FedRE: A Representation Entanglement Framework for Model-Heterogeneous Federated Learning

Yuan Yao[1] Lixu Wang[2] Jiaqi Wu[3,†] Jin Song[4] Simin Chen[5] Zehua Wang[6] Zijian Tian[7] Wei Chen[8] Huixia Li[9] Xiaoxiao Li[6]

[1]Teleinfo, CAICT, [2]NTU, [3]THU, [4]NJUPT, [5]UTD, [6]UBC, [7]CUMTB, [8]CUMT, [9]BJTU

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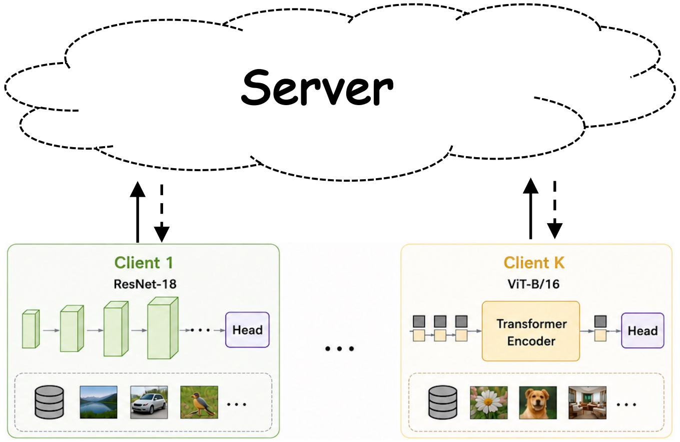
Problem Statement

Background: In practical federated learning, clients often adopt heterogeneous model architectures due to varying resources.



Setup: In model-heterogeneous FL settings, clients use different representation extractors but share a homogeneous classifier.

Problem: How to balance performance, privacy, and communication in model-heterogeneous FL?

Proposed Method：Motivation

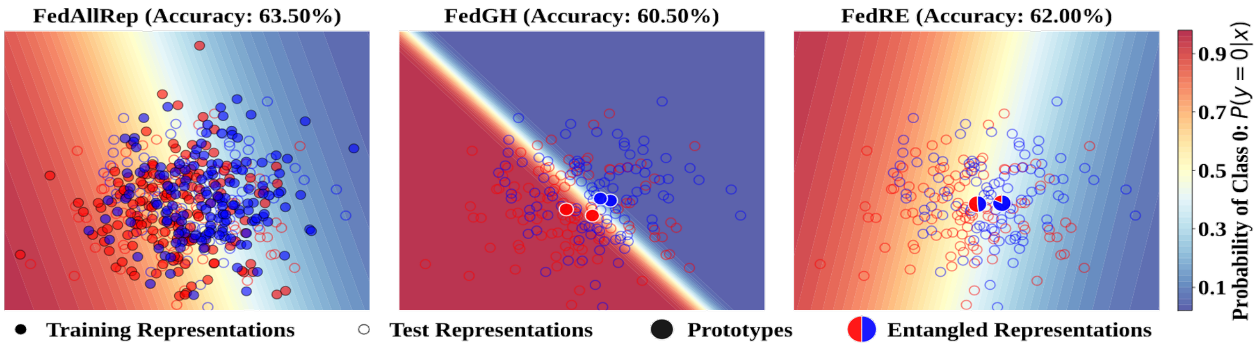


Figure 2. A toy experiment with 300 training and 200 test two-dimensional samples distributed across two clients. Red and blue indicate the predicted probabilities for classes 0 and 1, respectively, with darker shades representing higher confidence. FedAllRep uploads all 300 representations and achieves the best performance (63.50%). FedGH uploads 4 prototypes, resulting in sharper decision boundaries with abrupt color transitions and slightly lower performance (60.50%). FedRE uploads 2 entangled representations providing cross-category supervision, resulting in smoother decision boundaries with gradual color transitions and competitive performance (62.00%).

FedAllRep uploads all sample representations to the server to train the global classifier.

- ✅ Performance
- ❌ Privacy
- ❌ Communication

FedGH uploads class prototypes to the server to train the global classifier.

- ❌ Performance
- ✅ Privacy
- ✅ Communication

FedRE (ours) uploads entangled representations to the server to train the global classifier.

