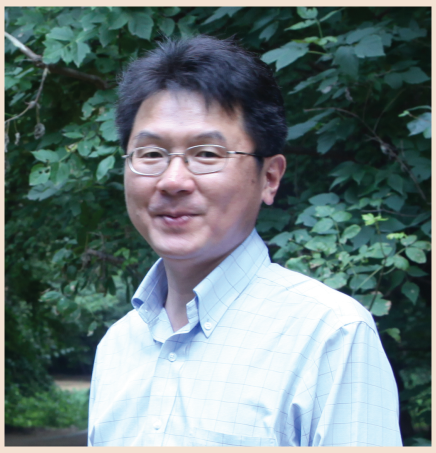
香港浸會大學
HONG KONG BAPTIST UNIVERSITY

Department of Mathematics

Distinguished Lecture Series

A Geometric Understanding of Deep Learning



Professor David Xianfeng Gu

New York Empire Innovation Professor at the Department of Computer Science, Stony Brook University

Biography:
David Gu is a New York Empire Innovation Professor at the Department of Computer Science, Stony Brook University. He received his Ph.D degree from the Department of Computer Science, Harvard University in 2003, supervised by the Fields medalist Prof. Shing-Tung Yau, and B.S. degree from the Tsinghua University, Beijing, China in 1995.
His research focuses on applying modern geometry in engineering and medical fields. With his collaborators, David systematically develops discrete theories and computational algorithms in the interdisciplinary field: Computational Conformal Geometry, and apply them for solving real problems, such as global surface parameterization in graphics, deformable shape registration in vision, manifold spline in geometric modeling, curvature convergence analysis in geometric processing, efficient routing in networking, brain mapping and virtual colonoscopy in medical imaging, and so on.
He is a recipient of Morningside Gold Medal of Applied Mathematics 2013; National Science Foundation (NSF) Faculty Early Career Award, 2005.

Date: 6 April 2022 (Wednesday)
Time: 10:00-11:00 a.m. GMT+8 (Hong Kong Time)
Venue: Online via Zoom (Meeting ID: 965 6623 4311)

Abstract

This work introduces an optimal transportation (OT) view of generative adversarial networks (GANs). Natural datasets have intrinsic patterns, which can be summarized as the manifold distribution principle: the distribution of a class of data is close to a low-dimensional manifold. GANs mainly accomplish two tasks: manifold learning and probability distribution transformation. The latter can be carried out using the classical OT method. From the OT perspective, the generator computes the OT map, while the discriminator computes the Wasserstein distance between the generated data distribution and the real data distribution; both can be reduced to a convex geometric optimization process. Furthermore, OT theory discovers the intrinsic collaborative—instead of competitive—relation between the generator and the discriminator, and the fundamental reason for mode collapse. We also propose a novel generative model, which uses an autoencoder (AE) for manifold learning and OT map for probability distribution transformation. This AE–OT model improves the theoretical rigor and transparency, as well as the computational stability and efficiency; in particular, it eliminates the mode collapse. The experimental results validate our hypothesis, and demonstrate the advantages of our proposed model.

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