Learning with Structural Labels for Learning with Noisy Labels

Supplementary Material

A. Effectiveness of Reverse k-NN

In the learning with noisy labels environment, as shown in Fig. 1, the feature manifold appears in a highly complex. In such environments, it is difficult to estimate feature distributions with a parametric estimator. Among non-parametric estimators, since k-NN is known to be more influenced by outlier samples compared to reverse k-NN [21, 50], we adopt reverse k-NN.

In Tab. 6, we conducted comparative experiments with k-NN in extracting structural labels. Using k-NN to obtain structural labels shows lower performance compared to our proposed method. It indicates that using reverse k-NN is more suitable for the LNL environment.

Method	IDN - CIFAR100				
	0.20	0.30	0.40	0.45	0.50
SSR	78.84	78.60	76.95	74.98	72.83
LSL w/ k-NN	77.87	78.33	75.92	72.96	72.83
LSL (Ours)	80.94	79.90	78.60	78.08	77.95

Table 6. Accuracy of our LSL based on reverse k-NN and k-NN

B. Learning Strategies

Strong augmentation and mixup are commonly employed in most LNL approaches [15, 33, 46] to mitigate overfitting on noisy samples and enhance robustness to label noise. Table 7 shows the ablation study on strong augmentaion and mixup. It can be noted that strong augmentation and mixup are helpful in noisy environments.

Method	IDN - CIFAR100				
	0.20	0.30	0.40	0.45	0.50
LSL w/o strong aug.	79.45	77.87	76.75	76.64	73.25
LSL w/o mixup	75.97	72.89	72.87	71.85	71.35
LSL (Ours)	80.94	79.90	78.60	78.08	77.95

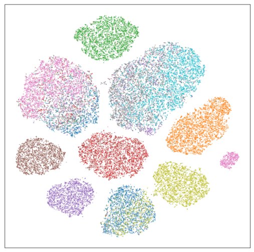
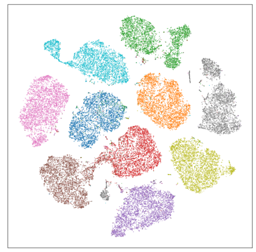
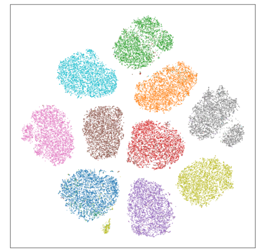
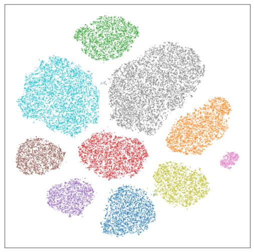
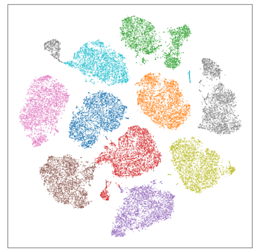
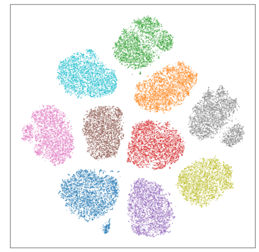
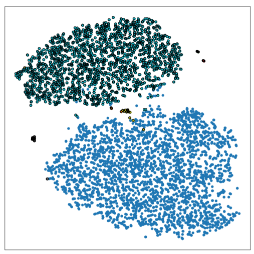
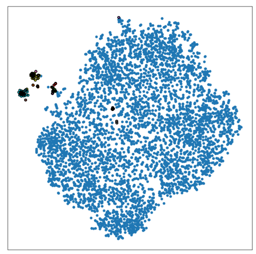
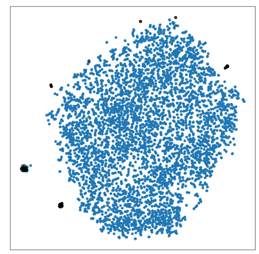
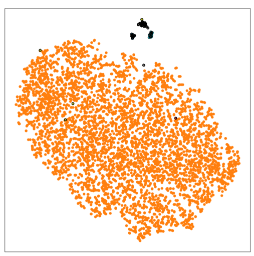
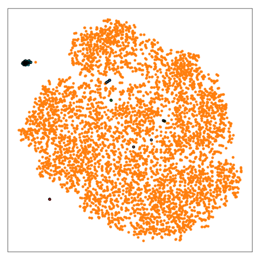
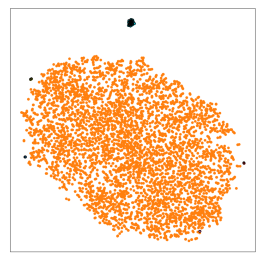
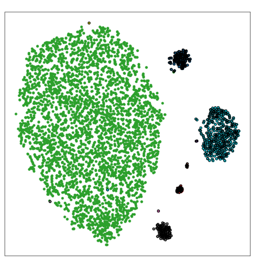
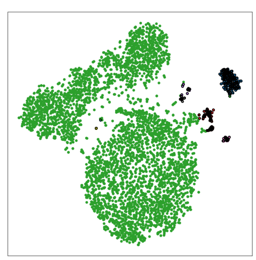
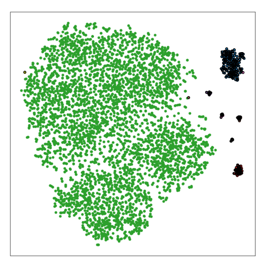
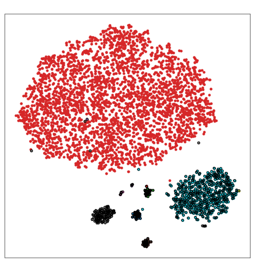
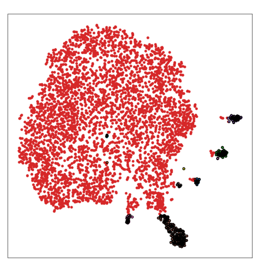
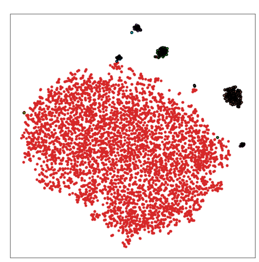
Table 7. Accuracy with various learning strategies

