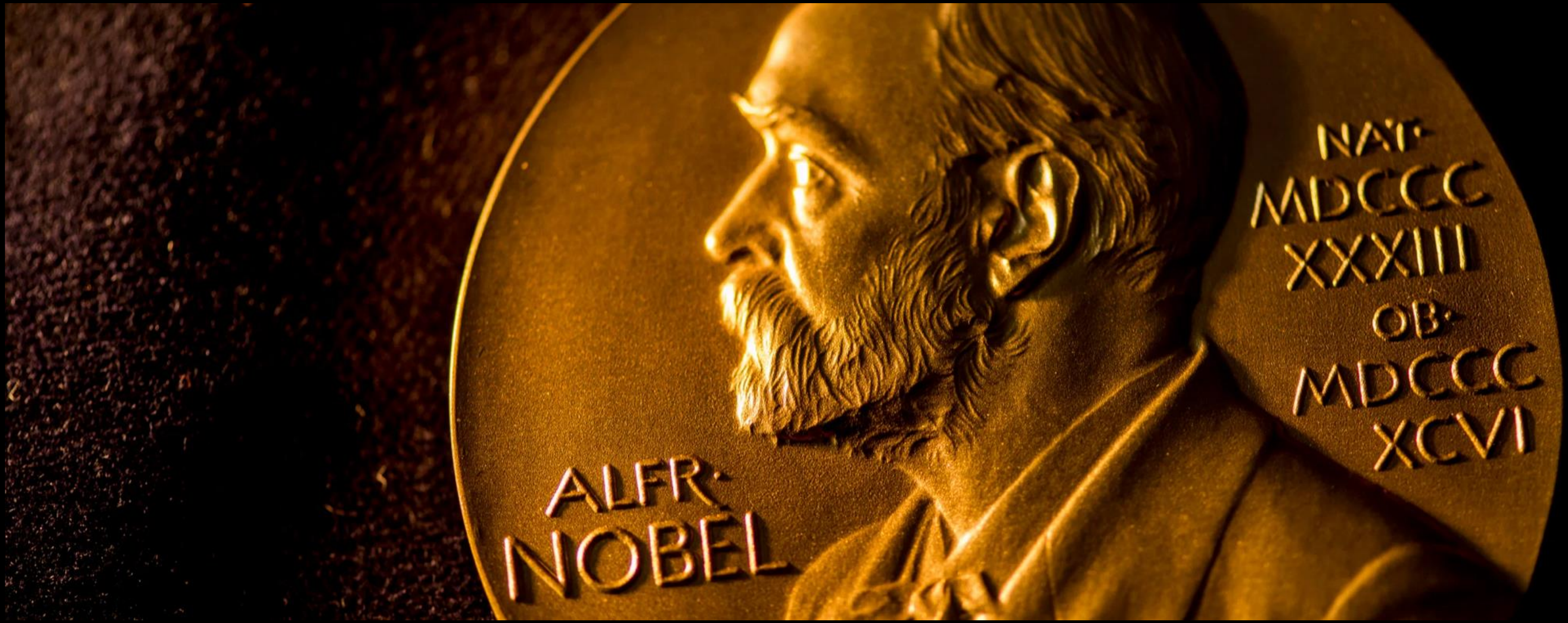
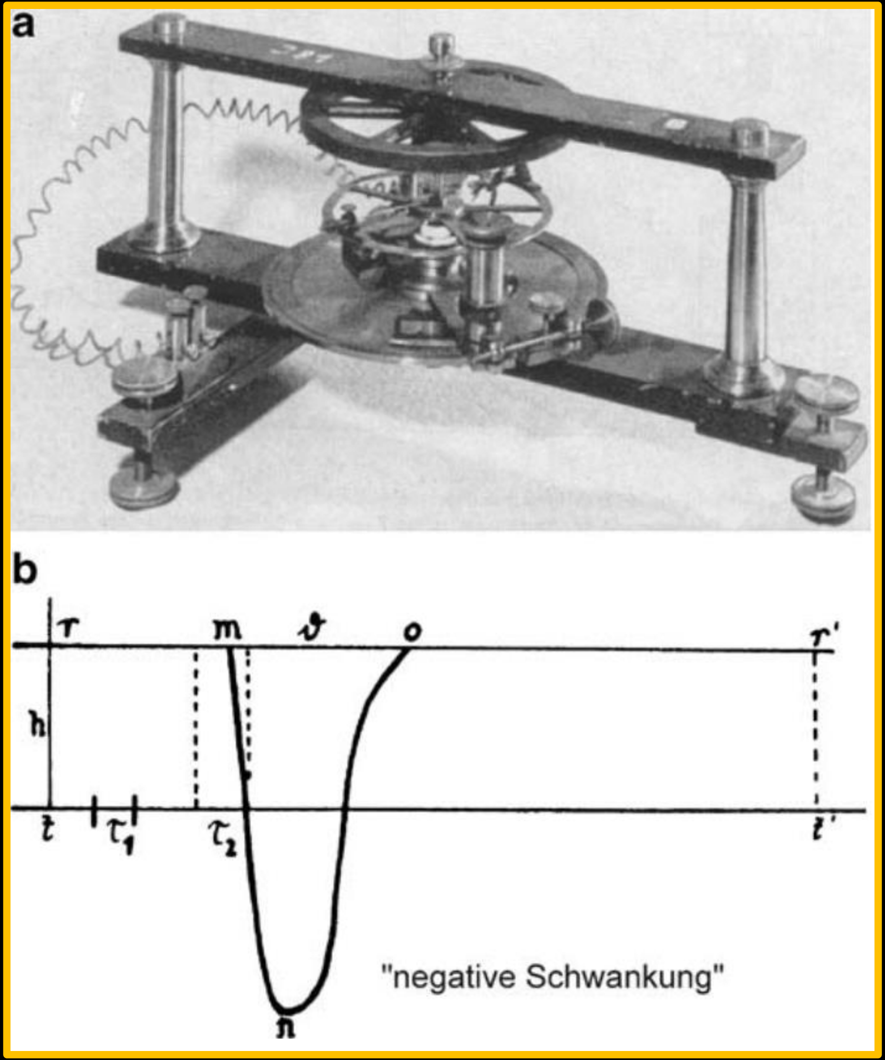


The Nobel Prize in Physics 2024 was awarded jointly to John J. Hopfield and Geoffrey E. Hinton "for foundational discoveries and inventions that enable machine learning with artificial neural networks"

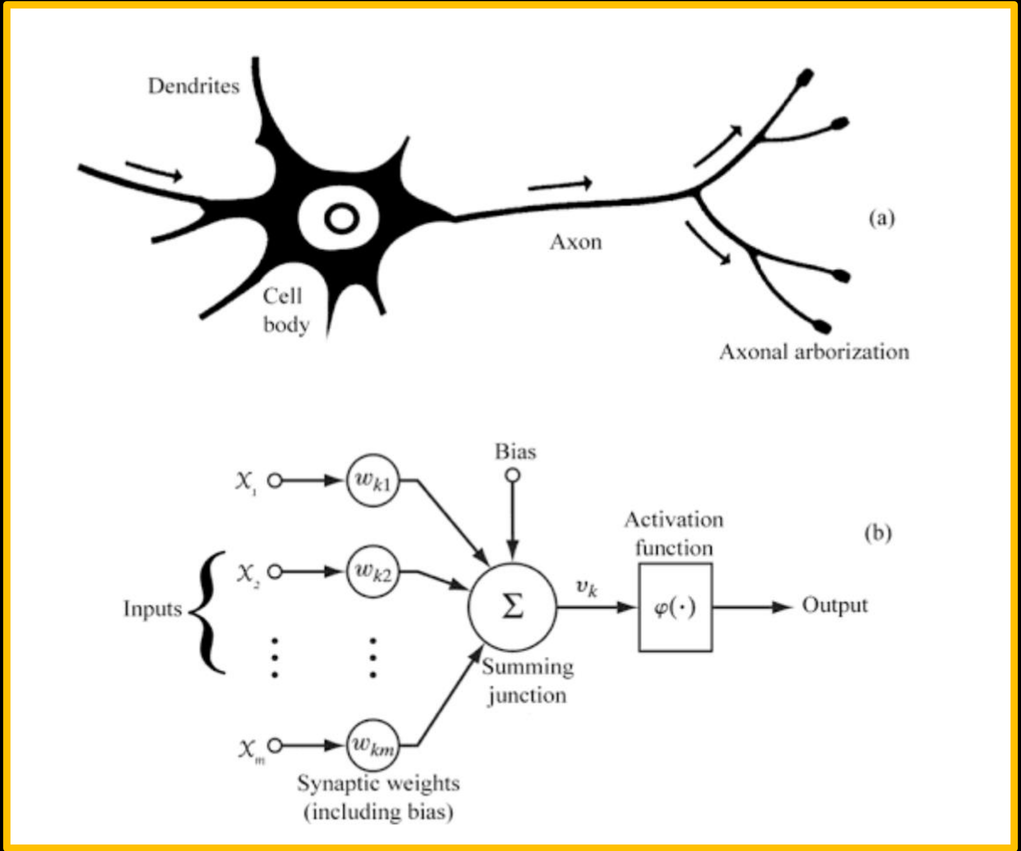
Los “unidades” del sistema nervioso, y su fisiologia

