DMQA Open Seminar (2023.08.18)

Introduction to Universal Domain Adaptation

Data Mining & Quality Analytics Lab.

정용태

발표자 소개

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- M. S. Student (2023.03 ~ Present)

❖ **Research Interest**

- Domain Adaptation
- Domain Generalization

❖ **Contact**

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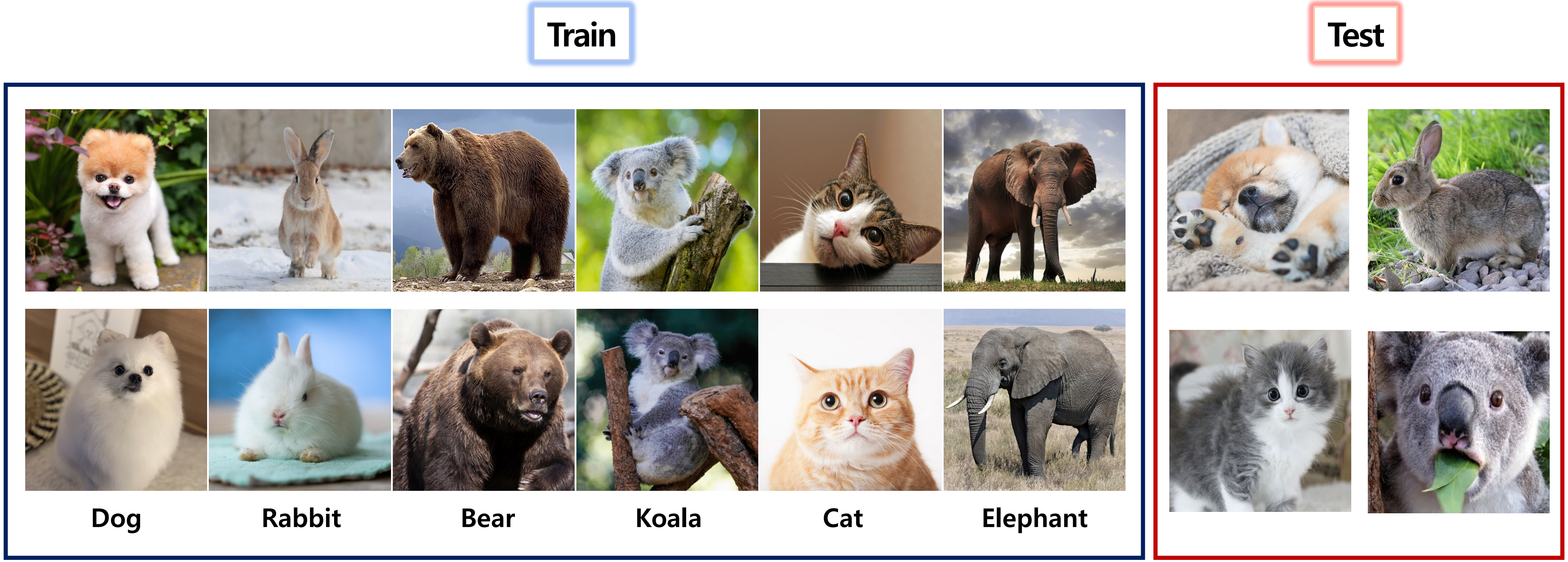
❖ Traditional Machine Learning

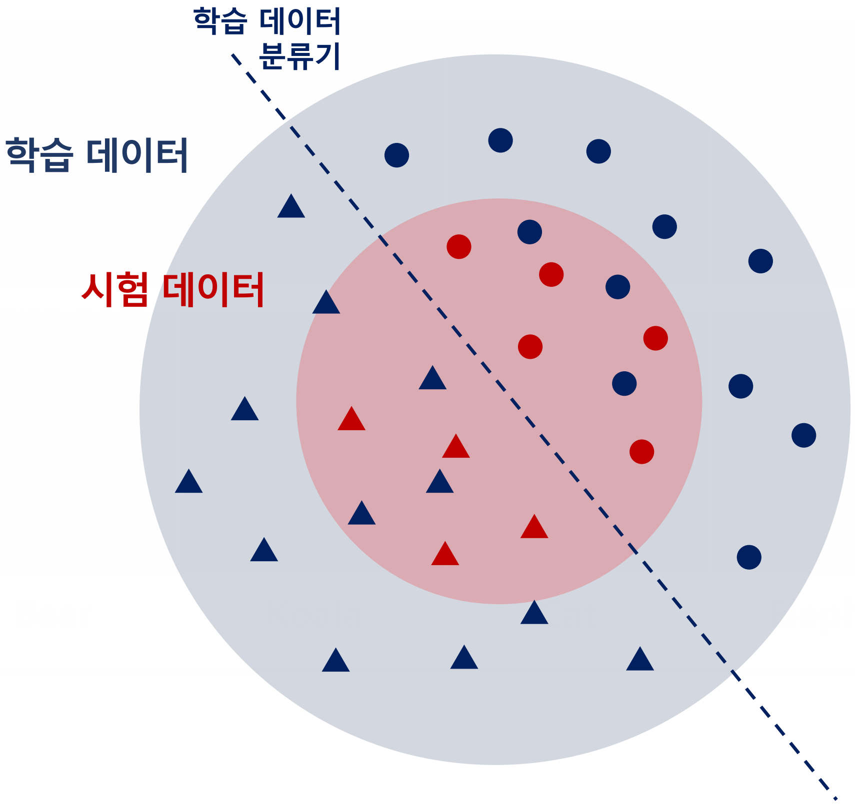


Introduction

Background of Universal Domain Adaptation

❖ Traditional Machine Learning

- 학습데이터와 시험데이터의 분포가 유사함
- 학습데이터를 통해 학습된 모델을 통해 시험 데이터를 예측하는 것이 가능함



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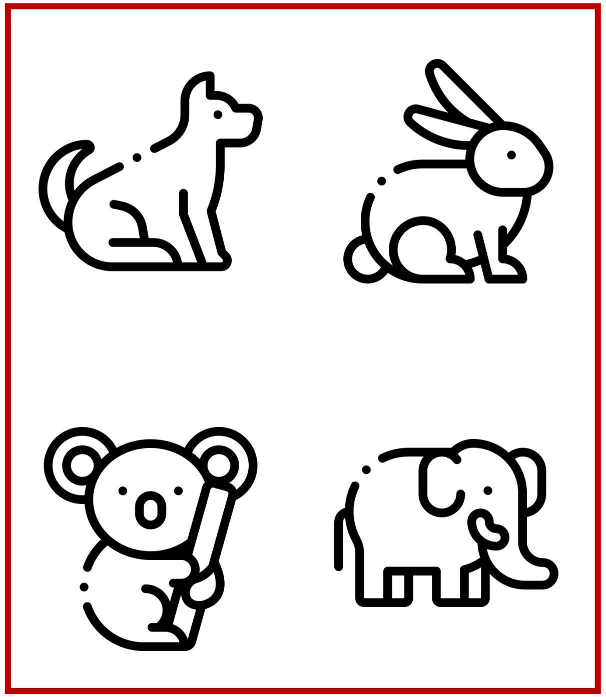
Background of Universal Domain Adaptation

❖ Domain Adaptation

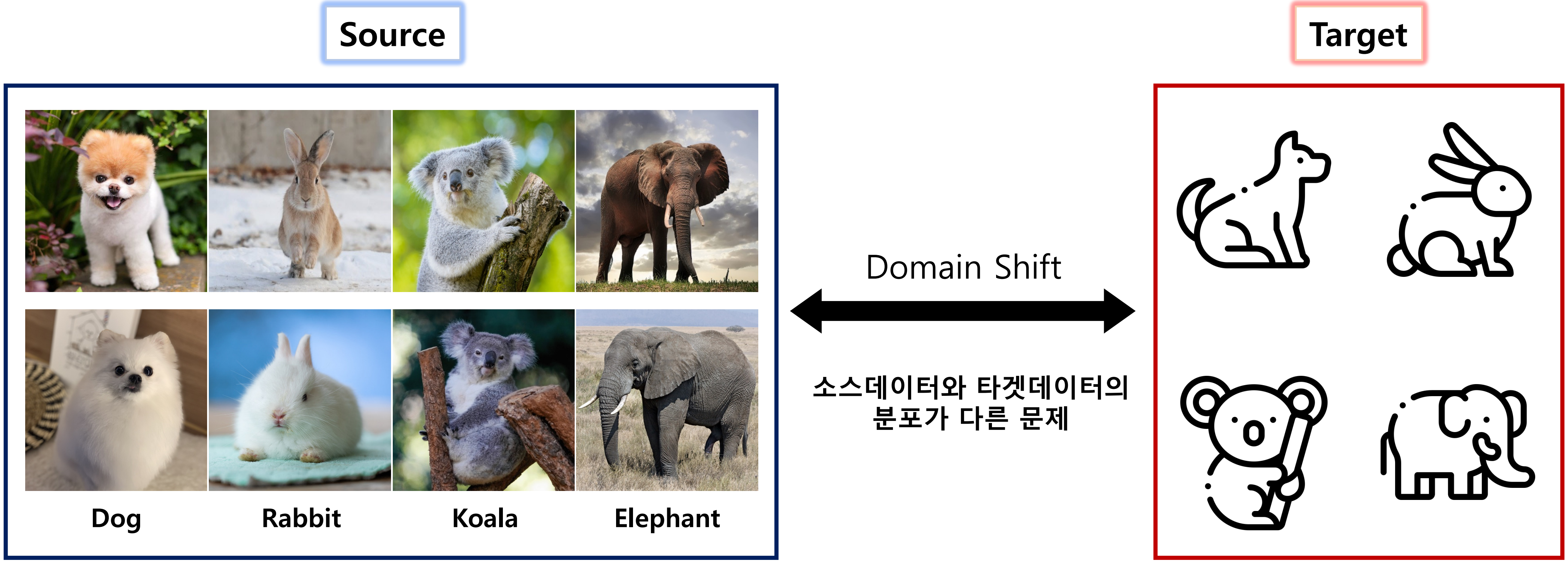
Train

Test



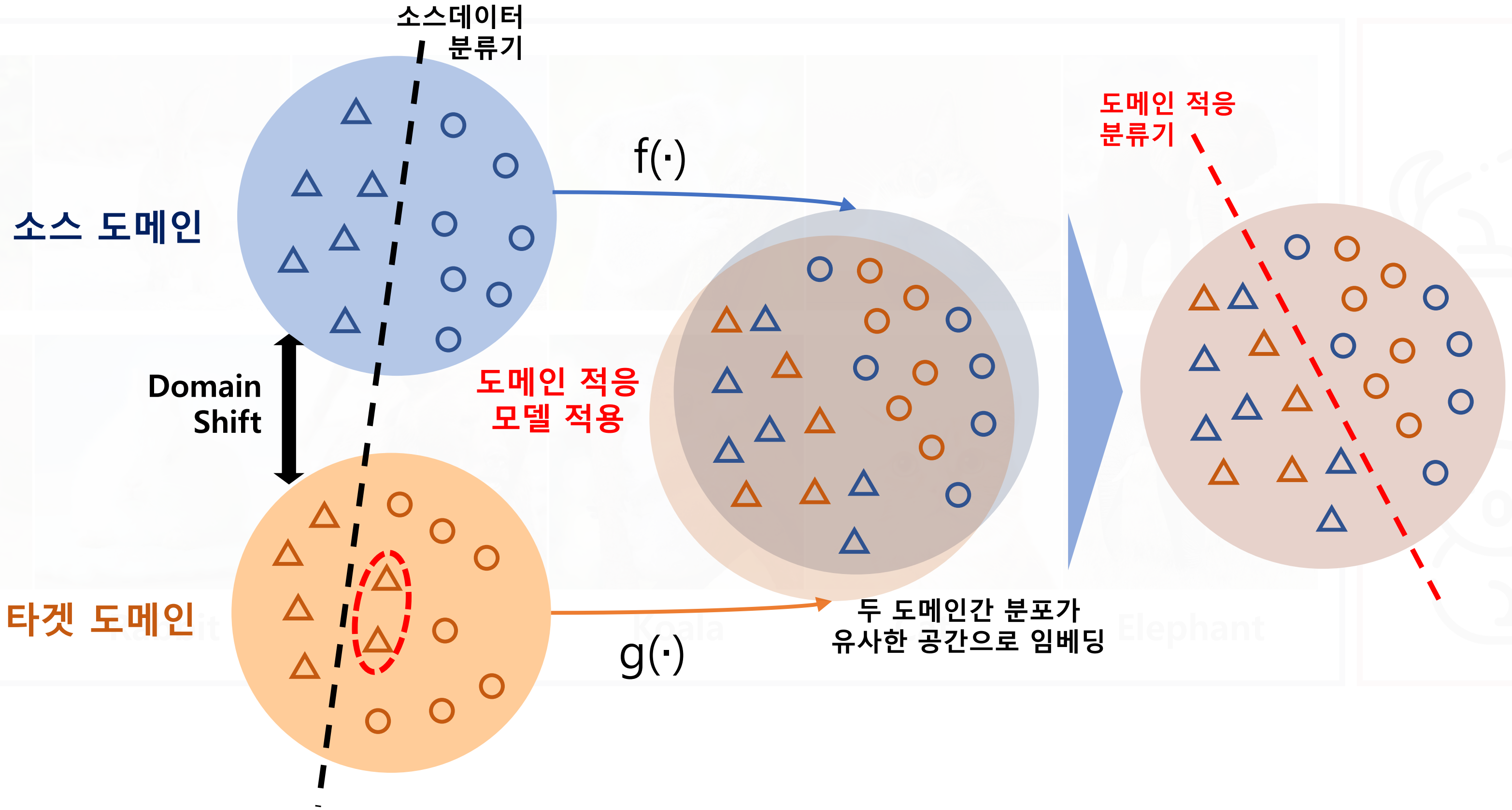
Background of Universal Domain Adaptation

❖ Domain Adaptation



❖ Domain Adaptation

- 소스데이터와 타겟데이터의 분포가 다르기 때문에, 소스데이터로 학습한 모델로 예측하는 것이 어려움
- 이에 따라 두 데이터의 분포가 유사해지도록 학습하여 타겟데이터에 대한 예측이 가능함



