

Condition Number

Consider $Ax=b$ where A is $n \times n$ and invertible.

Example

Say A^{-1} is perturbed (e.g. due to roundoff errors) to obtain a new matrix B .

Then the solution $x=A^{-1}b$ is perturbed to $\tilde{x}=Bb$. $\|Ax\| \leq \|A\| \|x\|$

Abs. Error = $\|x-\tilde{x}\| = \|x-Bb\| = \|x-BAx\| = \|(I-BA)x\| \leq \|I-BA\| \|x\|$

Thus, Relative Error = $\frac{\|x-\tilde{x}\|}{\|x\|} \leq \|I-BA\|$ $B \approx A^{-1}$

Example

Suppose b is perturbed to \tilde{b} , $Ax=b$ (exact) and $A\tilde{x}=\tilde{b}$ (approximate)

Then Abs. Error = $\|x-\tilde{x}\| = \|A^{-1}b - A^{-1}\tilde{b}\| = \|A^{-1}(b-\tilde{b})\| \leq \|A^{-1}\| \|b-\tilde{b}\|$

$$\|x-\tilde{x}\| \leq \|A^{-1}\| \|b\| \frac{\|b-\tilde{b}\|}{\|b\|} = \|A^{-1}\| \|Ax\| \frac{\|b-\tilde{b}\|}{\|b\|}$$

$$\leq \|A^{-1}\| \|A\| \|x\| \frac{\|b-\tilde{b}\|}{\|b\|}$$

Thus, Relative Error = $\frac{\|x-\tilde{x}\|}{\|x\|} \leq K(A) \frac{\|b-\tilde{b}\|}{\|b\|}$ where $K(A) = \|A^{-1}\| \|A\|$ is called the condition number.

Note that $I = A^{-1}A$

$\Rightarrow \|I\| = \|A^{-1}A\| \leq \|A^{-1}\| \|A\| = K(A)$

Example

Let $A = \begin{pmatrix} 1 & 1+\epsilon \\ 1-\epsilon & 1 \end{pmatrix}$ $A^{-1} = \frac{1}{\epsilon^2} \begin{pmatrix} 1 & -1-\epsilon \\ -1+\epsilon & 1 \end{pmatrix}$ ($\epsilon > 0$)

Then $\|A\|_\infty = 2+\epsilon$ $\|A^{-1}\|_\infty = \frac{1}{\epsilon^2} (2+\epsilon)$

Hence $K(A) = \frac{(2+\epsilon)^2}{\epsilon^2} > \frac{4}{\epsilon^2}$. If $\epsilon \leq 10^{-2}$ then

$K(A) \geq 4 \cdot 10^4 = 40000$

Thus a small error in b may induce a perturbation of x that is 40000 times larger.

Let \tilde{x} be the numerical approximation to $Ax=b$. Let $r = b - A\tilde{x}$ called the residual vector. Set $e = x - \tilde{x}$ to be the error vector.

Note

$Ae = Ax - A\tilde{x} = b - A\tilde{x} = r$

Set $\tilde{b} = A\tilde{x}$ then $\tilde{b} = b - r$ is the perturbed right hand side vector.

Now, $\frac{\|x-\tilde{x}\|}{\|x\|} = \frac{\|e\|}{\|x\|}$ and $\frac{\|b-\tilde{b}\|}{\|b\|} = \frac{\|r\|}{\|b\|}$

Thm When solving $Ax=b$ (for invertible A) we have

$$\frac{1}{K(A)} \frac{\|r\|}{\|b\|} \leq \frac{\|e\|}{\|x\|} \leq K(A) \frac{\|r\|}{\|b\|}$$

Note that we have already proved the inequality on the right above

The inequality on the left can be proved as follows:

$\|Mv\| \leq \|M\| \|v\|$

$\|r\| \|x\| = \|Ae\| \|A^{-1}b\| \leq \|A\| \|e\| \|A^{-1}\| \|b\| = K(A) \|e\| \|b\|$

thus $\frac{1}{K(A)} \frac{\|r\|}{\|b\|} \leq \frac{\|e\|}{\|x\|}$

4.5 Neumann Series and Iterative Refinement

Given a normed vector space $(V, \|\cdot\|)$ and a sequence $\{v^{(n)}\}$ in V , we say that $\{v^{(n)}\}$ converges to v if

