Welcome to the CIL online training

Thank you for joining, while we wait to get started:

- Check out our HackMD: https://hackmd.io/@ccpi/cil-online-25
    - Answer the question: If you could scan anything, what would you scan?
- Make sure your zoom name is correct
- Check your video and microphone (you will need them later)

CIL Discord

CIL GitHub

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
Danica Sugic – STFC
Hannah Robarts - STFC
Evangelos Papoutsellis – Finden
Edoardo Pasca – STFC
Margaret Duff – STFC
Franck Vidal – STFC
Casper da Casta-Luis - STFC

CIL Team

Scientific Computing @ STFC
Technical University of Denmark (DTU)

Finden

Our goals with this course

- Introduction to iterative methods for XCT with CIL
- Support you in trying out CIL with our Jupyter notebook demos on the cloud
- Set you up to continue exploring CIL for your own data

Your feedback from yesterday

CIL
CORE IMAGING LIBRARY
UKRI Science and Technology Facilities Council
Scientific Computing

Name one thing we could improve about today's course?

10 11

- More ellaborate explaination of functions/methods
- No, it was really interesting and well supported, thank you!
- All was quite right and well organised.
- more time on exercise to allow exploration.
- Keep up the good work
- Slower paced
- More time for exercises 😅
- Maybe some recommended reading a few weeks back would have been nice
- I think it was very good and I enjoyed the course very much.
- Well organized!
- Very well organized! Thanks!

Training Program

Welcome, intro and cloud set-up 1-1:15 – Edo

Intro to optimisation – 1:15-2:15 – Edo

- Intro lecture
- Time to explore: demos/1_Introduction/04_FBP_CGLS_SIRT.ipynb
- Extension: demos/1_Introduction/05_USB
- **Break**

Intro to regularisation 2:30-3:45 – Jakob

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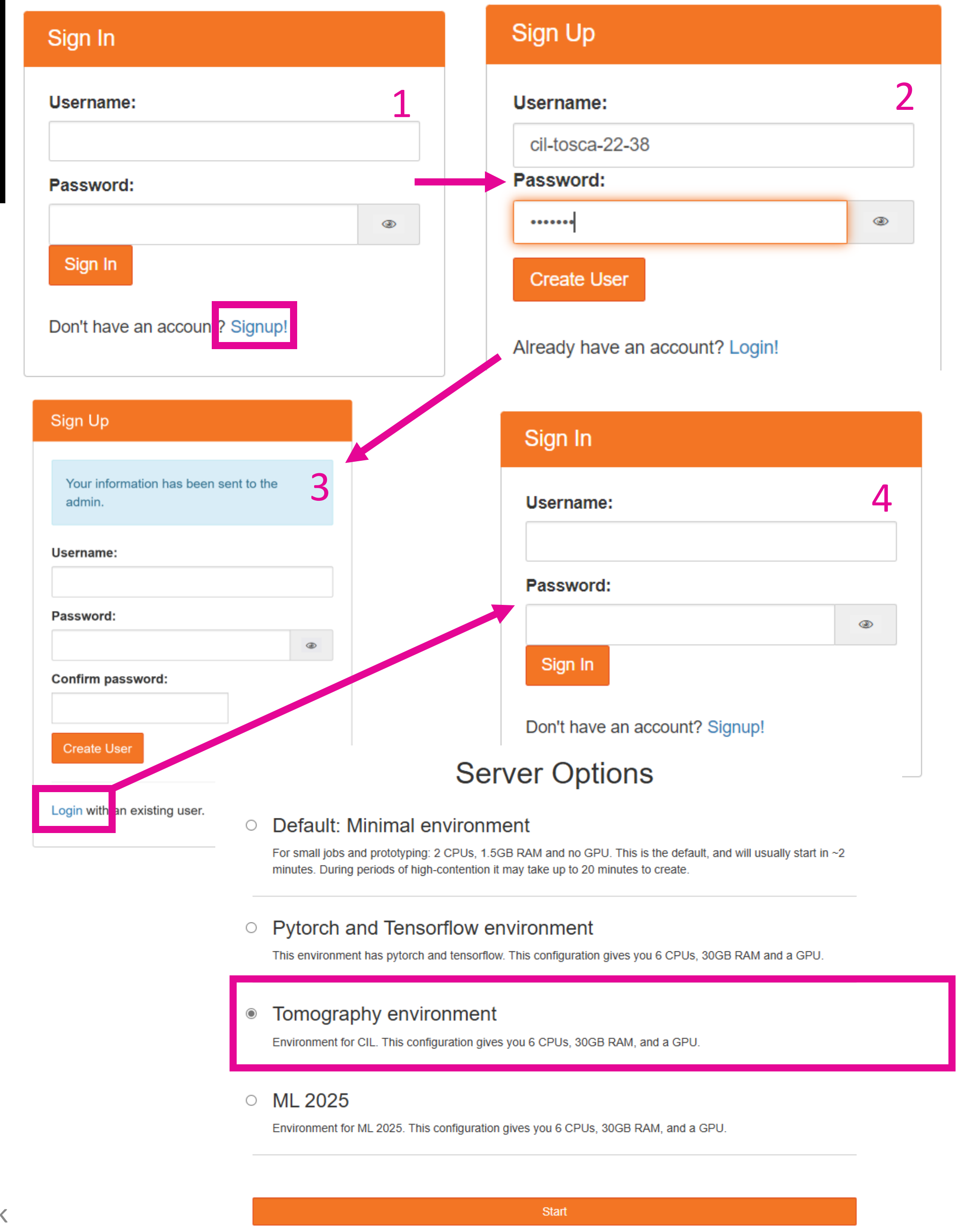
Time to explore and discuss – 4:00-4:45 – Jakob

- Notebook: 2_Iterative/05_Laminography_with_TV.ipynb
- Notebook: 3_Multichannel/03_Hyperspectral_reconstruction.ipynb

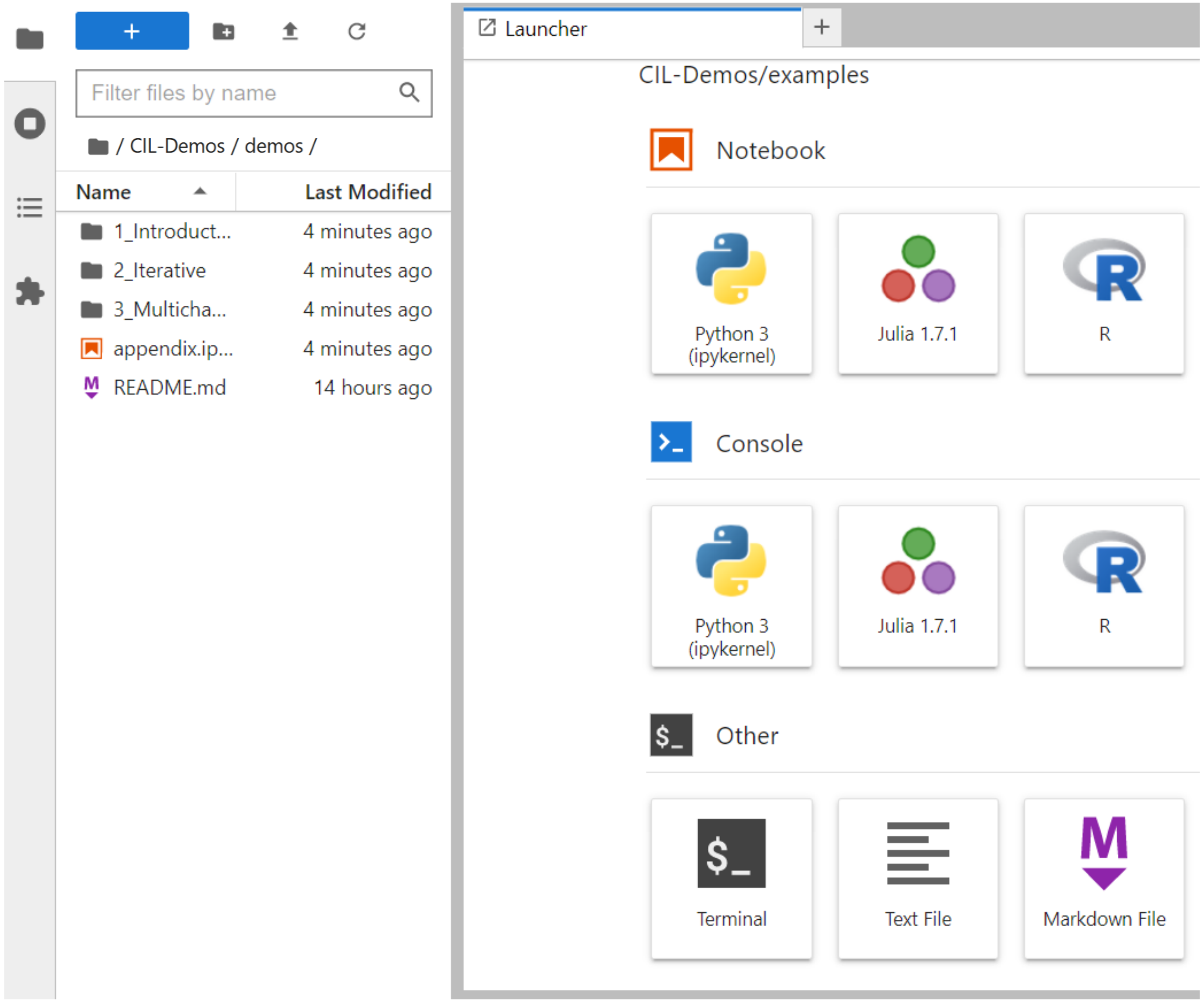
Conclusions 4:45-5 – Edo

Log in to JupyterHub

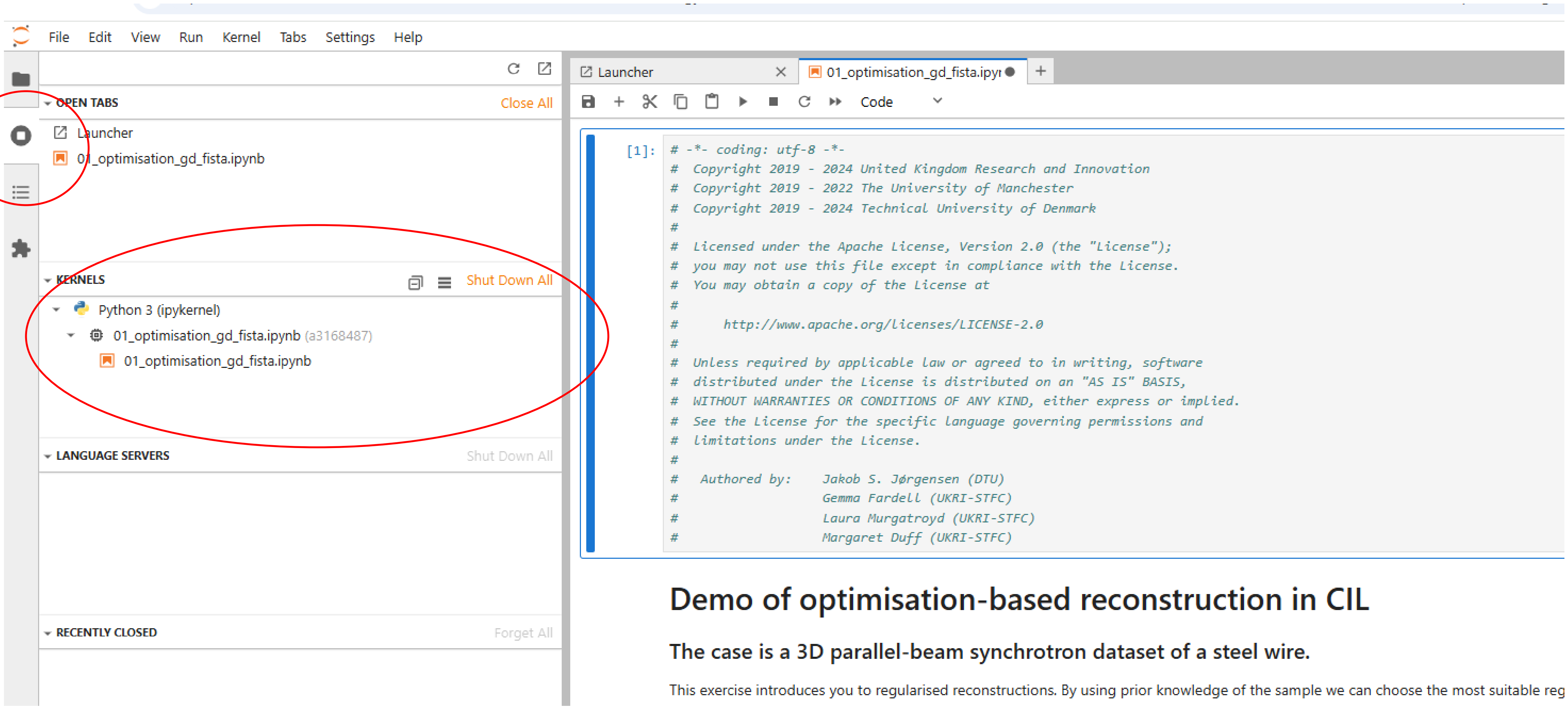
- Go to: https://tinyurl.com/cil-online-25
  and write your name next to a **username** to claim it for the exercises
- Go to: https://training.jupyter.stfc.ac.uk/
- **Sign up with the username** you claimed and a password of your choice.
- No password reset option, so remember your password!
- Then log in with the username and password you set.
- Select the **Tomography environment** server and press "start":



Once you've logged in …

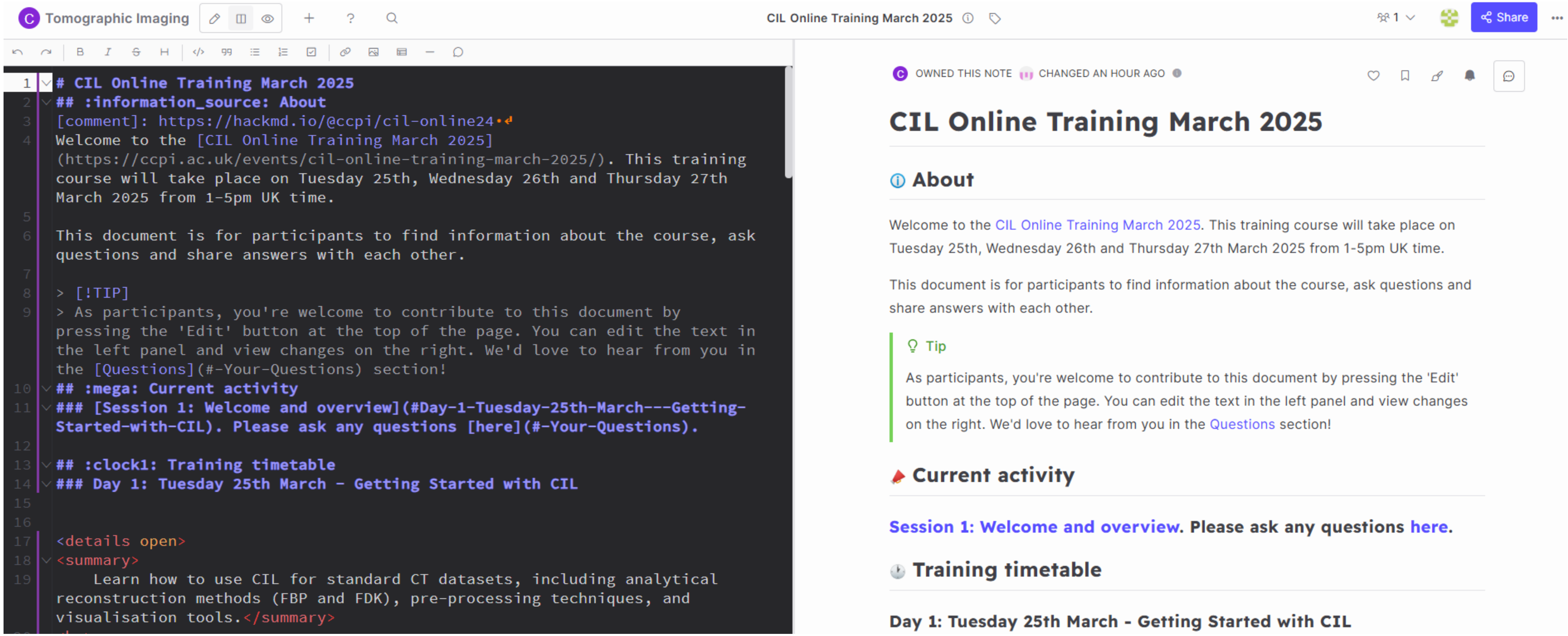


Killing kernels – IMPORTANT



HackMD

https://hackmd.io/@ccpi/cil-online-25



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Conclusions 4:45-5 – Edo

CIL reminder

tomography@stfc.ac.uk

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

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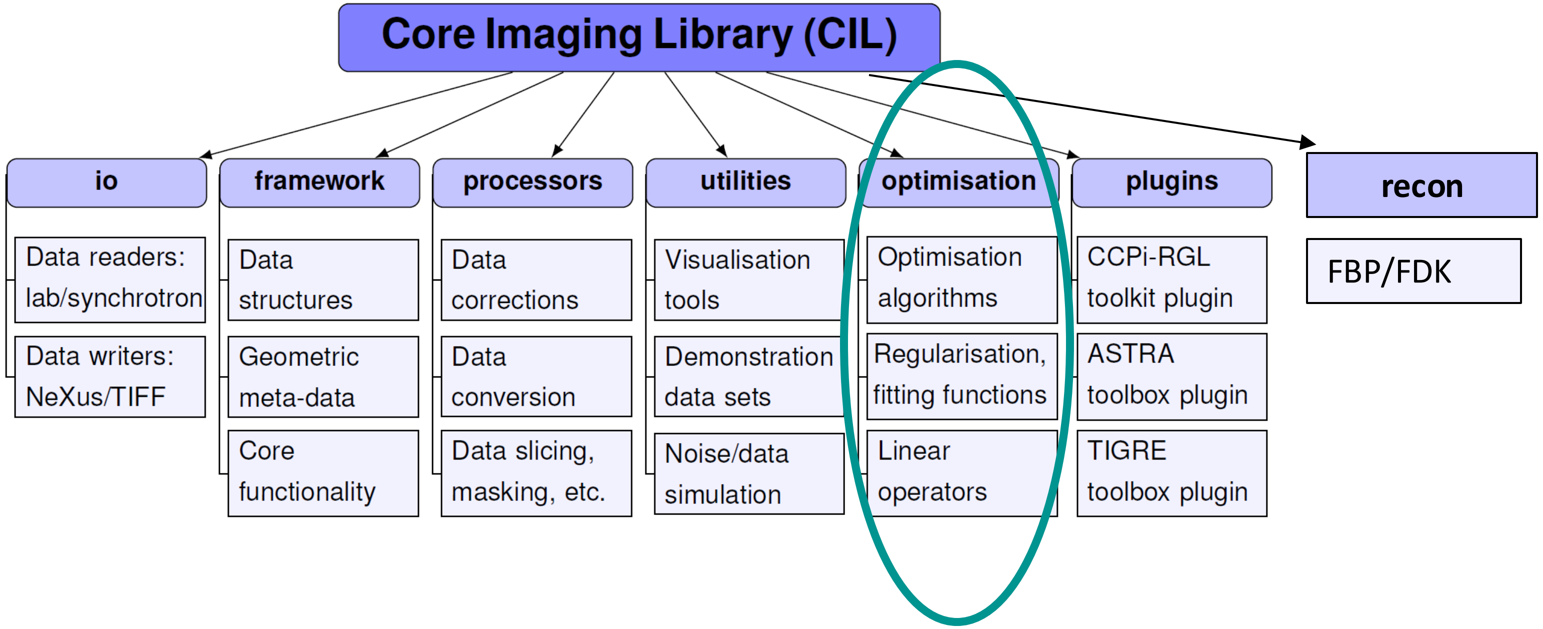
CIL Module Structure and Contents



