

SCAD: Super-Class-Aware Debiasing for Long-Tailed Semi-Supervised Learning

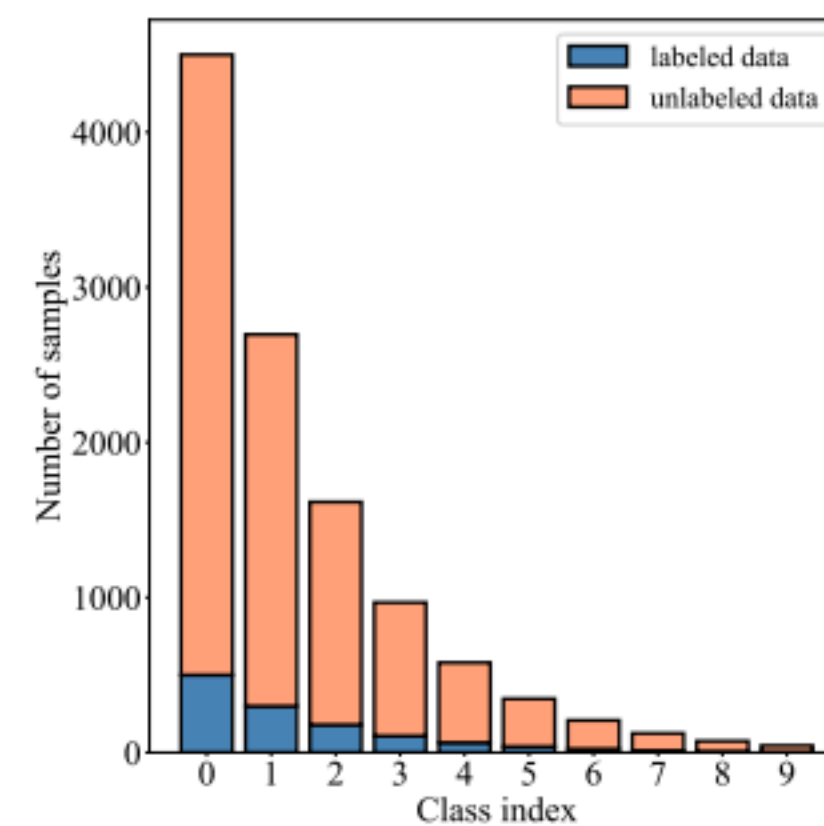
Sunguk Jang*, Jinwoo Jeon*, Byung-Jun Lee

Korea University, AITRICS

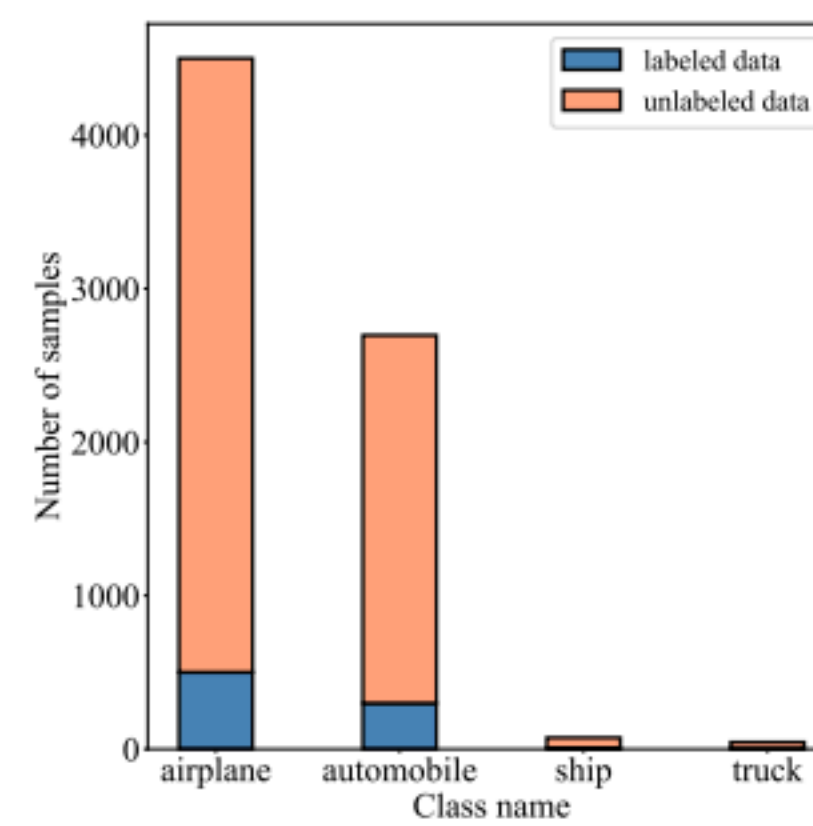


Motivation

- Existing long-tailed learning methods focus on global class imbalance, but overlook semantic relationships among classes.
- This leads to biased predictions within semantically related groups, even when global prior is addressed.



