

An Auto-Encoder Strategy for Adaptive Image Segmentation

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Challenge

- Annotations costs time, money and requires expertise
- Weeks to manually label a dataset
- Growing segmentation protocol or imaging technology
- **Objective:** Segmentation framework with one manual segmentations or labels

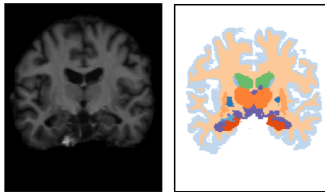


Figure 1: Structural brain MRI and its delineation

Setup

- Consider a dataset of N MRI scans $\{\mathbf{x}^{(i)}\}_{i=1}^N$
- Let \mathbf{s} be latent segmentation
- By Bayes' rule:

$$\log p(\mathbf{x}^{(i)}) = \log \sum_{\mathbf{s}} p(\mathbf{x}^{(i)}|\mathbf{s})p(\mathbf{s}), \quad (1)$$

- Evidence Lower Bound (ELBO):

$$\begin{aligned} \log p(\mathbf{x}^{(i)}) \geq & -\text{KL}(q(\mathbf{s}|\mathbf{x}^{(i)})||p(\mathbf{s})) \\ & + \mathbb{E}_{\mathbf{s} \sim q(\mathbf{s}|\mathbf{x}^{(i)})} \left[\log p(\mathbf{x}^{(i)}|\mathbf{s}) \right]. \end{aligned} \quad (2)$$

Segmentation Autoencoder (SAE)

- Variational Autoencoder (VAE)

$$\mathcal{L} = \text{KL}(q_\phi(\mathbf{s}|\mathbf{x}^{(i)})||p(\mathbf{s})) - \mathbb{E}_{\mathbf{s} \sim q_\phi(\mathbf{s}|\mathbf{x}^{(i)})} \left[\log p_\theta(\mathbf{x}^{(i)}|\mathbf{s}) \right]. \quad (3)$$

- Typical VAE uses representation \mathbf{s} that is typically continuous
- **Our model** maps \mathbf{s} to a semantic meaningful representation:

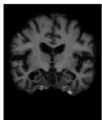
$$q_\phi(\mathbf{s}|\mathbf{x}^{(i)}) = \prod_{j=1}^V \text{Cat}(s_j|\mathbf{x}^{(i)}, \phi). \quad (4)$$

- Likelihood:

$$p_\theta(\mathbf{x}|\mathbf{s}) = \prod_{j=1}^V \mathcal{N}(\mathbf{x}; \hat{\mathbf{x}}_j(\mathbf{s}; \theta), \sigma^2). \quad (5)$$

