# Deep Learning for Medical Image Analysis

COMP5423

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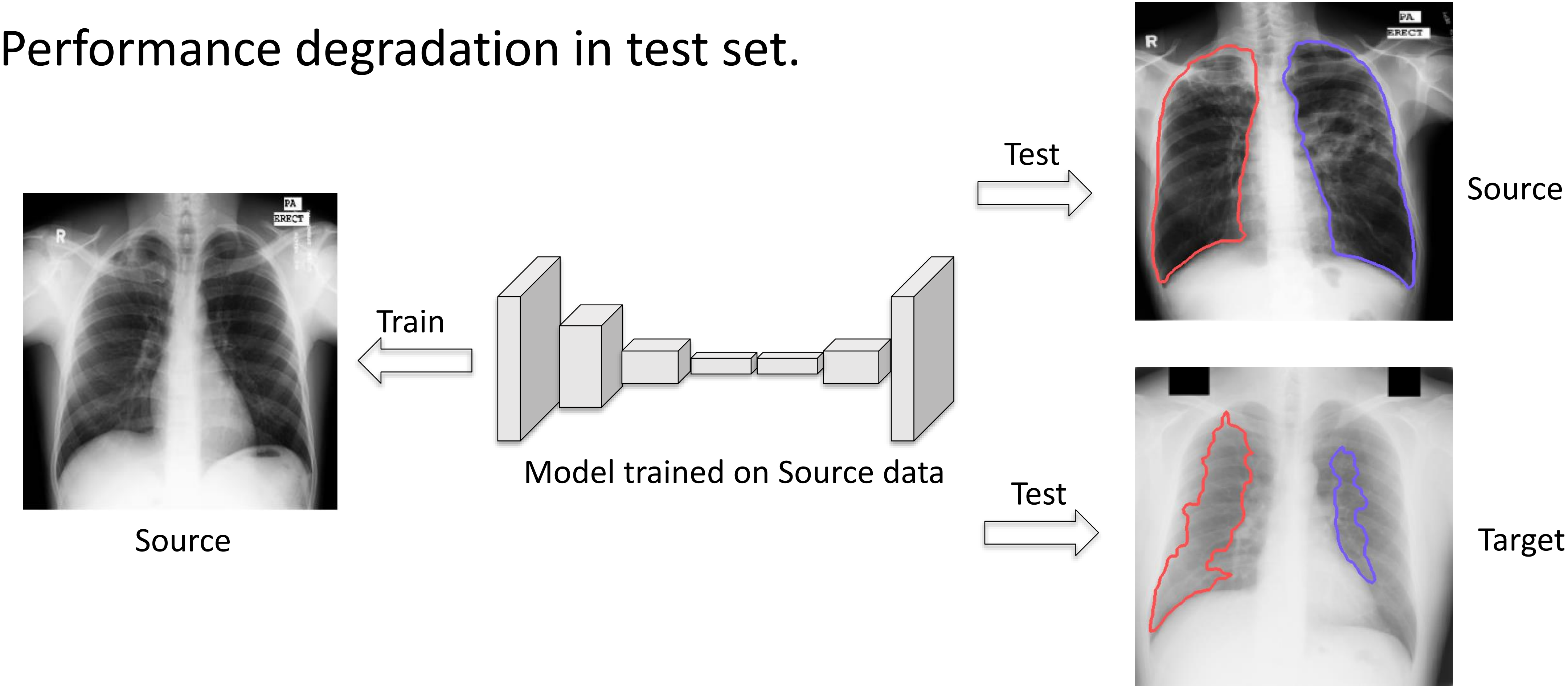
# Domain Adaptation in MIA

- Introduction
- Shallow domain adaptation model
- Deep domain adaptation model
- Challenge and future direction

# Introduction

## Problem in MIA

- Performance degradation in test set.




Chen C, et al. Semantic-Aware Generative Adversarial Nets for Unsupervised Domain Adaptation in Chest X-ray Segmentation. MICCAI, 2018.

# Introduction

**Problem**

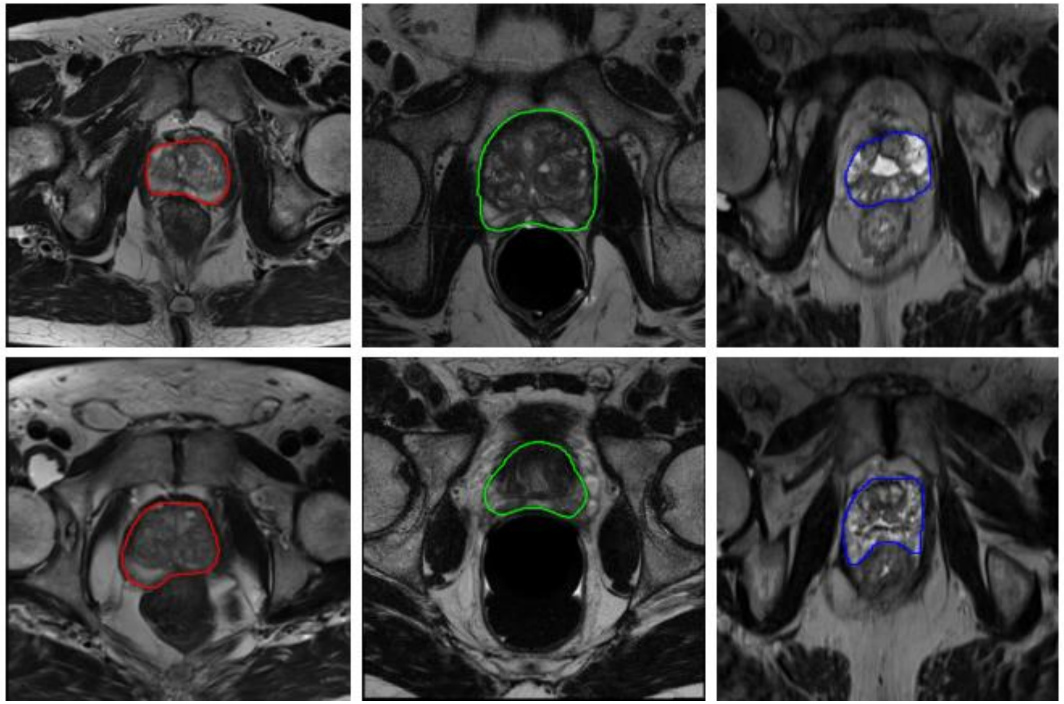
- Data heterogeneity
- Domain shift: training and testing data are from **different distributions**.
  - Caused by different centers, imaging protocols, modalities, patient populations, etc.
  - Common in medical applications.

Patel V M, et al. Visual domain adaptation: A survey of recent advances. IEEE SIGNAL PROC MAG, 2015.

# Introduction

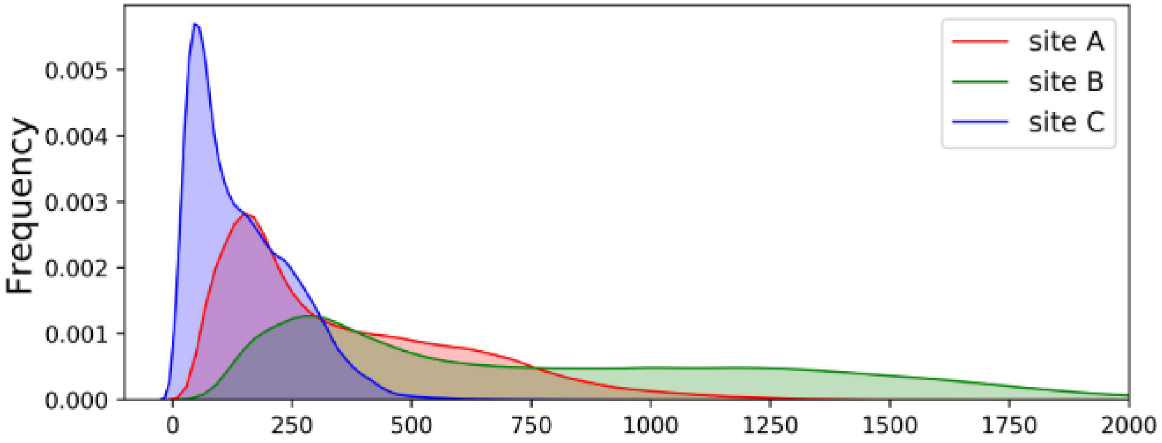
## Domain shift (1): cross-center

Prostate MRI



Center A Center B Center C

Histogram




Liu Q, et al. MS-Net: multi-site network for improving prostate segmentation with heterogeneous MRI data. TMI 2020.

