Inverse Problems 1: Convolution and Deconvolution

Lesson 5: Minimum norm solutions and TSVD

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Review

Pseudoinverse or Moore-Penrose Inverse

Minimum norm solution

Ill-posedness of the Inverse Problem.

• Condition Number Cond(A) := $\frac{d_1}{d_k}$

• Singular Value Decomposition (SVD) $A = UDV^T$

• Singular value Decomposition (SVD)
$$A = ODV$$

• Hadamard's conditions with respect to SVD matrix
$${\it D}$$

 $A^{-1} = VD^{-1}U^{T};$ $D^{-1} = \operatorname{diag}\left(\frac{1}{d_{1}}, \frac{1}{d_{2}}, \dots, \frac{1}{d_{k}}\right)$

A theorem

Theorem

Suppose that a continuum measurement is modelled by a sequence of matrices A_k of the size $k \times k$ for $k = k_0, k_0 + 1, k_0 + 2, \dots$ such that approximation to the forward problem becomes better as k grows. Then, Hadamard's third condition fails if

$$\lim_{k\to\infty} \mathit{Cond}(A_k) = \infty$$

Review

Pseudoinverse or Moore-Penrose Inverse

Minimum norm solution

 Let A be a k × n matrix. Let the SVD of matrix A be denoted by A = UDV^T Then the pseudoinverse (or Moore-Penrose inverse) of A is denoted by A⁺ is defined by

$$A^+$$
m = VD^+U^T m

where

$$D^{+} = \begin{bmatrix} \frac{1}{d_{1}} & 0 & \dots & 0 & \dots & 0 \\ 0 & \frac{1}{d_{2}} & \ddots & & & \vdots \\ \vdots & & & \frac{1}{d_{r}} & & & \\ & & & 0 & & \\ \vdots & & & & \ddots & \vdots \\ 0 & \dots & & & \dots & 0 \end{bmatrix} \in \mathbb{R}^{n \times k}.$$

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Pseudoinverse or Moore-Penrose Inverse

Minimum norm solution

Minimum Norm solution

• A vector $\mathcal{L}(\mathbf{m}) \in \mathbb{R}^n$ is called a least squares solution of the equation $A\mathbf{f} = \mathbf{m}$ if

$$||AL(\mathbf{m}) - \mathbf{m}|| = \min_{\mathbf{z} \in \mathbb{R}^n} ||(A\mathbf{z} - \mathbf{m})||$$

• $L(\mathbf{m})$ is called the mimimum norm solution if

$$\|\mathcal{L}(\mathbf{m})\| = \inf\{\|\mathbf{z}\| : \mathbf{z} \text{ is a least-squares solution of } A\mathbf{f} = \mathbf{m}\}$$

Theorem

Let A be a $k \times n$ matrix. Denote the SVD of the matrix A by $A = UDV^T$. The minimum norm solution of the equation $A\mathbf{f} = \mathbf{m}$ is given by $A^+\mathbf{m}$, where

$$A^+\mathbf{m} = VD^+U^T\mathbf{m}$$

Review

Pseudoinverse or Moore-Penrose Inverse

Minimum norm solution

A system of equations

Consider the system:

$$y = x;$$
$$y = 2x + 3$$

- Find the solution of the system by matrix inversion.
- ▶ Find the SVD of A
- Find the condition number of A
- Plot the system and the solution
- Consider the System

$$y = x;$$
$$y = x + 3$$

- Find the solution of the system by matrix inversion.
- ► Find the SVD of *A*
- ► Find the condition number of A
- ▶ Plot the system and the solution

Previous Example

• Consider the example of the signal

$$f=1 \quad \text{for} \quad n=[25:75] \qquad f=0 \quad \text{otherwise}$$
 (Here $n=[1:100]$).

- Consider the point spread function given by $PSF = [1, 1, 1, 1, 1]^T$ and normalise the point spread function.
- Create data for the inverse problem that involves inverse crime and with added noise.
- Now find f using naive inversion and with pseudo inverse and plot them on a graph