

# Hands-on training for the Core Imaging Library (CIL)



an open-source reconstruction platform for challenging  
and novel data.

**Gemma Fardell – STFC**

**Jakob Sauer Jørgensen – DTU**

**Laura Murgatroyd – STFC**

**Evangelos Papoutsellis – STFC**

**Edoardo Pasca – STFC**



# CIL Team



# Training School Program

## Morning

### 9:00 Introduction to XCT and CIL

- CIL-Demos Notebook
- Exercise

### 10:30 Break

### 11:00 Pre-processing of XCT data

- CIL-Demos Notebook
- Exercise
- CIL GUI sneak preview

### 12:30 Lunch

## Afternoon

### 13:30 Introduction to iterative reconstruction methods for standard XCT data

- CIL-Demos Notebook
- Exercise

### 14:45 Break

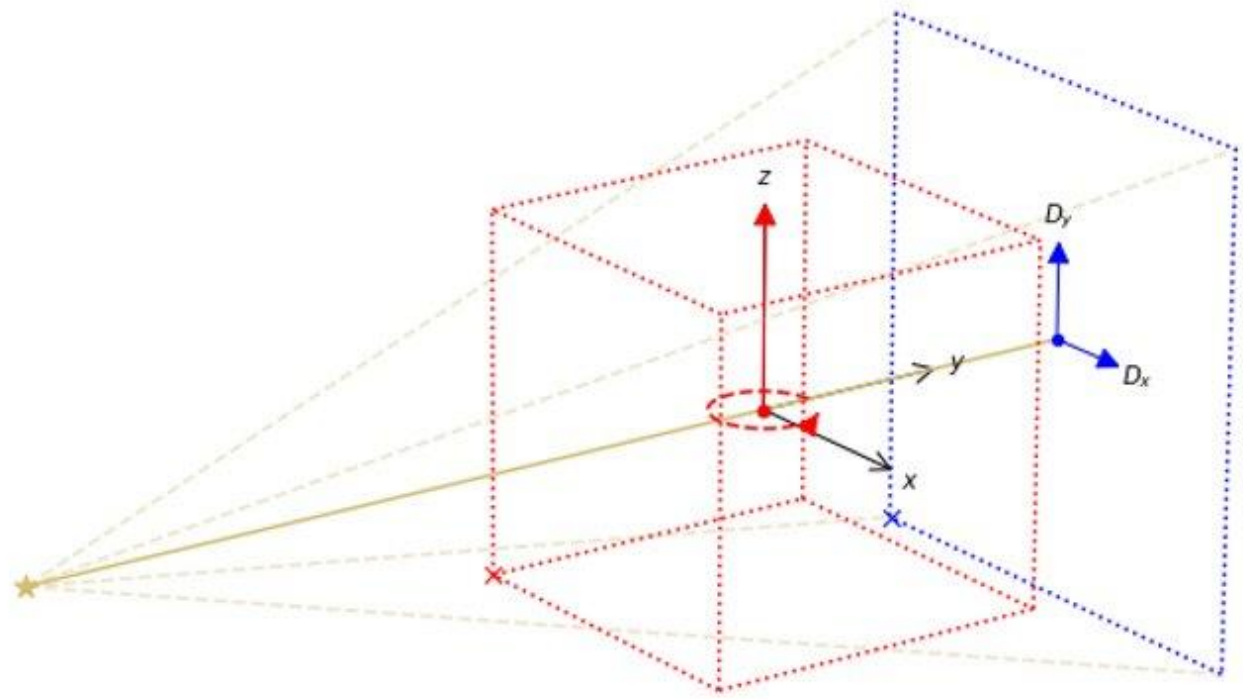
### 15:15 Choose an exercise

- Reconstruct data from gxVR
- Hyperspectral XCT
- Laminography
- Reduced data

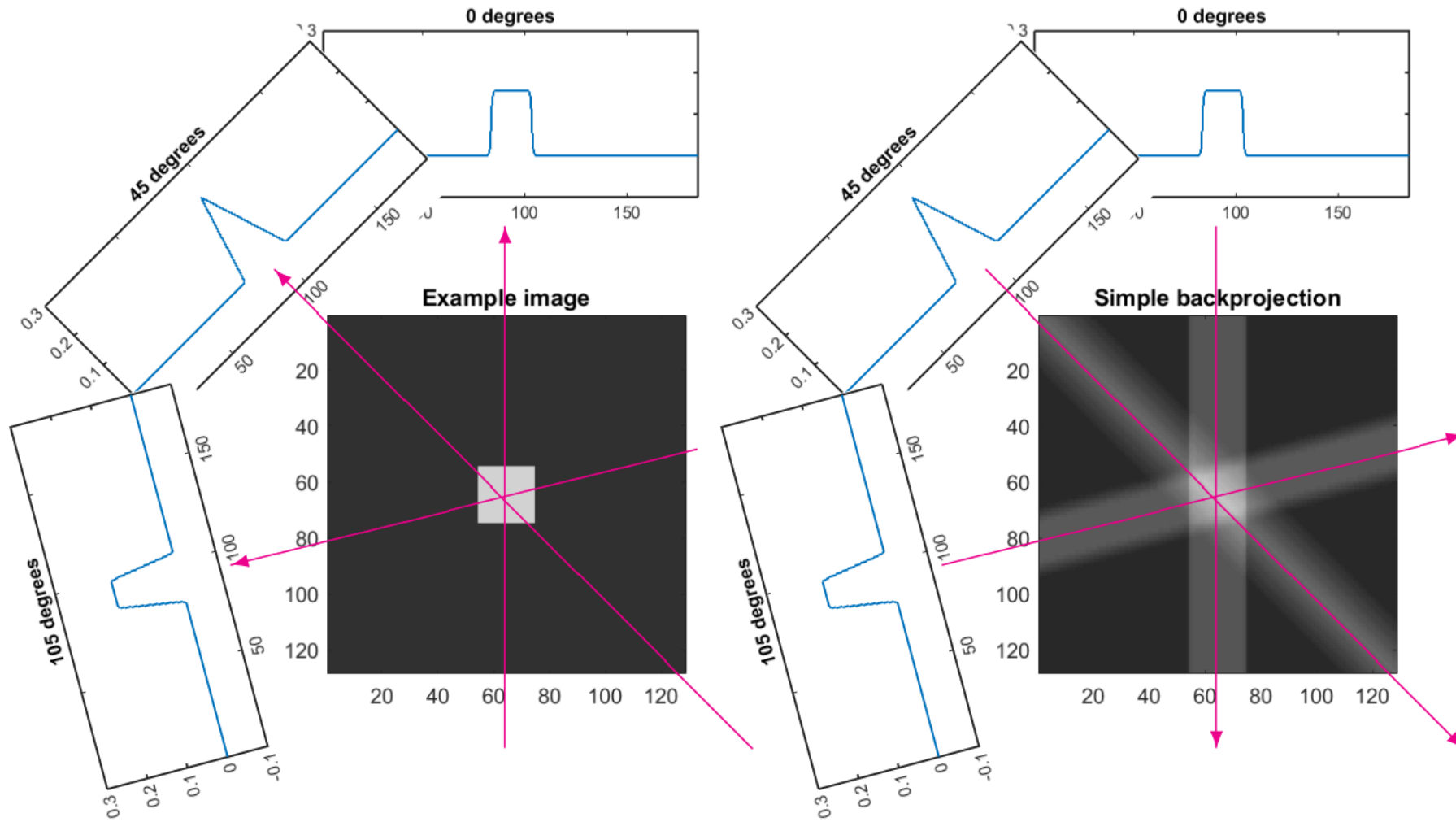
### 17:00 End of workshop

# Tomography

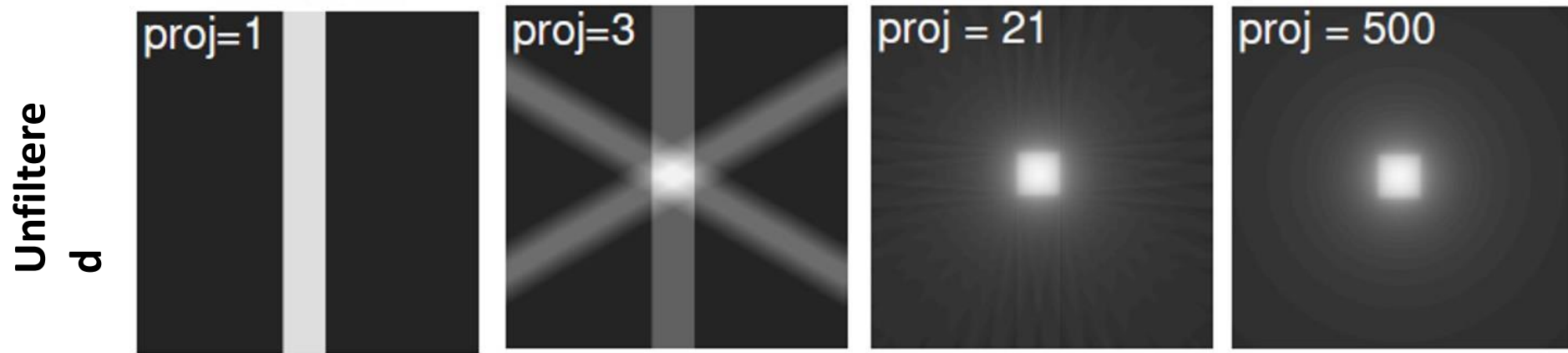
- world coordinate system
- ★ source position
- rotation axis position
- rotation axis direction
- ⋯ image geometry
- × data origin (voxel 0)
- rotation direction  $\theta$
- detector position
- detector direction
- ⋯ detector
- × data origin (pixel 0)



