Quantmetry
Building AI with pioneers

IRSN

EpibrainRad project

A Bayesian approach to brain segmentation

AppliBUGS Seminar

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High grade glioma

A very aggressive type of brain cancer

The disease

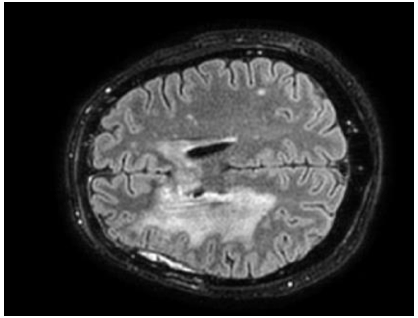
- 3000 new cases each year in France
- A median life expectancy of 30 months
- A heavy impact on the patient's life quality

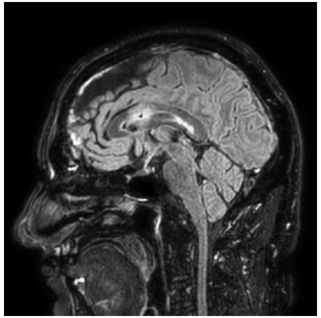
The treatment

- Surgical removal of the tumor
- **Radiotherapy** around the area
- Chemotherapy

Secondary effects of radiotherapy

- Behavioral disorders
- Temporary edema
- Leucopathy = alteration of the white matter
- Brain atrophy





Brain segmentation for the EpibrainRad cohort

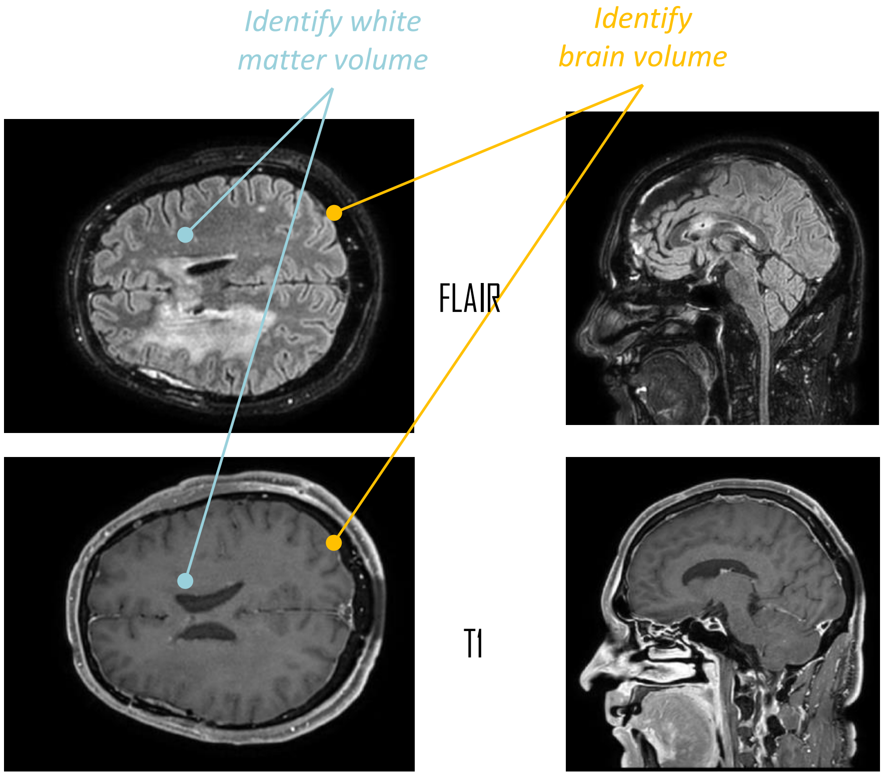
Context

- Study of a cohort set up in 2015 with patients treated for a high grade glioma
- Automatization of the lesions quantification

Data

- ~500 MRI sequences
- 3D images with 1M-10M voxels
- 135 patients : 4-10 exams / patient

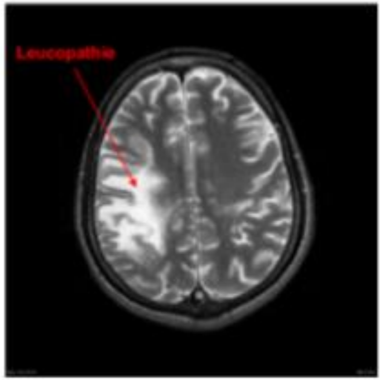
No labeled data means **non-supervised segmentation**



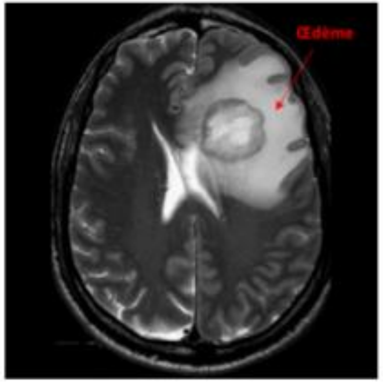
Why create a custom algorithm?

Hypersignal: leukopathy or edema?

