Big and Integrated Artificial Intelligence 2

M. Hadi Amini *Editor*

Distributed Machine Learning and Computing

Theory and Applications

Springer

Big and Integrated Artificial Intelligence

Volume 2

Series Editor

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ISSN 2662-4133 ISSN 2662-4141 (electronic)
Big and Integrated Artificial Intelligence
ISBN 978-3-031-57566-2 ISBN 978-3-031-57567-9 (eBook)
https://doi.org/10.1007/978-3-031-57567-9

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

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Preface

There has been an emerging concern regarding the optimal decision-making in large-scale networks. In this book, we focus on the wide range of novel distributed machine learning and computing algorithms and their applications in real-world applications, such as healthcare. To this end, this book includes contributions that explore distributed computing methods for a wide range of applications, including healthcare, drone networks, and energy systems.

Miami, FL, USA — M. Hadi Amini

Contents

About the Editor

M. Hadi Amini is an Assistant Professor at the Knight Foundation School of Computing and Information Sciences, College of Engineering and Computing, Florida International University. He is the Director of Sustainability, Optimization, and Learning for InterDependent Networks laboratory (www.solidlab.network), the Director of the ADvanced education and research for Machine learning-driven critical Infrastructure REsilience (ADMIRE) Center (funded by the US DHS), and the Associate Director of the USDOT Transportation Center for Cybersecurity and Resiliency (TraCR). He received his PhD in Electrical and Computer Engineering from Carnegie Mellon University in 2019, where he received his MSc degree in 2015. He also holds a doctoral degree in Computer Science and Technology. Prior to that, he received MSc degree from Tarbiat Modares University in 2013, and the BSc degree from Sharif University of Technology in 2011. His research interests include distributed learning and optimization algorithms, distributed computing and intelligence, interdependent networks, and cyber-physical-social security and resilience. Application domains include smart cities, energy systems, transportation networks, and healthcare.

Dr. Amini is a Senior Member of IEEE, and a life member of IEEE-Eta Kappa Nu (IEEE-HKN), the honor society of IEEE. He also serves/has served as Associate Editor of *IEEE Transactions on Information Forensics and Security*, SN *Operations Research*

Forum, Data Science for Communications (*Frontiers in Communications and Networks*), and *International Transactions on Electrical Energy Systems*. He edited/authored eight books and is the recipient of the best paper award from "2019 IEEE Conference on Computational Science and Computational Intelligence," "2024 Florida International University Top Scholar Award, Research and Creative Activities, Junior Faculty with Significant Grants (Sciences)," "2023 Florida International University Faculty Excellence in Teaching Award," 2021 best journal paper award from "Springer Nature *Operations Research Forum* Journal," FIU's Knight Foundation School of Computing and Information Sciences' "Excellence in Teaching Award," best reviewer award from four IEEE Transactions, the best journal paper award in "*Journal of Modern Power Systems and Clean Energy*," and the dean's honorary award from the President of Sharif University of Technology.

Chapter 1
Distributed Machine Learning and Computing: An Overview

M. Hadi Amini

The proliferation of sensing and monitoring systems and devices, such as IoT devices, autonomous vehicles, smart homes, and smart cities, is leading to a significant increase in the complexity of decision-making problems. There has been an emerging concern regarding the optimal decision-making in large-scale networks, such as critical infrastructures and healthcare systems. In the first volume of this book series, we focused on a wide range of novel federated decision-making, computing, and machine learning algorithms, and their applications in real-world problems, including drones, healthcare, Internet-of-Things, and power and energy systems. To this end, the present volume of this book series includes contributions from experts in federated learning, distributed computing, and blockchain technologies. As the purpose of this edited volume is mainly on applications of distributed machine learning and computing, readers may refer to the following comprehensive surveys and studies for more details on distributed optimization from theory [1, 2] and application [3, 4] perspectives, as well as federated learning [5–7] and its applications [8–10].

