OpenMatch: Open-set Consistency Regularization for Semi-supervised Learning with Outliers

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• Contents

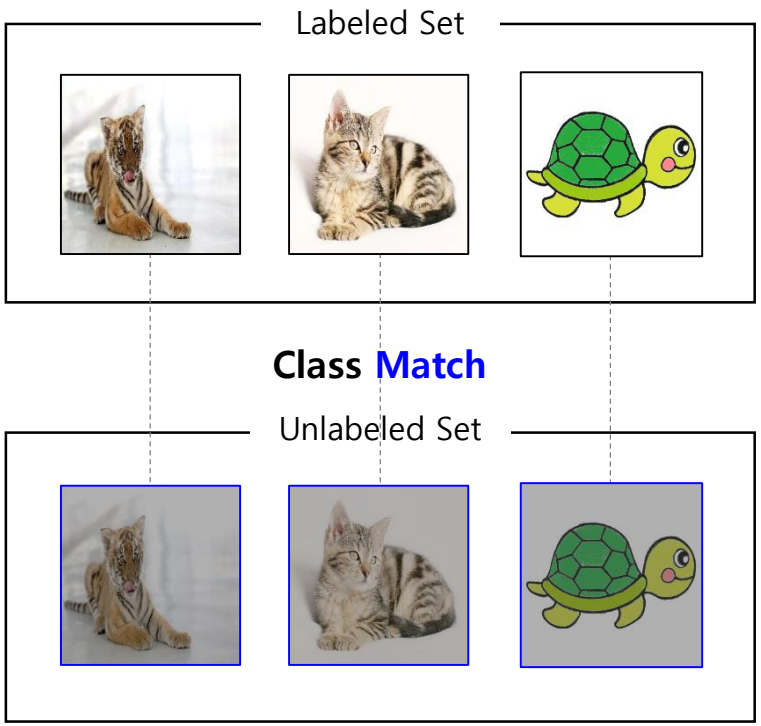
1. Introduction
2. Paper Review
3. Summary & Conclusions

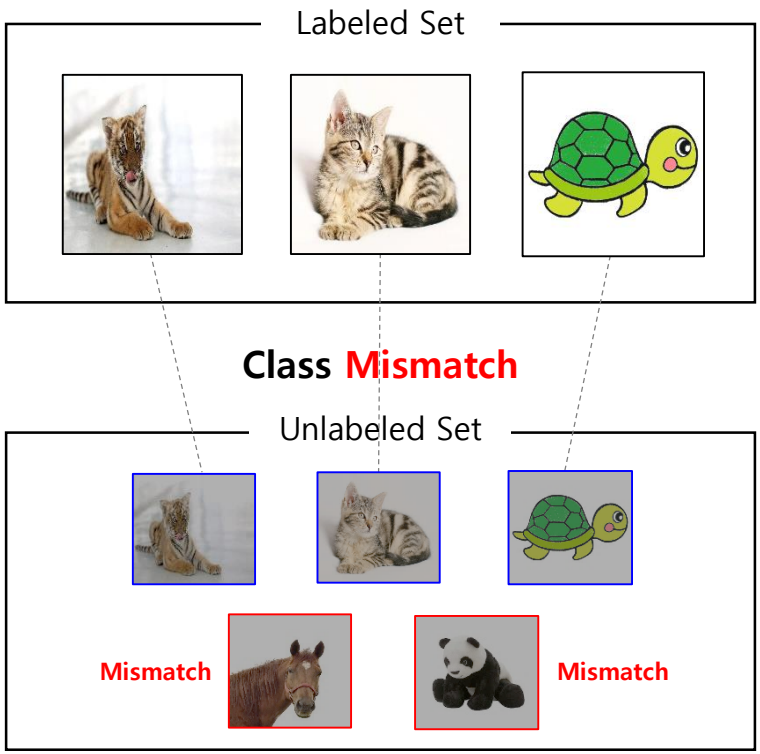
Introduction

Problem Definition

❖ Class mismatch between labeled data and unlabeled data

- 기존 semi-supervised learning(SSL)에서는 unlabeled data의 class를 labeled data의 class 중 하나로 가정 (class match)
- 하지만 real-world에서는 unlabeled data에 다른 class가 존재하는 class mismatch 상황이 자주 발생
- Class mismatch 상황에서 SSL을 바로 적용하면 성능 하락이 발생하게 됨





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Introduction

OpenMatch: Open-set Consistency Regularization for Semi-supervised Learning with Outliers

❖ **OpenMatch: Open-set Consistency Regularization for Semi-supervised Learning with Outliers**

- neurIPS2021에서 게재, 2022년 10월 07일 기준 5회 인용
- Labeled data와 class match인 data를 inlier, mismatch인 data를 outlier로 정의
- Labeled data로 One-vs-All(OVA) detector를 학습하여 unlabeled data가 입력되었을 때 outlier를 잘 탐지하는 것이 목적
- 학습된 detector를 통해서 unlabeled data가 inlier로 판단되면 pseudo label을 부여하고 fixmatch task 진행

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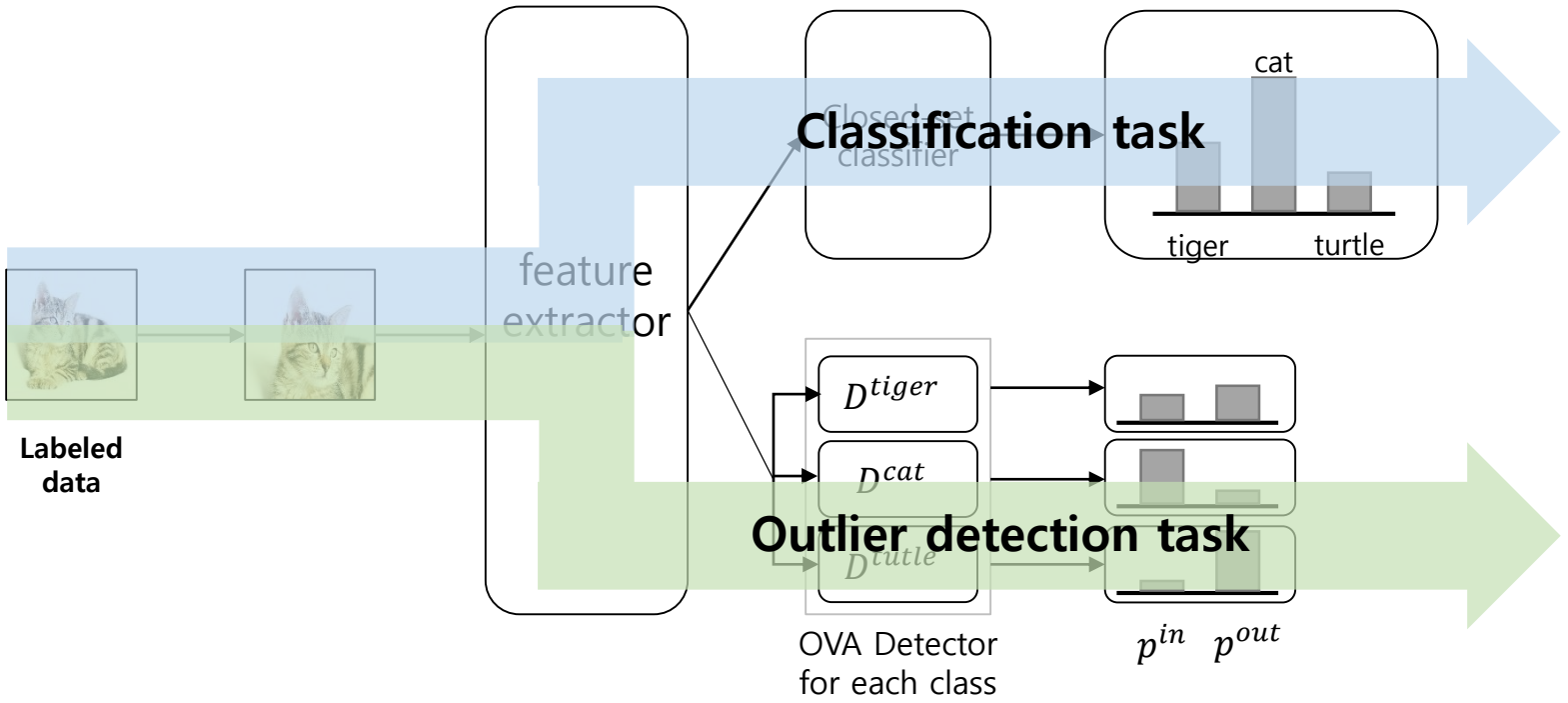
Paper Review

OpenMatch: Open-set Consistency Regularization for Semi-supervised Learning with Outliers

