

# Inverse Problems

## Sommersemester 2023

---

Vesa Kaarnioja  
[vesa.kaarnioja@fu-berlin.de](mailto:vesa.kaarnioja@fu-berlin.de)

FU Berlin, FB Mathematik und Informatik

Third lecture, May 2, 2023

## Numerical example: X-ray tomography

As an application, we consider X-ray tomography and describe here the construction of the tomography matrix. We will return to this example on Tuesday May 30 when we will discuss total variation regularization for X-ray tomography.

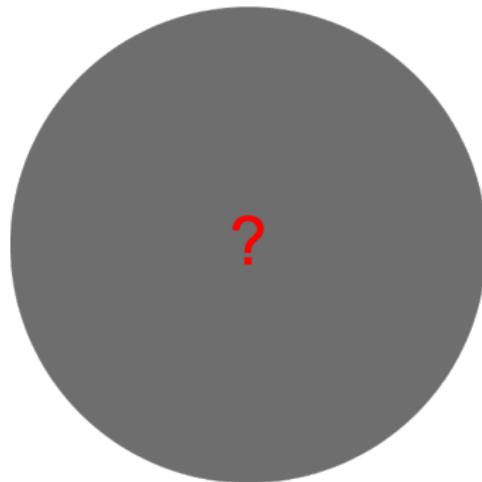
The following content follows roughly the material presented in the following monographs.

-  J. Kaipio and E. Somersalo. Statistical and Computational Inverse Problems. 2005.
-  J. L. Mueller and S. Siltanen. Linear and Nonlinear Inverse Problems with Practical Applications. 2012.

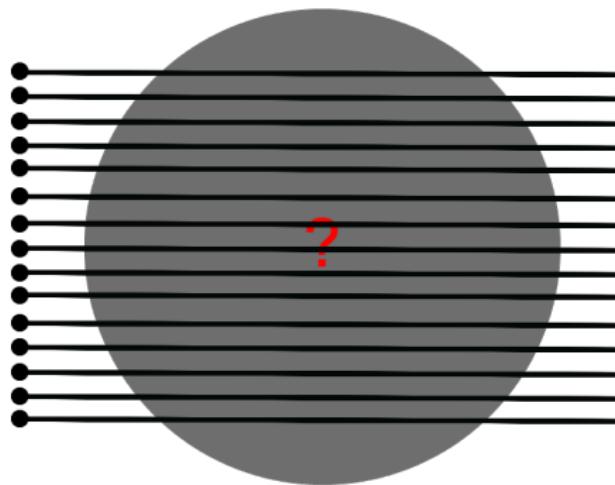
ASTRA Toolbox for 2D and 3D tomography:

<https://www.astra-toolbox.com/>

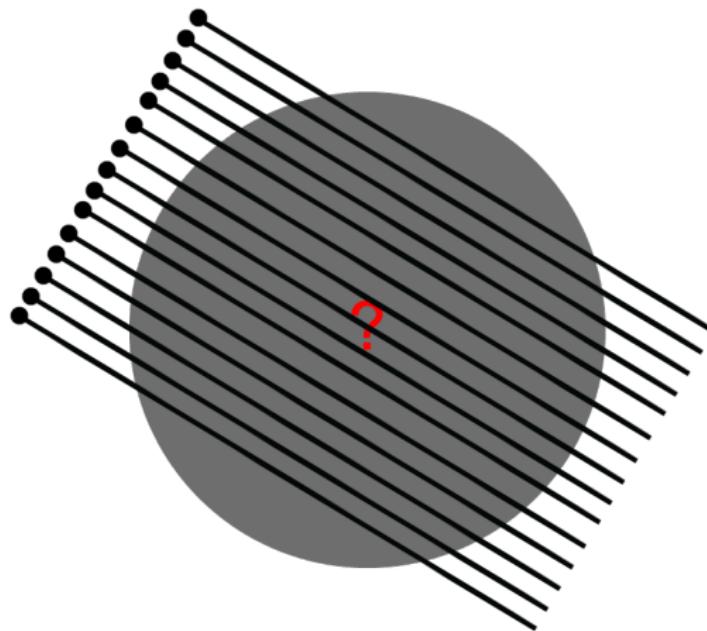
# Parallel-beam X-ray tomography



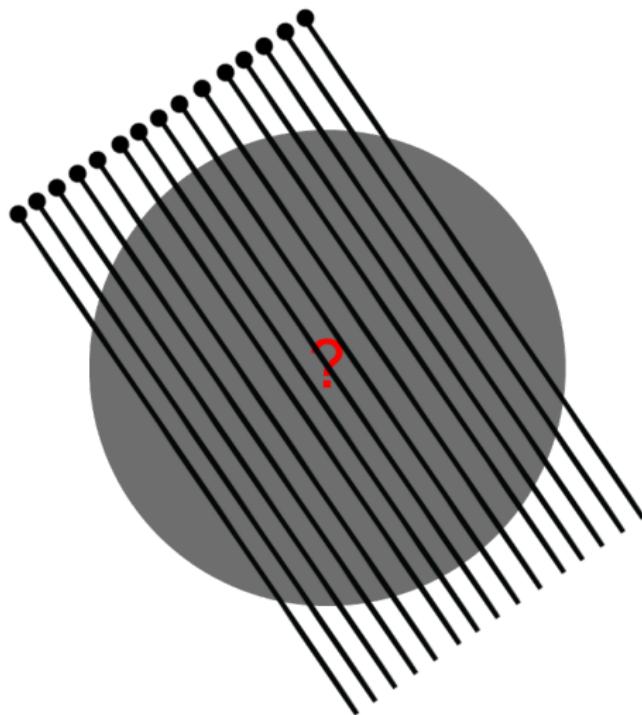
# Parallel-beam X-ray tomography



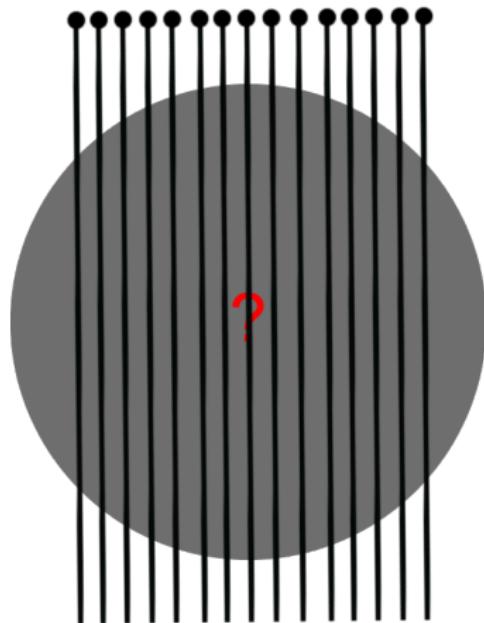
# Parallel-beam X-ray tomography



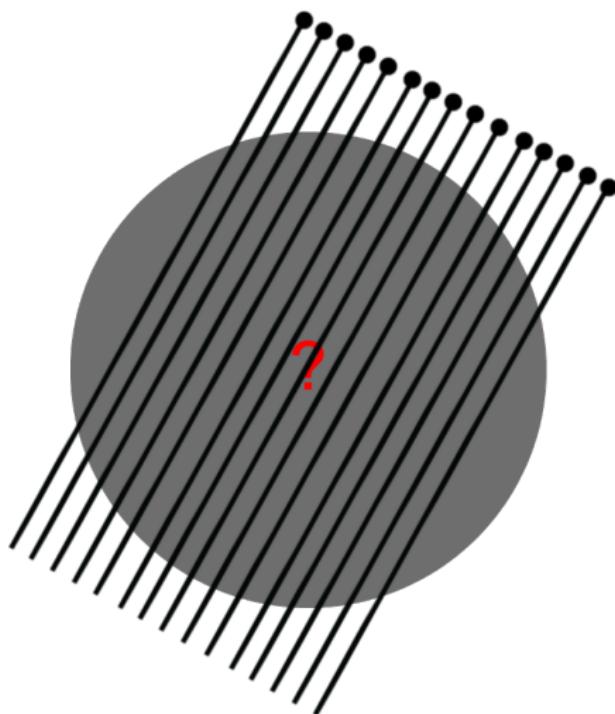
