Exploring Optimal Learning Rates and Convergence in Coded Federated Learning Using Lyapunov's Theorem

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Federated Learning (FL) has emerged as an innovative and critical machine learning (ML) framework for addressing data privacy and security concerns in training ML models. Unlike traditional approaches that centralize sensitive data, FL permits users to send training updates to train a model iteratively across devices without exploiting user data. Despite its potential, FL systems face challenges, such as training complicated ML models on resource-limited devices, as these devices lack sufficient computational power. To address this issue, two novel encoding schemes, RFF-Random-1 and RFF-Random-2, were developed to enhance FL systems by using coding techniques Random Fourier Features (RFF), one-hot encoding, and random matrix encoding for secure, efficient data processing. These schemes achieved a 91.76% training accuracy on the MNIST dataset after a significantly reduced time frame, demonstrating the impact and potential of these techniques on enhancing FL systems. However, FL systems still face challenges, such as straggling nodes (when a node cannot return the training rate and results on time) and the need for timely convergence. To overcome these issues, this research investigates the impact of learning rates on gradient descent-based training and explores the application of the Lyapunov stability theorem to optimize convergence. Under Lyapunov stability conditions, good learning rates can be found (this learning rate can be constant or adaptive). By addressing accuracy and convergence issues, this research provides theoretical and practical improvements for enhancing FL systems, paving the way for broader applications of FL.

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