Emphasis Regularisation by Gradient Rescaling for Training Deep Neural Networks Robustly

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Abstract

It is fundamental and challenging to train robust and accurate Deep Neural Networks (DNNs) when noisy labels exist. Although great progress has been made, there is still one crucial research question which is not thoroughly explored yet: What training examples should be focused and how much more should they be emphasised when training DNNs under label noise? In this work, we study this question and propose gradient rescaling (GR) to solve it. GR modifies the magnitude of logit vector’s gradient to emphasise on relatively easier training data points when severe noise exists, which functions as explicit emphasis regularisation to improve the generalisation performance of DNNs. Apart from regularisation, we also interpret GR from the perspectives of sample reweighting and designing robust loss functions. Therefore, our proposed GR helps connect these three approaches in the literature. We empirically demonstrate that GR is highly noise-robust and outperforms the state-of-the-art noise-tolerant algorithms by a large margin, e.g., increasing 7% on CIFAR-100 with 40% noisy labels. It is also significantly superior to standard regularisers. Furthermore, we present comprehensive ablation studies to explore the behaviours of GR under different cases, which is informative for applying GR in real-world scenarios.

1 Introduction

DNNs have been successfully applied in diverse applications [1–3]. However, their success is heavily reliant on the quality of training data, especially accurate semantic labels for learning supervision. Unfortunately, on the one hand, maintaining the quality of semantic labels as the scale of training data increases is expensive and almost impossible when the scale becomes excessively large. On the other hand, it has been demonstrated that DNNs are capable of memorising the whole training data even when all training labels are semantically unrelated to their inputs [4]. Therefore, DNNs struggle to discern meaningful data patterns and tackle overfitting to noisy training examples at the same time [5, 6]. Consequently, it becomes an inevitable demand for DNNs to hold robustness when learning from training data where corrupted labels exist [7–14].

One training example is composed of one input and its corresponding label. A noisy training example means the input data is semantically unrelated to its label, which may come from corrupted input or label. In this work, we focus on corrupted labels.

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Recently, great progress has been made towards robustness against corrupted labels when training DNNs [5, 6]. Three main perspectives are appealing in terms of their simplicity and effectiveness: 1) Some proposals reweight training examples by knowledge distilling from auxiliary models [14–18]. However, it is vital and challenging for them to select and train reliable auxiliary models in practice. 2) Robust loss functions [19–22]; 3) Explicit regularisation techniques [6, 23]. Although adopting robust losses or explicit regularisation is even easier in practice, the performance is not optimal yet.

In this work, we connect these three perspectives together to train robust and accurate DNNs under label noise. Specifically, we propose gradient rescaling (GR), which modifies the magnitude of logit vector’s gradient. The logit vector is the output of the last fully connected (FC) layer of a network. We explain how GR is connected to sample reweighting, robust losses, and explicit regularisation: 1) The gradient magnitude of logit vector can be regarded as a sample weighting scheme that is built-in in loss functions [24–27]. Therefore, rescaling the gradient magnitude equals to reweighting training examples; 2) A specific loss function owns a fixed gradient derivation. Making the gradient robust serves as improving a loss function to be noise-robust; 3) We design two controllers, one for what training examples to be emphasised, termed emphasis focus, and another for how much training examples to be differentiated, termed emphasis spread. Instead of focusing on harder examples by default, we can adjust emphasis focus to relative easier ones when noise is severe. GR serves as emphasis regularisation and is different from standard regularisers, e.g., L2 weight decay constraints on weight parameters and Dropout samples neural units randomly [32].

Furthermore, there is a core research question which is not well answered yet when label noise exists:

**What training examples should be focused and how large the emphasis spread should be?**

The incorporated two key components in our proposed GR, i.e., emphasis focus and spread with explicit definition in Sec. 3.2, help us study and analyse this question better. In more detail, the reasons why we need to consider emphasis focus and spread are as follows:

**Emphasis focus.** It is a common practice to focus on harder instances when training DNNs [28, 33]. When training labels are correct, it achieves faster convergence and better performance to emphasise on harder examples because they own larger gradient magnitude, which means more information and a larger update step for model’s parameters. However, when severe noise exists, as demonstrated in [5, 6], DNNs learn simple meaningful patterns first before memorising noisy ones. In other words, noisy training examples are harder to fit and own larger gradient magnitude as well. Consequently, if we use the default sample weighting in categorical cross entropy (CCE) where harder samples obtain higher weights, noisy training examples can be fitted well finally [4]. That is why we need to move the emphasis focus towards relatively easier ones, which serves as emphasis regularisation.

**Emphasis spread.** We term the weighting variance of training examples emphasis spread. As shown in [33], choosing a proper weighting variance can improve the performance a lot when emphasis focus is harder samples. The key is that we should not treat all examples equally, neither should we let only a few be emphasised and contribute to the training. Therefore, when emphasis focus changes, the emphasis spread should be adjusted accordingly.

We show the effectiveness of GR by outperforming the state-of-the-art under different classification scenarios: 1) Clean CIFAR-10 and CIFAR-100 [34]; 2) CIFAR-10 and CIFAR-100 with synthetic symmetric label noise, which is more challenging than asymmetric one [35, 11] evaluated by [12, 36]; 3) Clothing 1M [10] with real-world unknown label noise, which may contain open-set noise [37], e.g., images with only background, or outliers, etc. Additionally, we show GR is notably better than present standard regularisers, e.g., L2 weight decay and dropout. To comprehensively understand GR’s behaviours, we present extensive ablation studies, which is valuable for applying GR in practice.

**Main contribution.** Intuitively and principally, we claim that two basic factors, what examples get higher weights (emphasis focus) and how large variance over examples’ weights (emphasis spread), should be babysit simultaneously when it comes to sample differentiation and reweighting. Unfortunately, these two intuitive and indispensable factors are not studied together in the literature.

