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CDMAD: Class-Distribution-Mismatch-Aware Debiasing for Class-Imbalanced Semi-Supervised Learning

Hyuck Lee

Heeyoung Kim

Department of Industrial and Systems Engineering, KAIST

Daejeon 34141, Republic of Korea

{dlgur0921, heeyoungkim}@kaist.ac.kr

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Background



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Classifiers trained on a class-imbalanced set suffer from being **biased** toward the **majority** classes.

Under semi-supervised learning (SSL) settings, the use of **biased pseudo-labels** for training:

- Classifiers of pseudo-label-based algorithms tend to be **further biased**.
- The use of biased pseudo-labels also decreases the quality of representations.

The biased problem becomes more serious when the class **distributions** of the labeled and unlabeled sets **differ significantly**.

Background



Many class imbalanced SSL (CISSL) algorithms have been proposed.

1. Fan et al. [7], Lee et al. [17], Wei et al. [26] assumed that the class distribution of the unlabeled set is **known** and the **same** as that of the labeled set, although the class distribution of the unlabeled set can be unknown in practice. E.g., STL-10 is collected from **different periods** are likely to have a class **distribution mismatch**.

2. Some algorithms after the main training stage, they additionally used technique (proposed for fully **supervised** class-imbalanced learning) of Classifier Retraining (cRT) [11] or post-hoc logit-adjustment (LA).

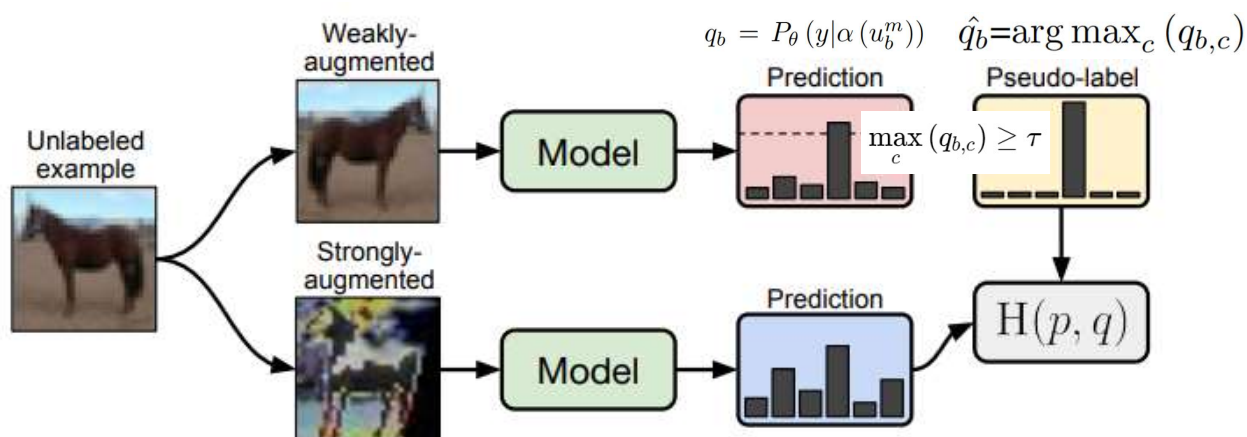
cRT: only **the labeled set** is used for training the classifier, cannot be learned interactively with (unlabeled) .

LA: **not consider** the unknown class distribution of the unlabeled set. When the class distribution of the **unlabeled** set is **unknown** and **differs** from that of the labeled set, may not re-balance the classifier.

Background



FixMatch



- 1) The proposed algorithm does **not use hard** pseudo-labels because entropy minimization of class predictions may cause the classifier to be biased towards certain classes.
- 2) The proposed algorithm does not use confidence threshold τ for FixMatch, enabling the utilization of all unlabeled samples.

$$loss_F(\mathcal{MX}, \mathcal{MU}, \hat{q}, \tau; \theta),$$

Background



ReMixMatch

the class distribution of the labeled set

denotes the moving average of the class probabilities predicted over the last 128 unlabeled minibatches.

distribution alignment $\tilde{q}_b = \text{Normalize}(q_b \times P_l(y) / q(y))$

sharpens

$$\bar{q}_b = \text{Normalize}(\tilde{q}_b^{1/T})$$

$\text{Normalize}(x)_i = x_i / \sum_j x_j$ and $q(y)$

Does **not employ** the distribution alignment when the class distribution of the unlabeled set is **unknown**.

