

# LEARNING WITH NEIGHBOR CONSISTENCY FOR NOISY LABELS

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Paper under double-blind review

## ABSTRACT

Recent advances in deep learning have relied on large, labelled datasets to train high-capacity models. However, collecting large datasets in a time- and cost-efficient manner often results in label noise. We present a method for learning from noisy labels that leverages similarities between training examples in feature space, encouraging the prediction of each example to be similar to its nearest neighbours. Compared to training algorithms that use multiple models or distinct stages, our approach takes the form of a simple, additional regularization term. It can be interpreted as an inductive version of the classical, transductive label propagation algorithm. We compare our approach to relevant baselines under both synthetic and realistic noise, and demonstrate that our simple approach achieves state-of-the-art accuracy under the realistic conditions of mini-ImageNet-Red, mini-WebVision and Clothing1M.

## 1 INTRODUCTION

While deep learning can achieve unprecedented accuracy in image classification tasks, it requires a large, supervised dataset that is often expensive to obtain. Unsupervised and semi-supervised learning seek to alleviate this requirement by incorporating unlabelled examples. However, these approaches cannot take advantage of the various sources of *noisy* labels in the modern world, such as images with hashtags in social media or images contained in webpages retrieved by a textual query. Training algorithms that are robust to label noise are therefore highly attractive for deep learning.

The dominant approach to learning with noisy labels in recent work is to use the predictions of the model itself to reject or modify training examples (*e.g.* Reed et al. (2015); Tanaka et al. (2018); Arazo et al. (2019); Yang et al. (2020); Liu et al. (2020); Nguyen et al. (2020); Han et al. (2018); Li et al. (2020)). This is inherently risky due to the ability of deep networks to fit arbitrary labels (Zhang et al., 2016) and it is important to take significant measures against overfitting. Moreover, this paradigm often leads to complicated training procedures, such as maintaining multiple models or alternating between updating the model and updating the training set.

This paper proposes Neighbor Consistency Regularization (NCR) for the specific problem of learning with noisy labels, illustrated in Figure 1. Rather than adopt model predictions as pseudo-labels, NCR introduces an additional consistency loss that encourages each example to have similar predictions to its neighbors. Concretely, the neighbor consistency loss penalizes the divergence of each example’s prediction from a weighted combination of its neighbors’ predictions, with the weights determined by their similarity in feature space. The motivation of NCR is to enable incorrect labels to be improved or at least attenuated by the labels of their neighbors, relying on the assumption that the noise is sufficiently weak or unstructured so as not to overwhelm the correct labels. Compared to the popular approach of bootstrapping the model predictions (Reed et al., 2015), NCR can be seen as instead bootstrapping the learned feature representation, which may reduce its susceptibility to overfitting and improve its stability at random initialization.

NCR is inspired by label propagation algorithms for semi-supervised learning (Zhou et al., 2003; Kipf & Welling, 2017; Iscen et al., 2019), which seek to transfer labels from supervised examples to neighboring unsupervised examples according to their similarity in feature space. However, whereas label propagation is typically performed in a batch setting over the entire dataset, our method effectively performs label propagation online within mini-batches during stochastic gradient descent. This results in a simple, single-stage training procedure. Moreover, whereas existing methods for label propagation represent *transductive* learning in that they only produce labels for the specific examples

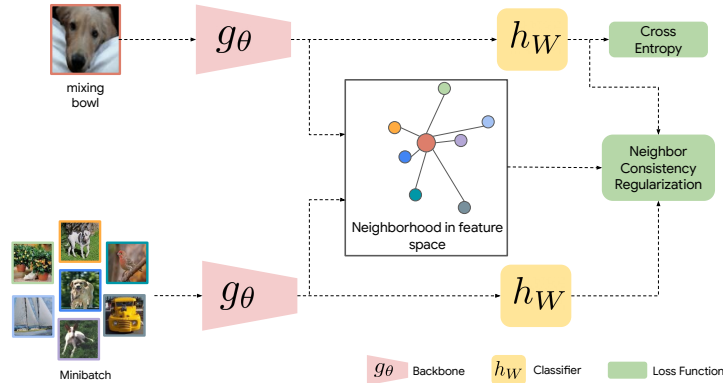


Figure 1: To address the problem of noisy labels in the training set, we propose Neighbor Consistency Regularization. This regularizer encourages examples with similar feature representations to have similar outputs, thus mitigating the impact of training examples with incorrect labels.

which are provided during training, NCR can be understood as an *inductive* form of label propagation in that it produces a model which can later be applied to classify unseen examples.

The key contributions of the paper are as follows.

- We propose Neighbor Consistency Regularization, a novel loss term for deep learning with noisy labels that encourages examples with similar feature representations to have similar predictions.
- We verify empirically that NCR achieves better accuracy than several important baselines at a wide range of noise levels from both synthetic and real distributions, and is complementary to the popular regularization technique of mixup (Zhang et al., 2018).
- We demonstrate that NCR achieves state-of-the-art accuracy on the mini-ImageNet-Red (Jiang et al., 2020), mini-WebVision (Li et al., 2020) and Clothing1M (Xiao et al., 2015) datasets, which contain realistic web noise.

## 2 RELATED WORK

This section reviews related work with a focus on image classification using deep learning and draws comparisons to our proposed approach. Note that, while there is a significant body of work examining the problem of noisy labels under the assumption that a small, trusted set of clean examples is available, this paper considers the variant where this is not the case.

**Regularization.** Regularization has an integral role under label noise as it limits the ability of a high-capacity model to fit arbitrary labels. Indeed, regularization alone can provide considerable robustness to label noise and many algorithms couple an effective regularization strategy with an explicit noise-handling technique to further robustness. One particularly effective form of regularization is mixup augmentation of Zhang et al. (2018), which generates additional examples by linearly interpolating between pairs of examples in both the image and label space. It was originally demonstrated to provide robustness to synthetic label corruption on CIFAR-10.

