IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom

M2 INTERNSHIP PROPOSAL

Physics Based Neural Networks for Studying Turbulence

Keywords : Turbulence ; Neural Networks ; PINNs ; Signal processing ; Multiscale analysis ;

Several end-of-studies internships at the interface between turbulence and machine learning are proposed.

1. Scientific context

Turbulence is an omnipresent phenomenon in nature, influencing a wide range of processes, such as chemical reactions, atmospheric and oceanic flows, and galactic dynamics. However, due to its multiscale and nonlinear behavior, leading to long-range correlations, non-Gaussian statistics at small scales and intermittency, turbulence remains a challenge for science.

Today, Neural Networks are used in a wide variety of applications, including super-resolution, forecasting, and data generation. Moreover, the versatility of these models, along with their ability to capture nonlinearities and complex behaviors, makes them a promising tool for studying turbulence [1, 2]. In particular, the use of state-of-the-art Neural Networks, such as transformers and the self-attention mechanism, presents a significant potential for improving the model's capacity to capture intricate multiscale interactions. In the context of working with physical fields (e.g., velocity, vorticity), we aim to leverage generative networks (such as diffusion models and Energy-Based Models) that have recently gained popularity in image generation.

The main goal of these internships is to create novel Neural Network models based on physics and capable of learning new representations of turbulence. Special interest will be placed on Physics Informed Neural Networks (PINNs) [3].

2. Specific Objectives

Generation : Using deep learning models to generate stochastic fields mimicking turbulence, i.e. presenting the same statistical behavior as turbulence.

Forecasting : Using deep learning to learn dynamical models able to produce, from a given state of the flow, an ensemble of possible future states.

Multiscale decomposition : Learning a mapping of turbulent velocity from the real space to a latent space where we can easily model the interactions between scales. This mapping would be equivalent to an intelligent definition of scales in a given space where the interactions are known. Co-advised by C. Furthlener and S. Chibbaro from LISN (Saclay).

Lagrangian to Eulerian reconstruction : Using deep learning to solve an ill posed inverse problem consisiting in reconstructing the full Eulerian velocity field from sparse Lagrangian observations of the velocity flow. Co-advised by A. Ponte from Ifremer.

3. Eligibility Criteria

Candidates are required to be in the Master 2 (or third year engineering school) level education in the field of either applied mathematics or physics. Good knowledge of Python programming language with previous experiences in programming is required, as well as previous experience in machine learning and deep learning, especially using pytorch library. Background in fluid dynamics and/or turbulence will be a plus.

4. Supervision

The internship will be advised by Carlos Granero-Belinchon and Eugenio Cutolo (IMT Atlantique). Motivated students should send a CV and a motivation letter to : carlos.granero-belinchon@imt-atlantique.fr.

References

[1] Li, T., Biferale, L., Bonaccorso, F. et al. Synthetic Lagrangian turbulence by generative diffusion models. Nat Mach Intell 6, 393–403 (2024)

[2] Granero-Belinchon, C. and Cabeza-Gallucci, M. A multiscale and multicriteria Generative Adversarial Network to synthesize 1-dimensional turbulent fields. Mach. Learn.: Sci. Technol. 5, 025032 (2024)

[3] M. Raissi, P. Perdikaris, G.E. Karniadakis, Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations, Journal of Computational Physics, 378, 686-707 (2019)