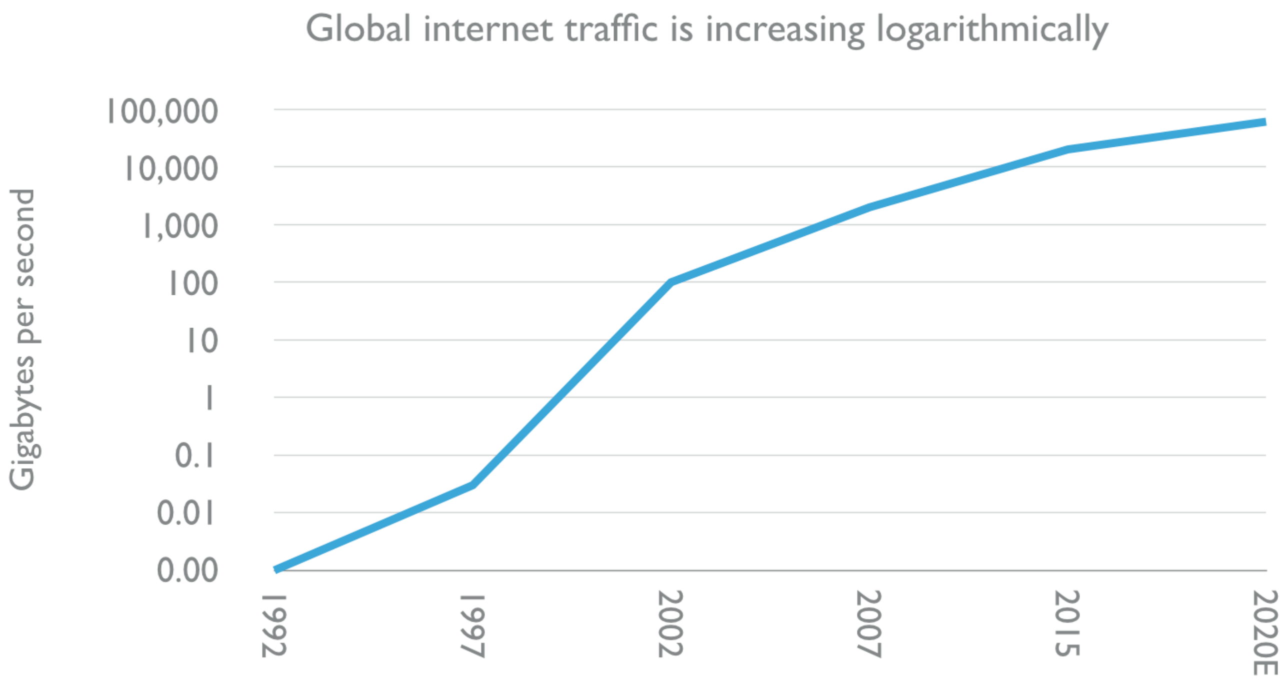
S1: Introducción

Diego García
diegogm@faculty.mioti.es

Madrid Internet
of Things Institute
Make-build-learn

Machine Learning



Madrid Internet
of Things Institute
Make-build-learn

Explosión de los datos

Madrid Internet
of Things Institute
Make-build-learn

- “We are creating so much data, so quickly, that 90% of the data in the world today has been created in the last 2 years”.
  Petter Bae Brandtzæg
  SINTEF ICT

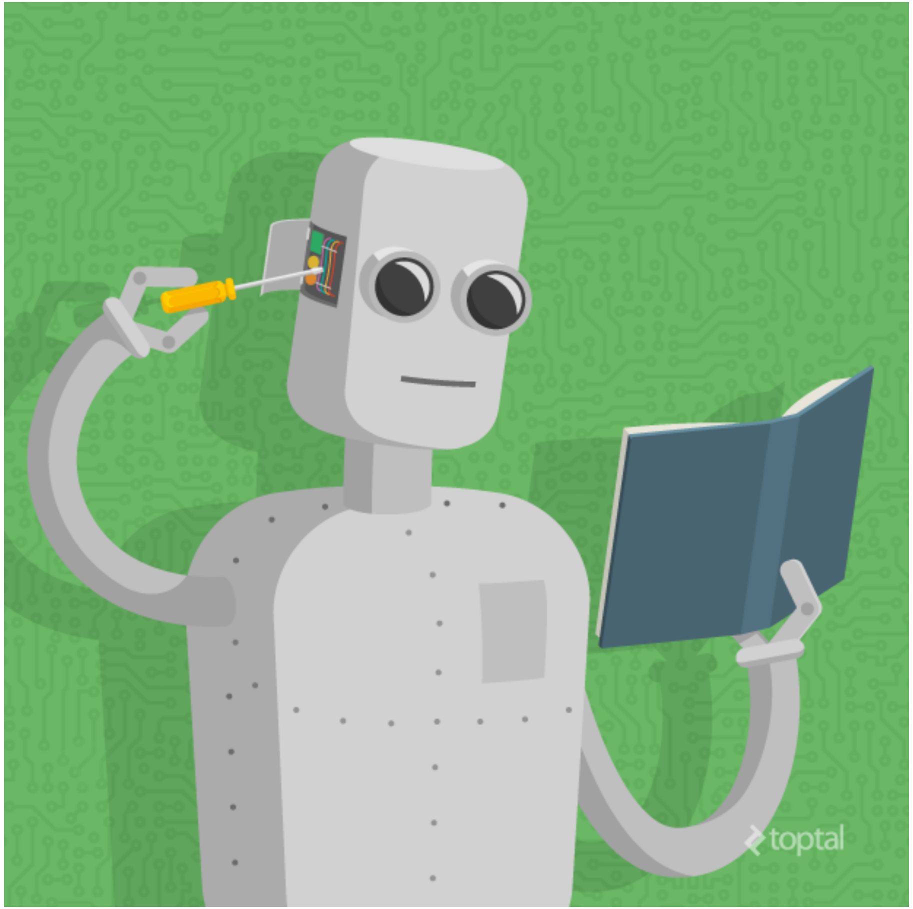
- Pero esto se cumple desde los últimos 30 años.
  - **Cada 2 años generamos 10 veces más datos.**


Inteligencia
Conocimiento
Información
Datos

Grandes cuestiones

Madrid Internet
of Things Institute
Make-build-learn

- ¿Cómo podemos resolver el problema de la explosión de la información?
- ¿Cómo podemos abordar un futuro cada vez más rápido, menos predecible y con más individualizado?



Madrid Internet
of Things Institute
Make-build-learn

¿Qué nos permite la AI?

