Towards Personalized Federated Learning via Heterogeneous Model Reassembly

Jiaqi Wang[1], Xingyi Yang[2], Suhan Cui[1], Liwei Che[1], Lingjuan Lyu[3], Dongkuan Xu[4], Fenglong Ma[1]
[1]The Pennsylvania State University, [2]National University of Singapore,[3]Sony AI, [4]North Carolina State University
{jqwang,sxc6192,lfc5481,fenglong}@psu.edu, xyang@u.nus.edu, lingjuan.lv@sony.com, dxu27@ncsu.edu

• Introduction

This paper focuses on addressing the practical yet challenging problem of **model heterogeneity in federated learning**, where **clients possess models with different network structures**. We propose a novel framework called pFedHR, which leverages **heterogeneous model reassembly** to achieve **personalized** federated learning. We approach the problem of heterogeneous model personalization as a model-matching optimization task on the server side. Moreover, pFedHR automatically and dynamically generates informative and diverse personalized candidates with minimal human intervention. Furthermore, our proposed heterogeneous model reassembly technique mitigates the adverse impact introduced by using public data with different distributions from the client data to a certain extent. Experimental results demonstrate that pFedHR outperforms baselines on three datasets under both IID and Non-IID settings. Additionally, pFedHR effectively reduces the adverse impact of using different public data and dynamically generates diverse personalized models in an automated manner.

• Method

○ Reassembly Candidate Generation

- Layer-wise Decomposition
- Function-driven Layer Grouping

$$\min \mathcal{L}_t = \min_{\delta^a_{b,h}\in\{0,1\}} \sum_{k=1}^{K}\sum_{b=1}^{B}\sum_{h=1}^{H} \delta^k_{b,h}(\text{dis}(\mathbf{L}^k_t,\mathbf{L}^b_{t,h})),$$

$$\text{dis}(\mathbf{L}^n_{t,i},\mathbf{L}^b_{t,j}) = (\text{CKA}(\mathbf{X}^n_{t,i},\mathbf{X}^b_{t,j})+\text{CKA}(\mathbf{L}^n_{t,i}(\mathbf{X}^n_{t,i}),\mathbf{L}^b_{t,i}(\mathbf{X}^b_{t,j})))^{-1}$$

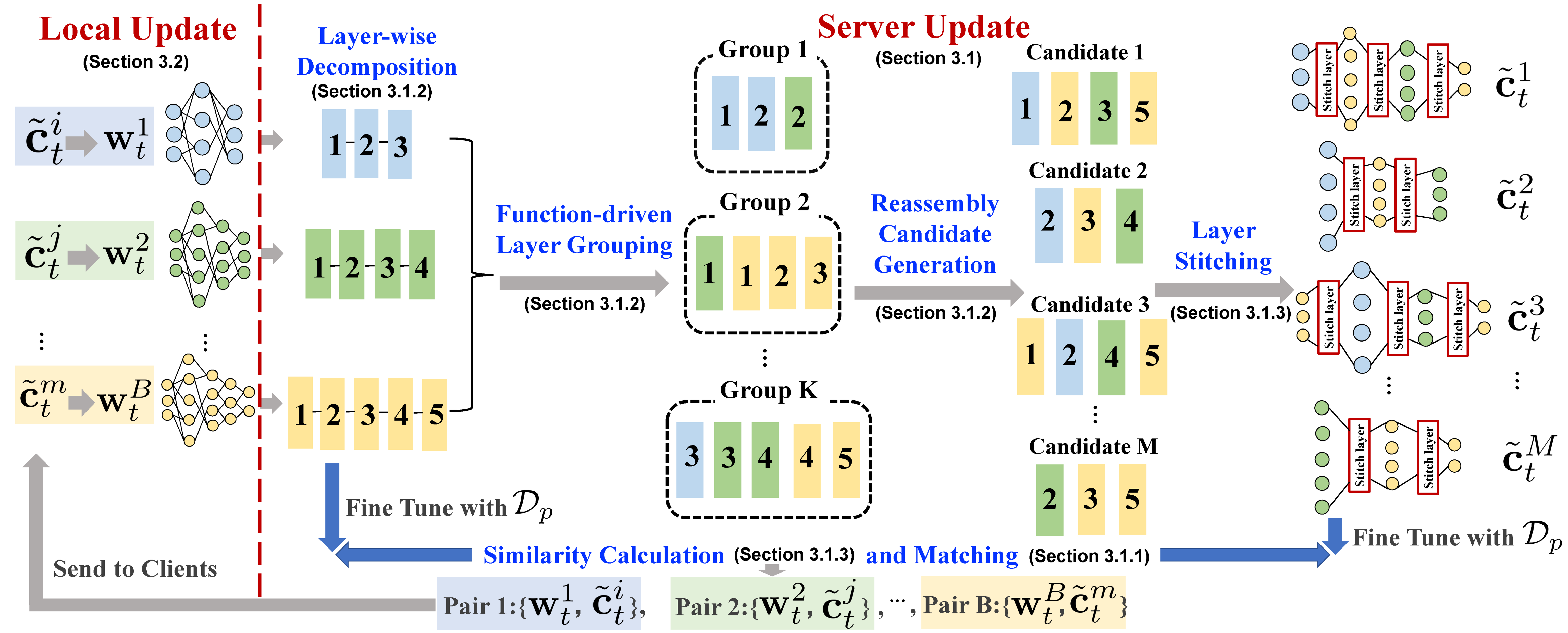
- Reassembly Candidate Generation

○ Layer Stitching

○ Similarity-based Model Matching

$$\text{sim}(\mathbf{w}^n_t,\mathbf{c}^m_t;\mathcal{D}_p) = \text{sim}(\mathbf{w}^n_t,\tilde{\mathbf{c}}^m_t;\mathcal{D}_p) = \frac{1}{P}\sum_{p=1}^{P}\cos(\boldsymbol{\alpha}^n_t(\mathbf{x}_p),\boldsymbol{\alpha}^m_t(\mathbf{x}_p))$$

