FCFL

A Fairness Compensation-based Federated Learning Scheme with Accumulated Queues

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Research Paper

[FCFL: A Fairness Compensation-Based Federated Learning Scheme with Accumulated Queues]

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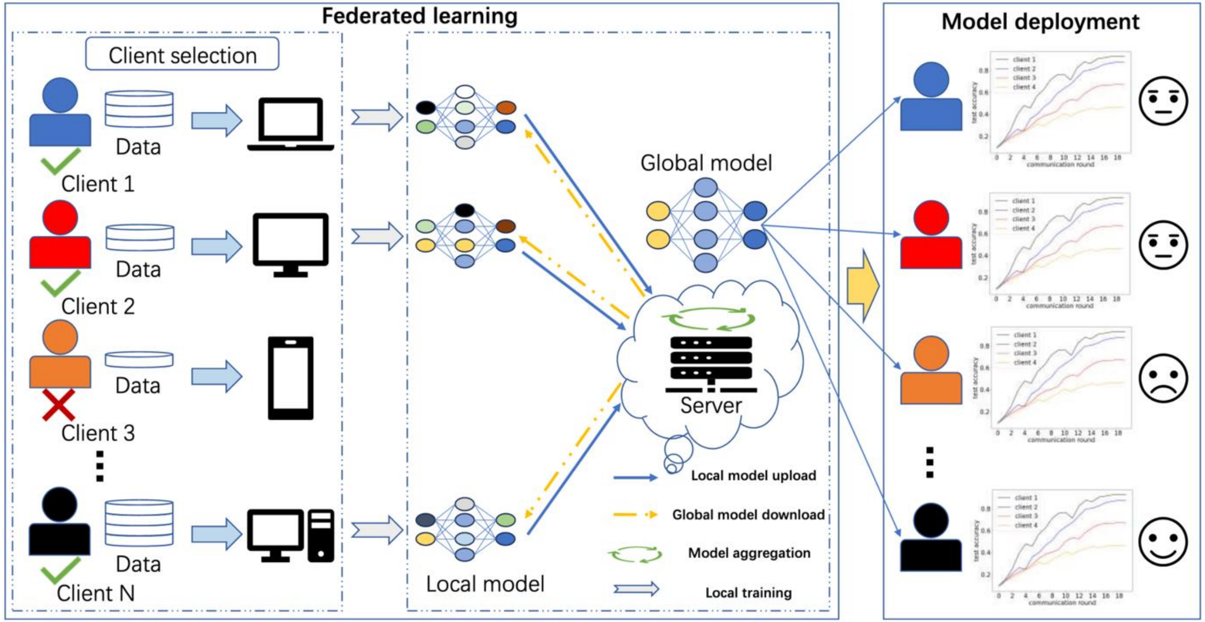
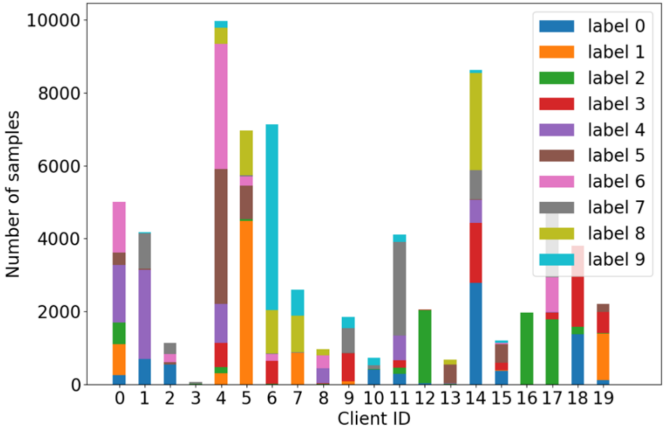
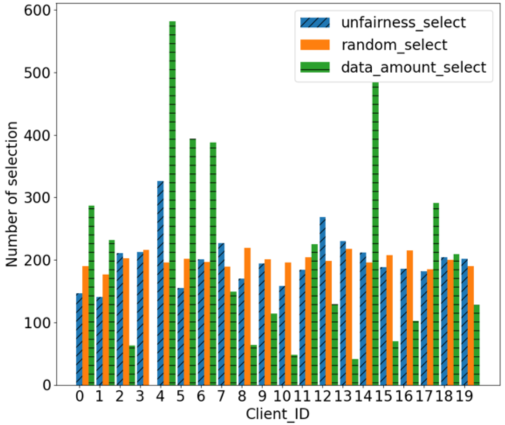


