Interactive Brain Tumor Segmentation

Jens Petersen
Medical Image Computing (E132)

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A Life Without Cancer

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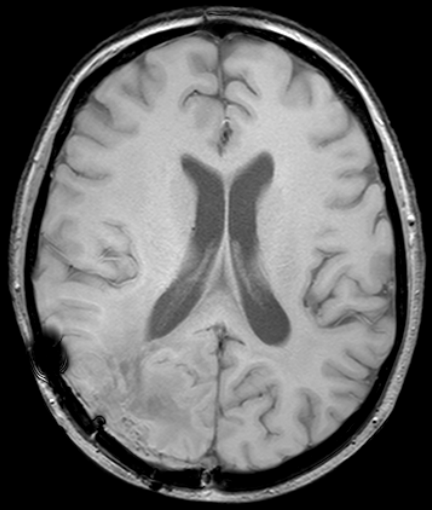
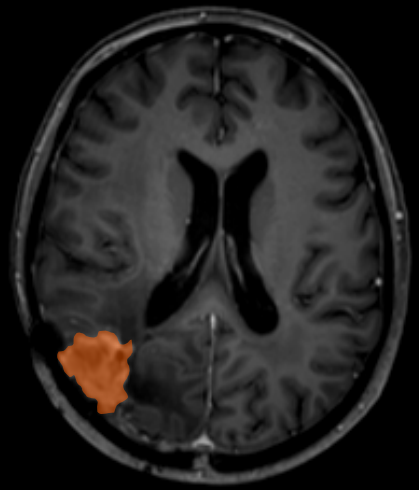
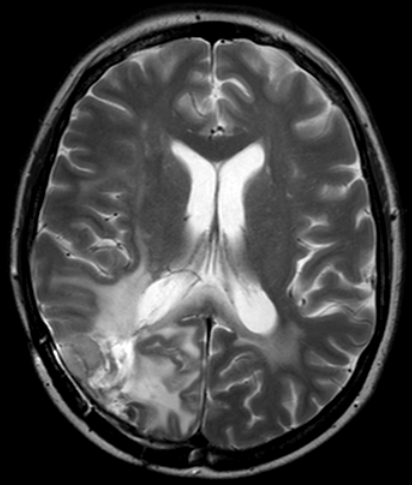
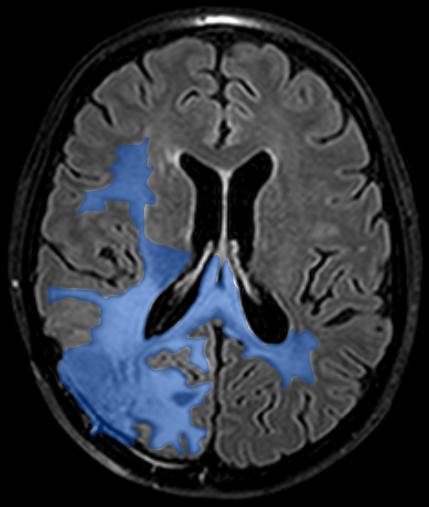
MRI Glioblastoma Segmentation









Field Strength:

3T	52.5%
1.5T	46.0%
1T	1.5%

Vendors:

Siemens	73.9%
GE	16.1%
Philips	10.0%

Common Flaws:

Missing sequences
Missing data

DWI PWI SWI T2* T2ce PD

The Foundation – EORTC 26101 Study

EORTC 26101 BOVAREC

437 Patients

First recurrence of GBM

Chemotherapy

Radiotherapy

Lomustine (CCNU)
alkylating agent
+
Bevacizumab (Avastin)
angiogenesis inhibitor

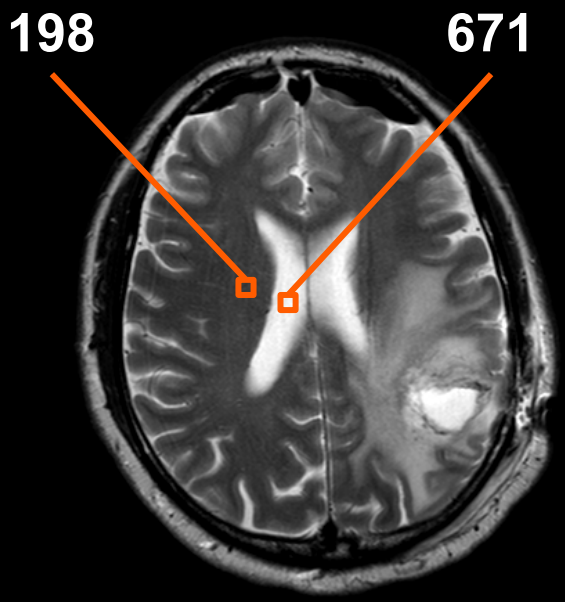
2

Lomustine (CCNU)
alkylating agent

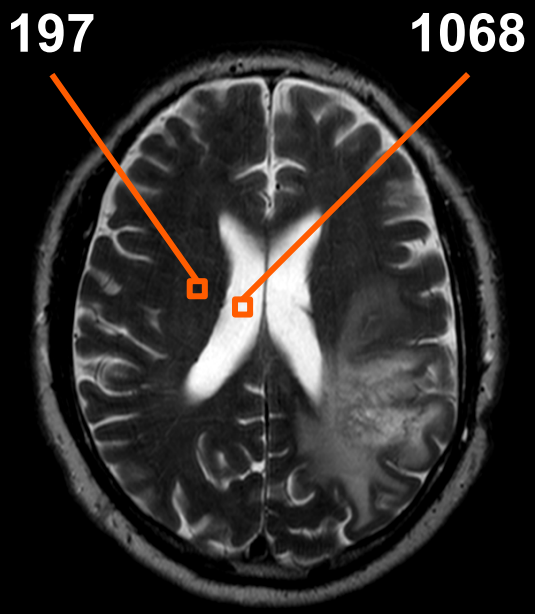
1

Wick, W. et al.: *LB-05. PHASE III TRIAL EXPLORING THE COMBINATION OF BEVACIZUMAB AND LOMUSTINE IN PATIENTS WITH FIRST RECURRENCE OF A GLIOBLASTOMA: THE EORTC 26101 TRIAL,* Neuro-Oncology 17(suppl. 5), 2015, pp. v1

