Adaptive Sample Selection for Robust Learning under Label Noise

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- These labelling errors can be due to automated labelling processes, crowdsourced annotations, human errors, etc.
- The training of deep networks is adversely affected by label noise and hence robust learning* under label noise is an important problem of current interest.

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Sample Reweighting – A popular approach

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- This idea is very similar to that of 'curriculum learning'.

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- Motivated by this, several strategies of 'curriculum learning' have been devised for robustness against label noise

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- However, loss value of any specific sample is itself a function of the current state of learning and it evolves with epochs.
- Loss values of even clean samples may change over a significant range during the course of learning for different classes.
- In addition, these methods require knowledge of noise rates, access to extra data with clean labels or availability of high computation resources. Quite often, these are not available.

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- We show through empirical studies the effectivenes of our method.

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- So, for robust learning under label noise, the objective is to learn a classifier from noisy training data, S_η, drawn from $\mathcal{D}_\eta$, such that the classifier performs well on clean training data, S, drawn from $\mathcal{D}$. Here,
  - $S = \{(\boldsymbol{x}_i, y_i^{cl})\}_{i=1}^m$ – training set with true labels
  - $S_\eta = \{(\boldsymbol{x}_i, y_i)\}_{i=1}^m$ – training set with noisy labels

Modelling Label Noise

The y_i here are the corrupted or noisy labels and they are random variables dependent on the clean labels, y_i^{cl}, through the following conditional probability relations:

$$\eta_{kk'} = P(y_i = e_{k'} | y_i^{cl} = e_k) \tag{1}$$

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- A special case of this is **symmetric noise** where we assume $\eta_{kk} = (1 - \eta)$ and $\eta_{kk'} = \frac{\eta}{K-1}$ $\forall k' \neq k$. η here represents the probability of a 'wrong' label.

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- Assumption: $\eta_{kk} > \eta_{kk'}$, $\forall k' \neq k$

An adaptive curriculum

- General curriculum can be viewed as minimization of a weighted loss [20, 14]:

$$\min_{\theta, \mathbf{w} \in [0,1]^m} \mathcal{L}_{\text{wtd}}(\theta, \mathbf{w}) = \frac{1}{m} \sum_{i=1}^{m} w_i \mathcal{L}(f(x_i; \theta), y_i) + G(\mathbf{w}) + \beta ||\theta||^2$$

where $G(\mathbf{w})$ represents the curriculum, $f(\cdot; \theta) \in \Delta^{K-1}$ ($\Delta^{K-1} \subset [0,1]^K$ is the probability simplex) is a classifier function parameterized by θ, and $\mathcal{L}(f(\cdot; \theta), \cdot)$ is a loss function. We use CCE loss here.

An adaptive curriculum (contd.)

- One simple choice for the curriculum is [20] $G(\mathbf{w}) = -\lambda||\mathbf{w}||_1,\ \lambda > 0$. Putting this in the above, omitting the regularization term and taking $l_i = \mathcal{L}(f(x_i;\theta), y_i)$, the optimization problem becomes

$$\begin{aligned}\min_{\theta,\mathbf{w}\in[0,1]^m} \mathcal{L}_{\text{wtd}}(\theta,\mathbf{w}) &= \frac{1}{m}\sum_{i=1}^{m}(w_i l_i - \lambda w_i) \\ &= \sum_{i=1}^{m}(w_i l_i + (1-w_i)\lambda) - m\lambda\end{aligned}$$

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- Under the usual assumption that loss function is non-negative, for the above problem, the optimal $\mathbf{w}$ for any fixed θ is: $w_i = 1$ if $l_i < \lambda$ and $w_i = 0$ otherwise.

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  - The optimal w_i (for any fixed θ) are still given by the same relation even if λ depend on the class label: for an i with $y_i = e_j$, $w_i = 1$ when $l_i < \lambda_j$. $(\lambda_j = \lambda(e_j))$
  - True even if λ_j a function of θ and of all x_i with $y_i = e_j$ and the current θ.
  - This is what we want. How to do that?