C. t-SNE Visualization

On CIFAR10 IDN at noise rate 0.50, the t-SNE visualizations of the training features for the DivideMix [31], SSR [15], and our proposed method are shown in Tab. 8.

First of all, in the first and second rows, there are t-SNE visualizations of all samples with golden labels and predictions from each model. In the case of DivideMix, samples for some classes are not distinctly clustered, and there is a significant amount of overlap. SSR demonstrates relatively better feature representation and better generalization performance compared to DivideMix. However, the distribution of features looks relatively complex. In contrast, the proposed method, LSL, exhibits a well-clustered result separated by class.

Below the second row, the t-SNE visualizations for each class are presented. Samples plotted with black borders indicate that the model's prediction disagree with the golden labels, while samples with no border color indicate agreement. In DivideMix, not only are features organized into multiple clusters within a single class of feature distribution, but incorrectly predicted samples are also distributed across a wide range. In contrast, most features for SSR are located around a main cluster, but it still shows poor generalization performance, with incorrectly predicted samples falling within the main cluster. In the proposed LSL, It is evident that each class exhibits a distinct and prominent main cluster. Moreover, only a small number of sub-cluster samples are misclassified. It confirms that our method for learning structural information can effectively learn feature representations well in noisy environments, and it also improves generalization performance.

Class	(a) DivideMix	(b) SSR	(c) LSL (Ours)
All classes (Golden Labels)			
All classes (Predictions)			
0 (airplane)			
1 (automobile)			
2 (bird)			
3 (cat)			