Madrid Internet
of Things Institute
Make-build-learn

- Aprender nuevas formas de resolver los problemas
- Decisiones en tiempo real.
- Mayor efectividad que los humanos en muchas tareas
- Capacidad de procesar datasets enormes
- Reducción de los tiempos de ciclo
- Eficiencias de coste
- Procesamiento sin “errores” o sesgos

MIOTI

Madrid Internet
of Things Institute
Make-build-learn

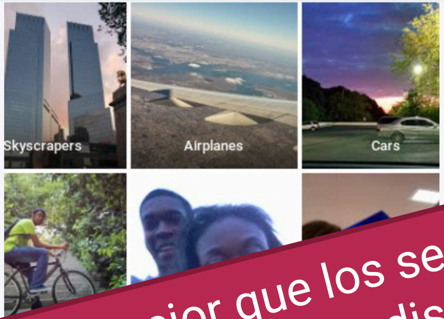
Una IA no es mejor que los sesgos de los humanos que la han diseñado.

TOM SIMONITE BUSINESS 01.11.18 07:00 AM

WHEN IT COMES TO GORILLAS, GOOGLE PHOTOS REMAINS BLIND

In WIRED's tests, Google Photos did identify some primates, but ... one were to be found. RICK MADONIK/TORONTO STAR/GETTY ...

IN 2015, A black software developer embarrassed Google by tweeting that the company's Photos service had labeled photos of him with a black friend as "gorillas." Google declared itself "appalled and genuinely sorry." An engineer who became the public face of the clean-up operation said the label gorilla would no longer be applied to groups of images, and that Google was "working on longer-term fixes."



...ed up. My friend's not a gorilla.

... 29, 2015

2,276 3,622 people are talking about this

Google 'fixed' its racist algorithm by removing gorillas from i... ge-labeling tech

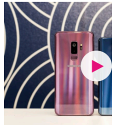
Near... called out, it hasn't gone beyond a quick workaround

The AI algorithms in Google Photos sort images by a number of categories. | Photo by Vjeran Pavic / The Verge

Back in 2015, software engineer Jacky Alciné pointed out that the image recognition algorithms in Google Photos were classifying his black friends as "gorillas." Google said it was "appalled" at the mistake, apologized to Alciné, and promised to fix the problem. But, as a new report from *Wired* shows, nearly three years on and Google hasn't really fixed anything. The company has simply blocked its image recognition algorithms from identifying gorillas altogether — preferring, presumably, to limit the service rather than risk another miscategorization.

NOW TREN

50 Cent admits in ban... document that he nev... owned any bitcoin



Samsung announces ... an upgraded camera i... body

“La calidad de un modelo está limitado por la calidad de los datos utilizados para entrenarlo”

Principio GIGO

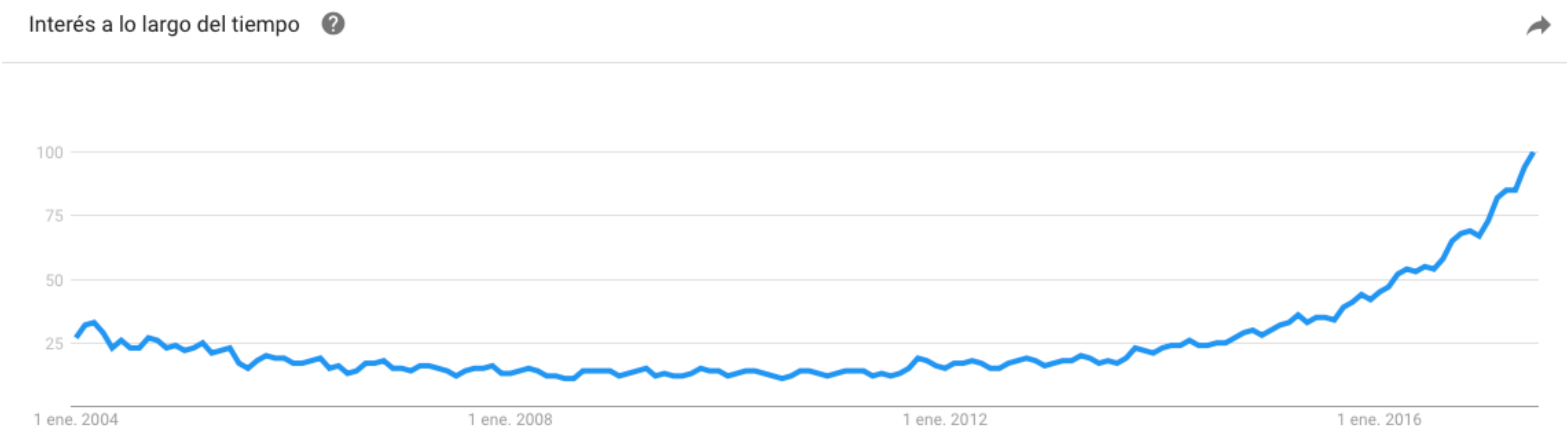
This isn't the first time that algorithm systems have appeared to be sexist


SKYNET
NEURAL NET-BASED ARTIFICIAL INTELLIGENCE
Inteligencia artificial
Aprendizaje automático
Analítica predictiva
Siri
Google!
Estadística
$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$


¿Qué está pasando con el
Machine Learning?