# Introduction

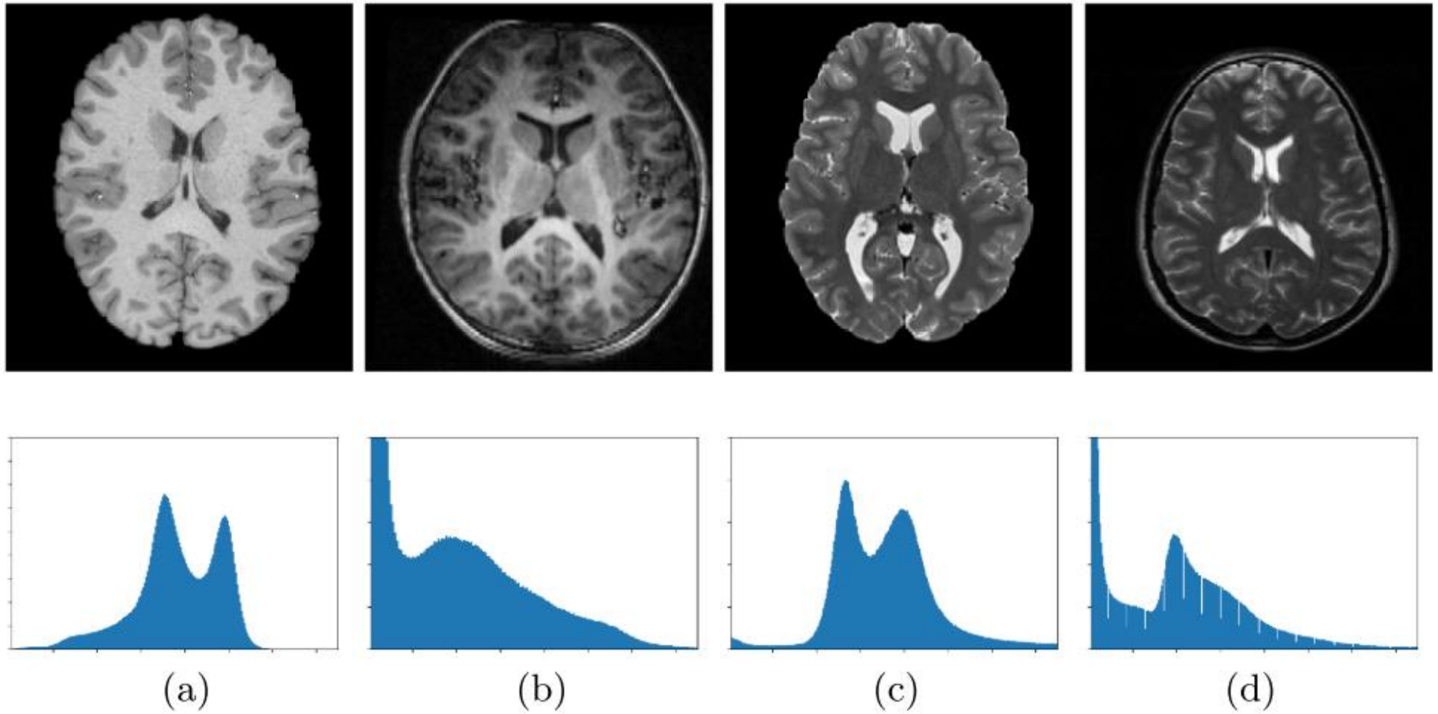
**Domain shift (2): cross-modality**

- Different sequences in MRI

T1-weighted T2-weighted

Brain MR

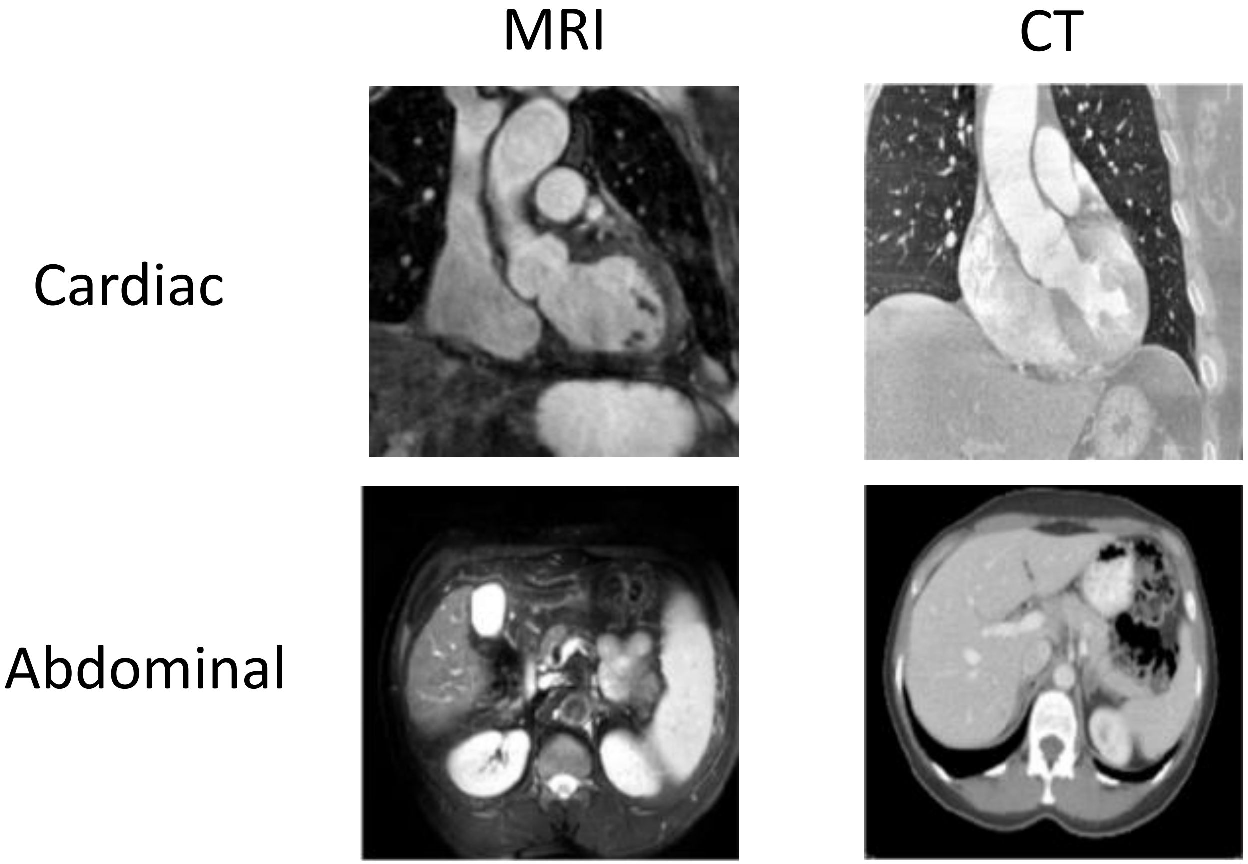
Histogram




Karani N, et al. A lifelong learning approach to brain MR segmentation across scanners and protocols. MICCAI 2018.

