Offre de stage :

Machine Learning methods for non-stationary systems: applications to climate simulations

Niveau : M2

Cadre :

- encadrant principal : Davide FARANDA (CNRS, LSCE équipe ESTIMR)
- co-encadrant(s) : F D'Andrea (LMD)

Durée et Période : 5-6 mois, idéalement 03/02/2020 au 02/08/2020

Résumé :

The goal of the internship is to develop Echo State Networks (ESN) learning algorithms methods for nonstationary systems, moving towards climate-change oriented applications. During the internship the student will include instantaneous information on the changing forcing as covariate of the ESN model and evaluate the capability of ESN in learning non stationary dynamics. Tests will be performed on both Lorenz 1963 equations, and on climate data issued from model simulations.

Sujet :

The advent of high-performance computing has paved the way for advanced analyses of high-dimensional datasets. Those successes have naturally raised the question of whether it is possible to learn the dynamical behavior of a system without simulating the underlying evolution equations. Several efforts have recently been done to apply machine learning to the prediction of geophysical data, to learn parameterizations of subgrid processes in climate models [1], for nowcasting [2] and forecasting of weather variables [3] . However, these attempts mainly consist of complementing deterministic models, or short term prediction of time series data: while their utilitymay be substantial, they are still far from learning the dynamics of a complex system such as the Earth's climate. A first great step in this direction was the use of Echo State Networks (ESN) to forecast the behavior of chaotic systems, such as the Lorenz 1963 and the Kuramoto-Sivashinsky dynamics. It was shown that ESN predictions of both systems attain performances comparable to those obtained with the real equations [4]. This success motivated several follow up studies with a focus on meteorological and climate data. The LSCE has participated to this effort with a proof of concept of the applicability of ESN forecast in the short term forecasts and long term reconstruction of stationary signals such as the global sea-level pressure fields [5]. In order to have useful machine learning algorithms for climate change we need to extend these results to non-stationary systems, where external forcing varies with time. The goal of the internship is therefore to adapt the ESN algorithm devised in [4, 5] to a nonstationary framework. The student will

1. Start from simple systems such as the chaotic Lorenz 1963 equations and add the information of changing forcing as a covariate of the ESN learning algorithm, evaluate theperformance of the learning algorithm

2. Explore the possibility of adding additional layers (deep learning) to take into account the high nonlinearity introduced by the time-changing forcing.

3. Apply the developed algorithms on real climate data issued from CMIP5/CMIP6 datasets issued from different anthropogenic emission scenarios.

The applicant should possess a M2 level with a background in climate sciences, mathematics, statistics or physics, a basic knowledge of machine learning algorithms and of chaos theory. A good programming skill (Python or Matlab) is highly recommended.

<u>Références bibliographiques :</u>

[1] P. Gentine et al., Geophysical Research Letters 45, 5742 (2018).
[2] S. Xingjian et al., Advances in neural information processing systems (2015) pp. 802–810
[3] S. Scher and G. Messori, QJRMS 144, 2830 (2018).
[4] J. Pathak et al., Physical review letters 120, 024102 (2018).
[5] D. Faranda et al., Physical review letters (submitted) (2019).

<u>Autres :</u> prolongement en thèse non prévu.