MRI – Intensities are not comparable



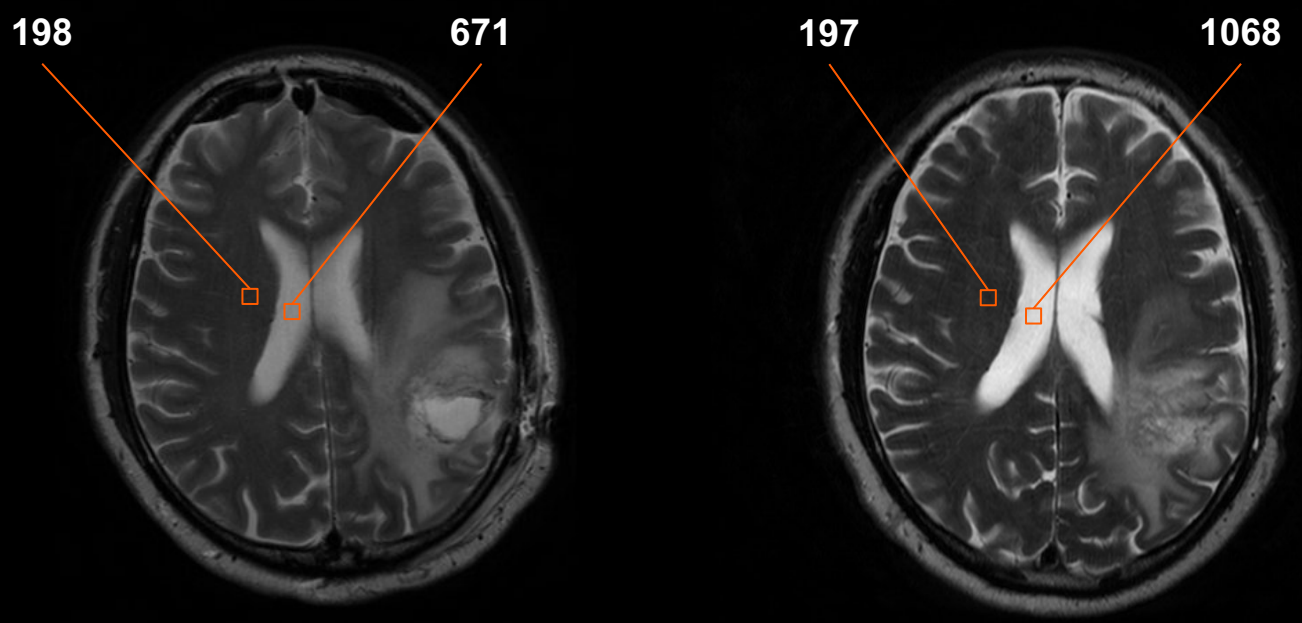
512 x 512
4mm spacing
[0, 874]



800 x 800
5mm spacing
[0, 1202]

Shinohara, R. T. et al.: *Statistical normalization techniques for magnetic resonance imaging,* NeuroImage: Clinical 6, 2014, pp. 9-19

MRI – Intensities are not comparable



Can we model bias field and transfer functions to learn invariant representation?
Works well for noise correction.

Burger, H. et al.: *Image Denoising: Can plain neural networks compete with BM3D?,* Computer Vision and Pattern Recognition, Proceedings, 2012, pp. 2392-2399

Shinohara, R. T. et al.: *Statistical normalization techniques for magnetic resonance imaging,* NeuroImage: Clinical 6, 2014, pp. 9-19

Goal

„Interactive Segmentation of very large image datasets with minimal effort“

Overview

- Brain Tumor Segmentation Overview
- Artificial Neural Networks
- Active Learning
- Milestones

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Brain Tumor Segmentation – Overview

Voxel			Volume
Handcrafted Features			Learned Features
Supervised			Unsupervised
Atlas			No Atlas
Interactive			Automatic

Random Forest

Neural Network

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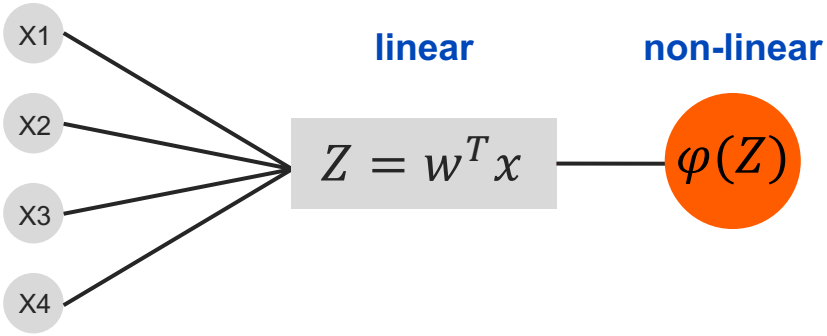
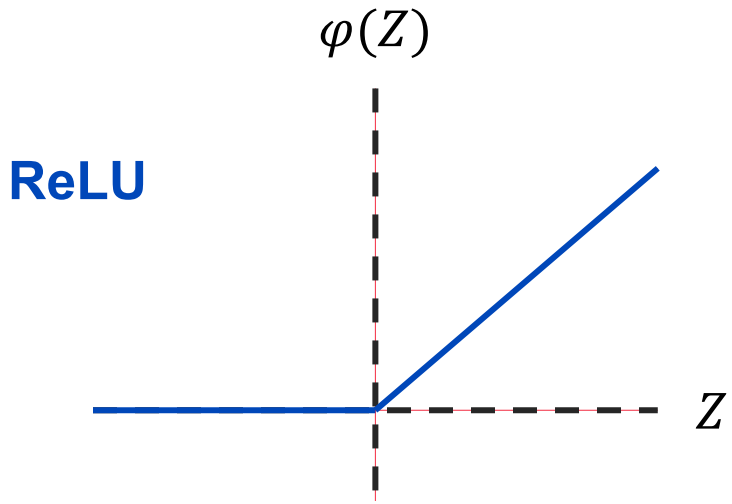
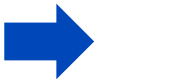
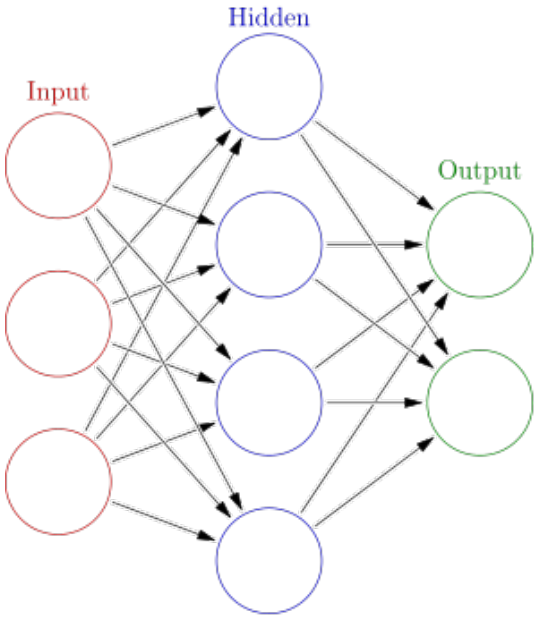
Artificial Neural Networks – Introduction



