Semi-Supervised Domain Adaptation

2023. 10. 06

Data Mining & Quality Analytics Lab.

황순혁

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- Data Mining & Quality Analytics Lab. (김성범 교수님)
- 석 · 박사 통합과정 4학기차 (2022. 03 ~)

❖ Research Interest
- Semi Domain Adaptation
- Representation Learning for Time-series data
- Self-supervised Learning

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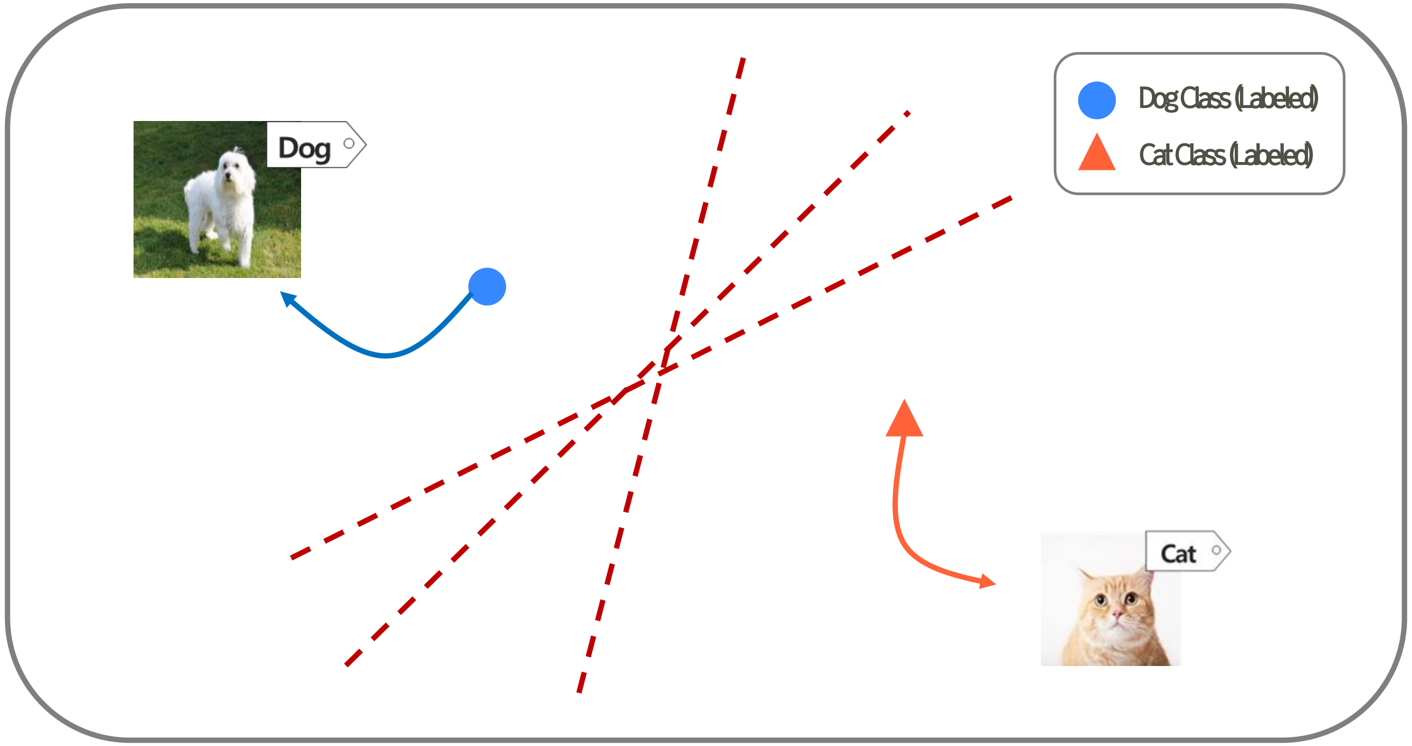
1. Introduction

준지도학습 (Semi-Supervised Learning)

→ **Unlabeled Data**를 활용해서 **일반화 성능**을 높이는 방법론



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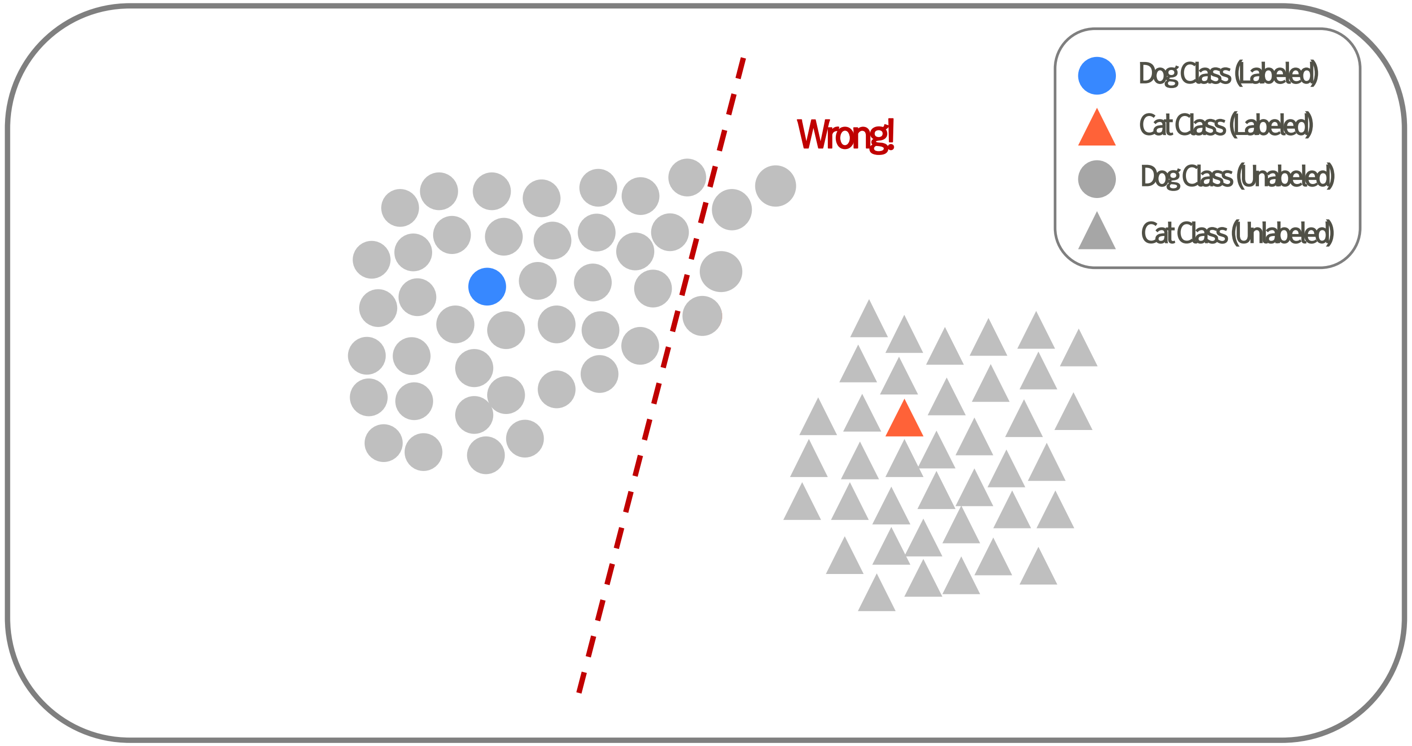

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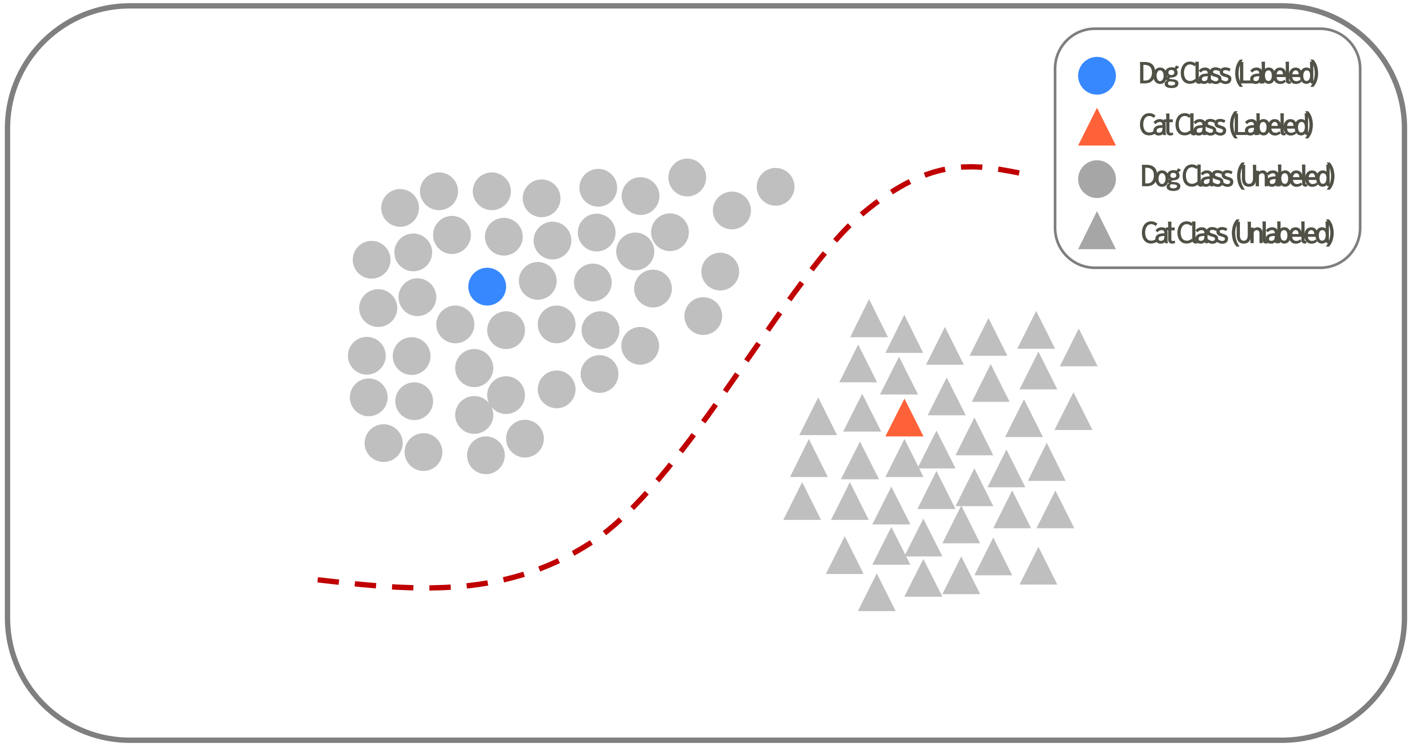

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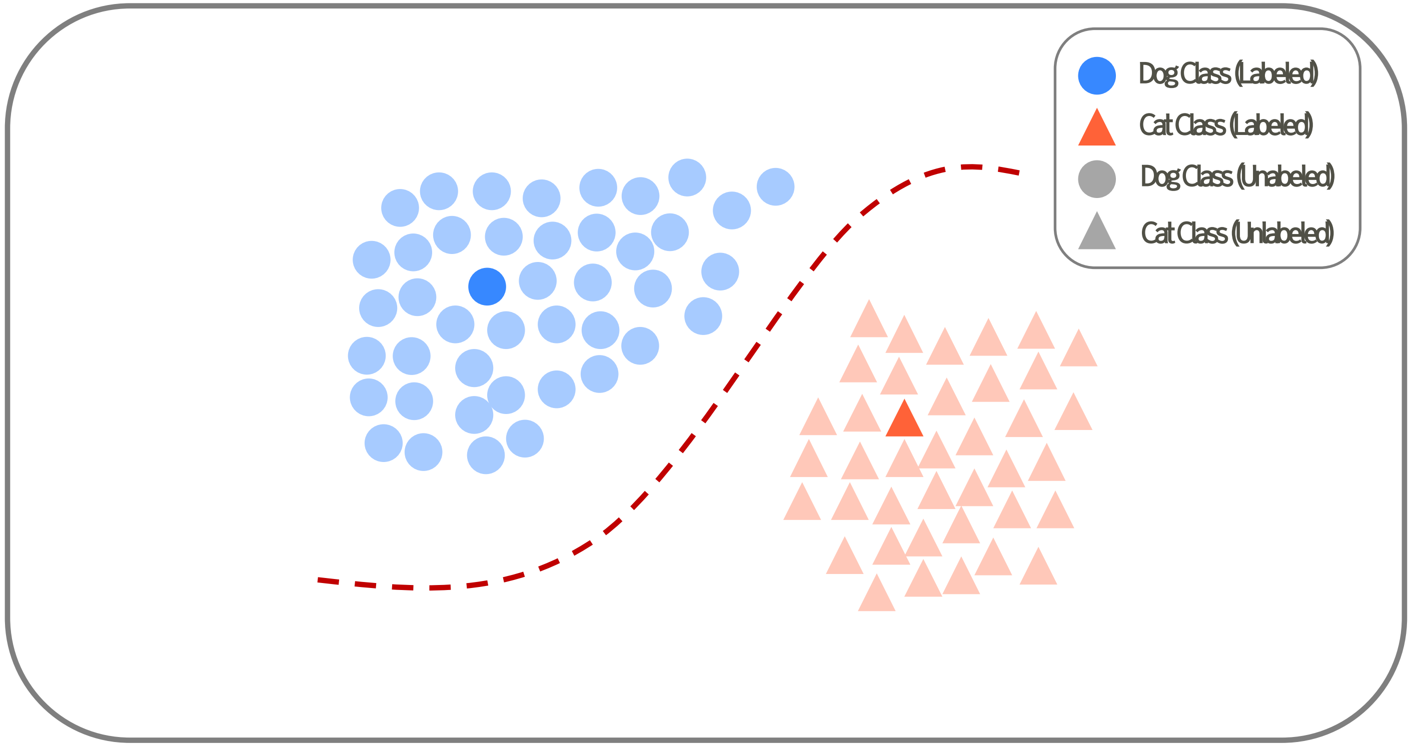
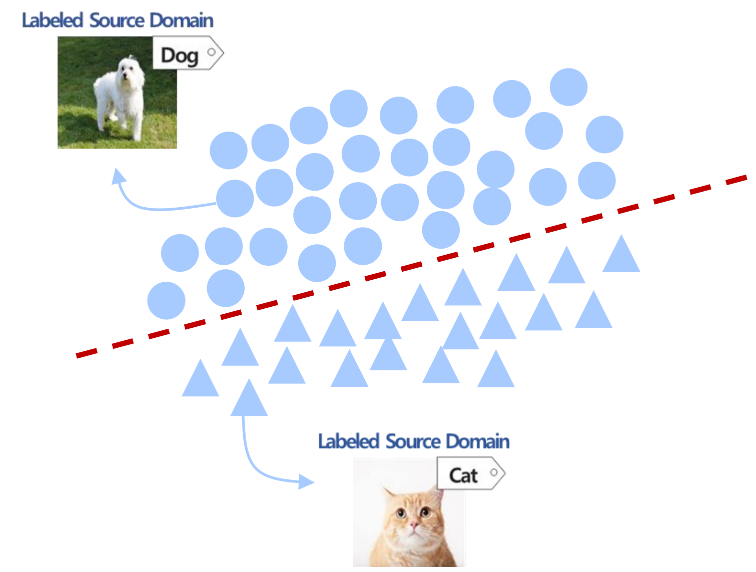


도메인 적응 방법론 (Domain Adaptation)

→ **서로 다른 도메인** 데이터셋간 **일반화 성능**을 높이는 방법론

특징 : 유사하지만 분포가 서로 약간 다름



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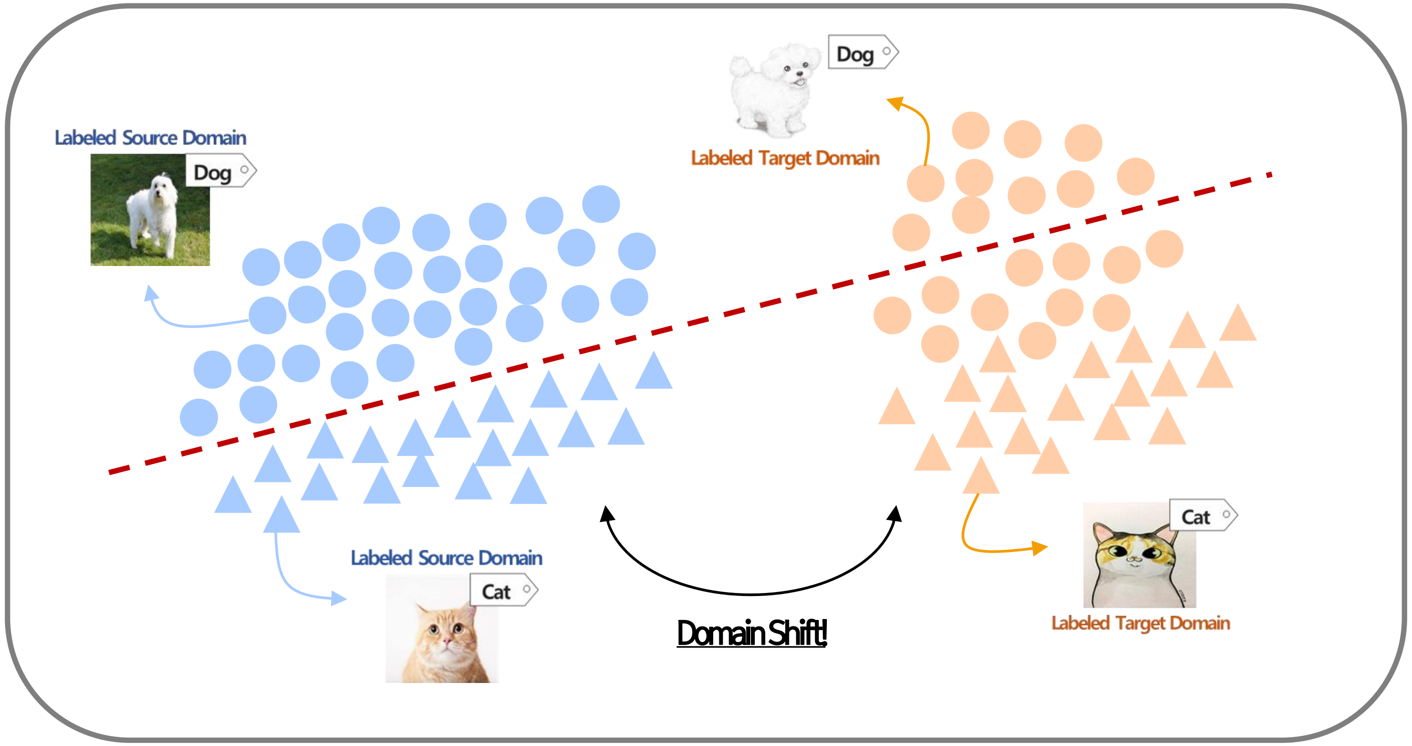

Introduction

Background

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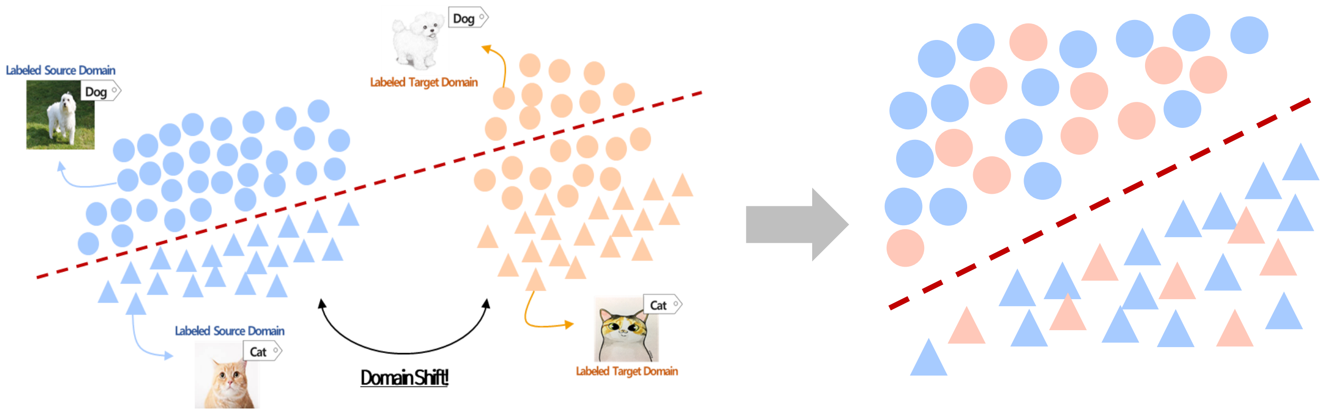


✓ 두 도메인을 잘 Alignment해서 모두 잘 분류되도록 만들자!

