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Harnessing Feature Distribution Consistency for Federated Learning with Noisy Labels

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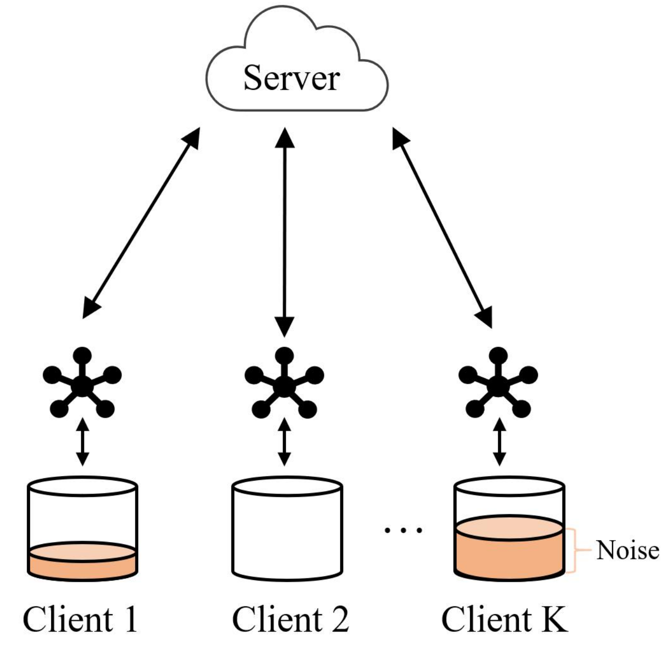
Background

Federated learning (FL) allows clients to train a generalized model without sharing local data, thereby effectively protecting client privacy. However, annotators may wrongly demarcate different categories due to a lack of experience or cognitive biases.

clients with noisy data

Local models are susceptible to interference from erroneous information, leading to a **decrease** in their generalization performance and **harming** the globally aggregated model.



Federated Learning with Noisy Labels

Related Work

- The **client-based methods** [1-3] recognize clean clients without any noisy labels and then utilize the model trained on clean clients to correct the labels of noisy clients. As clean clients are regarded as references for noisy label detection, these methods are inapplicable **in real-world scenarios where all the clients contain noisy labels.**

- Many **sample-based methods** [4-5] directly detect noisy labels. However, limited information is considered for noisy label detection, these methods are **less effective when labels are seriously poisoned**.

[1] Xu, Jingyi, et al. "Fedcorr: Multi-stage federated learning for label noise correction ".in CVPR 2022.
[2] Nannan Wu, Li Yu, et al. "Fednoro: Towards noise-robust fed-erated learning by addressing class imbalance and labelnoise heterogeneity" .in IJCAI 2023.
[3] Lu, Yang, et al. "Federated learning with extremely noisy clients via negative distillation. " in AAAI 2024.
[4] FedRN: Exploiting k-reliable neighbors towards robust federated learning. In CIKM 2022.
[5] Learning cautiously in federated learning with noisy and heterogeneous clients. In ICME 2023