# Parallel-beam X-ray tomography



# Parallel-beam X-ray tomography



## Parallel-beam X-ray tomography



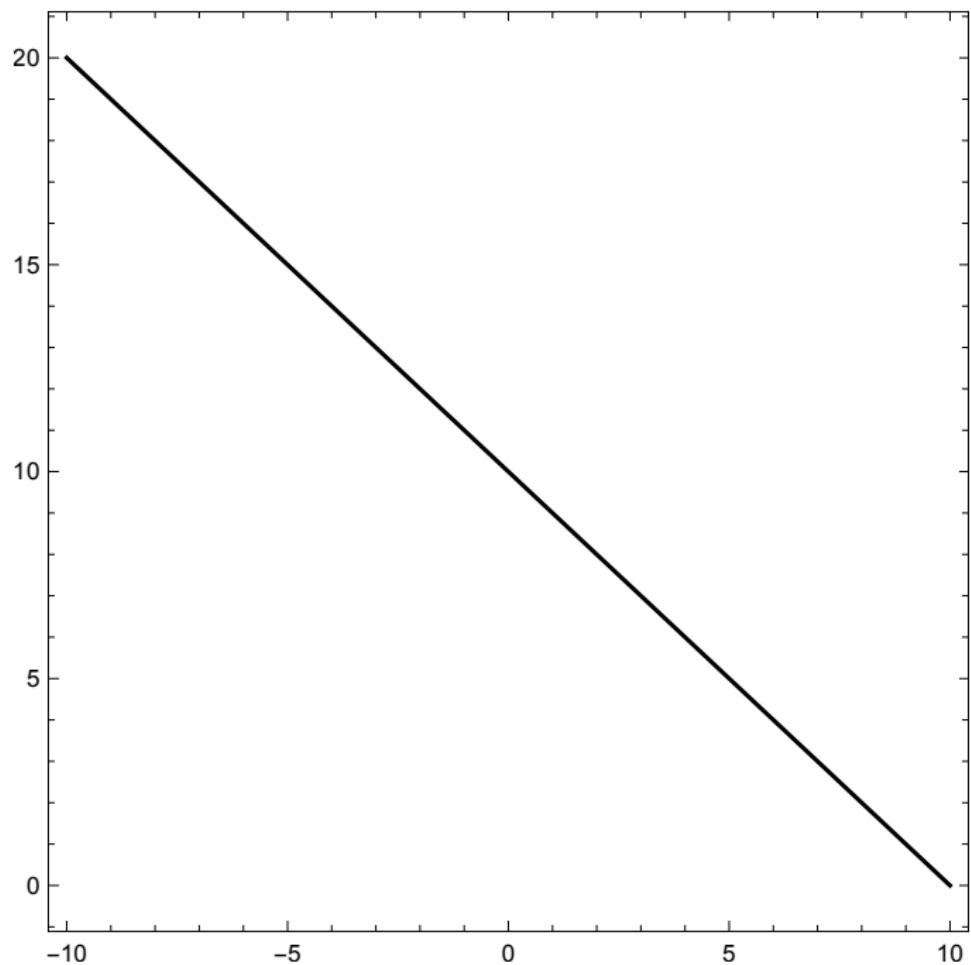
## Radon transform in $\mathbb{R}^2$

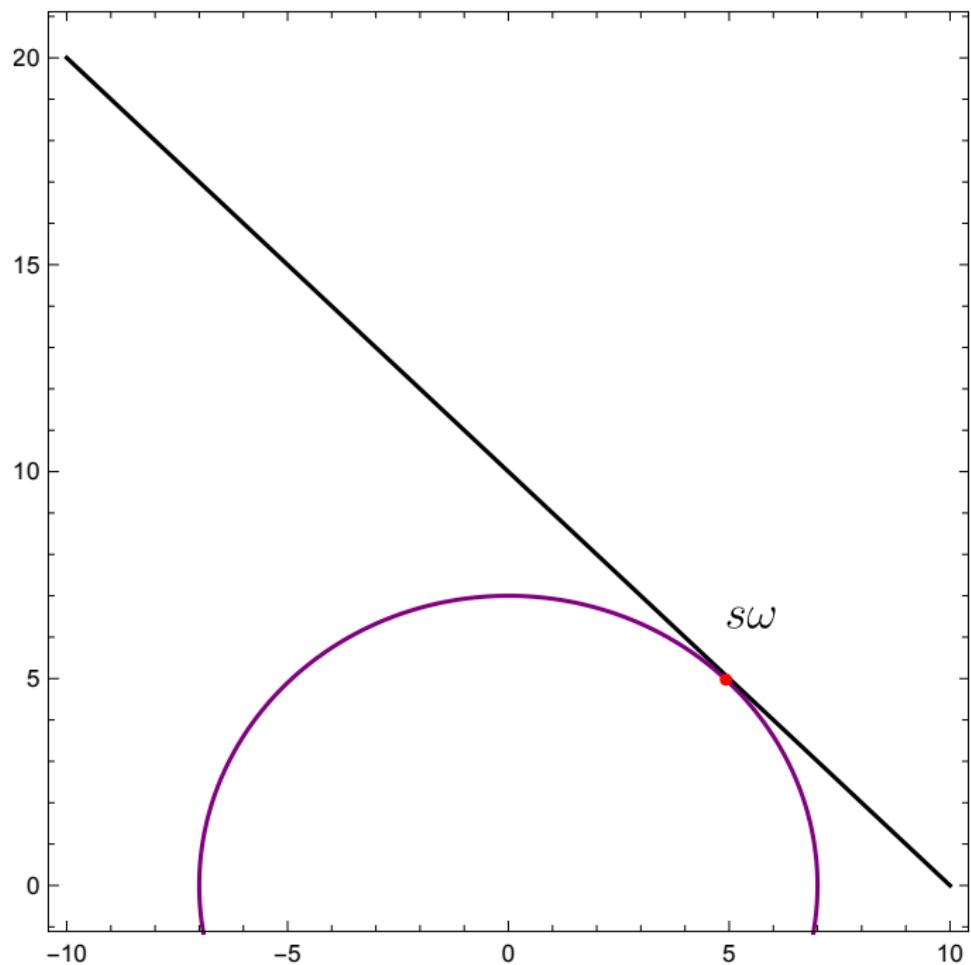
Let  $L$  be a straight line in  $\mathbb{R}^2$ .

