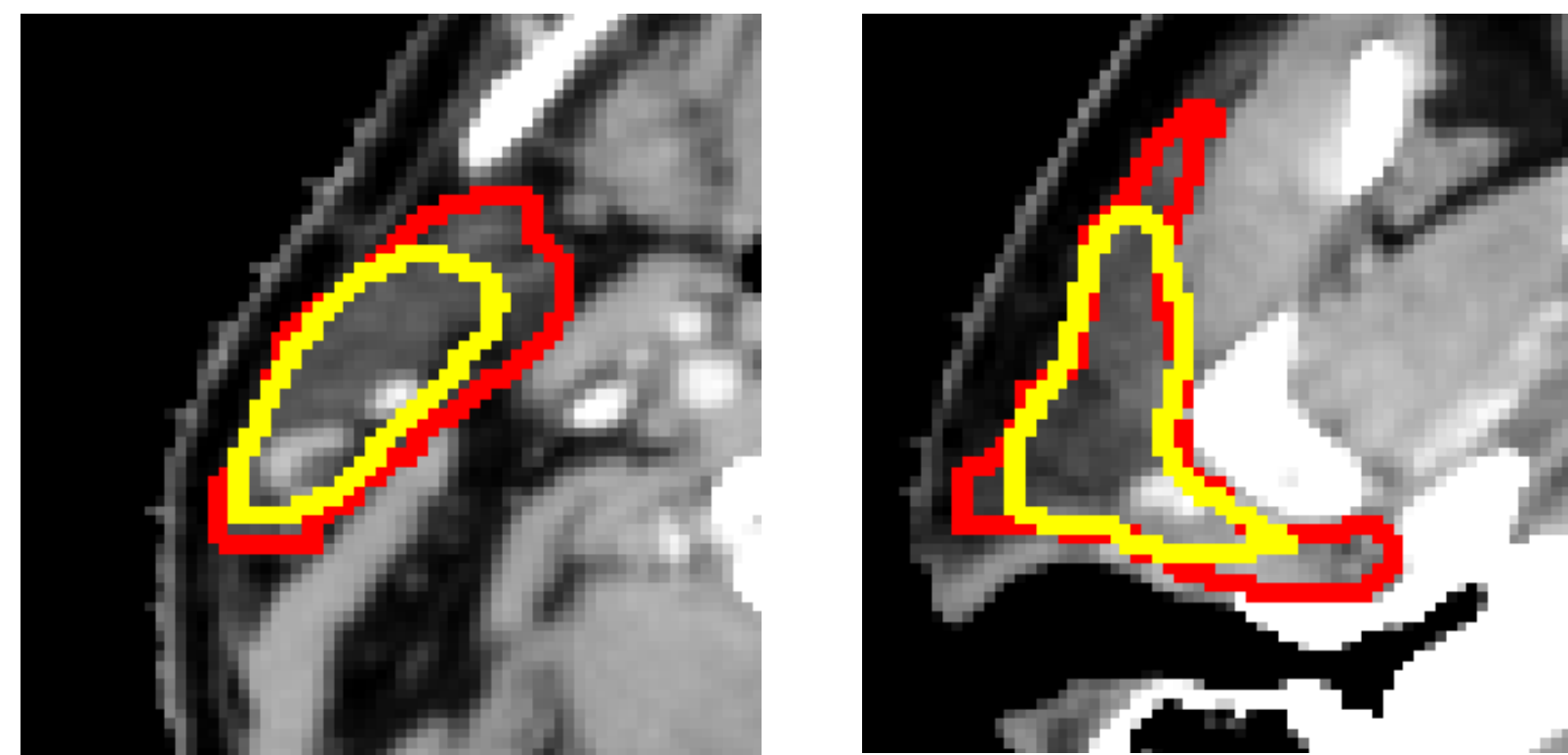


Introduction

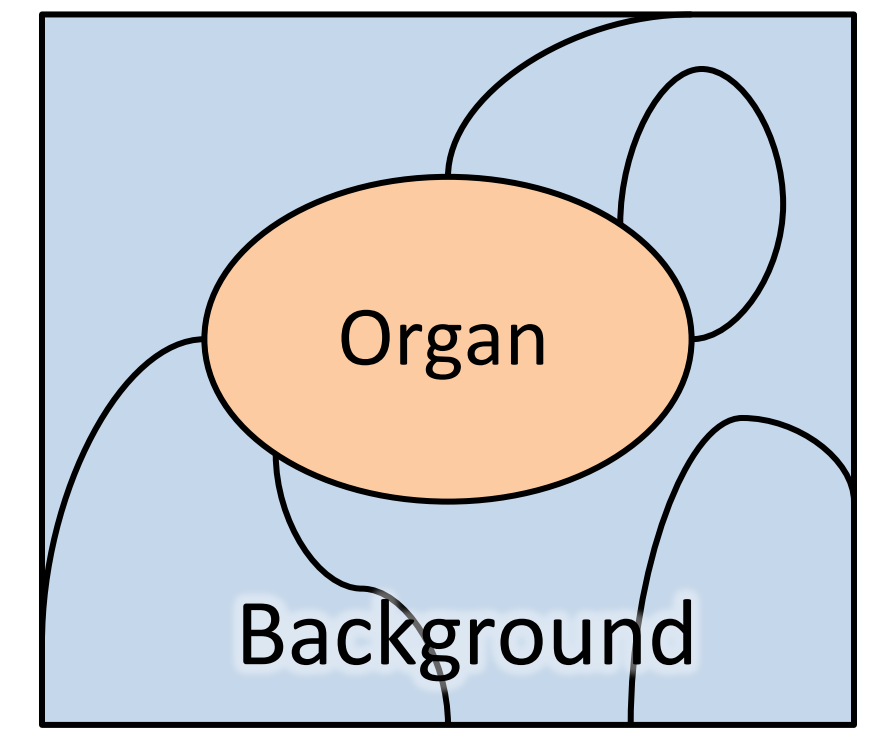
- Atlas-based segmentation is commonly used in medical image analysis
- Tendency of atlas-based segmentation to under-segment structures
- Dice overlap and Hausdorff distance do not measure under-segmentation
- Wang, Yushkevich (2012) proposed deconvolution of label maps
- Contributions:
 - Volume overlap measures to quantify under-segmentation
 - **Hypothesis: asymmetry in single organ segmentation as cause**
 - Generative model of background to correct under-segmentation