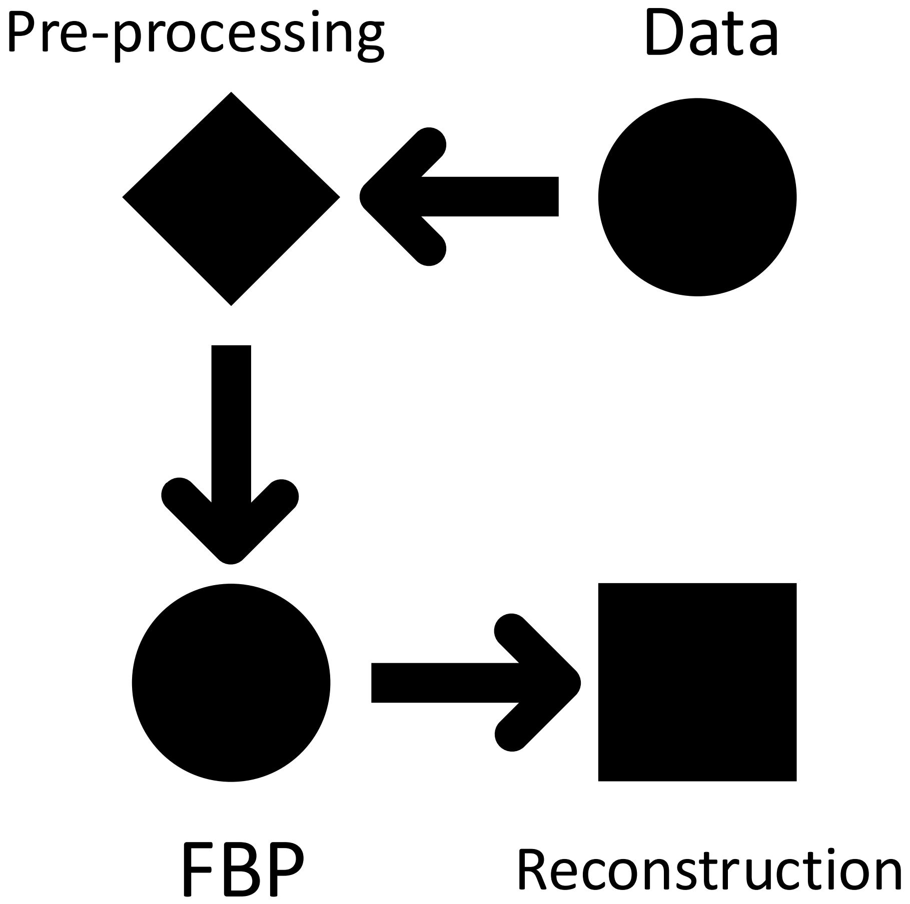
Jørgensen et al. 2021: *Core Imaging Library - Part I: a versatile Python framework for tomographic imaging*, Phil. Trans. R. Soc. A, **379**, 20200192: https://doi.org/10.1098/rsta.2020.0192

Iterative Reconstruction

Filtered Back Projection (FBP)

Pros

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



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Filtered Back Projection (FBP)

Pros

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- Few parameters
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From hackmd:

Are FDK and FBP the only reconstruction options available from CIL directly?

Physicist joke

$$\alpha|\text{Yes}\rangle + \beta|\text{No}\rangle$$

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- 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

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Take-away messages

Filtered back-projection is very good!

If data is good, look no further!

If data is *bad*, iterative reconstruction may help, but

Different kinds of *bad* need different methods.

CIL provides a range of iterative reconstruction methods for CT

and other inverse problems

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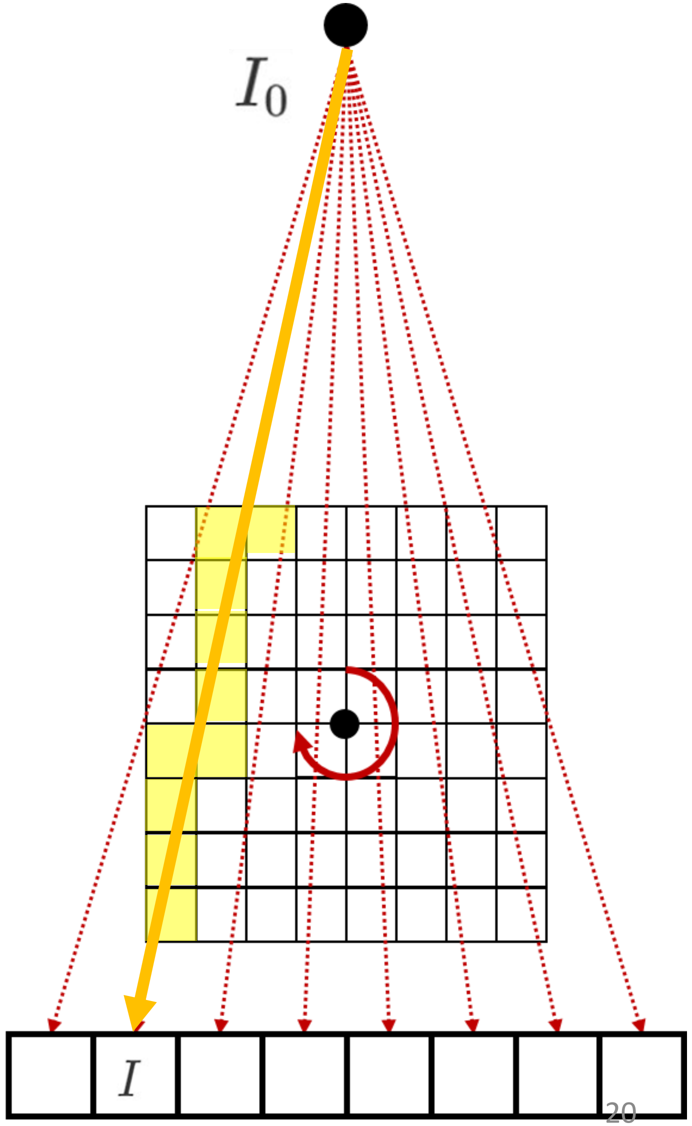
Imaging Model for Iterative Reconstruction

$$\frac{I}{I_0} = \exp \int_{L_i} -\mu(s)ds$$

$$b_i = -\log \frac{I_i}{I_0} = \int_{L_i} \mu(s)ds$$

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

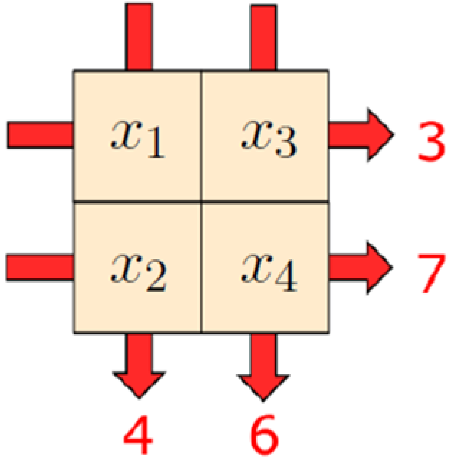
- Assume the object is constant in each pixel
- u_j is the j-th pixel value
- a_{ij} is the path length in the j-th pixel



Imaging Model for Iterative Reconstruction

Extremely large set of linear equations

$$b_i = \sum_j a_{ij} u_j \qquad Au = b$$



$$\begin{pmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{pmatrix} = \begin{pmatrix} 3 \\ 7 \\ 4 \\ 6 \end{pmatrix}$$

Imaging Model for Iterative Reconstruction

Extremely large set of linear equations

$$b_i = \sum_j a_{ij} u_j \qquad Au = b$$

Iterative reconstruction is based on optimisation algorithms and objective functions

Plan on how to minimise

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

What you want to minimise

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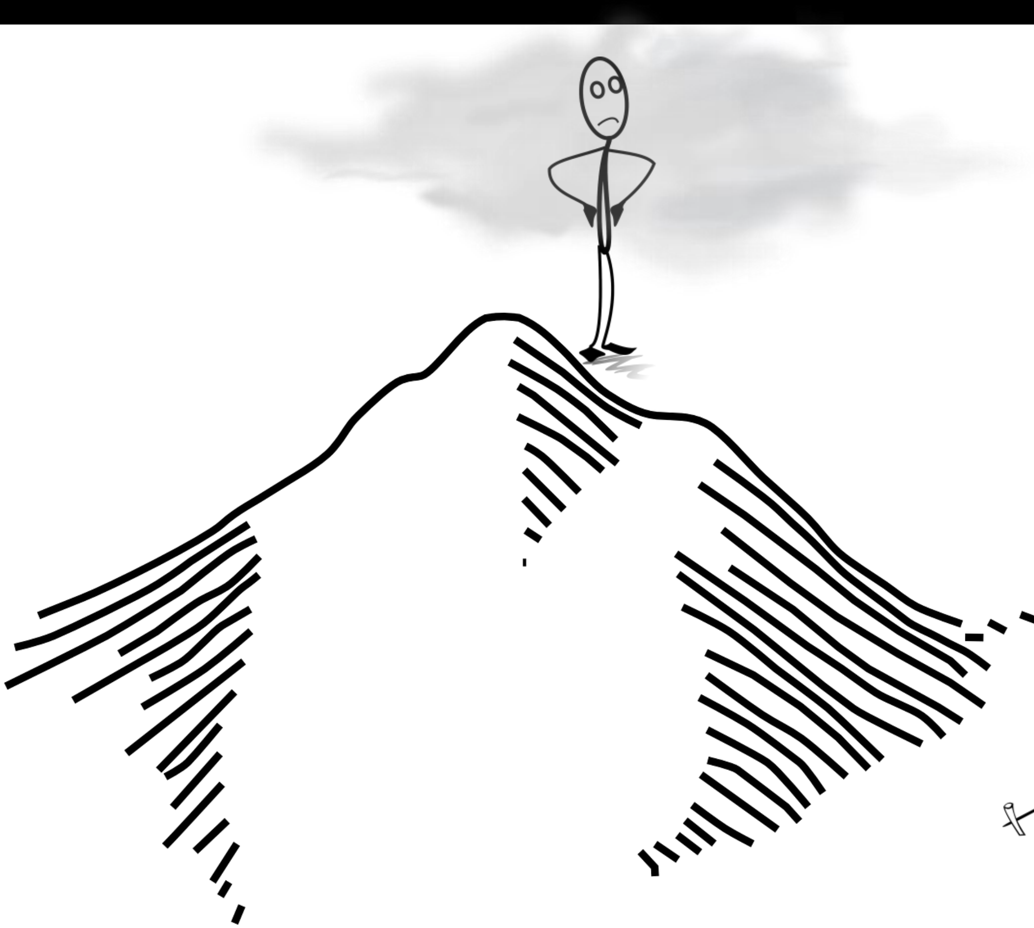
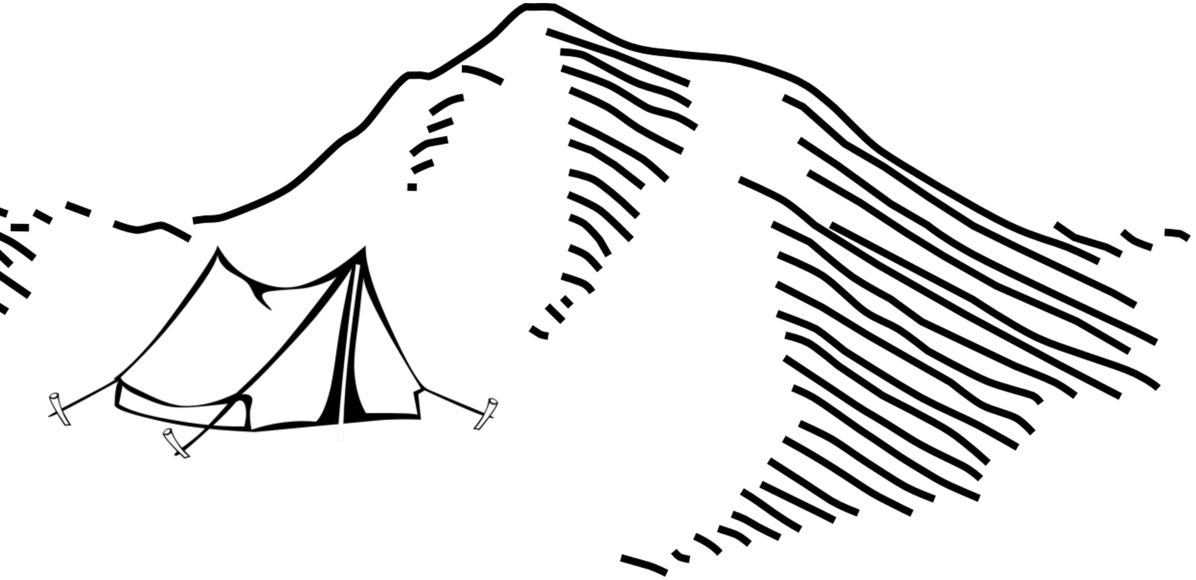
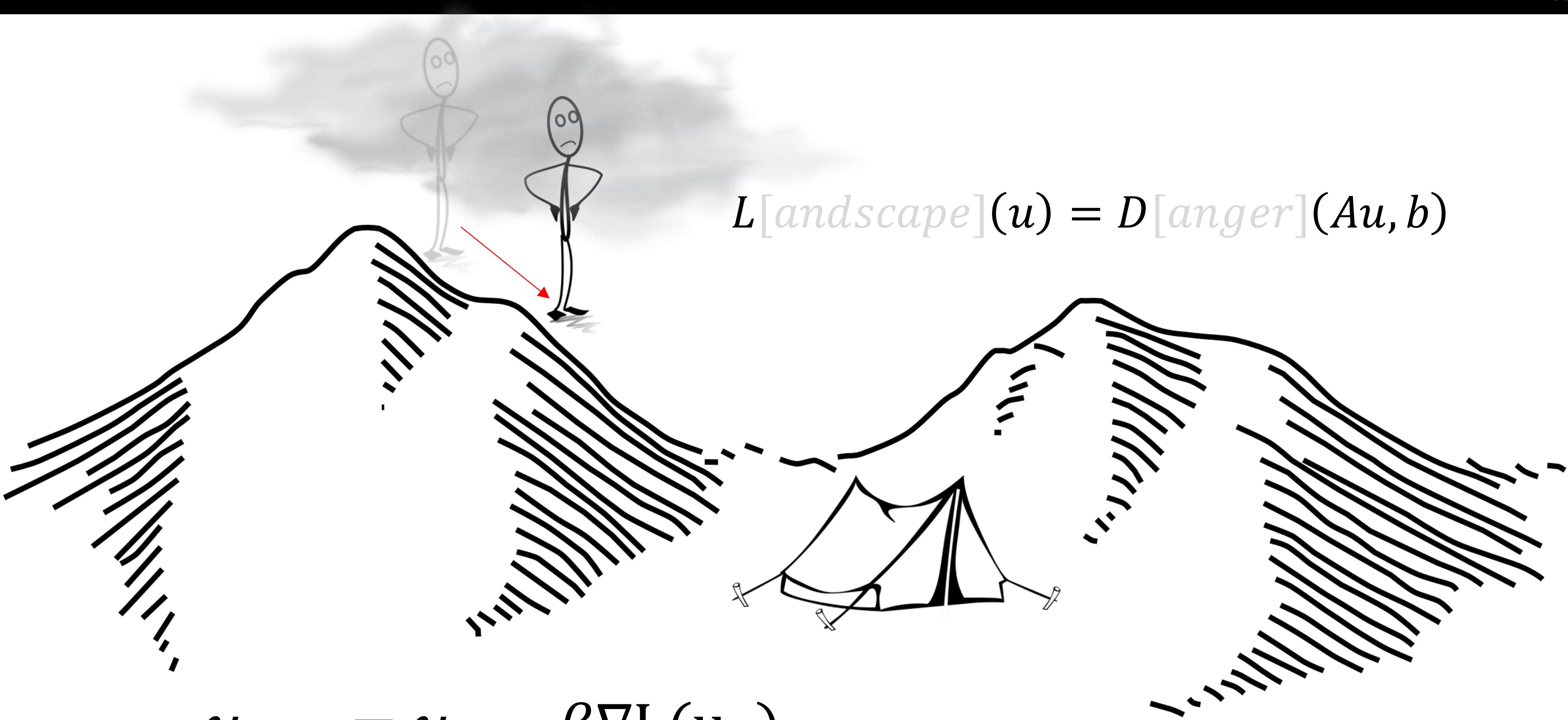
Optimisation algorithms



