Machine Learning for the Automatic Analysis of Medical Images

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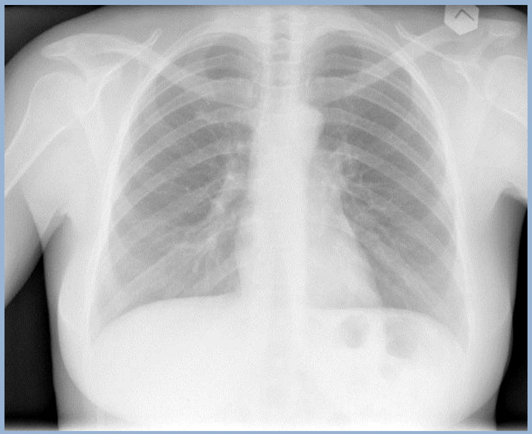
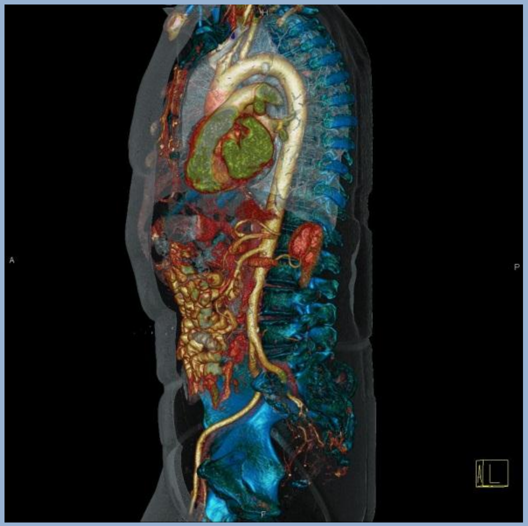
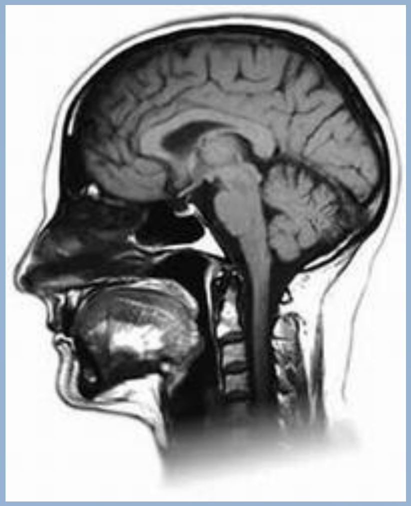
Machine learning for medical image analysis

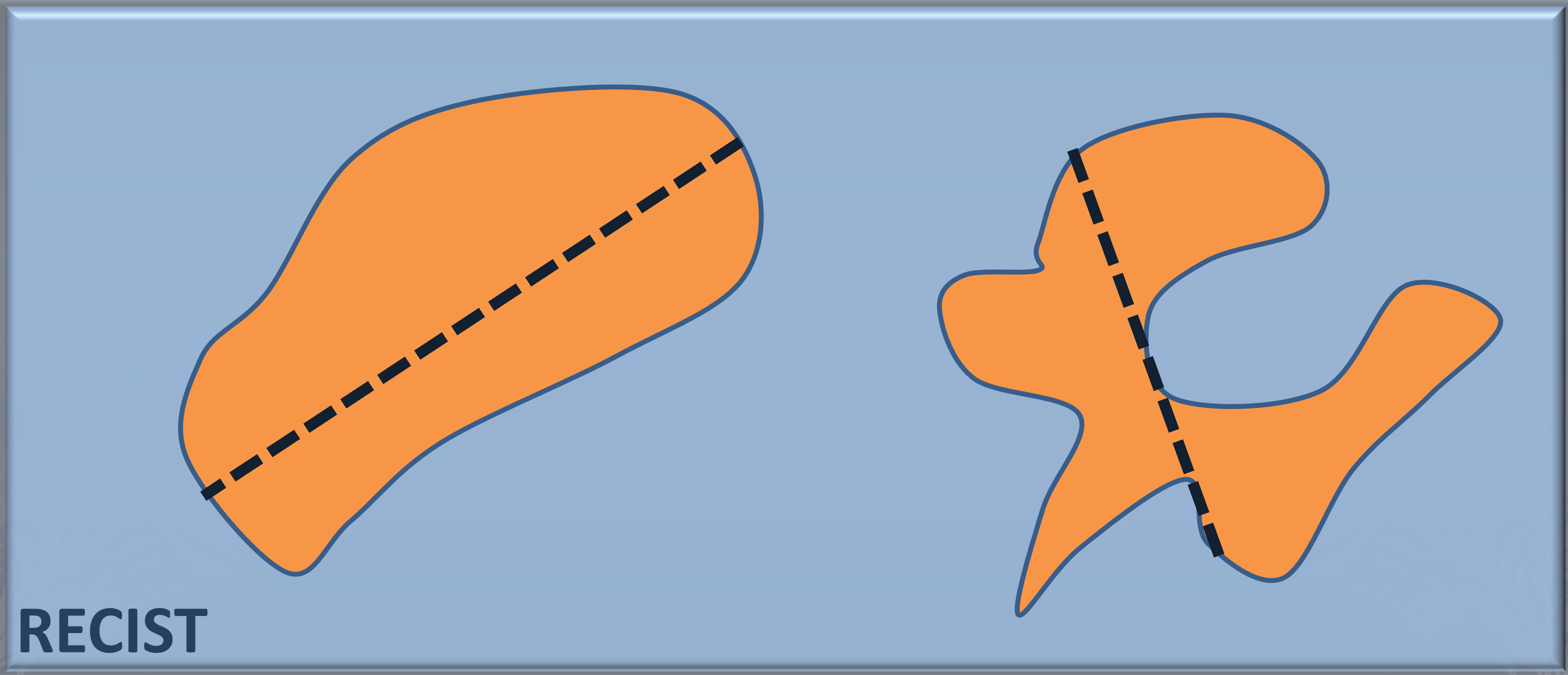






What is wrong with my patient?
What is the best treatment?

Machine learning for medical image analysis



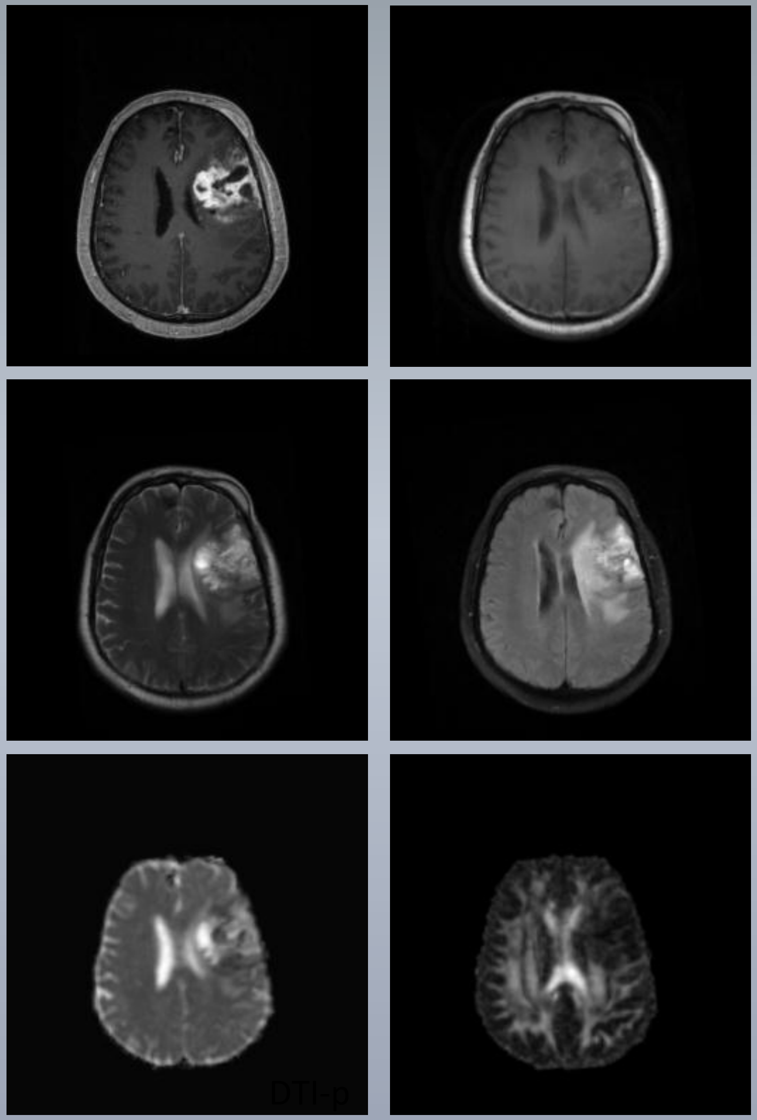
The problem of quantifying disease progression

Machine learning for medical image analysis

- **Project 1.** Automatic delineation of brain tumor in multi-channel MR images

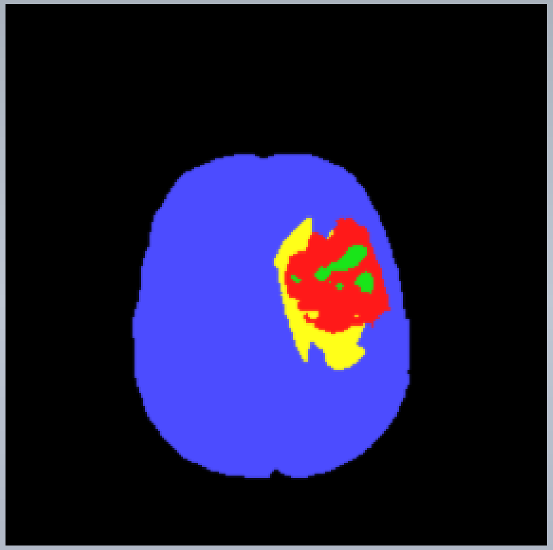
- **Project 2.** Automatic localization and identification of vertebrae in CT scans

Automatic 3D segmentation of glioblastoma



3D MRI input data

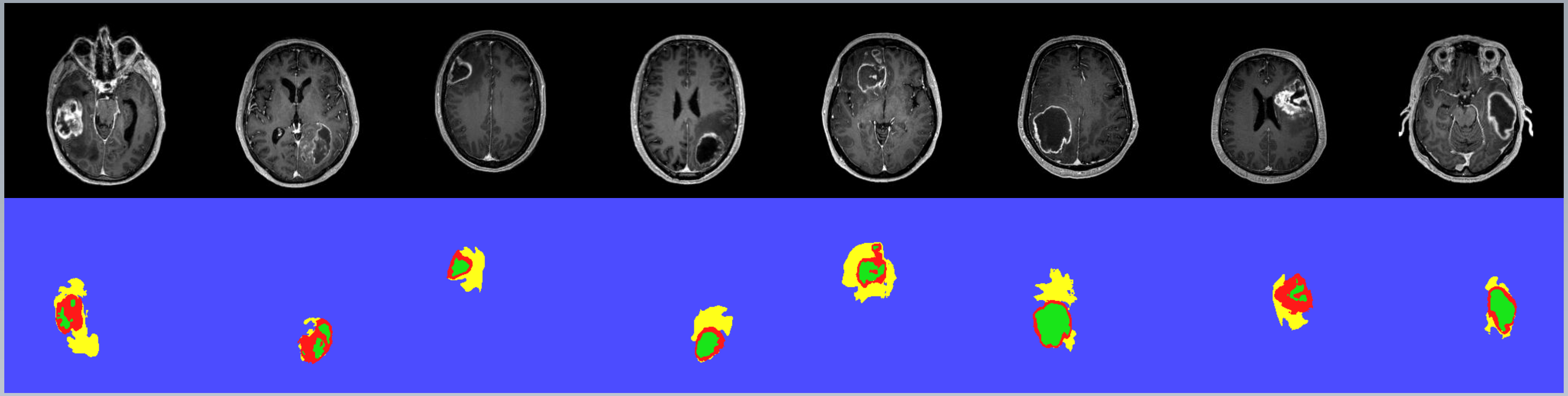
Segmentation of tumorous tissues:



---- Active cells
---- Necrotic core
---- Edema
---- Background

Overview of the method

Training a pixel-wise classifier



Tumour
Tissue
Classification

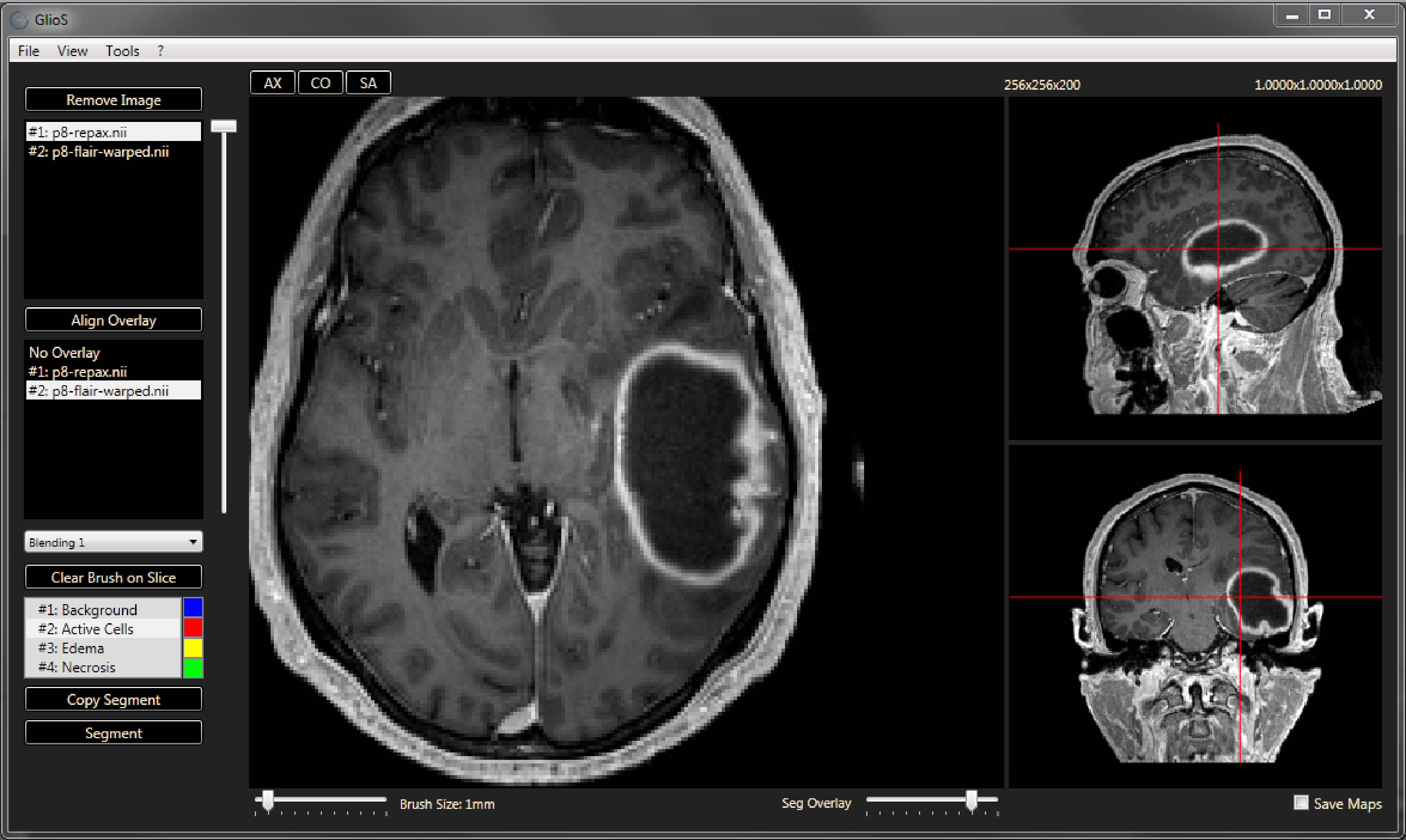
Testing a pixel-wise classifier

New Patient,
previously unseen

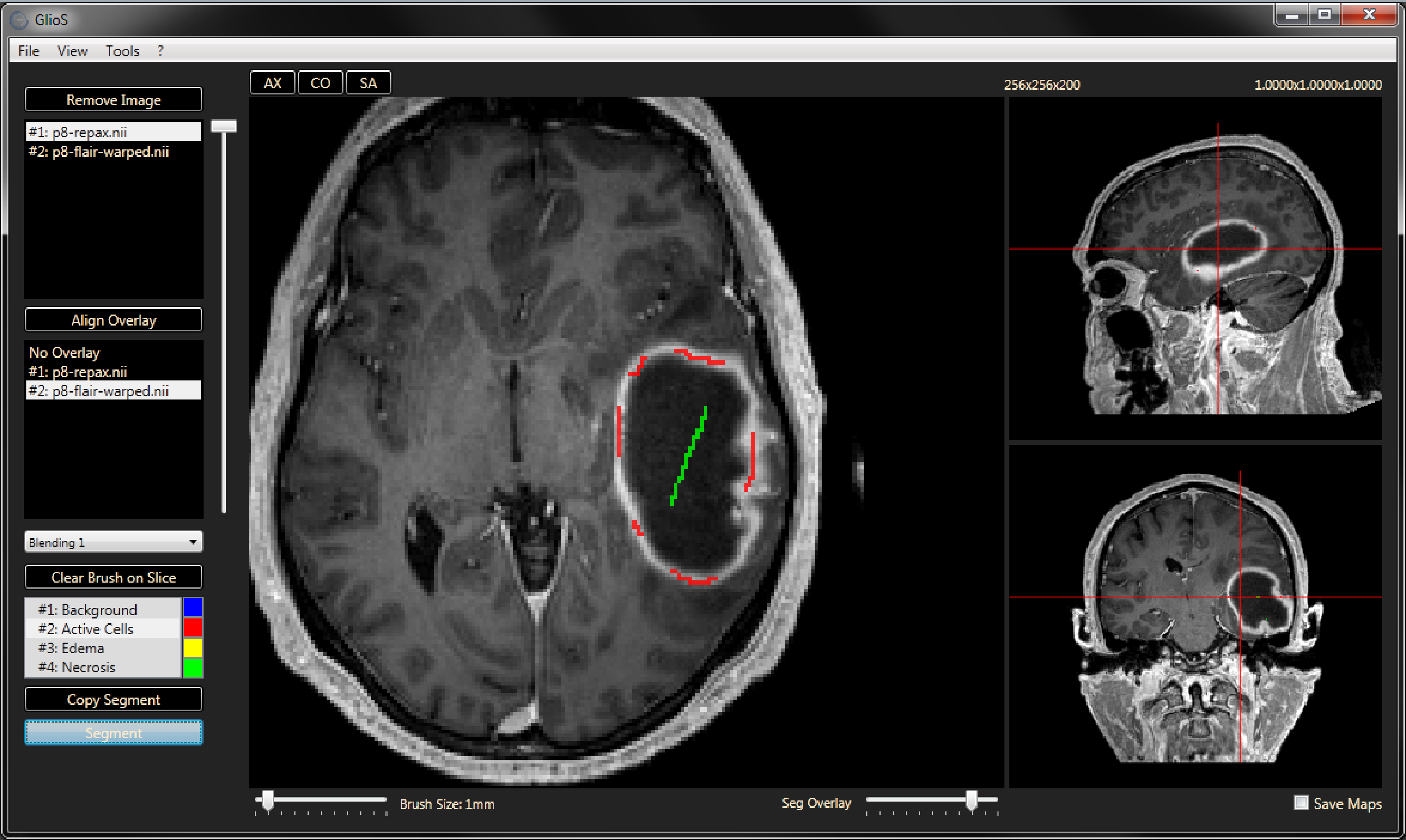
Tumour Tissue Classification

The labelled database

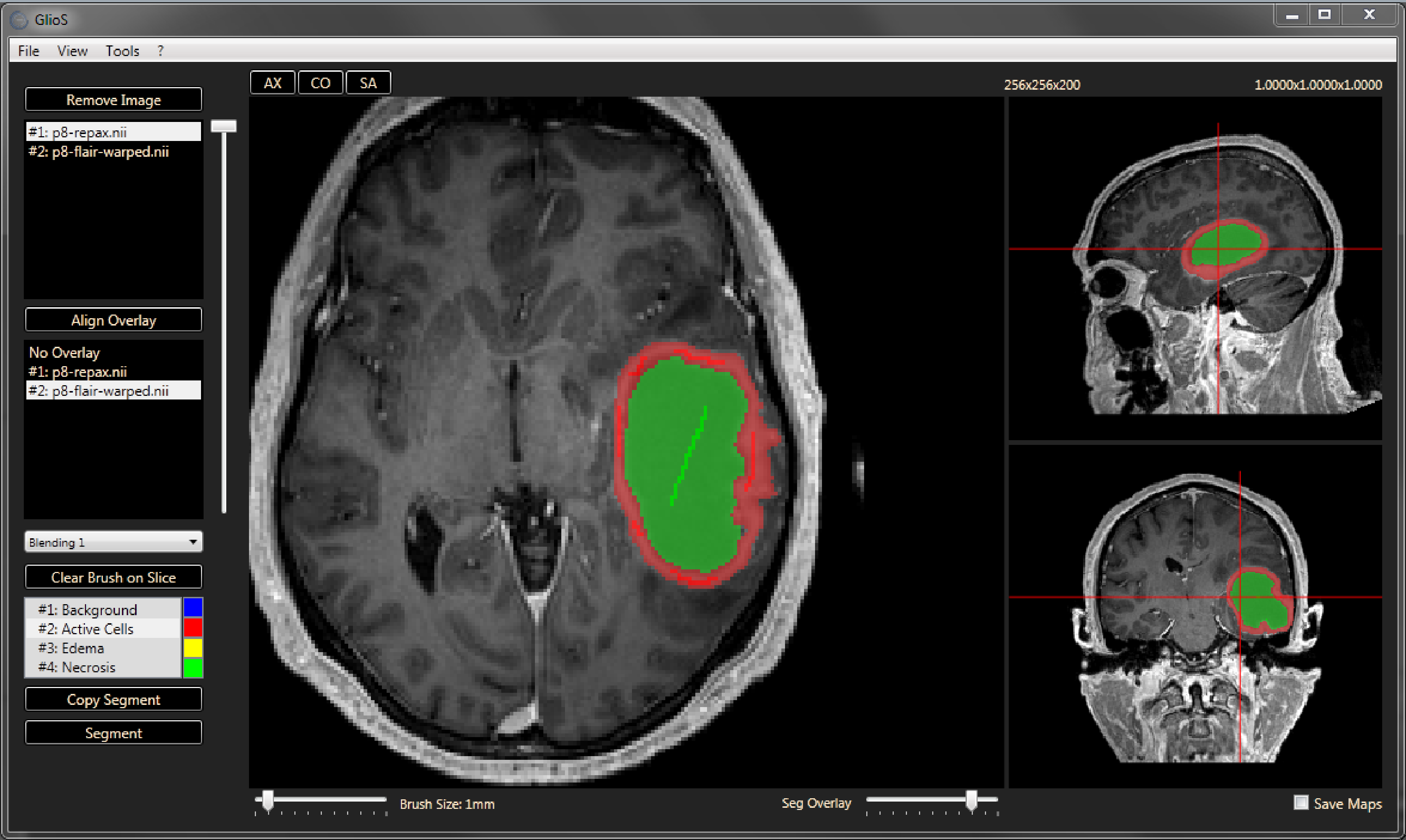
1st Step: Obtain Expert Segmentation



1st Step: Obtain Expert Segmentation



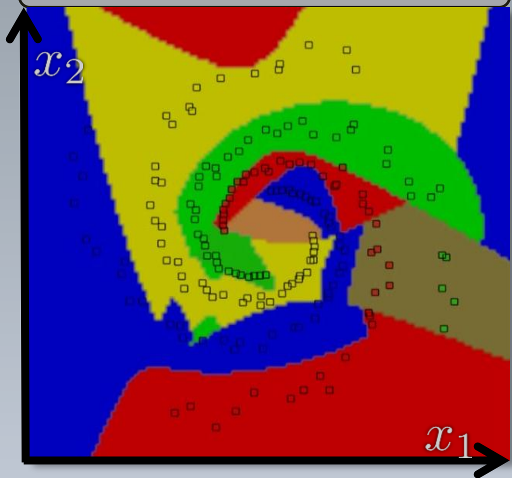
1st Step: Obtain Expert Segmentation



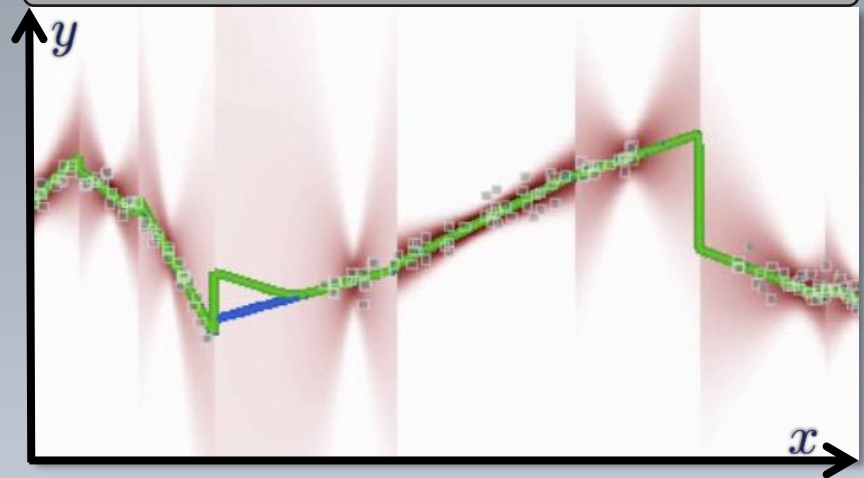
Decision forests for pixel-wise classification