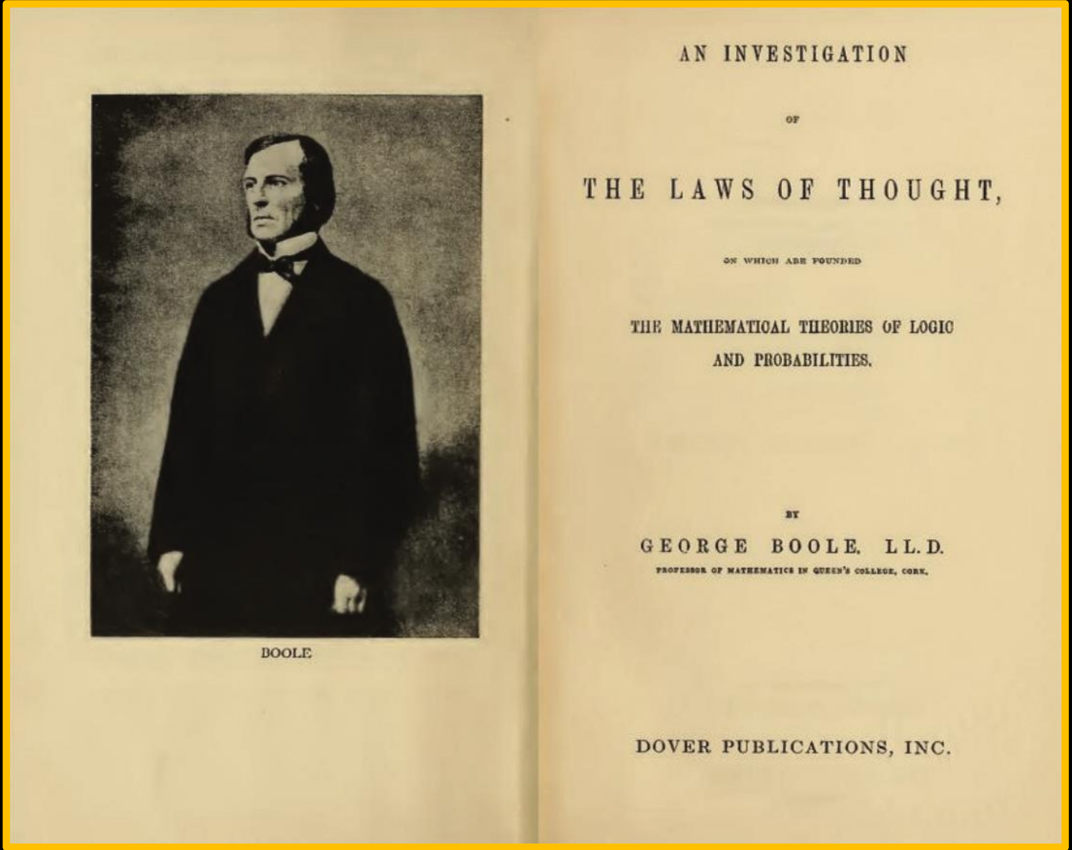
Ramon y Cajal, 1888



Bernstein, 1865

El camino “computacional” hacia la "computacion por medio de la materia”





Implementacionde puertas logicas

Aprendiendo por ejemplos, y no por diseño logico

NEW NAVY DEVICE LEARNS BY DOING

Psychologist Shows Embryo of Computer Designed to Read and Grow Wiser

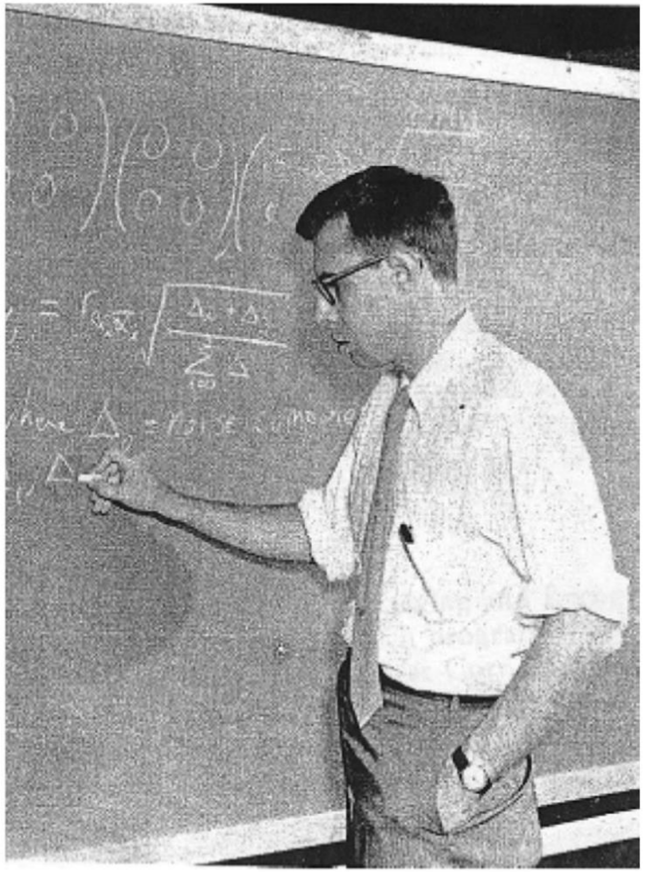
WASHINGTON, July 7 (UPI) —The Navy revealed the embryo of an electronic computer today that it expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence.

The embryo—the Weather Bureau's $2,000,000 "704" computer—learned to differentiate between right and left after fifty attempts in the Navy's demonstration for newsmen.

The service said it would use this principle to build the first of its Perceptron thinking machines that will be able to read and write. It is expected to be finished in about a year at a cost of $100,000.

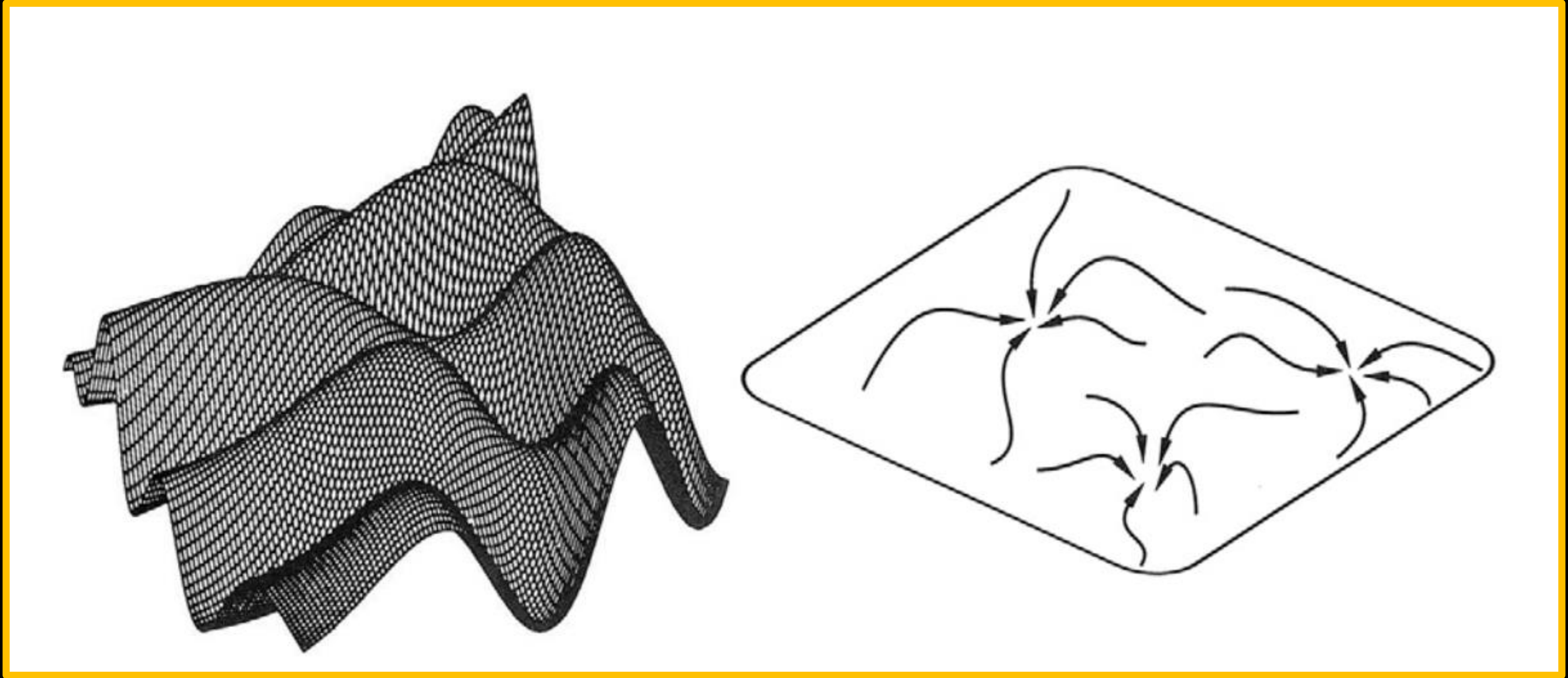
Dr. Frank Rosenblatt, designer of the Perceptron, conducted the demonstration. He said the machine would be the first device to think as the human brain. As do human beings, Perceptron will make mistakes at first, but will grow wiser as it gains experience, he said.

