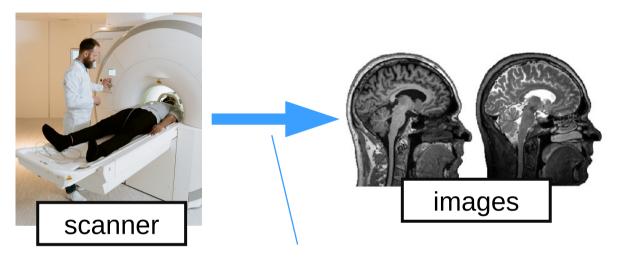
# Medical Image Analysis NBE-E4010



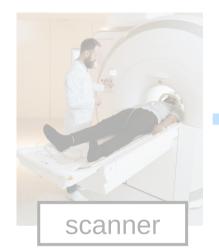
Koen Van Leemput Fall 2023

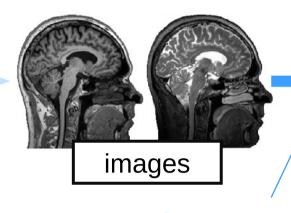
### AI in medical imaging



- acquire images faster
- visualize more details

### Al in medical imaging

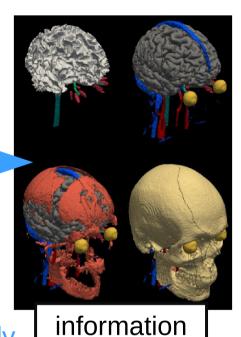




- expose the "unseeable"

