

Hilbert Matrix

Define $H_n \in \mathbb{R}^{n \times n}$ by $h_{ji} = 1/(i+j-1)$, $i, j = 1, 2, \dots, n$

Note: $H_n^T = H_n$. Moreover, possible to show $\lambda_i(H_n) > 0$ for all i .

Can be shown that $\lambda_{\min} \rightarrow 0$ as $n \rightarrow \infty$. This causes

$$\kappa_2(H_n) \sim \frac{(2\sqrt{2}+1)^{4n+4}}{2^{15/4} \cdot (\pi n)^{1/2}} \quad \text{as } n \rightarrow \infty$$

exponential growth!

Consider $b_i = \sum_{j=1}^n j/(i+j-1)$. ($b \in \mathbb{R}^n$) Note that:

$$\sum_{j=1}^n h_{ji} \cdot j = \sum_{j=1}^n \left(\frac{j}{i+j-1} \right) = b_i$$

So $x \in \mathbb{R}^n$ with $x_i = i$ solves $H_n \cdot x = b$.

Solve $H_n x = b$ for $x + \delta x$ via LU.
due to rounding error

n	$\ \delta b\ _2 / \ b\ _2$	$\ \delta x\ _2 / \ x\ _2$
5	1.2×10^{-15}	8.5×10^{-11}
10	1.7×10^{-15}	1.3×10^{-3}
15	2.8×10^{-15}	4.1
20	6.3×10^{-15}	8.7
25	1.9×10^{-13}	5.5×10^2

Note: for $n > 15$, error is larger than the solution itself!

Least Squares Problems

Often (e.g. data fitting), want to solve:

$$(P) \quad \min_x \|Ax - b\|_2 \quad \begin{matrix} x \in \mathbb{R}^n, & b \in \mathbb{R}^m \\ A \in \mathbb{R}^{m \times n} \end{matrix}$$

$m > n$? $\underline{A}\underline{x} = \underline{b}$ does not exist in general!

Ex: $\begin{pmatrix} 3 & 1 \\ 1 & 1 \\ 4 & 2 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \\ 2 \end{pmatrix}$ A

$m < n$? Infinitely many solutions!

Ex: $\begin{pmatrix} 3 & 1 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \underline{I} \Rightarrow \underline{x} = \begin{pmatrix} \mu \\ 1-3\mu \end{pmatrix}$ for $\mu \in \mathbb{R}$. A

Note: Convenient to solve instead:

$$\min_{\underline{x}} \frac{1}{2} \|\underline{Ax} - \underline{b}\|_2^2$$

By expansion,

$$\begin{aligned} \frac{1}{2} \|\underline{Ax} - \underline{b}\|_2^2 &= \frac{1}{2} (\underline{Ax} - \underline{b})^T (\underline{Ax} - \underline{b}) \\ &= \frac{1}{2} \underline{x}^T \underline{A}^T \underline{A} \underline{x} - 2 \underline{x}^T \underline{A}^T \underline{b} + \underline{b}^T \underline{b} \end{aligned}$$

Minimum can be found by setting gradient wrt $\underline{x} = \underline{0}$!

This gives the **normal equations**

$$\underline{A}^T \underline{A} \underline{x} = \underline{A}^T \underline{b} \quad \text{note: } \underline{A}^T \underline{A} \in \mathbb{R}^{n \times n}$$
$$\underline{A}^T \underline{b} \in \mathbb{R}^n$$

square system!

Problem: $\kappa(\underline{A}^T \underline{A}) = \kappa(\underline{A})^2$! The condition # of \underline{A} gets squared, making the normal equations often quite ill-conditioned.

Ex: $\underline{A} = \begin{pmatrix} \epsilon & 0 \\ 0 & 1 \end{pmatrix}, \quad \epsilon \in (0, 1) \quad \underline{A}^{-1} = \begin{pmatrix} 1/\epsilon & 0 \\ 0 & 1 \end{pmatrix}$

$$\|\underline{A}\| = 1, \quad \|\underline{A}^{-1}\| = 1/\epsilon \Rightarrow \kappa_2(\underline{A}) = 1/\epsilon$$

$$\underline{A}^T \underline{A} = \underline{A}^2 = \begin{pmatrix} \epsilon^2 & 0 \\ 0 & 1 \end{pmatrix} \Rightarrow \kappa_2(\underline{A}^T \underline{A}) = 1/\epsilon^2 \quad A$$

For ϵ small (e.g. $10^{-2}, 10^{-3}$), extra factor of $1/\epsilon$ huge!

Q: Can we devise a method that avoids squaring $\kappa(\underline{A})$, e.g. by working directly w/ the matrix \underline{A} ?