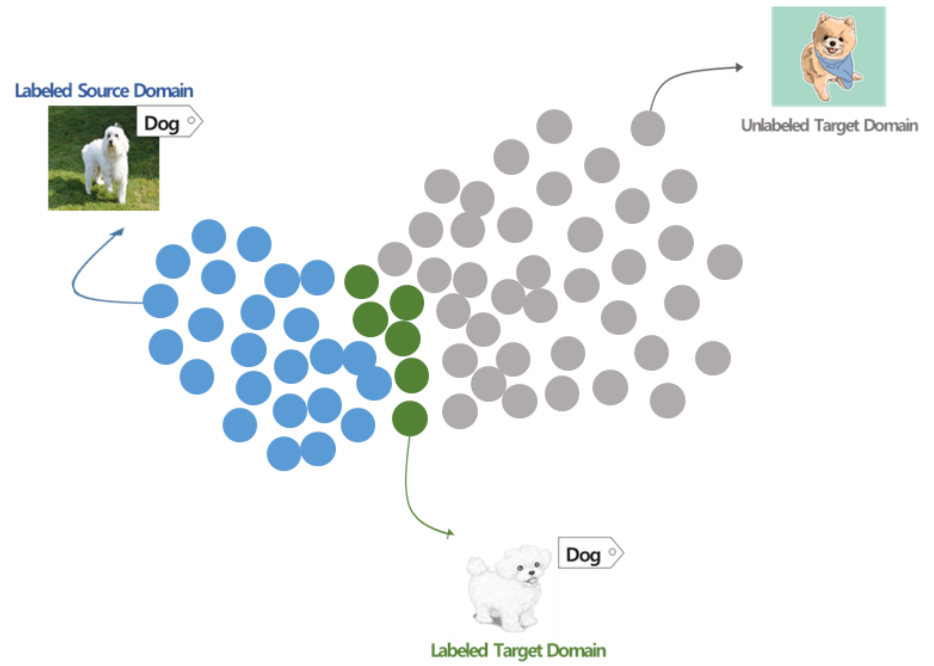
Introduction

Background

준지도 도메인 적응 방법론 (Semi-Supervised Domain Adaptation)

→ **Domain Inter Discrepancy** / Domain Intra Discrepancy를 해결하자!

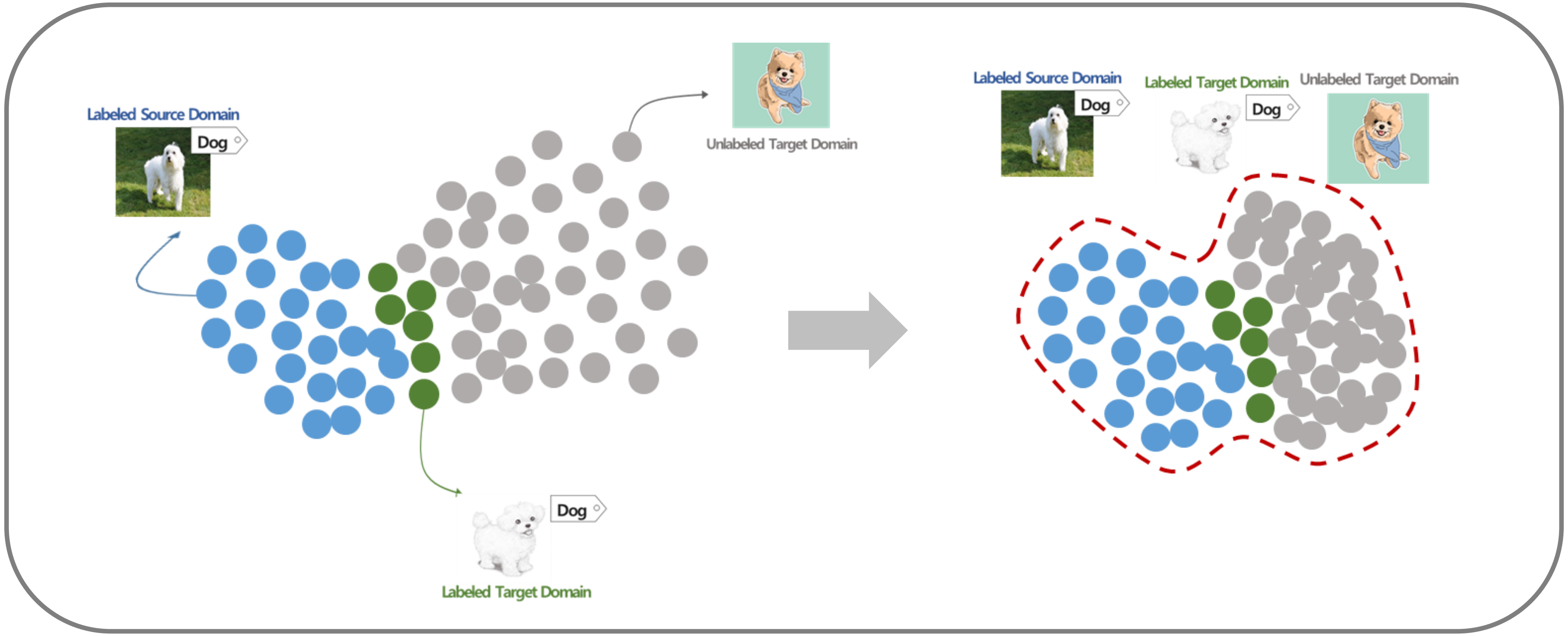
서로 다른 두 도메인 간 발생하는 분포 차이



준지도 도메인 적응 방법론 (Semi-Supervised Domain Adaptation)

→ Domain Inter Discrepancy / Domain Intra Discrepancy를 해결하자!

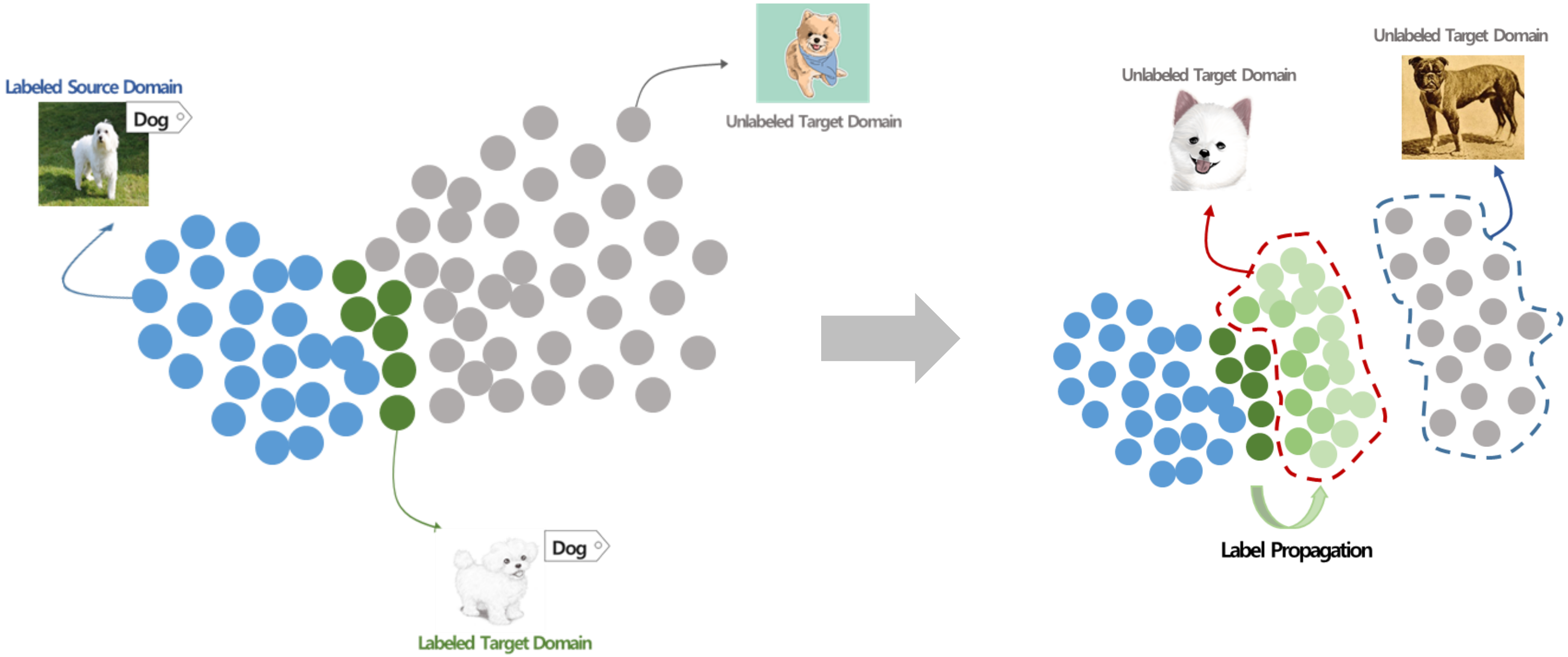
서로다른두도메인간발생하는분포차이



준지도 도메인 적응 방법론 (Semi-Supervised Domain Adaptation)

→ Domain Inter Discrepancy / **Domain Intra Discrepancy**를 해결하자!

Unlabeled Target Domain 내 발생하는 분포 차이



2. Semi-Supervised Domain Adaptation Methods

Methods

Semi-Supervised Domain Adaptation via Minimax Entropy

❖ Semi-Supervised Domain Adaptation via Minimax Entropy [1]

- 2019년에 제안된 Semi-Supervised Domain Adaptation 방법론(ICCV, 2023년 10월 기준 547회 인용)
- Entropy의 최소화 및 최대화를 적대적으로 학습하는 개념을 활용하여 Domain 간 차이 최소화

Semi-supervised Domain Adaptation via Minimax Entropy

Kuniaki Saito[1], Donghyun Kim[1], Stan Sclaroff[1], Trevor Darrell[2] and Kate Saenko[1]
[1]Boston University, [2]University of California, Berkeley
[1]{keisaito, donhk, sclaroff, saenko}@bu.edu, [2]trevor@eecs.berkeley.edu

Abstract

Contemporary domain adaptation methods are very effective at aligning feature distributions of source and target domains without any target supervision. However, we show that these techniques perform poorly when even a few labeled examples are available in the target domain. To address this semi-supervised domain adaptation (SSDA) setting, we propose a novel Minimax Entropy (MME) approach that adversarially optimizes an adaptive few-shot model. Our base model consists of a feature encoding network, followed by a classification layer that computes the features' similarity to estimated prototypes (representatives of each class). Adaptation is achieved by alternately maximizing the conditional entropy of unlabeled target data with respect to the classifier and minimizing it with respect to the feature encoder. We empirically demonstrate the superiority of our method over many baselines, including conventional feature alignment and few-shot methods, setting a new state of the art for SSDA. Our code is available at `http://cs-people.bu.edu/keisaito/research/MME.html`.

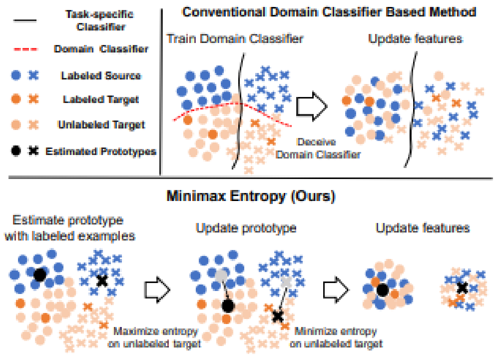
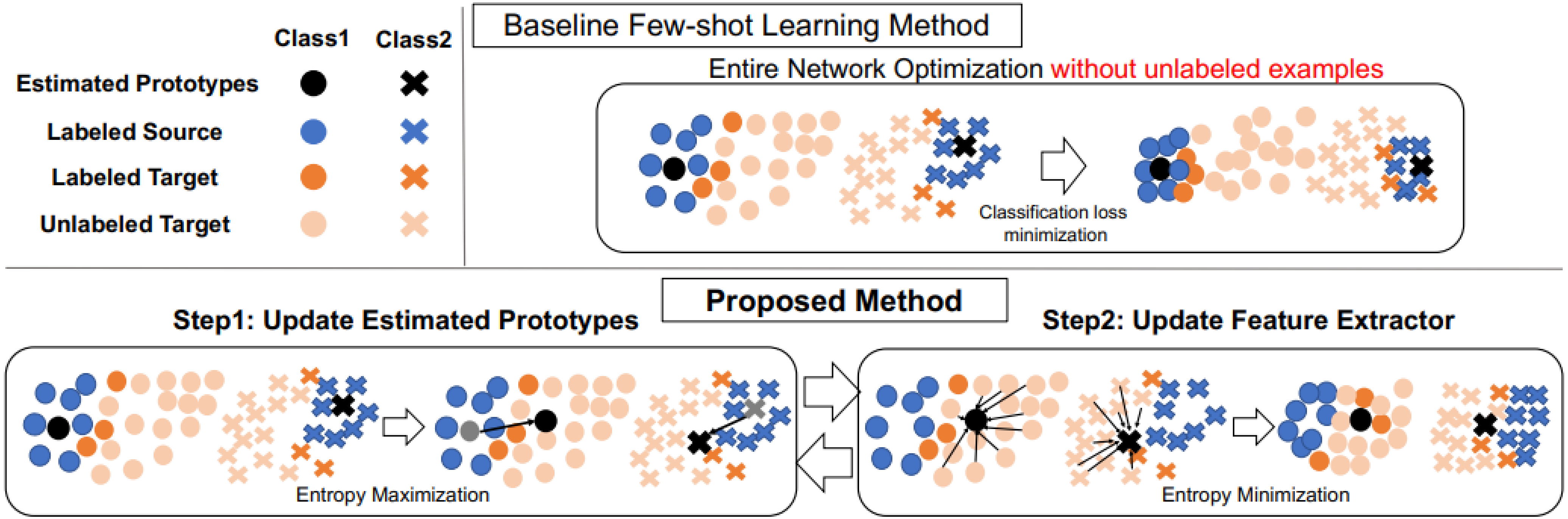


Figure 1: We address the task of semi-supervised domain adaptation. Top: Existing domain-classifier based methods align source and target distributions but can fail by generating ambiguous features near the task decision boundary. Bottom: Our method estimates a representative point of each class (prototype) and extracts discriminative features using a novel minimax entropy technique.

[1] Saito, K., Kim, D., Sclaroff, S., Darrell, T., & Saenko, K. (2019). Semi-supervised domain adaptation via minimax entropy. In Proceedings of the IEEE/CVF international conference on computer vision (pp. 8050-8058).

