Guest Editorial Special Issue on Distributed Learning Over Wireless Edge Networks—Part I

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ANALYZING massive amounts of data using complex machine learning models requires significant computational resources. The conventional approach to such problems involves centralizing training data and inference processes in the cloud, i.e., in data centers. However, with the proliferation of mobile devices and increasing application of the Internet-of-Things (IoT) paradigm, very large amounts of data are collected at the edges of wireless networks, and due to privacy constraints and limited communication resources, it is undesirable or impractical to upload this data from mobile devices to the cloud for centralized learning. This problem can be solved by distributed learning at the network edge, by which edge devices collaboratively train a shared learning model using real-time mobile data. The avoidance of raw-data uploading not only helps to preserve privacy but may also alleviate network-traffic congestion and minimize latency. With that said, distributed training still requires a substantial amount of information exchange between devices and edge servers over wireless links. In the process, wireless impairments such as noise, interference, and imperfect knowledge of channel states can significantly slow down distributed learning (e.g., convergence speed) and degrades its performance (e.g., learning accuracy). This makes it crucial to optimize wireless network performance so as to support the efficient deployment of distributed learning algorithms. On the other hand, distributed learning algorithms provide a powerful tool-set for solving complex problems in wireless communication and networking. One important framework, called federated learning (FL), enables users to collaboratively learn a shared model while helping to preserve local data privacy. The application of FL can endow edge devices with capabilities of user behavior prediction, user identification, and wireless environment analysis. As another example, distributed reinforcement learning is capable of leveraging distributed computation power and data to solve complex optimization and control problems that arise in various use cases, such as network control, user clustering, resource management, and interference alignment. To cover this paradigm of distributed learning over wireless networks, this two-part Special Issue features papers dealing with two main research challenges: a) optimization of wireless network performance for efficient implementation of distributed learning in wireless networks, and b) distributed learning for solving communication problems and optimizing network performance.

Our call for papers received a strong response from the community, and 104 papers have been received, many of which were of extremely high quality. However, due to the tight publication schedule of this Special Issue and the limited number of papers that can be accepted, 35 papers finally have been accepted and will be published in a double-issue. The accepted papers have been grouped into three topics: 1) network optimization for FL, 2) network optimization for other distributed learning methods, and 3) distributed reinforcement learning for wireless network optimization. In this guest editorial for Part I of the double-issue, we review the key contributions of the papers in the first cluster.

The first issue starts with an overview paper [A1] written by the team of guest editors. We provide therein a comprehensive study of how distributed learning can be efficiently and effectively deployed in wireless networks. In particular, we introduce four distributed learning frameworks, namely, FL, federated distillation, inference, and multi-agent reinforcement learning. The discussion of each framework comprises its motivation, basic principles, detailed literature review, illustrative examples, and future research opportunities. The contributions made by other papers in Part I are summarized as follows.

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I. Resource Management

In [A2], Luo *et al.* minimize the weighted sum of energy and time consumption of training a federated averaging algorithm via optimizing the subset of devices that participate in FL at each iteration of the algorithm, the number of FL updates at each device per iteration, and the number of global updates that FL needs to converge. The authors first analyze the relationship between these control variables and the weighted sum of energy and time consumption. Since this relationship contains several FL parameters related to local datasets, which are not known by the server, a low-cost sampling-based algorithm is proposed to estimate these FL parameters. Given this relationship, the optimal subset of devices that should participate in FL at each iteration and the optimal number of local FL updates at each device per iteration are determined by an iterative algorithm.

In [A3], Wan *et al.* optimize spectrum bandwidth allocation, the subset of devices that participate in FL, the processor frequency of each device, and the number of local updates per iteration so as to minimize the time and energy consumption of training a federated averaging algorithm.

In [A4], Lim *et al.* propose a hierarchical game framework to study the dynamics of edge association and resource allocation for a hierarchical FL network, which consists of edge devices, edge servers, and a central controller.

In [A5], Ma *et al.* propose a semi-asynchronous federated learning mechanism that enables the parameter server to aggregate a certain number of local models of edge devices by their arrival order in each round. The authors analyze how the number of participating devices per iteration, the data distribution, and edge heterogeneity affect the convergence of the proposed FL. Given the FL convergence analysis, the authors optimize the subset of participating devices to minimize the convergence time.

In [A6], Lee and Lee design three device selection schemes for asynchronous federated learning according to the network and FL information obtained by the parameter server.

