

Inverse Problems 1: Convolution and Deconvolution

Lesson 4: Inversion of the ill-posed problem

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Outline

Discretization

Singular Value Decomposition

Condition Number

Discretization

- Consider Fredholm integral equation of the first kind, where we wish to find $f(t)$

$$\int_0^1 K(s, t)f(t)dt = g(s), \quad 0 \leq s \leq 1, \quad \|K\|_{L^2([0,1] \times [0,1])}^2 \leq C$$

Quadrature Method

- Consider M discrete points $0 \leq s_1 < s_2 < s_3 < \dots < s_M \leq 1$
- Consider the quadrature method on

$$\int_0^1 K(s, t)f(t)dt = \sum_{j=1}^n w_j K(s_i, t_j)f(t_j)$$

- Then the integral equation reduces to M linear equations

$$\sum_{j=1}^n w_j K(s_i, t_j)f(t_j) = g(s_i)$$

Linear System

- Define a matrix \mathbf{A} with entries $a_{ij} \equiv w_j K(s_i, t_j)$
- Define a vector \mathbf{g} with entries $g_i \equiv g(s_i)$
- Define a vector \mathbf{f} with entries $f_j \equiv f(t_j)$
- The system of equations becomes $\mathbf{A}\mathbf{f} = \mathbf{g}$ with M equations in n unknowns.

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Singular Value Decomposition

- Consider an approximated discrete model of the form $\mathbf{m} = \mathbf{A}\mathbf{f} + \epsilon$ where \mathbf{A} is a matrix, $\mathbf{f} \in \mathbb{R}^n$, $\mathbf{m} \in \mathbb{R}^k$
- Singular Value Decomposition (SVD) is a tool that allows for the explicit analysis of the Hadamard's condition.
- Matrix Algebra tells us that any matrix $\mathbf{A} \in \mathbb{R}^{k \times n}$ can be written in the form of

$$\mathbf{A} = \mathbf{U}\mathbf{D}\mathbf{V}^T$$

- The right hand side of the above equation is called Singular Value Decomposition (SVD) of a matrix \mathbf{A}
- Here $\mathbf{U} \in \mathbb{R}^{k \times k}$ and $\mathbf{V} \in \mathbb{R}^{n \times n}$ are orthogonal matrices.
- $\mathbf{D} \in \mathbb{R}^{k \times n}$ is a diagonal matrix ; The diagonal elements d_j are the singular values of \mathbf{A} .

Orthogonality of U and V

- The matrices U and V are orthogonal means that

$$U^T U = U U^T = I, \quad V^T V = V V^T = I$$

- The columns of U form an orthonormal basis for \mathbb{R}^k .
- The columns of V form an orthonormal basis for \mathbb{R}^n .
- $U^{-1} = U^T$

Three possibilities for Diagonal matrix

- If $k = n$, The matrix \mathbf{D} is square.
- If $k > n$, then

$$\mathbf{D} = \begin{bmatrix} \text{diag}(d_1, \dots, d_n)_{k \times n} \\ (0, \dots, 0)_{(k-n) \times n} \end{bmatrix}$$

- If $k < n$, then

$$\mathbf{D} = \begin{bmatrix} \text{diag}(d_1, \dots, d_k), (0, \dots, 0)_{k \times (n-k)} \end{bmatrix}$$

- The diagonal elements d_j are non-negative and in decreasing order:

$$d_1 \geq d_2 \geq \dots \geq d_{\min(k,n)} \geq 0$$

- Note that some or all of d_j can be zeros.

Some basic Linear Algebra Definitions

Linear Subspaces related to \mathbf{A}

- $\text{Ker}(\mathbf{A}) = \{\mathbf{f} \in \mathbb{R}^n : \mathbf{A}\mathbf{f} = \mathbf{0}\}$
- $\text{Range}(\mathbf{A}) = \{\mathbf{m} \in \mathbb{R}^k : \text{there exists } \mathbf{f} \in \mathbb{R}^n \text{ such that } \mathbf{A}\mathbf{f} = \mathbf{m}\}$
- $\text{Coker}(\mathbf{A}) = (\text{Range}(\mathbf{A}))^\perp \subset \mathbb{R}^k$

Hadamard's condition and the matrix D

- if $n < k$, then by rank-nullity theorem, $\dim(\text{Range}(\mathbf{A})) < k$. Thus we can find a non-zero $\mathbf{m}_0 \in \text{Coker}(\mathbf{A})$ for which there is no \mathbf{f} . Thus existence condition is not satisfied.
- If $n > k$, then $\dim(\text{Ker}(\mathbf{A})) > 0$, that is there is a non-zero $\mathbf{f}_0 \in \text{Ker}(\mathbf{A})$ such that $\mathbf{A}(\mathbf{A}^{-1}\mathbf{m}) = \mathbf{m} = \mathbf{A}(\mathbf{A}^{-1}\mathbf{m} + \mathbf{f}_0)$. Thus the uniqueness is not satisfied.
- Consider $k = n$ and \mathbf{A} is invertible. Now we have,

$$\mathbf{A}^{-1}\mathbf{m} = \mathbf{A}^{-1}(\mathbf{A}\mathbf{f} + \epsilon) = \mathbf{f} + \mathbf{A}^{-1}\epsilon$$

- The error $\mathbf{A}^{-1}\epsilon$ can be bounded by

$$\|\mathbf{A}^{-1}\epsilon\| \leq \|\mathbf{A}^{-1}\| \|\epsilon\|$$

Example1 of class 2

1. Define a vector $\mathbf{f} \in \mathbb{R}^{100}$ such that $f_i = 1$ if $25 \leq i \leq 75$, $f_i = 0$. Plot the signal.
2. Define a point spread function $\mathbf{p} \in \mathbb{R}^5$ obtained by normalizing the vector $[1, 2, 3, 2, 1]'$.
3. Find the convolution matrix
4. Do the naive inversion. Plot the results
5. Let us analyse the failure of naive inversion with the help of SVD
6. Compute \mathbf{A}^{-1}
7. Compute the norm of \mathbf{A}^{-1} using norm command
8. Find SVD of \mathbf{A} using svd command

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Condition number

- Question is what is the problem when we can find the inverse of a matrix?
- Note that inverse of a matrix is

$$\mathbf{A}^{-1} = \mathbf{V}\mathbf{D}^{-1}\mathbf{U}^T, \quad \mathbf{D}^{-1} = \text{diag}\left(\frac{1}{d_1}, \frac{1}{d_2}, \dots, \frac{1}{d_k}\right)$$

- The problem for inversion arises from *Condition Number*

$$\text{Cond}(\mathbf{A}) := \frac{d_1}{d_k}$$

Example2 of Class2

1. Consider the same function as in the previous example.
2. Now define a different point spread function as $\mathbf{p} = [1, 1, 1, 1, 1]$, convolved with itself and normalized.
3. Find the Convolution Matrix
4. Add noise and do the naive inversion.
5. Analyse the results with norm of \mathbf{A}^{-1} , SVD, Condition number of \mathbf{A}
6. Compute \mathbf{A}^{-1}
7. Compute the norm of \mathbf{A}^{-1} using norm command
8. Find SVD of \mathbf{A} using svd command
9. Find Condition number of \mathbf{A}