

Orchestra: Unsupervised Federated Learning via Globally Consistent Clustering

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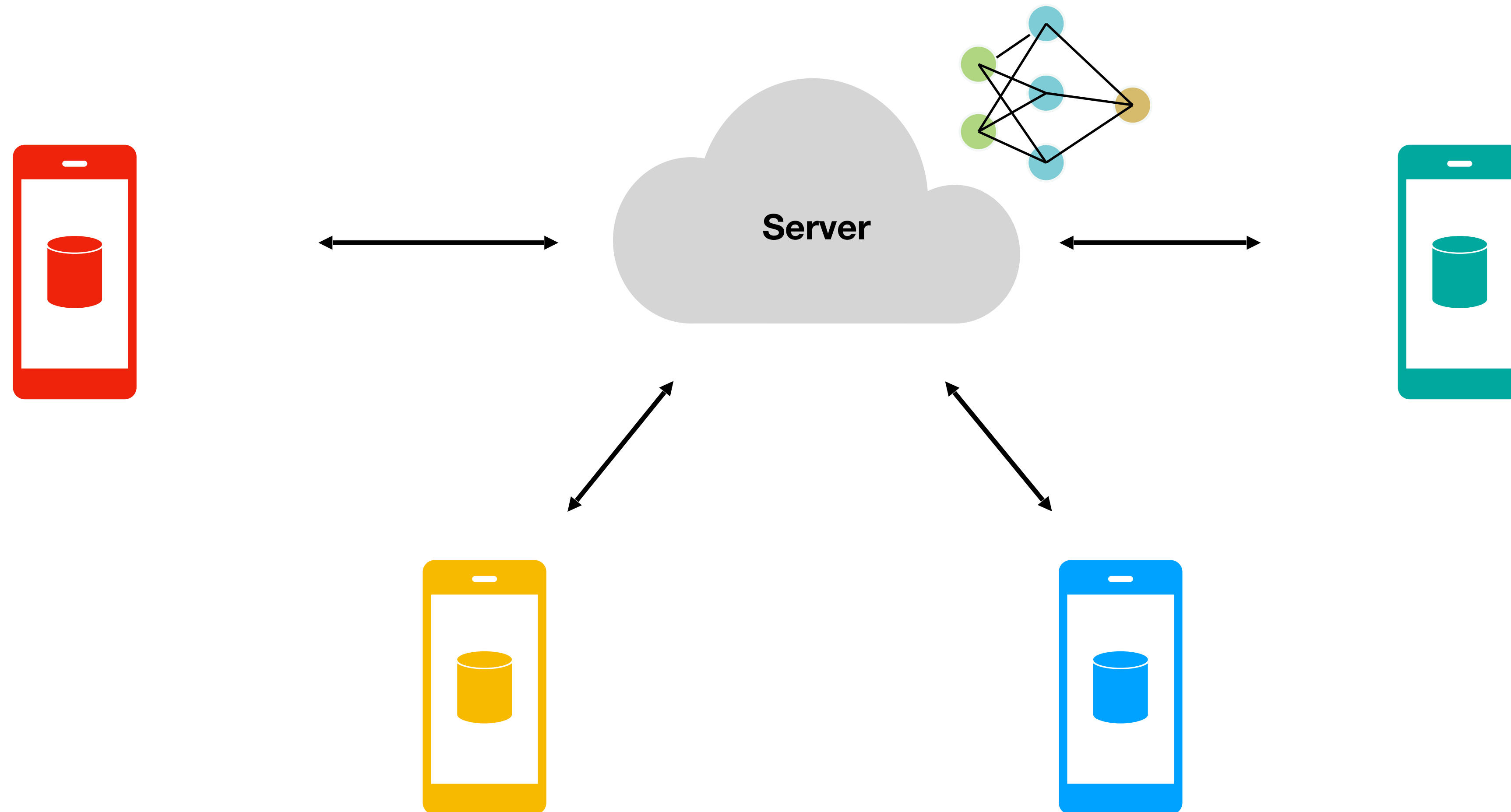


Smart Devices: Perpetual Data Generators

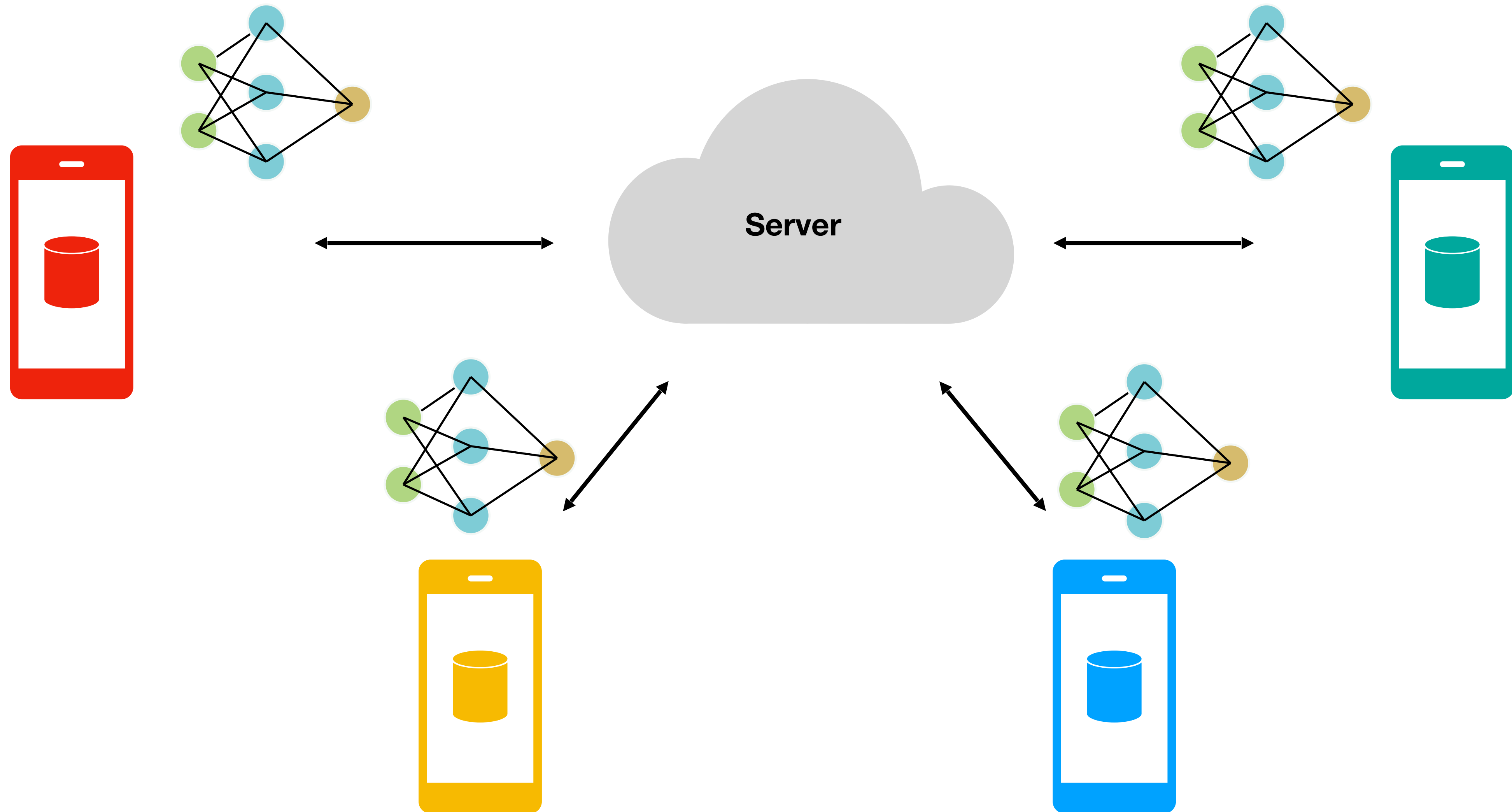


Federated Learning: Collaborative Training

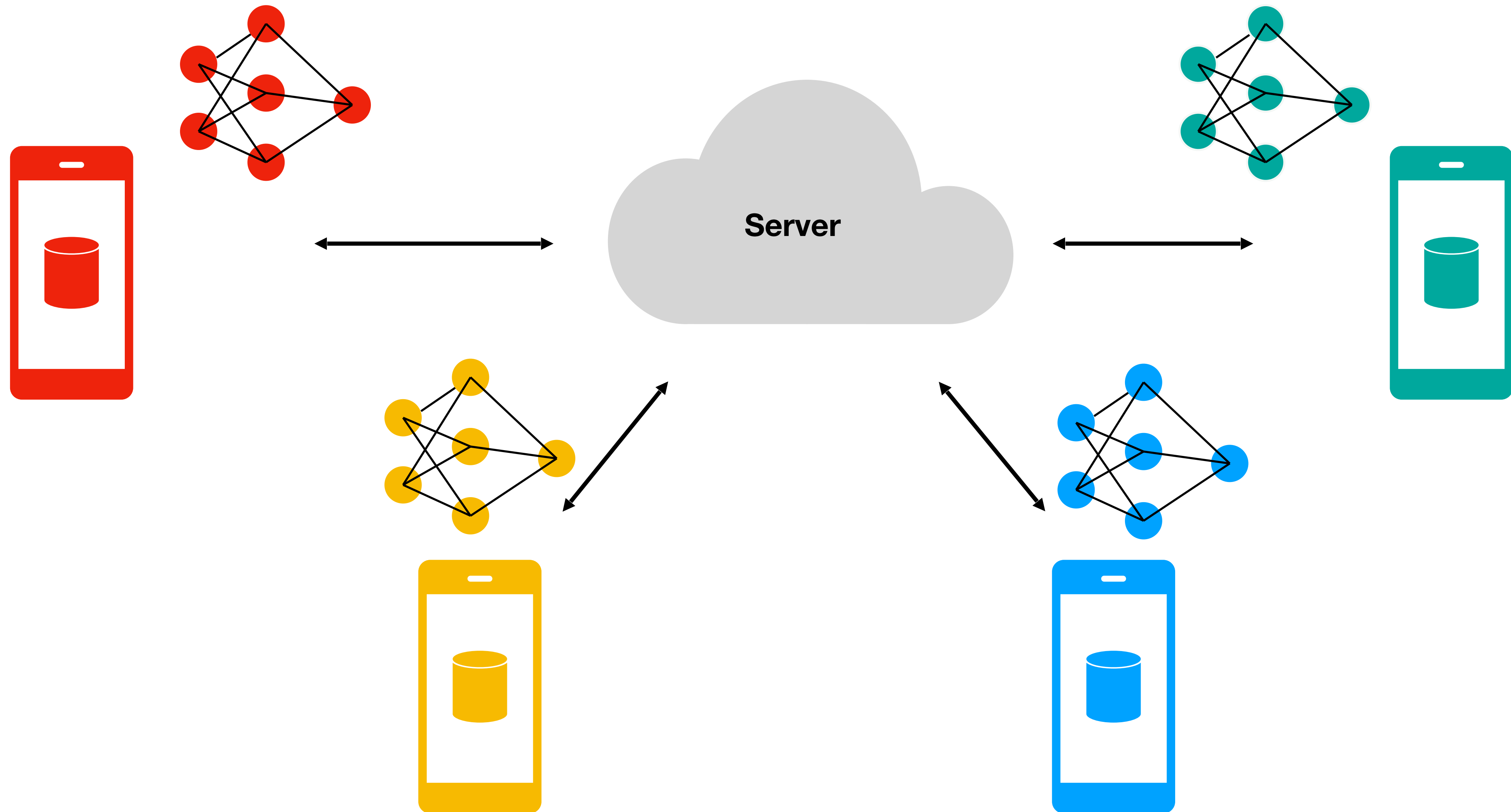
- Goal: Distributed, privacy-preserving, resource-efficient learning



