CWI

Centrum Wiskunde & Informatica

Tomosipo tutorial

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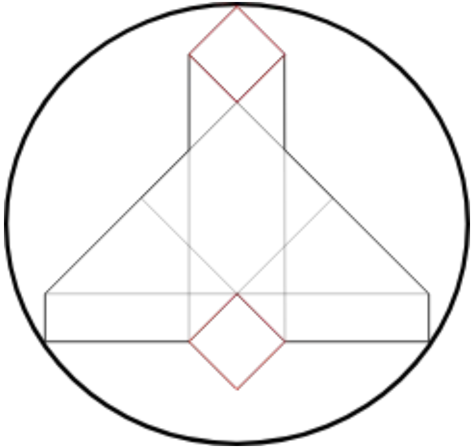
This presentation

1. What is Tomosipo
2. Installing Tomosipo
3. Three examples
   a. Projection operator in simple 2D geometry
   b. Unconventional geometry and visualization
   c. FleX-ray FDK reconstruction
4. Deep learning
5. Questions

All scripts are available on git: https://github.com/D1rk123/tomosipo_examples

What is Tomosipo?

- CT projection library in Python
  - Astra backend
- Pytonic interface
- Flexible in defining geometries
- Good integration with other libraries



Interacting libraries

- PyTorch compatibility
  - Use Tomosipo operators in neural networks
  - Very fast CPU/GPU operations from pytorch available
- Reconstruction algorithms available in ts_algorithms repository
  - Implemented in Python -> flexible and readable
  - Using PyTorch -> fast
- Visualisation options
  - Render your geometry to mp4 or svg file
  - Visualize data using PyQtGraph

My experience with Tomosipo

- Implemented Noise2Inverse neural network variations for Allard at the start of my PhD
- Used Tomosipo for my own research on carousel geometry CT
- Contributed FDK-implementation to ts_algorithms
    - Optimized this code to handle big FleX-Ray datasets

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- Disclaimer: I haven’t used Astra/ODL/Flexbox, so I can’t compare

Installing Tomosipo

- Tomosipo and ts_algorithms can be installed using pip
- Required packages:
  - Latest Astra 1.9.x development version
  - For ts_algorithms: pytorch version >= 1.7
  - For visualisation: ffmpeg, ffmpeg-python, pyqtgraph, pyqt, pyopengl

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  - For visualisation: ffmpeg, ffmpeg-python, pyqtgraph, pyqt, pyopengl
- Both Pytorch and Astra rely on the cudatoolkit package:
  - at most version 10.1 for the cluster
  - at least version 11.0 for RTX3070 cards in new workstations
  - at most version 11.0 for Astra
  - version 11.0 not supported in pytorch 1.8 so use pytorch 1.7 instead

