

FedDiv: Collaborative Noise Filtering for Federated Learning with Noisy Labels (Supplementary Document (abbr. Supp))

Jichang Li^{1,2}, Guanbin Li^{1,3*}, Hui Cheng⁴, Zicheng Liao^{2,5}, Yizhou Yu^{2*}

¹School of Computer Science and Engineering, Research Institute of Sun Yat-sen University in Shenzhen, Sun Yat-sen University, Guangzhou, China

²Department of Computer Science, The University of Hong Kong, Hong Kong

³Guangdong Province Key Laboratory of Information Security Technology

⁴UM-SJTU Joint Institute, Shanghai Jiao Tong University, Shanghai, China

⁵Zhejiang University, Hangzhou, China

csjcli@connect.hku.hk, liguanbin@mail.sysu.edu.cn, chenghui.123@sjtu.edu.cn
zichengliao@gmail.com, yizhouy@acm.org

In this supplementary material, we detail additional experimental setups encompassing data partitions, implementation specifics, and the baseline F-LNL methods. Furthermore, we provide further analysis of our proposed method, FedDiv. For a comprehensive understanding, we summarize the key notations of F-LNL and FedDiv in Table 7. Additionally, detailed training procedures of FedDiv and the specifics of local filter training are outlined in Algorithm 1 and Algorithm 2, respectively. To further enhance clarity, we present hyper-parameter summaries for each dataset in Table 8. Consistency in hyper-parameter settings is maintained across different label noise settings for both IID and non-IID data partitions on each dataset. It’s worth noting that all experiments are conducted on the widely-used PyTorch platform¹ and executed on an NVIDIA GeForce GTX 2080Ti GPU with 12GB memory.

Additional Experimental Setups

Non-IID data partitions. We employ Dirichlet distribution (Lin et al. 2020) with the fixed probability p and the concentration parameter α_{Dir} to construct non-IID data partitions. Specifically, we begin by introducing an indicator matrix $\Phi \in \mathbb{R}^{C \times K}$, and each entry Φ_{ck} determines whether the k -th client has samples from the c -th class. For every entry, we assign a 1 or 0 sampled from the Bernoulli distribution with a fixed probability p . For the row of the matrix Φ that corresponds to the c -th class, we sample a probability vector $q_c \in \mathbb{R}^{Q_c}$ from the Dirichlet distribution with a concentration parameter $\alpha_{Dir} > 0$, where $Q_c = \sum_k \Phi_{ck}$. Then, we assign the k' -th client a $q_{ck'}$ proportion of the samples that belong to the c -th category, where k' denotes the client index with $\Phi_{ck} = 1, k = 1, \dots, K$, and $\sum_{k'=1}^{|q_c|} q_{ck'} = 1$.

Additional Implementation Details. Similar to FedCorr (Xu et al. 2022), we select ResNet-18 (He et al. 2016), ResNet-34 (He et al. 2016) and Pre-trained

ResNet-50 (He et al. 2016) as the network backbones for CIFAR-10, CIFAR-100 and Clothing1M, respectively. During the local model training sessions, we train each local client model over $T = 5$ local training epochs per communication round, using an SGD optimizer with a momentum of 0.5 and a mini-batch size of 10, 10, and 16 for CIFAR-10, CIFAR-100, and Clothing1M, respectively. For each optimizer, we set the learning rate as 0.03, 0.01, and 0.001 on CIFAR-10, CIFAR-100, and Clothing1M, respectively. In addition, during data pre-processing, the training samples are first normalized and then augmented by hiring random horizontal flipping and random cropping with padding of 4. For most thresholds conducted on the experiments, we set them to default as in FedCorr (Xu et al. 2022), e.g. $\delta_k = 0.1$ in Eq. (11), the probability of a sample being clean/noisy = 0.50 in Eq. (7), $\xi = 0.5$ in Eq. (9), etc. Additionally, we determine ζ in Eq. (8) using a small validation set, where $\zeta = 0.70$ meets the peak of validation accuracies.

Baselines. We compare FedDiv with existing state-of-the-art (SOTA) F-LNL methods, including FedAvg (McMahan et al. 2017), FedProx (Li et al. 2020), RoFL (Yang et al. 2022), ARFL (Yang et al. 2022), JointOpt (Tanaka et al. 2018), DivideMix (Li, Socher, and Hoi 2019), FedCorr (Xu et al. 2022), borrowing the reported experimental results from (Xu et al. 2022). Specifically, FedAvg and FedProx are both classic FL algorithms, while RoFL, ARFL and FedCorr are three existing F-LNL methods. Besides, DivideMix and JointOpt are two exiting representative C-LNL algorithms, which are adapted by FedCorr into the FL scenarios.

