FEDERATED LEARNING FOR IMAGE CLASSIFICATION WITH DYNAMIC DATA DISTRIBUTION AND ADAPTIVE CLIENT PARTICIPATION

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OBJECTIVES

•Investigate Dynamic Data Distribution: Explore how time-varying, non-IID data (e.g., due to device mobility or environmental changes) affects model performance and convergence in federated learning.

•Analyze Adaptive Client Participation: Study the impact of adaptive client participation (based on device heterogeneity) and varying aggregation frequencies on federated learning performance in resource-constrained environments.

Contributions:

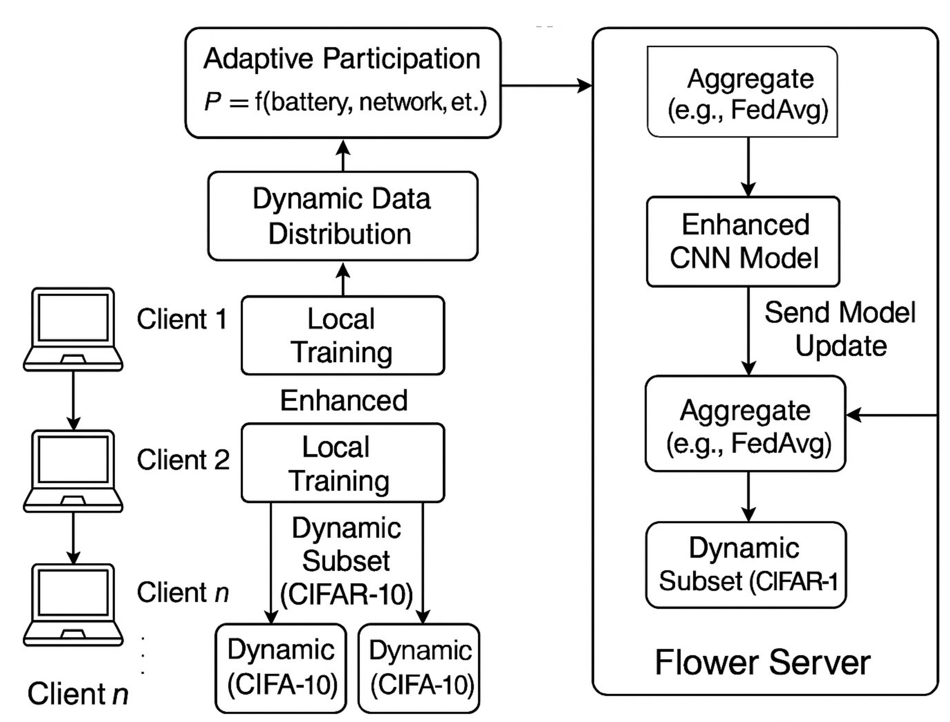
•Dynamic Data Distribution: Introduce time-varying, non-IID data distributions to simulate real-world scenarios like device mobility and environmental changes.