What can decision forests do? tasks

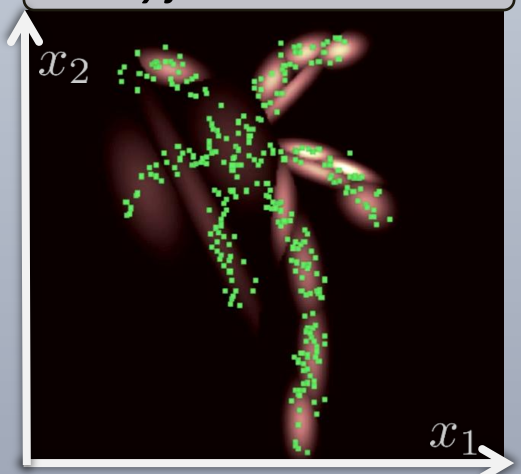
Classification forests



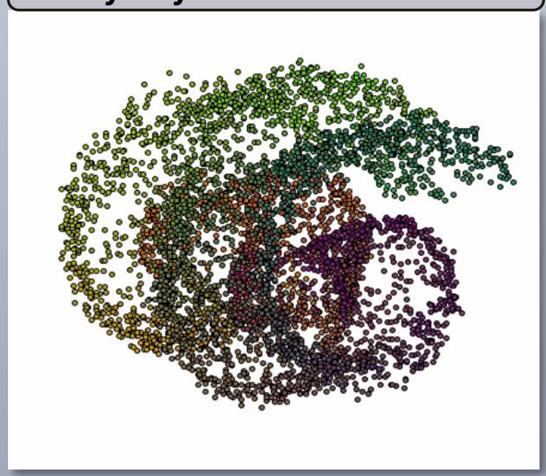
Regression forests



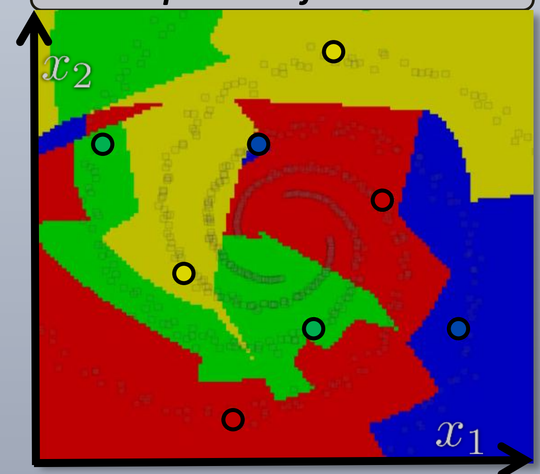
Density forests



Manifold forests



Semi-supervised forests



What can decision forests do? applications

Classification forests

e.g. semantic segmentation

Regression forests

e.g. object localization

Density forests

e.g. novelty detection

Manifold forests

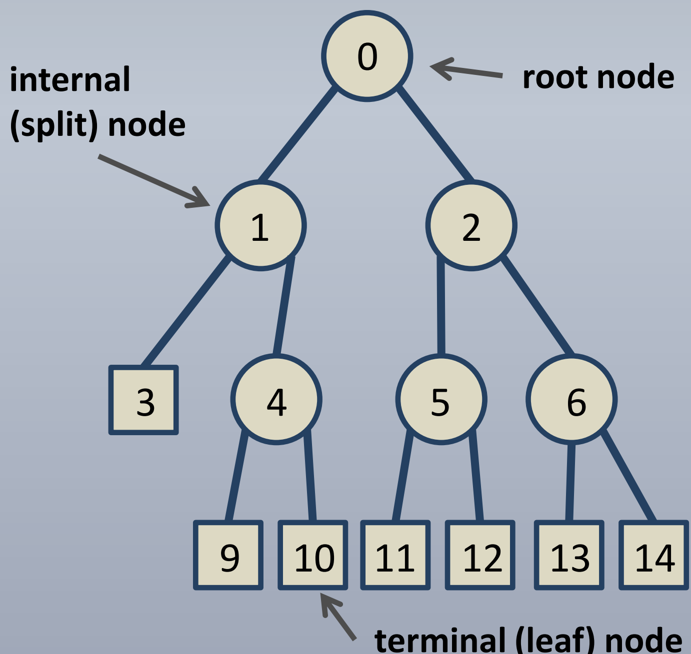
e.g. dimensionality reduction

Semi-supervised forests

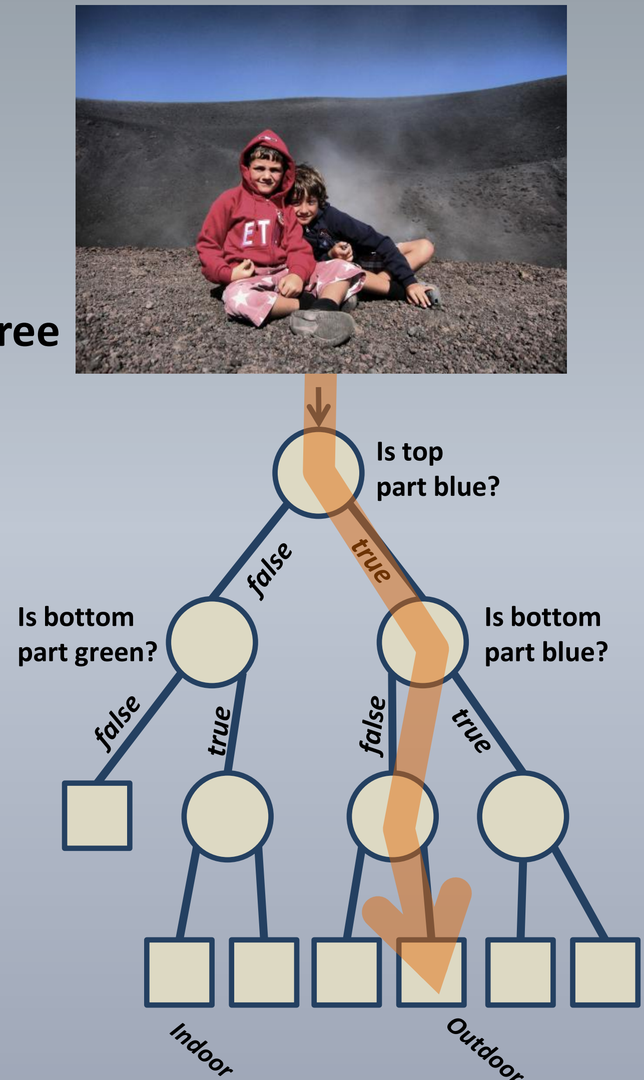
e.g. semi-sup. semantic segmentation

Generic trees and decision trees

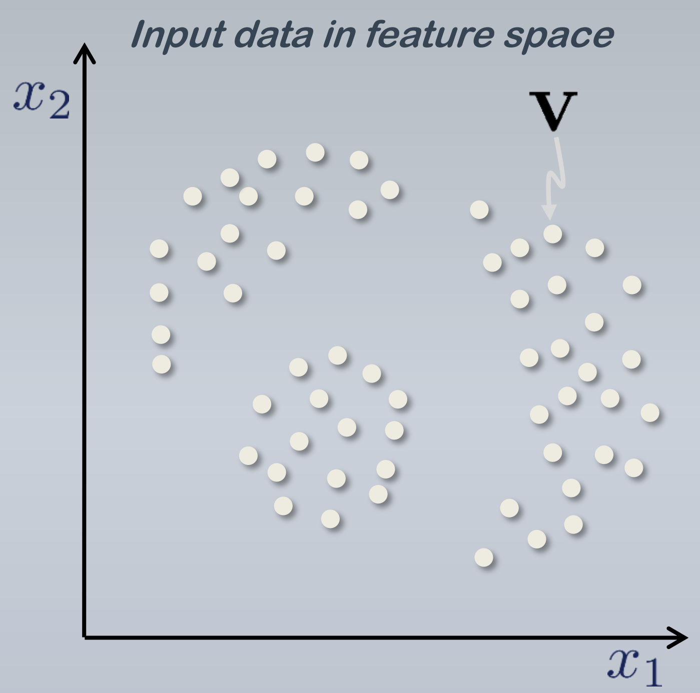
A general tree structure



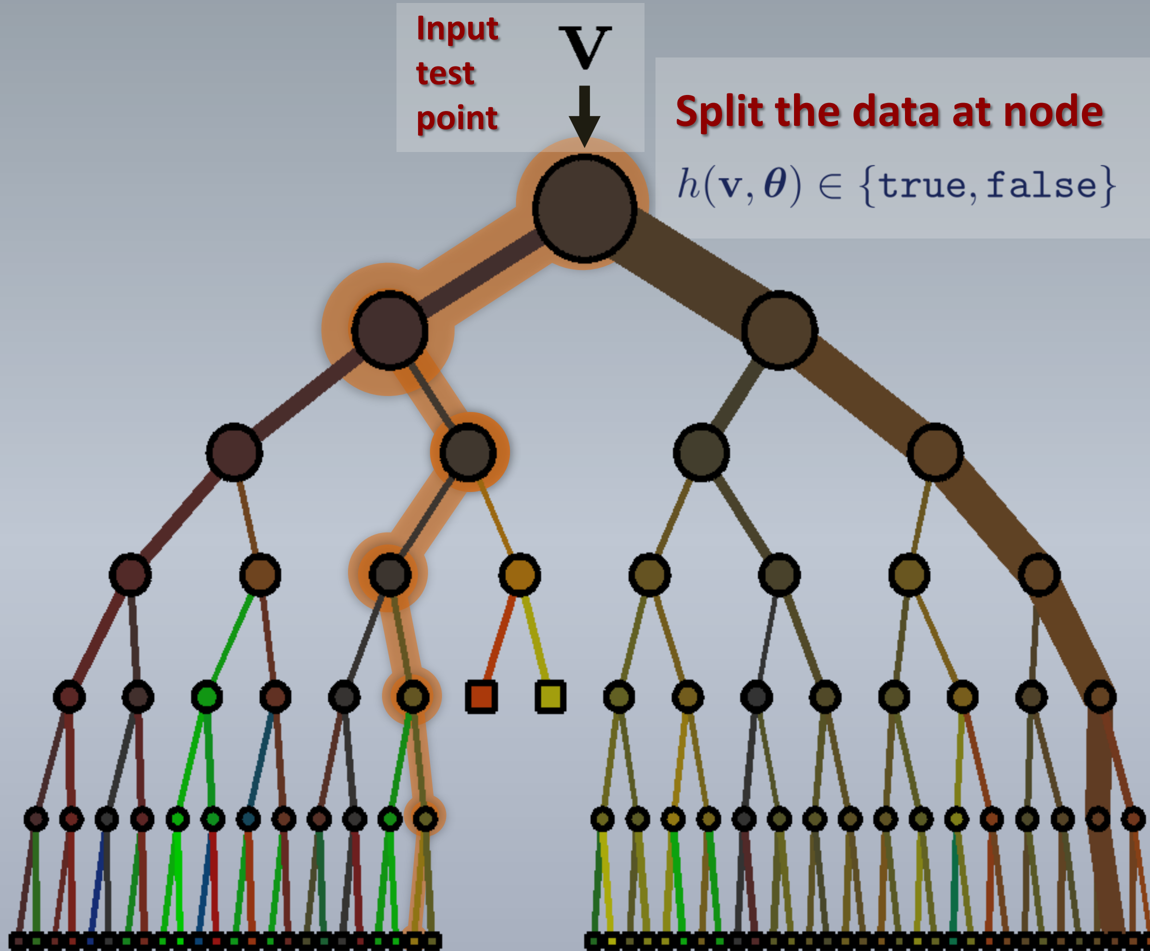
A decision tree



Decision tree testing (runtime)