Federated Learning

- Diverse Data Sources
- Data Security or Privacy
- Data Transfer costs

Federated Learning - Issues





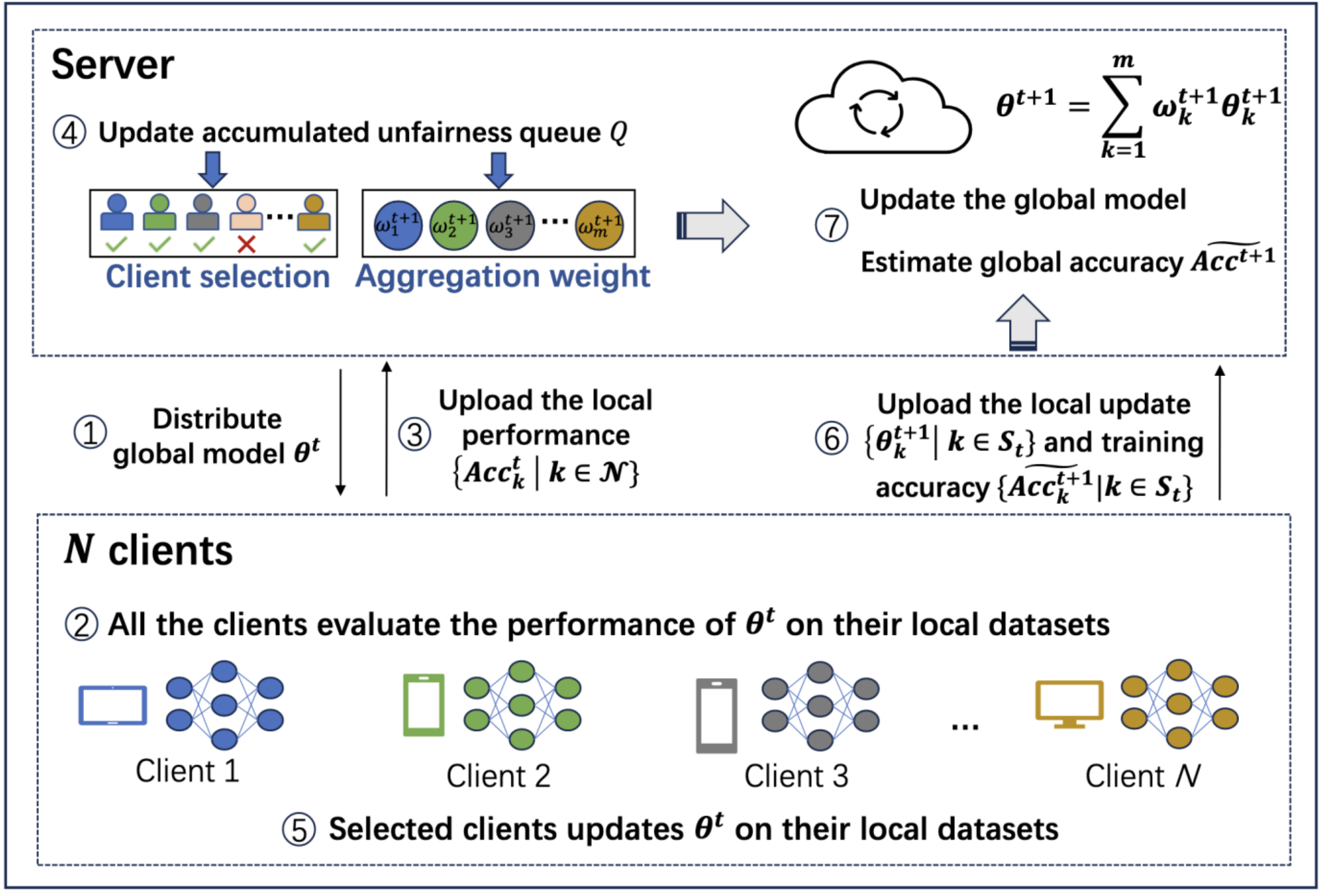
- **Data and System Heterogeneity**
- **Unfairness**
- **Participation Imbalance**

Previous Works

- Designing Novel Objective Functions
- Reweighting
- Eliminating Gradient Conflicts
- Multi-objective Optimization

