2024년 2월 2일 DMQA 연구실 오픈 세미나

Hybrid methods for semi-supervised learning under class distribution mismatch

고려대학교 산업경영공학부 배진수

발표자

❖ 배진수

- 건국대학교 수학과 학부 졸업
- 고려대학교 산업경영공학과 박사 과정
- 고려대학교 DMQA 연구실 (지도교수:김성범)
- wlstn215@korea.ac.kr

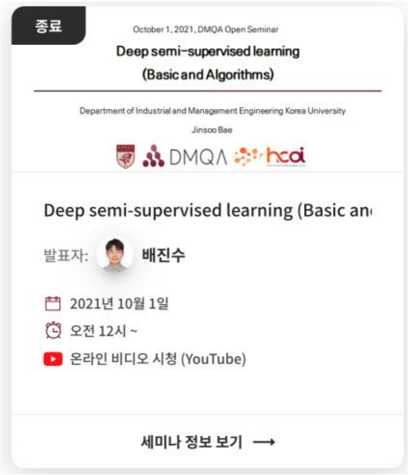
❖ 연구분야

- Calibration of deep neural network
- Semi-supervised learning under class distribution mismatch

세미나 내용

- 배경 지식
  - Semi-supervised learning under class distribution mismatch
  - Hybrid methods for semi-supervised learning
- 방법론 소개
  - Openmatch: Open-set semi-supervised learning with open-set consistency regularization, 2021, NeurIPS
  - Iomatch: Simplifying open-set semi-supervised learning with joint inliers and outliers utilization, 2023, ICCV
- 결론

추천 세미나



Consistency regularization 기반

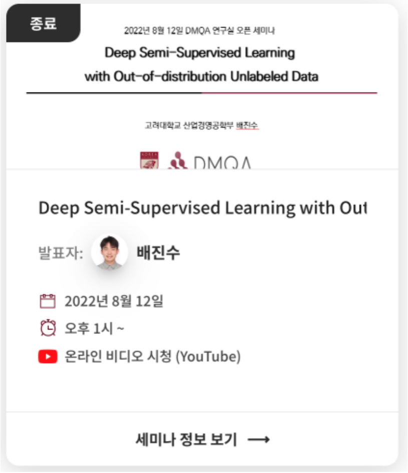
중요 준지도학습 알고리즘 설명

Pseudo label, 2013, ICML

Temporal ensemble, 2017, ICLR

Mean teacher, 2017, NeurIPS

Virtual adversarial training, 2018, TPAMI



Consistency regularization 기반

클래스 불일치 상황 속

안전한 준지도학습 알고리즘

UASD, 2020, AAAI

DS3L, 2020, PLMR

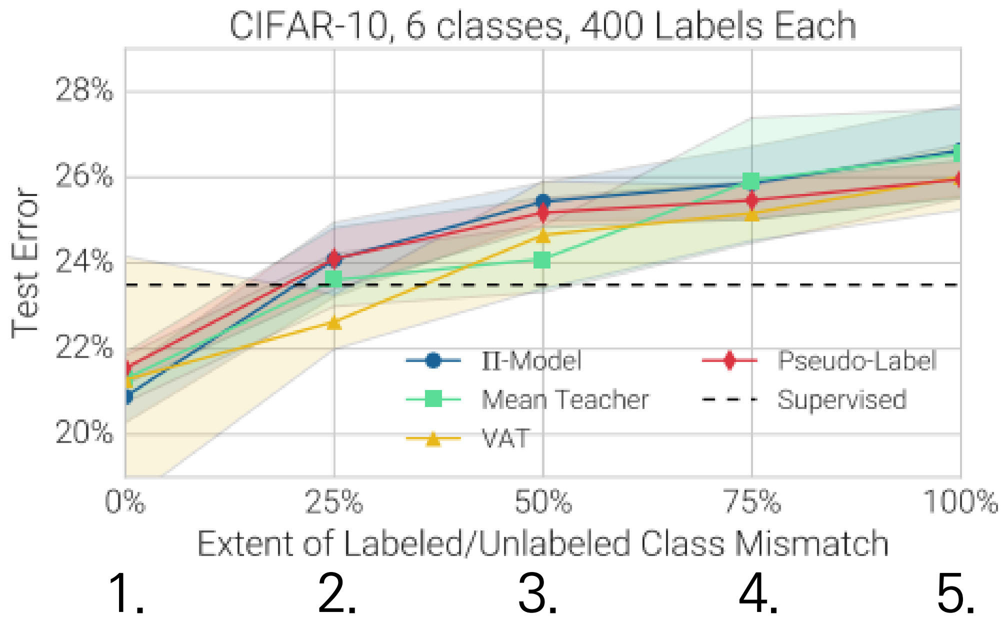
SafeUC, 2022, Information Sciences

Semi-supervised learning under class distribution mismatch

"Google Brain 연구원들의 연구 결과에 따르면 [1],
Unlabeled out of distribution data는 SSL 학습에 부정적인 영향을 끼침"

	CIFAR 10 class info		Mismatch ratio
	Labeled data (400)	Unlabeled data (4100)	
1.	Bird,cat,deer,dog,fog,horse	Deer, dog, fog, horse	0%
2.	Bird,cat,deer,dog,fog,horse	Airplane, dog, fog, horse	25%
3.	Bird,cat,deer,dog,fog,horse	Airplane, automobile, fog, horse	50%
4.	Bird,cat,deer,dog,fog,horse	Airplane, automobile, ship, horse	75%
5.	Bird,cat,deer,dog,fog,horse	Airplane, automobile, ship, truck	100%

O.O.D Unlabeled Data (⊇ Open-set Data)

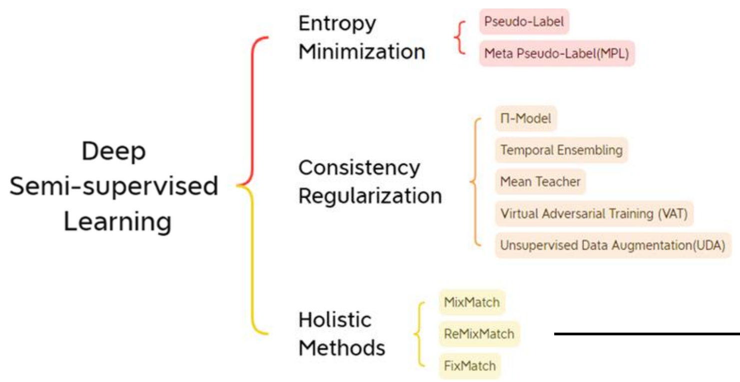


[1] Oliver, Avital, et al. "Realistic evaluation of deep semi-supervised learning algorithms." Advances in neural information processing systems 31 (2018).

Semi-supervised learning under class distribution mismatch

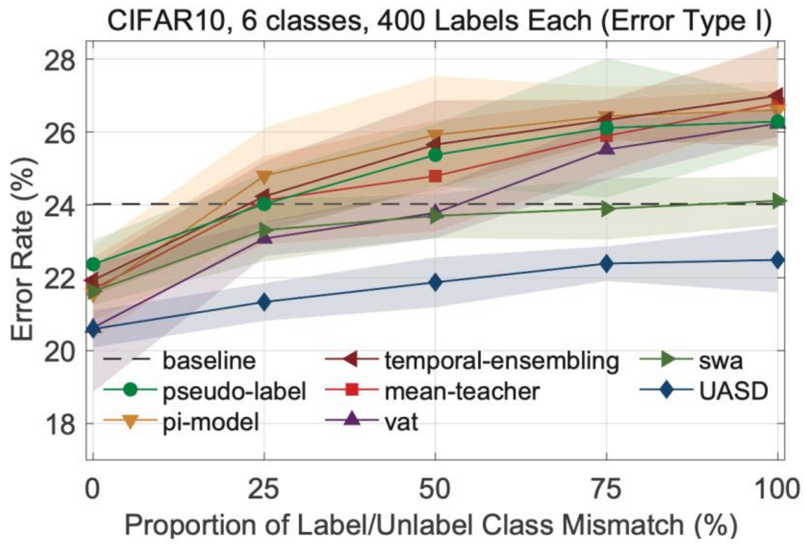
Safe semi-supervised learning
against unlabeled out-of-distribution data

= Unlabeled 데이터셋 내의 Open set data에 강건하고 지도학습 대비 우수한 성능을 낼 수 있는



[2-4]

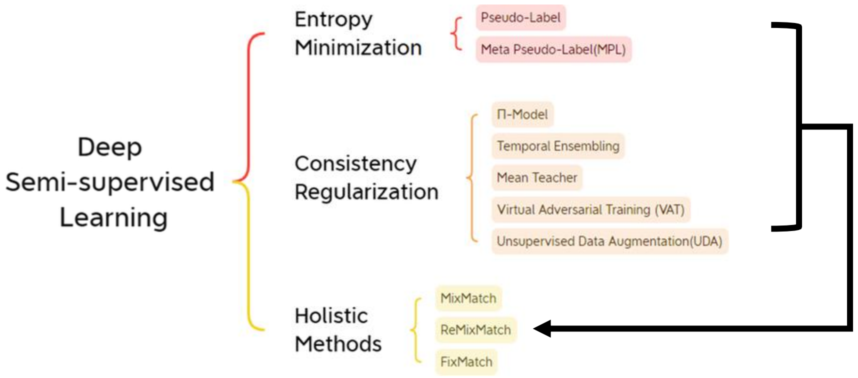
[5-10]



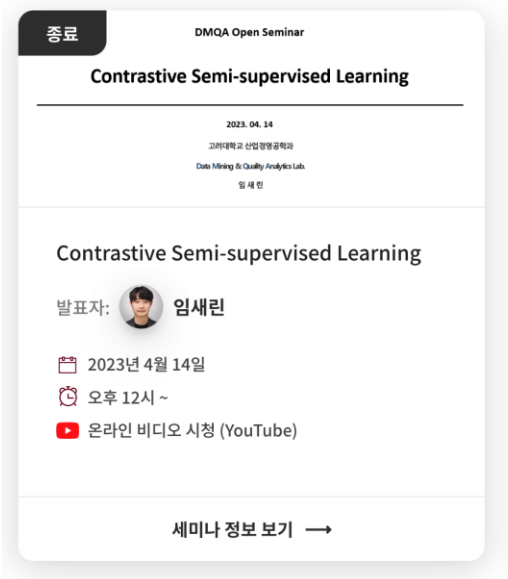
[2] Chen, Yanbei, et al. "Semi-supervised learning under class distribution mismatch." 2020, AAAI, Cited 127 times
[3] Guo, Lan-Zhe, et al. "Safe deep semi-supervised learning for unseen-class unlabeled data." 2020, PMLR, Cited 176 times
[4] Bae, jinsoo, et al. "Safe semi-supervised learning using a bayesian neural network." 2022, Information Sciences, Cited 3 times