❖ Overall Framework

- 총 5개의 task를 통해 모델을 학습

  → Labeled data를 활용한 task : Classification task & Outlier detection task



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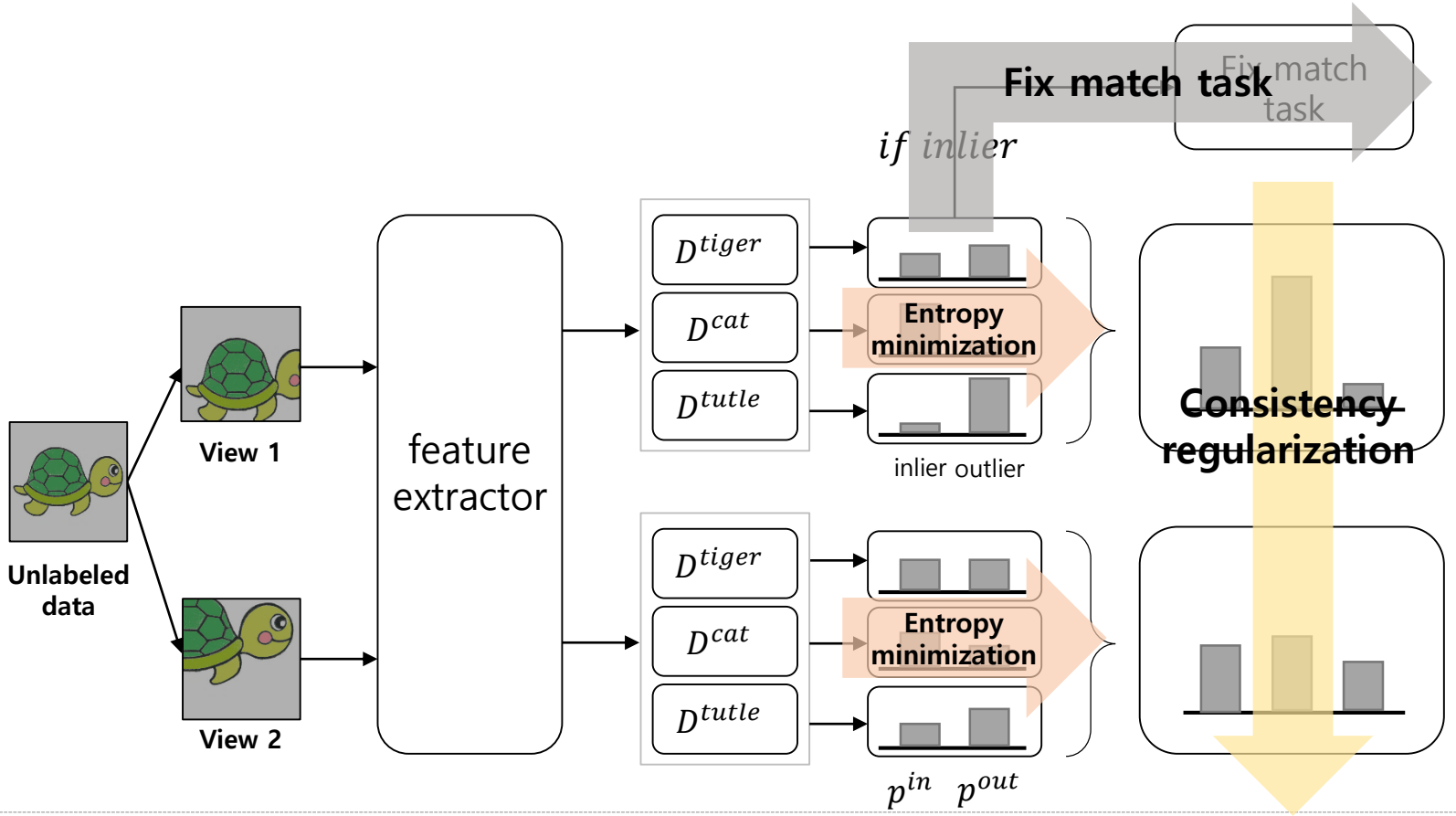
OpenMatch: Open-set Consistency Regularization for Semi-supervised Learning with Outliers

❖ Overall Framework

- 총 5개의 task를 통해 모델을 학습

  → Unlabeled data를 활용한 task : Entropy minimization & Consistency regularization & Fixmatch task



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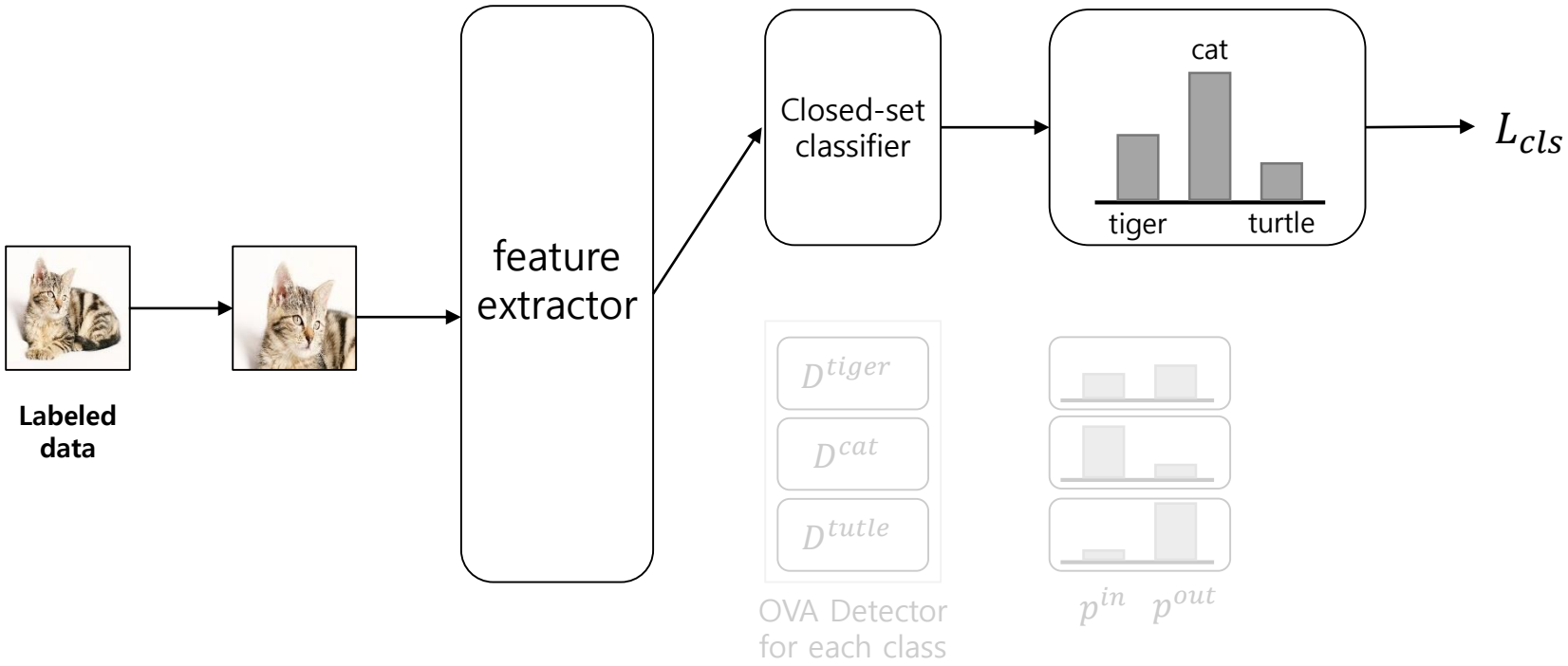
❖ Classification task with labeled data

- Labeled data를 통해서 일반적인 classification task 진행
- Target과 prediction간의 cross-entropy를 loss로 활용 (L_{cls})
- 모델이 이미지의 class를 잘 구분하도록 학습