$$\mathbf{v} = (x_1, \cdots, x_d) \in \mathbb{R}^d$$



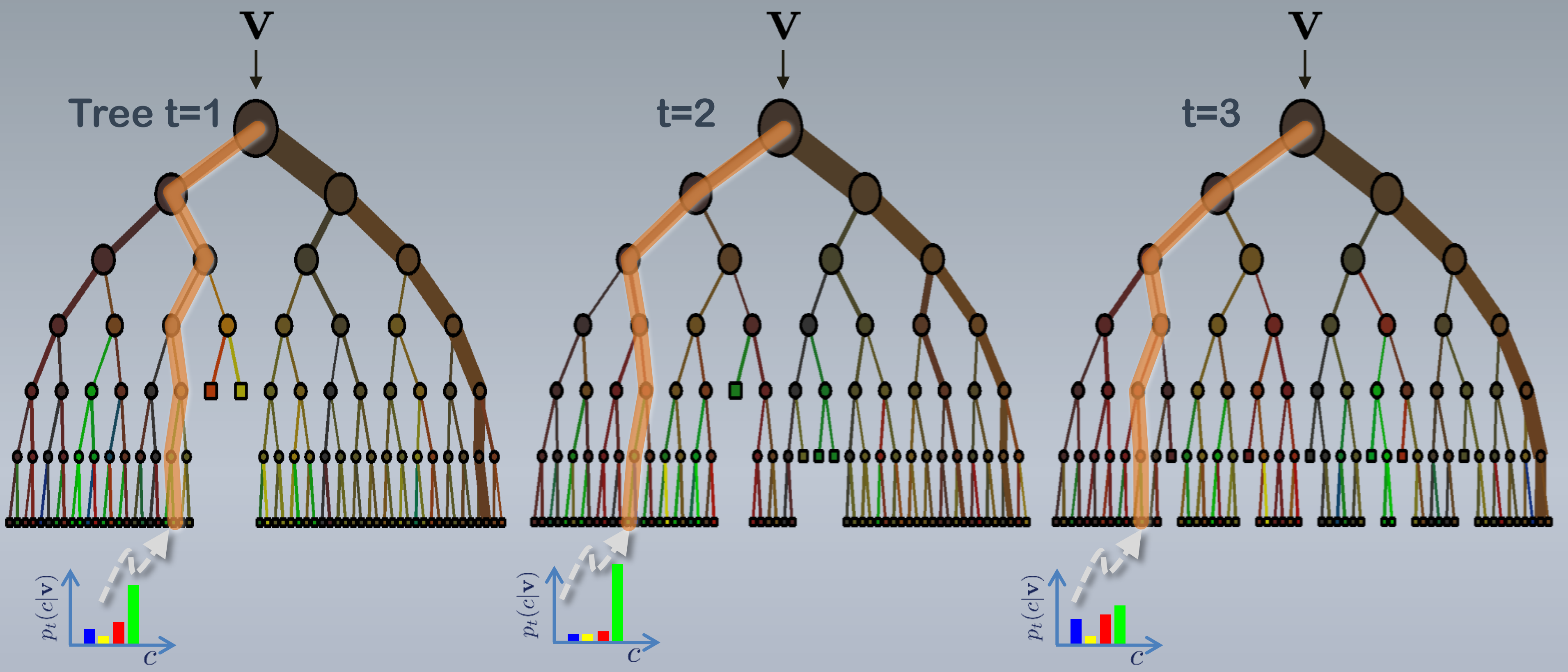
Split the data at node

$$h(\mathbf{v}, \boldsymbol{\theta}) \in \{\texttt{true}, \texttt{false}\}$$

Prediction at leaf

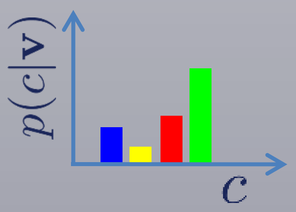
$$p(c|\mathbf{v}) = \sum_j p(c|j)p(j|\mathbf{v})$$

Classification forest: the ensemble model



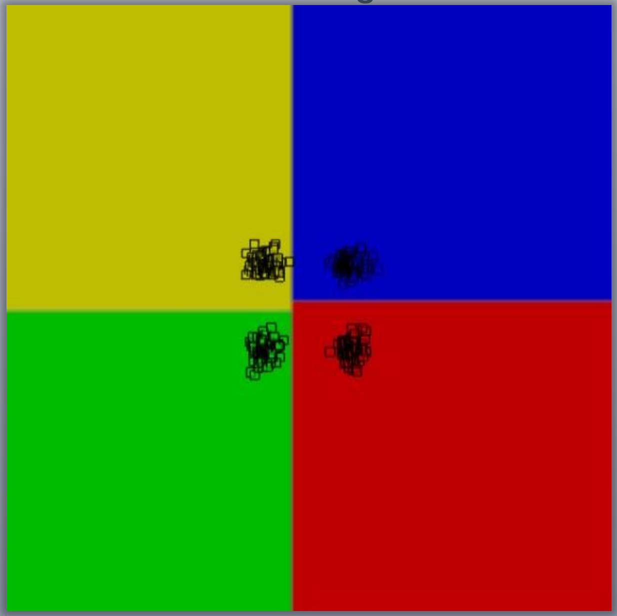
The ensemble model

Forest output probability $$p(c|\mathbf{v}) = \frac{1}{T}\sum_{t}^{T} p_t(c|\mathbf{v})$$

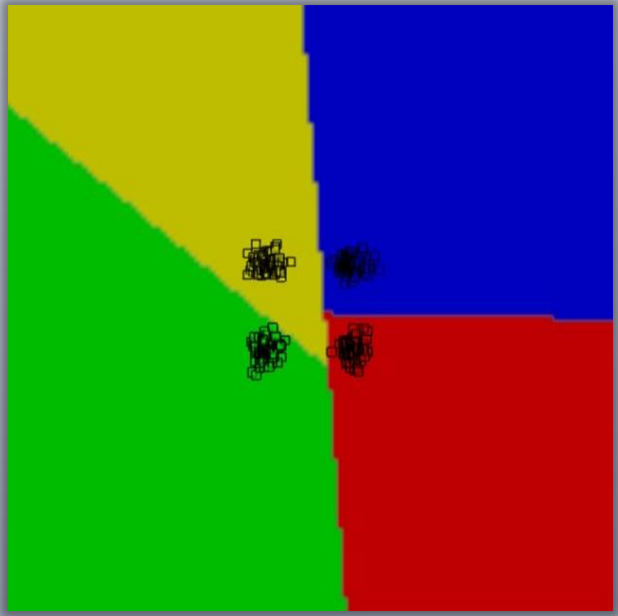


Classification forest: analysing generalization

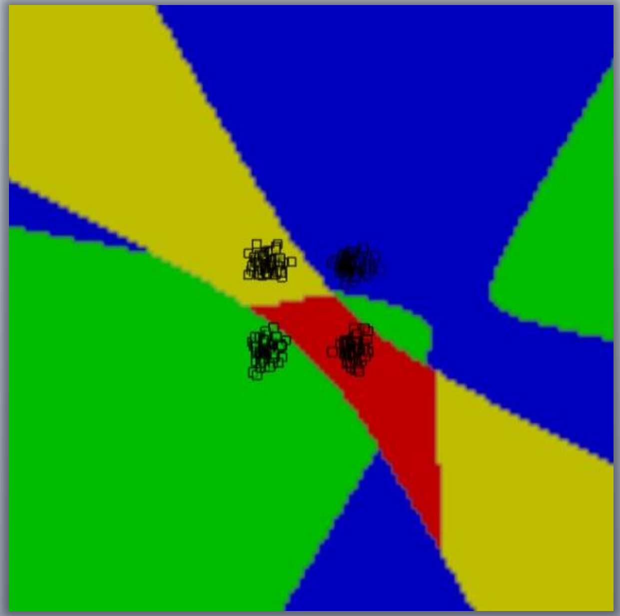
Weak learner: axis aligned



Weak learner: oriented line



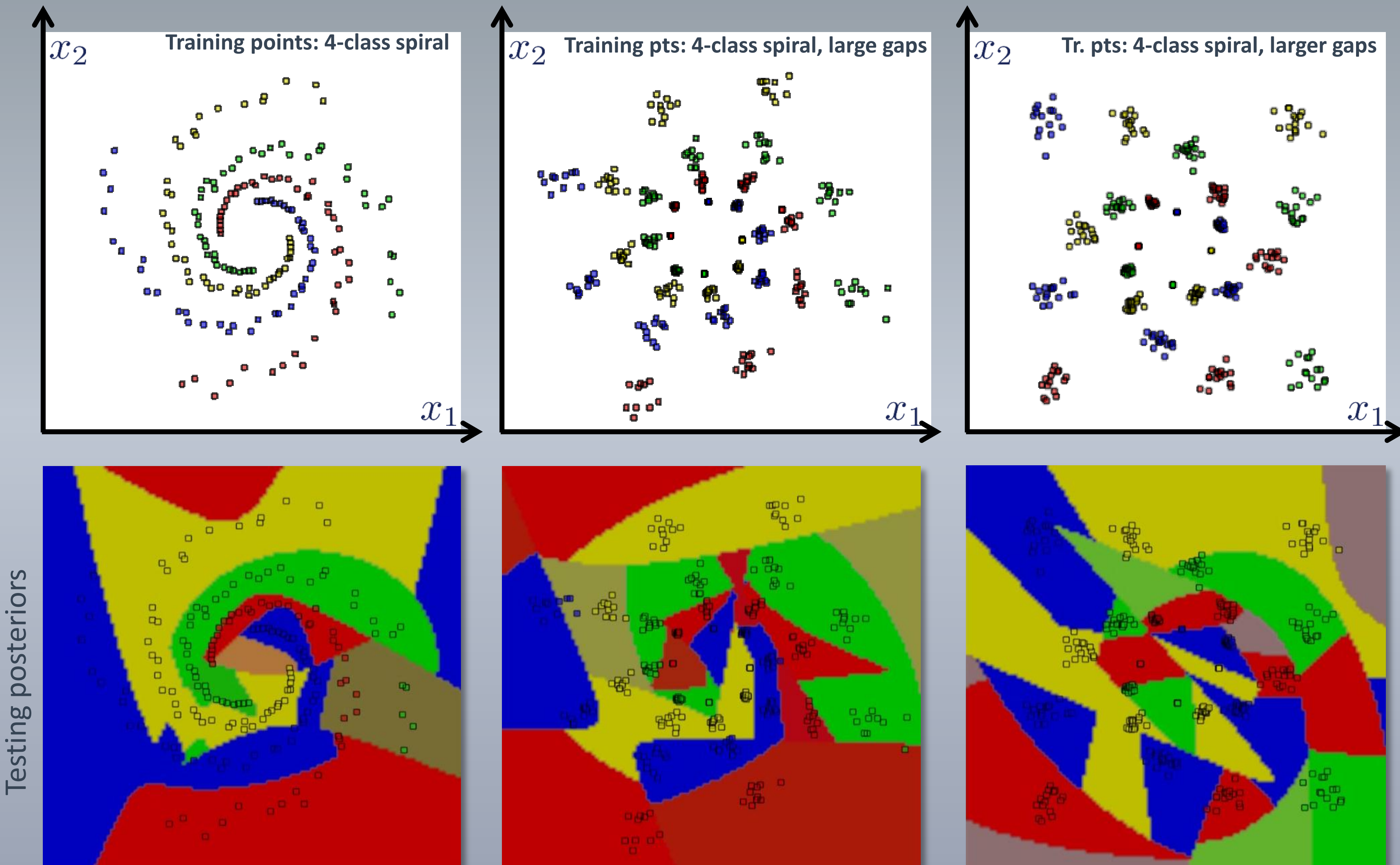
Weak learner: conic section



(3 videos in this page. Increasing T)

Parameters: T=200, D=3, leaf model = probabilistic

Classification forest: analysing generalization



(3 videos in this page)

Parameters: T=200, D=13, w. l. = conic, predictor = prob.

