

# Unsupervised Domain Adaptation for Cardiac Segmentation: Towards Structure Mutual Information Maximization Supplementary Material

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## 1. Compact Lower Bound Proof

Proof of Eq.4:

Firstly, We follow the deduction from UDA-VAE [2].

$$\begin{aligned}
 & \log p_{\theta_S}(x, y) \\
 &= \int q_{\phi_S}(z | x, y) \log \left[ \frac{q_{\phi_S}(z | x, y)}{p_{\theta_S}(z | x, y)} \cdot \frac{p_{\theta_S}(z)}{q_{\phi_S}(z | x, y)} \cdot p_{\theta_S}(x, y | z) \right] dz \\
 &= D_{KL}(q_{\phi_S}(z | x, y) \| p_{\theta_S}(z | x, y)) - \\
 & \quad D_{KL}(q_{\phi_S}(z | x, y) \| p_{\theta_S}(z)) + \\
 & \quad E_{q_{\phi_S}(z|x,y)} \log [p_{\theta_S}(x, y | z)]
 \end{aligned} \tag{1}$$

Note that UDA-VAE [2] neglects the term  $D_{KL}(q_{\phi_S}(z | x, y) \| p_{\theta_S}(z | x, y))$  as it is greater than 0. In comparison, we deduce a compact lower bound with the following term.

$$\begin{aligned}
 & D_{KL}(q_{\phi_S}(z | x, y) \| p_{\theta_S}(z | x, y)) \\
 &= \int q_{\phi_S}(z | x, y) \log \frac{q_{\phi_S}(z | x, y)}{p_{\theta_S}(z | x, y)} dz \\
 &= \int \frac{q_{\phi_S}(x, y, z)}{q_{\phi_S}(x, y)} \log \frac{q_{\phi_S}(x, y, z) p_{\theta_S}(x, y)}{p_{\theta_S}(x, y, z) q_{\phi_S}(x, y)} dz \\
 &= \frac{1}{q_{\phi_S}(x, y)} \left[ \int q_{\phi_S}(x, y, z) \log \frac{q_{\phi_S}(x, y, z)}{p_{\theta_S}(x, y, z)} + q_{\phi_S}(x, y, z) \log \frac{p_{\theta_S}(x, y)}{q_{\phi_S}(x, y)} dz \right] \\
 &= \frac{1}{q_{\phi_S}(x, y)} \int q_{\phi_S}(x, y, z) \log \frac{q_{\phi_S}(x, y, z)}{p_{\theta_S}(x, y, z)} dz + \log \frac{p_{\theta_S}(x, y)}{q_{\phi_S}(x, y)} \\
 &= \frac{1}{q_{\phi_S}(x, y)} D_{KL}(q_{\phi_S}(x, y, z) \| p_{\theta_S}(x, y, z)) + \log \frac{p_{\theta_S}(x, y)}{q_{\phi_S}(x, y)} \\
 &\geq D_{KL}(q_{\phi_S}(x, y, z) \| p_{\theta_S}(x, y, z)) + \log \frac{p_{\theta_S}(x, y)}{q_{\phi_S}(x, y)}
 \end{aligned} \tag{2}$$

Consider the reconstruction error [1]:

$$\mathcal{R} = \mathbb{E}_{(x,y,z) \sim q_{\phi_S}(x, y, z)} \log \frac{q_{\phi_S}(x, y, z)}{p_{\theta_S}(x, y, z)} - \mathbb{E}_{(x,y,z) \sim q_{\phi_S}(x, y, z)} \log q_{\phi_S}(x, y, z) + \mathbb{E}_{z \sim q_{\phi_S}(z)} \log p_{\theta_S}(z) \tag{3}$$

The second term is the joint entropy  $H_q(x, y, z)$ .