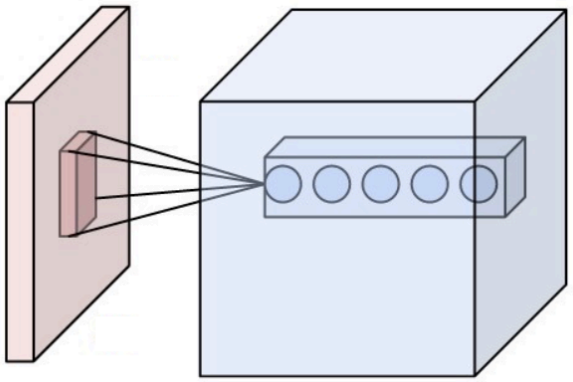






Convolutional Neural Networks

1. Convolutional Layer

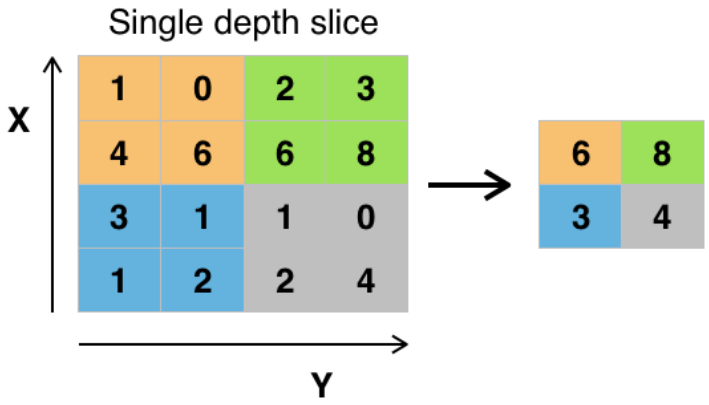


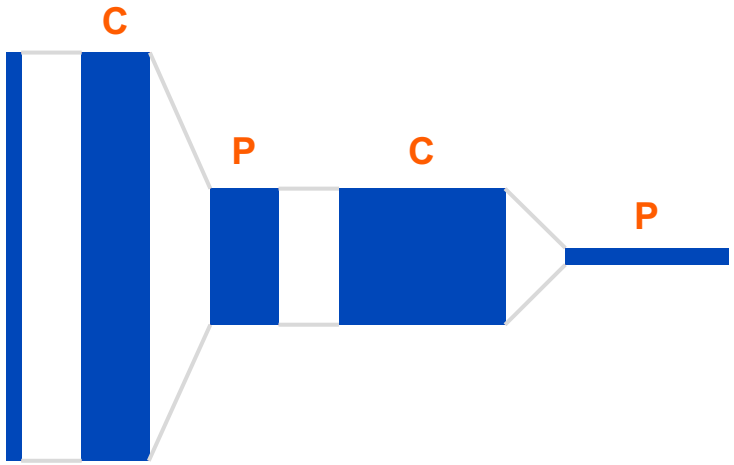
Receptive field

Weight sharing

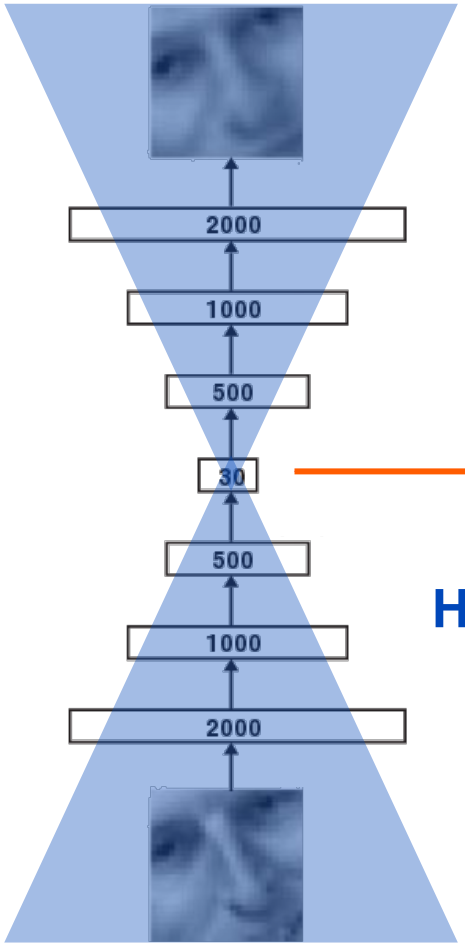
Multiple filters per layer

2. (Max-) Pooling Layer





Autoencoder



Reconstruction

2 Eyes, 1 Nose, 0.5 Mouth, Position

Hierarchical Information Compression

Shapes

Edges etc…

Pixels

Hinton, G. E. and Salakhutdinov, R. R.: *Reducing the Dimensionality of Data with Neural Networks,* Science 313, 2006

Example: Separation of Style & Content

Gatys, L. A., Ecker, A. S. and Bethge, M.: *A Neural Algorithm of Artistic Style,* arXiv:1508.06576, 2015

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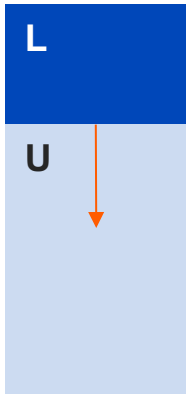
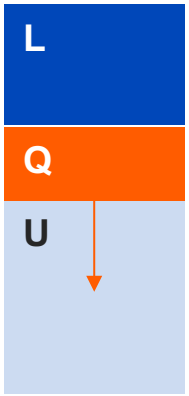
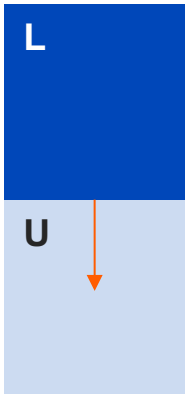
Active Learning Principle



Cost(U)



Cost(Q)



Cost(U) + Cost(Q)
= TotalCost

minimize TotalCost

Settles, B.: *Active Learning Literature Survey*, Computer Sciences Technical Report 1648, University of Wisconsin – Madison, 2010, accessed 4.3.16

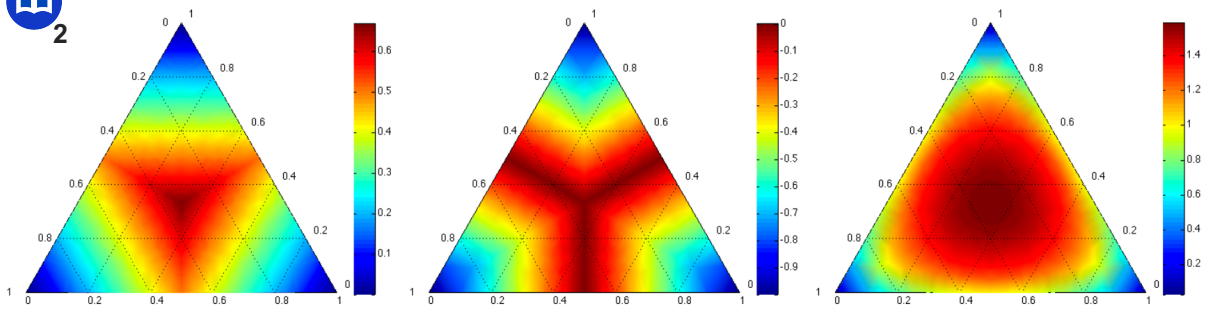
How to select Query Data

Uncertainty Sampling

Expected Model Change

Query by Committee

3 class problem



Confidence Margin Entropy

Lewis, D. and Gale, W.: *A sequential algorithm for training text classifiers*, Proceedings of the 17th ACM SIGIR Conference, 1994

