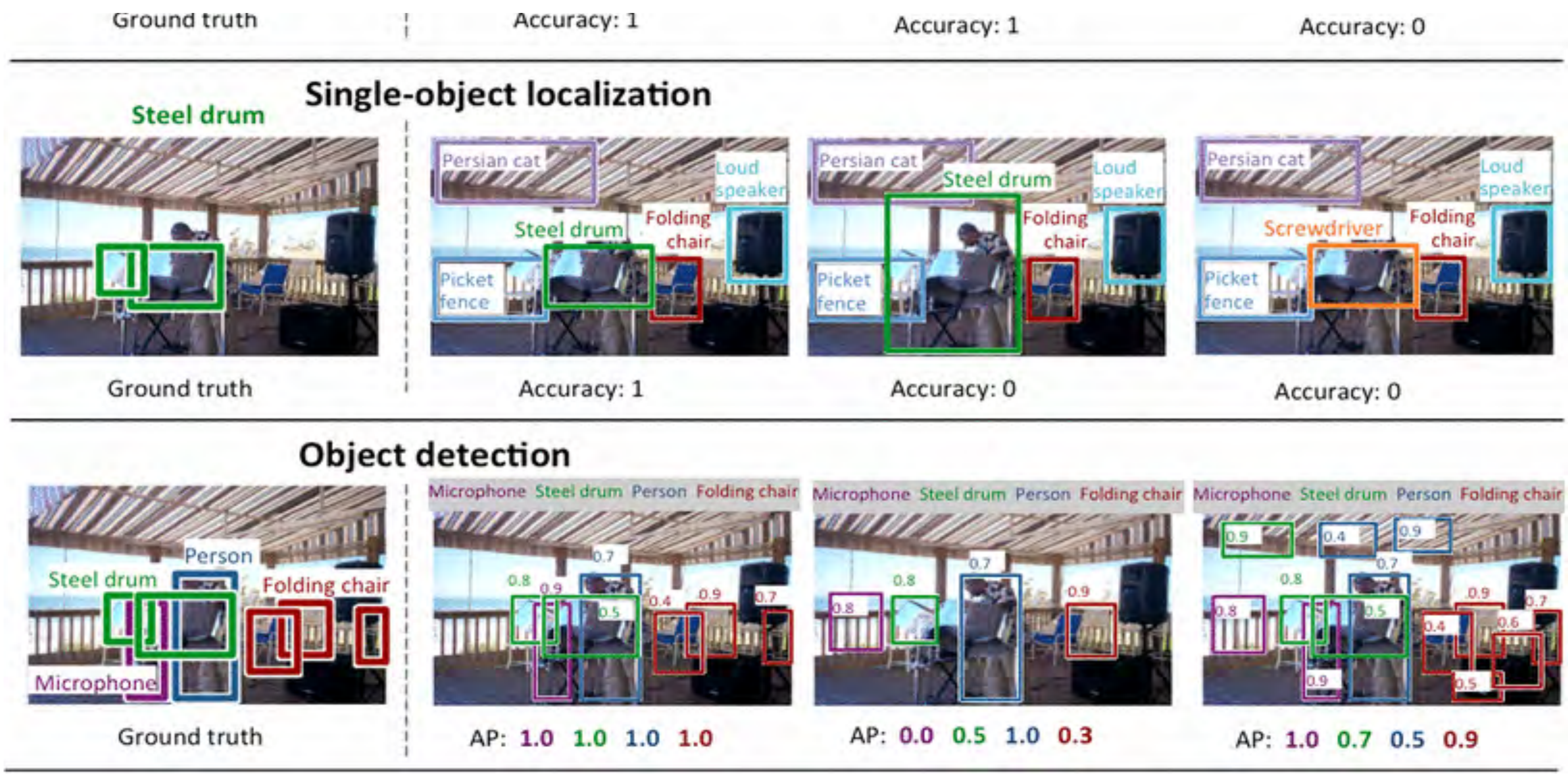
ImageNet is an image database organized according to the (nouns of the) WordNet hierarchy, in which each node of the hierarchy is depicted by an average of over five hundred images.

#synsets: 21841
#images: 14197122

150 GB [kaggle]



David G. Lowe, **Distinctive Image Features from Scale-Invariant Keypoints**. *International Journal of Computer Vision, 2004.*

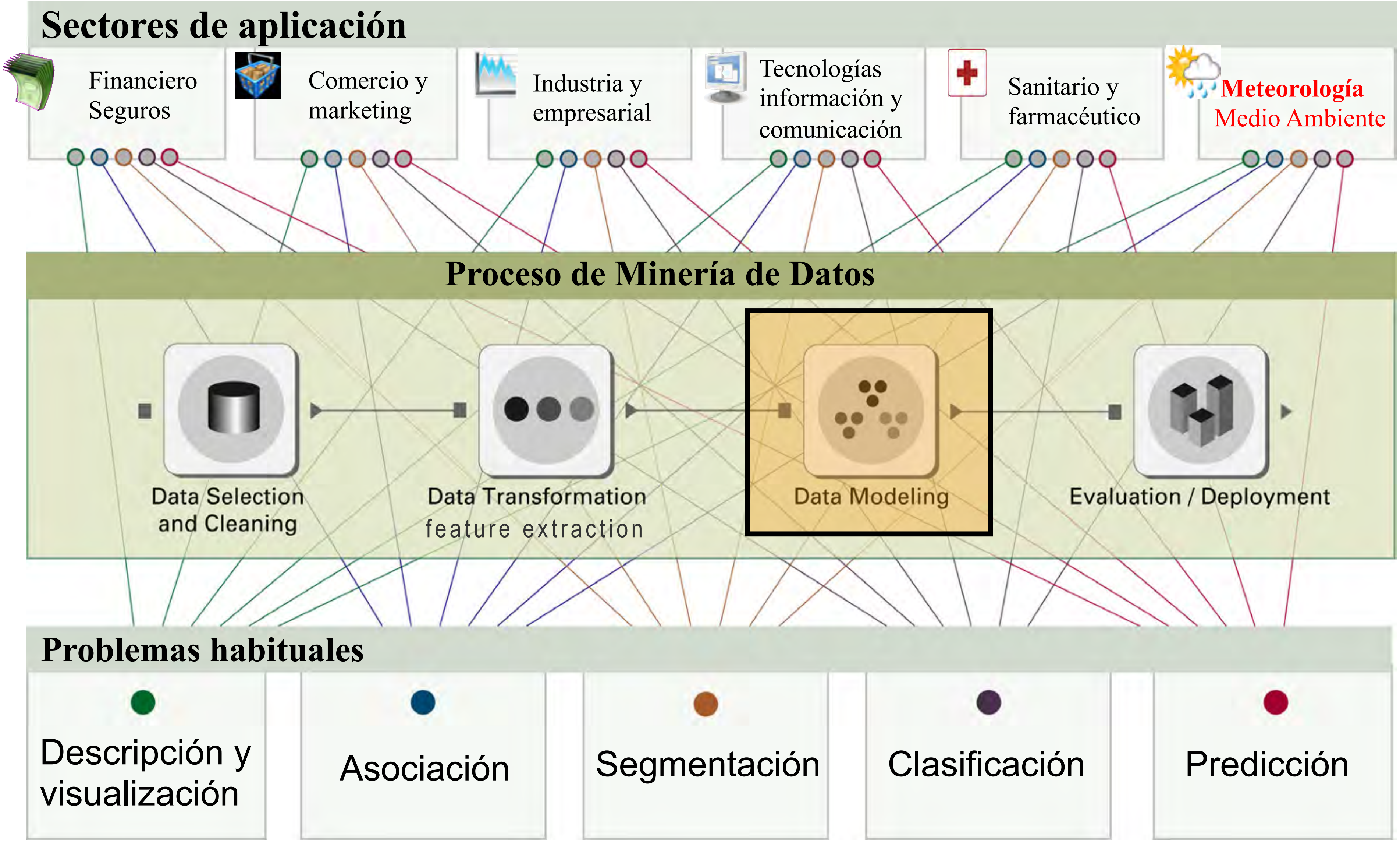


Validation: top-5 error rate

2017 video included

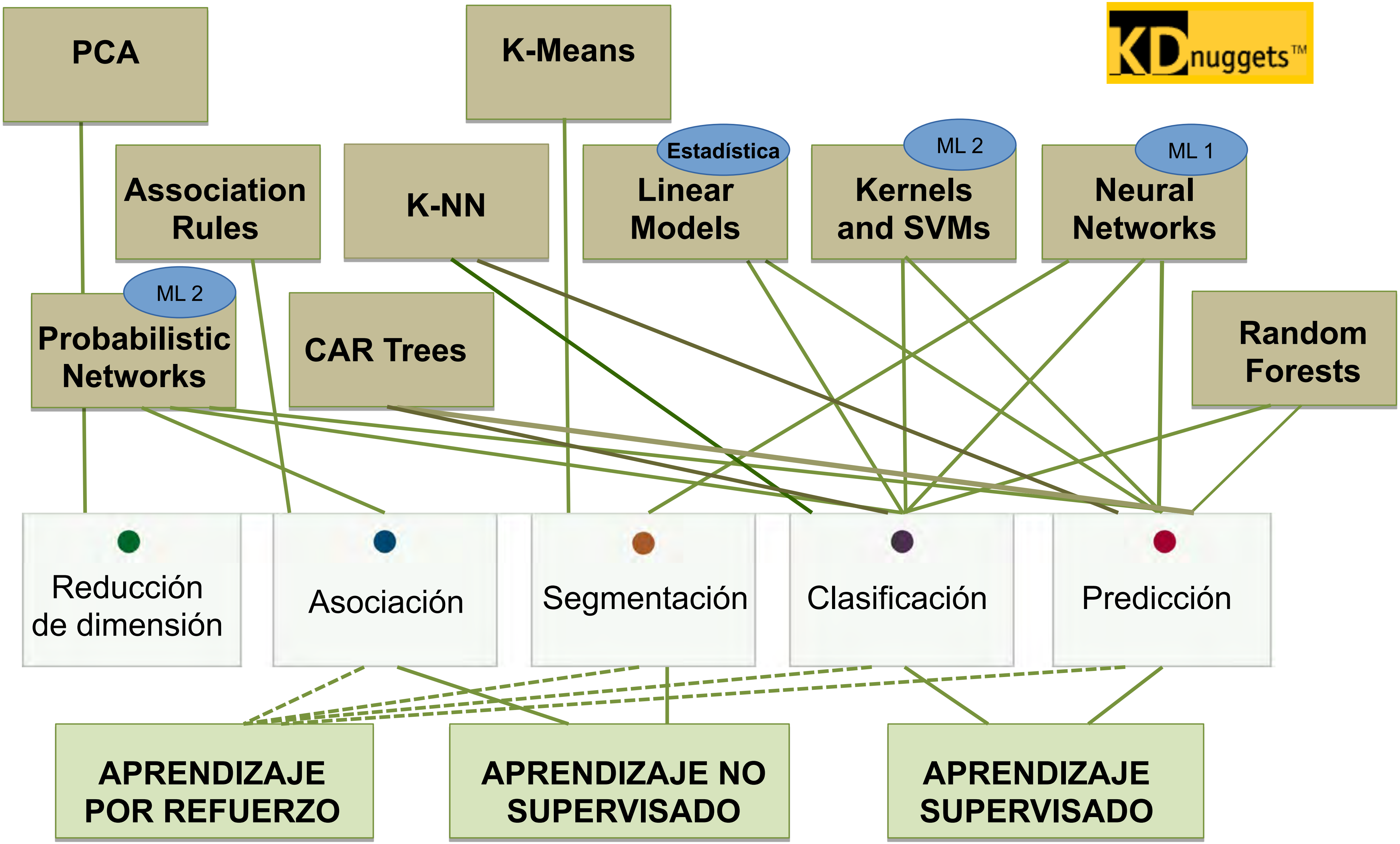
[Inception-v3](): 3.46% top-5 and 17.3% top-1 (25 million parameters). [Inception In [kaggle]()]

