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OVERVIEW OF PHYSICS-INFORMED NEURAL NETWORKS APPLICATIONS

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Abstract: When simulating various physical phenomena, the law of the phenomenon is often known in advance, in the form of a partial differential equation, that needs to be solved. Numerical methods, such as the finite element method, have been developed over decades, and these methods approximate the solution to the partial differential equation. However, these methods can be computationally demanding. On the other hand, neural networks, can provide predictions that approximate the given partial differential equation. Neural networks are computationally more efficient than numerical methods, but they often face issues of generalization and consequently problems with solution accuracy. Insufficient generalization, among other things, can result from data collected from numerical simulations. In the last few years, physics-informed neural networks are being developed, for which it's not necessary to gather data from simulations. These networks use automatic differentiation and during training, they minimize the residuals of the partial differential equation, its initial, and boundary conditions. After training, these neural networks can be used as a replacement for traditional numerical solvers.

Keywords: physics-informed neural networks, numerical analysis, machine learning.

1. INTRODUCTION

Physics-Informed Neural Networks (PINNs) represent a powerful synergy between machine learning and physics, blending the predictive capabilities of neural networks with the governing laws of the physical world. PINNs are designed to solve problems that involve partial differential equations (PDEs) or other physics-based constraints, making them particularly suitable for scenarios where accurate modeling of underlying physical processes is essential.

Unlike traditional neural networks that solely learn from data, PINNs embed domain knowledge and fundamental physics principles directly into their architecture. By incorporating these principles as constraints during training, PINNs can significantly enhance their predictive accuracy, even when data is sparse or noisy. This hybrid approach enables them to provide reliable solutions, especially in cases where purely data-driven models might struggle.

The applications of Physics-Informed Neural Networks are wide-ranging and impactful. They find use in fields such as fluid dynamics, heat transfer, structural mechanics, geophysics, quantum mechanics, medical imaging, renewable energy, material science, climate modeling, and more. By marrying the strengths of machine learning and physics, PINNs offer a versatile toolset to tackle complex, real-world problems that demand both accurate data-driven insights and a deep understanding of the underlying physical phenomena.

2. METHODS

Physics-informed neural networks (PINNs) are trained to solve supervised learning tasks while respecting any given law of physics described by general nonlinear partial differential equations [1-5].

These neural networks form a new class of data-efficient universal function approximators that naturally encode any underlying physical laws as prior information [1]. The major innovation with PINN is the introduction of a residual network that encodes the governing physics equations, takes the output of a deep-learning network, called surrogate, and calculates a residual value [2]. The residual of the differential equation is minimized by training the neural network. PINNs calculate differential operators on graphs using automatic differentiation.

The basic formulation of the PINN training does not require labeled data, results from other simulations or experimental data, and is unsupervised. PINNs only require the evaluation of the residual function. Providing simulation data or experimental data for training the network in a supervised manner is also possible and necessary in some cases, especially inverse problems. The supervised approach is often used for solving ill-defined problems when for instance we lack boundary conditions or an Equation of State to close a system of equations.

Once a PINN is trained, the inference from the trained PINN can be used to replace traditional numerical solvers in scientific computing [2]. PINNs are a gridless method because any point in the domain can be taken as input without requiring the definition of a mesh. Moreover, the trained PINN network can be used for predicting the values on simulation grids of different resolutions without the need of being retrained [2,3]. PINNs can also be used for time-dependent problems. Since time is represented as any other variable, it's possible to have a prediction of output at the specified time without solving for previous time steps.

3. APPLICATIONS

In this section we will list some of the applications of physics-informed neural networks, divided into following categories:

1. **Fluid Dynamics and Aerodynamics**: PINNs Fluid dynamics and aerodynamics represent fields where Physics-Informed Neural Networks (PINNs) have demonstrated remarkable potential. In these areas, understanding the behavior of fluid flows around complex geometries is crucial for designing efficient and safe transportation systems, optimizing energy usage, and enhancing performance in various applications. PINNs provide a unique advantage by combining data-driven learning with the governing equations of fluid dynamics, such as the Navier-Stokes equations. The Navier-Stokes equations describe the motion of fluid substances and are fundamental in understanding fluid flow behavior. PINNs incorporate these equations as constraints during training, allowing the neural network to learn not only from available data but also from the underlying physical laws. This hybrid approach enables accurate predictions and simulations of fluid flows

