Université Paris-Dauphine / LAMSADE
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Neural Ordinary Differential Equations (ODE)

Duration: 4 to 6 months
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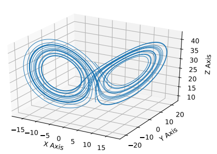
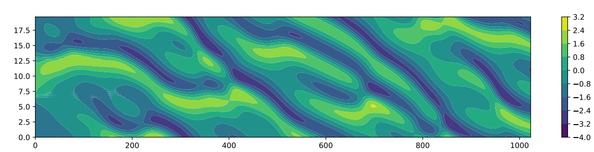
URL: https://allauzen.github.io/research/positions/

Context: The recent success of the paper called *Neural Ordinary Differential Equation*[1] (or Neural ODE for short) reveals the importance of the relation between numerical methods and deep-learning [2]. Neural ODE can be seen as the continuous limit in depth of architectures like ResNet and previous papers investigated this relation, for instance by deriving new state of the art architecture of deep nets from numerical methods to solve ODEs [3]. While these ideas are not new, they open new perspectives in deep learning [4].
Outline: The goals of this internship is to explore different aspects of this new kind of approach and different topics can be investigated. First, the link between the architecture and the numerical methods used to solve ODEs can be important to design new architectures or new training startegies. Another important question we want to address is the experimental evaluation of this kind of approach for time series prediction or classification. For this purpose we plan to explore simulated datasets that relies on physical processes for which the solutions are known or documented. We plan to vary the complexity of the process, starting for instance with the heat diffusion process to explore turbulent or chaotic systems like Lorentz or Kuramoto-Sivashinsky. Beyond the performances, we also analyse the solutions found by Neural ODE.





Organisation : Depending on your skills, the tradeo-off between the experimental and the theorical parts can be adapted. For the experiments we will rely on pytorch and existing data simulators. The internship can be extended with a funded PhD position.

References

[1] Tian Qi Chen, Yulia Rubanova, Jesse Bettencourt, and David K Duvenaud. Neural ordinary differential equations. In *Advances in Neural Information Processing Systems 31*, pages 6571–6583. 2018.

[2] Eldad Haber and Lars Ruthotto. Stable architectures for deep neural networks. *Inverse Problems*, 34(1):014004, Dec 2017.

[3] Yiping Lu, Aoxiao Zhong, Quanzheng Li, and Bin Dong. Beyond finite layer neural networks: Bridging deep architectures and numerical differential equations. In *Proceedings of the 35th International Conference on Machine Learning, ICML 2018*, volume 80, pages 3282–3291, 2018.

[4] Jinkyoo Park Atsushi Yamashita Hajime Asama Stefano Massaroli, Michael Poli. Dissecting neural ODEs. In *Advances in Neural Information Processing Systems 33*. 2020.