World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:18, No:06, 2024

Federated Knowledge Distillation with Collaborative Model Compression for Privacy-Preserving Distributed Learning

Authors : Shayan Mohajer Hamidi

Abstract : Federated learning has emerged as a promising approach for distributed model training while preserving data privacy. However, the challenges of communication overhead, limited network resources, and slow convergence hinder its widespread adoption. On the other hand, knowledge distillation has shown great potential in compressing large models into smaller ones without significant loss in performance. In this paper, we propose an innovative framework that combines federated learning and knowledge distillation to address these challenges and enhance the efficiency of distributed learning. Our approach, called Federated Knowledge Distillation (FKD), enables multiple clients in a federated learning setting to collaboratively distill knowledge from a teacher model. By leveraging the collaborative nature of federated learning, FKD aims to improve model compression while maintaining privacy. The proposed framework utilizes a coded teacher model that acts as a reference for distilling knowledge to the client models. To demonstrate the effectiveness of FKD, we conduct extensive experiments on various datasets and models. We compare FKD with baseline federated learning methods and standalone knowledge distillation techniques. The results show that FKD achieves superior model compression, faster convergence, and improved performance compared to traditional federated learning approaches. Furthermore, FKD effectively preserves privacy by ensuring that sensitive data remains on the client devices and only distilled knowledge is shared during the training process. In our experiments, we explore different knowledge transfer methods within the FKD framework, including Fine-Tuning (FT), FitNet, Correlation Congruence (CC), Similarity-Preserving (SP), and Relational Knowledge Distillation (RKD). We analyze the impact of these methods on model compression and convergence speed, shedding light on the trade-offs between size reduction and performance. Moreover, we address the challenges of communication efficiency and network resource utilization in federated learning by leveraging the knowledge distillation process. FKD reduces the amount of data transmitted across the network, minimizing communication overhead and improving resource utilization. This makes FKD particularly suitable for resource-constrained environments such as edge computing and IoT devices. The proposed FKD framework opens up new avenues for collaborative and privacy-preserving distributed learning. By combining the strengths of federated learning and knowledge distillation, it offers an efficient solution for model compression and convergence speed enhancement. Future research can explore further extensions and optimizations of FKD, as well as its applications in domains such as healthcare, finance, and smart cities, where privacy and distributed learning are of paramount importance.

Keywords : federated learning, knowledge distillation, knowledge transfer, deep learning
Conference Title : ICAINN 2024 : International Conference on Artificial Intelligence and Neural Networks
Conference Location : Montreal, Canada
Conference Dates : June 13-14, 2024