Expert insight is needed to interprete MRIs



Radiotherapy secondary effects



Side effects induces by the tumor

Available software and limitations

Dipy[1]:
- Free and open software
- Frequentist approach
- Few parameters
- Only T1 sequences

→ Fails

Deep Brain[2]:
- Free and open software
- Deep neural networks
- No parameters
- Only T1 sequences

→ Fails

Brain Suite[3]:
- Free software
- Nice interface

→ Classifies only sane tissues

FreeSurfer[4]:
- Free software
- Possible python API

→ Classifies only sane tissues

[1] http://nipy.org/dipy/examples_built/tissue_classification.html#example-tissue-classification
[2] https://pypi.org/project/deepbrain/
[3] http://brainsuite.org/
[4] https://surfer.nmr.mgh.harvard.edu/

Outline

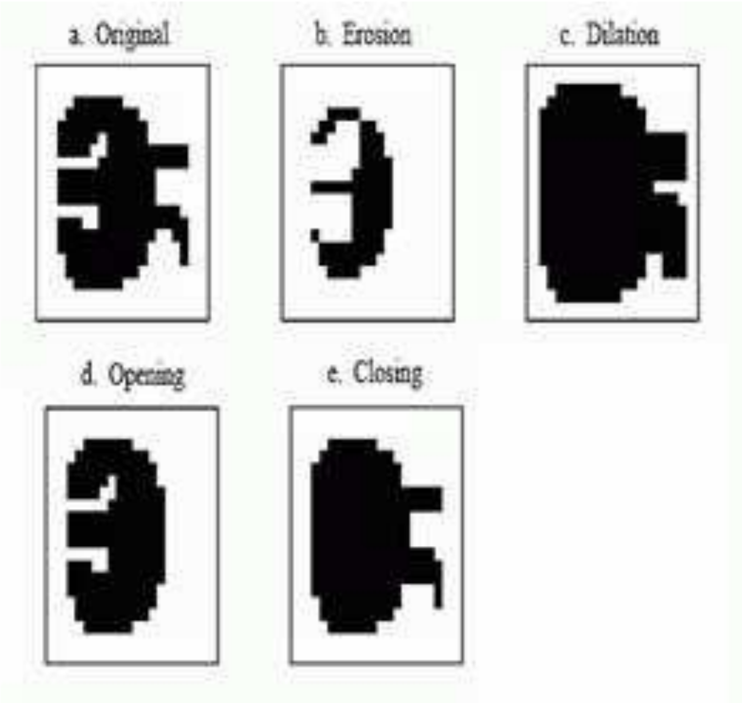
1. Brain extraction
- Morphological operations
- Results

2. Segmentation of brain tissues
- Hidden Markov random field model
- Sampling
- Results

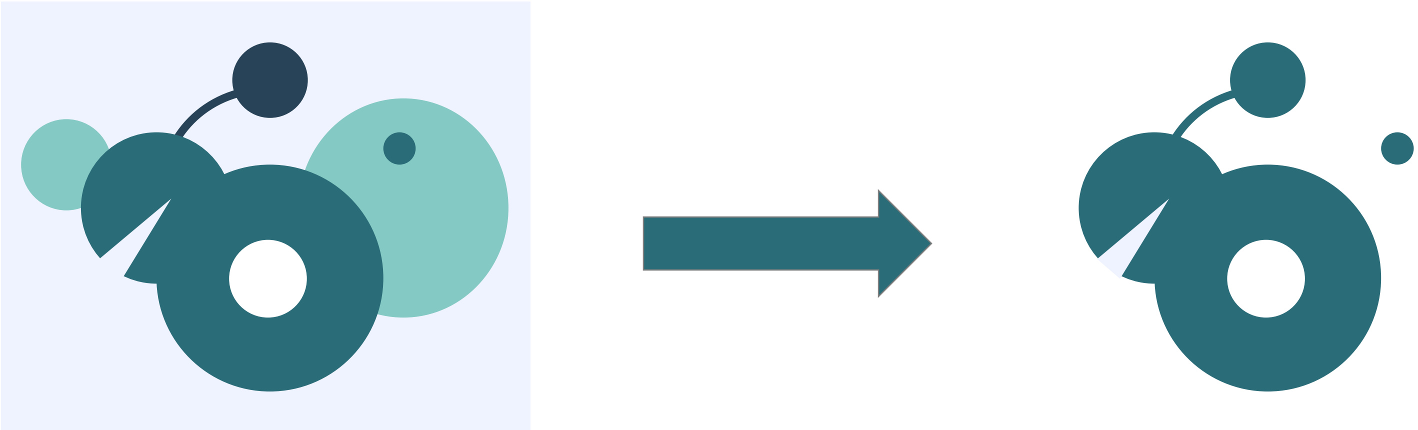
3. Data augmentation

1 | Brain extraction

Morphological operations



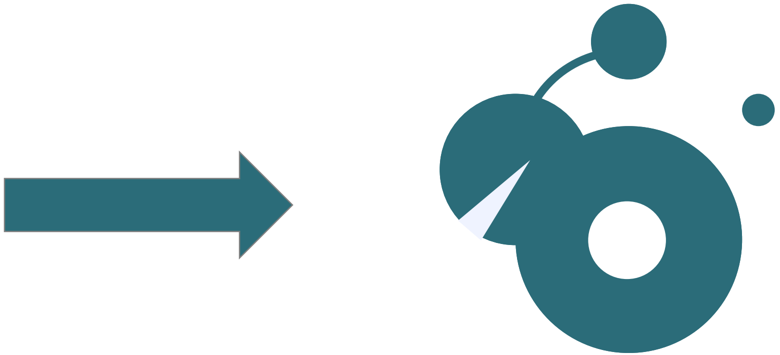
Brain extraction - Otsu thresholding (1/5)



Intensity threshold **maximizing** the **interclass** variance while **minimizing** the **intraclass** variance

VALA, Hetal J. et BAXI, Astha. A review on Otsu image segmentation algorithm. *International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)*, 2013, vol. 2, no 2, p. 387-389.