Interés en machine learning

Madrid Internet
of Things Institute
Make-build-learn



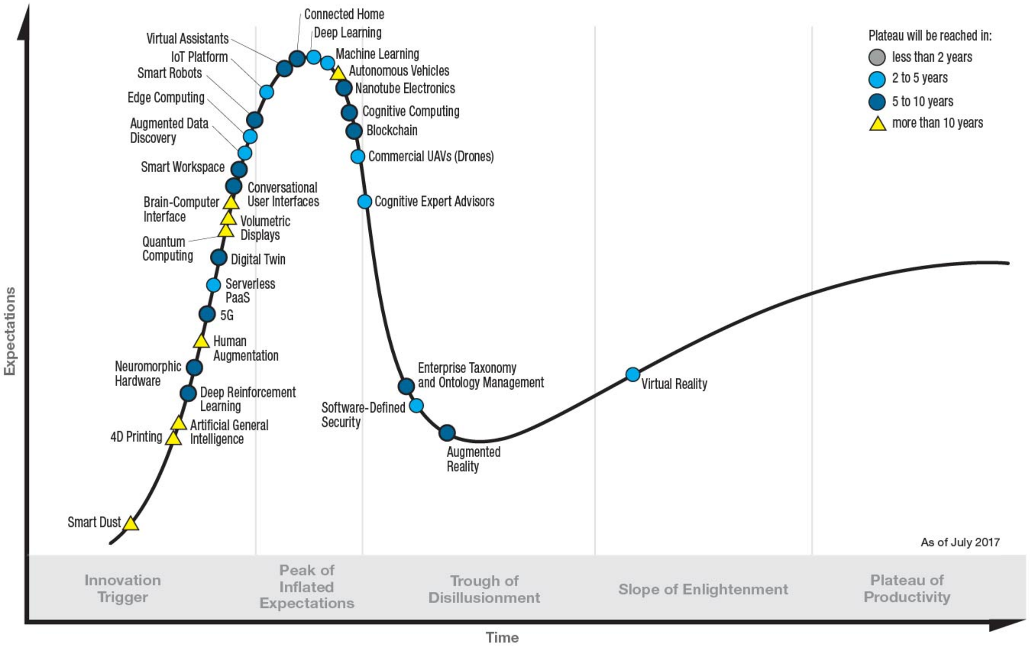
MIOTI

Madrid Internet
of Things Institute
Make-build-learn

“AI is the new electricity”

Andrew NG.
Fundador de Coursera

Gartner Hype Cycle for Emerging Technologies, 2017

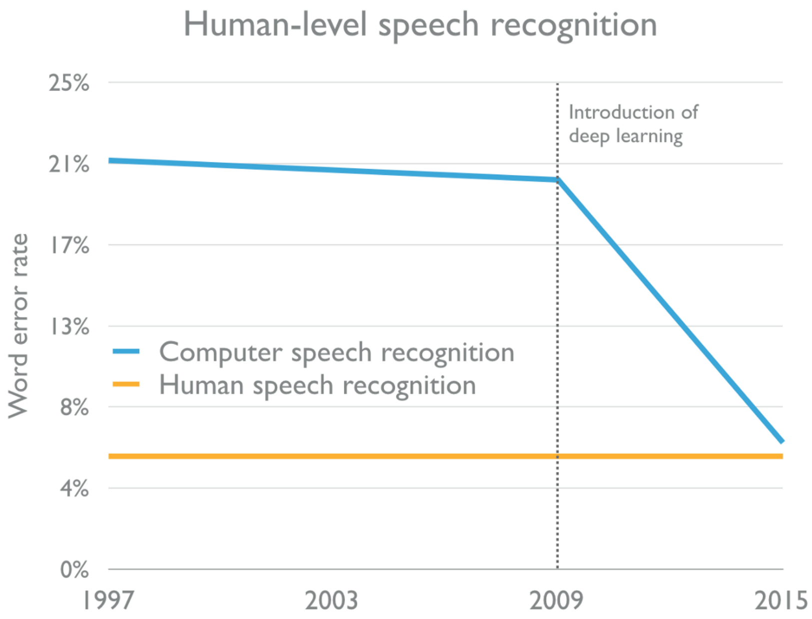


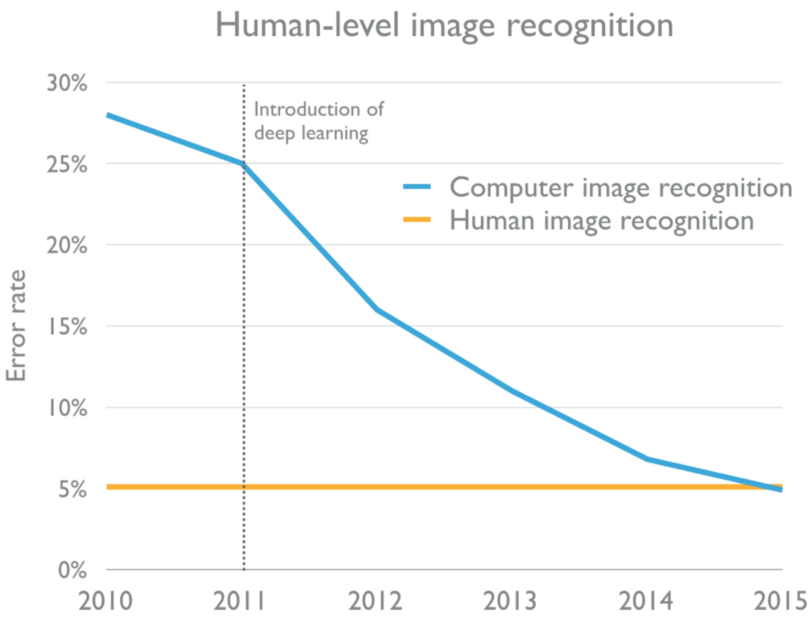
gartner.com/SmarterWithGartner

Source: Gartner (July 2017)

Ordenadores vs humanos

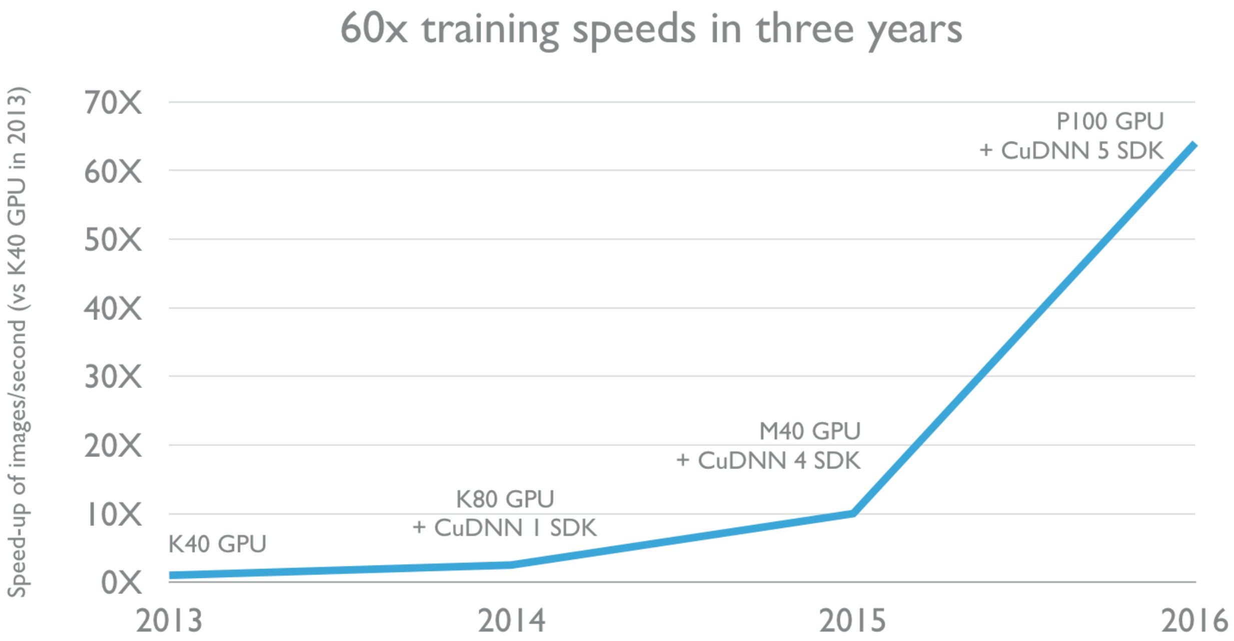
Madrid Internet
of Things Institute
Make-build-learn





