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Fairness-guided federated training for generalization and personalization in cross-silo federated learning

Key words: Generalized and personalized federated learning; Performance distribution fairness; Domain shift

Corresponding authors: Ya ZHANG; Yanfeng WANG
E-mail: ya_zhang@sjtu.edu.cn; wangyanfeng622@sjtu.edu.cn
ORCID: https://orcid.org/0000-0002-5390-9053
https://orcid.org/0000-0002-3196-2347

Motivation

Cross-silo federated learning faces the challenge of balancing generalization and personalization due to domain shifts across clients. Existing methods typically optimize either generalization (global model performance) or personalization (client-specific performance), but fail to address both simultaneously. Our motivations are to explore the relationship between generalization gaps and aggregation weights and to design an approach that not only improves global model generalization but also ensures personalization at the local client level.

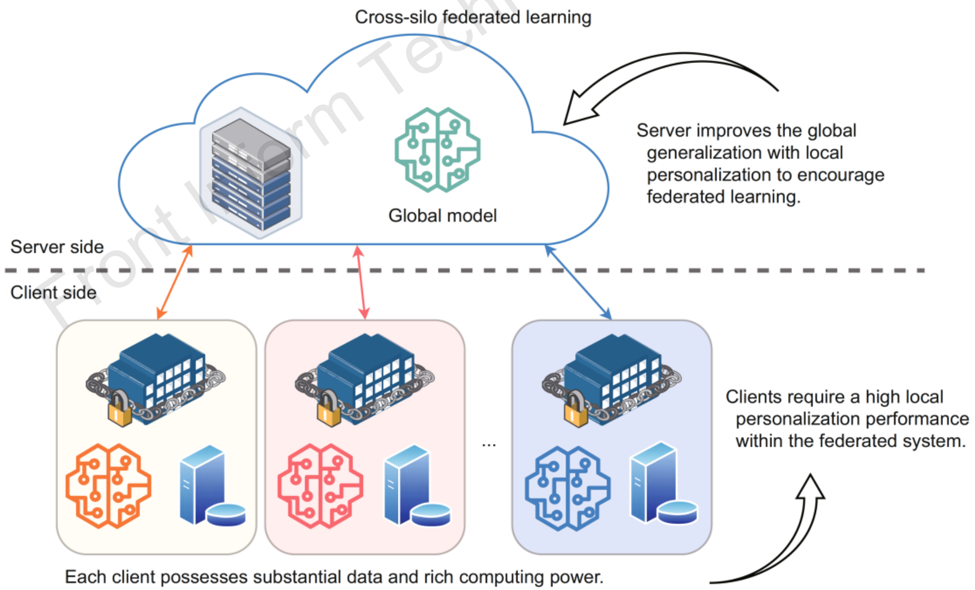


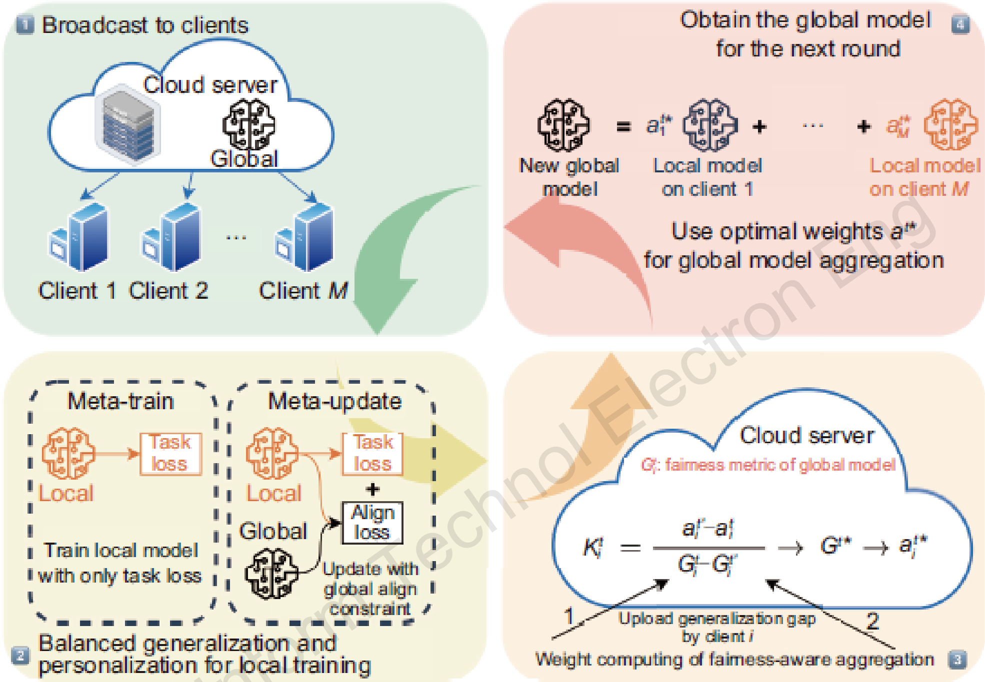
Fig. 1 Illustration of cross-silo FL. It has fewer clients than the cross-device FL, but each client has substantial data and computational resources. From the client perspective, FL needs to enhance each client's personalization performance while maintaining fairness among clients. On the server side, advancing FL requires improving the generalization capability of the global model to foster collaboration. FL: federated learning