Back to tumour segmentation

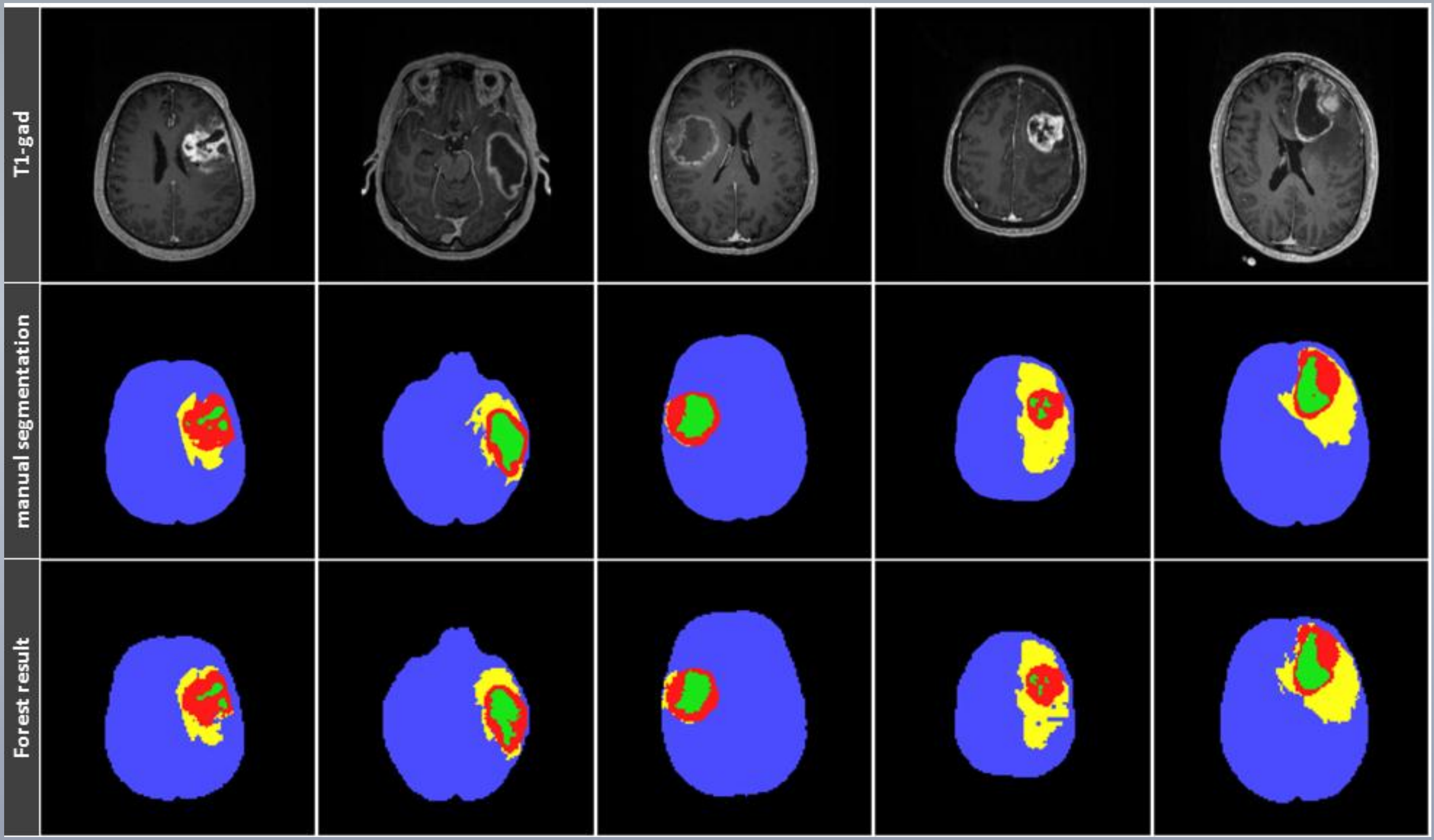
Evaluation

Evaluation framework

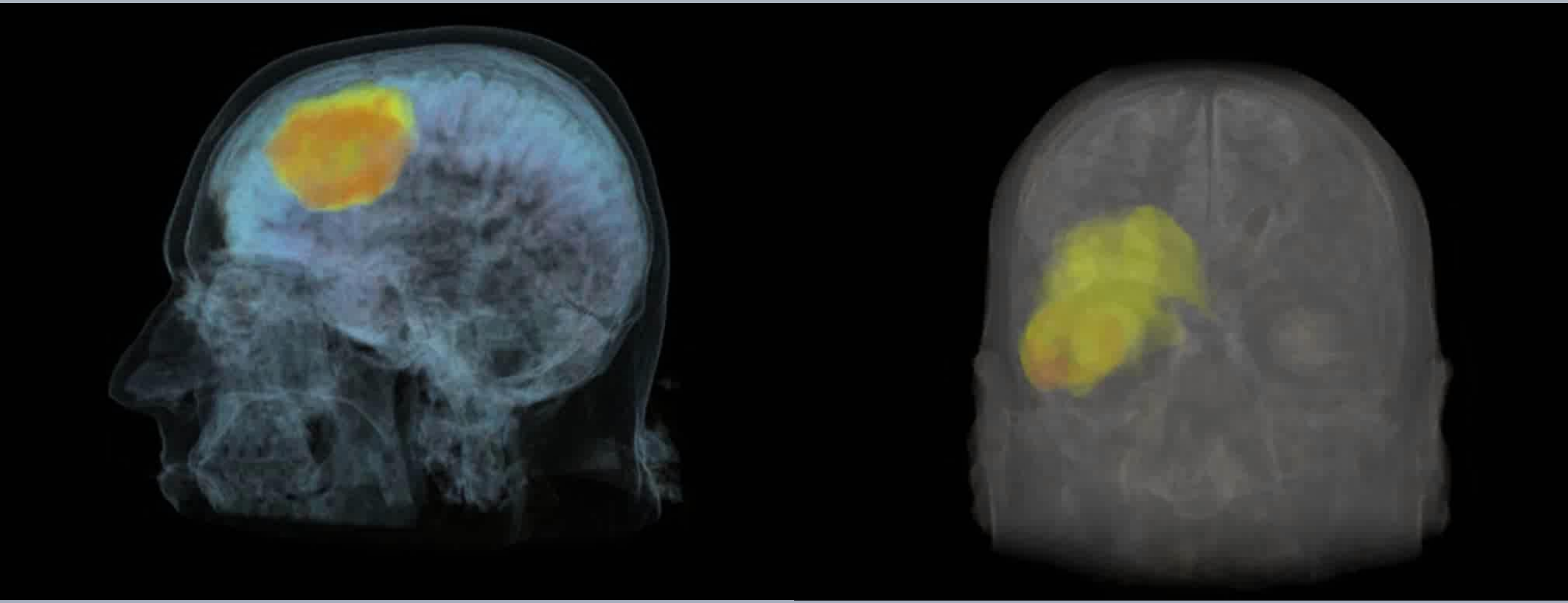
- **40** labelled patient images (training/testing splits: **10/30, 20/20, 30/10**)
  → good performance even with small amount of training data
- Evaluation of robustness of algorithm
  → method is robust to setting of key parameters
- Multiple random splits into training and testing data
  (10 random folds per training/testing split → **600 experiments**)
- With 40 patients and our experiment setup → **Largest evaluation** for this problem so far

Our combination of *high-quality input data* and *segmentation methodology* achieves significantly better quantitative results than previous state of the art methods

Glioblastoma segmentation: Qualitative results



Glioblastoma segmentation: Qualitative results



Comparative, quantitative results

DICE: mean and std.	GT	AC	NC	E
Bauer *et al.*	77±9	64±13	45±23	60±16
Our method 30/10	90±9	85±9	75±16	80±18
Our method 10/30	89±9	84±9	70±19	72±23

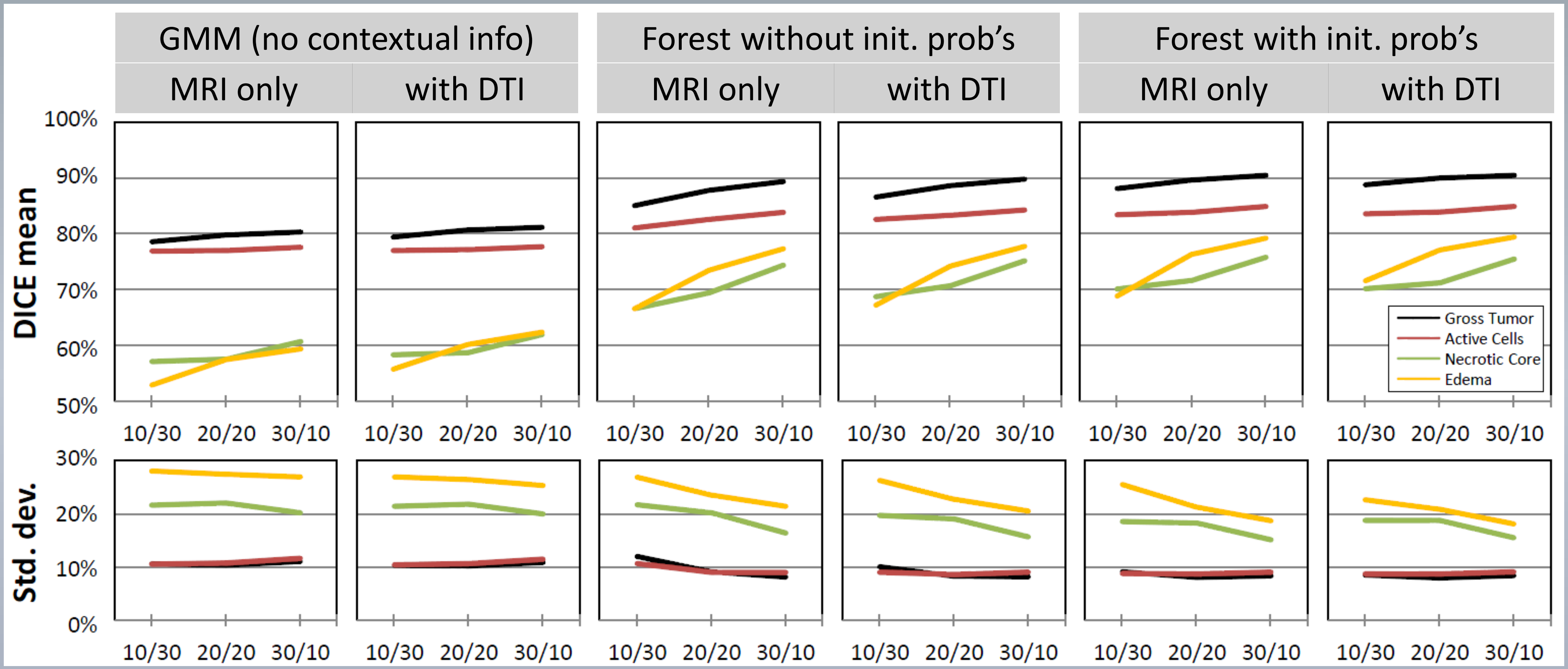
Accuracy: mean and std.	AC	NC	E
Verma *et al.*	89±29	34±39	93±9
Our method 30/10	99.6±0.3	98.6±0.7	99.8±0.2
Our method 10/30	99.4±0.3	98.4±0.8	99.7±0.4

[Bauer et al.] S. Bauer, L.-P. Nolte, and M. Reyes.
Fully automatic segmentation of brain tumor images using support vector machine classification in combination with hierarchical conditional random field regularization. In MICCAI, 2011.

[Verma et al.] R. Verma, E. I. Zacharaki, Y. Ou, H. Cai, S. Chawla, A.-K. Lee, E.R. Melhem, R. Wolf, and C. Davatzikos.
Multi-parametric tissue characterisation of brain neoplasm and their recurrence using pattern classification of MR images. Acad. Radiol., 15(8), 2008.

