



Weakly Supervised Segmentation: Models and Optimization

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Christian Desrosiers
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Data-driven priors: Advanced

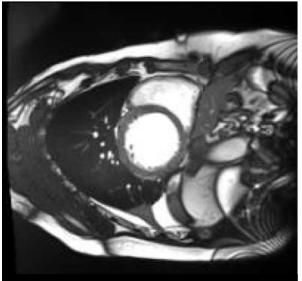
- 1) Adversarial learning
- 2) Consistency regularization
- 3) Unsupervised representation learning

Adversarial learning

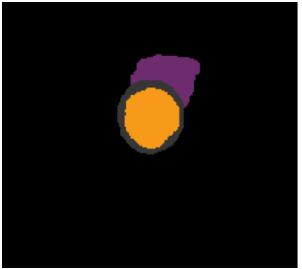
for weakly-supervised segmentation

Learning with unlabeled images

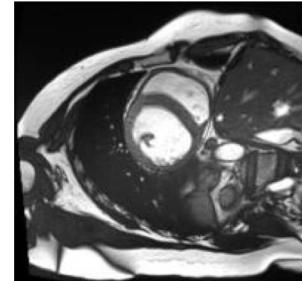
Labeled images (few)



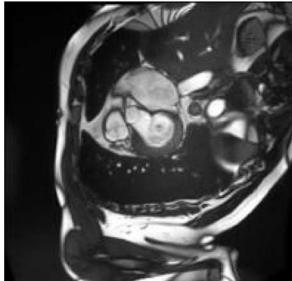
...



Unlabeled images (many)

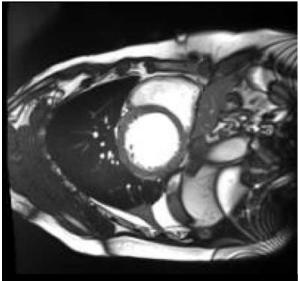


...

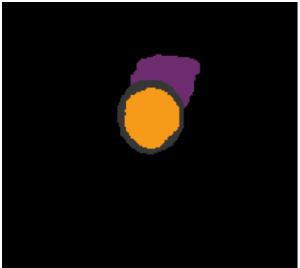
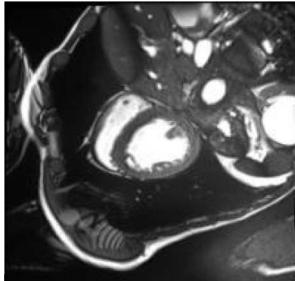


Learning with unlabeled images

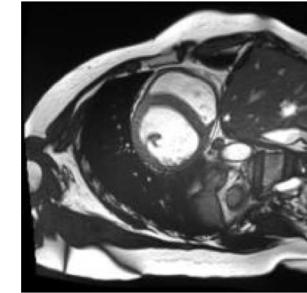
Labeled images (few)



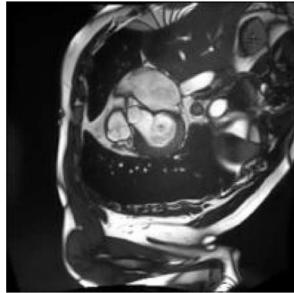
...



Unlabeled images (many)



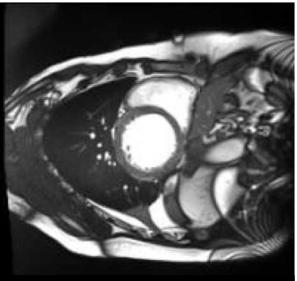
...



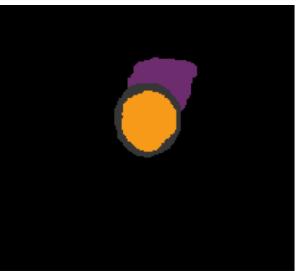
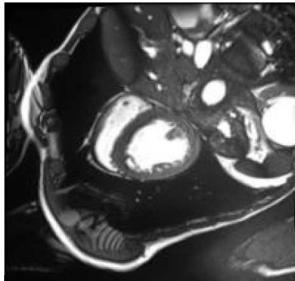
How can we use this information
to learn segmentation ?

Learning with unlabeled images

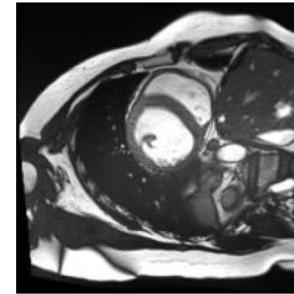
Labeled images (few)



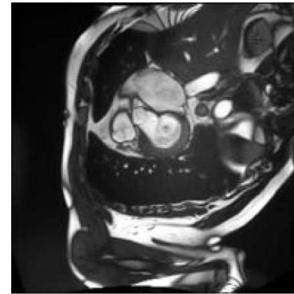
...



Unlabeled images (many)



...



How can we use this information
to learn segmentation ?



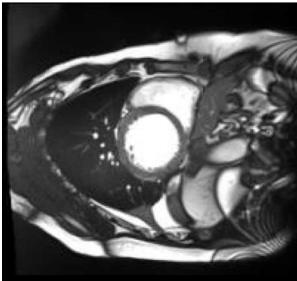
1) Knowledge-based priors:

- Size bounds, shape atlas, boundary smoothness, etc.
- Difficult to adapt to new domains or tasks

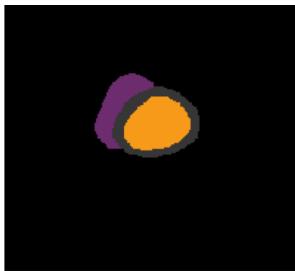
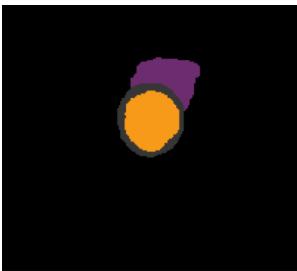
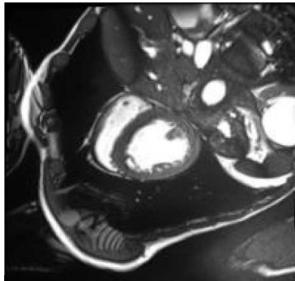
Presented in previous slides

Learning with unlabeled images

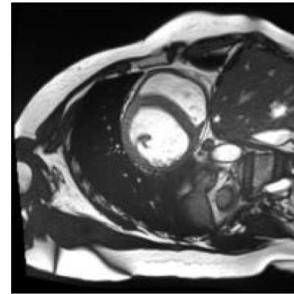
Labeled images (few)



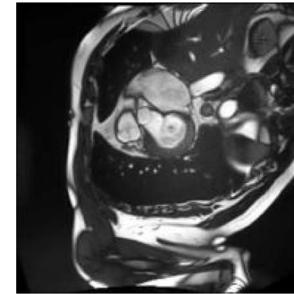
...



Unlabeled images (many)



...



How can we use this information
to learn segmentation ?



1) Knowledge-based priors:

- Size bounds, shape atlas, boundary smoothness, etc.
- Difficult to adapt to new domains or tasks

Presented in previous slides

2) Adversarial learning:

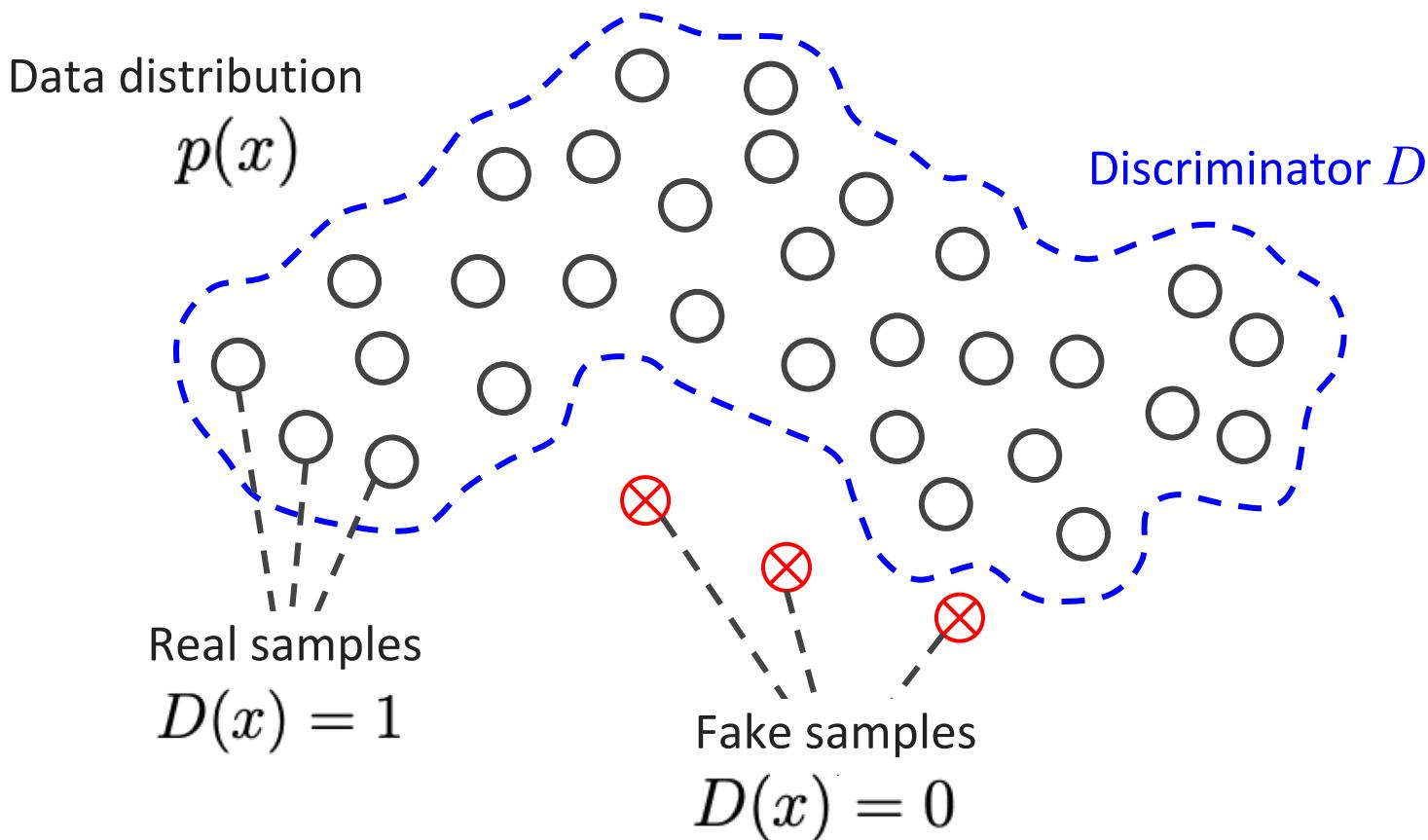
- Learn priors directly from training data
- Easily adapts to new domains or tasks

Discussed in next slides

Adversarial learning

Basic idea:

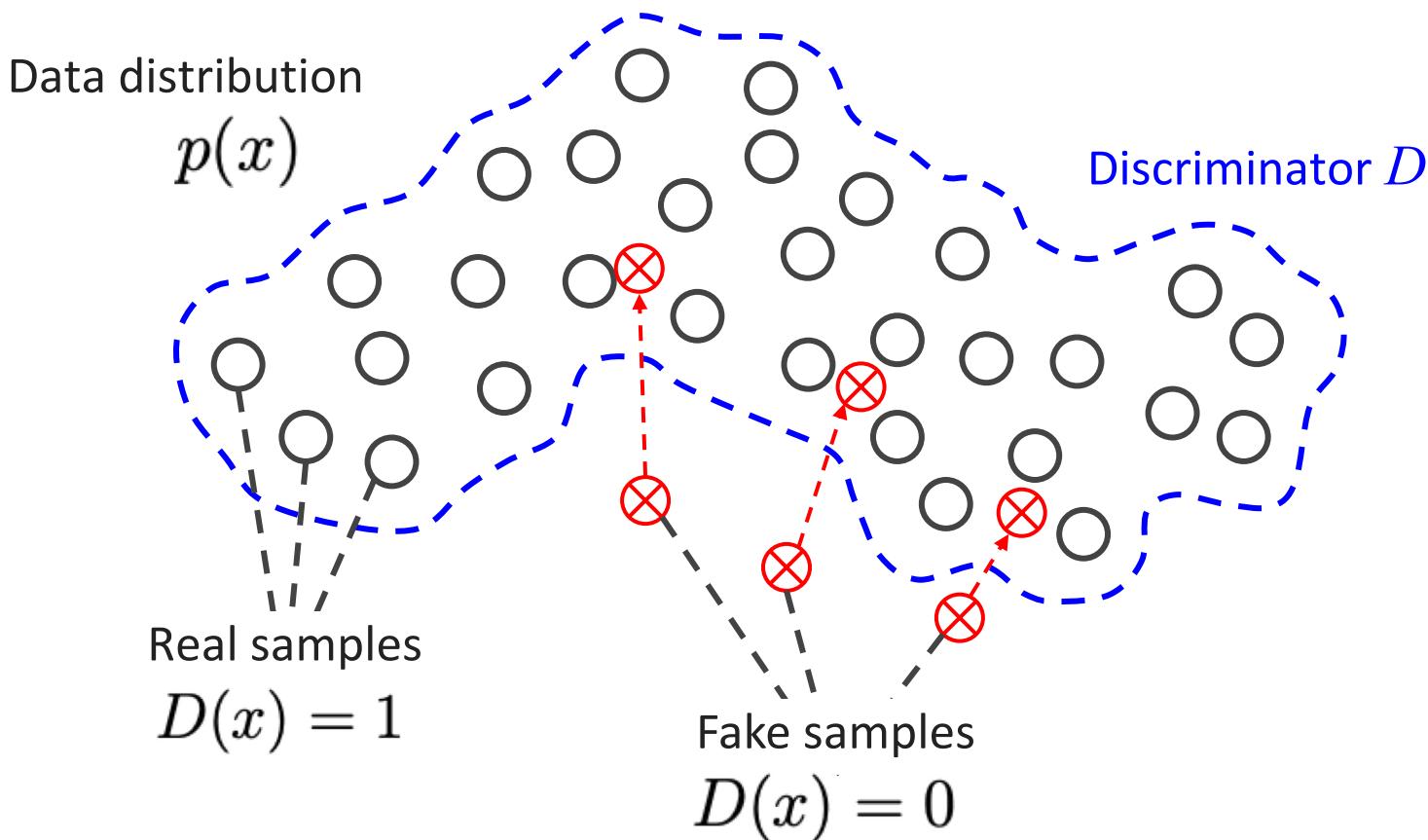
Learn the data distribution using a classifier (the discriminator)



Adversarial learning

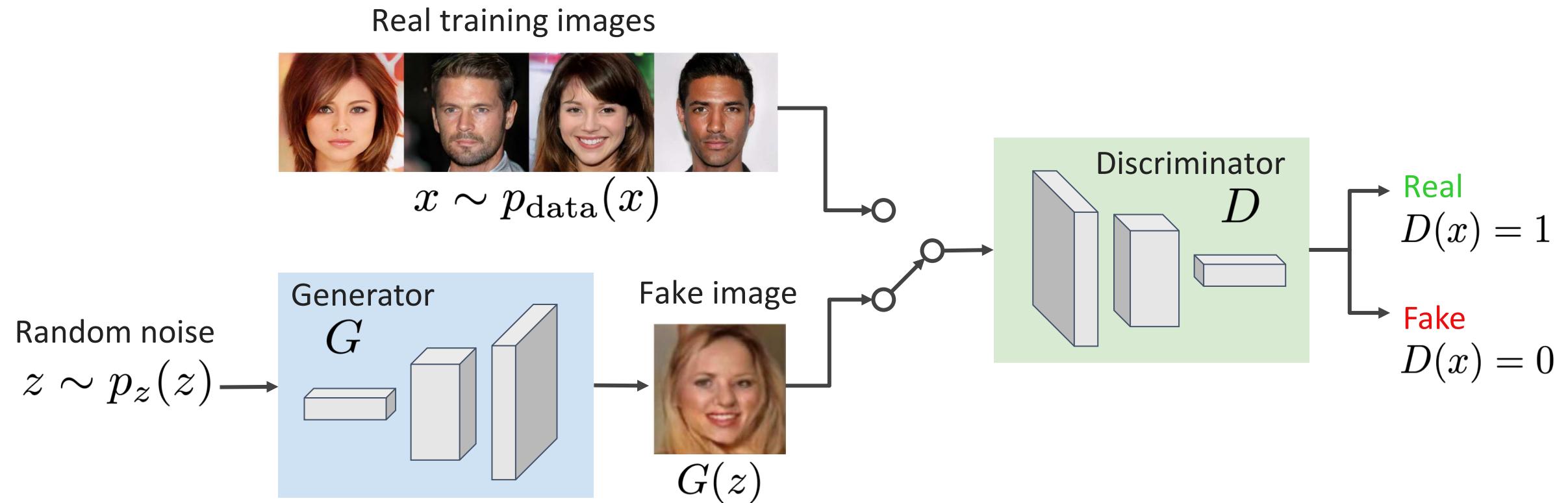
Basic idea:

Learn the data distribution using a classifier (the discriminator)

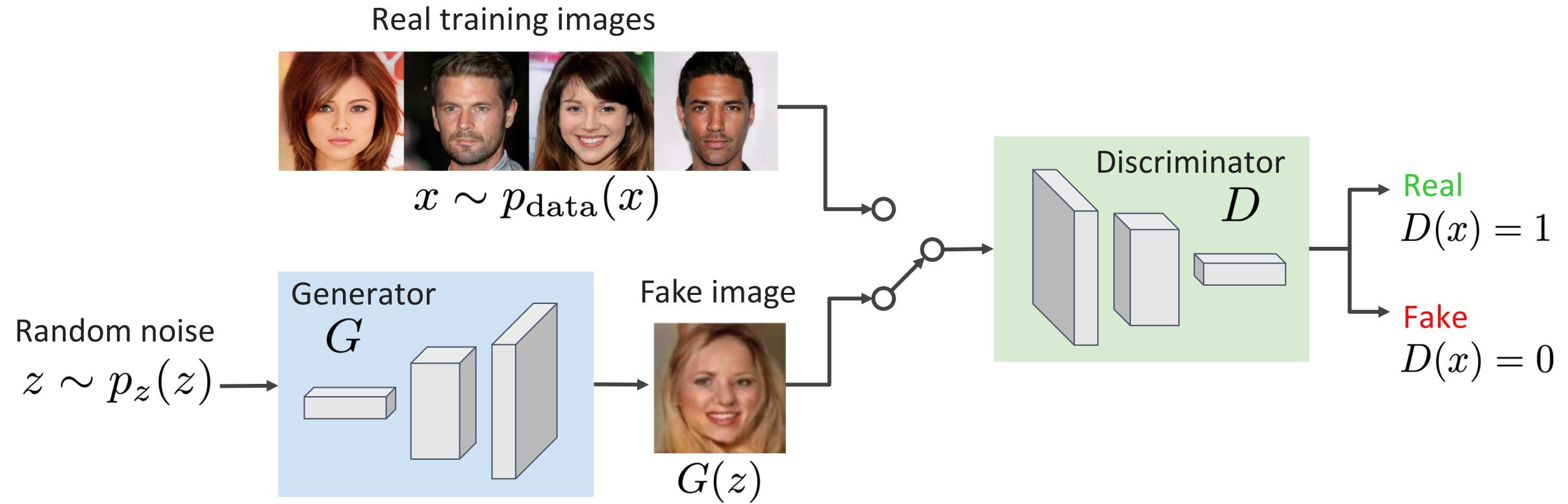


Objective: Generate samples in the distribution of real data

Generative adversarial network (GAN)

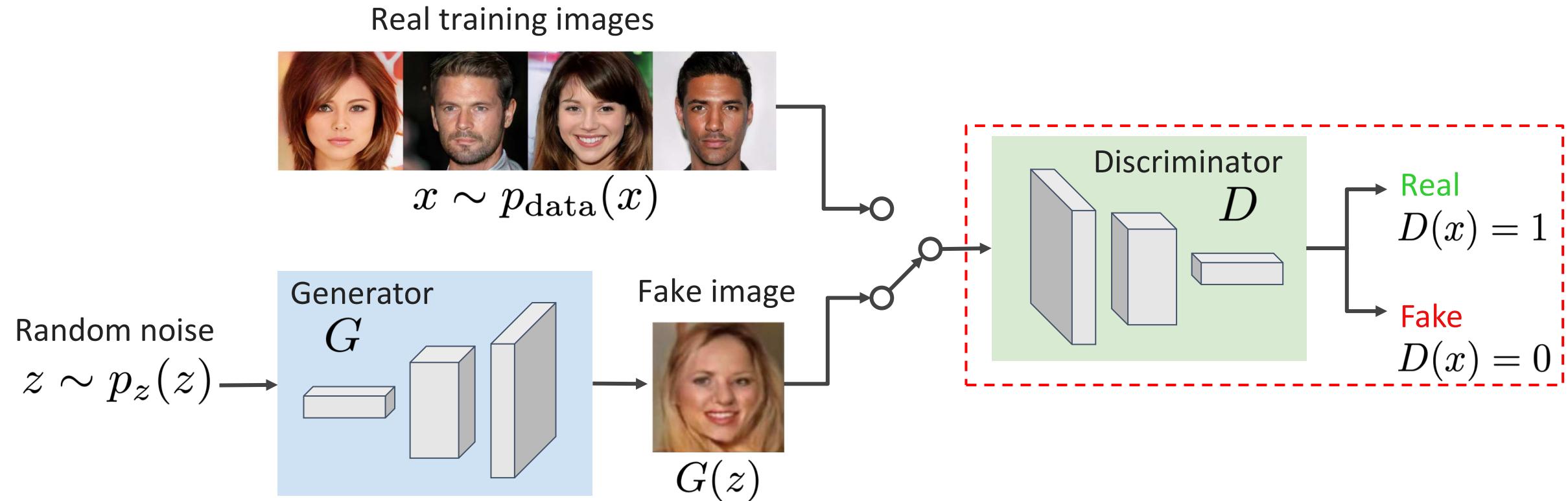


Generative adversarial network (GAN)



How to make sure that generated images look real ?

Generative adversarial network (GAN)



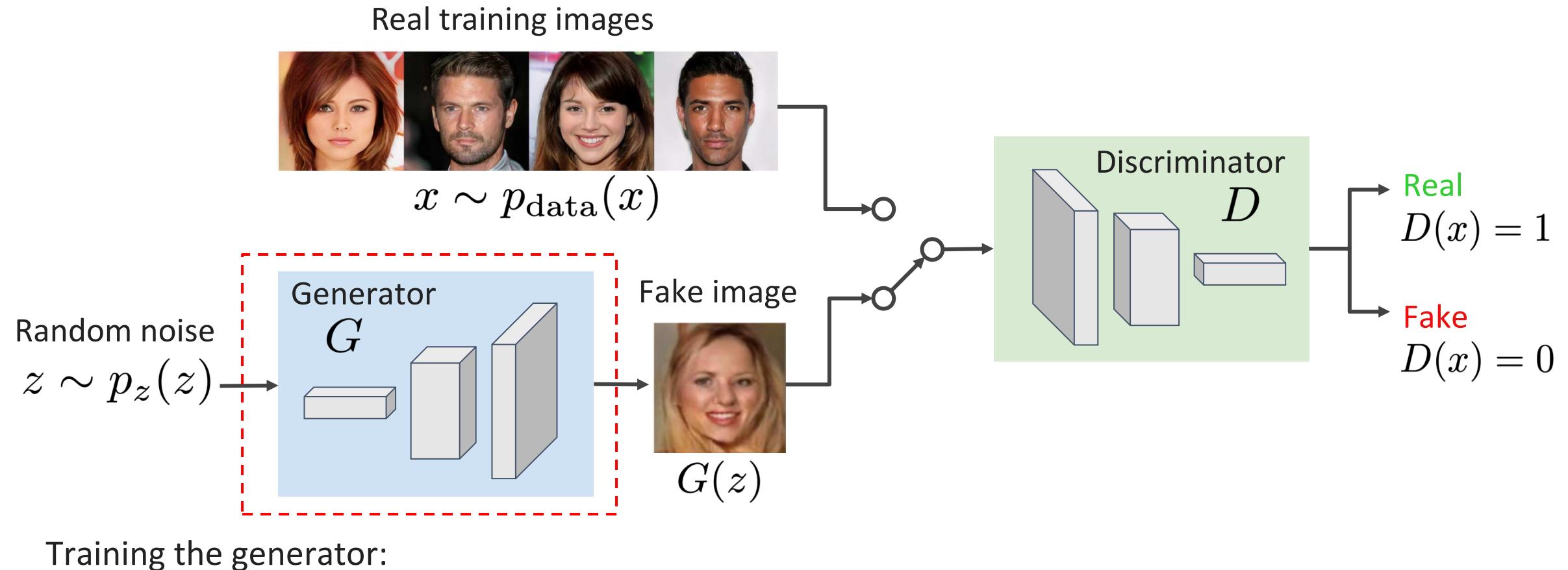
Training the discriminator (cross-entropy):

$$\max_D \mathbb{E}_{x \sim p_{\text{data}}(x)} [\log D(x)] + \mathbb{E}_{z \sim p_z(z)} [\log(1 - D(G(z)))]$$

Output '1' for real images

Output '0' for generated images

Generative adversarial network (GAN)

