Post-Doctoral Position:

Modeling, Optimization and Transfer for Physics-based Machine Learning

Location: Hubert Curien Lab, Saint-Etienne, France
Team: MALICE Inria
Duration: 12 months
Gratuity: About €2823 gross per month
Starting date: Early 2024 - at your earliest convenience

Keywords: Physics-guided models; Neural networks; Sparsity; Transfer learning; Optimization

Context In many physical systems, the governing partial differentiation equations (PDEs) are known with high confidence, but simulating a numerical solution can be prohibitively expensive. In other contexts, the PDEs are unknown (or partly known to some extent) and unveiling them from experimental data is the central goal since they could help in shedding some lights on the underlying physical process [1]. Recently, physics-guided machine learning models have shown to be a promising tool in both above-mentioned scenarios. They rely on neural networks in order to simulate the physical quantities of interest at various temporal and spatial positions. Training such neural networks entails to incorporate physical constraints, usually in the form of a PDE and boundary conditions, and/or to be able to generate plausible simulated data reproducing the experimental data at hand [2].

Mission Depending on the candidate's profile and interests, different research directions may be envisaged to foster the development of new joint methodological contributions at the interface between machine learning and physics. *(Modeling)* Design of new differentiable and frugal neural network based architectures, possibly multi-tasks [3, 4]. *(Optimization)* Develop fast and efficient novel optimization techniques to jointly unveil the underlying physics and learn the numerical solution, bilevel optimization approaches are a possible promising direction [5]. *(Transfer)* Design new transfer learning methods able to take into account physics-based knowledge [6]. Do not hesitate to contact us to discuss other research axes more suited to your profile.

Host team The selected candidate will join the MALICE Inria project-team whose goal is to combine the interdisciplinary skills present at the Hubert Curien laboratory in statistical learning and laser-matter interaction to foster the development of new joint methodological contributions at the interface between machine learning and surface engineering. Created in 2006, the Hubert Curien laboratory is a joint research unit (UMR 5516) of the Jean Monnet University, Saint-Étienne, the National Research Centre "CNRS" and the Institut d'Optique Graduate School. In addition, the present postdoctoral position will benefit from the research environment associated to the Manutech-Sleight graduate school.
- `https://labhc-malice.github.io/` - `https://manutech-sleight.com`
- `https://laboratoirehubertcurien.univ-st-etienne.fr`

Candidate profile

- PhD in computer science, machine learning, applied mathematics or related. Outstanding applications from physicists will also be considered,
- Good Python/PyTorch programming skills,
- Good knowledge of neural networks and optimization,
- Basic knowledge of partial differential equations is welcome,
- High proficiency in English.

Application Candidate must send the following documents to jordan.frecon.deloire@univ-st-etienne.fr and amaury.habrard@univ-st-etienne.fr as soon as possible:

- Cover letter with justification of your skills for the topic,
- A complete Curriculum Vitae,
- Top 3 publications,
- PhD diploma and thesis,
- Any additional document: letter(s) of recommendation, publications, etc.

Please feel free to contact us beforehand for any further pieces of information.

References

[1] Brandao, E. et al (2022). Learning PDE to Model Self-Organization of Matter. In *Entropy*.

[2] Raissi, M. et al. (2019). Physics-Informed Neural Networks: A deep Learning Framework for Solving Forward and Inverse Problems Involving Nonlinear Partial Differential Equations. In *Journal of Computational physics*.

[3] Li, Z. et al. (2021). Fourier Neural Operator for Parametric Partial Differential Equations. In *International Conference on Learning Representations*.

[4] Frecon, J. et al. (2022). Bregman Neural Networks. In *International Conference on Machine Learning*.

[5] Frecon, F. et al. (2020). Unveiling Groups of Related Tasks in Multi-Tasks Learning. In *International Conference on Pattern Recognition*.

[6] Pellegrin, R. et al (2022). Transfer Learning with Physics-Informed Neural Networks for Efficient Simulation of Branched Flows. In *Machine Learning and the Physical Sciences workshop, NeurIPS*.