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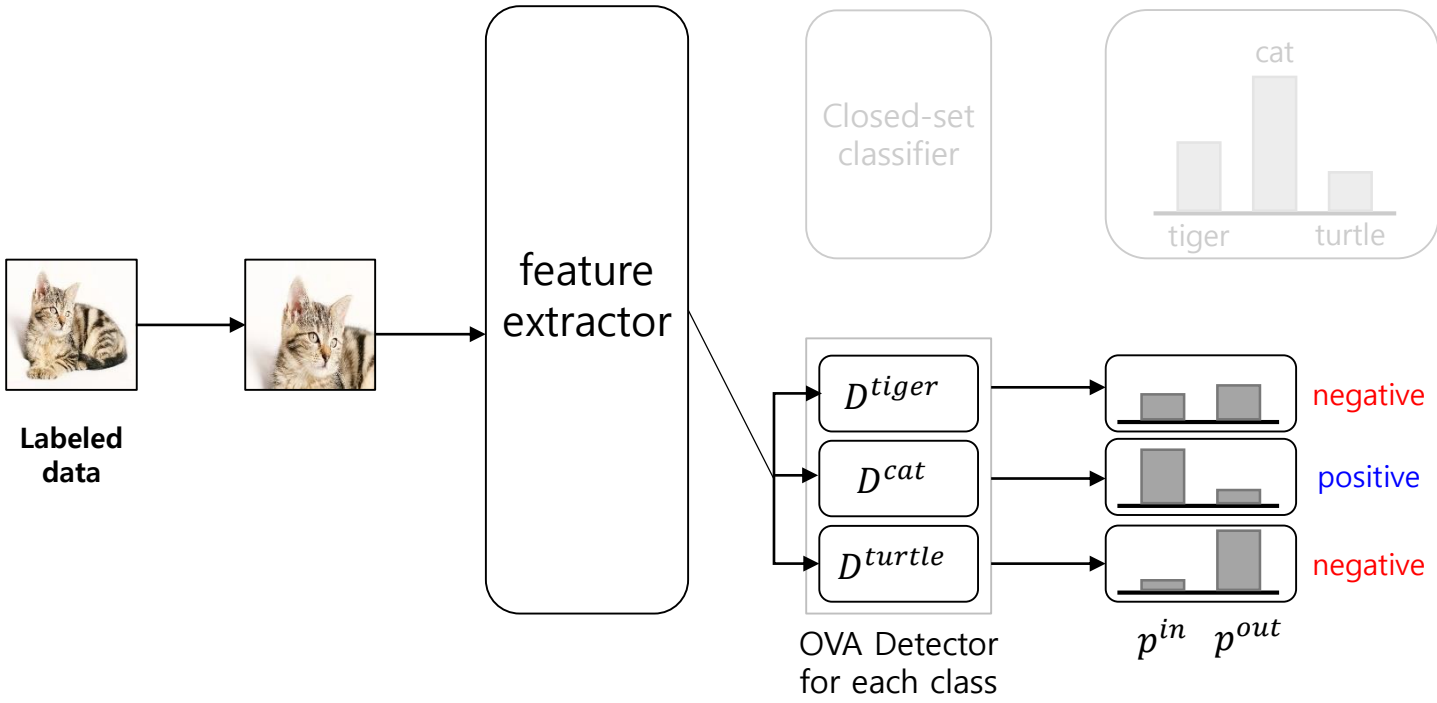
❖ Outlier detection task with labeled data using OVA detectors

- 각 class마다 MLP로 detector를 생성하며 labeled data를 통해서 detection task 진행
- 각 detector는 입력된 이미지가 같은 class인지(inlier) 아닌지(outlier) 구분할 수 있도록 학습
- 같은 class detector logit값을 positive로 나머지 class detector logit값을 negative로 정의



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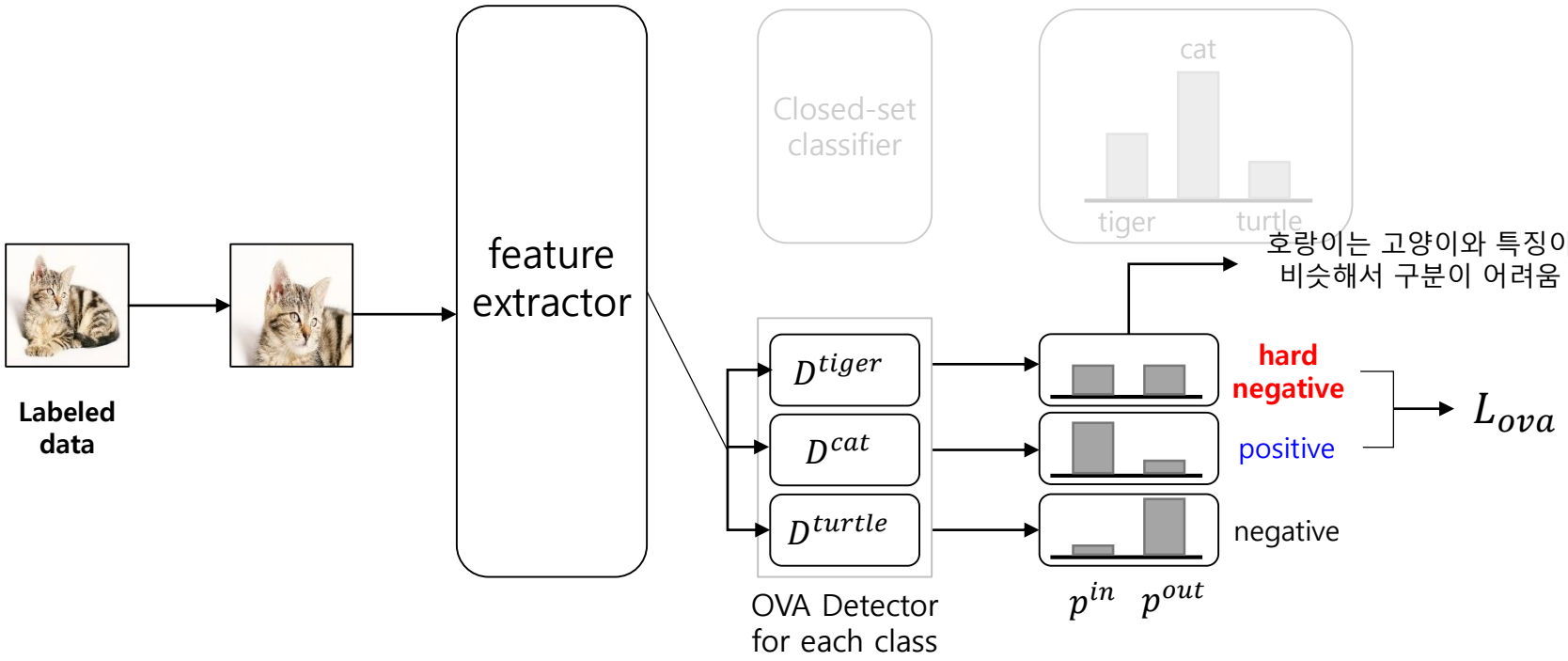
❖ Outlier detection task with labeled data using OVA detectors

- 본 연구에서는 유사한 class와의 결정 경계를 compact하게 만드는 것이 중요하다고 가정하고 Hard Negative Classifier Sampling (HNCS) 기법을 제안
- 다른 class detector의 p^{in} 이 크다는 것은 입력 class와 유사도가 크다는 의미이기 때문에 **hard negative**로 정의



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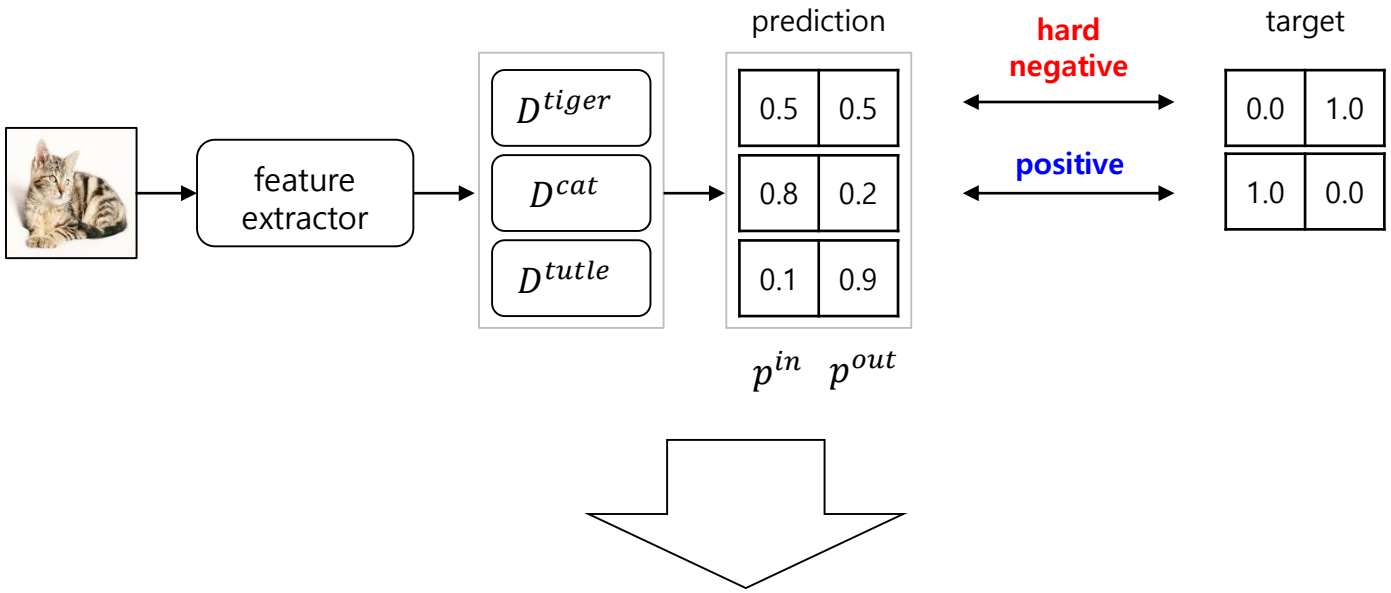
❖ Outlier detection task with labeled data using OVA detectors

