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MACHINE LEARNING, REDUCED ORDER MODELING AND UNCERTAINTY QUANTIFICATION IN BIOLOGICAL SYSTEMS

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MINI-SYMPOSIUM PROPOSAL

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Life sciences and computational medicine are currently witnessing a shift from solving forward problems based on sparse data towards model personalization [2], data assimilation and solving inverse problems to explain large datasets [4]. Very often, multi-scale or multi-physics simulations in bioengineering aim at describing and predicting the behavior of a system, assuming access to massive amounts of data, while the governing equations and their parameters may be uncertain [5]. This is where reduced-order modeling and machine learning may become critical: machine learning allows us to systematically preprocess massive amounts of data, integrate and analyze it from different input modalities and different levels of fidelity, identify correlations, discover hidden physics and infer the dynamics of the overall system [7]; on the other hand, reduced order models enable us dramatic computational speedups when addressing forward and inverse uncertainty quantification tasks [3]. Machine learning (and deep learning) are nowadays at the corner of the construction of data-driven surrogate models, physics-informed emulators and non-intrusive reduced order modeling [1, 6]. The application of these techniques to challenging problems arising from the description of biological systems, such as the description of the cardiac function, might enhance the solution of problems that would be otherwise unfeasible.

This mini-symposium aims to showcase current advances in machine learning, reduced-order modeling and uncertainty quantification methods for biological systems, including (but not limited to) topics in data fusion, Bayesian inference, systems identification, real-time simulation, multi-fidelity modeling, hybrid model- and data-driven approaches, parameter estimation, data assimilation, and model personalization in computational medicine.

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