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Learning interpretable stochastic models with sparse regression[1]

JARED CALLAHAM, University of Washington, JEAN-CHRISTOPHE LOISEAU, Arts et Metiers ParisTech, J. NATHAN KUTZ, STEVEN BRUNTON, University of Washington — Low-dimensional modeling is a promising avenue for enabling design, control, and physical understanding of complex flows. Data-driven approaches, which leverage the increasing availability of numerical and experimental data, are of particular interest. Recent results on laminar flows show that sparse Galerkin regression can be an effective tool for developing accurate minimum-complexity models. However, the separation of scales in turbulence presents a challenge for these fully resolved models. Alternatively, only dominant global variables may be explicitly modeled with smaller scales treated as stochastic forcing. When the dominant behavior is thought to be well-described by stereotypical dynamics such as the normal form of a bifurcation, the model parameters may be estimated using physical arguments or least-squares regression. More generally, we may not know the form of the equations a priori, and would like to discover a model directly from data. We describe an approach to learning interpretable stochastic models, devoting particular attention to practical considerations such as low sampling rates and time-correlated forcing. We apply our approach to prototypical nonlinear dynamics and demonstrate more accurate recovery than existing stochastic model discovery methods.

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