MRI Segmentation

MRI Bootcamp, 14th of January 2019

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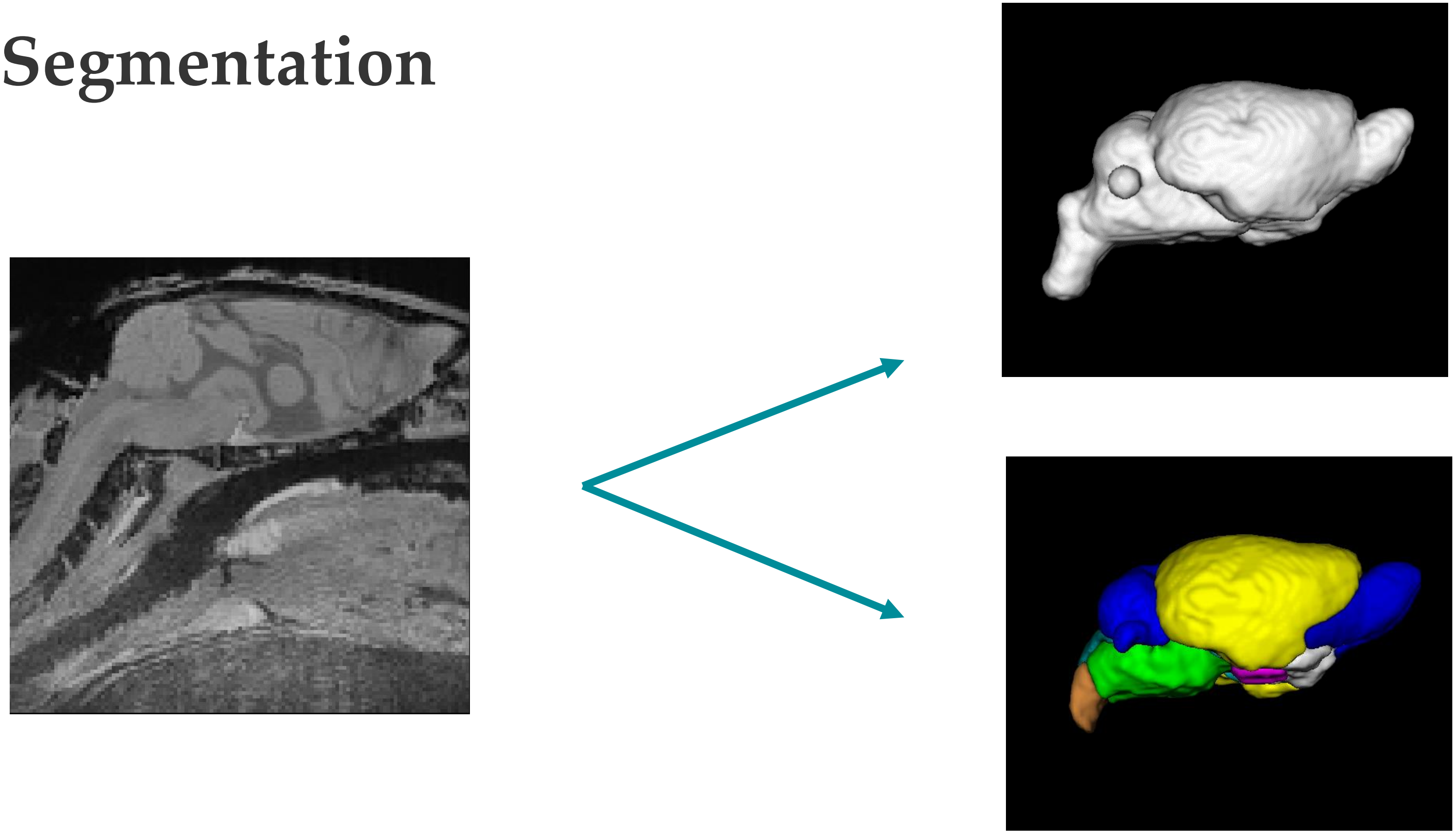
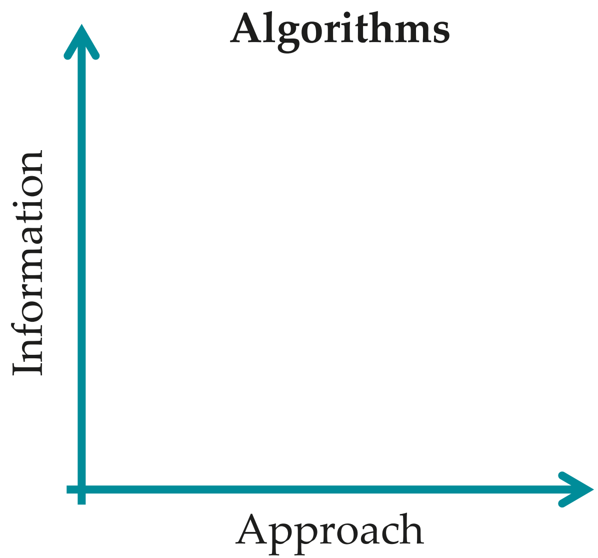
Segmentation

