Fairness Aware Federated Learning for Text Classification

Shubham Gupta (112103046) , Manas Jorvekar(112103058), Dr. Y.V.Haribhakta (College Guide)

Aim

- To develop a fairness-aware federated learning framework for text classification that reduces bias and ensures consistent model performance across all clients, even under non-IID (not independent and identically distributed) data conditions while maintaining high overall accuracy.

Objective

- Design and implement a federated learning(FL) architecture for multi-class text classification using Flower framework on non-IID data distributions.
- Analyse the limitations of existing aggregation algorithms in handling data heterogeneity.
- Explore dual-metric monitoring by analysing both intra-client and inter-client performance to guide adaptive behaviour.
- Propose **DualMetric-Adaptive FL**, a fairness aware algorithm that leverages these metrics to dynamically adjust client side regularization.

Introduction

- Federated Learning (FL) enables collaborative model training across decentralized clients without sharing raw data, ensuring privacy.
- In real-world scenarios, client data is often non-IID causing FL algorithms to struggle with both performance and fairness.
- Fairness is critical: Without it, models may favour certain clients, leading to biased or unreliable text classification outcomes.
- Our work addresses the challenge of achieving both high accuracy and fairness in federated text classification systems.

Literature Review

Title	Key Contributions
Federated Learning for Mobile Keyboard Prediction, February 2019 [1]	One of the first large-scale applications of FL using on-device RNN for next-word prediction in Google's Gboard keyboard.
Federated Optimization in Heterogeneous Networks, August 2020 [2]	This paper introduces FedProx, a generalized version of FedAvg that improves FL convergence in heterogeneous networks by adding a proximal term on server-side aggregation. Improved test accuracy by 22% compared to FedAvg.
Federated Learning on Non-IID Data Silos: Experimental Study, October 2021 [3]	This paper systematically evaluates performance on different FL algorithms. Concludes that no single algorithm works best for all non-IID settings.
Flower: A friendly Federated Learning Framework, March 2022 [4]	Flower- A novel Federated Learning framework, facilitating large-scale training. Bridging the gap between FL research and deployment.

Dataset

Instruction	Label
i got to add an item to the cart	Add Product
wanna add products to the basket can help me	Add product
i got to see the availability of an item i need assistance	Availability
i want to see the item availability can you help me	Availability
i got to cancel an online order i need assistance	Cancel Order
i got to delete my user account where can i do it	Close Account
i did not receive my shipment can you help me report a delivery issue	Delivery Issue
one of the items from my delivery isnt included will help me to report it	Missing Item
one of the items from my shipment isnt included could i report it	Missing Item
wanna know about ur money back policy where could i get more info	Refund Policy
id like to check ur reimbursement policy can i get some help	Refund Policy

