ABSTRACT
Instance-dependent label noise is realistic but rather challenging, where the label-corruption process depends on instances directly. It causes a severe distribution shift between the distributions of training and test data, which impairs the generalization of trained models. Prior works put great effort into tackling the issue. Unfortunately, these works always highly rely on strong assumptions or remain heuristic without theoretical guarantees. In this paper, to address the distribution shift in learning with instance-dependent label noise, a dynamic distribution-calibration strategy is adopted. Specifically, we hypothesize that, before training data are corrupted by label noise, each class conforms to a multivariate Gaussian distribution at the feature level. Label noise produces outliers to shift the Gaussian distribution. During training, to calibrate the shifted distribution, we propose two methods based on the mean and covariance of multivariate Gaussian distribution respectively. The mean-based method works in a recursive dimension-reduction manner for robust mean estimation, which is theoretically guaranteed to train a high-quality model against label noise. The covariance-based method works in a distribution disturbance manner, which is experimentally verified to improve the model robustness. We demonstrate the utility and effectiveness of our methods on datasets with synthetic label noise and real-world unknown noise.

CCS CONCEPTS
• Computing methodologies → Computer vision; Machine learning.

KEYWORDS
Instance-dependent label noise, distribution shift, distribution calibration, robustness

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1 INTRODUCTION
Learning with label noise is one of the hottest topics in weakly-supervised learning [7, 11, 36]. In real life, large-scale datasets are likely to contain label noise. The main reason is that manual high-quality labeling is expensive [42, 43, 59]. Large-scale datasets are always collected from crowdsourcing platforms [33] or crawled from the internet [67], which inevitably introduces label noise.

Instance-dependent label noise [5, 6, 63] is more realistic and applicable than instance-independent label noise, where the label-flipping process depends on instances/features directly. It is because, in real-world scenes, an instance whose features contain less discriminative information or are of poorer quality may be more likely to be mislabeled. Instance-dependent label noise is more challenging owing to its inherent complexity [76]. Compared with instance-independent label noise, it leads to a more severe distribution shift problem for trained models [2]. That is to say, this kind of noise makes the distributions of training and test data significantly different. If the models are trained with instance-dependent label noise, it is pessimistic that they would generalize poorly on test data [62].

The recent methods on handling instance-dependent label noise are generally divided into two main categories. The first one is to estimate the instance-dependent transition matrix [20, 60, 63], which tends to characterize the behaviors of clean labels flipping into noisy labels. However, these methods are limited to the case with a small number of classes [64, 76]. Besides, they highly rely on strong assumptions to achieve an accurate estimation, e.g., the assumptions on anchor points, bounded noise rates, and extra trusted data. It is hard or even infeasible to check these assumptions, which hinders the validity of these methods [20]. The second one tends to heuristically identify clean data based on the memorization effect of deep models [1] for subsequent operations, e.g., label correction [52, 52, 75]. Unfortunately, due to the complexity of instance-dependent label noise, label correction will be much weaker in the
Covariate shift is a subclass of distribution shift. It is when the distribution of instances shifts between training and test environments. Although the instance distribution may change, the labels remain the same.

Therefore, the labels mismatch to ground-truth distributions. (c) Label correction mainly corrects data far from decision boundaries. However, the mislabeled data near decision boundaries are still not corrected, making learned distributions biased. (d) By using our distribution calibration, the learned distributions are closer to ground-truth distributions, naturally following better generalization abilities.

Method works in a distribution disturbance manner, which is experimentally verified. It introduces an interference in the empirical covariance of given data. In this way, we can increase the diversity of training data to mitigate the distribution shift and improve generalization. After achieving multivariate Gaussian distributions for all classes, we sample examples from them for training, which calibrates the shifted distributions.

We conduct extensive experiments across various settings on CIFAR-10, CIFAR-100, WebVision, and Clothing1M. The results consistently exhibit substantial performance improvements compared to state-of-the-art methods, which support our claims well.

