Adaptive Test-Time Personalization for Federated Learning

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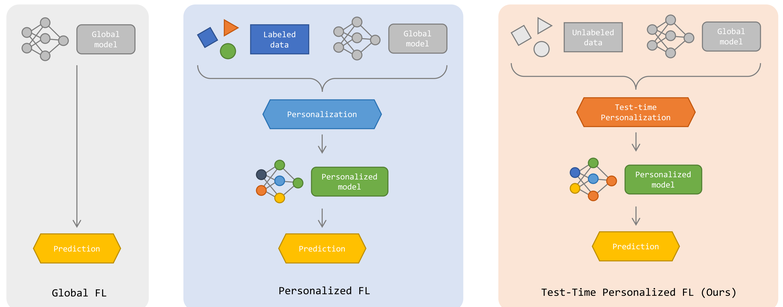
Background

Cross-device federated learning A very large number of mobile/IoT devices collaborate to train machine learning models under the orchestration of a central server, without sharing their raw data.

- Only a small part of clients have labeled data and are sampled for training.
- However, the model also needs to be deployed on clients that do not participate in FL training.
- Clients typically have their own distributions with distribution shifts, e.g., feature shift, label shift.

Question: How to generalize to unparticipating clients under distribution shifts?

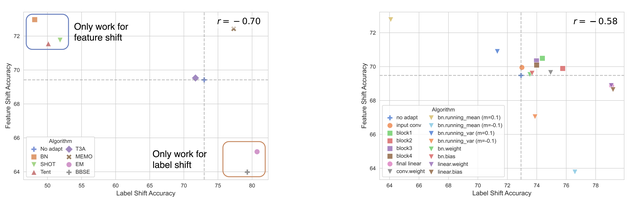
Test-Time Personalized Federated Learning (TTPFL)



Framework	Global FL	Personalized FL	Test-Time Personalized FL
Adaptation to each client	No :(	Yes :)	Yes :)
Data requirement	No :)	Additional labeled data :(	Unlabeled testing data :)

Test-time adaptation (TTA) methods can be applied to TTPFL, with **two drawbacks**:

- *Neglection of multiple sources*: TTA assumes single source domain and neglects the interrelationship among source clients, resulting in sub-optimal generalization.
- *Inflexibity to various distribution shifts*. Most TTA methods are customized for specific distribution shifts and lack the flexibility to address diverse types of distribution shifts.



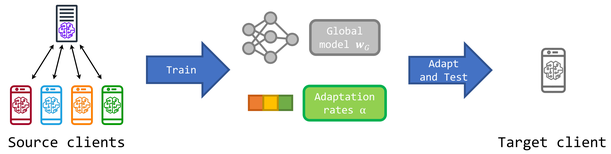
Motivation: Which modules to adapt should depend on the type of distribution shifts among clients, which can be inferred from source clients.

Paper Summary

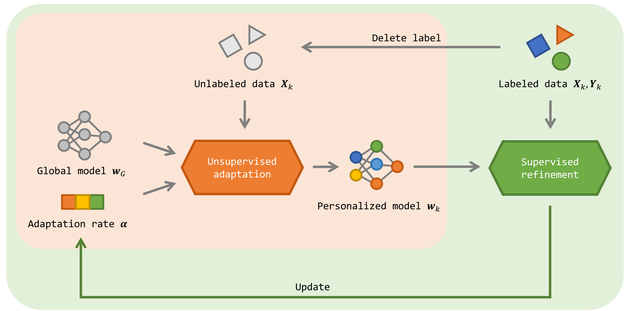
- We consider a novel setting named *Test-Time Personalized Federated Learning*, addressing the challenge of personalizing a global model to each *unparticipating client* during test-time, without requiring any labeled data.
- We propose *ATP*, which adaptively learns the adaptation rate for each module, enabling it to handle different types of distribution shifts among FL clients.

Proposed Method: ATP

Adaptive test-time personalization (ATP) learns the adaptation rates for each module.