Dr. Rosenblatt, a research psychologist at the Cornell Aeronautical Laboratory, Buffalo, said Perceptrons might be fired to the planets as mechanical space explorers.



Frank Rossenblatt

La gran idea de **Hopfield**
(o de por que esto cayo en Fisica)



1. Una representacion mas abstracta de lo que es una tarea cognitiva
(como que la recuperacion de una memoria sea converger a atractores en un espacio de fases)
2. Una regla dinamica para el proceso de recuperacion
3. Una regla para el entrenamiento del dispositivo para el almacenamiento de dicha memoria

John Hopfield (Chicago, 1933)

Ph.D. Cornell

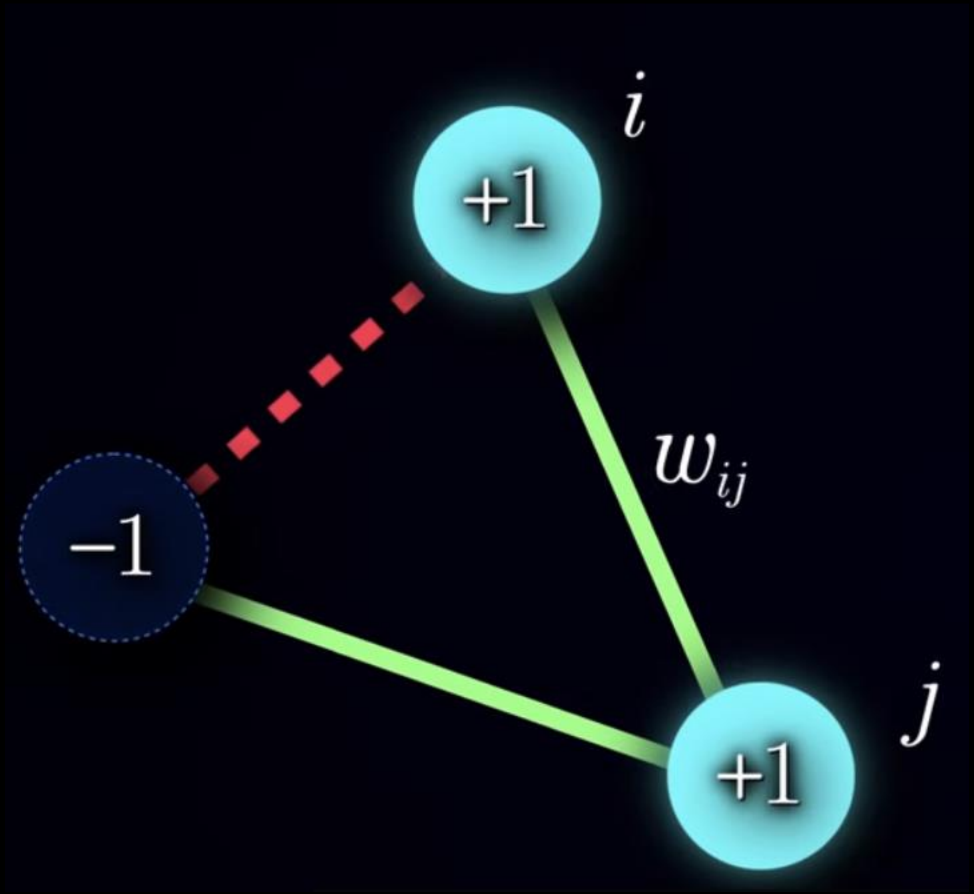
Faculty en Princeton

Materia condensada, biofisica (mecanismos de replicacion)

Importancia del Neuroscience Research Program (Boston)

Publica en 1982 “Neural networks and physical systems with emergent collective computational abilities”

