

# FedReLa: Imbalanced Federated Learning via Re-Labeling

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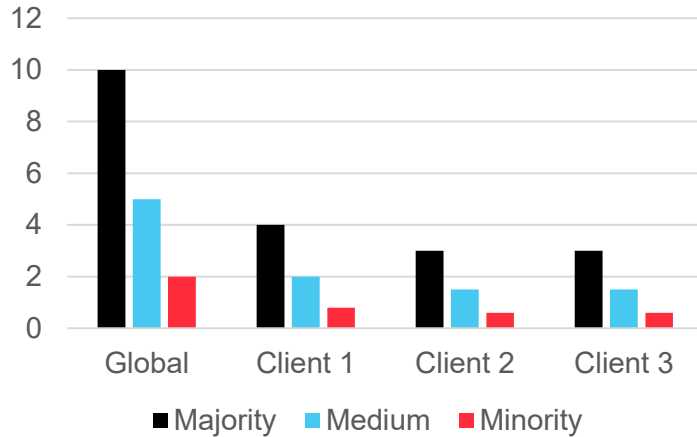
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# Imbalanced Federated Learning



## Heterogeneous + Imbalanced Data Distribution

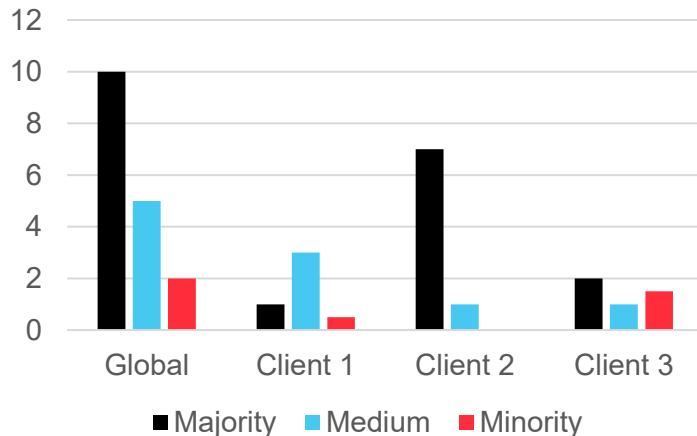
Homogeneous Class Distribution



### Rise New Challenges:

- No global class priors
- No local data / class priors exchanges
- Class absence
- Local computation is limited
- Communicational cost
- Global-local distribution mismatch

Heterogeneous Class Distribution



### No data-level method in Federated Learning:

- **Requires global class priors knowledge:** need to identify minority first
- Some clients has **zero seed samples**
- Fixed hyperparameters can not deal with heterogeneous data
- Misaligned multiple biased decision boundaries

# Correcting Aggregated Decision Boundary



**Parameter Aggregation Perspective:** FedAvg, FedNova, FedProx, MOOM, CLIMB

**Decision Boundary Aggregation Perspective:**

- Local model converges on local data
- Changing local data distribution directly rectifies local decision boundaries

**For a local dataset  $\tilde{\mathcal{D}}^{(k)}$  and classes  $j$  and  $\ell$ , we define**

- Local sample relabelling probabilities:

$$\rho_{\ell \rightarrow j}^{(k)}(x) = \Pr(\tilde{Y}^{(k)} = j \mid X^{(k)} = x, Y^{(k)} = \ell)$$

$$\rho_{j \rightarrow \ell}^{(k)}(x) = \Pr(\tilde{Y}^{(k)} = \ell \mid X^{(k)} = x, Y^{(k)} = j)$$

- Local decision boundaries with relabelling

$$\tilde{\mathcal{S}}^{(k)} = \left\{ x^* \in \mathcal{X} : \frac{P_j(x^*)}{P_\ell(x^*)} = \frac{1 - 2\rho_{\ell \rightarrow j}^{(k)}(x^*)}{1 - 2\rho_{j \rightarrow \ell}^{(k)}(x^*)} \cdot \frac{\pi_\ell^{(k)}}{\pi_j^{(k)}} \right\}$$

- Global Aggregated decision boundary on relabelled local datasets

$$\tilde{\mathcal{S}}^{[w]} = \left\{ x^* \in \mathcal{X} : \frac{P_j(x^*)}{P_\ell(x^*)} = \frac{\sum_{k=1}^K w_k \pi_\ell^{(k)} [1 - 2\rho_{\ell \rightarrow j}^{(k)}(x)] / \pi_\ell}{\sum_{k=1}^K w_k \pi_j^{(k)} / \pi_j} \cdot \frac{\pi_\ell}{\pi_j} \right\}$$

