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Conflict-free Client Update Aggregation for Personalized Federated Learning

Hao Zheng[1,2], Zhigang Hu[1], Liu Yang[1*], Meiguang Zheng[1], Aikun Xu[1], Boyu Wang[2*]

1. Central South University 2. University of Western Ontario

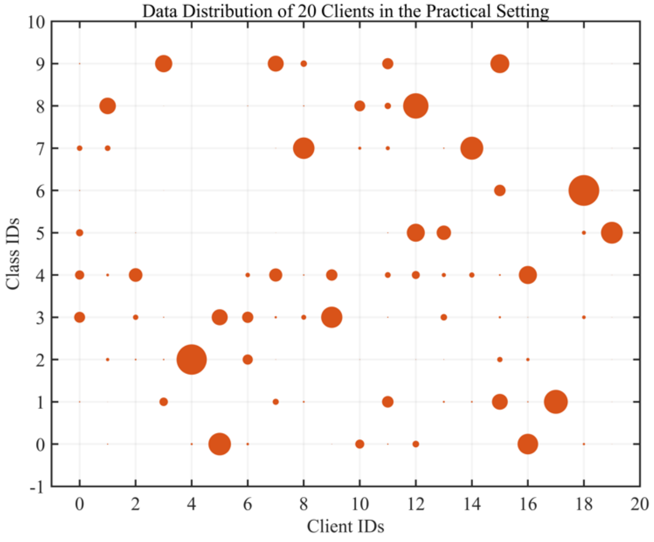
zhenghaocsu@gmail.com

Introduction

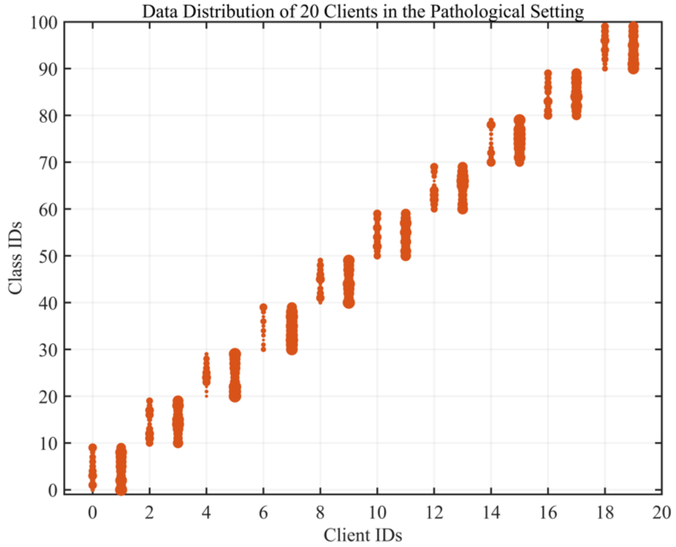
Personalized Federated Learning aims to learn a tailored model for each client while still benefiting from the global model to enhance their models and address data scarcity.

Key Challenge:

- The non-independent and identically distributed (non-IID) nature of real-world data.