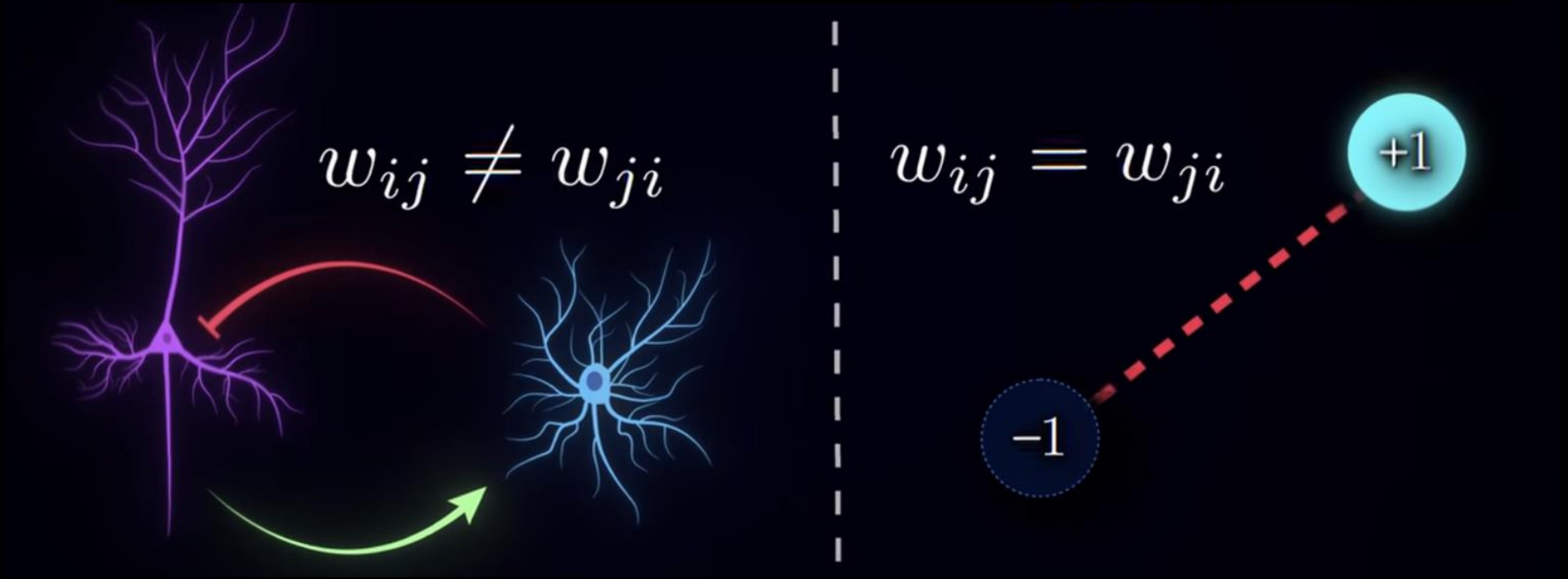
Unidades que toman valor +1, -1



Artem Kirsanov

Cerebro

Red de Hopfield



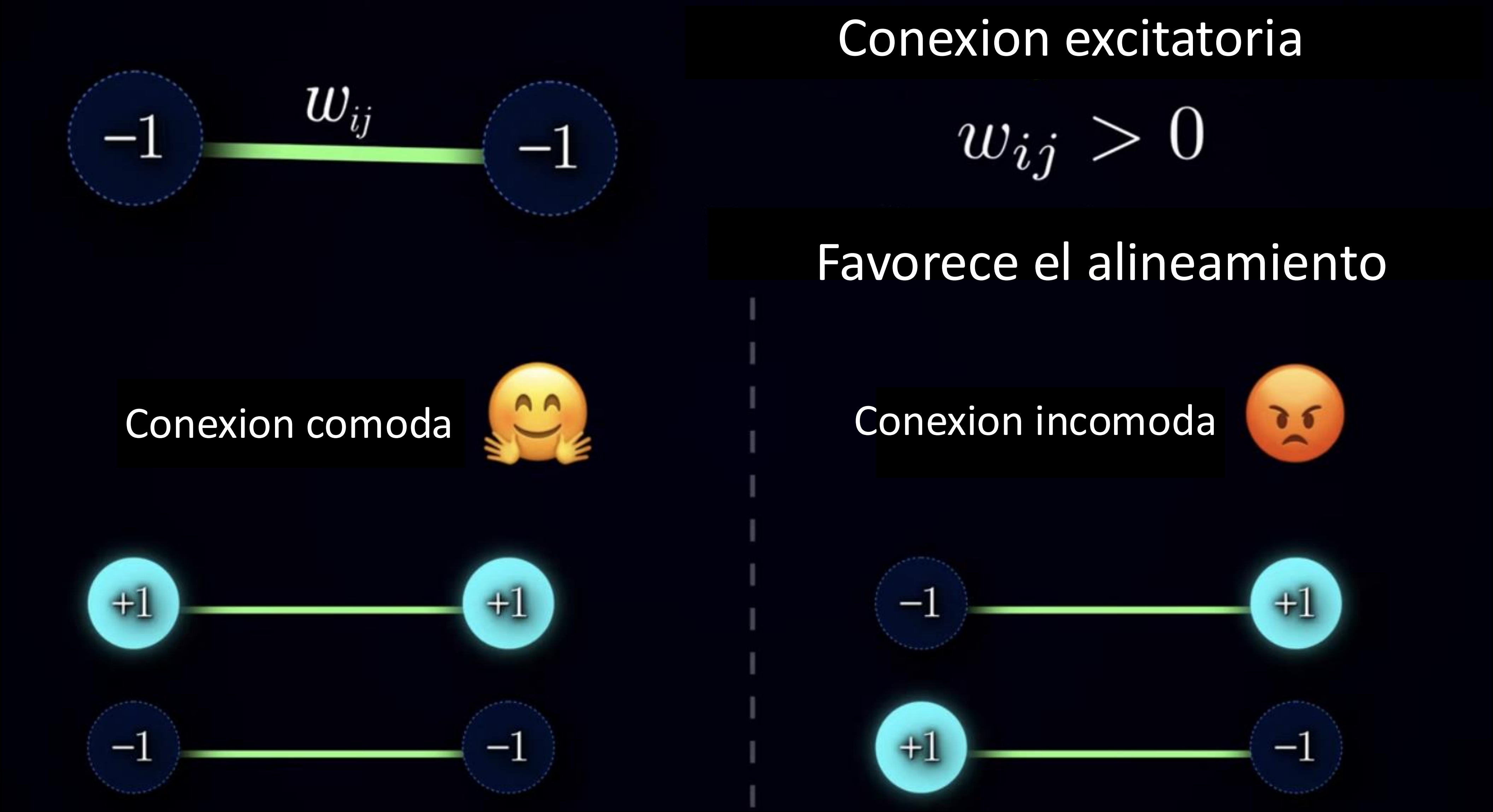
Conexion excitatoria

$$w_{ij} > 0$$

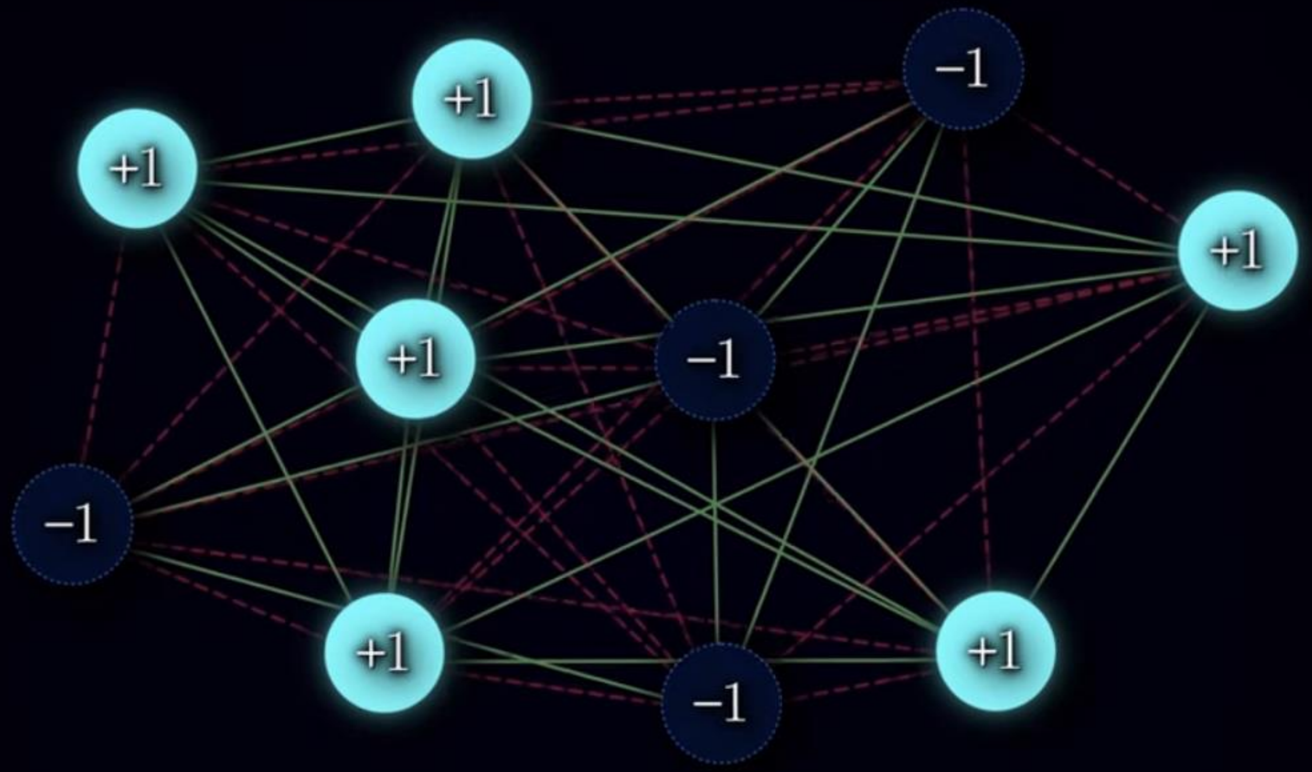
Favorece el alineamiento

Conexion comoda

Conexion incomoda

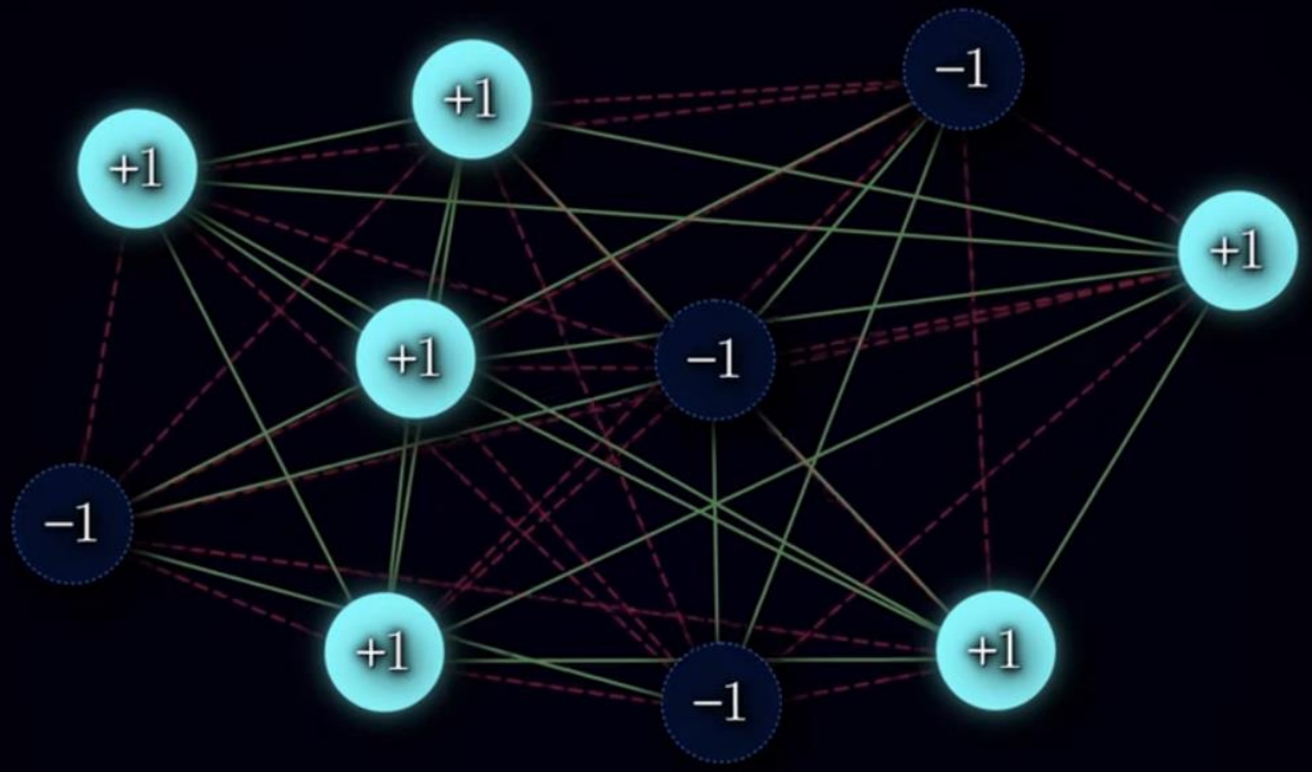


Artem Kirsanov



conexiones

$$\text{"Comodidad del arreglo"} = \sum_{ij} w_{ij} x_i x_j$$

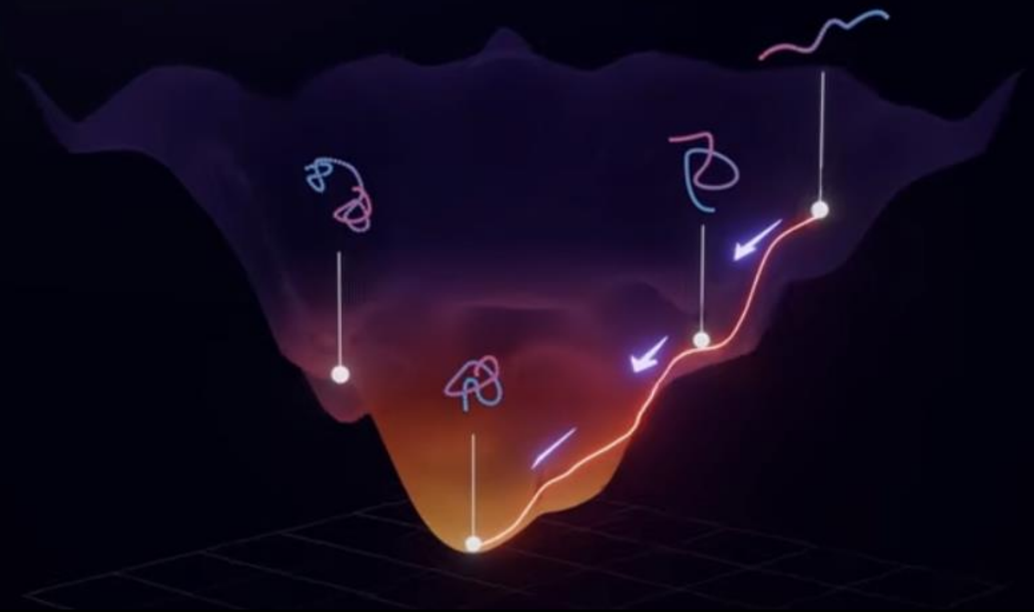


$$\text{“Comodidad” del arreglo} = \sum_{ij}^{\text{conexiones}} w_{ij} x_i x_j$$

