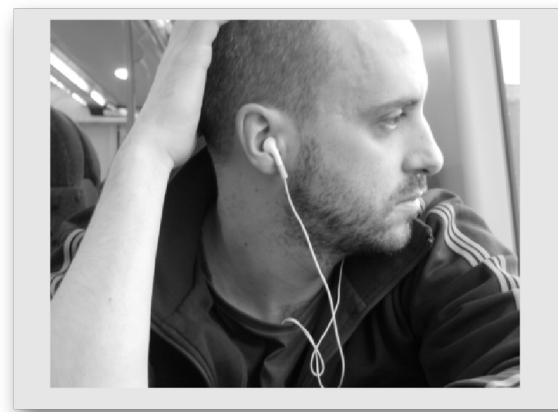


# FÍSICA Y AI: EL PREMIO NOBEL DE HOPFIELD Y HINTON Y EL FUTURO TECNOLÓGICO

Isaac Pérez Castillo



- Introducción
- Emergencia
- Estados Múltiples y vidrios de espín
- Redes Neuronales: diseñando atractores
- Máquinas de Boltzmann
- Cornucopia



The Nobel Prize in Chemistry 2024 was divided, one half awarded to David Baker "for computational protein design", the other half jointly to Demis Hassabis and John Jumper "for protein structure prediction"

Ill. Niklas Elmehed © Nobel Prize Outreach

**John J. Hopfield**

Prize share: 1/2

Ill. Niklas Elmehed © Nobel Prize Outreach

**Geoffrey Hinton**

Prize share: 1/2

The Nobel Prize in Physics 2024 was awarded jointly to John J. Hopfield and Geoffrey E. Hinton "for foundational discoveries and inventions that enable machine learning with artificial neural networks"