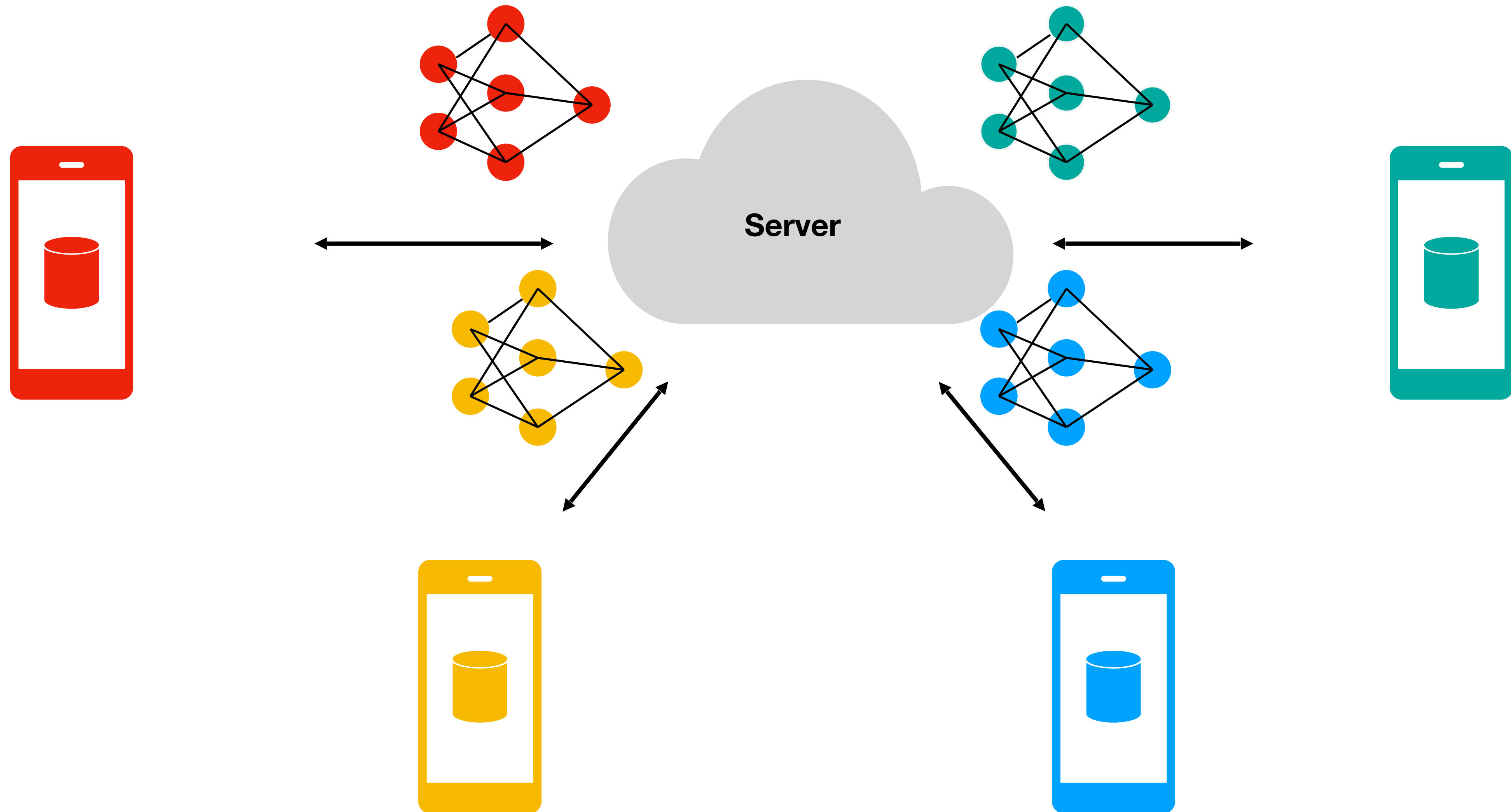
Step 1: Share Model with Clients



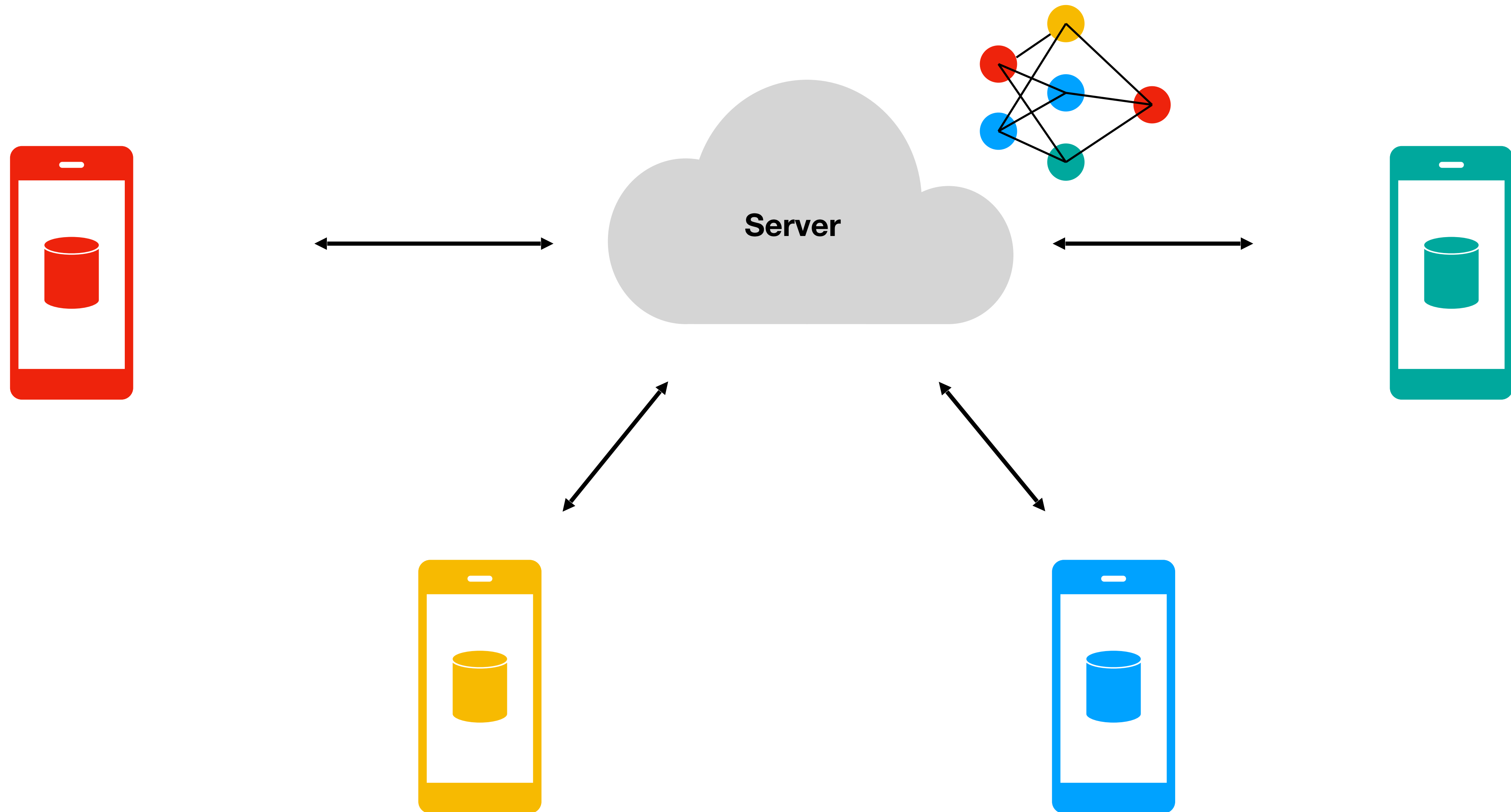
Step 2: Train Models on Local Data



Step 3: Aggregate Models in a Secure Manner



Step 4: Repeat Process with New Global Model



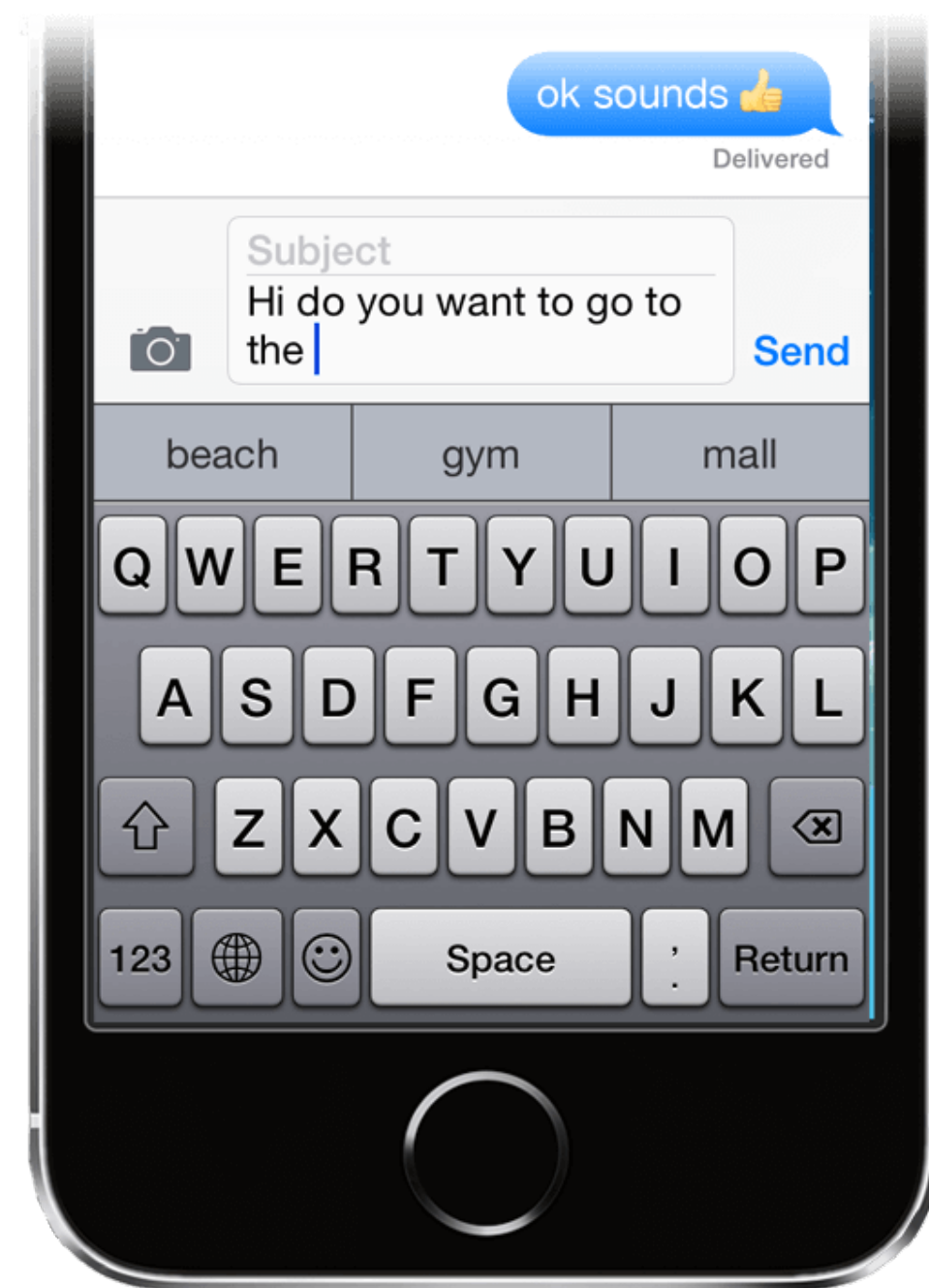
What's the catch?

