Data Mining
Quality Analytics

Introduction to Unsupervised Domain Adaptation

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  - Data Mining & Quality Analytics Lab (김성범 교수님 연구실)
  - 석·박사 통합과정 (2017.03~)
- 관심 연구 분야
  - Deep learning for multivariate sensor data
  - Incomplete multivariate sensor data
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A Review of Single-Source Deep Unsupervised Visual Domain Adaptation

Sicheng Zhao, *Senior Member, IEEE*, Xiangyu Yue, Shanghang Zhang, Bo Li, Han Zhao, Bichen Wu, Ravi Krishna, Joseph E. Gonzalez, Alberto L. Sangiovanni-Vincentelli, *Fellow, IEEE*, Sanjit A. Seshia *Fellow, IEEE*, and Kurt Keutzer, *Fellow, IEEE*

***Abstract*—Large-scale labeled training datasets have enabled deep neural networks to excel across a wide range of benchmark vision tasks. However, in many applications, it is prohibitively expensive and time-consuming to obtain large quantities of labeled data. To cope with limited labeled training data, many have attempted to directly apply models trained on a large-scale labeled source domain to another sparsely labeled or unlabeled target domain. Unfortunately, direct transfer across domains often performs poorly due to the presence of *domain shift* or *dataset bias*. Domain adaptation is a machine learning paradigm that aims to learn a model from a source domain that can perform well on a different (but related) target domain. In this paper, we review the latest single-source deep unsupervised domain adaptation methods focused on visual tasks and discuss new perspectives for future research. We begin with the definitions of different domain adaptation strategies and the descriptions of existing benchmark datasets. We then summarize and compare different categories of single-source unsupervised domain adaptation methods, including discrepancy-based methods, adversarial discriminative methods, adversarial generative methods, and self-supervision-based methods. Finally, we discuss future research directions with challenges and possible solutions.**

***Index Terms*—Domain adaptation, discrepancy-based methods, adversarial learning, self-supervised learning, transfer learning**

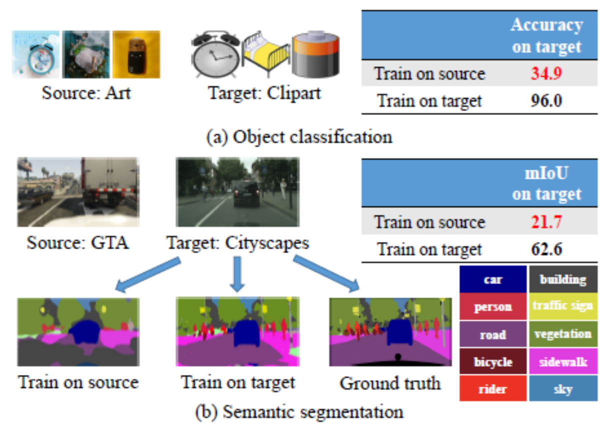
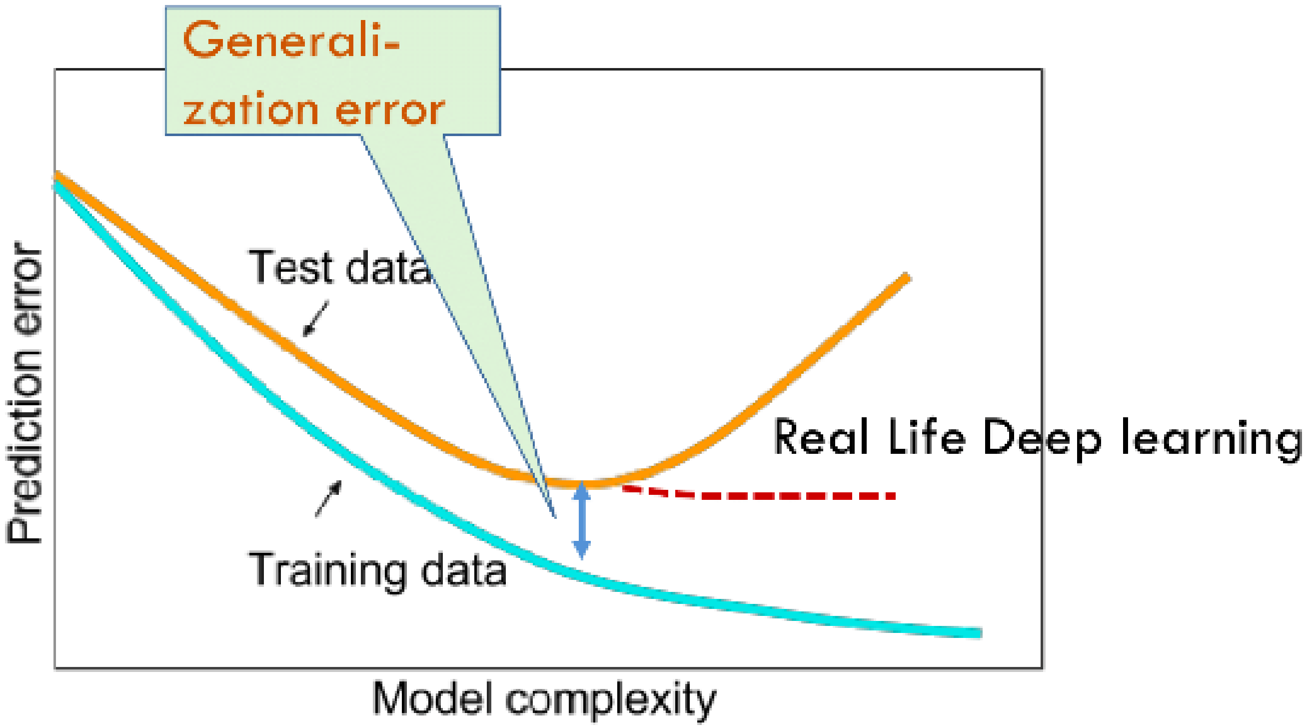


Fig. 1. An example of *domain shift*. For both image-level object classification and pixel-wise semantic segmentation tasks, direct transfer of the models trained on the labeled source domain to the unlabeled target domain results in a dramatic performance drop.

Zhao, S., Yue, X., Zhang, S., Li, B., Zhao, H., Wu, B., ... & Keutzer, K. (2020). A review of single-source deep unsupervised visual domain adaptation. IEEE Transactions on Neural Networks and Learning Systems.

Introduction

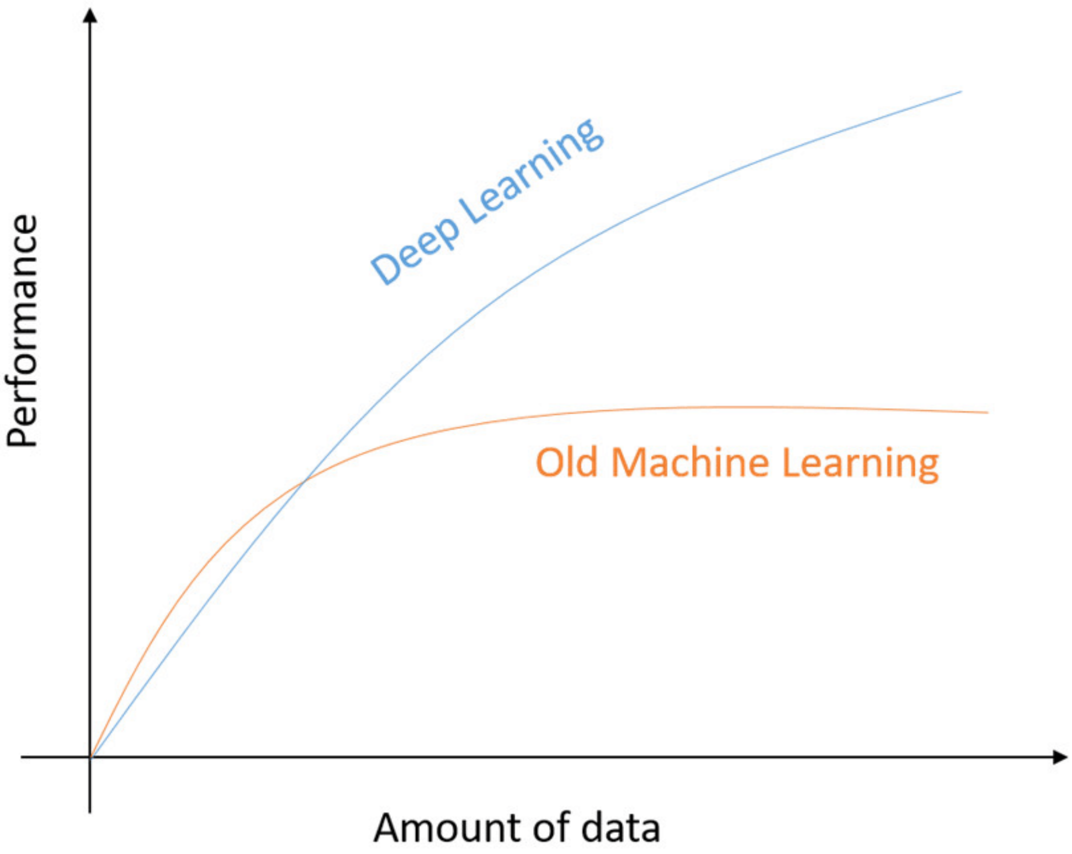
- 딥러닝 모델의 일반화 성능



이미지 출처 : https://desh2608.github.io/2018-07-27-deep-learning-theory-2/

Introduction

- 딥러닝 모델의 일반화 성능



이미지 출처 : https://www.researchgate.net/figure/The-performance-of-deep-learning-with-respect-to-the-amount-of-data_fig3_331540139

Introduction

- Domain shift/discrepancy 문제 예시

연구원 이모씨

숫자 인식 딥러닝 모델 개발

MNIST

이미지 출처 : https://www.researchgate.net/figure/The-noisy-MNIST-datasets-Examples-of-noisy-MNIST-samples-background-image-noise_fig3_333013233

