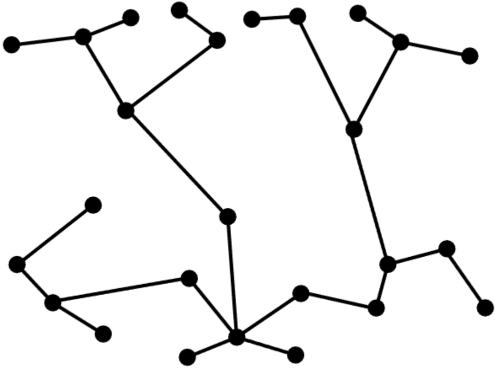
# Federated Learning with Unbiased Gradient Aggregation and FedMeta

# Decentralized learning

The group of nodes is not coordinated by any centralized server. Each node locally holds $f_i$ and exchanges information only with its immediate neighbors.

$$\min_{x_1,\ldots,x_m \in \mathbb{R}^d} \sum_{i=1}^{m} f_i(x_i)$$
$$\text{s.t. } x_1 = \ldots = x_m.$$



The optimal point in the decentralized sense should be consensual and optimal, i.e.

$$x_1 = \ldots = x_m = x^* = \arg\min_{x \in \mathbb{R}^d} \frac{1}{m} \sum_{i=1}^{m} f_i(x).$$

# Problem statement

The article focuses on two key issues in federated learning:

1. **Gradient Biases**: The multiple steps of local model updating on edge devices can lead to gradient biases, affecting the quality of the aggregated global model.
2. **Inconsistent Optimization Objectives**: Selecting a subset of clients for computation in each round may result in an inconsistency between the optimization objectives and the real target data distribution, particularly problematic in non-IID (non-identically distributed) FL settings.

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1. **Gradient Biases** -> Unbiased Gradient Aggregation (UGA)
2. **Inconsistent Optimization Objectives** -> Controllable FedMeta Updating

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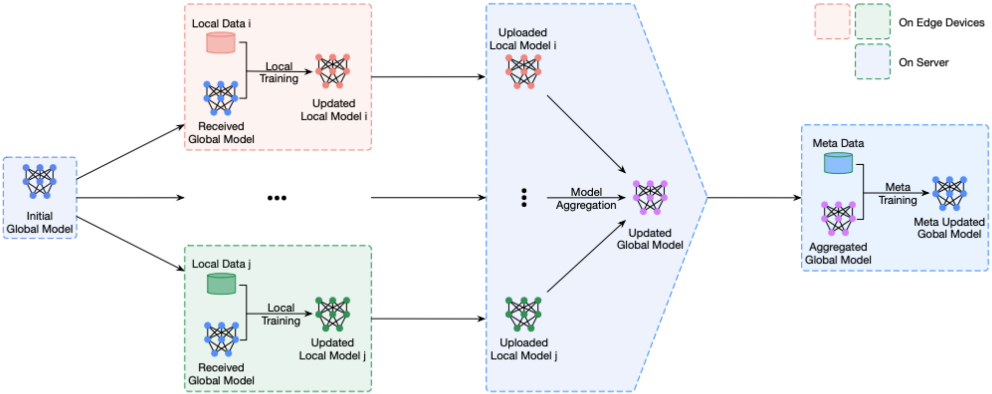



Figure 1: A typical round in FedMeta: model distributing, local training with either FedAvg [25] or UGA (Section 3.1), model aggregating and meta updating. (Better viewed in color)

# Unbiased Gradient Aggregation (UGA)

This technique leverages a keep-trace gradient descent and gradient evaluation strategy to calculate gradients against the initial global model parameters, effectively reducing gradient biases:

**Algorithm 1** Unbiased Gradient Aggregation

**Server Executes:**
1: Initialize $\omega_0$
2: **for** each round $t = 0, 1, \ldots$ **do**
3: $\quad m \leftarrow \max(C \cdot K, 1)$
4: $\quad S_t \leftarrow$ (random set of $m$ clients)
5: $\quad$ **for** each client $k \in S_t$ **do in parallel**
6: $\quad\quad g_t^k \leftarrow$ **ClientUpdate**$(k, \omega_t)$
7: $\quad$ **end for**
8: $\quad \omega_{t+1} \leftarrow \omega_t - \eta_g \sum_{k \in S_t} \frac{n_k}{n_{S_t}} g_t^k$ $\qquad \triangleright$ *Equation (14)*
9: **end for**

**ClientUpdate**$(k, \omega_t)$**:** $\qquad \triangleright$ *Run on client $k$*
1: **for** $i$ in the total steps of the first $E - 1$ epochs **do**
2: $\quad \omega_t^{k(i)} \leftarrow \omega_t^{k(i-1)} - \eta g_t^{k(i)}$ $\qquad \triangleright$ with *Keep-trace GD*
3: **end for**
4: $g_t^k = \nabla_{\omega_t} \mathcal{L}(\omega_t^k; \mathcal{D}_k)$ $\qquad \triangleright$ *Equation (13)*
5: return $g_t^k$ to server

# Controllable FedMeta Updating

This approach introduces an additional meta updating procedure using a small set of data samples after model aggregation in each round:

**Algorithm 2** FedMeta

**Server Executes:**

Initialize $\omega_0$

**for** each round $t = 0, 1, \ldots$ **do**

  $m \leftarrow \max(C \cdot K, 1)$

  $S_t \leftarrow$ (random set of $m$ clients)

  **for** each client $k \in S_t$ **do in parallel**

    $g_t^k \leftarrow$ **ClientUpdate**$(k, \omega_t)$

   *// Compatible with both FedAvg and Algorithm 1*

  **end for**

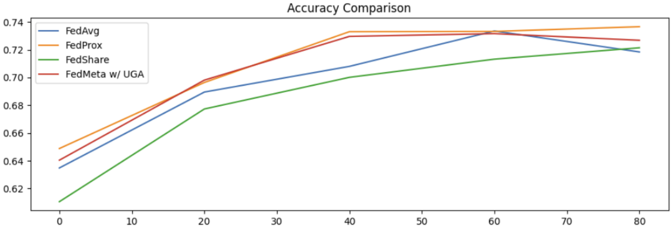
  $\omega_{t+1} \leftarrow \omega_t - \eta_g \sum_{k \in S_t} \frac{n_k}{n_{S_t}} g_t^k$ ▷ *Equation (14)*

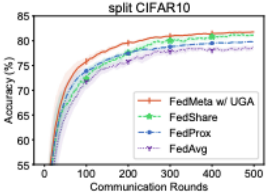
  $\omega_{t+1}^{meta} = \omega_{t+1} - \eta_{meta} \nabla_{\omega_{t+1}} \mathcal{L}(\omega_{t+1}; \mathcal{D}_{meta})$