An adaptive curriculum (contd)

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- So, we set the sample weights in the following manner:

$$w_i = \begin{cases} 1 & \text{if } f_{y_i}(x_i;\theta) \geq \frac{1}{|\mathcal{S}_{y_i}|}\sum_{s\in\mathcal{S}_{y_i}} f_{y_s}(x_s;\theta) + \sigma_{y_i} \\ 0 & \text{else} \end{cases} \tag{2}$$

where $\mathcal{S}_{y_i} = \{k \in [m] \mid y_k = y_i\}$ and σ_{e_j} indicates the sample variance of the class posterior probabilities for class-j in the given mini-batch.

BARE - The Algorithm

Keeping in mind that the neural networks are trained in a mini-batch manner, the BARE algorithm consists of three parts:

- Computing sample selection threshold, $T_{K\times 1}$, for a given mini-batch of data (Equation 2)
- Sample selection based on this threshold as per Equation 2
- Parameter updation using these selected samples

Experimental Setup

Datasets:

- MNIST [21] (– No data augmentation)
- CIFAR-10 [18] (– random cropping with size 4 padding and random horizontal flips)
- Clothing-1M [43] (– random cropping while ensuring fixed image size)

Table 1: Dataset details

	TRAIN SIZE	TEST SIZE	# CLASS	SIZE
MNIST	60,000	10,000	10	28×28
CIFAR-10	50,000	10,000	10	32×32
CLOTHING-1M	10,00,000	10,000	14	224×224

Experimental Setup (contd.)

Baselines: We compare the proposed algorithm with the following algorithms from literature:

- Co-Teaching (CoT) [10]
- Co-Teaching+ (CoT+) [47]
- Meta-Ren (MR) [36]
- Meta-Net (MN) [37]
- Curriculum Loss (CL) [24]
- Standard (CCE)

Experimental Setup (contd.)

- All the simulations are run for 5 trials.
- All experiments use PyTorch [32], NumPy [12], scikit-learn [34], and NVIDIA Titan X Pascal GPU with CUDA 10.0.

Experimental Setup (contd.)

Types of Label Noise simulated

- Symmetric Label Noise
- Class-conditional Label Noise
  - For MNIST, the following flipping is done: $1 \leftarrow 7$, $2 \rightarrow 7$, $3 \rightarrow 8$, and $5 \leftrightarrow 6$
  - For CIFAR10, the following flipping is done: TRUCK $\rightarrow$ AUTOMOBILE, BIRD $\rightarrow$ AIRPLANE, DEER $\rightarrow$ HORSE, CAT $\leftrightarrow$ DOG

Performance Metrics

- For all algorithms we compare **test accuracies** on a separate test set with clean labels.

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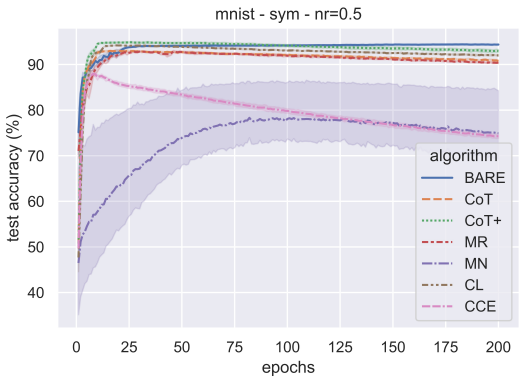
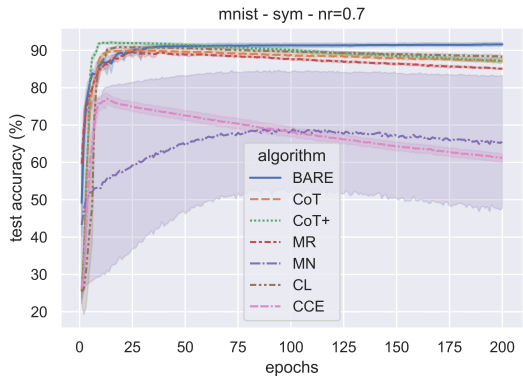
- For all algorithms we compare **test accuracies** on a separate test set with clean labels.
- The main idea in all sample selection schemes is to identify noisy labels. Hence, in addition to test accuracies, we also compare:
  - **precision** (# *clean labels selected* / # *of selected labels*)
  - **recall** (# *clean labels selected* / # *of clean labels*)