$$L[andscape](u) = D[anger](Au, b)$$



Optimisation algorithms – Gradient Descent



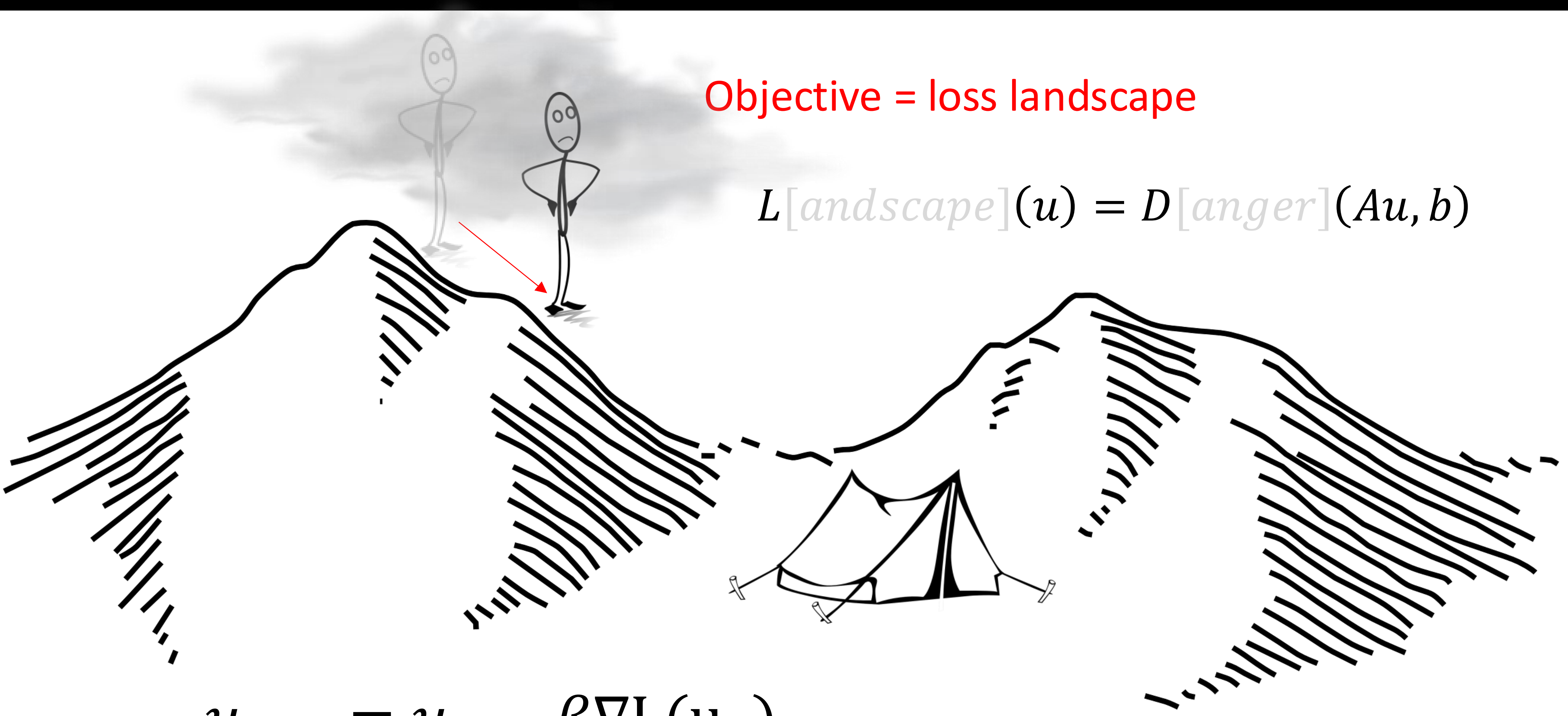
$$L[andscape](u) = D[anger](Au, b)$$

$$u_{k+1} = u_k - \beta \nabla \mathrm{L}(\mathrm{u_k})$$

Optimisation algorithms – Gradient Descent

Objective = loss landscape

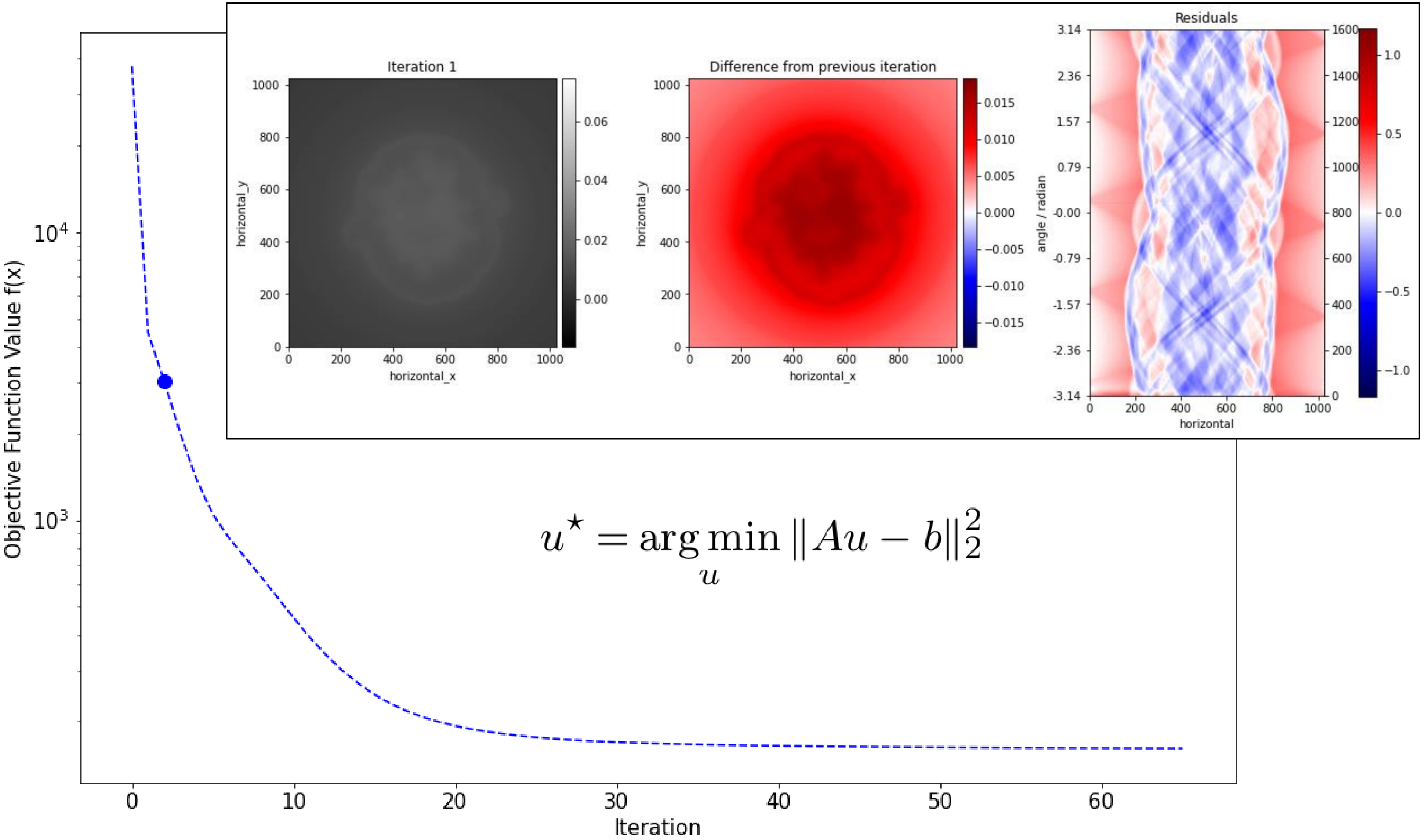
$$L[andscape](u) = D[anger](Au, b)$$



$$u_{k+1} = u_k - \beta \nabla \mathrm{L}(\mathrm{u_k})$$

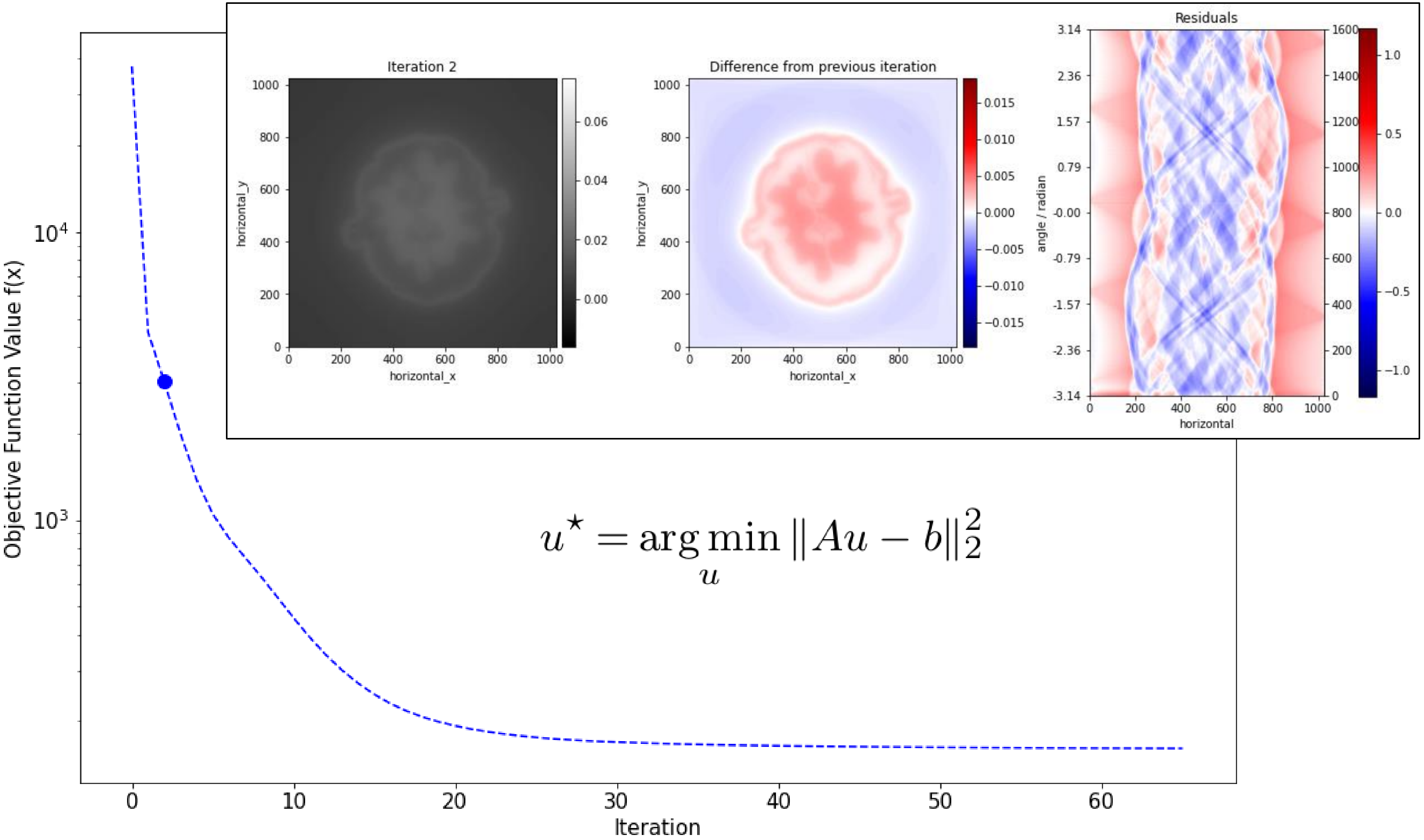
Optimisation algorithm = plan to get to the bottom

Solve optimisation problem iteratively



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

Solve optimisation problem iteratively



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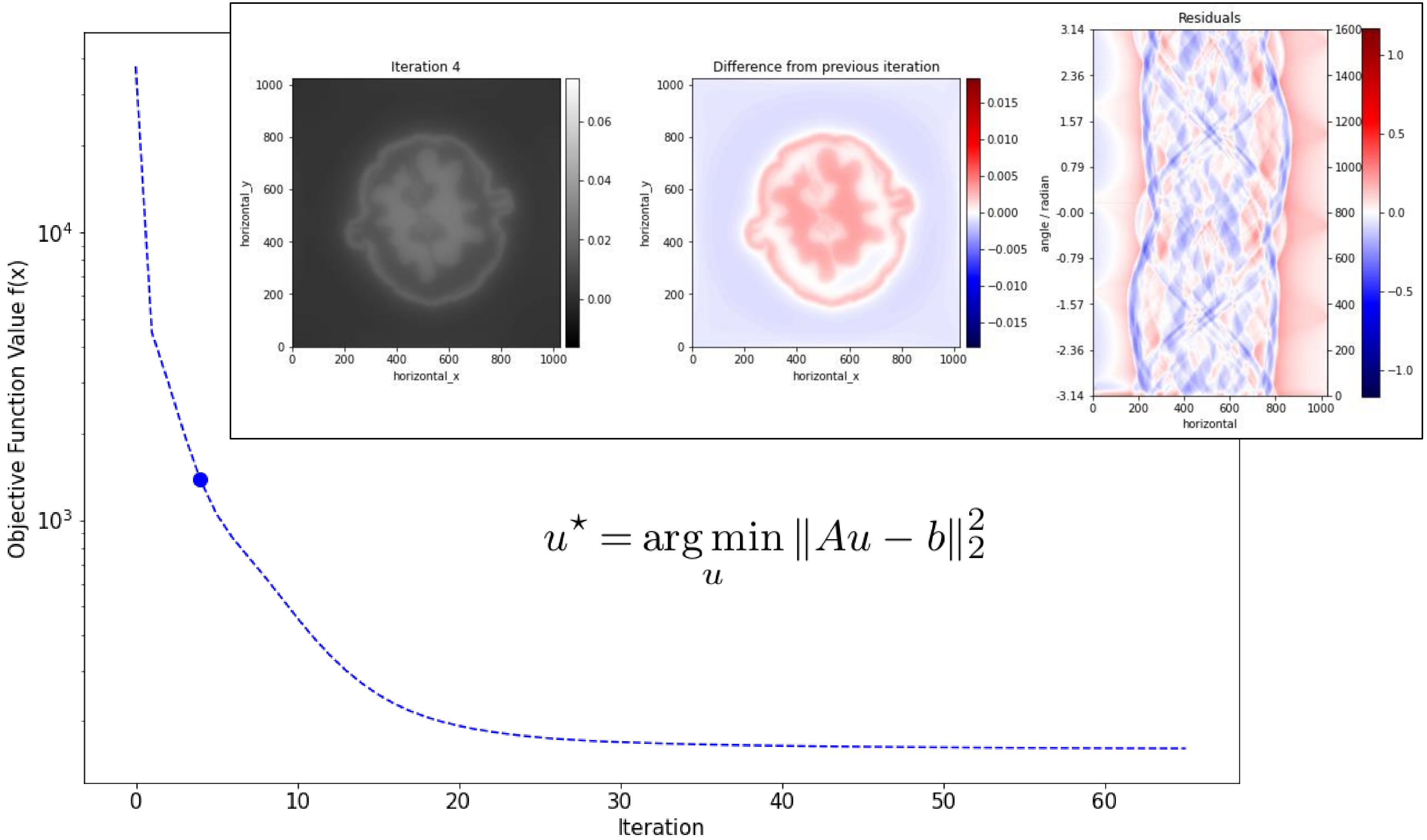
Solve optimisation problem iteratively



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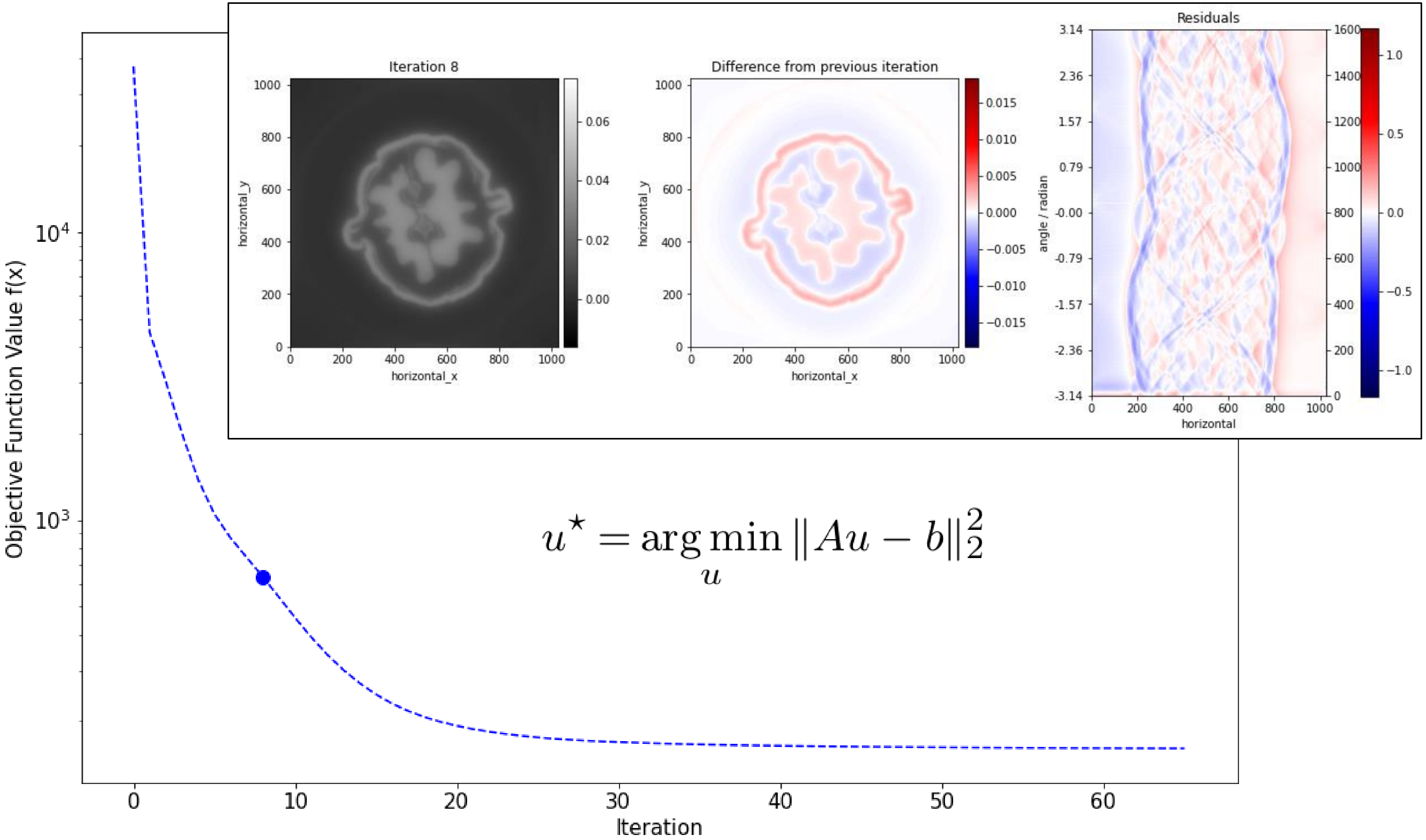
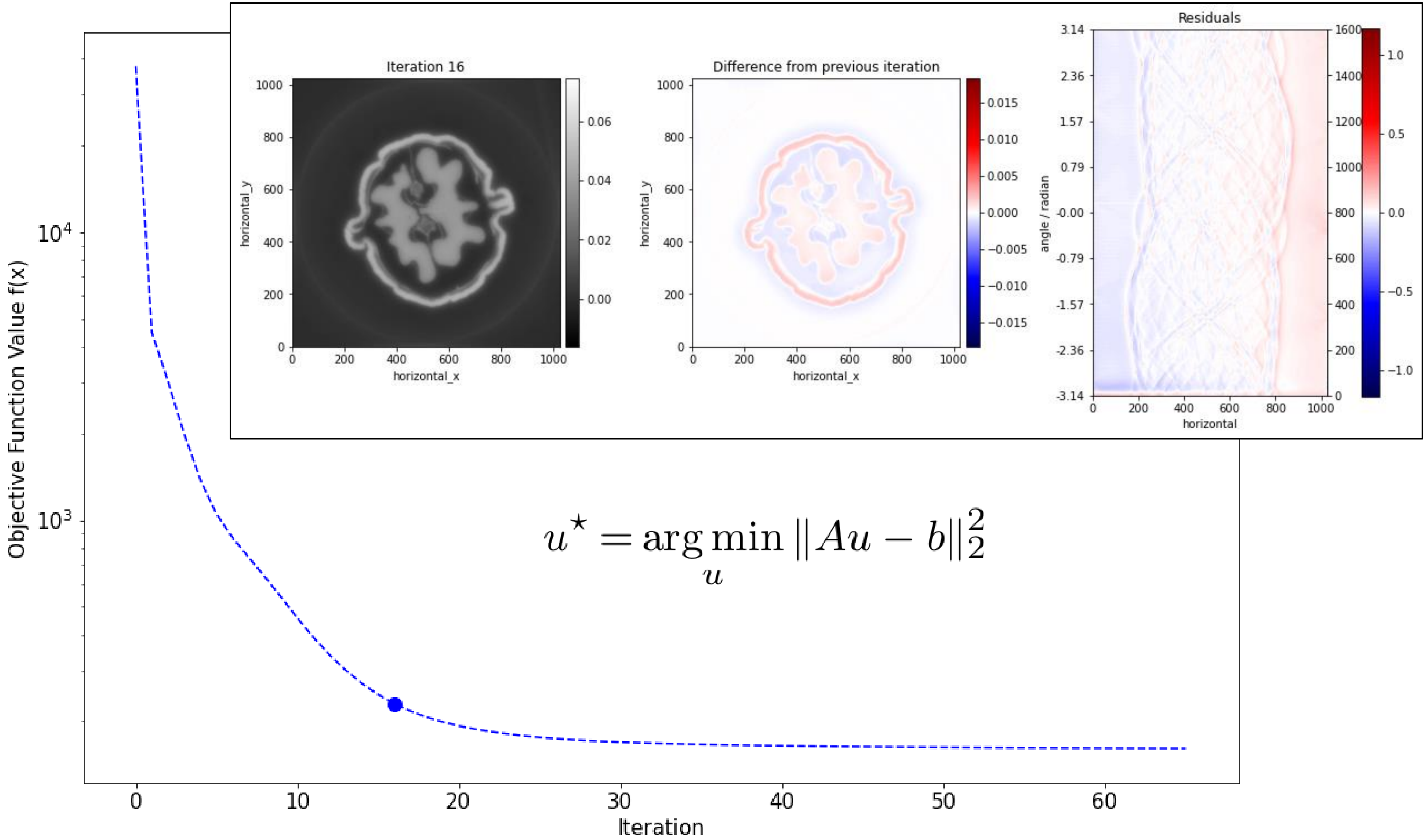