How to set ω , \mathcal{T} and \mathcal{T}_{wu} . In this work, we streamlined the multi-stage F-LNL process proposed in FedCorr (Xu et al. 2022) into a one-stage process, avoiding the complexity of executing multiple intricate steps across different stages as in FedCorr. However, for fair comparisons, we maintained an equivalent number of communication rounds as in FedCorr. This totals \mathcal{T}_{wu} , encompassing federated pre-processing from FedCorr’s training iterations, and \mathcal{T} , covering both federated fine-tuning and usual training stages

*Corresponding Authors are Guanbin Li and Yizhou Yu.

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¹<https://pytorch.org/>

Symbol	Definition
t	Current communication round
\mathcal{M}	Collection of all clients
\mathcal{S}	Collection of randomly selected clients at current round
k	Current index from the client randomly selected from \mathcal{M} or \mathcal{S}
\mathcal{D}_k	Given local samples for client k
$\mathcal{D}_k^{\text{clean}}$	Clean samples classified from \mathcal{D}_k
$\mathcal{D}_k^{\text{noisy}}$	Noisy samples classified from \mathcal{D}_k
$\mathcal{D}_k^{\text{relab}}$	Relabeled samples produced from $\mathcal{D}_k^{\text{noisy}}$
$\hat{\mathcal{D}}_k$	Obtained labeled samples with higher reliability generated by PCS
δ_k	Actual noise level at client k
$\hat{\delta}_k$	Estimated noise level at client k
$\theta^{(t)}$	Global network parameters at round t
$\hat{\theta}_k^{(t)}$	Local network parameters being optimized during local training for client k at round t
$\theta_k^{(t)}$	Local network parameters for client k at round t
$\mathcal{W}^{(t)}$	Global filter parameters for client k at round t
\mathcal{W}_k	Server-cached local filter parameters for client k
$\mathcal{W}_k^{(t)}$	Local filter parameters for client k obtained at round t
\hat{p}_k	Overall bias of the local model for client k w.r.t all classes

Table 7: Key notations of F-LNL and FedDiv.

involving FedCorr. Notably, within \mathcal{T}_{wu} , we solely utilize standard cross-entropy loss to warm up the local neural network models for faster convergence.

Below, we will begin by introducing the multi-stage F-LNL pipeline proposed by FedCorr, followed by an analysis of fraction scheduling and the construction of the training rounds of FedDiv.

- **FedCorr.** FedCorr comprises three FL stages: federated pre-processing, federated fine-tuning, and federated usual training. During the pre-processing stage, the FL model is initially pre-trained on all clients for \mathcal{T}_{wu} iterations (not training round) to guarantee initial convergence of model training. At the same time, FedCorr evaluates the quality of each client’s dataset and identifies and relabels noisy samples. After this stage, a dimensionality-based filter (Ma et al. 2018) is proposed to classify clients into clean and noisy ones. In the federated fine-tuning stage, FedCorr only fine-tunes the global model on relatively clean clients for \mathcal{T}_{ft} rounds. At the end of this stage, FedCorr re-evaluates and relabels the remaining noisy clients. Finally, in the federated

Hyper-parameter	CIFAR-10	CIFAR-100	Clothing1M
# of clients (K)	100	50	500
# of classes (C)	10	100	14
# of samples	50,000	50,000	1,000,000
Architecture	ResNet-18	ResNet-34	Pre-trained ResNet-50
Mini-batch size	10	10	16
Learning rate	0.03	0.01	0.001
\mathcal{T}_{wu}	5	10	2
\mathcal{T}_{ft}	500	450	50
\mathcal{T}_{ut}	450	450	50
\mathcal{T}	950	900	100
T	5	5	5
ω	0.1	0.1	0.02

Table 8: Hyper-parameters on different datasets.