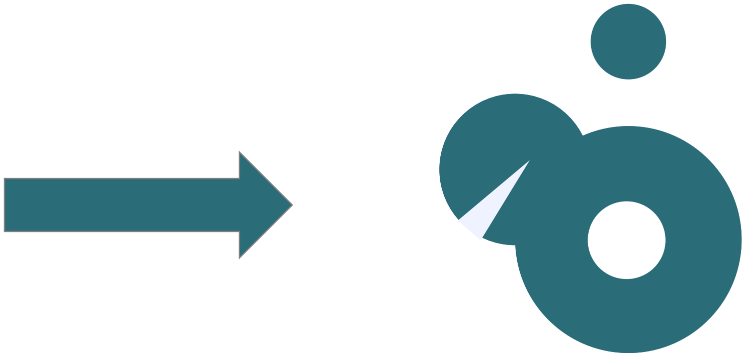
Brain extraction - Morphological opening (2/5)



Suppresses any detail with a characteristic length under $\ell = 2\text{mm}$

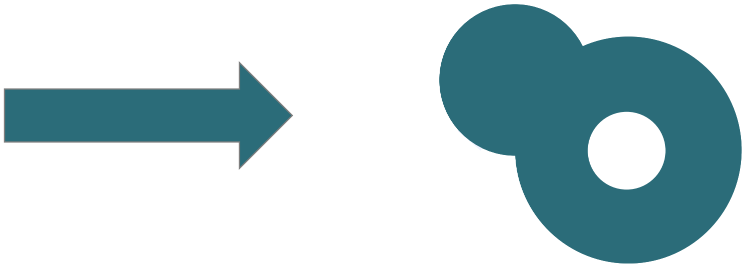
C. W. Chen, J. Luo and K. J. Parker, "Image segmentation via adaptive K-mean clustering and knowledge-based morphological operations with biomedical applications," in IEEE Transactions on Image Processing, vol. 7, no. 12, pp. 1673-1683, Dec. 1998. doi: 10.1109/83.730379

Brain extraction - Largest connected part (3/5)



Only preserves the largest connected part, removes any smaller component

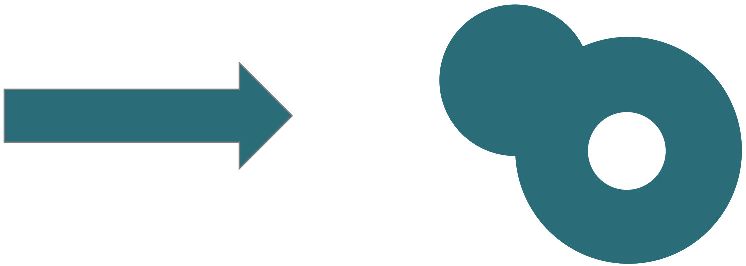
Brain extraction - Morphological closing operation (4/5)



Suppresses any holes and cracks with a characteristic length under $\ell = 2\text{mm}$

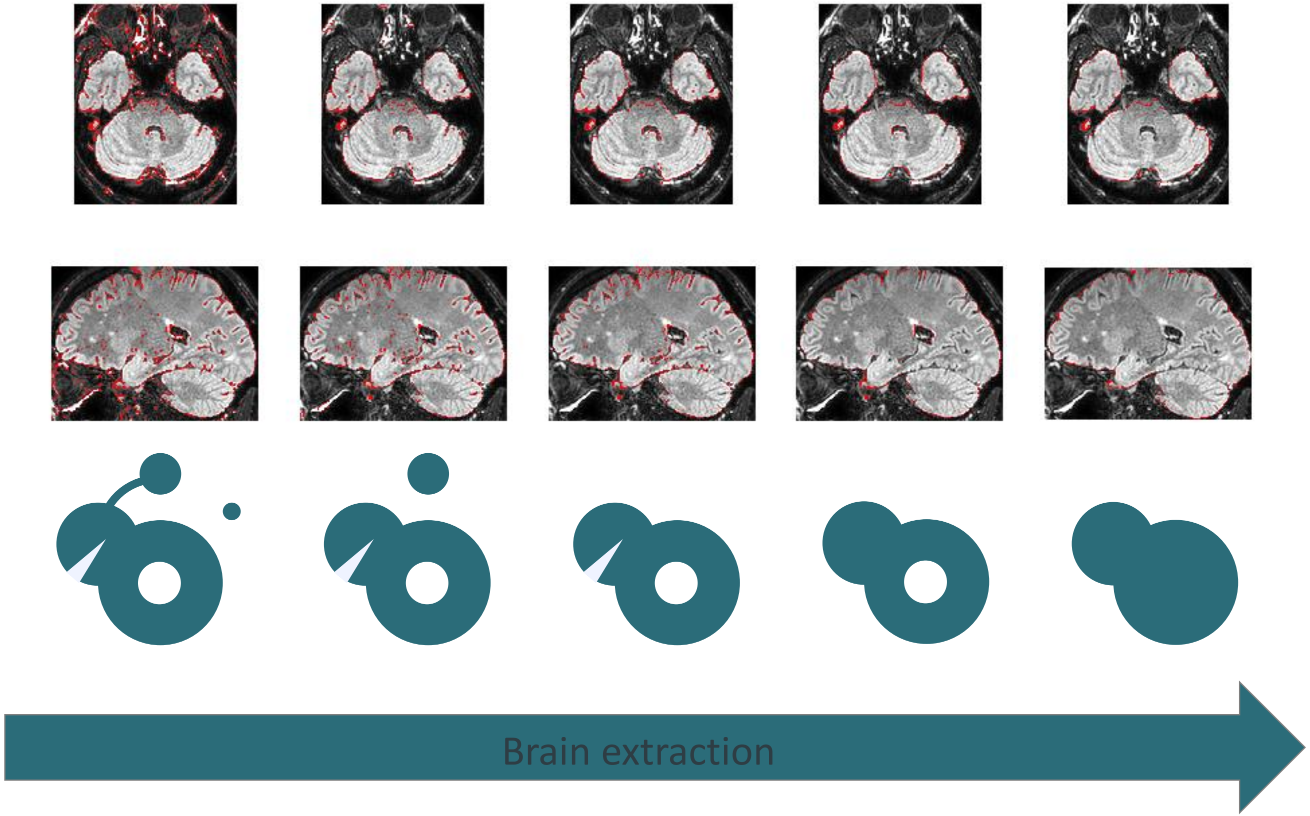
C. W. Chen, J. Luo and K. J. Parker, "Image segmentation via adaptive K-mean clustering and knowledge-based morphological operations with biomedical applications," in IEEE Transactions on Image Processing, vol. 7, no. 12, pp. 1673-1683, Dec. 1998. doi: 10.1109/83.730379