- Needs **user interaction**: Interaction patterns form labels

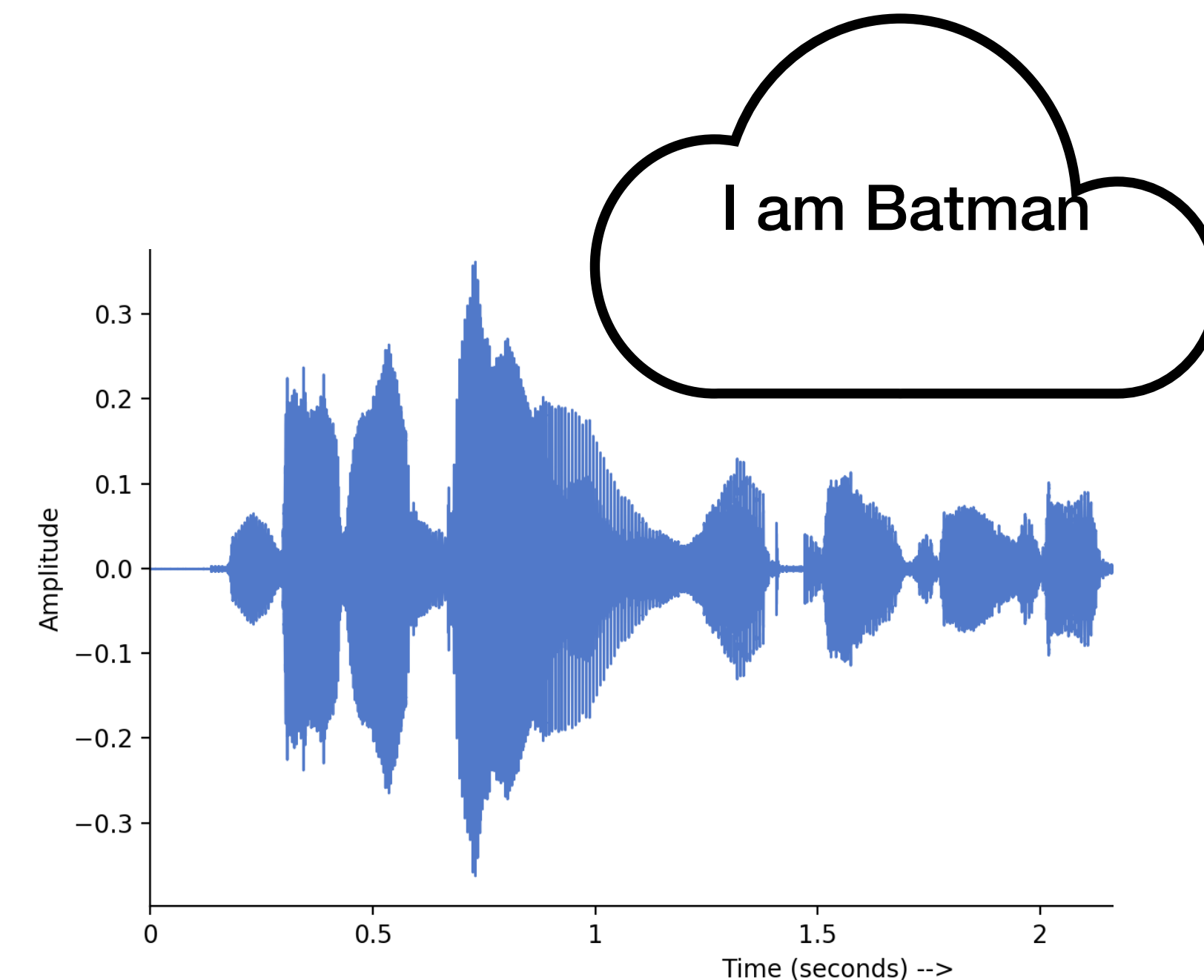


What's the catch?

- Needs **user interaction**: Interaction patterns form labels
- Most sensors collect data in **non-interactive** manners



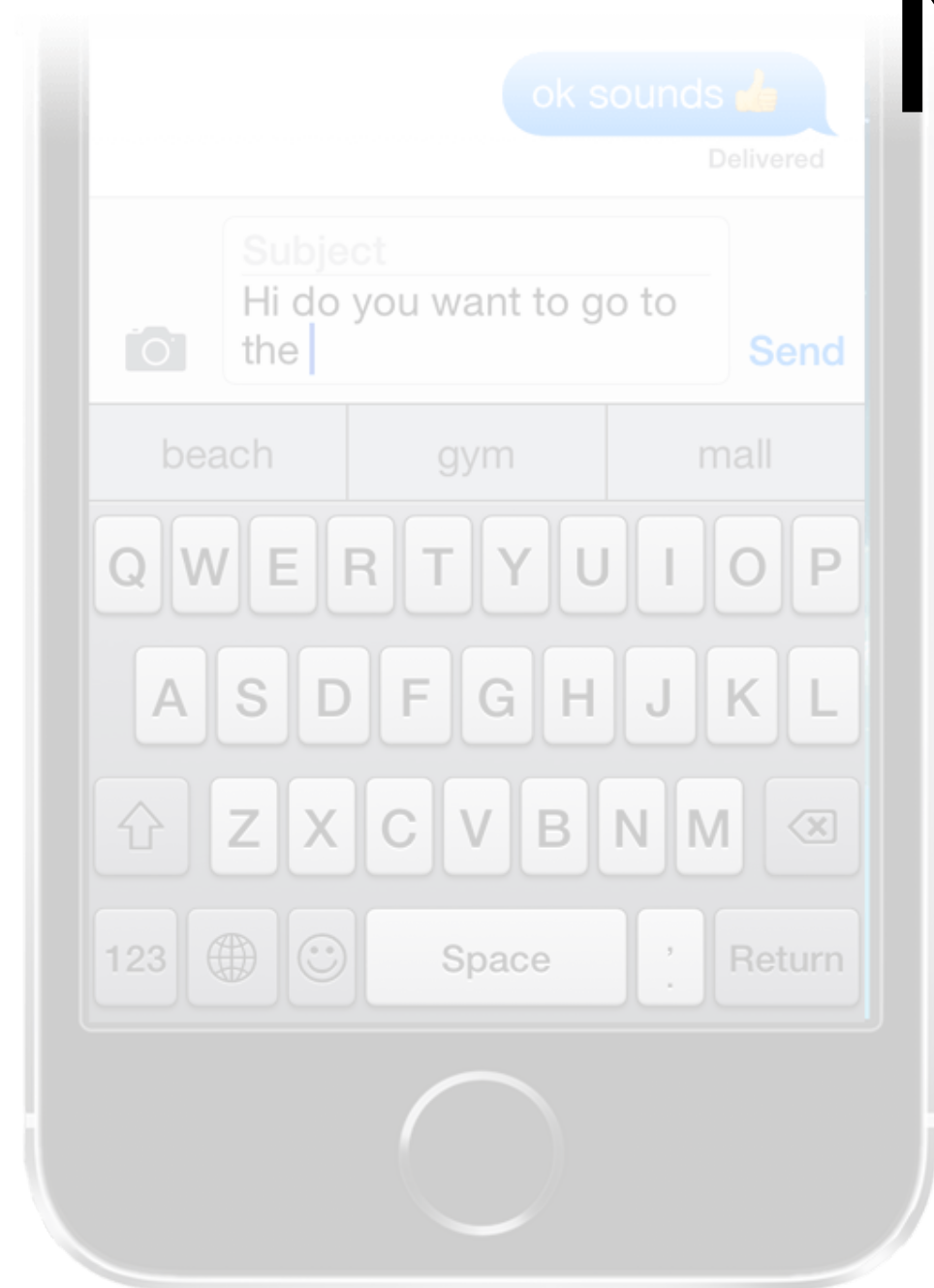
Who am I
again?