[2] Settles, B.: *Active Learning Literature Survey*, Computer Sciences Technical Report 1648, University of Wisconsin – Madison, 2010, accessed 4.3.16

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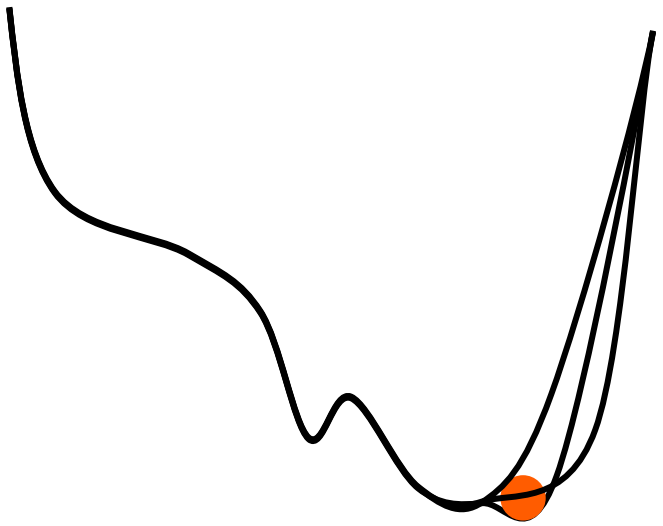
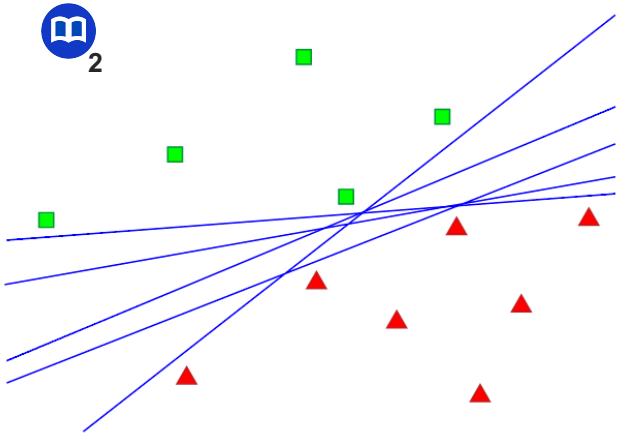


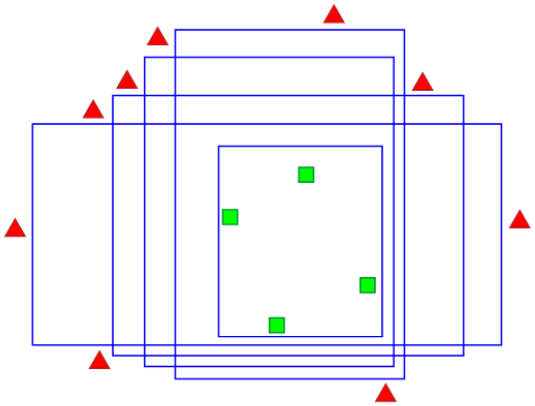
Applicable in almost all gradient based optimizations

Computationally expensive

Settles, B., Craven, M. and Ray, S.: *Multiple-instance Active Learning*, Advances in NIPS, 2008

How to select Query Data





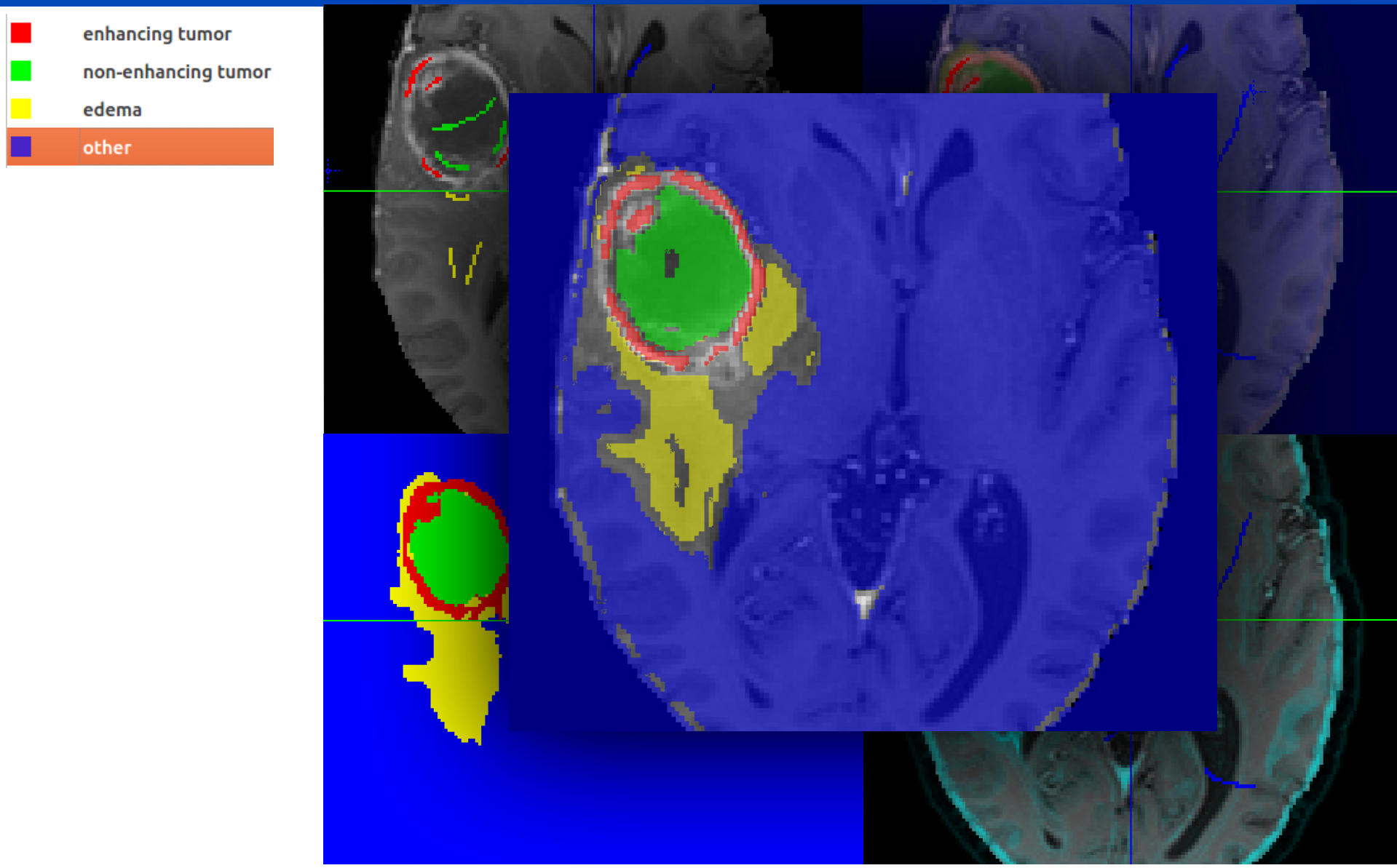
1. **Multiple models that describe known data**
2. **Measure of disagreement**