❖ Semi-Supervised Domain Adaptation via Minimax Entropy [1]

- **Motivation** : Unlabeled Target Domain 데이터의 Entropy를 활용해서 Target Domain의 특징을 파악하자
  - ✓ Source Domain 데이터와 소량의 Labeled Target Domain 데이터는 **전체 Target Domain 데이터를 대변하지 못함**



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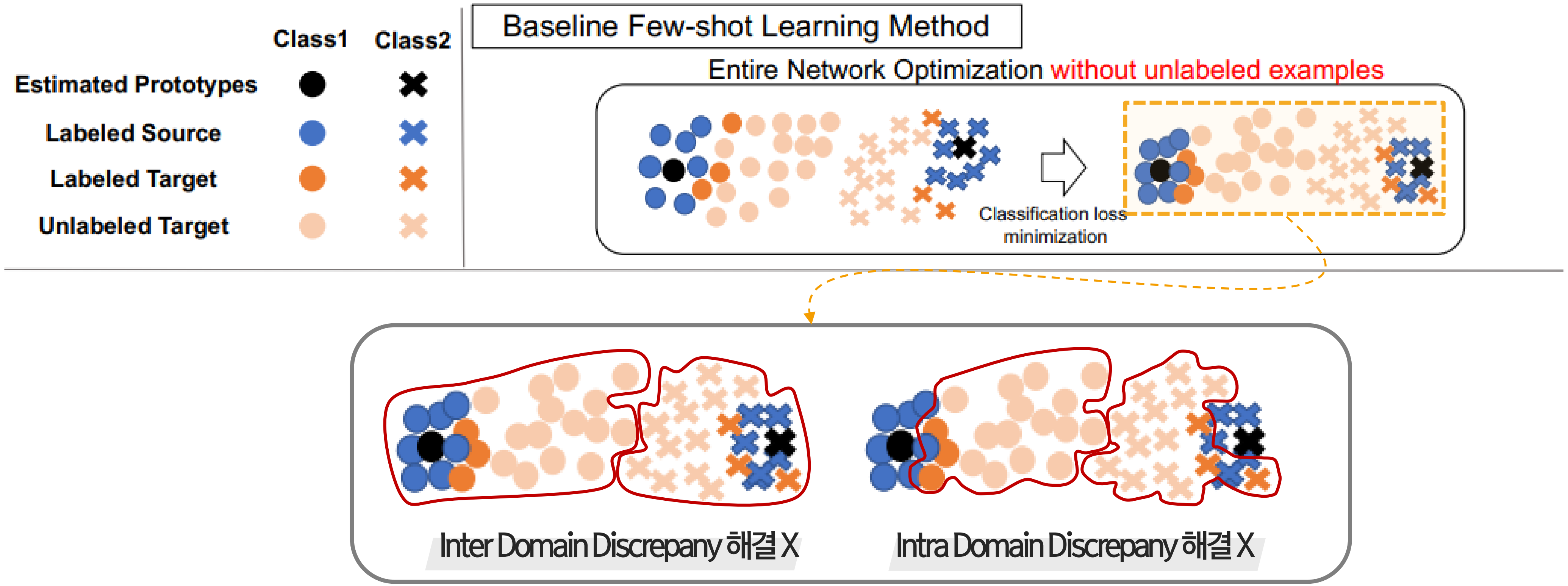
Methods

Semi-Supervised Domain Adaptation via Minimax Entropy

❖ Semi-Supervised Domain Adaptation via Minimax Entropy [1]

- 기존 Baseline Few-shot Learning Method은 **Unlabeled Target Domain 데이터를 고려하지 않음**
  - ✓ Labeled Source & Target Domain 데이터를 제외하고, Unlabeled Target Domain 데이터는 **Alignment 되지 않는 한계 존재**



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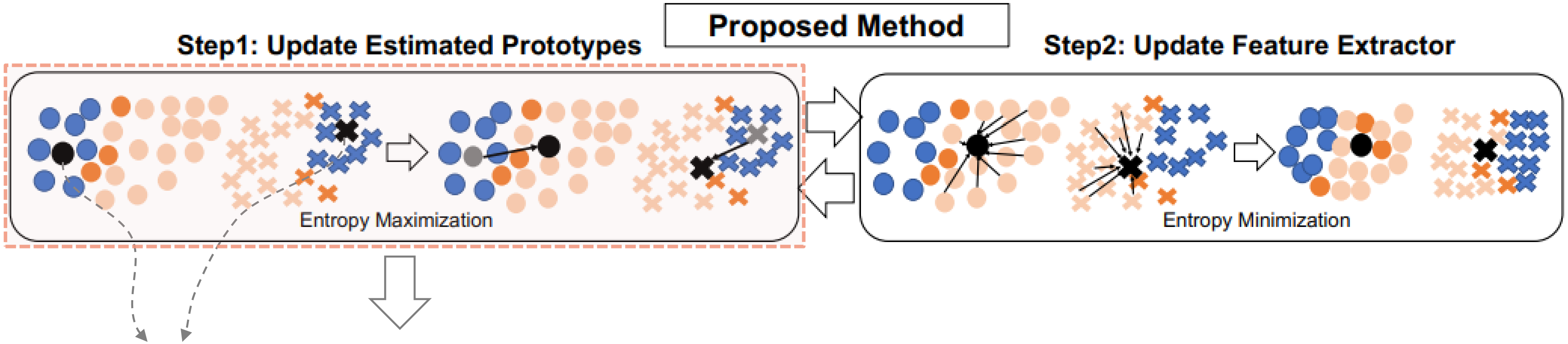
Semi-Supervised Domain Adaptation via Minimax Entropy

❖ Semi-Supervised Domain Adaptation via Minimax Entropy [1]

- Unlabeled Target Domain의 Entropy를 최소화 및 최대화하는 과정을 통해 Alignment 유도

Step 1 : Entropy Maximization



기존 Estimated Prototypes을 Unlabeled Target Examples을 반영하여 Update

[1] Saito, K., Kim, D., Sclaroff, S., Darrell, T., & Saenko, K. (2019). Semi-supervised domain adaptation via minimax entropy. In Proceedings of the IEEE/CVF international conference on computer vision (pp. 8050-8058).

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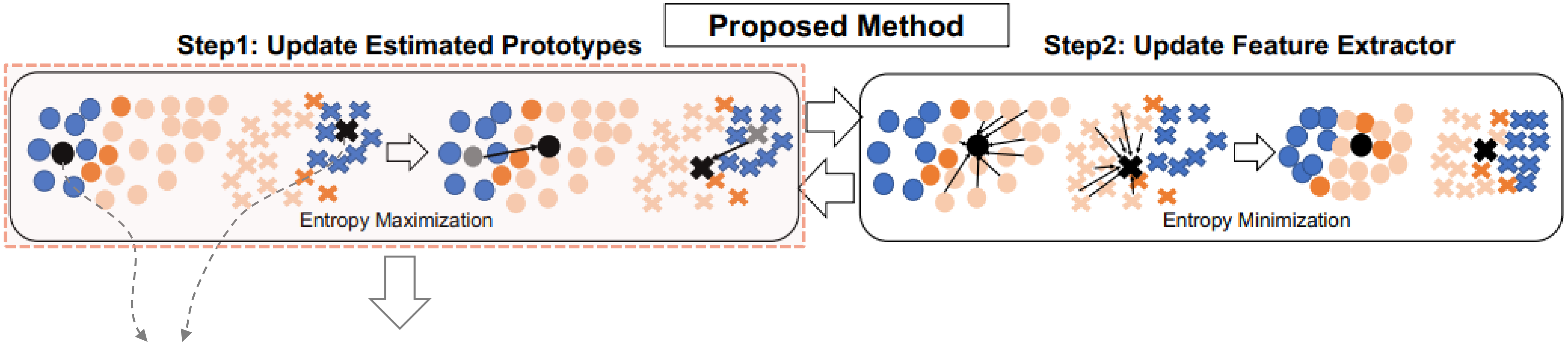

기존 Estimated Prototypes을 Unlabeled Target Examples을 반영하여 Update

$$Entropy\ H = -\mathbb{E}_{(x,y)\in D_U} \sum_{i=1}^{K} p(y=i|x) \log p(y=i|x)$$

Maximize

✓ Domain-invariant한 Discriminative Feature 학습 가능!

[1] Saito, K., Kim, D., Sclaroff, S., Darrell, T., & Saenko, K. (2019). Semi-supervised domain adaptation via minimax entropy. In Proceedings of the IEEE/CVF International conference on computer vision (pp. 8050-8058).

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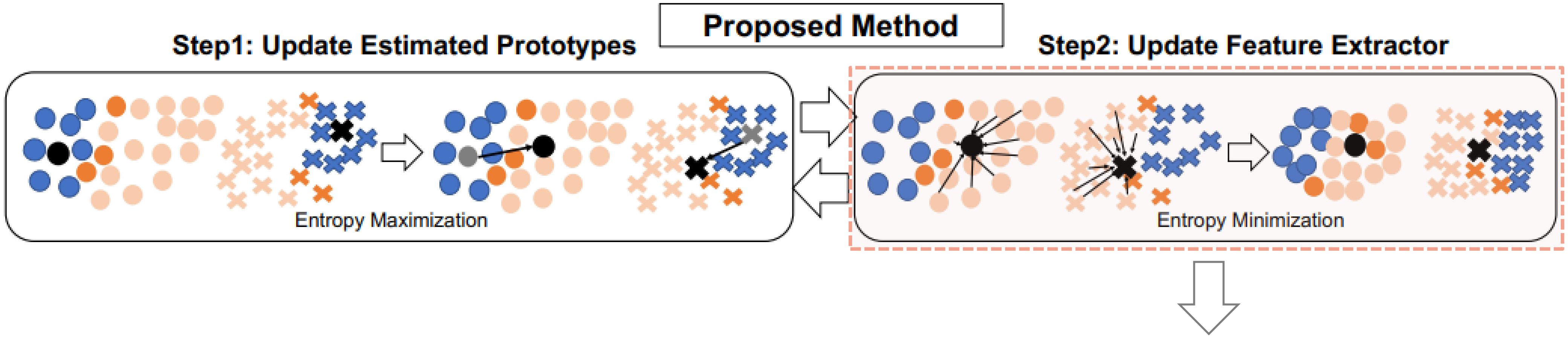
Step 2 : Entropy Minimization



Update된 Prototype으로 Unlabeled Target Examples을 Alignment하도록
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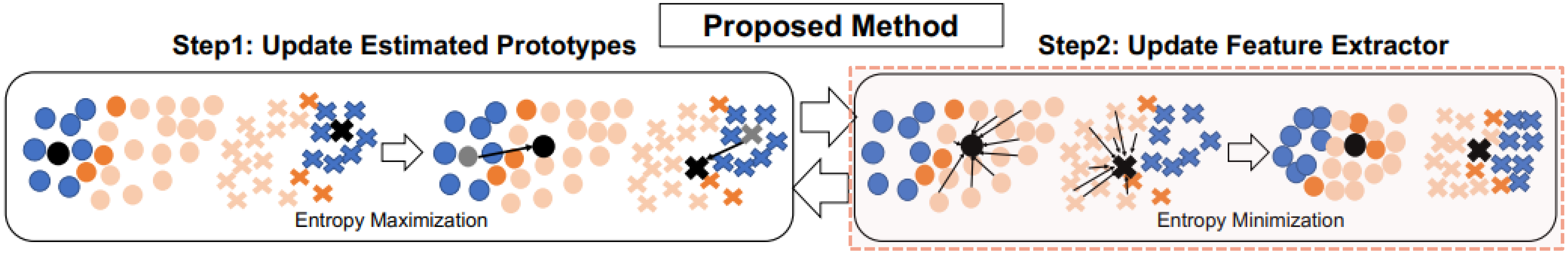

✓ Inter / Intra Domain Discrepancy 문제 해결 가능!

Update된 Prototype으로 Unlabeled Target Examples을 Alignment하도록 Feature Extractor을 Update

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Minimize

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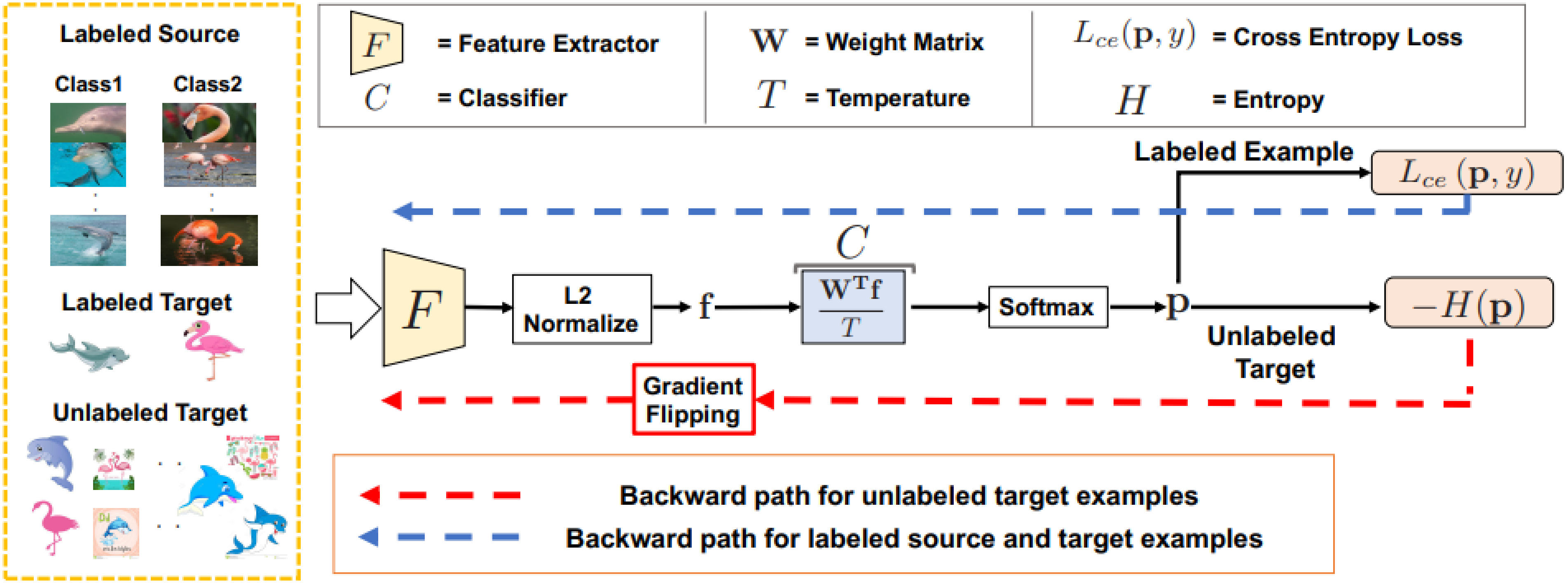

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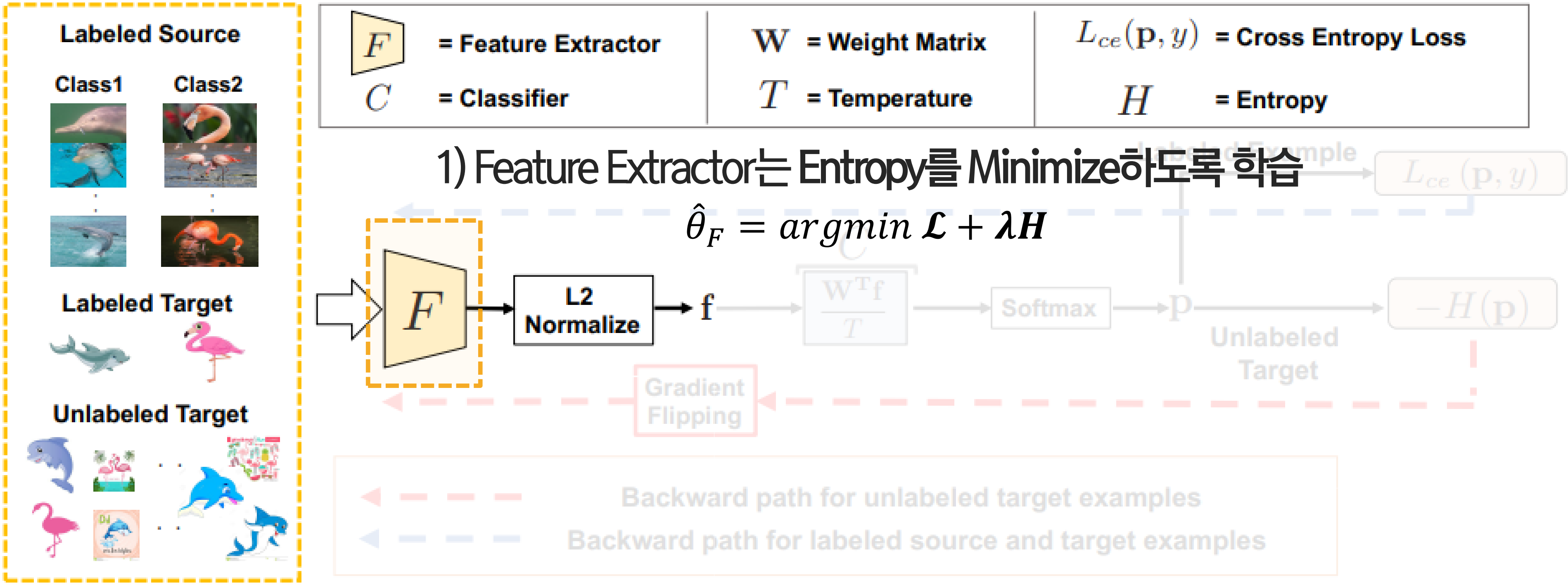

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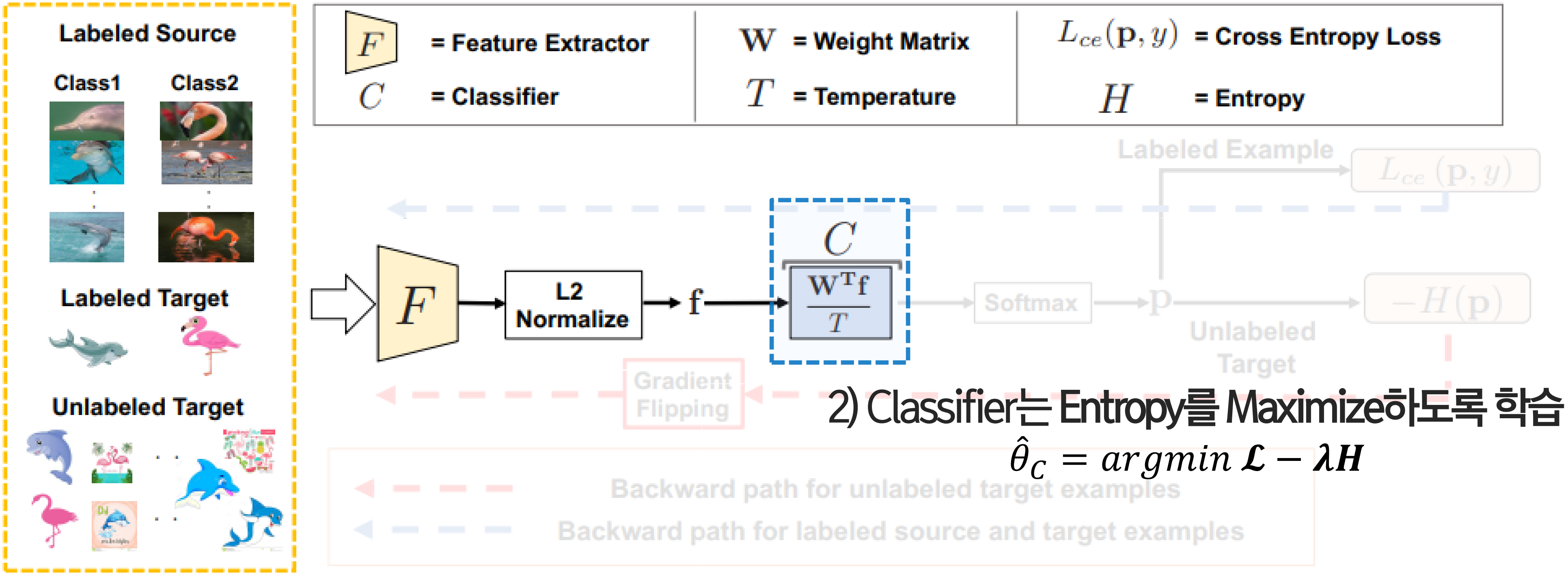

