Fengda ZHANG, Kun KUANG, Long CHEN, Zhaoyang YOU, Tao SHEN, Jun XIAO, Yin ZHANG, Chao WU, Fei WU, Yueting ZHUANG, Xiaolin LI, 2023. Federated unsupervised representation learning. *Frontiers of Information Technology & Electronic Engineering*, 24(8):1181-1193.
http://doi.org/10.1631/FITEE.2200268

Federated unsupervised representation learning

Key words: Federated learning; Unsupervised learning; Representation learning; Contrastive learning

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Motivation

1. Most of existing studies on federated learning focus on supervised learning. How to use the unlabeled data scattered in each node is an important problem.
2. An important challenge in decentralized unsupervised learning is the inconsistency of the representation space. Since the data distribution of different nodes is quite different, the spatial semantics encoded by different local models are different.
3. Another challenge with decentralized unsupervised learning is the misalignment of representations. Even though the spatial structures of different nodes are similar, there may be differences in location.

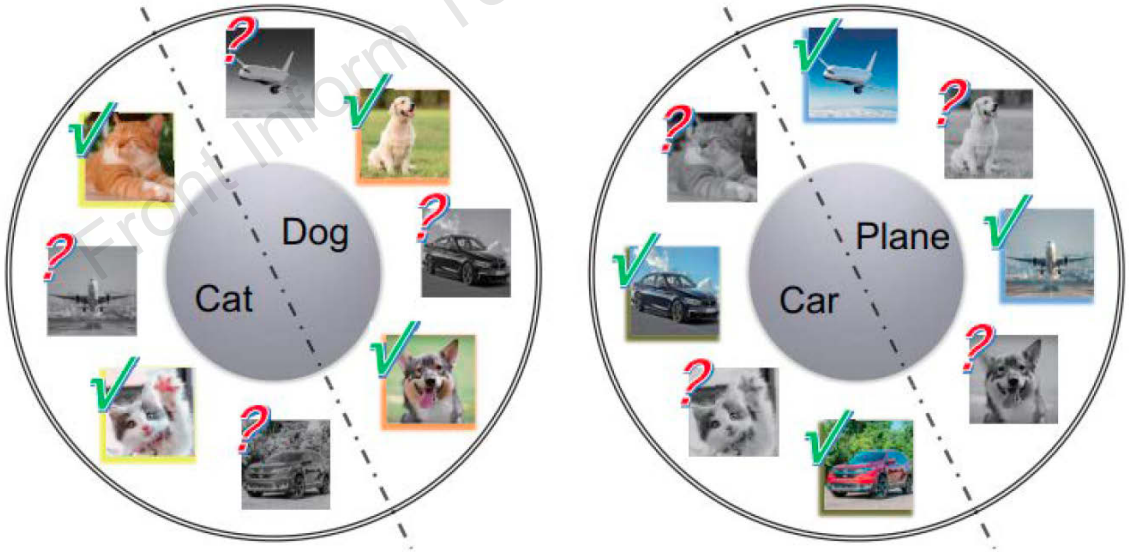
Main idea

1. We propose a new problem in federated learning called federated unsupervised representation learning (FURL) to learn a common representation model without supervision while preserving data privacy.
2. We introduce a dictionary module recording the historied data representations. The dictionary can be shared with all clients to solve the inconsistency of the representation space.
3. We propose an alignment module, which leverages a public model to encourage different local models to be aligned.