- measure more consistently

- analyze images faster

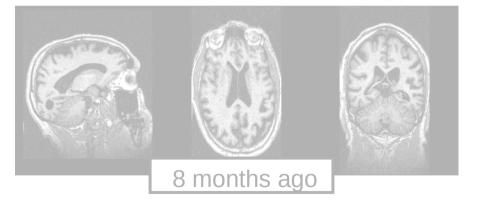


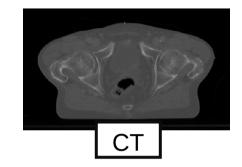
### **Exposing the "unseeable"**

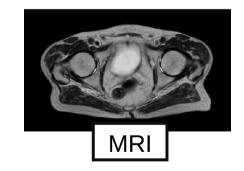


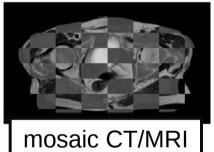
### **Exposing the "unseeable"**





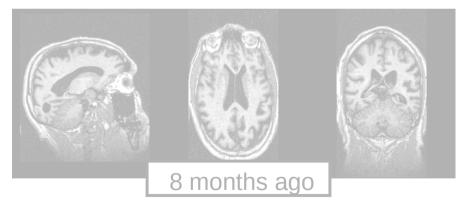


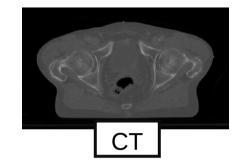


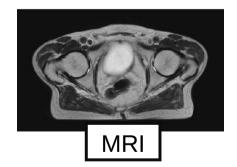


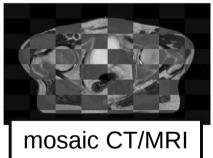
### **Exposing the "unseeable"**







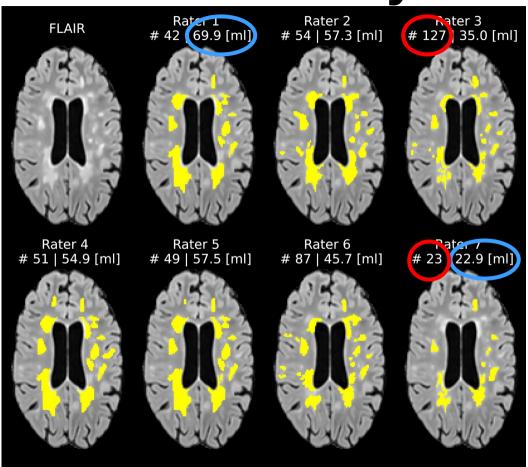




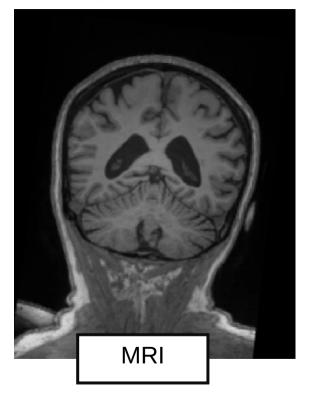
### Measuring more consistently

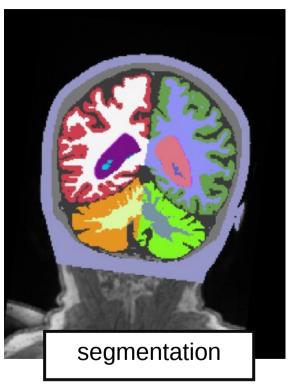
Quantifying lesions in multiple sclerosis (MS):

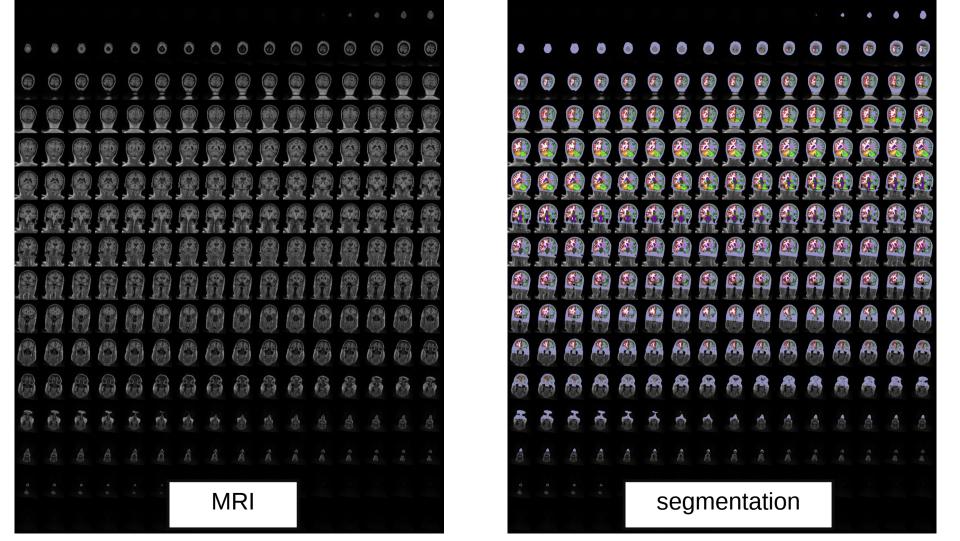
- number (#)
- volume (ml)



### **Analyzing images faster**







### Who are we?

- ✓ Koen Van Leemput (Professor, Neuroscience and Biomedical Engineering, Aalto University)
- ✓ Ida Granö (Doctoral Researcher, Neuroscience and Biomedical Engineering, Aalto University)
- ✔ Raymond Khazoum (Doctoral Researcher, Computer Science, Aalto University)







- Axel Thielscher (Professor, Health Technology, Technical University of Denmark)
- Oula Puonti (Postdoctoral Researcher, Health Technology, Technical University of Denmark)
- Merle Diedrichsen (Doctoral Researcher, Health Technology, Technical University of Denmark)









### Who are you?

- MSc in Life Science Technologies: 46
- Exchange studies: 8
- ✓ BSc in Electrical Engineering: 4
- ✓ MSc in Computer, Communication and Information Sciences: 3
- ✔ PhD in Science: 2
- BSc in Chemical Technology: 2
- MSc in Engineering Physics: 1
- BSc in Engineering: 1

67 students at Aalto

37 students at the Technical University of Denmark



### Learning objectives

### After this course you should be able to:

- ✓ Implement smoothing and interpolation operations in images
- Explain coordinate systems used in medical imaging
- ✔ Perform landmark-based and intensity-based image registration
- ✓ Select the most appropriate similarity measure for specific image registration problems
- ✓ Implement rigid, affine and nonlinear spatial transformation models
- ✓ Solve segmentation problems using generative models
- Perform image segmentation using example-based learning
- ✓ Weigh the advantages and limitations of model- vs. example-based techniques