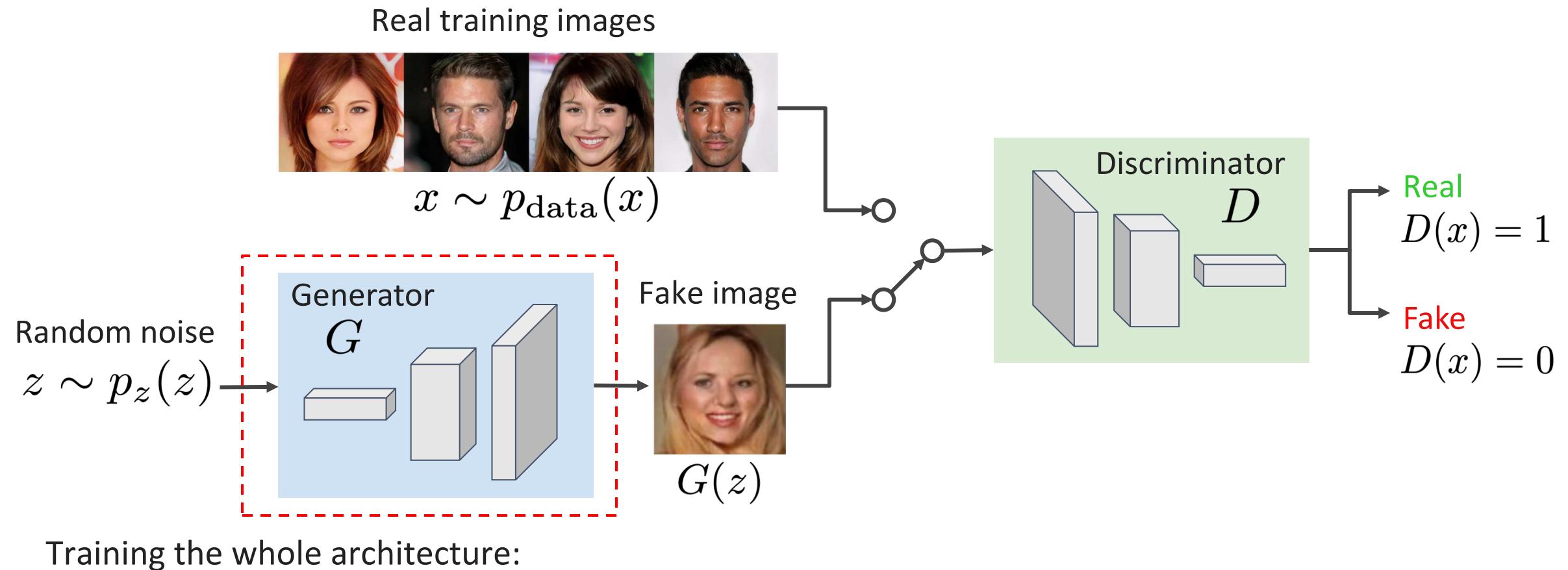


Training the generator:

$$\min_G \mathbb{E}_{z \sim p_z(z)} [\log(1 - D(G(z)))]$$

Fool the discriminator into predicting '1' for fake images

Generative adversarial network (GAN)

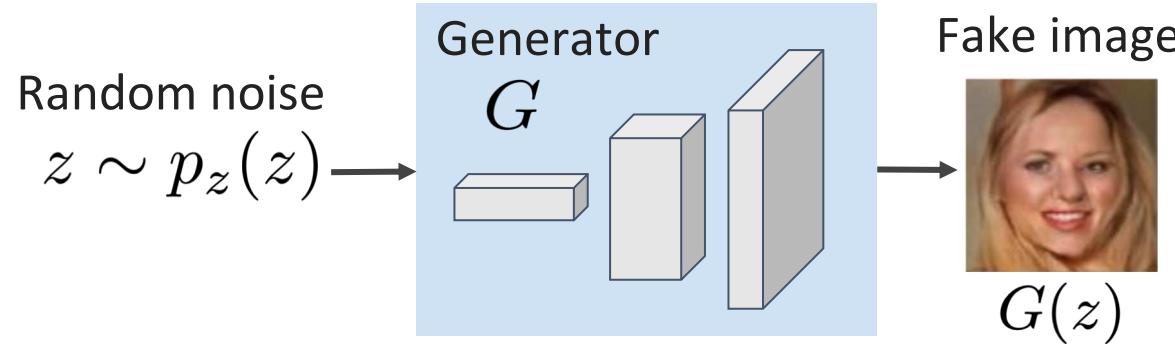


$$\min_G \max_D \mathbb{E}_{x \sim p_{\text{data}}(x)} [\log D(x)] + \mathbb{E}_{z \sim p_z(z)} [\log(1 - D(G(z)))]$$

Corresponds to a minimax problem (*more on this later...*)

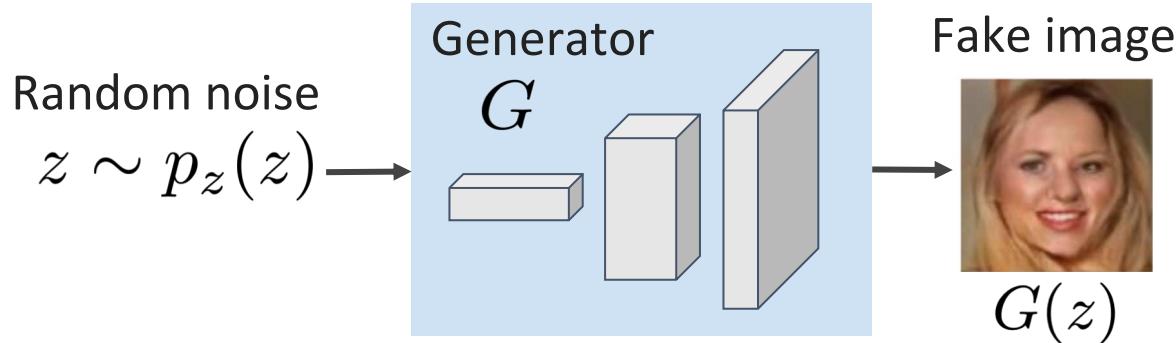
GANs for segmentation

GAN for image generation:

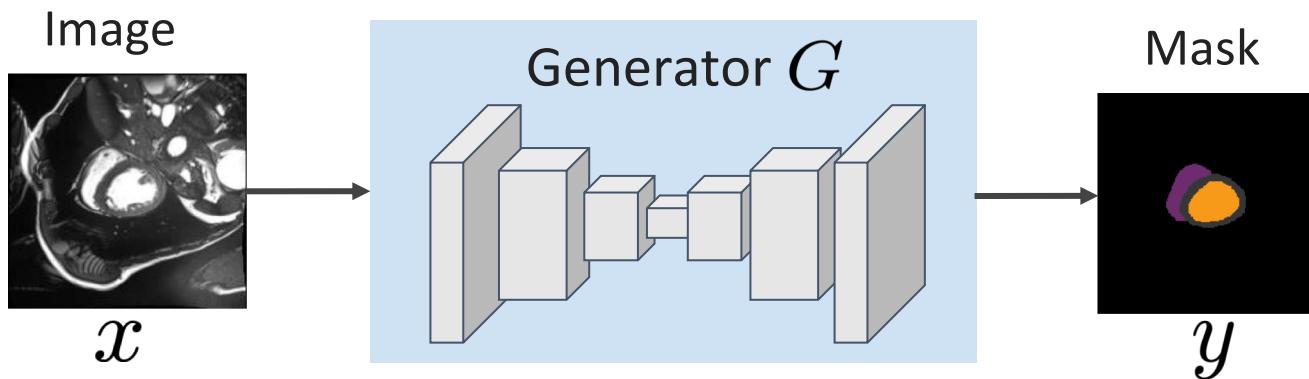


GANs for segmentation

GAN for image generation:

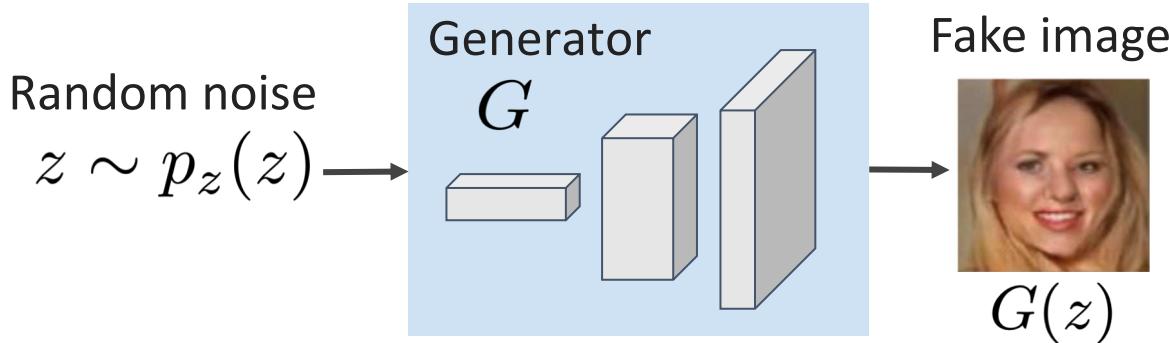


GAN for image segmentation:

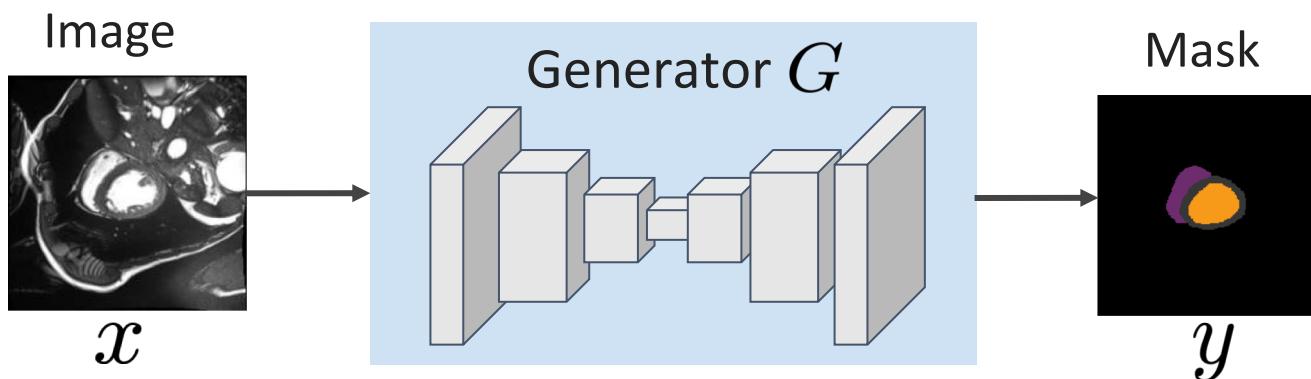


GANs for segmentation

GAN for image generation:



GAN for image segmentation:

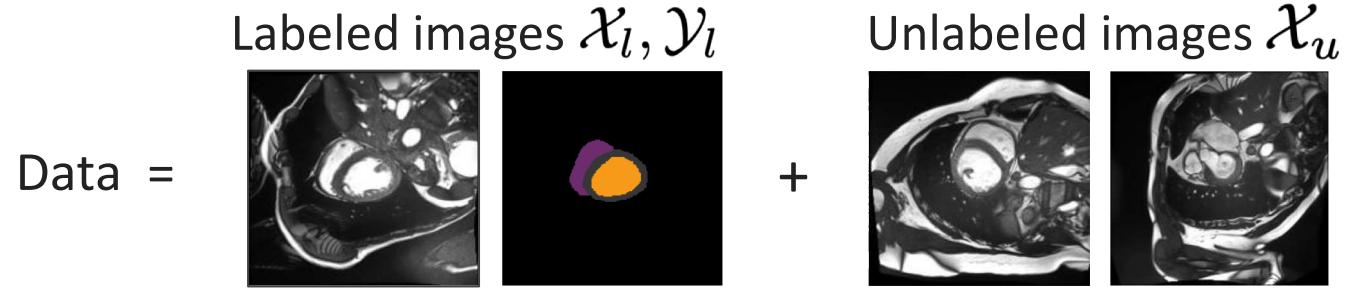


We are now modeling
the distribution of
segmentation masks

The generator is a segmentation network (encoder-decoder)

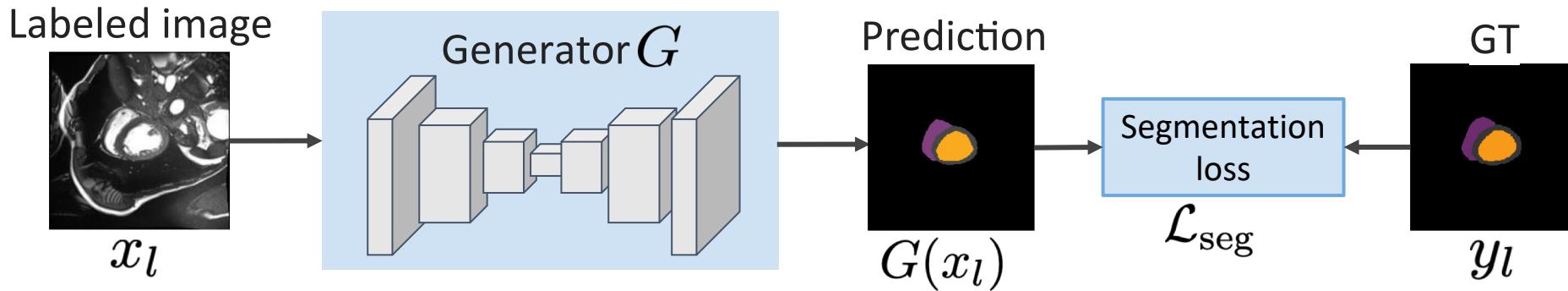
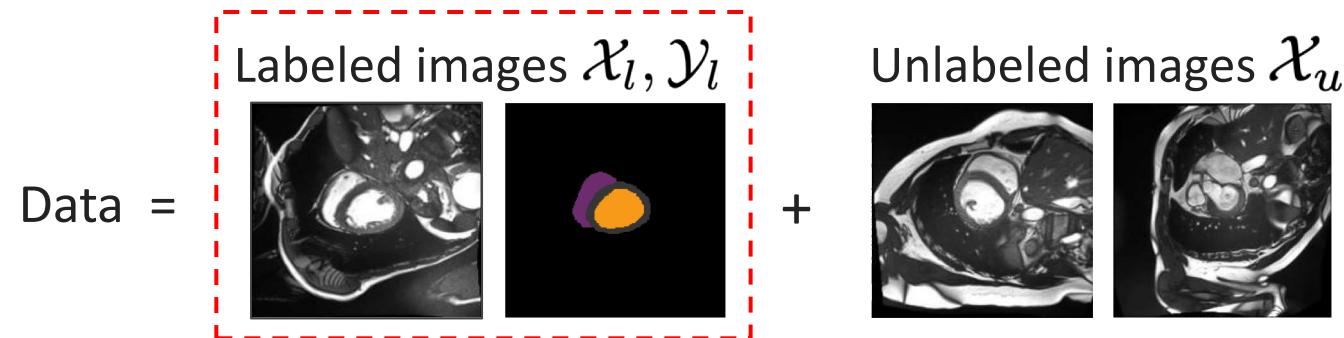
Adversarial semi-supervised segmentation

Basic idea: Learn to generate segmentation masks which can't be differentiated from ground-truth (GT)



Adversarial semi-supervised segmentation

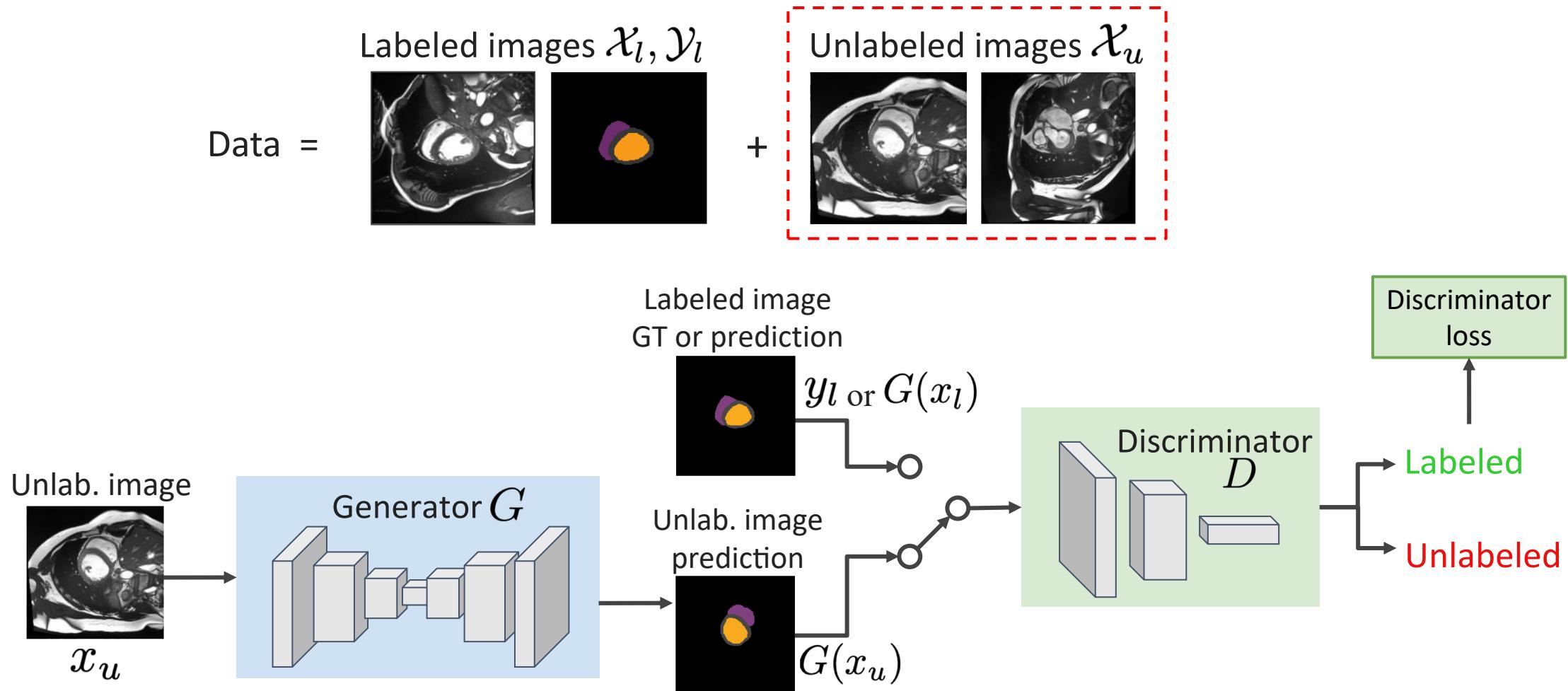
Basic idea: Learn to generate segmentation masks which can't be differentiated from ground-truth (GT)



$$\mathcal{L}_{\text{sup}}(G) = \mathbb{E}_{(x_l, y_l) \sim \mathcal{X}_l, \mathcal{Y}_l} [\mathcal{L}_{\text{seg}}(G(x_l), y_l)]$$

Adversarial semi-supervised segmentation

Basic idea: Learn to generate segmentation masks which can't be differentiated from ground-truth (GT)



Adversarial semi-supervised segmentation

Basic idea: Learn to generate segmentation masks which can't be differentiated from ground-truth (GT)



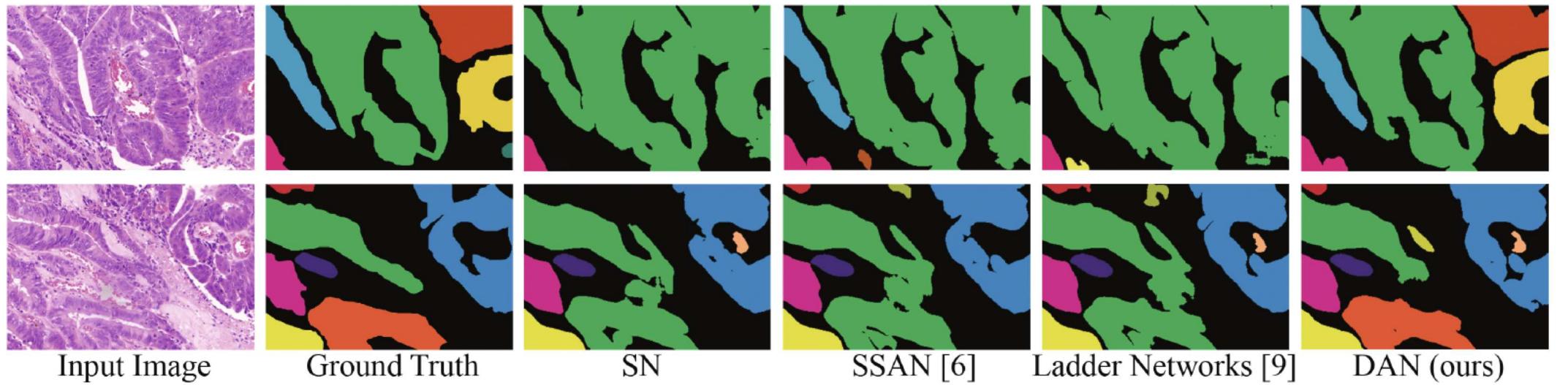
Both labeled and unlabeled:

$$\min_G \max_D \mathcal{L}(G, D) = \underbrace{\frac{1}{|\mathcal{X}_l|} \sum_{l=1}^{|\mathcal{X}_l|} \mathcal{L}_{\text{seg}}(G(x_l), y_l)}_{\text{Supervised loss}} - \underbrace{\frac{\lambda}{|\mathcal{X}_l| + |\mathcal{X}_u|} \left(\sum_{l=1}^{|\mathcal{X}_l|} \mathcal{L}_{\text{dis}}(D(G(x_l)), 1) + \sum_{u=1}^{|\mathcal{X}_u|} \mathcal{L}_{\text{dis}}(D(G(x_u)), 0) \right)}_{\text{Adversarial loss}}$$

Controls the trade-off between the two losses

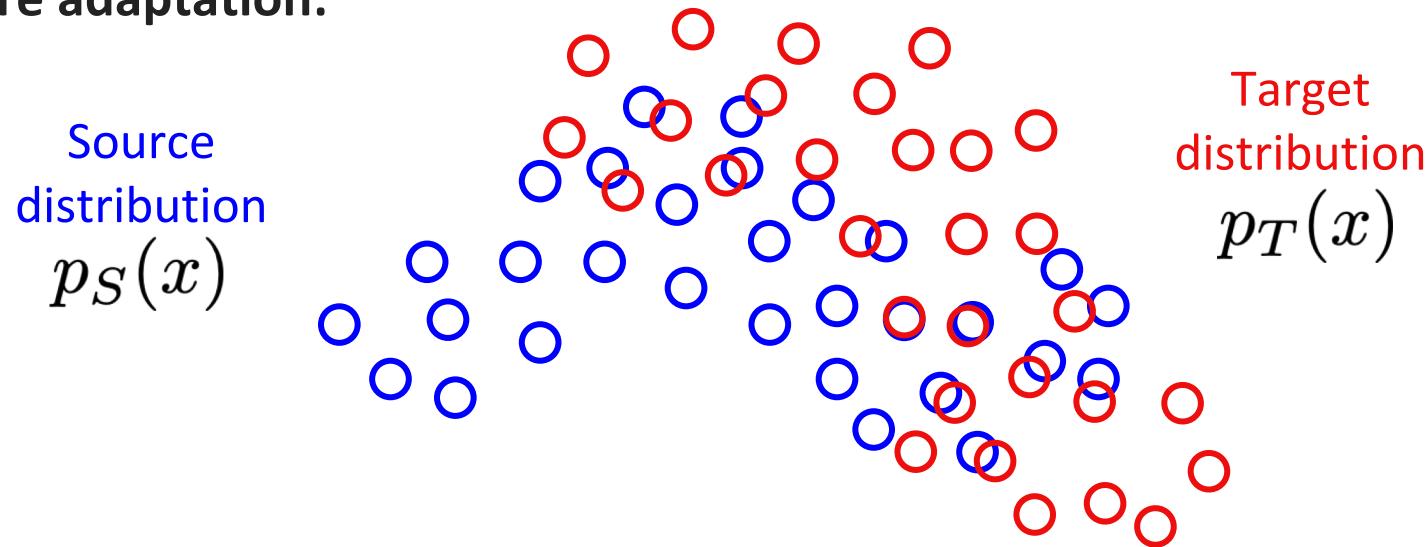
Adversarial semi-supervised segmentation

Adversarial network for semi-supervised segmentation of histological images



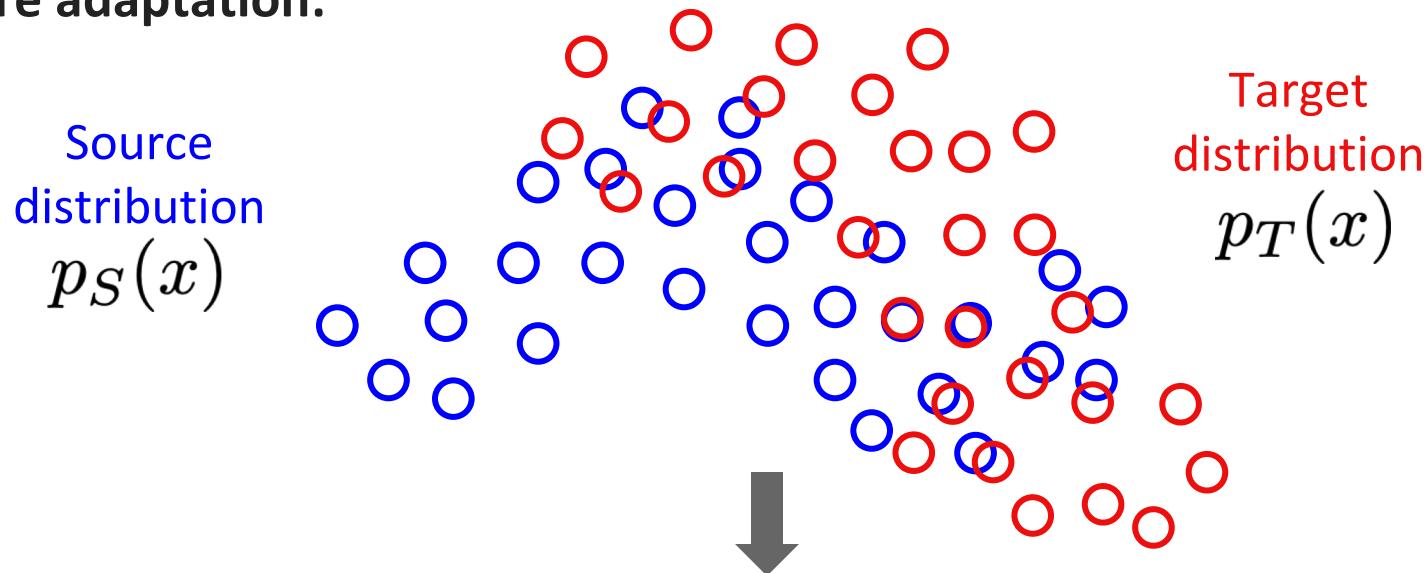
Domain adaptation

Before adaptation:

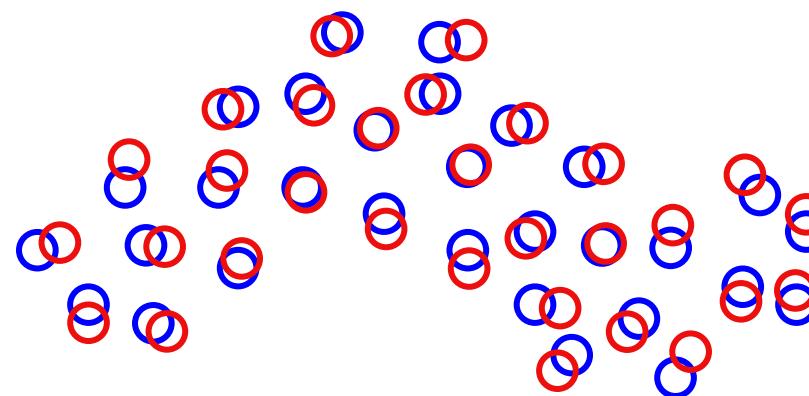


Domain adaptation

Before adaptation:



After adaptation:



$$p_S(x) = p_T(x)$$

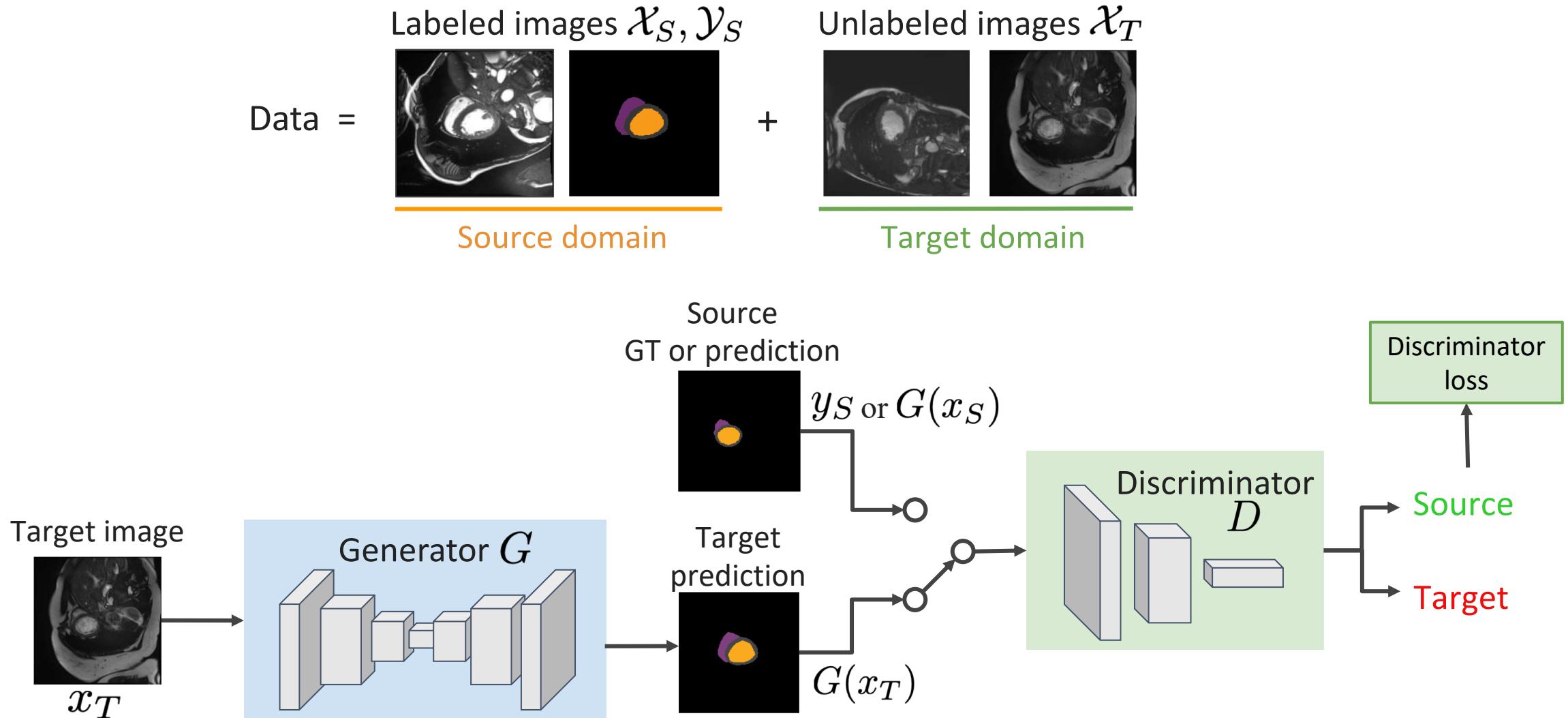
Objective

Align the distributions (input, output or representation) so that a model trained on Source data also works on Target data

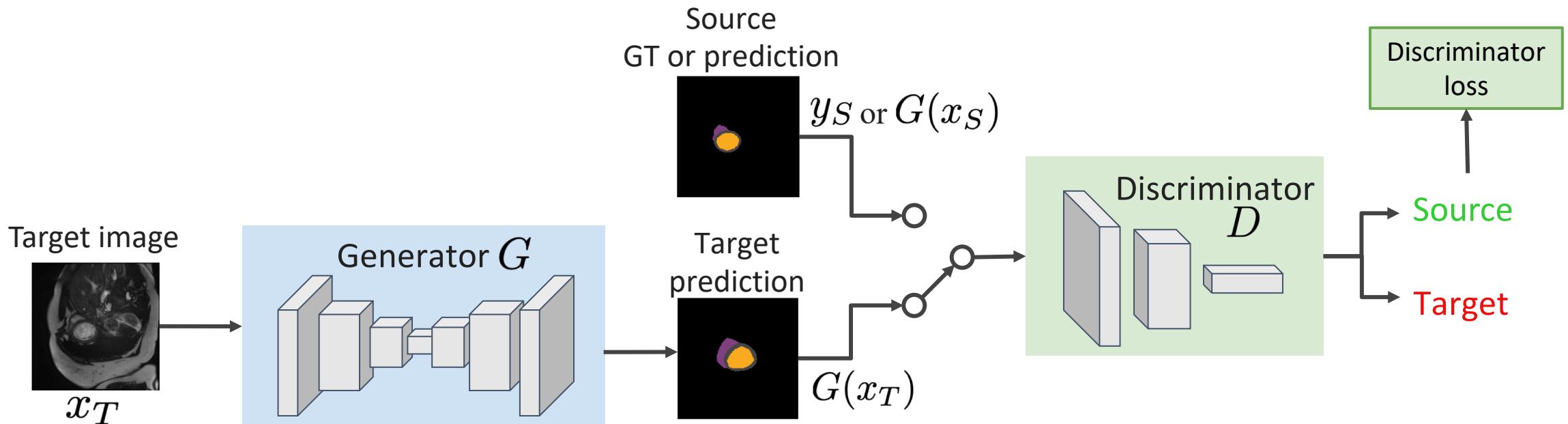
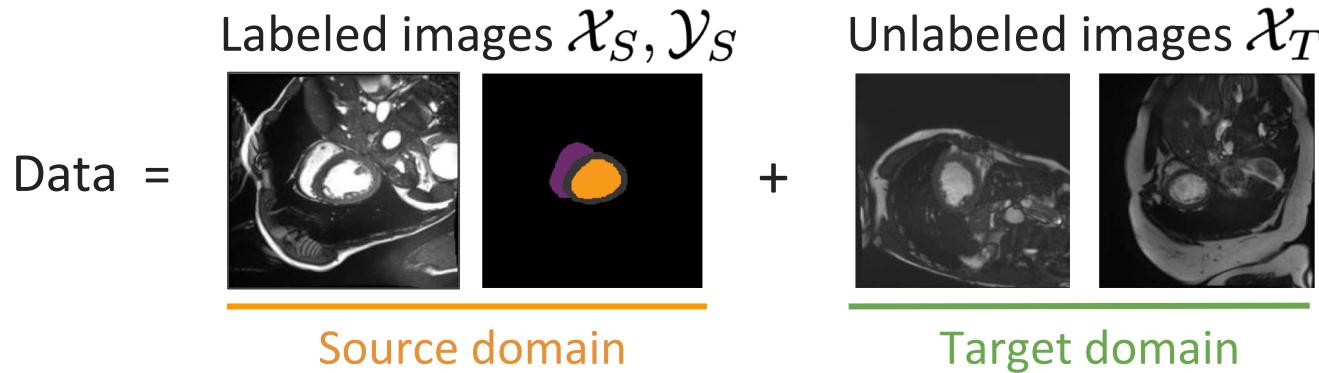
Adversarial domain adaptation



Adversarial domain adaptation



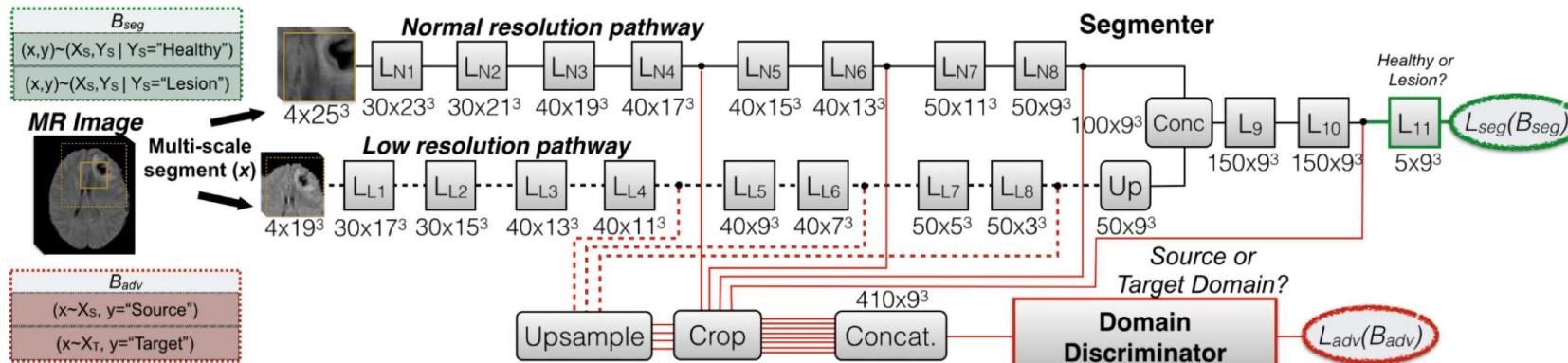
Adversarial domain adaptation



Like semi-supervised segmentation except target images are from a different domain

Adversarial domain adaptation

Adversarial domain adaptation for brain lesion segmentation



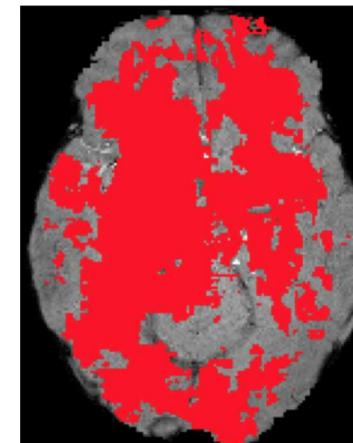
Source domain (Database 1):

- GE, FLAIR, T2, MPRAGE, PD

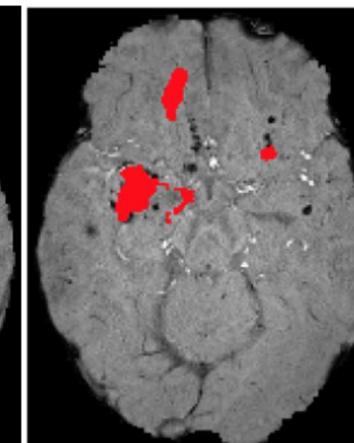
Target domain (Database 2):

- SWI, FLAIR, T2, MPRAGE, PD

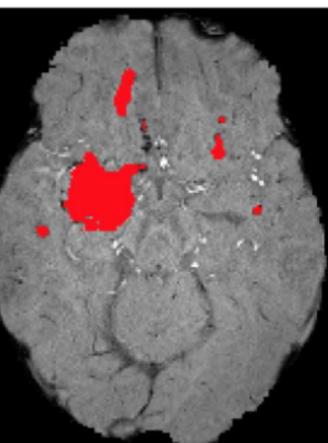
No adaptation
(All sequences)



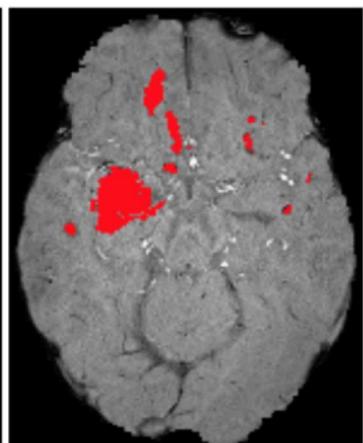
No adaptation
(No GE/SWI)



Adaptation S→T

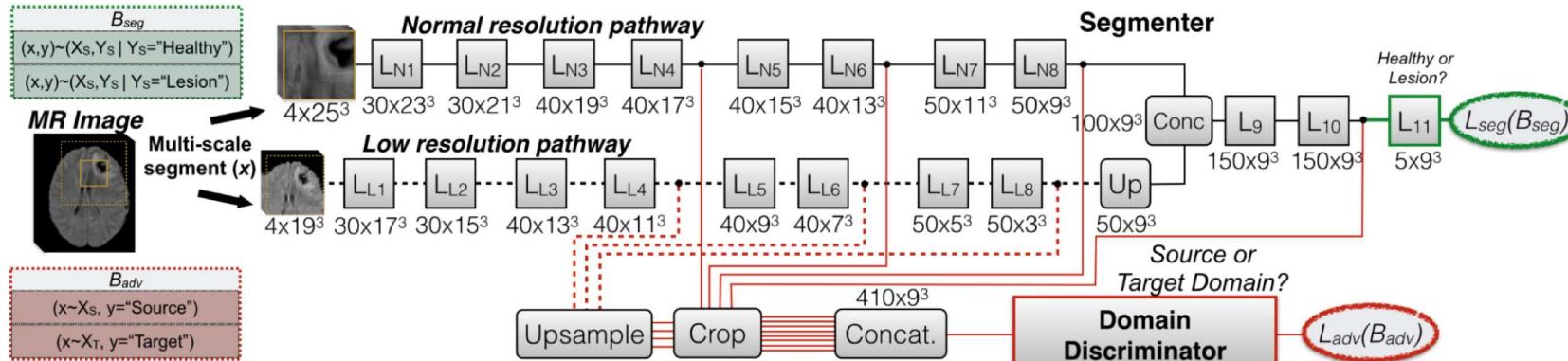


Ground-truth



Adversarial domain adaptation

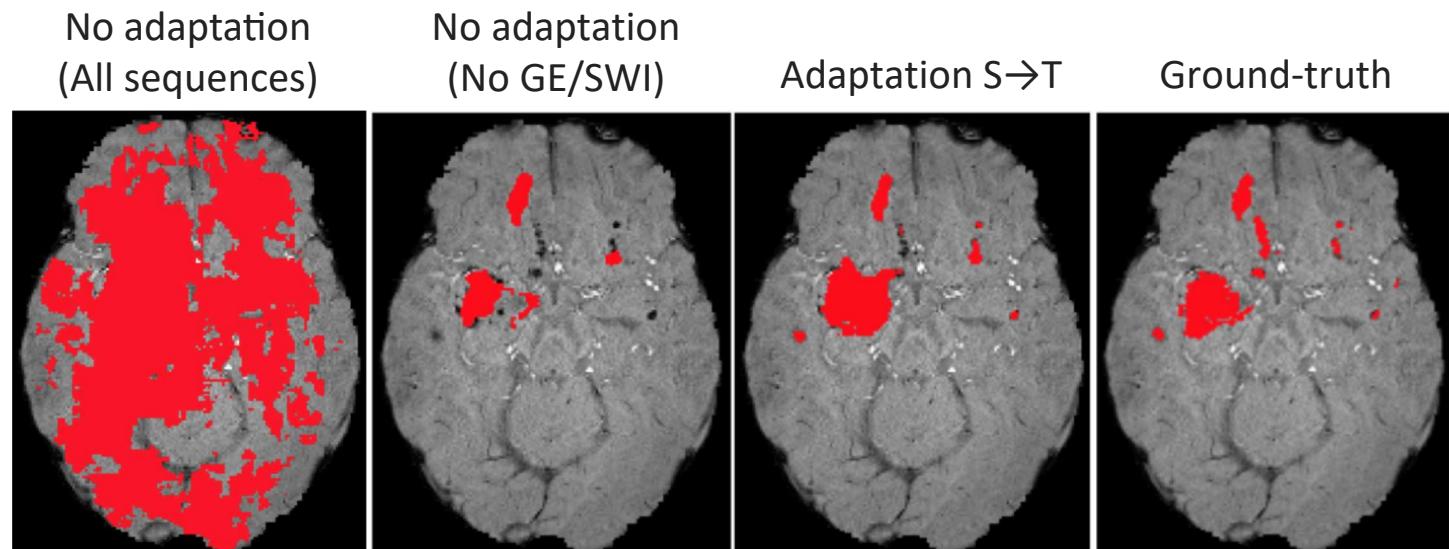
Adversarial domain adaptation for brain lesion segmentation



Adaptation done on
multi-scale feature
representation

Source domain (Database 1):
• GE, FLAIR, T2, MPRAGE, PD

Target domain (Database 2):
• SWI, FLAIR, T2, MPRAGE, PD

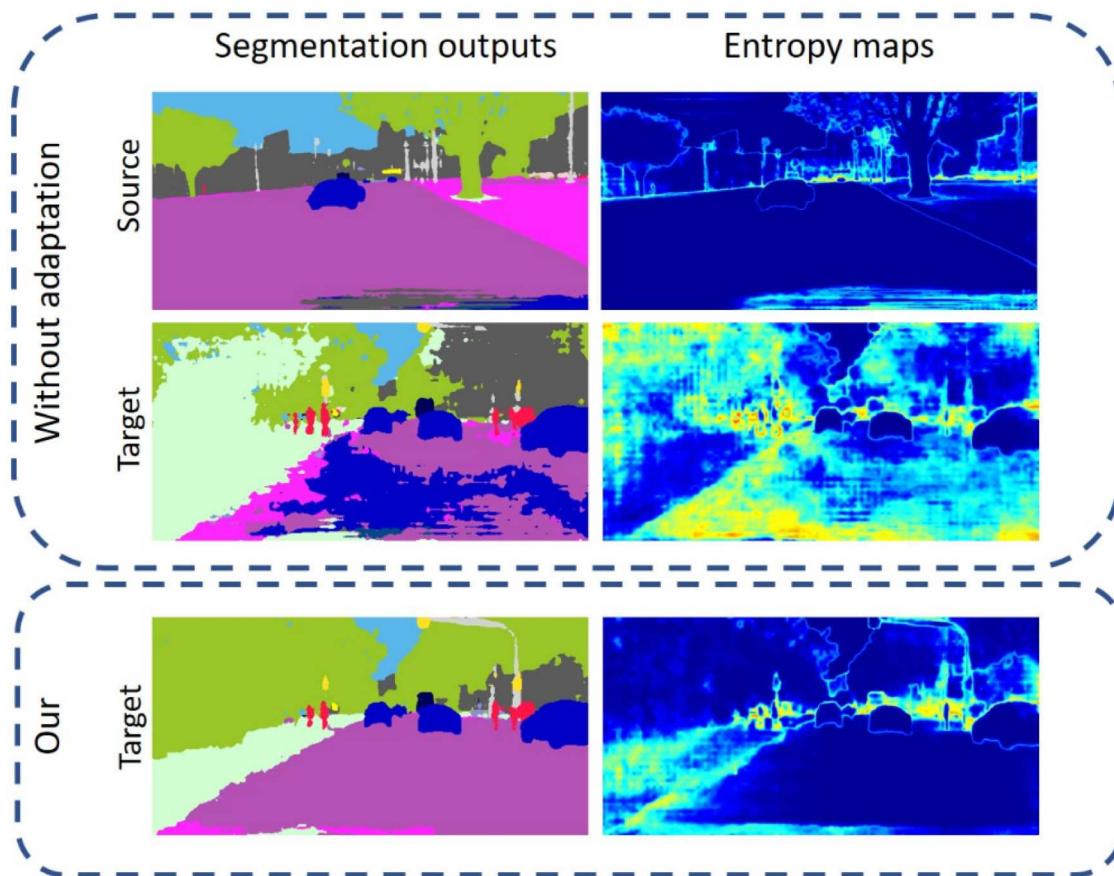


Adversarial domain adaptation

Adaptation on feature *representation* or *softmax output*. What else ?

Adversarial domain adaptation

Adaptation on feature *representation* or softmax output. What else ?



Adversarial entropy minimization

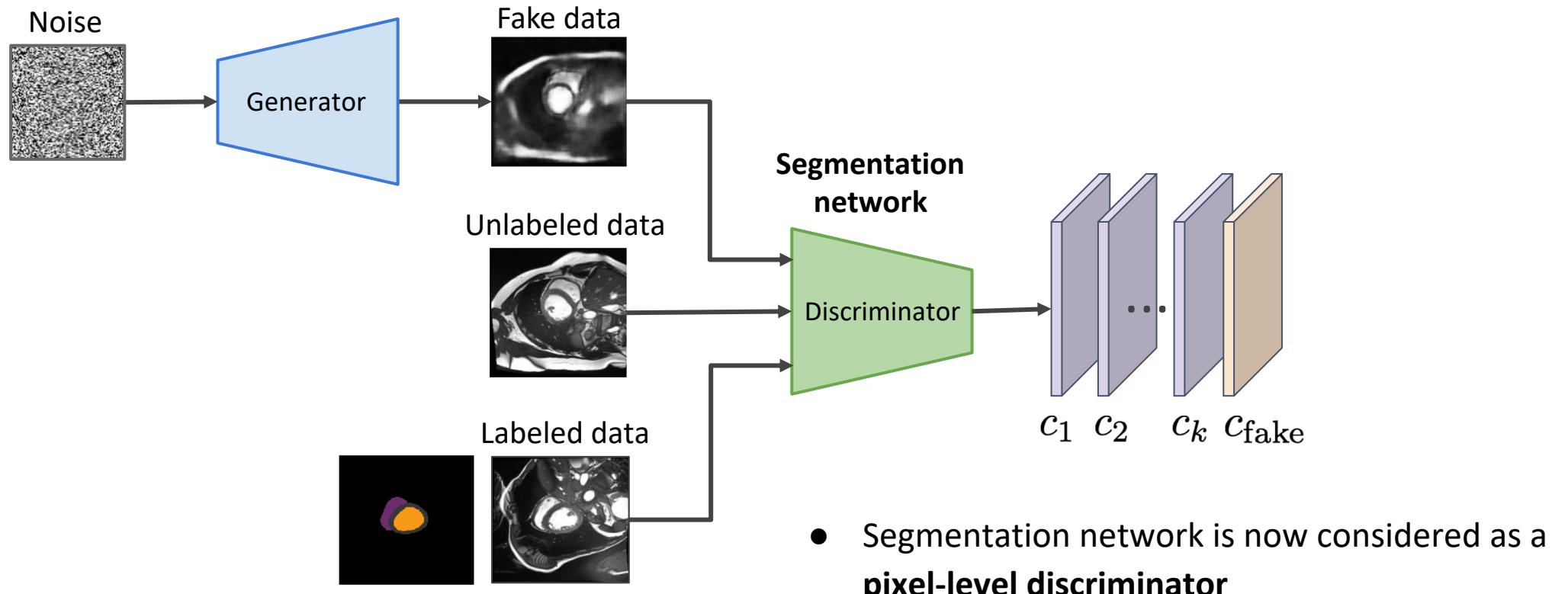
- The discriminator must differentiate between source and target examples using the entropy spatial maps
- Forces the segmentation model to be consistent in its confidence across different semantic regions

Semi-supervised segmentation with GANs

Can we use GAN-generated images to boost learning in a semi-supervised setting ?