In [A7], Zhang *et al.* aim to minimize the training loss of a hierarchical FL algorithm, while considering the energy and time consumption of each device in transmitting and updating the FL parameters. The authors study the use of a policy gradient-based multi-agent reinforcement learning method to find the device selection vector, the uplink and downlink bandwidth allocation vectors, and the computational resource allocation vector to minimize FL training loss.

In [A8], Jin *et al.* study the deployment of FL over a network in which devices will continuously receive new data samples. The authors introduce an FL convergence time minimization problem via optimizing the number of local updates, gradient-descent steps, and edge server selection. To solve the proposed problem, the authors first decouple it and design an online learning algorithm for controlling the number of local model updates and rectified gradient-descent steps. Then, the authors design a bandit learning algorithm for selecting the edge server for global model aggregations so as to minimize the FL convergence time.

II. FL Parameter Optimization

In [A9], Xing *et al.* study the deployment of FL over wireless device-to-device (D2D) networks by providing theoretical insights into the performance of digital and analog implementations of decentralized stochastic gradient descent (DSGD).

In [A10], Xu *et al.* study the deployment of FL in an AirComp-based network and propose a learning rate optimization scheme to reduce the FL model errors caused by fading channels.

In [A11], Fan *et al.* investigate over-the-air model aggregation for FL. The authors introduce a Markovian probability model to characterize the intrinsic temporal structure of the global FL model series. Given this temporal probability model, the authors formulate the global FL model estimation problem as an online Bayesian inference problem and develop a message-passing-based solution with low complexity and near-optimal performance.

In [A12], Li *et al.* analyze the distribution of the convergence time of FL implemented over wireless networks, where the time-varying nature of wireless channels affects the FL parameter transmission delay.

III. Privacy and Security Issues

In [A13], Zhang *et al.* first analyze how unbalanced and independent and identically distributed (Non-IID) data affect devices' incentives to voluntarily participate in FL and then design two faithful federated learning algorithms that satisfy economic properties, scalability, and privacy.

In [A14], Sun *et al.* propose a contract-based personalized privacy-preserving incentive for FL. In particular, the authors derive a set of optimal contracts analytically under both complete and incomplete information models, which could optimize the convergence performance of the finally learned global model, while bearing some desired economic properties, such as budget feasibility, individual rationality, and incentive compatibility.

In [A15], Seif *et al.* consider the optimization of training federated stochastic gradient descent (FedSGD) over fading multiple access channels, subject to central and local differential privacy constraints. The authors propose a wireless FedSGD scheme with user sampling, where users are sampled uniformly or based on their channel conditions. The authors also analyze the convergence rate of the proposed scheme and study the tradeoffs between wireless resources, convergence, and privacy theoretically and empirically for the two scenarios in which the number of sampled participants are either known or unknown at the parameter server.

IV. Training Method Design

In [A16], Yang *et al.* consider training binary neural networks (BNNs) in an FL setting, and hence, each device needs to upload only the binary parameters to the server, thus fulfilling the stringent delay and efficiency requirements in wireless edge networks. The authors also propose a novel parameter updating scheme based on the maximum likelihood estimation that preserves the performance of the BNNs even without the availability of aggregated real-valued auxiliary parameters that are usually needed during BNN training.

In [A17], Lin *et al.* propose a semi-decentralized learning architecture that combines the consensus-based method with the FL training. In each global FL iteration, devices perform multiple local stochastic gradient descent updates and aperiodically use consensus-based methods to update their model parameters through cooperative, distributed D2D communications. With a new general definition of gradient diversity, the authors analyze the convergence of the proposed FL. Given the convergence analysis, the authors design an adaptive control algorithm that tunes the step size, D2D communication rounds, and global aggregation period to target a sublinear convergence rate while minimizing network resource utilization.

In [A18], Han *et al.* minimize the convergence time of FL implemented by multiple wireless edge servers that have their own local coverage. The authors utilize the devices located in the overlapping coverage areas among adjacent edge servers to improve FL model synchronization, thus reducing FL convergence time.

Acknowledgment

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Appendix: Related Articles

[A1] M. Chen *et al.*, "Distributed learning in wireless networks: Recent progress and future challenges," *IEEE J. Sel. Areas Commun.*, early access, 2021.

[A2] B. Luo, X. Li, S. Wang, J. Huang, and L. Tassiulas, "Cost-effective federated learning in mobile edge networks," 2021, *arXiv:2109.05411*. [Online]. Available: https://arxiv.org/abs/2109.05411

[A3] S. Wan, J. Lu, P. Fan, Y. Shao, C. Peng, and K. B. Letaief, "Convergence analysis and system design for federated learning over wireless networks," *IEEE J. Sel. Areas Commun.*, early access, Oct. 7, 2021, doi: 10.1109/JSAC.2021.3118351.