Reduce version space

Seung, H. S., Opper, M. and Sompolinsky, H.: *Query by committee*, Proceedings of the ACM Workshop on Computational Learning Theory, 1992, pp. 287-294

Settles, B.: *Active Learning Literature Survey*, Computer Sciences Technical Report 1648, University of Wisconsin – Madison, 2010, accessed 4.3.16

Example – Pixel Classification in *ilastik*



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Milestones

Implementation State of the Art

- Random Forest based pixel classification (extend Michael‘s & Jonas‘ work)
- GUI with active user guidance
- Single image volume
- Handcrafted & fixed features

Milestones

Implementation
State of the Art

Multi-Volume Segmentation

- **Focus on querying next volume**
- **Transfer learning**
- **Extend to other modalities (User defined features)**

Milestones

Implementation
State of the Art

Multi-Volume
Segmentation

Neural Network
Active Learning

- Autoencoder for large enough datasets
- Learn features
- Use low-dimensional similarity measure

Summary

„Interactive Segmentation of Very Large Image Datasets with Minimal Effort“

Available

- Random Forest Classifier
- Autoencoder
- Active Learning Query Strategies
- Domain Adaptation Strategies

New

- Software with Active User Guidance
- Active Learning with Pre-Training
- Efficient Low-Dimensional Query
- Hierarchical Query

Thank you for your attention!

Further information on www.dkfz.de

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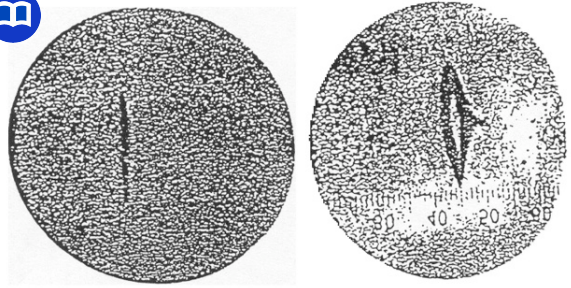
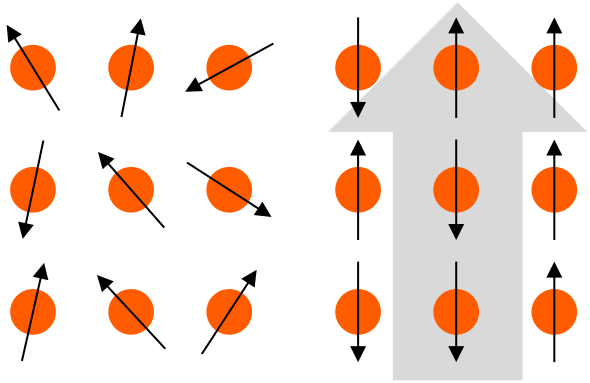
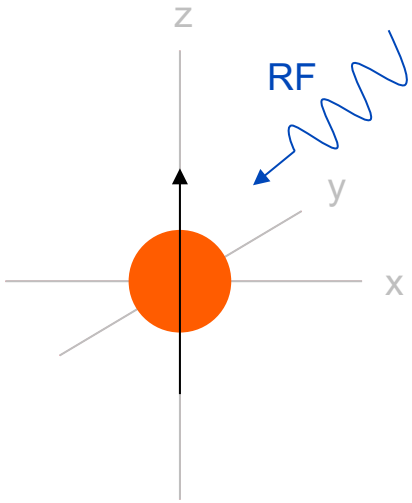
Quick MRI Review

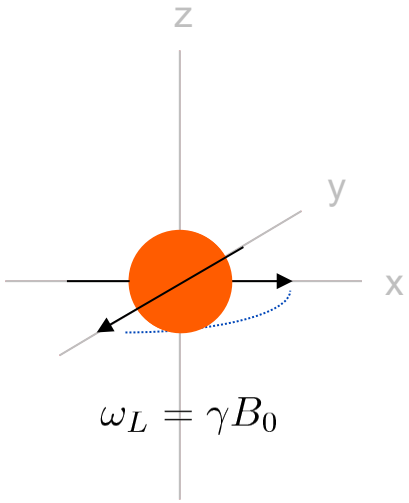




$$\frac{N_{\uparrow\uparrow}}{N_{\uparrow\downarrow}} = e^{\frac{\Delta E}{kT}}$$