2) Classifier는 Entropy를 Maximize하도록 학습

$$\hat{\theta}_C = argmin\ \mathcal{L} - \lambda H$$

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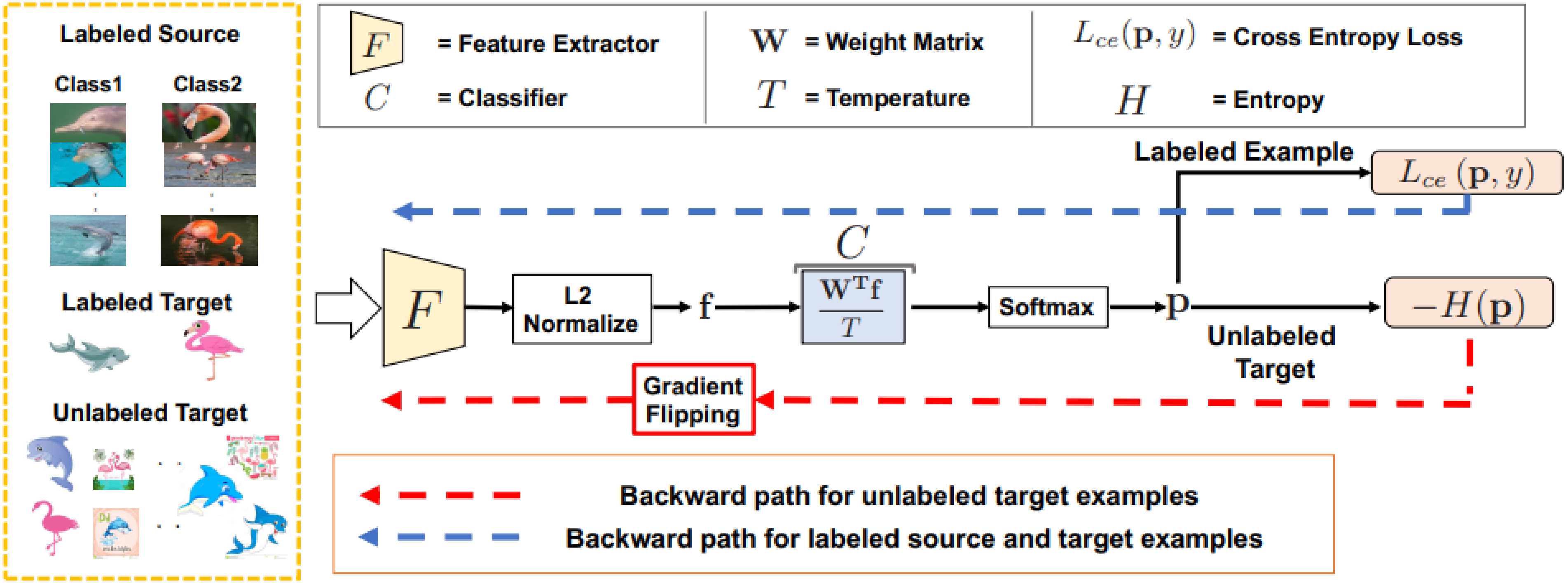

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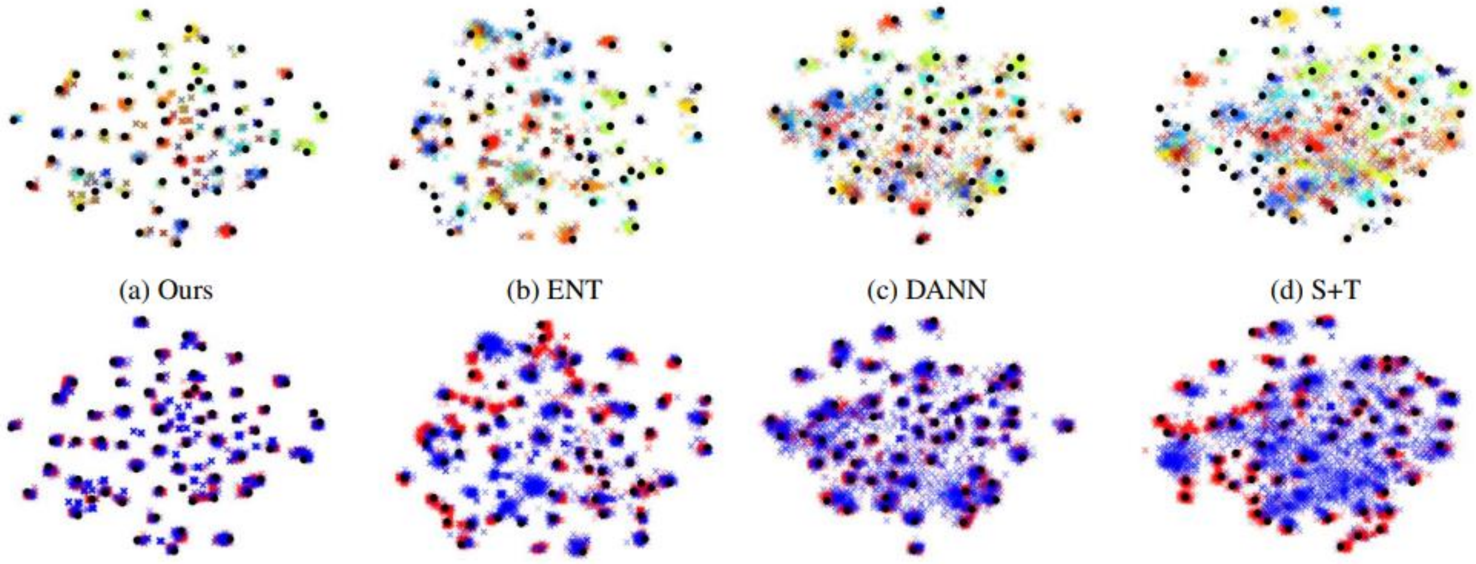
❖ Semi-Supervised Domain Adaptation via Minimax Entropy [1]

- t-SNE Visualization 결과
  - ✓ (a) ~ (d) → Class Prototype 기준 다른 비교 방법론에 비해 상대적으로 잘 Alignment됨
  - ✓ (e) ~ (h) → Source Domain(Red)과 Target Domain(Blue)가 다른 비교 방법론에 비해 서로 잘 겹쳐서 Alignment됨



(a) Ours (b) ENT (c) DANN (d) S+T

(e) Ours (f) ENT (g) DANN (h) S+T

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AdaMatch: A Unified Approach to Semi-Supervised Learning and Domain Adaptation

❖ AdaMatch: A Unified Approach to Semi-Supervised Learning and Domain Adaptation [2]

- 2022년에 제안된 Semi-Supervised Learning & Domain Adaptation 방법론 (ICLR, 2023년 10월 기준 70회 인용)
- Semi-Supervised Learning 및 Domain Adaptation(Unsupervised, Semi-Supervised) 상황에 모두 적용 가능한 알고리즘

Published as a conference paper at ICLR 2022

ADAMATCH: A UNIFIED APPROACH TO SEMI-SUPERVISED LEARNING AND DOMAIN ADAPTATION

David Berthelot†*, **Rebecca Roelofs**†*, **Kihyuk Sohn**†, **Nicholas Carlini**†, **Alex Kurakin**†
† Google Research

ABSTRACT

We extend semi-supervised learning to the problem of domain adaptation to learn significantly higher-accuracy models that train on one data distribution and test on a different one. With the goal of generality, we introduce AdaMatch, a unified solution for unsupervised domain adaptation (UDA), semi-supervised learning (SSL), and semi-supervised domain adaptation (SSDA). In an extensive experimental study, we compare its behavior with respective state-of-the-art techniques from SSL, SSDA, and UDA and find that AdaMatch either matches or significantly exceeds the state-of-the-art in each case using the same hyper-parameters regardless of the dataset or task. For example, AdaMatch nearly doubles the accuracy compared to that of the prior state-of-the-art on the UDA task for DomainNet and even exceeds the accuracy of the prior state-of-the-art obtained with pre-training by 6.4% when AdaMatch is trained completely from scratch. Furthermore, by providing AdaMatch with just one labeled example per class from the target domain (i.e., the SSDA setting), we increase the target accuracy by an additional 6.1%, and with 5 labeled examples, by 13.6%.[1]

[2] Berthelot, D., Roelofs, R., Sohn, K., Carlini, N., & Kurakin, A. (2021). Adamatch: A unified approach to semi-supervised learning and domain adaptation. arXiv preprint arXiv:2106.04732.

Methods

AdaMatch: A Unified Approach to Semi-Supervised Learning and Domain Adaptation

❖ Motivation

- 기존의 SSL SoTA 모델들은 Labeled Data와 Unlabeled Data의 분포 차이가 있는 경우(Domain Shift) 강건한 성능을 내지 못하는 한계
- Domain Adaptation을 통해 Labeled Data(Source Domain)와 Unlabeled Data(Target Domain) 간 차이를 좁히고 강건한 성능을 내고자 함

❖ Proposed Method

- Semi-Supervised Learning: Relative Confidence Threshold & Distribution Alignment
  - ✓ FixMatch를 기반으로 하되, Pseudo Label의 Confidence Threshold 산출 방식과 ReMixMatch의 Distribution Alignment 방식 변경
- Domain Adaptation: Radom Logit Interpolation
  - ✓ 각 Domain 별 Batch Norm Statics를 기반으로 내부 공분산 변화를 줄이고 Domain Shift 해결[1]

Task	Labeled	Unlabeled	Distributions
SSL	source	target	source $=$ target
UDA	source	target	source $\neq$ target
SSDA	source+target	target	source $\neq$ target

SSL: Semi Supervised Learning
UDA: Unsupervised Domain Adaptation
SSDA: SSL + UDA

[2] Berthelot, D., Roelofs, R., Sohn, K., Carlini, N., & Kurakin, A. (2021). Adamatch: A unified approach to semi-supervised learning and domain adaptation. arXiv preprint arXiv:2106.04732.

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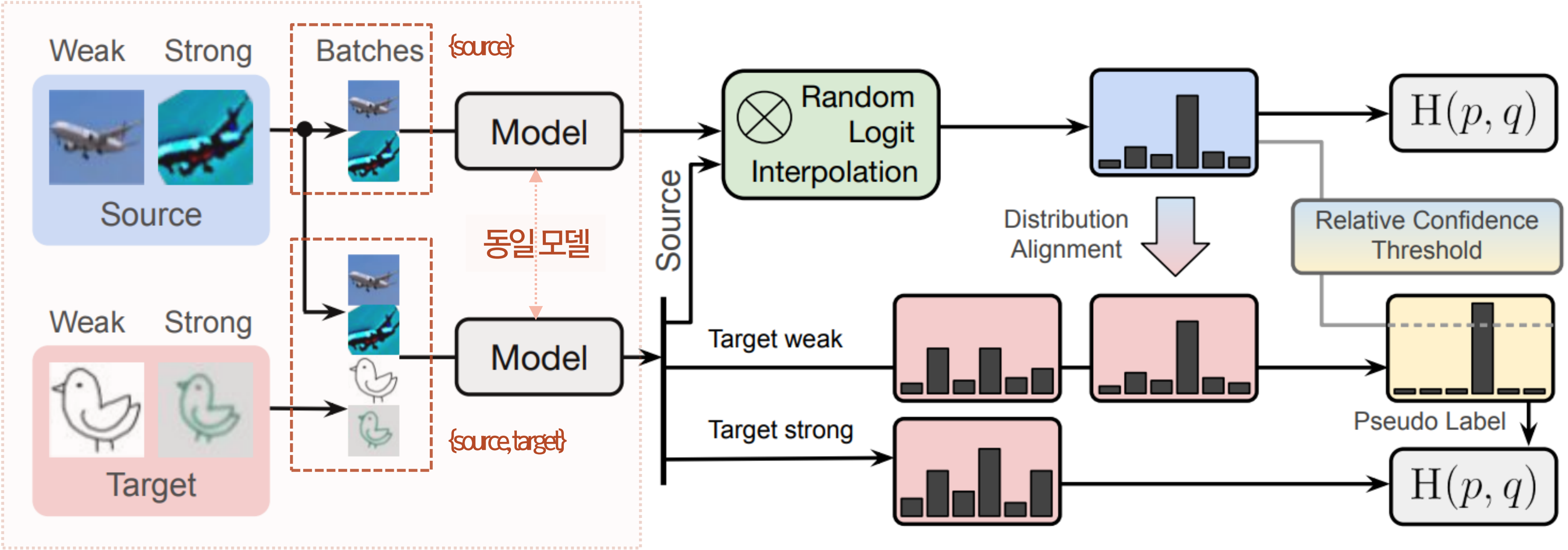
AdaMatch: A Unified Approach to Semi-Supervised Learning and Domain Adaptation

❖ Overall Framework of AdaMatch

- Labeled Source Domain과 Unlabeled Target Domain 모두 Weak/Strong Augmentation 수행
  - ✓ Weak Augmentation: (1) Shift, (2) Mirror about the x-axis
  - ✓ Strong Augmentation: Weak Augmentation + Cutout
- 동일 모델에 대하여 2번의 Forward Pass({source, target}, {source}) 수행



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AdaMatch: A Unified Approach to Semi-Supervised Learning and Domain Adaptation

$$\mathcal{L}_{\text{source}}(\theta) = \frac{1}{n_{SL}} \sum_{i=1}^{n_{SL}} H(Y_{SL}^{(i)}, Z_{SL,w}^{(i)}) + \frac{1}{n_{SL}} \sum_{i=1}^{n_{SL}} H(Y_{SL}^{(i)}, Z_{SL,s}^{(i)})$$

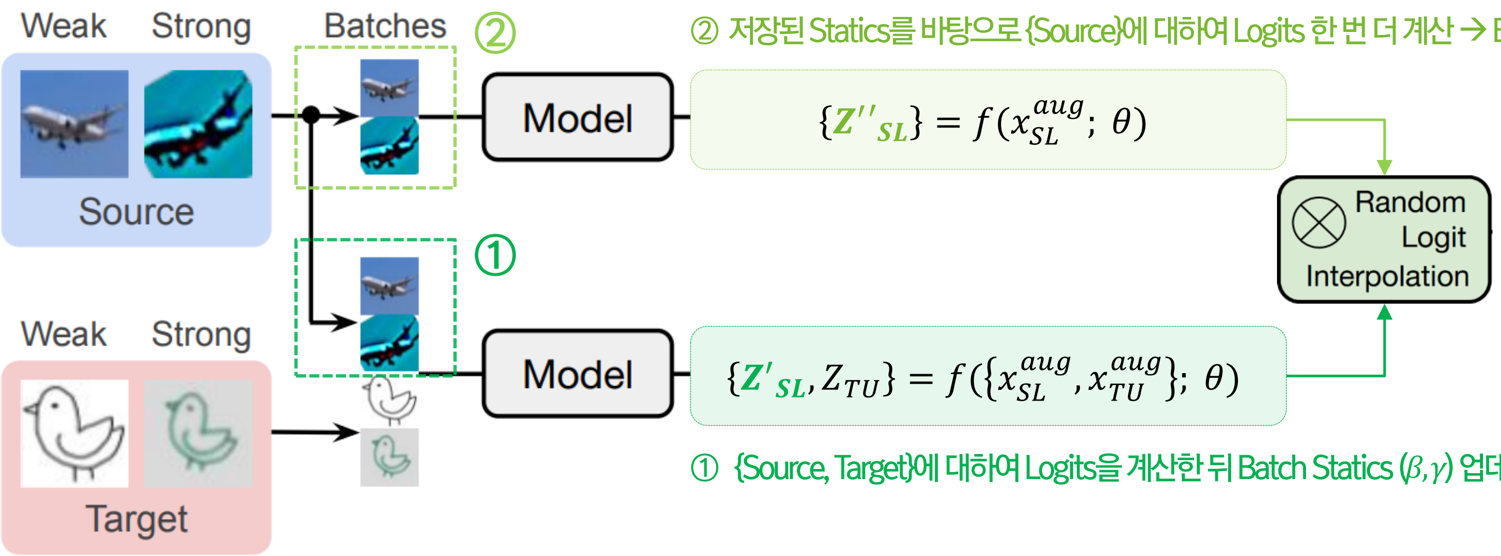
$$\mathcal{L}_{\text{target}}(\theta) = \frac{1}{n_{TU}} \sum_{i=1}^{n_{TU}} H\left(\text{stop\_gradient}(\tilde{Y}_{TU,w}^{(i)}), Z_{TU,s}^{(i)}\right) \cdot mask^{(i)}$$

$$\mathcal{L}(\theta) = \mathcal{L}_{\text{source}}(\theta) + \mu(t)\mathcal{L}_{\text{target}}(\theta)$$

❖ Random Logit Interpolation

- Random Vector λ로 + BN으로 달라진 모델의 Logits들을 + Interpolation 해보자!
- 같은 Input에 대해서, Batch Normalization으로 인해 달라진 Logits(Z'_{SL}, Z''_{SL})을 맞추기 위해 보간법 수행
  - ✓ Z'_{SL}과 Z''_{SL} 사이의 모든 점에 대하여 Loss를 산출하는 것이 아닌, [0, 1] 값을 가지는 Random Vector λ로 하나의 Interpolation Value만을 산출
  - ✓ Source Domain에 대한 Loss는 Logit Z_{SL} 을 이용하여 최소화