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2 An example's difficulty can be indicated by its loss [28–30], gradient magnitude [24, 25], or input-to-label relevance score [31]. The input-to-label relevance score means the probability of an input belonging to its labelled class predicted by a current model. The difficulty of an example may change as the model learns. In summary, higher difficulty = larger loss or larger gradient magnitude = lower input-to-label relevance score.
We show 3 settings of GR: (β = 2, λ = 0), (β = 8, λ = 0.5) and (β = 12, λ = 1). Their corresponding emphasis focuses are 0, 0∼0.5 and 0.5.

(b) GR when fixing λ = 0.5 (emphasis focus is within 0∼0.5) or λ = 2 (emphasis focus is within 0.5∼1).

c) GR when fixing β = 8. When λ increases, the emphasis focus moves towards 1 and emphasis spread drops.

Figure 1: A sample’s weight \( w_i \) along with its input-to-label relevance score \( p_i \). GR is a unified sample reweighting framework from the perspective of gradient rescaling, where the emphasis focus and spread can be adjusted by choosing proper \( \lambda \) and \( \beta \) in practice. Better viewed in colour.

Table 1: Comparison between GR and other learning supervisions. 0∼0.5 and 0∼1 indicate the emphasis focus is adjustable and ranges from 0 to 0.5 and 0 to 1, respectively. Note that GR manipulates the gradients and is independent of specific losses, e.g., CCE, MAE and GCE.

| Supervision | Empirical loss | Gradient rescaling | Emphasis focus | Adjustable emphasis spread |
|-------------|----------------|--------------------|----------------|---------------------------|
| CCE         | CCE            | No                 | 0              | No                        |
| MAE         | MAE            | No                 | 0.5            | No                        |
| GCE         | GCE            | No                 | 0∼0.5          | No                        |
| GR          | CCE/MAE/GCE    | Yes               | 0∼1            | Yes                       |

2 Related Work

Aside from reweighting [14–18], robust loss functions [19–22] and explicit regularisation techniques [6, 23], there are another two main perspectives for training robust and accurate DNNs under label noise: 1) Some methods focus on noise-aware modelling for correcting noisy labels or empirical losses [7–10, 12–16, 38, 39]. However, it is non-trivial and time-consuming to learn a noise-aware model, which also requires prior extra information or some specific assumptions. For example, Masking [39] is assisted by human cognition to speculate the noise structure of noise-aware matrix while some [13–16, 31, 40] exploit an extra clean dataset, which is a hyper-factor and hard to control in practice; 2) Some algorithms iteratively train the model and infer latent true labels [37, 41, 36, 35]. Nonetheless, it is hard to decide the status change between model training and label inference in practice. Moreover, alternative optimisation is time-consuming. Compared with noise-aware modelling and alternative optimisation, the first three are simpler and easier for practice. However, their connections are not explored in the literature. In this work, our proposal GR merges the first three angles and achieves new state-of-the-art while embracing simplicity and intuitive interpretation. Compared with existing sample reweighting techniques [14–18], neither knowledge from extra networks nor auxiliary clean labels are required in GR.

3 Emphasis Regularisation by Gradient Rescaling

Notation. We are given \( N \) training examples \( \mathbf{X} = \{(x_i, y_i)\}_{i=1}^N \), where \( (x_i, y_i) \) denotes \( i \)-th sample with input \( x_i \in \mathbb{R}^D \) and label \( y_i \in \{1, 2, ..., C\} \). \( C \) is the number of classes. Let’s consider a deep neural network \( z \) composed of an embedding network \( f(\cdot): \mathbb{R}^D \rightarrow \mathbb{R}^K \) and a linear classifier \( g(\cdot): \mathbb{R}^K \rightarrow \mathbb{R}^C \), i.e., \( z_i = z(x_i) = g(f(x_i)) : \mathbb{R}^D \rightarrow \mathbb{R}^C \). Generally, the linear classifier is the last FC layer which produces the final output of \( z \), i.e., logit vector \( z \in \mathbb{R}^C \). To obtain probabilities of a sample belonging to different classes, logit vector is normalised by a softmax function:

\[
p(m|x_i) = \frac{\exp(z_{im})}{\sum_{j=1}^C \exp(z_{ij})},
\]

\( p(m|x_i) \) is the probability of \( x_i \) belonging to class \( m \). A sample’s input-to-label relevance score is defined by \( p_i = p(y_i|x_i) \). In what follows, we will uncover the sample weighting in popular losses: CCE, Mean Absolute Error (MAE) and Generalised Cross Entropy (GCE) [21].
3.1 Analysing intrinsic sample weighting in CCE, MAE and GCE

CCE. The CCE loss with respect to \((x_i, y_i)\) and its gradient with respect to \(z_{im}\) are defined as:

\[
L_{\text{CCE}}(x_i, y_i) = -\log p(y_i | x_i) \quad \text{and} \quad \frac{\partial L_{\text{CCE}}}{\partial z_{im}} = \begin{cases} p(y_i | x_i) - 1, & m = y_i \\ p(m | x_i), & m \neq y_i. \end{cases}
\]

Therefore, we have \(\| \frac{\partial L_{\text{CCE}}}{\partial x_{im}} \|_1 = 2(1 - p(y_i | x_i)) = 2(1 - p_i)\). Here we choose L1 norm to measure the magnitude of gradient because of its simpler statistics and computation. Since we back-propagate \(\frac{\partial L_{\text{CCE}}}{\partial z_i}\) to update the model’s parameters, an example’s gradient magnitude determines how much impact it owns, i.e., its weight \(w_i^{\text{CCE}} = \| \frac{\partial L_{\text{CCE}}}{\partial x_{im}} \|_1 = 2(1 - p_i)\). In CCE, more difficult examples with smaller \(p_i\) get higher weight. So CCE is inclined to fit noisy training examples well [4–6].

