A Training Process

Algorithm 1 The training process with $\mathcal{L}_{\text{DMI}}$

Require: A training dataset $\mathcal{D} = \{(x_i, \tilde{y}_i)\}_{i=1}^{D}$, a validation dataset $\mathcal{V} = \{(x_i, \tilde{y}_i)\}_{i=1}^{V}$, a classifier modeled by deep neural network h_Θ, the running epoch number T, the learning rate γ and the batch size N.

1: Pretrain the classifier h_Θ on the dataset $\mathcal{D}$ with cross entropy loss
2: Initialize the best classifier: $h_{\Theta^*} \leftarrow h_\Theta$
3: Randomly sample a batch of samples $\mathcal{B}_v = \{(x_i, \tilde{y}_i)\}_{i=1}^{N}$ from the validation dataset
4: Initialize the minimum validation loss: $L^* \leftarrow \mathcal{L}_{\text{DMI}}(\mathcal{B}_v; h_\Theta)$
5: **for** epoch $t = 1 \rightarrow T$ **do**
6:     **for** batch $b = 1 \rightarrow \lceil D/B \rceil$ **do**
7:         Randomly sample a batch of samples $\mathcal{B}_t = \{(x_i, \tilde{y}_i)\}_{i=1}^{N}$ from the training dataset
8:         Compute the training loss: $L \leftarrow \mathcal{L}_{\text{DMI}}(\mathcal{B}_t; h_\Theta)$
9:         Update Θ: $\Theta \leftarrow \Theta - \gamma \frac{\partial L}{\partial \Theta}$
10:     **end for**
11:     Randomly sample a batch of samples $\mathcal{B}_v = \{(x_i, \tilde{y}_i)\}_{i=1}^{N}$ from the validation dataset
12:     Compute the validation loss: $L \leftarrow \mathcal{L}_{\text{DMI}}(\mathcal{B}_v; h_\Theta)$
13:     **if** $L < L^*$ **then**
14:         Update the minimum validation loss: $L^* \leftarrow L$
15:         Update the best classifier: $h_{\Theta^*} \leftarrow h_\Theta$
16:     **end if**
17: **end for**
18: **return** the best classifier h_{Θ^*}

B Other Proofs

Claim B.1.
$$\mathbb{E}\mathbf{U}_{c\tilde{c}} = \Pr[h(X) = c, \tilde{Y} = \tilde{c}]$$

where

$$\mathbf{U}_{c\tilde{c}} := \frac{1}{N}\sum_{i=1}^{N} \mathbf{O}_{ci}\mathbf{L}_{i\tilde{c}} = \frac{1}{N}\sum_{i=1}^{N} h(x_i)_c \mathbb{1}[\tilde{y}_i = \tilde{c}].$$

Proof. Recall that the randomness of $h(X)$ comes from both h and X and the randomness of h is independent of everything else.

$$
\begin{aligned}
\mathbb{E}\mathbf{U}_{c\tilde{c}} &= \mathbb{E}\frac{1}{N}\sum_{i=1}^{N} h(x_i)_c \mathbb{1}[\tilde{y}_i = \tilde{c}] \\
&= \mathbb{E}_{X,\tilde{Y}} h(X)_c \mathbb{1}[\tilde{Y} = \tilde{c}] &\text{(i.i.d. samples)} \\
&= \sum_{x,\tilde{y}} \Pr[X = x, \tilde{Y} = \tilde{y}] h(x)_c \mathbb{1}[\tilde{y} = \tilde{c}] \\
&= \sum_{x} \Pr[X = x, \tilde{Y} = \tilde{c}] h(x)_c \\
&= \sum_{x} \Pr[X = x, \tilde{Y} = \tilde{c}] \Pr[h(X) = c | X = x] &\text{(definition of randomized classifier)} \\
&= \sum_{x} \Pr[X = x, \tilde{Y} = \tilde{c}] \Pr[h(X) = c | X = x, \tilde{Y} = \tilde{c}] \\
&\qquad\qquad\qquad \text{(fixing } x \text{, the randomness of } h \text{ is independent of everything else)} \\
&= \Pr[h(X) = c, \tilde{Y} = \tilde{c}].
\end{aligned}
$$

$\square$

Claim B.2. *Under the the performance measure based on Shannon mutual information, the measurement based on noisy labels $MI(h(X), \tilde{Y})$ is not consistent with the measurement based on true labels $MI(h(X), Y)$. i.e., for every two classifiers h and h',*

$$I(h(X), Y) > I(h'(X), Y) \not\Rightarrow I(h(X), \tilde{Y}) > I(h'(X), \tilde{Y}).$$