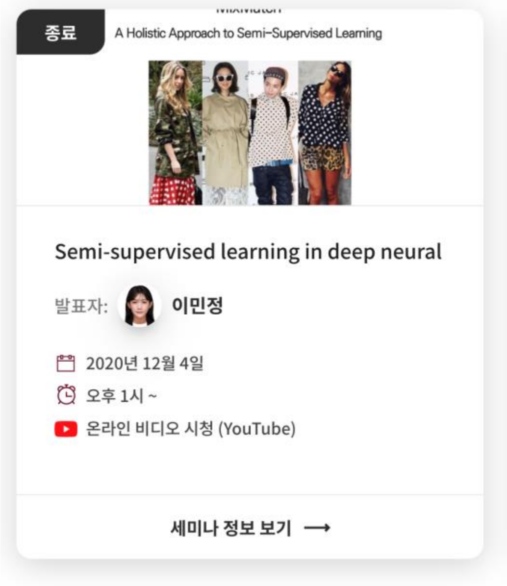
[5] Saito, Kuniaki, et al. "Openmatch: Open-set consistency regularization for semi-supervised learning with outliers." 2021, NeurIPS, Cited 40 times
[6] Li, Zekun, et al. "IOMatch: Simplifying open-set semi-supervised learning with joint inliers and outliers utilization." 2023, ICCV, Cited 3 times
[7] He, Rundong, et al. "Safe-student for safe deep semi-supervised learning with unseen-class unlabeled data." 2022, CVPR, Cited 19 times
[8] Yu, Qing, et al. "Multi-task curriculum framework for open-set semi-supervised learning." 2020, ECCV, Cited 103 times
[9] Ma, Qiankun, et al. "Rethinking Safe Semi-supervised Learning: Transferring the Open-set Problem to A Close-set One." 2023, ICCV, Cited 0 times
[10] Du, Pan, et al. "Semi-Supervised Learning via Weight-aware Distillation under Class Distribution Mismatch." 2023, ICCV, Cited 0 times

Hybrid methods for semi-supervised learning



"In recent years, many hybrid methods have been proposed, which combine ideas, such as consistency regularization, data augmentation, entropy minimization, and pseudo labeling." [11]

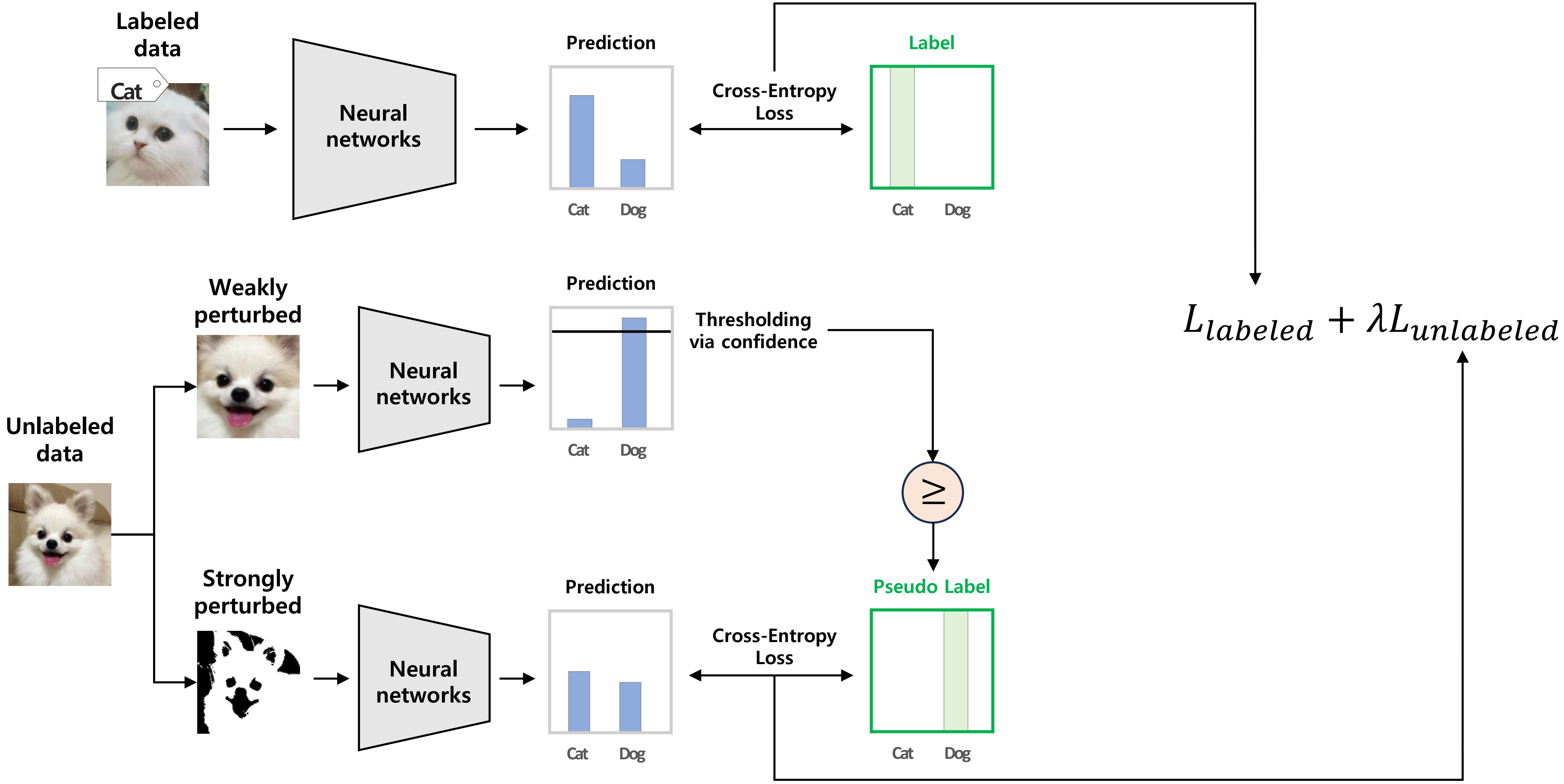




[11] Yang, Xiangli, et al. "A survey on deep semi-supervised learning." IEEE Transactions on Knowledge and Data Engineering (2022).

Hybrid methods for semi-supervised learning

- Fixmatch, 2020, NeurIPS



Hybrid methods for semi-supervised learning

- Fixmatch, 2020, NeurIPS

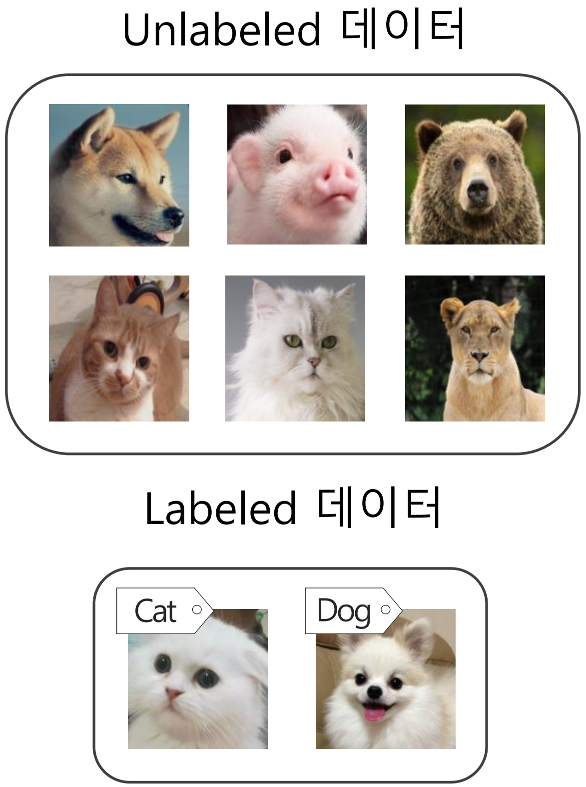
	CIFAR-10			CIFAR-100			SVHN			STL-10
Method	40 labels	250 labels	4000 labels	400 labels	2500 labels	10000 labels	40 labels	250 labels	1000 labels	1000 labels
Π-Model	-	54.26±3.97	14.01±0.38	-	57.25±0.48	37.88±0.11	-	18.96±1.92	7.54±0.36	26.23±0.82
Pseudo-Labeling	-	49.78±0.43	16.09±0.28	-	57.38±0.46	36.21±0.19	-	20.21±1.09	9.94±0.61	27.99±0.83
Mean Teacher	-	32.32±2.30	9.19±0.19	-	53.91±0.57	35.83±0.24	-	3.57±0.11	3.42±0.07	21.43±2.39
MixMatch	47.54±11.50	11.05±0.86	6.42±0.10	67.61±1.32	39.94±0.37	28.31±0.33	42.55±14.53	3.98±0.23	3.50±0.28	10.41±0.61
UDA	29.05±5.93	8.82±1.08	4.88±0.18	59.28±0.88	33.13±0.22	24.50±0.25	52.63±20.51	5.69±2.76	**2.46**±0.24	7.66±0.56
ReMixMatch	**19.10**±9.64	**5.44**±0.05	4.72±0.13	**44.28**±2.06	**27.43**±0.31	**23.03**±0.56	**3.34**±0.20	**2.92**±0.48	2.65±0.08	**5.23**±0.45
FixMatch (RA)	**13.81**±3.37	**5.07**±0.65	**4.26**±0.05	48.85±1.75	28.29±0.11	**22.60**±0.12	**3.96**±2.17	**2.48**±0.38	**2.28**±0.11	7.98±1.50
FixMatch (CTA)	**11.39**±3.35	**5.07**±0.33	**4.31**±0.15	49.95±3.01	28.64±0.24	23.18±0.11	7.65±7.65	**2.64**±0.64	**2.36**±0.19	**5.17**±0.63

Table 2: Error rates for CIFAR-10, CIFAR-100, SVHN and STL-10 on 5 different folds. FixMatch (RA) uses RandAugment [11] and FixMatch (CTA) uses CTAugment [3] for strong-augmentation. All baseline models (Π-Model [43], Pseudo-Labeling [25], Mean Teacher [51], MixMatch [4], UDA [54], and ReMixMatch [3]) are tested using the same codebase.

