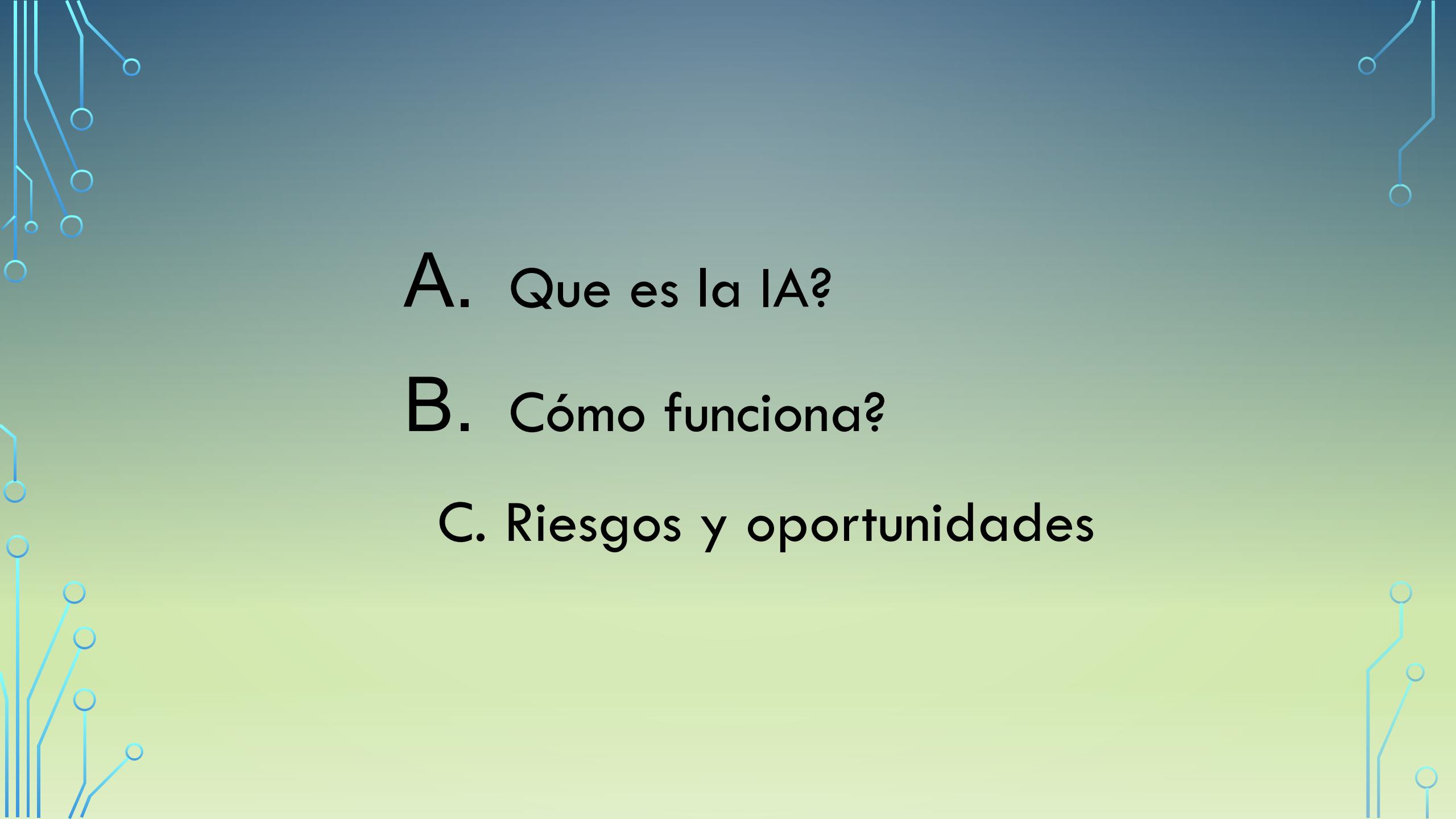


ABC DE LA INTELIGENCIA ARTIFICIAL

Raúl Benítez
raul.benitez@upc.edu

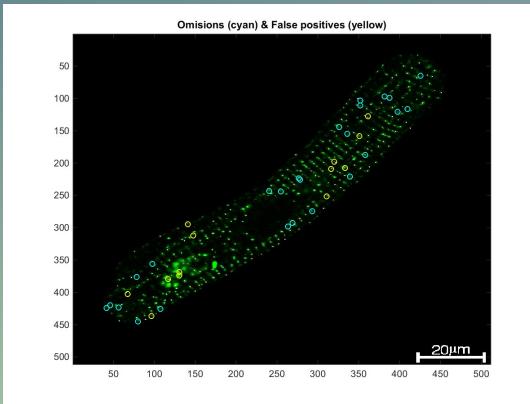


- 
- A. Que es la IA?
- B. Cómo funciona?
- C. Riesgos y oportunidades

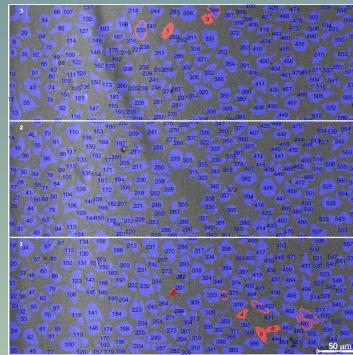
ANÁLISIS DE IMÁGENES MEDICINA Y BIOLOGÍA