Organization. The rest of this paper is organized as follows. In Section 2, we introduce some background knowledge. In Section 3, we present our methods step by step, with theoretical justifications. In Section 4, empirical evaluations are provided. In Section 5, we summarize this paper.

2 PRELIMINARIES

Notations. Let $\mathbb{I}[\mathcal{A}]$ be the indicator of the event $\mathcal{A}$. Let $[z] = \{0, \ldots, z - 1\}$. Besides, $|\mathcal{B}|$ denotes the total number of elements in the set $\mathcal{B}$.

Problem setup. We consider a $k$-classification problem ($k \geq 2$). Let $\mathcal{X}$ and $\mathcal{Y} = [k]$ be the instance and class label spaces respectively. We assume the dataset $\{(x_i, y_i)\}_{i=1}^n$ is sampled from the underlying joint distribution $\mathcal{D}$ over $\mathcal{X} \times \mathcal{Y}$, where $n$ is the sample size. Before observation, partial clean labels are flipped due to instance-dependent label noise. As a result, we are provided with a noisy training dataset $\{(x_i, \tilde{y}_i)\}_{i=1}^n$ obtained from a noisy joint distribution $\tilde{\mathcal{D}}$ over $\mathcal{X} \times \mathcal{Y}$. For each instance $x_i$, its label $\tilde{y}_i$ may be incorrect. Our goal is to learn a robust classifier by only exploiting the noisy dataset, which can assign clean labels to test data precisely.

Label noise model. In this paper, we consider polynomial-margin diminishing noise (PMD noise) [73]. The PMD noise is one of the instance-dependent label noise, which is realistic but rather challenging. Although the noise setting and analyses naturally generalize to the multi-class case ($k > 2$), for simplicity, we first focus on the binary case ($k = 2$) to improve legibility. Specifically, let $\eta(x) = \mathbb{P}(y = 1|x)$ be the clean class posterior. Let $\rho_{0,1}(x) = \mathbb{P}[^\eta(y = 1|y = 0, x)\}$ and $\rho_{1,0}(x) = \mathbb{P}[^\eta(y = 0|y = 1, x)]$
be the noise functions where \( \hat{y} \) denotes the noisy label. For example, an instance \( x \) has the true label \( y = 0 \), the noisy label is flipped to 1 with the probability of \( \rho_0,1(x) \). We give the formal definition of PMD noise as follows.

**Definition 1 (PMD noise).** The noise functions \( \rho_0,1(x) \) and \( \rho_1,0(x) \) are PMD, if there are constants \( 0 < t_0 < \frac{1}{2} \) and \( c_1, c_2 > 0 \) such as
\[
\rho_0,1(x) \leq c_1 \eta(x)^{1+c_2}; \forall \eta(x) \leq \frac{1}{2} - t_0; \\
\rho_1,0(x) \leq c_1 [1 - \eta(x)]^{1+c_2}; \forall \eta(x) \geq \frac{1}{2} + t_0.
\]

We denote \( t_0 \) as the margin of \( \rho \). In the restricted region \( \{ x : |\eta(x) - \frac{1}{2} | > t_0 \} \), the PMD noise requires the upper bound on \( \rho \) to be polynomial and monotonically decreasing \([73]\). Meanwhile, in the unrestricted region \( \{ x : \eta(x) - \frac{1}{2} | \leq t_0 \} \), both \( \rho_0,1 \) and \( \rho_1,0 \) can be arbitrary. For a clearer understanding, Figure 2 provides the noise level curve of the PMD noise. The PMD noise is consistent with real-world noisy scenarios: data near the decision boundary is \( f \) bounded.

