Una zambullida al mundo del "Aprendizaje automático" y "La Mineria de Datos"

@frikio3
#haciafsmm2019
#frikio #Alworkshop

Sergio Villordo
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FREE SOFTWARE MEETUP 2019

FRIKIO

UNIVERSIDAD Gastón Dachary

Una zambullida al mundo del "Machine Learning" y el "Data Mining"

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Una zambullida al mundo de la "Artificial Intelligence" y el "Data Science"

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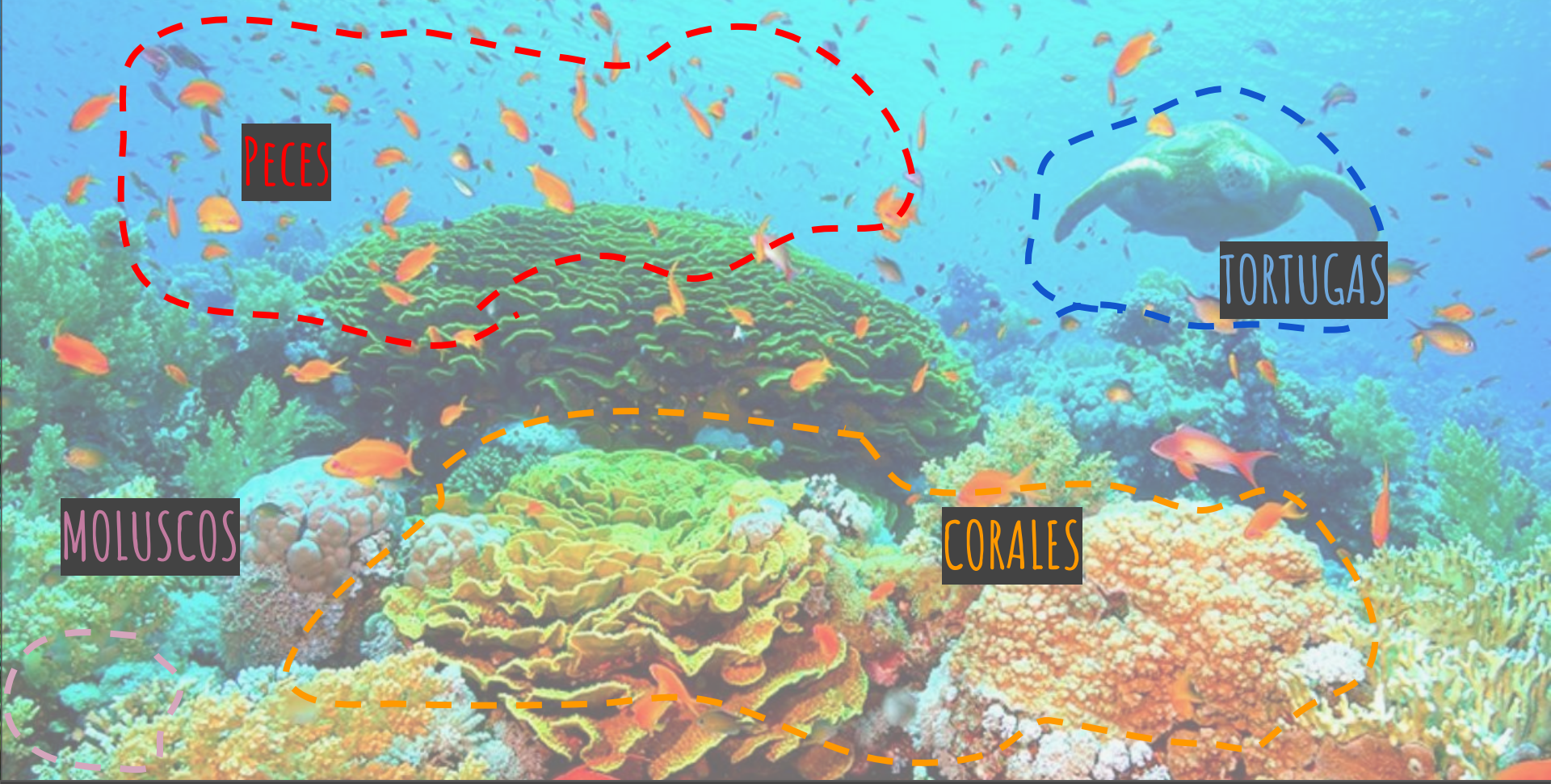
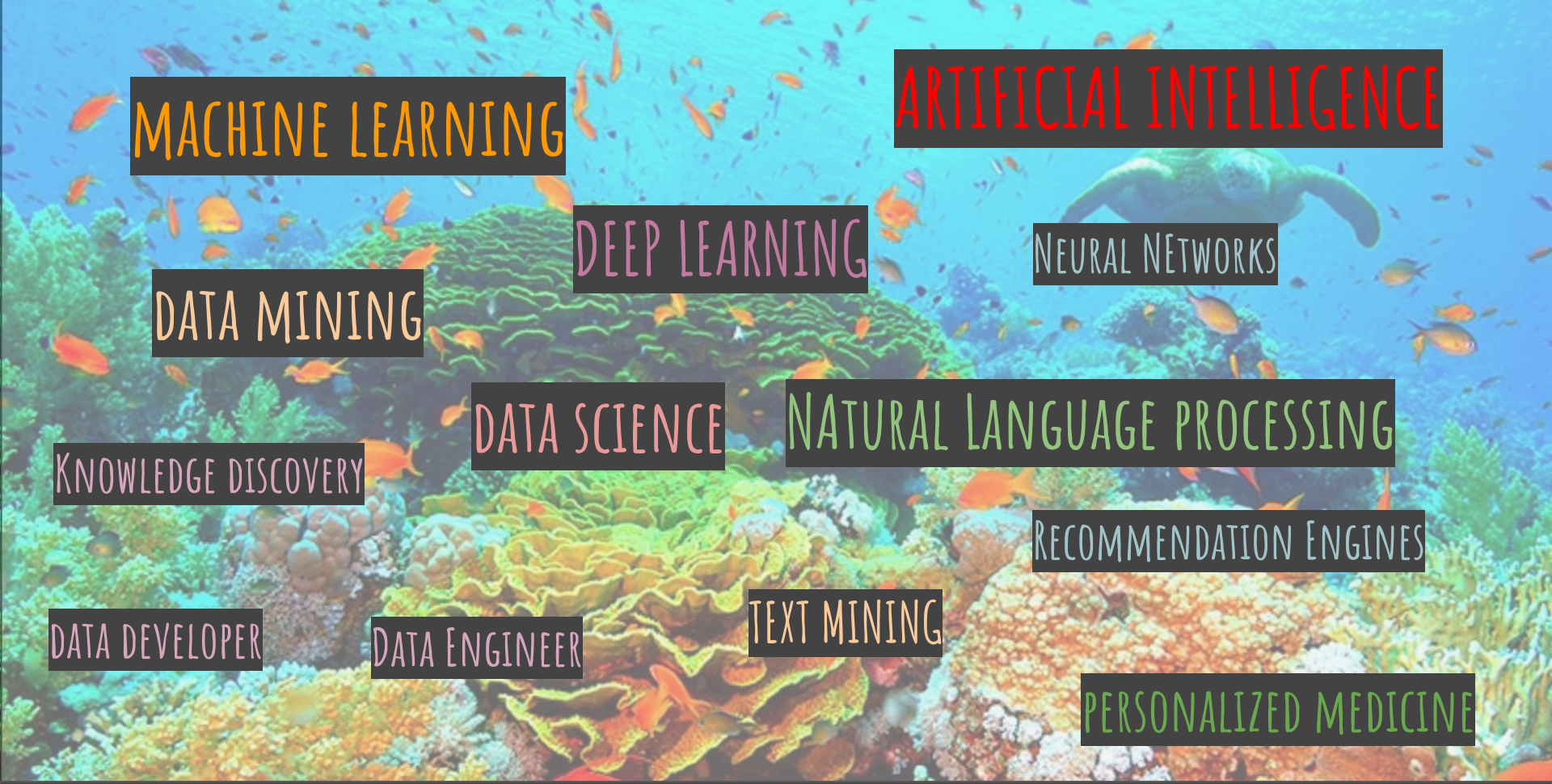

PECES
TORTUGAS
MOLUSCOS
CORALES

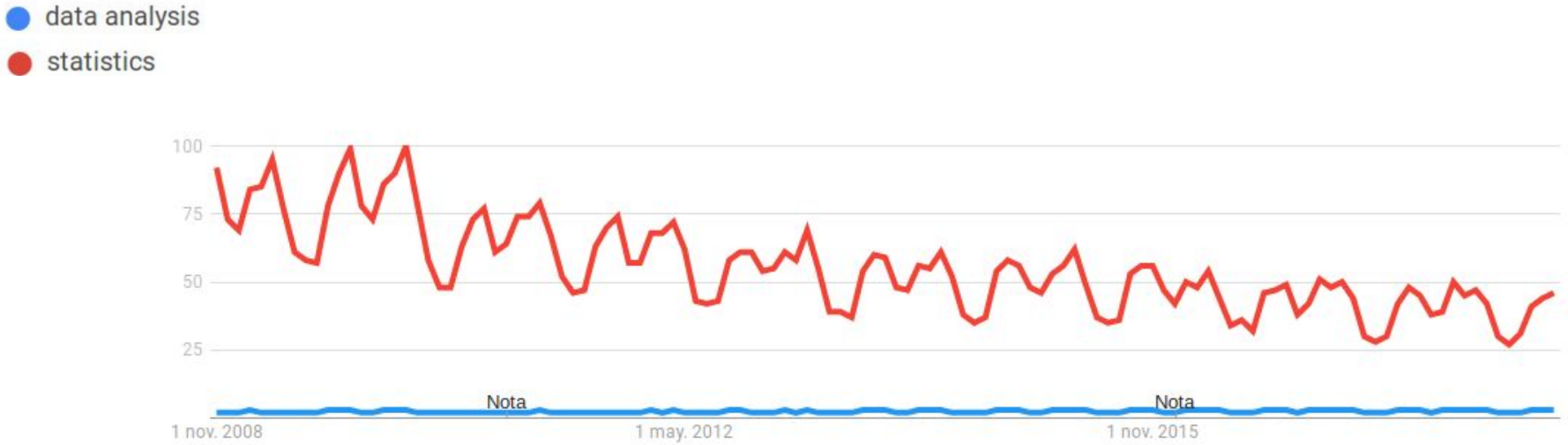

MACHINE LEARNING
ARTIFICIAL INTELLIGENCE
DEEP LEARNING
NEURAL NETWORKS
DATA MINING
DATA SCIENCE
NATURAL LANGUAGE PROCESSING
KNOWLEDGE DISCOVERY
RECOMMENDATION ENGINES
DATA DEVELOPER
DATA ENGINEER
TEXT MINING
PERSONALIZED MEDICINE

Un Poco de Historia...

I keep saying the ***sexy job*** *in the next ten years will be* ***statisticians****.* ***The ability to take data—to be able to understand it, to process it, to extract value from it, to visualize it, to communicate it—that's going to be a hugely important skill in the next decades****, not only at the professional level but even at the educational level for elementary school kids, for high school kids, for college kids.*

Hal Varian, Google's Chief Economist, 2008

Google Trend



Totem
Data Science

The New York Times

AUG. 5, 2009

TECHNOLOGY

For Today's Graduate, Just One Word: Statistics

By STEVE LOHR AUG. 5, 2009

MOUNTAIN VIEW, Calif. — At Harvard, Carrie Grimes majored in anthropology and archaeology and ventured to places like Honduras, where she studied Mayan settlement patterns by mapping where artifacts were found. But she was drawn to what she calls "all the computer and math stuff" that was part of the job.

"People think of field archaeology as Indiana Jones, but much of what you really do is data analysis," she said.

Now Ms. Grimes does a different kind of digging. She works at Google, where she uses statistical analysis of mounds of data to come up with ways to improve its search engine.

Ms. Grimes is an Internet-age statistician, one of many who are changing the image of the profession as a place for dronish number nerds. They are finding themselves increasingly in demand — and even cool.

"I keep saying that the sexy job in the next 10 years will be statisticians," said Hal Varian, chief economist at Google. "And I'm not kidding."

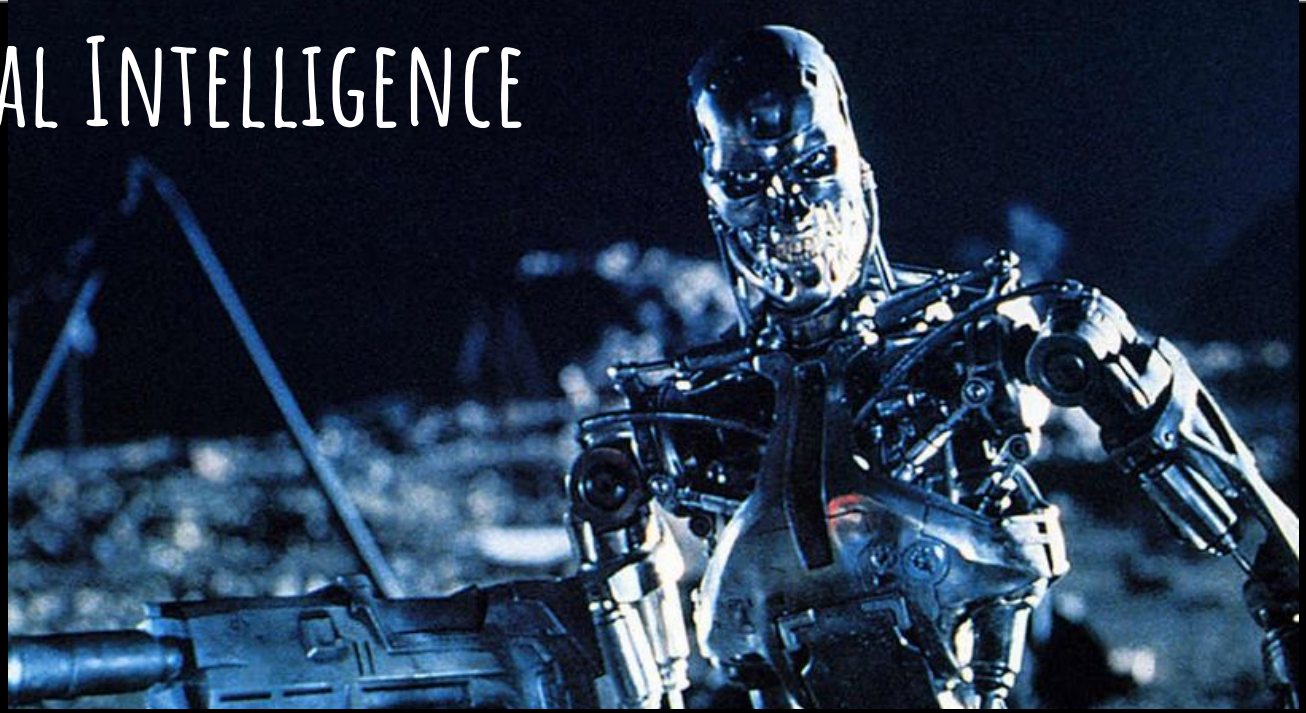
"People think of field archaeology as Indiana Jones, but much of what you really do is data analysis," she said.

"I keep saying that the sexy job in the next 10 years will be statisticians," said Hal Varian, chief economist at Google. "And I'm not kidding."

Yet data is merely the raw material of knowledge. "We're rapidly entering a world where everything can be monitored and measured," said Erik Brynjolfsson, an economist and director of the Massachusetts Institute of Technology's Center for Digital Business. "But the big problem is going to be the ability of humans to use, analyze and make sense of the data."

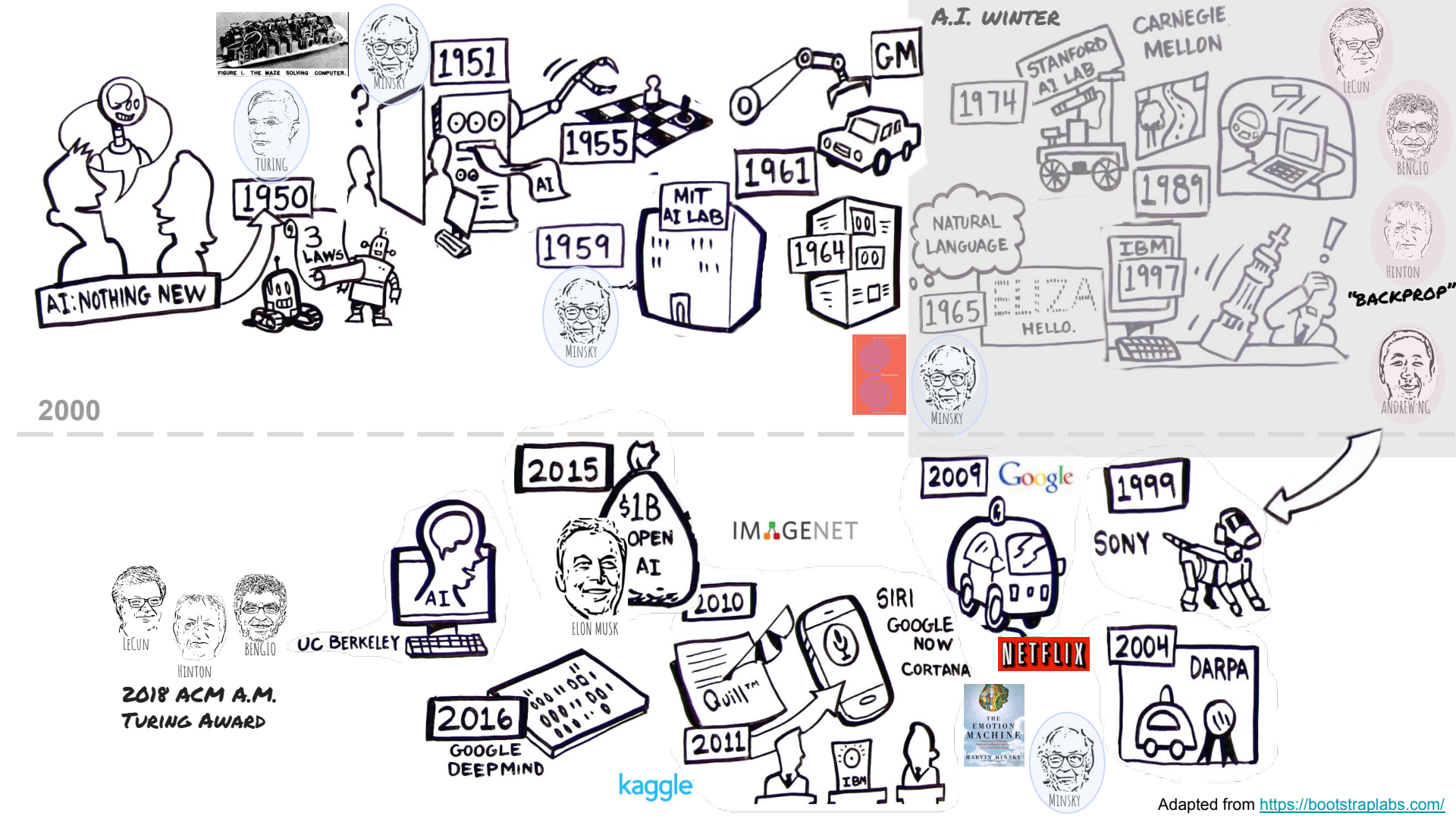
Even the recently ended Netflix contest, which offered $1 million to anyone who could significantly improve the company's movie recommendation system, was a battle waged with the weapons of modern statistics.

Artificial Intelligence



Once the computers got control, we might never get it back. We would survive at their sufferance. If we're lucky, they might decide to keep us as pets.

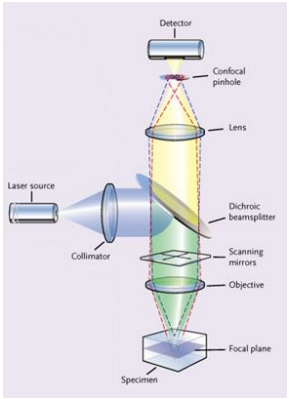
Marvin Minsky, 1970

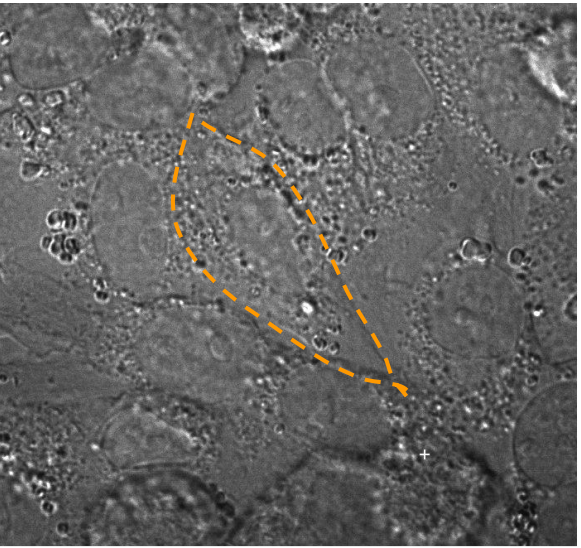


Adapted from https://bootstraplabs.com/

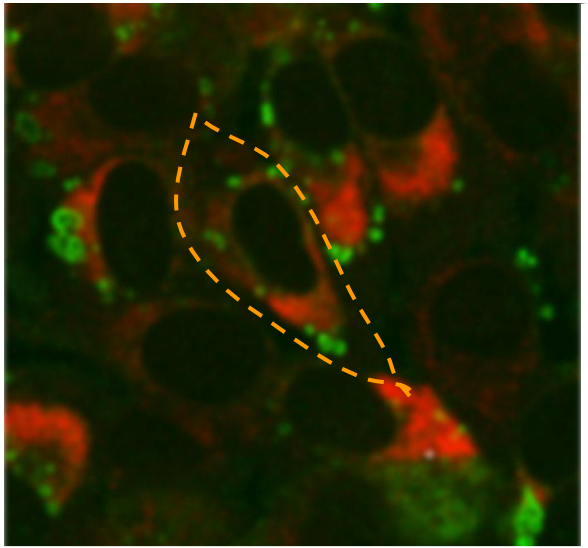
padre de la Inteligencia Artificial
...pero también de la Microscopía Confocal

marvin Minsky

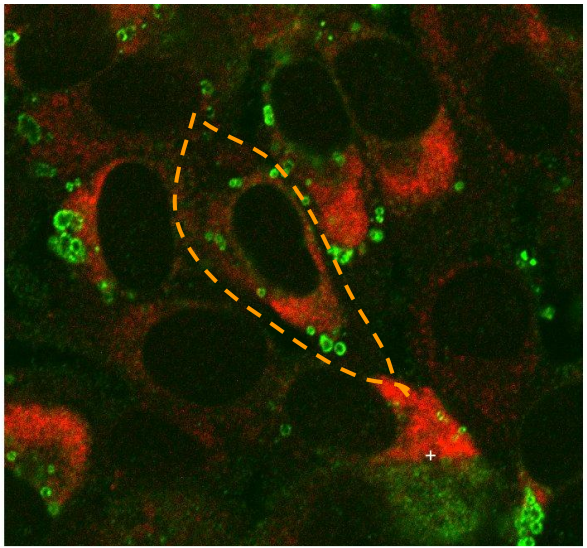




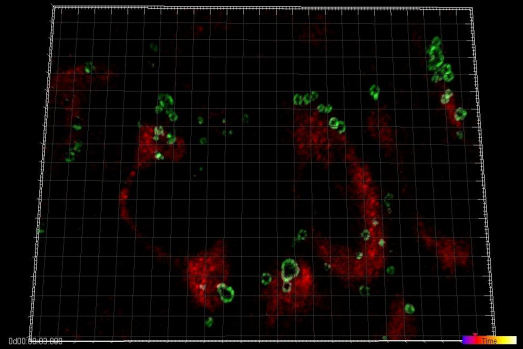
Contraste de Fases



Fluorescencia



Confocal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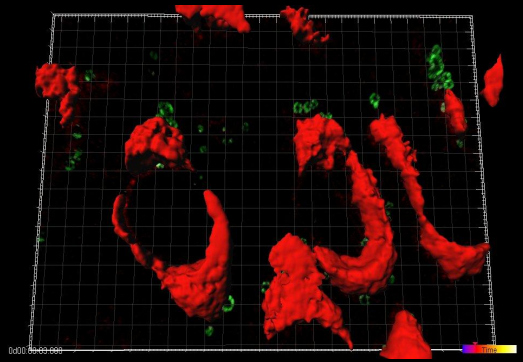
Time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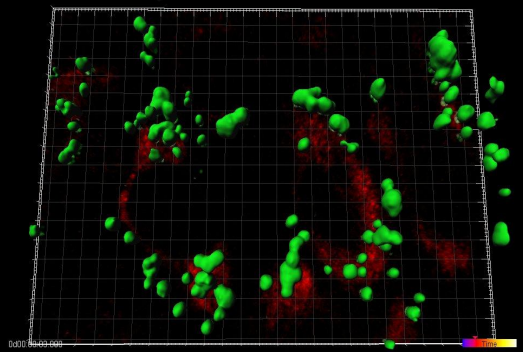
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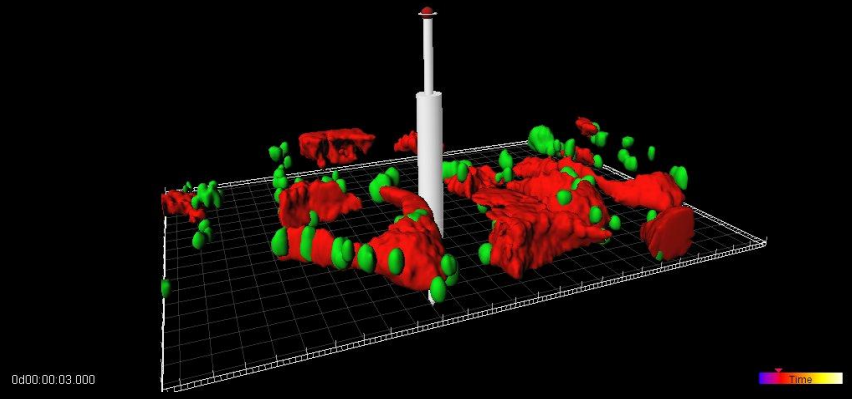
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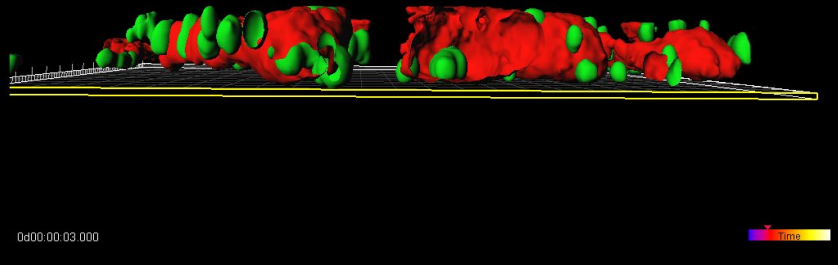
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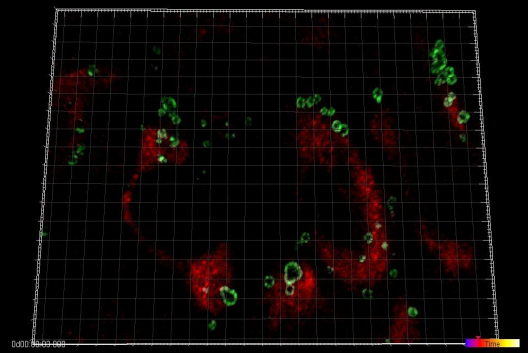

