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SCIENTIFIC MACHINE LEARNING GUIDED BY NUMERICAL ANALYSIS

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ABSTRACT

Scientific machine learning has rapidly emerged as a powerful paradigm for solving challenging problems in science and engineering, including partial differential equations, inverse problems, multiscale modeling, data assimilation, uncertainty quantification, and the discovery of governing laws from data. In particular, it is becoming increasingly important in applied mathematics and computational fluid dynamics, where one aims to model, simulate, and predict complex flow phenomena such as turbulence, multiphase flows, fluid–structure interaction, geophysical flows, and high-dimensional parametric fluid systems. Despite remarkable empirical success, many SciML methods still face fundamental challenges related to stability, accuracy, convergence, generalization, interpretability, and robustness, especially when available data are sparse, noisy, high-dimensional, or expensive to obtain.

The objective of this Minisymposium is to highlight the essential role of numerical analysis in developing reliable, efficient, and mathematically grounded scientific machine learning methods, with particular emphasis on applications to fluid mechanics and flow-related scientific computing. Classical concepts from numerical analysis, such as discretization, stability, convergence, structure preservation, error estimation, and efficient solvers, provide a natural framework for understanding and improving modern learning-based approaches to scientific computing. Rather than viewing machine learning as a replacement for traditional numerical methods, this Minisymposium emphasizes hybrid approaches in which data-driven models are guided, constrained, or enhanced by numerical principles and physical laws governing fluid flows. Topics of interest include physics-informed neural networks [1], neural operators [2], operator learning [3], reduced-order modeling [4], inverse problems, data assimilation, uncertainty quantification, turbulence modeling, flow control, and foundation models for scientific and fluid dynamical systems.

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