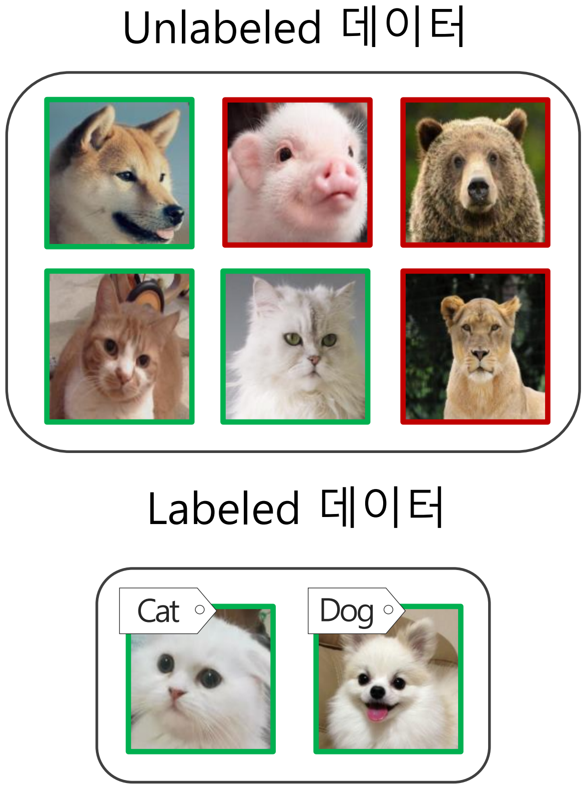
Hybrid methods for semi-supervised learning

- Under class distribution mismatch

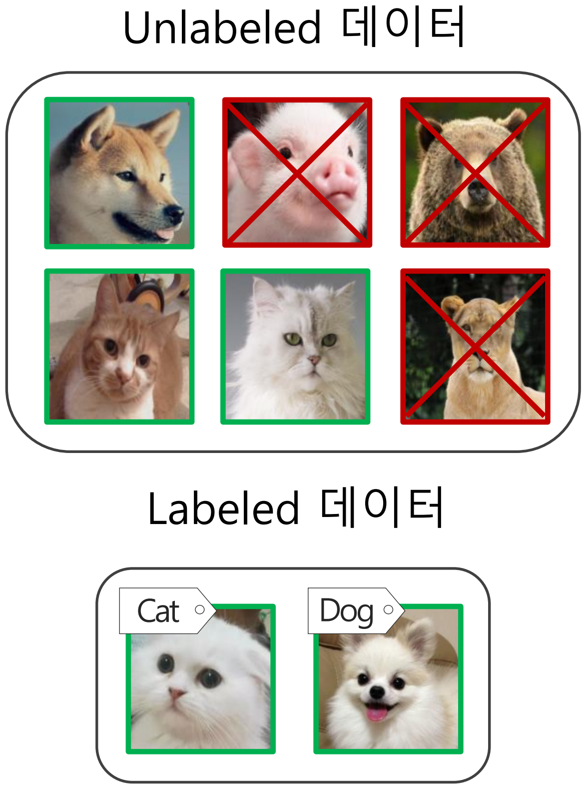
1. Preparing training dataset



2. Open-set detection



3. Fixmatch



Hybrid methods for semi-supervised learning

- Under class distribution mismatch

Unlabeled 데이터

❖ OpenMatch = Open-set detection + FixMatch

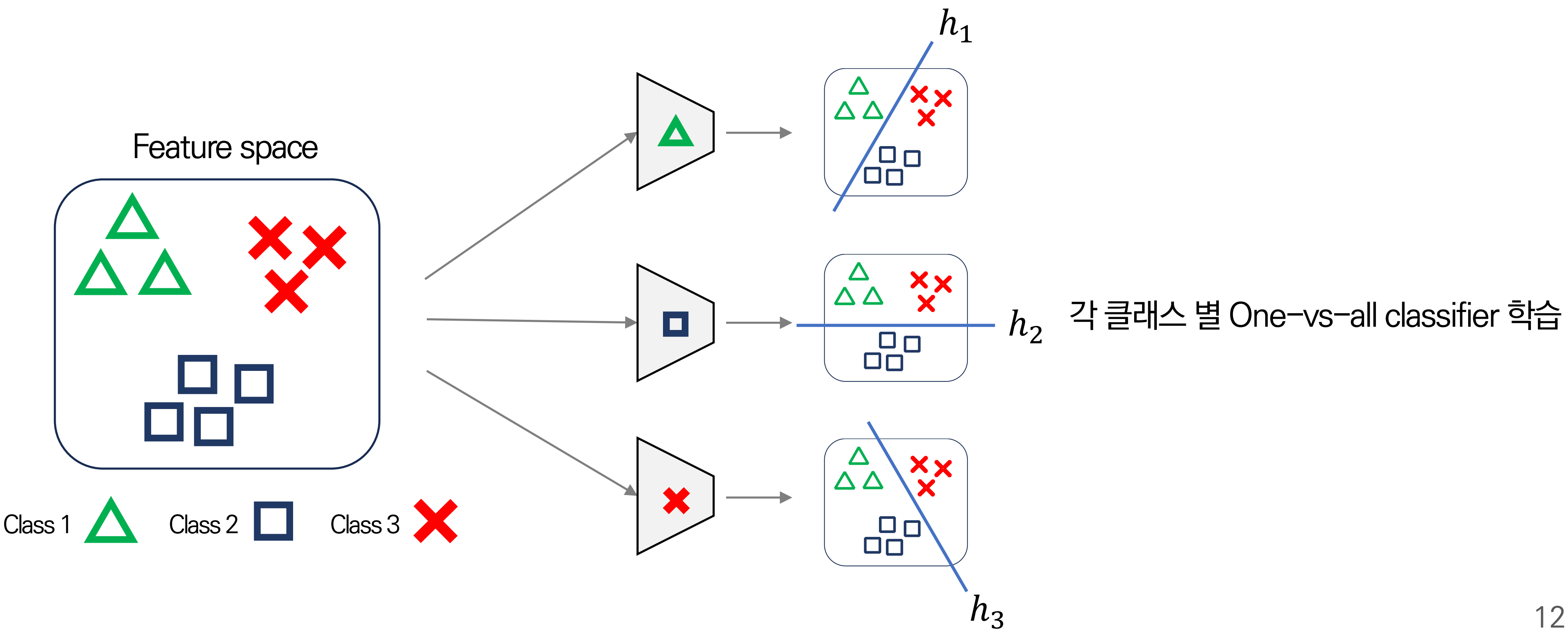
- ➢ One-vs-all classifiers들을 토대로 Unlabeled open-set 데이터 판단 방법 제안
- ➢ One-vs-all classifiers 성능 향상을 위해 Unlabeled data 기반 Open-set consistency regularization 기법 제안

Hybrid methods for semi-supervised learning

- Under class distribution mismatch

❖ One-vs-all classifiers for multi-class classification

1. 모든 클래스에 대하여, 각 클래스 별 “맞아요/아니에요”를 판단하는 이진 분류기를 학습 함

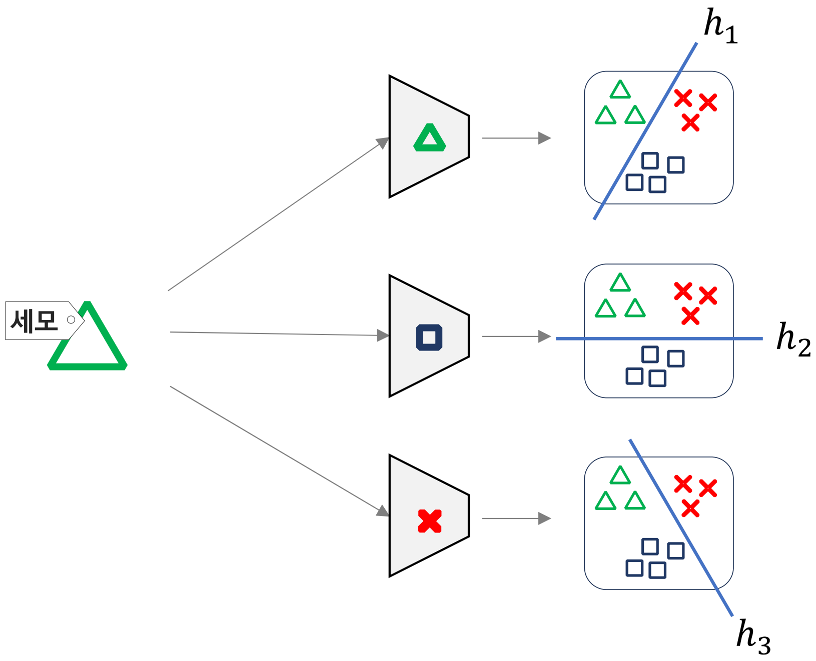


Hybrid methods for semi-supervised learning

- Under class distribution mismatch

❖ One-vs-all classifiers for multi-class classification

1. 모든 클래스에 대하여, 각 클래스 별 “맞아요/아니에요”를 판단하는 이진 분류기를 학습 함



세모

네모 및 엑스가 아닐 확률

$$\mathcal{L}_{ova}(\mathcal{X}) := \frac{1}{B}\sum_{b=1}^{B} -\underline{\log(p^{y_b}(t=0|x_b))} - \min_{i\neq y_b} \overline{\log(p^{i}(t=1|x_b))}.$$