Practical Setting



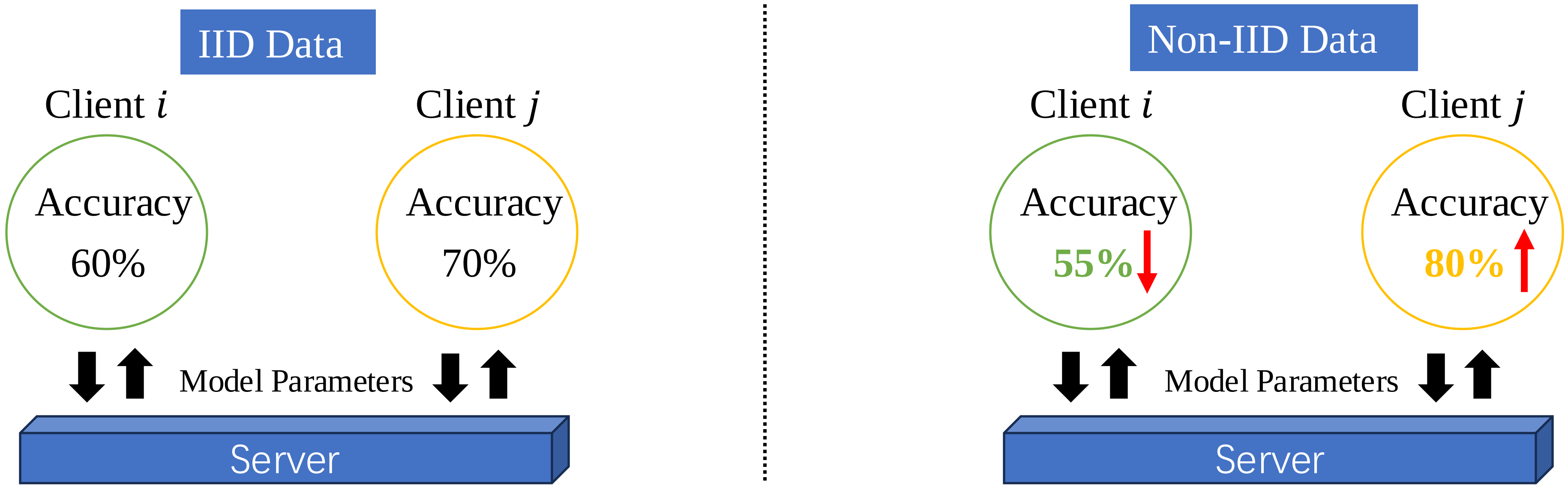
Pathological Setting

Introduction

Personalized Federated Learning aims to learn a tailored model for each client while still benefiting from the global model to enhance their models and address data scarcity.

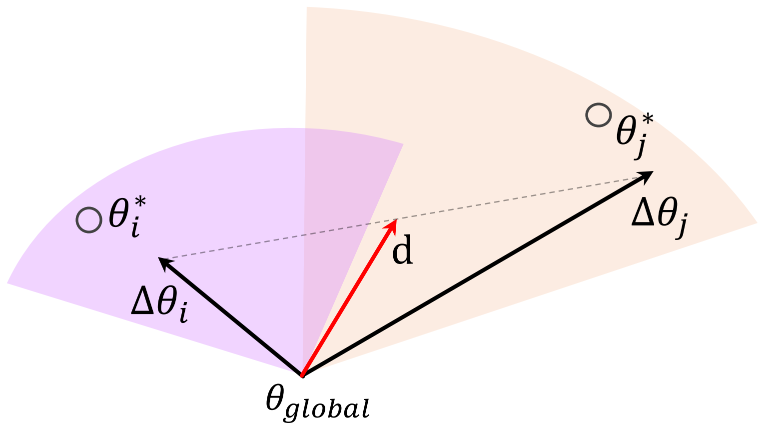
Key Challenge:

- Non-IID.
- Negative transfer: refers to the situation when models are shared between different clients and the performance is degraded because some client updates negatively affect the shared model.



Motivation

Negative transfer is caused by **update conflicts** among clients during server aggregation.



FedAvg

$$d = \frac{1}{N}\sum_{i=1}^{N}\Delta\theta_i$$

- **Client Update Conflicts**: when $\Delta\theta_i \cdot \Delta\theta_j < 0$, the parameter update from client i has a negative impact on client j because it leads to an increase in the loss of client j.

$$\Delta\mathcal{L}_j = \mathcal{L}_j(h_j, \theta_g + \Delta\theta_i) - \mathcal{L}_j(h_j, \theta_g) = -\frac{1}{\alpha}\Delta\theta_i \cdot \Delta\theta_j \quad (1)$$

$$\Delta\mathcal{L}_{\text{total}} = -\frac{1}{\alpha}\sum_{i=1}^{N}\sum_{j=1}^{N} p_i p_j \Delta\theta_i \cdot \Delta\theta_j \quad (2)$$