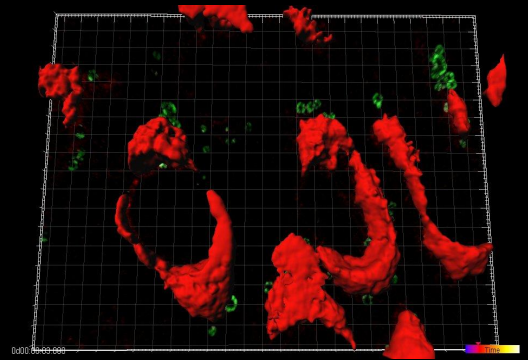

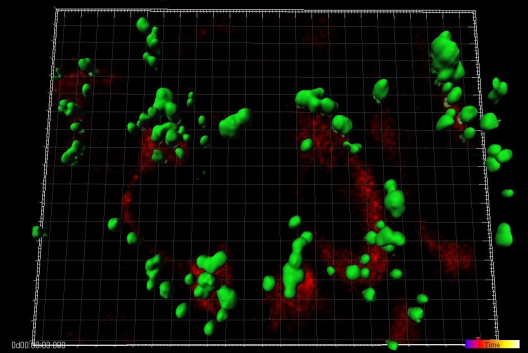

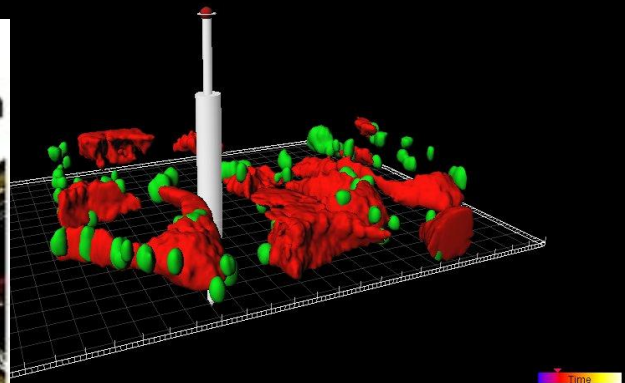

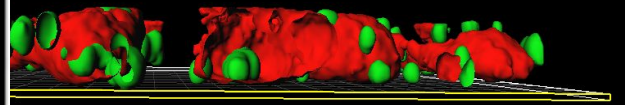

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Time

Artificial Intelligence (AI)

Intelligence Amplification (IA)

airbnb Google
Dropbox houzz
hudl
Spotify amazon
Quora Baidu 百度

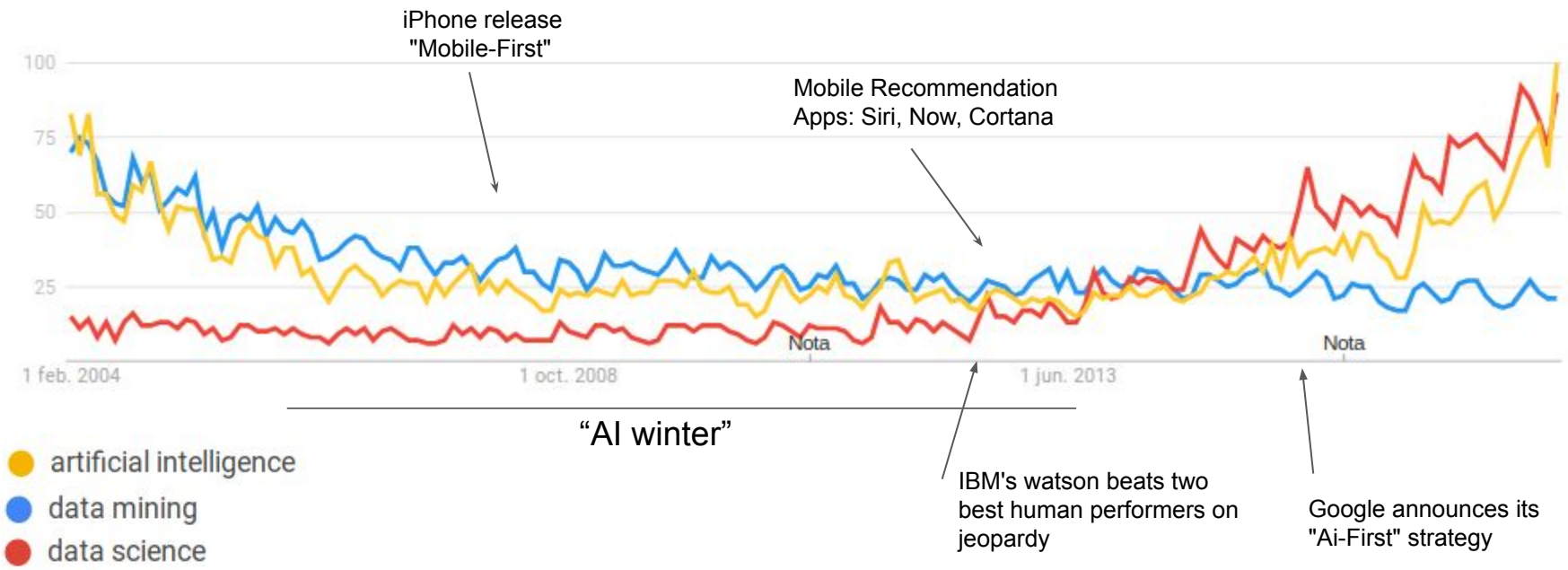
WIKIPEDIA
The Free Encyclopedia

Artificial intelligence (**AI**), sometimes called machine intelligence, is intelligence demonstrated by machines, in contrast to the natural intelligence displayed by humans and other animals. In computer science AI research is defined as the study of "intelligent agents": any device that perceives its environment and takes actions that maximize its chance of successfully achieving its goals. ***Colloquially, the term "artificial intelligence" is applied when a machine mimics "cognitive" functions that humans associate with other human minds, such as "learning" and "problem solving".***

WIKIPEDIA
The Free Encyclopedia

Intelligence amplification (**IA**) (also referred to as cognitive augmentation and **machine augmented intelligence**) refers to the effective use of information technology in augmenting human intelligence. The idea was first proposed in the 1950s and 1960s by cybernetics and early computer pioneers.
IA is sometimes contrasted with **AI** (**artificial intelligence**), that is, the project of building a human-like intelligence in the form of an autonomous technological system such as a computer or robot.

Google Trend



1956 - Term "Artificial Intelligence" coined by John McCarthy
1981 - First commercial expert system
1997- IBM's Deep Blue beats world champion Garry Kasparov at chess

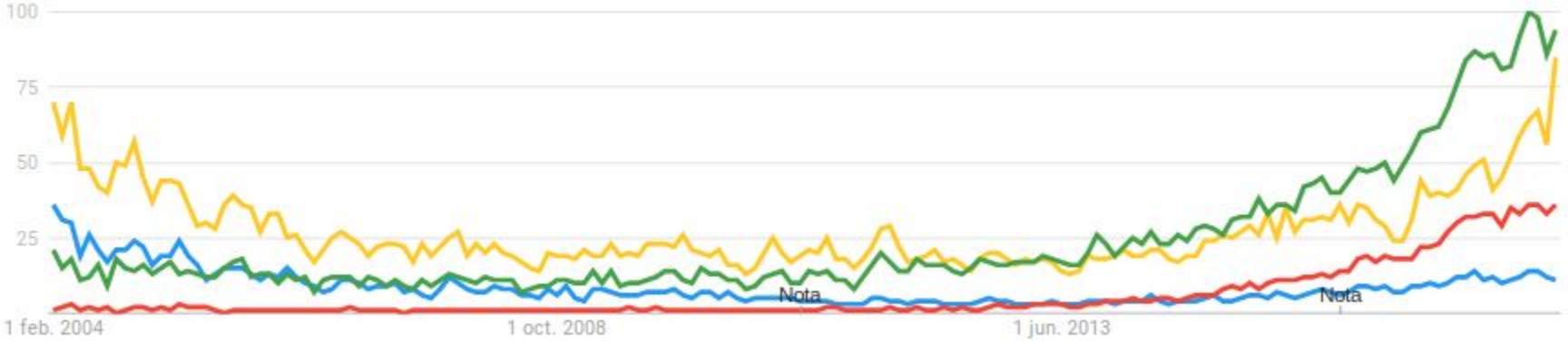
WIKIPEDIA
The Free Encyclopedia

Data mining is the process of discovering patterns in large data sets involving methods at the intersection of **machine learning, statistics, and database systems**. Data mining is an **interdisciplinary** subfield of computer science with an overall goal to **extract information** (with intelligent methods) from a data set and transform the information into a comprehensible structure for further use. Data mining is the analysis step of the "**knowledge discovery in databases**" process, or KDD.

Data science is an **interdisciplinary** field that uses scientific methods, processes, algorithms and systems to **extract knowledge** and insights from data in various forms, both structured and unstructured, **similar to data mining**.

Data science is a "concept to unify **statistics, data analysis, machine learning and their related methods**" in order to "understand and analyze actual phenomena" with data. It employs techniques and theories drawn from many fields within the context of mathematics, statistics, information science, and computer science.

Google Trends



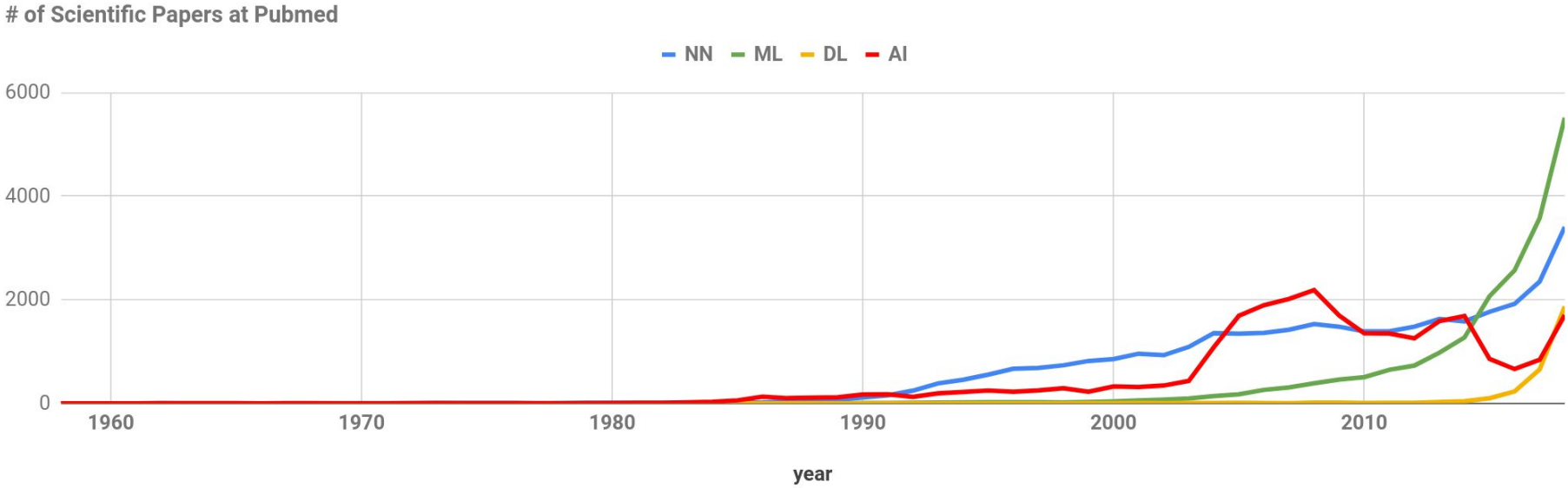
- artificial intelligence
- neural networks
- deep learning
- machine learning

WIKIPEDIA
The Free Encyclopedia

Machine learning (**ML**) is a field of artificial intelligence that **uses statistical techniques to give computer systems the ability to learn from data**, without being explicitly programmed.

Deep learning (DL) (also known as deep structured learning or hierarchical learning) **is part of a broader family of machine learning methods based on artificial neural networks**. Learning can be supervised, semi-supervised or unsupervised.

Artificial neural networks (ANN) or connectionist systems are computing systems that are inspired by, but not necessarily identical to, **the biological neural networks** that constitute animal brains. **Such systems "learn" to perform tasks by considering examples,** generally without being programmed with any task-specific rules.


# of Scientific Papers at Pubmed
NN
ML
DL
AI
6000
4000
2000
0
1960
1970
1980
1990
2000
2010
year


MACHINE LEARNING
MACHINE LEARNING EVERYWHERE!

"*Just as electricity transformed almost everything 100 years ago, today I actually have a hard time thinking of an industry that I don't think AI will transform in the next several years*"

Andrew Ng, 2017

"***Artificial Intelligence*** *is probably the most important thing humanity has ever worked on.* ***I think of it as something more profound than electricity or fire***."

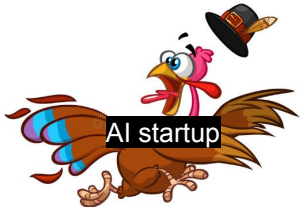
Sundar Pichai, Google's CEO, 2018

In last 6 year…

14 Billions of dollars...

2000 companies...

50% at initial stage….



Marcos Galperin ✓
@marcos_galperin

muy contentos de sumar al equipo de 60 desarrolladores de @machinalis a nuestro centro de desarrollo en Córdoba que ya suma 500 programadores.
Bienvenidos!lavoz.com.ar/negocios/merca...

♡ 487 17:31 - 9 sept. 2018

Mercado Libre compró una "startup" nacida en la UNC | La Voz
Se quedó con Machinalis, incubada en la Famaf y proveedora de desarrollos de "machine learning". Su exCEO, Juan Chacón,
lavoz.com.ar

67 personas están hablando de esto

Debora Slotnisky ✓
@deboraslot

Seguir

¡Primicia! @etermax (creadora del juego @Preguntados) compró la firma de #InteligenciaArticial Cognitiva. Toda, toda la información, en un extenso informe que publiqué en la revista Infotechnology, que ya está en la calle.

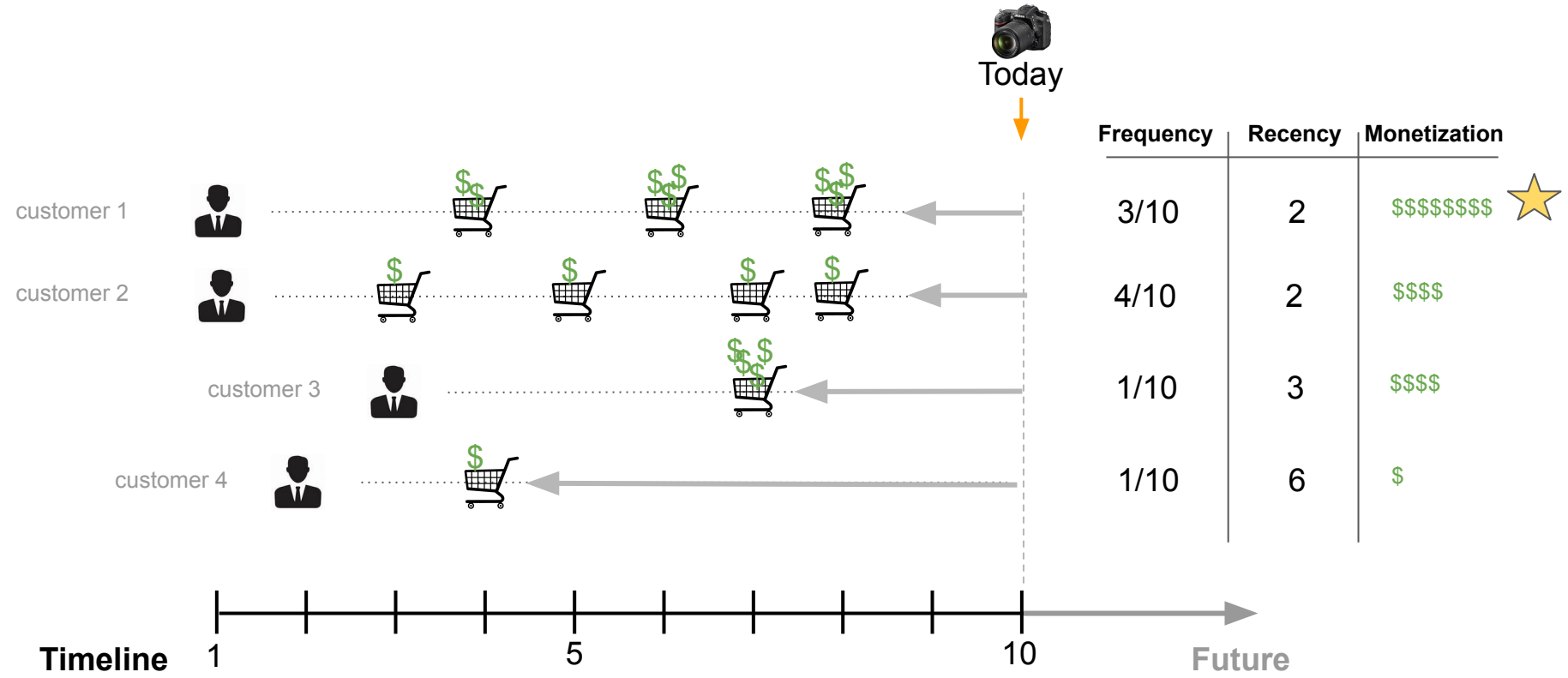
2:54 - 28 ene. 2019

16 Retweets **48** Me gusta

¿ A qué se debe la explosión del Machine Learning?

PARADIGMA PREVIO

CUSTOMER VALUE (CV)



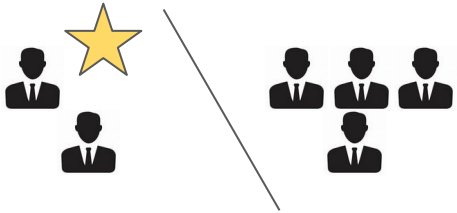
RFM : CUSTOMER VALUE ESTIMATION

Data

Data coming from **RFM análisis**

Rules and heuristics

Segmentation

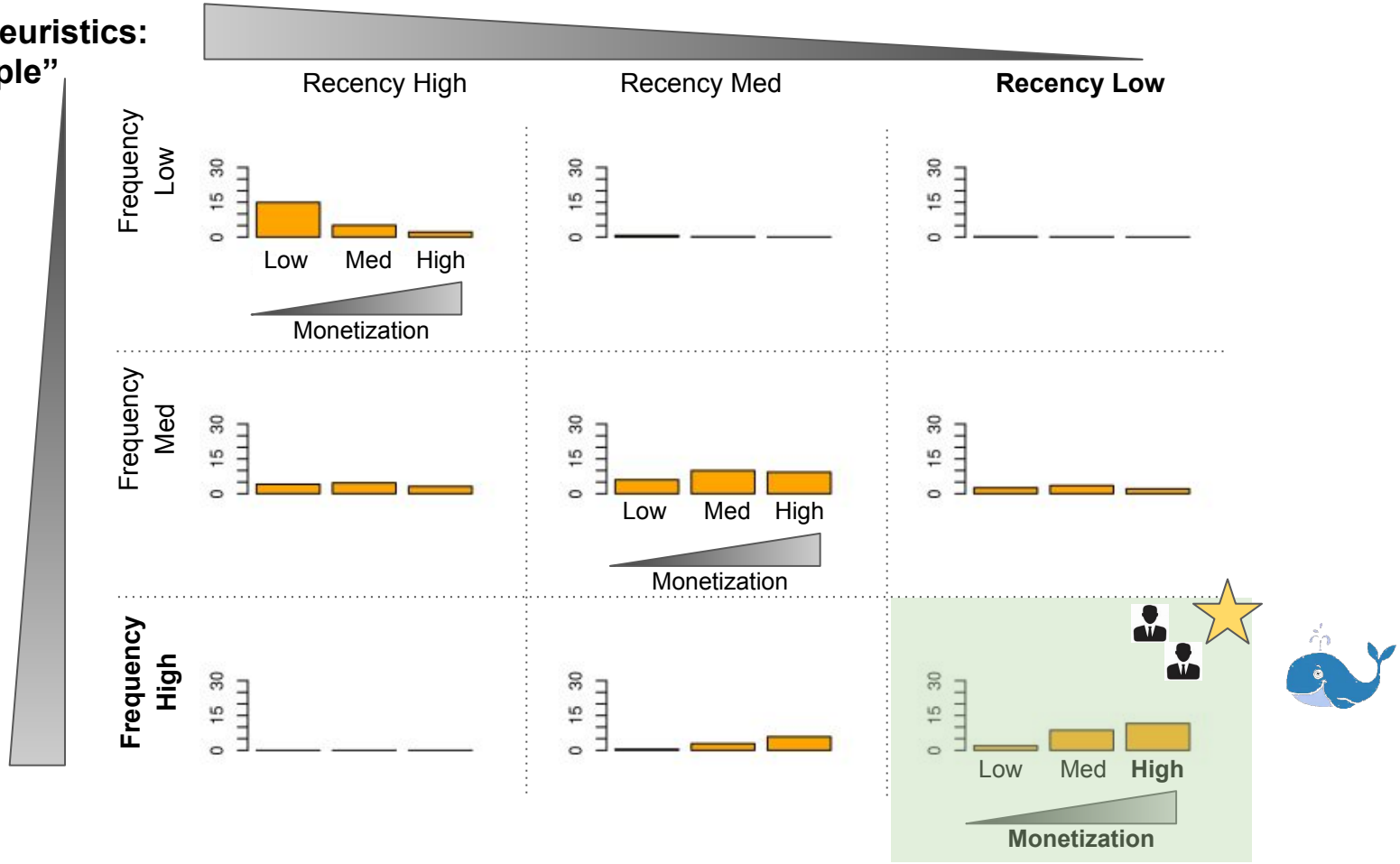


Recency – *¿Cuando fue la última compra?*
Frequency – ¿Con que frecuencia compran los usuarios?
Monetary Value – ¿ Cuanta plata gastan?

Group A
High frequency
High monetization
Low recency

Group B
(other)

Rules and heuristics: “RFM example”



Group A

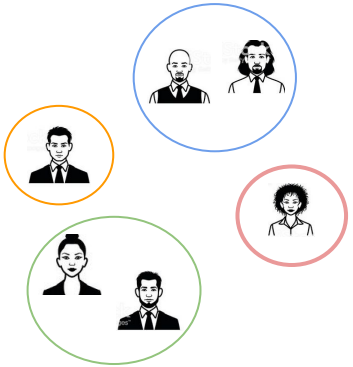
```
-- SQL Query

select  AVG(Monetization)
where
Frequency = “High” (Los que compran más frecuentemente)  AND
Recency = “Low”   (Los que han comprado más frecuentemente)  AND
Monetization = “High” (Los que realizan compras de mayor valor)
```

Cambio de Paradigma !

ML
Algorithms

Decisiones personalizadas



Data coming from user history, social networks, surveys, forecasting realtime demand, etc,

Customer Segmentation and Personalized Recommendation

Otro Ejemplo...
moderación de contenidos

DS de @CFK

filter if ... “kuka”

DS de @mauriciomacri

filter if ... “MMLPQTP”

DS de @CFK

filter if ... “kuka”

?

DS de @mauriciomacri

filter if ... “MMLPQTP”

?

DS de @CFK

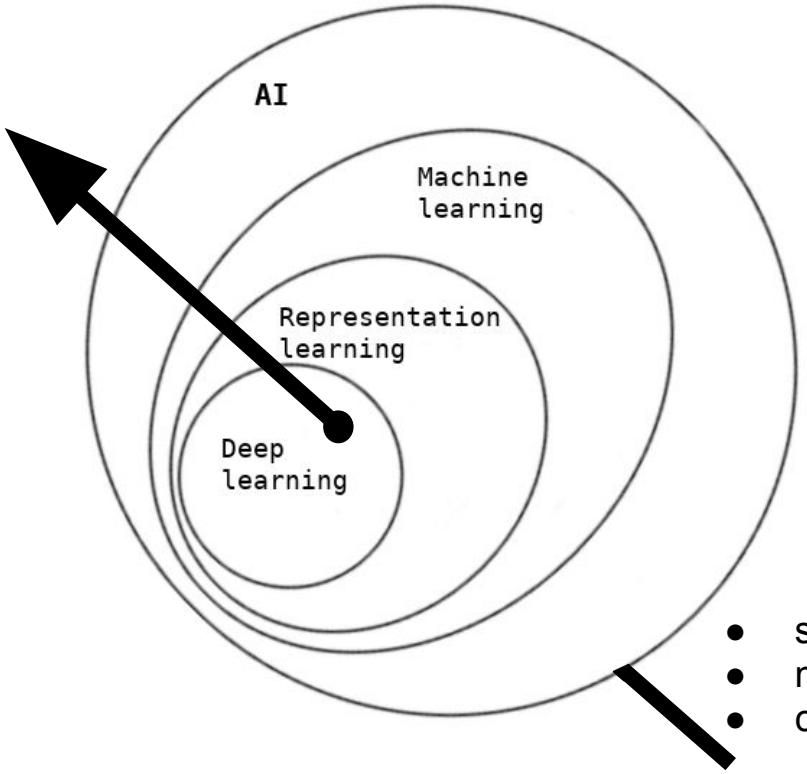
?

DS de @mauriciomacri

?

Un poco más de claridad con mayor profundidad!

“*Artificial intelligence World*”



- statistics
- maths
- computing

AI

(ex. **knowledge base**)

└— **Machine Learning**

(**ex. logistic regression, linear regression, decision trees, clustering**)

└— **Representation Learning**

(ex. **autoencoders**)

└— **Deep Learning**

(ex. **Multilayers Perceptrons**)

Adapted from Goodfellow et. al., 2016

Una breve introducción al los algoritmos de AI utilizados

Utilización de algoritmos de AI dentro de una startup que organiza eventos deportivos...

Datos históricos de participación en **eventos previos**:

1. x_1 : ¿Como estaba el tiempo?
2. x_2 : ¿Le resultó costoso el ticket promedio?
3. x_3: ¿Qué tan distante le quedaba el estadio?
4. x_4: ¿Que tan fanático es de su equipo ?
5. x_5: ¿Si ha ido previamente a ver a su equipo?

Respuesta $\mathbf{X}_n$: un valor entre 1 to 10

Machine Learning

(logistic regression, linear regression, decision trees, clustering)

Usuarios con datos históricos previos:

julio

Roberto

Tita

Carlos

Usuario nuevo

Jorge

Datos de los usuarios:

	Person	tiempo (x_1)	costo (x_2)	distancia (x_3)	fanatismo (x_4)	previa (x_5)	Va ?	precio ticket ?
training	Julio	9.00	2.00	7.00	3.00	0.00	yes	800
	Roberto	4.00	8.00	9.00	10.00	2.00	yes	1500
	Tita	8.00	6.00	9.00	5.00	0.00	no	0
testing	Carlos	8.00	4.00	6.00	5.00	0.00	yes	1000
to predict	Jorge	9.00	2.00	7.00	3.00	0.00	?	?

pasado

datos de hoy

tiempo

OBJETIVO 1: PREDECIR SI UN USUARIO ASISTIRÁ A UN PRÓXIMO EVENTO

Features:

1. x_1 : ¿Como esta el tiempo?
2. x_2 : ¿Le resultan costoso el ticket promedio?
3. x_3: ¿Qué tan distante le resulta el estadio?
4. x_4: ¿Que tan fanático es ?
5. x_5: ¿ Ha ido previamente a ver a su equipo?