Brain extraction - Addition of inclusions for each axial slice (5/5)

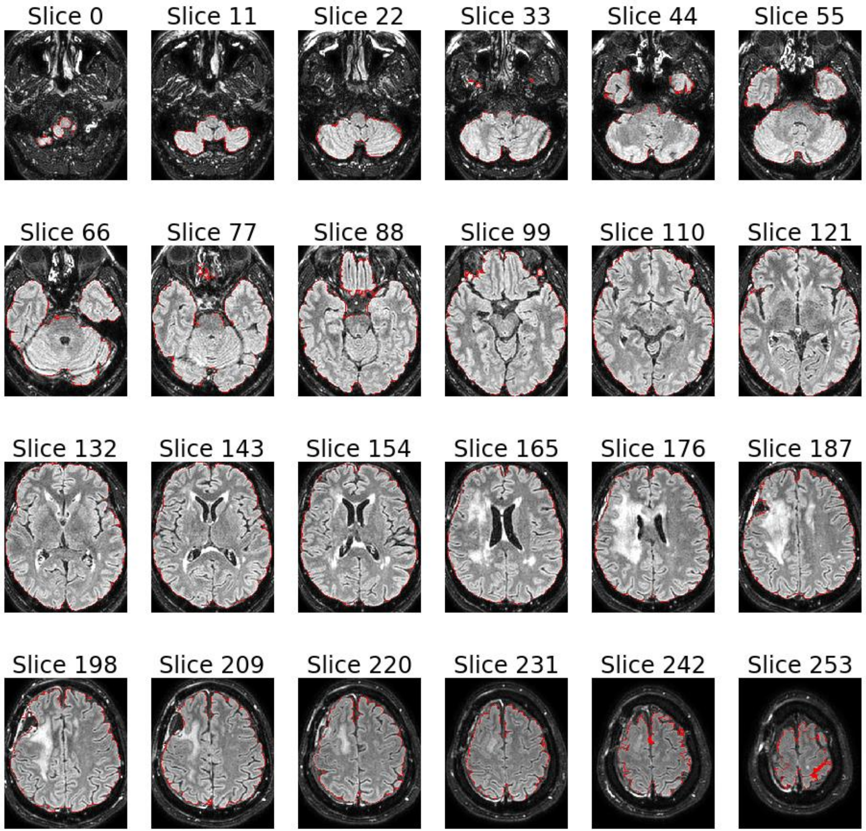


Fill any remaining hole (to do on every axial slice on a 3D scene)

Brain extraction – 5 steps on a brain MRI



Brain extraction – results



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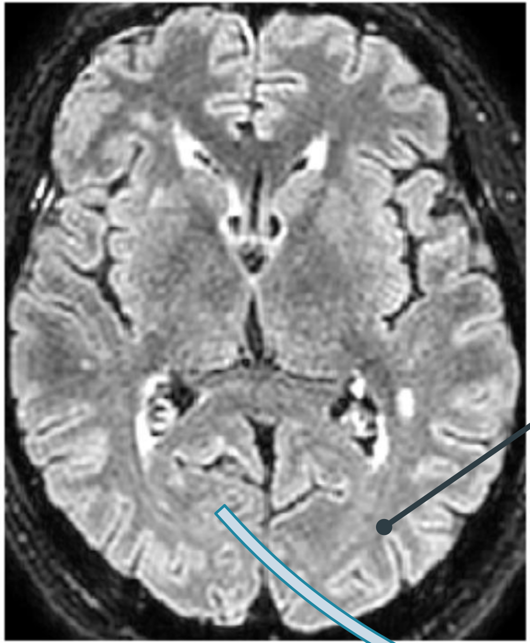
2 | Brain tissues segmentation

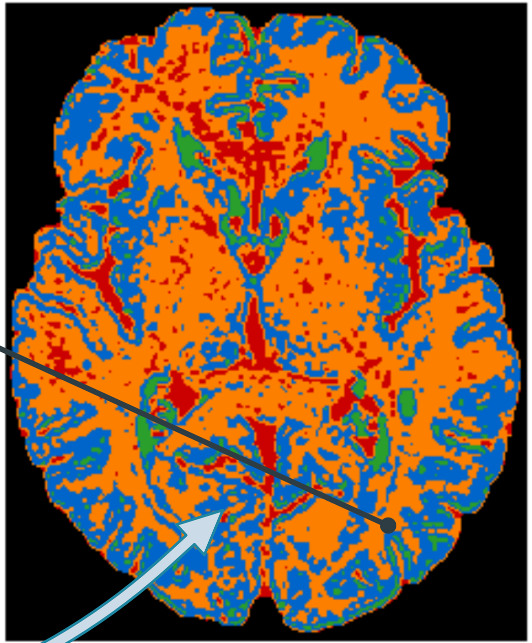
Variables



Voxel s

Intensity Y_s

Label X_s



labelling

MRI Intensities $Y = (Y_s)_{s \in S}$

Labeling $X = (X_s)_{s \in S}$

Bayesian model

Posterior probability:

$\pi(X\ |Y)$: probability of the labeling X knowing the MRI intensity Y

Goal:

1. Draw $\left(X^i\right)_{1\leq i\leq N} \sim \pi(X|Y)$
2. Compute the mean volume $\frac{1}{\mathrm{N}}\sum_{i=1}^{N} VolWhiteMatter\ (X^i)$

Bayes formula

Posterior = **Likelihood** X **Prior**

$$\pi(X|Y)$$

$$\pi(Y|X) = \prod_{s \in S} \underbrace{\pi(Y_s = y | X_s = k)}_{f_k(y)}$$

Need to define

$$\pi(X)$$

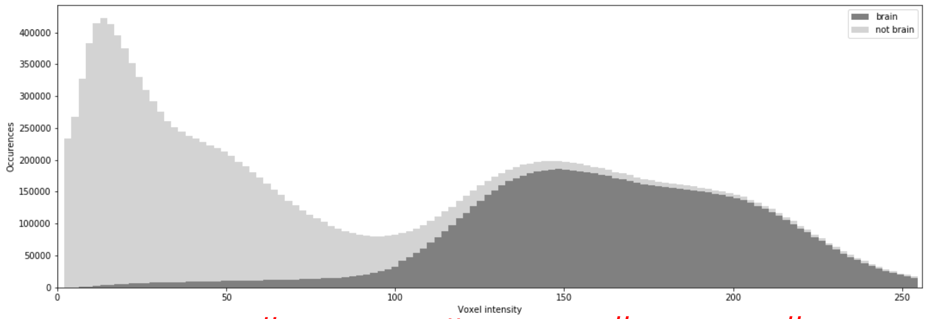
Need to define

Likelihood

Gaussian mixture model

Hypothèse

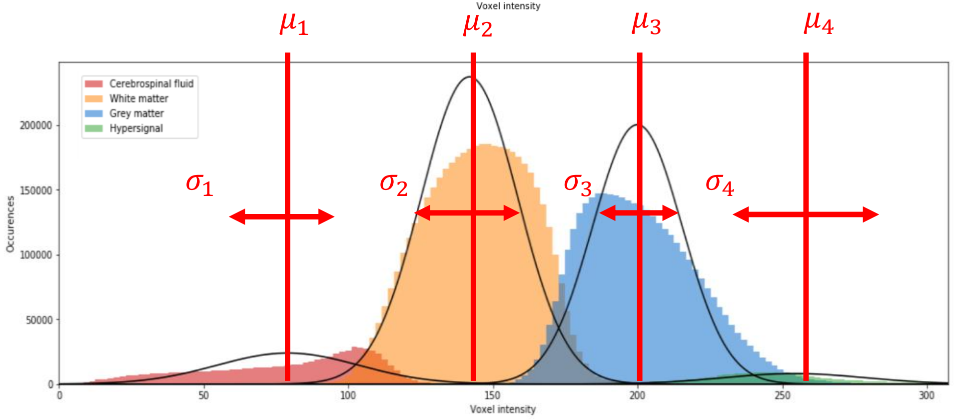
La distribution des intensités de chaque classe est gaussienne.



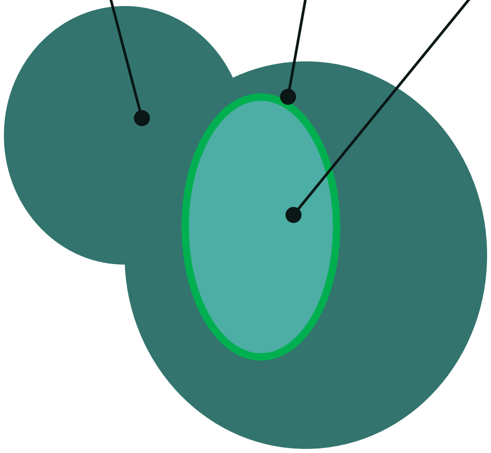
Need for variable parameters $\theta = (\mu_1, \mu_2, \cdots, \sigma_1, \sigma_2, \cdots)$:

$$\pi(Y_s | X_s = k, \theta) \sim \mathrm{Normal}(\mu_k, \sigma_k^2)$$

$$\pi(Y|X,\theta) = \prod_{s \in S} \frac{1}{\sqrt{2\pi\sigma_{X_s}^2}} \exp\left(-\frac{(Y_s - \mu_{X_s})^2}{2\sigma_{X_s}^2}\right)$$



Prior term for the labeling
Hidden random Markov field



Prior term:

$$\pi(X) = \prod_{s \sim s'} v(X_s, X_{s'})$$

where $s \sim s'$ means that these two sites are neighbors.

If for example $v(X_s, X_{s'}) = \begin{cases} 1 \; if \; X_s = X_{s'} \\ \exp(-\beta) \; if \; X_s \neq X_{s'} \end{cases}$

then the log-prior $\log \pi(X) = -\beta \; card(\{s \sim s' | X_s \neq X_{s'}\})$ is proportional to the length of the frontier.

Note: This model is closely related to the graph cut method.