# Introduction

## **Domain shift (3): cross-modality**




Chen C, et al. Synergistic image and feature adaptation: Towards cross-modality domain adaptation for medical image segmentation. AAAI 2019.

# Introduction

**Domain Adaptation and Transfer Learning**

- Domain adaptation can be regarded as a special type of transfer learning.

**Concept**

- Domain: the feature and distribution of specific dataset.
- Source domain denoted as *S*.
- Target domain denoted as *T*.
- Task: the label space of a dataset.

Guan H, et al. Domain adaptation for medical image analysis: a survey. TBME 2022.

# Introduction

## Formulation

- Given: a source domain *S* and a target domain *T* with different distributions $P_s$ and $P_t$.

$$\mathcal{D}_S = \{(\mathbf{x}_i^S, y_i^S)\}_{i=1}^{n_s} \qquad \mathcal{D}_T = \{(\mathbf{x}_j^T)\}_{j=1}^{n_t}$$

- Assumption: the source and target domains have different data distributions

$$P_s \neq P_t$$

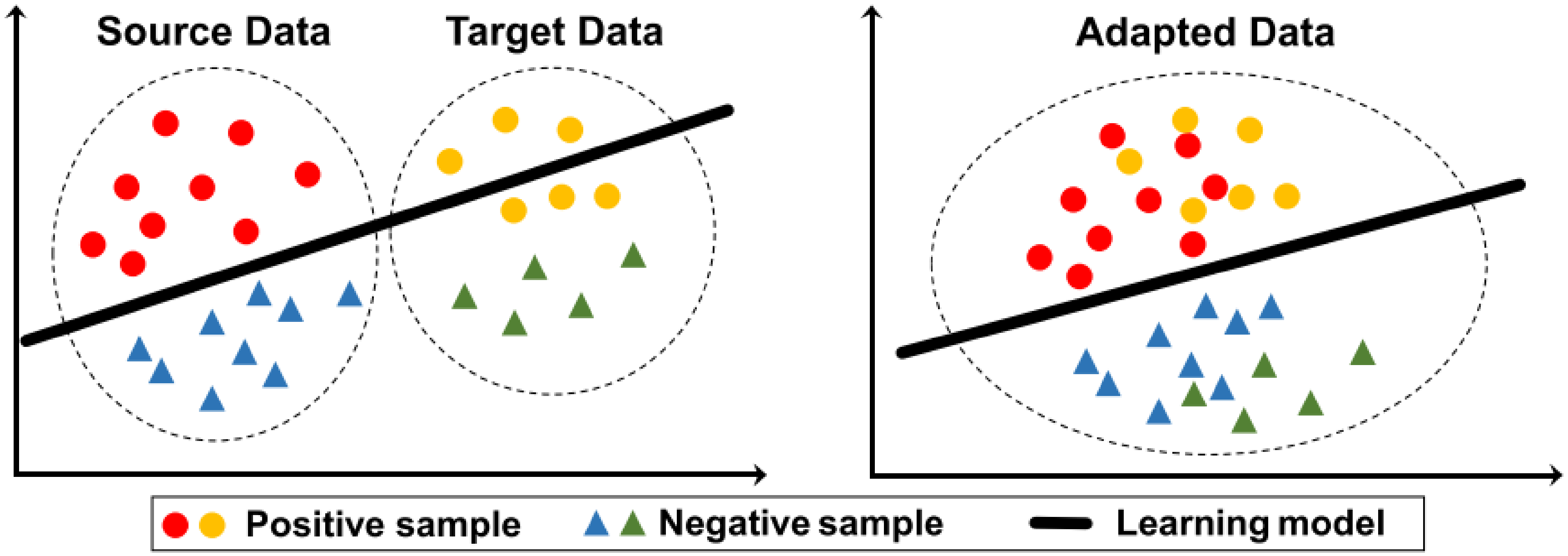
- Goal: transfer knowledge learned from *S* to *T* to perform a specific task on *T*, and this task is shared by *S* and *T*.

Guan H, et al. Domain adaptation for medical image analysis: a survey. TBME 2022.

# Introduction

## Formulation

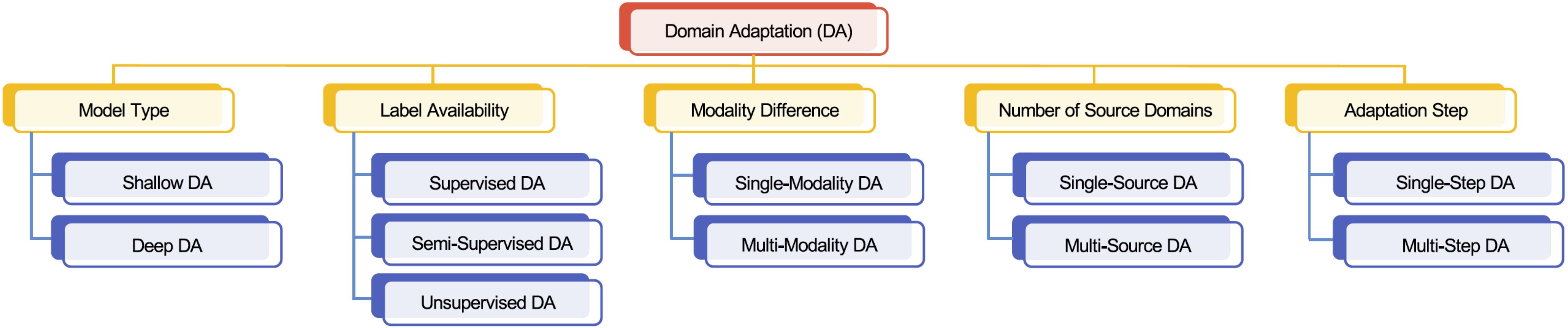
- Distributions of source and target domain before/after DA




Guan H, et al. Domain adaptation for medical image analysis: a survey. TBME 2022.

# Introduction

## Categorization




Guan H, et al. Domain adaptation for medical image analysis: a survey. TBME 2022.

# Domain Adaptation in MIA

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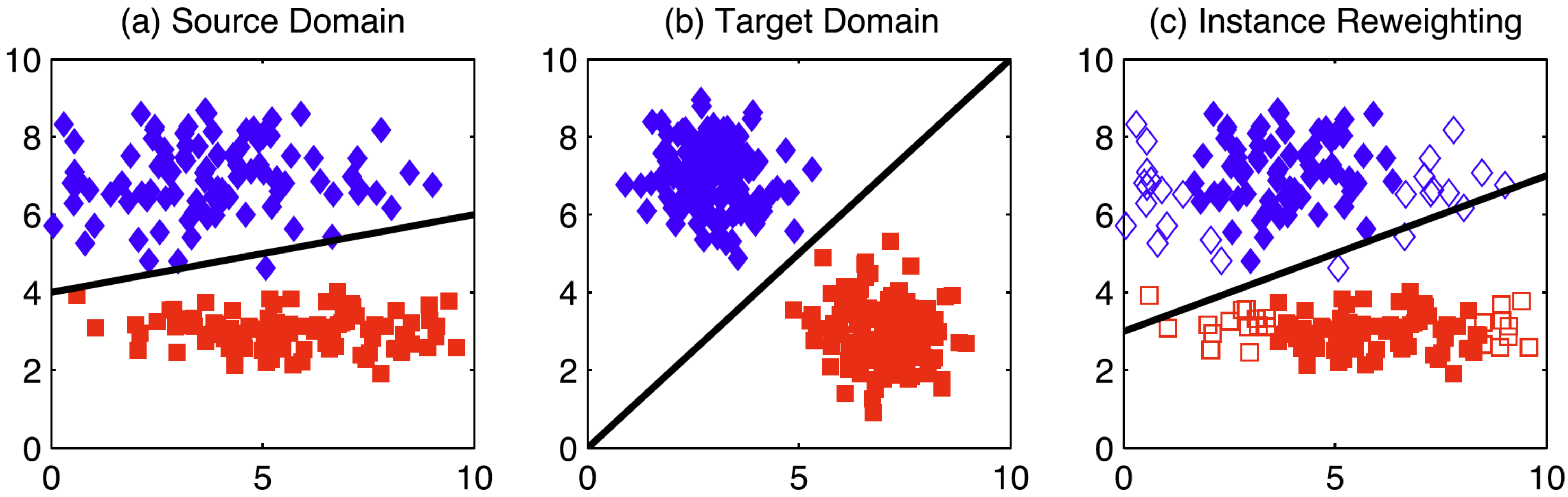
- Challenge and future direction

