Data-Driven Reduced Order Models As Deep Prior Neural Networks In Inverse Scattering

Mikhail Zaslavsky, Schlumberger

In this talk we discuss the framework of a data-driven model order reduction for solving inverse scattering problem when only a significantly limited training set (even composed of just a single data element) is available. We formulate our reduced order model (ROM) as a deep prior neural network with a specific physics-based architecture. It is inspired by 1950's works of M. Krein who developed mechanical interpretation of synthesized networks and constructed the data embedding into the state space. This allows networks to learn efficiently the underlying PDE system directly from the measured data, hence the data-driven designation. Unlike conventional optimization-based training of deep networks, our network hyperparameters can be computed directly from the data using existing powerful tools of data-driven ROMs . To show the advantages of using such networks, we consider time-domain acoustic and electromagnetic inverse problems in multiple-scattering environments. We focus on two such applications: 1) a transform that linearizes the dependency of the data on the medium therefore suppressing nonlinear artifacts, such as multiple reflections in acoustic and elastic full waveform data. It can be used as a preprocessing step in conventional linearized (Born) inversion algorithms. 2) inversion of high-frequency radar and low-frequency diffusive electromagnetic data preconditioned via ROM-based autoencoder. Numerical examples will be presented to verify the performance of the framework.