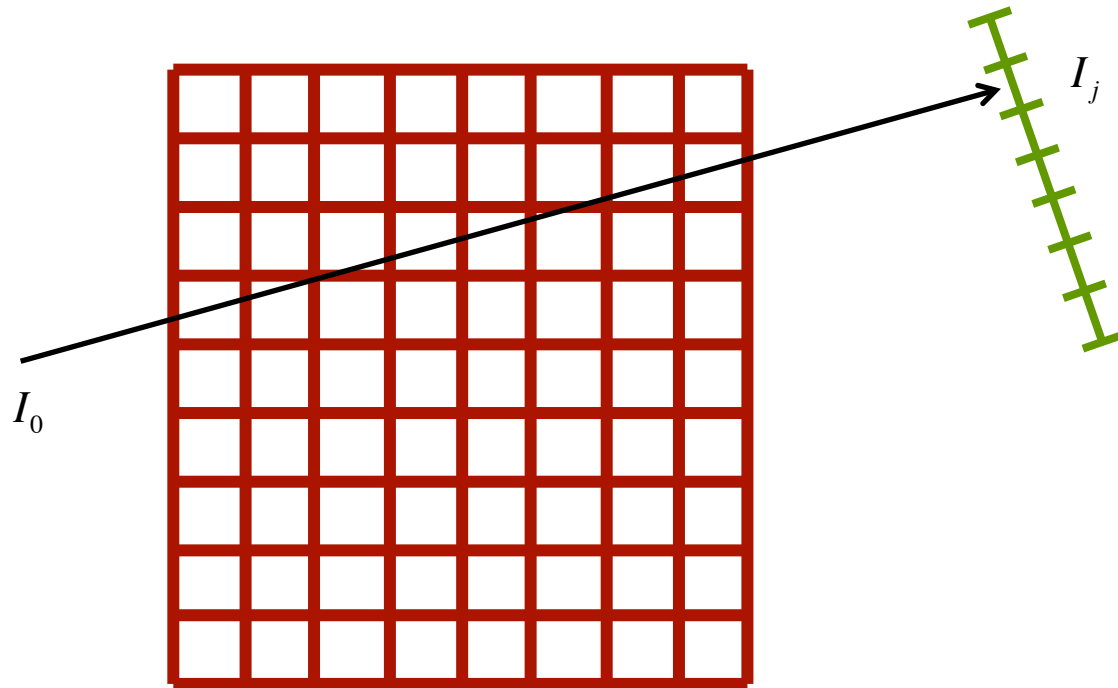




# Iterative CT reconstruction

A short introduction



# Analytic reconstruction

Previous lectures:

## Analytic reconstruction techniques

- analytic description of the forward problem

$$\lambda(p, \phi) = \int_A f(\mathbf{x}) \delta(p - \mathbf{x} \cdot \hat{\mathbf{n}}_\phi) d^2x = \Re \{f(\mathbf{x})\}$$

- solve by analytically inverting the Radon transform operator

$$f(\mathbf{x}) = \int_0^\pi \int_{-\infty}^\infty |\nu| \Lambda_\phi(\nu) \exp(2\pi i \nu \mathbf{x} \cdot \hat{\mathbf{n}}_\phi) d\nu d\phi$$

# Algebraic reconstruction

Now:

