A Bayesian Approach to Weakly-supervised Laparoscopic Image Segmentation - Supplementary Material -

Proof. As for $p(\mathbf{x}, \mathbf{y})$, we have:

$$\log p\left(\mathbf{x}, \mathbf{y}\right) = \log \int_{\mathbf{z}} p\left(\mathbf{x}, \mathbf{y}, \mathbf{z}\right) \, d\mathbf{z} = \log \int_{\mathbf{z}} \frac{p\left(\mathbf{x}, \mathbf{y}, \mathbf{z}\right) q\left(\mathbf{z}|\mathbf{x}\right)}{q\left(\mathbf{z}|\mathbf{x}\right)} \, d\mathbf{z}$$
$$\geq \mathbb{E}_{\mathbf{z} \sim q} \left[\log \frac{p\left(\mathbf{x}, \mathbf{y}, \mathbf{z}\right)}{q\left(\mathbf{z}|\mathbf{x}\right)} \right] = \mathbb{E}_{\mathbf{z} \sim q} \left[\log \frac{p\left(\mathbf{y}|\mathbf{x}, \mathbf{z}\right) p\left(\mathbf{x}|\mathbf{z}\right) p\left(\mathbf{z}\right)}{q\left(\mathbf{z}|\mathbf{x}\right)} \right] \quad (10)$$
$$= \mathbb{E}_{\mathbf{z} \sim q} \left[\log p\left(\mathbf{y}|\mathbf{x}, \mathbf{z}\right) + \log p\left(\mathbf{x}|\mathbf{z}\right) \right] - \mathbb{E}_{\mathbf{z} \sim q} \left[\log \frac{q\left(\mathbf{z}|\mathbf{x}\right)}{p\left(\mathbf{z}\right)} \right],$$

where $q(\mathbf{z}|\mathbf{x})$ is a variational distribution, and $\mathbb{E}_{\mathbf{z}\sim q}$ denotes the expectation over $q(\mathbf{z}|\mathbf{x})$. We finish the proof by deriving the ELBO in Eq. (5).

Dataset	CholecSeg8k	AutoLaparo	ACDC
Backbone	U-Net	U-Net	U-Net
Preprocessing	Resized each image to $432 \times$	Resized each image to $480 \times$	Resized each slice to 256 \times
	240 pixels and normalized	240 pixels and normalized	256 pixels and normalized
	the intensities to $[0,1]$	the intensities to $[0,1]$	the intensities to $[0,1]$
Input size	432×240	480×240	256×256
Optimizer	Adam with a weight decay of	Adam with a weight decay of	SGD with a weight decay of
	10^{-4}	10^{-4}	10^{-4} and a momentum of 0.9
Batch size	8	8	8
Training epochs or	1st stage: \mathbf{e}_1 , \mathbf{d}_1 , \mathbf{e}_2 , and \mathbf{d}_2	1st stage: \mathbf{e}_1 , \mathbf{d}_1 , \mathbf{e}_2 , and \mathbf{d}_2	1st stage: \mathbf{e}_1 , \mathbf{d}_1 , \mathbf{e}_2 , and
iterations	were jointly trained for 100	were jointly trained for 200	\mathbf{d}_2 were jointly trained for
	epochs,	epochs,	90000 iterations,
	2nd stage: ${\bf w}$ was trained for	2nd stage: \mathbf{w} was trained for	2nd stage: ${\bf w}$ was trained for
	100 epochs	200 epochs	90000 iterations
Learning rate	1st stage: 10^{-4} ,	1st stage: 10^{-4} ,	1st stage: $10^{-2} \times (1 - 1)^{-2}$
	2nd stage: 10^{-4}	2nd stage: 10^{-4}	$\eta/90000)^{0.9},$
			2nd stage: $10^{-2} \times (1 - 1)^{-2}$
			$\eta/90000)^{0.9},$
			η is the current iteration
Dimension of \mathbf{z}	256	256	256
α	10^{-3}	10^{-3}	10^{-3}
β	10^{-1}	10^{-1}	10^{-1}
γ	10^{-8}	10^{-8}	10^{-8}
N	3	3	3
T	15	15	15
Execution manner	5-fold cross validation	5-trial repeats	5-fold cross validation

Table 4. Implementation details. Experiments were performed on PyTorch.



Fig. 2. Network configuration for modeling $p(\mathbf{x}, \mathbf{y}|\mathbf{z})$. For simplicity, specifics of the encoder and decoder layers are excluded, and skip connections are omitted.





Fig. 4. An example slice of the ACDC dataset.



Fig. 5. Visualization results of various methods.