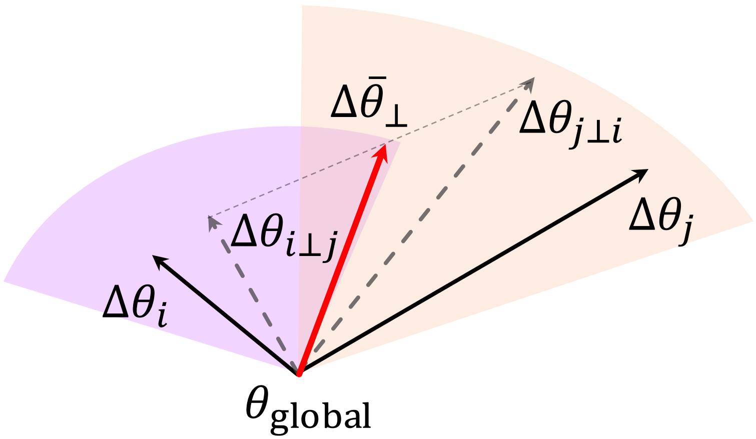
The classical FedAvg d tends to be dominated by the $\Delta\theta_j$ from clients with more data, leading to insufficient optimization for client i.

Methodology: ConFREE

Stage 1:

- **Guidance Vector $\Delta\bar{\theta}_{\perp}$:**

when $\cos\theta_{ij} < 0$**,** conflict occurs.



minimizes negative conflicts with parameter updates from other clients.

$$\Delta\bar{\theta}_{\perp} = \frac{1}{N}\sum_{i=1}^{N}\left(\Delta\theta_i - \sum_{j\neq i,\cos\theta_{ij}<0}\frac{\Delta\theta_i \cdot \Delta\theta_j}{\|\Delta\theta_j\|^2}\Delta\theta_j\right) \tag{3}$$

Methodology : ConFREE

Stage 2:

- Maximize the worst-performing clients near the guidance vector to regularize server aggregation.

$$\min \Delta\mathcal{L}_{\text{total}} \approx \max_{\mathbf{d}\in\mathbf{\Theta}} \frac{1}{N}\sum_{j=1}^{N} \min_{j\in[N]} \mathbf{d}\cdot\Delta\theta_j \qquad \text{s.t.} \quad \left\|\mathbf{d}-\Delta\bar{\theta}_\perp\right\| \leq c\|\Delta\bar{\theta}_\perp\| \tag{4}$$

- **Dual Problem**:

$$\begin{aligned} &\min_{w\in\mathcal{W},\lambda\geq 0}\ \max_{\mathbf{d}\in\Theta} \quad \mathbf{d}\cdot\Delta\theta_w - \frac{\lambda}{2}\left(\|\mathbf{d}-\Delta\bar{\theta}_\perp\|^2 - c^2\|\Delta\bar{\theta}_\perp\|^2\right) \\ &\implies \quad d^* = \Delta\bar{\theta}_\perp + \frac{c\|\Delta\bar{\theta}_\perp\|}{\|\Delta\theta_{w^*}\|}\Delta\theta_{w^*} \text{ and } \lambda = \frac{\|\Delta\theta_{w^*}\|}{c\|\Delta\bar{\theta}_\perp\|}. \end{aligned} \tag{5}$$

