Generative models by Hamiltonian and non-reversible stochastic flows (Funded Master internship and PhD via selective funding)

Motivation: Generative modeling aims to capture and sample complex high-dimensional data distributions, playing a central role in machine learning, Bayesian inference and computational physics. Among generative methods, Normalizing Flows (NF) have gained prominence by training neural networks to map a simple prior distribution onto the desired target distribution through a sequence of invertible transformations. They come with interesting characteristics, such as stability and correctness. However, traditional NF approaches often face significant computational bottlenecks, particularly in high dimensions, where calculating Jacobian determinants can be costly. Normalizing Hamiltonian Flows (NHFs) have emerged as a promising alternative, leveraging symplectic integration for volume-preserving transformations and enabling flexible neural network architectures [1, 2]. These methods exhibit advantages such as reduced computational costs, robustness through explicit kinetic energy design, and interpretability. Despite their potential, challenges remain in scaling NHFs to complex models and comparing their efficiency to other generative approaches, such as diffusion models.

Goal: The internship project builds on recent findings that NHFs require shorter dynamics integrations compared to diffusion models, making them computationally attractive. By further improving the flexibility of these methods but also investigating an alternative based on non-reversible flow implementations, the project seeks to develop state-of-the-art generative tools.

This opportunity is open to Master's students, including first-year students (Master 1), who are eager to explore advanced topics in generative modeling. For Master 2 students, the internship will aim to lay the foundation for a PhD project focused on the development and analysis of Hamiltonian and stochastic flow-based generative models through quantitative analytical and numerical approaches.

Environment: The intern will join the Université Clermont-Auvergne at the Laboratoire de Mathématiques Blaise Pascal (UMR 6620) and will be part of the interdisciplinary ANR project *SuSa*. The project will be supervised by Arnaud Guillin (UCA, LMBP) and Manon Michel (CNRS, LMBP). They will join a local interdisciplinary dynamics revolving around stochastic processes, machine learning, and statistical physics. Additionally, the intern will be part of the broader research ecosystem of the MIAI (Multidisciplinary Institute in Artificial Intelligence) Cluster, which fosters cutting-edge AI research and its applications. This dynamic setting offers rich opportunities for collaboration and exposure to innovative methodologies.

Profile: We are looking for a motivated candidate with a background in probability, statistical physics, or computational statistics, and an interest in generative modeling and stochastic processes. Programming experience is highly desirable. For more details, contact Manon Michel (manon.michel@uca.fr).

Webpages:

Manon Michel's webpage: `http://manon-michel.perso.math.cnrs.fr`
Arnaud Guillin's webpage: `http://math.univ-bpclermont.fr/~guillin`
SuSa project's webpage: `https://anr-susa.math.cnrs.fr`
MIAI's webpage: `https://miai.univ-grenoble-alpes.fr/`

References:

[1] P. Toth, D.J. Rezende, A. Jaegle. S. Racanière, A. Botev and I. Higgins. *Hamiltonian Generative networks*, *International Conference on Learning Representations*, 2020.

[2] V. Souveton, A. Guillin, J. Jasche, G. Lavaux, and M. Michel, *Fixed-kinetic Neural Hamiltonian Flows for enhanced interpretability and reduced complexity*, *Proceedings of The 27th International Conference on Artificial Intelligence and Statistics*, PMLR 238:3178-3186, 2024.