Quantitative results (II)

- training/testing data splits with set sizes of 10/30, 20/20, and 30/10
- 10 random folds per split



→ Clear improvement through use of Decision Forests over GMMs (contextual information)

→ Further improvement through use of initial probabilities in Decision Forests

→ DTI influence currently very pronounced (however not fully explored yet either) seems to show improvement for Edema and smaller amounts of training data

Project 2. Vertebrae Localization in Arbitrary Field-of-View CT Scans

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David R. Haynor

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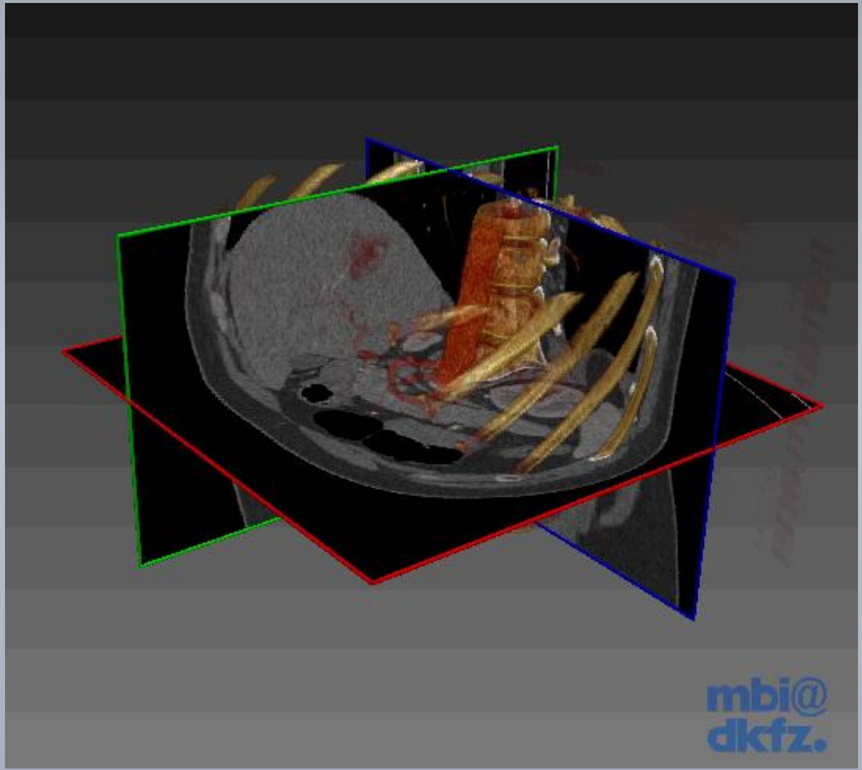
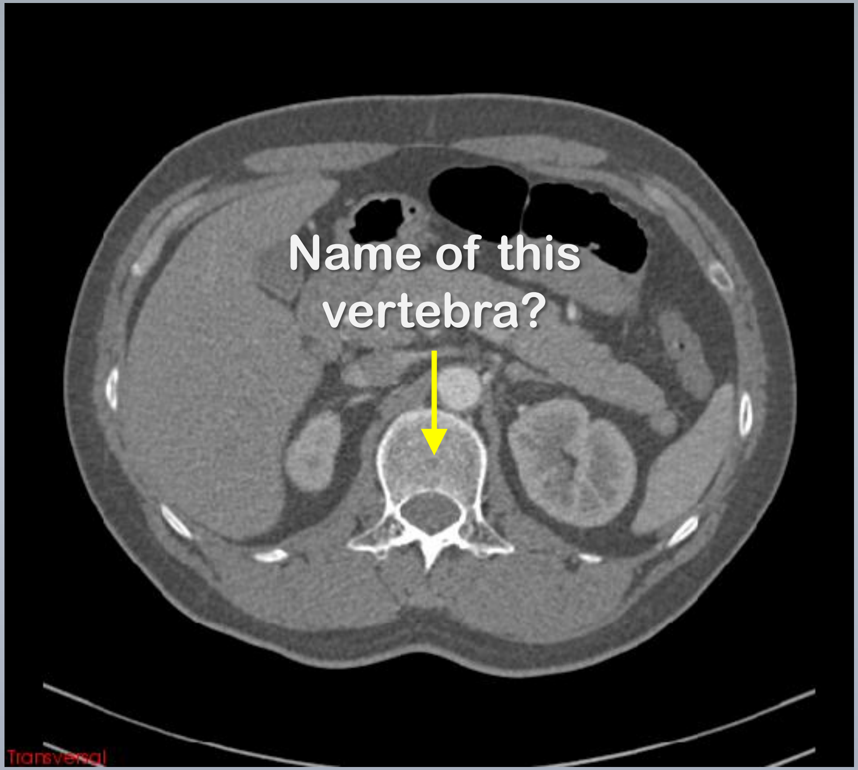
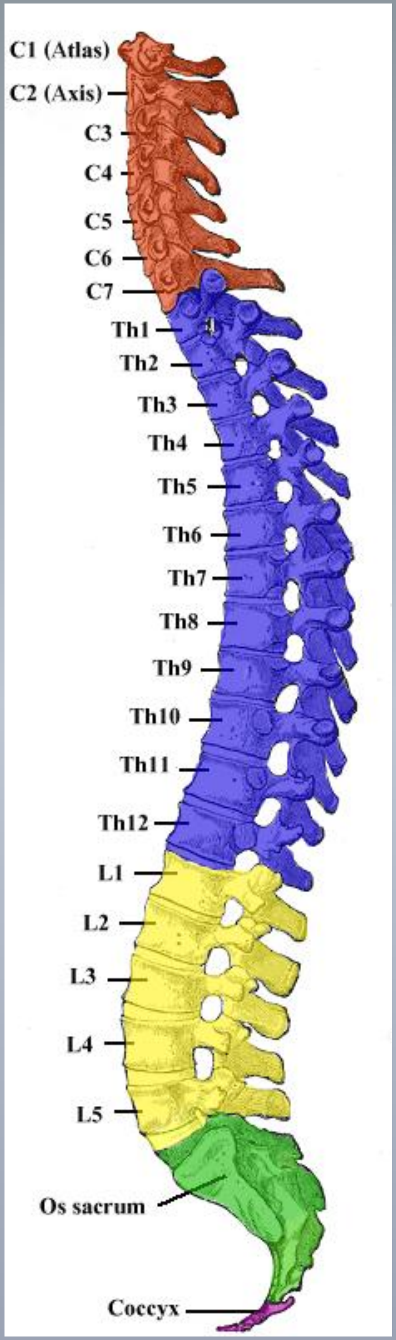
Radiology Department, Seattle

Problem Statement

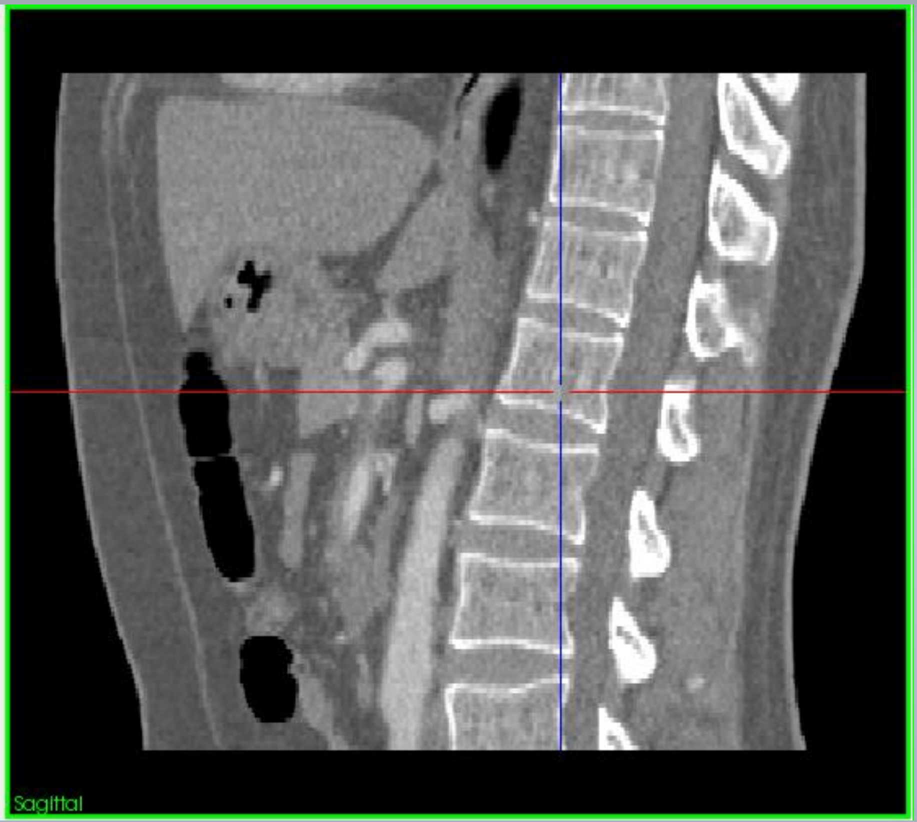


Problem Statement





The Difficulty of Counting



Clinical Motivation

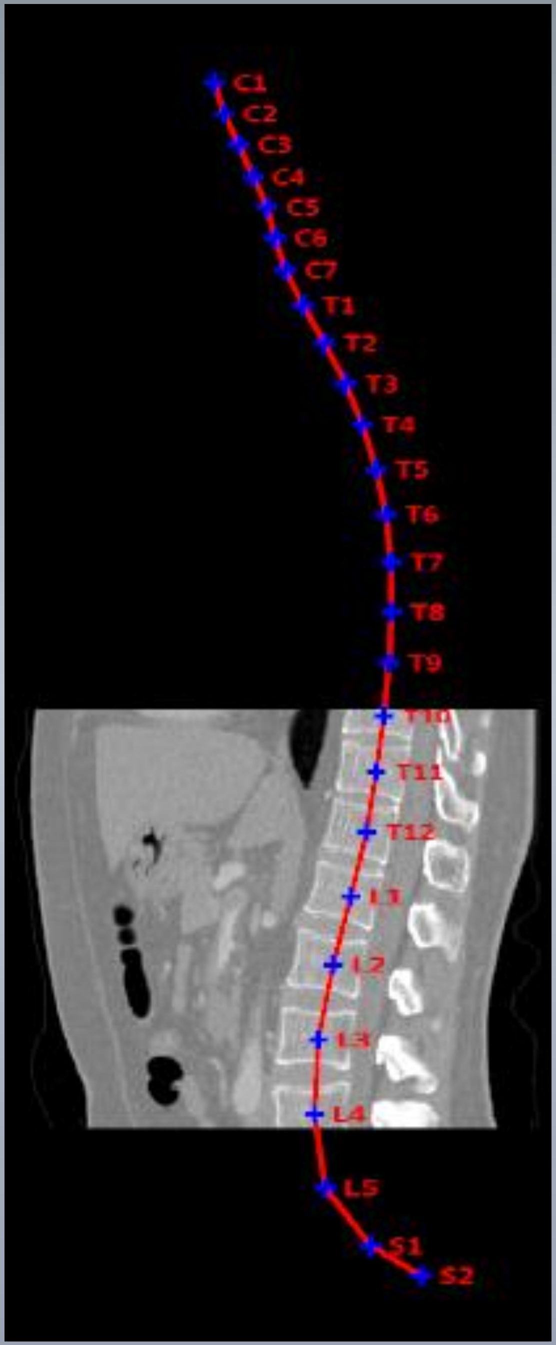
Patient-specific coordinate system

- Guided visualization/navigation in diagnostic tools

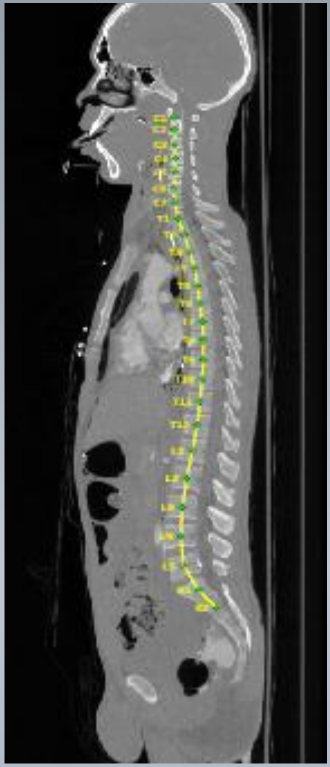
Impact on Clinical Routine!

- Longitudinal assessment after surgical Intervention
- Shape/population analysis for disease modelling

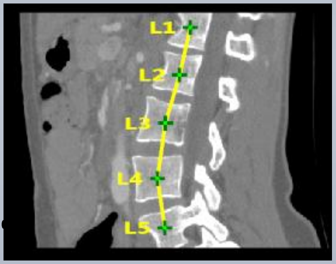
Impact on Clinical Research!