MAE. When it comes to MAE, the loss of \((x_i, y_i)\) and gradient with respect to \(z_{im}\), are:

\[
L_{\text{MAE}}(x_i, y_i) = 2(1 - p(y_i | x_i)) \quad \text{and} \quad \frac{\partial L_{\text{MAE}}}{\partial z_{im}} = \begin{cases} 2p(y_i | x_i)(p(y_i | x_i) - 1), & m = y_i \\ 2p(y_i | x_i)p(m | x_i), & m \neq y_i. \end{cases}
\]

Therefore, \(w_i^{\text{MAE}} = \| \frac{\partial L_{\text{MAE}}}{\partial z_i} \|_1 = 4p(y_i | x_i)(1 - p(y_i | x_i)) = 4p_i(1 - p_i)\). In MAE, those images whose input-to-label relevance scores are 0.5 become the emphasis focus. Consequently, MAE is more robust to label noise than CCE as proved in [20].

GCE. In GCE, the loss calculation of \((x_i, y_i)\) and gradient with respect to logit vector \(z_i\) are:

\[
L_{\text{GCE}}(x_i, y_i) = \frac{1}{q} - \frac{p(y_i | x_i)^q}{q} \quad \text{and} \quad \frac{\partial L_{\text{GCE}}}{\partial z_{im}} = \begin{cases} p(y_i | x_i)^q(p(y_i | x_i) - 1), & m = y_i \\ p(y_i | x_i)^q p(m | x_i), & m \neq y_i, \end{cases}
\]

where \(q \in [0, 1]\). Therefore, \(w_i^{\text{GCE}} = \| \frac{\partial L_{\text{GCE}}}{\partial z_i} \|_1 = 2p(y_i | x_i)(1 - p(y_i | x_i)) = 2p_i^q(1 - p_i)\). In this case, the emphasis focus can be adjusted from 0 to 0.5 when \(q\) ranges from 0 to 1. However, in their practice [21], instead of using this naive version, a truncated one is applied:

\[
L_{\text{GCE-trunc}}(x_i, y_i) = \begin{cases} L_q(p_i), & p_i > 0.5 \\ L_q(0.5), & p_i \leq 0.5 \text{ and } L_q(\gamma) = (1 - \gamma^q)/q, \end{cases}
\]

The loss of an example with \(p_i \leq 0.5\) is constant so that its gradient is zero, which means it is dropped and does not contribute to the training. The main drawback is that the model cannot be trained directly. Because at the initial stage, the model is not well learned so that the predicted \(p_i\) of most samples are smaller than 0.5. To address it, alternative convex search is exploited for iterative data pruning and parameters optimisation, making it quite complex and less appealing in practice.

3.2 Gradient rescaling for reweighting unification and emphasis regularisation

A loss function provides supervision information by its derivative with respect to a network’s output. Therefore, there are two perspectives for improving the supervision information: 1) Modifying the loss format to improve its corresponding derivative; 2) Manipulating the gradient straightforwardly. In this work, we choose to improve the gradient, which is more direct to control and easier to understand.

According to Eq. (2), (3), (4), the gradients of CCE, MAE and GCE share the same direction. Our proposal GR unifies them from the gradient perspective. Being independent of loss computation, a sample’s gradient is rescaled linearly based on its weight \(w_i^{GR}\):

\[
w_i^{GR} = g(\beta \cdot p_i^\lambda (1 - p_i)) \Rightarrow \frac{\partial L}{\partial z_i} = \frac{\partial L_{\text{CCE}}}{\partial z_i} \cdot w_i^{GR} \text{CCE} = \frac{\partial L_{\text{MAE}}}{\partial z_i} \cdot w_i^{GR} \text{MAE} = \frac{\partial L_{\text{GCE}}}{\partial z_i} \cdot w_i^{GR} \text{GCE},
\]

where \(\lambda, \beta\) are hyper-parameters for controlling the emphasis focus and spread, respectively. Choosing a larger \(\lambda\) when severe noise exists, GR regularises sample reweighting by moving emphasis focus toward relatively easier training data points, thus embracing noise-robustness.

For clarification, we explicitly define the emphasis focus and spread over training examples. With these definitions, we differentiate GR with other methods in Table 1. We show the sample weighting curves of GR with different settings in Figure 1, with comparison to CCE, MAE, GCE.

**Definition 1 (Emphasis Focus).** The emphasis focus refers to those examples that own the largest weight. Since an example’s weight is determined by its input-to-label relevance score \(p_i\), for simplicity, we define the emphasis focus to be an input-to-label score to which the largest weight is assigned, i.e., \(\arg \max_{p_i} w_i^{GR}\).

**Definition 2 (Emphasis Spread).** The emphasis spread is the weight variance over all training instances in a mini-batch.
As shown in Figure 1c, the emphasis spread declines as \( \lambda \) increases. Therefore, we explore larger \( \beta \) values when \( \lambda \) is larger in Sec. 4.2.1.

