



# **Nobel Prizes awarded to AI-Pioneers: The Deep link between Computing and Physics (and Chemistry)**

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## **► To cite this version:**

Daniel Brunner, John M. Dudley, Demetri Psaltis. Nobel Prizes awarded to AI-Pioneers: The Deep link between Computing and Physics (and Chemistry). *Photoniques*, 2024, 128, pp.12-14. <10.1051/photon/202212812>. <hal-04847804>

**HAL Id: hal-04847804**

**<https://hal.science/hal-04847804v1>**

Submitted on 19 Dec 2024

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# Nobel Prizes awarded to AI-Pioneers:

## The Deep link between Computing and Physics (and Chemistry)

**Daniel BRUNNER<sup>1\*</sup>, John M. DUDLEY<sup>1</sup>, Demetri PSALTIS<sup>2</sup>**

<sup>1</sup> FEMTO-ST/Optics Department, UMR CNRS 6174, Université Franche-Comté, 25030 Besançon Cedex, France

<sup>2</sup> Optics Laboratory, École Polytechnique Fédérale de Lausanne, Lausanne, Switzerland

\* [daniel.brunner@femto-st.fr](mailto:daniel.brunner@femto-st.fr)

**The 2024 Nobel Prize in Physics has been awarded to John J. Hopfield and Geoffrey E. Hinton for their pioneering contributions to harnessing principles from physics to establish foundational methods in machine learning. Their work catalysed ground-breaking computing concepts, establishing the basis for unconventional computing architectures that directly exploit the physics of their underlying hardware. Today, these novel paradigms promise to drive next-generation hardware with enhanced performance and efficiency, while advanced neural network architectures open doors to transformative scientific discoveries. In this review, we outline the broader context of their contributions to unconventional computing and emphasize the integration of physics-based concepts in modern machine learning architectures.**

<https://doi.org/10.1051/photon/202212812>

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**T**he human brain, a biological marvel, has inspired the development of physical computers with extraordinary capabilities. Notably, it is highly energy-efficient, capable of complex problem-solving, supports creativity and can solve certain problems with remarkable reliability. Research into brain function has long had two interwoven goals: to understand the brain itself, and to develop technologies that mirror its capabilities. This dual interest has influenced generations of scientists, including the 2024 Nobel laureates in Physics, Geoffrey Hinton and John Hopfield, whose work has highlighted the profound link between brain-inspired computing and fundamental physical principles [1, 2]. Early computing began with special-purpose devices that leveraged analogue physics to perform calculations, usually with a rather direct mapping of the computational task onto the physical laws of the machines. This approach, though relatively simple to implement, limited such devices in their ability to evaluate/solve/compute/mimic specific functions to the ones embedded in their physical construction. The breakthrough

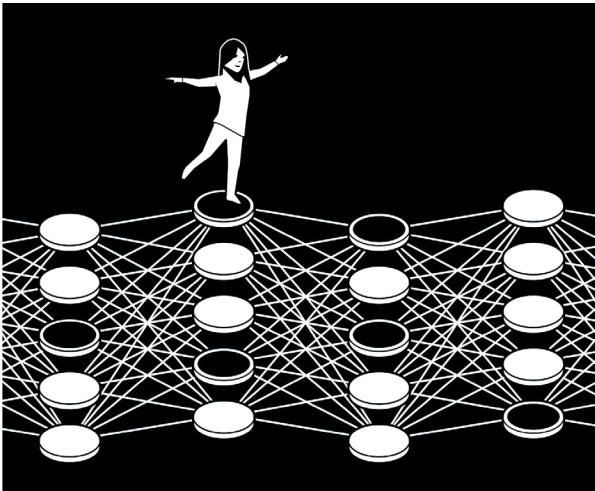
in general-purpose computing emerged with Alan Turing's concepts, which abstracted computation using binary logic [3]. By reducing computation to simple, hence more readily reproducible operations, Turing's model made computing robust against physical imperfections,

enabling the development of reliable hardware that operated largely independent of the specifics of the underlying physics.

However, this direct task-mapping approach, linking computational objectives to Turing algorithms, diverges



| John J. Hopfield and Geoffrey Hinton © Niklas Elmeheed - Nobel Prize Outreach



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significantly from the mechanisms underlying human intelligence. This discrepancy has intrigued researchers seeking to bridge the gap between conventional computing and brain function. Santiago Ramón y Cajal's pioneering studies in neuroscience (for which he received the Nobel Prize in Physiology or Medicine in 1906) provided an initial view of the brain's network structure, hypothesizing how neural connections could grow to support learning [4]. Later, McCulloch and Pitts associated neural function with computation using Boolean logic, interpreting neurons' binary firing patterns as a justification for representing neural activity in symbolic terms [5]. While this approach integrated computer science with networked computation, it failed to capture the deep connections to physics.

