SemiNLL: A Framework of Noisy-Label Learning by Semi-Supervised Learning

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Abstract

Deep learning with noisy labels is a challenging task, which has received much attention from the machine learning and computer vision communities. Recent prominent methods that build on a specific sample selection (SS) strategy and a specific semi-supervised learning (SSL) model achieved state-of-the-art performance. Intuitively, better performance could be achieved if stronger SS strategies and SSL models are employed. Following this intuition, one might easily derive various effective noisy-label learning methods using different combinations of SS strategies and SSL models, which is, however, simply reinventing the wheel in essence. To prevent this problem, we propose *SemiNLL*, a versatile framework that investigates how to naturally combine different SS and SSL components based on their effects and efficiencies. Our framework can absorb various SS strategies and SSL backbones, utilizing their power to achieve promising performance. We also instantiate our framework with different combinations, which sets the new state of the art on benchmark-simulated and real-world datasets with noisy labels.

1 Introduction

Deep Neural Networks (DNNs) have achieved great success in various real-world applications, such as image classification (Krizhevsky et al., 2012), detection (Ren et al., 2015), and semantic segmentation (Long et al., 2015). Such a great success is demanding for large datasets with clean human-annotated labels. However, it is costly and time-consuming to correctly label massive images for building a large-scale dataset like ImageNet (Deng et al., 2009). Some common and less expensive ways to collect large datasets are through online search engines (Schroff et al., 2010) or crowdsourcing (Yu et al., 2018), which would, unfortunately, bring noisy labels to the collected datasets. Besides, an in-depth study (Zhang et al., 2016) showed that deep learning with noisy labels can lead to severe performance deterioration. Thus, it is crucial to alleviate the negative effects caused by noisy labels for training DNNs.

A typical strategy is to conduct *sample selection* (SS) and to train DNNs with selected samples (Han et al., 2018; Jiang et al., 2018; Song et al., 2019; Yu et al., 2019; Wei et al., 2020; Yao et al., 2020a; Xia et al., 2022). Since DNNs tend to learn simple patterns first before fitting noisy samples (Arpit et al., 2017), many studies utilize the small-loss trick, where the samples with smaller losses are taken as clean ones. For example, *Co-teaching* (Han et al., 2018) leverages two networks to select small-loss samples within each mini-batch for training each other. Later, Yu et al. (2019) pointed out the importance of the disagreement between two networks and proposed *Co-teaching+*, which updates the two networks using the data on which the two networks hold different predictions. By contrast, *JoCoR* (Wei et al., 2020) proposes to reduce the diversity between two networks by training them simultaneously with a joint loss calculated from the selected small-loss samples. Although these methods have achieved satisfactory performance by training with selected small-loss samples, they simply discard other large-loss samples which may contain potentially useful information for the training process.

To make full use of all given samples, a prominent strategy is to consider selected samples as labeled "clean" data and other samples as unlabeled data, and to perform *semi-supervised learning* (SSL) (Laine & Aila, 2016; Tarvainen & Valpola, 2017; Berthelot et al., 2019; Arazo et al., 2020; Xie et al., 2020; Sohn et al., 2020;

Zhang et al., 2021). Following this strategy, *SELF* (Nguyen et al., 2020) detects clean samples by removing noisy samples whose self-ensemble predictions of the model do not match the given labels in each iteration. With the selected labeled and unlabeled data, the problem becomes an SSL problem, and a *Mean-Teacher* model (Tarvainen & Valpola, 2017) can be trained. Another recent method, *DivideMix* (Li et al., 2020), leverages Gaussian Mixture Model (GMM) (Permuter et al., 2006) to distinguish clean (labeled) and noisy (unlabeled) data, and then uses a strong SSL backbone called *MixMatch* (Berthelot et al., 2019).

As shown above, both methods rely on a specific SS strategy and a specific SSL model. The two components play a vitally important role for combating label noise, and stronger components are expected to achieve better performance. This motivates us to investigate a versatile algorithmic framework that can leverage various SS strategies and SSL models. In this paper, we propose *SemiNLL*, which is a versatile framework to bridge the gap between SSL and *noisy-label learning* (NLL). Our framework can absorb various SS strategies and SSL backbones, utilizing their power to achieve promising performance. Guided by our framework, one can easily instantiate a specific learning algorithm for NLL, by specifying a commonly used SSL backbone with an SS strategy. The key contributions of our paper can be summarized as follows:

- Our framework can not only provide an important prototype in the NLL community for further exploration into SS and SSL, but can also act as a conclusive work to prevent future researchers from simply reinventing the wheel.
- To instantiate our framework, we propose *DivideMix+* by replacing the epoch-level selection strategy of *DivideMix* (Li et al., 2020) with a mini-batch level one. We also propose *GPL*, another instantiation of our framework that leverages a two-component ***G**aussian mixture model* (Li et al., 2020; Permuter et al., 2006) to select labeled (unlabeled) data and uses ***P**seudo-**L**abeling* (Arazo et al., 2020) as the SSL backbone.
- We conduct extensive experiments on benchmark-simulated and real-world datasets with noisy labels. Our instantiations, *DivideMix+* and *GPL*, outperform other state-of-the-art noisy-label learning methods. We also analyze the effects and efficiencies of different instantiations of our framework.

The rest of this paper is organized as follows. In Section 2, we first review the related works. Then, the overview of the framework is introduced in Section 3. Section 4 illustrates the instantiations of our framework in detail. After that, we demonstrate the experimental results in Section 5 and give detailed ablation studies and discussions in Section 6. The conclusion is in Section 7.

2 RELATED WORK

In this section, we briefly review several related aspects on which our framework builds.

2.1 Learning with noisy labels

For NLL, most of the existing methods could be roughly categorized into the following groups:

Sample selection. This family of methods regards samples with small loss as "clean" and trains the model only on selected clean samples. For example, *self-paced MentorNet* (Jiang et al., 2018), or equivalently *self-teaching*, selects small-loss samples and uses them to train the network by itself. To alleviate the sample-selection bias in *self-teaching*, Han et al. (2018) proposed an algorithm called *Co-teaching*, where two networks choose the next batch of data for each other for training based on the samples with smaller loss values. *Co-teaching+* (Yu et al., 2019) bridges the *disagreement strategy* (Malach & Shalev-Shwartz, 2017) with *Co-teaching* (Han et al., 2018) by updating the networks over data where two networks make different predictions. In contrast, Wei et al. (2020) leveraged the agreement maximization algorithm (Kumar et al., 2010) by designing a joint loss to train two networks on the same mini-batch data and selected small-loss samples to update the parameters of both networks. The mini-batch SS strategy in our framework belongs to this direction. However, instead of ignoring the large-loss unclean samples, we just discard their labels and exploit the associated images in an SSL setup.

Noise transition estimation. Another line of NLL is to estimate the noise transition matrix for loss correction (Natarajan et al., 2013; Menon et al., 2015; Xiao et al., 2015; Goldberger & Ben-Reuven, 2016; Patrini et al., 2017; Hendrycks et al., 2018; Wang et al., 2020; Yao et al., 2020b; Wu et al., 2021a). Patrini et al. (2017) first estimated the noise transition matrix and trained the network with two different loss corrections. Hendrycks et al. (2018) proposed a loss correction technique that utilizes a small portion of trusted samples to estimate the noise transition matrix. Wang et al. (2020) proposed a model-agnostic approach to learn the transition matrix directly from data via meta-learning. However, the limitation of these methods is that they do not perform well on datasets with a large number of classes.