Respuesta $\mathbf{X}_n$: un valor entre 1 to 10

1 - Selección de un algoritmo de Machine learning
2 - Fase de Entrenamiento con datos históricos
3 - Fase de testeo
4 - Generación de una predicción

Algoritmo

Supervisado

Respuesta $\mathbf{X_n}$: un valor entre 1 to 10

Person	tiempo (x_1)	costo (x_2)	distancia (x_3)	fanatismo (x_4)	previa (x_5)	Va ?
Julio	9.00	2.00	7.00	3.00	0.00	yes
Roberto	4.00	8.00	9.00	10.00	2.00	yes
Tita	8.00	6.00	9.00	5.00	0.00	no
Carlos	8.00	4.00	6.00	5.00	0.00	yes
Jorge	9.00	2.00	7.00	3.00	0.00	?

Algoritmo = Multiplicación del valor de cada feature por un peso (w)

$\mathbf{W_n}$: un valor arbitrario entre -1 to 1,

$$\sum_{x_i=1}^{n} = x_1w_1 + x_2w_2 + x_3w_3 + x_4w_4 + x_5w_5$$

Fase de Entrenamiento (train)

Julio: yes

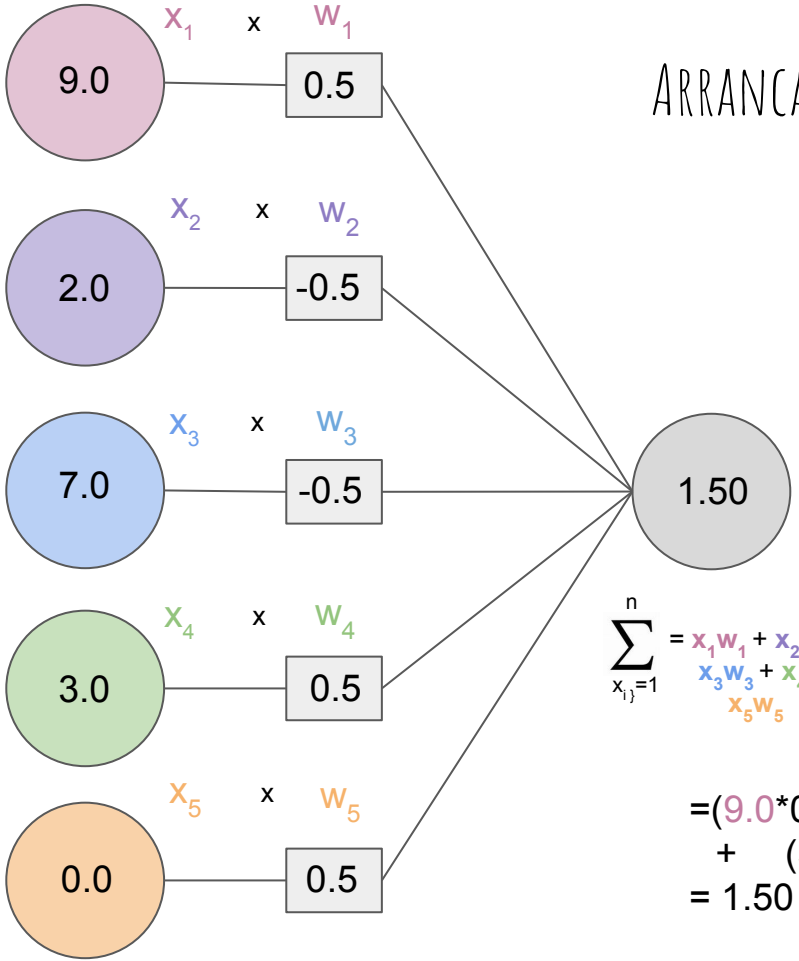
tiempo

costo

distancia

fan

previa

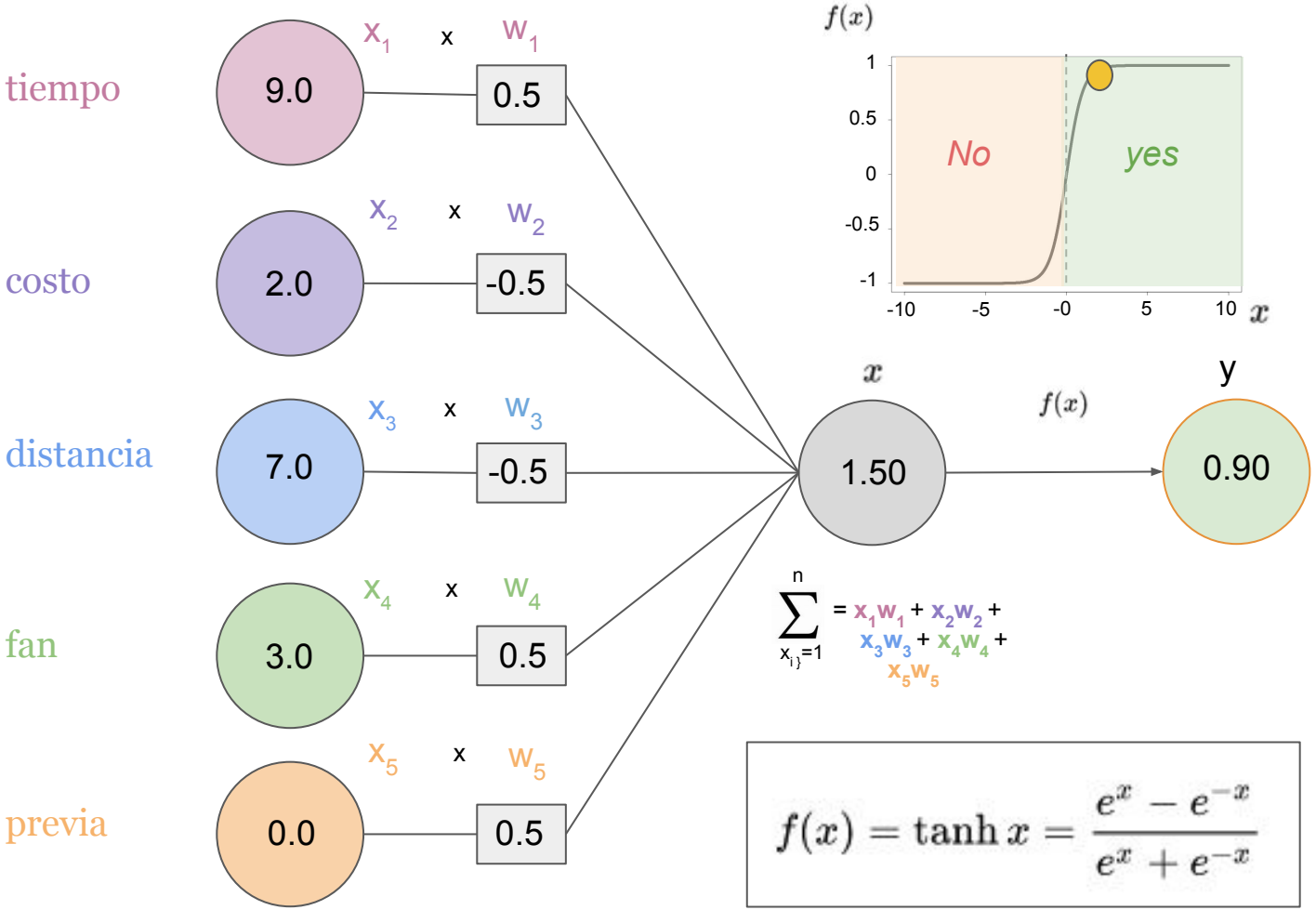


Arrancamos los pesos w en 0.5

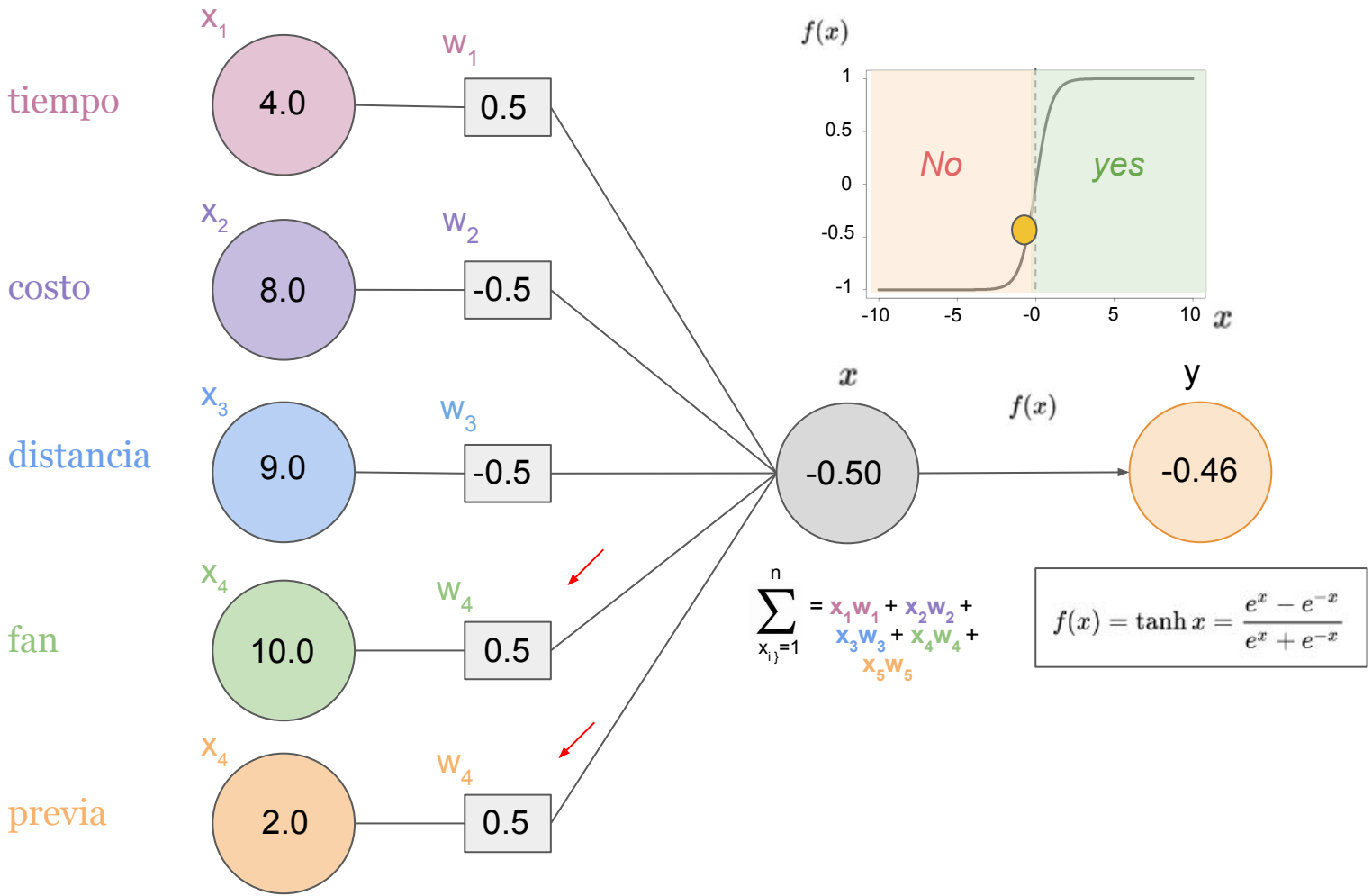
$$\sum_{x_i}^{n=1} = x_1w_1 + x_2w_2 + x_3w_3 + x_4w_4 + x_5w_5$$

=(9.0*0.5) + (2.0* -0.5) + (7.0*-0.5)
+ (3.0 +0.5) + (0.0*0.5)
= 1.50

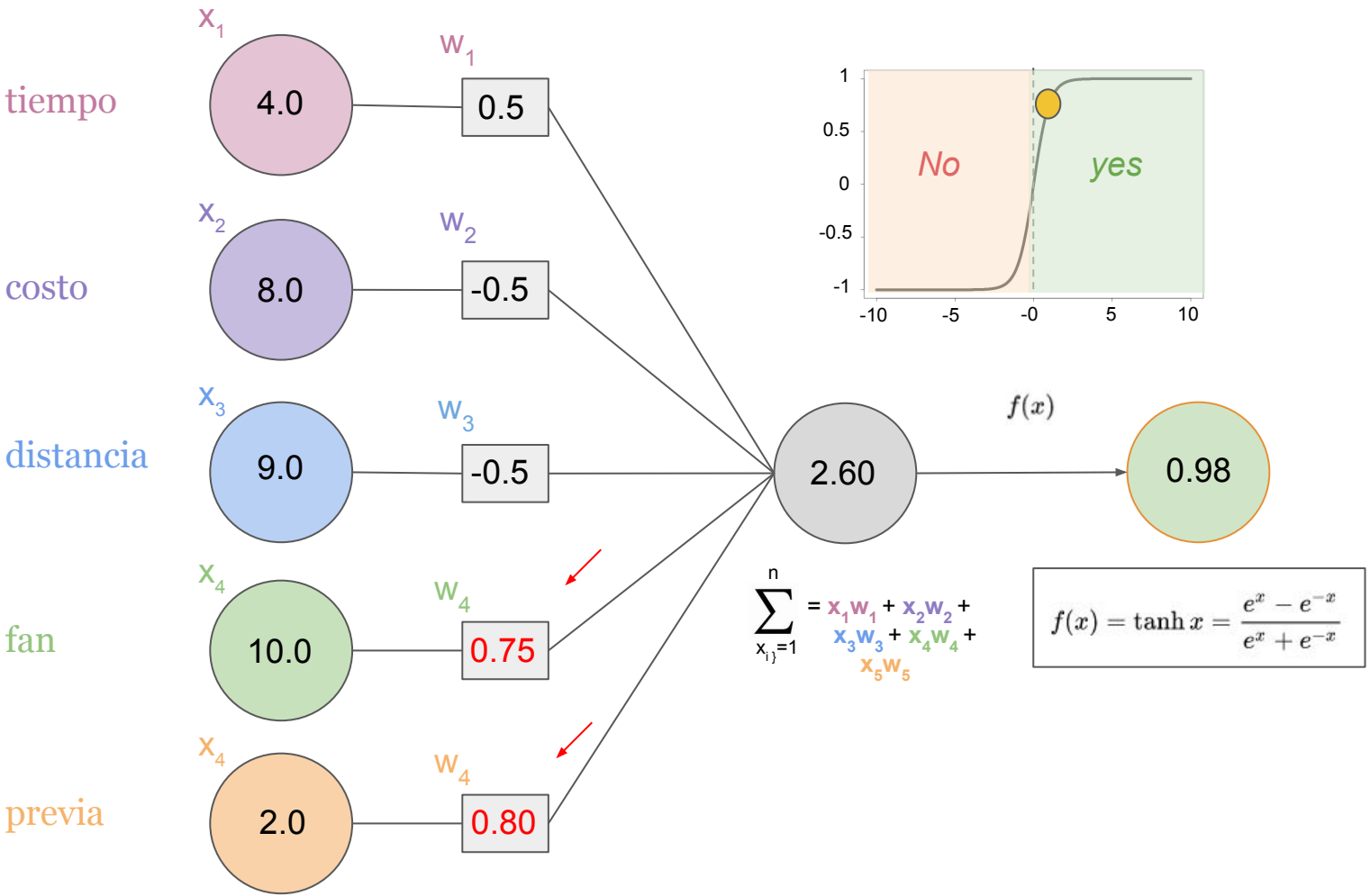
Julio: yes


tiempo
costo
distancia
fan
previa
9.0
2.0
7.0
3.0
0.0
x1 x w1
x2 x w2
x3 x w3
x4 x w4
x5 x w5
0.5
-0.5
-0.5
0.5
0.5
1.50
x
f(x)
y
0.90
f(x)
1
0.5
0
-0.5
-1
-10
-5
-0
5
10
x
No
yes
n
∑
xi}=1
= x1w1 + x2w2 +
x3w3 + x4w4 +
x5w5
f(x) = tanh x = (e^x − e^−x) / (e^x + e^−x)

Roberto: yes


tiempo
costo
distancia
fan
previa
x_1
x_2
x_3
x_4
x_4
4.0
8.0
9.0
10.0
2.0
w_1
w_2
w_3
w_4
w_4
0.5
-0.5
-0.5
0.5
0.5
$f(x)$
1
0.5
0
-0.5
-1
-10
-5
-0
5
10
x
No
yes
x
-0.50
$f(x)$
y
-0.46
$\sum_{x_i}^{n} = x_1w_1 + x_2w_2 + x_3w_3 + x_4w_4 + x_5w_5$
$f(x) = \tanh x = \frac{e^x - e^{-x}}{e^x + e^{-x}}$

Roberto: yes


x1
w1
tiempo
4.0
0.5
x2
w2
costo
8.0
-0.5
x3
w3
distancia
9.0
-0.5
x4
w4
fan
10.0
0.75
x4
w4
previa
2.0
0.80
2.60
f(x)
0.98
No
yes
1
0.5
0
-0.5
-1
-10
-5
-0
5
10
$\sum_{x_i}^{n} = x_1w_1 + x_2w_2 + x_3w_3 + x_4w_4 + x_5w_5$
$f(x) = \tanh x = \frac{e^x - e^{-x}}{e^x + e^{-x}}$

Julio: yes

tiempo

distancia

costo

fan

previa

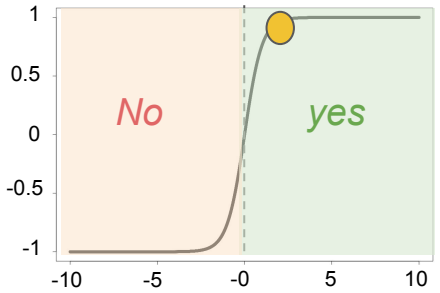
x_1 9.0 w_1 0.5

x_2 2.0 w_2 -0.5

x_3 7.0 w_3 -0.5

x_4 3.0 w_4 0.75

x_5 0.0 w_5 0.80



2.25

$f(x)$

0.97

$$\sum_{x_i}^{n=1} = x_1w_1 + x_2w_2 + x_3w_3 + x_4w_4 + x_5w_5$$

$$f(x) = \tanh x = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

Tita: no

tiempo

costo

distancia

fan

previa

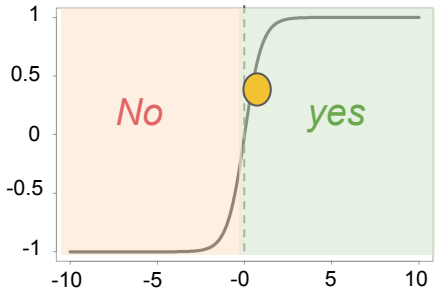
x_1 8.0 w_1 0.5

x_2 6.0 w_2 -0.5

x_3 9.0 w_3 -0.5

x_4 5.0 w_4 0.75

x_4 0.0 w_4 0.80



0.25

$f(x)$

0.24

$$\sum_{x_i}^{n} = x_1w_1 + x_2w_2 + x_3w_3 + x_4w_4 + x_5w_5$$

$$f(x) = \tanh x = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

Tita: no

tiempo

costo

distancia

fan

previa

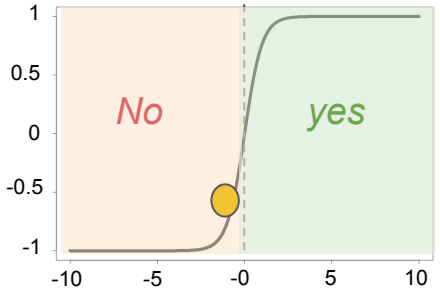
x_1 8.0 w_1 0.5

x_2 6.0 w_2 -0.65

x_3 9.0 w_3 -0.5

x_4 5.0 w_4 0.75

x_4 0.0 w_4 0.80



-0.65

$f(x)$

-0.57

$$\sum_{x_i}^{n} = x_1w_1 + x_2w_2 + x_3w_3 + x_4w_4 + x_5w_5$$

$$f(x) = \tanh x = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

Julio: yes

tiempo

costo

distancia

fan

previa

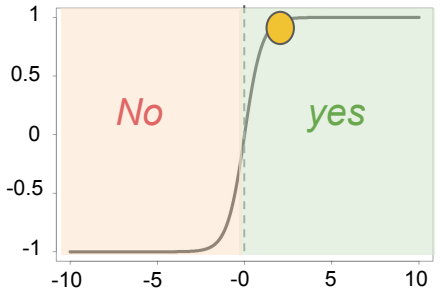
x_1 6.0 w_1 0.5

x_2 2.0 w_2 -0.65

x_3 6.0 w_3 -0.5

x_4 3.0 w_4 0.75

x_5 0.0 w_5 0.80



0.95

$f(x)$

0.73

$$\sum_{x_i}^{n} = x_1w_1 + x_2w_2 + x_3w_3 + x_4w_4 + x_5w_5$$

$$f(x) = \tanh x = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

Roberto: yes

tiempo

costo

distancia

fan

previa

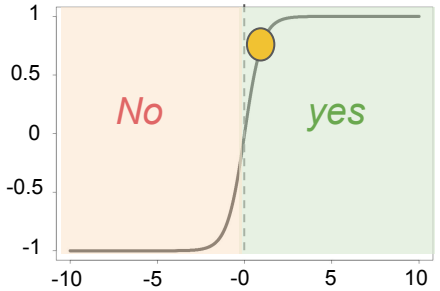
x_1 4.0 w_1 0.5

x_2 8.0 w_2 -0.65

x_3 9.0 w_3 -0.5

x_4 10.0 w_4 0.75

x_4 2.0 w_4 0.80



1.40

$f(x)$

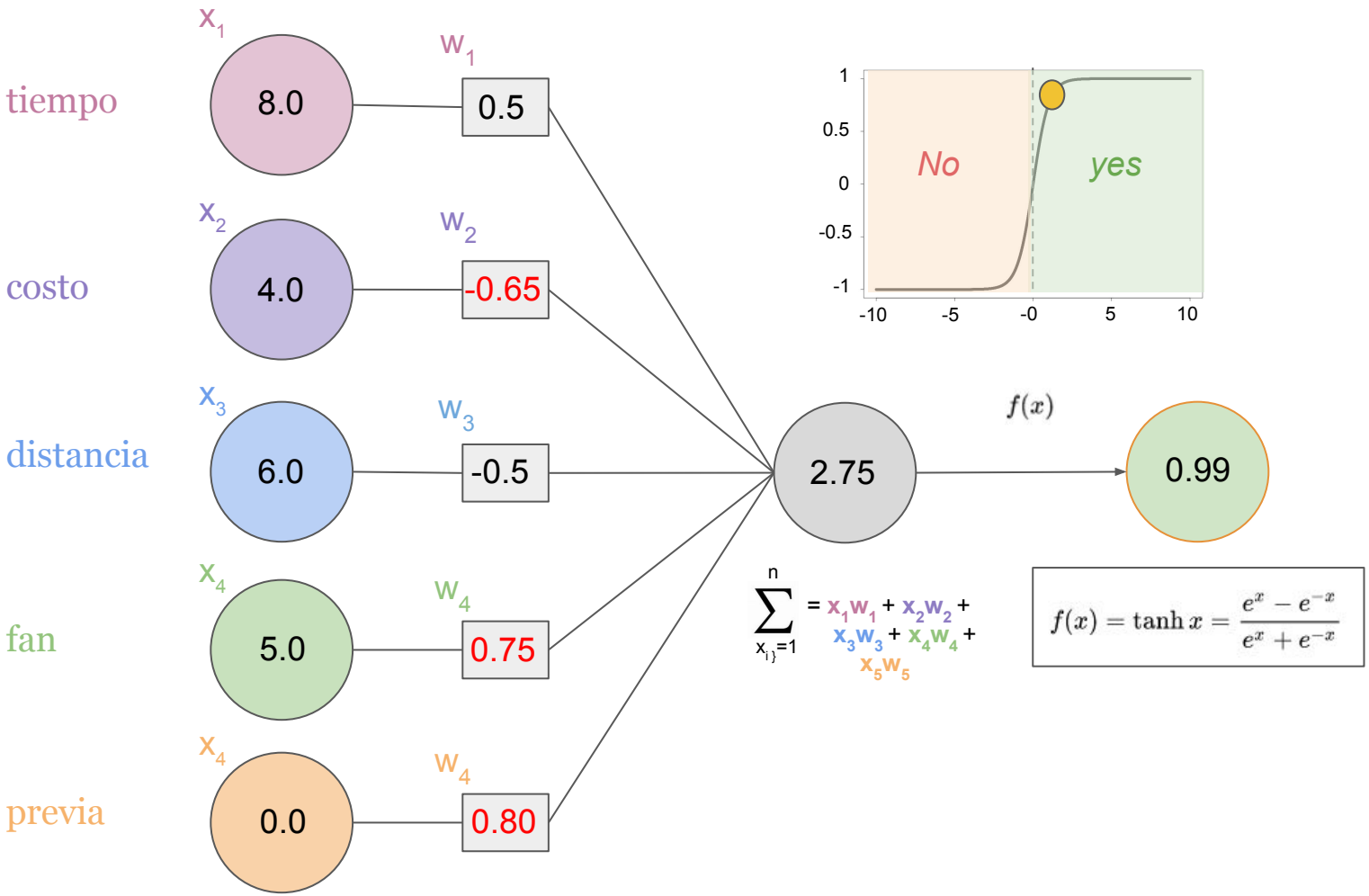
0.88

$$\sum_{x_i}^{n} = x_1w_1 + x_2w_2 + x_3w_3 + x_4w_4 + x_5w_5$$

$$f(x) = \tanh x = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

Fase de Testeo
(test)

Carlos: yes


x1
w1
tiempo
8.0
0.5
x2
w2
costo
4.0
-0.65
x3
w3
distancia
6.0
-0.5
x4
w4
fan
5.0
0.75
x4
w4
previa
0.0
0.80
2.75
f(x)
0.99
No
yes
1
0.5
0
-0.5
-1
-10
-5
-0
5
10
$\sum_{x_i}^{n} = x_1w_1 + x_2w_2 + x_3w_3 + x_4w_4 + x_5w_5$
$f(x) = \tanh x = \frac{e^x - e^{-x}}{e^x + e^{-x}}$

Generación de predicciones

¿Que predice el modelo para Jorge?

Jorge: ?

