IOMatch: Simplifying Open-Set Semi-Supervised Learning with Joint Inliers and Outliers Utilization

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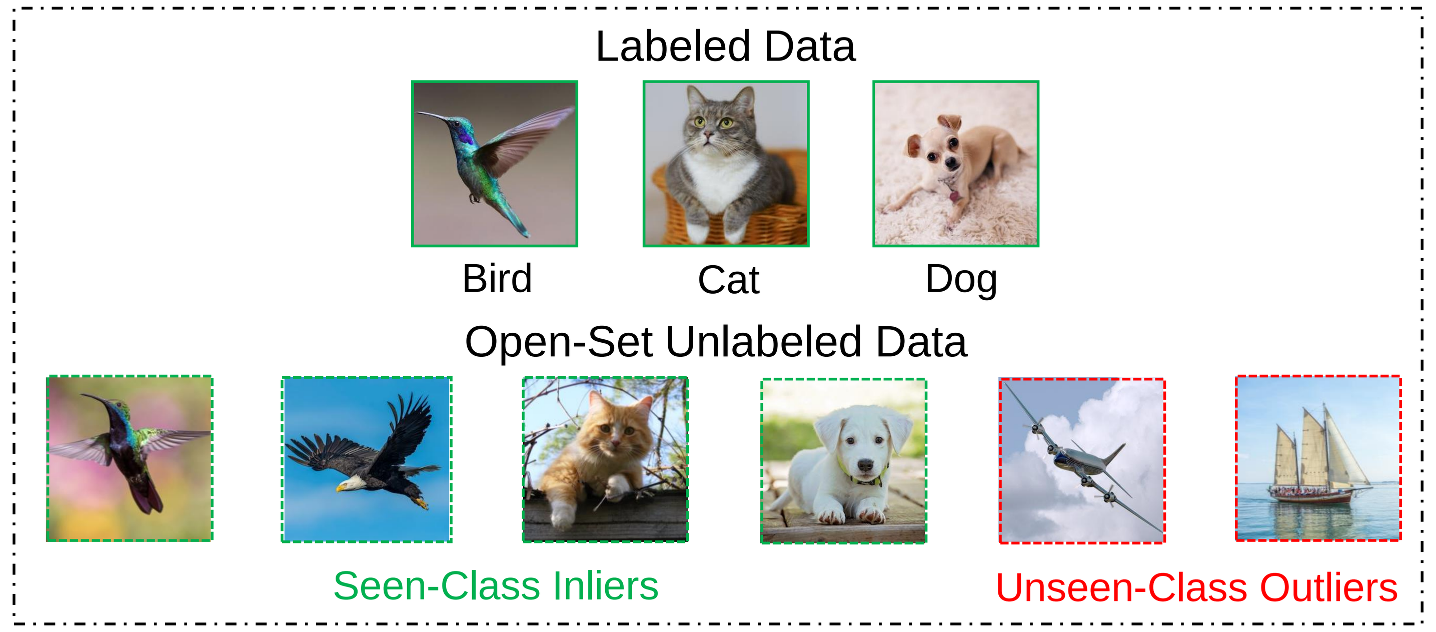
Background

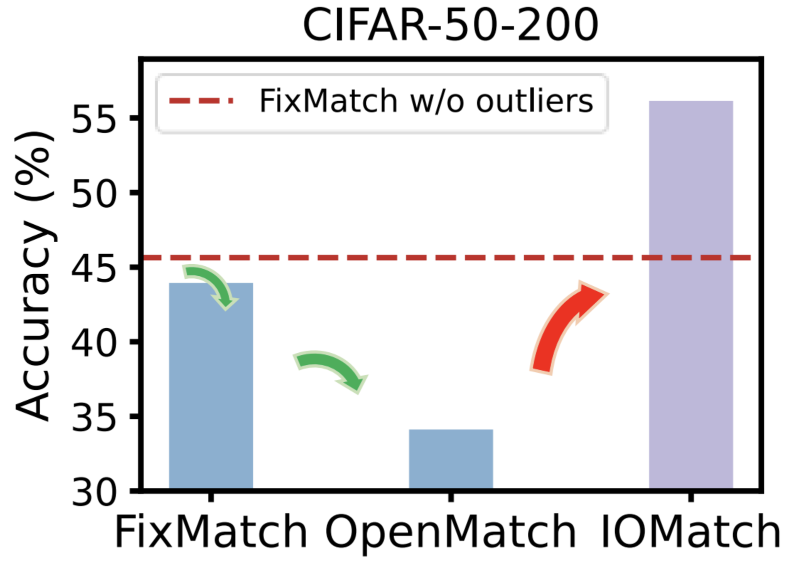
When open-set unlabeled data contain outliers from unseen classes, mainstream SSL methods experience significant performance drops, as it is impossible to generate correct closed-set pseudo-labels for outliers.