$$u^{\star} = \arg\min_{u} \|Au - b\|_2^2$$

Solve optimisation problem iteratively



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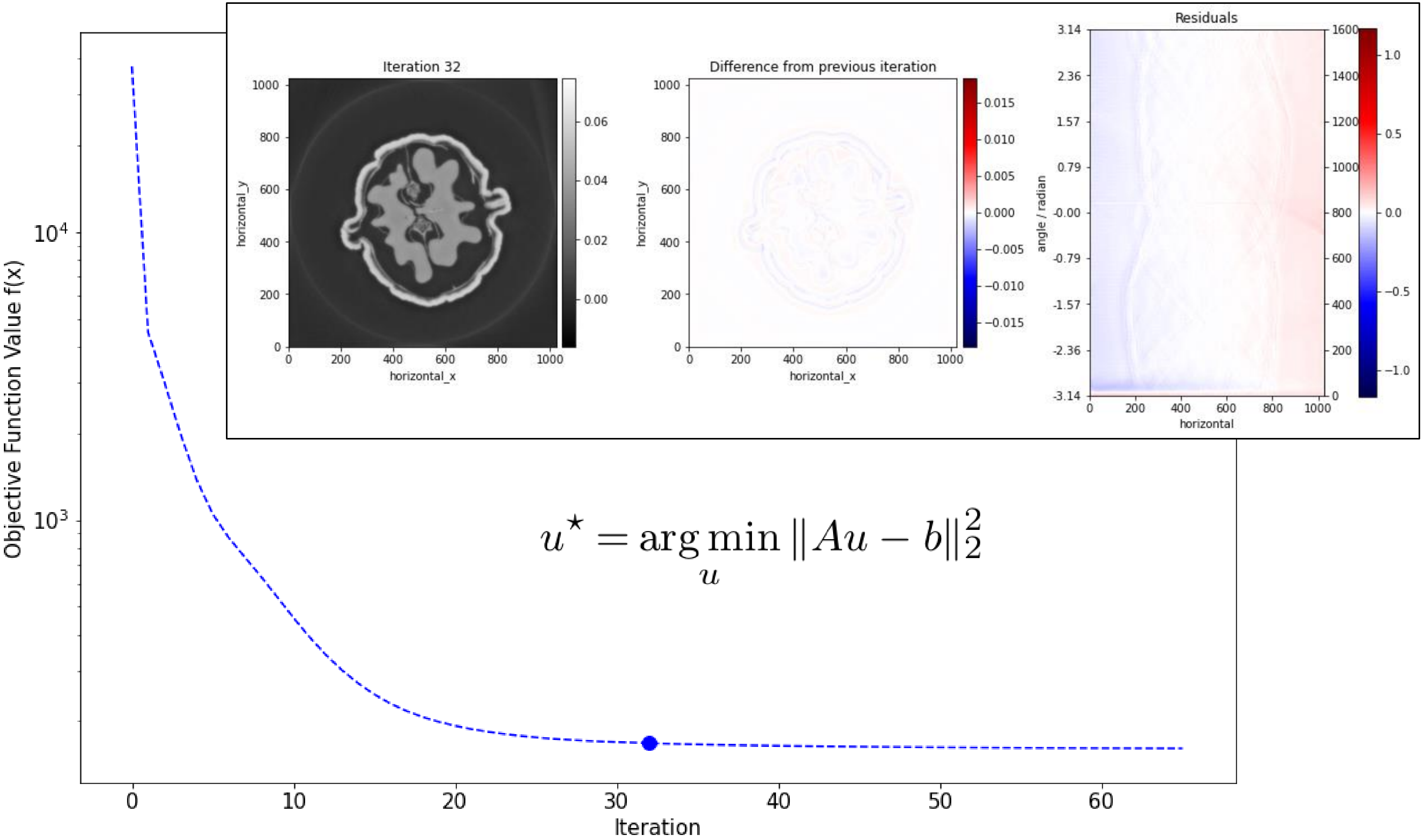
Solve optimisation problem iteratively



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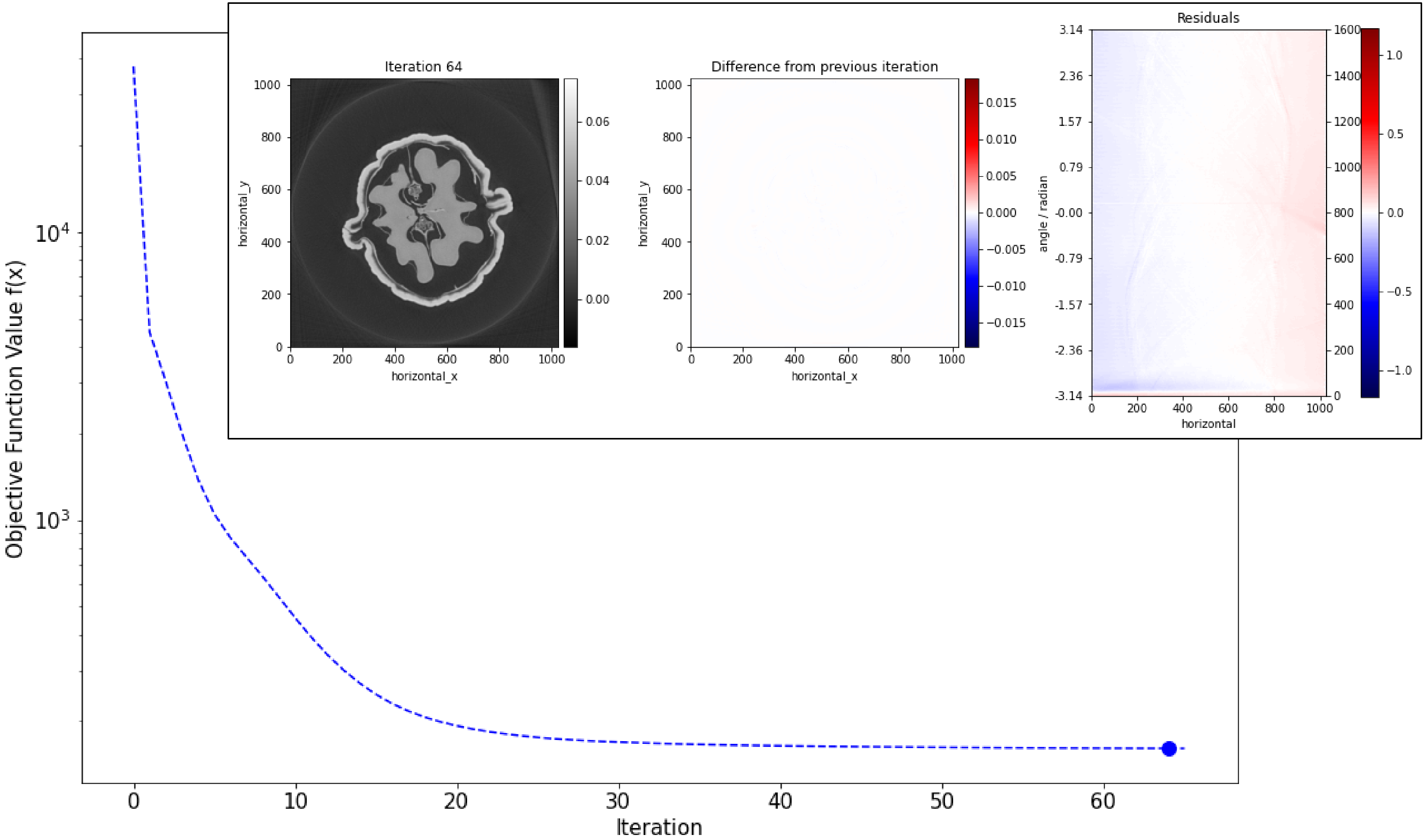
Solve optimisation problem iteratively



Try this out in breakout rooms

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

Learning Objectives:

In the end of this session, participants will be able to:

- formulate CT reconstruction as an optimisation problem and solve it iteratively
- introduce constraints in the optimisation problem
- visualise final and intermediate reconstruction results

- Go to: https://tinyurl.com/cil-online-25 write your name next to a **username** to claim it for the exercises
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Extension: CIL-Demos/demos/1_Introduction/05_usb_limited_angle_fbp_sirt.ipynb

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- Reconstruction behaviour well understood

Cons

- Number of projections needed proportional to acquisition panel size
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- Fixed scan geometries
- Cannot make use of prior knowledge such as non-negativity

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Summary and questions

We have seen:

- how to formulate CT reconstruction as an optimisation problem and solve it iteratively
- how to introduce constraints in the optimisation problem in CIL
- comparisons of CGLS, SIRT and FBP reconstructions in CIL
- the terms optimisation objective and optimisation algorithm

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Break

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Conclusions 4:45-5 – Jakob and Margaret

Regularisation

Iterative Reconstruction with Regularisation

Extremely large set of linear equations

$$b_i = \sum_j a_{ij} u_j \qquad Au = b$$

Ill posed problem

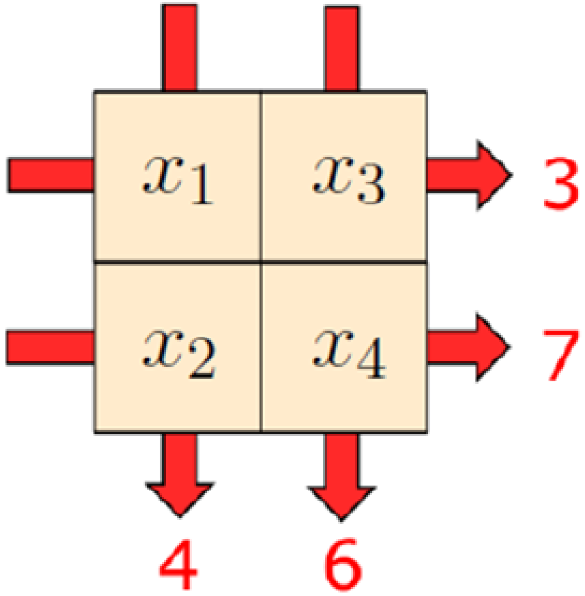
In case either:

1. No solution
2. Not unique solution
3. Solution sensitive to noise

Iterative reconstruction is based on optimisation algorithms and objective functions

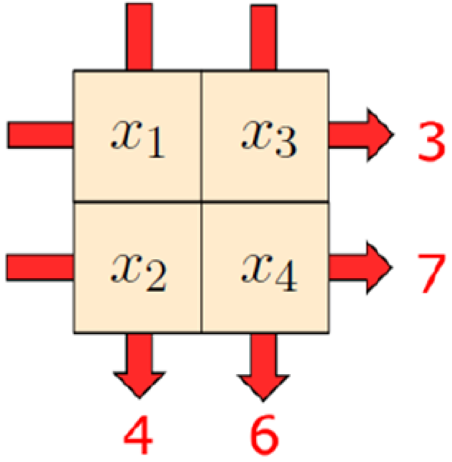
$$u^\star = \underset{u}{\operatorname{argmin}} \left\{ \mathcal{D}(Au, b) + \alpha \cdot \mathcal{R}(u) \right\}$$

Sudoku analogy



$$Au = b$$

Sudoku analogy



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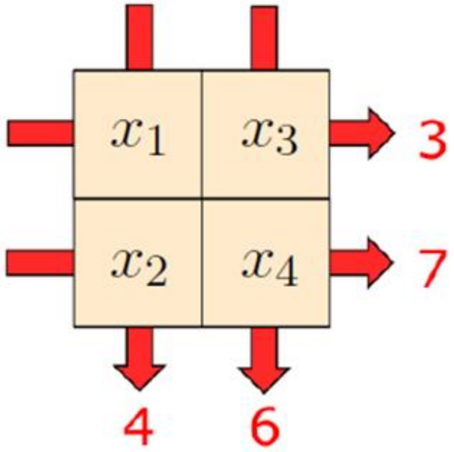
Sudoku analogy

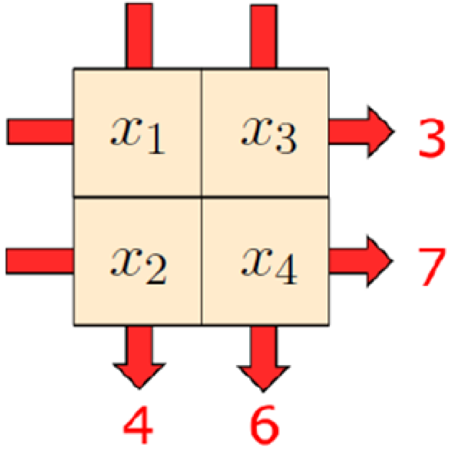


$$\begin{pmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{pmatrix} = \begin{pmatrix} 3 \\ 7 \\ 4 \\ 6 \end{pmatrix}$$

<u>Infinitely many solutions ($k \in \Re$):</u>

$$\begin{array}{|c|c|} \hline x_1 & x_3 \\ \hline x_2 & x_4 \\ \hline \end{array} = \begin{array}{|c|c|} \hline 1 & 2 \\ \hline 3 & 4 \\ \hline \end{array} + k \times \begin{array}{|c|c|} \hline -1 & 1 \\ \hline 1 & -1 \\ \hline \end{array}$$

Sudoku analogy



$$\begin{pmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{pmatrix} = \begin{pmatrix} 3 \\ 7 \\ 4 \\ 6 \end{pmatrix}$$

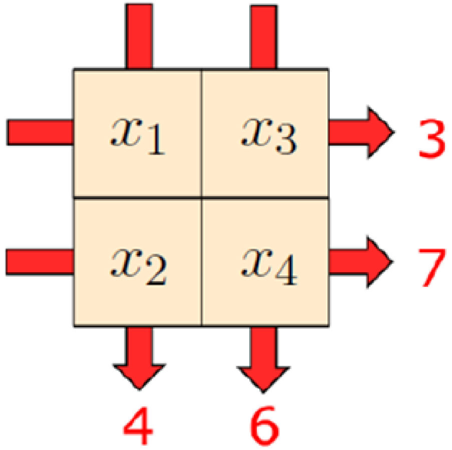
Infinitely many solutions ($k \in \Re$):

$$\begin{bmatrix} x_1 & x_3 \\ x_2 & x_4 \end{bmatrix} = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} + k \times \begin{bmatrix} -1 & 1 \\ 1 & -1 \end{bmatrix}$$

Prior: solution is integer and non-negative →

$$\begin{bmatrix} 0 & 3 \\ 4 & 3 \end{bmatrix} \quad \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \quad \begin{bmatrix} 2 & 1 \\ 2 & 5 \end{bmatrix} \quad \begin{bmatrix} 3 & 0 \\ 1 & 6 \end{bmatrix}$$

Sudoku analogy



$$\begin{pmatrix}1 & 0 & 1 & 0\\ 0 & 1 & 0 & 1\\ 1 & 1 & 0 & 0\\ 0 & 0 & 1 & 1\end{pmatrix}\begin{pmatrix}x_1\\ x_2\\ x_3\\ x_4\end{pmatrix} = \begin{pmatrix}3\\ 7\\ 4\\ 6\end{pmatrix}$$

Infinitely many solutions ($k \in \Re$):

$$\begin{bmatrix}x_1 & x_3\\ x_2 & x_4\end{bmatrix} = \begin{bmatrix}1 & 2\\ 3 & 4\end{bmatrix} + k \times \begin{bmatrix}-1 & 1\\ 1 & -1\end{bmatrix}$$

0	3
4	3

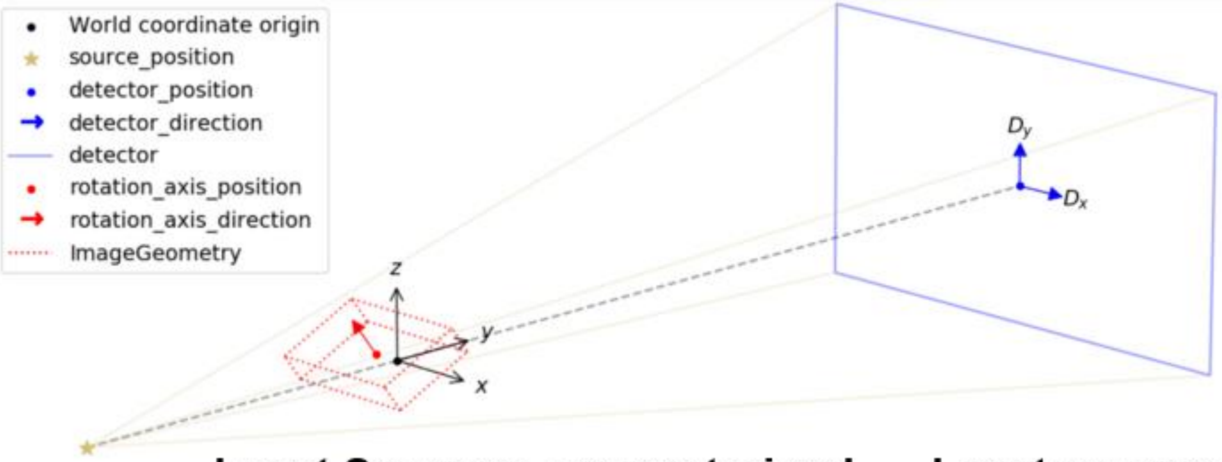
1	2
3	4

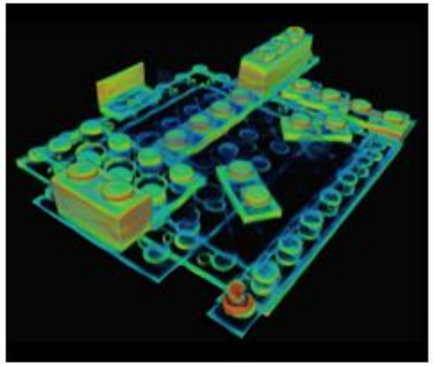
2	1
2	5

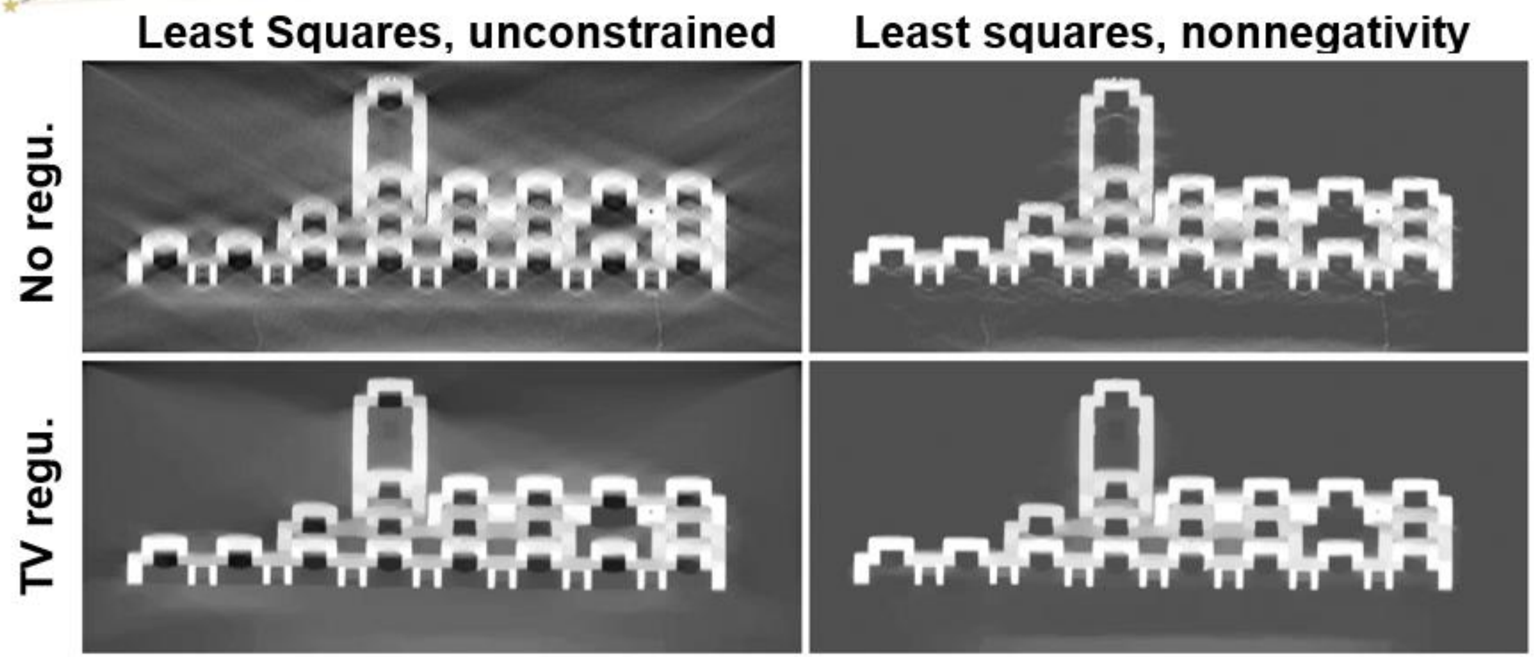
Prior: solution is integer and non-negative →