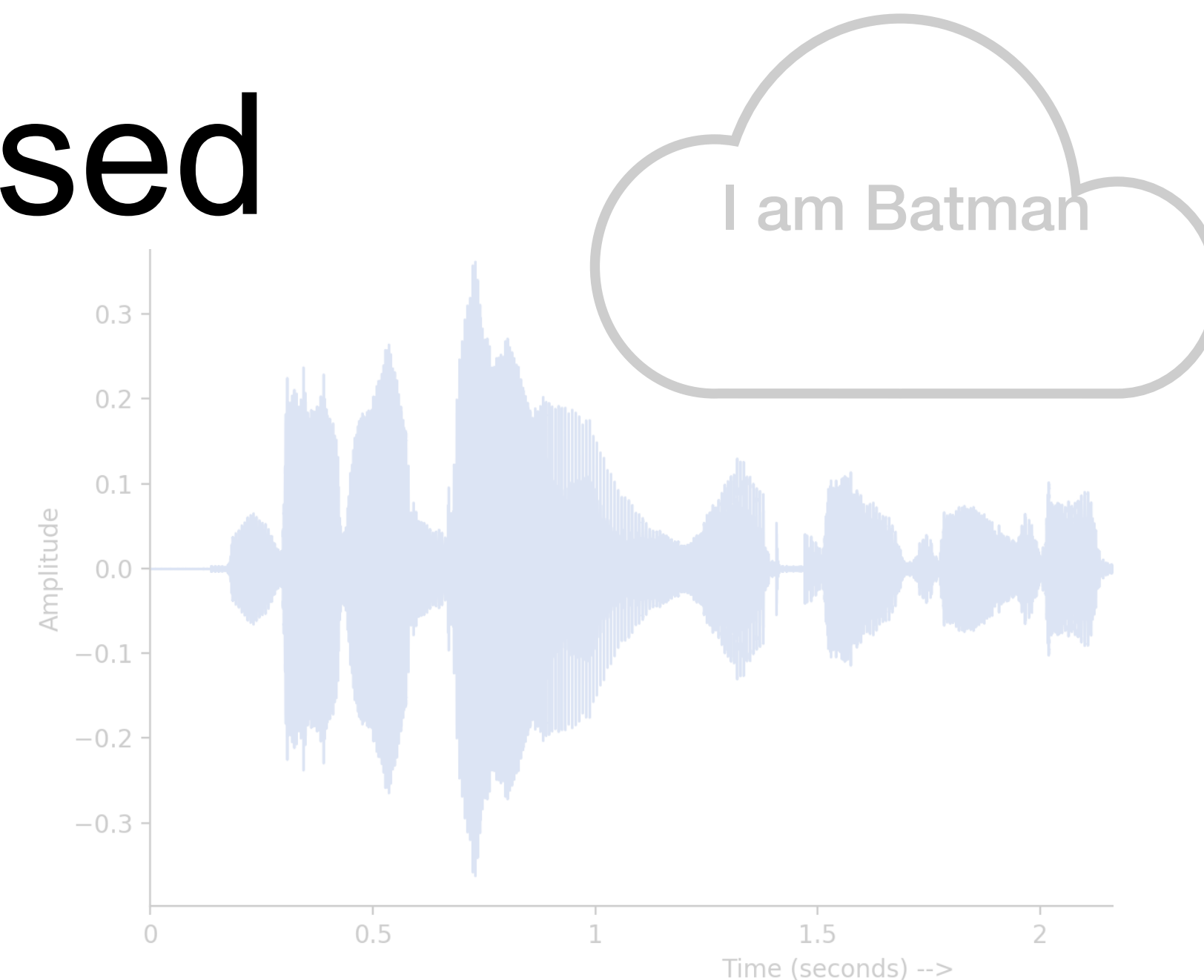
Seems too simple... what's the catch?

- Needs **user interaction**: Interaction patterns form labels
- Most sensors collect data in **non-interactive** manners

Need to go Unsupervised

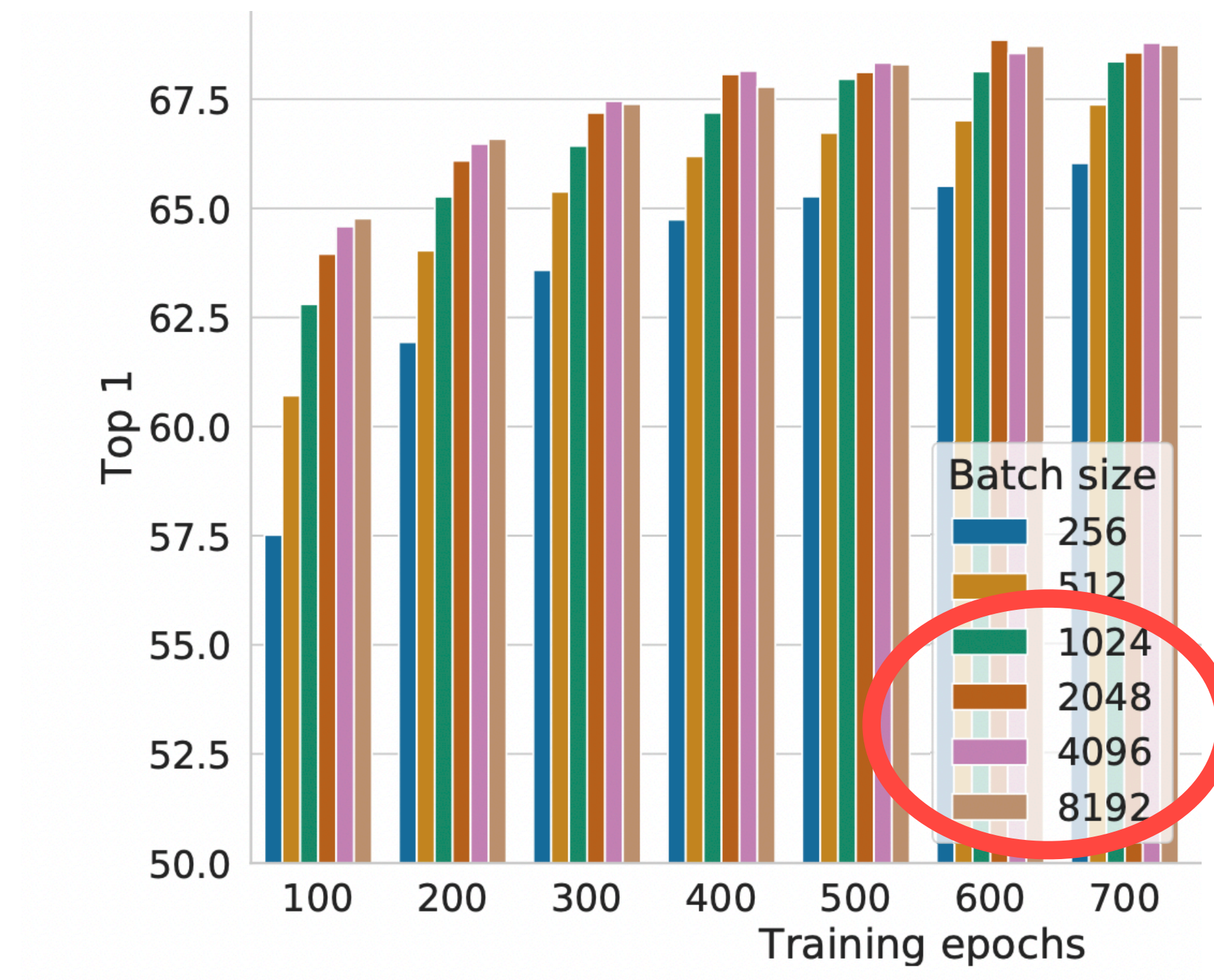


again?



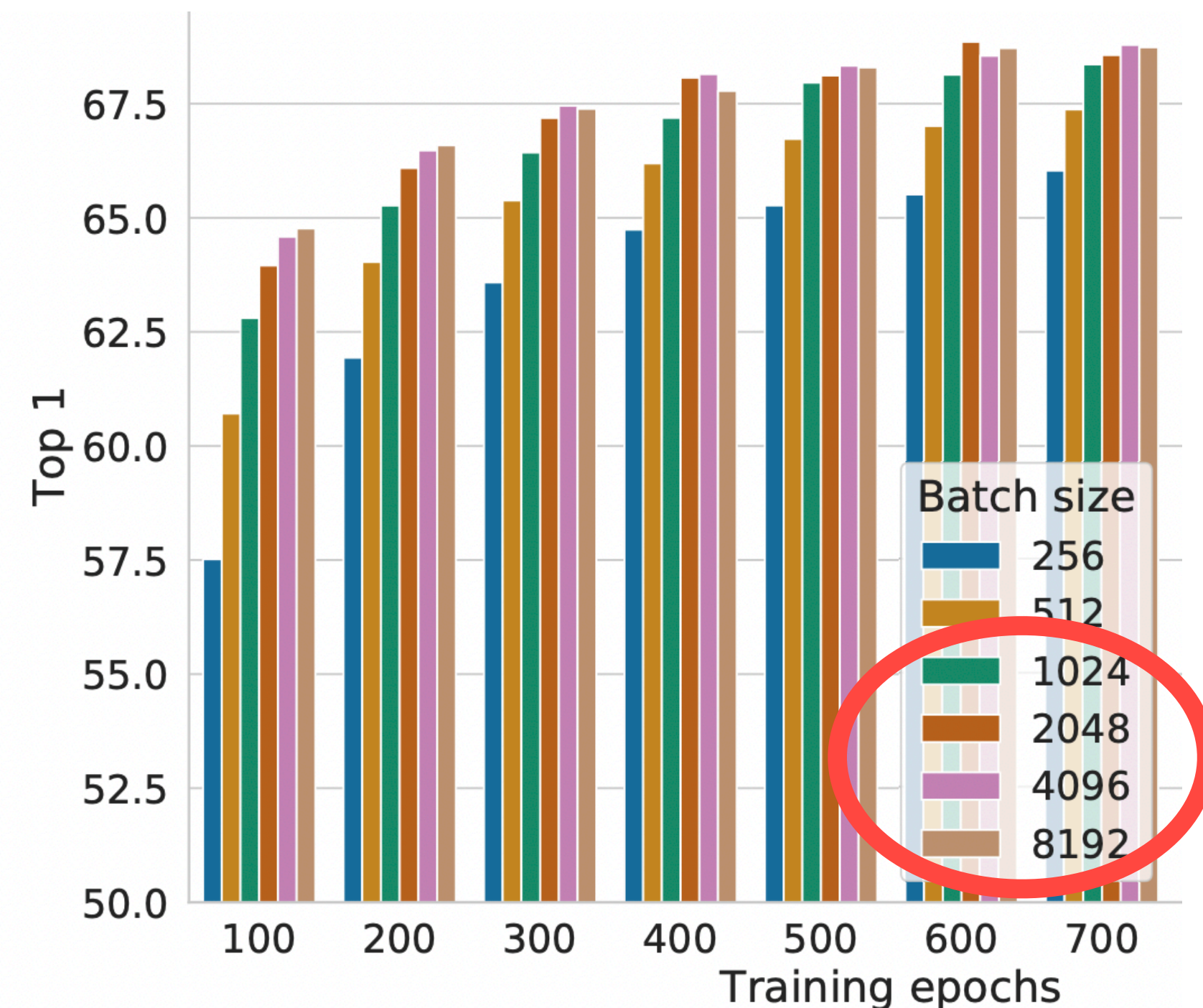
Limitations of Conventional Unsupervised Learning

- Useful unsupervised learning algorithms traditionally require **large amounts of compute and data**