Proposed Method

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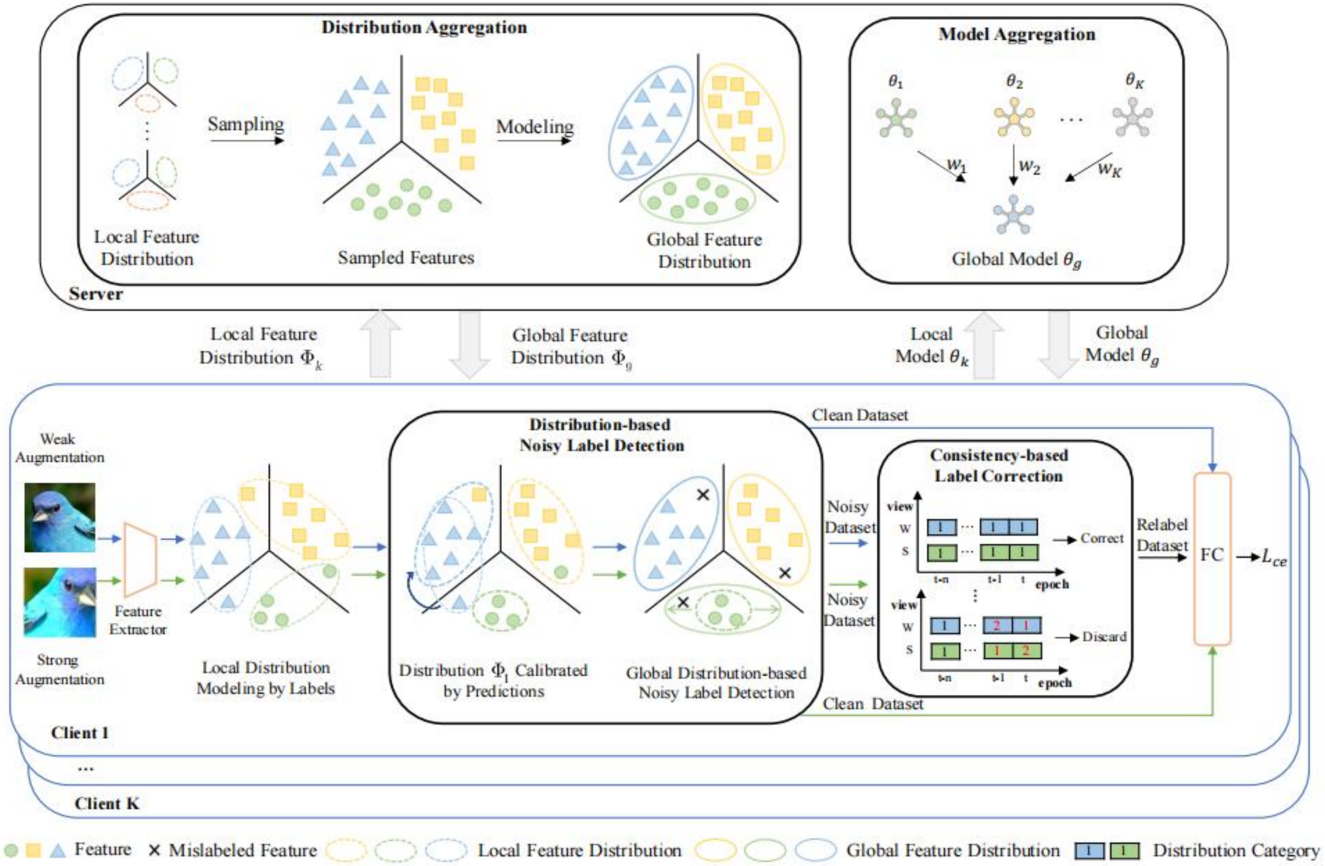
- We propose a distribution-based noisy label detection method, **FedFDC**, which enhances noisy label detection with the help of global feature distribution, thus improving the FL performance.

- We design a **TDC** mechanism to correct noisy labels in FL. It considers the consistency of the distributions to which the dual views belong and the continuity of label correction, thereby increasing sample utilization and improving reliability.



Experimental Setting

Datasets: We validate FedFDC on three classic benchmark datasets, which include two synthetic noisy label datasets: CIFAR-10 and CIFAR-100 , as well as one real-world noisy label dataset, Animal-10N .

Label Noise Settings: For CIFAR10 and CIFAR100 datasets, two widely-used corruption methods, symmetric flipping (Sym) and pair flipping (Pair), are applied to simulate the wrongly labeled cases. The images in Animal-10N are crawled from multiple online search engines, with a label noise rate of approximately 8%.

Experimental Results

Table 1: Test Accuracies (%) on the CIFAR10, CIFAR100 and Animal-10N datasets.

Dataset	CIFAR10				CIFAR100				Animal-10N
Sym Noise Ratio (η^l, η^u)	(0.3,0.5)		(0.5,0.7)		(0.3,0.5)		(0.5,0.7)		-
Noise Client Ratio ρ	0.5	1	0.5	1	0.5	1	0.5	1	-
FedAvg (AISTATS 2017)	82.52	62.69	75.63	38.67	53.26	34.73	45.97	18.36	72.99
RoFL (IEEE IS 2022)	83.88	79.37	80.04	61.16	55.20	41.44	48.41	22.95	72.23
FedRN (CIKM 2022)	90.12	85.46	85.77	54.77	60.74	46.89	55.39	26.82	74.00
FedCorr (CVPR 2022)	87.67	78.55	86.06	53.80	65.86	51.60	64.81	33.73	72.37
FedNoRo (IJCAI 2023)	89.76	66.94	89.77	45.13	58.17	37.31	56.06	24.30	72.87
FedNed (AAAI 2024)	86.87	63.52	86.63	38.78	55.11	35.17	52.67	18.20	72.55
Ours	**92.51**	**90.11**	**91.33**	**84.71**	**69.7**	**61.84**	**66.86**	**47.97**	**85.95**

