Federated Learning on Heterogeneous Sensor Data

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This project explores Federated Learning (FL) using the MNIST dataset, addressing challenges in data heterogeneity, system optimization, and robustness to adversarial conditions. A flexible Non-IID data distribution strategy was implemented, utilizing Dirichlet partitioning to simulate varying levels of heterogeneity. Adversarial robustness was analyzed by introducing Byzantine attacks, where malicious clients disrupt training through gradient manipulation, and countermeasures such as robust aggregation methods (e.g., median and trimmed mean) were implemented to mitigate these effects.

The project initially experimented with multiple setups, including distributed training using Google Colab and a single-window simulation on local systems. After evaluating the trade-offs in efficiency, compatibility, and debugging, the single-window simulation approach was chosen for its robustness and ease of deployment. Technical challenges, such as gradient alignment, data partitioning inconsistencies, and environment configuration, were addressed, enabling significant performance improvements, with model accuracy increasing from 13.02

This study contributes practical insights into federated optimization by presenting systematic approaches for handling Non-IID data, mitigating adversarial influences, and optimizing performance under realistic constraints. Future directions include achieving over 90

Additional Key Words and Phrases: Federated Learning (FL), Non-IID Data Distribution, Byzantine Attacks, Robust Aggregation Methods, Dirichlet Partitioning, Adversarial Robustness, Global Model Convergence

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1 Introduction

Federated Learning (FL) has emerged as a promising paradigm for decentralized machine learning, allowing collaborative model training across multiple devices while preserving data privacy. By keeping data localized, FL eliminates the need for centralized storage, making it particularly appealing for privacy-sensitive applications such as healthcare, finance, and user-generated content. However, real-world deployment of FL faces significant challenges, including heterogeneous data distributions, adversarial threats, and system configuration complexities.

1.1 Motivation

The decentralized nature of FL introduces unique challenges. Real-world data generated by different devices is rarely independent and identically distributed (IID), leading to skewed distributions that impact global model performance. Additionally, FL systems are susceptible to adversarial threats, such as Byzantine attacks, where malicious clients intentionally manipulate gradient updates to disrupt training. Furthermore, configuring robust and scalable FL systems often requires balancing trade-offs in compatibility, computational resources, and debugging ease.

1.2 Problem Statement

This project aims to address key challenges in FL, focusing on:

- Evaluating system configurations (e.g., Google Colab vs. single-window simulation) to identify the most efficient and compatible setup for experimentation.
- Designing a Non-IID data distribution strategy using Dirichlet partitioning to simulate diverse heterogeneity levels.
- Introducing Byzantine attacks to analyze their impact on model robustness and accuracy.
- Developing robust aggregation methods to mitigate adversarial effects and improve convergence stability.

1.3 System Specifications

The project employs the MNIST dataset as a benchmark for FL training under heterogeneous and adversarial conditions. Key components of the system include:

- Data Partitioning: Flexible control over Non-IID data distribution using an adjustable alpha parameter to model varying heterogeneity levels.
- Adversarial Simulation: Implementation of gradient manipulation attacks, including random noise injection and gradient scaling, to simulate malicious client behavior.
- Robust Aggregation: Integration of methods like median and trimmed mean to counter adversarial gradients while maintaining system scalability.
- Environment Setup: Experiments were conducted using both distributed platforms (Google Colab) and local single-window simulations, with the latter chosen for its stability and debugging efficiency.

By addressing these challenges, this study contributes valuable insights into FL's robustness and scalability, offering practical solutions for real-world applications in decentralized environments.

2 Literature Review

Federated Learning (FL) has evolved significantly to address challenges such as communication efficiency, data heterogeneity, and adversarial robustness. Various methods have been proposed to optimize FL performance, ranging from foundational algorithms like FedSGD and FedAvg to advanced techniques for enhancing robustness and privacy. This section explores alternative designs and strategies that have shaped the development of FL systems, analyzing their strengths, limitations, and relevance to this project.

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2.1 Alternative Design

1. FederatedSGD (FedSGD): FedSGD is one of the simplest FL algorithms, where each client computes a single gradient update on its local data and transmits it to the server. The server aggregates these updates to optimize the global model. While straightforward and computationally efficient, FedSGD has notable limitations:

- Communication Overhead: Frequent communication between clients and the server increases network load, particularly in large-scale systems.
- Convergence Instability: FedSGD struggles with non-IID data distributions, as gradients from different clients may diverge significantly, slowing convergence.