## **Algebraic reconstruction techniques**

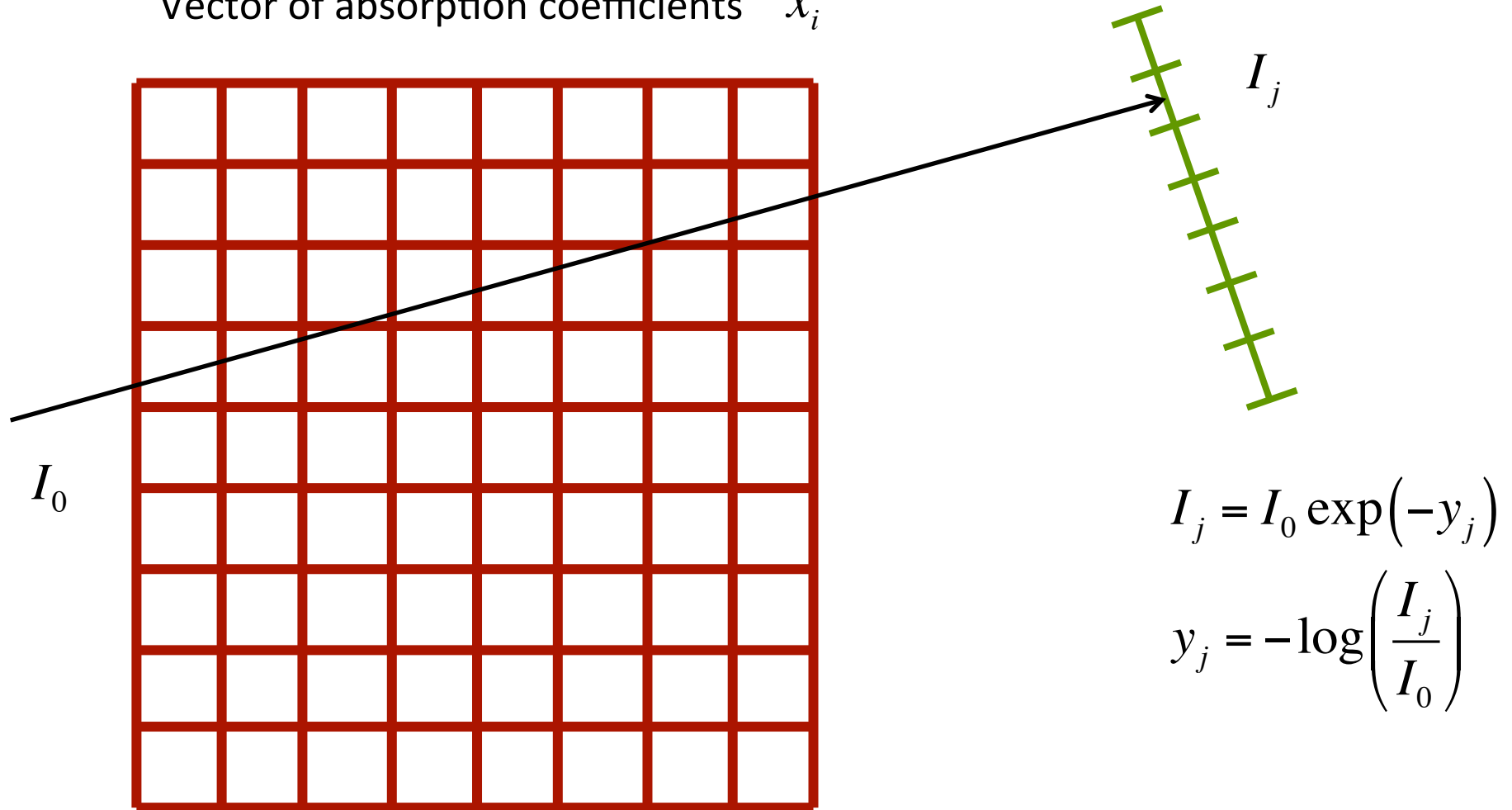
- discrete problem representation  
(through algebraic equations)
- optimization based reconstruction techniques