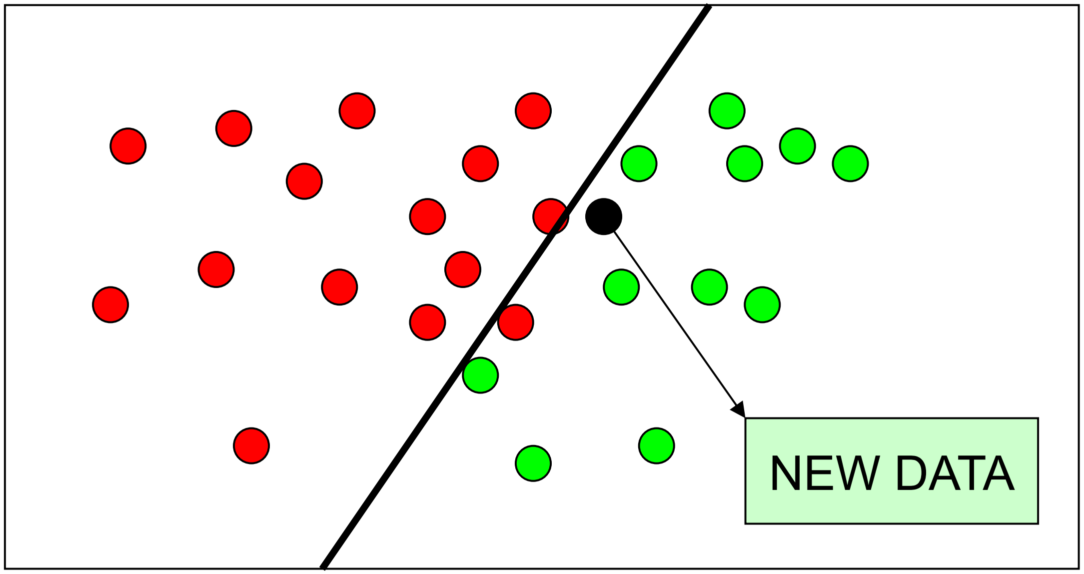
O. Russakovsk (2015) [ImageNet Large Scale Visual Recognition Challenge](), International Journal of Computer Vision, 115, 211–252



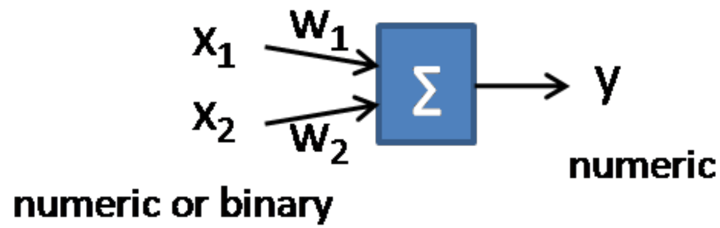
Machine learning develop methods for data modelling and prognosis.

https://www.kdnuggets.com/2017/10/top-10-machine-learning-algorithms-beginners.html



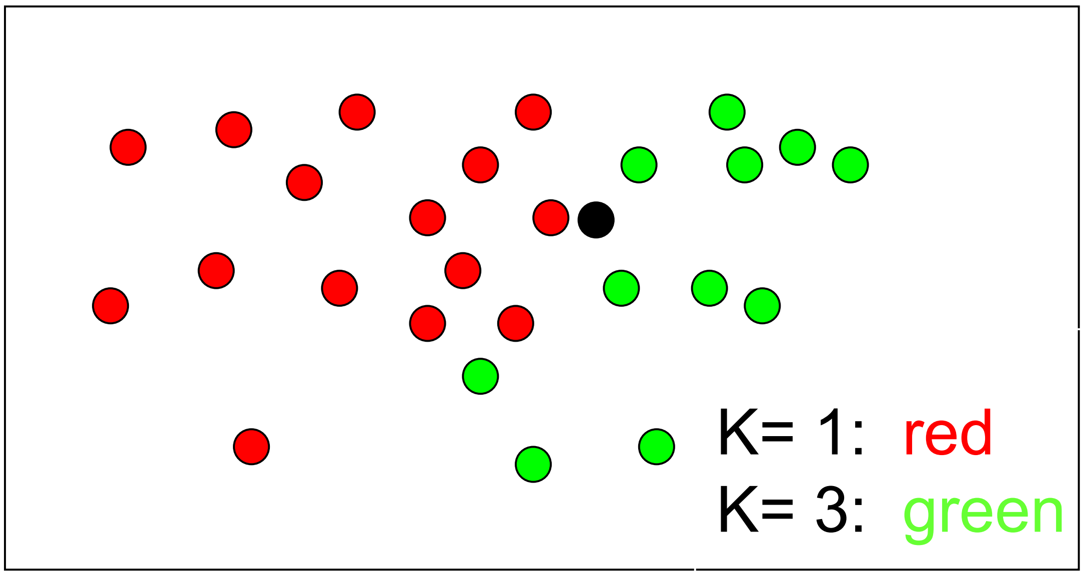


GENERATIVE METHODS:
Linear models are the simplest family for machine learning and have good generalization properties.