Introduction

- Domain shift/discrepancy 문제 예시

연구원 이모씨

숫자 인식 딥러닝 모델 개발 **완료 (평가 데이터 정확도 99.9% 확인)**

학습 데이터

MNIST

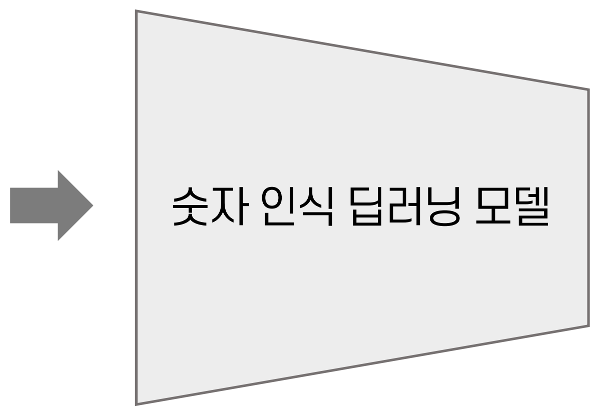
Introduction

- Domain shift/discrepancy 문제 예시

숫자 인식 딥러닝 모델 개발 **완료 (?)**

연구원 이모씨

평가 데이터



정확도 15.1%

Introduction

- Domain shift/discrepancy 문제 예시

Domain shift
Domain discrepancy

Source domain

≠

Target domain

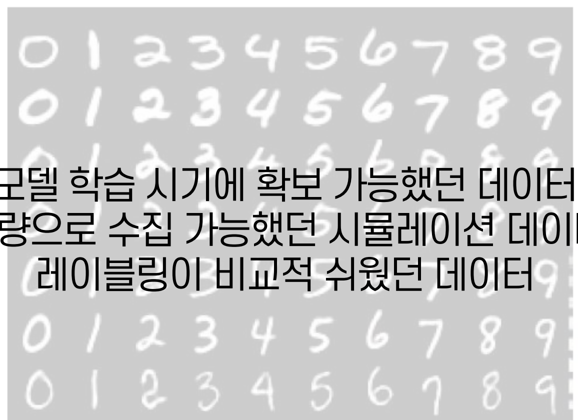
기존에 모델이 우수한 성능으로 동작하던 영역

모델이 우수한 성능으로 작동되어야 하는 영역

Introduction

- 현실에서 빈번한 domain shift/discrepancy 문제

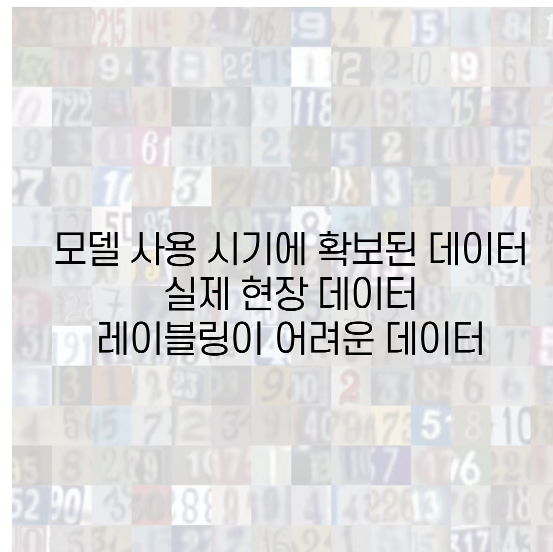
Source domain



모델 학습 시기에 확보 가능했던 데이터
다량으로 수집 가능했던 시뮬레이션 데이터
레이블링이 비교적 쉬웠던 데이터

≠

Target domain



모델 사용 시기에 확보된 데이터
실제 현장 데이터
레이블링이 어려운 데이터

기존에 모델이 우수한 성능으로 동작하던 영역

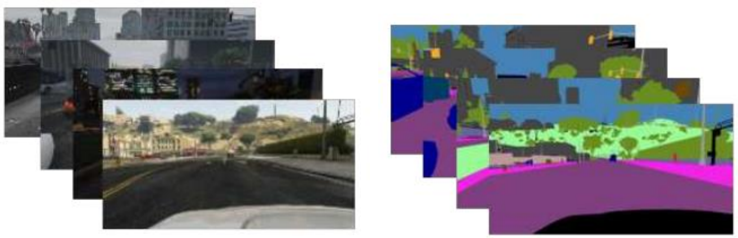
모델이 우수한 성능으로 작동되어야 하는 영역

Introduction

- 현실에서 빈번한 domain shift/discrepancy 문제

<자율주행을 위해 도로 상황에 대해서 semantic segmentation 모델 개발>

Source domain



Road	Traffic light	Rider
Sidewalk	Traffic sign	Car
Building	Vegetation	Truck
Wall	Terrain	Bus
Fence	Sky	Train
Pole	Person	Motorcyle

GTA 데이터

Target domain

실제 도로 데이터

Introduction

- 현실에서 빈번한 domain shift/discrepancy 문제

<자율주행을 위해 도로 상황에 대해서 semantic segmentation 모델 개발>

Source domain

Target domain

≠

GTA 데이터

실제 도로 데이터

Introduction

- 현실에서 빈번한 domain shift/discrepancy 문제

<자율주행을 위해 도로 상황에 대해서 semantic segmentation 모델 개발>

Source domain **Target domain**

≠

이미지 데이터에만 발생하는 문제일까?

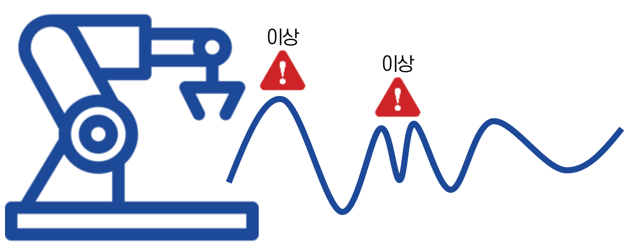
GTA 데이터 실제 도로 데이터

Introduction

- 현실에서 빈번한 domain shift/discrepancy 문제

<센서 데이터를 사용해서 장비 고장 (정상/이상) 여부를 판단하는 classification 모델 개발>

Source domain **Target domain**



장비 A

≠

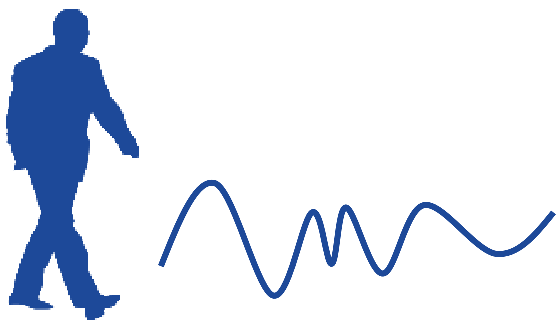
신규 장비

Introduction

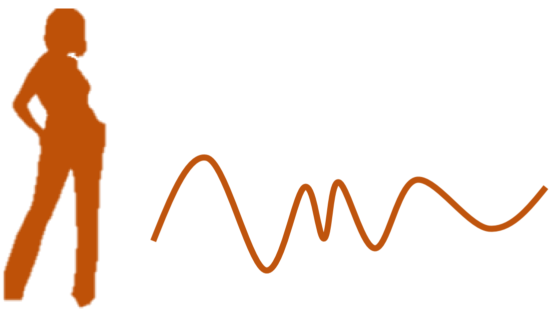
- 현실에서 빈번한 domain shift/discrepancy 문제

<센서 데이터를 사용해서 인간의 동작(걷기, 뛰기, 앉아있음, 누워있음…)을 탐지하는 모델 개발>

Source domain **Target domain**



≠

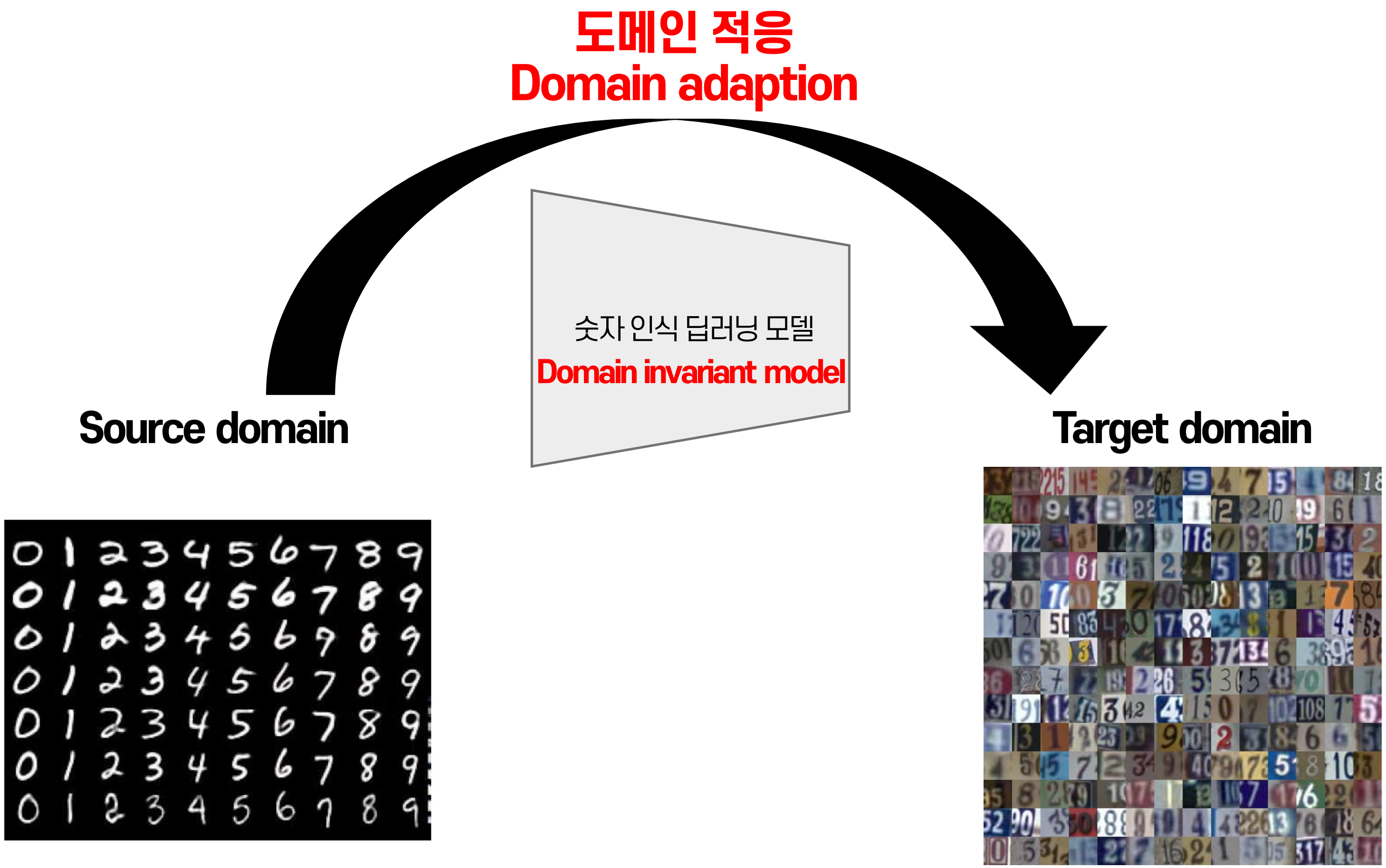


피실험자 A

다른 성별/연령/신체 조건의 피실험자

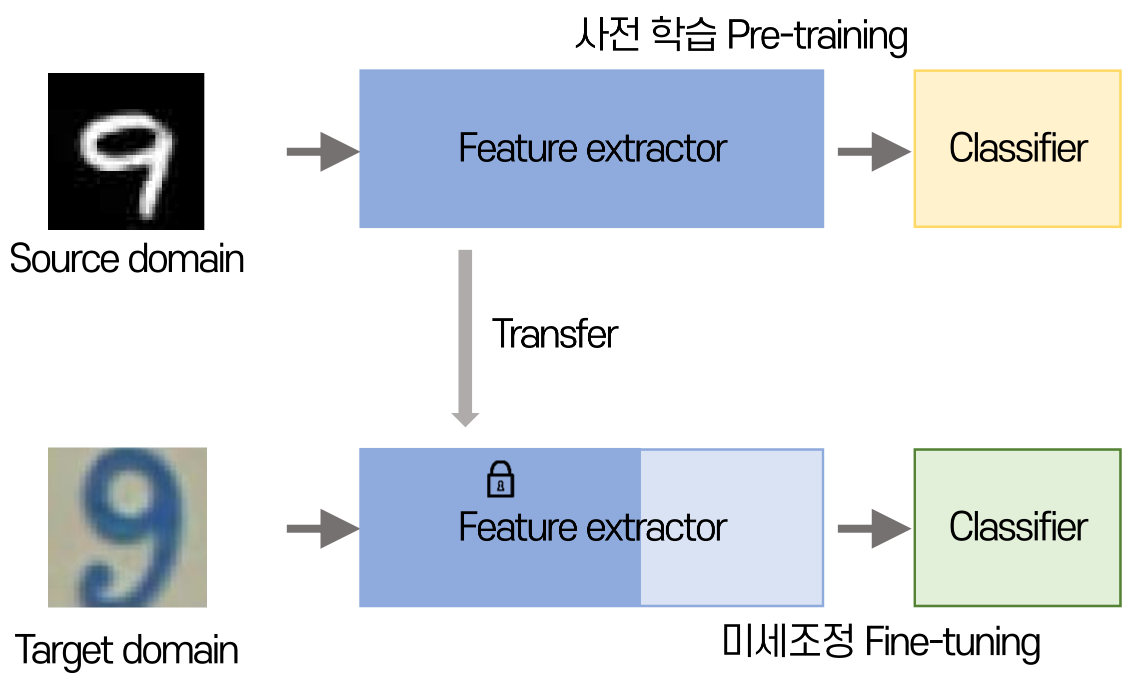
Introduction

- Domain adaptation



Introduction

- 전이학습(Transfer learning)은 해결책이 될 수 없는가?
  - Pre-training with source domain & fine-tuning with target domain
  - **However, fine-tuning still requires considerable quantities of labeled data**