1.00002
H_1 @ 3T, 300K





$$\omega_L = \gamma B_0$$

$$M_z(t) = M_z(0) \cdot \left(1 - c \cdot e^{-\frac{t}{T_1}}\right)$$

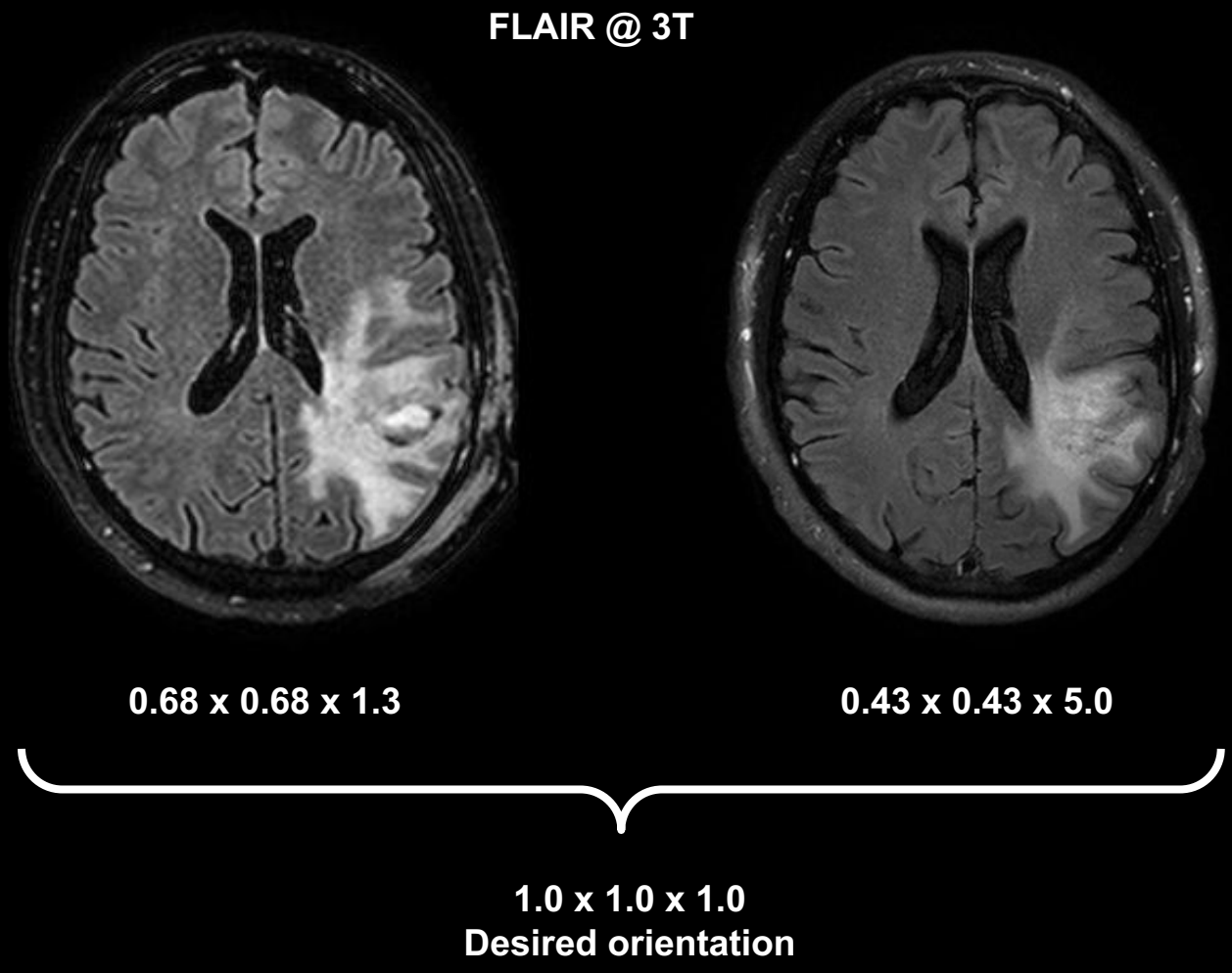
$$M_{xy}(t) = M_{xy}(0) \cdot e^{-\frac{t}{T_2}}$$

Lauterbur, P. C. and Mansfield, P.: *Nobel Prize in Physiology or Medicine 2003*

Gerlach, W. and Stern, O.: *Der experimentelle Nachweis der Richtungsquantelung im Magnetfeld*. Zeitschrift für Physik 9, 1922, pp. 349-352

Preprocessing

- **Resampling**
- Registration
- Brain Extraction
- Bias Field Correction
- Normalization



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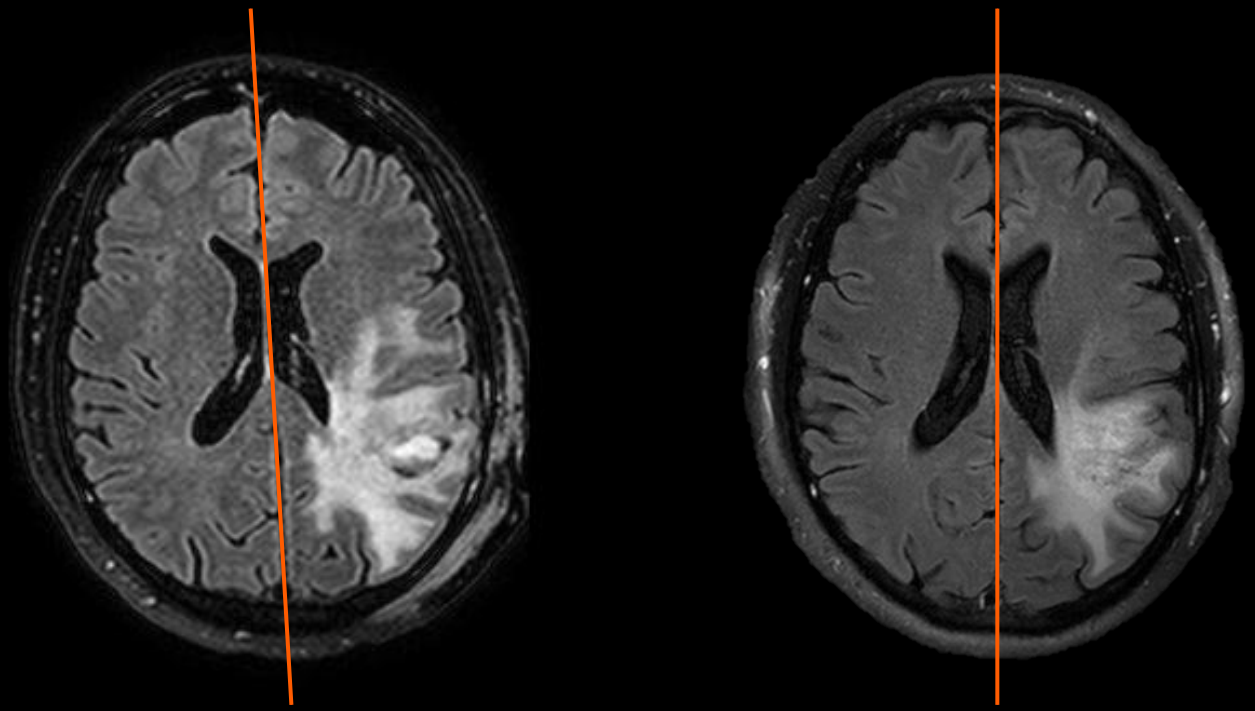

Rigid: 3T + 3R
Non-rigid: +3S (+arbitrary deformation)