- With

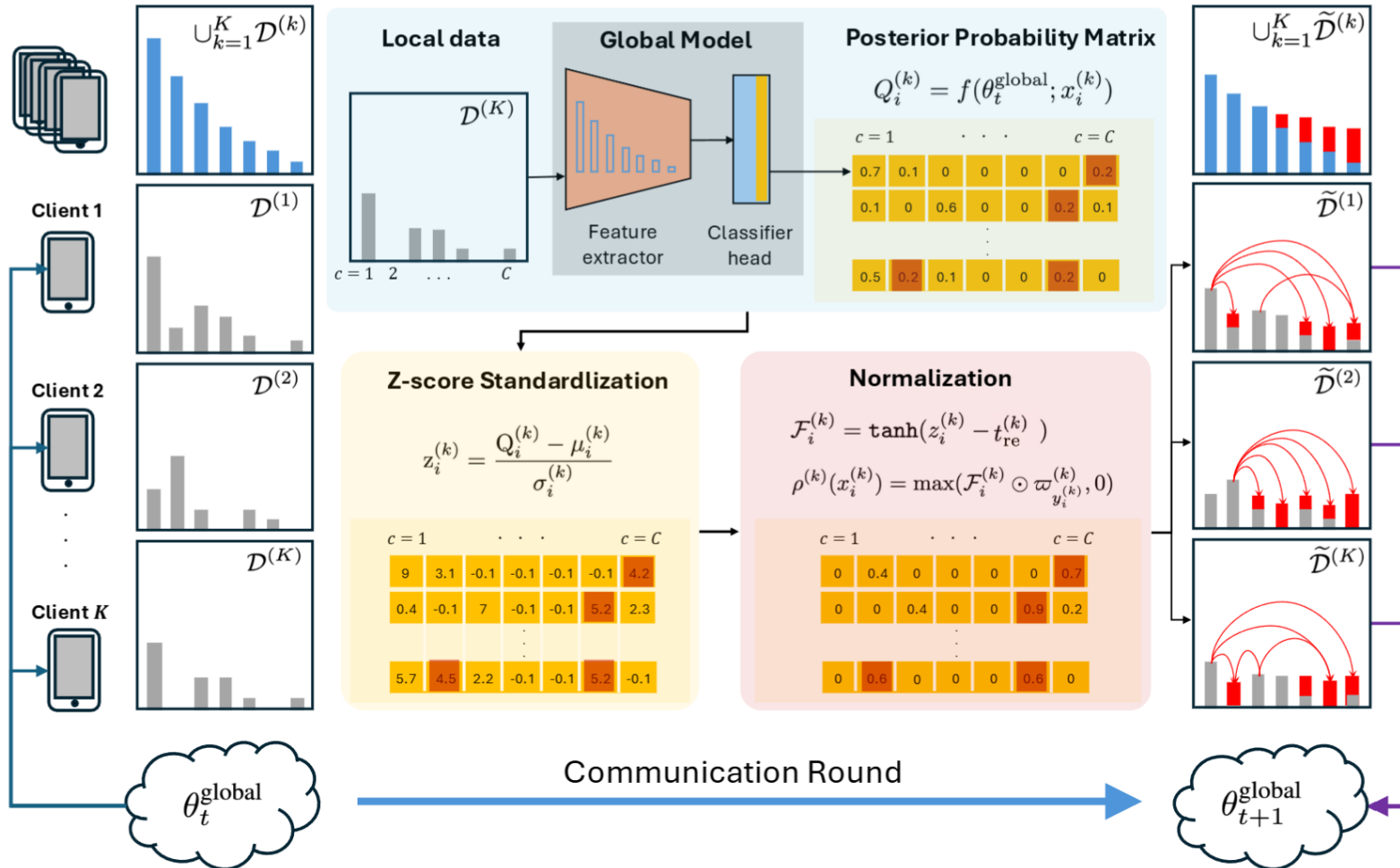
$$w_k = |\mathcal{D}^{(k)}| / |\mathcal{D}|, \sum_{k=1}^K w_k \pi_j^{(k)} / \pi_j = 1.$$

- We have proven that

$$\sum_{k=1}^K w_k \pi_\ell^{(k)} [1 - 2\rho_{\ell \rightarrow j}^{(k)}(x)] / \pi_\ell < 1$$

when  $\rho_{\ell \rightarrow j}^{(k)}(x) > 0$  for all  $k \in \{1, \dots, K\}$

# FedReLa: Adaptive Re-Labeling



Adaptive Threshold:

$$t_{re,j}^{(k)} = \text{Quantile}_{1-\tau}(\mathbf{z}_{:,j}^{(k)}), \quad j = 1, \dots, C,$$