Anatomia patológica

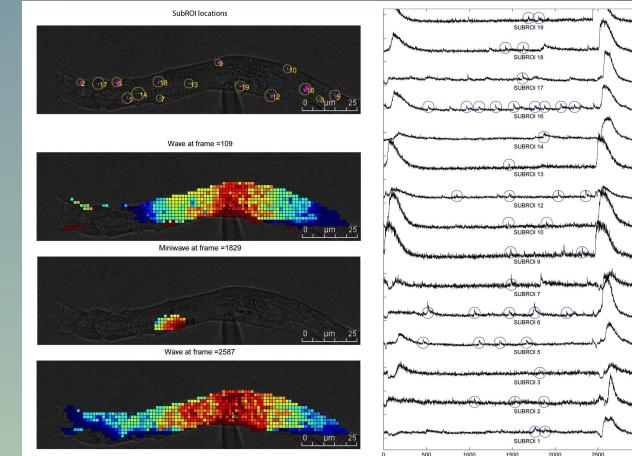
Receptores moleculares



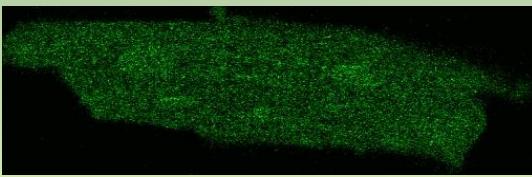
Cultivos celulares



Dinámica de calcio intracelular



Eventos dinámicos

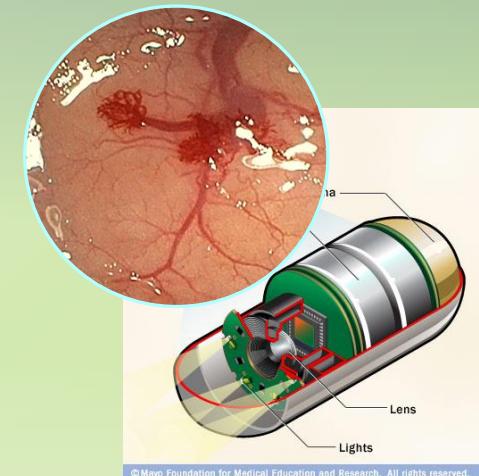


Transporte de mitocondrias

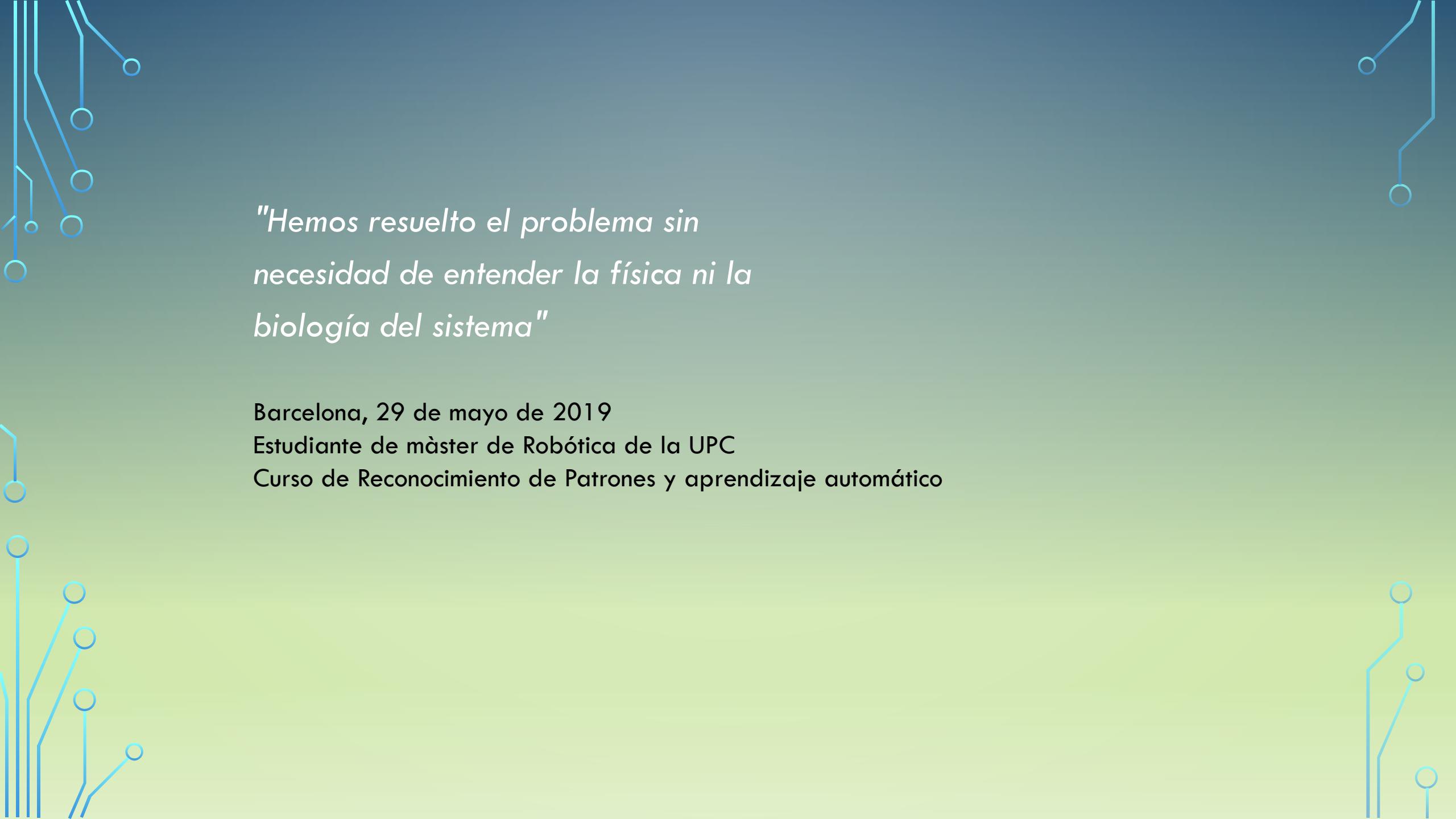


Extracción de biomarcadores funcionales multiescalas

Endoscopia



A. QUÉ ES LA IA?

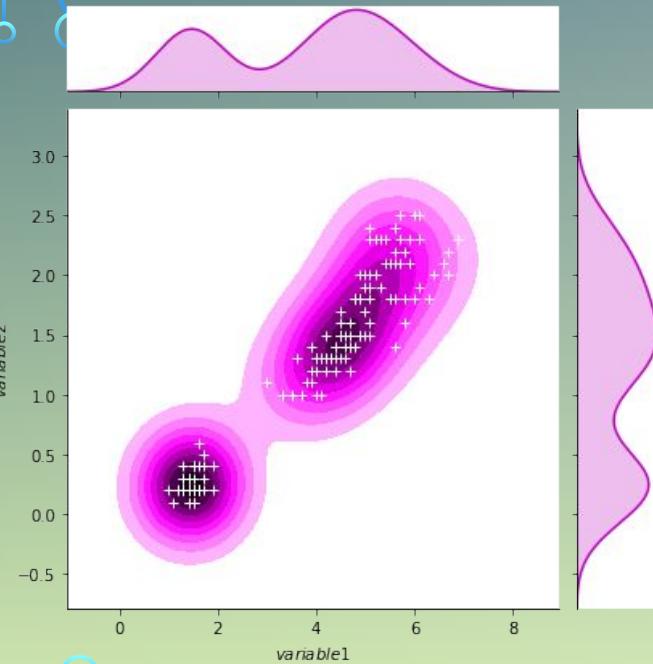


*"Hemos resuelto el problema sin
necesidad de entender la física ni la
biología del sistema"*

Barcelona, 29 de mayo de 2019
Estudiante de màster de Robòtica de la UPC
Curso de Reconocimiento de Patrones y aprendizaje automático

artificial Intelligence
data analysis
machine learning
unsupervised learning
pattern recognition
data modeling
expert systems
statistical inference
deep learning
big data
business intelligence
knowledge retrieval
cybernetics
data analytics

Datos



Textos
Imágenes
Datos numéricos multivariados
Datos genética
Señales temporales (audio, video)
DATOS HETEROGÉNEOS

Matemáticas

$$\begin{aligned} p(\mathcal{D}|\theta) &= p(x_1, x_2, \dots, x_n | \mu, \sigma^2) \\ &= \prod_{i=1}^n p(x_i | \theta) \\ &= \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x_i - \mu)^2}{2\sigma^2}\right) \\ &= \left(\frac{1}{2\pi\sigma^2}\right)^{\frac{n}{2}} \exp\left(-\frac{\sum_{i=1}^n (x_i - \mu)^2 + n(\frac{1}{n} \sum_{i=1}^n x_i - \mu)^2}{2\sigma^2}\right) \end{aligned}$$

Estadística
Geometría
Optimización
Procesos estocásticos

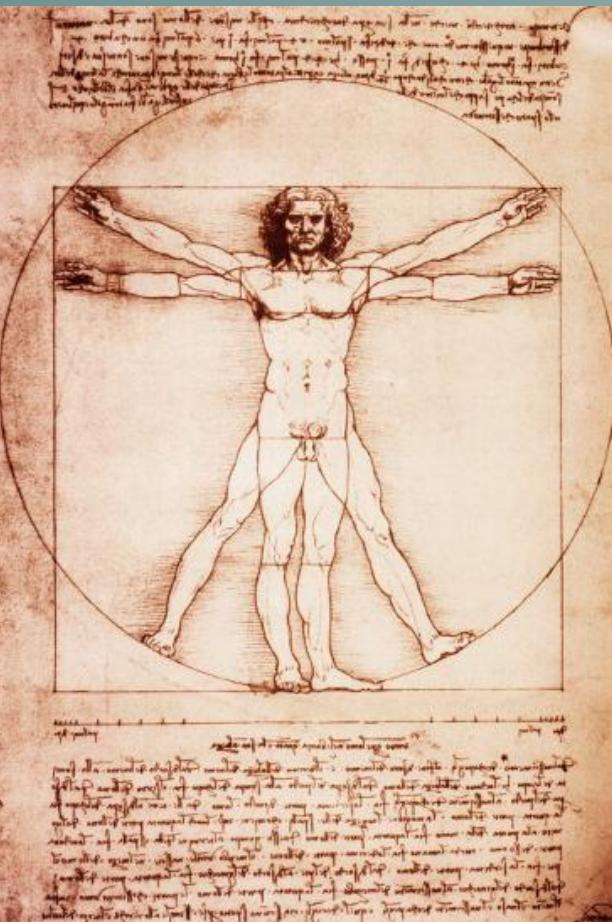
Informática

```
1 import numpy as np
2 from sklearn import decomposition
3 from sklearn import datasets
4
5 iris = datasets.load_iris()
6 X = iris.data
7 y = iris.target
8
9 pca = decomposition.PCA(n_components=2)
10 pca.fit(X)
11 Xproj = pca.transform(X)
```

Algorítmica
Complejidad computacional
Teoría de la información
Teoría de redes y grafos

Imitamos el cuerpo humano

Biomecánica del cuerpo humano



Robótica humanoide

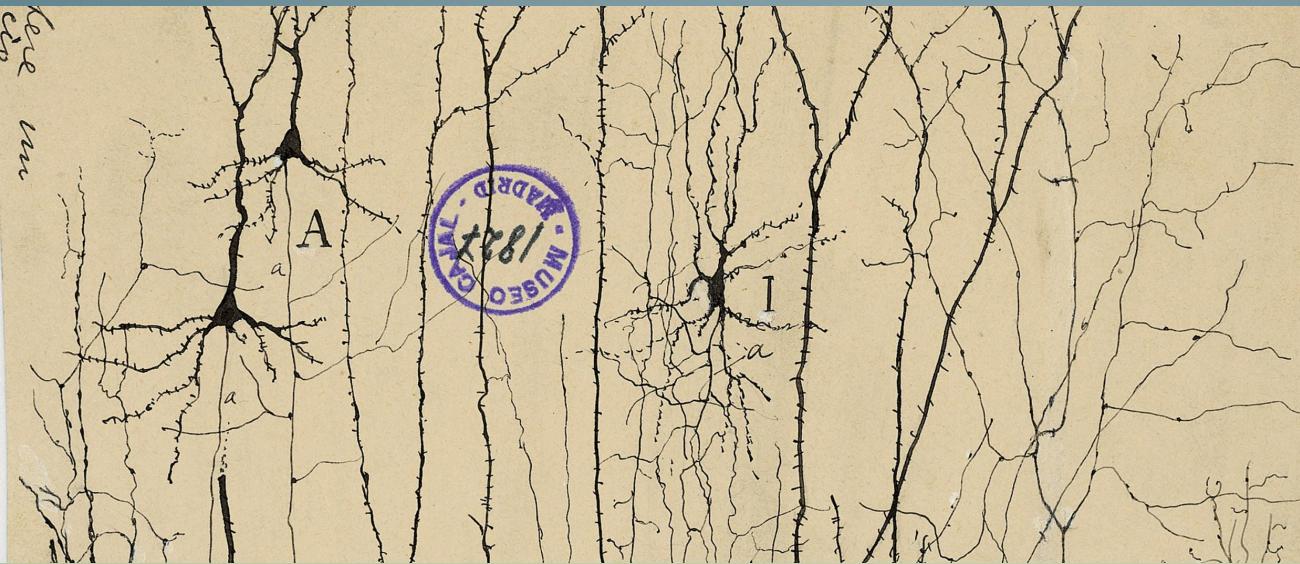


[imgflip.com](#)

Robótica



IMITAMOS LA MENTE HUMANA



Cajal & Golgi Nobel 1906

Aprendentatge Hebbià 1949

Hodkin & Huxley 1952 Nobel 1963

Hubel & Wiesel 1959 Cortex Visual Nobel 1981

Tecnología y IA

Calculadoras
mecánicas
(s.XVII)



Relé
electromecánico
(s. XIX)



Telégrafo
Eléctrico
1830



Máquina
Enigma
1918

Relé
electromecánico
(s. XIX)

Relé
electromecánico
(s. XIX)

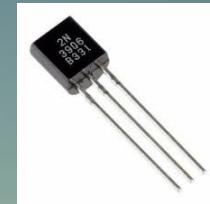
Válvula termoiónica
de vacío (1904)



ENIAC 1946



El transistor (1947)
Nobel 1956



IBM 608
1957



GPUs (2018)



IA hoy



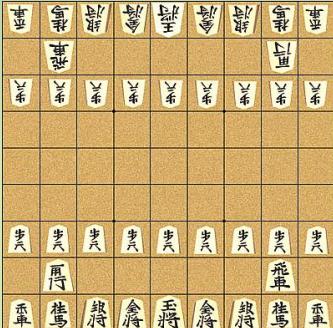
RESEARCH
COMPUTER SCIENCE

A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play

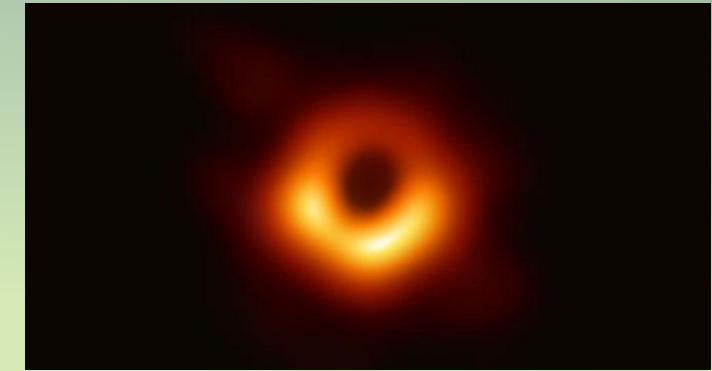
David Silver^{1,2*†}, Thomas Hubert^{1*}, Julian Schrittwieser^{1*}, Ioannis Antonoglou¹, Matthew Lai¹, Arthur Guez¹, Marc Lanctot¹, Laurent Sifre¹, Dharshan Kumaran¹, Thore Graepel¹, Timothy Lillicrap¹, Karen Simonyan¹, Demis Hassabis^{1,†}

The game of chess is the longest-studied domain in the history of artificial intelligence. The strongest programs are based on a combination of sophisticated search techniques, domain-specific adaptations, and handcrafted evaluation functions that have been refined by human experts over several decades. By contrast, the AlphaGo Zero program recently achieved superhuman performance in the game of Go by reinforcement learning from self-play. In this paper, we generalize this approach into a single AlphaZero algorithm that can achieve superhuman performance in many challenging games. Starting from random play and given no domain knowledge except the game rules, AlphaZero convincingly defeated a world champion program in the games of chess and shogi (Japanese chess), as well as Go.