Objetivo: minimizar la “incomodidad” ≡ $- \sum_{ij} w_{ij} x_i x_j$

El desafio era definir una regla de evolucion local que fuera compatible con minimizar esta cantidad ("energia")

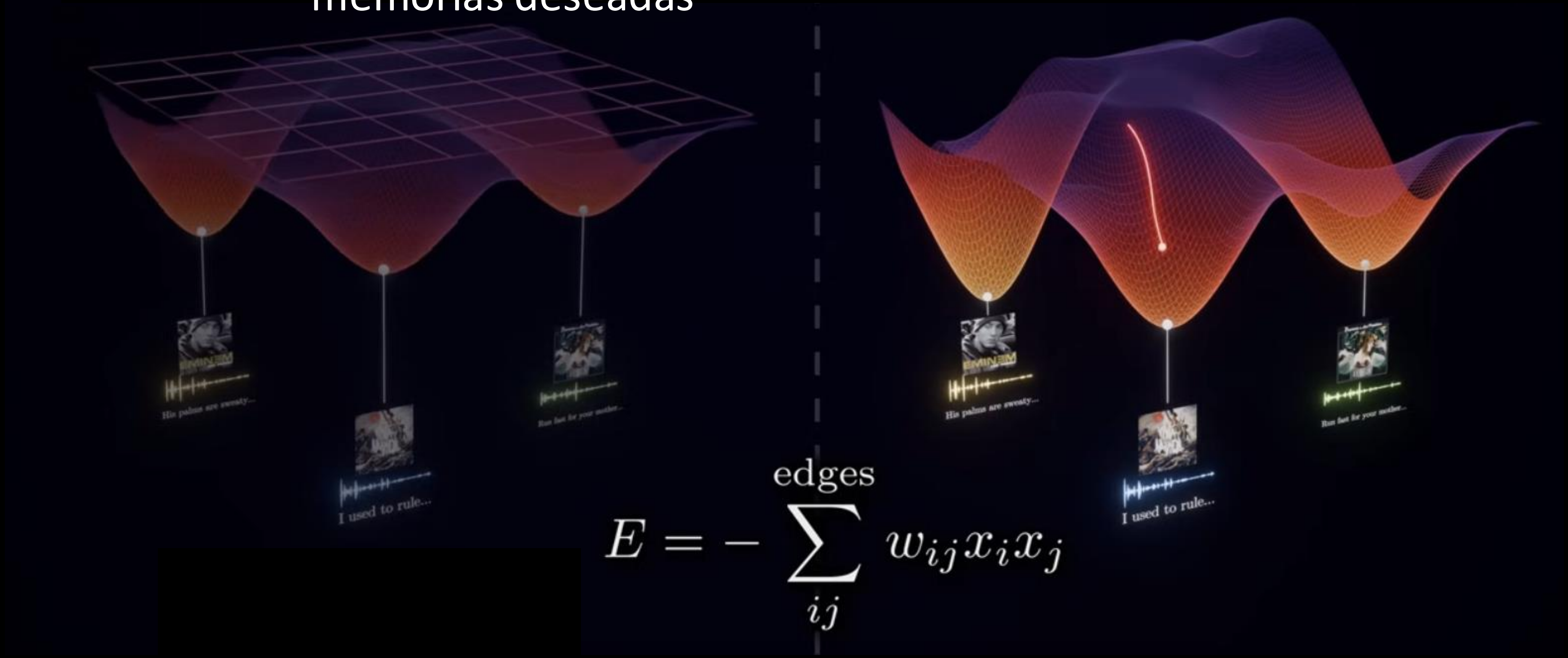
$$\text{“Energia”} = -\sum_{ij}^{\text{edges}} w_{ij} x_i x_j$$



Dos tareas

"Esculpir" el paisaje energetico eligiendo los pesos (aprender) para que los minimos sean las memorias deseadas

Evolucionar, para un conjunto de pesos, hacia los minimos, recuperando las memorias

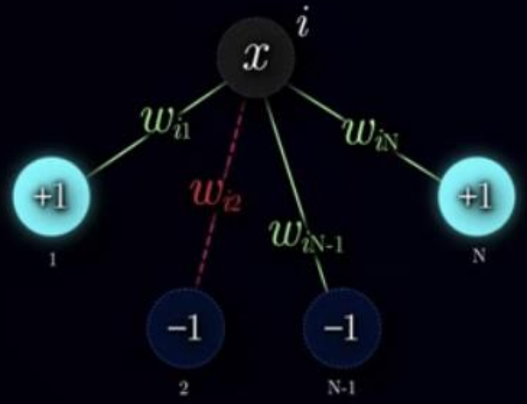


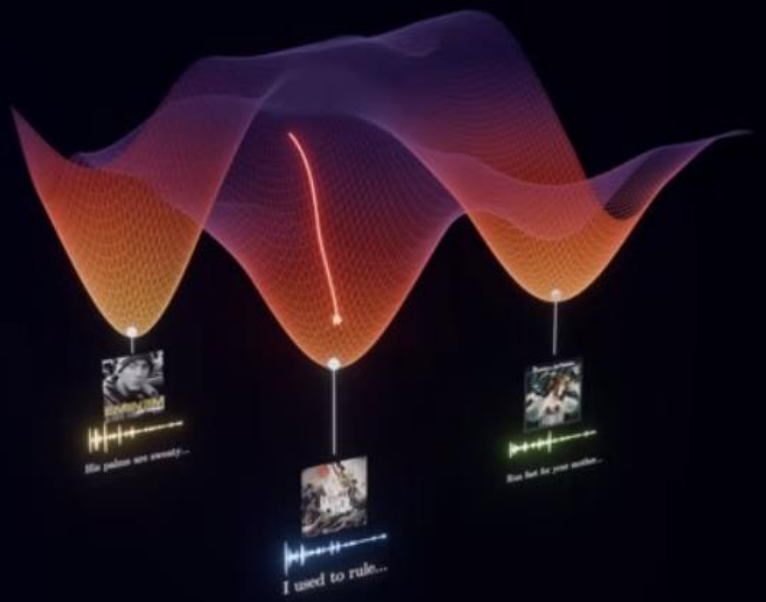
Hopfield demostro que con esta regla local, Y ciertas restricciones a las conectividades (simetrias) lograba que el sistema evolucionara minimizando la “energia” definida

Regla de evolucion

$$h_i = \sum_{j \neq i} w_{ij}\ x_j$$

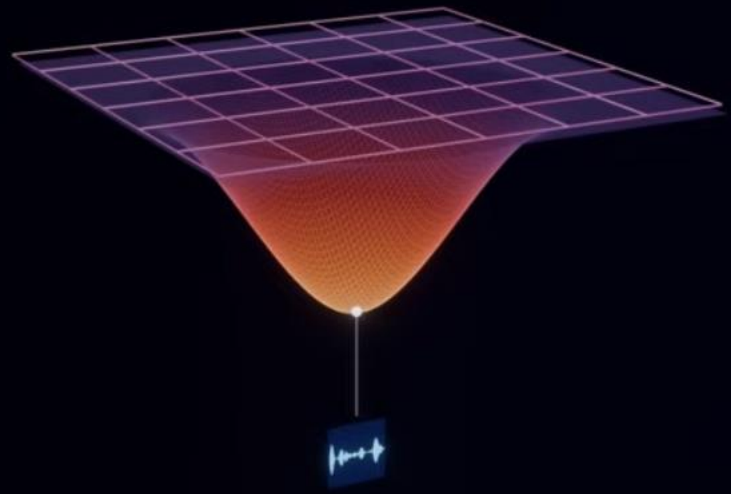
$$x_i = \begin{cases} +1 & \text{if } h_i > 0 \\ -1 & \text{if } h_i < 0 \end{cases}$$





Como grabar una memoria?

$$E(\cdot) < E_{\text{other}}$$

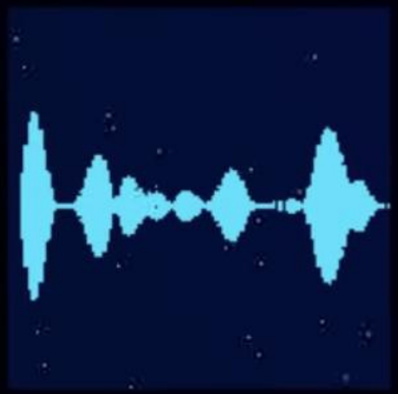


[redacted]

$$E(\cdot) = -\sum_{(ij)} w_{ij}\,\xi_i \xi_j$$

[redacted]

$$w_{ij} \leftarrow \xi_i \xi_j$$



[redacted]

$$E(\cdot) = -\sum_{(ij)} \xi_i^2 \xi_j^2 = -N$$

Como se incorporo la “creatividad” caracteristica de la IA?