# Filtered Back Projection (FBP)

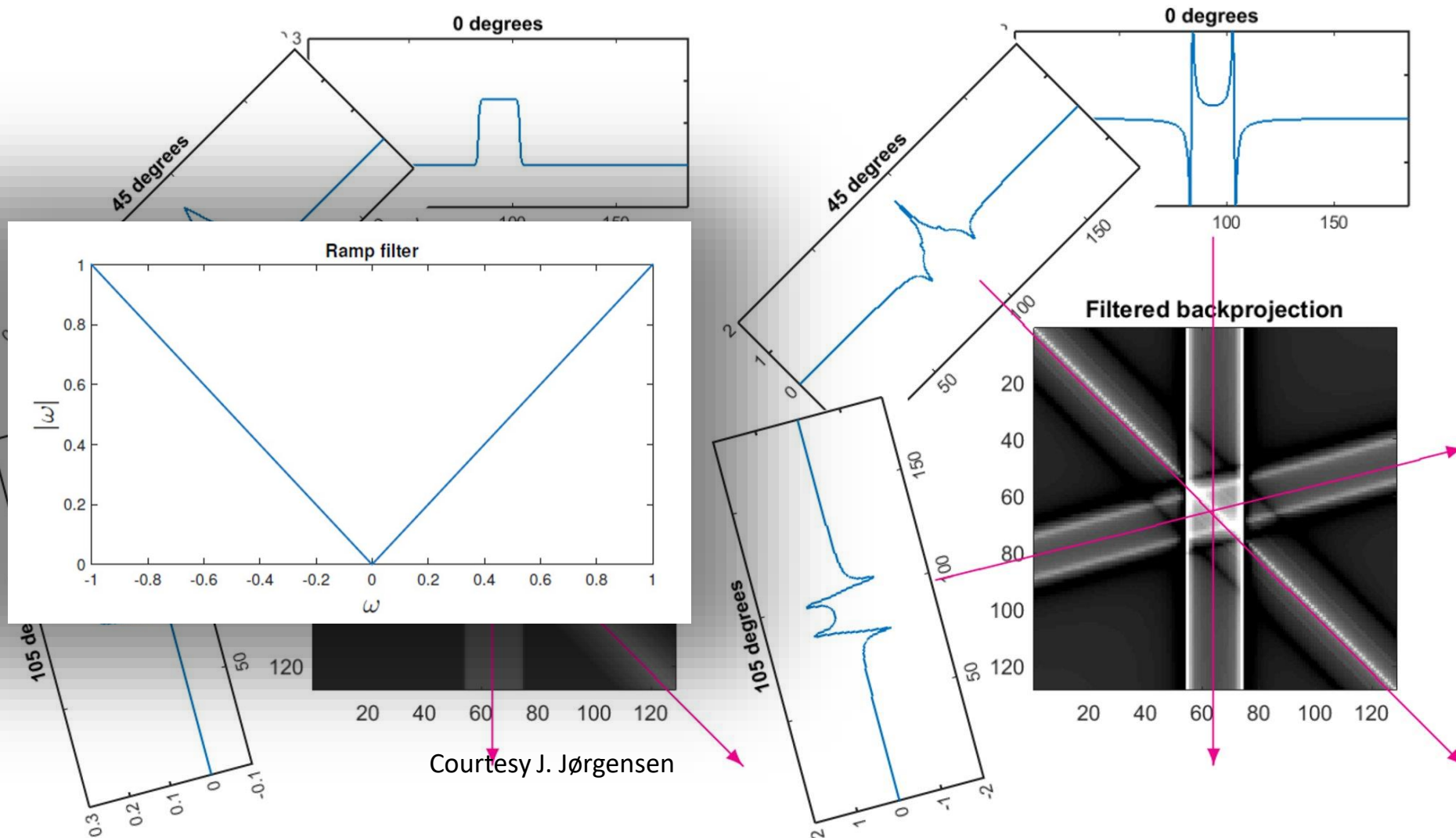


# Filtered Back Projection (FBP)

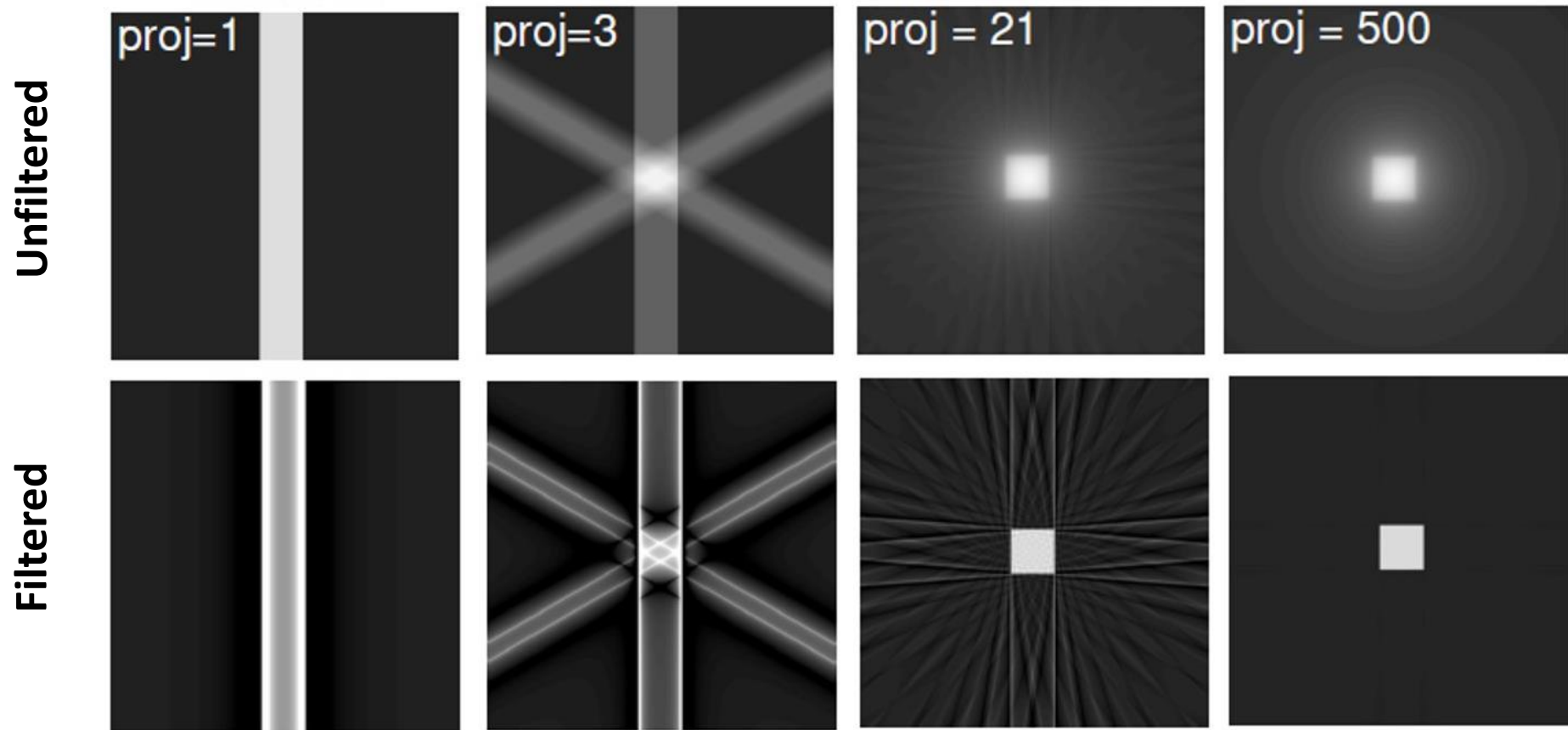


Courtesy J. Jørgensen

# Filtered Back Projection (FBP)



# Filtered Back Projection (FBP)



Courtesy J. Jørgensen



# Filtered Back Projection (FBP)

## Pros

- Fast as based on FFT and backprojection
- Few parameters
- Typically works very well
- Reconstruction behaviour well understood

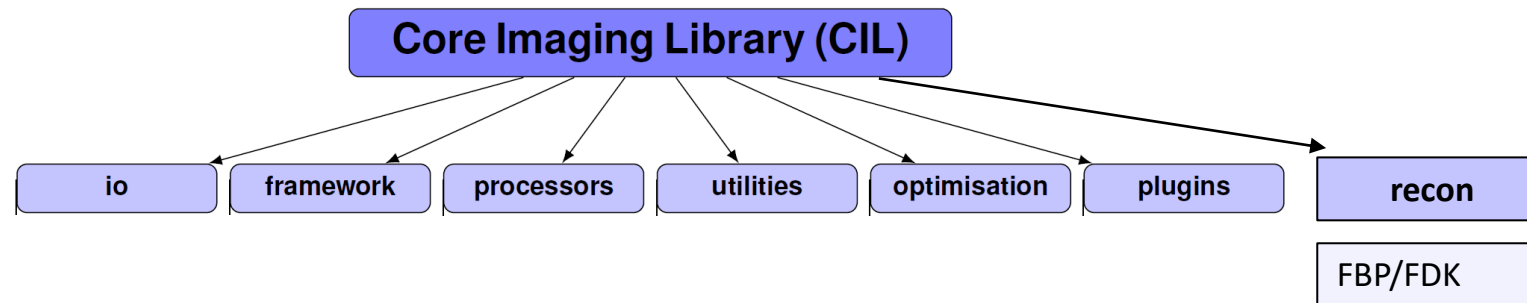
# What is the Core Imaging Library?

- A Python library for **processing** and **reconstruction** of tomography data.
- Optimised standard methods, such as **Filtered Back Projection**
- Special emphasis on *challenging data sets*: noisy, non-standard, incomplete, multi-channel, ...
- Highly modular to allow creation of bespoke pipelines.
- Apache v2 license.
- Actively developed on GitHub: <https://github.com/TomographicImaging/CIL>

# Who is CIL for?

- CT experimentalists
  - **Optimised** standard algorithms for large data
  - Batch processing
  - To utilise reconstruction algorithms for **poor data quality** or to handle novel imaging modalities
- image processing specialists
  - to easily implement new reconstruction algorithms
  - **assess** them against existing ones.

# CIL Module Structure and Contents



Jørgensen et al. 2021: *Core Imaging Library - Part I: a versatile Python framework for tomographic imaging*, Phil. Trans. R. Soc. A, **379**, 20200192: <https://doi.org/10.1098/rsta.2020.0192>

The **cil.plugins** module contains wrapper code for other software and third-party libraries that need to be installed separately to be used by CIL.

<https://tomographicimaging.github.io/CIL>

Framework Read/ write AcquisitionData and ImageData **Optimisation framework** Processors Recon Utilities D

## Table of Contents

Contents:

- Framework
- Read/ write AcquisitionData and ImageData
- Optimisation framework
  - Algorithm
  - Operator
    - Operator base classes
    - Trivial operators
    - GradientOperator
  - Function
    - Base classes
    - Simple functions
    - Composition of operator and a function
    - Indicator box
    - KullbackLeibler
    - L1 Norm
    - Squared L2 norm squared
    - Least Squares
    - Mixed L21 norm
    - Smooth Mixed L21 norm
    - Total variation
- Block Framework
  - BlockDataContainer
  - Block Function
  - Block Operator
- Processors
- Recon
- Utilities
- Developer's guide

### Note

Currently, the strongly convex constants are passed as parameters of PDHG. In the future, these parameters will be properties of the corresponding functions.

### Notes

A first-order primal-dual algorithm for convex optimization problems with known saddle-point structure with applications in imaging.

The general problem considered in the PDHG algorithm is the generic saddle-point problem

$$\min_{x \in X} \max_{y \in Y} (Kx, y) + g(x) - f^*(y)$$

where  $f$  and  $g$  are convex functions with "simple" proximal operators.

$X$  and  $Y$  are two finite-dimensional vector spaces with an inner product and representing the domain of  $g$  and  $f^*$ , the convex conjugate of  $f$ , respectively.

The operator  $K$  is a continuous linear operator with operator norm defined as

$$\|K\| = \max\{\|Kx\| : x \in X, \|x\| \leq 1\}$$

The saddle point problem is decomposed into the primal problem:

$$\min_{x \in X} f(Kx) + g(x),$$

and its corresponding dual problem

$$\max_{y \in Y} -g^*(-K^*y) - f^*(y).$$

The PDHG algorithm consists of three steps:

- gradient ascent step for the dual problem,
- gradient descent step for the primal problem and
- an over-relaxation of the primal variable.

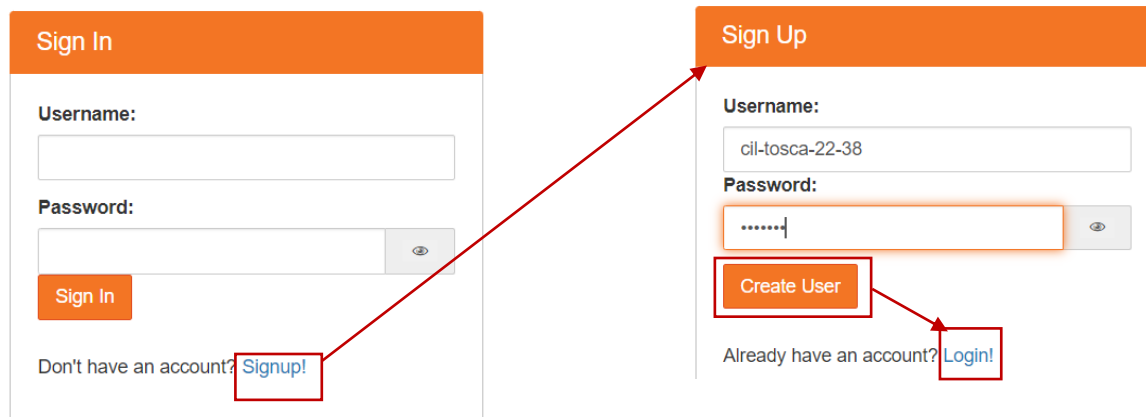
$$y^{n+1} = \text{prox}_{\sigma f^*}(y^n + \sigma Kx^n)$$

$$x^{n+1} = \text{prox}_{\tau g}(x^n - \tau K^*y^{n+1})$$

$$\bar{x}^{n+1} = x^{n+1} + \theta(x^{n+1} - x^n)$$

# Log in to JupyterHub

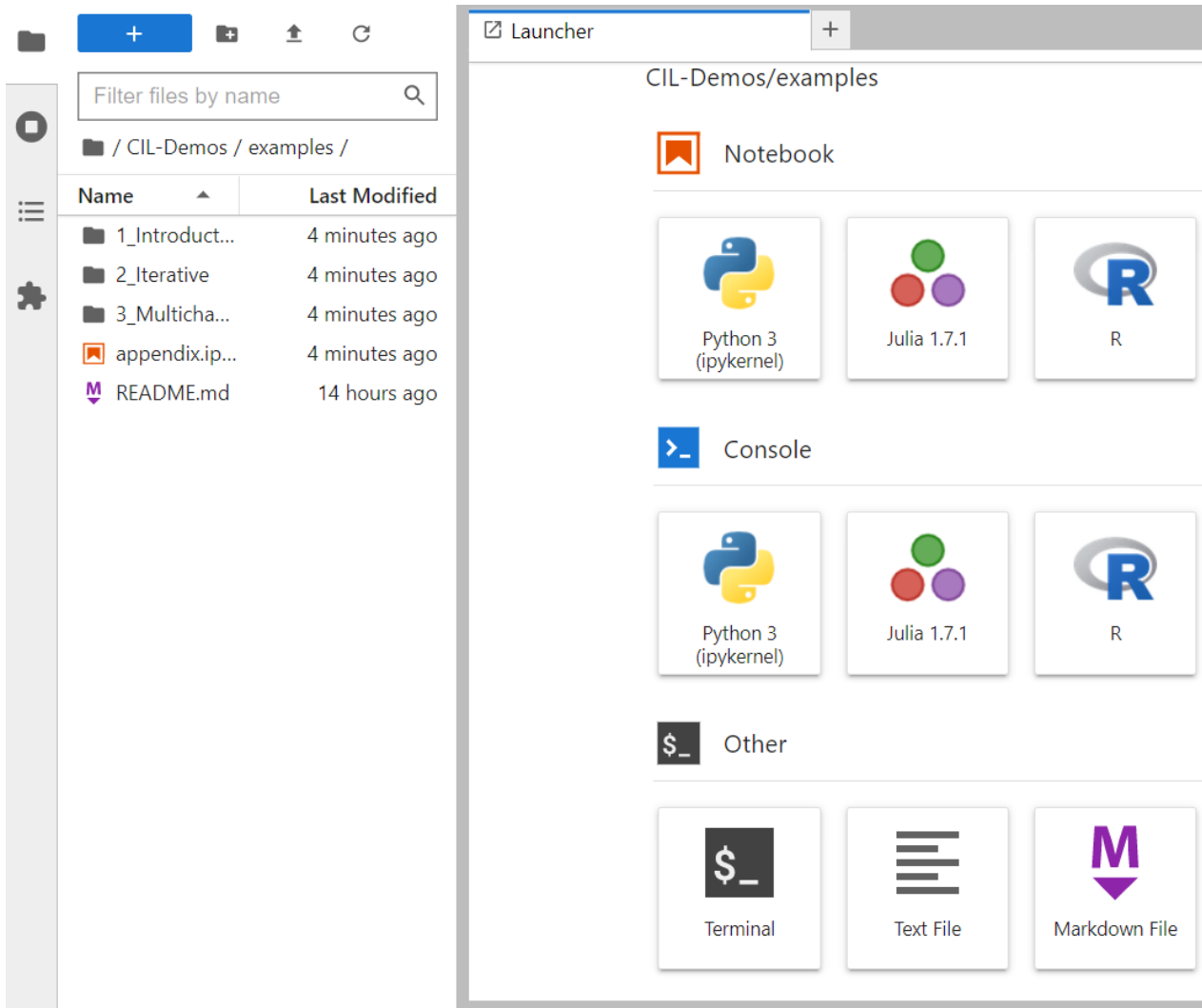
- Go to: <https://ibsim.co.uk/training> and write your name next to a username to claim it for the exercises
- Hands-on exercises at CIL Jupyter notebook server: <https://training.jupyter.stfc.ac.uk/>
- Sign up with the username you claimed and a password of your choice.
- No password reset option, so remember your password!
- Then log in with the username and password you set.
- Select the **OpenGL GPU environment** server and press "start":