Because:

- The labeled and unlabeled sets can potentially have **different** class distributions.
- This modification helps prevent the generation of **low-quality pseudo-labels** in situations.

$$\text{loss}_R(\mathcal{MX}, \mathcal{MU}, \bar{q}; \theta),$$



Motivation

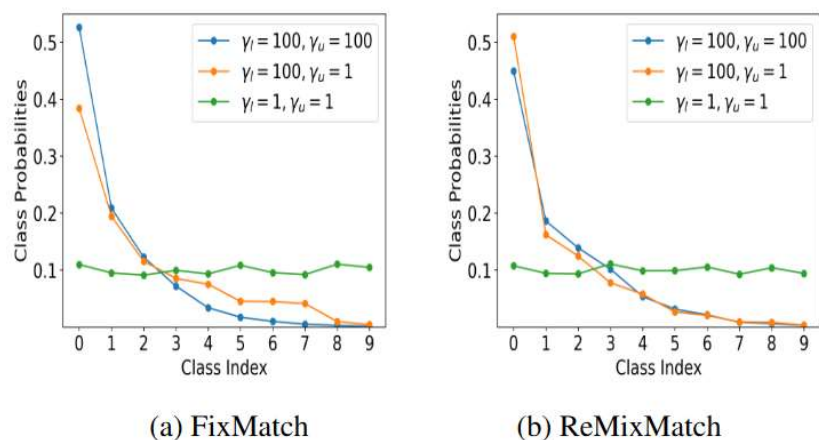


Figure 1. Class probabilities on an image without any patterns.

For an image irrelevant to the learned features, the predicted class probabilities are expected to be **uniform** across classes.

However, this may not be true when the training set is class imbalanced because the classifier tends to be **biased** towards the majority classes.

It assume that the solid color image does **not have the features** learned from the training set.

Then, the class probabilities for the solid color image can be thought of as **predicted based** solely on the classifier's **biased degree** towards each class

Method



Refinement of pseudo-labels during training

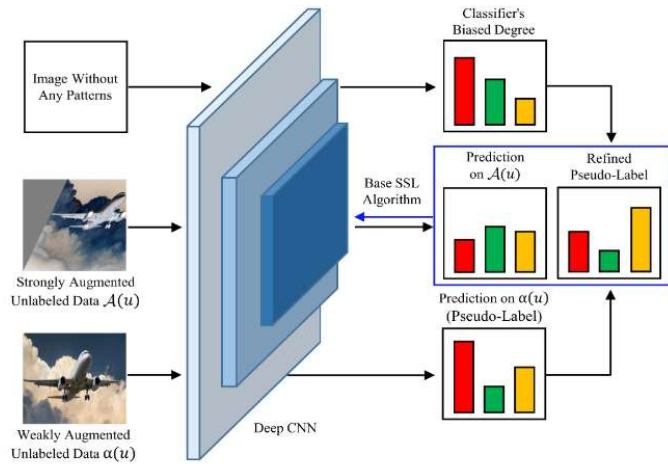


Figure 2. Pseudo-label refinement process using CDMAD.

