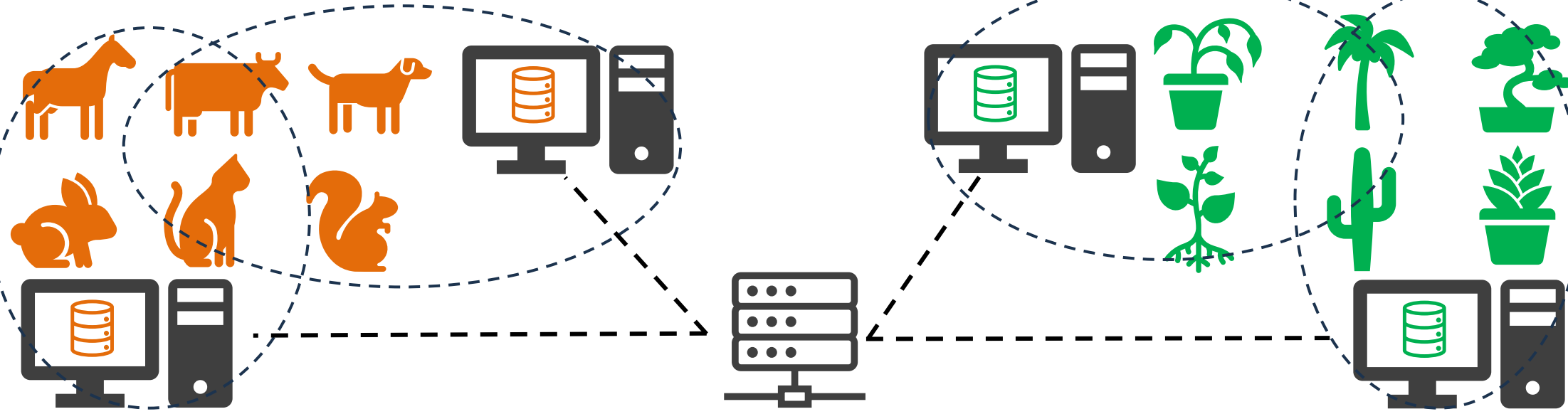


## TL;DR

Q

**CFL Problems:** When training multiple models for diverse data distributions (clients), how do we cluster clients?



The Clients are connected to a central unit but **no local dataset is shared**.

①

**Accumulate client gradients** over multiple learning iterations **for a set of models**.

**CFL-GP (Ours)**

②

**Apply spectral clustering** to the accumulated gradient information

Q

What **advantages** does your approach offer over existing clustered federated learning algorithms?

①

Rapidly identifies cluster identities, **often within just a few rounds**.