## Server Options

- Default: Normal Size**  
For small jobs and prototyping: 2 CPUs, 1.5GB RAM and no GPU.
- Tensorflow GPU environment**  
This configuration gives you 10 CPUs, 70GB of RAM, and a GPU, Tensorflow environment
- OpenGL GPU environment**  
This configuration gives you 10 CPUs, 70GB of RAM, and a GPU and sets up an OpenGL environment

# Once logged in ...



Filter files by name

/ CIL-Demos / examples /

Name	Last Modified
1_Introduct...	4 minutes ago
2_Iterative	4 minutes ago
3_Multicha...	4 minutes ago
appendix.ip...	4 minutes ago
README.md	14 hours ago

Launcher

CIL-Demos/examples

Notebook

- Python 3 (ipykernel)
- Julia 1.7.1
- R

Console

- Python 3 (ipykernel)
- Julia 1.7.1
- R

Other

- Terminal
- Text File
- Markdown File

# Let's Try Out the Walnut Notebook!

Go to:

`CIL-Demos/examples/1_Introduction/01_intro_walnut_conebeam.ipynb`

Learning Objectives:

- Load and investigate a ZEISS data set.
  - Apply CIL's TransmissionAbsorptionConverter.
  - Compute FDK reconstruction using CIL and compare with a reconstruction made from fewer projections.
  - Write out the reconstructed image to a TIFF stack.
- 
- Go to: <https://ibsim.co.uk/training> - write your name next to a username to claim it for the exercises
  - CIL Jupyter notebook server: <https://training.jupyter.stfc.ac.uk/>
  - Sign up with the username you claimed and a password of your choice.



# Questions?

# Exercise 1

- Make your own reconstruction as the Walnut with a Nikon dataset

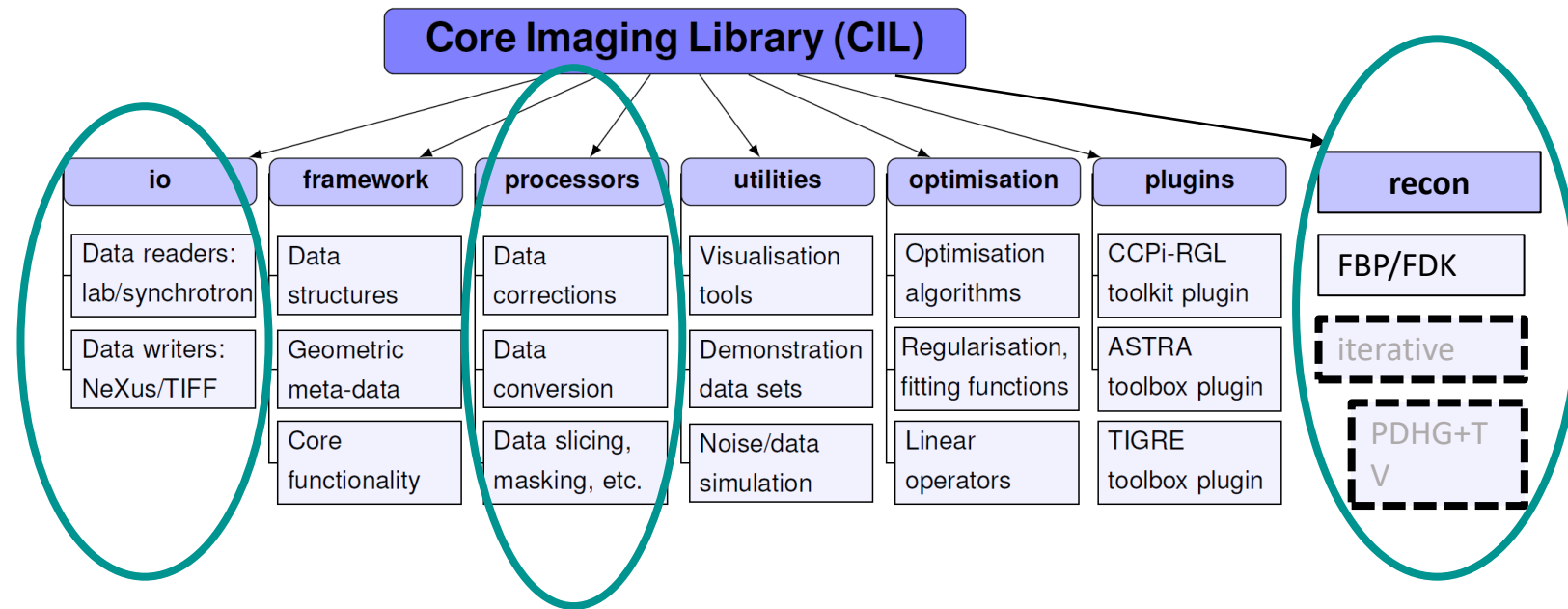
# Questions?



# Session 2

## Pre-processing of XCT data

# CIL Module Structure and Contents



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# Typical XCT Data Pre-Processing

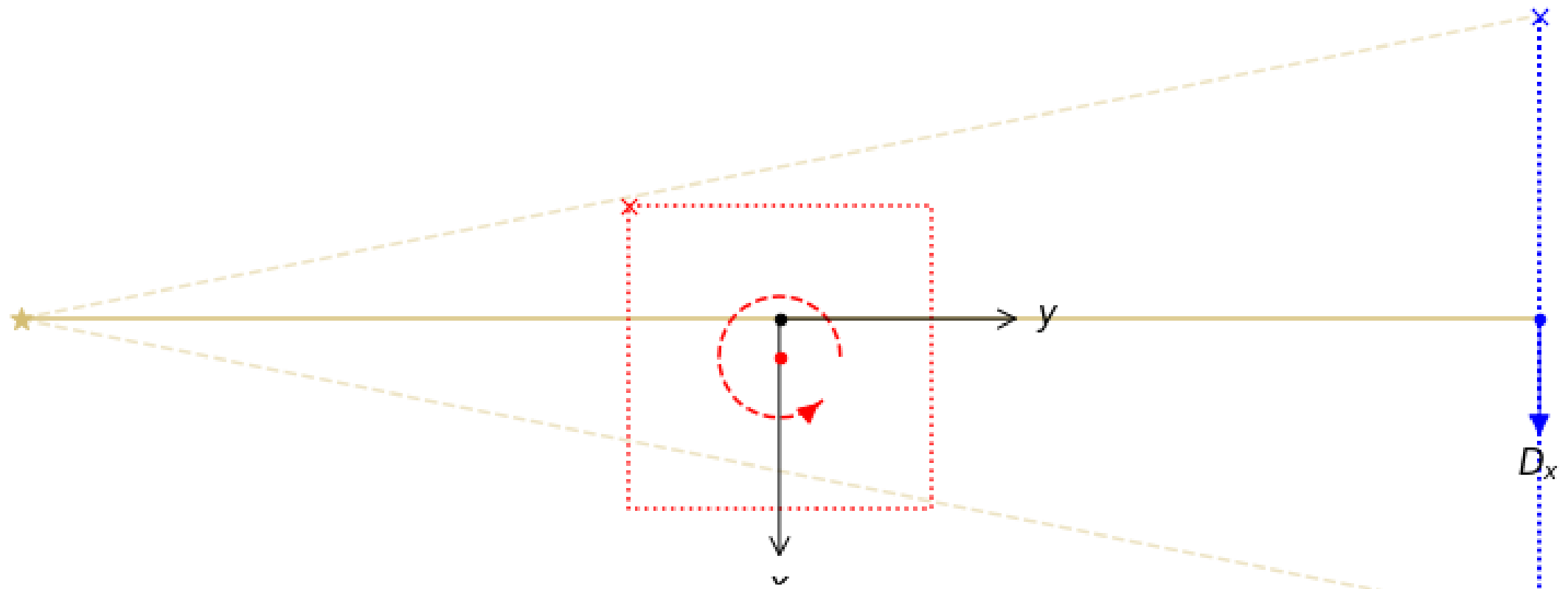
## Data Manipulation

- Data Slicer
- Data Binner
- Data Padder
- Mask Generator from Data
- Data Masking

## Pre-processors

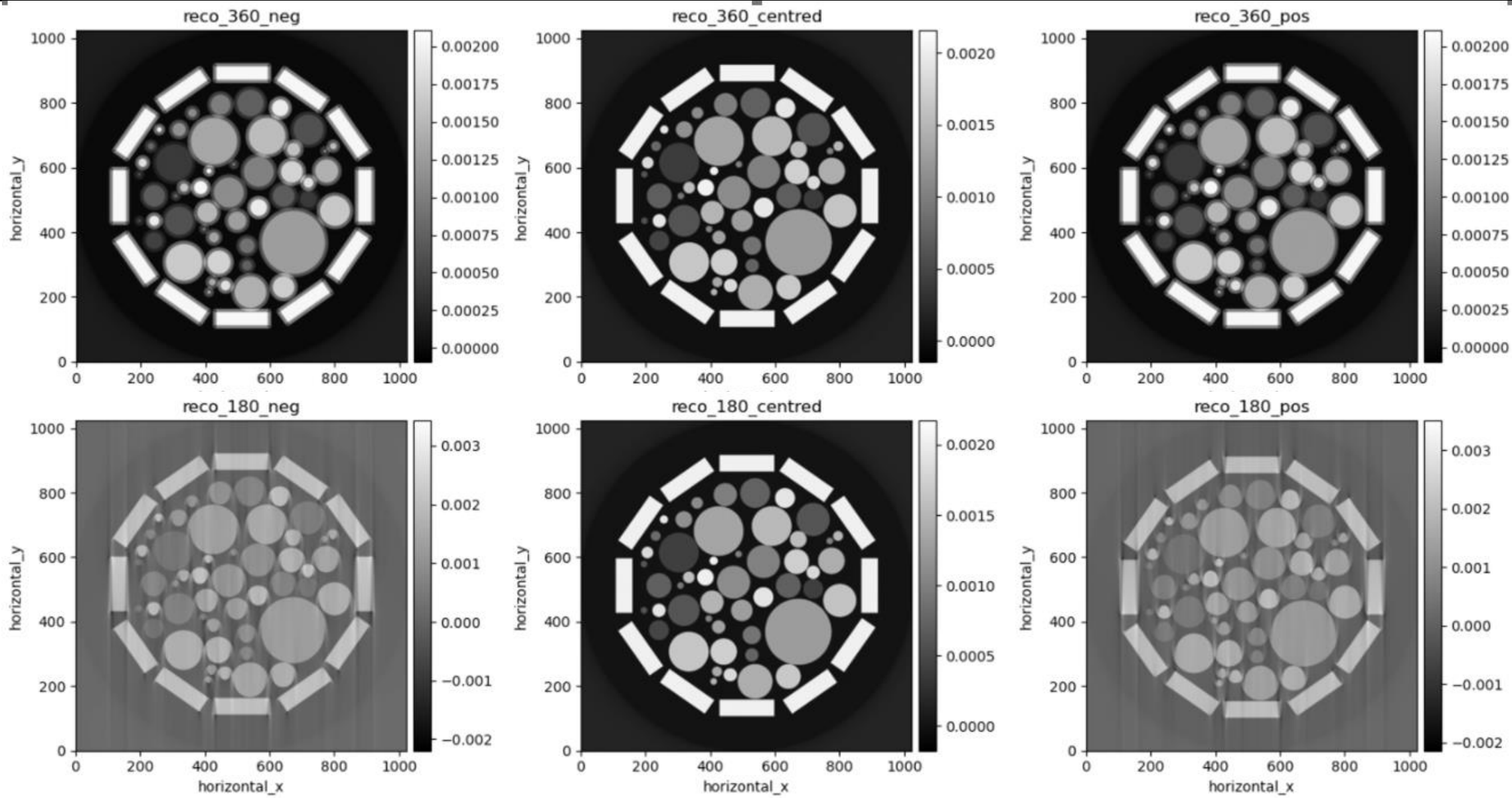
- Centre Of Rotation Correction
- Data Normaliser
- Transmission to Absorption Converter
- Absorption to Transmission Converter
- Ring Remover

# Centre of Rotation



- world coordinate system
- ★ source position
- rotation axis position
- rotation axis direction
- ⋯ image geometry
- × data origin (voxel 0)
- - - rotation direction  $\theta$
- detector position
- detector direction
- ⋯ detector
- × data origin (pixel 0)

# Centre of Rotation





# Let's Pre-Process

Go to:  
`CIL-Demos/examples/1_Introduction /02_intro_sandstone_parallel_roi.ipynb`

## Learning Objectives:

- Load and investigate a real data set.
  - Determine geometric information of the data and set up CIL data structures.
  - Apply CIL processors to pre-process the data, including normalisation, negative log, region-of-interest and centre of rotation correction.
  - Compute FBP reconstruction using CIL and compare with reconstruction provided.
- 
- Go to: <https://ibsim.co.uk/training> - write your name next to a username to claim it for the exercises
  - CIL Jupyter notebook server: <https://training.jupyter.stfc.ac.uk/>
  - Sign up with the username you claimed and a password of your choice.