### 3.1 Feature Extraction and Label Correction

Given a training example \((x, \hat{y})\), we employ a deep network to finish the encoding and classification for it. In more detail, first, the instance \( x \) is fed into the deep network to obtain its deep features, \( \tilde{x} \). We denote \( h(x) \) as the margin of \( \rho \) to be polynomial and monotonically decreasing \([73]\). We map the deep features to the class label space with the classifier \( f(h(x)) \). For simplicity, we use \( f(x) \) to substitute \( f(h(x)) \). In binary classification, \( f(x) : X \rightarrow [0,1] \). Let \( y_f(x) := \mathbb{I}(f(x) \geq \frac{1}{2}) \) be the label predicted by \( f \).

In this paper, we build our methods based on label correction \([73]\), mainly considering its sample-efficiency \([52]\). Specifically, we first warm up the deep network within a few epochs. The warm-up phase is used to initialize the model for the following operations. Then, we correct the label, where \( f \) has high confidence in it. With a threshold \( \tau \), if \( |f(x) - \frac{1}{2}| > \tau \), we flip \( \hat{y} \) to the prediction \( y_f(x) \) of \( f \). We repeatedly correct labels and improve the network within the epoch, until no label can be corrected. In the next epoch, we slightly relax the threshold \( \tau \) for label correction. The above procedure can be easily extended to the multi-class scenario (see Appendix B for more details).

Recall that we assume that before training data are corrupted by label noise, the features of each class conform to a multivariate Gaussian distribution. That is, for \( k \) classes, we define \( k \) multivariate Gaussian distributions in total. The distribution for the \( c \)-th class is denoted by \( N_c(h(x)|\mu^c,\Sigma^c) \), where \( \mu^c \in \mathbb{R}^d \) and \( \Sigma^c \in \mathbb{R}^{d \times d} \).

Note that when all deep feature distributions are ideal, i.e., they are not corrupted by label noise, the empirical mean \( \bar{\mu} \) is well-known to be an optimal estimator of the true mean \( \mu^c \) at most \( O(\sqrt{d/n_c}) \), where \( n_c \) is the number of examples belonging to the \( c \)-th class. The existence of label noise makes the empirical mean fail: even a single corrupted data can arbitrarily mislead the mean estimation. However, as discussed, the label correction approach cannot handle distribution shift caused by instance-dependent label noise in two aspects: (1) The labels corrected by the current predictions would likely be erroneous; (2) The training data in identified clean regions in this way is relatively monotonous, leading to covariate shift. The two issues motivate us to explore more robust solutions.

### 3.2 Mean-Based Method

Based on the Huber’s contamination model \([18]\) and our assumption, we introduce the algorithm \textit{AgnosticMean} \([27]\). In summary, the algorithm consists of two steps: (1) the outlier damping step; (2) the projection step. In the outlier damping step, we assign different weights to each data point where outliers will get smaller weights. In the projection step, we project data points onto the span (denoted as \( \mathcal{V} \)) of the top \( \frac{d}{2} \) principal components. Two steps are **alternately implemented** to achieve robust mean estimation, which mitigates the side effect of instance-dependent label noise. In the following, we give mathematical descriptions of our mean-based method.

Given the noisy dataset \( \{(x_i, \hat{y}_i)\}_{i=1}^n \) after label correction at the \( t \)-th epoch, we obtain the dataset \( \{(x_i, \bar{y}_i)\}_{i=1}^n \). For building the multivariate Gaussian distribution on deep features \( h(x) \), we take instances whose labels are \( c \) as examples, the rest classes are the same procedure. We group these instances into a set \( S \). Due to the corruption caused by label noise, we have \( S = S_N \cup S_Q \), where \( S_N \) and \( S_Q \) include the instances sampled from the underlying multivariate Gaussian distribution and arbitrary noise distribution respectively. If the noise rate is \( \epsilon \), we have \( |S_Q| = \epsilon |S| \). We assume that the underlying distribution is \( N(h(x)|\mu, \sigma^2 I) \). Note that the assumption on the covariance is practical in statistical/machine learning and related tasks (c.f. \([8, 24, 25]\)). The notations \( \mu_S \) (resp. \( \mu_Q \)) and \( \Sigma_S \) (resp. \( \Sigma_Q \)) denote the mean and covariance of the set \( S \) (resp. \( S_Q \)). We then have
\[
\Sigma_S = (1 - \epsilon)\sigma^2 I + \epsilon \Sigma_Q + \epsilon (1 - \epsilon)(\mu_S - \mu_Q)(\mu_S - \mu_Q)\top.
\]

