CMAI: Interface of Math and Artificial Intelligence Seminar
The Chinese University of Hong Kong

This CMAI Interface of Math and AI Seminar is organized by Centre for Mathematical Artificial Intelligence (CMAI), under Department of Mathematics at CUHK.

Date: June 7, 2024 (Friday)
Time: 2:00 pm-3:30 pm (Hong Kong Time)
Zoom Meeting: 905 330 9693

Towards Decentralized Learning over Digraphs: Effective metrics, lower bound, and optimal algorithms

Speaker: Prof. Kun Yuan
Peking University

Abstract: In this talk, we will investigate the influence of directed networks on the convergence of decentralized learning associated with column-stochastic mixing matrices. We find that the canonical spectral gap, a widely-used metric in undirected networks, alone fails to adequately characterize the impact of directed networks. Through a new analysis of the Push-Sum strategy, a fundamental building block for decentralized algorithms over directed graphs, we identify another novel metric called the equilibrium skewness. Next, we establish the first convergence lower bound for non-convex stochastic decentralized algorithms over directed networks, which explicitly manifests the impact of both the spectral gap and equilibrium skewness and justifies the imperative need for both metrics in analysis. Moreover, by jointly considering the spectral gap and equilibrium skewness, we present the state-of-the-art convergence rate for the Push-DIGing algorithm, which, however, is far worse than the established lower bound. We further integrate the technique of multi-round gossip to Push-DIGing to obtain MG-Push-DIGing, which nearly achieves the established lower bound, demonstrating its convergence optimality, best-possible resilience to directed networks, and the tightness of our lower bound. Experiments verify our theoretical findings.

Bio: Dr. Kun Yuan is an Assistant Professor at Center for Machine Learning Research (CMLR) in Peking University. He completed his Ph.D. degree at UCLA in 2019, and was a staff algorithm engineer in Alibaba (US) Group between 2019 and 2022. His research focuses on the development of fast, scalable, reliable, and distributed algorithms with applications in large-scale optimization, deep neural network training, federated learning, and Internet of Things. He was the recipient of the 2017 IEEE Signal Processing Society Young Author Best Paper Award, and the 2017 ICCM Distinguished Paper Award.