Deep-learning time-prediction of chaotic dynamical systems

Keywords: Machine learning, nonlinear dynamical systems, chaos, time prediction

Contexte

The reliable prediction of the time behavior of complex systems is required in numerous fields ranging from the engineering applications to finance, epidemiology or fluid and solid mechanics. In many cases, the governing equations describing the physics of the system under consideration are not accessible or – when known – their solution requires a computational time often incompatible with the prediction horizon. However, recent successes in the application of deep Neural Networks (NN) are boosting the interest in using deep Machine Learning techniques to simulate complex systems and produce long time forecast[1]. Nevertheless, several open questions have to be addressed: For instance, when following a trajectory, it is not *a-priori* guaranteed that the amount of data used during the training process is sufficient to faithfully reproduce the real system. How to choose the architecture of the neural network and a relevant objective (loss function) to obtain reliable and generalizable results?

Objectives

The internship will focus on studying the quality of a deep NN reduced-order model for simulating chaotic dynamical systems. We will consider the well known Lorenz system and the chaotic dynamics of the Kuramoto-Sivashinsky (KS) partial differential equation, often used in fluid mechanics to model the diffusive instabilities in laminar flames. The intership is part of an effort in our group[2] and it will take place at LIMSI (`www.limsi.fr`) in Saclay (91), benefiting from its multidisciplinary environment and expertise in machine learning, dynamical systems and computational fluid mechanics.

Organization

The candidate should have a good mathematical background; basic knowledge in Python language and rudiments in nonlinear systems will be beneficial. Python scripts are already available, for the numerical simulations of the aforementioned models as well as several NN architectures and training strategies (multi-layer perceptrons, long short-term memory (LSTM), generative adversarial network (GAN)) in combination with several strategies of optimization.

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Duration: 5 months, starting early Spring 2020.
Internship bonus: ≈ 600 euros /month (+up to 50% for the transport costs)

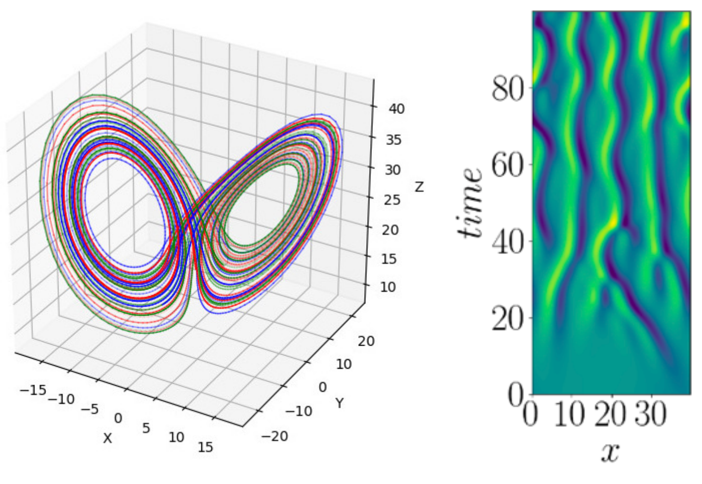

Figure 1: Lorenz attractor (left) and Kuramoto-Sivashinsky (KS) solution (right).

[1] Pathak J., Hunt B., Girvan M., Lu Z., & Ott E. (2018). Model-free prediction of large spatiotemporally chaotic systems from data: a reservoir computing approach, *Physical review letters*, **120**(2), 024102.

[2] https://mathelin3.wixsite.com/flowconproject