Challenge 1

Inconsistency of representation spaces

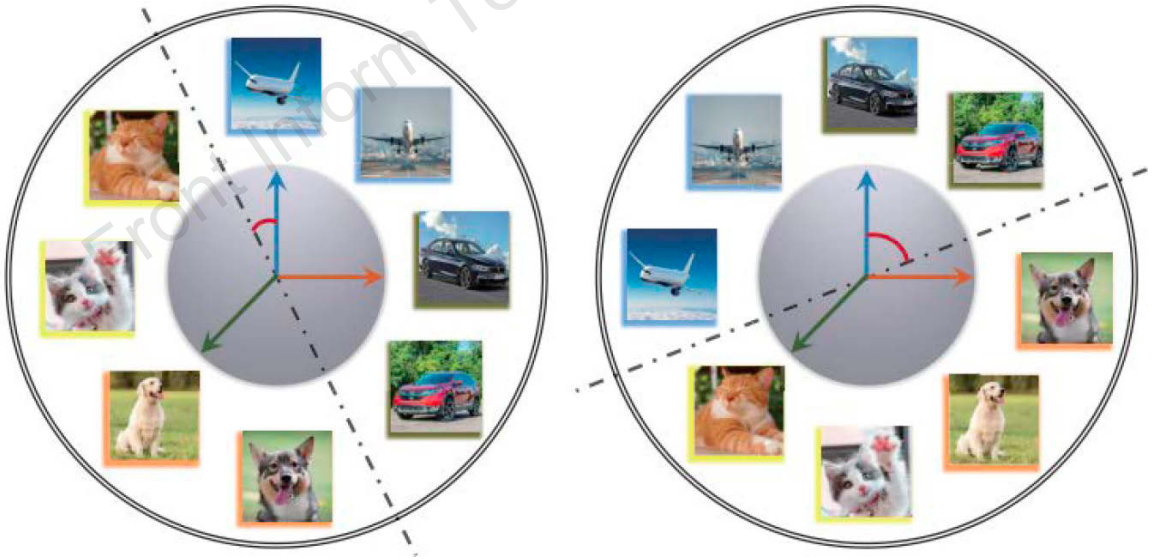
Different clients have different data. Then, the locally trained models encode different representation spaces. As a result, the performance of the global model aggregated by these inconsistent local models may fall short of expectations.



Challenge 2

Misalignment of representations

Even if the representation spaces encoded by different local models are consistent, there may be misalignment between representations due to randomness in the training process.



Method

To address these challenges, we propose a contrastive loss-based FURL algorithm called the federated contrastive averaging with dictionary and alignment (FedCA), which consists of two main novel modules: a dictionary module for addressing the inconsistency of representation spaces and an alignment module for aligning the representations across clients.

Specifically, the dictionary module, which is maintained by the server, aggregates the abundant representations of samples from clients, and these can be shared with each client for local model optimization.

In the alignment module, we first train a base model based on small public data, and then require all local models to mimic the base model such that the representations generated by different local models can be aligned.

Method (Cont'd)

Overall, in each round, FedCA involves two stages: (1) clients train local representation models on their own unlabeled data via contrastive learning with the two modules mentioned above, and then generate local dictionaries, and (2) the server aggregates the trained local models to obtain a shared global model and integrates the local dictionaries into a global dictionary.