세모일 확률

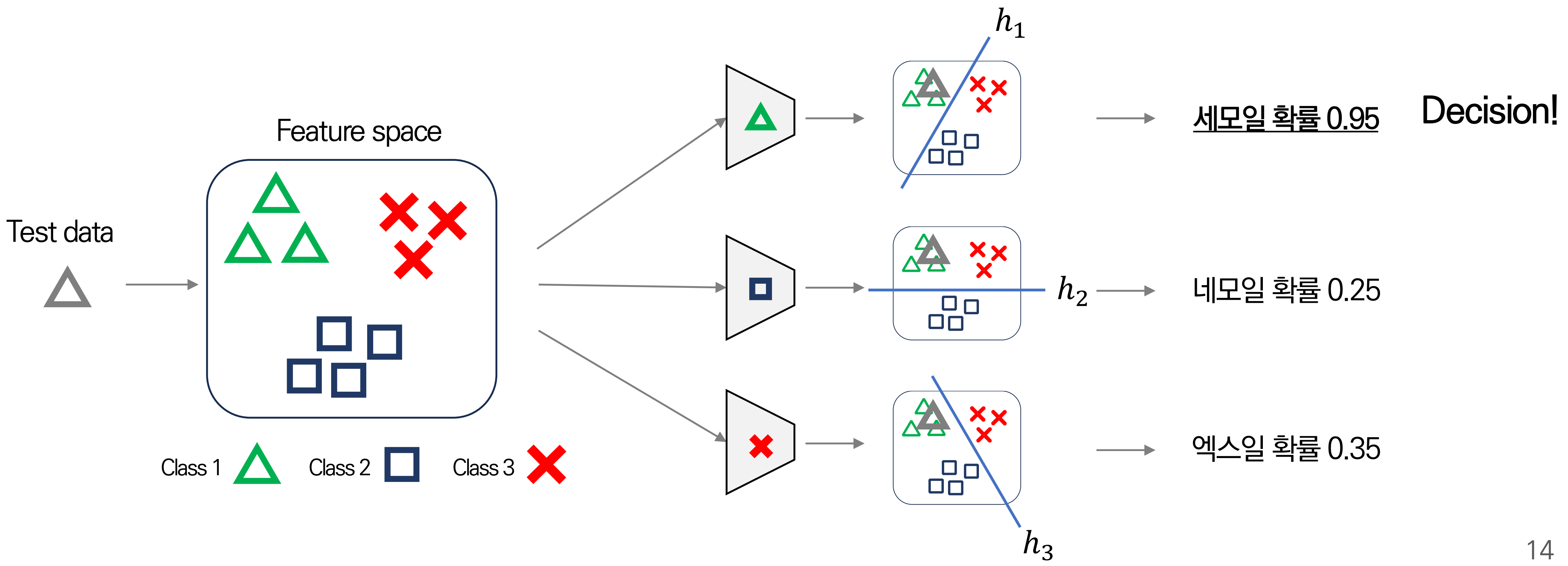
네모, 엑스

Hybrid methods for semi-supervised learning

- Under class distribution mismatch

❖ One-vs-all classifiers for multi-class classification

2. 클래스 개수만큼 해당되는 이진 분류기들의 결과를 종합하여 최종 결론을 내림 ➔ 결론적으로, multi-class classification 가능

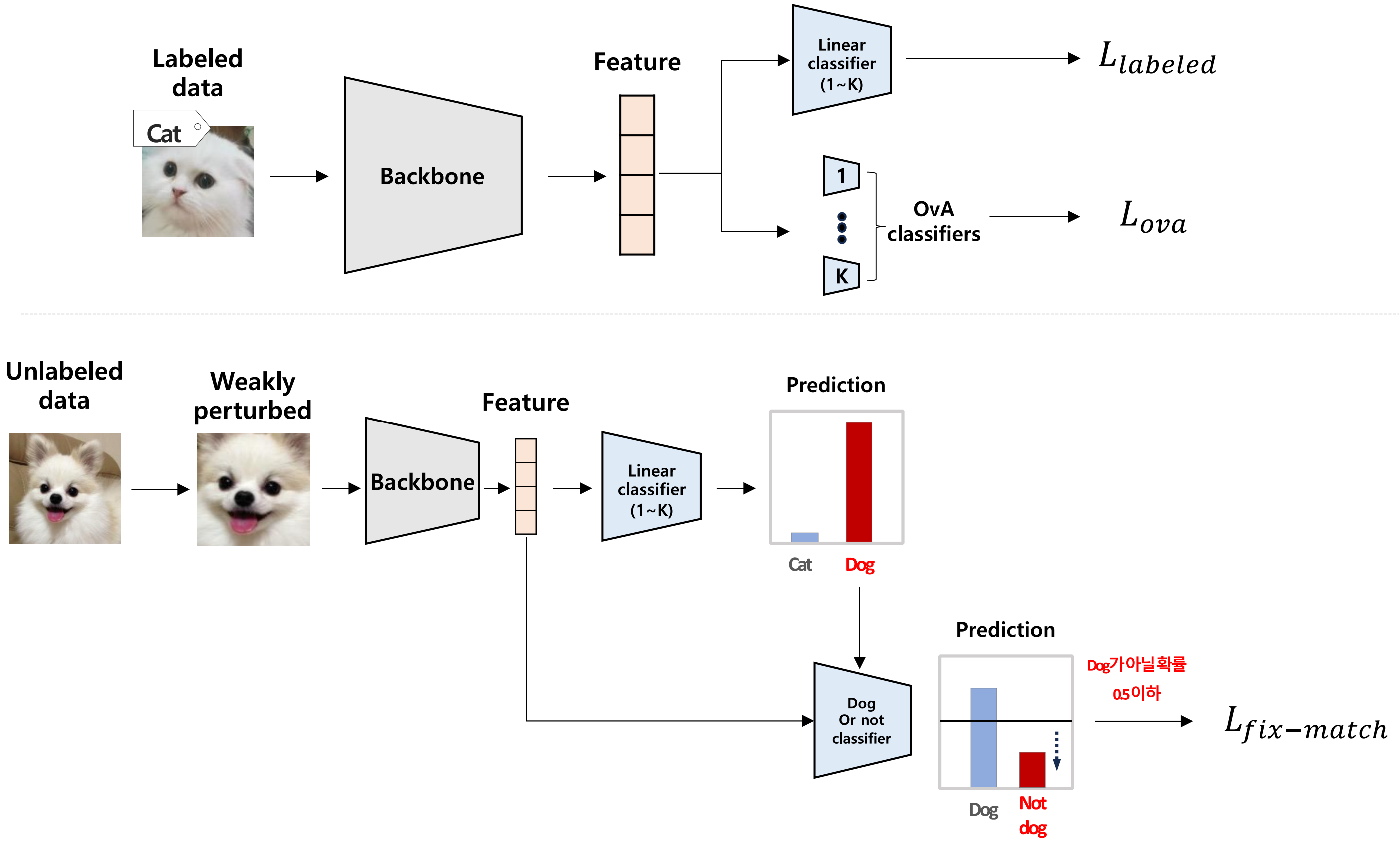


Hybrid methods for semi-supervised learning

- Under class distribution mismatch

❖ OpenMatch = <u>Open-set detection</u> + FixMatch

➢ One-vs-all classifiers들을 토대로 Unlabeled open-set 데이터 판단 방법 제안

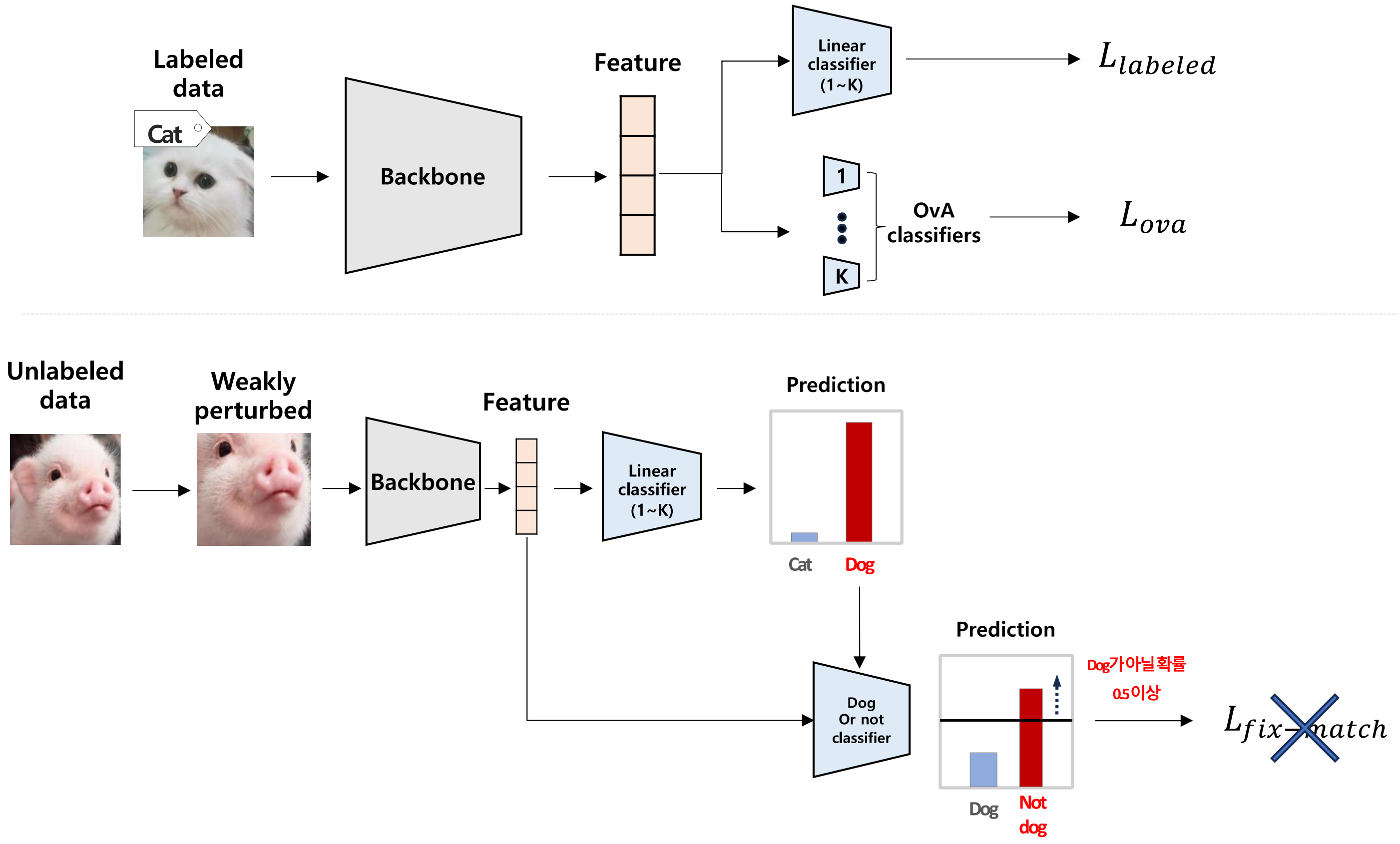


Hybrid methods for semi-supervised learning

- Under class distribution mismatch

❖ OpenMatch = Open-set detection + FixMatch

➢ One-vs-all classifiers들을 토대로 Unlabeled open-set 데이터 판단 방법 제안



Hybrid methods for semi-supervised learning

- Under class distribution mismatch

❖ OpenMatch = Open-set detection + FixMatch

➢ One-vs-all classifiers 성능 향상을 위해 Unlabeled data 기반 Open-set consistency regularization 기법 제안