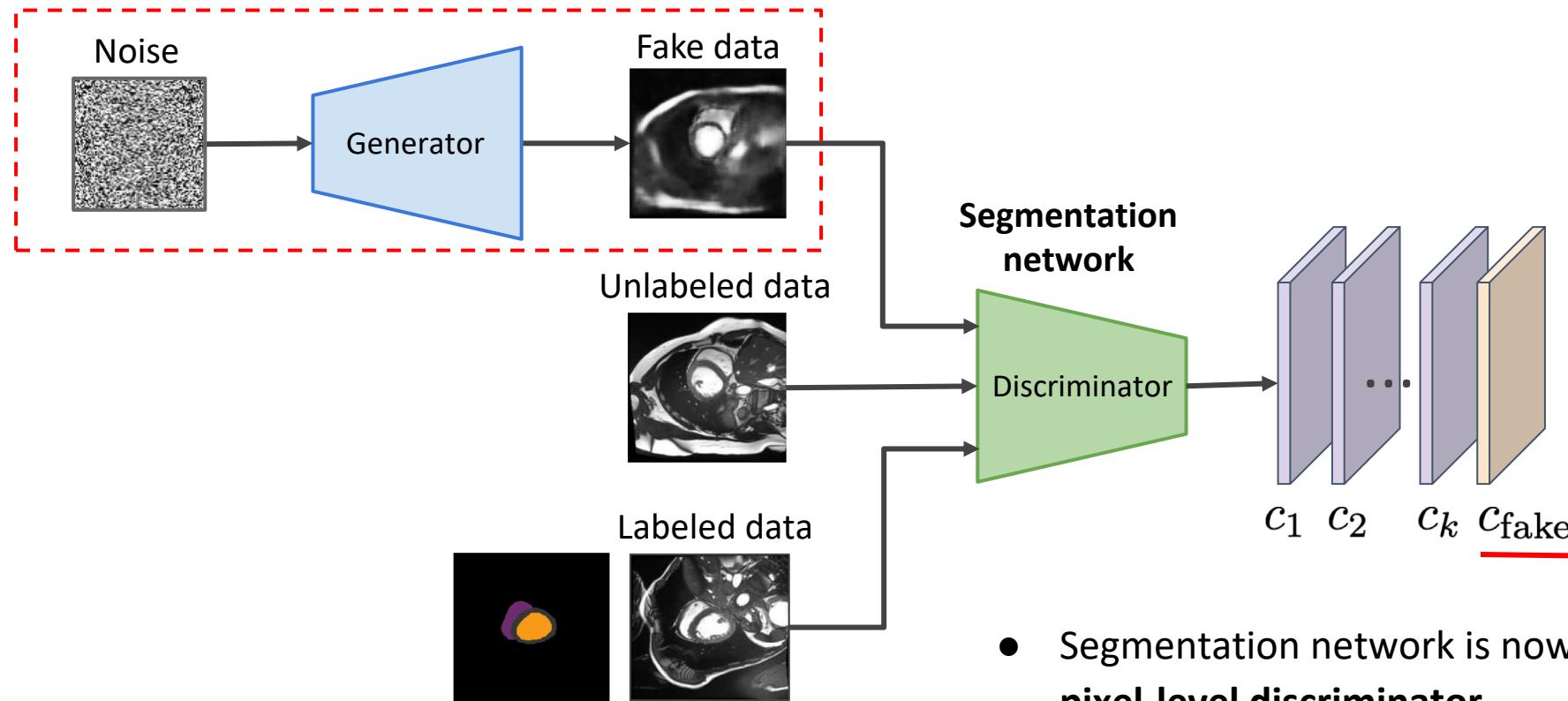
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Semi-supervised segmentation with GANs

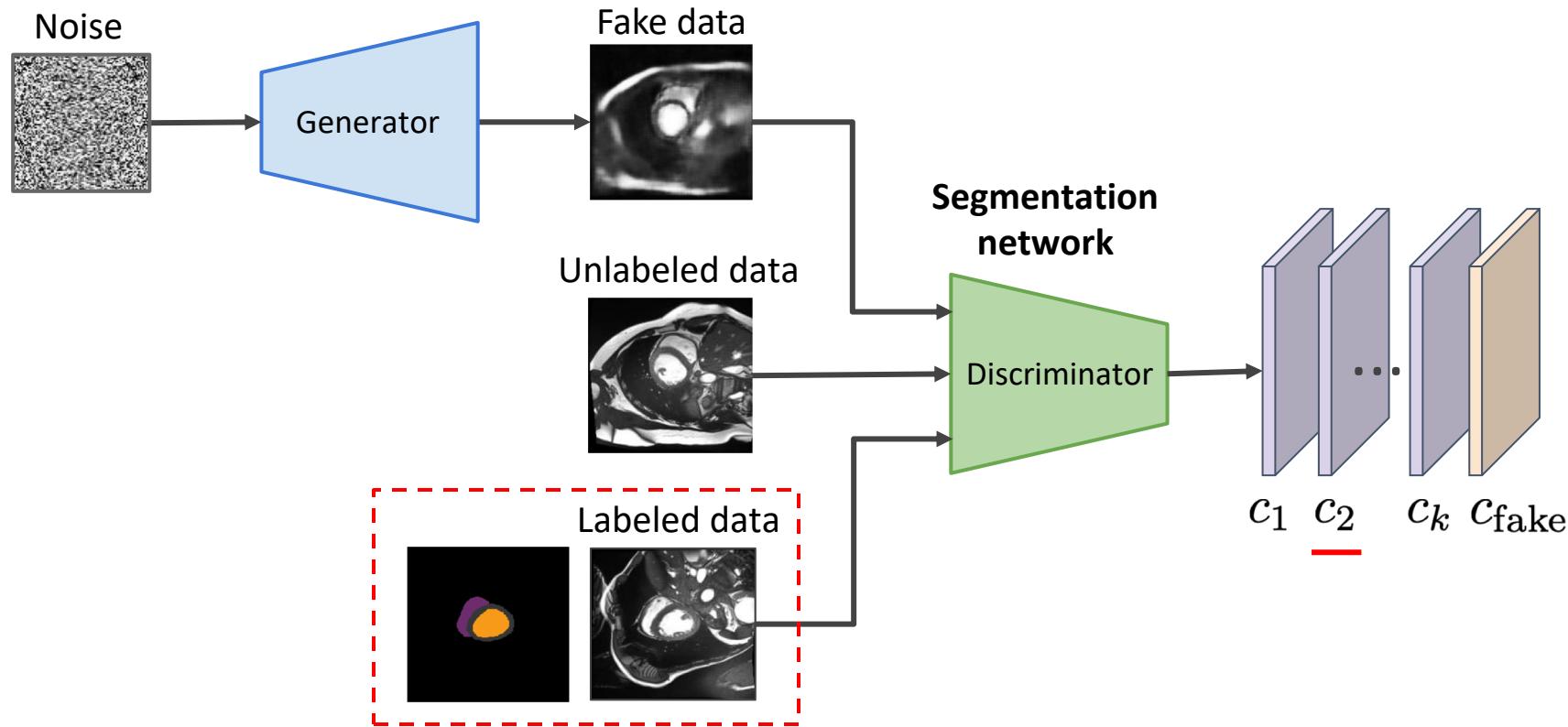
Can we use GAN-generated images to boost learning in a semi-supervised setting ?



- Segmentation network is now considered as a **pixel-level discriminator**
- For each pixel, predicts the class label or an extra *fake* label

Semi-supervised segmentation with GANs

Can we use GAN-generated images to boost learning in a semi-supervised setting ?

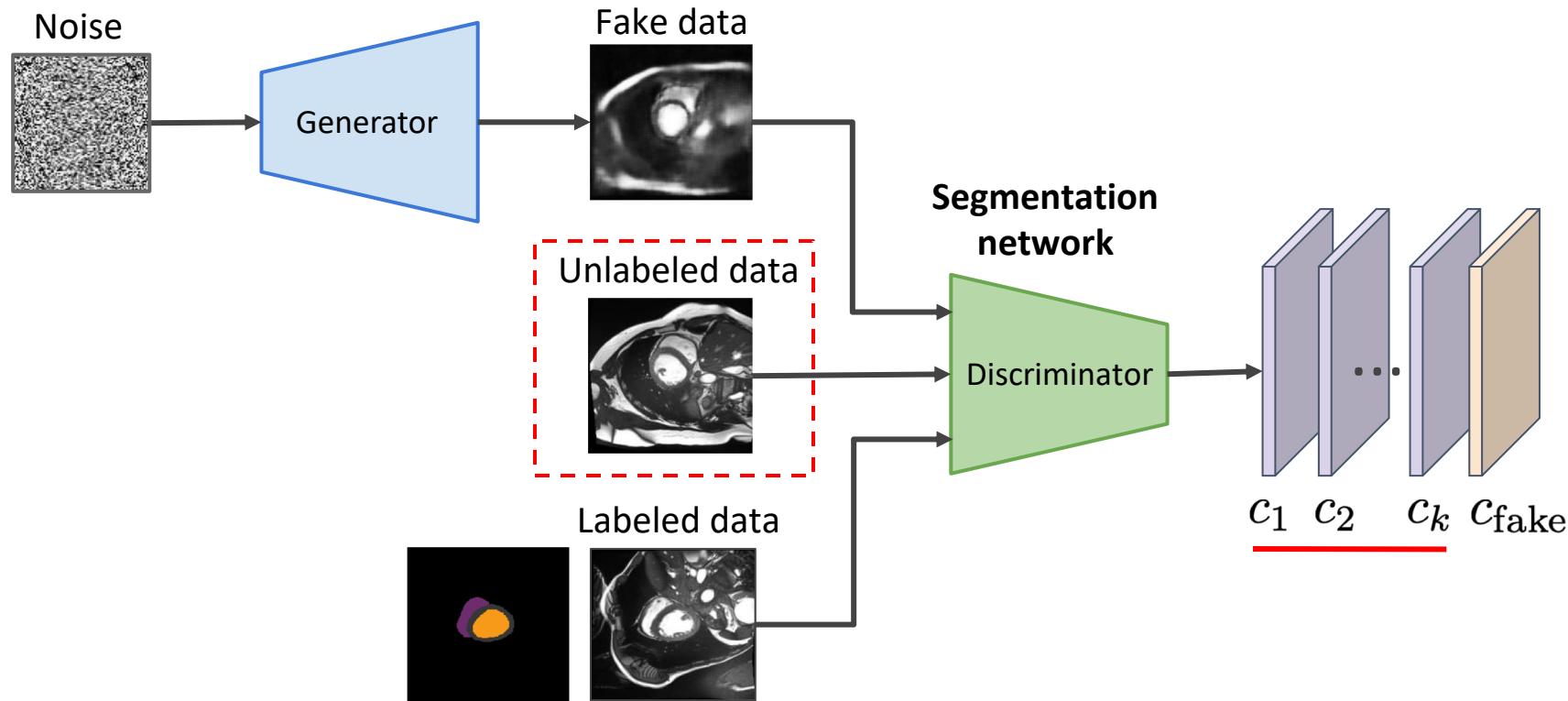


Labeled data: Predict the ground-truth label as in standard supervised segmentation

$$\mathcal{L}_{\text{sup}}(D) = \mathbb{E}_{(x,y) \sim p_{\text{data}}(x,y)} \left[- \sum_i \log p(Y_i = y_i | x) \right]$$

Semi-supervised segmentation with GANs

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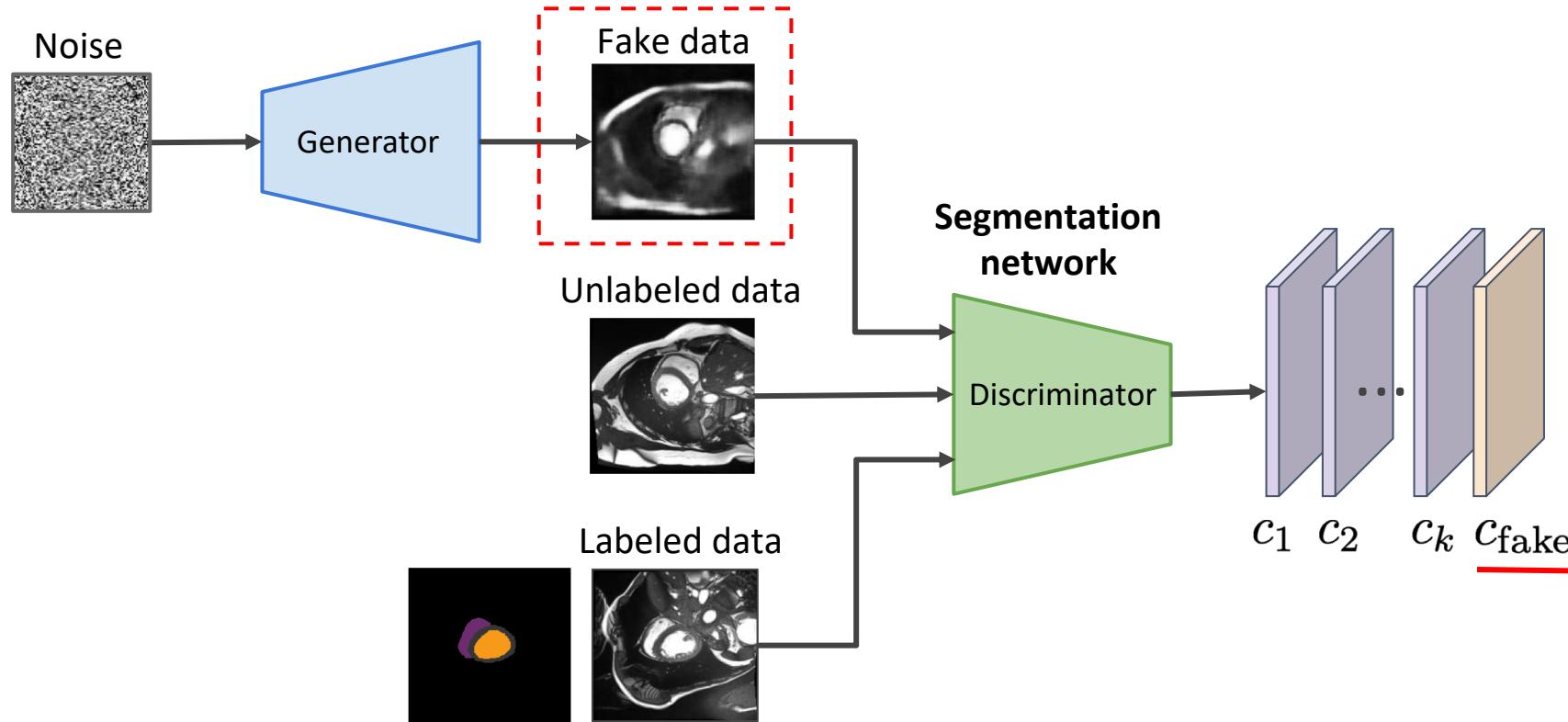


Unlabeled data: Predict the any label except fake

$$\mathcal{L}_{\text{unsup}}(D) = \mathbb{E}_{x \sim p_{\text{data}}(x)} \left[- \sum_i \log p(Y_i \neq \text{fake} | x) \right] = \mathbb{E}_{x \sim p_{\text{data}}(x)} \left[- \sum_i \log (1 - p(Y_i = \text{fake} | x)) \right]$$

Semi-supervised segmentation with GANs

Can we use GAN-generated images to boost learning in a semi-supervised setting ?

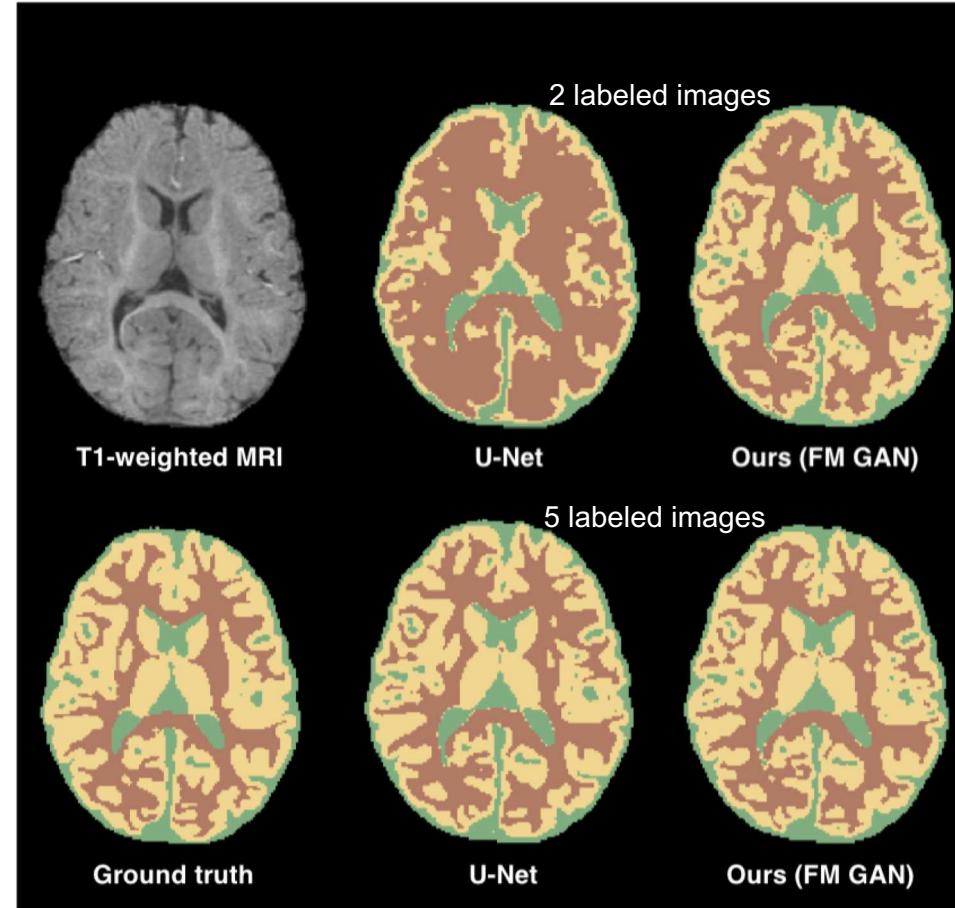
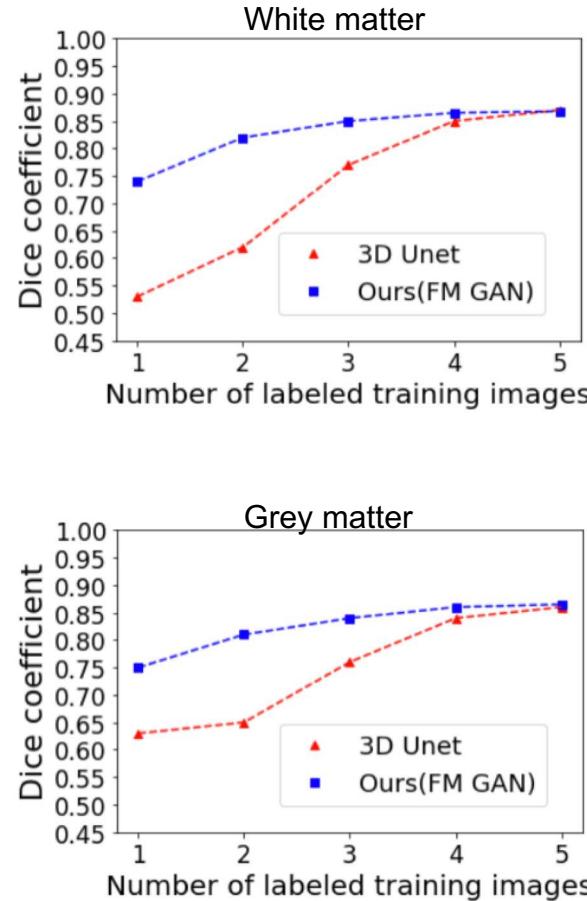


Fake data: Predict the label fake at every pixel

$$\mathcal{L}_{fake}(G, D) = \mathbb{E}_{z \sim p_z(z)} \left[- \sum_i \log p(Y_i = \text{fake} | G(z)) \right]$$

Semi-supervised segmentation with GANs

Application to brain segmentation with very few training images

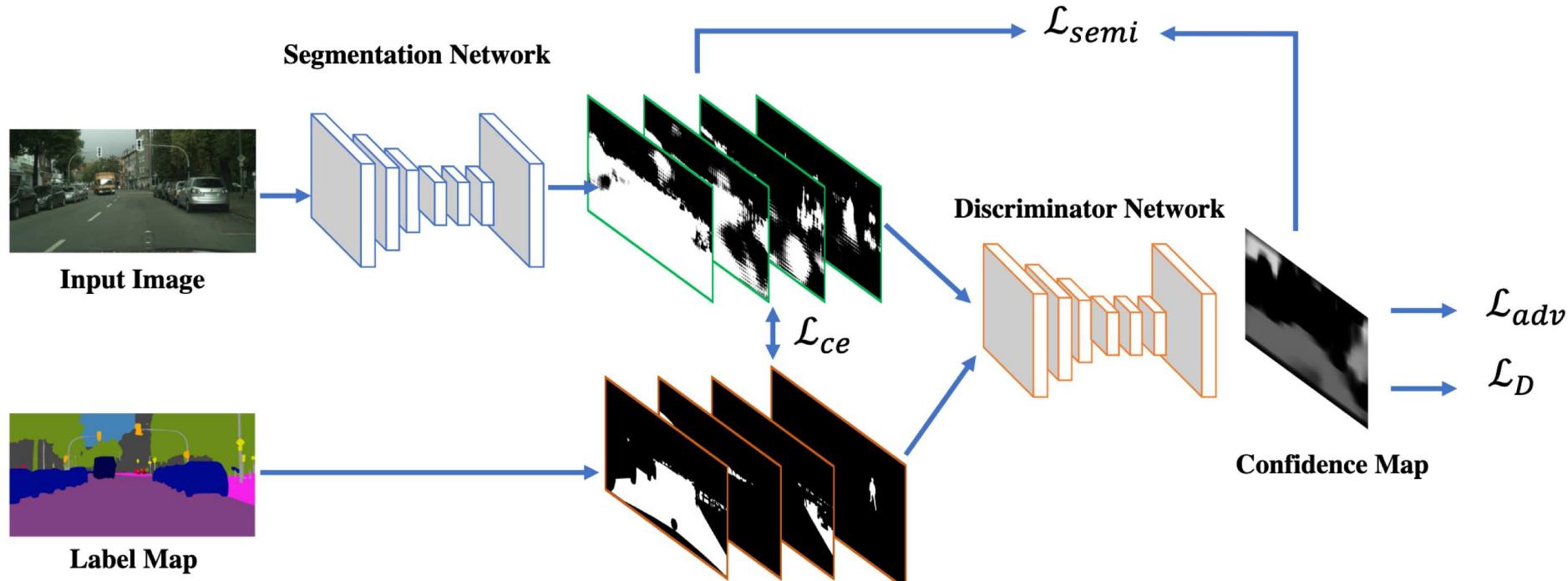


Adversarial model for self-training

How else can we leverage discriminator predictions at the pixel-level ?

Adversarial model for self-training

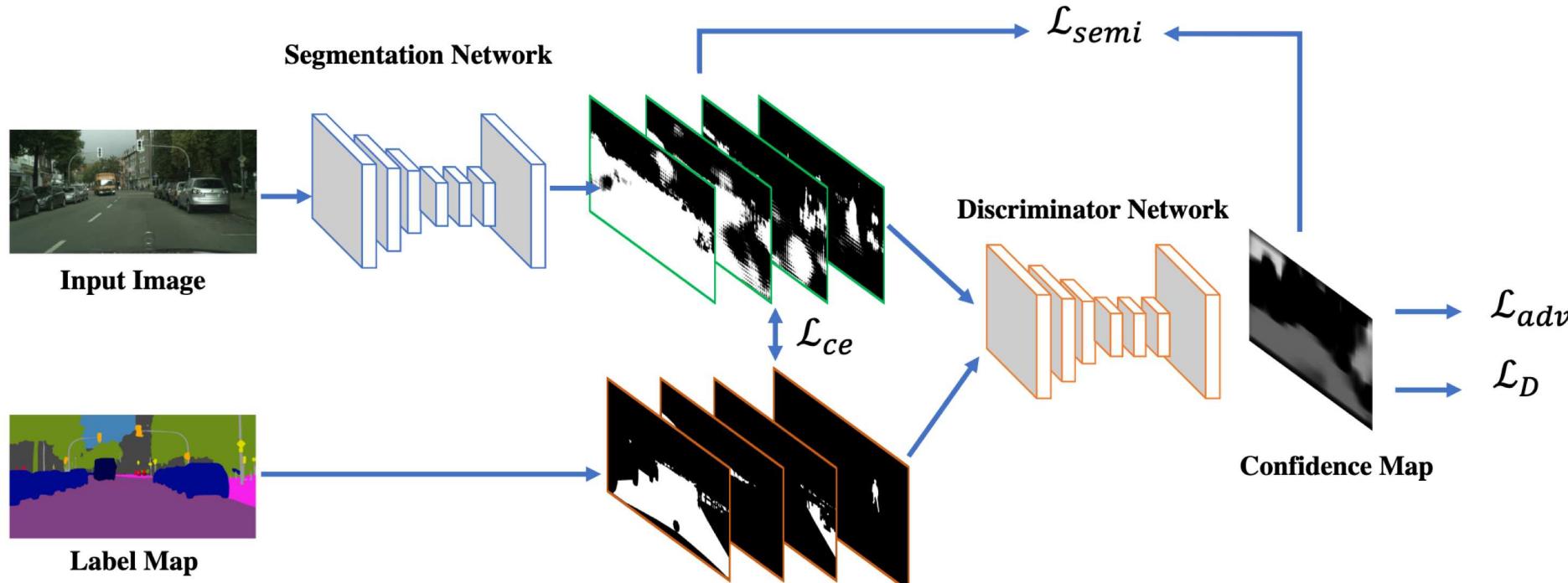
How else can we leverage discriminator predictions at the pixel-level ?



- The discriminator must discriminate between prediction and ground-truth (GT) at each pixel
- Consider the discriminator GT-class probabilities as confidence scores
- Use high-confidence predictions on unlabeled images as pseudo-labels for self-training

Adversarial model for self-training

How else can we leverage discriminator predictions at the pixel-level ?

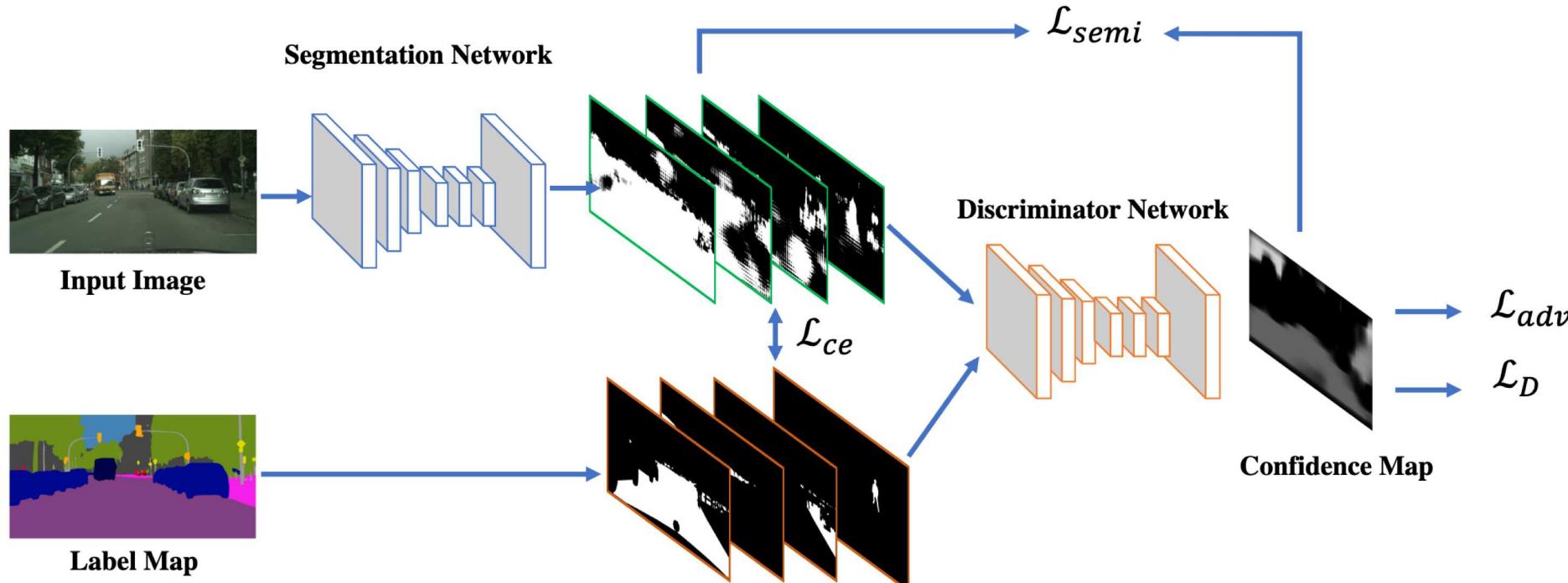


Select pixels with confidence above a given threshold

$$\mathcal{L}_{semi} = - \sum_{h,w} \sum_{c \in C} I(D(S(\mathbf{X}_n))^{(h,w)} > T_{semi}) \cdot \hat{\mathbf{Y}}_n^{(h,w,c)} \log(S(\mathbf{X}_n)^{(h,w,c)})$$
$$\hat{\mathbf{Y}}_n^{(h,w,c^*)} = 1 \text{ if } c^* = \arg \max_c S(\mathbf{X}_n)^{(h,w,c)}$$

Adversarial model for self-training

How else can we leverage discriminator predictions at the pixel-level ?



