

EchoAlign: Bridging Generative and Discriminative Learning under Noisy Labels

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Problems & Ideas

- Ambiguous instance features make clean-label inference unreliable, so direct label correction can fail under instance-dependent noise.
- Instance modification introduces two challenges: preserving class-defining characteristics and avoiding distribution shift between original and modified data.
- EchoAlign changes the perspective: treat the observed noisy label as the supervision target, generate a label-aligned instance, and then select reliable original samples for training.

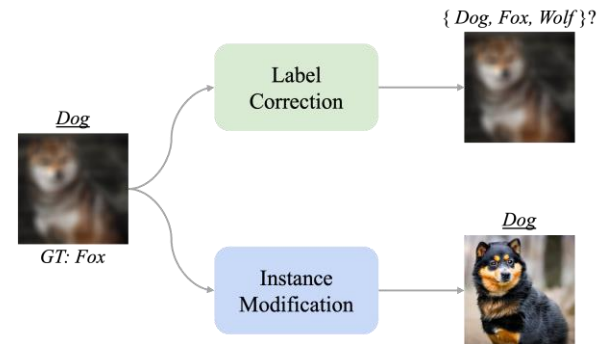


Fig. 1. Label correction may stay ambiguous, whereas instance modification can align the sample with the observed label.

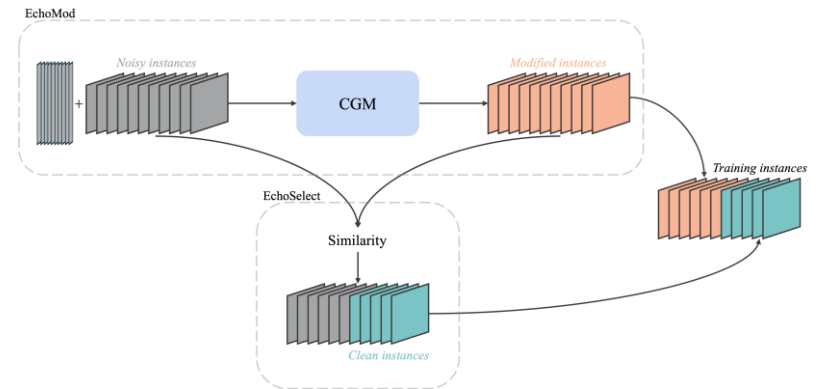


Fig. 2. EchoMod generates label-aligned instances and EchoSelect retains reliable original samples to control distribution shift.

Main Results

- EchoAlign delivers the best or near-best accuracy in most evaluated settings on CIFAR-10, CIFAR-100, and CIFAR-10N.
- Strong gains under hard noise: 77.81% on CIFAR-10 (50% instance-dependent noise), 60.31% on CIFAR-100 (45% pair-flip), and 84.35% on the CIFAR-10N worst-label split.
- EchoSelect keeps substantially more useful data: under 30% instance-dependent noise, it retains 19,010 samples at 99% selection accuracy, versus 10,673 for BLTM.

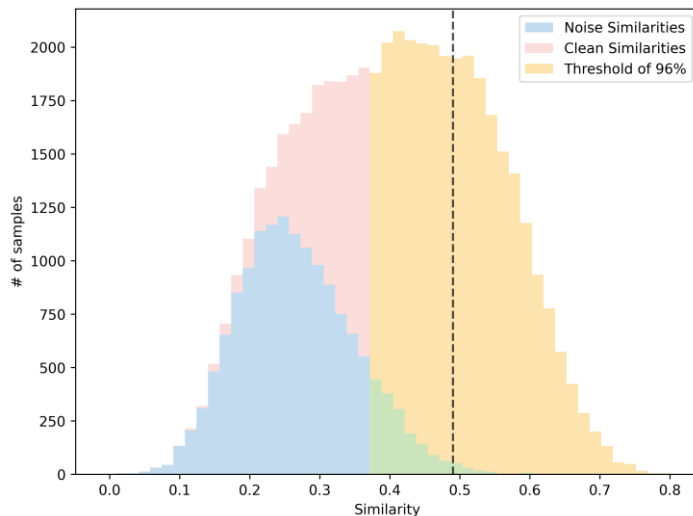


Fig. 3. Feature similarity between original and modified samples separates clean and noisy examples, enabling robust sample selection.

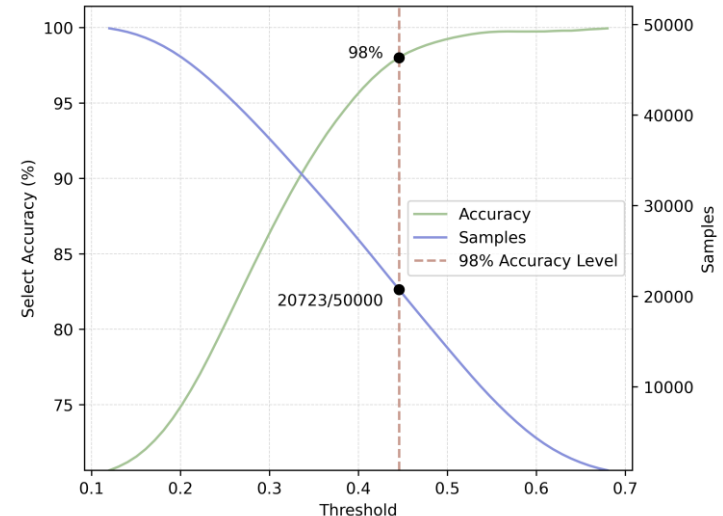


Fig. 4. Threshold calibration reveals the precision-coverage trade-off for sample selection under 30% instance-dependent noise.