Unsupervised Domain Generalization

Data Mining & Quality Analytics Lab.

2025. 11. 21

발표자: 정진용

발표자 소개

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❖ 관심 연구 분야

- Out-Of-Distribution Generalization & Domain Generalization
- Semi-Supervised Learning & Class-Imbalanced Semi-Supervised Learning

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목차

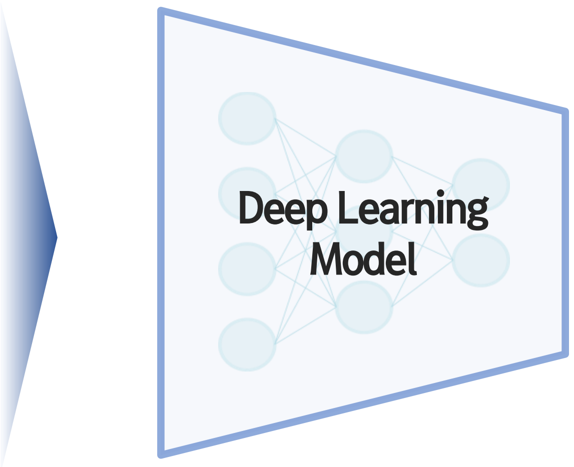
Introduction

Background of domain generalization

❖ Train dataset을 사용해서 일반화 성능이 좋은 모델을 구축해보자

Train dataset

모델 학습



Test dataset

$$P_{train}(X, Y) = P_{train}(Y|X) \cdot P_{train}(X)$$

$$\mathcal{Y}_{train} = \{\text{강아지, 고양이}\}, Y \in \mathcal{Y}$$

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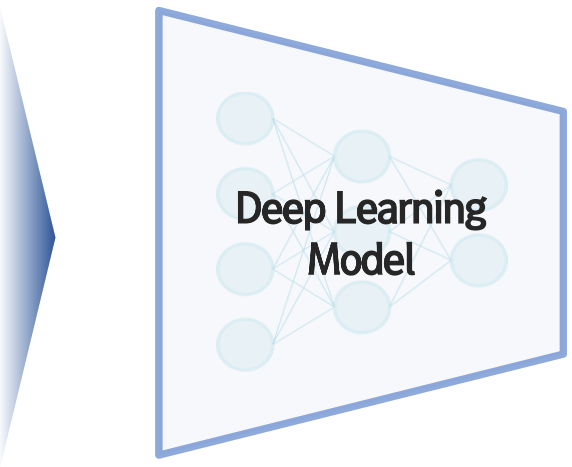
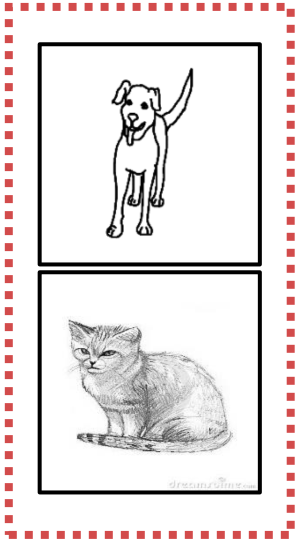


Test dataset



$P_{train}(X,Y) = P_{train}(Y|X) \cdot \boxed{P_{train}(X)}$

$\mathcal{Y}_{train} = \{\text{강아지, 고양이}\}, Y \in \mathcal{Y}$

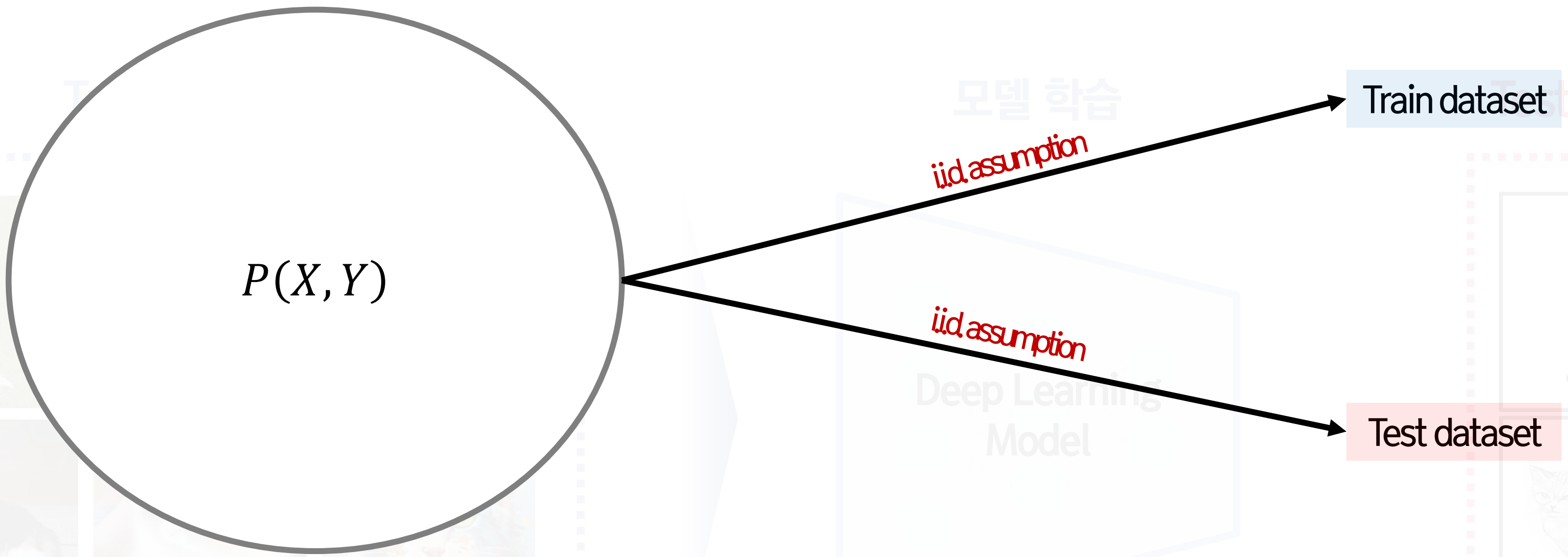
$P_{test}(X,Y) = P_{test}(Y|X) \cdot \boxed{P_{test}(X)}$

$\neq$

Introduction

Background of domain generalization

❖ Distribution shift가 있는 상황에서는 모델 일반화 성능 저하로 이어짐



'독립적이고 동일한 확률로'

기존 머신러닝 및 딥러닝 학습에서는 train dataset과 test dataset이 같은 분포에서 샘플링 되었다는 가정이 있음

→ 만약 i.i.d 가정이 깨진다면, 지도 학습을 통해 학습된 모델은 예측 성능이 저하될 수 있음

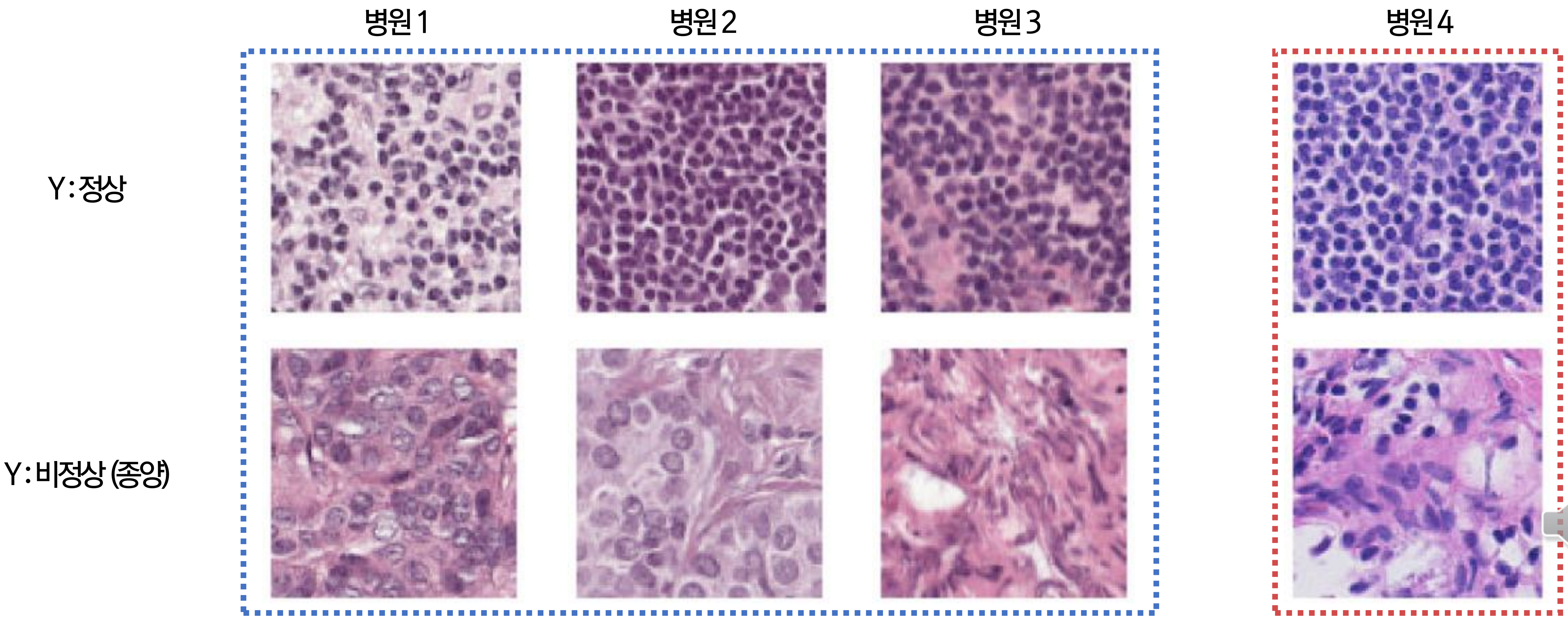
'Distribution shift'

Introduction

Background of domain generalization

❖ 현실에서도 distribution shift 문제를 자주 접할 수 있음

- 병원을 하나의 도메인으로 본다면 distribution shift = domain shift

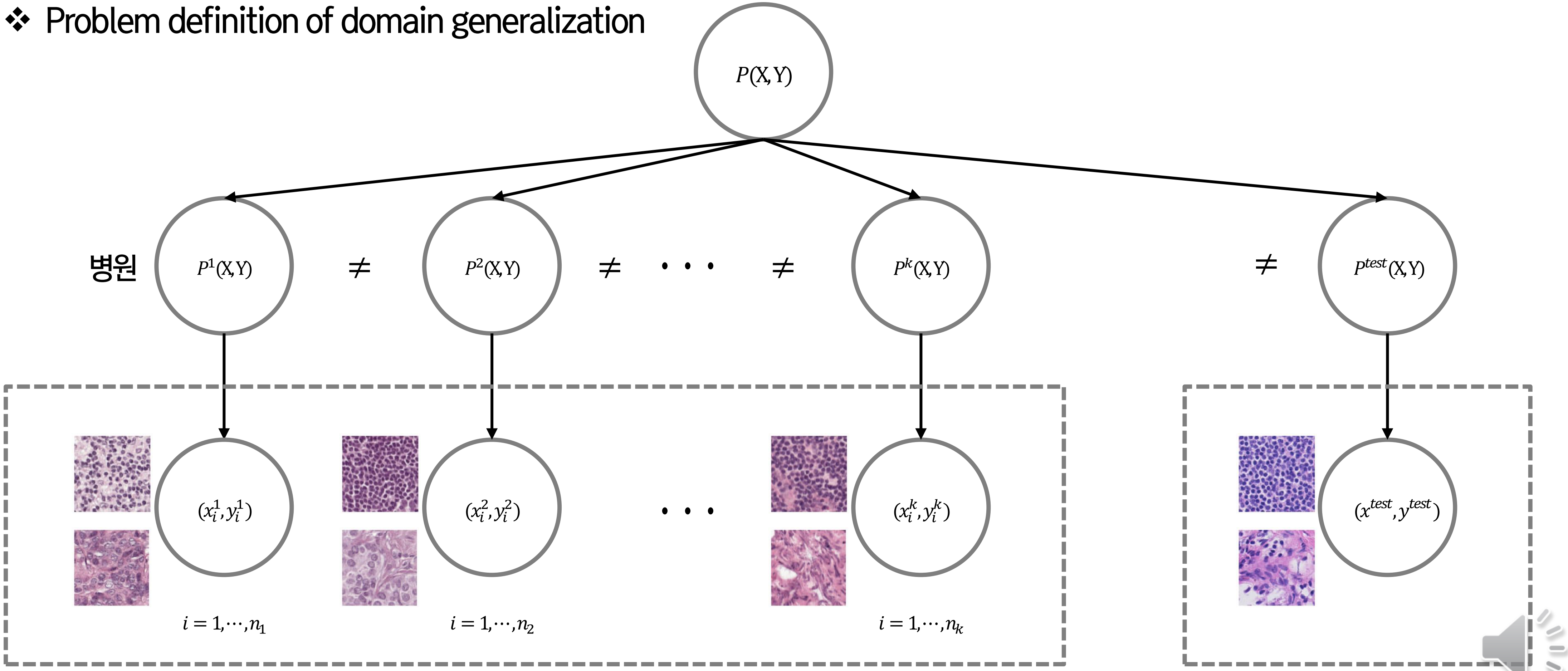


Koh, P. W., Sagawa, S., Marklund, H., Xie, S. M., Zhang, M., Balsubramani, A., ... & Liang, P. (2021, July). Wilds: A benchmark of in-the-wild distribution shifts. In International conference on machine learning (pp. 5637-5664). PMLR.