1) Hardware especializado

Madrid Internet
of Things Institute
Make-build-learn



Source: NVIDIA

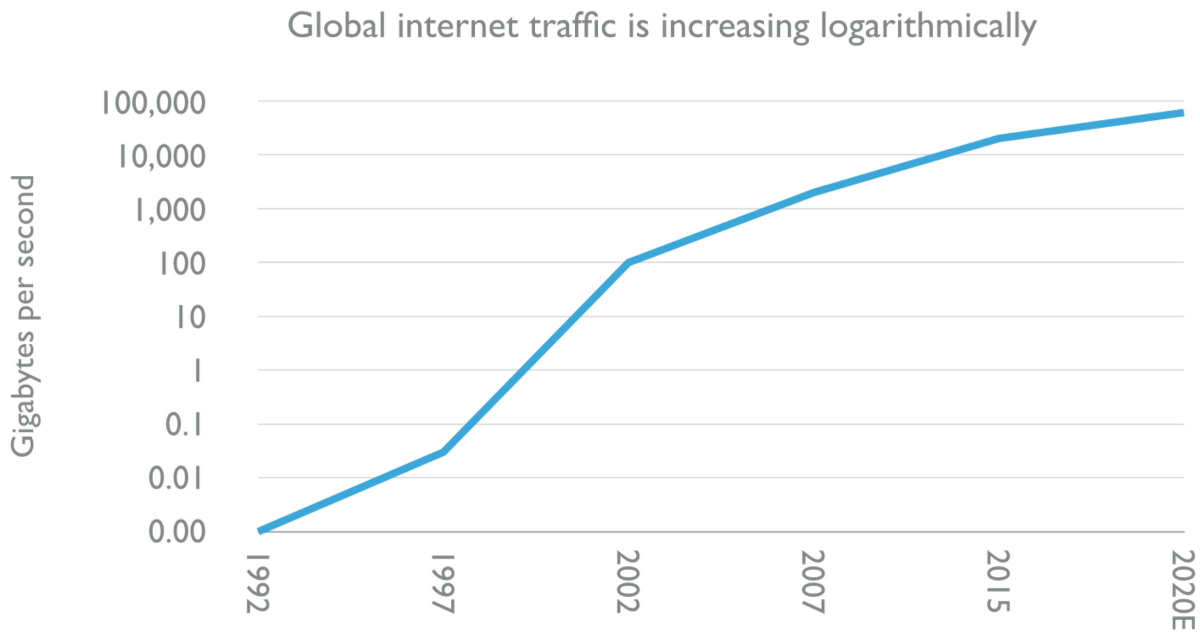
1) Hardware especializado

Madrid Internet
of Things Institute
Make-build-learn

1) Hardware especializado

2) Datasets más grandes

Madrid Internet
of Things Institute
Make-build-learn



Datasets vs Algorithms

Madrid Internet
of Things Institute
Make-build-learn

Year	Breakthroughs in AI	Datasets (First Available)	Algorithms (First Proposed)
1994	Human-level spontaneous speech recognition	Spoken Wall Street Journal articles and other texts (1991)	Hidden Markov Model (1984)
1997	IBM Deep Blue defeated Garry Kasparov	700,000 Grandmaster chess games, aka "The Extended Book" (1991)	Negascout planning algorithm (1983)
2005	Google's Arabic- and Chinese-to-English translation	1.8 trillion tokens from Google Web and News pages (collected in 2005)	Statistical machine translation algorithm (1988)
2011	IBM Watson became the world Jeopardy! champion	8.6 million documents from Wikipedia, Wiktionary, Wikiquote, and Project Gutenberg (updated in 2010)	Mixture-of-Experts algorithm (1991)
2014	Google's GoogLeNet object classification at near-human performance	ImageNet corpus of 1.5 million labeled images and 1,000 object categories (2010)	Convolution neural network algorithm (1989)
2015	Google's Deepmind achieved human parity in playing 29 Atari games by learning general control from video	Arcade Learning Environment dataset of over 50 Atari games (2013)	Q-learning algorithm (1992)
Average No. of Years to Breakthrough:		**3 years**	**18 years**

Learning representations by back-propagating errors

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

* Institute for Cognitive Science, C-015, University of California, San Diego, La Jolla, California 92093, USA
† Department of Computer Science, Carnegie-Mellon University, Pittsburgh, Philadelphia 15213, USA

We describe a new learning procedure, back-propagation, for networks of neurone-like units. The procedure repeatedly adjusts the weights of the connections in the network so as to minimize a measure of the difference between the actual output vector of the net and the desired output vector. As a result of the weight adjustments, internal 'hidden' units which are not part of the input or output come to represent important features of the task domain, and the regularities in the task are captured by the interactions of these units. The ability to create useful new features distinguishes back-propagation from earlier, simpler methods such as the perceptron-convergence procedure[1].

There have been many attempts to design self-organizing neural networks. The aim is to find a powerful synaptic modification rule that will allow an arbitrarily connected neural network to develop an internal structure that is appropriate for a particular task domain. The task is specified by giving the desired state vector of the output units for each state vector of the input units. If the input units are directly connected to the output units it is relatively easy to find learning rules that iteratively adjust the relative strengths of the connections so as to progressively reduce the difference between the actual and desired output vectors[2]. Learning becomes more interesting but more difficult when we introduce hidden units wh
desired states are not specified by the task. (In
there are 'feature analysers' between the input an
are not true hidden units because their input co
fixed by hand, so their states are completely dete
input vector: they do not learn representations.)
procedure must decide under what circumstanc
units should be active in order to help achiev
input–output behaviour. This amounts to decidi
units should represent. We demonstrate that a ge
and relatively simple procedure is powerful enoug
appropriate internal representations.