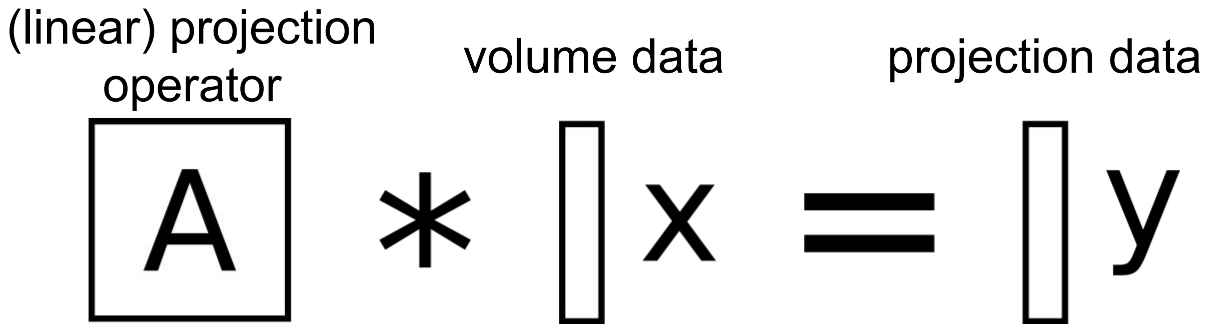
Conda installation script

11.0 for RTX30XX cards

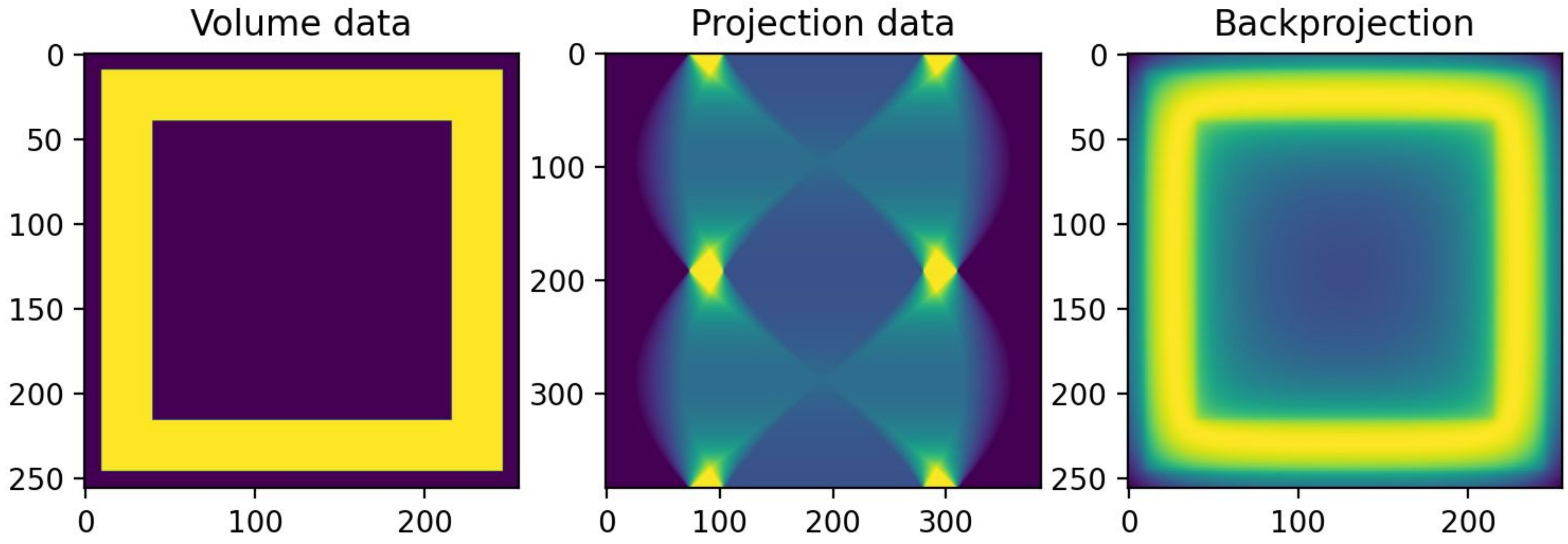
```
conda create -n to_ex python=3.8 cudatoolkit=10.1 pytorch=1.7
astra-toolbox numpy scikit-image matplotlib tifffile tqdm ffmpeg
ffmpeg-python pyqtgraph pyqt pyopengl -c pytorch -c
astra-toolbox/label/dev -c defaults -c conda-forge

conda activate to_ex

pip install git+https://github.com/ahendriksen/tomosipo.git@develop

pip install git+https://github.com/ahendriksen/ts_algorithms.git
```

