



Reconstructing 3D data from 2D observations with deep learning

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Dynamical numerical models have, over the span of the past decades, provided ever more accurate predictions of the evolution of environmental variables such as temperature and pressure in meteorology, and sea currents in oceanography. However, the chaotic nature of natural processes, combined with sub-scale phenomena that are not fully incorporated in present-day models, make accurate long-term predictions impossible. In effect, these models are periodically re-initialized close to the observed evolution of the monitored parameters before being re-used for forecasting.

A multitude of approaches have, in the past been developed to attempt to perform this, such as the field of data assimilation. Such techniques have their advantages and inconveniences but in general can be quite computationally expensive. Synchronizing observed data (such as those issued from satellite imaging) with numerical models, remains an optimizable endeavor.

In the past we have shown (such as in Charantonis et al. 2015) that a combination of machine learning with Hidden Markov models has essentially provided a cost-efficient method to simulate the temporal evolution of vertical profiles of physical parameters such as Chlorophyll-A and Temperature that dynamical numerical model would forecast, given a concordant sequence of satellite data at a given location.

The CNN and LSTM deep learning architectures have, over the past years have been highly performing. They can address some essential issues of the previous approach, namely the ability to modulate your profile reconstructions, the ability to simultaneously train the spatial and temporal aspects of your model and the ability to expand the predictions to a 4D field reconstruction of the ocean's dynamics from sea-surface images.

In this work, we compared a "shallow-learning" and deep-learning approach for spatio-temporal reconstructions. It showed that the performance of the methods are dependent on the size and nature of the parameters being forecasted.