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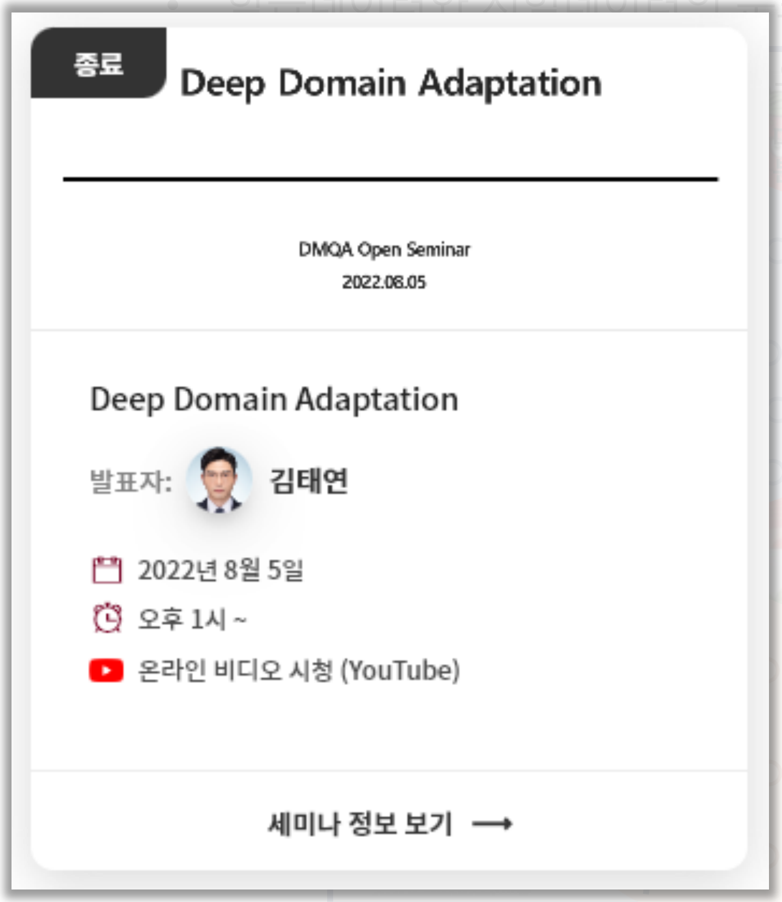
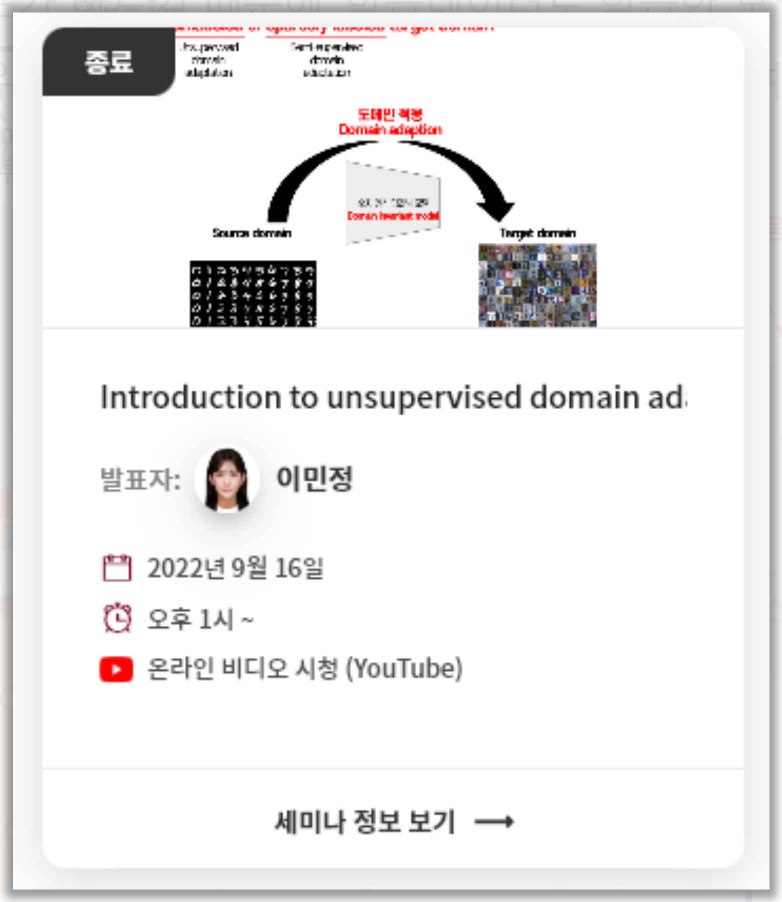
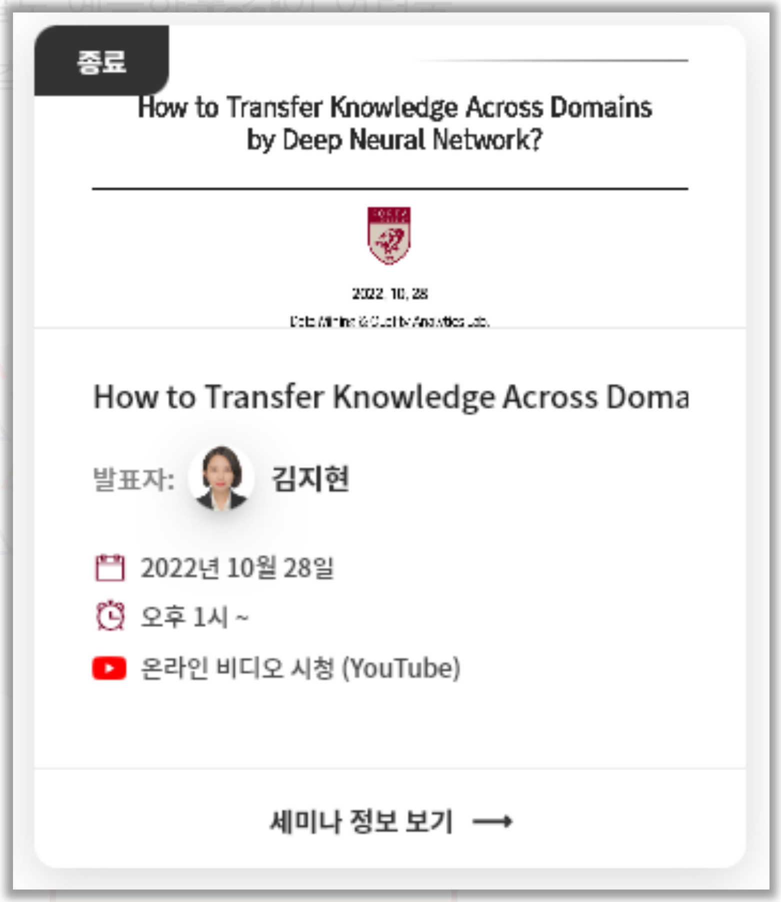
Background of Universal Domain Adaptation

❖ Domain Adaptation







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Background of Universal Domain Adaptation

❖ Limitation of Domain Adaptation

- 소스도메인과 타겟도메인의 Class의 분포가 동일한 상황을 가정함

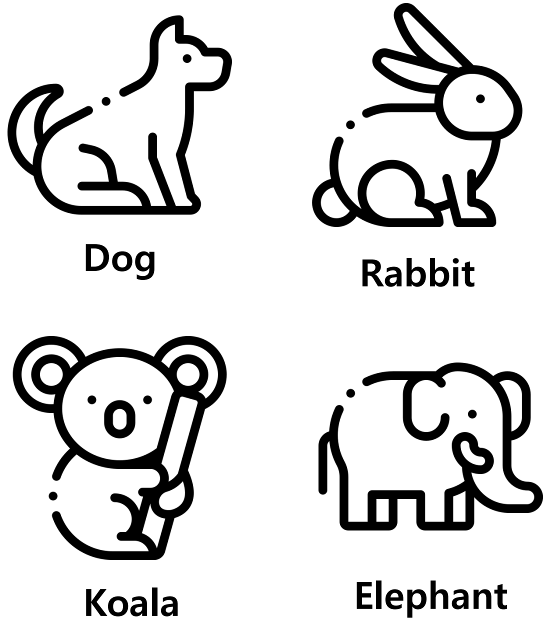
Source

Dog Rabbit Koala Elephant

Same Category

=

Target



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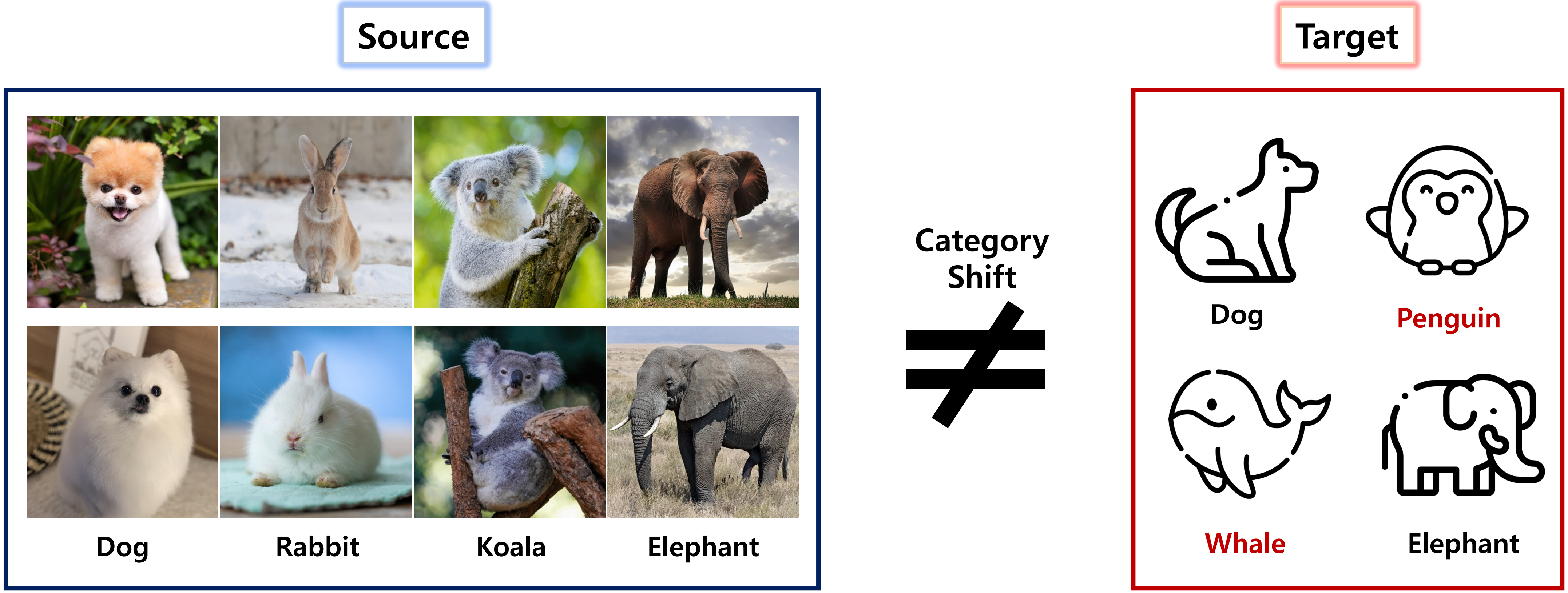
Background of Universal Domain Adaptation

❖ Limitation of Domain Adaptation

- 다양한 현실문제에서 소스도메인과 타겟도메인의 Class의 분포가 달라질 수 있음



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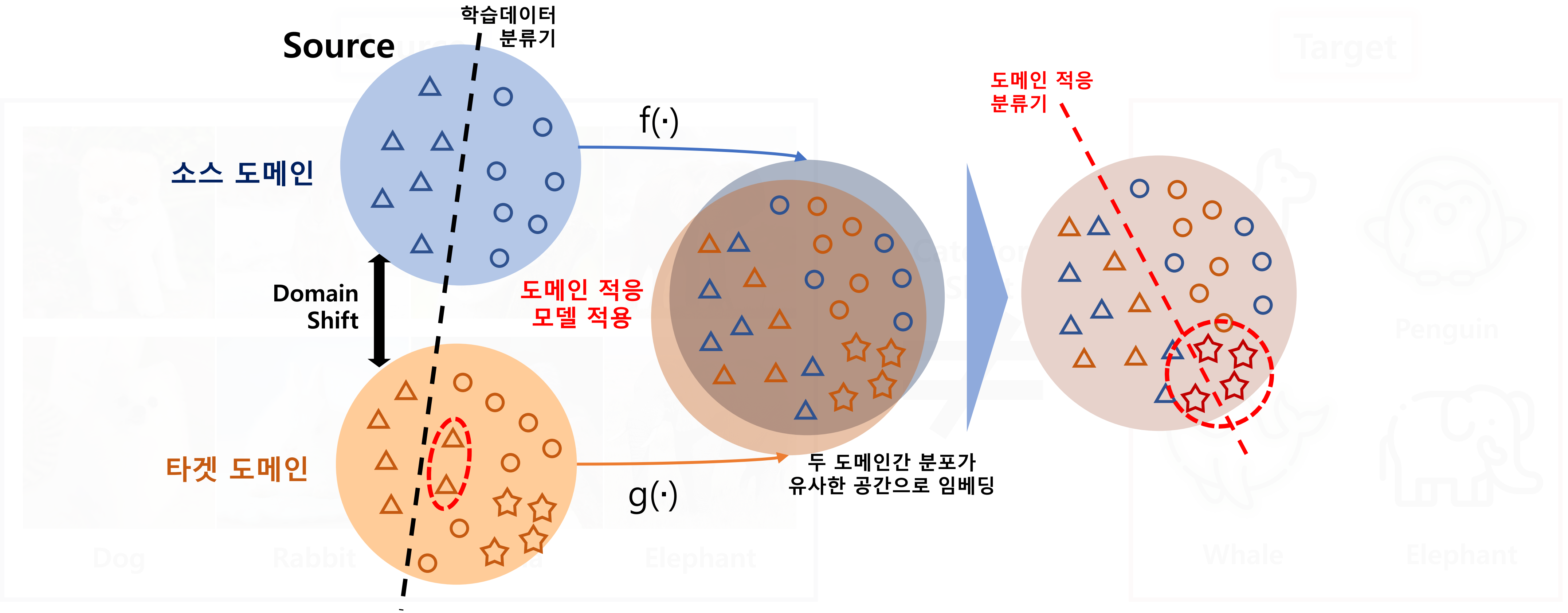