Geometries in tomosipo

- Volume geometry specifies the volume
  - Properties: size, position, resolution
- Projection geometry specifies the projection setup
  - Type: Cone or parallel beam
- Geometries are always 3D
  - [z, y, x] coordinates are used for volume data, and [height, time, width] for projection data, so the first dimension can be 1 for 2D setups
- Operator can be derived from a volume and projection geometry



```python
import numpy as np
import tomosipo as ts
from matplotlib import pyplot as plt

# Setup 2D volume and parallel projection geometry
vg = ts.volume(shape=(1, 256, 256))
pg = ts.parallel(angles=384, shape=(1, 384))

# Create an operator from the geometries
A = ts.operator(vg, pg)

# Create hollow cube phantom
x = np.zeros(A.domain_shape)
x[:, 10:-10, 10:-10] = 1.0
x[:, 40:-40, 40:-40] = 0.0

# Project the volume data to obtain the projection data and backproject it again
y = A(x)
b = A.T(y)

plt.figure(figsize=(9, 3))
plt.subplot(131); plt.imshow(x[0, ...]); plt.title("Volume data")
plt.subplot(132); plt.imshow(y[0, ...]); plt.title("Projection data")
plt.subplot(133); plt.imshow(b[0, ...]); plt.title("Backprojection")
plt.show()
```


Volume data
Projection data
Backprojection
0
50
100
150
200
250
0
100
200
300
0
100
200
300
0
50
100
150
200
250
0
100
200

Making geometries just as complex as you need to

- All geometries have a standard form and a more flexible vector form
  - Standard forms assume a still volume and a rotating detector setup
  - In vector form the orientation can change for every projection
- Standard geometries have good defaults
  - If only shape is provided, 1x1x1 voxels are assumed
  - If no position is defined, position at the origin is assumed
- Vector form geometries can be created in two ways
  - Create a vector geometry directly by providing the parameters as a vector over time
  - Convert a standard geometry and apply a transformation

Visualizing geometries

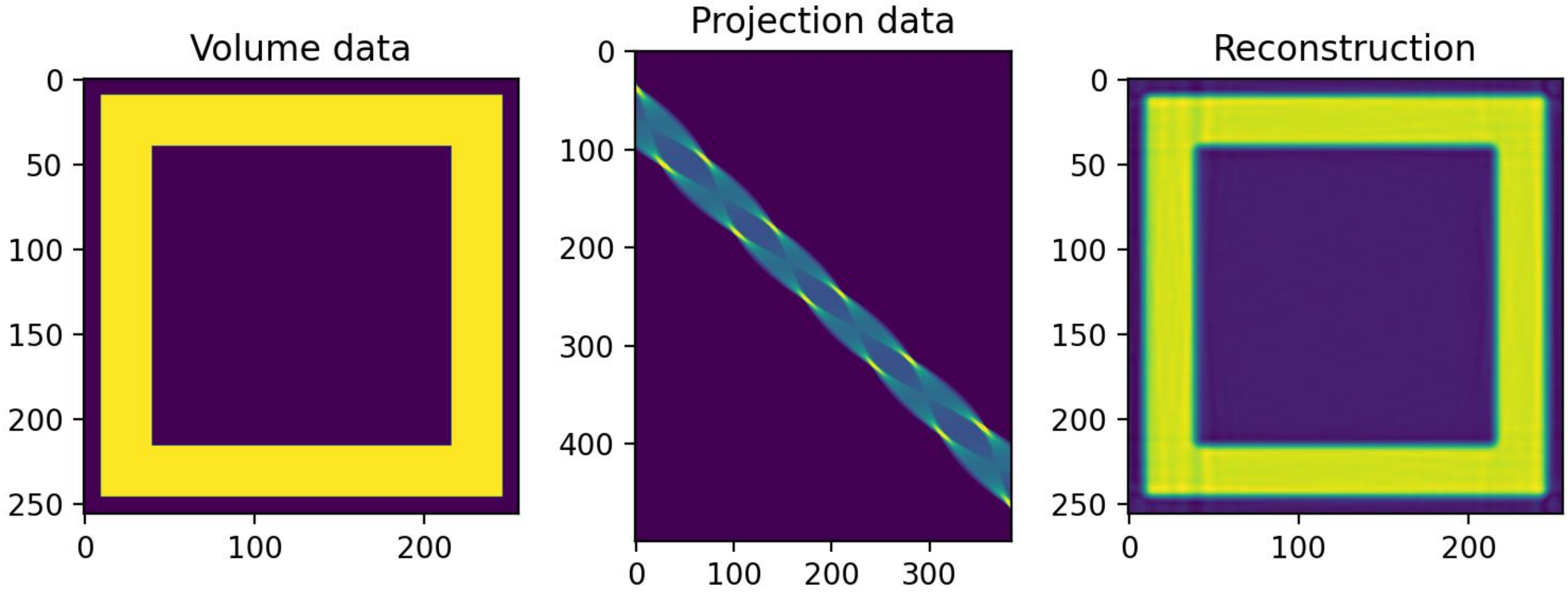
- Two possibilities:
  - .mp4 video
  - animated .svg vector graphics
- Very simple
  - Just call ts.qt.animate or ts.svg functions with any number of geometries as arguments
- Displaying
  - save to file
  - show in Jupyter notebook