2. FederatedAveraging (FedAvg): FedAvg extends FedSGD by allowing clients to perform multiple local updates before transmitting their model parameters. This approach reduces communication frequency and improves scalability. FedAvg is robust to non-IID data distributions, making it a more suitable choice for real-world FL applications. However, its performance is sensitive to:

- Data Partitioning: Non-IID data distributions can still lead to skewed updates, particularly when local datasets are small.
- Adversarial Behavior: Malicious clients can manipulate model updates, compromising global model performance.

3. Robust Aggregation Methods: To address the vulnerabilities of FedAvg in adversarial settings, several robust aggregation methods have been proposed:

- Median Aggregation: Aggregates gradients by computing the median for each parameter, effectively reducing the impact of outliers (e.g., Byzantine clients).
- Trimmed Mean: Discards a fixed percentage of the highest and lowest parameter updates before averaging, offering enhanced robustness.
- Krum Algorithm: Selects the set of updates that are closest to one another in Euclidean space, ensuring resilience to adversarial noise.

While these methods enhance robustness, they introduce additional computational complexity, making them less efficient in large-scale systems.

4. Differential Privacy and Secure Aggregation: Advanced privacy-preserving techniques, such as differential privacy and secure multi-party computation, have been explored to further protect user data. These methods encrypt model updates or add noise to ensure privacy but may impact model accuracy and increase computation overhead.

2.2 Relevance to This Project

This project adopts the FedAvg algorithm due to its scalability and adaptability to non-IID data. To address the challenges posed by adversarial behaviors and heterogeneity, robust aggregation methods, including median and trimmed mean, are integrated. Additionally, a Dirichlet-based partitioning method is implemented to systematically control data heterogeneity, allowing detailed evaluation of FL performance under varying conditions. This approach balances computational efficiency, communication costs, and robustness, aligning with the practical constraints of FL in real-world scenarios.

3 Background

In this project, several challenges were encountered during the implementation of Federated Learning (FL) with the MNIST dataset. These challenges, stemming from data heterogeneity, adversarial behaviors, and system configuration trade-offs, significantly influenced the design choices, experimental framework, and evaluation methods. This section outlines the key problems faced during the project and highlights their impact on the FL workflow.

3.1 Problem Statement

1. Data Heterogeneity and Its Impact on Model Performance

- In real-world FL systems, data generated by clients is rarely independent and identically distributed (IID). Clients often hold datasets that vary in size, distribution, and class composition, referred to as non-IID data.
- This data heterogeneity can lead to skewed model updates, slower convergence, and suboptimal performance of the global model. Without strategies to manage heterogeneity, FL systems may fail to generalize across diverse client datasets.

2. Adversarial Threats in FL

- The decentralized and distributed nature of FL makes it susceptible to adversarial attacks. Among these, Byzantine attacks are particularly critical, where malicious clients intentionally submit incorrect or misleading model updates to compromise the global model.
- Such attacks can lead to significant degradation in model performance, especially in the absence of robust aggregation mechanisms to mitigate their impact.

3. System Configuration and Trade-offs

- The deployment of FL systems often requires balancing computational efficiency, compatibility, and scalability. For example, this project initially experimented with distributed training on Google Colab but faced challenges such as connection timeouts and system inconsistencies. A single-window simulation approach was eventually chosen for its simplicity and reliability.
- These trade-offs highlight the importance of adaptable system configurations that can accommodate the unique requirements of FL experiments.

4. Evaluation Under Diverse Conditions

- To comprehensively evaluate FL systems, it is crucial to simulate and analyze their performance under various conditions: (a). Non-IID settings: Different levels of data heterogeneity. (b). Adversarial environments: The presence of malicious clients with varying attack strengths.
- These evaluations provide insights into how FL systems can be optimized for robustness, accuracy, and efficiency.

4 System design

This section outlines the overall architecture and strategic considerations for addressing the challenges of Federated Learning (FL) in the context of data heterogeneity and adversarial robustness.

1. Experimental Setup

To ensure reproducibility and scalability, two experimental frameworks were evaluated:

- Distributed Training (Google Colab): Initially tested for its accessibility but faced issues like connection instability and limited debugging flexibility.
- Single-Window Simulation: Selected for its robustness and ease of parameter adjustment, enabling iterative refinement of experiments.