Beyond the choice of regularization, there are numerous possible approaches to handle noisy labels. Early investigation into deep learning with label noise concentrated on either estimation of the label transition matrix (Sukhbaatar et al., 2014; Patrini et al., 2017) or loss functions that are robust to outliers (Reed et al., 2015; Ghosh et al., 2017; Xu et al., 2019). More recently, numerous methods have been proposed that re-weight or re-label the examples that are believed to have incorrect labels. We briefly review this body of work in the following paragraphs.

**Model predictions for noisy labels.** Many methods have used the predictions of the model itself during training to either generate pseudo-labels or to identify incorrect examples (or both). For deep learning, this often leverages the phenomenon that correct labels tend to be fit earlier than incorrect ones (Liu et al., 2020). Reed et al. (2015) first proposed the bootstrapping loss, in which a fixed linear combination of the annotated label and the current prediction are adopted as the regression

target for each example. Our method can be considered a bootstrapping approach which uses the learned *similarity* rather than the actual predictions. Extensions of this work have included setting the proportion of annotated and predicted labels adaptively using the model confidence (Arazo et al., 2019; Yang et al., 2020) and averaging model weights and predictions over time (Liu et al., 2020; Nguyen et al., 2020). Lukasik et al. (2020) showed that some robustness to noise could be obtained by label smoothing, which instead interpolates between the annotated label and a uniform distribution. To avoid overfitting, several works have proposed to split the training set in half and train two models, with each used to assess the training examples of the other (Han et al., 2018; Li et al., 2020).

**Identifying noisy examples using neighbors.** Whereas our method, in effect, uses neighbors to modify the supervision of each example, several approaches have rather used neighbors with the aim of identifying and eliminating noisy examples. Both Wang et al. (2018) and Guo et al. (2018) proposed to identify and re-weight examples with incorrect labels using the local density of examples with the same annotation. Wu et al. (2020) constructed a  $k$ -NN graph and kept only the examples which constituted the core of the largest connected component per class. Bahri et al. (2020) eliminated examples whose labels did not agree with the prediction of a  $k$ -NN classifier. Ortego et al. (2020) proposed Multi-Objective Interpolation Training (MOIT), which identifies mislabelled examples by comparing the predictions of each example to the average prediction of its neighbors and then replaces the least reliable labels with the model’s current predictions. MOIT+ incorporates an additional stage of semi-supervised learning, in which the labels believed to be noisy are discarded.

**Label propagation.** Variants of label propagation (Zhou et al., 2003) have been applied to various computer vision tasks, including retrieval (Donoser & Bischof, 2013; Iscen et al., 2017), semi-supervised learning (Kipf & Welling, 2017; Iscen et al., 2019) and few-shot learning (Douze et al., 2018; Liu et al., 2019; Rodríguez et al., 2020). For semi-supervised learning in particular, Iscen et al. (2019) used it to obtain labels for unsupervised examples based on their neighbors in feature space. While most methods perform label propagation over large graphs containing many examples in a batch fashion, Liu et al. (2019) and Rodríguez et al. (2020) considered label propagation within stochastic gradient descent for episodic few-shot learning (Vinyals et al., 2016). This is a meta-learning approach which seeks a suitable feature representation with which to *later* perform label propagation during meta-testing. It is not directly applicable for learning with noisy labels and it does not scale to large sets of examples.

For learning with noisy labels, although neighbors have often been used to *identify* mislabelled examples (see above), few works have considered the use of neighbors to generate pseudo-labels. Iscen et al. (2020) used graph convolution to propagate labels from a small set of examples with trusted labels to a large set of examples with noisy labels. By comparison, our approach does not require a clean set and is inductive in nature. Perhaps the most similar method to our own is that of Yang et al. (2020), in which graph filtering is applied once to the global graph of all examples to refine the predictions of an initial model. In contrast, our consistency loss encourages similar examples to have similar labels throughout training and is much simpler to implement.

**Consistency.** The idea of constraining a network to produce consistent outputs as a way to leverage unlabelled data has appeared in several previous works. Verma et al. (2019) and Berthelot et al. (2019) proposed variants of mixup for semi-supervised learning in which predictions replace the labels for unsupervised examples. Xie et al. (2020) introduced Unsupervised Data Augmentation for semi-supervised image classification, where a model is encouraged to be robust to label-preserving transformations even when labels are not available by minimizing the divergence between predictions for transformed and non-transformed images. Most relevant to our work, Engleson & Azizpour (2021) used prediction consistency with respect to image transformations for the express purpose of learning with noisy labels. While these forms of consistency are effective regularizers, neighbor consistency offers the ability to transfer supervision directly to mislabelled examples.

### 3 PRELIMINARIES

We first define our notation and formulate the task of learning with noisy labels. We then describe label propagation, a graph-based semi-supervised learning method designed to work with closed datasets.

**Problem formulation.** We assume a dataset defined by  $X := \{x_1, \dots, x_n\}$ . Each example, e.g. an image,  $x_i$ , has a corresponding true label  $\tilde{y}_i \in \mathcal{C}$ . In our task, some of the labels,  $y_i$ , are noisy:  $y_i \neq \tilde{y}_i$  and do not correctly reflect the visual content of the example  $x_i$ . During training, we do not know

whether  $y_i$  is noisy ( $y_i \neq \tilde{y}_i$ ) or clean ( $y_i = \tilde{y}_i$ ). Our goal is to learn a model with the highest accuracy on the true labels,  $\tilde{y}$ , although an unknown number of labels in our training set are noisy.