$$g_{\theta}^*(\alpha(u_b^m)) = g_{\theta}(\alpha(u_b^m)) - g_{\theta}(\mathcal{I}),$$

$$q_b^* = \phi(g_{\theta}^*(\alpha(u_b^m))).$$

Method



Refinement of biased class predictions during testing

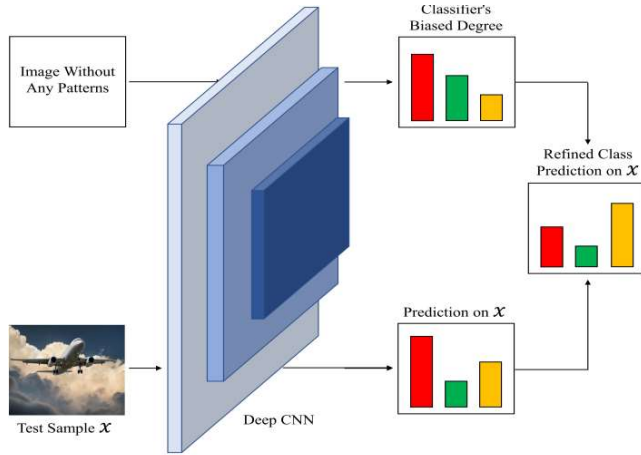


Figure 6. Refinement of biased class predictions on test samples using CDMAD

$$g_{\theta}^* (x_k^{test}) = g_{\theta} (x_k^{test}) - g_{\theta} (\mathcal{I}).$$

$$\begin{aligned} f_{\theta}^* (x_k^{test}) &= \arg \max_c g_{\theta}^* (x_k^{test})_c \\ &= \arg \max_{y \in [C]} P_{\theta} (y | x_k^{test}) / P_{\theta} (y | \mathcal{I}). \end{aligned}$$

CDMAD as a CISSL extension of post-hoc logitadjustment (LA)

$$g_{\theta}^* (x_k^{test}) = g_{\theta} (x_k^{test}) - \log \pi.$$

$$\begin{aligned} &\downarrow \\ g_{\theta} (\mathcal{I}) + constant &= \log P_{\theta} (y | \mathcal{I}) \end{aligned}$$

proven to be Fisher consistent for minimizing the balanced error rate (BER)

$$\text{BER} (f_{\theta}^*) = \frac{1}{C} \sum_{y \in [C]} P_{x|y} (y \neq f_{\theta}^* (x)).$$



