Interpretable data-driven model reduction for multiscale nonlinear dynamics

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Many systems of practical and basic research interest are characterized by strongly nonlinear dynamics across a wide range of scales. Even when first principles physical arguments can be used to derive highly accurate governing equations, these are often too complicated to be directly useful in practice For example, the Naver-Stokes equations give an essentially complete physical description of fluid dynamics, but engineering applications typically rely on a host of approximation techniques to reduce their complexity. We are interested in developing methods which can use the increasing wealth of experimental and numerical data to augment centuries of progress in physical modeling; in this talk we describe two such approaches. From one perspective, we seek to automatically identify spatiotemporal regions in which the observed behavior is dominated by a balance between subsets of terms in the governing equations, by analogy with the classical separation of aerodynamic flows into boundary layers and inviscid wakes. In another example, we identify low-dimensional stochastic models which approximate the evolution of coherent structures with simple nonlinear dynamics driven by random forcing from unobserved degrees of freedom. We explore these complexity reduction techniques in a wide range of systems: turbulence, nonlinear optics, ocean circulation, and neuroscience.