We learn a convolutional neural network for classification. The network, denoted by  $f_{\theta, W} : \mathcal{X} \rightarrow \mathbb{R}^c$ , takes a dataset example  $x_i$  as the input and outputs *logits* for softmax classification. Its two learnable variables  $\theta$  and  $W$  correspond to the feature extractor and classifier, respectively. The feature extractor maps an image  $x_i$  to a  $d$ -dimensional vector  $\mathbf{v}_i := g_{\theta}(x_i) \in \mathbb{R}^d$ . The classifier maps the  $d$ -dimensional vector to class scores  $\mathbf{z}_i := h_W(\mathbf{v}_i) \in \mathbb{R}^c$ . Typically, the network parameters are learned by minimizing a loss function for supervised classification:

$$L_S(X, Y; \theta, W) := \frac{1}{m} \sum_{i=1}^m \ell(\sigma(\mathbf{z}_i), y_i), \quad (1)$$

where  $X$  and  $Y$  correspond to the set of examples in the mini-batch,  $m = |X| = |Y|$  denotes the size of the mini-batch,  $\sigma$  is the softmax function and  $\ell(\mathbf{q}, \mathbf{p})$  is the cross-entropy loss function for predictions  $\mathbf{q}$ . When the target distribution  $\mathbf{p}$  is a single label  $y \in \mathcal{C}$ , we adopt the short-hand  $\ell(\mathbf{q}, y) = \ell(\mathbf{q}, \delta_y)$  for cross-entropy with a one-hot vector  $\delta_y$ .

**Label propagation** is a graph-based technique used in semi-supervised learning (Zhou et al., 2003). We assume that we are given labeled and unlabeled examples in a dataset, and that the dataset is also defined by a graph which is either given or created from the  $k$ -nearest neighbours of each example (Donoser & Bischof, 2013). This method spreads the label information of each node to the other nodes based on the connectivity in the graph. This process is repeated until a global equilibrium state is achieved. Finally, unlabeled examples are assigned to the class from which they have received the most information.

Formally, for a graph of dataset  $X$ , represented by an affinity matrix  $W$ , where  $W_{ij} = \text{similarity}(x_i, x_j)$ , Zhou et al. (2003) show that label propagation can be computed by minimizing

$$\mathcal{Q}(F) = \frac{1}{2} \mu \sum_{i=1}^n \|F_i - Y\|^2 + \frac{1}{2} \sum_{i,j=1}^n W_{ij} \left\| \frac{1}{\sqrt{D_{ii}}} F_i - \frac{1}{\sqrt{D_{jj}}} F_j \right\|^2, \quad (2)$$

where  $D$  is the degree matrix (a diagonal matrix with entries  $D_{ii} = \sum_j W_{ij}$ ),  $Y$  is the matrix of one-hot labels for all examples and  $\mu$  is a regularization parameter. This objective function comprises two terms: a *fitting constraint*, which encourages the classification of each point to their assigned label, and a *smoothing* term, which encourages the outputs of nearby points in the graph to be similar.

One of the main limitations of label propagation is its *transductive* property. In transductive learning, the goal is to classify *seen* unlabeled examples. This is different to *inductive* learning, which learns a generic classifier to classify any unseen data. To apply label propagation on new test examples, a new graph  $W$  needs to be constructed each time a new test example is seen. This makes it inefficient in practice.

Another requirement for label propagation is that the feature space needs to be fixed to compute the affinity matrix  $W$ . This requires the feature extractor to be learned beforehand, potentially from the noisy data. Existing work (Isken et al., 2019) has tried to overcome this issue by alternating between optimizing the feature space, and performing label propagation. However, this does not directly enforce smoothness, as the optimization of two components are done separately.

Our goal is to overcome the limitations of label propagation by 1) adapting it to an inductive setting 2) applying the smoothness constraint directly during optimization. In Section 4, we propose a simple and efficient approach which generalizes label propagation by enforcing smoothness in the form of a regularizer. As a result, we avoid constructing an explicit graph to propagate the information, and inference can be performed on any unseen test example.

## 4 METHOD

We now present our method *Neighbor Consistency Regularization* and compare it to classical label propagation. We then highlight its relationship to similar, online techniques.

#### 4.1 NEIGHBOR CONSISTENCY REGULARIZATION

When learning with noisy labels, the network is prone to overfit, or *memorize*, the mapping from  $x_i$  to a noisy label  $y_i$  for the training data (Liu et al., 2020). This behavior typically results in a non-optimal classification performance in a clean evaluation set, as the network does not generalize well.

To overcome this issue, we propose *Neighbor Consistency Regularization* (NCR). Our main assumption is that the over-fitting occurs less dramatically before the classification layer  $h_W$ . This is supported by the work of Ortego et al. (2020), which shows that feature representations are robust enough to discriminate between noisy and clean examples when training a network. With that assumption, we can design a smoothness constraint similar to label propagation (2) when training the network. The overview of our method is shown in Figure 1.

Let us define the *similarity* between two examples by the cosine similarity of their feature representations, *i.e.*  $s_{i,j} = \cos(\mathbf{v}_i, \mathbf{v}_j) = \mathbf{v}_i^T \mathbf{v}_j / (\|\mathbf{v}_i\| \|\mathbf{v}_j\|)$ . Note that the feature representations contain non-negative values when obtained after a ReLU non-linearity, and therefore the cosine similarity is bounded in the interval  $[0,1]$ . Our goal is to enforce *neighbor consistency regularization* by leveraging the structure of the feature space produced by  $g_\theta$  to enhance the classifier  $h_W$ . More specifically,  $h_W(\mathbf{v}_i)$  and  $h_W(\mathbf{v}_j)$  should behave similarly if  $s_{i,j}$  is high, regardless of their labels  $y_i$  and  $y_j$ . This would prevent the network from over-fitting to an incorrect mapping between an example  $x_i$  and a label  $y_i$ , if either (or both)  $y_i$  and  $y_j$  are noisy.