Science, 362 (6419), 1140-1144 (2018)

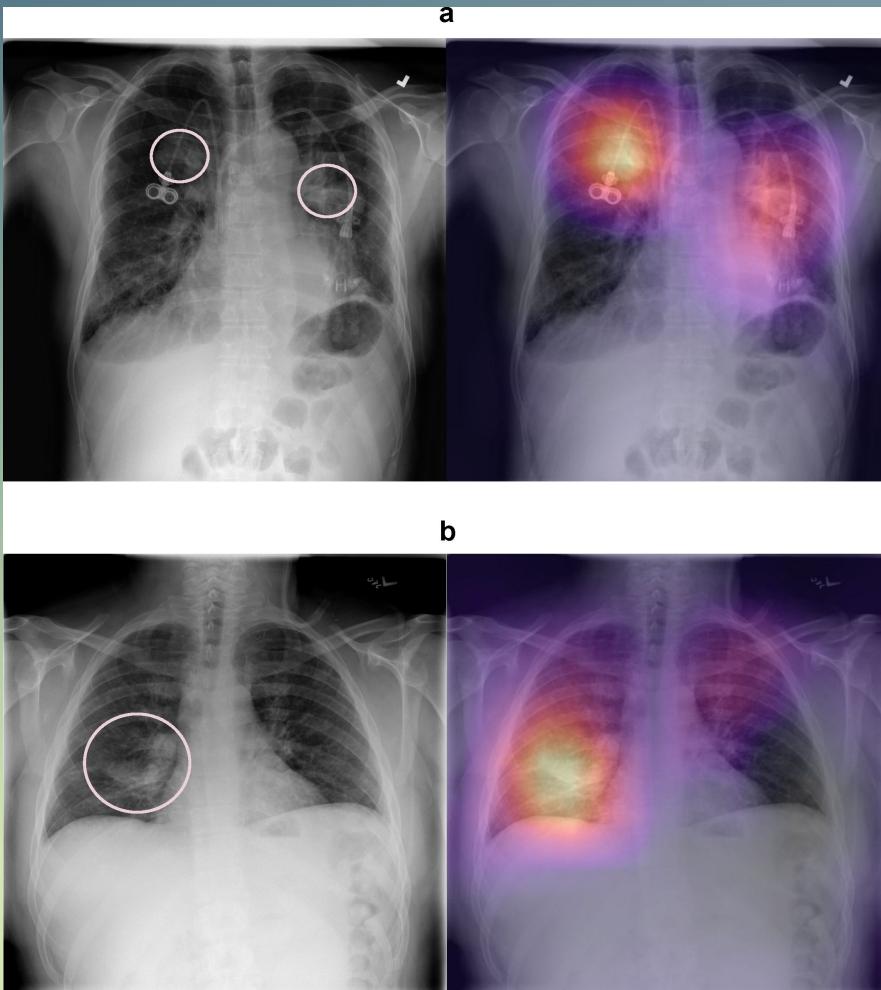


COMPLEJIDAD COMPUTACIONAL



Primera imagen de un agujero negro 2019
Event Horizon Telescope (EHT)
The Astrophysical Journal Letters

IA en medicina



14 patologías 69,682,060 parámetros

PLOS Medicine 15(11): e1002686 (2018)

PLOS MEDICINE

RESEARCH ARTICLE

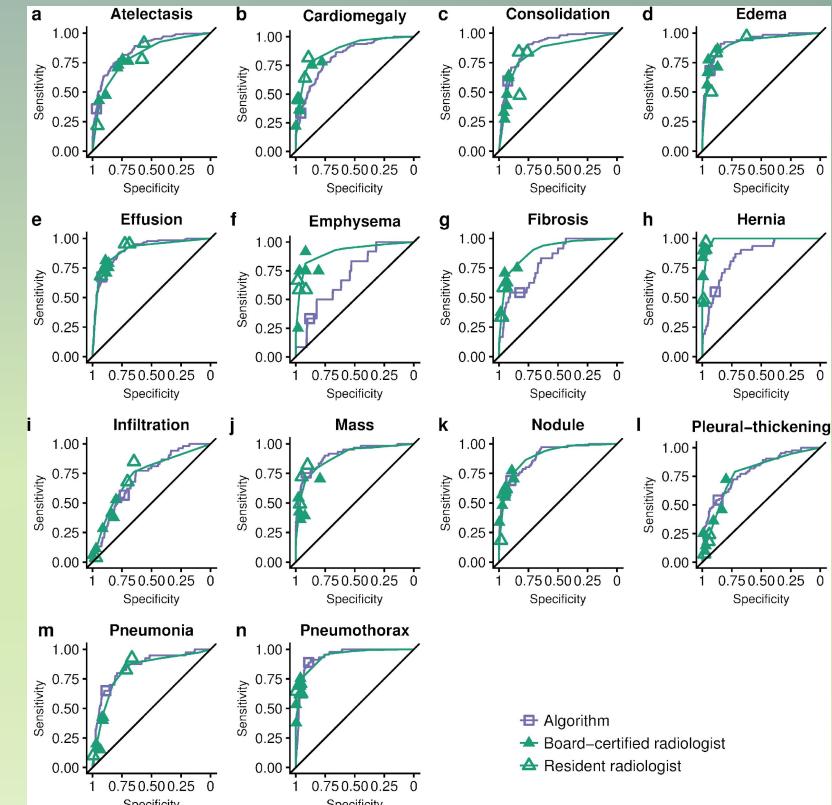
Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists

Pranav Rajpurkar^{1,2*}, Jeremy Irvin^{1,1†}, Robyn L. Bell², Kaylie Zhu¹, Brandon Yang¹, Hershel Mehta¹, Tony Duan¹, Daisy Ding¹, Aarti Bagul¹, Curtis P. Langlotz^{3,4}, Bhavik N. Patel⁵, Kristen W. Yeom³, Katie Shpanskaya³, Francis G. Blankenberg³, Jayne Seekins³, Timothy J. Amrein³, David A. Mong³, Sawsan S. Halabi³, Evan J. Zucker³, Andrew Y. Ng^{1,6}, Matthew P. Lungren^{3,6}

1 Department of Computer Science, Stanford University, Stanford, California, United States of America, 2 Department of Medicine, Quantitative Sciences Unit, Stanford University, Stanford, California, United States of America, 3 Department of Radiology, Stanford University, Stanford, California, United States of America, 4 Department of Radiology, Duke University, Durham, North Carolina, United States of America, 5 Department of Radiology, University of Colorado, Denver, Colorado, United States of America

* These authors contributed equally to this work.
†These authors share first authorship on, and contributed equally to, this work.
* pranavr@cs.stanford.edu

Check for updates

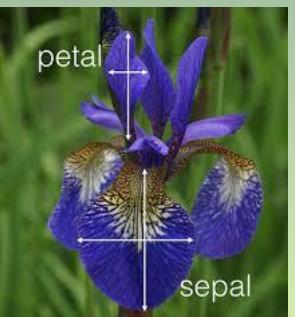


B. CÓMO FUNCIONA?

REPRESENTAR LOS DATOS MATEMÀTICAMENTE

A: m observations \times n features

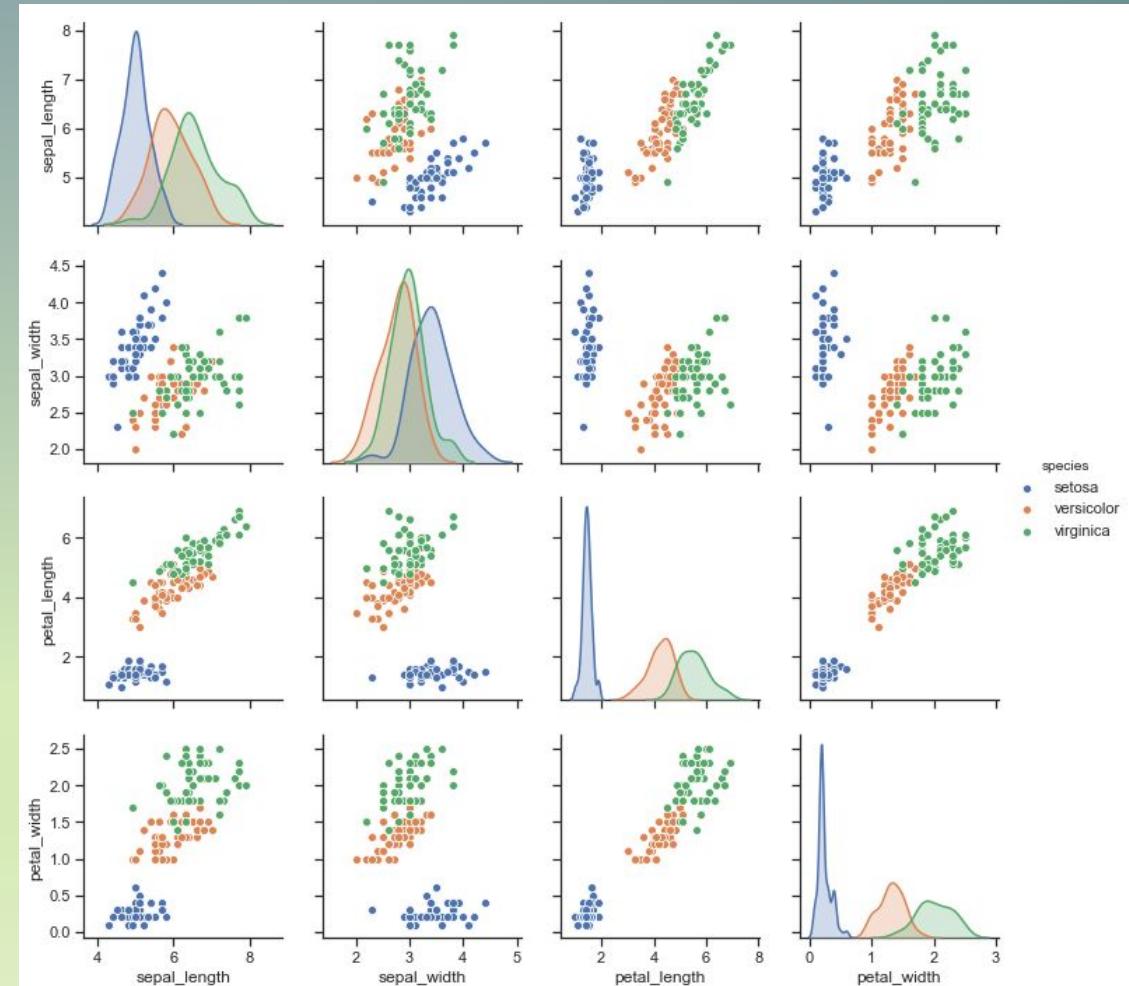
$$A_{m \times n} = \begin{pmatrix} x_1^1 & x_2^1 & \cdots & x_n^1 \\ x_1^2 & x_2^2 & \cdots & x_n^2 \\ x_1^3 & x_2^3 & \cdots & x_n^3 \\ \vdots & & & \\ x_1^m & x_2^m & \cdots & x_n^m \end{pmatrix}$$