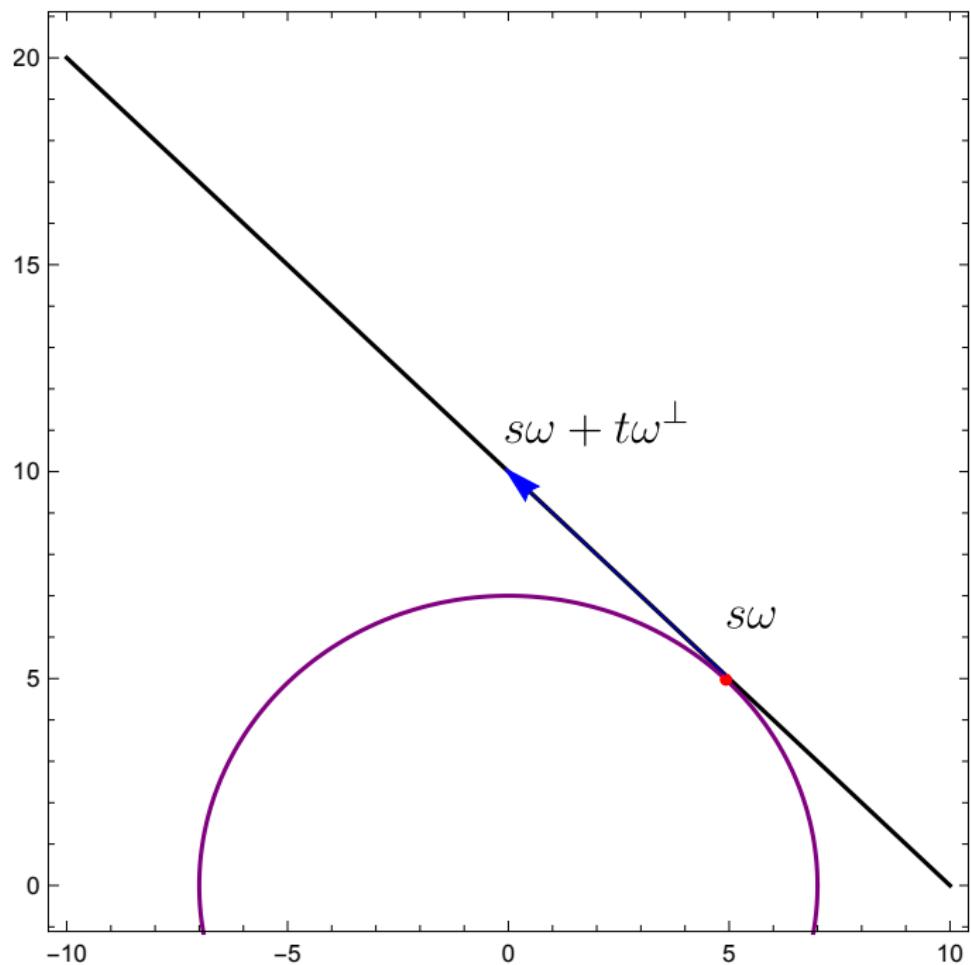
Any line in  $\mathbb{R}^2$  can be parameterized as

$$L = \{sw + t\omega^\perp; t \in \mathbb{R}\} \quad \text{for some } s \in \mathbb{R} \text{ and } \omega \in S^1,$$

where  $\omega^\perp \perp \omega$ .







## Radon transform in $\mathbb{R}^2$

Let  $L$  be a straight line in  $\mathbb{R}^2$ .

Any line in  $\mathbb{R}^2$  can be parameterized as

$$L = \{sw + t\omega^\perp; t \in \mathbb{R}\} \quad \text{for some } s \in \mathbb{R} \text{ and } \omega \in S^1,$$

where  $\omega^\perp \perp \omega$ .

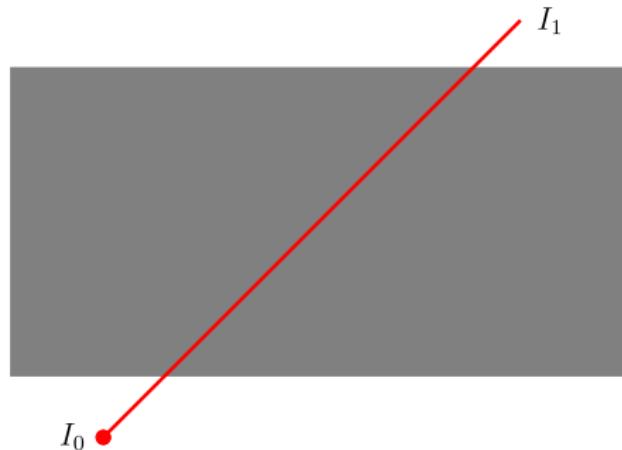
Writing  $\omega = \begin{bmatrix} \cos \theta \\ \sin \theta \end{bmatrix}$ , we get

$$L = L(s, \theta) = \left\{ s \begin{bmatrix} \cos \theta \\ \sin \theta \end{bmatrix} + t \begin{bmatrix} \sin \theta \\ -\cos \theta \end{bmatrix}; t \in \mathbb{R} \right\}, \quad s \in \mathbb{R} \text{ and } \theta \in [0, \pi).$$

The *Radon transform* of a continuous function  $f: \mathbb{R}^2 \rightarrow \mathbb{R}$  on  $L$  is defined as

$$\mathcal{R}f(L) = \int_L f(\mathbf{x}) |\mathrm{d}\mathbf{x}| = \int_{-\infty}^{\infty} f(s \cos \theta + t \sin \theta, s \sin \theta - t \cos \theta) dt.$$

Let  $f$  be a nonnegative function modeling X-ray attenuation (density) inside a physical body.