- **hard negative**와 **positive**의 log likelihood를 최대화하여 **hard negative**와 **positive**를 잘 구분하도록 학습



$$L_{ova}(x^k, y^k) = -\log(p_k^{in}) - \min_{c \neq k} \log(1 - p_c^{in})$$

Positive는 1, Negative 중 가장 헷갈리는 것은 0 이 되도록 학습
k & c = class

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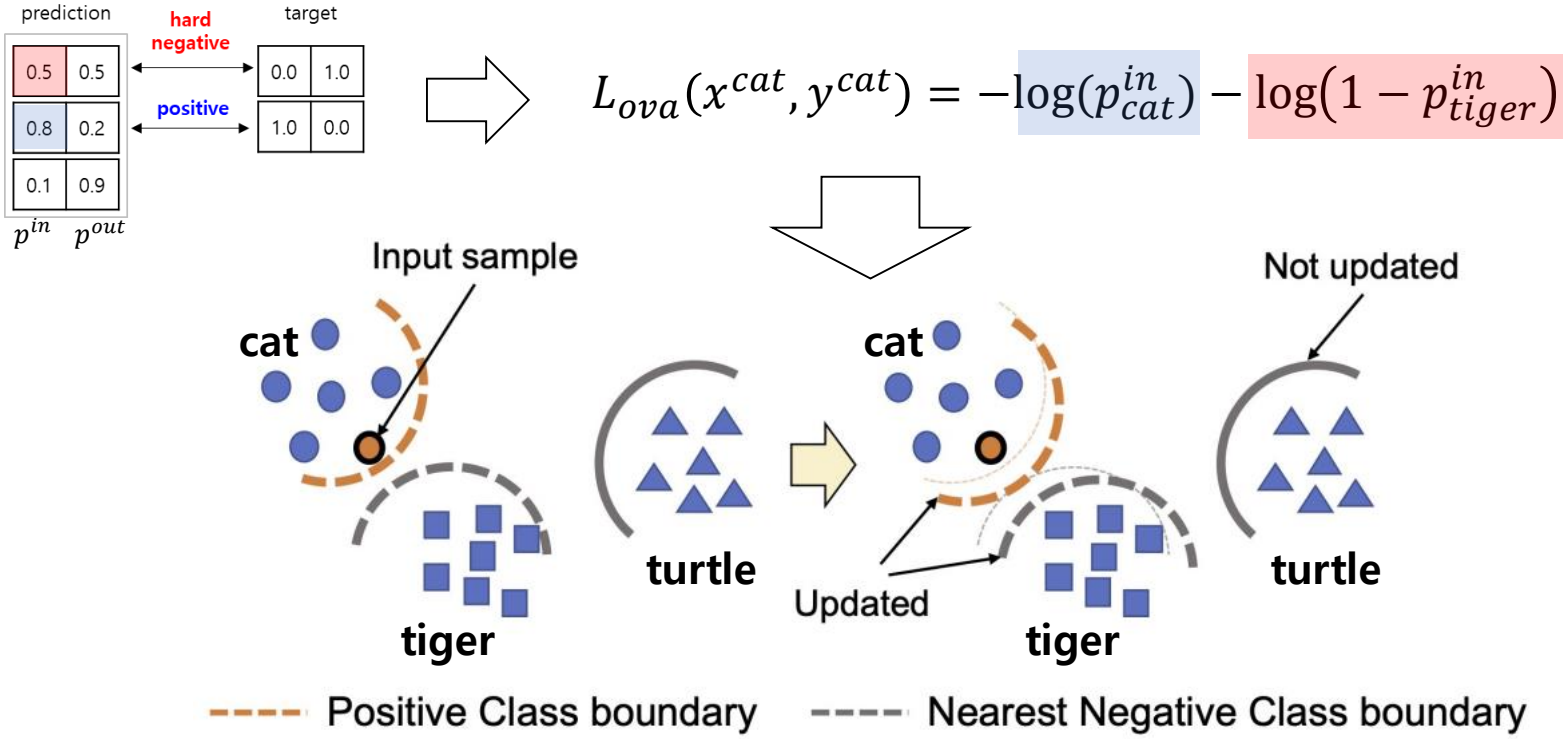
❖ Outlier detection task with labeled data using OVA detectors

- 고양이가 입력으로 들어온다면 cat detector의 logit이 **positive**
- tiger detector의 p^{in}이 가장 크기 때문에 **hard negative**이며 실제로 고양이와 호랑이는 비슷한 특징을 가짐
- 결과적으로 cat과 tiger의 결정 경계가 더 compact하게 업데이트



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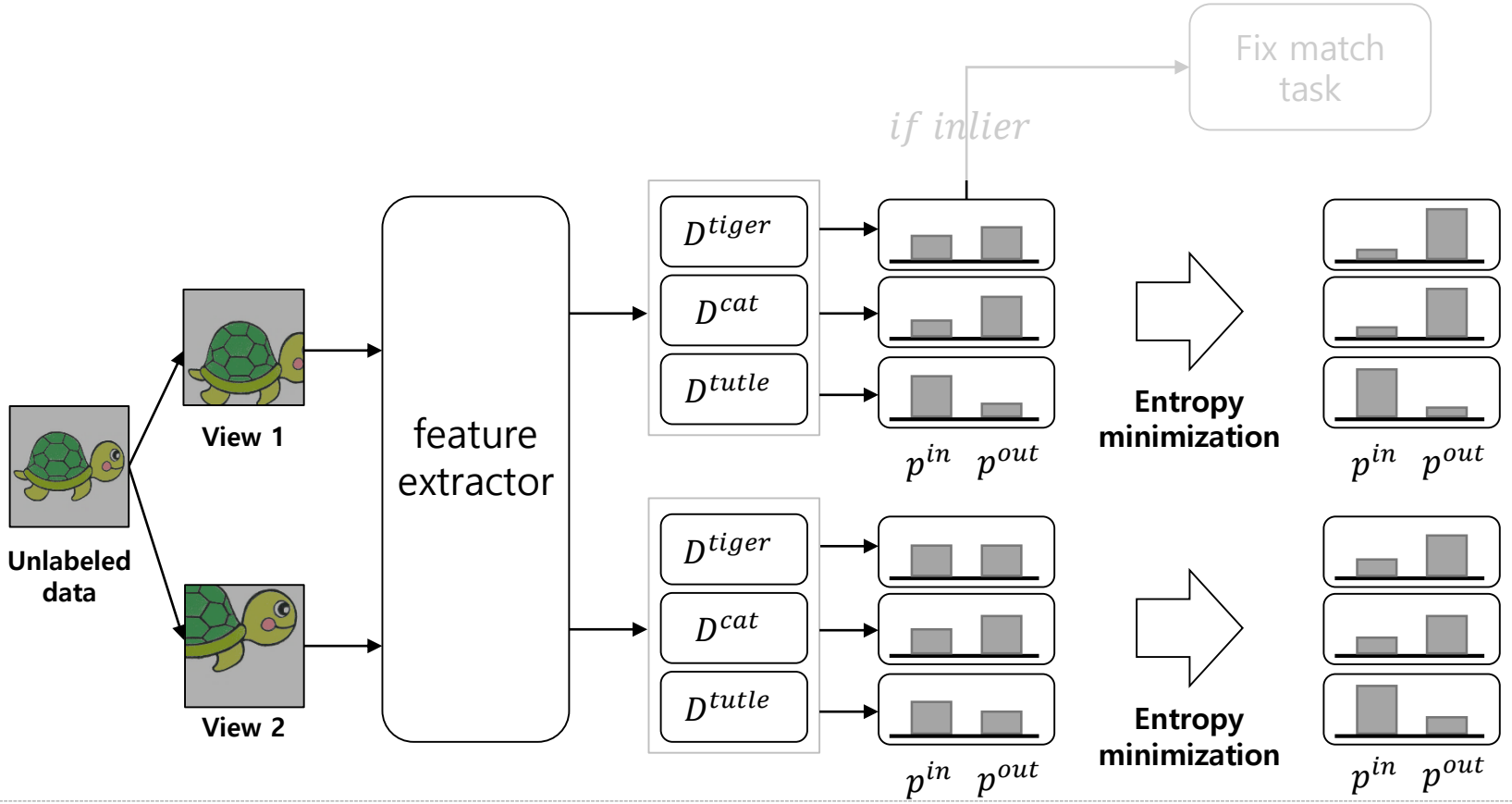
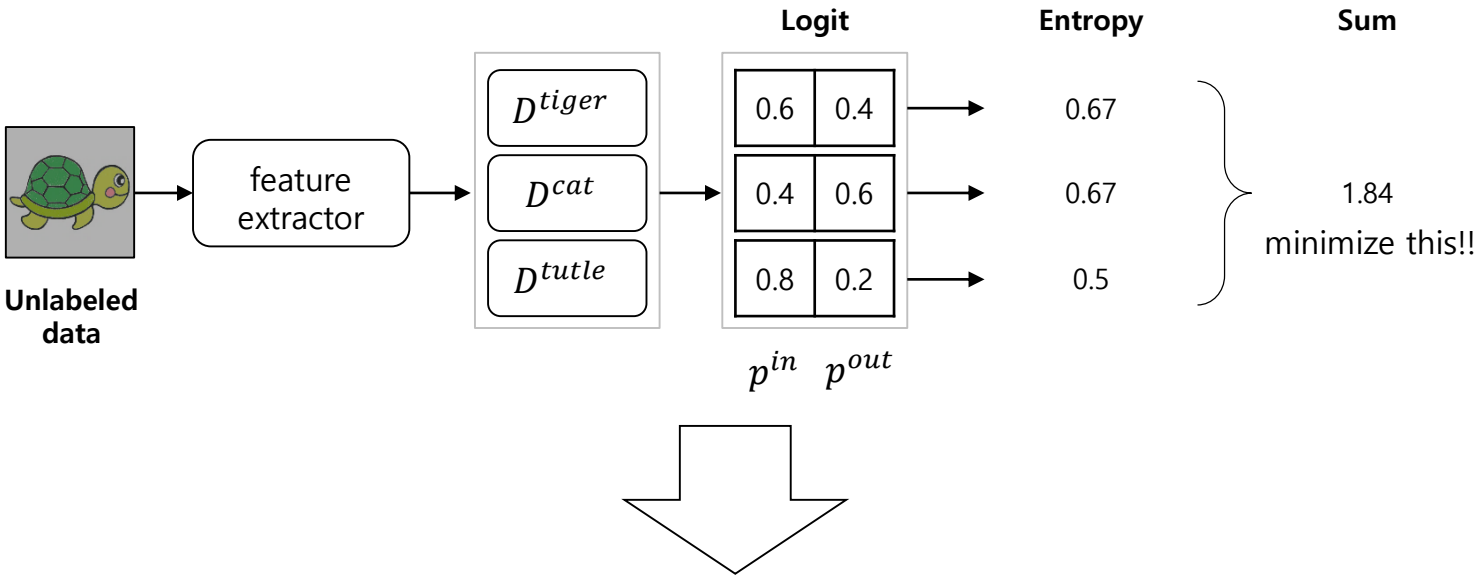
❖ Open-set Entropy Minimization