The simplest form of the learning procedure
networks which have a layer of input units at the
number of intermediate layers; and a layer of o
the top. Connections within a layer or from hi
layers are forbidden, but connections can skip
layers. An input vector is presented to the netwo
the states of the input units. Then the states of the
layer are determined by applying equations (1) a
connections coming from lower layers. All units
have their states set in parallel, but different lay
states set sequentially, starting at the bottom
upwards until the states of the output units are d

The total input, x_j, to unit j is a linear function o
y_i, of the units that are connected to j and of the
on these connections

$$x_j = \sum_i y_i w_{ji}$$

Units can be given biases by introducing an extra
unit which always has a value of 1. The weight
input is called the bias and is equivalent to a thr
opposite sign. It can be treated just like the other

A unit has a real-valued output, y_j, which is
function of its total input

$$y_j = \frac{1}{1+e^{-x_j}}$$

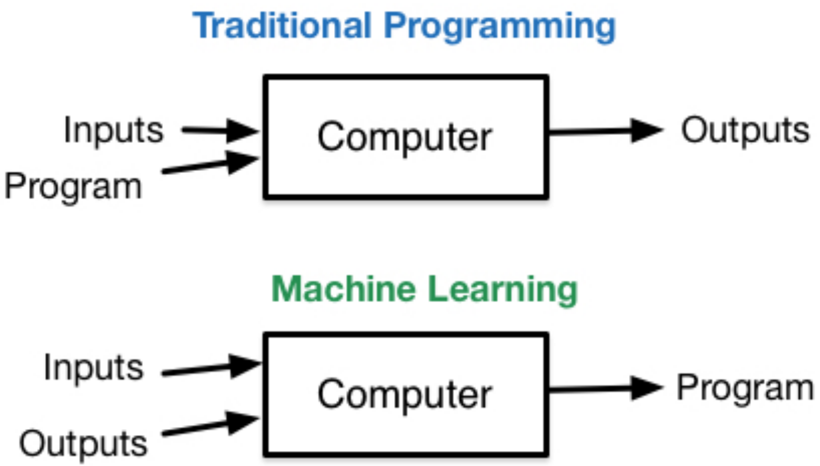
† To whom correspondence should be addressed.

3) Open source

TensorFlow
scikit learn
Keras
kaggle
PYTORCH
theano
gensim
arXiv.org
Caffe
Chainer
SM
将軍
sho gun

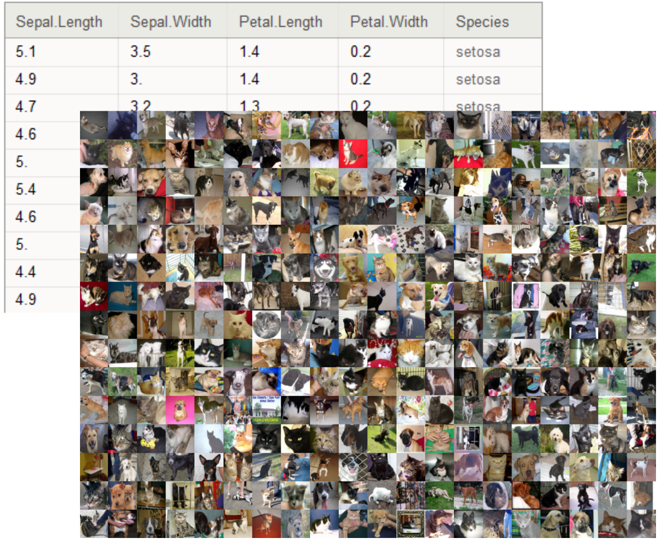
¿En qué consiste el machine learning?

- Las técnicas de aprendizaje automático permiten a los ordenadores aprender de la experiencia.



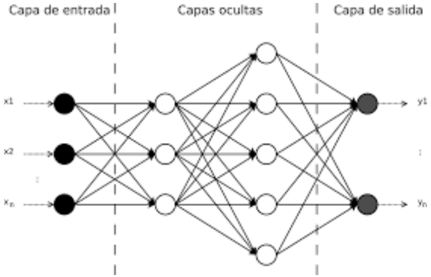
Vocabulario

- A partir de un **dataset**, mediante un **algoritmo entreno** un **modelo** que utilizo para **predecir** otros datos.

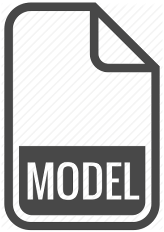


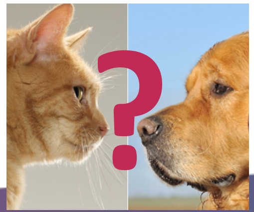
Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
5.1	3.5	1.4	0.2	setosa
4.9	3.	1.4	0.2	setosa
4.7	3.2	1.3	0.2	setosa
4.6				
5.				
5.4				
4.6				
5.				
4.4				
4.9				

dataset



algoritmo



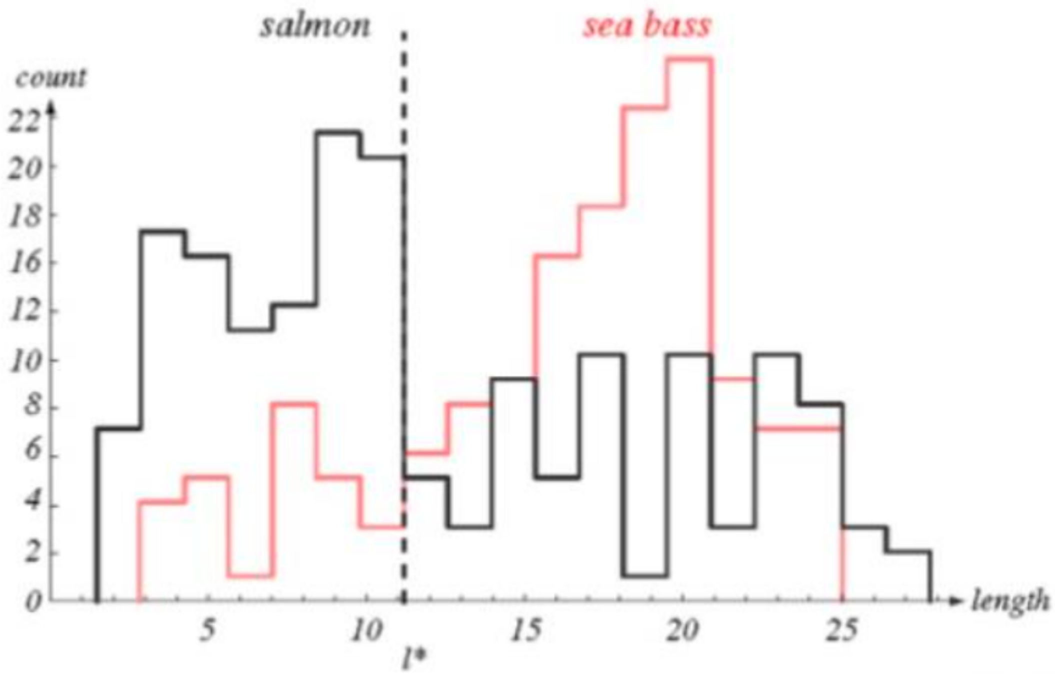


¿Cómo diferenciar salmones de corvinas?