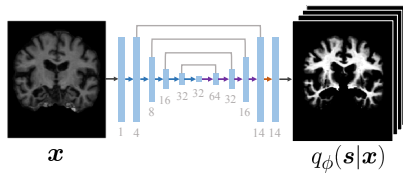
- Spatial Prior

$$p_{\text{spatial}}(\mathbf{s}) = \prod_{j=1}^V p_j(s_j). \quad (6)$$

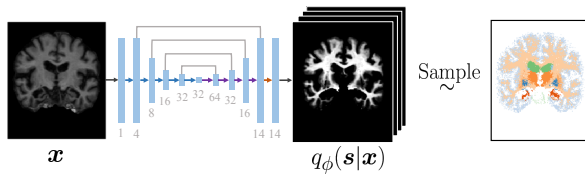


x

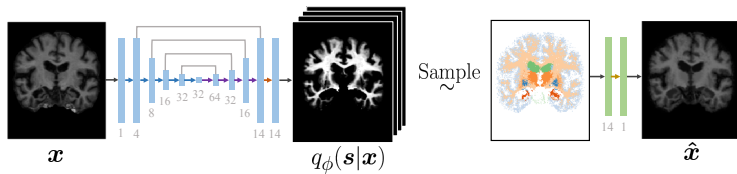
Architecture



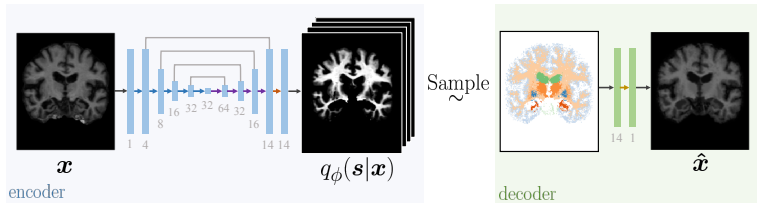
Architecture



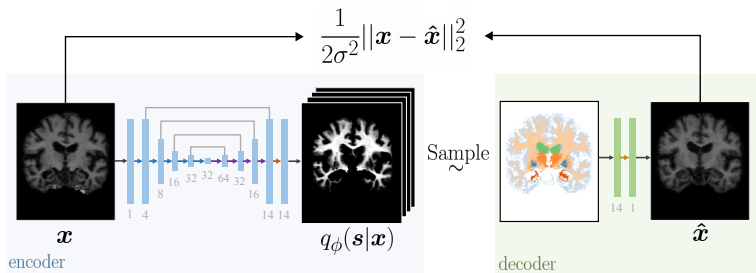
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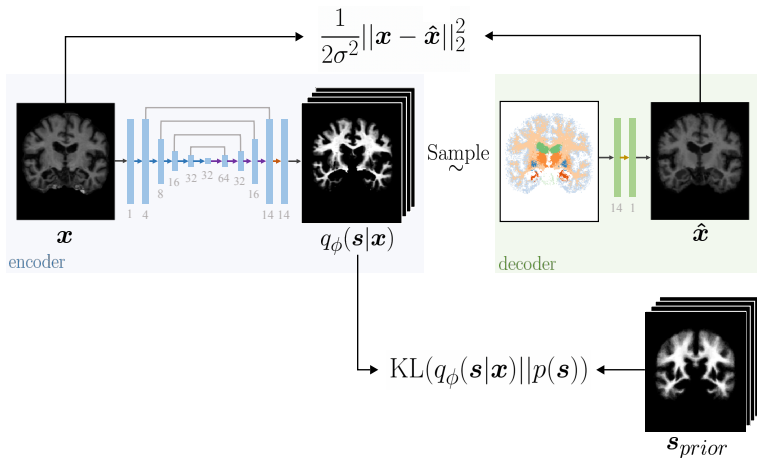
Architecture



Architecture



Architecture



- Buckner dataset
- T1 MRI scans and 12 manual labels
- 1 probabilistic label atlas
- 30 training subjects and 8 testing subjects
- Repeated the experiment 5 times with different random subject assignments to the train/test partitioning.

Qualitative Results

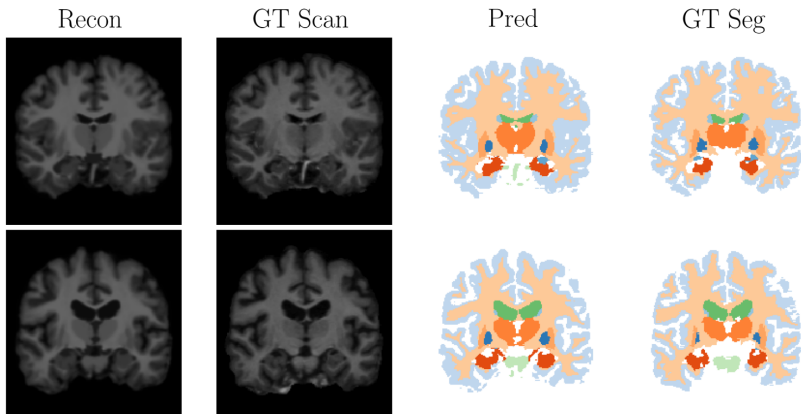


Figure 2: Representative segmentation results obtained with SAE (w/ MRF) on two subjects.

Model	Performance Measure	
	Hausdorff (mm)	Dice Overlap (%)
Baseline	3.50 ± 0.06	71.45 ± 0.65
EM Baseline	2.65 ± 0.05	79.70 ± 0.54
SAE (w/o MRF)	2.73 ± 0.04	79.94 ± 0.34
SAE (w MRF)	2.68 ± 0.05	80.54 ± 0.36
Supervised	2.23 ± 0.07	84.60 ± 0.26

Table 1: Mean performance of all methods with their standard errors.

Thank You

More experiments + Implementation:
<https://github.com/evanmy/sae>

