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A nonlocal physics-informed deep learning framework using the peridynamic differential operator. (English) Zbl 07415658

Summary: The Physics-Informed Neural Network (PINN) framework introduced recently incorporates physics into deep learning, and offers a promising avenue for the solution of partial differential equations (PDEs) as well as identification of the equation parameters. The performance of existing PINN approaches, however, may degrade in the presence of sharp gradients, as a result of the inability of the network to capture the solution behavior globally. We posit that this shortcoming may be remedied by introducing long-range (nonlocal) interactions into the network’s input, in addition to the short-range (local) space and time variables. Following this ansatz, here we develop a nonlocal PINN approach using the Peridynamic Differential Operator (PDDO) – a numerical method which incorporates long-range interactions and removes spatial derivatives in the governing equations. Because the PDDO functions can be readily incorporated in the neural network architecture, the nonlocality does not degrade the performance of modern deep-learning algorithms. We apply nonlocal PDDO-PINN to the solution and identification of material parameters in solid mechanics and, specifically, to elastoplastic deformation in a domain subjected to indentation by a rigid punch, for which the mixed displacement-traction boundary condition leads to localized deformation and sharp gradients in the solution. We document the superior behavior of nonlocal PINN with respect to local PINN in both solution accuracy and parameter inference, illustrating its potential for simulation and discovery of partial differential equations whose solution develops sharp gradients.

MSC:
35-XX Partial differential equations
82-XX Statistical mechanics, structure of matter

Keywords:
deep learning; peridynamic differential operator; physics-informed neural networks; surrogate models

Software:
AlexNet; PyTorch; SciANN; Theano; AdaGrad; TensorFlow; GitHub; MXNet; Adam; Keras; ImageNet; COMSOL; SciPy; DiffSharp

Full Text: DOI arXiv

References:


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