- unlabeled data에 대한 class별 detector의 logit값을 sharp하게 만들기 위해 open-set entropy minimization (OME) 제안



❖ Open-set Entropy Minimization

- unlabeled data에 대한 class별 detector의 logit값을 sharp하게 만들기 위해 open-set entropy minimization (OME) 제안
- 각 class별 detector가 입력된 unlabeled data에 대해 **inlier와 outlier의 구분을 확실하게** 하도록 학습



$$L_{ome}(u) = \sum_{k} p_k^{in} * \log(p_k^{in}) + p_k^{out} * \log(p_k^{out})$$

Class k detector logit에 대한 entropy

모든 detector logit에 대한 entropy 합

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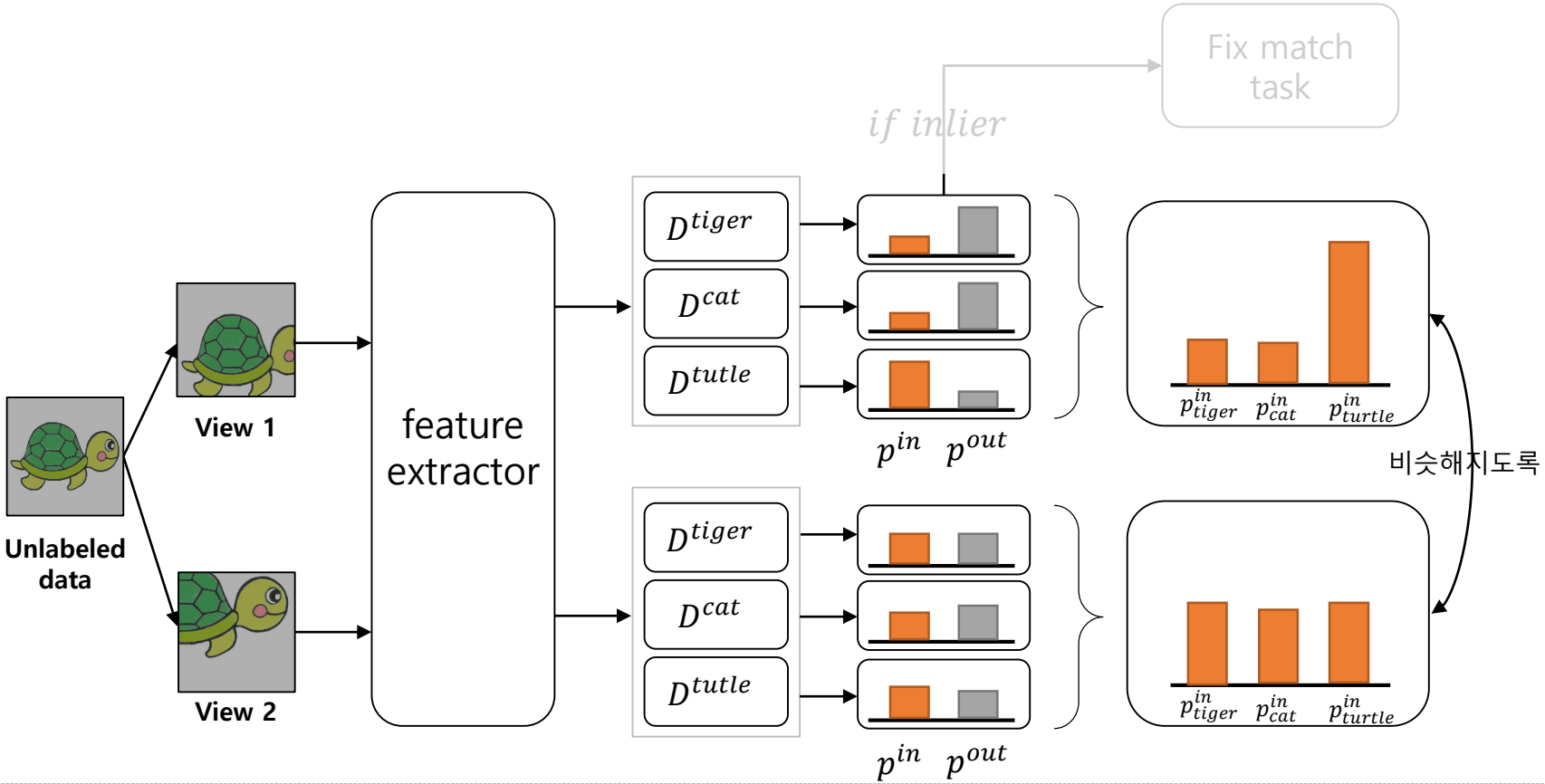
❖ Soft Open-set Consistency Regularization

- 입력된 unlabeled data가 변형되어도 비슷한 detection logit을 가질 수 있도록 consistency regularization 수행



