MATHEMATICS COLLOQUIUM

THURSDAY

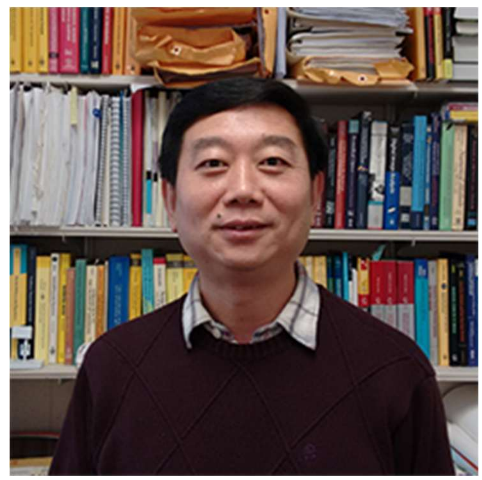
MARCH

27

4:30 - 5:30PM
LECONTE COLLEGE
ROOM 444

Computing high dimensional Wasserstein geometric flows in neural network parameter space

Machine learning based strategies have impacted computational mathematics significantly in recent years. Many used-to-be intractable tasks such as solving high dimensional PDEs or computing solution operators for differential equations can be tackled by methods using artificial neural network (ANN). In this presentation, I will use Wasserstein geometric flows as examples to illustrate several new mathematical questions and methodologies that are designed to handle certain classes of PDEs in high dimensions. More precisely, a parameterization framework has been developed for simulating geometric flows on the Wasserstein manifold, the probability density space equipped with optimal transport metric. The framework leverages the theory of optimal transport and techniques like the push-forward operators and ANNs, leading to a system of ODEs for the parameters of neural networks. The resulting methods are mesh-less, basis-less, sample-based schemes that can scale up well to higher dimensional problems. The strategy works for Wasserstein gradient flows such as Fokker-Planck and porous media equations, and Wasserstein Hamiltonian flows like Schrodinger equation. Theoretical error bounds measured in Wasserstein metric are established too. This presentation is based on joint work with Yijie Jin (Math, GT), Wuchen Li (South Carolina), Shu Liu (UCLA), Hao Wu (Wells Fargo), Xiaojing Ye (Georgia State), and Hongyuan Zha (CUHK-SZ).



Haomin Zhou
Professor
School of Mathematics
Georgia Institute of Technology

UNIVERSITY OF South Carolina

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