Physics-aware deep neural networks for surrogate modeling of turbulent natural convection

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Abstract

Recent works have explored the potential of machine learning as data-driven turbulence closures for RANS and LES techniques. Beyond these advances, the high expressivity and agility of physics-informed neural networks (PINNs) make them promising candidates for full fluid flow PDE modeling. An important question is whether this new paradigm, exempt from the traditional notion of discretization of the underlying operators very much connected to the flow scales resolution, is capable of sustaining high levels of turbulence characterized by multi-scale features? We investigate the use of PINNs surrogate modeling for turbulent Rayleigh-Bénard (RB) convection flows in rough and smooth rectangular cavities, mainly relying on DNS temperature data from the fluid bulk. We carefully quantify the computational requirements under which the formulation is capable of accurately recovering the flow hidden quantities. We then propose a new padding technique to distribute some of the scattered coordinates - at which PDE residuals are minimized - around the region of labeled data acquisition. We show how it comes to play as a regularization close to the training boundaries which are zones of poor accuracy for standard PINNs and results in a noticeable global accuracy improvement at iso-budget. Finally, we propose for the first time to relax the incompressibility condition in such a way that it drastically benefits the optimization search and results in a much improved convergence of the composite loss function. The RB results obtained at high Rayleigh number $Ra = 2 \cdot 10^9$ are particularly impressive: the predictive accuracy of the surrogate over the entire half a billion DNS coordinates yields errors for all flow variables ranging between $[0.3\% - 4\%]$ in the relative L_2 norm, with a training relying only on 1.6% of the DNS data points.

Keywords: deep learning, machine learning, PINNs, DNS, turbulence, convection