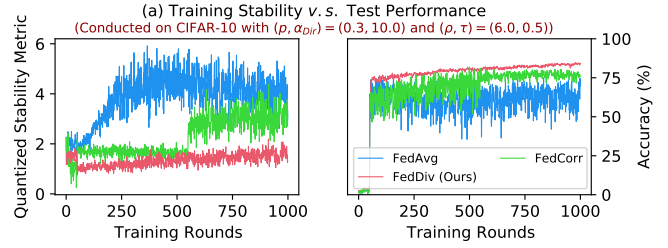


Figure 4: The evolution of quantized training stability v.s. test classification performance across epochs for various F-LNL algorithms. We quantitatively assess training stability in F-LNL by computing the average proximal regularization metric (Li et al. 2020; Xu et al. 2022) between the weights of local and global neural network models in the current training round.

usual training stage, the global model is trained over \mathcal{T}_{ut} rounds using FedAvg (McMahan et al. 2017) on all the clients, incorporating the labels corrected in the previous two training stages.

- **Fraction scheduling and communication rounds of FedDiv.** During FL training, a fixed fraction of clients will be selected at random to participate in local model training at the beginning of each round. Here, we set a fraction parameter ω to control the fraction scheduling, which is the same as the fine-tuning and usual training stages in FedCorr. However, during the pre-processing stage of FedCorr, every client must participate in local training exactly once in each iteration. Hence, any one client may be randomly sampled from all the clients with a probability of $\frac{1}{K} \cdot 100\%$ to participate in local model training, without replacement. As three stages of FedCorr have been merged into one in FedDiv, to ensure fairness in training, we convert the training iterations of the pre-processing stage into the training rounds we used, which gives us the corresponding training rounds $\mathcal{T}'_{wu} = (\mathcal{T}_{wu} \times K) / (w \times K) = \mathcal{T}_{wu} / w$. Therefore, in our work, the total number of communication rounds in the entire training process is $\mathcal{T}'_{wu} + \mathcal{T}$, where $\mathcal{T} = \mathcal{T}_{ft} + \mathcal{T}_{ut}$.

Algorithm 1: The training procedure of FedDiv

Input: $\mathcal{M}; \{\mathcal{D}_k | k \in \mathcal{M}\}; \mathcal{T}; T; \omega$; Initialized $\theta^{(0)}$; Initialized $\mathcal{W}^{(0)}$; Initialized $\{\mathcal{W}_k | k \in \mathcal{M}\}$; Initialized $\{\hat{p}_k | k \in \mathcal{M}\}$