Segmentation



Segmentation



Types of Information

- Local

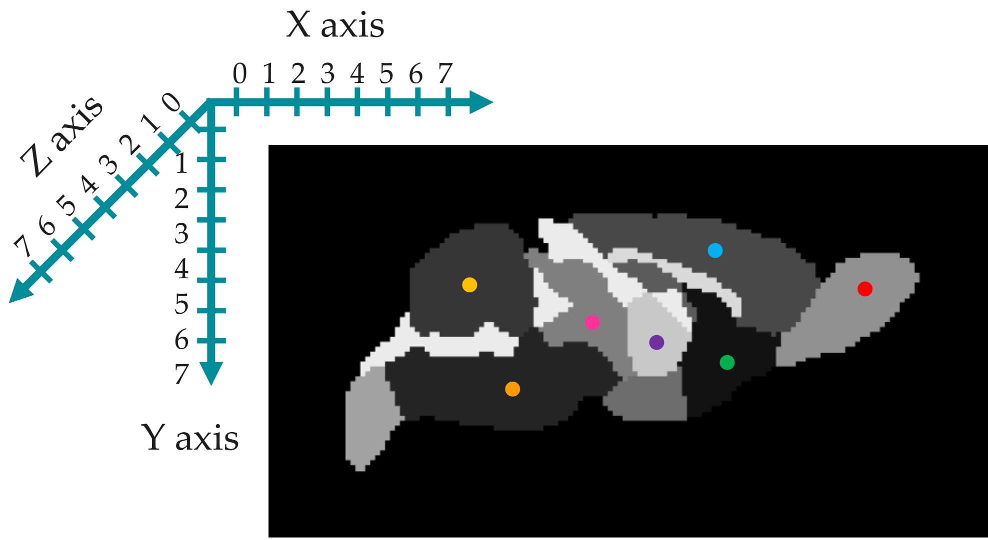
4	45	100	110	80	50	76
42	27	186	177	120	167	111
56	79	200	208	211	180	90
53	142	211	209	242	201	76
160	180	200	222	239	190	100
43	233	201	200	166	186	75
25	65	58	37	22	52	90

Types of Information

- Local
- Contextual

Types of Information

- Local
- Contextual
- Spatial



Approaches classification

- Atlas registration based
- Hand-crafted features (Machine Learning)
- Learnt features (Deep Learning)

Chen H. et al. NeuroImage 2018.

Atlas registration based

Overview

Image

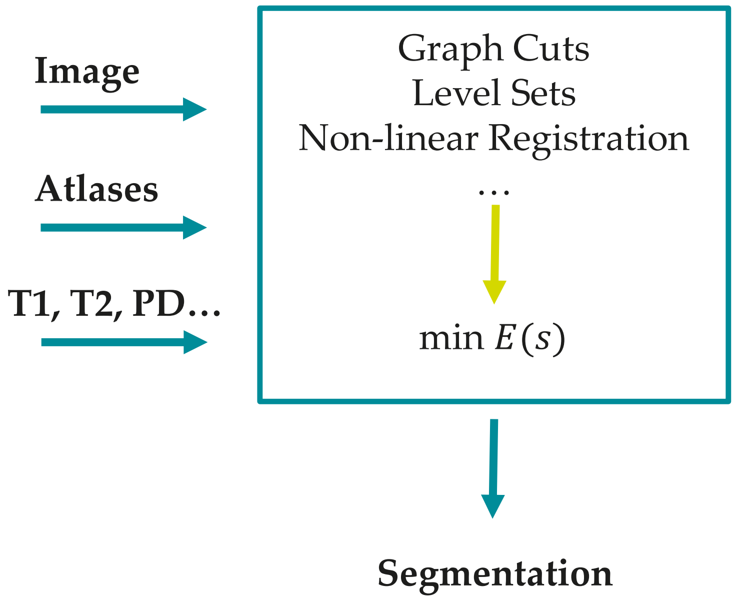
Graph Cuts
Level Sets
Non-linear Registration
...

$\min E(s)$

Segmentation

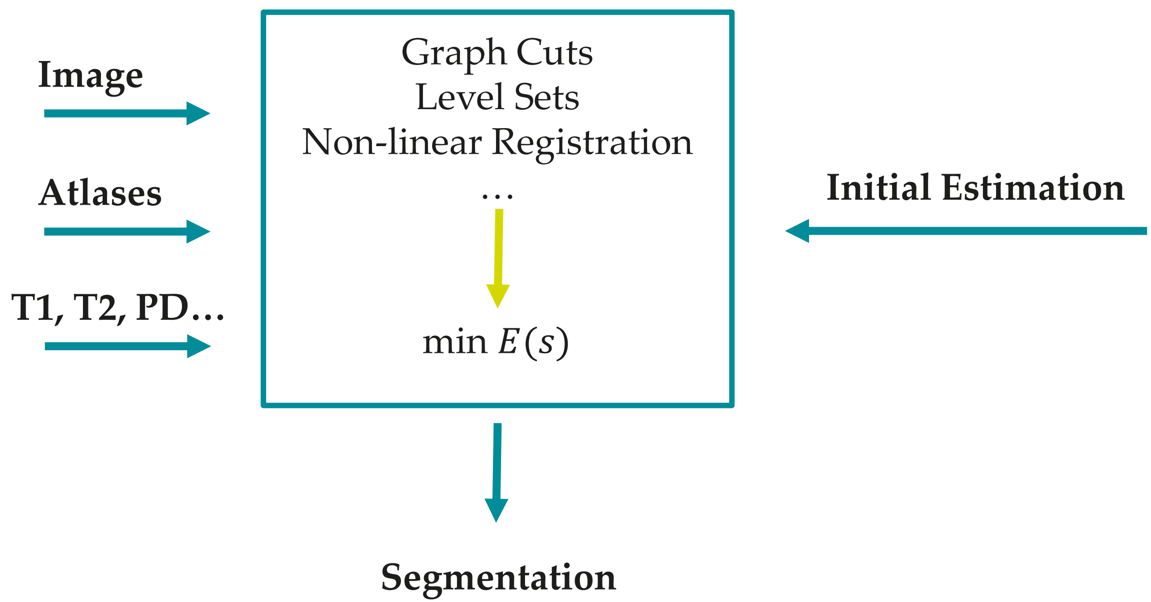
Atlas registration based

Overview



Atlas registration based

Overview



Atlas registration based

- Single-atlas approach
  - Average
  - Most similar

Atlas registration based

- Single-atlas approach
  - **Average**
  - Most similar

Not realistic
Sensitive to outliers

Atlas registration based

- Single-atlas approach
  - Average
  - **Most similar** **Biased**

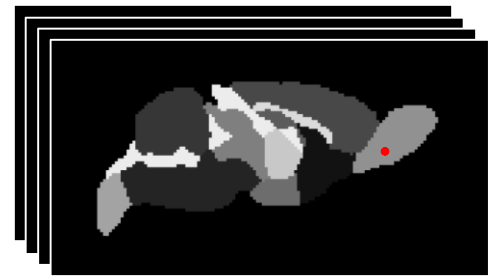
Atlas registration based

- Single-atlas approach
  - Average
  - Most similar
- Multi-atlas approach
  - N most similar
  - Use many as single-atlas