- ✅ Performance
- ✅ Privacy
- ✅ Communication

Proposed Method：Formulation & Workflow

Entangled Representation: $$\widetilde{\mathbf{r}}_k = \sum_{i=1}^{|\mathcal{D}_k|} w_i^k \mathrm{RM}\left[\boldsymbol{g}_k(\boldsymbol{\phi}_k; \mathbf{x}_i^k)\right]$$

Entangled-Label Encoding: $$\widetilde{\mathbf{y}}_k = \sum_{i=1}^{|\mathcal{D}_k|} w_i^k \mathbf{y}_i^k$$

Representation Mapping (RM):

- **Average Pooling (AP)**
- Max Pooling (MP)
- Fully Connection (FC)

Representation Entanglement (RE):

- Random Select Representation (RSR)
- Vanilla Average Representation (VAR)
- Random Average Representation (RAR)
- Random Select Prototype (RSP)
- Vanilla Average Prototype (VAP)
- **Random Average Prototype (RAP)**

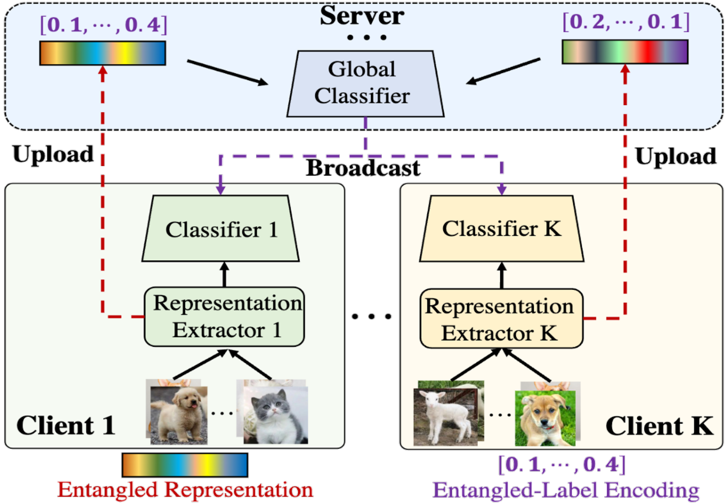


Figure 1. FedRE framework. Each client maintains a local model consisting of a representation extractor and a classifier. The client's local representations and their corresponding one-hot label encodings are integrated into a single entangled representation and entangled-label encoding, respectively, which are then uploaded to the server for training the global classifier.

Experiments: Performance

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Table 1. Accuracy (%) comparison on three datasets under the model-heterogeneous setting. In each column, the best results are **bolded**, and the second-best results are <u>underlined</u>.

Method	PRA			PAT			Average
	CIFAR-10	CIFAR-100	TinyImageNet	CIFAR-10	CIFAR-100	TinyImageNet	
LG-FedAvg [21]	80.90 ± 0.17	<u>41.96 ± 0.03</u>	25.16 ± 0.42	85.35 ± 0.25	<u>58.24 ± 0.33</u>	32.26 ± 0.28	53.98
FedGH [48]	78.66 ± 0.34	40.91 ± 0.26	25.04 ± 0.11	<u>85.43 ± 0.03</u>	58.07 ± 0.33	31.98 ± 0.29	53.35
FedKD [42]	80.79 ± 0.38	41.33 ± 0.25	25.39 ± 0.36	84.03 ± 0.17	55.61 ± 0.10	31.73 ± 0.20	53.15
FedGen [59]	81.16 ± 0.12	41.46 ± 0.10	25.45 ± 0.19	84.88 ± 0.18	57.87 ± 0.67	31.96 ± 0.21	53.80
FedProto [36]	78.36 ± 0.52	35.00 ± 0.34	18.16 ± 0.08	83.81 ± 0.18	56.72 ± 0.11	29.61 ± 0.02	50.28
FPL [11]	77.40 ± 0.23	36.66 ± 0.45	22.64 ± 0.46	83.89 ± 0.38	53.21 ± 0.25	29.16 ± 0.19	50.49
FedMRL [49]	81.28 ± 0.05	34.41 ± 0.04	20.92 ± 0.09	83.30 ± 0.41	54.25 ± 0.21	27.37 ± 0.10	50.26
FedTGP [56]	<u>81.32 ± 0.47</u>	35.89 ± 0.22	<u>28.70 ± 0.49</u>	84.68 ± 0.27	54.67 ± 1.34	<u>35.64 ± 0.37</u>	53.48
Local	81.20 ± 0.05	41.57 ± 0.10	25.81 ± 0.15	84.68 ± 0.07	57.96 ± 0.12	33.02 ± 0.14	<u>54.04</u>
FedRE	**82.60 ± 0.01**	**46.36 ± 0.09**	**30.48 ± 0.13**	**86.20 ± 0.14**	**62.56 ± 0.32**	**38.52 ± 0.08**	**57.79**

Table 11. Accuracy (%) comparison on three datasets in the model-homogeneous setting. In each column, the best results are **bolded**, and the second-best results are <u>underlined</u>.