# Questions?

# Exercise 2

- As above, with different dataset from Nikon? (seeds in a box, uncentred?, centring? Slicer? Binner? Reconstruction volumes?, advanced exercise, do the same with a different dataset?)
- GUI demo with seeds in the box

# Questions?

# Session 3

## Iterative reconstruction methods for standard XCT data

# Filtered Back Projection (FBP)

## Pros

- Fast as based on FFT and backprojection
- Few parameters
- Typically works very well
- Reconstruction behaviour well understood

## Cons

- Number of projections needed proportional to acquisition panel size
- Full angular range required (limited angle problem)
- Modest amount of noise tolerated
- Fixed scan geometries
- Cannot make use of prior knowledge such as non-negativity

# Imaging model for iterative reconstruction

Beer-Lambert for  $i$ th ray (along line  $L_i$ ):

$$\frac{I}{I_0} = \int e^{-\mu(x)} dx \quad \int_{L_i} \mu ds = -\log \frac{I_i}{I_0} = b_i$$

Assume object constant in each pixel:

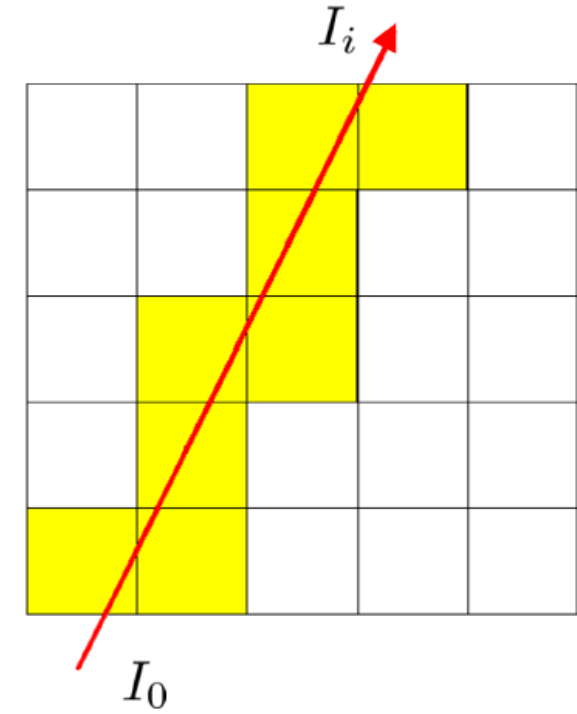
- ▶  $u_j$  is the  $j$ th pixel value.
- ▶  $a_{ij}$  is path length through  $j$ th pixel.

Approximate line integral by sum:

$$\sum_j a_{ij} u_j = b_i$$

Extremely large set of linear equations:

$$Au = b$$



### Operator A:

- Direct  $Au$ : Projection
- Adjoint  $A^T b$ : Backprojection

# Iterative reconstruction is based on optimisation problems and algorithms

Discrete imaging model:

$$Au = b$$

Typical CT images:

- ▶ Regions of homogeneous tissue.
- ▶ Separated by sharp boundaries.



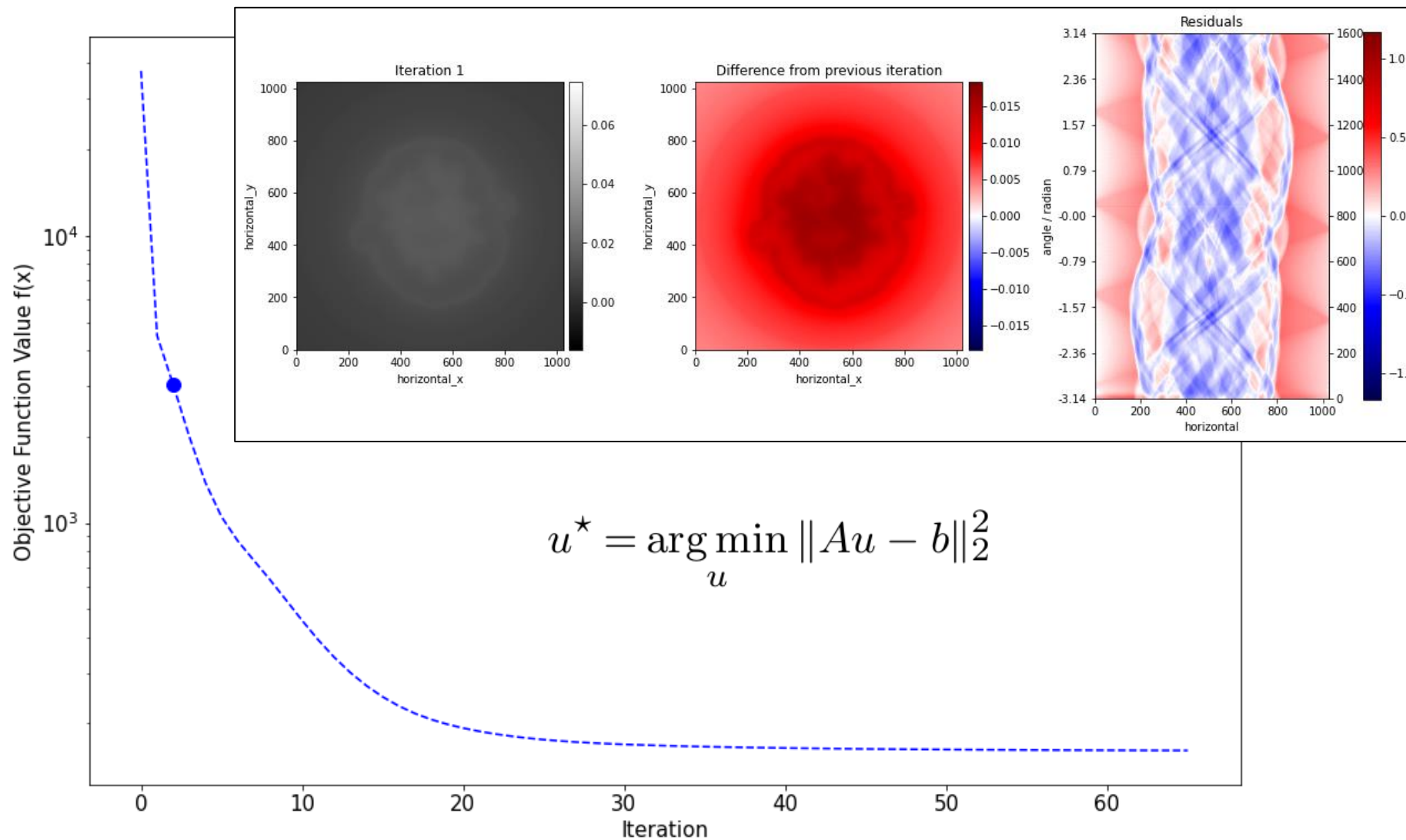
Reconstruction

$$u^* = \operatorname{argmin}_u \{ \mathcal{D}(Au, b) \}$$

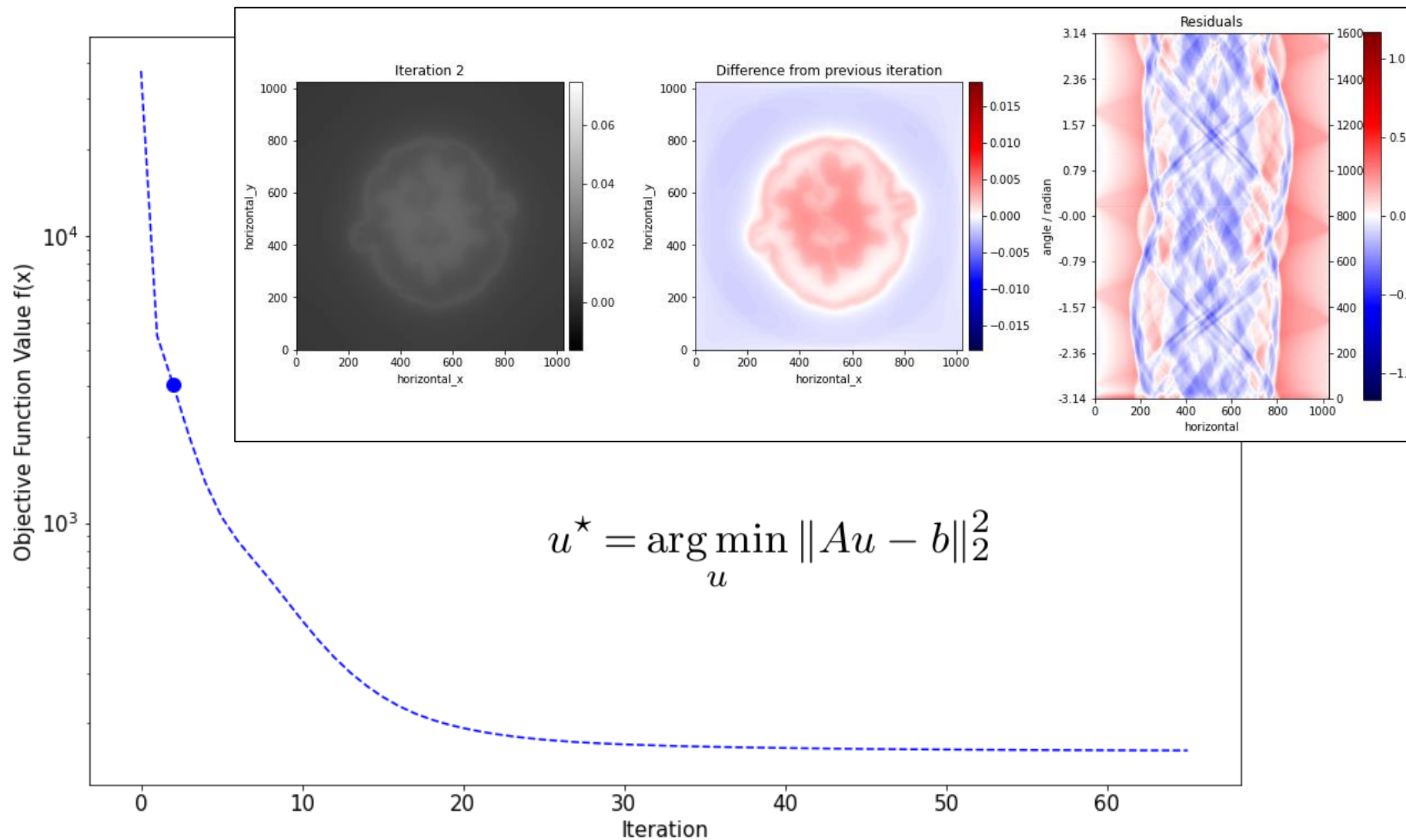
$$u^* = \operatorname{argmin}_u \|Au - b\|_2^2 = \sum_i ((Au)_i - b_i)^2$$