- Localized relabelling
- Safeguarded relabelling

Adaptive Direction of Relabelling:

$$\varpi^{(k)} = 1 - \min_{\max}(n_y^{(k)})$$

$$\varpi_j^{(k)} = \max(\varpi^{(k)} - \varpi^{(k)}[j], 0)$$

- Only majority to minority
- Localized balancing

# FedReLa: Adaptive Re-Labeling



**Algorithm 1** Re-Allocator re-labels local data

**Input:** local datasets  $\mathcal{D}^{(k)} = \{(x_i^{(k)}, y_i^{(k)})\}_{i=1}^{n_k}$ , classifier  $f(\cdot; \cdot)$ , global model  $\theta_t^{\text{global}}$

**Parameters:** Threshold  $t_{\text{re}}^{(k)}$ , re-labeling round  $T_{\text{relabel}}$

**for** client  $k \in K$  at communication round  $t = T_{\text{relabel}}$  **do:**

    Compute  $\varpi^{(k)}$  by (3) with  $n_{\mathcal{Y}}^{(k)}$

**for**  $(x_i^{(k)}, y_i^{(k)}) \in \tilde{\mathcal{D}}^{(k)}$  **do:**

$Q_i^{(k)} \leftarrow f(\theta_t^{\text{global}}; x_i^{(k)})$

**for**  $(x_i^{(k)}, y_i^{(k)}) \in \mathcal{D}^{(k)}$  **do:**

        Compute  $z_i^{(k)}$  by (3) with  $Q_i^{(k)}$

$\varpi_{y_i^{(k)}}^{(k)} \leftarrow \max(\varpi^{(k)} - \varpi^{(k)}[y_i^{(k)}], 0)$











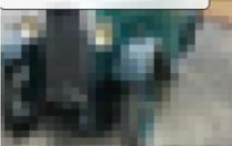
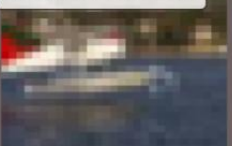
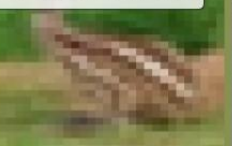
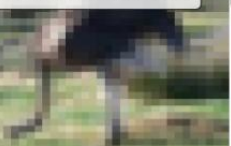

        Compute  $\rho^{(k)}(x_i^{(k)})$  by (4)

$\mathcal{U} \in \mathbb{R}^{|\mathcal{Y}|} \leftarrow \text{Bernoulli}(\rho^{(k)}(x_i^{(k)}))$

**if**  $\mathcal{U}$  contains 1 **then:**

$\tilde{y}_i^{(k)} \leftarrow \mathcal{Y}[\text{argmax}(\rho^{(k)}(x_i^{(k)}))]$

**return**  $\tilde{\mathcal{D}}^{(k)} \leftarrow \{(x_i^{(k)}, \tilde{y}_i^{(k)})\}_{i=1}^{n_k}$

automobile	airplane	bird	deer	
Posterior: 0.30 Re-label Prob: 0.99	Posterior: 0.02 Re-label Prob: 1.00	Posterior: 0.01 Re-label Prob: 0.97	Posterior: 0.15 Re-label Prob: 1.00	Posterior: 0.26 Re-label Prob: 0.99
				
Posterior: 0.23 Re-label Prob: 1.00	Posterior: 0.03 Re-label Prob: 0.99	Posterior: 0.01 Re-label Prob: 0.91	Posterior: 0.10 Re-label Prob: 1.00	Posterior: 0.14 Re-label Prob: 0.81
				
Posterior: 0.02 Re-label Prob: 0.99	Posterior: 0.11 Re-label Prob: 1.00	Posterior: 0.03 Re-label Prob: 0.81	Posterior: 0.10 Re-label Prob: 0.89	Posterior: 0.22 Re-label Prob: 0.93
				
