Sujet de thèse

Titre de la thèse : Learning Generative World Models of Physical Dynamics

Directrice ou directeur de thèse : Patrick Gallinari, patrick.gallinari@sorbonne-universite.fr

Collaboration dans le cadre de la thèse : INRIA Paris, Institut d'Alembert Sorbonne Université,

Laboratoire d'accueil : ISIR (*Institut des Systèmes Intelligents et de Robotique*), Campus Pierre et Marie Curie, 4 place Jussieu, 75005 Paris.

Start date: November/ December 2026

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

Keywords: AI4Science, deep learning, physics-aware deep learning, world models, generative models, foundation models

Personne à contacter

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Date limite de dépôt de la candidature : 20/12/2026

Description du sujet (en anglais)

Project Description:

Context

AI4Science is an emerging research field that investigates the potential of AI methods to advance scientific discovery, particularly through the modeling of complex natural phenomena. This fast-growing area holds the promise of transforming how research is conducted across a broad range of scientific domains. One especially promising application is in modeling complex dynamical systems that arise in fields such as climate science, earth science, biology, and fluid dynamics. A diversity of approaches is currently being developed, but this remains an emerging field with numerous open research challenges in both machine learning and domain-specific modeling.
This PhD project aims to investigate the next generation of AI models for physical dynamics. The objective is to develop generative world models that learn structured representations of physical systems and can efficiently model, predict, and reason about their evolution. The research will focus on applications such as fluid mechanics and climate science while addressing fundamental questions at the intersection of machine learning and scientific computing.

Research Directions

The main objective of this PhD is to develop generative world models for physical dynamics that combine scalability, uncertainty modeling, and scientific consistency.
The research will explore several complementary directions:

Learning transferable representations of physical dynamics, by developing latent representations that capture the underlying structure of physical systems and can generalize across multiple physical regimes and downstream tasks.

Generative modeling of physical trajectories, using recent approaches such as diffusion models, flow matching, and stochastic interpolants to represent uncertainty, multimodality, and long-term evolution of complex dynamical systems.

Physically consistent generative models, by integrating physical constraints and scientific priors into generative learning in order to produce solutions that remain both accurate and scientifically valid.

The exact research direction will be adapted to the candidate's interests and background and may emphasize either methodological developments or applications to scientific domains such as fluid dynamics and climate modeling.

Position and Working Environment

The PhD studentship is a three years position starting in October/ November 2026. It does not include teaching obligation, but it is possible to engage if desired. The PhD candidate will work at Sorbonne Université (S.U.), in the center of Paris. He/She will integrate the MLIA team (Machine Learning and Deep Learning for Information Access) at ISIR (Institut des Systèmes Intelligents et de Robotique).

References

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Required Profile:

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