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ÉTS Le génie pour l'industrie

Erasmus MC University Medical Center Rotterdam

UC SANTA CRUZ

Learning with Limited Supervision

- *Constrained CNNs* -

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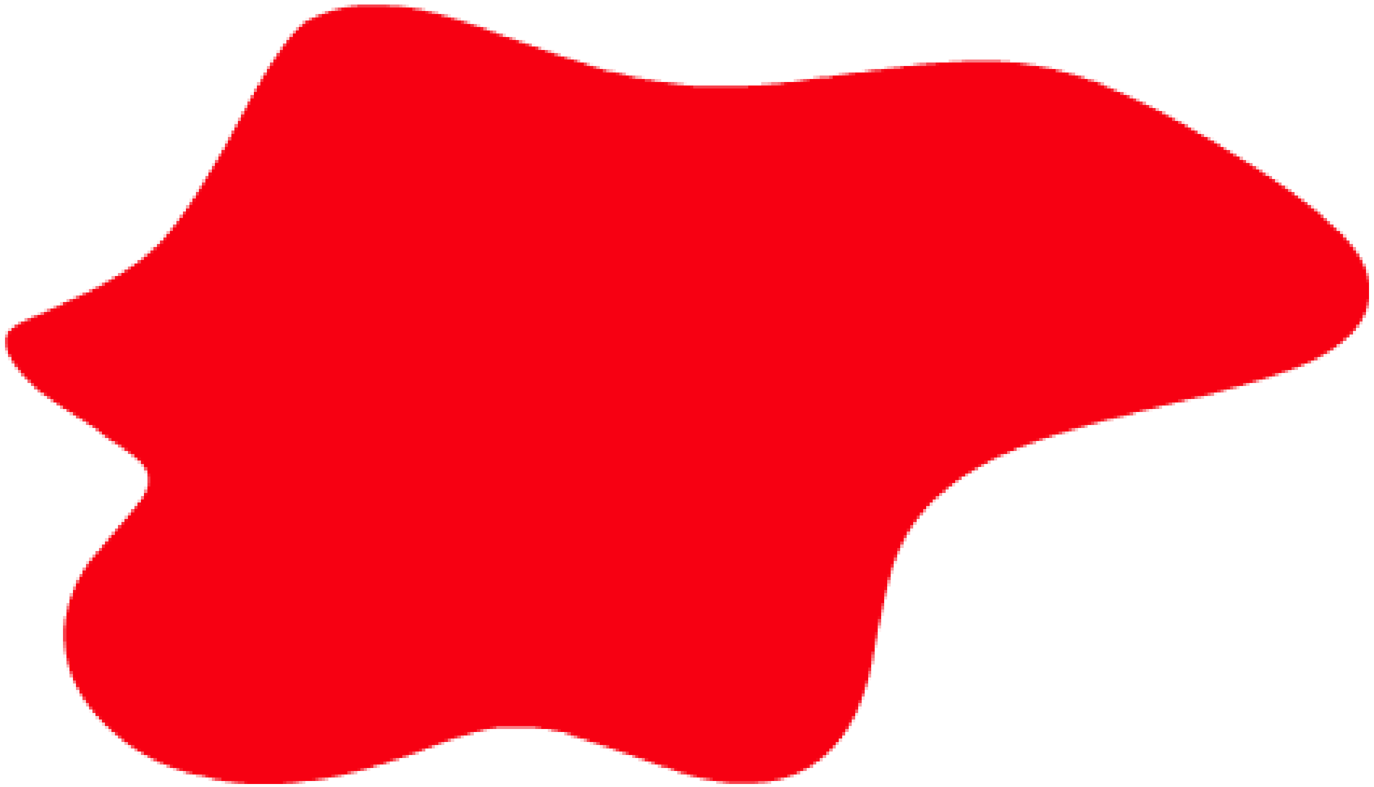
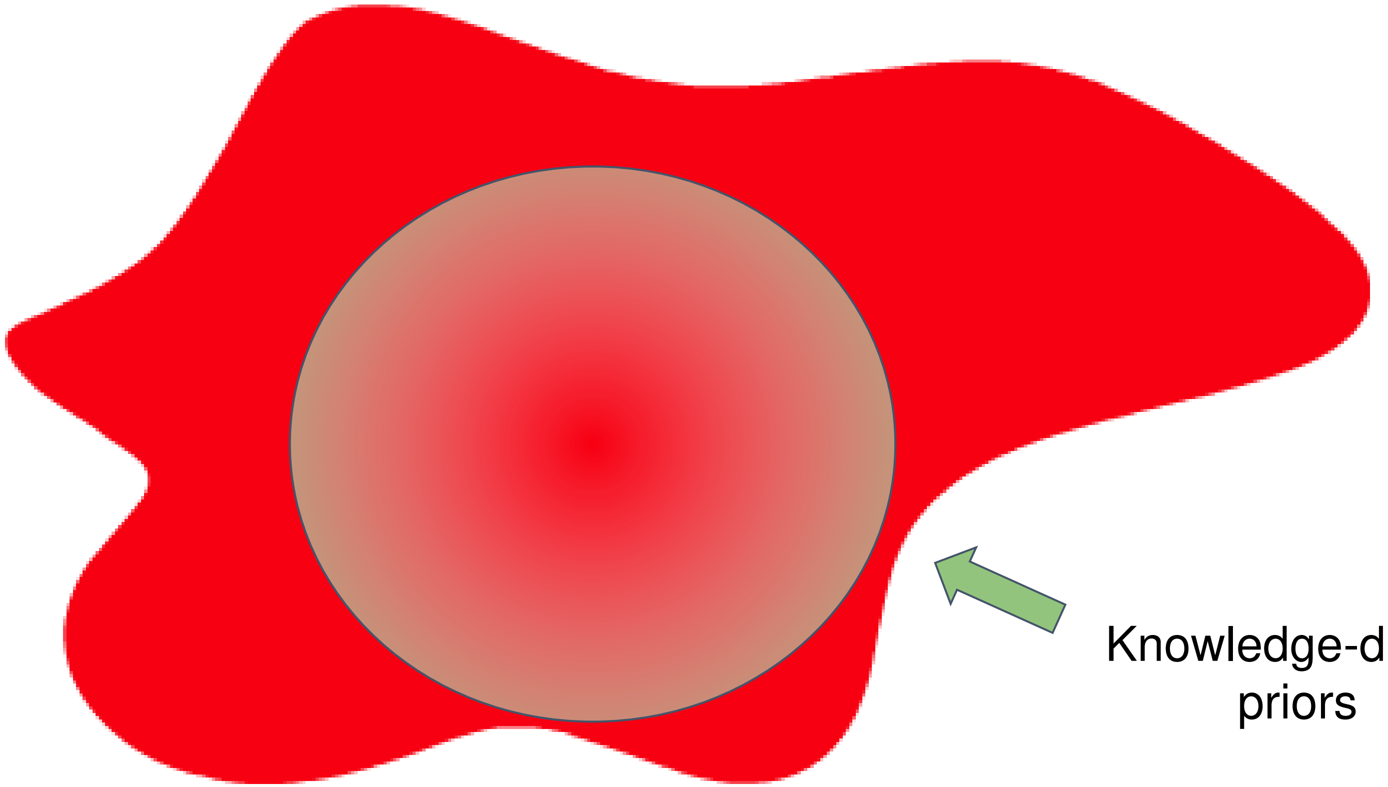
Jose Dolz
Christian Desrosiers
Marleen de Bruijne
Hoel Kervadec

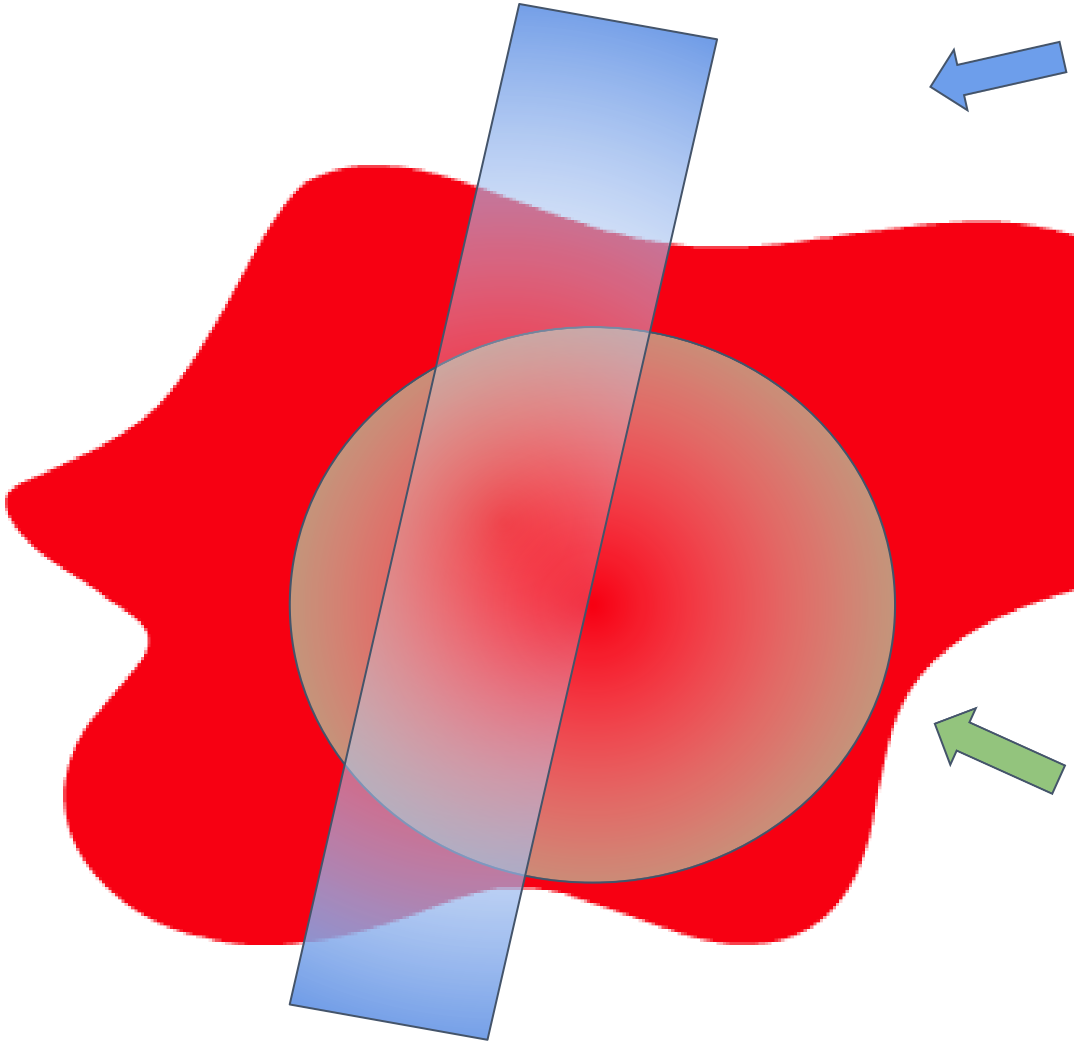
Knowledge vs data driven priors



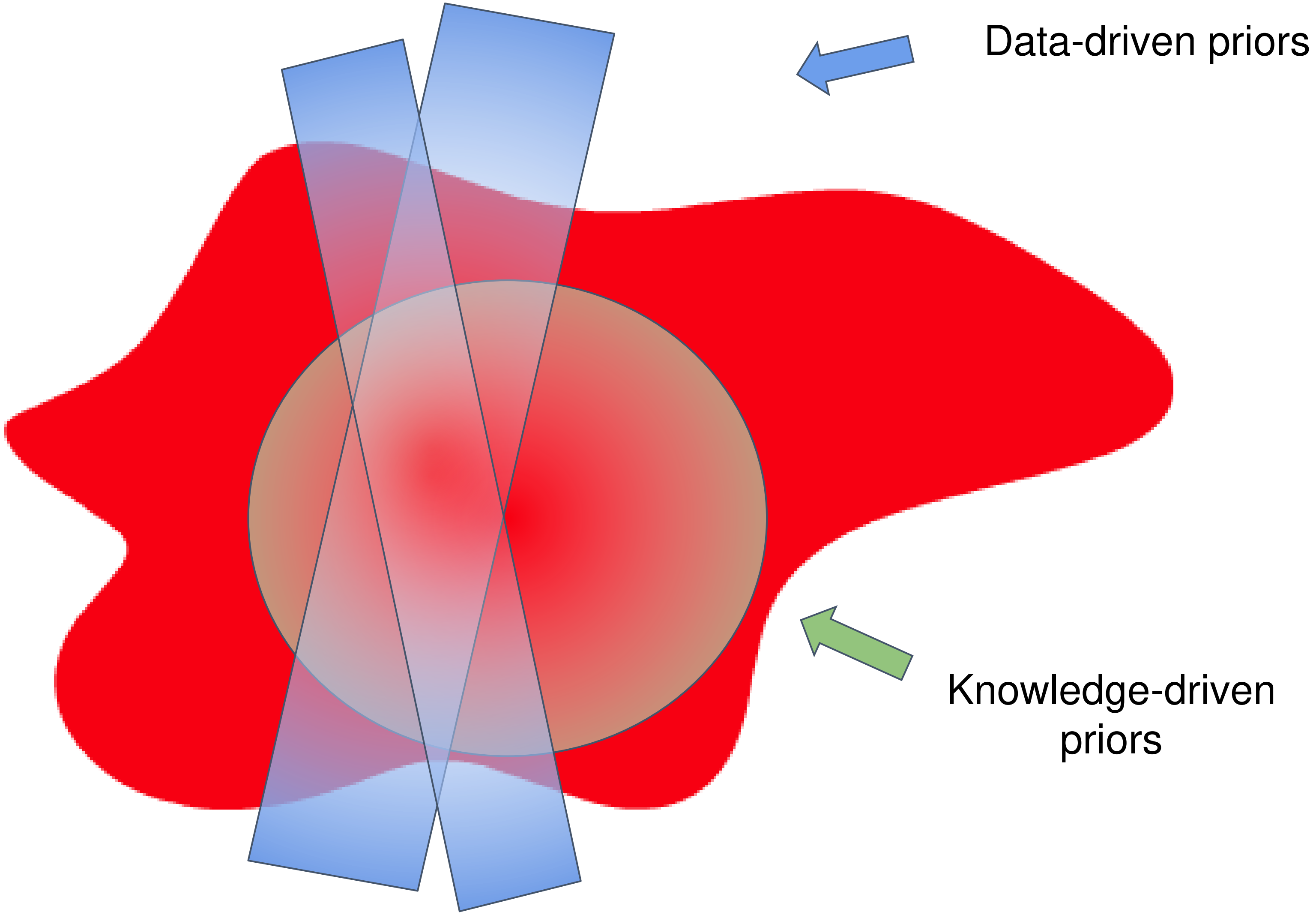
Knowledge vs data driven priors



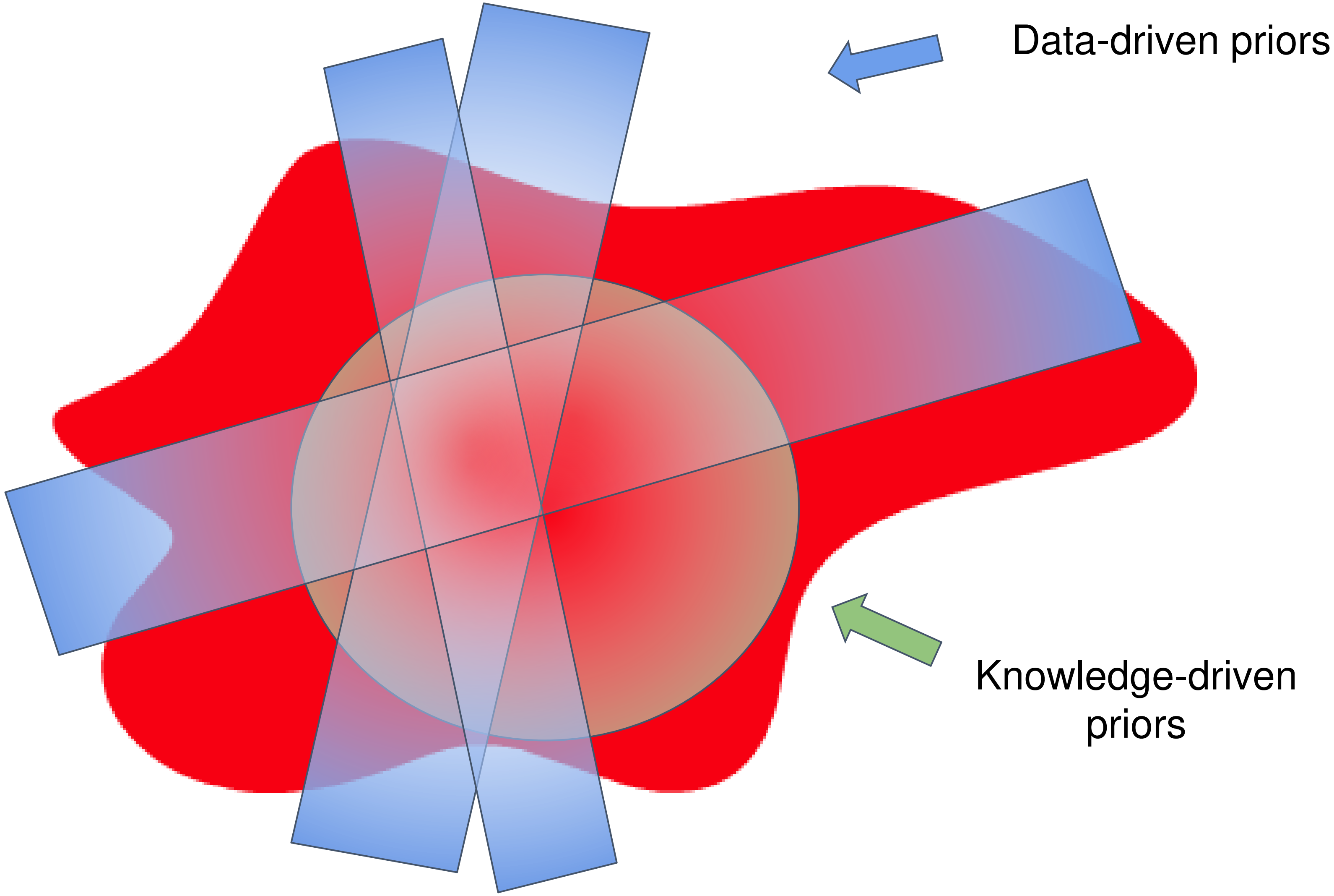
Knowledge vs data driven priors



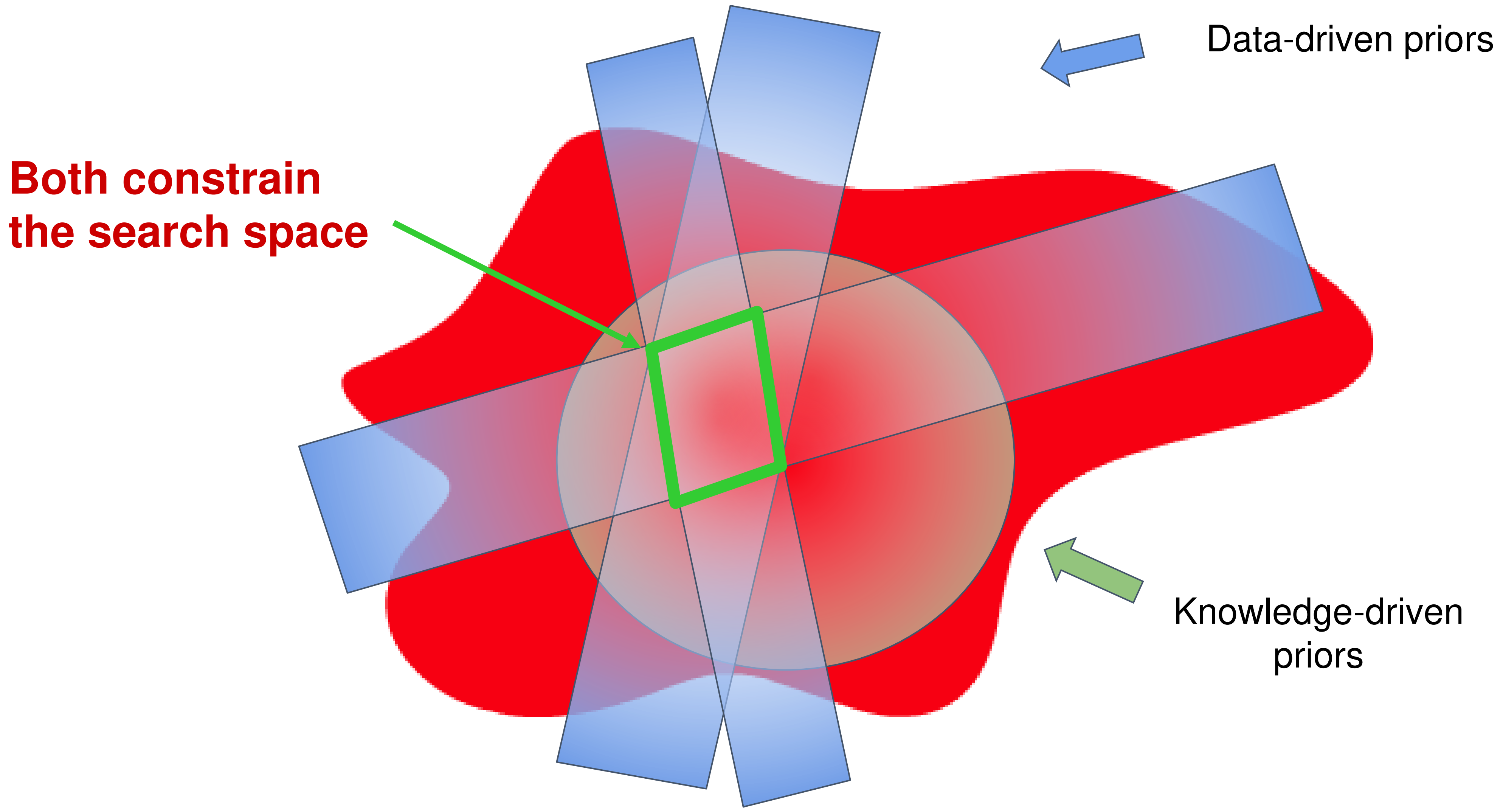
Knowledge vs data driven priors



Knowledge vs data driven priors

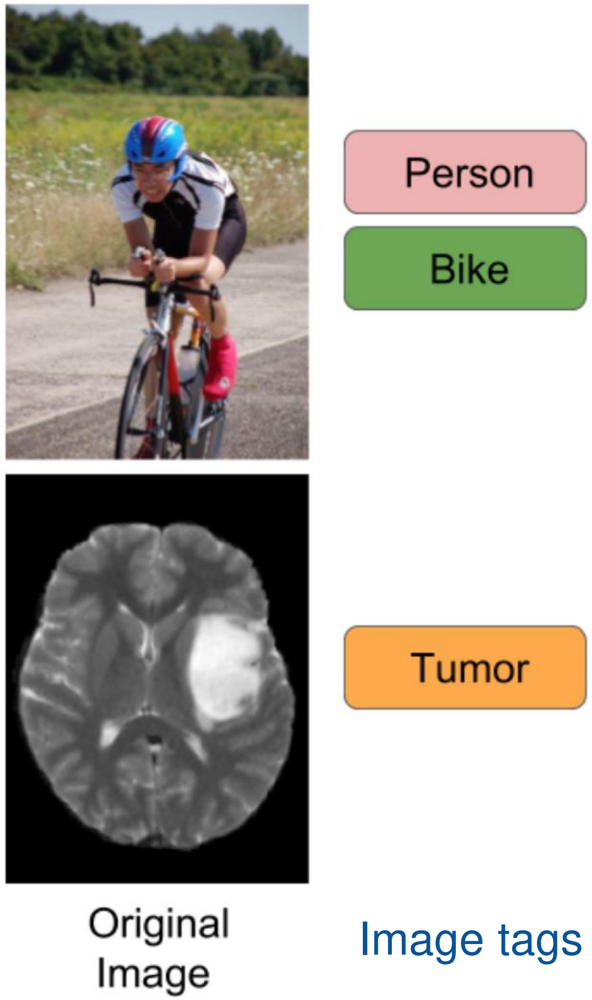


Knowledge vs data driven priors



Data-driven priors (cues)

Image tags

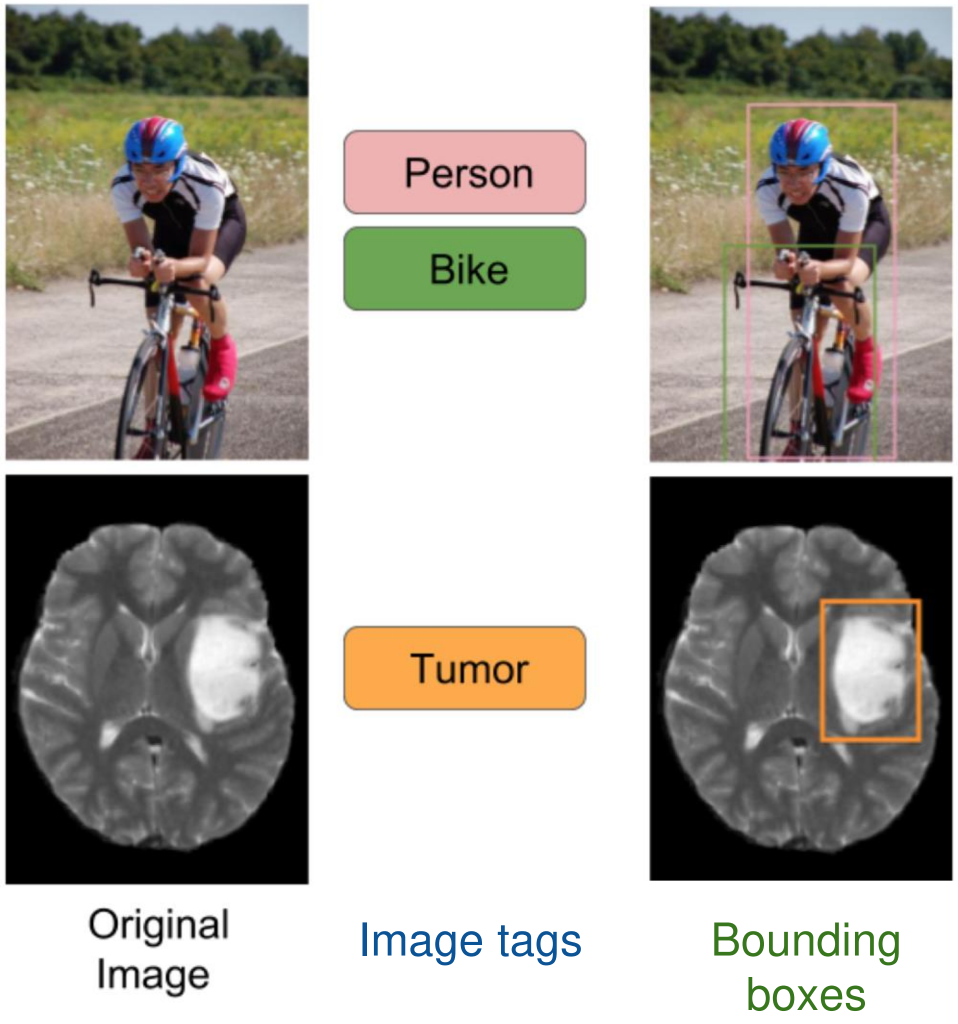


- Pathak et al., Constrained convolutional neural networks for weakly supervised segmentation, ICCV 2015
- Kervadec et al., Constrained-CNN losses for weakly supervised segmentation, MedIA 2019.