Segmentation of parotid glands in CT images



Red: manual, Yellow: automatic

Merging several structures to one background label



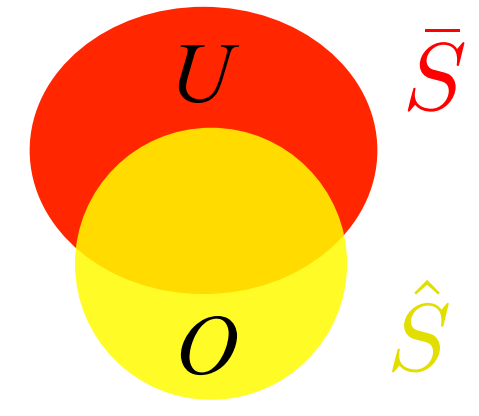
Under-Segmentation

Measures to quantify over- and under-segmentation:

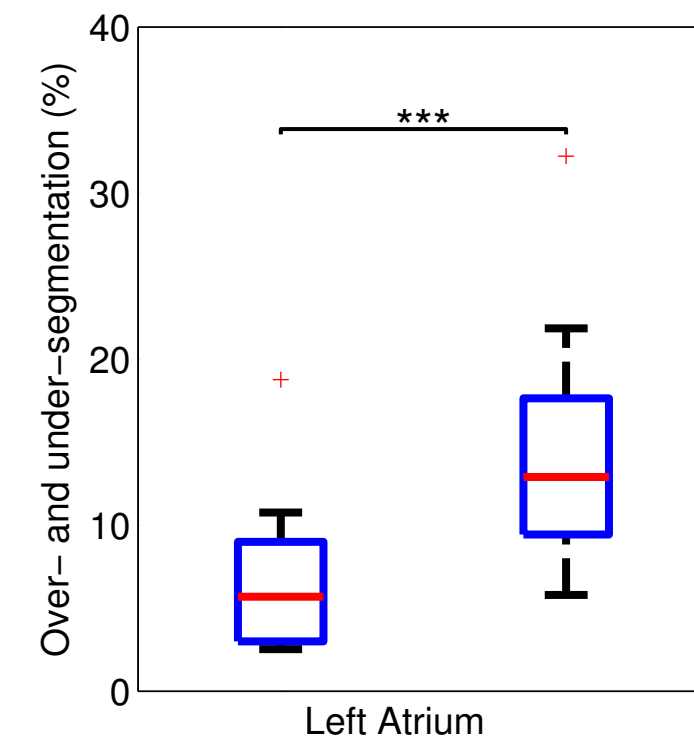
$$O(\hat{S}, \bar{S}) = \frac{|\hat{S} \setminus \bar{S}|}{|\hat{S}|} \quad U(\hat{S}, \bar{S}) = \frac{|\bar{S} \setminus \hat{S}|}{|\bar{S}|}$$

\bar{S} : Manual \hat{S} : Automatic segmentation

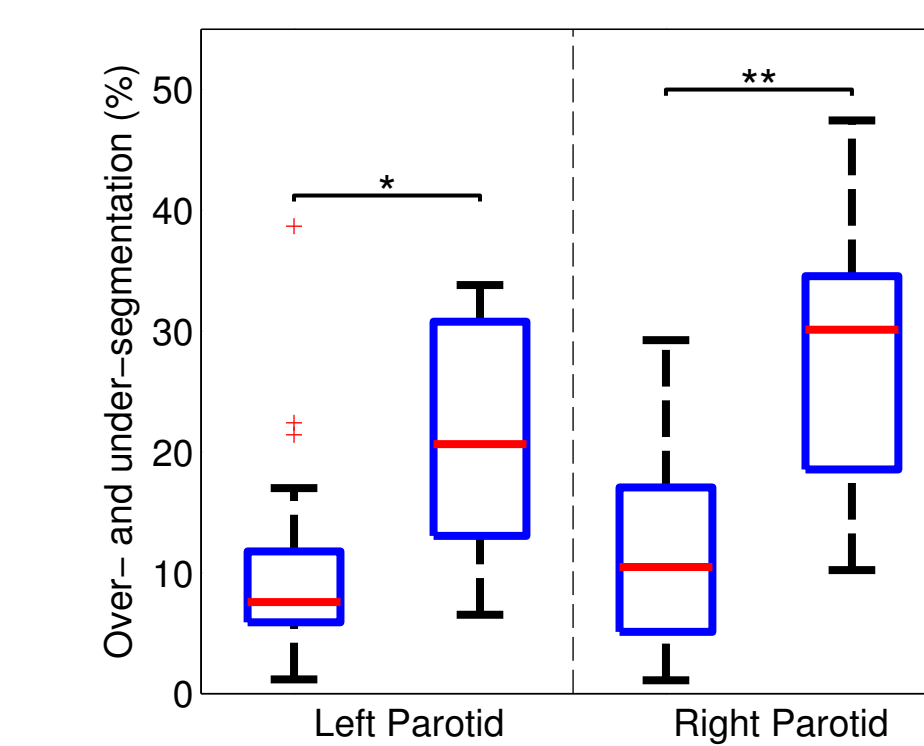
- Quantitative segmentation results for three applications
- Under-segmentation errors significantly higher than over-segmentation errors