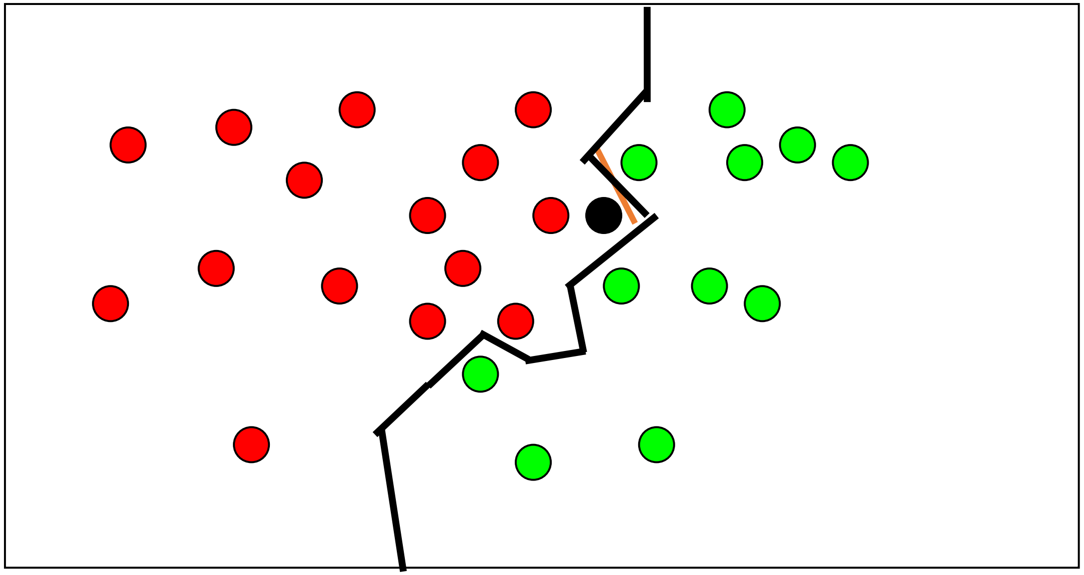
$$y = w_0 + w_1 x_1 + w_2 x_2$$

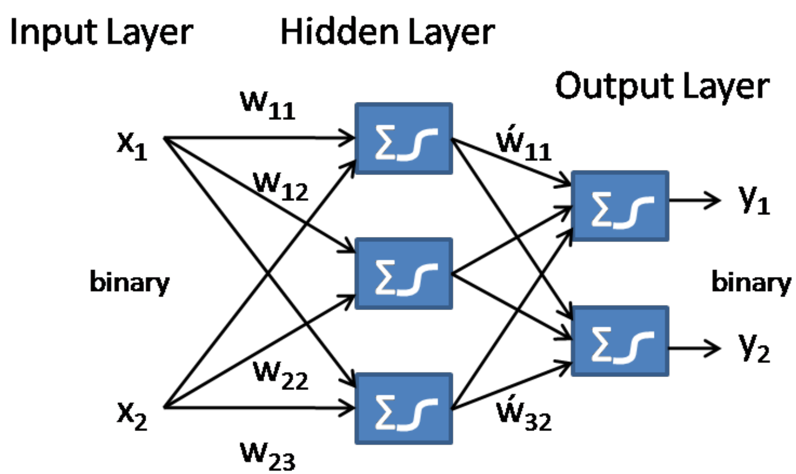
$$y = f(X, W) = X^T . W$$

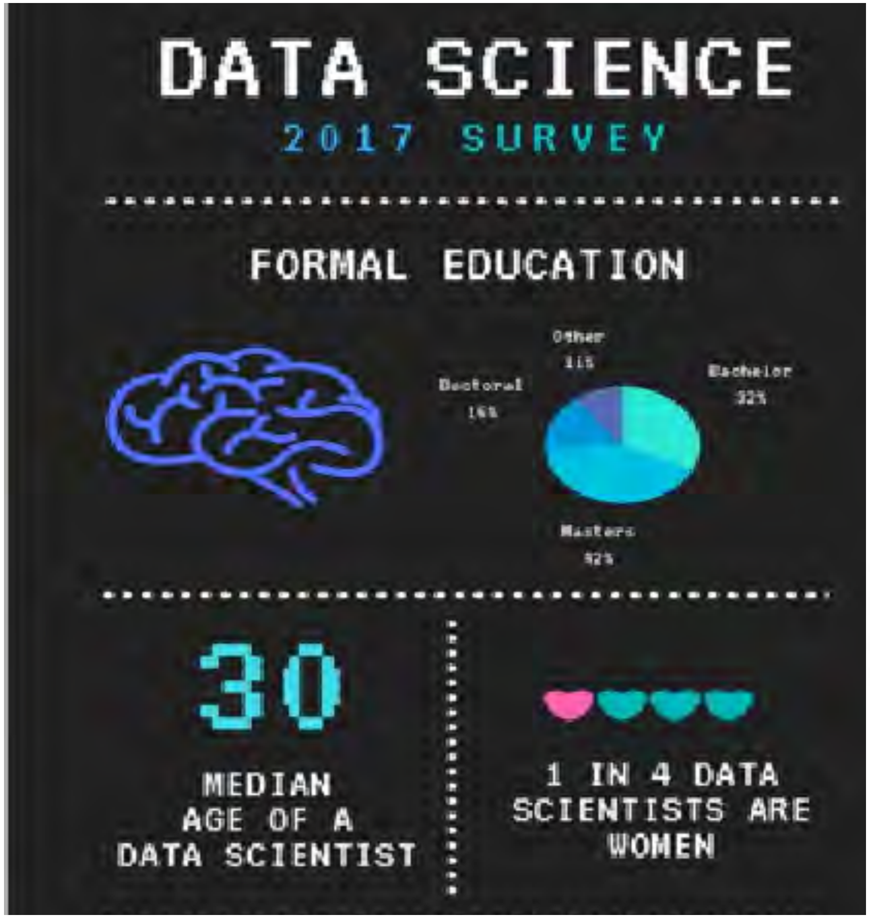


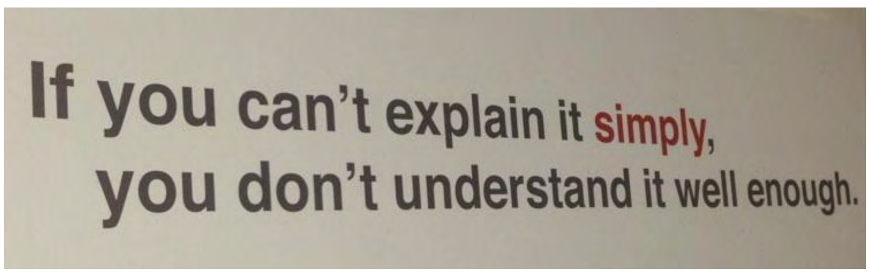
NON-GENERATIVE (OR ALGORITHMIC)
K Nearest Neighbours is the simples non-generative method. It depends on a single parameter (K) to be tunned (generalization depends on K).

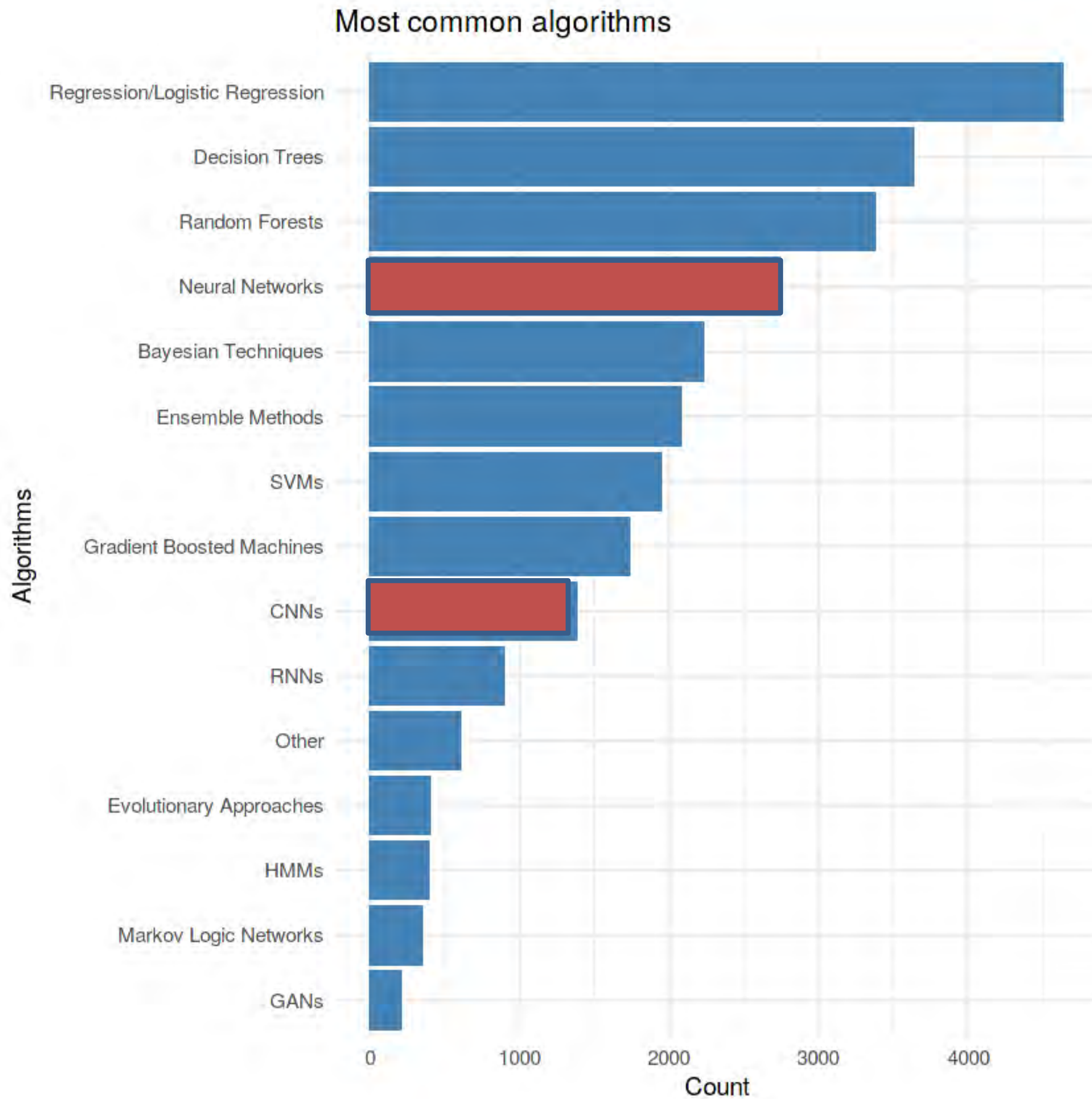
Increasing model complexity (e.g. number of parameters) can result in **overfitting** (lack of generalization).









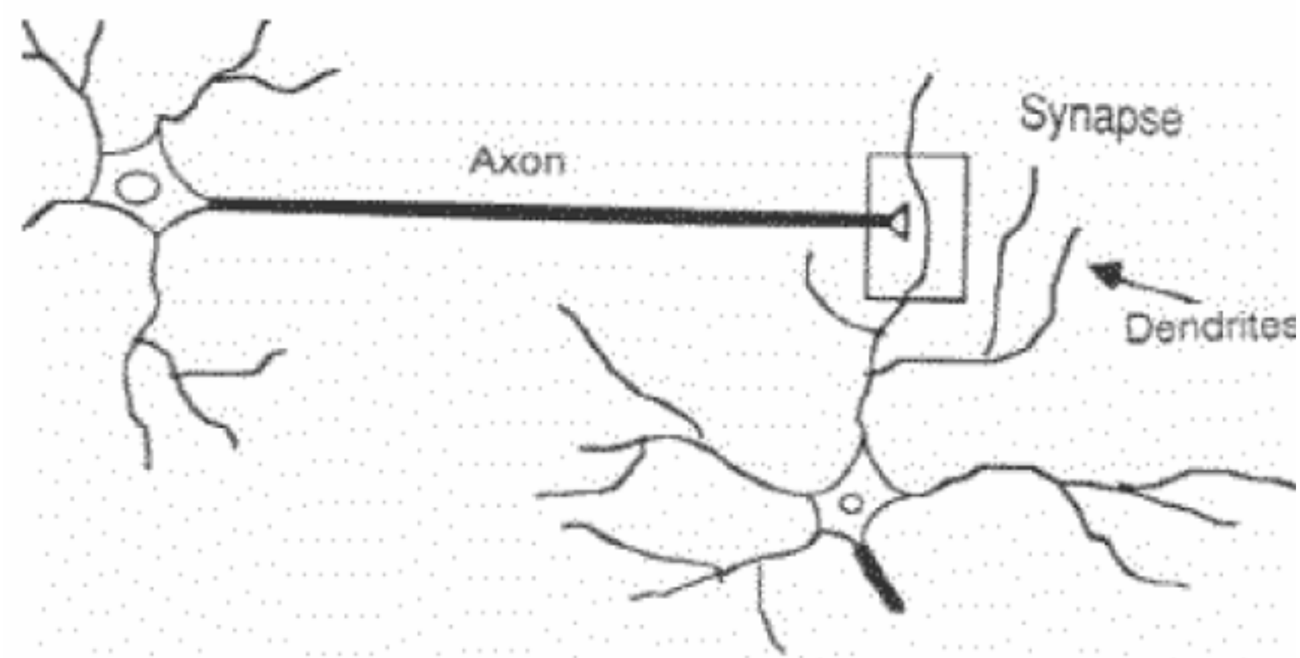


https://www.kaggle.com/kaggle/kaggle-survey-2017

NEURAL NET: **KAGGLE SURVEY**

Artificial Neural Networks are inspired in the structure and functioning of the **brain**, which is a collection of **interconnected neurons** (the simplest computing elements performing information processing):

- ✓Each neuron consists of a cell body, that contains a cell **nucleus**.
- ✓There are number of fibers, called **dendrites**, and a single long fiber called **axon** branching out from the cell body.
- ✓The axon connects one neuron to others (through the dendrites).
- ✓The connecting junction is called **synapse**.



