Abstract:
Current medical practice heavily relies on population data and physician experience, with ”one-size-fits-all” strategies that have a limited ability to assess inter-subject variations in the underlying physiological processes. In contrast, computer simulation models – customized to individual anatomy and physiology – provide physicians with a patient-specific virtual organ to predict therapeutic responses, at minimal to no risk to the patient. However, healthcare industry has been slow in embracing simulation models. A key barrier is the variability in model predictions that, if not quantified, will hamper decision support.

Probabilistic inference at the presence of these models is challenging, because standard Markov Chain Monte Carlo (MCMC) sampling requires repeated model simulations that are computationally infeasible. Surrogate modeling is an important building block in uncertainty quantification in these models, with the goal to construct an efficient approximation of the expensive simulation model. To build a “globally accurate” approximation of a highly nonlinear model, however, is computationally infeasible without sacrificing local approximation accuracy. In this talk, we describe our recent effort in cast surrogate modeling as a machine-learning problem, in which the training data are virtually infinite (in a continuous space) but expensive to obtain (incurring model evaluations). We highlight our concept and developments in “active surrogate modeling” which, during the construction of the surrogate, will actively search the optimal training points (samples) at which to query the model. This high-dimensional active search is further embedded into a low-dimensional latent space through probabilistic generative modeling. Finally, we present surrogate-accelerated MCMC algorithms that utilize the surrogate to theoretically accelerate the convergence of MCMC sampling. We demonstrate the efficacy of these developments in the application context of patient-specific cardiac modeling. These developments are highly novel at several aspects. In the area of surrogate modeling, this is the first time active learning concepts are introduced to intelligently realize a locally-focused approximation. In the general area of active learning, this is the first integration of generative modeling to realize active learning over a high-dimensional continuous space.