	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa

Etiquetas de clase

$w(i)$

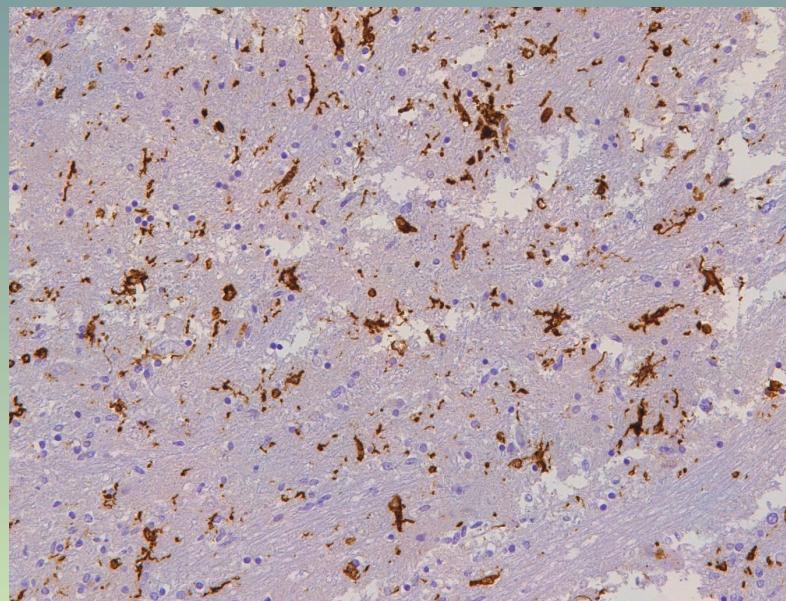


DATOS EN FORMA DE IMÁGENES

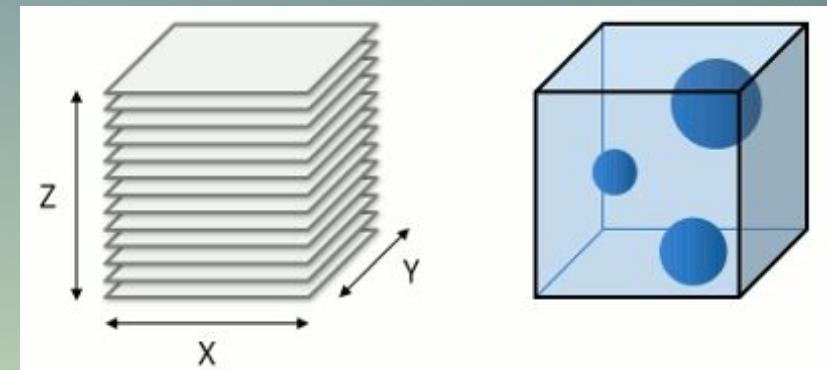
Escala de grises



Imágenes en color



volumenes 3D



Secuencias temporales 2D/3D

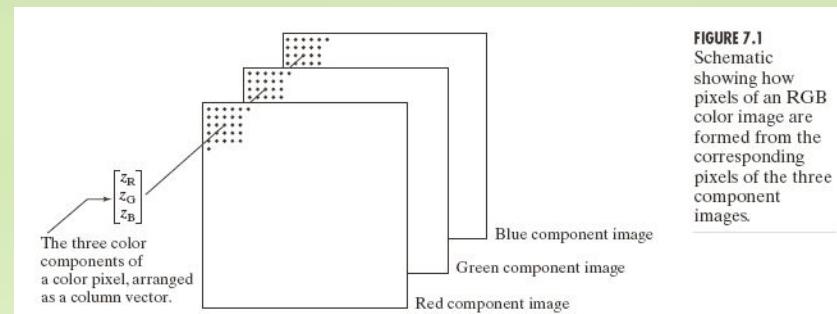
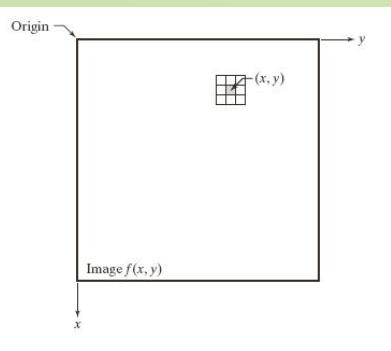
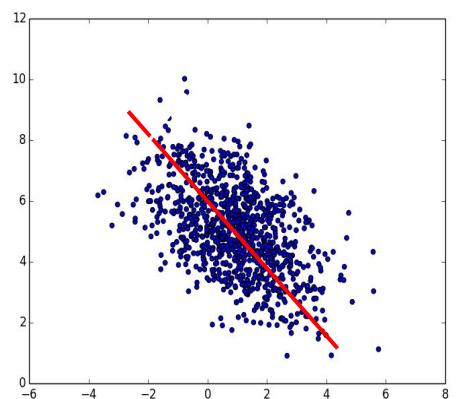


FIGURE 7.1
Schematic
showing how
pixels of an RGB
color image are
formed from the
corresponding
pixels of the three
component
images.

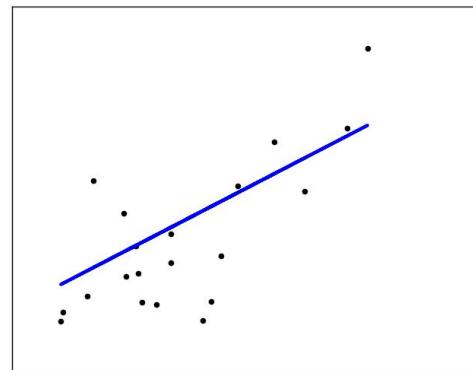
RECONOCIMIENTO DE PATRONES

DIMENSIONALITY REDUCTION



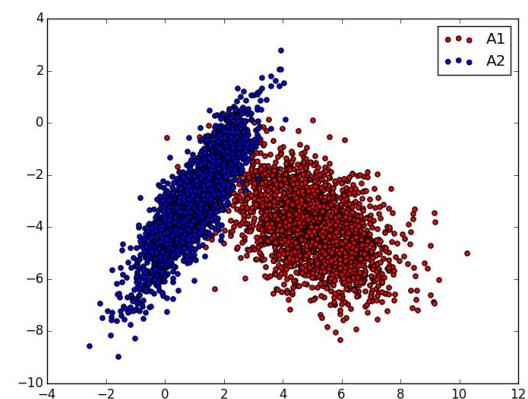
Principal Component Analysis
Singular Value Decomposition
Independent Component Analysis

MULTIVARIATE REGRESSION



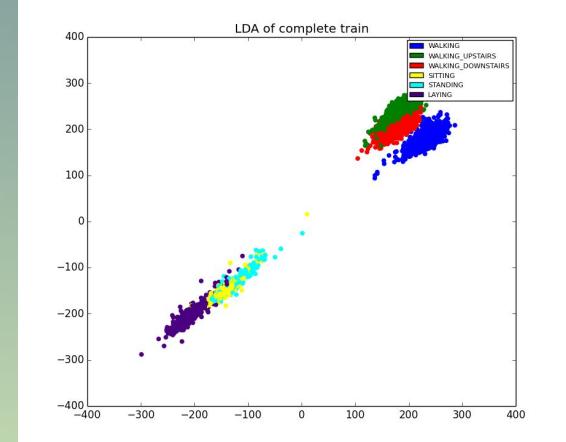
Multivariate linear regression
Regression using decision trees
Support Vector Machines

SUPERVISED CLASSIFICATION



Discriminant Analysis
Artificial Neural Networks
Support Vector Machines
Bayesian methods
Decision Trees
Ensemble classifiers
Deep Learning

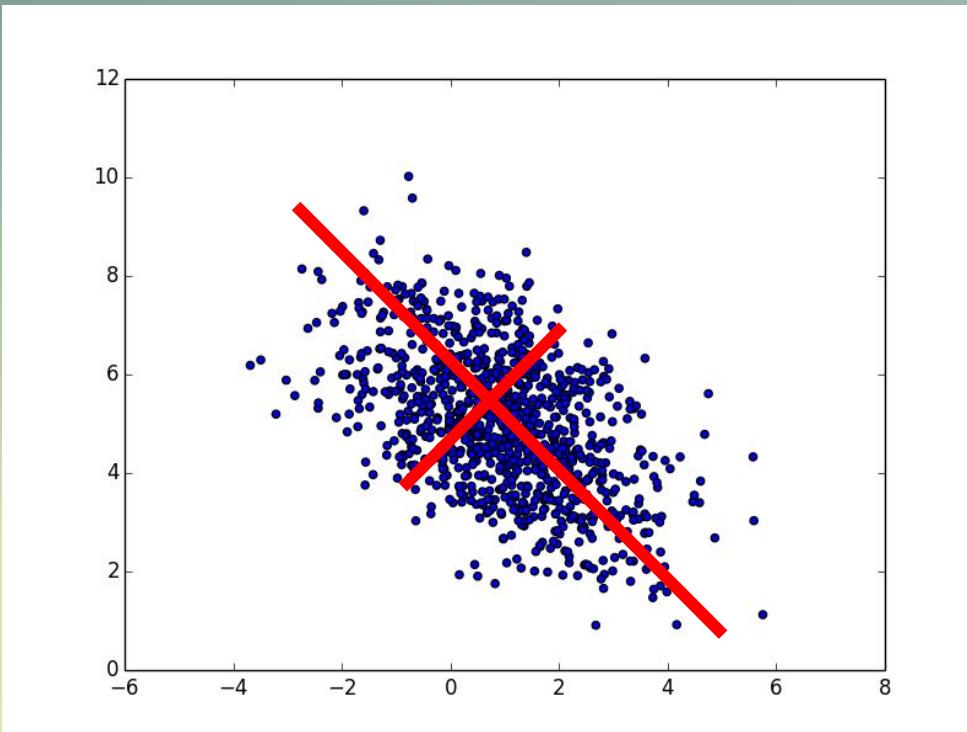
CLUSTER ANALYSIS



K-means
Hierarchical clustering
Gaussian Mixture Methods

EJEMPLO: REDUCCIÓN DE DIMENSIONALIDAD PRINCIPAL COMPONENT ANALYSIS (PCA)

Reduce dimensionality of data



Matemáticas

$$C_{n \times n} = (A - \bar{A})^T (A - \bar{A})$$

$$C \cdot \vec{v}_i = \lambda_i \cdot \vec{v}_i, \quad i = 1 \dots n$$

Informática



```
21 # Obtain covariance matrix:  
22 A1 = A - A.mean(0)  
23 matcov = dot(A1.transpose(),A1)  
24  
25 # Diagonalization of covariance matrix:  
26 valp,vecp = linalg.eig(mtcov)  
27  
28 ind_creciente = argsort(valp) # sort eigenvalues
```

APRENDIZAJE AUTOMÁTICO TRADICIONAL

Procesado de imágenes

Filtrado del ruido
Eliminación de artefactos

Segmentación
de estructuras

Extracción
de atributos

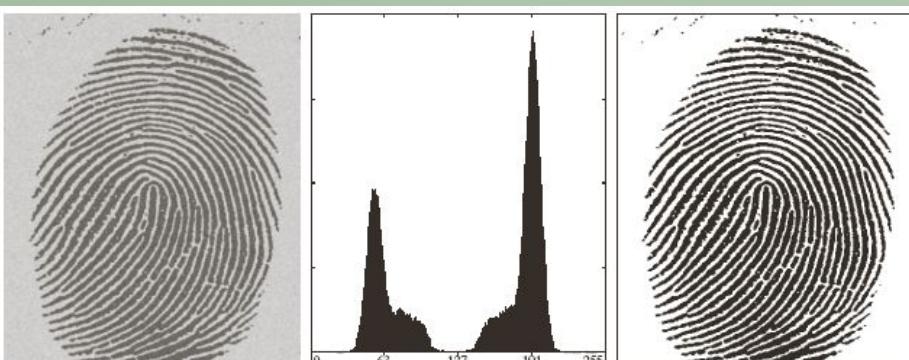


FIGURE 11.13 (a) Noisy fingerprint. (b) Histogram. (c) Segmented result using a global threshold (the border was added manually for clarity). (Original courtesy of the National Institute of Standards and Technology.)