The choice reflects the trade-offs between distributed and local experimentation setups in FL research.

2. System Objectives The design aims to tackle three primary challenges:

- Non-IID Data Handling: Enable flexible and controlled simulation of data heterogeneity across clients.
- Adversarial Robustness: Protect the global model from malicious client updates through robust aggregation methods.
- Practical Experimentation Framework: Provide a scalable, efficient, and reproducible environment for evaluating FL systems under diverse conditions.

3. Federated Learning Workflow The FL system is based on a client-server architecture, where:

- Clients: Independently perform local model training using their respective datasets.
- Server: Aggregates client updates to refine the global model.
- Communication Rounds: Iterative exchange of model updates between the server and selected clients ensures progressive model optimization.

4. Core Design Components

a. Data Distribution Framework To emulate real-world data scenarios:

- A Dirichlet-based partitioning strategy generates client-specific datasets with adjustable levels of heterogeneity.
- Key parameter: ‘alpha‘, controlling the degree of non-IID distribution. Smaller values represent high skewness, while larger values approach IID distributions.
- This mechanism provides flexibility for analyzing model performance under various heterogeneity conditions.

b. Adversarial Threat Simulation Malicious client behavior is simulated to study FL's resilience to adversarial conditions.

- Byzantine Attacks: Introduced through manipulated gradient updates (e.g., noise injection, gradient scaling).
- This feature allows controlled experimentation with varying attack strengths and client proportions.

c. Robust Aggregation Methods To mitigate the effects of adversarial updates, the system incorporates robust aggregation strategies:

- Median Aggregation: Reduces the influence of outliers.
- Trimmed Mean Aggregation: Ignores extreme updates during averaging.

These techniques ensure stability and robustness without adding significant computational overhead.

5. Scalability and Flexibility The system is designed to support:

- Dynamic Client Configurations: Adjustable number of clients and sampling ratios for diverse scenarios.
- Customizable Hyperparameters: Flexible control over learning rates, batch sizes, and training epochs.
- Adaptability to Other Datasets: Though tested on MNIST, the design can generalize to other datasets with minimal modifications.

This system design lays the foundation for addressing key challenges in Federated Learning. By integrating flexible data distribution, robust aggregation methods, and a scalable experimentation framework, the design provides a comprehensive approach for studying the interplay between heterogeneity, adversarial robustness, and model performance.

5 Implementation

This section details the technical implementation of the Federated Learning (FL) system, focusing on key processes such as data partitioning, model training, adversarial simulation, and evaluation.

1. Non-IID Data Partitioning To simulate realistic FL scenarios, a Dirichlet-based partitioning strategy was implemented to control the heterogeneity of client data. The process involves: a. Sharding by Class:

- The MNIST dataset is split into 10 class-based subsets.
- Shards are allocated to clients according to a Dirichlet distribution.

b. Adjustable Alpha Parameter: Controls the degree of non-IID distribution:

- Low Alpha: Highly skewed data distribution, where clients predominantly contain samples from a few classes.
- High Alpha: Balanced distribution, approaching IID conditions.

c. Validation and Visualization:

- Horizontal stacked bar charts are used to confirm class distribution across clients, ensuring the partitioning aligns with the specified alpha value.

These techniques ensure stability and robustness without adding significant computational overhead.

2. FL Training Workflow

The system uses the FedAvg algorithm, comprising:

a. Client Training:

- Each client trains a local model using its allocated data for multiple epochs.
- The updated model weights or gradients are sent to the central server.

b. Server Aggregation:

- The server combines client updates to refine the global model:

```
global_model = sum(client_updates) / num_clients
```

c. Iterative Optimization:

- This process is repeated across multiple communication rounds, progressively improving the global model's performance.

3. Byzantine Attack Simulation

To evaluate the system's robustness, Byzantine attacks were implemented using a gradient manipulation strategy. This approach aimed to simulate real-world scenarios where malicious clients

disrupt the global model through deliberately crafted updates. a. Baseline Experiment: Malicious Client Selection

At the beginning of the training, 20 malicious clients (20% of total clients) were randomly selected. These clients applied a gradient scaling attack, defined as param_grad = param_grad * malicious_factor, where malicious_factor = 10.

