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Vincenzo Schiano Di Cola
F. Giampaolo
G. Rozza
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<tr><th>volume</th><td>92</td></tr>
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<tr><th>abstract</th><td>Physics-Informed Neural Networks (PINN) are neural networks (NNs) that encode model equations, like Partial Differential Equations (PDE), as a component of the neural network itself. PINNs are nowadays used to solve PDEs, fractional equations, integral-differential equations, and stochastic PDEs. This novel methodology has arisen as a multi-task learning framework in which a NN must fit observed data while reducing a PDE residual. This article provides a comprehensive review of the literature on PINNs: while the primary goal of the study was to characterize these networks and their related advantages and disadvantages. The review also attempts to incorporate publications on a broader range of collocation-based physics informed neural networks, which stars form the vanilla PINN, as well as many other variants, such as physics-constrained neural networks (PCNN), variational hp-VPINN, and conservative PINN (CPINN). The study indicates that most research has focused on customizing the PINN through different activation functions, gradient optimization techniques, neural network structures, and loss function structures. Despite the wide range of applications for which PINNs have been used, by demonstrating their ability to be more feasible in some contexts than classical numerical techniques like Finite Element Method (FEM), advancements are still possible, most notably theoretical issues that remain unresolved.</td></tr>
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