In practice, transformation \( g \) could be designed as any monotonically increasing function. Because the non-linear exponential mapping can change the overall weights’ variance and relative weights between any two examples, we choose \( g(\cdot) = \exp(\cdot) \), which works well in our practice. By integral, the exact loss format is an error function (non-elementary). We summarise several existing cases as follows (the ellipsis refers to other potential options which can be explored in the future):

\[
\begin{align*}
    w^\text{GR}_i &= \\
    &\begin{cases}
        w^{\text{CCE}}_i, & \beta = 2, \lambda = 0, g = \text{identity} \\
        w^{\text{MAE}}_i, & \beta = 4, \lambda = 1, g = \text{identity} \\
        w^{\text{GCE}}_i, & \beta = 1, 1 \geq \lambda \geq 0, g = \text{identity} \\
        \exp(\beta \cdot p^\lambda_1 \cdot (1 - p_i)), & \beta \geq 0, \lambda \geq 0, g = \exp
    \end{cases}
\end{align*}
\]  

(7)

3.3 Why does GR contribute to robust learning?

GR unifies CCE, MAE and GCE as presented in Table 1, thus sharing the same theoretical insights and justification as the prior work, MAE and GCE. Let’s regard a deep network \( f \) as a black box, which produces \( C \) logits. \( C \) is the class number. Then during gradient back-propagation, an example’s impact on the update of \( f \) is determined by its gradient w.r.t. the logit vector. The impact can be decomposed into two factors, i.e., gradient direction and magnitude. To reduce the impact of a noisy sample, we can either reduce its gradient magnitude or amend its gradient direction. In this work, inspired by the analysis of CCE, MAE and GCE whose gradient directions are the same, we explore rescaling the gradient magnitude as illustrated in Figure 1. It is also worth studying amending gradient directions in the future.

4 Experiments

4.1 Image classification with clean labels

Datasets. We test on CIFAR-10 and CIFAR-100 [34], which contain 10 and 100 classes, respectively. In CIFAR-10, the training data contains 5k images per class while the test set includes 1k images per class. In CIFAR-100, there are 500 images per class for training and 100 images per class for testing.

Implementation details. On CIFAR-10, following [42], we adopt ResNet-20 and ResNet-56 as backbones so that we can compare fairly with their reported results. On CIFAR-100, we follow D2L [36] to choose ResNet-44 and compare with its reported results. We also use a SGD optimiser with momentum 0.9 and weight decay \( 10^{-4} \). The learning rate is initialised with 0.1, and multiplied with 0.1 every 5k iterations. We apply the standard data augmentation as in [42, 36]: The original images are padded with 4 pixels on every side, followed by a random crop of \( 32 \times 32 \) and horizontal flip.

Results. Here, our intention is to show GR can achieve competitive performance with CCE under clean labels to demonstrate its general applicability. As reported in D2L, all noise-tolerant proposals [11, 35, 36] perform similarly with CCE when training labels are clean. Therefore we do not present other related competitors here. Our implemented results are shown in Table 2. For reference, the reported results in [42] on CIFAR-10 with CCE are 91.3% for ResNet-20 and 93.0% for ResNet-56. In D2L, the result on CIFAR-100 with ResNet-44 is 68.2%. Our reimplemented performance of CCE is only slightly different. For GR, we observe the best performance when emphasis focus is 0, i.e., \( \lambda = 0 \). Furthermore, it is insensitive to a wide range of emphasis spreads according to our observations in Figure 4 in the supplementary material.

Table 2: Classification accuracies (%) of CCE, and GR on clean CIFAR-10 and CIFAR-100. \( \lambda = 0 \) means the emphasis focus is 0 where we fix \( \beta = 2 \). \( \beta = 0 \) means all examples are treated equally.

| Dataset   | Backbone | CCE  | GR (\( \lambda = 0 \)) | GR (\( \beta = 0 \)) |
|-----------|----------|------|------------------------|----------------------|
| CIFAR-10  | ResNet-20| 91.8 | 91.8                   | 91.0                 |
|           | ResNet-56| 92.4 | 92.5                   | 91.9                 |
| CIFAR-100 | ResNet-44| 68.1 | 68.4                   | 66.4                 |

Treating training examples equally. As shown in Table 2, we obtain competitive performance by treating all training examples equally when \( \beta = 0 \). This is quite interesting and motivates us that sample differentiation and reweighting work much better only when noise exists.
Table 3: Results of CCE, GR on CIFAR-10 with corrupted labels. For every model, we show its best test accuracy during training and the final test accuracy when training terminates, which are indicated by ‘Best’ and ‘Final’, respectively. We also present the results on corrupted training sets and original intact one. The overlap rate between corrupted and intact sets is (1 − r). Therefore, we can regard the intact training set as a validation set. When λ is larger, β should be larger as shown in Figure 1c.

| Noise Rate r | Emphasis Focus | Model | Testing Accuracy (%) | Accuracy on Training Sets (%) |
|--------------|----------------|-------|----------------------|-------------------------------|
|              |                |       | Best     | Final | Corrupted/Fitting | Intact/Validation |
| 20%          | None           | CCE   | 86.5     | 76.8  | 95.7             | 80.6             |
|              | 0 (λ = 0)      | GR (β = 0) | 83.5     | 58.1  | 50.6             | 60.2             |
|              | 0.5 (λ = 0.5)  | GR (β = 12) | 89.4    | 87.8  | 81.5             | **95.0**         |
|              | 0.5 (λ = 1)    | GR (β = 16) | 87.3    | 86.7  | 78.4             | 93.8             |
|              | 0.5~1 (λ = 2)  | GR (β = 24) | 85.8    | 85.5  | 76.0             | 91.4             |
| 40%          | None           | CCE   | 82.8     | 60.9  | **83.0**         | 64.4             |
|              | 0 (λ = 0)      | GR (β = 0) | 71.8    | 44.9  | 31.3             | 45.8             |
|              | 0.5 (λ = 0.5)  | GR (β = 12) | 85.1    | 79.9  | 67.7             | 85.7             |
|              | 0.5 (λ = 1)    | GR (β = 16) | 84.7    | **83.3** | 60.3 | **88.9**         |
|              | 0.5~1 (λ = 2)  | GR (β = 20) | 52.7    | 52.7  | 35.4             | 53.6             |
| 60%          | None           | CCE   | 69.5     | 37.2  | **84.1**         | 40.5             |
|              | 0 (λ = 0)      | GR (β = 0) | 69.9    | 57.9  | 40.1             | 58.6             |
|              | 0.5 (λ = 0.5)  | GR (β = 12) | 72.3    | 53.9  | 42.1             | 55.1             |
|              | 0.5 (λ = 1)    | GR (β = 16) | 71.9    | 70.0  | 41.0             | 73.9             |
|              | 0.5~1 (λ = 2)  | GR (β = 20) | 80.2    | **72.5** | 44.9 | **75.4**         |
| 80%          | None           | CCE   | 36.1     | 16.1  | **54.3**         | 18.4             |
|              | 0 (λ = 0)      | GR (β = 0) | 44.4    | 28.2  | 20.6             | 28.8             |
|              | 0.5 (λ = 0.5)  | GR (β = 8) | 51.6    | 22.4  | 16.1             | 24.4             |
|              | 0.5 (λ = 1)    | GR (β = 8) | 35.5    | 31.5  | 19.8             | 32.3             |
|              | 0.5~1 (λ = 2)  | GR (β = 12) | 33.0    | **32.8** | 14.2 | **32.6**         |