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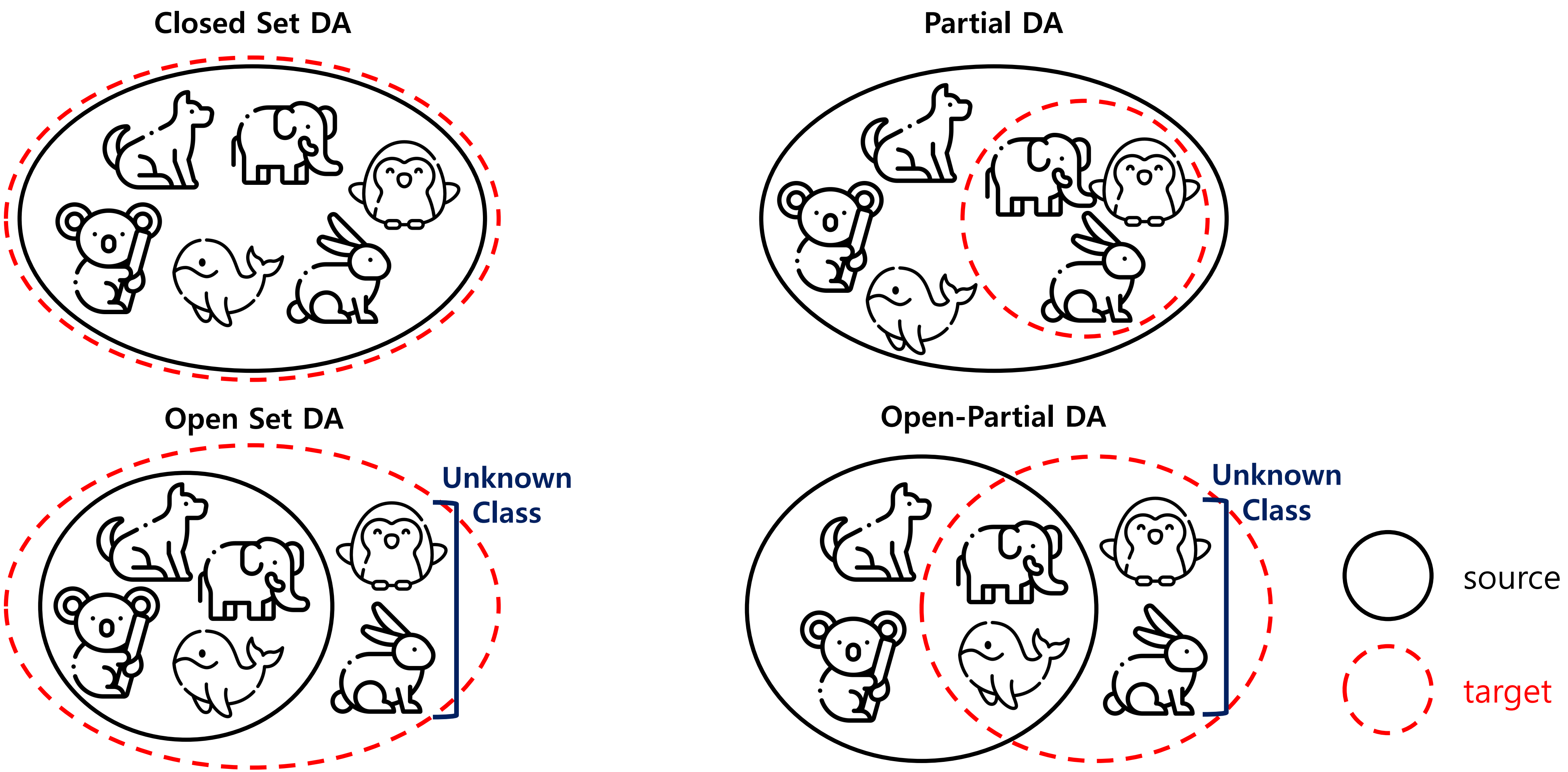
Background of Universal Domain Adaptation

❖ Existing Domain adaptation Setting[1]



[1] Saito, Kuniaki, et al. "Universal domain adaptation through self supervision." *Advances in neural information processing systems* 33 (2020): 16282-16292.

Introduction

Background of Universal Domain Adaptation

❖ Existing Domain adaptation Setting

- 타겟도메인의 레이블이 없는 상황에서 어떤 방법론을 사용할지 결정하는 것은 어려움

Background of Universal Domain Adaptation

Universal Domain Adaptation

모든 문제상황에 통합적으로 적용가능한 방법론

Introduction

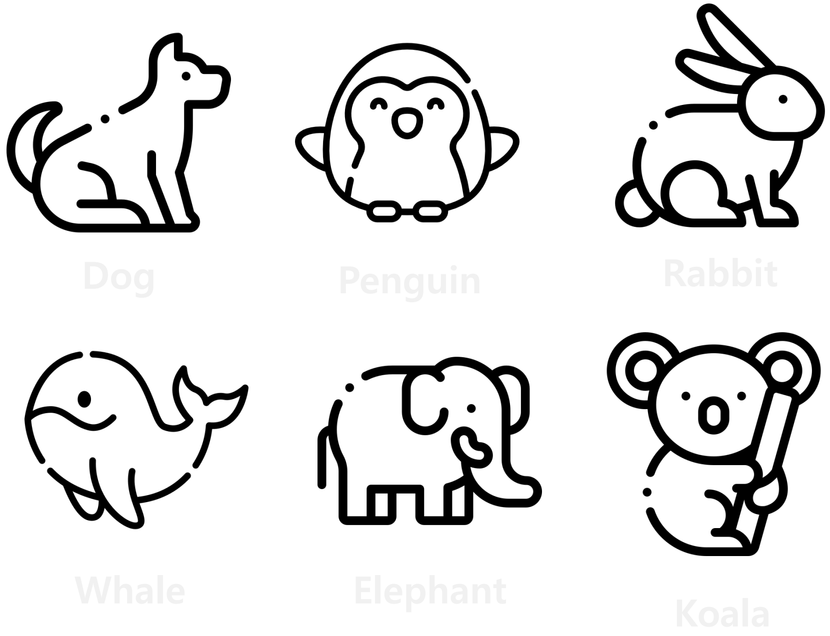
Preliminaries

❖ Problem Setting

$Source : D_s = \{(x_i^s, y_i^s)\} \sim p$

Dog Rabbit Koala Elephant

$Target : D_t = \{(x_i^t)\} \sim q$



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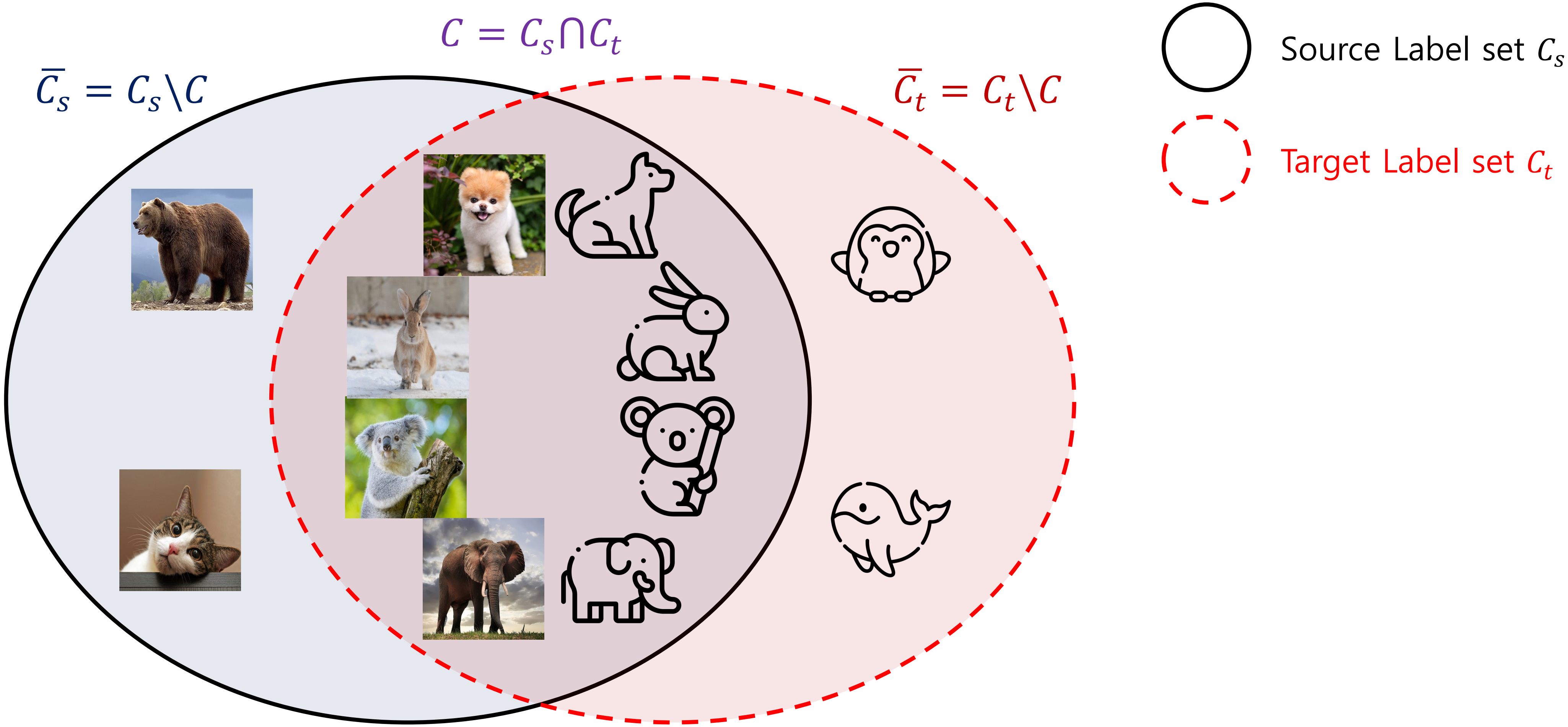
Preliminaries

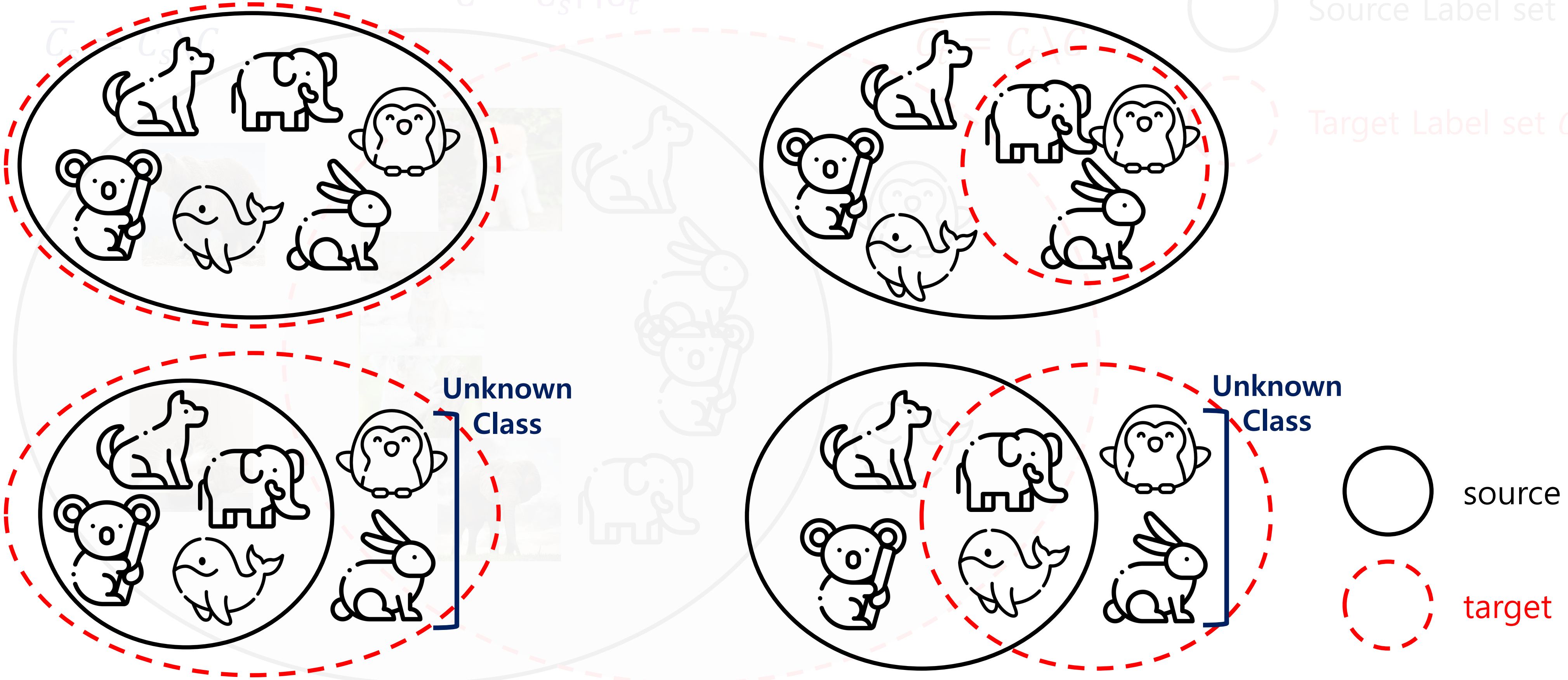
❖ **Problem Setting**



Introduction

Preliminaries

❖ Problem Setting



Introduction

Preliminaries

❖ Problem Definition

$$\textbf{Minimize}_h \; \mathbf{E}_{x^t, y^t \sim D_T} L(h(x), y)$$

타겟 도메인에 대한 분류 성능 향상

소스데이터와 공통된 Class는 해당 Class로 분류하고, Unknown Class는 Unknown으로 분류

Methods

Methods

1. Universal Domain Adaptation

❖ Universal Domain Adaptation[2]

- 2019년에 제안된 Universal Domain Adaptation 방법론(CVPR, 23년 8월 기준 349회 인용)
- Universal Domain Adaptation의 문제상황을 처음으로 제시한 논문

Universal Domain Adaptation

Kaichao You, Mingsheng Long, Zhangjie Cao, Jianmin Wang, Michael I. Jordan; Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 2720-2729

Abstract

Domain adaptation aims to transfer knowledge in the presence of the domain gap. Existing domain adaptation methods rely on rich prior knowledge about the relationship between the label sets of source and target domains, which greatly limits their application in the wild. This paper introduces Universal Domain Adaptation (UDA) that requires no prior knowledge on the label sets. For a given source label set and a target label set, they may contain a common label set and hold a private label set respectively, bringing up an additional category gap. UDA requires a model to either (1) classify the target sample correctly if it is associated with a label in the common label set, or (2) mark it as "unknown" otherwise. More importantly, a UDA model should work stably against a wide spectrum of commonness (the proportion of the common label set over the complete label set) so that it can handle real-world problems with unknown target label sets. To solve the universal domain adaptation problem, we propose Universal Adaptation Network (UAN). It quantifies sample-level transferability to discover the common label set and the label sets private to each domain, thereby promoting the adaptation in the automatically discovered common label set and recognizing the "unknown" samples successfully. A thorough evaluation shows that UAN outperforms the state of the art closed set, partial and open set domain adaptation methods in the novel UDA setting.

