Data-Free One-Shot Federated Regression: An Application to Bone Age Assessment

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Introduction and our proposal

- One-shot federated learning
  - Allowing single-round communication
- Data-free one-shot federated learning
  - Requiring no additional proxy datasets
- FL in classification vs regression
  - Classification is widely explored
  - Regression is less investigated
- ➢ We consider a novel task: data-free one-shot federated regression.
- ➢ We simulate four different settings under this task by considering independent and identical distribution (IID) and non-IID settings with model homogeneity and heterogeneity.

Our proposed method comprises three stages

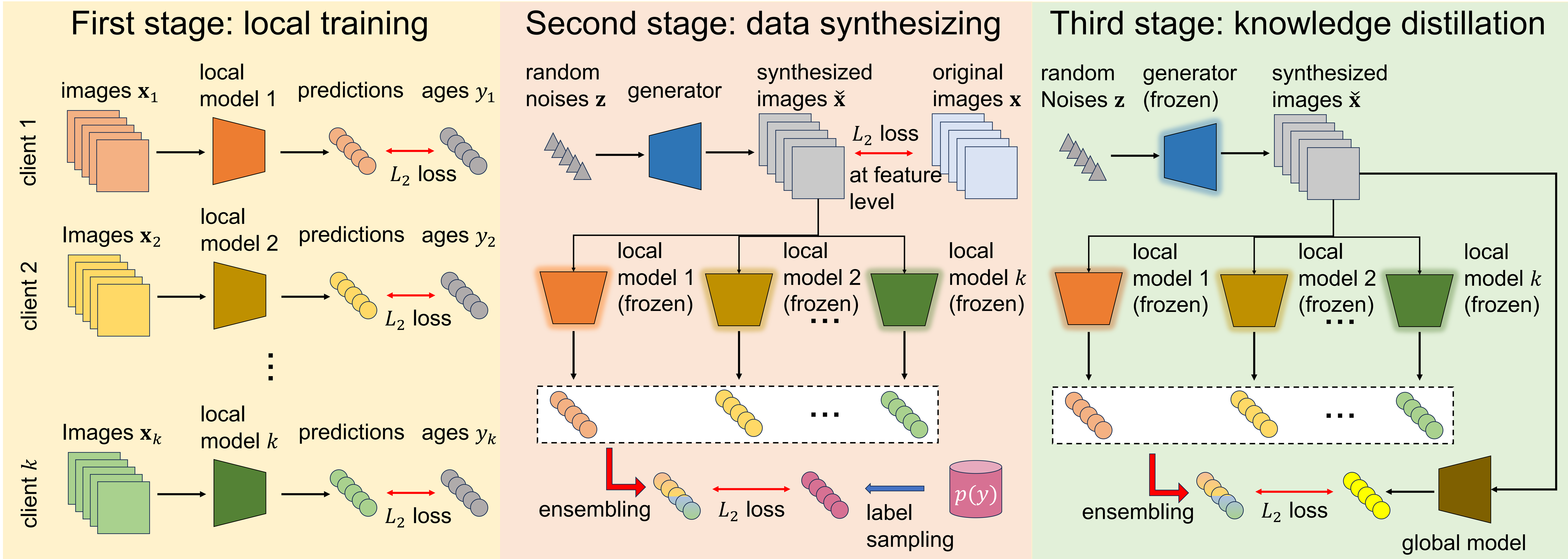

Figure 1: Overview of our framework, which contains three stages. In our study, bone ages range from 1 to 228 months. Let $\mathbf{x}$ denote images, and y denote the corresponding ages, we assume ages y follow a discrete uniform distribution $p(y)$ over the set of {1, 2, 3, ..., 228}.

Experiments and results

- Dataset and metric
  - RNSA-BAA, hand radiograph
  - 12,661 / 1,425 / 200 for training / validation / testing
  - Mean absolute difference (MAD)