3	0
1	6

CIL example - non-standard scan

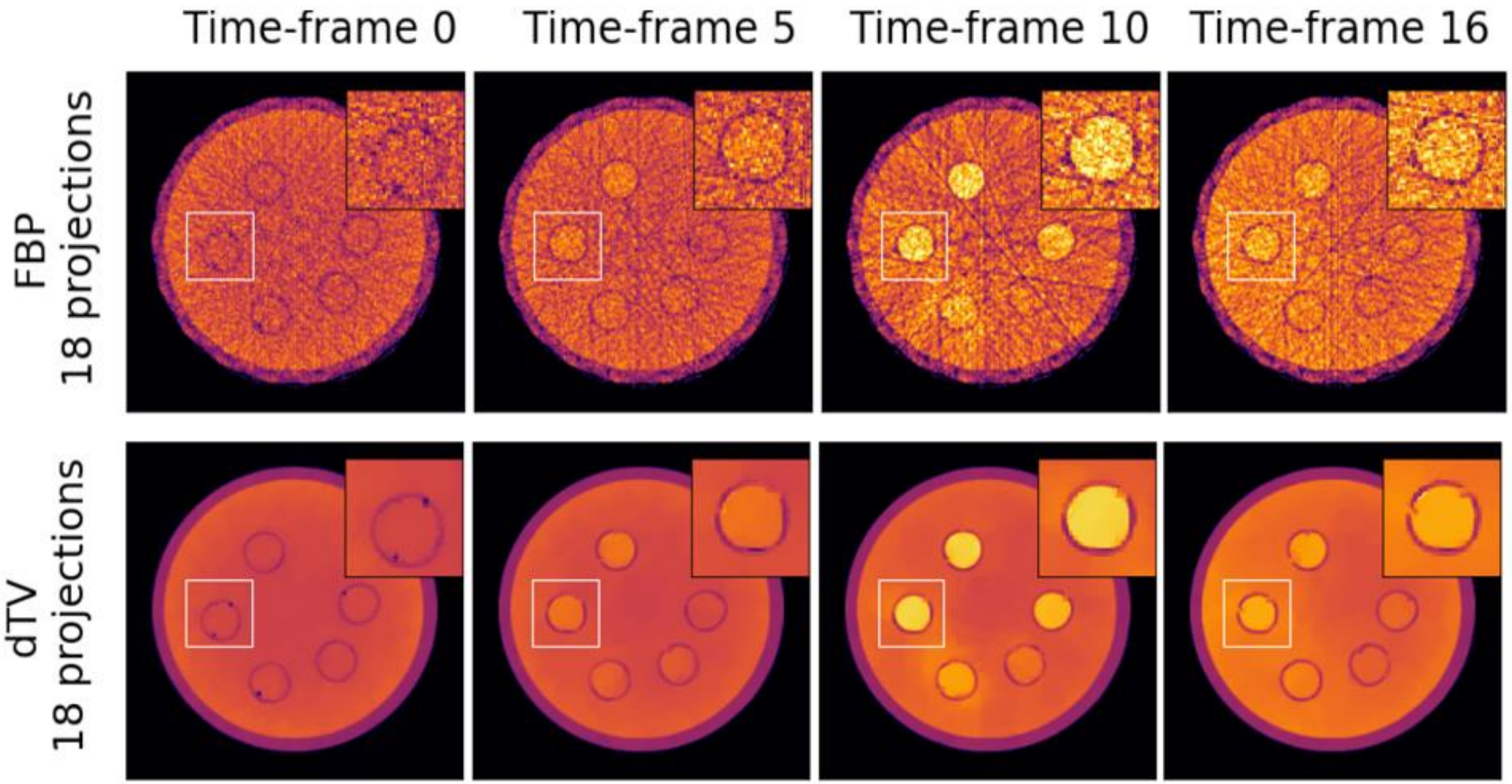






Jørgensen et al. 2021: *Core Imaging Library - Part I: a versatile Python framework for tomographic imaging*, Phil Trans A. https://doi.org/10.1098/rsta.2020.0192

CIL example - few-view dynamic CT



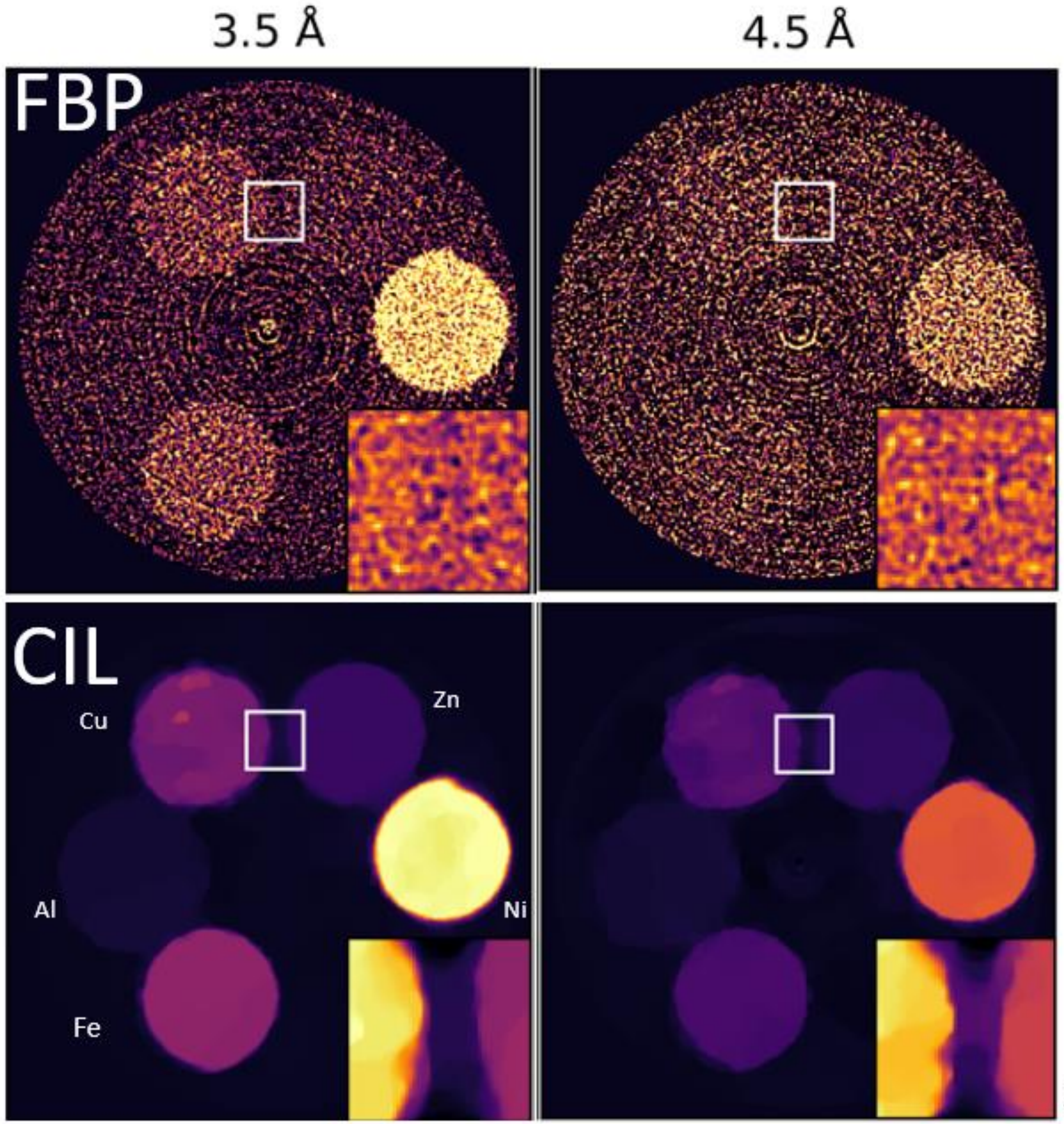
Filtered back-projection

Directional TV propagating edges from pre and post scan

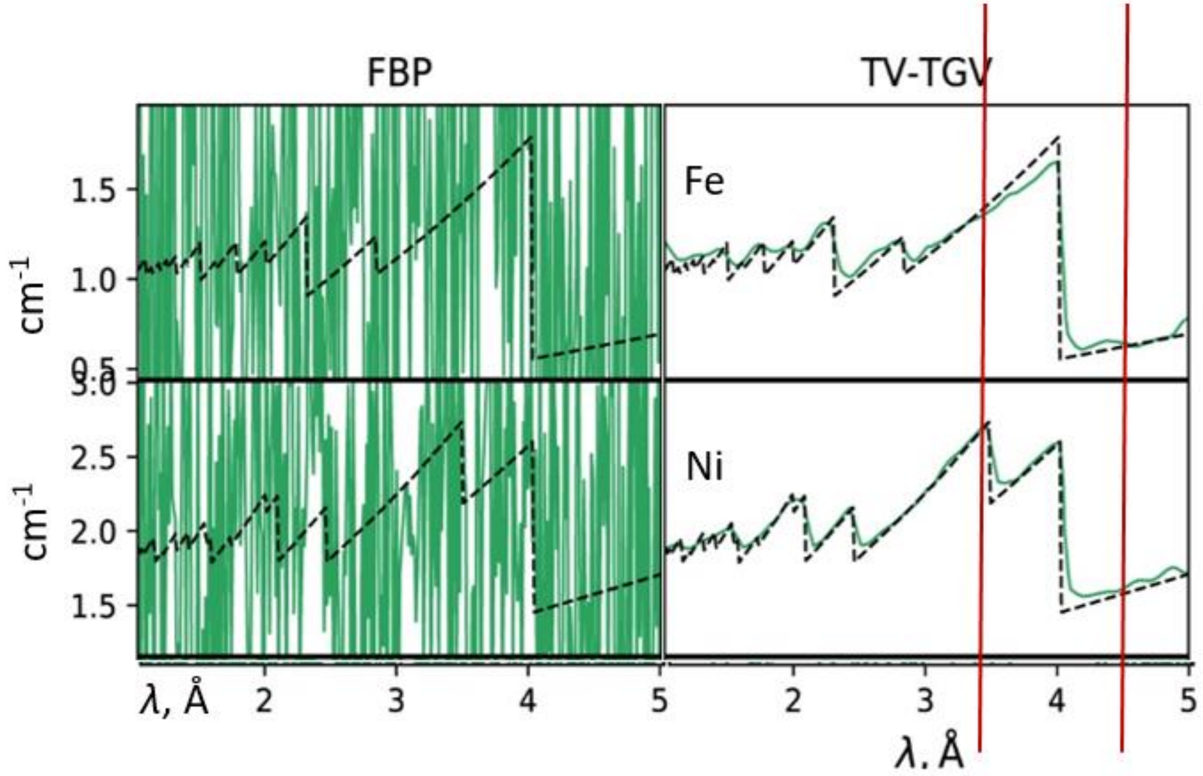
Papoutsellis et al. 2021: *Core Imaging Library - Part II: multichannel reconstruction for dynamic and spectral tomography*, Phil. Trans. R. Soc. A, **379**, 20200193: https://doi.org/10.1098/rsta.2020.0193

FIPS dataset: Tommi Heikkilä, Hanna Help and Alexander Meaney: "Gel phantom data for dynamic X-ray tomography" https://doi.org/10.5281/zenodo.4540623

Energy-resolved neutron CT



- Proposed spatio-spectral TV-TGV regularization
- Enables clear identification of Bragg edges in 3D



Ametova et al. 2021: *Crystalline phase discriminating neutron tomography using advanced reconstruction methods*, J. Physics D, https://doi.org/10.1088/1361-6463/ac02f9

Regularization notebook walk-through

PyData22_deblurring.ipynb

Demo notebook

Go to:
CIL-Demos/binder/PyData22_deblurring.ipynb

Learning Objectives:
- Load a CIL example dataset
- Set-up a deblurring inverse problem
- Compare the results of different regularisation choices : Tikhonov, L1-Norm, Total-Variation
- Solve different optimisation problems with the same algorithm: FISTA

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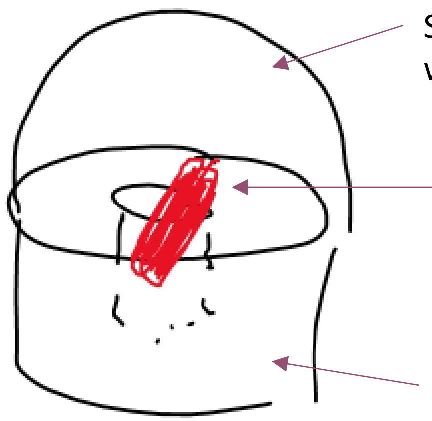
Functions in CIL

name	description
BlockFunction	separable sum of multiple functions
ConstantFunction	function taking the constant value
OperatorCompositionFunction	compose function f and operator A: $f(Ax)$
IndicatorBox	indicator function for box (lower/upper) constraints
KullbackLeibler	Kullback–Leibler divergence data fidelity
L1Norm	L^1-norm: $\|x\|_1 = \sum_i \|x_i\|$
L2NormSquared	squared L^2-norm: $\|x\|_2^2 = \sum_i x_i^2$
LeastSquares	least-squares data fidelity: $\|Ax - b\|_2^2$
MixedL21Norm	mixed $L^{2,1}$-norm: $\|(U_1; U_2)\|_{2,1} = \|(U_1^2 + U_2^2)^{1/2}\|_1$
SmoothMixedL21Norm	smooth $L^{2,1}$-norm: $\|(U_1; U_2)\|_{2,1}^S = \|(U_1^2 + U_2^2 + \beta^2)^{1/2}\|_1$
WeightedL2NormSquared	weighted squared L^2-norm: $\|x\|_w^2 = \sum_i (w_i \cdot x_i^2)$
TotalVariation	$\mathrm{TV}(u) = \|Du\|_{2,1} = \sum_{i,j} \left(\sqrt{(D_y u)^2 + (D_x u)^2}\right)_{i,j}$
WeightedL1Norm	$\|x\|_{1,w} = \sum_i \|x_i\, w_i\|$
ApproximateGradientSumFunction	…
SGFunction	…

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°

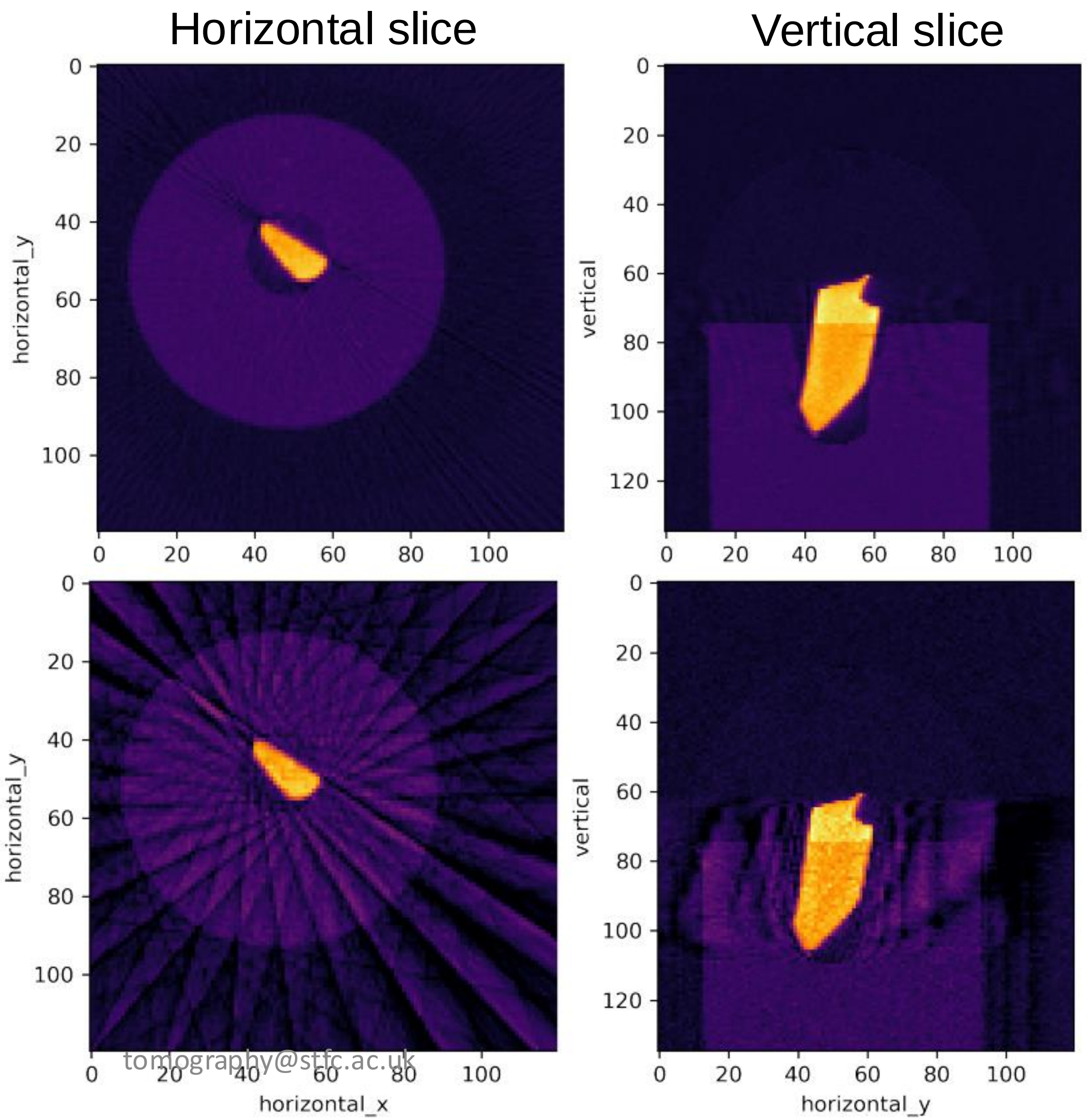
Jørgensen et al.: *Core Imaging Library - Part I: a versatile Python framework for tomographic imaging* Phil. Trans. R. Soc. A. **379** 20200192 (2021) DOI: [10.1098/rsta.2020.0192](https://doi.org/10.1098/rsta.2020.0192)