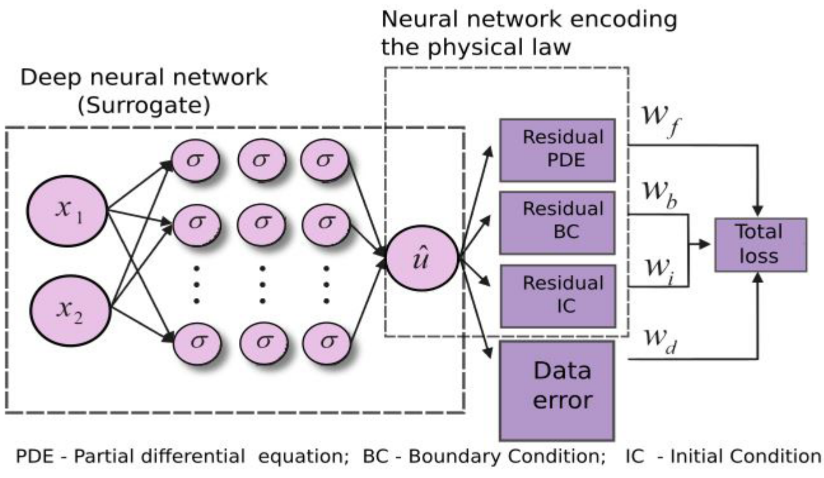

Figure 1. *Schematic of the Physics-informed neural network*

that can be challenging to achieve using traditional methods alone. One noteworthy application is in predicting aerodynamic characteristics [6]. By leveraging PINNs, researchers can analyze and optimize the shapes of aircraft, vehicles, and other objects interacting with a fluid medium. This leads to improved efficiency, reduced drag, and enhanced overall performance. PINNs have also shown promise in simulating turbulent flows, which are notoriously complex and computationally demanding. Their ability to capture turbulent behavior accurately and efficiently has the potential to revolutionize aerodynamic research and design processes.

2. **Heat Transfer**: PINNs can model heat conduction, convection, and radiation in various materials. This is useful in designing cooling systems, predicting temperature distributions, and optimizing thermal management in electronic devices. In the context of heat transfer, PINNs allow the incorporation of governing equations such as the heat equation or the energy conservation equation [7]. These equations describe how heat is transferred within materials and between different mediums. By embedding these physics-based constraints into the neural network architecture, PINNs can accurately predict temperature profiles, heat fluxes, and other thermal characteristics in complex scenarios. One of the key advantages of using PINNs in heat transfer analysis is their ability to handle intricate geometries and material properties. Traditional analytical or numerical methods often struggle with complex geometries and nonlinear material behavior, which can be common in real-world applications. PINNs, however, can learn and adapt to these complexities from data, making them versatile tools for simulating heat transfer in a wide range of situations.

3. **Structural Mechanics**: PINNs can simulate the behavior of structures under mechanical loads. By incorporating principles from mechanics and elasticity, they can predict stress, strain, deformation, and failure in structures, aiding in design optimization and safety analysis. In structural mechanics, PINNs allow the incorporation of fundamental equations governing the behavior of materials and structures, such as the equations of linear elasticity. By encoding these equations as constraints during training, the neural network can learn how different forces and loads affect the mechanical response of structures. One significant advantage of using PINNs in this context is their ability to handle complex geometries and nonlinear material behavior. They can predict structural responses in scenarios where traditional analytical or numerical methods may fall short. Moreover, PINNs can reduce the computational cost associated with solving complex structural problems, making them an efficient tool for design and analysis.

4. **Geophysics and Seismic Imaging**: In the field of geophysics, PINNs can help solve inverse problems related to seismic imaging. By incorporating wave equations and boundary conditions, they can enhance the accuracy and speed of seismic image reconstruction.

5. **Quantum Mechanics and Chemistry**: PINNs can be used to solve Schrödinger's equation to predict molecular and quantum mechanical properties of materials. This has applications in drug discovery, material design, and quantum chemistry.

6. **Inverse Problems in Medical Imaging**: PINNs can help in solving inverse problems encountered in medical imaging, such as tomography. By incorporating knowledge of the imaging physics and constraints, they can enhance the quality of reconstructed images and reduce the required measurements.

7. **Renewable Energy Modeling**: PINNs can simulate and optimize the behavior of renewable energy systems, such as solar panels and wind turbines. They can predict power output, efficiency, and optimal operating conditions.

8. **Material Science and Engineering**: By integrating material properties and physical behavior into the network, PINNs can help design new materials with desired properties or optimize existing ones.

9. **Oceanography and Climate Modeling**: PINNs can model ocean currents, heat transfer in oceans, and interactions between oceanic and atmospheric processes. This aids in climate modeling and predicting the effects of climate change.

10. **Optimization in Engineering**: PINNs can be used for shape optimization and design in various engineering domains. By incorporating physics-based constraints, they can find optimal designs that meet specific performance criteria.

4. CONCLUSIONS

In all these applications, Physics-Informed Neural Networks bridge the gap between data-driven machine learning techniques and the underlying physical principles governing the systems. They offer a way to leverage both data and domain knowledge to achieve accurate and reliable predictions in complex physical scenarios.

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ОСВРТ НА УПОТРЕБУ НЕУРОНСКИХ МРЕЖА ПОДРЖАНИХ ФИЗИЧКИМ ЗАКОНИМА

Сажетак: Закон функционисања физичке појаве која се симулира често је познат у виду парцијалне диференцијалне једначине, коју треба решити. Нумеричке методе за решавање ових једначина, као што је метод коначних елемената, развијане су деценијама. Међутим, ове методе могу бити веома рачунски захтевне. Са друге стране, неуронске мреже, након обуке, могу дати предикције које приближно решавају дату парцијалну диференцијалну једначину. Неуронске мреже су рачунски ефикасније од нумеричких метода, али се често јављају проблеми генерализације и последично проблеми са прецизношћу решења. Недовољно добра генерализација, између осталог, може бити последица прикупљених података из нумеричких симулација. Последњих неколико година, развијају се неуронске мреже подржане физичким законима, за које није неопходно прикупљати податке из симулација. Ове мреже користе аутоматску диференцијацију и приликом обуке се минимизују резидуали парцијалне диференцијалне једначине, њених почетних и граничних услова. Након обуке ове неуронске мреже могу се користити као замена за традиционалне нумеричке солвере.

Кључне речи: неуронске мреже подржане физичким законима, нумеричка анализа, машинско учење.

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