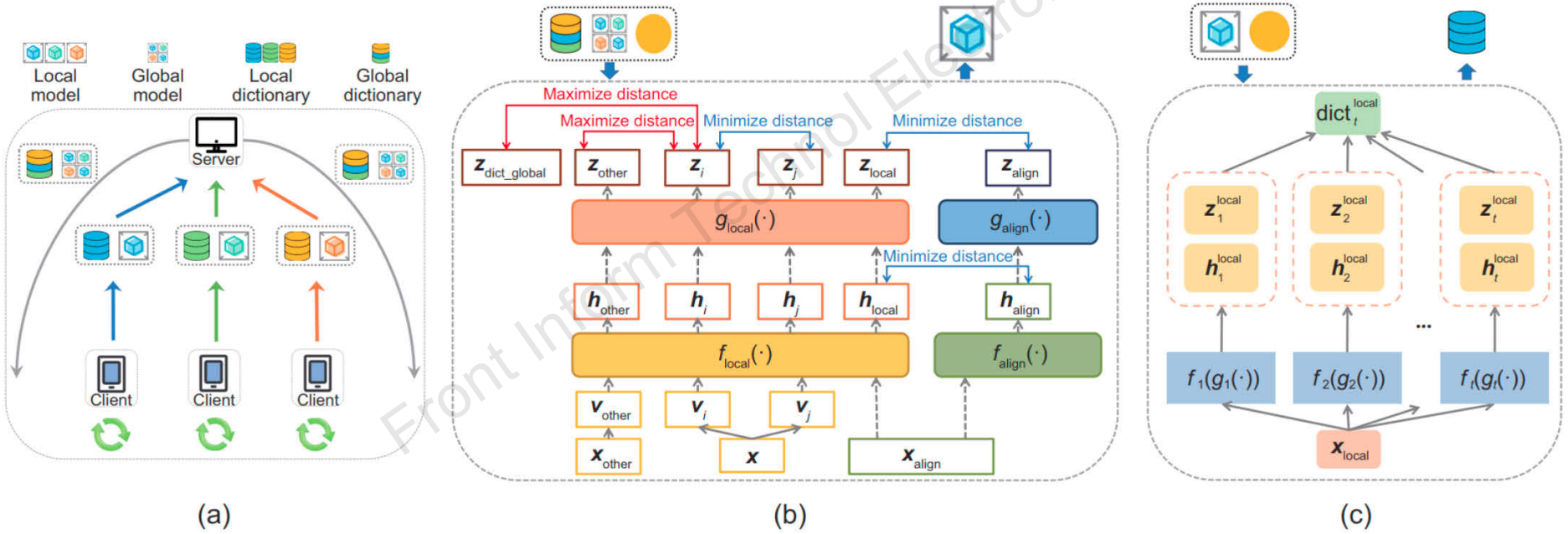


Fig. 3 Illustration of FedCA: (a) overview of FedCA (in each round, clients generate local models and dictionaries, and then the server gathers them to obtain the global model and dictionary); (b) local update of model (clients update local models by contrastive leaning with the dictionary and alignment modules); (c) local update of dictionary (clients generate local dictionaries via temporal ensembling). In (b), x_{other} is a sample different from sample x, x_{align} is a sample from the additional public dataset for alignment, f is the encoder, and g is the projection head

Major results

Dictionary module for inconsistency challenge

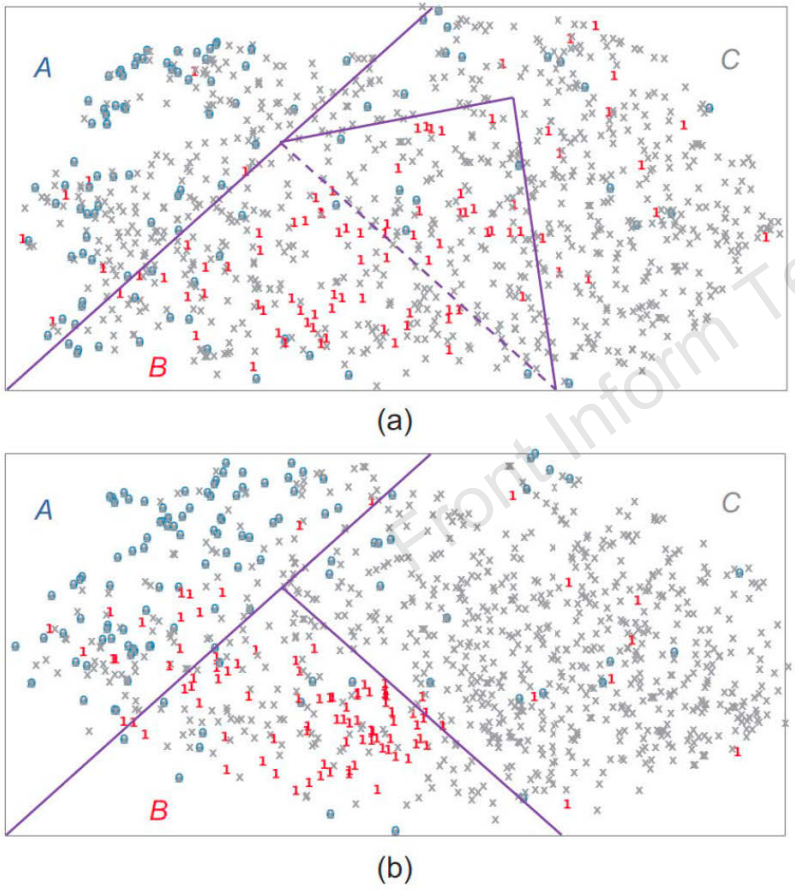
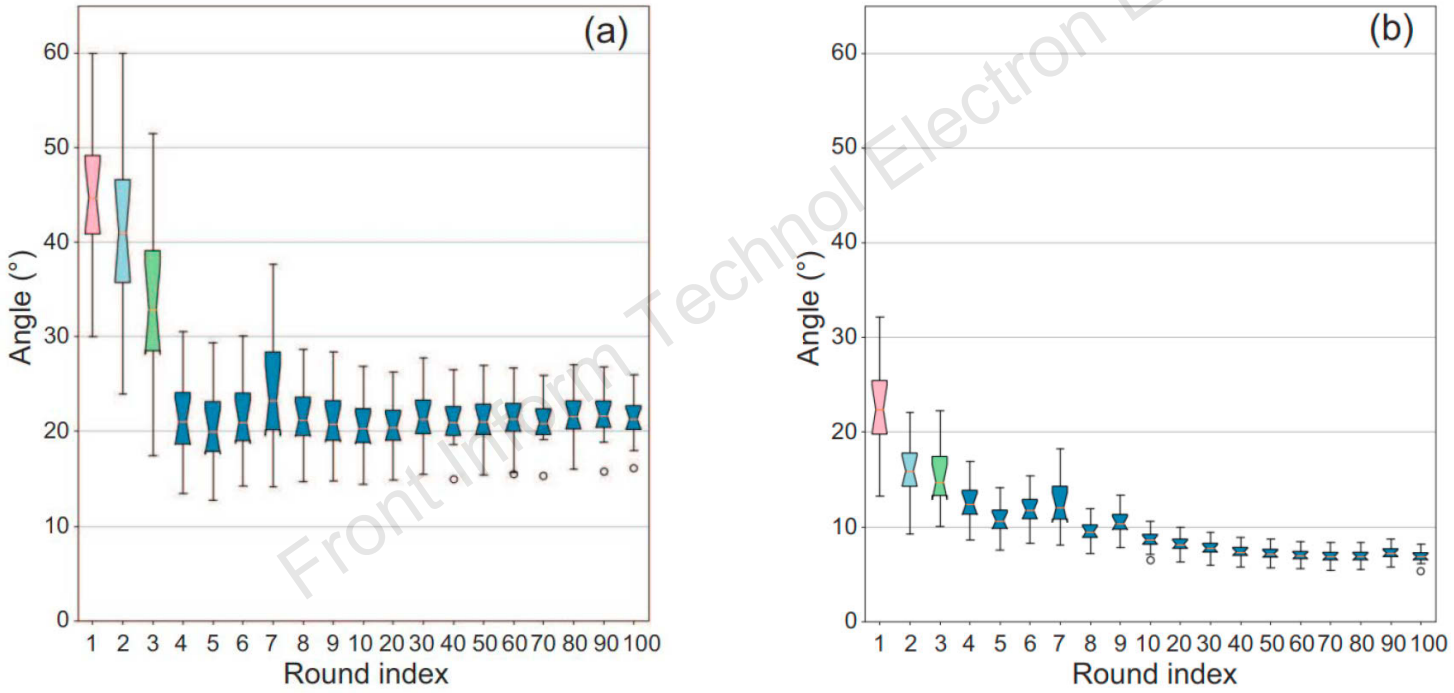