[A4] W. Y. B. Lim, J. S. Ng, Z. Xiong, D. Niyato, C. Miao, and D. I. Kim, "Dynamic edge association and resource allocation in self-organizing hierarchical federated learning networks," *IEEE J. Sel. Areas Commun.*, early access, Oct. 6, 2021, doi: 10.1109/JSAC.2021.3118401.

[A5] Q. Ma, Y. Xu, H. Xu, Z. Jiang, L. Huang, and H. Huang, "FedSA: A semi-asynchronous federated learning mechanism in heterogeneous edge computing," *IEEE J. Sel. Areas Commun.*, early access, Oct. 6, 2021, doi: 10.1109/JSAC.2021.3118435.

[A6] H.-S. Lee and J.-W. Lee, "Adaptive transmission scheduling in wireless networks for asynchronous federated learning," 2021, *arXiv:2103.01422*. [Online]. Available: https://arxiv.org/abs/2103.01422

[A7] W. Zhang *et al.*, "Optimizing federated learning in distributed industrial IoT: A multi-agent approach," *IEEE J. Sel. Areas Commun.*, early access, Oct. 7, 2021, doi: 10.1109/JSAC.2021.3118352.

[A8] Y. Jin, L. Jiao, Z. Qian, S. Zhang, and S. Lu, "Budget-aware online control of edge federated learning on streaming data with stochastic inputs," *IEEE J. Sel. Areas Commun.*, early access, Oct. 7, 2021, doi: 10.1109/JSAC.2021.3118421.

[A9] H. Xing, O. Simeone, and S. Bi, "Federated learning over wireless device-to-device networks: Algorithms and convergence analysis," 2021, *arXiv:2101.12704*. [Online]. Available: https://arxiv.org/abs/2101.12704

[A10] C. Xu, S. Liu, Z. Yang, Y. Huang, and K.-K. Wong, "Learning rate optimization for federated learning exploiting over-the-air computation," 2021, *arXiv:2102.02946*. [Online]. Available: https://arxiv.org/abs/2102.02946

[A11] D. Fan, X. Yuan, and Y.-J. A. Zhang, "Temporal-structure-assisted gradient aggregation for over-the-air federated edge learning," 2021, *arXiv:2103.02270*. [Online]. Available: http://arxiv.org/abs/2103.02270

[A12] L. Li *et al.*, "Delay analysis of wireless federated learning based on saddle point approximation and large deviation theory," 2021, *arXiv:2103.16994*. [Online]. Available: http://arxiv.org/abs/2103.16994

[A13] M. Zhang, E. Wei, and R. Berry, "Faithful edge federated learning: Scalability and privacy," *IEEE J. Sel. Areas Commun.*, early access, Oct. 11, 2021, doi: 10.1109/JSAC.2021.3118423.

[A14] P. Sun *et al.*, "Pain-FL: Personalized privacy-preserving incentive for federated learning," *IEEE J. Sel. Areas Commun.*, early access, Oct. 8, 2021, doi: 10.1109/JSAC.2021.3118354.

[A15] M. Seif, W.-T. Chang, and R. Tandon, "Privacy amplification for federated learning via user sampling and wireless aggregation," 2021, *arXiv:2103.01953*. [Online]. Available: http://arxiv.org/abs/2103.01953

[A16] Y. Yang, Z. Zhang, and Q. Yang, "Communication-efficient federated learning with binary neural networks," *IEEE J. Sel. Areas Commun.*, early access, Oct. 6, 2021, doi: 10.1109/JSAC.2021.3118415.

[A17] F. P.-C. Lin, S. Hosseinalipour, S. S. Azam, C. G. Brinton, and N. Michelusi, "Semi-decentralized federated learning with cooperative D2D local model aggregations," *IEEE J. Sel. Areas Commun.*, early access, Oct. 6, 2021, doi: 10.1109/JSAC.2021.3118344.

[A18] D.-J. Han, M. Choi, J. Park, and J. Moon, "FedMes: Speeding up federated learning with multiple edge servers," *IEEE J. Sel. Areas Commun.*, early access, Oct. 6, 2021, doi: 10.1109/JSAC.2021.3118422.

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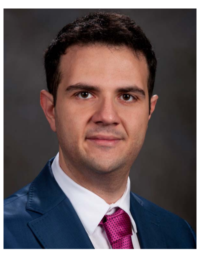

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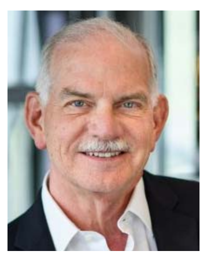

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