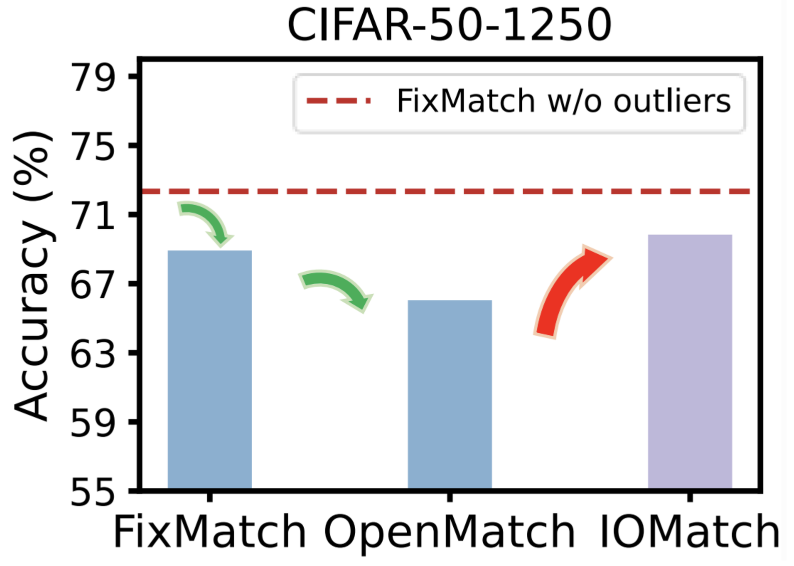


Motivation

A common strategy employed in prior research is to first detect and then filter outliers out. However, it is quite challenging to obtain a reliable outlier detector at the outset, especially when labels are extremely scarce.

We observed that ***an unreliable detector can be more harmful than the outliers themselves***, since it may wrongly exclude numerous inliers.



