

Edge Federated Learning for Smart HealthCare Systems

Abstract:

With the wide usage of smart wearable devices and mobile health care application, the total amount of healthcare data is increasing rapidly. To manage health care data and to recommend healthy advices in time critical cases, data is getting collected at cloud and analyzed using machine learning approaches, which takes more time to compute and huge cost to transfer the data over the network, as well there is possibility of data privacy leakage. To solve communication, computation and privacy issues we can use Edge computing, which is primarily concerned with transmitting data among the devices at the edge, closer to where user applications are located, rather than to a centralized server. To train the data for health advices in time critical cases Federated learning can be used, it is a collaborative machine learning framework allowing devices from different resources with different private datasets working together to study and train a global model. So, we propose a Edge federated learning solves the data island problem by fully exploring the huge potential of the data on terminal devices without infringing on user's privacy, and it greatly improves the efficiency of model learning in edge computing systems. In this research work, it is to explore some issues of Communication, computation, security, privacy, migration and scheduling for an efficient edge federated learning.

Keywords: Cloud Computing, Edge Computing, Federated Learning, Edge Federated Learning

References

1. Qi Xia, Winson Ye, Zeyi Tao, Jindi Wu, QunLi, A survey of federated learning for edge computing: Research problems and solutions, High-Confidence Computing, Volume 1, Issue 1, 2021, 100008, ISSN 2667-2952, <https://doi.org/10.1016/j.hcc.2021.100008>.
2. Abreha, H.G.; Hayajneh, M.; Serhani, M.A. Federated Learning in Edge Computing: A Systematic Survey. *Sensors* 2022, 22, 450. <https://doi.org/10.3390/s22020450>.
3. Keith Bonawitz, Hubert Eichner, Wolfgang Grieskamp, Dzmitry Huba, Alex Ingerman, Vladimir Ivanov, Chloe Kiddon, Jakub Konečný, Stefano Mazzocchi, H. Brendan McMahan, Timon Van Overveldt, David Petrou, Daniel Ramage, Jason Roselander, Towards Federated Learning at Scale: System Design. <https://doi.org/10.48550/arXiv.1902.01046>.
4. M. Duan, D. Liu, X. Chen, R. Liu, Y. Tan and L. Liang, "Self-Balancing Federated Learning With Global Imbalanced Data in Mobile Systems," in *IEEE Transactions on Parallel and Distributed Systems*, vol. 32, no. 1, pp. 59-71, 1 Jan. 2021, doi: 10.1109/TPDS.2020.3009406.
5. Chaoyang He, Songze Li, Jinhyun So, Xiao Zeng, Mi Zhang, Hongyi Wang, Xiaoyang Wang, Praneeth Vepakomma, Abhishek Singh, Hang Qiu, Xinghua Zhu, Jianzong Wang, Li Shen, Peilin Zhao, Yan Kang, Yang Liu, Ramesh Raskar, Qiang Yang, Murali Annavaram, Salman Avestimehr, FedML: A Research Library and Benchmark for Federated Machine Learning, <https://doi.org/10.48550/arXiv.2007.13518>.
6. X. Li, X. Huang, C. Li, R. Yu and L. Shu, "EdgeCare: Leveraging Edge Computing for Collaborative Data Management in Mobile Healthcare Systems," in *IEEE Access*, vol. 7, pp. 22011-22025, 2019, doi: 10.1109/ACCESS.2019.2898265.