Geoffry Hinton, Wimbledon 1947

King’s college, Cambridge
Universidad de Edimburgo
Sussex

UCSD
Carnegie Mellon

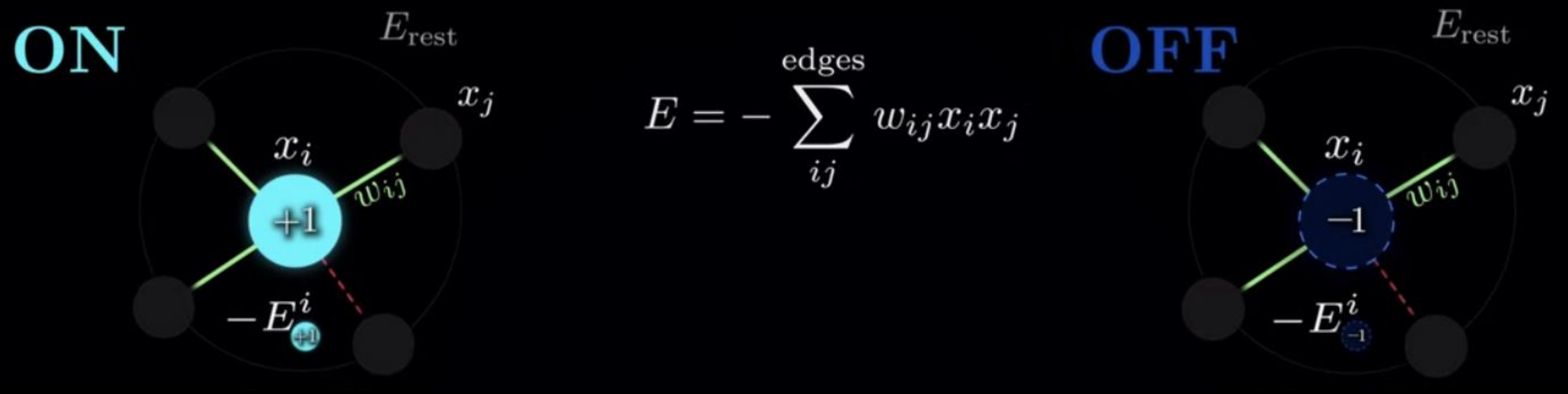
Maquinas de Boltzmann
backpropagation

Toronto

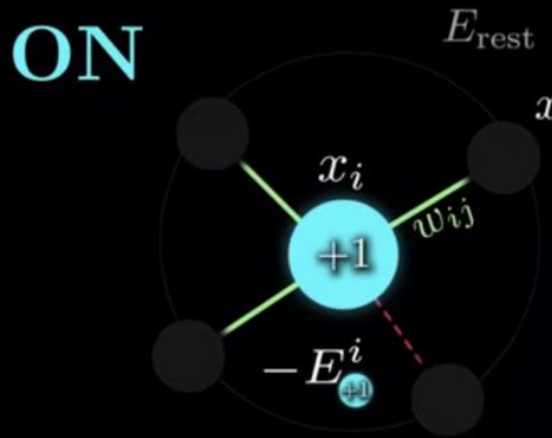
Hopfield

Boltzmann machines

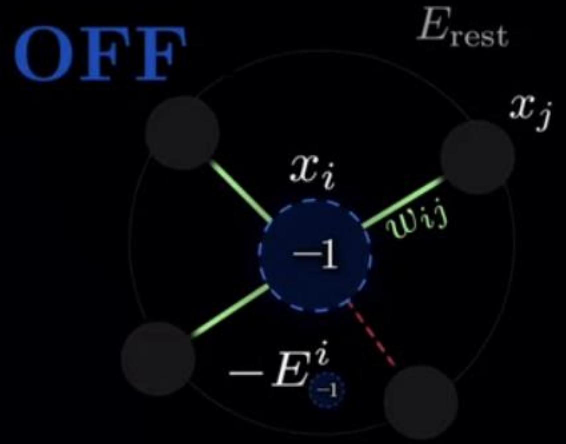
La regla de evolucion no es determinista: hay una probabilidad asignada por la distribucion de Boltzmann



La regla de evolucion no es determinista: hay una probabilidad asignada por la distrib ucion de Boltzmann



$$E = -\sum_{ij}^{\text{edges}} w_{ij} x_i x_j$$



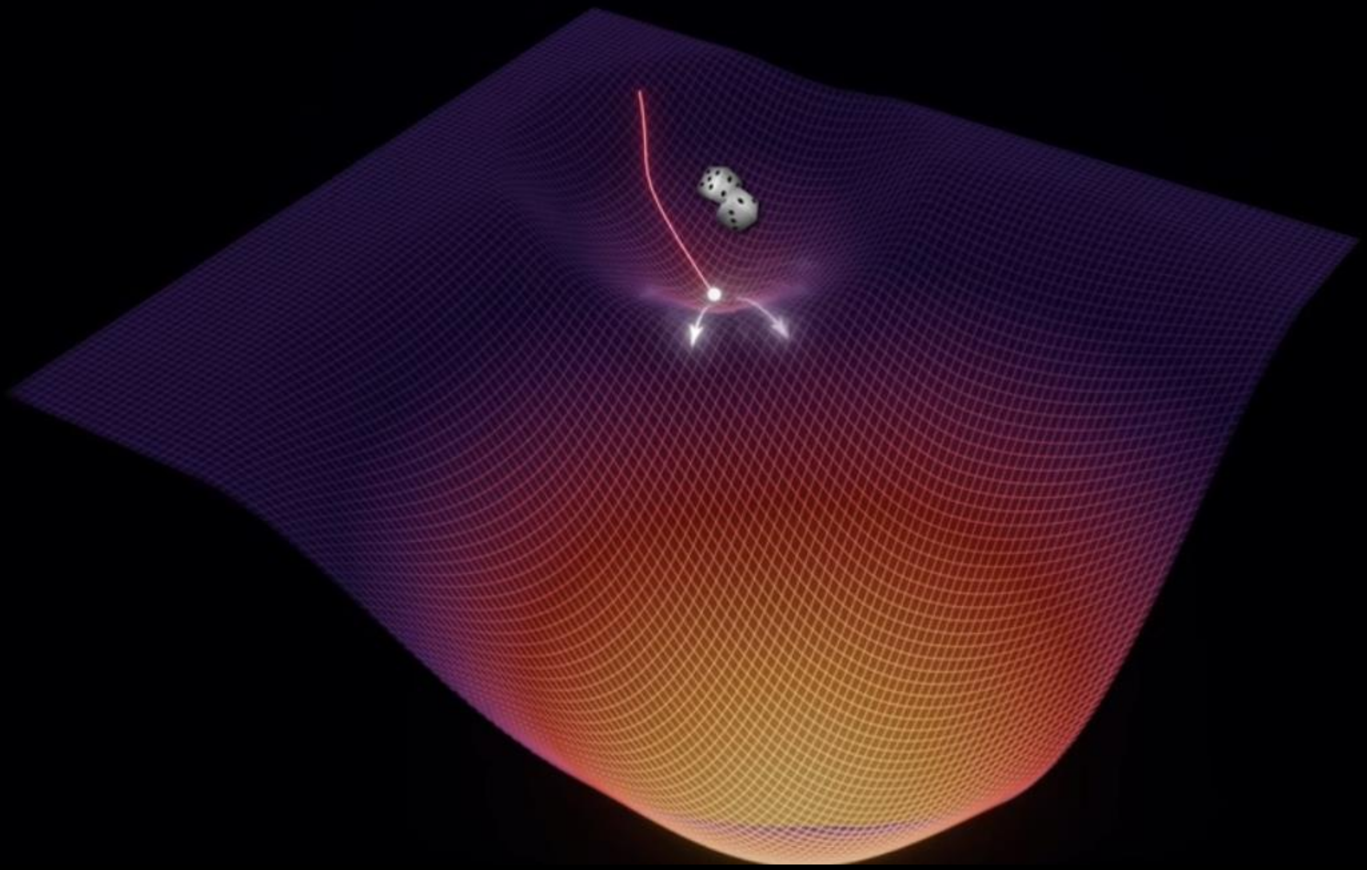
$$E_{\text{on}} = \overbrace{\sum_{j \neq i} -w_{ij}\; x_j}^{E(x_i = +1)} + E_{\text{rest}} \quad \xrightarrow{\Delta E = E_{\text{off}} - E_{\text{on}}} \quad E_{\text{off}} = \overbrace{\sum_{j \neq i} w_{ij}\; x_j}^{E(x_i = -1)} + E_{\text{rest}}$$

$$p_{\text{on}} = \frac{1}{Z} e^{-E_{\text{on}}}$$

$$Z = e^{-E_{\text{on}}} + e^{-E_{\text{off}}}$$

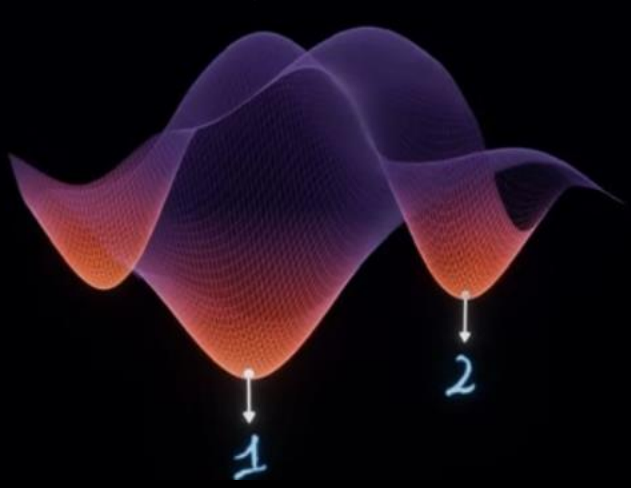
$$\Longrightarrow \quad p_{\text{on}} = \frac{e^{-E^i_{+1}}}{e^{-E^i_{+1}} + e^{-E^i_{-1}}} = \frac{1}{1 + e^{-2\sum w_{ij} x_j}}$$