Our main goal is to find the mean shift, i.e., \( \mu_S - \mu_Q \). The rationale behind this is that if outliers substantially move \( \mu_S \) far away from \( \mu \), it must move \( \mu_S \) in the direction of \( \mu_S - \mu \). The outlier damping step can effectively limit the effect of outliers. The projection step contributes to find the direction of the mean shift.

**Outlier damping step.** In this step, we impose different weights on different instances. Specifically, the instances that are far away from the coordinate-wise median are endowed with smaller weights. Here, the coordinate-wise median simply takes the median in each dimension. Subsequently, we use \( m \) to denote the coordinate-wise median of \( S \). Let \( s^2 = C \text{Tr}(\Sigma_S) \), where \( C \) is a constant, \( \text{Tr}(\Sigma_S) \) is the trace of \( \Sigma_S \). The weight of each instance can be obtained by the following equation:
\[
omega_i = \exp(-\frac{||h(x_i) - m||_2^2}{s^2}), x_i \in S.
\]
Algorithm 1 AgnosticMean

Require: The set $S = \{h(x_1), \ldots, h(x_n)\}$ with $h(x_i) \in \mathbb{R}^d$.
1: if $d = 1$ then
2: return median($S$).
3: end if
4: Let $s^2 = \text{CTr}(\Sigma_S)$;
5: Compute the weight $\omega_i$ for every $h(x_i) \in S$ with Eq. (4),
6: $\omega = (\omega_1, ..., \omega_n)$;
7: Reset the covariance of the set $S$ as $\Sigma_{S,\omega}$ with Eq. (5);
8: Project $S$ onto the span $\mathcal{V}$ and $\mathcal{W}$ to obtain $P_{\mathcal{V}}S$ and $P_{\mathcal{W}}S$,
9: $P_{\mathcal{V}}S \in \mathbb{R}^d$, $P_{\mathcal{W}}S \in \mathbb{R}^d$;
10: Set $\hat{\mu}_V = \text{AgnosticMean}(P_{\mathcal{V}}S)$ recursively and $\hat{\mu}_W = \text{mean}(P_{\mathcal{W}}S)$;
11: Obtain $\hat{\mu} \in \mathbb{R}^d$, where $P_{\mathcal{V}}\hat{\mu} = \hat{\mu}_V$ and $P_{\mathcal{W}}\hat{\mu} = \hat{\mu}_W$.

After obtaining different weights of all instances, we reset the covariance of the set $S$ with the weights. That is,

$$
\Sigma_{S,\omega} = \sum \omega_i \frac{(h(x_i) - \mu_{S,\omega})^\top(h(x_i) - \mu_{S,\omega})}{nc},
$$

where $\mu_{S,\omega} = \sum \omega_i \frac{h(x_i)}{nc}$ and $nc$ denotes the number of examples belonging to the $c$-th class.

**Projection step.** With the aim of containing a large projection of $\mu_S - \mu$, we project $S$ onto the span $\mathcal{V}$ of the top $\frac{d}{2}$ principal components of $\Sigma_{S,\omega}$. For the span of the bottom $\frac{d}{2}$ principal components (denoted as $\mathcal{W}$), $P_{\mathcal{W}}\mu_S$ is just approximated by $P_{\mathcal{W}}\mu_S$, where $P_{\mathcal{W}}$ represents the operation projecting to the space $\mathcal{W}$. After determining the projection of $\mu$ in space $\mathcal{W}$, we still need to ensure the mean in space $\mathcal{V}$. We recursively perform the outlier damping step and projection step in $\mathcal{V}$. To the end, there will be only a one-dimensional space which is treated as the direction of $\mu_S - \mu$. Note that when the dimension of deep features is 1, the median of $S$ is known to be a robust estimator of the mean with the error of $O(\epsilon x)$ [10, 19]. So we just compute the median as the robust mean estimator.