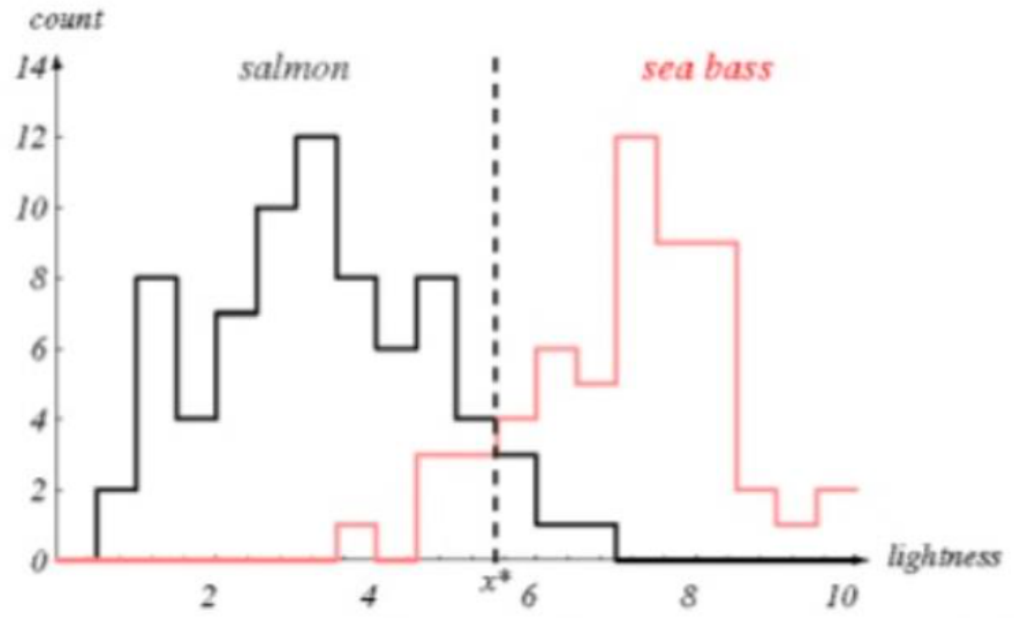
- Sólo mirando sus datos

¿Por su longitud?

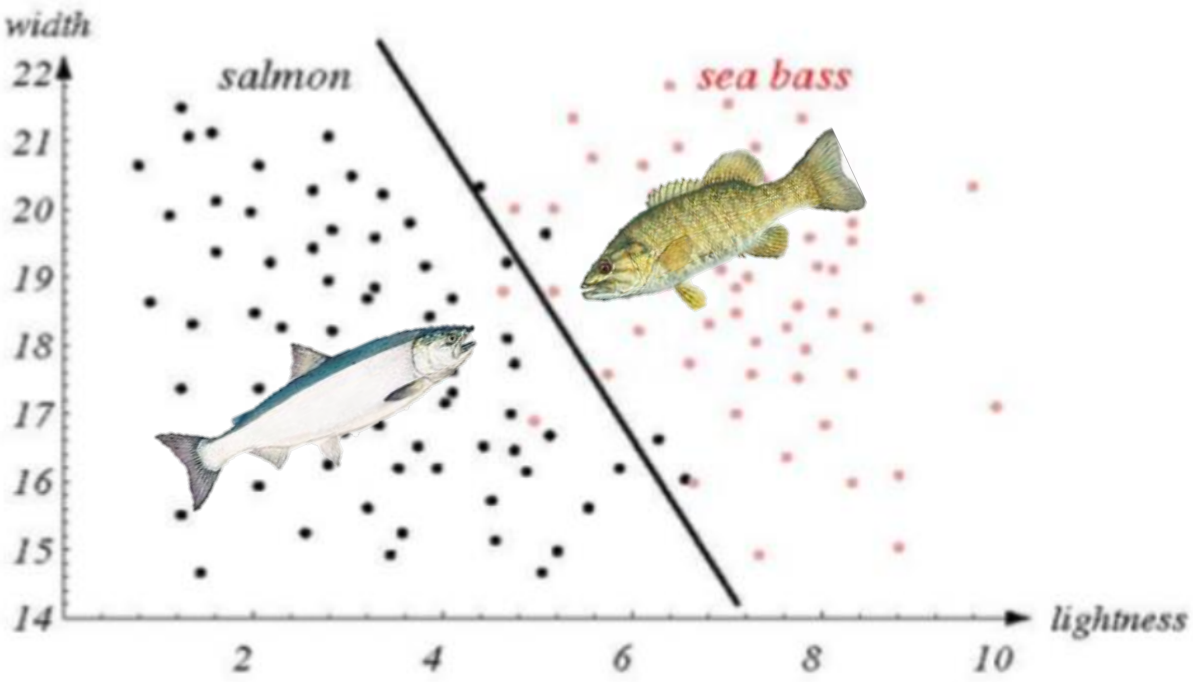
Madrid Internet
of Things Institute
Make-build-learn



¿Por su peso?



¿Y si agrupamos las dos variables?



Cuestiones importantes

Madrid Internet
of Things Institute
Make-build-learn

- ¿Cómo podemos obtener esas líneas de separación?
- ¿Qué tipo de problemas podemos resolver con machine learning?

Tipos de aprendizajes

- Machine learning
  - Aprendizaje supervisado
    - Clasificación
    - Regresión
  - Aprendizaje no supervisado

Aprendizaje supervisado

- El aprendizaje supervisado permite al ordenador **aprender a resolver problemas** a partir de ejemplos

- Principales problemas a resolver:
  - Clasificación
  - Regresión

Clasificación

- Tengo un individuo ¿a qué clase pertenece?

- **Idea**: entrenar un **modelo** automáticamente a partir de individuos ya etiquetados y utilizarlo para etiquetar nuevos casos

- Aplicaciones:
  - Detección de impagos, fraude…
  - Detección de enfermedades
  - Clasificación de imágenes, reconocimiento de voz, etc…

Ejemplo de clasificación

- Tenemos un dataset con datos de distintos sensores de un coche (temperatura del motor, nivel de aceite...)

