Internship offers (MSc./Eng. Degree)

Deep learning for the space-time reconstruction of geophysical dynamics: application to space oceanography

Supervisor: Ronan Fablet (ronan.fablet@imt-atlantique.fr) Research team: IMT Atlantique, Lab-STICC, INRIA team Odyssey, Brest Expected duration: 6 months

Scientific context and specific objectives:

We open internship offers in the framework of AI chair OceaniX (<u>https://cia-oceanix.github.io/</u>) to develop Physics-Informed AI for Ocean Monitoring and Surveillance.

Data-driven and learning-based strategies for the analysis, modeling and reconstruction of dynamical systems are currently emerging as promising research directions as an alternative to classic model-driven approaches for a wide variety of application fields, including atmosphere and ocean science, remote sensing, computer vision.... [2,3,4]. Especially, deep learning schemes [1] are currently investigated to address inverse problems, i.e. reconstruction of signals or images from observations. Especially, recent works [e.g., 3,4] have shown that one can learn variational models and solvers for the reconstruction.

These internships will specifically investigate the development of deep learning inverse models for the space-time reconstruction of geophysical dynamics from partial observations. We aim to explore and understand how end-to-end neural schemes, such as 4DVarNets [3,5], provide new means to address limitations of operational data assimilation systems, especially for applications to ocean modeling and forecasting using satellite and in situ observations. Both simulated and real case-studies will be of interest.

Keywords: deep learning, inverse problems, data assimilation, space oceanography.

Candidate profile

MSc. and/or engineer degree in Applied Math., Data Science and/or Computer Science with a strong theoretical background, proven programming skills (Python).

Advanced knowledge of deep learning models and a first experience with Pytorch would be a plus.

References

[1] LeCun et al. Deep learning. Nature, 521(7553) :436-444, May 2015.

[2] Lguensat et al. The Analog Data Assimilation. Monthly Weather Review, 2017.

[3] R. Fablet, L. Drumetz, F. Rousseau. Learning variational data assimilation models and solvers. JAMES, 2021.

[4] Kobler et al. Total Deep Variation for Linear Inverse Problems. arXiv, 2020.

[5] Ronan Fablet, Quentin Febvre, Bertrand Chapron, Multimodal 4DVarNets for the reconstruction of sea surface dynamics from SST-SSH synergies. arXiv, 2022.