Physics and machine learning: mutual benefits

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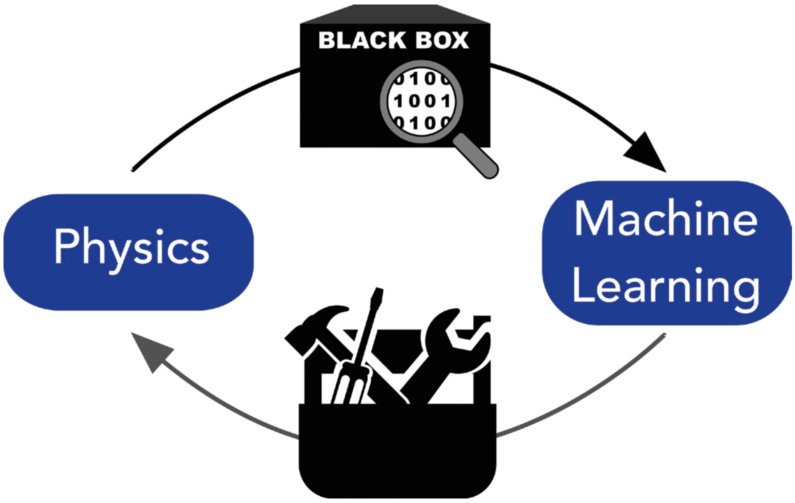
Physics has relied on data-driven discoveries since the Scientific Revolution, exemplified by Kepler's groundbreaking work based on Tycho Brahe's precise astronomical observations.

This reliance on empirical evidence laid the foundation for the scientific method in physics, where observations and experiments are central to uncovering fundamental principles and constructing predictive theories. As data collection methods have become more precise and extensive, they have continued to drive progress in physics, advancing our understanding from Newtonian mechanics to quantum theory and beyond.

Today, as the volume of data continues to grow exponentially, machine learning (ML) has emerged as a powerful tool for advancing discoveries in physics. The goal of ML is to develop a model that accurately captures the underlying patterns and intrinsic properties of the external world as reflected in observed data [1]. This closely mirrors the goals of physics, where the aim is to formulate mathematical models that describe the fundamental laws of nature based on empirical observations. Thus, ML methods can be naturally incorporated into physics.

ML technologies enable physicists to analyse huge datasets, identify complex patterns and discover relationships that may be missed by traditional methods. ML is transforming physics, providing powerful tools to accelerate discovery and deepen understanding of physical phenomena, helping to uncover governing equations, solve inverse problems and optimise experimental designs. Methodologies such as supervised learning, deep learning, generative modelling and reinforcement learning are being used to explore new horizons and solve complex problems that were previously inaccessible [1].

▸ Machine learning can provide new tools for physics, while physics can help explain machine learning algorithms.



These methods have been successfully applied to a wide range of problems in physics, including processing atmospheric data, predicting the behaviour of particle systems, discovering new materials, studying phase transitions, generating experimental designs, and even automatically uncovering physical laws [1]. By harnessing vast amounts of data, ML techniques have enabled scientists to identify hidden patterns and relationships that would have been difficult or impossible to detect using traditional methods. These advances have significantly improved our understanding of complex systems and opened up new avenues of research. Indeed, in recognition of the transformative role of machine learning in physics, the 2024 Nobel Prize was awarded to the pioneers of neural networks for their groundbreaking discoveries and inventions that enabled the development of machine learning with artificial neural networks.

Physics also plays a central role in machine learning. For example, optimisation techniques (*e.g.* gradient descent, simulated annealing) are based on physical principles. In addition, new areas of ML are emerging where physics plays a central role, such as physics-informed machine learning, which incorporates established physical laws and constraints into ML algorithms, enabling models to learn from data while ensuring consistency with known physical principles. Therefore, theoretical physicists must also be involved in understanding deep learning.

Although machine learning methods are becoming increasingly important in physics, they are still unknown to most physicists. In our recent work [1], we provide an insight into how these methods are used and a brief guide to the main concepts and computational tools. The application of machine learning in physics is still in its infancy, but the future looks very promising. A new revolution is on the horizon, and we need to be ready for it. ■

Reference

[1] F.A. Rodrigues, *Europhysics Letters* **144** (2), 22001