Internship Master or Engineering degree

Transfer Learning for Modeling Ocean Dynamics

https://mlia.lip6.fr/available-positions/

Informations

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Where : Machine Learning and Information Access team - MLIA - *https://mlia.lip6.fr*, Sorbonne University, Paris, Fr

Dates and duration : 6 months starting in spring 2022

Supervisor : **Patrick Gallinari, Sylvie Thiria, Marie Dechelle** marie.dechelle@sorbonne-universite.fr

Candidate profile: Master or engineering degree in computer science or applied mathematics. The candidate should have a strong scientific background with good technical skills in programming.

Stipend : classical French academic internship gratification around 550 E/ month

Context

The topic of the Internship concerns the modeling of complex physical processes characterizing climate dynamics and more precisely ocean dynamics. Classical models rely on differential equations that incorporate physical knowledge on the underlying phenomenon. These equations are solved via numerical solvers and data assimilation. More recently, with the increasing availability of large amounts of data collected from satellites, researchers have started to explore the use of data intensive methods like neural networks for complementing or replacing the classical physical models. While they offer an interesting alternative or complement to classical physics, their deployment poses new problems. For example, they require large quantities of training data and they often poorly generalize to data from new environments.

Objectives

A classical strategy for training with sufficient amounts of data is to train the models, here the neural networks, on simulated data and then adapt the model to real data or more generally to data from a new source with different statistics than those from the training set. This is an instance of transfer learning. This idea has been developed in different domains. The objective of the internship is to push this idea for the modeling and forecasting of spatio-temporal dynamics. Physicist have developed sophisticated simulators that allow them to generate large amounts of data. This makes possible to train dynamic models with good forecasting abilities. The objective is then to transfer the knowledge gained on this data to new data with different statistics. We will examine different transfer strategies, starting with ideas from adversarial learning as in (Zhu 2017, de Bezenac 2021).

References

Zhu, J.-Y., Park, T., Isola, P., & Efros, A. A. (2017). Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks. *ICCV*, 2223–2232.

de Bézenac, E., Ayed, I., & Gallinari, P. (2021). CycleGAN through the lens of (Dynamical) Optimal Transport. *ECML*.

Additional readings :

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Ayed, I., de Bézenac, E., Pajot, A., Brajard, J., and Gallinari, P. 2020. Learning Dynamical Systems from Partial Observations. ICASSP 2020

de Bezenac, E., Pajot, A., and Gallinari, P. 2018. Deep Learning For Physical Processes: Incorporating Prior Scientific Knowledge. ICLR.

Thuerey, N., Holl, P., Mueller, M., Schnell, P., Trost, F. and Um, K. 2021. Physics-based Deep Learning, arXiv:2109.05237

(Yin et al. 2021a)Yin, Y., Le Guen, V., Dona, J., de Bezenac, E., Ayed, I., Thome, N. and Gallinari, P. 2021. Augmenting Physical Models with Deep Networks for Complex Dynamics Forecasting. *ICLR* (2021).