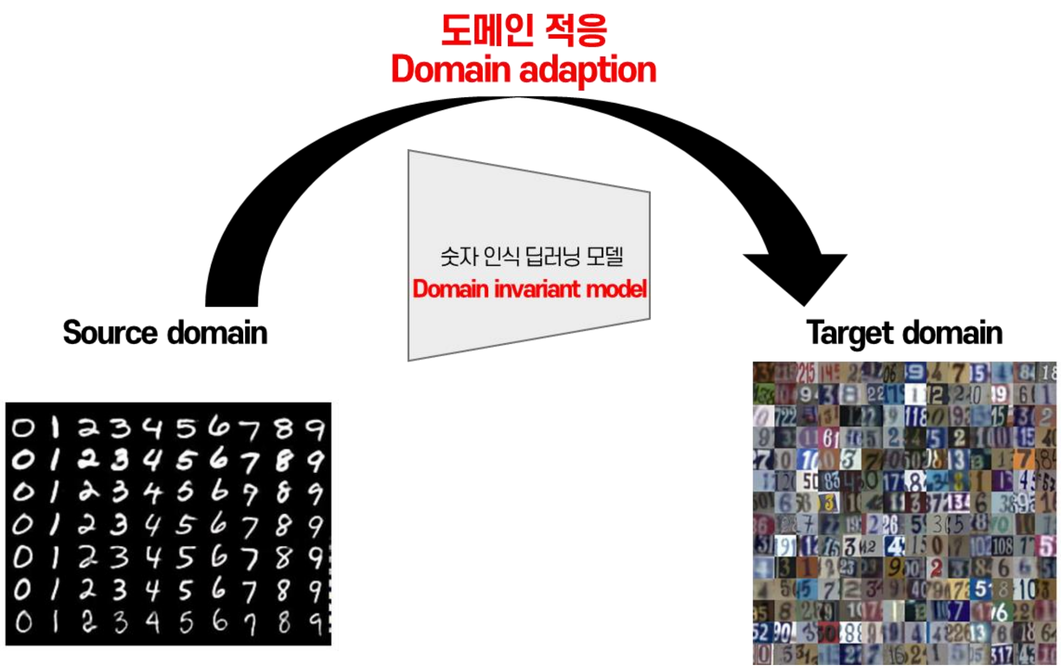


Introduction

- Domain adaptation
  - Specialized form of transfer learning that aims to learn a model that can **generalized well to unlabeled or sparsely labeled target domain**

Unsupervised domain adaptation

Semi-supervised domain adaptation



Labeled dataset

Unlabeled dataset

Sparsely labeled dataset

Introduction

- **Unsupervised domain adaptation**
  - Specialized form of transfer learning that aims to learn a model that can **generalized well to unlabeled target domain**

Unsupervised domain adaptation

Unsupervised Domain Adaptation

- 가정 및 목표를 정리해보자!

Source domain

Labeled dataset

Target domain

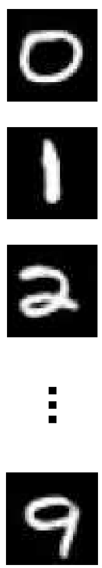
Unlabeled dataset

Unsupervised Domain Adaptation

- 가정 및 목표를 정리해보자!

Source domain labeled dataset

$$D^S = \{X_i^S, y_i^S\}_{i=1}^{N_s}$$



0

1

2

9

Target domain unlabeled dataset

$$D^T = \left\{X_i^T\right\}_{i=1}^{N_T}$$

Unsupervised Domain Adaptation

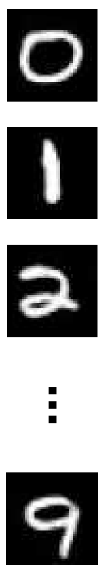
- 가정 및 목표를 정리해보자!

Source domain labeled dataset

$$D^S = \{X_i^S, y_i^S\}_{i=1}^{N_s}$$

Target domain unlabeled dataset

$$D^T = \{X_i^T\}_{i=1}^{N_T}$$



Domain shift/discrepancy

$$p(X) \neq q(X)$$

$X^S \sim p(X)$

$X^T \sim q(X)$

Unsupervised Domain Adaptation

- 가정 및 목표를 정리해보자!

Training dataset

Source domain labeled dataset

$$D^S = \{X_i^S, y_i^S\}_{i=1}^{N_S}$$

Target domain unlabeled dataset

$$D^T = \{X_i^T\}_{i=1}^{N_T}$$

$Minimize_\theta$ **Target risk**

θ classifier

The goal of the learning algorithm is to build a classifier with **a low target risk**

Unsupervised Domain Adaptation

- 가정 및 목표를 정리해보자!
  - 이번 세미나에서 다루는 범위
    - ✓ Non-deep UDA vs **deep UDA**

Training dataset

Source domain labeled dataset

$$D^S = \{X_i^S, y_i^S\}_{i=1}^{N_S}$$

Target domain unlabeled dataset

$$D^T = \{X_i^T\}_{i=1}^{N_T}$$

$Minimize_\theta$ **Target risk**

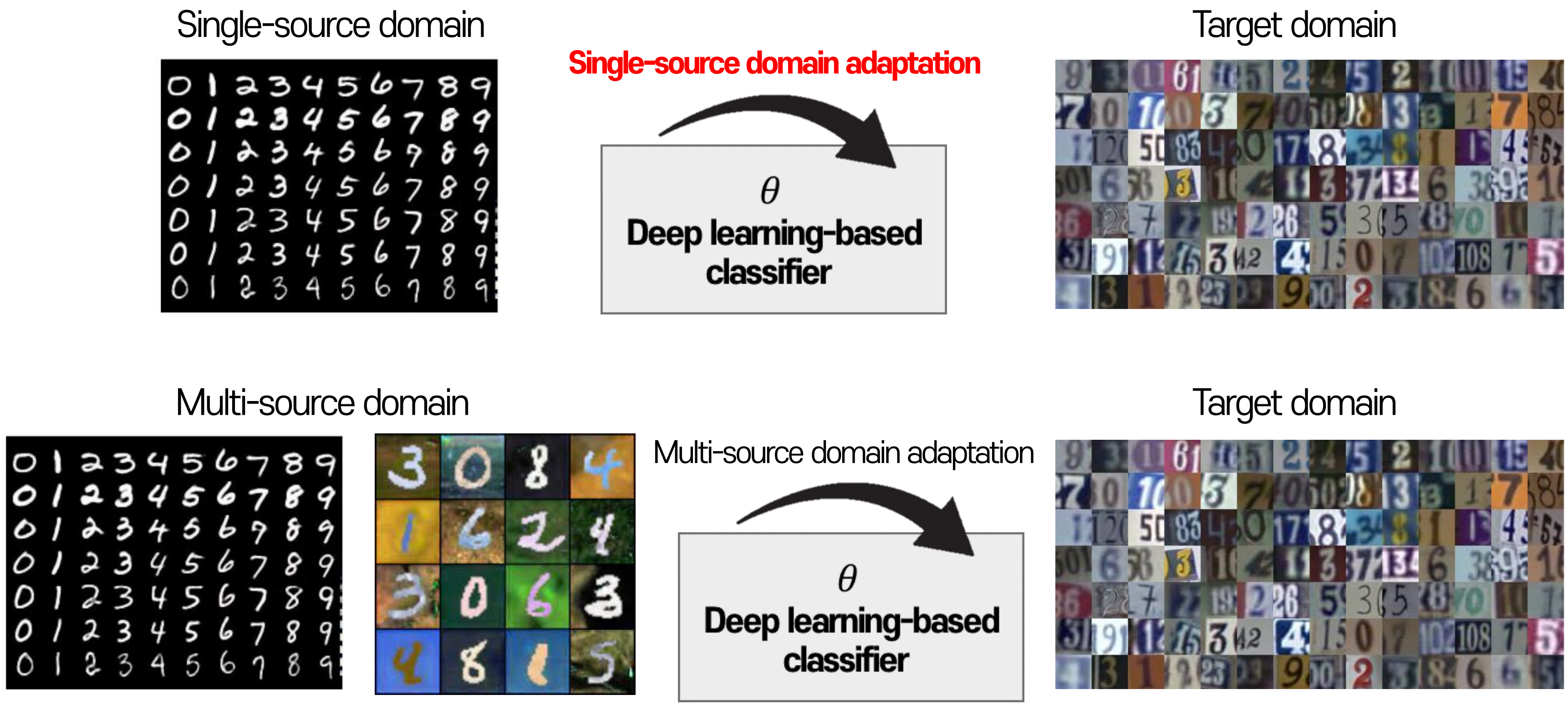
θ

Deep learning-based classifier

The goal of the learning algorithm is to build a classifier with **a low target risk**

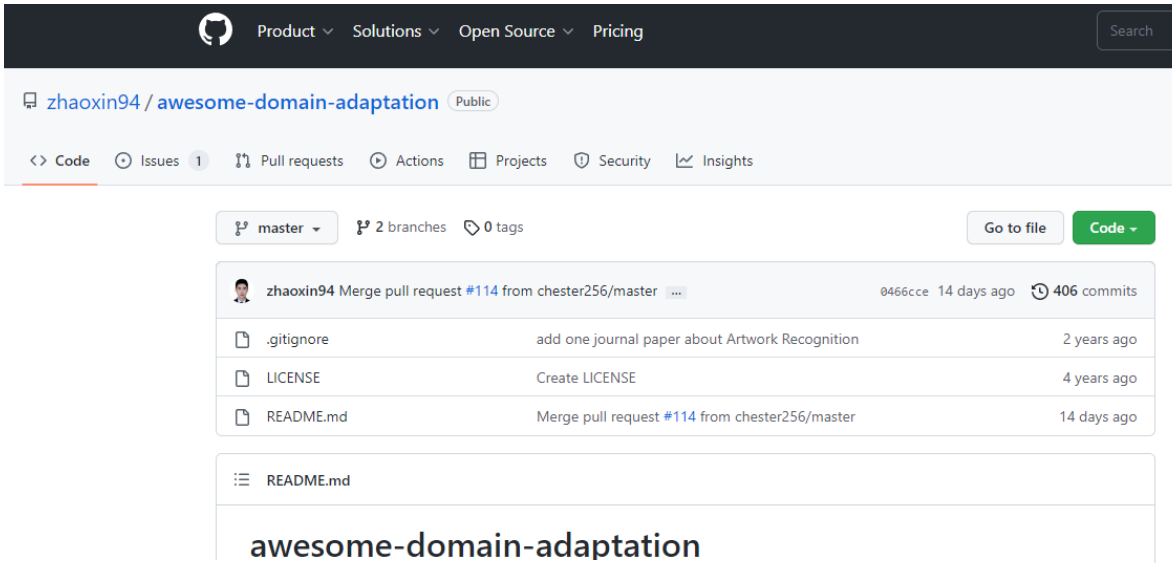
Unsupervised Domain Adaptation

- 가정 및 목표를 정리해보자!
  - 이번 세미나에서 다루는 범위
    - ✓ Non-deep UDA vs **deep UDA**
    - ✓ **Single-source UDA** vs multi-source UDA



Unsupervised Domain Adaptation

- 가정 및 목표를 정리해보자!
  - 이번 세미나에서 다루는 범위
    - ✓ 이외에도 관심이 생기는 분들은 다음 사이트 참고해주세요 ☺



Semi-supervised DA

Conference

- Multi-level Consistency Learning for Semi-supervised Domain Adaptation [IJCAI 2022]
- AdaMatch: A Unified Approach to Semi-Supervised Learning and Domain Adaptation [ICLR 2022]
- CLDA: Contrastive Learning for Semi-Supervised Domain Adaptation [NeurIPS]
- Deep Co-Training With Task Decomposition for Semi-Supervised Domain Adaptation [ICCV2021]
- ECACL: A Holistic Framework for Semi-Supervised Domain Adaptation [ICCV2021]
- Cross-Domain Adaptive Clustering for Semi-Supervised Domain Adaptation [CVPR2021]
- Semi-supervised Domain Adaptation based on Dual-level Domain Mixing for Semantic Segmentation [CVPR2021]
- Learning Invariant Representations and Risks for Semi-supervised Domain Adaptation [CVPR2021]

Multi Source DA

Conference

- Confident Anchor-Induced Multi-Source Free Domain Adaptation [NeurIPS2021] [code is coming soon]
- mDALU: Multi-Source Domain Adaptation and Label Unification With Partial Datasets [ICCV2021]
- STEM: An Approach to Multi-Source Domain Adaptation With Guarantees [ICCV2021]
- T-SVDNet: Exploring High-Order Prototypical Correlations for Multi-Source Domain Adaptation [ICCV2021]
- Multi-Source Domain Adaptation for Object Detection [ICCV2021]
- Information-Theoretic Regularization for Multi-Source Domain Adaptation [ICCV2021]
- Partial Feature Selection and Alignment for Multi-Source Domain Adaptation [CVPR2021]
- Wasserstein Barycenter for Multi-Source Domain Adaptation [CVPR2021] [Code]
- Unsupervised Multi-source Domain Adaptation Without Access to Source Data [CVPR2021]
- Dynamic Transfer for Multi-Source Domain Adaptation [CVPR2021] [Pytorch]
- Multi-Source Domain Adaptation with Collaborative Learning for Semantic Segmentation [CVPR2021]

https://github.com/zhaoxin94/awesome-domain-adaptation

Unsupervised Domain Adaptation

- 알고리즘 분류
  - **Discrepancy-based method**
    - ✓ DAN (Deep Adaptation Networks), ICML, 2015
  - **Adversarial-based method**
    - ✓ DANN (Domain-Adversarial Neural Networks), JMLR, 2016
  - **Self-supervision-based method**
    - ✓ JiGen (Jigsaw puzzle based Generalization), CVPR, 2019
  - **Combination method for time series data**
    - ✓ SLARDA (SeLf-supervised AutoRegressive Domain Adaptation), TNNLS, 2022

Long, M., Cao, Y., Wang, J., & Jordan, M. (2015, June). Learning transferable features with deep adaptation networks. In International conference on machine learning (pp. 97-105). PMLR.
Ganin, Y., Ustinova, E., Ajakan, H., Germain, P., Larochelle, H., Laviolette, F., ... & Lempitsky, V. (2016). Domain-adversarial training of neural networks. The journal of machine learning research, 17(1), 2096-2030.
Carlucci, F. M., D'Innocente, A., Bucci, S., Caputo, B., & Tommasi, T. (2019). Domain generalization by solving jigsaw puzzles. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 2229-2238).
Ragab, M., Eldele, E., Chen, Z., Wu, M., Kwoh, C. K., & Li, X. (2022). Self-Supervised Autoregressive Domain Adaptation for Time Series Data. IEEE Transactions on Neural Networks and Learning Systems.

