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Transforming Physics Through Artificial Intelligence: A Comparative Study of Pre-AI and Post-AI Eras

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Abstract
This research paper looks at how physics has changed over time from the way of doing things before artificial intelligence to the new way of doing things with artificial intelligence. For a time, physicists used mathematical solutions to understand the world. With artificial intelligence physicists can now use machine learning and artificial neural networks to do their work. This paper looks at two areas of physics: non-linear dynamics and astrophysics. It shows how artificial intelligence can help physicists do their work faster and better. It also shows that artificial intelligence has its own problems. This paper says that the future of physics is not about using artificial intelligence but about using artificial intelligence and classical physics together.

Keywords: Artificial Intelligence, Computational Physics, Exoplanets, Machine Learning, Non-linear Dynamics

Introduction

Physics has always tried to make sense of the world by using powerful mathematical ideas. From Isaac Newton to today physicists have used these ideas to understand the world. As physics has gotten more complex it has become harder to use just mathematical solutions. Physicists have had to use computers to help them. Now they are using artificial intelligence.

The old way of doing physics before intelligence used numerical methods like the Runge-Kutta method. These methods were good. They had problems. They were slow. Could not handle complex systems. With intelligence physicists can now use machine learning and artificial neural networks to do their work. These new methods are faster. Can handle complex systems but they also have problems. They are not transparent. It is hard to understand how they work.

Review of Related Literature

The way physicists do their work has changed over time. Before computers physicists used solutions to understand the world. With computers physicists started using methods like the Runge-Kutta method. In the 1960s physicists started using computers to simulate systems. With artificial intelligence physicists can now use machine learning and artificial neural networks to do their work. One of the papers on using artificial intelligence in physics was written by Carleo and Troyer in 2017. They showed how artificial neural networks could be used to solve the many-body problem. Since then many papers have been written on using intelligence in physics. Pathak et al. showed how reservoir computing could be used to learn the phase space of chaotic systems. Shallue and Vanderburg showed how a Convolutional Neural Network could be used to detect exoplanets.

Objectives

The first objective of this paper is to compare the way of doing physics with the new way of doing physics with artificial intelligence. The second objective is to evaluate the effectiveness of intelligence in experimental data analysis. The third objective is to construct a reference matrix that outlines the operational methodologies, primary applications and fundamental limitations of both paradigms. The fourth objective is to analyze the epistemological shift in physics addressing the transition from explicit transparent mathematical derivation to implicit opaque algorithmic optimization. The research questions are: How do iterative solvers and trained neural networks differ in terms of computational cost? When there is a lot of noise in data at what point do traditional analytical models stop working? Does relying on intelligence that is not transparent compromise the main goal of physics?

Methodology

To compare the pre-AI and post-AI eras in a way that is robust and scientifically valid this research uses a comparative methodology that looks at two case studies. This framework is designed to contrast algorithmic processing with stochastic data-driven optimization. By focusing on two sub-fields non-linear dynamics and experimental astrophysics the study ensures that the findings are applicable to both computational simulation and data analysis.

The Pre-AI Framework

The pre-AI methodology is based on deduction. It assumes that the laws governing the system are perfectly known, such as Newtons Second Law or Maxwells equations. The process involves translating these differential equations into discrete difference equations that a computer can process iteratively. In this study the pre-AI framework is represented by the 4th-order Runge-Kutta method. This method calculates the state of a system at a given time by evaluating the derivative at four points computing a weighted average to achieve a highly accurate prediction. However, this framework has a limitation: it is sequential meaning that the state at a later step cannot be computed without first computing all previous steps.

The Post-AI Framework

The post-AI methodology is based on induction. Than explicitly programming the physical equations a machine learning architecture is instantiated with randomized internal parameters. The framework relies on a training phase, where the model is fed amounts of data either from real-world experiments or generated by high-fidelity pre-AI simulations. Through the process of backpropagation and gradient descent the algorithm iteratively adjusts its weights to minimize a predefined loss function.

Findings and Discussion

The application of the methodology yields insights into the differences between the pre-AI and post-AI eras of computational physics. This section presents an in-depth analysis of the two case studies highlighting the divergence in error handling, speed and feature extraction.

Case Studies Analysis

In simulating the double pendulum, the pre-AI Runge-Kutta method demonstrates the value of mathematical rigor. However the analysis reveals a critical failure point to deterministic methods in chaotic regimes. The post-AI neural network approach redefines the problem creating a topological map correlating inputs to outputs. The training phase requires computational power but once trained the inference time is fractions of a millisecond.

The analysis of astrophysics data provides a compelling argument for the integration of artificial intelligence. The post-AI application of a Convolutional Neural Network resolves the issue of noise through feature extraction. The neural network learns what a transit looks like under an array of noisy conditions isolating only the specific 'U-shape' characteristic of a planetary transit.

Table 1. Reference Table of Methodological Comparisons

Parameter	**Pre-AI Era**	**Post-AI Era**
Core Mechanism	Explicit deduction, formulas	Implicit induction, data-driven algorithms
Computational Speed	Slow at execution scales poorly	Slow at training nearly instantaneous at execution
Interpretability	Complete transparency	Severe opacity neural weights
Handling of Noise	Highly susceptible	Highly robust convolutional layers

Epistemology of the Black Box

The move from physics to physics that uses artificial intelligence is changing the way we think about knowledge. For a time physics has been about breaking down complex systems into smaller parts and describing them with math. With artificial intelligence we can get the right answer without really understanding how it works. This is because artificial intelligence models are like boxes. We put in the data and get out the answer but we do not really know what is going on inside. One solution to this problem is to use something called Physics-Informed Neural Networks. These are intelligence models that are designed to follow the basic laws of physics.

Conclusion

The move from physics to physics that uses artificial intelligence is a big deal. Traditional methods are still important because they are transparent and follow the laws of physics. Artificial intelligence can do things that traditional methods cannot. It can handle huge amounts of data and do simulations really fast. The problem is that artificial intelligence can be a box and we need to be careful not to lose sight of what is really going on.

So what does this mean for the future of physics? It means that physicists need to be able to speak two languages. The language of physics and the language of artificial intelligence. They need to know how to use intelligence to get results but also how to understand what those results mean. This is especially important for students who are just starting out in physics.

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