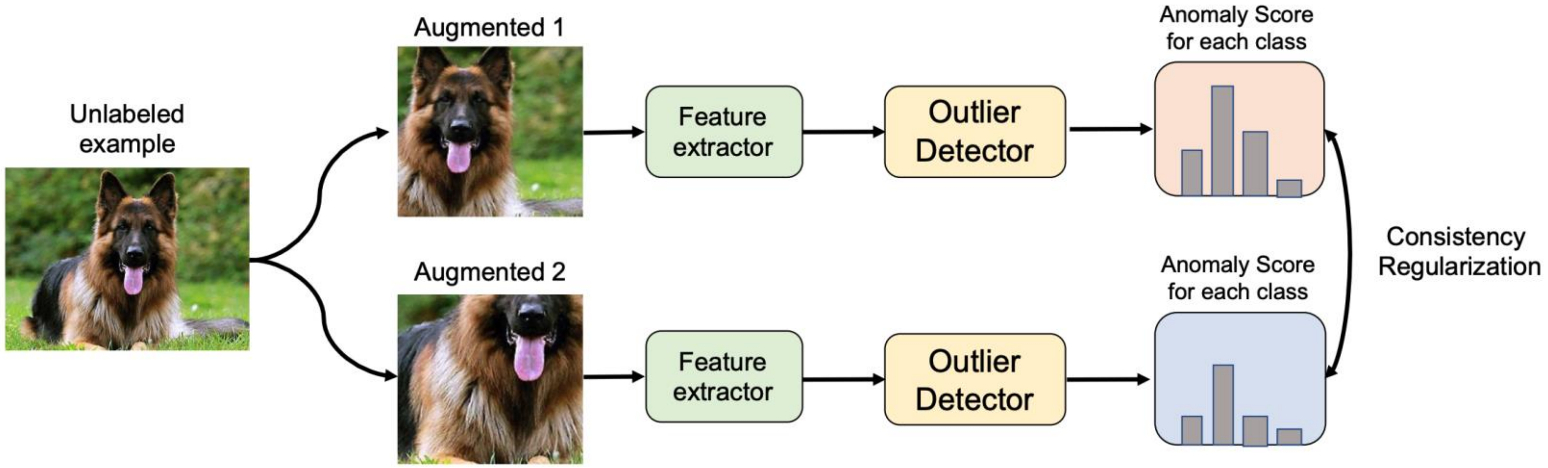


Figure 1: An illustration of our proposed open-set soft-consistency loss used to enhance outlier detection. Two differently augmented inputs are fed into the network to obtain the predictions of the outlier detector. The detector consists of one-vs-all classifiers and is able to detect outliers in an unsupervised way. The consistency loss is computed in a soft manner, *i.e.*, without sharpening logits.

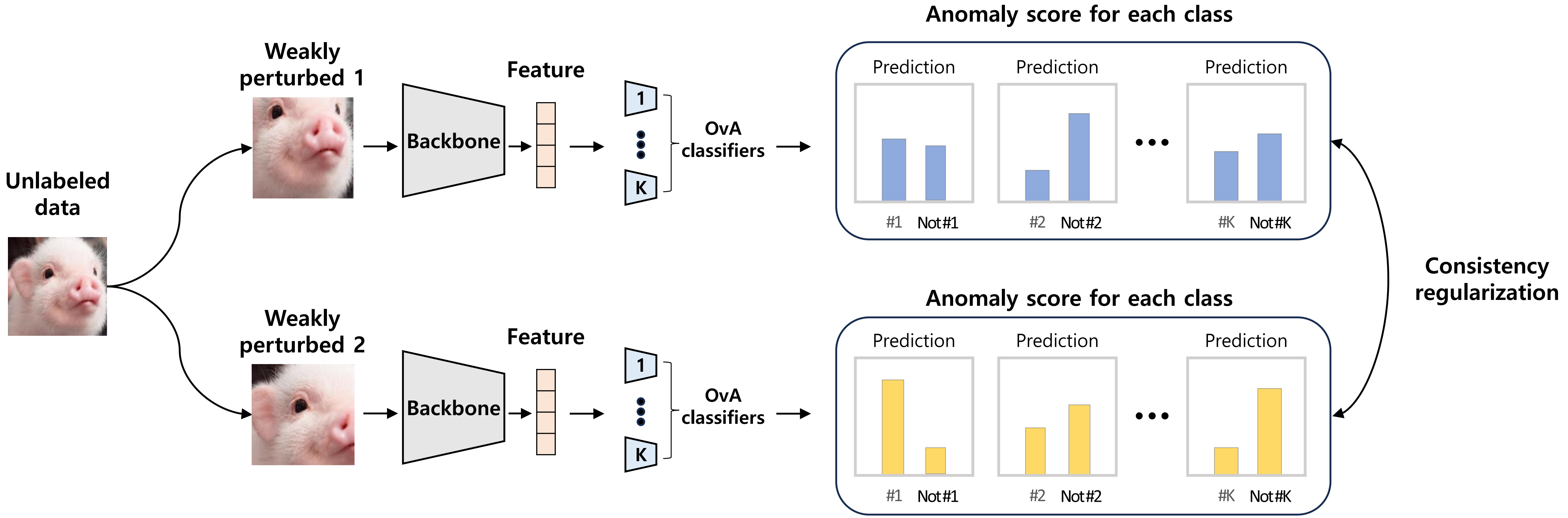
Hybrid methods for semi-supervised learning

- Under class distribution mismatch

$$\mathcal{L}_{oc}(\mathcal{U},\mathcal{T}) := \frac{1}{\mu B}\sum_{b=1}^{\mu B}\sum_{j=1}^{K}\sum_{t\in(0,1)} |p^j(t|\mathcal{T}_1(u_b)) - p^j(t|\mathcal{T}_2(u_b))|^2.$$

❖ OpenMatch = <u>Open-set detection</u> + FixMatch

➢ One-vs-all classifiers 성능 향상을 위해 <u>Unlabeled data 기반 Open-set consistency regularization 기법 제안</u>



Hybrid methods for semi-supervised learning

- Under class distribution mismatch

❖ OpenMatch = <u>Open-set detection</u> + FixMatch

Dataset	CIFAR10			CIFAR100		CIFAR100		ImageNet-30
No. of Known / Unknown	6 / 4			55 / 45		80 / 20		20 / 10
No. of labeled samples	50	100	400	50	100	50	100	10 %
Labeled Only	35.7±1.1	30.5±0.7	20.0±0.3	37.0±0.8	27.3±0.5	43.6±0.5	34.7±0.4	20.9±1.0
FixMatch [35]	43.2±1.2	29.8±0.6	16.3±0.5	35.4±0.7	27.3±0.8	41.2±0.7	34.1±0.4	12.9±0.4
MTC [44]	20.3±0.9	13.7±0.9	9.0±0.5	33.5±1.2	27.9±0.5	40.1±0.8	33.6±0.3	13.6±0.7
OpenMatch	**10.4±0.9**	**7.1±0.5**	**5.9±0.5**	**27.7±0.4**	**24.1±0.6**	**33.4±0.2**	**29.5±0.3**	**10.4±1.0**

Table 1: Error rates (%) with standard deviation for CIFAR10, CIFAR100 on 3 different folds. Lower is better. For ImageNet, we use the same fold and report averaged results of three runs. Note that the number of labeled samples *per each class* is shown in each column.

Dataset	CIFAR10			CIFAR100		CIFAR100		ImageNet-30
No. of Known / Unknown	6 / 4			55 / 45		80 / 20		20 / 10
No. of labeled samples	50	100	400	50	100	50	100	10 %
Labeled Only	63.9±0.5	64.7±0.5	76.8±0.4	76.6±0.9	79.9±0.9	70.3±0.5	73.9±0.9	80.3±1.0
FixMatch [35]	56.1±0.6	60.4±0.4	71.8±0.4	72.0±1.3	75.8±1.2	64.3±1.0	66.1±0.5	88.6±0.5
MTC [44]	96.6±0.6	98.2±0.3	98.9±0.1	81.2±3.4	80.7±4.6	79.4±2.5	73.2±3.5	93.8±0.8
OpenMatch	**99.3±0.3**	**99.7±0.2**	**99.3±0.2**	**87.0±1.1**	**86.5±2.1**	**86.2±0.6**	**86.8±1.4**	**96.4±0.7**

Table 2: AUROC of Table 1. Higher is better. Note that the number of labeled samples *per each class* is shown in each column.

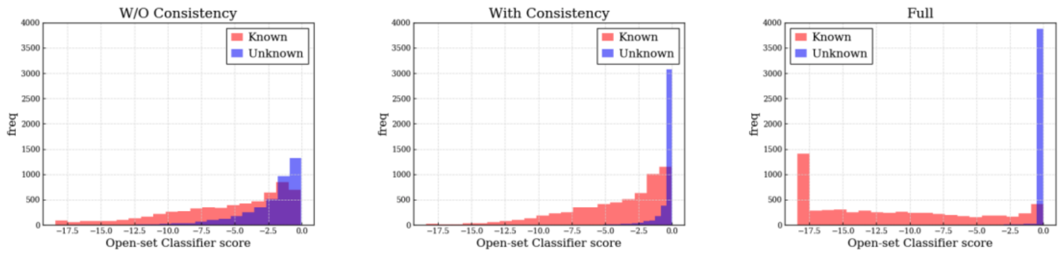
Hybrid methods for semi-supervised learning

- Under class distribution mismatch

❖ OpenMatch = <u>Open-set detection</u> + FixMatch

Dataset	CIFAR10		CIFAR100		ImageNet-30
No. Known / Unknown	6 / 4		80 / 20		20 / 10
No. Labeled samples	50	400	50	100	10 %
without SOCR	60.5$\pm$2.8	75.8$\pm$0.8	70.4$\pm$0.1	73.2$\pm$0.2	81.3$\pm$0.4
with SOCR	**81.3**$\pm$2.9	**96.8**$\pm$0.6	**78.9**$\pm$0.1	**85.0**$\pm$0.8	**89.3**$\pm$0.3

Table 3: Ablation study of our soft consistency regularization (SOCR, $\mathcal{L}_{oc}$). We report AUROC scores (%). In this study, we do not apply FixMatch to pseudo-inliers to see the pure gain from SOCR.