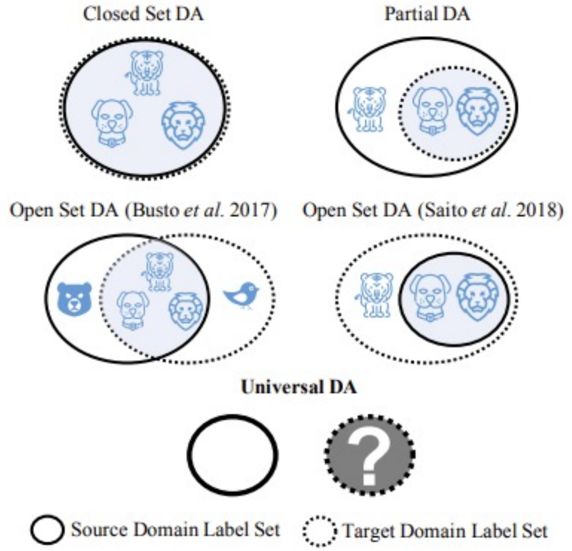


Figure 1. Universal Domain Adaptation (UDA) and existing domain adaptation settings with respect to label sets of source and target domains (blue shades indicate shared labels). Only UDA is able to deal with the setting that the label set of target domain is unknown.

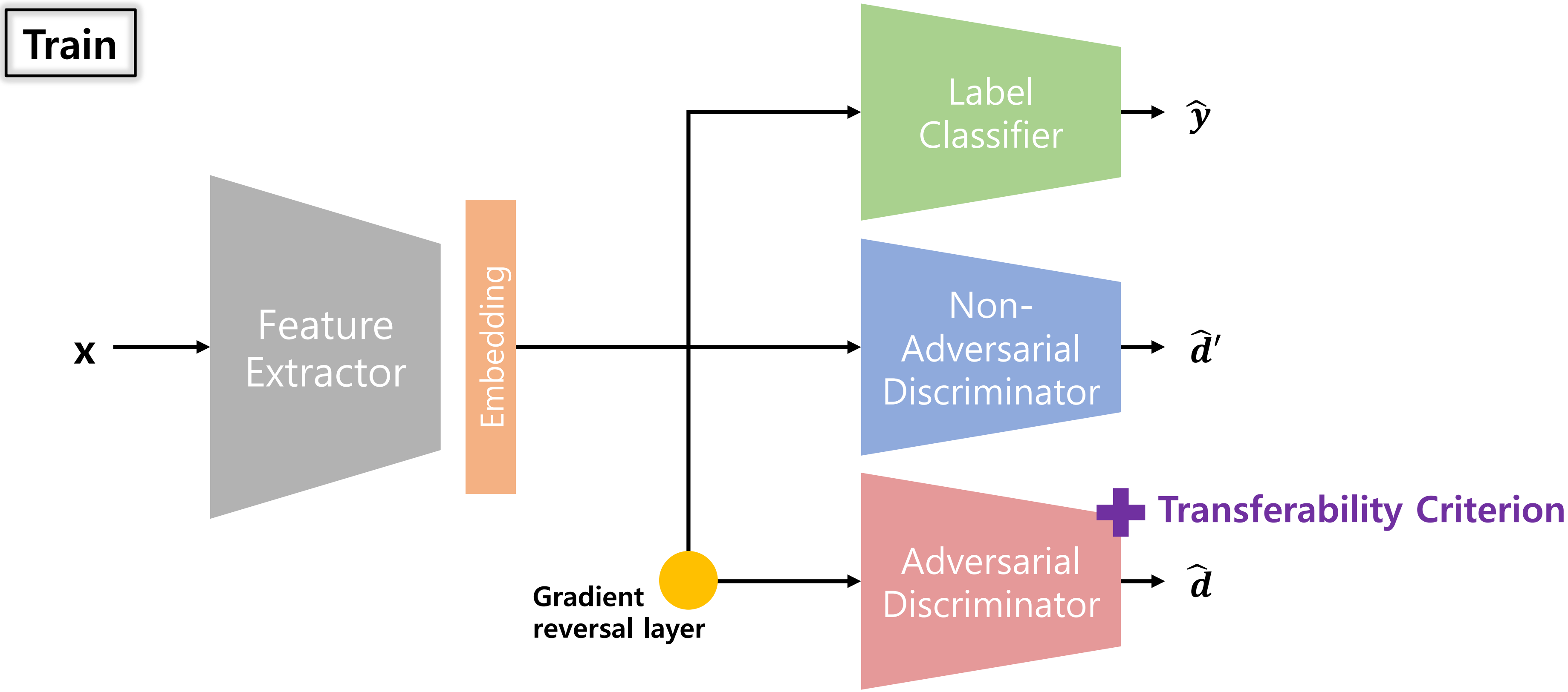
[2] You, Kaichao, et al. "Universal domain adaptation." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition.* 2019.

Methods

1. Universal Domain Adaptation

❖ Universal Domain Adaptation[2]

- Universal Domain Adaptation 문제는 Domain 차이와 Category 차이를 해결하는 것이 핵심
- Domain Adversarial Learning 구조[3]에 Transferability Criterion을 추가하여 "Unknown" 탐지



[2] You, Kaichao, et al. "Universal domain adaptation." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition.* 2019.
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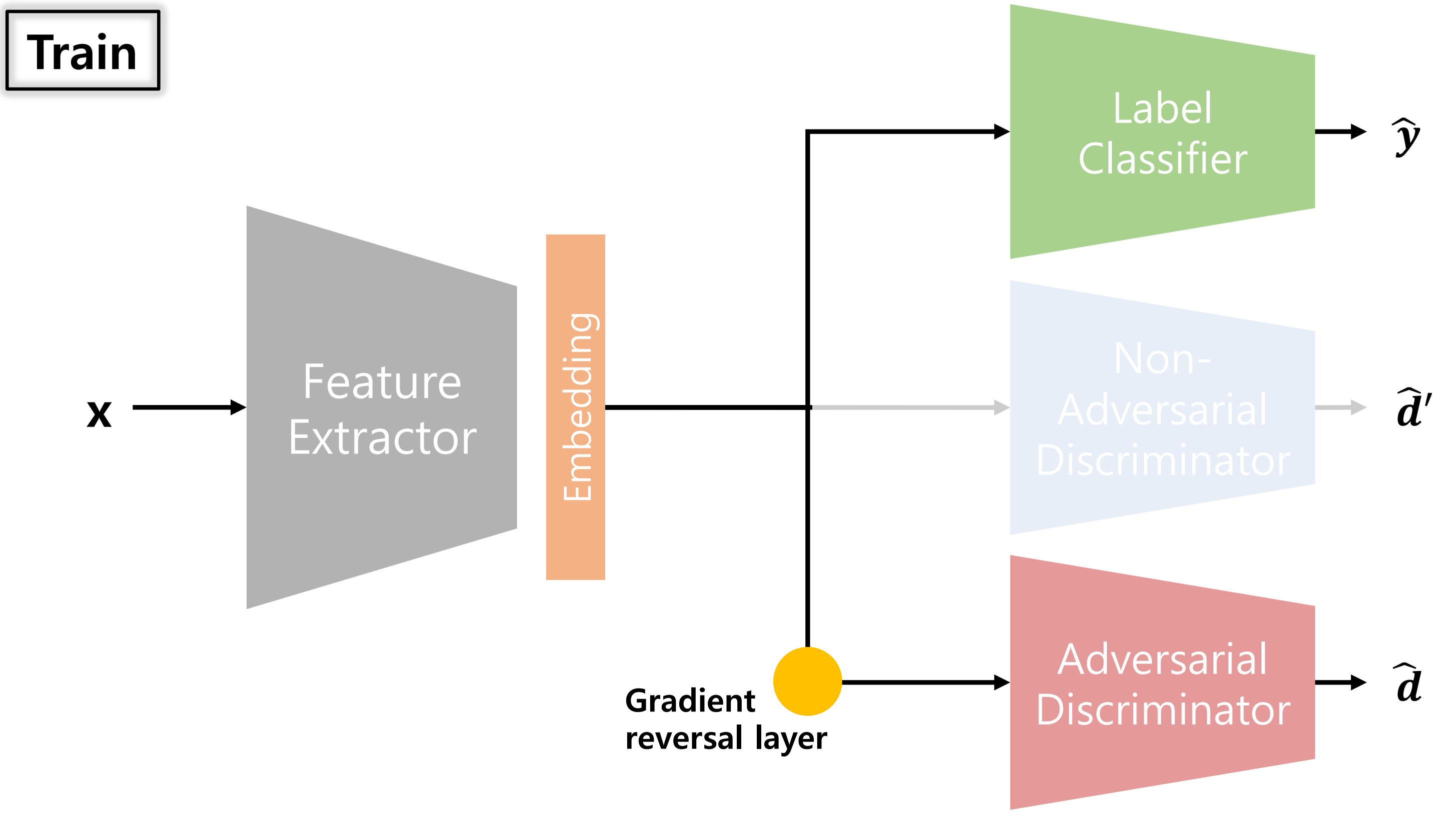

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- **Adaptation Target Error** (Ben-David et al., 2006) [4]

$$R_{D_T}(\eta) \leq \underbrace{R_{D_S}(\eta) + \hat{d}_H(S,T)}_{\text{Objective}} + \Omega$$

$$\hat{d}_H(S,T) = 2\sup_{\eta \in H} \left| \Pr_{x \sim D_S^X}[\eta(x) = 1] - \Pr_{x \sim D_T^X}[\eta(x) = 1] \right| = 2(1 - 2\varepsilon)$$

$R_{D_S}(\eta)$: 소스 도메인 분류 오류
$R_{D_T}(\eta)$: 타겟 도메인 분류 오류
$\hat{d}_H(S,T)$: 두 확률분포사이의 거리
ε : 두 도메인 간 분류 오류

Objective Minimize $R_S(\eta)$, $\hat{d}_H(S,T)$ → Minimize $R_S(\eta)$, Maximize ε

[4] Shai Ben-David, John Blitzer, Koby Crammer, Fernando Pereira “Analysis of Representations for Domain Adaptation” Part of Advances in Neural Information Processing Systems 19 (NIPS 2006)

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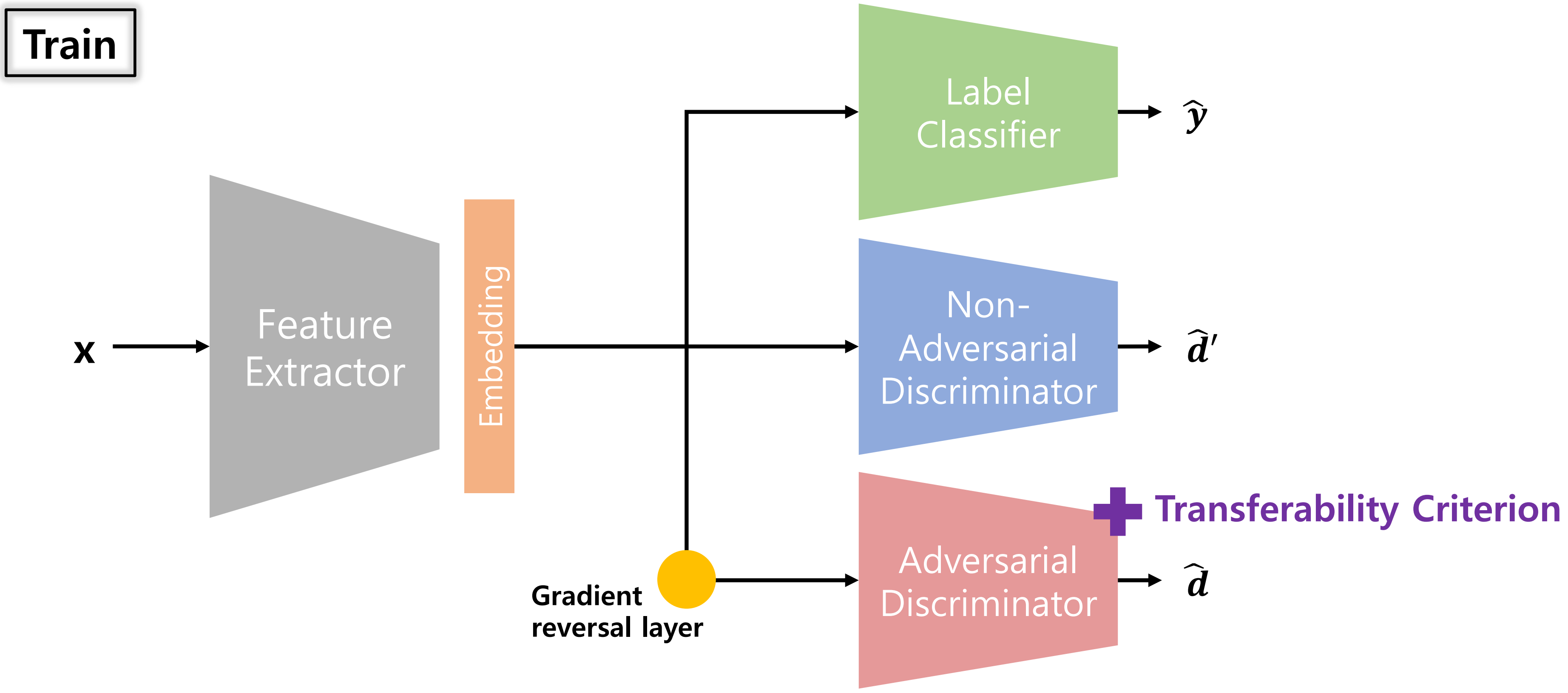

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Transferability Criterion

$$w^s = w^s(x), \qquad w^t = w^t(x)$$

→ **공통 레이블을 갖는** 소스도메인과 타겟도메인의 차이를 줄이고, 타겟 도메인의 **"Unknown"레이블을 식별하는 가중치**

$$\mathrm{E}_{x\sim p_c} w^s(x) > \mathrm{E}_{x\sim p_{\overline{C_s}}} w^s(x), \qquad \mathrm{E}_{x\sim q_c} w^t(x) > \mathrm{E}_{x\sim q_{\overline{C_t}}} w^t(x)$$