Proof. See a counterexample:

The matrix format of the joint distribution $Q_{h(X),Y}$ is $\mathbf{Q}_{h(X),Y} = \begin{bmatrix} 0.1 & 0.4 \\ 0.2 & 0.3 \end{bmatrix}$, the matrix format of the joint distribution $Q_{h'(X),Y}$ is $\mathbf{Q}_{h'(X),Y} = \begin{bmatrix} 0.2 & 0.6 \\ 0.1 & 0.1 \end{bmatrix}$ and the noise transition matrix is $\mathbf{T}_{Y \to \tilde{Y}} = \begin{bmatrix} 0.8 & 0.2 \\ 0.4 & 0.6 \end{bmatrix}$.

Given these conditions, $\mathbf{Q}_{h(X),\tilde{Y}} = \begin{bmatrix} 0.24 & 0.26 \\ 0.28 & 0.22 \end{bmatrix}$ and $\mathbf{Q}_{h'(X),\tilde{Y}} = \begin{bmatrix} 0.40 & 0.40 \\ 0.12 & 0.08 \end{bmatrix}$.

If we use Shannon mutual information as the performance measure,

$$\text{MI}(h(X), Y) = 2.4157 \times 10^{-2},$$
$$\text{MI}(h'(X), Y) = 2.2367 \times 10^{-2},$$
$$\text{MI}(h(X), \tilde{Y}) = 3.2085 \times 10^{-3},$$
$$\text{MI}(h'(X), \tilde{Y}) = 3.2268 \times 10^{-3}.$$

Thus we have $\text{MI}(h(X), Y) > \text{MI}(h'(X), Y)$ but $\text{MI}(h(X), \tilde{Y}) < \text{MI}(h'(X), \tilde{Y})$.

Therefore, $\text{MI}(h(X), Y) > \text{MI}(h'(X), Y) \not\Rightarrow \text{MI}(h(X), \tilde{Y}) > \text{MI}(h'(X), \tilde{Y})$.

□

C Noise Transition Matrices

Here we list the explicit noise transition matrices.

On Fashion-MNIST, case (1): $\mathbf{T}_{Y \to \tilde{Y}} = \begin{bmatrix} 1 - \frac{r}{2} & \frac{r}{2} \\ \frac{r}{2} & 1 - \frac{r}{2} \end{bmatrix}$;

On Fashion-MNIST, case (2): $\mathbf{T}_{Y \to \tilde{Y}} = \begin{bmatrix} 1-r & r \\ 0 & 1 \end{bmatrix}$;

On Fashion-MNIST, case (3): $\mathbf{T}_{Y \to \tilde{Y}} = \begin{bmatrix} 1 & 0 \\ r & 1-r \end{bmatrix}$;

On CIFAR-10, $\mathbf{T}_{Y \to \tilde{Y}} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ r & 0 & 1-r & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1-r & 0 & r & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1-r & 0 & 0 & r & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & r & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1-r \end{bmatrix}$;

On Dogs vs. Cats, $\mathbf{T}_{Y \to \tilde{Y}} = \begin{bmatrix} 1 & 0 \\ r & 1-r \end{bmatrix}$.

On MR, $\mathbf{T}_{Y \to \tilde{Y}} = \begin{bmatrix} 1 & 0 \\ r & 1-r \end{bmatrix}$.

For Fashion-MNIST case (1), $r = 0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0, 9$ are diagonally dominant noises. For other cases, $r = 0.0, 0.1, 0.2, 0.3, 0.4$ are diagonally dominant noises and $r = 0.5, 0.6, 0.7, 0.8, 0, 9$ are diagonally non-dominant noises.