Fig 1: Sample of Bitext Retail eCommerce Dataset

Project Architecture

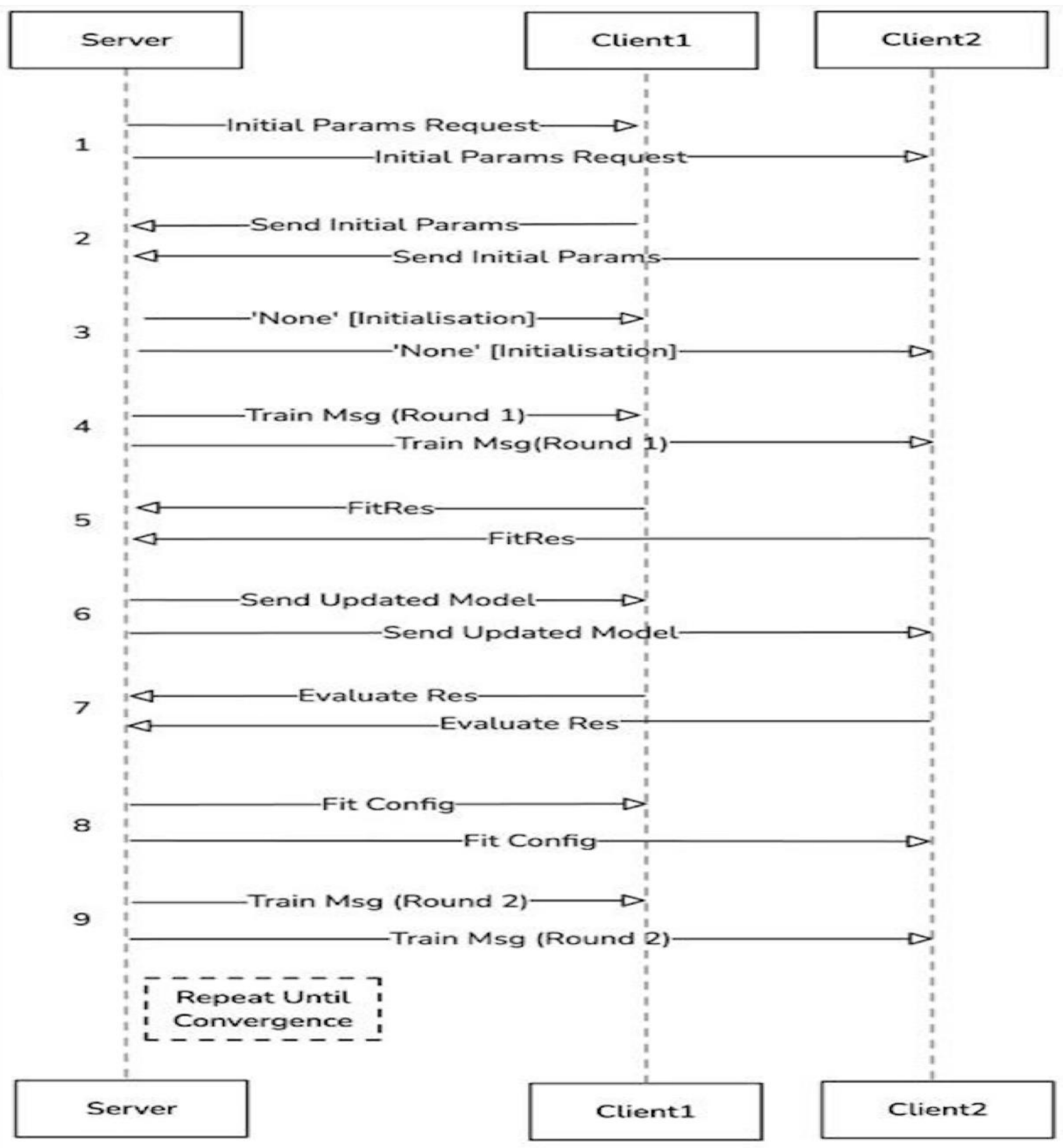


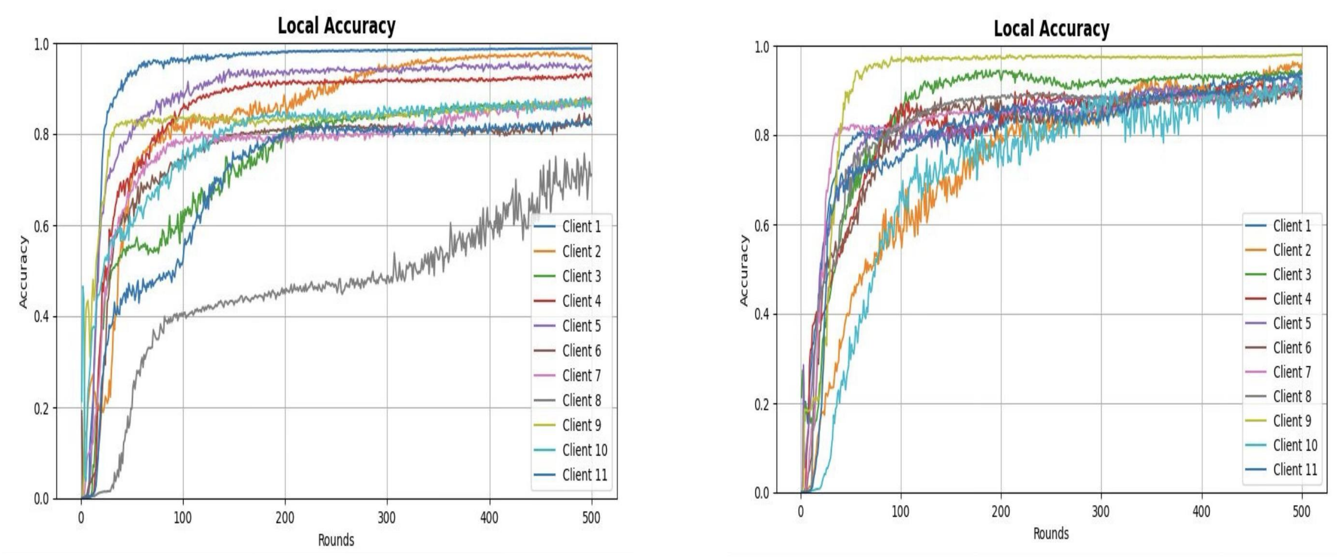
Fig 2 : Client-Server Architecture in Flower Framework

- The server requests initial parameters from all clients.
- Each client sends its local model parameters to the server.
- The server initializes a None model with a combined set of parameters from all clients and matches parameters of all clients.
- The server sends a training request to all clients, instructing them to perform local training on their respective datasets.
- Each client responds with a Fit Response packet, containing local model metrics, weights, and biases.
- The server applies a mathematical aggregation function to combine the model updates and distributes the updated global model to all clients for synchronization.
- Clients evaluate the global model on their local data and global test set and send back an Evaluate Response packet containing performance metrics.
- The server evaluates the metric and dynamically changes regularization parameter of clients and sends them via Configuration Fit packet.
- The process continues until convergence.

Methodology

- Perform client-specific evaluation analysing global model and individual client performance with the help of global accuracy and local accuracy metric .
- Applying proximal regularization term on client side, preventing extreme divergence in non-IID settings.
- To reduce bias, we designed DualMetric-Adaptive FL using intra-client and inter-client analysis where we increment or decrement the regularization value.