Working with PyTorch

- Torch Tensors behave very similarly to Numpy arrays
- Computations on the gpu also possible
  - Call tensor_name.cuda() to copy a tensor to the gpu
  - Call tensor_name.cpu() to copy a tensor to RAM
- Tomosipo operators can act on Torch Tensors just like Numpy arrays
  - You get back the same type as you put in (numpy, gpu tensor, cpu tensor)
- ts_algorithms requires tensor input

```python
import numpy as np
import torch
import tomosipo as ts
import tomosipo.torch_support
from tomosipo.qt import animate
import ts_algorithms as tsa
from matplotlib import pyplot as plt

nump_proj = 500

# Setup 2D volume and fan beam projection geometry
vg = ts.volume(shape=(1, 256, 256), size=(0.1, 0.5, 0.5))
pg = ts.cone(shape=(1, 384), size=(0.1, 5), src_orig_dist=2.25, src_det_dist=3)

# Setup the a rotation and translation transform
tra = ts.translate(axis=np.array((0, 0, 1)), alpha=np.linspace(-2.5, 2.5, nump_proj))
rot = ts.rotate(pos=0, axis=np.array((1, 0, 0)), angles=np.linspace(0, 3*np.pi, nump_proj))

# Apply transformations to the volume geometry
vg = tra * rot * vg.to_vec()
pg = pg.to_vec()

# Create an operator from the transformed geometries
A = ts.operator(vg, pg)
```

```python
# Make an animation of the geometries and save it
s = ts.scale(1.8)
animation = animate(s * vg, s * pg)
animation.save("geometry_video.mp4")

# Create hollow cube phantom and copy it to the GPU
x = torch.zeros(A.domain_shape)
x[:, 10:-10, 10:-10] = 1.0
x[:, 40:-40, 40:-40] = 0.0
x = x.cuda()

# Project the volume data to obtain the projection data
y = A(x)

# Reconstruct using SIRT and copy everything back to RAM
recon = tsa.sirt(A, y, num_iterations=100)
recon = recon.cpu(); x = x.cpu(); y = y.cpu()

plt.figure(figsize=(9, 3))
plt.subplot(131); plt.imshow(x[0, ...]); plt.title("Volume data")
plt.subplot(132); plt.imshow(y[0, ...]); plt.title("Projection data")
plt.subplot(133); plt.imshow(recon[0, ...]); plt.title("Reconstruction")
plt.show()
```


Volume data
Projection data
Reconstruction
0
50
100
150
200
250
0
100
200
0
100
200
300
400
0
100
200
300

FleX-ray example

- Datasets take up a lot of memory
  - FDK algorithm
- Load the geometry from scan_settings.txt file

Working with large FleX-ray data

- High resolution FleX-ray dataset
  - Full resolution 1912 x 1520
  - 3600 projections
  - 21 GB on harddisk stored as 16 bit ints
  - 42 GB in memory stored as 32 bit floats
- Reconstruction volume of 1912x1912x1520 is also 22GB
- FDK algorithm optimized to work on CWI workstations
  - 64GB memory available
- Only works when no other copies are made

