Domain Adaptation for the Segmentation of Confidential Medical Images

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Motivation

Unsupervised Domain Adaptation (UDA) addresses scenarios when the application domain (*target domain*) of a model has a different data distribution (*domain shift*) from the training domain (*source domain*), which negatively impacts generalization

Domain shift can be particularly impactful for medical image segmentation, as labeling new images requires expert knowledge, and joint access to the source and target datasets may violate privacy regulations

Objective

We develop an UDA algorithm which mitigates domain shift without the need for joint source and target domain access (*source-free*):

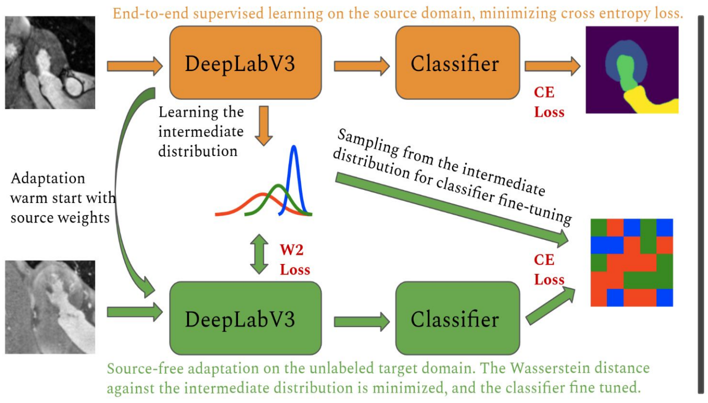
➔ We approximate the class conditional source embeddings via GMM distributions.

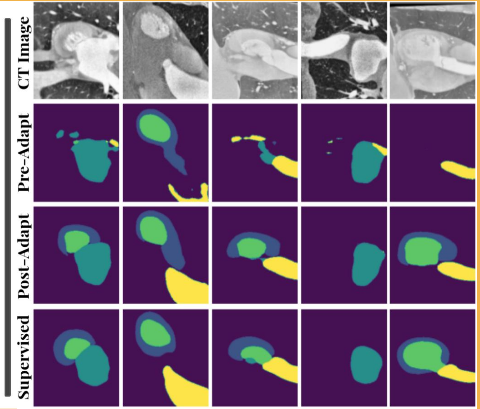
$$\mathcal{P}_{\mathcal{Z}}(z) = \sum_{c=1}^{\omega K} \alpha_c p_c(z) = \sum_{c=1}^{\omega K} \alpha_c \mathcal{N}(z|\mu_c, \Sigma_c)$$

➔ We ensure classifier generalization on the target domain by minimizing the distributional distance between source and target in the latent space using an optimal transport metric

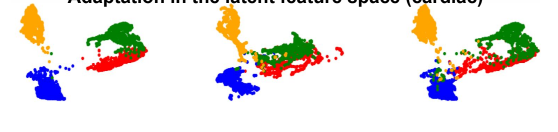
$$\mathcal{L}_{SWD}(P,Q) = \frac{1}{V}\sum_{i=1}^{V} WD(\langle\gamma_i, P\rangle, \langle\gamma_i, Q\rangle)$$

Approach



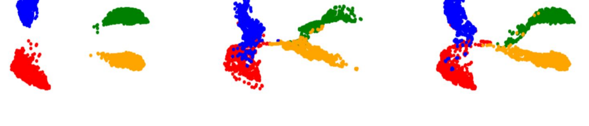


Adaptation in the latent feature space (cardiac)



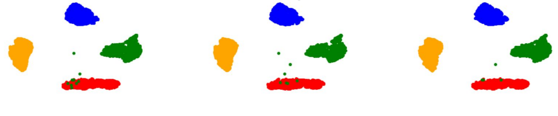
(a) GMM samples (b) Pre-adaptation (c) Post-adaptation

Adaptation in the latent feature space (abdomen)



(a) GMM samples (b) Pre-adaptation (c) Post-adaptation

Confidence based sampling and GMM separation



(a) $\rho = 0$ (b) $\rho = 0.8$ (c) $\rho = .97$

Performance when increasing the number of Gaussians ω

	Dice					Average Symmetric Surface Distance				
ω-SFS	AA	LAC	LVC	MYO	Average	AA	LAC	LVC	MYO	Average
1-SFS	86.2	83.5	75.4	70.9	79.0	11.1	5.0	10.8	3.6	9.8
3-SFS	88.0	83.7	81.0	72.5	81.3	6.3	7.2	4.7	6.1	6.1
5-SFS	88.0	83.8	81.9	73.3	81.7	6.2	7.4	4.8	5.7	6.0
7-SFS	86.8	84.8	82.0	73.5	81.8	4.8	7.2	4.4	5.6	5.9