Fig. 2 *t*-distributed stochastic neighbor embedding (T-SNE) visualization results of representations on CIFAR-10. In federated learning (FL) with a non-independent and identically distributed (non-IID) setting, we use the local model of the client who has only samples of class 0 and class 1 to generate representations. We compare two methods: (a) vanilla federated unsupervised approach FedSimCLR (SimCLR is combined with FedAvg directly) and (b) FedCA (ours). A and B are the regions where representations of samples of class 0 and class 1 cluster, respectively, and C is the remaining region

Major results (Cont'd)

Alignment module for misalignment challenge



Box plots of the angles between the representations encoded by local models on the CIFAR-10 dataset in FL with an IID setting: (a) FedSimCLR; (b) FedCA. FL: federated learning; IID: independent and identically distributed

Major results (Cont'd)

Classification results

Table 2 Top-1 accuracies of algorithms for FURL on linear evaluation

Setting	Method	Accuracy (%)					
		CIFAR-10		CIFAR-100		MiniImageNet	
		Five-layer CNN	ResNet-50	Five-layer CNN	ResNet-50	Five-layer CNN	ResNet-50
IID	FedAE	61.23	65.47	34.07	36.56	28.21	31.97
	FedPR	55.75	63.52	29.74	30.89	24.76	26.63
	FedSimCLR	61.62	68.10	34.18	39.75	29.84	32.18
	FedCA (ours)	**64.87**	**71.25**	**39.47**	**43.30**	**35.27**	**37.12**
Non-IID	FedAE	60.14	63.74	33.94	37.27	29.00	30.44
	FedPR	54.94	60.31	30.70	32.39	24.74	25.91
	FedSimCLR	59.21	64.06	33.63	38.70	29.24	30.47
	FedCA (ours)	**63.02**	**68.01**	**38.94**	**42.34**	**34.95**	**35.01**

Values in bold are the best performance. FedAvg is combined with AutoEncoder (named FedAE), predicting rotation (named FedPR), and SimCLR (named FedSimCLR). CNN: convolutional neural network; FURL: federated unsupervised representation learning; IID: independent and identically distributed

Our method outperforms all of the baseline methods due to the modules designed for FURL

Conclusions

1. We formulate a significant and challenging problem, termed federated unsupervised representation learning (FURL), and show the two main challenges (inconsistency of representation spaces and misalignment of representations).

2. We propose a contrastive learning based FL algorithm named FedCA, composed of the dictionary module and alignment module, to tackle the above challenges.

3. Our experimental results demonstrate that FedCA outperforms those algorithms that combine solely FL with unsupervised approaches and provides a stronger baseline for FURL.

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