# Instance Weighting

- Instances in the source domain are assigned with different weights according to their relevance with target samples/instances.
- Source instances that are more relevant to the target instances will be assigned larger weights.
- After instance weighting, a learning model is trained on the re-weighted source samples, thus reducing domain shift between the source and target domains.

Guan H, et al. Domain adaptation for medical image analysis: a survey. TBME 2022.

# Instance Weighting




(a) Source domain after feature matching (i.e., discovering a shared feature representation by jointly reducing the distribution difference and preserving the important properties of input data). (b) Target domain after feature matching. (c) Source domain after joint feature matching and instance weighting, with unfilled markers indicating irrelevant source instances that have smaller weights.

Guan H, et al. Domain adaptation for medical image analysis: a survey. TBME 2022.

# Histogram Matching

- Obtain $p_r(r)$ from the input image and then obtain the values of $s$

$$s = (L-1)\int_0^r p_r(w)dw$$

- Use the to be matched PDF and obtain the transformation $G(z)$

$$G(z) = (L-1)\int_0^z p_z(t)dt = s$$

- Mapping from $s$ to $z$

$$z = G^{-1}(s) = G^{-1}[T(r)]$$

- The output image with $z$ values is then of the matched histogram.

Gonzalez R C. Digital Image Processing, 2009.

# Domain Adaptation in MIA

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# Unsupervised Domain Adaptation (UDA)

- Manually annotating new data for each test domain is not a feasible solution.
- Unsupervised deep domain adaptation has attracted increasing attention in the field of medical image analysis, due to its advantage that does not require any labeled target data.
- We will cover two typical UDA methods based on the feature-level and image-level alignment.

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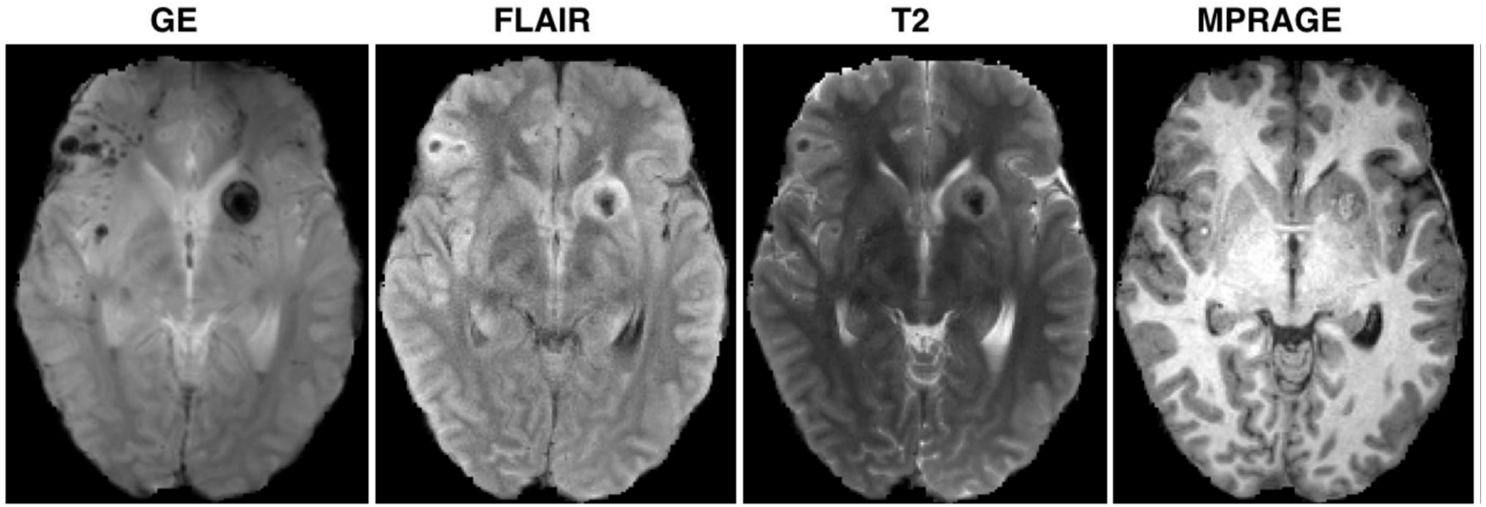
# Feature-level Alignment

**Introduction**

- Goal: learn domain-invariant features across domains by adversarial network.