Table 2: Test Accuracies (%) on CIFAR10, CIFAR100 with Pair label noise (η^l, η^u) = (0.3, 0.5) settings.

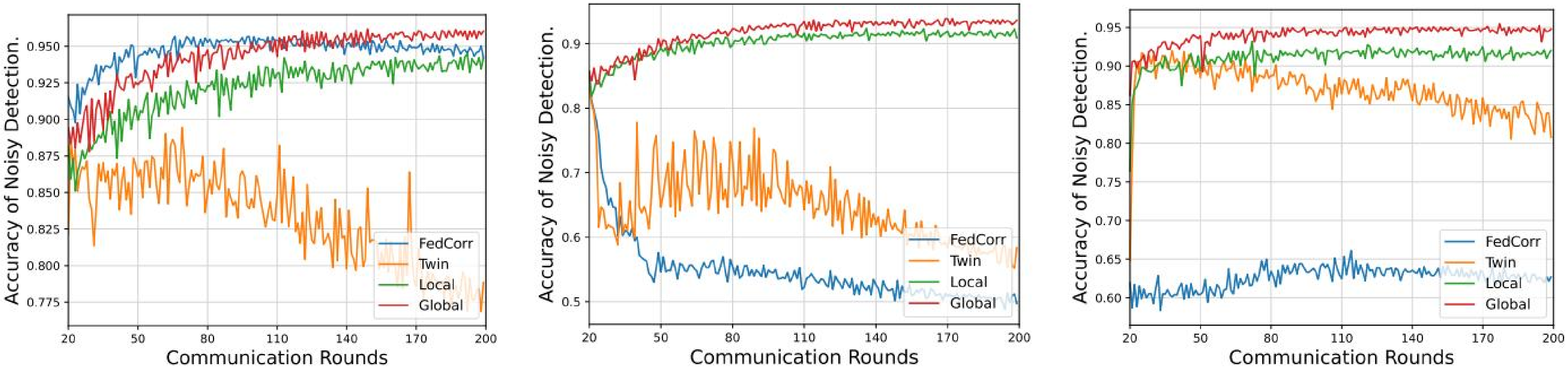
Dataset	CIFAR10		CIFAR100	
Noise Client Ratio ρ	0.5	1	0.5	1
FedAvg (AISTATS 2017)	83.38	58.67	57.36	38.19
RoFL (IEEE IS 2022)	83.88	78.04	56.48	40.58
FedRN (CIKM 2022)	86.47	61.82	63.64	38.72
FedCorr(CVPR 2022)	88.00	63.73	67.09	40.86
FedNoRo (IJCAI 2023)	90.73	60.79	62.05	37.58
FedNed (AAAI 2024)	87.96	60.17	60.25	37.69
Ours	**92.64**	**90.01**	**70.3**	**59.31**

Overall, FedFDC consistently achieves the best test accuracies across different noise levels for Sym and Pair noise types, with particularly significant outperformance in extremely noisy scenarios.

Ablation Study

Table 3: Ablation study of FedFDC with $\rho = 1$. *(CIFAR10: Sym label noise (0.5,0.7); CIFAR100: Pair label noise (0.3,0.5))*

Base	Dual-View	ND	NC	CIFAR10	CIFAR100
✓				38.67	38.19
✓	✓			47.33	44.18
✓		✓		70.36	50.63
✓	✓	✓		84.21	58.44
✓	✓	✓	✓	**84.71**	**59.31**



(a) $\rho = 1$, Sym label noise (0.3, 0.5)   (b) $\rho = 1$, Sym label noise (0.5, 0.7)   (c) $\rho = 1$, Pair label noise (0.3, 0.5)

Fig. 3: Accuracy of noisy label detection on CIFAR-10 datasets.

Thank you!

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