

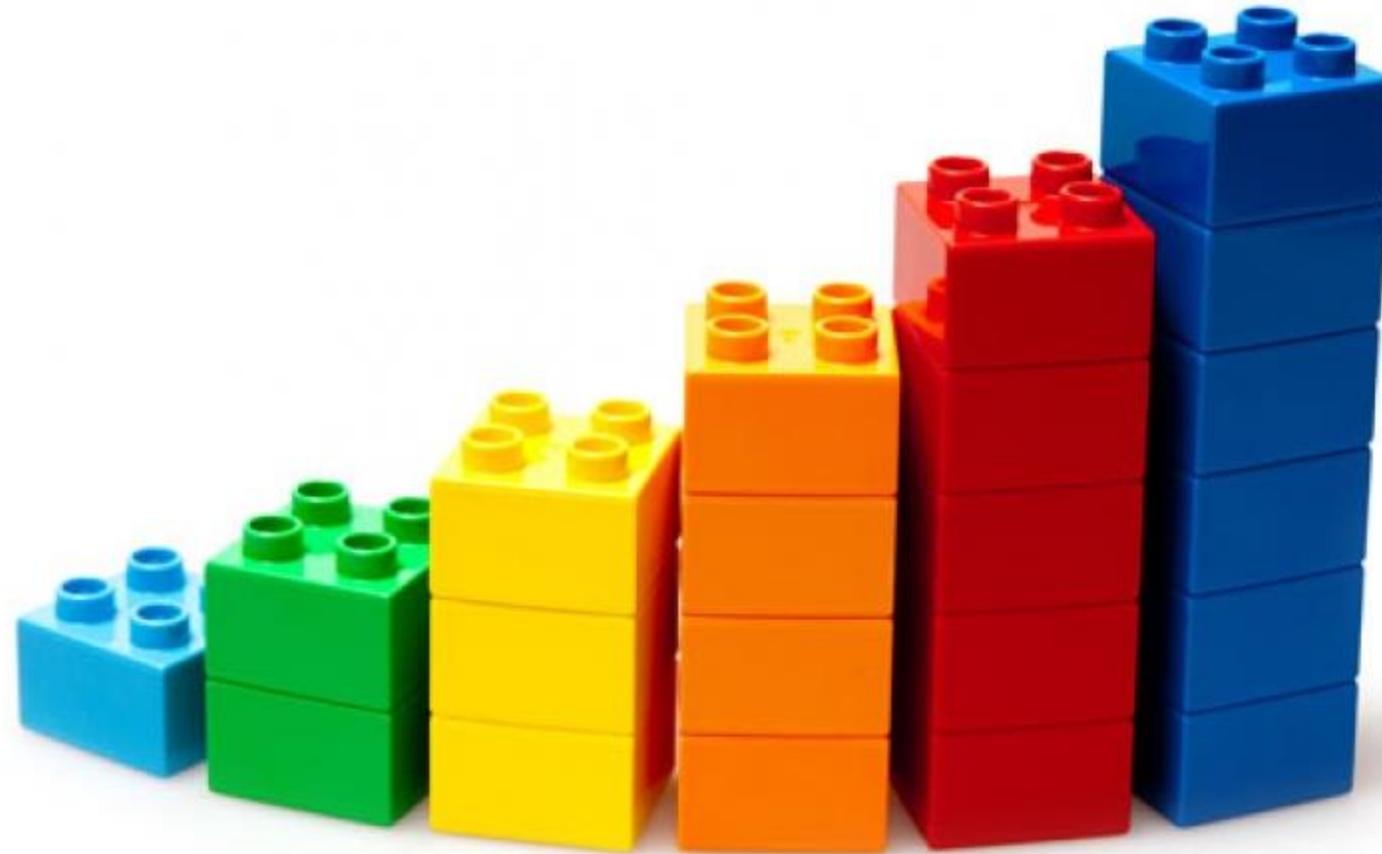
Aplicación de tecnologías emergentes para la extracción, tratamiento y análisis de datos en tiempo real durante la pandemia COVID 19



Dra. Alba Naya Prieto

Adjunto de Neumología

Unidad de Cuidados Intermedios Respiratorios UCIR



2021

Qué hacemos con estos datos

El progreso y la innovación **no** se ven limitados por la **recopilación de datos**



Sino por la capacidad de extraer el **valor** de los datos y obtener **conocimiento**

Inteligencia artificial

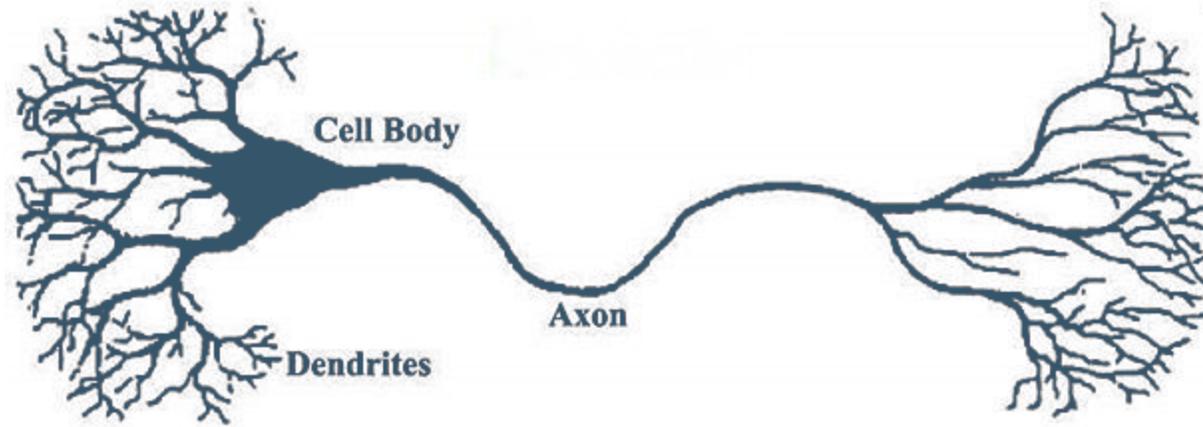


Redes neuronales
Redes Bayesianas
Modelos de Markov

Redes neuronales

McCulloch y Pitts 1943

Base del
funcionamiento
cerebral

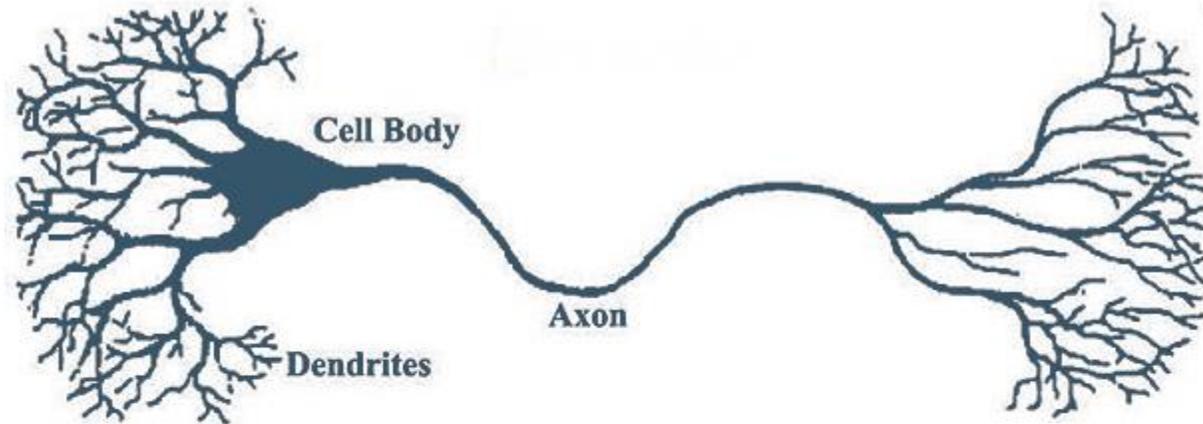


Procesamiento no
lineal, complejo y
paralelo

Redes neuronales

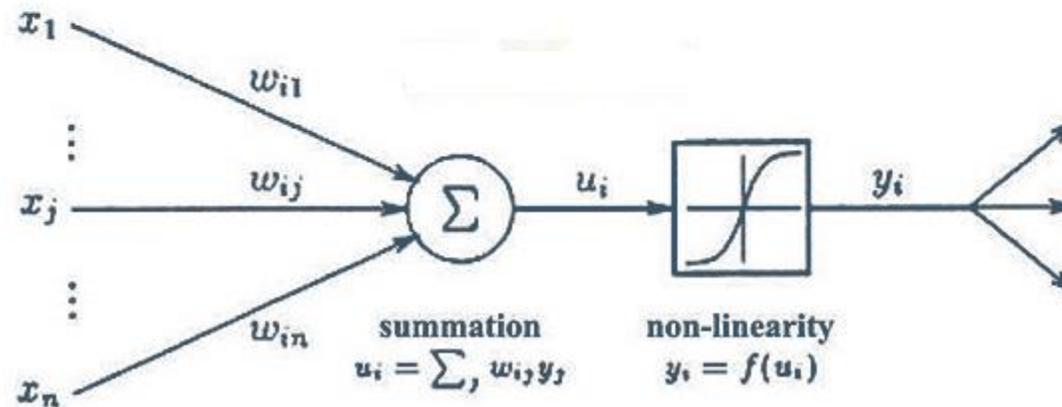
McCulloch y Pitts 1943

Base del funcionamiento cerebral



Procesamiento no lineal, complejo y paralelo

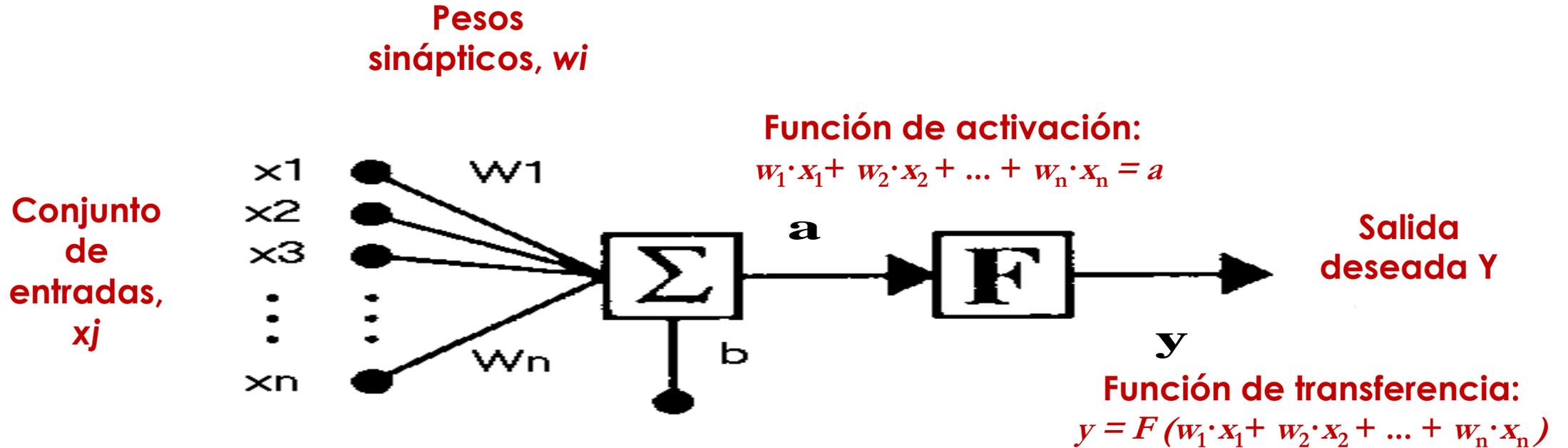
Dispositivo simple de cálculo



Varios vectores proporcionan una única salida

perceptrón

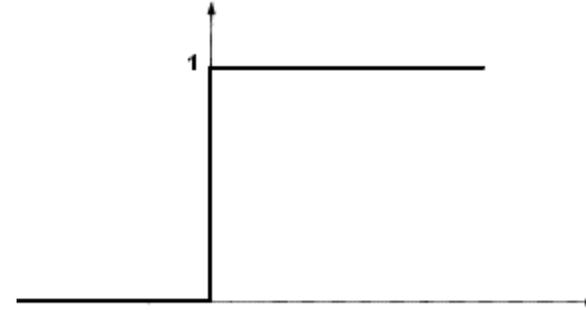
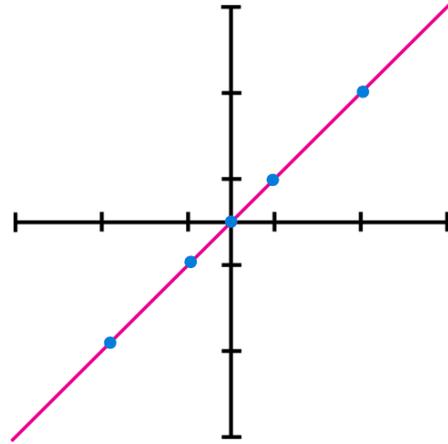
Perceptrón



Bias, umbral o polarización: entrada constante de magnitud 1, y peso b que se introduce en el sumador

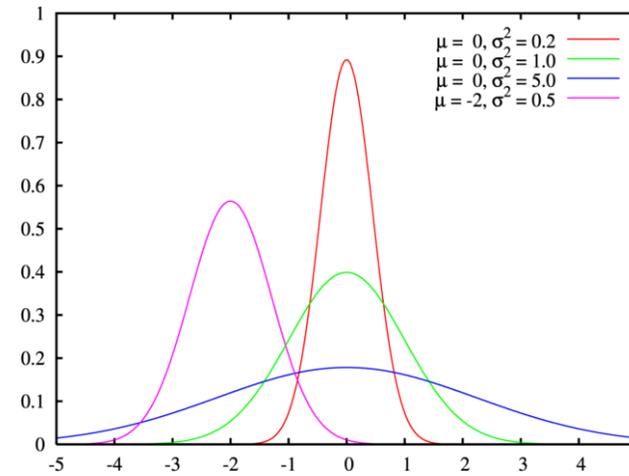
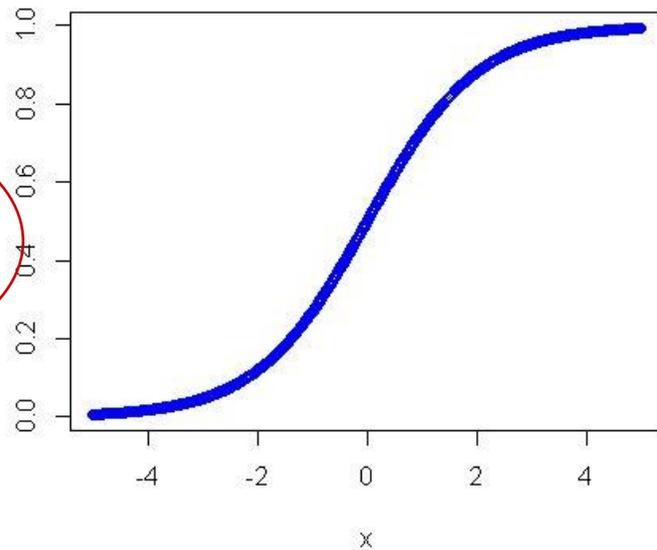
Funciones de transferencia