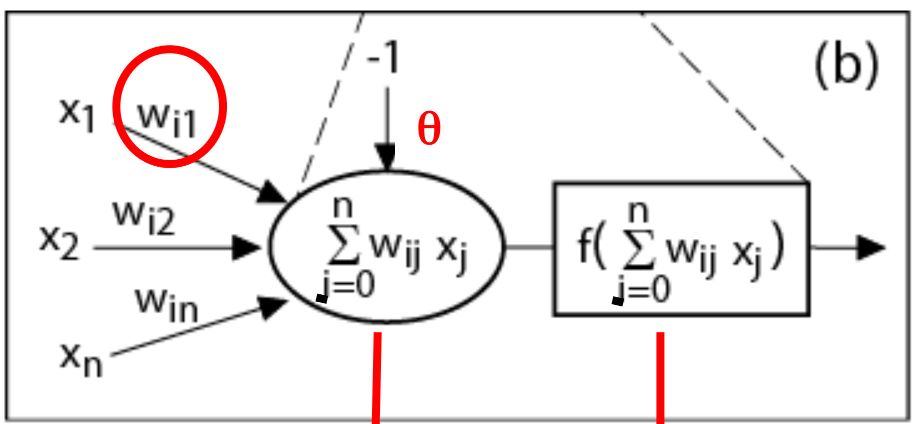
There are over **10^{11} neurons** in a human brain, each **connected with 1000** on average.

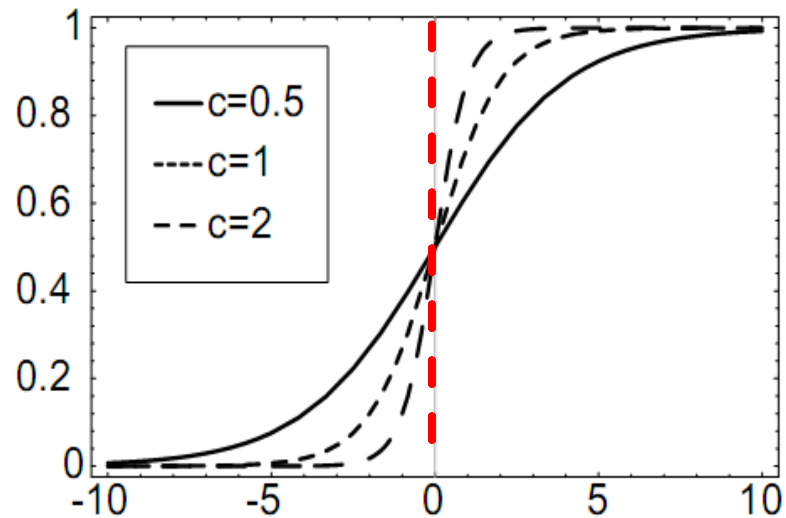
- The synapses releases chemical transmitter substances, entering the dendrite, raising or lowering (**excitatory and inhibitory synapses**) the electrical potential of the cell body.
- When the potential **reaches a threshold**, an electric pulse or action potential is sent down to the axon affecting other neurons *(there is a* ***nonlinear activation****)*.

$$y = f(w^T x), \text{ with } x_0 = -1 \text{ to account for } \theta\text{: } f(w^T x - \theta).$$

McCulloc & Pitts (1943)

weights (+ or -, excitatory or inhibitory)





neuron potential: **mixed input of neighboring neurons**

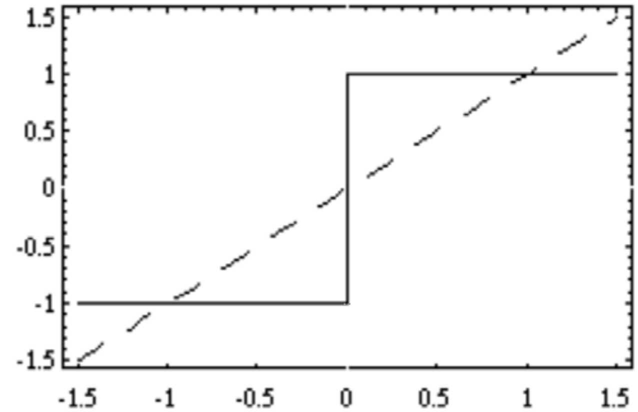
nonlinear activation function

(threshold = θ)

- **Funciones lineales:** $f(x) = x$.

- **Funciones paso:** Dan una salida binaria dependiente de si el valor de entrada está por encima o por debajo del valor umbral.

$$sgn(x) = \begin{cases} -1, & \text{si } x < 0, \\ 1, & \text{sino}, \end{cases} \quad , \quad \Theta(x) = \begin{cases} 0, & \text{si } x < 0, \\ 1, & \text{sino}. \end{cases}$$

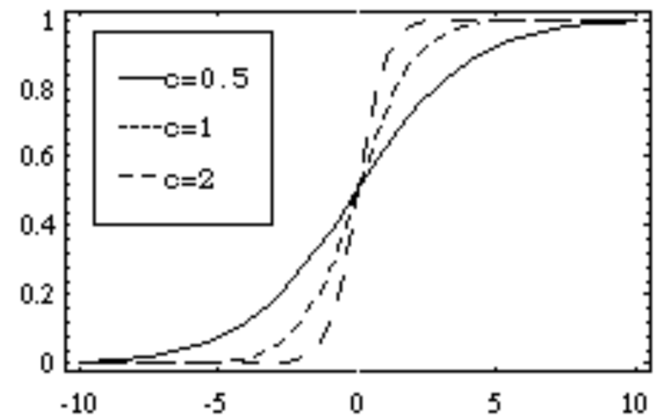


- **Funciones sigmoidales:** Funciones monótonas acotadas que dan una salida gradual no lineal.

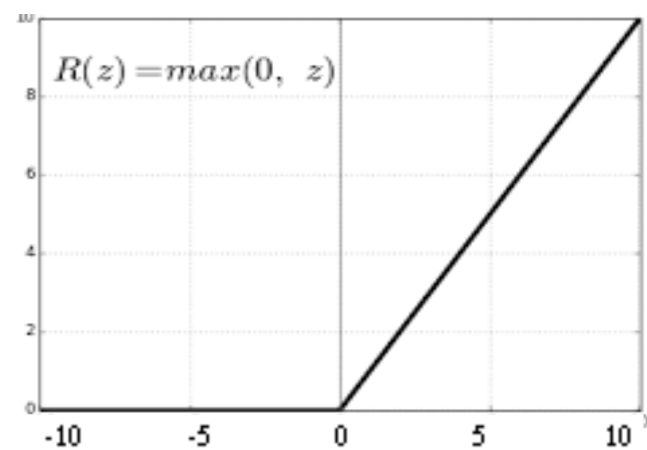
  1. La función logística de 0 a 1:

$$f_c(x) = \frac{1}{1 + e^{-c\,x}}.$$

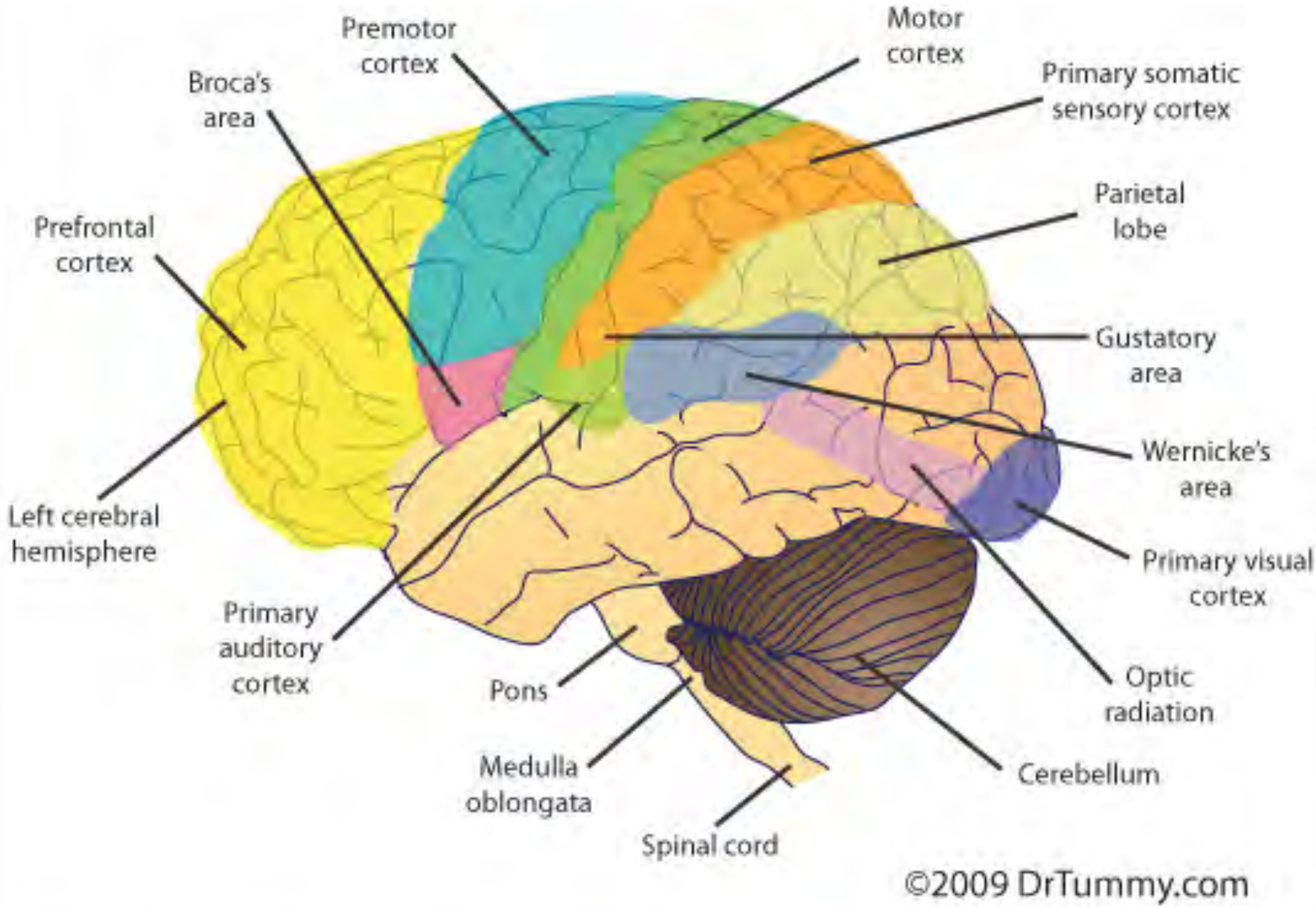
  2. La función tangente hiperbólica de -1 a 1 $f_c(x) = tanh(c\,x)$.