Demonstration dataset

90
projections

15
projections



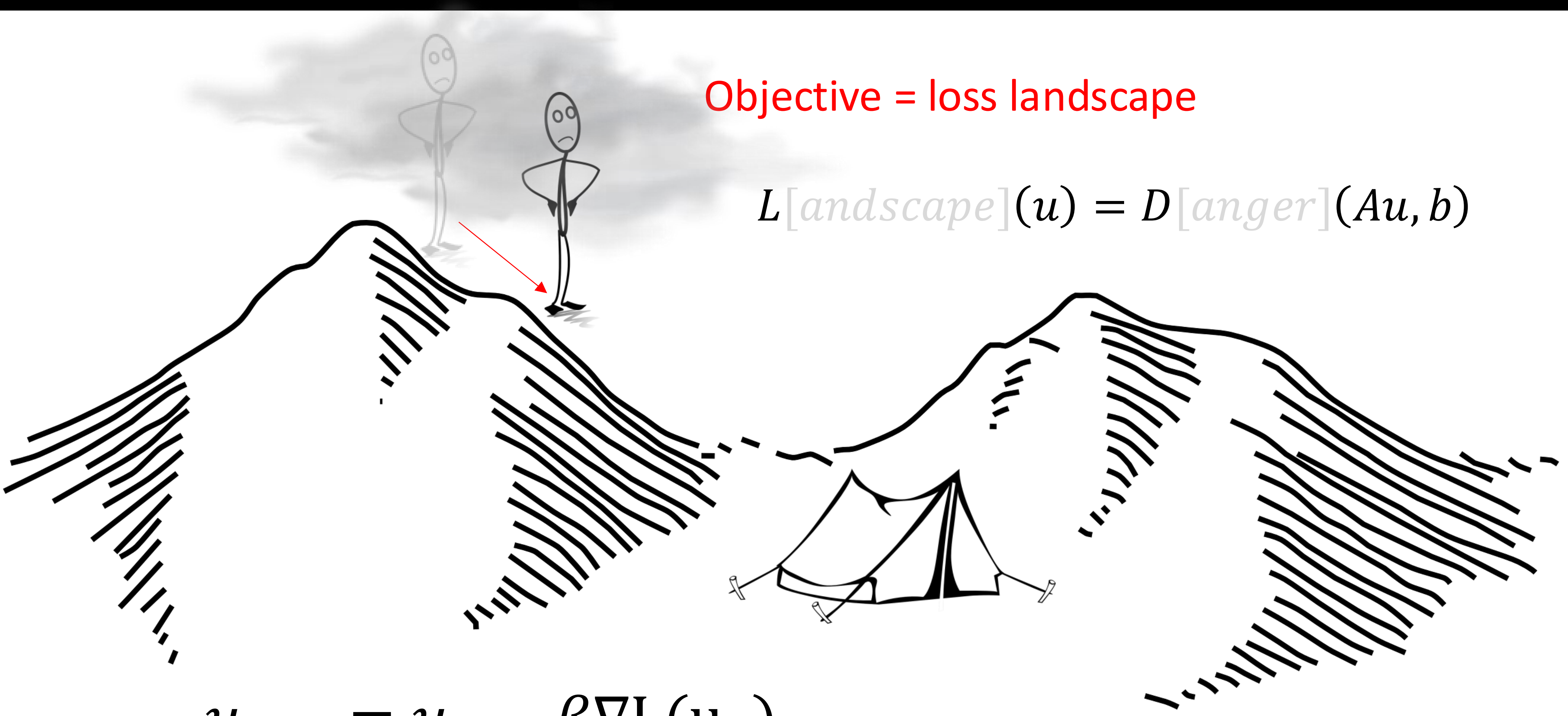
Try that out in breakout rooms:

Go to:
CIL-Demos/demos/2_Iterative/01_optimisation_gd_fista.ipynb

Learning Objectives:
- Load a dataset and reconstruct with FBP
- Set-up a least-squares problem to solve using CIL's algorithms, a projection operator and objective function
- Add regularisation to the least-squares problem and compare the results: Tikhonov, Non-negativity, L1-Norm, Total-Variation
- Solve the optimisation problem with the appropriate algorithm: Gradient Descent, FISTA, PDHG

- Go to: https://tinyurl.com/cil-online-25 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.

Optimisation algorithms – Gradient Descent



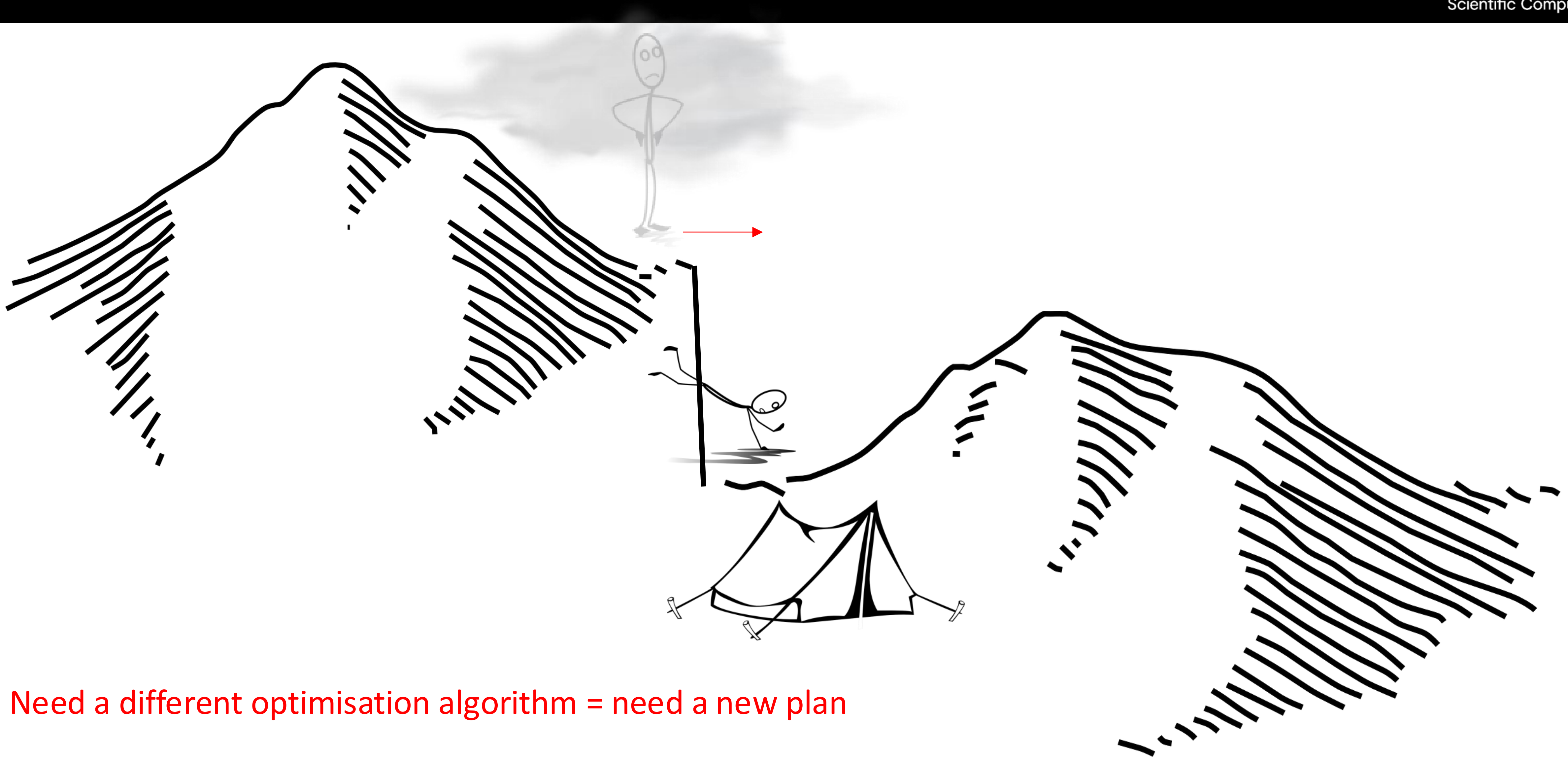
Objective = loss landscape

$$L[landscape](u) = D[anger](Au, b)$$

$$u_{k+1} = u_k - \beta \nabla \mathrm{L}(\mathrm{u_k})$$

Optimisation algorithm = plan to get to the bottom

Optimisation algorithms – Non smooth



Need a different optimisation algorithm = need a new plan

CIL Optimisation module

name	description	problem type solved
CGLS	conjugate gradient least squares	least squares
SIRT	simultaneous iterative reconstruction technique	weighted least squares
GD	gradient descent	smooth
FISTA	fast iterative shrinkage-thresholding algorithm	smooth + non-smooth
LADMM	linearized alternating direction method of multipliers	non-smooth
PDHG	primal dual hybrid gradient	non-smooth
SPDHG	stochastic primal dual hybrid gradient	non-smooth

MaskOperator
SymmetrisedGradientOperator
ZeroOperator
ProjectionOperator
ProjectionOperator

L2NormSquared	squared L^2-norm: $\|x\|_2^2 = \sum_i x_i^2$
LeastSquares	least-squares data fidelity: $\|Ax - b\|_2^2$
MixedL21Norm	mixed $L^{2,1}$-norm: $\|(U_1; U_2)\|_{2,1} = \|(U_1^2 + U_2^2)^{1/2}\|_1$
SmoothMixedL21Norm	smooth $L^{2,1}$-norm: $\|(U_1; U_2)\|_{2,1}^S = \|(U_1^2 + U_2^2 + \beta^2)^{1/2}\|_1$
WeightedL2NormSquared	weighted squared L^2-norm: $\|x\|_w^2 = \sum_i (w_i \cdot x_i^2)$
TotalVariation	$\mathrm{TV}(u) = \|Du\|_{2,1} = \sum_{i,j} \left(\sqrt{(D_y u)^2 + (D_x u)^2} \right)_{i,j}$

Optimisation algorithms in CIL

Gradient Descent (GD)	When your objective is convex and differentiable
Conjugate Gradient Least Squares (CGLS)	For minimising a least squares problem e.g. $\min_u \|\|Au - b\|\|_2^2$
Simultaneous Iterative Reconstruction Technique (SIRT)	To solve problems of the form $Au = b$ with optional constraints
Iterative Shrinkage-Thresholding Algorithm (ISTA)	To solve problems of the form $\min_u f(u) + g(u)$ where f is convex and differentiable and g is convex with a simple proximal operator
Fast Iterative Shrinkage-Thresholding Algorithm (FISTA)	Like ISTA but accelerated
Primal Dual Hybrid Gradient (PDHG)	To solve problems of the form $\min_u f(Au) + g(u)$ where f is convex and has a "simple" proximal method of its conjugate and g is convex with a "simple" proximal.
Stochastic Primal Dual Hybrid Gradient (SPDHG)	Similar to PDHG but where f can be written as a separable sum
Linearized Alternating Direction Method of Multipliers (LADMM)	To solve problems of the form $\min_u f(u) + g(v)$ $f(x)$ subject to $Au + Bv = b$ where both f and g are convex and have "simple" proximals.
Stochastic algorithms…	Training coming soon…

Optimisation algorithms in CIL

Gradient Descent (GD)	When your objective is convex and differentiable
Conjugate Gradient Least Squares (CGLS)	For minimising a least squares problem e.g. $\min_u \lVert Au - b \rVert_2^2$
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Stochastic algorithms…	Training coming soon…

$$\operatorname{prox}_{\tau g}(u) = \arg\min_v \left\{ \tau g(v) + \frac{1}{2}\lVert v - u \rVert_2^2 \right\}$$

Summary and questions

We have seen:

- How additional regularisation terms in your optimisation objective can change the reconstruction
- How to implement Tikhonov, Non-negativity, L1-Norm, Total-Variation regularisation in CIL and compare the results
- That different choices of optimisation objective require different optimisation algorithms

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Break

Training Program

Welcome, intro and cloud set-up 1-1:15 – Edo

Intro to optimisation – 1:15-2:15 – Edo

- Intro lecture
- Time to explore: demos/1_Introduction/04_FBP_CGLS_SIRT.ipynb
- Extension: demos/1_Introduction/05_USB
- **Break**

Intro to regularisation 2:30-3:45 – Jakob

- Intro lecture
- Demo: binder/PyData22_deblurring.ipynb
- Notebook: 2_Iterative/Optimisation_gd_fista.ipynb
- **Break**

Time to explore and discuss – 4:00-4:45 – Jakob

- Notebook: 2_Iterative/05_Laminography_with_TV.ipynb
- Notebook: 3_Multichannel/03_Hyperspectral_reconstruction.ipynb

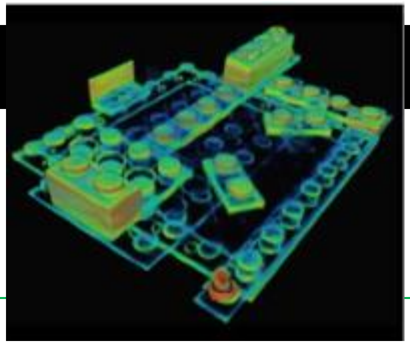
Conclusions 4:45-5 – Edo

Time to explore and discuss

Time to explore

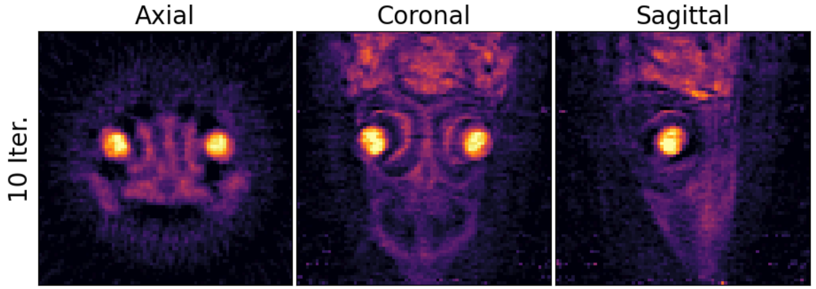
Option 1 : CIL-Demos/demos/2_Iterative/05_Laminography_with_TV.ipynb

- Construct an advanced AcquisitionGeometry by-hand to describe the tilted and offset data
- Use this geometry to read in a tiff stack and create an AcquisitionData object
- Create a custom ImageGeometry around the flat sample
- Reconstruct the data with LS and TV



Option 2: CIL-Demos/demos/3_Multichannel/03_Hyperspectral_reconstruction.ipynb

- Identify the key differences in building Image/Acquisition Geometries and Operators for hyperspectral datasets
- Build your own reconstructions using FDK, CGLS and PDHG
- Determine optimum regularisation parameters based on reconstruction method
- Evaluate the effectiveness of each reconstruction routine using spatial and energy profiles.



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- CIL Jupyter notebook server: https://training.jupyter.stfc.ac.uk/
- **Sign up with the username** you claimed and a password of your choice.

CIL User Showcase

- 001 – Multibang regularisation
- 002 – Deblurring with CIL
- 003 – 1D integral inverse problem
- 004 – Dynamic CT example
- 005 – Dynamic MR example (with SIRF)
- 006 – CT simulation with gVXR
- 007 – Hyperspectral regularisation
- 008 - Poisson noise models for the data discrepancy term
- 009 – Offset CT reconstruction of an apple
- 010 – Bruker Skyscan reader and reconstruction
- 011 – Phase contrast Exciscope data
- 012 – Wavelet sparsity control regularization
- 013 – anisotropic regularization for FILD measurements
- 014 – GVXR simulation and CIL CPU reconstruction
- One more currently in review!

https://github.com/TomographicImaging/CIL-User-Showcase

Questions?

Feedback and next steps

Tomorrow

Welcome, intro and cloud set-up 1-1:15

Building your own optimisation problem using the block framework– 1:15-2:30 – Jakob

- Demo: 2_Iterative/02_tikhonov_block_framework.ipynb
- Block framework example lecture
- Notebook: 4_Deep_Dives/03_htc_2022.ipynb
- **Break**

Customising your optimisation method- 2:45-3:30 – Margaret

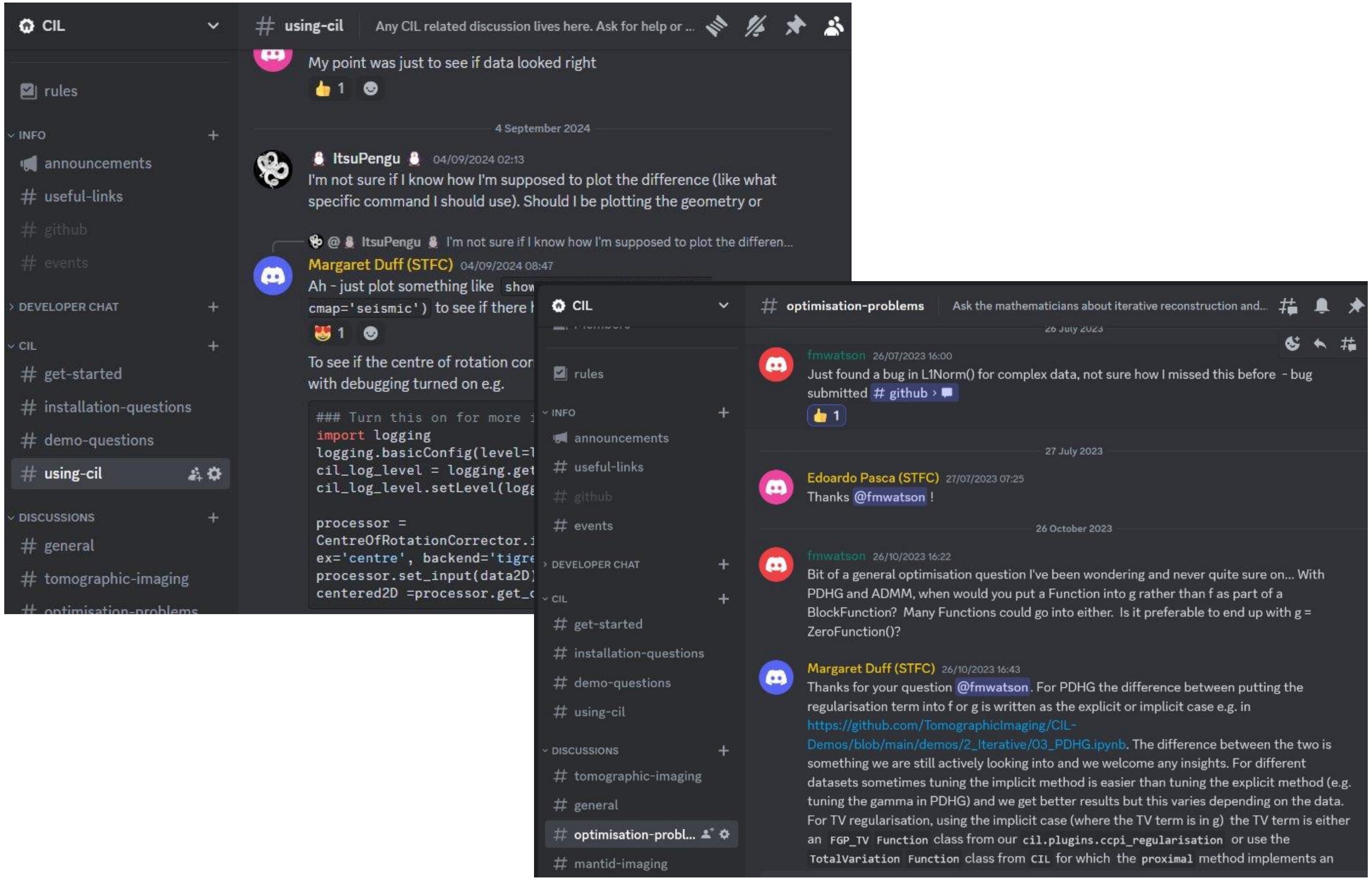
- Demo notebook: 4_Deep_Dives/01_callbacks.ipynb
- Notebook: 4_Deep_Dives/04_preconditioner_stepsize.ipynb
- **Break**