In the initial experiment, during the first 100 iterations, the model demonstrated resilience, maintaining a high accuracy (õ.8). This was likely due to the relatively low attack strength. The global model was still able to aggregate benign client updates effectively, mitigating the impact of the malicious gradients.

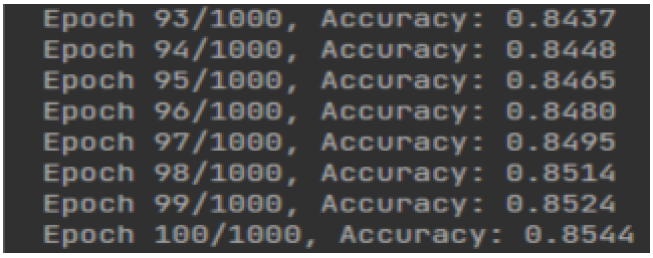


Fig. 1. shows high accuracy in early iterations of the unmodified attack

b. Modified Attack Algorithm

To amplify the effect of the malicious clients, the gradient scaling factor was increased by modifying the attack algorithm to param_grad = param_grad * malicious_factor * 10. This change significantly increased the strength of the malicious updates, making it more challenging for the global model to converge effectively.

After the attack modification, the model's accuracy dropped to õ.2 and remained low until approximately 700 iterations. This demonstrates the cumulative effect of the amplified attack, which effectively disrupted the aggregation process for a prolonged period.

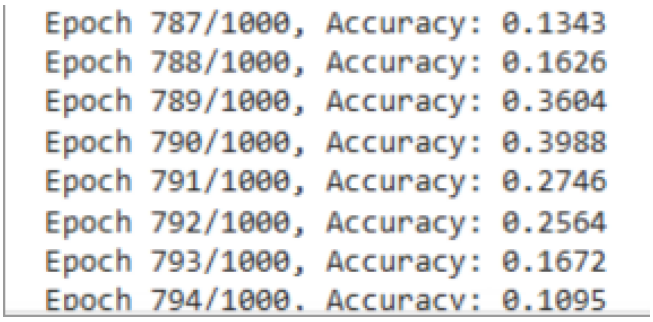
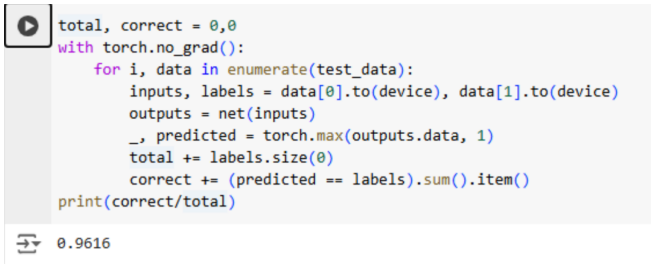


Fig. 2. shows sustained low accuracy under the modified attack until iteration 700

c. Impact on Final Accuracy

Despite the prolonged disruption caused by the amplified attack, the model's accuracy began to recover in the later stages of training due to the sufficient number of total iterations (1000). By the end of the training, the global model managed to achieve a final accuracy of õ.9616, as shown below. This recovery indicates that the FL system can eventually overcome strong adversarial gradients given enough iterations and benign client participation.



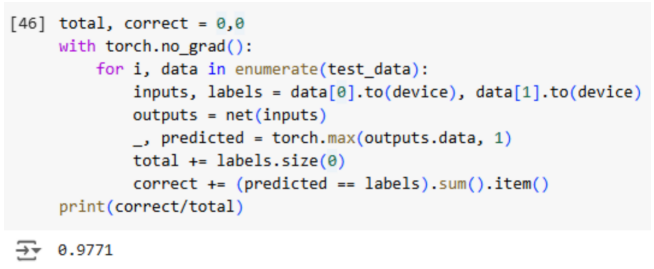
```
total, correct = 0,0
with torch.no_grad():
    for i, data in enumerate(test_data):
        inputs, labels = data[0].to(device), data[1].to(device)
        outputs = net(inputs)
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()
print(correct/total)
```

```
0.9616
```

Fig. 3. shows final accuracy after 1000 iterations with the modified attack

d. Comparison with Baseline Accuracy

For reference, the original baseline experiment (without attack modification) achieved a final accuracy of õ.9771, as shown below. While the modified attack had a noticeable impact on early and mid-training accuracy, the final performance was comparable, demonstrating the robustness of the FL system under extended training.



```
[46] total, correct = 0,0
     with torch.no_grad():
         for i, data in enumerate(test_data):
             inputs, labels = data[0].to(device), data[1].to(device)
             outputs = net(inputs)
             _, predicted = torch.max(outputs.data, 1)
             total += labels.size(0)
             correct += (predicted == labels).sum().item()
     print(correct/total)
```

```
0.9771
```