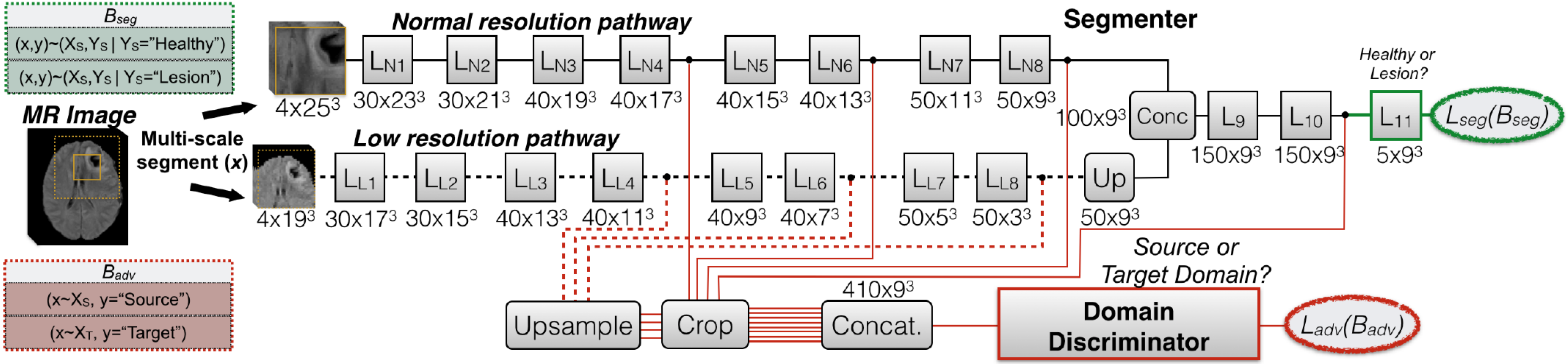



Multi-sequence MR brain scans

K. Kamnitsas et al. Unsupervised domain adaptation in brain lesion segmentation with adversarial networks. IPMI 2017.

# Feature-level Alignment

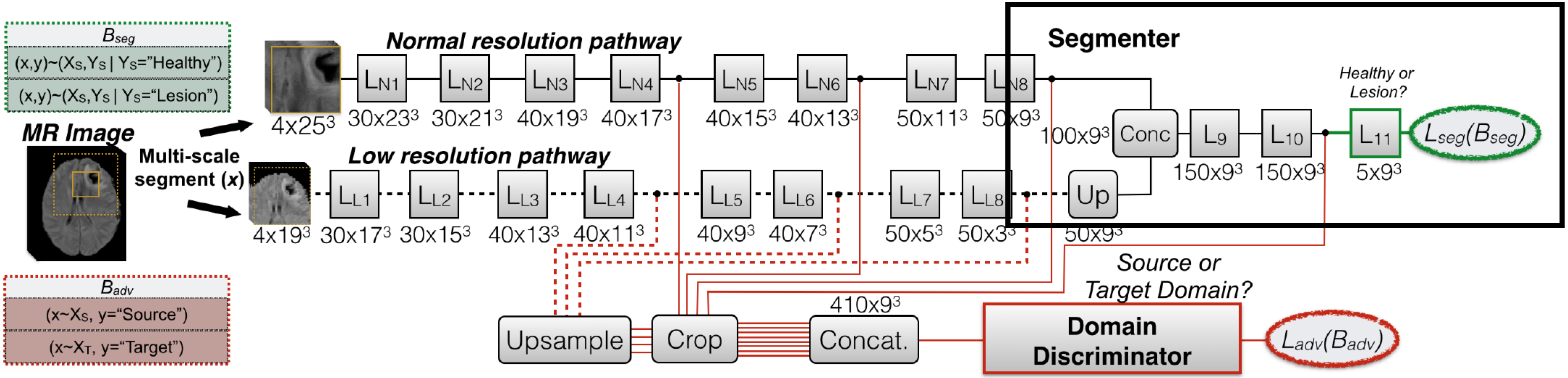
## Overview




K. Kamnitsas et al. Unsupervised domain adaptation in brain lesion segmentation with adversarial networks. IPMI 2017.

# Feature-level Alignment

## Overview




Segmenter: 3D CNN architecture

Segmentation loss $L_{seg}$: cross-entropy



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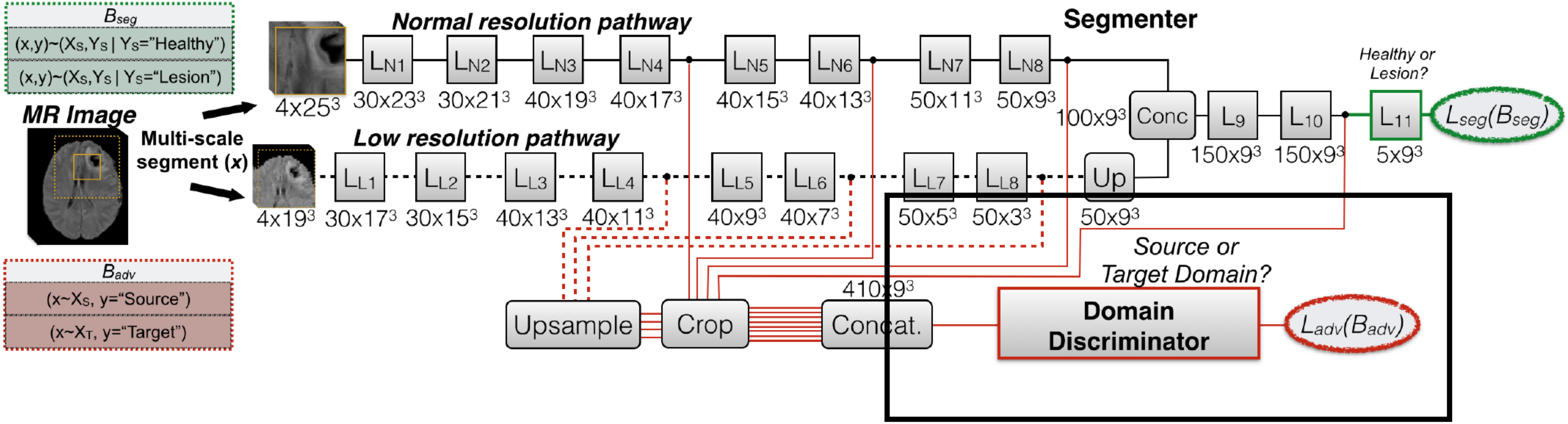
# Feature-level Alignment

## Overview




Domain discriminator: 3D CNN for classifying the domain of input *x*, by processing activations at multiple layers of the segmenter.

K. Kamnitsas et al. Unsupervised domain adaptation in brain lesion segmentation with adversarial networks. IPMI 2017.

# Feature-level Alignment

**Domain adaptation via adversarial training**

- Incorporating the domain-discriminator's loss $L_{adv}$ into the training objective of the segmenter, which aims to simultaneously maximize the domain classification loss and minimize the segmentation loss $L_{seg}$:

$$\mathcal{L}_{segAdv}(\theta_{seg}) = \mathcal{L}_{seg}(\theta_{seg}) - \alpha\mathcal{L}_{adv}(\theta_{seg})$$