Training phase: Learn to adapt with source clients



Unsupervised adaptation: Simulate adapting the global model with *unlabeled data*.

$$\boldsymbol{w}_k \leftarrow \boldsymbol{w}_G + (\boldsymbol{A}\boldsymbol{\alpha}) \odot \boldsymbol{h}_k \quad \text{i.e.,} \quad \boldsymbol{w}_k^{[l]} \leftarrow \boldsymbol{w}_G^{[l]} + \alpha^{[l]} \boldsymbol{h}_k^{[l]} \text{ for each module } l, \text{ where}$$

- For trainable parameters, $\boldsymbol{h}_k^{[l]} = -\nabla_{\boldsymbol{w}^{[l]}} \ell_H(f(\boldsymbol{X}_k; \boldsymbol{w}_G))$ (negative gradient of entropy)
- For BatchNorm running statistics, $\boldsymbol{h}_k^{[l]} = \hat{\boldsymbol{w}}_k^{[l]} - \boldsymbol{w}_G^{[l]}$ (batch stat $-$ global stat)

Supervised refinement: Refine the adaptation rates $\boldsymbol{\alpha}$ with *labeled data* and cross entropy

$$\boldsymbol{\alpha} \leftarrow \boldsymbol{\alpha} - \eta \nabla_{\boldsymbol{\alpha}} \ell_{CE}(f(\boldsymbol{X}_k; \boldsymbol{w}_k), \boldsymbol{Y}_k)$$

Server aggregation: Local adaptation rates are uploaded to and aggregated by the server.

Testing phase: Exploit adaptation rates on target clients

ATP-batch processes each batch independently. It is identical to unsupervised adaptation.

ATP-online processes a stream of batches $[\boldsymbol{X}_1, \boldsymbol{X}_2, \cdots]$. It uses update directions on previous batches $[\boldsymbol{h}_1, \boldsymbol{h}_2, \cdots, \boldsymbol{h}_k]$ to assist the adaptation to the current batch.

$$\boldsymbol{w}_k \leftarrow \boldsymbol{w}_G + (\boldsymbol{A}\boldsymbol{\alpha}) \odot \left(\frac{1}{k} \sum_{s=1}^{k} \boldsymbol{h}_s \right)$$

Experiments

ATP can handle different types of distribution shifts

We train ResNet-18 on CIFAR-10(C) with different types of distribution shifts:

- Feature shift: Each client has a random type of image corruption.
- Label shift: Each client has 2 majority classes and 8 minority classes.
- Hybrid shift: Feature + label shifts.

Table 1:Accuracy (mean $\pm$ s.d. %) on target clients under various distribution shifts on CIFAR-10(C)

Method	Feature shift	Label shift	Hybrid shift	Avg. Rank
No adaptation	69.42 ± 0.13	72.98 ± 0.24	63.68 ± 0.24	7.7
BN-Adapt	73.52 ± 0.22	54.54 ± 0.10	50.42 ± 0.39	7.0
SHOT	71.76 ± 0.17	48.13 ± 0.18	44.68 ± 0.32	9.3
Tent	71.76 ± 0.09	50.13 ± 0.21	46.05 ± 0.26	8.3
T3A	69.53 ± 0.08	71.70 ± 0.32	62.17 ± 0.17	8.0
MEMO	72.43 ± 0.22	77.30 ± 0.15	68.07 ± 0.28	4.3
EM	65.18 ± 0.12	80.73 ± 0.18	69.85 ± 0.43	5.0
BBSE	63.98 ± 0.17	79.30 ± 0.17	67.96 ± 0.43	6.7
Surgical	69.85 ± 0.22	76.00 ± 0.17	66.94 ± 0.43	6.3
ATP-batch	73.68 ± 0.10	79.90 ± 0.22	73.05 ± 0.35	2.3
ATP-online	**74.06 ± 0.18**	**81.96 ± 0.14**	**75.37 ± 0.22**	**1.0**

ATP consistently improves the performance across different types of distribution shifts. We also conduct experiments on more datasets (CIFAR-100(C), Digits-5, PACS), and try different models (Shallow-CNN, ResNet-18, ResNet-50).

ATP learns shift-specific adaptation rates

Table 2:Train and test adaptation rates with different distribution shifts, accuracy (mean $\pm$ s.d. %)

Train	Test		
	Feature shift	Label shift	Hybrid shift
No adaptation	69.42 ± 0.13	72.98 ± 0.24	63.68 ± 0.24
Feature shift	**73.68 ± 0.10**	65.05 ± 1.82	60.64 ± 1.43
Label shift	67.99 ± 0.28	**79.90 ± 0.22**	69.50 ± 0.52
Hybrid shift	72.69 ± 0.14	78.92 ± 0.34	**73.05 ± 0.35**

- ATP performs the best when training and testing under the same type of distribution shift.
- The adaptation rates trained under feature shifts have negative impact on label shifts, and vice versa.
- The adaptation rates trained under hybrid shift are also beneficial for feature and label shifts.

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