② 저장된 Statics를 바탕으로 {Source}에 대하여 Logits 한 번 더 계산 → Batch Statics (β, γ) 업데이트 수행 X



$$Z_{SL} = \lambda \cdot Z'_{SL} + (1-\lambda)Z''_{SL}$$

① {Source, Target}에 대하여 Logits을 계산한 뒤 Batch Statics (β, γ) 업데이트

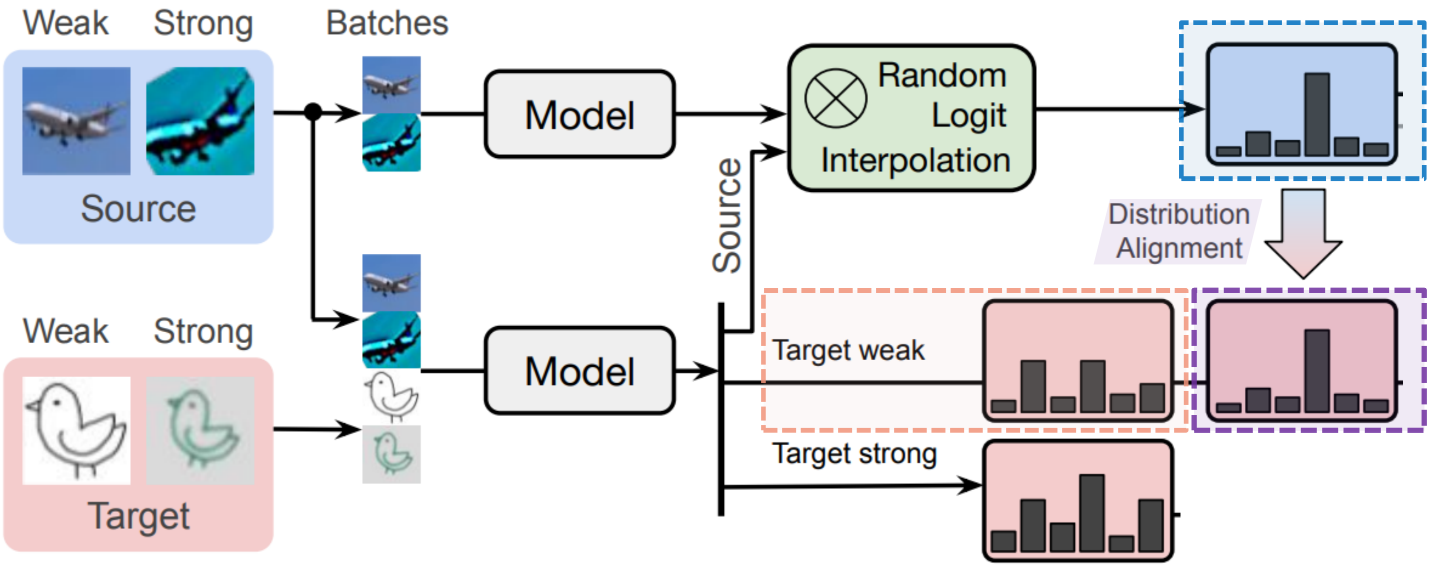
[2] Berthelot, D., Roelofs, R., Sohn, K., Carlini, N., & Kurakin, A. (2021). Adamatch: A unified approach to semi-supervised learning and domain adaptation. arXiv preprint arXiv:2106.04732.

Methods

AdaMatch: A Unified Approach to Semi-Supervised Learning and Domain Adaptation

❖ Distribution Alignment

- Unlabeled Data의 Class 예측에 대한 분포를 Labeled Data의 분포와 맞추는 과정이 필요
  - ✓ 맞추기 쉬운 Class에 대해서만 잘 예측하는 것을 방지하기 위함
- 실제 y 분포와의 조정을 시도했던 ReMixMatch(2019. 11)와는 달리, Source Domain의 Prediction output과의 조정(align)을 시도
  - ✓ Weakly Augmented Source Domain의 Output과 Weakly Augmented Target Domain의 Output 조정으로 최종 Pseudo Label 생성



$$\hat{Y}_{SL,w} = \texttt{softmax}(Z_{SL,w}) \in \mathbb{R}^{n_{SL} \cdot k}$$

Source에 대한 예측 평균과 Target에 대한 예측 평균 사이 비율

$$\tilde{Y}_{TU,w} = \texttt{normalize}\left(\hat{Y}_{TU,w} \frac{\mathbb{E}[\hat{Y}_{SL,w}]}{\mathbb{E}[\hat{Y}_{TU,w}]}\right)$$

$$\hat{Y}_{TU,w} = \texttt{softmax}(Z_{TU,w}) \in \mathbb{R}^{n_{TU} \cdot k}$$

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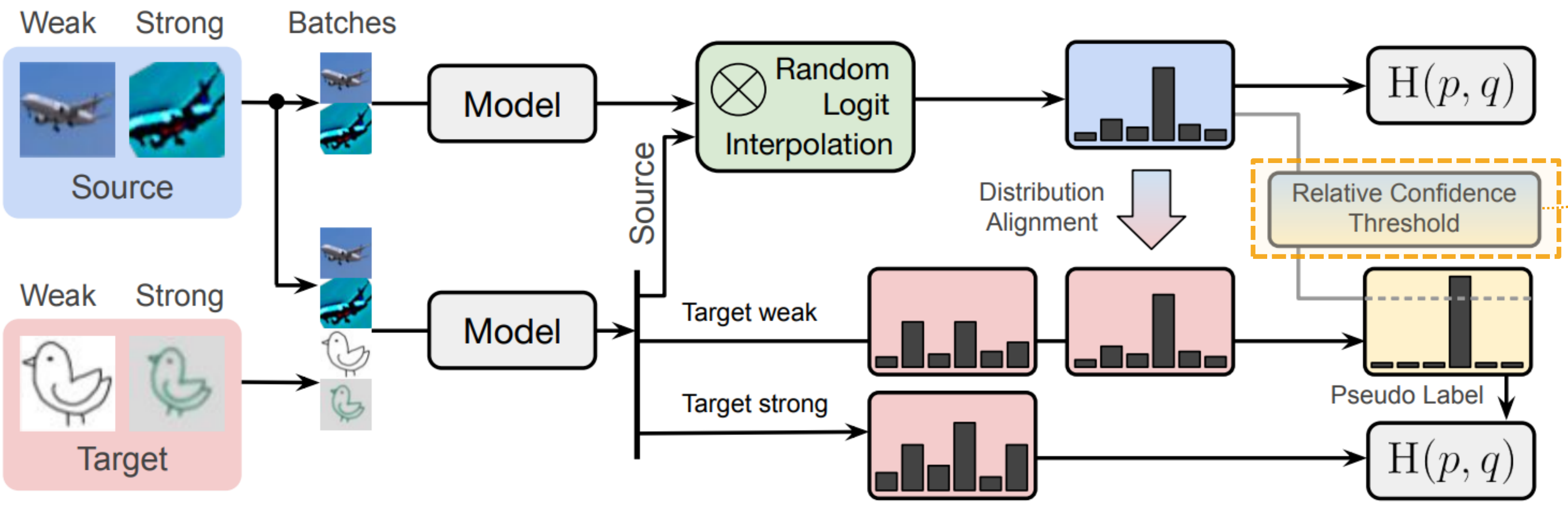
AdaMatch: A Unified Approach to Semi-Supervised Learning and Domain Adaptation

❖ Relative Confidence Threshold

- Domain이 다른 경우 모델의 Confidence Threshold가 데이터셋마다 다른 점을 감안
- Weakly Augmented Source Domain의 Confidence 수준에 따른 상대적인 Threshold 제안 (c_τ)
  - ✓ Weakly Augmented Source Domain의 top-1 예측 값을 사전에 지정한 Threshold(τ)에 곱함

$$c_\tau = \frac{\boxed{\tau}}{n_{SL}} \sum_{i=1}^{n_{SL}} \boxed{\max_{j\in[1..k]} (\hat{Y}_{SL,w}^{(i,j)})}$$



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Methods

Semi-Supervised Domain Adaptation

❖ Attract, Perturb, and Explore: Learning a Feature Alignment Network for Semi-supervised Domain Adaptation [3]

- 2020년에 제안된 Semi-Supervised Domain Adaptation 방법론 (ECCV, 2023년 10월 기준 102회 인용)
- Intra-domain Discrepancy 문제의 발생 과정 및 원인과 이를 해결하는 과정을 체계적으로 제시한 논문

Attract, Perturb, and Explore: Learning a Feature Alignment Network for Semi-supervised Domain Adaptation

Taekyung Kim[0000−0001−7401−098X] and Changick Kim

Korea Advanced Institute of Science and Technology, Daejeon, South Korea
{tkkim93, changick}@kaist.ac.kr

Abstract. Although unsupervised domain adaptation methods have been widely adopted across several computer vision tasks, it is more desirable if we can exploit a few labeled data from new domains encountered in a real application. The novel setting of the semi-supervised domain adaptation (SSDA) problem shares the challenges with the domain adaptation problem and the semi-supervised learning problem. However, a recent study shows that conventional domain adaptation and semi-supervised learning methods often result in less effective or negative transfer in the SSDA problem. In order to interpret the observation and address the SSDA problem, in this paper, we raise the intra-domain discrepancy issue within the target domain, which has never been discussed so far. Then, we demonstrate that addressing the intra-domain discrepancy leads to the ultimate goal of the SSDA problem. We propose an SSDA framework that aims to align features via alleviation of the intra-domain discrepancy. Our framework mainly consists of three schemes, i.e., attrac-

[3] Kim, T., & Kim, C. (2020). Attract, perturb, and explore: Learning a feature alignment network for semi-supervised domain adaptation. In Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XIV 16 (pp. 591-607).

Methods

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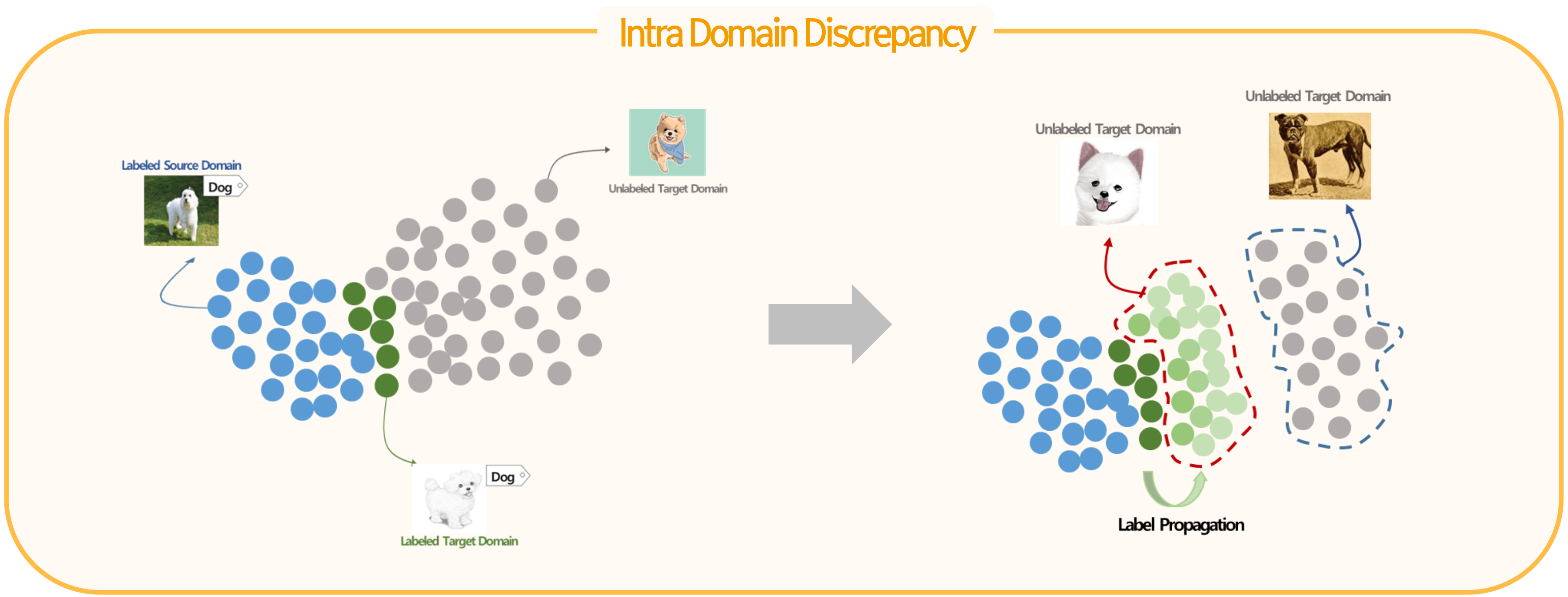
- Motivation : Semi-Supervised Domain Adaptation 상황에서 발생할 수 있는 Intra Domain Discrepancy 문제를 해결하자!
  - ✓ Intra Domain Discrepancy 문제는 악화될 경우 Labeled Target Domain을 아예 사용하지 않는 UDA의 경우보다 성능이 저조해질 수 있음



Methods

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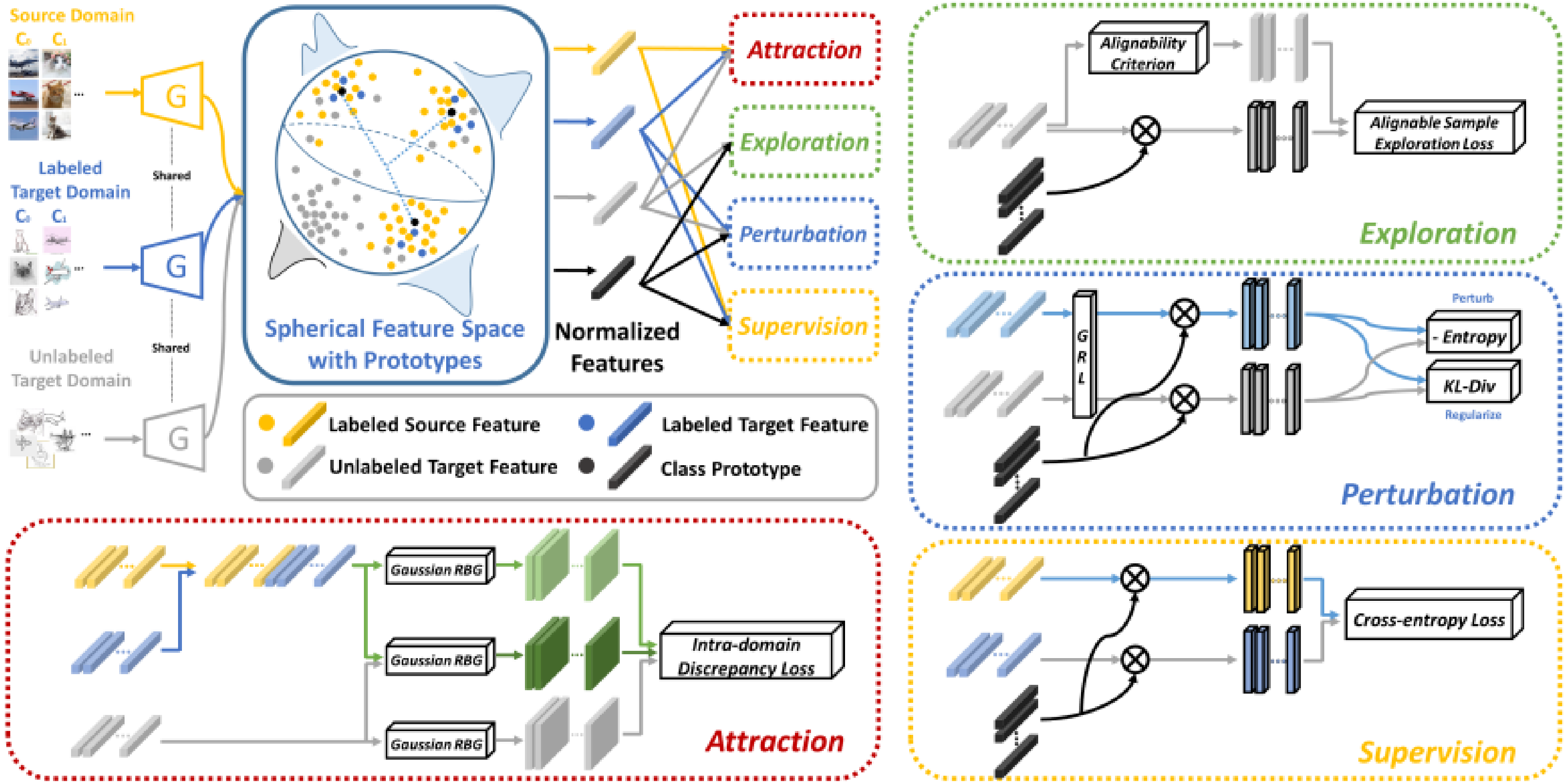
- 본 논문은 아래의 네 가지 과정에서의 Loss를 산정하여 Intra Domain Discrepancy 문제를 해결하고자 함
  - ✓ 1) Supervision 2) Attract 3) Perturb 4) Explore



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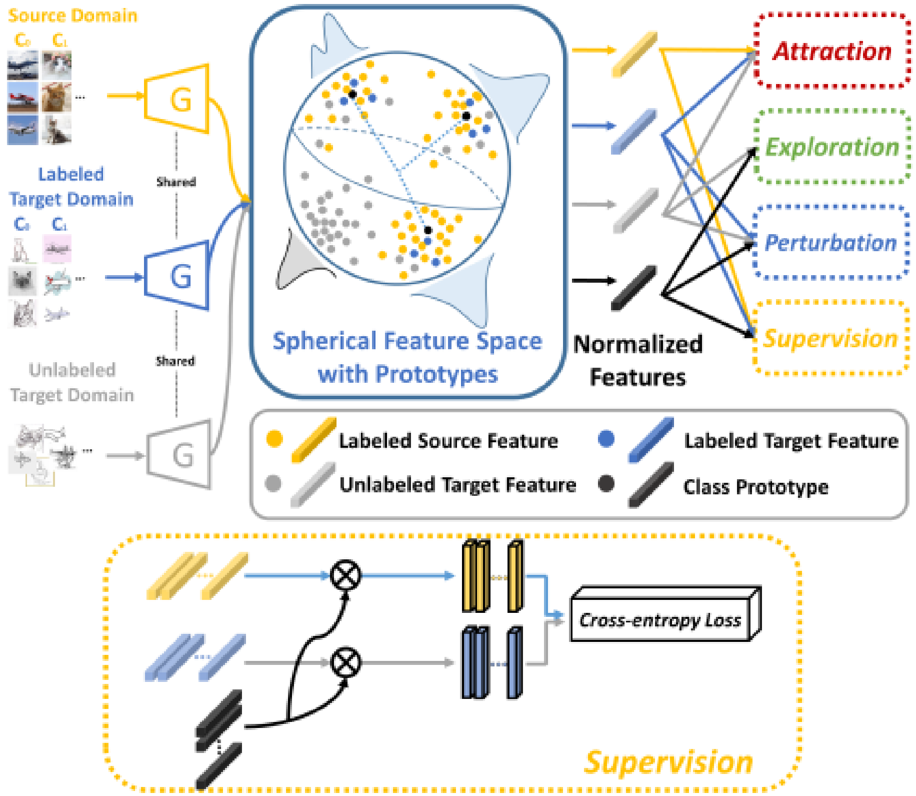

