

Forward to the Special Topic on “Solving Differential Equations with Deep Learning”

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The concept of artificial intelligence (AI) was first presented at the Dartmouth Summer Research Project on AI hosted by McCarthy and Minsky in 1956. After that, the development of AI has experienced ups and downs due to some limited conditions including intelligent computing techniques, computer and hardware and software^[1, 2]. In particular, with the rapid of deep artificial neural networks, machine learning (ML) and deep learning (DL) techniques^[3, 4] have been applied in many fields of science and engineering, including machine translation, image recognition, genomics, scientific computing and atmospheric science, etc^[5].

More recently, some DL techniques were presented to study the forward and inverse problems of various models of mathematical physics (see, e.g., Refs. [6–10] and references therein). This special issue focuses on the DL methods and applications in some linear/nonlinear differential models: Guo and Ming^[11] studied the eigenvalues of the fractional Schrodinger operator (alias fractional Hamiltonian) via a novel deep learning method; Chen, et al.^[12] presented a Neumann series neural operator method to learn the solution operator of Helmholtz equation from inhomogeneity coefficients and source terms to solutions; Xiao, et al.^[13] proposed a structure-preserving recurrent Neural networks to study a Class of Birkhoffian systems; Wang and Cui^[14] used the deep learning method to predict the number of solitons of the KdV equation with a given initial value; Sun, et al.^[15] developed a physics-informed liquid networks to solve nonlinear partial differential equations; Liu, et al.^[16] proposed a pre-training physics-informed neural network with mixed sampling to study the higher-dimensional systems; Zhou^[17] developed a parallel physics-informed neural networks (PINNs) method to study the forward-inverse problems of the variable coefficient mKdV equation; Sun, et al.^[18] used the PINNs with two weighted loss functions to investigate interactions of two-dimensional oceanic internal waves.

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