Beer–Lambert law:

$$\mathcal{R}f(L) = \log \frac{I_0}{I_1}.$$

$f_{9,0}$	$f_{9,1}$	$f_{9,2}$	$f_{9,3}$	$f_{9,4}$	$f_{9,5}$	$f_{9,6}$	$f_{9,7}$	$f_{9,8}$	$f_{9,9}$
$f_{8,0}$	$f_{8,1}$	$f_{8,2}$	$f_{8,3}$	$f_{8,4}$	$f_{8,5}$	$f_{8,6}$	$f_{8,7}$	$f_{8,8}$	$f_{8,9}$
$f_{7,0}$	$f_{7,1}$	$f_{7,2}$	$f_{7,3}$	$f_{7,4}$	$f_{7,5}$	$f_{7,6}$	$f_{7,7}$	$f_{7,8}$	$f_{7,9}$
$f_{6,0}$	$f_{6,1}$	$f_{6,2}$	$f_{6,3}$	$f_{6,4}$	$f_{6,5}$	$f_{6,6}$	$f_{6,7}$	$f_{6,8}$	$f_{6,9}$
$f_{5,0}$	$f_{5,1}$	$f_{5,2}$	$f_{5,3}$	$f_{5,4}$	$f_{5,5}$	$f_{5,6}$	$f_{5,7}$	$f_{5,8}$	$f_{5,9}$
$f_{4,0}$	$f_{4,1}$	$f_{4,2}$	$f_{4,3}$	$f_{4,4}$	$f_{4,5}$	$f_{4,6}$	$f_{4,7}$	$f_{4,8}$	$f_{4,9}$
$f_{3,0}$	$f_{3,1}$	$f_{3,2}$	$f_{3,3}$	$f_{3,4}$	$f_{3,5}$	$f_{3,6}$	$f_{3,7}$	$f_{3,8}$	$f_{3,9}$
$f_{2,0}$	$f_{2,1}$	$f_{2,2}$	$f_{2,3}$	$f_{2,4}$	$f_{2,5}$	$f_{2,6}$	$f_{2,7}$	$f_{2,8}$	$f_{2,9}$
$f_{1,0}$	$f_{1,1}$	$f_{1,2}$	$f_{1,3}$	$f_{1,4}$	$f_{1,5}$	$f_{1,6}$	$f_{1,7}$	$f_{1,8}$	$f_{1,9}$
$f_{0,0}$	$f_{0,1}$	$f_{0,2}$	$f_{0,3}$	$f_{0,4}$	$f_{0,5}$	$f_{0,6}$	$f_{0,7}$	$f_{0,8}$	$f_{0,9}$

Let us consider the computational domain  $[-1, 1]^2$ . We divide this region into  $n \times n$  pixels and approximate the density by a piecewise constant function with constant value

$f_{i,j}$  in pixel  $P_{i,j}$

for  $i, j \in \{0, \dots, n - 1\}$ .

$$P_{i,j} := \{(x, y); -1 + 2 \frac{j}{n} < x < -1 + 2 \frac{j+1}{n}, -1 + 2 \frac{i}{n} < y < -1 + 2 \frac{i+1}{n}\}$$

$x_{90}$	$x_{91}$	$x_{92}$	$x_{93}$	$x_{94}$	$x_{95}$	$x_{96}$	$x_{97}$	$x_{98}$	$x_{99}$
$x_{80}$	$x_{81}$	$x_{82}$	$x_{83}$	$x_{84}$	$x_{85}$	$x_{86}$	$x_{87}$	$x_{88}$	$x_{89}$
$x_{70}$	$x_{71}$	$x_{72}$	$x_{73}$	$x_{74}$	$x_{75}$	$x_{76}$	$x_{77}$	$x_{78}$	$x_{79}$
$x_{60}$	$x_{61}$	$x_{62}$	$x_{63}$	$x_{64}$	$x_{65}$	$x_{66}$	$x_{67}$	$x_{68}$	$x_{69}$
$x_{50}$	$x_{51}$	$x_{52}$	$x_{53}$	$x_{54}$	$x_{55}$	$x_{56}$	$x_{57}$	$x_{58}$	$x_{59}$
$x_{40}$	$x_{41}$	$x_{42}$	$x_{43}$	$x_{44}$	$x_{45}$	$x_{46}$	$x_{47}$	$x_{48}$	$x_{49}$
$x_{30}$	$x_{31}$	$x_{32}$	$x_{33}$	$x_{34}$	$x_{35}$	$x_{36}$	$x_{37}$	$x_{38}$	$x_{39}$
$x_{20}$	$x_{21}$	$x_{22}$	$x_{23}$	$x_{24}$	$x_{25}$	$x_{26}$	$x_{27}$	$x_{28}$	$x_{29}$
$x_{10}$	$x_{11}$	$x_{12}$	$x_{13}$	$x_{14}$	$x_{15}$	$x_{16}$	$x_{17}$	$x_{18}$	$x_{19}$
$x_0$	$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$	$x_7$	$x_8$	$x_9$

It is convenient to reshape the matrix/image ( $f_{i,j}$ ) into a vector  $x$  of length  $n^2$  so that

$$x_{in+j} = f_{i,j}, \quad i, j \in \{0, \dots, n-1\}.$$

The image on the left illustrates the new numbering corresponding to the pixels.

Note that  $x = f.\text{reshape}((n*n, 1))$  and  $f = x.\text{reshape}((n, n))$ .  
 (In MATLAB:  $x = f(:)$  and  $f = \text{reshape}(x, n, n)$ ).