Atlas registration based

- Single-atlas approach
  - Average
  - Most similar
- Multi-atlas approach
  - N most similar
  - Use many as single-atlas
    - Majority voting (Artaechevarria X. et al. Trans. Med. Im. 2009.)

Majority voting



$$Y_v = \arg\max_{y} \sum_{i=0}^{N} f(A_v^i, y)$$

where

$$f(A_v^i, y) = \begin{cases} 1 \; if \; A_v^i = y \\ 0 \; if \; A_v^i \neq y \end{cases}$$

Y_v final label at voxel v, N number of atlases

A_v^i atlas A^i at voxel v, y label

Atlas registration based

- Single-atlas approach
  - Average
  - Most similar
- Multi-atlas approach
  - N most similar
  - Use many as single-atlas
    - Majority voting (Artaechevarria X. et al. Trans. Med. Im. 2009.)
    - Bayes (Ali AA. et al. NeuroImage 2005.)

Bayesian statistics

$$P(Y|X) = \frac{P(X|Y)P(Y)}{P(X)}$$

where

X voxel

Y label

Atlas registration based

- Single-atlas approach
  - Average
  - Most similar
- Multi-atlas approach
  - N most similar
  - Use many as single-atlas
    - Majority voting (Artaechevarria X. et al. Trans. Med. Im. 2009.)
    - Bayes (Ali AA. et al. NeuroImage 2005.)
    - MRF (Bae MH. et al. NeuroImage 2009.)
    - …

Markov Random Field

$$P(y_v|y_{S-\{v\}}) = P(y_v|y_{N_v})$$

where

v voxel
S set of all voxels
N_v neighbor voxels of v

Atlas registration based

Disadvantages:

- Registration is needed (affine and/or non-linear).
- Computationally expensive.
- **Very** sensitive to registration.

Hand-crafted features (Machine Learning)

1. Generate a feature collection

```
for voxel in allVoxels:
    f = generateFeatureVector(voxel)
    allFeatures.append(f)
```

Hand-crafted features (Machine Learning)

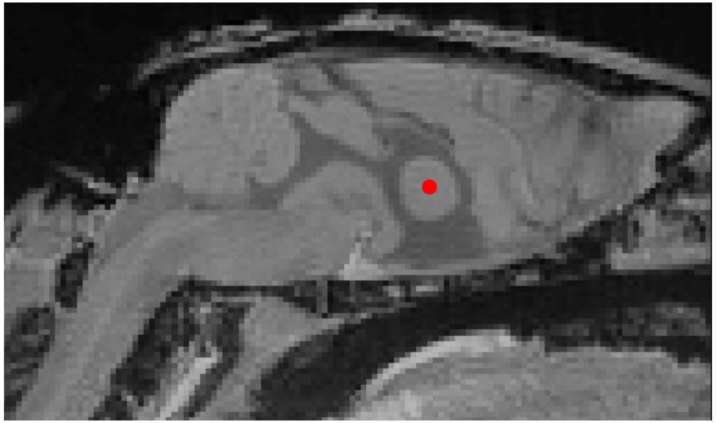
```
# 1. Generate a feature collection
for voxel in allVoxels:
    f = generateFeatureVector(voxel)
    allFeatures.append(f)

# 2. Train a model
model = SVM(parameters)
model.fit(allFeatures)
```

Hand-crafted features (Machine Learning)

Vector of features:

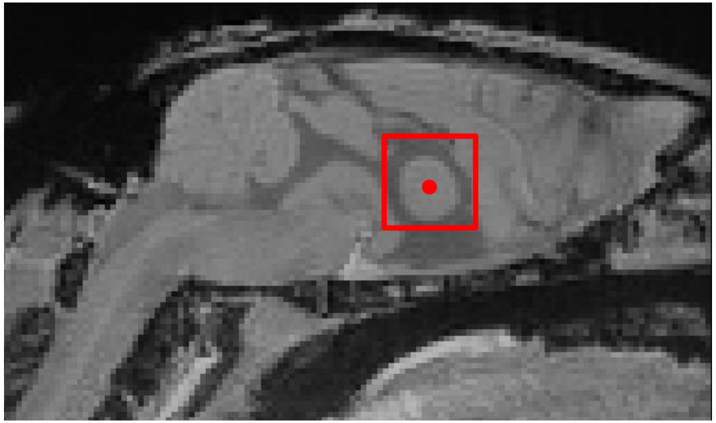
- Local intensities (Wu T. et al. NeuroImage 2012.)