Other deep learning methods. Some other interesting and promising directions for NLL include meta-learning (Finn et al., 2017; Snell et al., 2017) based, pseudo-label estimation (Lee, 2013) based, and robust loss (Feng et al., 2020; Ghosh et al., 2017; Ma et al., 2020; Wang et al., 2019; Xu et al., 2019; Zhang & Sabuncu, 2018; Hu et al., 2021) based approaches. For meta-learning based approaches, most studies fall into two main categories: training a model that *adapts fast to different learning tasks* without overfitting to corrupted labels (Garcia et al., 2016; Li et al., 2019), and *learning to reweight* loss of each mini-batch to alleviate the adverse effects of corrupted labels (Ren et al., 2018; Shu et al., 2019; Zhang et al., 2020; Wu et al., 2021b; Zheng et al., 2021). Pseudo-label estimation based approaches reassign the labels for noisy samples. For example, *Joint-Optim* (Tanaka et al., 2018) corrects labels during training and updates network parameters simultaneously. *PENCIL* (Yi & Wu, 2019) proposes a probabilistic model, which can update network parameters and reassign labels as label distributions. The family of pseudo-label estimation has a close relationship with semi-supervised learning (Han et al., 2019; Lee, 2013; Tanaka et al., 2018; Yi & Wu, 2019). Robust loss based approaches focus on designing loss functions that are robust to noisy labels.

2.2 Semi-supervised learning

SSL methods leverage unlabeled data to provide additional information for the training model. A line of work is based on the concept of consistency regularization: if a perturbation is given to an unlabeled sample, the model predictions of the same sample should not be too different. Laine & Aila (2016) applied consistency between the output of the current network and the exponential moving average (EMA) of the output from the past epochs. Instead of averaging the model outputs, Tarvainen & Valpola (2017) proposed to update the network on every mini-batch using an EMA of model parameter values. Berthelot et al. (2019) introduced a holistic approach that well combines *MixUp* (Zhang et al., 2018), entropy minimization, and consistency regularization. Another line of SSL is pseudo-labeling, the objective of which is to generate pseudo-labels for unlabeled samples to enhance the learning process. Arazo et al. (2020) proposed a method to improve previous pseudo-labeling methods (Iscen et al., 2019) by adding *MixUp* augmentation (Zhang et al., 2018). Xie et al. (2020) and Sohn et al. (2020)used a confidence-based strategy pseudo labeling to select unlabeled data with high confidence. Zhang et al. (2021) proposed a curriculum learning method to leverage unlabeled data for SSL.

2.3 Combination of SS and SSL

Some previous studies that combine a specific SS strategy and a specific SSL backbone could be regarded as special cases in our framework. Ding et al. (2018) used a pre-trained DNN on the noisy dataset to select labeled samples. In the SSL stage, *Temporal Ensembling* (Laine & Aila, 2016) was used to handle labeled and unlabeled data. Nguyen et al. (2020) proposed a progressive noise filtering mechanism based on the *Mean-Teacher* model (Tarvainen & Valpola, 2017) and its self-ensemble prediction. Li et al. (2020) used a Gaussian Mixture Model (GMM) to divide noisy and clean samples based on their training losses and fitted them into a recent SSL algorithm called *MixMatch* (Berthelot et al., 2019). Each specific component used in these methods has its own pros and cons. This motivates us to propose a versatile framework that can build on various SS strategies and SSL backbones. In other words, many recent publications (Arazo et al., 2019; Li et al., 2020; Nguyen et al., 2020) or preprints (Cordeiro et al., 2021; Wei et al., 2021) could be taken as special instantiations of our framework, which indicates that a conclusive work like this paper is vitally necessary to prevent future researchers from simply reinventing the wheel.

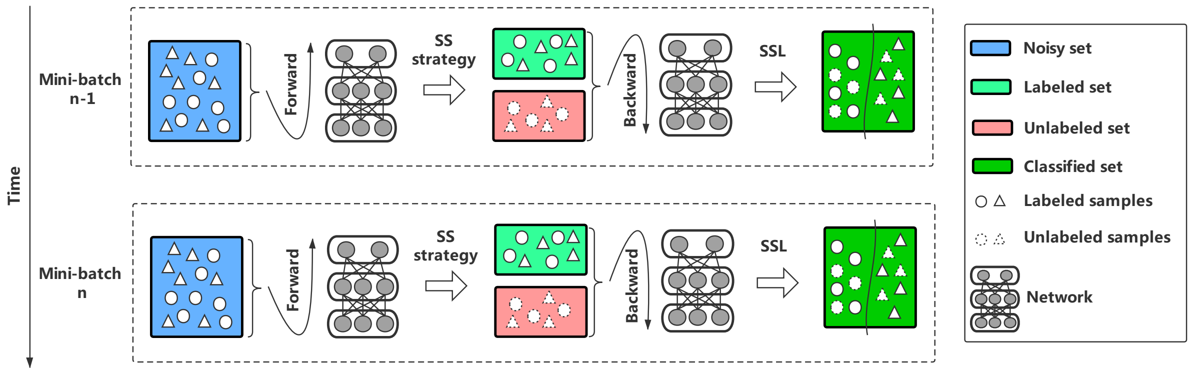


Figure 1: The schematic of *SemiNLL*. First, each mini-batch of data is forwarded to the network to conduct SS, which divides the original data into the labeled/unlabeled sets. Second, labeled/unlabeled samples are used to train the SSL backbone to produce accurate model output.

3 The Overview of SemiNLL

In this section, we present *SemiNLL*, a versatile framework of learning with noisy labels by SSL. The idea behind our framework is that we effectively take advantage of the whole training set by trusting the labels of undoubtedly correct samples and utilizing only the image content of potentially corrupted samples. Previous sample selection methods (Han et al., 2018; Jiang et al., 2018; Yu et al., 2019; Wei et al., 2020) train the network only with selected clean samples, and they discard all potentially corrupted samples to avoid the harmful memorization of DNNs caused by the noisy labels of these samples. In this way, the feature information contained in the associated images might be discarded without being exploited. Our framework, alternatively, makes use of those corrupted samples by ignoring their labels while keeping the associated image content, transforming the NLL problem into an SSL setup. The mechanism of SSL that leverages labeled data to guide the learning of unlabeled data naturally fits well in training the model with the clean and noisy samples divided by our SS strategy. We first discuss the advantages of the mini-batch SS strategy in our framework and then introduce several SSL backbones used in our framework. The schematic of our framework is shown in Figure 1.

Algorithm 1 SemiNLL

Input: Network f_θ, SS strategy SELECT, SSL method SEMI, epoch $T_{\max}$, iteration $I_{\max}$;
1: **for** $t = 1,2,\ldots,T_{\max}$ **do**
2:   **Shuffle** training set $\mathcal{D}_{train}$;
3:   **for** $n = 1, \ldots, I_{\max}$ **do**
4:     **Fetch** mini-batch D_n from $\mathcal{D}_{train}$;
5:     **Obtain** $\mathcal{X}_m, \mathcal{U}_m \leftarrow \text{SELECT}(D_n, f_\theta)$;
6:     **Update** $f_\theta \leftarrow \text{SEMI}(\mathcal{X}_m, \mathcal{U}_m, f_\theta)$;
7:   **end for**
8: **end for**
Output: f_θ

3.1 Mini-batch sample selection

During the SS process, a hazard called confirmation bias (Tarvainen & Valpola, 2017) is worth noting. Since the model is trained using the selected clean (labeled) and noisy (unlabeled) samples, wrongly selected clean samples in this iteration may keep being considered clean ones in the next iteration due to the model overfitting to their labels. Most existing methods (Li et al., 2020; Nguyen et al., 2020) divide the whole training set into the clean/noisy set on an epoch level. In this case, the learned selecting knowledge is incorporated into the SSL phase and will not be updated till the next epoch. Thus, the confirmation bias induced from those wrongly divided samples will accumulate within the whole epoch. To overcome this problem, our mini-batch SS strategy divides each mini-batch of samples into the clean subset $\mathcal{X}_m$ and the noisy subset $\mathcal{U}_m$ (Line 5 in Algorithm 1) right before updating the network using SSL backbones. In the next mini-batch, the network can know better to distinguish clean and noisy samples, alleviating the confirmation bias mini-batch by mini-batch.