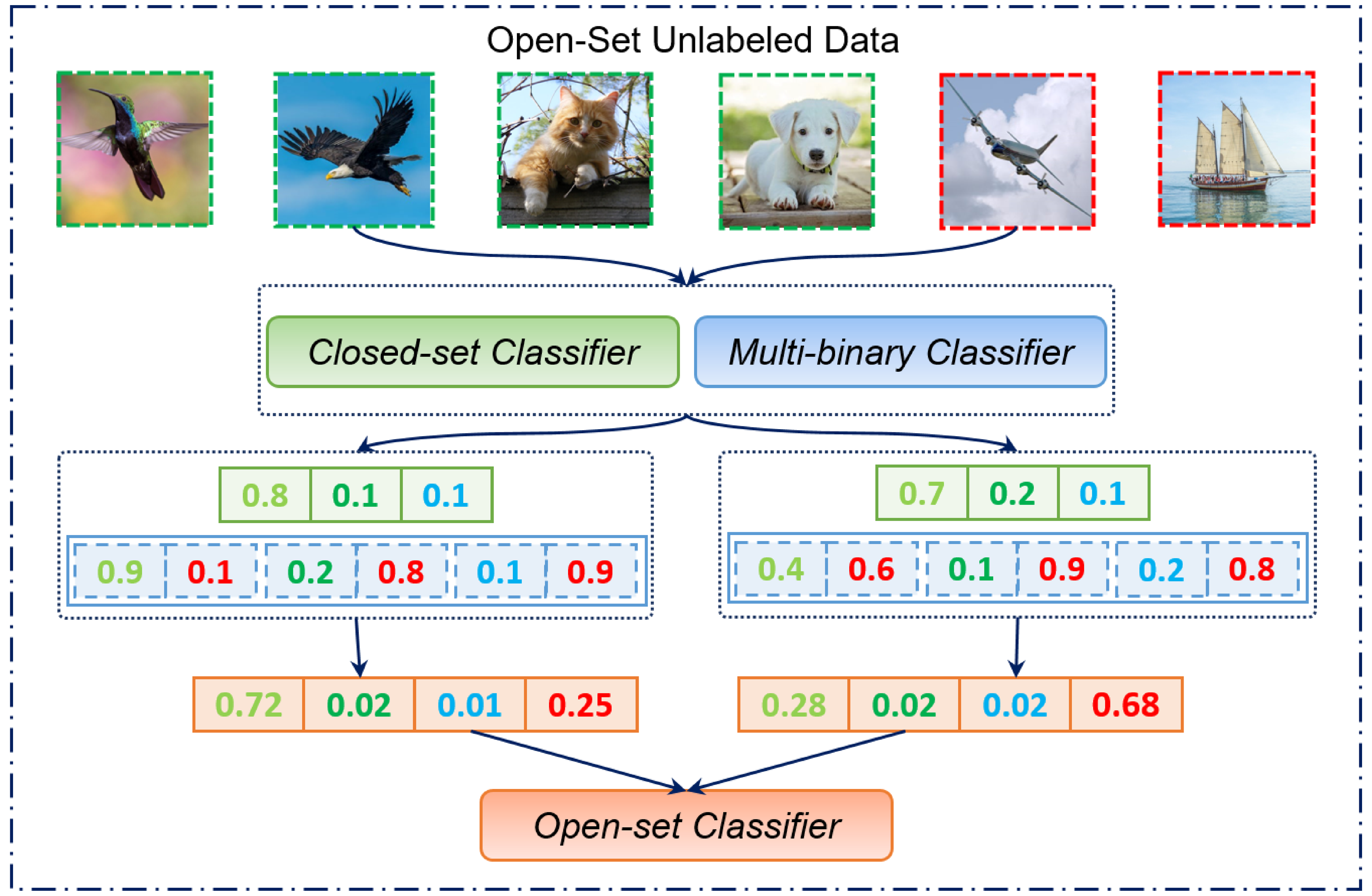


Core Approach of IOMatch

Can we ***jointly utilize open-set unlabeled data without the need for precise differentiation between inliers and outliers***?

We achieve this by leverage ***unified open-set targets*** as pseudo-labels:

- A standard closed-set classifier is used to predict the most likely seen class for an unlabeled sample, with the proability $\boldsymbol{p} = (p_1, \dots, p_k, \dots, p_K)$.
- An additional multi-binary classifier is incoporated. Each binary classifier is designed to determine whether an unlabeled sample truly belongs to each seen class or not, with the proability $\boldsymbol{o}_k = (o_k, \overline{o_k})$.
- By combining these two predictions, we can estimate the likelihood of an unlabeled sample being an inlier ($p_k \times o_k$) of each seen class or an outlier ($\sum p_k \times \overline{o_k}$).
- We optimize an open-set classifier with these unified targets, via the consistency-regularized pseudo-labeling scheme.



Code available in: https://github.com/nukezil/IOMatch

Experiments

Dataset			CIFAR-10		CIFAR-100					
Class split (Seen / Unseen)			6 / 4		20 / 80		50 / 50		80 / 20	
Number of labels per class			4	25	4	25	4	25	4	25
Standard SSL	MixMatch [3]	NeurIPS'19	43.08 ± 1.79	63.13 ± 0.64	28.13 ± 5.06	51.28 ± 1.45	26.97 ± 0.46	56.93 ± 0.84	28.35 ± 0.83	53.77 ± 0.97
	ReMixMatch [2]	ICLR'20	72.82 ± 1.81	87.08 ± 1.12	36.02 ± 3.56	61.83 ± 0.81	37.57 ± 1.54	65.80 ± 1.33	40.64 ± 2.97	62.90 ± 1.07
	FixMatch [28]	NeurIPS'20	81.58 ± 6.63	92.94 ± 0.80	46.27 ± 0.64	66.45 ± 0.74	48.93 ± 5.05	68.77 ± 0.89	43.06 ± 1.21	64.44 ± 0.51
	CoMatch [20]	ICCV'21	86.08 ± 1.08	92.57 ± 0.47	43.53 ± 3.01	66.82 ± 1.37	43.17 ± 0.55	67.85 ± 1.17	37.89 ± 1.22	62.04 ± 0.08
	FlexMatch [41]	NeurIPS'21	73.34 ± 4.42	86.44 ± 3.72	37.93 ± 4.49	62.68 ± 2.02	44.10 ± 1.88	68.98 ± 0.94	43.44 ± 2.40	64.34 ± 0.64
	SimMatch [43]	CVPR'22	79.84 ± 4.76	90.07 ± 2.44	36.93 ± 5.72	67.23 ± 1.13	51.53 ± 2.02	69.71 ± 1.44	50.32 ± 2.57	**65.68 ± 1.43**
	FreeMatch [34]	ICLR'23	79.26 ± 4.11	92.27 ± 0.15	45.18 ± 8.36	64.62 ± 0.79	50.26 ± 1.92	68.57 ± 0.27	47.34 ± 0.57	64.41 ± 0.55
Open-Set SSL	UASD [7]	AAAI'20	35.25 ± 1.07	56.42 ± 1.34	29.78 ± 4.28	53.78 ± 0.67	29.08 ± 1.44	54.24 ± 1.10	26.41 ± 2.16	50.33 ± 0.62
	DS^{3}L [10]	ICML'20	39.09 ± 1.24	51.83 ± 1.06	19.70 ± 1.98	41.78 ± 1.45	21.62 ± 0.54	47.41 ± 0.61	20.10 ± 0.48	40.51 ± 1.02
	MTCF [39]	ECCV'20	49.15 ± 6.12	74.42 ± 2.95	32.58 ± 3.36	55.93 ± 1.66	35.35 ± 2.39	57.72 ± 0.20	25.40 ± 1.20	54.59 ± 0.49
	T2T [16]	ICCV'21	73.89 ± 1.55	85.69 ± 1.90	44.23 ± 2.27	65.60 ± 0.71	39.31 ± 1.16	68.59 ± 0.92	38.16 ± 0.59	63.86 ± 0.32
	OpenMatch [25]	NeurIPS'21	43.63 ± 3.26	66.27 ± 1.86	37.45 ± 2.67	62.70 ± 1.76	33.74 ± 0.38	66.53 ± 0.54	28.54 ± 1.15	61.23 ± 0.81
	SAFE-STUDENT [14]	CVPR'22	59.28 ± 1.18	77.87 ± 0.14	34.53 ± 0.67	58.07 ± 1.40	35.84 ± 0.86	62.75 ± 0.38	34.17 ± 0.69	57.99 ± 0.34
	IOMatch	**Ours**	**89.68 ± 2.04**	**93.87 ± 0.16**	**53.73 ± 2.12**	**67.28 ± 1.10**	**56.31 ± 2.29**	**69.77 ± 0.58**	**50.83 ± 0.99**	64.75 ± 0.52

