

Wireless Networks

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Wei Yang Bryan Lim • Jer Shyuan Ng •
Zehui Xiong • Dusit Niyato • Chunyan Miao

Federated Learning Over Wireless Edge Networks

 Springer

Wei Yang Bryan Lim
Alibaba-NTU Joint Research Institute
Singapore, Singapore

Jer Shyuan Ng
Alibaba-NTU Joint Research Institute
Singapore, Singapore

Zehui Xiong
Singapore University of Technology and
Design
Singapore, Singapore

Dusit Niyato
School of Computer Science and
Engineering
Nanyang Technological University
Singapore, Singapore

Chunyan Miao
School of Computer Science and
Engineering
Nanyang Technological University
Singapore, Singapore

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Preface

The confluence of edge computing and artificial intelligence (AI) has driven the rise of edge intelligence, which leverages the storage, communication, and computation capabilities of end devices and edge servers to empower AI implementation at scale closer to where data is generated. An enabling technology of edge intelligence is the privacy-preserving machine learning paradigm known as federated learning (FL). Amid the increasingly stringent privacy regulations, FL will enable the development of applications that have to be built using sensitive user data and will continue to revolutionize service delivery in finance, Internet of Things (IoT), healthcare, and transport industries, among others. However, the implementation of FL is envisioned to involve thousands of heterogeneous distributed end devices that differ in terms of communication and computation resources, as well as the levels of willingness to participate in the collaborative model training process. The potential node failures, device dropouts, and stragglers effect are key bottlenecks that impede the effective, sustainable, and scalable implementation of FL.

In Chap. 1, we will first present a tutorial and survey on FL and highlight its role in enabling edge intelligence. This tutorial and survey provide readers with a comprehensive introduction to the forefront challenges and state-of-the-art approaches towards implementing FL at the edge. In consideration of resource heterogeneity at the edge networks, we then provide multifaceted solutions formulated via the interdisciplinary interplay of concepts derived from network economics, optimization, game theory, and machine learning towards improving the efficiency of resource allocation for implementing FL at scale amid information asymmetry. In Chap. 2, we devise a multi-dimensional contract-matching approach for optimized resource allocation for federated sensing and learning amid multi-dimensional sources of heterogeneities. In Chap. 3, we propose a joint-auction coalition formation framework towards facilitating communication-efficient FL networks aided by unmanned aerial vehicles (UAVs). In Chap. 4, we propose a two-level evolutionary game theoretic and auction approach to allocate and price resources to facilitate efficient edge intelligence. In Chap. 5, we recap the key points and discuss the promising research directions for future works.

We sincerely thank our collaborators for their contributions to the presented research works. Special thanks also go to the staff at Springer Nature for their help throughout the publication preparation process. Finally, we would like to take the chance to dedicate this book to celebrate the birth of Lim Chen Huan Theodore, son of Dr. Lim Wei Yang Bryan and Foo Feng Lin.

Singapore, Singapore
Singapore, Singapore
Singapore, Singapore
Singapore, Singapore
Singapore, Singapore

Wei Yang Bryan Lim
Jer Shyuan Ng
Zehui Xiong
Dusit Niyato
Chunyan Miao

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