Lineal: $y=ka$



Escalón: $y = 0$ si $a < 0$; $y = 1$ si $a \geq 0$

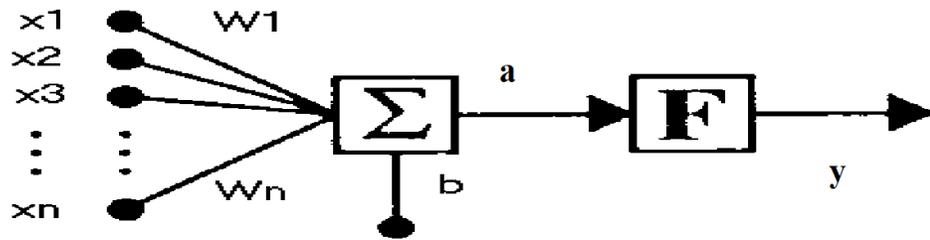
Sigmoide



Gaussiana

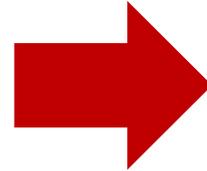
Potencia de cálculo: las capas

Una neurona aislada dispone de poca potencia de cálculo

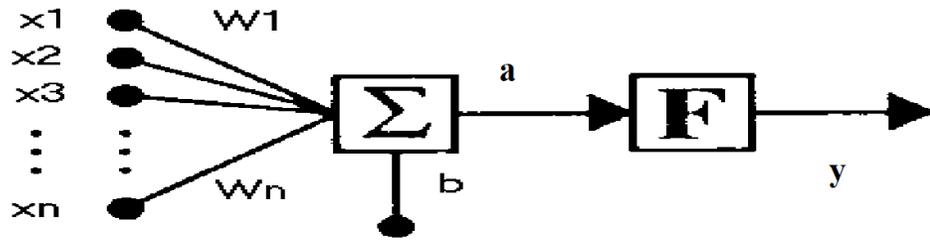


Potencia de cálculo: las capas

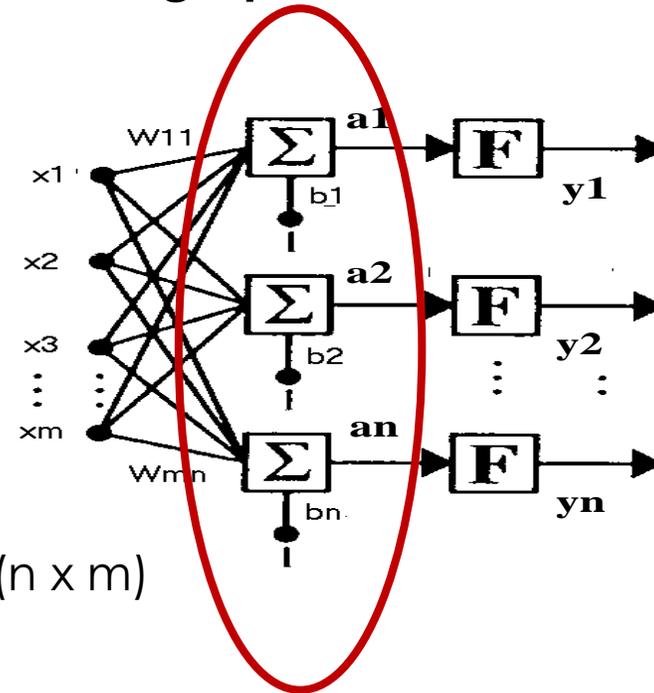
Una neurona aislada dispone de poca potencia de cálculo



Aumentar potencia mediante la agrupación de varias



Los pesos pasan a ser matrices W ($n \times m$)



capa

La salida de la red es un vector:

$$Y = (y_1, y_2, \dots, y_n)^T$$
$$Y = F(W \cdot X + b)$$

Tipos de redes neuronales según aprendizaje

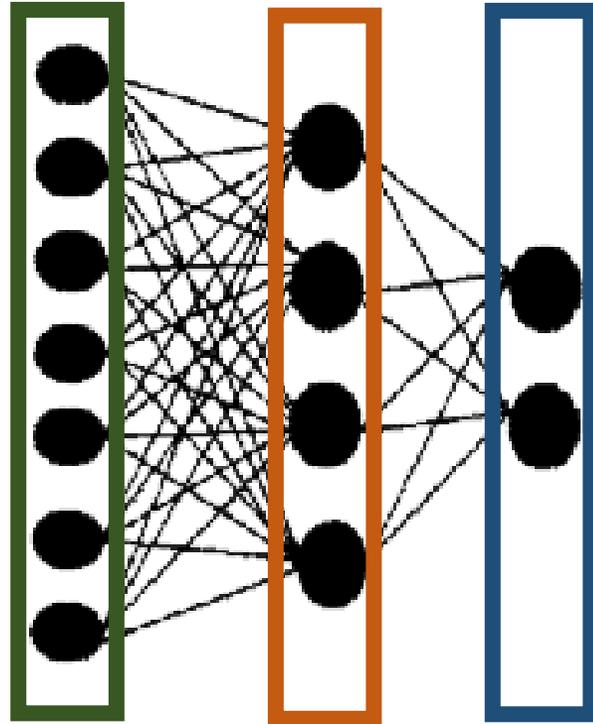
Capas en cascada

Tipos de capas

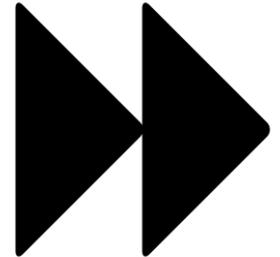
Entrada

Salida

Oculto

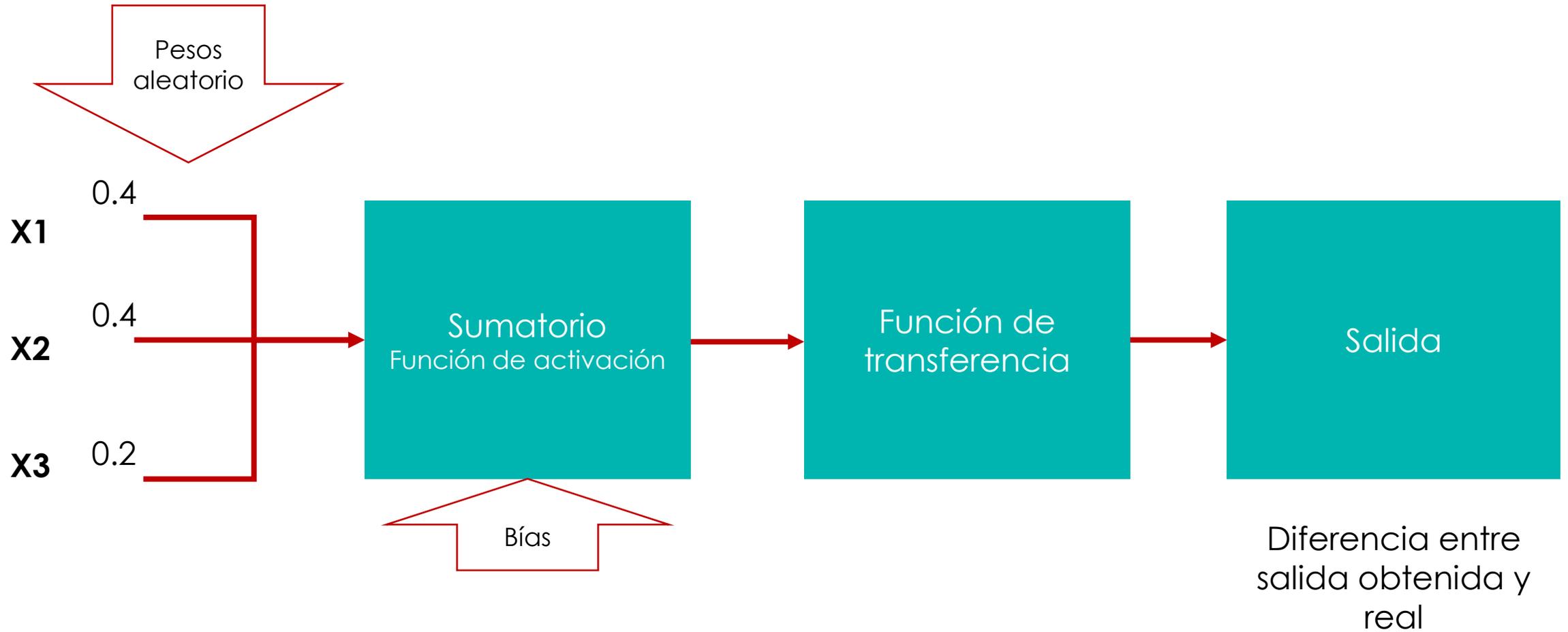


red feedforward

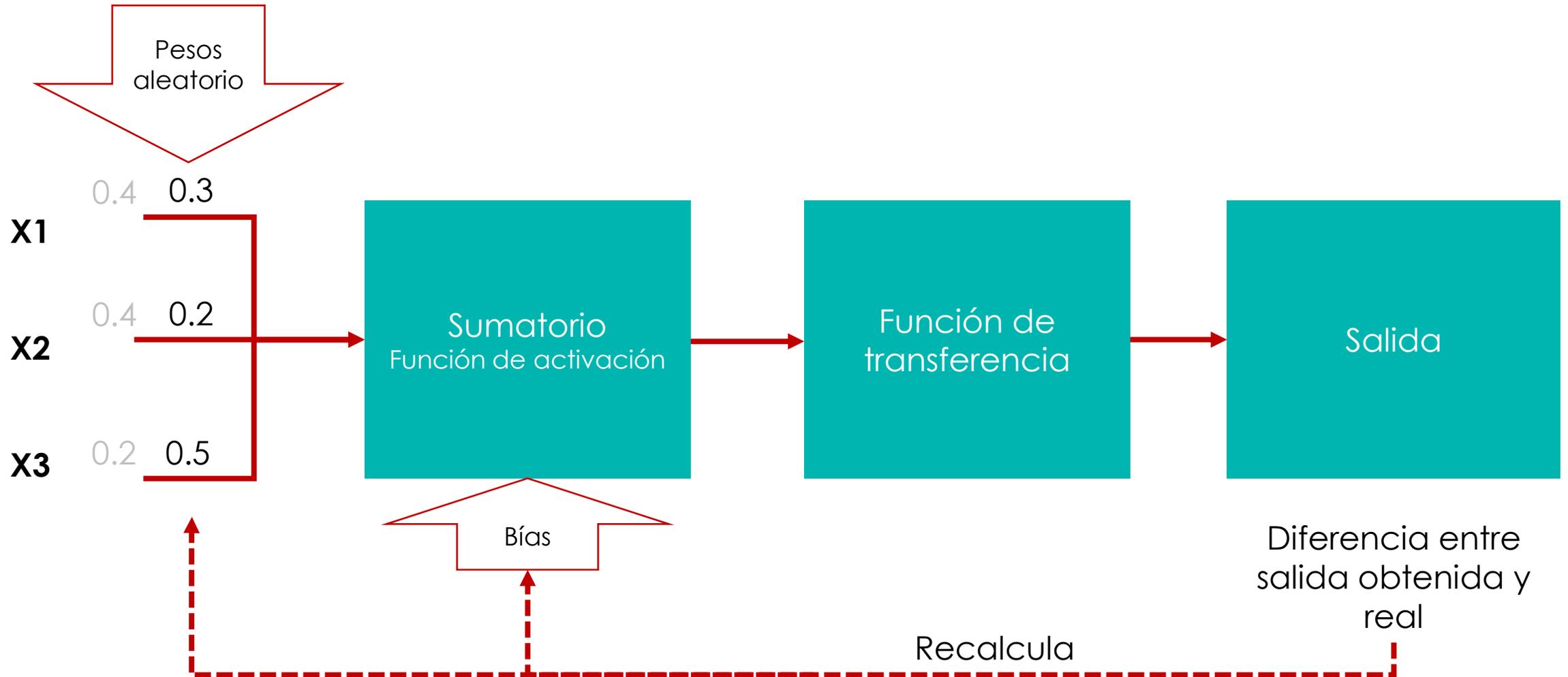


red recurrente

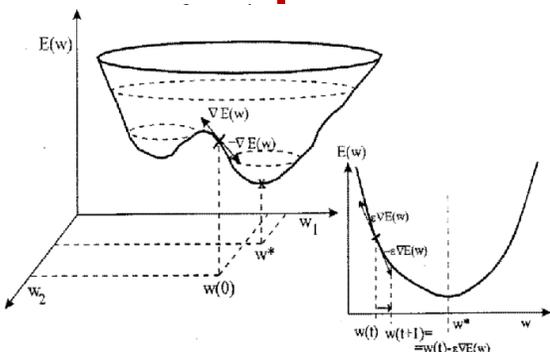
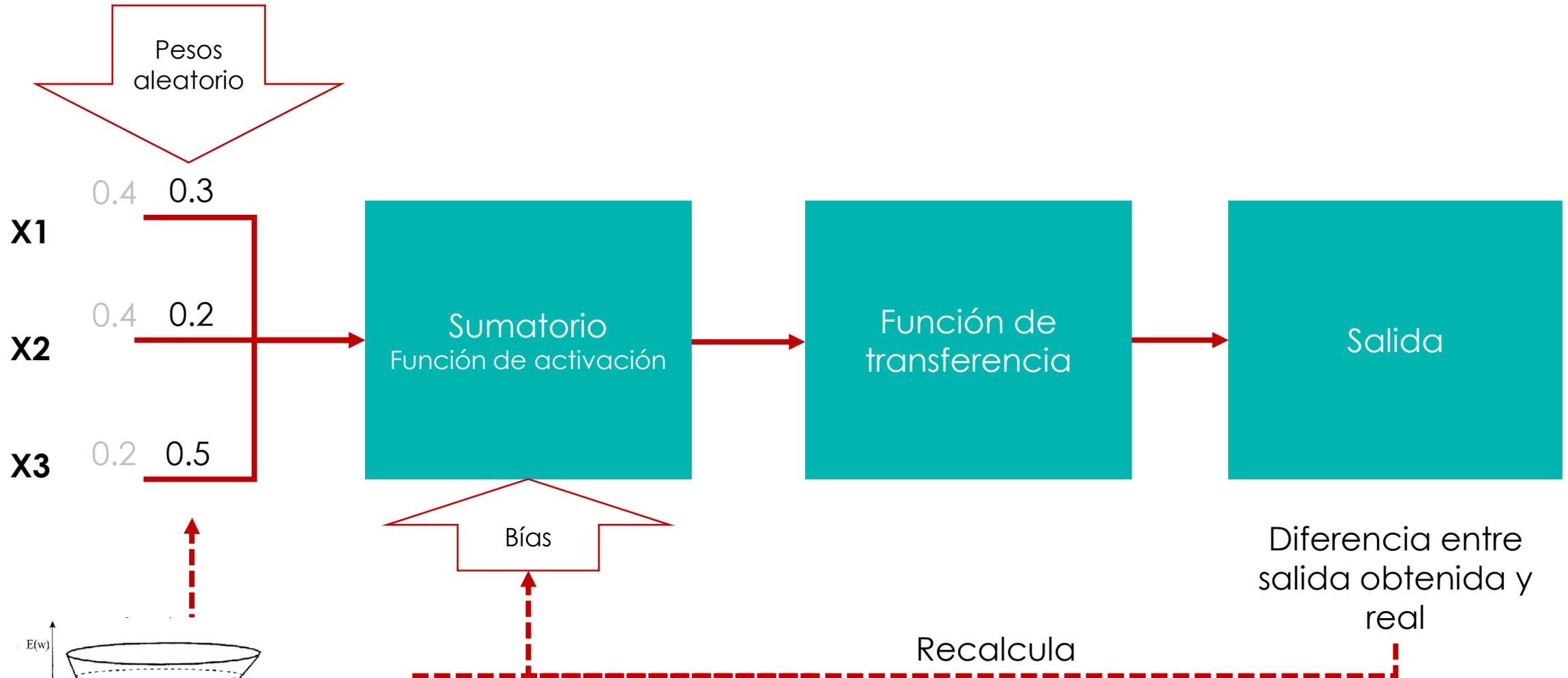
Redes recurrentes: backpropagation



