Frontier of Artificial Network

CityU Department of Data Science

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# From Fair Unlearning Algorithms to Incentive-Compatible Mechanisms in Federated Unlearning


**Invited Speaker**

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**Date:** December 3, 2025 (Wednesday)

**Time:** 14:00-15:30 (Hong Kong Time)

**Zoom Meeting:** 756 768 6492

## Biography

Ningning Ding is a Tenure-Track Assistant Professor in the Data Science and Analytics Thrust and the Internet of Things Thrust at the Hong Kong University of Science and Technology (Guangzhou). Before that, she was a Postdoctoral Scholar in the Department of Electrical and Computer Engineering at Northwestern University, USA, and she received her Ph.D. in Information Engineering from The Chinese University of Hong Kong. Her research focuses on on trustworthy learning and efficient coordination in distributed environments. Her work has been published in top-tier journals and conferences such as IEEE JSAC, COMST, and TMC. Some of her research outcomes have been applied in industry, including Huawei and DiDi. She has led or participated in projects funded by the National Natural Science Foundation of China and the Ministry of Industry and Information Technology. Dr. Ding has received several honors, including the CCF-DiDi Gaia Scholar and Rising Star Woman in Engineering. She is actively looking for self-motivated Ph.D. students. https://ningningding.com/

## Abstract


Federated unlearning is becoming essential for safeguarding users' "right to be forgotten" by removing the influence of leaving clients' data from collaboratively trained models. While existing research has emphasized unlearning accuracy and computational efficiency, two critical yet underexplored dimensions—fairness in algorithmic unlearning and incentive compatibility in user participation—determine whether federated unlearning can be both effective and sustainable in practice. We first introduce fair federated unlearning algorithms through the lens of FedShard, the first method designed to ensure both efficiency fairness and performance fairness across heterogeneous clients. FedShard adaptively navigates the trade-offs between convergence speed, unlearning cost, and fairness constraints, preventing risks such as cascaded departures and poisoning behaviors. Building on these insights, we develop an incentive-compatible unlearning mechanism based on a four-stage game that captures learning, unlearning strategies, and information updates. By connecting fair unlearning algorithms with incentive-aligned mechanisms, this talk provides a perspective on achieving efficient, equitable, and strategically robust federated unlearning.