16th World Congress on Computational Mechanics and 4th Pan American Congress on Computational Mechanics

July 21-26, 2024, Vancouver Convention Centre, Vancouver, British Columbia, Canada

TRUSTWORTHY MULTI-FIDELITY AND DATA-DRIVEN MODELS FOR COMPUTATIONAL APPLICATIONS

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MINISYMPOSIUM

Emulators constructed from deep neural networks trained on data, have recently emerged as acomputationally efficient alternative to solving complex systems of ordinary/partial differentialequations that are often utilized in single- or multi-physics computational applications in science andengineering. However, the efficient, accurate, and stable training of state-of-the-art models requireslarge volumes of data extracted from high-fidelity numerical simulations or costly experiments, whicheffectively prohibits the application of these methods on high-fidelity applications. At the same time,there exists an opportunity to generate simplified models to generate multiple data sources bysimplifying the high-fidelity numerical model, e.g., the discretization of PDEs or the underlyinggoverning equations. Consequently, a limited quantity of high-fidelity outputs or experimental datacan be supplemented with a substantial volume of results obtained from simplified models. The maindrawback of these so-called “low-fidelity” models is that they are typically biased and do not retain thehigh-fidelity prediction capabilities necessary for trustworthy predictions. As a consequence, augmenting sparse, high-fidelity datasets with these less-expensive simulations requires carefulconsideration to avoid the corruption of information contained in the original high-fidelity model. Thisis often called “negative transfer” in the machine learning community.Several recent advancements in the areas of multi-fidelity and transfer learning have demonstrated thepotential benefits of this approach. In this minisymposium, we will welcome contributions thatdevelop, discuss and/or demonstrate approaches designed to lower the computational budget associatedto the multi-fidelity training of high-fidelity data-driven models. We are particularly interested incontributions that assess the trustworthiness and reliability of the proposed emulators.

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