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 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. This is still an emerging field with numerous open research challenges in both machine learning and domain-specific modeling.

Generative modeling is transforming machine learning by enabling the synthesis of plausible, high-dimensional data across modalities like text, images, and audio. A similarly profound shift is underway in the sciences, where generative deep learning is being leveraged to model complex physical dynamics , especially in cases where traditional simulations are computationally expensive.

The central goal of the PhD project is to investigate whether deep generative architectures—such as diffusion, flow-matching, or autoregressive transformer-based sequence models—can be designed to simulate, generalize, and interpolate physical dynamics across a wide range of parametric and multiphysics regimes. Building on recent advances in neural surrogate modeling, this research will aim to advance generalizable, cross-physics generative modeling.

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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