Learning Reduced-Order Ocean Forecasting Models

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Hosting team: IMT Atlantique, Brest, INRIA Odyssey team
Expected starting date: fall 2022

Keywords: ocean modelling and forecasting, deep learning, model compression, upper ocean dynamics, underwater acoustic propagation

This PhD position is open in the framework of AI Chair OceaniX (https://cia-oceanix.github.io/) and a collaboration between OceaniX chair and SHOM (https://www.shom.fr/) on AI approaches for the modelling of ocean dynamics and their impact on underwater acoustic propagation. The PhD candidate will be hosted on IMT Atlantique campus in Brest by the newly created INRIA team Odyssey (https://team.inria.fr/odyssey).

Recent developments in artificial intelligence (AI) open many interesting opportunities in the context of operational oceanography and ocean forecasting systems. Current operational forecasting systems face important challenges. Ocean models and data assimilation methods, which are the scientific underpinning of these operational systems, are highly computationally-demanding when addressing large ensemble simulations with increasingly fine spatial resolution and their ability to fully exploit available data sources remains limited. Deep learning and differentiable programming are opening many opportunities in computational fluid dynamics and ocean science (Vinuesa and Brunton, 2021; Zanna and Bolton 2021) as well as to solve inverse problems (Cranmer et al. 2021; Fablet et al. 2021, Hartfield et al., 2021). Deep learning especially benefits GPU acceleration as well as from an application-centric viewpoint to better address specific application-dependent requirements.

This PhD aims to explore and develop such deep learning paradigms for ocean forecasting. The specific objectives are three-fold: (i) learning and benchmarking reduced-order (or compressed) representations for ocean forecasting ensembles, (ii) exploring how these representations could benefit from available in situ and/or remote sensing data, (iii) accounting for underwater acoustic propagation in the learning and benchmarking of the proposed representations. From a methodological point of view, the PhD will consider both purely data-driven deep learning schemes (e.g., auto-encoder, CNN, ResNet, UNet,...) and physics-informed ones (Ouala et al., 2020; Fablet et al., 2021). Numerical experiments will exploit numerical simulations with simplified geophysical dynamics such as quasi-geostrophic dynamics (Lapeyre & Klein, 2006) as well as state-of-the-art high-resolution ocean simulations from the resolution of primitive equations such as NATL60/NEMO simulations.

Skills: Applications are encouraged from candidates with a MSc./engineer degree in applied math/data science/AI with interest in ocean science or a MSc./engineer in ocena science and a strong interest in data science and deep learning..

Application: Send CV, statement of research interests and the contact information of at least two references to ronan.fablet@imt-atlantique.fr. Review of applications will begin immediately and continue until the position is filled.

Specs: The PhD fellowship position covers the salary and a scholarship for visiting periods in international labs up to 6 months as well as the possibility to participate to teaching activities.

References

Brunton, S. L., et al. (2020). Machine learning for fluid mechanics. Annual Review of Fluid Mechanics, 52(1), 477–508. https://doi.org/10.1146/annurev-fluid-010719-060214

Cranmer, K., Brehmer, J., & Louppe, G. (2020a). The frontier of simulation-based inference. *PNAS*, *117*(48), 30055–30062. https://doi.org/10.1073/pnas.1912789117

Fablet, R. et al. (2021). Learning variational data assimilation models and solvers. *JAMES*, *13*(10). https://doi.org/10.1029/2021MS002572

Hatfield, S. et al (2021). Building Tangent Linear and Adjoint Models for Data Assimilation With Neural Networks. JAMES. https://doi.org/10.1029/2021ms002521

Kochkov, D. et al, S. (2021). Machine learning–accelerated computational fluid dynamics. *PNAS*, *118*(21), e2101784118. https://doi.org/10.1073/pnas.2101784118

Lapeyre, G. & Klein, P. (2006) Dynamics of the upper oceanic layers in terms of surface quasi-geostrophy theory. JPO, 36, 165-176.

Ouala, S. et al. Learning Latent Dynamics for Partially-Observed Chaotic Systems. Chaos, 2020.

Vinuesa, R., & Brunton, S. L. (2021). The potential of machine learning to enhance computational fluid dynamics. *ArXiv:2110.02085 [Physics]*. http://arxiv.org/abs/2110.02085

Zanna, L., & Bolton, T. (2021). Deep learning of unresolved turbulent ocean processes in climate models. In G. Camps Valls, D. Tuia, X. X. Zhu, & M. Reichstein (Eds.), *DL for the Earth Sciences*. https://doi.org/10.1002/9781119646181.ch20