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Artificial boundaries

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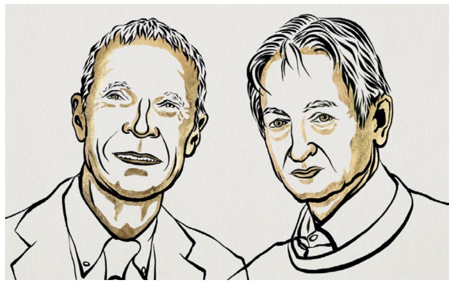
The 2024 Nobel prize for Physics was awarded for foundational contributions to the development of artificial neural networks. The award reflects a shift in how we understand boundaries between scientific fields — or whether such boundaries are still useful at all.



The Nobel Prize committee awarded this year's Physics prize to John J. Hopfield and Geoffrey E. Hinton "for foundational discoveries and inventions that enable machine learning with artificial neural networks". Their work, inspired by physics principles and models, has contributed significantly to machine learning with artificial neural networks. But the choice of the committee also opens up a conversation about the compartmentalization of knowledge and the arbitrary boundaries of what we consider physics.

In 1982, Hopfield introduced an approach to understanding associative memory by applying concepts from statistical physics[1]. His eponymous network used a recurrent neural network architecture in which neurons functioned as binary units. The strength of the connections between neurons determined the stability of certain configurations, which can be thought of as memories. Hopfield's main insight was to frame memory retrieval as an energy minimization process.

When a partially corrupted or incomplete input is fed into the network, the neurons adjust their states asynchronously to reduce the overall system's energy, guiding the network to a low-energy configuration that corresponds to a stored memory. This process mimics how physical systems evolve toward states of lower energy, such as a magnet settling into a stable configuration. This allowed for several properties of the model to be captured by analytical tools coming from the theory of spin glasses[2].

Hinton and colleagues extended Hopfield's ideas by developing the Boltzmann machine[3] — a neural network model that incorporates stochasticity through a probabilistic learning rule. Instead of binary updates, each node in the machine is updated according to a Boltzmann probability distribution that depends on its energy state, with lower-energy states being more probable.

The introduction of hidden units — nodes that do not directly correspond to the data but help capture more general distributions — allowed the Boltzmann machine to model intricate dependencies within the data. However, the machine's hefty computational demands made it mostly impractical for large-scale learning tasks until the invention of restricted Boltzmann machines, which simplified the original architecture by limiting the connections between visible and hidden layers of neurons. This restriction proved instrumental for the efficient pre-training of deep networks layer by layer.

This year's award has raised more than one eyebrow among physics researchers and commentators. Although the work of the two laureates is undoubtedly rooted in statistical physics, many argue that the greatest practical impact of their work has been in computer science, where it laid the foundation for what Hinton has described as something akin to a new Industrial Revolution.

On the other hand, the fruits of Hopfield and Hinton's work have circled back to physics. Machine learning techniques are routinely employed to sift through the enormous datasets generated by particle detectors[4]. Restricted Boltzmann machines and other neural network architectures have been used as a variational approach to the quantum many-body problem[5], and convolutional neural networks have been shown to help identify phases and phase transitions in condensed matter models[6,7]. The list goes on, but whether the work of Hopfield and Hinton has produced a Nobel-worthy advance in our understanding of the systems and laws traditionally associated with physics remains debatable.

The recognition of this work raises broader questions about the evolving nature of scientific disciplines. For much of the 20th century, science moved towards increased specialization, driven by the institutionalization of research into distinct departments and focused funding streams. This specialization was highly effective in enabling deep expertise and technological advances. However, the complexity of contemporary scientific problems — think of climate change — calls for the synthesis of knowledge from separate domains.

At *Nature Physics*, we endorse the interdisciplinary nature of contemporary physics research. In recent years, we have discussed the benefits and challenges of a multidisciplinary approach in biophysics, explored the dialogue between physics and economics, and network science has been increasingly featured on our pages. In the Editorial of our previous issue, we highlighted how experimental tools developed in a given field can be successfully ported to another. As a journal serving the physics community, we adapt to how the field evolves and expands. We thus welcome the committee's decision to acknowledge the blurring of the traditional boundaries of physics.

Perhaps the debate over the appropriateness of this year's award stems from the compartmentalization of the prize itself. It may seem paradoxical that the work of Hopfield and Hinton is being recognized from an institution that remains formally tied to distinct disciplinary categories. The Nobel Prize is not just a scientific award; it is a cultural institution that carries great symbolic weight. It plays a large role in shaping the public perception of what constitutes important scientific progress. At a time when arbitrarily defined boundaries between fields appear less and less productive, we hope that the award to Hopfield and Hinton might signal a decisive shift away from a rigidly reductionist view of science.

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