Ill. Niklas Elmehed © Nobel Prize Outreach

**David Baker**

Prize share: 1/2



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**Demis Hassabis**

Prize share: 1/4



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**John Jumper**

Prize share: 1/4

## Memoria asociativa

Original



Degraded



Reconstruction



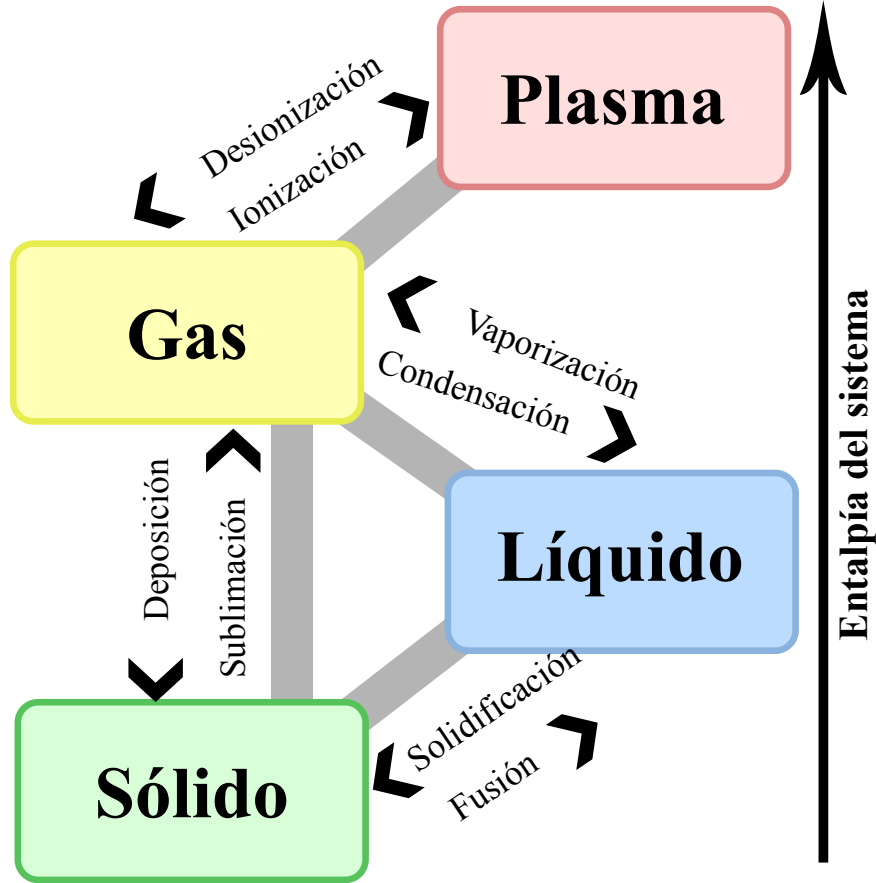
Patrones

estado neuronal inicial

evolución

estado neuronal final

Transiciones de fase



Descripción microscópica

$$E(\mathbf{s}) = \sum_{i,j} J_{ij} s_i s_j$$

$s_j$

Grado de libertad

$J_{ij}$

Interacciones

$$P(\mathbf{s}) = e^{-\beta E(\mathbf{s})} / Z(\beta)$$

# Emergencia

## Descripción microscópica

$$E(\mathbf{s}) = \sum_{i,j} J_{ij} s_i s_j$$

$s_j$

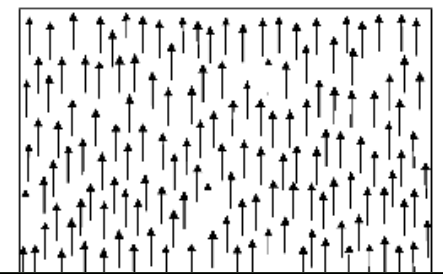
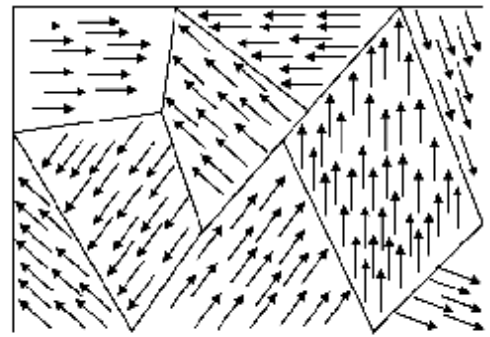
espín

$J_{ij}$

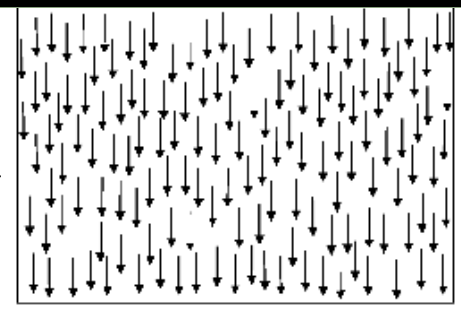
Interacción  
magnética



## Ferromagnetismo



## Un bit the información





**Ferromagnetismo**

$$J_{ij}$$

**Interacción magnética**

$$s_j$$

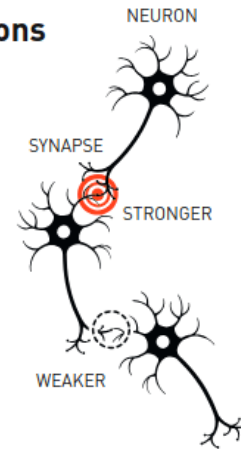
**espín**

**Un bit the información**

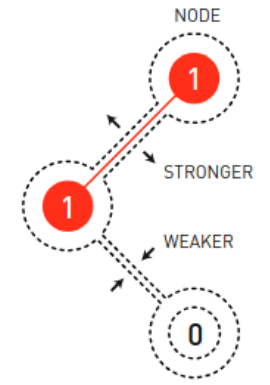
¿Es posible tener interacciones  $J_{ij}$  de tal forma que guardamos mas de un bit de información?

### Natural and artificial neurons

The brain's neural network is built from living cells, neurons, with advanced internal machinery. They can send signals to each other through the synapses. When we learn things, the connections between some neurons get stronger, while others get weaker.



Artificial neural networks are built from nodes that are coded with a value. The nodes are connected to each other and, when the network is trained, the connections between nodes that are active at the same time get stronger, otherwise they get weaker.