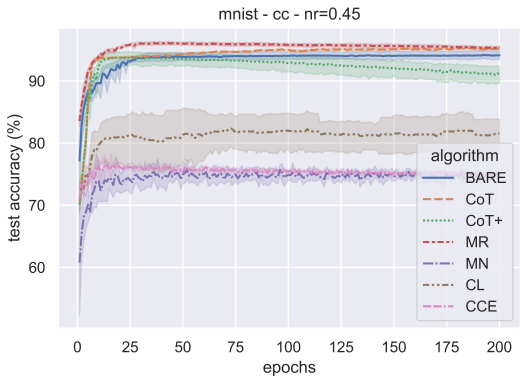
Results on MNIST - Test Accuracy



(a)



(b)

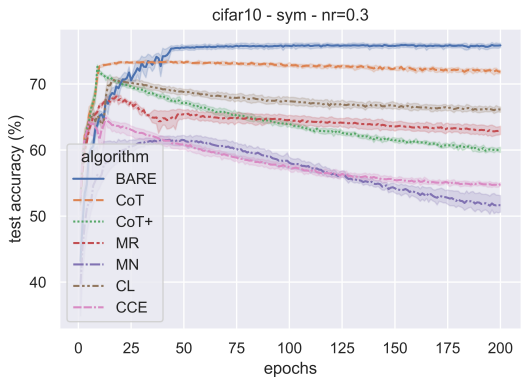


(c)

Figure 1: Test Accuracies - MNIST - Symmetric ((a) & (b)) & Class-conditional ((c)) Label Noise

- BARE outperforms the baselines for symmetric noise.
- For class-conditional noise, the test accuracy of BARE is marginally less than the best of the baselines, namely CoT and MR.

Results on CIFAR10 - Test Accuracy



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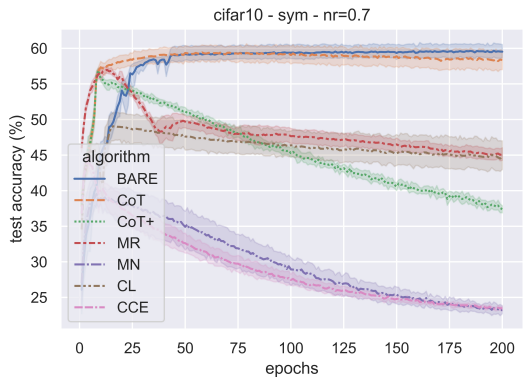

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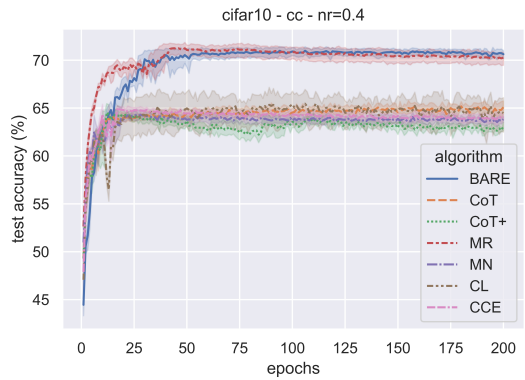


(c)

Figure 2: Test Accuracies - CIFAR10 - Symmetric ((a) & (b)) & ((c)) Class-conditional Label Noise

- BARE outperforms the baseline schemes and its test accuracies are uniformly good for all types of label noise.

Results on Clothing-1M – Test Accuracy

Table 2: Test accuracies on Clothing-1M dataset

Algorithm	Test Accuracy (%)
CCE	68.94
D2L [27]	69.47
GCE [50]	69.75
Forward [33]	69.84
CoT [10]†	70.15
SEAL [6]	70.63
DY [2]	71.00
SCE [40]	71.02
LRT [51]	71.74
PTD-R-V [42]	71.67
Joint Opt. [39]	72.23
BARE (Ours)	**72.28**
DivideMix [22]	74.76

†as reported in [6]

Results on Clothing-1M – Test Accuracy (contd.)

