Post-Doctoral position

Control of multi-agent systems via deep learning-based surrogate modeling

Subject: The research activities will be grounded in scientific machine learning, with a focus on developing and analyzing surrogate models for the efficient approximation and control of multi-agent systems.
Duration: 12 months, with possibility of extension for another year.
Gross Salary: between 3000€ and 3300€ per month, according to experience.
Work place: CentraleSupélec, Paris-Saclay University.
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Introduction

Multi-agent systems (MAS) consist of multiple autonomous agents, interacting within a shared environment and depending on several parameters describing the current configuration. Modeling MAS involves capturing both the dynamics of individual agents and their interactions to understand the emergent behavior of the collective system as a unicum. Depending on the scale of the observed quantities and the required level of detail, MAS can be modeled using different mathematical tools. In practice, hybrid approaches that combine microscopic and macroscopic scales are often adopted to comprehensively capture MAS evolution. These strategies leverage insights from both perspectives to develop more accurate and scalable models. For example, agent-based models may be coupled with fluid dynamics equations to study traffic flow and crowd evacuation during emergencies, enabling researchers to simultaneously analyze both individual vehicle/person behavior and macroscopic traffic/crowd patterns.

Usually, at the microscopic level, agent behavior and interactions are explicitly modeled using Ordinary Differential Equations (ODEs). These equations describe the dynamics of individual agents in terms of their state variables, such as position, velocity, and internal states. In contrast, the macroscopic perspective focuses on describing the collective behavior of the entire system rather than individual agents. Here, the emphasis is on understanding global patterns, such as traffic flow, crowd dynamics, or information dissemination, emerging from the interactions of many agents. Macroscopic models often rely on Partial Differential Equations (PDEs) to describe how aggregated quantities, such as density, flow, or concentration, evolve over space and time.

However, many MAS applications involve nonlinear interactions and complex spatial-temporal dynamics thus leading to high, if not prohibitive, computational costs, particularly when dealing with large-scale systems or highly heterogeneous environments with evolving boundary conditions. These issues may render it intractable for applying analytical tools, commonly found in optimal control literature.

Job description

The successful postdoc will be expected to work on the development of a deep learning-based surrogate models (SM) for the solution of the parametrized time-dependent nonlinear PDE (tacking into account the MAS macroscopic perspective) thus enabling real-time control. The SM should maintain high-level of accuracy, comparable to the one provided by high fidelity models, e.g. analytical solutions or finite element method, with a significantly lower computational cost, thereby facilitating more efficient and scalable MAS simulations. Deep learning techniques rooted in physics will be exploited, leading to the integration of the governing equations describing the simulated phenomena, in the form of either hard constraints in the definition of the neural networks, either as weak constraints in the loss function formulation. These constraints will ensure the connection between ODE and PDE descriptions, so to inform the SM with fine-grained phenomena (the dynamics of individual agents) described by the ODEs.

Desired experience

1. PhD in applied math or computer science;
2. Experience in scientific machine learning, reinforcement learning, control theory;
3. Experience in publishing high quality research papers;
4. Knowledge of libraries for deep learning (PyTorch, Tensorflow, Keras, JAX);
5. Experience in the design and analysis of networked control systems is a plus.

The position is available immediately and applications will be accepted until this position is filled. A National Security clearance is needed, and it can require approximately 2 months.

References

[1] S. Fresca and A. Manzoni, “POD-DL-ROM: Enhancing deep learning-based reduced order models for nonlinear parametrized pdes by proper orthogonal decomposition,” Computer Methods in Applied Mechanics and Engineering, vol. 388, p. 114181, 2022.
[2] S. Brivio, S. Fresca, A. Manzoni "PTPI-DL-ROMs: pre-trained physics-informed deep learning-based reduced order models for nonlinear parametrized PDEs". https://arxiv.org/abs/2405.08558. 2024
[3] F. Lehmann, F. Gatti, D. Clouteau. "Multiple-Input Fourier Neural Operator (MIFNO) for source-dependent 3D elastodynamics". https://arxiv.org/abs/2404.10115. 2024
[4] L. P. Njoua Dongmo, J. Auriol, A. Iovine, "Smart traffic manager for speed harmonisation and stop-and-go waves mitigation dedicated to connected autonomous vehicles", to appear on IEEE Transactions on Control Systems Technology, https://hal.science/hal-04680301v1/document
[5] M. Mirabilio, A. Iovine, E. De Santis, M. D. Di Benedetto and G. Pola, "Scalable Mesh Stability of Nonlinear Interconnected Systems," in IEEE Control Systems Letters, vol. 6, pp. 968-973, 2022.

Contacts
Interested applicants should contact Stefania Fresca, Filippo Gatti, and Alessio Iovine, and provide in PDF format (a) a CV, (b) the names of three or more references, (c) a one page description of their earlier work and (d) a one paragraph statement about their interest in the advertised position.