Redes recurrentes: backpropagation



Redes recurrentes: backpropagation



Entrenamiento de redes neuronales

Proceso de aprendizaje = entrenamiento

Supervisado

Entrada y salida conocida

Automatizar

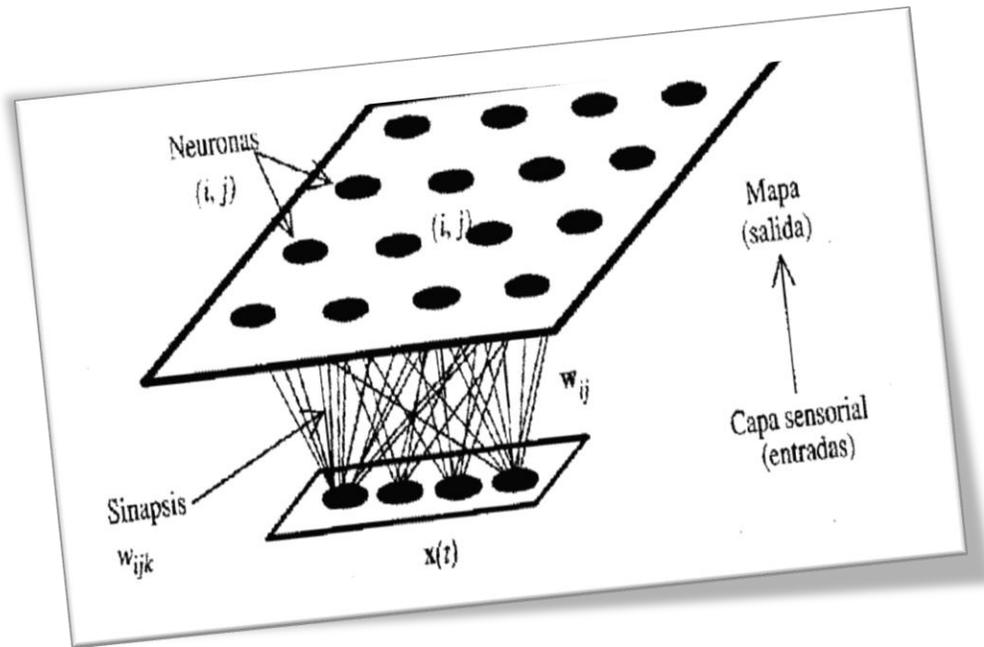
No supervisado

Descubre por si misma
Competitivo

Reforzado

Objetivo = comportamiento deseado

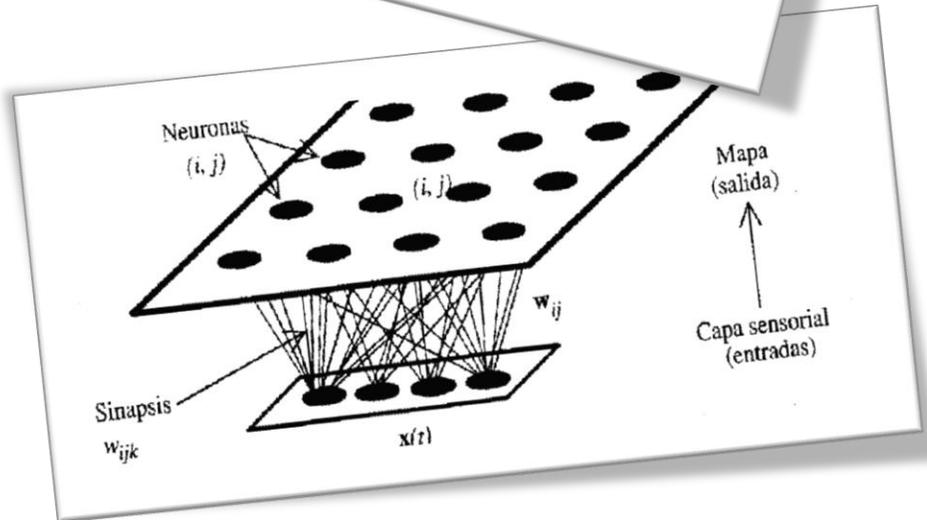
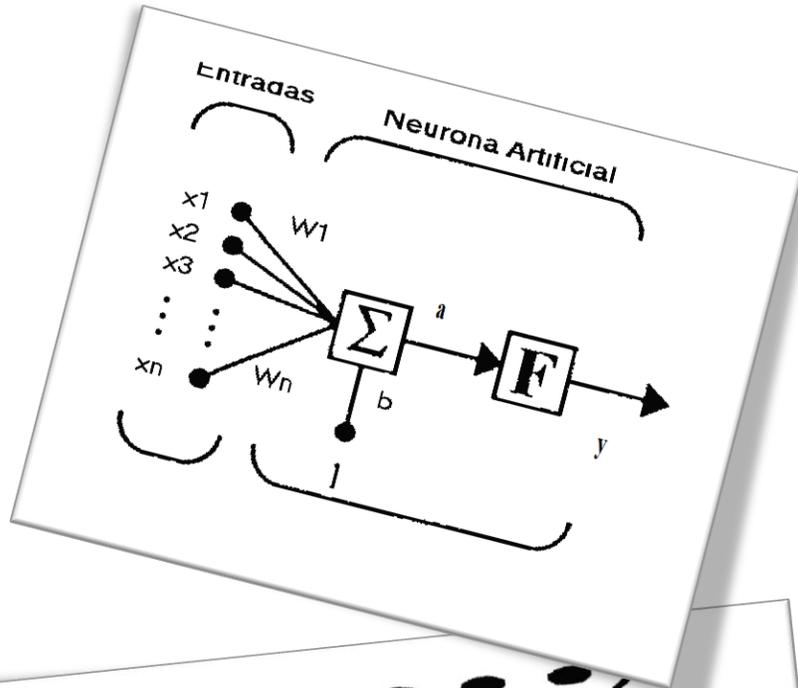
Entrenamiento redes no supervisadas



- Autoorganizativas: durante el proceso de aprendizaje la red debe descubrir por si misma regularidades o categorías
- Competitiva: quedará activa aquella que sea capaz de acercarse al vector de entrada con menos error

Ideales para sacar a la luz posible conocimiento oculto

Ventajas de las redes neuronales



- Aprendizaje adaptativo
- Auto-organización
- Aprenden incluso de patrones distorsionados o incompletos
- Operaciones en tiempo real
- Facilidad de inserción en tecnología ya existente

Investigación en UCIR basada en redes neuronales

Arch Bronconeumol. 2020;56(9):564-570

 **ARCHIVOS DE Bronconeumología**
www.archbronconeumol.org

Original Article

Patient Management Assisted by a Neural Network Reduces Mortality in an Intermediate Care Unit

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¹Intermediate Respiratory Care Unit, IIS-Fundación Jiménez Díaz Quirón Salud, Madrid, CIBER de enfermedades respiratorias (CIBERES), REVA Network, Madrid, Spain, Avda Reyes Católicos nº 2, CP 28040 Madrid, Spain
²Genetics and Genomics Department, IIS-Fundación Jiménez Díaz, Madrid, Center for Biomedical Network Research on Rare Diseases (CIBERER), ESCIII, Madrid, Spain
³Department of Biostatistics and Epidemiology, IIS-Fundación Jiménez Díaz UAM, Madrid, Spain
⁴Thoracic Surgery Department, Sanchinarro University Hospital, HM Hospitals Group, Madrid, Spain
⁵ITC Ingeniería y Técnicas Clínicas, CIBER de Enfermedades Respiratorias (CIBERES), Madrid, Spain
⁶Civil Engineering, Sorbonne-Paris, Paris, France

2019

  
THE PREPRINT SERVER FOR HEALTH SCIENCES

COVID-19 Outcomes in 4712 consecutively confirmed SARS-CoV2 cases in the city of Madrid

Sarah Heili-Frades, Pablo Minguez, Ignacio Mahillo Fernández, Tomás Prieto-Rumeau, Antonio Herrero González, Lorena de la Fuente, María Jesús Rodríguez Nieto, Germán Peces-Barba Romero, Mario Peces-Barba, María del Pilar Carballosa de Miguel, Itziar Fernández Ormaechea, Alba Naya prieto, Farah Ezzine de Blas, Luis Jiménez Hiscock, Cesar Perez Calvo, Arnoldo Santos, Luis Enrique Muñoz Alameda, Fredeswinda Romero Bueno, Miguel Górgolas Hernández-Mora, Alfonso Cabello Úbeda, Beatriz Álvarez Álvarez, Elizabet Petkova, Nerea Carrasco, Dolores Martín Ríos, Nicolás González Mangado, Olga Sánchez Pernaute, and the COVID FJD-TEAM

doi: <https://doi.org/10.1101/2020.05.22.20109850>

2020

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DOI: 10.23937/2378-3516/1410147
Volume 7 | Issue 4
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 **International Journal of Respiratory and Pulmonary Medicine**

RESEARCH ARTICLE

The Role of Intermediate Respiratory Care Units in Preventing ICU Collapse during the COVID Pandemic

Sarah Heili Frades, MD^{1,*}, María del Pilar Carballosa de Miguel, MD¹, Alba Naya Prieto, MD¹, Itziar Fernández Ormaechea, MD¹, Farah Ezzine de Blas, MD¹, Pablo Lopez Yeste, MD¹, Francisco Jos Laso Del Hierro, MD¹, Alinhao Izquierdo Perez, MD¹, Marwan Mohamed Choukri, MD¹, Herminia Ortiz Mayoral, MD¹, Abdulkader El Hachem Debek, MD¹, Andres Gimenez Velando, MD¹, Marcel Jose Rodriguez Guzman, MD¹, Elena Cabezas Pastor², Pablo Minguez, PhD¹, Ignacio Mahillo Fernández, PhD¹, Antonio Herrero González², Lorena de la Fuente, PhD¹, Luis Jiménez Hiscock, MD¹, Sandra Pelicano Vizuetes³, Rebeca Armenta⁴, María José Checa Venegas⁵ and Germán Peces Barba Romero, MD, PhD¹

¹Intermediate Respiratory Care Unit, IIS-Fundación Jiménez Díaz Quirón Salud, Spain
²Pulmonology Department, Fundación Jiménez Díaz Quirón Salud, Spain
³Genetics and Genomics Department, IIS-Fundación Jiménez Díaz-Universidad Autónoma de Madrid UAFJ, Spain
⁴Center for Biomedical Network Research on Rare Diseases (CIBERER), Spain

2020

1- Patient management assisted by a Neural Network reduces mortality in an Intermediate Care Unit



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Hb	12.14	2.66	0.15
PL	258.37	130.19	0.20
INR	1.55	1.32	40.18
CREA	1.01	1.57	0.15
NA	138.35	5.43	0.15
K	4.34	1.92	0.31
PH	7.23	0.47	0.66
PCO2	59.34	22.00	0.66
PO2	58.33	33.14	0.66
BE	4.38	7.10	0.92
SBC	28.48	6.04	0.92

1- Patient management assisted by a Neural Network reduces mortality in an Intermediate Care Unit

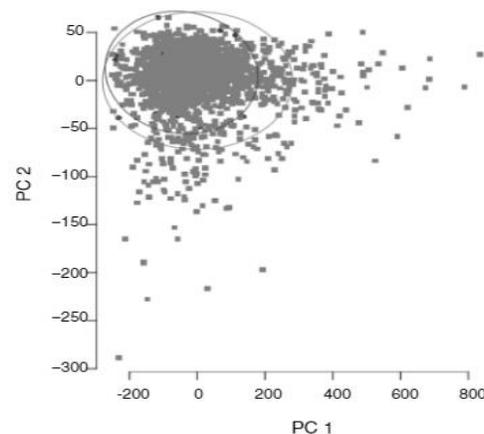


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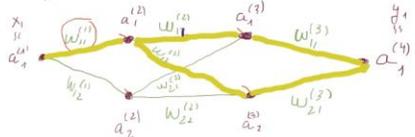
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Las redes neuronales son derivadas....

Back Propagation



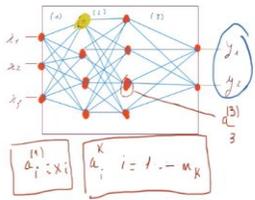
$$\frac{\partial y_1}{\partial w_{11}^{(1)}} = a_1^{(1)}(1-a_1^{(1)}) \cdot w_{11}^{(2)} \cdot a_1^{(2)}(1-a_1^{(2)}) \cdot w_{11}^{(3)} \cdot a_2^{(2)}(1-a_2^{(2)}) \cdot a_1^{(3)} +$$

$$a_1^{(1)}(1-a_1^{(1)}) \cdot w_{21}^{(2)} \cdot a_2^{(2)}(1-a_2^{(2)}) \cdot w_{21}^{(3)} \cdot a_1^{(2)}(1-a_1^{(2)}) \cdot a_1^{(3)}$$

$$\frac{\partial y_1}{\partial w_{11}^{(1)}} = a_1^{(1)} a_1^{(2)} (1-a_1^{(1)}) w_{11}^{(2)} a_1^{(3)} (1-a_1^{(2)}) w_{11}^{(3)} a_1^{(4)} (1-a_1^{(3)}) +$$

$$a_1^{(1)} a_1^{(2)} (1-a_1^{(1)}) w_{12}^{(2)} a_2^{(2)} (1-a_2^{(2)}) w_{21}^{(3)} a_1^{(3)} (1-a_1^{(2)}) \rightarrow i, e, s, q \dots$$

$$\frac{\partial y_1}{\partial w_{11}^{(1)}} = x_1 a_1^{(2)} (1-a_1^{(1)}) \sum_{j=1}^2 w_{1j}^{(2)} a_j^{(2)} (1-a_j^{(2)}) \sum_{k=1}^2 w_{kj}^{(3)} a_k^{(3)} (1-a_k^{(3)}) y_1 (1-y_1)$$



$$a_i = F(\mu + |w_{1i}| + w_{2i} z_2 + w_{3i} z_3)$$

$$a = F(\mu)$$

$$\frac{\partial a}{\partial \mu} = \frac{dF}{d\mu} \cdot \mathbb{1} = F'(\mu) = F'(\mu) \cdot (1-F(\mu)) = a(1-a)$$

$$\frac{\partial a}{\partial w_1} = a(1-a) z_1$$

$$a_i^{(k)} = F\left(\mu_i^{(k)} + \sum_{j=1}^{M_{k-1}} a_j^{(k-1)} \cdot w_{ji}^{(k)}\right)$$

```

1 rm(list=ls())
2
3 library(DMwR)
4 library(GGally)
5 library(ggplot2)
6 library(pROC)
7 library(caret)
8
9 # PARAMETERS TO CUSTOMIZE
10
11
12
13
14
15:1 (Top Level)
R Script

