

SIMULTANEOUS LEARNING OF DYNAMICS AND COORDINATES, WITH EXAMPLES IN FLUID DYNAMICS

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This work describes how machine learning may be used to develop accurate and efficient nonlinear dynamical systems models for complex natural and engineered systems. We explore the sparse identification of nonlinear dynamics (SINDy) algorithm, which identifies a minimal dynamical system model that balances model complexity with accuracy, avoiding overfitting. This approach tends to promote models that are interpretable and generalizable, capturing the essential “physics” of the system. We also discuss the importance of learning effective coordinate systems in which the dynamics may be expected to be sparse. These coordinate systems are typically learned within the framework of a deep neural network autoencoder. Such autoencoders may also be used to learn coordinate systems where the dynamics become linear, related to Koopman operator theory. We will demonstrate this learning approach on a range of challenging modeling problems in fluid dynamics, and we will discuss how to incorporate these models into existing model-based control efforts. Because fluid dynamics is central to transportation, health, and defense systems, we will emphasize the importance of machine learning solutions that are interpretable, explainable, generalizable, and that respect known physics.

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