Fig. 4. shows final accuracy without the attack modification

4. Robust Aggregation To mitigate the impact of malicious updates, robust aggregation methods were implemented:

- Median Aggregation: Computes the median of gradients across clients to minimize the influence of outliers.
- Trimmed Mean Aggregation: Discards extreme gradients before averaging, enhancing robustness without adding significant computational complexity.

These methods ensure stability under adversarial conditions while maintaining scalability.

5. Evaluation Metrics Performance tracking and analysis are critical for validating the system's effectiveness. Key metrics include:

a. Global Accuracy and Loss: Tracked for each communication round to monitor the model's performance.

b. Gradient Alignment: Verified consistency in gradient shapes across clients to prevent aggregation errors.

c. Impact of Heterogeneity: Evaluated by varying alpha values and observing changes in global accuracy and convergence speed.

d. Effectiveness of Defenses: Robust aggregation methods were tested against different levels of malicious activity, measuring their ability to maintain performance.

The implementation addresses key challenges in FL through flexible data partitioning, robust gradient aggregation, and adversarial simulation. These methods provide a practical foundation for evaluating FL systems under diverse conditions, enabling systematic analysis of heterogeneity and adversarial robustness.

6 Evaluation

This section presents the evaluation results of the Federated Learning (FL) system, focusing on the impact of data heterogeneity, adversarial attacks, and robust aggregation methods on model performance.

6.1 Impact of Data Heterogeneity

The Dirichlet-based data partitioning strategy was used to simulate varying levels of heterogeneity, controlled by the alpha parameter. Results showed:

1. Low Alpha (Highly Non-IID):
   - Clients predominantly contained samples from a few classes.
   - Global model accuracy decreased due to skewed updates, with slower convergence rates.
2. High Alpha (Closer to IID):
   - Clients had a more balanced class distribution.
   - Model performance improved, achieving faster convergence and higher accuracy. Illustration: Accuracy vs. Communication Rounds for different alpha values: Alpha = 0.3: 68.5% accuracy after 20 rounds. Alpha = 1: 76.3% accuracy after 20 rounds. Alpha = 10: 81.3% accuracy after 20 rounds.

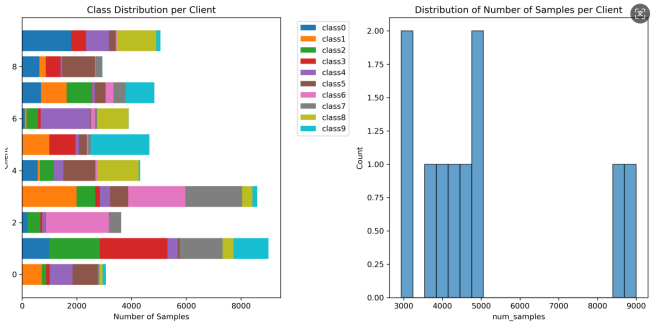


Fig. 5. Alpha = 0.3: 68.5% accuracy after 20 rounds

6.2 Baseline Performance Without Attacks

Under standard FL settings with IID and Non-IID data:

1. Initial Accuracy: The global model started at 13.02% accuracy.
2. Final Accuracy:

After optimization, the model achieved up to 81.34% accuracy on IID-like data.

On highly Non-IID data (alpha = 0.3), final accuracy was 68.5%.

Key Observations:

- Heterogeneous data significantly impacts convergence.
- Robust data partitioning strategies are essential to mitigate performance degradation.