Left atrium in heart MRA

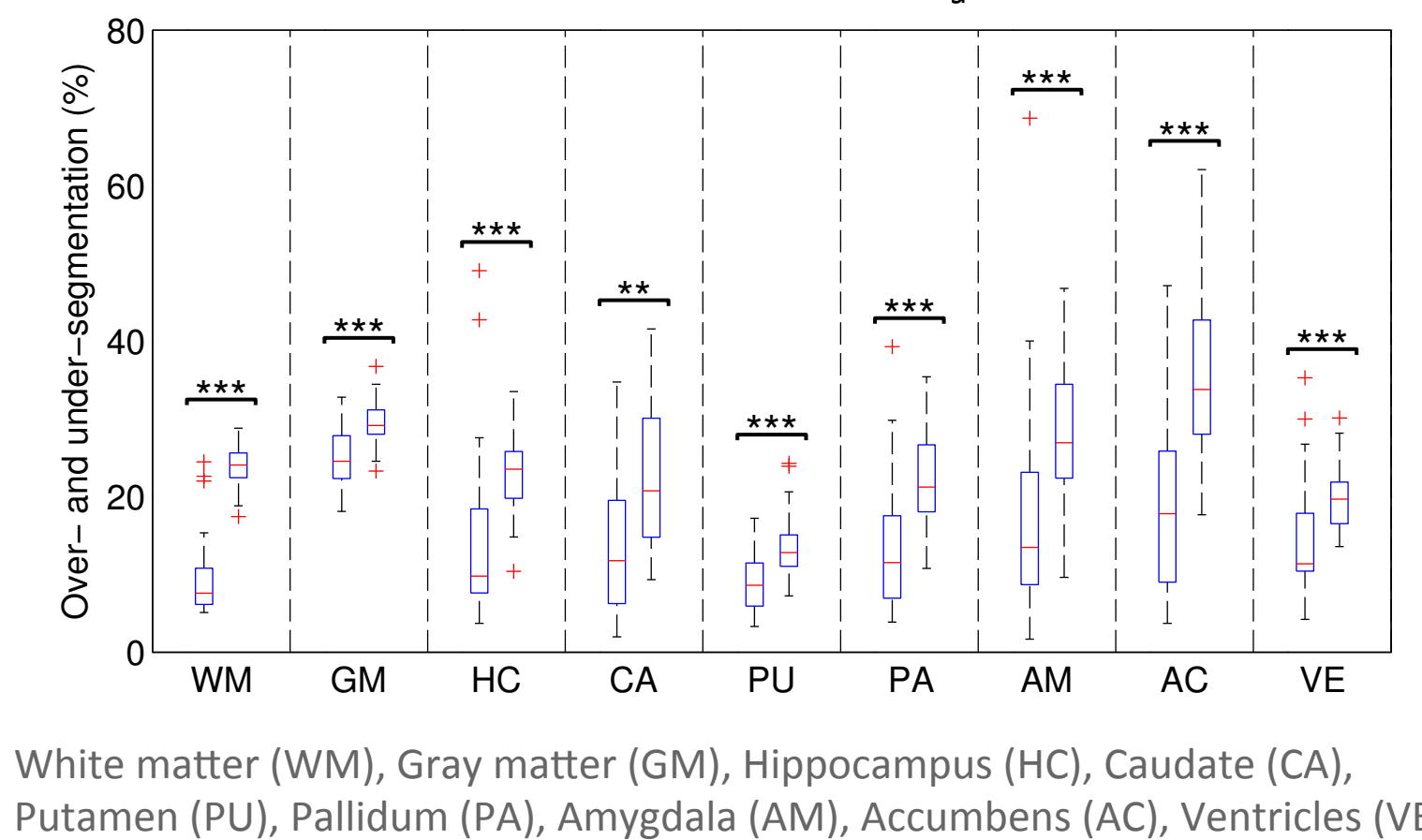


Parotid glands in head & neck CT



First column: over-segmentation
Second column: under-segmentation

Nine brain structures in MRI
Foreground-background segmentation

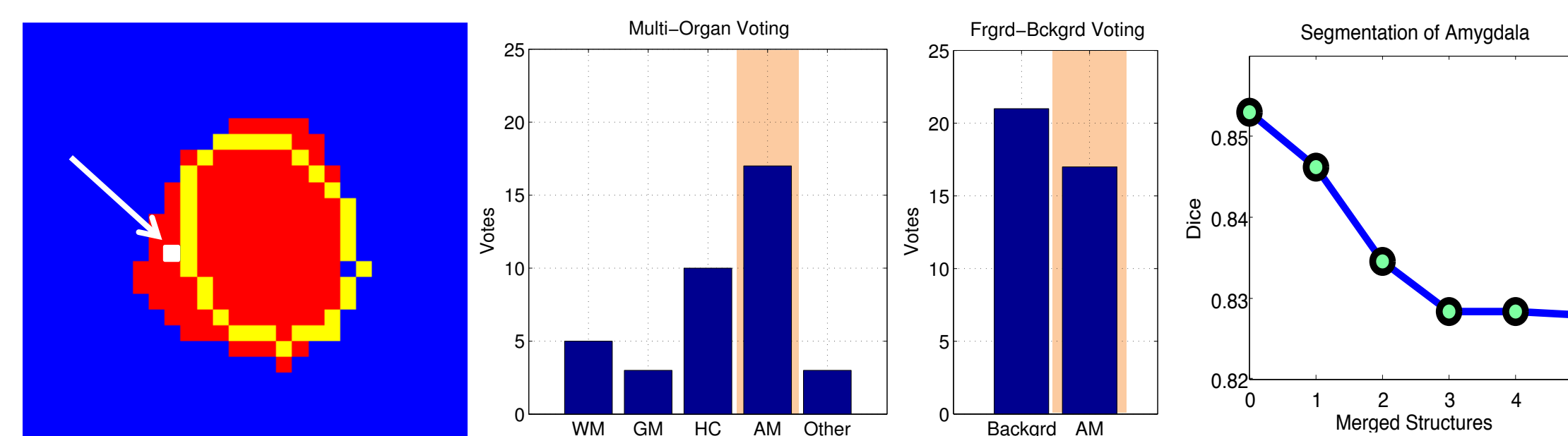


White matter (WM), Gray matter (GM), Hippocampus (HC), Caudate (CA), Putamen (PU), Pallidum (PA), Amygdala (AM), Accumbens (AC), Ventricles (VE)