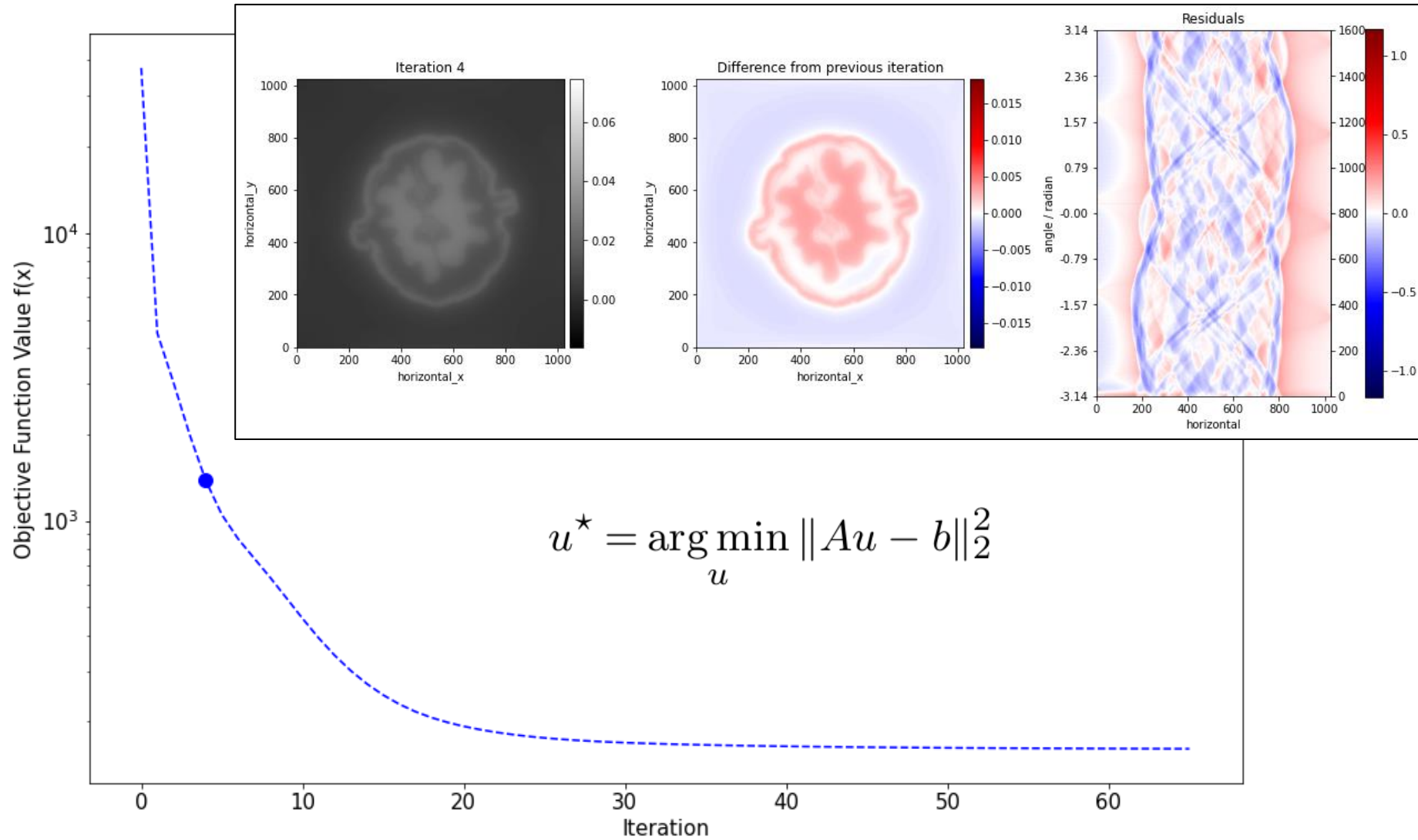
# Solve optimisation problem iteratively



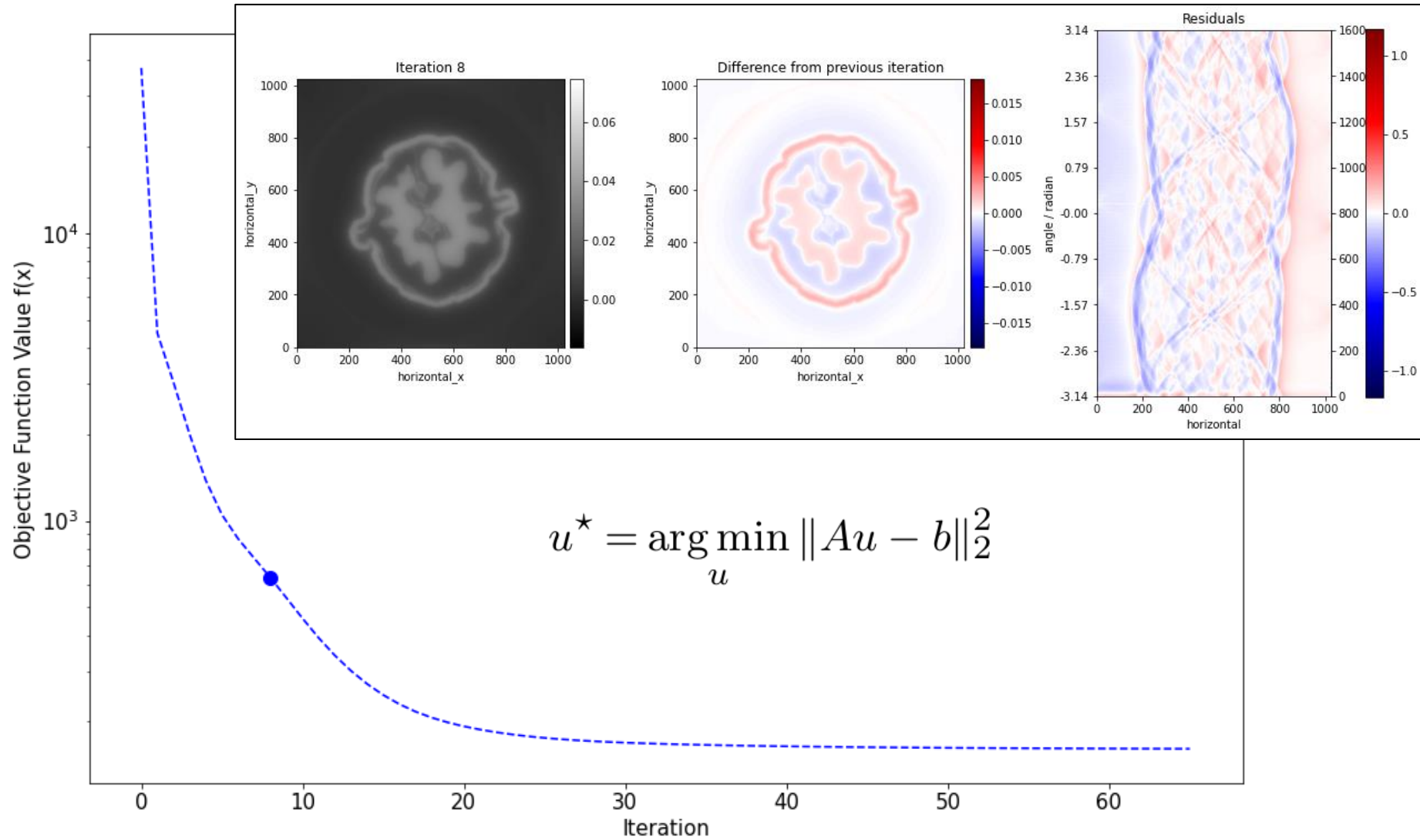
# Solve optimisation problem iteratively



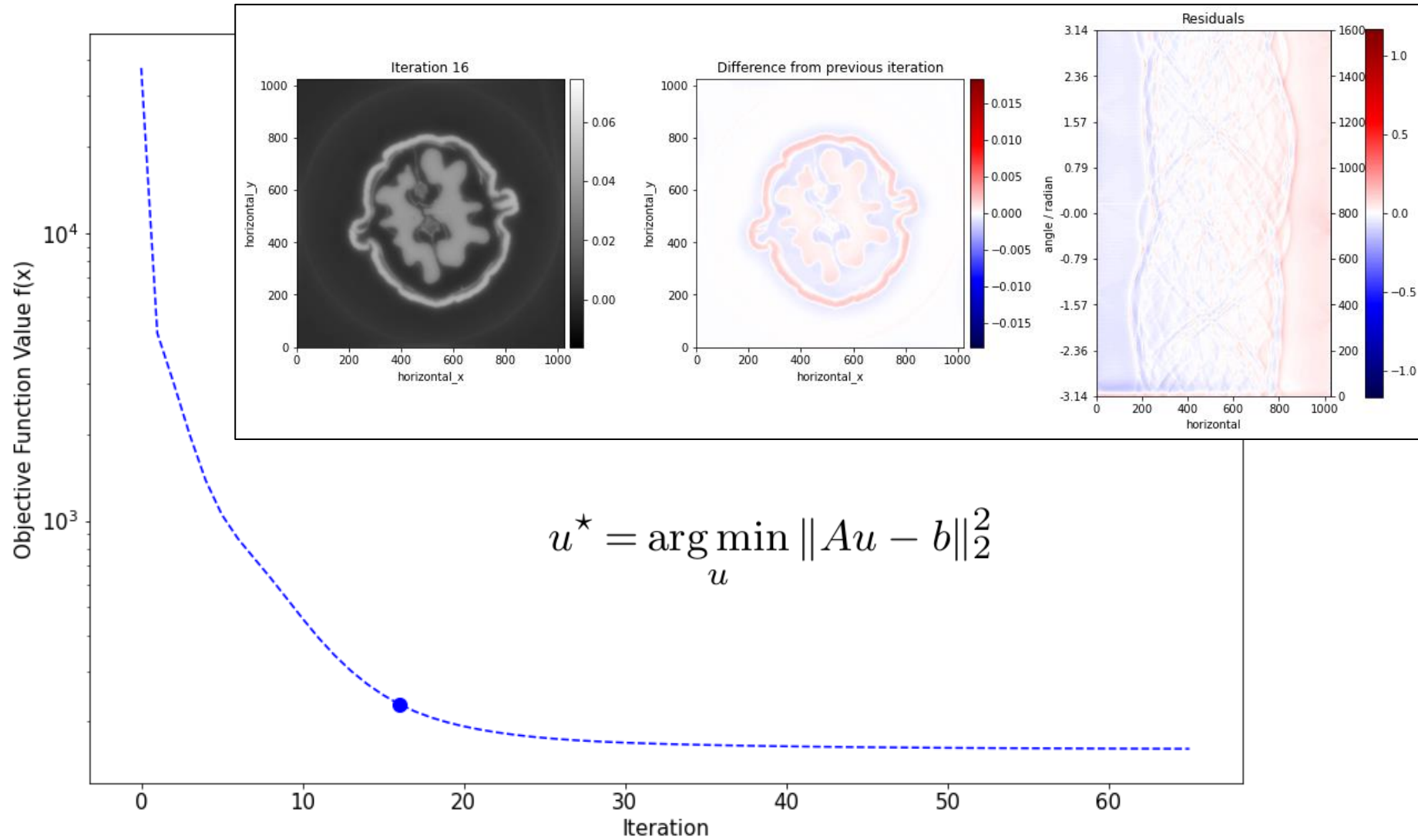
# Solve optimisation problem iteratively



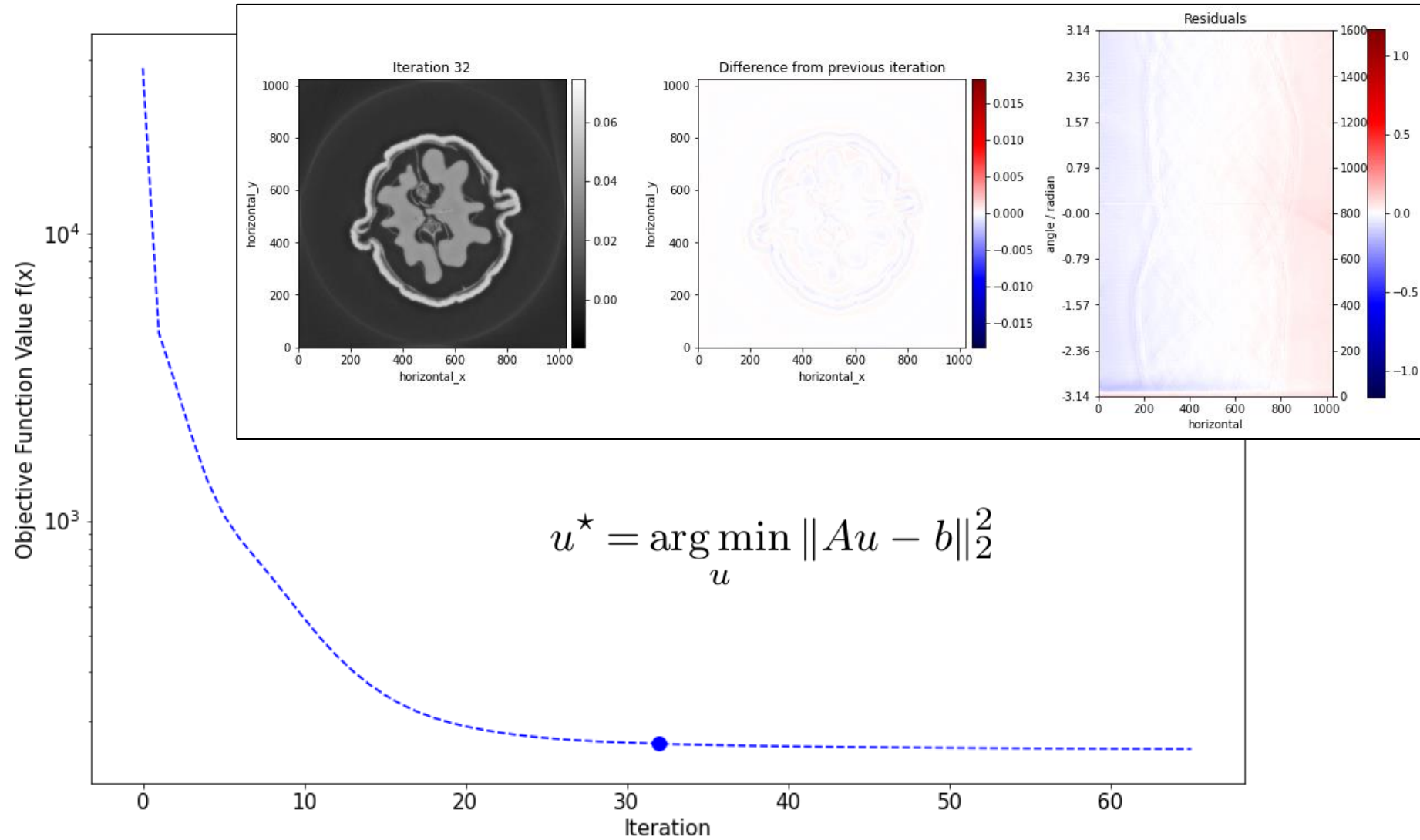
# Solve optimisation problem iteratively



