SIMAI 2025
1-5 September 2025, Trieste, Italy

NUMERICAL ISSUES IN MACHINE LEARNING FOR DYNAMICAL SYSTEMS

PASQUALE DE LUCA[*], LIVIA MARCELLINO[*], GIOVANNI PAGANO[†] AND LEILI SHAHRIYARI[††]

[*] Parthenope University of Naples
I-80143
{pasquale.deluca,livia.marcellino}@uniparthenope.it

[†] Department of Agricultural Sciences of University Federico II of Naples
I-80055
giovanni.pagano5@unina.it

[††] University of Massachussetts Amherst
01003-3010
lshahriyari@umass.edu

ABSTRACT

Recent advances in machine learning have been driven by the rapid growth of its applications in various fields, facilitated by the increasing availability of high-performance computing to handle large data. This session will explore the use of machine learning methods for the calibration and solution of problems related to dynamical systems. Topics of interest include reinforcement learning, online learning, supervised and unsupervised learning. Special attention will be given to physics-informed neural networks (PINNs), which offer a powerful approach for the solution of partial differential equations over complex domains. Additionally, PINNs show promise in solving inverse problems, where the goal is to find unknown parameters or behaviours of a system from observed data. In this regard, we will also explore how machine learning can help estimate parameters in dynamical systems, e.g. by convolutional neural networks for image analysis. The session aims to encourage the exchange of ideas and methodologies that will advance both the theoretical understanding and practical applications of AI-enhanced computational methods for dynamical systems, with a special focus on differential equations.

Topics of interest include, but are not limited to:

- theoretical foundations of neural solvers;
- convergence analysis and error estimation in AI-methods;
- architectural innovations in PINNs;
- integration of domain-specific physical constraints;
- numerical methods designed for neural networks;
- data-driven approaches for discovering governing equations in dynamical systems;
- automatic differentiation.

REFERENCES

[1] Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational physics*, 378, 686-707.

[2] Li, Q., Lin, T., & Shen, Z. (2022). Deep learning via dynamical systems: An approximation perspective. *Journal of the European Mathematical Society*, 25(5), 1671-1709.