Output: Global network model $\theta^{(T)}$

```

1: for  $k \in \mathcal{M}$  do
2:    $[k] \leftarrow (\mathcal{D}_k, \hat{p}_k)$  ▷ Packaging
3: end for
4: /* Warm-Up Stage */
5: for  $t = 1$  to  $\mathcal{T}_{wu}$  do
6:   Warm up  $\theta^{(t)}$  for each client  $k \in \mathcal{M}$ 
7: end for
8: /* Model-Train Stage */
9: for  $t = 1$  to  $T$  do
10:   $\mathcal{S} \leftarrow$  Randomly select  $\omega \times 100\%$  clients from  $\mathcal{M}$ 
11:  for  $k \in \mathcal{S}$  do
12:     $(\mathcal{D}_k, \hat{p}_k) \leftarrow [k]$  ▷ Unpackaging
13:    Obtain  $\mathcal{D}_k^{\text{clean}}$  and  $\mathcal{D}_k^{\text{noisy}}$  via the federated noise filter model  $\mathcal{W}^{(t)}$  using Eq. (7)
14:    Estimate  $\hat{\delta}_k = |\mathcal{D}_k^{\text{noisy}}|/|\mathcal{D}_k|$ 
15:    Obtain  $\mathcal{D}_k^{\text{relabel}}$  using Eq. (8)
16:     $\hat{\theta}_k^{(t)} \leftarrow \theta^{(t)}$ 
17:    for  $t' = 1$  to  $T$  do
18:      Obtain  $\hat{\mathcal{D}}_k$  using Eqs. (9), (10), (11)
19:      Optimize  $\hat{\theta}_k^{(t')}$  using Eq. (15)
20:    end for
21:     $\theta_k^{(t)} \leftarrow \hat{\theta}_k^{(t)}$ 
22:    Update  $\hat{p}_k^{(t)}$  using Eq. (12)
23:    Update  $[k] \leftarrow (\mathcal{D}_k, \hat{p}_k^{(t)})$  ▷ Repackaging
24:    Obtain the local filter parameters  $\mathcal{W}_k^{(t)}$  using Algorithm 2
25:    Upload  $\theta_k^{(t)}$  and  $\mathcal{W}_k^{(t)}$  to the server
26:  end for
27:  Update the network  $\theta^{(t+1)}$  using Eq. (1)
28:  for  $k \in \mathcal{S}$  do
29:     $\mathcal{W}_k \leftarrow \mathcal{W}_k^{(t)}$ 
30:  end for
31:  Update the global filter  $\mathcal{W}^{(t+1)}$  using Eq. (5)
32: end for

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Additional Analysis

Quantized training stability. To better grasp the motivation behind this approach, we propose using “Quantized training stability” to quantify the impact of data heterogeneity and noise heterogeneity (Kim et al. 2022; Yang et al. 2022) on the training instability experienced during local training sessions. Technically, quantized training stability can be measured by the average proximal regularization metric between local and global model weights, denoted as $\theta_k^{(t)}$ and $\theta^{(t)}$ respectively, at round t . This is calculated by $\frac{1}{|\mathcal{S}|} \sum_{k \in \mathcal{S}} |\theta_k^{(t)} - \theta^{(t)}|^2$. As depicted in Figure 4, this instability results in notable discrepancies in weight divergence between local and global models, potentially hindering the performance enhancement of the aggregated model if left unaddressed. Additionally, considering the efficacy of different noise filtering strategies, our proposed federated noise filtering demonstrates superior performance in label noise

Algorithm 2: Local filter training