Hand-crafted features (Machine Learning)

Vector of features:

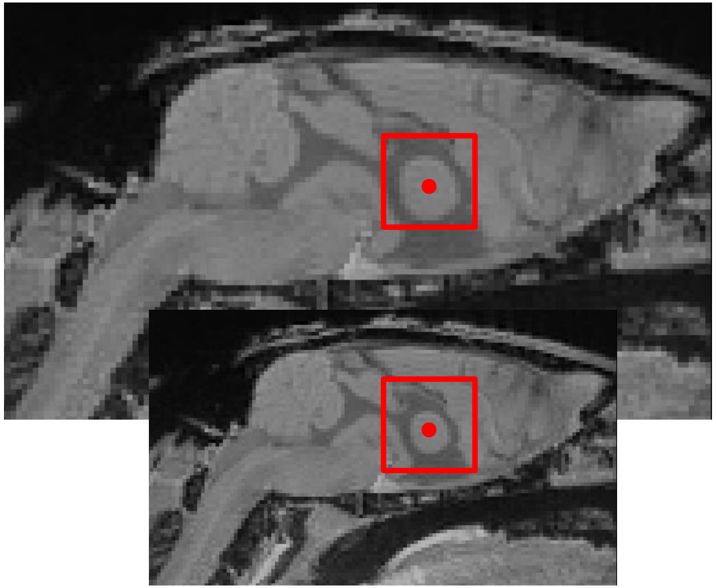
- Local intensities (Wu T. et al. NeuroImage 2012.)
- Neighbour intensities, gradients (Pereira S. et al. Journal of Neuroscience Methods 2016)



Hand-crafted features (Machine Learning)

Vector of features:

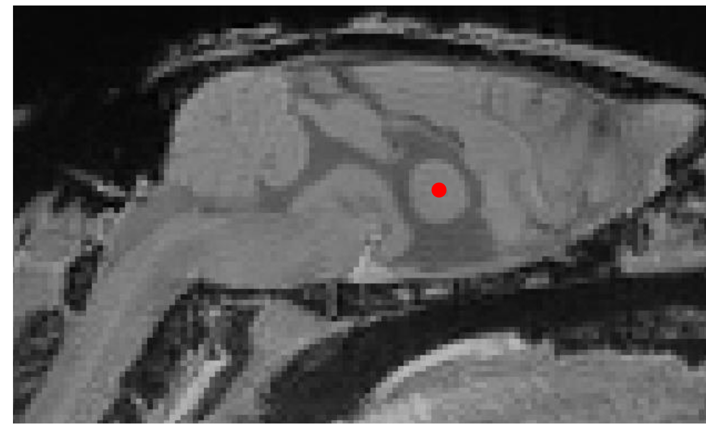
- Local intensities (Wu T. et al. NeuroImage 2012.)
- Neighbour intensities, gradients (Pereira S. et al. Journal of Neuroscience Methods 2016)
- Multi-scale (Bae MH. et al. NeuroImage 2009.)



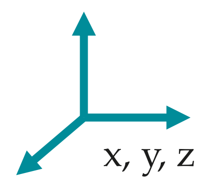
Hand-crafted features (Machine Learning)

Vector of features:

- Local intensities (Wu T. et al. NeuroImage 2012.)
- Neighbour intensities, gradients (Pereira S. et al. Journal of Neuroscience Methods 2016)
- Multi-scale (Bae MH. et al. NeuroImage 2009.)
- Coordinates (Wachinger C. et al. IEEE Trans. Biomed. Eng. 2017.)



Requires Registration!

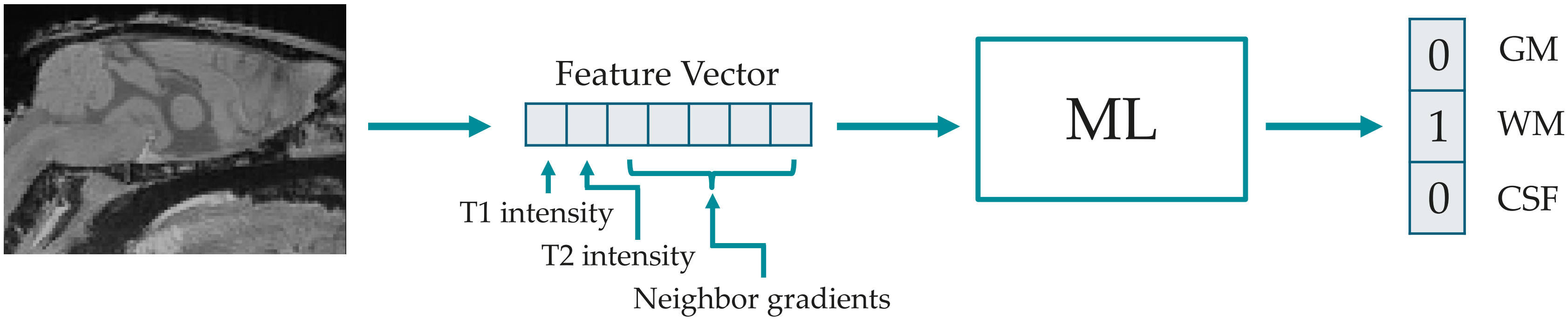


Hand-crafted features (Machine Learning)

