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**Abstract Text:**

I will define three basic mathematical problems we encounter in applications involving partial differential equations (PDEs): the uncertainty propagation problem, the inverse problem, and the design under uncertainty problem. In the uncertainty propagation problem, one knows the system of PDEs governing the physical system, but may be uncertain about model parameters, boundary or initial conditions. The objective is to propagate this uncertainty through the PDE to characterize the uncertainty in quantities of interest. We will use an example from reconstructive skin surgery modeling to introduce the concepts. The inverse problem goes the other way. One has some experimental data which can be thought as noisy, incomplete measurements of some physical quantities of interest that satisfy a system of PDEs. The objective here is to calibrate the model parameters and reconstruct the unobserved physical fields. The motivating example will be reconstructing the velocity and pressure fields from 4D MRI aneurism data. The design under uncertainty problem consists of optimizing the expectation of a quantity of interest that depends on the solution of a system of PDEs. The motivating example will also be from reconstructive skin surgery where one wishes to identify the optimal flap design that minimizes a complications index. After introducing the basic problems, I will argue why existing techniques are inadequate to solve realistic problems due to the curse of dimensionality. Finally, I will introduce the idea of physics-informed machine learning through a toy, but very challenging, uncertainty propagation example involving a stochastic elliptic PDE with thousands of uncertain variables.