Domain Similarity와 **Prediction Uncertainty**를 통해 Transferability Criterion 정의

[2] You, Kaichao, et al. "Universal domain adaptation." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2019.
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Domain Similarity

→ Non-Adversarial Discriminator을 통해 **소스도메인은 1, 타겟 도메인은 0**로 예측하는 값 $\hat{\boldsymbol{d}}'$

$$\mathrm{E}_{x\sim p_{\overline{C}_s}}\hat{d}' > \mathrm{E}_{x\sim p_C}\hat{d}' > \mathrm{E}_{x\sim q_C}\hat{d}' > \mathrm{E}_{x\sim q_{\overline{C}_t}}\hat{d}'$$

Prediction Uncertainty

→ 엔트로피는 예측 불확실성을 정량화하고, **엔트로피가 작을 수록 더욱 확실한 예측을 의미**

$$\mathrm{E}_{x\sim q_{\overline{C}_t}}H(\hat{y}) > \mathrm{E}_{x\sim q_C}H(\hat{y}) > \mathrm{E}_{x\sim p_C}H(\hat{y})' > \mathrm{E}_{x\sim p_{\overline{C}_s}}H(\hat{y})$$

[2] You, Kaichao, et al. "Universal domain adaptation." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2019.
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$$w^s = \frac{H(\hat{y})}{\log|C_s|} - \hat{d}'(x), \qquad w^t = \hat{d}'(x) - \frac{H(\hat{y})}{\log|C_s|}$$

$$\mathrm{E}_{x\sim p_c} w^s(x) > \mathrm{E}_{x\sim p_{\overline{C_s}}} w^s(x), \qquad \mathrm{E}_{x\sim q_c} w^t(x) > \mathrm{E}_{x\sim q_{\overline{C_t}}} w^t(x)$$

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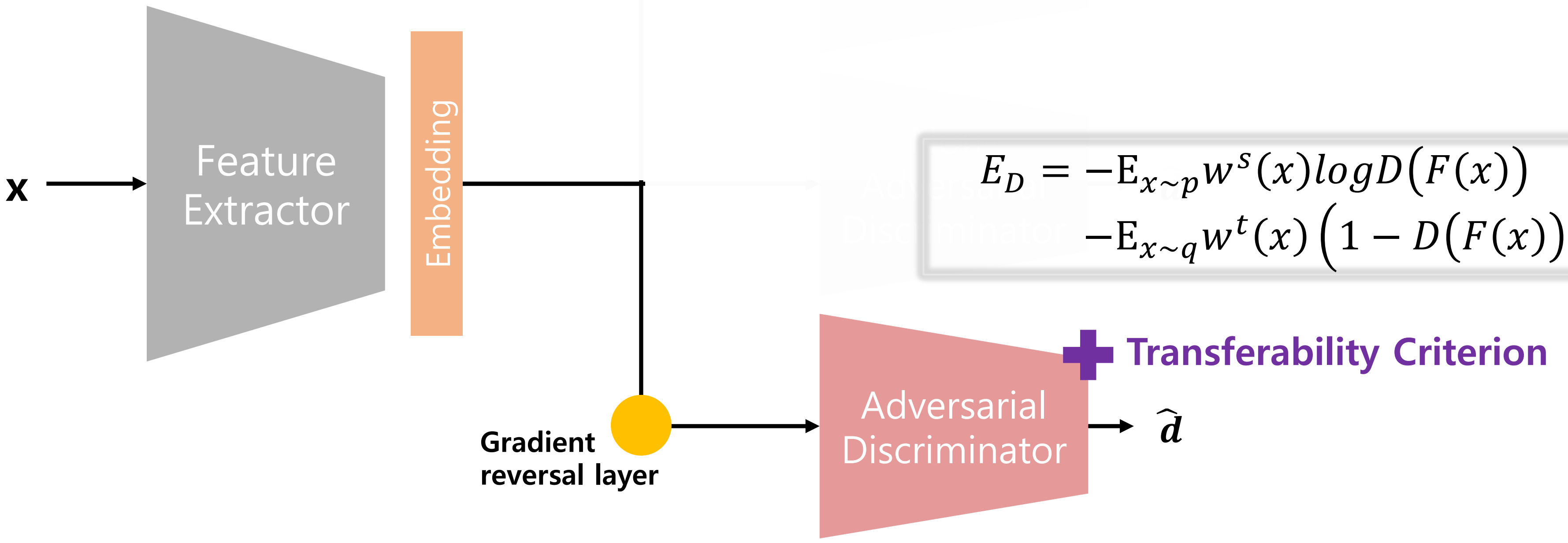
Train



$$E_D = -\mathrm{E}_{x\sim p} w^s(x) log D\big(F(x)\big) - \mathrm{E}_{x\sim q} w^t(x)\Big(1 - D\big(F(x)\big)\Big)$$

[2] You, Kaichao, et al. "Universal domain adaptation." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2019.
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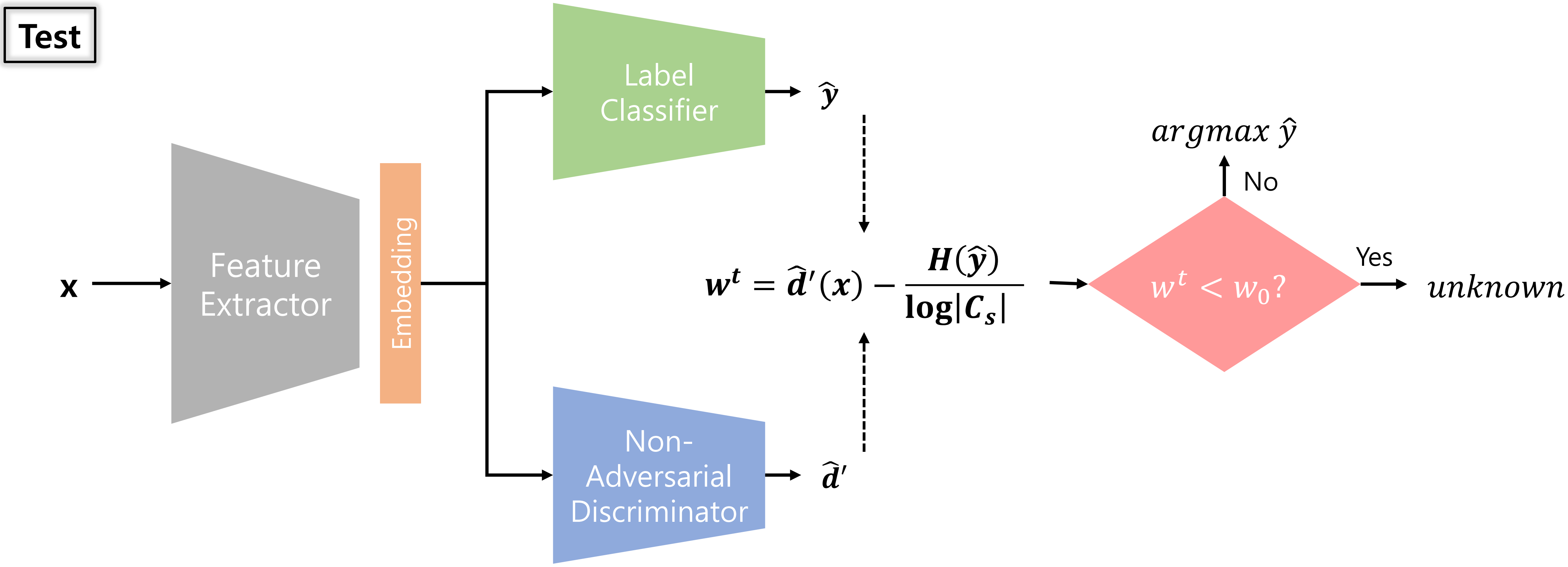

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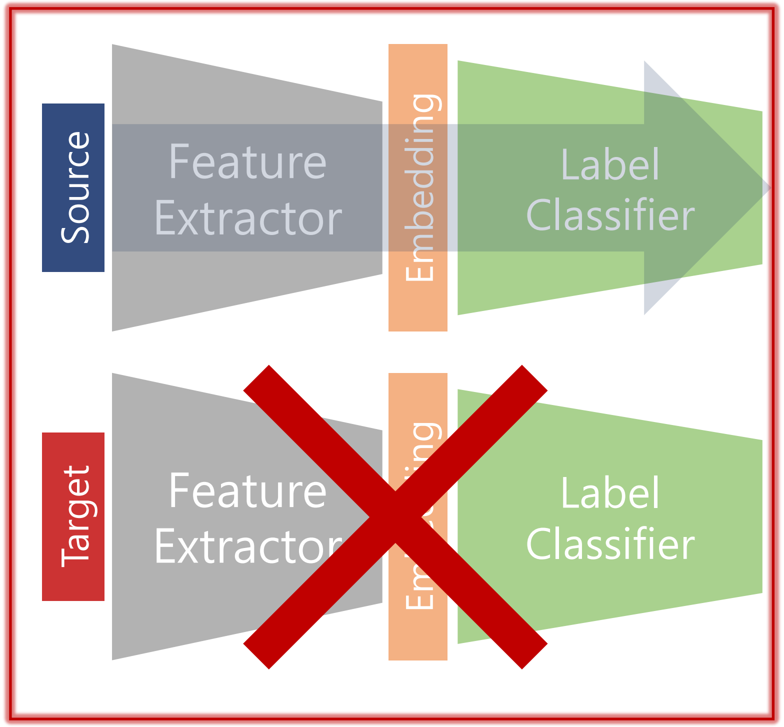
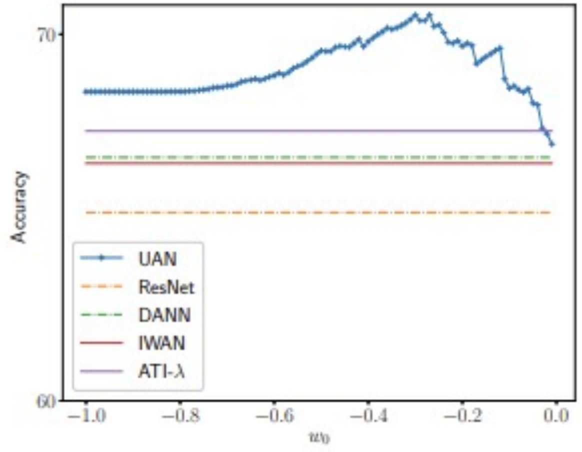
❖ Limitation of Universal Domain Adaptation

1. 레이블 분류기의 학습이 소스도메인 데이터를 통해서만 진행됨
2. “Unknown”의 Threshold을 수동으로 설정하는 것은 성능에 민감한 영향을 줌

① **“Unknown”에 대한 분류기 학습 부재**



② ***Threshold*** w_0**이 정확도에 민감한 영향**



(c) Sensitivity to w_0

1. Universal Domain Adaptation

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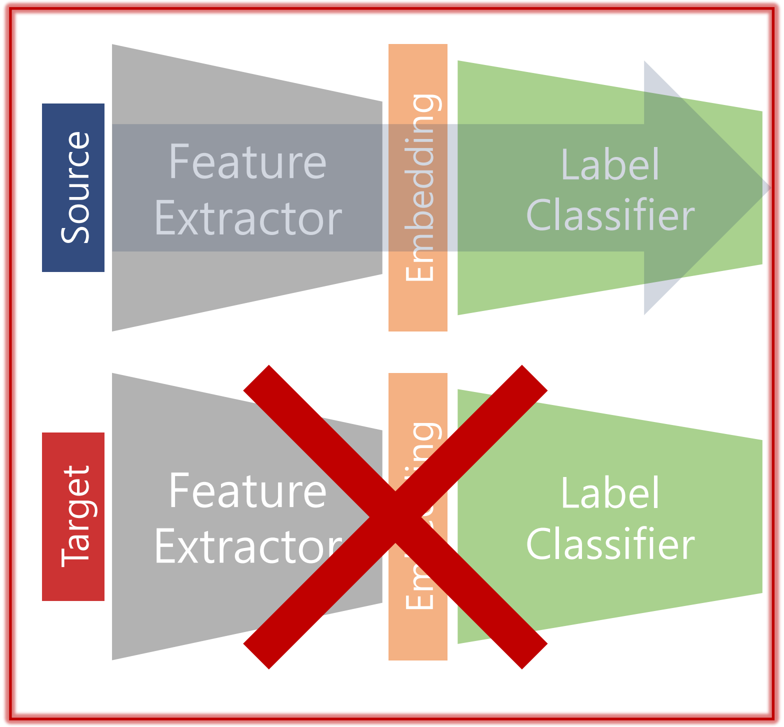
① “Unknown”에 대한 분류기 학습 부재



② *Threshold* w_0이 정확도에 민감한 영향

(c) Sensitivity to w_0

Methods

2. Universal Domain Adaptation through Self-Supervision

❖ Universal Domain Adaptation through Self-Supervision[4]

- 2020년에 제안된 Universal Domain Adaptation 방법론(NeurIPS, 23년 8월 기준 217회 인용)
- 소스데이터에 대한 분류의존도가 높은 문제를 해결함

Universal Domain Adaptation through Self-Supervision

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Abstract

Unsupervised domain adaptation methods traditionally assume that all source categories are present in the target domain. In practice, little may be known about the category overlap between the two domains. While some methods address target settings with either partial or open-set categories, they assume that the particular setting is known a priori. We propose a more universally applicable domain adaptation framework that can handle arbitrary category shift, called Domain Adaptative Neighborhood Clustering via Entropy optimization (DANCE). DANCE combines two novel ideas: First, as we cannot fully rely on source categories to learn features discriminative for the target, we propose a novel neighborhood clustering technique to learn the structure of the target domain in a self-supervised way. Second, we use entropy-based feature alignment and rejection to align target features with the source or reject them as unknown categories based on their entropy. We show through extensive experiments that DANCE outperforms baselines across open-set, open-partial, and partial domain adaptation settings. Implementation is available at https://github.com/VisionLearningGroup/DANCE.

Figure 1: We propose *DANCE*, which combines a self-supervised clustering loss (red) to cluster neighboring target examples and an entropy separation loss (gray) to consider alignment with source (best viewed in color).