Introduction

Background of domain generalization

❖ Problem definition of domain generalization



Training domains (environments)

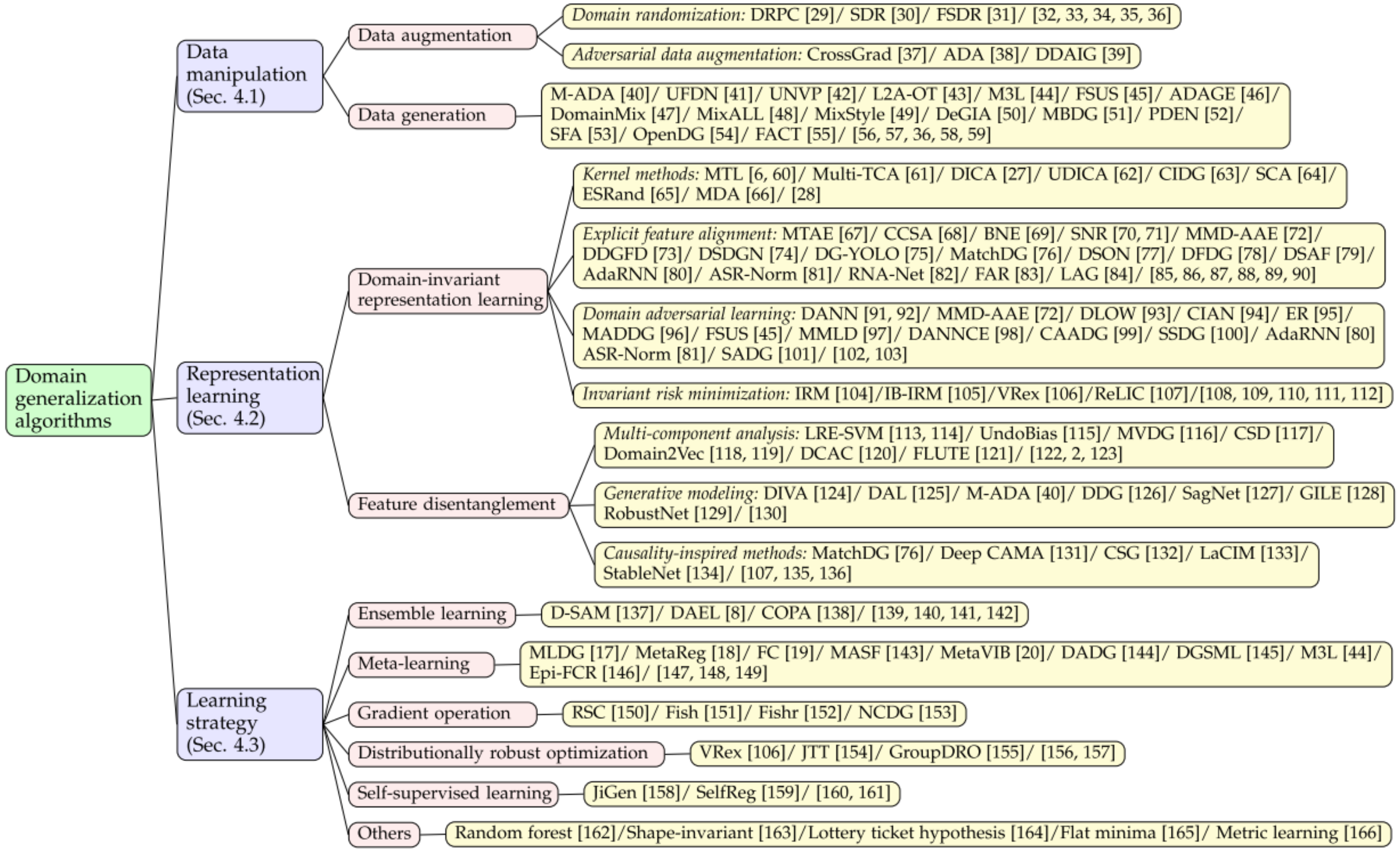
'Unseen' Test domain (environment)

Introduction

Background of domain generalization

❖ Taxonomy of domain generalization methods

- Domain generalization 문제를 해결하기 위한 다양한 방법론들이 존재함



Introduction

Background of domain generalization

❖ Taxonomy of domain generalization methods

• Domain generalization 문제를 해결하기 위한 다양한 방법론들이 존재함

종료

DMQA Open Seminar (2023.07.21)

Data Mining & Quality Analytics Lab.

Domain Generalization: How to improve t

발표자: 김지현

2023년 7월 21일

오후 12시 ~

온라인 비디오 시청 (YouTube)

세미나 정보 보기 ⟶

종료

DMQA Open Seminar (2024.04.26)

Model Selection in Domain Generalization

Data Mining & Quality Analytics Lab.

정용태

Model Selection in Domain Generalizatio

발표자: 정용태

2024년 4월 26일

오전 12시 ~

온라인 비디오 시청 (YouTube)

세미나 정보 보기 ⟶

종료

Domain Generalization : Domain-invariant Representation Learning

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2024. 01. 19

Domain Generalization : Domain-invariar

발표자: 정진용

2024년 1월 19일

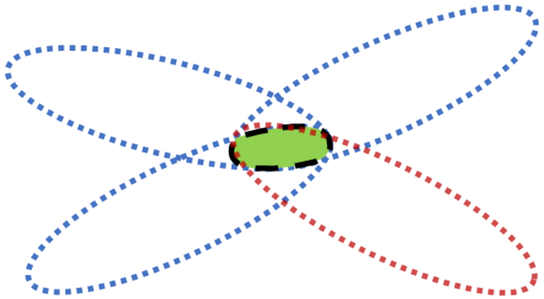
오전 12시 ~

온라인 비디오 시청 (YouTube)

세미나 정보 보기 ⟶

Introduction

Background of domain generalization

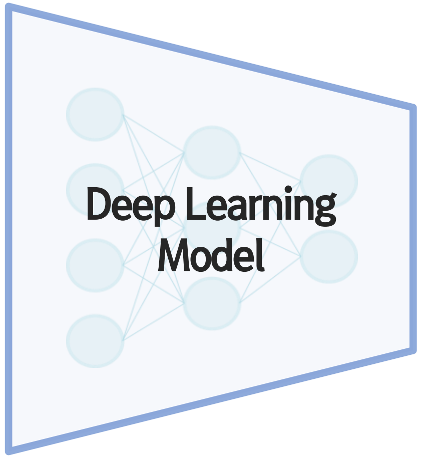


❖ Domain-invariant 특징이란?

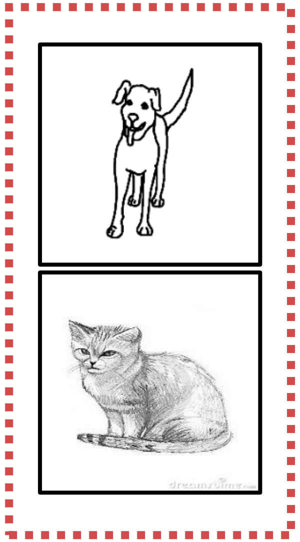
- 도메인에 상관없이 사물 또는 객체를 표현할 수 있는 특징
  - ➢ 눈, 코, 입 등 강아지와 고양이 자체를 표현하는 특징들
  - ➢ Domain-specific: 배경, 글씨, 이미지 스타일 등 강아지, 고양이와는 거의 관련이 없는 특징들

Train dataset

모델 학습 시 domain-invariant 반영



Test dataset



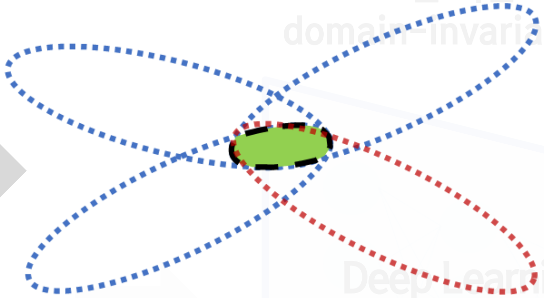
➔ 일반화(generalization) 성능개선

Introduction

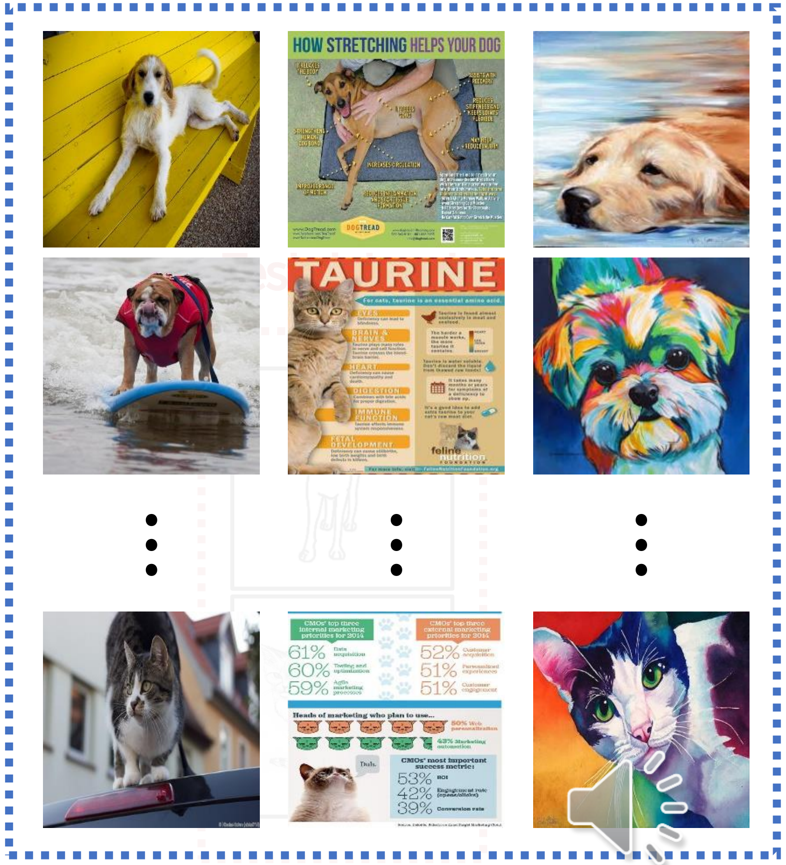
Background of unsupervised domain generalization

❖ 만약 학습을 위한 labeled dataset을 충분히 수집하기 어려운 상황에서는?

Labeled dataset



Unlabeled dataset



→ Labeled dataset이 충분하지 않다면 invariant 학습이 힘들 수 있음

→ Unlabeled dataset 활용해서 invariant 학습을 해보자

Unsupervised domain generalization

❖ Domain-Aware Representation LearnING: Towards unsupervised domain generalization (CVPR, 2022)

- Unsupervised domain generalization 문제 상황 및 unlabeled dataset 구축 케이스들을 정의한 논문
    - ➢ All correlated, domain correlated, uncorrelated
- Contrastive learning 기반으로 domain-invariant 표현들을 학습하는 방법론

Towards Unsupervised Domain Generalization

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xingxuanzhang@hotmail.com, zhoulj16@mails.tsinghua.edu.cn, xrz199721@gmail.com
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Abstract

Domain generalization (DG) aims to help models trained on a set of source domains generalize better on unseen target domains. The performances of current DG methods largely rely on sufficient labeled data, which are usually costly or unavailable, however. Since unlabeled data are far more accessible, we seek to explore how unsupervised learning can help deep models generalize across domains. Specifically, we study a novel generalization problem called unsupervised domain generalization (UDG), which aims to learn generalizable models with unlabeled data and analyze the effects of pre-training on DG. In UDG, models are pretrained with unlabeled data from various source domains before being trained on labeled source data and eventually tested on unseen target domains. Then we propose a method named Domain-Aware Representation LearnING (DARLING) to cope with the significant and misleading heterogeneity within unlabeled pretraining data and severe distribution shifts between source and target data. Surprisingly we observe that DARLING can not only counterbalance the scarcity of labeled data but also further strengthen the generalization ability of models when the labeled data are insufficient. As a pretraining approach, DARLING shows superior or comparable performance compared with ImageNet pretraining protocol even when the available data are unlabeled and of a vastly smaller amount compared to ImageNet, which may shed light on improving generalization with large-scale unlabeled data.

domain generalization (DG) proposes algorithms that have access to labeled data from multiple domains or environments during training and generalize well to unseen test domains [18, 32, 36, 37, 43, 63].