The rest of this book is organized as follows:

(i) Chapter 2 proposes a novel *distributed multi-agent meta learning mechanism* to solve the problem of trajectory design for energy-constrained drones operating in dynamic wireless network environments.
(ii) Chapters 3 and 4 mainly focus on distributed learning and parallel computing for healthcare applications. Specifically, Chap. 3 focuses on developing distributed machine learning solutions for health IoT applications with an emphasis on EEG data as use case. Chapter 4 provides a comprehensive survey

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M. H. Amini (ed.), *Distributed Machine Learning and Computing*, Big and Integrated Artificial Intelligence 2, https://doi.org/10.1007/978-3-031-57567-9_1

of AI and Machine Learning, and their applications in healthcare, with an emphasis on federated learning methods.

(iii) Chapter 5 provides a review of vertical federated learning (VFL) which vertically partitions data features and labels across clients.

(iv) Chapters 6 and 7 focus on distributed computing solutions for power and energy systems. Specifically, Chap. 6 focuses on restructuring the current operational architecture of the electricity grid in view of the ongoing decentralization trends with an emphasis on peer-to-peer energy trading. Chapter 7 explores the transition from centralized to decentralized approaches in the electricity industry, with a particular focus on how machine learning advancements play a crucial role in empowering renewable energy sources and improving grid management.

The following includes list of chapters, and their brief abstract is provided below:

- Chapter 2: "*Distributed Multi-agent Meta Learning for Trajectory Design in Wireless Drone Networks*" by Hu and Chen: *This chapter proposes a value decomposition-based reinforcement learning (RL) coupled with a meta training mechanism that allows RL agents to dynamically learn their policies while generalizing their learning to unseen environments. It also explores the use of the designed RL algorithm to solve the problem of the trajectory design for energy-constrained drones operating in dynamic wireless network environments. The trajectory design problem is posed as an optimization framework with the goal of finding optimal trajectories that maximize the fraction of users served by all drone base stations. Then, authors explain how to use the designed RL algorithm to solve this trajectory design problem.*
- Chapter 3: "*Heterogeneity Aware Distributed Machine Learning at the Wireless Edge for Health IoT Applications: An EEG Data Case Study*" by Mohammad and Saeed: *This chapter proposes a mobile edge learning (MEL) framework that enables multiple end user devices or learners to cooperatively train a machine learning model in a wireless edge environment. It develops a heterogeneity aware synchronous (HA-Sync) approach with time-constraints and extend the framework to consider dual time and energy constraints. The proposed MEL framework includes commonly known federated learning and parallelized learning. For the problem with dual time and energy constraints, this chapter proposes solutions based on the suggest and improve (SAI) approach. As an application focus, authors demonstrate a real-time medical event prediction by showing the applicability of personalized MEL for epileptic seizure detection and predictions—using EEG data.*
- Chapter 4: "*A Comprehensive Review of Artificial Intelligence and Machine Learning Methods for Modern Healthcare Systems*" by Ahmed et al.: "*Artificial Intelligence (AI) and Machine Learning (ML) methods have been applied significantly in modern healthcare systems in the last few years. AI and its subfields, such as ML, Deep Learning (DL) and Reinforcement Learning (RL) are driving a paradigm shift in modern healthcare systems, including disease*

detection, diagnosis, treatment, and outcome prediction, supported by good quality healthcare datasets. Research domains such as telemedicine, precision medicine, and healthcare monitoring have become pioneers in deploying AI methods for advancing medical sectors. Additionally, the emerging subfield of AI, Federated Learning (FL) removes the barrier of data sharing and enhances privacy which is gaining increasing attention as a mainstream technology in healthcare research and utilizing patients' data efficiently. This paper provides a comprehensive study of the use of AI, ML, and FL methods in smart healthcare systems, their contributions to this paradigm shift, their current status, and their recent challenges. In addition, this study outlines a roadmap for future research in this domain."