### **Teaching form**

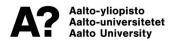
### Lectures:

- ✓ Tuesdays 14:15-16:00
- ✓ Live-streamed to/from Denmark
- ✓ Konetekniikka 1, 216 (until mid-October); Terveysteknologian talo, F239a (from mid-October)
- ✓ Two guest lectures: Jyrki Lötjönen (Combinostics) and Eero Salli (HUS Radiology)

### **Exercises:**

- ✓ Mondays 12:15-14:00
- Terveysteknologian talo, luentosali 1 F175a
- Python + Jupyter notebooks
- ✓ Group-work (max. 3 students per group)
- 2-3 weeks to submit a group report (6 reports in total)
- ✓ Grading: Peergrade + teachers' final assessment

no exam!



### Logistics

### https://mycourses.aalto.fi/

- Course material (lecture slides, book, ...)
- Announcements
- Discussion fora
- Submission of exercise reports

### ✓ Week 1

Lecture: Introduction to the course, Python and Jupyter notebooks

### ✓ Week 2

Lecture: Image smoothing and interpolation

### Week 3

Exercise session: Image smoothing and interpolation

Discussion forum: Image smoothing and interpolation exercise

Lecture: Coordinate systems, spatial transformations, landmarkbased registration

### ✓ Week 4

Exercise session: Image smoothing and interpolation (cont.)

Lecture: Intensity-based methods for registration

### ✓ Week 5

Exercise session: Landmarkbased registration

Discussion forum: Landmark-based registration exercise

Lecture: Nonlinear registration with Gauss-Newton

### ✓ Week 6

Exercise session:Mutual Information-based registration

Discussion forum: Mutual information-based registration

Lecture: Model-based segmentation I

### ✓ Week 7

Exercise session: Nonlinear registration

Discussion forum: Nonlinear registration exercise

Lecture: Model-based segmentation II

### ✓ Week 8

Exercise session: Modelbased segmentation

Discussion forum: Modelbased segmentation

Neural Networks

### ✓ Week 9

Exercise session: Modelbased segmentation (cont.)

Guest lecture: Jyrki Lötjönen (Combinostics)

### ✓ Week 10

Exercise session: Neural networks

Discussion forum: Neural networks exercise

Guest lecture: Eero Salli (HUS)

### ✓ Week 11

Exercise session: Neural networks (cont.)

Lecture: Neural networks in practice I

### ∨ Week 12

Lecture: Neural networks in practice II



## Python and Jupyter Notebooks

- Python: https://lectures.scientific-python.org/
- Jupyiter Notebooks: https://www.dataquest.io/blog/jupyter-notebook-tutorial/



### Image Smoothing and Interpolation

### Linear regression

-0.75

Let  $\mathbf{x}=(x_1,\dots,x_D)^T$  denote the spatial position in a D-dimensional space. In medical imaging, D is typically 2 or 3. Given N measurements  $\{r_n\}_{n=1}^N$  at locations  $\{\mathbf{x}_n\}_{n=1}^N$ , a frequent task is to predict the value i at a new location  $\mathbf{x}$ . A simple model, known as lemph[linear regression], uses the function value  $\mathbf{y}(\mathbf{x}_i, \mathbf{x}_i) = u_0 + u_1, \mathbf{x}_i + \dots + u_D \mathbf{x}_i + \dots + u_D \mathbf{x}_i$ 

as its prediction, where  $w_0, \dots, w_D$  are tunable weights that need to be estimatated from the available measurements. A more general form uses nonlinear functions of the input locations instead:

$$y(\mathbf{x}; \mathbf{w}) = w_0 + \sum_{m=1}^{M-1} w_m \phi_m(\mathbf{x}).$$

which greatly increases the flexibility of the model. Here the functions  $\phi_m(\mathbf{x})$  are known as \emph{basis functions}, and it is often convenient to define an additional ``dummy'' basis function  $\phi_n(\mathbf{x}) = 1$ , so that the model can be written as

$$y(\mathbf{x}; \mathbf{w}) = \sum_{m=0}^{M-1} w_m \phi_m(\mathbf{x}),$$

where  $\mathbf{w} = (w_0, \dots, w_{M-1})^T$  are M tunable parameters.