- **Rectified linear unit (ReLU):** Utilizadas para evitar el "desvanecimiento del gradiente".



TanH	$f(x) = tanh(x) = \frac{2}{1+e^2x} - 1$	$f'(x) = 1 - f(x)^2$	$(-1, 1)$	C^∞
SoftSign	$f(x) = \frac{x}{1+\lvert x\rvert}$	$f'(x) = 1 - f(x)^2$	$(-1, 1)$	C^1
SoftPlus	$f(x) = \ln(1 + e^x)$	$f'(x) = \frac{1}{1 + e^{-x}}$	$(0, \infty)$	C^∞
SoftExponential	$f(\alpha, x) = \begin{cases} -\frac{\ln(1-\alpha(x+\alpha))}{\alpha} \text{ for } \alpha < 0 \\ x \text{ for } \alpha = 0 \\ \frac{e^{\alpha x}-1}{\alpha} + \alpha \text{ for } \alpha > 0 \end{cases}$	$f'(\alpha, x) = \begin{cases} \frac{1}{1-\alpha(\alpha+x)} \text{ for } \alpha < 0 \\ e^{\alpha x} \text{ for } \alpha \geq 0 \end{cases}$	$(-\infty, \infty)$	C^∞
Sinusoid	$f(x) = \sin(x)$	$f'(x) = \cos(x)$	$[-1, 1]$	C^∞
Sinc	$f(x) = \begin{cases} 1 \text{ for } x = 0 \\ \frac{\sin(x)}{x} \text{ for } x \neq 0 \end{cases}$	$f'(x) = \begin{cases} 0 \text{ for } x = 0 \\ \frac{\cos(x)}{x} - \frac{\sin(x)}{x^2} \text{ for } x \neq 0 \end{cases}$	$[\approx -.217234, 1]$	C^∞
Scaled exponential linear unit (SELU)	$f(\alpha, x) = \lambda \begin{cases} \alpha(e^x - 1) \text{ for } x < 0 \\ x \text{ for } x \geq 0 \end{cases}$ $\lambda = 1.0507$ y $\alpha = 1.67326$	$f'(\alpha, x) = \lambda \begin{cases} f(\alpha, x) + \alpha \text{ for } x < 0 \\ 1 \text{ for } x \geq 0 \end{cases}$	$(-\lambda\alpha, \infty)$	C^0
Rectified linear unit (ReLU)	$f(x) = \begin{cases} 0 \text{ for } x < 0 \\ x \text{ for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for} & x < 0 \\ 1 & \text{for} & x \geq 0 \end{cases}$	$[0, \infty)$	C^0
Randomized leaky rectified linear unit (RReLU)	$f(\alpha, x) = \begin{cases} \alpha x \text{ for } x < 0 \\ x \text{ for } x \geq 0 \end{cases}$	$f'(\alpha, x) = \begin{cases} \alpha \text{ for } x < 0 \\ 1 \text{ for } x \geq 0 \end{cases}$	$(-\infty, \infty)$	C^0
Parametric rectified linear unit (PReLU)	$f(\alpha, x) = \begin{cases} \alpha x \text{ for } x < 0 \\ x \text{ for } x \geq 0 \end{cases}$	$f'(\alpha, x) = \begin{cases} \alpha \text{ for } x < 0 \\ 1 \text{ for } x \geq 0 \end{cases}$	$(-\infty, \infty)$	C^0
Logistic (a.k.a soft step)	$f(x) = \frac{1}{1+e^{-x}}$	$f'(x) = f(x)(1 - f(x))$	(0,1)	C^∞


Premotor cortex
Motor cortex
Broca's area
Primary somatic sensory cortex
Parietal lobe
Prefrontal cortex
Gustatory area
Wernicke's area
Left cerebral hemisphere
Primary visual cortex
Primary auditory cortex
Pons
Optic radiation
Medulla oblongata
Cerebellum
Spinal cord
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Neural Network Study (1988, AFCEA International Press, p. 60):

*... a neural network is a system composed of **many simple processing elements operating in parallel** whose function is determined by network structure, connection strengths, and the processing performed at computing elements or nodes.*

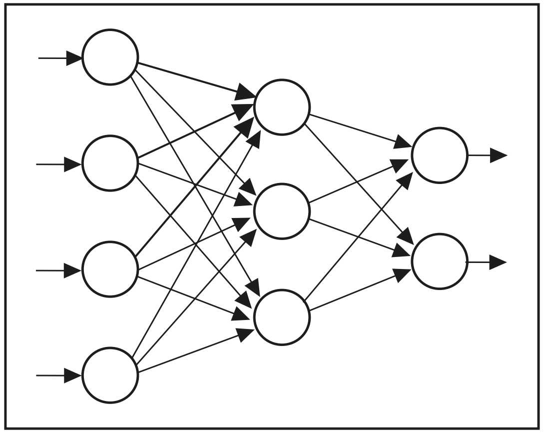
Haykin, S. (1994), Neural Networks: A Comprehen- sive Foundation, NY: Macmillan, p. 2:

A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects:

1. ***Knowledge is acquired through a learning process.***
2. ***Neuron weights are used to store the knowledge.***

Supervised Problems. Input-Output pairs are provided:
(x1,y1), (x2,y2), ..., (xn,yn) and the network learns y = f(x+ε).

***Multilayer* Networks or *Feedforward* Nets.**
Several layers connected (input+hidden+output)



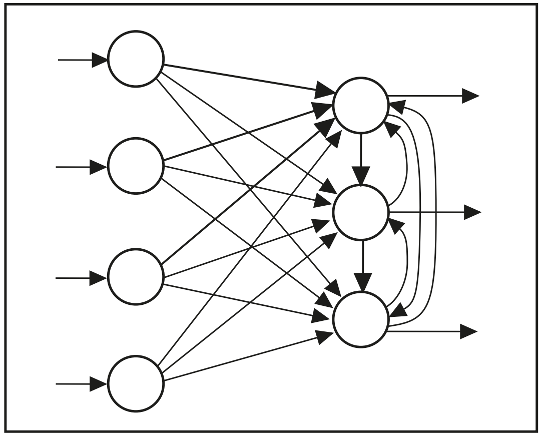
Pattern Recognition
OCR, images
Interpolation and fitting

Prediction: Input => Output

Learning: Backpropagation

Unsupervised Problems. Only input data is provided:
x1, x2, ..., xn and the network self-organizes it to provide a clustering.

***Competitive* Networks**
Multilayer networks with lateral connections (competitive) in the last layer.



Segmentation

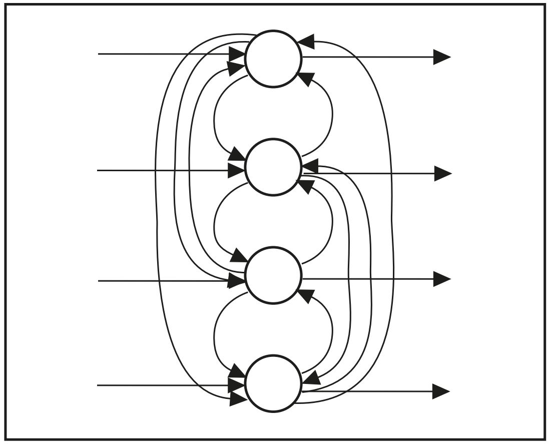
Feature extraction.

Prediction: Input => Clusters

Learning: Ad hoc
Winner-takes-all

Supervised Problems. Input-Input pairs are provided:
(x1,x1), (x2,x2), ..., (xn,xn) and the network learns $x = f(x+\varepsilon)$.

Autoassociative memories (Hopfield).
Single layer with lateral delayed connections.



Pattern Recognition
OCR, images
Memories (robust to noise)

Prediction: Input => Input

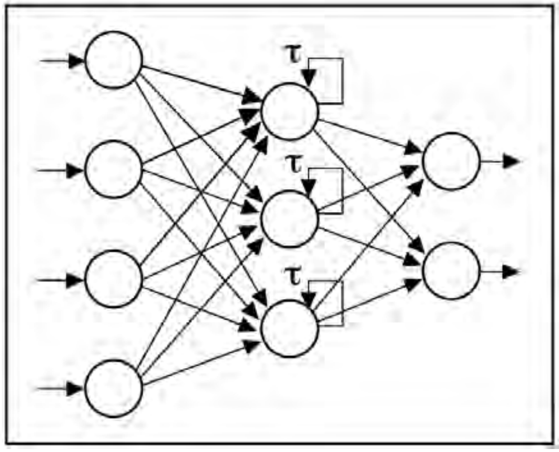
Learning: Hegg

Autoencoders (later)

Feature extraction, compression.

Supervised Problems (with memory). Input-Output pairs are provided:
(x1,y1), (x2,y2), ..., (xn,yn) and the network learns $y_t = f(x_{t-1,t-2,\ldots}+\varepsilon)$.

Recurrent Networks or Elman/Jordan nets.
Multilayer network with hidden/output delayed lines.