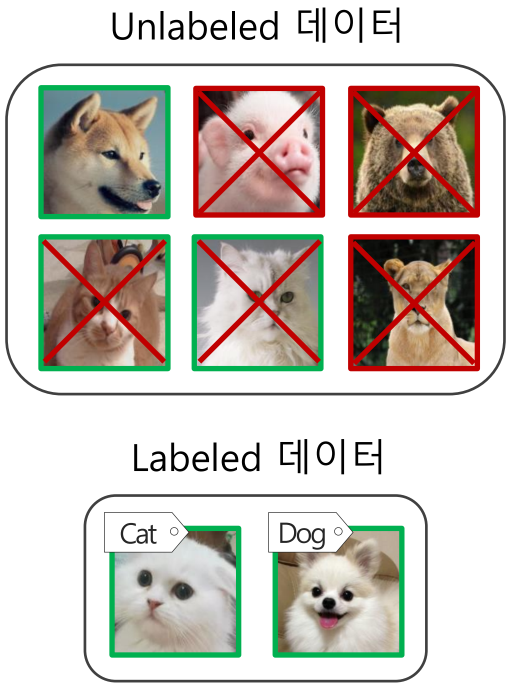
(a) w/o FixMatch, SOCR. (b) w/o FixMatch (c) FULL (OpenMatch)

Figure 3: The histograms of the outlier detector's scores obtained with ablated models. Red: Inliers, Blue: Outliers. From left to right, a model without FixMatch and SOCR, a model without FixMatch, and a model with all objectives. These results show that SOCR ensures separation between inliers and outliers, and FixMatch added to SOCR can further enhance this separation.

Hybrid methods for semi-supervised learning

- Under class distribution mismatch

❖ Open-set detection 성능 저하 → Unlabeled valuable data 제거 → 성능 저하 → 새로운 방법론 필요 (IOMatch, 2023, ICCV)



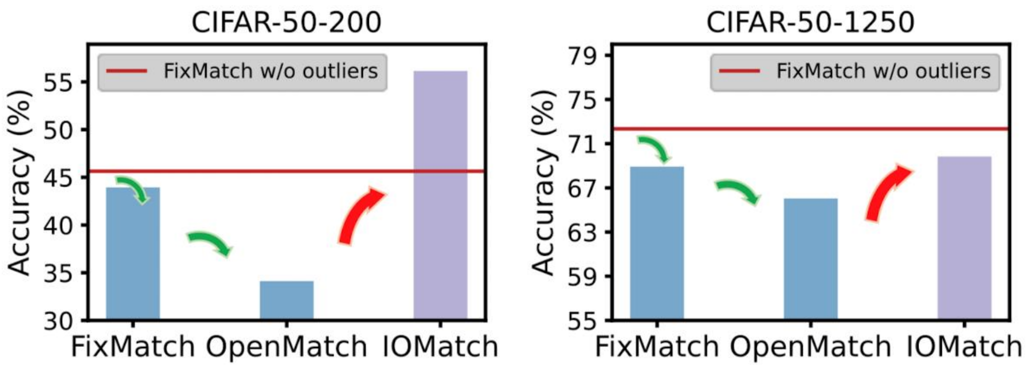


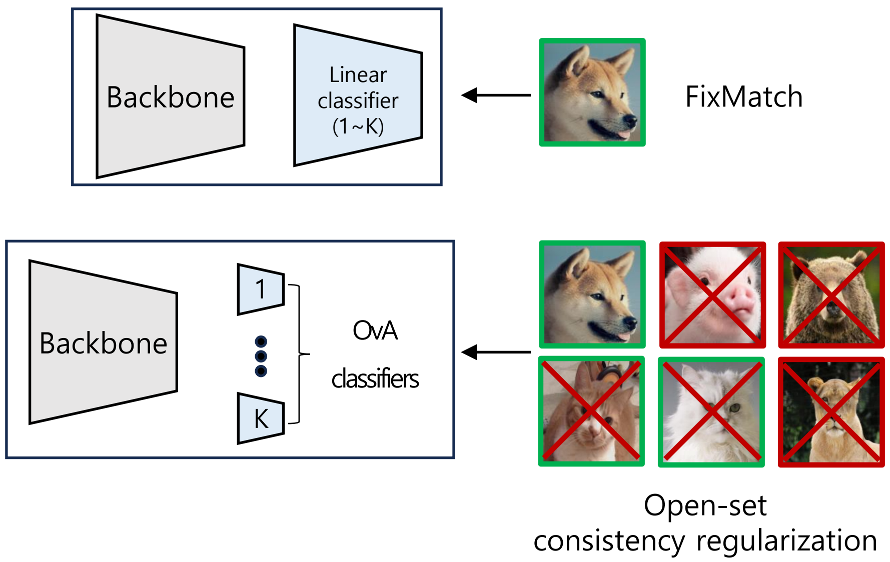
Figure 1. The motivation of our work comes from a surprising fact in open-set semi-supervised learning tasks: An unreliable outlier detector can be more harmful than outliers themselves, because it will wrongly exclude valuable inliers from subsequent training. For this issue, we consider a unified paradigm for utilizing open-set unlabeled data, even when it is difficult to distinguish exactly between inliers and outliers, and thus we propose IOMatch.

Hybrid methods for semi-supervised learning

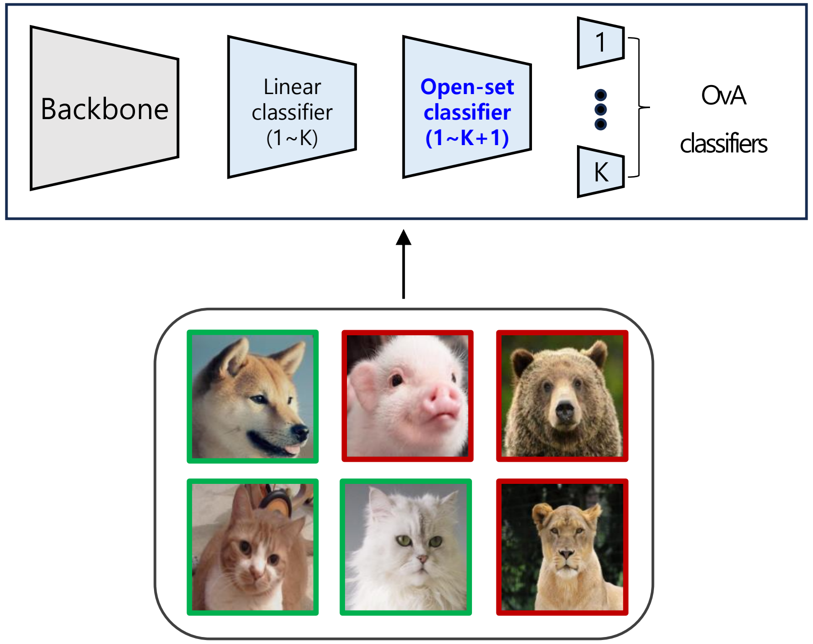
- Under class distribution mismatch

❖ Open-set detection 성능 저하 → Unlabeled valuable data 제거 → 성능 저하 → 새로운 방법론 필요 (IOMatch, 2023, ICCV)

OpenMatch의 Unlabeled data 사용 방법



IOMatch의 Unlabeled data 사용 방법

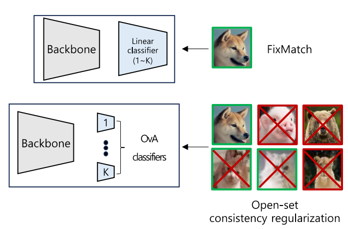


joint inliers and outliers utilization

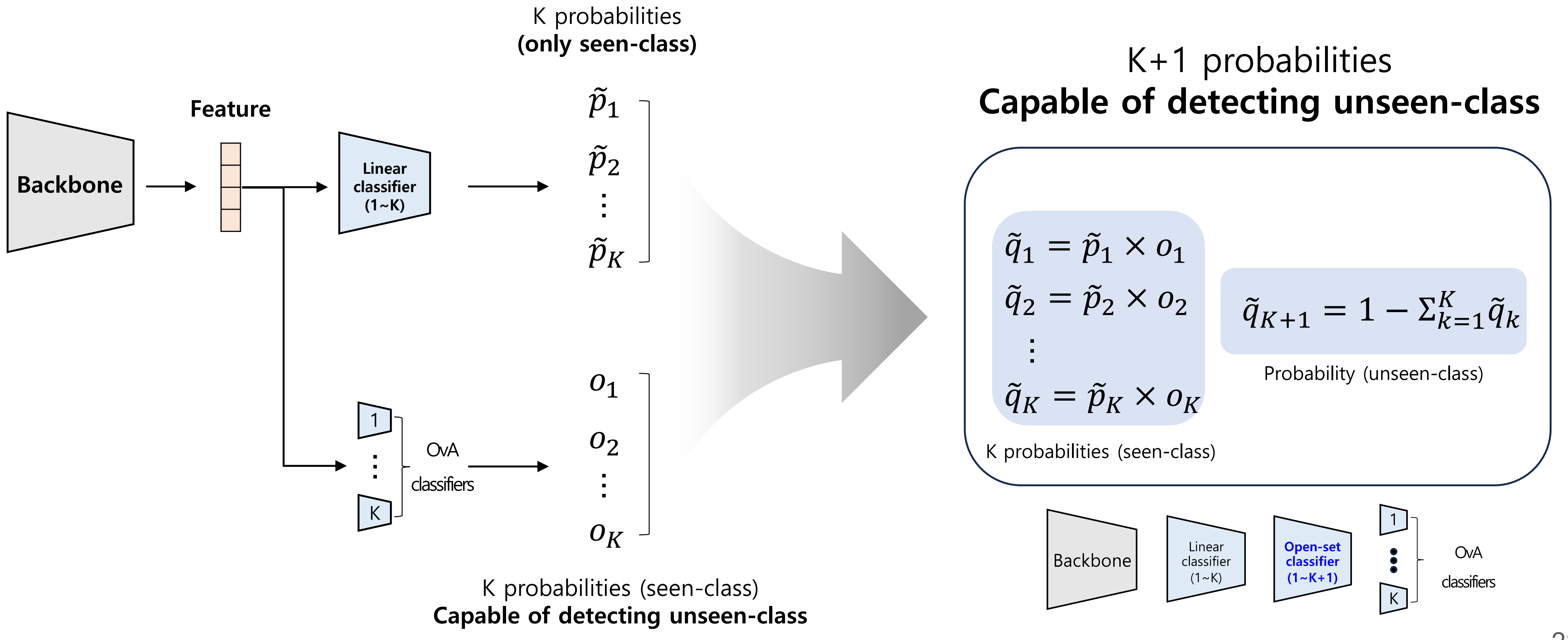
Hybrid methods for semi-supervised learning

