Auto-differentiable Data Assimilation and Neural ODEs for learning latent dynamics

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ABSTRACT

The development of data-informed predictive models for dynamical systems is of widespread interest in many disciplines. First, we will present a unifying framework for blending mechanistic and machine-learning approaches for identifying dynamical systems from data [1]. This framework is agnostic to the chosen machine learning model parameterization, and casts the problem in both continuous- and discrete-time. Second, we will focus on recent developments that fuse data assimilation with auto-differentiable ODE solvers which, when combined, allow us to learn from noisy, partial observations. Finally, we will conclude with examples on simulated Lorenz dynamics, and propose simple, yet challenging benchmarks for these systems that highlight a method's ability to cope with non-Markovianity induced by partial observations.

REFERENCES

[1] M. E. Levine and A. M. Stuart, A framework for machine learning of model error in dynamical systems, *Communications of the American Mathematical Society*, **2**, 283-344, 2017.