K. Kamnitsas et al. Unsupervised domain adaptation in brain lesion segmentation with adversarial networks. IPMI 2017.

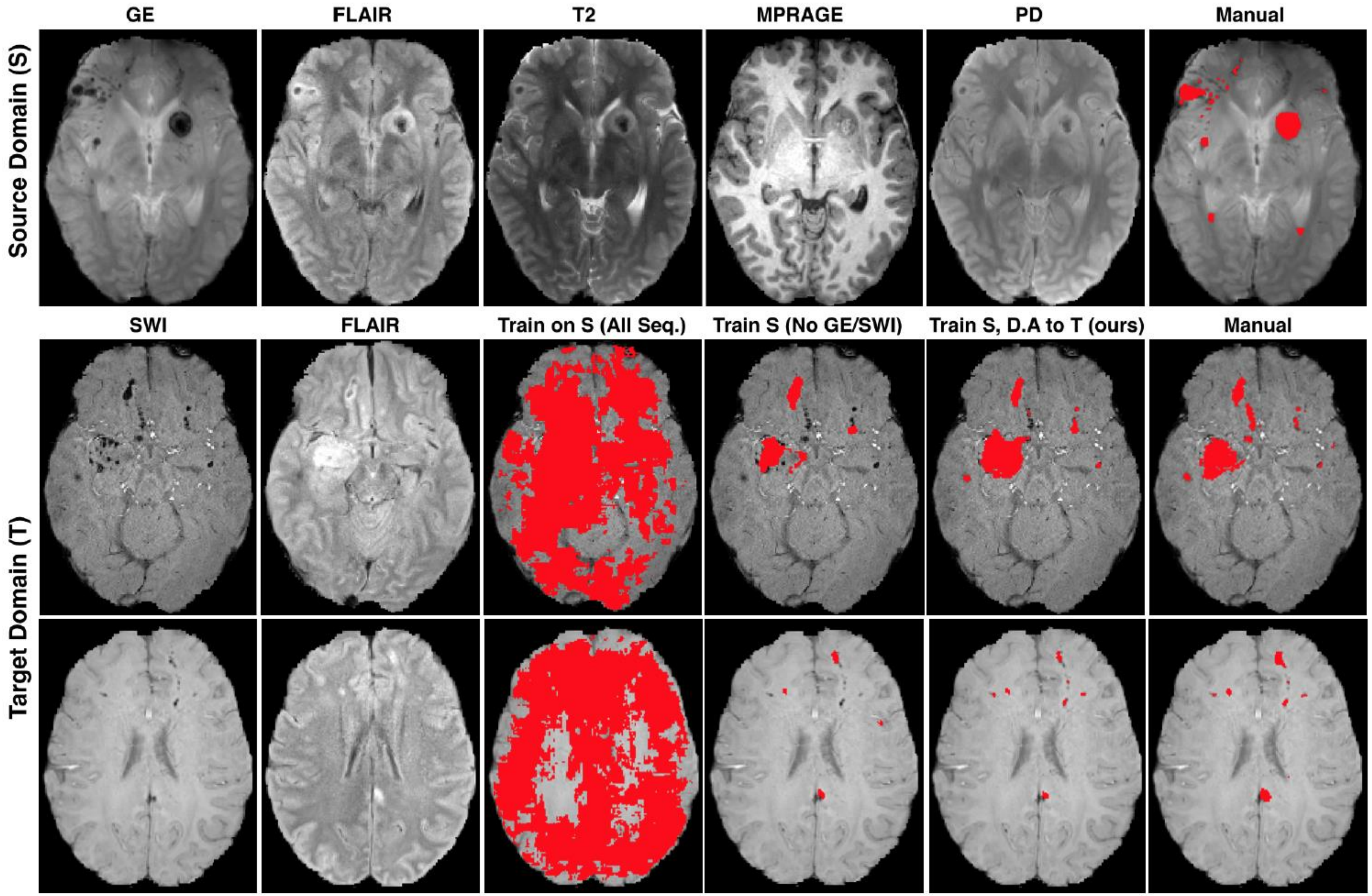
# Feature-level Alignment

## Experiments

| | DSC | Recall | Precision |
|---|---|---|---|
| Train on S | 15.7(13.5) | 80.4(12.3) | 09.5(09.0) |
| Train on S (No GE/SWI) | 59.7(22.1) | 55.7(22.6) | 69.7(21.5) |
| **Train on S → UDA to T (ours)** | 62.7(19.8) | 58.9(21.2) | 71.6(18.4) |
| Train on T | 63.5(20.2) | 60.6(21.1) | 71.5(19.8) |
| Train on S+T | 66.5(17.7) | 66.6(19.1) | 69.4(19.0) |
| Train on S+T (GE/SWI diff chan.) | 64.7(19.2) | 65.7(20.2) | 67.0(20.8) |

K. Kamnitsas et al. Unsupervised domain adaptation in brain lesion segmentation with adversarial networks. IPMI 2017.

# Feature-level Alignment

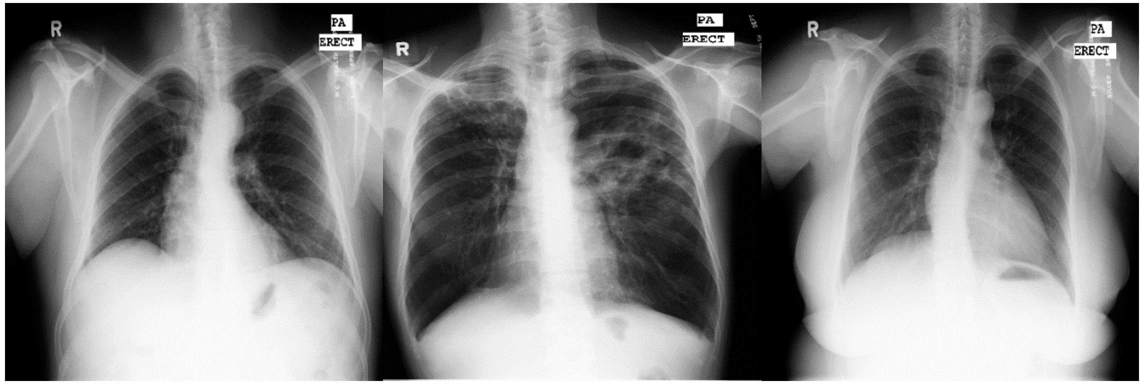



K. Kamnitsas et al. Unsupervised domain adaptation in brain lesion segmentation with adversarial networks. IPMI 2017.

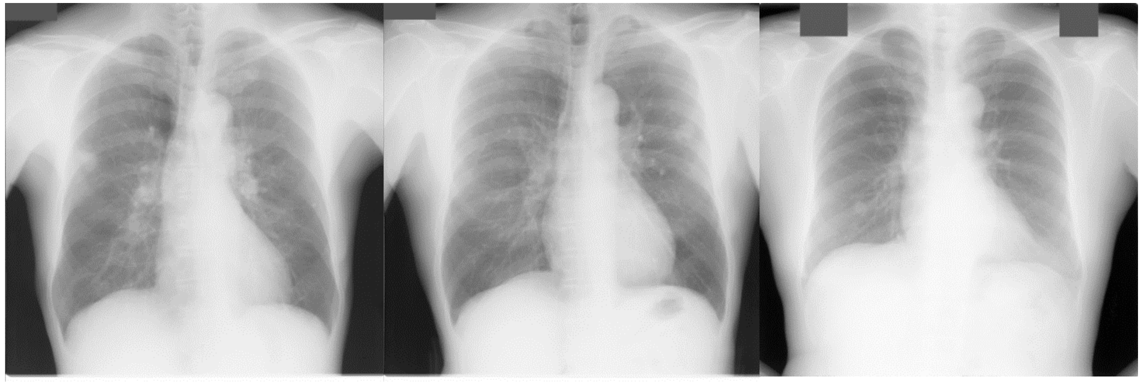
# Image-level Alignment

- **Image-to-image** transformation
- A novel semantic-aware loss for segmentation task
- Transforming target images to appear like source images, which can be directly forwarded to the established source model for test
- Two chest X-ray datasets for lung segmentation

*Source Domain*



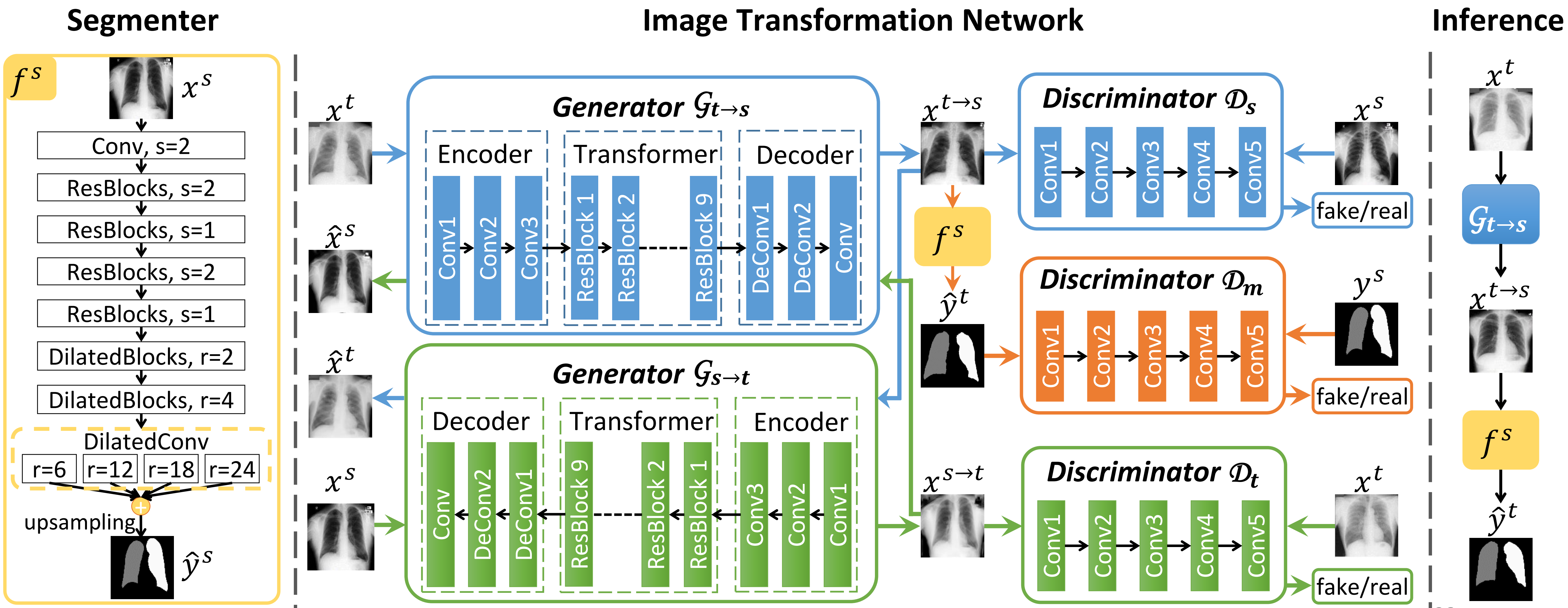

*Target Domain*



Chen C, et al. Semantic-Aware Generative Adversarial Nets for Unsupervised Domain Adaptation in Chest X-ray Segmentation. MICCAI, 2018.

