SIAM Conference on Uncertainty Quantification (UQ20)

Thursday – 26.03.2020

08:30

MS741: Machine learning methods for reliability analysis and risk assessment (Part I of II)

Chair(s)

Qifeng Liao (ShanghaiTech University)
Jinglai Li (University of Liverpool)

Room:
MW ZS 2050

Topic:
Rare events and Risk

Form of presentation:
Mini-symposium

Duration:
120 Minutes

Reliability analysis and risk assessment for complex physical and engineering systems governed by partial differential equations (PDEs) are computationally intensive, especially when high-dimensional random parameters are involved. Since standard numerical schemes for solving these complex PDEs are expensive, traditional Monte Carlo methods which require repeatedly solving PDEs are infeasible. Alternative approaches which are typically the surrogate based methods suffer from the so-called ``curse of dimensionality", which limits their application to problems with high-dimensional parameters. The purpose of this mini-symposium is to bring researchers from different fields to discuss the recent machine learning methods for such problems, focusing on both novel machine learning surrogates and alternative Monte Carlo methods.

08:30

A modified Multicanonical Monte Carlo method for failure probability estimation

Jinglai Li | University of Liverpool | United Kingdom

Author:

Jinglai Li | University of Liverpool | United Kingdom

In this talk we shall discuss the implementation of Multicanonical Monte Carlo (MMC) method for estimating rare failure probability. Here we present certain treatment to avoid constructing bins in the output space, an important step that has substantial impact on the estimation accuracy in the original MMC algorithm. The proposed method is based on Gaussian process regression and kernel density estimation. We provide numerical examples to illustrate the performance of the proposed method.

09:00

Coupling the reduced-order model and the generative model for an importance sampling estimator

Xiaoliang Wan | Louisiana State University | United States

Author:

Xiaoliang Wan | Louisiana State University | United States

In this work, we develop an importance sampling estimator by coupling the reduced-order model and the generative model in a problem setting of uncertainty quantification. The target is to estimate the probability that the quantity of interest (QoI) in a complex system is beyond a given threshold. To avoid the prohibitive cost of sampling a large scale system, the reduced-order model is usually considered for a trade-off between efficiency and accuracy. However, the Monte Carlo estimator given by the reduced-order model is biased due to the error from dimension reduction. To correct the bias, we still need to sample the fine model. An effective technique to reduce the variance reduction is importance sampling, where we employ the generative model to estimate the distribution of the data from the reduced-order model and use it for the change of measure in the importance sampling estimator. To compensate the approximation errors of the reduced-order model, more data that induce a slightly smaller QoI than the threshold need to be included into the training set. Although the amount of these data can be controlled by a posterior error estimate, redundant data, which may outnumber the effective data, will be kept due to the epistemic uncertainty. To deal with this issue, we introduce a weighted empirical distribution to process the data from the reduced-order model.

09:30

- CANCELED - A model reduction method for multiscale elliptic PDEs with random coefficients using an optimization approach

Zhiwen Zhang | University of Hong Kong | Hong Kong

Author:

Zhiwen Zhang | University of Hong Kong | Hong Kong

We propose a model reduction method for solving multiscale elliptic PDEs with random coefficients setting using an optimization approach. The optimization approach enables us to construct a set of localized multiscale data-driven stochastic basis functions that give optimal approximation property of the solution operator. Our method consists of offline and online stages. In the offline stage, we construct the localized multiscale data-driven stochastic basis functions by solving an optimization problem. In the online stage, using our basis functions, we can efficiently solve multiscale elliptic PDEs with random coefficients with relatively small computational costs. Therefore, our method is very efficient in solving target problems with many different force functions. The convergence analysis of the proposed method is also presented and has been verified by the numerical simulations.

10:00

A Hierarchical Neural Hybrid Method for Failure Probability Estimation

Ke Li | ShanghaiTech University | China

Author:

Ke Li | ShanghaiTech University | China

Failure probability evaluation for complex physical and engineering systems governed by
partial differential equations (PDEs) are computationally intensive, especially when high-dimensional random parameters are involved. Since standard numerical schemes for solving these complex PDEs are expensive, traditional Monte Carlo methods which require repeatedly solving PDEs are infeasible.
Alternative approaches which are typically the surrogate based methods suffer from the so-called ``curse of dimensionality'', which limits their application to problems with high-dimensional parameters. For this purpose, we develop a novel hierarchical neural hybrid (HNH) method to efficiently compute failure probabilities of these challenging high-dimensional problems. Especially, multifidelity surrogates are constructed based on neural networks with different levels of layers, such that expensive highfidelity surrogates are adapted only when the parameters are in the suspicious domain. The efficiency of our new HNH method is theoretically analyzed and is demonstrated with numerical experiments. From numerical results, we show that to achieve an accuracy in estimating the rare failure probability (e.g., 1e-5), the traditional Monte Carlo method needs to solve PDEs more than a million times, while our HNH only requires solving them a few thousand times.