Gibbs sampling

$$\pi(Y|X,\theta) = \prod_{s\in S} \frac{1}{\sqrt{2\pi\sigma_{X_s}^2}} \exp\left(-\frac{\left(Y_s - \mu_{X_s}\right)^2}{2\sigma_{X_s}^2}\right)$$

Intensity likelihood term

Prior on X

$$\pi(X) = \prod_{s\sim s'} v(X_s, X_{s'})$$

Spatial coherence term

New posterior $\pi(X,\theta|Y)$

Partial density in X

$$\pi(X|Y,\theta) \propto \pi(Y|X,\theta)\,\pi(X)$$

Likelihood

Partial density in θ

$$\pi(\theta|Y,X) \propto \pi(Y|X,\theta)\,\pi(\theta)$$

Prior on θ

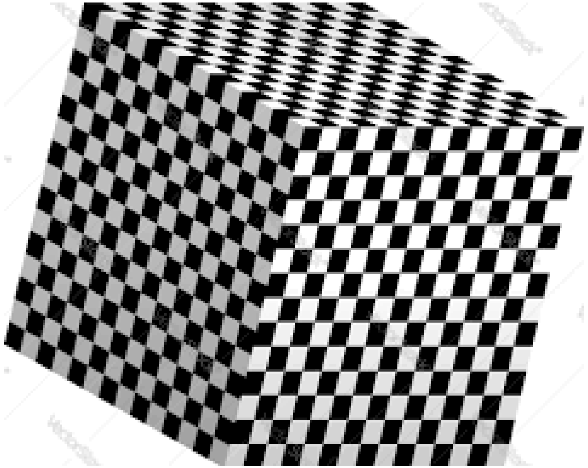
$\pi(\theta)$ A priori knowledge on the tissue intensities

$$\sigma_k^2|\mathbf{Y}=\mathbf{y}^*,\mathbf{X}=\mathbf{x},\mu_k \sim \text{InvGamma}\left(\frac{N_k(\mathbf{x})}{2}+a, \frac{1}{2}N_k(x)\left(\mu_k-\widehat{y}_k(x)\right)^2+\frac{1}{2}\sum_{s|x_s=k}(y_s-\widehat{y}_k(\mathbf{x}))^2+\frac{1}{2}\widetilde{N}_k(\mu_k-\widetilde{\mu}_k)^2+(a-1)\widetilde{\sigma}_k^2\right)$$

$$\mu_k|\mathbf{Y}=\mathbf{y}^*,\mathbf{X}=\mathbf{x},\sigma_k^2 \sim \text{Normal}\left(\frac{N_k(\mathbf{x})\widehat{y}_k(\mathbf{x})+\widetilde{N}_k\widetilde{\mu}_k}{N_k(\mathbf{x})+\widetilde{N}_k}, \frac{\sigma_k^2}{N_k(\mathbf{x})+\widetilde{N}_k}\right)$$

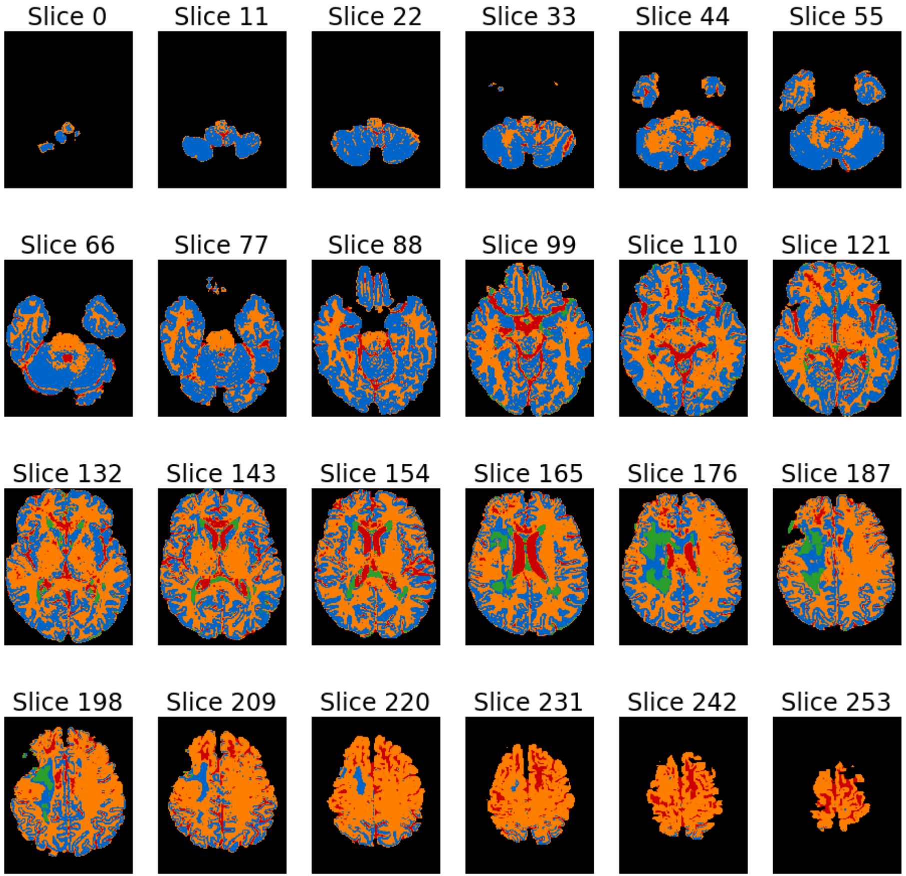
Generate labels using
Gibbs Sampler + Markov-Chain Monte Carlo