**Red Neuronal**

$$J_{ij}$$

**Interacción entre neuronas**

$$s_j$$

**estado neuronal**

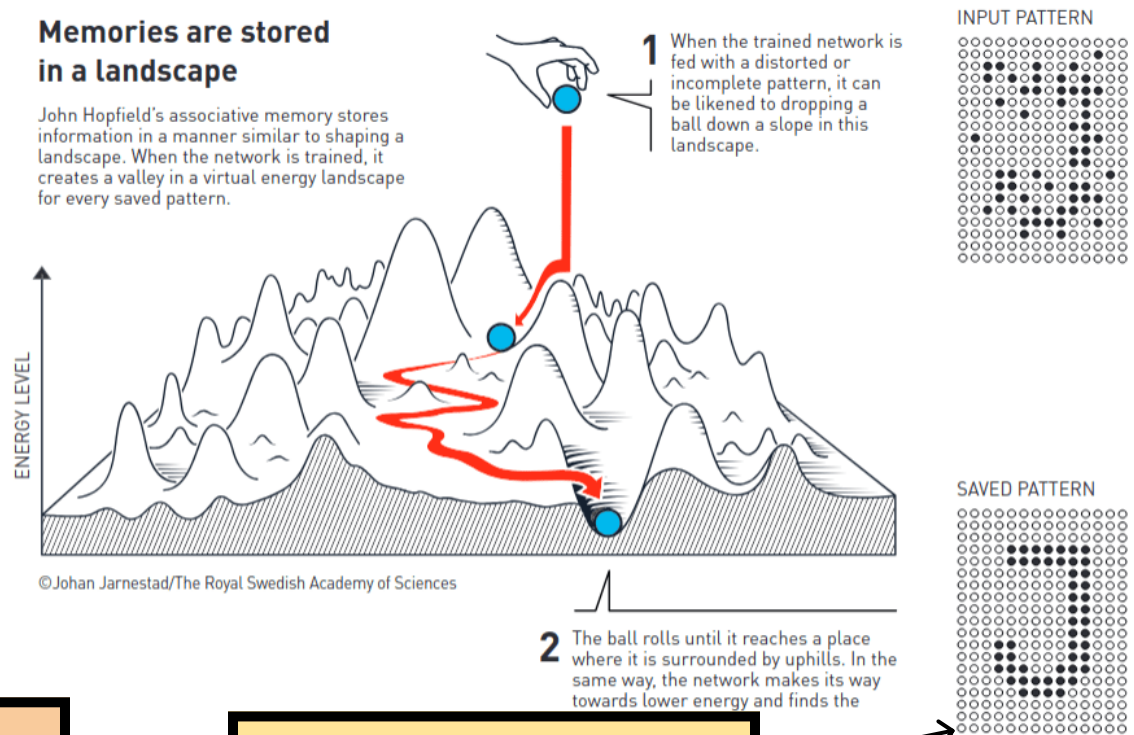
$$J_{ij} = \sum_{\mu=1}^p \xi_i^{\mu} \xi_j^{\mu}$$

Regla de Hebb

$$\xi^{\mu} = (\xi_1^{\mu}, \dots, \xi_N^{\mu})$$

## Memories are stored in a landscape

John Hopfield's associative memory stores information in a manner similar to shaping a landscape. When the network is trained, it creates a valley in a virtual energy landscape for every saved pattern.



$$E(\mathbf{s}) = \sum_{i,j} J_{ij} s_i s_j$$

Modelo de Hopfield

$$\xi^{\mu} = (\xi_1^{\mu}, \dots, \xi_N^{\mu})$$

$$s(t)$$

Evolución temporal

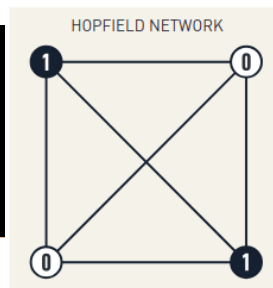
$$\xi^{\mu} = (\xi_1^{\mu}, \dots, \xi_N^{\mu})$$

## Different types of network

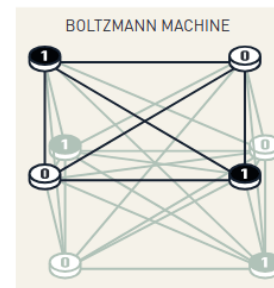
$$E(\mathbf{s}) = \sum_{i,j} J_{ij} s_i s_j + \sum_i \theta_i s_i$$

$$P(\mathbf{s}) = e^{-\beta E(\mathbf{s})} / Z(\beta)$$

Máquina de Boltzmann

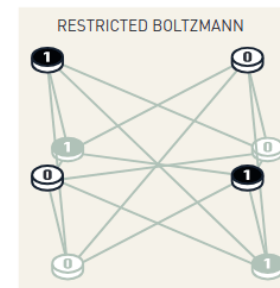


John Hopfield's associative memory is built so that all the nodes are connected to each other. Information is fed in and read out from all the nodes.



Visible nodes Hidden nodes

Geoffrey Hinton's Boltzmann machine is often constructed in two layers, where information is fed in and read out using a layer of *visible* nodes. They are connected to *hidden* nodes, which affect how the network functions in its entirety.



In a restricted Boltzmann machine, there are no connections between nodes in the same layer. The machines are frequently used in a chain, one after the other. After training the first restricted Boltzmann machine, the content of the hidden nodes is used to train the next machine, and so on.

$$\mathbf{s} = (s_1, \dots, s_N)$$

Neuronas ocultas  $h$

Neuronas visibles  $v$

$$P(\mathbf{v}) = \sum_h P(\mathbf{v}, h)$$

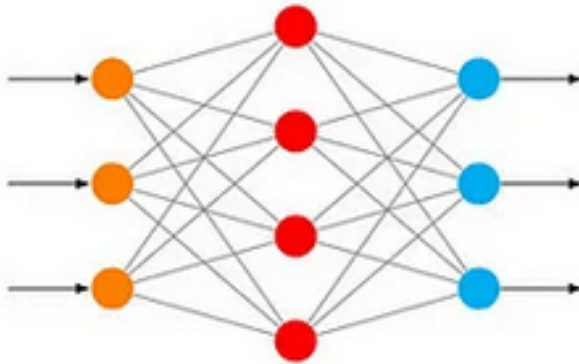
Entrenamiento: encontrar las  $\{J_{ij}, \theta_i\}$  tal que:  
 $P(\mathbf{v}) \rightarrow P_{\text{training}}(\mathbf{v})$