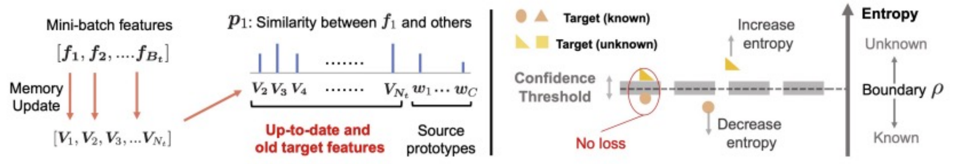

Figure 2: **Left**: Similarity distribution calculation in neighborhood clustering (best viewed in color). We minimize the entropy of the similarity distribution between each point (as shown for f_1), the prototypes, and the other target samples. Since most target samples are absent in the mini-batch, we store the their features in a memory bank, updating it with each batch. **Right**: An overview of the entropy separation loss (best viewed in color). We further decrease small entropy to move the sample to a "known"-class prototype, and increase large entropy to move it farther away. Since distinguishing "known" vs "unknown" samples near the boundary is hard, we introduce a confidence threshold that ignores such ambiguous samples.

[4] Saito, Kuniaki, et al. "Universal domain adaptation through self supervision." *Advances in neural information processing systems* 33 (2020): 16282-16292.

Methods

2. Universal Domain Adaptation through Self-Supervision

❖ Universal Domain Adaptation through Self-Supervision[4]

- 소스데이터 뿐 아니라 레이블이 없는 타겟데이터를 사용하여 레이블 분류기를 학습
- 레이블이 없는 타겟데이터를 활용하기 위하여, 클러스터링 기반 분류 모델 활용

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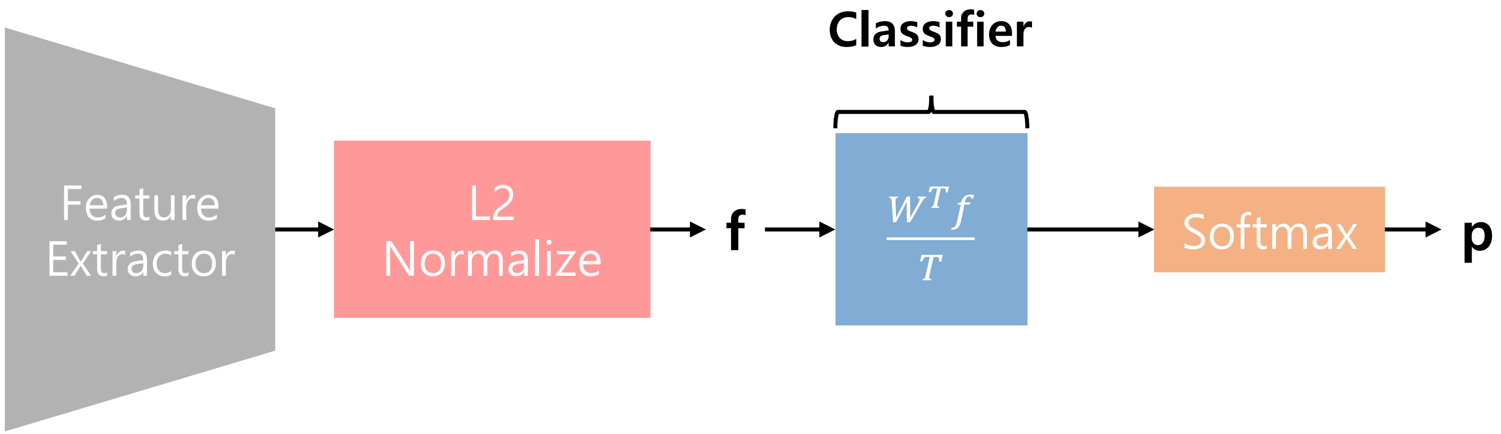
Network Architecture[5]

→ 레이블이 있는 소스도메인 데이터를 학습하여, 분류기의 가중치를 **각 Class의 Prototype 특징으로 사용**



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$$D_s = \{(x_i^s, y_i^s)\}_{i=1}^{N_s}$$

$$L_{cls} = L\left(y, softmax\left(W^T F(x)\right)\right)$$

$$W = (w_1, w_2, \dots, w_K)$$

→ **Prototype :** 각 Class를 대표하는 점

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Neighborhood Clustering(NC)

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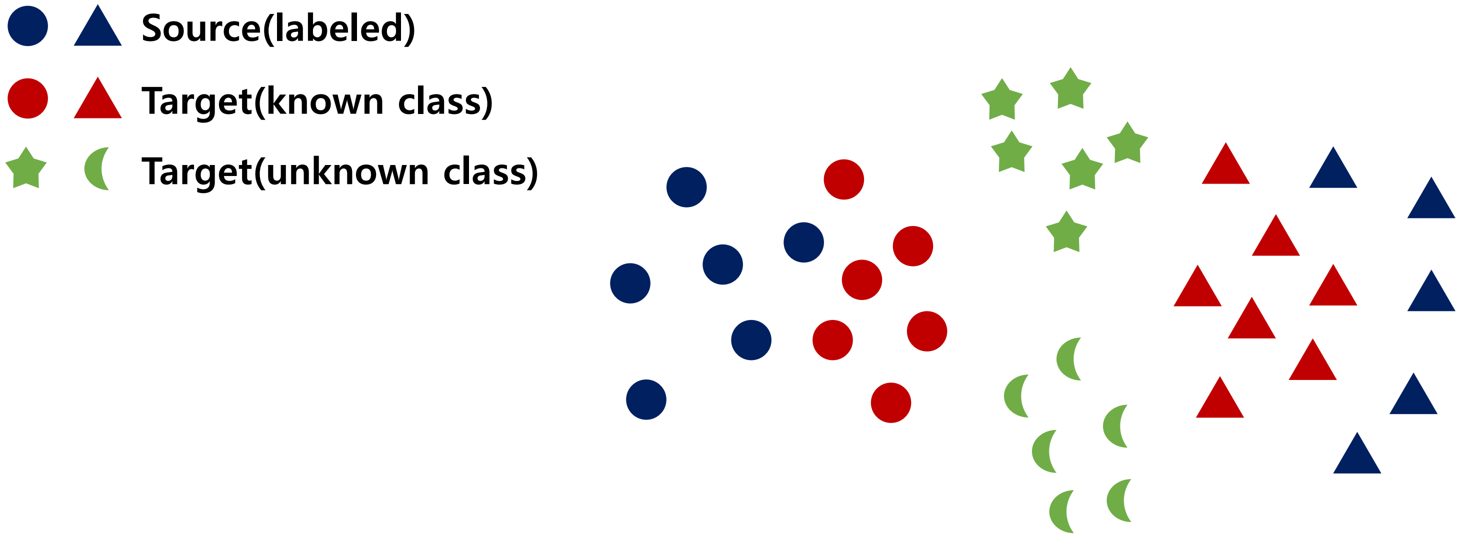

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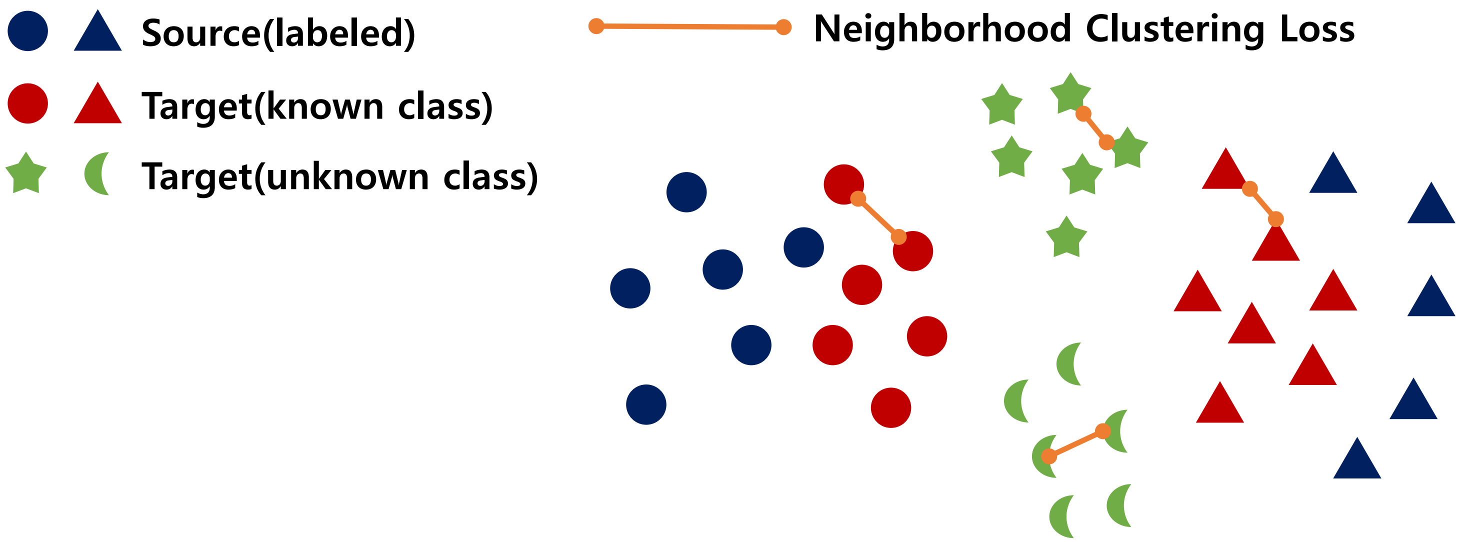

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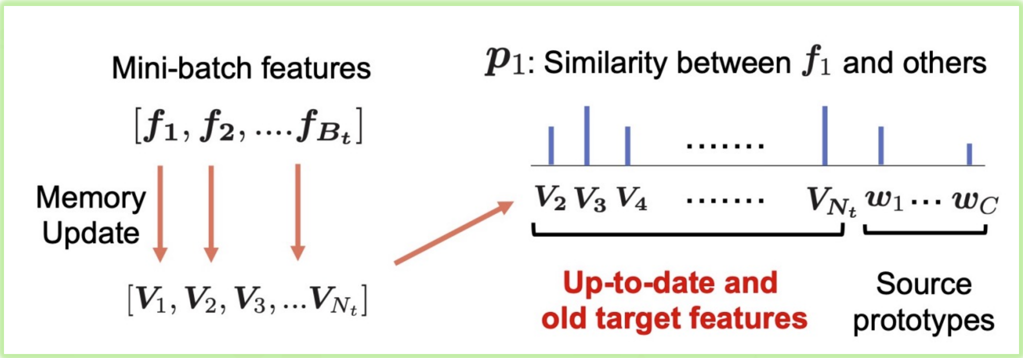
$$D_t = \{(x_i^t)\}_{i=1}^{N_t}$$

$$L_{nc} = -\frac{1}{|B_t|}\sum_{i \in B_t}\sum_{j=1, j\neq i}^{N_t+K} p_{i,j}\log(p_{i,j})$$

$$p_{i,j} = \frac{\exp(F_j^{\top} f_i/\tau)}{Z_i}, \qquad Z_i = \sum_{j=1, j\neq i}^{N_t+K}\exp(F_j^{\top} f_i/\tau)$$



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→ **Known Class와 Unknown Class를 더욱 분리**

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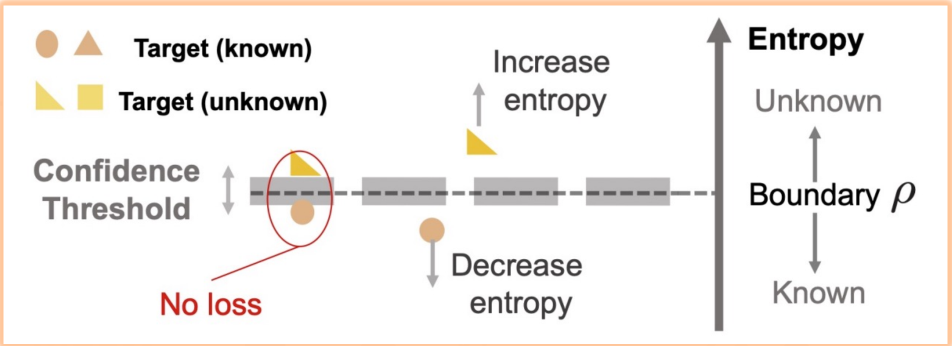

$$L_{es}(p_i) = \begin{cases} -|H(p_i) - \rho| & (|H(p_i) - \rho| > m), \\ 0 & otherwise. \end{cases} \qquad \rho = \frac{\log(K)}{2}$$

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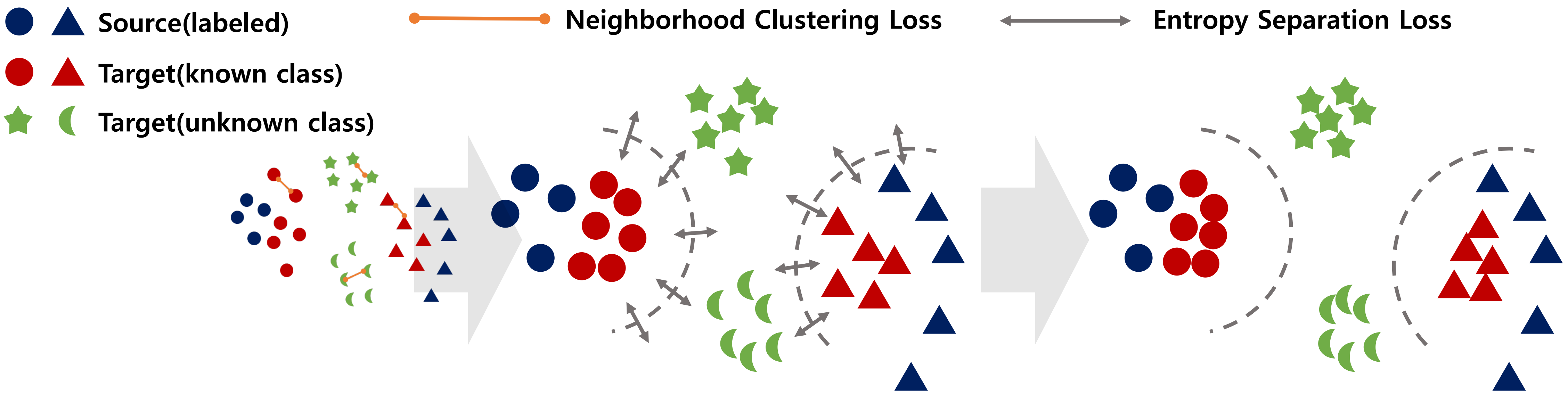

