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INNOVATIONS IN MACHINE LEARNING-ENHANCED UNCERTAINTY QUANTIFICATION FOR COMPUTATIONAL MECHANICS

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In practice, computational mechanics simulations involve uncertainties due to imprecise measurements, sparse data, and natural variability. UQ provides a systematic framework to quantify, characterize, and propagate these uncertainties, enabling a more comprehensive understanding of plausible model predictions. Through UQ, scientists and engineers can quantitatively gauge confidence in outcomes, perform robust optimization, assess design reliability, identify critical parameters within a model, guide future experimental efforts, and more. This, in turn, leads to risk-informed decision-making and more robust designs, making UQ an essential tool for computational mechanics in real-world scenarios.

A primary drawback of UQ is the associated computational costs. Recent integrations of machine learning (ML) with UQ have introduced novel avenues for expediting assessments and completing formerly intractable analyses. We aim to explore how the integration of these disciplines is leading to more efficient, accurate, and insightful uncertainty assessments. Topics of interest include but are not limited to the following:

1. Uncertainty Propagation: ML can expedite simulations, enabling tractable uncertainty propagation. Examples include active learning strategies for rare event predictions and multi-fidelity UQ methods that leverage low-fidelity ML models.
2. Model Calibration: Traditional probabilistic model calibration techniques such as Bayesian inference can often be intractable given expensive computational mechanics simulations. ML enables calibration through, for example, surrogate modeling or likelihood-free inference techniques.
3. Generative Modeling: Deep learning methods such as Denoising Diffusion Probabilistic Models (DDPM) and Generative Adversarial Networks (GANs) have been used to learn complex probability distributions from data to address uncertainty quantification challenges. The potential to extend these methods using physics informed learning is of particular interest.
4. Uncertainty Reduction: ML can accelerate approximation of sensitivity measures, allowing for the rapid identification of critical input parameters that drive uncertainty in model predictions. ML-assisted, optimal experimental design can then be utilized to reduce uncertainty through targeted experiments.