Experiment

Table 1. Comparison of bACC/GM on CIFAR-10-LT

CIFAR-10-LT ($\gamma = \gamma_l = \gamma_u$, γ_u is assumed to be known)			
Algorithm	$\gamma = 50$	$\gamma = 100$	$\gamma = 150$
Vanilla	65.2 $\pm$ 0.05 / 61.1 $\pm$ 0.09	58.8 $\pm$ 0.13 / 58.2 $\pm$ 0.11	55.6 $\pm$ 0.43 / 44.0 $\pm$ 0.98
Re-sampling	64.3 $\pm$ 0.48 / 60.6 $\pm$ 0.67	55.8 $\pm$ 0.47 / 45.1 $\pm$ 0.30	52.2 $\pm$ 0.05 / 38.2 $\pm$ 1.49
LDAM-DRW	68.9 $\pm$ 0.07 / 67.0 $\pm$ 0.08	62.8 $\pm$ 0.17 / 58.9 $\pm$ 0.60	57.9 $\pm$ 0.20 / 50.4 $\pm$ 0.30
cRT	67.8 $\pm$ 0.13 / 66.3 $\pm$ 0.15	63.2 $\pm$ 0.45 / 59.9 $\pm$ 0.40	59.3 $\pm$ 0.10 / 54.6 $\pm$ 0.72
FixMatch	79.2 $\pm$ 0.33 / 77.8 $\pm$ 0.36	71.5 $\pm$ 0.72 / 66.8 $\pm$ 1.51	68.4 $\pm$ 0.15 / 59.9 $\pm$ 0.43
/++DARP+cRT	85.8 $\pm$ 0.43 / 85.6 $\pm$ 0.56	82.4 $\pm$ 0.26 / 81.8 $\pm$ 0.17	79.6 $\pm$ 0.42 / 78.9 $\pm$ 0.35
/+CRcST+LA	85.6 $\pm$ 0.36 / 81.9 $\pm$ 0.45	81.2 $\pm$ 0.70 / 74.5 $\pm$ 0.99	71.9 $\pm$ 2.24 / 64.4 $\pm$ 1.75
/+ABC	85.6 $\pm$ 0.26 / 85.2 $\pm$ 0.29	81.1 $\pm$ 1.14 / 80.3 $\pm$ 1.29	77.3 $\pm$ 1.25 / 75.6 $\pm$ 1.65
/+CoSSL	86.8 $\pm$ 0.30 / 86.6 $\pm$ 0.25	83.2 $\pm$ 0.49 / 82.7 $\pm$ 0.60	80.3 $\pm$ 0.55 / 79.6 $\pm$ 0.57
/+SAW+LA	86.2 $\pm$ 0.15 / 83.9 $\pm$ 0.35	80.7 $\pm$ 0.15 / 77.5 $\pm$ 0.21	73.7 $\pm$ 0.06 / 71.2 $\pm$ 0.17
/+Adsh	83.4 $\pm$ 0.06 / -	76.5 $\pm$ 0.35 / -	71.5 $\pm$ 0.30 / -
/+DebiasPL	- / -	80.6 $\pm$ 0.50 / -	- / -
/+UDAL	86.5 $\pm$ 0.29 / -	81.4 $\pm$ 0.39 / -	77.9 $\pm$ 0.33 / -
/+L2AC	- / -	82.1 $\pm$ 0.57 / 81.5 $\pm$ 0.64	77.6 $\pm$ 0.53 / 75.8 $\pm$ 0.71
/+CDMAD	87.3$\pm$0.12 / 87.0$\pm$0.15	83.6$\pm$0.46 / 83.1$\pm$0.57	80.8$\pm$0.86 / 79.9$\pm$1.07
ReMixMatch	81.5 $\pm$ 0.26 / 80.2 $\pm$ 0.32	73.8 $\pm$ 0.38 / 69.5 $\pm$ 0.84	69.9 $\pm$ 0.47 / 62.5 $\pm$ 0.35
/+DARP+cRT	87.3 $\pm$ 0.61 / 87.0 $\pm$ 0.11	83.5 $\pm$ 0.07 / 83.1 $\pm$ 0.09	79.7 $\pm$ 0.54 / 78.9 $\pm$ 0.49
/+CRcST+LA	84.2 $\pm$ 0.11 / -	81.3 $\pm$ 0.34 / -	79.2 $\pm$ 0.31 / -
/+ABC	87.9 $\pm$ 0.47 / 87.6 $\pm$ 0.51	84.5 $\pm$ 0.32 / 84.1 $\pm$ 0.36	80.5 $\pm$ 1.18 / 79.5 $\pm$ 1.36
/+CoSSL	87.7 $\pm$ 0.21 / 87.6 $\pm$ 0.25	84.1 $\pm$ 0.56 / 83.7 $\pm$ 0.66	81.3 $\pm$ 0.83 / 80.5 $\pm$ 0.76
/+SAW+cRT	87.6 $\pm$ 0.21 / 87.4 $\pm$ 0.26	85.4 $\pm$ 0.32 / 83.9 $\pm$ 0.21	79.9 $\pm$ 0.15 / 79.9 $\pm$ 0.12
/+CDMAD	88.3$\pm$0.35 / 88.1$\pm$0.35	85.5$\pm$0.46 / 85.3$\pm$0.44	82.5$\pm$0.23 / 82.0$\pm$0.30

mitigated class imbalance but did not significantly improve the classification performance compared to the vanilla algorithm

importance of using the unlabeled set



Experiment

Table 2. Comparison of bACC/GM on CIFAR-10-LT and STL-10-LT under $\gamma_l \neq \gamma_u$ (γ_u is assumed to be unknown). ReMixMatch* denotes ReMixMatch with the estimated class distribution of the unlabeled set [12].