Datos de los **usuarios**:

	Person	tiempo (x_1)	costo (x_2)	distancia (x_3)	fanatismo (x_4)	previa (x_5)	Va ?
training	Julio	9.00	2.00	7.00	3.00	0.00	yes
	Roberto	4.00	8.00	9.00	10.00	2.00	yes
	Tita	8.00	6.00	9.00	5.00	0.00	no
testing	Carlos	8.00	4.00	6.00	5.00	0.00	yes
submit	Jorge	9.00	2.00	7.00	3.00	0.00	?

pasado

datos de hoy

Jorge: ?

tiempo

costo

distancia

fan

previa

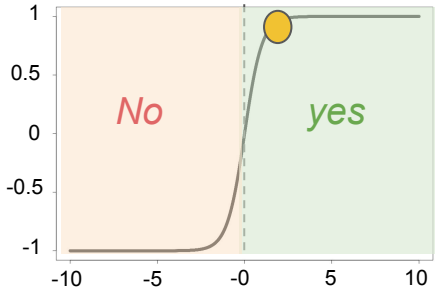
x_1 9.0 w_1 0.5

x_2 2.0 w_2 -0.65

x_3 7.0 w_3 -0.5

x_4 3.0 w_4 0.75

x_5 0.0 w_5 0.80



2.15

$f(x)$

0.97

$$\sum_{x_i}^{n} = x_1w_1 + x_2w_2 + x_3w_3 + x_4w_4 + x_5w_5$$

$$f(x) = \tanh x = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

Jorge: ?

tiempo

costo

distancia

fan

previa

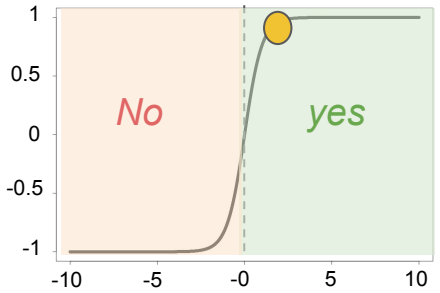
x_1 9.0 w_1 0.5

x_2 2.0 w_2 -0.65

x_3 7.0 w_3 -0.5

x_4 3.0 w_4 0.75

x_5 0.0 w_5 0.80



2.15

$f(x)$

0.97

$$\sum_{x_i}^{n}=1 = x_1w_1 + x_2w_2 + x_3w_3 + x_4w_4 + x_5w_5$$

$$f(x) = \tanh x = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

Regresión Logística

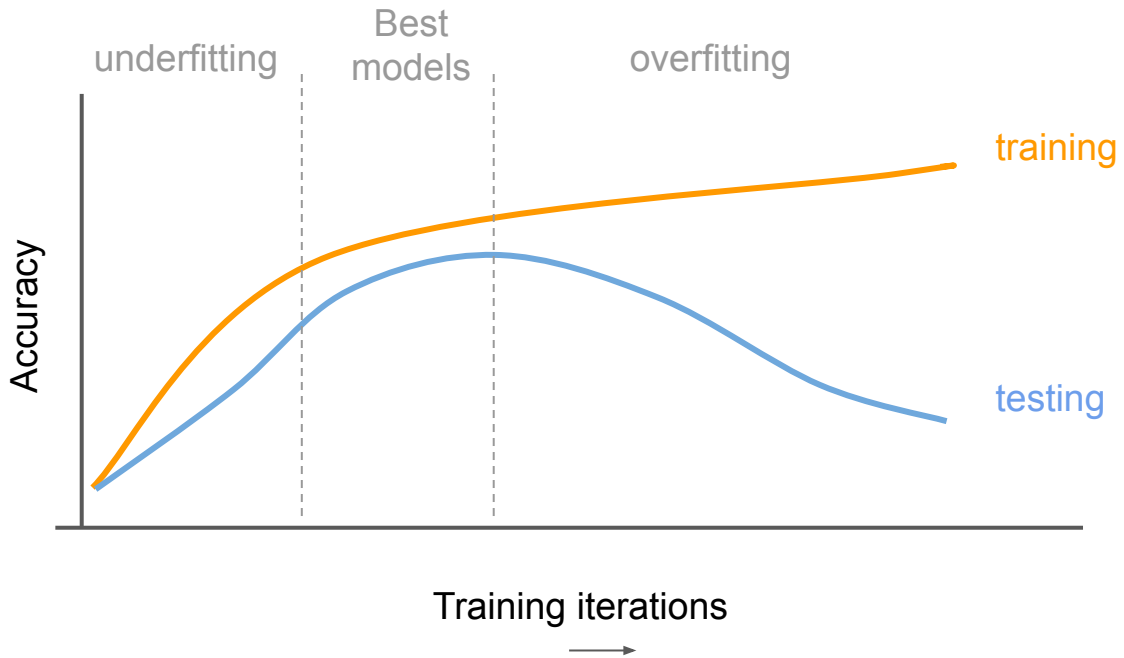
El algoritmo predice que el nuevo usuario irá al evento!

Predicción : Yes

Métricas utilizadas para evaluar la performance algoritmo:

Accuracy = Cantidad de predicciones correctas / total de predicciones

Regresión Logística

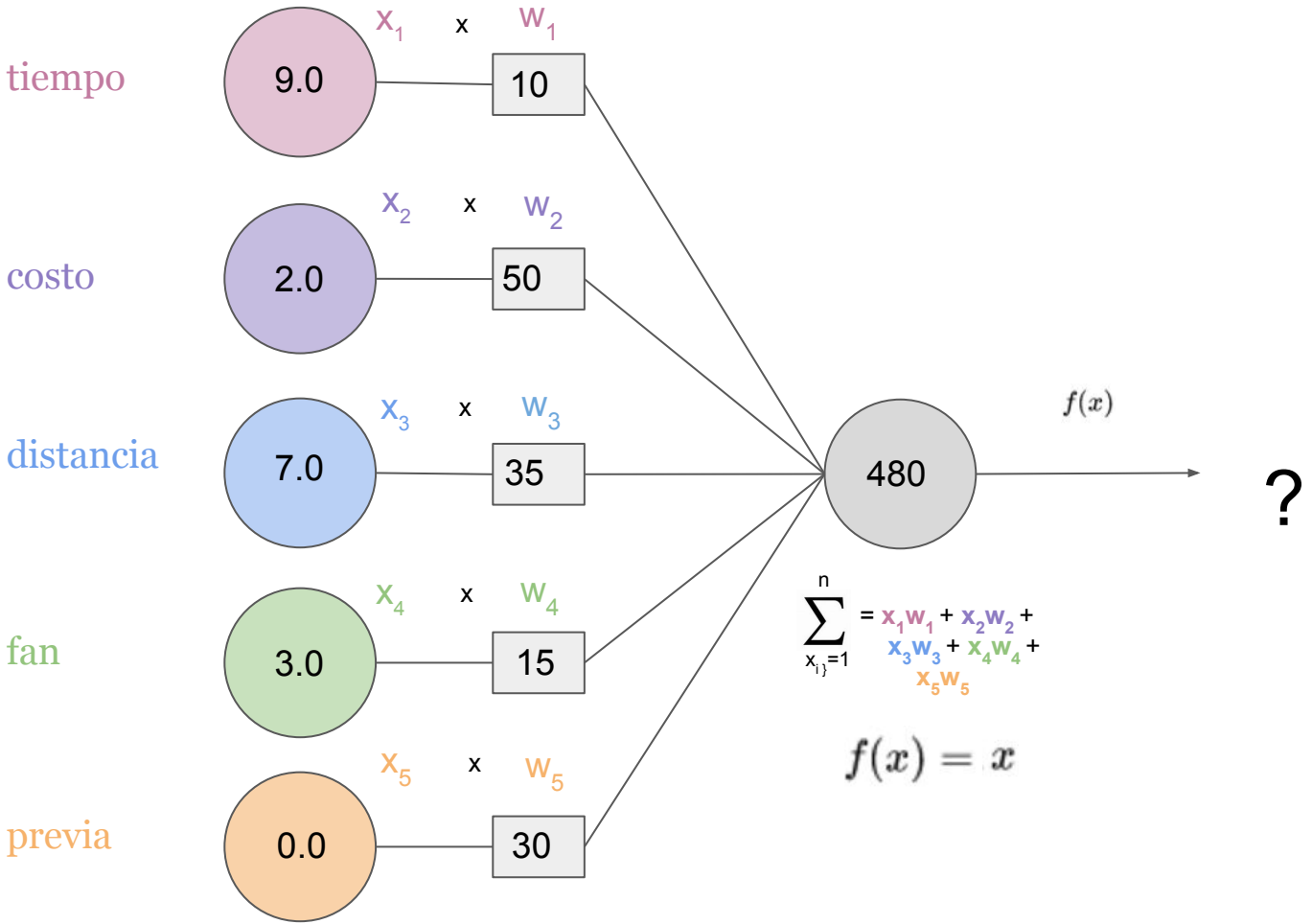

underfitting
Best models
overfitting
training
testing
Accuracy
Training iterations

OBJETIVO 2: PREDECIR VALOR DEL TICKET QUE PAGARÁN LOS USUARIOS

Datos de los **usuarios**:

	Person	tiempo (x_1)	costo (x_2)	distancia (x_3)	fanatismo (x_4)	previa (x_5)	Va ?	precio ticket ?	
training	Julio	9.00	2.00	7.00	3.00	0.00	yes	800	pasado
	Roberto	4.00	8.00	9.00	10.00	2.00	yes	1500	
testing	Tita	8.00	6.00	9.00	5.00	0.00	no	0	
	Carlos	8.00	4.00	6.00	5.00	0.00	yes	1000	
submit	Jorge	9.00	2.00	7.00	3.00	0.00	?	?	datos de hoy

Julio: 800


tiempo
costo
distancia
fan
previa
9.0
2.0
7.0
3.0
0.0
x_1 x w_1
x_2 x w_2
x_3 x w_3
x_4 x w_4
x_5 x w_5
10
50
35
15
30
480
$f(x)$
?
$\sum_{x_i}^{n} = x_1w_1 + x_2w_2 + x_3w_3 + x_4w_4 + x_5w_5$
$f(x) = x$

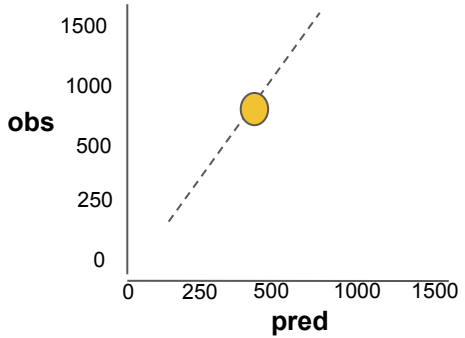
Julio: 800

TRAIN
TEST
PREDICCIÓN

tiempo
costo
distancia
fan
previa

x_1 x w_1 : 9.0 x 10
x_2 x w_2 : 2.0 x 50
x_3 x w_3 : 7.0 x 35
x_4 x w_4 : 3.0 x 15
x_5 x w_5 : 0.0 x 30

$y = x_1w_1 + ..+ x_5w_5$



480

$f(x)$

y

480

$$\sum_{x_i}^{n} = x_1w_1 + x_2w_2 + x_3w_3 + x_4w_4 + x_5w_5$$

$$f(x) = x$$

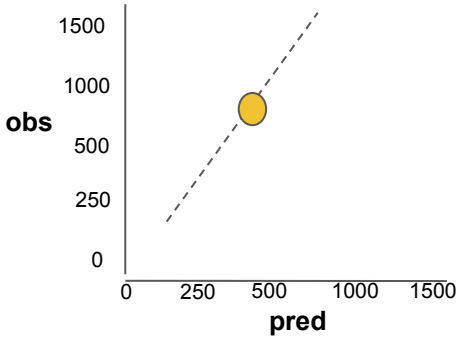
Julio: 800

TRAIN
TEST
PREDICCIÓN

tiempo
costo
distancia
fan
previa

x_1 x w_1 : 9.0 x 10
x_2 x w_2 : 2.0 x 50
x_3 x w_3 : 7.0 x 35
x_4 x w_4 : 3.0 x 15
x_5 x w_5 : 0.0 x 30

$y = x_1w_1 + ..+ x_5w_5$



480

$f(x)$

y

480

$$\sum_{x_i}^{n} = x_1w_1 + x_2w_2 + x_3w_3 + x_4w_4 + x_5w_5$$

$$f(x) = x$$

REGRESIÓN LINEAL

Métricas utilizadas para evaluar la performance algoritmo:

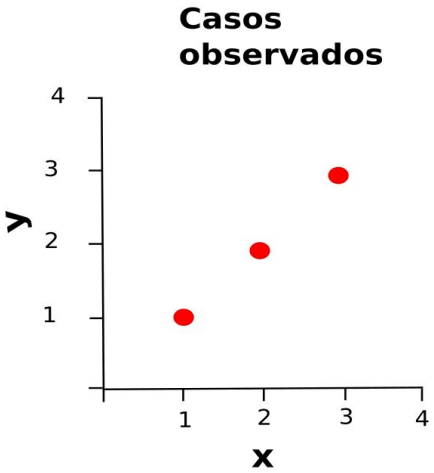
Root Mean Square Error

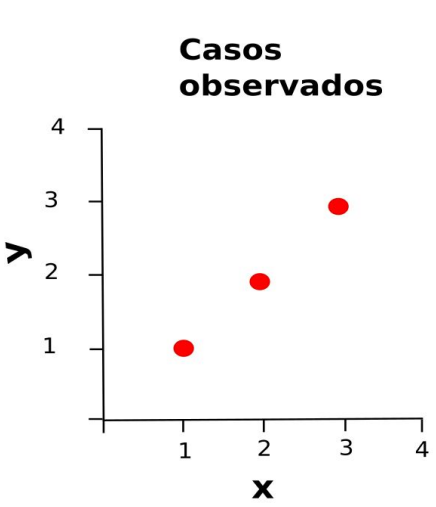
RMSE = sqrt (∑(pred -obs)^2 / N)

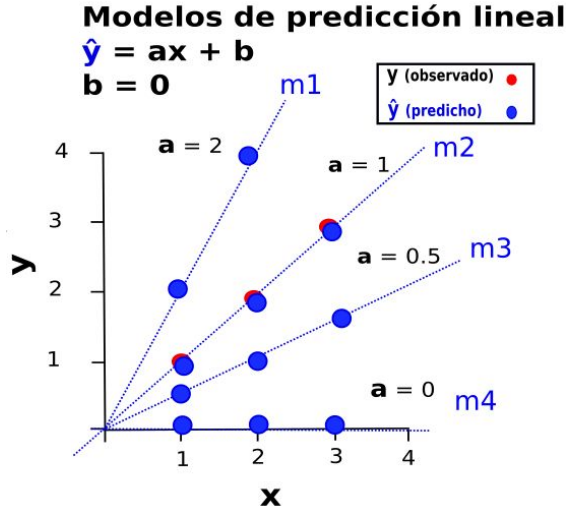
	Precio ticket		Error	
Persona	**obs**	**pred**	**(pred - obs)**	**RMSE**
Julio	800	480	-320	400
Roberto	1500	678	-822	750
Tita	0	350	350	0
Carlos	1000	1200	200	500

Regresión Lineal

Cómo se actualizan los pesos?

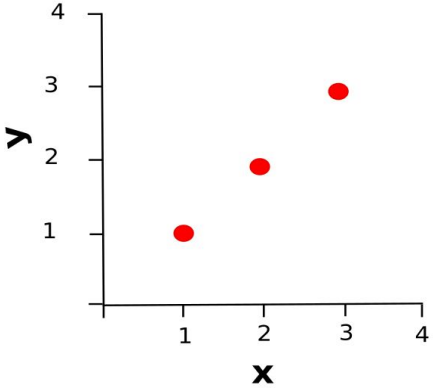

Casos
observados
4
3
2
1
y
1
2
3
4
x

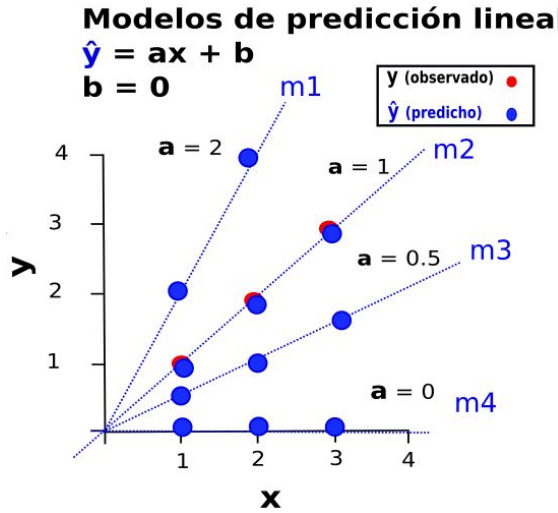


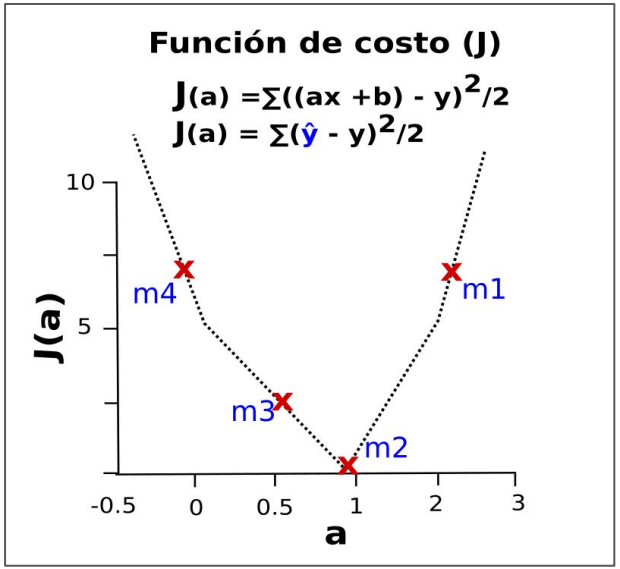


Modelos lineales

X	Y	m1 = X * 2	m2 = X * 1	m3 = X * 0.5	m1 = X *0
1	1	2	1	0.5	0
2	2	4	2	1	0
3	3	6	3	1.5	0







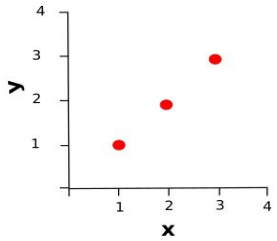
Modelos lineales

X	Y	m1 = X * 2	m2 = X * 1	m3 = X * 0.5	m1 = X *0
1	1	2	1	0.5	0
2	2	4	2	1	0
3	3	6	3	1.5	0

Función de costo

J(m1)	J(m2)	J(m3)	J(m4)
7	0	1.75	7

Derivando..



$$\delta = \frac{1}{2} \sum_{i=1}^{3} (y^{(i)} - (ax^{(i)} + b))^2$$

$$\delta = \frac{1}{2} (1 - (a(1) + b))^2 + (2 - (a(2) + b))^2 + (3 - (a(3) + b))^2$$

$$\delta = \frac{1}{2} (1 - a - b)^2 + (2 - 2a - b)^2 + (3 - 3a - b)^2)$$

Derivada parcial respecto de a

$$\frac{\partial \delta}{\partial a} = \frac{2}{2} ((-1)(1 - a - b) + (-2)(2 - 2a - b) + (-3)(3 - 3a - b))$$

$$\frac{\partial \delta}{\partial a} = \frac{2}{2} (-1 + a + b - 4 + 4a + 2b + -9 + 9a + 3b)$$

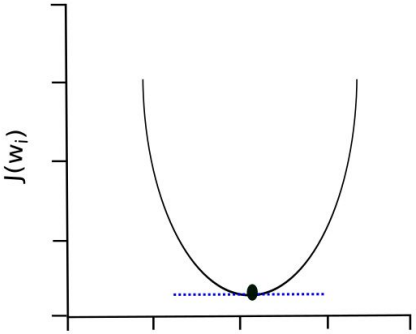
$$\frac{\partial \delta}{\partial a} = 14a + 6b - 14$$

Derivada parcial respecto de b

$$\frac{\partial \delta}{\partial b} = \frac{2}{2} ((-1)(1 - a - b) + (-1)(2 - 2a - b) + (-1)(3 - 3a - b))$$

$$\frac{\partial \delta}{\partial b} = \frac{2}{2} (-1 + a + b - 2 + 2a + b + -3 + 3a + b)$$

$$\frac{\partial \delta}{\partial b} = 6a + 3b - 6$$



$\frac{\partial \delta}{\partial b} = 6a + 3b - 6 = 0$, luego

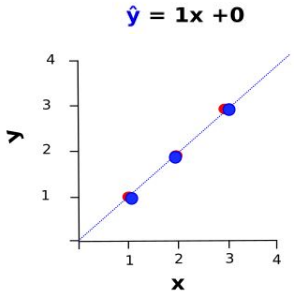
$b = \frac{6-6a}{3} = 2 - 2a$, y

$\frac{\partial \delta}{\partial a} = 14a + 6(2 - 2a) - 14 = 0$

$14a + 12 - 12a - 14 = 0$

$a = \frac{2}{2} = 1$

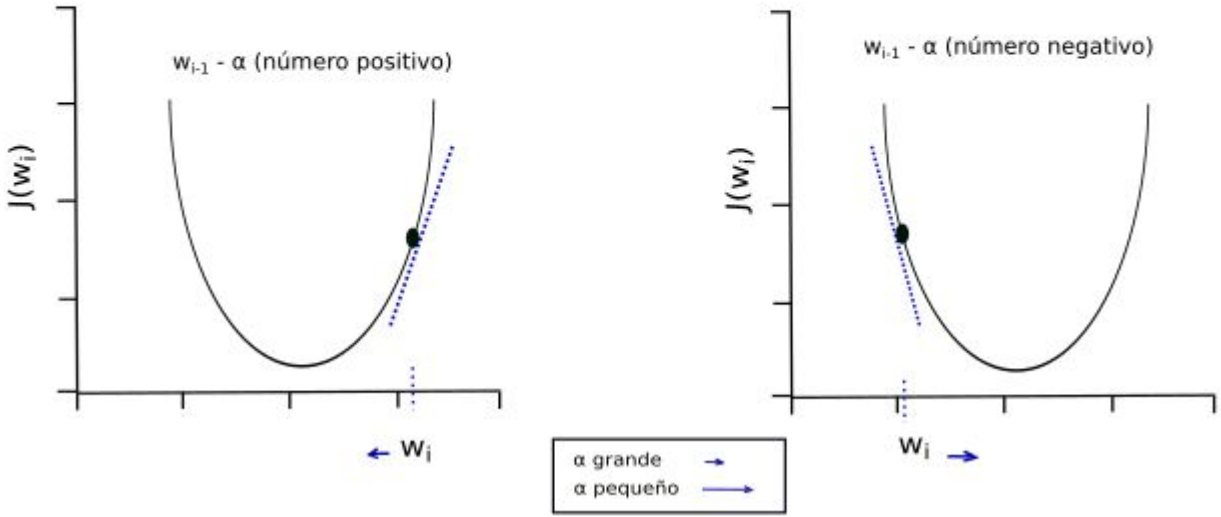
$b = 2 - 2a = 0$



Gradient descent

$$w_i = w_{i-1} - \Delta w_{i-1}$$

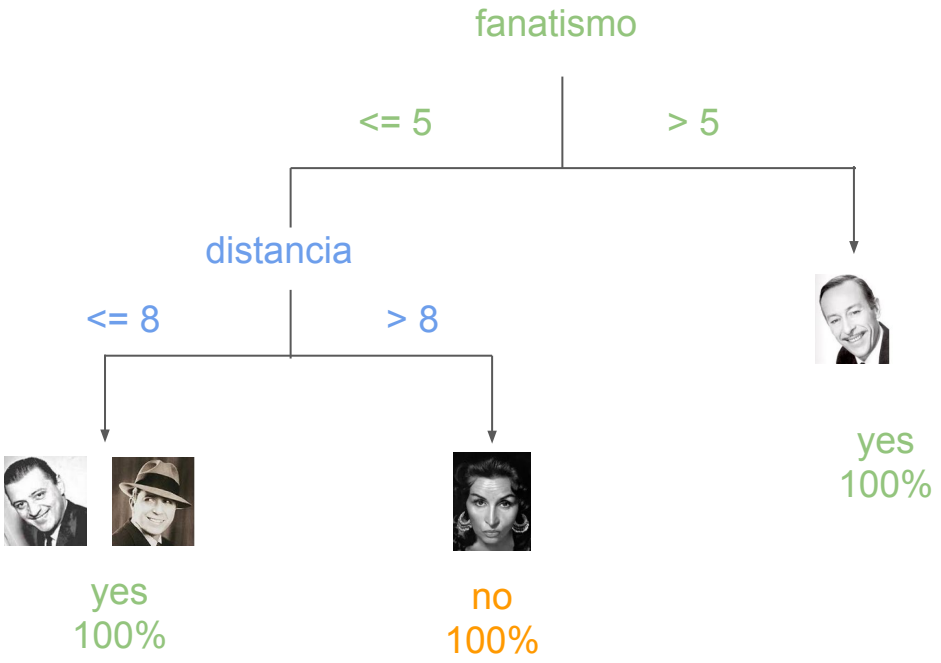
$$w_i = w_{i-1} - \alpha \nabla J(w_{i-1})$$



Δw_{i-1} = Gradient

Otros Modelos de Machine Learning muy utilizados

Person	tiempo (x_1)	costo (x_2)	distancia (x_3)	fanatismo (x_4)	previa (x_5)	Va ?	precio ticket ?
Julio	9.00	2.00	7.00	3.00	0.00	yes	800
Roberto	4.00	8.00	9.00	10.00	2.00	yes	1500
Tita	8.00	6.00	9.00	5.00	0.00	no	0
Carlos	8.00	4.00	6.00	5.00	0.00	yes	1000
Jorge	9.00	2.00	7.00	3.00	0.00	?	?