Methodology : ConFREE

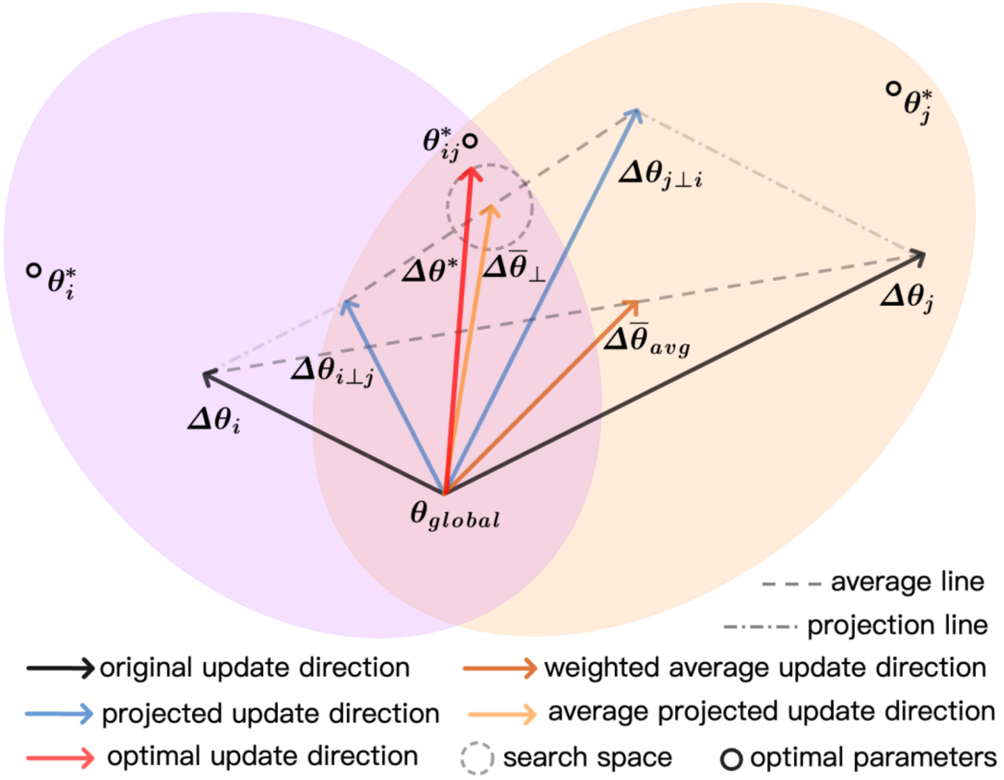
- **Final Objective Function:**

$$w^* = \arg\min_{w \in \mathcal{W}} \; \mathbf{d} \cdot \Delta\theta_w + c\|\Delta\bar{\theta}_\perp\|\|\Delta\theta_w\| \quad (6)$$

the optimization problem for w can be solved using the Minimize function provided by the scientific computing library Scipy

- **Overall Process:**

ConFREE projects conflicting updates onto a normal plane, creates a conflict-free guiding vector $\Delta\bar{\theta}_\perp$. The optimal $\Delta\theta^*$ is then found within a ball centered around $\Delta\bar{\theta}_\perp$, which maximizes the local improvement of the worst performing client in the neighborhood. This ensures the updated global model is closer to the global optimum θ^*_{ij} and balances the update across clients.



Experiments

- Comparison of eight SOTA methods combined with ConFREE. #S: communication overhead (MB), #T: computation overhead (s).

Methods	Pathological heterogeneous		Practical heterogeneous($\beta = 0.1$)				#S.	#T.
	Flowers102	CIFAR100	CIFAR10	CIFAR100	TINY	Flowers102		
Per-FedAvg	67.04	61.77	87.76	41.49	25.62	55.33	151.72	66.86
+ ConFREE	67.64 (↑ 0.60)	62.45 (↑ 0.68)	88.23 (↑ 0.47)	41.76 (↑ 0.27)	27.42 (↑ 1.80)	55.96 (↑ 0.63)	148.19	67.38
LG-FedAvg	63.89	63.32	89.23	47.63	33.75	51.48	148.39	46.71
+ ConFREE	64.09 (↑ 0.20)	63.48 (↑ 0.16)	89.52 (↑ 0.29)	47.88 (↑ 0.25)	33.96 (↑ 0.21)	52.72(↑ 1.24)	144.86	46.94
APFL	68.87	63.53	89.45	54.18	41.16	63.65	292.85	56.27
+ ConFREE	70.79 (↑ 1.92)	63.71 (↑ 0.18)	89.64 (↑ 0.19)	55.44 (↑ 1.26)	41.97 (↑ 0.81)	65.11 (↑ 1.46)	289.32	56.66
FedROD	69.21	63.79	89.93	51.02	39.74	61.02	159.55	54.30
+ ConFREE	69.56 (↑ 0.35)	64.02 (↑ 0.23)	90.80 (↑ 0.87)	52.57 (↑ 1.55)	40.98 (↑ 1.24)	61.52(↑ 0.50)	156.02	54.81
FedRep	68.62	67.41	90.40	51.33	41.72	57.52	151.52	56.90
+ ConFREE	68.92 (↑ 0.30)	67.92 (↑ 0.51)	90.61 (↑ 0.21)	51.41 (↑ 0.08)	42.31 (↑ 0.59)	57.81(↑ 0.29)	147.99	56.97
FedCP	71.38	70.47	91.30	55.33	44.87	60.73	539.17	99.49
+ ConFREE	71.73 (↑ 0.35)	70.98 (↑ 0.51)	91.72 (↑ 0.42)	55.68 (↑ 0.35)	45.62 (↑ 0.75)	61.51(↑ 0.78)	535.64	99.59
FedALA	68.82	67.33	90.67	57.24	44.56	62.92	683.23	55.91
+ ConFREE	70.64 (↑ 1.82)	67.52 (↑ 0.19)	91.32 (↑ 0.65)	57.70 (↑ 0.46)	45.01 (↑ 0.45)	63.94 (↑ 1.02)	679.72	56.39
FedPAC	74.48	72.60	90.86	61.94	46.63	68.56	160.01	110.67
+ ConFREE	74.68 (↑ 0.20)	73.01 (↑ 0.41)	91.42 (↑ 0.56)	62.85 (↑ 0.91)	46.83 (↑ 0.20)	69.10 (↑ 0.54)	156.48	147.20

