Data-driven numerical and reduced order modeling of flows

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ABSTRACT

Machine learning changes paradigms in computational fluid mechanics through many different and fundamental ways. Traditional computational methods that have been around for decades may not be able to directly deal with noisy and dynamic big or small data, and it is worth exploring novel combinations of traditional and emerging machine learning techniques to reach beyond the current state of the art [1, 2]. The proposed minisymposium will provide a platform for exchange on most recent developments at the interface between data-driven learning, numerical method development for flow simulation and knowledge-driven approaches for reduced-order modelling of complex flow phenomena. The proposers have addressed aspects of these fields in their recent work, e.g. the development of nonlinear discretization schemes for physically complex flows [3]. Recurrent neural networks, such as long short-term memory or echo state networks, have been used to process sequential data, such that the dynamics and low-order statistics can be reproduced without solving the original nonlinear partial differential equations of fluid motion [4]. With the minisymposium we intend to span the full scope of machine-learning infused prediction of flows at the interface with physical knowledge and the fusion of experimental and numerical data, beyond traditional Kriging approaches. The minisymposium will bring together experts in this vital field of current research coming from fluid mechanics, applied mathematics, and physics who will present their recent work on the foundations and increasingly complex applications of machine learning.

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