# Image-level Alignment

## Overview



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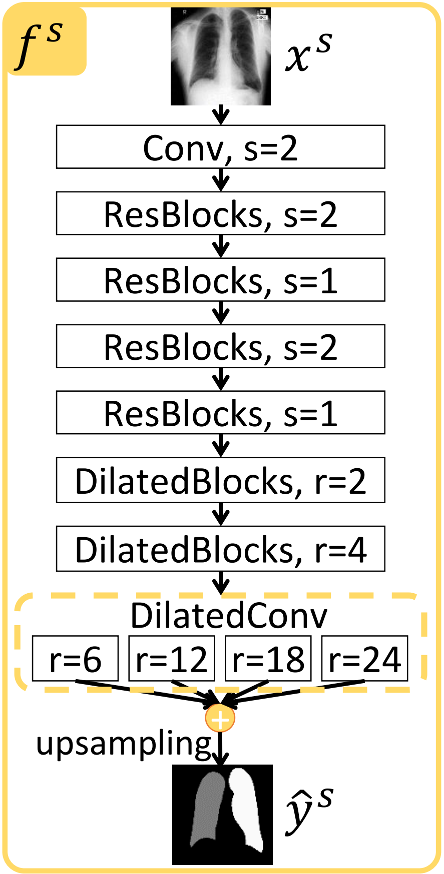
# Image-level Alignment

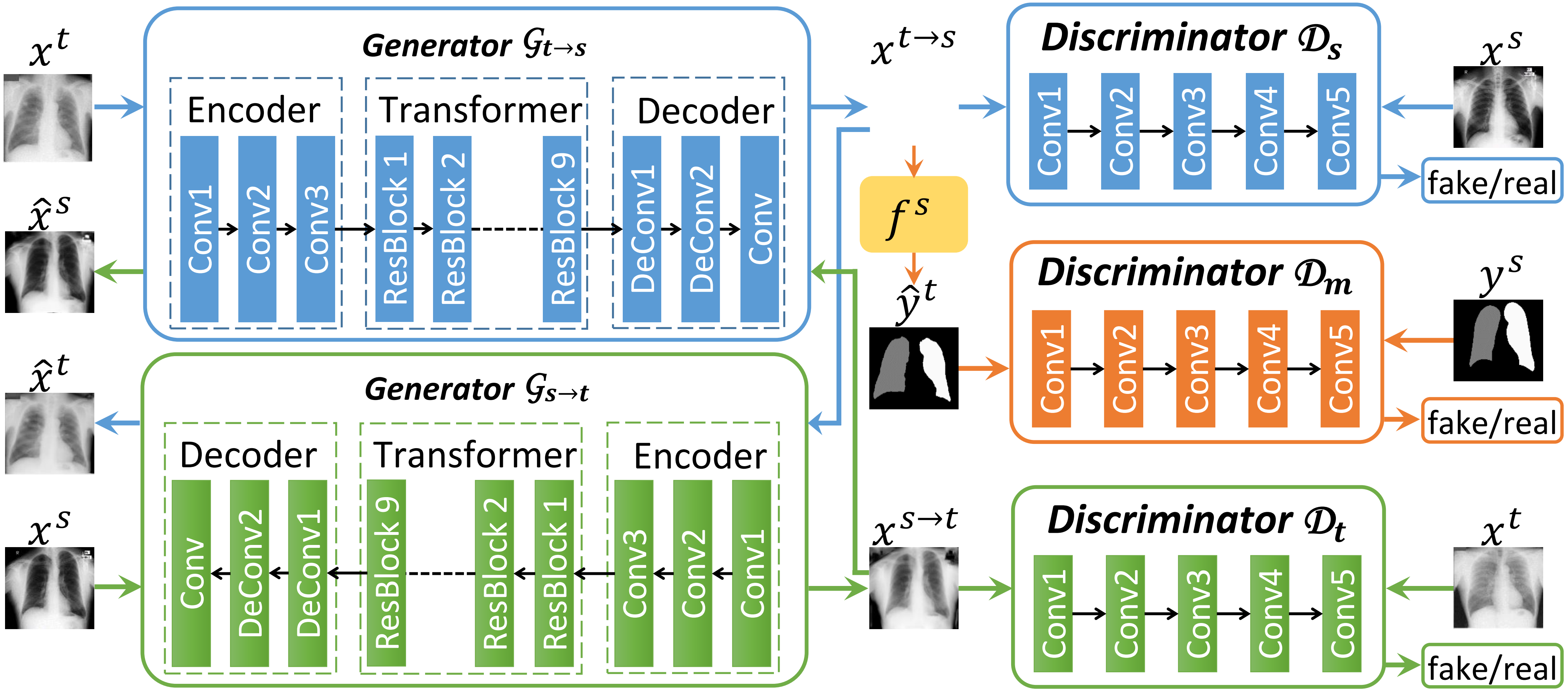
## Segmentation network




- Detached from the learning of domain adaptation GANs
- Established on source domain
- No further update in the process of image transformation
- Network architecture:
  - Residual blocks
  - Dilated convolutions
  - Multi-scale feature fusion

# Image-level Alignment

## Image transformation network




Chen C, et al. Semantic-Aware Generative Adversarial Nets for Unsupervised Domain Adaptation in Chest X-ray Segmentation. MICCAI, 2018.

# Image-level Alignment

**Overall loss functions**

- GAN loss

$$\mathcal{L}_{\text{GAN}}(\mathcal{G}_{t\to s}, \mathcal{D}_s) = \mathbb{E}_{x^s}[\log \mathcal{D}_s(x^s)] + \mathbb{E}_{x^t}[\log(1 - \mathcal{D}_s(\mathcal{G}_{t\to s}(x^t)))]$$

$$\mathcal{L}_{\text{GAN}}(\mathcal{G}_{s\to t}, \mathcal{D}_t) = \mathbb{E}_{x^t}[\log \mathcal{D}_t(x^t)] + \mathbb{E}_{x^s}[\log(1 - \mathcal{D}_t(\mathcal{G}_{s\to t}(x^s)))]$$

- Cycle-consistency loss

$$\mathcal{L}_{\text{cyc}}(\mathcal{G}_{t\to s}, \mathcal{G}_{s\to t}) = \mathbb{E}_{x^t}[||\mathcal{G}_{s\to t}(\mathcal{G}_{t\to s}(x^t)) - x^t||_1] + \mathbb{E}_{x^s}[||\mathcal{G}_{t\to s}(\mathcal{G}_{s\to t}(x^s)) - x^s||_1]$$

- Semantic-aware loss

$$\mathcal{L}_{\text{sem}}(\mathcal{G}_{t\to s}, \mathcal{D}_m) = \mathbb{E}_{y^s}[\log \mathcal{D}_m(y^s)] + \mathbb{E}_{x^t}[\log(1 - \mathcal{D}_m(f^s(\mathcal{G}_{t\to s}(x^t))))]$$

- Overall objective

$$\begin{aligned}\mathcal{L}(\mathcal{G}_{s\to t}, \mathcal{G}_{t\to s}, \mathcal{D}_s, \mathcal{D}_t, \mathcal{D}_m) = \; & \mathcal{L}_{GAN}(\mathcal{G}_{s\to t}, \mathcal{D}_t) + \alpha \mathcal{L}_{GAN}(\mathcal{G}_{t\to s}, \mathcal{D}_s) + \\ & \beta \mathcal{L}_{\text{cyc}}(\mathcal{G}_{t\to s}, \mathcal{G}_{s\to t}) + \lambda \mathcal{L}_{\text{sem}}(\mathcal{G}_{t\to s}, \mathcal{D}_m)\end{aligned}$$

Chen C, et al. Semantic-Aware Generative Adversarial Nets for Unsupervised Domain Adaptation in Chest X-ray Segmentation. MICCAI, 2018.