(a) Global Distribution



(b) Local Distribution

Intra-Super-Class Imbalance Problem

- We identify a new challenge called intra-super-class imbalance, where imbalance persists within semantically similar classes.
- To address this, we propose SCAD, which dynamically adjusts logits based on each sample's predicted super-class.

airplane	984	2	1	0
automobile	3	994	0	3
ship	227	81	643	11
truck	80	481	6	411
	airplane	automobile	ship	truck

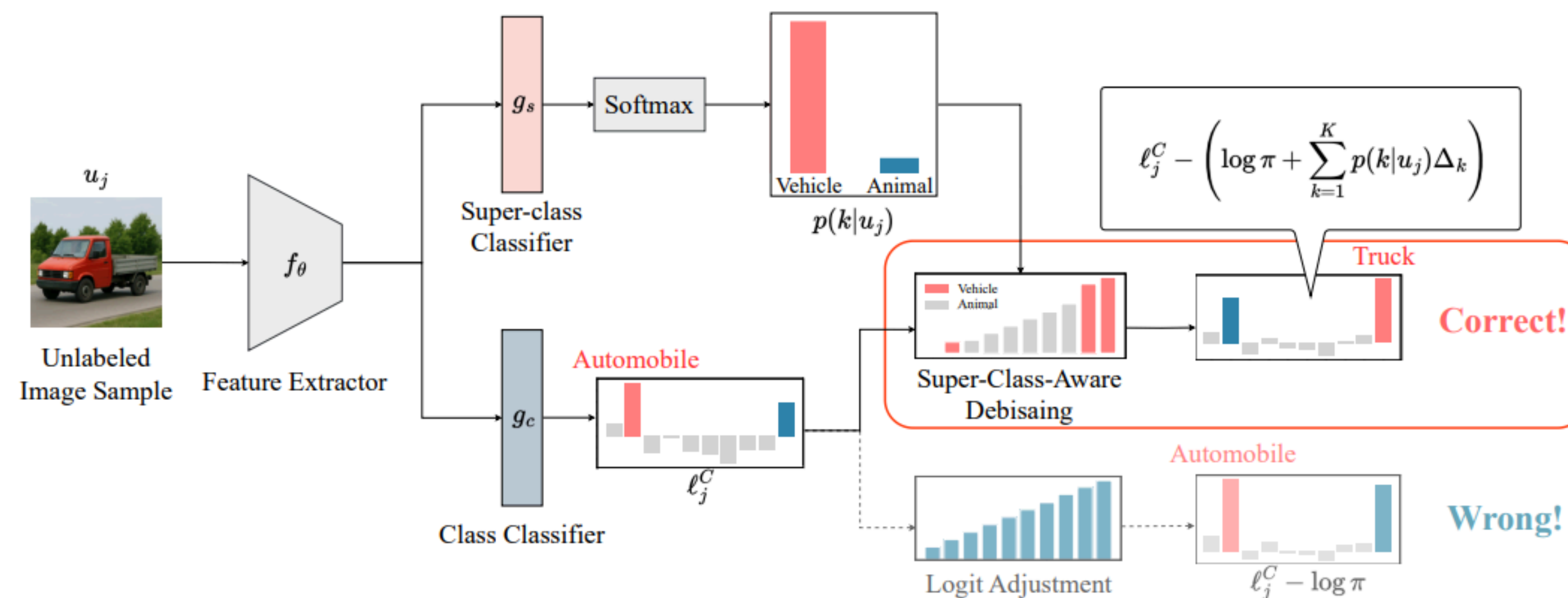
(c) FixMatch + LA

airplane	969	3	10	5
automobile	3	986	1	9
ship	170	55	745	14
truck	53	301	19	609
	airplane	automobile	ship	truck

(d) FixMatch + SCAD

Method

- We construct superclass groups using a pretrained text model (e.g., CLIP) to capture semantic relationships between classes, and then introduce an additional superclass classifier
- SCAD decomposes the adjustment into a global class prior and a local intra-super-class prior. While the global prior corrects overall class imbalance, the intra-super-class prior captures frequency within each semantic group, enabling debiasing among similar classes.



