What can artificial intelligence do for physics?

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Introduction

In recent years, governments all over the world have launched research initiatives for artificial intelligence (AI). These range from Australia, Canada and the United States to the People's Republic of China, Denmark, the European Commission, France, Germany and the United Kingdom. Everyone suddenly has a strategy for "AI made in", whatever happens to be their own part of the planet. In the coming decades, it is likely that tens of billions of public and private dollars, euros and Yuan renminbi will flow into the field. However, ask physicists what they think of AI, and they will probably be surprised. For them, AI was trendy in the 1980s. They prefer to call it "machine learning" and pride themselves on having used that term for decades. This essay summarises different applications for which AI physicists use AI, classifying them roughly into data analysis, modelling and model analysis.

The evolution of machine learning in physics

Already in the mid-1980s, researchers working in statistical mechanics – a field concerned with the interaction of large numbers of particles – set out to better understand how machines learn. They noticed that magnets with disorderly magnetisation (known as "spin glasses") can serve as a physical realisation for certain mathematical rules used in machine learning. This, in turn, means the physical behaviour of these magnets sheds light on some properties of machines that learn, such as their storage capacity (Peretto, 1984). Back then, physicists also used techniques from statistical mechanics to classify the learning abilities of algorithms.

Particle physicists, too, were at the forefront of machine learning. The first workshop on Artificial Intelligence in High Energy and Nuclear Physics was held as early as 1990. Workshops in this series still take place but have since been renamed to Advanced Computing and Analysis Techniques. This may be because the new acronym, ACAT, is catchier. However, it also illustrates the phrase "artificial intelligence" is no longer in common use among researchers in physics.

Physicists avoid the term "artificial intelligence" because it reeks of hype and because the analogy to natural intelligence is superficial at best, misleading at worst. True, the current models are loosely based on the human brain's architecture. The term "neural networks" refers not to an actual structure, such as a neuron, but to algorithms based on mathematical representations of "neurons" connected by "synapses". Using feedback about its performance – the "training" – the algorithm then "learns" to optimise a quantifiable goal, such as recognising an image or predicting a data-trend.

This type of iterative learning is certainly one aspect of intelligence, but it is far from complete. The current algorithms rely heavily on humans to provide suitable input data. They do not formulate their own goals.

They do not propose models. They are, for what physicists are concerned, simply elaborate ways of fitting and extrapolating data.

So, what novelty can AI bring to physics? A lot, it turns out. The techniques are not new – even deep learning, a neural network with three or more layers, dates back to the early 2000s. However, today's ease of use and sheer computational power mean that computers can perform tasks previously reserved for humans.

Developments in AI have also enabled scientists to explore entirely new research directions. Until a few years ago, other computational methods often outperformed machine learning, but now it leads in many different areas. This is why, in recent years, interest in machine learning has spread into seemingly every niche of physics.

Most applications of AI in physics loosely fall into three main categories: data analysis, modelling and model analysis.

Data analysis

Data analysis is the most widely known application of machine learning. Neural networks can be trained to recognise specific patterns, and can also learn to find new patterns on their own. In physics, this is used in image analysis, such as when astrophysicists search for signals of gravitational lensing. Gravitational lensing happens when space-time around an object is deformed so much that it noticeably distorts the light coming from behind it. The recent, headline-making, black hole image is an extreme example. However, most gravitational lensing events are more subtle, resulting in smears or partial arcs of light. AIs can learn to identify them.

Particle physicists also use neural networks to find patterns, both specific and unspecific. Highly energetic particle collisions, like those done at the Large Hadron Collider, produce huge amounts of data. Neural networks can be trained to flag interesting events. Similar techniques have been used to identify certain types of gamma-ray bursts (Chen and Bo-Qiang, 2021). They may also soon help to find gravitational waves (George and Huerta, 2018).

Data analysis is not necessarily passive. Achieving fusion power requires solutions to the challenge of suspending a super-heated plasma in a torus of powerful magnets. Using AI to analyse the dynamics of the plasma and predict instabilities can help control a potentially chaotic system (Degrave et al., 2022).

Modelling

Machine learning aids the modelling of physical systems by both speeding up existing calculations and enabling new types. For example, simulations for the formation of galaxies take a long time even on the current generation of supercomputers. However, neural networks can learn to extrapolate from the existing simulations without re-running the full simulation each time. This technique was successfully used to match the amount of dark matter to the amount of visible matter in galaxies (Moster et al., 2021). Neural networks have also been used to reconstruct what happens when cosmic rays hit the atmosphere (Erdmann et al., 2018), or how elementary particles are distributed inside composite particles (Forte et al., 2002).

Model analysis

Machine learning is applied to better understand the properties of known theories that cannot be extracted by other mathematical methods or to speed up computation. For example, the interaction of many quantum particles can result in a variety of phases of matter beyond the commonly known gases, liquid, solids and superfluids. However, existing mathematical methods have not allowed physicists to calculate these phases. Neural nets can encode the many quantum particles and then classify the different types of behaviour.

Similar ideas underlie neural networks that seek to classify the properties of materials, such as conductivity or compressibility. The theory for materials' atomic structure is known in principle. However, many calculations needed to operationalise the theory are so vast that they have exceeded computational resources. Machine learning is beginning to change that. Many hope it may one day allow physicists to find materials that are superconducting at room temperature. Success in this search would have major practical applications, from medicine to computing. Another fertile area for applications of neural nets is "quantum tomography", i.e. the reconstruction of quantum state from the measurements performed on it, a problem of high relevance for quantum computing.

Machine learning advances physics, but physics can in return advance machine learning. At present, it is not well understood just why neural nets work as well as they do. Since some neural networks can be represented as physical systems, knowledge from physics may shed light on how they operate.

Conclusion

The use of AI in physics is not new. However, today's ease of use, technical progress and enormous computational power mean that machine learning can rather suddenly allow physicists to tackle a lot of problems that were previously intractable. What does this mean for the future of physics? Will we see the "end of theory" predicted by Chris Anderson in his much-cited paper (Anderson, 2008)?

It is unlikely. There are many different types of neural networks, which differ in their architecture and learning schemes. Physicists have to understand which algorithm works for which situation and how well, the same process they went through for theory. Rather than spelling the end of theory, machine learning will take it to the next level.

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