# Problem formulation

Unknown image

Vector of absorption coefficients  $x_i$

Observation



# Problem formulation

Unknown image

Vector of attenuation coefficients  $x_i$

Observation

$y_j$

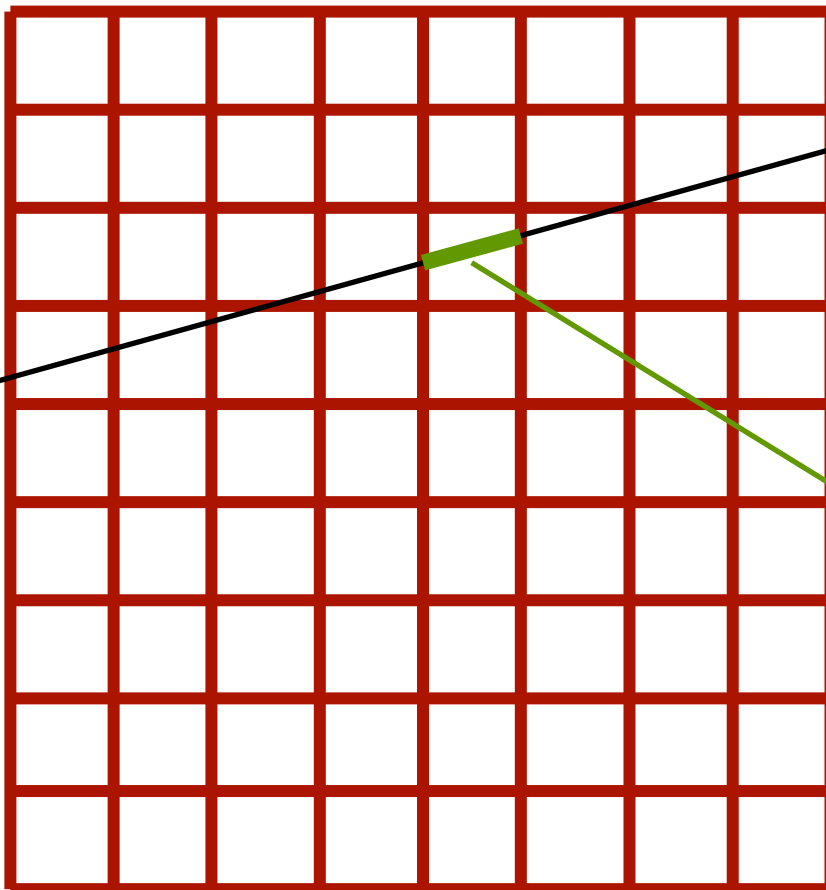
Total attenuation  $y_j$ :

sum over the attenuation in every voxel that ray  $j$  passes through

$A_{ij}$  length of the segment of ray  $j$  that falls into voxel  $i$

$$y_j = \sum_i A_{ij} x_i$$

note:  $A$  is sparse



# Problem formulation

- $y_j$  is measured
- $A_{ij}$  can be constructed (similar to ray tracing in dose calculation)

**CT reconstruction task:**

**Find a solution to the linear system of equations**

$$y_j = \sum_i A_{ij} x_i$$

## 1. One difficulty: Problem size

$$y_j = \sum_i A_{ij} x_i$$

$(\text{\#pixels})^2 \times \text{\#angles}$

$512 \times 512 \times 200$

$A_{ij}$  is sparse but still very large (may not fit in memory)

## 2. Problem is ill-posed

- underdetermined (many solutions) (reconstruction from undersampled projections)
- overdetermined (no solution)