truck	ship	frog	horse	

# Results



Dataset	IF	Heterogeneity Method/Metrics	$\alpha = 0.1$		$\alpha = 0.3$		$\alpha = 10$	
			H/M/T-shots	Overall	H/M/T-shots	Overall	H/M/T-shots	Overall
CIFAR-10	50	FedETF	85.07/41.03/5.40	47.96	79.60/67.93/43.10	65.15	88.77/73.22/56.81	74.52
		+(FedReLa)	78.70/65.20/35.57	<b>61.71</b>	74.95/71.57/55.63	<b>68.14</b>	86.80/76.62/71.59	<b>79.18</b>
		FedLOGE	56.51/58.98/59.74	58.22	82.81/76.90/67.98	76.59	88.32/81.32/72.40	81.45
		+(FedReLa)	69.55/70.13/53.09	<b>64.78</b>	80.09/78.47/76.86	<b>78.63</b>	83.79/83.32/84.12	<b>83.75</b>
	100	FedETF	66.90/36.80/24.40	40.87	72.05/37.13/25.32	42.88	92.16/69.52/50.13	68.56
		+(FedReLa)	57.60/44.53/36.95	<b>45.42</b>	72.59/40.11/30.47	<b>46.00</b>	90.17/70.73/66.91	<b>75.04</b>
100	FedLOGE	44.93/50.27/41.30	45.08	86.71/67.52/57.89	69.43	91.90/75.07/62.50	75.09	
	+(FedReLa)	70.60/59.60/57.75	<b>62.16</b>	78.62/68.10/69.39	<b>71.77</b>	84.58/75.48/79.70	<b>79.90</b>	
CIFAR-100	50	FedETF	62.97/44.65/20.12	42.35	68.89/46.87/20.28	44.83	71.11/48.78/18.80	44.83
		+(FedReLa)	56.81/48.60/29.20	<b>44.71</b>	61.79/51.20/30.38	<b>47.41</b>	56.37/53.09/34.30	<b>47.18</b>
		FedLOGE	32.92/37.70/34.64	35.09	59.40/47.76/31.40	45.87	68.37/52.31/26.45	47.88
		+(FedReLa)	51.22/46.82/30.37	<b>42.73</b>	63.93/51.99/30.04	<b>48.25</b>	67.65/51.30/29.77	<b>48.57</b>
	100	FedETF	64.48/42.64/13.72	37.11	68.75/48.13/14.93	39.63	71.76/47.48/16.45	39.67
		+(FedReLa)	56.10/46.73/24.14	<b>40.19</b>	61.01/51.24/25.02	<b>42.70</b>	56.05/50.78/29.86	<b>42.51</b>
100	FedLOGE	27.00/36.41/25.62	29.21	50.80/43.67/25.26	37.75	69.55/50.40/22.98	42.87	
	+(FedReLa)	49.25/47.98/23.11	<b>38.08</b>	62.36/52.15/23.98	<b>42.89</b>	66.28/50.43/25.92	<b>43.36</b>	

Table 2. Test accuracies (in %) of different methods on long-tailed CIFAR-10/100.

Method	50 Clients		100 Clients	
	Overall Accuracy (%)	H/M/F Accuracy (%)	Overall Accuracy (%)	H/M/F Accuracy (%)
FedLC (Zhang et al., 2022)	32.81	56.20/32.42/9.74	23.72	46.41/20.74/4.23
+FedReLa	<b>34.76</b>	49.92/ <b>35.24/17.21</b>	<b>25.13</b>	39.82/ <b>28.34/7.02</b>
FedYoYo (Yan et al., 2025)	40.89	54.32/41.95/24.12	30.73	34.12/29.64/27.92
+FedReLa	<b>41.31</b>	53.62/ <b>42.24/25.91</b>	<b>32.13</b>	33.90/ <b>32.72/29.22</b>
FedETF	31.89	60.67/40.45/9.22	28.71	59.00/33.72/9.73
+FedReLa	<b>33.94</b>	55.12/ <b>43.61/15.12</b>	<b>31.50</b>	52.21/ <b>38.73/16.53</b>
FedLoGe	34.83	57.12/42.21/17.29	33.08	62.71/38.78/13.75
+FedReLa	<b>35.62</b>	57.01/ <b>44.32/18.00</b>	<b>34.32</b>	59.90/ <b>42.22/16.00</b>

Method	IF	Med+Tail Gain (%)			Overall Gain (%)		
		$\alpha=0.1$	$\alpha=0.3$	$\alpha=10$	$\alpha=0.1$	$\alpha=0.3$	$\alpha=10$
+FedReLa							
FedETF	50	<b>+54.34</b>	+16.17	+18.18	<b>+13.75</b>	+2.99	+4.66
FedETF	100	<b>+20.28</b>	+8.13	+17.99	+4.55	+3.12	<b>+6.48</b>
FedLoGe	50	+4.50	+10.45	<b>+13.72</b>	<b>+6.56</b>	+2.04	+2.30
FedLoGe	100	<b>+25.78</b>	+12.08	+17.61	<b>+17.08</b>	+2.34	+4.81