- Chapter 5: "*Vertical Federated Learning: Principles, Applications, and Future Frontiers*" by Saadati et al.: "*This chapter explores vertical federated learning (VFL), a paradigm that diverges from traditional horizontal FL by vertically partitioning data features and labels across entities. It starts with an introduction, providing context for VFL within the broader landscape of Federated Learning. Highlighting the differences between HFL and VFL architecture. Delving into the principles of VFL, we uncovered the basic pipeline of VFL and various stages of this platform. Some of the main applications of VFL are explored to showcase its unique suitability for scenarios involving dependent entities, such as organizations with shared user data.*"
- Chapter 6: "*Decentralization of Energy Systems with Blockchain: Bridging Top-Down and Bottom-Up Management of the Electricity Grid*" by Mishra et al.: *The electricity grid has operated in a centralized top-down fashion. However, as distributed energy resources penetration grows, the grid edge is increasingly infused with intelligent computing and communication capabilities. Decentralization refers to transferring control and decision-making from a centralized entity (individual, organization, or group thereof) to a distributed network. This chapter aims to highlight the need for and outline a credible path toward restructuring the current operational architecture of the electricity grid in view of the ongoing decentralization trends with an emphasis on peer-to-peer energy trading. Authors further introduce blockchain technology in the context of decentralized energy systems problems. They also suggest that blockchain is an effective technology for facilitating the synergistic operations of top-down and bottom-up approaches to grid management.*
- Chapter 7: "*Empowering Distributed Solutions in Renewable Energy Systems and Grid Optimization*" by Mohammadi and Mohammadi: *This chapter delves into the shift from centralized to decentralized approaches in the electricity industry, with a particular focus on how machine learning (ML) advancements play a crucial role in empowering renewable energy sources and improving grid management. ML models have become increasingly important in predicting renewable energy generation and consumption, utilizing various techniques like artificial neural networks, support vector machines, and decision trees. Furthermore, data preprocessing methods, such as data splitting, normalization, decomposition, and discretization, are employed to enhance prediction accuracy.*

This research demonstrates the evolving landscape of the electricity sector as it shifts from centralized to decentralized solutions through the application of ML innovations and distributed decision-making, ultimately shaping a more efficient and sustainable energy future.

Acknowledgments This work is based upon the work partly supported by the National Center for Transportation Cybersecurity and Resiliency (TraCR) (a U.S. Department of Transportation National University Transportation Center) headquartered at Clemson University, Clemson, South Carolina, the USA. Any opinions, findings, conclusions, and recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of TraCR, and the US Government assumes no liability for the contents or use thereof.

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Chapter 2
Distributed Multi-agent Meta-Learning for Trajectory Design in Wireless Drone Networks

Ye Hu and Mingzhe Chen

2.1 Introduction

Aerial wireless communication platforms carried by drones can provide a cost-effective, flexible approach to boost the coverage and capacity of future wireless networks [1–3]. However, effectively deploying a group of drone base stations (DBSs) for providing timely on-demand wireless connectivity to ground users in dynamic wireless environments is still an important open problem. In particular, designing trajectories for a group of independent DBSs is challenging particularly when the DBSs only have limited information on the wireless requests of the ground users, which are often highly unpredictable and dynamic.

2.1.1 Related Works

The existing literature in [4–17] studied a number of problems related to trajectory design for drone-based wireless networks. The work in [4] studies the drone trajectory optimization problem by jointly considering both the drone's communication

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M. H. Amini (ed.), *Distributed Machine Learning and Computing*, Big and Integrated Artificial Intelligence 2, https://doi.org/10.1007/978-3-031-57567-9_2

throughput and its energy consumption. The authors in [5] design the trajectory of a solar-powered DBS to enhance its wireless communication performance. In [6], the problem of trajectory design and user association in a multi-drone communication system is solved with a block coordinate descent solution. The authors in [7] propose a dynamic trajectory control algorithm to improve the communication performance of the DBSs. The authors in [8] jointly optimize resource allocation and the deployment of DBSs in visual light-assisted networks. Despite their promising results, these existing works [4–8] do not consider practical DBS-assisted wireless networks in which the ground user requests for wireless service follow unpredictable patterns. Indeed, the optimization-based solutions in [4–8] are not suitable to design DBS trajectories when the user requests are unknown and unforeseeable.