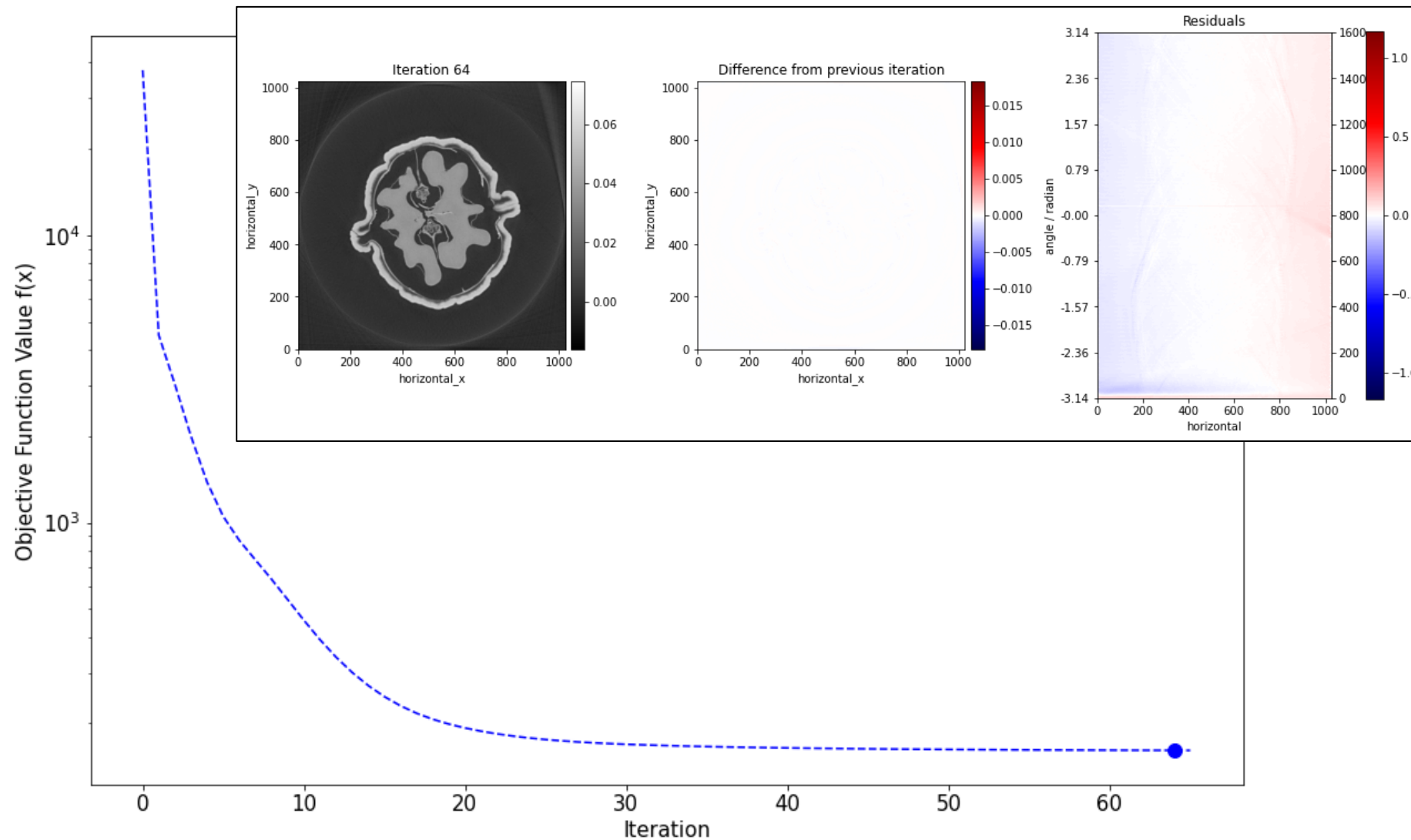
# Solve optimisation problem iteratively



# Solve optimisation problem iteratively



# Solve optimisation problem iteratively



# Let's Get Iterative!

Go to:  
`CIL-Demos/examples/1_Introduction/04_FBP_CGLS_SIRT.ipynb`

## Learning Objectives:

- formulate CT reconstruction as an optimisation problem and solve it iteratively
- introduce constraints in the optimisation problem
- visualise final and intermediate reconstruction results
- get familiar with the CIL `Algorithm` and `Operator` classes
- Use of the CGLS, SIRT algorithms

- Go to: <https://ibsim.co.uk/training> - write your name next to a username to claim it for the exercises
- CIL Jupyter notebook server: <https://training.jupyter.stfc.ac.uk/>
- Sign up with the username you claimed and a password of your choice.



# Questions?

# Iterative reconstruction with Regularisation

Discrete imaging model:

$$Au = b$$

Typical CT images:

- ▶ Regions of homogeneous tissue.
- ▶ Separated by sharp boundaries.



Reconstruction

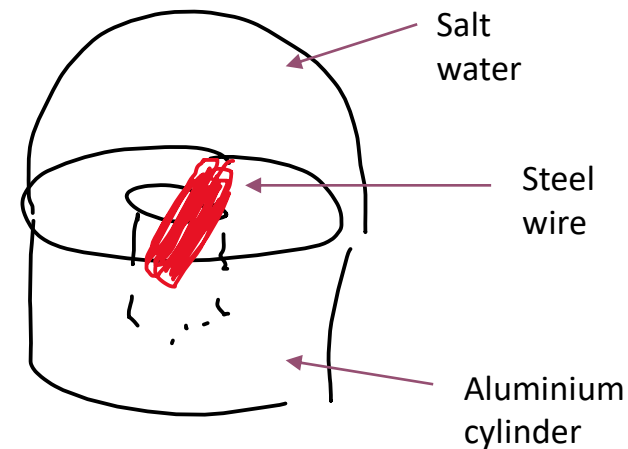
$$u^* = \underset{u}{\operatorname{argmin}} \{ \mathcal{D}(Au, b) + \alpha \cdot \mathcal{R}(u) \}$$

$$u^* = \underset{u}{\operatorname{argmin}} \|Au - b\|_2^2 = \sum_i ((Au)_i - b_i)^2$$

# Demonstration dataset

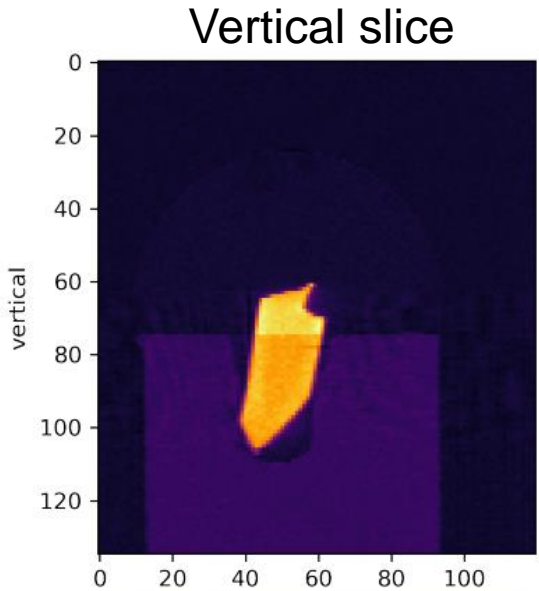
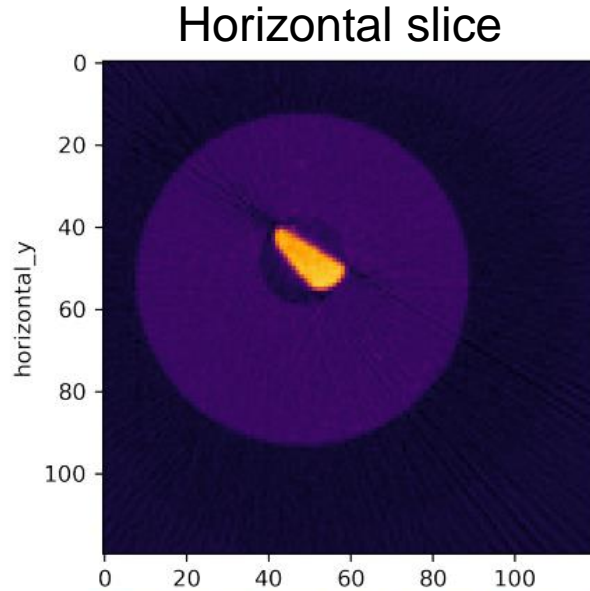
- 3D parallel-beam X-ray CT dataset from Beamline I13-2, Diamond Light Source.
- 0.5 mm aluminium cylinder with a piece of steel wire embedded in a small drilled hole. A droplet of salt water was placed on top, causing corrosion to form hydrogen bubbles.
- 160x135 15 projections over 180°

Jørgensen et al.: *Core Imaging Library - Part I: a versatile Python framework for tomographic imaging* Phil. Trans. R. Soc. A. **379** 20200192 (2021) DOI: [10.1098/rsta.2020.0192](https://doi.org/10.1098/rsta.2020.0192)

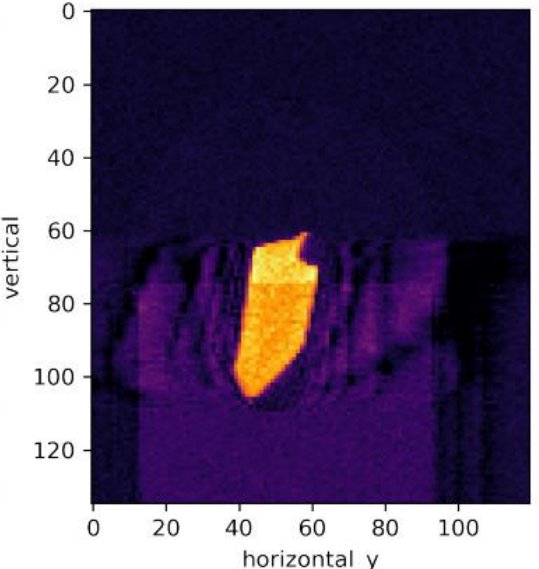
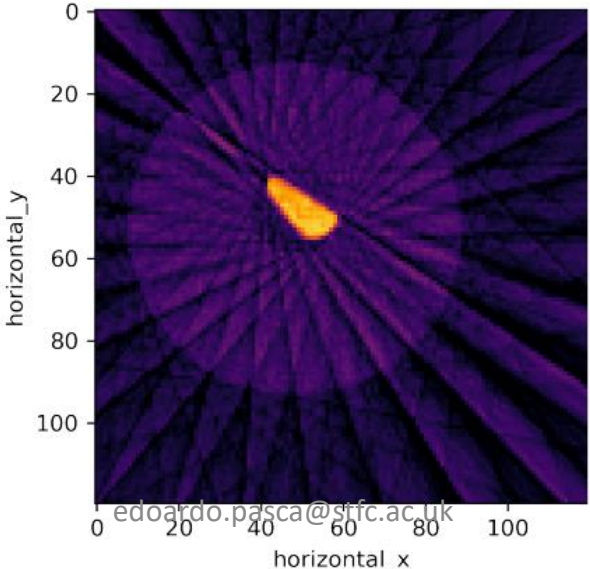