Input: $\mathcal{D}_k; \theta_k^{(t)}; \mathcal{W}^{(t)}$

Output: Optimal local filter parameters $\mathcal{W}_k^{(t)}$

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1: Initialize  $\mathcal{W}_k^{(t)} = (\mu_k^{(t)}, \sigma_k^{(t)}, \pi_k^{(t)})$  using  $\mathcal{W}^{(t)}$ 
2: while  $\mathcal{W}_k^{(t)}$  is not converged do
3:   /* E step: */
4:    $\gamma_{kg}(x, y; \theta_k^{(t)}) = \frac{\pi_{kg}^{(t)} \cdot \mathcal{N}(\ell(x, y; \theta_k^{(t)}); \mu_{kg}^{(t)}, \sigma_{kg}^{(t)})}{\sum_{g'=1}^2 \pi_{kg'}^{(t)} \cdot \mathcal{N}(\ell(x, y; \theta_k^{(t)}); \mu_{kg'}^{(t)}, \sigma_{kg'}^{(t)})}$ 
5:   /* M step: */
6:    $\mu_{kg}^{(t)} = \frac{\sum_{(x, y) \in \mathcal{D}_k} \gamma_{kg}(x, y; \theta_k^{(t)}) \cdot \ell(x, y; \theta_k^{(t)})}{\sum_{(x, y) \in \mathcal{D}_k} \gamma_{kg}(x, y; \theta_k^{(t)})}$ 
7:    $\sigma_{kg}^{(t)} = \frac{\sum_{(x, y) \in \mathcal{D}_k} \gamma_{kg}(x, y; \theta_k^{(t)}) \cdot [\ell(x, y; \theta_k^{(t)}) - \mu_{kg}^{(t)}]^2}{\sum_{(x, y) \in \mathcal{D}_k} \gamma_{kg}(x, y; \theta_k^{(t)})}$ 
8:    $\pi_{kg}^{(t)} = \frac{\sum_{(x, y) \in \mathcal{D}_k} \gamma_{kg}(x, y; \theta_k^{(t)})}{n_k}$ 
9: end while

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identification per client, leading to decreased training instability during local training sessions and thus achieving higher classification performance of the aggregated model.

Further evaluation of federated noise filtering. To further verify the capability of our proposed label noise filtering strategy, we again compare FedDiv with FedDiv(Local filter) and FedDiv(Degraded) in Figure 5 and Figure 6. Both experiments are conducted on CIFAR-100 with the noise setting $(\rho, \tau) = (0.4, 0.5)$ for the IID data partition. Specifically, Figure 5 shows the accuracy of label noise filtering over all 50 clients at different communication rounds, while Figure 6 provides two examples to illustrate the noise filtering performance of different noise filters on clean and noisy clients.

As depicted in both Figure 5 and Figure 6, the proposed strategy consistently produces stronger label noise filtering capabilities on the vast majority of clients than the alternative solutions. Additionally, Figure 5 also shows that all these three noise filtering schemes significantly improve the label noise identification performance as model training proceeds, especially on clean clients—possibly because the network model offers greater classification performance—but ours continues to perform the best. These results once again highlight the feasibility of our proposed noise filtering strategy.