Data-driven priors (cues)

Image tags

Bounding boxes



- Pathak et al., Constrained convolutional neural networks for weakly supervised segmentation, ICCV 2015
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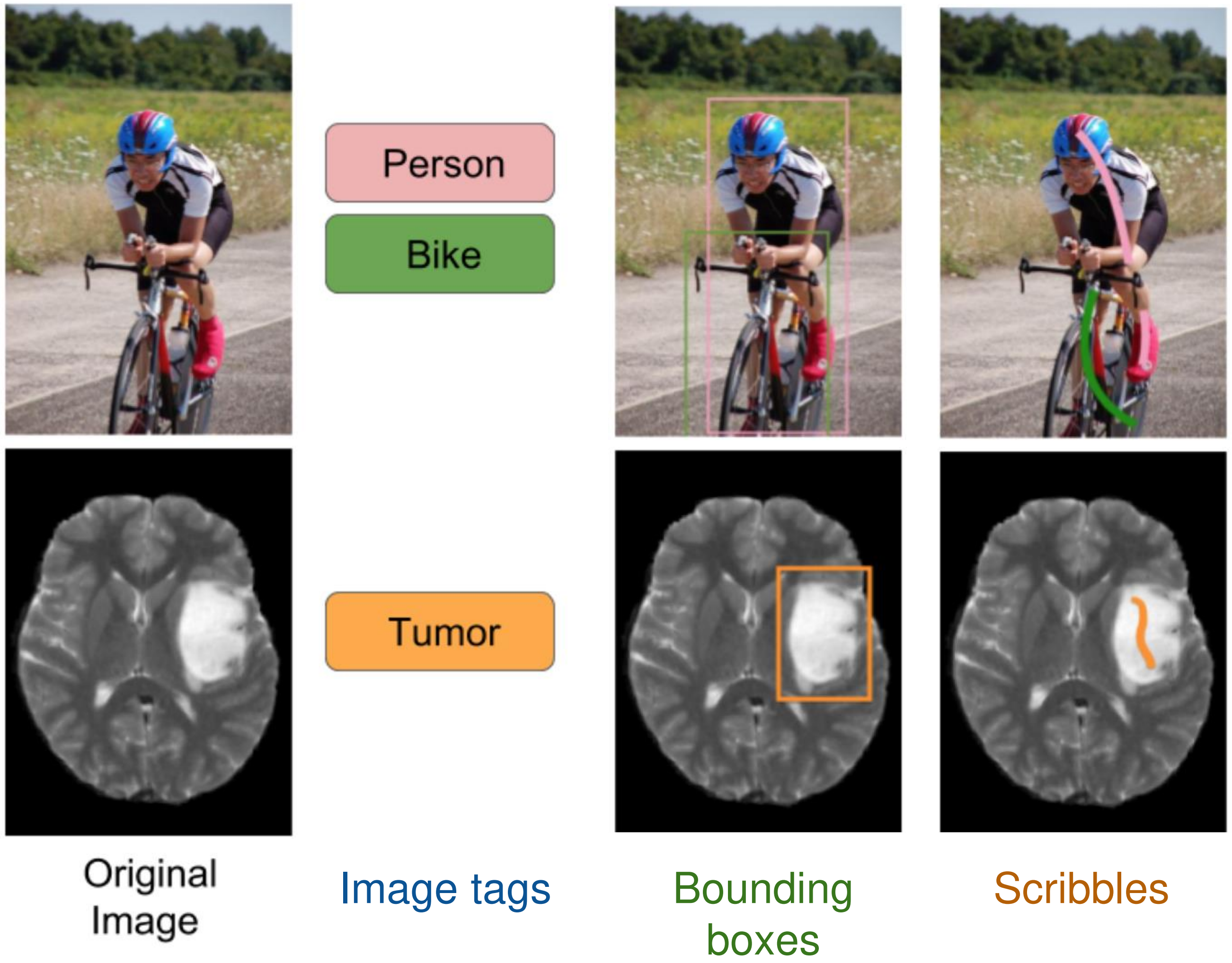
Data-driven priors (cues)

Image tags

Bounding boxes

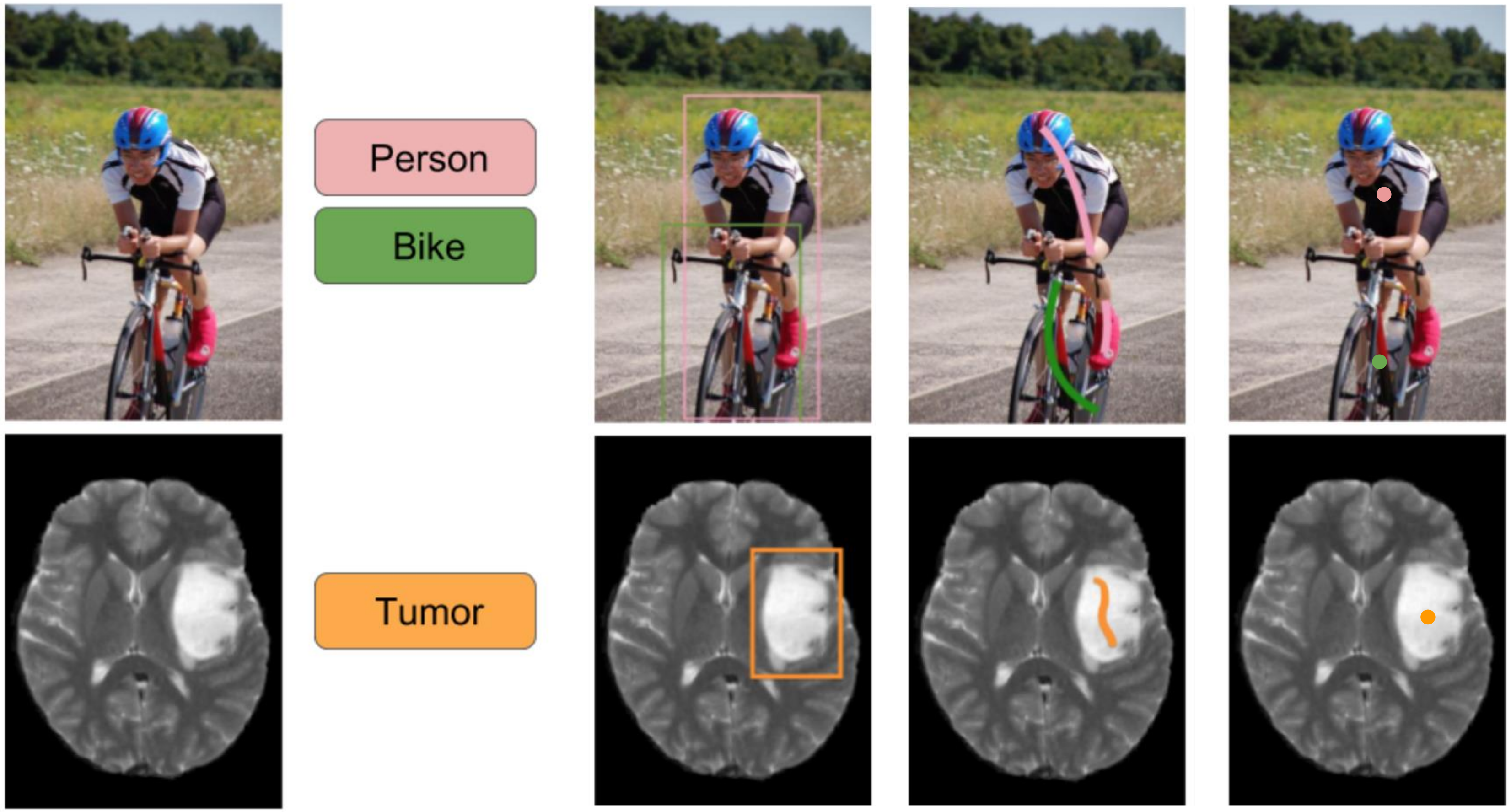
Scribbles



- Pathak et al., Constrained convolutional neural networks for weakly supervised segmentation, ICCV 2015
- Kervadec et al., Constrained-CNN losses for weakly supervised segmentation, MedIA 2019.

Data-driven priors (cues)

- Image tags
- Bounding boxes
- Scribbles
- Points



Original Image | Image tags | Bounding boxes | Scribbles | Points

- Pathak et al., Constrained convolutional neural networks for weakly supervised segmentation, ICCV 2015
- Kervadec et al., Constrained-CNN losses for weakly supervised segmentation, MedIA 2019.

Data-driven priors (cues)

Another data-driven priors

Image captions

A boy jumping on a skateboard

Extreme points

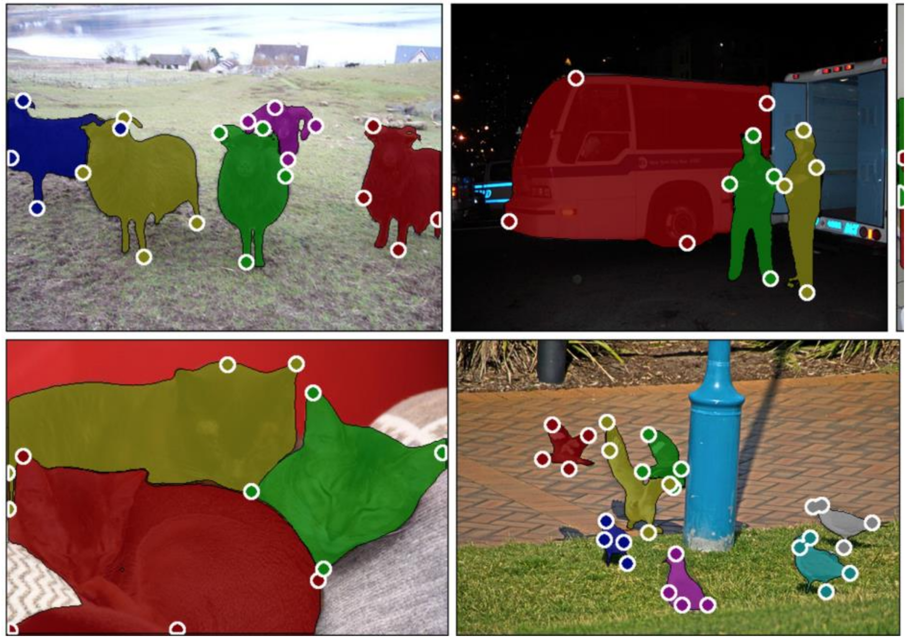
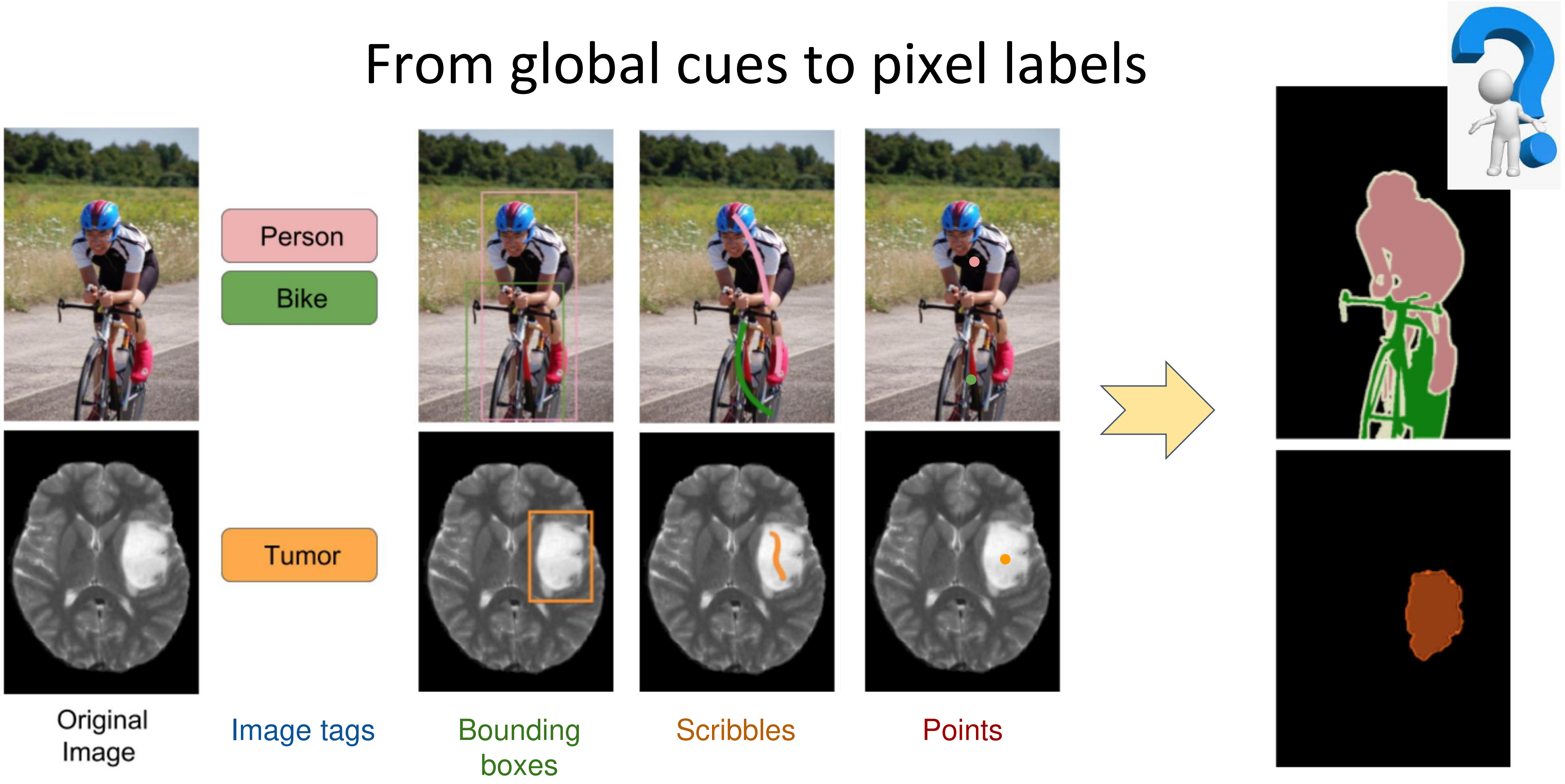


Image from Maninis et al, CVPR'18

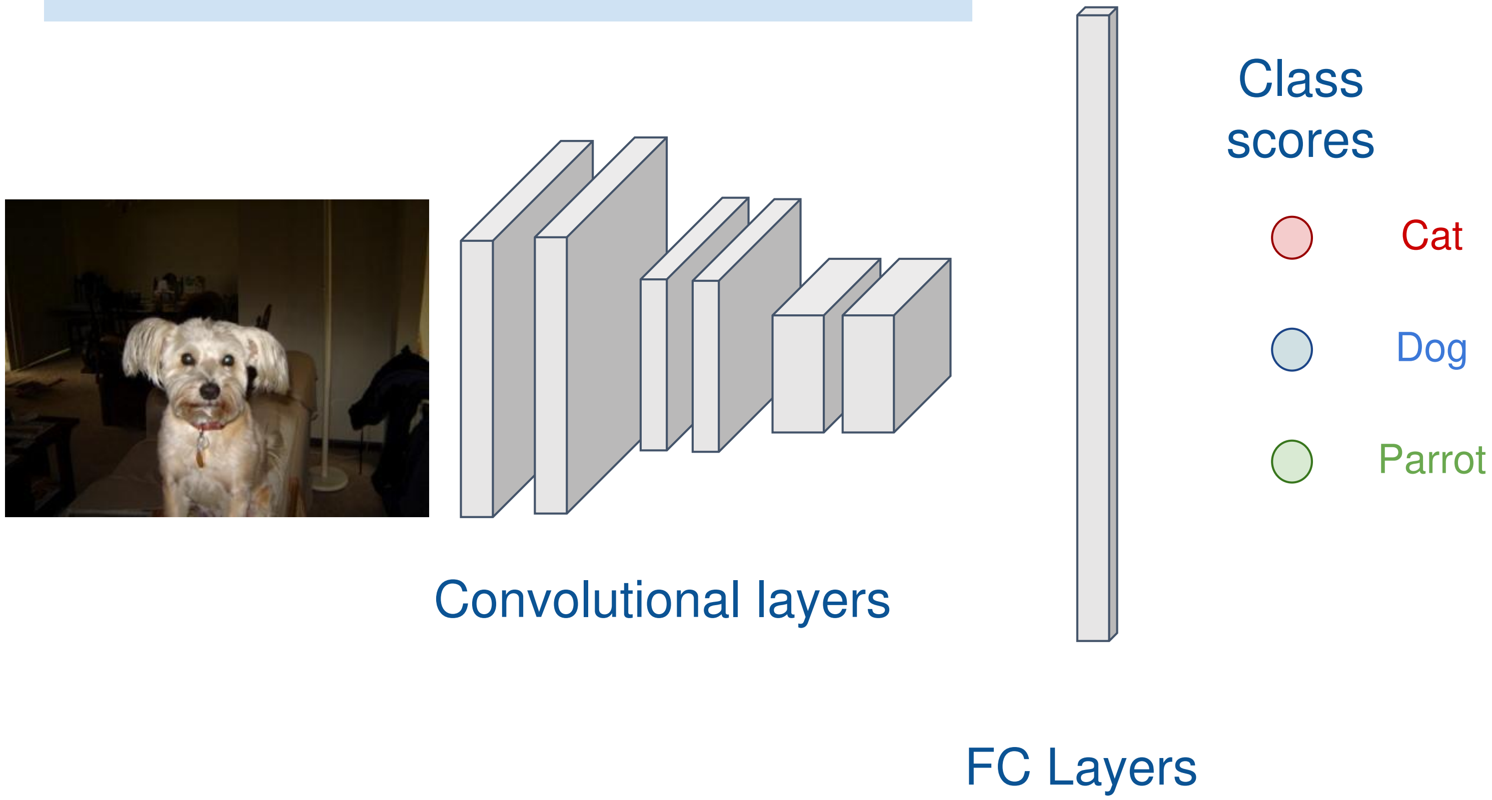
- Maninis et al. Deep extreme cut: From extreme points to object segmentation. CVPR 2018

From global cues to pixel labels



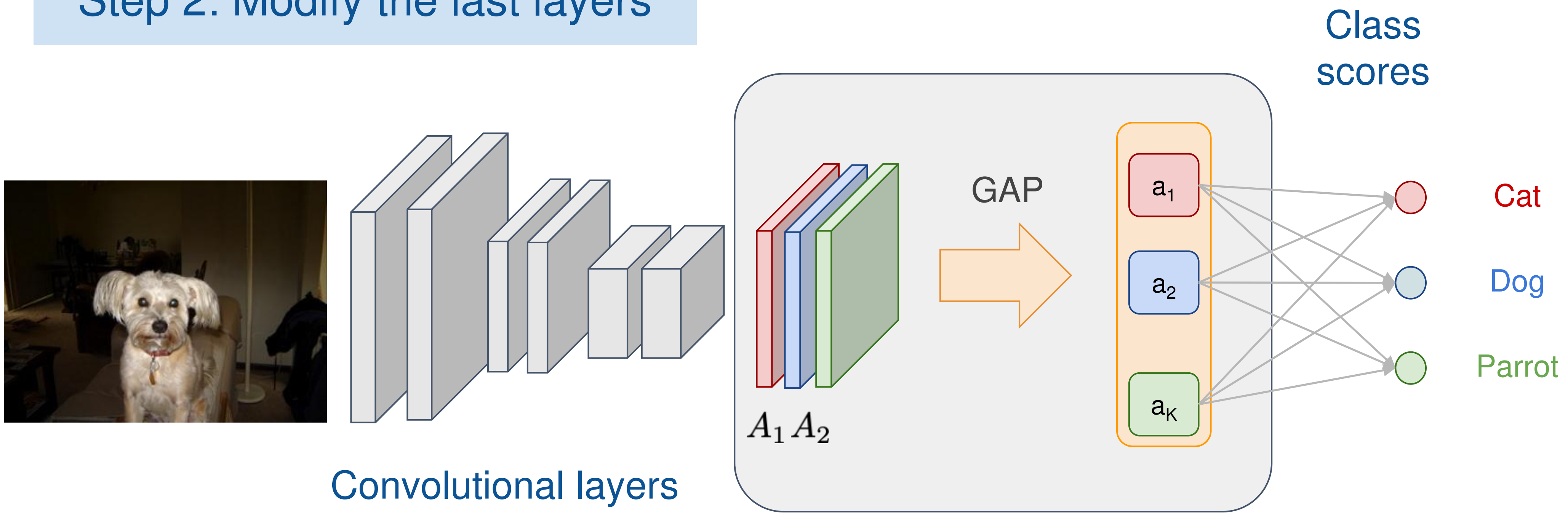
From global cues to pixel labels

Step 1: Get a classification CNN



From global cues to pixel labels

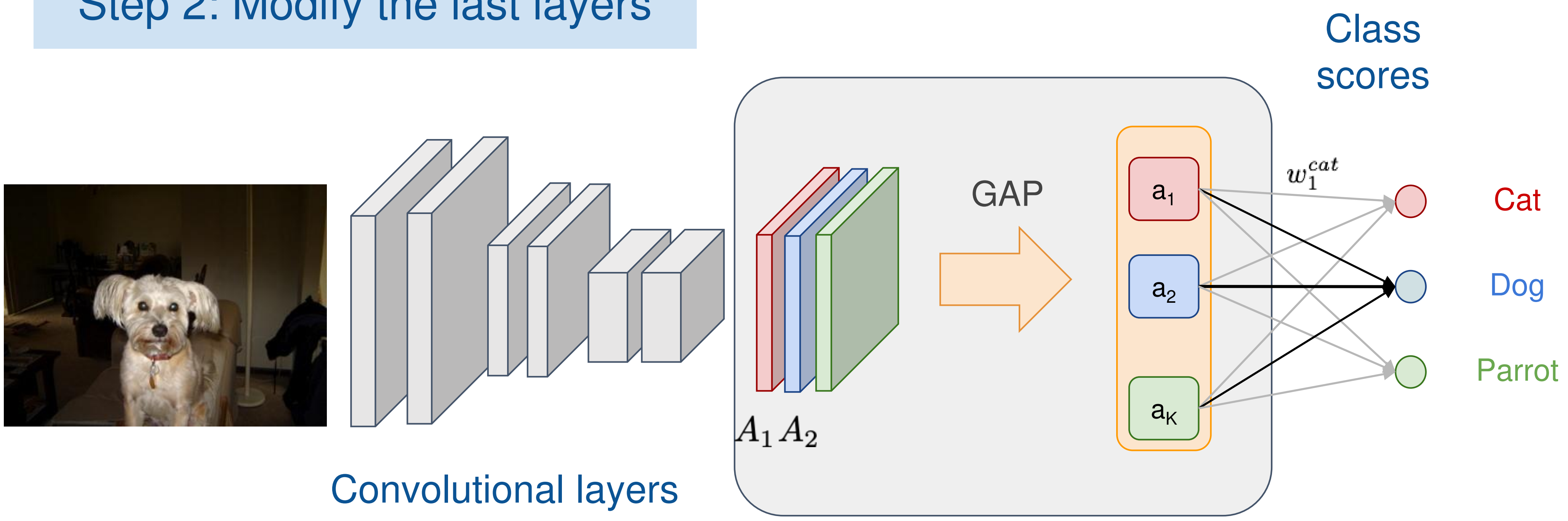
Step 2: Modify the last layers



$$GAP(A_k) = a_k = \frac{1}{|N|}\sum_{x,y} A_k(x,y)$$

From global cues to pixel labels

Step 2: Modify the last layers



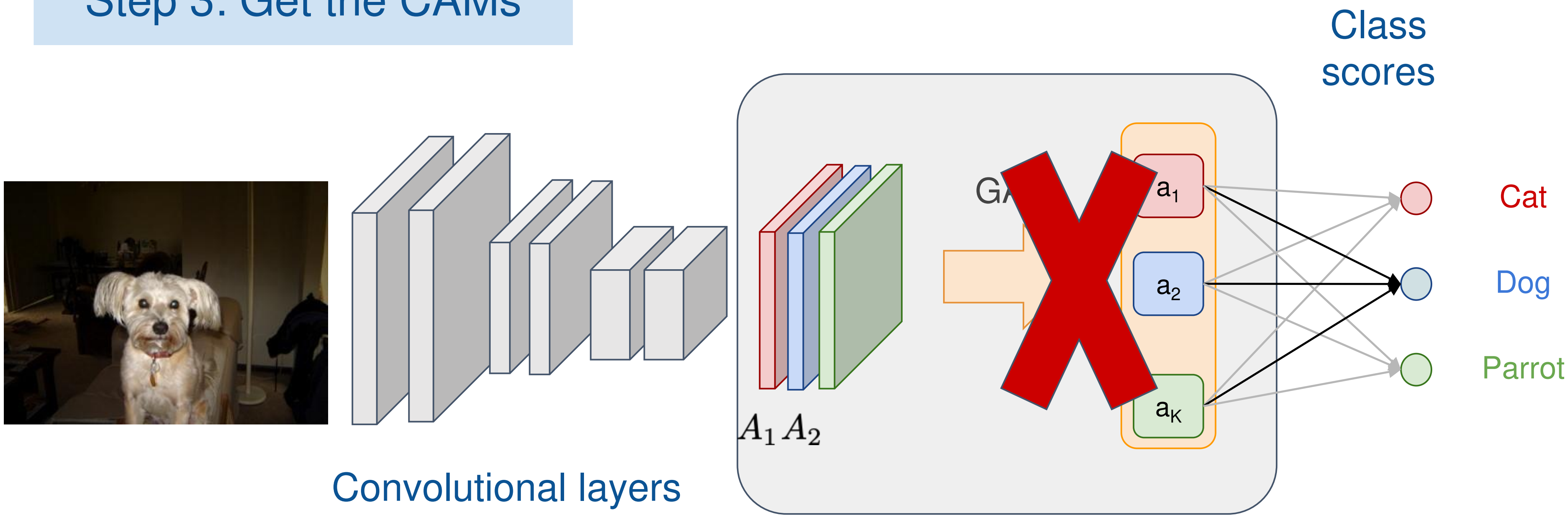
$$GAP(A_k) = a_k = \frac{1}{|N|}\sum_{x,y} A_k(x,y)$$