Chromatic sampling

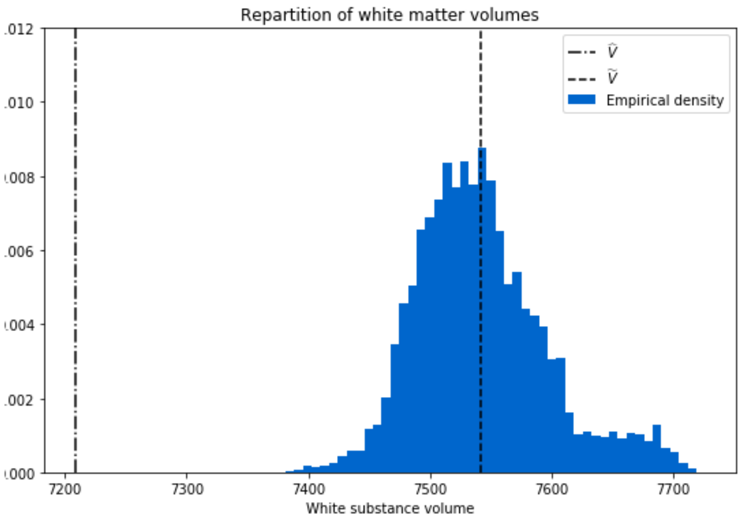


- Fixons $X^{-1,J-1} = \mathbf{x}^*$,
- Pour i de 0 à $I-1$:
  1. simuler $\theta^i \sim \pi(\theta|\mathbf{Y} = \mathbf{y}^*, \mathbf{X} = \mathbf{X}^{i-1,J-1})$;
  2. Pour j allant de 0 à $J-1$:
     (a) simuler $\mathbf{X}_+^{i,j} \sim \pi(\mathbf{X}_+|\mathbf{Y} = \mathbf{y}^*, \theta^i, \mathbf{X}_- = \mathbf{x}_-^{i,j-1})$
     (b) simuler $\mathbf{X}_-^{i,j} \sim \pi(\mathbf{X}_-|\mathbf{Y} = \mathbf{y}^*, \theta^i, \mathbf{X}_+ = \mathbf{x}_+^{i,j})$
     (c) définir $\mathbf{X}^{i,j}$ par combinaison de $\mathbf{X}_+^{i,j}$ et $\mathbf{X}_-^{i,j}$
- Produire l'échantillon $(\mathbf{X}^{i,j}, \theta^i)_{0 \leqslant i < I, 0 \leqslant j < J}$.

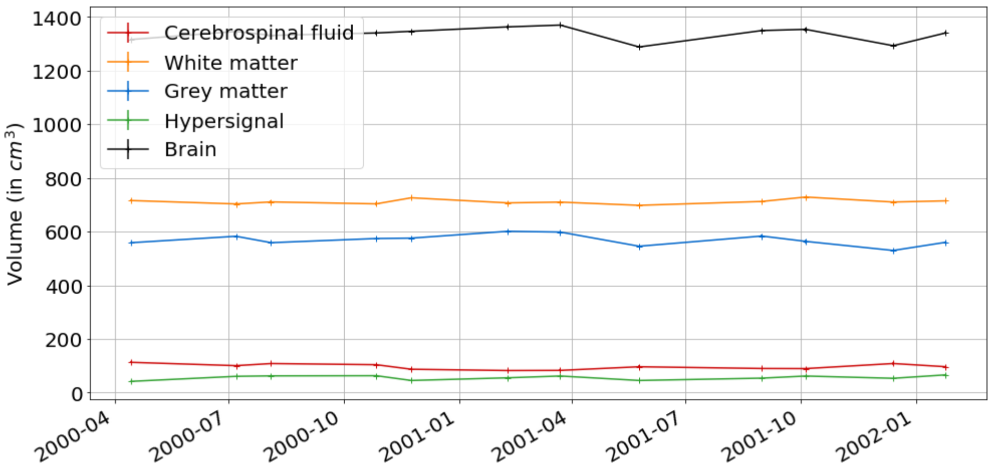
Segmentation results: a generated label



Segmentation results: white matter volume



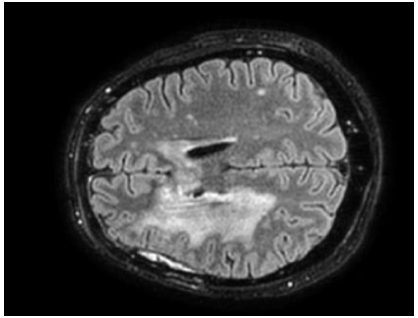
White matter volume with confidence interval