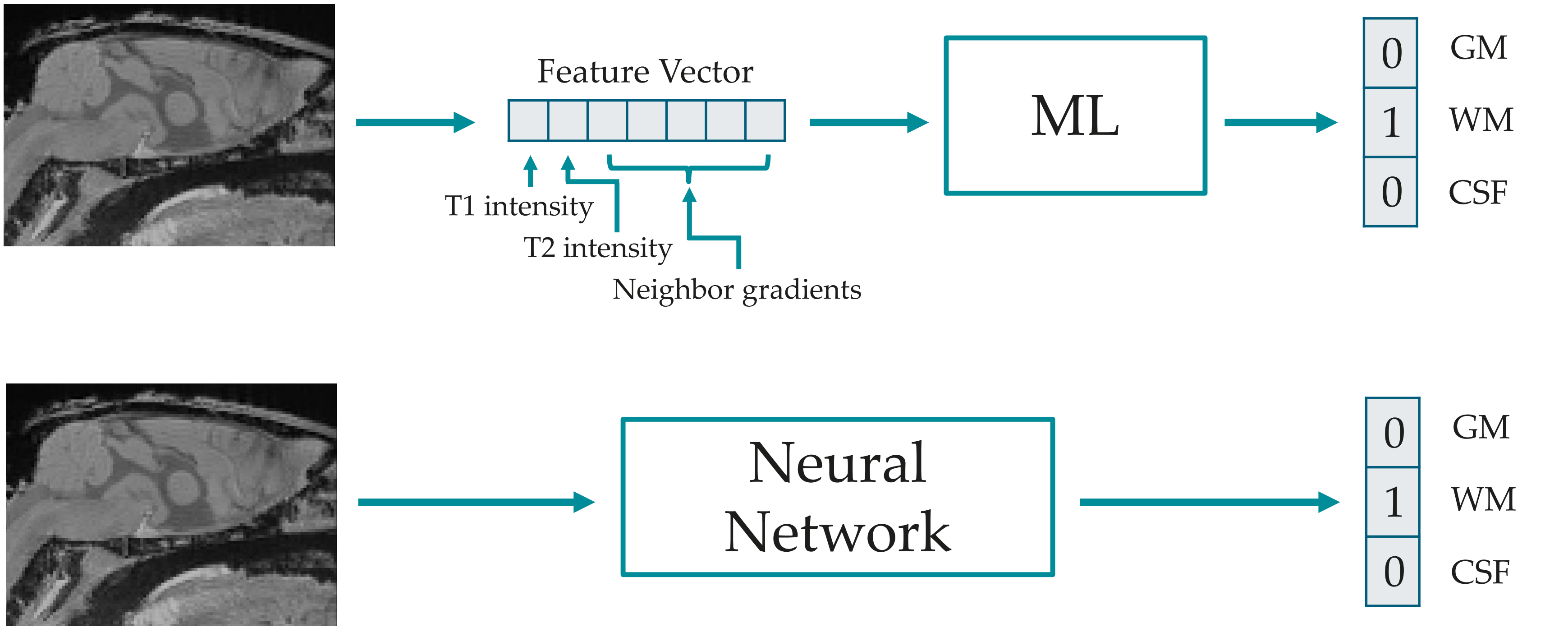
Advantages

- No registration needed (in principle).
- Rotational invariant
- Understanding of the features.
- Can easily try different ML algorithms.

Learnt features (Deep Learning)

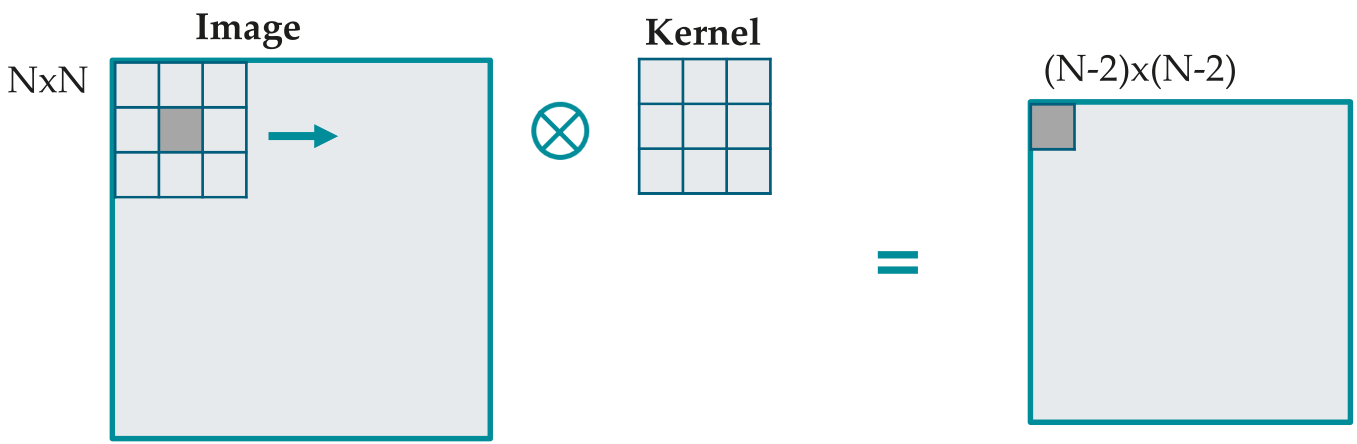


Learnt features (Deep Learning)