```

Environment History Connections

Global Environment

Variable	Value
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resampling	"yes"
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times.the.size	1

Files Plots Packages Help Viewer

~/Desktop/

1- Patient management assisted by a Neural Network reduces mortality in an Intermediate Care Unit

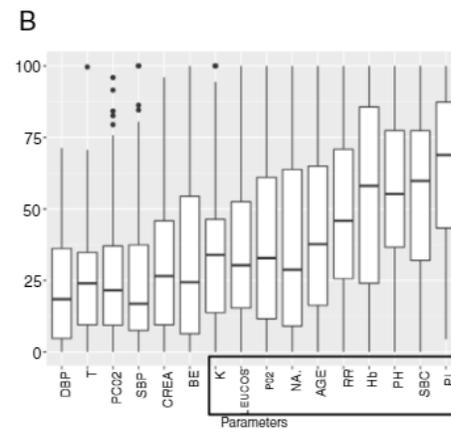
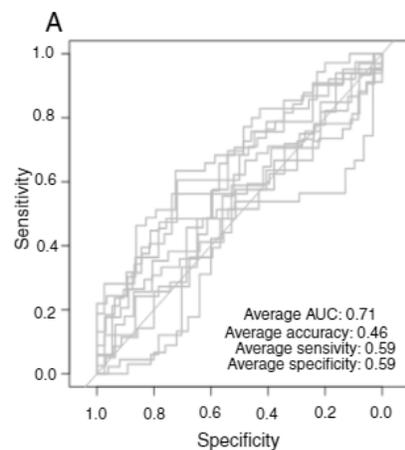
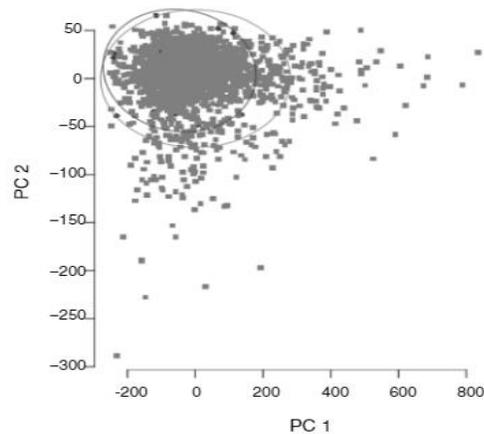


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Modificamos algunos criterios de ingreso

- Datos de infección grave
 - Hipoxia grave refractaria durante las primeras horas en SU
 - Paciente oncohematológico

UCI



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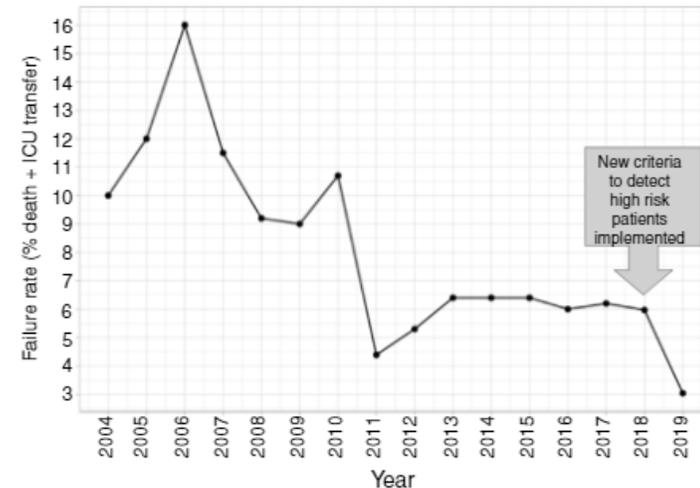
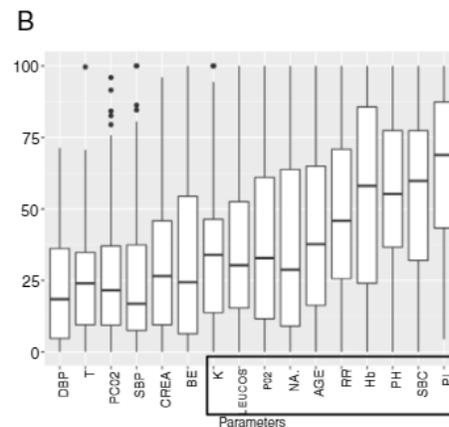
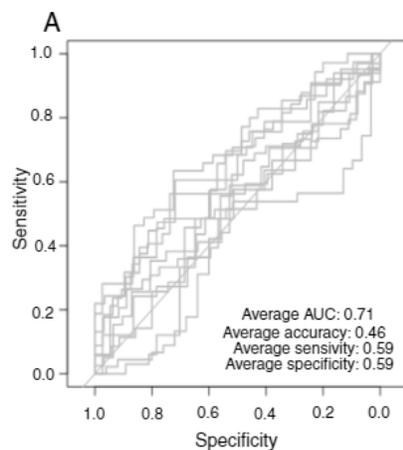
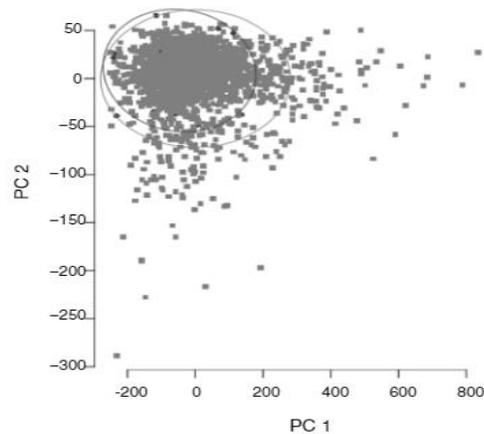


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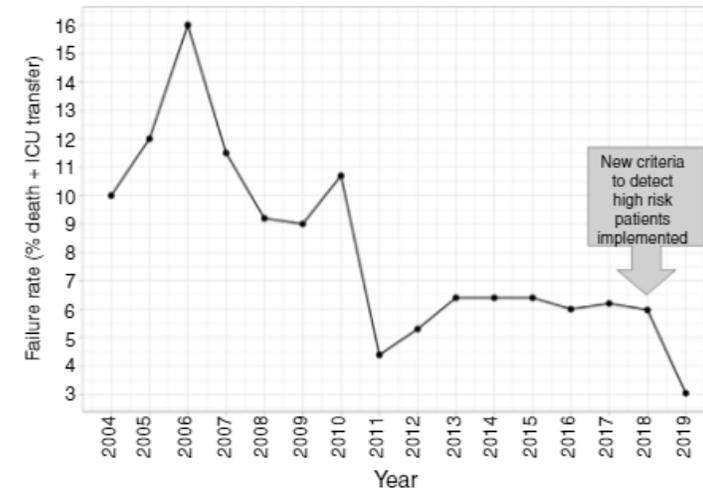
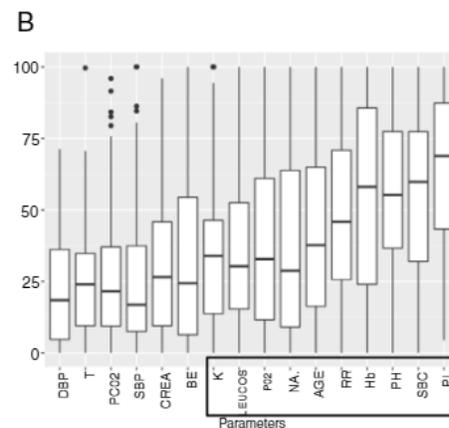
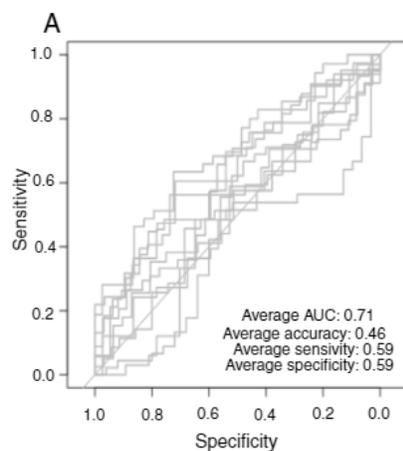
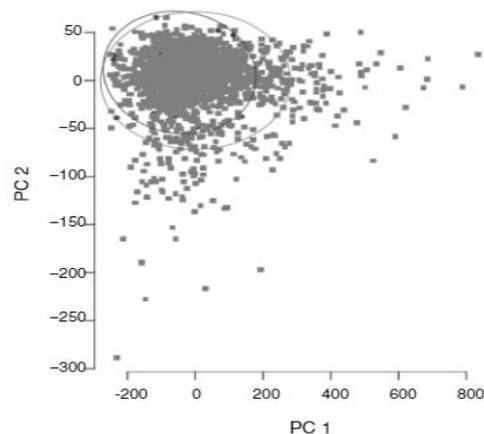


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Vasoactive drugs (%)	26

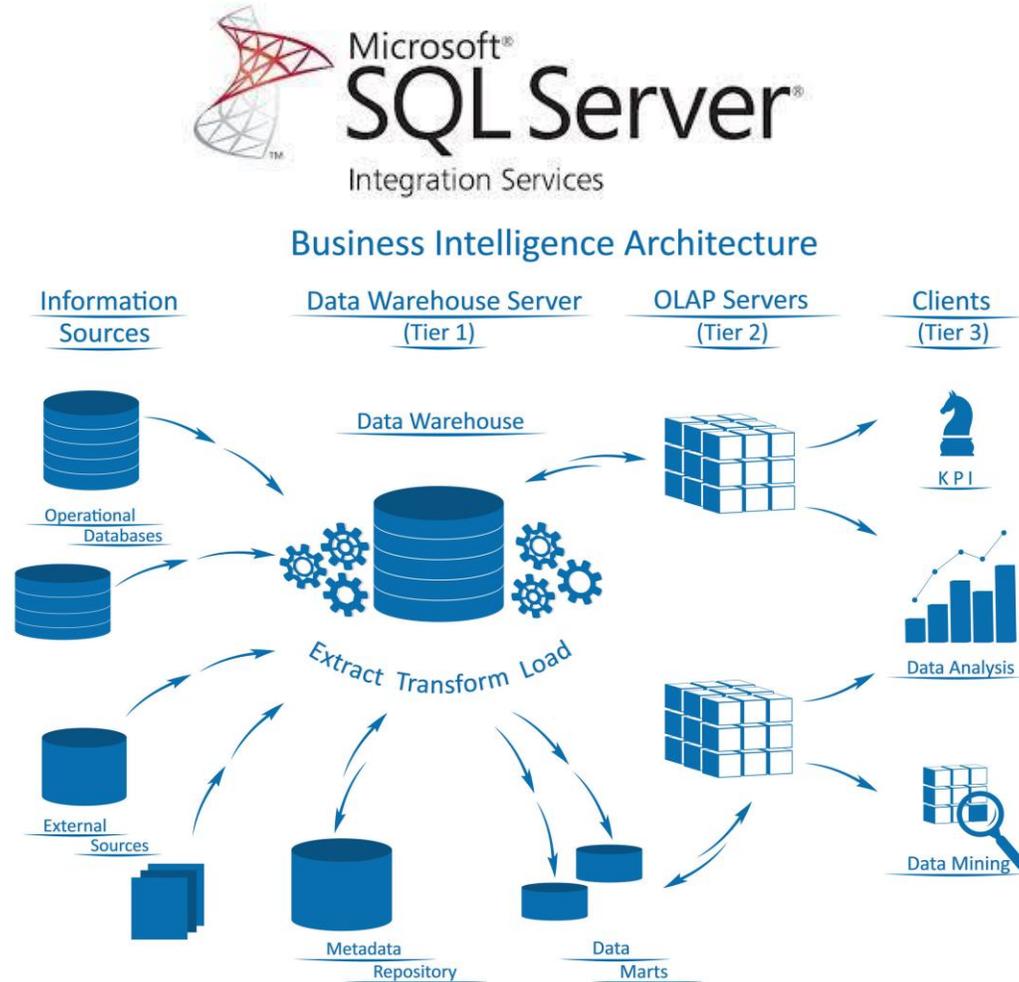
Table 2
Description of the Variables and Their Values Introduced in the Analysis. Percentage of NAs (Not Available Value) Indicates the Missing Values of Every Variable.

Variable	Mean	SD	%NA
AGE	75.3	14.8	7.38
SBP	127.43	20.35	0
DBP	70.42	23.19	0
T	37.34	0.54	0
RR	19.41	2.38	0
LEUCOS	12.25	9.79	0.15
Hb	12.14	2.66	0.15
PL	258.37	130.19	0.20
INR	1.55	1.32	40.18
CREA	1.01	1.57	0.15
NA	138.35	5.43	0.15
K	4.34	1.92	0.31
PH	7.23	0.47	0.66
PCO2	59.34	22.00	0.66
PO2	58.33	33.14	0.66
BE	4.38	7.10	0.92
SBC	28.48	6.04	0.92



Reducción de la mortalidad desde 7% a 3%

2- The role of intermediate respiratory care units in preventing ICU collapse during the COVID pandemic

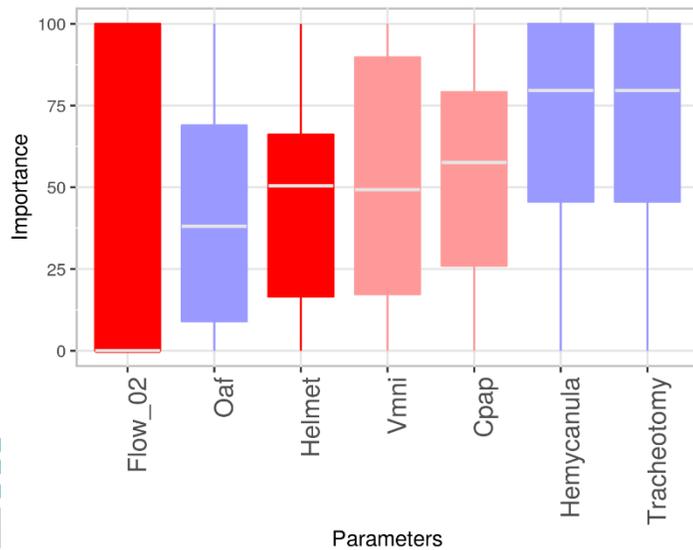
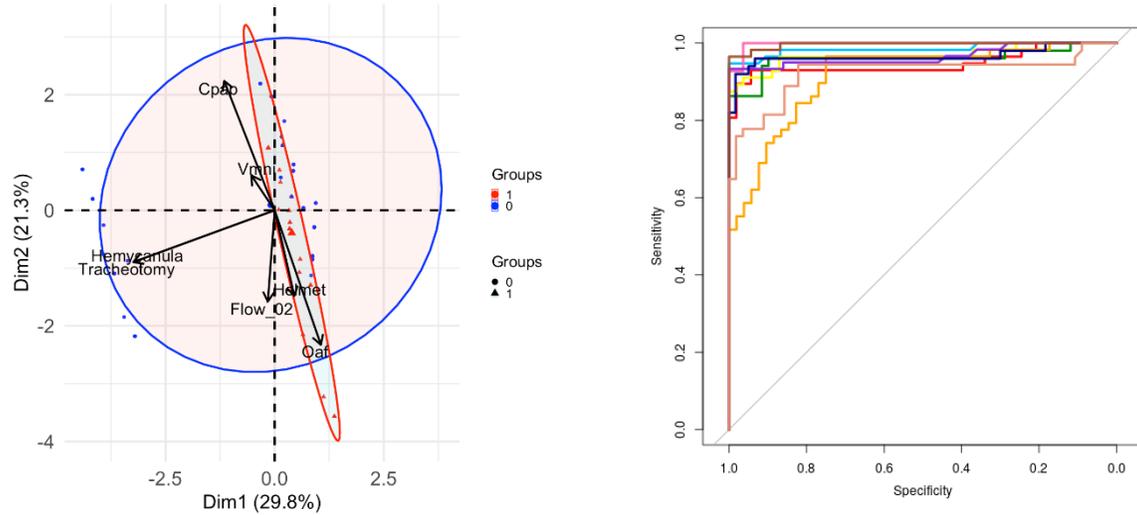