## Measurement model

Let us consider a measurement setup where we take X-ray measurements of an object using  $K$  X-rays  $L(s_0, \theta), \dots, L(s_{K-1}, \theta)$  taken at angles  $\theta \in \{\theta_0, \dots, \theta_{M-1}\}$ . The total number of X-rays is  $Q = MK$ .

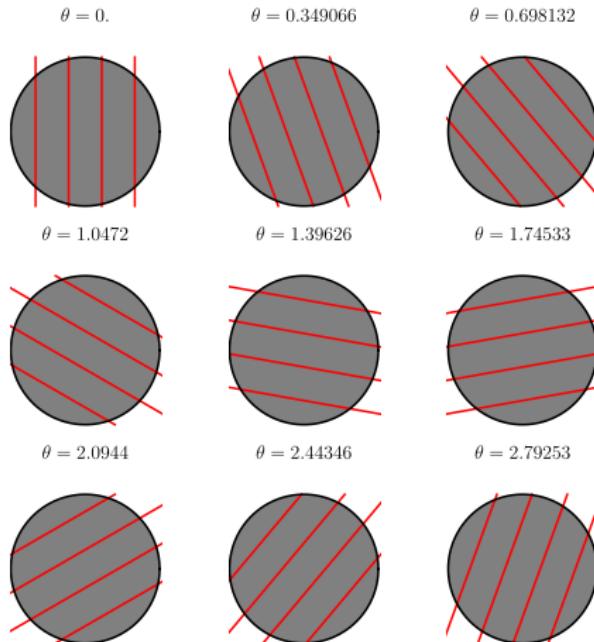
For brevity, let us write  $L_{mK+k} := L(s_k, \theta_m)$  for  $k \in \{0, \dots, K-1\}$  and  $m \in \{0, \dots, M-1\}$ .

The measurement model is

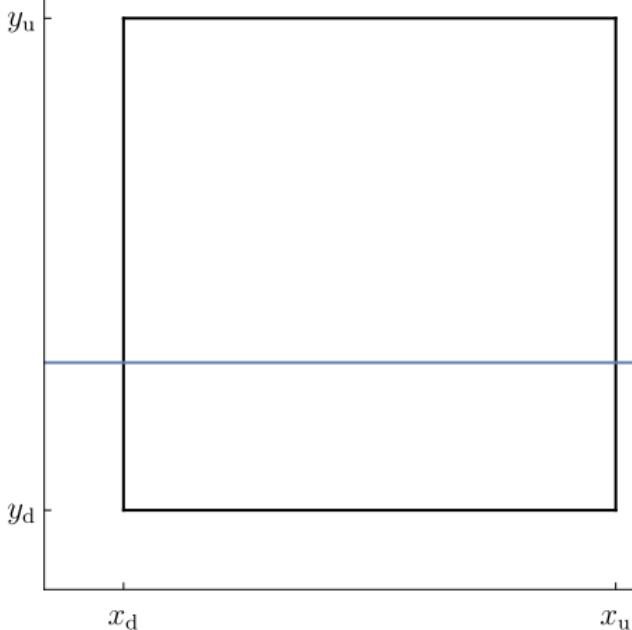
$$y = \begin{bmatrix} \int_{L_0} f(\mathbf{x}) |\mathrm{d}\mathbf{x}| \\ \vdots \\ \int_{L_{Q-1}} f(\mathbf{x}) |\mathrm{d}\mathbf{x}| \end{bmatrix} + \eta \approx \begin{bmatrix} \sum_{j=0}^{n^2-1} A_{0,j} x_j \\ \vdots \\ \sum_{j=0}^{n^2-1} A_{Q-1,j} x_j \end{bmatrix} + \eta = Ax + \eta,$$

where  $A \in \mathbb{R}^{Q \times n^2}$  and  $A_{i,j}$  is the distance that ray  $L_i$  travels through pixel  $j$ . Here,  $x$  is a vector containing the (piecewise constant) densities within each pixel and  $\eta$  is measurement noise.

$$L_{mK+k} = \left\{ s_k \begin{bmatrix} \cos \theta_m \\ \sin \theta_m \end{bmatrix} + t \begin{bmatrix} \sin \theta_m \\ -\cos \theta_m \end{bmatrix}; \quad t \in \mathbb{R} \right\}, \quad k = 0, \dots, K-1, \quad m = 0, \dots, M-1.$$



Pixel-by-pixel construction of the tomography matrix  $A$   
(See the files `tomodemo.py/tomodemo.m` on the course page!)



Case  $\cos \theta = 0$  and  $\sin \theta = 1$ :