Decision Trees

(supervisado)

Los Árboles de decisión Generan Reglas de decision

Regla 1 : If fan > 5,
then class = yes

Regla 2 : If fan <= 5 AND distance <= 8,
then class = yes

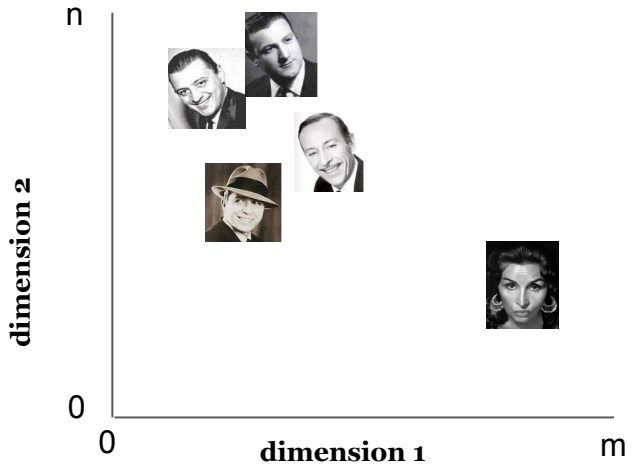
Regla 3 : If fan <=5 AND distance > 8,
then class = no

Decision Trees

(supervisado)

Person	tiempo (x_1)	costo (x_2)	distancia (x_3)	fanatismo (x_4)	previa (x_5)
Julio	9.00	2.00	7.00	3.00	0.00
Roberto	4.00	8.00	9.00	10.00	2.00
Tita	8.00	6.00	9.00	5.00	0.00
Carlos	8.00	4.00	6.00	5.00	0.00
Jorge	9.00	2.00	7.00	3.00	0.00

k-means
k=2

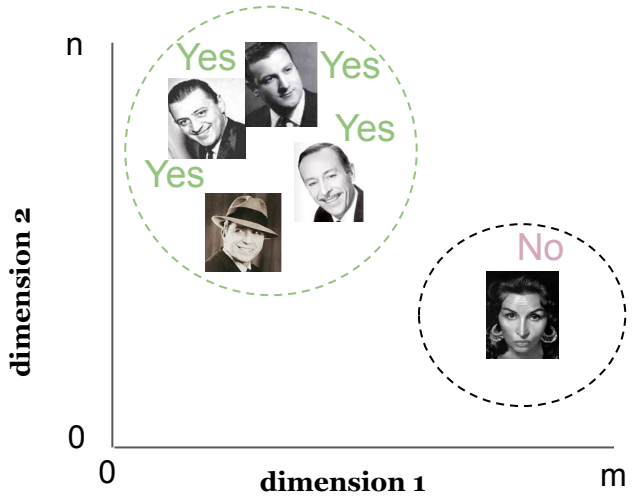


ALGORITMOS DE CLUSTERING

(NO SUPERVISADO)

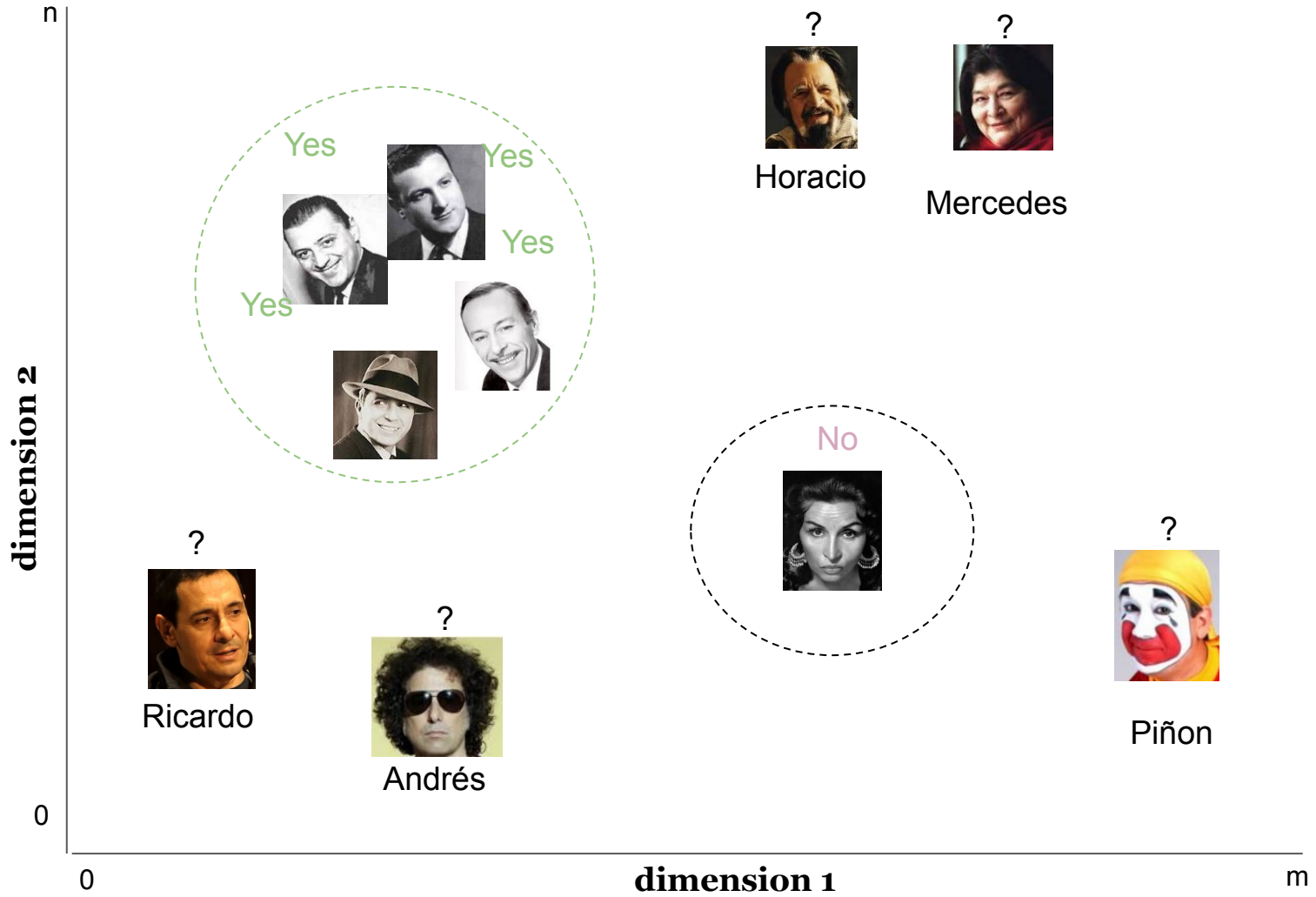
Person	tiempo (x_1)	costo (x_2)	distancia (x_3)	fanatismo (x_4)	previa (x_5)
Julio	9.00	2.00	7.00	3.00	0.00
Roberto	4.00	8.00	9.00	10.00	2.00
Tita	8.00	6.00	9.00	5.00	0.00
Carlos	8.00	4.00	6.00	5.00	0.00
Jorge	9.00	2.00	7.00	3.00	0.00

k-means
k=2



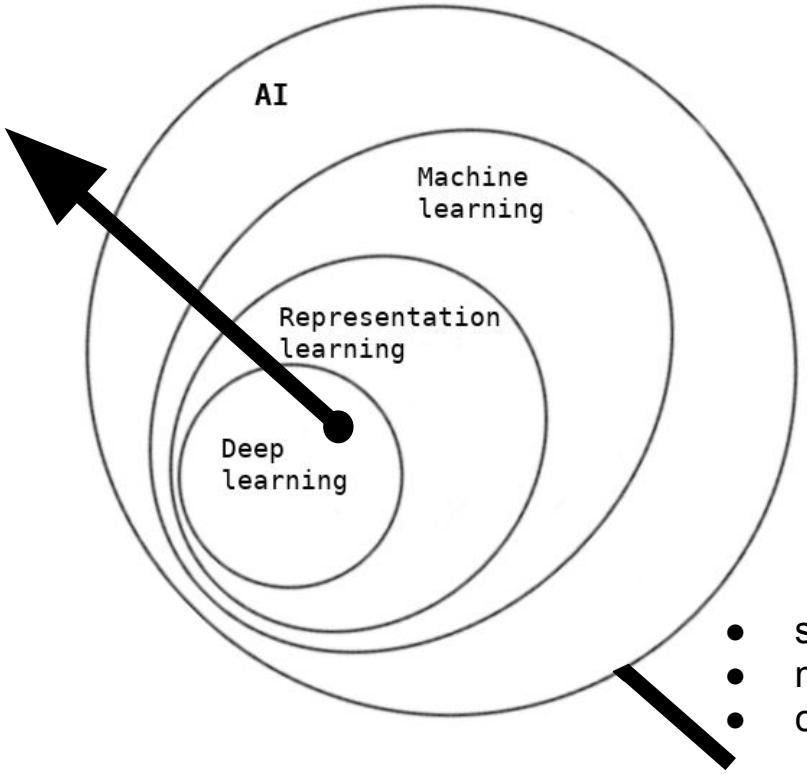
ALGORITMOS DE CLUSTERING

….Porque necesitamos muchos datos?


n
dimension 2
0
0
dimension 1
m
?
?
Horacio
Mercedes
Yes
Yes
Yes
Yes
No
?
?
?
Ricardo
Andrés
Piñon

Porque necesitamos muchos datos?

“*Artificial intelligence World*”



- statistics
- maths
- computing

AI

(ex. **knowledge base**)

└— **Machine Learning**

(**ex. logistic regression, linear regression, decision trees, clustering**)

└— **Representation Learning**

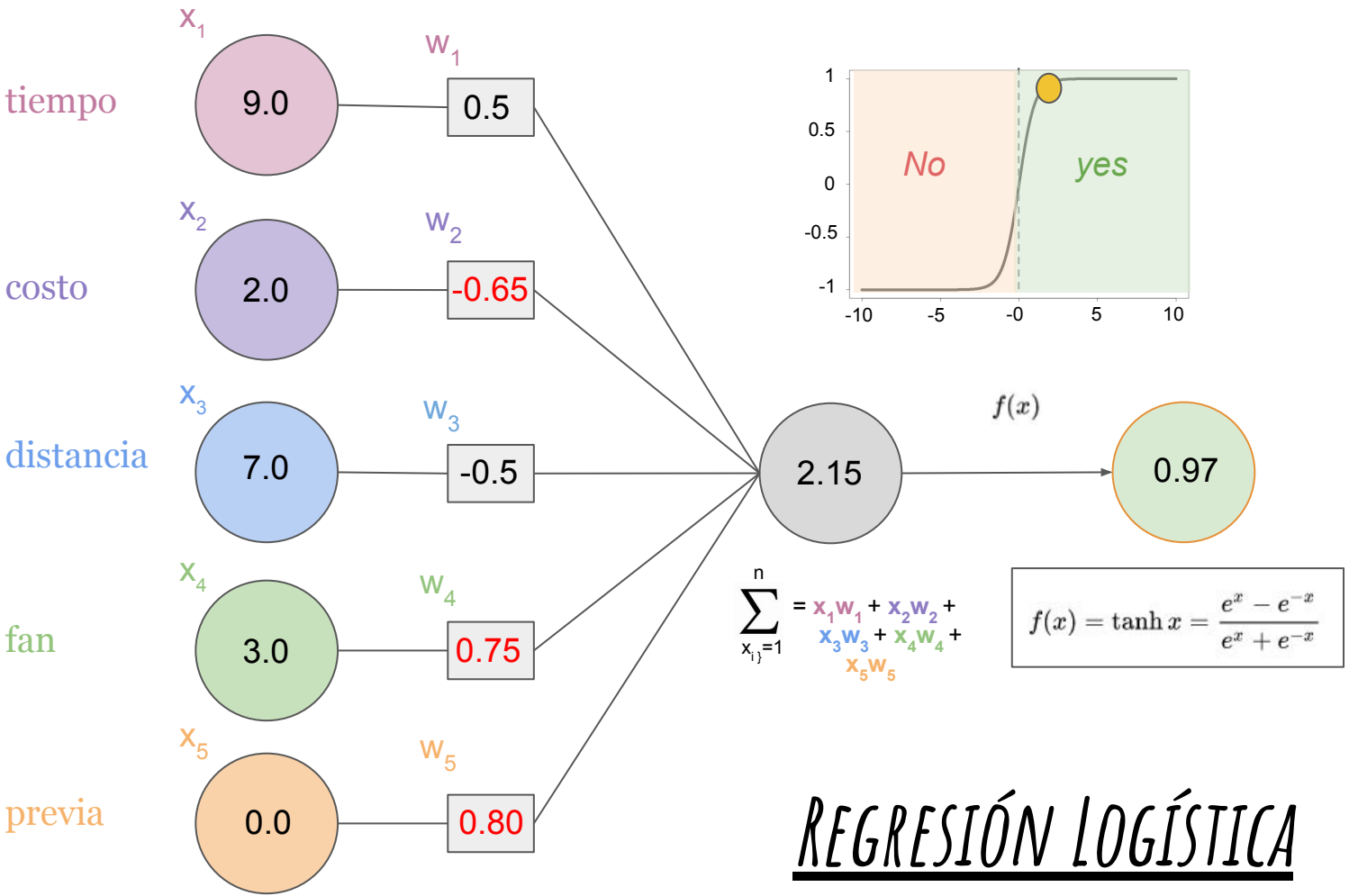
(ex. **autoencoders**)

└— **Deep Learning**

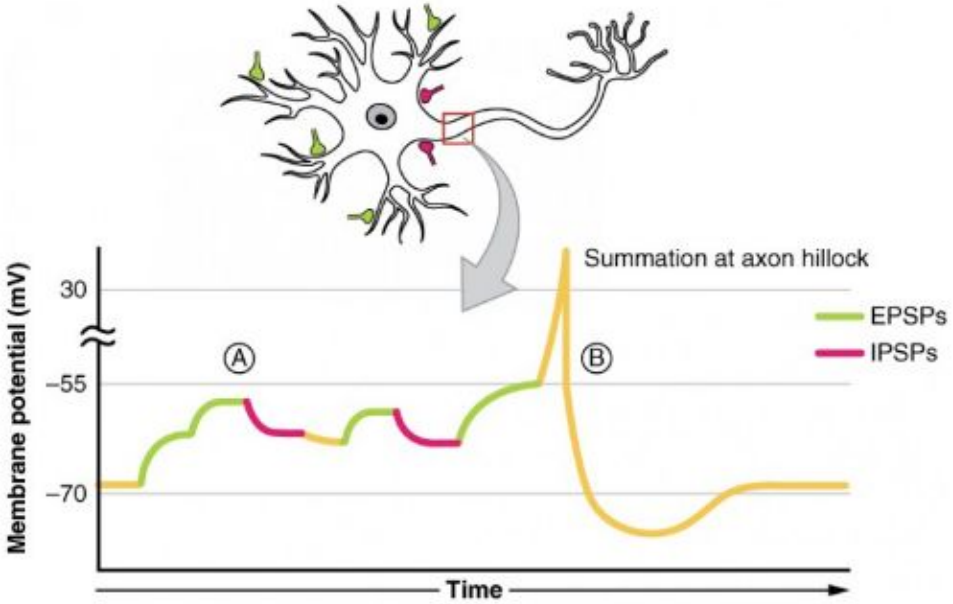
(ex. **Multilayers Perceptrons**)

Adapted from Goodfellow et. al., 2016

Deep Learning
MLPs, CNNs, RNN

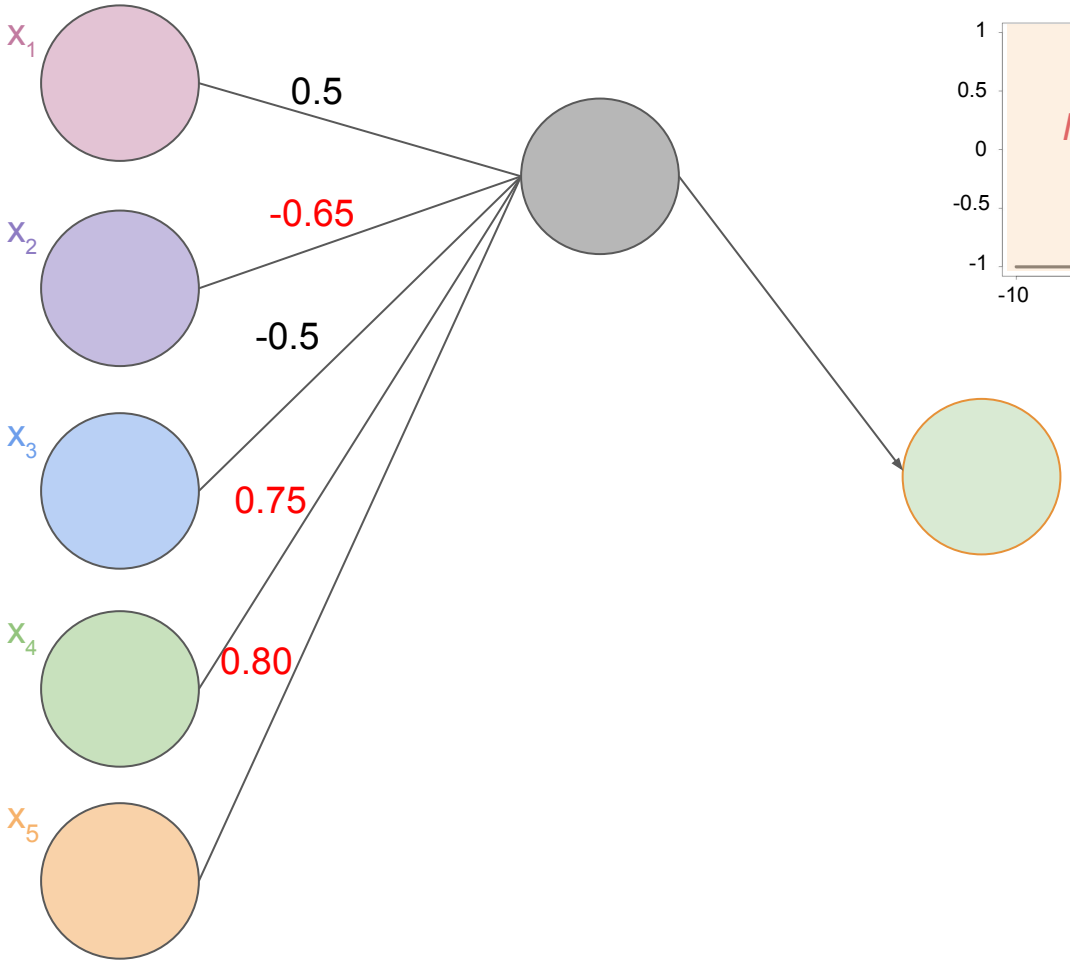

x1
tiempo
9.0
w1
0.5
x2
costo
2.0
w2
-0.65
x3
distancia
7.0
w3
-0.5
x4
fan
3.0
w4
0.75
x5
previa
0.0
w5
0.80
2.15
f(x)
0.97
1
0.5
0
-0.5
-1
-10
-5
-0
5
10
No
yes
n
Σ
xi}=1
= x1w1 + x2w2 + x3w3 + x4w4 + x5w5
f(x) = tanh x = (e^x − e^−x) / (e^x + e^−x)
REGRESIÓN LOGÍSTICA

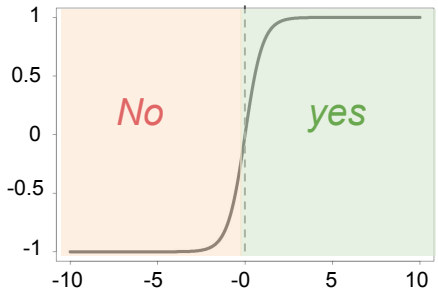
Fuerte similitud con las Neuronas del cerebro



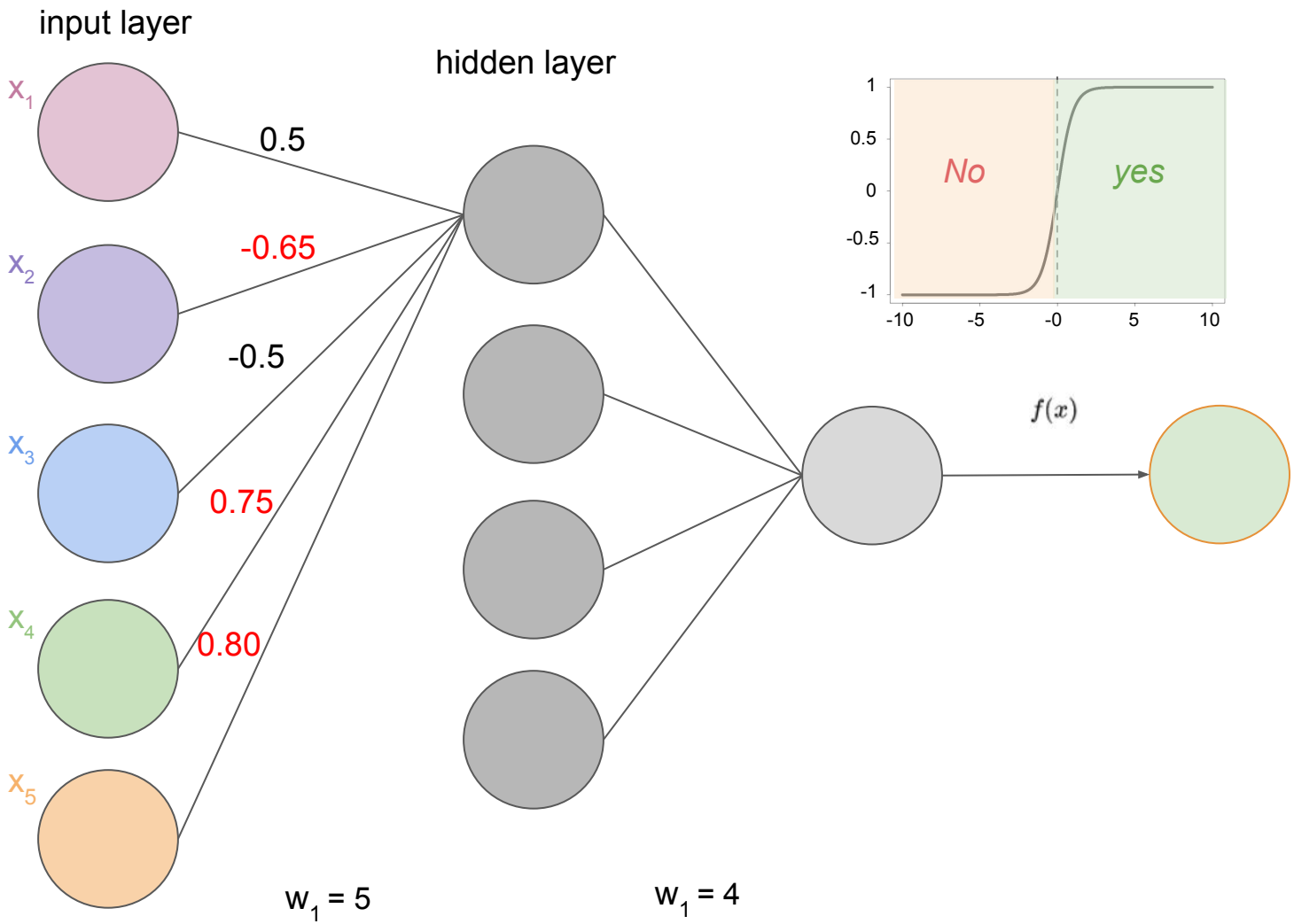
OpenStax Biology 2nd Edition, 2018

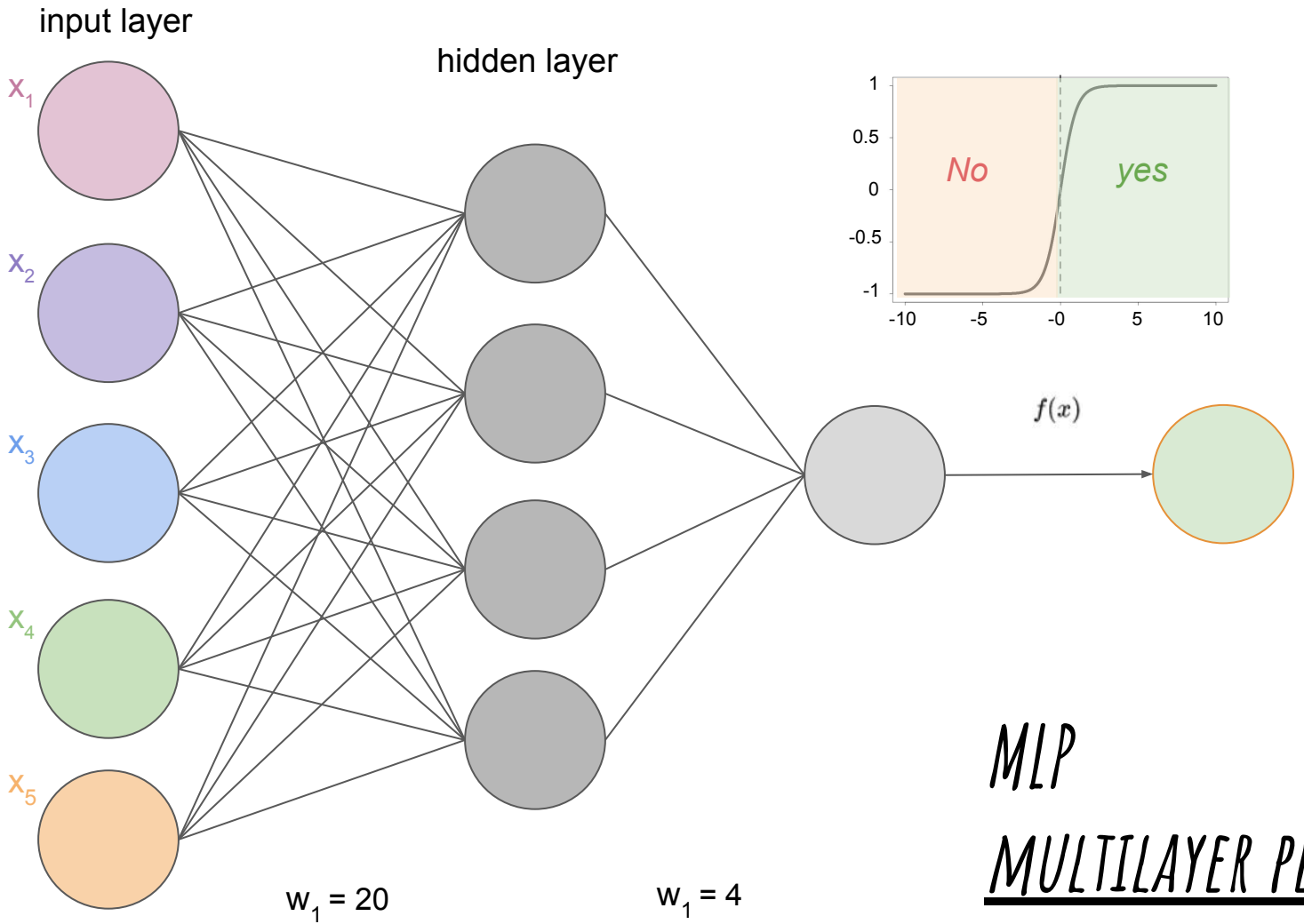
input layer





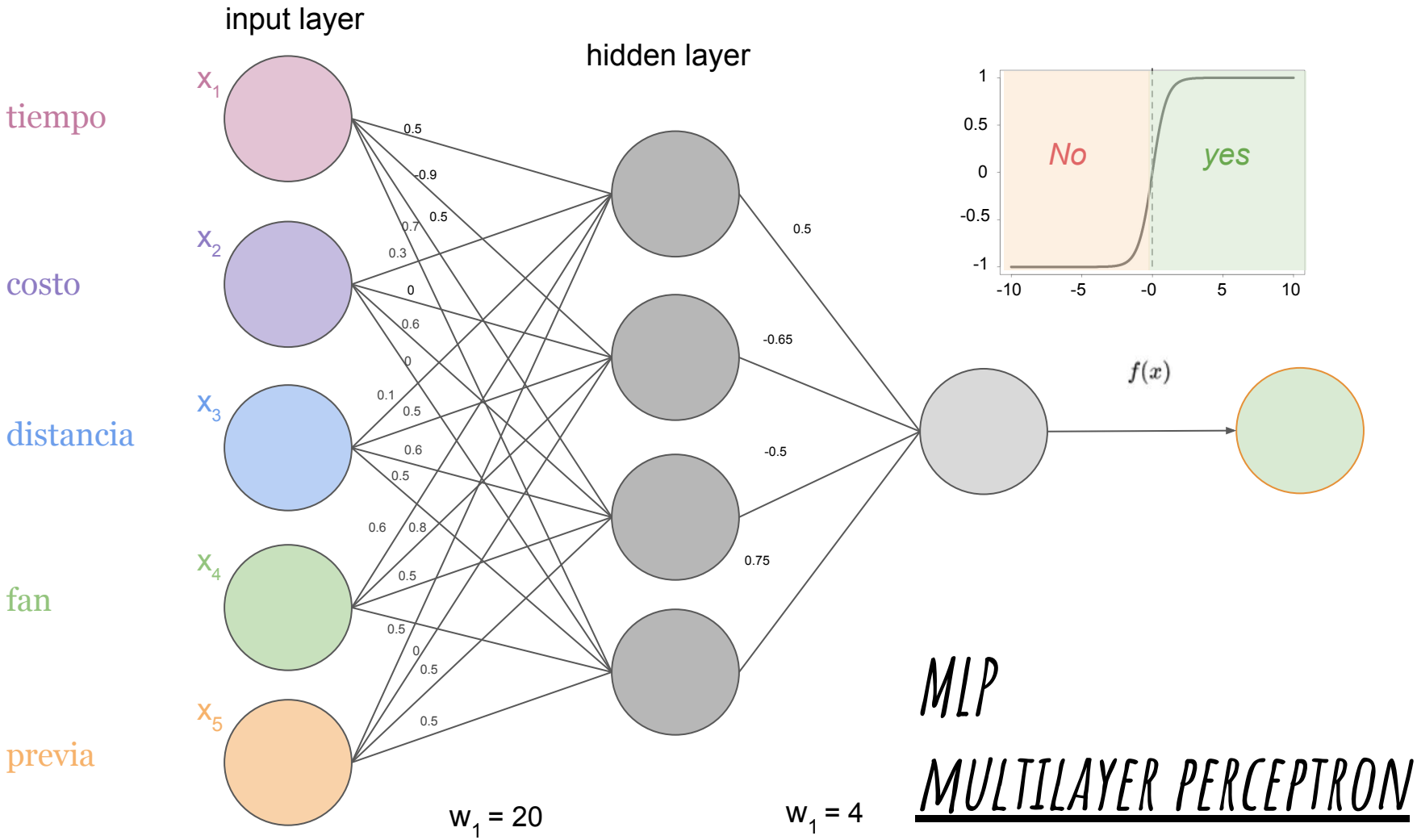
$f(x)$


input layer
hidden layer
x_1
x_2
x_3
x_4
x_5
0.5
-0.65
-0.5
0.75
0.80
1
0.5
0
-0.5
-1
-10
-5
-0
5
10
No
yes
$f(x)$
$w_1 = 5$
$w_1 = 4$