To enforce NCR, we design an objective function which minimizes the distance between logits  $\mathbf{z}_i$  and  $\mathbf{z}_j$ , if the corresponding feature representations  $\mathbf{v}_i$  and  $\mathbf{v}_j$  are similar:

$$L_{\text{NCR}}(X, Y; \theta, W) := \frac{1}{m} \sum_{i=1}^m D_{\text{KL}} \left( \sigma(\mathbf{z}_i/T) \left\| \sum_{j \in \text{NN}_k(\mathbf{z}_i)} \frac{s_{i,j}}{\sum_k s_{i,k}} \cdot \sigma(\mathbf{z}_j/T) \right. \right), \quad (3)$$

where  $D_{\text{KL}}$  is the KL-divergence loss to measure the difference between two distributions,  $T$  is the temperature and  $\text{NN}_k(\mathbf{z}_i)$  denotes the set of  $k$  nearest neighbors of  $i$  in the feature space. We set  $T=2$  throughout our experiments. We normalize the similarity values so that the second term of the KL-divergence loss remains a probability distribution. We set the self-similarity  $s_{i,i}=0$  so that it does not dominate the normalized similarity. Gradients will be back-propagated to all inputs.

The objective (3) ensures that the output of  $x_i$  will be consistent with the output of its neighbors regardless of its potentially noisy label  $y_i$ . We combine it with the supervised classification loss function (1) to obtain the final objective to be minimized during the training:

$$L(X, Y; \theta, W) := (1-\alpha) \cdot L_S(X, Y; \theta, W) + \alpha \cdot L_{\text{NCR}}(X, Y; \theta, W), \quad (4)$$

where the hyper-parameter  $\alpha \in [0,1]$  controls the impact of the each loss term. Similar to label propagation, the final loss objective (4) has two terms. The first term is the classification loss term  $L_S$ . This is analogous to the fitting constraint in (2). The second term is the NCR loss  $L_{\text{NCR}}$ , which is also similar to the *smoothness* constraint in (2). We find that it sometimes helps to train the network with  $\alpha=0$  for several epochs (denoted by  $e$  in our experiments) before enabling the NCR term.

However, the main difference between label propagation and our method is that label propagation applies smoothness based on the graph edges  $W_{ij}$  computed over the entire dataset. On the other hand, our method is online, and does not require a global graph  $W$ . We enforce the NCR through the local neighborhood as the feature space is being learned. As a result, our method does not require a learned feature representation with noisy examples. It enriches the learned feature representation by reducing the negative impact of noisy examples.

Compared to standard training, NCR incurs an additional computational cost of order  $O(m^2(d+c))$  where  $m$  is the batch size,  $d$  is the feature dimension and  $c$  is the number of classes. This arises in the computation of the similarity values and weighted predictions in (3). However, this operation is relatively fast to compute for moderate values of  $m$  because it is a dense matrix multiplication, for which modern GPUs are optimized.

#### 4.2 RELATION TO OTHER METHODS

**Bootstrapping** introduces an additional loss that adopts the model’s own predictions as labels (Reed et al., 2015). Its motivation is to discourage the model from overfitting to examples which are difficult

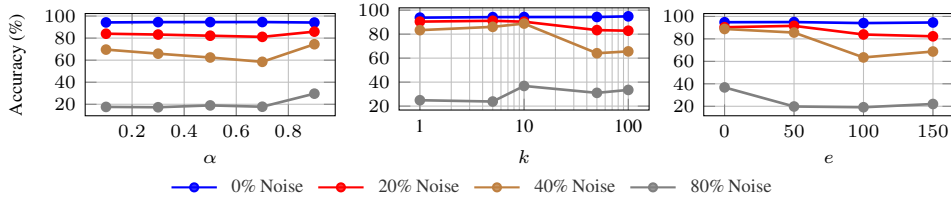


Figure 2: **Ablation study.** Impact of hyperparameters  $\alpha$ ,  $k$  and  $e$  are evaluated on the CIFAR-10 validation set. The ResNet-18 architecture is used.

to fit. The overall loss combines the supervised loss and the bootstrap loss in fixed proportion:

$$L_B(X, Y; \theta, W) := \frac{1}{m} \sum_{i=1}^m (1-\alpha) \cdot \ell(\sigma(\mathbf{z}_i), y_i) + \alpha \cdot \ell(\sigma(\mathbf{z}_i), \sigma_B(\mathbf{z}_i)), \quad (5)$$

where  $\sigma_B$  is the bootstrap activation function, which may be argmax or softmax (with optional temperature). NCR can be understood as bootstrapping from the neighborhood structure induced by the representation rather than from the model’s predictions. This eliminates the dependency on the classifier parameters  $W$ , which may be particularly advantageous as it has been shown that linear models can fit random labels given a sufficiently high-dimensional representation (Liu et al., 2020).

**Label smoothing** is a regularization method (Szegedy et al., 2016) that mixes the ground truth labels with a uniform distribution. It has been shown capable of denoising corrupted labels (Lukasik et al., 2020). Under label smoothing, the supervised classification loss function becomes:

$$L_{LS}(X, Y; \theta, W) := \frac{1}{m} \sum_{i=1}^m (1-\alpha) \cdot \ell(\sigma(\mathbf{z}_i), y_i) + \alpha \cdot \ell(\sigma(\mathbf{z}_i), \frac{1}{C} \mathbf{1}). \quad (6)$$

Note that the linear combination of losses is equivalent to a linear combination of labels due to the linearity of  $\ell(\mathbf{q}, \mathbf{p}) = -\mathbf{p}^T \log \mathbf{q}$  with respect to  $\mathbf{p}$ . Our method can be considered a modified version of label smoothing where the uniform distribution is replaced with a distribution defined by the neighboring examples. It would collapse to label smoothing if the neighbors were random or if a high temperature  $T$  were used.