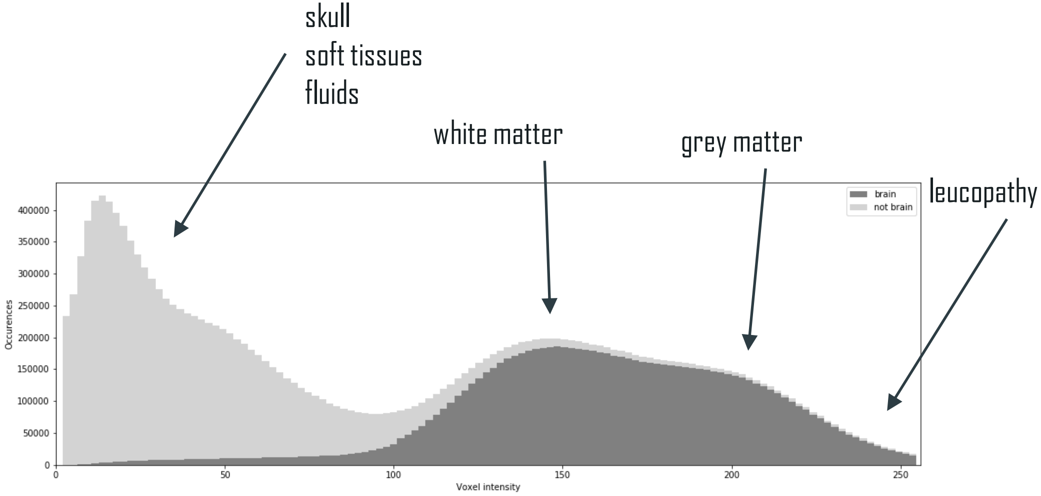
Longitudinal study

3 | Data augmentation

Limitation: low contrast

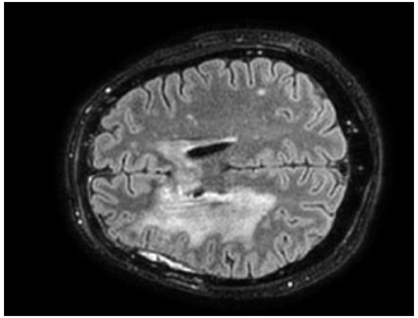


FLAIR MRI



Intensity distribution

Using both T2 FLAIR and T1 MRIs



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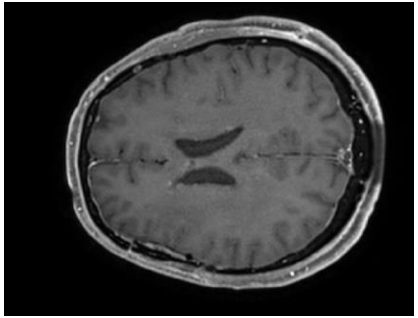
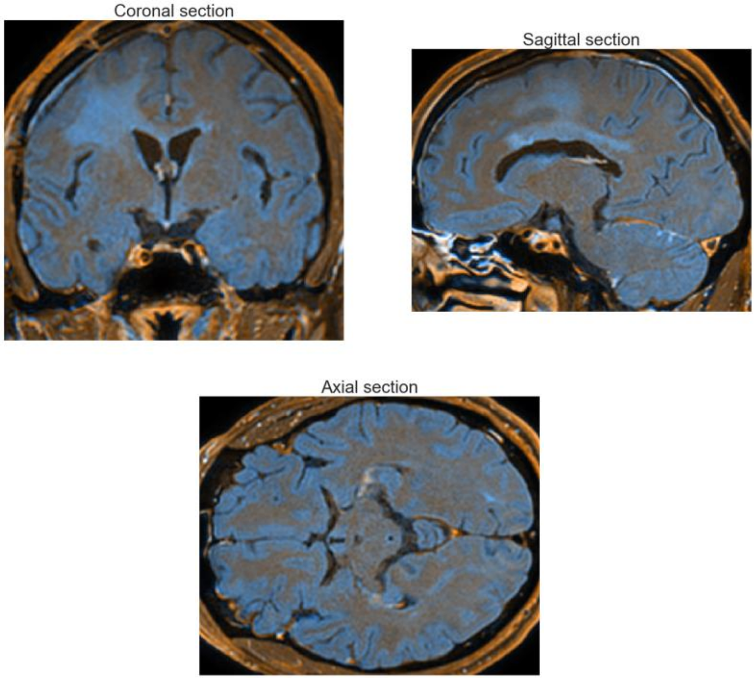
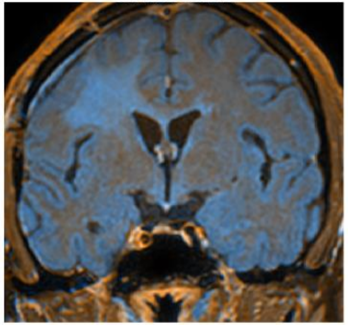


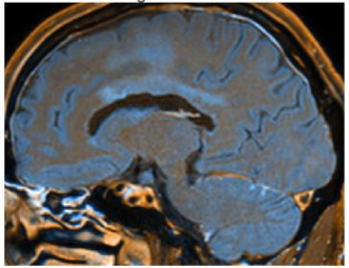


Using both T2 FLAIR and T1 MRIs

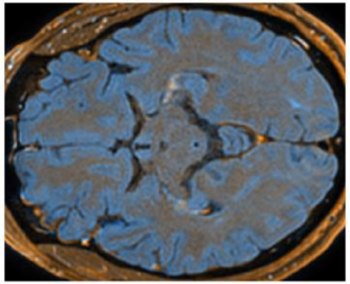
Coronal section



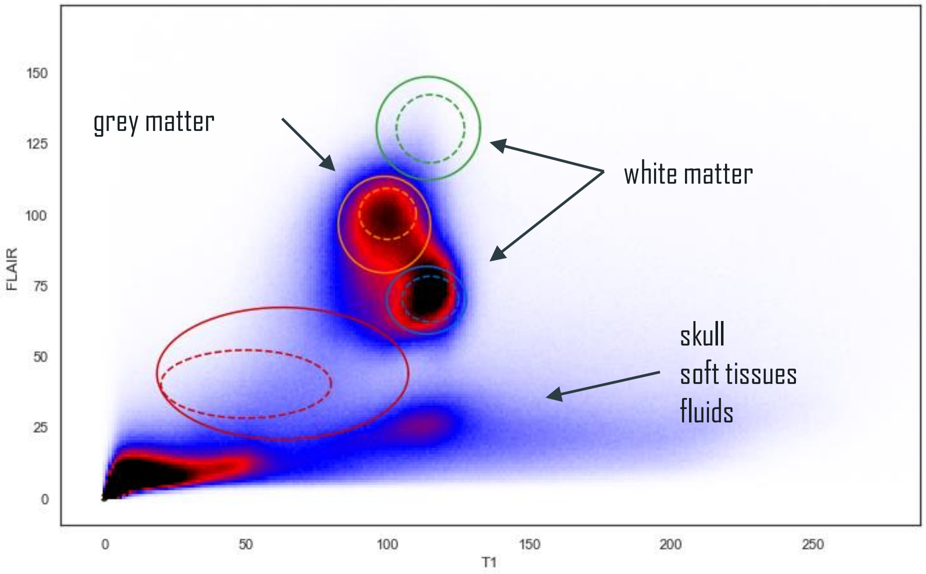
Sagittal section



Axial section



2D intensity histogram



Conclusion and perspectives

- Bayesian models offer great flexibility and confidence intervals

- Computation efficiency requires careful algorithm implementation

- Brain MRI normalization and standardization is tricky, limiting estimation accuracy

- We can use simultaneously T1 and FLAIR MRI modalities to improve accuracy.