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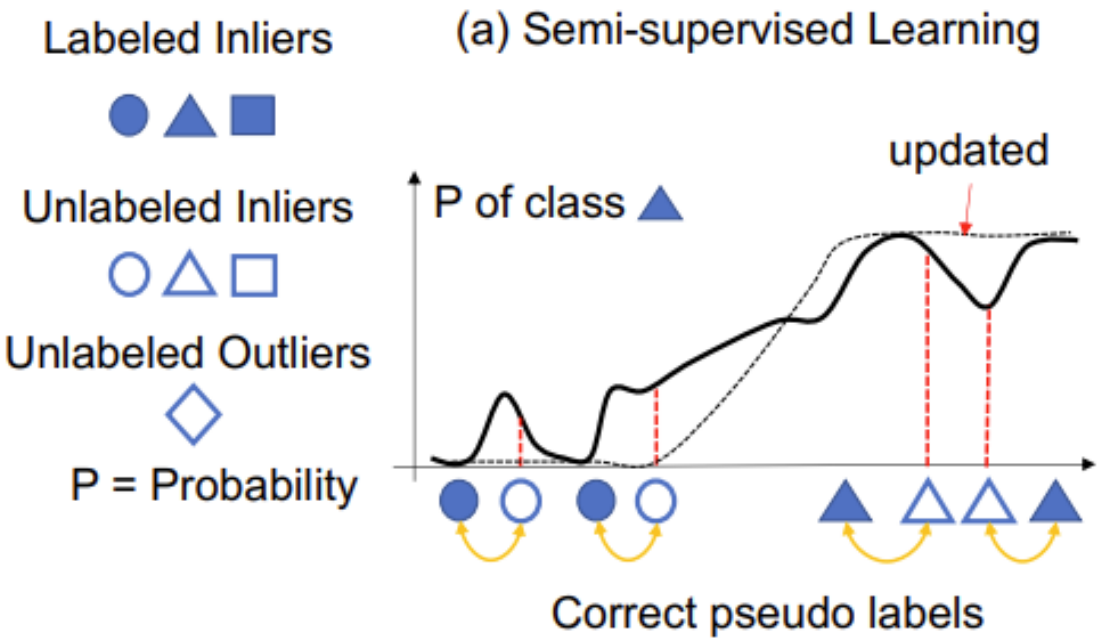
❖ Soft Open-set Consistency Regularization

- 일반적인 closed-set SSL에서 unlabeled data에 대해 가장 가까운 labeled data의 class를 비슷하게 하는 (ex. Pseudo labeling) hard consistency regularization은 unlabeled data에 효과적으로 label propagation을 할 수 있게 해줌



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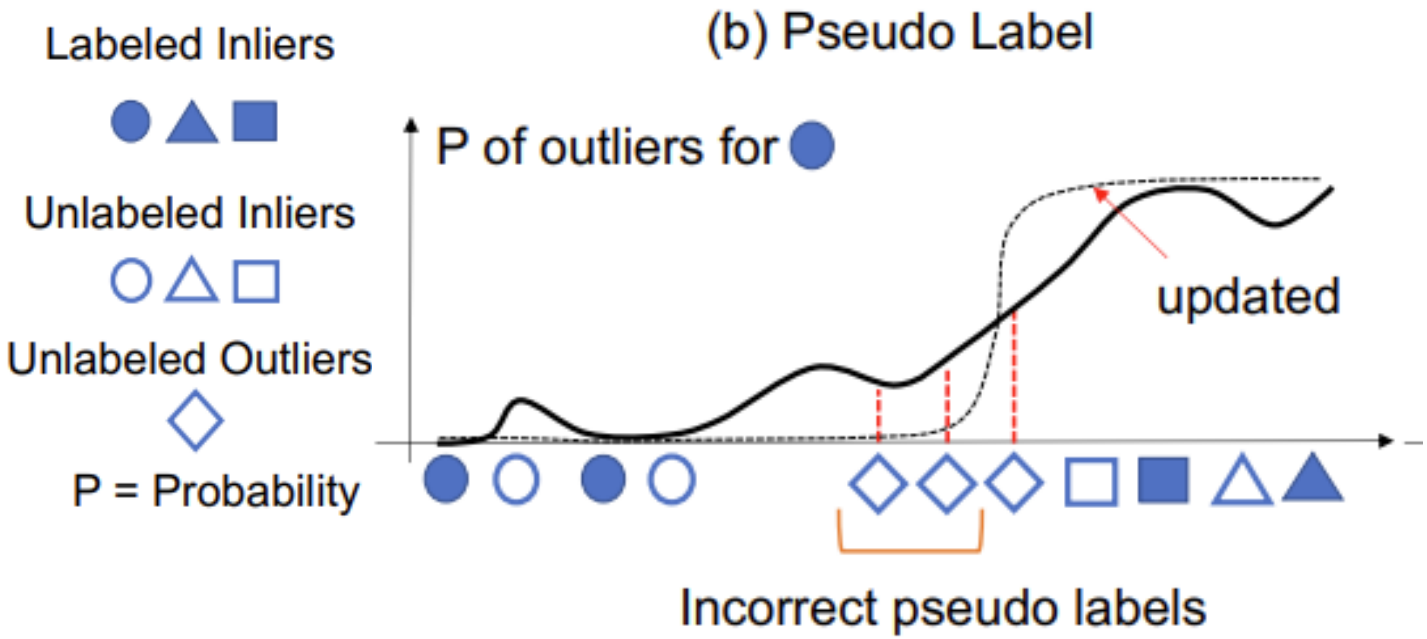
❖ Soft Open-set Consistency Regularization

- 하지만 open-set SSL에서 unlabeled outlier는 가장 가까운 labeled data가 항상 다른 class이기 때문에 hard consistency regularization을 사용하면 잘못된 pseudo label(=pseudo inlier)을 가지게 됨

One-vs-All detector score



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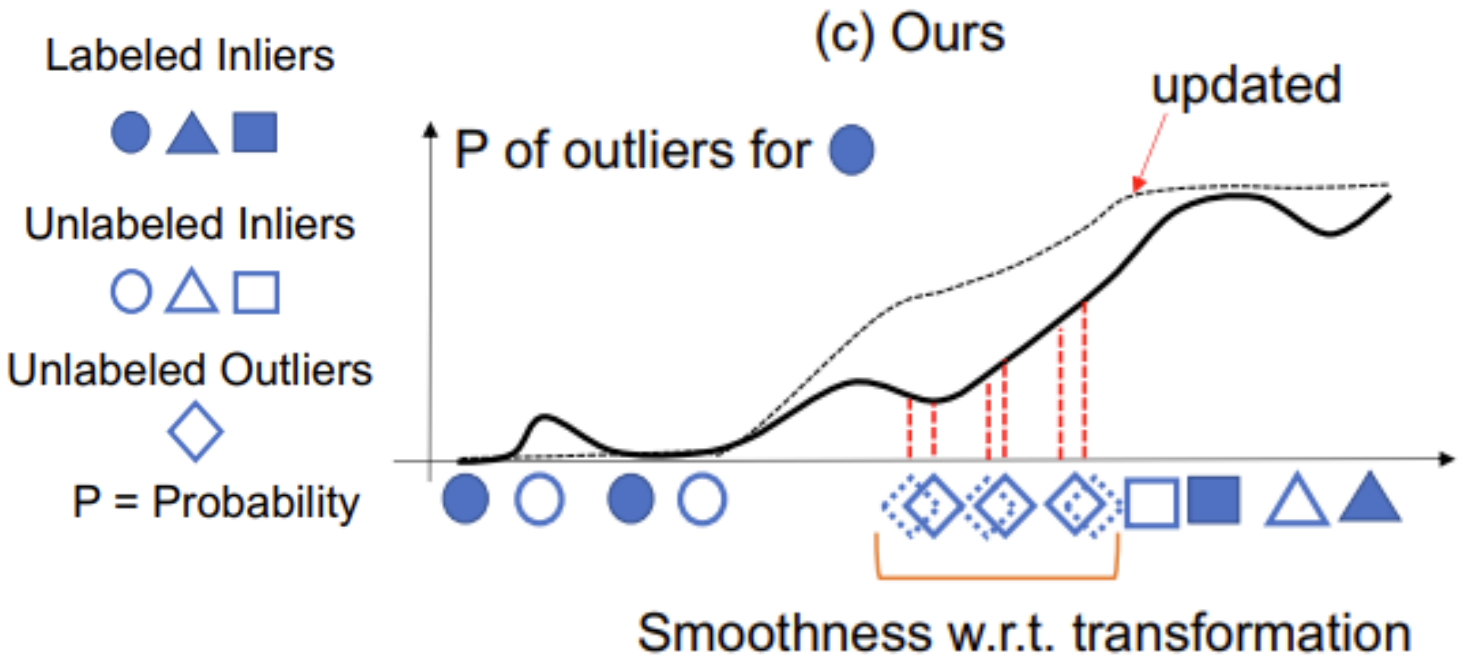
❖ Soft Open-set Consistency Regularization

- 본 연구에서는 이 문제를 해결하기 위해 soft logit을 사용하는 soft open-set consistency regularization (SOCR) 제안
- 또한 data transformation을 활용하여 outlier detector의 smoothness를 강화하고 잘못된 label propagation을 방지