In order to find suitable values of the parameters of the model, the following energy can be minimzed with respect to w:

$$E(\mathbf{w}) = \sum_{n=1}^{N} \left( t_n - \sum_{n=1}^{M-1} w_m \phi_m(\mathbf{x}_n) \right)^2,$$

which simply sums of the squared distances between the measurements  $t_n$  and the model's predictions  $y(\mathbf{x}_n; \mathbf{w})$ .

```
In [4]: #
        import numpy as np
        from matplotlib import pyplot as plt
        plt.ion()
        ns = np.arange( N ).reshape( -1, 1 )
        A = np.cos(np.pi * (ns + 0.5) * np.arange(3) / N
        A[:, 0] *= 1/np.sqrt(2) # DC component is scaled differently
        plt.figure()
        plt.plot( ns, A )
Out[4]: [<matplotlib.lines.Line2D at 0x7fdf2fc61a60>,
         <matplotlib.lines.Line2D at 0x7fdf2fc6la90>
         <matplotlib.lines.Line2D at 0x7fdf2fc6fc70>]
          0.75
          0.50
         0.25
          0.00
         -0.25
         -0.50
```



### Jupyter notebooks at Aalto

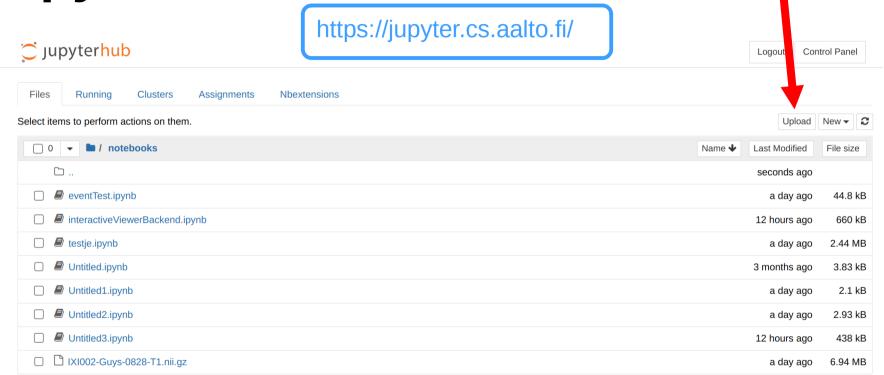
https://jupyter.cs.aalto.fi/

### Server Options

- Python: General use (JupyterLab) v6.1.4
- Python: General use (classic notebook) v6.1.4
- R: General use (JupyterLab) v5.0.25-jh401
- O Julia: General use (JupyterLab) v5.0.16-jh401
- (testing) Python: General use (JupyterLab) v6.0.0
- Old version (Junyterlah) vs 0.26

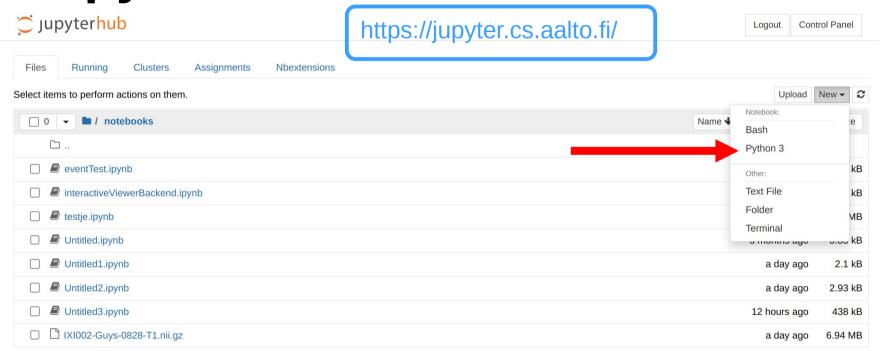


### Jupyter notebooks at Aalto





### Jupyter notebooks at Aalto





### Copyrights

"Accurate and robust whole-head segmentation from magnetic resonance images for individualized head modeling" by Puonti et al. NeuroImage (2020), licensed under CC-BY-NC-ND