3.2 SSL backbones

The mechanism of SSL that uses labeled data to guide the learning of unlabeled data fits well when dealing with clean/noisy data in NLL. The difference lies in an extra procedure, as introduced in Subsection 3.1, that divides the whole dataset into clean and noisy data. After the SS process, clean samples are considered labeled data and keep their annotated labels. The others are considered noisy samples, and their labels are discarded to be treated as unlabeled ones in SSL backbones. *SemiNLL* can build on a variety of SSL algorithms without any modifications to form an end-to-end training scheme for NLL. Concretely, we consider the following representative SSL backbones ranging from weak to strong according to their performance in SSL tasks: (i) *Temporal Ensembling* (Laine & Aila, 2016). The model uses an exponential moving average (EMA) of label predictions from the past epochs as a target for the unsupervised loss. It enforces consistency of predictions by minimizing the difference between the current outputs and the EMA outputs. (ii) *MixMatch* (Berthelot et al., 2019). MixMatch is a holistic method that combines *MixUp* (Zhang et al., 2018), entropy minimization, consistency regularization, and other traditional regularization tricks. It guesses low-entropy labels for augmented unlabeled samples and mixes labeled and unlabeled data using *MixUp* (Zhang et al., 2018). (iii) *Pseudo-Labeling* (Arazo et al., 2020). This method learns from unlabeled data by combining soft *pseudo-label* generation (Tanaka et al., 2018) and *MixUp* augmentation (Zhang et al., 2018) to reduce confirmation bias in training. In the next section, we will instantiate our framework by applying specific SS strategies and SSL backbones to the SELECT and SEMI placeholders in Algorithm 1.

4 The Instantiations of SemiNLL

4.1 Instantiation 1: DivideMix+

In Algorithm 1, if we (i) specify the SELECT placeholder as a GMM (Permuter et al., 2006), (ii) specify the SEMI placeholder as *MixMatch* (Berthelot et al., 2019) mentioned in Subsection 3.2, and (iii) train two independent networks wherein each network selects clean/noisy samples in the SS phase and predicts labels in the SSL phase for the other network, then our framework is instantiated into a mini-batch version of *DivideMix* (Li et al., 2020). Specifically, during the SS process, *DivideMix* (Li et al., 2020) fits a two-component GMM to the loss of each sample using the Expectation-Maximization technique and obtains the posterior probability of a sample being clean or noisy. During the SSL phase, the clean set $\mathcal{X}_e$ and the noisy set $\mathcal{U}_e$ are fit into an improved *MixMatch* (Berthelot et al., 2019) strategy with label co-refinement and co-guessing. As shown in Figure 4 (b) in Appendix, the SS strategy (GMM) of *DivideMix* (Li et al., 2020) is conducted on an epoch level. Since $\mathcal{X}_e$ and $\mathcal{U}_e$ are updated only once per epoch, the confirmation bias induced from the wrongly divided samples will be accumulated within the whole epoch. However, our mini-batch version, which is called *DivideMix+* (Figure 4 (c) in Appendix), divides each mini-batch of data into a clean subset $\mathcal{X}_m$ and a noisy subset $\mathcal{U}_m$, and updates the networks using the SSL backbone right afterwards. In the next mini-batch, the updated networks could better distinguish clean and noisy samples.

4.2 Instantiation 2: GPL

Intuitively, the choice of stronger SS strategies and SSL models would achieve better performance based on our framework. Thus, we still choose GMM to distinguish clean and noisy samples due to its flexibility in the sharpness of distribution (Li et al., 2020). As for the SSL backbone, we choose the strongest *Pseudo-Labeling* (Arazo et al., 2020) introduced in Subsection 3.2. We call this instantiation *GPL* (***G****MM* + ***P****seudo-* ***L****abeling*). Note that we do not train two networks in *GPL* as in *DivideMix* (Li et al., 2020) and *DivideMix+*. To our understanding, training two networks simultaneously might provide significant improvements in performance. However, this is outside the scope of this paper, since our goal is to demonstrate the versatility of our framework.

4.3 Self-prediction divider

Inspired by *SELF* (Nguyen et al., 2020), we introduce the *self-prediction divider*, a simple yet effective SS strategy which leverages the information provided by the network's own prediction to distinguish clean and noisy samples. Based on the phenomenon that DNN's predictions tend to be consistent on clean samples and inconsistent on noisy samples in different training iterations, we select the correctly annotated samples via the consistency between the original label set and the model's own predictions. The *self-prediction divider* determines potentially clean samples in a mini-batch if the samples' maximal likelihood predictions of the network match their annotated labels. Specifically, the samples are divided into the labeled set only if the model predicts the annotated label to be the correct class with the highest likelihood. The others are considered noisy samples, and their labels will be discarded to be regarded as unlabeled ones in SSL backbones. Compared to previous small-loss SS methods (Han et al., 2018; Wei et al., 2020; Yu et al., 2019), which depend on a known noise ratio to control how many small-loss samples should be selected in each training iteration, *self-prediction divider* does not need any additional information to perform SS strategy where the clean subset and the noisy subset are determined by the network itself. Concretely, we instantiate three learning algorithms by combining our ***s**elf-**p**rediction **d**ivider (SPD)* with three SSL backbones introduced in Subsection 3.2 and denote them as *SPD-Temporal Ensembling*, *SPD-MixMatch*, and *SPD-Pseudo-Labeling*, respectively.

4.4 Effects of the two components

This section demonstrates the effects of SS strategies and SSL backbones in our framework. To prove that a more robust SS strategy can boost performance for our framework, we propose *DivideMix-* (Figure **??**) by replacing the GMM in *DivideMix* (Li et al., 2020) with our *self-prediction divider* on an epoch level. Since *self-prediction divider* is supposed to be weaker than GMM, *DivideMix-* is expected to achieve lower performance than *DivideMix* (Li et al., 2020). To prove the effectiveness of the SSL backbone, we remove it after the SS process and only update the model using the supervised loss calculated from the clean samples. We will give detailed discussions in Section 6.

5 Experiment

5.1 Experiment setup

Datasets. We compare our method with five state-of-the-art algorithms in PU learning: We thoroughly evaluate our proposed *DivideMix+* and *GPL* on six datasets, including MNIST (Lecun et al., 1998), FASHION-MNIST (Xiao et al., 2017), CIFAR-10, CIFAR-100 (Krizhevsky & Hinton, 2009), Clothing1M (Xiao et al., 2015), and WebVision (Li et al., 2017). The detailed characteristics of the datasets in the experiments are shown in Table 8. MNIST and FASHION-MNIST contain 60K training images and 10K test images of size 28×28. CIFAR-10 and CIFAR-100 contain 50K training images and 10K test images of size 32×32 with three channels. According to previous studies (Zhang & Sabuncu, 2018; Li et al., 2020; Wei et al., 2020), we experiment with two types of label noise: symmetric noise and asymmetric noise. Symmetric label noise is produced by changing the original label to all possible labels randomly and uniformly according to the noise ratio. Asymmetric label noise is similar to real-world noise, where labels are flipped to similar classes. Clothing1M is a large-scale real-world dataset that consists of one million training images from online shopping websites with labels annotated from surrounding texts. The estimated noise ratio is about 40%. WebVision is a large-scale dataset which consists of real-world web noise. We follow Chen et al. (2019); Li et al. (2020) to create a mini version of WebVision that uses the Google subset images of the top 50 classes.

