



Data-driven inference of the ordinary differential equation representation of a chaotic dynamical model using data assimilation

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Recent progress in machine learning has shown how to forecast and, to some extent, learn the dynamics of a model from its output, resorting in particular to neural networks and deep learning techniques. We will show how the same goal can be directly achieved using data assimilation techniques without leveraging on machine learning software libraries, with a view to high-dimensional models. The dynamics of a model are learned from its observation and an ordinary differential equation (ODE) representation of this model is inferred using a recursive nonlinear regression. Because the method is embedded in a Bayesian data assimilation framework, it can learn from partial and noisy observations of a state trajectory of the physical model. Moreover, a space-wise local representation of the ODE system is introduced and is key to deal with high-dimensional models.

The method is illustrated on several chaotic discrete and continuous models of various dimensions, with or without noisy observations, with the goal to identify or improve the model dynamics, build a surrogate or reduced model, or produce forecasts from mere observations of the physical model.

It has recently been suggested that neural network architectures could be interpreted as dynamical systems. Reciprocally, we show that our ODE representations are reminiscent of deep learning architectures. Furthermore, numerical analysis considerations on stability shed light on the assets and limitations of the method.