Sufficient labeled data are crucial for current DG methods to learn domain invariant features, which are proved to be generalizable to unseen domains [1, 43, 54, 64]. A common and effective approach to learning discriminative features in DG is to enlarge the available data space with augmentations of source domains [5, 69, 70]. With sufficient source data and strong augmentations, even empirical risk minimization (ERM) can outperform previous state-of-the-art methods [21]. Nevertheless, both augmentation-based methods and carefully hyperparameter tuned ERM assume adequate labeled data from multiple domains available for representation learning.

As manually labeled data can be costly or unavailable while unlabeled data are far more accessible, we study a novel generalization problem called unsupervised domain generalization (UDG). UDG aims to unsupervised learn discriminative representations that generalize well across domains and thus reduce the dependence of DG methods on labeled data. Specifically, models are trained with unlabeled heterogeneous data before finetuned and evaluated on labeled data, so that methods for UDG can be easily assembled with current DG methods as pretraining and study how pre-training affects models' generalization ability.

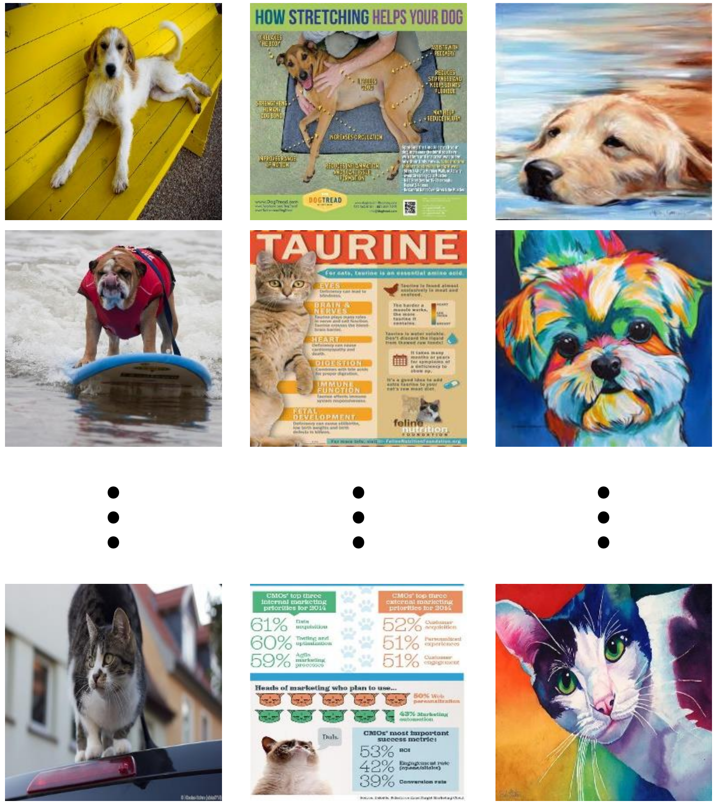
In the field of unsupervised learning [22, 50, 65], contrastive learning (CL) advances in discriminative represen-

Unsupervised domain generalization

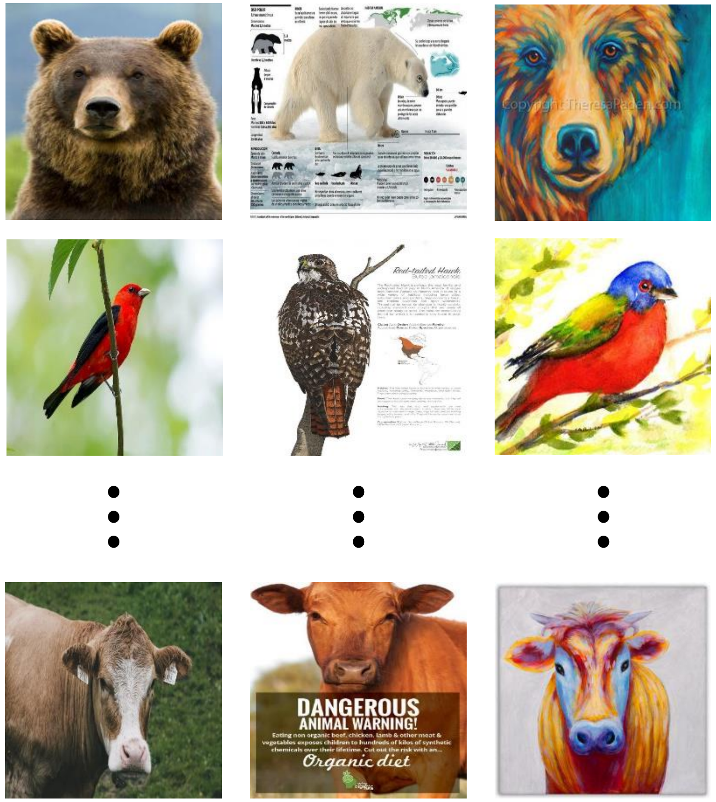
Labeled dataset

- Domain: (real-photo, info, painting)

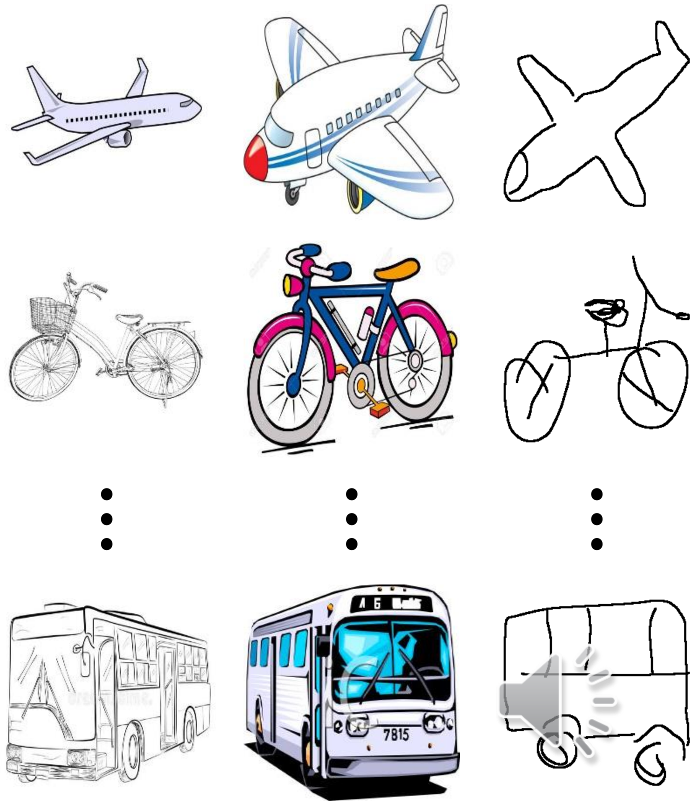
All correlated Unlabeled dataset



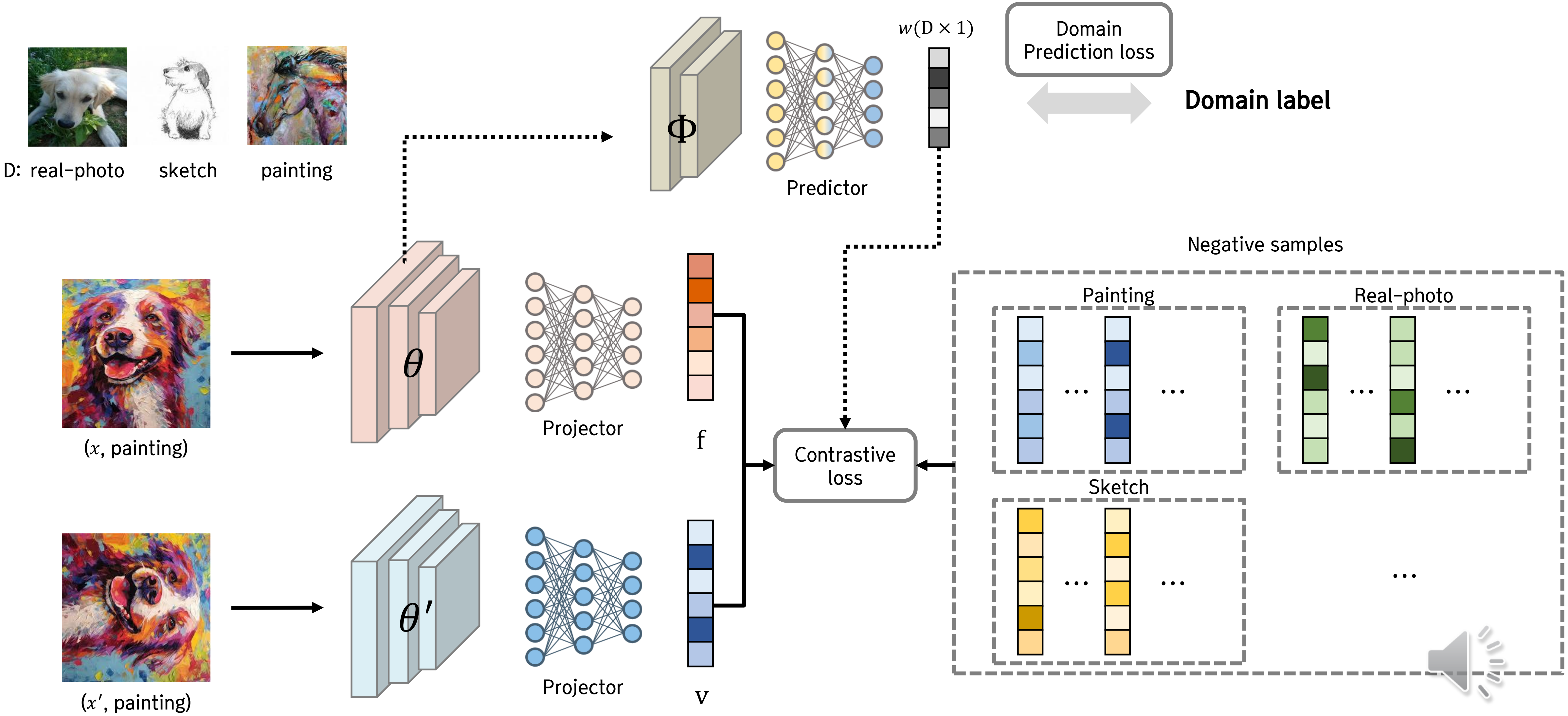
Domain correlated Unlabeled dataset



Uncorrelated Unlabeled dataset



Towards unsupervised domain generalization



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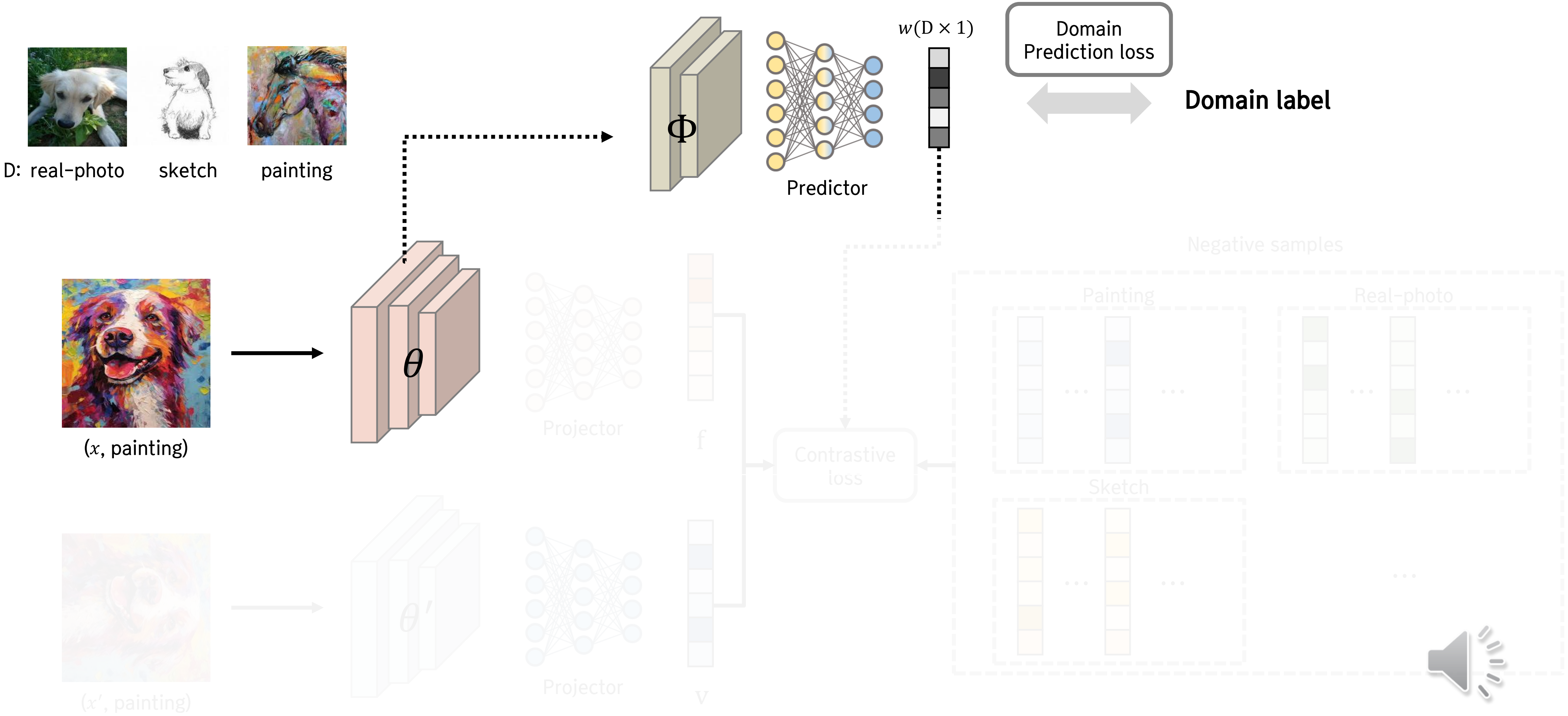