Network structure and optimizer. Following previous works (Arazo et al., 2020; Li et al., 2020; Wei et al., 2020; Zhang & Sabuncu, 2018), we use a 2-layer MLP for MNIST, a ResNet-18 (He et al., 2016) for FASHION-MNIST, the well-known "13-CNN" architecture (Tarvainen & Valpola, 2017) for CIFAR-10 and CIFAR-100, a ResNet-50 (He et al., 2016) for Clothing1M and the inception-resnet v2 (Szegedy et al., 2017) for mini WebVision. To ensure a fair comparison between the instantiations of our framework and other methods, we keep the training settings for MNIST, CIFAR-10, CIFAR-100, Clothing1M, and mini WebVision as close as possible to *DivideMix* (Li et al., 2020) and FASHION-MNIST close to *GCE* (Zhang & Sabuncu, 2018). For FASHION-MNIST, the network is trained using stochastic gradient descent (SGD)

Table 1: Average test accuracy (%) and standard deviation (5 runs) in various datasets under symmetric label noise. The best accuracy is **bold-faced**. The second-best accuracy is underlined.

Datasets	Method	Symmetric Noise ratio				Mean
		20%	40%	60%	80%	
MNIST	Cross-Entropy	86.16 ± 0.34	70.39 ± 0.59	50.35 ± 0.51	23.41 ± 0.96	57.58
	Co-teaching	91.20 ± 0.03	90.02 ± 0.02	83.21 ± 0.71	25.33 ± 0.84	72.44
	F-correction	93.93 ± 0.10	84.30 ± 0.43	65.06 ± 0.64	29.81 ± 0.63	68.27
	JoCoR	94.30 ± 0.09	92.66 ± 0.13	89.94 ± 0.24	75.37 ± 0.74	88.07
	GCE	94.36 ± 0.11	93.61 ± 0.17	92.46 ± 0.20	85.04 ± 0.66	91.37
	M-correction	$\mathbf{97.25 \pm 0.03}$	96.63 ± 0.04	95.07 ± 0.08	86.19 ± 0.42	93.79
	DivideMix	96.80 ± 0.08	96.53 ± 0.06	96.47 ± 0.04	95.15 ± 0.25	96.24
	GPL (ours)	96.67 ± 0.09	96.27 ± 0.08	95.82 ± 0.09	94.81 ± 0.15	95.89
	DivideMix+ (ours)	96.83 ± 0.06	$\mathbf{96.79 \pm 0.06}$	$\mathbf{96.69 \pm 0.03}$	$\mathbf{95.91 \pm 0.10}$	**96.56**
FASHION MNIST	Cross-Entropy	90.83 ± 0.26	86.44 ± 0.11	77.27 ± 0.56	61.84 ± 1.27	79.10
	Co-teaching	89.18 ± 0.32	89.13 ± 0.05	80.08 ± 0.25	60.36 ± 2.15	79.69
	F-correction	$\mathbf{93.37 \pm 0.17}$	92.27 ± 0.06	90.32 ± 0.30	85.78 ± 0.06	90.43
	JoCoR	91.43 ± 0.14	90.55 ± 0.11	86.89 ± 0.29	79.61 ± 0.41	87.12
	GCE	93.35 ± 0.09	92.58 ± 0.11	91.30 ± 0.20	88.01 ± 0.22	91.31
	M-correction	93.03 ± 0.15	92.74 ± 0.42	91.61 ± 0.02	85.25 ± 0.23	90.66
	DivideMix	92.98 ± 0.17	92.55 ± 0.13	91.55 ± 0.31	88.55 ± 0.24	90.66
	GPL (ours)	92.94 ± 0.20	91.38 ± 0.54	89.97 ± 0.16	87.14 ± 0.65	90.36
	DivideMix+ (ours)	93.20 ± 0.08	$\mathbf{92.89 \pm 0.15}$	$\mathbf{92.15 \pm 0.16}$	$\mathbf{88.70 \pm 0.17}$	**91.74**
CIFAR-10	Cross-Entropy	83.48 ± 0.17	68.49 ± 0.40	48.65 ± 0.06	27.56 ± 0.43	57.05
	Co-teaching	67.73 ± 0.71	62.83 ± 0.72	48.81 ± 0.78	27.56 ± 2.71	51.73
	F-correction	83.27 ± 0.04	73.67 ± 0.30	77.64 ± 0.11	63.95 ± 0.32	74.63
	JoCoR	85.22 ± 0.06	80.27 ± 0.37	58.72 ± 0.29	29.67 ± 0.68	63.47
	GCE	89.72 ± 0.10	87.75 ± 0.05	84.11 ± 0.26	72.84 ± 0.30	83.61
	M-correction	92.01 ± 0.40	90.09 ± 0.68	85.90 ± 0.22	70.57 ± 0.85	84.64
	DivideMix	94.82 ± 0.09	93.95 ± 0.14	92.28 ± 0.08	89.30 ± 0.17	92.59
	GPL (ours)	94.45 ± 0.20	94.00 ± 0.22	$\mathbf{93.32 \pm 0.10}$	91.76 ± 0.23	93.38
	DivideMix+ (ours)	$\mathbf{94.84 \pm 0.12}$	$\mathbf{94.03 \pm 0.20}$	93.08 ± 0.19	$\mathbf{91.91 \pm 0.07}$	**93.47**
CIFAR-100	Cross-Entropy	60.93 ± 0.40	46.24 ± 0.74	29.00 ± 0.38	11.42 ± 0.19	36.90
	F-correction	60.49 ± 0.29	48.93 ± 0.21	48.74 ± 0.41	22.93 ± 0.78	45.27
	JoCoR	65.89 ± 0.08	49.65 ± 0.51	32.38 ± 0.60	16.91 ± 0.63	41.21
	GCE	69.20 ± 0.10	65.90 ± 0.25	57.33 ± 0.18	18.19 ± 1.15	52.66
	M-correction	67.96 ± 0.17	64.48 ± 0.76	55.37 ± 0.72	24.21 ± 1.06	53.01
	DivideMix	73.17 ± 0.28	71.01 ± 0.16	66.61 ± 0.18	43.25 ± 0.82	63.51
	GPL (ours)	71.24 ± 0.24	68.89 ± 0.07	65.80 ± 0.63	$\mathbf{59.96 \pm 0.15}$	66.47
	DivideMix+ (ours)	$\mathbf{73.22 \pm 0.21}$	$\mathbf{71.03 \pm 0.32}$	$\mathbf{67.52 \pm 0.19}$	58.07 ± 0.71	**67.46**

with 0.9 momentum and a weight decay of 1×10^{-4} for 120 epochs. For MNIST, CIFAR-10, and CIFAR-100, all networks are trained using SGD with 0.9 momentum and a weight decay of 5×10^{-4} for 300 epochs.