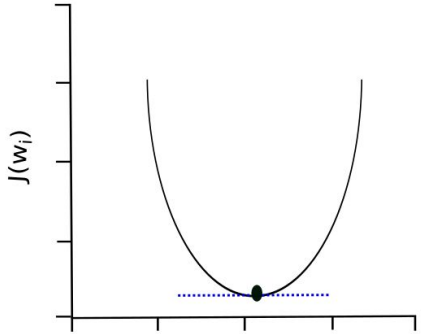


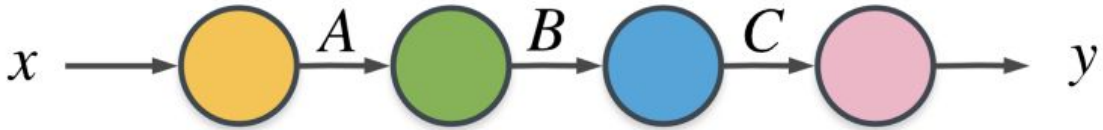
MLP

MULTILAYER PERCEPTRON


input layer
hidden layer
tiempo
costo
distancia
fan
previa
x_1
x_2
x_3
x_4
x_5
0.5
-0.9
0.5
0.7
0.3
0
0.6
0
0.1
0.5
0.6
0.5
0.6
0.8
0.5
0.5
0
0.5
0.5
0.5
-0.65
-0.5
0.75
1
0.5
0
-0.5
-1
-10
-5
-0
5
10
No
yes
$f(x)$
$w_1 = 20$
$w_1 = 4$
MLP
MULTILAYER PERCEPTRON

Backpropagation

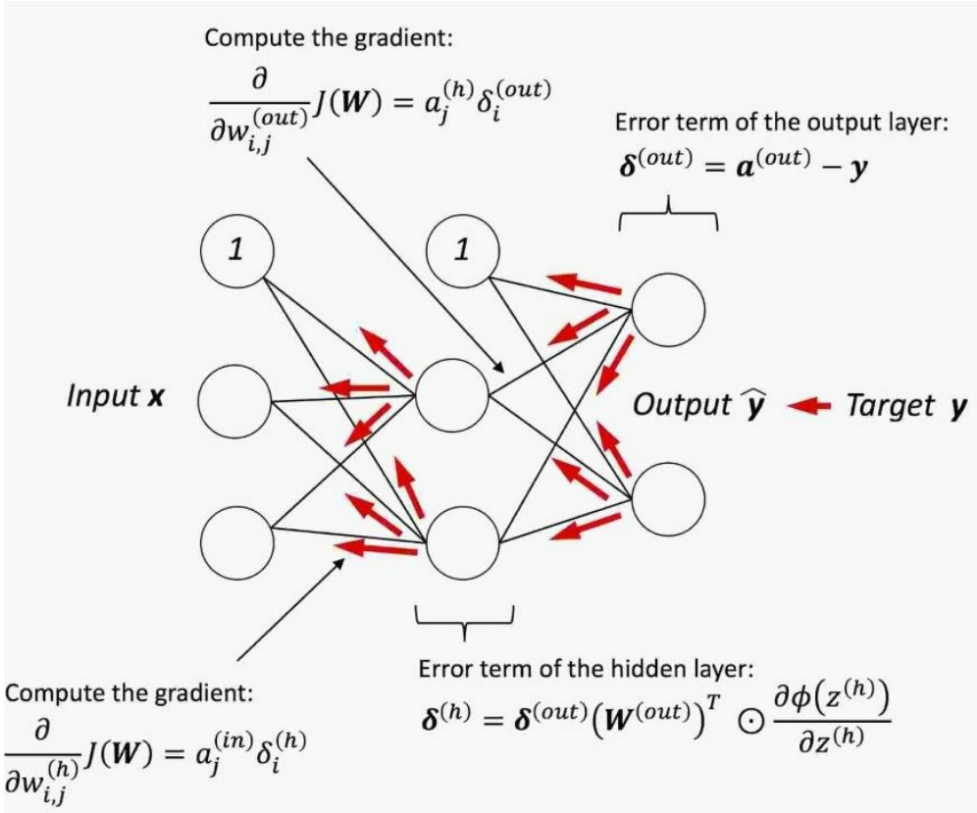




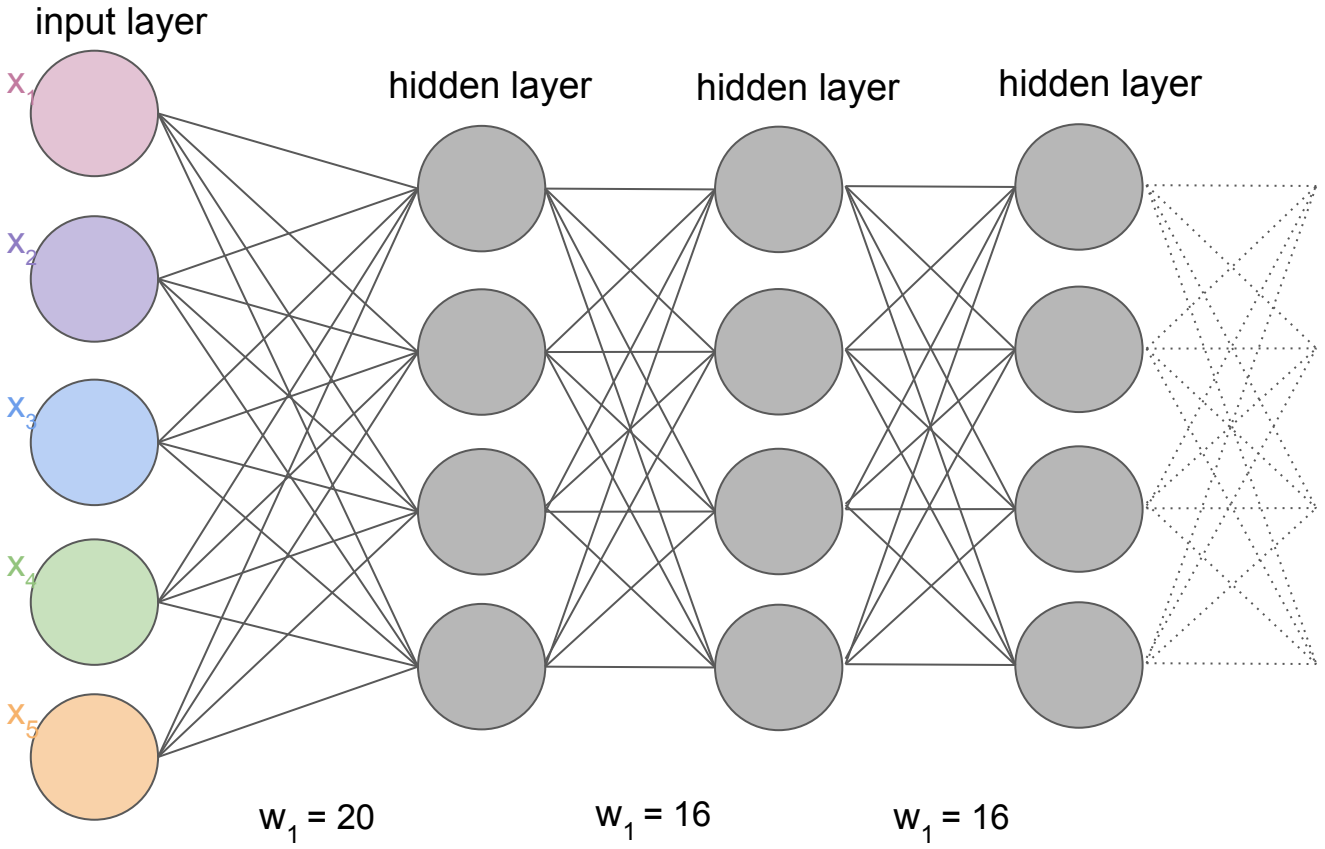
$$\frac{\partial y}{\partial x} = \frac{\partial y}{\partial C} \times \frac{\partial C}{\partial B} \times \frac{\partial B}{\partial A} \times \frac{\partial A}{\partial x}$$

Backpropagation

$$\frac{\partial J}{\partial w_{ij}^{(l)}} \quad , \quad \frac{\partial J}{\partial b_{ij}^{(l)}} \qquad \delta_{ij}^{(l)}$$

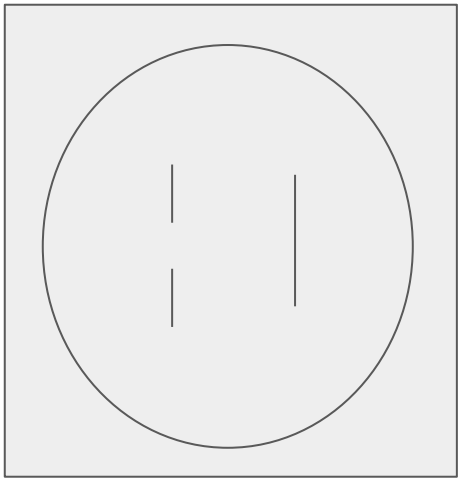


Una cuestion de Pesos

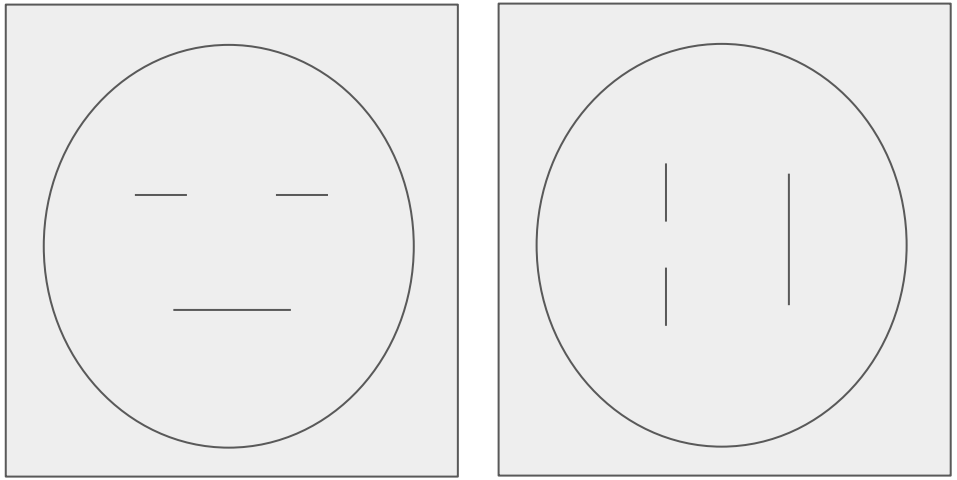


CNNs
Convolutional Neural Networks

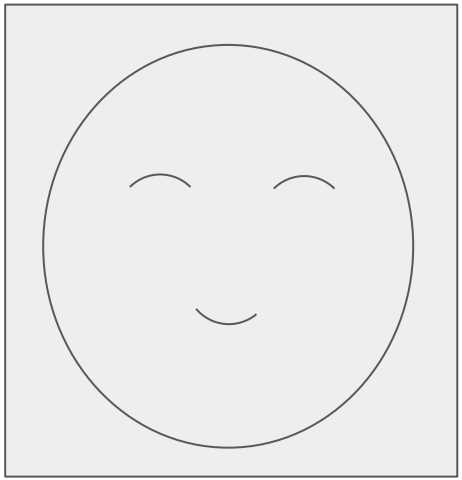
PATRONES BÁSICOS DE LA PERCEPCIÓN

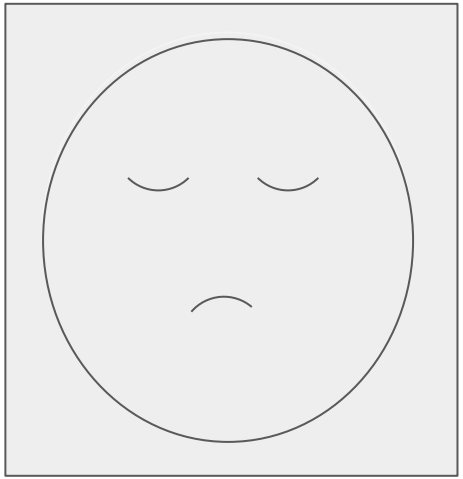


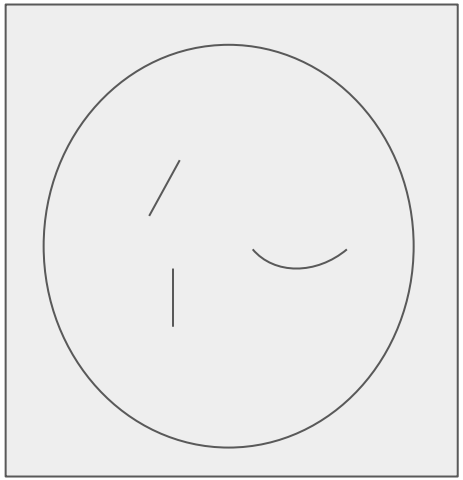
PATRONES BÁSICOS DE LA PERCEPCIÓN



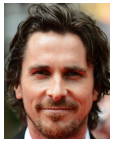
PATRONES BÁSICOS DE LA PERCEPCIÓN

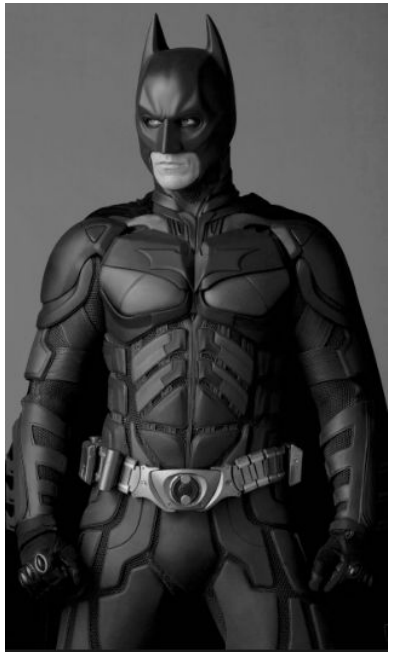






Christian bale ??





https://quickdraw.withgoogle.com/data

Quick, Draw! The Data

Get the data Play the game

What do 50 million drawings look like?

Over 15 million players have contributed millions of drawings playing Quick, Draw! These doodles are a unique data set that can help developers train new neural networks, help researchers see patterns in how people around the world draw, and help artists create things we haven't begun to think of. That's why we're open-sourcing them, for anyone to play with.

Select a drawing

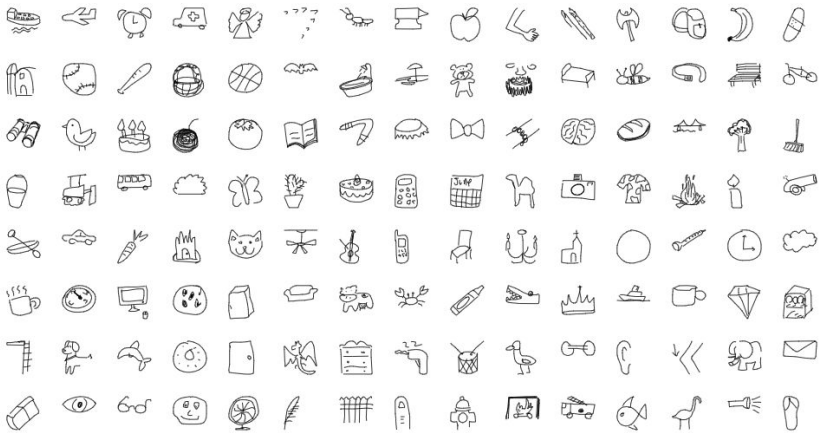
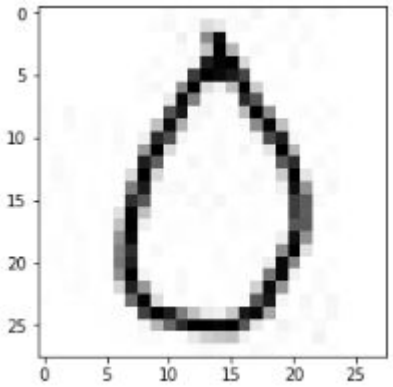


Image as matrix



$f(x)$

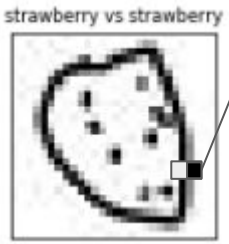
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
0	0	0	0	0	0	0	0	0	0	0	8	0	3	2	0	6	0	16	0	0	15	0	0	7	0	0	0	0
1	0	0	0	0	0	0	0	0	0	6	11	0	7	58	40	6	10	0	0	6	0	5	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	27	0	139	243	5	0	0	3	5	0	7	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	1	7	0	88	255	104	0	10	0	0	8	0	4	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	10	0	2	21	230	250	255	63	0	0	0	12	0	5	1	0	0	0	0
5	0	0	0	0	0	0	0	0	5	0	3	8	207	254	246	232	200	0	2	1	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	5	14	0	138	255	57	24	94	253	77	3	5	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	4	0	38	248	147	10	3	0	221	189	0	0	1	0	4	0	0	0	0	0
8	4	0	14	0	2	1	1	0	0	0	188	234	11	16	0	5	97	255	137	0	1	6	0	8	0	0	0	0
9	4	0	7	0	3	0	5	1	0	90	244	106	11	0	3	0	7	137	249	92	0	0	6	0	0	0	0	0
10	3	0	0	1	3	0	9	0	29	220	193	16	0	0	7	0	0	19	196	228	14	3	0	0	0	0	0	0
11	0	1	0	2	2	0	6	0	123	255	61	0	0	4	7	0	17	0	47	255	99	0	0	5	0	0	0	0
12	0	8	0	0	1	0	0	4	230	175	0	0	13	0	7	0	0	0	5	182	218	0	7	0	0	0	0	0
13	0	9	4	0	0	2	0	60	255	64	1	1	2	3	0	2	0	9	4	79	255	43	0	6	0	0	0	0
14	0	3	4	0	1	0	0	148	231	11	7	11	0	8	0	2	8	5	0	27	240	130	0	13	0	0	0	0
15	3	0	2	0	3	0	5	216	185	0	4	0	11	0	15	0	0	2	1	6	205	181	7	0	0	0	0	0
16	1	0	3	0	0	5	51	252	90	7	0	0	0	8	0	4	0	2	0	0	206	178	0	0	0	0	0	0
17	0	0	5	2	0	4	91	255	29	0	3	4	1	4	0	5	2	3	0	1	186	183	0	7	0	0	0	0
18	0	2	0	5	0	3	131	248	0	0	4	3	1	2	0	1	0	0	2	33	240	131	2	0	0	0	0	0
19	3	3	0	3	0	2	149	217	0	11	1	0	0	0	6	0	0	5	0	135	255	50	0	0	0	0	0	0
20	2	3	0	3	0	3	154	227	0	1	0	0	0	0	6	0	2	5	34	247	141	2	0	6	0	0	0	0
21	0	2	2	6	0	3	133	253	20	0	0	9	0	0	2	3	0	1	156	248	24	0	10	0	0	0	0	0
22	0	0	4	5	0	0	68	226	126	11	0	11	0	0	0	4	0	71	244	128	0	0	7	0	0	0	0	0
23	4	0	0	1	1	0	1	166	250	58	0	4	0	6	0	0	10	187	233	16	0	17	0	15	0	0	0	0
24	0	0	0	0	0	1	1	1	203	255	230	149	91	38	29	81	233	248	114	0	0	7	0	13	0	0	0	0
25	0	0	0	0	0	1	1	1	17	101	169	219	255	255	249	255	185	39	0	20	8	0	9	0	0	0	0	0
26	0	0	0	0	0	0	1	1	6	8	0	3	41	73	85	92	24	0	1	7	0	0	22	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	3	10	6	0	0	10	5	0	0	2	0	3	0	0	0	0

Algunas técnicas muy utilizadas en clasificación de IMG.

Input

50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100

output



-1	0	1
-2	0	2
-1	0	1

Filtros de contornos

FILTER= (-1x50) + (-2*50) + (-1*50) + (0+50) + (0*50) + (0*50) + (50*1) + (50*2) + (50*1)

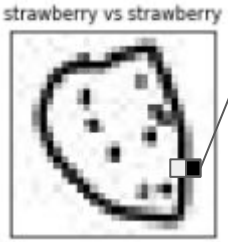
= -50 -100 -50 +0 + 0 + 0 + 50 +100 +50

= 0

50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100

	0	

-1	0	1
-2	0	2
-1	0	1



Filtros de contornos

FILTER = (-1x50) + (-2*50) + (-1*50) + (0+50) + (0*50) + (0*50) + (100*1) + (100*2) + (100*1)

= -50 -100 -50 +0 + 0 + 0 + 100 +200 +100

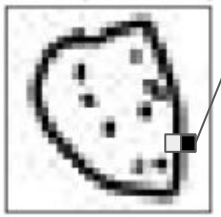
= 200

50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100

-1	0	1
-2	0	2
-1	0	1

	0	200		

strawberry vs strawberry



Filtros de contornos

FILTER = (-1x50) + (-2*50) + (-1*50) + (0+100) + (0*100) + (0*100) + (100*1) + (100*2) + (100*1)

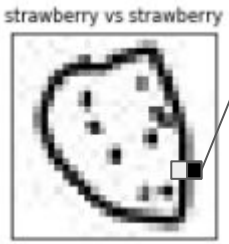
= -50 -100 -50 +0 + 0 + 0 + 100 +200 +100

= 200

50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100

	0	200	200	

-1	0	1
-2	0	2
-1	0	1



Filtros de contornos

FILTER = (-1x100) + (-2*100) + (-1*100) + (0+100) + (0*100) + (0*100) + (100*1) + (100*2) + (100*1)

= -100 -200 -100 +0 + 0 + 0 + 100 +200 +100

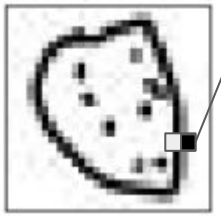
= 0

50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100

-1	0	1
-2	0	2
-1	0	1

	0	200	200	0

strawberry vs strawberry



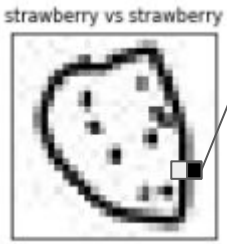
Input

50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100
50	50	50	100	100	100

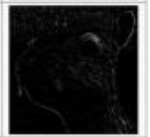
output

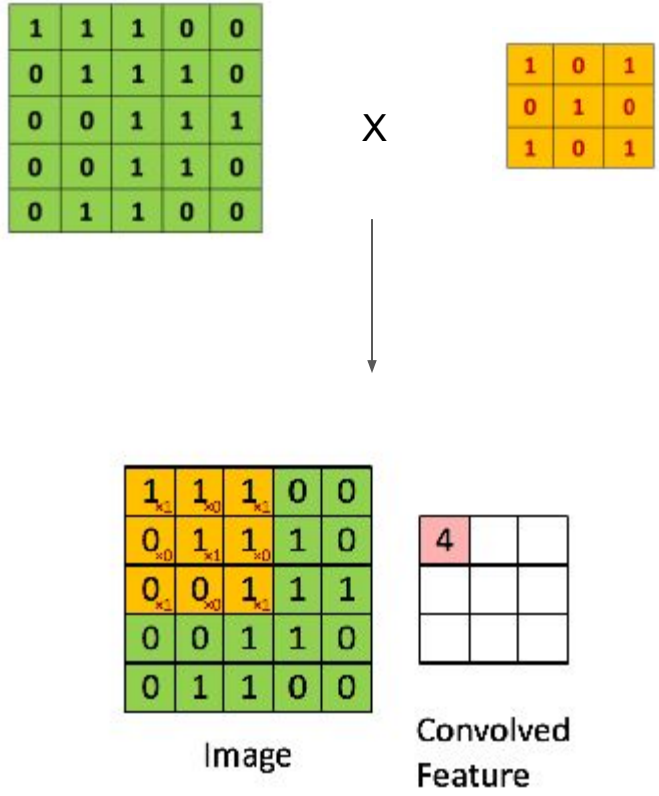
0	0	200	200	0
0	0	200	200	0
0	0	200	200	0
0	0	200	200	0

edge



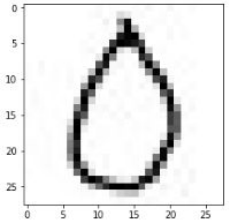
-1	0	1
-2	0	2
-1	0	1

Operation	Filter	Convolved Image
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	
Gaussian blur (approximation)	$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	

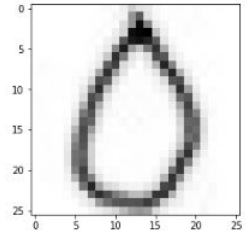


https://ezyang.github.io/convolution-visualizer/index.html

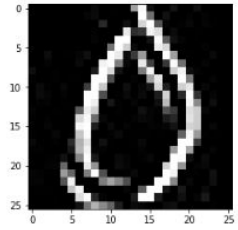
Ejemplos del set de Frutas



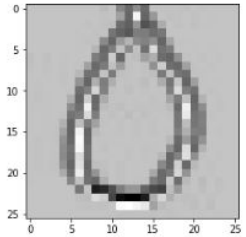
$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$



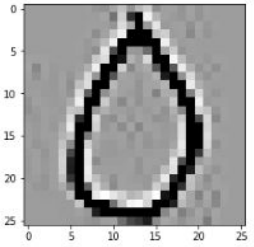
$$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$$



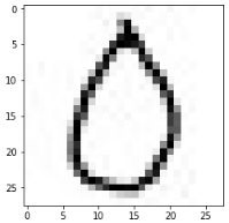
$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$