4.2 Image classification with synthetic symmetric label noise

Noisy labels generation. Following [41, 36], we generate symmetric label noise. That is, given a probability r, the original label of an image is changed to one of the other class labels uniformly. r denotes noise rate. Symmetric label noise generally exists in large-scale real-world applications where the dataset scale is so large that label quality is hard to guarantee. It is also demonstrated in [12] that it is more challenging than asymmetric noisy labels [35, 11], which assume that label errors only exist within a predefined set of similar classes. The batch size is 128 in Sec. 4.2.1 and 4.2.3.

4.2.1 Empirical analysis of GR on CIFAR-10

To understand GR well empirically, we explore the behaviours of GR on CIFAR-10 with r = 20%, 40%, 60%, 80%, respectively. We use ResNet-56 which has larger capacity than ResNet-20.

Design choices. We mainly focus on analysing the impact of different emphasis focuses for different noise rates. We explore 5 emphasis focuses by setting β = 0 or different λ: 1) None: β = 0. There is no emphasis focus since all examples are treated equally; 2) 0: λ = 0; 3) 0~0.5: λ = 0.5; 4) 0.5: λ = 1; 5) 0.5~1: λ = 2. Note that a higher emphasis focus by setting a larger λ functions as focusing on relatively easier training data points. As shown in Figure 1, when emphasis focus changes, emphasis spread changes accordingly. Therefore, to set a proper spread for each emphasis focus, we try 4 emphasis spread and choose the best one to compare the impact of emphasis focus.

Results analysis. We show the results in Table 9. The intact training set serves as a validation set and we observe that its accuracy is always consistent with the final test accuracy. This motivates us

3Since there is a large interval between different β in our four trials, we deduce that the chosen one is not the optimal. For every λ, four corresponding β values are shown in Figures 6-9 in the supplementary material. The focus of this work is not to optimize the hyper-parameters.
that we can choose our model’s hyper-parameters $\beta, \lambda$ via a validation set in practice. We display the training dynamics in Figure 2. We summarise our observations as follows:

**Fitting and generalisation.** We observe that CCE always achieves the best accuracy on corrupted training sets, which indicates that CCE has a strong data fitting ability even if there is severe noise [4, 6]. However, fitting too well incurs bad generalisation when noise exists. According to our observations, CCE has much worse final test accuracy than most models.

**Emphasising on harder examples.** When there exist noisy training examples, we obtain the worst final test accuracy if emphasis focus is 0, i.e., CCE and GR with $\lambda = 0$. This unveils that in applications where we have to learn from noisy training data, it will hurt the model’s generalisation dramatically if we use CCE or simply focus on harder training data points.

**Emphasis focus.** When noise rate is 0, 20%, 40%, 60%, and 80%, we obtain the best final test accuracy when $\lambda = 0$, $\lambda = 0.5$, $\lambda = 1$, $\lambda = 2$, and $\lambda = 2$, respectively. This demonstrates that when noise rate is higher, we can improve a model’s robustness by moving emphasis focus towards relatively less difficult examples with a larger $\lambda$, which is informative in practice.

**Emphasis spread.** As displayed in Table 9 and Figures 6-9 in the supplementary material, emphasis spread also matters a lot when fixing emphasis focus, i.e., fixing $\lambda$. For example in Table 9, when $\lambda = 0$, although focusing on harder examples similarly with CCE, GR can outperform CCE by modifying the emphasis spread. As shown in the Figures 6-9, some models even collapse and cannot converge if the emphasis spread is not rational under severe noise.

### 4.2.2 Competing with the state-of-the-art on CIFAR-10

**Implementation details.** We follow exactly the same settings as MentorNet [15] to compare fairly with its reported results. Optimiser and data augmentation are described in Section 4.1. All augmented training examples share the same label as the original one.

**Competitors.** FullModel is the most basic one trained using L2 weight decay and dropout [32]. Forgetting [6] searches the dropout parameter in the range of (0.2-0.9). Self-paced [43], Focal Loss [33], and MentorNet [15] are representatives of example reweighting algorithms. Reed Soft [35] is a weakly-supervised learning method.