Baselines. We compare *DivideMix+* and *GPL* to previous state-of-the-art algorithms from *Co-teaching* (Han et al., 2018), *F-correction* (Patrini et al., 2017), *GCE* (Zhang & Sabuncu, 2018), *M-correction* (Arazo et al., 2019), and *DivideMix* (Li et al., 2020). We implement all methods by PyTorch on NVIDIA Tesla V100 GPUs. (1) *Cross-Entropy*, which trains the network using the cross-entropy loss. (2) *Coteaching* (Han et al., 2018), which trains two networks and cross-updates the parameters of peer networks. (3) *F-correction* (Patrini et al., 2017), which corrects the prediction by the label transition matrix. As suggested by the authors, we first train a standard network using the cross-entropy loss to estimate the transition matrix. (4) *JoCoR* (Wei et al., 2020), which uses a joint loss to train two networks on the same mini-batch data and selects small-loss samples to update the networks. (5) *GCE* (Zhang & Sabuncu, 2018), which uses a theoretically grounded and easy-to-use loss function, the $\mathcal{L}_q$ loss, for NLL. (6) *M-correction* (Arazo et al., 2019), which models clean and noisy samples by fitting a two-component BMM and applies *MixUp* data augmentation (Zhang et al., 2018). (7) *DivideMix* (Li et al., 2020), which divides clean and noisy samples by using a GMM on an epoch level and leverages *MixMatch* (Berthelot et al., 2019) as the SSL backbone.

Table 2: Average test accuracy (%) and standard deviation (5 runs) in various datasets under asymmetric label noise. The best accuracy is **bold-faced**. The second-best accuracy is underlined.

Datasets	Method	Asymmetric Noise ratio 10%	20%	30%	40%	Mean
MNIST	Cross-Entropy	95.78 ± 0.19	91.15 ± 0.26	86.01 ± 0.25	79.92 ± 0.32	88.22
	Co-teaching	90.32 ± 0.02	89.03 ± 0.02	79.80 ± 0.27	64.94 ± 0.02	81.02
	F-correction	96.39 ± 0.04	94.27 ± 0.21	89.33 ± 0.94	81.61 ± 0.42	90.40
	JoCoR	95.43 ± 0.04	94.39 ± 0.13	90.15 ± 0.24	87.31 ± 0.05	91.82
	GCE	94.61 ± 0.13	94.43 ± 0.07	94.00 ± 0.12	93.42 ± 0.12	94.12
	M-correction	96.74 ± 0.03	96.70 ± 0.10	$\mathbf{96.67 \pm 0.07}$	94.85 ± 0.40	96.24
	DivideMix	96.17 ± 0.06	96.11 ± 0.09	95.88 ± 0.05	95.83 ± 0.05	96.00
	GPL (ours)	$\mathbf{96.76 \pm 0.04}$	$\mathbf{96.71 \pm 0.03}$	96.49 ± 0.08	96.45 ± 0.04	**96.60**
	DivideMix+ (ours)	96.67 ± 0.04	96.66 ± 0.07	96.50 ± 0.04	$\mathbf{96.46 \pm 0.04}$	96.57
FASHION MNIST	Cross-Entropy	93.88 ± 0.16	92.20 ± 0.33	90.41 ± 0.67	84.56 ± 0.41	90.26
	Co-teaching	88.01 ± 0.03	78.88 ± 0.20	70.07 ± 0.38	61.97 ± 0.21	74.73
	F-correction	$\mathbf{94.17} \pm 0.12$	$\mathbf{93.88 \pm 0.10}$	$\mathbf{93.50 \pm 0.10}$	$\mathbf{93.25 \pm 0.16}$	**93.7**
	JoCoR	91.54 ± 0.13	88.60 ± 0.47	84.37 ± 0.24	81.68 ± 0.62	86.55
	GCE	93.51 ± 0.17	93.24 ± 0.14	92.21 ± 0.27	89.53 ± 0.53	92.12
	M-correction	92.11 ± 0.93	91.26 ± 1.35	89.79 ± 1.28	89.58 ± 2.20	90.69
	DivideMix	91.83 ± 0.24	91.09 ± 0.08	89.90 ± 0.26	87.58 ± 0.26	90.10
	GPL (ours)	92.52 ± 0.22	92.23 ± 0.09	92.15 ± 0.26	91.64 ± 0.31	92.14
	DivideMix+ (ours)	92.56 ± 0.39	92.25 ± 0.21	91.62 ± 0.08	89.67 ± 0.44	91.53
CIFAR-10	Cross-Entropy	90.85 ± 0.06	87.23 ± 0.40	81.92 ± 0.32	76.23 ± 0.45	84.06
	Co-teaching	62.85 ± 2.20	61.04 ± 1.31	54.50 ± 0.39	51.68 ± 1.66	57.52
	F-correction	89.79 ± 0.33	86.79 ± 0.67	83.34 ± 0.30	76.81 ± 1.08	84.18
	JoCoR	88.62 ± 0.21	89.79 ± 0.17	82.37 ± 0.12	77.90 ± 0.69	84.67
	GCE	90.40 ± 0.09	89.30 ± 0.13	86.89 ± 0.22	82.60 ± 0.17	87.30
	M-correction	92.28 ± 0.12	92.13 ± 0.17	91.38 ± 0.11	90.43 ± 0.23	91.56
	DivideMix	93.61 ± 0.15	92.99 ± 0.21	91.79 ± 0.36	90.57 ± 0.31	92.24
	GPL (ours)	$\mathbf{94.32 \pm 0.01}$	$\mathbf{94.23 \pm 0.07}$	$\mathbf{93.79 \pm 0.06}$	$\mathbf{93.02 \pm 0.30}$	**93.84**
	DivideMix+ (ours)	94.27 ± 0.23	93.92 ± 0.20	92.82 ± 0.28	91.91 ± 0.24	93.23
CIFAR-100	Cross-Entropy	68.58 ± 0.34	68.82 ± 0.22	53.99 ± 0.50	44.31 ± 0.23	58.93
	F-correction	68.87 ± 0.06	64.11 ± 0.37	56.45 ± 0.59	46.44 ± 0.50	58.97
	JoCoR	69.44 ± 0.16	66.91 ± 0.54	54.71 ± 0.42	39.76 ± 0.97	57.71
	GCE	70.77 ± 0.14	69.22 ± 0.15	64.60 ± 0.25	51.72 ± 1.17	64.08
	M-correction	69.44 ± 0.52	67.25 ± 0.81	63.16 ± 1.55	52.90 ± 1.79	63.19
	DivideMix	$\mathbf{74.00 \pm 0.29}$	73.28 ± 0.42	$\mathbf{72.84 \pm 0.36}$	54.33 ± 0.69	68.61
	GPL (ours)	71.94 ± 0.29	71.22 ± 0.11	70.56 ± 0.23	$\mathbf{69.84 \pm 0.41}$	**70.89**
	DivideMix+ (ours)	73.49 ± 0.31	$\mathbf{73.30 \pm 0.22}$	72.36 ± 0.43	55.63 ± 0.60	68.70

5.2 Performance comparison

The results of all the methods under symmetric and asymmetric noise types on MNIST, FASHION-MNIST, CIFAR-10, and CIFAR-100 are shown in Table 1 and Table 2. The results on Clothing1M and mini WebVision are shown in Table 3 and Table 4. Furthermore, We delve into the reasons beyond these results in Section 6.

Table 3: Test accuracy (%) on Clothing1M.