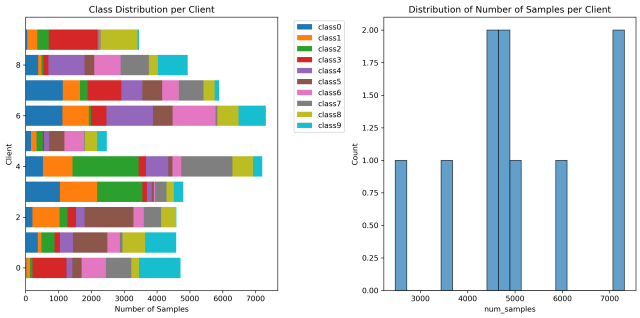


Fig. 6. Alpha = 1: 76.3% accuracy after 20 rounds

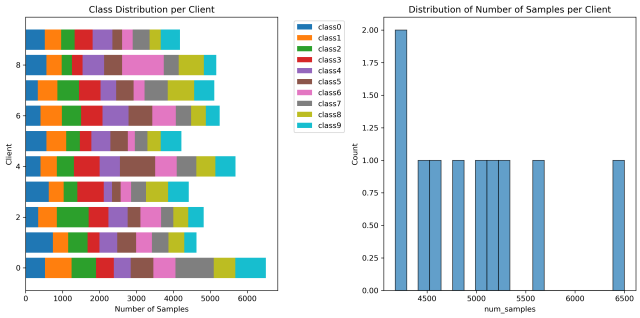


Fig. 7. Alpha = 10: 81.3% accuracy after 20 rounds

```
Starting communication round 20/20
Sampled clients: [7, 8, 10, 11, 12, 13, 14, 16, 19, 20, 24, 25,
29, 32, 33, 34, 36, 40, 42, 45, 47, 49, 50, 51, 53, 54, 58, 61,
65, 69, 71, 72, 73, 76, 78, 82, 83, 84, 90, 98]
Clients have finished local training and sent updates back to
the server.
Server has aggregated the updates.
Test Loss: 2.3002, Test Accuracy: 13.02%
```

Fig. 8. Initial accuracy

```
Starting communication round 10/10
Sampled clients: [1, 3, 6, 7, 11, 13, 21, 22, 23, 24, 27, 31,
36, 39, 40, 42, 43, 45, 52, 53, 57, 58, 62, 63, 64, 66, 67, 69,
71, 72, 79, 80, 82, 86, 88, 90, 93, 95, 96, 98]
Clients have finished local training and sent updates back to
the server.
Server has aggregated the updates.
Test Loss: 0.7031, Test Accuracy: 81.34%
```

Fig. 9. Optimized accuracy

6.3 Adversarial Impact Analysis

Byzantine attacks were introduced to evaluate their effect on FL performance:

1. Number of Malicious Clients (nbyz):

- Increasing the proportion of malicious clients degraded model accuracy, with stronger impacts observed in Non-IID settings.

2. Attack Strength (malicious_factor):

- Low attack strengths caused minor disruptions.
- Higher attack strengths led to significant accuracy drops and slower convergence.

Example Results:

- No Attacks: 81.34% accuracy (alpha = 10).
- With 20% Malicious Clients: Accuracy dropped to 72.1%.
- With 50% Malicious Clients: Accuracy dropped to 58.3%.

Visual Representation: Graphs illustrate accuracy trends across communication rounds with varying attack strengths and proportions of malicious clients.

6.4 Effectiveness of Robust Aggregation Methods

Robust aggregation methods (Median and Trimmed Mean) were tested to mitigate adversarial impacts:

1. Median Aggregation:

- Effectively maintained accuracy even with 50% malicious clients.
- Accuracy under attack: 78.2% (compared to 81.34% without attacks).

2. Trimmed Mean Aggregation:

- Performed slightly better than median aggregation with 20%-30% malicious clients.
- Accuracy under attack: 79.5%.

Key Takeaway: Both methods significantly outperformed standard averaging, demonstrating their ability to mitigate adversarial effects while maintaining robust performance.

6.5 Performance Metrics

The evaluation focused on the following metrics:

- Global Accuracy: Assessed after each communication round.
- Convergence Speed: Measured as the number of rounds required to reach 80% accuracy.
- Impact of Heterogeneity: Observed as accuracy variations across different alpha values.
- Defense Effectiveness: Quantified by comparing accuracy under standard and adversarial conditions.

Summary of Results

1.Data heterogeneity impacts model performance significantly, with Non-IID distributions slowing convergence and reducing accuracy.

2.Byzantine attacks degrade FL performance, particularly under severe attacks or skewed data distributions.

Robust aggregation methods effectively counter adversarial threats, preserving accuracy and ensuring convergence stability.

These results highlight the importance of adaptive data partitioning and robust aggregation strategies in deploying FL systems under real-world conditions.