**Results.** Comparison of validation accuracy on CIFAR-10 under different noise rates is shown in Table 4. We observe that GR with fixed hyper-parameters $\beta = 8, \lambda = 0.5$ outperforms the state-of-the-art GCE by a large margin, especially when label noise becomes severe.
Table 4: The results of GR and other noise-robust approaches on CIFAR-10 using GoogLeNet V1 [44]. We follow exactly the same settings as MentorNet [15]. We remark that FullModel (naive CCE) [15] was trained with L2 weight decay and dropout [32]. The hyper-parameters of GR are fixed: $\beta = 8, \lambda = 0.5$.

| Noise rate $r$ | FullModel [6] | Forgetting [43] | Self-paced [43] | Focal Loss [33] | Reed [35] | MentorNet [15] | Mentor [15] | GCE [21] $(\beta = 8, \lambda = 0.5)$ | GR $(\beta = 8, \lambda = 0.5)$ |
|---------------|---------------|----------------|----------------|----------------|----------|----------------|------------|----------------------------------|----------------|
| 0%            | 0.81          | –              | –              | –              | –        | 0.83           | 0.85       | 0.85                             | 0.85           |
| 20%           | 0.76          | 0.76           | 0.80           | 0.77           | 0.78     | 0.79           | 0.79       | 0.81                             | 0.83           |
| 40%           | 0.73          | 0.71           | 0.74           | 0.74           | 0.74     | 0.74           | 0.78       | 0.78                             | 0.79           |
| 80%           | 0.42          | 0.44           | 0.33           | 0.40           | 0.39     | 0.44           | 0.46       | 0.50                             | 0.57           |

4.2.3 Competing with the state-of-the-art on CIFAR-100

Implementation details. Most baselines have been reimplemented in [36] with the same settings. Therefore, for direct comparison, we follow exactly their experimental configurations on CIFAR-100 with ResNet-44 [42]. Optimiser and data augmentation are described in Section 4.1. All augmented training examples share the same label as the original one. We repeat training and evaluation 5 times where different random seeds are used for generating noisy labels and model initialisation. The mean test accuracy and standard deviation are reported.

Competitors. We compare with D2L [36], GCE [21], and other baselines reimplemented in D2L: 1) Standard CCE [36]; 2) Forward [11] uses a noise-transition matrix to multiply the network’s predictions for label correction; 3) Backward [11] applies the noise-transition matrix to multiply the CCE losses for loss correction; 4) Bootstrapping [35] trains models with new labels generated by a convex combination of the original ones and their predictions. The convex combination can be soft (Bootstrap-soft) or hard (Bootstrap-hard); 5) D2L [36] achieves noise-robustness from a novel perspective of restricting the dimensionality expansion of learned subspaces during training and is the state-of-the-art; 6) Since GCE outperforms MAE [21], we only reimplement GCE for comparison.

Results. We compare the results of GR and other algorithms in Table 5. GR outperforms other competitors by a large margin, especially when label noise is severe, e.g., $r = 40\%$ and 60\%. More importantly, we highlight that GR is much simpler without any extra information. Compared with Forward and Backward, GR does not need any prior knowledge about the noise-transition matrix or estimate it, which is quite difficult on CIFAR-100 although it contains only 100 classes. Bootstrapping targets at label correction and is time-consuming. D2L estimates the local intrinsic dimensionality every $b$ mini-batches and checks the turning point for dimensionality expansion every $e$ epochs, where $b$ and $e$ are difficult to choose and iterative monitoring is time-consuming.

Table 5: The accuracies (%) of GR and recent approaches on CIFAR-100. The results of fixed parameters $(\beta = 8, \lambda = 0.5)$ are shown in the second last column. With a little effort for optimising $\beta, \lambda$ via the validation set, the results and corresponding parameters are presented in the last column. The trend is consistent with Table 9. When $r$ raises, we can increase $\beta, \lambda$ for better robustness. The increasing scale is much smaller. This is because CIFAR-100 has 100 classes so that its distribution of $p_i$ (input-to-label relevance score) is different from CIFAR-10 after softmax normalisation.

| Noise rate $r$ | CCE [36] | GCE [21] | Forward [11] | Backward [11] | Bootstrap-soft [35] | Bootstrap-hard [35] | D2L [36] | GR $(\beta = 8, \lambda = 0.5)$ | GR $(\beta, \lambda)$ |
|---------------|----------|----------|---------------|----------------|---------------------|---------------------|----------|-------------------------------|---------------------|
| 20%           | 52.9±0.2 | 53.4±0.3 | 50.6±0.2      | 58.7±0.2       | 58.5±0.4            | 57.3±0.3            | 62.2±0.4 | 62.6±0.3                      | 64.1±0.2            |
| 40%           | 42.9±0.2 | 47.0±0.2 | 51.3±0.3      | 45.4±0.2       | 44.4±0.1            | 41.9±0.1            | 52.0±0.3 | 59.3±0.2                      | 60.9±0.1            |
| 60%           | 30.1±0.2 | 41.0±0.2 | 41.2±0.3      | 34.5±0.2       | 36.7±0.3            | 32.3±0.1            | 42.3±0.2 | 49.9±0.3                      | 49.9±0.3            |

4.3 Image classification with real-world label noise

Dataset. Clothing 1M [10] contains 1 million images with noisy labels. It is an industrial-level dataset and its noise structure is agnostic. According to [10], around 61.54% training labels are reliable, i.e., noise rate is about 38.46%. There are 14 classes from several online shopping websites. In addition, there are 50k, 14k, and 10k images with clean labels for training, validation, and testing, respectively. Here, we follow and compare with existing methods that only learn from noisy training data since we would like to avoid exploiting auxiliary information.
Implementation details. We only train on the noisy training data with ResNet-50 \[42\] so that we can compare directly with the results reported in \[11, 41\]. We follow exactly same training settings in \[11, 41\]: 1) Initialisation: ResNet-50 is initialised by publicly available model pretrained on ImageNet \[45\]; 2) Optimisation: A SGD optimiser with a momentum of 0.9 and a weight decay of \(10^{-3}\) is applied. The learning rate starts at \(10^{-3}\) and is divided by 10 after 5 epochs. Training terminates at 10 epochs; 3) Standard data augmentation: We first resize a raw input image to \(256 \times 256\), and then crop it randomly at \(224 \times 224\) followed by random horizontal flipping. The batch size is 64 due to memory limitation. Since the noise rate is around 38.46%, we simply set \(\lambda = 1, \beta = 16\) following Table 9 when noise rate is 40%.