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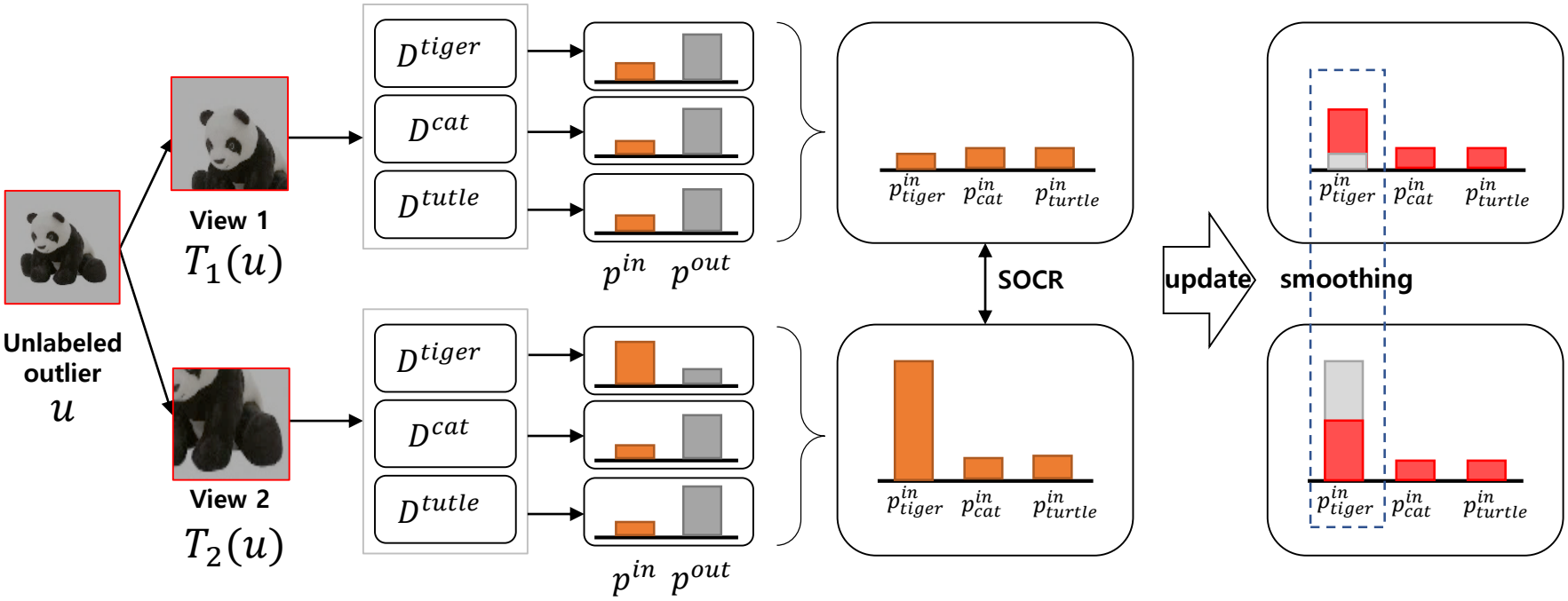

$$L_{oc}(u,T) = \sum_{k} \sum_{s\in(in,out)} \left| p_k^s(T_1(u)) - p_k^s(T_2(u)) \right|^2$$

view1,2의 class k detector에 대한 p^{in}/p^{out}의 MSE

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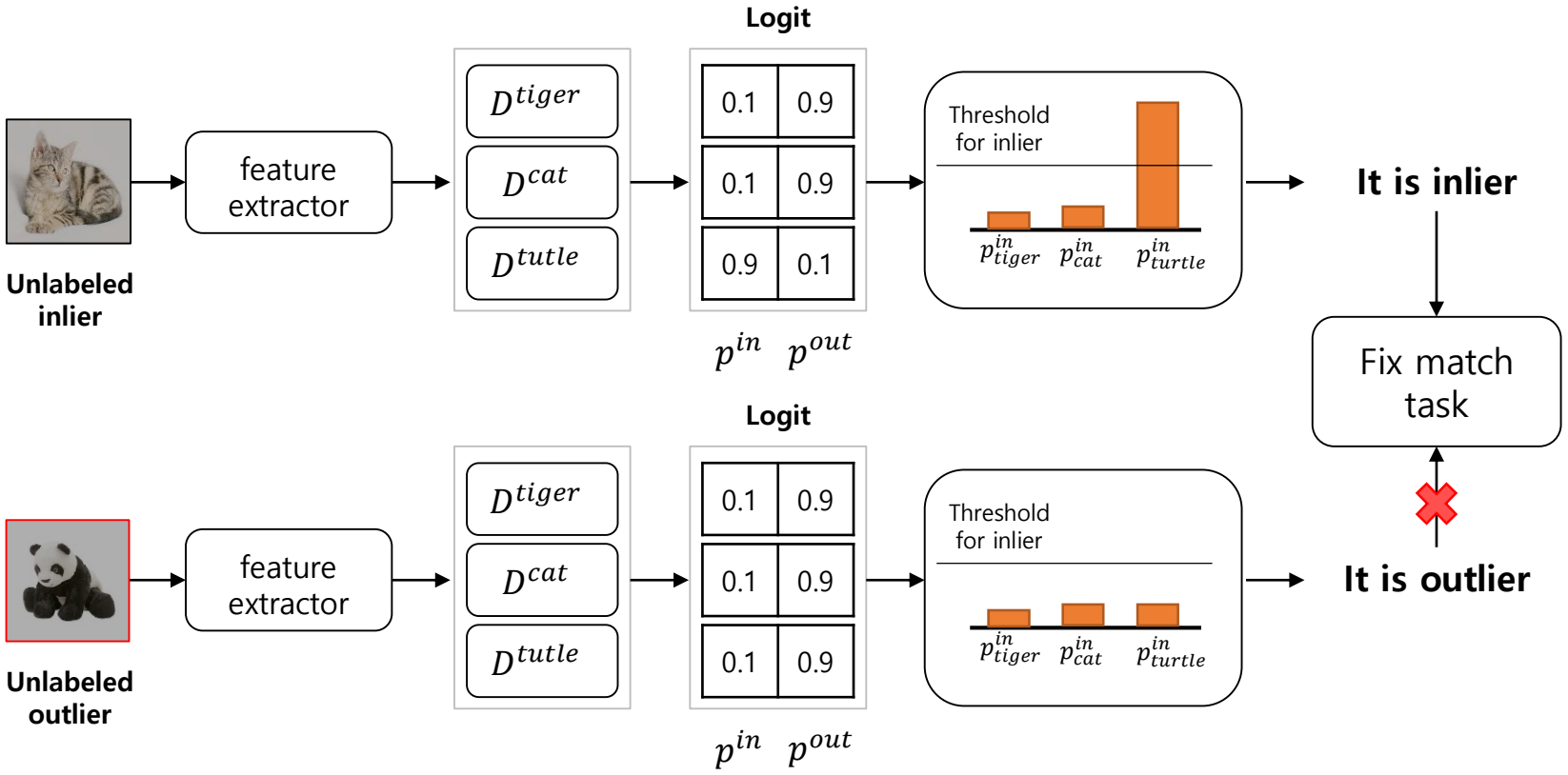
❖ Fixmatch task

- 학습된 OVA detector들을 이용해 unlabeled data의 inlier/outlier 유무를 파악(threshold = 0.5)
- Inlier로 판단된 unlabeled data는 일반적인 fixmatch task를 수행
- 학습 초기에는 OVA detector가 잘 작동하지 않기 때문에 특정 에폭 이후 fixmatch 적용



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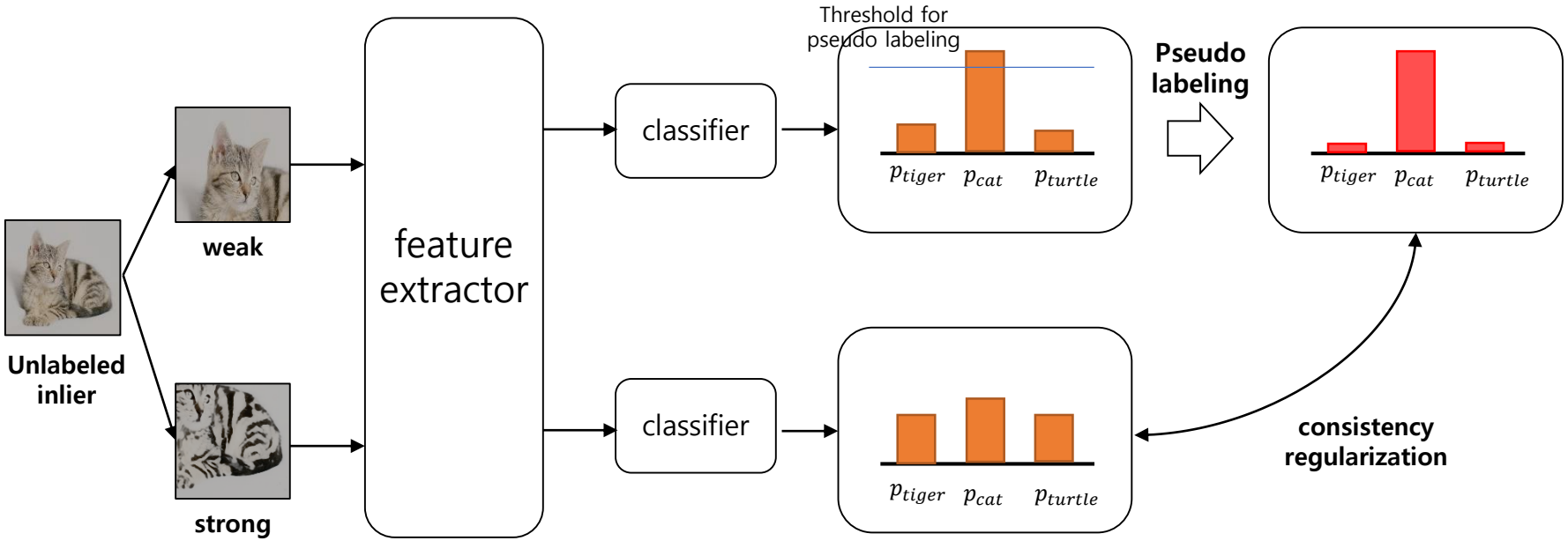