Use class with highest probability as pseudo-label

$$\mathcal{L}_{semi} = - \sum_{h,w} \sum_{c \in C} I(D(S(\mathbf{X}_n))^{(h,w)} > T_{semi}) \cdot \hat{\mathbf{Y}}_n^{(h,w,c)} \log(S(\mathbf{X}_n)^{(h,w,c)})$$
$$\hat{\mathbf{Y}}_n^{(h,w,c^*)} = 1 \text{ if } c^* = \arg \max_c S(\mathbf{X}_n)^{(h,w,c)}$$

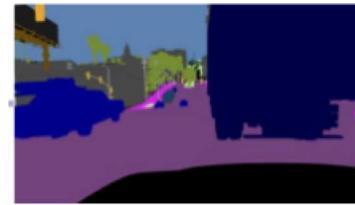
Cycle GANs for domain adaptation

How can we learn a model to segment target images without paired images or GT ?

Source domain



Image



Ground-truth

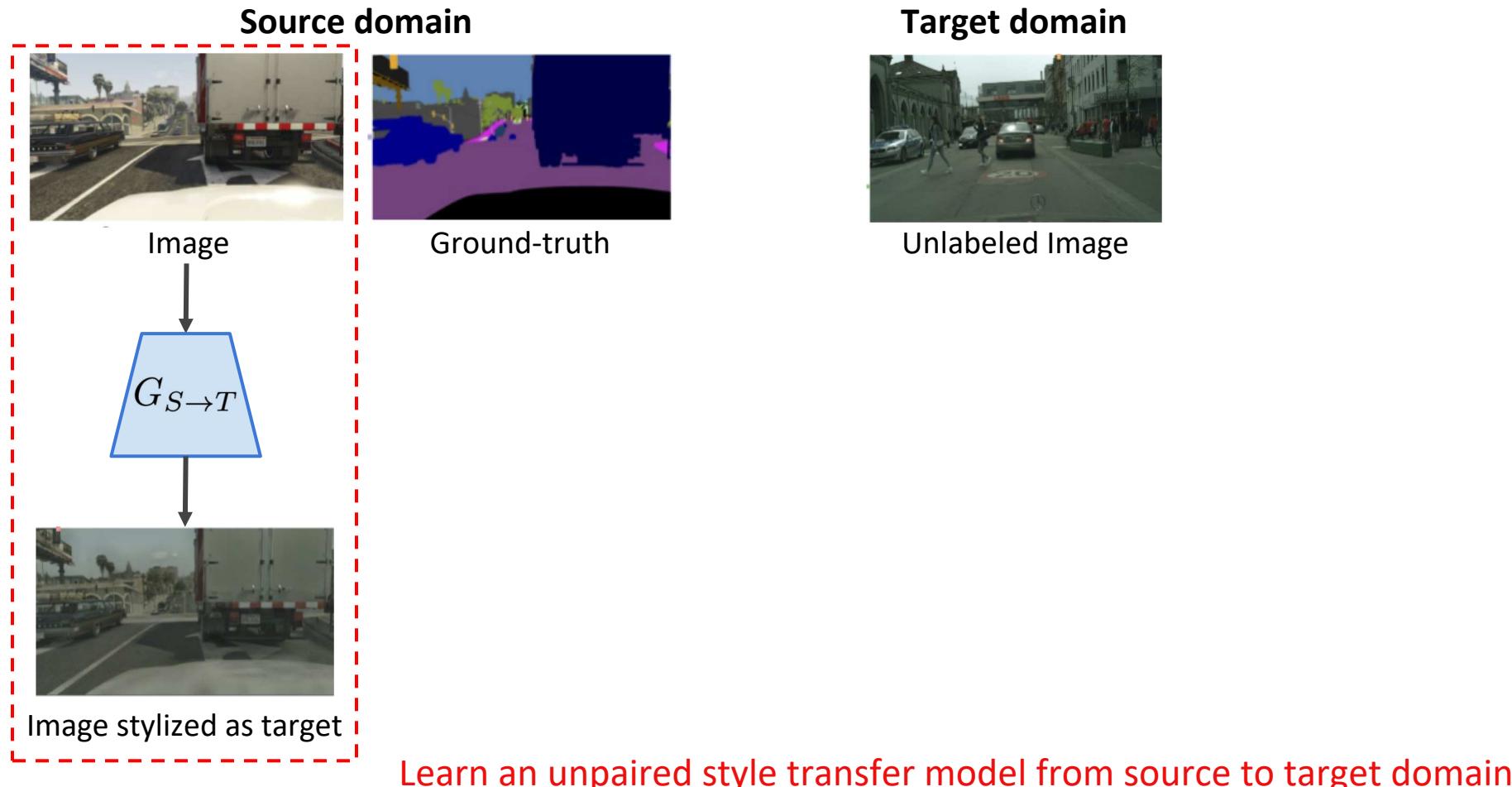
Target domain



Unlabeled Image

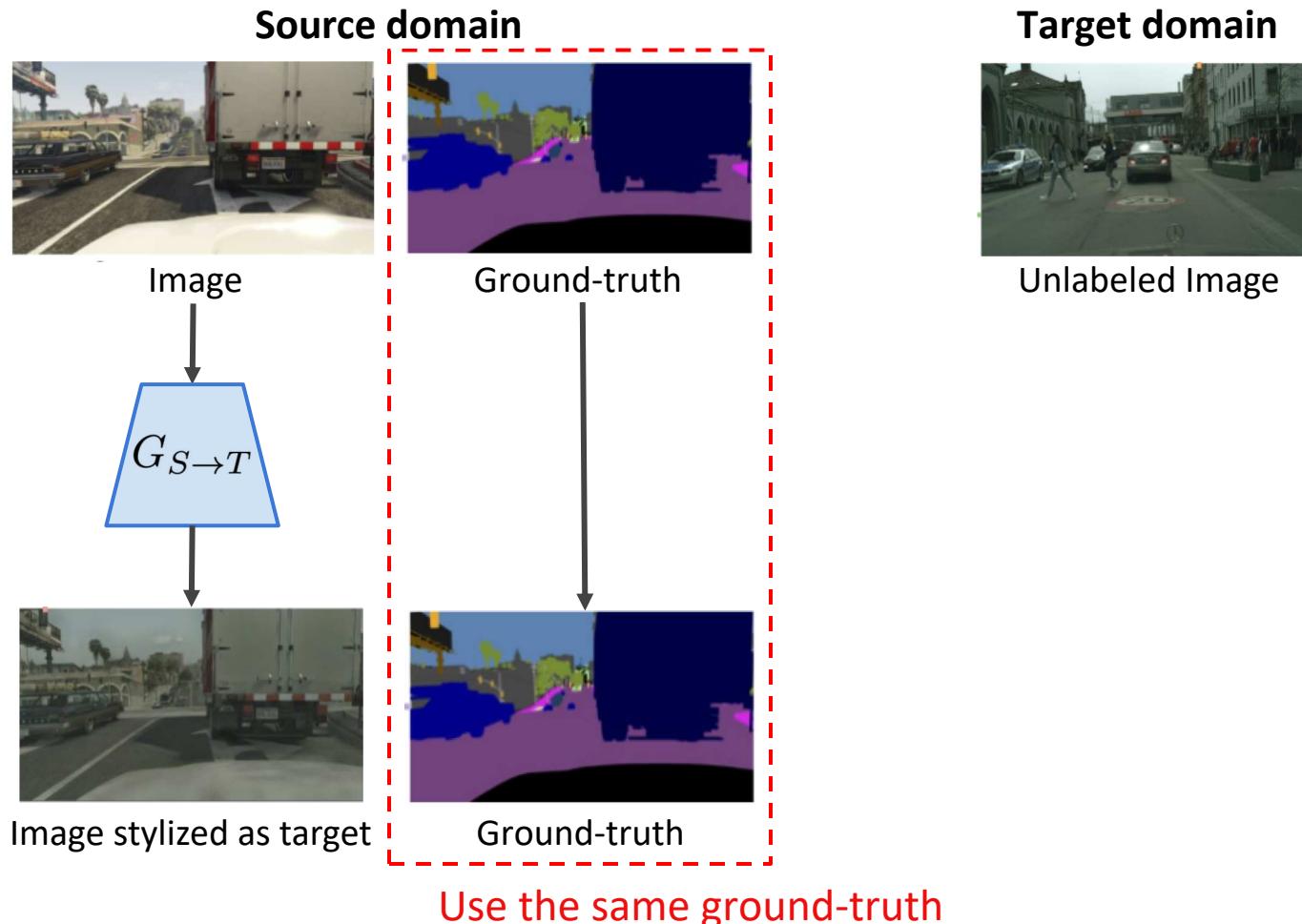
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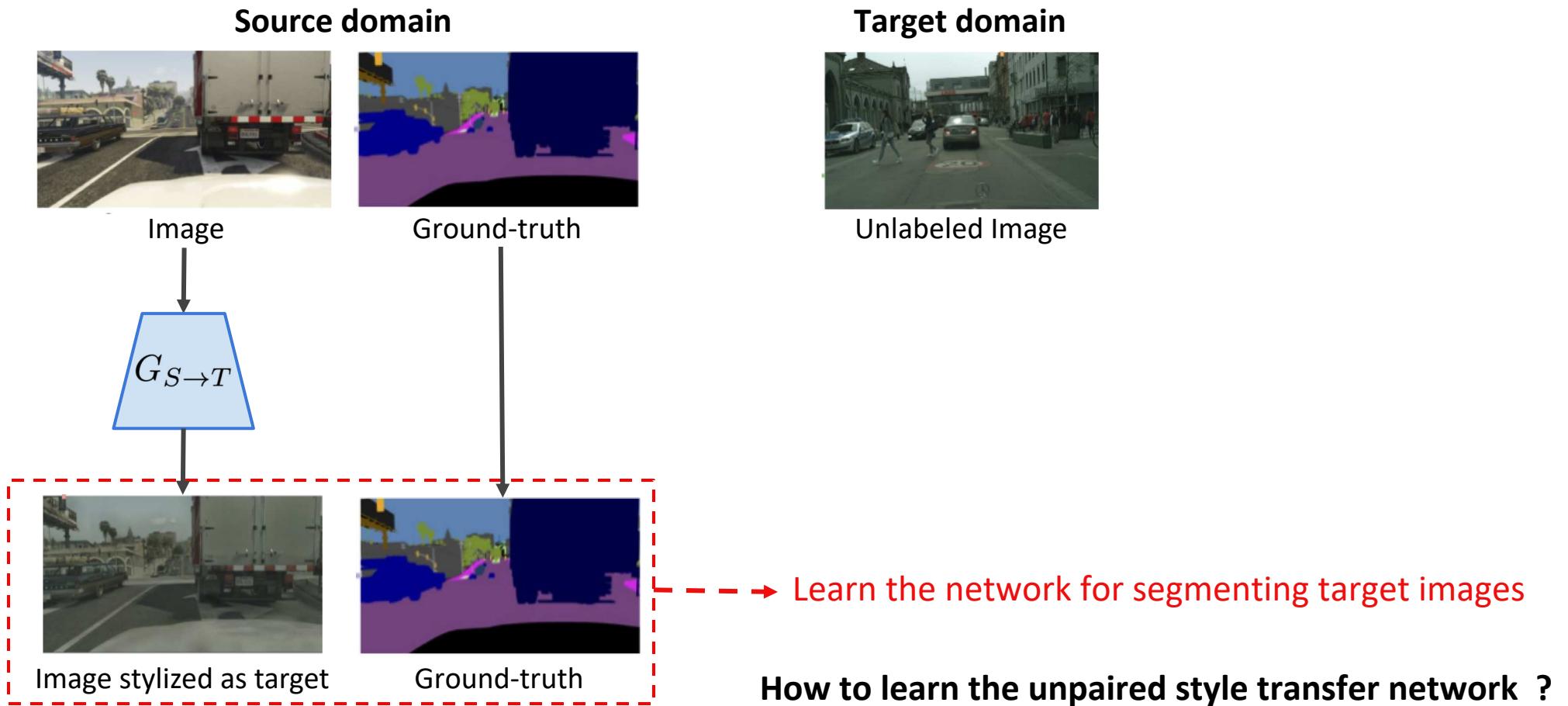
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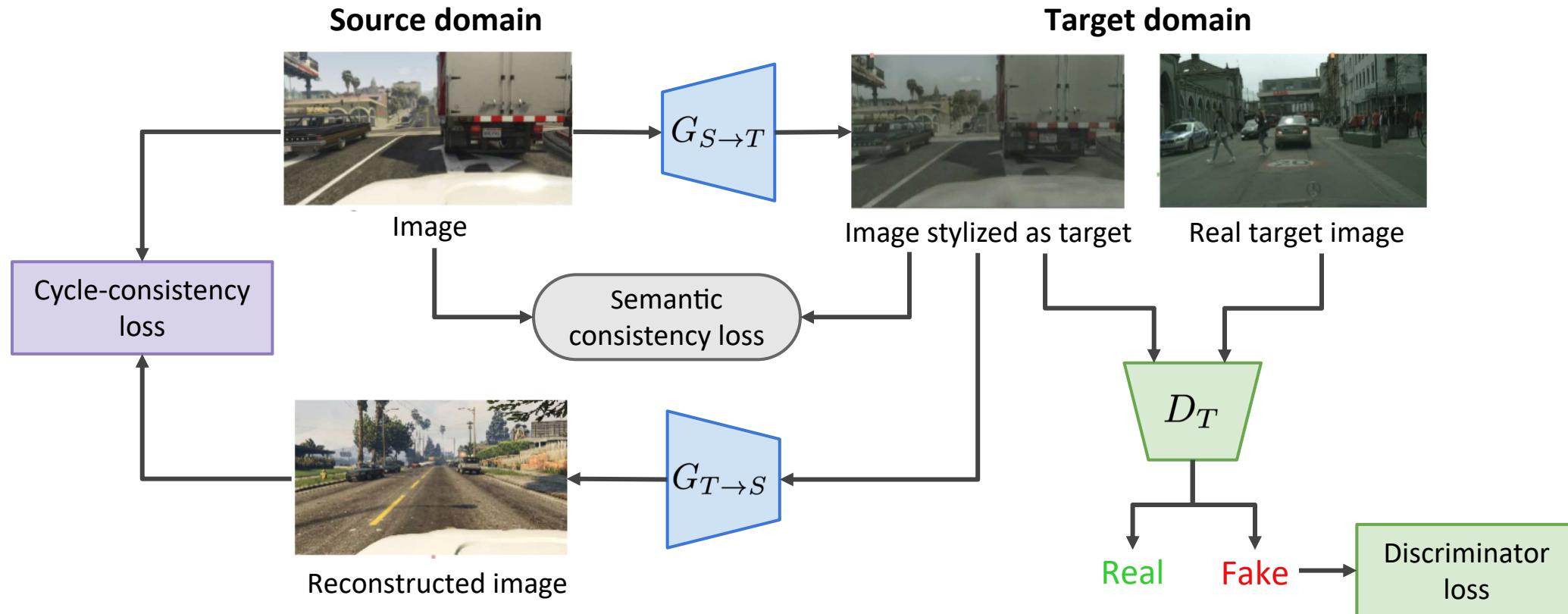
Cycle GANs for domain adaptation

How can we learn a model to segment target images without paired images or GT ?



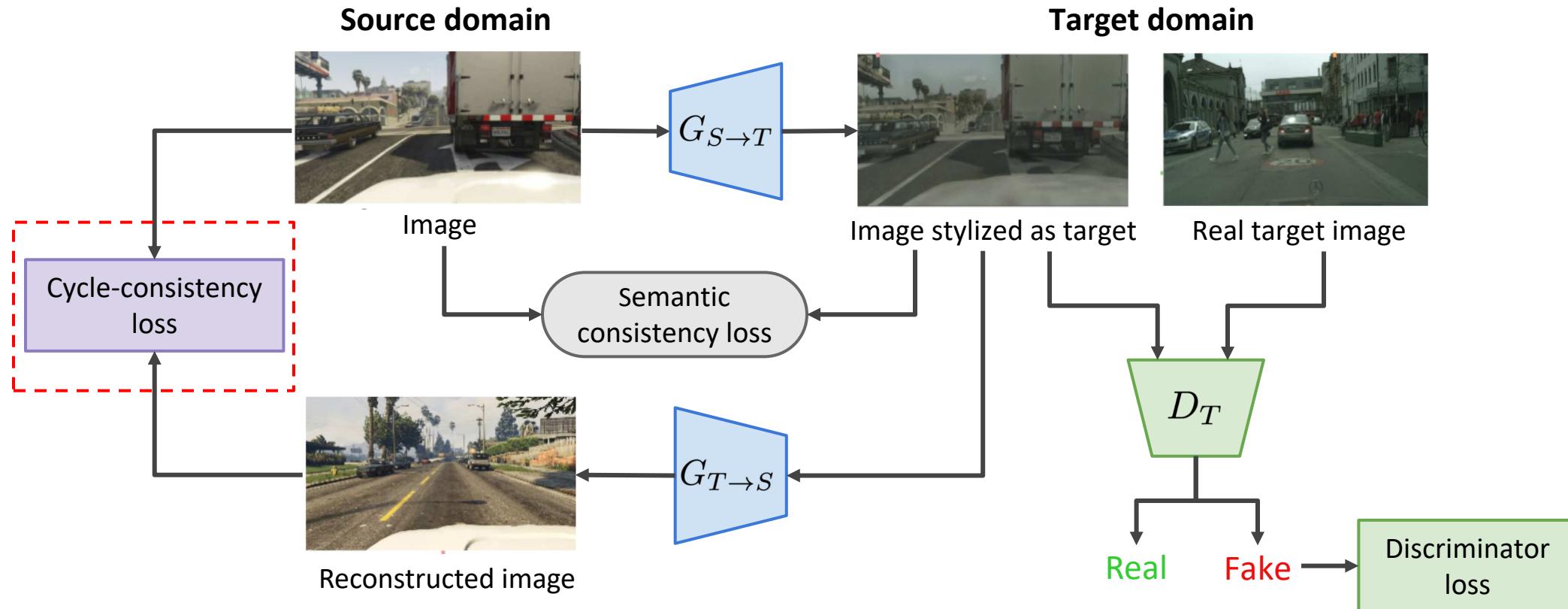
Cycle GANs for domain adaptation

How can we learn a model to segment target images without paired images or GT ?



Cycle GANs for domain adaptation

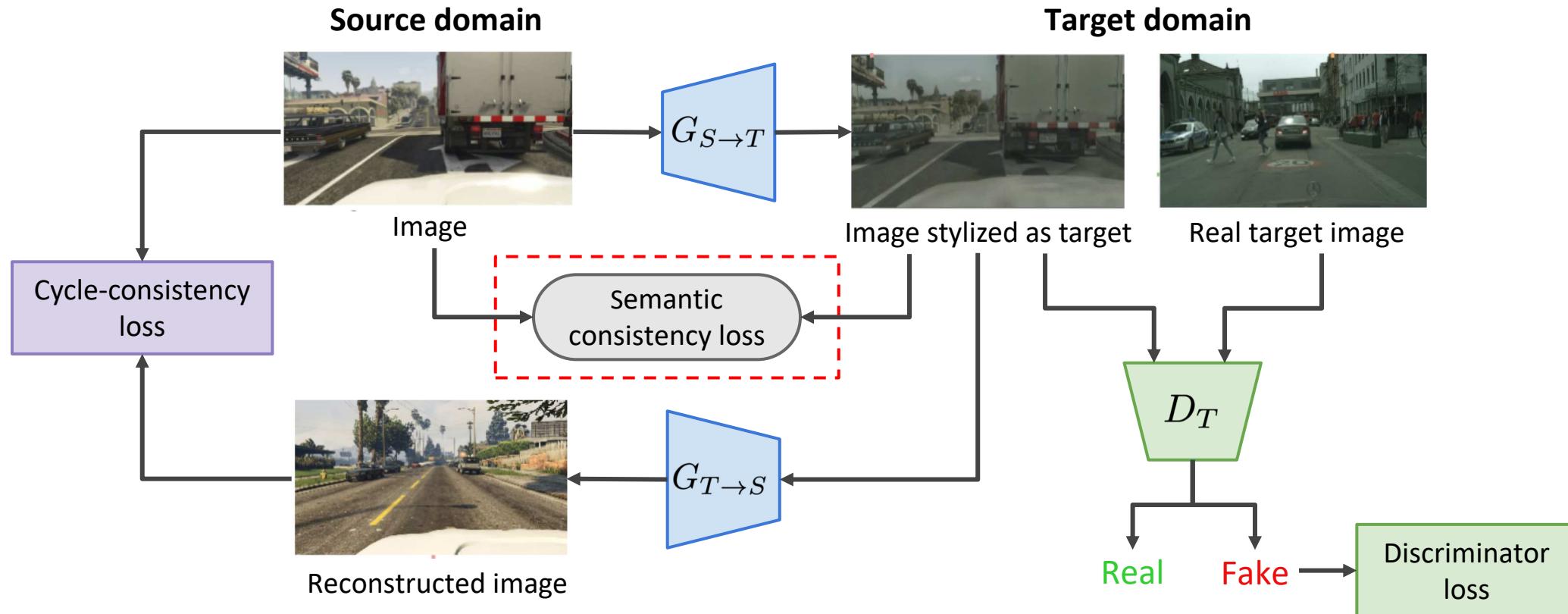
How can we learn a model to segment target images without paired images or GT ?



$$\text{Cycle consistency loss: } L_{\text{cycle}}(G_{S \rightarrow T}, G_{T \rightarrow S}) = \mathbb{E}_{x \sim p_S(x)} \left[\|x - G_{T \rightarrow S}(G_{S \rightarrow T}(x))\|_1 \right]$$

Cycle GANs for domain adaptation

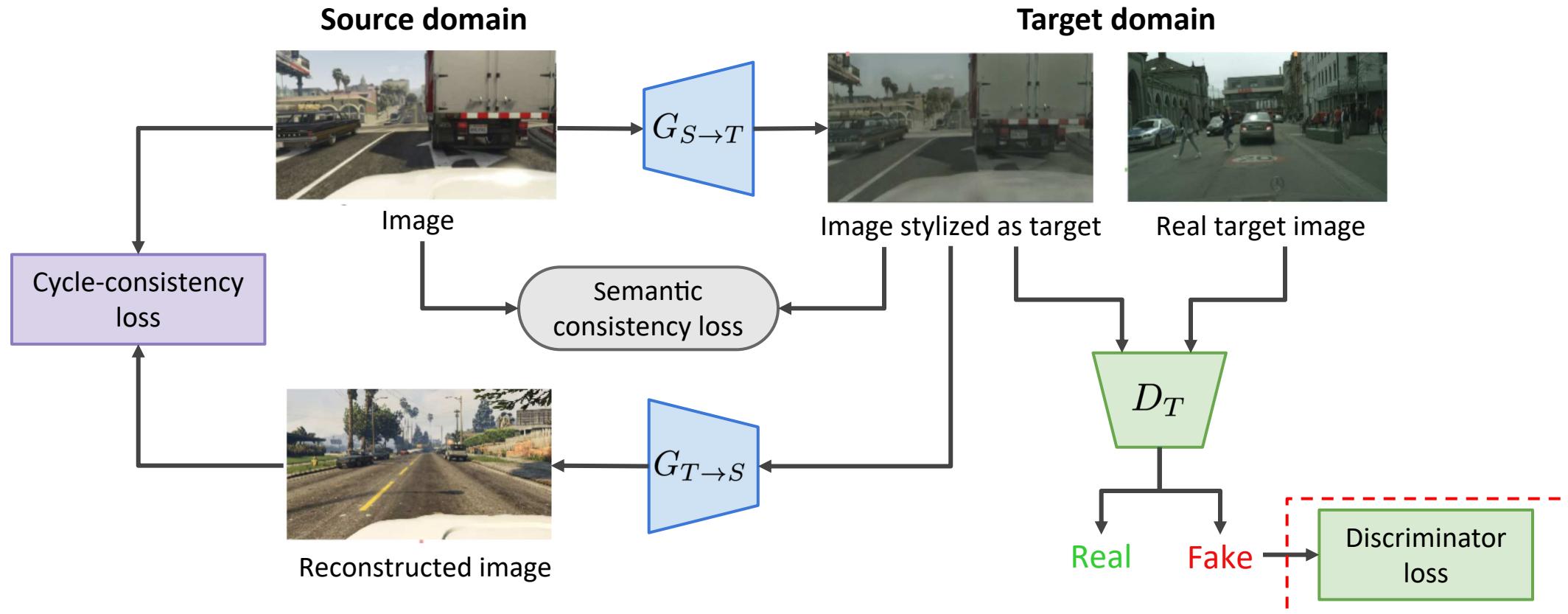
How can we learn a model to segment target images without paired images or GT ?



Semantic consistency loss: Segmentation for the source image and its stylized target version should be consistent

Cycle GANs for domain adaptation

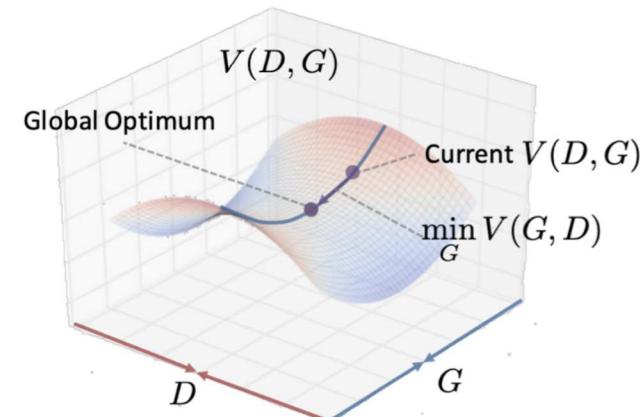
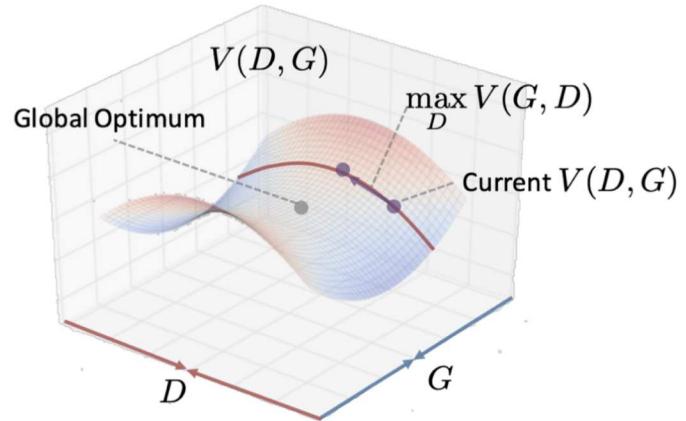
How can we learn a model to segment target images without paired images or GT ?