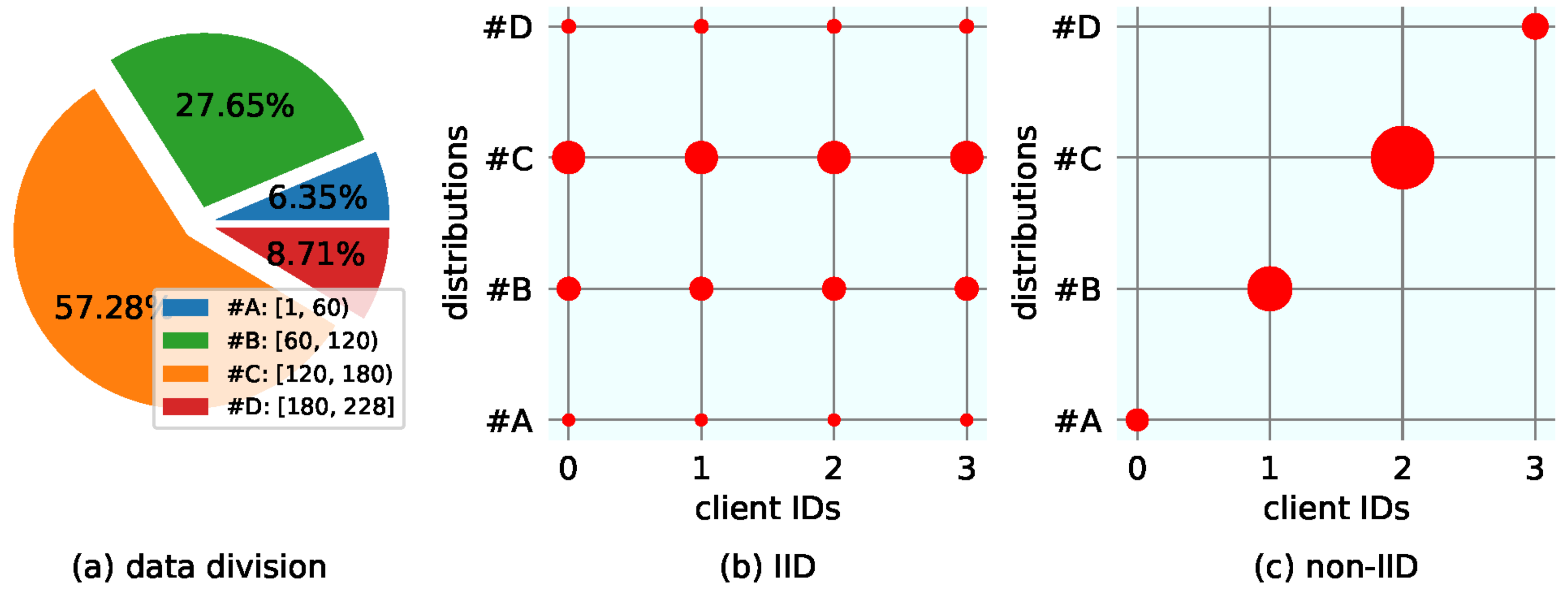

Figure 2: Details of experimental setup: (a) Training set was divided into four subsets with bone age values falling within four ranges. (b) Simulated independent and identically distributed (IID) setting. (c) Simulated non-IID setting. Size of each red circle is proportional to number of samples.

- Experimental setup
  - One central server and four local clients
  - IID and non-IID simulation (see Figure 2)
  - Model homogeneity (same local models) and model heterogeneity (different local models)

Formating four different settings

(1) homo-IID (2) homo-non-IID
(3) hetero-IID (4) hetero-non-IID

- Baselines
  - Centralization (centralization training)
  - FedAvg
  - FedAvgOneShot (averaging model weights after local training)
  - FLNoisyKD (using random noise images)
  - FedOneShot (using a proxy dataset)

Table 1: Quantitative comparison among different methods under four different settings. Centralization represents the upper-bound accuracy derived from centralized training. Results are reported as average (standard deviation) on test set based on three runs.

method	MAD (↓)			
centralization	10.15 (0.46)			
	homo-IID	homo-non-IID	hetero-IID	hetero-non-IID
FedAvg	11.68 (0.48)	36.80 (1.23)	-	-
FedAvgOneShot	62.15 (2.75)	68.35 (2.75)	-	-
FedNoisyKD	116.41 (1.78)	116.46 (1.57)	117.15 (2.07)	117.59 (2.44)
FedOneShot	59.92 (3.31)	**46.55 (1.69)**	**55.87 (2.67)**	**46.29 (1.10)**
Ours	**42.65 (4.40)**	49.49 (5.45)	58.52 (30.01)	52.60 (5.98)

Conclusions

- We made a first attempt to explore data-free one-shot FL in regression, and we show the efficacy of our method in this setting.

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