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MACHINE LEARNING FOR LARGE SCALE MODELS IN PHYSICS

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MINISYMPOSIUM

In this mini-symposium, we propose to meet around the recent advances in the fields of reduced order modeling and machine learning applied to industrial and mechanical large-scale problems.
Nowadays, we need to give a response to the environmental requirements in almost all the mechanical domains. Typically, for the aeronautical industry, a new design process exhibits large-scale multi-disciplinary problems often solved in a highly coupled fashion in order to explore a number of configurations of aeronautical components. As we like to provide new industrial designs that are less consuming and less polluting, the design process must fulfill the same exigencies. The large-scale problems – based design exploration is highly consuming in CPU resources. High Performance Computing is inevitably an important tool for the verification and the validation of a design of interest. However, we need to leverage the exploration phase with even more efficient methods. Hence, the exploration phase is a machine learning – like inference one and the verification phase is a high-fidelity large-scale problem – like resolution one.
This mini-symposium is the opportunity to discuss how these machine-learning approaches are becoming unavoidable. A discussion about the possible numerical certification of these techniques is required in the light of the recent advances in uncertainty quantification in reduced order modeling and machine learning.
The subjects addressed in this mini-symposium include, but are not limited to:

- Physics-based machine learning for regression of scalar and field quantities of interest
- Physical reduced-order modeling and its hybridation with AI technologies
- Uncertainty propagation and predictive uncertainty quantification
- Nonparameterized variability – including the geometry
- Application to structural mechanics and thermics, computational fluid mechanics, electromagnetism
- Efficiency in training and inference stages