$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$



Aproximaciones de computer Vision



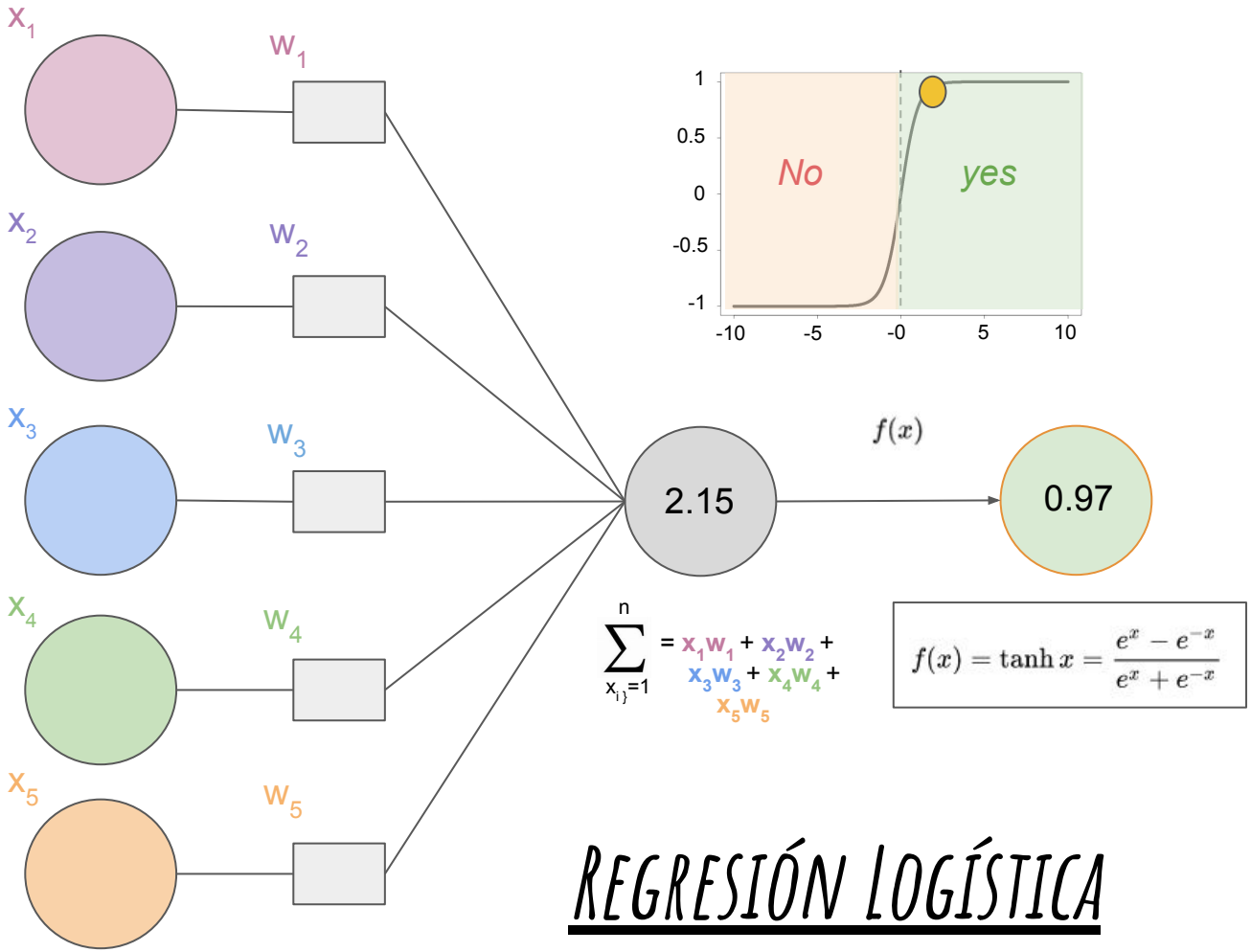
Aplicación de Filtros

Generación de Features

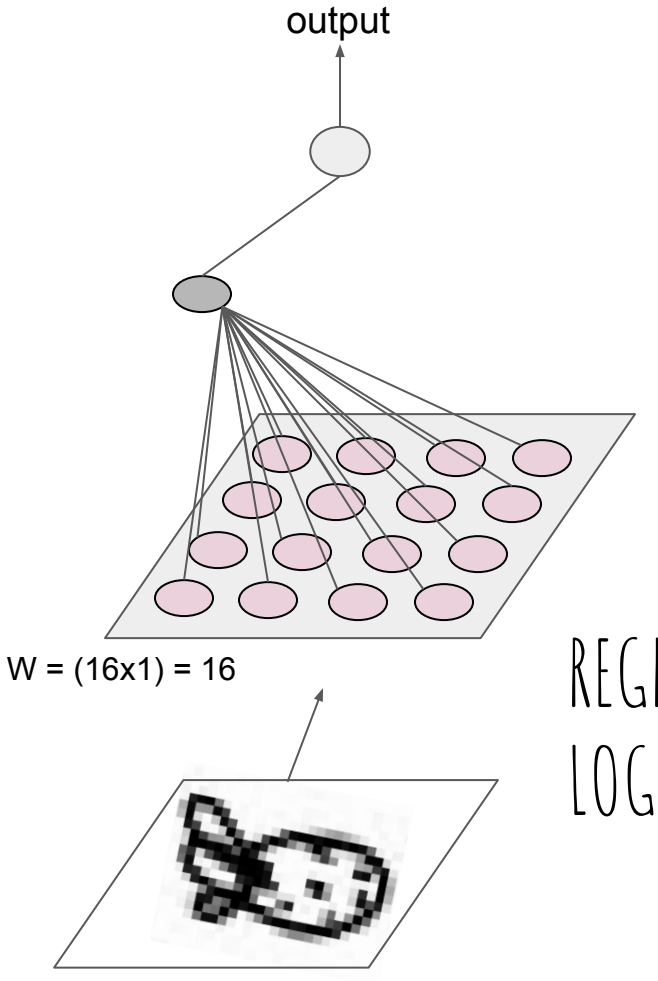
Ejemplo:
Promedio intensidad de pixels

MLP , Regresión logística, SVM

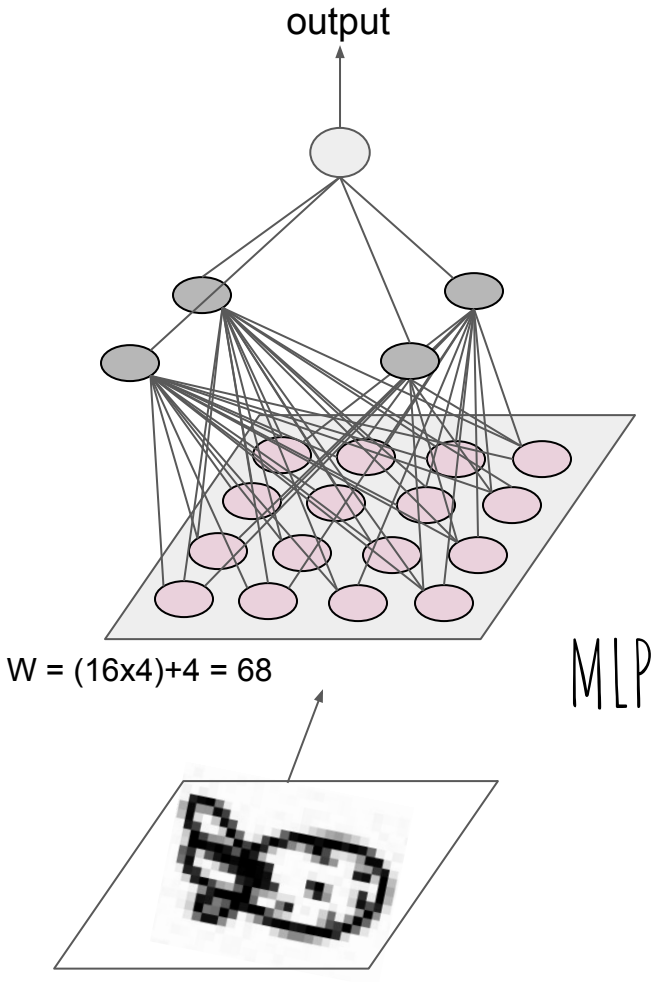
CNNs

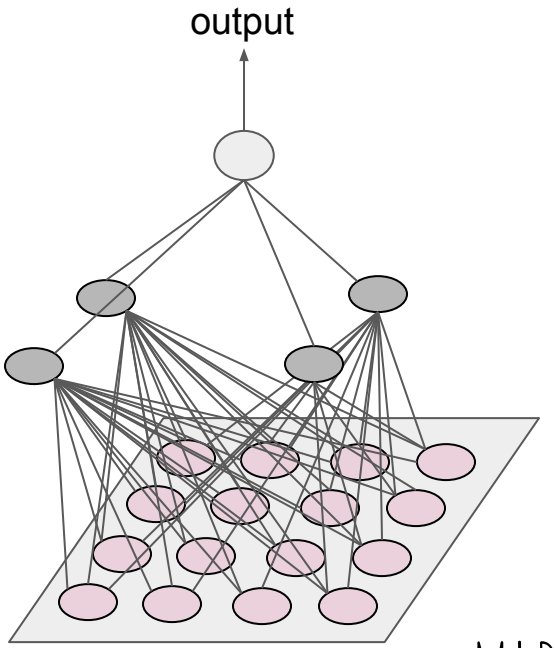


Regresión Logística



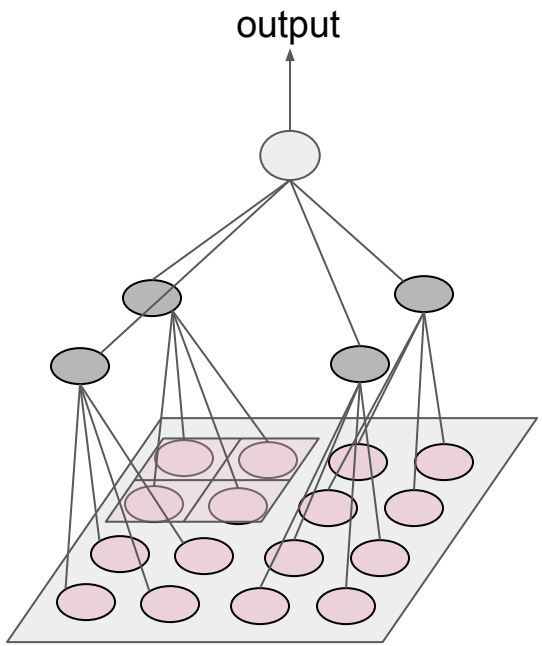
REGRESIÓN LOGISTICA


output
W = (16x4)+4 = 68
MLP

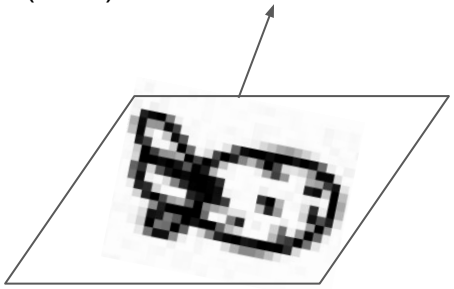


W = (16x4)+4 = 68

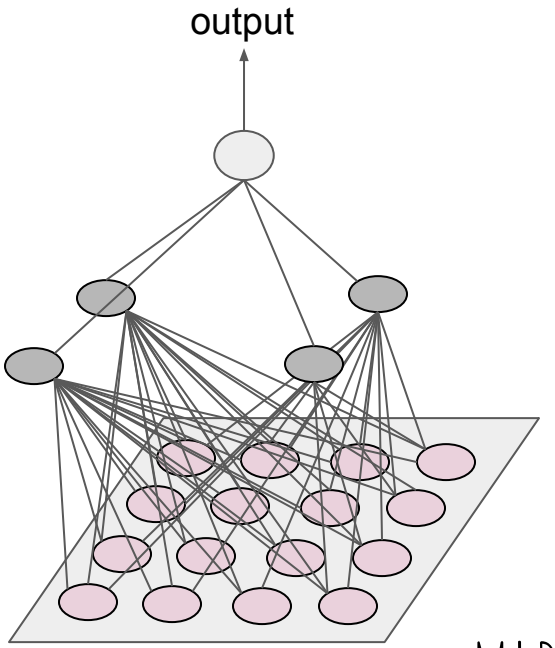
MLP



W = (2x2)+4 = 13

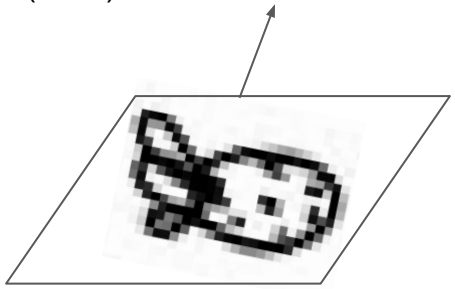


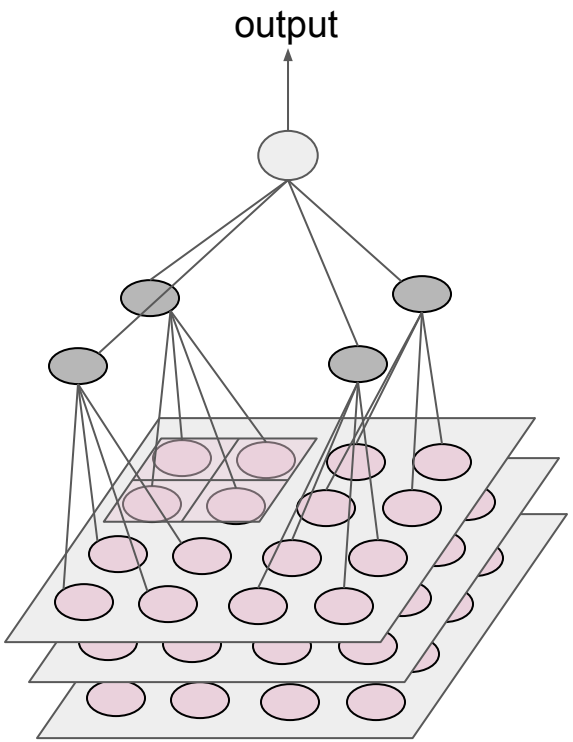
Convolutional Neural Networks(CNNs)



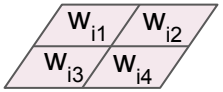
W = (16x4)+4 = 68

MLP



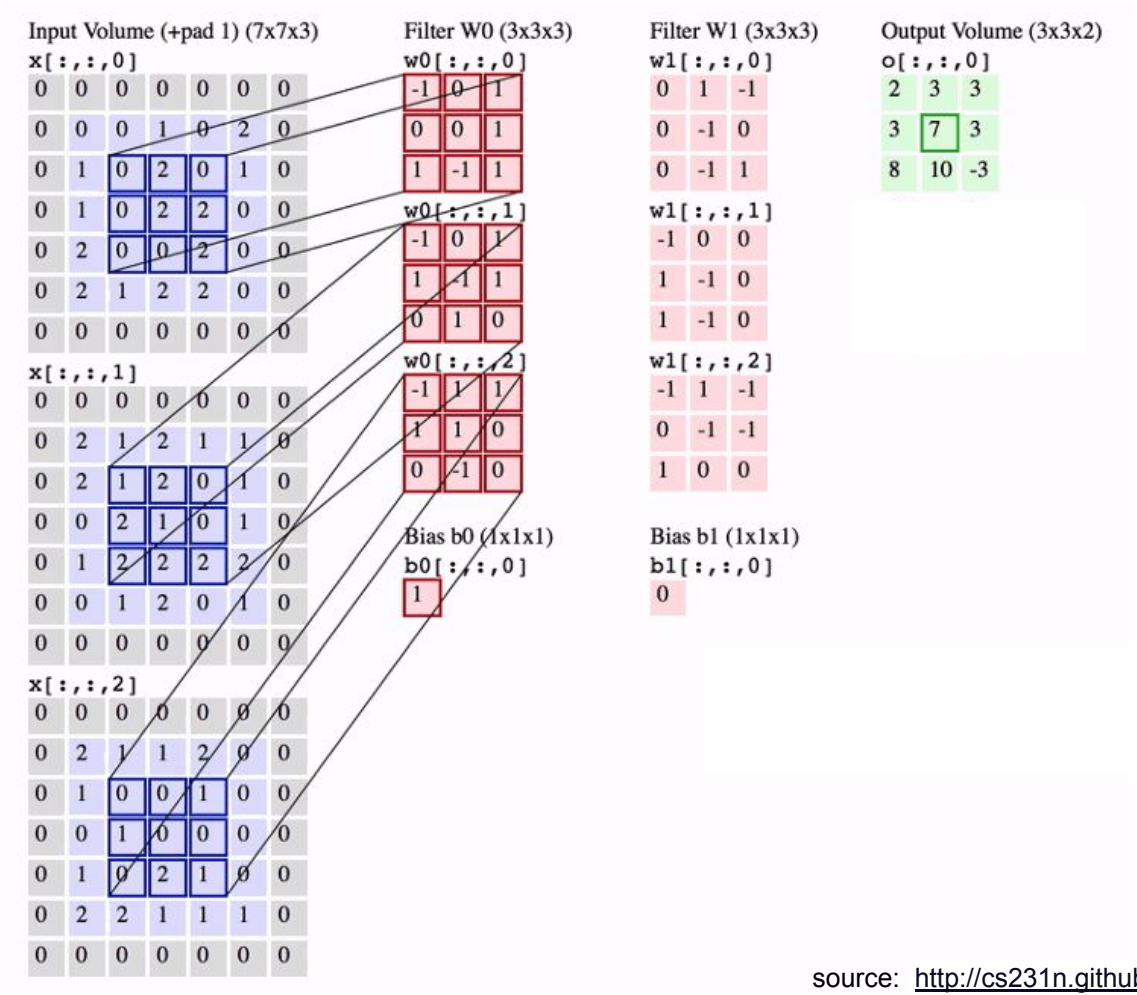


W = (2x2)+(2x2)+(2x2)+4 = 16

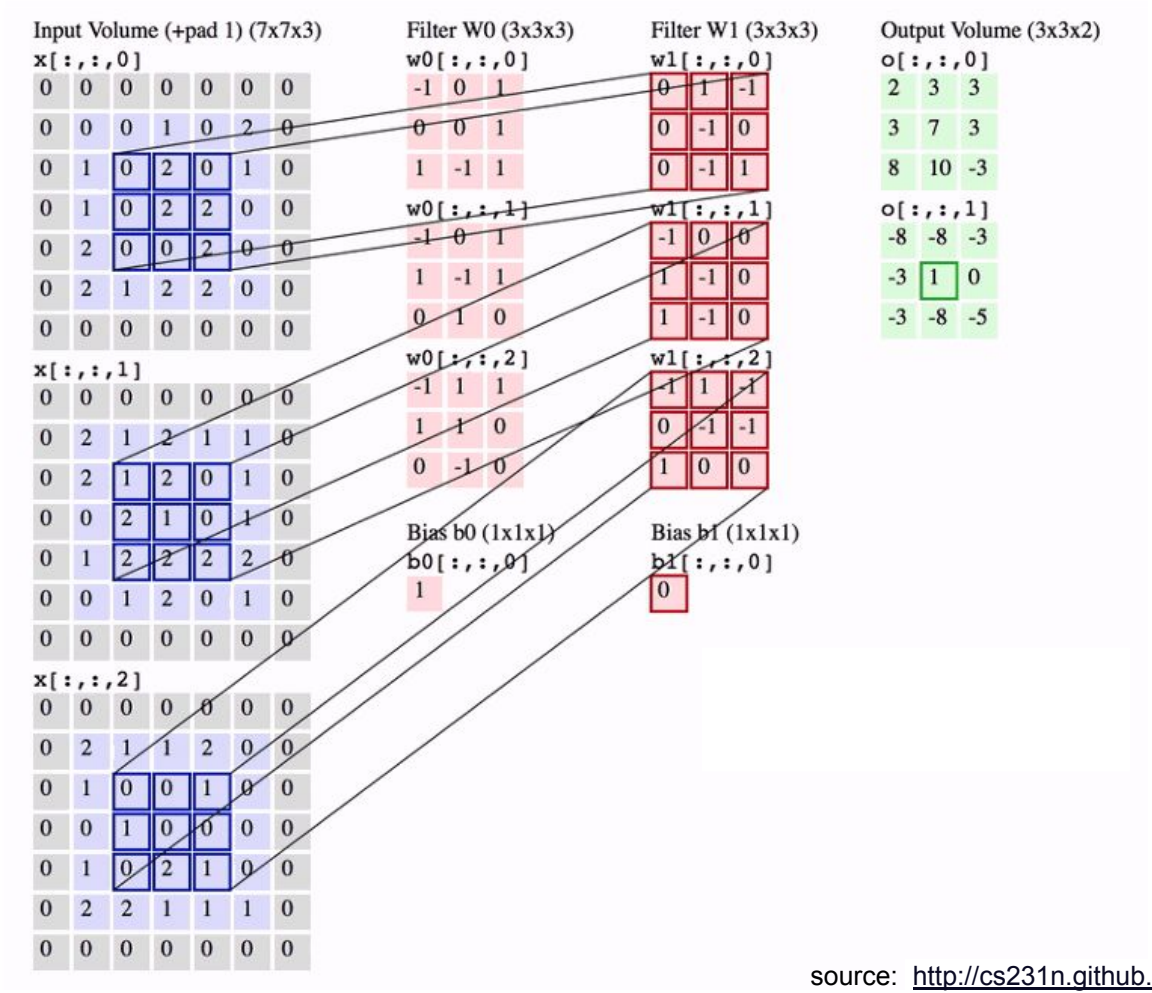


Convolutional Neural Networks(CNNs)

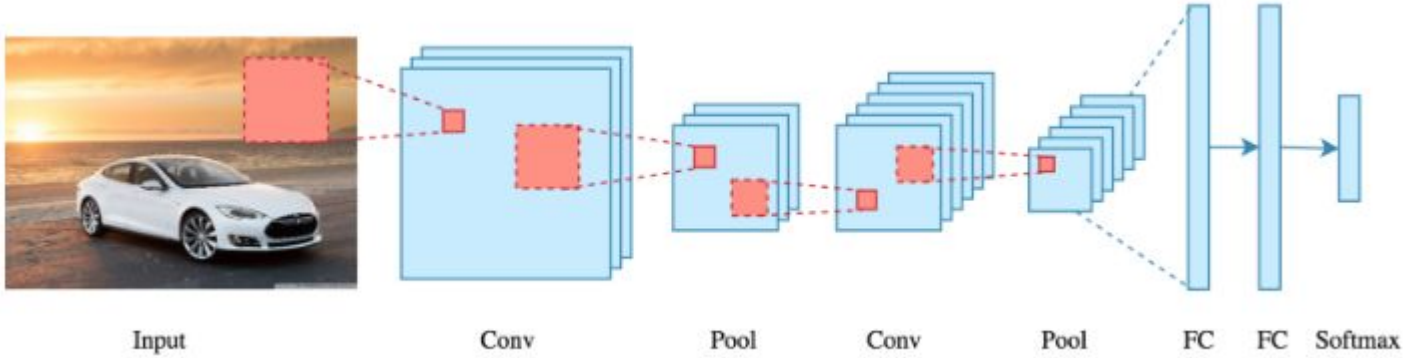
RGB image

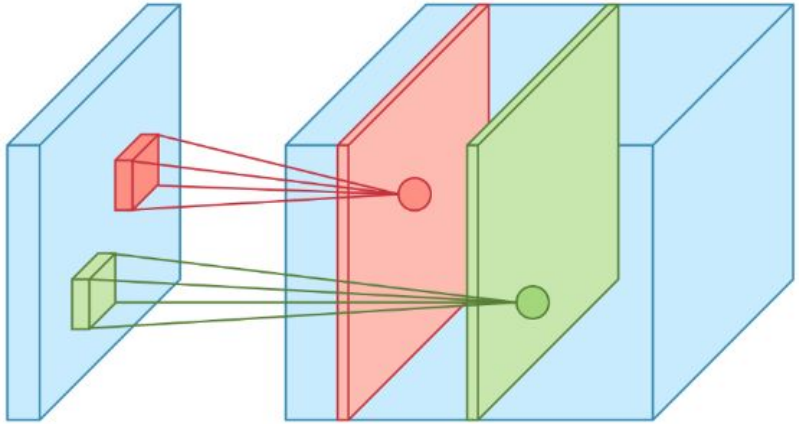


source: http://cs231n.github.io/convolutional-networks/

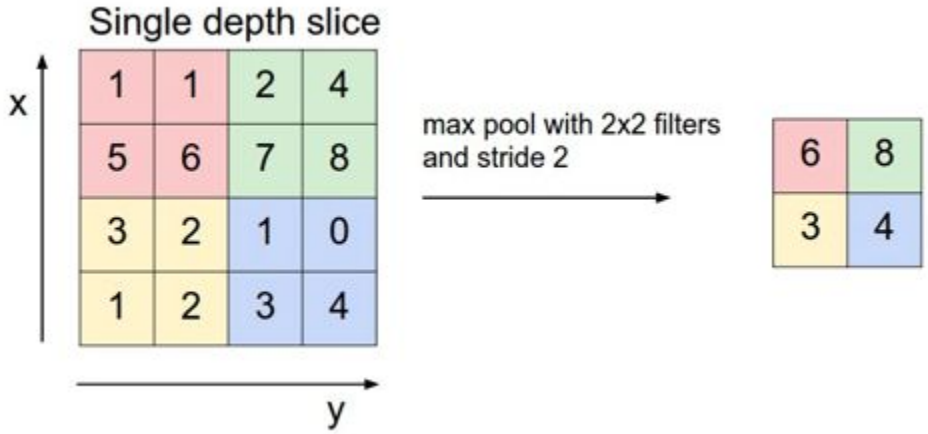


source: http://cs231n.github.io/convolutional-networks/


Input
Conv
Pool
Conv
Pool
FC
FC
Softmax

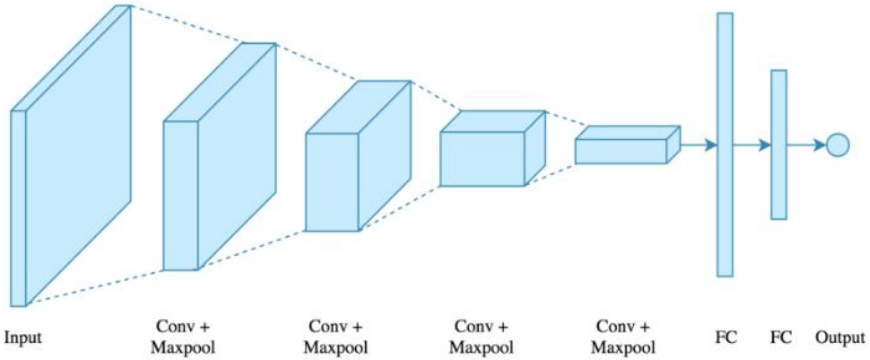


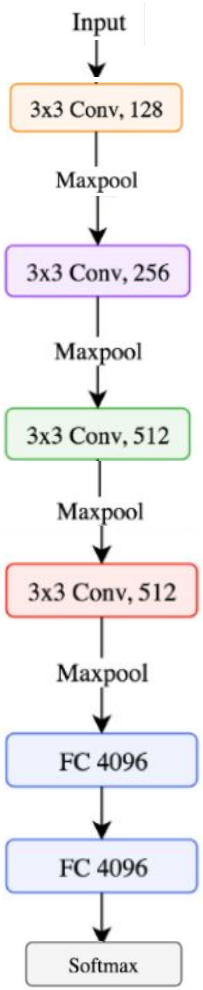
SUB-SAMPLEO (POOLING)