Temp motor (ºC)	Nivel aceite (ml)	Suciedad inyectores	Estado
93	3409	Baja	Bueno
104	3509	Media	Malo
93	1500	Media	Malo

- Queremos saber a partir de esos sensores si el coche está funcionando **bien** o **mal**. ¿Cómo podríamos hacerlo?.

Ejemplo de clasificación

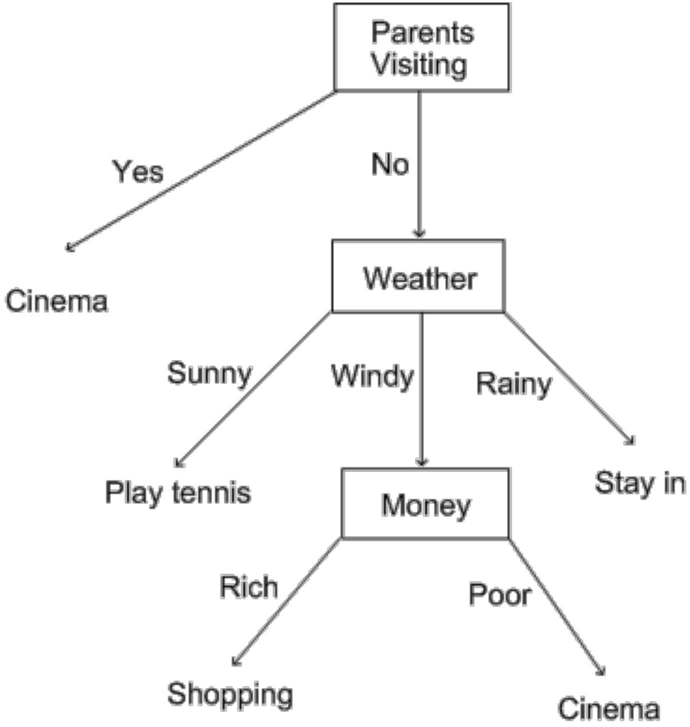
Madrid Internet
of Things Institute
Make-build-learn

- Podemos crear reglas que relacionen los distintos sensores y que definan que rangos de funcionamiento son buenos o malos.

```
Si temp_motor entre (70, 100) -> estado bueno
Si nivel_aceite entre (3000, 4000) -> estado bueno
Si suciedad_inyectores != ‘Alta’ -> estado bueno
Else -> estado malo
```

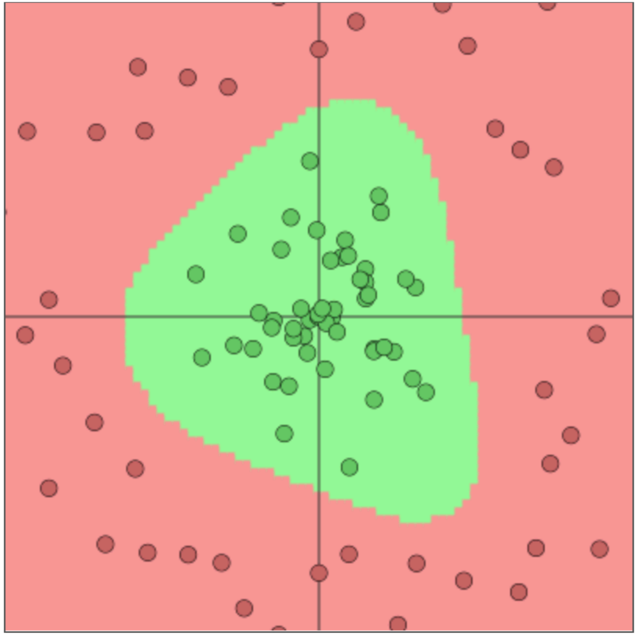
Ejemplo de modelo

Madrid Internet
of Things Institute
Make-build-learn



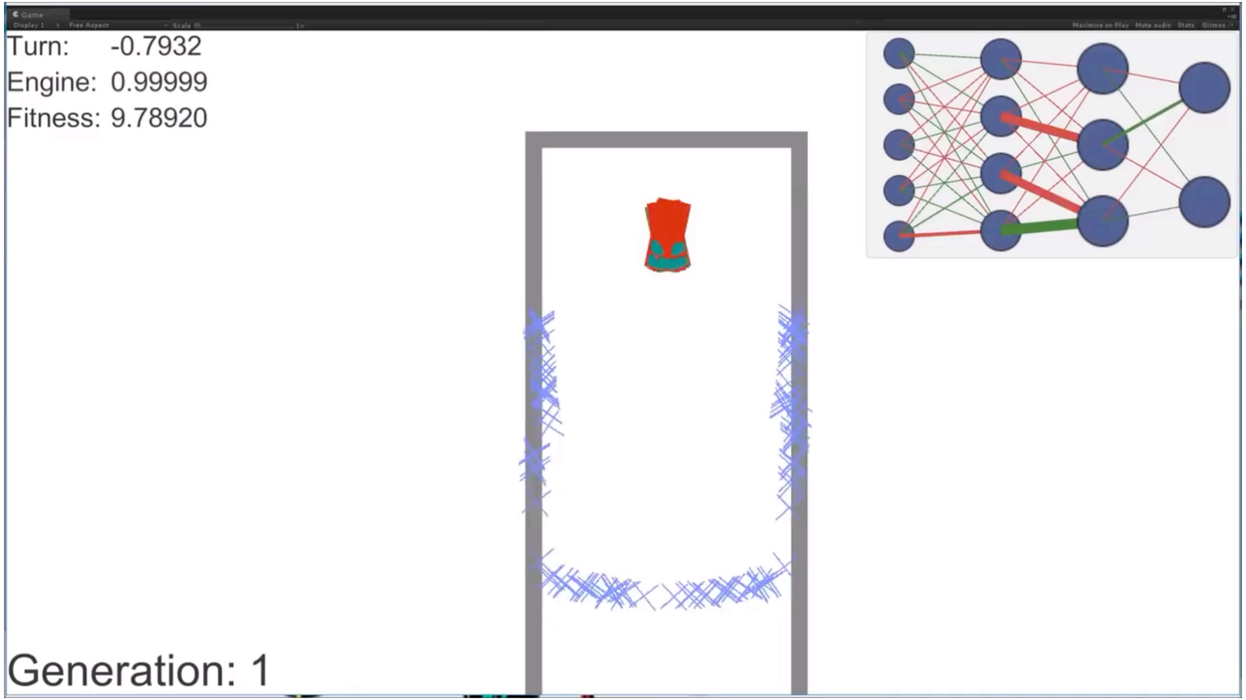
Clasificación

- El objetivo es que ese modelo nos determine automáticamente las líneas de separación entre los individuos