- Under class distribution mismatch

OpenMatch의 Unlabeled data 사용 방법



❖ IOMatch: Simplifying open-set semi-supervised learning <u>with joint inliers and outliers utilization</u>



Hybrid methods for semi-supervised learning

- Under class distribution mismatch

❖ IOMatch: Simplifying open-set semi-supervised learning <u>with joint inliers and outliers utilization</u>

3.3. Joint Inliers and Outliers Utilization

For all the open-set unlabeled samples, we adopt the open-set targets as supervision to train the open-set classifier $\psi(\cdot)$ with its predictions $\boldsymbol{q}_i^s = \psi(\boldsymbol{z}_s^i) \in \mathbb{R}^{K+1}$ on the strongly augmented samples:

$$\mathcal{L}_{op}(\mathcal{U}) = \frac{1}{\mu B} \sum_{i=1}^{\mu B} \mathbb{1}(\max_k(\tilde{q}_{i,k}) > \tau_q) \cdot \mathrm{H}(\tilde{\boldsymbol{q}}_i, \boldsymbol{q}_i^s), \quad (6)$$

where $\mathbb{1}(\cdot)$ is the indicator function and τ_q is the confidence threshold. In practice, we usually choose a low value for τ_q so that most of the unlabeled samples can be utilized. Different from the traditional consistency regularization technique, we use $\tilde{\boldsymbol{q}}_i$ instead of the predictions $\boldsymbol{q}_i^w$ on the weakly augmented samples as supervision. In this way, the generation and utilization of pseudo-labels can be disentangled to alleviate the accumulation of confirmation bias.

K+1 probabilities

Capable of detecting unseen-class

$$\tilde{q}_1 = \tilde{p}_1 \times o_1$$

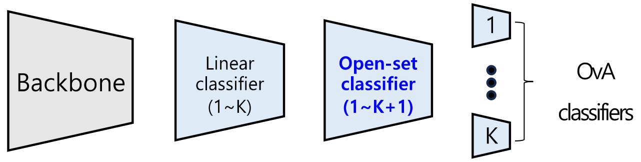
$$\tilde{q}_2 = \tilde{p}_2 \times o_2$$

$$\vdots$$

$$\tilde{q}_K = \tilde{p}_K \times o_K$$

$$\tilde{q}_{K+1} = 1 - \Sigma_{k=1}^{K} \tilde{q}_k$$

Probability (unseen-class)



Hybrid methods for semi-supervised learning

- Under class distribution mismatch

❖ IOMatch: Simplifying open-set semi-supervised learning <u>with joint inliers and outliers utilization</u>

Then, for the closed-set classifier, we propose a double filtering strategy to select high-quality seen-class pseudo-labels of inliers:

$$\mathcal{L}_{ui}(\mathcal{U}) = \frac{1}{\mu B} \sum_{i=1}^{\mu B} \mathcal{F}(\boldsymbol{u}_i) \cdot \mathrm{H}(\widetilde{\boldsymbol{p}}_i, \boldsymbol{p}_i^s). \tag{7}$$

$\mathcal{F}(\cdot)$ is the filtering function, which is defined as $\mathcal{F}(\boldsymbol{u}_i) = \mathbb{1}(\max_k(\widetilde{p}_{i,k}) > \tau_p) \cdot \mathbb{1}(\mathcal{S}_i < 0.5)$, where τ_p is another confidence threshold. We use $\mathcal{S}_i$ to exclude the likely outliers and use τ_p to ignore incorrect pseudo-labels of inliers. As these temporarily excluded samples have been utilized by the open-set classifier, the true inliers will be gradually involved in the training, which prevents IOMatch from falling into the same issue as the previous OSSL methods.

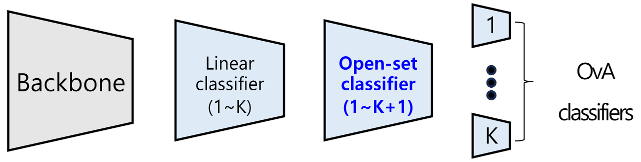
K+1 probabilities

Capable of detecting unseen-class

$$\tilde{q}_1 = \tilde{p}_1 \times o_1$$
$$\tilde{q}_2 = \tilde{p}_2 \times o_2$$
$$\vdots$$
$$\tilde{q}_K = \tilde{p}_K \times o_K$$

$$\tilde{q}_{K+1} = 1 - \Sigma_{k=1}^{K} \tilde{q}_k$$

Probability (unseen-class)

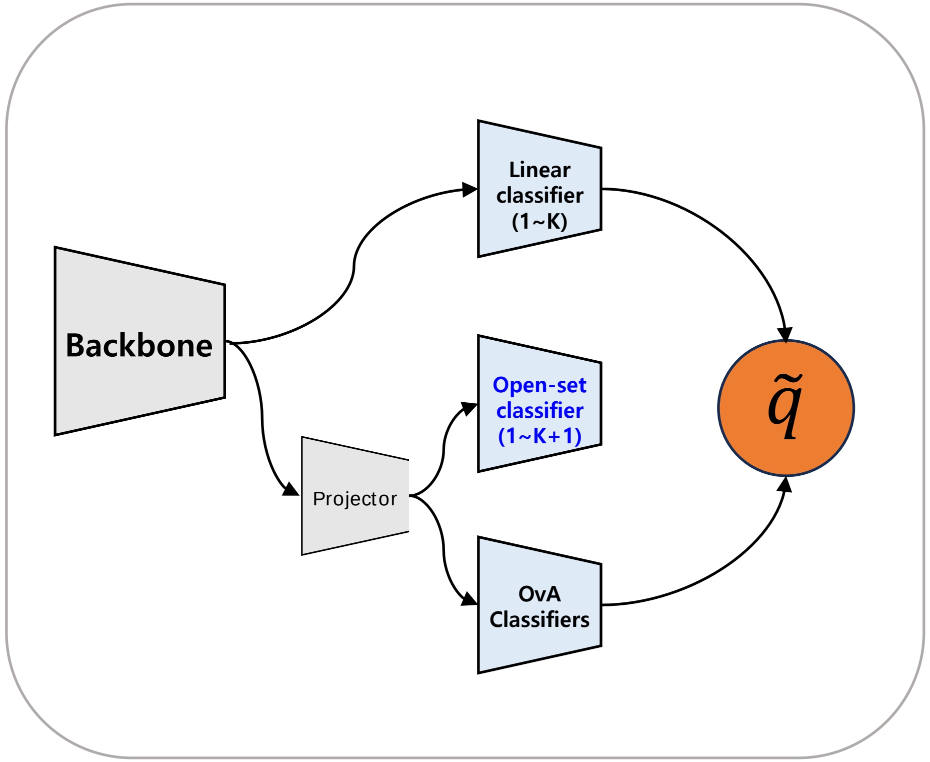


Hybrid methods for semi-supervised learning

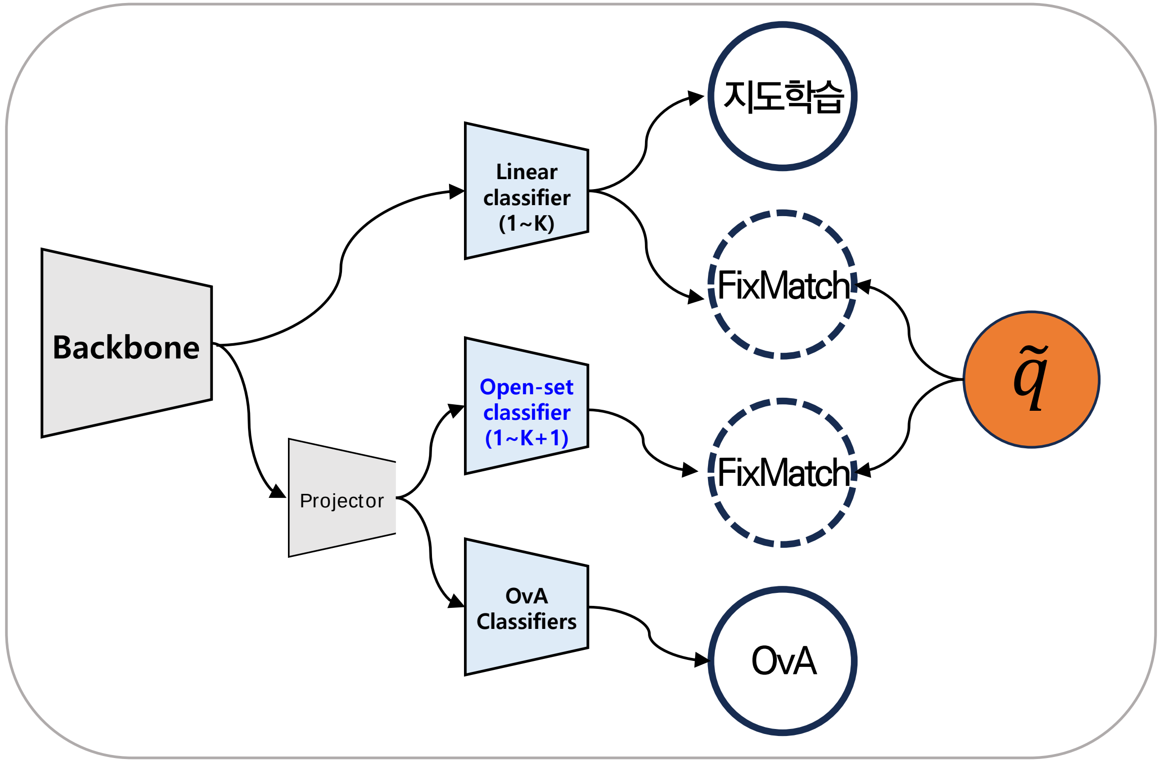
- Under class distribution mismatch

❖ IOMatch: Simplifying open-set semi-supervised learning <u>with joint inliers and outliers utilization</u>