Características clínicas
Fechas
Analítica
Terapias administradas

Lenguaje natural

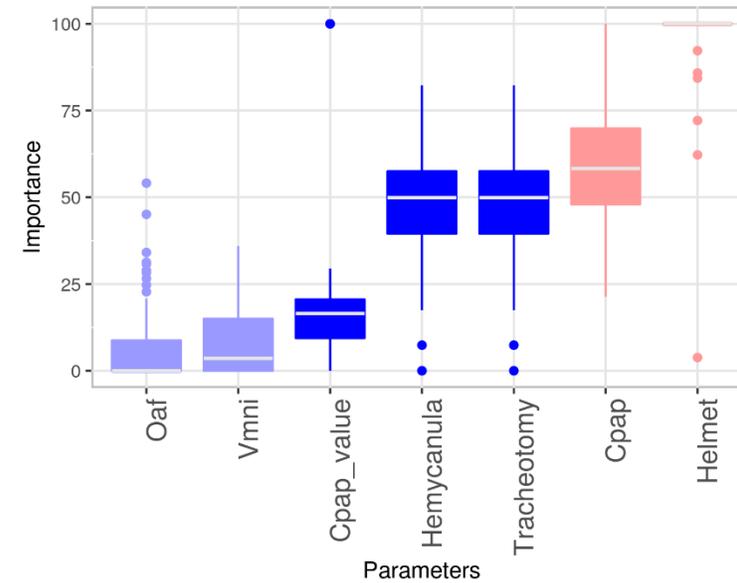
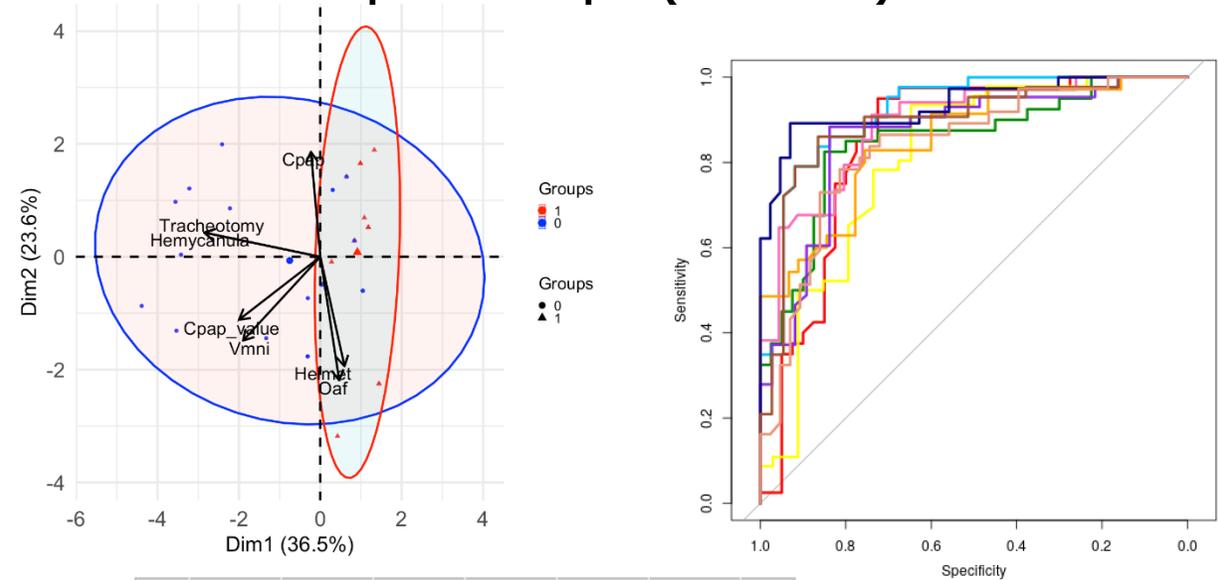
2- The role of intermediate respiratory care units in preventing ICU collapse during the COVID pandemic

Tipo de terapia (todas las edades)



Average AUC: 0.97
 Average Accuracy: 0.91
 Average Sensitivity: 0.71
 Average Specificity: 0.71

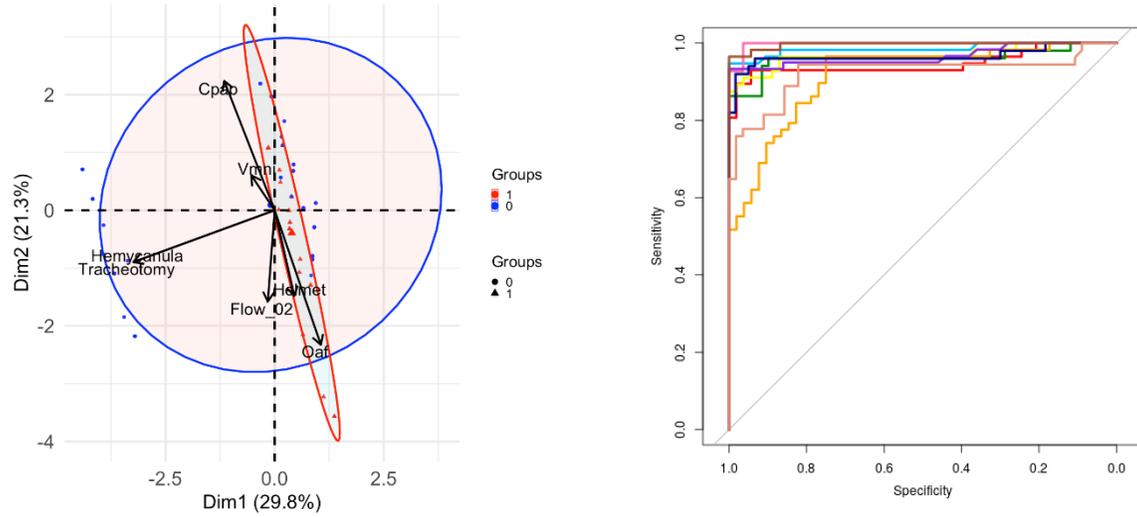
Tipo de terapia (> 70 años)



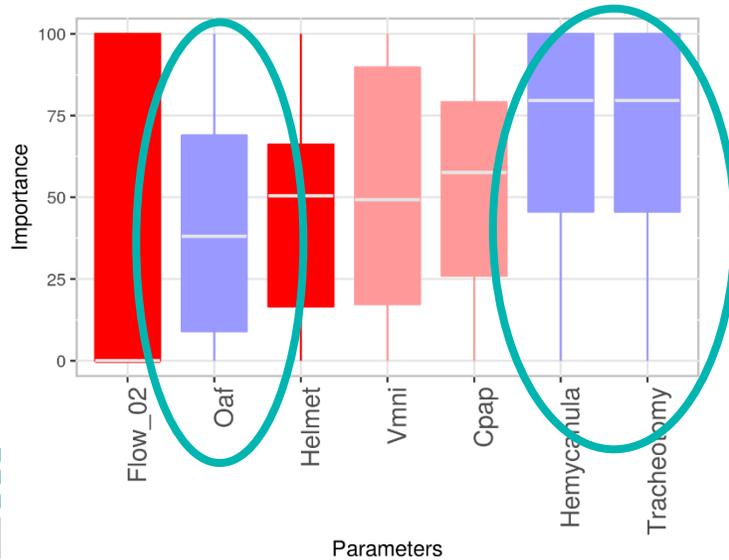
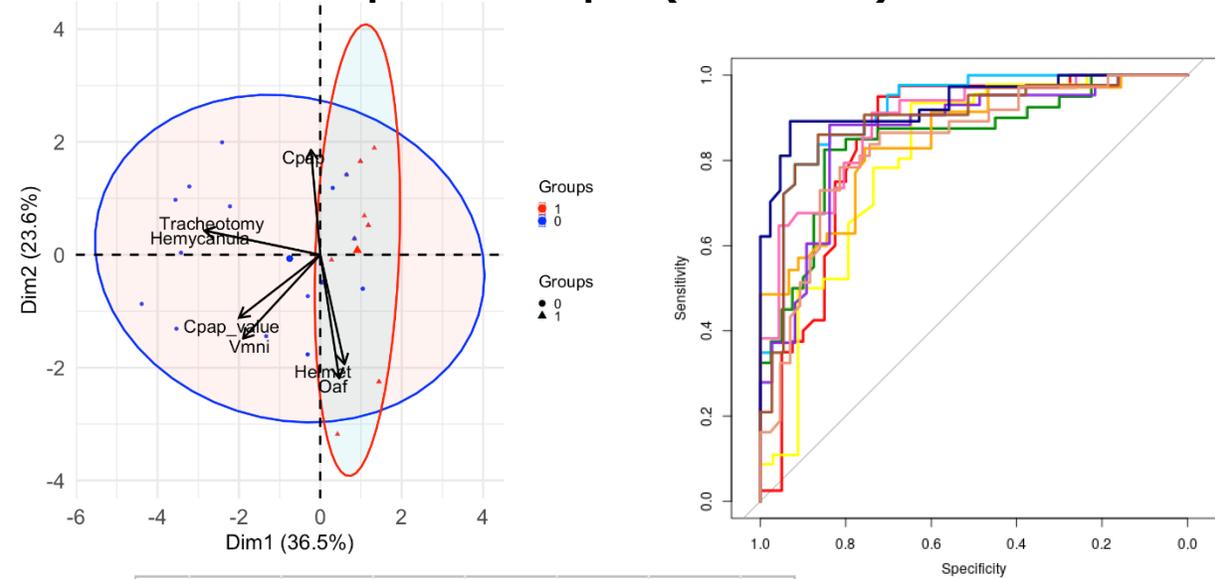
Average AUC: 0.92
 Average Accuracy: 0.8
 Average Sensitivity: 0.69
 Average Specificity: 0.67

2- The role of intermediate respiratory care units in preventing ICU collapse during the COVID pandemic

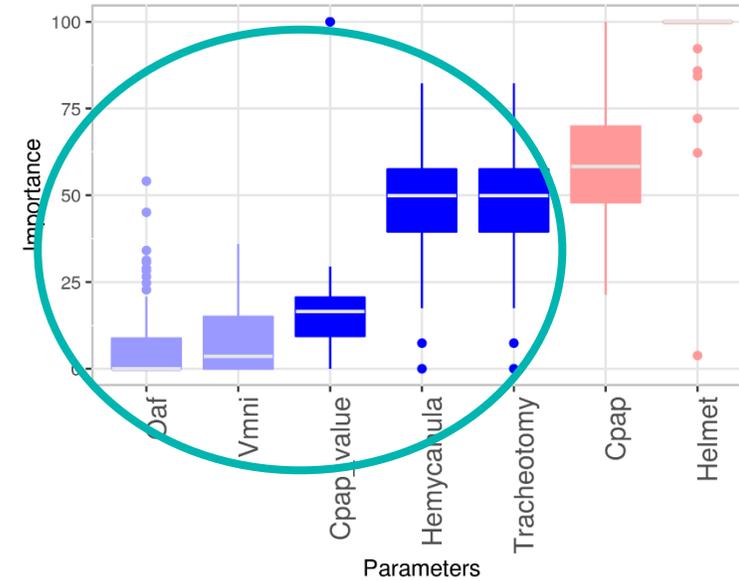
Tipo de terapia (todas las edades)



Tipo de terapia (> 70 años)

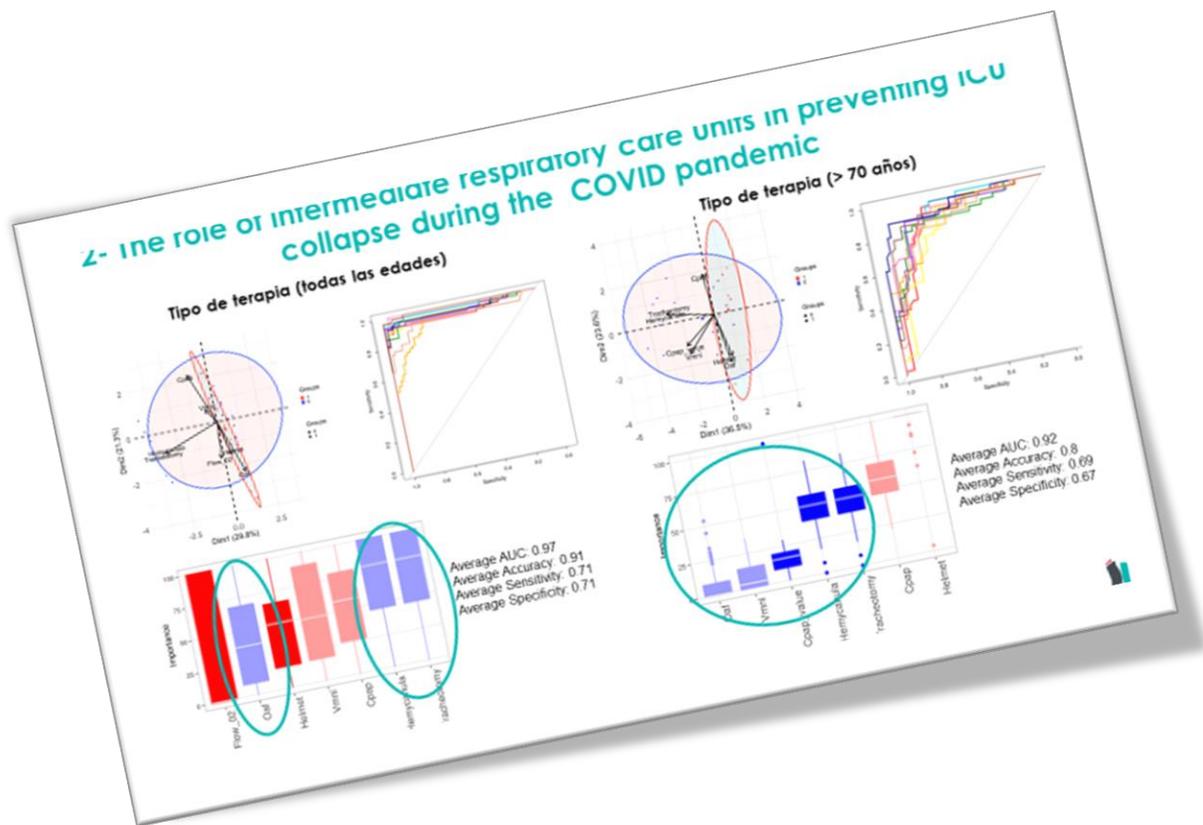


Average AUC: 0.97
 Average Accuracy: 0.91
 Average Sensitivity: 0.71
 Average Specificity: 0.71