1) Supervision

Labeled Sample(Source & Target)과 이들의 Prototype간 Cross-entropy

$$\mathcal{L}_{cls} = \mathbb{E}_{(x,y)\in D_S \cup D_t}[-\log p\,(y|x, p)]$$

$$= \mathbb{E}_{(x,y)\in D_S \cup D_t}[-\log(\frac{\exp\left(p_y * \frac{f_\theta(x)}{T}\right)}{\sum_{i=1}^{K}\exp\left(p_i * \frac{f_\theta(x)}{T}\right)})]$$

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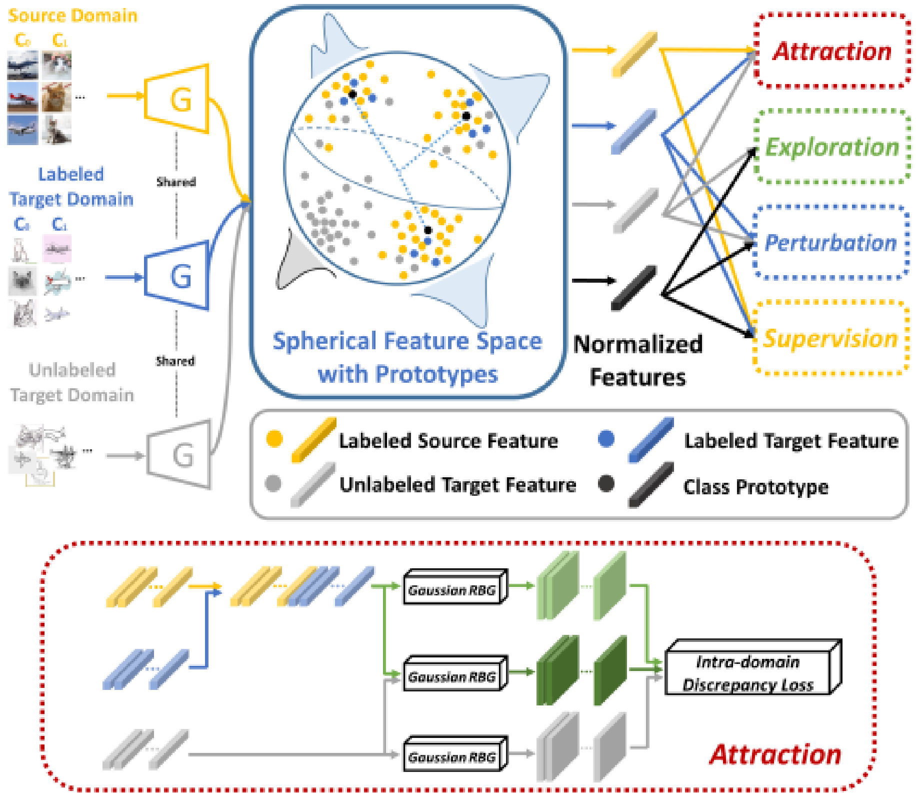
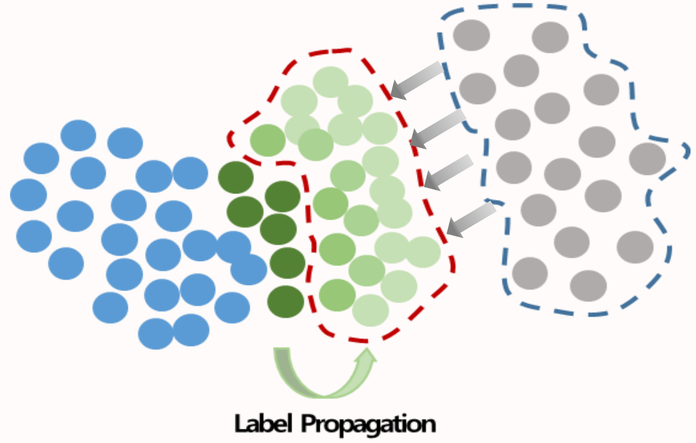


2) Attraction

Align되지 않은 Target Unlabeled Domain sample을 Align하자!



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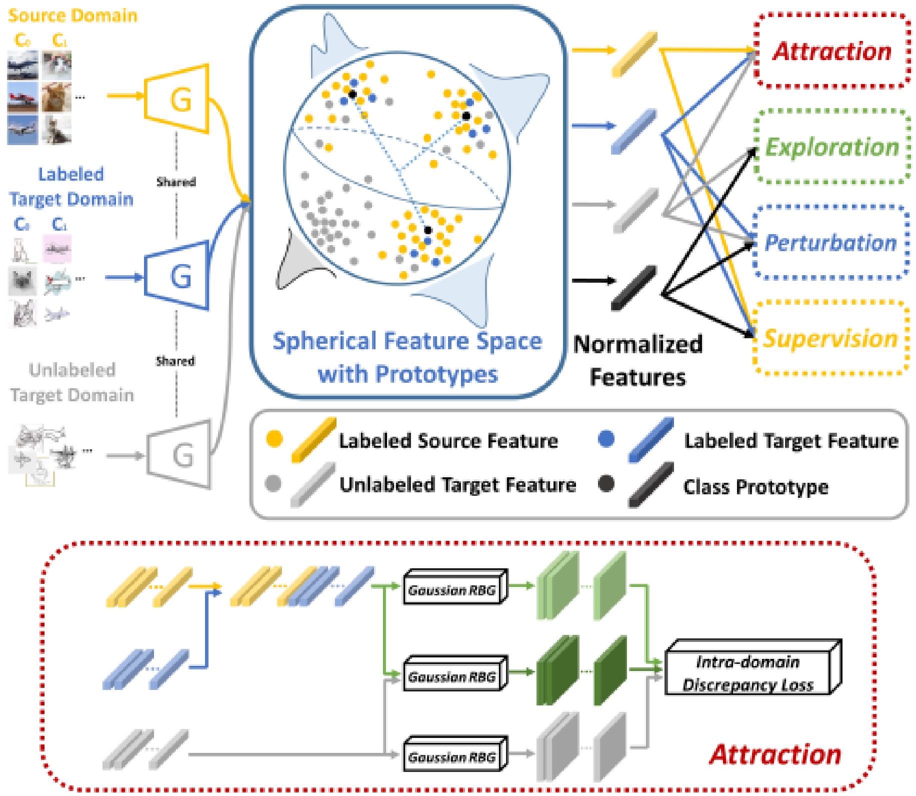

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Intra-domain Discrepancy $d(\cdot)$

$$d(D_s \cup D_t, D_U) = \mathbb{E}_{(x,y),(x',y') \in D_s \cup D_t}\left[k\left(f_\theta(x), f_\theta(x')\right)\right] + \mathbb{E}_{(z,w),(z',w') \in D_U}\left[k\left(f_\theta(z), f_\theta(z')\right)\right] - 2\mathbb{E}_{(x,y) \in D_s \cup D_t, (z,w) \in D_U}\left[k\left(f_\theta(x), f_\theta(z)\right)\right]$$

✓ Mean Maximum Discrepancy

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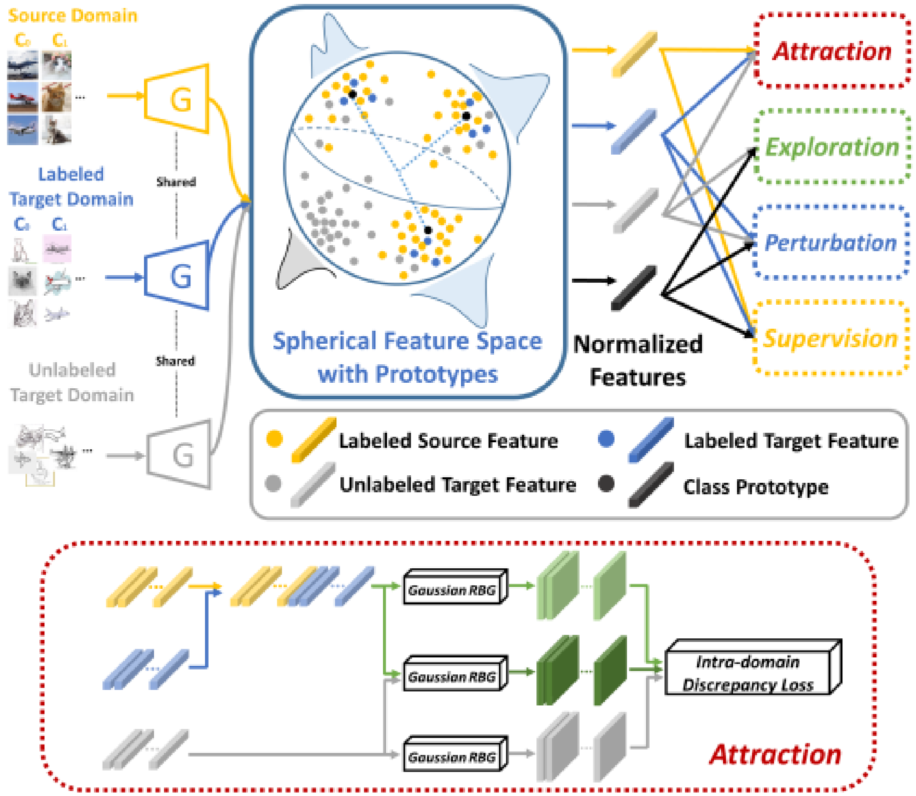

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Intra-domain Discrepancy $d(\cdot)$

Labeled Sample(Source & Target)끼리 유사도가 크고,

$$\boxed{d(D_s \cup D_t, D_U)} = \boxed{\mathbb{E}_{(x,y),(x',y')\in D_s \cup D_t}[k(f_\theta(x), f_\theta(x'))]}$$
$$+\ \mathbb{E}_{(z,w),(z',w')\in D_U}[k(f_\theta(z), f_\theta(z'))]$$
$$-2\mathbb{E}_{(x,y)\in D_s \cup D_t,(z,w)\in D_U}[k(f_\theta(x), f_\theta(z))]$$

d값이 크다면

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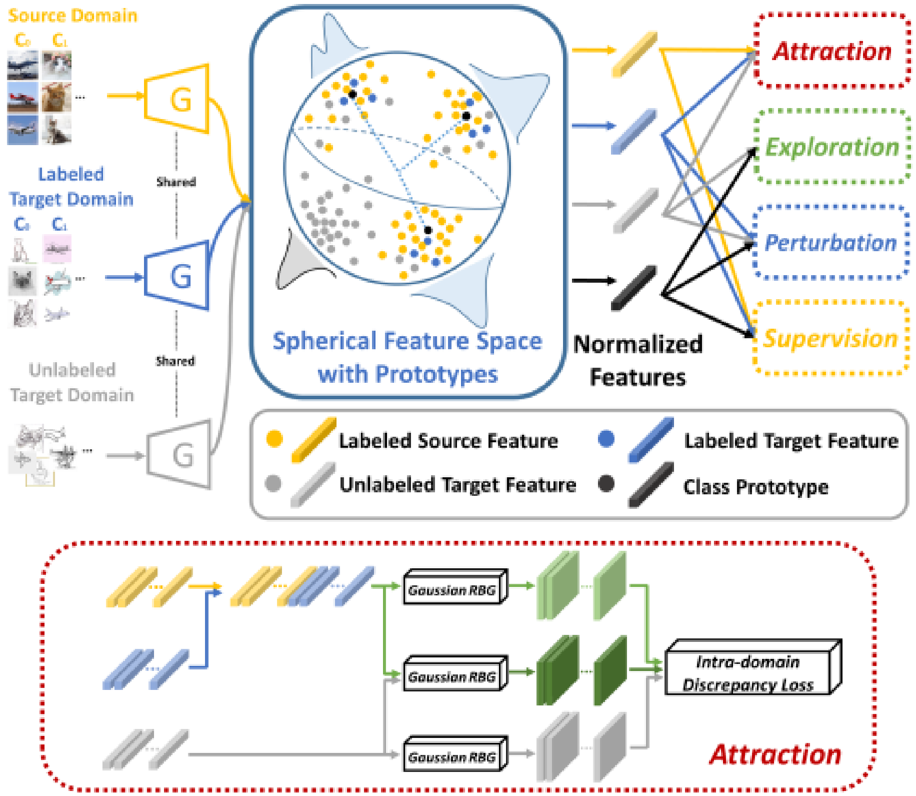

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d값이 크다면

Unlabeled Sample(Target)끼리 유사도가 크고,

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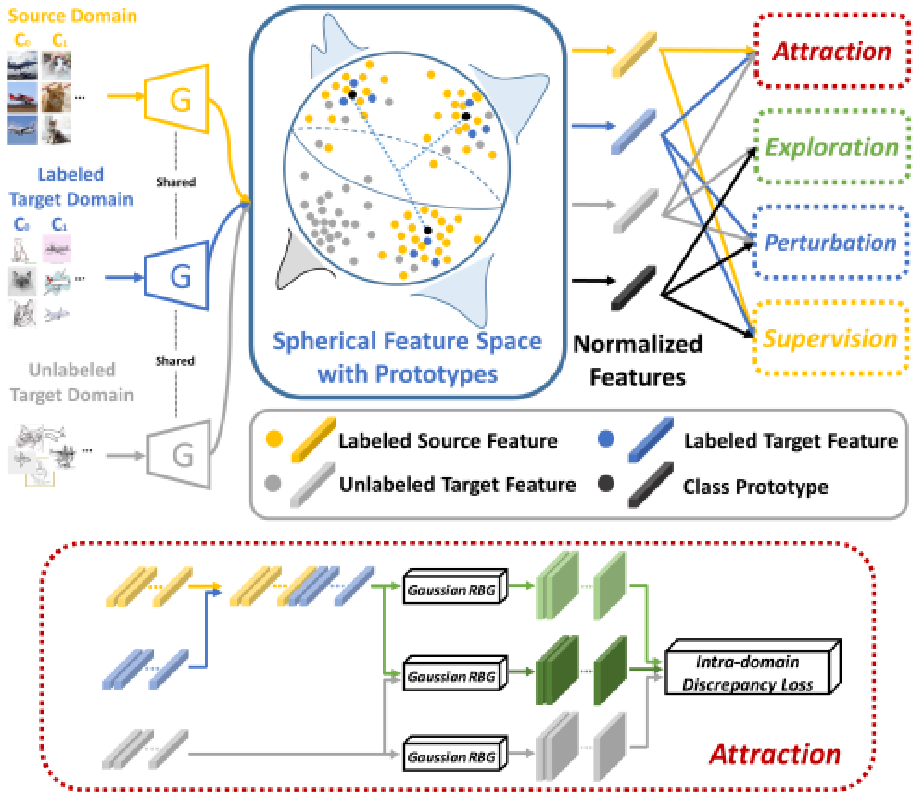

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d값이 크다면

Labeled Sample(Source & Target)과
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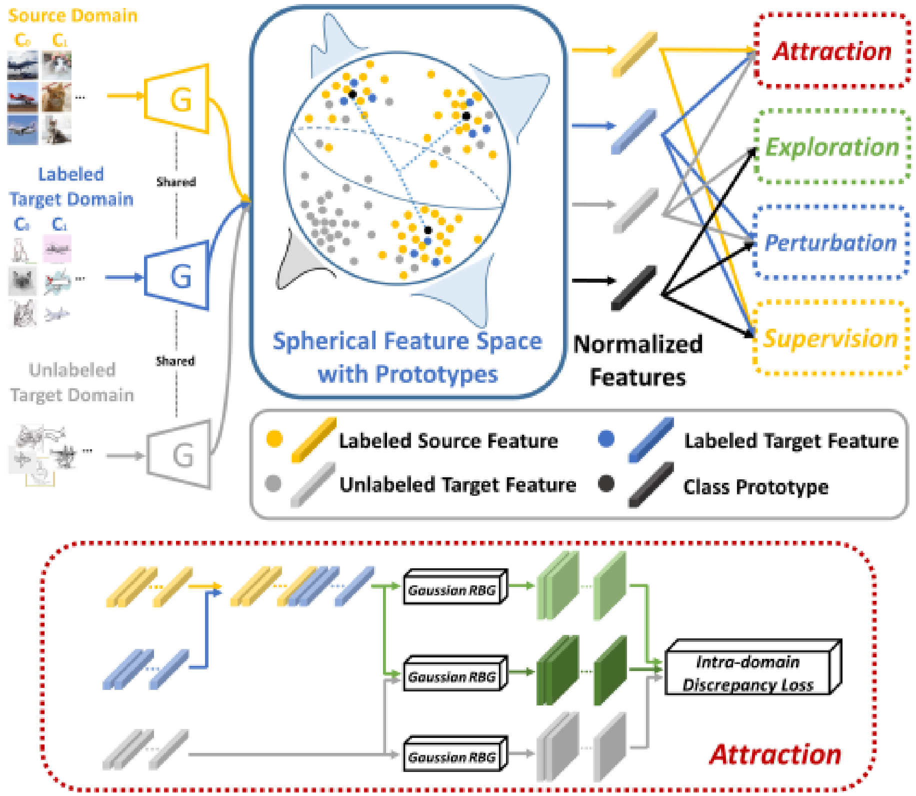

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d값이 크다면

Intra-domain Discrepancy 문제가 해결되지 못함!