# Image-level Alignment

## Experiments

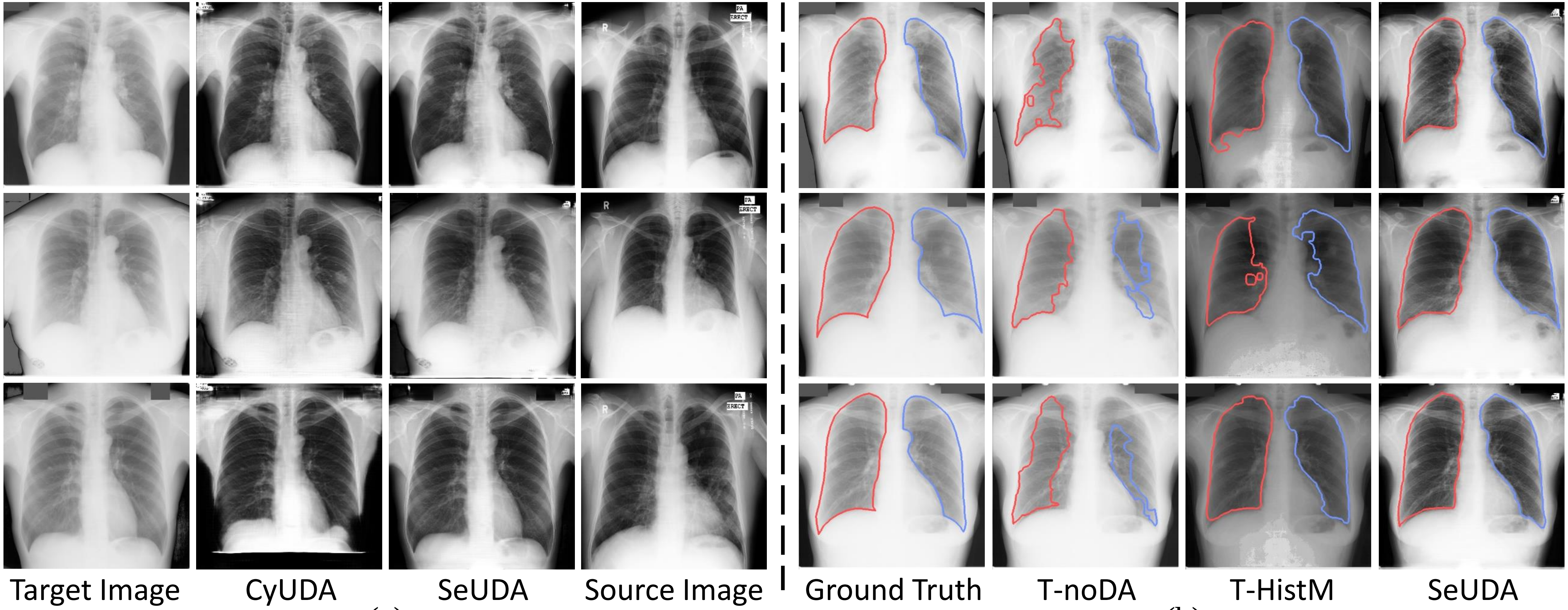
**Table 1.** Quantitative evaluation results of domain adaptation methods for both lung segmentations from chest X-ray images.

| Methods | Right Lung | | | | Left Lung | | | |
|---|---|---|---|---|---|---|---|---|
| | Dice | Recall | Precision | ASD | Dice | Recall | Precision | ASD |
| S-test | 95.98 | 97.98 | 94.23 | 2.23 | 95.23 | 96.56 | 94.01 | 2.45 |
| T-noDA | 82.29 | 98.40 | 73.38 | 10.68 | 76.65 | 95.06 | 69.15 | 11.40 |
| T-HistM [15] | 90.05 | 92.96 | 88.05 | 5.72 | 91.03 | 94.35 | 88.45 | 4.66 |
| T-FeatDA[9] | 94.85 | 93.66 | 96.42 | 3.26 | 92.93 | 91.67 | 94.46 | 3.80 |
| T-STL [6] | 96.91 | 98.47 | 95.46 | 1.93 | 95.84 | 97.48 | 94.29 | 2.20 |
| CyUDA | 94.09 | 96.31 | 92.28 | 3.88 | 91.59 | 92.28 | 91.70 | 4.57 |
| SeUDA | 95.59 | 96.55 | 94.77 | 2.85 | 93.42 | 92.40 | 94.70 | 3.51 |

[6] M. Ghafooria et al. Transfer learning for domain adaptation in mri: Application in brain lesion segmentation. MICCAI, 2017.
[9] K. Kamnitsas et al. Unsupervised domain adaptation in brain lesion segmentation with adversarial networks. IPMI, 2017.
[15] L. Wang et al. Correction for variations in mri scanner sensitivity in brain studies with histogram matching. Magn Reson Med, 1998.

# Image-level Alignment

## Experiments




(a) (b)

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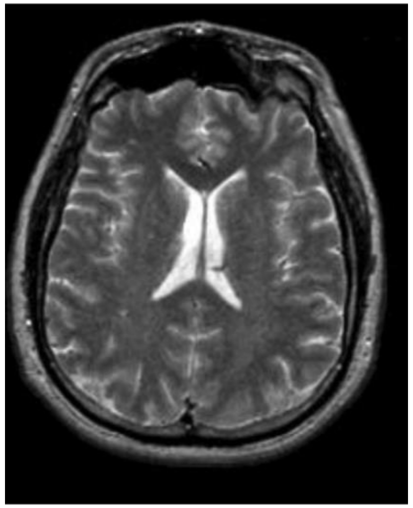
- Challenge and future direction

# Challenges and Potential Directions

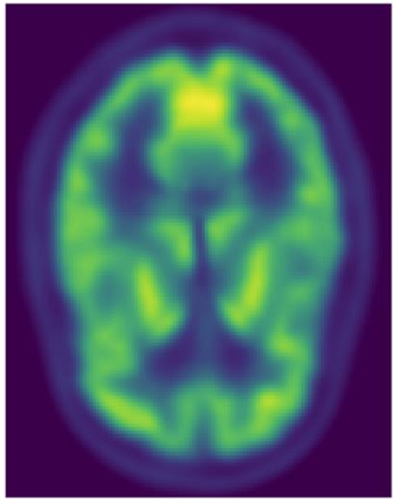
- Inter-Modality Heterogeneity

The large inter-modality difference brings difficulties for efficient knowledge transfer between different domains, such as CT, structural MRI, function MRI, and positron emission tomography (PET).

CT



MRI



PET



Kotte S et al. Optimal multilevel thresholding selection for brain MRI image segmentation based on adaptive wind driven optimization. Measurement 2018.

# Challenges and Potential Directions

- Unsupervised Domain Adaptation with Extreme Settings

Completely avoiding any target data (even those unlabeled ones) for model training is an interesting research topic, i.e., domain generalization, zero-shot learning, etc.

- Multi-Source/Multi-Target Domain Adaptation

Leveraging training data from multi-source domains to improve models' transferability on the target domain is of great clinical significance.

Guan H, et al. Domain adaptation for medical image analysis: a survey. TBME 2022.