Discriminator loss: Target images generated from source should look like real target ones

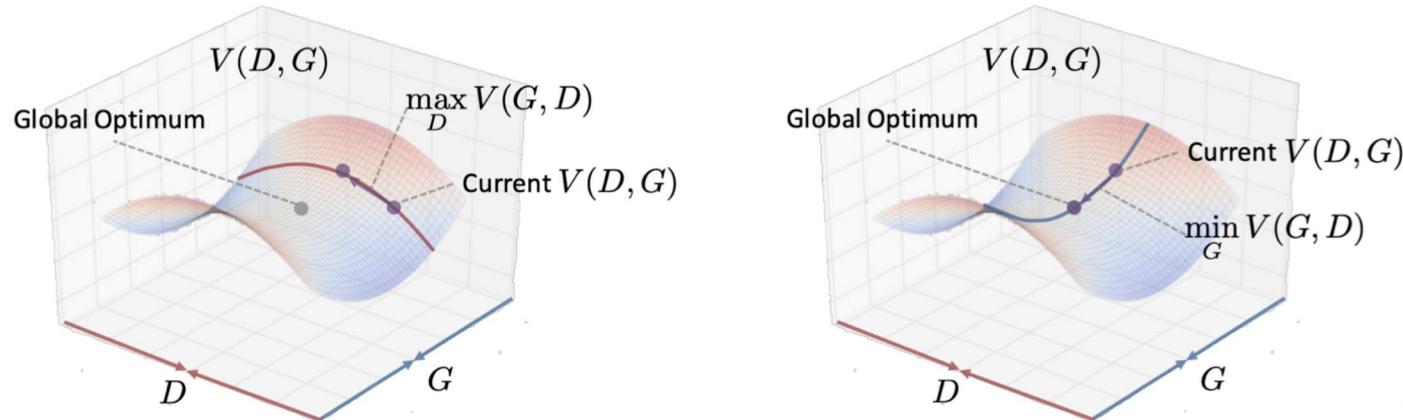
Challenges of adversarial learning

1) Unstable optimization of minimax problem

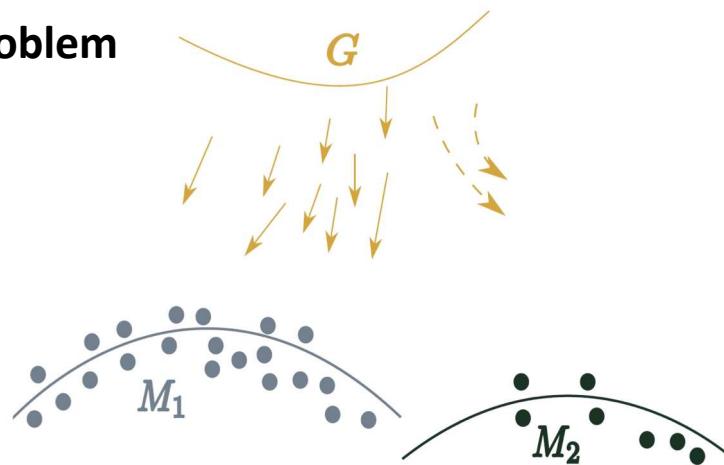


Challenges of adversarial learning

1) Unstable optimization of minimax problem

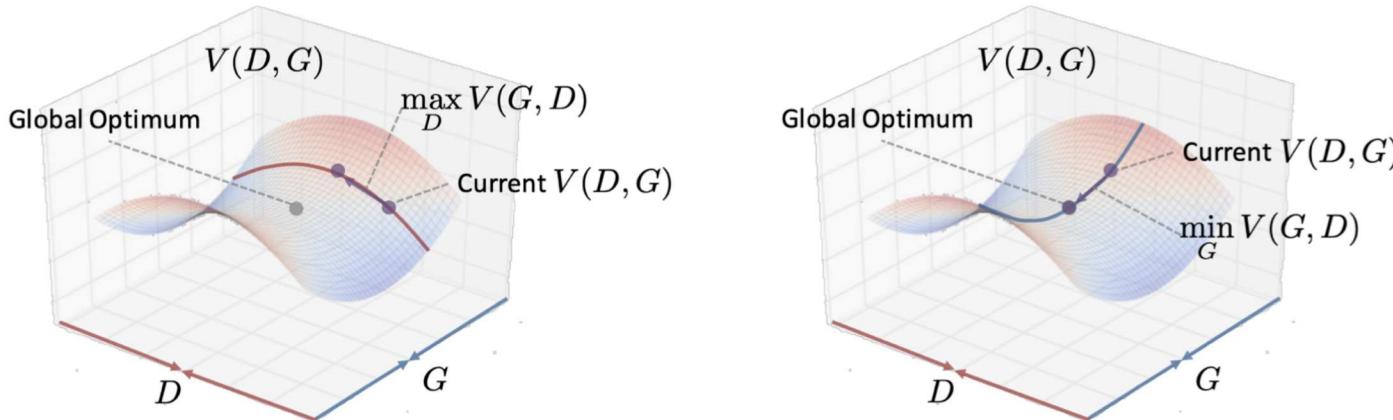


2) Mode collapse problem

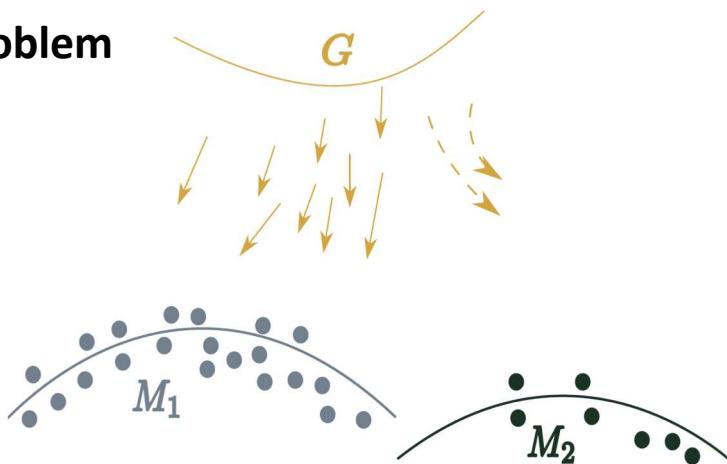


Challenges of adversarial learning

1) Unstable optimization of minimax problem



2) Mode collapse problem



Various solutions:

- Spectral normalization (Miyato *et al.*, 2018)
- Wasserstein GANs (Arjovsky *et al.*, 2017)
- LSGANs (Mao *et al.*, 2017)
- etc.

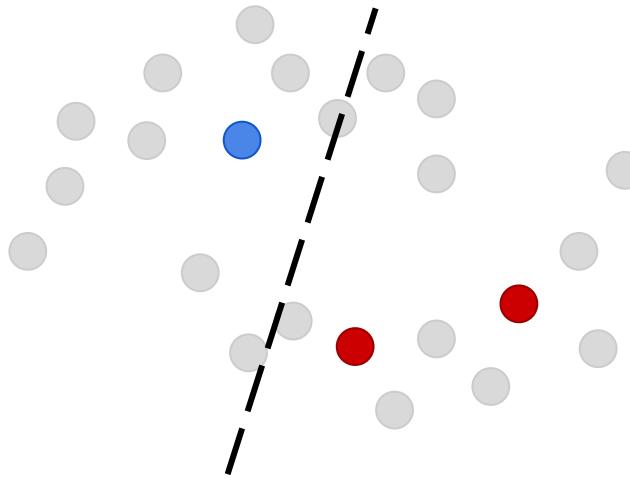
Consistency regularization

for weakly-supervised segmentation

Consistency regularization for SSL

How to better use unlabeled data ?

Vanilla supervised learning

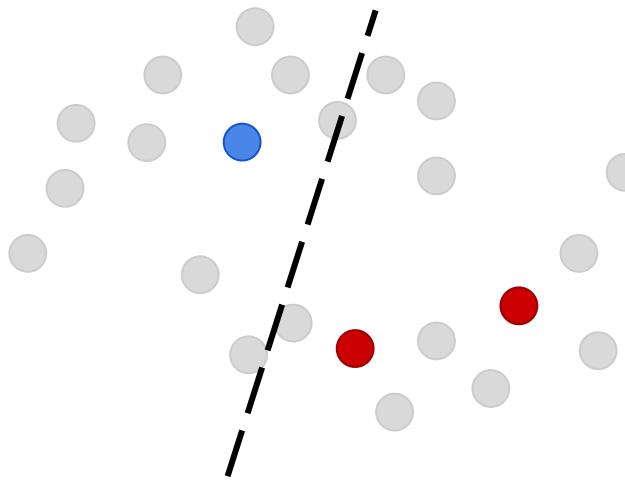


- Consider only labeled samples
- Overfits when few training samples

Consistency regularization for SSL

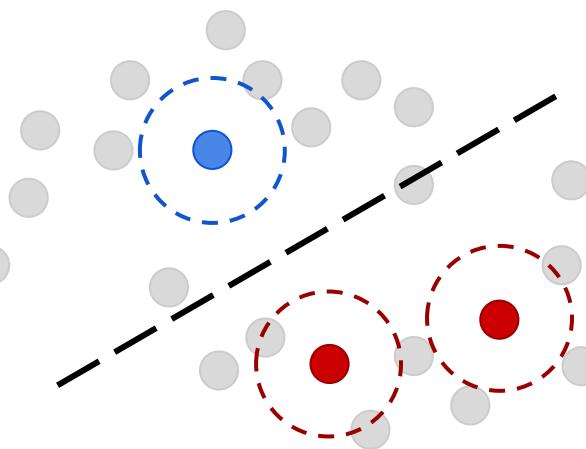
How to better use unlabeled data ?

Vanilla supervised learning



- Consider only labeled samples
- Overfits when few training samples

Data augmentation

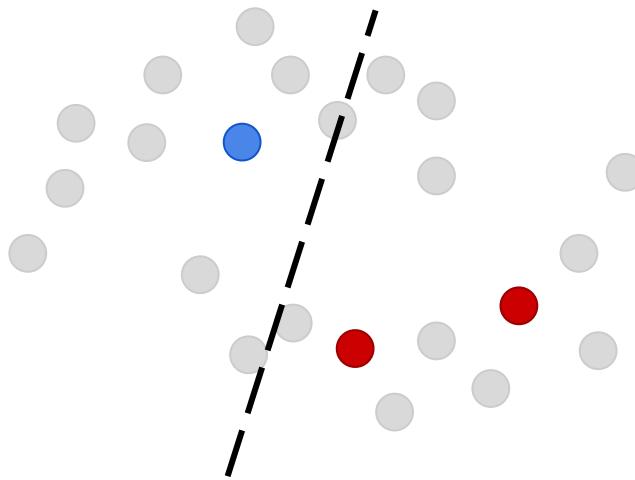


- Transform labeled examples to augment the training set
- Better generalization, but not enough for semi-supervised learning

Consistency regularization for SSL

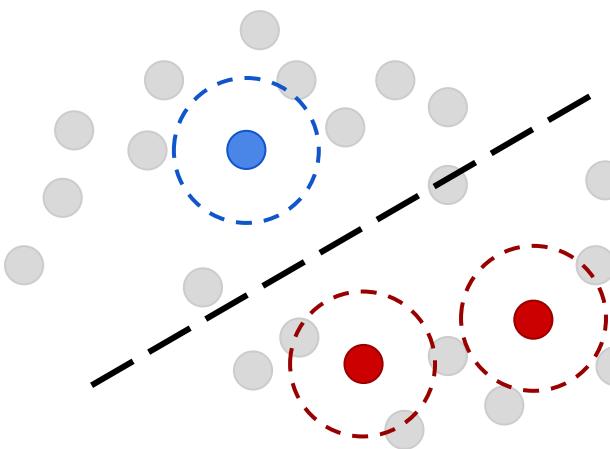
How to better use unlabeled data ?

Vanilla supervised learning



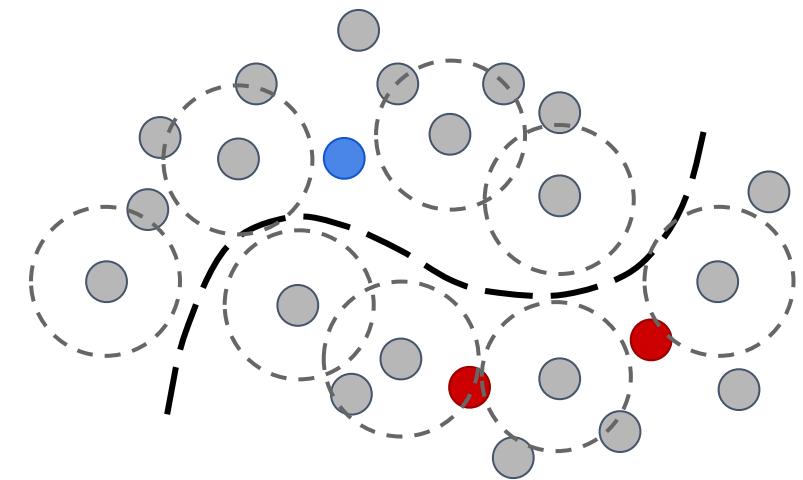
- Consider only labeled samples
- Overfits when few training samples

Data augmentation



- Transform labeled samples to augment the training set
- Better generalization, but not enough for semi-supervised learning

Consistency regularization



- Perturb unlabeled samples with noise or guided transformations
- Impose the network to have consistent outputs for perturbed samples

SSL methods using consistency regularization

Basic transformation consistency (Γ -model)

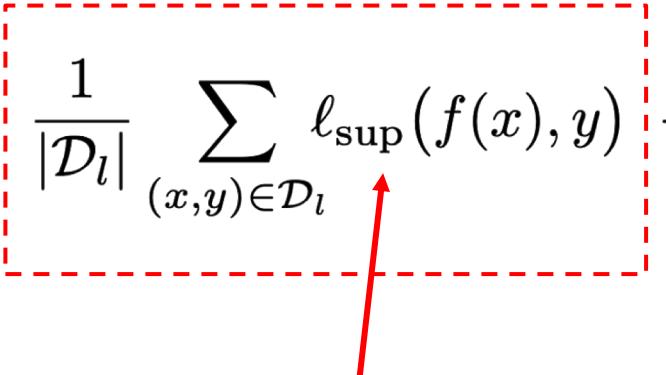
$$\mathcal{L}(\theta; \mathcal{D}_l, \mathcal{D}_u) = \frac{1}{|\mathcal{D}_l|} \sum_{(x,y) \in \mathcal{D}_l} \ell_{\text{sup}}(f(x), y) + \frac{\lambda}{|\mathcal{D}_u|} \sum_{x \in \mathcal{D}_u} \mathbb{E}_{T \sim p_T} [\ell_{\text{reg}}(T(f(x)), f(T(x)))]$$

SSL methods using consistency regularization

Basic transformation consistency (Γ -model)

$$\mathcal{L}(\theta; \mathcal{D}_l, \mathcal{D}_u) = \underbrace{\frac{1}{|\mathcal{D}_l|} \sum_{(x,y) \in \mathcal{D}_l} \ell_{\text{sup}}(f(x), y)}_{\text{Standard supervised loss}} + \frac{\lambda}{|\mathcal{D}_u|} \sum_{x \in \mathcal{D}_u} \mathbb{E}_{T \sim p_T} [\ell_{\text{reg}}(T(f(x)), f(T(x)))]$$

Cross-entropy, Dice, etc.



SSL methods using consistency regularization

Basic transformation consistency (Γ -model)

$$\mathcal{L}(\theta; \mathcal{D}_l, \mathcal{D}_u) = \frac{1}{|\mathcal{D}_l|} \sum_{(x,y) \in \mathcal{D}_l} \ell_{\text{sup}}(f(x), y) +$$

Transformation consistency loss

$$\frac{\lambda}{|\mathcal{D}_u|} \sum_{x \in \mathcal{D}_u} \mathbb{E}_{T \sim p_T} [\ell_{\text{reg}}(T(f(x)), f(T(x)))]$$

Random transformation:
rotation, flip, crop, etc.

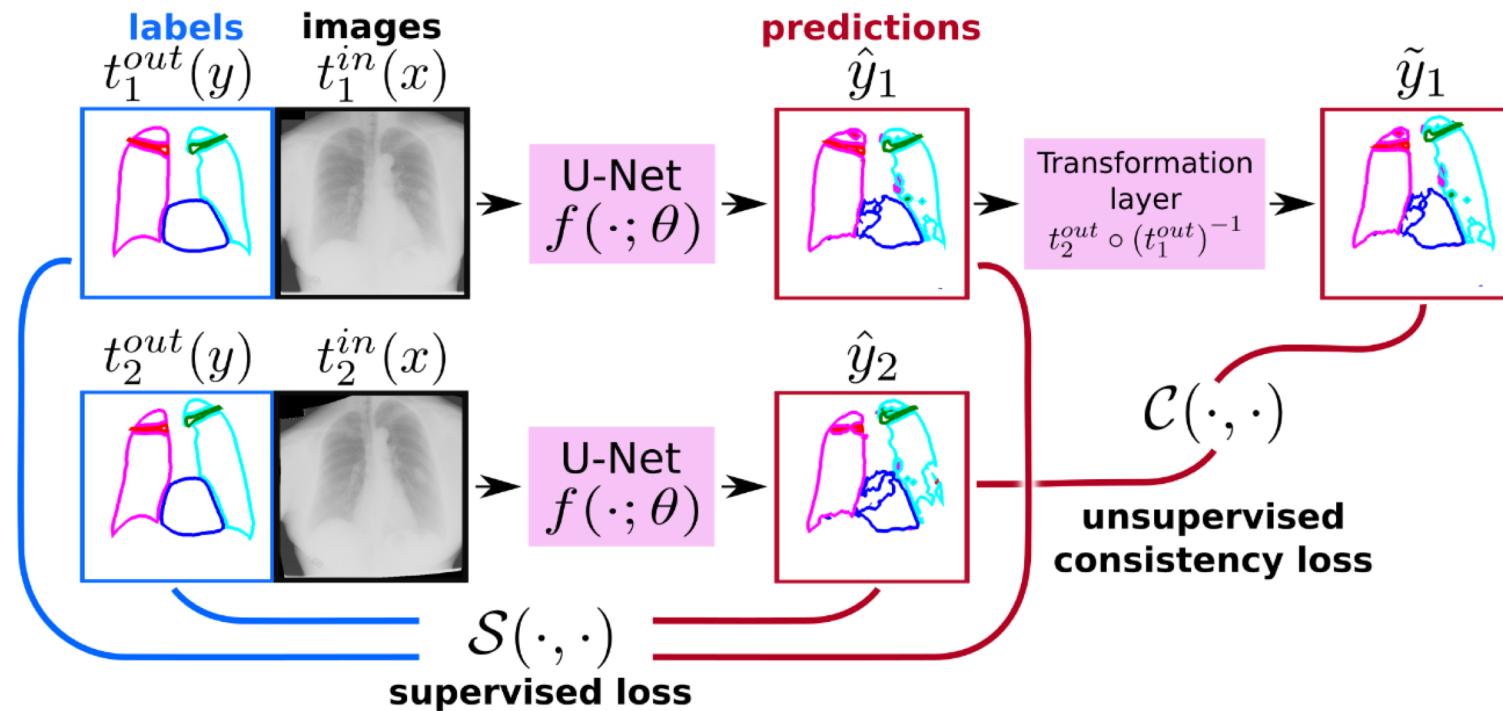
Regularization loss
imposing transformation equivariance

L2 regularization loss:

$$\ell_{\text{reg}}(T(f(x)), f(T(x))) = \|T(f(x)) - f(T(x))\|_2^2$$

SSL methods using consistency regularization

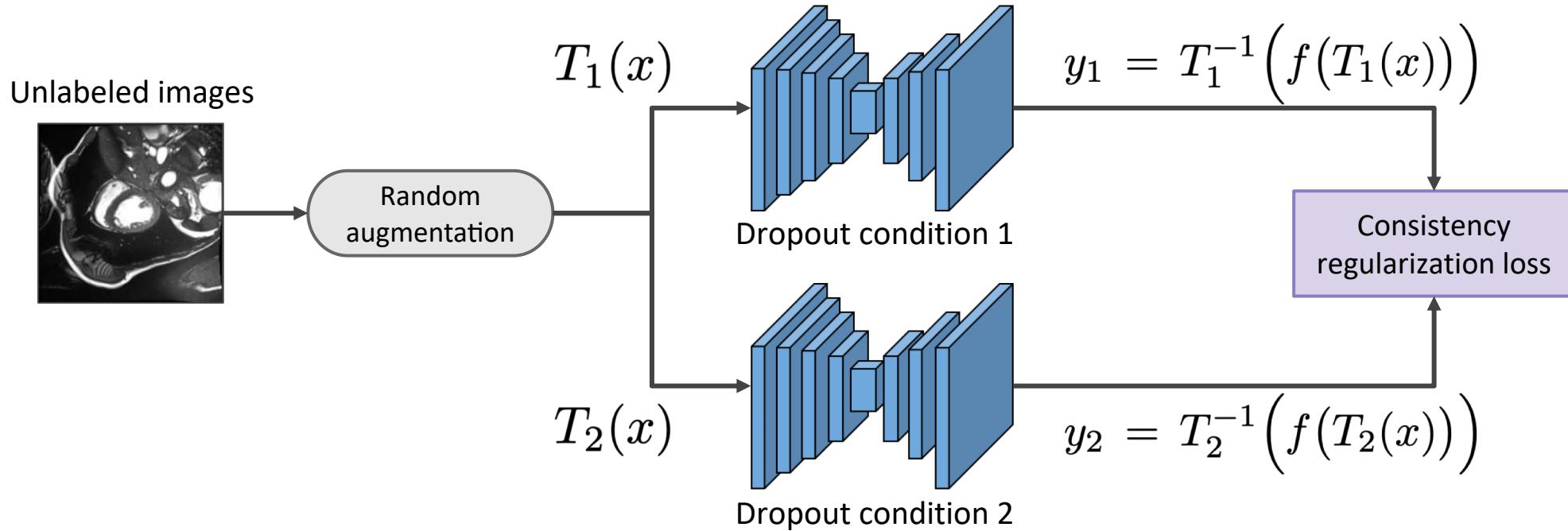
Application to chest X-ray segmentation:



Transformations are random elastic deformations

SSL methods using consistency regularization

Self-ensembling (Π -model):

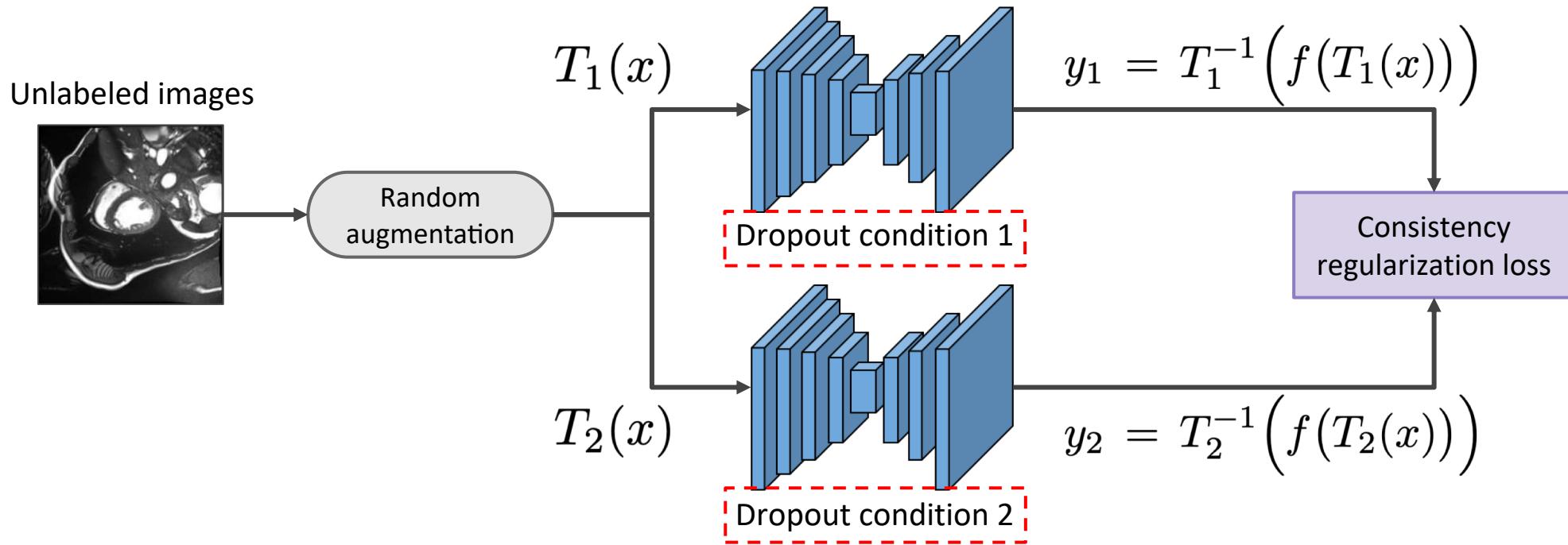


Key idea:

- Applying different dropouts on the same network gives an ensemble of models
- Also leverages random image transformations

SSL methods using consistency regularization

Self-ensembling (Π -model):