References	Method	Dataset
AFL (2019) [16]	Minimax optimization	Fashion MNIST; Adult; Cornell movie; PTB
q-FedAvg (2019) [11]	Reweighting	Synthetic; Vehicle; Sent 140; Shakespeare
FedGini (2023) [12]	Objective function	Synthetic; CIFAR-10; Sent 140
DRFL (2022) [30]	Reweighting	Synthetic; Fashion MNIST; Adult
Ada-FFL (2023) [2]	Reweighting	Synthetic; Vehicle; Sent 140
FedFa (2022) [8]	Reweighting	MNIST; FEMNIST; Synthetic; Sent 140; Shakespeare
PG-FFL (2022) [21]	Reweighting	Fashion MNIST; CIFAR-10; CIFAR-100
FedFV (2021) [23]	Gradient projection	MNIST; Fashion MNIST; CIFAR-10
GIFAIR (2023) [28]	Reweighting; Objective function	FEMNIST; Shakespeare;
FedMGDA (2022) [6]	Multi-objective optimization	Fashion MNIST; CIFAR-10; Shakespeare; Adult
FedMDFG (2023) [17]	Multi-objective optimization	MNIST; Fashion MNIST; CIFAR-10; CIFAR-100
FairWire+ (2024) [5]	Multi-objective optimization	CIFAR-10; CIFAR-100; FEMNIST

FCFL - Overview



FCFL – Accm Unfairness Queues

- Qi(t) accumulates per-round unfairness or low-accuracy clients
- Not selected ⇒ queue increases
- Small aggregation weight
  ⇒ minor penalty
  → queue remains high

$$uf_i^t = \begin{cases} \widetilde{Acc}^t - Acc_i^t, & if \ \ \widetilde{Acc}^t > Acc_i^t \\ 0, & otherwise \end{cases}$$

$$Q_i(t) = \max\left\{Q_i(t-1) + \alpha u f_i^t - \omega_i^t \cdot \mathbf{1}_{[x_i(t-1)=1]}, 0\right\}$$

Client Selection and Aggregation Reweighting

$$\omega_i^{t+1} = \begin{cases} \dfrac{n_i}{\sum_{i=1}^{m} n_i}, & if \quad Q_1(t) = \ldots = Q_m(t) = 0 \\[2ex] \dfrac{Q_i(t)}{\sum_{i=1}^{m} Q_i(t)}, & otherwise \end{cases}$$

- Biasness towards vulnerable clients.
- \+ Randomly selected r% clients.

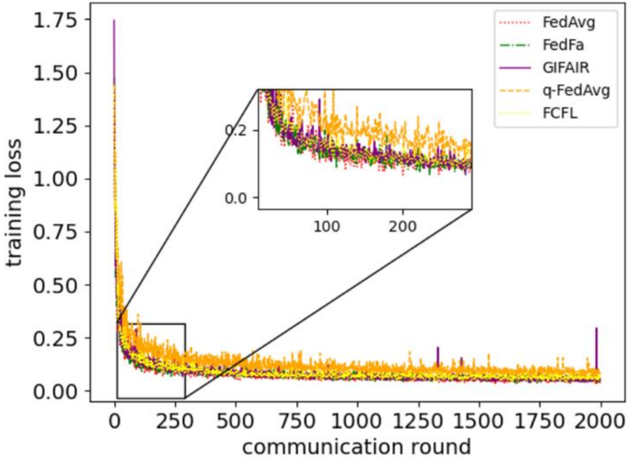
Experiment Setup

- Datasets & Models
  - MNIST – CNN
  - CIFAR10 – MLP
  - Shakespeare – RNN + LSTM Layer
- Baseline Methods
  - FedAvg
  - Q-FedAvg
  - FedFa
  - GIFAIR