- We combine both analysis to adapt regularization dynamically and define our final update rule for DualMetric-Adaptive FL on client side in FL settings.

Results



a. FedProx b. DualMetric-Adaptive FL

Fig 3 : Comparison of client-side performance showing Reduced client divergence across 500 rounds.

Conclusion

- Using dynamically adjusted regularization parameters for each client according to intra-client and inter-client trends makes DualMetric-Adaptive FL successful in minimizing bias by 89% among clients.
- The proposed approach delivers improved global performance by 5.25% alongside tight local accuracy clusters which results in better collaborative text classification than standard FedProx.

References

[1] Ramaswamy, Swaroop, Rajiv Mathews, Kanishka Rao, and Fran¸coise Beaufays. ”Federated learning for emoji prediction in a mobile keyboard.” arXiv preprint arXiv:1906.04329 (2019).
[2] T. Li, A. K. Sahu, M. Zaheer, M. Sanjabi, A. Talwalkar, and V. Smith, "Federated Optimization in Heterogeneous Networks," arXiv preprint arXiv:1812.06127, 2018
[3] Li, Qinbin, Yiqun Diao, Quan Chen, and Bingsheng He. ”Federated learning on non-iid data silos: An experimental study.” In 2022 IEEE 38th international conference on data engineering (ICDE), pp. 965-978. IEEE, 2022.
[4] D. J. Beutel et al., "Flower: A Friendly Federated Learning Framework," arXiv preprint arXiv:2007.14390, 2020.
[5] Bitext Gen AI Retail eCommerce Dataset.

Department of Computer Science and Engineering, COEP Technological University