Class score (logits)

$$S_c = \sum_k w_k^c a_k = \frac{1}{N}\sum_k w_k^c \sum_{x,y} a_k(x,y)$$

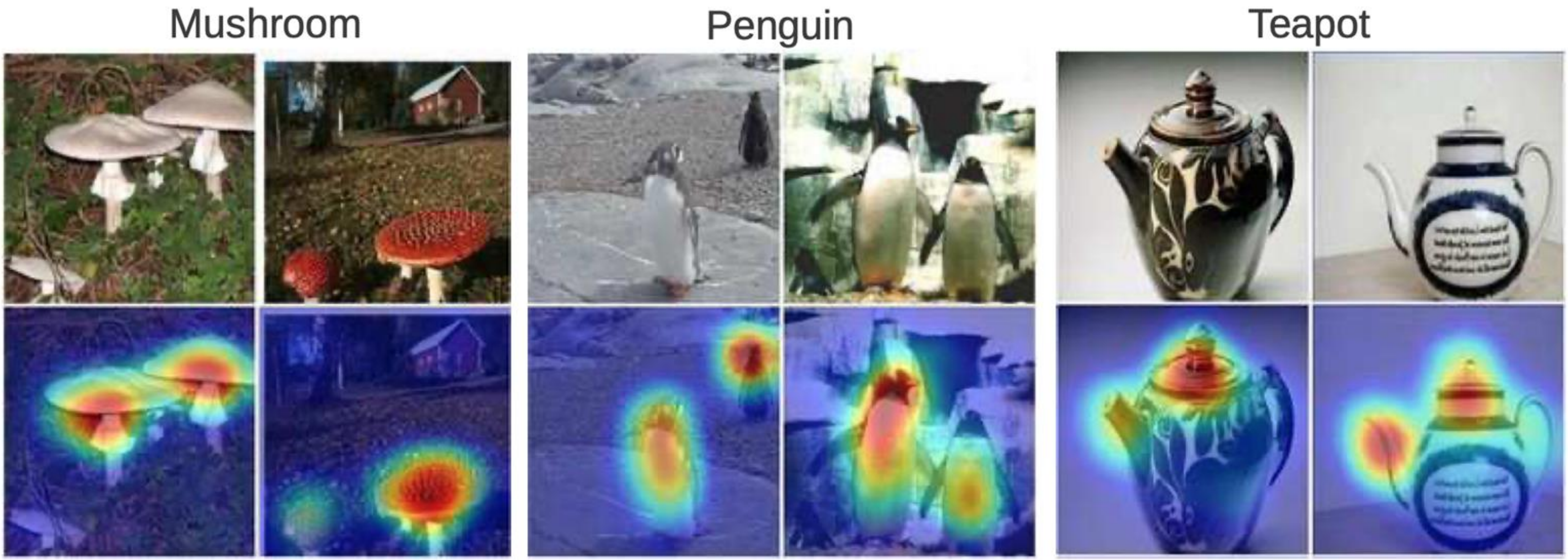
From global cues to pixel labels

Step 3: Get the CAMs



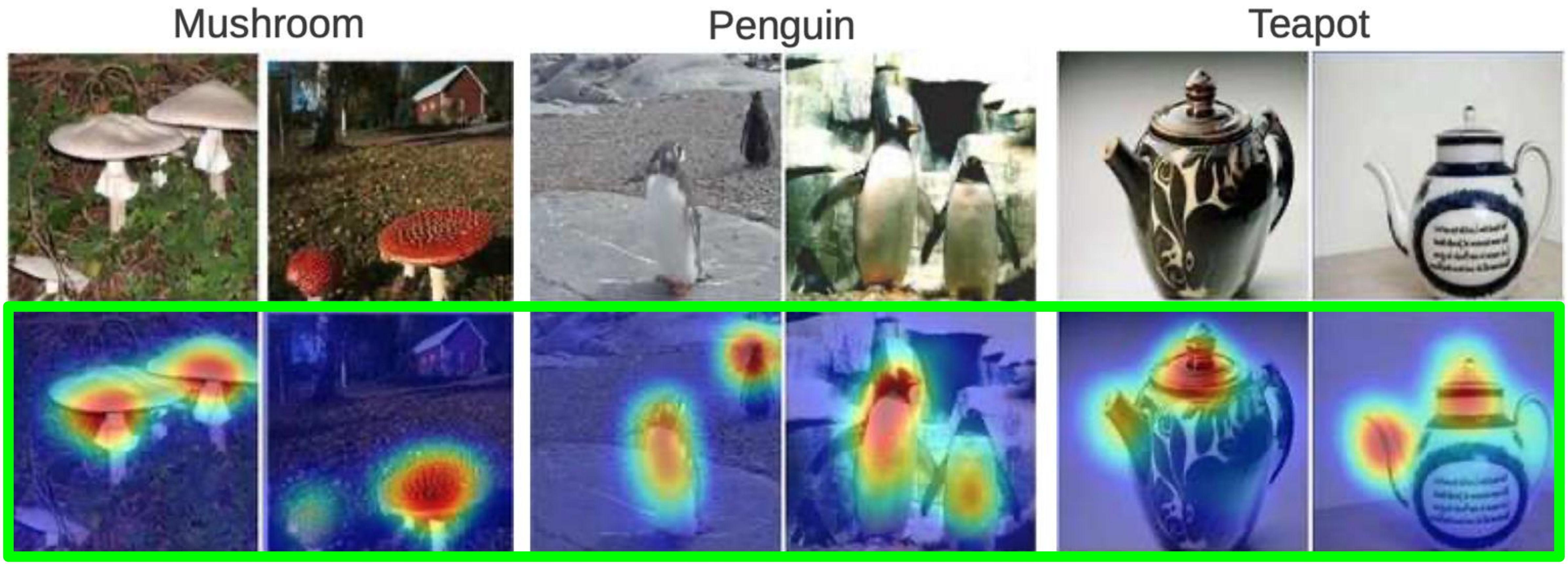
$$CAM_{Dog}(x,y) = \sum_k w_k^{Dog} A_k(x,y) =$$

From global cues to pixel labels



- Zhou et al., Learning deep features for discriminative localization. CVPR 2016

From global cues to pixel labels



These activations maps can be used as **pseudo-masks**

- Zhou et al., Learning deep features for discriminative localization. CVPR 2016

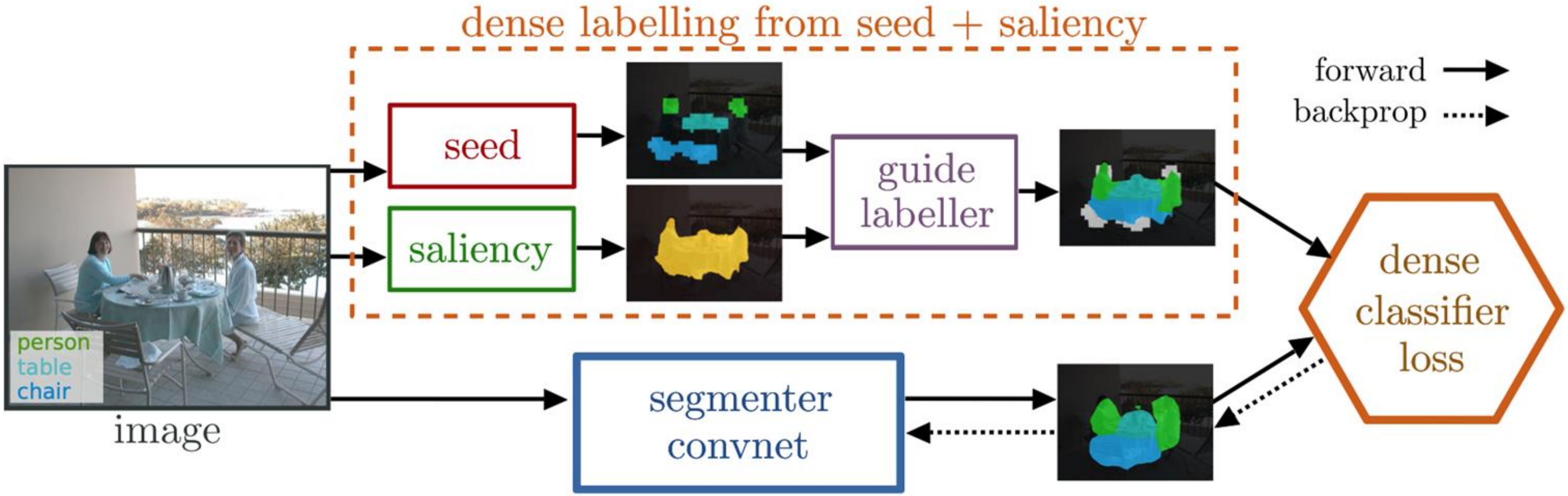
From global cues to pixel labels

Problem: they focus only on highly discriminative regions

From global cues to pixel labels

Problem: they focus only on highly discriminative regions

Incorporate saliency maps

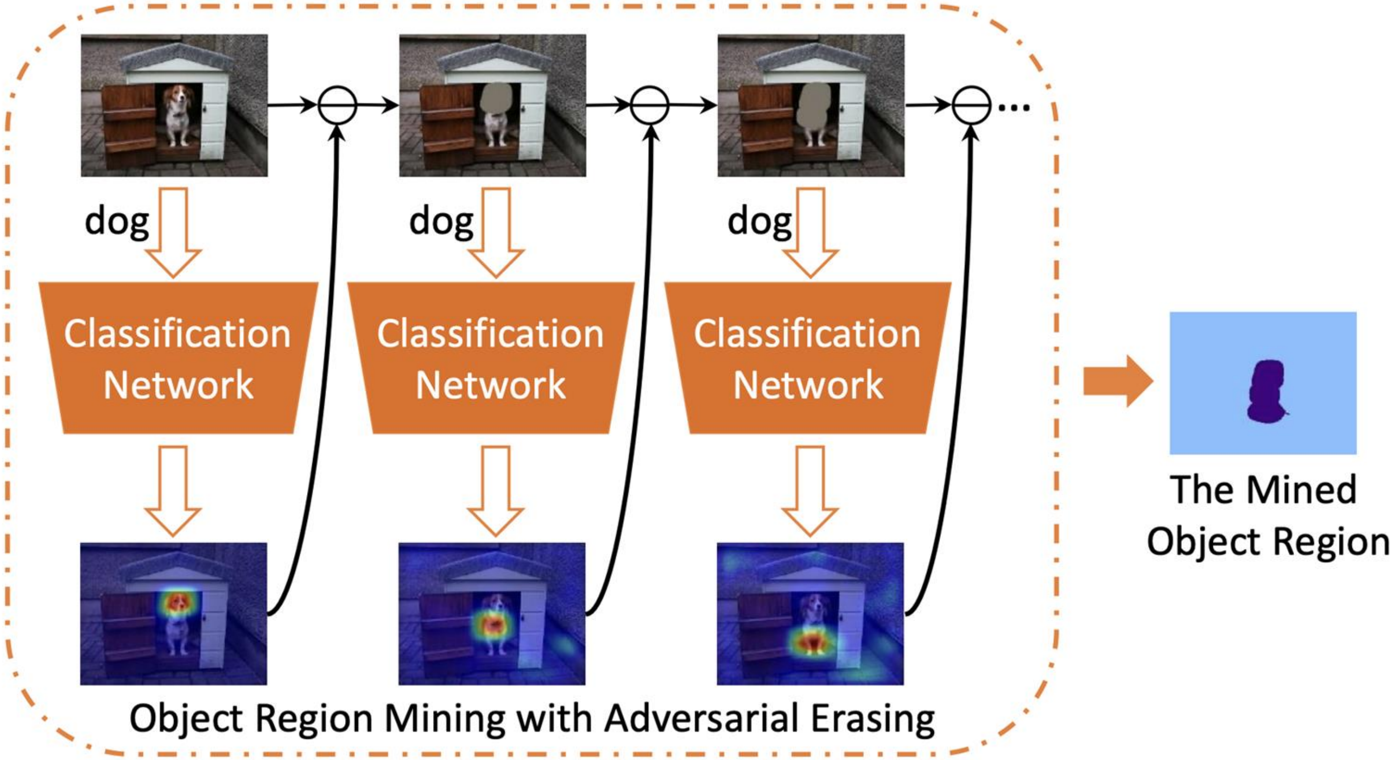


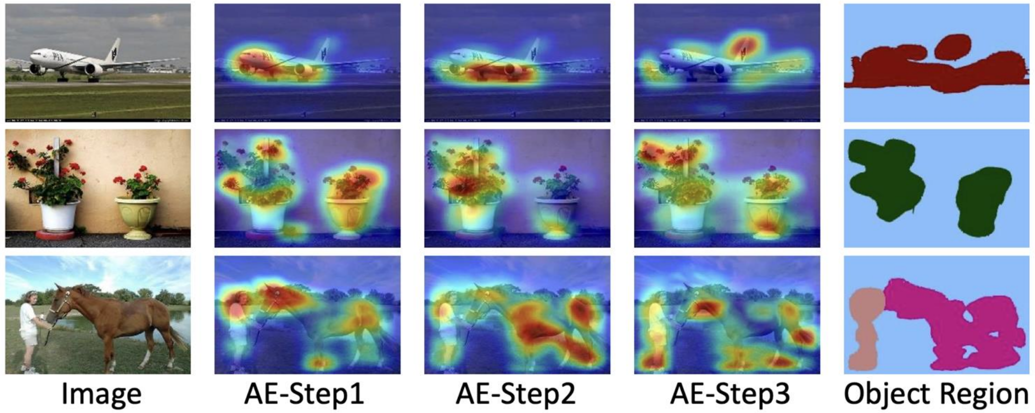
- Oh et al. Exploiting Saliency for Object Segmentation from Image Level Labels. CVPR 2017
- Fan et al. Learning Integral Objects With Intra-Class Discriminator for Weakly-Supervised Semantic Segmentation. CVPR 2020

From global cues to pixel labels

Problem: they focus only on highly discriminative regions

Region mining

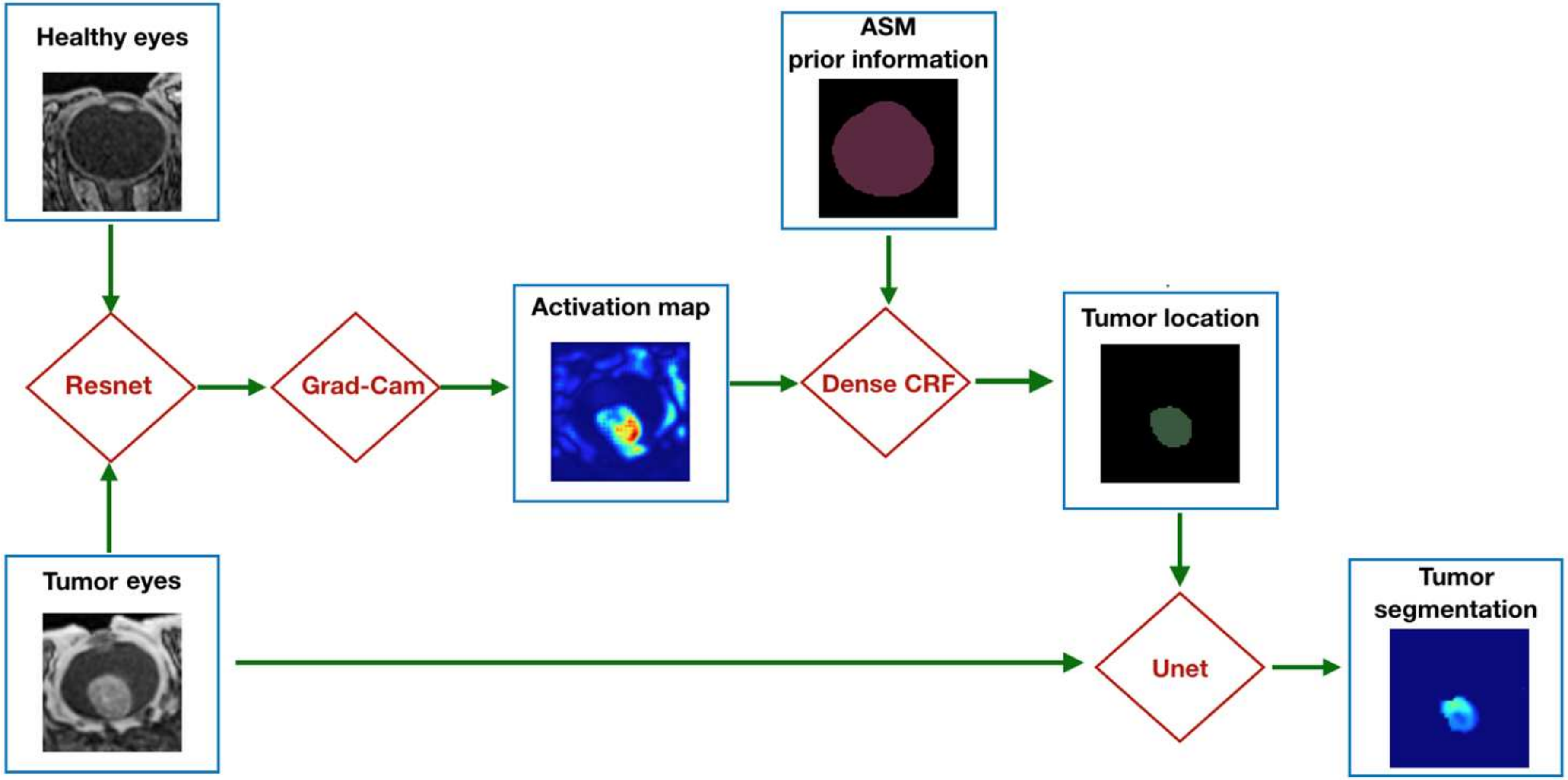




- Wei et al. Object Region Mining with Adversarial Erasing: A Simple Classification to Semantic Segmentation Approach. CVPR 2017
- Wang et al. Weakly-Supervised Semantic Segmentation by Iteratively Mining Common Object Features. CVPR 2018

From global cues to pixel labels

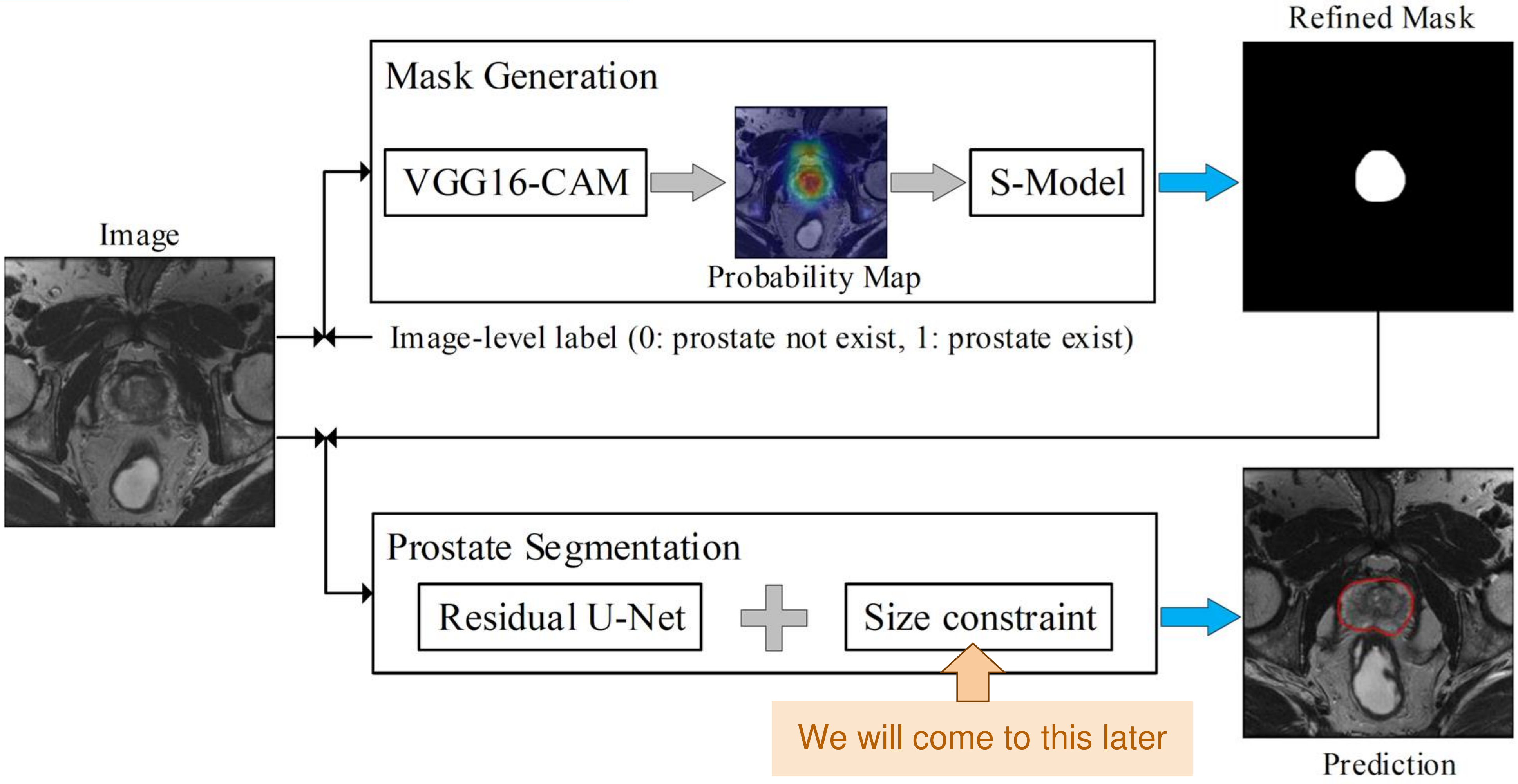
CAMs in the medical domain



Nguyen et al. A novel segmentation framework for uveal melanoma based on magnetic resonance imaging and class activation maps. MIDL 2019.

From global cues to pixel labels

CAMs in the medical domain

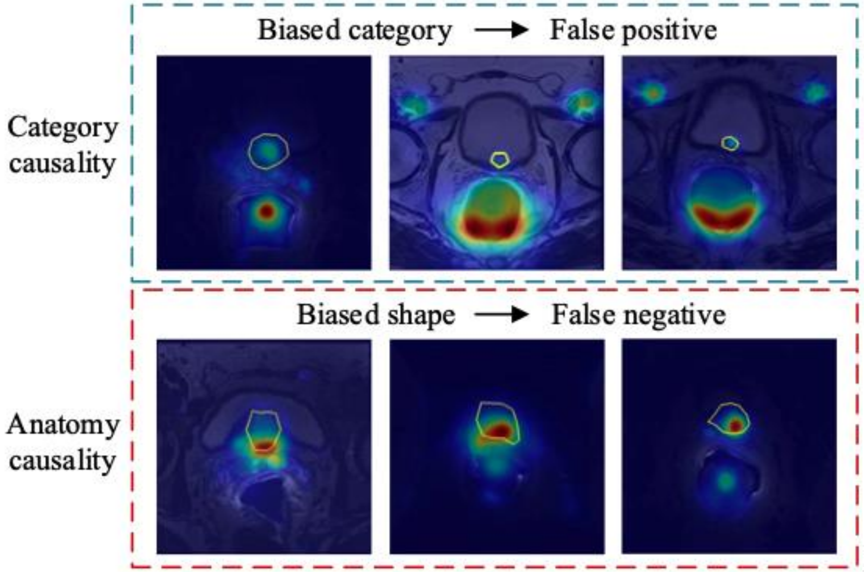


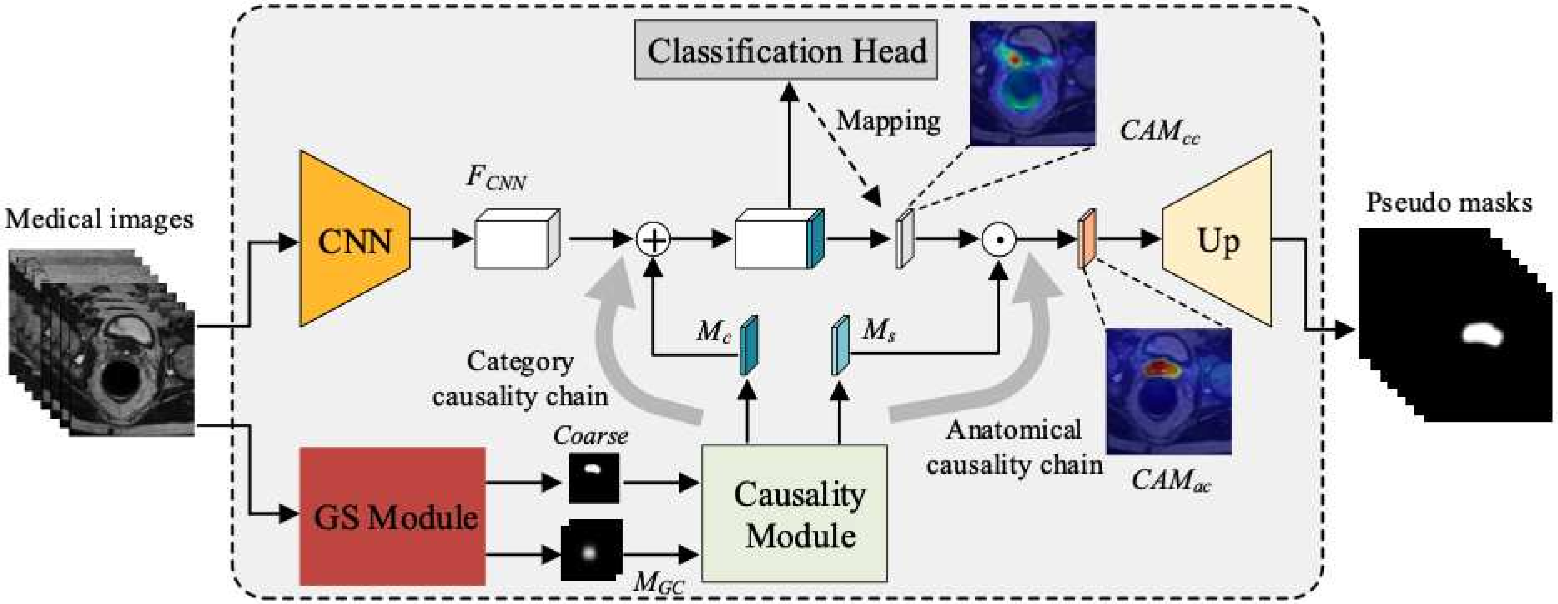
We will come to this later

Chen et al. Exploiting confident information for weakly supervised prostate segmentation based on image-level labels. SPIE Medical Imaging 2020

From global cues to pixel labels

CAMs in the medical domain





Chen et al. C-CAM: Causal CAM for Weakly Supervised Semantic Segmentation on Medical Image. CVPR’22

Knowledge-driven priors

Common priors in natural images

Target Size

Incorrect sizes

Correct sizes

- Pathak et al., Constrained convolutional neural networks for weakly supervised segmentation, ICCV 2015
- Xu et al., Learning to Segment Under Various Forms of Weak Supervision, CVPR 2015
- Zhang et al., Curriculum Domain Adaptation for Semantic Segmentation of Urban Scenes. ICCV’17

