PostDoc Operator Learning

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1 Context

This PostDoc is co-funded by the two Chairs of the Toulouse AI Cluster ANITI 'Madlads' (F. Gamboa) and 'PILearnWater' (J. Monnier, O. Roustant).

Operator learning is an emerging paradigm in machine learning that aims at approximating mappings between infinite-dimensional spaces, such as functions or fields, rather than simple vectors. Instead of predicting scalar or finite-dimensional outputs, these models learn the action of an operator that maps one function to another, for instance mapping boundary conditions to solutions of a PDE. This framework is particularly powerful for scientific computing, where physical systems are naturally described by operators. However, current approaches often rely on abundant training data, which is rarely available in real-world applications.

2 Objectives

- **To produce new methods for learning operators in the context of scarce data**

  The objective is to study approximation by neural operators for operational applications and for complex, high-dimensional problems. In particular, we will examine the following issues:

  - the adaptation of neural operator methodology to general boundary conditions. At present, neural operators approximate functions with periodic boundary conditions, relying on periodic convolutions and the Fourier transform.
  - the incorporation into neural operators of physical constraints such as the preservation of quantities (e.g., mass, momentum) and inequalities (e.g., positivity, entropy dissipation).
  - the study of neural network approximation for phenomena involving the formation of discontinuities. Indeed, current neural operators are effective only for sufficiently regular solutions, for which the Fourier transform has compact support and therefore good encoding properties.

- **To challenge and hybrid neural networks with Gaussian process techniques**
  Neural networks provide expressive representations, while Gaussian processes (GPs) offer principled uncertainty modeling and interpretability. We propose to combine these strengths by creating hybrid models for operator learning. The neural component will capture complex nonlinearities, while the GP part will ensure statistical rigor and robustness. This synergy can help mitigate overfitting and improve extrapolation. Comparative studies will challenge standard deep models with these hybrid approaches. The outcome will be a new class of methods blending flexibility with reliability.

- **To add uncertainty quantification in the paradigm of operator learning**
  Uncertainty quantification (UQ) is critical when learned operators are used in decision-making or high-risk domains. Current operator learning frameworks often focus only on accuracy, neglecting confidence estimates. This project will develop techniques to provide calibrated UQ within operator learning models. The integration of UQ is expected to improve trust and usability of operator learning in practice.

- **To put in action these techniques on the applications of the Chairs, in water and electromagnetism problems**
  The proposed methods will be validated on real applications from the Chairs, ensuring relevance beyond synthetic benchmarks. In water-related problems, operator learning can accelerate flow simulations, improve forecasting, and support risk analysis. In electromagnetism, these methods can model wave propagation or material interactions with high precision. Both domains present scarce data scenarios, making them ideal testbeds.

3 Duration and condition

- Timing and duration. The project is expected to start in early 2026 and will run for at least one year. The first year will be funded by ANITI with a possible prolongation.
- Locations: Toulouse.

4 Application agenda

- Send your application to Fabrice Gamboa (`fabrice.gamboa@math.univ-toulouse.fr`) and Olivier Roustant (`roustant@insa-toulouse.fr`). The application file should include a CV, transcripts of Master's grades, and the contact details of two academic referees.
- Application files must be submitted by December 1, 2026.
- Interviews will be held before the Christmas break.
- Results will be announced on January 15, 2026.

References

[1] Pau Batlle, Matthieu Darcy, Bamdad Hosseini, and Houman Owhadi. Kernel methods are competitive for operator learning. *Journal of Computational Physics*, 496:112549, 2024.

[2] Nikola Kovachki, Zongyi Li, Burigede Liu, Kamyar Azizzadenesheli, Kaushik Bhattacharya, Andrew Stuart, and Anima Anandkumar. Neural operator: Learning maps between function spaces with applications to PDEs. *Journal of Machine Learning Research*, 24(89):1–97, 2023.