**CFL-GP (Ours)**

②

Highly robust (**both clustering/model convergence**) without dataset sharing

## Theoretical results

Under assumptions (Gaussian SGN, convexity...),

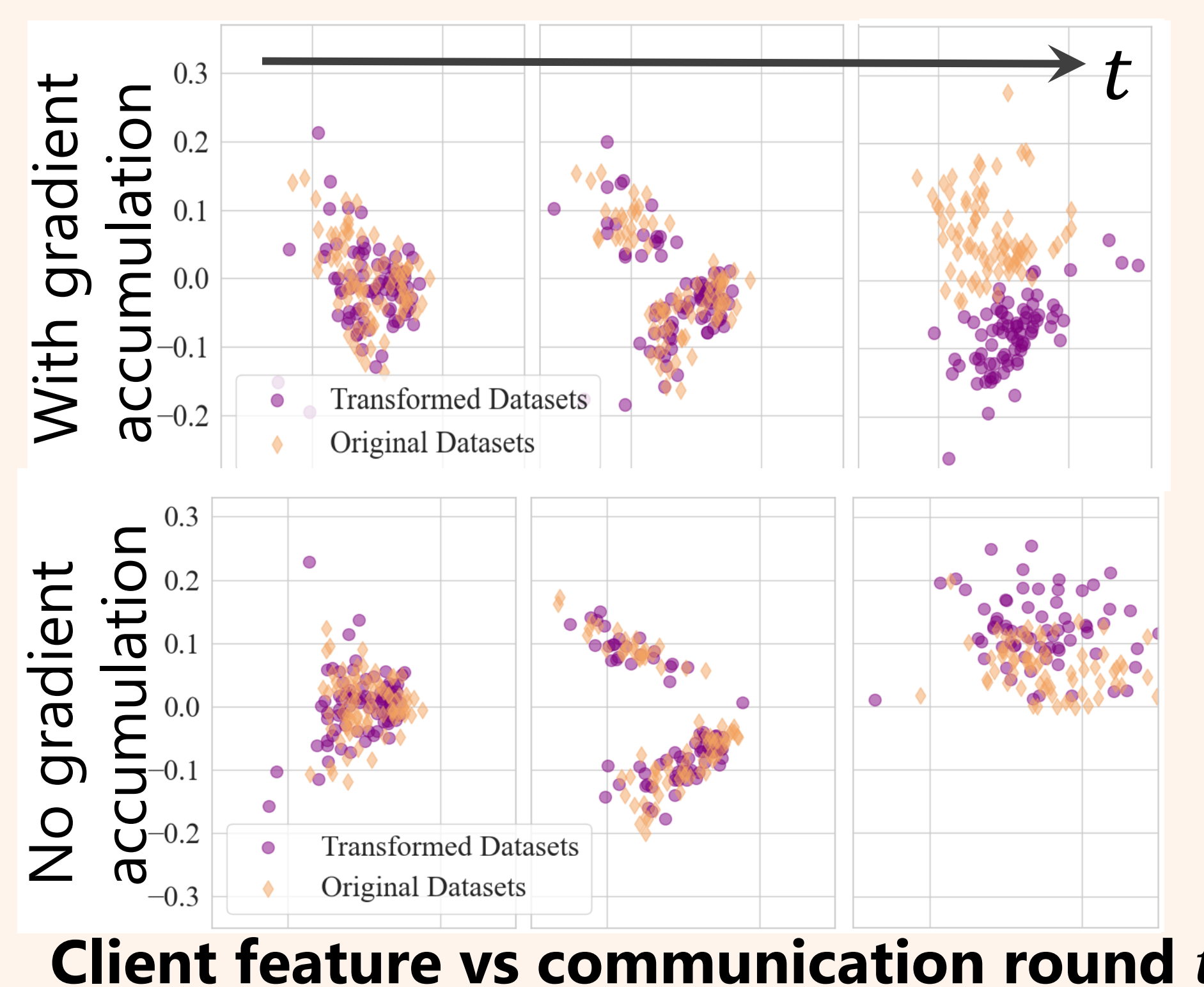