Knowledge-driven priors

Common priors in natural images

Target Location

Incorrect location

Correct location

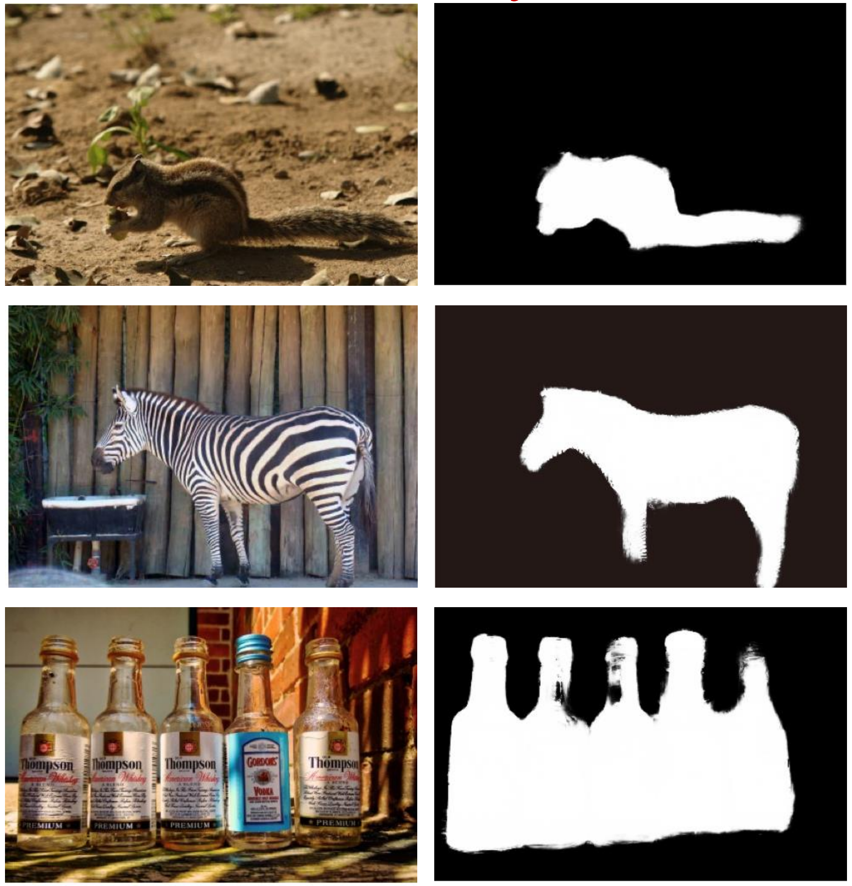
- Remez et al. Learning to segment via cut-and-paste. ECCV 2018
- Georgakis et al Synthesizing training data for object detection in indoor scenes. RSS 2017

Knowledge-driven priors

Common priors in natural images

Contrast
Foreground/Background

Saliency



Images from Hou et al, CVPR'17

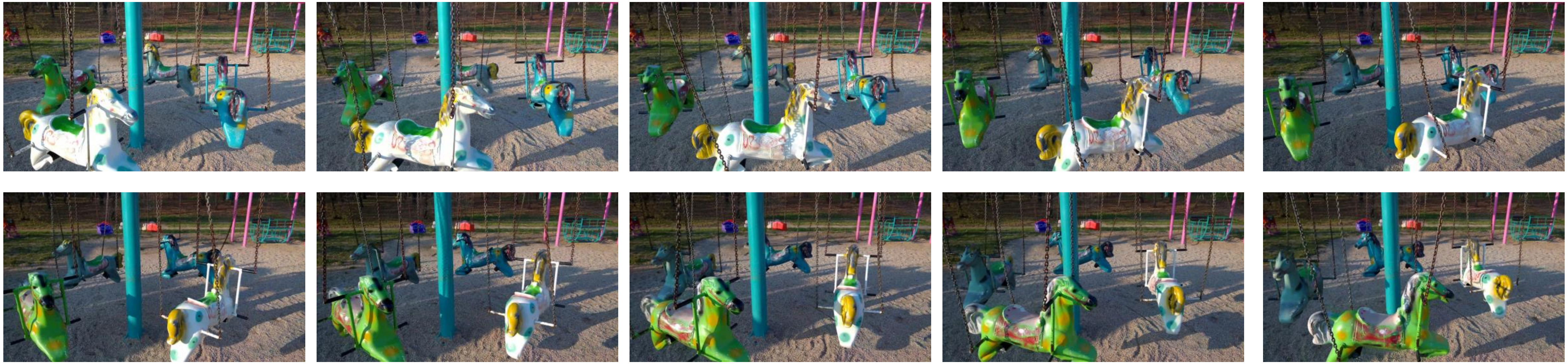
- Hou et al. Deeply supervised salient object detection with short connections. CVPR 2017
- Li et al. Instance-level salient object segmentation. CVPR 2017

Knowledge-driven priors

Common priors in natural images

Motion

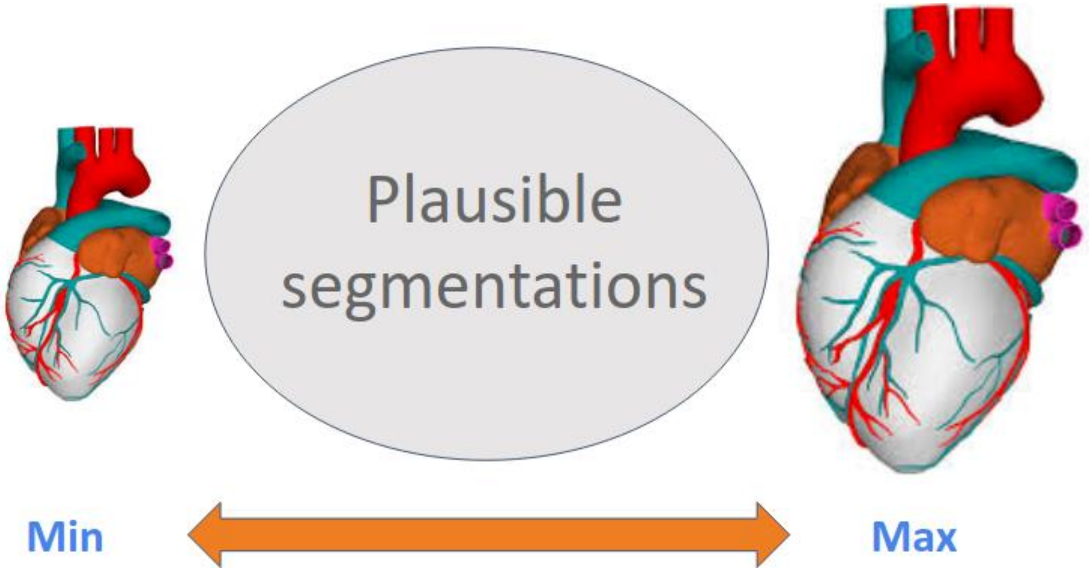
Images from the DAVIS Challenge Dataset

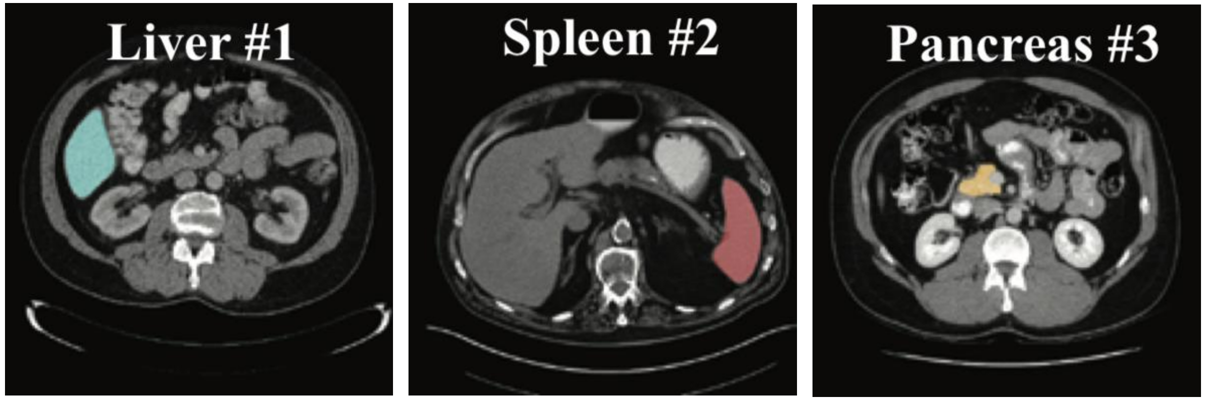


- Tokmakov et al. Weakly-supervised semantic segmentation using motion cues. ECCV 2016
- Pathak et al. Learning features by watching objects move. CVPR 2017

Knowledge-driven priors

What about priors in the medical domain?





Anatomical priors

Partial labeled data
(exploit target relationships)

Constrained optimization (CNN)

Optimize (A) such that (B)

Task

Set of constraints

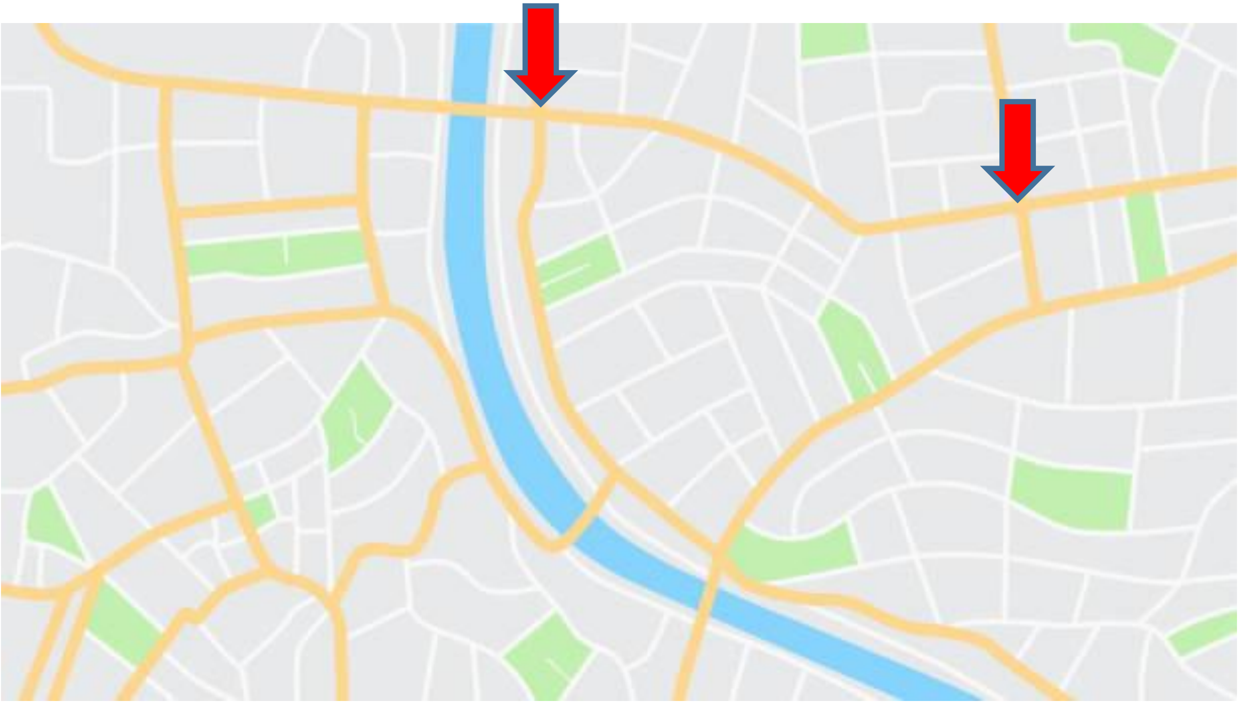
Constrained optimization (CNN)

Optimize (A) such that (B)

Task

Set of constraints

How we can go from point A to B?



Constrained optimization (CNN)

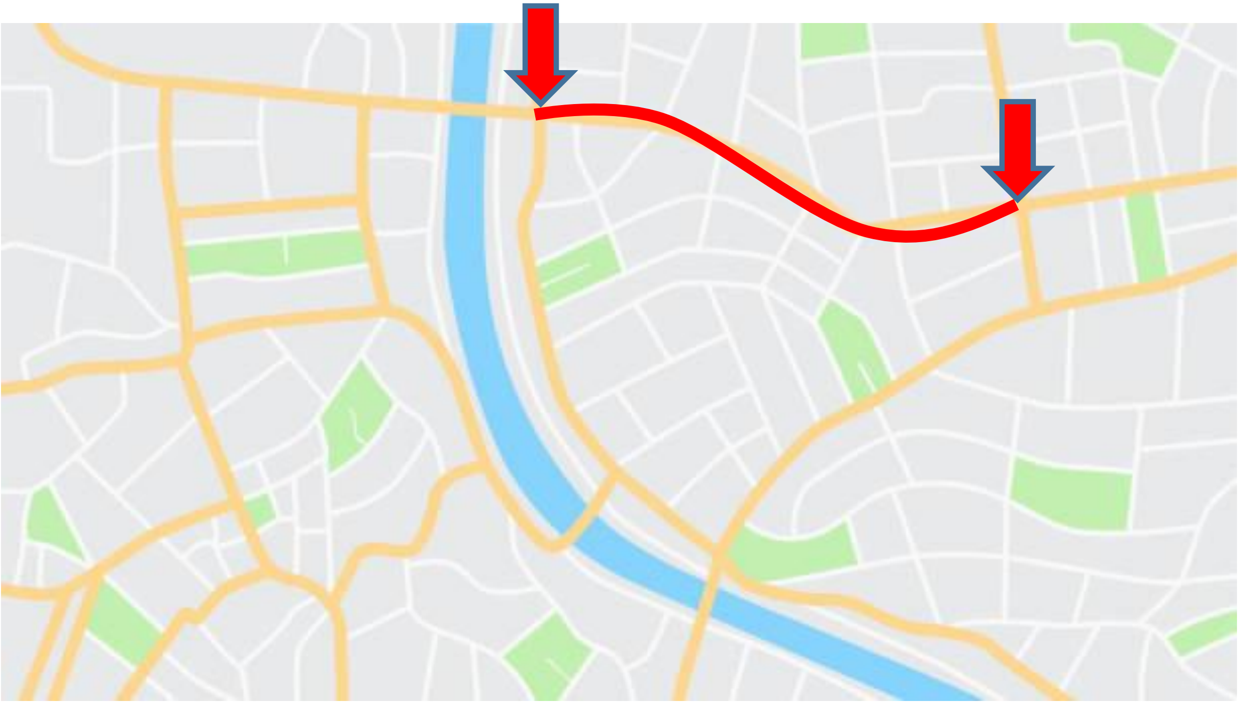
Optimize (A)

Task

such that (B)

Set of constraints

How we can go from point A to B?



Constrained optimization (CNN)

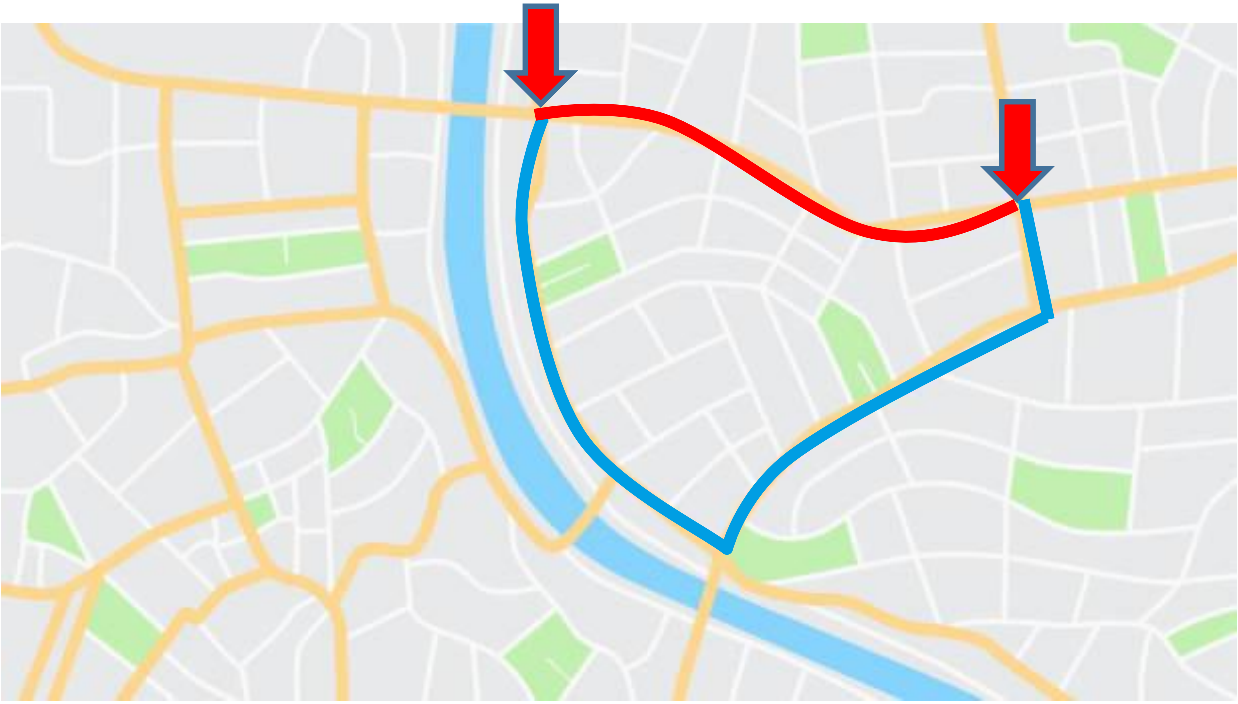
Optimize (A)

Task

such that (B)

Set of constraints

How we can go from point A to B?

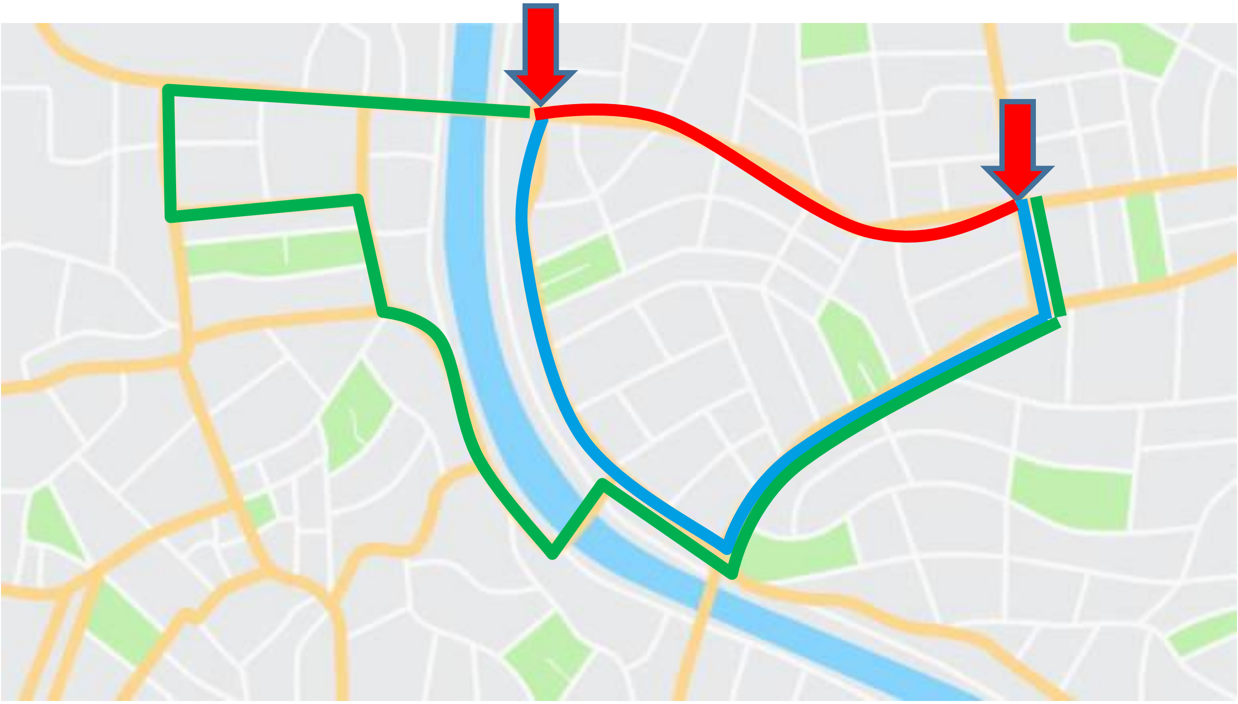


Constrained optimization (CNN)

Optimize (A) such that (B)

Task

Set of constraints



How we can go from point A to B?

Which is the best route?

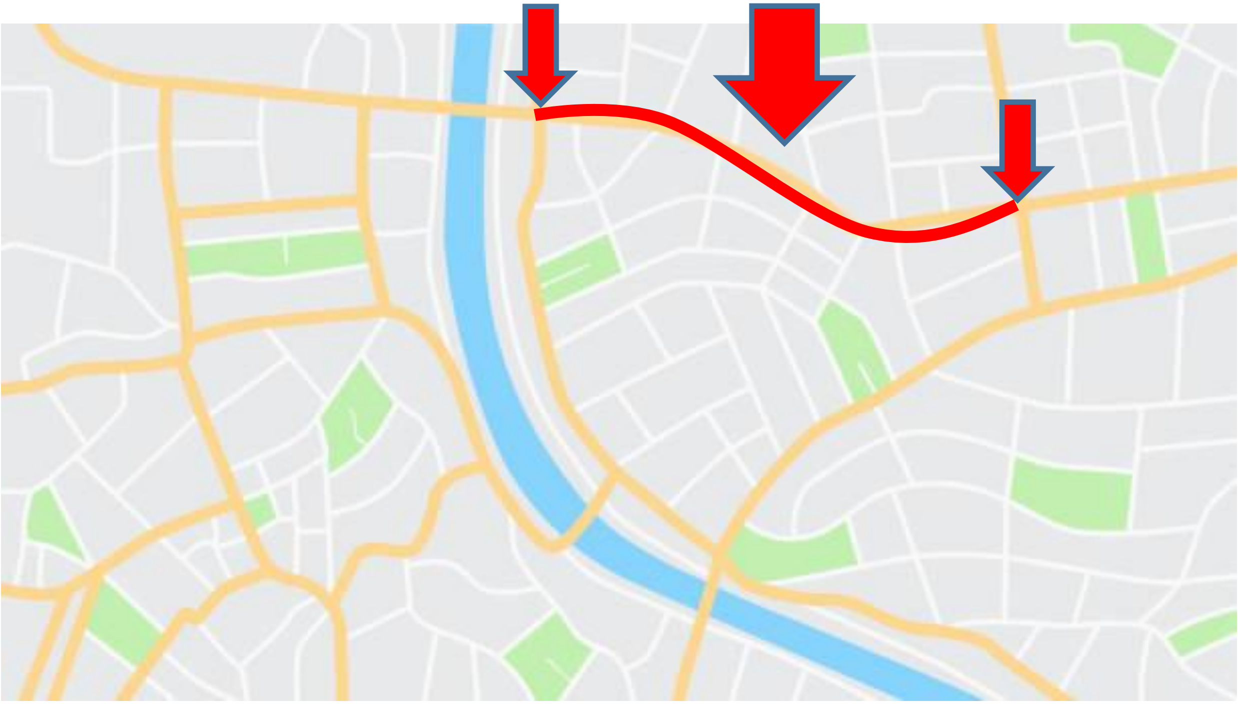
Constrained optimization (CNN)

Optimize (A)

Task

such that (B)

Set of constraints



How we can go from point A to B?

Which is the best route?

Constraint: shortest

Constrained optimization (CNN)

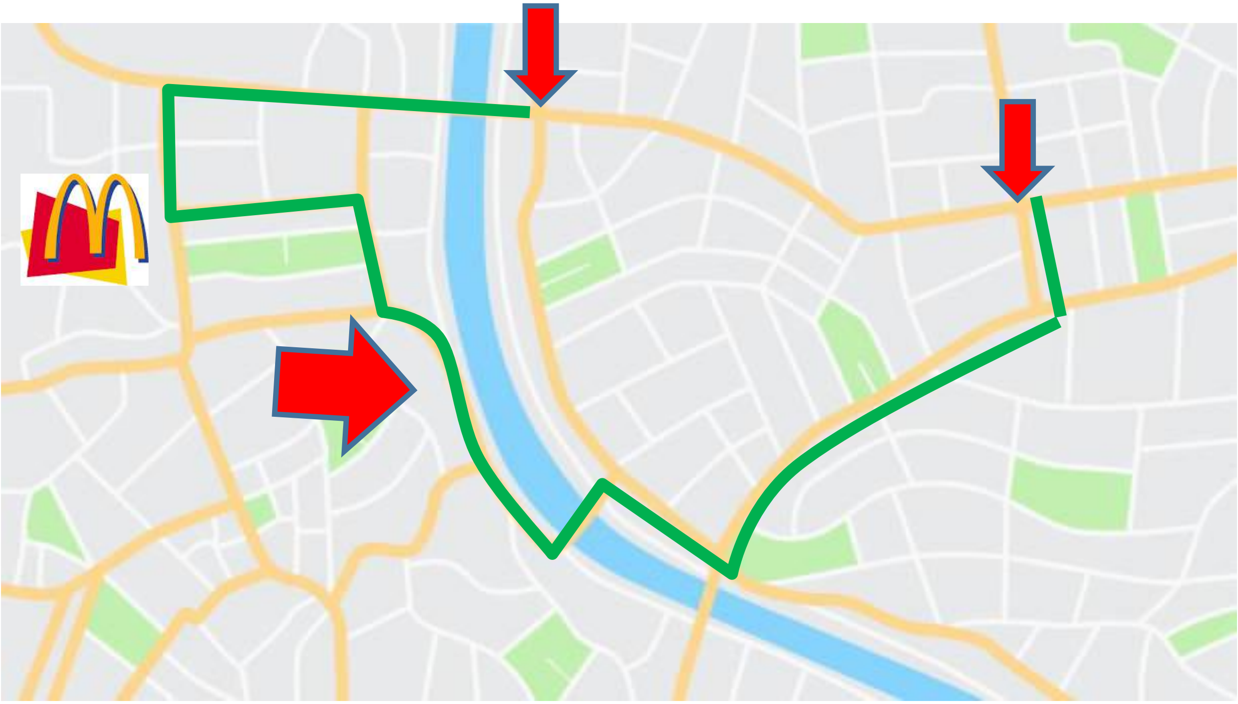
Optimize (A)

Task

such that (B)

Set of constraints

How we can go from point A to B?



Which is the best route?