Discrepancy-based method

- Deep Adaptation Networks (DAN) ICML 2015

Target risk = source risk + domain discrepancy

Source domain distribution과
target domain distribution의 차이를 줄이는 함수 학습

Training dataset

Source domain labeled dataset

$$D^S = \{X_i^S, y_i^S\}_{i=1}^{N_S}$$

Target domain unlabeled dataset

$$D^T = \{X_i^T\}_{i=1}^{N_T}$$

$Minimize_{\theta}$ **Target risk**

θ

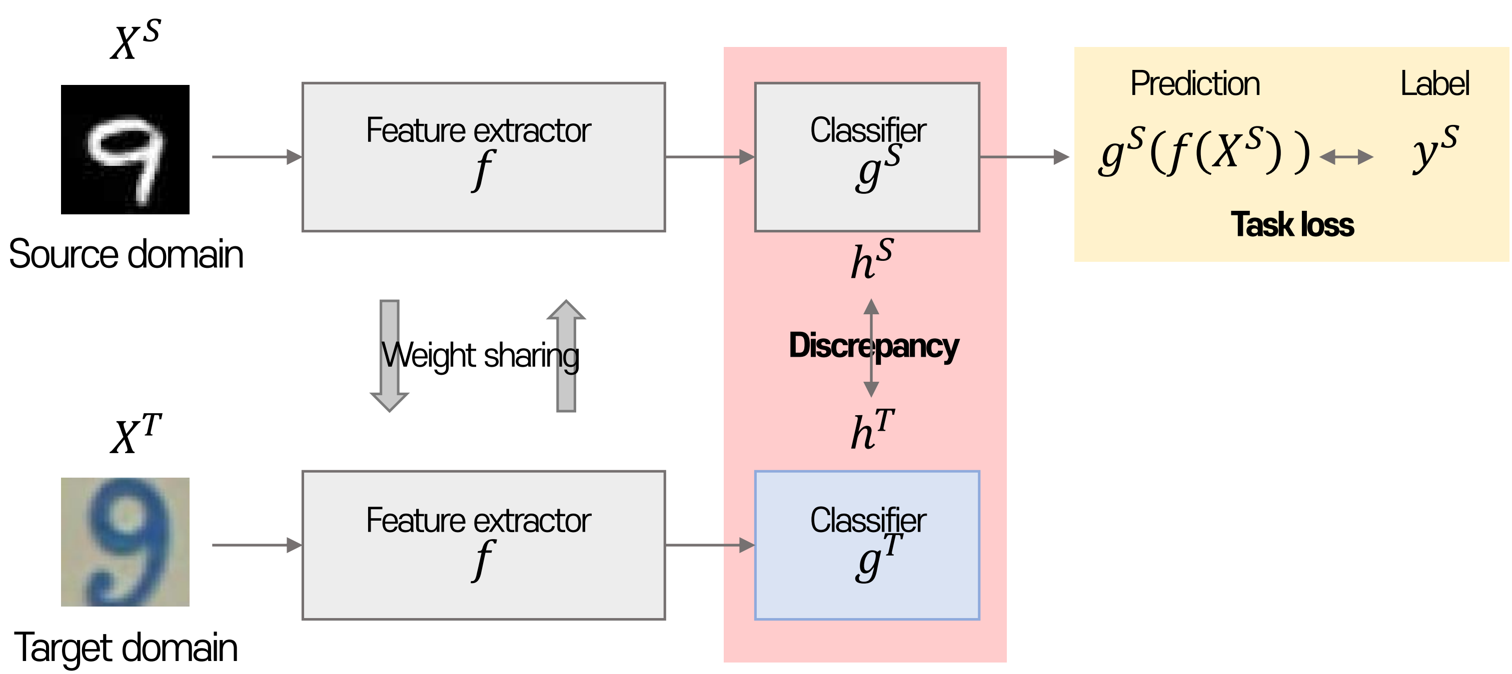
Deep learning-based classifier

The goal of the learning algorithm is to build a classifier with **a low target risk**

Discrepancy-based method

- Deep Adaptation Networks (DAN) ICML 2015

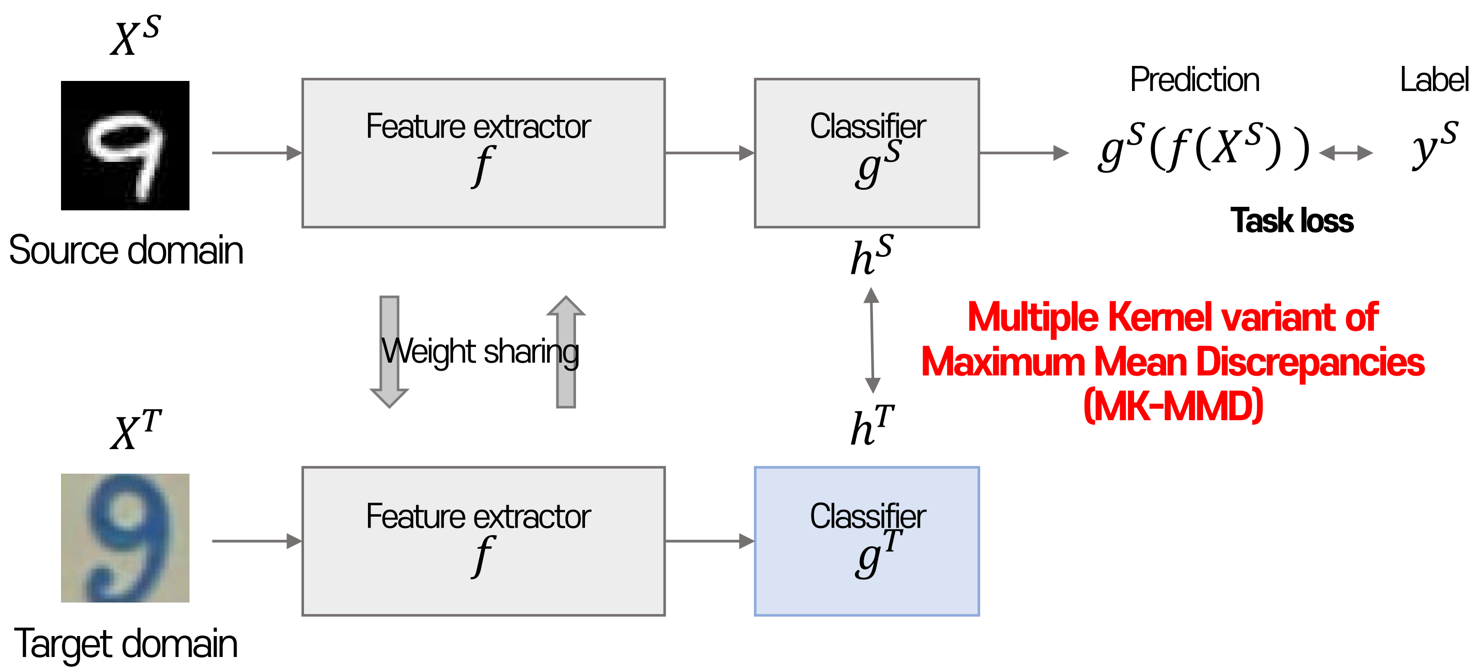
Target risk = source risk + domain discrepancy



Discrepancy-based method

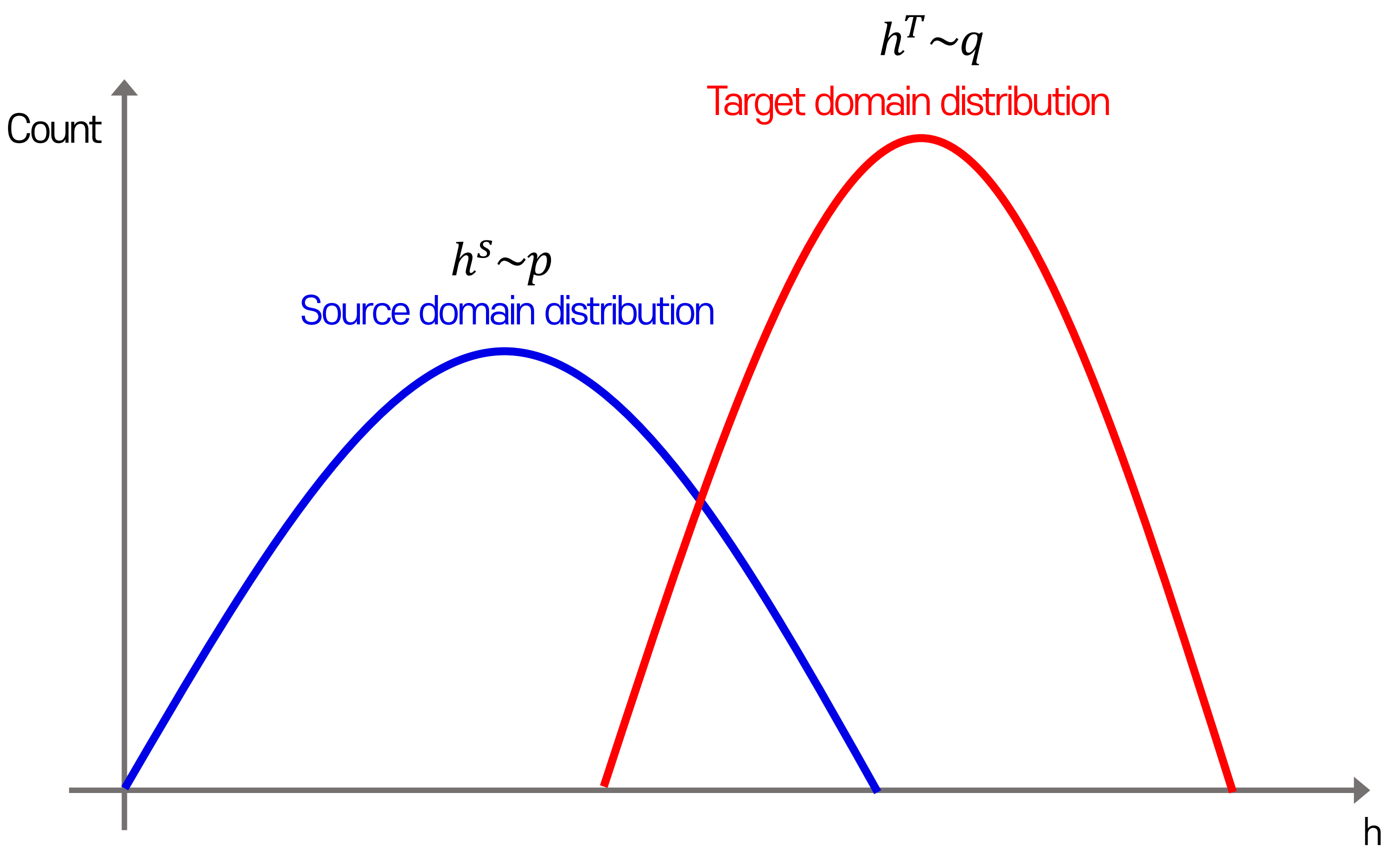
- Deep Adaptation Networks (DAN) ICML 2015