• Framework

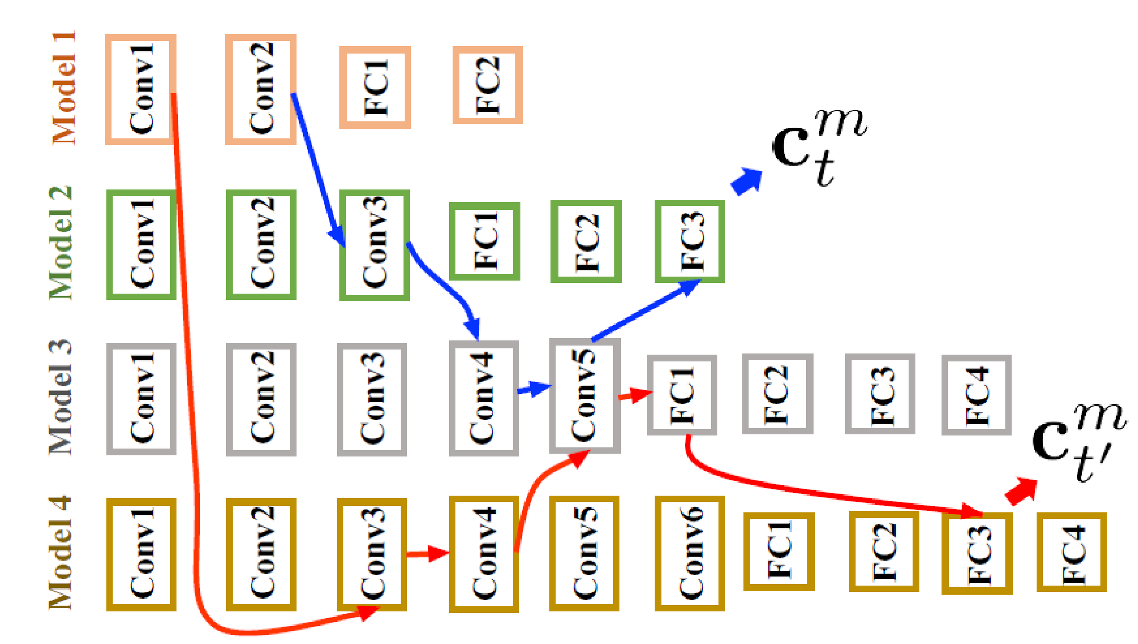


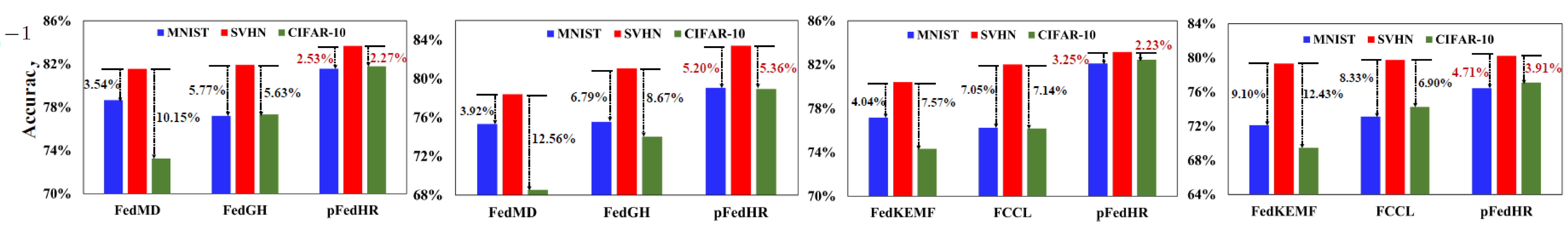
• Selected Results

Performance comparison with baselines under the heterogeneous setting.

Public Data	Dataset / Model	MNIST IID	MNIST Non-IID	SVHN IID	SVHN Non-IID	CIFAR-10 IID	CIFAR-10 Non-IID
Labeled	FedMD [17]	93.08%	91.44%	81.55%	78.39%	68.22%	66.13%
	FedGH [22]	94.10%	93.27%	81.94%	81.06%	72.69%	70.27%
	pFedHR	**94.55%**	**94.41%**	**83.68%**	**83.40%**	**73.88%**	**71.74%**
Unlabeled	FedKEMF [20]	93.01%	91.66%	80.41%	79.33%	67.12%	66.93%
	FCCL [18]	93.62%	92.88%	82.03%	79.75%	68.77%	66.49%
	pFedHR	**93.89%**	**93.76%**	**83.15%**	**80.24%**	**69.38%**	**68.01%**

Candidate models





(a) IID with labeled public dataset (b) Non-IID with labeled public dataset (c) IID with unlabeled public dataset (d) Non-IID with unlabeled public dataset

Performance changes when using different public data. pFedHR is our proposed model.