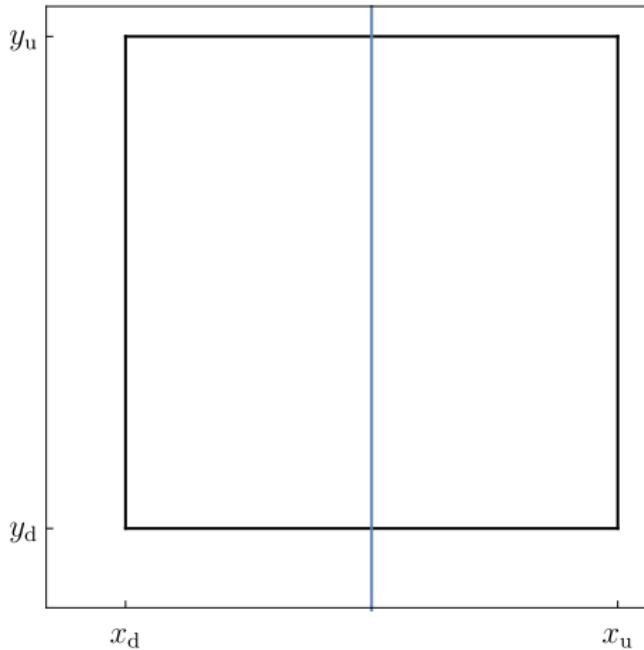
$$\begin{bmatrix} x_d \\ y_d \end{bmatrix} \leq \begin{bmatrix} s \cos \theta + t \sin \theta \\ s \sin \theta - t \cos \theta \end{bmatrix} < \begin{bmatrix} x_u \\ y_u \end{bmatrix}$$

$$\Leftrightarrow \begin{bmatrix} x_d \\ y_d \end{bmatrix} \leq \begin{bmatrix} t \\ s \end{bmatrix} < \begin{bmatrix} x_u \\ y_u \end{bmatrix}.$$

The distance that ray  $L_m$  travels through pixel  $k$  is

$$A_{m,k} = \int_{L_m} \chi_k |\mathrm{d}\mathbf{x}| = \int_{\substack{x_d \leq t < x_u \\ y_d \leq s < y_u}} dt = \begin{cases} x_u - x_d & \text{if } y_d \leq s < y_u, \\ 0 & \text{otherwise.} \end{cases}$$

N.B. In here and in the following,  $\chi_k = \chi_k(\mathbf{x})$  denotes the characteristic function of the  $k^{\text{th}}$  pixel. In the above illustration, the pixel is denoted by the rectangle  $[x_d, x_u) \times [y_d, y_u)$ .

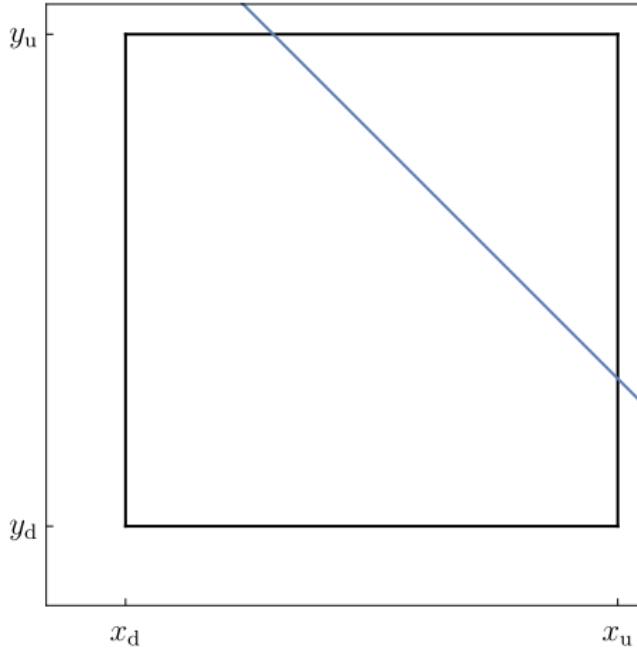


Case  $\cos \theta = 1$  and  $\sin \theta = 0$ :

$$\begin{aligned} \begin{bmatrix} x_d \\ y_d \end{bmatrix} &\leq \begin{bmatrix} s \cos \theta + t \sin \theta \\ s \sin \theta - t \cos \theta \end{bmatrix} < \begin{bmatrix} x_u \\ y_u \end{bmatrix} \\ \Leftrightarrow \begin{bmatrix} x_d \\ y_d \end{bmatrix} &\leq \begin{bmatrix} s \\ -t \end{bmatrix} < \begin{bmatrix} x_u \\ y_u \end{bmatrix} \\ \Leftrightarrow \begin{bmatrix} x_d \\ -y_u \end{bmatrix} &< \begin{bmatrix} s \\ t \end{bmatrix} \leq \begin{bmatrix} x_u \\ -y_d \end{bmatrix}. \end{aligned}$$

The distance that ray  $L_m$  travels through pixel  $k$  is

$$A_{m,k} = \int_{L_m} \chi_k |\mathrm{d}\mathbf{x}| = \int_{\substack{-y_u < t \leq -y_d \\ x_d < s \leq x_u}} dt = \begin{cases} y_u - y_d & \text{if } x_d < s \leq x_u, \\ 0 & \text{otherwise.} \end{cases}$$



Case  $\cos \theta > 0$ :