# Projection methods

**First approach:**

**Find a solution to the system of linear equations**

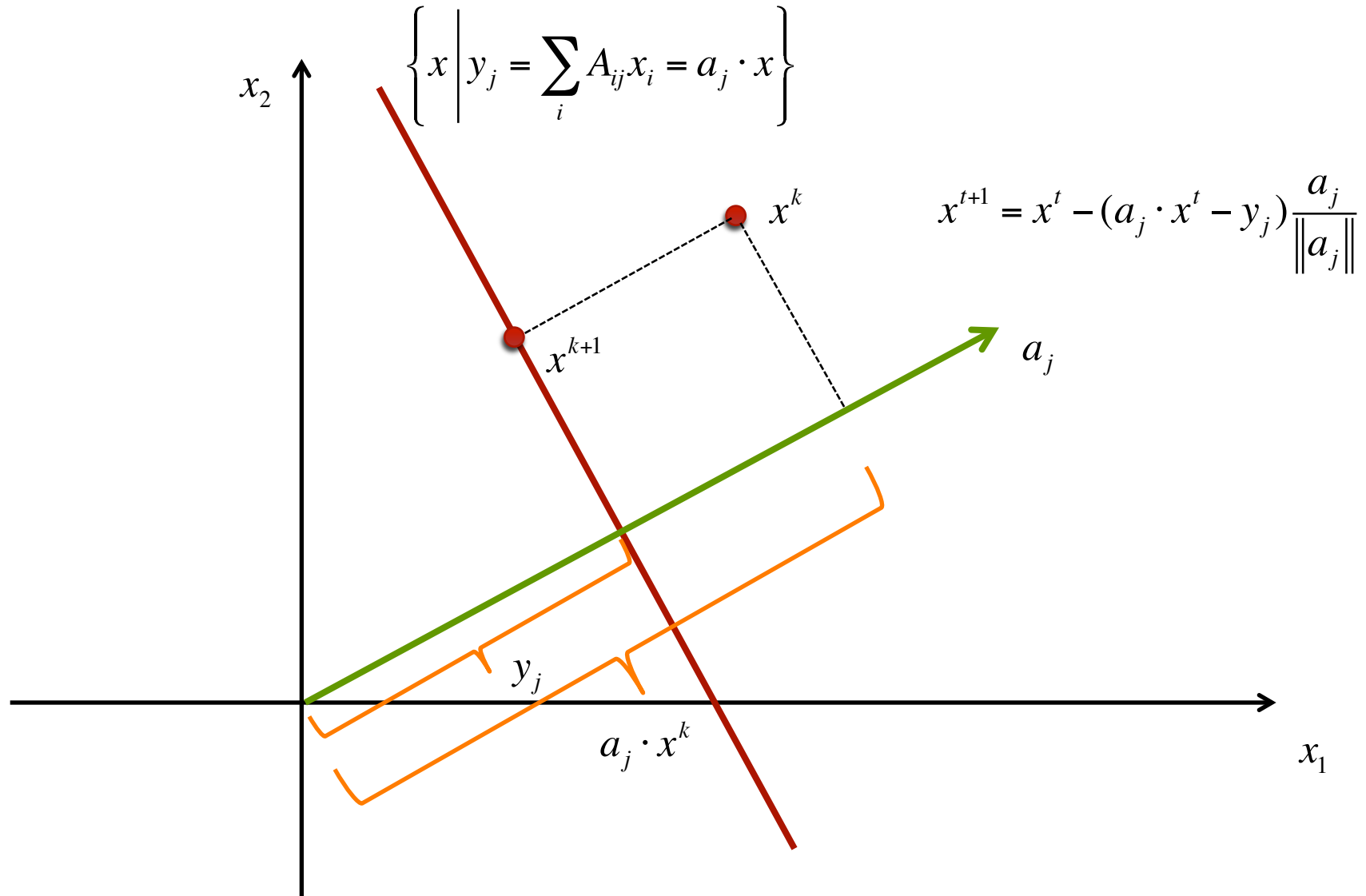
- $x$  is a  $N$ -dimensional vector
- each measurement  $y_j$  defines in  $(N-1)$ -dimensional hyper-plane