Maximize Mutual Information
Combine with resampling

Preprocessing

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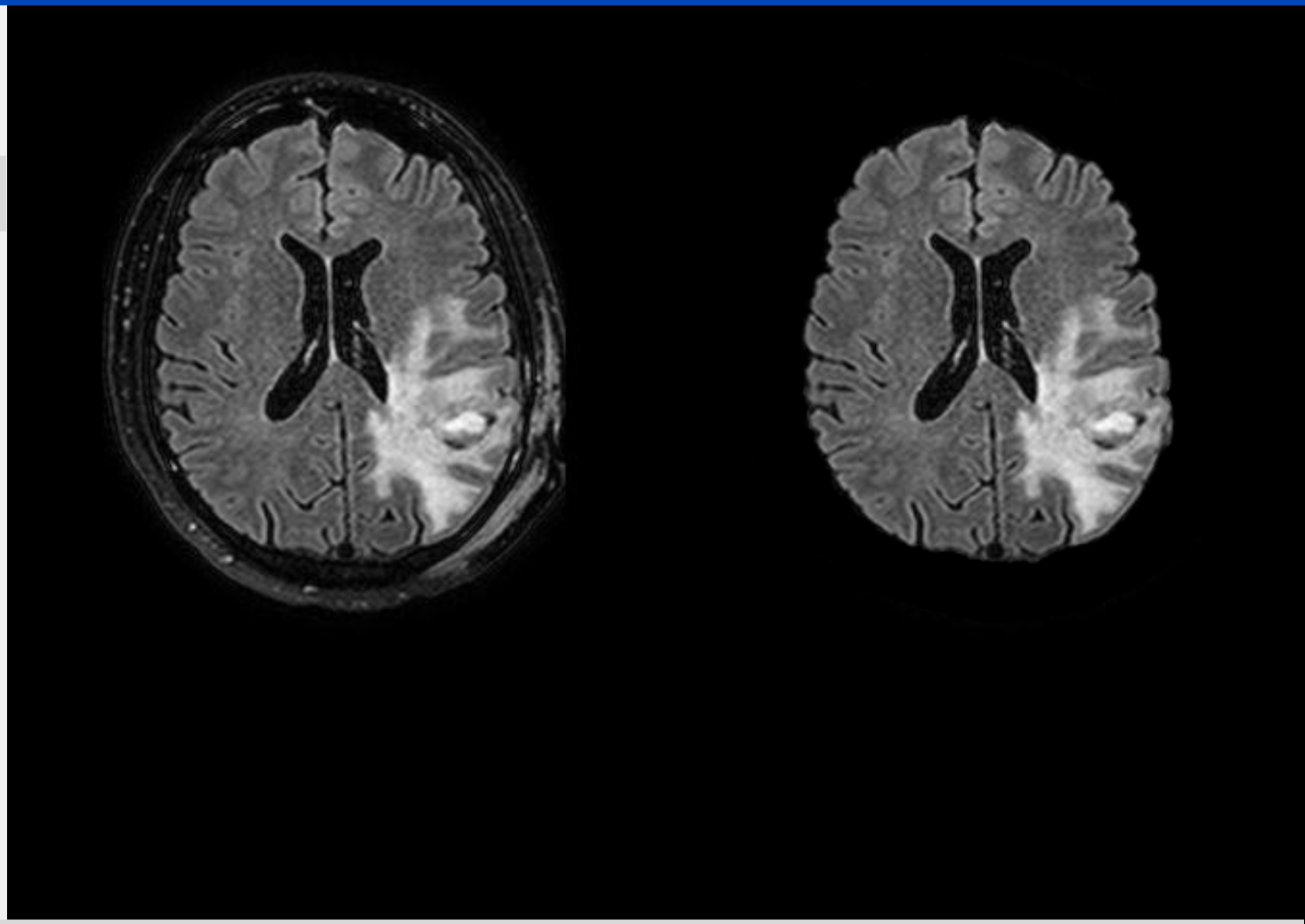

ROBEX BEaST FSL-BET FREESURFER-HWA AFNI-3dSkullStrip BrainSuite-BSE ITK

Kleesiek, J. et al.: *Deep MRI brain extraction: A 3D convolutional neural network for skull stripping,* NeuroImage 129, 2016, pp. 460-469

Preprocessing

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- **Bias Field Correction**
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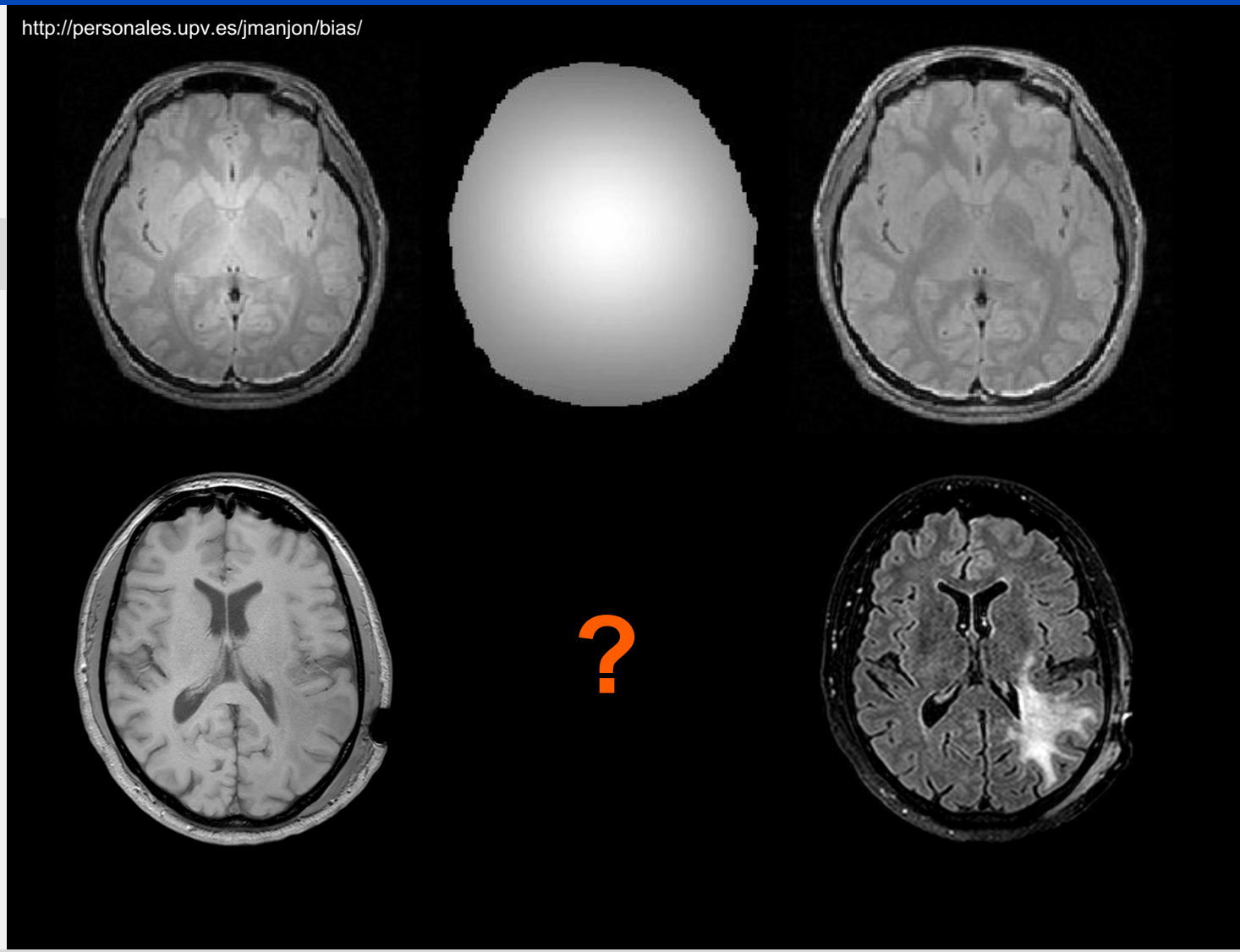
http://personales.upv.es/jmanjon/bias/