Competitors. We compare with present noise-robust algorithms that have been evaluated on Clothing 1M with similar settings: 1) Standard CCE \[11\]; 2) Since Forward outperforms Backward on Clothing 1M \[11\], we only present the result of Forward; 3) S-adaptation applies an additional softmax layer to estimate the noise-transition matrix \[38\]; 4) Masking is a human-assisted approach that conveys human cognition to speculate the structure of the noise-transition matrix \[39\]. 5) Label optimisation \[41\] learns latent true labels and model’s parameters iteratively. Two regularisation terms are added for label optimisation and adjusted in practice.

Results. The results are compared in Table 6. Under real-world agnostic noise, GR also outperforms the state-of-the-art. It is worth mentioning that the burden of noise-transition matrix estimation in Forward and S-adaptation is heavy due to alternative optimisation steps, and such estimation is non-trivial without big enough data. Masking exploits human cognition of a structure prior and reduces the burden of estimation, nonetheless its performance is not competitive. Similarly, Label Optimisation requires alternative optimisation steps and is time-consuming. Instead, GR is simple, efficient and effective.

Table 6: The classification accuracy on Clothing 1M with ResNet-50.

| Method                  | CCE   | Bootstrapping | Forward | S-adaptation | Masking | Label Optimisation | GR   |
|-------------------------|-------|---------------|---------|--------------|---------|--------------------|------|
| Accuracy (%)            | 68.9  | 69.1          | 69.8    | 70.4         | 71.1    | 72.2               | 72.9 |

4.4 Beating standard regularisers under label noise

In Table 7, we compare our proposed regularisor GR with current standard ones, i.e., L2 weight decay and Dropout \[32\]. We set the dropout rate to 0.2 and L2 weight decay rate to \(10^{-4}\) based on the validation performance. For GR, as mentioned in Section 4.2.3, we fix \(\beta = 8, \lambda = 0.5\). Interestingly, Dropout+L2 achieves 52.8% accuracy, which is even better than the state-of-the-art in Table 5, i.e., D2L with 52.0% accuracy. However, GR is better than current standard regularisers and their combination significantly. GR works best when it is together with L2 weight decay.

Table 7: Comparing GR with standard regularisers on CIFAR-100 with \(r = 40\%\), i.e., the label noise is severe but not belongs to the majority. The backbone is ResNet-44. We report the average test accuracy and standard deviation (%) over 5 trials. Baseline means CCE without regularisation.

| Method                  | Baseline | L2      | Dropout | Dropout+L2 | GR       | GR+L2    | GR+Dropout | GR+L2+Dropout |
|-------------------------|----------|---------|---------|------------|----------|----------|------------|---------------|
| Accuracy (%)            | 44.7±0.1 | 51.5±0.4| 46.7±0.5| 52.8±0.4   | 55.7±0.3 | 59.3±0.2 | 54.3±0.4   | 58.3±0.3      |

5 Conclusion

In this work, we propose a simple yet effective gradient rescaling framework for emphasis regularisation, where the emphasis focus and spread are adjustable in practice. We present three main contributions: 1) We conduct extensive empirical studies to analyse an unanswered core question when training robust DNNs under noise: What training examples should be focused and how large emphasis spread should be? 2) By gradient rescaling, we achieve new state-of-the-art performance when training DNNs under synthetic and real-world label noise. 3) Our gradient rescaling also significantly outperforms standard regularisers, i.e., L2 weight decay, Dropout and their combination.

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Supplementary Material for
Emphasis Regularisation by Gradient Rescaling for
Training Deep Neural Networks with Noisy Labels

Question: What training examples should be focused and how much more should they be emphasised when training DNNs under label noise?

Proposal: Gradient rescaling incorporates emphasis focus (centre/focal point) and emphasis spread, and serves as explicit regularisation in terms of sample reweighting/emphasis.

Finding: When noise rate is higher, we can improve a model’s robustness by moving emphasis focus towards relatively less difficult examples.

More detailed results for our key finding by studying the core research question:

Table 8: Exploration of GR with different emphasis focuses (centres) and spreads on CIFAR-100 when \( r = 20\% , 40\% , 60\% \), respectively. This table presents detailed information of optimising \( \lambda , \beta \) mentioned in Table 5 in the paper. Specifically, for each \( \lambda \), we try 5 \( \beta \) values from \( \{2, 4, 6, 8, 10\} \) and select the best one as the final result of the \( \lambda \). We report the mean test accuracy over 5 repetitions.

| Noise rate \( r \) | \( \lambda \) | \( \beta \) | Testing accuracy (%) |
|------------------|--------|--------|---------------------|
| 20%              | 0.1    | 4      | 61.3                |
|                  | 0.2    | 4      | 63.3                |
|                  | 0.3    | 6      | **64.1**            |
|                  | 0.4    | 6      | 63.6                |
|                  | 0.5    | 8      | 62.6                |
|                  | 0.6    | 8      | 62.5                |
| 40%              | 0.1    | 4      | 55.5                |
|                  | 0.2    | 4      | 58.2                |
|                  | 0.3    | 6      | 59.1                |
|                  | 0.4    | 6      | **60.0**            |
|                  | 0.5    | 8      | 59.3                |
|                  | 0.6    | 8      | 58.5                |
| 60%              | 0.1    | 4      | 44.9                |
|                  | 0.2    | 4      | 47.5                |
|                  | 0.3    | 6      | 49.7                |
|                  | 0.4    | 6      | **49.9**            |
|                  | 0.5    | 8      | **49.9**            |
|                  | 0.6    | 8      | 47.3                |
Figure 3: The training and test accuracies on clean CIFAR-10 along with training iterations. The training labels are clean. We fix $\lambda = 0$ to focus on harder examples while changing emphasis spread controller $\beta$. The backbone is ResNet-20. The results of ResNet-56 are shown in Figure 4. Better viewed in colour.