# Demonstration dataset

90  
projections



15  
projections



# Algebraic Iterative Methods

regularising by number of iterations

## CGLS

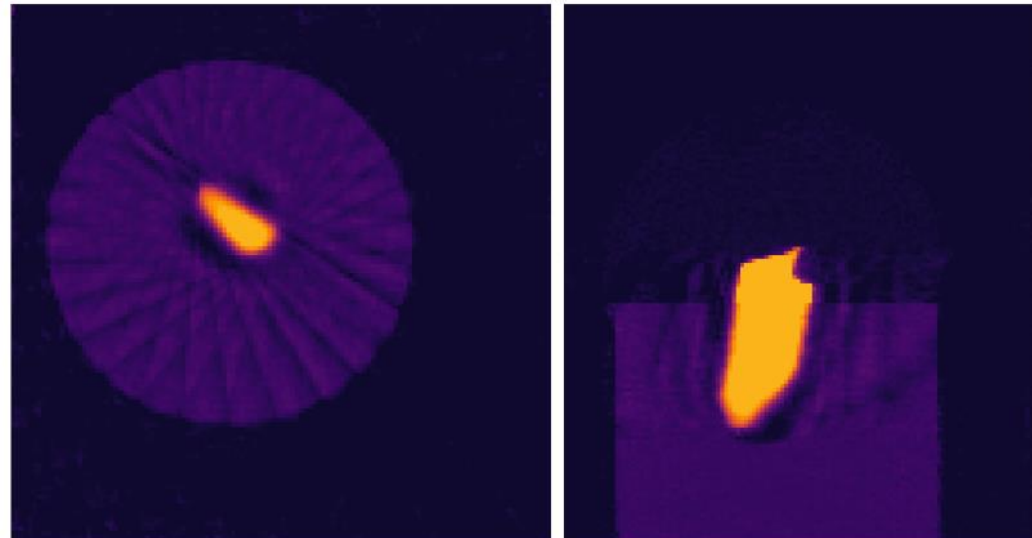
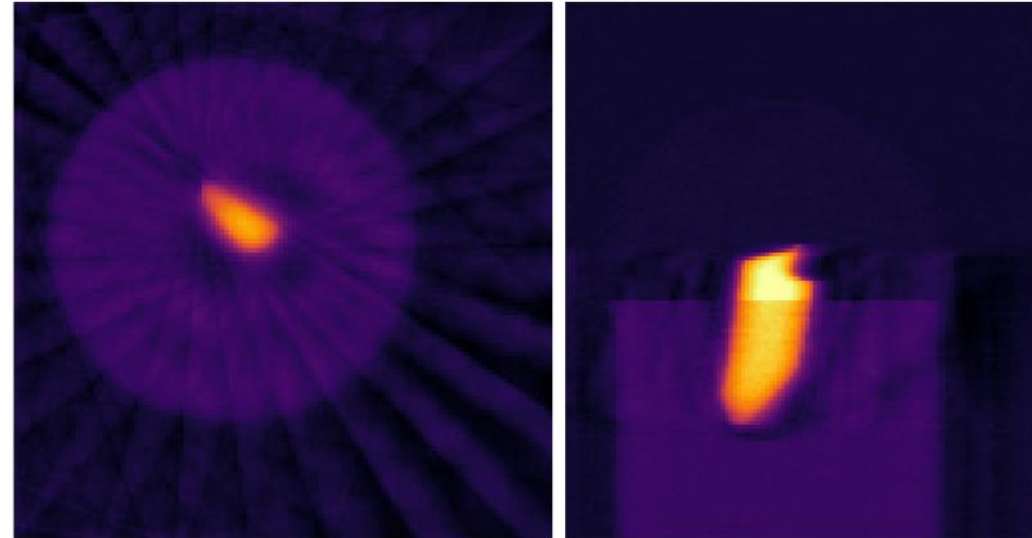
$$u^* = \arg \min_u \|Au - b\|_2^2$$

Typically 10s of iterations

## SIRT

As above and allowing lower and upper bounds on pixel values, here Non-negative and  $\leq 0.9$

Typically 100s of iterations



# Smooth Regularisation: Tikhonov

$$u^* = \arg \min_u \left\{ \|Au - b\|_2^2 + \alpha^2 \|Lu\|_2^2 \right\}$$

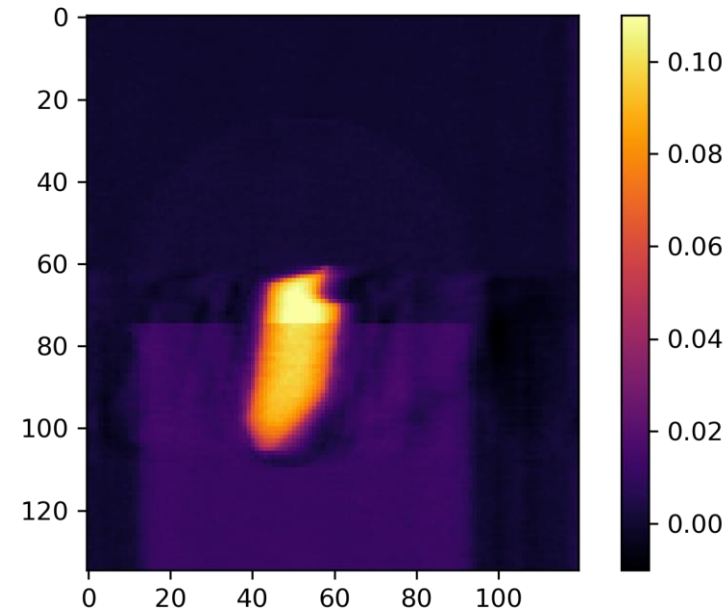
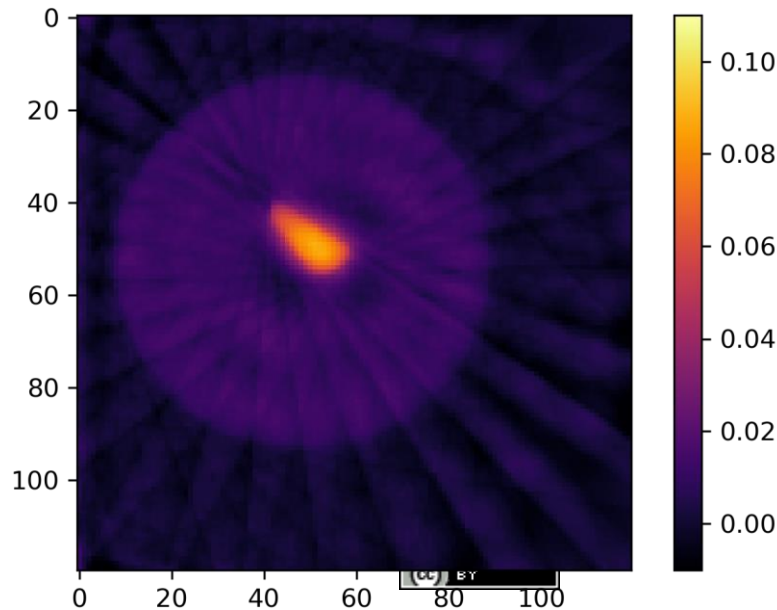
Minimiser: Solution image

Unknown image TBD

Data fidelity

Regulariser

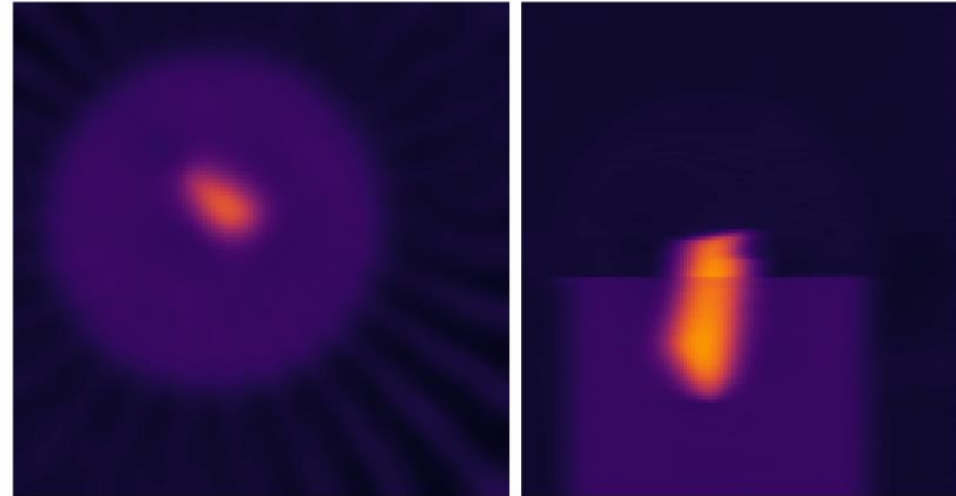
Regularisation parameter



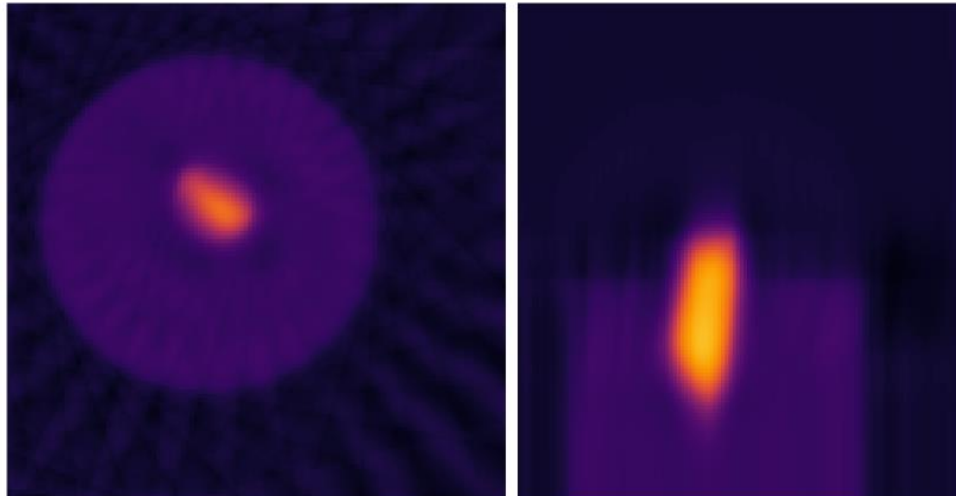
# Smooth Regularisation: Anisotropic Tikhonov

$$u^* = \arg \min_u \left\{ \|Au - b\|_2^2 + \alpha_x^2 \|L_x u\|_2^2 + \alpha_y^2 \|L_y u\|_2^2 + \alpha_z^2 \|L_z u\|_2^2 \right\}$$

**Large horizontal,  
small vertical smoothing**



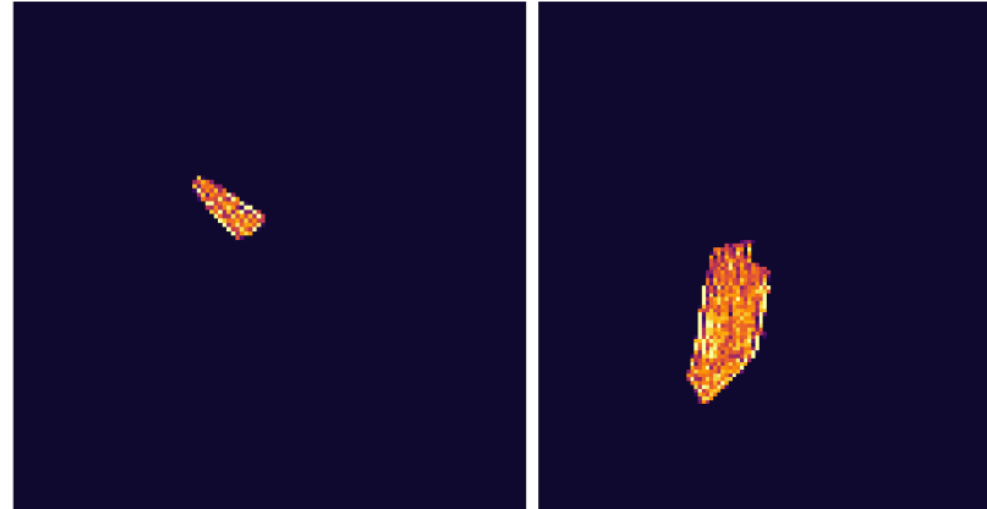
**Small horizontal,  
large vertical smoothing**