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- Reconstruction volume of 1912x1912x1520 is also 22GB
- FDK algorithm optimized to work on CWI workstations
  - 64GB memory available
- Only works when no other copies are made
- Memory use not the runtime bottleneck
  - +-13.5 minutes on workstation, +-26 minutes on voxel1 (with 128GB memory)
  - 72.5s with half the resolution and half the projections

Avoiding copies

- Load images directly into array
- Preprocess in place
- Do FDK weighting and filtering in place
  - Use overwrite_y=True in the FDK call
- Converting between torch and numpy does not copy the data

```python
# Preprocesses the projection data without making copies
def preprocess_in_place(y, dark, flat):
    dark = dark[:, None, :]
    flat = flat[:, None, :]
    y -= dark
    y /= (flat - dark)
    torch.log_(y)
    y *= -1
```

Parse the scan settings

- Three settings needed for FDK reconstruction
  - Source detector distance
  - Source object distance
  - Binned pixel size
- Available in `scan settings.txt` file
  - `Name : value` format

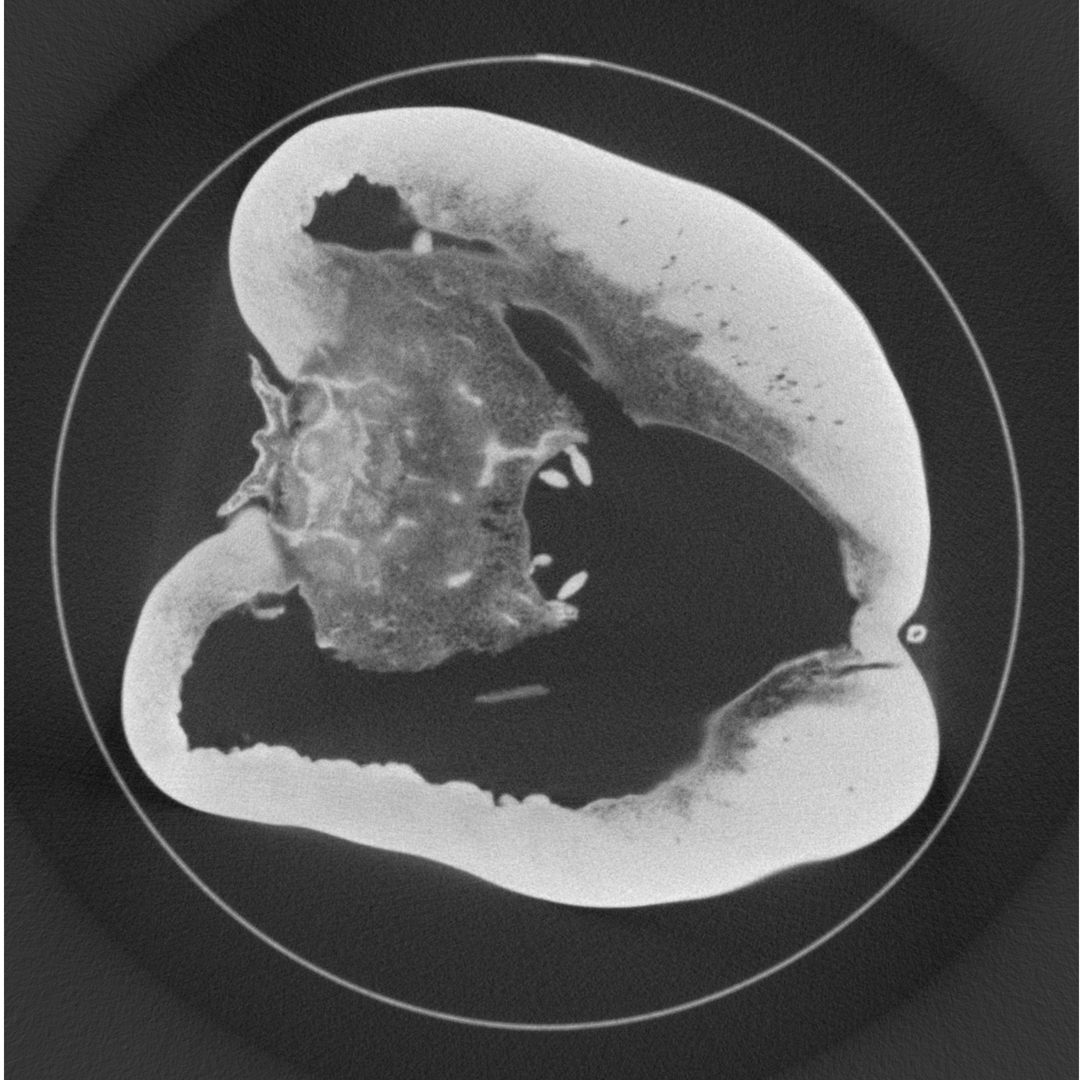
```
SCAN DURATION : 7 minutes
COR : 478.000497
VC : 383.056383
HC : 478.000394
SDD : 1098.000000
SOD : 1001.305645
Voxel size : 136.425614
Magnification : 1.096568
```

```python
# The function parse_scan_settings reads the scan settings.txt into a dictionary
scan_settings = parse_scan_settings(data_path / "scan settings.txt")
# Read the required settings from the file
src_det_dist = float(scan_settings["SDD"])
src_obj_dist = float(scan_settings["SOD"])
pixel_size = float(scan_settings["Binned pixel size"])
# Derive the other settings from the input data
detector_hor_res = y.shape[2]
detector_ver_res = y.shape[0]
num_angles = y.shape[1]

# Make volume and projection geometries with the parameters
vg = ts.volume(
    shape=(detector_ver_res, detector_hor_res, detector_hor_res),
    size=np.array((detector_ver_res, detector_hor_res, detector_hor_res))*pixel_size
)
pg = ts.cone(
    angles=num_angles,
    shape=(detector_ver_res, detector_hor_res),
    size=np.array((detector_ver_res, detector_hor_res))*pixel_size,
    src_det_dist = src_det_dist,
    src_orig_dist = src_obj_dist
)
# Combine the geometries into an operator
op = ts.operator(vg, pg)
```

```python
# Make an FDK reconstruction
# If you are using large projection data you may want to use overwrite_y=True
reconstruction = tsa.fdk(A=op, y=y, overwrite_y=True)
print("Finished reconstruction")
# Variable y was overwritten with a filtered version of y because overwrite_y=True
# You probably don't want to use this so delete y to free up memory
del y

save_stack(save_path, reconstruction.numpy(), exist_ok=True)
```



