

# Accepted Manuscript

Hidden Physics Models: Machine Learning of Nonlinear Partial Differential Equations

Maziar Raissi, George Em Karniadakis

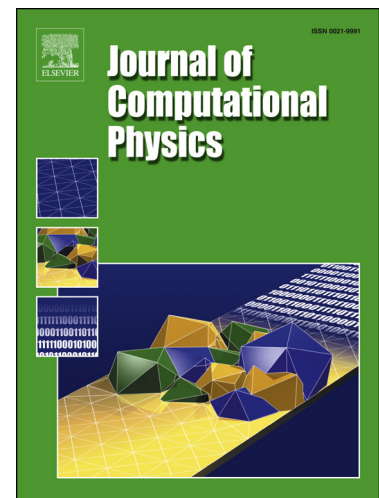
PII: S0021-9991(17)30901-4  
DOI: <https://doi.org/10.1016/j.jcp.2017.11.039>  
Reference: YJCPH 7754

To appear in: *Journal of Computational Physics*

Received date: 22 August 2017  
Revised date: 11 October 2017  
Accepted date: 7 November 2017

Please cite this article in press as: M. Raissi, G.E. Karniadakis, Hidden Physics Models: Machine Learning of Nonlinear Partial Differential Equations, *J. Comput. Phys.* (2017), <https://doi.org/10.1016/j.jcp.2017.11.039>

This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.



# Hidden Physics Models: Machine Learning of Nonlinear Partial Differential Equations

Maziar Raissi and George Em Karniadakis

*Division of Applied Mathematics, Brown University,  
Providence, RI, 02912, USA*

---

## Abstract

While there is currently a lot of enthusiasm about “big data”, useful data is usually “small” and expensive to acquire. In this paper, we present a new paradigm of learning partial differential equations from *small* data. In particular, we introduce *hidden physics models*, which are essentially data-efficient learning machines capable of leveraging the underlying laws of physics, expressed by time dependent and nonlinear partial differential equations, to extract patterns from high-dimensional data generated from experiments. The proposed methodology may be applied to the problem of learning, system identification, or data-driven discovery of partial differential equations. Our framework relies on Gaussian processes, a powerful tool for probabilistic inference over functions, that enables us to strike a balance between model complexity and data fitting. The effectiveness of the proposed approach is demonstrated through a variety of canonical problems, spanning a number of scientific domains, including the Navier-Stokes, Schrödinger, Kuramoto-Sivashinsky, and time dependent linear fractional equations. The methodology provides a promising new direction for harnessing the long-standing developments of classical methods in applied mathematics and mathematical physics to design learning machines with the ability to operate in complex domains without requiring large quantities of data.

**Keywords:** probabilistic machine learning, system identification, Bayesian modeling, uncertainty quantification, fractional equations, small data

---

Download English Version:

<https://daneshyari.com/en/article/6929122>

Download Persian Version:

<https://daneshyari.com/article/6929122>

[Daneshyari.com](https://daneshyari.com)