PHYSICS-BASED SURROGATE MODELS AND SCIENTIFIC MACHINE LEARNING

FEDERICO PICHI[*], FRANCESCO REGAZZONI[†] AND DAVIDE TORLO[^]

[*] SISSA
Via Bonomea. 265, 34136, Trieste
fpichi@sissa.it, https://fpichi.github.io/

[†] MOX, Dep. of Mathematics, Politecnico di Milano
p.za Leonardo da Vinci 32, 20133 Milano
francesco.regazzoni@polimi.it, https://regazzoni.faculty.polimi.it/

[^] Dipartimento di Matematica "Guido Castelnuovo", Sapienza Università di Roma
p.le Aldo Moro, 5, 00185 Roma
davide.torlo@uniroma1.it, https://davidetorlo.it/

ABSTRACT

Reduced Order Methods (ROMs) aim to build surrogate models to generate efficient and reliable approximations of complex parametric systems, enabling real-time simulations and many-query contexts, which are essential for both academic and industrial applications.

Physics-based models are usually intrusive approaches based on Galerkin projection, and require the knowledge of the system equations. These methods are highly accurate, but their efficiency is hindered when dealing with non-linear problems or advection-dominated phenomena.

Non-intrusive methods, commonly based on data-driven and machine learning techniques, exploit data from measurements or simulations, efficiently handling a wide range of applications. Despite this, they may require a large amount of data, long training times, and usually lack error certification, physics consistency, and structure-preserving properties.

Scientific Machine Learning (SciML) aims at bridging data-driven and physics-based approaches by investigating their approximation properties, enhancing their interpretability and modeling capabilities, while enabling consistent, efficient, and accurate predictions for complex time-dependent and parametric systems.

The goal of this mini-symposium is to foster idea exchange and bring together researchers actively working on ROMs and SciML approaches, illustrating their practical benefits and limitations across a wide range of academic, industrial, and engineering applications.