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# FLUID DYNAMICS AND SCIML: NAVIGATING CHALLENGES AND SEIZING OPPORTUNITIES

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## MINISYMPOSIUM

Computational Fluid Dynamics (CFD) with well-established numerical schemes such as finite difference, finite volume, and finite/spectral element methods, along with experimental measurements and analyses, have long been the cornerstones of research in fluid mechanics and engineering applications. They offer valuable insights into fluid flow phenomena. Turbulent flows, characterized by the nonlinear interaction of a wide range of spatial and temporal scales, are now better predicted thanks to High-Performance Computing (HPC) and improved turbulence modeling and dynamics learning.
However, the enormous amount of potentially noisy data generated, the modeling complexity of multi-scale/phase/physics high-dimensional real-world problems, and the need for parametric explorations call for a shift in paradigm in which scientific machine learning (SciML) plays an increasingly important role alongside more traditional physical modeling. This becomes particularly relevant for multi-query approaches required for uncertainty quantification, robust design optimization, reduced-order modeling, manifold learning, and adaptive control in fluid flow applications.
Recent AI techniques have demonstrated their potential for data-driven modeling in the era of big data, enhancing efficiency and providing data-driven insights. In this mini-symposium (MS), we are also keenly interested in physics-informed modeling and the combination of these techniques at the interface between traditional methods and emerging data-driven approaches. Furthermore, we aim to understand how essential CFD components, such as adaptivity, mesh refinement, error control, multi-fidelity, super resolution, HPC efficiency, and storage, transition into the era of scientific machine learning.
In this MS, all classes of machine learning methods, including Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), AutoEncoders, U-Net, Reinforcement Learning (RL), Generative Adversarial Networks (GANs), and Reduced-Order Models (ROMs), will be very welcome, especially if they incorporate physical knowledge. Envisioned applications are diverse and include the development and calibration of turbulence modeling, simulations of shocked flows, wall modeling, active flow control, aerodynamic and aeroelastic optimization, modeling biological and cardiovascular flows, fluid-structure interactions, and uncertainty quantification in fluid flow phenomena.