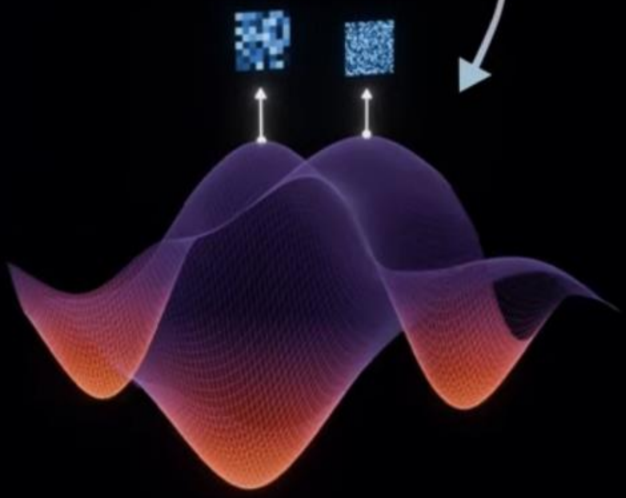
Asi, en terminos de la evolucion, esto permite una primera flexibilidad



Uno se propone maximizar una distribucion de probabilidad *P(Datos)* inferida de los datos, no patrones dados

$$\underbrace{\log P(\text{data})}_{\substack{\text{maximizar} \\ \text{(variando los pesos)}}} = -\frac{1}{T} \sum_{n=1}^{N} \underbrace{E(x^{(n)})}_{\text{minimizar}} - N \underbrace{\log Z}_{\text{minimizar}}$$





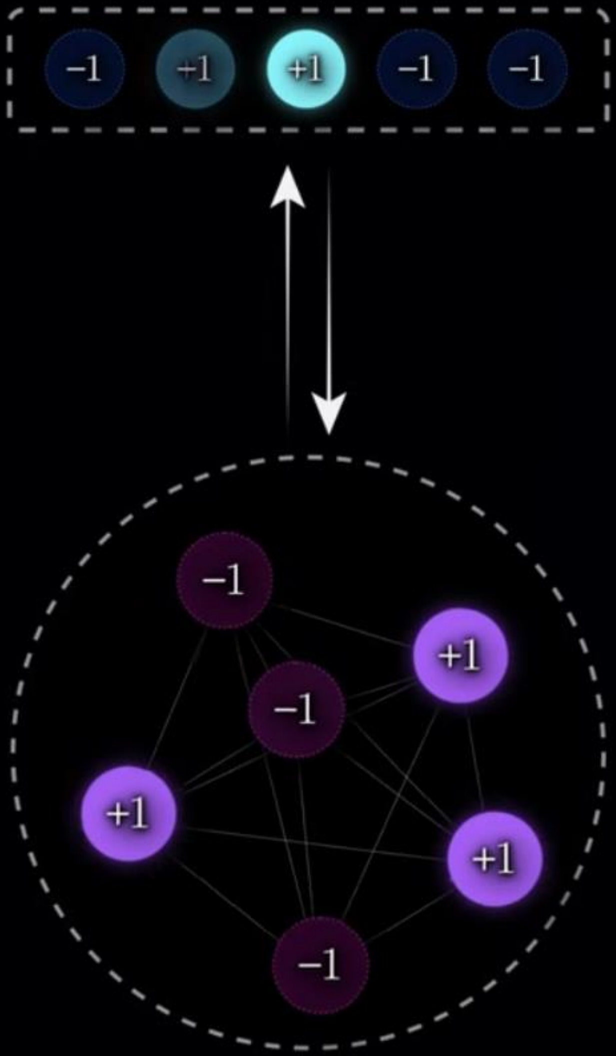
La esculpida de los pesos es en dos tiempos:
una fase “despierta”, atenta al mundo exterior,
y otra “dormida”, sin input del mundo exterior

$$\Delta w_{ij} \propto \langle x_i x_j \rangle_{data} - \langle x_i x_j \rangle_{model}$$

Hebbian

Anti-Hebbian

Otro cambio importante de la maquina de Boltzmann



Unidades visibles

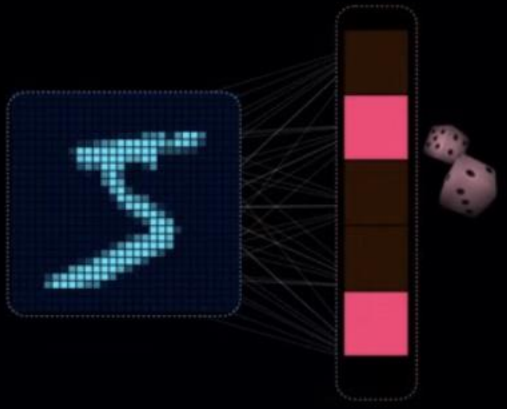
En contacto con el mundo externo

Unidades ocultas

Nunca en contacto, de modo de poder encontrar propiedades mas alla de lo obvio

Fase despierta

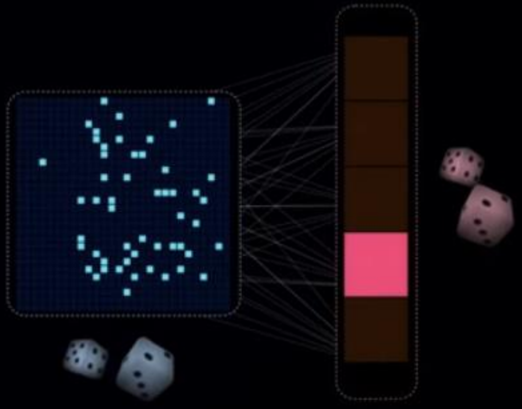
Fijamos las unidades visibles, y hacemos evolucionar las ocultas