Hypothesis for under-segmentation

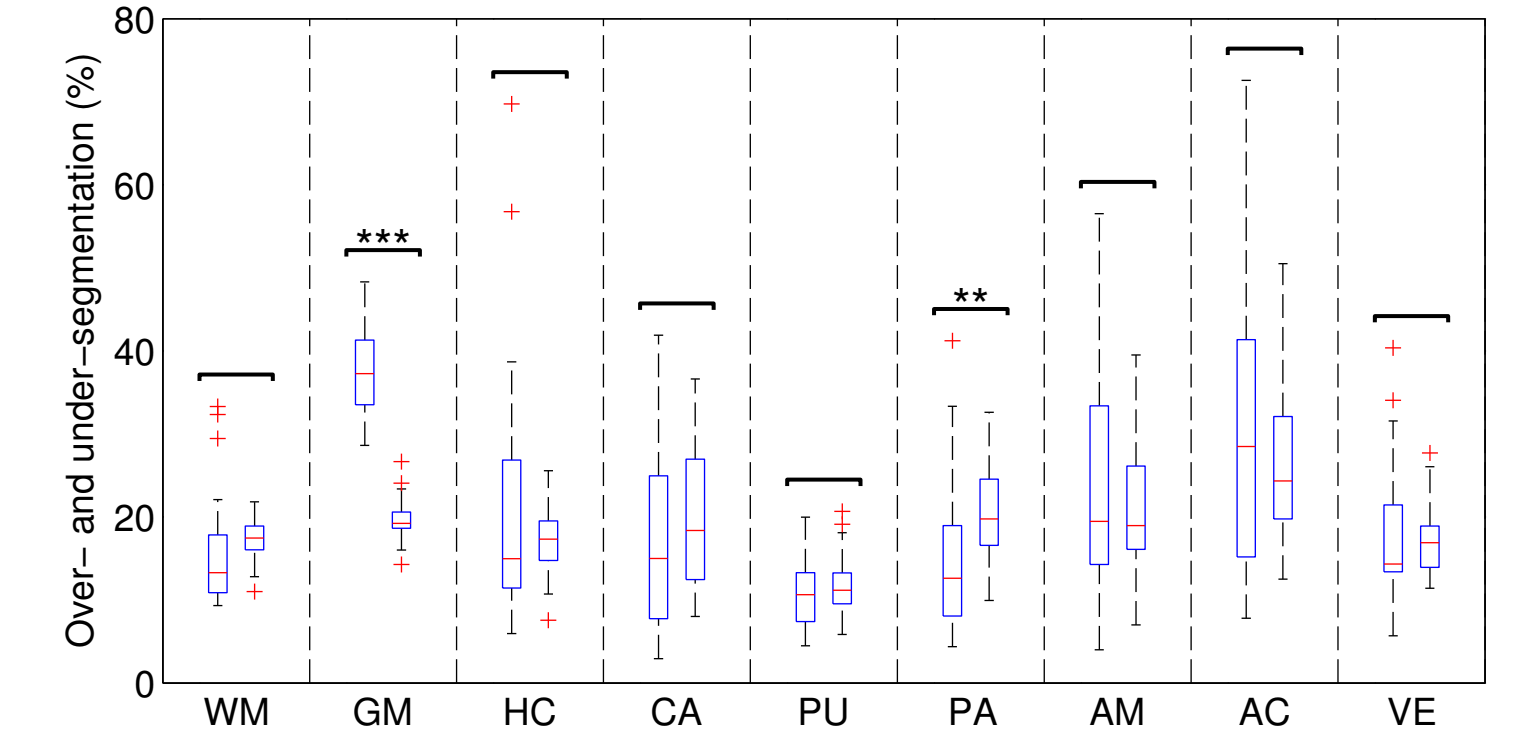
- Under-segmentation is caused by asymmetry in foreground-background segmentation
- Merging all surrounding labels into background creates a new meta-label that dominates the voting process
- Multi-organ segmentation of brain supports hypothesis