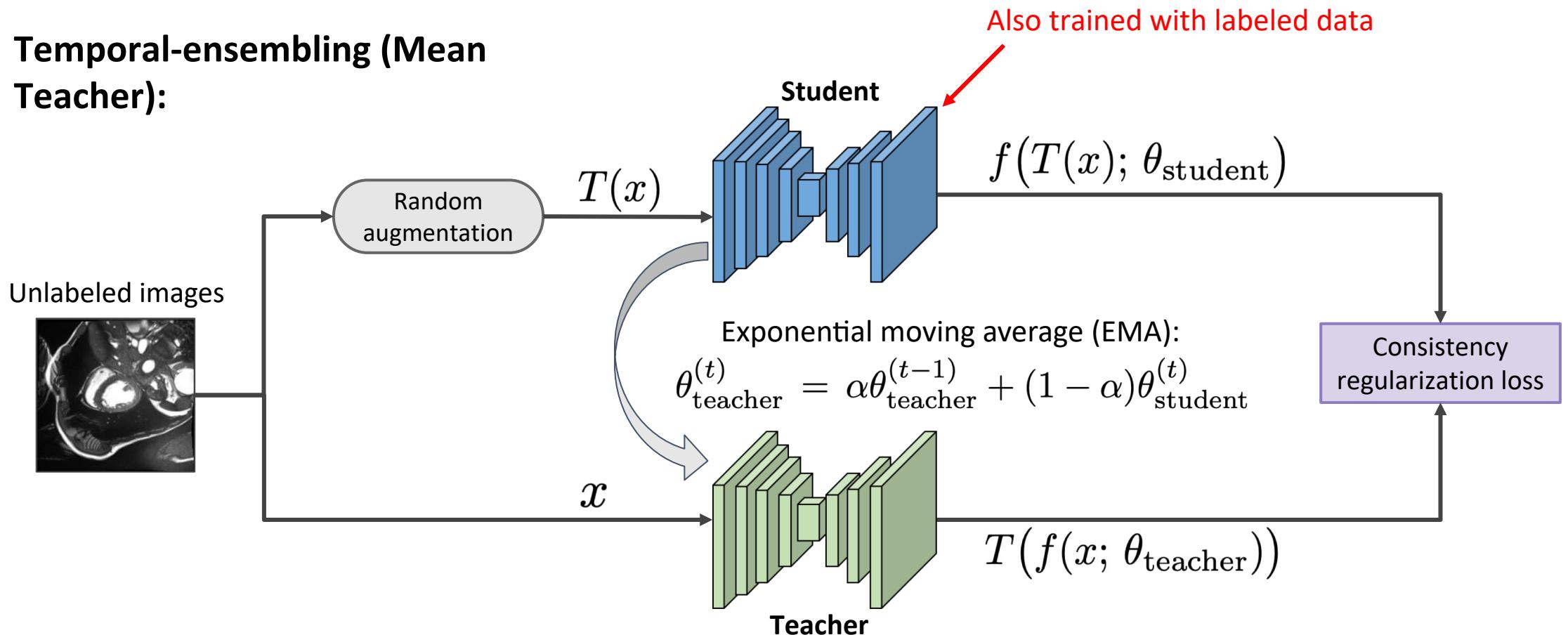


Key idea:

- Applying different dropouts on the same network gives an ensemble of models
- Also leverages random image transformations

SSL methods using consistency regularization

Temporal-ensembling (Mean Teacher):

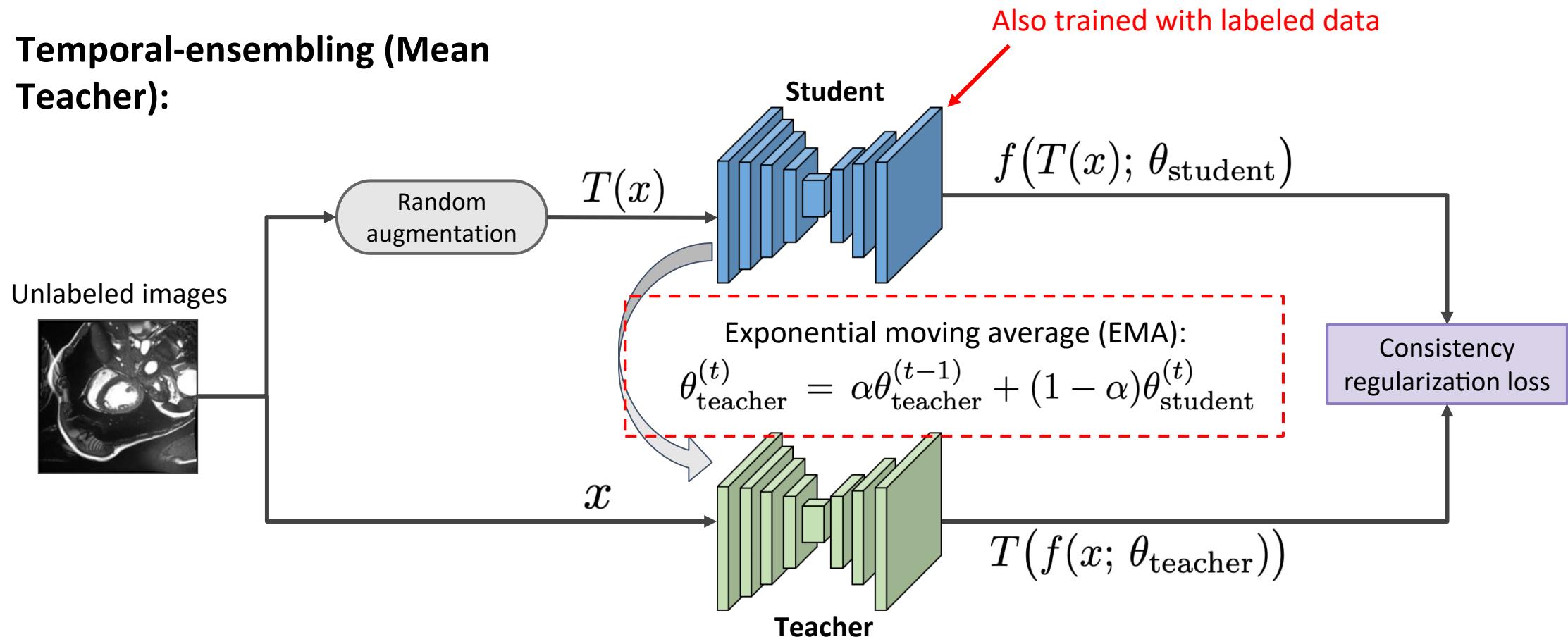


Key idea:

- Consistency between the predictions of a Teacher and a Student network
- The Teacher's weights are an EMA of the Student's at previous training iterations ($\alpha \approx 1$)
- Note: original Temporal Ensembling computes the EMA on outputs for each sample

SSL methods using consistency regularization

Temporal-ensembling (Mean Teacher):

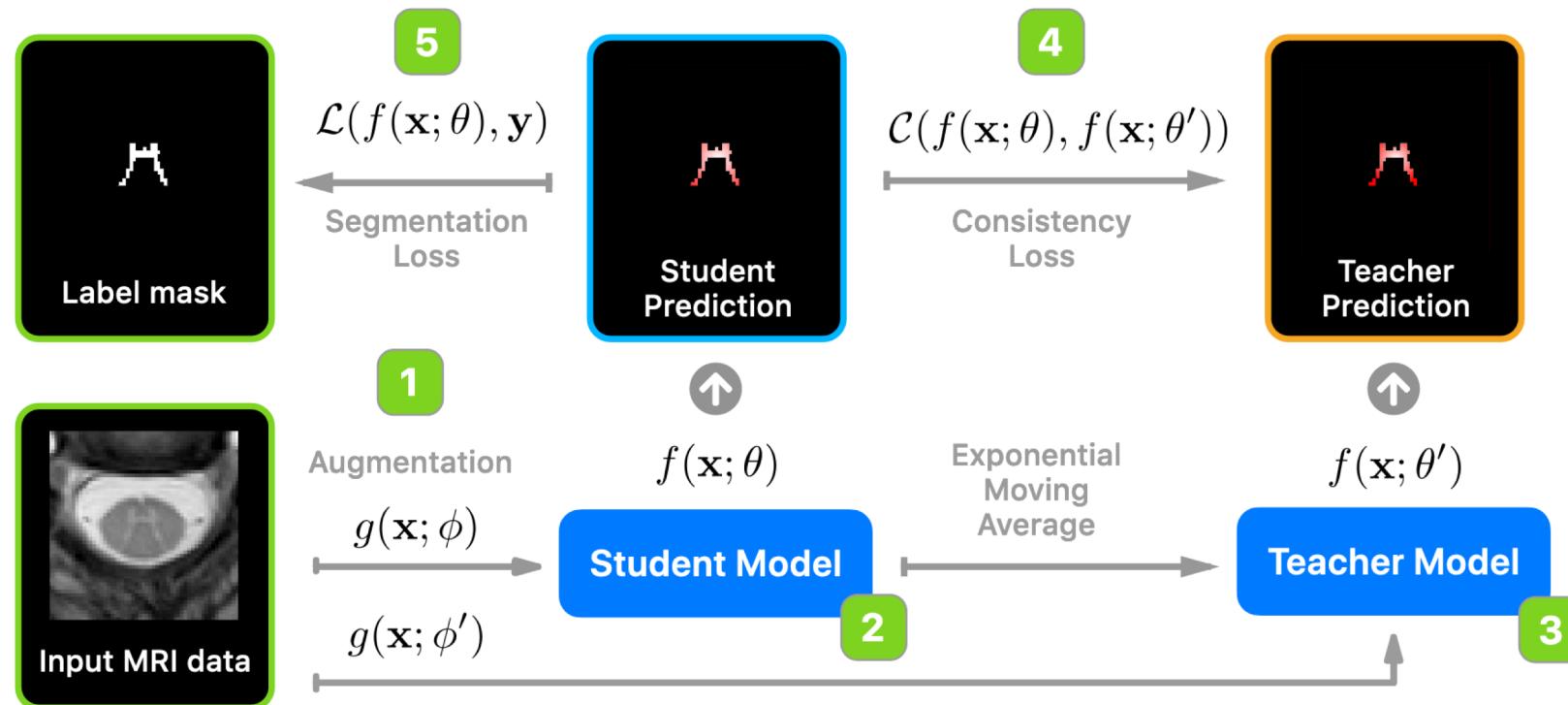


Key idea:

- Consistency between the predictions of a Teacher and a Student network
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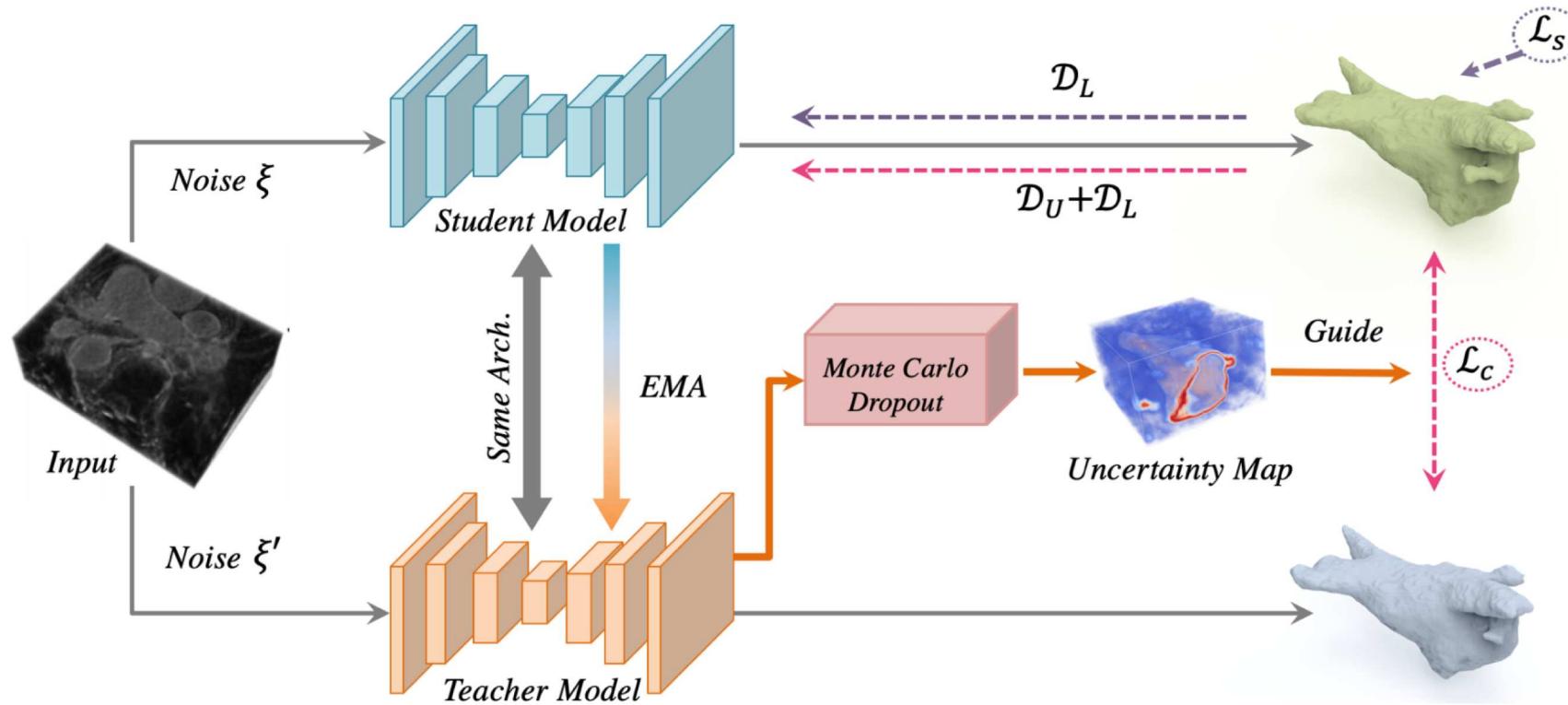
SSL methods using consistency regularization

Application of Mean Teacher to segmenting MRI spinal cord gray matter



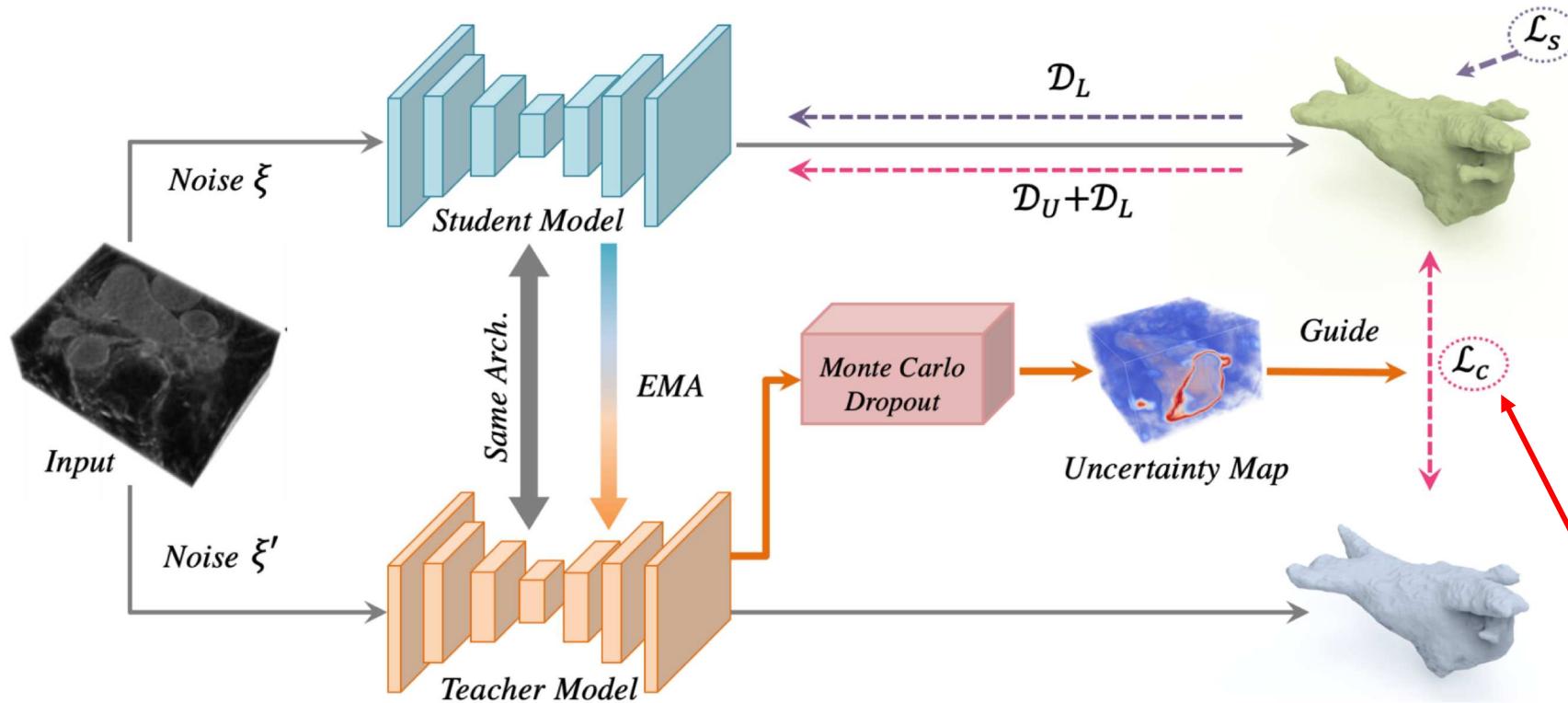
SSL methods using consistency regularization

Uncertainty-aware self-ensembling



SSL methods using consistency regularization

Uncertainty-aware self-ensembling

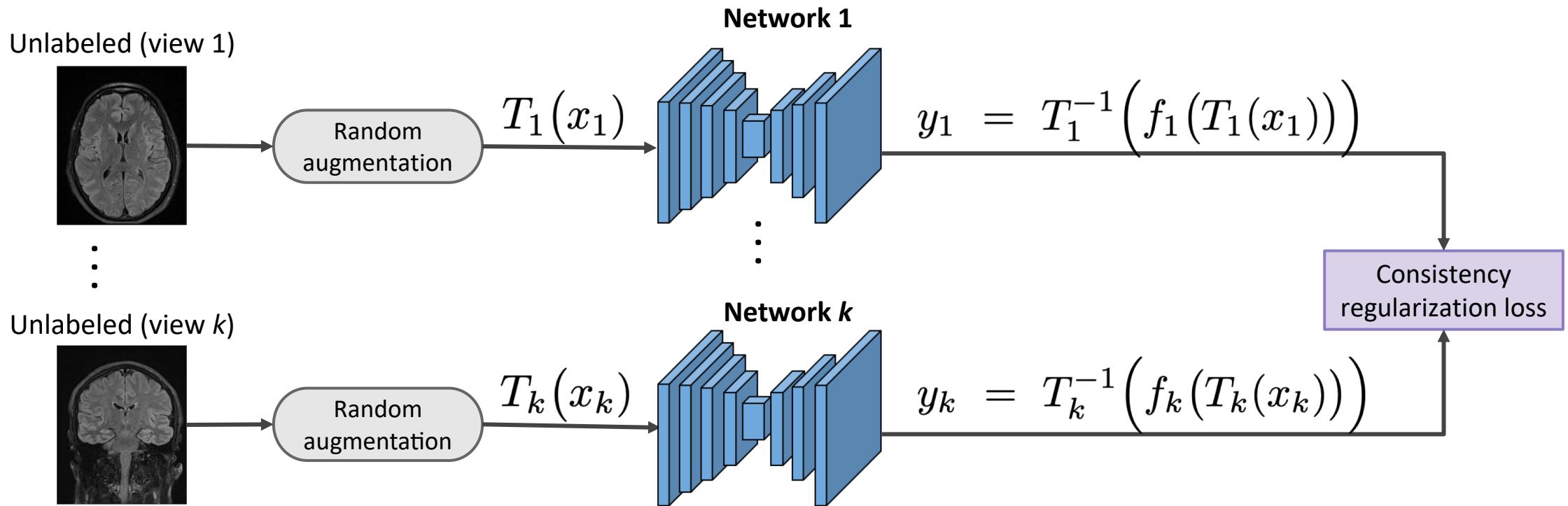


Enforces consistency only in low-uncertainty regions of the image

$$\mathcal{L}_c(f', f) = \frac{\sum_v \mathbb{I}(u_v < H) \|f'_v - f_v\|^2}{\sum_v \mathbb{I}(u_v < H)},$$

SSL methods using consistency regularization

Muti-view co-training

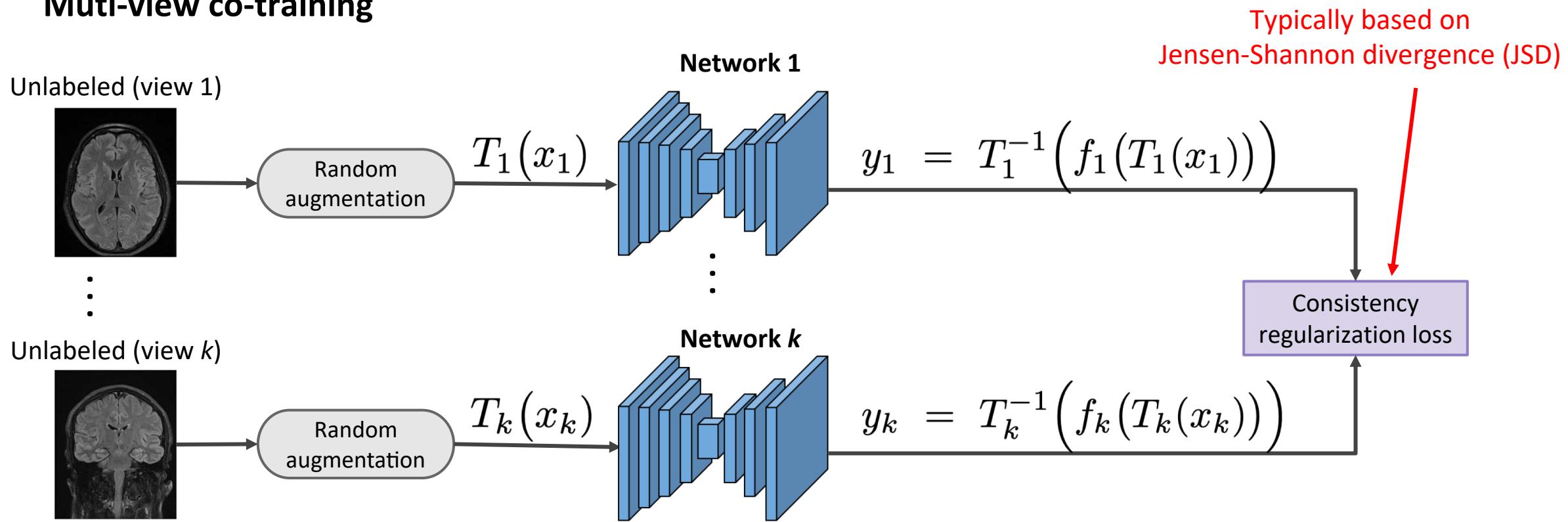


Key idea:

- Supposes the existence of separate, complementary views of the data
- Use high-confidence predictions for a given view as pseudo-labels in other views

SSL methods using consistency regularization

Muti-view co-training

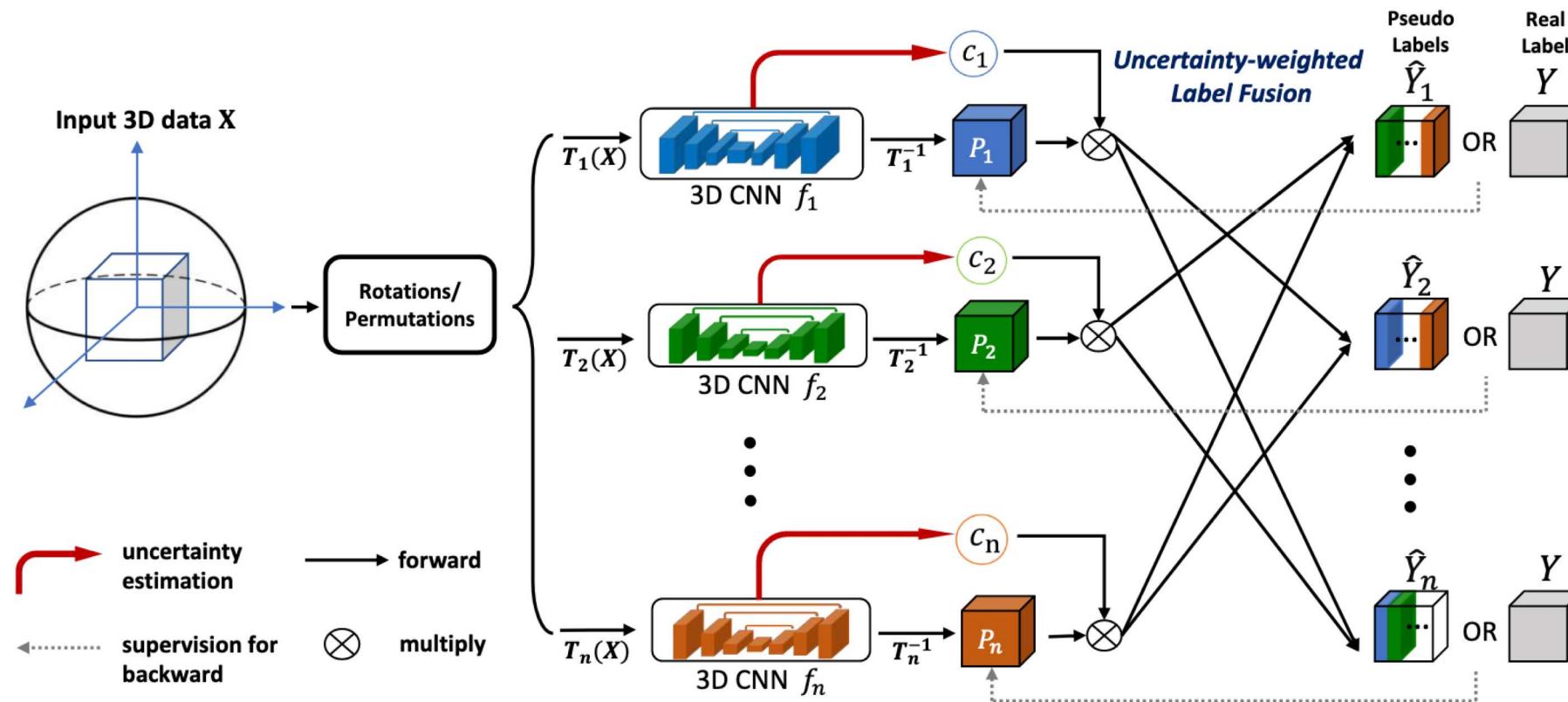


Key idea:

- Supposes the existence of separate, complementary views of the data
- Use high-confidence predictions for a given view as pseudo-labels in other views

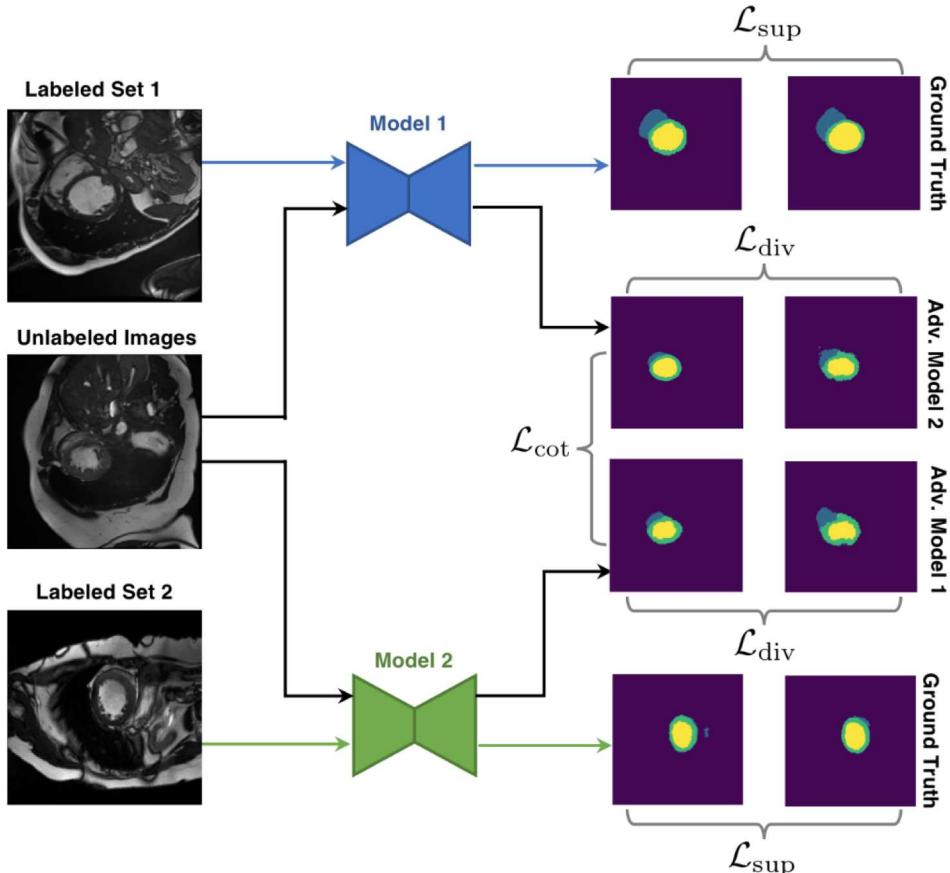
SSL methods using consistency regularization

Application of multi-view co-training for pancreas and liver tumor segmentation



SSL methods using consistency regularization

How to apply co-training without different views ?

