Embedded model learning for fluid flows with scientific machine learning

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ABSTRACT

Many fluid flow models feature differential equations with terms that are partially unknown. For example, turbulent flows are usually solved with LES or RANS models, in which a closure term appears as a consequence of averaging the Navier-Stokes equations. Similarly, in (non-intrusive) reduced order models (NIROMs), operators are being derived in such a way to closely match (projected) snapshot data. Common in many approaches is that these unknown terms are being approximated in an 'offline' fashion, e.g. through a supervised learning approach, and then substituted back into the differential equation in order to give predictions in an 'online' setting [1]. An ongoing issue with this approach is that it is difficult to guarantee stability [2]: small deviations in the approximated terms can lead to large discrepancies or instabilities on long time intervals, depending on the nature of the dynamical system.

Recently, an alternative to this "derivative-fitting" approach has been proposed, known as "embedded model learning", "solver-in-the-loop", or "trajectory-fitting" [3,4]. In this approach, one learns a model in such a way that, upon embedding in the solver, it results in accurate predictions of the solution trajectory. This has the promise to lead to more stable models, but comes at the price of increased computational costs associated with differentiating through the entire differential equation solver (e.g. by using fully differentiable solvers or adjoints). Such fully differentiable solvers are actively being developed in the Scientific Machine Learning community [5].

In this minisymposium we bring together researchers working on learning models while being embedded into a differential equation solver. We welcome contributions on the topic of learning turbulence models, reduced order models, and other types of 'closure' models that appear in fluid flow equations. We also invite researchers with an interest in scientific machine learning for fluid flows to join the minisymposium.

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