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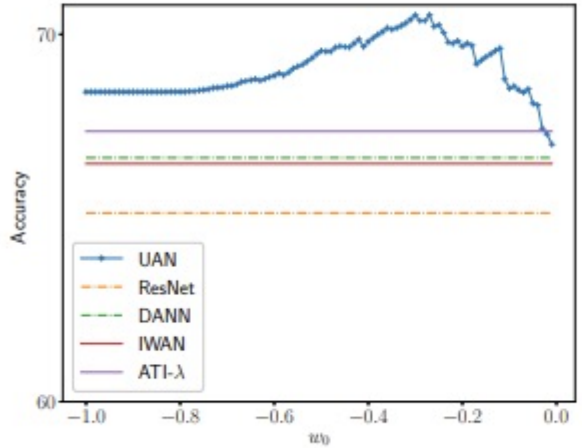
❖ Limitation of Universal Domain Adaptation

1. 레이블 분류기의 학습이 소스도메인 데이터를 통해서만 진행됨
2. "Unknown"의 Threshold을 수동으로 설정하는 것은 성능에 민감한 영향을 줌

① "Unknown"에 대한 분류기 학습 부재

② **$Threshold\ w_0$이 정확도에 민감한 영향**



(c) Sensitivity to w_0

Methods

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- 2021년에 제안된 Universal Domain Adaptation 방법론(ICCV, 23년 8월 기준 70회 인용)
- 수동으로 “unknown” Threshold를 선정하는 문제를 해결

OVANet: One-vs-All Network for Universal Domain Adaptation

Kuniaki Saito, Kate Saenko; Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), 2021, pp. 9000-9009

Abstract

Universal Domain Adaptation (UNDA) aims to handle both domain-shift and category-shift between two datasets, where the main challenge is to transfer knowledge while rejecting "unknown" classes which are absent in the labeled source data but present in the unlabeled target data. Existing methods manually set a threshold to reject "unknown" samples based on validation or a pre-defined ratio of "unknown" samples, but this strategy is not practical. In this paper, we propose a method to learn the threshold using source samples and to adapt it to the target domain. Our idea is that a minimum inter-class distance in the source domain should be a good threshold to decide between "known" or "unknown" in the target. To learn the inter- and intra-class distance, we propose to train a one-vs-all classifier for each class using labeled source data. Then, we adapt the open-set classifier to the target domain by minimizing class entropy. The resulting framework is the simplest of all baselines of UNDA and is insensitive to the value of a hyper-parameter, yet outperforms baselines with a large margin.

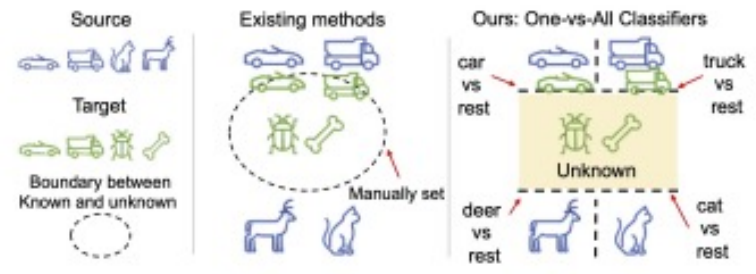

Figure 1: Existing open-set or universal domain adaptation methods handle unknown samples by manually setting a threshold to reject them, either by validation or prior knowledge about the target domain. If set incorrectly, it can mistakenly reject known classes as shown here, *e.g.*, car and truck. Instead, we propose to learn the threshold by training one-vs-all classifiers for each class.

[6] Saito, Kuniaki, and Kate Saenko. "Ovanet: One-vs-all network for universal domain adaptation." *Proceedings of the ieee/cvf international conference on computer vision*. 2021.

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❖ OVANet: One-vs-All Network for universal Domain Adaptation[6]

- 각 Class 사이의 거리는 좋은 Threshold로 사용이 가능함
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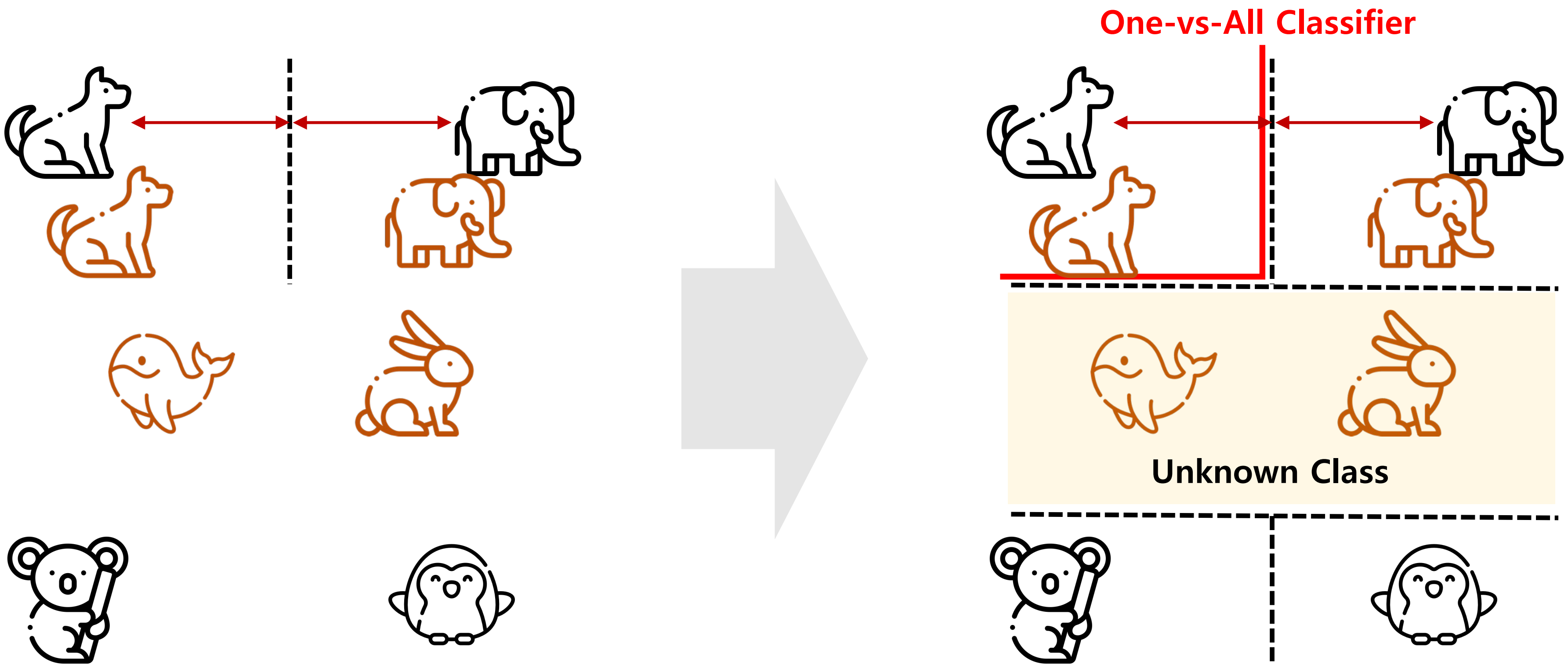

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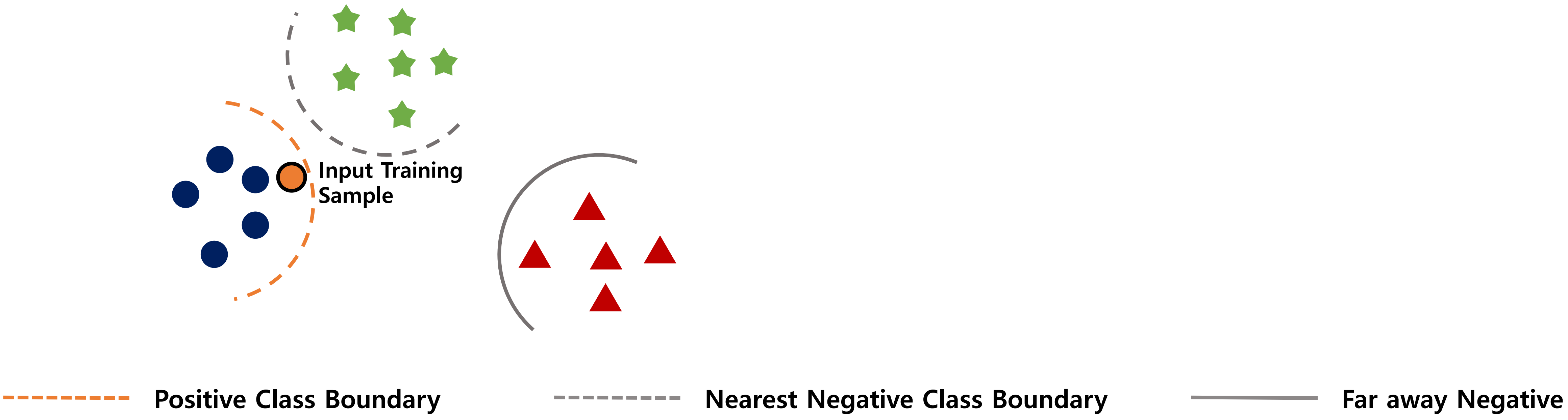
Hard Negative Classifier Sampling



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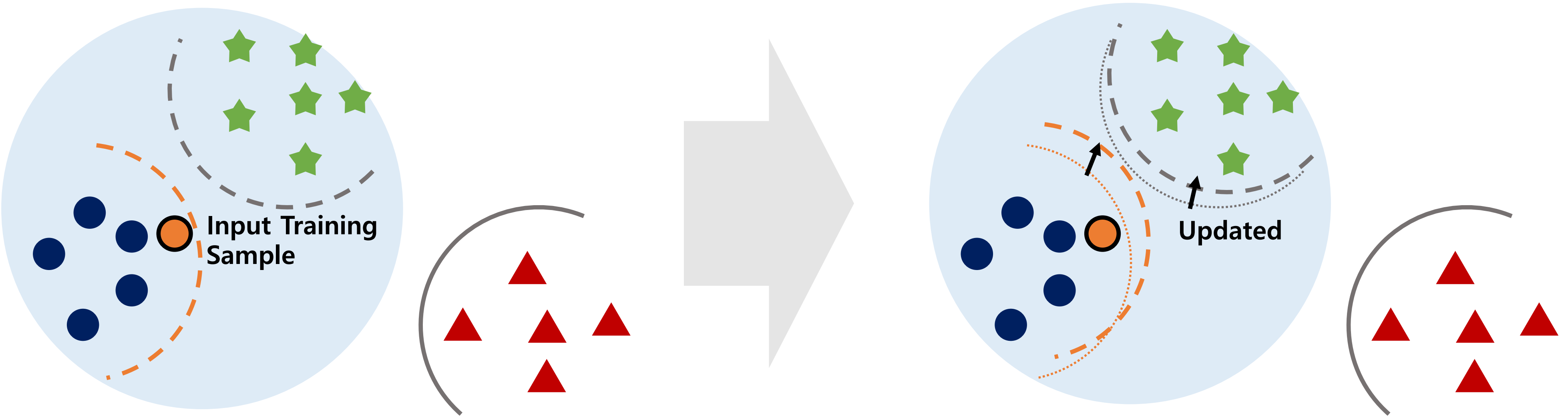

Positive Class Boundary   Nearest Negative Class Boundary   Far away Negative

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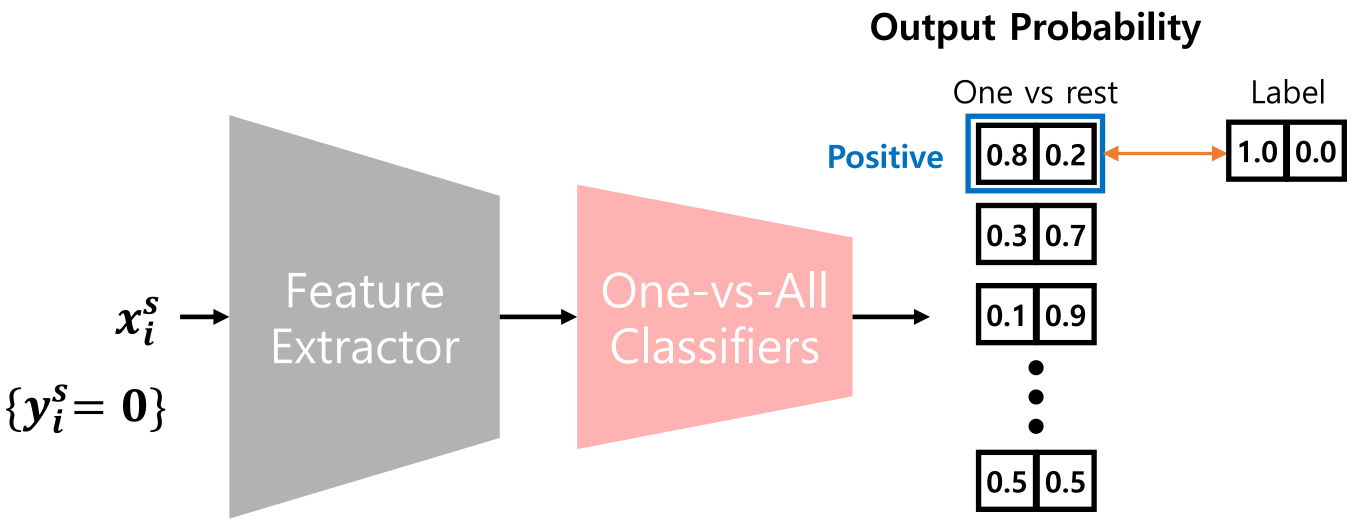

