CRUNCH Seminars at Brown, Division of Applied Mathematics

Friday – April 12, 2019

Paper Review: Assessment of End-to-End and Sequential Data-driven Learning of Fluid Flows

Ameya Jagtap

In this work we explore the advantages of end-to-end learning of multilayer maps offered by feed forward neural-networks (FFNN) for learning and predicting dynamics from transient fluid flow data. While machine learning in general depends on data quality and quantity relative to the underlying dynamics of the system, it is important for a given learning architecture to make the most of this available information. To this end, we focus on data-driven problems where there is a need to predict over reasonable time into the future with limited data availability. Such function approximation or time series prediction is in contrast to many applications of machine learning such as pattern recognition and parameter estimation that leverage vast datasets. In this study, we interpret the suite of recently popular data-driven learning approaches that approximate the dynamics as Markov linear model in a higher-dimensional feature space as a multilayer architecture similar to neural networks. However, there exists a couple of key differences: (i) Markov linear models employ layer-wise learning in the sense of linear regression whereas neural networks represent end-to-end learning in the sense of nonlinear regression. We show through examples of data-driven modeling of canonical fluid flows that FFNN-like methods owe their success to leveraging the extended learning parameter space available in end-to-end learning without overfitting the data. In this sense, the Markov linear models behave as shallow neural networks. (ii) The second major difference is that while the FFNN is by design a forward architecture, the class of Markov linear methods that approximate the Koopman operator are bi-directional, i.e., they incorporate both forward and backward maps in order to learn a linear map that can provide insight into spectral characteristics. In this study, we assess both reconstruction as well as predictive performance of temporally evolving dynamic using limited snapshots of data for canonical nonlinear fluid flows including the transient limit-cycle attractor in a cylinder wake and the instability-driven dynamics of buoyant Boussinesq flow.
arXiv link: https://arxiv.org/abs/1806.08234