Average AUC: 0.92
 Average Accuracy: 0.8
 Average Sensitivity: 0.69
 Average Specificity: 0.67

¿- The role of intermediate respiratory care units in preventing ICU collapse during the COVID pandemic



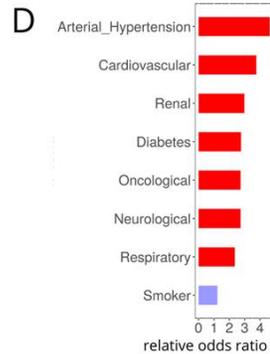
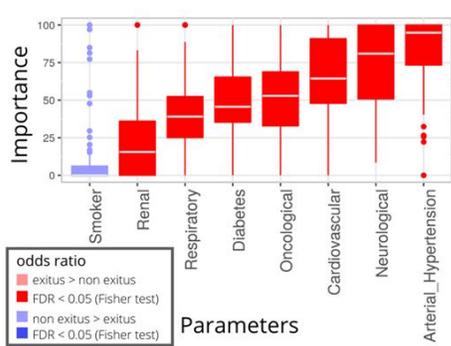
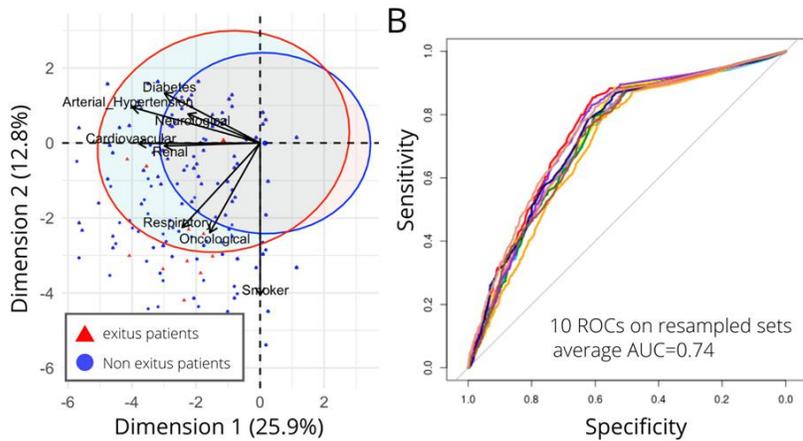
En la 2,3,4 ola...

- Utilización de alto flujo +++
- Minimizar VMNI
- CPAP con parámetros ajustados
- Traqueostomía

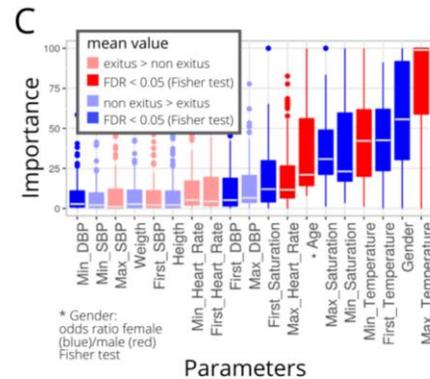
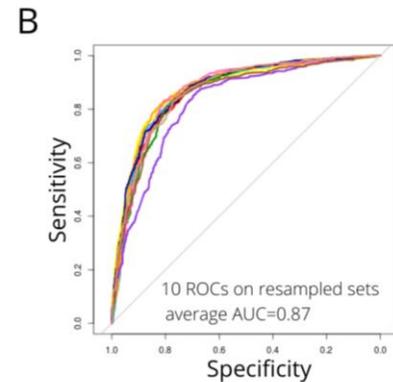
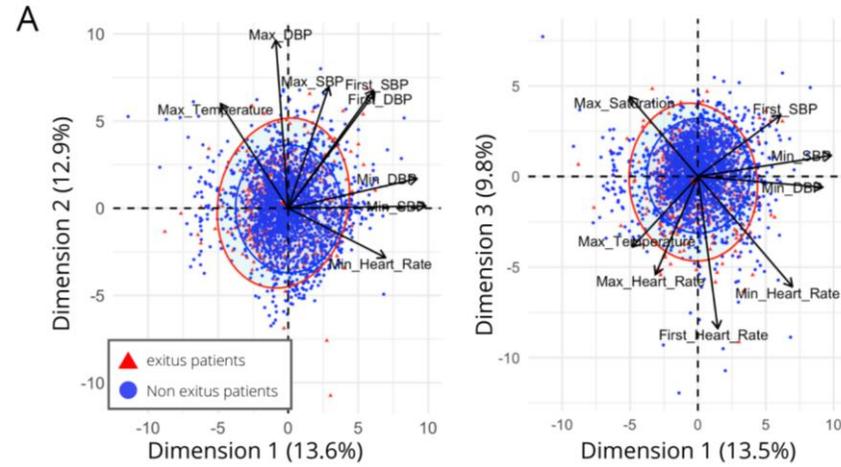
Reducción de la mortalidad

3- COVID19 outcomes in 4712 consecutively confirmed SARS-COV2 cases in the city of Madrid

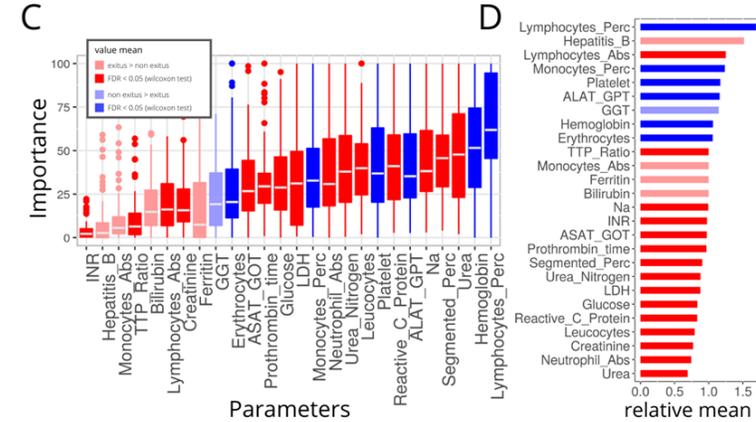
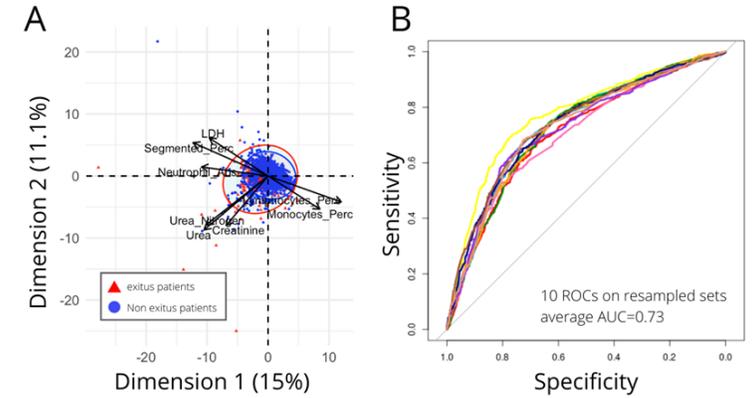
Comorbilidades vivos vs fallecidos todas las edades



Signos vitales, edad y sexo vivos vs fallecidos todas las edades

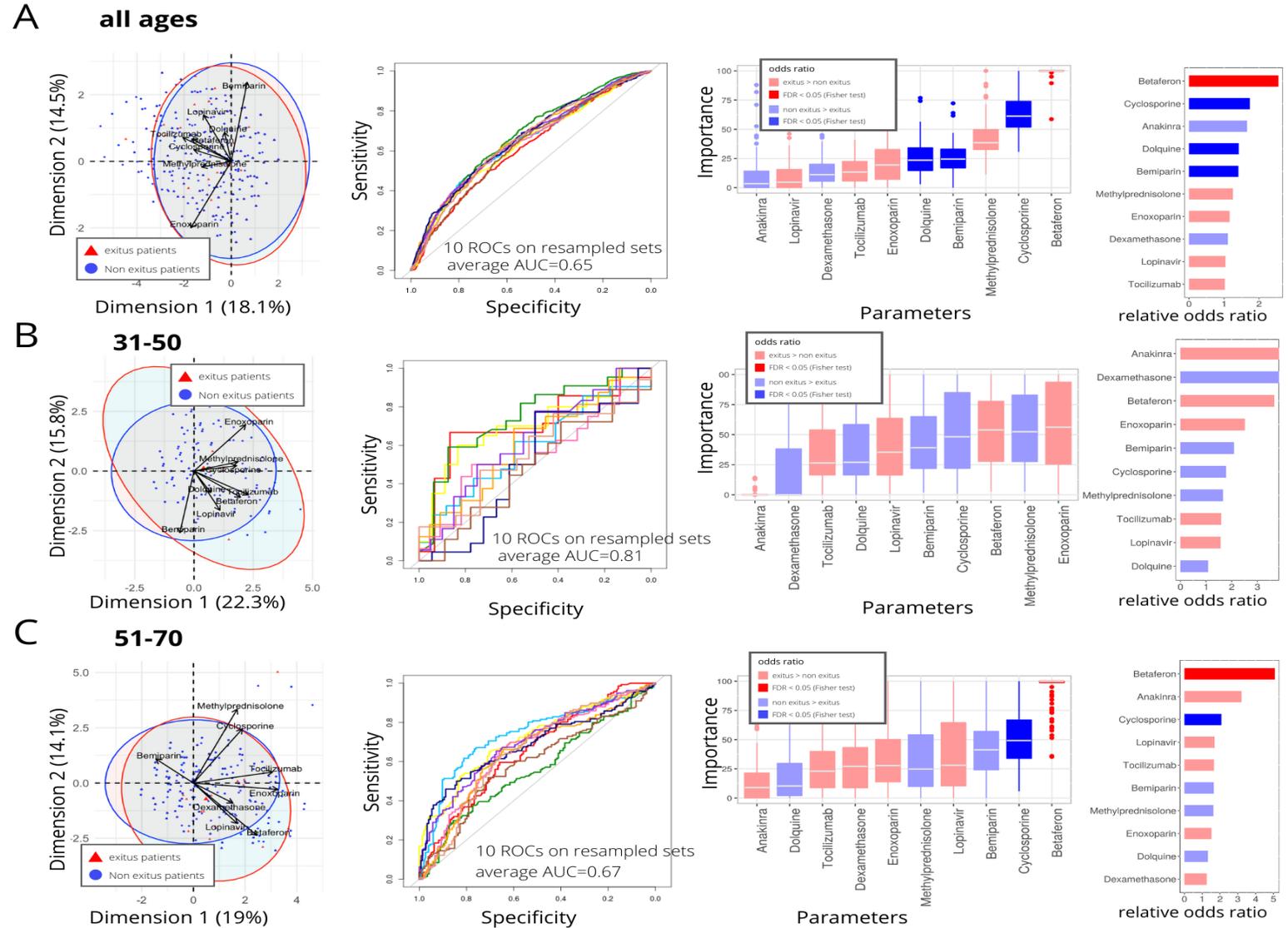


Biomarcadores vivos vs fallecidos todas las edades



3- COVID19 outcomes in 4712 consecutively confirmed SARS-COV2 cases in the city of Madrid

Tratamientos administrados.
vivos vs fallecidos todas las
edades



3- COVID19 outcomes in 4712 consecutively confirmed SARS-COV2 cases in the city of Madrid

Tratamientos administrados
vivos vs fallecidos todas
edades

Actualización de protocolos Ensayos clínicos



Inteligencia artificial

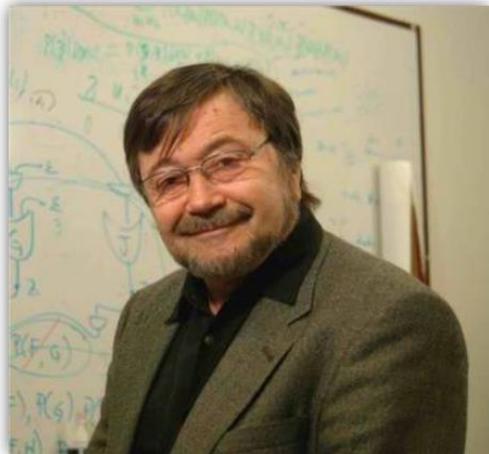


Redes neuronales
Redes Bayesianas
Modelos de Markov

Redes Bayesianas



Thomas Bayes
(1702-1761)



Judea Pearl
4 de Septiembre 1936

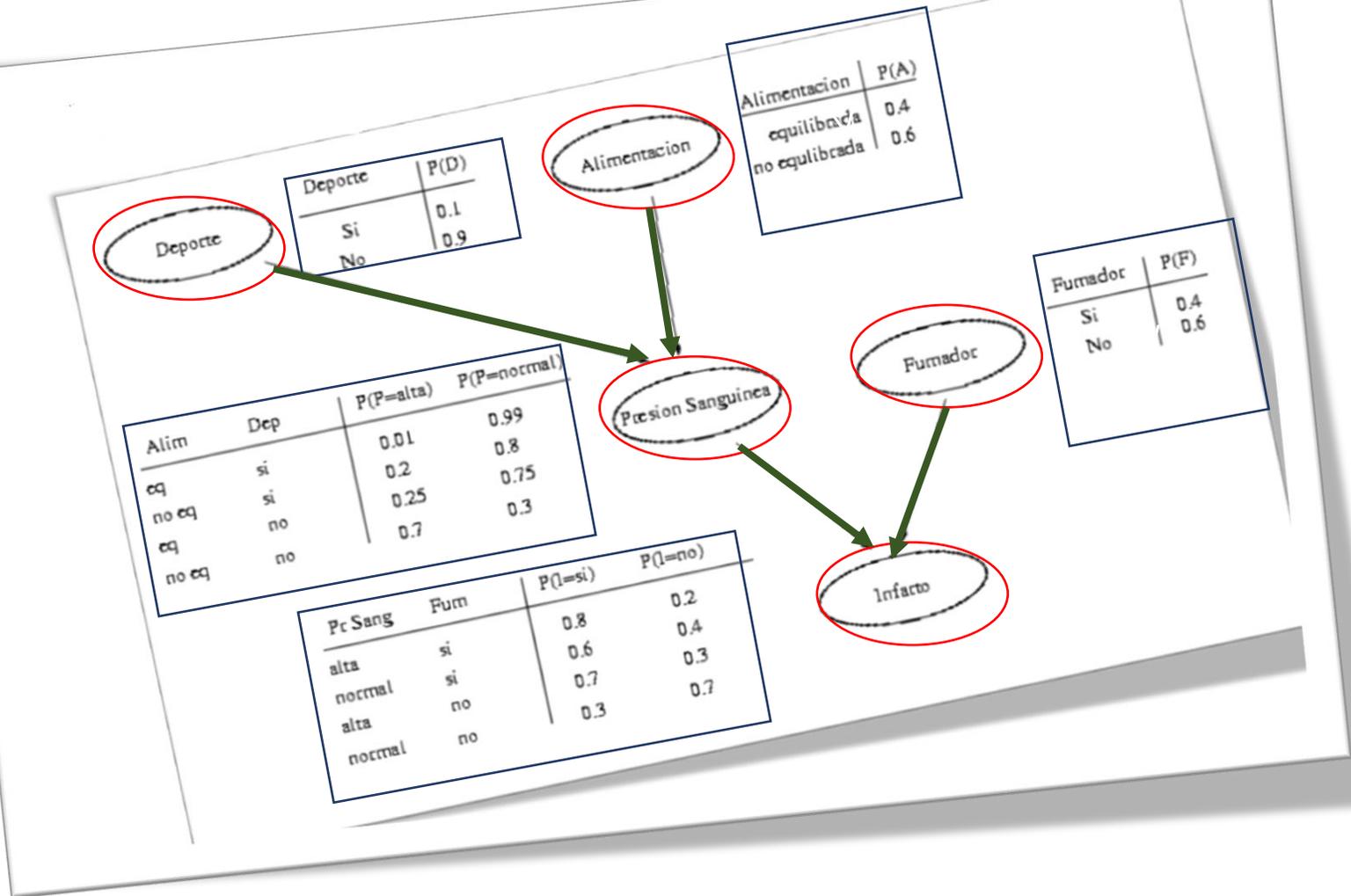
- **Modelos: Simplificación** del mundo para explicarlo de forma sencilla
 - **No** tiene en cuenta **todas las variables** posibles, solo las variables e interacciones mas significativas
 - Todos los modelos son **erróneos**, pero son útiles para tratar problemas
- Se basa en **probabilidad**
- A partir de evidencias (variables aleatorias observables) permiten realizar razonamientos sobre variables aleatorias ocultas o desconocidas
- Permite descubrir distribuciones complejas a partir de distribuciones condicionales locales simples
- Es la forma **más básica y robusta** de obtener conocimiento de **entornos locales inciertos**



