PAN Yi, CUI Laizhong, CAI Zhipeng, LI Wei

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

Guest Editors >>>

PAN Yi is currently a Chair Professor and the Dean of Faculty of Computer Science and Control Engineering at Shenzhen Institute of Advanced Technology, Chinese Academy of Sciences, China and a Regents' Professor Emeritus at Georgia State University, USA. He served as Chair of Computer Science Department at Georgia State University from 2005 to 2020. Dr. PAN received his BE and ME degrees in computer engineering from Tsinghua University, China, in 1982 and 1984, respectively, and his PhD degree in computer science from the University of Pittsburgh, USA in 1991. His profile has been featured as a distinguished alumnus in both Tsinghua and University of Pittsburgh CS Alumni Newsletters. His current research interests mainly include bioinformatics and health informatics using big data analytics, cloud computing, and machine learning technologies. Dr. PAN has published more than 450 papers including over 250 journal papers published in IEEE/ACM Transactions/Journals. In addition, he has edited/authored 43 books. His work has been cited more than 19 000 times based on Google Scholar and his current h-index is 88. He has served as an Editor-in-Chief or editorial board member for 20 journals including seven IEEE Transactions. He is the recipient of many awards including one IEEE Transactions Best Paper Award, five IEEE and other international conference or journal Best Paper Awards, four IBM Faculty Awards, two JSPS Senior Invitation Fellowships, IEEE BIBE Outstanding Achievement Award, IEEE Outstanding Leadership Award, NSF Research Opportunity Award, etc. He has organized numerous international conferences and delivered keynote speeches at over 70 international conferences around the world. Dr. PAN is a member of the Academy of the United Nations Sciences and Technology Organization, foreign member of Ukrainian Academy of Engineering Sciences, Fellow of American Institute for Medical and Biological Engineering, Fellow of Institute of Engineering Technology, and Fellow of Royal Society for Public Health.

CUI Laizhong is currently a professor in the College of Computer Science and Software Engineering at Shenzhen University, China. He received his BS degree from Jilin University, China in 2007 and PhD degree in computer science and technology from Tsinghua University, China in 2012. His research interests include future Internet architecture and protocols, edge computing, multimedia systems and applications, blockchain, Internet of Things, cloud and big data computing, computational intelligence, and machine learning. He led more than 10 scientific research projects, including National Key Research and Development Plan of China, National Natural Science Foundation of China, etc. He has published more than 100 papers in prestigious journals, including *IEEE JSAC*, *IEEE TC*, *IEE TKDE*, *IEEE TMM*, *IEEE IoT Journal*, *IEEE TII*, *IEEE TVT*, *IEEE TNSM*, *ACM TOIT*, *IEEE TCBB*, etc. He serves as an associate editor or a member of editorial boards for several international journals, including *IEEE IoT Journal*, *IEEE TNSM*, and *International Journal of Machine Learning and Cybernetics*. He is a senior member of the IEEE and a senior member of the CCF.

CAI Zhipeng received his PhD and MS degrees from the Department of Computing Science at University of Alberta, Canada and BS degree from the Department of Computer Science and Engineering at Beijing Institute of Technology, China. Dr. CAI is currently a professor in the Department of Computer Science and the College of Business at Georgia State University, USA. His research areas focus on machine learning, Internet of Things, privacy, and big data. Dr. CAI is the recipient of an NSF CAREER Award. His research has been supported by the National Science Foundation, the U. S. Department of State, and other academic and industrial sponsors. Dr. CAI has published more than 100 papers in top journals and conferences including more than 70 IEEE/ACM transaction papers. His publications have been cited for more than 11 000 times. He is the Editor-in-Chief for *Wireless Communications and Mobile Computing* and Associate Editor-in-Chief for Elsevier *High-Confidence Computing Journal*. He serves as an editor for several prestigious journals including *IEEE TKDE*, *IEEE TVT*, *IEEE TWC*, *IEEE TCSS*, *IEEE Internet of Things Journal*, etc. Dr. CAI is a Steering Committee Co-Chair for the international conferences of WASA, IPCCC and COCOON. He has served as a General/Program Chair for many international conferences.

LI Wei received his PhD from The University of Sydney, Australia. He is currently an ARC DECRA Fellow with the Center for Distributed and High Performance Computing, School of Computer Science, The University of Sydney. He is the technical lead of the Australia-China Joint Research Center on Energy Informatics

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.**

and Demand Response Technologies. His research interests include edge computing, sustainable computing, task scheduling, decision making, Internet of Things, energy informatics, and medical informatics. He is the recipient of Australian Research Council Discovery Early Career Researcher Award in 2020, the IEEE TCSC Award for Excellence in Scalable Computing for Early Career Researchers in 2018, and the IEEE Outstanding Leadership Award in 2018. He serves as the information director for ACM Computing Surveys and the editors and PC members of tens of journals and conferences.

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 information 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 multi-center 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.