Figure 3 illustrates the effectiveness of the mean-based method. After the outlier damping step, outliers are assigned with smaller weights. The mean shift $\mu_S - \mu$ onto the space $\mathcal{W}$ has very small projection, which implies that the contribution of outliers in space $\mathcal{W}$ on average cancels out and the sample mean lead to a small error. Therefore, we just need to perform the outlier damping step and projection step in space $\mathcal{V}$ at the next procedure until there is only one dimension. The procedure of the algorithm AgnosticMean is presented in Algorithm 1. Emphatically, Steps 4-6 belong to outlier damping. Step 7 belongs to projection. In Step 8, the outlier damping and projection steps are performed recursively, until there will be only a one-dimensional space. The procedure of AgnosticMean is executed for any $c$-th class to obtain its robust mean $\hat{\mu}_c$. We will provide theoretical insights for the mean-based method in Section 3.4.

### 3.3 Covariance-Based Method

As discussed, if we exploit the memorization effect of deep networks [1], the training data in identified clean regions in this way is relatively monotonous, leading to covariate shift. In other words, the training data in identified clean regions are sampled from a biased distribution and cannot cover the underlying distribution well [31, 55, 66].

To relieve the above issue, we add some disturbance to the empirical covariance of the biased distribution. Intuitively, in this way, we can increase the diversity of training data to mitigate the overfitting to the biased distribution. Specifically, for any $c$-th class, we first compute the mean and covariance of the corresponding distribution of the $c$-th class, i.e.,

$$
\hat{\mu} = \sum \frac{h(x_i)}{nc},
\hat{\Sigma} = \sum \frac{(h(x_i) - \hat{\mu})^\top(h(x_i) - \hat{\mu})}{nc}.
$$

Then, we add the disturbance to the covariance $\hat{\Sigma}$, which can expand the features’ regions, rendering the model gains robustness against covariate shift. That is,

$$
\hat{\Sigma}' = \sum \frac{(h(x_i) - \hat{\mu})^\top(h(x_i) - \hat{\mu})}{nc} + \alpha I,
$$

where $\alpha \in \mathbb{R}^+$ is a hyperparameter that controls the degree of the disturbance, and $I \in \mathbb{R}^{d \times d}$ is a matrix of ones. Note that it is rather hard to set an optimal $\alpha$ from a theoretical view. It is because, without strong assumptions, the determination of the optimal covariance is an open problem in robust statistics. Therefore, in this paper, we determine the value of $\alpha$ by simply employing a (noisy) validation set. Experimental results prove the feasibility of this way.

**Algorithm flow.** We present the overall paradigm of our methods in Algorithm 2. For the setting of $\tau(t)$, we follow the setting in [73]. In summary, we first use warm-up training to make the model predictions more reliable (Step 1). Then, in each epoch, we exploit label correction to obtain a corrected dataset (Steps 3-7) for the following extraction of deep features (Step 8). Next, we perform the proposed two methods (described in Section 3.2 and 3.3) to build multivariate Gaussian distributions for all classes (Steps 9-11). At last, extra data points are sampled from the built multivariate Gaussian distributions for training, which finishes the distribution.
We can approximate the error of the classifier $f$ by:

$$\text{error}(f) = O(\tau).$$

We provide theoretical analyses of MDDC based on PLC [73], which shows that: 1) a classifier trained with our strategy converges to be consistent with the Bayes optimal classifier with high probability. In this work, we focus on the asymptotic case [39].