Constraint: shortest but going through a McDonnalds

Constrained optimization (CNN)

Optimize (A) such that (B)

$$\min_{\theta} \mathcal{H}(S, Y) \quad s.t. \quad \sum_{n=0}^{N} s_n = A$$

Constrained problem

Constrained optimization (CNN)

Optimize (A) such that (B)

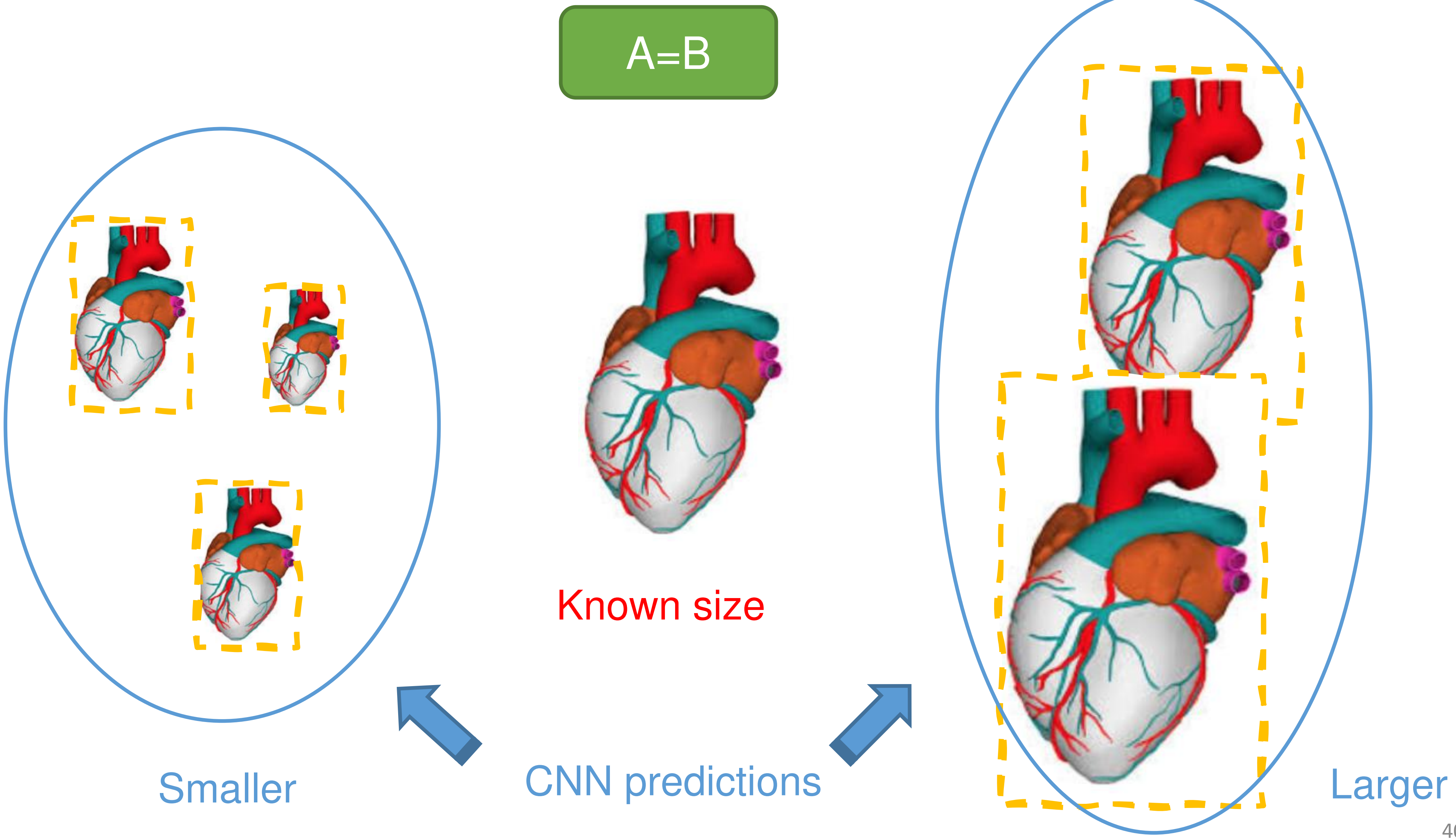
$$\min_{\theta} \mathcal{H}(S, Y) \quad s.t. \quad \sum_{n=0}^{N} s_n = A$$

Constrained problem

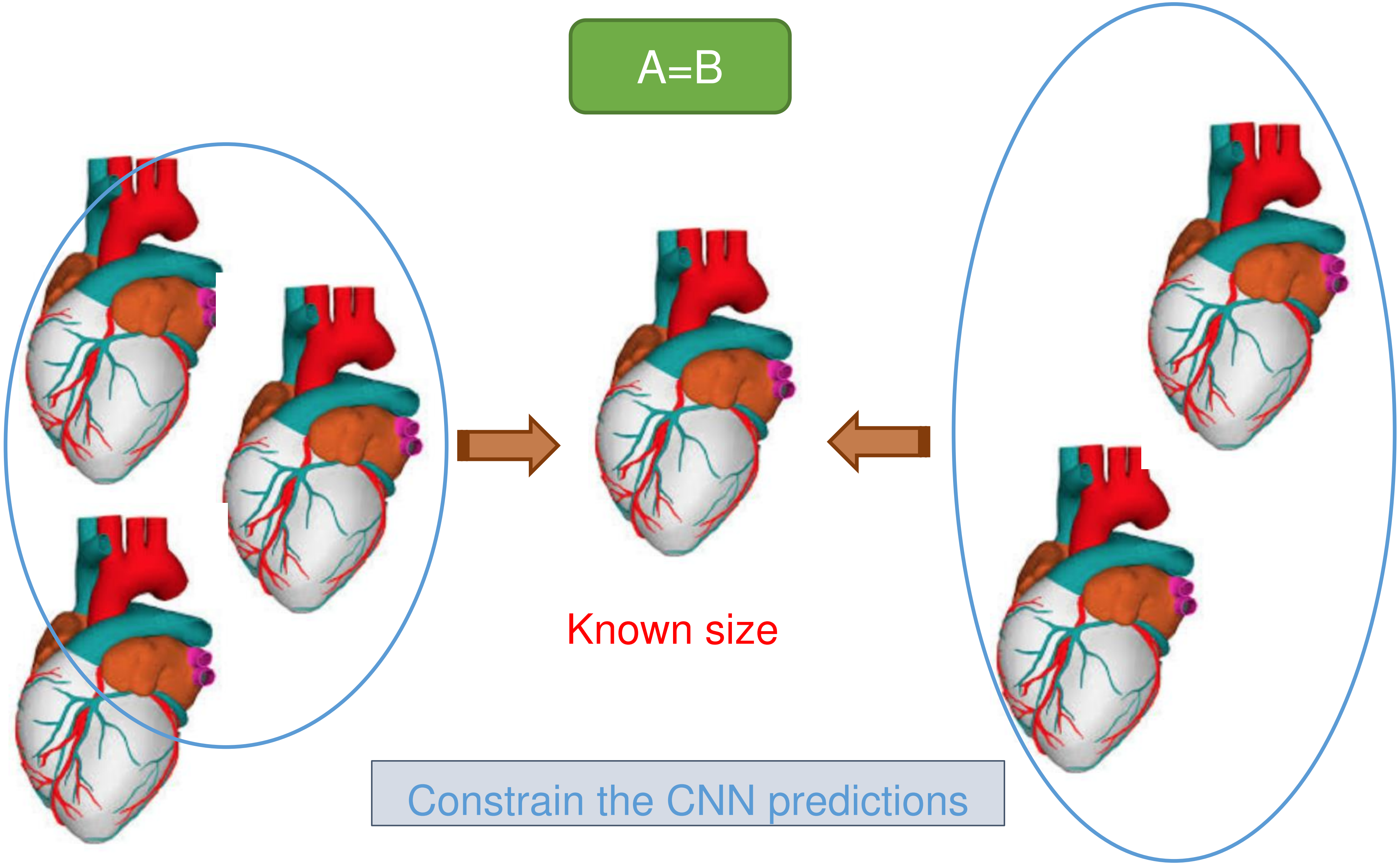
$$\min_{\theta} \mathcal{H}(S, Y) - \lambda(\sum_{n=0}^{N} s_n - A)$$

Unconstrained problem

Equality constraints



Equality constraints



Equality constraints

L2 Penalty

Input
(Histology image)

Any CNN architecture

Output
(Pixel-wise prediction)

Jia et al. Constrained deep weak supervision for histopathology image segmentation. IEEE TMI 2017

Equality constraints

L2 Penalty

Input
(Histology image)

Any CNN architecture

Output
(Pixel-wise prediction)

Additional term

$$l_{ac} = \boldsymbol{I}(Y_i = 1) \sum_i (v_i - a_i)^2$$

Predicted relative size (%)

$$v_i = \frac{1}{N} \sum_{p \in \Omega} s_\theta^{p,1}$$

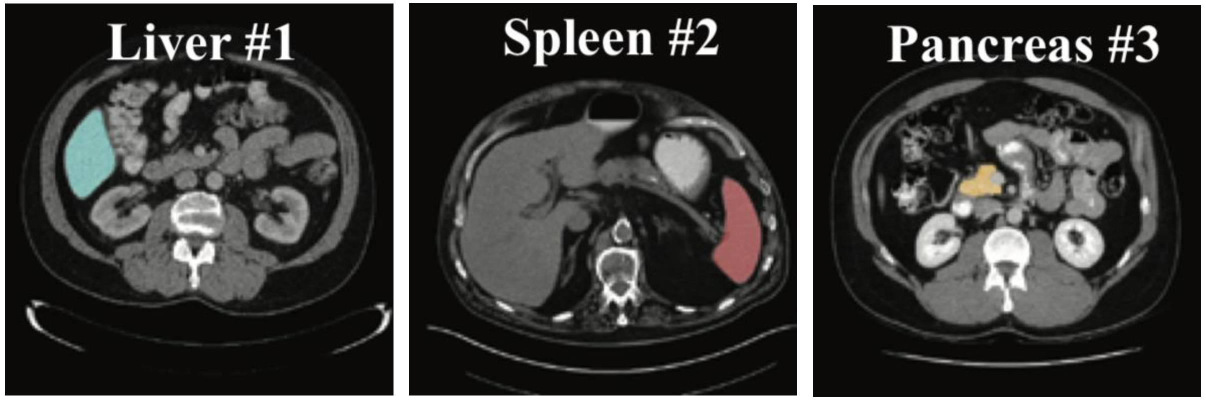
Predicted size given by experts

Jia et al. Constrained deep weak supervision for histopathology image segmentation. IEEE TMI 2017

Equality constraints

Kullback-Leibler (KL) Divergence

Partial annotations

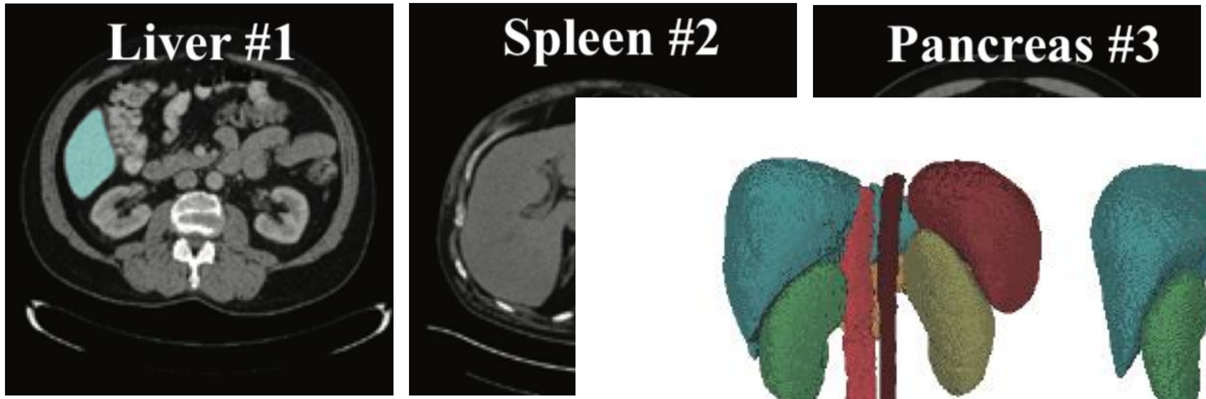


[Zhou et al., Prior-aware Neural Network for Partially-Supervised Multi-Organ Segmentation, ICCV'19]

Equality constraints

Kullback-Leibler (KL) Divergence

Partial annotations



Prior on the proportion

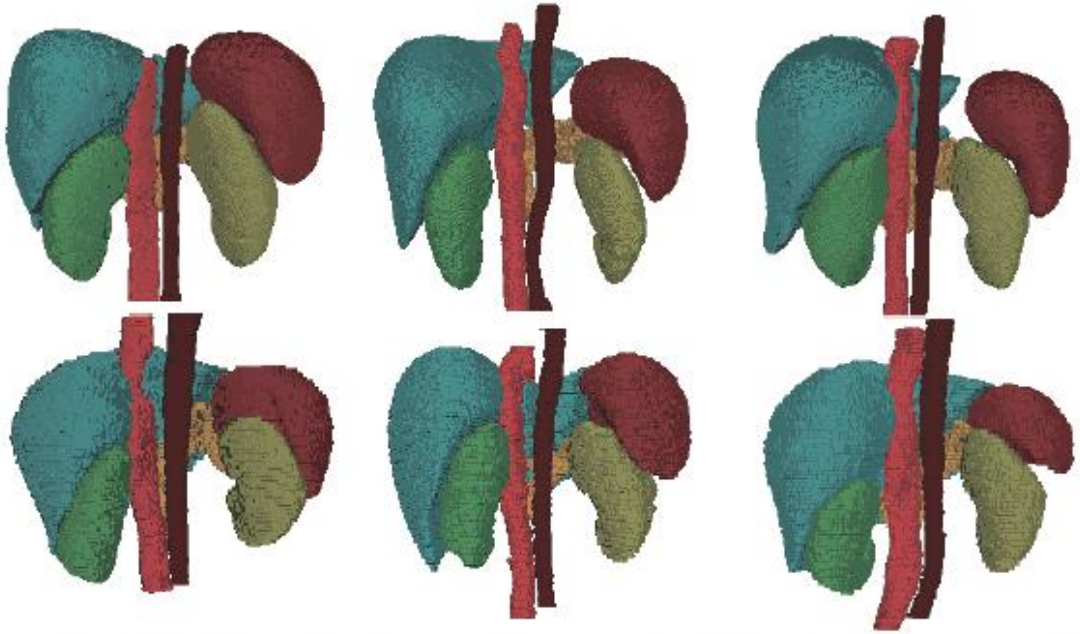


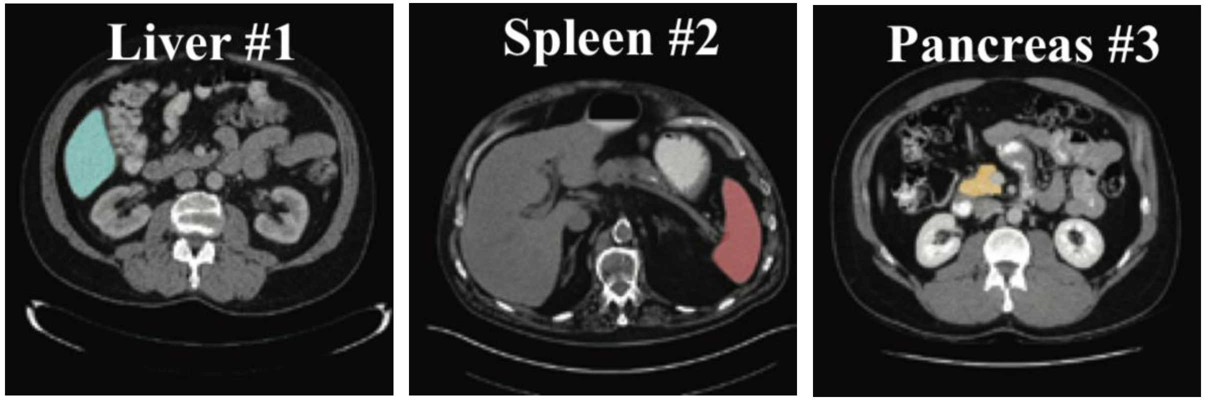
Figure 1. 3D Visualization of several abdominal organs (liver, spleen, left kidney, right kidney, aorta, inferior vena cava) to show the similarity of patient-wise abdominal organ size distributions.

[Zhou et al., Prior-aware Neural Network for Partially-Supervised Multi-Organ Segmentation, ICCV’19]

Equality constraints

Kullback-Leibler (KL) Divergence

Partial annotations



Main objective:

$$min\frac{1}{|\mathcal{L}|}\sum_{p\in\mathcal{L}} l(\mathbf{y}^p,\mathbf{s}^p_\theta) + \lambda_1\frac{1}{|\mathcal{P}|}\sum_{q\in\mathcal{P}} l(\mathbf{y}^q,\mathbf{s}^q_\theta) + \lambda_2\mathcal{J}(\theta)$$

Prior-aware loss

Fully labeled images

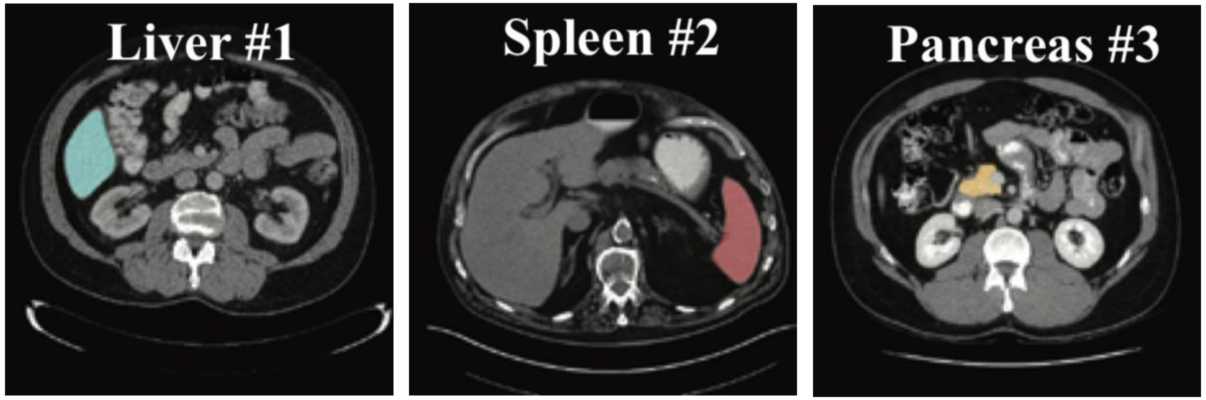
Partially labeled images

[Zhou et al., Prior-aware Neural Network for Partially-Supervised Multi-Organ Segmentation, ICCV'19]

Equality constraints

Kullback-Leibler (KL) Divergence

Partial annotations



Prior-aware loss

Averaged predicted distribution

$$\hat{\mathbf{p}} = \frac{1}{N} \sum_{p \in \mathcal{P}} \mathbf{s}_\theta^p$$

$$[s_\theta^{p,0}, s_\theta^{p,1}, \ldots, s_\theta^{p,|K|}]$$

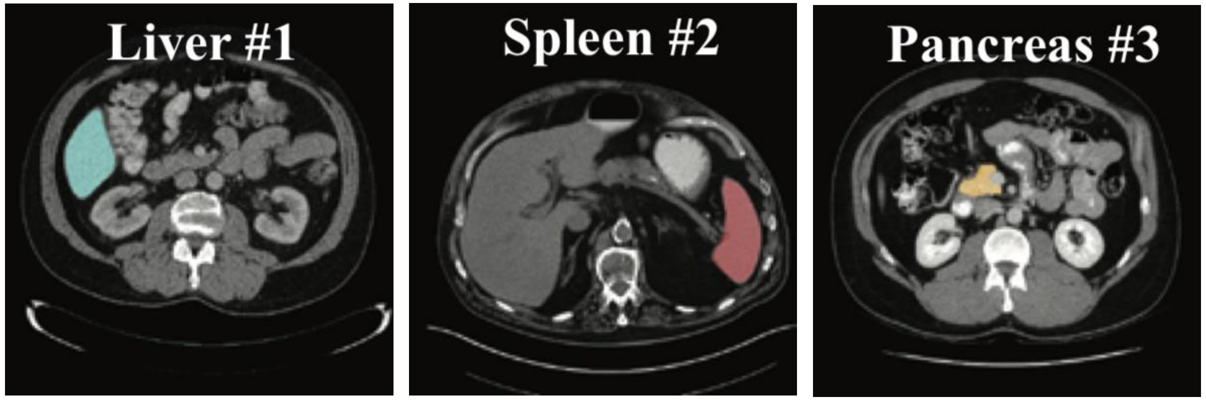
On partially labeled images

[Zhou et al., Prior-aware Neural Network for Partially-Supervised Multi-Organ Segmentation, ICCV'19]

Equality constraints

Kullback-Leibler (KL) Divergence

Partial annotations



Prior-aware loss

Embed prior knowledge

$$KL(\mathbf{q}|\hat{\mathbf{p}})$$

Real label distribution

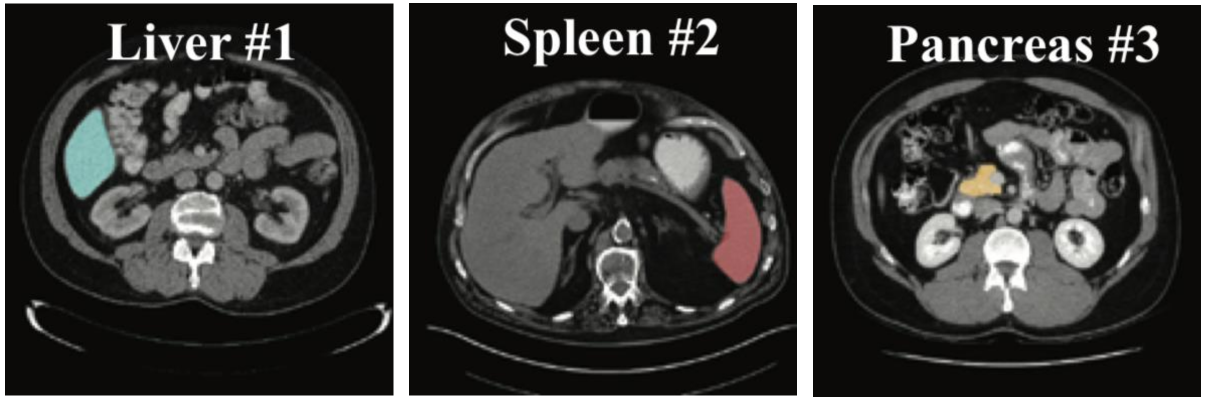
Average predicted distribution

[Zhou et al., Prior-aware Neural Network for Partially-Supervised Multi-Organ Segmentation, ICCV'19]

Equality constraints

Kullback-Leibler (KL) Divergence

Partial annotations



KL can be expanded

$$\sum_c KL(q^c|\hat{p}^c) = -\sum_c (q^c \log \hat{p}^c + ((1-q^c)\log(1-\hat{p}^c)) + const$$

$$\hat{p}_c = \frac{1}{N}\sum_{p\in\mathcal{P}} \mathbf{s}_\theta^{p,c}$$

Prior-aware loss

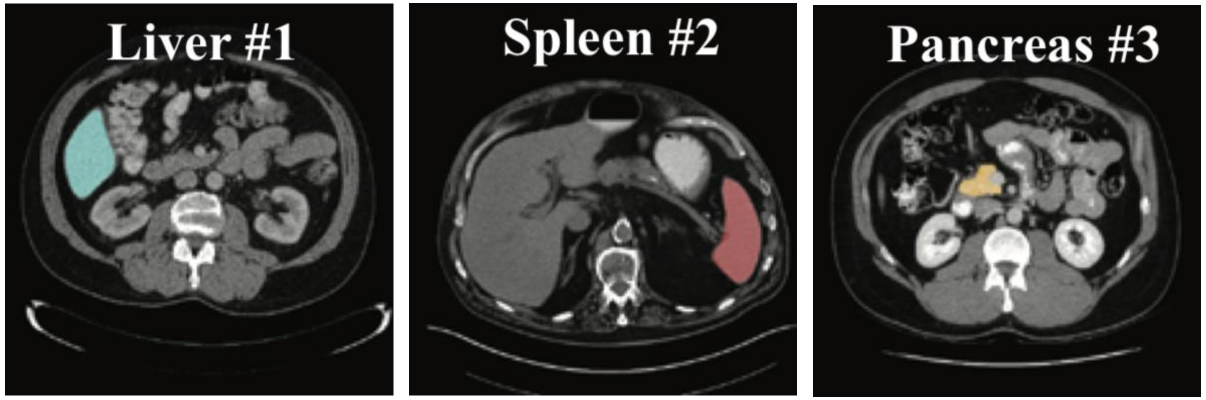
$$-\sum_{c=0}^{|K|}\{q^c log \frac{1}{N}\sum_{p\in\mathcal{P}} \mathbf{s}_\theta^{p,c} + (1-q^c)log(1-\frac{1}{N}\sum_{p\in\mathcal{P}} \mathbf{s}_\theta^{p,c})\} + const$$

[Zhou et al., Prior-aware Neural Network for Partially-Supervised Multi-Organ Segmentation, ICCV'19]

Equality constraints

Kullback-Leibler (KL) Divergence

Partial annotations



$$\sum_c KL(q^c|\hat{p}^c) = -\sum_c (q^c \log \hat{p}^c + ((1-q^c)\log(1-\hat{p}^c)) + const$$

Prior-aware loss

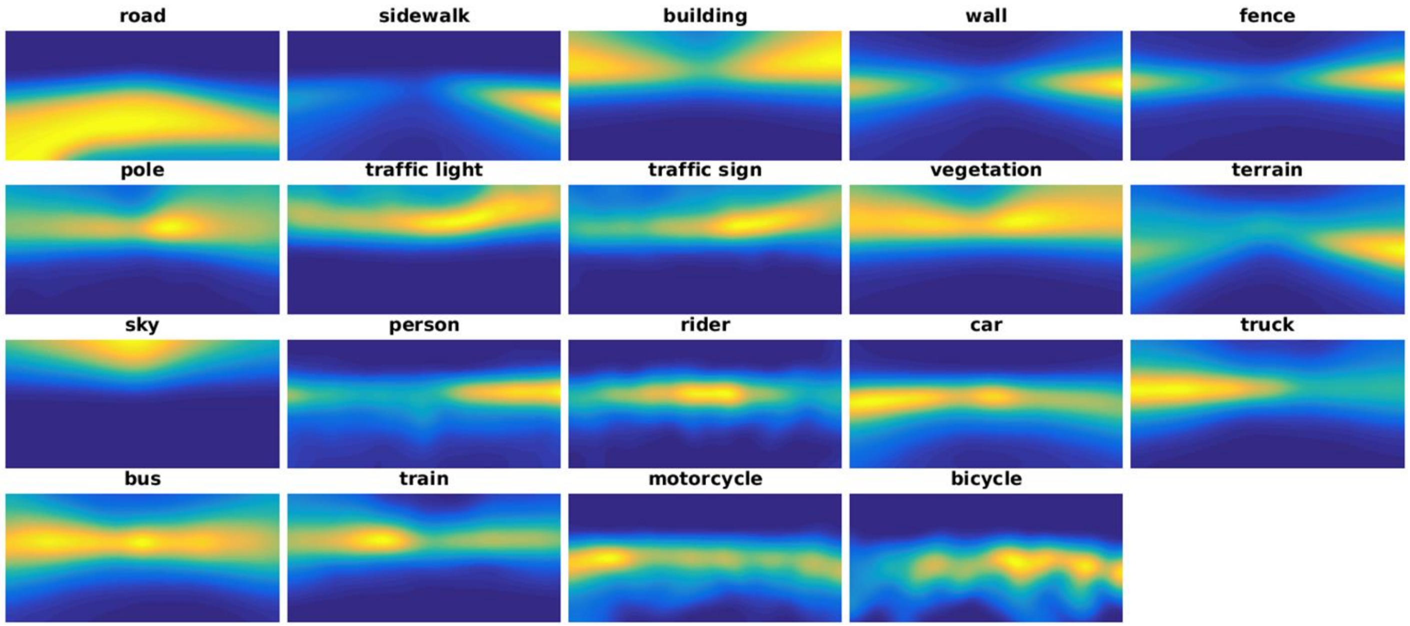
$$-\sum_{c=0}^{|K|}\{q^c log \frac{1}{N}\sum_{p\in\mathcal{P}} \mathbf{s}_\theta^{p,c} + (1-q^c) log(1-\frac{1}{N}\sum_{p\in\mathcal{P}} \mathbf{s}_\theta^{p,c})\} + const$$

This is problematic (average distribution of p̂ organ sizes inside log!!)