**Mixup** (Zhang et al., 2018) bears some resemblance to our method in that it takes a convex combination of labels. However, mixup uses this combination as the regression target for a novel example obtained as the convex combination of the inputs, whereas NCR uses it as the target for an existing example.

## 5 EXPERIMENTS

### 5.1 EXPERIMENTAL SETUP

We first perform experiments on datasets with synthetic noise, where the noise level can be varied, before considering datasets with organic noise, where the noise level is fixed and unknown. For experiments with synthetic noise, we use the standard variants of CIFAR-10 and -100 (Krizhevsky & Hinton, 2009) as well as mini-ImageNet with “Blue” and “Red” noise (Jiang et al., 2020). The CIFAR and mini-ImageNet-Blue datasets are contaminated with uniform label noise, whereas mini-ImageNet-Red is constructed by replacing some examples in each class with false positives from an image search engine, representing more realistic noise. For experiments with organic noise, we use mini-WebVision (Li et al., 2020) and Clothing1M (Xiao et al., 2015). All datasets include a clean validation and/or final evaluation set. Implementation details and hyperparameters are described in Section A.1.

### 5.2 ABLATION STUDY

We first study the effect of the key hyperparameters of NCR at different noise levels using the CIFAR-10 validation set. Specifically, we investigate the impact of  $\alpha$ , which controls the strength of the NCR term in (4), the number of neighbors  $k$  and the number of initialization epochs  $e$ . We first set the number of neighbors  $k = m$  (the batch size) and the number of initialization epochs to zero while varying  $\alpha$ . Subsequently, we select the optimal  $\alpha$  for each noise level and vary  $k$ . Finally, we adopt the optimal  $k$  and vary  $e$ .

Table 1: **Baseline and oracle comparison.** Classification accuracy is reported on the mini-ImageNet-{Blue, Red} datasets with the ResNet-18 architecture. The accuracy is reported for each individual noise ratio (0%, 20%, 40%, 80%). We present the mean accuracy and standard deviation from five trials. The oracle model is trained on only the known, clean examples in the training set using a cross-entropy loss.

Method	mini-ImageNet-Blue				mini-ImageNet-Red			
	0%	20%	40%	80%	0%	20%	40%	80%
<b>BASELINES</b>								
Standard	65.8±0.4	49.5±0.4	36.6±0.5	13.1±1.0	63.5±0.5	55.3±0.9	49.5±0.7	36.4±0.4
Mixup	67.4±0.4	60.1±0.2	51.6±0.8	<b>21.0±0.5</b>	65.5±0.5	61.6±0.5	57.2±0.6	43.7±0.3
Bootstrap	66.4±0.4	54.4±0.5	44.8±0.5	2.9±0.3	64.3±0.3	56.2±0.2	51.3±0.6	38.2±0.3
Bootstrap + Mixup	67.5±0.3	61.9±0.4	51.0±0.7	1.3±0.1	65.9±0.4	62.7±0.2	58.3±0.5	43.5±0.6
LS	67.5±0.8	60.2±0.5	50.2±0.4	20.9±0.8	65.7±0.5	59.7±0.4	54.0±0.6	39.7±0.5
LS + Mixup	<b>68.6±0.3</b>	63.3±1.0	57.1±0.2	14.4±0.3	<b>66.9±0.2</b>	63.4±0.4	59.2±0.4	45.5±0.7
<b>OURS</b>								
<b>Ours</b> : NCR	66.5±0.2	61.7±0.3	54.1±0.4	20.7±0.5	64.0±0.4	60.9±0.3	56.1±0.7	40.9±0.2
<b>Ours</b> : NCR + Mixup	67.9±0.6	<b>64.3±0.1</b>	<b>59.2±0.6</b>	14.2±0.4	66.3±0.5	<b>64.6±0.6</b>	60.4±0.3	45.4±0.4
<b>OTHER WORKS</b>								
D-Mix (Li et al., 2020)	-	-	-	-	55.8	50.3	50.9	35.4
ELR (Liu et al., 2020)	-	-	-	-	57.4	58.1	50.6	41.7
MOIT (Ortego et al., 2020)	-	-	-	-	64.7	63.1	<b>60.8</b>	<b>45.9</b>
<b>ORACLE: CLEAN SUBSET</b>								
Standard	65.8±0.4	63.9±0.5	60.6±0.4	45.4±0.8	63.5±0.5	61.7±0.1	58.4±0.3	41.5±0.5
Mixup	67.4±0.4	64.2±0.5	61.5±0.3	46.9±0.8	65.5±0.5	63.1±0.6	59.7±0.7	43.6±0.4

Figure 2 shows the validation accuracy for different noise ratios. The performance remains relatively stable over different hyperparameters for 0% and 20% noise ratios. It is optimal to set  $\alpha$  to be high (0.9) for any non-zero noise ratio, indicating that the greater influence of NCR benefits these settings. Similarly, smaller  $k$  (e.g.  $k = 10$ ) leads to higher accuracy when the noise ratio is above 0%. We also observe that  $e = 0$  performs better for higher noise ratios (i.e. 40% and 80%). This shows that the NCR needs to be enabled early in training to prevent the network from memorizing the noisy labels when the noise ratio is high.

### 5.3 BASELINE COMPARISON

We now compare NCR against the baselines defined in Section 4.2. The results are reported on the official validation set of mini-ImageNet-{Red, Blue} datasets. We run each experiment five times and report the mean accuracy at the completion of training. We do not report the peak validation accuracy attained during training as the conclusions may be less likely to generalize to an unseen test set.

Table 1 shows the final accuracy for each method on the mini-ImageNet-{Red, Blue} datasets across different noise splits. When compared with the *standard* baseline, our method significantly improves the performance, up to 17.5% across all noise ratios. Furthermore, we show that our method is compatible with some of the existing baselines. Combining mixup with our method leads to further improvements in almost all scenarios. We observe that NCR improves the accuracy of the method even at 0% noise. This suggests that it has a general regularization effect. However, the improvement in accuracy is much more pronounced in the training sets which contain label noise.