Target risk = source risk + domain discrepancy



Discrepancy-based method

- Deep Adaptation Networks (DAN) ICML 2015
  - Multiple Kernel variant of Maximum Mean Discrepancies (MK-MMD)



Discrepancy-based method

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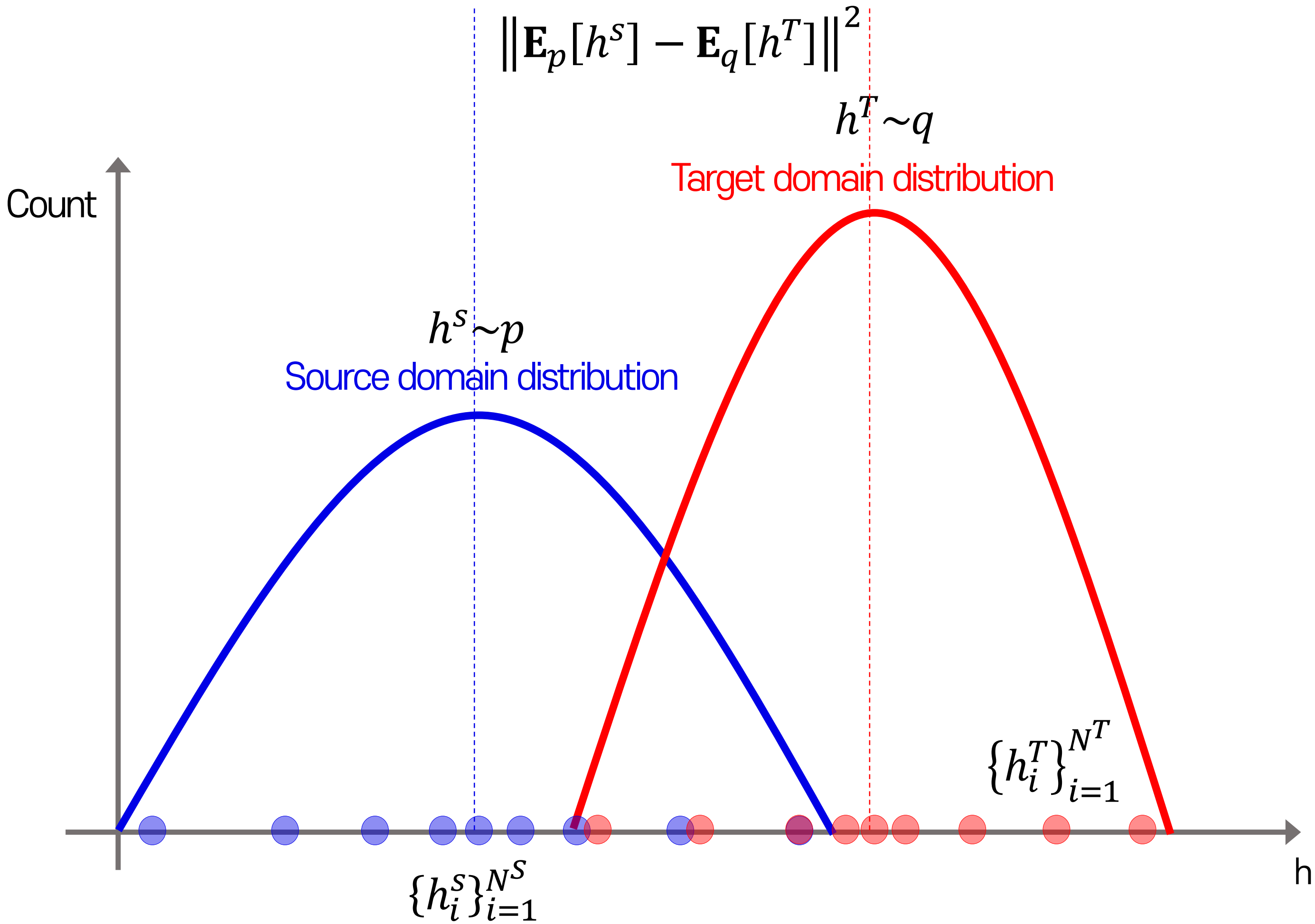
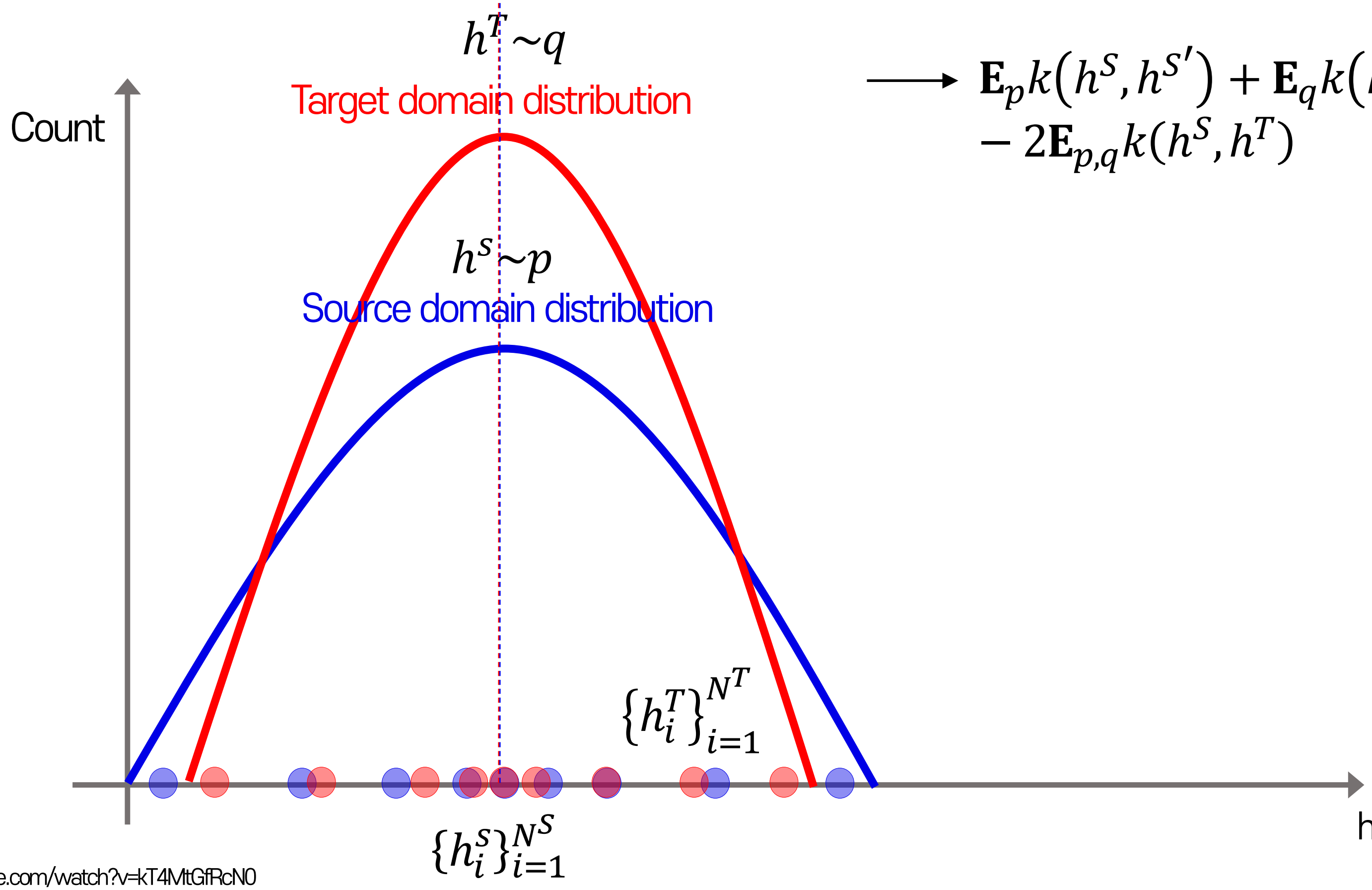


Discrepancy-based method

- Deep Adaptation Networks (DAN) ICML 2015
  - Multiple Kernel variant of Maximum Mean Discrepancies (MK-MMD)

$$\left\|\mathbf{E}_p[h^S] - \mathbf{E}_q[h^T]\right\|^2 \longrightarrow \left\|\mathbf{E}_p[\phi(h^S)] - \mathbf{E}_q[\phi(h^T)]\right\|^2$$

$$\longrightarrow \mathbf{E}_p k\left(h^S, h^{S'}\right) + \mathbf{E}_q k\left(h^T, h^{T'}\right) - 2\mathbf{E}_{p,q} k\left(h^S, h^T\right)$$