[Zhou et al., Prior-aware Neural Network for Partially-Supervised Multi-Organ Segmentation, ICCV'19]

Equality constraints

At pixel level

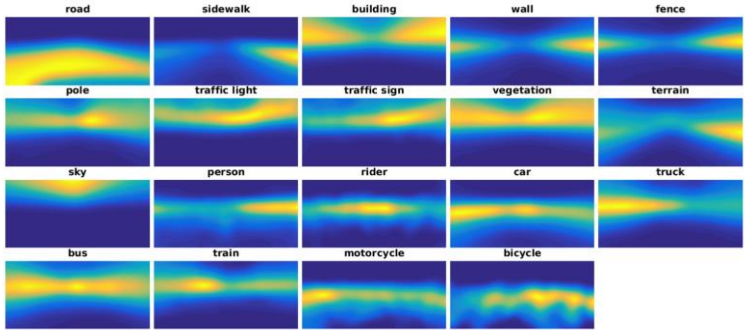


Spatial priors on GTA5

Images from [Zou et al., Unsupervised Domain Adaptation for Semantic Segmentation via Class-Balanced Self-Training, ECCV'18]

Equality constraints

At pixel level



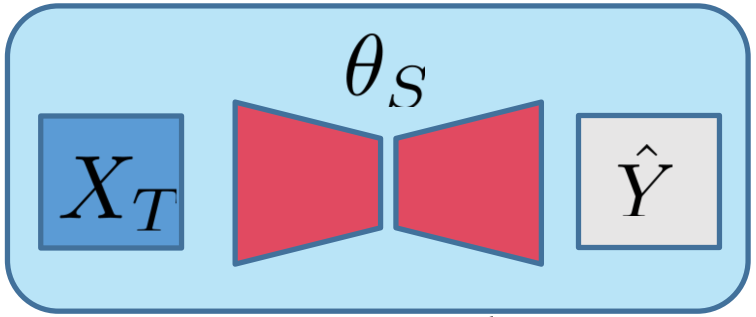
Objective:

$$-\sum_{p\in\mathcal{L}} l(\mathbf{y}^p, s_\theta^p) - \sum_{q\in\mathcal{U}}\sum_{c=1}^{K}(\hat{y}^{q,c} log(prior^{q,c} s_\theta^{q,c}) + w_c \hat{y}^{q,c})$$

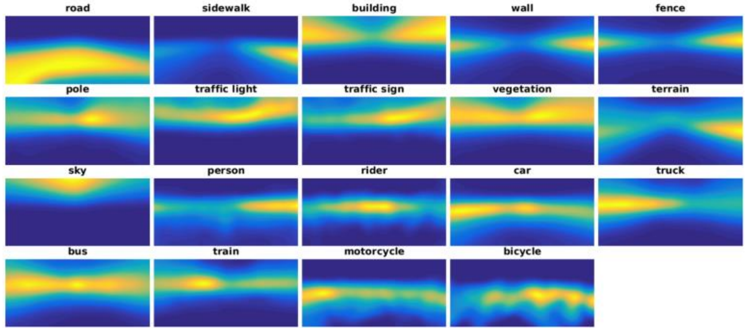
Zou et al., Unsupervised Domain Adaptation for Semantic Segmentation via Class-Balanced Self-Training, ECCV’18

Equality constraints

At pixel level



Proposals



Objective:

$$-\sum_{p\in\mathcal{L}} l(\mathbf{y}^p, s_\theta^p) - \sum_{q\in\mathcal{U}}\sum_{c=1}^{K}(\hat{y}^{q,c}log(prior^{q,c}s_\theta^{q,c}) + w_c\hat{y}^{q,c})$$

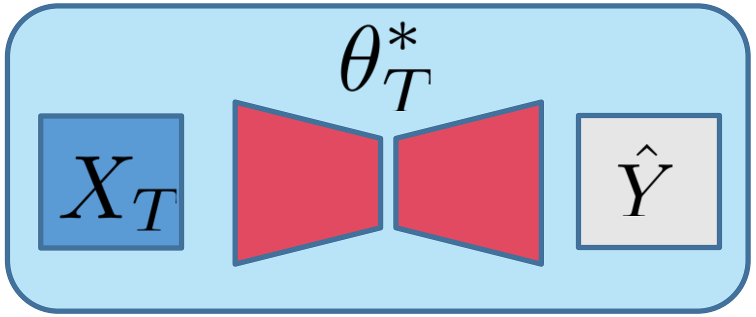
Source images

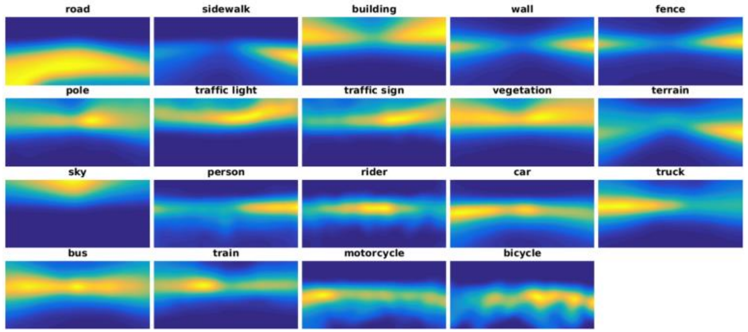
Target images

Zou et al., Unsupervised Domain Adaptation for Semantic Segmentation via Class-Balanced Self-Training, ECCV'18

Equality constraints

At pixel level





Objective:

$$-\sum_{p\in\mathcal{L}} l(\mathbf{y}^p, s^p_\theta) - \sum_{q\in\mathcal{U}}\sum_{c=1}^{K}(\underbrace{\hat{y}^{q,c}log(prior^{q,c}s^{q,c}_\theta)} + w_c\hat{y}^{q,c})$$

2-steps minimization process

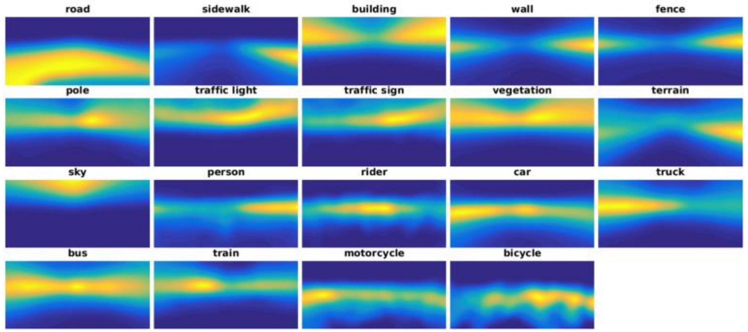
This becomes two KL

$$KL(\hat{y}^{q,c}|prior^{q,c}) \qquad KL(\hat{y}^{q,c}|s^{q,c}_\theta)$$

Zou et al., Unsupervised Domain Adaptation for Semantic Segmentation via Class-Balanced Self-Training, ECCV'18

Equality constraints

At pixel level



Objective:

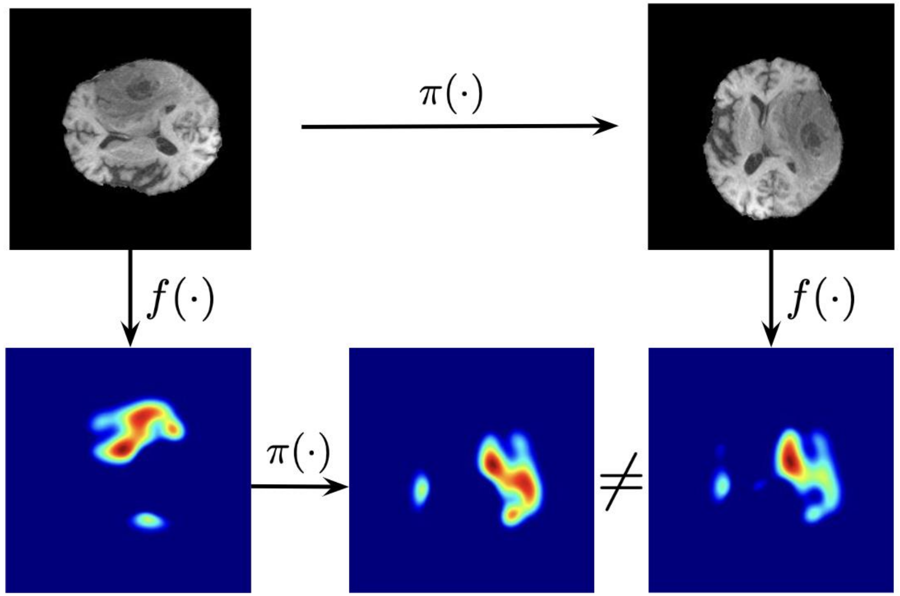
$$-\sum_{p\in\mathcal{L}} l(\mathbf{y}^p, s_\theta^p) - \sum_{q\in\mathcal{U}}\sum_{c=1}^{K}(\hat{y}^{q,c} log(prior^{q,c} s_\theta^{q,c}) + \underbrace{w_c \hat{y}^{q,c}}_{\text{Weights the proposals}})$$

Zou et al., Unsupervised Domain Adaptation for Semantic Segmentation via Class-Balanced Self-Training, ECCV'18

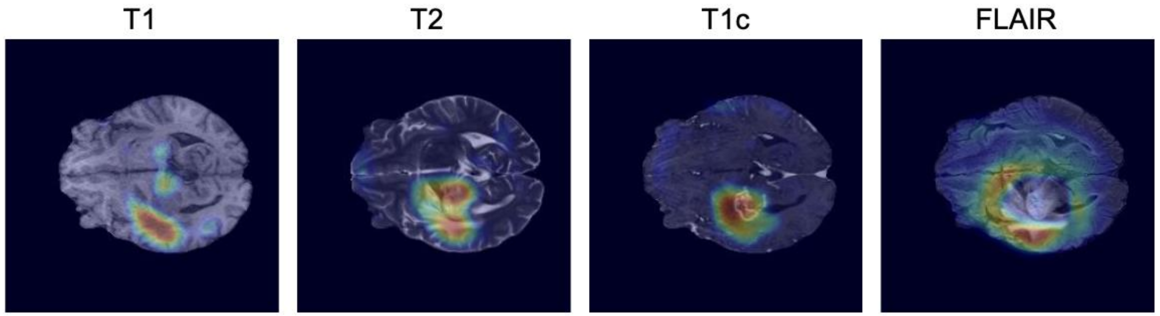
Equality constraints

At pixel level

Imposing Consistency across image modalities



CAMs not equivariant to spatial transformations



CAMs not consistent across modalities

Patel and Dolz, Weakly supervised segmentation with equivariant constraints. MedIA'22

Equality constraints

At pixel level

Consistency regularization term on the CAMs and between modalities

Same-modality equivariant constraints	Cross-modality equivariant constraints
$l_{reg}(T(f(M_1)), f(T(M_1)))$	$l_{reg}(T(f(M_1)), f(T(M_2)))$

Patel and Dolz, Weakly supervised segmentation with equivariant constraints. MedIA'22

Equality constraints

At pixel level

Consistency regularization term on the CAMs and between modalities

Same-modality equivariant constraints

$$l_{reg}(T(f(M_1)), f(T(M_1)))$$

Cross-modality equivariant constraints

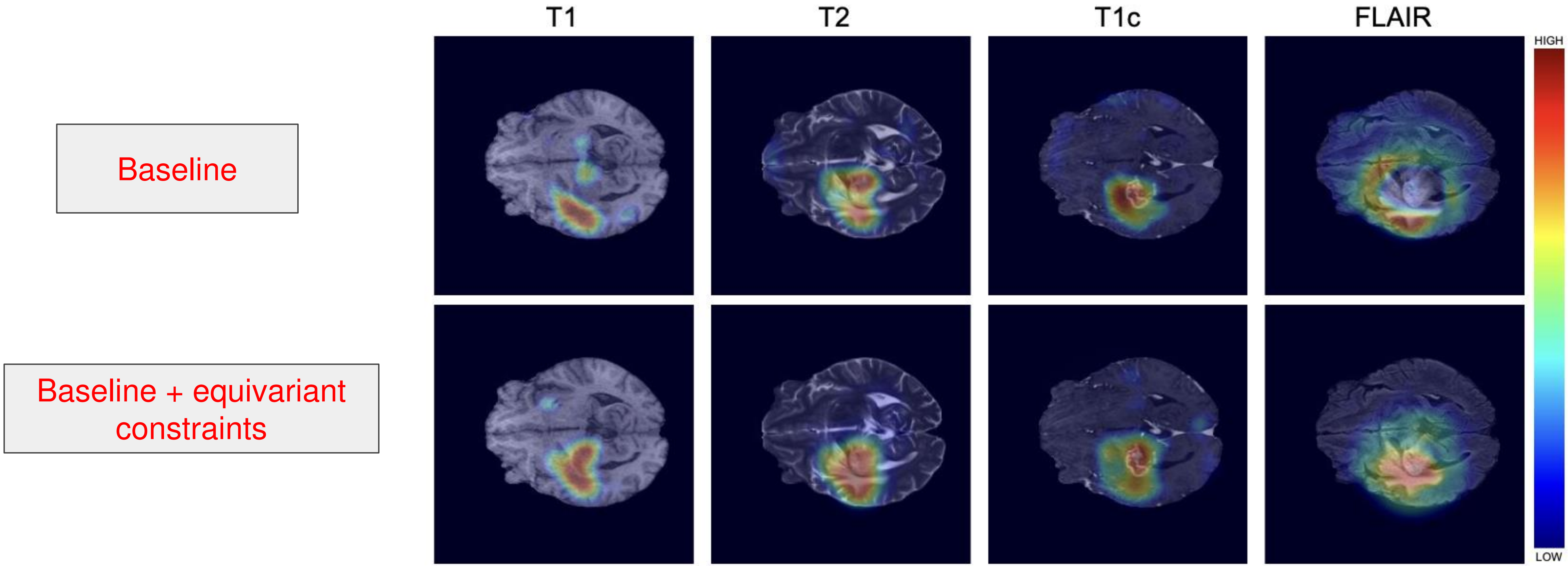
$$l_{reg}(T(f(M_1)), f(T(M_2)))$$

$$\mathcal{L}_{class} + \quad l_{reg}(T(f(M_m)), f(T(M_m))) + + l_{reg}(T(f(M_m)), f(T(M_n)))$$

Patel and Dolz, Weakly supervised segmentation with equivariant constraints. MedIA'22

Equality constraints

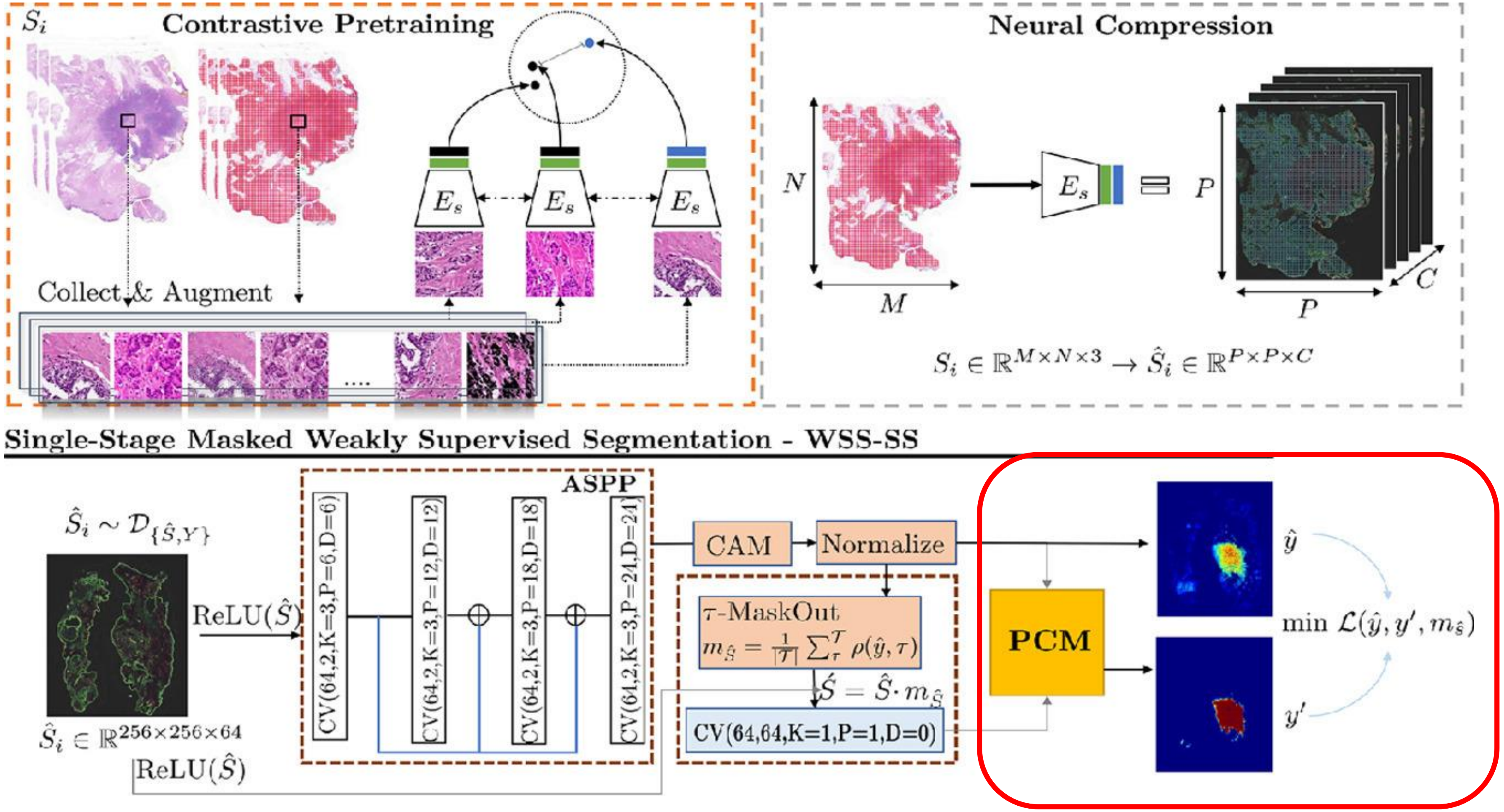
At pixel level



Patel and Dolz, Weakly supervised segmentation with equivariant constraints. MedIA'22

Equality constraints

At pixel level



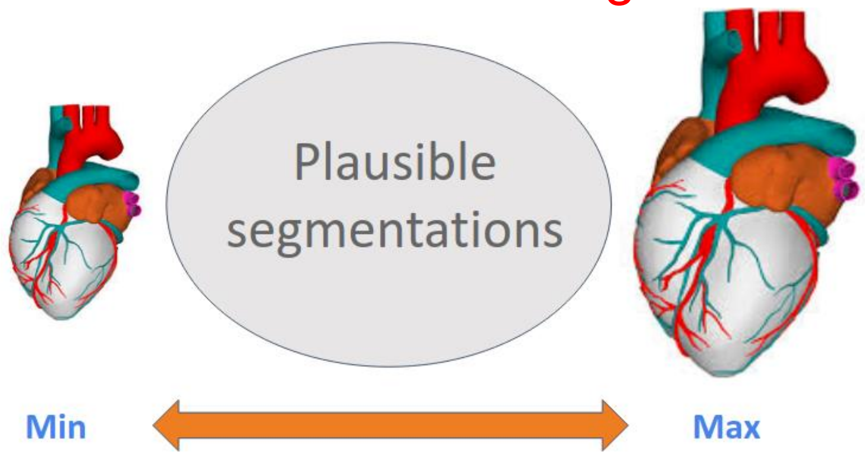
Equivariant regularization

Chikontwe et al. Weakly Supervised Segmentation on Neural Compressed Histopathology with Self-Equivariant Regularization. MedIA’22