Methods	Test Accuracy
Cross-Entropy	69.21
F-correction (Patrini et al., 2017)	69.84
M-correction (Arazo et al., 2019)	71.00
Joint-Optim (Tanaka et al., 2018)	72.16
Meta-Learning Li et al. (2019)	73.47
PENCIL Yi & Wu (2019)	73.49
Dividemix (Li et al., 2020)	73.91
GPL(ours)	73.89
Dividemix+(ours)	**74.14**

Results on MNIST. *DivideMix+* surpasses *DivideMix* across symmetric and asymmetric noise at all noise ratios, showing the effectiveness of the mini-batch SS strategy in our framework. In the cases of Symmetric 20% and 40%, *DivideMix+* and *M-correction* perform better than the other methods. When it comes to Asymmetric noise, *GPL* and *M-correction* demonstrate better performance. However, the performance of *M-correction* drops dramatically in the more challenging Symmetric 80% case where *DivideMix+* surpasses all the other algorithms.

Results on FASHION-MNIST. FASHION-MNIST is quite similar to MNIST but more complicated. *DivideMix+* still outperforms *DivideMix* on symmetric and asymmetric noise at all noise ratios. Under symmetric noise, *DivideMix+* outperforms most of other methods, while *F-correction* has better performance under asymmetric noise.

Results on CIFAR-10. *DivideMix+* constantly outperforms *DivideMix*, especially in the cases with higher noise ratios. *DivideMix+* achieves an improvement in the accuracy of +2.61% in Symmetric 80% and +1.34% in Asymmetric 40% over *DivideMix*. We believe the reason is that the mini-batch SS strategy used in our framework can better mitigate the confirmation bias induced from wrongly divided samples in more challenging scenarios. In the easiest Symmetric 20%, 40%, *DivideMix*, *DivideMix+* and *GPL* tie closely with *DivideMix+* slightly working better than the other two. In the harder cases (symmetric 60%, symmetric 80% and all asymmetric cases), *GPL* and *DivideMix+* surpass the other methods over a large margin.

Results on CIFAR-100. There are 100 classes in CIFAR-100, making it more challenging to train than CIFAR-10. *Coteaching* tends to fail in CIFAR-100 even under low noise ratios. In most cases, *DivideMix+* and *DivideMix* achieve higher test accuracy than the other approaches, with *DivideMix+* performing better. Specifically, *DivideMix+* surpasses *DivideMix* by 14.82% in the hardest symmetric 80% case. An interesting phenomenon is that all the approaches suffer from performance deterioration in the asymmetric 40% cases except *GPL*, which significantly outperforms the second-best algorithm over +14%.

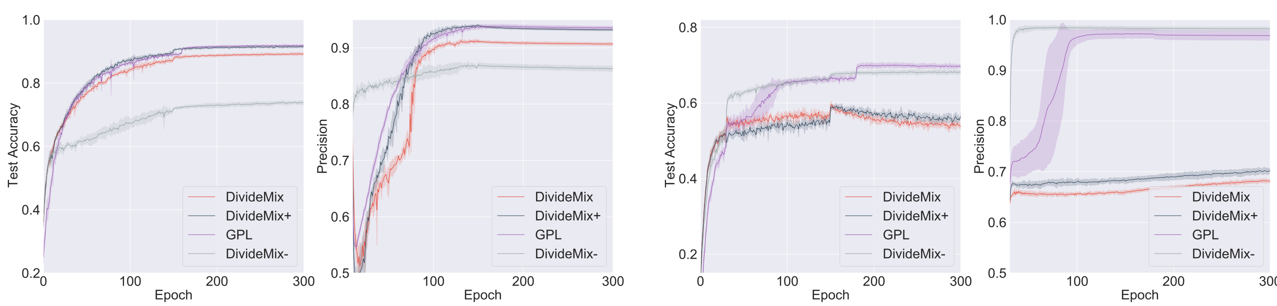
Table 4: Test accuracy (%) on (mini) WebVision.

Methods	Test Accuracy
F-correction (Patrini et al., 2017)	61.12
Decoupling (Malach & Shalev-Shwartz, 2017)	62.54
D2L (Ma et al., 2018)	62.68
MentorNet (Jiang et al., 2018)	63.00
Co-teaching (Han et al., 2018)	63.58
Iterative-CV (Chen et al., 2019)	65.24
Dividemix (Li et al., 2020)	77.32
GPL(ours)	77.84
Dividemix+(ours)	**78.28**

Results on real-world datasets. To show the robustness of our framework under real-world noisy labels, we demonstrate the effectiveness of *DivideMix+* and *GPL* on Clothing1M and mini WebVision. As shown in Table 3, the performance of *DivideMix+* is better than that of *DivideMix* and other methods. In Table 4, both *DivideMix+* and *GPL* outperform compared methods.

6 Ablation Studies and Discussions

In this section, we investigate our framework in depth to gain more insights. Specifically, we analyze the pros and cons of different SS and SSL components, and also analyze the effects and efficiencies of the instantiations of our framework, which sheds light on how SSL components affect SS process.



(a) CIFAR-10 sym 80%　　(b) CIFAR-100 asym 40%

Figure 2: Results of ablation study. For (a) and (b), left: accuracy vs. epochs; right: precision vs. epochs.

6.1 The effects of mini-batch mechanism

In Table 5, the test accuracy of *DivideMix+* constantly outperforms *DivideMix* in most cases. This is because our mini-batch mechanism injects more stochasticity in training and reduces the harm of confirmation bias. In Figure 2 (a) and (b), the precision of *DivideMix+* outperforms *DivideMix* during the training process, showing that our approach is better at finding clean instances.

Table 5: Test accuracy (%) of *DivideMix-*, *DivideMix*, and *DivideMix+*.

Datasets	Method	Symmetric				Asymmetric			
		Noise ratio				Noise ratio			
		20%	40%	60%	80%	10%	20%	30%	40%
CIFAR-10	DivideMix-	94.49 ± 0.02	93.64 ± 0.12	91.65 ± 0.34	76.61 ± 1.26	93.58 ± 0.02	92.87 ± 0.14	91.21 ± 0.21	90.42 ± 0.23
	DivideMix	94.82 ± 0.09	93.95 ± 0.14	92.28 ± 0.08	89.30 ± 0.17	93.61 ± 0.15	92.99 ± 0.21	91.79 ± 0.36	90.57 ± 0.31
	DivideMix+ (ours)	$\mathbf{94.84 \pm 0.12}$	$\mathbf{94.03 \pm 0.20}$	$\mathbf{93.08 \pm 0.19}$	$\mathbf{91.91 \pm 0.07}$	$\mathbf{94.27 \pm 0.23}$	$\mathbf{93.92 \pm 0.20}$	$\mathbf{92.82 \pm 0.28}$	$\mathbf{91.91 \pm 0.24}$
CIFAR-100	DivideMix-	72.51 ± 0.32	69.27 ± 0.46	61.13 ± 0.60	25.96 ± 0.78	73.62 ± 0.12	72.32 ± 0.24	70.64 ± 0.20	$\mathbf{68.04 \pm 1.24}$
	DivideMix	73.17 ± 0.28	71.01 ± 0.16	66.61 ± 0.18	43.25 ± 0.82	$\mathbf{74.00 \pm 0.29}$	73.28 ± 0.42	$\mathbf{72.84 \pm 0.36}$	54.33 ± 0.69
	DivideMix+ (ours)	$\mathbf{73.22 \pm 0.21}$	$\mathbf{71.03 \pm 0.32}$	$\mathbf{67.52 \pm 0.19}$	$\mathbf{58.07 \pm 0.71}$	73.49 ± 0.31	$\mathbf{73.30 \pm 0.22}$	72.36 ± 0.43	55.63 ± 0.60

Table 6: Test accuracy (%) of the baseline and three SSL backbones integrated into our proposed framework.