biomarcadores



- Forma
- Tamaño
- Color
- Textura
- Orientación
- Contornos
- Intensidad

Reconocimiento de patrones

Classificación
supervisada

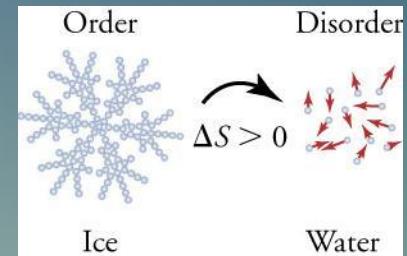
$$A_{m \times n} = \begin{pmatrix} x_1^1 & x_2^1 & \cdots & x_n^1 \\ x_1^2 & x_2^2 & \cdots & x_n^2 \\ x_1^3 & x_2^3 & \cdots & x_n^3 \\ \vdots & & & \\ x_1^m & x_2^m & \cdots & x_n^m \end{pmatrix} \quad w(i)$$

Fase 1: ENTRENAMIENTO
Fase 2: VALIDACIÓN

EJEMPLO DE ATRIBUTO: ENTROPIA

Física: Medida del desorden de un sistema

$$S = k \log W$$



Teoría de la información: Contenido información de un missatge

Conjunto de símbolos (alfabeto): $a_1, a_2, a_3, \dots, a_n$

Probabilidad de aparición de cada símbolo en el mensaje: $p_1, p_2, p_3, \dots, p_n$

$$S = - \sum_{i=1}^n p_i \log p_i$$

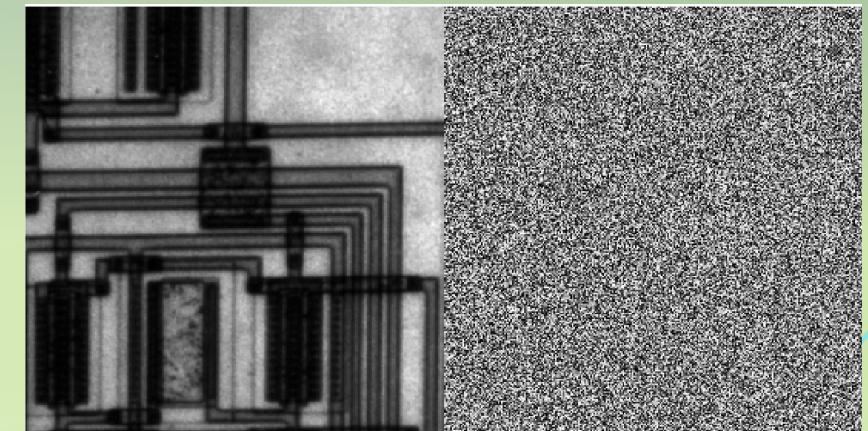
$$S = 6.9439 \text{ bits/pixel}$$

$$S = 8 \text{ bits/pixel}$$

Ejemplo: Imagen escala de grises

Alfabeto: niveles de intensidad de grises $0, 1, 2, \dots, 255$

Probabilidad de aparición: Histograma $p_1, p_2, p_3, \dots, p_n$



Entropía menor ➔ se requieren menos bits per codificar-la ➔ compresión de imágenes

CLASSIFICACIÓN AUTOMÁTICA DE IMÁGENES



Base de dades imágenes etiquetadas

- **Imágenes** $I(i), i = 1, \dots N_{im}$
- **Etiquetas de clase** (nombre, feliz/triste, enfermo/sano, etc.) $w(i)$

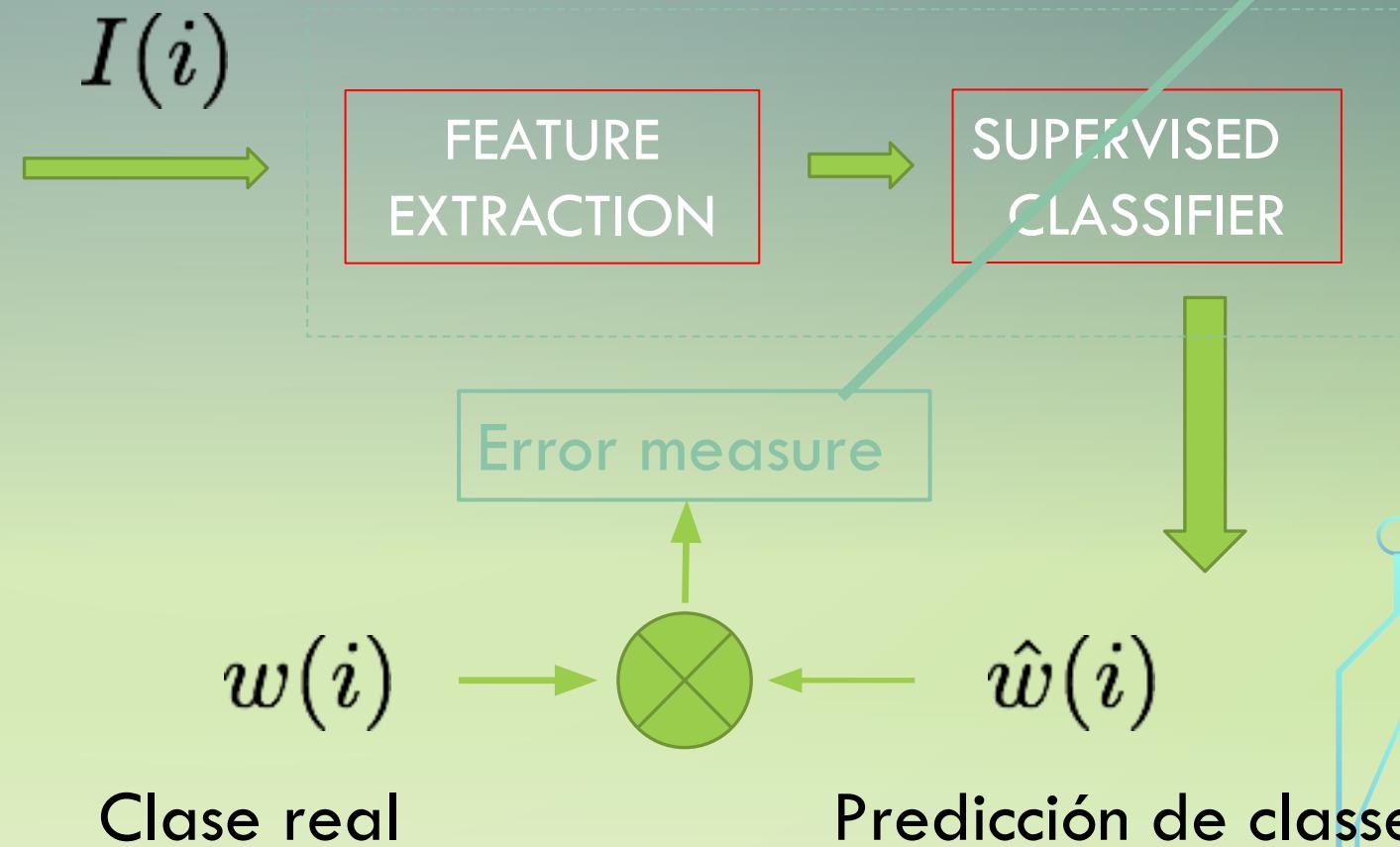
Representar la variabilidad intra i inter-classe (100-1000 imágenes)