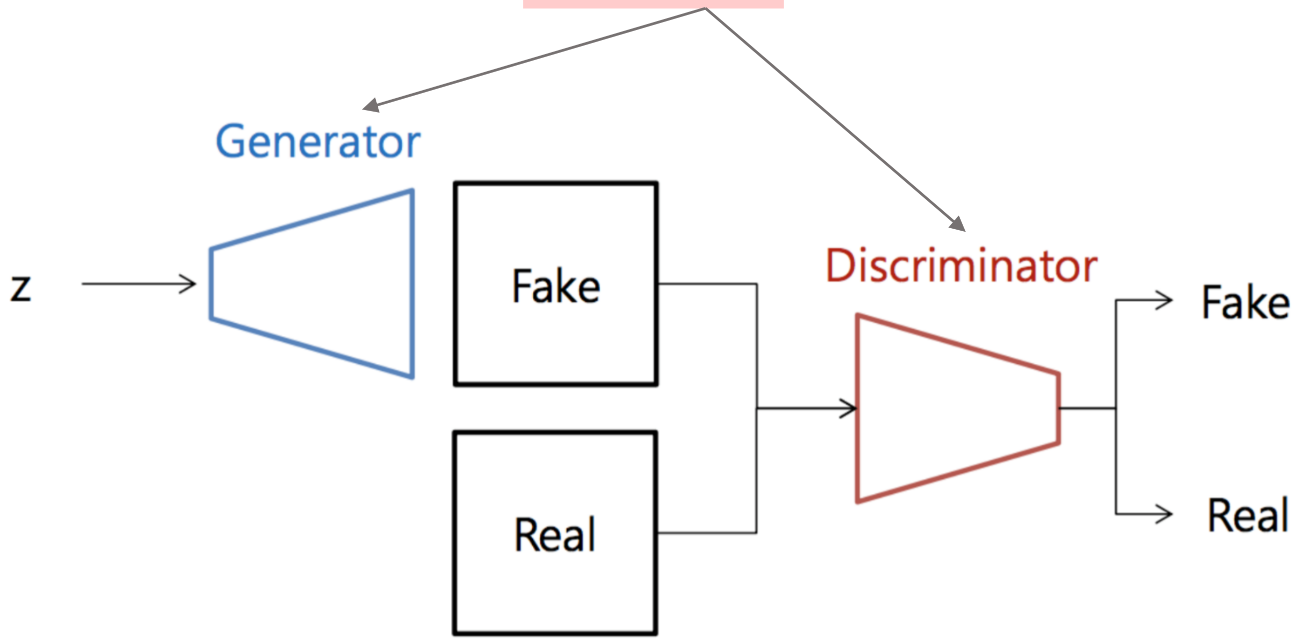


https://www.youtube.com/watch?v=kT4MtGfRcN0

Adversarial-based method

- Adversarial

Generative Adversarial Networks (GAN)
적대적인

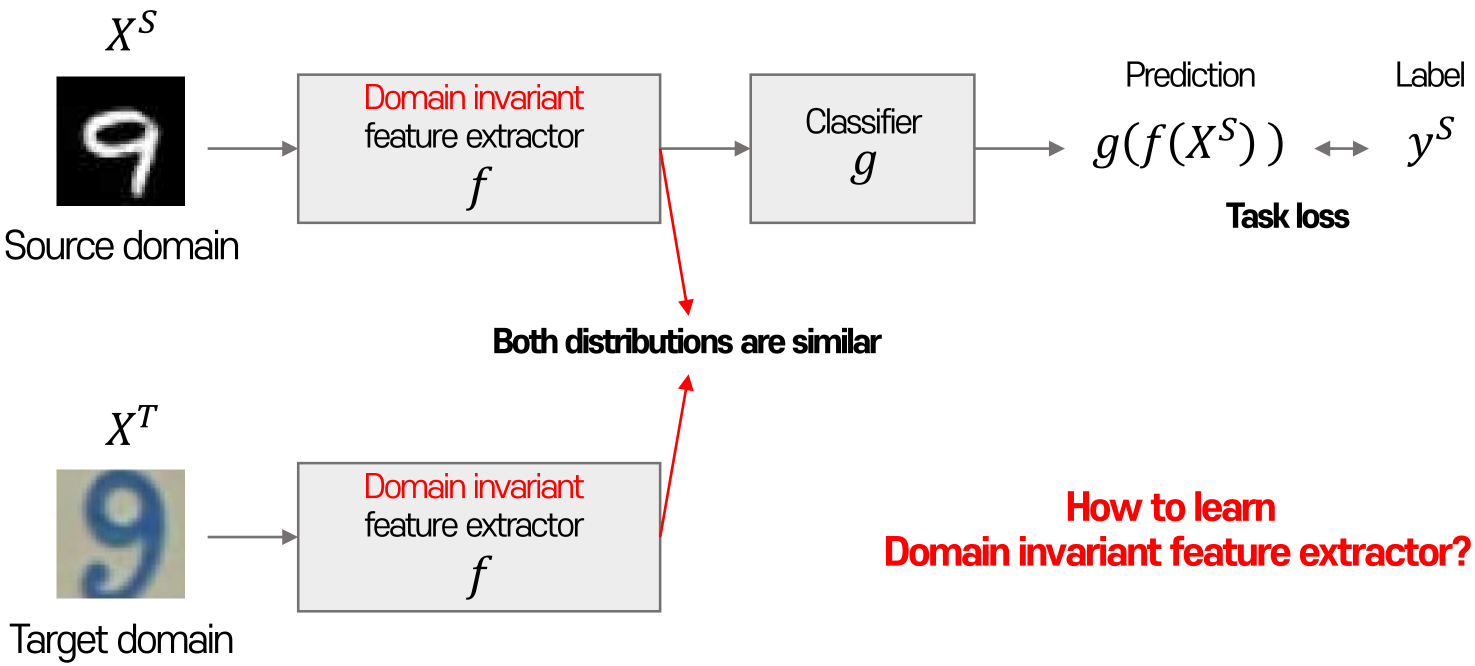


$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

Adversarial-based method

- Deep-Adversarial Neural Networks (DANN) JMLR 2016

The source risk is expected to be a good indicator of the target risk when both distributions are similar.

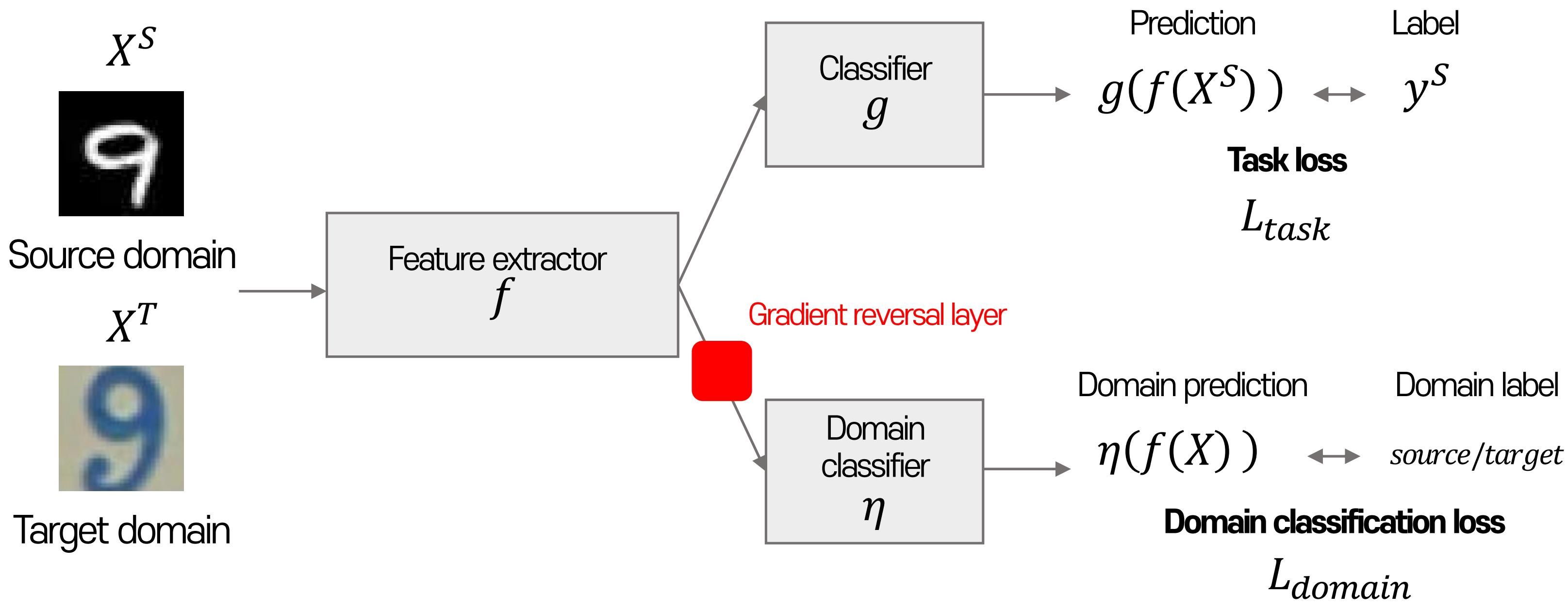


How to learn
Domain invariant feature extractor?

Ganin, Y., Ustinova, E., Ajakan, H., Germain, P., Larochelle, H., Laviolette, F., ... & Lempitsky, V. (2016). Domain-adversarial training of neural networks. The journal of machine learning research, 17(1), 2096-2030.

Adversarial-based method

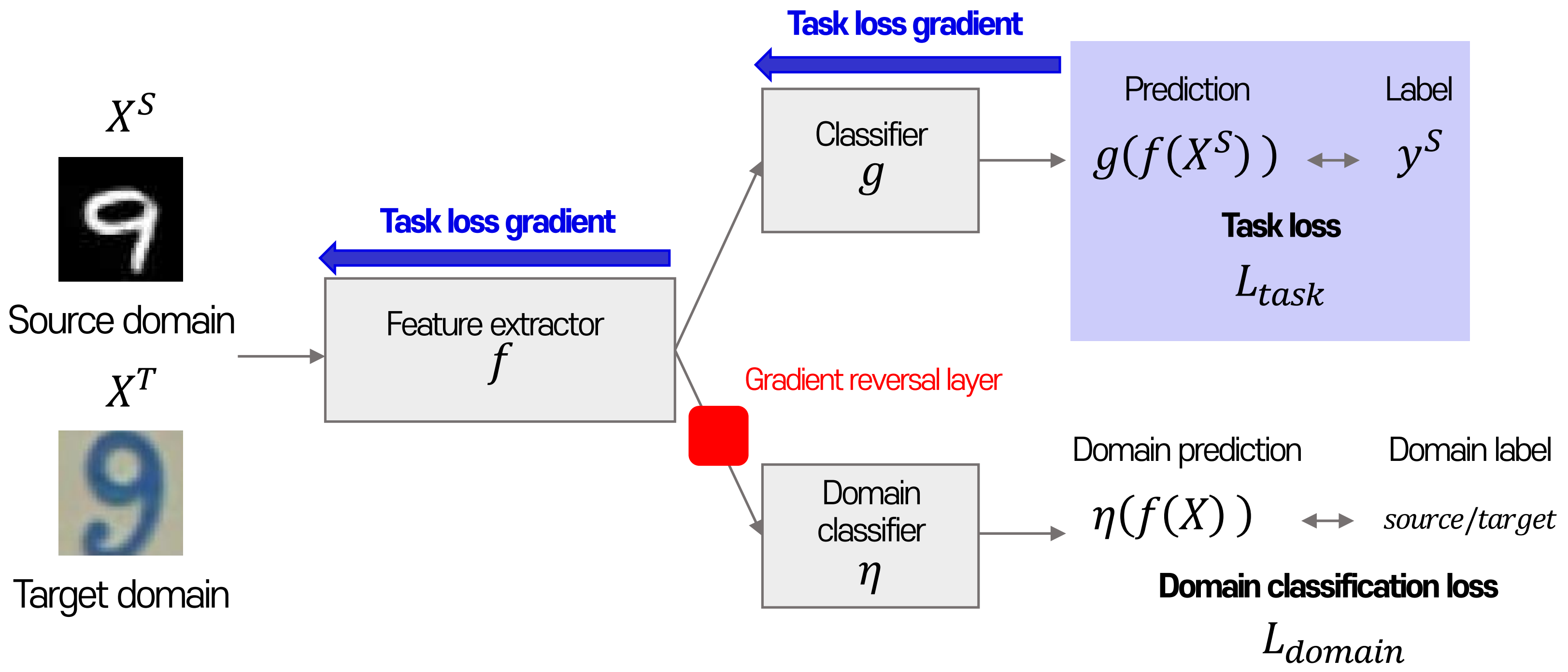
- Deep-Adversarial Neural Networks (DANN) JMLR 2016



Ganin, Y., Ustinova, E., Ajakan, H., Germain, P., Larochelle, H., Laviolette, F., ... & Lempitsky, V. (2016). Domain-adversarial training of neural networks. The journal of machine learning research, 17(1), 2096-2030.

Adversarial-based method

- Deep-Adversarial Neural Networks (DANN) JMLR 2016



Ganin, Y., Ustinova, E., Ajakan, H., Germain, P., Larochelle, H., Laviolette, F., ... & Lempitsky, V. (2016). Domain-adversarial training of neural networks. The journal of machine learning research, 17(1), 2096-2030.

Adversarial-based method

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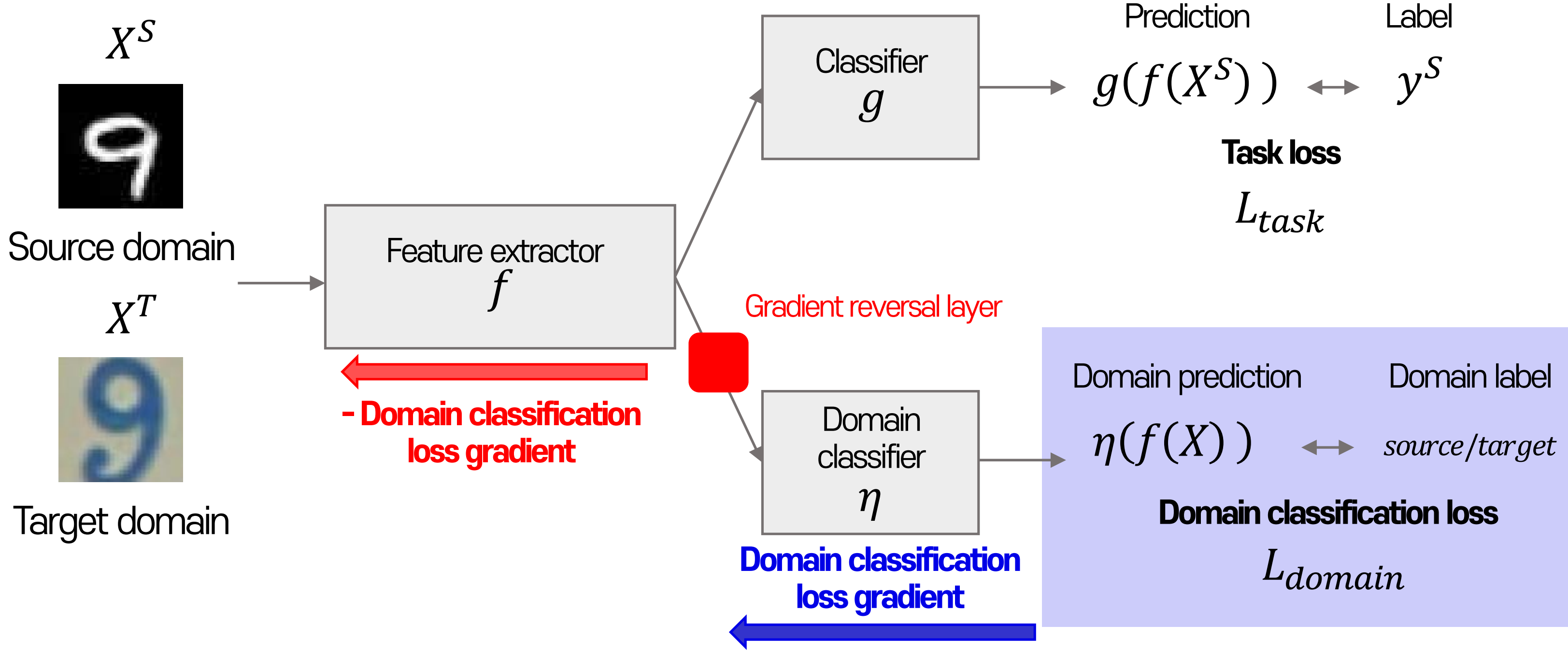