Dataset	CIFAR-10			CIFAR-100		
Method/Noise rate	20%	50%	80%	20%	50%	80%
SPD-Cross-Entropy	83.13 ± 0.16	79.74 ± 0.10	49.14 ± 0.15	45.07 ± 0.55	35.02 ± 0.57	10.22 ± 0.10
SPD-Temporal Ensembling	83.15 ± 0.06	80.16 ± 0.36	49.10 ± 0.13	46.16 ± 0.12	39.91 ± 0.60	12.37 ± 0.67
SPD-MixMatch	93.53 ± 0.52	90.22 ± 0.18	88.77 ± 0.20	72.89 ± 0.30	68.57 ± 0.20	33.92 ± 0.20
SPD-Pseudo-Labeling	$\mathbf{94.52 \pm 0.06}$	$\mathbf{93.24 \pm 0.36}$	$\mathbf{90.27 \pm 0.34}$	$\mathbf{73.84 \pm 0.48}$	$\mathbf{68.61 \pm 0.40}$	$\mathbf{55.37 \pm 0.34}$

6.2 The effects of different SS strategies

To study how SS strategies can affect the performance of our framework, we propose *DivideMix-* by replacing the GMM component in *DivideMix* with our *self-prediction divider* yet maintaining the epoch-level SS strategy for a fair comparison. In CIFAR-10, the difference between *DivideMix-* and *DivideMix* is not obvious in the lower noise ratios. However, in the most difficult symmetric 80% case, the test accuracy of *DivideMix* is +12.69% higher than *DivideMix-* and the precision of *DivideMix* in Figure 2 (a) outperforms *DivideMix-*. In CIFAR-100, the difference of test accuracy is even greater under symmetric noise. An impressive phenomenon to note is that *DivideMix-* excels in the asymmetric 40% case in CIFAR-100 with the highest precision and accuracy. This is because *GMM* distinguishes clean and noisy samples by fitting their loss distribution, which works effectively for symmetric noise. However, for asymmetric noise, most samples have near-zero normalized loss due to the low entropy predictions of the network, causing performance deterioration for *GMM*. Since *SPD* leverages the prediction of its own network to choose clean samples, its performance is more sensitive to noisy rates rather than noise type.

6.3 The effects of different SSL backbones

We evaluate the effects of SSL backbones in our framework by combining the *self-prediction divider (SPD)* with three different SSL methods and a baseline which only updates the model using the cross-entropy loss calculated from clean samples. We denote them as *SPD-Temporal Ensembling (TE)*, *SPD-MixMatch (MM)*, *SPD-Pseudo-Labeling (PL)*, and *SPD-Cross-Entropy (CE)*, respectively. For a fair comparison, we use the "13-CNN" architecture (Tarvainen & Valpola, 2017) for all methods across different datasets. We keep most hyperparameters introduced by the SSL methods close to their original papers (Arazo et al., 2020; Berthelot et al., 2019; Laine & Aila, 2016), since they can be easily integrated into our framework without massive adjustments. In Table 6, *SPD-MM* and *SPD-PL* outperform *SPD-TE* by a large domain in both CIFAR-10 and CIFAR-100, especially under 80% noise ratio. This phenomenon is reasonable because *TE* (Laine & Aila, 2016) only uses consistency regularization for unsupervised loss, while *MM* (Berthelot et al., 2019) and *PL* (Arazo et al., 2020) also leverage entropy regularization as well as *MixUp* data augmentation (Zhang et al., 2018). Moreover, *SPD-PL* achieves remarkable test accuracy under 80% noise ratio in CIFAR-100. This is due to the additional loss used in *SPD-PL* that prevents the model from assigning all labels to a single class at the early training stage. From the results of *SPD-CE*, we can see that after the removal of the SSL backbone, the test accuracy drops dramatically compared to *SPD-MM* and *SPD-PL*. This is due to the substantial amount of data that has been removed by the *SPD*, leaving very few samples per class. Thus, instead of discarding noisy samples, transferring them to unlabeled ones in SSL backbones is an effective way to combat noisy labels.

The benefits of using SSL methods in our framework are in these aspects: (i) improving SS performance incrementally and (ii) leveraging the potentially noisy samples to learn feature representation. **For (i)**, as shown in Figure 2 (a) and (b), the precision of *GPL* is higher than *DivideMix+* and *DivideMix*. This is because the SSL backbone used in *GPL*, i.e., *Pseudo-Labeling*, can better alleviate the confirmation bias induced during the SS process and improve the prediction results. In this way, *GPL* can achieve competitive test accuracy in CIFAR-10 sym 80% without co-training two models. This finding is more prominent in CIFAR-100 asym 40%. **For (ii)**, we visualize feature representations of *GPL* and *DivideMix+* in 2-dimensional embeddings using t-SNE (der Maaten & Hinton, 2008). Figure 3 presents the normalised 2D embeddings of 500 randomly selected samples from each of two classes in CIFAR-10 sym 80%. We can see that both *GPL* and *DivideMix+* can accurately separate the clean instances of two classes (blue vs red). As for noisy instances (magenta and cyan), the representations learned by *GPL* are more fragmented and pushed away from clean clusters, showing that the SSL backbones of *GPL* is more effective in isolating noisy samples from clean ones. However, *DivideMix+* outperforms *GPL* in test accuracy because *DivideMix+* leverage two models for training and testing to improve accuracy.

6.4 Efficiency analysis

In Table 7, we study the efficiency of these two components by dividing all our instantiations into two parts and calculating their training time on CIFAR-10 sym 20% using an NVIDIA RTX 6000 GPU. We also break down the computation time per epoch (measured in seconds) for the SS process (Alg. 1, line 5) and SSL process (Alg. 1, line 6). **For the efficiency of SS**, *DivideMix+* is much faster than *DivideMix* because our per-minibatch SS strategy extracts and divides each minibatch of data faster. We can conclude that instantiations from our framework work more efficiently than simply combining SS and SSL components. *DivideMix-* is faster than *DivideMix*, which shows that *SPD* (used by *DivideMix-*) is faster than *GMM*. Moreover, *GPL* is much faster because only one network is trained. **For the efficiency of SSL**, *SPD-TE* is faster than *SPD-MM* and *SPD-PL* because the last two methods need to take an additional *MixUp* operation. The small time differences between these three instantiations indicate that various SSL backbones can be integrated into our framework efficiently.

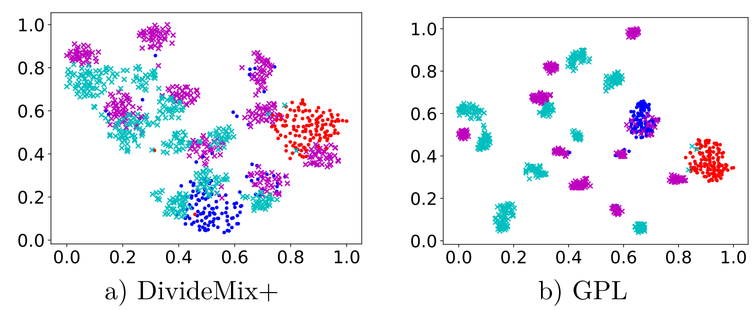


Figure 3: Representations (t-SNE 2D embeddings) of two CIFAR-10 classes, 'cat' and 'truck', learned by DivideMix+ (left) and GPL (right), with 80% noise rate. Blue/red dots represent clean samples of cat/truck, while magenta and cyan crosses represent corrupted samples.

Table 7: Comparison of training time on CIFAR-10.