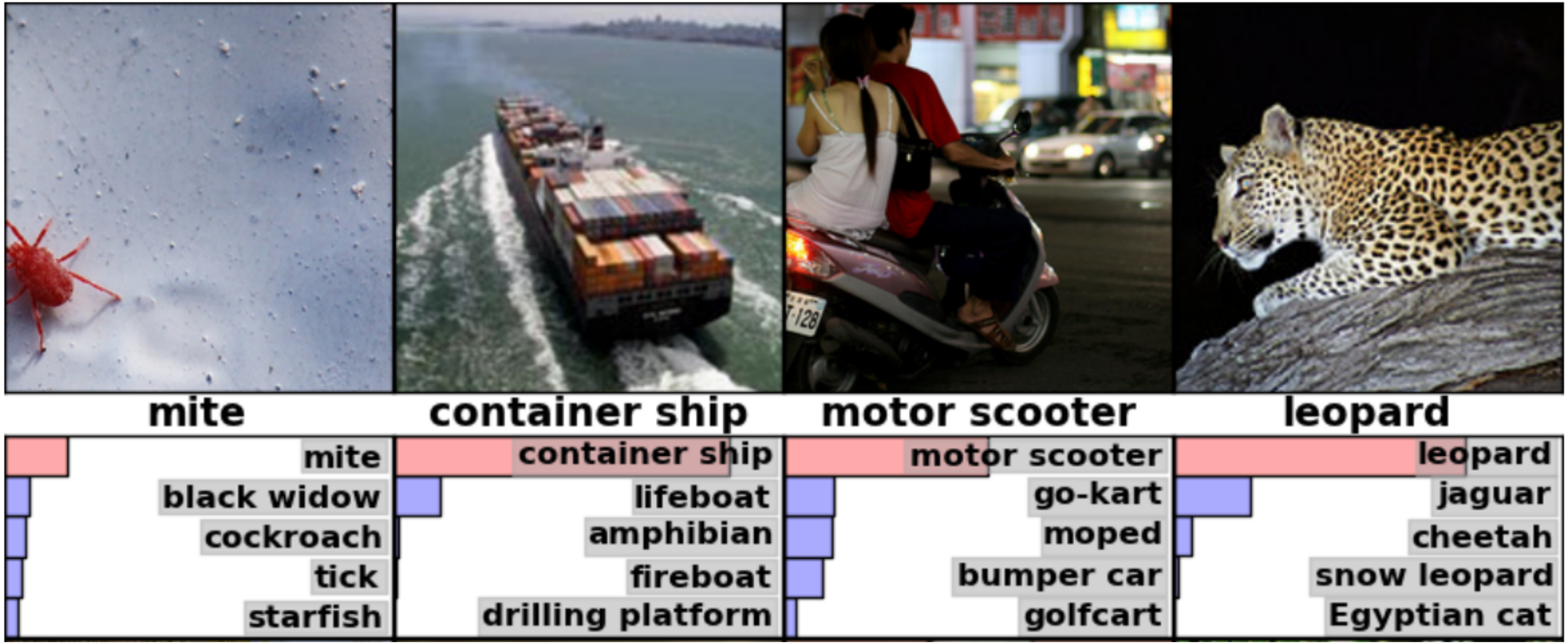
http://cs.stanford.edu/people/karpathy/convnetjs/demo/classify2d.html

Ejemplo: enseñando a un ordenador a conducir




Videocore
HDMI
Audio : LPCM
Video : 1080p 24Hz

Clasificación



Regresión

- Tengo una serie temporal, ¿cuál es el siguiente valor?

- **Idea**: Construir un **modelo** automáticamente a partir de los valores actuales y utilizarlo para **predecir** los siguientes valores

- Aplicaciones:

  - Previsión de consumo eléctrico
  - Previsión en bolsa
  - Previsión de demanda, etc..

Regresión

0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
0
50
100
150
200
250
300
350
400
450
True Data
Prediction
Prediction
Prediction
Prediction
Prediction
Prediction
Prediction
Prediction

Aprendizaje no supervisado

- El aprendizaje no supervisado nos ayuda a encontrar **patrones ocultos o relaciones ocultas en los datos**.
- Se aplica sobre conjuntos de **datos no etiquetados, no requiere conjunto de entrenamiento.**
- Los problemas más habituales que resuelve son:
  - Clusterización
  - Reglas de asociación

Pilares de la IA aplicada

Generar, recopilar y etiquetar dataset
Entrenar la red neuronal.

Entrenamiento

Producción

Ejecutar el modelo en escala e intentar llegar a los niveles de rendimiento esperados.

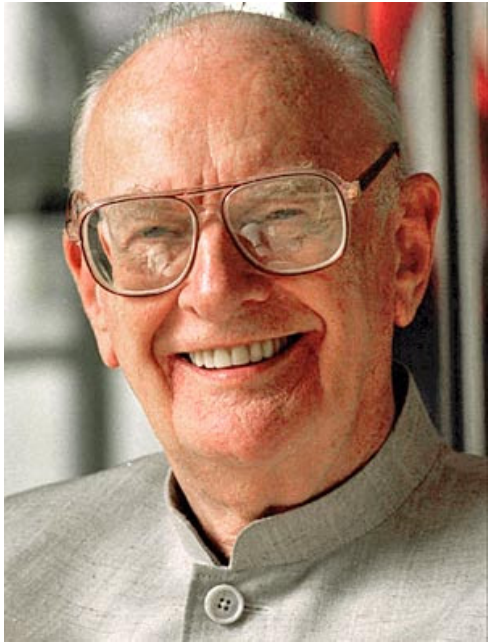
Aprendizaje activo

Corregir errores de predicción para mejorar el modelo a lo largo del tiempo.

Take aways

Madrid Internet
of Things Institute
Make-build-learn

- Los **algoritmos** son un **commodity**, el verdadero **valor** se encuentra en los **datasets** y en crear **modelos de negocio** basados en estas tecnologías
- En los últimos **10** años hemos avanzado más que en los últimos **40** en muchas áreas
- **Superamos ya a los humanos** en varios problemas
- Existen **muchos problemas** muy concretos aún **por resolver**



“Cualquier tecnología suficientemente avanzada es indistinguible de la magia”.

Arthur C. Clarke

Make
build
learn_

Calle Rufino González 25
28037 Madrid
+34810527241
www.mioti.es