Limitations of Conventional Unsupervised Learning

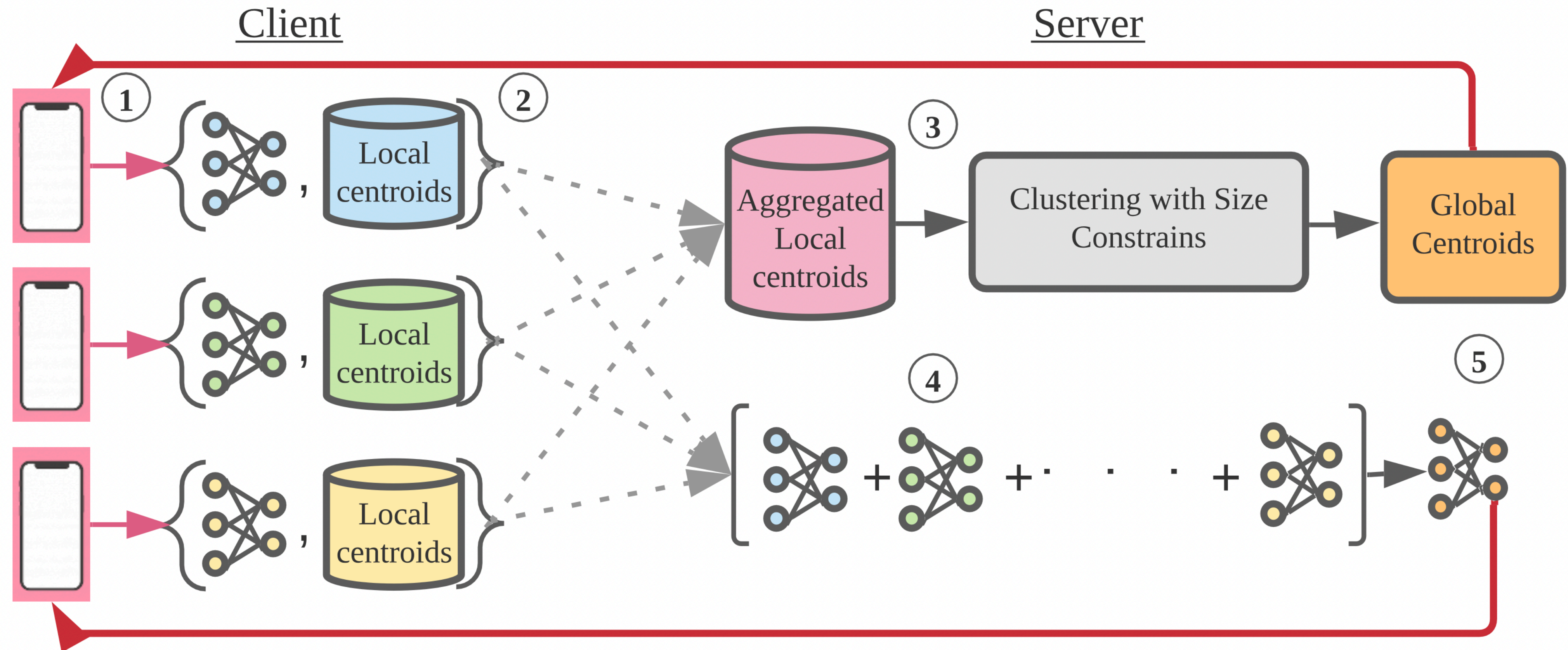
- Useful unsupervised learning algorithms traditionally require **large amounts of compute and data**



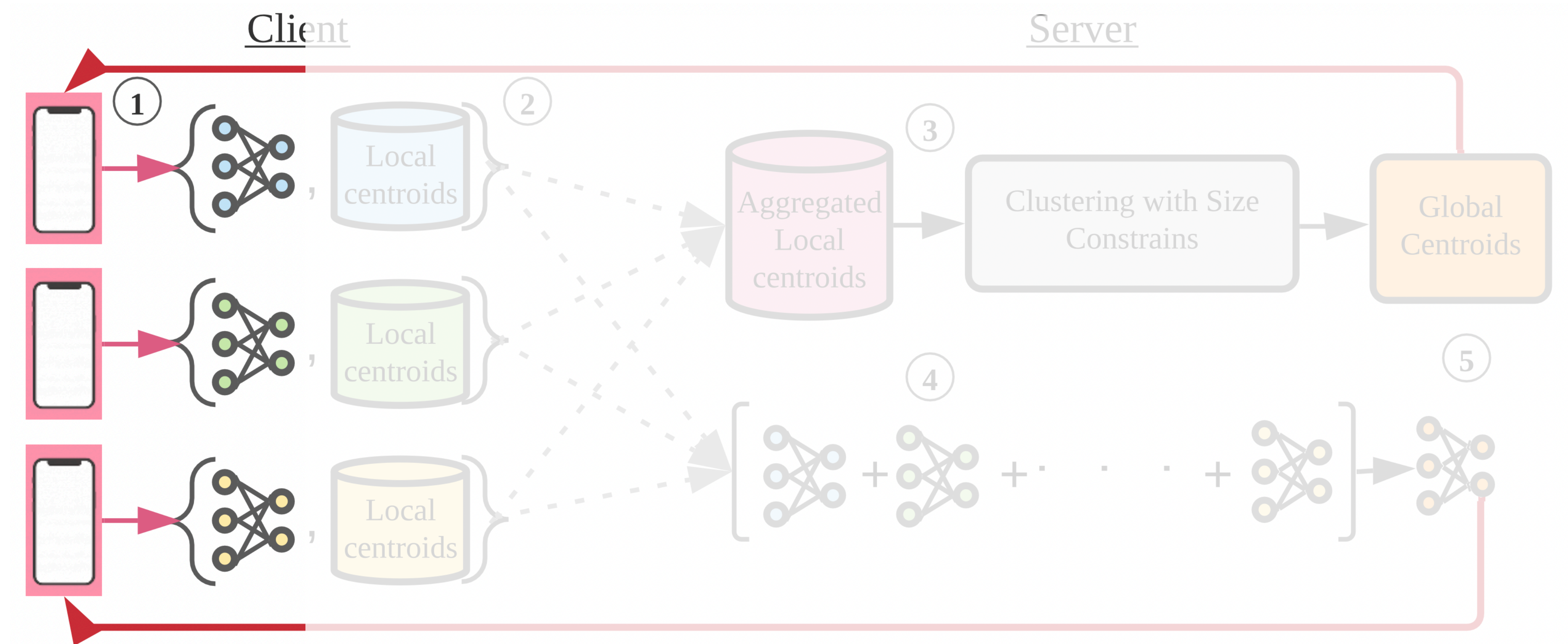
- Edge devices have small memories and few data points
- Minimal compute resources necessitate small batch-sizes
- Federated algorithms need to work with non-IID datasets

Our Proposition:

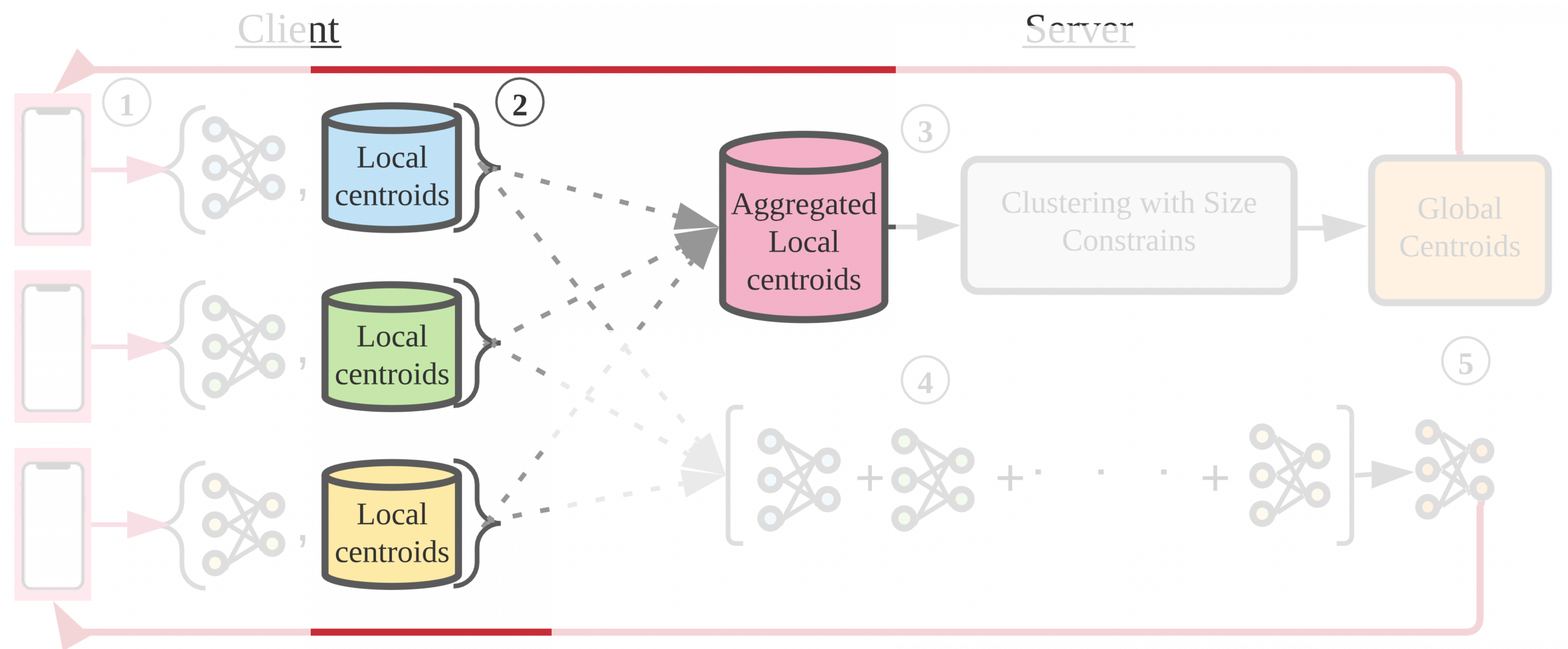
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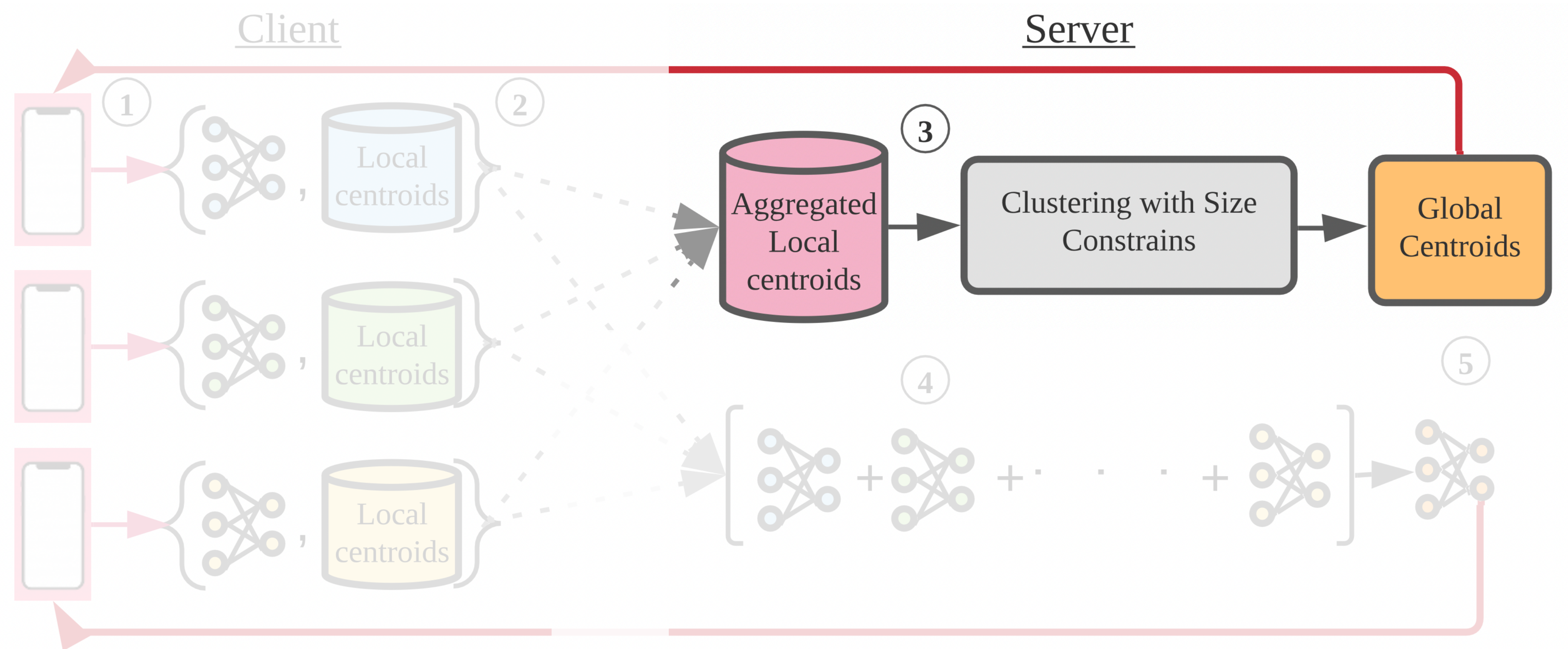
Step 1: Compute data representations



