THE 2024 PHYSICS NOBEL PRIZE: THE FOUNDATIONS OF ARTIFICIAL INTELLIGENCE

EL PREMIO NOBEL DE FISICA DEL 2024: LOS FUNDAMENTOS DE LA INTELIGENCIA ARRTIFICIAL

R. Mulet[a†] and C. Díaz-Faloh[a]

Centro de Sistemas Complejos y Departamento de Física Teórica. Facultad de Física, Universidad de La Habana, Cuba. roberto.mulet@gmail.com[†]
† corresponding author

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The 2024 Nobel Prize in Physics was jointly awarded to John Hopfield and Geoffrey Hinton "for foundational discoveries and inventions that enable machine learning with artificial neural networks". Here we try to explain the meaning of this statement and why we consider their contribution to be an important advance for Physics. This prize is probably the definitive demostration that once again in History, Physics is more than the study of innanimate natural objects.

El Premio Nobel de Física del año 2024 fue entregado a John Hopfield y Geoffrey Hinton por "descubrimientos fundacionales e invenciones que permiten el aprendizaje automático con redes neuronales artificiales". Aquí tratamos de explicar el significado de esta sentencia, y por qué consideramos que sus contribuciones son importantes avances para la Física. Este premio es probablemente la demonstración definitiva de que la Física, una vez más en la historia, es más que el estudio de los objetos inanimados de la naturaleza.

PACS: Physics Nobel prize, artificial intelligence, neural networks

I. INTRODUCTION

In 2024, every educated person with internet access has heard about ChatGPT. It entered our worldwide web with such prominence that many believe it may be as disruptive, or even more so, than the Google search engine. This impact likely contributed to the Nobel Prize Foundation awarding a (for some) surprising Nobel Prize in Physics this year.

According to the Nobel Foundation: *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."*

If the corresponding question is posed to an artificial intelligence on the web, the answer tends to be more detailed and specific: *The 2024 Nobel Prize in Physics was awarded to John J. Hopfield and Geoffrey E. Hinton for their foundational discoveries and inventions that enable machine learning through artificial neural networks. According to the Royal Swedish Academy of Sciences, their work has utilized tools from physics to develop methods that form the basis of today's powerful machine learning technologies.*

Still, it may not be clear to everyone what ChatGPT has to do with Physics. Let us explain it in more detail.

II. JOHN HOPFIELD: THE MEMORY

John Hopfield has had an extraordinary career in Physics. Like many who began their training in the late 1950's, he worked extensively in Solid State Physics, where one of his main contributions was the introduction of the concept of polariton [1]. After a few years, he became interested in Biological Physics, particularly in the accuracy of DNA replication, leading him to introduce the concept of kinetic proofreading [2].

However, it was in the early 1980's that he began working on the subject that earned him this Nobel Prize. Two of his articles [3, 4] presented an artificial network that could serve as a memory and that would later be refered to as Hopfield Network, after him. In short, the system that he proposed consists of a collection of interconnected artificial neurons (or nodes), where each neuron can represent a binary state, typically +1 or −1. The network is fully connected, meaning each neuron is connected to every other neuron, except for self-connections. The behavior of a Hopfield Network is governed by an energy function that quantifies the network's state. The energy E can be expressed mathematically as:

$$E = -\frac{1}{2}\sum_{i,j} w_{ij}x_i x_j - \sum_i b_i x_i \tag{1}$$

where w_{ij} are the weights between neurons i and j, and x_i is the state of neuron i. Notice that the states of the neurons in the Hopfield model are analogous to the orientations of spins in the Ising model. The weights of the neural network represent interaction terms, while biases b_i play the role of external fields. From this expression for E, it is clear that this field of research is intimately connected with Spin Glass Theory, which granted Giorgio Parisi a Nobel Prize in 2021 (Rev. Cubana Fis. 28, 128 (2021)).

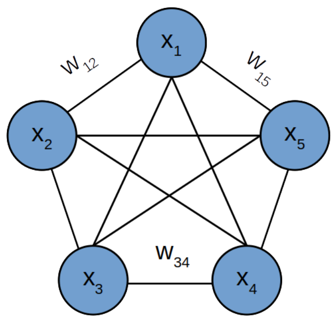

Figure 1. Hopfield network with five neurons. Each neuron is connected with the other four. Only a few weights are represented for visual porpouses.

Hopfield had an important intuition that was not previously explored by the Spin Glass community. He proposed that the states of the network could evolve following a simple rule. Define for each neuron a field $h_i = \sum_j w_{ij}x_j$, such that $x_i = 1$ if $h_i > 0$ or -1 when $h_i < 0$. This is known as the Hebb rule; if the weights are symmetric, such dynamics are guaranteed to lead to stationary states identified as memories.

The clear connection with Physics goes beyond metaphorical inspiration; soon it became possible to exploit techniques developed in disordered systems to analytically compute relevant quantities. For example, Gardner computed the storage capacity of a Hopfield Network [5], which is always $P < 0.15N$, where N is the number of nodes in the network and P is the number of patterns that can be reliably stored. Such analytical results inspired others to seek networks with larger storage capacities [6] and turned this subject into a new field of research [7].