Figure 3 presents further evidence that NCR inhibits memorization of noisy labels. After the training is complete, we perform one last forward-pass and obtain the confidence  $p$  that the model assigns to the annotated label for each training example. The top row shows that the baseline model overfits to the noisy labels, resulting in  $p = 1$  for both clean and noisy images. On the other hand, NCR avoids overfitting and assigns low confidence  $p = 0$  to most of the noisy training labels. Some of the noisy examples are still classified as their assigned label on mini-Imagenet-Red. This is likely due to the dataset containing realistic and correlated noise: the mislabelled class and the true class often have visual patterns in common.

For the synthetic noise (mini-Imagenet-Blue), NCR separates the clean and noisy examples up to 40% noise ratio. However, the model underfits with 80% synthetic noise, resulting in  $p$  being close to 0

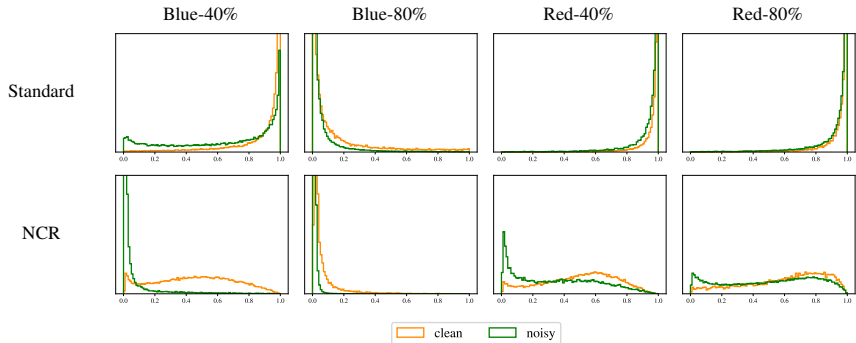


Figure 3: **Predicted confidence of training examples.** Whereas the baseline assigns similar confidence scores to clean and mislabelled examples (usually all high), NCR more often assigns lower confidence to mislabelled examples and higher confidence to correct examples.

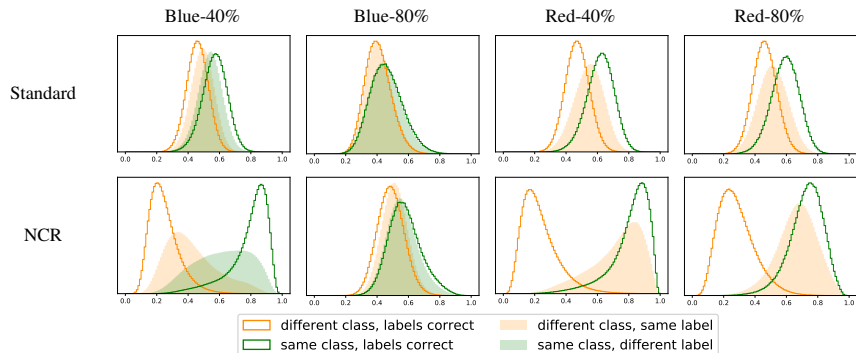


Figure 4: **Similarity distributions.** We compare the distribution of cosine similarities for training examples in mini-ImageNet that are correctly and incorrectly labelled as the same class or different classes. For mini-ImageNet-Blue, the features learned using NCR achieve significantly better class separation with 40% noise (or less, not pictured). For the more realistic mini-ImageNet-Red, NCR still achieves better separation of the clean examples but fails to separate examples that are incorrectly labelled as the same class.

for both clean and noisy examples. This results in a small relative improvement for NCR in terms of test accuracy, see mini-ImageNet-Blue with 80% noise in Table 1.

Table 1 also includes an *oracle* that is obtained by excluding the mislabelled examples from the training set, reducing its size by 20%, 40% or 80% accordingly. Under *realistic* noise (mini-ImageNet-Red), the results show that NCR outperforms the oracle across all noise ratios when using mixup. While this may be surprising, it can be explained by the observation that the noisy examples for each class are often visually similar to the clean examples, and thus still contain some useful information. However, the performance of NCR is significantly less than the oracle under synthetic noise (mini-ImageNet-Blue), where the noisy examples are often entirely dissimilar to the clean examples.

#### 5.4 EFFECT ON FEATURE EMBEDDINGS

Using the datasets with known noise, we can compare the feature similarity of training examples that are correctly or incorrectly labelled as belonging to the same or different classes. In the ideal case, the distributions of within-class and between-class similarities for clean examples would have zero overlap, and would be identical to the true within-class and between-class similarities for mislabelled examples. Figure 4 presents the similarity distributions for mini-ImageNet-Blue and -Red. (Note that, for mini-ImageNet-Red, the set of clean examples is known but the true class of the mislabelled examples is not known, so we cannot obtain the true within-class similarity for mislabelled examples.) We compare the distributions for a baseline model and a model trained with NCR. While the distributions for the baseline model overlap, they are not identical, showing that the feature similarities contain some signal for NCR



Table 2: **State-of-the-art comparison.** We compare NCR and our baseline implementation to other methods on mini-WebVision, Clothing1M, CIFAR-10 and CIFAR-100. We report the mean accuracy and standard deviation from five trials. The symbols denote: <sup>†</sup>result obtained using Inception-ResNet instead of ResNet-50, \*result obtained from a publication other than the original. CIFAR results for GJS,  $\mathcal{L}_{DMI}$  and the original ELR paper were not included because they use ResNet-34 instead of -18. Additional data augmentation (+DA) can help when using a larger backbone.