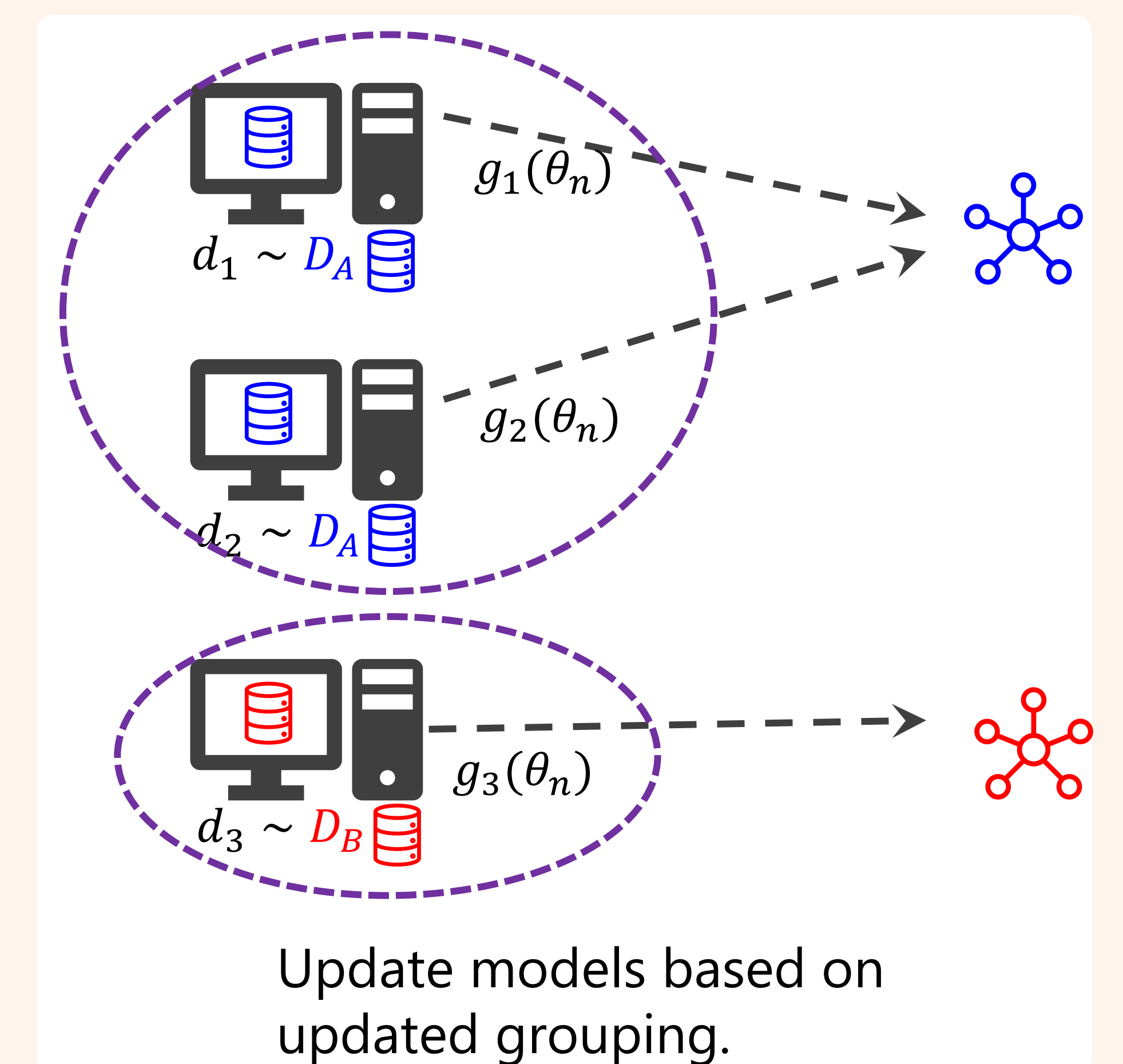
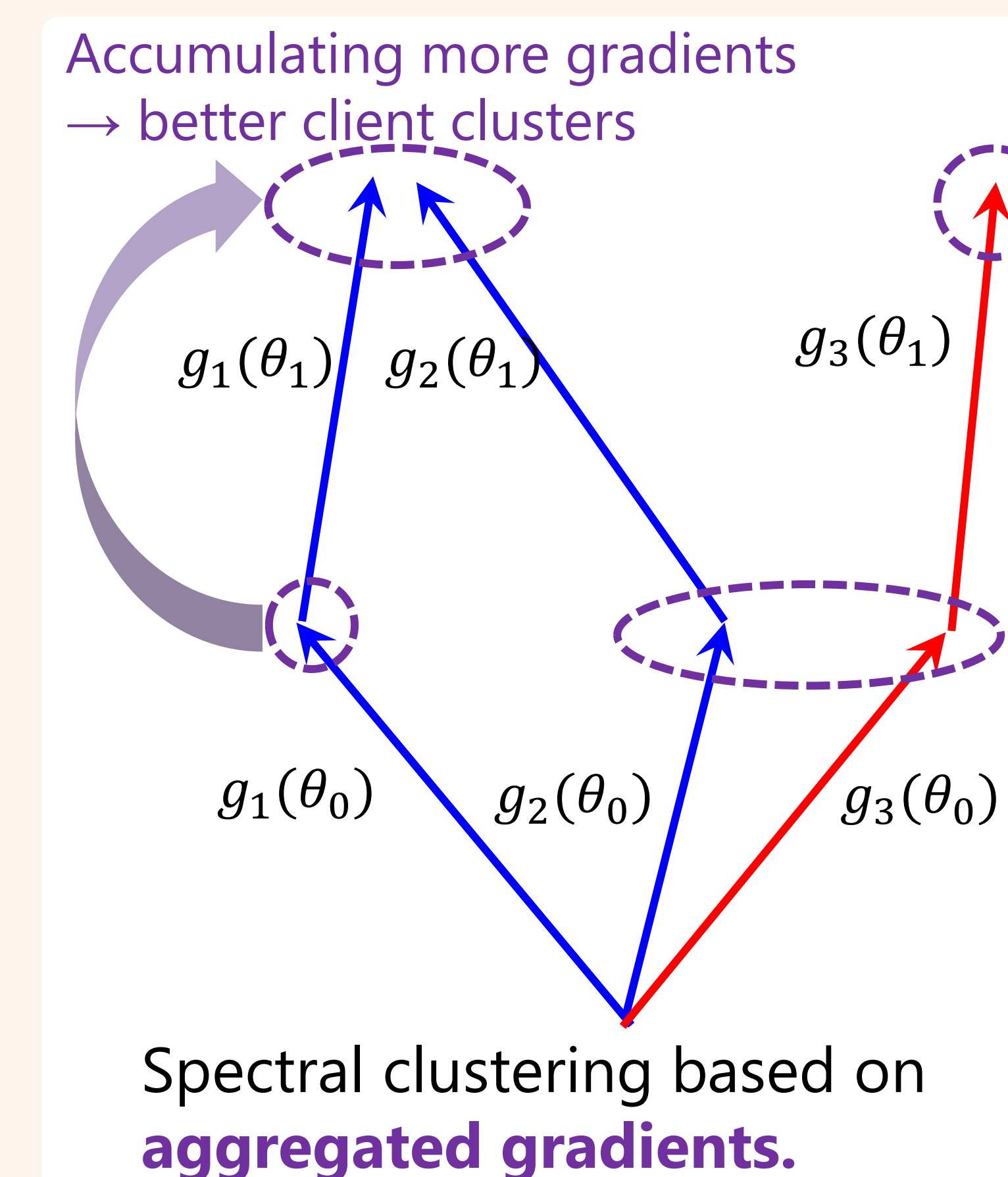
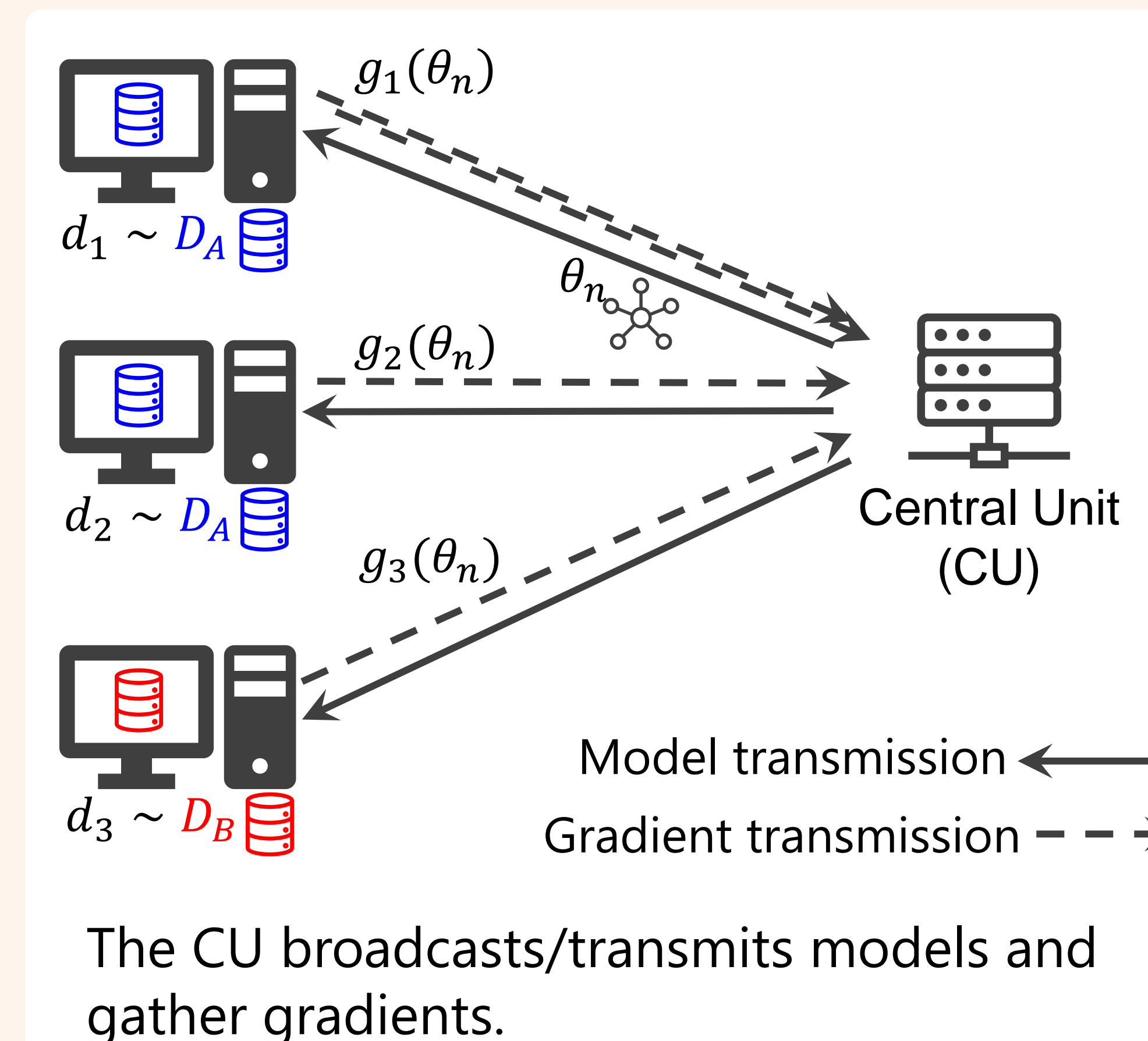
① **Cluster convergence:** As  $t \rightarrow \infty$ , **all clients are correctly clustered** with high probability.