Method	GPL	DivideMix+	DivideMix-	DivideMix	SPD-CE	SPD-TE	SPD-PL	SPD-MM
Total	3.3 h	8.2 h	9.1 h	9.4 h	2.5 h	3.0 h	3.2 h	3.6 h
SS/epoch	9.2 s	12.1 s	15.5 s	18.2 s	-	37.2 s	39.5 s	44.1 s

7 Conclusion

This paper proposes a versatile framework called *SemiNLL* for NLL. This framework consists of two main parts: the mini-batch SS strategy and the SSL backbone. We conduct extensive experiments on benchmark-simulated and real-world datasets to demonstrate that *SemiNLL* can absorb a variety of SS strategies and SSL backbones, leveraging their power to achieve state-of-the-art performance in different noise scenarios. Moreover, we throughly analyze the effects of the two components in our framework. In future work, we hope to develop more advanced algorithms guided by this framework to tackle noisy labels.

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A Datasets

MNIST and FASHION-MNIST contain 60K training images and 10K test images of size 28×28. CIFAR-10 and CIFAR-100 contain 50K training images and 10K test images of size 32×32 with three channels. Clothing1M is a large-scale real-world dataset that consists of one million training images of size 224×224 from online shopping websites with labels annotated from surrounding texts. The estimated noise ratio is approximately 40% Xiao et al. (2015). Webvision Li et al. (2017) contains 2.4 million images crawled from the websites using the 1,000 concepts in ImageNet ILSVRC12Deng et al. (2009). Since the dataset is quite large, for quick experiments, we use the first 50 classes of the Google image subset. We test the trained models on the human-annotated WebVision validation set. The detailed characteristics of the datasets in the experiments are shown in Table 8.

Table 8: Summary of datasets used in the experiments.

	# of training	# of test	# of class	size
MNIST	60,000	10,000	10	$1 \times 28 \times 28$
F-MNIST	60,000	10,000	10	$1 \times 28 \times 28$
CIFAR-10	50,000	10,000	10	$3 \times 32 \times 32$
CIFAR-100	50,000	10,000	100	$3 \times 32 \times 32$
Clothing1M	1,000,000	10,000	14	$3 \times 224 \times 224$

B Network Structure

For MNIST, we use a simple 2-layer MLP following *Jocor* Wei et al. (2020). For FASHION-MNIST, we use a ResNet-18 He et al. (2016) following *GCE* Zhang & Sabuncu (2018). For CIFAR-10 and CIFAR-100, we use the "13-CNN" architecture Tarvainen & Valpola (2017), which is shown in Table 9. For Clothing1M, we use a ResNet-50 He et al. (2016) following *DivideMix* Li et al. (2020). For mini WebVision, we use the inception-resnetv2 Szegedy et al. (2017).

C Illustrations

To better understand the differences between *DivideMix-*, *DivideMix*, and *DivideMix+*, their illustrations are shown in Figure 4 (a), (b), and (c), respectively.

Table 9: The "13-CNN" network architecture used in CIFAR-10 and CIFAR-100.

Layer	Hyperparameters
Input	32×32 RGB image
Convolutional	128 filters, 3×3, *same* padding
Convolutional	128 filters, 3×3, *same* padding
Convolutional	128 filters, 3×3, *same* padding
Pooling	Maxpool 2×2
Convolutional	256 filters, 3×3, *same* padding
Convolutional	256 filters, 3×3, *same* padding
Convolutional	256 filters, 3×3, *same* padding
Pooling	Maxpool 2×2
Convolutional	512 filters, 3×3, *valid* padding
Convolutional	256 filters, 1×1, *same* padding
Convolutional	128 filters, 1×1, *same* padding
Pooling	Average pool ($6 \times 6 \rightarrow 1\times1$ pixels)
Softmax	Fully connected $128 \rightarrow 10$ (100)

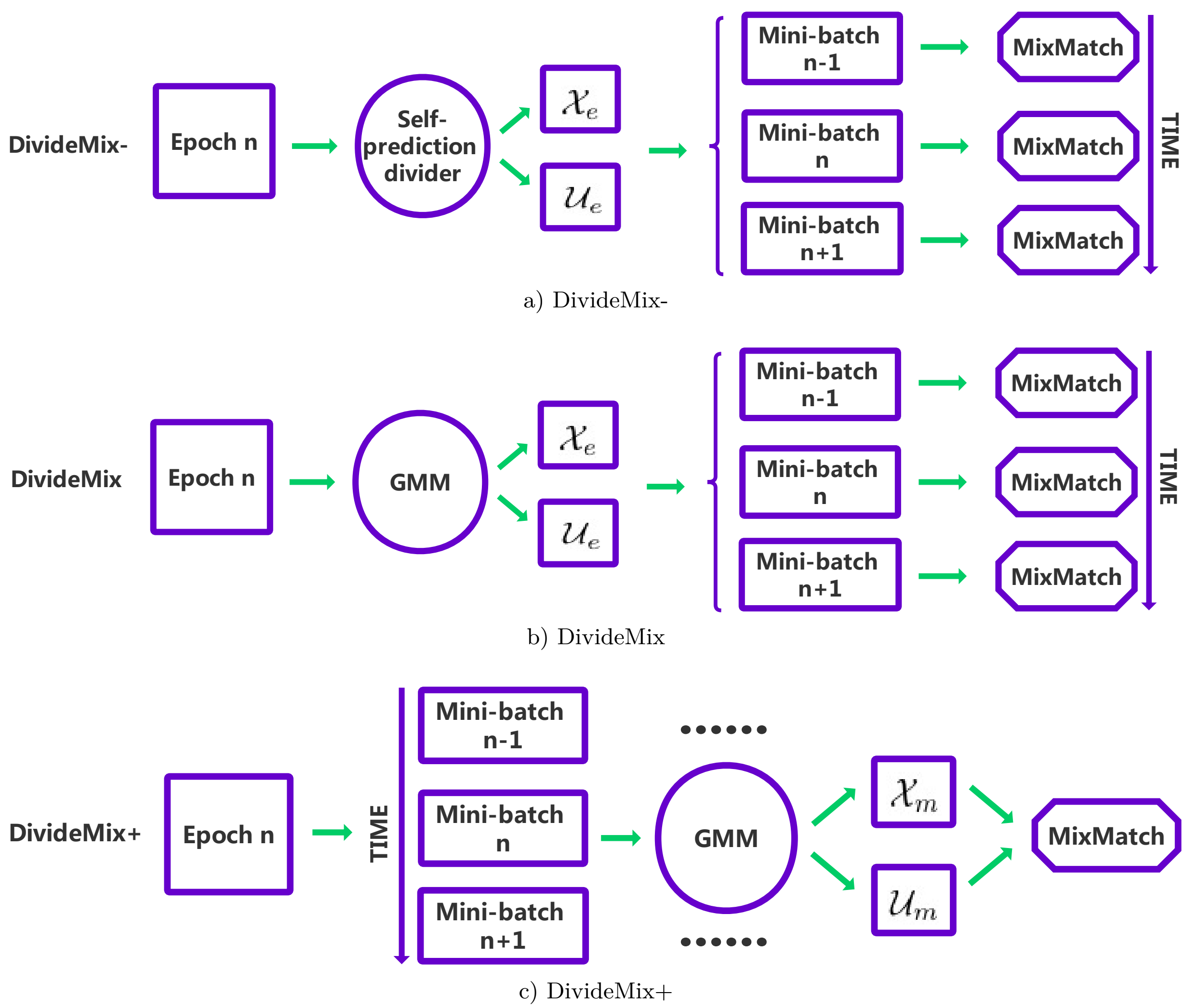

Figure 4: Comparisons between: (a) *DivideMix-*, (b) *DivideMix*, and (c) *DivideMix+*. Squares represent data. Circles represent SS strategy. Octagons represent SSL backbone.