Backbone	mini-WebVision	Clothing 1M	CIFAR-10				CIFAR-100			
	R-50	R-50	0%	20%	40%	80%	0%	20%	40%	80%
Standard	75.8±0.9	71.7	94.2±0.1	80.0±0.6	57.7±0.3	18.0±0.3	74.2±1.7	60.6±0.6	46.3±0.5	8.9±0.3
Mixup	77.2±0.2	72.2	95.6±0.1	87.2±0.4	72.9±0.5	56.3±0.6	76.7±0.2	68.6±0.2	56.5±0.2	17.8±0.3
<b>Ours: NCR</b>	77.1	74.4	94.4±0.2	91.8±0.3	88.3±0.2	34.2±2.3	75.8±0.3	70.1±0.5	64.5±0.3	15.1±7.9
<b>Ours: NCR+Mixup</b>	79.4	74.5	<b>95.7±0.1</b>	92.5±0.1	90.0±0.2	55.8±1.5	<b>78.1±0.3</b>	72.5±0.3	66.8±0.3	30.4±0.4
<b>Ours: NCR+Mixup+DA</b>	<b>80.5</b>	74.6	95.5±0.1	92.0±0.1	89.3±0.3	54.7±2.7	77.8±0.2	72.3±0.5	65.8±0.4	33.1±0.5
MLNT; 3 iter.	-	73.5	-	-	-	-	-	-	-	-
CleanNet	-	<b>74.7</b>	-	-	-	-	-	-	-	-
$\mathcal{L}_{DMI}$	-	72.5	-	-	-	-	-	-	-	-
LongReMix	-	73.0	-	96.0	-	93.4	-	77.5	-	62.3
ELR	76.3 <sup>†</sup>	-	95.5*	94.5*	92.6*	38.2*	<b>78.0*</b>	75.9*	72.9*	36.8*
ELR+	77.8 <sup>†</sup>	<b>74.8</b>	-	94.6	-	91.1	-	77.5	-	60.8
DMix	76.3±0.4*	<b>74.8</b>	-	<b>96.2</b>	<b>94.9</b>	79.8	-	77.2	<b>75.2</b>	60.0
DMix+C2D	79.4±0.3	74.3	-	<b>96.2±0.1</b>	-	<b>94.3±0.1</b>	-	<b>78.3±0.4</b>	-	<b>67.4±0.3</b>
GJS	79.3±0.2	-	-	-	-	-	-	-	-	-
MOIT	-	-	95.2	92.9	90.6	70.5	75.8	72.8	67.4	45.6
MOIT+	-	-	<b>95.7</b>	94.1	92.0	75.8	77.1	75.9	70.9	51.4

to take advantage of. Training with NCR is shown to achieve greater separation of the classes in feature space, which must be due to the backpropagation of gradients through the feature similarities in (3).

## 5.5 STATE-OF-THE-ART COMPARISON

In addition to Table 1, which shows the state of the art comparison on mini-ImageNet-Red, we compare NCR against the state of the art on mini-WebVision, Clothing1M and CIFAR- $\{10, 100\}$  datasets in Table 2. We also present a Data Augmentation (DA) variant of NCR in these comparisons, where we generate a second view of each example in the minibatch by applying random color jittering. NCR achieves state-of-the-art accuracy in datasets with realistic noise such as mini-WebVision and mini-ImageNet-Red. We observe up to 1.5% improvement on mini-ImageNet-Red, and 1.1% improvement on mini-WebVision. Our method is also competitive on Clothing1M, where it is only 0.2% less than the state of the art.

Note that unlike most of the existing work in the literature, NCR does not involve additional steps, such as dividing the dataset into multiple splits, learning multiple models, applying semi-supervised learning, or a second-stage with additional training. While NCR is orthogonal to these strategies, we show that we achieve state of the art results with minimal additional processing (*e.g.* data augmentation). Furthermore, NCR achieves higher performance compared to GJS (Engleson & Azizpour, 2021) which applies a similar consistency regularization only on different augmentation of each example. This confirms that the neighbor consistency brings further improvements on top of augmentation consistency.

## 6 CONCLUSION

This work has introduced Neighborhood Consistency Regularization and demonstrated that it is an effective strategy for deep learning with label noise. In particular, neighbor consistency compares favorably against label smoothing and the bootstrapping loss as a technique to temper the influence of incorrect labels. While our approach draws inspiration from multi-stage training procedures for semi-supervised learning that employ transductive label propagation, it consists of a comparatively simple training procedure, requiring only that an extra loss be added to the objective which is optimized in stochastic gradient descent. NCR has been shown to achieve state-of-the-art results on the mini-WebVision dataset, outperforming methods that use neighbors in feature space purely for the purpose of rejecting mislabelled examples. Promising directions for future research include coupling NCR with a technique to reject out-of-distribution examples and applying NCR to the problem of semi-supervised learning.

**Ethics statement.** Our work presents a method for learning image classifiers from noisy data. Image classification is a general technology with a wide range of potential applications. While we are unaware of all potential applications, it is important to be aware that each application has its own merits and societal implications depending on the intentions of the individuals building and using the system.

Our proposed method is suited to learning from noisy data, as could be obtained by automatic scraping of the internet (illustrated by our experiments on mini-ImageNet-Red and mini-WebVision). Data collected in this fashion may contain bias (Birhane & Prabhu, 2021; de Vries et al., 2019) and a method which is able to more effectively learn from such data may inadvertently cause these biases to be amplified. Furthermore, when using training data automatically scraped from the web, it is possible that the data is being used for a purpose to which the original owner did not consent, potentially infringing on their privacy.

**Reproducibility statement.** We have included exhaustive descriptions of our datasets, training hyperparameters and remaining experimental details in the main paper and appendices. All of our experiments are also on publicly available datasets. We will release code and models upon acceptance.