**Pre-knowledge.** For completeness, we first reproduce the relevant background knowledge.

**Definition 2** ($\beta, \nu$)-consistency [73]). Suppose that a set of data $(x, \tilde{y})$ is sampled from $D(x, \tilde{y}(x))$, where $\tilde{y}(x)$ outputs the noisy posterior probability for $x$. Given a hypothesis class $M$ with sufficient examples, and $f(x) = \arg \min_{m \in M} \mathbb{E}_{(x, y) \sim D(x, \tilde{y}(x))} \text{Loss}(m(x), \tilde{y})$, we define $M$ is $(\beta, \nu)$-consistency if:

$$|\mathbb{E}_{(x, y) \sim D(x, \tilde{y}(x))} \mathbb{E}_{(x, z) \sim D(x, \tilde{y}(x))} \hat{\eta}(z) = \frac{1}{2} - \frac{1}{2} \beta(v) + o(v),$$

where $v$ outputs the clean posterior probability for $z$ and $\eta^*(z)$ is the Bayes optimal classifier for $z$.

**Definition 3** $(c, c^*)$-bounded distribution [73]). Denote the cumulative distribution function of $\eta(x) = \frac{1}{2} + O(\epsilon)$ as $R(\epsilon)$. For a random variable $\epsilon$, $R(\epsilon) = \mathbb{P}(|\eta(x) - \frac{1}{2}| \leq \epsilon)$. The corresponding probability density function is $r(\epsilon)$. We denote the distribution $D$ as $\epsilon$-bounded if $0 < \epsilon \leq \epsilon^* \leq \epsilon^* \leq \epsilon_0^*$. The worst-case density-imbalance ratio of $D$ is denoted by $\epsilon$. The bounded condition enforces the continuity of the density function. The continuity allows one example to borrow useful information from its (clean) neighborhood region, which can help handle mislabeled data.

**Definition 4** (Pure $(\tau, f, \eta)$-level set). We say a set $\mathbb{S}(\tau, f, \eta) := \{x \mid \eta(x) - \frac{1}{2} \geq \tau\}$ is pure for the classifier $f$, if $y_{f(x)} = \eta^*(x)$ for all $x \in \mathbb{S}(\tau, f, \eta)$, where $y_{f(x)}$ denotes the label predicted by $f$, i.e., $y_{f(x)} = \frac{1}{2} (f(x) \geq \frac{1}{2})$.

**Theorem 1.** As training on the noisy dataset, the proposed method will return the trained classifier $f$ such that:

$$\mathbb{P}_{x \sim D} |y_{f(x)} = \eta^*(x)| \geq 1 - 3\epsilon^* c^* 
u.$$  

The proofs are provided in Appendix A. Lemma 1 tells us that the cleansed region will be enlarged by at least a constant factor after one training round. Theorem 1 states that the classifier trained with our method converges to be consistent with the Bayes optimal classifier with high probability. Note that since $\epsilon < 1, 1 - 3\epsilon^* c^* \nu > 0 - 3\epsilon^* c^* \nu$ holds, which indicates our method can help the classifier converge to be consistent with the Bayes optimal classifier with a higher probability than PLC [73]. The theoretical results verify the effectiveness of our method well. In the next section, we use comprehensive experiments to support our claims.

**4 EXPERIMENTS**

In this section, we first introduce the used baselines in this paper (Section 4.1). The evaluations on synthetic and real-world label-noise datasets are then provided (Section 4.2 and 4.3). Finally, a comprehensive ablation study is provided (Section 4.4).

**4.1 Baselines**

In this paper, we compare our methods with five representative baselines and implement all methods with default parameters by PyTorch. The baselines include: (i) Standard; (ii) Co-teaching+ [70];
We leave out 10% of noisy examples for validation. Note that the clean labels are dominating in noisy classes and that noisy labels are random, the accuracy on the noisy validation set and the accuracy on the clean test set are positively correlated. The noisy validation set can thus be used [40, 47, 61].

