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Data assimilation schemes as a framework for learning dynamical model from partial and noisy observations

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The constantly increasing wealth of simulation and observation data on geophysical dynamics make more and more appealing data-driven strategies as new means to address key issues in ocean and atmosphere science, including for instance forecasting and assimilation issues. In this respect, recent studies have investigated data-driven strategies to identify governing equations from data using different machine learning frameworks, especially sparse regression models and neural networks. Among others, such data-driven representations of dynamical operators have shown to be of key interest for data assimilation issues, especially the spatio-temporal interpolation of geophysical fields from ocean remote sensing data.

The availability of representative training datasets is a strong requirement for the development of such approaches. When considering observation datasets (e.g., satellite-derived data or in-situ observations), the question whether one may learn such data-driven representations from noisy and partial observation data naturally arises. For instance, regarding sea surface dynamics, beyond observation noise patterns, satellite sensors also involve irregular space-time sampling patterns due to their intrinsic characteristics or their sensitivity to the atmospheric conditions. In this work, we investigate these issues. We show that the effectiveness of previously proposed learning-based methods is strongly affected when applied to noisy and partial observation datasets. Within a neural-network-based framework, we address the data-driven identification of governing equations as the joint learning of dynamical models and the assimilation of the hidden states from noisy and partial observations. We restate state-of-the-art assimilation schemes (e.g., Ensemble Kalman Filters, Variational schemes) as neural network architectures, such that the identification of the dynamical operator comes to the minimization of a data assimilation cost, rather than a simple forecasting error. From numerical experiments on Lorenz-63 dynamics and sea surface dynamics, we demonstrate the relevance of the proposed approaches for the data-driven identification of dynamical operators, both in terms of forecasting performance and long-term topological patterns, within respect to the state-of-the-art. These experiments also illustrate that different assimilation-inspired neural-network-based architectures may be of interest depending on the noise levels.