N4ITK FSL-FAST FREESURFER BrainSuite-BFC AFNI-3duniformize

Preprocessing – Normalization

- Resampling
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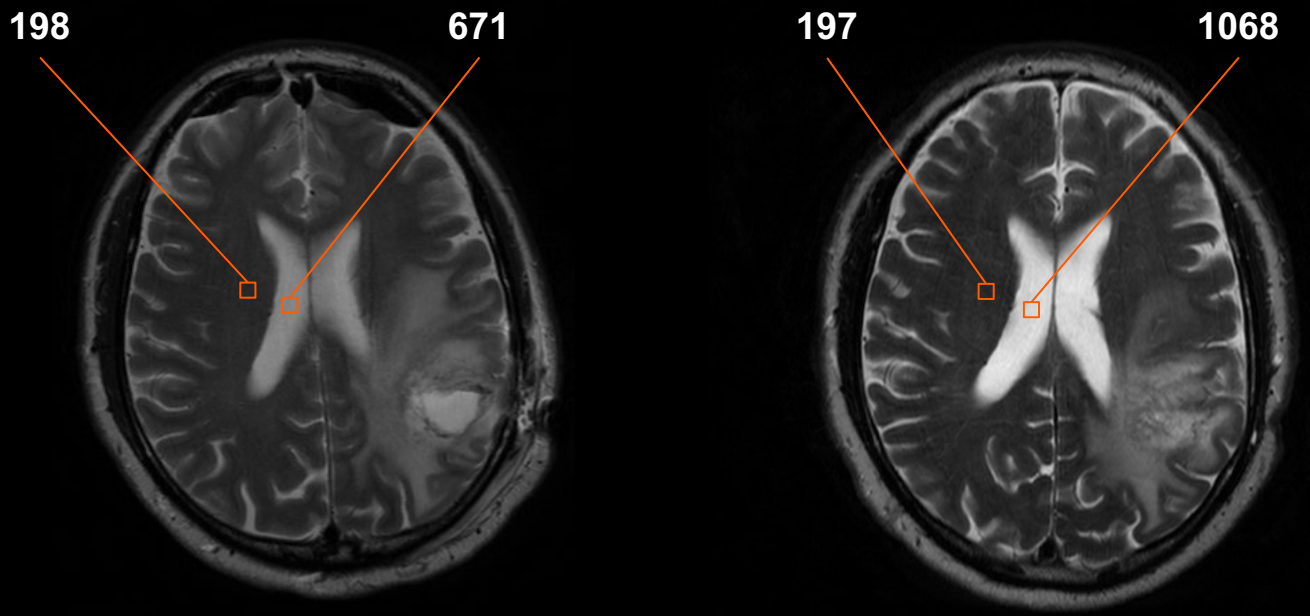

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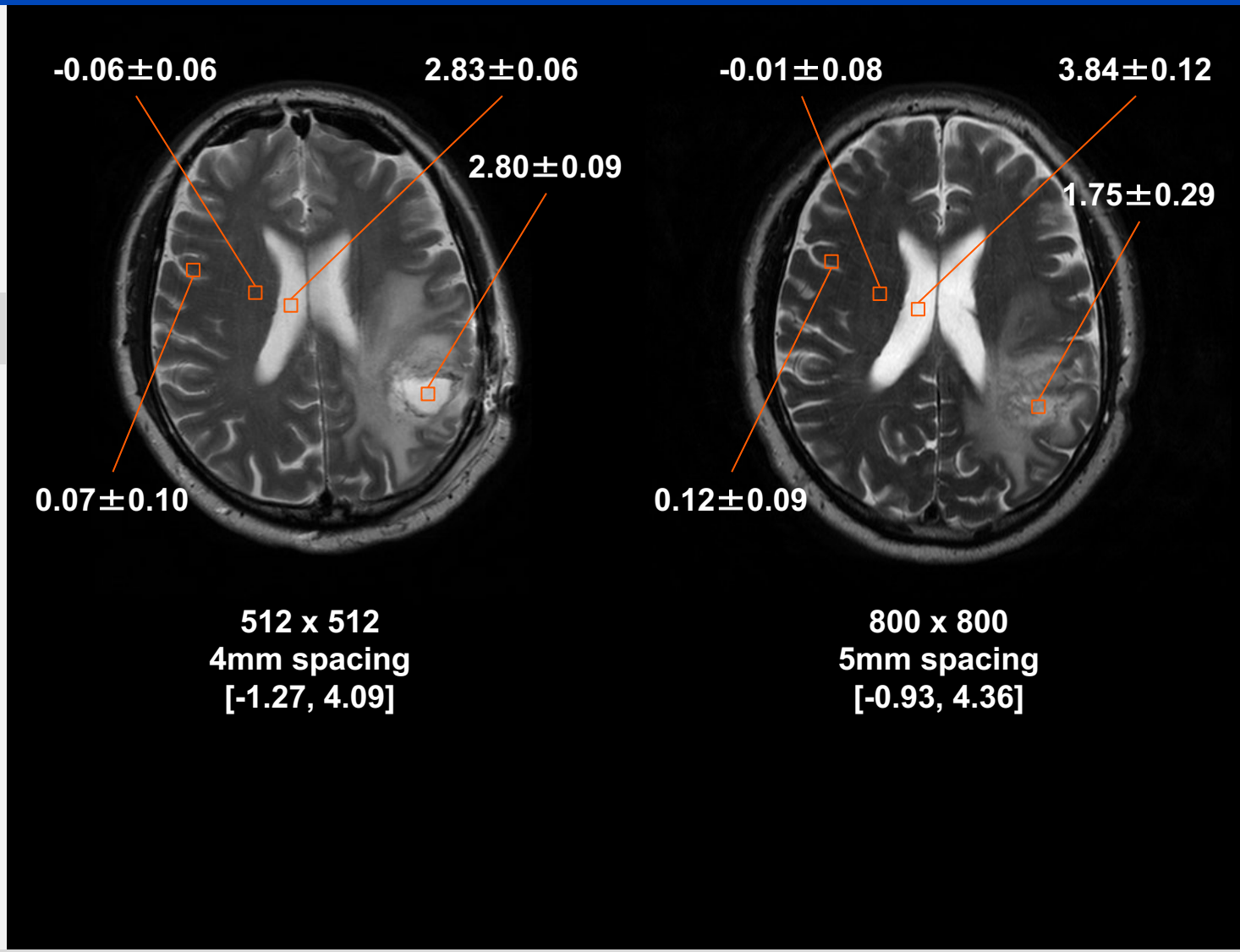

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