Model and configurations. For CIFAR-10 and CIFAR-100, we use a preact ResNet-34 network. We perform data augmentation by horizontal random flips and 32×32 random crops after padding 4 pixels on each side. The batch size is set to 128 and we run 100 epochs CIFAR-10, and 180 epochs for CIFAR-100. We adopt SGD optimizer (momentum=0.9). It should be noted that, since the data sampled from Gaussian distribution are penultimate layer’s features, we adopt two SGD optimizers for the corrected dataset and the new sampled dataset. The initialized learning rates are set to 0.01 and 0.0001 for two SGD optimizers. We divide learning rates by 0.5 at 40–th and 80–th epochs. All experiments are repeated three times with different random seeds. We report the mean and standard deviation of experimental results.

Measurement. To measure the performance, we use the test accuracy, i.e. \( \text{test accuracy} = \frac{\text{# of correct predictions}}{\text{# of testing}} \). Intuitively, the higher test accuracy means that a method is more robust to label noise.

Experimental results. Table 1 shows the results of our methods and other baselines under three types of PMD noise with noise levels 35% and 70%. For CIFAR-10, as can be seen, our methods, i.e., MDDC and CDDC, outperform baselines in almost all cases. Although the baseline LRT can achieve comparable performance in the case Type-II (35%), its performance decreases drastically as the noise rate increases. For CIFAR-100, we observe that our methods exhibit a more distinct improvement. In addition, in partial noise settings, our methods can achieve over 7% higher test accuracy than all baselines. Table 2 summarizes the test accuracy achieved on the datasets corrupted with a combination of PMD noise and class-dependent noise. As can be seen, our methods work significantly better than baselines in all cases. In more detail, for CIFAR-100, our methods can achieve more than 10% lead over baselines in the case of combining PMD noise and additional 60% symmetric noise.

4.3 Experiments on Real-World Datasets

Datasets. In this paper, we exploit two large-scale real-world label-noise datasets, i.e., WebVision [33] and Clothing1M [65]. WebVision contains 2.4 million images crawled from the websites using the 1,000 concepts in ImageNet ILSVRC12. Following the “mini” setting in [3, 38], we take the first 50 classes of the Google resized image subset, and evaluate the trained networks on the same 50 classes of the WebVision and ILSVRC12 validation sets, which are exploited as test sets. Meanwhile, Clothing1M consists of 1M noisy training examples collected from online shopping websites.

Model and configurations. For WebVision, we use Inception-ResNet V2 [49]. For Clothing1M, we exploit ResNet-50 with ImageNet pretrained weights. The networks are trained using SGD with a momentum of 0.9, a weight decay of 0.001, and a batch size of 32. For WebVision, we train the network for 100 epochs. The initial learning rate is set as 0.01 and reduced by a factor of 10 after 50 epochs. For Clothing1M, we train the network for 20 epochs. The initial learning rate is set as 0.001 and reduced by a factor of 10 after 5 epochs. In experiments, we boost DivideMix by applying our methods after the DivideMix paradigm.

Results. Table 3 shows the results on WebVision and Clothing1M. Compared MDDC and CDDC with the baselines without...
We study the effect of removing multiple techniques, we can see our methods outperform them clearly. Second, from Table 4, we observe that with our methods, the performance of the state-of-the-art method, i.e., DivideMix, is further enhanced. All results support our claims well.

### 4.4 Ablation Study

The role of different parts. We study the effect of removing distribution-calibration components to provide insights into what makes our methods successful. Note that without the mean-based and covariance-based methods, MDDC and CDDC will degenerate to the label correction method PLC [73]. We analyze the results in Table 5 as follows. As we can see, our methods, i.e., MDDC and CDDC, achieve clear improvements in classification performance over PLC.

The influence of $\alpha$. For CDDC, the value of hyperparameter $\alpha$ controls the degree of the disturbance and can be determined with a noisy validation set. Results have shown the effectiveness of the determination. Here, Figure 4 shows the influence of $\alpha$ with different values. Specifically, the value of hyperparameter $\alpha$ is chosen in $[0.1, 0.2, 0.3, 0.4]$.