**Solution method:**

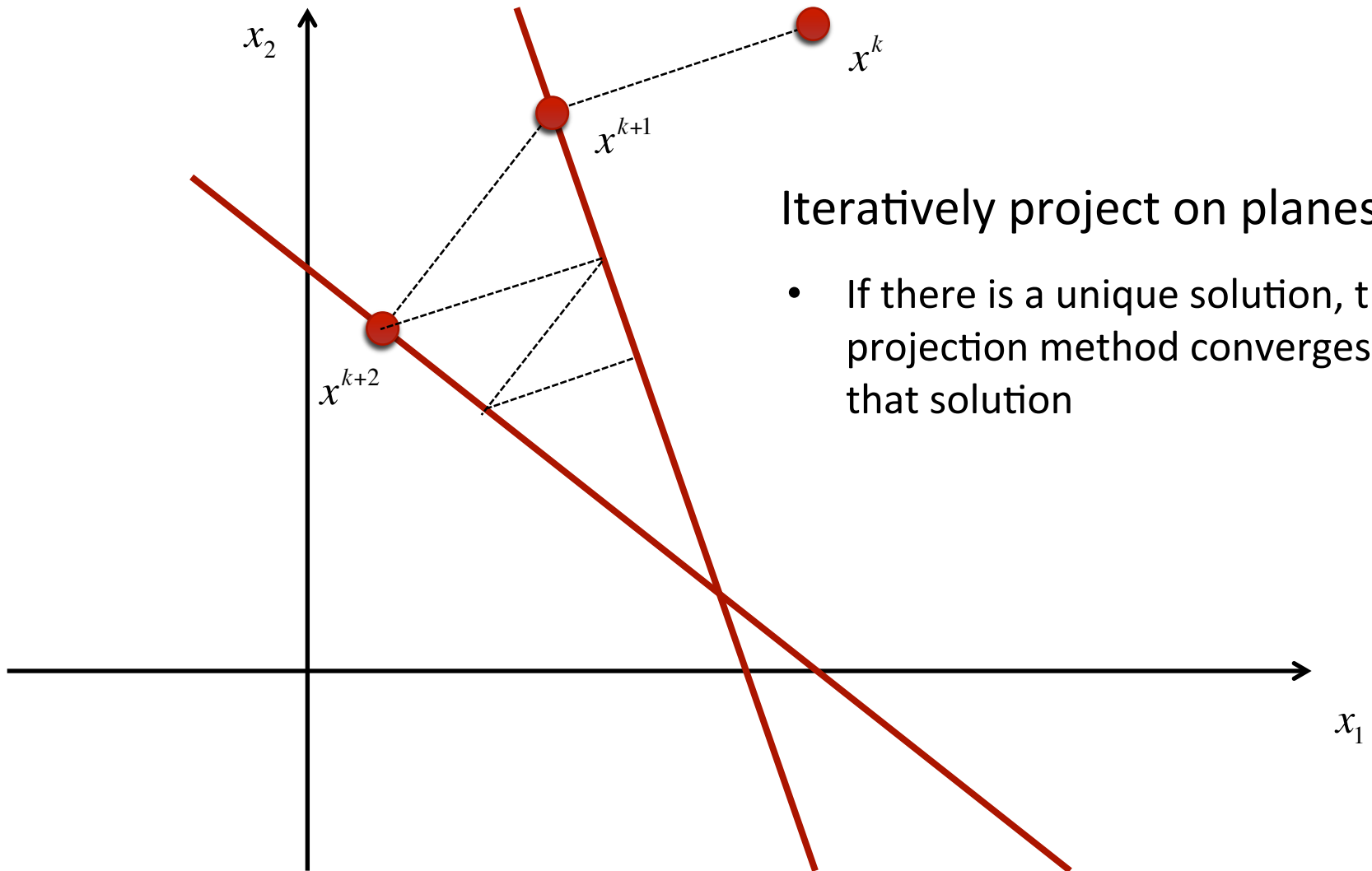
**Iteratively project on hyper-planes**



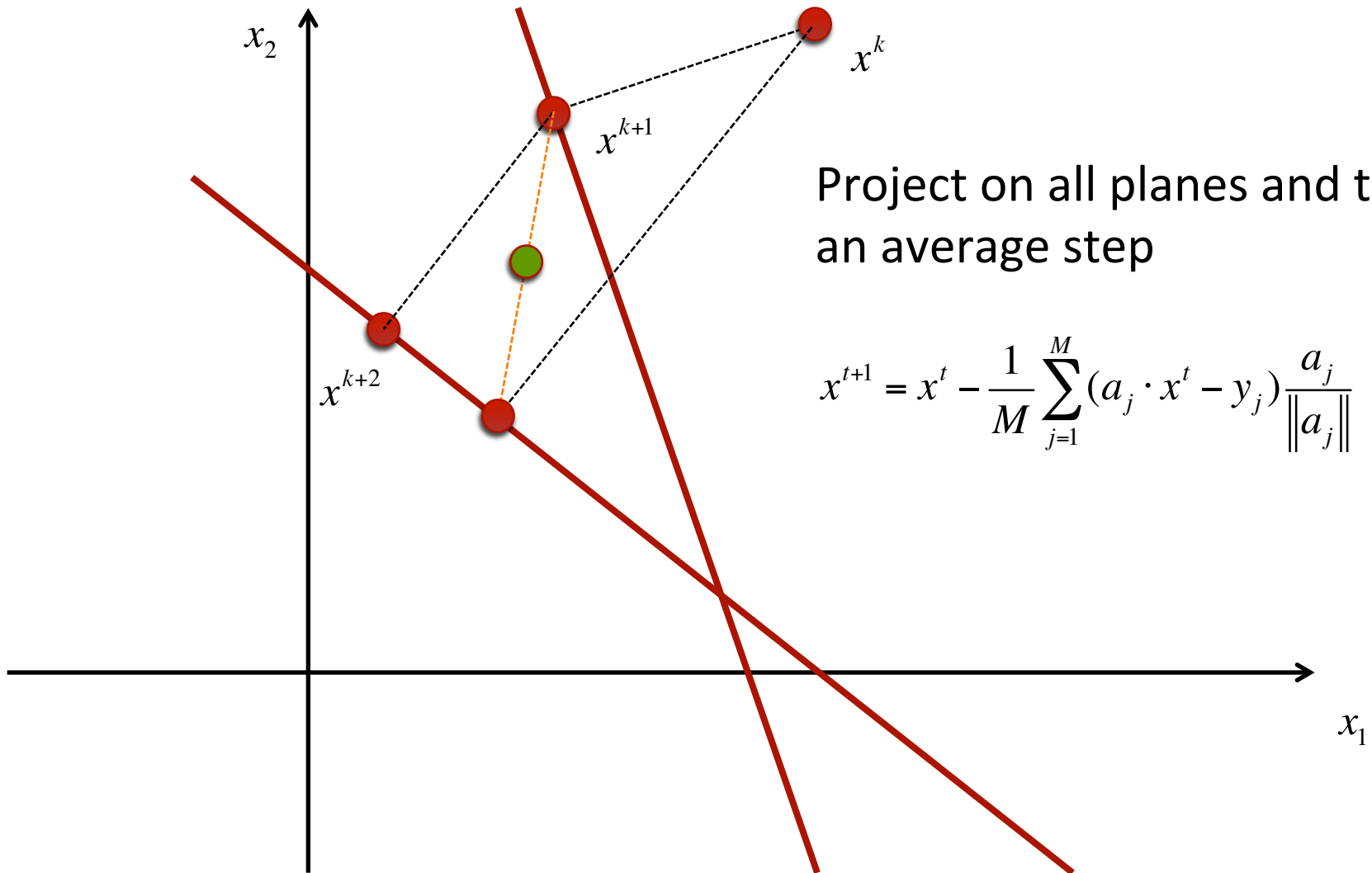
# Projection



# Iterative Projection



# Variation



# Optimization methods

**Second approach:**

**Look at this as an optimization problem**

(can address the ill-posed-ness this way)

$$y_j = \sum_i A_{ij} x_i$$

System of linear equations



minimize <sub>$x$</sub>   $\sum_j \left( y_j - \sum_i A_{ij} x_i \right)^2$  Least square minimization problem

# Gradient descent

**Most basic optimization method: Gradient descent**

$$C(x) = \sum_j \left( y_j - \sum_i A_{ij} x_i \right)^2$$

**Gradient vector points in the direction of steepest ascent**

$$\nabla_x C = \begin{pmatrix} \frac{\partial C}{\partial x_1} \\ \vdots \\ \frac{\partial C}{\partial x_n} \end{pmatrix} \quad x^{t+1} \leftarrow x^t - \alpha \nabla_x C(x^t)$$

# Gradient descent

**Objective function**

$$C(x) = \sum_j \left( y_j - \sum_i A_{ij} x_i \right)^2$$

**Calculate gradient**

$$\frac{\partial C}{\partial x_i} = - \sum_j 2 \left( y_j - \sum_i A_{ij} x_i \right) A_{ij}$$