$$\langle x_i x_j \rangle_{data}$$

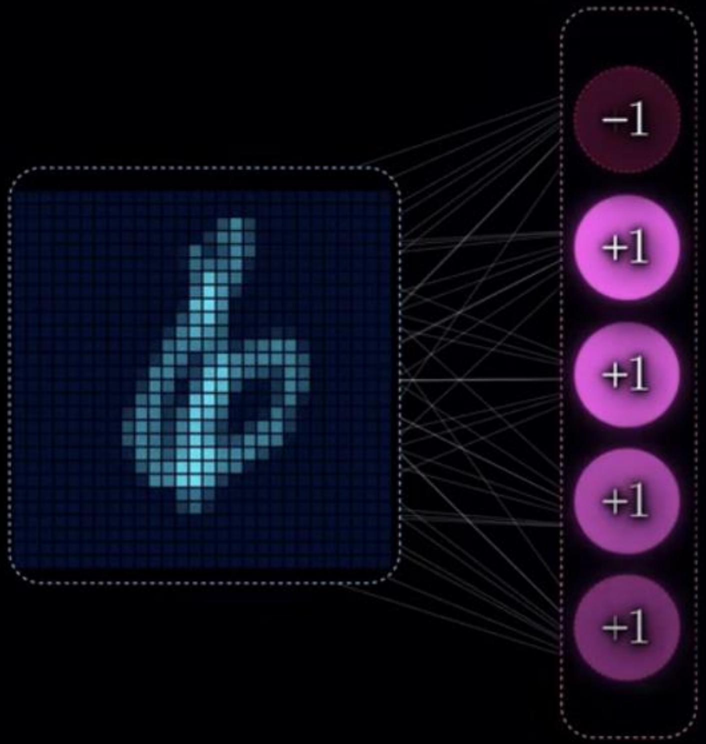
Fase dormida

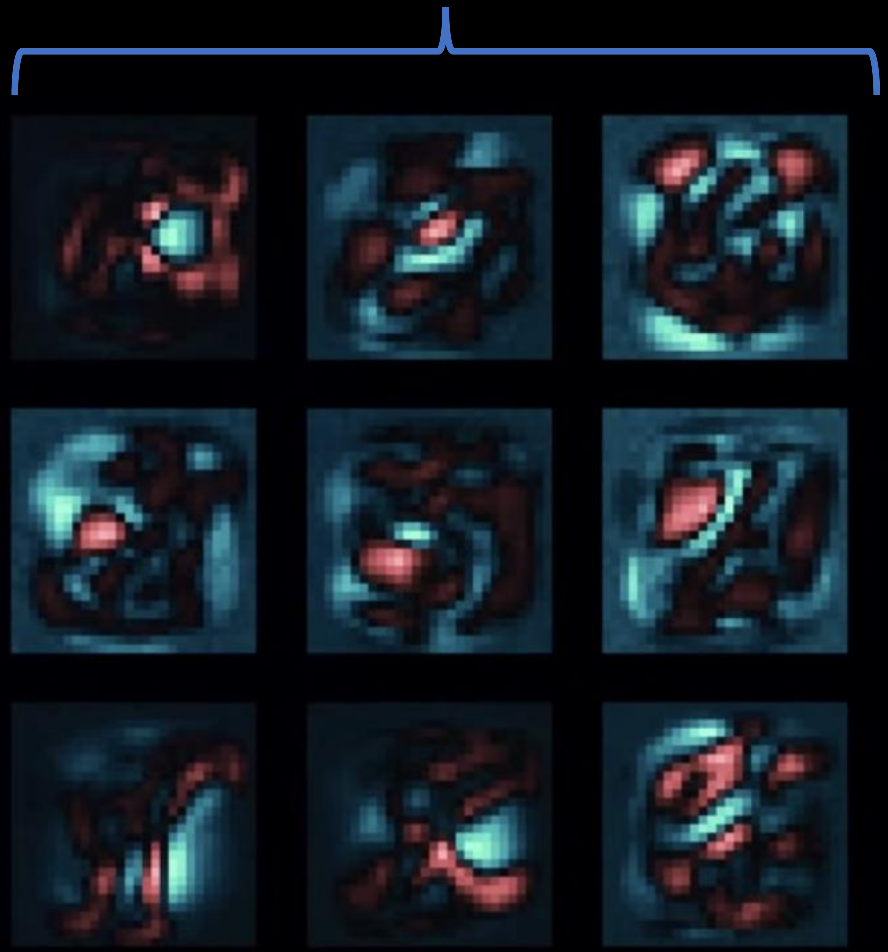
hacemos evolucionar las ocultas y las visibles



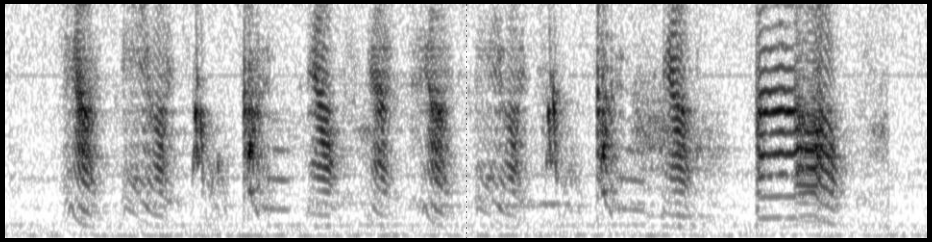
$$\langle x_i x_j \rangle_{model}$$

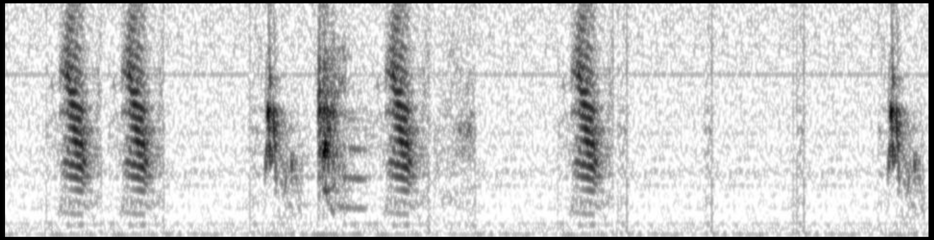
$$\Delta w_{ij} = \langle x_i x_j \rangle_{data} - \langle x_i x_j \rangle_{model}$$

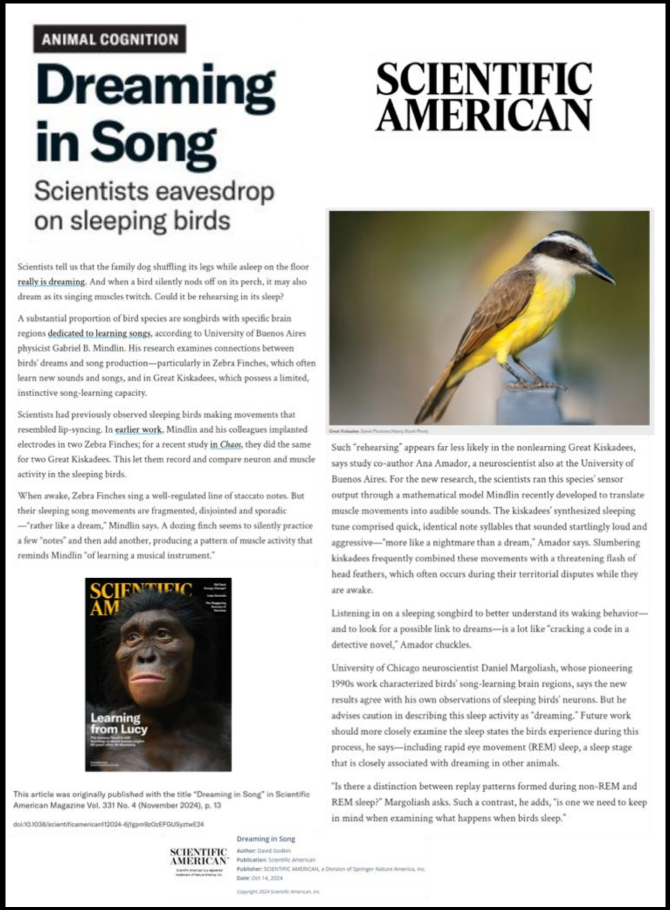




Weights connecting a particular
hidden neuron to visidble units







ANIMAL COGNITION

Dreaming in Song

Scientists eavesdrop on sleeping birds

SCIENTIFIC AMERICAN

Scientists tell us that the family dog shuffling its legs while asleep on the floor really is dreaming. And when a bird silently nods off on its perch, it may also dream as its singing muscles twitch. Could it be rehearsing in its sleep?

A substantial proportion of bird species are songbirds with specific brain regions dedicated to learning songs, according to University of Buenos Aires physicist Gabriel B. Mindlin. His research examines connections between birds' dreams and song production—particularly in Zebra Finches, which often learn new sounds and songs, and in Great Kiskadees, which possess a limited, instinctive song-learning capacity.

Scientists had previously observed sleeping birds making movements that resembled lip-syncing. In earlier work, Mindlin and his colleagues implanted electrodes in two Zebra Finches; for a recent study in *Chaos*, they did the same for two Great Kiskadees. This let them record and compare neuron and muscle activity in the sleeping birds.

When awake, Zebra Finches sing a well-regulated line of staccato notes. But their sleeping song movements are fragmented, disjointed and sporadic —"rather like a dream," Mindlin says. A dozing finch seems to silently practice a few "notes" and then add another, producing a pattern of muscle activity that reminds Mindlin "of learning a musical instrument."

Such "rehearsing" appears far less likely in the nonlearning Great Kiskadees, says study co-author Ana Amador, a neuroscientist also at the University of Buenos Aires. For the new research, the scientists ran this species' sensor output through a mathematical model Mindlin recently developed to translate muscle movements into audible sounds. The kiskadees' synthesized sleeping tune comprised quick, identical note syllables that sounded startlingly loud and aggressive—"more like a nightmare than a dream," Amador says. Slumbering kiskadees frequently combined these movements with a threatening flash of head feathers, which often occurs during their territorial disputes while they are awake.

Listening in on a sleeping songbird to better understand its waking behavior—and to look for a possible link to dreams—is a lot like "cracking a code in a detective novel," Amador chuckles.

University of Chicago neuroscientist Daniel Margoliash, whose pioneering 1990s work characterized birds' song-learning brain regions, says the new results agree with his own observations of sleeping birds' neurons. But he advises caution in describing this sleep activity as "dreaming." Future work should more closely examine the sleep states the birds experience during this process, he says—including rapid eye movement (REM) sleep, a sleep stage that is closely associated with dreaming in other animals.

"Is there a distinction between replay patterns formed during non-REM and REM sleep?" Margoliash asks. Such a contrast, he adds, "is one we need to keep in mind when examining what happens when birds sleep."

This article was originally published with the title "Dreaming in Song" in Scientific American Magazine Vol. 331 No. 4 (November 2024), p. 13

doi:10.1038/scientificamerican112024-6j1gpm9zOzEFGUSyztwE24

Dreaming in Song
Author: David Godkin
Publication: Scientific American
Publisher: SCIENTIFIC AMERICAN, a Division of Springer Nature America, Inc.
Date: Oct 14, 2024

Table S2: Average occurrence of each SLA type with standard error.

Category	1 Syllable	Syllable + unknown	Two or more syllables	Two or more + unknown	Complete motifs	Partial syllables	Incorrect timing
Percent occurrence	20±6.6%	12±4.2%	15±4.3%	5.5±2.2%	6.1±2.2%	33±7.4%	8.1±2.0%

David Ackley

Geoffrey Hinton

Terry Sejnowski


“Esta linea esta muerta”
“La IA nunca pasara por las redes neuronales”
“Esos modelos de juguete nunca enseñaran nada sobre el cerebro, y menos serviran para nada”
Durante mi año en San Diego, cuna de “backpropagation”…

Y entonces fue el invierno…