Open-Set Target 생성



IOMatch 학습 프레임워크



Hybrid methods for semi-supervised learning

- Under class distribution mismatch

❖ IOMatch: Simplifying open-set semi-supervised learning <u>with joint inliers and outliers utilization</u>

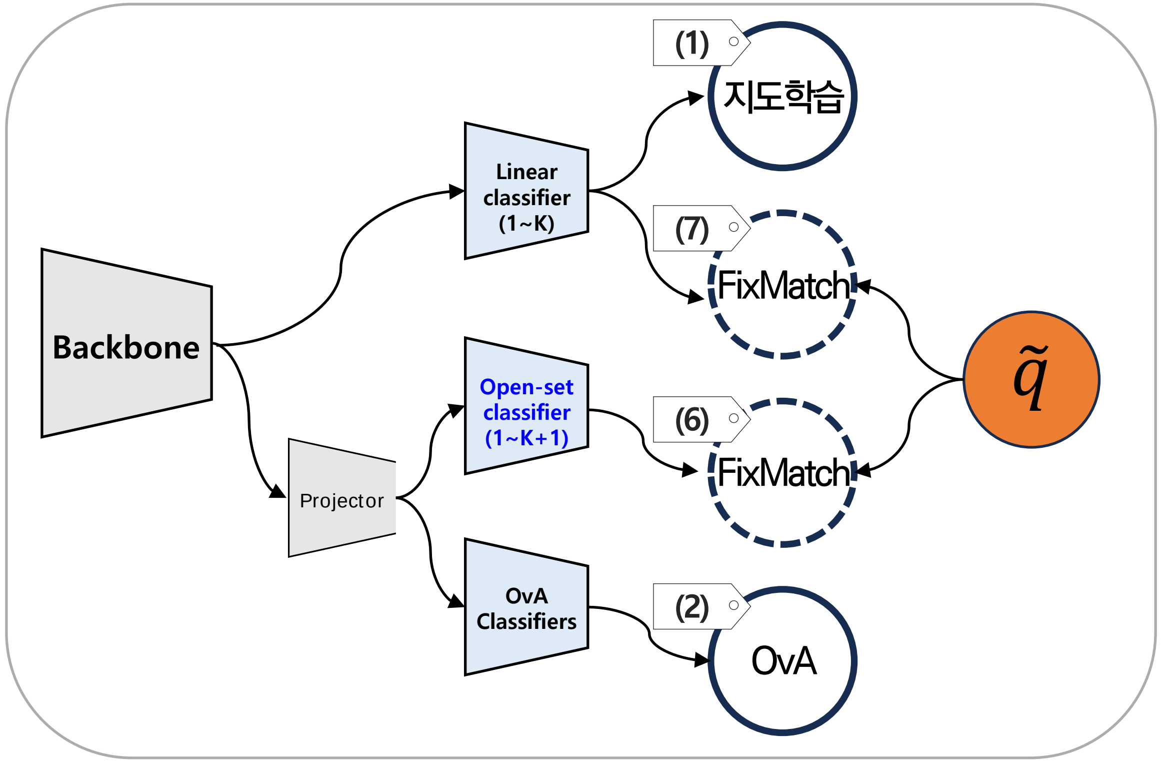
$$\mathcal{L}_s(\mathcal{X}) = \frac{1}{B}\sum_{i=1}^{B} \mathrm{H}(y_i, \boldsymbol{p}_i). \quad (1)$$

$$\mathcal{L}_{op}(\mathcal{U}) = \frac{1}{\mu B}\sum_{i=1}^{\mu B} \mathbb{1}(\max_k(\widetilde{q}_{i,k}) > \tau_q) \cdot \mathrm{H}(\widetilde{\boldsymbol{q}}_i, \boldsymbol{q}_i^s), \quad (6)$$

$$\mathcal{L}_{ui}(\mathcal{U}) = \frac{1}{\mu B}\sum_{i=1}^{\mu B} \mathcal{F}(\boldsymbol{u}_i) \cdot \mathrm{H}(\widetilde{\boldsymbol{p}}_i, \boldsymbol{p}_i^s). \quad (7)$$

$$\mathcal{L}_{mb}(\mathcal{X}) = \frac{1}{B}\sum_{i=1}^{B} \left(-\log(o_{i,y_i}) - \min_{k \neq y_i} \log(\bar{o}_{i,k})\right). \quad (2)$$

IOMatch 학습 프레임워크



Hybrid methods for semi-supervised learning

- Under class distribution mismatch

❖ IOMatch: Simplifying open-set semi-supervised learning with joint inliers and outliers utilization

Table 1. Closed-set classification accuracy (%) on the *seen-class* test data of CIFAR-10/100 with varying seen/unseen class splits and labeled set sizes. We report the mean with standard deviation over 3 runs of different random seeds.

	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

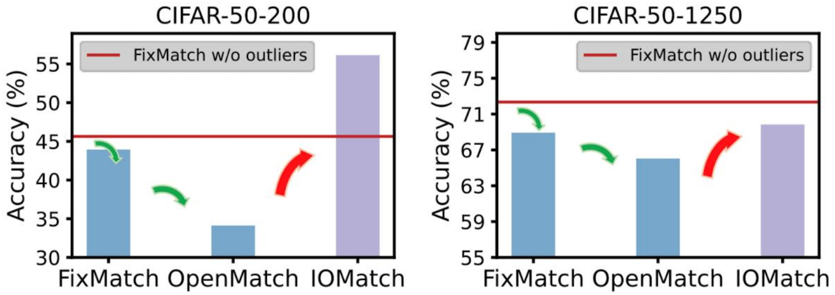


Figure 1. The motivation of our work comes from a surprising fact in open-set semi-supervised learning tasks: An unreliable outlier detector can be more harmful than outliers themselves, because it will wrongly exclude valuable inliers from subsequent training. For this issue, we consider a unified paradigm for utilizing open-set unlabeled data, even when it is difficult to distinguish exactly between inliers and outliers, and thus we propose IOMatch.

Hybrid methods for semi-supervised learning

- Under class distribution mismatch

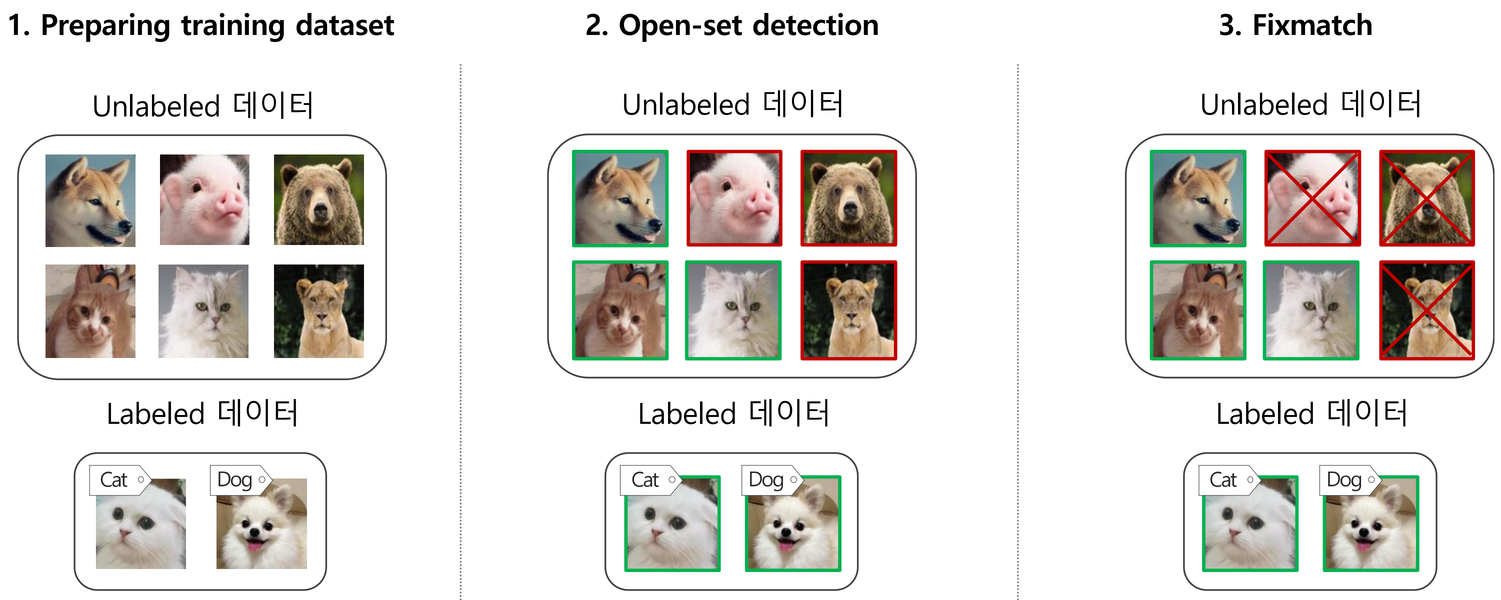
❖ IOMatch: Simplifying open-set semi-supervised learning with joint inliers and outliers utilization

Table 2. Open-set classification balanced accuracy (%) on the *open-set* test data of CIFAR-10/100, which consist of samples from all the seen and unseen classes. We report the mean with standard deviation over 3 runs of different random seeds.

	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

Conclusion

Hybrid methods for semi-supervised learning under class distribution mismatch




Thank you