Learning Guarantees for Data-Driven Sparse Sensing and System Identification

BIOGRAPHY

Krithika Manohar is an Assistant Professor of Mechanical Engineering at the University of Washington. Her research lies at the intersection of machine learning and dynamical systems, with a focus on data-driven methods for sensing, estimation, and control of complex engineering systems. She received her Ph.D. in Applied Mathematics from the University of Washington, followed by a postdoctoral appointment and von Kármán Instructorship at Caltech. She is a recipient of the NSF Mathematical Sciences Postdoctoral Research Fellowship and the Boeing Award for Excellence in Research at the University of Washington.

ABSTRACT

A core challenge in scientific machine learning is how to learn from limited, noisy, or strategically chosen data. This talk presents the mathematics of sparse sensing—the problem of choosing maximally informative measurements for high-dimensional estimation and control. Sensor placement defines a highly nonconvex optimization landscape and, in general, is NP-hard. Existing methods provide limited insight into the underlying landscape of sensing objectives. Our framework characterizes this landscape explicitly: at each iteration, it yields a spatial map of the objective, revealing how information gain varies across possible sensor locations.

We formulate this problem through the lens of statistical mechanics, deriving a Hamiltonian whose minima corresponds to optimal sensor configurations under uncertainty and physical constraints. This approach unifies ideas from information theory, D-optimal design, and statistical physics, producing scalable algorithms with estimation guarantees. The resulting methods enable robust field reconstruction and uncertainty quantification in safety-critical environments, while exposing structure in the dynamics of physical systems. These ideas further extend to nonlinear system identification, where sparse discovery of governing equations (SINDy) can be interpreted as a learning problem with an underlying energy landscape.