Calibrating the projection geometry

- Use a vector cone beam projection geometry to describe the exact setup

- FDK implementation is flexible
  - Allows off axis rotations
  - Allows non centered detectors
  - FDK approximations get worse further from the cone beam center

Including operators in PyTorch neural networks

- Tomosipo operators can be converted to a differentiable PyTorch layer
    - tomosipo.torch_support.to_autograd(operator)
- Usable in a neural network like any other layer

Recap

- Tomosipo is useful in many situations
  - FleX-ray reconstructions
  - Unconventional geometries
  - CT operators in neural networks
- Pytorch integration allows fast reconstruction algorithms in Python
  - Both on CPU and GPU
- ts_algorithms already implements some reconstruction algorithms
  - FBP, FDK, SIRT, Chambolle-Pock based 2D TV minimization

Useful links

- Tomosipo examples
  - https://github.com/D1rk123/tomosipo_examples
- Tomosipo documentation
  - https://aahendriksen.gitlab.io/tomosipo/topics/index.html
- Tomosipo online tutorial by Allard
  - https://blog.allardhendriksen.nl/cwi-ci-group/advent-of-tomosipo-introduction/
- Git repositories
  - https://github.com/ahendriksen/tomosipo
  - https://github.com/ahendriksen/ts_algorithms

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