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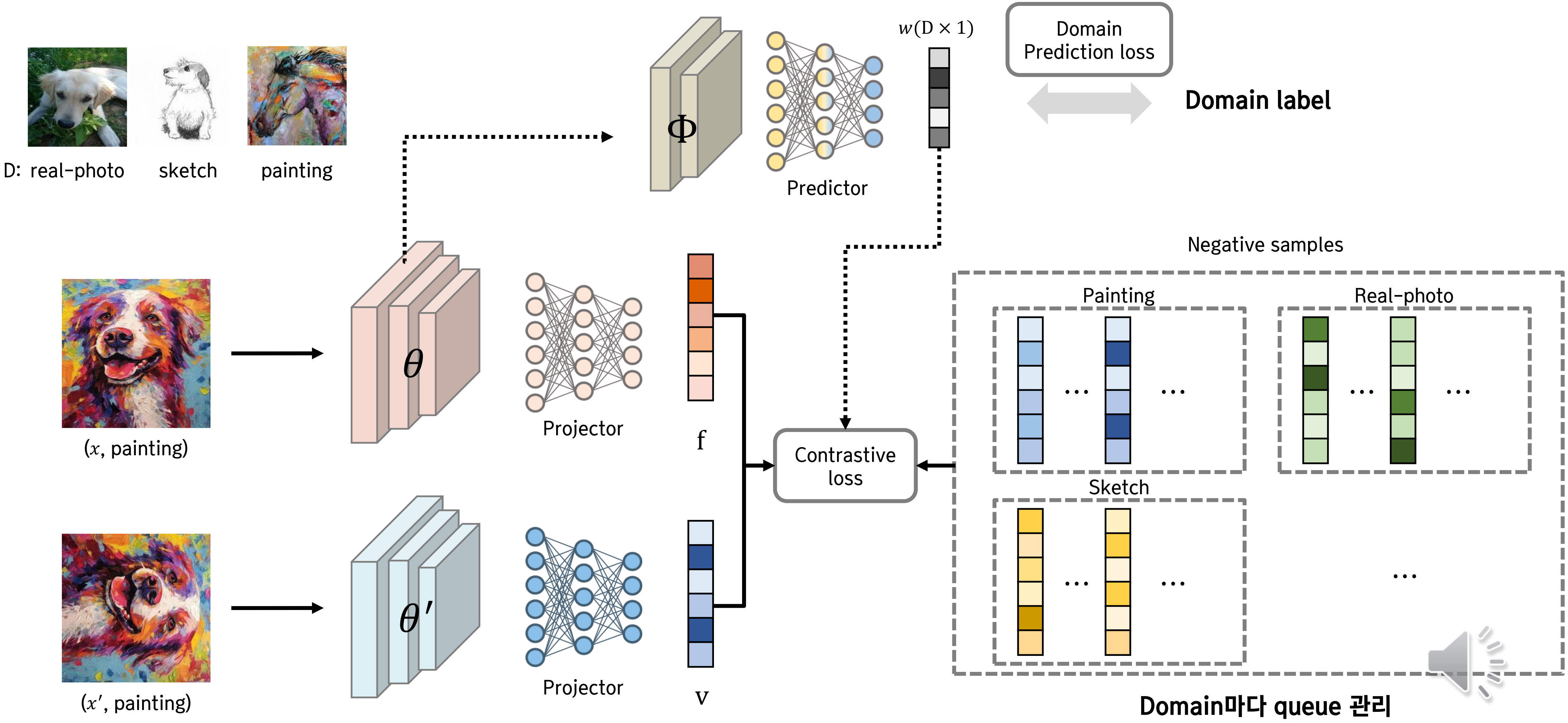
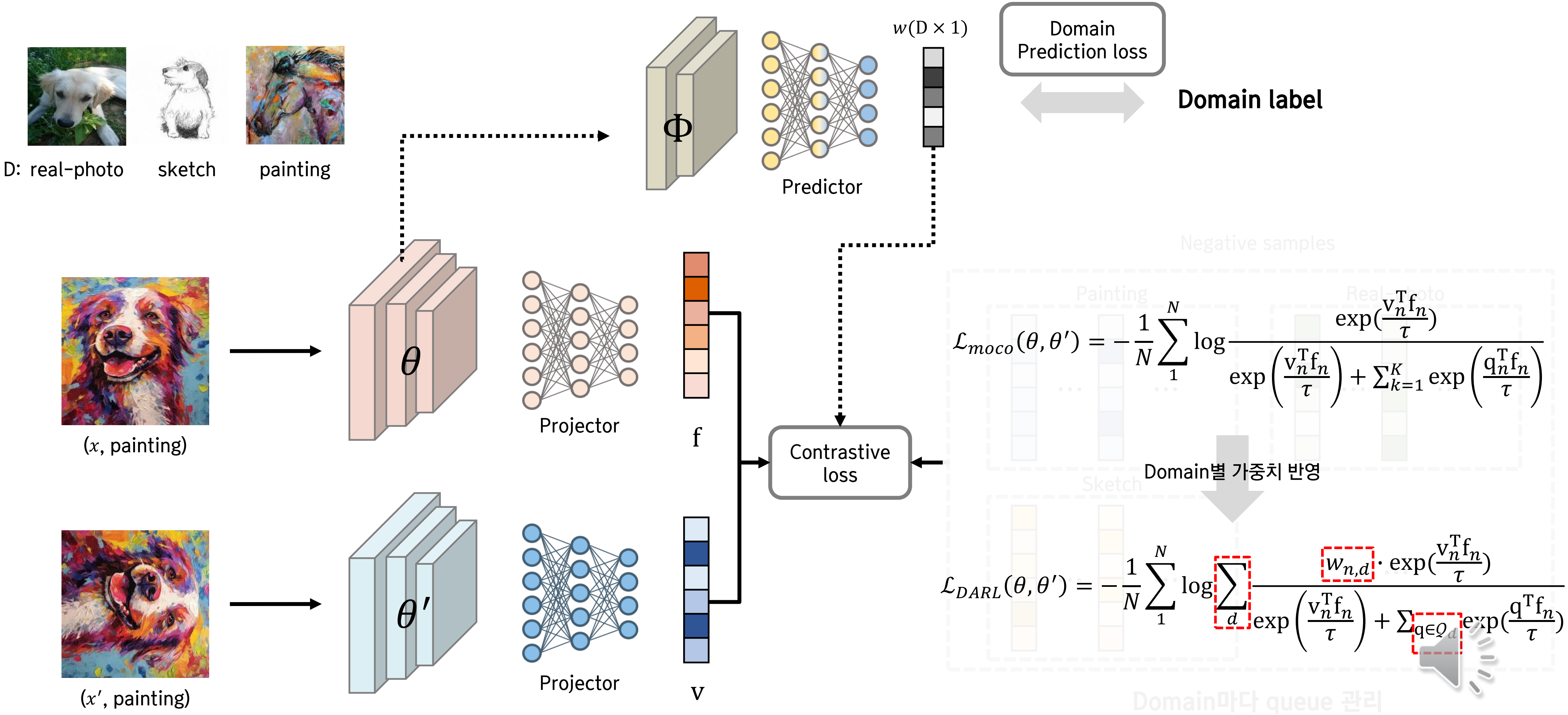


Towards unsupervised domain generalization



$$\mathcal{L}_{moco}(\theta,\theta') = -\frac{1}{N}\sum_{1}^{N}\log\frac{\exp(\frac{\mathrm{v}_n^{\mathrm{T}}\mathrm{f}_n}{\tau})}{\exp\left(\frac{\mathrm{v}_n^{\mathrm{T}}\mathrm{f}_n}{\tau}\right)+\sum_{k=1}^{K}\exp\left(\frac{\mathrm{q}_n^{\mathrm{T}}\mathrm{f}_n}{\tau}\right)}$$

$$\mathcal{L}_{DARL}(\theta,\theta') = -\frac{1}{N}\sum_{1}^{N}\log\boxed{\sum_{d}}\frac{\boxed{w_{n,d}}\cdot\exp(\frac{\mathrm{v}_n^{\mathrm{T}}\mathrm{f}_n}{\tau})}{\exp\left(\frac{\mathrm{v}_n^{\mathrm{T}}\mathrm{f}_n}{\tau}\right)+\sum_{\boxed{\mathrm{q}\in Q_d}}\exp(\frac{\mathrm{q}^{\mathrm{T}}\mathrm{f}_n}{\tau})}$$

Towards unsupervised domain generalization

Domain weighting 효과

$$\mathcal{L}_{DARL}(\theta,\theta') = -\frac{1}{N}\sum_{1}^{N}\log \boxed{\sum_{d}} \frac{\boxed{w_{n,d}}\cdot \exp(\frac{v_n^T f_n}{\tau})}{\exp\left(\frac{v_n^T f_n}{\tau}\right) + \sum_{\boxed{q\in Q_d}} \exp(\frac{q^T f_n}{\tau})}$$

같은 domain일 때,
Contrastive learning 집중

(x, painting)

Domain-aware representation learning

Negative samples (Painting)

Domain-specific 특징으로 구분하기 힘듦
→ **Invariance 표현 학습 유도**

Towards unsupervised domain generalization

Adversarial queue update 기법

$$q_k \leftarrow q_k + \eta_N \frac{\partial \mathcal{L}(\theta, \mathcal{Q}_{painting}, \mathcal{Q}_{real-photo}, \mathcal{Q}_{sketch})}{\partial q_k}$$

(x, painting)

Query embedding vector에 가까워 지도록

→ **Encoder가 더 정교한 표현들을 학습**

Negative samples (Painting)

Towards unsupervised domain generalization

❖ DomainNet 데이터셋에 대한 실험 결과 – All correlated case

- 총 6가지 도메인으로 구성된 데이터셋
  - ➢ 학습 도메인: painting, real-photo, sketch
  - ➢ 테스트 도메인: clipart, infograph, quickdraw

	Label Fraction 1%					Label Fraction 5%				
method	Clipart	Infograph	Quickdraw	Overall	Avg.	Clipart	Infograph	Quickdraw	Overall	Avg.
MoCo V2 [8, 23]	18.85	10.57	6.32	10.05	11.92	28.13	13.79	9.67	14.56	17.20
SimCLR V2 [7]	**23.51**	**15.42**	5.29	11.80	**14.74**	34.03	17.17	**10.88**	17.32	20.69
BYOL [20]	6.21	3.48	4.27	4.45	4.65	9.60	5.09	6.02	6.49	6.90
AdCo [29]	16.16	12.26	5.65	9.57	11.36	30.77	18.65	7.75	15.44	19.06
ERM	6.54	2.96	5.00	4.75	4.83	10.21	7.08	5.34	6.81	7.54
DARLING (ours)	18.53	10.62	**12.65**	**13.29**	13.93	**39.32**	**19.09**	10.50	**18.73**	**22.97**
	Label Fraction 10%					Label Fraction 100%				
method	Clipart	Infograph	Quickdraw	Overall	Avg.	Clipart	Infograph	Quickdraw	Overall	Avg.
MoCo V2	32.46	18.54	8.05	15.92	19.69	64.18	27.44	25.26	33.76	38.96
SimCLR V2	**37.11**	19.87	12.33	19.45	23.10	68.72	27.60	30.56	37.47	42.29
BYOL	14.55	8.71	5.95	8.46	9.74	54.44	23.70	20.42	28.23	32.86
AdCo	32.25	17.96	11.56	17.53	20.59	62.84	26.69	26.26	33.80	38.60
ERM	15.10	9.39	7.11	9.36	10.53	52.79	23.72	19.05	27.19	31.85
DARLING (ours)	35.15	**20.88**	**15.69**	**21.08**	**23.91**	**72.79**	**32.01**	**33.75**	**41.19**	**46.18**

