Weakly supervised segmentation

Jose Dolz

Data-driven priors (cues)

Image tags

Person

Bike

Tumor

Original Image

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

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Data-driven priors (cues)

Image tags

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Scribbles

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Data-driven priors (cues)

Image tags

Bounding boxes

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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

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)

Knowledge vs data driven priors

Recall from an optimization standpoint

Knowledge vs data driven priors

Recall from an optimization standpoint

Knowledge vs data driven priors

Ideally we want to reach this point (And we have a lot of data for this!!)

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

From global cues to pixel labels

From global cues to pixel labels

Step 1: Get a classification CNN

Convolutional layers

FC Layers

Class scores

Cat

Dog

Parrot

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

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**

$$-\sum_{i \in \Omega_i} \hat{y}_i \log(s_i)$$

- 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

How to improve CAMs?

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

How to improve CAMs?

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

How to improve CAMs?

Region mining

1 - Obtain CAM
2 - Mask image with that region
3 - Repeat

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- Wang et al. Weakly-Supervised Semantic Segmentation by Iteratively Mining Common Object Features. CVPR 2018

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From global cues to pixel labels

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From global cues to pixel labels

How to improve CAMs?

Equivariant constraints

Wang et al. Self-supervised Equivariant Attention Mechanism for Weakly Supervised Semantic segmentation. CVPR'20

From global cues to pixel labels

Integrating language-vision models

How to improve CAMs?

Xie et al, CLIMS: Cross Language Matching for weakly supervised semantic segmentation

From global cues to pixel labels

Integrating language-vision models

How to improve CAMs?

Xie et al, CLIMS: Cross Language Matching for weakly supervised semantic segmentation

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.

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

CAMs in the medical domain

Equivariant constraints

CAMs not equivariant to spatial transformations

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

CAMs in the medical domain

Equivariant constraints

CAMs not equivariant to spatial transformations

CAMs not consistent across modalities

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

CAMs in the medical domain

Equivariant constraints

Same-modality equivariant constraints

$$\mathcal{L}_{reg}(\tau(f(M_1)), f(\tau(M_1)))$$

transformations

Cross-modality equivariant constraints

$$\mathcal{L}_{reg}(\tau(f(M_1)), f(\tau(M_2)))$$

transformations

Modality 1

Modality 2

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

CAMs in the medical domain

Equivariant constraints

Same-modality equivariant constraints

$$\mathcal{L}_{reg}(\tau(f(M_1)), f(\tau(M_1)))$$

Cross-modality equivariant constraints

$$\mathcal{L}_{reg}(\tau(f(M_1)), f(\tau(M_2)))$$

Classification loss

$$\mathcal{L}_{class} + \mathcal{L}_{reg}(\tau(f(M_1)), f(\tau(M_1))) + \mathcal{L}_{reg}(\tau(f(M_1)), f(\tau(M_2)))$$

Intra-modal regularization

Inter-modal regularization

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

CAMs in the medical domain

Equivariant constraints

Baseline

Baseline
+ equivariant constraints

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

Constrained optimization (CNN)

Optimize (A) such that (B)

Task

Set of constraints

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

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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?

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

A=B

General definition

$$\min_{\theta} \mathcal{H}(S) \quad s.t. \quad g(\mathbf{s}) = C$$

Constraint

Equality constraints

A=B

General definition

$$\min_{\theta} \mathcal{H}(S) \quad s.t. \quad g(\mathbf{s}) = C$$

Constraint

$$\min_{\theta} \mathcal{H}(S) + \lambda(g(\mathbf{s}) - C)$$

Penalty

Equality constraints

A=B

General definition

$$\min_{\theta} \mathcal{H}(S) \quad s.t. \quad g(\mathbf{s}) = C$$

Constraint

$$\min_{\theta} \mathcal{H}(S) + \lambda(g(\mathbf{s}) - C)$$

Penalty

This can be modeled with linear/quadratic penalties, KL divergence, etc

Equality constraints

L2 Penalty

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

Equality constraints

L2 Penalty

Input
(Histology image)

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:

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

Fully labeled images

Partially labeled images

Prior-aware loss

[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 $\hat{p}$ organ sizes inside log!!)

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

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

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

Cross-modality equivariant constraints

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

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

Equality constraints

At pixel level

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,
A>B,
B1 < A < B2

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

Use case:
Size constraint

No cavity

Cavity

Image-tag information

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

For negative image tags

Inequality constraints

Use case:
Size constraint

No cavity

Cavity

Image-tag information

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

For negative image tags

Size information

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

For positive image tags

Inequality constraints

Formal definition

Use case:
Size constraint

$$\min_{\boldsymbol{\theta}} \mathcal{H}(S) \quad \text{s.t} \quad a \leqslant \sum_{p \in \Omega} S_p \leqslant b$$

Inequality constraint

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

Inequality constraints

Formal definition

Use case:
Size constraint

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

$$V_S = \sum_{p \in \Omega} \mathbf{s}_\theta^{p,c}$$

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

Inequality constraints

Formal definition

Use case:
Size constraint

$$\min_{\boldsymbol{\theta}} \mathcal{H}(S) \quad \text{s.t} \quad a \leqslant \sum_{p \in \Omega} S_p \leqslant b$$

$$\mathcal{H}(S) + \lambda \mathcal{C}(V_S)$$

$$V_S = \sum_{p \in \Omega} \mathbf{s}_\theta^{p,c}$$

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

CE on the labeled pixels (if any)

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

Inequality constraints

Formal definition

Use case:
Size constraint

$$\min_{\boldsymbol{\theta}} \mathcal{H}(S) \quad \text{s.t} \quad a \leqslant \sum_{p \in \Omega} S_p \leqslant b$$

$$\mathcal{H}(S) + \lambda \mathcal{C}(V_S)$$

$$V_S = \sum_{p \in \Omega} \mathbf{s}_\theta^{p,c}$$

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

CE on the labeled pixels (if any)

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

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

Inequality constraints

Visual intuition

Use case:
Size constraint

Constraint A satisfied

Constraint B violated

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

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

Information (proportion) is given as a prior

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

Class-ratio priors

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

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

Inequality constraints

KL divergence

Source-free Domain Adaptation

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

Inequality constraints

KL divergence

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

KL divergence

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

KL divergence

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'21]

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

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

Length

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

Laplacian

[Kervadec et al., Beyond pixel-wise supervision for segmentation: A few global shape descriptors might be surprisingly good!. MIDL'21]

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!

Thank you!