Closed-Set Classification Accuracy (%)

Dataset			CIFAR-10		CIFAR-100					
Class split (Seen / Unseen)			6 / 4		20 / 80		50 / 50		80 / 20	
Number of labels per class			4	25	4	25	4	25	4	25
Open-Set SSL	UASD [7]	AAAI'20	17.10 ± 0.32	36.01 ± 0.22	10.50 ± 0.83	26.96 ± 0.53	6.92 ± 0.55	32.23 ± 0.54	5.77 ± 0.21	27.61 ± 1.15
	DS3L [10]	ICML'20	30.89 ± 0.33	40.45 ± 0.77	12.56 ± 1.21	34.35 ± 0.41	12.14 ± 0.39	35.17 ± 0.48	11.10 ± 1.27	29.09 ± 0.31
	MTCF [39]	ECCV'20	33.35 ± 7.21	46.13 ± 0.54	8.12 ± 2.10	26.60 ± 3.66	4.13 ± 0.37	38.36 ± 0.29	1.46 ± 0.17	30.75 ± 0.52
	T2T [16]	ICCV'21	50.57 ± 0.38	61.10 ± 0.39	17.17 ± 1.37	37.18 ± 0.60	12.74 ± 2.66	44.24 ± 0.42	34.23 ± 0.57	51.41 ± 0.96
	OpenMatch [25]	NeurIPS'21	14.37 ± 0.05	20.35 ± 3.50	8.77 ± 2.84	39.89 ± 1.16	7.00 ± 0.02	49.75 ± 1.08	6.30 ± 0.87	44.83 ± 0.62
	SAFE-STUDENT [14]	CVPR'22	45.27 ± 0.36	52.78 ± 0.64	15.94 ± 1.07	28.83 ± 0.46	23.98 ± 0.88	46.71 ± 1.74	29.43 ± 0.66	50.48 ± 0.61
	IOMatch	**Ours**	**75.08 ± 1.92**	**78.96 ± 0.08**	**45.94 ± 1.70**	**58.52 ± 0.48**	**46.36 ± 1.93**	**60.78 ± 0.71**	**39.96 ± 0.95**	**54.39 ± 0.38**

Open-Set Classification Balanced Accuracy (%)

Task	CIFAR-50-200		CIFAR-50-1250	
Setting	OSSL	SSL	OSSL	SSL
FixMatch	43.94	45.64	68.92	72.74
SimMatch	49.98	51.76	69.70	**73.66**
OpenMatch	37.60	39.16	66.54	67.80
IOMatch	**56.14**	**55.94**	**69.84**	73.28

For Standard SSL

Dataset	CIFAR100			
Class split	50 / 50		80 / 20	
Number of labels	4	25	4	25
IOMatch	56.14	69.84	49.89	64.28
w/ Contrastive	57.08	70.80	50.25	65.92
w/ Rotation	**58.92**	**71.54**	**50.90**	**66.50**

Enhanced with Self-SL Techs.

Conclusion

We proposed a simple yet effective open-set SSL framework, IOMatch, and we found:

- ➢ It is challenging, but not mandatory, to identify outliers before performing pseudo-labeling.
- ➢ What truly matters is the idea of joint inliers and outliers utilization. Producing unified open-set targets is just one way, and we can explore stronger techniques for this.