

DECONFOUNDED NOISY LABELS LEARNING

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A APPENDIX

A.1 ERROR ESTIMATION

To estimate the bound of error in Section 3.3, the following theorem is used, and the proof of the theorem can be found in Wang et al. (2021); Abramovich & Persson (2016); Gao et al. (2017).

Theorem 1 *Given a non-linear function $f : G \rightarrow \mathbb{R}$, G is a closed subset of \mathbb{R} , and a random variable X with the probability distribution $p(X)$, the expectation μ , if the three conditions hold,*

- (1) f is bounded on any compact subset of \mathbb{R} ;
- (2) $|f(x) - f(\mu)| = O(|x - \mu|^a)$ at $x \rightarrow \mu$ for $a > 0$
- (3) $|f(x)| = O(|x|^b)$ at $x \rightarrow \infty$ for $b \geq a$

then,

$$|E[f(x)] - f(\mu)| \leq \sup_{x \in G, x \neq \mu} \frac{|f(x) - f(\mu)|}{|x - \mu|^a + |x - \mu|^b}$$

A.2 FIVE NOISY DATASETS.

Synthetic noise on CIFAR10 and CIFAR-100. According to previous works Han et al. (2018); Xia et al. (2019; 2020); Bai et al. (2021), the two synthetic noisy datasets contain 50k training images and 10k test images of size 32×32 with different levels of symmetric, pairflip, and instance-dependent label noise. Symmetric noise uniformly flips labels to all possible labels. Pairflip noise flips is generated by noisy labels into their adjacent class. Instance noise is generated by image features. More details of synthetic noise can be found in Bai et al. (2021).

Human-annotated real-world noisy labels CIFAR-10N and CIFAR-100N. In CIFAR-10N, each training image contains one clean label and three human annotated labels, with five different noisy-label sets. (1) Aggregate: aggregation of three noisy labels by majority voting. If the submitted three labels are different for an image, the aggregated label will be randomly selected among the three labels. (2) Random i ($i \in \{1, 2, 3\}$): the i -th submitted label for each image. (3) Worst: dataset with the highest noise rate. For each image, if there exist any wrongly annotated labels in three noisy labels, the worst label is randomly selected from wrong labels. Otherwise, the worst label is equal to the clean label. The noise rates of the above mentioned five noisy label sets are 9.03% (Aggregate), 17.23% (Random 1), 18.12% (Random 2), 17.64% (Random 3) and 40.21% (Worst). In CIFAR-10N, 60.27% of the training images have received unanimous label from three independent labelers. All three random sets have $\approx 18\%$ noise level. In CIFAR-100N dataset, each image contains a coarse label and a fine label given by a human annotator. Most batches have approximately 40% noisy fine labels and 25% noisy coarse labels. The overall noise level of coarse and fine labels are 25.60% and 40.20%, respectively.

Clothing1M Clothing1M consists of 1 million training images collected from online shopping websites with labels generated from surrounding texts. It contains 15k validation images, and 10k test images with clean labels.

A.3 NETWORK STRUCTURE AND HYPERPARAMETERS.

For experiments without semi-supervised learning, we follow previous works Bai et al. (2021); Li et al. (2019), and use ResNet-18 for CIFAR-10 and ResNet-34 for CIFAR-100. The network is trained for 200 epochs and utilize SGD with a 0.9 momentum. The initial learning rate is set to 0.1

and decayed with a factor of 10 at the 100th and 150th epoch respectively, and a weight decay is set to 10^{-4} . For finetuning, we employ an Adam optimizer with a learning rate of 10^{-4} .

For experiments with semi-supervised learning, we follow the setting of Bai et al. (2021) with PreAct Resnet-18. The network is trained for 300 epochs. For optimization, we use a single cycle of cosine annealing, and the learning rate begins from 0.02 and ends at $2 * 10^{-4}$, with a weight decay of $5 * 10^{-4}$. An Adam optimizer is adopted with a learning rate of 10^{-4} .

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