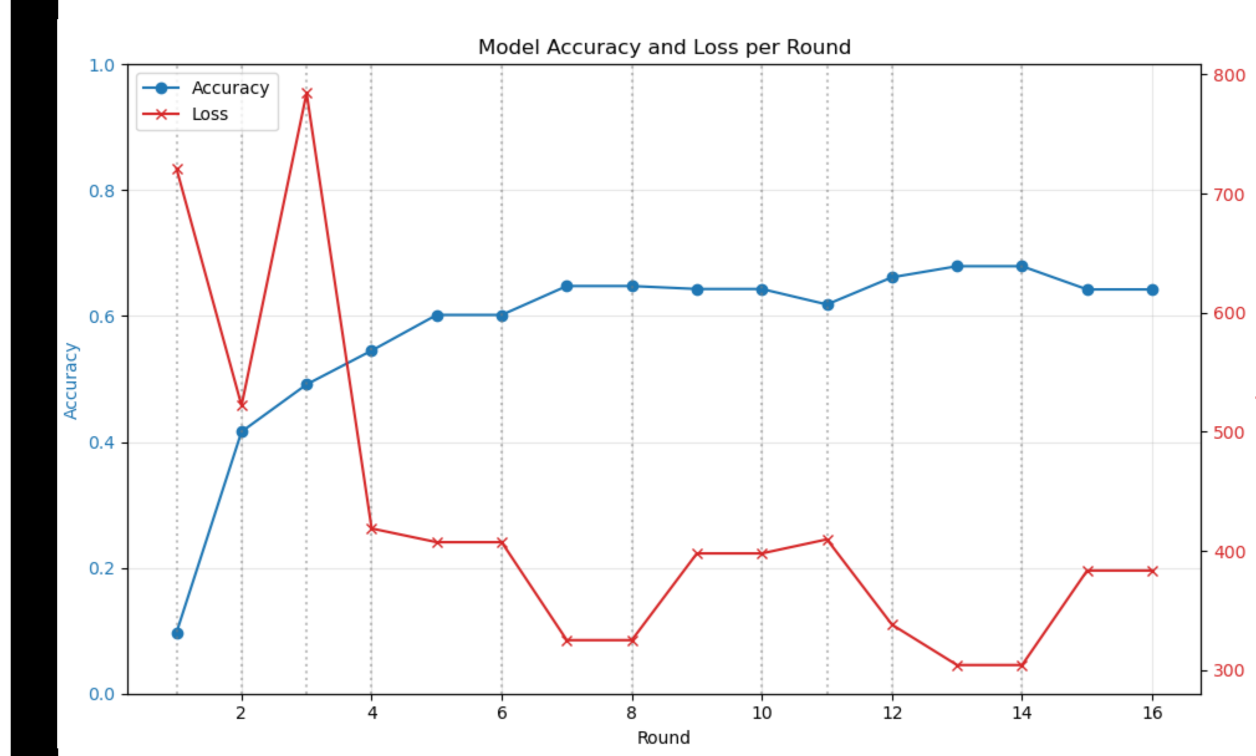
•Adaptive Client Participation: Develop a dynamic participation mechanism based on client heterogeneity (e.g., processing power, battery, and network conditions).

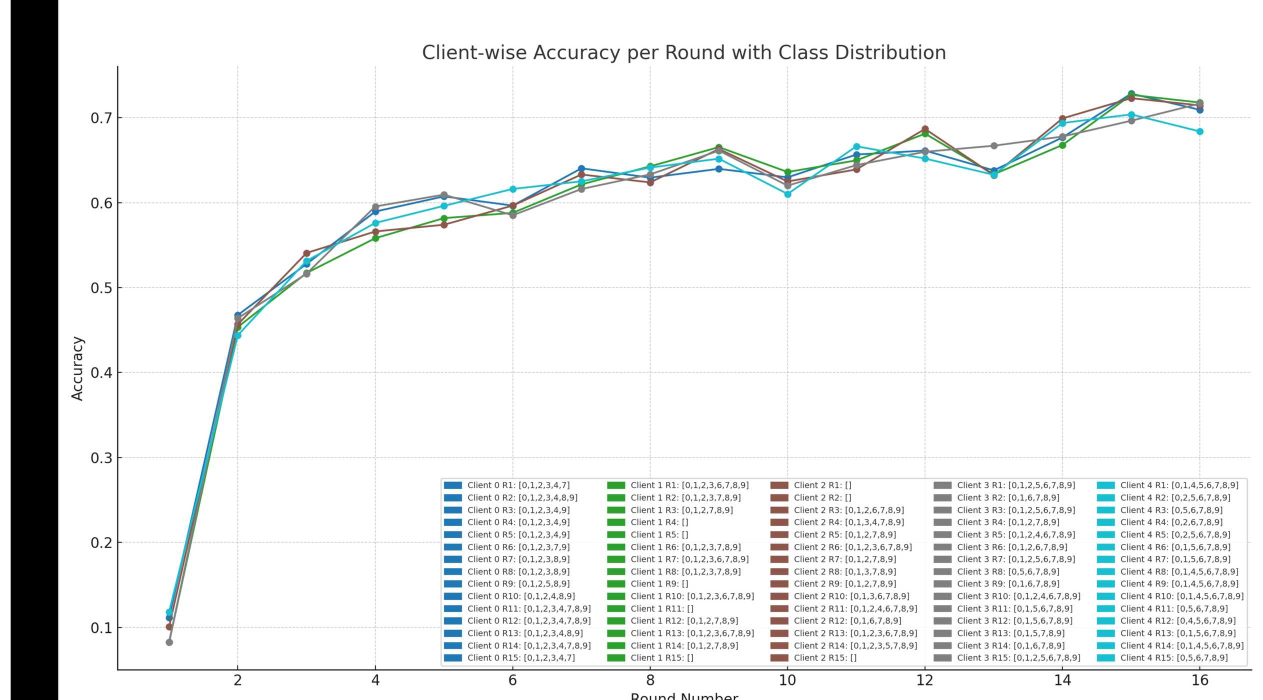
•Aggregation Frequency Evaluation: Optimize the balance between aggregation frequency and client participation to improve communication efficiency and model accuracy.