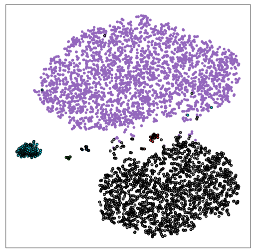
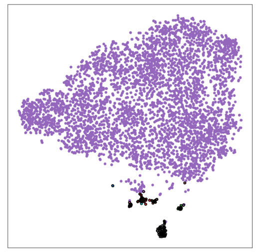
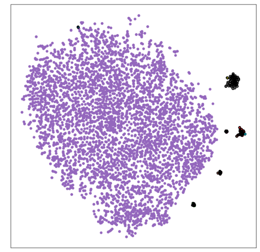
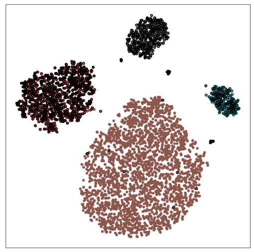
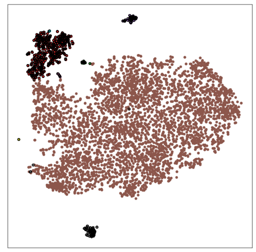
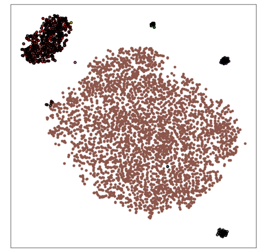
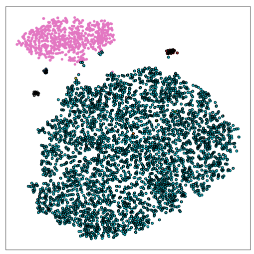
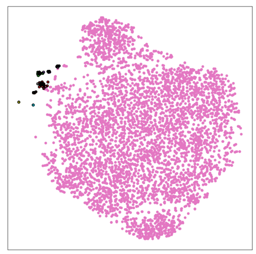
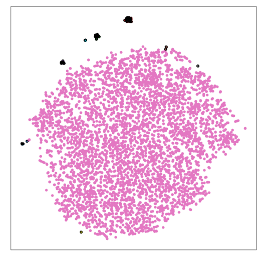
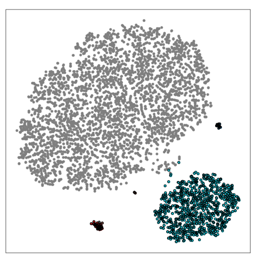
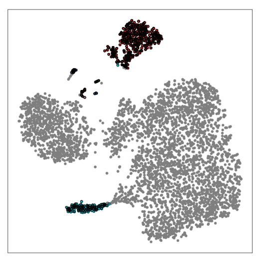
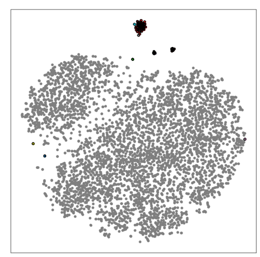
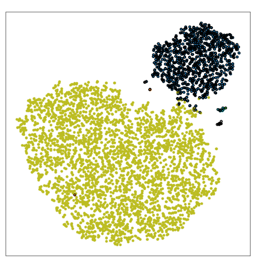
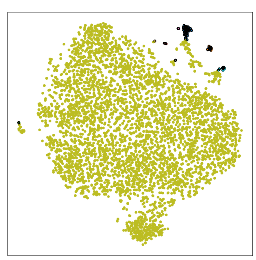
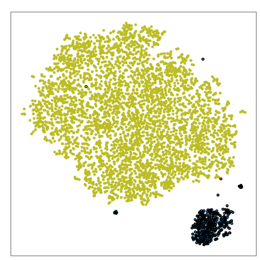
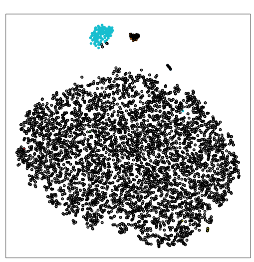
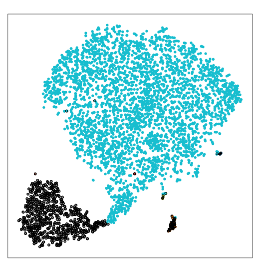
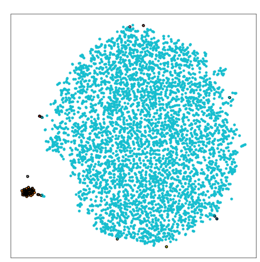
Class	(a) DivideMix	(b) SSR	(c) LSL (Ours)
4 (deer)			
5 (dog)			
6 (frog)			
7 (horse)			
8 (ship)			
9 (truck)			

Table 8. Comparison of t-SNE visualization on CIFAR10 IDN at noise rate 0.50. (a) DivideMix. (b) SSR. (c) Our proposed method. Black outlined circles are wrongly predicted samples.