The third term can be written as:

$$\mathbb{E}_{z \sim q_{\phi_S}(z)} \log p_{\theta_S}(z) = -D_{KL}(q_{\phi_S}(z) \| p_{\theta_S}) - H_{q_{\phi_S}}(z) \tag{4}$$

With

$$H_{q_{\phi_S(z)}}(x, y, z) - H_{q_{\phi_S}}(z) = H_{q_{\phi_S}}(z) - I_{q_{\phi_S}}(x, y, z) \quad (5)$$

where  $I$  is mutual information.

The reconstruction error can be written as:

$$\mathcal{R} \leq D_{KL}(q_{\phi_S(x,y,z)} \| p_{\theta_S(x,y,z)}) - I_{q_{\phi_S}}(x, y, z) + H_{q_{\phi_S}}(z) \quad (6)$$

which is compact when  $q_{\phi_S(z)}$  matches the prior distribution  $p_{\theta_S}(z)$ .

$$D_{KL}(q_{\phi_S(x,y,z)} \| p_{\theta_S(x,y,z)}) \geq \mathcal{R} + I_{q_{\phi_S}}(x, y, z) - H_{q_{\phi_S}}(z) \quad (7)$$

Thus, we obtain the bound,

$$\begin{aligned} & D_{KL}(q_{\phi_S}(z | x, y) \| p_{\theta_S}(z | x, y)) \\ & \geq D_{KL}(q_{\phi_S}(x, y, z) \| p_{\theta_S}(x, y, z)) + \log \frac{p_{\theta_S}(x, y)}{q_{\phi_S}(x, y)} \\ & \geq \mathcal{R} + I_{q_{\phi_S}}(x, y, z) - H_{q_{\phi_S}}(z) + \log \frac{p_{\theta_S}(x, y)}{q_{\phi_S}(x, y)} \end{aligned} \quad (8)$$

From, Eq.1 and Eq.8,

$$\begin{aligned} & \log p_{\theta_S}(x, y) \\ & \geq (\mathcal{R} + I_{q_{\phi_S}}(x, y, z) - H_{q_{\phi_S}}(z) + \log \frac{p_{\theta_S}(x, y)}{q_{\phi_S}(x, y)}) - D_{KL}(q_{\phi_S}(z | x) \| p_{\theta_S}(z)) + E_{q_{\phi_S}(z|x)} \log p_{\theta_S}(x, y | z) \\ & = (\mathcal{R} + I_{q_{\phi_S}}(x, y, z) - H_{q_{\phi_S}}(z) + \log \frac{p_{\theta_S}(x, y)}{q_{\phi_S}(x, y)}) - D_{KL}(q_{\phi_S}(z | x) \| p_{\theta_S}(z)) + E_{q_{\phi_S}(z|x)} \log p_{\theta_S}(x | y, z) \\ & \quad + E_{q_{\phi_S}(z|x)} \log p_{\theta_S}(y | z) \end{aligned} \quad (9)$$

where  $R$ ,  $\log \frac{p_{\theta_S}(x, y)}{q_{\phi_S}(x, y)}$  and  $H_{q_{\phi_S}}(z)$  are constant. The equation holds, as  $p_{\theta_S}(x, y | z) = p_{\theta_S}(y | z) \cdot p_{\theta_S}(x | y, z)$ .

Meanwhile,  $y_S$  and  $z_S$  are conditionally independent on  $x_S$  for distribution  $q_{\phi_S}$ , so that  $q_{\phi_S}(z | x, y) = q_{\phi_S}(z | x)$ .

Finally, We get the compact lower bound (plus red terms) than UDA-VAE .

The UDA-VAE++ maximizes the mutual information of  $I_{q_{\phi_S}}(x, y, z)$ .

Proved.

## References

- [1] Mohamed Ishmael Belghazi, Aristide Baratin, Sai Rajeshwar, Sherjil Ozair, Yoshua Bengio, Aaron Courville, and Devon Hjelm. Mutual information neural estimation. In *International conference on machine learning*, pages 531–540. PMLR, 2018.
- [2] Fuping Wu and Xiahai Zhuang. Unsupervised domain adaptation with variational approximation for cardiac segmentation. *IEEE Transactions on Medical Imaging*, 40(12):3555–3567, 2021.