$$x^{t+1} = x^t - (a_j \cdot x^t - y_j) \frac{a_j}{\|a_j\|}$$

$$\begin{aligned} \nabla_x C &= - \sum_j 2 \left( y_j - \sum_i A_{ij} x_i \right) a_j \\ &= - \sum_j 2 (y_j - a_j \cdot x) a_j \end{aligned}$$

**Calculate descent**

$$x^{t+1} = x^t - \alpha \nabla_x C(x^t)$$

# Gradient descent

## Compare to projection method

### Projection

$$x^{t+1} = x^t - \frac{1}{M} \sum_{j=1}^M (a_j \cdot x^t - y_j) \frac{a_j}{\|a_j\|}$$

### Calculate descent

$$\begin{aligned} x^{t+1} &= x^t - \alpha \nabla_x C(x^t) \\ &= x^t - \alpha \sum_{j=1}^M 2(a_j \cdot x^t - y_j) a_j \end{aligned}$$

- Projection method can be interpreted as gradient descent (for particular step size and weighting factors)

**Historically:** Different versions of projection methods  
(ART, SIRT, SART, ...)

**Contemporary topics:**

- Reconstruction from incomplete data, Compressed sensing methods

$$\underset{x}{\text{minimize}} \quad \sum_j \left( y_j - \sum_i A_{ij} x_i \right)^2 + \text{TV}(x) \quad \text{---} \quad \text{L}_1\text{-regularization}$$

- Reconstruction using prior knowledge
- Improved forward models, e.g. beam hardening