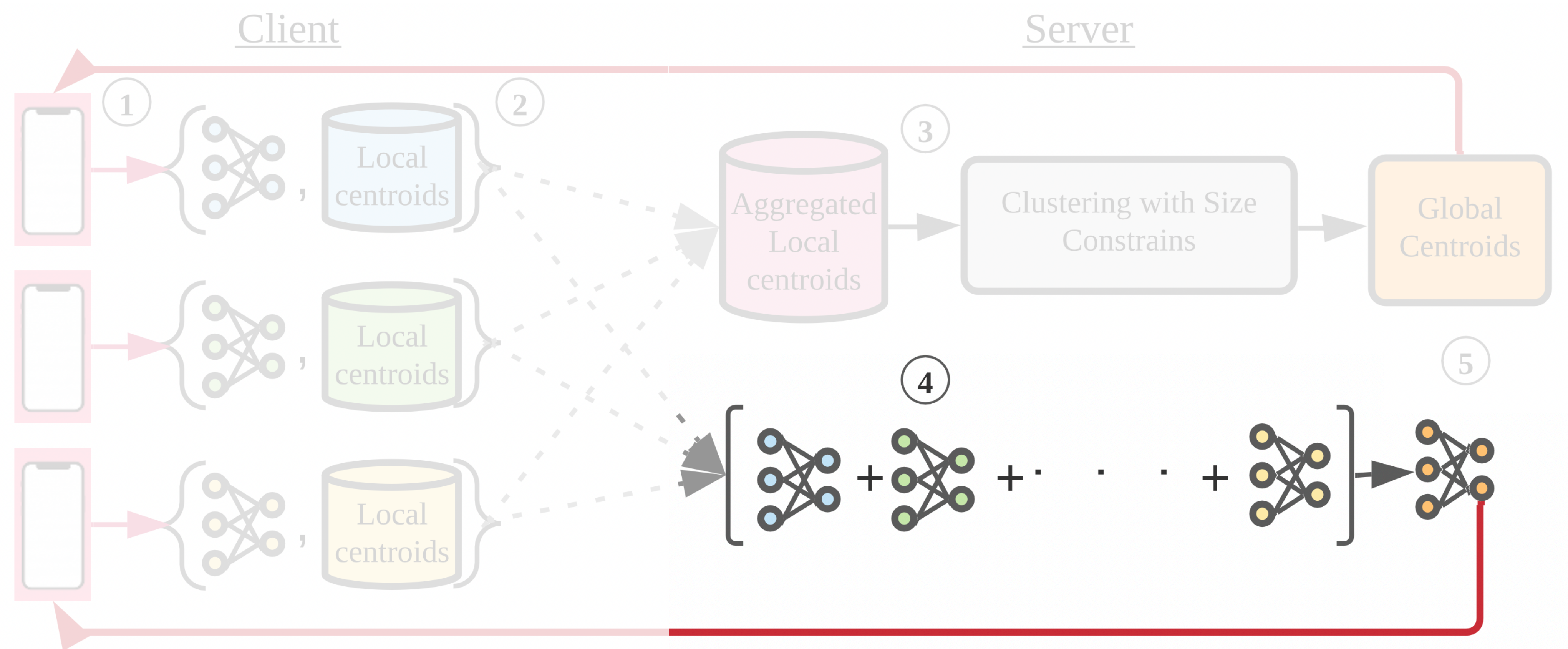
Step 2: Compute local centroids, share with server



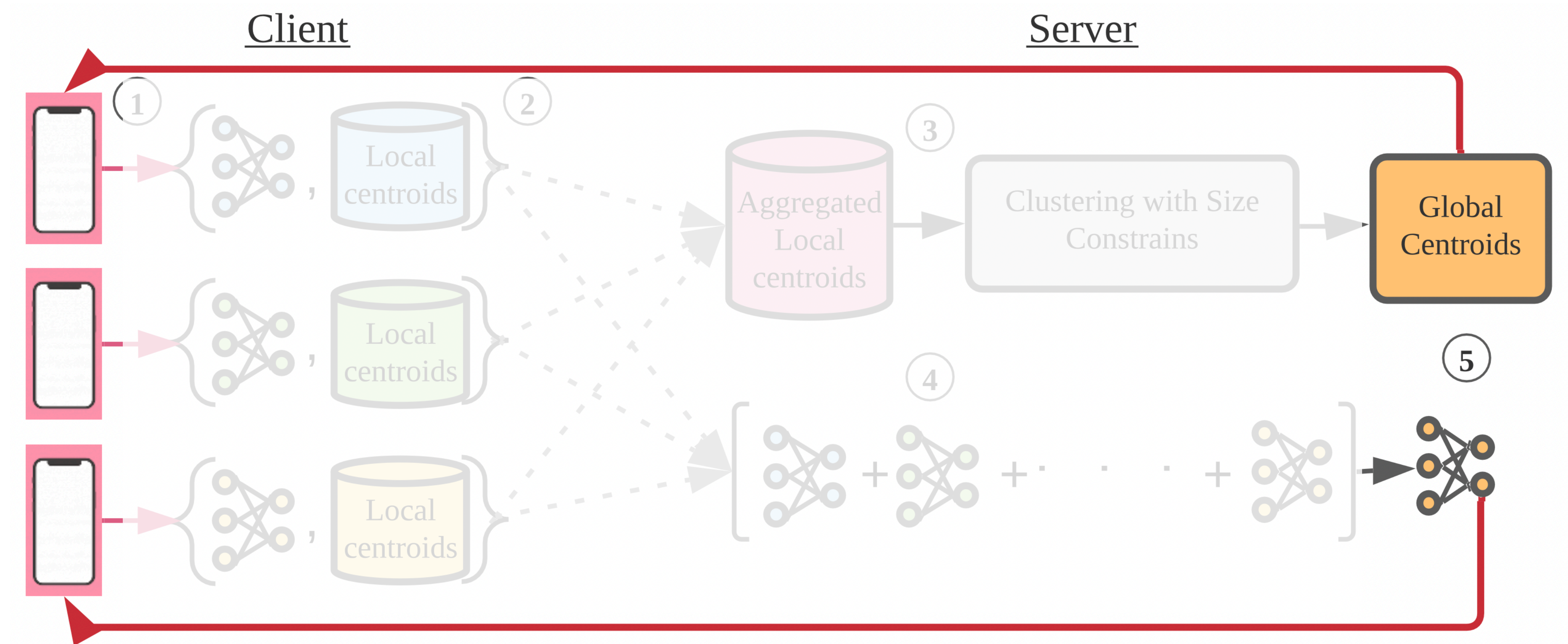
Step 3: Compute “global” centroids from “local” ones