Algorithm	CIFAR-10-LT ($\gamma_l = 100$, γ_u is assumed to be unknown)			STL-10-LT ($\gamma_u = \text{Unknown}$)	
	$\gamma_u = 1$	$\gamma_u = 50$	$\gamma_u = 150$	$\gamma_l = 10$	$\gamma_l = 20$
FixMatch	68.9 $\pm$ 1.95 / 42.8 $\pm$ 8.11	73.9 $\pm$ 0.25 / 70.5 $\pm$ 0.52	69.6 $\pm$ 0.60 / 62.6 $\pm$ 1.11	72.9 $\pm$ 0.09 / 69.6 $\pm$ 0.01	63.4 $\pm$ 0.21 / 52.6 $\pm$ 0.09
FixMatch+DARP	85.4 $\pm$ 0.55 / 85.0 $\pm$ 0.65	77.3 $\pm$ 0.17 / 75.5 $\pm$ 0.21	72.9 $\pm$ 0.24 / 69.5 $\pm$ 0.18	77.8 $\pm$ 0.33 / 76.5 $\pm$ 0.40	69.9 $\pm$ 1.77 / 65.4 $\pm$ 3.07
FixMatch+DARP+LA	86.6 $\pm$ 1.11 / 86.2 $\pm$ 1.15	82.3 $\pm$ 0.32 / 81.5 $\pm$ 0.29	78.9 $\pm$ 0.23 / 77.7 $\pm$ 0.06	78.6 $\pm$ 0.30 / 77.4 $\pm$ 0.40	71.9 $\pm$ 0.49 / 68.7 $\pm$ 0.51
FixMatch+DARP+cRT	87.0 $\pm$ 0.70 / 86.8 $\pm$ 0.67	82.7 $\pm$ 0.21 / 82.3 $\pm$ 0.25	80.7 $\pm$ 0.44 / 80.2 $\pm$ 0.61	79.3 $\pm$ 0.23 / 78.7 $\pm$ 0.21	74.1 $\pm$ 0.61 / 73.1 $\pm$ 1.21
FixMatch+ABC	82.7 $\pm$ 0.49 / 81.9 $\pm$ 0.68	82.7 $\pm$ 0.64 / 82.0 $\pm$ 0.76	78.4 $\pm$ 0.87 / 77.2 $\pm$ 1.07	79.1 $\pm$ 0.46 / 78.1 $\pm$ 0.57	73.8 $\pm$ 0.15 / 72.1 $\pm$ 0.15
FixMatch+SAW	81.2 $\pm$ 0.68 / 80.2 $\pm$ 0.91	79.8 $\pm$ 0.25 / 79.1 $\pm$ 0.32	74.5 $\pm$ 0.97 / 72.5 $\pm$ 1.37	-/-	-/-
FixMatch+SAW+LA	84.5 $\pm$ 0.68 / 84.1 $\pm$ 0.78	82.9 $\pm$ 0.38 / 82.6 $\pm$ 0.38	79.1 $\pm$ 0.81 / 78.6 $\pm$ 0.91	-/-	-/-
FixMatch+SAW+cRT	84.6 $\pm$ 0.23 / 84.4 $\pm$ 0.26	81.6 $\pm$ 0.38 / 81.3 $\pm$ 0.32	77.6 $\pm$ 0.40 / 77.1 $\pm$ 0.41	-/-	-/-
FixMatch+CDMAD	87.5$\pm$0.46 / 87.1$\pm$0.50	85.7$\pm$0.36 / 85.3$\pm$0.38	82.3$\pm$0.23 / 81.8$\pm$0.29	79.9$\pm$0.23 / 78.9$\pm$0.38	75.2$\pm$0.40 / 73.5$\pm$0.31