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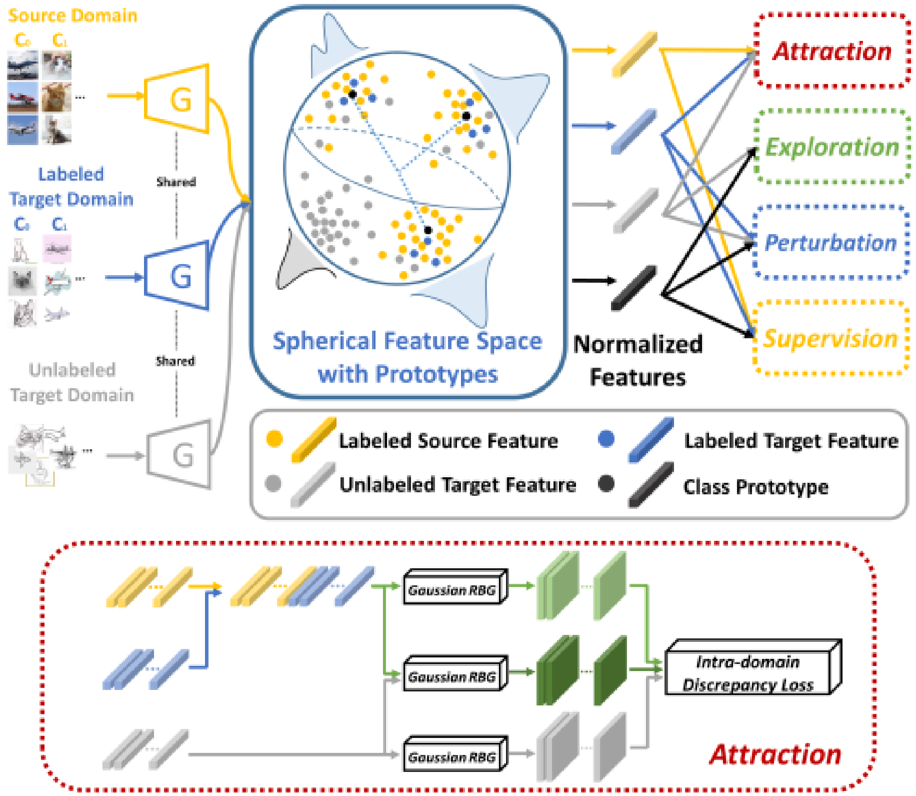

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$$\min \mathcal{L}_a = \min d(D_s \cup D_t, D_U)$$

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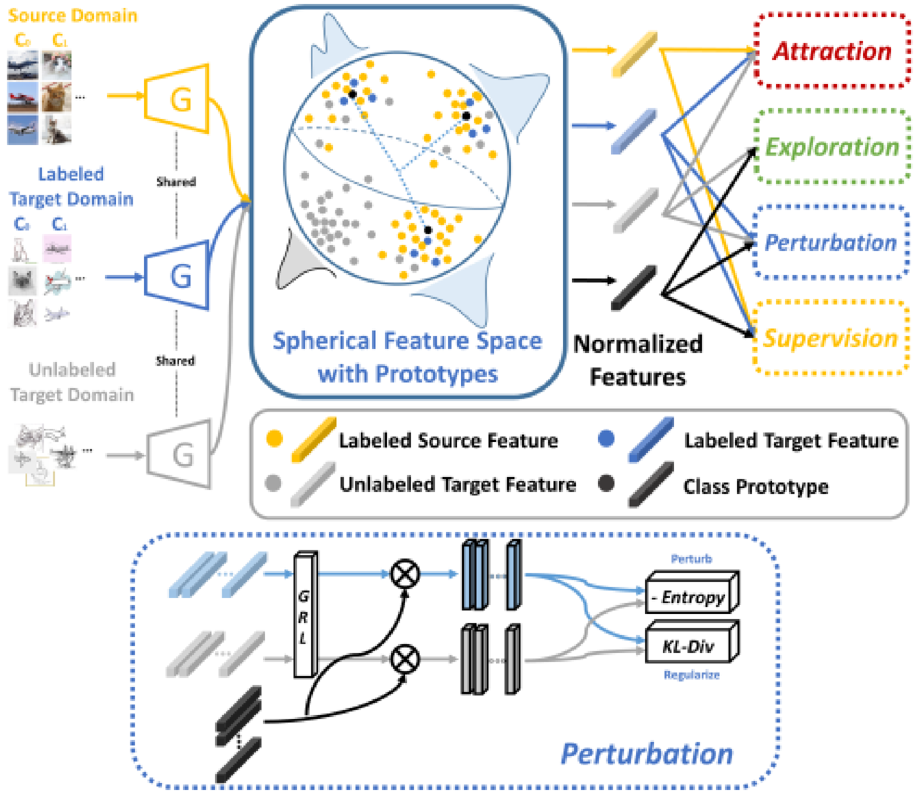

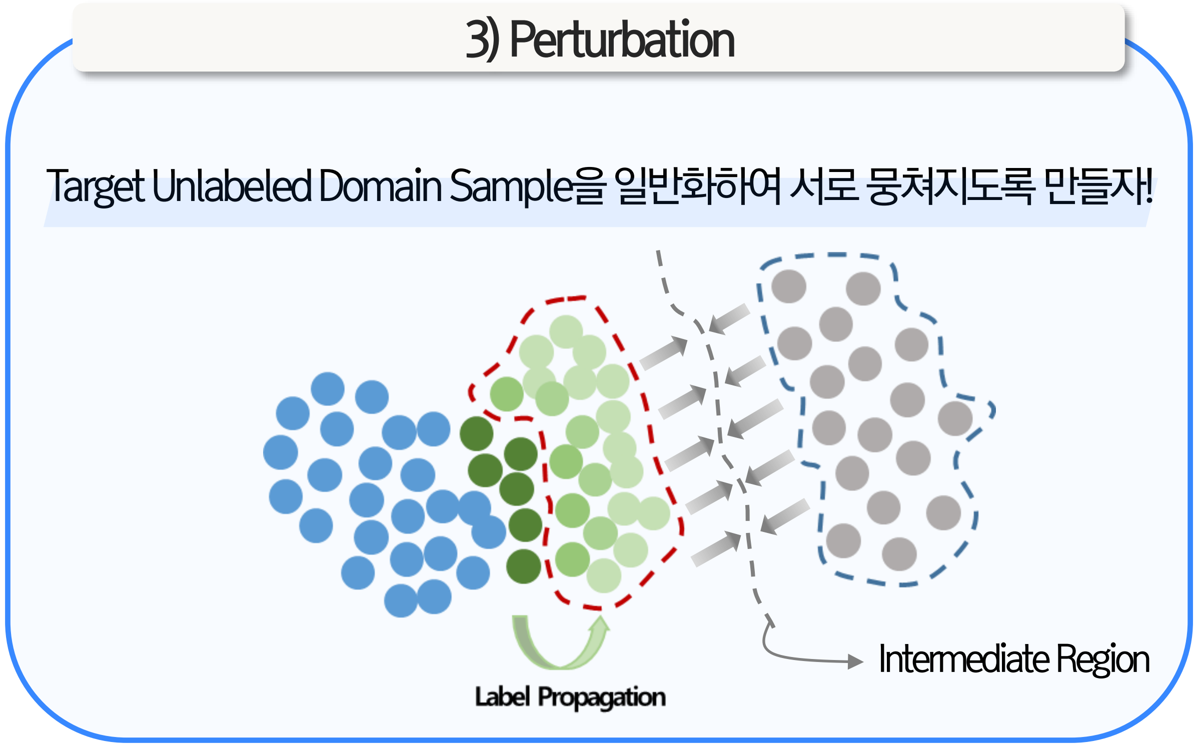

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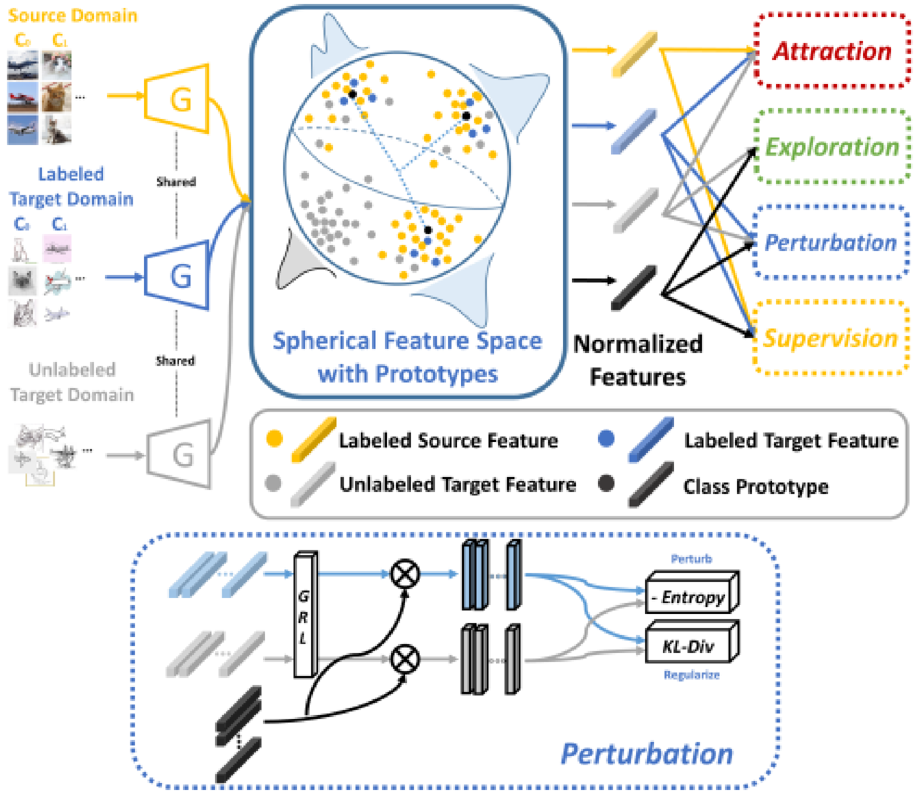

3) Perturbation

Target Unlabeled Domain Sample을 일반화하여 서로 뭉쳐지도록 만들자!

$$H_p(x) = -\sum_{i=1}^{K} p(y=i|x)\,\log p(y=i|x,p)$$

$$r_x = \underset{||r||<c}{\operatorname{argmin}}\,\max_{p} H_p(x+r)$$

$$\mathcal{L}_p = \mathbb{E}_{x\in D_u}\left[\sum_{i=1}^{K} D_{KL}[p(y=i|x,p), p(y=i|x+r_x,p)]\right] + \mathbb{E}_{(z,w)\in D_t}\left[\sum_{i=1}^{K} D_{KL}[p(y=i|z,p), p(y=i|z+r_z,p)]\right]$$

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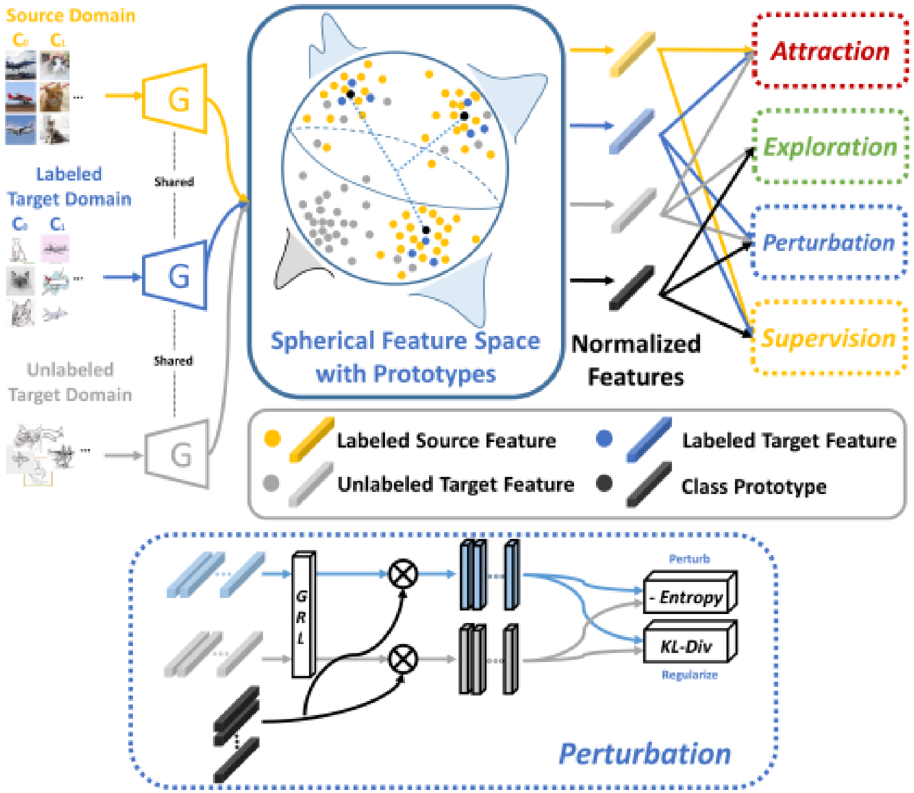

3) Perturbation

Target Unlabeled Domain Sample을 일반화하여 서로 뭉쳐지도록 만들자!

Sample (x)와 Prototype (p) 간 Entropy

$$\boxed{H_p(x) = -\sum_{i=1}^{K} p(y=i|x) \log p(y=i|x,p)}$$

$$r_x = \underset{||r||<c}{\operatorname{argmin}} \max_{p} H_p(x+r)$$

$$\mathcal{L}_p = \mathbb{E}_{x\in D_u}\left[\sum_{i=1}^{K} D_{KL}[p(y=i|x,p), p(y=i|x+r_x,p)]\right] + \mathbb{E}_{(z,w)\in D_t}\left[\sum_{i=1}^{K} D_{KL}[p(y=i|z,p), p(y=i|z+r_z,p)]\right]$$

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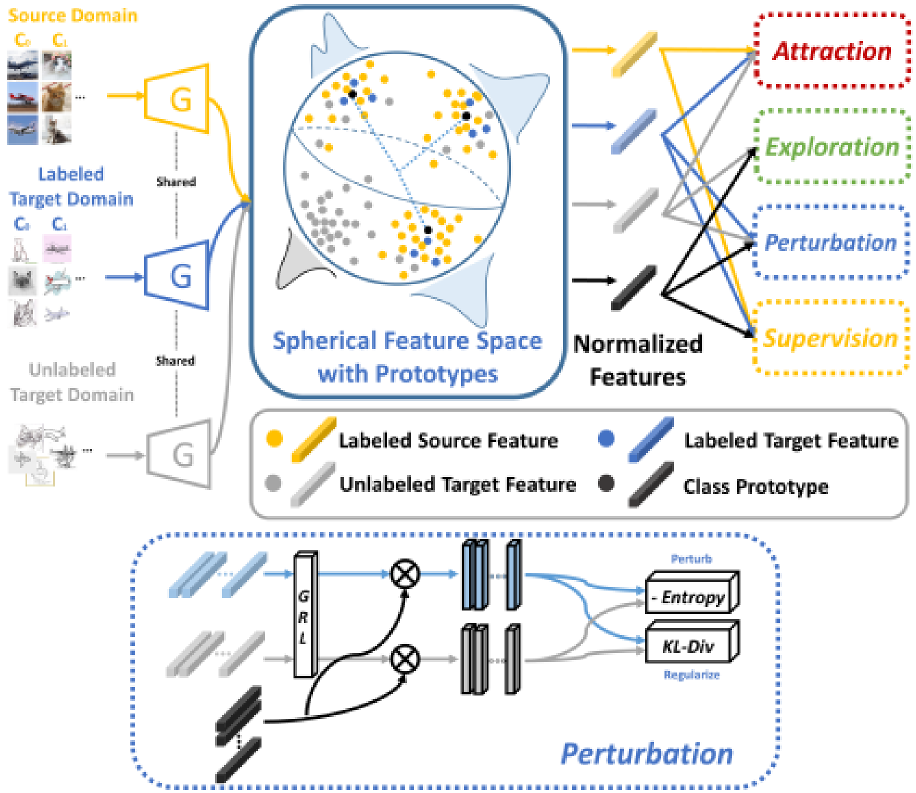
- 본 논문은 아래의 네 가지 과정에서의 Loss를 산정하여 Intra Domain Discrepancy 문제를 해결하고자 함

✓ 1) Supervision 2) Attraction 3) Perturbation 4) Exploration



3) Perturbation

Target Unlabeled Domain Sample을 일반화하여 서로 뭉쳐지도록 만들자!

$$H_p(x) = -\sum_{i=1}^{K} p(y=i|x)\log p(y=i|x,p)$$

$$r_x = \boxed{\underset{||r||<c}{\operatorname{argmin}}} \max_{p} H_p(x+r)$$

Perturbation value r이 특정값c를 넘지않으면서,

$$\mathcal{L}_p = \mathbb{E}_{x\in D_u}\left[\sum_{i=1}^{K} D_{KL}[p(y=i|x,p),p(y=i|x+r_x,p)]\right] + \mathbb{E}_{(z,w)\in D_t}\left[\sum_{i=1}^{K} D_{KL}[p(y=i|z,p),p(y=i|z+r_z,p)]\right]$$

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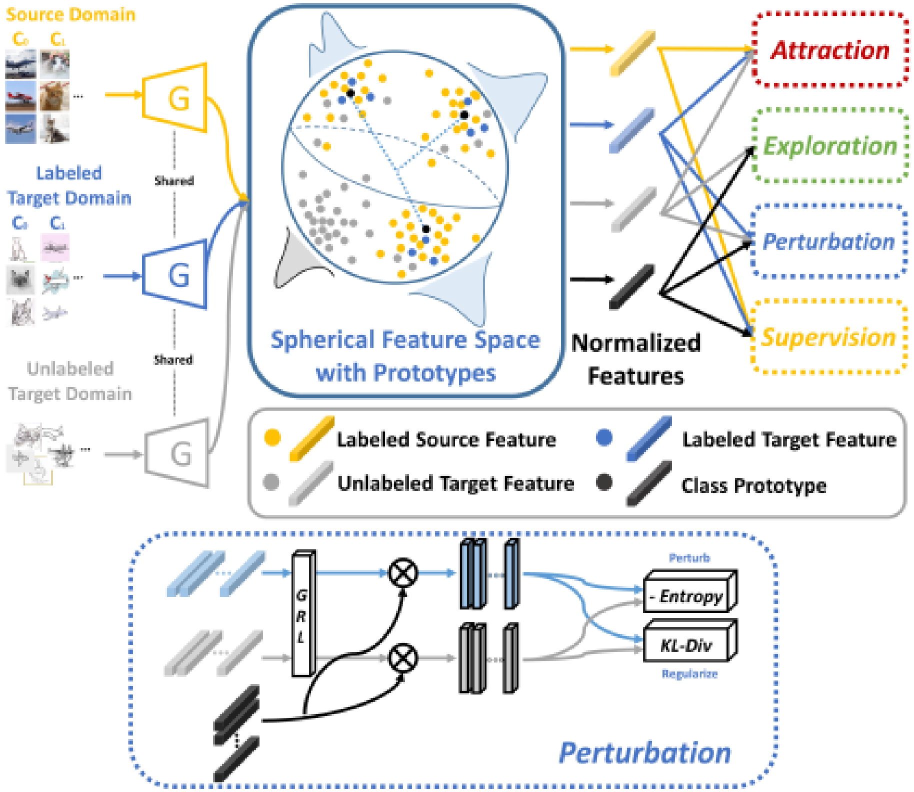