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	CIFAR- $\{10, 100\}$	mini-ImageNet- $\{\text{Red, Blue}\}$	mini-Webvision	Clothing1M
Optimizer	SGD			
Momentum	0.9			
Batch size	256	128	256	128
Learning Rate	0.1	0.1	0.1	0.002
LR Schedule	cosine decay with linear warmup			
Warmup epochs	5			
Epochs	250	130	130	80
Weight decay	$5e-4$	$5e-4$	$1e-3$	$1e-3$
Architecture	ResNet-18		ResNet-50	

Table 3: List of network hyperparameters used to train the network in our experiments.

	mini-ImageNet				CIFAR-10				CIFAR-100				Clothing1M
	0%	20%	40%	80%	0%	20%	40%	80%	0%	20%	40%	80%	
$\alpha$	0.7	0.7	0.7	0.5	0.7	0.9	0.9	0.9	0.1	0.9	0.9	0.9	0.9
$k$	50	1	1	1	50	10	10	10	1	1	1	50	1
$e$	100	50	50	0	150	50	0	0	50	50	0	100	40

Table 4: List of NCR hyperparameters used to train the network in our experiments.

## A APPENDIX

### A.1 TRAINING DETAILS

**Implementation details.** We use the ResNet-18 and -50 architectures (He et al., 2016) in our experiments. To be comparable to the existing state-of-the-art (Ortego et al., 2020), we mostly adopt the same training hyperparameters as Ortego et al. (2020), only changing the batch size of CIFAR experiments to accelerate the training. For Clothing1M, we follow the work of Li et al. (2020) and fine-tune a pre-trained ResNet-50 for 80 epochs, where each epoch contains 1000 mini-batches. Table 3 lists the network hyperparameters used to train the network throughout our experiments. We train the network with the typical dot-product linear classifier  $h_W(\cdot)$  in all datasets except for mini-WebVision. For the mini-WebVision experiments, we follow the work of Ortego et al. (2020) and use a *cosine classifier* for  $h_W(\cdot)$ . Cosine classifier is also a linear classifier, however, the features and the classifier weights are  $\ell_2$ -normalized unlike the dot-product classifier.

We employ random crop augmentation during training in all experiments and resize images to  $224 \times 224$  pixels. For experiments with CIFAR, we use  $32 \times 32$  images and reduce the strides. We trained each model on a single Nvidia V100 GPU, and will release all code upon acceptance.

**NCR hyperparameters.** We sweep over the NCR hyperparameters  $\alpha$ ,  $k$  and  $e$ , and choose a set of hyperparameter based on the validation set accuracy on CIFAR- $\{10, 100\}$  and Clothing1M. This hyperparameter sweep is done for each noise ratio separately. Since mini-ImageNet- $\{\text{Red, Blue}\}$  does not contain a held-out validation set, we create a *held-out* set from the mini-ImageNet-Red dataset which comprises the (clean) examples from the 0% noise dataset that do not appear in the datasets with 20%, 40% or 80% noise. The *held-out* set allows us to choose hyperparameters without overfitting on the final evaluation set. We use the same hyperparameters on mini-ImageNet-Blue as well. Table 4 shows the list of hyperparameters for each dataset.

### A.2 DATASET DETAILS

Mini-ImageNet-Red contains 50 000 training examples and 5 000 validation examples. The noisy images are retrieved by text-to-image and image-to-image search. They come from an open vocabulary outside of the set of classes in the training set. Depending on the noise ratio, a subset of clean images are replaced by the noisy images to construct the training set.

Mini-ImageNet-Blue contains 60 000 training examples. The validation set is the same as mini-ImageNet-Red. The noise in mini-ImageNet-Blue is synthetic. The label of each example is

Method	mini-ImageNet-Purple			
	0%	20%	40%	80%
<b>BASELINES</b>				
Standard	65.8±0.4	16.1±0.0	11.9±0.0	0.05±0.0
Data Aug.	67.8±0.3	28.3±0.0	23.2±0.0	12.7±0.0
Mix-Up Zhang et al. (2018)	67.4±0.4	35.4±0.0	30.9±0.0	14.3±0.0
DataAug.+MixUp	<b>69.7±0.4</b>	49.6±0.0	42.6±0.0	<b>18.4±0.0</b>
<b>ORACLE</b>				
Standard	-	63.9±0.5	60.6±0.4	45.4±0.8
Data Aug.	-	65.2±0.4	62.4±0.6	48.8±0.7
DataAug.+MixUp	-	67.1±0.3	64.0±0.3	49.9±0.5
<b>OURS</b>				
<b>NCR</b> - Standard	67.8±0.2	34.7±0.0	25.9±0.0	10.2±0.0
<b>NCR</b> - Data Aug	69.4±0.3	44.2±0.0	33.3±0.0	15.3±0.0
<b>NCR</b> - DataAug.+MixUp	69.4±0.4	<b>53.6±0.0</b>	<b>43.1±0.0</b>	16.1±0.0

Table 5: **Baseline and oracle comparison.** Classification accuracy is reported on the mini-ImageNet-Purple with the ResNet-18 architecture. The accuracy is reported for each individual noise ratio (0%, 20%, 40%, 80%). We present the mean accuracy and standard deviation from five trials. The oracle model is trained on only the known, clean examples in the training set using a cross-entropy loss.

independently and uniformly changed according to a probability. The noisy examples come from a fixed vocabulary, *i.e.* their true label belongs to another class in the training set.

Mini-Webvision contains a subset of the original Webvision dataset Li et al. (2017). It contains only the first 50 classes of the Google image subset. This corresponds to 65 944 training images. The validation set contains 2 500 images corresponding to the 50 training classes.

Clothing1M (Xiao et al., 2015) is a large-scale dataset containing 1 million images and 14 categories. Images are collected from the web, and the noisy labels are assigned based on the surrounding text. We do not use the clean training subset with human-verified labels. We follow the existing protocol (Li et al., 2019) and fine-tune a ResNet-50 model which is pre-trained on ImageNet.