ReMixMatch	48.3$\pm$0.14 / 19.5$\pm$0.85	75.1 $\pm$ 0.43 / 71.9 $\pm$ 0.77	72.5 $\pm$ 0.10 / 68.2 $\pm$ 0.32	67.8 $\pm$ 0.45 / 61.1 $\pm$ 0.92	60.1 $\pm$ 1.18 / 44.9 $\pm$ 1.52
ReMixMatch*	85.0 $\pm$ 1.35 / 84.3 $\pm$ 1.55	77.0 $\pm$ 0.12 / 74.7 $\pm$ 0.04	72.8 $\pm$ 0.10 / 68.8 $\pm$ 0.21	76.7 $\pm$ 0.15 / 73.9 $\pm$ 0.32	67.7 $\pm$ 0.46 / 60.3 $\pm$ 0.76
ReMixMatch*+DARP	86.9 $\pm$ 0.10 / 86.4 $\pm$ 0.15	77.4 $\pm$ 0.22 / 75.0 $\pm$ 0.25	73.2 $\pm$ 0.11 / 69.2 $\pm$ 0.31	79.4 $\pm$ 0.07 / 78.2 $\pm$ 0.10	70.9 $\pm$ 0.44 / 67.0 $\pm$ 1.62
ReMixMatch*+DARP+LA	81.8 $\pm$ 0.45 / 80.9 $\pm$ 0.40	83.9 $\pm$ 0.42 / 83.4 $\pm$ 0.45	81.1 $\pm$ 0.20 / 80.3 $\pm$ 0.26	80.6 $\pm$ 0.45 / 79.6 $\pm$ 0.55	76.8 $\pm$ 0.60 / 74.8 $\pm$ 0.68
ReMixMatch*+DARP+cRT	88.7 $\pm$ 0.25 / 88.5 $\pm$ 0.25	83.5 $\pm$ 0.53 / 83.1 $\pm$ 0.51	80.9 $\pm$ 0.25 / 80.3 $\pm$ 0.31	80.9 $\pm$ 0.53 / 80.0 $\pm$ 0.46	76.7 $\pm$ 0.50 / 74.9 $\pm$ 0.70
ReMixMatch+ABC	76.4 $\pm$ 5.34 / 74.8 $\pm$ 6.05	85.2 $\pm$ 0.20 / 84.7 $\pm$ 0.25	80.4 $\pm$ 0.40 / 80.0 $\pm$ 0.44	76.8 $\pm$ 0.52 / 74.8 $\pm$ 0.64	71.2 $\pm$ 1.37 / 67.4 $\pm$ 1.89
ReMixMatch*+SAW	87.0 $\pm$ 0.75 / 86.4 $\pm$ 0.85	80.6 $\pm$ 1.57 / 79.2 $\pm$ 2.19	77.6 $\pm$ 0.76 / 76.0 $\pm$ 0.93	-/-	-/-
ReMixMatch*+SAW+LA	74.2 $\pm$ 1.49 / 65.1 $\pm$ 2.36	84.8 $\pm$ 1.07 / 82.4 $\pm$ 2.32	81.3 $\pm$ 2.42 / 80.9 $\pm$ 2.47	-/-	-/-
ReMixMatch*+SAW+cRT	88.8 $\pm$ 0.79 / 88.6 $\pm$ 0.83	84.5 $\pm$ 0.78 / 83.6 $\pm$ 1.27	82.4 $\pm$ 0.10 / 82.0 $\pm$ 0.10	-/-	-/-
ReMixMatch+CDMAD	89.9$\pm$0.45 / 89.6$\pm$0.46	86.9$\pm$0.21 / 86.7$\pm$0.17	83.1$\pm$0.46 / 82.7$\pm$0.50	83.0$\pm$0.38 / 82.1$\pm$0.35	81.9$\pm$0.32 / 80.9$\pm$0.44