- Backbone: ResNet-18
- Learning rate: 0.03
- Batch size: 1024
- Epochs: 1000(pt), 30(ft)
- Augmentation: MoCo V2
- Temperature: MoCo V2

Towards unsupervised domain generalization

❖ DomainNet 데이터셋에 대한 실험 결과 – Domain correlated case

- Pre-training 도메인 & fine-tuning 도메인: {painting, real-photo, sketch}
- Pre-training 클래스 종류 (40개 또는 100개) ∩ fine-tuning 클래스 종류 (20개) = ∅
- 다른 클래스 간 transfer에서도 unsupervised pretraining이 효과적임
- Domain-invariant 반영 → 더 좋은 도메인 일반화 성능을 보임

	Pretraining with data from 40 categories					Pretraining with data from 100 categories				
method	Clipart	Infograph	Quickdraw	Overall	Avg.	Clipart	Infograph	Quickdraw	Overall	Avg.
MoCo V2	72.84	33.40	34.20	41.19	46.82	77.03	37.68	35.25	43.71	49.98
SimCLR V2	75.58	**35.52**	37.08	43.83	49.39	79.70	38.88	38.89	46.50	52.49
BYOL	58.39	23.99	28.56	32.87	36.98	58.27	24.14	27.83	32.49	36.75
AdCo	76.61	31.55	33.42	40.96	47.19	75.19	33.76	38.51	43.77	49.15
ERM	55.78	22.40	25.75	30.43	34.64	55.78	22.40	25.75	30.43	34.64
DARLING (ours)	**78.40**	33.98	**39.87**	**44.20**	**50.75**	**82.28**	**40.60**	**47.68**	**52.19**	**56.85**

Towards unsupervised domain generalization

❖ CIFAR 데이터셋에 대한 실험 결과 – Uncorrelated case

- Pre-training과 fine-tuning의 도메인 및 클래스는 서로 겹치지 않음
  - ➢ Pre-training: CIFAR-100-C, (Elastic, fog, impulse noise, motion blur)
  - ➢ Fine-tuning: CIFAR-10-C, (Contrast, frost, glass blur, blur, shot noise)
- 도메인 일반화가 가장 어려운 실험 세팅에서도 pretraining 및 domain-invariant learning 효과적임
- 준지도 학습은 클래스가 겹치지 않는 상황에서 다루기 힘듬
  - ➢ Label propagation 가정에 맞지 않은 상황

method	Brightness	Defocus Blur	Gaussian Noise	Snow	Avg.
MoCo V2	77.13	75.88	75.18	72.27	75.12
SimCLR V2	78.54	77.60	75.92	72.68	76.19
BYOL	58.10	57.07	56.31	53.96	56.36
AdCo	75.63	77.32	78.84	72.25	76.01
ERM	36.53	34.61	33.49	32.98	34.40
DARLING (ours)	**80.28**	**77.74**	**79.65**	**77.76**	**78.86**

Unsupervised domain generalization (UDG)

❖ DisMAE: Disentangling masked autoencoders for unsupervised domain generalization (ECCV, 2024)

- Masked autoencoder를 기반으로 domain-invariant 표현 학습을 하는 방법론
- Disentanglement principle: domain-invariant (또는 semantic)과 domain-specific (또는 variation)을 분리

Disentangling Masked Autoencoders for Unsupervised Domain Generalization

An Zhang[1 *†], Han Wang[2*], Xiang Wang[3], and Tat-Seng Chua[1]

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[2] Zhejiang University
[3] University of Science and Technology of China
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xiangwang1223@gmail.com, dcscts@nus.edu.sg

Abstract. Domain Generalization (DG), designed to enhance out-of-distribution (OOD) generalization, is all about learning invariance against domain shifts utilizing sufficient supervision signals. Yet, the scarcity of such labeled data has led to the rise of unsupervised domain generalization (UDG) — a more important yet challenging task in that models are trained across diverse domains in an unsupervised manner and eventually tested on unseen domains. UDG is fast gaining attention but is still far from well-studied.
To close the research gap, we propose a novel learning framework designed for UDG, termed the Disentangled Masked AutoEncoder (**DisMAE**), aiming to discover the disentangled representations that faithfully reveal the intrinsic features and superficial variations without access to the class label. At its core is the distillation of domain-invariant semantic features, which can not be distinguished by domain classifier, while filtering out the domain-specific variations (for example, color schemes and texture patterns) that are unstable and redundant. Notably, DisMAE co-trains the asymmetric dual-branch architecture with semantic and lightweight variation encoders, offering dynamic data manipulation and representation level augmentation capabilities. Extensive experiments on four benchmark datasets (*i.e.* DomainNet, PACS, VLCS, Colored MNIST) with both DG and UDG tasks demonstrate that DisMAE can achieve competitive OOD performance compared with the state-of-the-art DG and UDG baselines, which shed light on potential research line in improving the generalization ability with large-scale unlabeled data. Our codes are available at https://github.com/rookiehb/DisMAE.

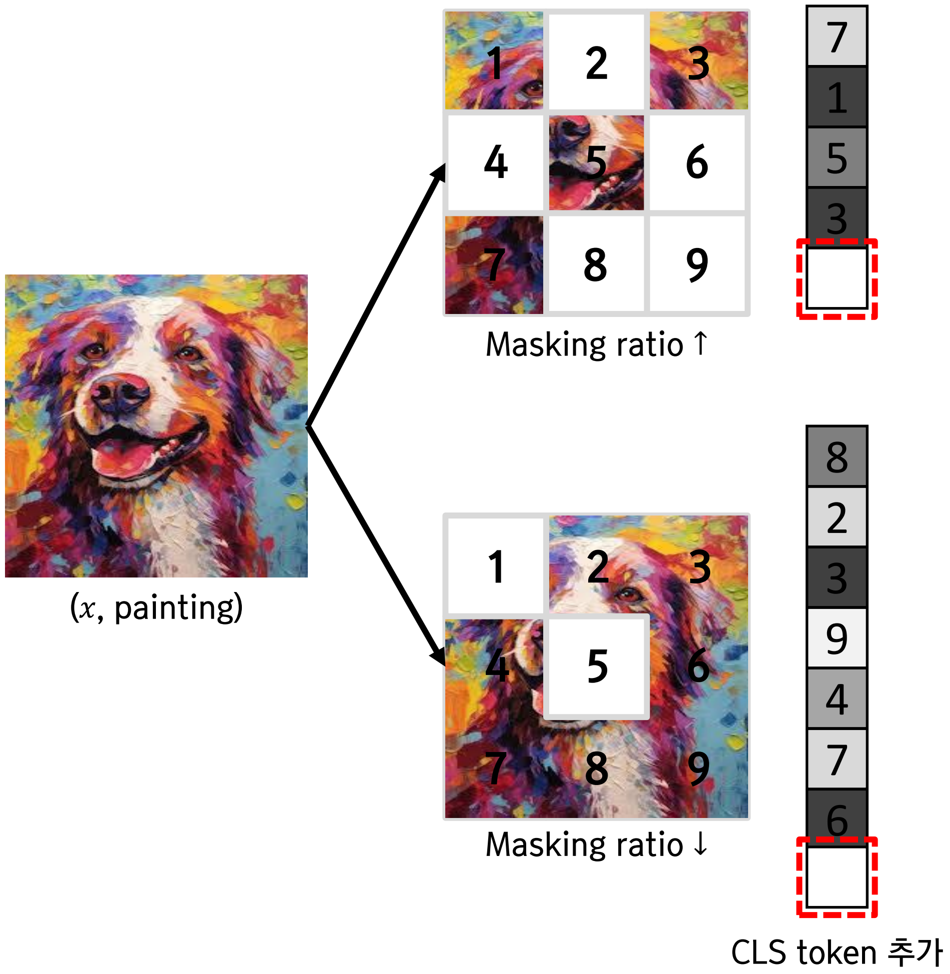
눈, 코, 입 등 강아지 자체를
표현하는 정보
→ Domain-invariant

Disentanglement

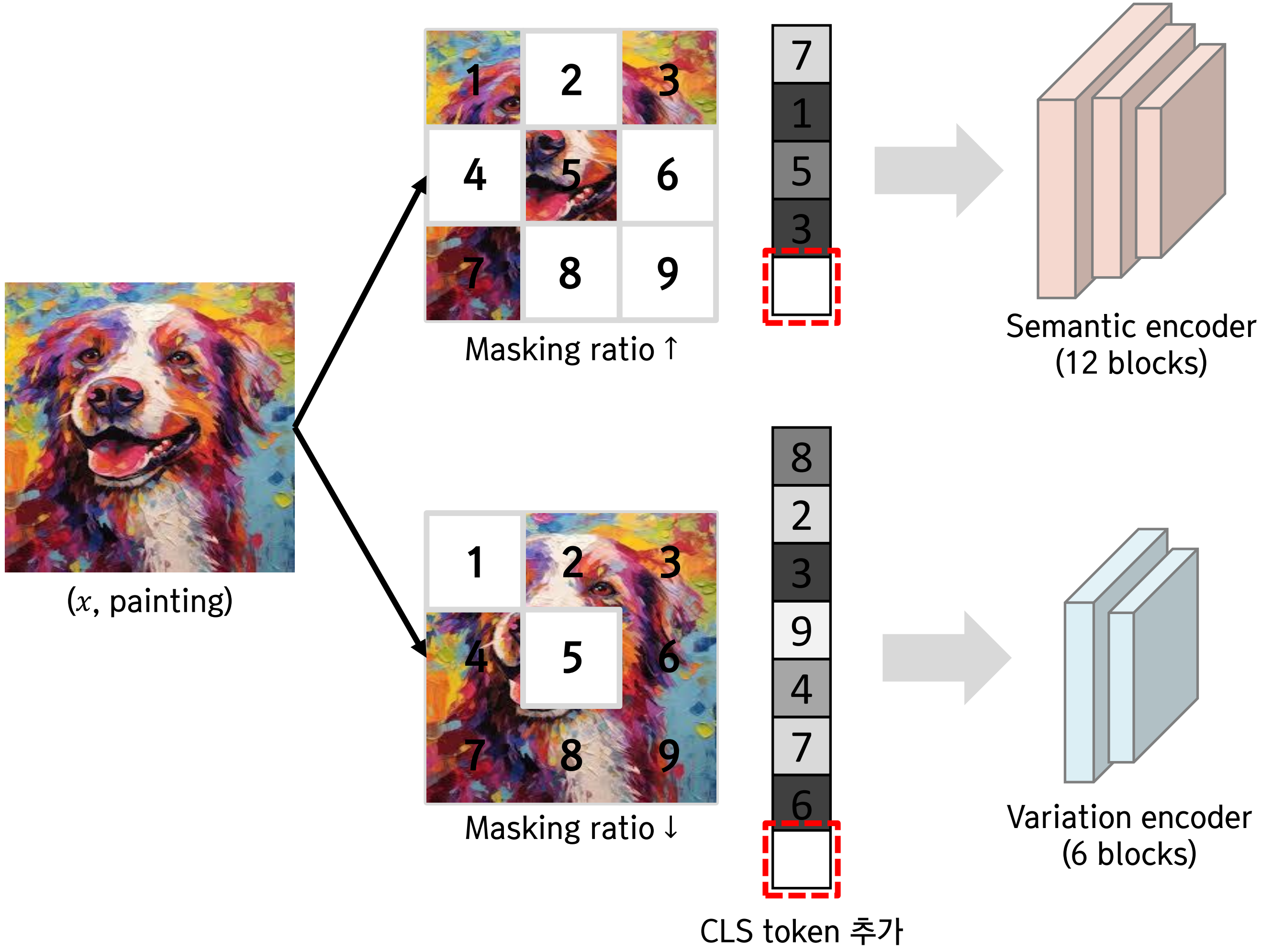
배경, 이미지 스타일 등
강아지와 관련 없는 정보
→ Domain-specific

Zhang, A., Wang, H., Wang, X., & Chua, T. S. (2024, September). Disentangling Masked Autoencoders for Unsupervised Domain Generalization. In European Conference on Computer Vision (pp. 126-151). Cham: Springer Nature Switzerland.