② **Contractive property:** As  $t \rightarrow \infty$ , the error rate of CFL-GP's gradient update converges to **the optimal error rate** with high probability.

③ **Model convergence:** As  $t \rightarrow \infty$ , all of models **converge to the optimal model** with high probability.

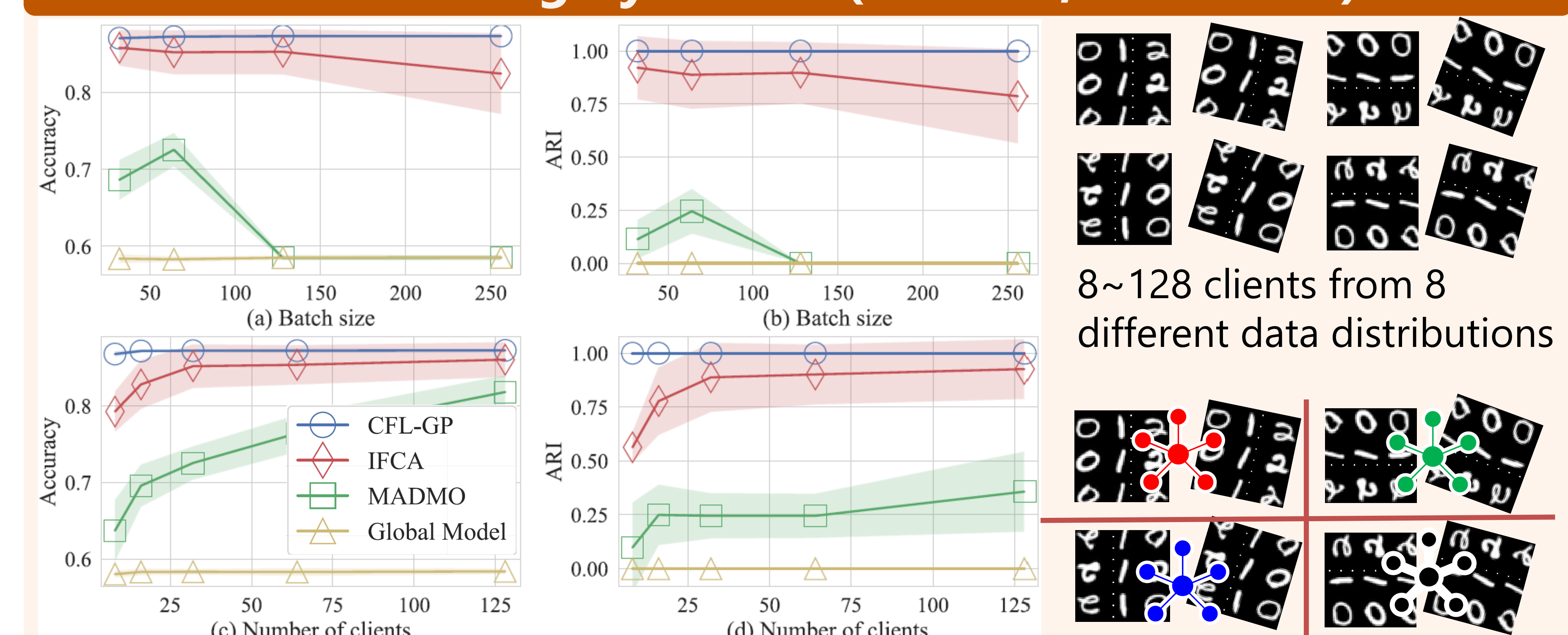
## Key Findings / Algorithm (CFL-GP)

- ① **Accumulating clients' gradient information** for a set of models reveals their cluster identities by effectively **denoising gradient noise**.
- ② **More accurate client clustering** yields better task performance.