Inequality constraints

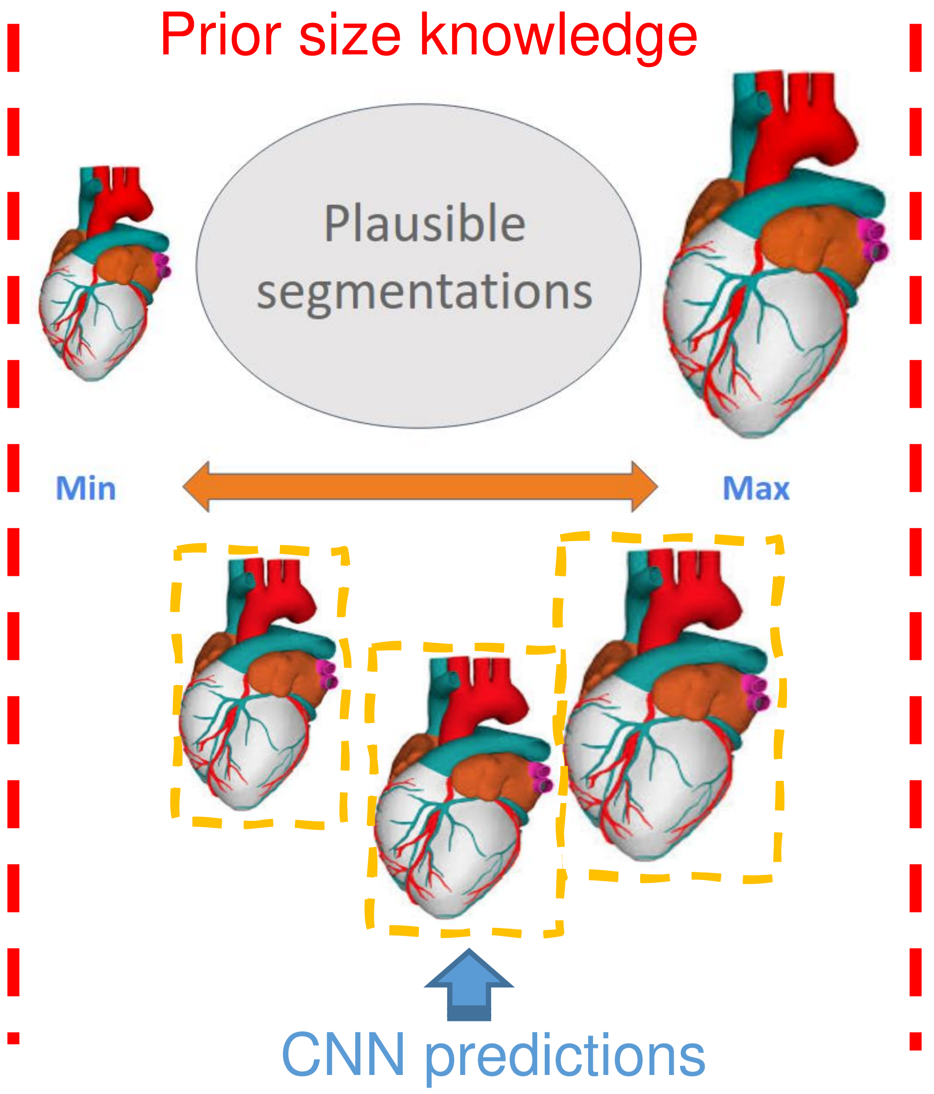
A<B,
A>B,
B1 < A < B2

Prior size knowledge



Inequality constraints

A<B,
A>B,
B1 < A < B2



Inequality constraints

$A<B$,
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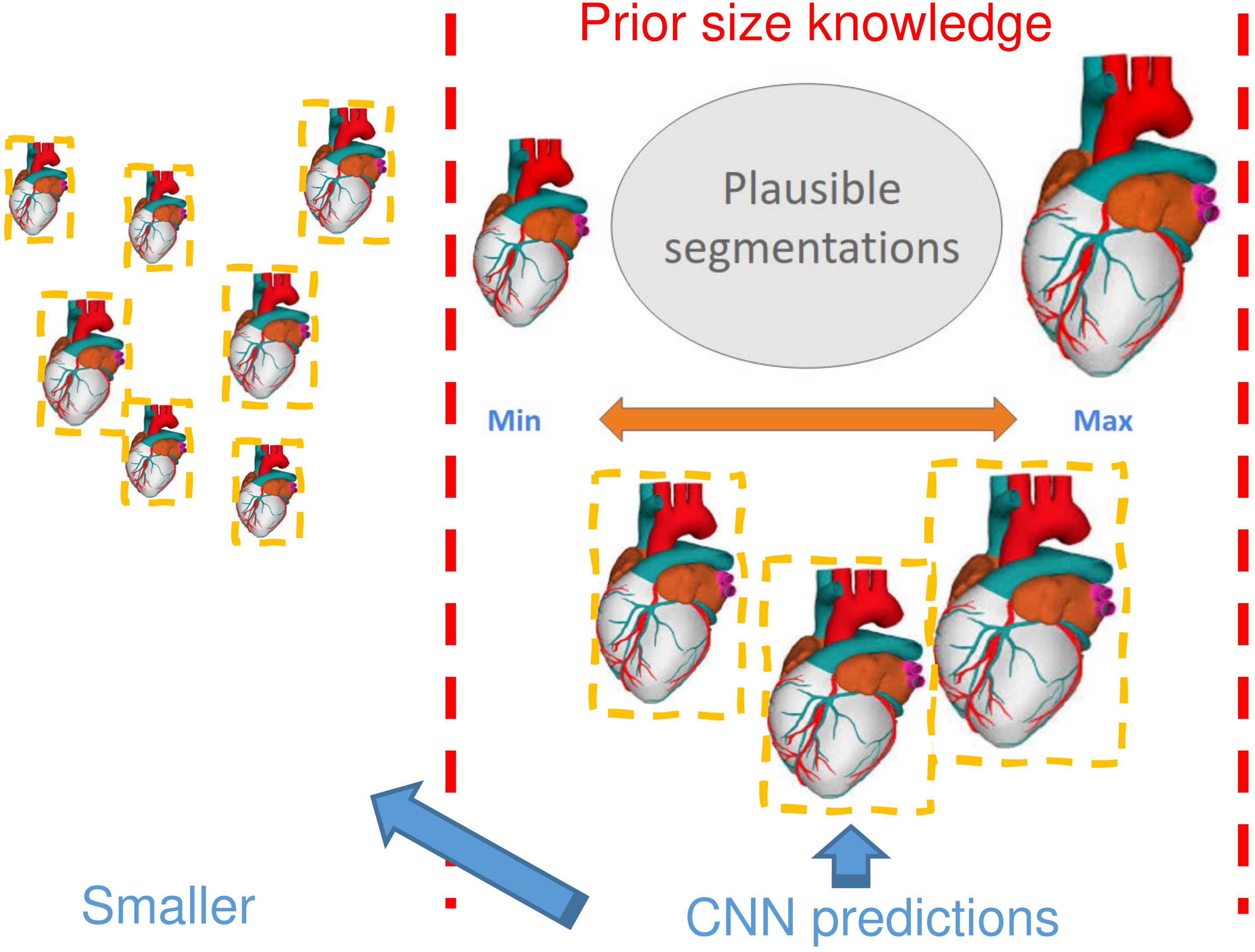
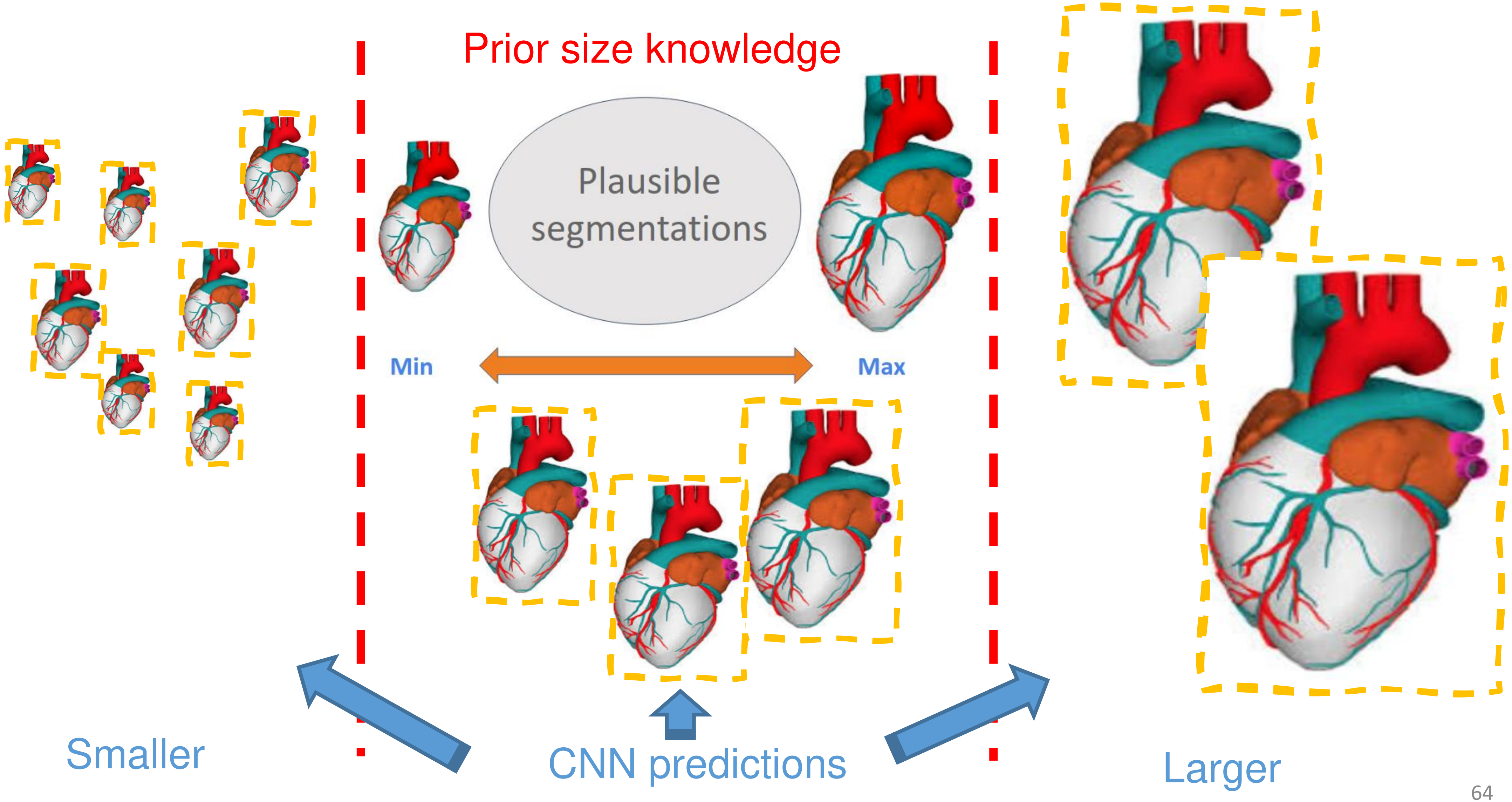
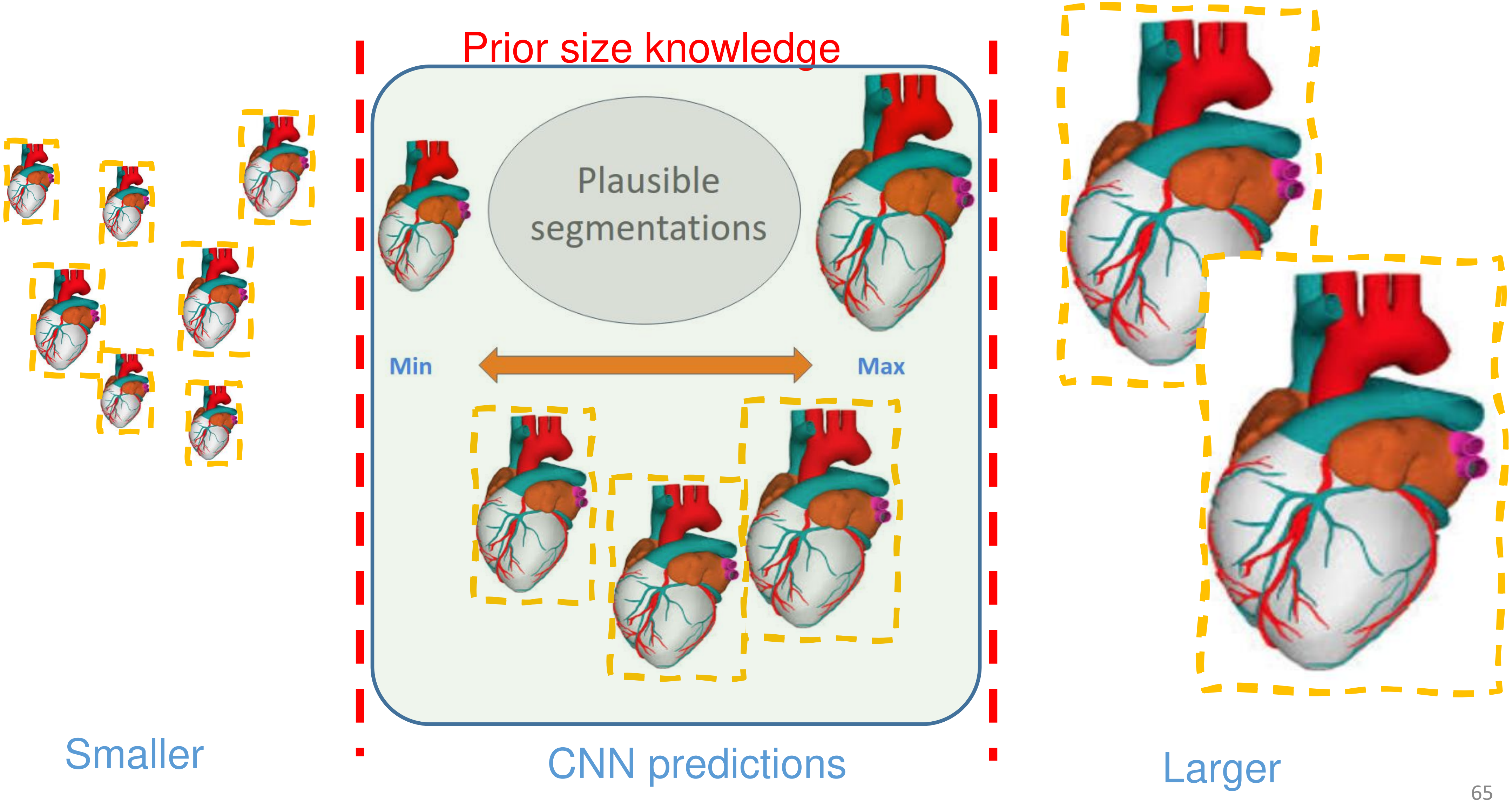


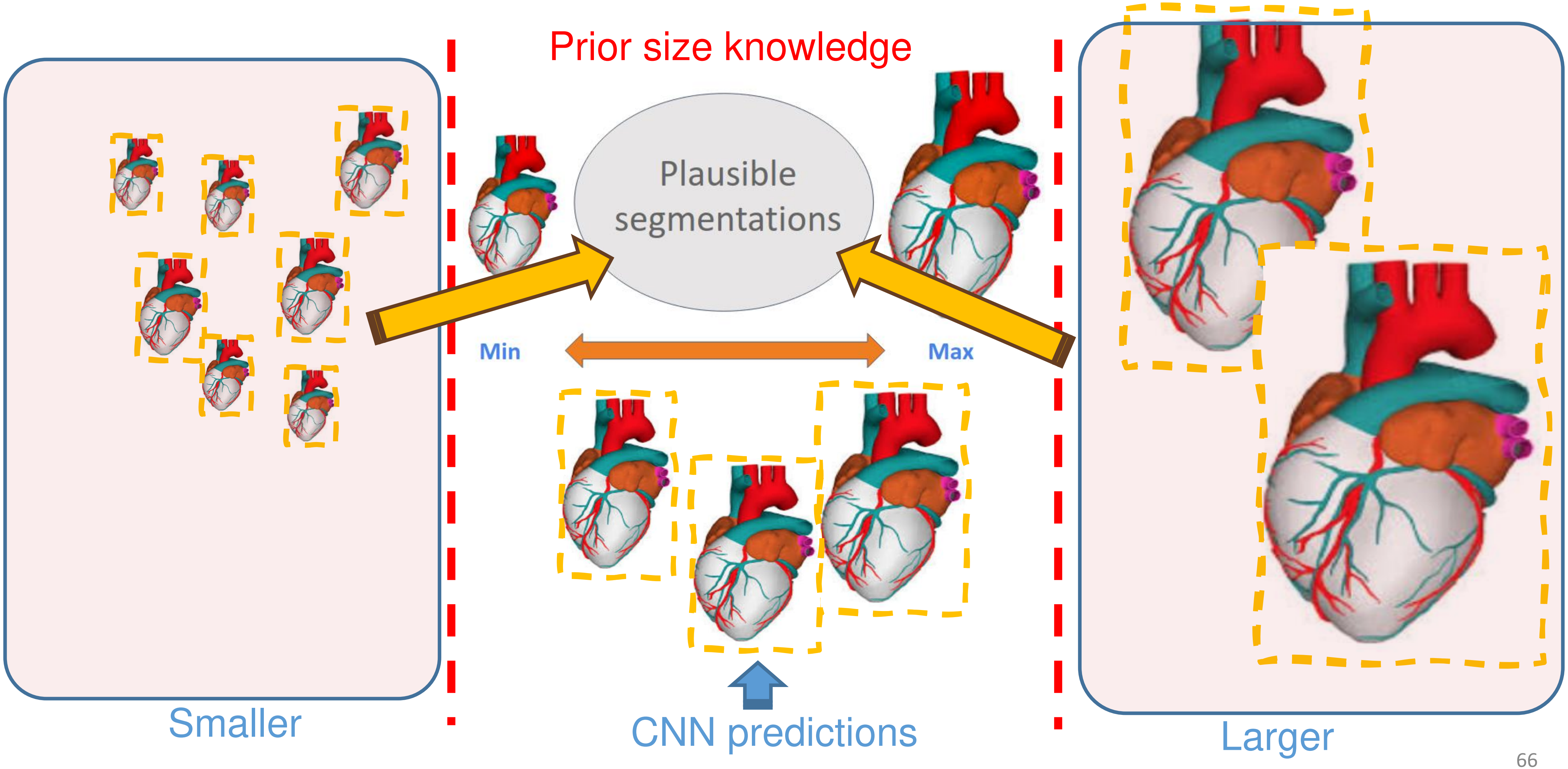
Inequality constraints



Inequality constraints



Inequality constraints



Inequality constraints

Information is given in the form of image-tags

Suppression $$\sum_{p\in\Omega} s_\theta^{p,c} \leq 0 \quad \forall c \notin C$$

“Person”

[Pathak et al., Constrained Convolutional Neural Networks for Weakly Supervised Segmentation, ICCV’15]

Inequality constraints

Information is given in the form of image-tags

Inclusion (or existence)

$$\sum_{p\in\Omega} s_\theta^{p,c} \geq 1 \quad \forall c \in C$$

"Car"

[Pathak et al., Constrained Convolutional Neural Networks for Weakly Supervised Segmentation, ICCV'15]

Inequality constraints

Information is given in
the form of image-tags

Target Size
a > 1

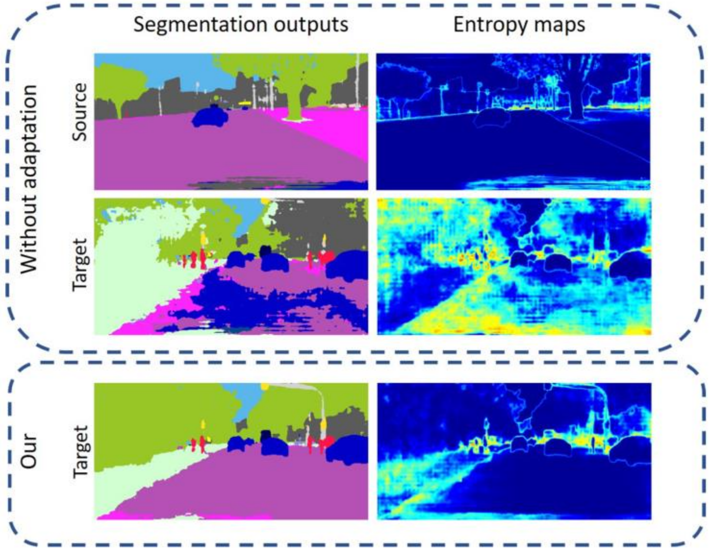
$$\sum_{p \in \Omega} s_{\theta}^{p,c} \geq a \quad \forall c \in C$$

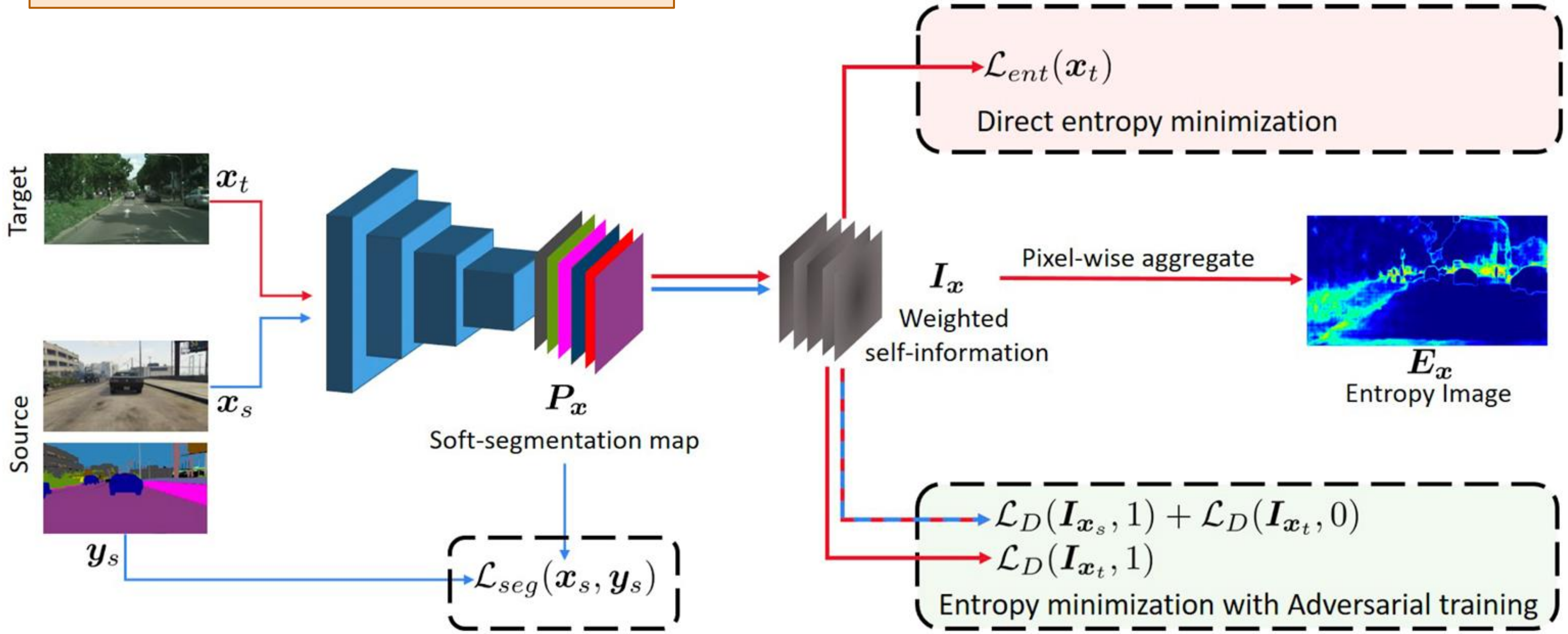
"Car"

[Pathak et al., Constrained Convolutional Neural Networks for Weakly Supervised Segmentation, ICCV'15]

Inequality constraints

Information (proportion)
is given as a prior





Images from [Vu et al., ADVENT: Adversarial Entropy Minimization for Domain Adaptation in Semantic Segmentation. CVPR’19]

Inequality constraints

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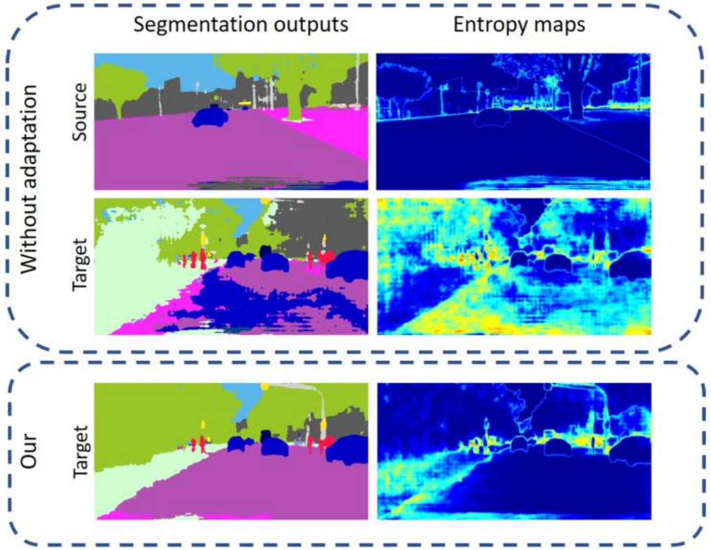
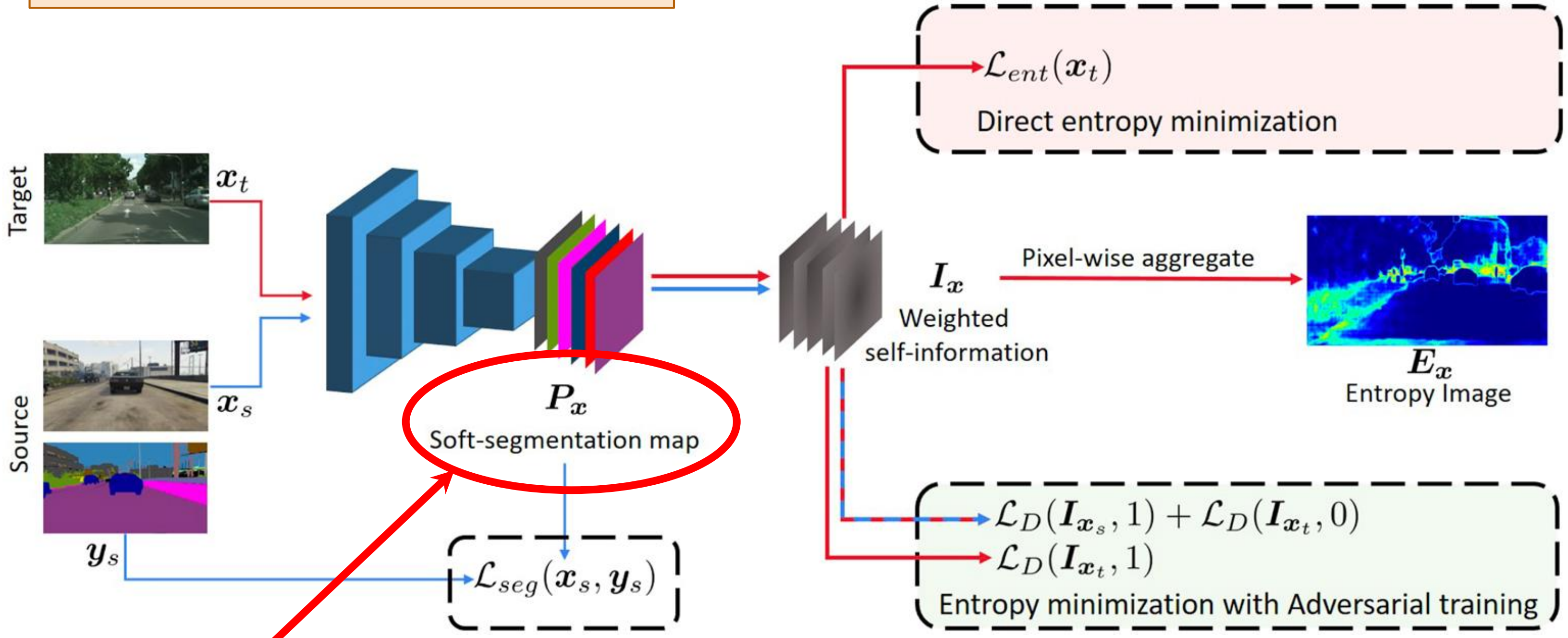


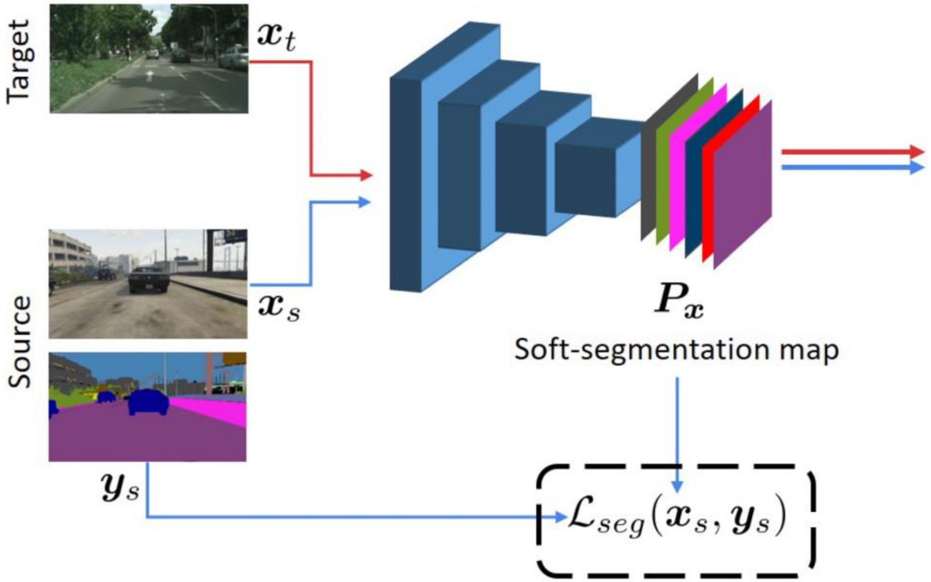


We focus on this now

Images from [Vu et al., ADVENT: Adversarial Entropy Minimization for Domain Adaptation in Semantic Segmentation. CVPR'19]

Inequality constraints

Information (proportion)
is given as a prior



Class-ratio priors

$$\mathcal{L}_{cp}(\boldsymbol{x}_t) = \sum_{c=1}^{C} \max\left(0, \mu \boldsymbol{p}_s^{(c)} - \mathbb{E}_c(\boldsymbol{P}_{\boldsymbol{x}_t}^{(c)})\right)$$

It relaxes the class prior constraint

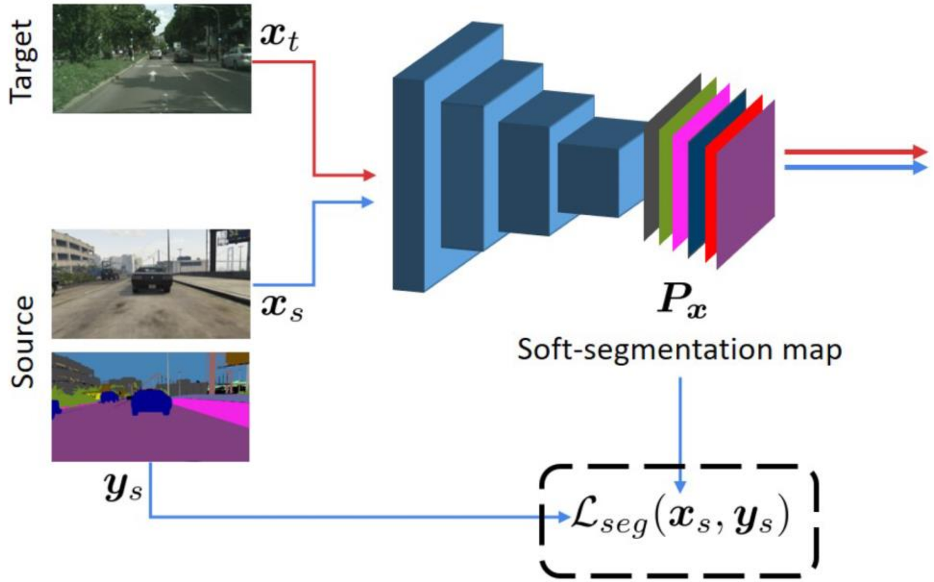
$\ell 1$-normalized histogram (source)

Estimated size on the prediction

Vu et al., ADVENT: Adversarial Entropy Minimization for Domain Adaptation in Semantic Segmentation. CVPR'19

Inequality constraints

Information (proportion)
is given as a prior



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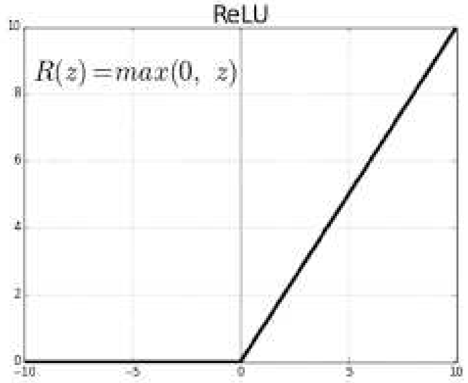


Vu et al., ADVENT: Adversarial Entropy Minimization for Domain Adaptation in Semantic Segmentation. CVPR'19

Inequality constraints

How we can benefit from this in the medical domain?