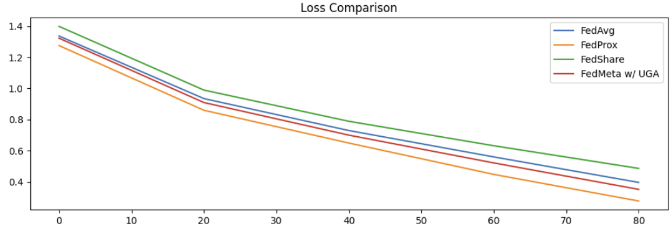
  *// Equation (20)*

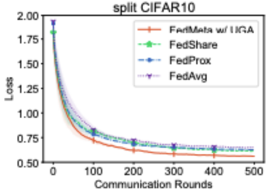
**end for**

# Experiments reproducing - CIFAR-10 dataset

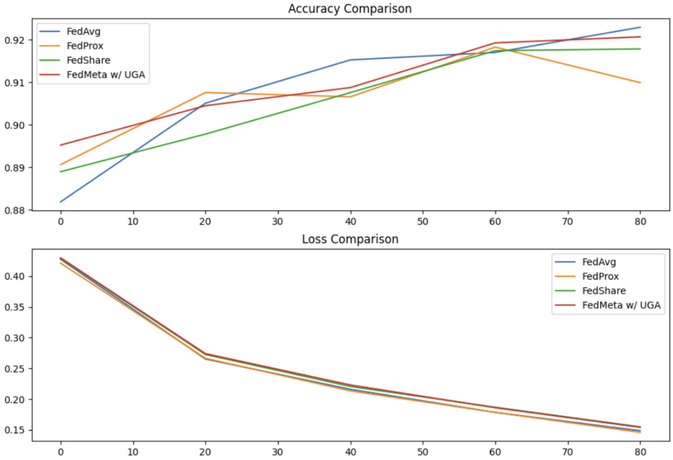


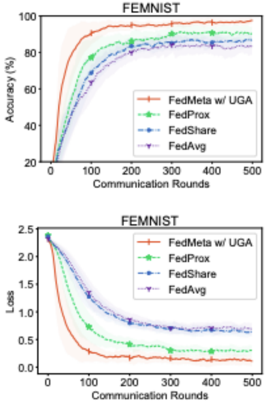



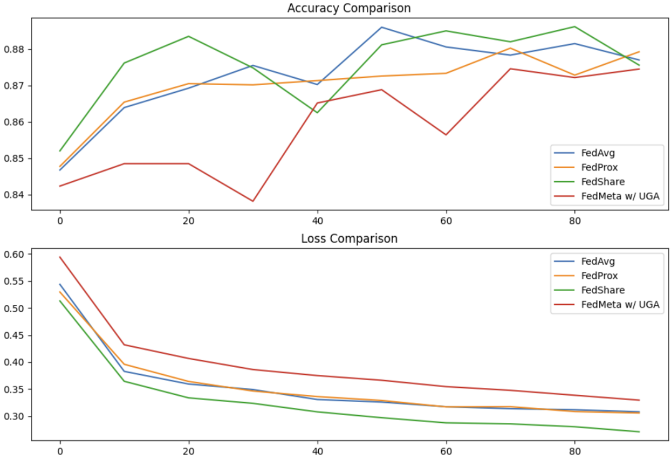



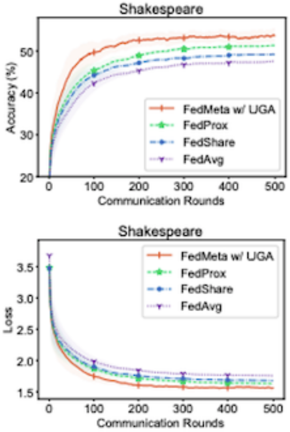
# Experiments reproducing - FEMNIST dataset



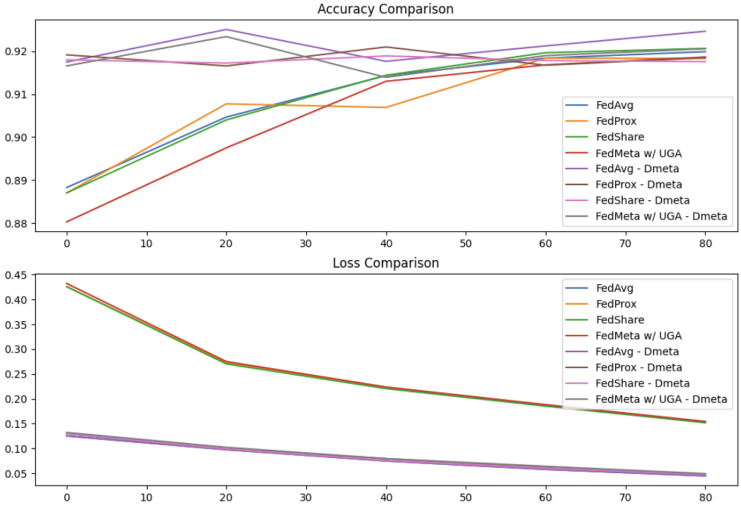



# Experiments reproducing - Shakespeare dataset



# Experiments reproducing - more experiments



*Questions?*