

July 2022



ARCHITECTURE AGNOSTIC FEDERATED LEARNING FOR NEURAL NETWORKS

International Conference of Machine Learning 2022

DISHA MAKHIJA, XING HAN, NHAT HO, JOYDEEP GHOSH

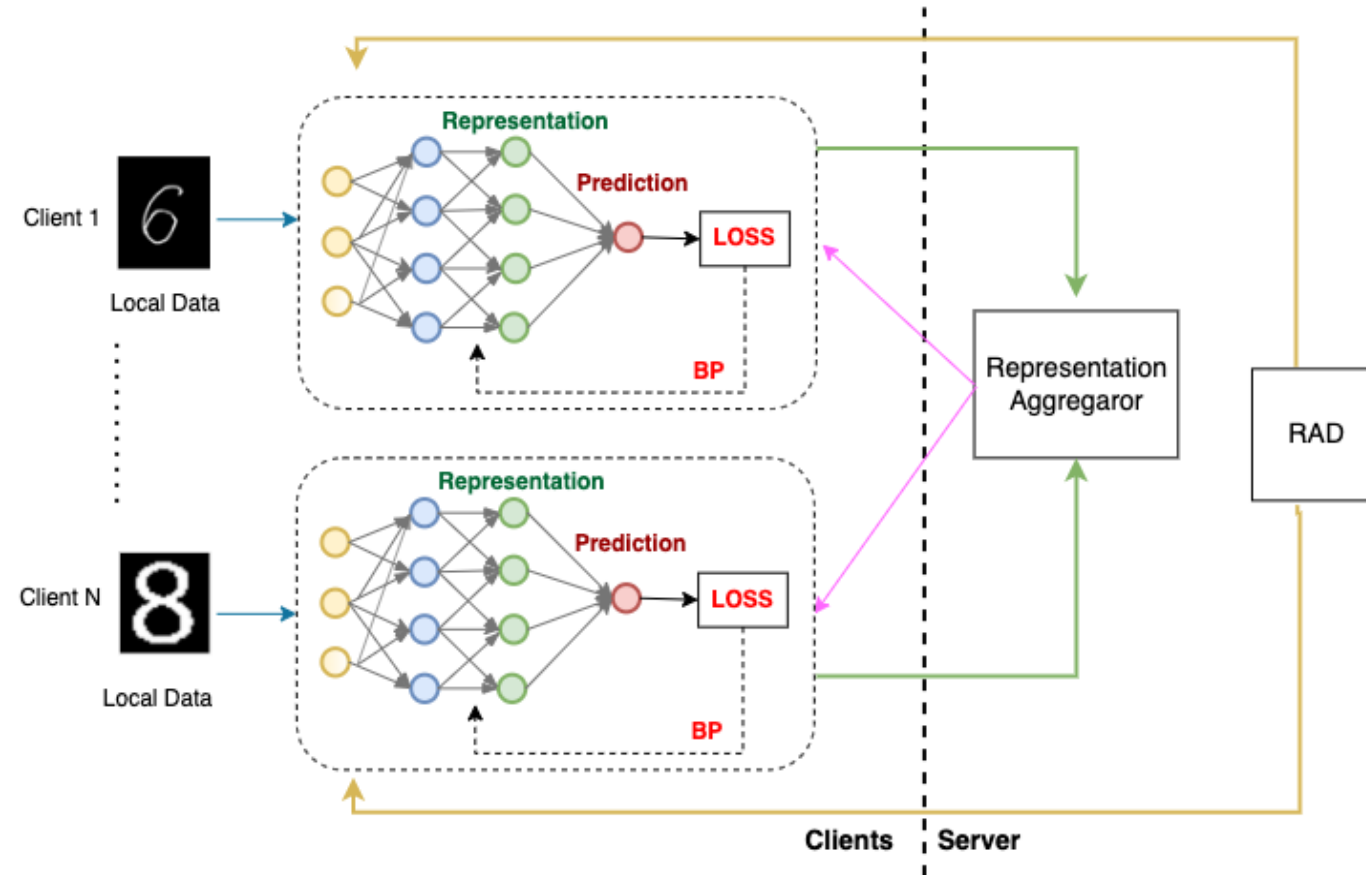
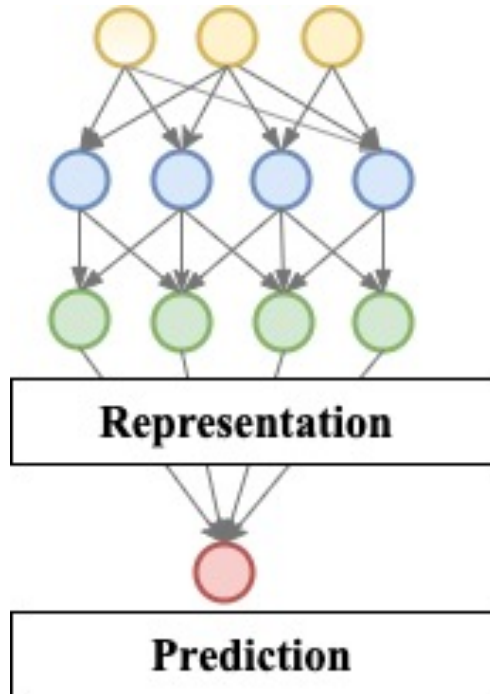
Outline