No cavity | Cavity

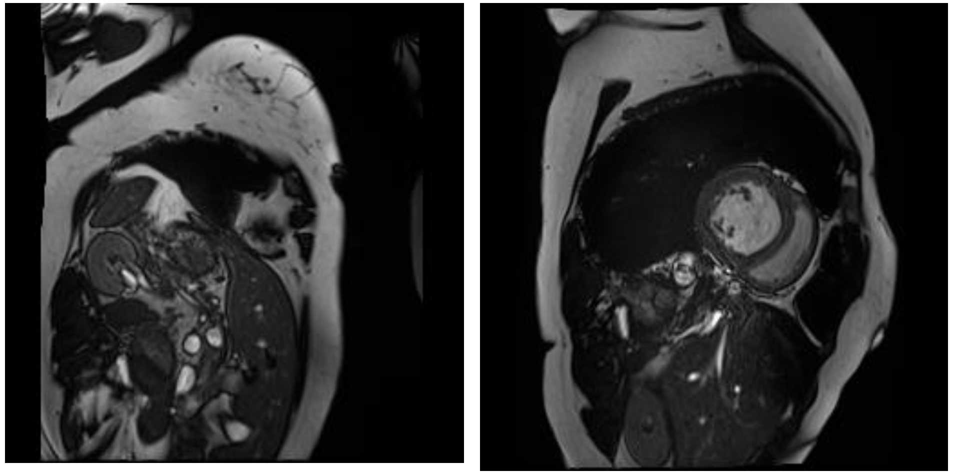


Image-tag information

$$\sum_{p \in \Omega} s_{\theta}^{p,c} \leq 0$$

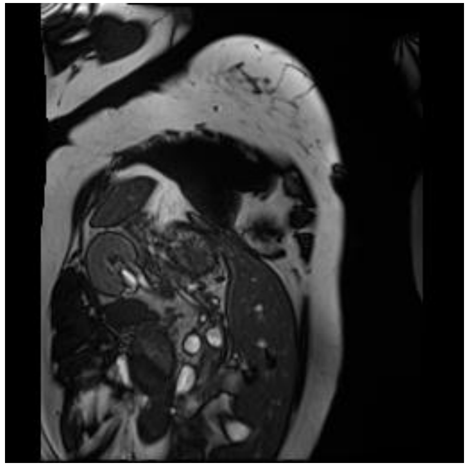
For negative image tags

[Kervadec et al., Constrained-CNN losses for weakly supervised segmentation. MedIA 2019]

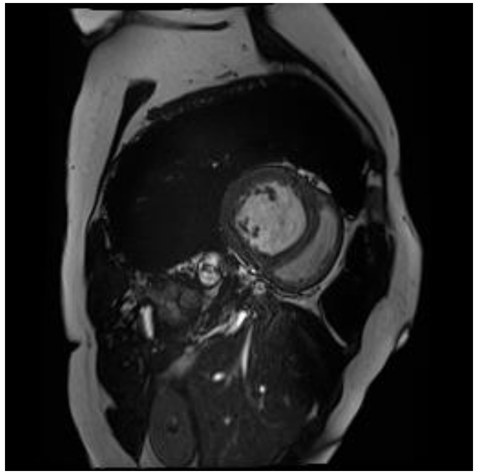
Inequality constraints

How we can benefit from this in the medical domain?

No cavity



Cavity



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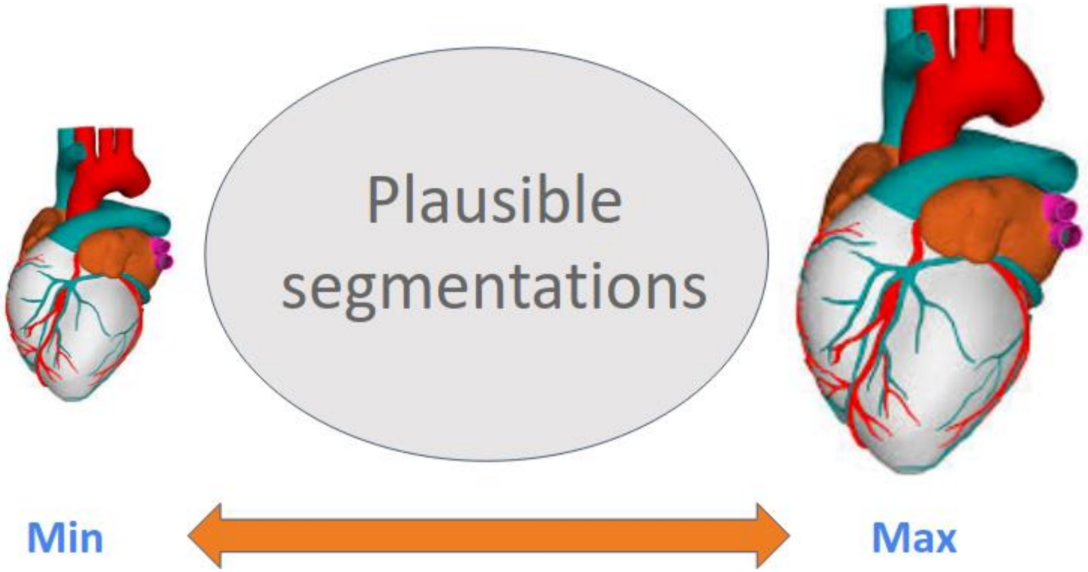


Size information

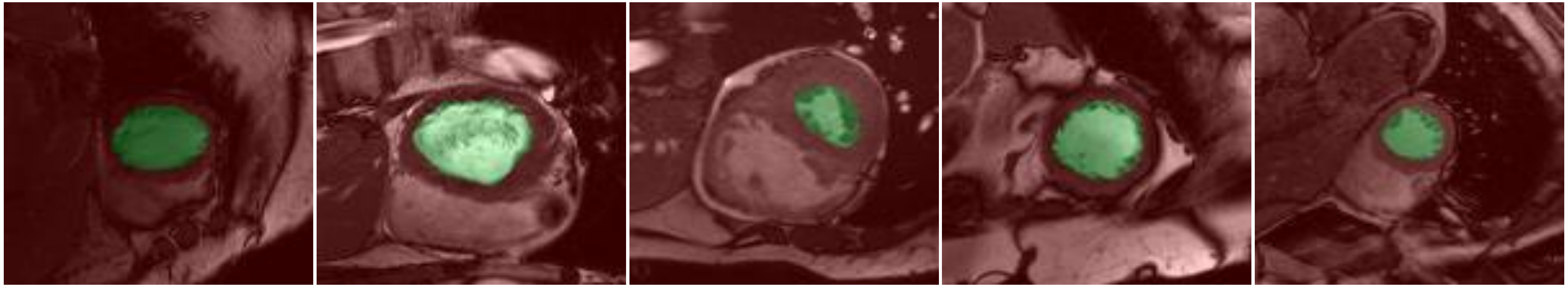
$$min \leq \sum_{p \in \Omega} s_{\theta}^{p,c} \leq max$$

For positive image tags

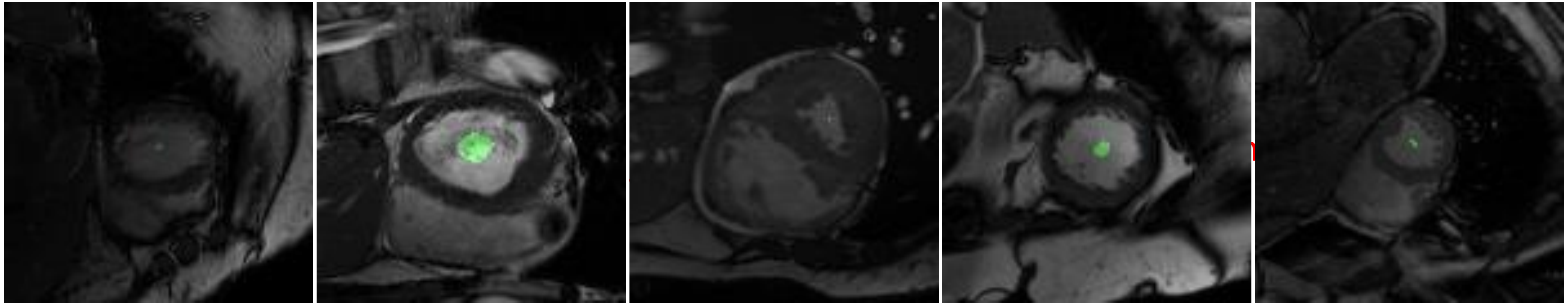
[Kervadec et al., Constrained-CNN losses for weakly supervised segmentation. MedIA 2019]

Inequality constraints

L2 Penalty



Full annotations



Partial annotations for cross-entropy

[Kervadec et al., Constrained-CNN losses for weakly supervised segmentation. MedIA 2019]

Inequality constraints

L2 Penalty

Objective

$$\min_{\boldsymbol{\theta}} \mathcal{H}(S) \quad \text{s.t} \quad a \leq \sum_{p \in \Omega} s_{\theta}^{p,c} \leq b \quad \Rightarrow \quad \mathcal{H}(S) + \lambda \mathcal{C}\left(V_S\right)$$

[Kervadec et al., Constrained-CNN losses for weakly supervised segmentation. MedIA 2019]

Inequality constraints

L2 Penalty

Objective

$$\min_{\boldsymbol{\theta}} \mathcal{H}(S) \quad \text{s.t} \quad a \leq \sum_{p \in \Omega} s_\theta^{p,c} \leq b \quad \Rightarrow \quad \mathcal{H}(S) + \lambda \mathcal{C}\left(V_S\right)$$

$$\mathcal{H}(S) = -\sum_{p \in \mathcal{L}} log(s_\theta^p)$$

On annotated pixels

[Kervadec et al., Constrained-CNN losses for weakly supervised segmentation. MedIA 2019]

Inequality constraints

L2 Penalty

Objective

$$\min_{\boldsymbol{\theta}} \mathcal{H}(S) \quad \text{s.t} \quad a \leq \sum_{p \in \Omega} s_\theta^{p,c} \leq b \quad \Rightarrow \quad \mathcal{H}(S) + \lambda \mathcal{C}(V_S)$$

$$\mathcal{H}(S) = -\sum_{p \in \mathcal{L}} log(s_\theta^p)$$

On annotated pixels

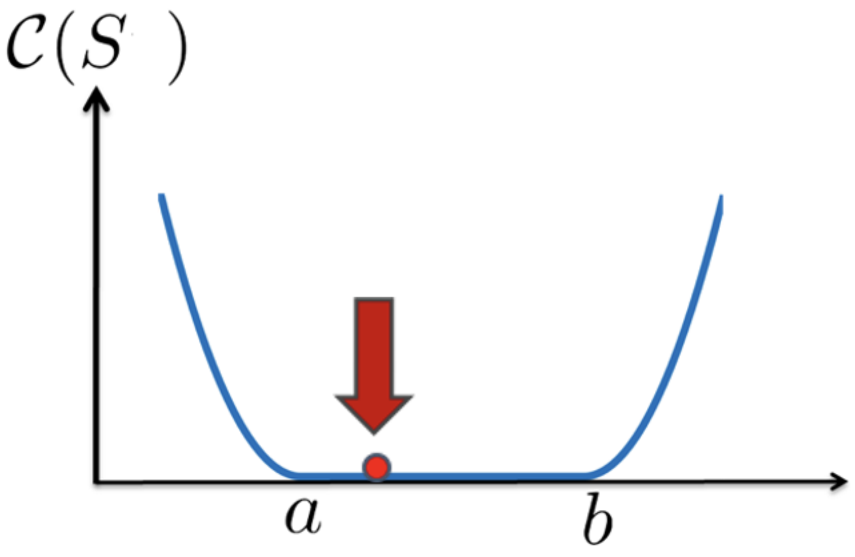
$$\mathcal{C}(V_S) = \begin{cases} (V_S - a)^2, & \text{if } V_S < a \\ (V_S - b)^2, & \text{if } V_S > b \\ 0, & \text{otherwise} \end{cases}$$

[Kervadec et al., Constrained-CNN losses for weakly supervised segmentation. MedIA 2019]

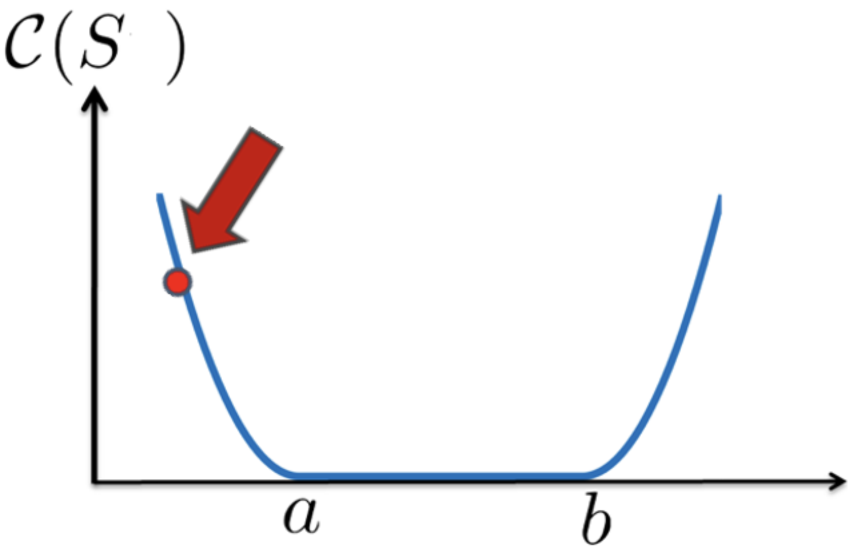
Inequality constraints

L2 Penalty

Visual intuition



Constraint A satisfied



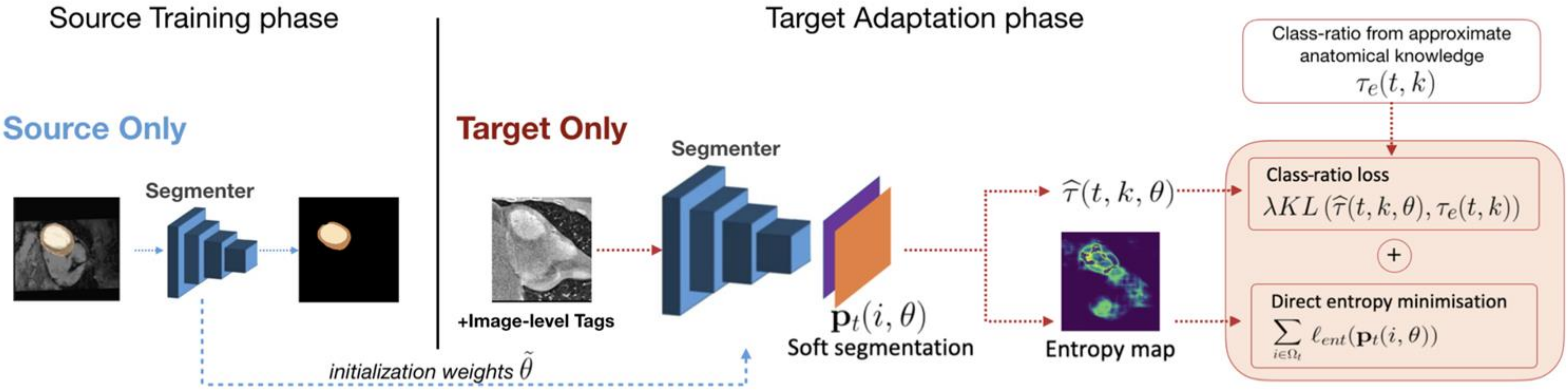
Constraint B violated

[Kervadec et al., Constrained-CNN losses for weakly supervised segmentation. MedIA 2019]

Inequality constraints

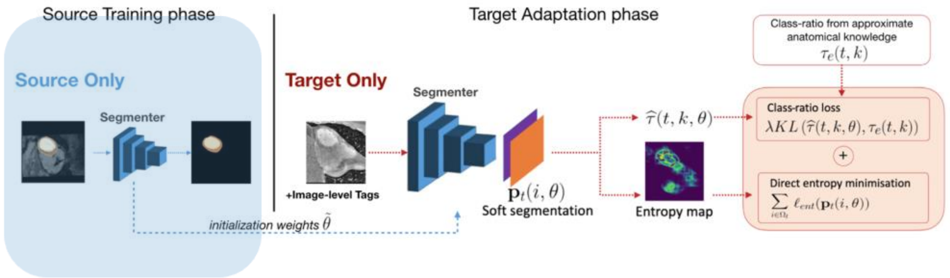
L2 Penalty

Source-free Domain Adaptation



Bateson et al. Source-relaxed domain adaptation for image segmentation. MICCAI'20

Inequality constraints



L2 Penalty

Source-free: no access to source data when adapting

1-Train the network on the source domain

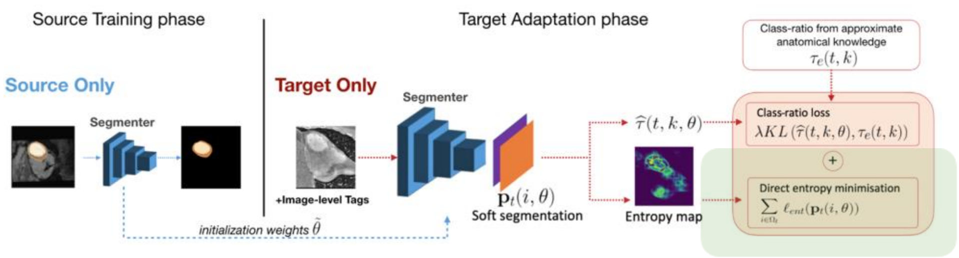
$$\min_{\theta} \sum_{p \in \mathcal{L}} l(\mathbf{y}^p, \mathbf{s}_\theta^p)$$

Set of labeled SOURCE pixels

Bateson et al., Source-Relaxed Domain Adaptation for Image Segmentation. MICCAI'19

Inequality constraints

L2 Penalty



Source-free: no access to source data when adapting

2-Adapt the model without accessing the source data

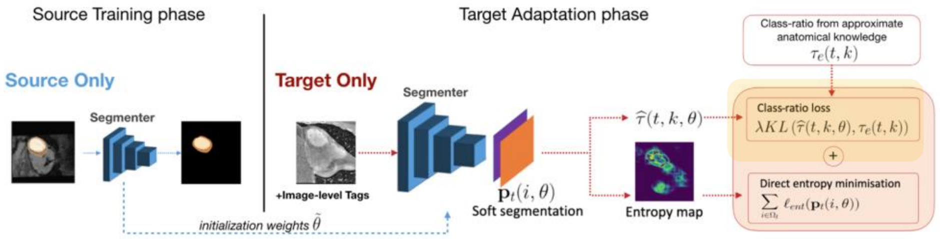
$$\mathcal{L}_{\mathcal{H}} = -\sum_{p \in \mathcal{T}} \sum_{k} \mathbf{s}_{\theta}^{p,k} \log \mathbf{s}_{\theta}^{p,k} + \mathcal{D}_{KL}(\hat{\tau}, \tau_e)$$

Minimize entropy on predicted TARGET pixels

Bateson et al., Source-Relaxed Domain Adaptation for Image Segmentation. MICCAI'19

Inequality constraints

L2 Penalty



Source-free: no access to source data when adapting

2-Adapt the model without accessing the source data

$$\mathcal{L}_{\mathcal{H}} = -\sum_{p\in\mathcal{T}}\sum_{k} \mathbf{s}_\theta^{p,k}\log \mathbf{s}_\theta^{p,k} + \mathcal{D}_{KL}(\hat{\tau}, \tau_e)$$

$$\tau_e(t,k)$$

Estimated size by an auxiliary network trained on the source

$$\hat{\tau}(t,k,\theta) = \frac{1}{|\Omega_t|}\sum_{i\in\Omega_t} \mathbf{s}_\theta^{i,k}$$

Minimize entropy on predicted TARGET pixels

Size regularizer

Computed size from the segmentation of the target image

Bateson et al., Source-Relaxed Domain Adaptation for Image Segmentation. MICCAI'19

Inequality constraints

L2 Penalty

But we can do more than simply the size

Shape moment $\mu_{p,q}^{(k)}(s_{\boldsymbol{\theta}}) := \sum_{i \in \Omega} s_{\boldsymbol{\theta}}^{(i,k)} x_{(i)}^{p} y_{(i)}^{q},$

Central moment $\bar{\mu}_{p,q}^{(k)} := \sum_{i \in \Omega} s_{\boldsymbol{\theta}}^{(i,k)} \left(x_{(i)} - \frac{\mu_{1,0}^{(k)}}{\mu_{0,0}^{(k)}} \right)^{p} \left(y_{(i)} - \frac{\mu_{0,1}^{(k)}}{\mu_{0,0}^{(k)}} \right)^{q}.$

[Kervadec et al., Beyond pixel-wise supervision for segmentation: A few global shape descriptors might be surprisingly good!. MIDL'22]

Inequality constraints

L2 Penalty

But we can do more than simply the size

From shape and central moment

Volume

$$\mathfrak{V}^{(k)}(s_{\boldsymbol{\theta}}) := \mu_{0,0}^{(k)}(s_{\boldsymbol{\theta}}).$$

Centroid

$$\mathfrak{C}^{(k)}(s_{\boldsymbol{\theta}}) := \left(\frac{\mu_{1,0}^{(k)}(s_{\boldsymbol{\theta}})}{\mu_{0,0}^{(k)}(s_{\boldsymbol{\theta}})}, \frac{\mu_{0,1}^{(k)}(s_{\boldsymbol{\theta}})}{\mu_{0,0}^{(k)}(s_{\boldsymbol{\theta}})} \right).$$

Laplacian

Length

$$\mathfrak{L}^{(k)}(s_{\boldsymbol{\theta}}) := \sum_{i,j \in \mathcal{G}_\Omega} |s_{\boldsymbol{\theta}}^{(i,k)} - s_{\boldsymbol{\theta}}^{(j,k)}| L_{\Omega,i,j}.$$

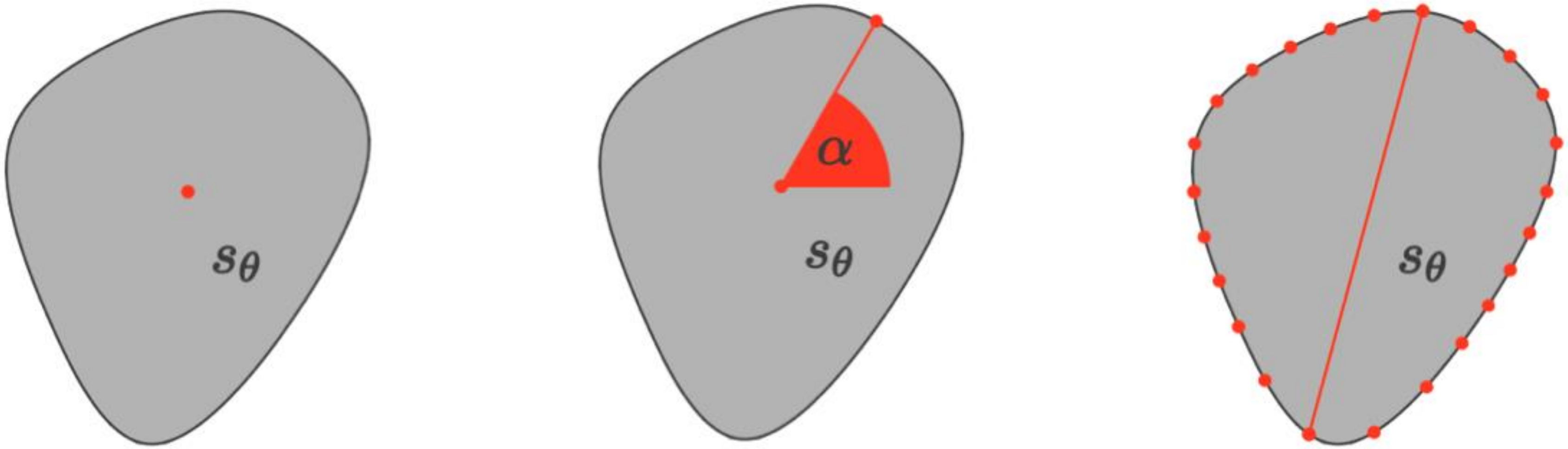
[Kervadec et al., Beyond pixel-wise supervision for segmentation: A few global shape descriptors might be surprisingly good!. MIDL'22]

Inequality constraints

L2 Penalty

But we can do more than simply the size

From shape and central moment



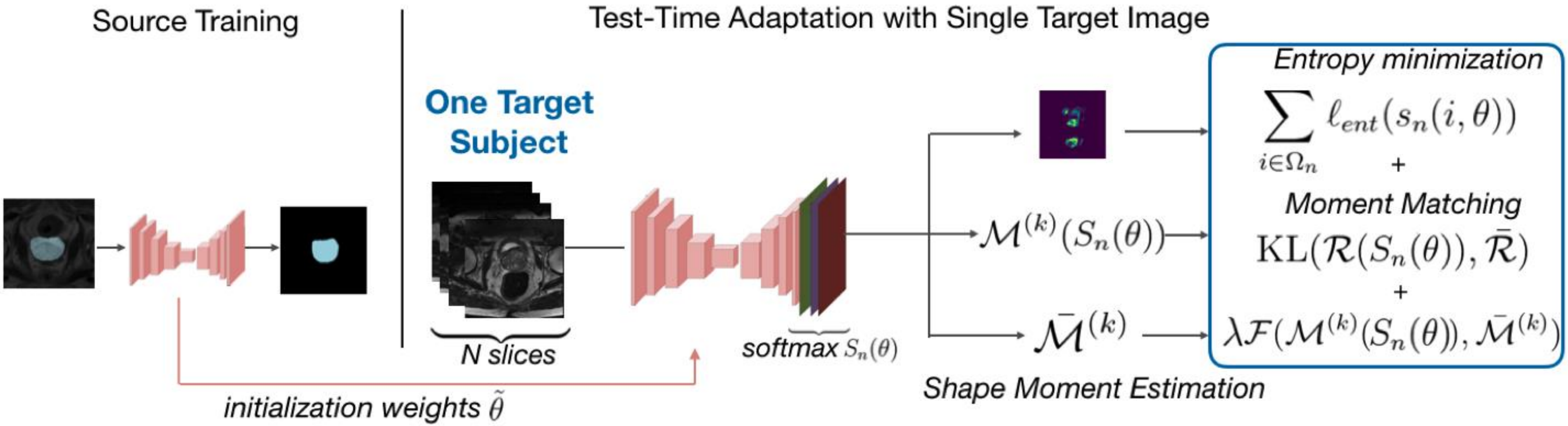
(a) Centroid $\mathfrak{C}(s_\theta)$ (b) Radius $\widehat{\mathfrak{R}}_\beta(s_\theta, \alpha)$ (c) Diameter $\mathfrak{D}(s_\theta)$

Camarasa et al. Differentiable Boundary Point Extraction for Weakly Supervised Star-shaped Object Segmentation. MIDL'22

Inequality constraints

L2 Penalty

Test-Time Adaptation (TTA)



Bateson et al., Test-Time Adaptation with Shape Moments for Image Segmentation. MICCAI'22

Take-home message

- Imposing constraints helps weakly-supervised segmentation learning by restricting plausible segmentations on weakly labeled and unlabeled images

- Few constraints have been explored under low-labeled data regime

- Room for improvement (many opportunities beyond weakly supervised segmentation)

Thank you!