Experiments

- Comparison on different numbers of clients C and participation rates P on the CIFAR100 and Flowers102.

Methods	CIFAR100				Flowers102			
	C = 20		C = 60		C = 20		C = 60	
	$P = 30\%$	$P = 60\%$	$P = 30\%$	$P = 60\%$	$P = 30\%$	$P = 60\%$	$P = 30\%$	$P = 60\%$
APFL	52.85	53.64	43.56	44.02	62.92	63.94	45.88	50.31
+ ConFREE	53.49 (↑ 0.64)	54.11 (↑ 0.47)	44.90 (↑ 1.34)	44.46 (↑ 0.44)	64.14 (↑ 1.22)	64.48 (↑ 0.54)	49.30 (↑ 3.42)	52.53 (↑ 2.22)
FedROD	53.91	53.06	52.49	50.59	61.41	61.46	56.87	55.28
+ ConFREE	54.18 (↑ 0.27)	53.29 (↑ 0.23)	53.23 (↑ 0.74)	52.29 (↑ 1.70)	62.41 (↑ 1.00)	62.69 (↑ 1.23)	57.74 (↑ 0.87)	56.34 (↑ 1.06)
FedRep	50.95	51.03	44.36	44.04	58.44	57.42	49.40	48.72
+ ConFREE	51.11 (↑ 0.16)	51.39 (↑ 0.36)	44.66 (↑ 0.30)	44.37 (↑ 0.33)	58.93 (↑ 0.49)	58.10 (↑ 0.68)	49.93 (↑ 0.53)	49.16 (↑ 0.44)
FedCP	56.25	56.10	50.20	48.95	62.19	61.31	53.30	51.81
+ ConFREE	56.38 (↑ 0.13)	56.20 (↑ 0.10)	50.29 (↑ 0.09)	49.02 (↑ 0.07)	63.03 (↑ 0.84)	61.80 (↑ 0.49)	53.69 (↑ 0.39)	52.29 (↑ 0.48)
FedALA	56.62	56.97	58.01	58.15	62.19	62.48	56.54	58.71
+ ConFREE	56.98 (↑ 0.36)	57.45 (↑ 0.48)	58.40 (↑ 0.39)	58.60 (↑ 0.45)	63.50 (↑ 1.31)	63.70 (↑ 1.22)	59.33 (↑ 2.79)	60.88 (↑ 2.17)
FedPAC	61.45	61.61	61.93	62.84	67.49	68.08	58.95	59.04
+ ConFREE	62.09 (↑ 0.64)	62.23 (↑ 0.62)	62.63 (↑ 0.70)	63.34 (↑ 0.50)	67.83 (↑ 0.34)	68.86 (↑ 0.78)	60.20 (↑ 1.25)	60.78 (↑ 1.74)

Conclusion

1. ConFREE is the first method to address client update conflicts in PFL. By optimizing global model aggregation, it provides each client with more effective and comprehensive global information.

2. ConFREE is model-agnostic, which requires a single modification to the server aggregation program that can be easily applied to enhance various client-side personalization techniques.

3. Through enhancing different SOTA methods and conducting extensive evaluations on real-world datasets with different data heterogeneity, ConFREE has been proven to significantly boost their overall performance.

Thanks for watching !

Reporter: Hao Zheng