Main idea

The fairness-guided federated training for generalization and personalization (FFT-GP) algorithm addresses both global and local challenges in cross-silo federated learning.

- **Fairness-aware aggregation:** By investigating the fairness of performance distribution across clients, we propose a new connection between generalization gaps and aggregation weights. FAA minimizes the variance of generalization gaps, ensuring a fairer distribution of performance across clients.
- **Meta-learning alignment:** To improve personalization during local training, we employ a meta-learning strategy to align the feature distributions between the global and local models, ensuring that local models are optimized for individual clients while still benefiting from global model generalization.

Method

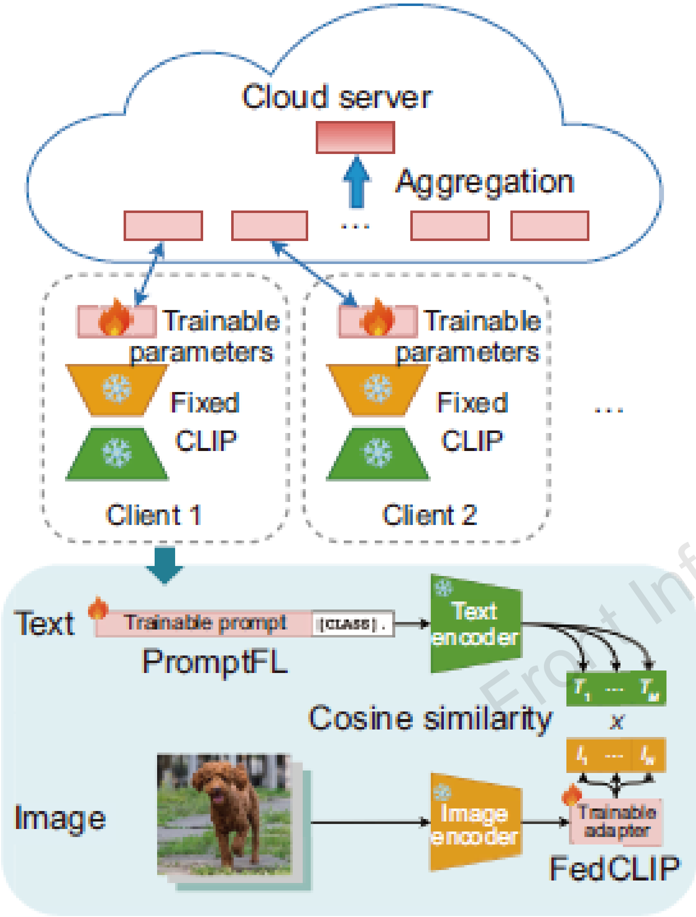


Our method operates in a cyclical sequence of four key steps:

1. **Broadcasting**: The global server sends the current global model to all clients.
2. **Local meta-learning**: Each client balances task-specific personalization with global alignment via meta-learning.
3. **Fairness-aware weight adjustment**: The server computes aggregation weights based on client-reported generalization gaps to ensure fairness.
4. **Aggregation**: Local models are aggregated with updated weights to produce the next global model.

Method

Federated learning with foundation models



The integration of foundation models (FMs) in federated learning:

- **Fine-tuning:** Clients fine-tune the trainable parameters of the FMs while keeping certain pre-trained components (e.g., CLIP) fixed to leverage their pre-trained knowledge.
- **FedCLIP & PromptFL:**
  - FedCLIP incorporates a trainable adapter into CLIP for improved local training.
  - PromptFL uses trainable prompts with CLIP to enhance the performance.

  Both approaches rely on contrastive language-image pre-training to adapt to client-specific tasks while contributing effectively to global model updates.