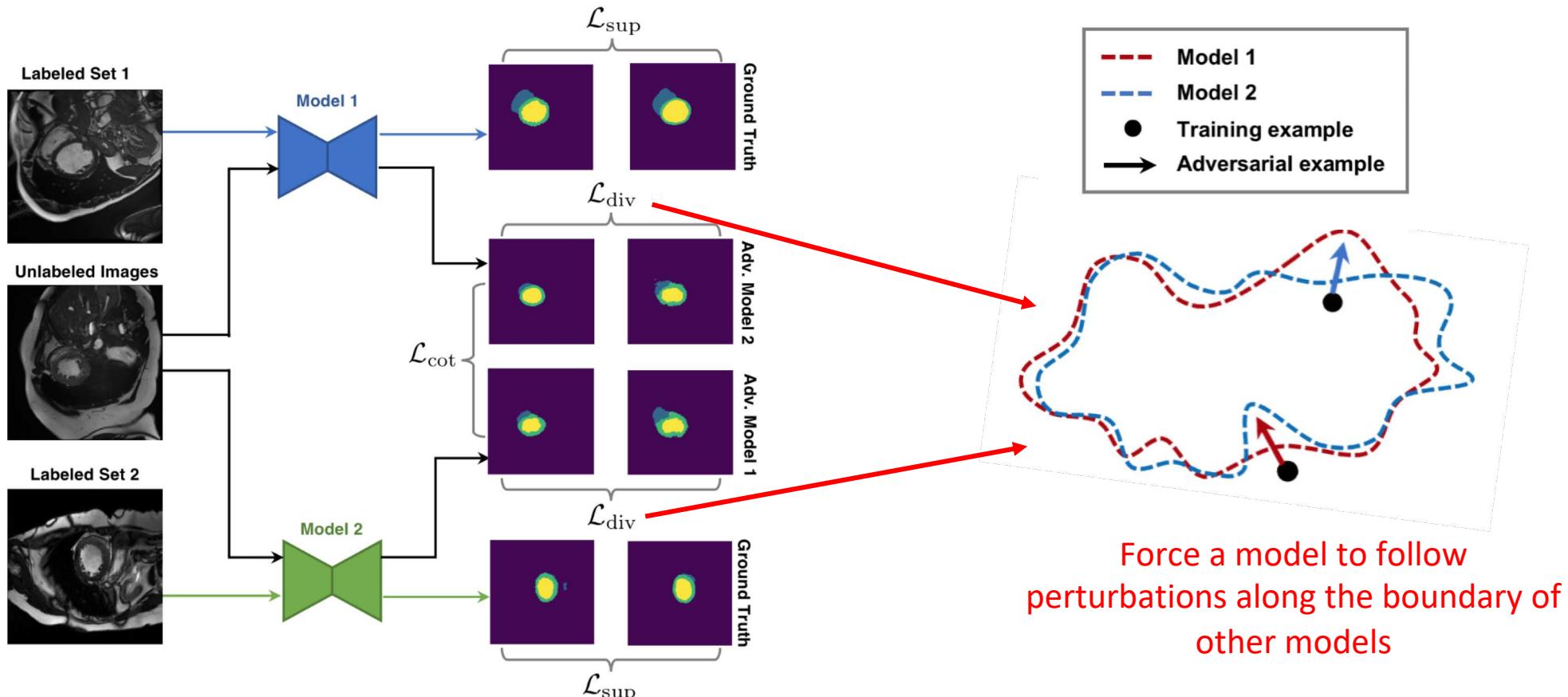


Basic idea:

- Use adversarial examples to generate diversity in the representation learned by models

SSL methods using consistency regularization

How to apply co-training without different views ?



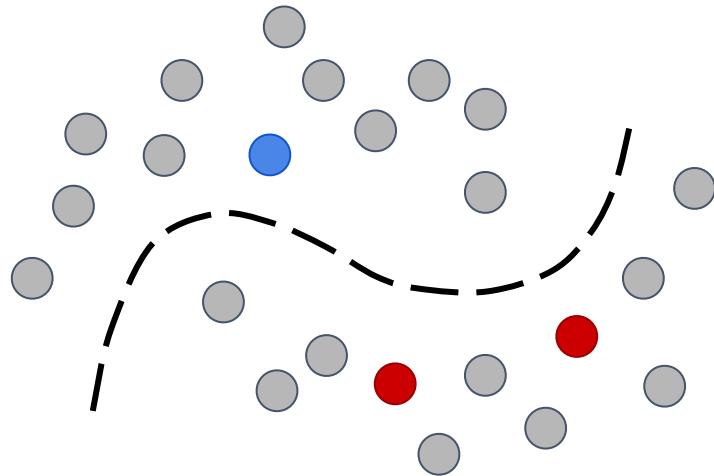
Basic idea:

- Use adversarial examples to generate diversity in the representation learned by models

Unsupervised representation learning for weakly-supervised segmentation

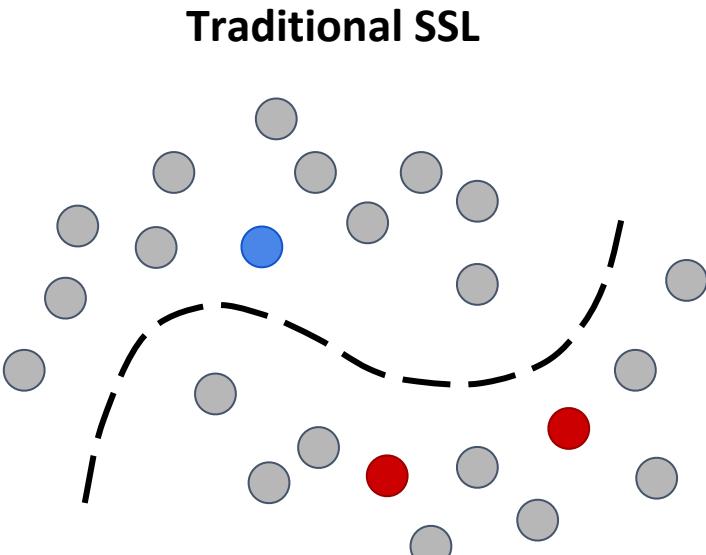
Unsupervised representation learning (URL)

Traditional SSL

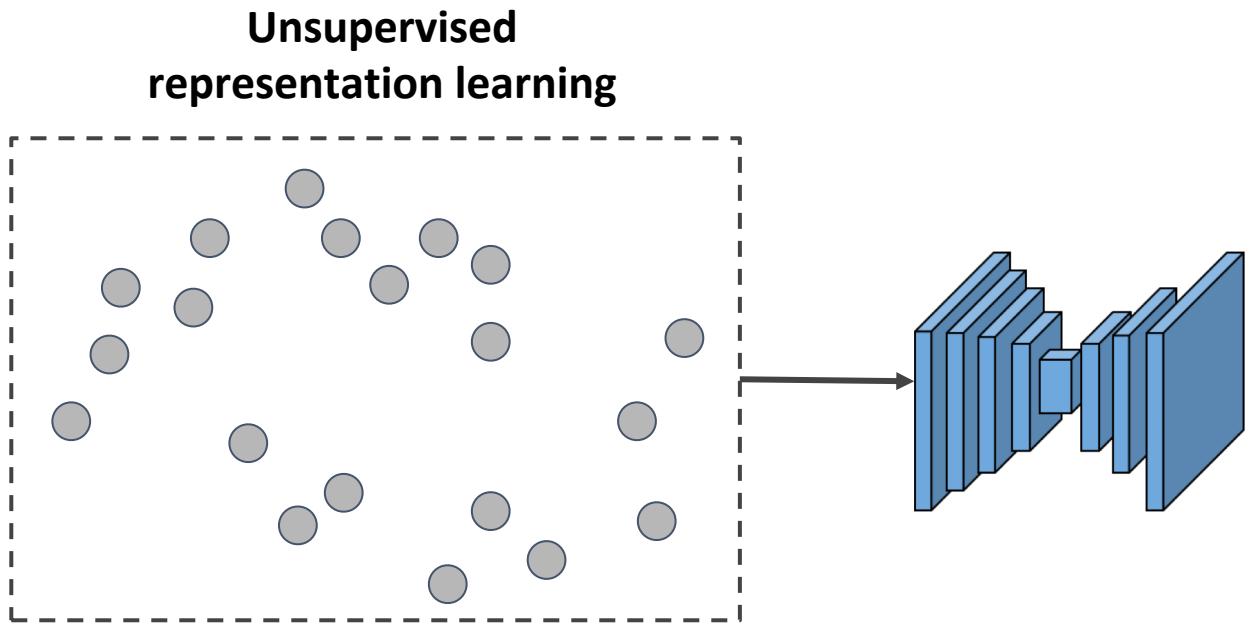


- Train a model simultaneously with both labeled and unlabeled data

Unsupervised representation learning (URL)

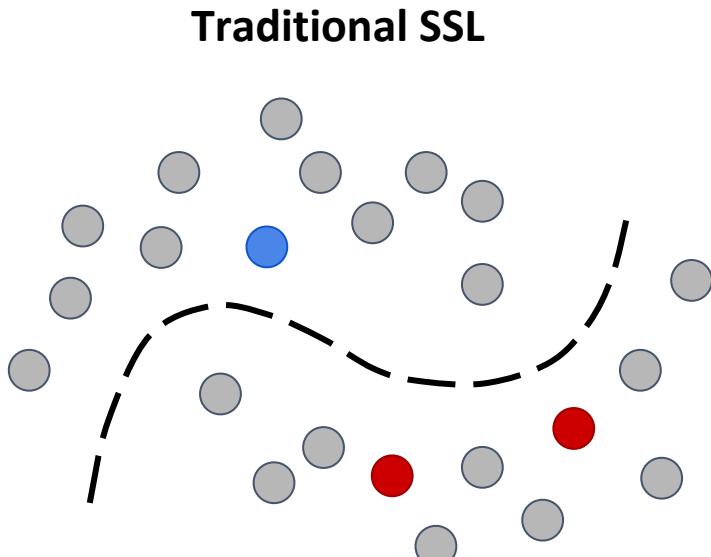


- Train a model simultaneously with both labeled and unlabeled data

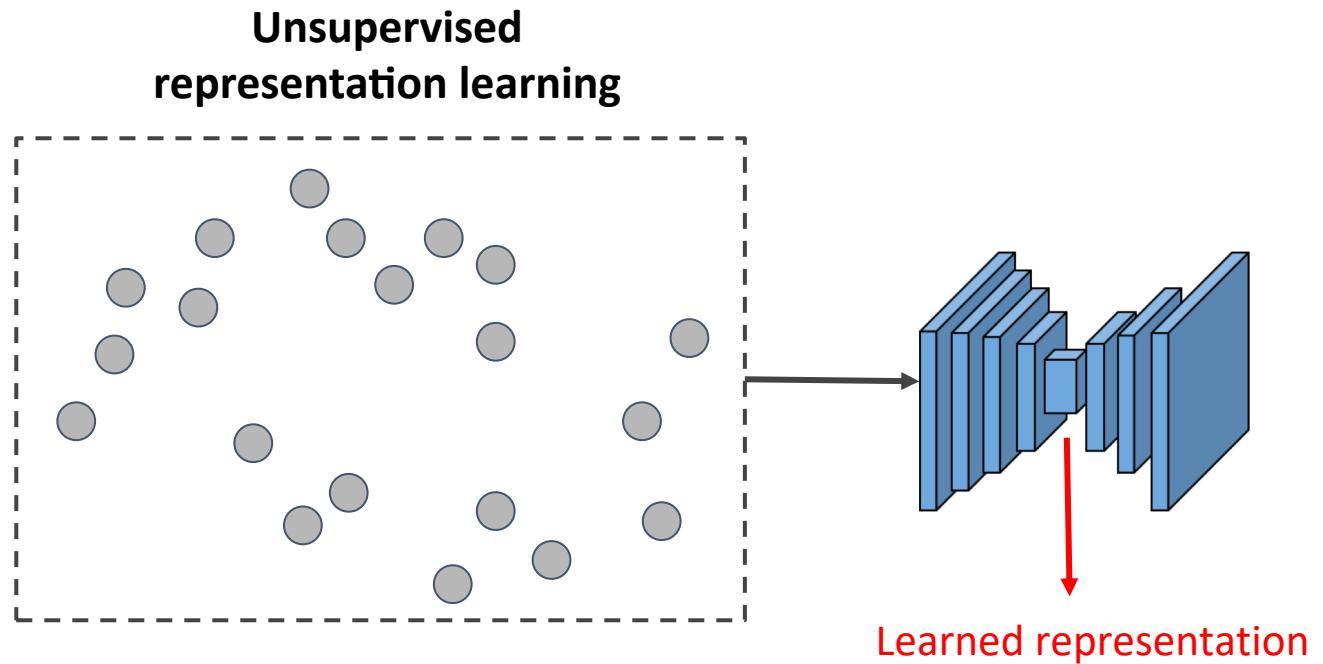


- In an upstream step, use only unlabeled data to learn a representation useful to downstream tasks
- **Examples:**
 - Self-supervised learning
 - Contrastive learning

Unsupervised representation learning (URL)



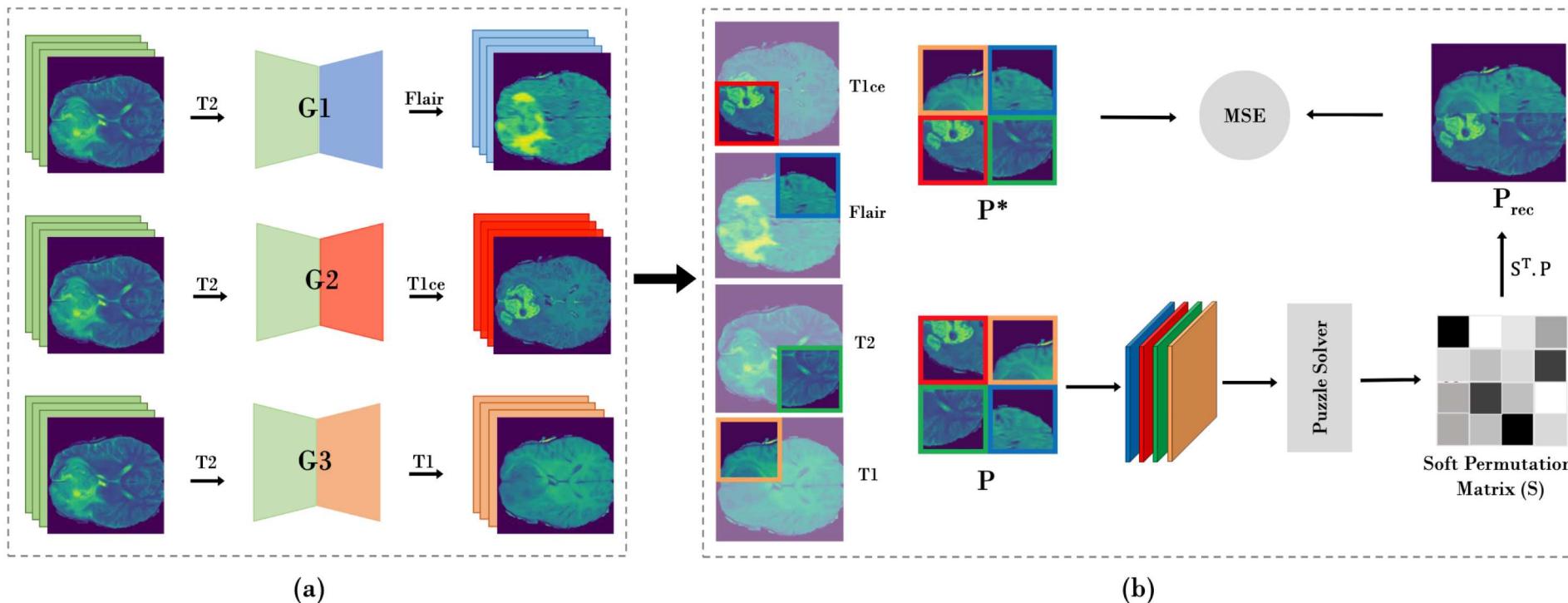
- Train a model simultaneously with both labeled and unlabeled data



- In an upstream step, use only unlabeled data to learn a representation useful to downstream tasks
- **Examples:**
 - Self-supervised learning
 - Contrastive learning

Approaches for URL

Self-supervised learning:

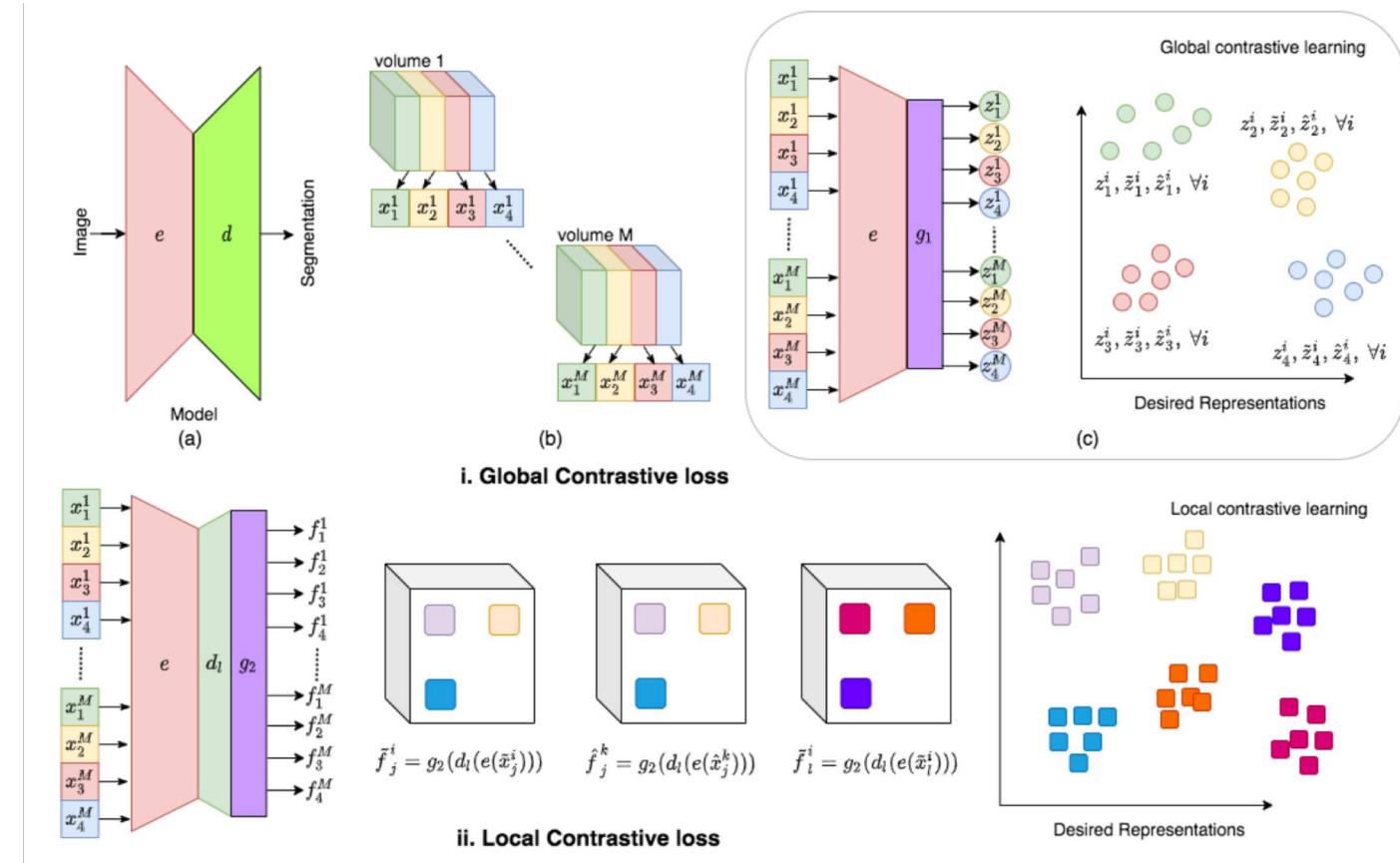


Basic idea:

- Learn to solve a pretext task which does not require annotations
- Example: find the correct order of permuted patches (*see above*)

Approaches for URL

Contrastive learning:

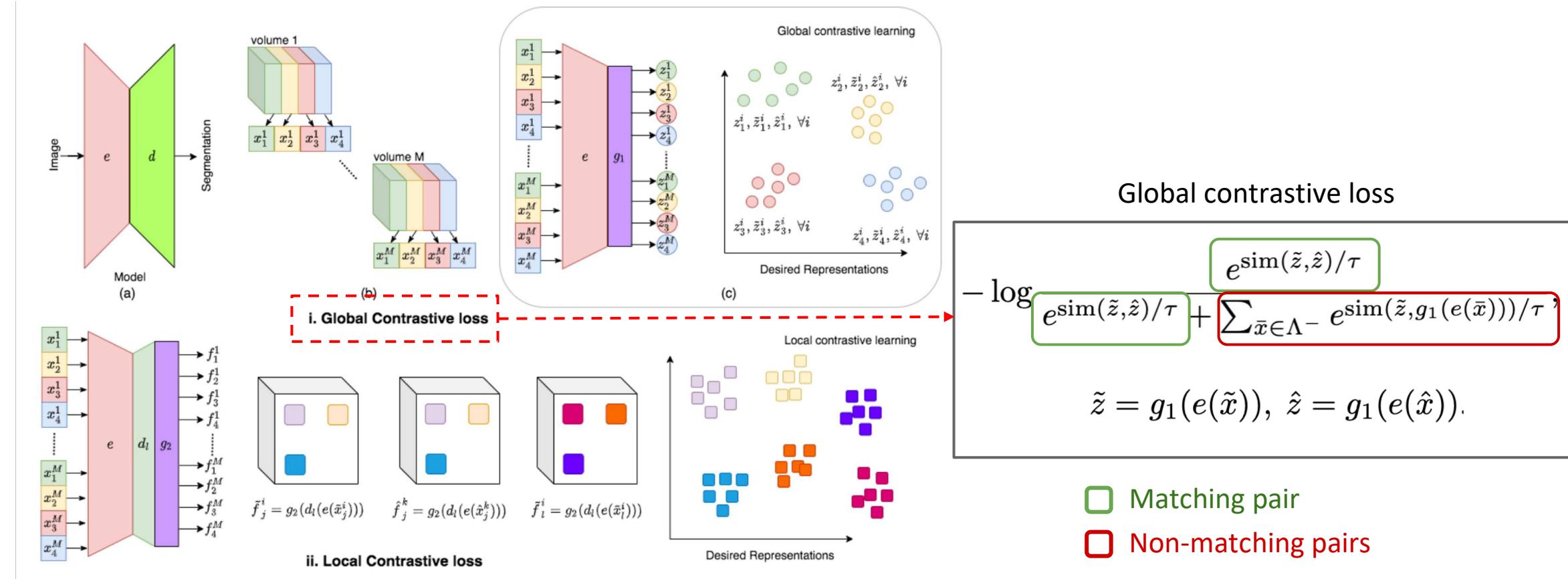


Basic idea:

- Train with pairs of images that can match (e.g., same position in volume, same image under different transformations, etc.) or not
- Find a representation that is similar for matching pairs and different for non-matching ones

Approaches for URL

Contrastive learning:



Basic idea:

- Train with pairs of images which match (e.g., same position in volume, same image under different transformations, etc.) or not
- Find a representation that is similar for matching pairs and different for non-matching ones

Thank you

Questions ?

https://github.com/LIVIAETS/miccai_2020-weakly_supervised_tutorial

A survey on the presented content is coming very soon!



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