III. HINTON: LEARNING STRUCTURES

Geoffrey Hinton studied experimental psychology before obtaining a PhD in Artificial Intelligence (AI) in 1978, at a time when personal computers were rare and laptops did not exist. Just a few years after his PhD, he examined Hopfield Networks and altered their dynamics. While Hopfield defined variable values s_i deterministically by local fields h_i, Hinton proposed that the Network's state follows a probabilistic (Boltzmann) distribution:

$$P(\{x\}) = \frac{e^{-\beta E(\{x\})}}{Z} \tag{2}$$

where β is a tuning parameter and Z is a normalization factor recognized by physicists as the partition function of this problem. This machine is called a Boltzmann Machine [8, 9] and does not act as memory; instead, it generates new patterns.

To clarify differences: once trained with P patterns, the Hopfield model can produce one of those patterns (this represents memory). In contrast, once trained, a Boltzmann machine can generate new patterns respecting the statistical distribution of the training data.

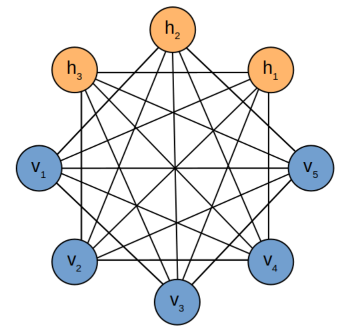

Figure 2. Boltzman Machine

Although initially slow and thus less utilized, a slightly modified version known as Restricted Boltzmann Machines (RBMs) [10–12] became versatile tools whose structure inspired more complex machines emerging in this field. While both Hopfield and Boltzmann machines are fully connected networks (each node connects with every other), RBMs consist of two consecutive layers; when people refer to Deep Learning, they usually mean machines with multiple consecutive connected layers—the idea was already there.

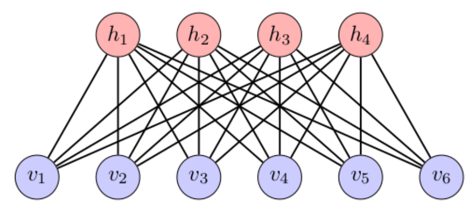

Figure 3. Restricted Boltzman Machine

Hinton continued advancing AI through inventions like backpropagation [13], Deep Belief Networks [14], AlexNet [15], etc., transforming basic science from the 1980's into real applications just a few years later.

IV. ARTIFICIAL INTELIGENCE IN PHYSICS

Artificial Neural Networks (ANNs) are playing an increasingly important role in modern physics, influencing a wide range of research areas.

In materials science, for instance, fundamental properties—from band gaps to emergent behaviors—are theoretically derived from solving the Schrödinger equation for electrons. However, the inherent computational complexity of quantum mechanics renders exact analytical solutions nearly impossible. ANNs have demonstrated their usefulness as function approximators [16], learning the energy landscapes of various models. This deep learning approach significantly reduces the computational resources required while maintaining high accuracy and resolution. As a result, ANNs have facilitated significant progress in tackling quantum-mechanical many-body problems [17,18], including the prediction of new photovoltaic materials.

Similarly, ANNs have improved the resolution of physics-based climate models without demanding additional computational power, leveraging the vast amount of data available on climate variables [19, 20].

Beyond simulation, ANNs serve as powerful tools for pattern recognition in data analysis. During the search for the Higgs boson, ANNs were trained to identify specific patterns in the massive datasets generated at the CERN Large Electron-Positron Collider (LEP) during the 1990s [21]. Neural networks also played a crucial role in analyzing the data that ultimately led to the discovery of the Higgs boson at CERN's Large Hadron Collider (LHC) in 2012 [22].

In astronomy and astrophysics, ANNs are widely employed for tasks such as spectral classification, image processing, and inference. A recent example is the use of ANNs in analyzing data from the IceCube neutrino detector at the South Pole, which led to the creation of a neutrino image of the Milky Way [23]. Exoplanet transits have been identified by the Kepler Mission using ANNs [24], and the Event Horizon Telescope relied on neural networks to process the data that produced the first-ever image of a black hole at the center of the Milky Way [25]. Additionally, the Square Kilometre Array (SKA) uses ANNs to perform regression on high-redshift data, a key task in its mission to study the universe at centimetre and metre wavelengths [26].

These are just a few examples of the many applications of ANNs in modern physics, showcasing their broad impact. Overall, ANNs have given physics a powerful boost in terms of simulation and data processing. Their use has lowered computational costs and made it easier to analyze complex systems, leading to faster and more accurate results across many areas of research.

V. CONCLUSIONS

This Nobel Prize in Physics represents more than the recognition for pioneers who conducted groundbreaking work; it certifies that Physics must be understood beyond traditional boundaries. Many were taught in high school that Physics was merely about studying the motion of inanimate objects. However, after three decades of active research, We can not agree more with those who awarded this prize: Physics encompasses not only problems but also methods, concepts, and ideas.

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