Time to explore and discuss – 3:45-4:45 – Margaret

- Notebook: 1_Introduction/exercises/03_where_is_my_reader.ipynb
- Notebook: 4_Deep_Dives/04_phase_retrieval.ipynb
- Notebook: 3_Multichannel/02_Dynamic_CT.ipynb
- Notebook: 4_Deep_Dives/06_directional_TV.ipynb

Conclusions and further support 4:45-5 – Edo

Discord Community



Join our Discord community:

tinyurl.com/cil-discord

CIL Publications

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Scientific Computing

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)

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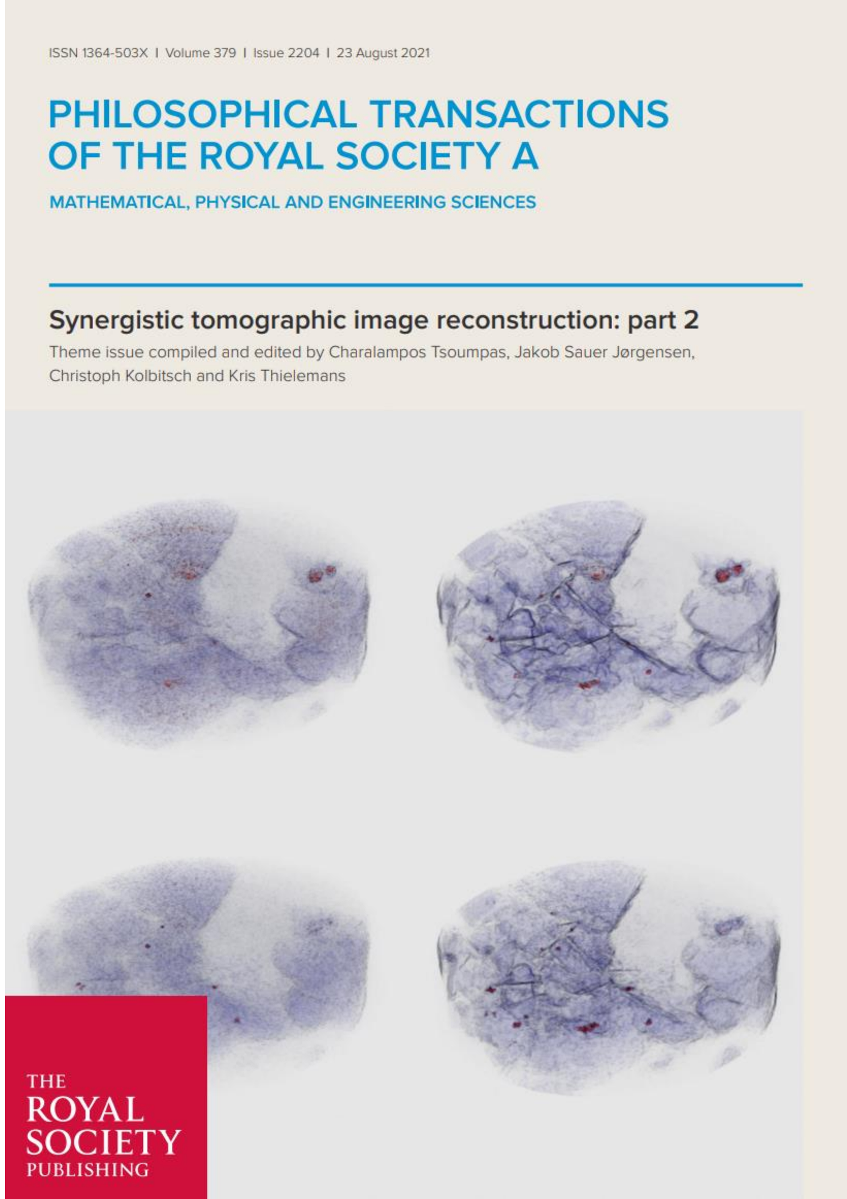

Tell us about your work!

If you publish or present - or win a prize - for work done using CIL, please:

- Tell us about it – tomography@stfc.ac.uk

- Cite CIL --> citations help us secure funding for more CIL!

https://github.com/TomographicImaging/CIL

Citing CIL

If you use CIL in your research, please include citations to **both** the software on Zenodo, and a CIL paper:

E. Pasca, J. S. Jørgensen, E. Papoutsellis, E. Ametova, G. Fardell, K. Thielemans, L. Murgatroyd, M. Duff and H. Robarts (2023)
Core Imaging Library (CIL)
Zenodo [software archive]
DOI: https://doi.org/10.5281/zenodo.4746198

Thank you - and see you again tomorrow!

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Scientific Computing

Come talk to us on the CIL Discord support forum:
https://tinyurl.com/cil-discord

Spare slides

Smooth Regularisation: Tikhonov

Data fidelity

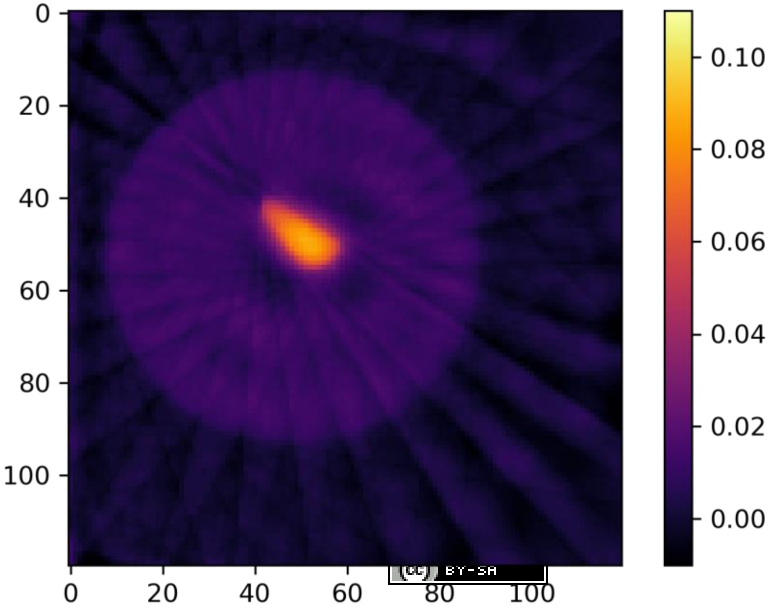
Regulariser

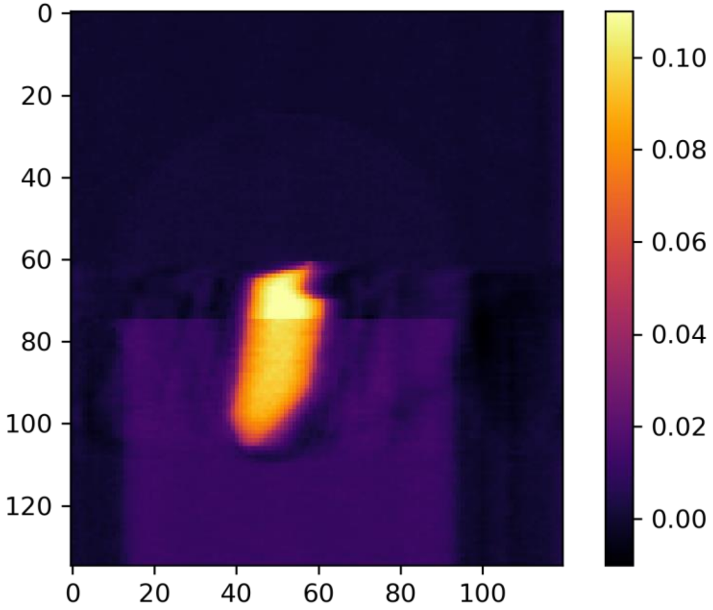
$$u^\star = \arg\min_{u} \left\{ \|Au - b\|_2^2 + \alpha^2 \|Lu\|_2^2 \right\}$$

Minimiser: Solution image

Unknown image TBD

Regularisation parameter



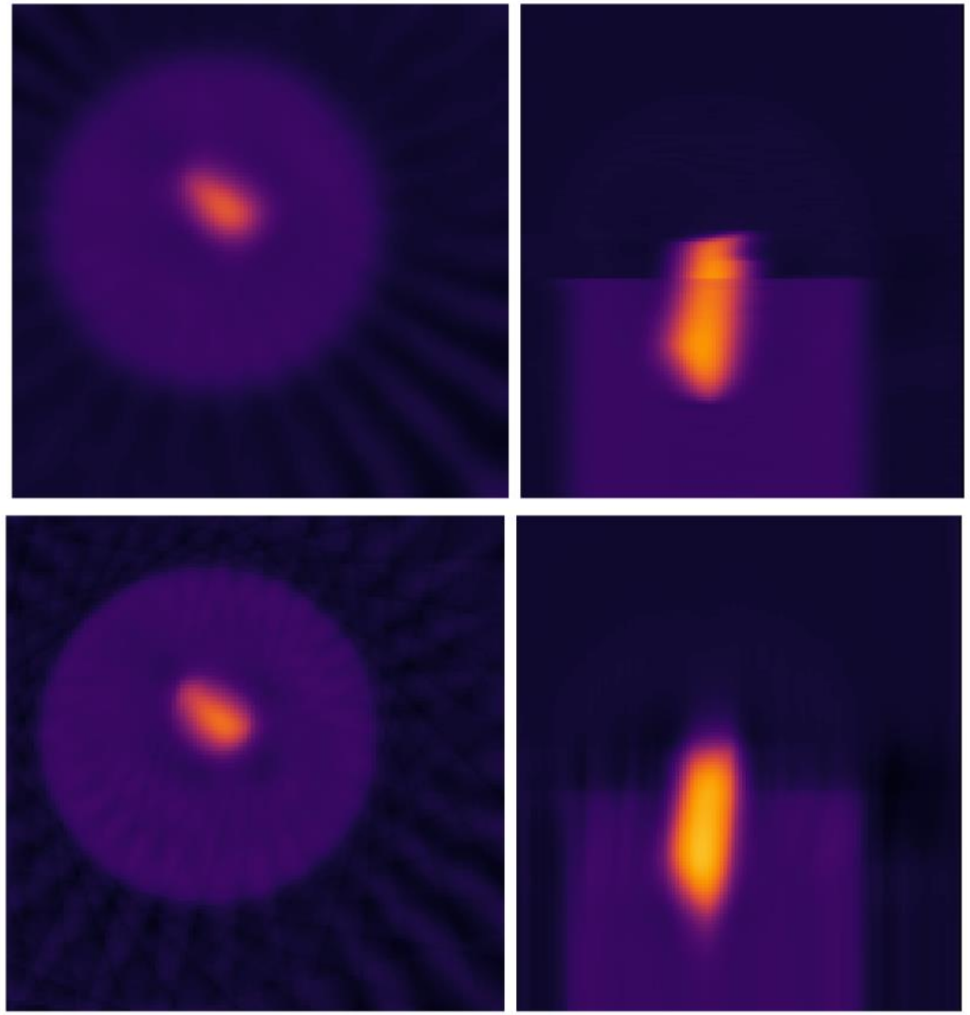


Smooth Regularisation: Anisotropic Tikhonov

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

Large horizontal,
small vertical smoothing

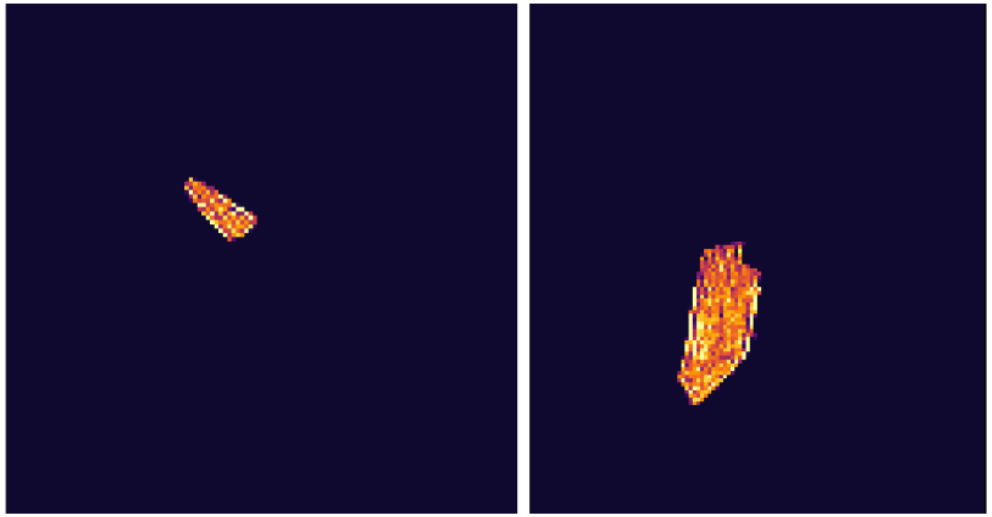
Small horizontal,
large vertical smoothing



Sparsity: L1 Regularization

L1-norm regularisation:

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



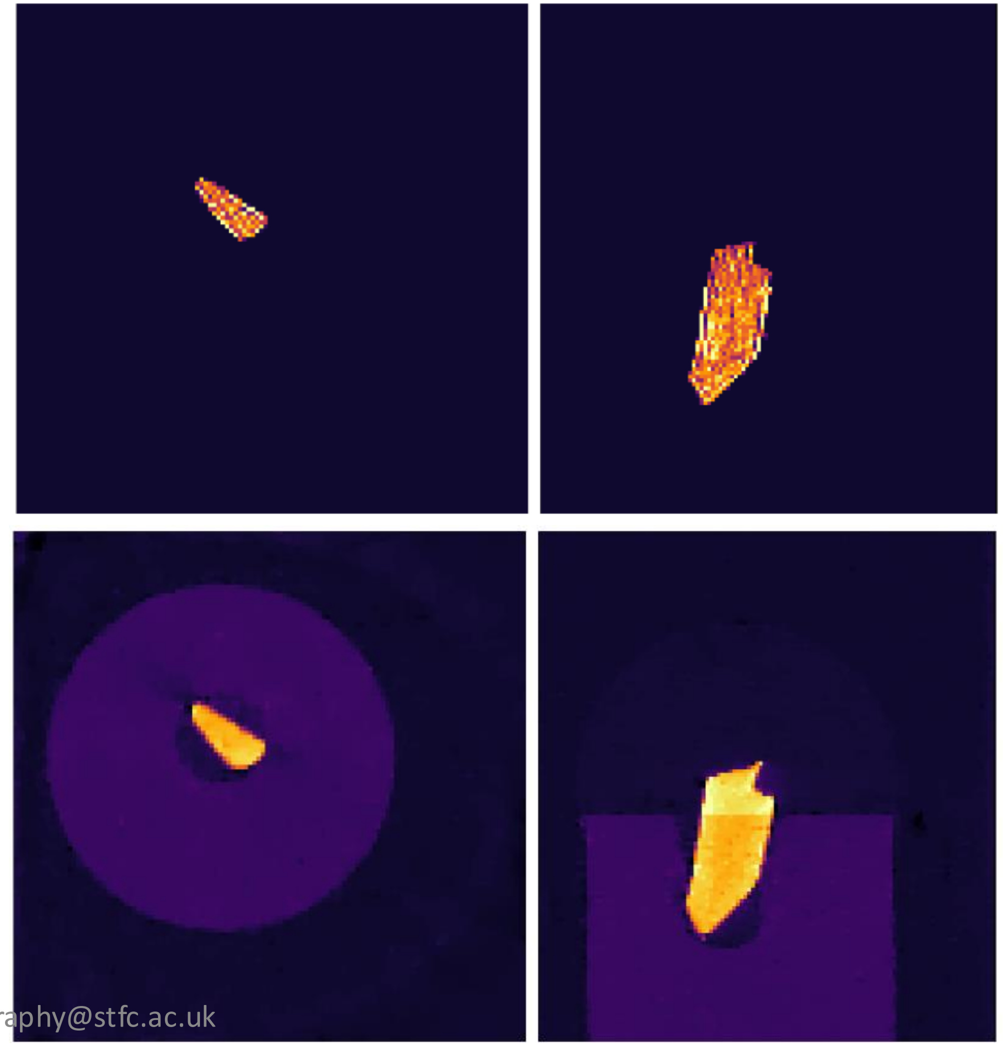
Sparsity and Total Variation Regularization

L1-norm regularisation:

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

Total variation regularisation:

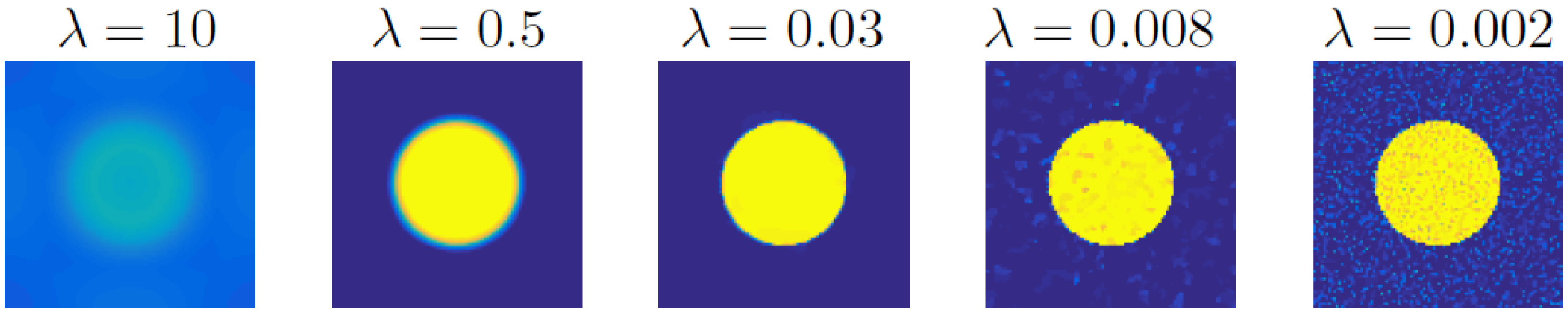
$$\sum_j \|D_j u\|_2$$



Effect of the Regularisation Parameter

Total variation regularization:

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



- Large λ: Almost only effect of regularizer. TV $\rightarrow$ Constant.
- Small λ: Almost just least-squares solution.
- Best trade-off?

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CIL community

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Scientific Computing

CIL "Bring Your Own Data" Hackathon
Isaac Newton Institute
Cambridge, UK – Mar 2023

First CIL User Meeting
Rutherford Appleton Laboratory
Harwell, UK – Nov 2023

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.