Disentangling masked autoencoders for UDG



Disentangling masked autoencoders for UDG

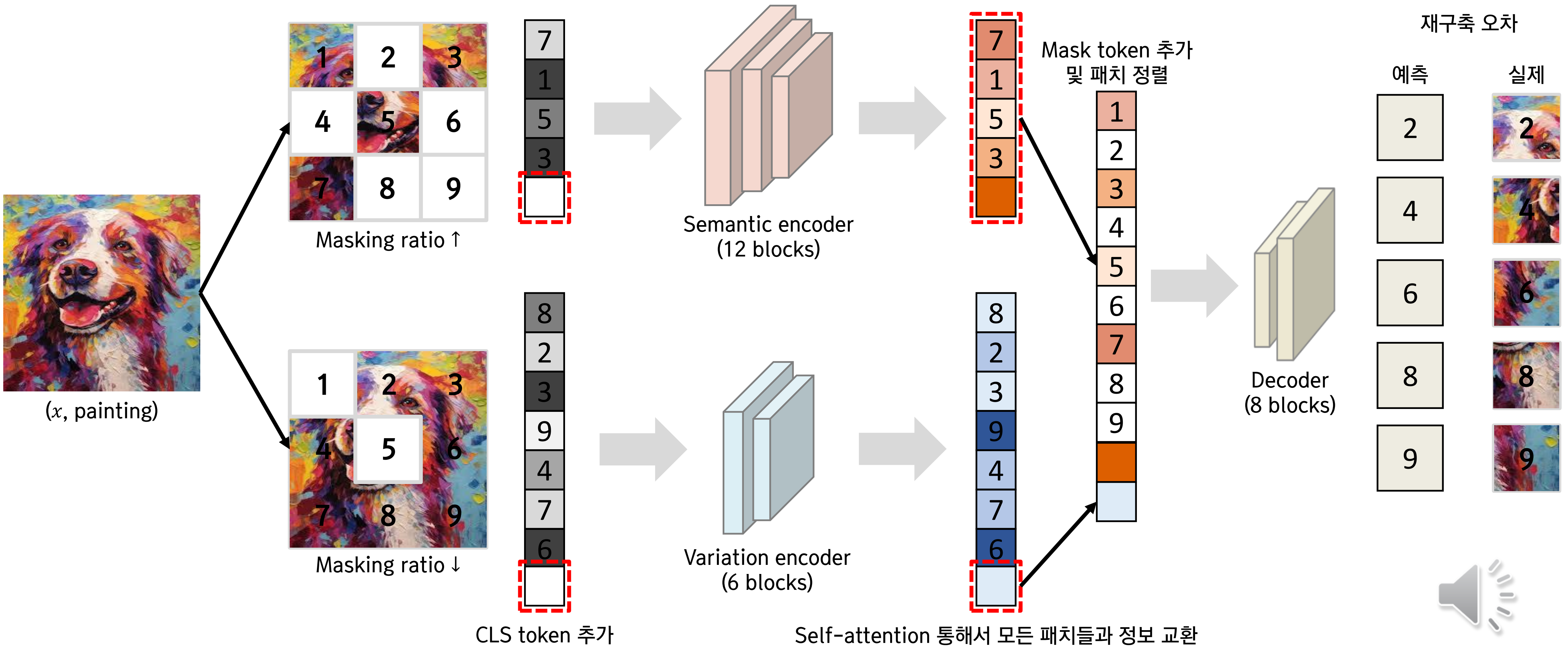


Forced disentanglement

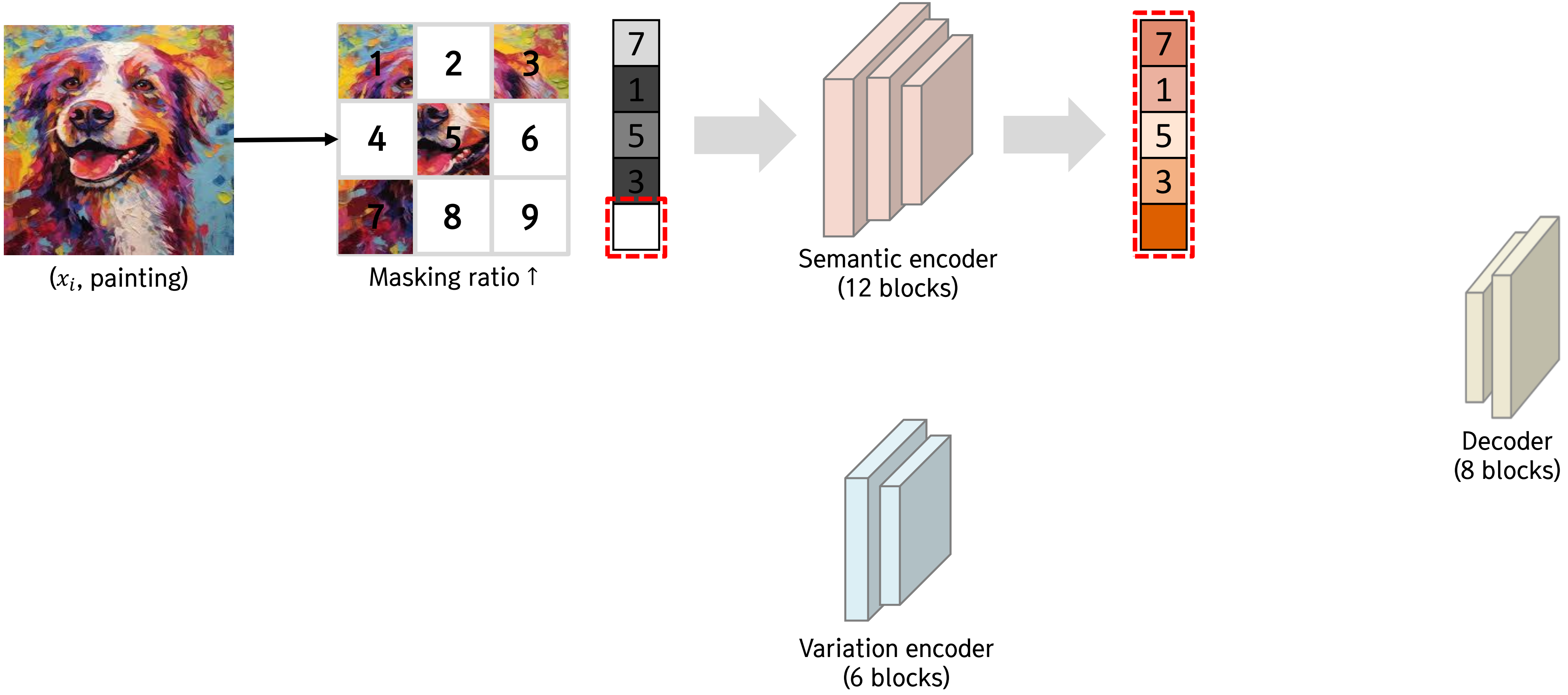
객체 자체를 인식할 수 있는 고차원 정보 학습

이미지 스타일 등 저차원 또는 표면적인 정보 학습

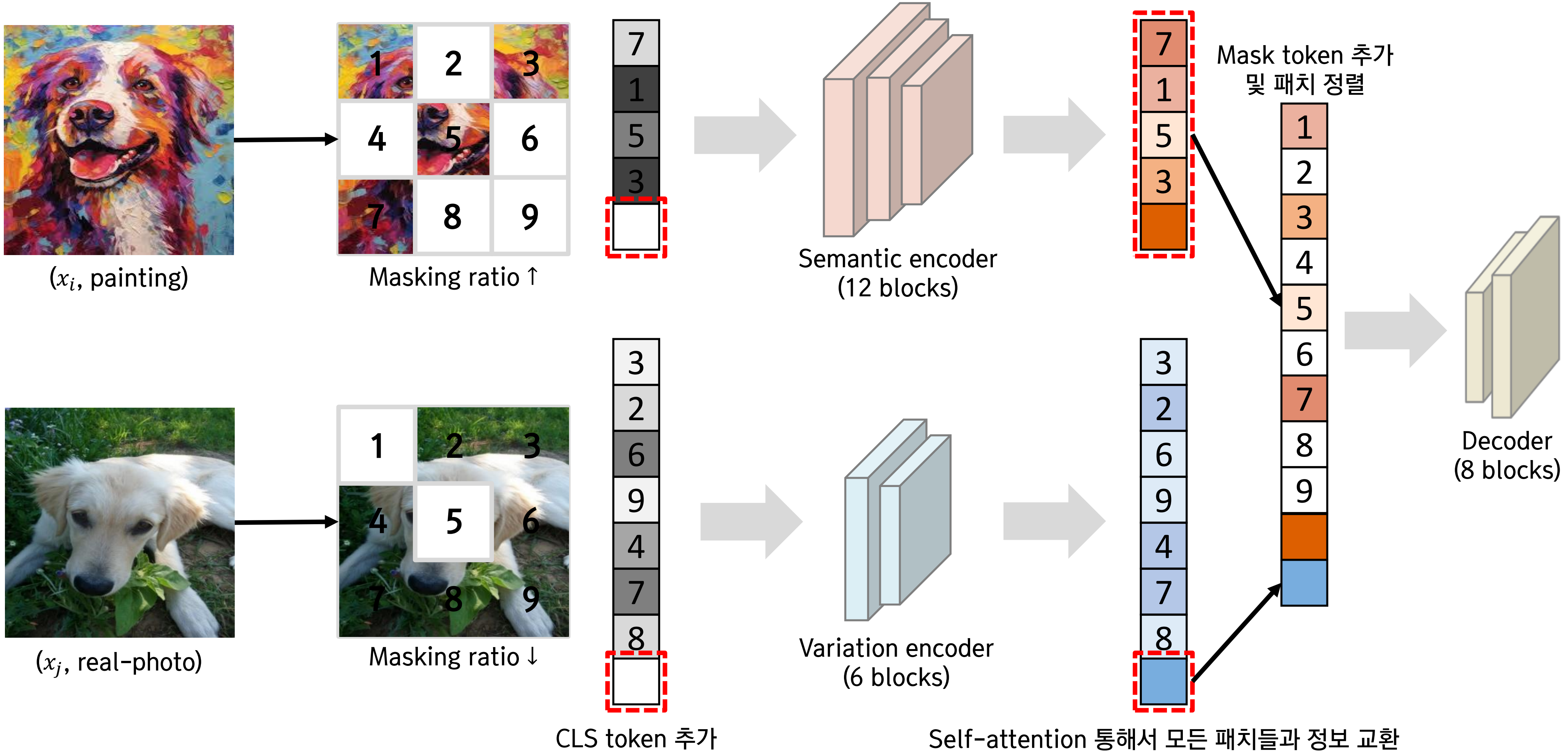
Disentangling masked autoencoders for UDG



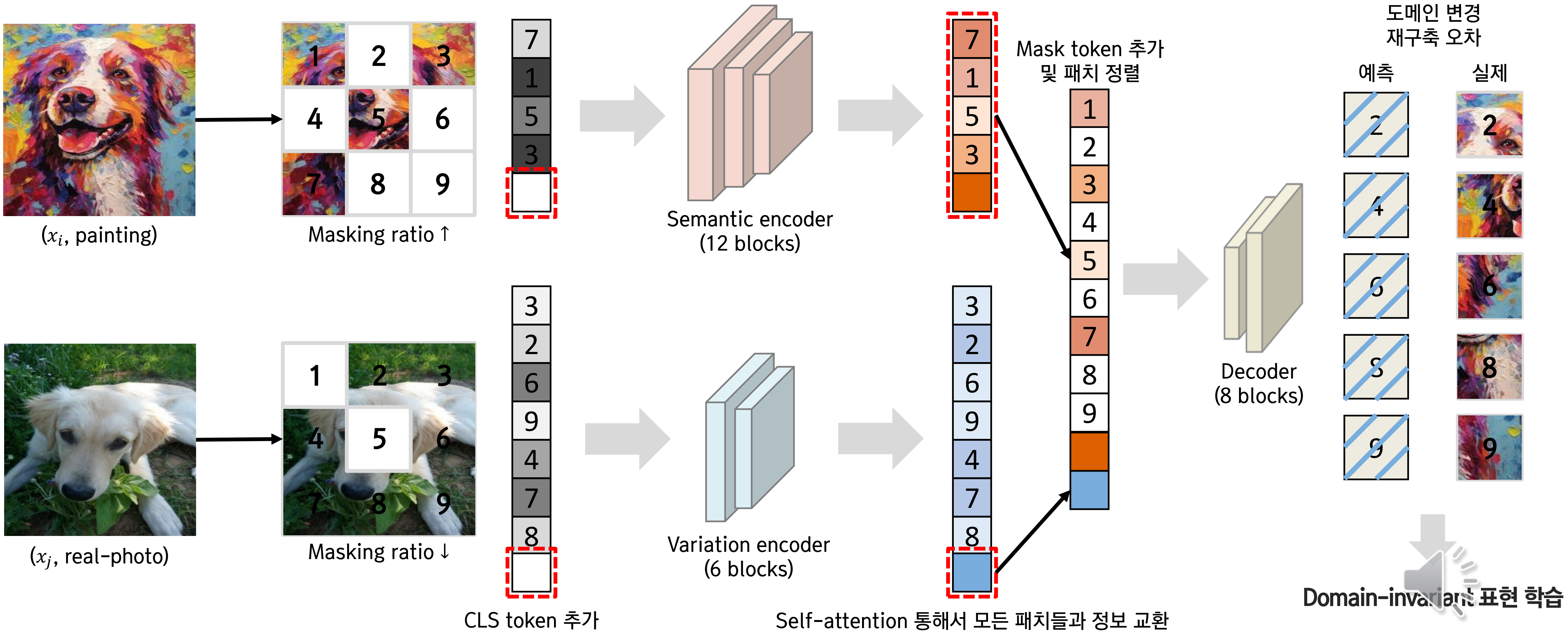
Disentangling masked autoencoders for UDG