METHODOLOGY

- Dataset: CIFAR-10 dataset used for image classification, simulating dynamic data distributions across clients.
- Dynamic Data Distribution: Data changes over time, simulating real-world factors like device mobility and environmental shifts.
- Adaptive Client Participation: Clients' participation in each round is dynamically adjusted based on device capabilities (e.g., processing power, battery, and network conditions).
- Model: Enhanced CNN used for classification, trained through federated learning with dynamic aggregation frequencies.
- Aggregation Frequency: Different aggregation frequencies tested to optimize the balance between communication overhead and model accuracy.







RELATION TO EXISTING RESEARCH

- Federated Learning with Non-IID Data and Communication Efficiency (McMahan et al., 2017):

Existing Method: McMahan et al. use FedAvg to reduce communication overhead in federated learning, where each client trains on local, non-IID data.

Our Approach: We build on this by introducing time-varying data distributions that simulate real-world changes (e.g., client mobility, environmental shifts). Additionally, we optimize aggregation frequency to balance communication efficiency and model accuracy, which enhances the FL setup's performance.

- Federated Learning with Heterogeneous Clients (Li et al., 2020):

Existing Method: Li et al. focus on optimizing federated learning in heterogeneous networks, considering client capabilities like processing power and network conditions.

Our Approach: We extend this by introducing adaptive client participation, dynamically adjusting client involvement based on their resources and past performance, allowing for more efficient federated training.

- Federated Learning with Non-IID Data (Zhao et al., 2018):

Existing Method: Zhao et al. investigate federated learning with non-IID data, primarily using static data distributions across clients.

Our Approach: We introduce dynamic data distributions, where client data changes each round to better reflect real-world scenarios, such as device location and environmental changes.

RESULTS

- Accuracy and Loss: Accuracy improved and loss decreased over rounds, demonstrating the effectiveness of dynamic data distributions and aggregation frequencies.
- Client Participation: Adaptive participation led to better convergence, with clients with higher resources contributing more, optimizing communication and training.

CONCLUSIONS

- Dynamic Data Distribution: Time-varying, non-IID data improves model performance by simulating real-world conditions like device mobility.
- Adaptive Client Participation: Dynamic participation based on client resources enhances model convergence and reduces communication costs.
- Aggregation Frequency: Optimizing aggregation frequency and client participation improves federated learning efficiency, especially in resource-constrained environments.

REFERENCES

- McMahan, B., et al. "Communication-efficient learning of deep networks from decentralized data." Proceedings of the 20th International Conference on Artificial Intelligence and Statistics, 2017.
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- Li, T., et al. "Federated optimization in heterogeneous networks." Proceedings of Machine Learning and Systems 2, 2020.