Further evaluation of filtering, relabeling and re-selection. To emphasize each FedDiv thread’s effectiveness in label noise filtering, noisy sample relabeling, and labeled sample re-selection, we compare confusion matrices before processing, after label noise filtering and noisy sample relabeling (Thread 1), and after labeled sample re-selection (Thread 2) in Figure 7. Figure 7 displays heat maps of these three confusion matrices on five representative clients. On clean or noisy clients with varying noise levels, each thread gradually eliminates label noise, confirming the performance of each FedDiv component.

Hyper-parameter sensitivity. We analyze hyper-parameter sensitivity to the confidence threshold ζ . As shown in Figure 8, the proposed approach consistently achieves higher

M-(#)	Dataset Noise level (ρ, τ) Method (ρ, a_{dir})	CIFAR-10		CIFAR-100		Mean
		(0.8, 0.0)	(0.6, 0.5)	(0.8, 0.5)	(0.4, 0.0)	
1	FedCorr§	91.52±0.50	81.57±3.68	59.10±5.12	72.73±1.02	76.23/75.31§
2	FedDiv (Ours)§	92.98±0.60	85.31±2.28	65.49±2.20	74.47±0.34	79.56/79.24§
3	FedCorr w/ \mathcal{L}_{ce}	90.17	79.36	57.42	70.70	74.41
4	FedDiv w/ \mathcal{L}_{ce}	91.78	84.40	64.02	73.68	78.47
5	FedDiv w/ \mathcal{L}_{reg}	92.47	-	61.94	-	77.21‡
6	FedCorr w/ “flip”	78.98	-	38.75	-	58.86‡
7	FedDiv w/ “flip”	86.46	-	56.81	-	71.63‡
8	FedCorr w/ “biased”	93.51	83.62	-	-	-
9	FedDiv w/ “biased”	95.22	90.45	-	-	-

Table 9: Additional ablation study results. § denotes their results derived from Table 6, while ‡ indicates the mean calculated under IID partition only. \mathcal{L}_{ce} , the cross-entropy loss, is used to replace \mathcal{L}_{mix} in both FedDiv and FedCorr.

classification performance when ζ is set to 0.75. Therefore, $\zeta = 0.75$ is an excellent choice for setting the confidence threshold for noisy sample relabeling when training the FL model on CIFAR-10 and CIFAR-100 under different label noise settings for both IID and non-IID data partitions.

Analysis on \mathcal{L}_{mix} and \mathcal{L}_{reg} . In Table 9, replacing \mathcal{L}_{mix} with \mathcal{L}_{ce} (M-(3) and M-(4)) led to significantly reduced performance in both FedCorr and our FedDiv. We also applied \mathcal{L}_{reg} under the IID partition (M-(5)), which does not meaningfully improve performance but instead decreases average accuracy by 2.03% compared to M-(2).

Evaluation of FedDiv on class-biased label noise. To conduct experiments with class-biased label noise, we follow “asymmetric noise” from (Li, Socher, and Hoi 2019) to achieve this. Specifically, while keeping other settings unchanged, on each noisy client, only $u \times 100\%$ (i.e. $u \sim U(\tau, 1)$ in Eq. (16)) of labels from samples belonging to candidate classes are replaced with similar classes (i.e. deer→horse, dog↔cat). As shown in Table 9, both FedCorr (M-(8)) and FedDiv (M-(9)) significantly improve their performance in this setting, possibly due to the quantity of label noise among their clients greatly reduced. Under non-IID data partition, our FedDiv markedly achieves more performance gains than FedCorr. This is possibly due to the significant efforts our method makes to mitigate local model bias towards certain classes and to address data heterogeneity.