Experiment

Algorithm	CIFAR10-LT				CIFAR100-LT			
	$\gamma = \gamma_l = \gamma_u = 100$		$\gamma = \gamma_l = \gamma_u = 150$		$\gamma = \gamma_l = \gamma_u = 10$		$\gamma = \gamma_l = \gamma_u = 20$	
	$N_1 = 500$ $M_1 = 4000$	$N_1 = 1500$ $M_1 = 3000$	$N_1 = 500$ $M_1 = 4000$	$N_1 = 1500$ $M_1 = 3000$	$N_1 = 50$ $M_1 = 400$	$N_1 = 150$ $M_1 = 300$	$N_1 = 50$ $M_1 = 400$	$N_1 = 150$ $M_1 = 300$
Supervised w/ LA	47.3 ± 0.95 53.3 ± 0.44	61.9 ± 0.41 70.6 ± 0.21	44.2 ± 0.33 49.5 ± 0.40	58.2 ± 0.29 67.1 ± 0.78	29.6 ± 0.57 30.2 ± 0.44	46.9 ± 0.22 48.7 ± 0.89	25.1 ± 1.14 26.5 ± 1.31	41.2 ± 0.15 44.1 ± 0.42
FixMatch	67.8 ± 1.13	77.5 ± 1.32	62.9 ± 0.36	72.4 ± 1.03	45.2 ± 0.55	56.5 ± 0.06	40.0 ± 0.96	50.7 ± 0.25
w/ DARP	74.5 ± 0.78	77.8 ± 0.63	67.2 ± 0.32	73.6 ± 0.73	49.4 ± 0.20	58.1 ± 0.44	43.4 ± 0.87	52.2 ± 0.66
w/ CReST+	76.3 ± 0.86	78.1 ± 0.42	67.5 ± 0.45	73.7 ± 0.34	44.5 ± 0.94	57.4 ± 0.18	40.1 ± 1.28	52.1 ± 0.21
w/ DASO	76.0 ± 0.37	79.1 ± 0.75	70.1 ± 1.81	75.1 ± 0.77	49.8 ± 0.24	59.2 ± 0.35	43.6 ± 0.09	52.9 ± 0.42
w/ DASO + Ours	75.1 ± 0.10	79.2 ± 1.60	69.0 ± 0.61	75.8 ± 0.33	50.0 ± 0.22	58.7 ± 0.28	44.5 ± 0.35	53.2 ± 0.50
FixMatch + LA	75.3 ± 2.45	82.0 ± 0.36	67.0 ± 2.49	78.0 ± 0.91	47.3 ± 0.42	58.6 ± 0.36	41.4 ± 0.93	53.4 ± 0.32
w/ DARP	76.6 ± 0.92	80.8 ± 0.62	68.2 ± 0.94	76.7 ± 1.13	50.5 ± 0.78	59.9 ± 0.32	44.4 ± 0.65	53.8 ± 0.43
w/ CReST+	76.7 ± 1.13	81.1 ± 0.57	70.9 ± 1.18	77.9 ± 0.71	44.0 ± 0.21	57.1 ± 0.55	40.6 ± 0.55	52.3 ± 0.20
w/ DASO	77.9 ± 0.88	82.5 ± 0.08	70.1 ± 1.68	79.0 ± 2.23	50.7 ± 0.51	60.6 ± 0.71	44.1 ± 0.61	55.1 ± 0.72
w/ DASO + Ours	81.6 ± 0.22	84.0 ± 0.99	74.5 ± 1.21	82.2 ± 0.14	51.8 ± 0.28	60.5 ± 0.21	45.7 ± 0.56	55.7 ± 0.57
FixMatch + ACR	81.6 ± 0.19	84.1 ± 0.39	77.0 ± 1.19	80.9 ± 0.22	51.3 ± 0.48	61.1 ± 0.11	44.8 ± 0.21	55.9 ± 0.31
w/ Ours	83.5 ± 0.16	85.5 ± 0.03	78.6 ± 0.56	83.3 ± 0.20	52.7 ± 0.11	61.8 ± 0.21	45.8 ± 0.20	56.4 ± 0.10