Results

Table 2 In-domain personalization result comparison for local models across five DomainBed benchmarks with state-of-the-art methods using the fully supervised ResNet50

Method	Accuracy (%)					
	PACS	VLCS	OfficeHome	TerraInc	DomainNet	Avg.
FedAvg	96.52	85.04	85.51	93.46	89.12	89.93
Ditto	97.69	86.14	**86.88**	95.52	90.88	91.42
AFL	96.56	86.36	86.26	95.21	90.94	91.07
q-FFL	97.50	86.35	85.20	91.88	90.88	90.36
PerFedAvg	97.23	86.87	85.76	94.81	90.27	90.99
GRACE	97.88	86.18	85.79	94.93	89.83	90.92
FFT-GP	**97.98**	**87.12**	86.26	**95.63**	**91.18**	**91.63**

Bold values indicate the maximum values, while underlined values represent the second-highest values

Table 3 Out-of-domain generalization result comparison for the global model across five DomainBed benchmarks with state-of-the-art methods using the fully supervised ResNet50

Method	Accuracy (%)					
	PACS	VLCS	OfficeHome	TerraInc	DomainNet	Avg.
FedAvg	86.16	78.21	70.64	44.55	77.27	71.37
FedProx	85.01	77.29	71.19	45.34	77.95	71.36
AFL	85.95	77.19	70.17	44.53	76.85	70.94
q-FFL	85.57	77.95	**71.82**	44.32	78.03	71.54
PerFedAvg	83.89	77.89	68.95	45.28	78.62	70.93
GA	86.62	79.29	69.98	48.67	80.98	73.11
GRACE	86.75	79.46	68.94	45.96	77.78	71.78
FFT-GP	**87.59**	**80.65**	71.43	**50.63**	**81.82**	**74.42**

Bold values indicate the maximum values, while underlined values represent the second-highest values

FFT-GP achieves the optimal performance in both **in-domain personalization** and **out-of-domain generalization** across multiple benchmarks.

Results

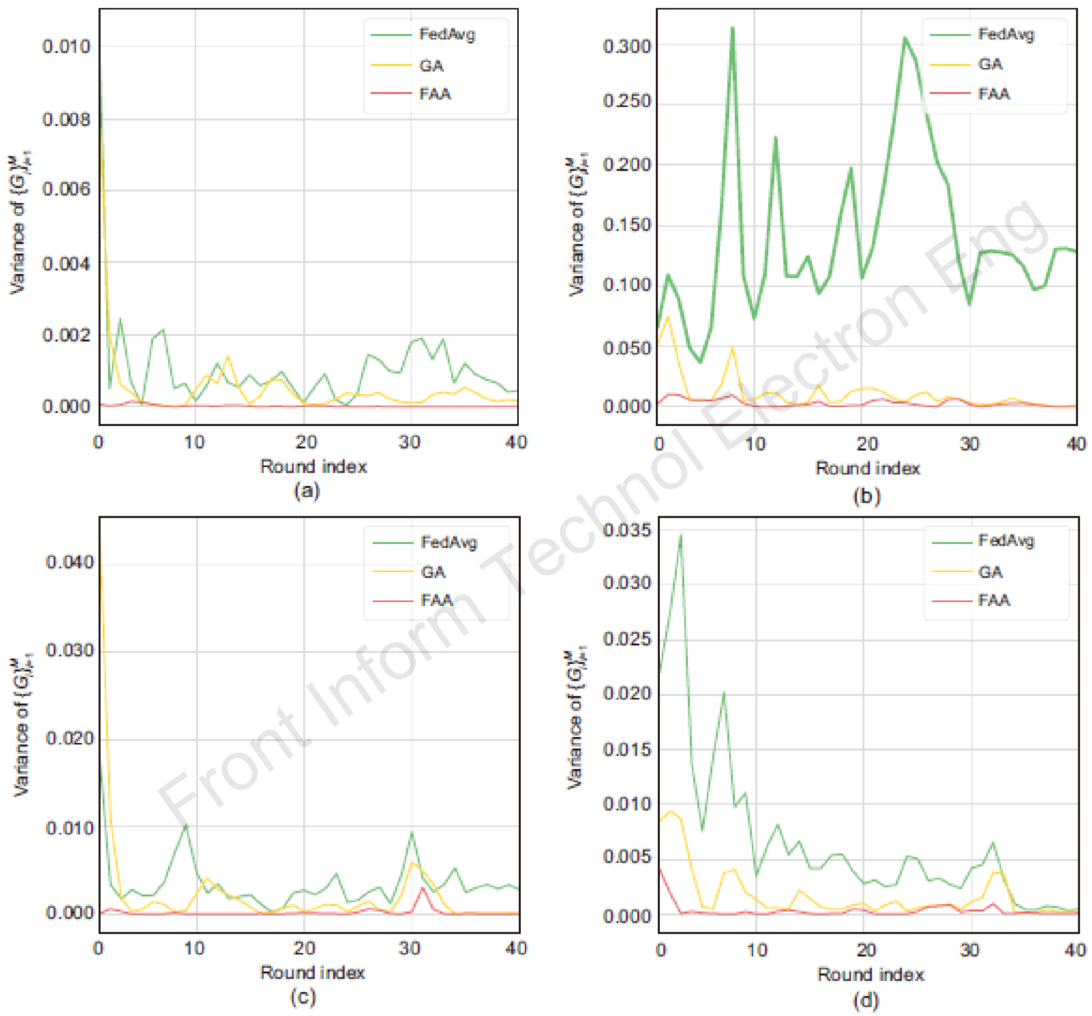
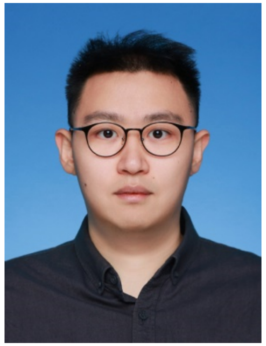