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Prototype의 Entropy를 최대화시키는 p, r_x를 찾자!

$$\mathcal{L}_p = \mathbb{E}_{x \in D_u}\left[\sum_{i=1}^{K} D_{KL}[p(y=i|x,p), p(y=i|x+r_x,p)]\right]$$
$$+\mathbb{E}_{(z,w) \in D_t}\left[\sum_{i=1}^{K} D_{KL}[p(y=i|z,p), p(y=i|z+r_z,p)]\right]$$

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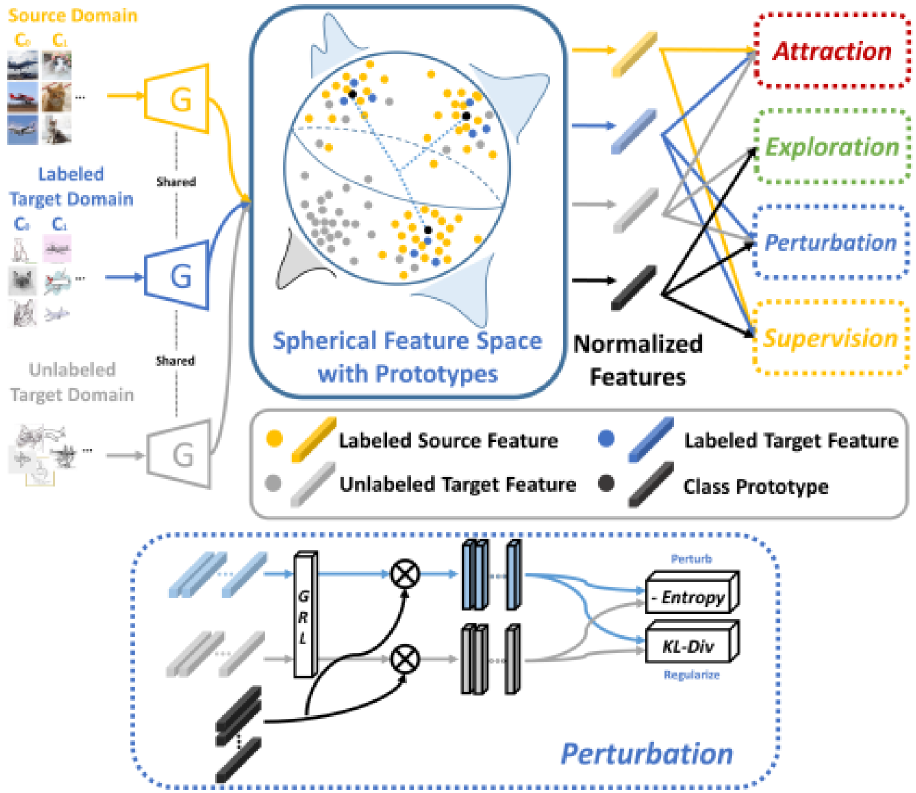

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KLdivergence → Perturbated Unlabeled Targetsample과 Given data간 Regularization

$$\mathcal{L}_p = \mathbb{E}_{x\in D_u}\left[\sum_{i=1}^{K} D_{KL}[p(y=i|x,p), p(y=i|x+r_x,p)]\right] + \mathbb{E}_{(z,w)\in D_t}\left[\sum_{i=1}^{K} D_{KL}[p(y=i|z,p), p(y=i|z+r_z,p)]\right]$$

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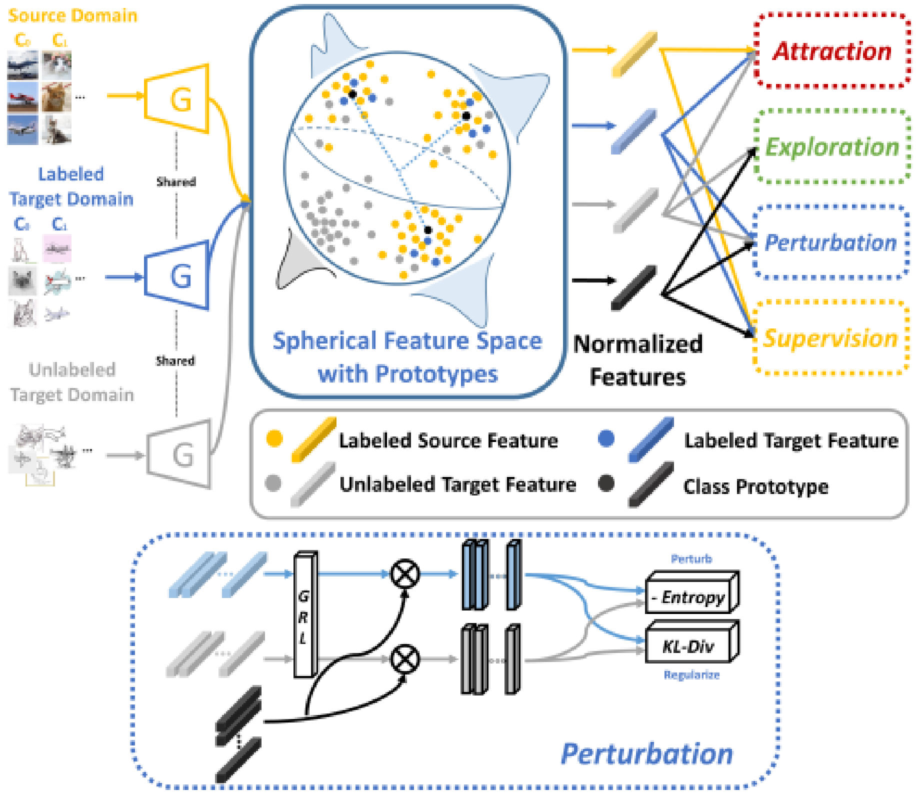

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KL divergence → Perturbated Labeled Target sample과 Given data간 Regularization

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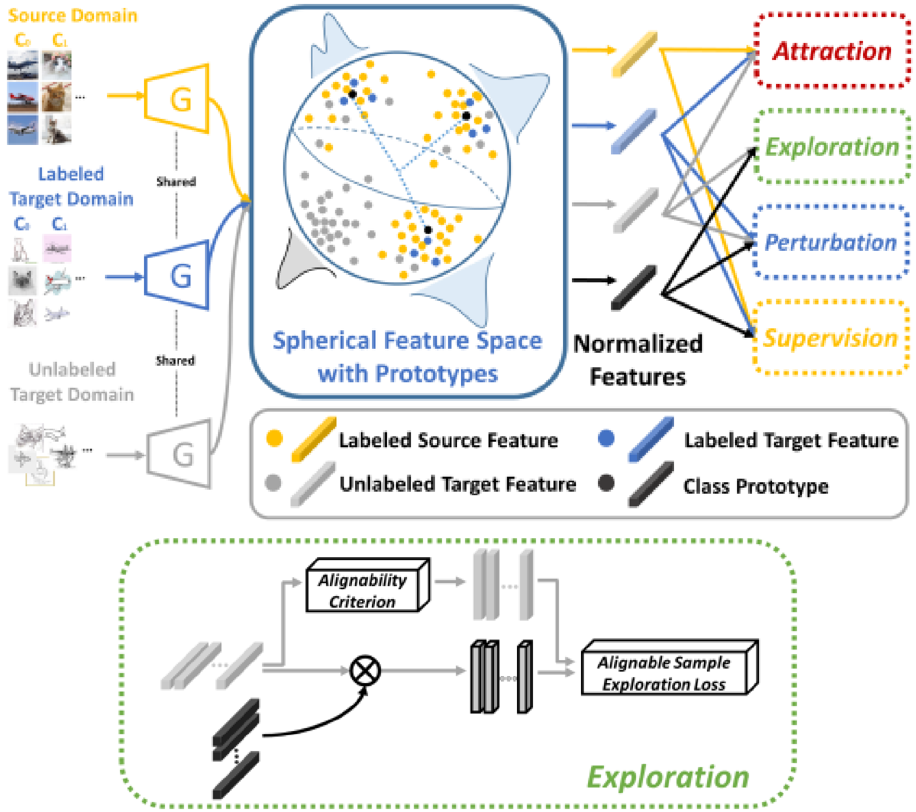

4) Exploration

Pseudo-labeling을 통해 모델을 학습시키자! → 일반적인 준지도학습

$$M_\epsilon = \{x \in D_u \,|\, H_p(x) < \epsilon\}$$

$$\hat{y}_x = \operatorname*{argmax}_{i\in\{1,\ldots,K\}} p(y=i|x,p)$$

$$\mathcal{L}_e = \mathbb{E}_{D_u}\left[-1_{M_\epsilon}(x)\log p(y=\hat{y}_x|x,p)\right]$$

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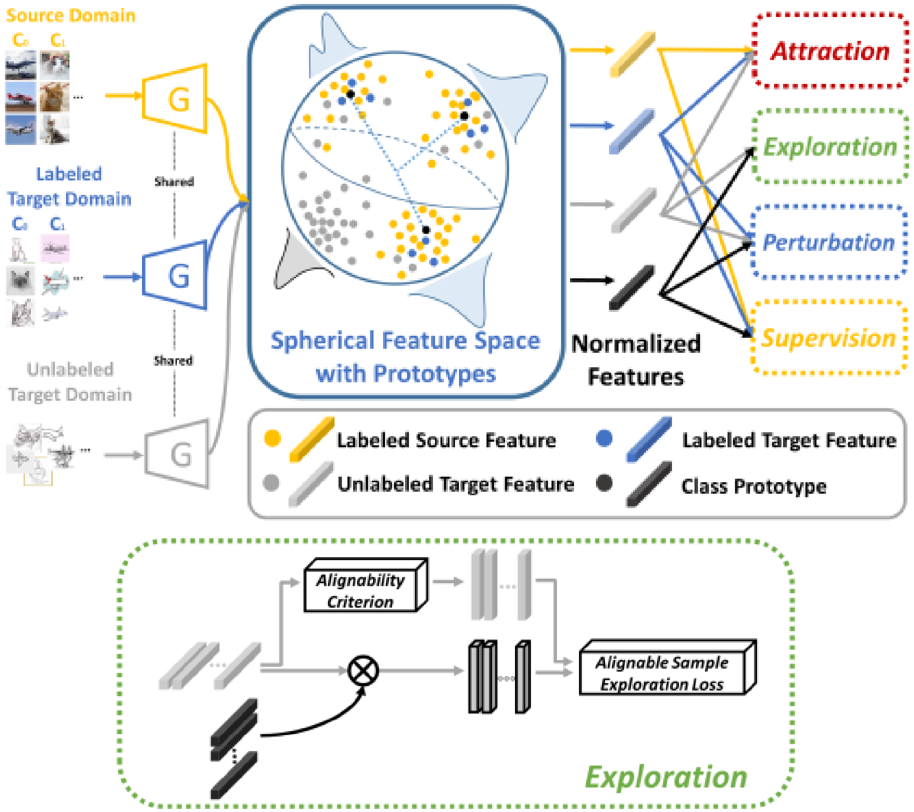

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Entropy가 ϵ보다 낮은 확실한 Unlabeled Target Domain Sample만 추출

$$M_\epsilon = \{x \in D_u \mid H_p(x) < \epsilon\}$$

$$\hat{y}_x = \underset{i \in \{1,\ldots,K\}}{\operatorname{argmax}}\, p(y = i \mid x, p)$$

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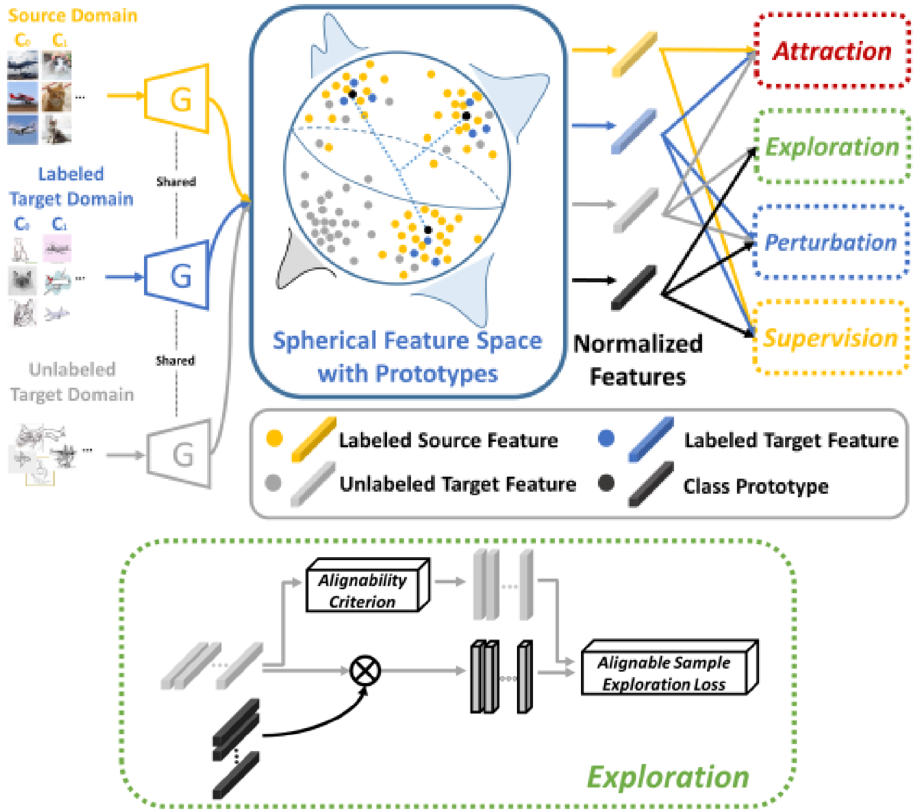

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Pseudo-labeling을 거쳐서

$$\hat{y}_x = \underset{i \in \{1,\ldots,K\}}{\operatorname{argmax}}\, p(y = i \mid x, p)$$

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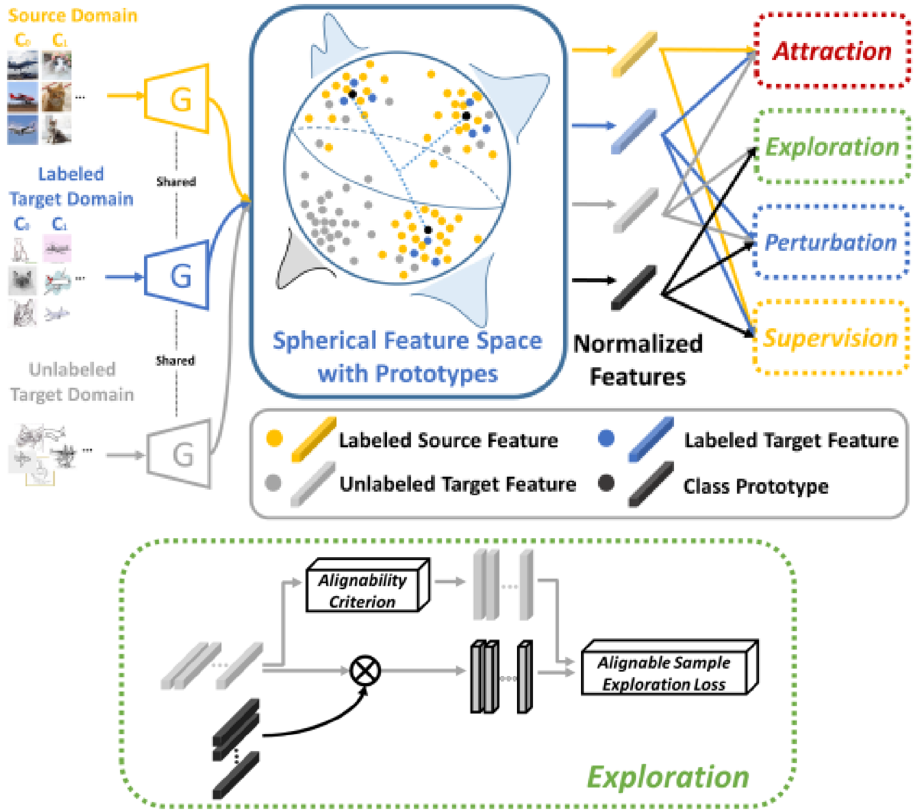

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Pseudo-labeling 결과와 Prototype 간 Cross-entropy를 Loss $\mathcal{L}_e$로 산정

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3. Conclusion

Conclusions

Semi-Supervised Domain Adaptation

❖ Semi-Supervised Domain Adaptation의 필요성

- 다양한 원인에 의해 실제 산업에서 기존 데이터의 분포에 대한 변화(Domain Shift)가 발생
- 분포 변화가 일어난 데이터는 일반적으로 Labeling이 적용된 데이터의 수가 극히 소수인 경우가 많음

❖ Semi-Supervised Domain Adaptation via Minimax Entropy

- Unlabeled Target Domain sample의 Entropy를 활용하여 Target Domain에 대한 일반화

❖ AdaMatch: A Unified Approach to Semi-Supervised Learning and Domain Adaptation

- Relative Confidence Threshold와 Distribution Alignment 및 Random Logit Interpolation을 활용하여 Target Domain에 대한 일반화

❖ Attract, Perturb, and Explore: Learning a Feature Alignment Network for Semi-supervised Domain Adaptation

- 세 단계(Attract, Perturb, Explore) 과정을 통해 Target Domain의 Inter/Intra Domain Discrepancy 문제 해결