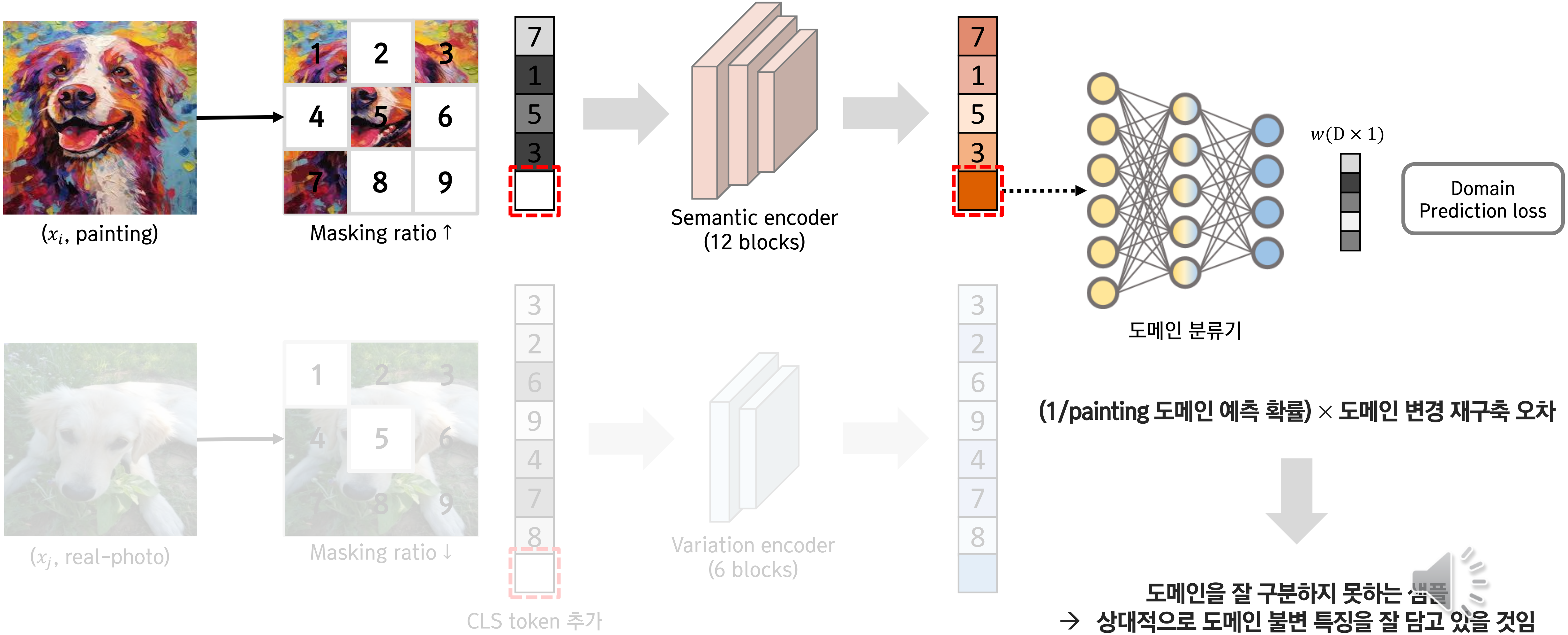
Disentangling masked autoencoders for UDG



Disentangling masked autoencoders for UDG



Disentangling masked autoencoders for UDG



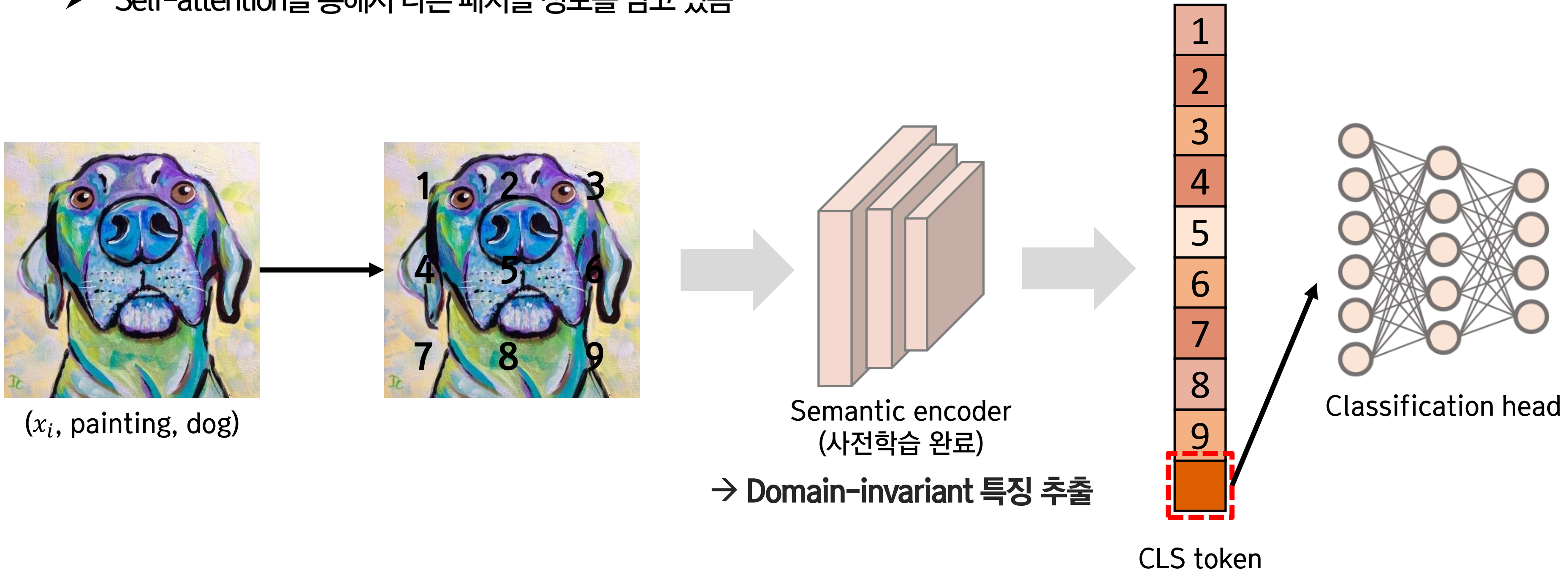
(1/painting 도메인 예측 확률) × 도메인 변경 재구축 오차

도메인을 잘 구분하지 못하는 샘플
→ 상대적으로 도메인 불변 특징을 잘 담고 있을 것임

Disentangling masked autoencoders for UDG

❖ Fine-tuning 단계 학습 방식

- Variation encoder, decoder, domain classifier를 모두 제거한 후 semantic encoder만 사용
- Semantic encoder는 domain-invariant 특징을 추출하는 데 집중함
- Classification head에는 CLS 토큰만 입력으로 사용
  - ➢ Self-attention을 통해서 다른 패치들 정보를 담고 있음



Disentangling masked autoencoders for UDG

❖ DomainNet 데이터셋에 대한 실험 결과 – All correlated case

- 총 6가지 도메인으로 구성된 데이터셋
  - ➢ 학습 도메인: painting, real-photo, sketch
  - ➢ 테스트 도메인: clipart, infograph, quickdraw


painting


real-photo


sketch


clipart

infograph


quickdraw

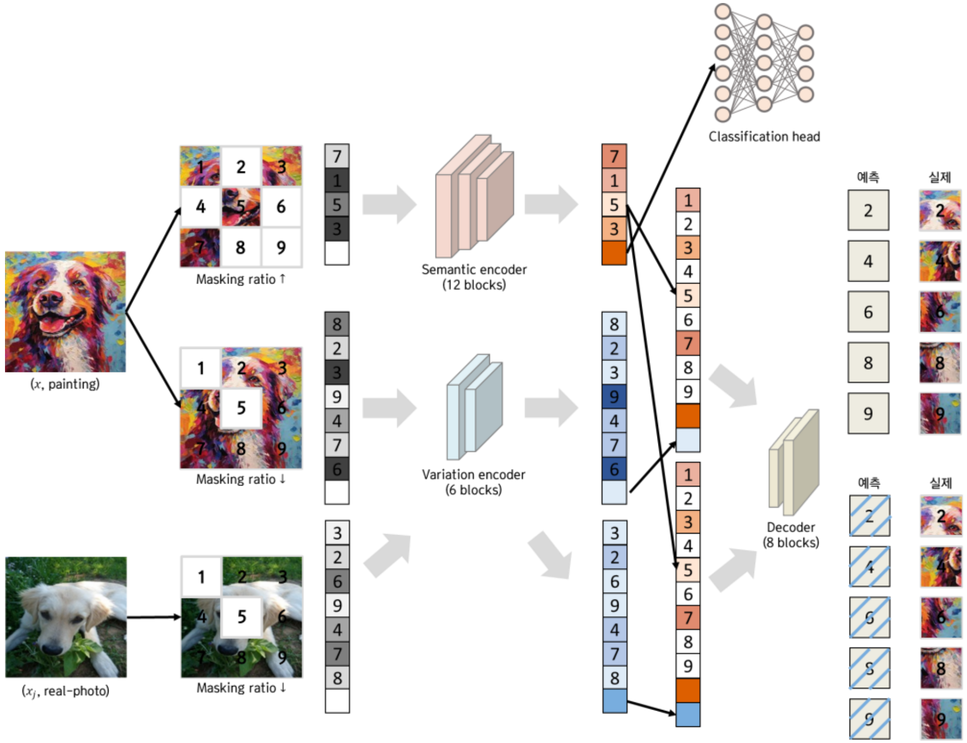
	Label Fraction 1% (Linear evaluation)					Label Fraction 5% (Linear evaluation)				
Methods	**Clip**	**Info**	**Quick**	**Overall**	**Avg.**	**Clip**	**Info**	**Quick**	**Overall**	**Avg.**
ERM [44]	9.38	**9.70**	6.64	8.04	8.57	11.27	8.58	6.90	8.25	8.92
MoCo V2 [14]	9.76	6.53	5.24	6.51	7.18	11.44	9.20	4.95	7.42	8.53
BYOL [20]	17.93	8.03	5.05	8.47	10.34	24.26	8.88	4.66	9.78	12.60
MAE [23]	19.69	8.85	**12.49**	12.96	13.68	29.12	8.88	13.71	15.52	17.24
DARLING [60]	13.77	6.33	7.24	8.41	9.18	19.02	8.49	9.59	11.19	12.36
CycleMAE [53]	11.68	6.82	8.06	8.46	8.85	22.06	**10.46**	12.07	13.66	14.86
DisMAE (Ours)	**24.55**	9.18	11.75	**13.64**	**15.16**	**31.70**	10.14	**19.06**	**19.19**	**20.30**
	Label Fraction 10% (Full finetuning)					**Label Fraction 100% (Full finetuning)**				
Methods	**Clip**	**Info**	**Quick**	**Overall**	**Avg.**	**Clip**	**Info**	**Quick**	**Overall**	**Avg.**
ERM [44]	27.57	13.32	8.29	13.60	16.39	48.61	18.37	20.06	25.38	29.01
MoCo V2 [14]	26.51	11.68	10.62	14.12	16.27	57.16	16.44	29.40	31.50	34.33
BYOL [20]	31.33	11.55	9.51	14.48	17.46	56.62	12.77	26.90	29.08	32.10
MAE [23]	41.76	12.91	18.98	21.94	24.55	63.90	19.34	33.00	35.54	38.75
DARLING [60]	30.68	11.66	13.93	16.69	18.75	55.20	17.04	33.30	33.22	35.18
CycleMAE [53]	33.84	12.06	15.41	18.23	20.43	56.10	19.15	28.60	31.60	34.62
DisMAE (Ours)	**49.06**	**15.82**	**22.68**	**26.16**	**29.19**	**72.99**	**23.40**	**38.20**	**41.22**	**44.86**