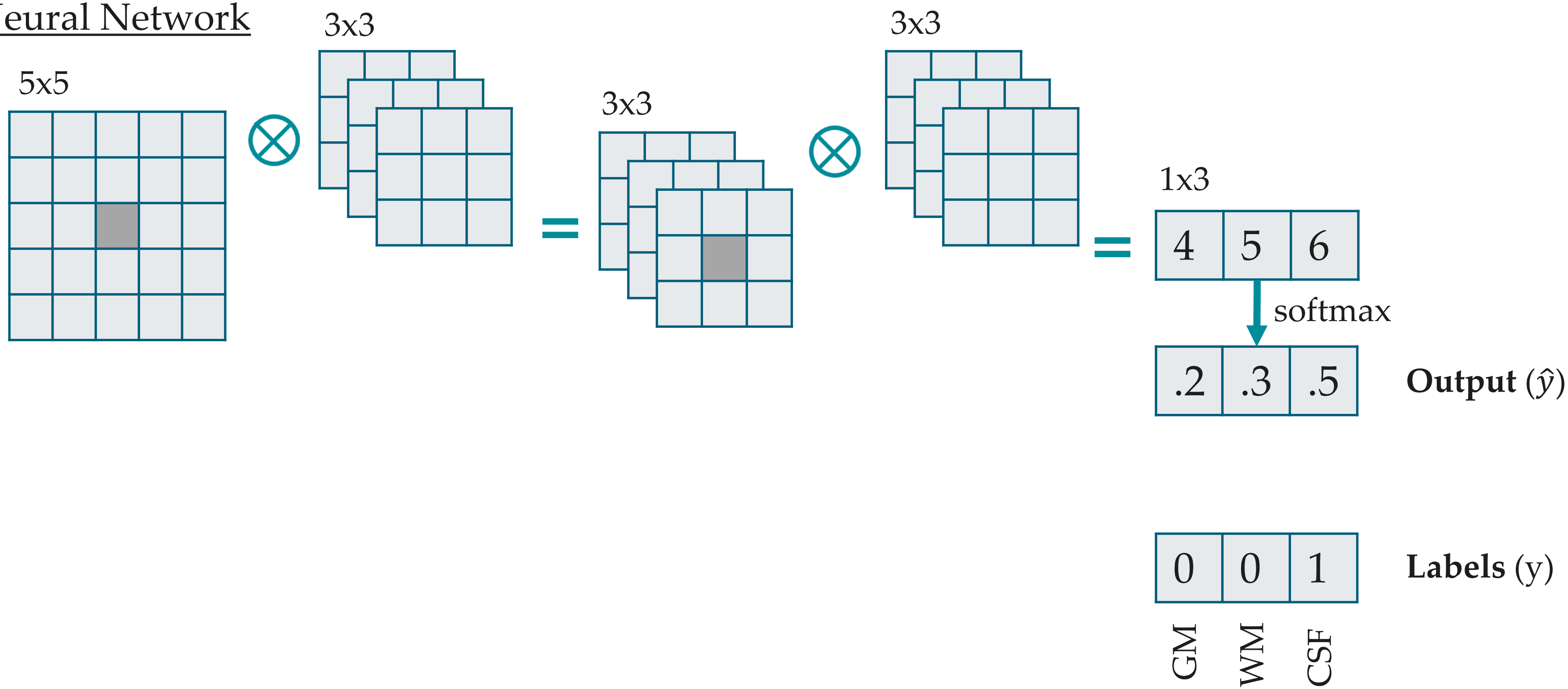
Learnt features (Deep Learning)

Convolutions



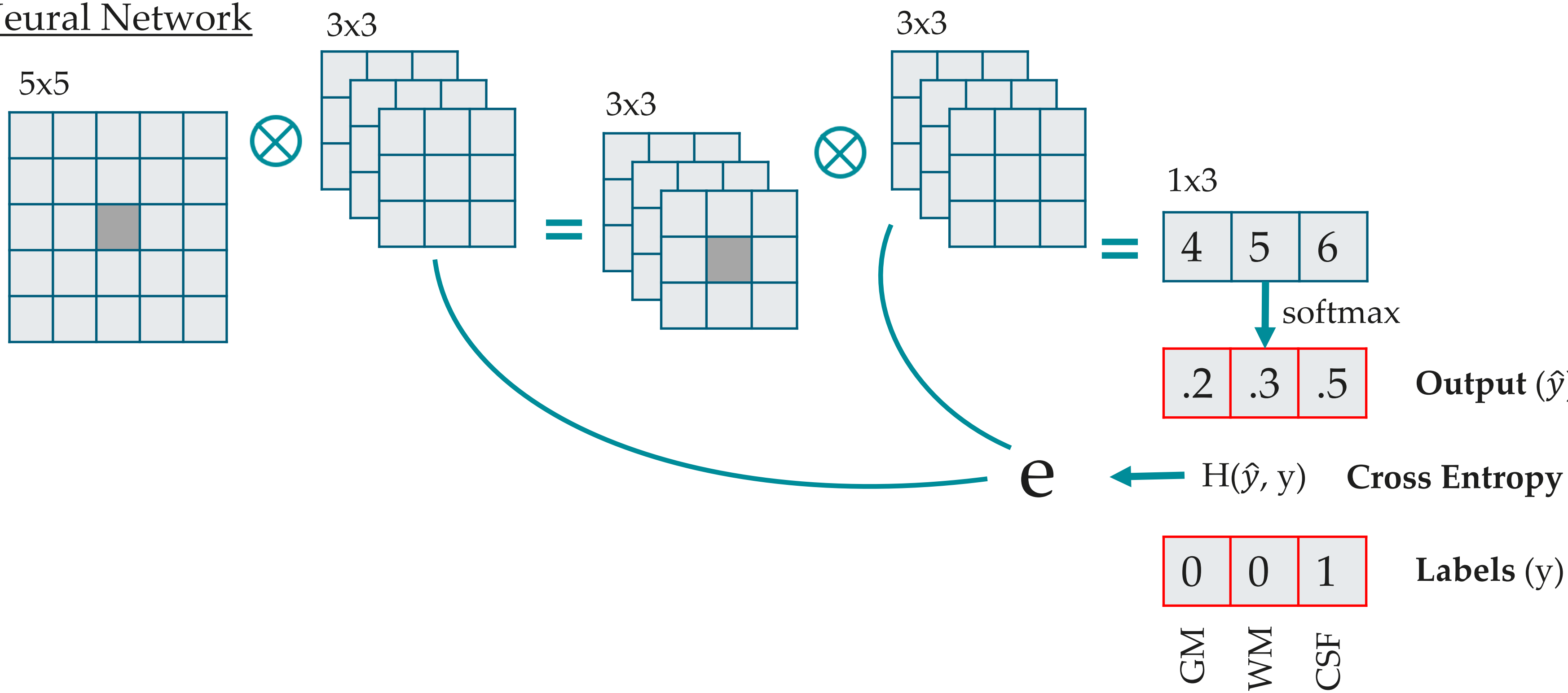
Learnt features (Deep Learning)

<u>Neural Network</u>



Learnt features (Deep Learning)