Redes Bayesianas: grafo directo acíclico

Método simbólico y conexionista

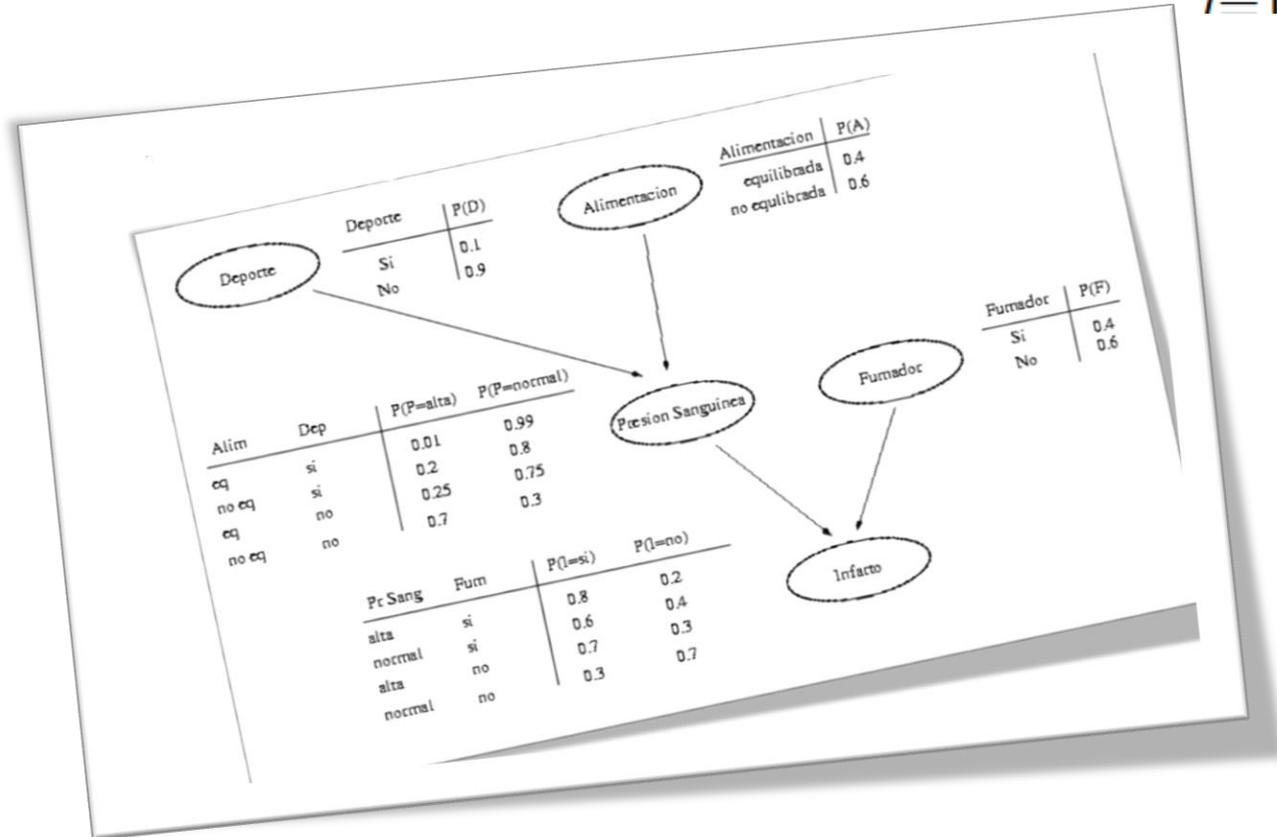
- **Nodo:** variable aleatoria
- Tabla de distribución de probabilidad condicional asociada
- **Arco:** **Influencia directa local** de una variable sobre otra
 - solo se define si es significativa
 - mínimo número de arcos posibles
 - exponencial



Debido a su representación es imposible crear una red que viole los axiomas de la probabilidad, dado que no existen probabilidades redundantes

Redes Bayesianas, probabilidad conjunta

$$P(x_1, x_2, \dots, x_n) = \prod_{i=1}^n P(x_i | \text{padres}(x_i))$$



TÉRMINO DE INDEPENDENCIA

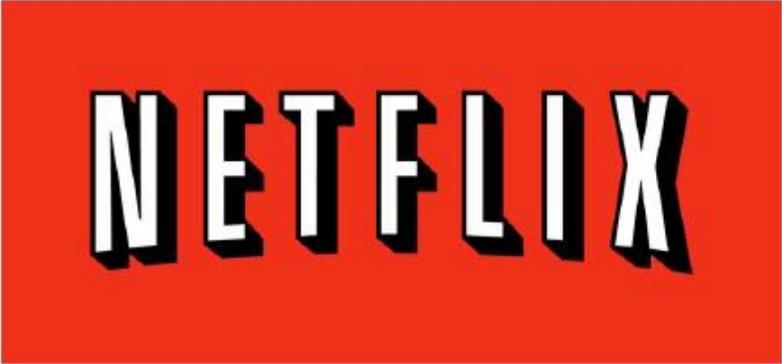
Regla de la cadena: $P(a/b) = P(a) \times P(b)$ cuando son independientes

Independencia condicional

Permite la factorización

Acumulativo, exponencial
Cantidades ingentes de datos

Redes Bayesianas



NETFLIX



Google



LinkedIn



amazon.com

COVID-19 Estado del arte

nature
machine intelligence

ARTICLES

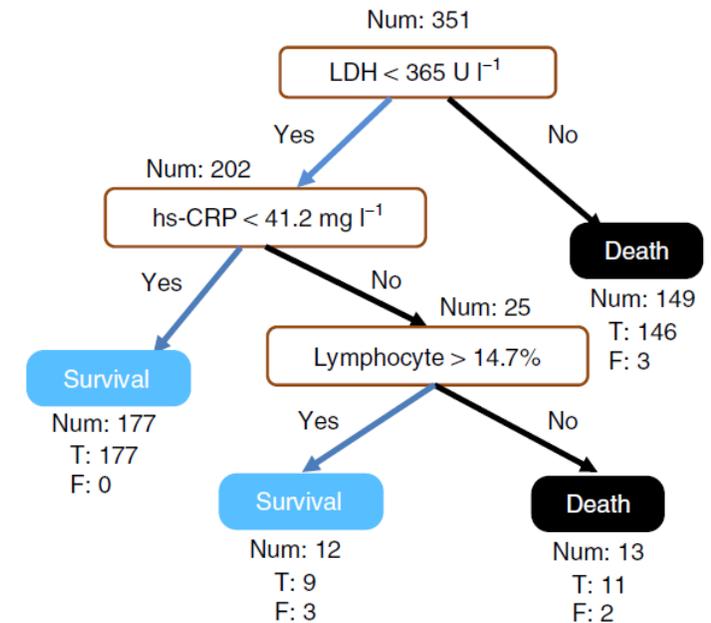
<https://doi.org/10.1038/s42256-020-0180-7>

Check for updates

An interpretable mortality prediction model for COVID-19 patients

Li Yan^{1,10}, Hai-Tao Zhang^{2,10}, Jorge Goncalves^{3,4,10}, Yang Xiao², Maolin Wang², Yuqi Guo², Chuan Sun², Xiuchuan Tang⁵, Liang Jing¹, Mingyang Zhang², Xiang Huang², Ying Xiao², Haosen Cao², Yanyan Chen⁶, Tongxin Ren⁷, Fang Wang¹, Yaru Xiao¹, Sufang Huang¹, Xi Tan⁸, Niannian Huang⁸, Bo Jiao⁸, Cheng Cheng², Yong Zhang⁹, Ailin Luo⁸, Laurent Mombaerts³, Junyang Jin⁷, Zhiguo Cao², Shusheng Li¹✉, Hui Xu⁸✉ and Ye Yuan²✉

The sudden increase in COVID-19 cases is putting high pressure on healthcare services worldwide. At this stage, fast, accurate and early clinical assessment of the disease severity is vital. To support decision making and logistical planning in healthcare systems, this study leverages a database of blood samples from 485 infected patients in the region of Wuhan, China, to identify crucial predictive biomarkers of disease mortality. For this purpose, machine learning tools selected three biomarkers that predict the mortality of individual patients more than 10 days in advance with more than 90% accuracy: lactic dehydrogenase (LDH), lymphocyte and high-sensitivity C-reactive protein (hs-CRP). In particular, relatively high levels of LDH alone seem to play a crucial role in distinguishing the vast majority of cases that require immediate medical attention. This finding is consistent with current medical knowledge that high LDH levels are associated with tissue breakdown occurring in various diseases, including pulmonary disorders such as pneumonia. Overall, this Article suggests a simple and operable decision rule to quickly predict patients at the highest risk, allowing them to be prioritized and potentially reducing the mortality rate.

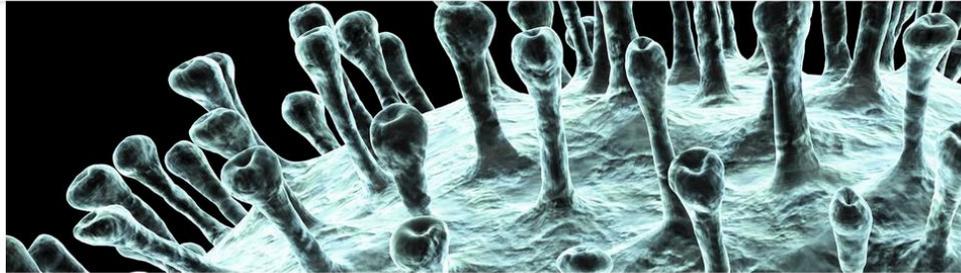


Mayo-2020

Investigación en UCIR basada en redes Bayesianas

Arranque del Proyecto de COVID-19
Financiado por FBBVA

Fundación BBVA Esp Q



Convocatoria 2020

Adjudicadas 4 Ayudas a Equipos de Investigación Científica sobre SARS-CoV-2 y COVID-19 en Big Data e Inteligencia Artificial

La comisión evaluadora de las [Ayudas a Equipos de Investigación Científica SARS-CoV-2 y COVID-19 de la Fundación BBVA](#) en Big Data e Inteligencia Artificial, reunida el día 29 de septiembre de 2020, y siguiendo los criterios establecidos en las [bases de la convocatoria](#), publicadas en mayo de 2020, acuerda conceder las ayudas que se relacionan a continuación.

28 septiembre, 2020

Solicitudes: 150

Ayudas concedidas: 4

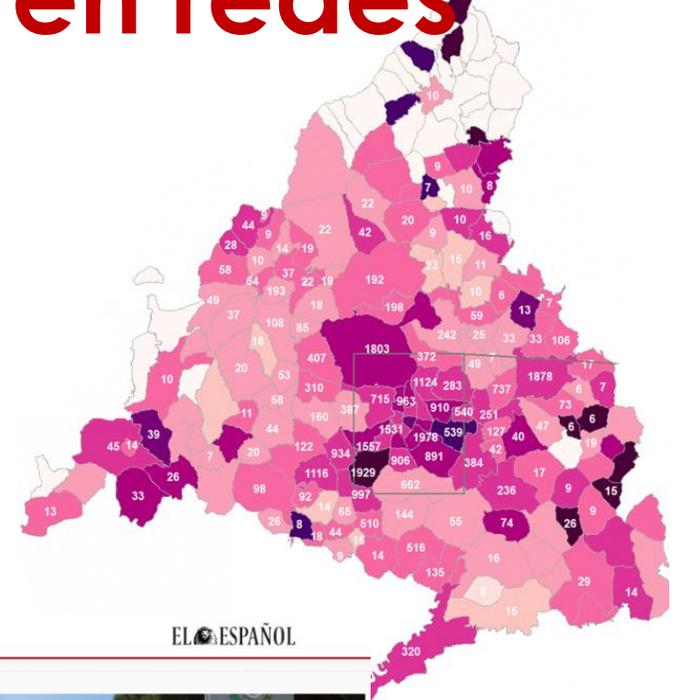
Proyectos seleccionados:

“Outcome prediction and treatment efficiency in patients hospitalized with COVID-19 in Madrid: A Bayesian network approach”

Investigadora principal: Concha Bielza, Departamento de Inteligencia Artificial, Universidad Politécnica de Madrid

Miembros del equipo: Pedro Larrañaga (Universidad Politécnica de Madrid); Juan A. Fernández del Pozo (Universidad Politécnica de Madrid); Bojan Mihaljevic (Universidad Politécnica de Madrid).

Importe de la ayuda: 125.465 euros.



EL ESPAÑOL



Concha Bielza, catedrática de Estadística e Investigación Operativa en el Departamento de Inteligencia Artificial de la Universidad Politécnica de Madrid. Fundación BBVA.

SALUD / FUNDACIÓN BBVA

La matemática que trata de acabar con el caos de datos de la Covid en España y salvar vidas

La catedrática Concha Bielza y su equipo trabajan en un modelo de predicción con datos de pacientes de los hospitales españoles.