Improved understanding of the distributed, interactive nature of brain function started to increasingly highlight the parallels to physical systems. In the 1980s, a seminal analogy connected fundamental computing operations to atomic spin-spin interactions [6, 7]. Early researchers recognized that Ising models, where spins could point up or down, evolve toward stable configurations through the minimization of free energy. The resulting spin patterns are influenced by the topology of interactions, the initial spin states, and random fluctuations akin to the effects of a temperature, yielding highly robust configurations. John Hopfield extended this concept to memory storage in neural networks. In these binary memory systems, each memory corresponds to a specific spin configuration [2] and a spin network can store a variety of memories due to multiple stable configurations. Hopfield showed how to design these spin-spin interactions, or the network topology, such that inherent physics establish these memories as stable points positioned at local minima within the system's energy landscape [8], c.f. Fig. 1A. When the system is initialized from a partial state, it naturally relaxes to the closest stable configuration, restoring the intended memory. Hopfield networks thus enable memory retrieval ●●●

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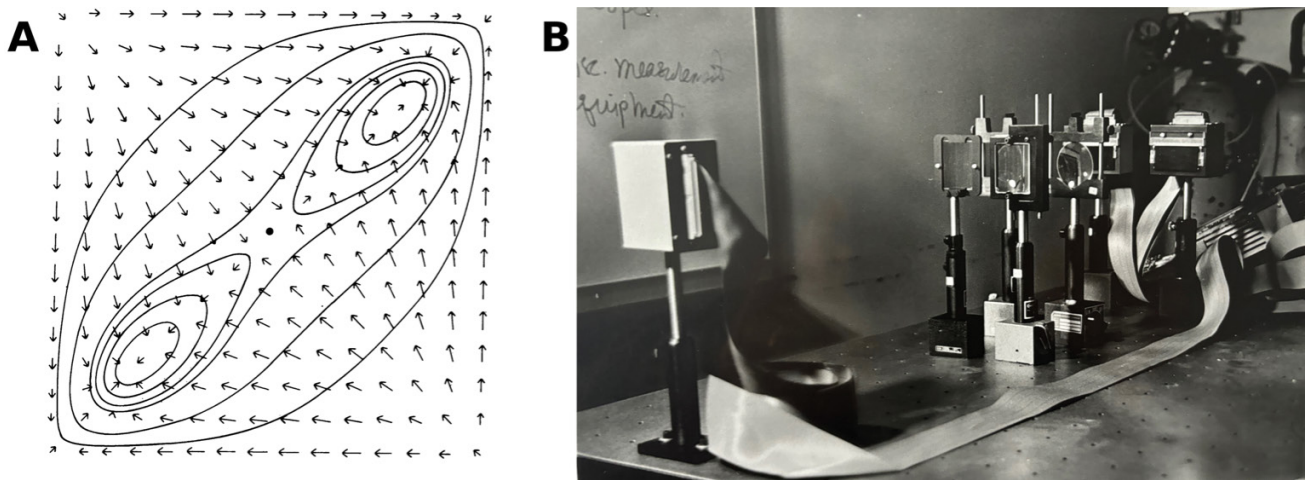
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**Figure 1.** A The energy contour map for a two-neuron network, *i.e.* two-spin Ising model. Arrows indicate the relaxation-direction towards the two memories stored in the Hopfield network's energy minima. Picture reproduced with permission from J.J. Hopfield. B The almost immediate implementation of a Hopfield network demonstrates the legacy of Hopfield's work: connecting computing and physics. Photo: courtesy D. Psaltis. See also Ref. [10]

from incomplete inputs, offering a unified framework for neuro-inspired memory reconstruction, Ising spin system dynamics, and bistable network interactions. This achievement underscores the deep link between neuro-inspired computing, memory dynamics, and physical systems [9].

Geoffrey Hinton's Boltzmann machine expands the use of these concepts by leveraging concepts of statistical mechanics. The Boltzmann machine is also based on an Ising system connected in such a way that it searches for low-energy configurations to represent meaningful content again as stable configurations. Drawing on the idea of an energy landscape, each stable network state corresponds to a point with an associated energy level. The machine seeks configurations that minimize this energy, akin to how physical systems settle into stable, low-energy states. However, Boltzmann machines incorporate a "temperature" concept, using simulated annealing to explore network configurations by initially allowing more randomness (high temperature) and then gradually cooling (lowering randomness). This process helps avoiding poor solutions by enabling the system to escape local energy minima. The Boltzmann machine exemplifies how the principle of energy minimization combined with thermal fluctuations can bridge the gap between physics and artificial intelligence in the context of probabilistic learning models, and the approach has been foundational for deep learning architectures, particularly in unsupervised learning.

The legacy of Hopfield networks and Boltzmann machines has significantly motivated the fields of artificial intelligence, machine learning and unconventional computing using physics. Their work contributed to the development of deep neural networks that are now widely used. In particular, Hopfield's initial publication was pivotal, sparking interest in optical neural networks and leading to the first experimental realization of a Hopfield network [10] just two years later – using optics (*c.f.* Fig. 1B). Driven by the urgent need for new and efficient neuro-inspired physical computing engines, optical neural networks flourish again today. The 2024 Nobel Prize in Chemistry awarded to Demis Hassabis and John Jumper for their work on AlphaFold highlights the importance of Hinton's and Hopfield's work for novel computing concepts. Including an energy landscape model of protein folding, AlphaFold 2 exemplifies the application potential of the computational techniques pioneered by the early neural network architectures. Beyond this, neural network methodologies permeate nearly every scientific discipline, driving advancements in automated optical design, enabling the rapid simulation of complex optical

systems and creating breakthroughs in computational imaging. Thus, the combined legacy of Hopfield networks and Boltzmann machines continues to inform advancements in artificial intelligence, illustrating the profound connections between physics and computational intelligence. ●

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