USACM Workshop on Establishing Benchmarks for Data-Driven Modeling of Physical Systems
April 6-7, 2023, University of Southern California,, Los Angeles, California, USA

SOLVING INVERSE PROBLEMS VIA NEURAL NETWORK FLOW MAP APPROXIMATION

Joseph Hart[1], Mamikon Gulian[1], and Indu Manickam[1]

[1]Sandia National Laboratories

ABSTRACT

Operator learning has gained significant interest thanks to its potential as a non-intrusive reduced order model. It is particularly appealing in applications where computationally expensive coupled multi-physics models are commonly used, but only a subset of the relevant physics is important for a given scientific question. In this work, we consider solving source inversion problems for large-scale atmospheric transport related to naturally occurring and engineered stratospheric aerosol injections. We use a neural network approximation of the flow map, also called the evolution operator, to approximate specific atmospheric components of a global earth system model. To understand benefits and limitations of the approach, we consider two benchmark problems which introduce various aspects of the final earth system application. Our first demonstration is on a regional atmospheric transport partial differential equation for which we can rigorously test the accuracy of the learned operator and its efficacy in solving the associated inverse problem to estimate aerosol sources. We then transition to a more complex global model which captures the spatial scales of a full earth system model but can be more easily analyzed because it is not coupled with topography and oceans. These benchmarks are used to understand and demonstrate which features of atmospheric transport can and cannot be reasonably learned or reconstructed in a limited data setting where earth system model evaluations are the primary bottleneck. We will present the benchmark problems, our approach to solving inverse problems via learned flow maps, our results to date, and future goals to enable inversion by learning components of earth system models.