PhD Position in Engineering and Computer Science, Sorbonne Université, Paris, France

Deep Generative Models of Physical Dynamics: Representation, Generalization, and Multiphysics Learning

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Machine Learning and Information Access team.

Candidate profile: Master degree 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 2025 for three years

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: Deep Learning, Generative Models, AI4Science

Context

AI4Science is an emerging field investigating the potential of AI to advance scientific discovery, with deep learning playing a central role in modeling complex natural phenomena. Within this context, *deep generative modeling*—which already enables the synthesis of high-dimensional data across modalities such as text, images, and audio—is now opening new avenues for simulating and understanding complex physical systems.

This PhD project aims to explore and advance generative deep learning architectures—such as diffusion models, flow-matching networks, and autoregressive transformers—for modeling complex physical dynamical systems arising in domains such as climate, biology, and fluid mechanics. These models hold strong potential for learning flexible, data-driven representations of physical laws. By developing generalizable, cross-physics generative models, this research contributes to the broader vision of AI4Science: accelerating scientific discovery through learned simulation and abstraction.

Research Objectives

The overarching research question is: Can we develop generative models that learn structured, physically grounded representations of dynamical systems—enabling synthesis, adaptation, and generalization across physical regimes and multiphysics settings? It unfolds into several complementary directions:

Latent Generative Models for Physical Dynamics

The objective is to design generative models—such as diffusion, flow-matching, or autoregressive models—that learn compact and interpretable latent representations of spatiotemporal dynamics governed by PDEs. These models should:

- Capture uncertainty and multimodality in solution trajectories.
- Generalize across parametric variations.

Learning Across Multiphysics Systems

To enable transfer learning across heterogeneous physics, we will explore shared latent representations across families of PDEs:

- Using encode–process–decode frameworks.
- Applying contrastive or multitask training to uncover reusable physical abstractions.

- Designing models invariant to space/time resolution and units.

This direction builds toward foundation-like models that capture generalizable physics priors across simulation families.

Few-Shot and In-Context Generalization to New Physics

To support scientific modeling in data-scarce settings, we will develop methods for few-shot generalization such as:

- Fine-tuning latent priors to new PDE systems using limited examples.
- Exploring meta-learning and prompt-based adaptation techniques (inspired by in-context learning in language models).
- Incorporating known physical constraints into the generative process.

The goal is to enable rapid and physically consistent adaptation to previously unseen dynamics with minimal data and supervision.

Position and Working Environment

The PhD studentship is a three years position starting in October/November 2025. 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).

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