Fig. 6 Fairness curves of global models, obtained using different aggregation methods (FedAvg, GA, and FAA) during local training: (a) PACS; (b) VLCS; (c) OfficeHome; (d) TerraInc. Notably, FFT-GP is the foundation of the training process. After each round of local training, we evaluate fairness through different aggregation algorithms, with the results from FAA guiding the aggregation strategy for the subsequent experimental round. FAA: fairness-aware aggregation; FFT-GP: fairness-guided federated training for generalization and personalization; GA: generalization adjustment. References to color refer to the online version of this figure

Conclusions

We propose FFT-GP, a novel approach that addresses the dual challenge of generalization and personalization in cross-silo federated learning. By leveraging the relationship between generalization gaps and aggregation weights in the global aggregation phase and aligning global and local model distributions in the local training phase, FFT-GP ensures a fair and effective balance between global performance and client-specific personalization. Extensive experiments show that FFT-GP outperforms existing methods in both global model generalization and local model personalization, making it a promising solution for cross-silo federated learning.



Ruipeng ZHANG is currently pursuing his PhD degree at Shanghai Jiao Tong University. He obtained his BS degree from University of Electronic Science and Technology of China in 2019. His research interests include domain generalization and federated learning.

Ziqing FAN is currently working toward his PhD degree at Shanghai Jiao Tong University. He obtained his BS degree from University of Electronic Science and Technology of China in 2022. His research interests include machine learning, federated learning, and multi-task reinforcement learning.

Jiangchao YAO is an assistant professor with Shanghai Jiao Tong University, Shnaghai, China. He received the BS degree in information engineering from South China University of Technology, Guangzhou, China, in 2013. He got a dual Ph.D. degree under the supervision of Ya ZHANG in Shanghai Jiao Tong University and Ivor W. TSANG in University of Technology Sydney. His research interests include deep representation learning and robust machine learning.

Ya ZHANG is a processor with the School of Artificial Intelligence, Shanghai Jiao Tong University. She obtained her BS degree from Tsinghua University and PhD degree in information sciences and technology from Pennsylvania State University. She is currently serving as an Assistant Dean of the School of Artificial Intelligence at Shanghai Jiao Tong University. She has published over 200 scholarly articles in high-impact international journals and conferences, with her work being cited over 10 000 times according to Google Scholar. Her achievements are recognized through various awards and honors, including earning a Leading Talent under the National High-Level Talent Special Support Program (2023) and receiving the First Prize of the Shanghai Technological Invention Award (2022). Her research focuses on machine learning applications in multimedia and healthcare.

Yanfeng WANG is currently a processor with the School of Artificial Intelligence, Shanghai Jiao Tong University. He obtained his BS degree from PLA Information Engineering University, the MS and PhD degrees in Antai College of Economics & Management from Shanghai Jiao Tong University. He is currently the Executive Dean of the School of Artificial Intelligence at Shanghai Jiao Tong University. His research interests are mainly on media big data, emerging commercial applications of information technology, and technology transfer.