70% Conjunto de entrenamiento / 30% conjunto de validación

LA FASE D'ENTRENAMENT

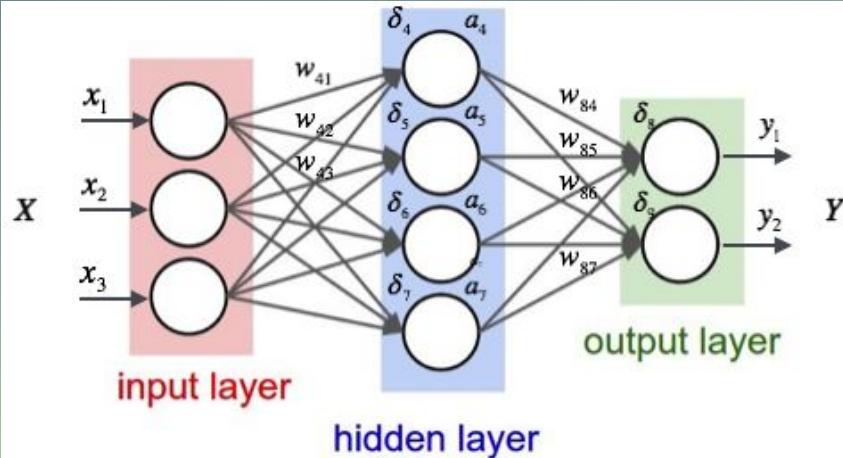


Conjunto
entrenamiento

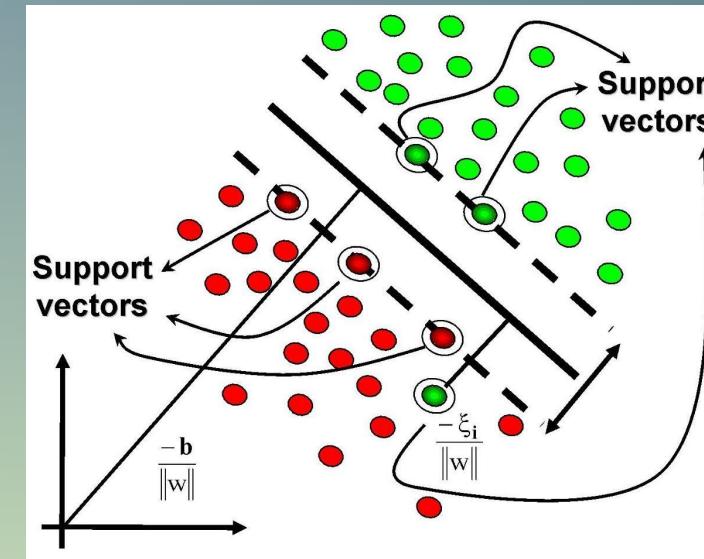


DIFERENTES CLASSIFICADORES SUPERVISADOS

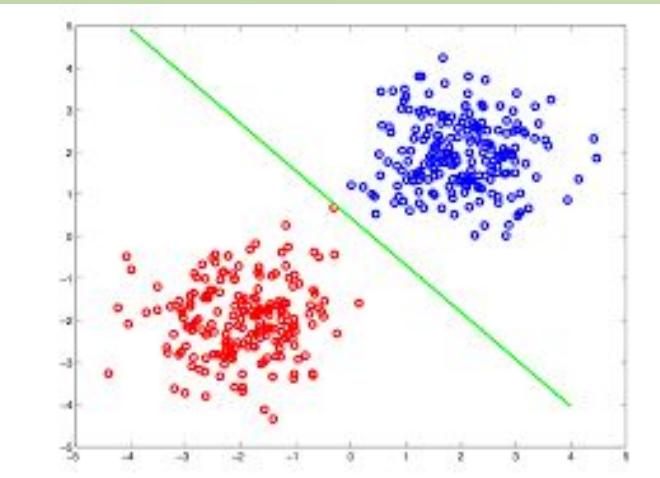
Redes Neuronales



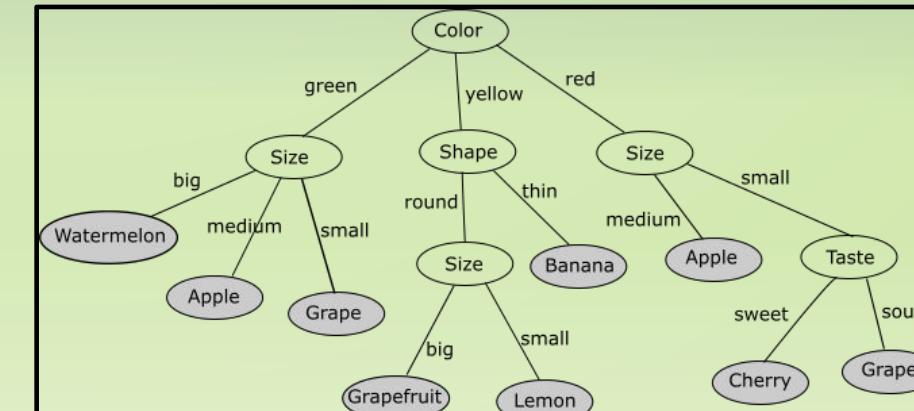
Support Vector Machines



Discriminantes probabilísticos



Árboles de decisión



FASE DE VALIDACIÓN

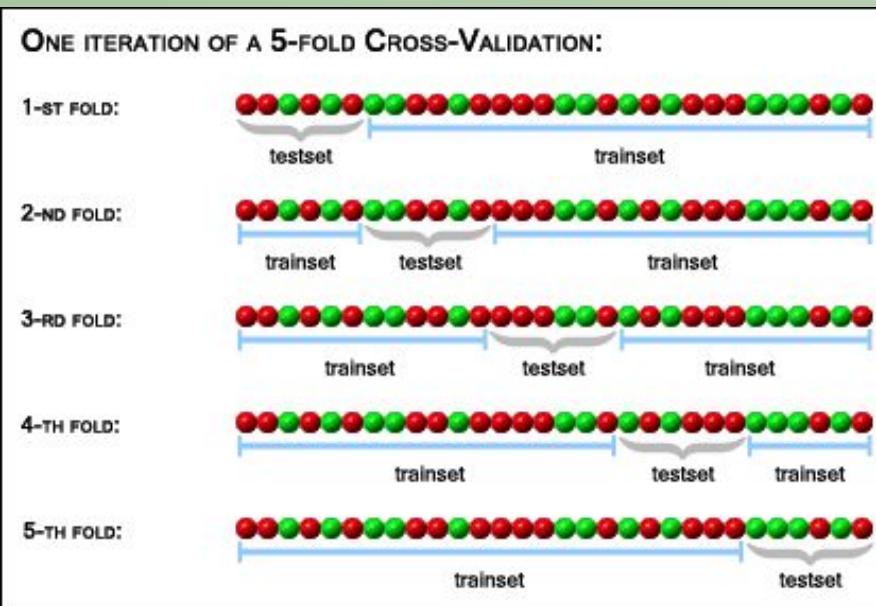


$I(i)$

FEATURE
EXTRACTION

SUPERVISED
CLASSIFIER

Conjunt de validació



$w(i)$

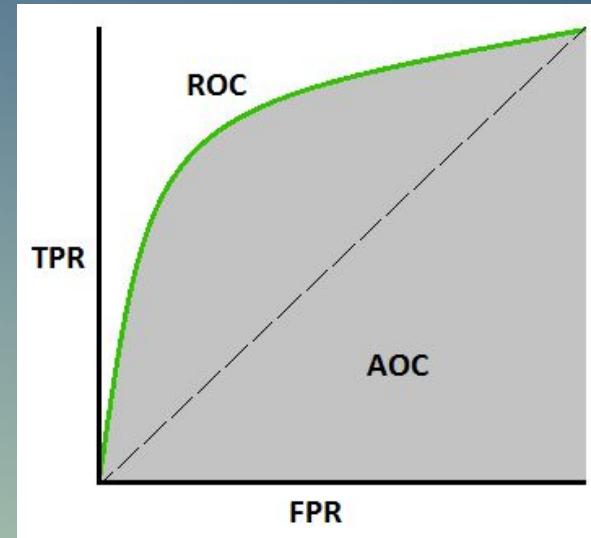
Clase
real

$\hat{w}(i)$

Predictió
de
clase

Medidas de error

MEDIDAS DE ERROR EN LA CLASIFICACIÓN



		True condition				
		Total population	Condition positive	Condition negative	Prevalence = $\frac{\sum \text{Condition positive}}{\sum \text{Total population}}$	Accuracy (ACC) = $\frac{\sum \text{True positive} + \sum \text{True negative}}{\sum \text{Total population}}$
Predicted condition	Predicted condition positive	True positive	False positive, Type I error	Falsa alarma	Positive predictive value (PPV), Precision = $\frac{\sum \text{True positive}}{\sum \text{Predicted condition positive}}$	False discovery rate (FDR) = $\frac{\sum \text{False positive}}{\sum \text{Predicted condition positive}}$
	Predicted condition negative	False negative, Type II error	Omissió	True negative	False omission rate (FOR) = $\frac{\sum \text{False negative}}{\sum \text{Predicted condition negative}}$	Negative predictive value (NPV) = $\frac{\sum \text{True negative}}{\sum \text{Predicted condition negative}}$
		True positive rate (TPR), Recall, Sensitivity, probability of detection, Power $= \frac{\sum \text{True positive}}{\sum \text{Condition positive}}$	False positive rate (FPR), Fall-out, probability of false alarm $= \frac{\sum \text{False positive}}{\sum \text{Condition negative}}$	Positive likelihood ratio (LR+) = $\frac{\text{TPR}}{\text{FPR}}$	Diagnostic odds ratio (DOR) = $\frac{\text{LR+}}{\text{LR-}}$	F_1 score = $2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$
		False negative rate (FNR), Miss rate $= \frac{\sum \text{False negative}}{\sum \text{Condition positive}}$	Specificity (SPC), Selectivity, True negative rate (TNR) = $\frac{\sum \text{True negative}}{\sum \text{Condition negative}}$	Negative likelihood ratio (LR-) = $\frac{\text{FNR}}{\text{TNR}}$		

Ejemplo: Reconocimiento de planos ecográficos

Dades:

Fetal ultrasound 1st trimester
506 RGB Images of size 960x720 pixels / class
3 class labels (fetal planes BPD, CLR, NT)



BPD - Biparietal Diameter



CLR - Crown-Rump-Length



NT - Nuchal translucency



CONJUNTOS ENTRENAMIENTO Y TEST

	BPD	CLR	NT
Training	406	406	406
Test	100	100	100
Total	506	506	506

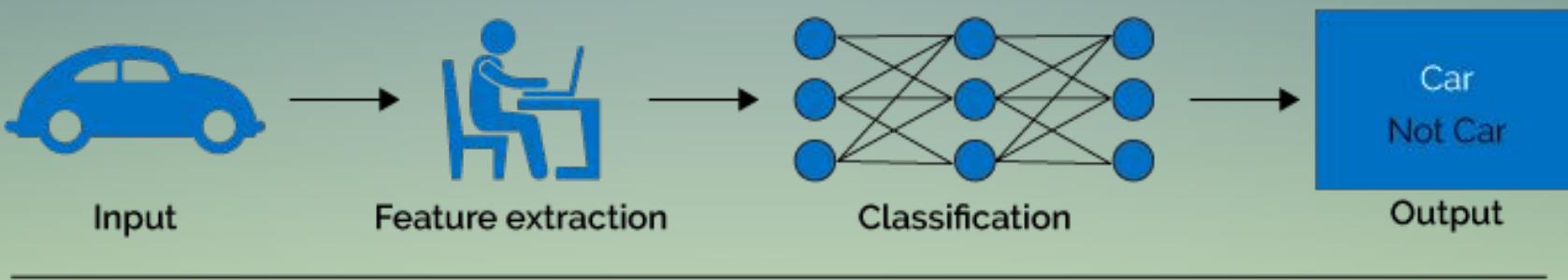
REAL

	BPD	CLR	NT
BPD	95	4	1
CLR	1	97	2
NT	2	6	92

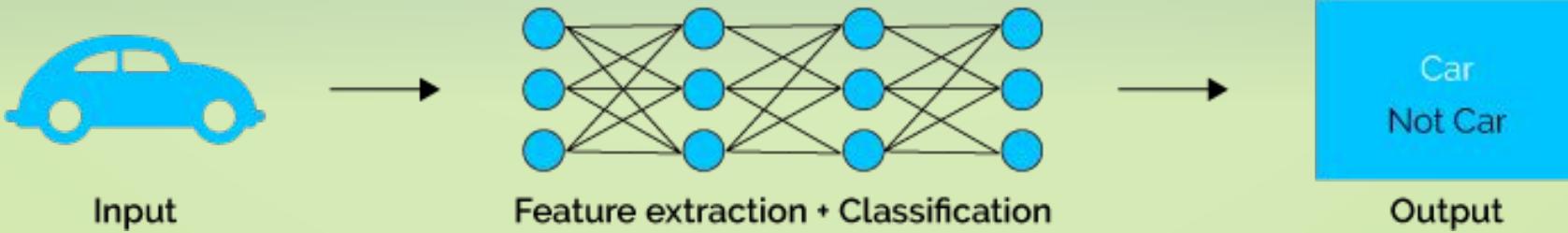
PREDICCIÓN

CAMBIO DE PARADIGMA

Machine Learning



Deep Learning

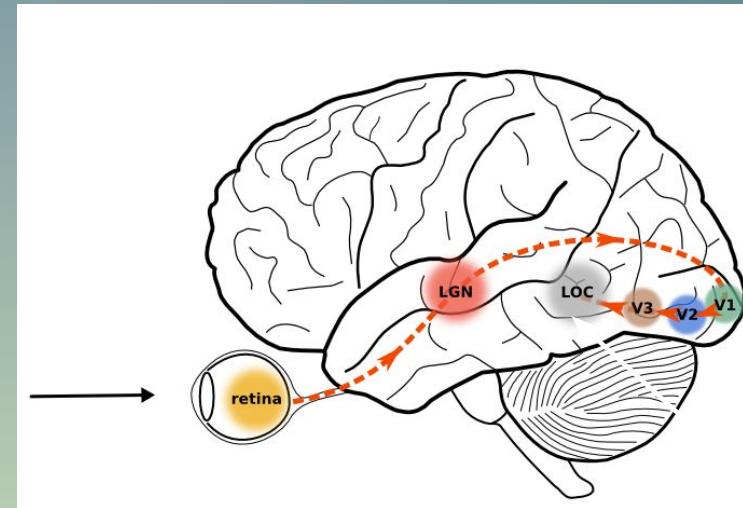


DEEP LEARNING – CONVOLUTIONAL NEURAL NETWORKS

Hubel & Wiesel: Neural basis of visual perception

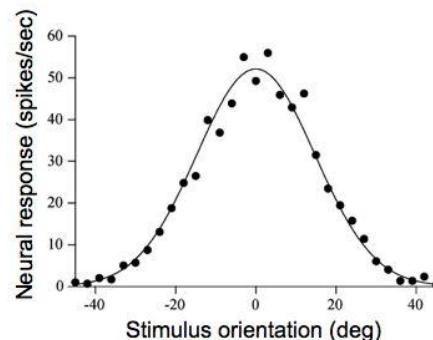
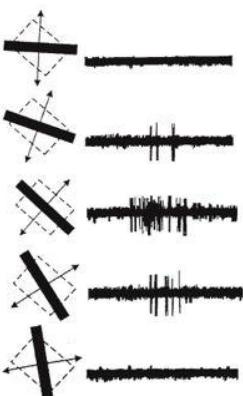
LGN: Lateral Geniculate Nucleus

