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Respecting Causality Is All You Need for Training Physics-informed Neural Networks

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While the popularity of physics-informed neural networks (PINNs) is steadily rising, to this date PINNs have not been successful in simulating dynamical systems whose solution exhibits multi-scale, chaotic or turbulent behavior. In this work we attribute this shortcoming to the inability of existing PINNs formulations to respect the spatio-temporal causal structure that is inherent to the evolution of physical systems. We argue that this is a fundamental limitation and a key source of error that can ultimately steer PINN models to converge towards erroneous solutions. We address this pathology by proposing a simple re-formulation of PINNs loss functions that can explicitly account for physical causality during model training. We demonstrate that this simple modification alone is enough to introduce significant accuracy improvements, as well as a practical quantitative mechanism for assessing the convergence of a PINNs model. We provide state-of-the-art numerical results across a series of benchmarks for which existing PINNs formulations fail, including the chaotic Lorenz system, the Kuramoto–Sivashinsky equation in the chaotic regime, and the Navier-Stokes equations in the turbulent regime. To the best of our knowledge, this is the first time that PINNs have been successful in simulating such systems, introducing new opportunities for their applicability to problems of industrial complexity.