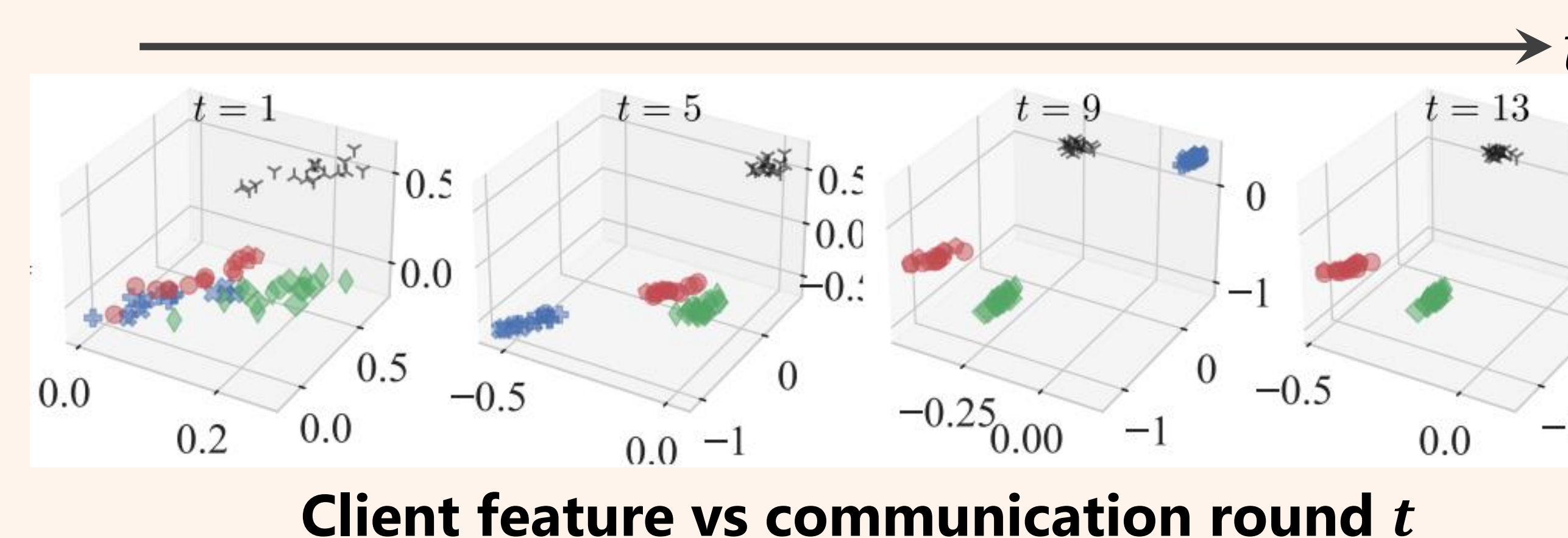
Client feature vs communication round  $t$

## CFL-GP is highly robust (#clients, batch size)

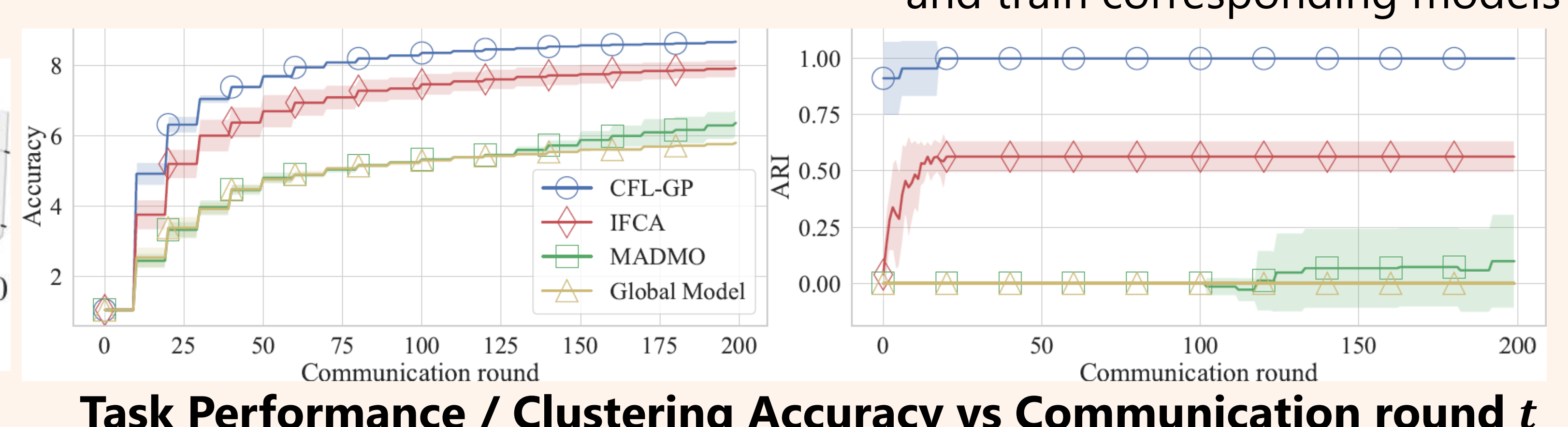


8~128 clients from 8 different data distributions

**Goal:** cluster them into 4 groups and train corresponding models



Client feature vs communication round  $t$



Task Performance / Clustering Accuracy vs Communication round  $t$