V1: Primary Visual cortex

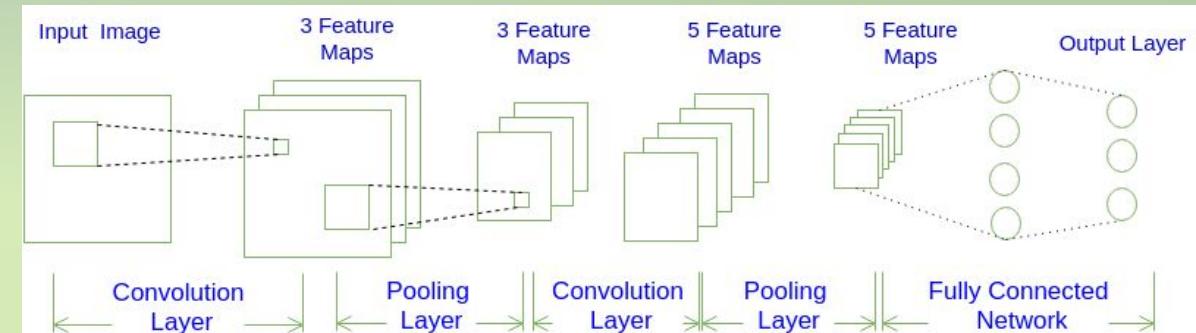


Mug

V1 physiology: orientation selectivity



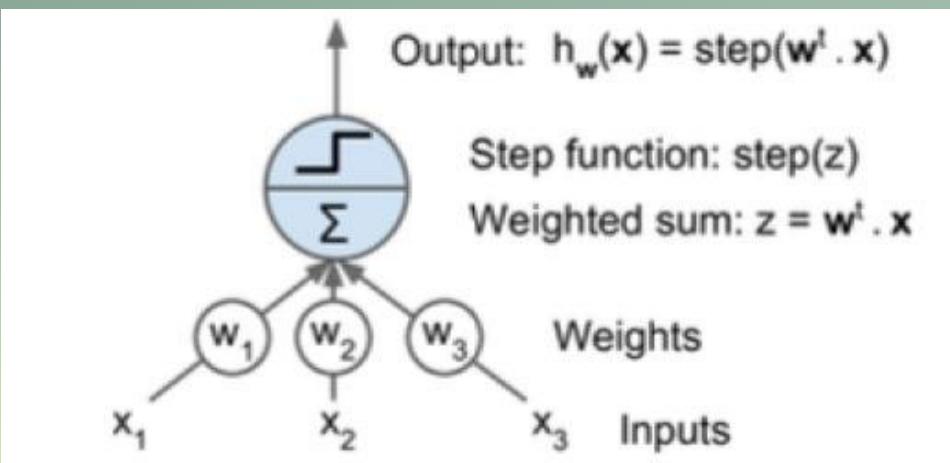
Hubel & Wiesel, 1968



CNN's: 1982 – Now become hot topic due to GPU's (gamers)
SUPERVISED LEARNING OF WEIGHTS

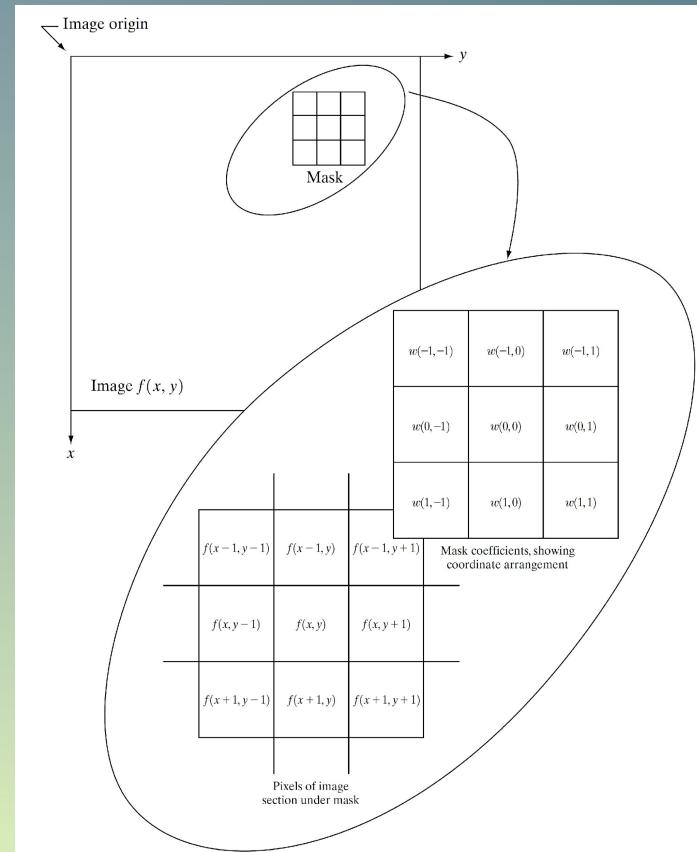
NEURAL NETWORK

Artificial neuron:
Soma, post-synaptic inputs, activation function



Training / learning weights:
Hebbian rule “wiring by firing”

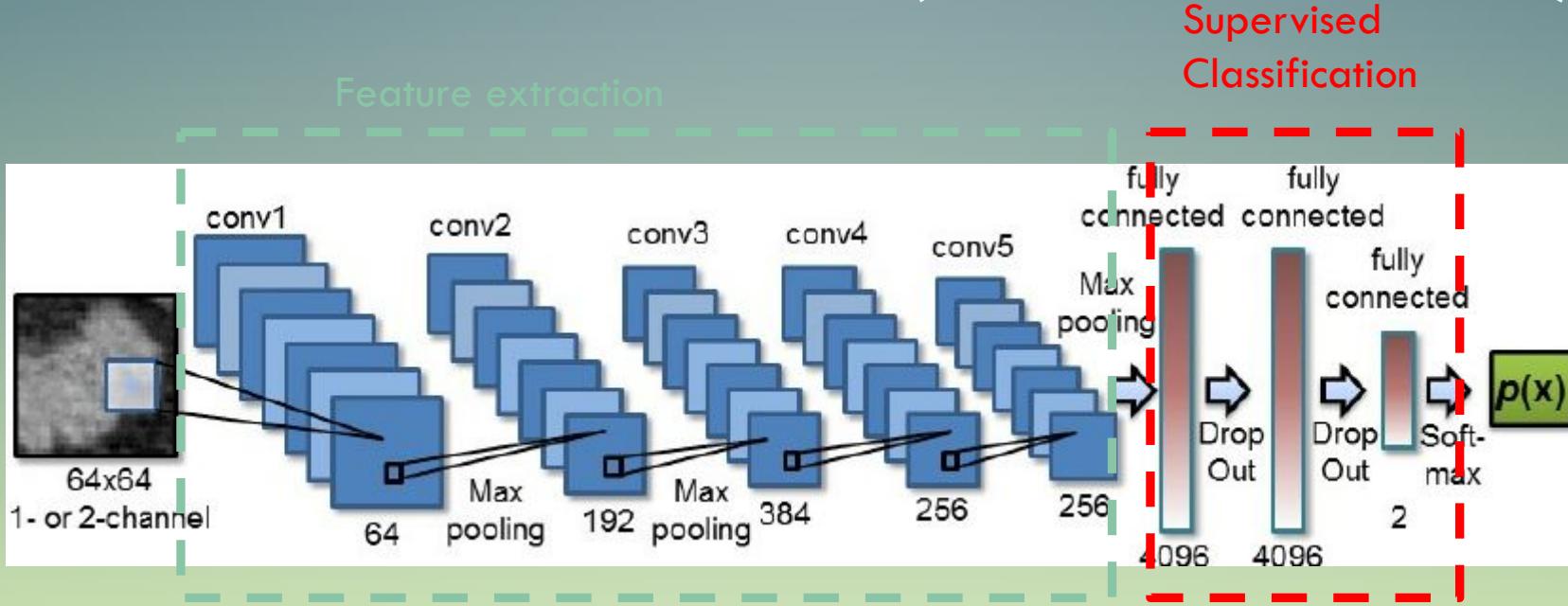
Convolutional filters



$$g(x, y) = \sum_{s=-a}^a \sum_{t=-b}^b w(s, t) \cdot f(x + s, y + t)$$

Mask Image

DL: BLACK-BOX LEARNING ! (DARK-LEARNING)



Learns both:

- Which features are more relevant
- How to classify the images

TRANSFER LEARNING: PRE-TRAINED MODELS

```
from keras.applications.inception_v3 import InceptionV3
from keras.layers import Input

# this could also be the output of a different Keras model or layer
input_tensor = Input(shape=(224, 224, 3)) # this assumes K.image_data_format() == 'channels_last'

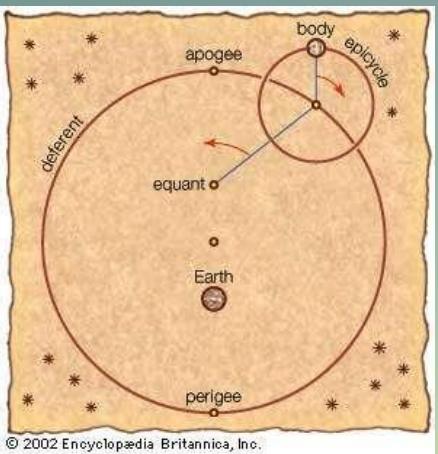
model = InceptionV3(input_tensor=input_tensor, weights='imagenet', include_top=True)
```

Documentation for individual models

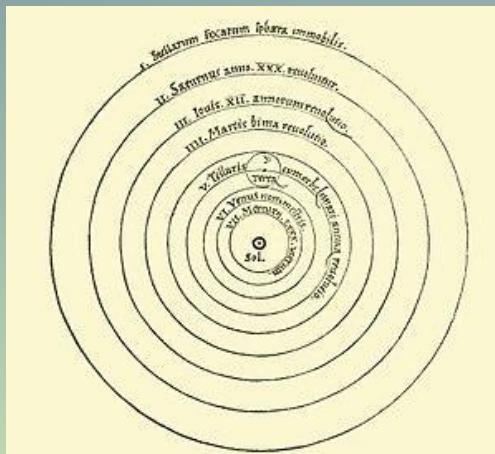
Model	Size	Top-1 Accuracy	Top-5 Accuracy	Parameters	Depth
Xception	88 MB	0.790	0.945	22,910,480	126
VGG16	528 MB	0.715	0.901	138,357,544	23
VGG19	549 MB	0.727	0.910	143,667,240	26
ResNet50	99 MB	0.759	0.929	25,636,712	168
InceptionV3	92 MB	0.788	0.944	23,851,784	159
InceptionResNetV2	215 MB	0.804	0.953	55,873,736	572
MobileNet	17 MB	0.665	0.871	4,253,864	88
DenseNet121	33 MB	0.745	0.918	8,062,504	121
DenseNet169	57 MB	0.759	0.928	14,307,880	169
DenseNet201	80 MB	0.770	0.933	20,242,984	201