- Even for real-world noisy datasets such as Clothing-1M where the label noise that isn't synthetic unlike that used for simulations on MNIST & CIFAR-10, BARE performs better than all but one baselines.
- Note that DivideMix requires about 2.4 times the computation time required for BARE. And, DivideMix requires tuning of 5 hyperparameters whereas no such tuning is required for BARE.

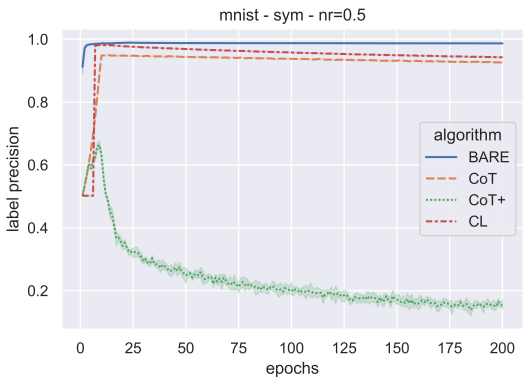
Efficiency of BARE

- Table 3 shows the typical run times for 200 epochs of training with all the algorithms.
- BARE takes roughly the same time as the usual training with CCE loss. Other baselines are significantly more expensive computationally.

Table 3: Algorithm run times for training (in seconds)

Algorithm	MNIST	CIFAR10
BARE	**310.64**	**930.78**
CoT	504.5	1687.9
CoT+	537.7	1790.57
MR	807.4	8130.87
MN	1138.4	8891.6
CL	730.15	1254.3
CCE	**229.27**	**825.68**

Efficacy of detecting clean samples - Label Precision



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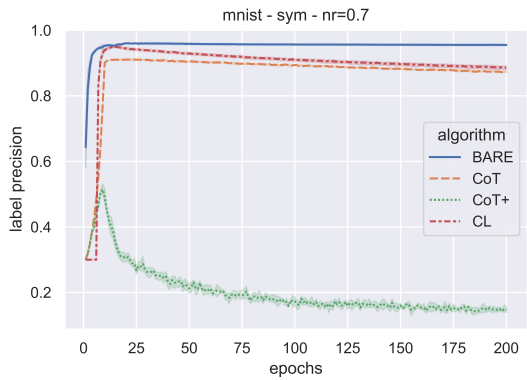

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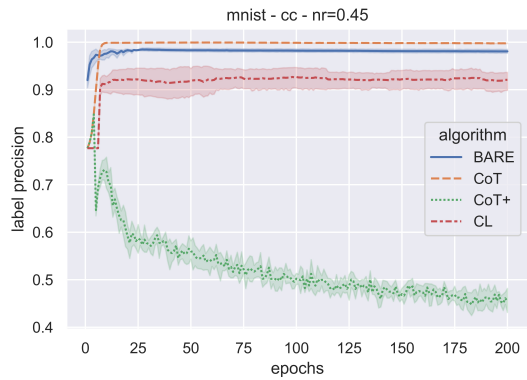
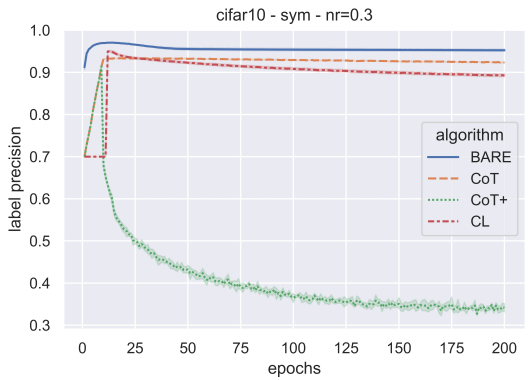


(c)

Figure 3: Label Precision - MNIST - Symmetric ((a) & (b)) & ((c)) Class-conditional Label Noise