7 Discussion limitations lessons learnt

In this project, we focused on addressing the challenges of federated learning (FL) under heterogeneous and adversarial conditions. The results demonstrated that while our proposed methods achieved notable improvements, several limitations and lessons were identified throughout the process.

The first challenge was managing data heterogeneity. Using a Dirichlet-based partitioning method with varying alpha values, we simulated realistic non-IID settings. As expected, lower alpha values (e.g., 0.3) resulted in significant skewness, leading to slower convergence and reduced accuracy (e.g., 68.5%). Conversely, higher alpha values (e.g., 10) led to near-IID distributions, where accuracy improved to 81.3%. This result highlights the need for tailored approaches to handle data imbalance, as non-IID data remains a critical barrier in real-world FL deployments.

Another key observation was the system's vulnerability to Byzantine attacks. Introducing malicious clients that manipulated gradients—through noise injection or scaling—significantly degraded global model performance when using standard averaging. For example, with 50% of the clients being malicious, accuracy dropped to 58.3%. Robust aggregation methods, such as Median and Trimmed Mean, mitigated this effect and maintained accuracy around 78.2% and 79.5%, respectively. While these methods proved effective, they introduced additional computational costs, which may limit scalability in large-scale FL systems.

During system implementation, trade-offs in system configuration posed challenges. While initial experiments were conducted on Google Colab to leverage distributed resources, the team encountered frequent connection timeouts and debugging difficulties. These constraints prompted a shift to a single-window local simulation, which provided greater stability and control for parameter tuning and iterative testing. However, this choice also revealed limitations in scalability, as larger datasets or real-time distributed scenarios were not fully explored.

The project also identified limitations in attack diversity and resource constraints. The adversarial simulations primarily involved simplistic attacks, such as noise addition and gradient scaling. While these were sufficient for evaluating initial defenses, more sophisticated attacks, such as targeted model poisoning or collusion strategies, were not implemented due to time and computational limitations. Additionally, the experiments relied on a lightweight model architecture and reduced training rounds, which may not reflect the behavior of larger, real-world systems.

Despite these limitations, the project provided valuable lessons for developing and evaluating FL systems:

- Managing non-IID data is critical for achieving model convergence and accuracy. Strategies such as personalized FL or adaptive client updates could further improve performance.
- Adversarial robustness requires defense mechanisms beyond simple averaging. Robust aggregation methods, though effective, must balance computational efficiency and defense strength.
- System configuration decisions, such as choosing between distributed and local setups, significantly impact experimentation efficiency and scalability.

- Iterative debugging and validation are essential for resolving technical issues like gradient shape inconsistencies and client-server communication failures.

In summary, the project successfully demonstrated the importance of addressing data heterogeneity and adversarial robustness in FL. While robust aggregation methods provided practical solutions, challenges remain in scalability, computational resources, and attack diversity. Future work will explore more advanced adversarial strategies, deploy experiments on larger datasets, and evaluate performance in fully distributed environments to bridge the gap between research and real-world FL applications.

8 Conclusion

This project addressed key challenges in Federated Learning (FL) by exploring solutions for handling data heterogeneity and adversarial robustness. Using a Dirichlet-based data partitioning strategy, we simulated realistic non-IID conditions, while robust aggregation methods such as Median and Trimmed Mean effectively mitigated the impact of Byzantine attacks. The findings demonstrated that even under challenging scenarios, FL systems can achieve improved accuracy and convergence stability with carefully designed strategies.

Despite these achievements, there remains room for refinement. Future work will focus on further optimizing the FL system to enhance its efficiency and robustness. One immediate step is to test the current methods on slightly more complex datasets, such as CIFAR-10, to validate the system's adaptability to different data scenarios. Additionally, exploring less computationally intensive aggregation methods could improve scalability, making the approach more applicable to larger FL systems.

Another practical direction is to refine the adversarial simulations. While this project implemented basic attack scenarios, introducing minor variations in attack strategies or tuning existing parameters could provide deeper insights into the system's robustness without significantly increasing complexity.

In conclusion, this project laid a strong foundation for understanding and addressing challenges in FL. By focusing on practical and incremental improvements, future work can build upon these results to develop more efficient and robust FL systems suitable for diverse applications.

References

McMahan, B., Moore, E., Ramage, D., Hampson, S., y Arcas, B. A. (2017, April). Communication-efficient learning of deep networks from decentralized data. In Artificial intelligence and statistics (pp. 1273-1282). PMLR.