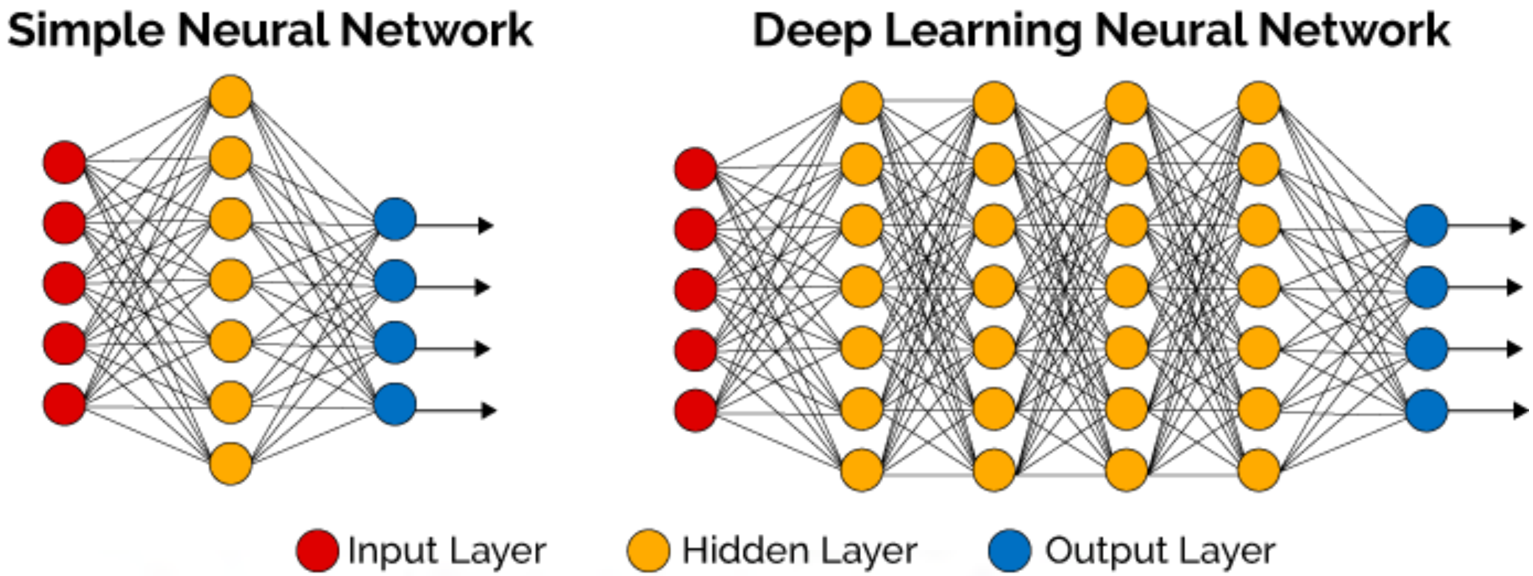
Time series analysis
Video, natural language
Interpolation and fitting

Prediction: Input => Output

Learning: Backpropagation in time

Deep Learning: Supervised and Reinforced Problems

(x1,y1), (x2,?), ..., (xn,yn) and the network self-organizes and learn y = f(x).



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

60000+10000 images 32x32

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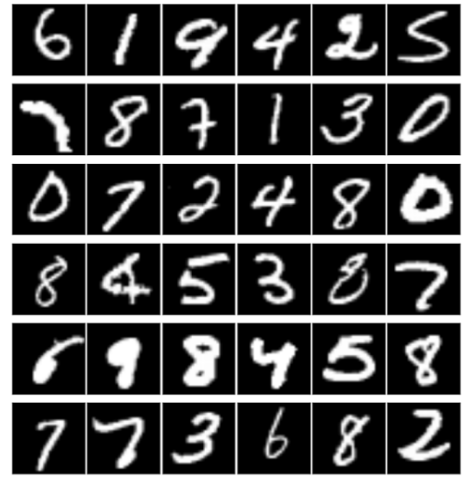

Lineal: 10%. k-NN: 3%. SVM: 1%.

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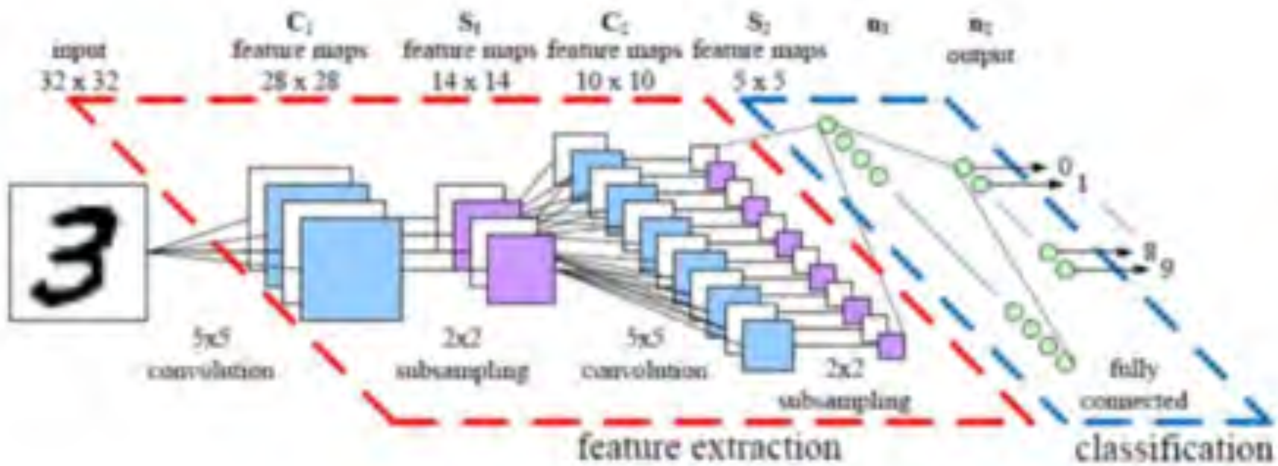
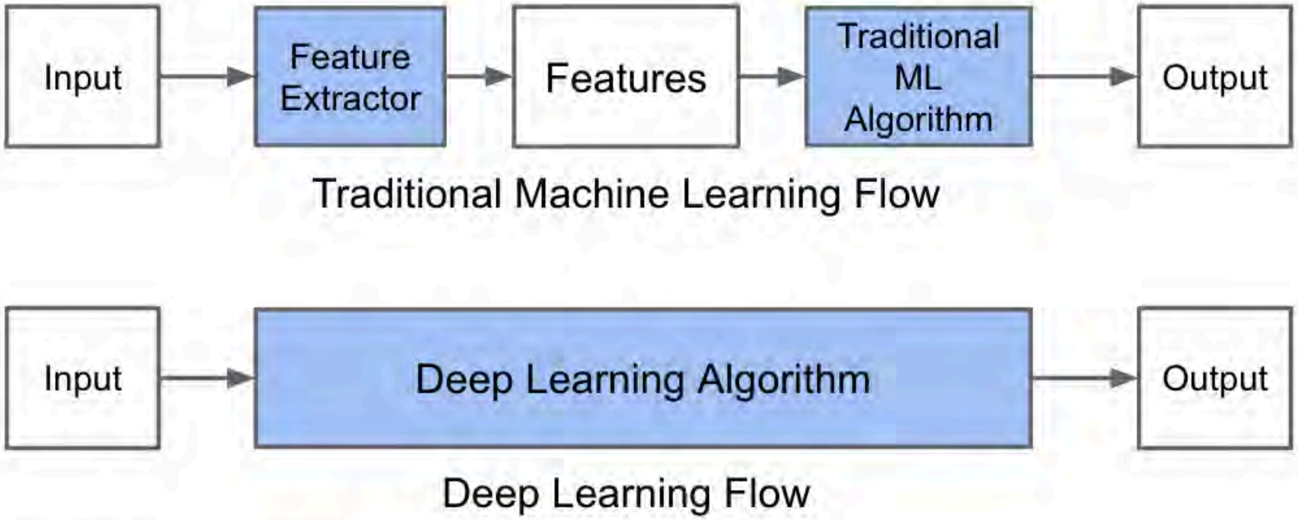


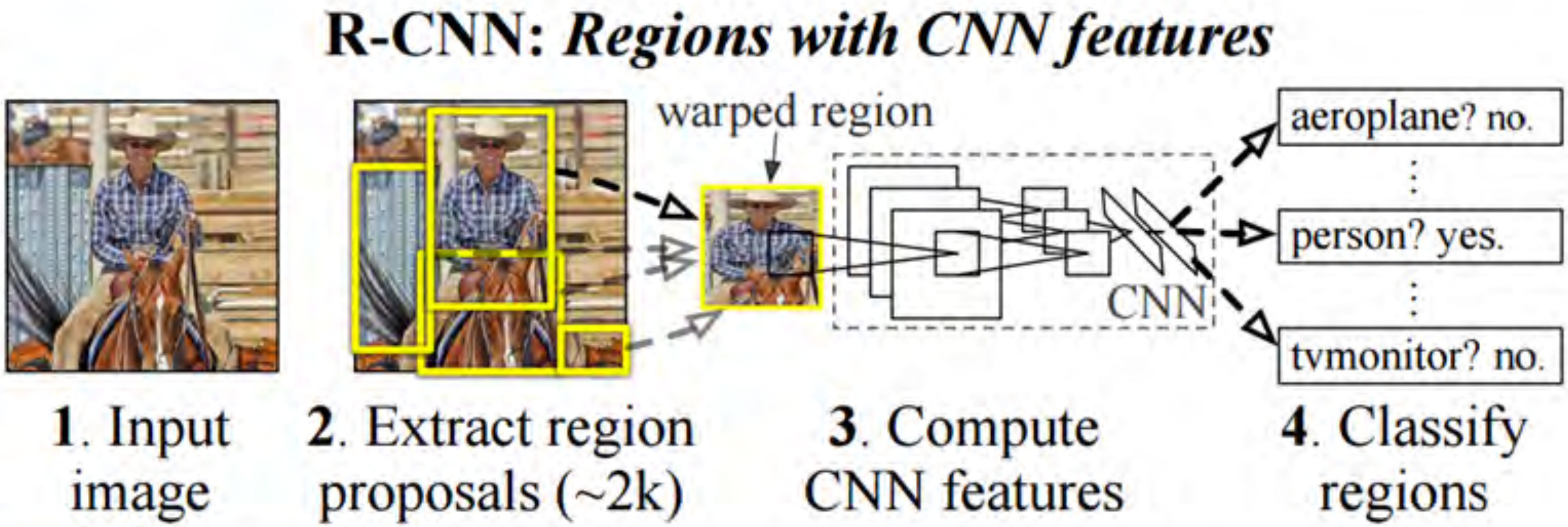
Include preprocessing layers for feature extraction:

- Convolutions
- Autoencoders

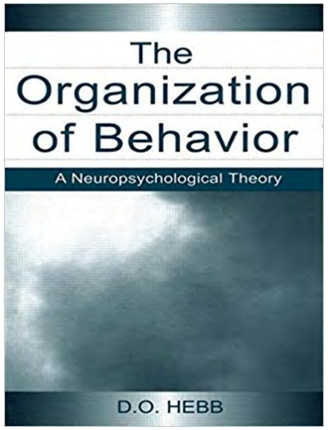
New optimization/learning.

http://www.kdnuggets.com/2017/08/convolutional-neural-networks-image-recognition.html





R-CNN workflow



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Letter

Learning representations by back-propagating errors

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

Nature **323**, 533–536 (09 October 1986)
doi:10.1038/323533a0
Download Citation

Received: 01 May 1986
Accepted: 31 July 1986
Published online: 09 October 1986

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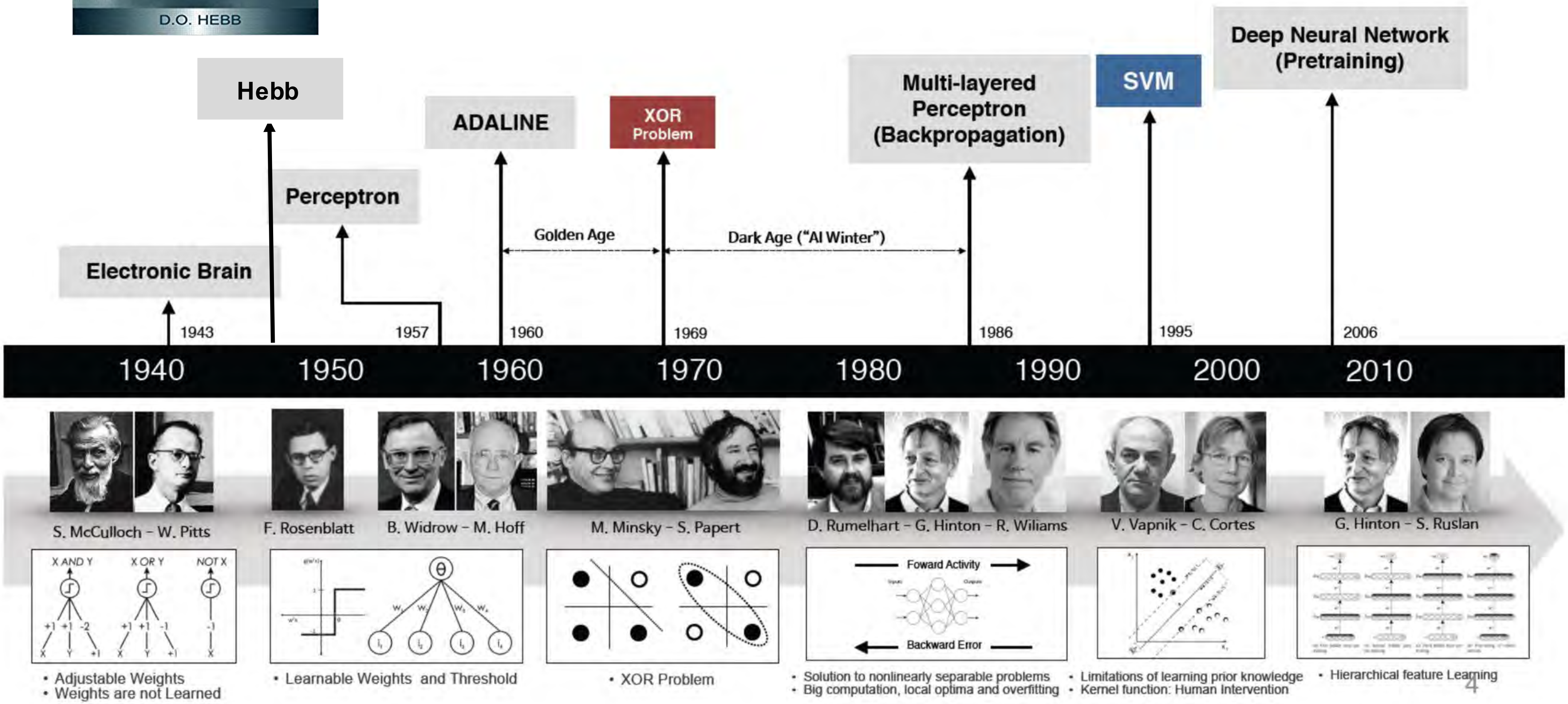
Review

Deep learning

Yann LeCun, Yoshua Bengio & Geoffrey Hinton

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

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



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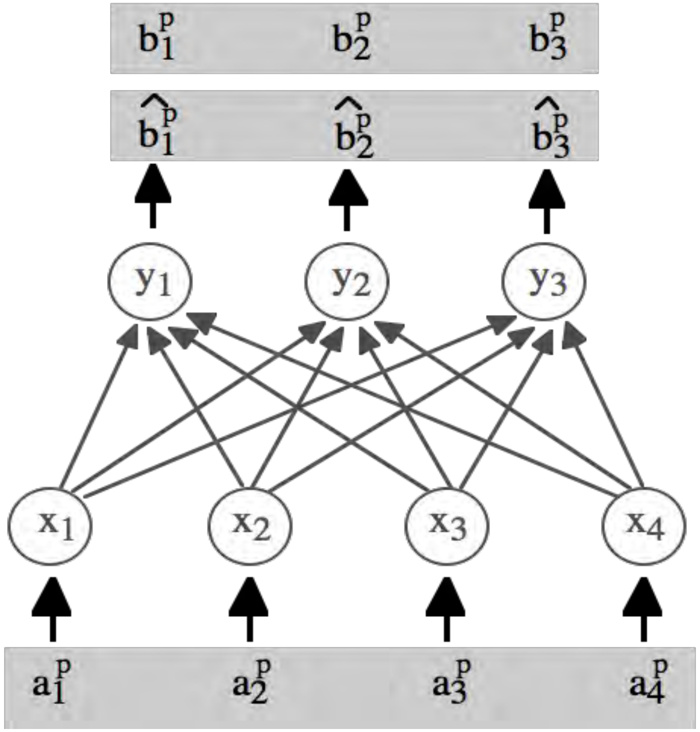
NEURAL NET: HISTORY



$$E(w) = \frac{1}{2}\sum_{i,p}(b_i^p - \hat{b}_i^p)^2.$$

Inicialmente se eligen valores aleatorios para los pesos.

Aprendizaje Hebbiano (1949): Se modifican los pesos acorde a la correlación entre las unidades. Se eligen los patrones (a^p, b^p) de uno en uno y se modifican los pesos de los nodos con salidas incorrectas:

$$\Delta w_{ij} = \eta(b_i^p - \hat{b}_i^p)a_j^p$$

Descenso de gradiente: Se modifican los pesos acorde la dirección del gradiente del error.

$$\Delta w_{ij} = -\eta\frac{\partial E}{\partial w_{ij}} = \eta\sum_p(b_i^p - \hat{b}_i^p)f'(B_i^p)a_j^p$$

η : Tasa de aprendizaje

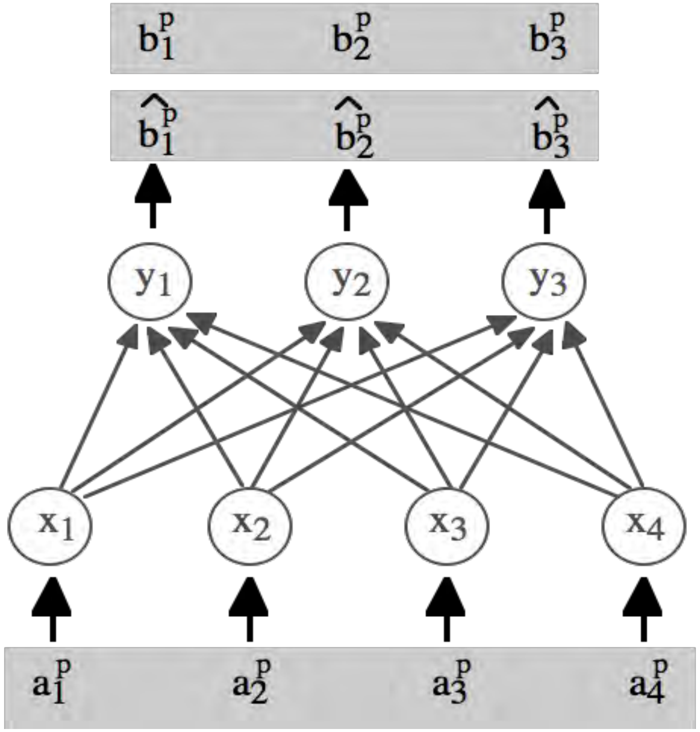
Inercia

$$\Delta w_{ij}(t+1) = -\eta\frac{\partial E}{\partial w_{ij}} + \alpha\Delta w_{ij}(t-1)$$

Regularización

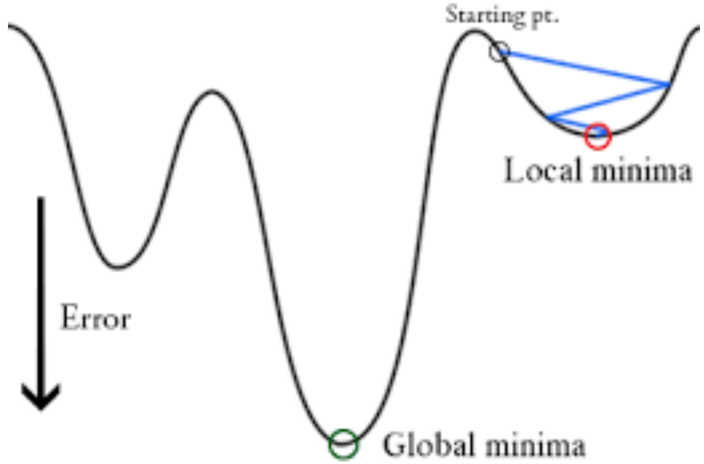
$$E(w) = \sum_{p=1}^{r}(y_p - \hat{y}_p)^2 + \lambda\sum_{i,j}w_{ij}^2$$