$$P_{\text{training}}(\mathbf{v})$$

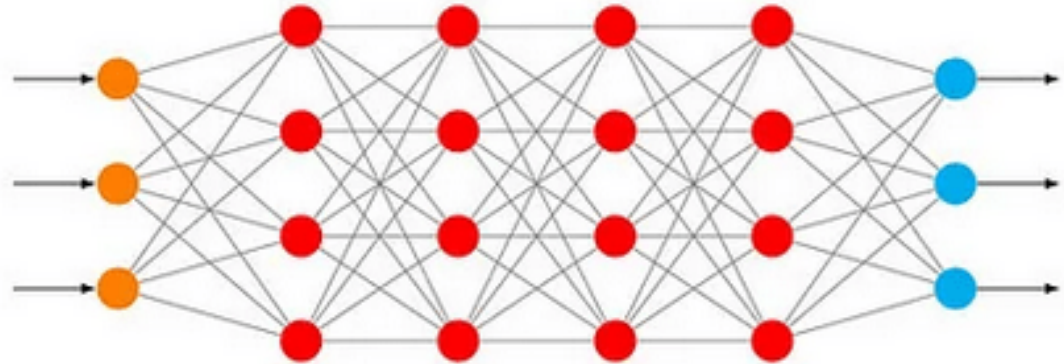
$$J_{ij}^*, \theta_i^* = \arg \min_{\{J_{ij}, \theta_i\}} \text{KL}(P_{\text{training}}(\mathbf{v}) || P(\mathbf{v}))$$

## Deep NNs

Neural Networks



Deep Neural Networks



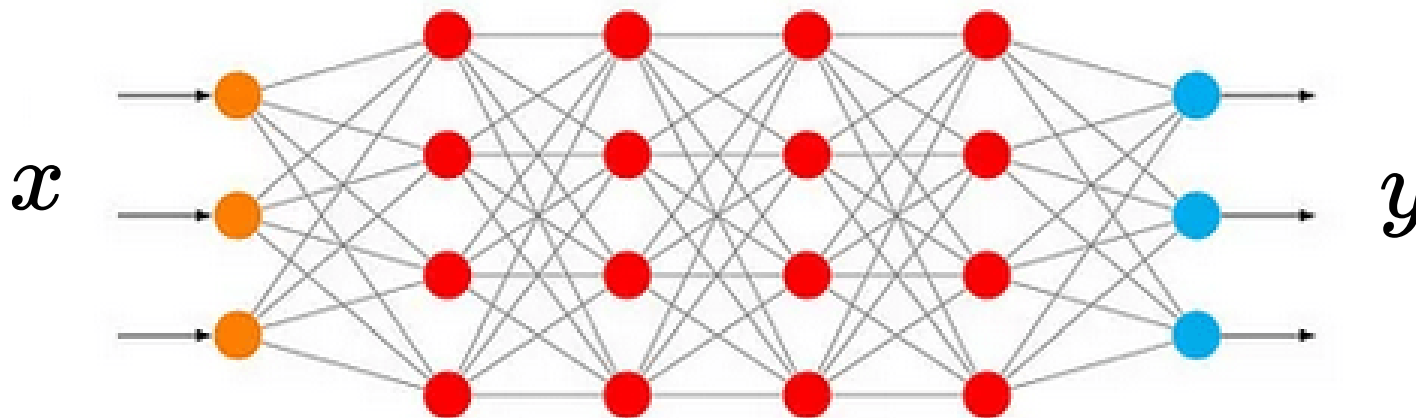
● Input Layer ● Hidden Layer ● Output Layer

- Reconocimiento de imágenes
- Procesamiento de lenguaje natural
- Síntesis de voz
- Sistemas de recomendación
- Aplicaciones en salud

- Aplicaciones en finanzas y trading
- Aplicaciones en comercio minorista
- Vehículos autónomos
- Monitoreo ambiental

## Deep NNs: Backpropagation

Deep Neural Networks



$$g(x) := f^L(W^L f^{L-1}(W^{L-1} \dots f^1(W^1 x) \dots))$$

Forward Propagation

Aprendizaje  
Minimizar función coste:  
 $\mathcal{C}(\{W\})$

$$W^{t+1} = W^t - \eta \nabla_W \mathcal{C}(\{W\})$$

Regla de la cadena

Back Propagation



Casa abierta al tiempo

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Unidad Iztapalapa

# Cornucopia

# B O U R B A K I

COLEGIO DE MATEMÁTICAS

¡Gracias!



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