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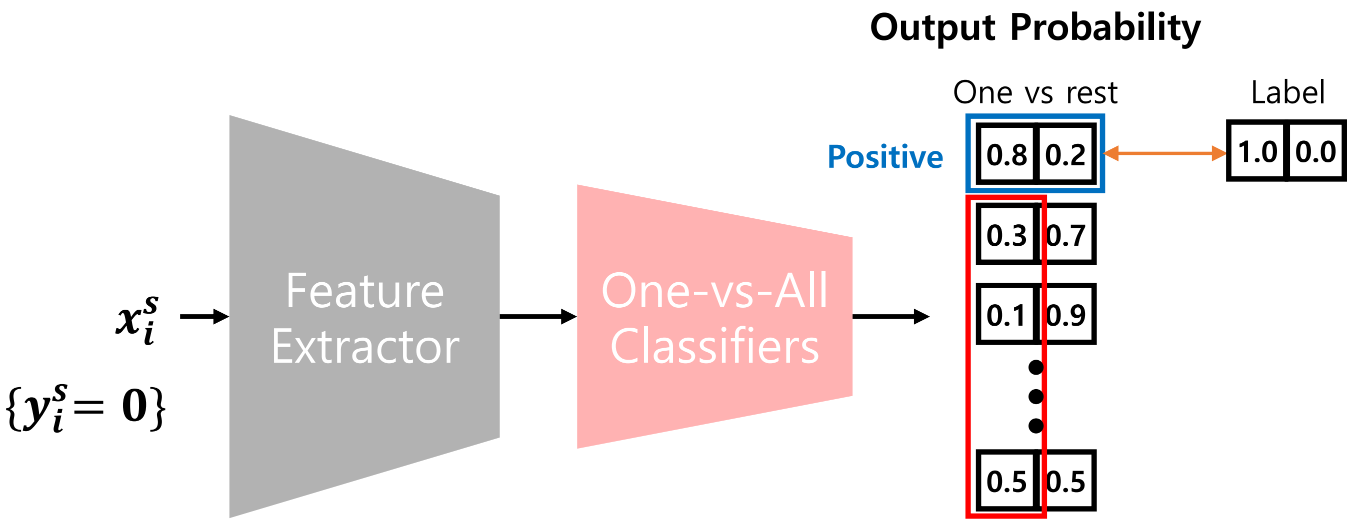

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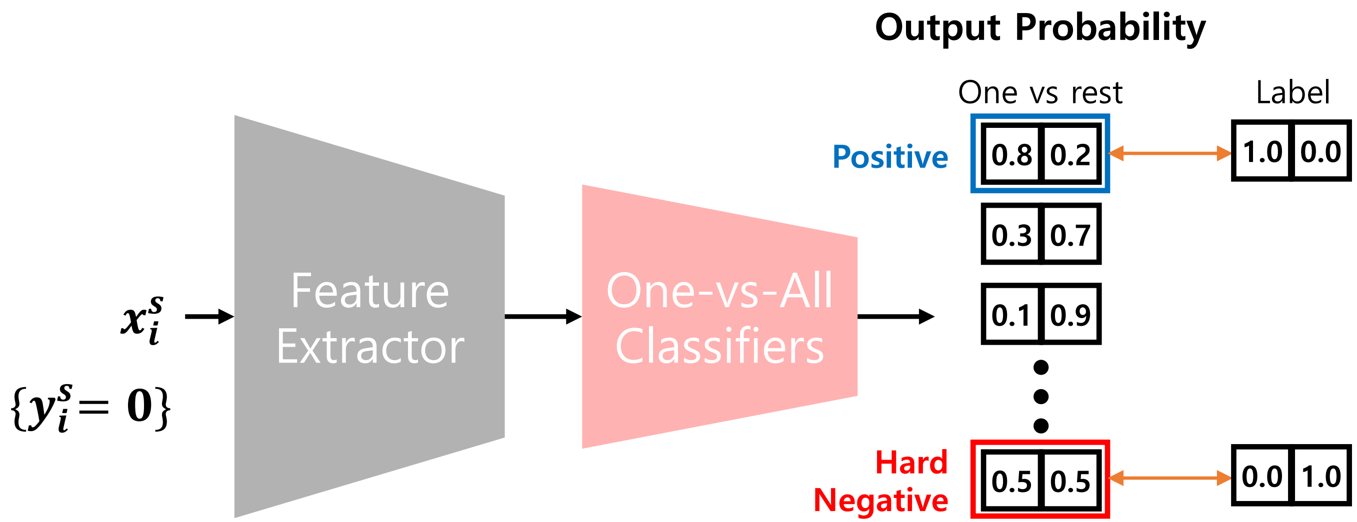

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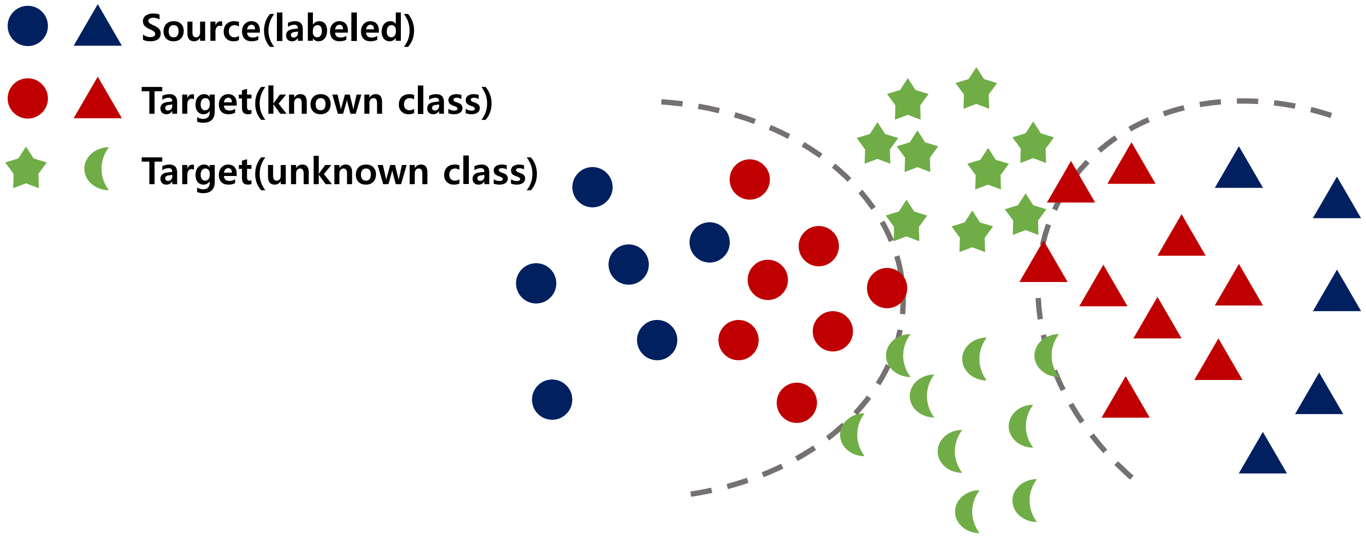

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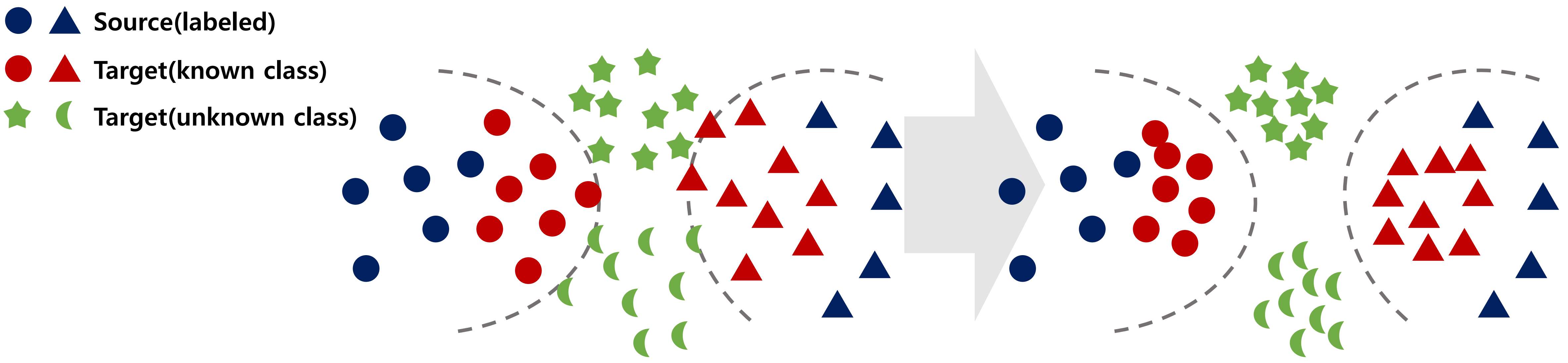

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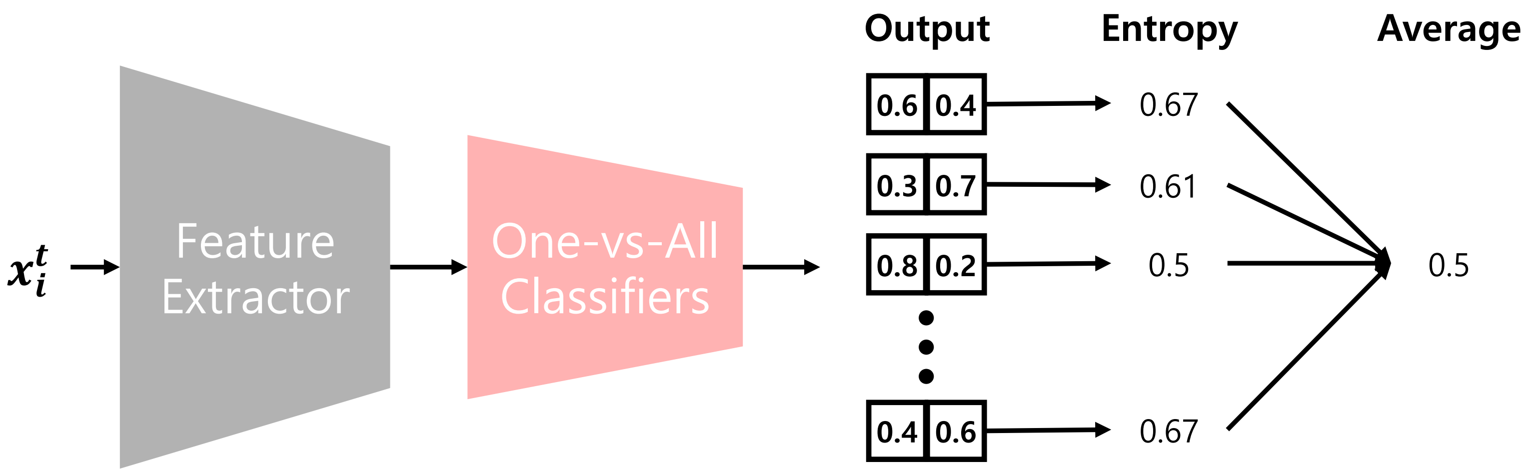

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Methods

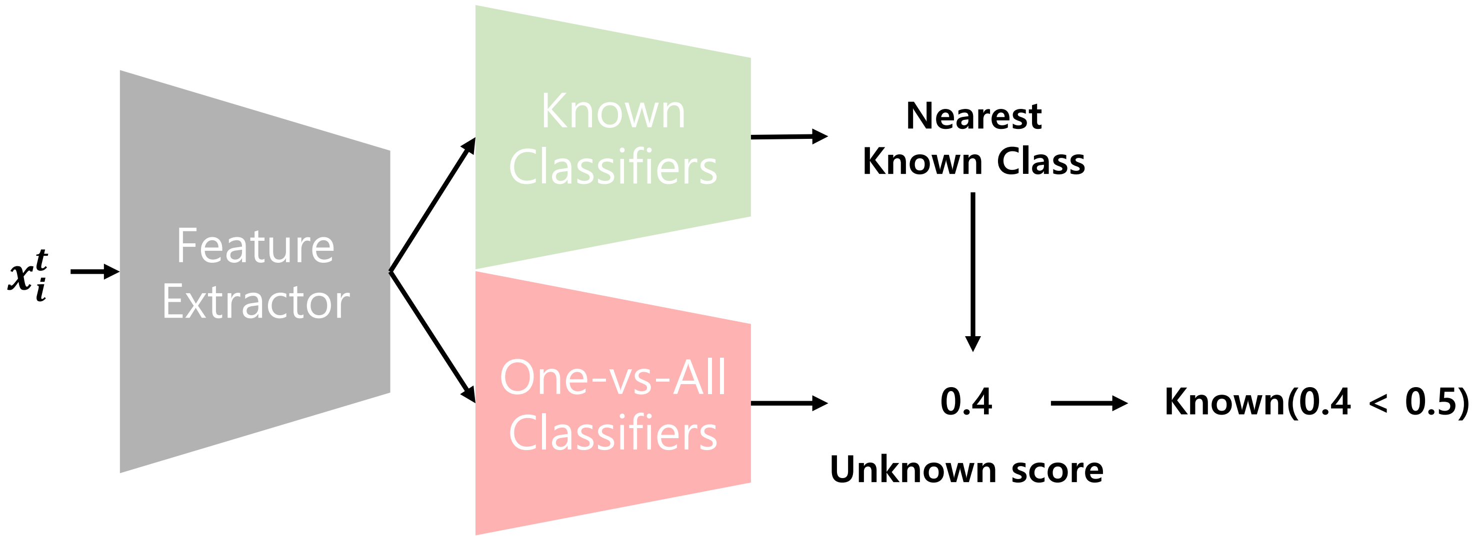
3. OVANet: One-vs-All Network for universal Domain Adaptation

❖ **OVANet: One-vs-All Network for universal Domain Adaptation[6]**

- 각 Class 사이의 거리는 좋은 Threshold로 사용이 가능함
- 각 Class에 대하여 One-vs-All Network를 학습하고, One-vs-All Classifiers를 통해 Threshold를 정의

Inference

→ 학습된 **One-vs-All Classifiers**을 통해서 **“unknown” 식별**



[6] Saito, Kuniaki, and Kate Saenko. "Ovanet: One-vs-all network for universal domain adaptation." *Proceedings of the ieee/cvf international conference on computer vision*. 2021.

Conclusion

Conclusion

❖ 기존 Domain Adaptation 방법론의 한계

- 대다수의 기존 방법론은 **소스도메인과 타겟도메인의 레이블 분포가 동일함을 가정함**
- 현실의 많은 문제에서 소스도메인과 타겟도메인의 분포가 동일하지 않은 경우가 존재함
- 이에 따라, 레이블의 분포가 다른 상황에서도 타겟도메인에 대한 높은 성능이 요구됨

❖ Universal Domain Adaptation

- 레이블의 분포가 다른 상황을 해결하기 위해 Open-set DA, Partial DA의 방법론이 존재함
- 하지만, 타겟도메인의 레이블이 없는 상황에서는 **어떤 방법론을 사용할지 결정하는 것이 불가함**
- **Universal Domain Adaptation**은 레이블의 분포차이가 존재하는 모든 상황에 적합한 방법론임
- 다양한 현실문제를 풀어가는데 유용하게 사용될 것으로 예상됨

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고맙습니다.