- Motivation
- Proposed Approach
- Experimental Results

Motivation

- Standard FL algorithms assume each client use the same architecture
 - But clients may differ in their compute resources and local data size/properties
 - May have pre-existing (uncoordinated) solutions
 - Identical architecture requirement is severe, even impractical
- Aggregation of client models to generate single global model is not straightforward due to facts like permutation invariance of neurons, non-linearities etc.
- We propose a systematic framework for **architecture-agnostic federated learning** called FedHeNN

Proposed Approach : FedHeNN



$$\text{Loss} = \text{Task Loss} + \text{Representation Dissimilarity Loss}$$

Proposed Approach : FedHeNN

- FedHeNN for Homogeneous Clients

$$\min_{\mathcal{W}_i} \mathcal{L}_i = \mathcal{F}(\mathcal{W}_i) + \eta d(\Phi_i(\mathbf{X}; \mathcal{W}_i), \Phi_{\text{global}}(\mathbf{X}; \hat{\mathcal{W}}(t-1))).$$

- FedHeNN for Heterogeneous Clients

$$\min_{\mathcal{W}_i} \mathcal{L}_i = \mathcal{F}(\mathcal{W}_i) + \eta d(\Phi_i(\mathbf{X}; \mathcal{W}_i), \bar{\Phi}(\mathbf{X}; (t-1))).$$

$$\text{where } \bar{\Phi}(\mathbf{X}; (t-1)) = \sum_{j=1}^N w_j \Phi_j(\mathbf{X}; \mathcal{W}_j(t-1))$$

Distance Function

- Use a kernel-based distance metric to allow comparison between NNs of different widths
- Specifically, we use CKA(centered kernel alignment) whose linear version is given by

Linear CKA(K_i, K_j) =

$$\text{Linear CKA}(A_i A_i^T, A_j A_j^T) = \frac{\|A_j^T A_i\|_F^2}{\|A_i^T A_i\|_F \|A_j^T A_j\|_F}.$$

Experimental Results

DATA SET(SETTING)	FEDAVG	FEDPROX	FEDHENN GLOBAL
CIFAR-10(100 CLIENTS, 2 CLS/CLIENT)	44.29 \pm 0.5	53.8 \pm 2.3	68.8 \pm 2.1
CIFAR-10(100 CLIENTS, 5 CLS/CLIENT)	58.14 \pm 0.7	63.3 \pm 2.0	70.19 \pm 2.0
CIFAR-10(500 CLIENTS, 2 CLS/CLIENT)	42.7 \pm 0.4	50.46 \pm 1.4	65.4 \pm 0.8
CIFAR-10(500 CLIENTS, 5 CLS/CLIENT)	56.8 \pm 0.5	55.2 \pm 1.2	64.7 \pm 0.7
CIFAR-100(100 CLIENTS, 20 CLS/CLIENT)	28.6 \pm 0.8	27.3 \pm 1.1	44.2 \pm 0.7
SENTIMENT140(100 CLIENTS, 2 CLS/CLIENT)	52.6 \pm 0.4	52.7 \pm 1.0	52.7 \pm 0.01

Table 1: Average test accuracy of FedHeNN computed for the common global model as compared to the baselines with global models.

DATA SET(SETTING)	FEDREP	FEDHENN HOMO	FEDHENN HETERO
CIFAR-10(100 CLIENTS, 2 CLS/CLIENT)	85.7 \pm 0.4	94.7 \pm 1.1	88.9 \pm 0.35
CIFAR-10(100 CLIENTS, 5 CLS/CLIENT)	72.4 \pm 1.2	84.37 \pm 1.5	73.01 \pm 0.3
CIFAR-10(500 CLIENTS, 2 CLS/CLIENT)	78.9 \pm 0.6	86.5 \pm 0.9	82.02 \pm 0.8
CIFAR-10(500 CLIENTS, 5 CLS/CLIENT)	58.14 \pm 0.21	73.32 \pm 1.23	61.74 \pm 0.6
CIFAR-100(100 CLIENTS, 20 CLS/CLIENT)	38.85 \pm 0.9	62.89 \pm 0.8	43.36 \pm 0.2
SENTIMENT140(100 CLIENTS, 2 CLS/CLIENT)	69.8 \pm 0.4	72.6 \pm 0.3	71.5 \pm 0.5

Table 2: Average test accuracy of FedHeNN computed for the personalised models as compared to the baselines with personalised models.

Thank you!