Geophysical Research Abstracts
Vol. 17, EGU2015-5776-1, 2015
EGU General Assembly 2015

Nonparametric and data-driven data assimilation for the reconstruction of complex geophysical dynamics

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Nowadays, ocean, atmosphere and climate sciences face a deluge of data pouring from space, in situ monitoring as well as numerical simulations. The availability of these different data sources offer new opportunities, still largely underexploited, to improve the understanding, modeling and reconstruction of geophysical dynamics. The classical way to reconstruct the space-time dynamics of a geophysical system from observation series relies on data assimilation methods, which perform multiple runs of the known dynamical model. This classical framework may have severe limitations including its computational cost, the lack of consistency of the model with respect to the observed data, modeling uncertainties.

Here, we explore an alternative approach and develop a fully data-driven framework. We assume that a representative catalog of examples of the space-time dynamics of the geophysical system of interest is available. Depending on the case-study, such a catalog may be issued from observations as well as numerical simulations. Based on this catalog, we combine machine learning and statistical sampling to address data assimilation as follows. The key idea is to design a nonparametric sampler of the dynamics of the considered geophysical system from the available catalog. We focus in this work on analog (also referred to as nearest-neighbor) methods. They provide us the mean for sampling forecast members with no online evaluation of the physical model. The combination of these members with the observations resorts to the classical stochastic filtering techniques, such as ensemble Kalman or particle filters and smoothers.

As a proof concept, we demonstrate the relevance of the proposed data assimilation method for Lorenz-63 and Lorenz-96 chaotic dynamics. We compare different nonparametric sampling schemes as well as stochastic filters and evaluate how the size of the catalog and the dimensionality of the system affect assimilation performance. We show that our nonparametric data-driven assimilation can reach state-of-the-art performances with no explicit online evaluation of the physical model. Compared to the classical model-driven assimilation, the key feature of our methodology is its computational efficiency and its flexibility. We further discuss the potential perspectives of this approach such as parameter and model error estimations as well as different applications, especially in spatial oceanography and meteorology.