distribution alignment technique employed in ReMixMatch significantly degraded the quality of pseudo-labels



Experiment

Table 3. Comparison of bACC/GM under $\gamma_l = \gamma_u = 100$ (reversed).

CIFAR-10-LT, $\gamma_l = 100, \gamma_u = 100$ (reversed)					
Algorithm	ABC	SAW	SAW+LA	SAW+cRT	CDMAD
FixMatch+	69.5/66.8	72.3/68.7	74.1/72.0	75.5/73.9	77.1/75.4
ReMixMatch+	63.6/60.5	79.5/78.5	50.2/14.8	80.8/79.9	81.7/81.0

Table 5. Comparison of bACC on Small-ImageNet-127 (size 32×32 and 64×64 , γ_u is assumed to be known)

Small-ImageNet-127 ($\gamma = \gamma_l = \gamma_u$, γ_u is assumed to be known)		
Algorithm	32×32	64×64
FixMatch	29.7	42.3
FixMatch+DARP	30.5	42.5
FixMatch+DARP+cRT	39.7	51.0
FixMatch+CReST	32.5	44.7
FixMatch+CReST+LA	40.9	55.9
FixMatch+ABC	46.9	56.1
FixMatch+CoSSL	43.7	53.8
FixMatch+CDMAD	48.4	59.3

Table 4. Comparison of bACC on CIFAR-100-LT.

CIFAR-100-LT ($\gamma = \gamma_l = \gamma_u$, γ_u is assumed to be known)			
Algorithm	$\gamma = 20$	$\gamma = 50$	$\gamma = 100$
FixMatch	49.6 $\pm$ 0.78	42.1 $\pm$ 0.33	37.6 $\pm$ 0.48
FixMatch+DARP	50.8 $\pm$ 0.77	43.1 $\pm$ 0.54	38.3 $\pm$ 0.47
FixMatch+DARP+cRT	51.4 $\pm$ 0.68	44.9 $\pm$ 0.54	40.4 $\pm$ 0.78
FixMatch+CReST	51.8 $\pm$ 0.12	44.9 $\pm$ 0.50	40.1 $\pm$ 0.65
FixMatch+CReST+LA	52.9 $\pm$ 0.07	47.3 $\pm$ 0.17	42.7 $\pm$ 0.70
FixMatch+ABC	53.3 $\pm$ 0.79	46.7 $\pm$ 0.26	41.2 $\pm$ 0.06
FixMatch+CoSSL	53.9 $\pm$ 0.78	47.6 $\pm$ 0.57	43.0 $\pm$ 0.61
FixMatch+UDAL	-	48.0 $\pm$ 0.56	43.7 $\pm$ 0.41
FixMatch+CDMAD	54.3$\pm$0.44	48.8$\pm$0.75	44.1$\pm$0.29
ReMixMatch	51.6 $\pm$ 0.43	44.2 $\pm$ 0.59	39.3 $\pm$ 0.43
ReMixMatch+DARP	51.9 $\pm$ 0.35	44.7 $\pm$ 0.66	39.8 $\pm$ 0.53
ReMixMatch+DARP+cRT	54.5 $\pm$ 0.42	48.5 $\pm$ 0.91	43.7 $\pm$ 0.81
ReMixMatch+CReST	51.3 $\pm$ 0.34	45.5 $\pm$ 0.76	41.0 $\pm$ 0.78
ReMixMatch+CReST+LA	51.9 $\pm$ 0.60	46.6 $\pm$ 1.14	41.7 $\pm$ 0.69
ReMixMatch+ABC	55.6 $\pm$ 0.35	47.9 $\pm$ 0.10	42.2 $\pm$ 0.12
ReMixMatch+CoSSL	55.8 $\pm$ 0.62	48.9 $\pm$ 0.61	44.1 $\pm$ 0.59
ReMixMatch+CDMAD	57.0$\pm$0.32	51.1$\pm$0.46	44.9$\pm$0.42