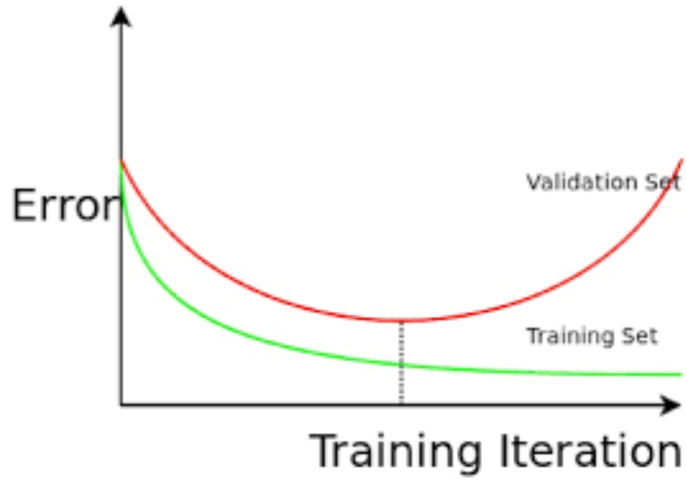
RSNNS

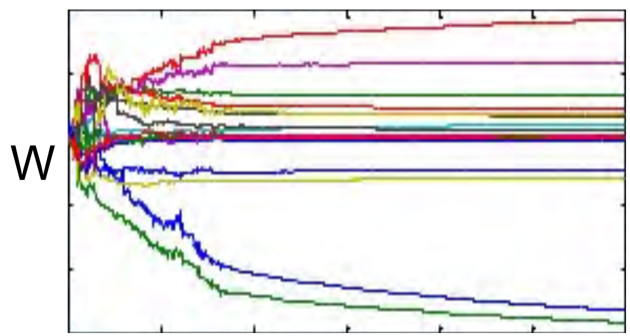


$$E(w) = \frac{1}{2}\sum_{i,p}(b_i^p - \hat{b}_i^p)^2.$$

Overfiting is a critical problem in neural networks. The network should be carefully designed and/or **early stopping** learning should be adopted.





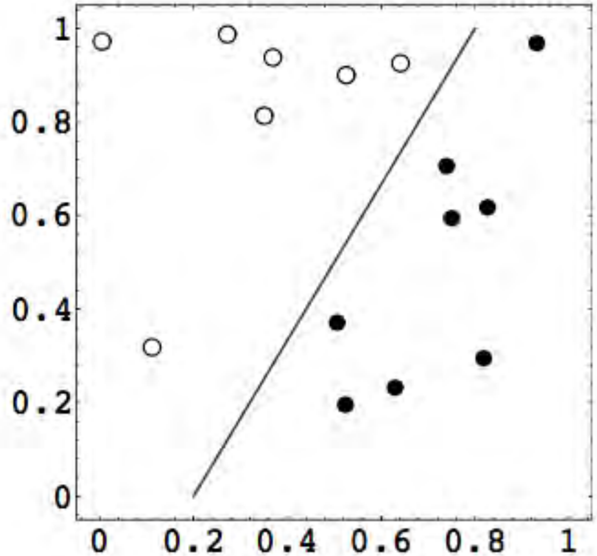


Error functions can be **highly nonlinear** and optimization can get trapped in local minima.

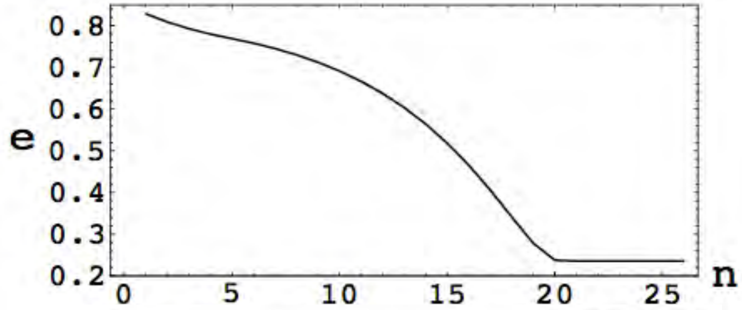
Several **replications** of the learning process are necessary (from different random initial weights).

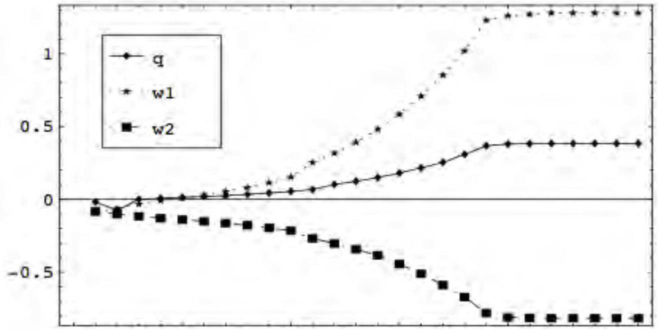
This process can be very **time consuming**.

Recent **advances** mitigate these problems.

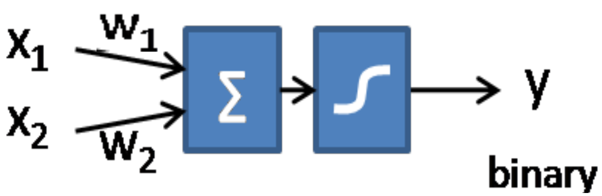


$$c_i = w_1 x_i + w_2 y_i + q,$$





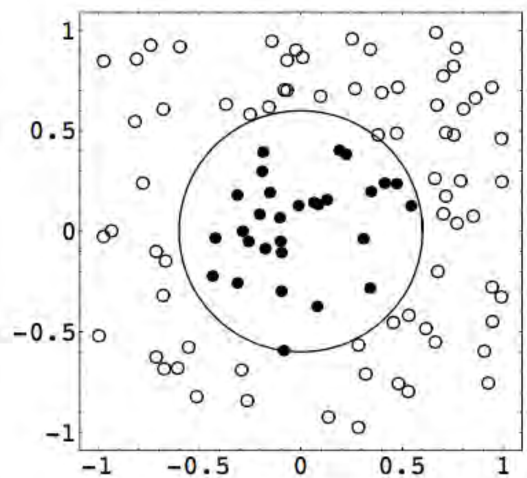
$$c_i = 1.28 x_i - 0.815 y_i + 0.384.$$



y = f(**X**,**W**) = sigmod(**X**^{T}.**W**)

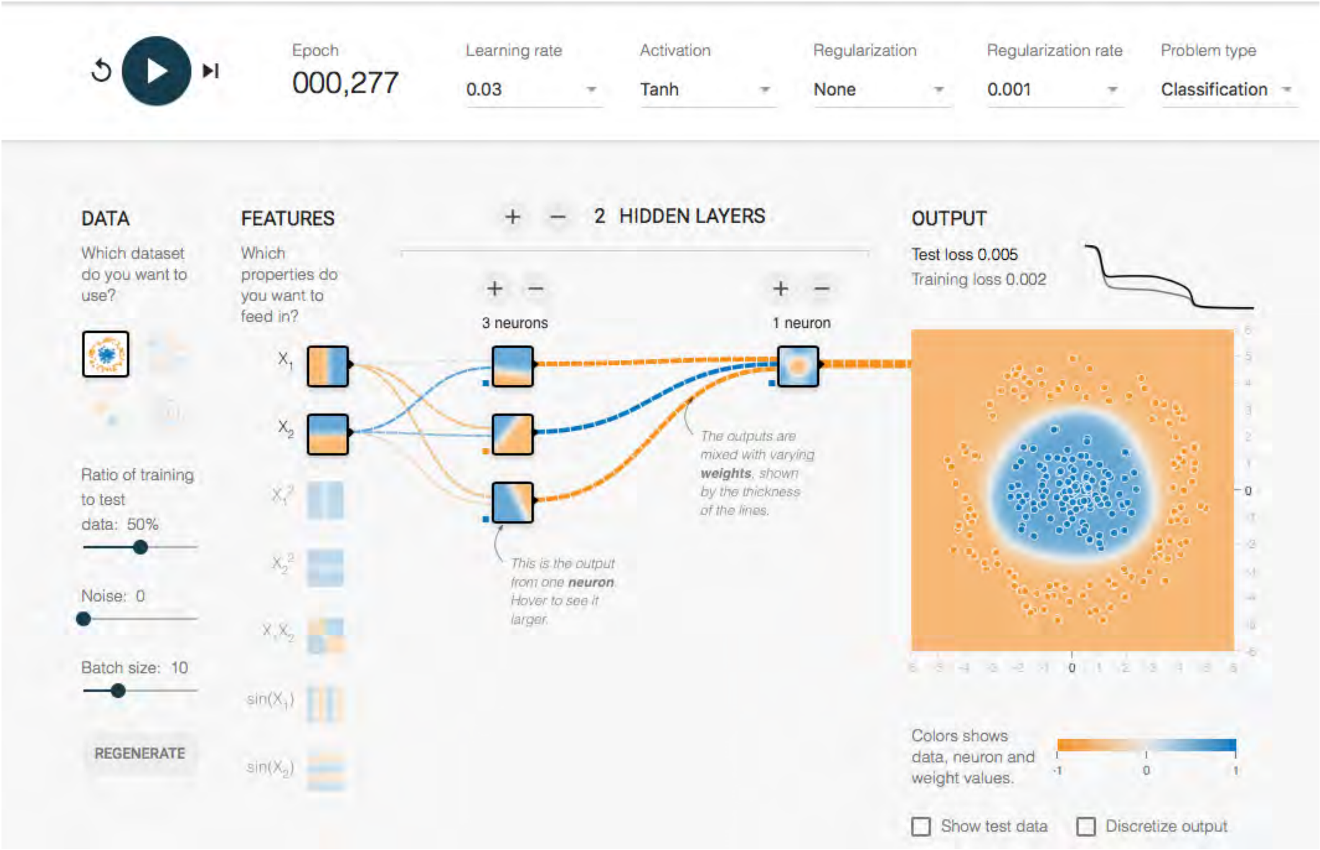
LOGISTIC REGRESSION

Single-layer networks cannot approximate nonlinear problems.



1. Watch an introductory video (19') on multi-layer neural networks.
2. Play around with the tensorflow illustrative tool.

Introductory video: https://www.youtube.com/watch?v=aircAruvnKk



http://playground.tensorflow.org/