The influence of $\lambda$. Recall that we sample $\lambda$ proportion data points from the built multivariate Gaussian distributions. Here, Figure 5 shows the influence of $\lambda$ with different values. Specifically, the value of hyperparameter $\lambda$ is chosen in $[0.10, 0.15, 0.20, 0.25]$.

The results with different networks. Before this, on CIFAR-10 and CIFAR-100, we have shown that our methods are effective with a
Table 3: Comparison with state-of-the-art methods trained on (mini) WebVision [3] and Clothing1M. The best two results on the WebVision validation set, the ImageNet ILSVRC12 validation set and the Clothing1M test set are in bold.

| Test Dataset | WebVision | ILSVRC12 | Clothing1M |
|--------------|-----------|----------|------------|
| Method       | Accuracy (%) | Accuracy (%) | Accuracy (%) |
| Standard     | 59.37     | 58.86    | 68.94      |
| Co-teaching+ | 61.72     | 59.72    | 64.02      |
| GCE          | 62.33     | 61.35    | 69.75      |
| SL           | 62.17     | 60.95    | 71.02      |
| LRT          | 62.96     | 62.09    | 71.74      |
| PLC          | 63.90     | 62.74    | 74.02      |
| MDDC         | 65.06     | 64.30    | 74.39      |
| CDDC         | 64.82     | 64.09    | 74.43      |

Table 4: Comparison with state-of-the-art method DivideMix [30] trained on real-world noisy datasets. Here, DivideMix-M and DivideMix-C mean that DivideMix is boosted with our methods MDDC and CDDC respectively. The best two results are in bold.

| Test Dataset | WebVision | ILSVRC12 | Clothing1M |
|--------------|-----------|----------|------------|
| Method       | Accuracy (%) | Accuracy (%) | Accuracy (%) |
| DivideMix    | 77.32     | 75.20    | 74.76      |
| DivideMix-M  | 77.45     | 75.30    | 74.85      |
| DivideMix-C  | 77.62     | 75.68    | 74.96      |

Table 5: Mean and standard deviations of test accuracy (%) on two synthetic noisy datasets. The improvement of MDDC and CDDC over PLC is highlighted.

| Dataset | Noise | Type-I (30%) | Type-II (35%) | Type-III (50%) | Type-I+30% Asym. | Type-I+30% Sym. | Type-II+30% Asym. | Type-II+30% Sym. | Type-III+30% Asym. | Type-III+30% Sym. |
|---------|-------|--------------|--------------|----------------|------------------|----------------|------------------|------------------|-------------------|------------------|
| CIFAR-10 | Noisy | 42.74±0.21 | 43.70±0.91 | 45.14±1.17 | 49.85±0.91 | 84.60±0.32 | 81.40±0.07 | 71.60±0.33 | 74.20±0.33 |
|         | 60%   | 42.74±0.21 | 43.70±0.91 | 45.14±1.17 | 49.85±0.91 | 84.60±0.32 | 81.40±0.07 | 71.60±0.33 | 74.20±0.33 |
|         | 70%   | 42.74±0.21 | 43.70±0.91 | 45.14±1.17 | 49.85±0.91 | 84.60±0.32 | 81.40±0.07 | 71.60±0.33 | 74.20±0.33 |

5 CONCLUSION

We propose a dynamic distribution-calibration strategy to handle the distribution shift problem brought by instance-dependent label noise. We suppose that before training data are corrupted by label noise, we exploit SENet18 [16], MobileNetV2 [15], WRN-40-2 [71], and EfficientNet [51]. The performance of our methods using these networks is shown in Table 6.

These results show that our methods are not sensitive to the value of $\alpha$ and $\lambda$. Moreover, our methods are robust to the choice of networks. The results imply that it is easy to apply our methods in real-world scenarios.
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