Efficacy of detecting clean samples - Label Precision



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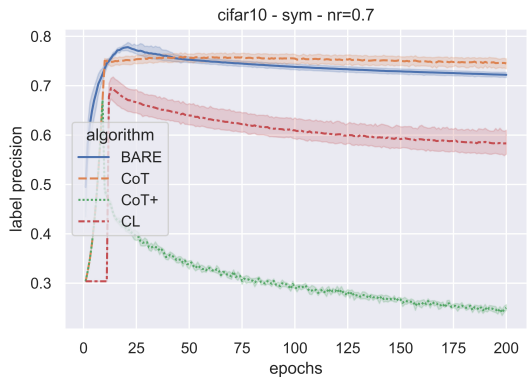

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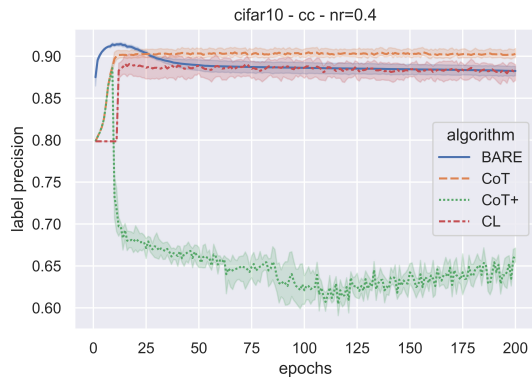
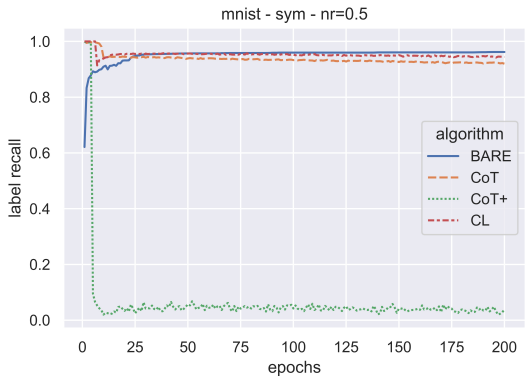


(c)

Figure 4: Label Precision - CIFAR10 - Symmetric ((a) & (b)) & ((c)) Class-conditional Label Noise

- Figures 3 and 4 show the label precision (across epochs) on MNIST and CIFAR-10 respectively.
- BARE has comparable or better precision.

Efficiency of detecting clean samples - Label Recall



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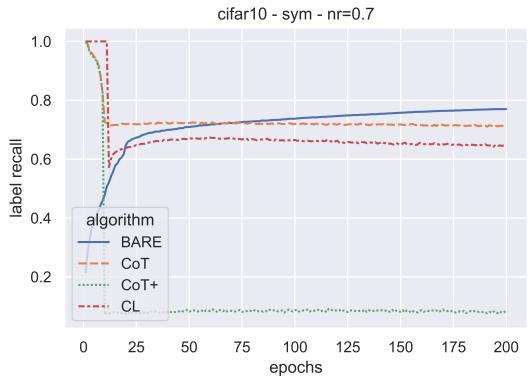

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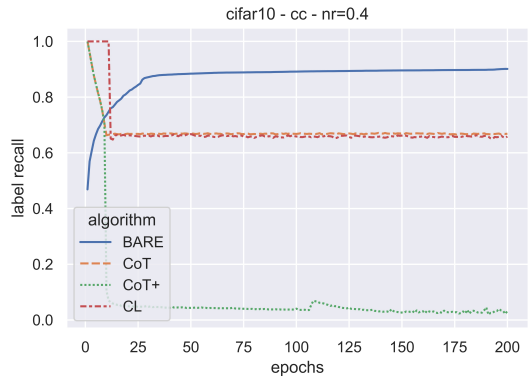
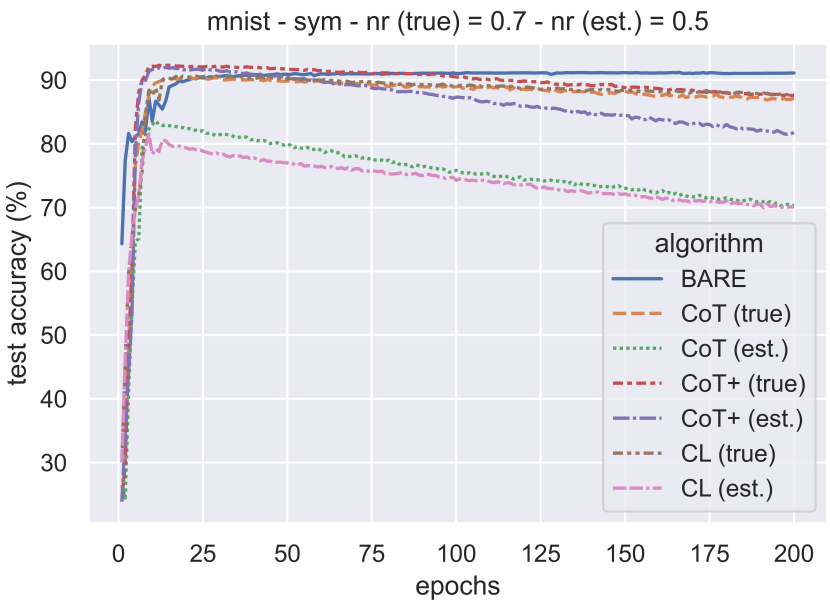