Experiment

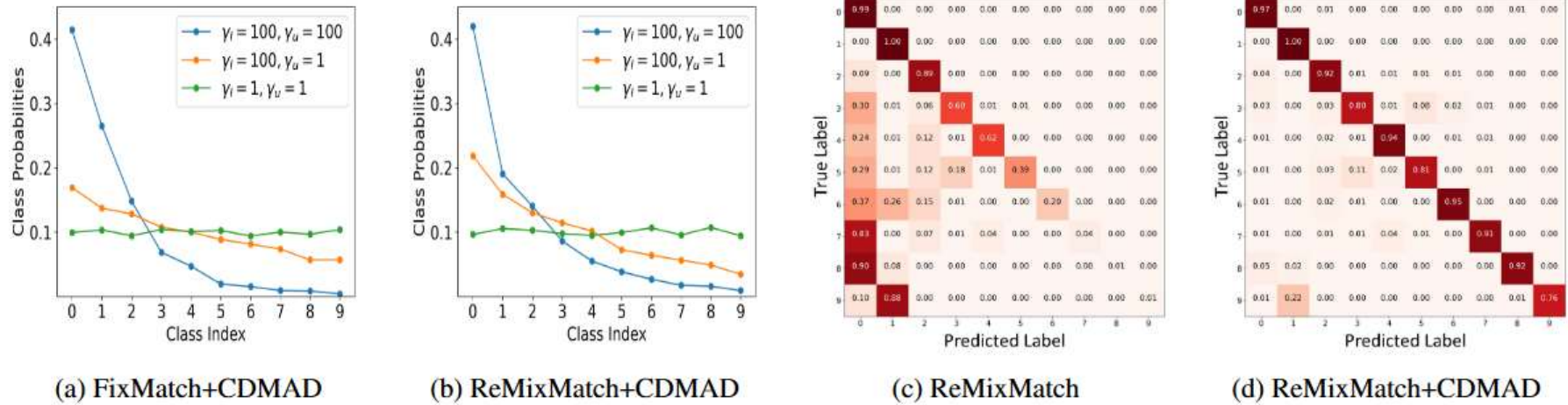


Figure 3. (a) and (b) present the class probabilities predicted on a white image using the proposed algorithm. (c) and (d) present the confusion matrices of the class predictions on test samples.

Based on the above findings, CDMAD can be considered as measuring the classifier's biased degree by **implicitly** incorporating the class distributions of **both labeled and unlabeled** sets.



Experiment

Table 8. Ablation study for the proposed algorithm on CIFAR-10-LT under $\gamma_l = 100$ and $\gamma_u = 1$

Ablation study ($\gamma_l = 100, \gamma_u = 1$)	bACC/GM		bACC/GM
FixMatch+CDMAD	87.5/87.1	ReMixMatch+CDMAD	89.9/89.6
Without CDMAD for refining pseudo-labels	78.2/75.8	Without CDMAD for refining pseudo-labels	72.3/65.9
Without CDMAD for test phase	84.9/84.1	Without CDMAD for test phase	88.2/87.7
With the use of hard pseudo-labels	86.7/86.3	With the use of sharpened pseudo-labels	88.9/88.6
With the use of confidence threshold $\tau = 0.95$	86.8/86.3	With the use of distribution alignment technique	80.4/78.5

Table 9. Experiments with the replacement of $\mathcal{I}$ by other inputs

ReMixMatch+CDMAD	CIFAR-10-LT	
Input	$\gamma_l = \gamma_u = 100$	$\gamma_l = 100, \gamma_u = 1$
Uniform	81.3/ 80.7	85.3/ 84.2
Bernoulli	82.5/ 82.0	83.6/ 82.8
Normal	78.4/ 77.5	84.0/ 83.2
Black	84.8/ 84.5	89.3/ 89.0
Red	84.8/ 84.6	90.1/ 89.9
Green	84.9/ 84.6	89.3/ 88.9
Blue	84.9/ 84.7	90.2/ 89.9
Gray	85.1/ 84.9	89.6/ 89.3
White	85.5/ 85.3	89.9/ 89.6

Table 10. Experiments with replacing $\mathcal{I}$ by non-image input

Algorithm	CIFAR-10-LT	$\gamma_l = \gamma_u = 100$	$\gamma_l = 100, \gamma_u = 1$
FixMatch+CDMAD	White image	83.6/83.1	87.5/87.1
	Non-image	84.0/83.6	87.4/87.0
ReMixMatch+CDMAD	White image	85.5/85.3	89.9/89.6
	Non-image	85.6/85.4	89.8/89.6

outside the range [0, 255]

the classification of images is related to their color.

This may be because the parameters of the distributions (e.g., mean and standard deviation of a normal distribution) used to generate random pixels may be related to specific classes.

Non-image > white > other solid color > distribution



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Thank you