D   Additional Experiments

For clean presentation, we only include the comparison between **CE** and **DMI** in section 5.1 and attach comparisons with other methods here. In the experiments in section 5.2, noise patterns are divided into two main cases, diagonally dominant and diagonally non-dominant and uniform noise is a special case of diagonally dominant noise. Thus, we did not emphasize the uniform noise results in section 5.2 and attach them here.
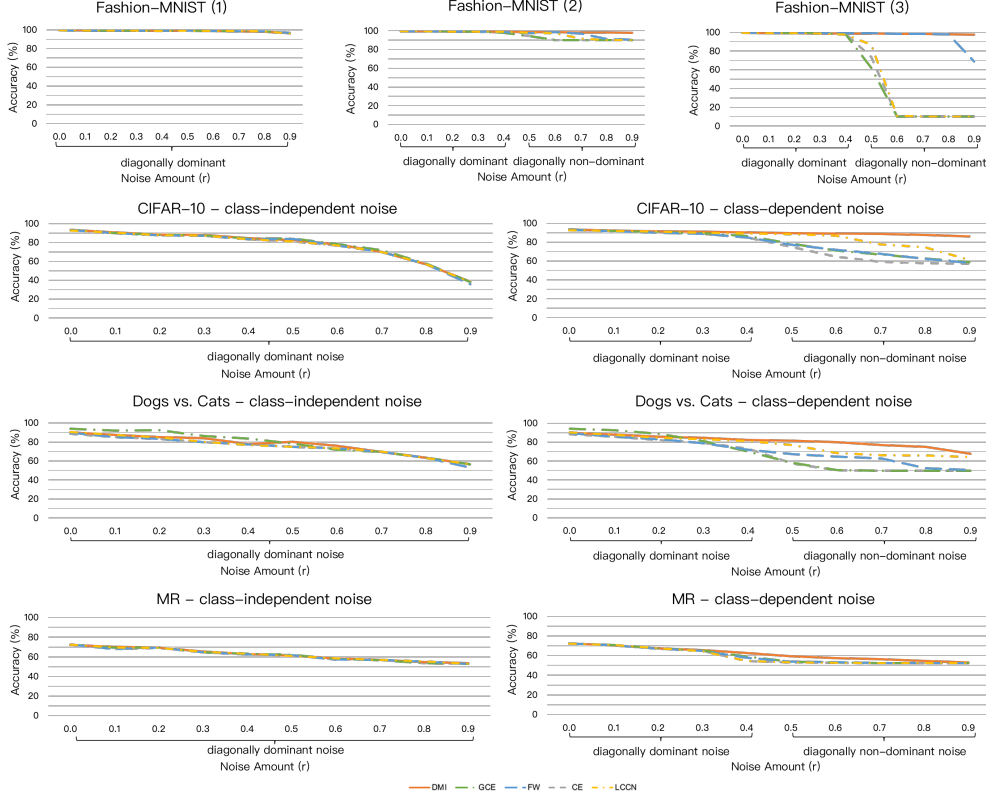

Figure 4: Additional experiments

We also compared our method to **MentorNet** (the sample reweighting loss [14]) and **VAT** (the regularization loss [25]). For clean presentation, we only attach them here. Our method still outperforms these two additional baselines in most of the cases. [4]

Table 2: Test accuracy on CIFAR-10 (mean ± std. dev.)

r	CE	MentorNet	VAT	FW	GCE	LCCN	DMI
0.0	93.29 ± 0.18	92.13 ± 1.22	92.25 ± 0.1	93.12 ± 0.16	$\mathbf{93.43 \pm 0.24}$	92.47 ± 0.36	93.37 ± 0.20
0.1	91.63 ± 0.32	91.35 ± 0.83	91.4 ± 0.68	91.54 ± 0.15	91.96 ± 0.09	91.88 ± 0.23	$\mathbf{92.08 \pm 0.08}$
0.2	90.36 ± 0.24	90.06 ± 0.52	91.19 ± 0.31	90.10 ± 0.22	90.87 ± 0.16	91.05 ± 0.43	$\mathbf{91.51 \pm 0.17}$
0.3	88.79 ± 0.40	88.47 ± 0.61	88.97 ± 0.41	88.77 ± 0.36	89.67 ± 0.21	89.88 ± 0.40	$\mathbf{91.12 \pm 0.30}$
0.4	84.76 ± 0.98	84.12 ± 1.29	84.09 ± 0.46	84.78 ± 1.53	86.6 ± 0.47	89.33 ± 0.58	$\mathbf{90.41 \pm 0.32}$
0.5	74.81 ± 3.37	78.43 ± 0.39	75.07 ± 0.66	77.2 ± 4.19	78.53 ± 1.93	88.30 ± 0.38	$\mathbf{89.45 \pm 0.99}$
0.6	64.61 ± 0.72	71.33 ± 0.13	65.02 ± 0.63	71.98 ± 1.83	71.14 ± 0.78	86.89 ± 0.51	$\mathbf{89.03 \pm 0.69}$
0.7	59.15 ± 0.64	66.28 ± 0.76	58.92 ± 1.49	67.59 ± 1.64	67.10 ± 0.82	77.50 ± 0.60	$\mathbf{88.82 \pm 0.89}$
0.8	57.65 ± 0.28	65.67 ± 0.57	57.78 ± 0.32	62.22 ± 1.80	62.56 ± 0.72	74.62 ± 1.16	$\mathbf{87.46 \pm 0.79}$
0.9	57.46 ± 0.08	59.49 ± 0.40	57.19 ± 1.25	58.23 ± 0.25	58.91 ± 0.46	61.32 ± 1.87	$\mathbf{85.94 \pm 0.74}$

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[4]**VAT** can not be applied to MR dataset.