Recently, there has been significant interest in realizing intelligent control of drones in dynamic networking environments, using machine learning tools [18, 19] for trajectory design [9–17, 20]. In [9], the problem of real-time dynamic maneuver design at a data collecting DBS is studied and solved using reinforcement learning (RL). The work in [10] employs two powerful deep neural networks to intelligently guide an energy-limited DBS under environmental dynamics. In [11], the authors develop an RL algorithm that enables a drone to act as a data-collection relay with the goal of maximize information freshness. The authors of [20] propose to use a neural network to predict user traffic for the optimal deployment of DBSs using rate-splitting multiple access. However, the work in [11] is restricted to the case of a single drone. For intelligently controlling multi-drone systems, the authors in [12] design interference-aware paths for a group of cellular-connected drones by using a multi-agent reinforcement learning (MARL) solution that relies on a deep echo state network (ESN) architecture. The work in [13] proposes a deep MARL architecture that directs drones within a continuous set of locations to accomplish time-sensitive sensing tasks. Meanwhile, in [14], the authors develop a MARL framework to allow drones dynamically manage resources according to their local observations. The authors in [15] propose an ESN-based learning architecture to predict the users' mobility patterns and, then, realize an optimal deployment of a group of DBSs. The works in [16] and [17] propose distributed multi-agent algorithms that allow a group of agents to update their individual strategies considering the team benefits. However, most of the existing MARL solutions such as those in [12] and [15–17] require DBSs to share their states and actions while searching for the optimal strategies. These traditional RL solutions have high complexity as they solve multi-agent problems by updating strategies based on the entire set of agents' actions and strategies whose dimension increases exponentially with the number of agents. Meanwhile, the MARL solutions in [13] and [14] allow the agents to search strategies independently based on their own actions and states. However, using these RL solutions, the DBSs cannot optimize the sum utilities of all DBSs and, thus, cannot maximize the overall coverage of the ground users since the DBSs are optimizing their individual utilities. In addition, traditional RL solutions such as those used in [12–17] cannot efficiently adapt the trajectories of the DBSs to unseen environments as they are often overfitted to their training tasks. This is because the hyper-parameters, exploration strategies, and initializations of traditional RL algorithms are manually adjusted for fitting the training tasks. Once the agent faces an unseen task, manually adjusted RL algorithms may not converge to the optimal solution and, even if they do, the convergence speed will be very slow. As a result, the traditional RL algorithms in [9–17, 20] cannot effectively find optimal DBS trajectories in unseen environments. Finally, we note that in [21], we studied the problem of trajectory design for a single DBS operating in a dynamic environment using meta-learning. However, this prior work relies on a simple algorithm that cannot be scaled to larger networks.

2.2 Preliminaries of RL

RL enables the wireless devices to learn the control and management strategies such as resource allocation schemes by interacting with their dynamic wireless environment [22]. Next, we introduce three basic RL algorithms that are generally used for wireless networks.

2.2.1 Single Agent RL

The formal model of a single agent RL can be described as a Markov decision process (MDP) [22]. Hence, the model of a single agent RL consists of four components: agent, state, action, and reward. The agent refers to the device that implements the RL algorithm. The state describes the environment observed by the agent at each time slot. A reward evaluates the immediate effect of an action given a state.

Single agent RL enables the agent to find a policy that maximizes the expected discounted reward while only receiving the immediate reward at each learning step. During the single agent RL training process, the agent first observes its current state and then performs an action. As a result, the agent receives its immediate reward together with its new state. The immediate reward and new state are used to update the agent's policy. This process will be repeated until the agent finds a policy that can maximize the expected discounted reward.

In wireless networks, single agent RL algorithms can be considered as the centralized algorithms used for network control and optimization. In particular, single RL algorithms that are implemented by a central controller are mainly used for solving non-convex or time-dependent optimization problems. For example, one can use single RL algorithms to optimize the trajectory of an unmanned aerial vehicle [23, 24]. However, as the number of mobile devices that are considered by single agent RL increases, the action and state space of the single agent RL will significantly increase, thus increasing the training complexity and decreasing the convergence speed. Meanwhile, as the number of the considered devices increases, the overhead of collecting state information of all devices increases which further