Evaluation of FedDiv on malicious clients with label flipping attacks. To achieve this, we conduct experiments under IID partitions only, where $\rho \times 100\%$ of clients are first chosen as malicious clients, on each of which labels of 50% samples are then randomly replaced with other classes. Here “ τ ” is invalid. M-(6) and M-(7) in Table 9 illustrate that FedDiv achieves higher accuracy than FedCorr when applied in the presence of malicious attacks. This showcases, confronted with label flipping attacks, FedDiv exhibits greater robustness compared to FedCorr.

References

He, K.; Zhang, X.; Ren, S.; and Sun, J. 2016. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, 770–778.

Kim, S.; Shin, W.; Jang, S.; Song, H.; and Yun, S.-Y. 2022.

FedRN: Exploiting k-Reliable Neighbors Towards Robust Federated Learning. *arXiv preprint arXiv:2205.01310*.

Li, J.; Socher, R.; and Hoi, S. C. 2019. DivideMix: Learning with Noisy Labels as Semi-supervised Learning. In *International Conference on Learning Representations*.

Li, T.; Sahu, A. K.; Zaheer, M.; Sanjabi, M.; Talwalkar, A.; and Smith, V. 2020. Federated optimization in heterogeneous networks. *Proceedings of Machine Learning and Systems*, 2: 429–450.

Lin, T.; Kong, L.; Stich, S. U.; and Jaggi, M. 2020. Ensemble distillation for robust model fusion in federated learning. *Advances in Neural Information Processing Systems*, 33: 2351–2363.

Ma, X.; Wang, Y.; Houle, M. E.; Zhou, S.; Erfani, S.; Xia, S.; Wijewickrema, S.; and Bailey, J. 2018. Dimensionality-driven learning with noisy labels. In *International Conference on Machine Learning*, 3355–3364. PMLR.

McMahan, B.; Moore, E.; Ramage, D.; Hampson, S.; and y Arcas, B. A. 2017. Communication-efficient learning of deep networks from decentralized data. In *Artificial intelligence and statistics*, 1273–1282. PMLR.

Tanaka, D.; Ikami, D.; Yamasaki, T.; and Aizawa, K. 2018. Joint optimization framework for learning with noisy labels. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, 5552–5560.

Xu, J.; Chen, Z.; Quek, T. Q.; and Chong, K. F. E. 2022. FedCorr: Multi-Stage Federated Learning for Label Noise Correction. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 10184–10193.

Yang, S.; Park, H.; Byun, J.; and Kim, C. 2022. Robust federated learning with noisy labels. *IEEE Intelligent Systems*, 37(2): 35–43.

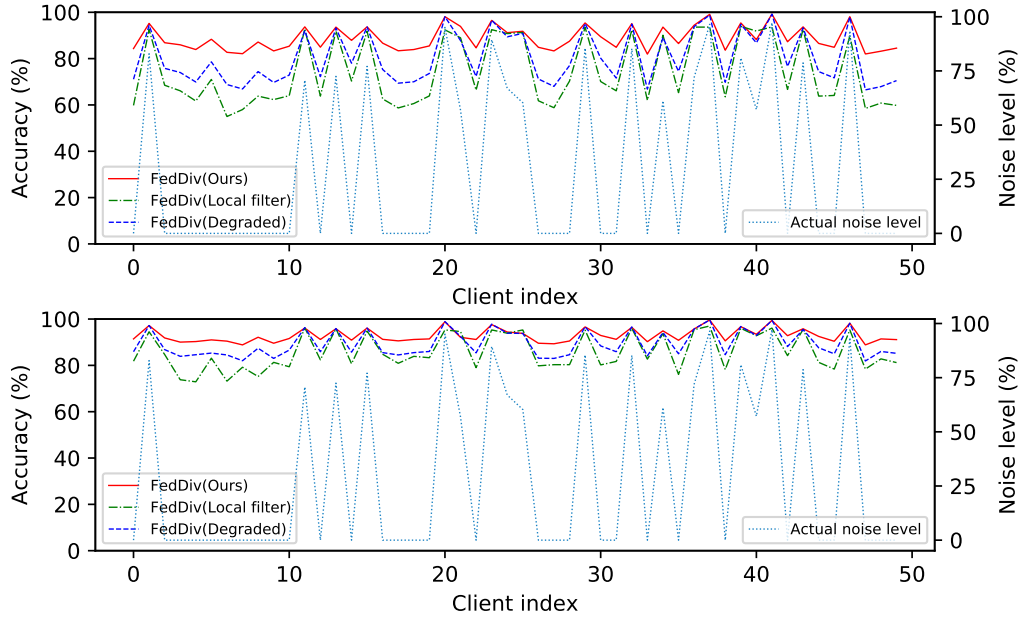