Fixmatch task framework

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❖ Overall Algorithms

- Fixmatch task를 제외한 4개의 task를 통해 OVA detectors를 어느정도 학습한 후, fixmatch task까지 추가해서 학습

Algorithm 1 OpenMatch Algorithm.

Input: Set of labeled data $\mathcal{S} = \big((x_b, y_b); b \in (1, \ldots, N)\big)$, set of unlabeled data $\mathcal{S}_u = \big(u_b; b \in (1, \ldots, N_u)\big)$, and set of pseudo-inlier data $\mathcal{K} = \emptyset$.
Data augmentation function $\mathcal{T}$. Model parameters w, learning rate η, epoch E_{fix} and $E_{\max}$, iteration $I_{\max}$, trade-off parameters, $\lambda_{em}, \lambda_{oc}, \lambda_{fm}$;
for *Epoch = 1 to* $E_{\max}$ **do**
  for *Iteration = 1 to* $I_{\max}$ **do**
    Sample a batch of labeled data $\mathcal{X} \in \mathcal{S}$ and unlabeled data $\mathcal{U} \in \mathcal{S}_u$;
    Compute $\mathcal{L}_{all} = \mathcal{L}_{sup}(\mathcal{X}) + \lambda_{em}\mathcal{L}_{em}(\mathcal{U}) + \lambda_{oc}\mathcal{L}_{oc}(\mathcal{U}, \mathcal{T})$; // Eq.1, 2 and 3
    if $Epoch > E_{fix}$ **then**
      Sample a batch of pseudo-inliers $\mathcal{I} \in \mathcal{K}$; // Sample pseudo-inliers.
      Compute $\mathcal{L}_{all} \mathrel{+}= \lambda_{fm}\mathcal{L}_{fm}(\mathcal{I})$; // FixMatch for pseudo-inliers.
    end
    Update $w = w - \eta\nabla_w L_{all}$; // Update weights
  end
  if $Epoch \geq E_{fix}$ **then**
    Update $\mathcal{K} = \text{Select}(w, \mathcal{D}_u)$; // Detect outliers and select pseudo-inliers.
  end
end
Output: Model parameters w.

$L_{cls} + L_{ova}$: classification task & outlier detection task using labeled data

SORC using unlabeled data

Entropy minimization using unlabeled data

OVA detector가 어느정도 학습이 된 후 fixmatch task 진행

Paper Review

OpenMatch: Open-set Consistency Regularization for Semi-supervised Learning with Outliers

❖ Experiments

- CIFAR10, CIFAR100, ImageNet-30를 통해 calssification error rate과 testset에 포함된 outlier탐지 성능(AUROC)을 평가
- 제안 방법론이 모든 데이터셋에서 훨씬 좋은 성능을 보이며 unknown도 잘 탐지함

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

Mismatch rate에 따른 실험
# of labeled data에 따른 실험

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 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

Mismatch rate에 따른 실험
# of labeled data에 따른 실험

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

OpenMatch: Open-set Consistency Regularization for Semi-supervised Learning with Outliers

❖ Experiments

- SOCR의 효과를 검증하기 위한 ablation study로 SOCR의 효과만을 보기 위해 fixmatch task는 수행하지 않음
- SOCR를 사용했을 때 큰 성능 향상을 보임

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±2.8	75.8±0.8	70.4±0.1	73.2±0.2	81.3±0.4
with SOCR	**81.3**±2.9	**96.8**±0.6	**78.9**±0.1	**85.0**±0.8	**89.3**±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.

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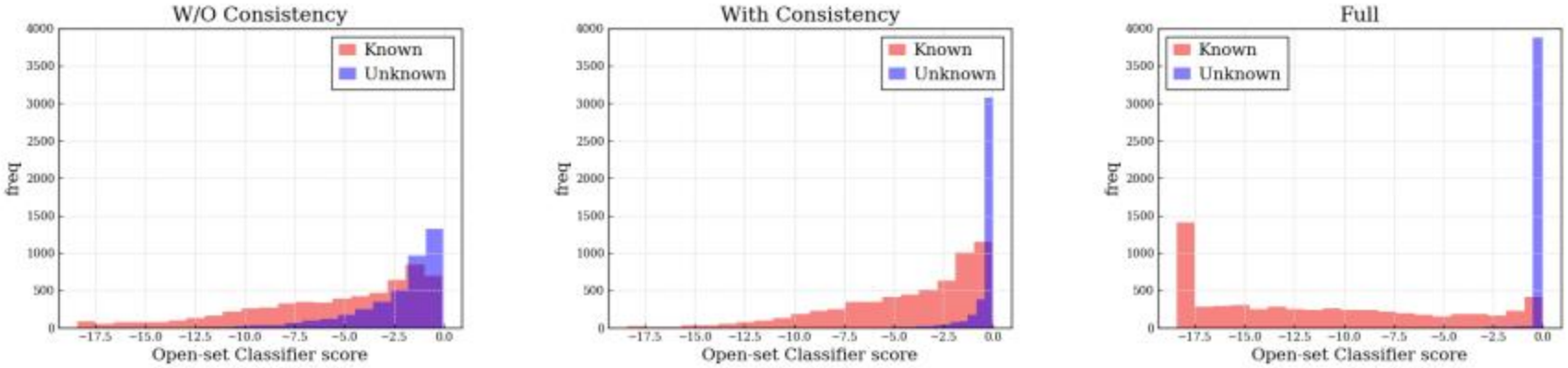
OpenMatch: Open-set Consistency Regularization for Semi-supervised Learning with Outliers

❖ Experiments

- SOCR의 효과를 검증하기 위한 outlier score 히스토그램 시각화(x축에서 오른쪽으로 갈수록 outlier일 확률이 상승)
- SOCR를 사용하면 대부분의 unknown을 outlier로 잘 분류하는 것을 볼 수 있음
- Fixmatch task를 추가하면 이 과정이 더 정교해지는 것을 확인(이유는 명확하지 않음)



(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.

OpenMatch: Open-set Consistency Regularization for Semi-supervised Learning with Outliers

❖ Experiments

- Openmatch의 representation capability를 보기 위한 t-SNE 시각화
- Openmatch가 unknown을 고려하여 representation을 생성하는 것을 볼 수 있음

(a) Partially labeled model (b) Fully labeled model (c) OpenMatch

Figure 4: Feature visualization with t-SNE [26]. Different colors indicate different classes. Pink dots represent outliers. (a): A model trained with 100 labeled samples per class. (b): A model trained with all labeled inliers. (c): A model trained with OpenMatch. (Best viewed in color)

Summary & Conclusions

OpenMatch: Open-set Consistency Regularization for Semi-supervised Learning with Outliers

❖ Summary

- 본 연구에서는 universal domain adaptation에 활용되는 OVA classifier를 open-set SSL 상황에 맞게 적용
- 각 클래스 별 OVA detector를 통해 unknown class까지 고려한 representation 학습을 진행
- 기존의 방법론보다 훨씬 우수한 성능을 보여줌

❖ Conclusions

- 좋은 아이디어와 심플한 방법으로 우수한 성능을 보여준 것은 좋음
- 하지만 SORC에 대한 설명이 부족하다고 생각함
- 또한, open-set entropy minimization의 효과를 검증할 수 있는 실험이 없음
- Class가 많아질수록 detector의 개수도 선형적으로 증가하기 때문에 large dataset에서 사용할 수 있을지 의문

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