Neural Network

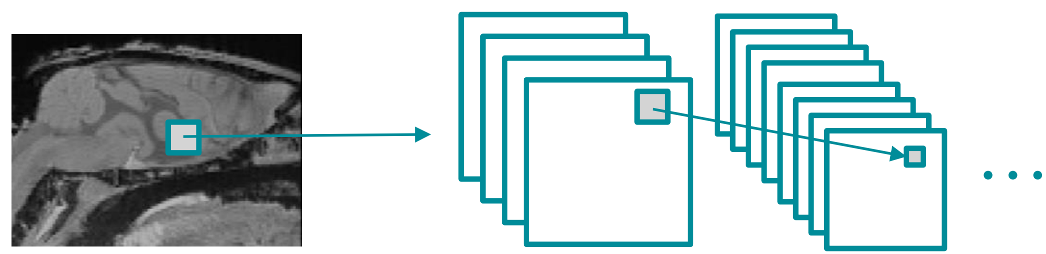


Learnt features (Deep Learning)

Types of information/data

- Convolutions (region)

Local + Contextual

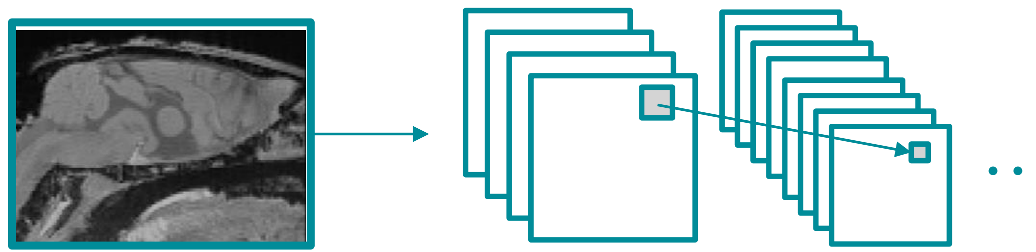


Learnt features (Deep Learning)

<u>Types of information/data</u>

- Convolutions (region)
- Convolutions (full)

Local + Contextual + Spatial

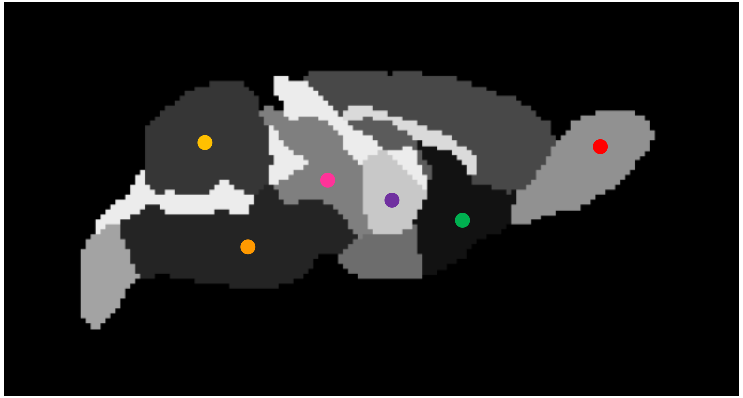


Learnt features (Deep Learning)

Types of information/data

- Convolutions (region)
- Convolutions (full)
- Other information
  - Distance to centroids (de Brebisson A. and Montana G. IEEE CVPR Workshop 2015.)

Spatial

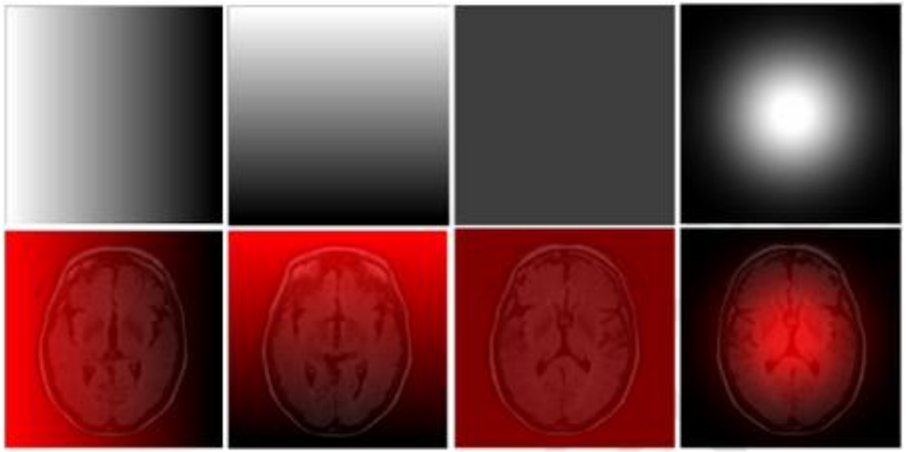


Learnt features (Deep Learning)

<u>Types of information/data</u>

- Convolutions (region)
- Convolutions (full)
- Other information
  - Distance to centroids (de Brebisson A. and Montana G. IEEE CVPR Workshop 2015.)
  - Encoded spatial information (Rachmadi MF. et al. Compu. Med. Imaging Graph 2018.)

Spatial



Learnt features (Deep Learning)

Advantages

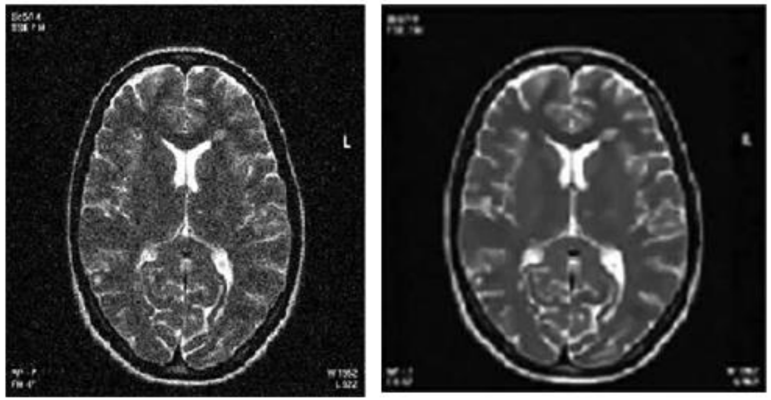
- No feature engineering needed.
- Extrapolate to other tasks.
- Parallel processing capabilities.