Method	PRA			PAT			Average
	CIFAR-10	CIFAR-100	TinyImageNet	CIFAR-10	CIFAR-100	TinyImageNet	
LG-FedAvg [21]	<u>86.92 ± 0.25</u>	49.82 ± 0.39	<u>32.00 ± 0.13</u>	90.59 ± 0.17	66.00 ± 0.27	38.43 ± 0.23	<u>60.63</u>
FedAvg [25]	55.21 ± 0.12	30.37 ± 0.02	13.66 ± 0.41	52.70 ± 0.11	24.89 ± 0.20	9.98 ± 0.48	31.14
FedALA [55]	55.02 ± 0.14	29.89 ± 0.22	13.63 ± 0.10	52.83 ± 0.19	24.91 ± 0.15	10.65 ± 0.15	31.16
FedGH [48]	86.02 ± 0.17	48.59 ± 0.60	28.64 ± 0.26	90.46 ± 0.22	65.14 ± 0.26	32.40 ± 0.19	58.54
FedKD [42]	86.23 ± 0.12	<u>51.91 ± 0.28</u>	29.47 ± 0.31	90.01 ± 0.09	67.23 ± 0.38	35.34 ± 0.33	60.03
FedAvgDBE [54]	78.10 ± 0.20	35.23 ± 0.24	16.92 ± 0.52	82.27 ± 0.45	35.21 ± 0.27	16.80 ± 0.23	44.09
FedGen [59]	55.21 ± 0.14	29.90 ± 0.17	13.76 ± 0.23	52.37 ± 0.22	24.82 ± 0.38	10.67 ± 0.54	31.12
FedProto [36]	85.63 ± 0.22	50.52 ± 0.19	28.67 ± 0.17	<u>91.04 ± 0.16</u>	<u>69.28 ± 0.07</u>	34.75 ± 0.49	59.98
FPL [11]	83.60 ± 0.03	49.10 ± 0.21	26.87 ± 0.09	90.59 ± 0.06	67.31 ± 0.03	32.95 ± 0.23	58.40
FedMRL [49]	82.55 ± 0.31	48.41 ± 0.09	26.78 ± 0.05	89.02 ± 0.23	65.97 ± 0.21	35.22 ± 0.05	57.99
FedTGP [56]	85.59 ± 0.12	47.05 ± 0.17	30.89 ± 0.21	90.49 ± 0.03	67.47 ± 0.07	<u>40.88 ± 0.20</u>	60.40
Local	86.33 ± 0.11	49.88 ± 0.40	31.44 ± 0.15	90.54 ± 0.12	66.57 ± 0.17	37.46 ± 0.27	60.37
FedRE	**86.99 ± 0.01**	**52.12 ± 0.04**	**36.12 ± 0.21**	**91.06 ± 0.01**	**70.52 ± 0.17**	**42.45 ± 0.17**	**63.21**

PRA: Dirichlet partition (α=0.1)

PAT: Partial-class partition

Experiments: Privacy & Communication

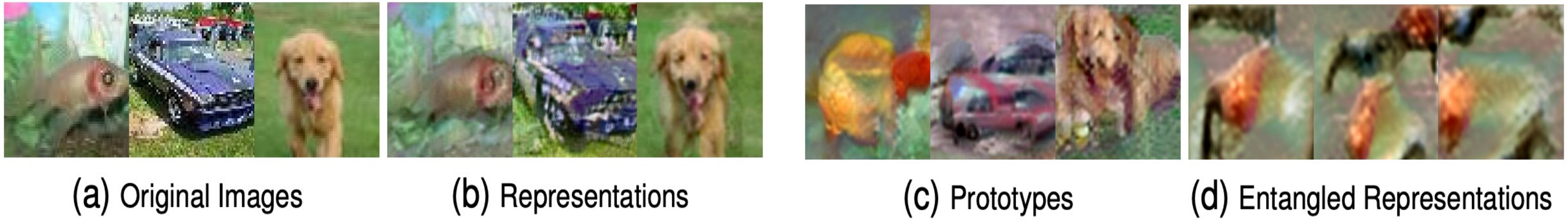

Figure 4. Comparison of privacy protection in restructuring results from **sample representations**, **class prototypes**, and **entangled representations** on the TinyImageNet dataset.

Table 2. Communication overhead (# Scalars $\times 10^3$) comparison on the CIFAR-100 dataset. In each row, the best results are **bolded**, and the second-best results are underlined.

Metric	LG-FedAvg	FedGH	FedKD	FedGen	FedProto	FedMRL	FedTGP	FPL	FedRE
Upload	513.00	<u>257.02</u>	4234.28	9247.08	<u>257.02</u>	8863.08	<u>257.02</u>	<u>257.02</u>	**5.12**
Broadcast	<u>513.00</u>	**512.00**	4234.28	<u>513.00</u>	**512.00**	8863.08	**512.00**	916.48	<u>513.00</u>

Thank you all for your time and participation!

Paper: https://arxiv.org/pdf/2511.22265

Code: https://github.com/AIResearch-Group/FedRE

Contact: yaoyuan.hitsz@gmail.com