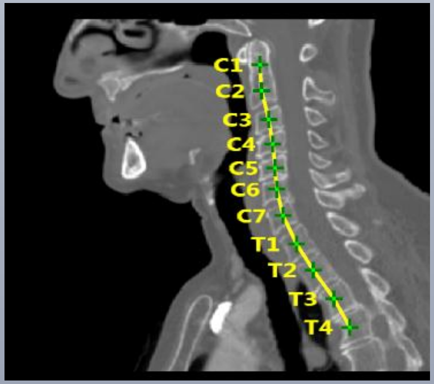


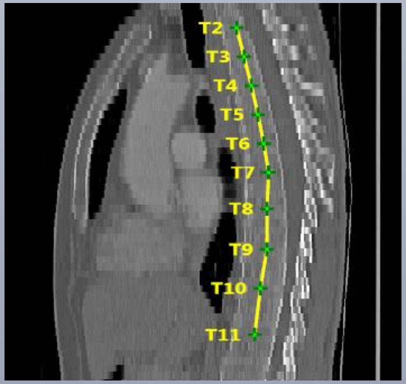
Challenges

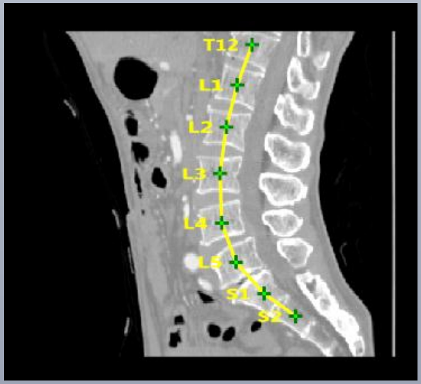


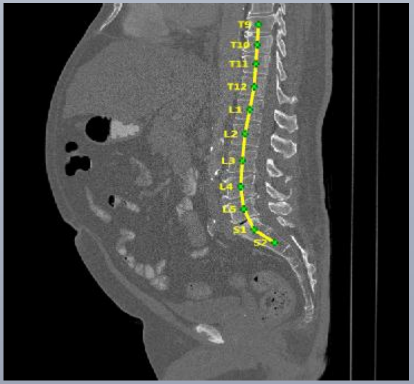
- Repetitive nature of structures
- Variability of normal anatomy
- Presence of pathologies
- Varying image acquisition (FOV, noise level, resolution, ..











Our Machine Learning Approach

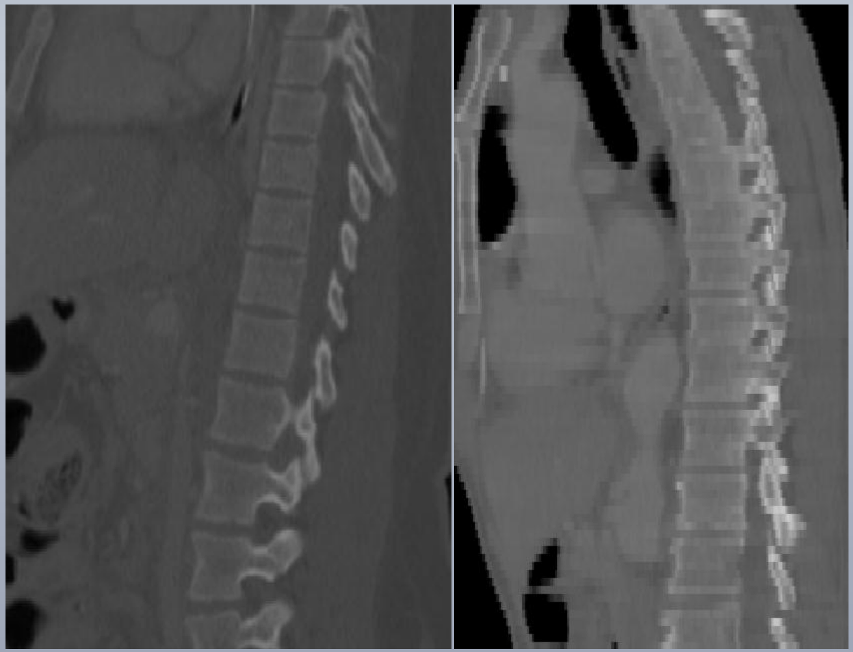
Two-stages:

1. Regression Forests
   – rough localization of visible part of the spine

2. Hidden Markov Model
   – accurate refinement using shape and appearance model

Experimental Setup

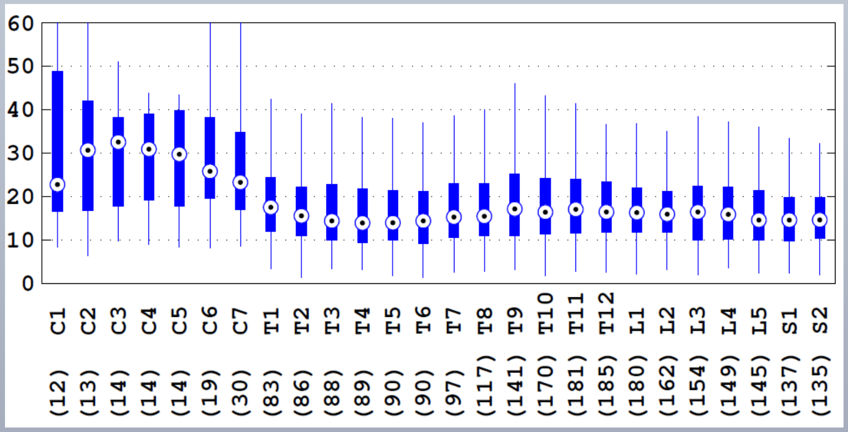
- 200 CT scans, trauma patients
- Slice distance [0.5, 6.5]mm (79 scans with 3.75mm)
- Number of slices: [51, 2058], 240 in average
- Visible parts: from 4 vertebrae up to whole-body scans
- Training/Testing split: 100/100

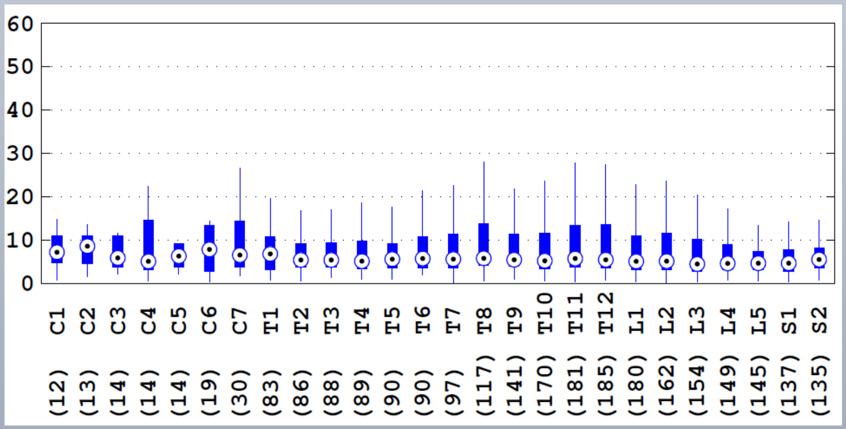


1mm 4mm

Quantitative Results

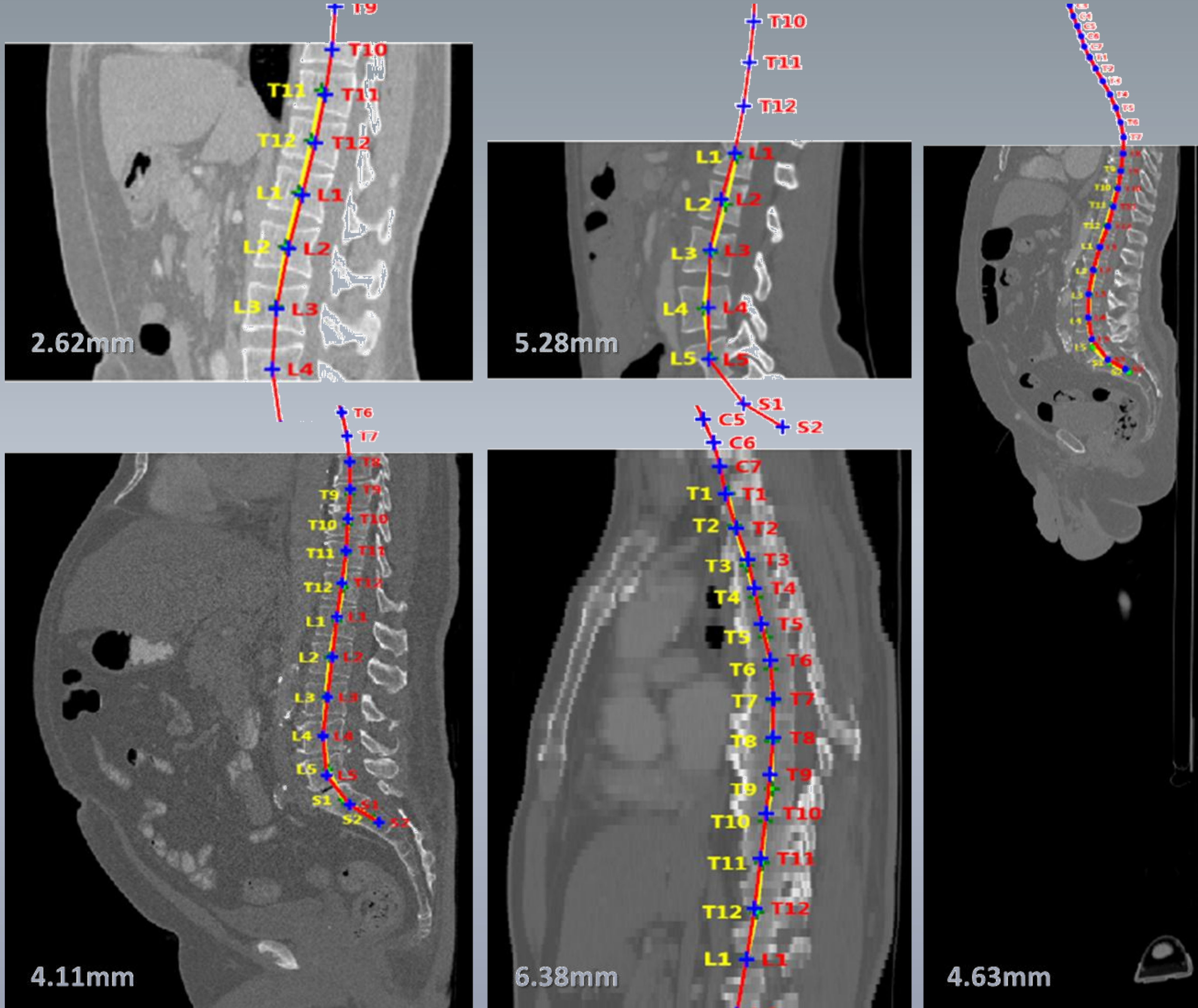
Vertebrae		Stage 1: Regression Forest			Stage 2: HMM			Distance to Closest			Identification	
Region	Counts	Median	Mean	Std	Median	Mean	Std	Median	Mean	Std	Correct	Rate
All	2595	15.91	18.35	11.32	5.31	9.50	10.55	4.79	6.10	5.53	2089	81%
Cervical	116	25.97	30.74	18.64	6.87	10.85	12.49	6.14	8.53	9.05	84	72%
Thoracic	1417	15.79	18.20	10.81	5.51	9.83	10.44	4.91	5.94	4.84	1100	78%
Lumbar	1062	15.40	17.20	10.07	4.88	8.92	10.45	4.59	6.06	5.82	905	85%