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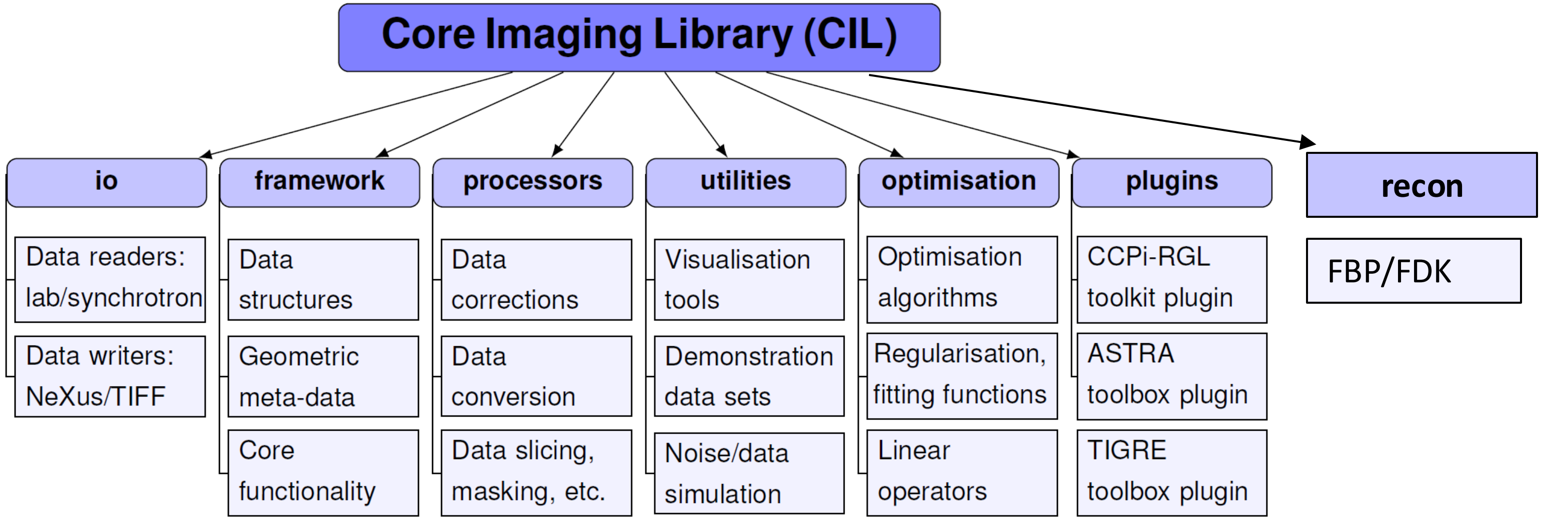
CIL Module Structure and Contents



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.

Documentation

CIL Introduction Framework Read/ write AcquisitionData and ImageData Optimisation framework Processors Recon Utilities CIL Plugins Developers' Guide More

Search the docs ... Ctrl + K

24.0.0

Table of Contents

Contents:

Edit on GitHub

Welcome to CIL's documentation!

The aim of this package is to enable rapid prototyping of optimisation-based reconstruction problems, i.e. defining and solving different optimization problems to enforce different properties on the reconstructed image, while being powerful enough to be employed on real scale problems.

Firstly, it provides a framework to handle acquisition and reconstruction data and metadata; it also provides a basic input/output package to read data from different sources, e.g. Nikon X-Radia, NeXus.

Secondly, it provides an object-oriented framework for defining mathematical operators and functions as well a collection of useful example operators and functions. Both smooth and non-smooth functions can be used.

Further, it provides a number of high-level generic implementations of optimisation algorithms to solve generically formulated optimisation problems constructed from operator and function objects.

Demos and Examples

A number of demos can be found in the CIL-Demos repository.

For detailed information refer to our articles and the repositories with the code to reproduce the article's results.

1. Jørgensen JS et al. 2021 Core Imaging Library Part I: a versatile python framework for tomographic imaging https://doi.org/10.1098/rsta.2020.0192 . Phil. Trans. R. Soc. A 20200192. The code to reproduce the article results. TomographicImaging/Paper-2021-RSTA-CIL-Part-I

2. Papoutsellis E et al. 2021 Core Imaging Library - Part II: multichannel reconstruction for dynamic and spectral tomography https://doi.org/10.1098/rsta.2020.0193 Phil. Trans. R. Soc. A 20200193. The code to reproduce the article results. TomographicImaging/Paper-2021-RSTA-CIL-Part-II

Cite this work

If you use this software please consider citing one or both of the articles above.

https://tomographicimaging.github.io/CIL

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

Algebraic Iterative Methods

regularising by number of iterations

CGLS

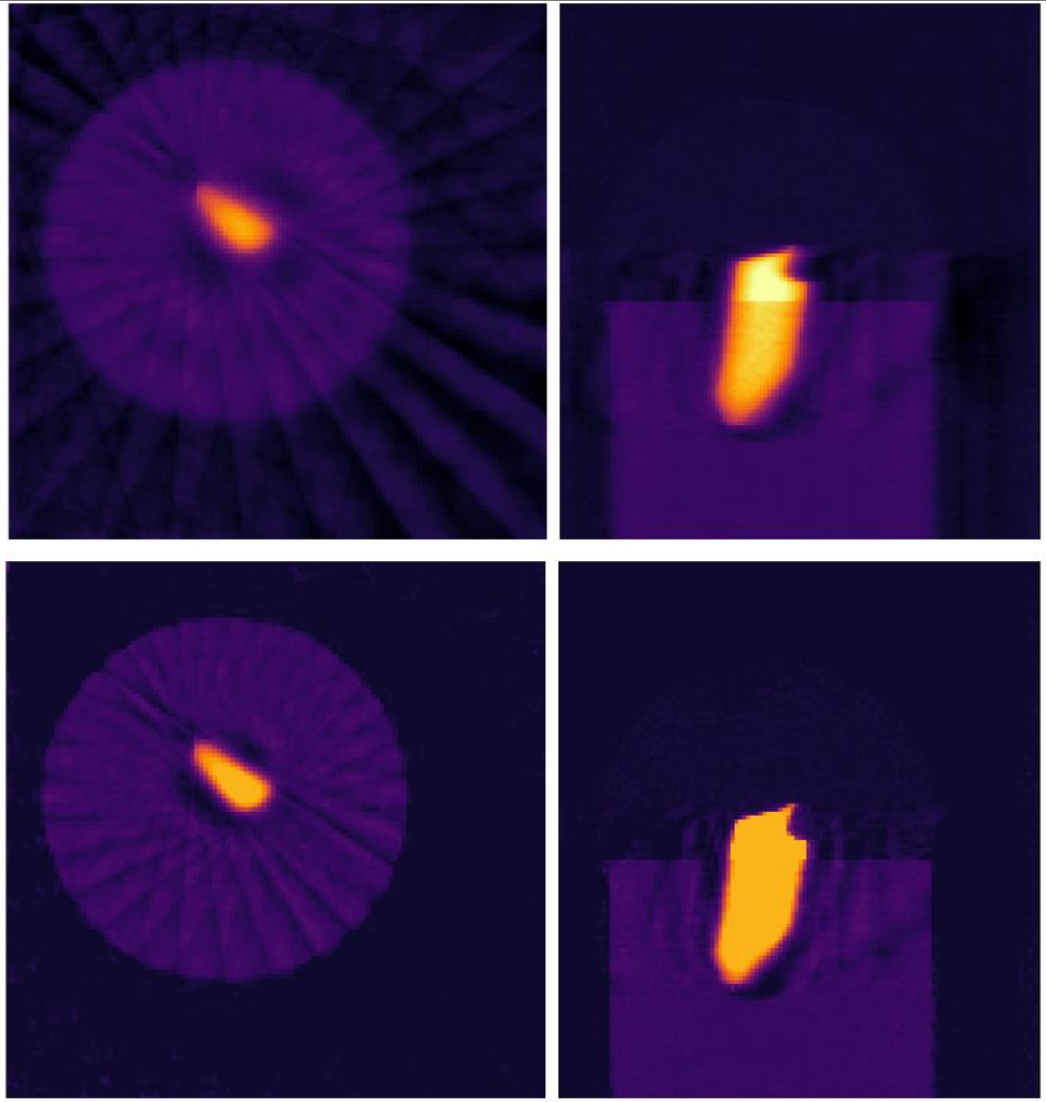
$$u^\star = \arg\min_u ||Au - b||_2^2$$

Typically 10s of iterations

SIRT

As above and allowing lower and upper bounds on pixel values, here Non-negative and <= 0.9

Typically 100s of iterations



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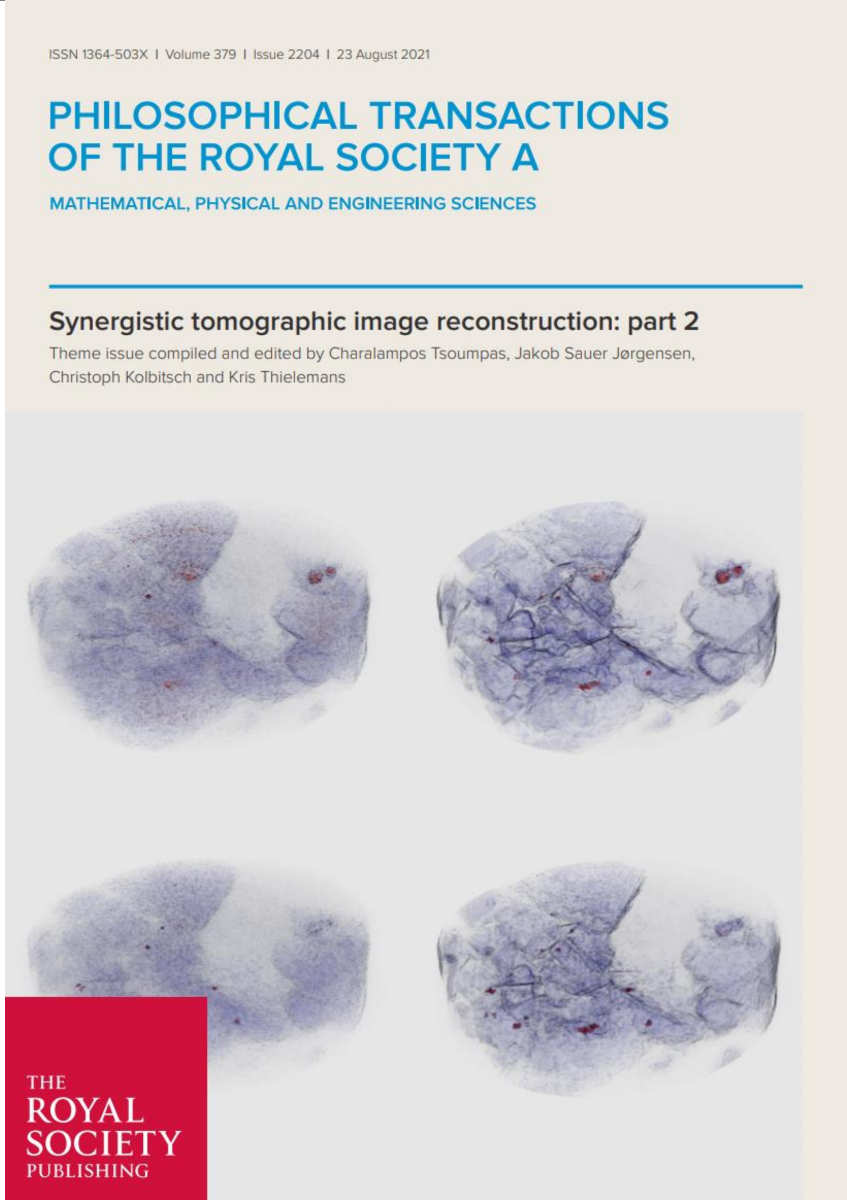

CCP*i* = CCP in Tomographic Imaging

- 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

Conclusion

- 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.ccpi.ac.uk/CIL

Discord community:
discord.gg/ky7yCqRcYn

tomography@stfc.ac.uk

Core Imaging Library for CT and other inverse problems

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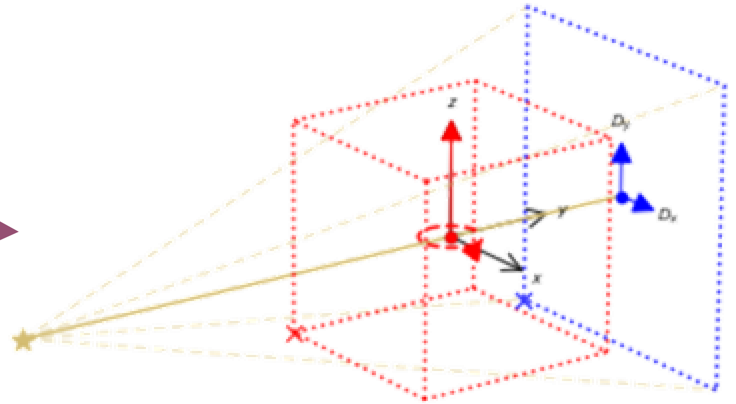
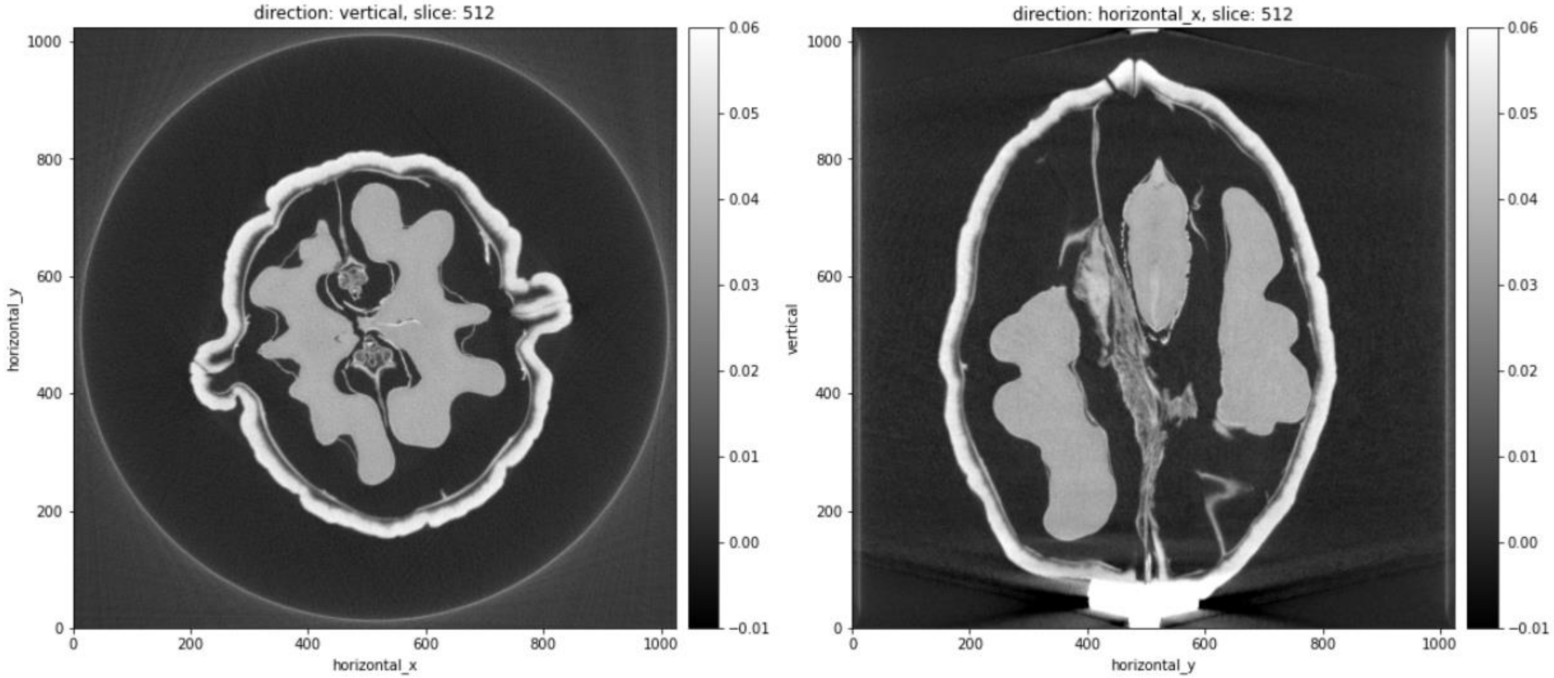
```
data = ZEISSDataReader(filename).read()
data = TransmissionAbsorptionConverter()(data)
show_geometry(data.geometry)
recon = FDK(data).run()
show2D(recon)
```

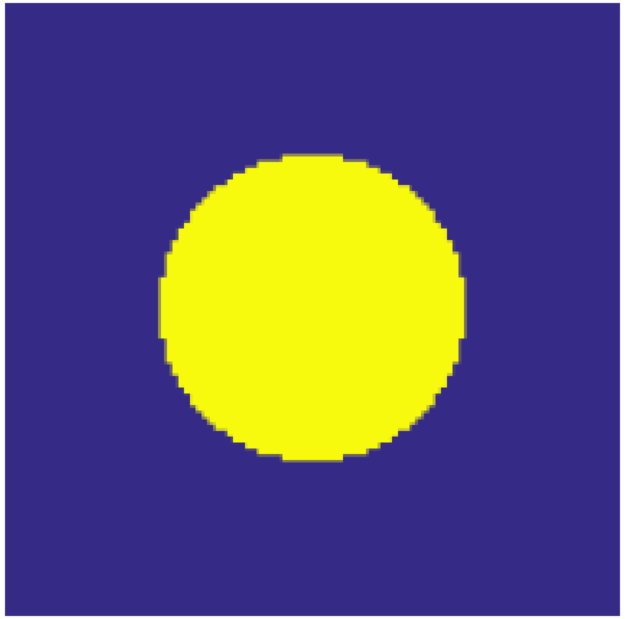


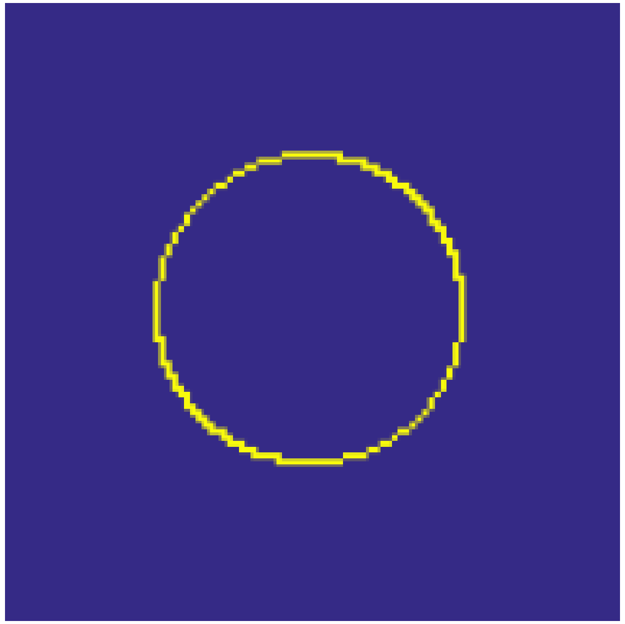


- Data readers/writers
- Pre-processing tools
- Image reconstruction
- *Near math* optimisation syntax
- Visualisation
- 2D, 3D and 4D data
- TIGRE and ASTRA backend

ccpi.ac.uk/CIL

What is Total Variation?





- Measures variation of an image
- Sum of gradient magnitude image

$$\mathrm{TV}(u) = \sum_j \|D_j u\|_2$$

- Prior: few homogeneous regions with simple boundaries
- Quite successful in tomography, in particular for reduced data