C. RIESGOS Y OPORTUNIDADES

SOBRAJUSTE DE LOS DATOS (OVERFITTING)



Models data-driven



knowledge-driven

Principio de parsimonia

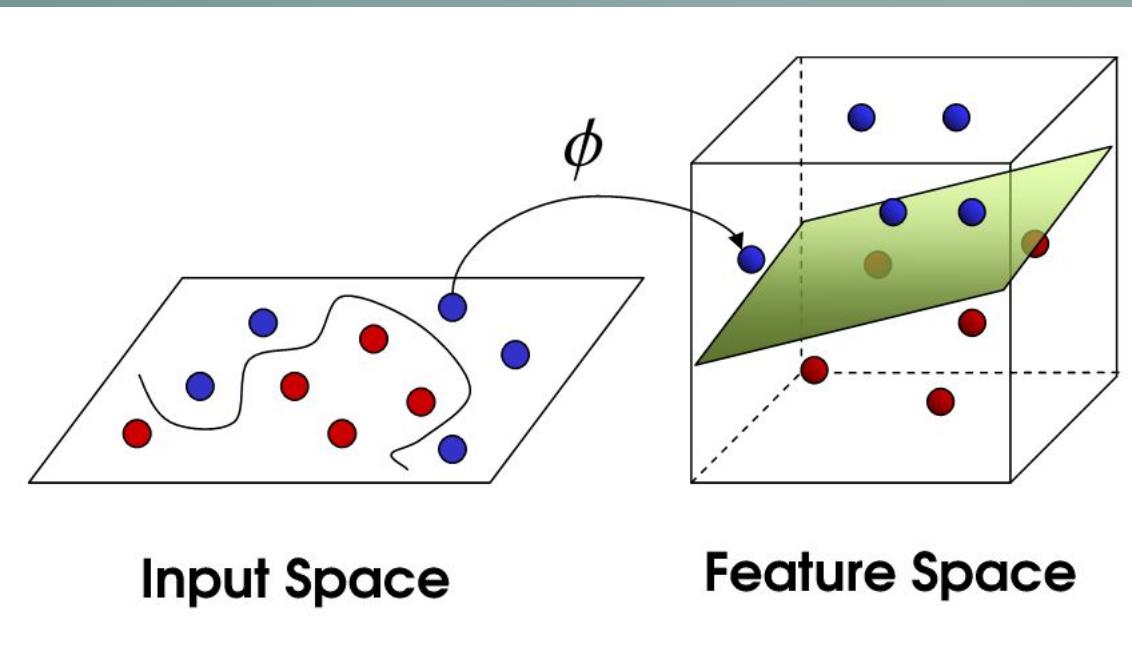
Rendimiento



complejidad

Errores por exceso o falta de complejidad

INTERPRETABILIDAD DE LOS MÉTODOS Y ATRIBUTOS



Los algoritmos deben ser poder interpretados por humanos

SÓLO FUNCIONA BIEN EN PROBLEMAS DE DOMINIO CERRADO



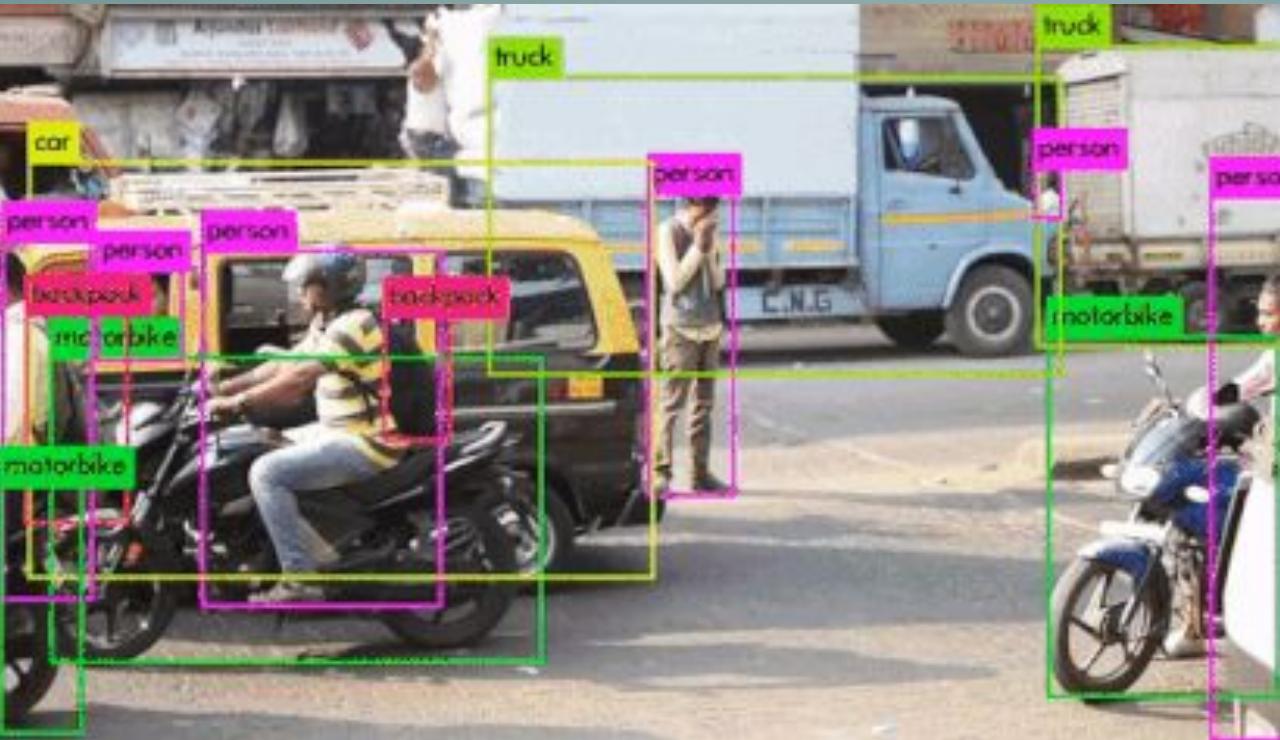
Incorporar información contextual, abierta, evolutiva

QUIÉN ES RESPONSABLE DE LOS ERRORES?



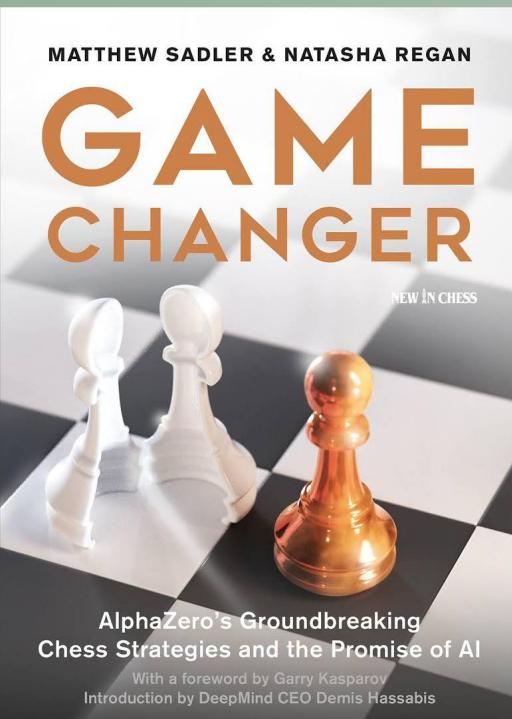
Introducción de consideraciones éticas y legales

YOU ONLY LOOK ONCE (YOLO)

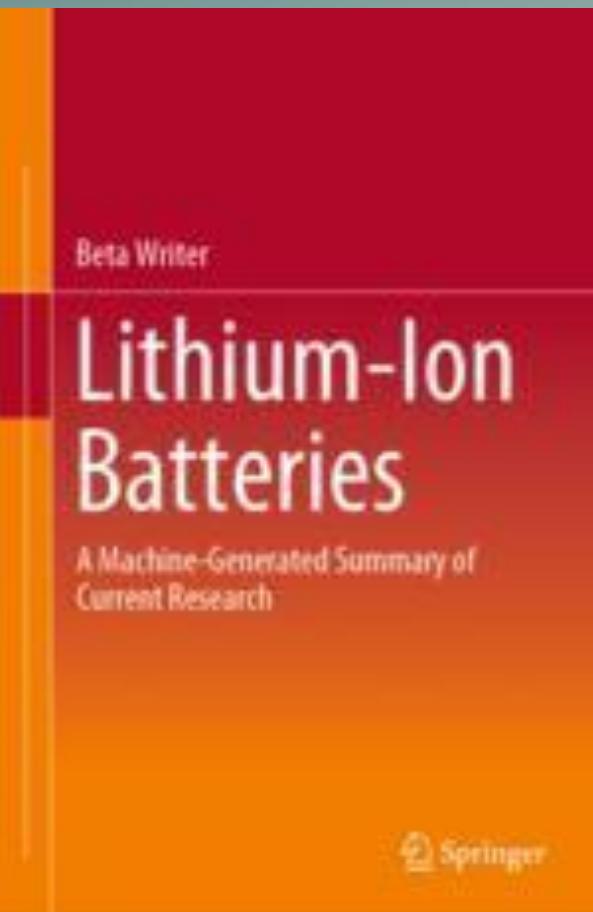


Reducción del coste en datos y recursos computacionales

LOS HUMANOS SEREMOS REPROGRAMADOS POR MÁQUINAS

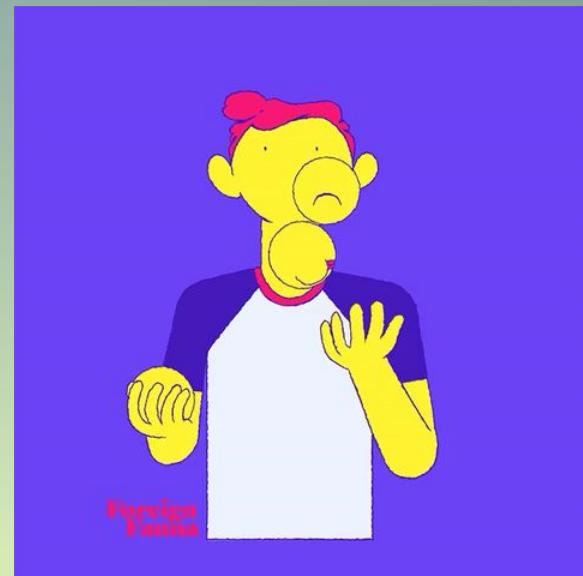


QUÉ MÁS PODRAN HACER LAS MÁQUINAS? Creatividad?



Lithium-Ion Batteries | © Springer
Nature

Empatía?
Compasión?
Complicidad?
Respeto?
Iniciativa?



Muchas gracias por vuestra atención!

