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Data-driven discovery of partial differential equations SAMUEL RUDY, Department of Applied Mathematics, University of Washington, Seattle, STEVEN BRUNTON, Department of Mechanical Engineering, University of Washington, Seattle, JOSHUA PROCTOR, Institute for Disease Modeling, J. NATHAN KUTZ, Department of Applied Mathematics, University of Washington, Seattle — Fluid dynamics is inherently governed by spatial-temporal interactions which can be characterized by partial differential equations (PDEs). Emerging sensor and measurement technologies allowing for rich, time-series data collection motivate new data-driven methods for discovering governing equations. We present a novel computational technique for discovering governing PDEs from time series measurements. A library of candidate terms for the PDE including nonlinearities and partial derivatives is computed and sparse regression is then used to identify a subset which accurately reflects the measured dynamics. Measurements may be taken either in a Eulerian framework to discover field equations or in a Lagrangian framework to study a single stochastic trajectory. The method is shown to be robust, efficient, and to work on a variety of canonical equations. Data collected from a simulation of a flow field around a cylinder is used to accurately identify the Navier-Stokes vorticity equation and the Reynolds number to within 1%. A single trace of Brownian motion is also used to identify the diffusion equation. Our method provides a novel approach towards data enabled science where spatial-temporal information bolsters classical machine learning techniques to identify physical laws.

Samuel Rudy
Department of Applied Mathematics, University of Washington, Seattle

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