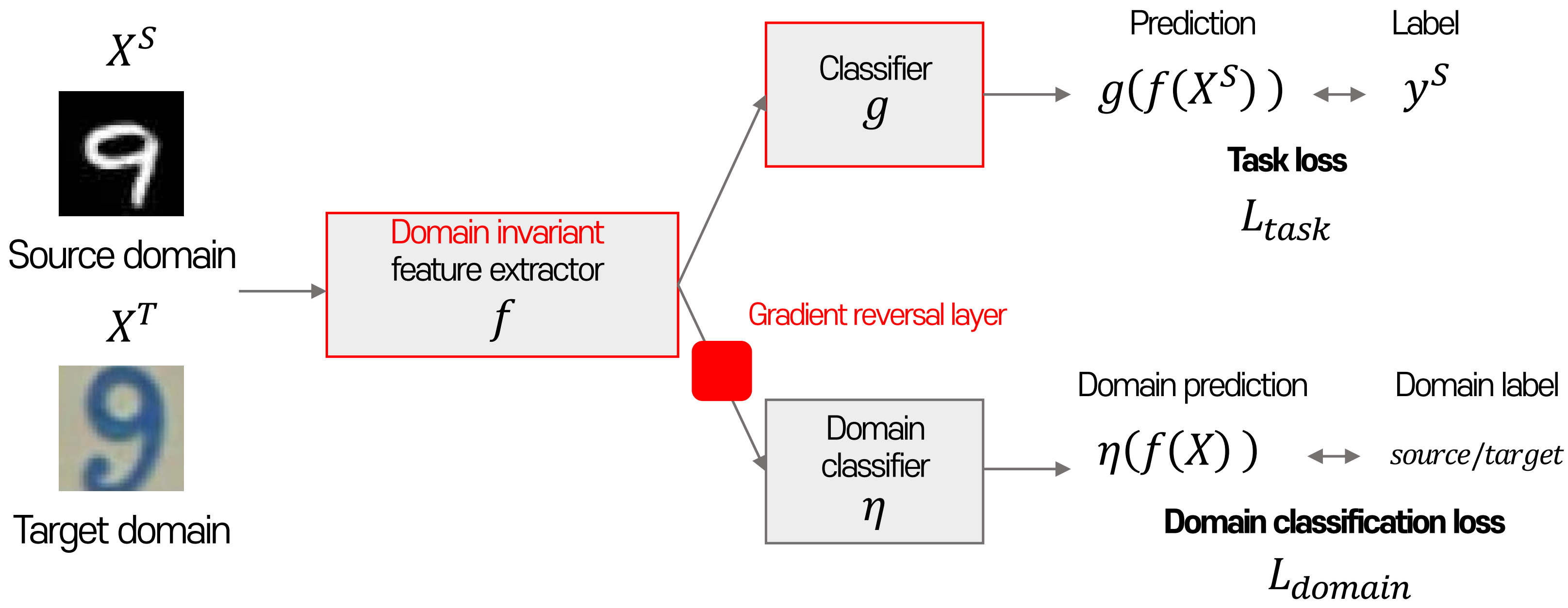
Feature extractor는 domain 구분이 어려운 방향으로
Domain classifier는 domain 구분을 잘하는 방향으로 서로 **적대적**으로 학습

Ganin, Y., Ustinova, E., Ajakan, H., Germain, P., Larochelle, H., Laviolette, F., ... & Lempitsky, V. (2016). Domain-adversarial training of neural networks. The journal of machine learning research, 17(1), 2096-2030.

Adversarial-based method

- Deep-Adversarial Neural Networks (DANN) JMLR 2016

The source risk is expected to be a good indicator of the target risk when both distributions are similar.



Ganin, Y., Ustinova, E., Ajakan, H., Germain, P., Larochelle, H., Laviolette, F., ... & Lempitsky, V. (2016). Domain-adversarial training of neural networks. The journal of machine learning research, 17(1), 2096-2030.

Adversarial-based method

- Deep-Adversarial Neural Networks (DANN) JMLR 2016

The source risk is expected to be a good indicator of the target risk when both distributions are similar.

Target domain

Domain invariant feature extractor f → Classifier g → Good prediction $g(f(X^T))$

Ganin, Y., Ustinova, E., Ajakan, H., Germain, P., Larochelle, H., Laviolette, F., ... & Lempitsky, V. (2016). Domain-adversarial training of neural networks. The journal of machine learning research, 17(1), 2096-2030.

Self-supervision-based method

- Jigsaw puzzle based Generalization (JiGen) CVPR 2019

Domain Generalization by Solving Jigsaw Puzzles

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Barbara Caputo[3,4] Tatiana Tommasi[4]

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[3]Italian Institute of Technology [4]Politecnico di Torino, Italy

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Abstract

Human adaptability relies crucially on the ability to learn and merge knowledge both from supervised and unsupervised learning: the parents point out few important concepts, but then the children fill in the gaps on their own. This is particularly effective, because supervised learning can never be exhaustive and thus learning autonomously allows to discover invariances and regularities that help to generalize. In this paper we propose to apply a similar approach to the task of object recognition across domains: our model learns the semantic labels in a supervised fashion, and broadens its understanding of the data by learning from self-supervised signals how to solve a jigsaw puzzle on the same images. This secondary task helps the network to learn the concepts of spatial correlation while acting as a regularizer for the classification task. Multiple experiments on the PACS, VLCS, Office-Home and digits datasets confirm our intuition and show that this simple method outperforms previous domain generalization and adaptation solutions. An ablation study further illustrates the inner workings of our approach.

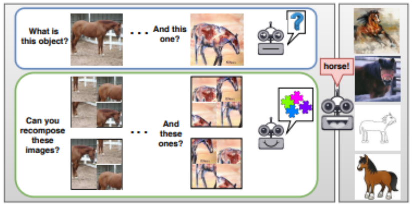


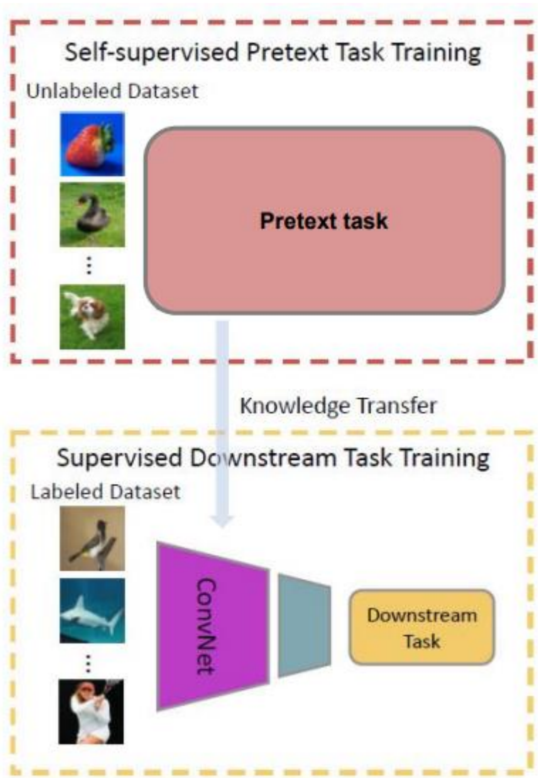
Figure 1. Recognizing objects across visual domains is a challenging task that requires high generalization abilities. Other tasks, based on intrinsic self-supervisory image signals, allow to capture natural invariances and regularities that can help to bridge across large style gaps. With JiGen we learn jointly to classify objects and solve jigsaw puzzles, showing that this supports generalization to new domains.

the community has attacked this issue so far mainly by *supervised learning* processes that search for semantic spaces able to capture basic data knowledge regardless of the specific appearance of input images. Existing methods range from decoupling image style from the shared object con-

Carlucci, F. M., D'Innocente, A., Bucci, S., Caputo, B., & Tommasi, T. (2019). Domain generalization by solving jigsaw puzzles. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 2229-2238).

Self-supervision-based method

- Jigsaw puzzle based Generalization (JiGen) CVPR 2019
  - Self-supervised learning 자기지도학습
    - ✓ 레이블이 없는 데이터로도 좋은 양질의 representation/feature를 얻고자 수행하는 학습 방식
    - ✓ 레이블없이 입력되는 원본 데이터에서 모델 학습의 target으로 쓰일 수 있는 것을 정하여 task를 정의
    - ✓ 'Task를 어떻게 정의하는가?'에 따라서 다양한 방법론이 발전되고 있음



Self-supervision-based method

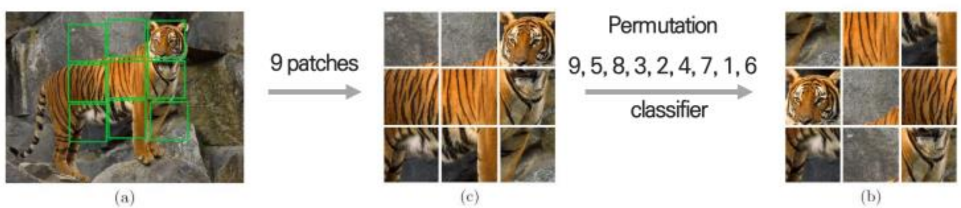
- Jigsaw puzzle based Generalization (JiGen) CVPR 2019
  - Self-supervised learning 자기지도학습 中 Jigsaw Puzzle, ECCV 2016

Pretext tasks

Unsupervised Learning of Visual Representations by Solving Jigsaw Puzzles

❖ Jigsaw Puzzle, 2016 ECCV

- Pretext task 과정
  1. Input 이미지로부터 9개의 patch들을 만들어 냄
  2. Patch들을 섞은 다음에 원래의 배치로 돌아가기 위한 순열을 예측하는 classifier를 학습



  3. 9개의 patch들로 만들 수 있는 순열 조합은 9!(약 35만 개)이므로 비슷한 순열끼리 제거하여 대표적인 100개의 순열만 class로 분류하도록 학습

종료

Self-Supervised Representation Learning

Seokho Moon

May 1, 2020

Self-Supervised Representation Learning

발표자: 문석호

2020년 5월 1일

오후 1시 ~

화상 프로그램 이용(Zoom)

세미나 정보 보기 ⟶

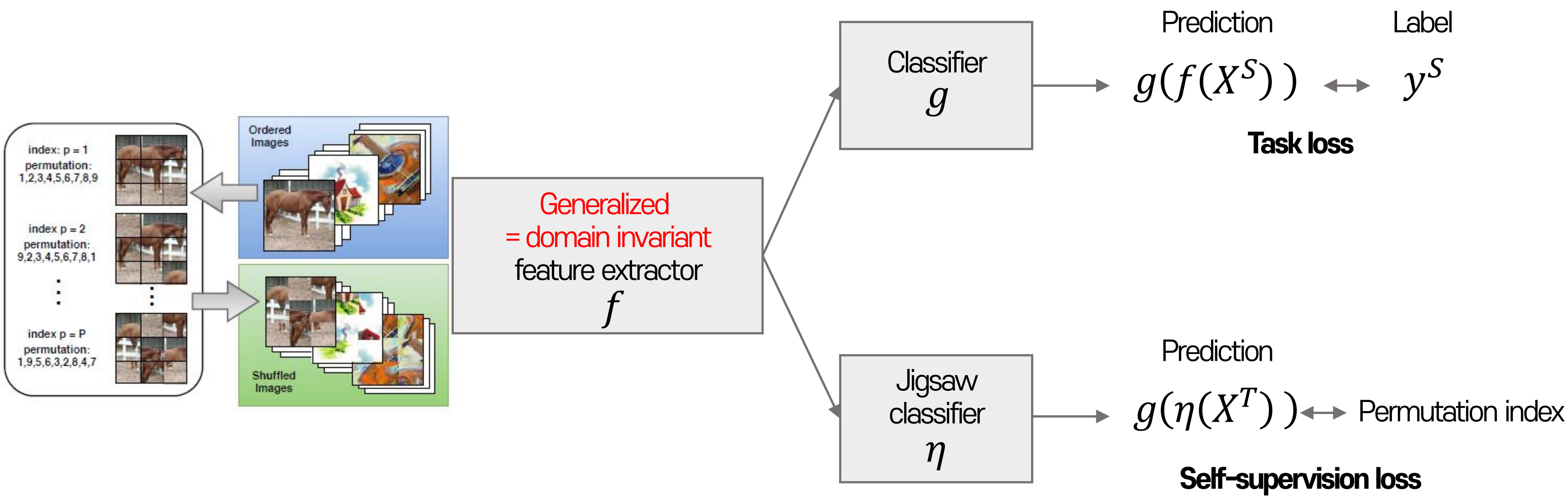
Data Mining Quality Analytics hcai

26

http://dmqa.korea.ac.kr/activity/seminar/284

Self-supervision-based method

- Jigsaw puzzle based Generalization (JiGen) CVPR 2019
  - Jigsaw puzzle을 푸는 self-supervision loss를 통해 domain invariant한 특징 추출



Carlucci, F. M., D'Innocente, A., Bucci, S., Caputo, B., & Tommasi, T. (2019). Domain generalization by solving jigsaw puzzles. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 2229-2238).