Default hyperparameters	
MoCo V2	lr=5e-4, BS=96, WD=0.05, K=65536, m=0.999, T=0.07
BYOL	lr=5e-4, BS=64, WD=0.05, m=0.996
MAE	lr=1e-3, BS=96, WD=0.00, mask ratio=0.75
DARLING	lr=5e-4, BS=96, WD=0.05, K=65536, m=0.995, T=0.07
CycleMAE	lr=7e-4, BS=96, WD=0.05, m=0.999, $\alpha = 2$, $\beta = 1$

Disentangling masked autoencoders for UDG

❖ Supervised learning 세팅에서 DG 방법론들과 비교 실험

- DisMAE 사전학습 모델 구조에서 추가적으로 classification head를 동시에 사용 (end-to-end 학습)
  - ➢ 전체 손실 함수 = 재구축 오차 + 도메인 변경 재구축 오차 + 클래스 분류 손실 오차
- Label 정보를 활용할 수 있는 상황에서도 semantic과 variation을 분리하려는 학습 방식이 효과적임

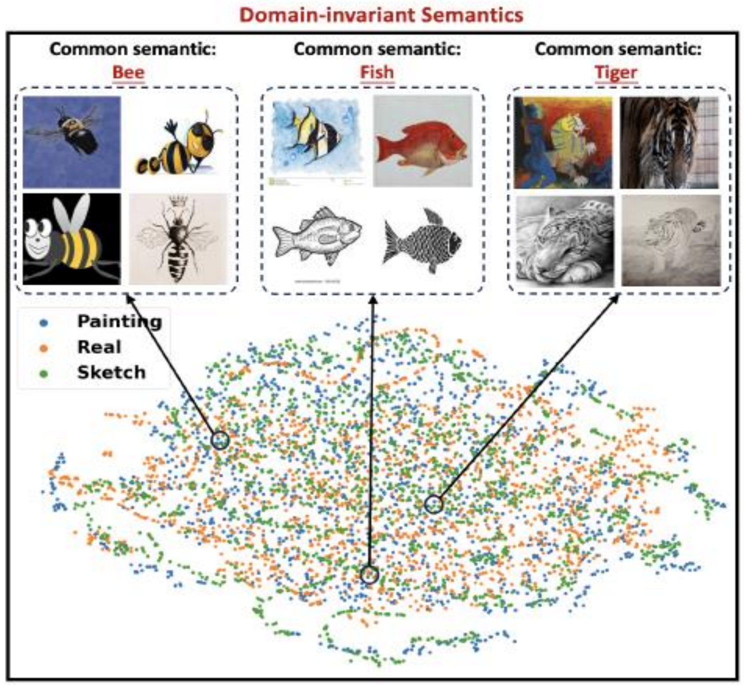


Methods	C	L	S	V	Avg.
ERM [44]	95.47	65.74	76.83	77.07	78.78
MMD [29]	94.61	65.85	73.70	77.26	77.86
GroupDRO [40]	95.49	65.80	76.28	77.37	78.74
IRM [2]	96.26	65.30	73.25	76.01	77.71
Mixup [52]	95.38	65.74	76.83	77.07	78.76
VREx [27]	96.94	63.67	73.34	76.10	77.51
Fishr [39]	96.17	65.19	74.77	78.06	78.55
DDG [58]	96.97	64.21	71.76	76.58	77.38
RIDG [10]	96.64	66.16	**77.57**	76.68	79.26
DisMAE (Ours)	**97.35**	**66.96**	77.10	**80.12**	**80.38**

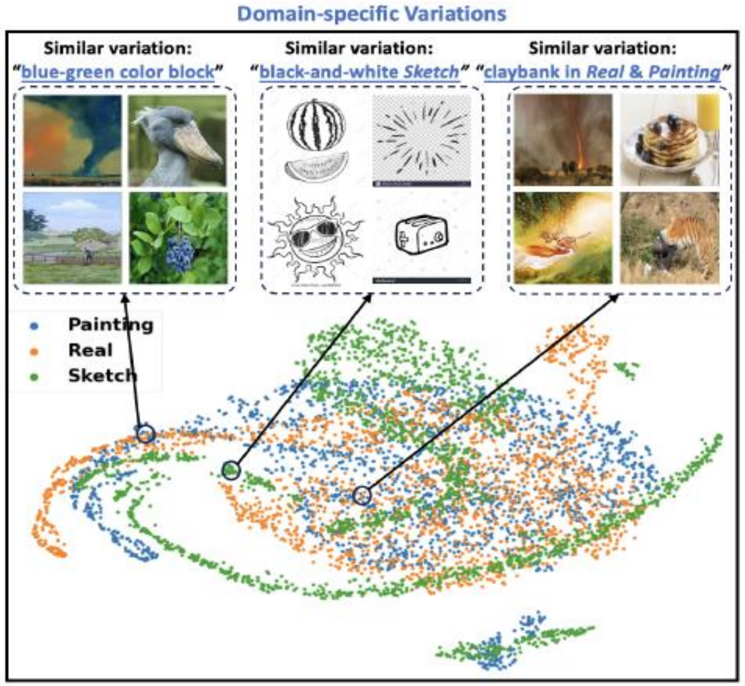
Disentangling masked autoencoders for UDG

❖ Semantic 특징과 variation 특징이 잘 분리되었는지 시각적으로 검증 → Disentanglement

- Semantic encoder가 도메인 정보(이미지 스타일 등)를 무시하고 있음을 확인할 수 있음
  - ➢ 도메인을 구분할 수 없게 만듦으로써, 이미지의 invariant 요소들에 집중하여 특징 추출
- Variation encoder가 도메인 정보를 잘 포착하고 있음을 알 수 있음



Semantic latent vectors

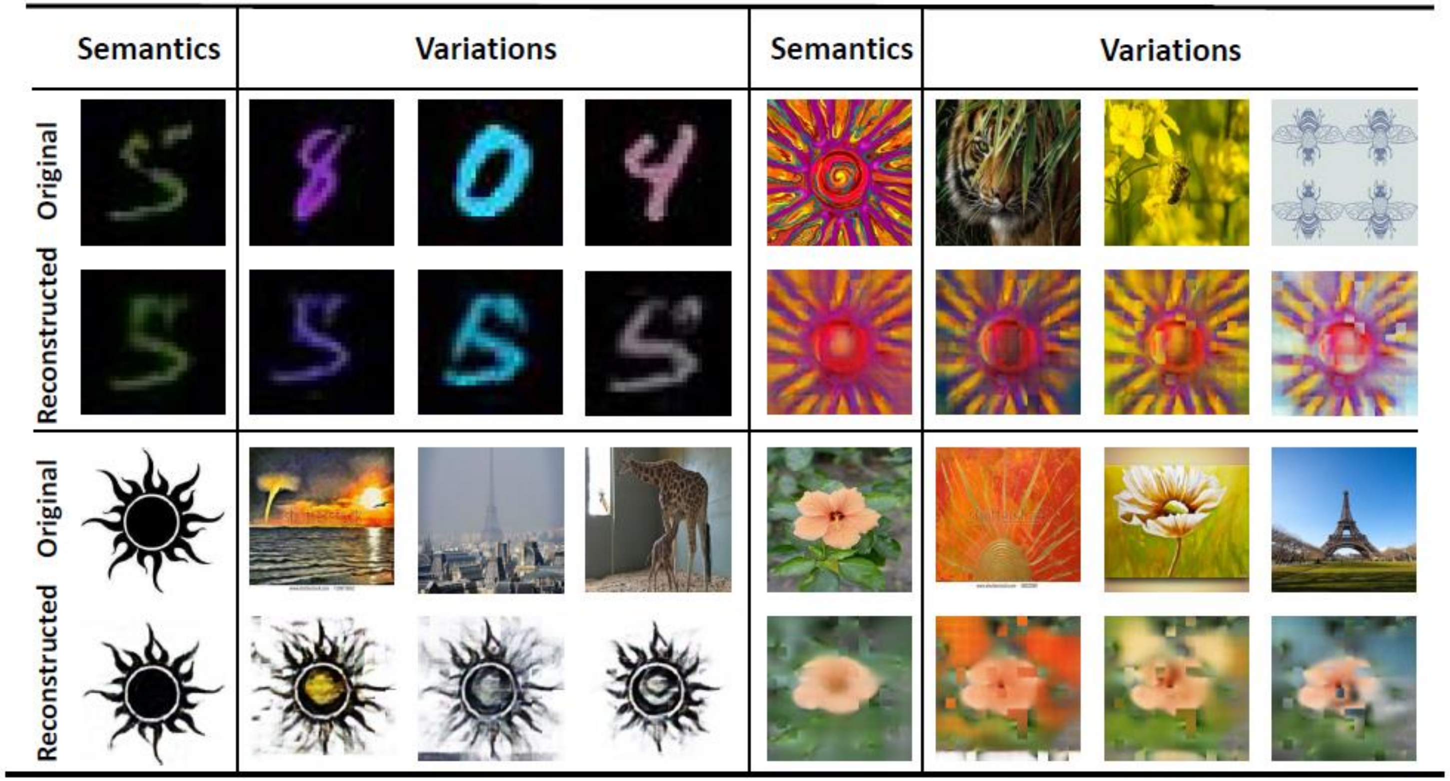


Variation latent vectors

Disentangling masked autoencoders for UDG

❖ 실제 이미지와 재구축된 이미지들 시각화 비교

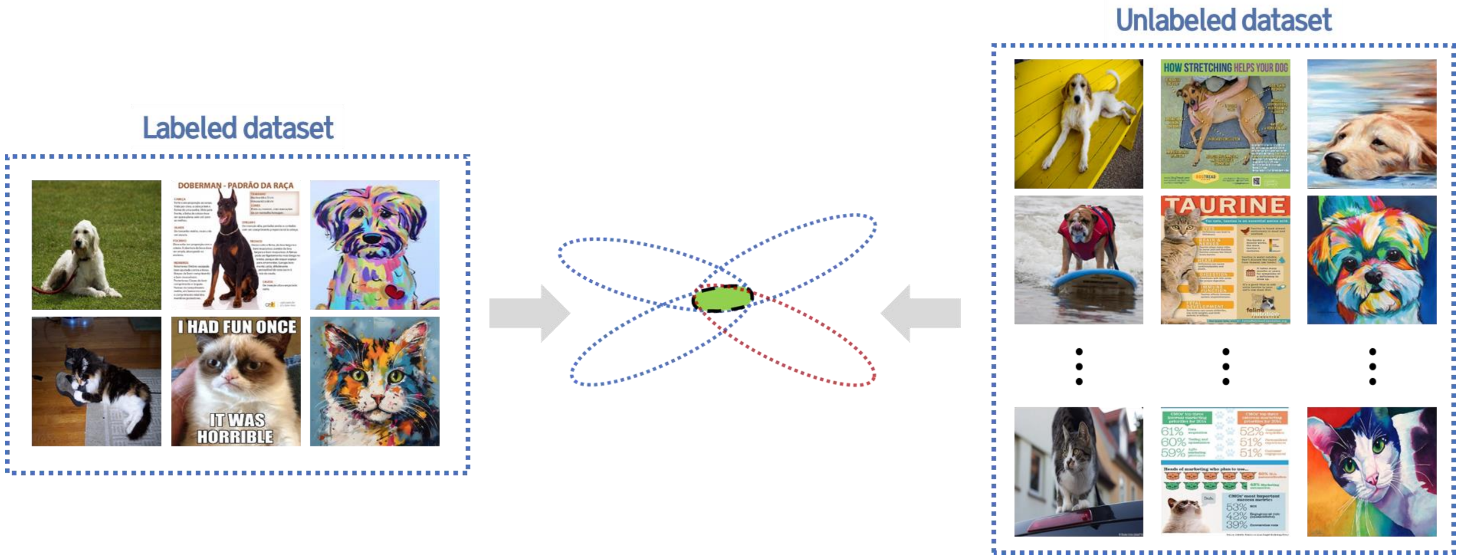
- Colored MNIST 등 단순한 이미지에서는 이미지 스타일 변경 재구축이 잘 되는 것을 확인할 수 있음
- 도메인 간 분포 차이가 심하거나 클래스가 다른 경우에는 한계를 보임



Conclusion

❖ Summary

- Domain generalization을 해결하기 위해서 대표적으로 domain-invariant 정보를 학습
- Labeled dataset이 충분하지 않을 경우에는 unlabeled dataset을 활용하여 domain-invariant 표현을 학습



- Contrastive learning에서 domain 정보를 반영한 negative sample 활용
- Masked autoencoder와 disentanglement 개념을 활용

고맙습니다