Disadvantages

- Black box

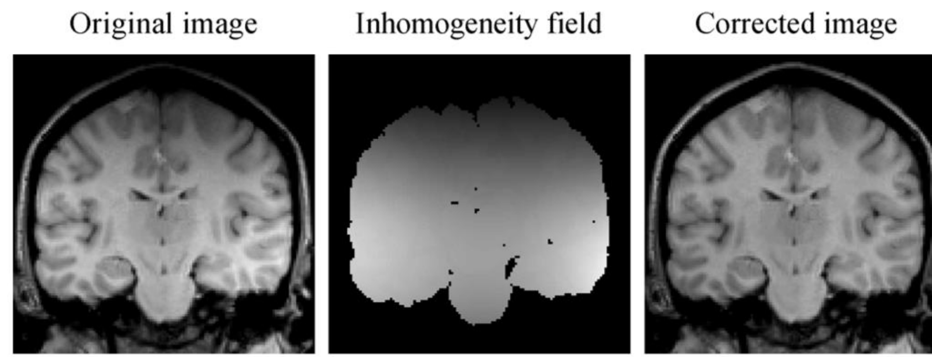
Pre-processing operations

- Denoising



Pre-processing operations

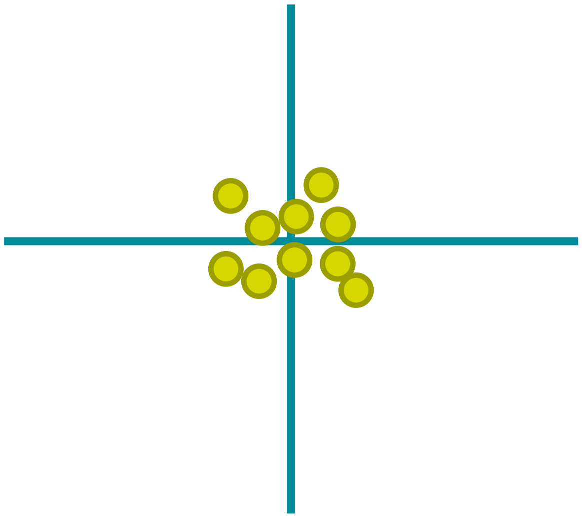
- Denoising
- Inhomogeneity correction



Intensity inhomogeneity in MR brain image. (Vovk U. et al. IEEE Trans. Med. Imag. 2007)

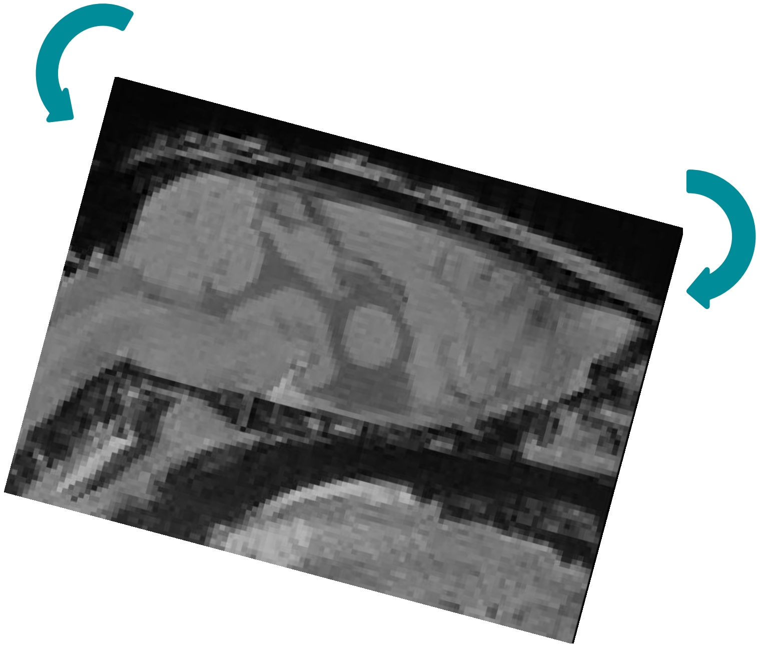
Pre-processing operations

- Denoising
- Inhomogeneity correction
- 0 mean, 1 variance



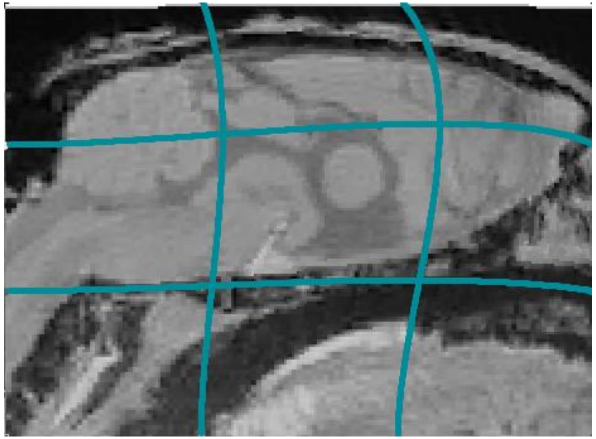
Pre-processing operations

- Denoising
- Inhomogeneity correction
- 0 mean, 1 variance
- Data augmentation
  - Rotation



Pre-processing operations

- Denoising
- Inhomogeneity correction
- 0 mean, 1 variance
- Data augmentation
  - Rotation
  - Non-linear transformations



Conclusion / Take home message

- Important to understand what we have and what we want.
- Check the data. Then, check the data again.