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Exploration of data-driven numerical methods for fluid flows by end-to-end optimization

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The compressible Navier-Stokes equations govern compressible flows and allow for complex phenomena like turbulence and shocks. The reliable computation of fluids has been a long-lasting challenge due to nonlinear interactions over multiple spatio-temporal scales. We are currently witnessing a paradigm shift towards machine learning supported design of numerical schemes as a means to tackle aforementioned problem [1]. While prior work has explored differentiable algorithms for one-dimensional or two-dimensional incompressible fluid flows [2, 3, 4], we present a fully-differentiable three-dimensional framework for the computation of compressible fluid flows using high-order state-of-the-art numerical methods [5]. Firstly, we demonstrate the efficiency of our framework as a classical phyiscs simulator by computing two- and three-dimensional test cases, including strong shocks and transition to turbulence. Secondly, and more importantly, we showcase how our framework allows for end-to-end optimization to improve existing numerical schemes inside computational fluid dynamics algorithms, e.g. flux functions or subgrid-scale models.

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