Plenary Talks

Haomin Zhou - Analysis and Computation of Parameterized Wasserstein Geometric Flow

We introduce a new parameterization strategy that can be used to design algorithms simulating geometric flows on Wasserstein manifold, the probability density space equipped with optimal transport metric. The framework leverages the theory of optimal transport and the techniques like the push-forward operators and neural networks, leading to a system of ODEs for the parameters of neural networks. The resulting methods are mesh-less, basis-less, sample-based schemes that scale well to higher dimensional problems. The strategy works for Wasserstein gradient flows such as Fokker-Planck equation, and Wasserstein Hamiltonian flow like Schrodinger equation. Theoretical error bounds measured in Wasserstein metric is established. This presentation is based on joint work with Yijie Jin (Math, GT), Shu Liu (UCLA), Has Wu (Wells Fargo), and Xiaojing Ye (Georgia State).

Sung Ha Kang - Identifying Differential Equations with Weak Form

We explore identifying underlaying differential equation from given single set of noisy time dependent data. We assume that the governing equation is a linear combination of linear and nonlinear differential term, and the identification can be formulated as a linear system, with the feature matrix multiplied by a coefficient vector. This talk will cover a couple of our recent work on this topic for ODE and PDE recovery. Using weak form shows robustness against higher level of noise and higher order derivative in underlying equation. We further consider Group subspace pursuit for varying coefficient cases and using Fourier domain for identification.

Peng Chen - Derivative-informed Neural Operators for PDE-Constrained Optimization under Uncertainty

In this talk I will present a class of Derivative-Informed Neural Operators (DINO) for solving optimization problems governed by large-scale partial differential equations (PDEs) with high-dimensional random parameters. Such optimization problems appear in Bayesian inverse problems for parameter estimation, optimal experimental design for data acquisition, and stochastic optimization for risk-averse optimal control and design, etc. I will provide error/convergence/complexity analysis and demonstrate the high accuracy, dimension scalability, and sampling efficiency of DINO by its applications in material science, computational fluid dynamics, and structure mechanics.

Zecheng Zhang - Multi-operator learning

Single operator learning learns a single operator which maps a function to another function. In this talk we will discuss multi-operator learning (MOL) which is an extension of the single operator learning: it identify the operator and construct the operator simultaneously. We will discuss several advantages of the MOL such as the extrapolations.