CIFAR10-LT, CIFAR100-LT

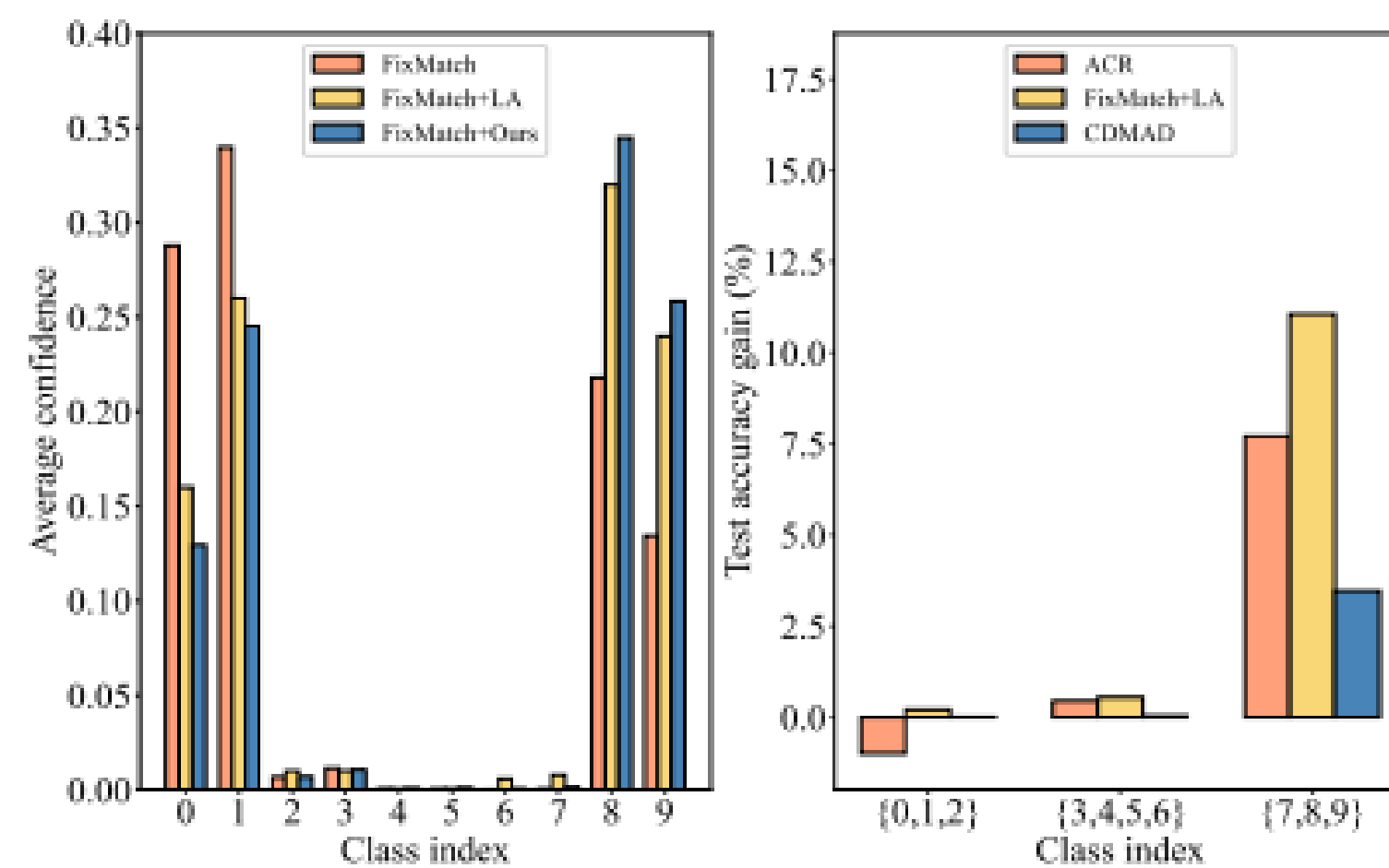
Algorithm / ImageNet-127	32 × 32	64 × 64
FixMatch	29.7	42.3
w/ DARP	30.5	42.5
w/ DARP+cRT	39.7	51.0
w/ CReST+	32.5	44.7
w/ CReST++LA	40.9	55.9
w/ CoSSL	43.7	53.9
w/ ACR	57.2	63.6
w/ Ours	60.1	66.7
w/ ACR + Ours	60.5	67.0

Imagenet-127

Experiment

Ablations	CIFAR10-LT	STL10-LT
FixMatch	67.8	56.1
+ Super-class learning	69.2	69.0
+ Logit-Adjustment (LA)	76.9	70.4
+ Super-class-Aware Debiasing (SCAD)	78.7	71.3

Algorithms	CIFAR100-LT
FixMatch + LA	47.3
w/ Ours with ground truth	50.3
w/ Ours with GloVe	49.7
w/ Ours with SBERT	50.1
w/ Ours with CLIP text encoder	50.4
w/ Ours with text-embedding-ada-002	50.5



Conclusion

- We introduce Super-Class-Aware Debiasing (SCAD), a novel framework designed to tackle the fundamental challenge of intra-super-class imbalance in long-tailed semi-supervised learning (LTSSL).
- SCAD outperforms strong baselines and debiasing methods across diverse datasets, demonstrating that leveraging semantic structure and local class relationships enables robust and generalizable learning in imbalanced settings.