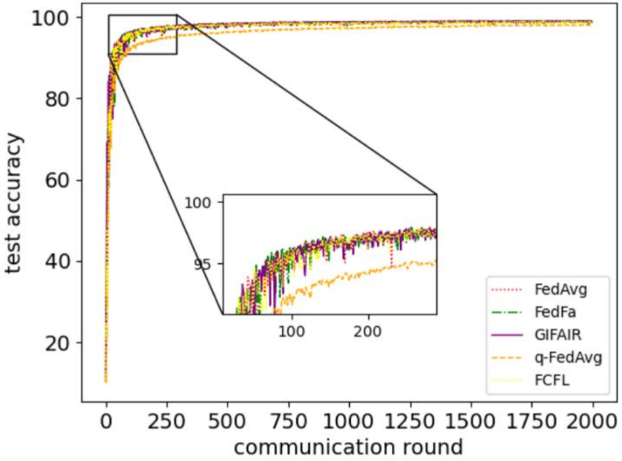
Fairness of FCFL

Dataset	Method	Accuracy	Best 10%	Worst 10%	Variance
MNIST	FedAvg	95.96	100.00	87.47	15.06
	q-FedAvg$\|q$=0.2	96.09	100.00	88.40	12.58
	FedFa$\|\alpha$=0.6,β=0.4	**96.23**	100.00	88.37	12.61
	GIFAIR$\|\lambda$=0.5	96.12	100.00	88.63	12.72
	FCFL$\|\alpha$=0.3,r=0.4	96.06	100.00	**89.17**	**11.03**
CIFAR-10	FedAvg	46.35	**68.67**	20.16	178.93
	q-FedAvg$\|q$=2.0	**47.14**	66.81	24.98	149.50
	FedFa$\|\alpha$=0.6,β=0.4	46.64	68.10	23.19	164.68
	GIFAIR$\|\lambda$=0.5	46.61	67.02	23.18	158.36
	FCFL$\|\alpha$=0.3,r=0.6	46.12	65.39	**28.03**	**114.59**
Shakespeare	FedAvg	49.16	**70.65**	35.34	89.87
	q-FedAvg$\|q$=2.0	50.24	69.77	37.92	75.99
	FedFa$\|\alpha$=0.5,β=0.5	49.03	69.06	36.23	79.54
	GIFAIR$\|\lambda$=0.3	50.01	68.50	36.24	78.25
	FCFL$\|\alpha$=0.1,r=0.6	**50.55**	68.74	**38.55**	**67.48**

Efficiency of FCFL

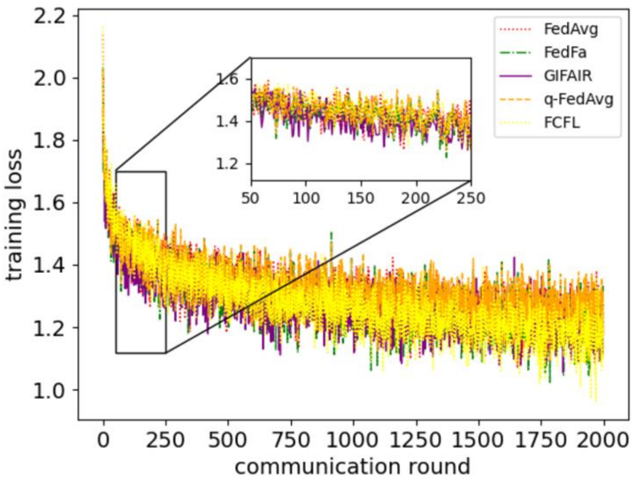


(a) MNIST training loss

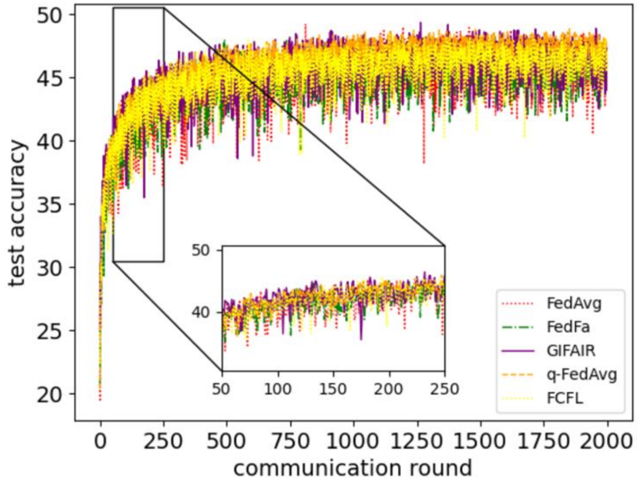


(b) MNIST test accuracy

Efficiency of FCFL



(c) CIFAR-10 training loss



(d) CIFAR-10 test accuracy

Table 4. Ablation studies of FCFL on CIFAR-10.

Method	Accuracy	Best 10%	Worst 10%	Variance
FCFL	**46.12**	65.39	**28.03**	114.59
FCFL|RS	46.06	**65.60**	22.91	151.31
FCFL|DAR	43.56	61.00	26.57	**96.31**

Limitations

- Not tested on large scale highly heterogenous datasets.
- Focused on accuracy based fairness.
- Potential for overcompensation for certain vulnerable clients.

Future Works

- Improving Unfairness Calculation
  - Incorporating global performance
- Multi fairness integration
- Adaptive Hyper Parameters (alpha, r) selection

Thank you