Illustration of multi-organ and foreground-background segmentation



Red: manual, Yellow: automatic, White: voxel of interest

Multi-organ brain segmentation

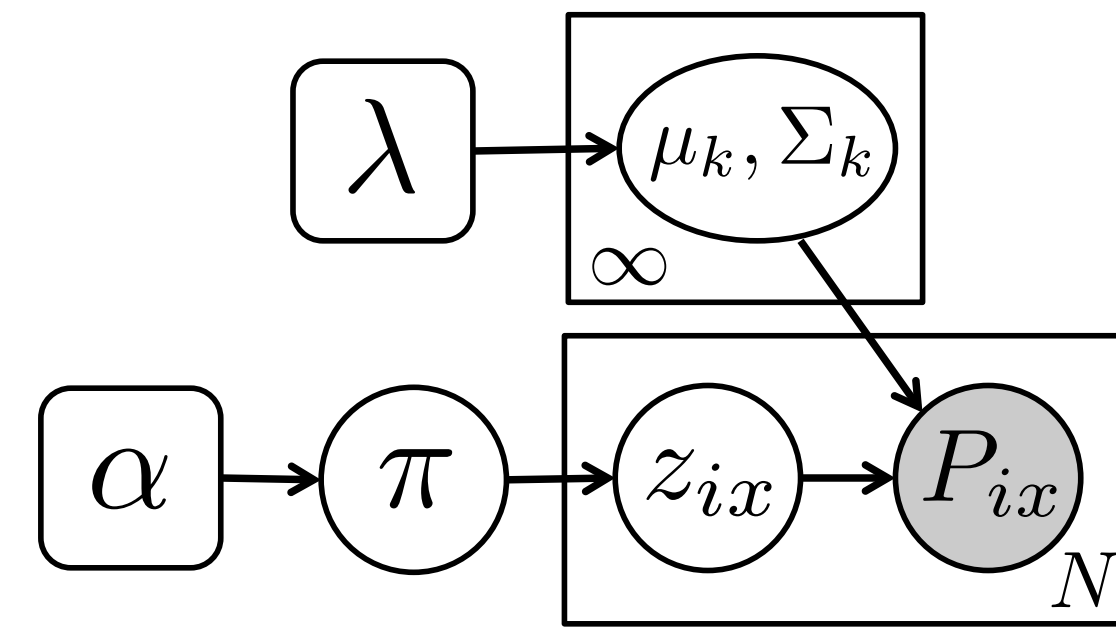


Latent multi-label model of the background

- Generative model for the unsupervised separation of the background in K components and simultaneous estimation of K
- Dirichlet process Gaussian mixture model (DP-GMM) on patches:

$$\mathcal{P} = \{P_{ix} : x \in \Gamma, S_i(x) = b\}$$
- Replace background label with mixture component:

$$S_i(x) = b \rightarrow S_i(x) = z_{ix} \quad z_{ix} \in \{1, \dots, K\}$$

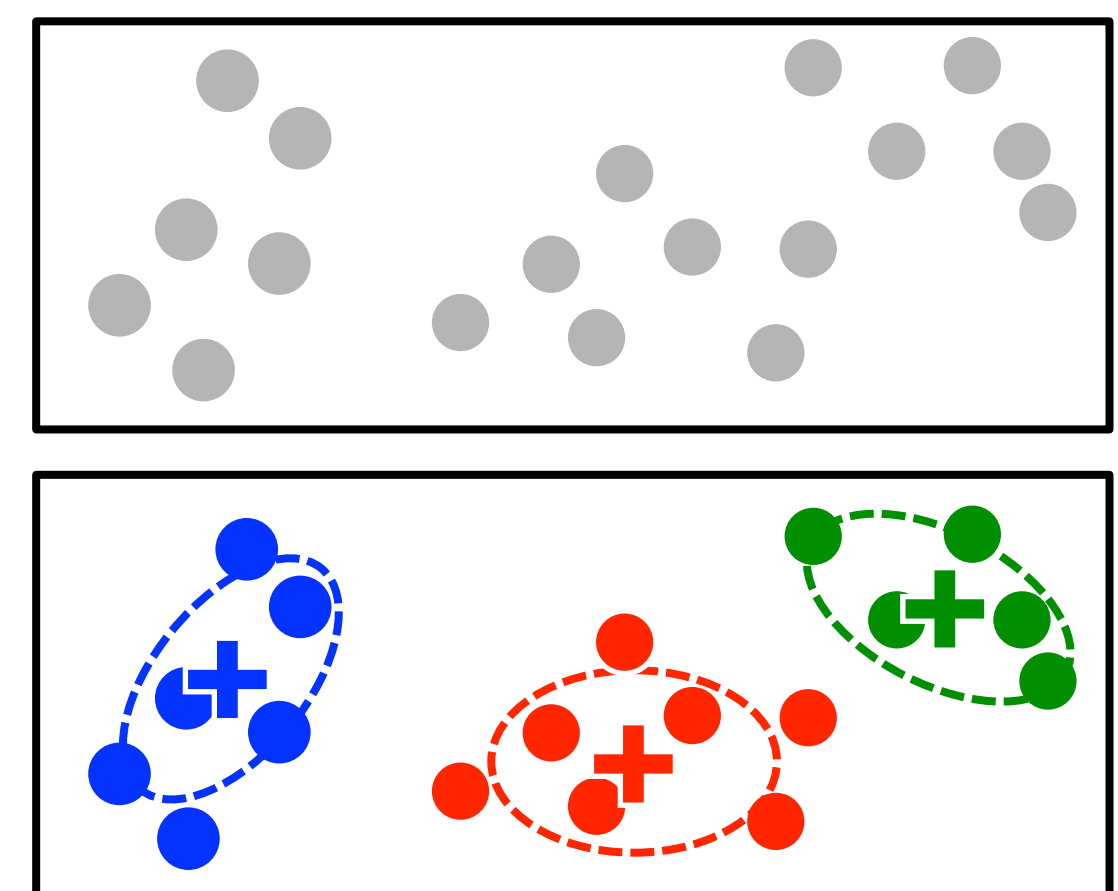


$$P_{ix} | z_{ix} \sim \mathcal{N}(\mu_{z_{ix}}, \Sigma_{z_{ix}})$$

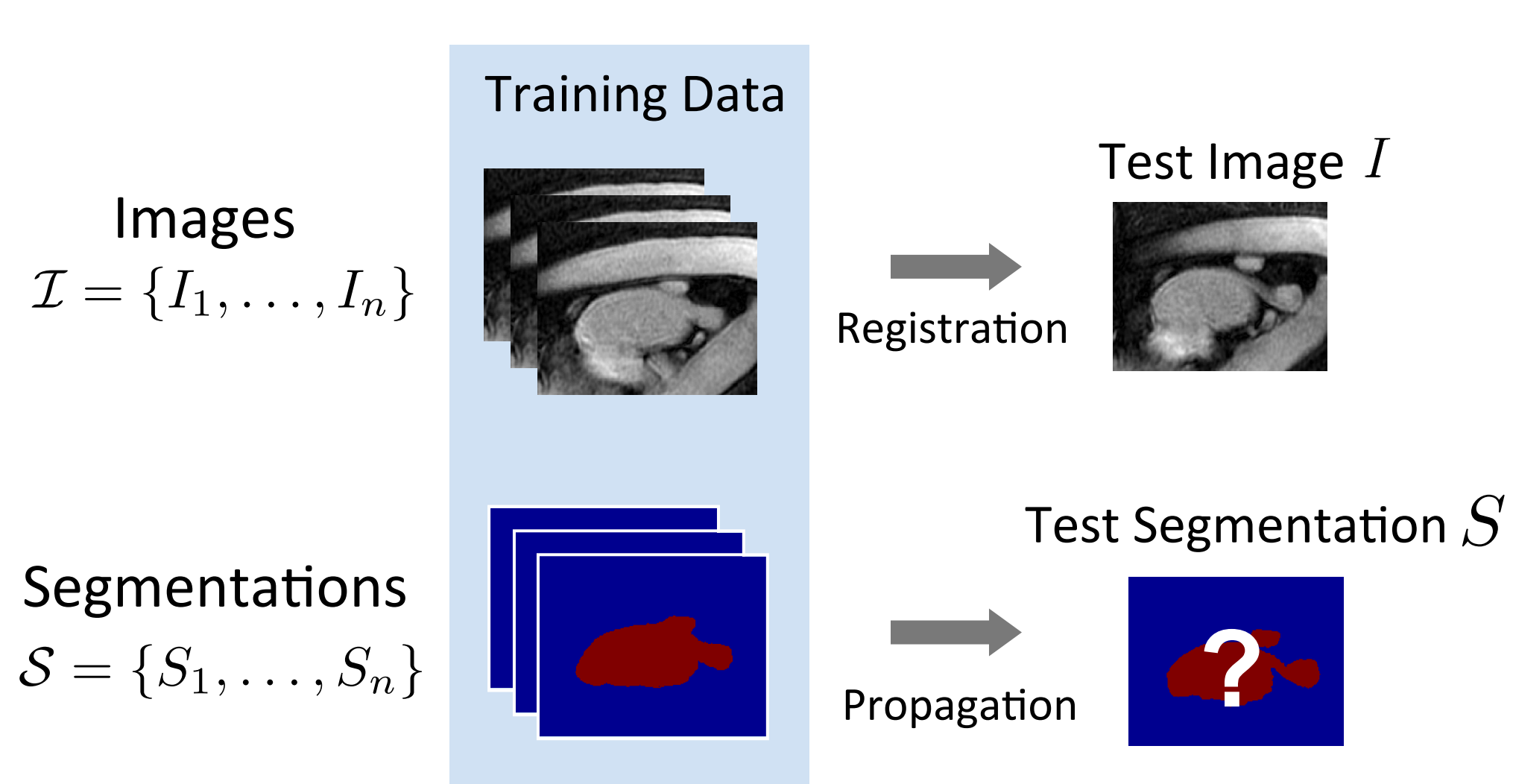
$$z_{ix} \sim \text{Cat}(\pi)$$

$$\pi \sim \text{GEM}(\alpha)$$

$$(\mu_k, \Sigma_k) \sim \mathcal{NW}(\lambda)$$



Multi-atlas segmentation



Label maps specify likelihood of each label:

$$L^l(x) = \sum_{i=1}^n p(S(x) = l | S_i) \cdot p(I(x) | I_i) \quad l \in \{1, \dots, \eta\}$$

Label likelihood term:

$$p(S(x) = l | S_i) = \begin{cases} 1 & \text{if } S_i(\phi_i(x)) = l, \\ 0 & \text{otherwise.} \end{cases}$$

Intensity likelihood term:

$$p(I(x) | I_i) \propto \exp\left(-\frac{(I(x) - I_i(\phi_i(x)))^2}{2\sigma^2}\right)$$

Most likely label yields segmentation:

$$\hat{S}(x) = \arg \max_l L^l(x)$$

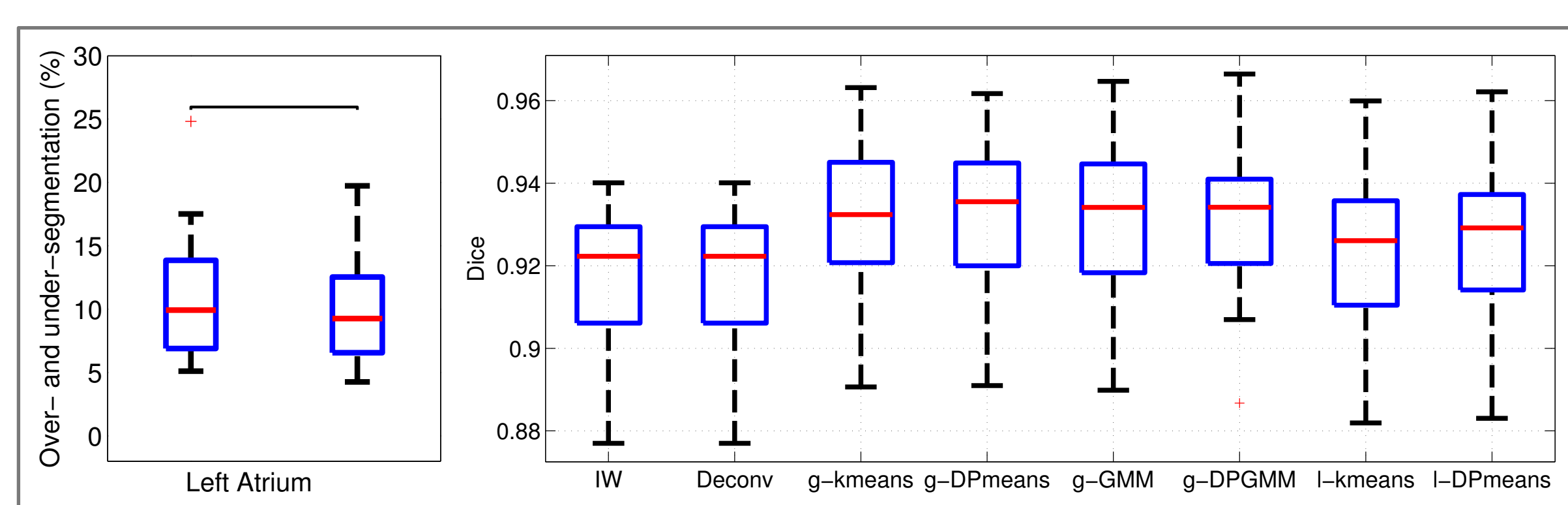
Foreground-Background segmentation:

$$L^f(x) > L^b(x)$$

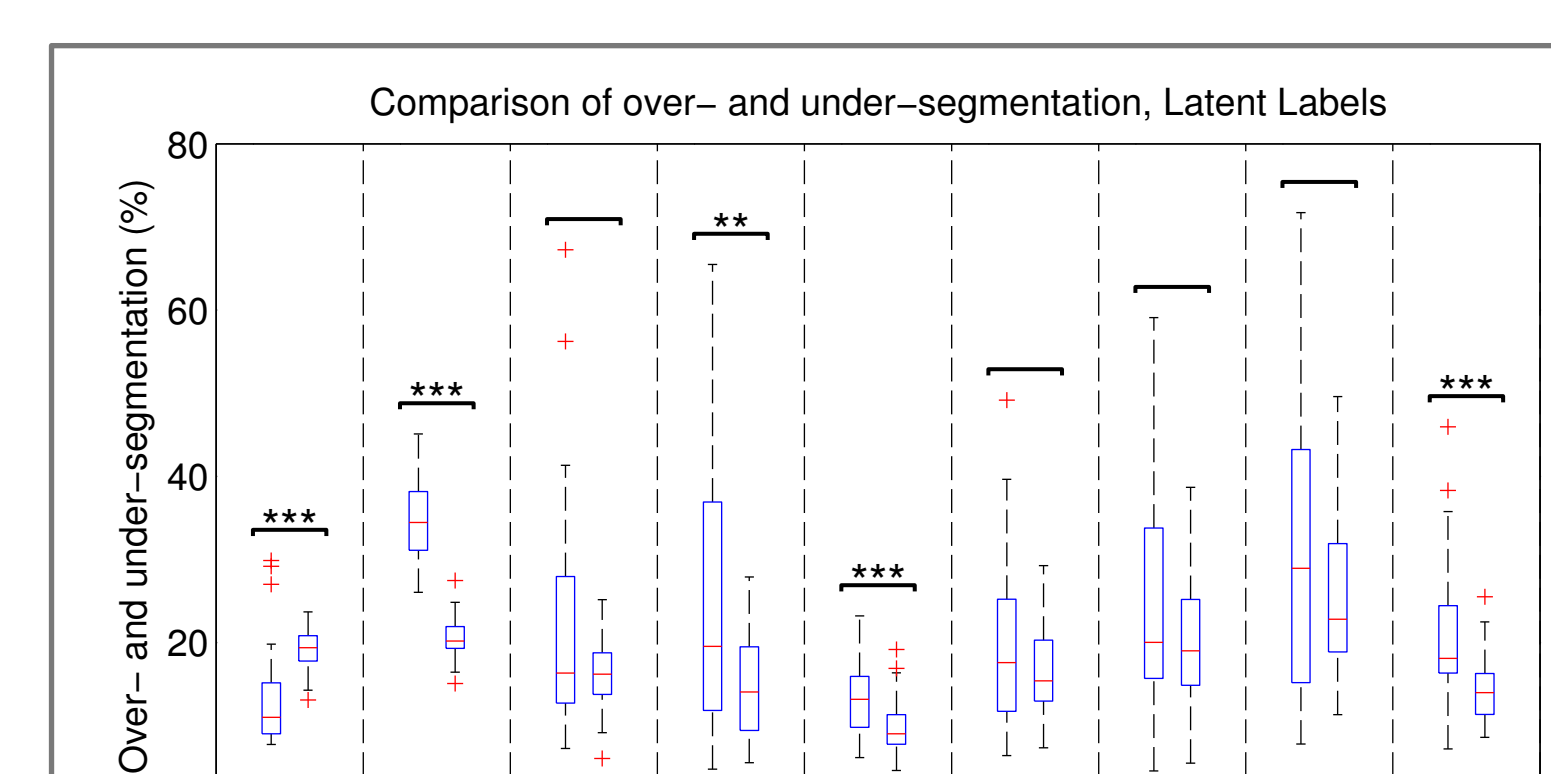
Results

- Datasets:
 - 16 heart MRA images (0.6x0.6x1.5mm)
 - 18 head and neck CT scans (0.9x0.9x2.5mm)
 - 39 brain MRI with 1mm isotropic resolution
- Comparison to deconvolution (Wang, 2012)
- Details:
 - DP-GMM, GMM, DP-means, k-means
 - Global and local approach
 - Patch size: 3 x 3 x 3