Figure 5: The accuracy of noisy label identification vs. different clients. The lightblue dotted line represents the actual noise level of each client, while the (dotted) lines in deep bright colors indicate the noise filtering performance with respect to different noise filters. The experiment is conducted on CIFAR-100 with the IID data partition under the noise setting $(\rho, \tau) = (0.4, 0.5)$. TOP: Evaluation in the 50-th communication round of the usual training stage; BOTTOM: Evaluation in the 500-th communication round of the usual training stage.

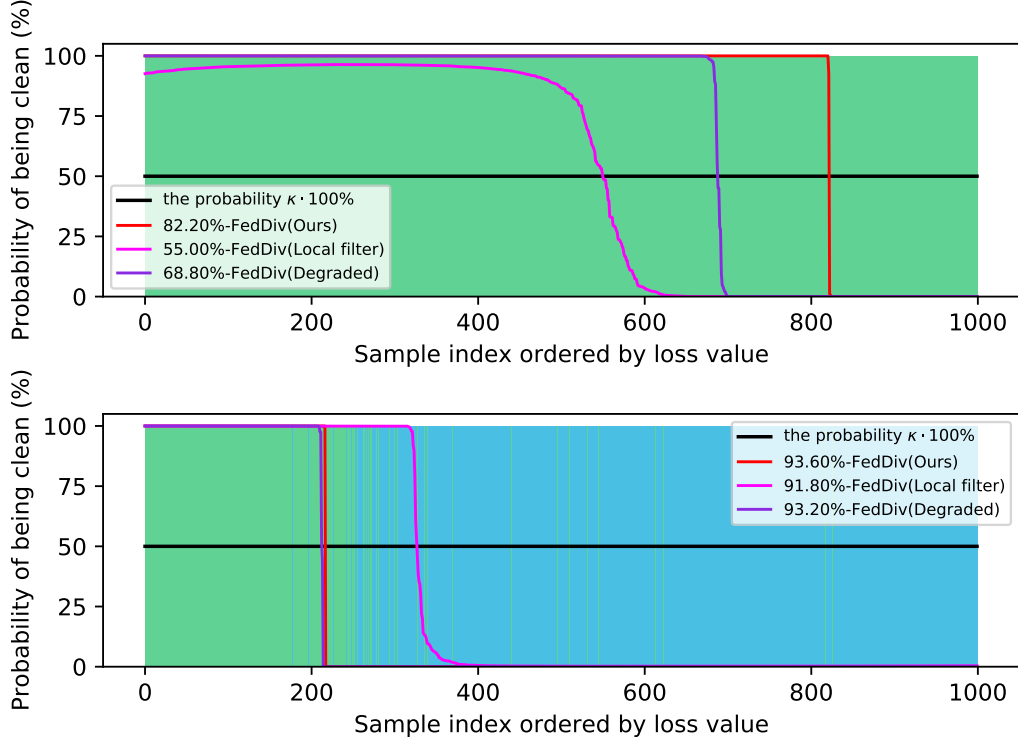


Figure 6: Two examples to illustrate the performance of three noise filters to identify label noise on a clean client (with the lowest accuracy of label noise filtering) and a noisy client. We show the probability distributions of samples being clean predicted by each filter, with the samples ranked according to the per-sample loss function values. In the legend, the percentages show the accuracy of noisy label identification with respect to each filter. In addition, as illustrated by the black line, a sample that is considered clean should have a predicted probability higher than $\kappa \cdot 100\%$. Furthermore, the green and blue bars represent, respectively, the distribution of the given **clean** and **noisy** samples. The evaluation is performed at the end of the 50-th communication round in the usual federated training stage. The experiment is conducted on CIFAR-100 with the IID data partition under the noise setting $(\rho, \tau) = (0.4, 0.5)$. TOP: Evaluation on the clean client; BOTTOM: Evaluation on the noisy client with $\delta = 0.725$. (**Best viewed zoomed in.**)

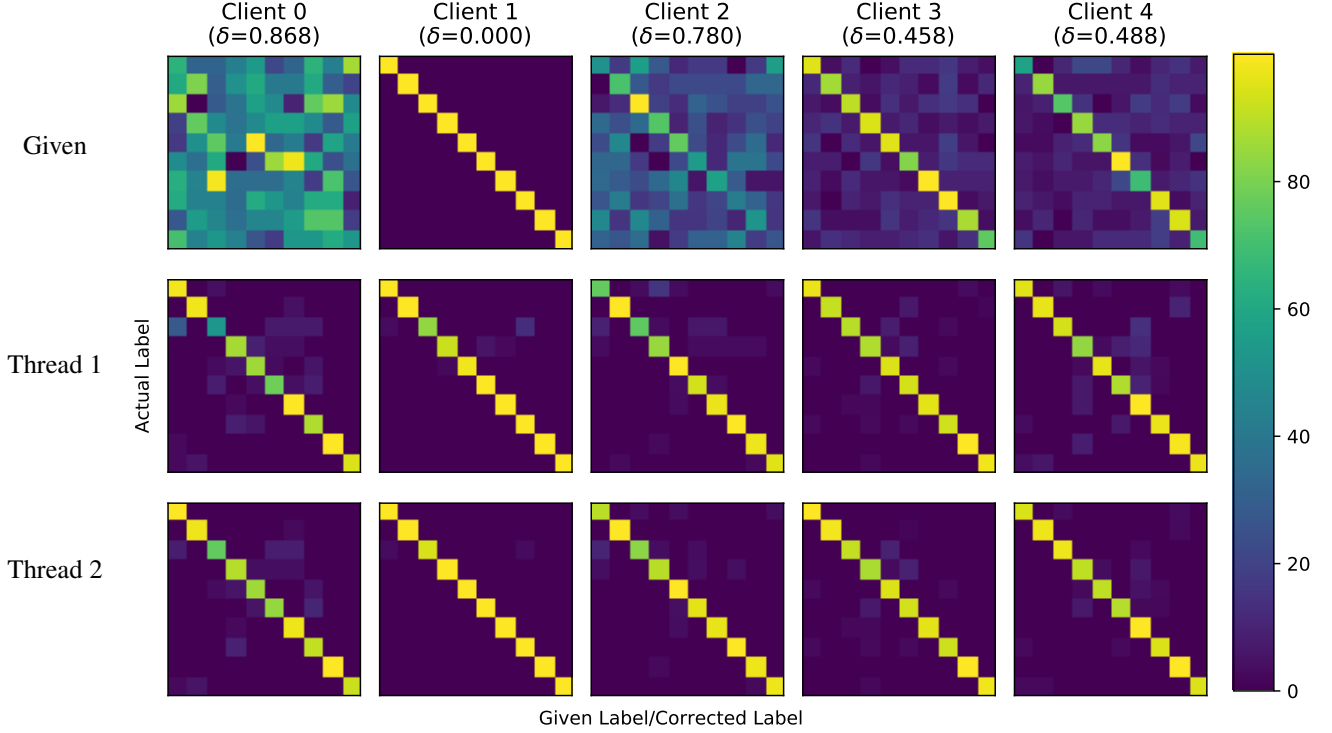


Figure 7: An evaluation of label noise filtering, noisy sample relabeling and labeled sample re-selection on five representative clients in the proposed FedDiv. As indicated by the heat maps, three confusion matrices for each client are associated to the actual labels v.s. the given labels before processing, the corrected labels after label noise filtering and noisy sample relabeling (named Thread 1), and the corrected labels after labeled sample re-selection (named Thread 2), respectively. Note that, in practice, noisy label relabeling and labeled sample re-selection may not necessarily be conducted on clean clients (e.g., Client 1) during local model training, in accordance with Eq. (10). The experiment is conducted on CIFAR-10 with the IID data partition under the noise setting $(\rho, \tau) = (0.8, 0.5)$.

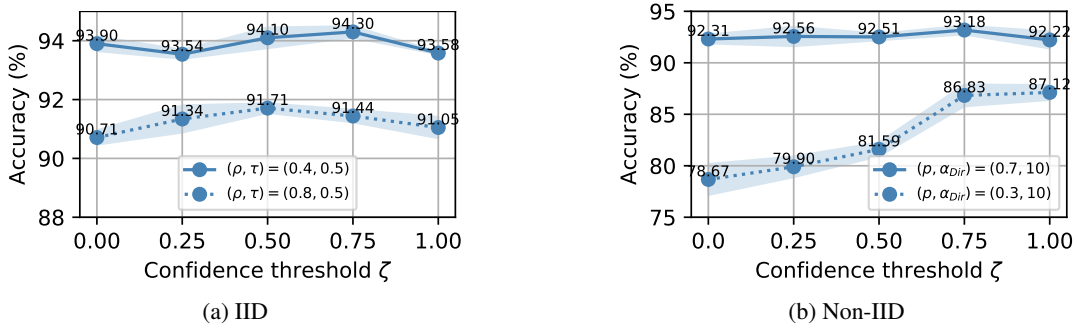


Figure 8: Sensitivity with respect to the hyper-parameter ζ . We show the test accuracy to illustrate the classification performance of the final FL model when we set ζ to 0.00, 0.25, 0.50, 0.75, and 1.00, respectively. We conduct these experiments on CIFAR-10 with both IID and non-IID data partitions. For the non-IID data partition, the noise level is set to $(\rho, \tau) = (0.6, 0.5)$.