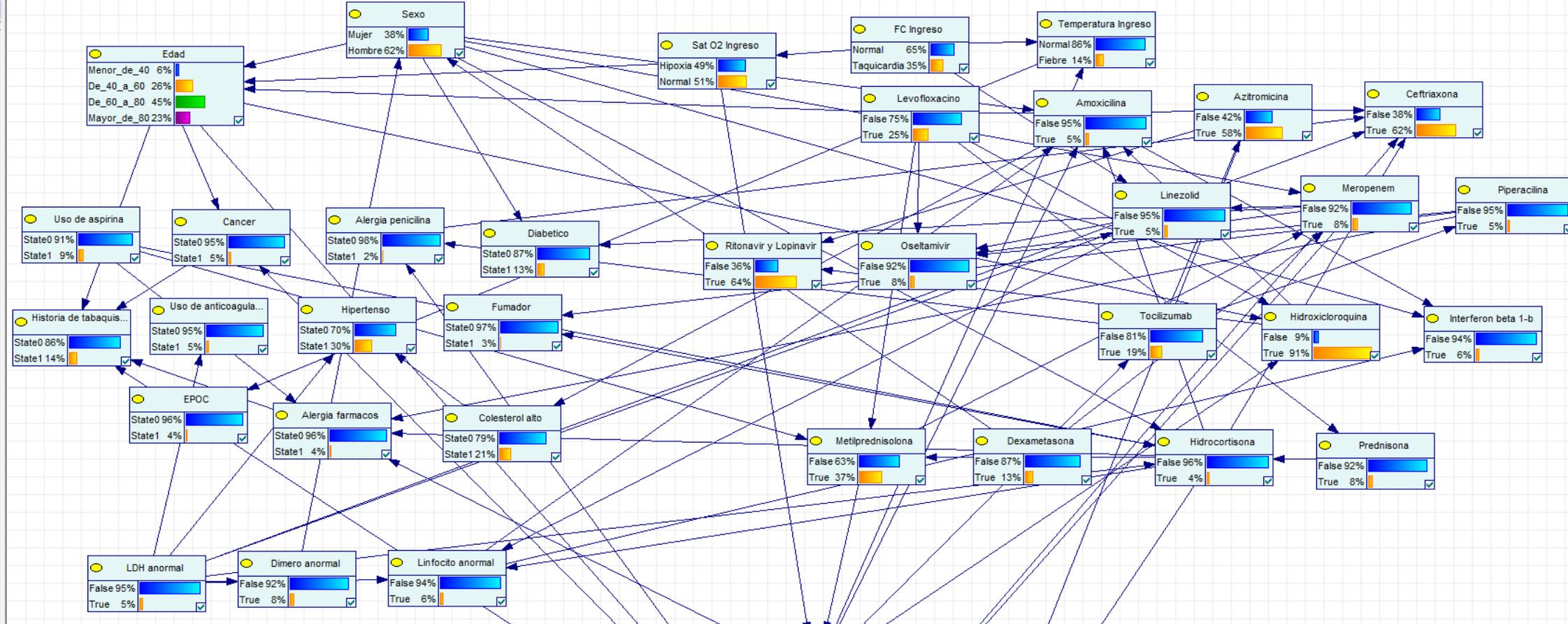
colaboradores y objetivos



- Predecir riesgo muerte (o intubación)
- Evaluar eficiencia del tratamiento
- Hacer razonamiento probabilístico (construir red bayesiana)
- Implementar plataforma web abierta para hacer consultas
- Riesgos de sobremedicar, efectos secundarios...
- RBD: evolución, tiempo ingresado, alta
- Comparación hospitales
- Comparación olas
- Comparación tratamientos
- Secuelas: fatiga, tromboembolismo, arritmias, depresión...



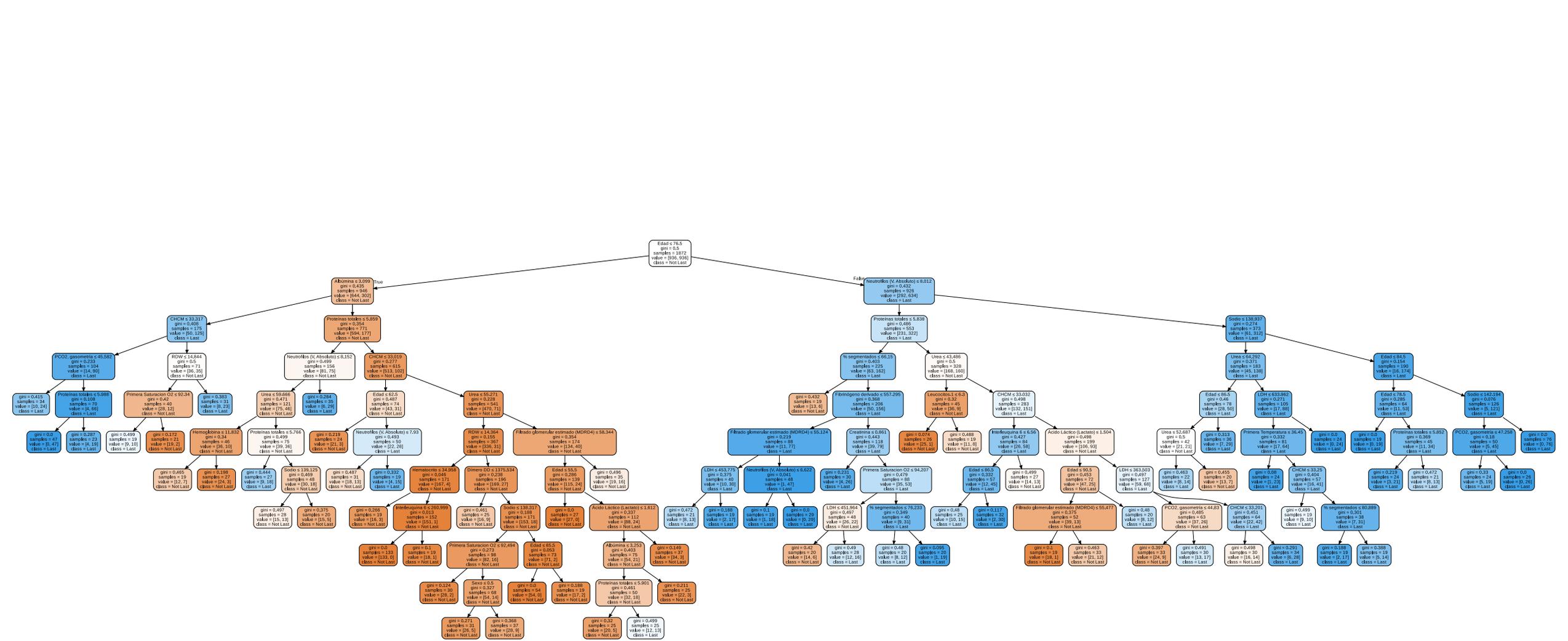
- data_covid (Red_COVID_cor)
- Alergia farmacos
- Alergia penicilina
- Amoxicilina
- Azitromicina
- Cancer
- Ceftriaxona
- Colesterol alto
- Dexametasona
- Diabetico
- Dimero anormal
- EPOC
- Edad
- FC Ingreso
- Fumador
- Hidrocloroquina
- Hipertenso
- Historia de tabaquismo
- Interferon beta 1-b
- LDH anormal
- Levofloxacino
- Linezolid
- Linfocito anormal
- Meropenem
- Metilprednisolona
- Muerto
- Osetamivir
- Piperacilina
- Prednisona
- Ritonavir y Lopinavir
- Sat O2 Ingreso
- Sexo
- TIEMPO_INGRESO
- Temperatura Ingreso
- UCI
- Uso de anticoagulantes
- Uso de aspirina



Input file: data_covid
Data rows: 1645
Elapsed time: 17.984s

Learning algorithm: Bayesian Search
Algorithm parameters:
Iterations: 50
Max parent count: 8
Sample size: 100
Link probability: 0.1
Prior link probability: 0.001
Seed: 1
Max search time: 0
Score by accuracy (5-fold), class variable: Muerto
Background knowledge was provided:
nodes assigned to tiers: 2

Best accuracy in iteration 32: 0.990881 (1630/1645)
EM Log Likelihood: -24273.8



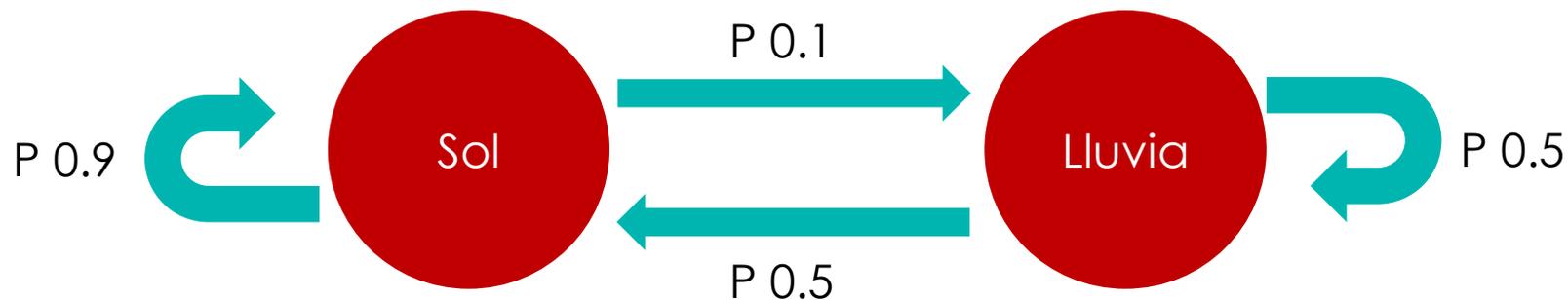
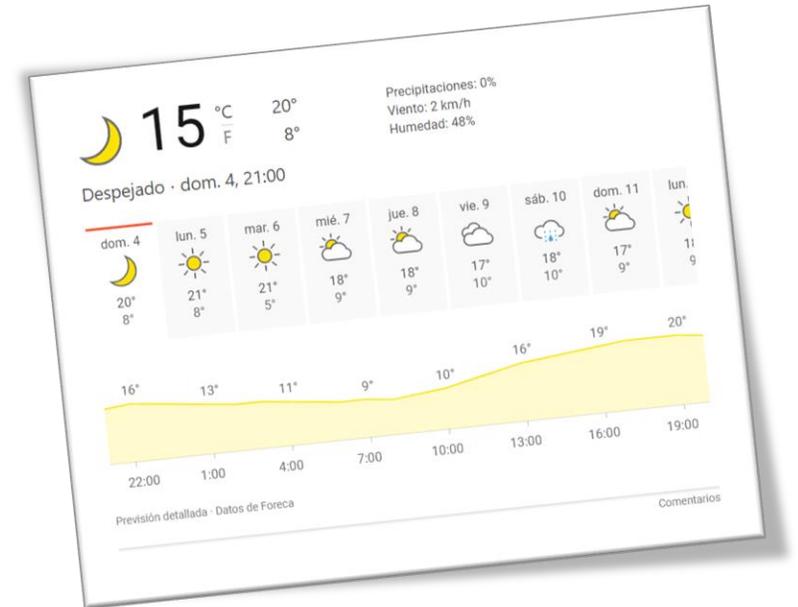
Inteligencia artificial

The image features a central graphic of a human brain. The left hemisphere is rendered as a glowing blue circuit board, while the right hemisphere is a glowing pink and purple organic shape. A human hand in a white shirt cuff points its index finger at the right side of the brain. In the upper left, a glowing blue robotic arm reaches towards the brain. The background is dark with faint binary code and circular patterns.

Redes neuronales
Redes Bayesianas
Modelos de Markov

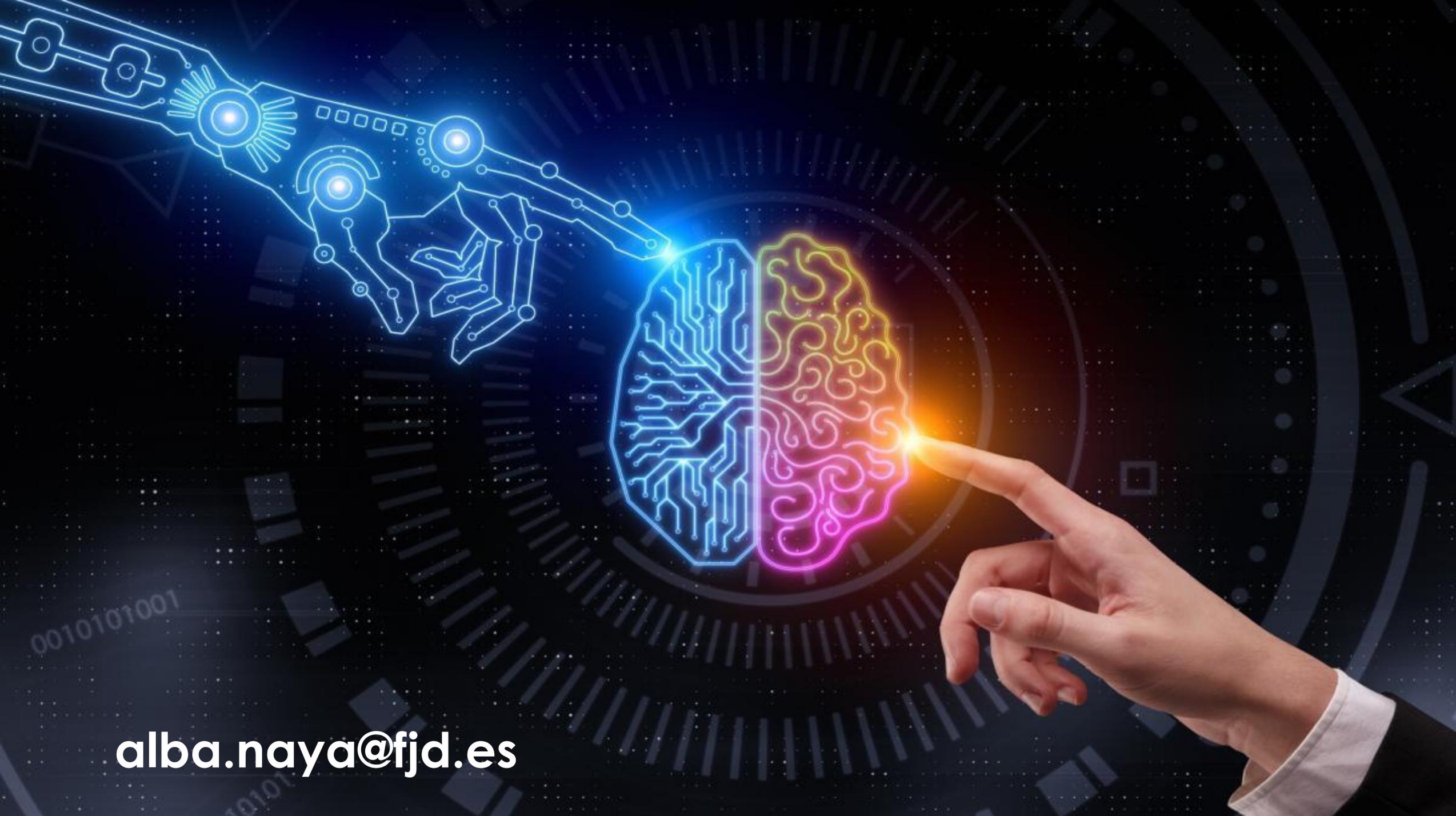
Modelos de Markov

- Modelo estocásticos \rightarrow tiempo
- El conjunto de sucesos posibles es finito
- La probabilidad de ocurrencia del siguiente suceso depende solamente del inmediatamente anterior
- Esta probabilidad permanece estable en el tiempo



Conclusiones

- IA = eficiencia
- Redes neuronales: son derivadas
 - aprendizaje adaptativo
 - capaces de extraer nuevo conocimiento
 - caja negra, en la que las relaciones no lineales causa/efecto pueden ser difícilmente interpretables
- Redes bayesianas: son probabilidades
 - simplicación de datos, ordenar y priorizar
 - fácil identificar asociación de datos y suposiciones
 - necesidad de conocer probabilidades a priori
- Modelos de Markov: probabilidad estocástica. Lectura lenguaje natural



alba.naya@fjd.es