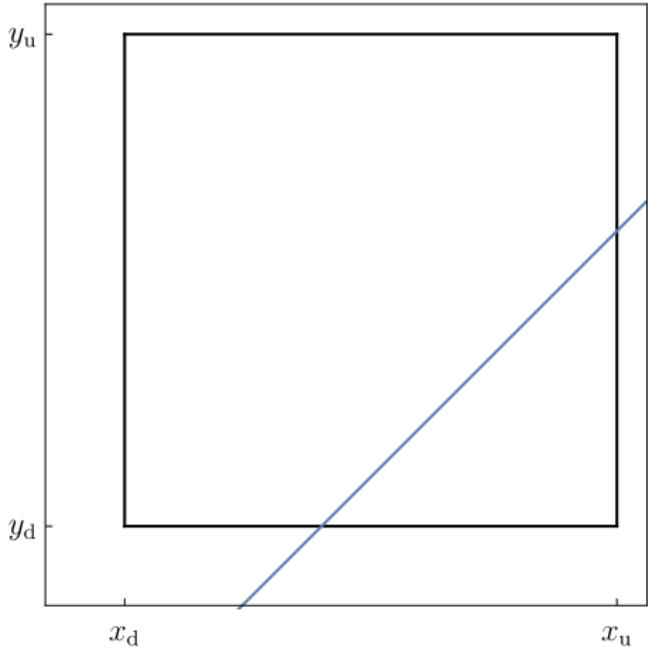
$$\begin{bmatrix} x_d \\ y_d \end{bmatrix} < \begin{bmatrix} s \cos \theta + t \sin \theta \\ s \sin \theta - t \cos \theta \end{bmatrix} < \begin{bmatrix} x_u \\ y_u \end{bmatrix}$$

$$\Leftrightarrow \begin{bmatrix} \frac{x_d - s \cos \theta}{\sin \theta} \\ \frac{s \sin \theta - y_u}{\cos \theta} \end{bmatrix} < \begin{bmatrix} t \\ t \end{bmatrix} < \begin{bmatrix} \frac{x_u - s \cos \theta}{\sin \theta} \\ \frac{s \sin \theta - y_d}{\cos \theta} \end{bmatrix}.$$

The distance that ray  $L_m$  travels through pixel  $k$  is

$$A_{m,k} = \int_{L_m} \chi_k |\mathrm{d}\mathbf{x}| = \int_{\max \left\{ \frac{x_d - s \cos \theta}{\sin \theta}, \frac{s \sin \theta - y_u}{\cos \theta} \right\}}^{\min \left\{ \frac{x_u - s \cos \theta}{\sin \theta}, \frac{s \sin \theta - y_d}{\cos \theta} \right\}} dt$$

$$= \left( \min \left\{ \frac{x_u - s \cos \theta}{\sin \theta}, \frac{s \sin \theta - y_d}{\cos \theta} \right\} - \max \left\{ \frac{x_d - s \cos \theta}{\sin \theta}, \frac{s \sin \theta - y_u}{\cos \theta} \right\} \right)_+$$



Case  $\cos \theta < 0$ :

$$\begin{aligned}
 \begin{bmatrix} x_d \\ y_d \end{bmatrix} &< \begin{bmatrix} s \cos \theta + t \sin \theta \\ s \sin \theta - t \cos \theta \end{bmatrix} < \begin{bmatrix} x_u \\ y_u \end{bmatrix} \\
 \Leftrightarrow \begin{bmatrix} \frac{x_d - s \cos \theta}{\sin \theta} \\ \frac{s \sin \theta - y_u}{\sin \theta} \end{bmatrix} &< \begin{bmatrix} t \\ t \cos \theta \end{bmatrix} < \begin{bmatrix} \frac{x_u - s \cos \theta}{\sin \theta} \\ \frac{s \sin \theta - y_d}{\sin \theta} \end{bmatrix} \\
 \text{!} \Leftrightarrow \begin{bmatrix} \frac{x_d - s \cos \theta}{\sin \theta} \\ \frac{s \sin \theta - y_d}{\sin \theta} \end{bmatrix} &< \begin{bmatrix} t \\ t \end{bmatrix} < \begin{bmatrix} \frac{x_u - s \cos \theta}{\sin \theta} \\ \frac{s \sin \theta - y_u}{\sin \theta} \end{bmatrix}.
 \end{aligned}$$

The distance that ray  $L_m$  travels through pixel  $k$  is

$$\begin{aligned}
 A_{m,k} &= \int_{L_m} \chi_k |\mathrm{d}\mathbf{x}| = \int_{\max \left\{ \frac{x_d - s \cos \theta}{\sin \theta}, \frac{s \sin \theta - y_d}{\cos \theta} \right\}}^{\min \left\{ \frac{x_u - s \cos \theta}{\sin \theta}, \frac{s \sin \theta - y_u}{\cos \theta} \right\}} \mathrm{d}t \\
 &= \left( \min \left\{ \frac{x_u - s \cos \theta}{\sin \theta}, \frac{s \sin \theta - y_u}{\cos \theta} \right\} - \max \left\{ \frac{x_d - s \cos \theta}{\sin \theta}, \frac{s \sin \theta - y_d}{\cos \theta} \right\} \right)_+.
 \end{aligned}$$

## Discussion

Tomography problems can be classified into three classes based on the nature of the measurement data:

- Full angle tomography
  - Sufficient number of measurements from all angles → not a very ill-posed problem.
- Limited angle tomography
  - Data collected from a restricted angle of view → reconstructions very sensitive to measurement error and it is not possible to reconstruct the object perfectly (even with noiseless data). Applications include, e.g., dental imaging.
- Sparse data tomography
  - The data consist of only a few projection images, possibly from any direction → extremely ill-posed inverse problem and prior knowledge necessary for successful reconstructions. (E.g., minimizing a patient's radiation dose.)