Combination method for time series data

- SeLf-supervised AutoRegressive Domain Adaptation (SLARDA) TNNLS 2022

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

Self-Supervised Autoregressive Domain Adaptation for Time Series Data

Mohamed Ragab, *Graduate Student Member, IEEE*, Emadeldeen Eldele, Zhenghua Chen, *Senior Member, IEEE*, Min Wu, *Senior Member, IEEE*, Chee-Keong Kwoh, and Xiaoli Li, *Senior Member, IEEE*

***Abstract*—Unsupervised domain adaptation (UDA) has successfully addressed the domain shift problem for visual applications. Yet, these approaches may have limited performance for time series data due to the following reasons. First, they mainly rely on the large-scale dataset (i.e., ImageNet) for source pretraining, which is not applicable for time series data. Second, they ignore the temporal dimension on the feature space of the source and target domains during the domain alignment step. Finally, most of the prior UDA methods can only align the global features without considering the fine-grained class distribution of the target domain. To address these limitations, we propose a SeLf-supervised AutoRegressive Domain Adaptation (SLARDA) framework. In particular, we first design a self-supervised (SL) learning module that uses forecasting as an auxiliary task to improve the transferability of source features. Second, we propose a novel autoregressive domain adaptation technique that incorporates temporal dependence of both source and target features during domain alignment. Finally, we develop an ensemble teacher model to align class-wise distribution in the target domain via a confident pseudo labeling approach. Extensive experiments have been conducted on three real-world time series applications with 30 cross-domain scenarios. The results demonstrate that our proposed SLARDA method significantly outperforms the state-of-the-art approaches for time series domain adaptation. Our source code is available at: https://github.com/mohamedr002/SLARDA.**

***Index Terms*—Autoregressive domain adaptation, ensemble teacher learning, self-supervised (SL) learning, time series data.**

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Mohamed Ragab and Xiaoli Li are with the Institute for Infocomm Research, Centre for Frontier AI Research (CFAR), Agency for Science, Technology and Research (A*STAR), Singapore 138632, and also with the School of Computer Science and Engineering, Nanyang Technological

I. Introduction

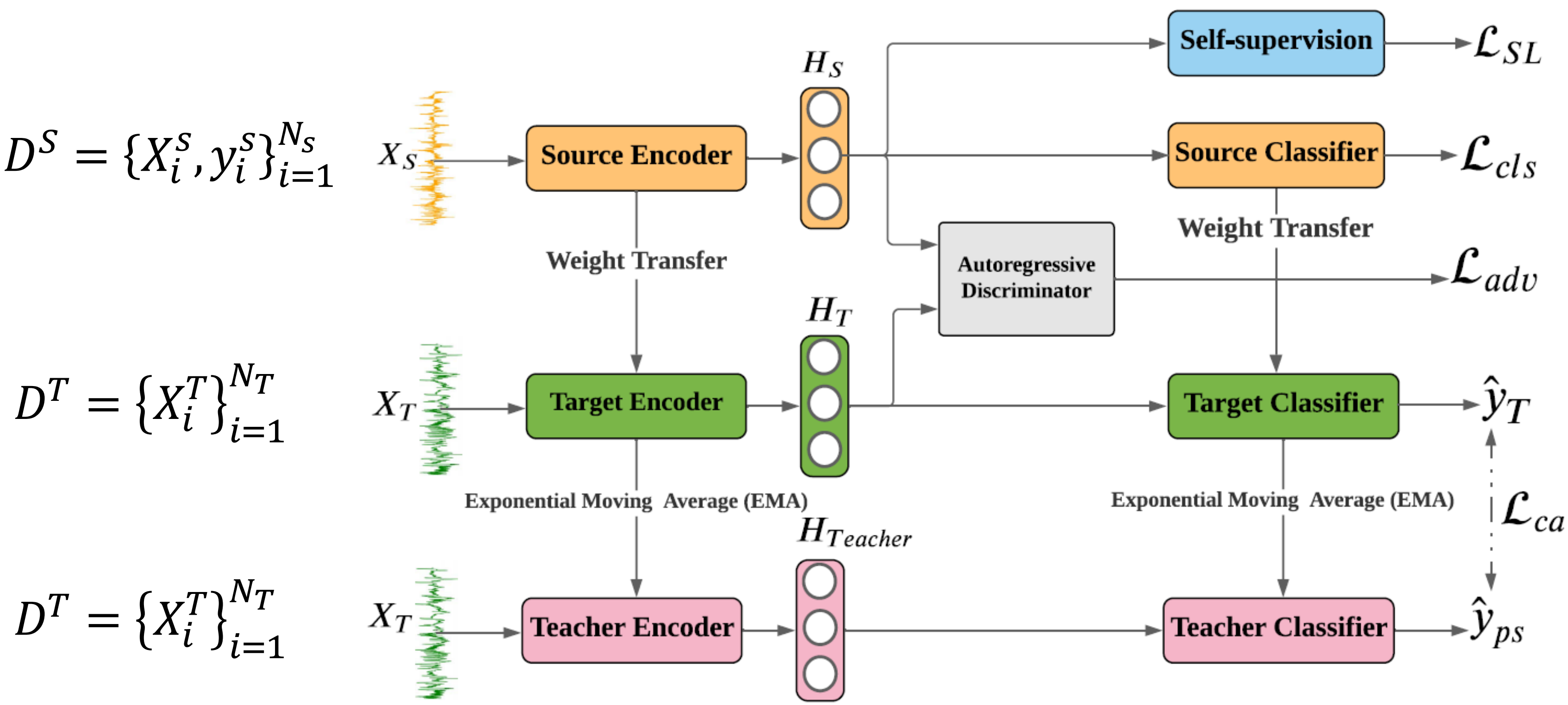
TIME series classification (TSC) is a pivotal problem in many real-world applications including healthcare services and smart manufacturing [1], [2]. Several conventional approaches tried to learn the dynamics of the time series data for the classification task including dynamic time warping (DTW), hidden Markov models (HMMs), and artificial neural networks (ANNs) [3]. Yet, these approaches cannot cope with evolving complexity of real-world applications. Deep learning (DL) has shown notable success for time-series-based applications [1], [4], [5]. However, its success comes at the expense of laborious data annotation. Moreover, DL-based approaches always assume that the training data (i.e., source domain) and testing data (i.e., target domain) are drawn from the same distribution. This may not hold for real applications under dynamic environments, which is well-known as the domain shift problem.

The unsupervised domain adaptation (UDA) methods have achieved remarkable progress in mitigating the domain shift problem for visual applications [6], [7]. To avoid extensive data labeling, UDA is designed to leverage previously labeled datasets (i.e., source domain) and transfer knowledge to an unlabeled dataset of interest (i.e., target domain) in a transductive domain adaptation scenario [8]. One popular paradigm is to reduce the distribution discrepancy between the source and target domains via matching moments of distributions at different orders. For instance, the most prevailing method is based on the maximum mean discrepancy (MMD) as a distance, which is calculated via the weighted sum of the distribution moments [9]. Another paradigm for mitigating the distribution shift is inspired by generative adversarial networks (GANs).

Ragab, M., Eldele, E., Chen, Z., Wu, M., Kwoh, C. K., & Li, X. (2022). Self-Supervised Autoregressive Domain Adaptation for Time Series Data. IEEE Transactions on Neural Networks and Learning Systems.

Combination method for time series data

- SeLf-supervised AutoRegressive Domain Adaptation (SLARDA) TNNLS 2022
  - Task + Adversarial + Self-supervision + Semi-supervision



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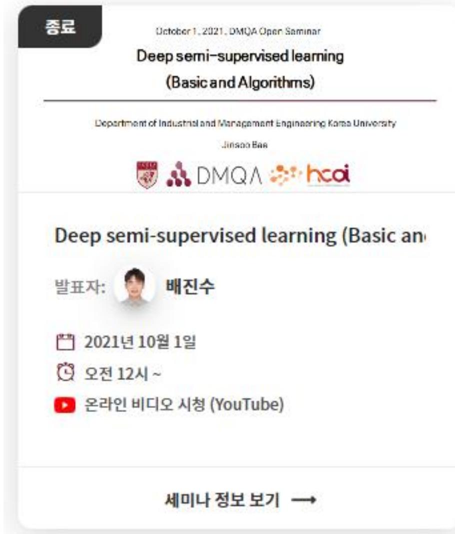
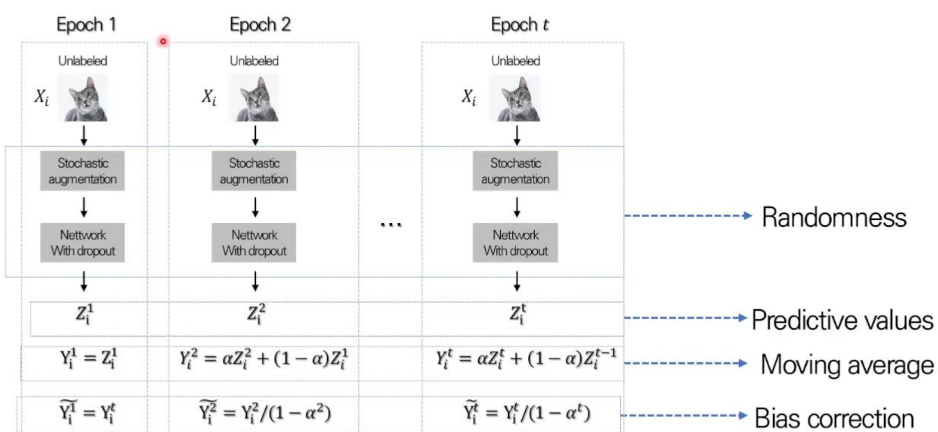


Main idea and algorithms in computer vision

Algorithms (3): "Temporal Ensembling for Semi-Supervised Learning", ICLR, 2017

❖ Propose self-ensembling using the outputs of the network-in-training on different epochs under different regularization and input augmentation conditions.



https://arxiv.org/pdf/1610.02242.pdf

16/30

http://dmqa.korea.ac.kr/activity/seminar/337

Conclusion

1) 본 세미나에서는 domain shift/discrepancy 문제를 설명하고 이를 적은 레이블링 비용으로 해결할 수 있는 domain adaptation의 필요성 및 개념을 살펴보았음

2) 특히, unsupervised domain adaptation에서 연구되고 있는 방법론 종류 3가지에 대해서 특징을 설명하고, 대표 알고리즘에 대한 간단한 설명 전달

3) 이미지 데이터 뿐만 아니라 센서 데이터 등 다양한 데이터 종류에 적용 가능하며 관련된 연구들이 발전되고 있음

Data Mining
Quality Analytics

감사합니다

2022. 09. 16.

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