**Experiment Setup Analysis**

**The configuration shows:**

Dataset: CIFAR-10 with Dirichlet distribution (α=0.05), creating highly non-IID data across 12 clients

Optimal parameters: Batch size 64, minibatch time 0.81 seconds

FL setup: 20 rounds, 3 clients selected randomly per round, FedAvg aggregation

Training: 3 local epochs per client per round, learning rate 0.0001

**Key Observations:**

1. **Significant Data Heterogeneity Across Clients The data distribution reveals extreme imbalance:**

Largest client (CID2): 6,761 training samples

Smallest client (CID3): 216 training samples

Ratio: ~31:1 difference in dataset sizes

This creates a natural disparity in client contributions and training times.

1. **Client Performance Variations**

Analyzing individual client performance patterns:

High-performing clients (consistently >95% local accuracy):

CID8, CID10, CID11: Large datasets, stable high accuracy

These clients likely have more balanced class distributions

Poor-performing clients:

CID3: Consistently 12 minibatches, ~45-55% accuracy

CID4: Small dataset, variable performance

These suffer from severe class imbalance due to non-IID distribution

1. **Training Time Utilization Issues The timing analysis reveals inefficiencies:**

Actual training time: Cumulative across all clients

Simulation round time: Bottlenecked by the slowest client

Large variance in training times (12 minibatches vs 318 minibatches)

Example from Round 7:

CID2: 318 minibatches (bottleneck)

CID3: 12 minibatches

CID6: 168 minibatches

The federation waits for the slowest client, leading to resource underutilization.

1. **Global Model Performance The global accuracy progression is concerning:**

Starts at 10% (Round 1-2)

Peaks at ~22% (Round 10)

Plateaus/degrades to ~20% by Round 20

This poor performance (20% on CIFAR-10) indicates:

Data heterogeneity challenges: Non-IID distribution severely impacts convergence

Client drift: Local models diverge due to skewed data distributions

Statistical heterogeneity: Each client sees different class distributions

**Critical Issues Identified**

1. Unequal Client Contributions Clients with larger, more balanced datasets (CID2, CID7, CID11) contribute significantly more meaningful updates

Small clients (CID3, CID4) provide noisy or limited updates that may hurt global performance

1. Training Time Inefficiency Federation synchronization waits for the bottleneck client

Resource waste as faster clients remain idle

Random selection doesn't consider client capabilities or data quality

1. Poor Convergence 20% accuracy suggests the random selection strategy fails to effectively aggregate knowledge

***High statistical heterogeneity from Dirichlet α=0.05 distribution exacerbates the problem.***