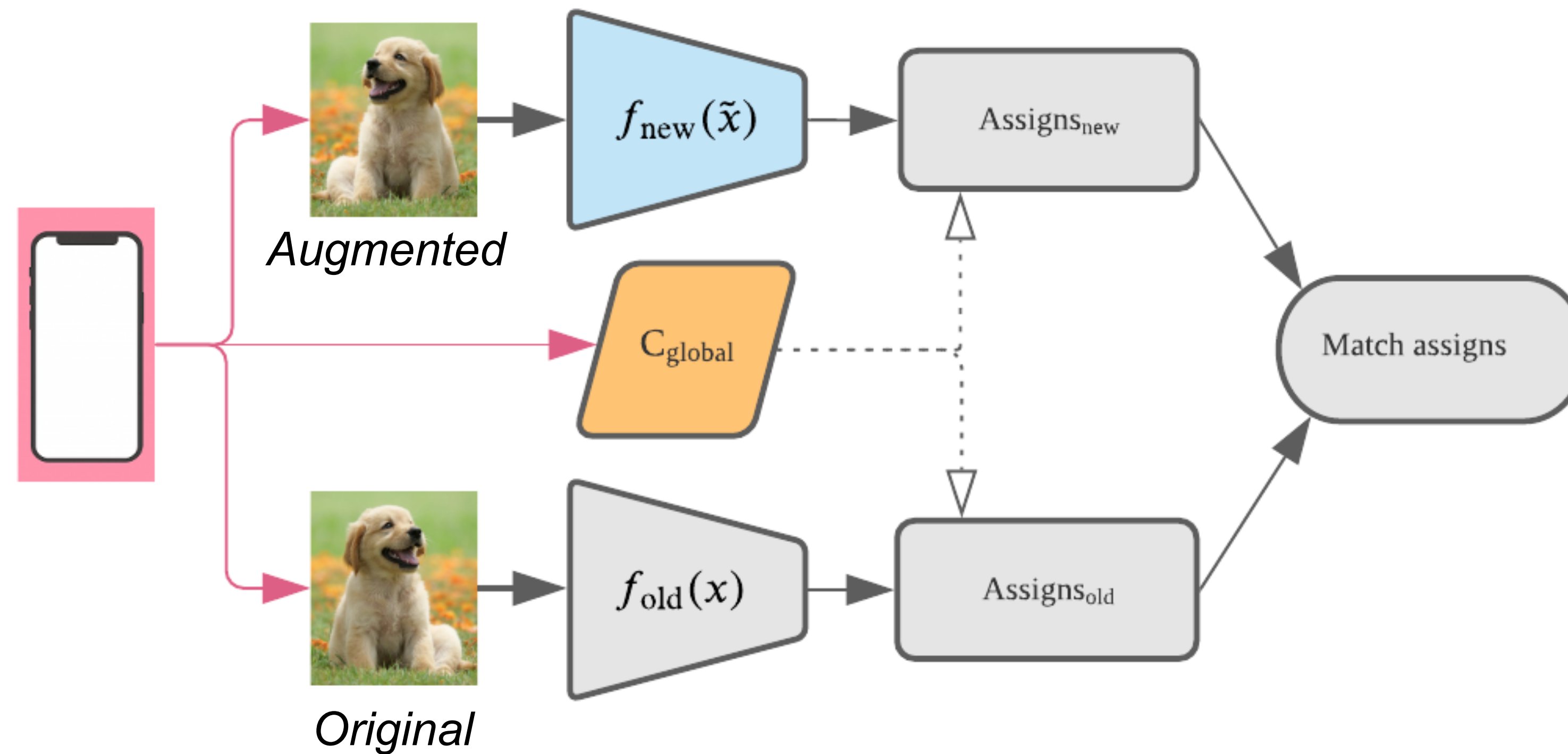
Step 4: Aggregate local models



Step 5: Share global centroids and model with clients



Step 6: Local training: Cluster Prediction Task

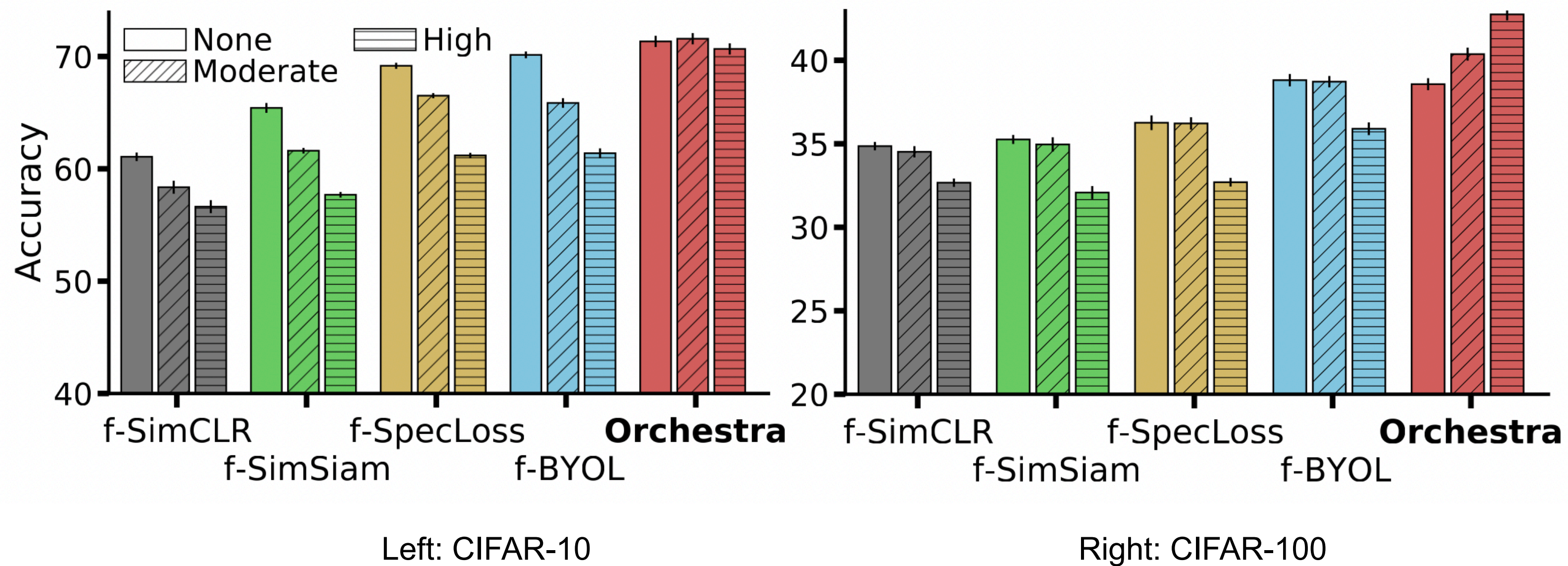


The Concert: Experimental Evaluation

- Datasets: CIFAR-10 (left) and CIFAR-100 (right)
- General Setting: Cross-device, 100 clients, 10 local epochs, 16 batch-size
- Baselines: Federated versions of SOTA unsupervised learning algorithms
- Implementation¹: Flower (Beutel et al., 2020)

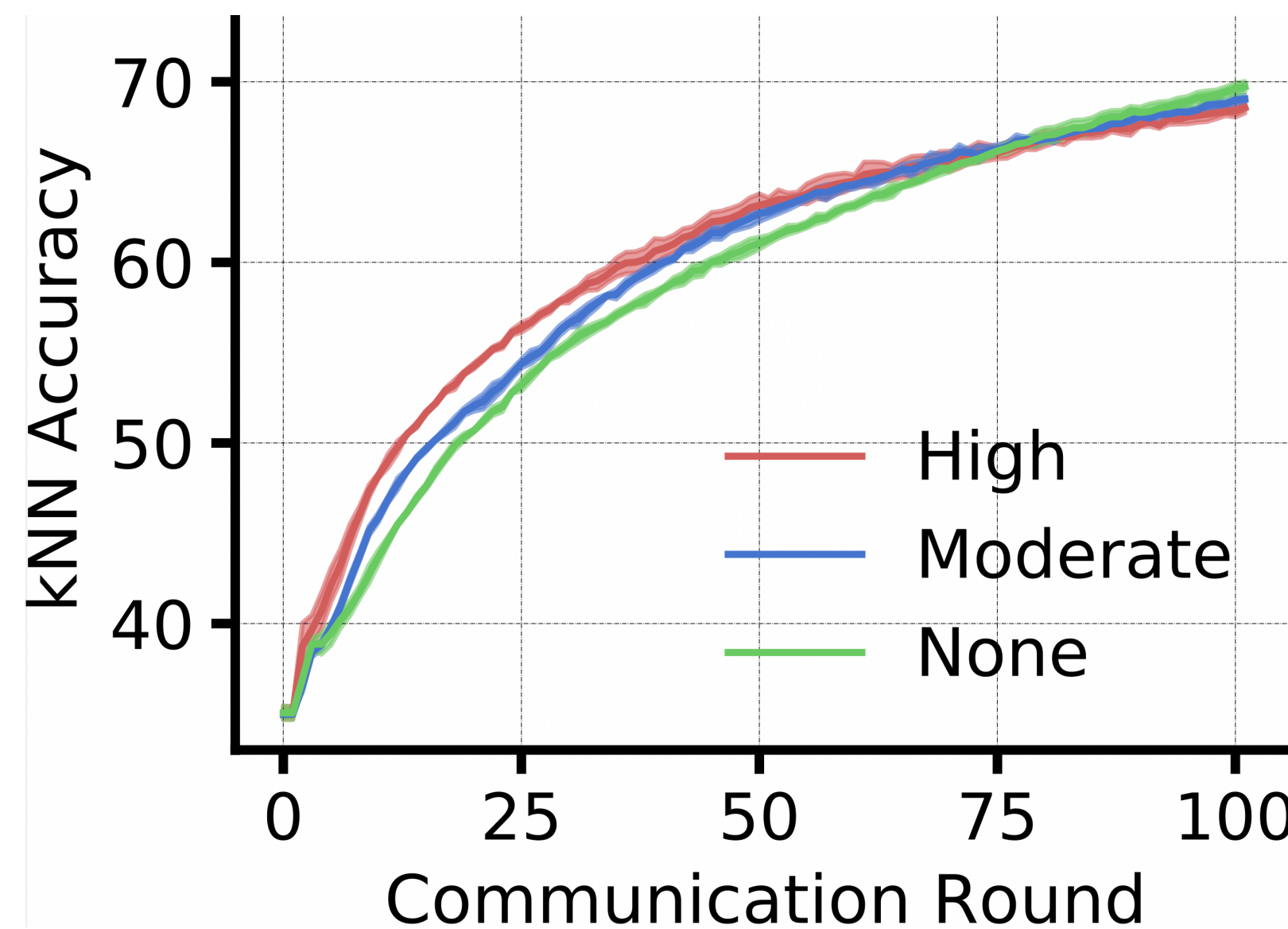
Evaluation 1: Sensitivity to Heterogeneity

- Better absolute accuracy
- Thrives under heterogeneity
- Robust under extreme settings too

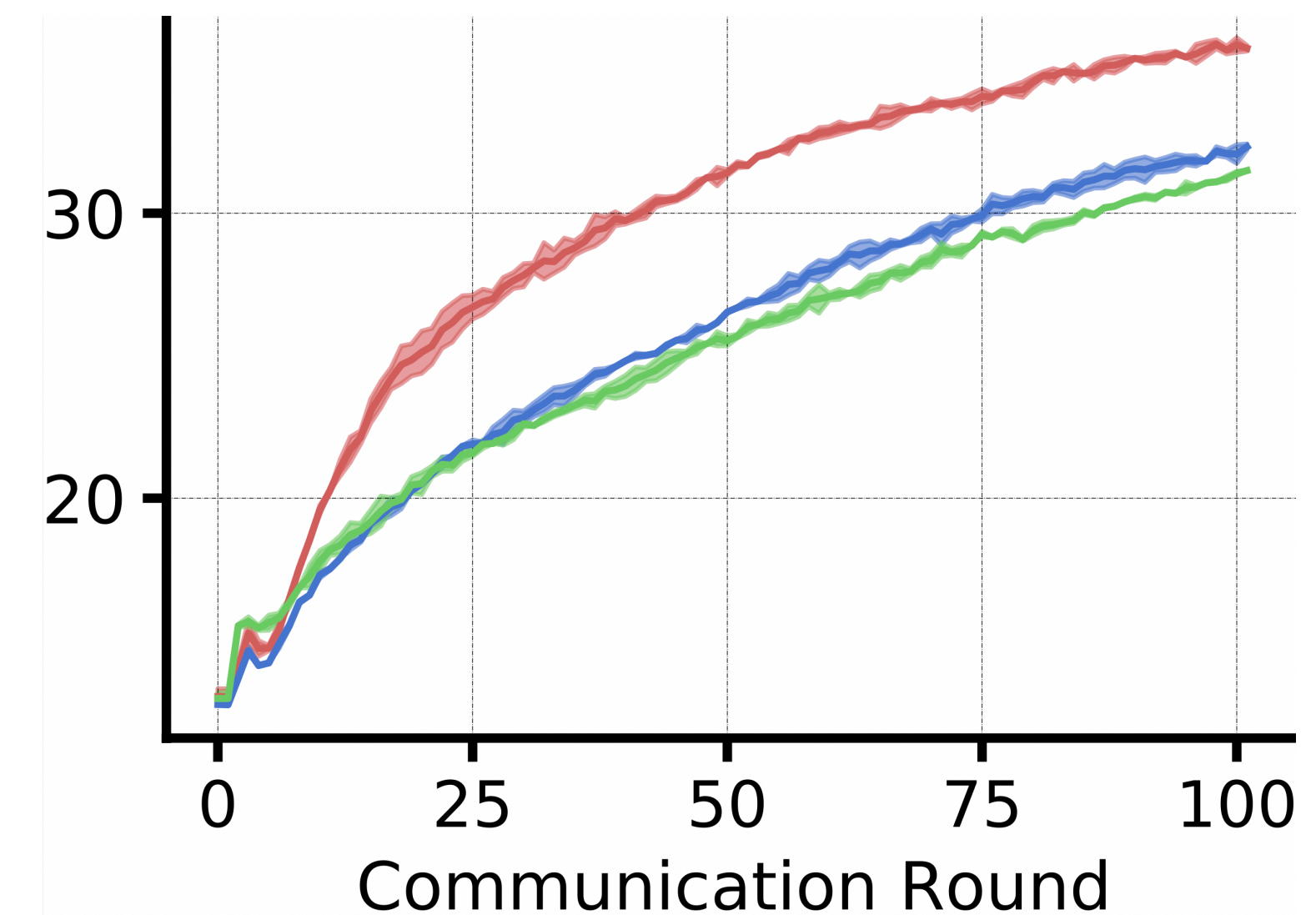


Evaluation 1: Sensitivity to Heterogeneity

- Orchestra's robustness to heterogeneity arises from its use of local clustering, a task that becomes easier with more non-IID data!
- See paper for detailed theoretical statements