(c)

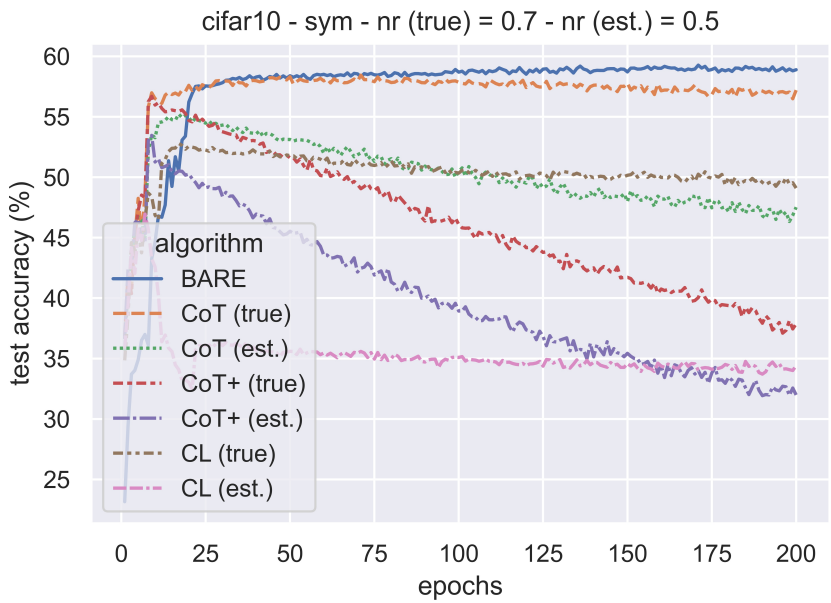
Figure 5: Label Recall - Symmetric ((a) & (b)) & ((c)) Class-conditional Label Noise

- Figure 5 show the label recall values for CoT, CoT+, CL, and BARE for MNIST (5(a)) and CIFAR-10 (5(b) & 5(c)).

Sensitivity to noise rates



(a)



(b)

Figure 6: ((a) & (b)):Test accuracies when estimated (symmetric) noise rate, $\eta = 0.5$, and true noise rate, $\eta = 0.7$, for MNIST & CIFAR-10 resp.

- So, similar performance trends are seen for the case of mis-specified noise rates and arbitrary noise rate matrices.

Conclusions

- We propose an adaptive, data-dependent sample selection scheme, BARE, for robust learning in the presence of label noise.
- The algorithm relies on statistics of assigned posterior probabilities of all samples in a minibatch to select samples from that minibatch.
- The mini-batch statistics are used as proxies for determining current state of learning here.
- Unlike other algorithms in literature, BARE neither needs an extra data set with clean labels nor does it need any knowledge of the noise rates. Further it has no hyperparameters in the selection algorithm.
- Comparisons with baseline schemes on benchmark datasets show the effectiveness of the proposed algorithm both in terms of performance metrics and computational complexity.

Thank You

Any Questions?

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