PhD position in Paris, France

Physics Based Deep Learning for Modeling Complex Dynamics. Applications to Climate

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Location: Sorbonne Université, Pierre et Marie Curie Campus, 4 Place Jussieu, Paris, Fr

Candidate profile: Master in computer science or applied mathematics, Engineering school. Background and experience in machine learning. Good technical skills in programming.

How to apply: please send a cv, motivation letter, grades obtained in master, recommendation letters when possible to patrick.gallinari@sorbonne-universite.fr

Start date: October/November 2022

Note: The research topic is open and depending on the candidate profile could be oriented more on the theory or on the application side.

Context

Deep Learning is beginning to be explored for scientific computing in domains traditionally dominated by physics models (first principles) like earth science, climate science, biological science, etc. It is particularly promising in problems involving processes that are not completely understood, or computationally too complex to solve by running the physics inspired model. The direct use of pure machine learning approaches has however met limited successes for scientific computing. Hence, researchers from different communities have started to explore (i) how to integrate physics knowledge and data, and (ii) how to push the limits of current ML methods and theory; two challenging directions. We consider here deep learning approaches for the modeling of complex dynamical systems characterizing natural phenomena, a recent and fast growing research topic (Willard et al. 2020, Thuerey et al. 2021). Motivating problems and applications will come from climate science (de Bezenac et al. 2018, Ayed et al. 2020).

Research directions

The global objective is the development of new models leveraging observation or simulation data for the modeling of complex spatio-temporal dynamics characterizing physical phenomena such as those underlying earth-science and climate observations. The classical modeling tools for such dynamics in physics and applied mathematics rely on partial differential equations (PDE). Despite their successes in different areas, current ML based approaches are notably insufficient for such problems. Using ML for physics raises new challenging problems and requires rethinking fundamental ML ideas.

Hybrid systems - Integrating Physics and Deep Learning

In many situations, there is available some prior physical knowledge provided by PDEs for characterizing the underlying phenomenon. A key issue is then how to combine this prior knowledge with information extracted from the data. ML could come as a complement to numerical models and allow us to take into account information not present in the model or to integrate observation data. Alternatively, it could come as a surrogate model for fast prototyping. From a ML perspective, physical priors help guide and constrain the learning process. Initial attempts to solve similar problems can be found in recent work such as (de Bezenac et al. 2018, Harlim et al. 2020, Yin et al. 2021, Dona et al. 2022). This will be further developed for the PhD project with the objective of analyzing and developing different integration frameworks.

Domain generalization for deep learning as dynamical models

Explicit physical models come with guarantees and can be used in any context (also called domain or environment) where the model is valid. This is not the case for DNNs, and we have no guarantee that they can be extrapolated to new physical environments. We propose here to tackle the problem by drawing inspiration from recent ML frameworks developed for handling the new research topic of domain generalization, such as (Yin et al. 2021b, Wang et al. 2021).

Learning at Multiple Scales

Modeling dynamical physical processes often requires considering multiple spatio-temporal scales. For example in climate, global phenomena are influenced by dynamics operating at a smaller scale. Similar problems occur e.g. in computational fluid dynamics. Learning at different scales is an open issue in ML. Most current DNN deployments for learning dynamics operate at a fixed spatio-temporal discretization. Recent advances (Sitzman 2020, , Lindel et al. 2021, Li 2021) relying on implicit representations, allow us learning a function space instead of discrete flows and open the possibility for generalizing at different spatio-temporal resolutions. This will be used as starting point for learning at different scales with DNNs.

Position and Working Environment

The PhD studentship is a three years position starting in October/November 2022. It does not include teaching obligation, but it is possible to engage if desired. The PhD candidate will work at Sorbonne Université (S.U.), Pierre et Marie Campus in the center of Paris. He/She will integrate the Machine Learning and Deep Learning for Information Accesss team at S.U. at the ISIR lab. (Institut des Systèmes Intelligents et de Robotique). On the Climate side, the candidate will be co-advised by M. Levy and S. Thiria from LOCEAN laboratory, https://www.locean-ipsl.upmc.fr/

References

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