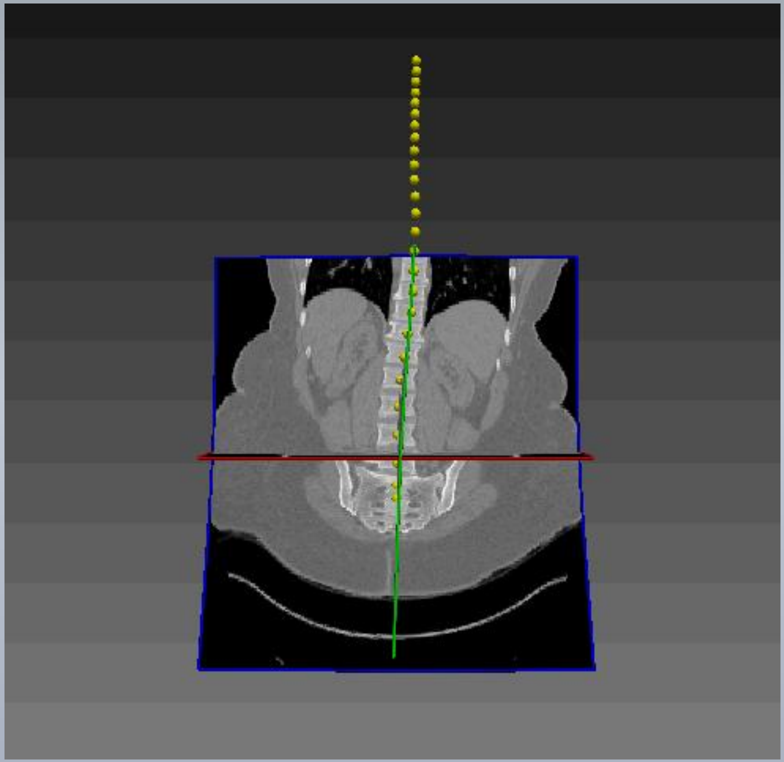


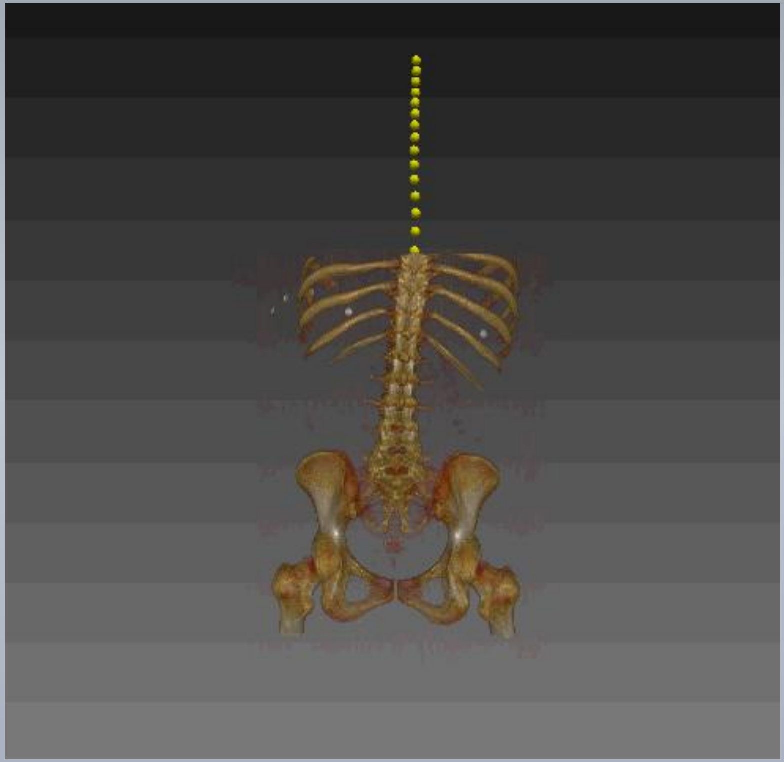


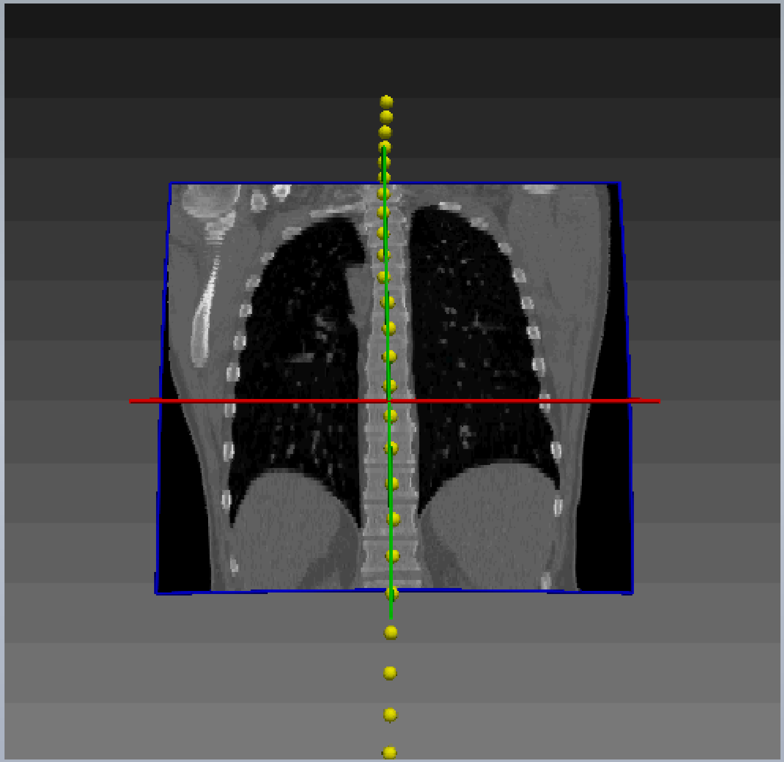
Stage 1: Forest
Run-Time: < 1s

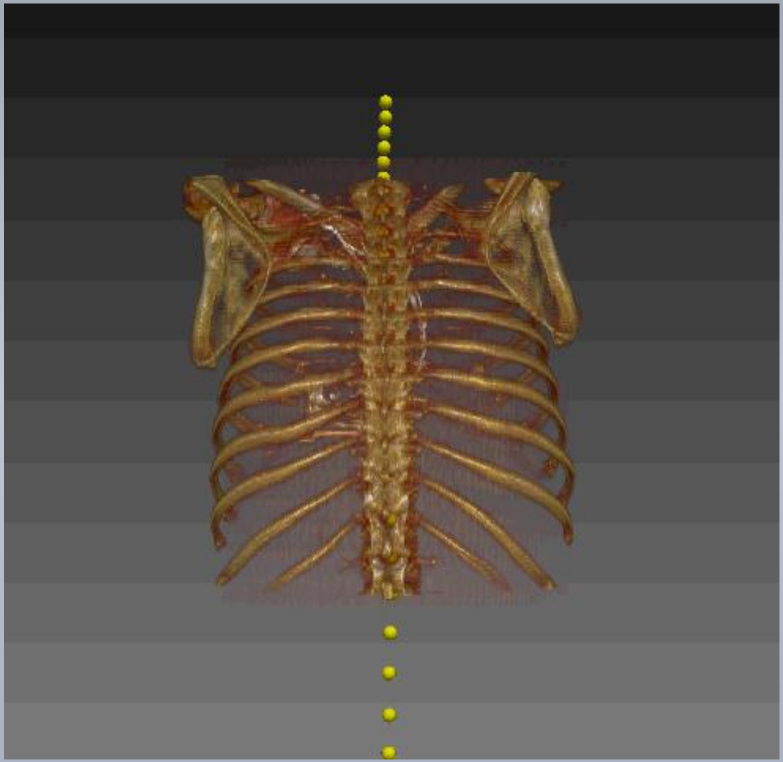
Stage 2: HMM
Run-Time: < 2min


2.62mm
5.28mm
4.63mm
4.11mm
6.38mm







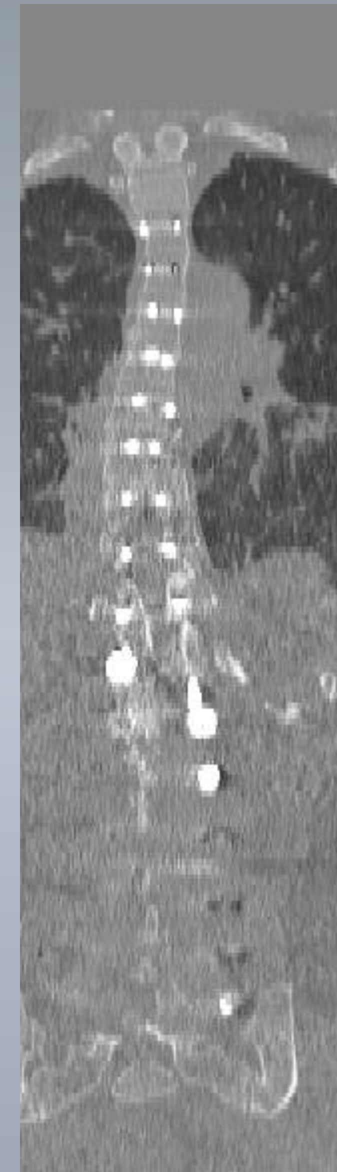


Outlook

Pre-op

Post-op

Pre-op



Post-op

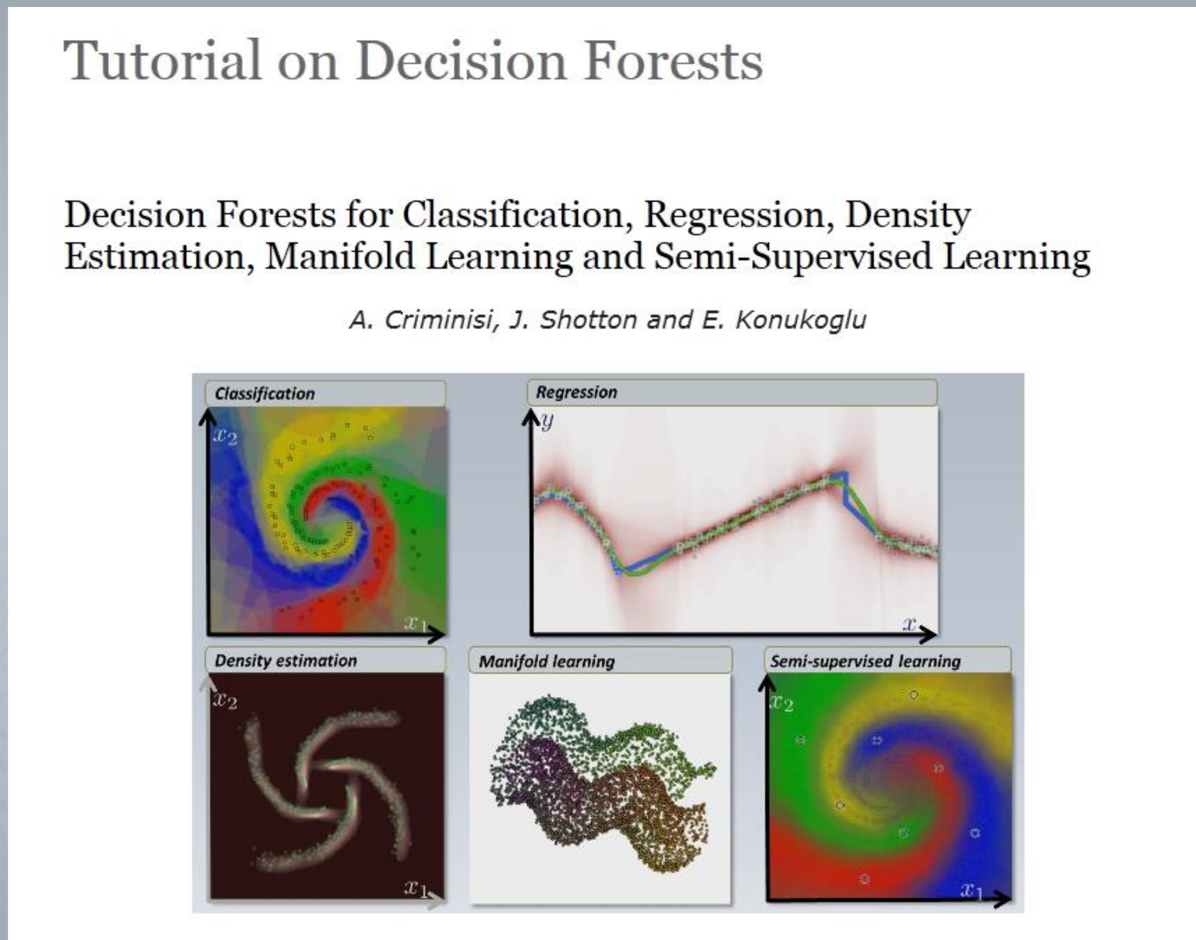
Summary

- **Glioblastoma:**
  - We achieve high-quality tissue-specific segmentations, surpassing quantitative results of previous state of the art

- **Spine:**
  - Accurate vertebra localization and identification. Automatic. Works for highly cropped images.

[Both papers to appear in MICCAI 2012, Nice, France, Oct 2012.]

More on decision forests



Tutorial on Decision Forests

Decision Forests for Classification, Regression, Density Estimation, Manifold Learning and Semi-Supervised Learning

A. Criminisi, J. Shotton and E. Konukoglu

http://research.microsoft.com/~antcrim