

# Supplementary material for Addressing out-of-distribution label noise in webly-labelled data

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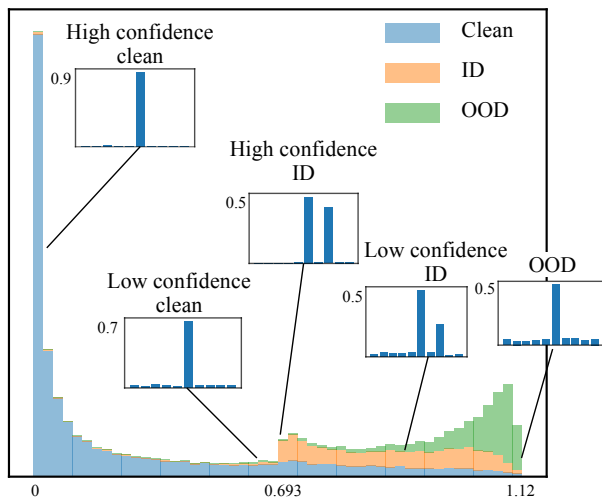


Figure 1: Clean/ID/OOD hierarchy established by the collision entropy of the interpolated label  $l_{detect}$

## 1. Additional explanation of the behavior of the ID/OOD measure

Figure 1 illustrates the behavior of our proposed metric  $l_{detect}$ . By studying the collision entropy of the interpolated label  $y_{inter}$  between the network prediction and the ground truth label, we establish a hierarchy from clean to ID noise to OOD noise. The pivot point  $-\log(.5) = 0.693$  marks the separation between low confidence clean samples and high confidence noisy samples. Although some clean samples will be detected as noisy at the pivot point, because we avoid OOD sample during this transition, we can correct the detected confident ID samples without concerns of labeling OOD data or corrupting the clean samples since we relabel correct but simply under-confident clean samples: this will not harm the training procedure (their label stays the same). By smoothing OOD samples, we also avoid correcting ID noisy samples with an under-confident corrected prediction.

## 2. Hyperparameter table

Table 1 details the hyperparameters used in every experiment reported in the state-of-the-art comparison. The configuration remains the same across different noise ratios for miniImageNet and Stanford Cars. The parameters common to all experiments are: entropy regularization [2], SGD optimizer, a learning rate decay factor of 10, random horizontal flips, mixup [3] data augmentation. To match the baseline of [1], we add a dropout layer before the fully connected layer in the case of the Stanford Cars experiments. We do not use dropout for other datasets as we manage to match the baselines without it.

## 3. Algorithm

Alg. 1 displays the DSOS algorithm.

## 4. Examples of labeled images from the mini-Webvision subset

Figures 2 and 3 display examples of images labeled from the mini-Webvision subset. The annotations are available together with our code at [github].

## References

- [1] Lu Jiang, Di Huang, Mason Liu, and Weilong Yang. Beyond Synthetic Noise: Deep Learning on Controlled Noisy Labels. In *International Conference on Machine Learning (ICML)*, 2020.
- [2] D. Tanaka, D. Ikami, T. Yamasaki, and K. Aizawa. Joint Optimization Framework for Learning with Noisy Labels. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2018.
- [3] H. Zhang, M. Cisse, Y.N. Dauphin, and D. Lopez-Paz. mixup: Beyond Empirical Risk Minimization. In *International Conference on Learning Representations (ICLR)*, 2018.





Figure 2: Samples annotated as clean, in-distribution noise, out-of-distribution noise.

Figure 3: Samples annotated as clean, in-distribution noise, out-of-distribution noise.