# Sparsity and Total Variation Regularization

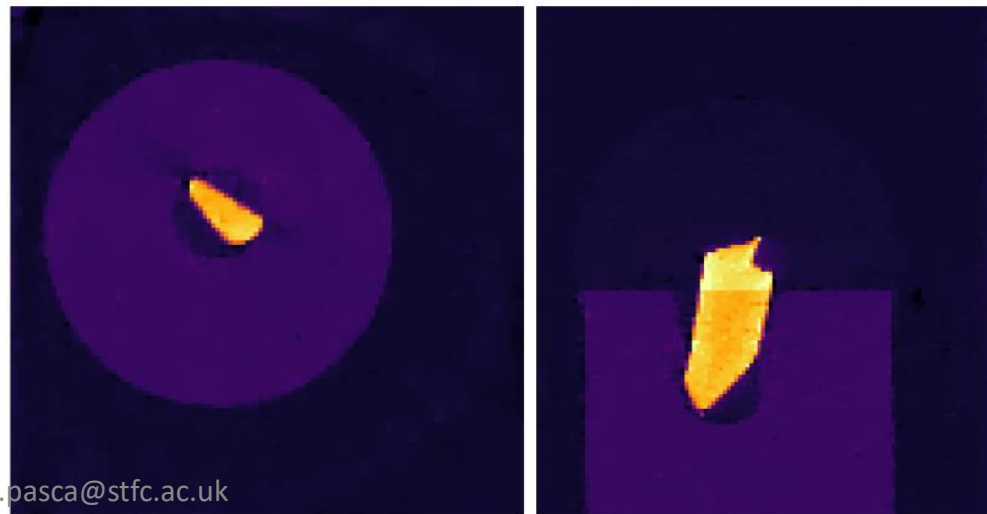
**L1-norm regularisation:**

$$\|u\|_1 = \sum_j |u_j|$$



**Total variation regularisation:**

$$\sum_j \|D_j u\|_2$$



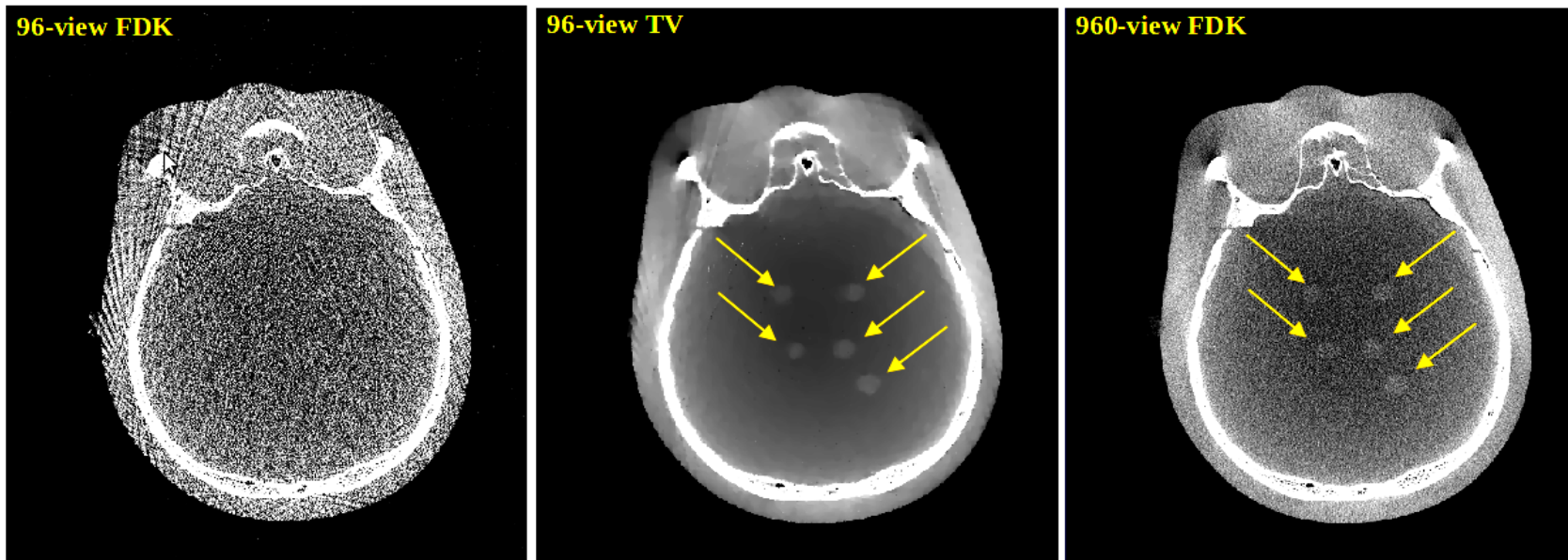


# Total Variation (TV) Regularised Reconstruction

**Total variation:** Homogeneous regions with sharp boundaries.

$$\min_u \|Au - b\|_2^2 + \lambda \cdot \text{TV}(u)$$

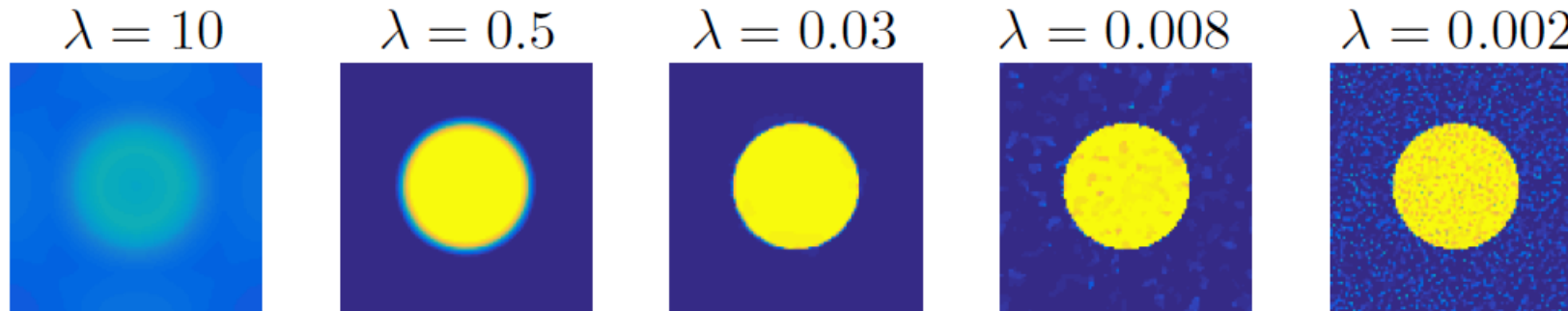
TV is an example of **sparsity-regularized reconstruction**.



# Effect of the Regularisation Parameter

## Total variation regularization:

$$\min_u \|Au - b\|_2^2 + \lambda \cdot \text{TV}(u)$$



- ▶ Large  $\lambda$ : Almost only effect of regularizer.  $\text{TV} \rightarrow \text{Constant}$ .
- ▶ Small  $\lambda$ : Almost just least-squares solution.
- ▶ Best trade-off?

# What is TV?

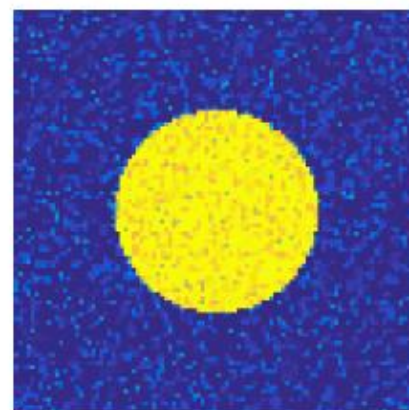
$\lambda = 10$



Original



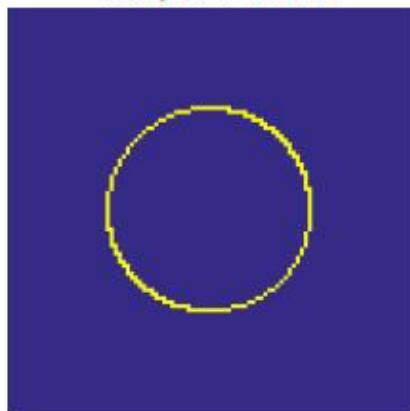
$\lambda = 0.002$



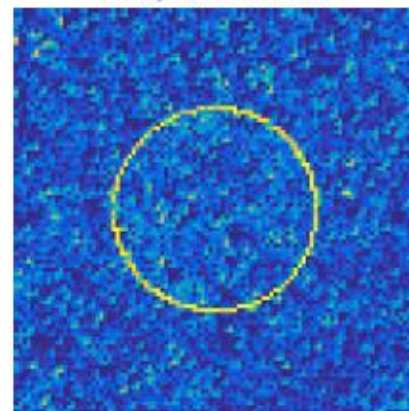
GMI, TV = 54.9



GMI, TV = 183.0



GMI, TV = 1475.6



- Measures variation of an image
- Sum of gradient magnitude image
$$\text{TV}(u) = \sum_j \|D_j u\|_2$$
- Prior: few homogeneous regions with simple boundaries
- Quite successful in tomography, in particular for reduced data

# Exercise 3

- Tomography: 2\_Iterative /01\_optimisation\_gd\_fista.ipynb

# Questions?

# Session 4

## Choose one from

1. Reconstruction of data simulated from gVXR
2. Advanced iterative reconstruction with spectral XCT data
  - 3\_Multichannel /03\_Hyperspectral\_reconstruction.ipynb
3. Advanced iterative reconstruction on laminography XCT data
  - 2\_Iterative /05\_Laminography\_with\_TV.ipynb
4. Reduced data reconstruction:
  - Use CIL processors (e.g. Slicer or Binner or Masker/MaskGenerator) to remove parts of or downsample data sets, for example to obtain a reduced number of projections, a limited angle problem, truncated projections (region of interest data), exterior problem, etc. Compare for example different regularised reconstruction methods at increasingly few projections.
5. Check in each folder for additional exercises and data resources

# Questions?

Jørgensen et al.: *Core Imaging Library - Part I: a versatile Python framework for tomographic imaging* Phil. Trans. R. Soc. A. **379** 20200192 (2021) DOI: [10.1098/rsta.2020.0192](https://doi.org/10.1098/rsta.2020.0192)

Papoutsellis et al.: *Core Imaging Library - Part II: multichannel reconstruction for dynamic and spectral tomography* Phil. Trans. R. Soc. A. **379** 20200193 (2021) DOI: [10.1098/rsta.2020.0193](https://doi.org/10.1098/rsta.2020.0193)

Ametova et al.: *Crystalline phase discriminating neutron tomography using advanced reconstruction methods*, J. Phys. D: Appl. Phys. **54** 325502 (2021) DOI [10.1088/1361-6463/ac02f9](https://doi.org/10.1088/1361-6463/ac02f9)

Warr R. et al.: *Enhanced hyperspectral tomography for bioimaging by spatio-spectral reconstruction* Sci Rep **11**, 20818 (2021) DOI: [10.1038/s41598-021-00146-4](https://doi.org/10.1038/s41598-021-00146-4)

Brown R. et al: *Motion estimation and correction for simultaneous PET/MR using SIRT and CIL* Phil. Trans. R. Soc. A. **379** 20200208 (2021) DOI: [10.1098/rsta.2020.0208](https://doi.org/10.1098/rsta.2020.0208)

19/10/2022



edoardo.pasca@stfc.ac.uk

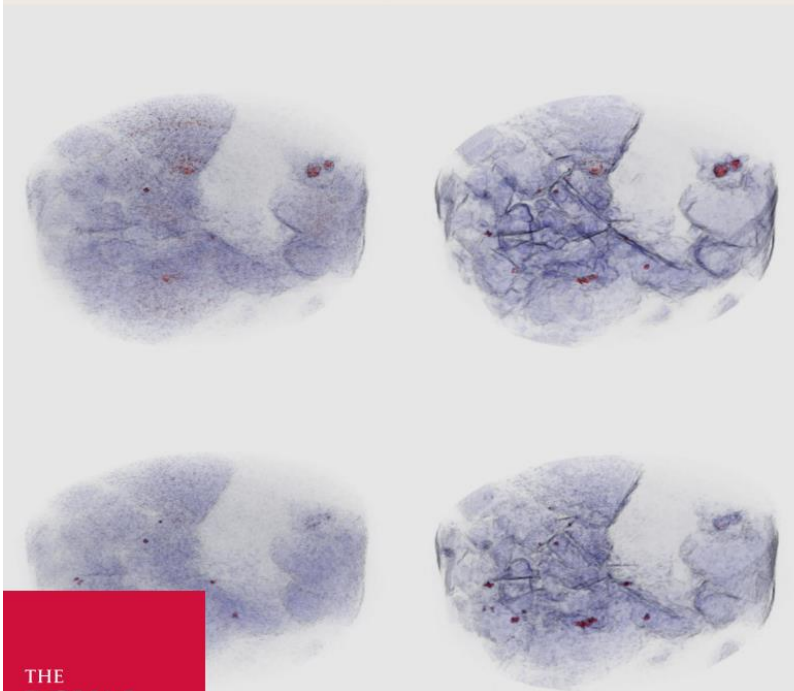
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## PHILOSOPHICAL TRANSACTIONS OF THE ROYAL SOCIETY A

MATHEMATICAL, PHYSICAL AND ENGINEERING SCIENCES

### Synergistic tomographic image reconstruction: part 2

Theme issue compiled and edited by Charalampos Tsoumpas, Jakob Sauer, Jørgensen, Christoph Kolbitsch and Kris Thielemans



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# CCPi = CCP in Tomographic Imaging

- The Collaborative Computational Projects (CCPs)
- UK Network of expertise in key computational research fields
- CCP's foster exchange by organising workshop, training, conferences ...
- Enable large-scale scientific software development, maintenance and distribution.
- Long term funding by EPSRC with a 5 years renewal cycle
- CCP's are supported by the Computational Science Centre for Research Communities (CoSeC).
- <https://www.ccpi.ac.uk>

- CIL is a Open Source mostly Python library for all your tomographic needs:
  - I/O
  - pre-processing
  - Reconstruction
  - visualisation
- Developer Support, user driven, long term funding
- Join the community Discord
- <https://www.ccpil.ac.uk/CIL>

# Thank you!

**Feedback form:**

<https://forms.office.com/r/2sHuckJeGV>



**Discord community:**

<https://discord.gg/ky7yCqRcYn>