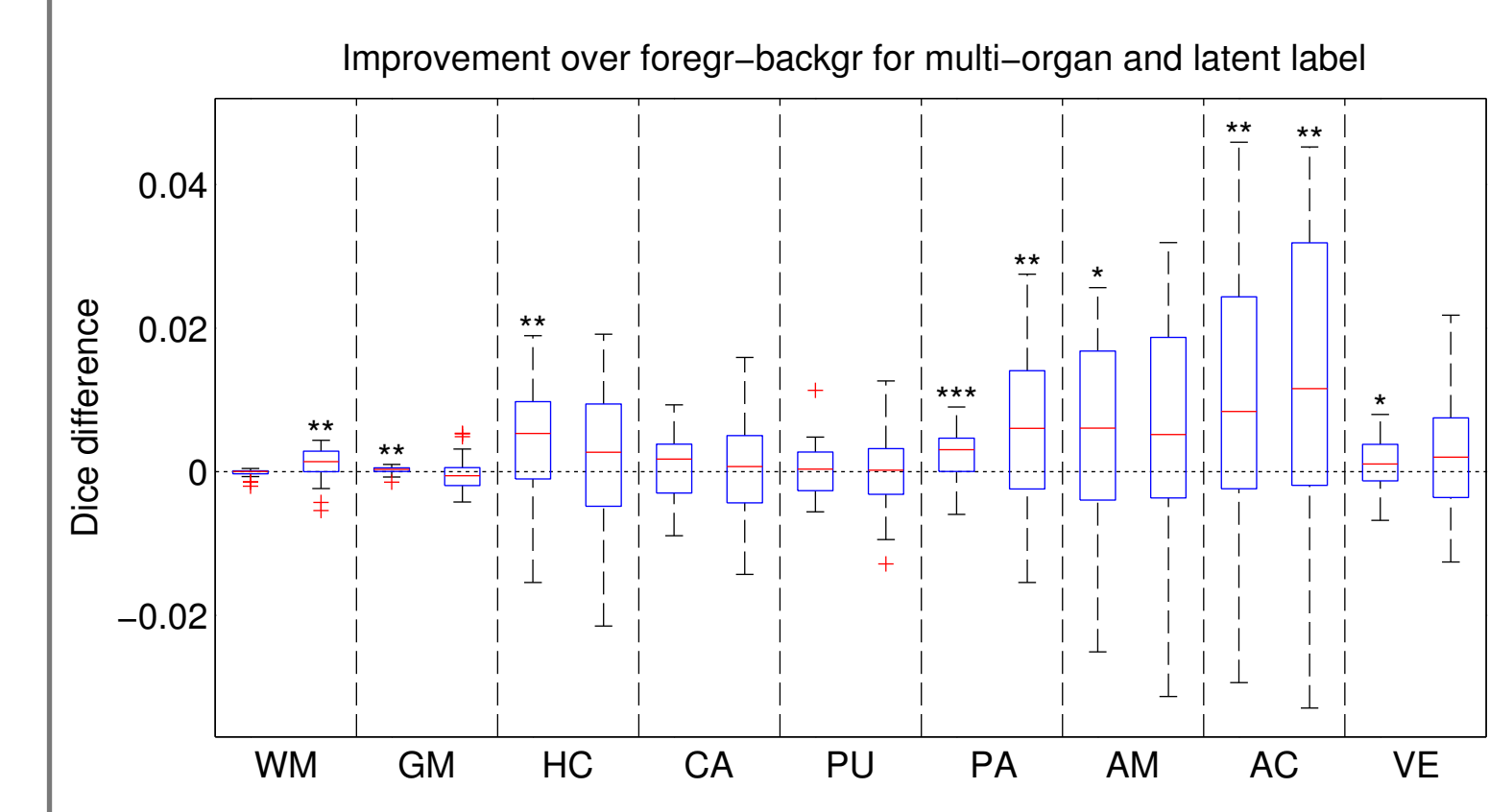
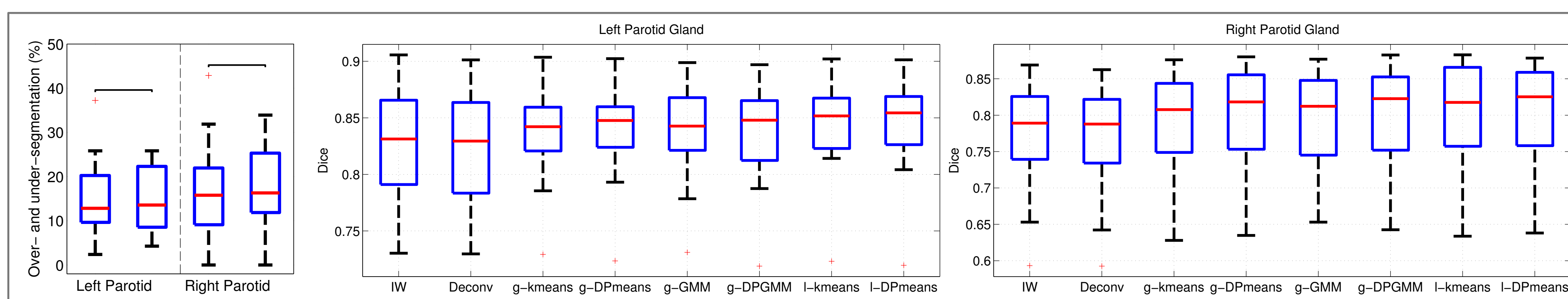
Left Atrium



Brain



Parotid Glands



Conclusions

- Significant bias in atlas-based segmentation to under-segmentation
- Asymmetry in foreground-background segmentation as new hypothesis
- Generative model to partition background reduces under-segmentation

Acknowledgement:

We thank Jason Chang and Greg Sharp. This work was supported in part by the National Alliance for Medical Image Computing (U54-EB005149) and the Neuroimaging Analysis Center (P41-EB015902).