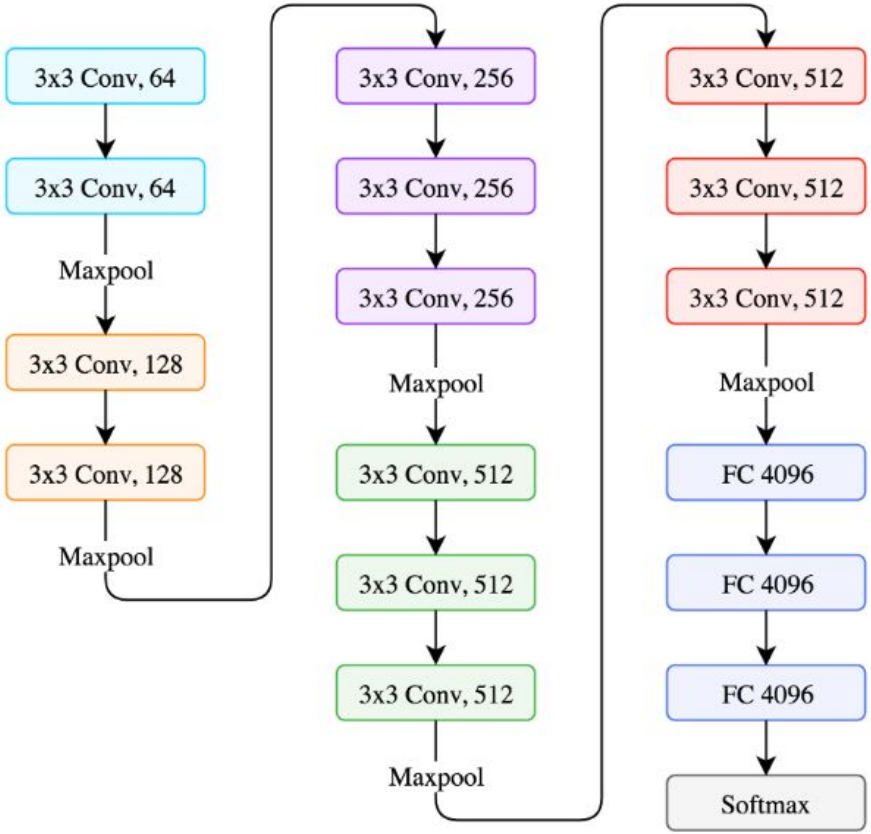
source: http://cs231n.github.io/convolutional-networks/

Deep learning architecture (Simple CNN)





Deep learning architecture (More complex CNN , ex. VGG16)



Places: A 10 million Image Database for Scene Recognition
Zhou et al., 2017
https://ieeexplore.ieee.org/document/7968387

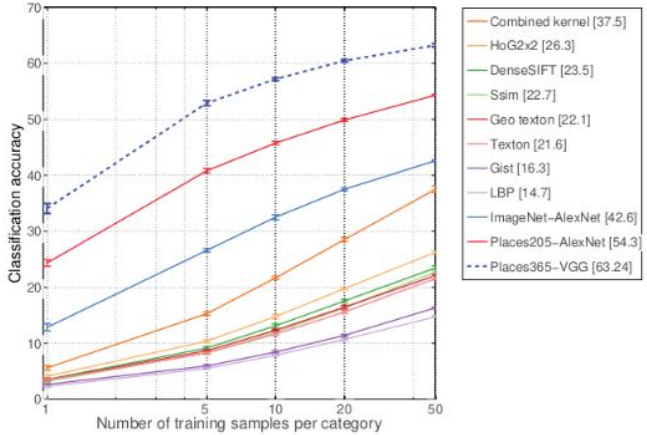


Fig. 14. Classification accuracy on the SUN397 Dataset. We compare the deep features of Places365-VGG, Places205-AlexNet (result reported in [1]), and ImageNet-AlexNet, to hand-designed features (HOG, gist, etc). The deep features of Places365-VGG outperforms other deep features and hand-designed features by a large margin. Results of other hand-designed features/kernels are fetched from [16].

https://s3-us-west-2.amazonaws.com/kinesis-helpers/selfie.html#1

Take a Photo

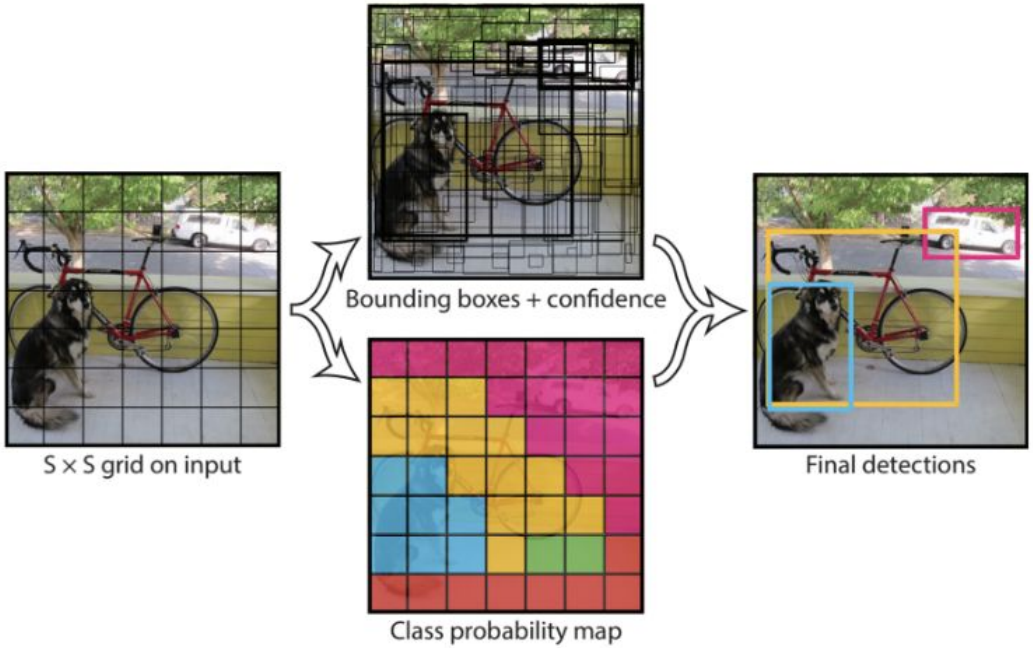
Person Details:

Age Range: 48 - 68
Beard: false
Eyeglasses: false
Gender: Male
Smile: false

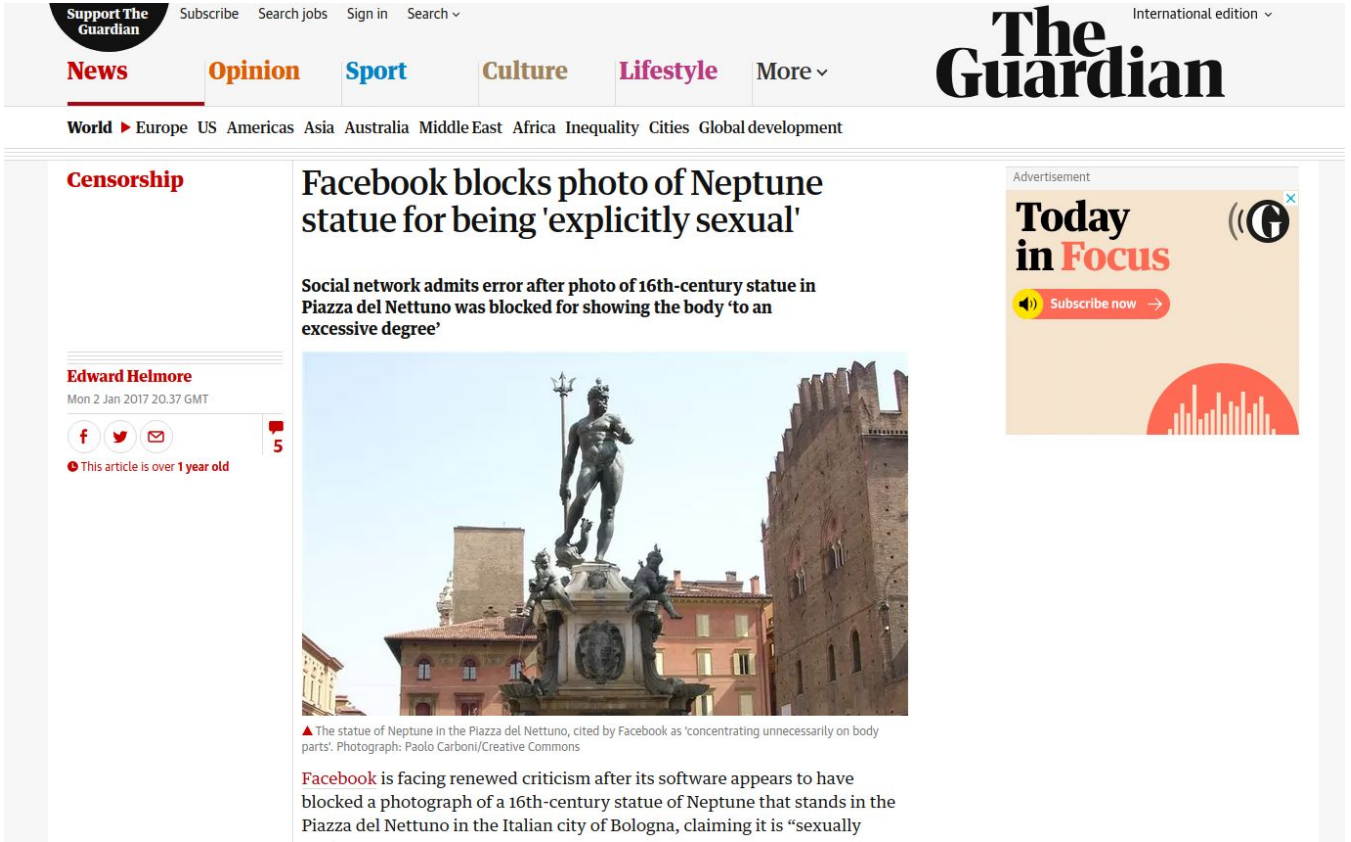
Items found in photo:

Clothing
Apparel
Swimwear
Human
Person
Skin
Shorts
Underwear

OBJECT DETECTION



No todo lo que brilla es oro!



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Censorship

Facebook blocks photo of Neptune statue for being 'explicitly sexual'

Social network admits error after photo of 16th-century statue in Piazza del Nettuno was blocked for showing the body 'to an excessive degree'

Edward Helmore

Mon 2 Jan 2017 20.37 GMT

5

This article is over 1 year old

▲ The statue of Neptune in the Piazza del Nettuno, cited by Facebook as 'concentrating unnecessarily on body parts'. Photograph: Paolo Carboni/Creative Commons

Facebook is facing renewed criticism after its software appears to have blocked a photograph of a 16th-century statue of Neptune that stands in the Piazza del Nettuno in the Italian city of Bologna, claiming it is "sexually

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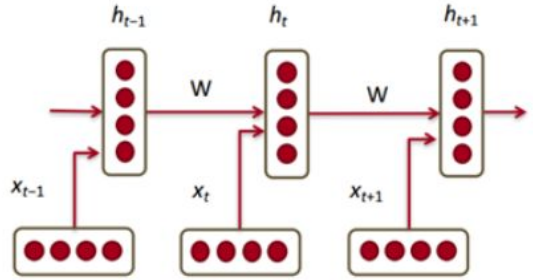
https://gizmodo.com/this-neural-networks-hilariously-bad-image-descriptions-1730844528
http://www.evolvingai.org/fooling

RNNs
Recurrent Neural Networks

Natural Language Processing (NLP)

$$h_t = \sigma\left(W^{(hh)} h_{t-1} + W^{(hx)} x_{[t]}\right)$$



$$p(y_1, \ldots, y_{T'} | x_1, \ldots, x_T) = \prod_{t=1}^{T'} p(y_t | v, y_1, \ldots, y_{t-1})$$

Representation Learning

Autoencoders

input layer

x_1 9.0

x_2 2.0

x_3 7.0

x_4 3.0

x_5 0.0

hidden layer

Dimensional reduction

AUTOENCODERS

$w_1 = 20$

$w_2 = 8$

input layer

error correction

output layer

x_1 9.0

x_2 2.0

x_3 7.0

x_4 3.0

x_5 0.0

hidden layer

Dimensional reduction

hidden layer

0.76

0.32

8.7

1.4

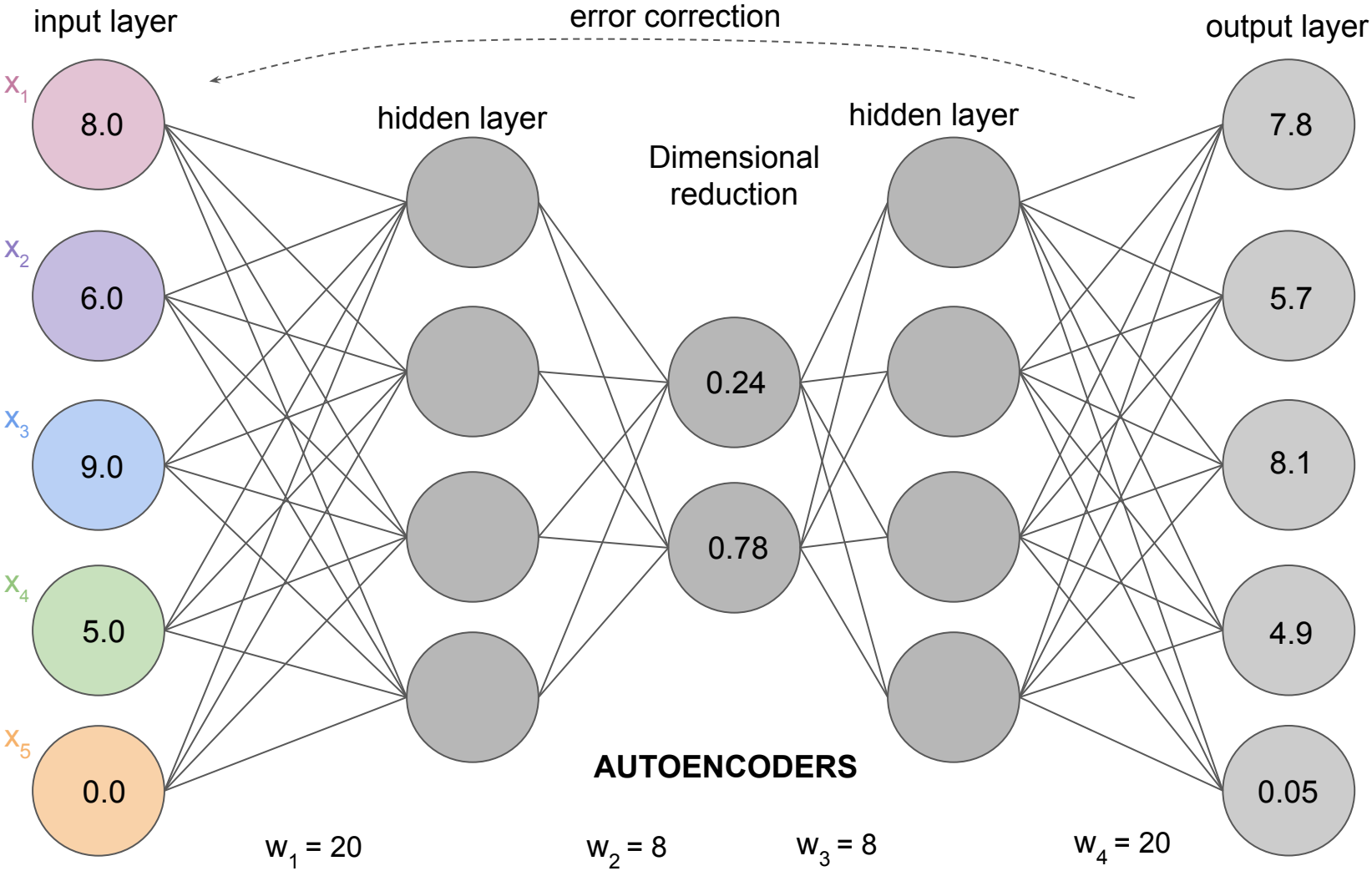
6.9

2.9

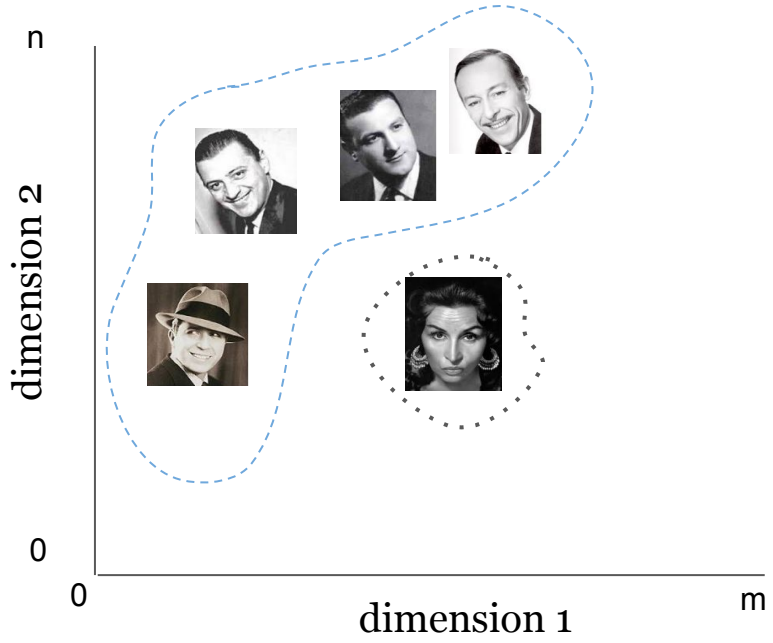
0.01

AUTOENCODERS

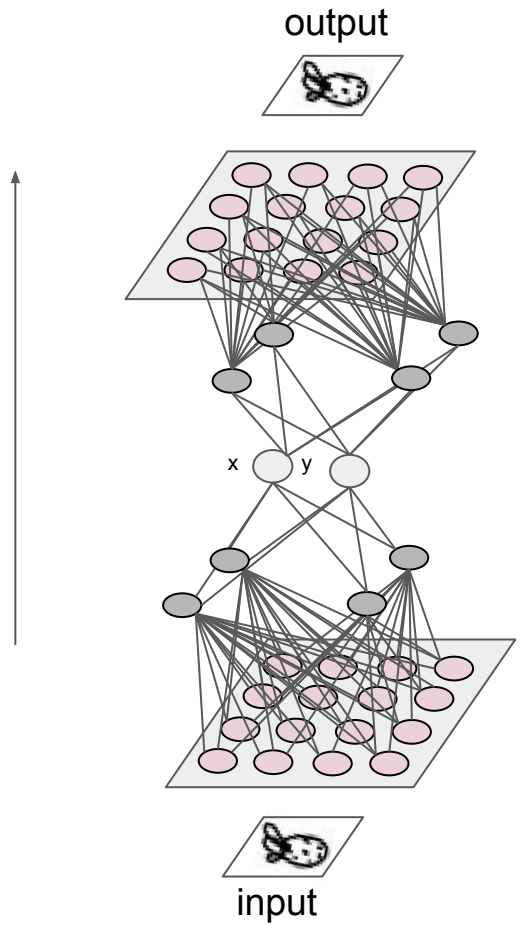
$w_1 = 20$ $w_2 = 8$ $w_3 = 8$ $w_4 = 20$


input layer
error correction
output layer
x_1
8.0
hidden layer
Dimensional reduction
hidden layer
7.8
x_2
6.0
5.7
x_3
9.0
0.24
8.1
x_4
5.0
0.78
4.9
x_5
0.0
0.05
AUTOENCODERS
$w_1 = 20$
$w_2 = 8$
$w_3 = 8$
$w_4 = 20$

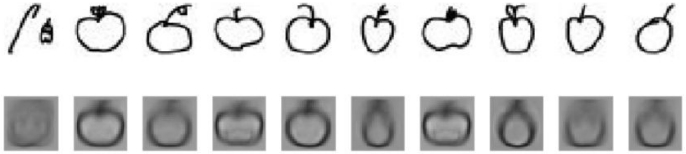
Las nuevas representaciones muchas veces permiten mejorar la performance de los algoritmos de clustering



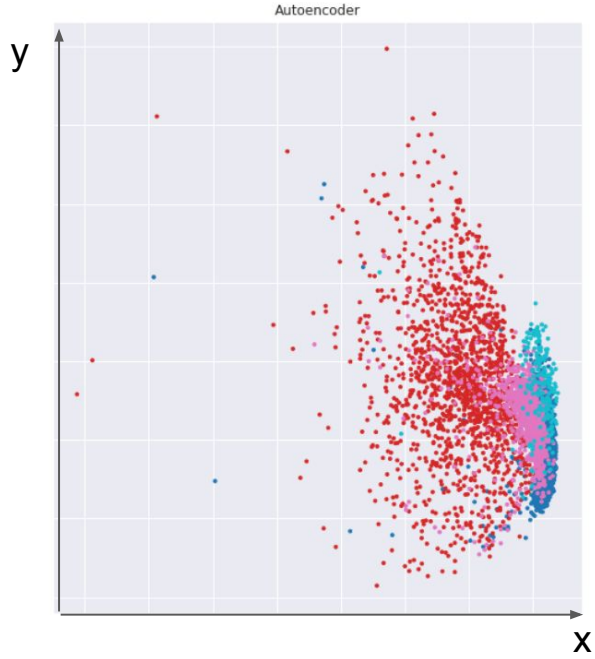
Autoencoder con el set de Frutas



Representaciones



Separación entre los grupos de frutas usando nuevas representaciones

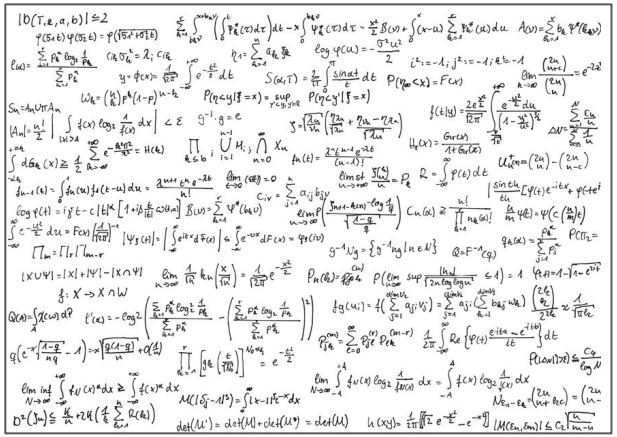


REFLEXIÓN FINAL

El imaginario popular de lo que es el ML ...

Un montón de información

Aplicamos un complejo algoritmo



Soluciones mágicas

~ $20 ~ $30 ~ $60 ~ $70 ~ $80

Lo que realmente es...

Colección de los datos

Procesamiento

Fase de Prototipado
Selección de Features y Modelos

Puesta en Producción

Resultado Final

~ $20 ~ $30 ~ $60 ~ $70 ~ $80

SQL PostgreSQL mongoDB

python R TensorFlow

Java Scala aws Spark

Algunas de las aplicaciones más conocidas de ML en distintos mundos del negocio:

Manufacturas:
Predicción de mantenimiento.
Monitoreo y generación de alertas.
Forecasting de demanda.
Optimización de packaging.

Retail en general:
Predicción de inventariado.
Sistemas de Recomendación.
Optimización de precios.
Segmentación de usuarios y mercados.
ROI de usuarios y lifetime value.
Cross-selling.
Campañas de promociones y marketing.
Encuestas de satisfacción, NPS, etc.
Moderación de contenido.
Modelos de attrition y drop-out de empleados.

Servicios de Finanzas:
Análisis de Riesgo.
Segmentación de usuarios.
Cross-selling.
Campañas de marketing.
Evaluación de créditos.

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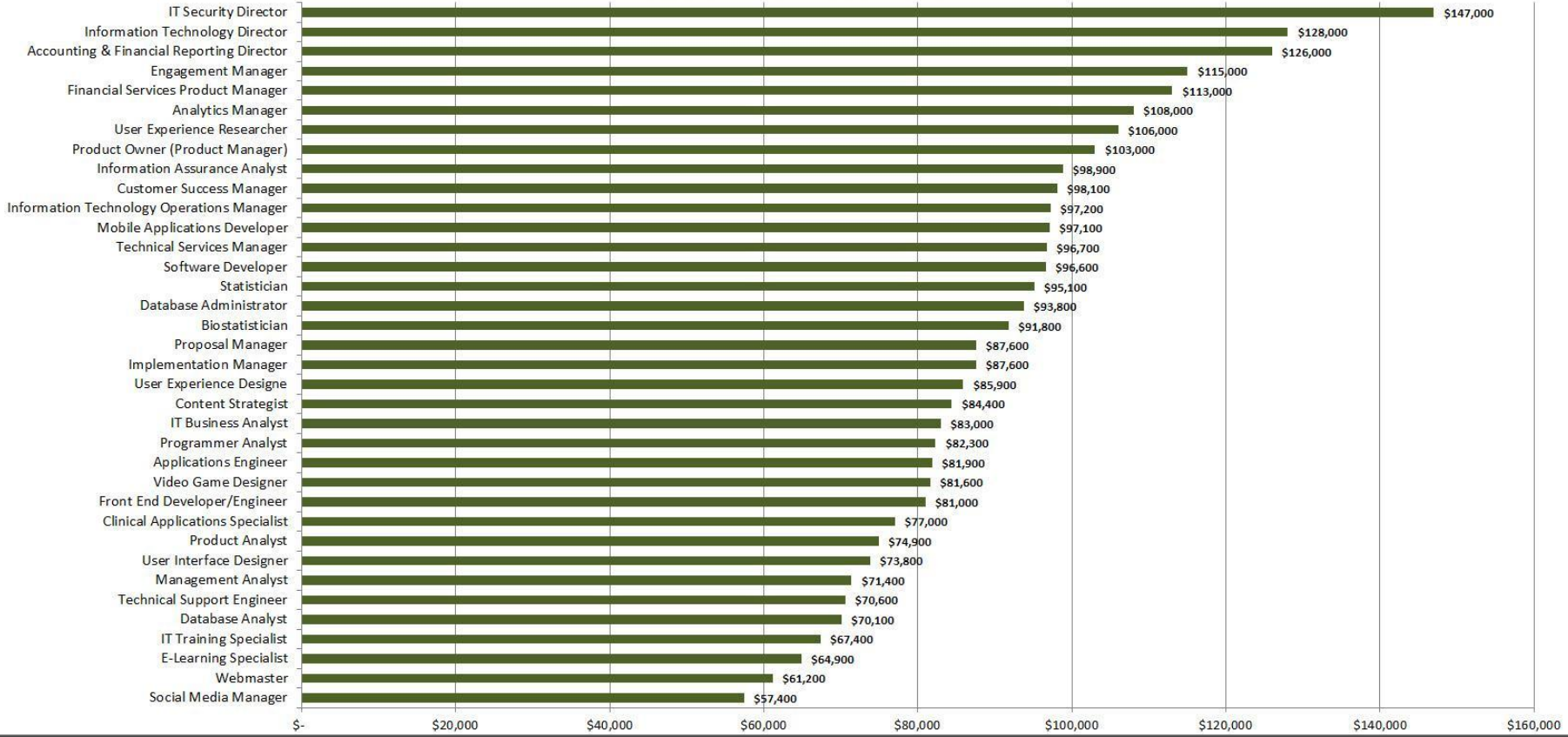
CNNMoney's 100 Best Jobs in America, 2017
Median Pay For 36 Technology-Related Positions
urce: http://money.cnn.com/pf/best-jobs/



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Gracias!