Table 3: Test accuracy on Dogs vs. Cats (mean ± std. dev.)

r	CE	MentorNet	VAT	FW	GCE	LCCN	DMI
0.0	88.50 ± 0.60	88.76 ± 0.32	88.32 ± 0.76	89.66 ± 0.63	**94.06 ± 0.41**	90.41 ± 0.38	90.21 ± 0.27
0.1	85.87 ± 0.79	87.33 ± 0.51	87.04 ± 1.53	85.87 ± 0.54	**92.75 ± 0.50**	87.72 ± 0.46	87.99 ± 0.41
0.2	82.50 ± 0.96	82.08 ± 0.60	82.36 ± 0.78	83.20 ± 0.83	**88.94 ± 0.70**	84.80 ± 0.93	85.88 ± 0.83
0.3	79.11 ± 1.08	80.14 ± 0.99	78.55 ± 0.76	78.71 ± 1.97	81.34 ± 3.23	83.16 ± 1.18	**84.61 ± 0.98**
0.4	73.05 ± 0.20	72.24 ± 0.75	74.72 ± 0.57	72.13 ± 2.42	70.13 ± 3.59	81.06 ± 1.05	**82.52 ± 1.01**
0.5	57.46 ± 3.71	63.62 ± 0.39	66.83 ± 0.75	67.50 ± 3.99	58.31 ± 1.19	76.88 ± 2.97	**81.50 ± 1.19**
0.6	49.98 ± 0.15	63.07 ± 0.93	55.02 ± 1.41	64.58 ± 5.21	50.39 ± 0.47	68.50 ± 3.40	**80.00 ± 0.72**
0.7	49.83 ± 0.09	52.38 ± 0.66	54.18 ± 0.72	62.87 ± 6.82	49.76 ± 0.00	66.10 ± 2.45	**77.01 ± 1.07**
0.8	49.80 ± 0.03	51.42 ± 0.75	51.88 ± 0.25	52.44 ± 1.52	49.76 ± 0.00	65.93 ± 2.76	**75.01 ± 0.88**
0.9	49.77 ± 0.01	51.31 ± 0.20	51.69 ± 0.70	50.56 ± 1.32	49.76 ± 0.00	64.29 ± 1.46	**67.96 ± 1.45**

Table 4: Test accuracy on MR (mean ± std. dev.)

r	CE	MentorNet	FW	GCE	LCCN	DMI
0.0	72.35 ± 0.00	**72.44 ± 0.32**	72.35 ± 0.00	72.24 ± 0.10	72.35 ± 0.00	72.07 ± 0.00
0.1	70.51 ± 0.97	69.54 ± 0.19	70.49 ± 0.94	**70.58 ± 1.03**	70.72 ± 1.02	70.42 ± 0.73
0.2	67.12 ± 1.19	66.72 ± 0.98	67.14 ± 1.21	**67.48 ± 1.02**	67.33 ± 1.61	67.44 ± 1.22
0.3	64.68 ± 1.22	65.13 ± 0.13	64.92 ± 1.37	65.19 ± 1.09	64.65 ± 1.58	**65.62 ± 1.04**
0.4	54.52 ± 1.74	54.73 ± 1.01	57.89 ± 2.51	58.97 ± 1.77	54.52 ± 1.74	**62.67 ± 2.27**
0.5	53.08 ± 0.64	53.70 ± 0.55	53.83 ± 0.68	53.81 ± 2.04	53.08 ± 0.64	**59.40 ± 0.63**
0.6	52.52 ± 0.57	53.15 ± 0.97	53.58 ± 0.35	53.08 ± 1.46	52.54 ± 0.59	**57.38 ± 0.81**
0.7	52.28 ± 0.12	52.76 ± 0.98	52.38 ± 0.19	52.22 ± 0.10	52.29 ± 0.13	**56.44 ± 0.78**
0.8	52.26 ± 0.08	52.29 ± 0.25	52.24 ± 0.08	52.31 ± 0.15	52.25 ± 0.08	**54.69 ± 0.65**
0.9	52.20 ± 0.00	52.20 ± 0.56	52.16 ± 0.14	52.20 ± 0.07	52.20 ± 0.00	**52.88 ± 0.33**

Table 5: Test accuracy (mean) on Clothing1M

Method	CE	MentorNet	VAT	FW	GCE	LCCN	DMI
Accuracy	68.94	69.30	69.57	70.83	69.09	71.63	**72.46**