cases	doc_1	doc_2	decision	id
authors	• Wayne Isaac Tan Uy • Mircea Grigoriu	• W. I. Uy • M. Grigoriu	DUPLICATES	283
title	Neural network representation of the probability density function of diffusion processes	Neural network representation of the probability density function of diffusion processes.		
publication_date	2020-04-19 00:00:00	2020-01-15 00:00:00		
source	SupportedSources.INTERNET_ARCHIVE	SupportedSources.SEMANTIC_SCHOLAR		
journal		Chaos		
volume		30 9		
doi		10.1063/5.0010482		
urls	• https://web.archive.org/web/20200508014248/https://arxiv.org/pdf/2001.05437v2.pdf	• https://www.semanticscholar.org/paper/40ec128be83548f20fccc5801c25a5eb195cd82e		
id	id1805920897457675023	id7733395427928289399		
abstract	Physics-informed neural networks are developed to characterize the state of dynamical systems in a random environment. The neural network approximates the probability density function (pdf) or the characteristic function (chf) of the state of these systems which satisfy the Fokker-Planck equation or an integro-differential equation under Gaussian and/or Poisson white noises. We examine analytically and numerically the advantages and disadvantages of solving each type of differential equation to characterize the state. It is also demonstrated how prior information of the dynamical system can be exploited to design and simplify the neural network architecture. Numerical examples show that: 1) the neural network solution can approximate the target solution even for partial integro-differential equations and system of PDEs describing the time evolution of the pdf/chf, 2) solving either the Fokker-Planck equation or the chf differential equation using neural networks yields similar pdfs of the state, and 3) the solution to these differential equations can be used to study the behavior of the state for different types of random forcings.	Physics-informed neural networks are developed to characterize the state of dynamical systems in a random environment. The neural network approximates the probability density function (pdf) or the characteristic function (chf) of the state of these systems, which satisfy the Fokker-Planck equation or an integro-differential equation under Gaussian and/or Poisson white noises. We examine analytically and numerically the advantages and disadvantages of solving each type of differential equation to characterize the state. It is also demonstrated how prior information of the dynamical system can be exploited to design and simplify the neural network architecture. Numerical examples show that (1) the neural network solution can approximate the target solution even for partial integro-differential equations and a system of partial differential equations describing the time evolution of the pdf/chf, (2) solving either the Fokker-Planck equation or the chf differential equation using neural networks yields similar pdfs of the state, and (3) the solution to these differential equations can be used to study the behavior of the state for different types of random forcings.		
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