



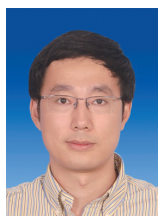
Editorial: Special Topic on Federated Learning for IoT and Edge Computing

Guest Editors >>>



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DOI: 10.12142/ZTECOM.202203001

Citation: Y. Pan, L. Z. Cui, Z. P. Cai, and W. Li, "Editorial: special topic on federated learning for IoT and edge computing," *ZTE Communications*, vol. 20, no. 3, pp. 1 – 2, Sept. 2022. doi: 10.12142/ZTECOM.202203001.

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Recent years have witnessed the proliferation of Internet of Things (IoT), in which billions of devices are connected to the Internet, generating an overwhelming amount of data. It is challenging and infeasible to transfer and process trillions and zillions of bytes using the current cloud-device architecture, due to bandwidth constraints of networks and potentially uncontrollable latency of cloud services. Edge computing, an emerging computing paradigm, has received a tremendous amount of interest to boost IoT. By pushing data storage, computing and controls closer to the network edge, edge computing has been widely recognized as a promising solution to meeting the current-day requirements of low latency, high scalability, and energy efficiency, as well as to mitigating the network traffic burdens.

However, with the emergence of diverse IoT applications (e.g., the smart city, industrial automation, and connected cars), it becomes challenging for edge computing to deal with these heterogeneous IoT environments and gather the data feasibly for training in a centralized manner. Furthermore, data privacy has become fast-growing concerns when data are being accessed and obtained from IoT devices.

The aforementioned issues necessitate Federated Learning (FL), which enables edge devices to collaboratively train a locally-standard model using mobile data generated in real time. Federated learning is well suited for IoT and edge computing applications and can leverage the computation power of edge servers and the data collected on widely dispersed edge devices. Instead of collecting data to some centralized servers, FL allows machine learning models to be deployed and trained on the user end to alleviate some potential privacy leakage. Building such FL systems into edge architecture poses many technical challenges that need to be addressed. The goal of this special issue is to stimulate discussions around open problems of FL for IoT and edge computing. It focuses on sharing of the most recent and groundbreaking work on the study and application of FL in IoT and network edge.

This special issue receives both theoretical and application-based contributions in FL for IoT and edge computing. The following five papers are accepted after rigorous reviews by several external reviewers and guest editors.

The paper “A Collaborative Medical Diagnosis System Without Sharing Patient Data” by NAN, et al. proposes and builds a secured and explainable machine learning framework to address the issue of current machine learning not being able to fully exploit its potentials because the data usually sit in data silos and privacy and security regulations restrict their access and use. Their approach can share valuable informa-

tion among different medical institutions to improve the learning results without sharing the patients’ data. It also reveals how the machine makes a decision through eigenvalues to offer a more insightful answer to medical professionals.

HAN et al. give an overview of numerous state-of-the-art methods in the literature related to FL on non-IID data in the paper “A Survey of Federated Learning on Non-IID Data”. This paper also proposes a motivation-based taxonomy, which classifies these methods into two categories, including heterogeneity reducing strategies and adaptability enhancing strategies. Moreover, the core ideas and main challenges of these methods are analyzed and several promising research directions are outlined.

The third paper “Federated Learning Based on Extremely Sparse Series Clinic Monitoring Data” by LU et al. designs a medical data resampling and balancing scheme for federated learning to eliminate model biases caused by sample imbalance and provide accurate disease risk prediction on multicenter medical data. Experimental results on a real-world clinical database demonstrate the improvement of accuracy and tolerance for missing data.

The fourth paper “MSRA-Fed: A Communication-Efficient Federated Learning Method Based on Model Split and Representation Aggregate” by LIU et al. verifies that the outputs of the last hidden layer can record the features of training data. Accordingly, they propose a communication-efficient strategy based on model split and representation aggregate. Specifically, the authors make the client upload the outputs of the last hidden layer instead of all model parameters when participating in the aggregation, and the server distributes gradients according to the global information to revise local models. Experimental results indicate that their new method can upload less than one-tenth of model parameters, while preserve the usability of the model.

The last paper “Neursafe-FL: A Reliable, Efficient, Easy-to-Use Federated Learning Framework” by TANG et al. introduces a reliable, efficient and easy-to-use federated learning framework named Neursafe-FL. Based on the unified application program interface (API), the framework is not only compatible with mainstream machine learning frameworks such as Tensorflow and Pytorch, but also supports further extensions, which can preserve the programming style of the original framework to lower the threshold of FL. At the same time, the design of componentization, modularization, and standardized interface makes the framework highly extensible. Their source code is also publicly available.

We would like to thank the authors and reviewers for their hard work and contributions. This special issue would not be possible without their help and collaboration.