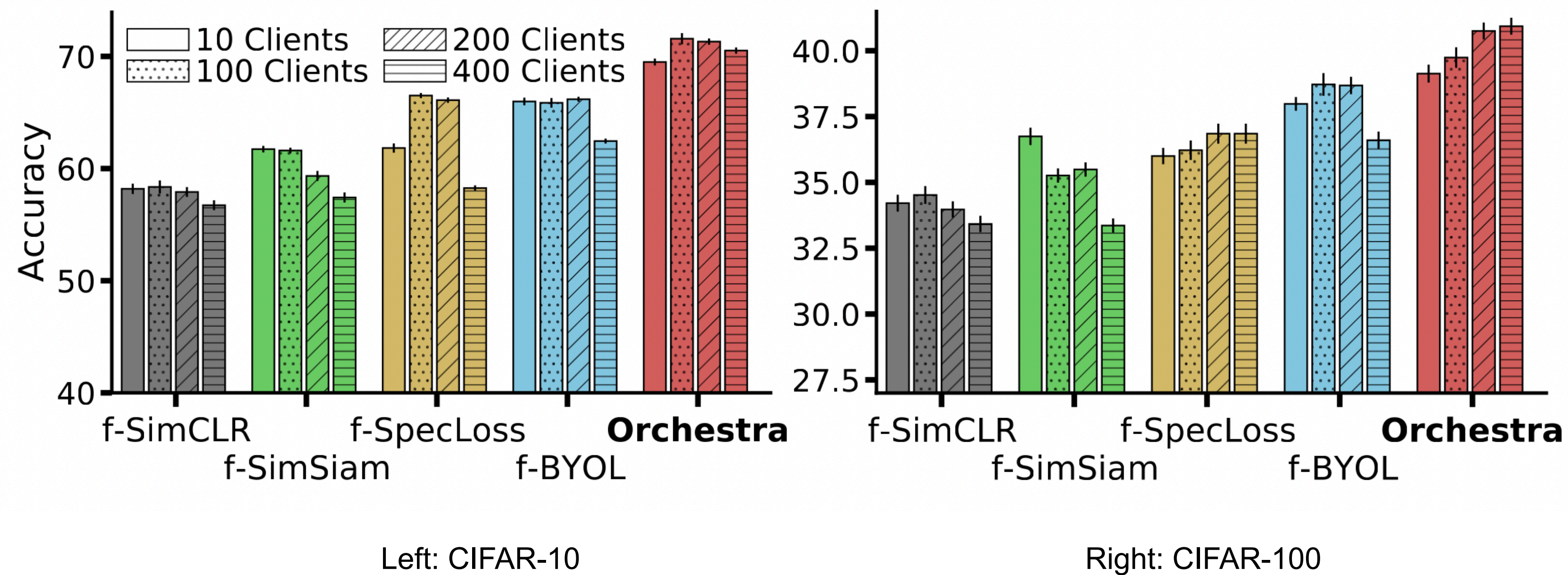
Left: CIFAR-10



Right: CIFAR-100

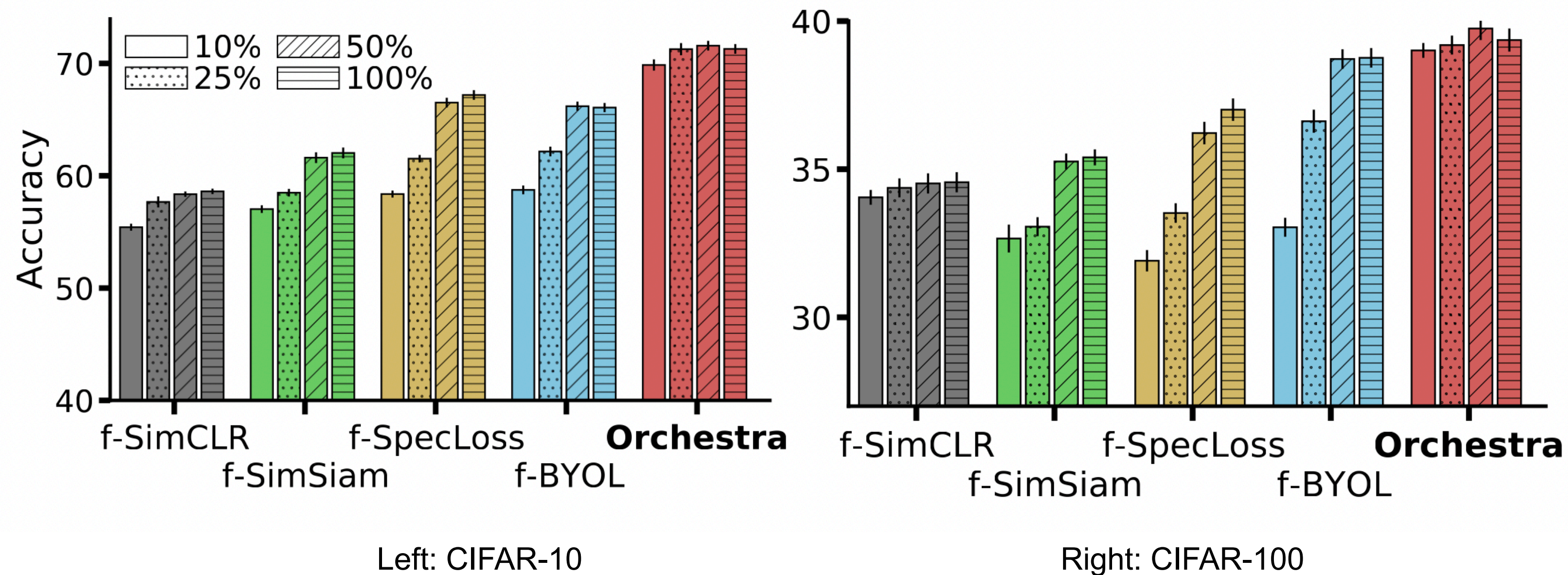
Evaluation 2: Scalability with Number of Clients

- Much better absolute accuracy in all settings
- Scales well with large number of clients



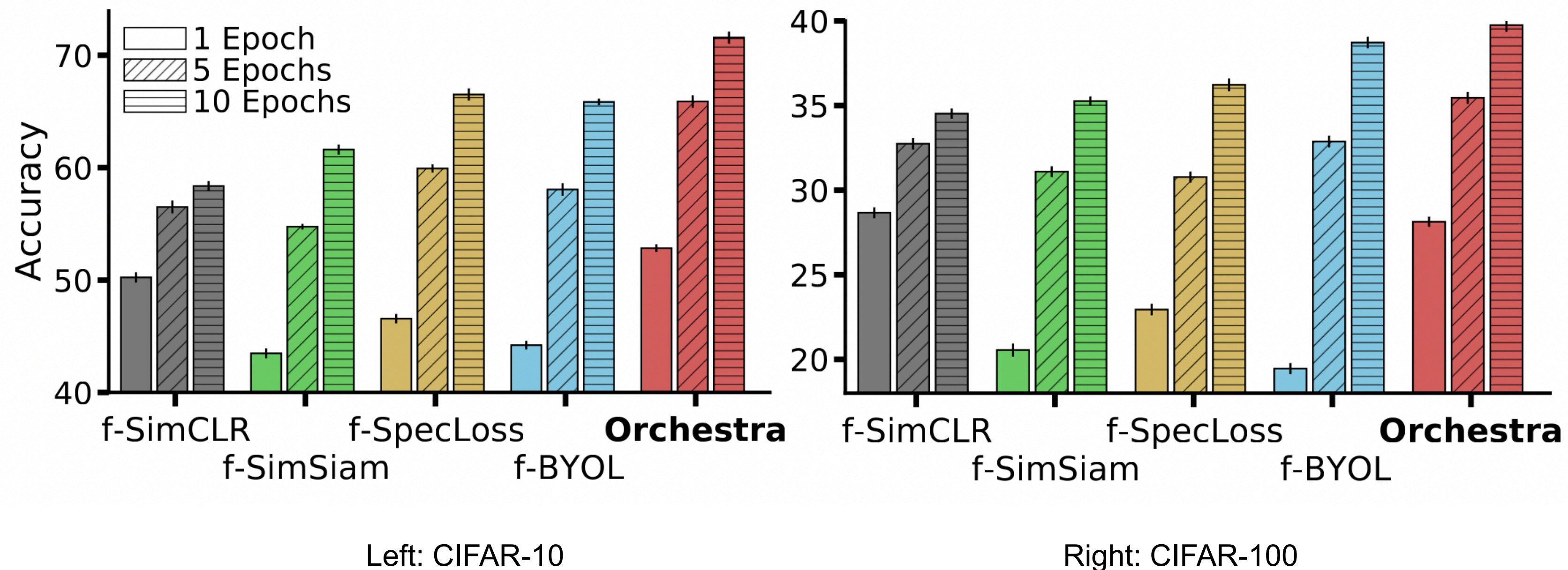
Evaluation 3: Participation Ratio

- Much higher robustness to participation ratio
- Especially more effective with smaller ratios, compared to other methods



Evaluation 4: Robustness to Local Epochs

- More compute efficient
- More communication efficient



Conclusion

- Orchestra provides a scalable, resource-efficient methodology for unsupervised federated learning
- The method is highly robust to heterogeneity and comes with guarantees
- For several more experiments, see the main paper

