Physics of Data. Part XI

Physics of Data. Part XI | Alfonso R. Reyes

Applications of Physics Learning Machines

a.k.a. Physics-Informed Neural Networks;
a.k.a. Neural ODEs;
a.k.a. Physics-informed deep learning;
a.k.a. Multi physics-informed neural networks;
a.k.a. Physics-integrated neural networks;
a.k.a. Physics-informed neural ODEs;
a.k.a. Physics-informed deep learning;
a.k.a. Physics-informed machine learning;
a.k.a. Deep hidden physics models;
a.k.a. Physics-Informed DeepONets;
a.k.a. Physics Graph Neural Networks;
a.k.a. Physics-informed Generative Adversarial Networks;
a.k.a. Hybrid Physics-informed neural networks;
a.k.a. Conservative physics-informed neural networks;
a.k.a. Self-adaptive physics-informed Quantum machine learning;
a.k.a. Bayesian physics-informed Korlmorov-Arnold networks;
a.k.a. Finite Basis physics-informed neural networks;
a.k.a. Stochastic physics-informed neural ODEs;
etc.

These are the top 10 applications of PINNs found in 200+ papers, exclusively, on Physics enforced neural networks:

1. inverse problems
2. Navier-Stokes equations
3. Burgers' equation
4. simulation
5. forward problems
6. surrogate modeling
7. fluid dynamics
8. time-series
9. uncertainty quantification
10. image classification

This research is still work in progress and may change as more papers are being documented in a dataset built with Obsidian. There are other 262 applications in the PDF attached.

The list still needs to be classified in super-classes, classes, and sub-classes.

SciML Neural Networks PINN Physics Physics Of Data SPE Petroleum Engineering

Alfonso R. Reyes • You
VP Artificial Intelligence Engineering - Energy Division
5mo • Edited •

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#SCiML #neuralNetworks #PINN #physics #PhysicsOfData #SPE #pet

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Object (272)	Count
inverse problems	47
Navier-Stokes Equations	46
Burgers' equation	28
Simulation	23
forward problems	17
surrogate modeling	17
fluid dynamics	14
time-series	13
uncertainty quantification	12
Image Classification	11
Nonlinear Allen-Cahn equation	11
Advection-diffusion-reaction system	10
Korteweg-de Vries equation	10
Poisson equation	10
Schrodinger's Equations	9
parameter estimation	9
continuous-time models	8
heat equation	8
Image Recognition	7
Lotka-Volterra model	7
biological systems	7
Brownian Motion	6
Darcy Flow	6