Figure 4: The training and test accuracies on clean CIFAR-10 along with training iterations. The training labels are clean. We fix $\lambda = 0$ to focus on more difficult examples while changing emphasis spread controller $\beta$. The backbone is ResNet-56. The results of ResNet-20 are shown in Figure 3. Better viewed in colour.

Figure 5: The learning dynamics on CIFAR-10 ($r = 80\%$) with ResNet-56, i.e., training and testing accuracies along with training iterations. The legend in the top left is shared by two subfigures. ‘xxx: yyy’ means ‘method: emphasis focus’. The results of $r = 20\%, 40\%, 60\%$ are shown in Figure 2 in the paper.
We have two key observations: 1) When noise rate increases, better generalisation is obtained with higher emphasis focus, i.e., focusing on relatively easier examples; 2) Both overfitting and underfitting lead to bad generalisation. For example, ‘CCE: 0’ fits training data much better than the others while ‘GR: None’ generally fits it unstably or a lot worse. Better viewed in colour.
Figure 6: ResNet-56 on CIFAR-10 ($r = 20\%$). From left to right, the results of four emphasis focuses $0, 0 \sim 0.5, 0.5, 0.5 \sim 1$ with different emphasis spreads are displayed in each column respectively. When $\lambda$ is larger, $\beta$ should be larger as displayed in Figure 1c in the paper. Specifically:
1) when $\lambda = 0$: we tried $\beta = 0.5, 1, 2, 4$;
2) when $\lambda = 0.5$: we tried $\beta = 4, 8, 12, 16$;
3) when $\lambda = 1$: we tried $\beta = 8, 12, 16, 20$;
4) when $\lambda = 2$: we tried $\beta = 12, 16, 20, 24$.

Figure 7: ResNet-56 on CIFAR-10 ($r = 40\%$). From left to right, the results of four emphasis focuses $0, 0 \sim 0.5, 0.5, 0.5 \sim 1$ with different emphasis spreads are displayed in each column respectively. When $\lambda$ is larger, $\beta$ should be larger as displayed in Figure 1c in the paper. Specifically:
1) when $\lambda = 0$: we tried $\beta = 0.5, 1, 2, 4$;
2) when $\lambda = 0.5$: we tried $\beta = 4, 8, 12, 16$;
3) when $\lambda = 1$: we tried $\beta = 8, 12, 16, 20$;
4) when $\lambda = 2$: we tried $\beta = 12, 16, 20, 24$. 
Figure 8: ResNet-56 on CIFAR-10 ($r = 60\%$). From left to right, the results of four emphasis focuses 0, 0~0.5, 0.5, 0.5~1 with different emphasis spreads are displayed in each column respectively.

When $\lambda$ is larger, $\beta$ should be larger as displayed in Figure 1c in the paper. Specifically:

1) when $\lambda = 0$: we tried $\beta = 0.5, 1, 2, 4$;
2) when $\lambda = 0.5$: we tried $\beta = 4, 8, 12, 16$;
3) when $\lambda = 1$: we tried $\beta = 8, 12, 16, 20$;
4) when $\lambda = 2$: we tried $\beta = 12, 16, 20, 24$.

Figure 9: ResNet-56 on CIFAR-10 ($r = 80\%$). From left to right, the results of four emphasis focuses 0, 0~0.5, 0.5, 0.5~1 with different emphasis spreads are displayed in each column respectively.

When $\lambda$ is larger, $\beta$ should be larger as displayed in Figure 1c in the paper. Specifically:

1) when $\lambda = 0$: we tried $\beta = 0.5, 1, 2, 4$;
2) when $\lambda = 0.5$: we tried $\beta = 4, 8, 12, 16$;
3) when $\lambda = 1$: we tried $\beta = 8, 12, 16, 20$;
4) when $\lambda = 2$: we tried $\beta = 12, 16, 20, 24$. 
Table 9: How much fitting of the clean training data? How much fitting of the noisy training data? Is it feasible to correct the labels of training data? 
Our results indicate the high label correction performance of using DNNs trained by GR. 
When retraining, we did not adjust the hyper-parameters. Therefore, the shown results of retraining on relabelled datasets are not the optimal.

| Noise Rate $r$ | Emphasis Focus | Model   | Testing Accuracy (%) | Accuracy on Training Sets (%) | Fitting degree of subsets (%) | Retrain after label correction |
|---------------|----------------|---------|-----------------------|-------------------------------|-------------------------------|-------------------------------|
|               |                |         | Best | Final | Noisy | Intact | Clean | Noisy | |
| 20%           | 0              | CCE     | 86.5 | 76.8  | 95.7  | 80.6   | 99.0  | 85.9  | –     |
|               | 0~0.5          | GR ($\beta = 12$) | **89.4** | **87.8** | 81.5 | **95.0** | 98.8 | 11.7  | 89.3 (+1.5) |
| 40%           | 0              | CCE     | 82.8 | 60.9  | **83.0** | 64.4 | 97.0  | 81.1  | –     |
|               | 0.5            | GR ($\beta = 16$) | 84.7 | **83.3** | 60.3 | **88.9** | 94.8 | 7.5   | 85.3 (+2)  |