$\lim_{n \rightarrow \infty} \|v^{(n)} - v\| = 0$

e.g. $v^{(n)} = \begin{pmatrix} 3 - \frac{1}{n} \\ -2 + \frac{1}{\sqrt{n}} \\ 1 \\ e^{-n} \end{pmatrix} \in \mathbb{R}^4$ let $v = \begin{pmatrix} 3 \\ -2 \\ 1 \\ 0 \end{pmatrix}$

Then $\|v^{(n)} - v\|_\infty = \max \left\{ \frac{1}{n}, \frac{1}{\sqrt{n}}, e^{-n} \right\} \rightarrow 0$ as $n \rightarrow \infty$

In fact, for finite dimensional V , the notion of convergence is independent of the norm. (If $v^{(n)} \rightarrow v$ using norm $\|\cdot\|$, then $v^{(n)} \rightarrow v$ using any norm $\|\cdot\|'$.)

Cauchy criterion

$a_n \in \mathbb{R}$ $\{a_n\}$ is Cauchy if $\forall \epsilon > 0$
 $\exists N$ s.t. $|a_i - a_j| < \epsilon$
 $\forall i, j \geq N$

$\{v^{(n)}\}$ converges (in finite dimensional V over \mathbb{R} or \mathbb{C}) iff $\lim_{n \rightarrow \infty} \sup_{i, j \geq n} \|v^{(i)} - v^{(j)}\| = 0$

Thm (Theorem on Neumann Series)

If A is $n \times n$ and $\|A\| < 1$, then $I - A$ is invertible

and $(I - A)^{-1} = \sum_{k=0}^{\infty} A^k$. Recall geometric series $|r| < 1$ then $\frac{1}{1-r} = \sum_{k=0}^{\infty} r^k$

Pf

Assume on the contrary that $I - A$ is not invertible.

Then $\exists x \in \mathbb{R}^n$ s.t. $\|x\| = 1$ and $(I - A)x = 0 \Rightarrow Ax = x$

Thus, $1 = \|x\| = \|Ax\| \leq \|A\| \|x\| = \|A\|$ which is a contradiction.

Next we want to show $\sum_{k=0}^m A^k \rightarrow (I-A)^{-1}$ or equivalently

$$(I-A) \sum_{k=0}^m A^k \rightarrow I$$

Note that $(I-A) \sum_{k=0}^m A^k = \sum_{k=0}^m A^k - A^{k+1} = A^0 - A^{m+1} = I - A^{m+1}$

Note that $\|A^{m+1}\| \leq \|A\| \|A^m\| \leq \|A\| \|A\| \|A^{m-1}\| \leq \dots \leq \|A\|^{m+1}$

Since $\|A\| < 1$, $\|A^{m+1}\| \leq \|A\|^{m+1} \rightarrow 0$

$\Rightarrow A^{m+1} \rightarrow 0$ which was to be shown.

Remark: $\|(I-A)^{-1}\| \leq \sum_{k=0}^{\infty} \|A^k\| \leq \sum_{k=0}^{\infty} \|A\|^k = \frac{1}{1-\|A\|}$

Example Find the inverse of $B = \begin{pmatrix} 0.9 & -0.3 \\ 0.3 & 1.1 \end{pmatrix}$ using Neumann series.

Set $A = I - B = \begin{pmatrix} 0.1 & 0.3 \\ -0.3 & -0.1 \end{pmatrix}$ Clearly $\|A\|_{\infty} = 0.4 < 1$

Thus, $B = I - A$ is invertible and $B^{-1} = \sum_{k=0}^{\infty} A^k$

Set $B_m = \sum_{k=0}^m A^k$ ($B_m \rightarrow B^{-1}$ as $m \rightarrow \infty$)

Then $B_0 = I$, $B_1 = I + A = I + AB_0$

$B_2 = I + A + A^2 = I + AB_1$ and so on. $B_{n+1} = I + AB_n$

$B_0 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$, $B_1 = \begin{pmatrix} 1.1 & 0.3 \\ -0.3 & 0.9 \end{pmatrix}$, $B_2 = \begin{pmatrix} 1.02 & 0.3 \\ -0.3 & 0.82 \end{pmatrix}$

$B_4 = \begin{pmatrix} 1.012 & 0.276 \\ -0.276 & 0.828 \end{pmatrix} \dots$

$B^{-1} \approx \begin{pmatrix} 1.0185 & 0.27778 \\ -0.27778 & 0.83333 \end{pmatrix}$

Thm 2 If A and B are $n \times n$ matrices s.t. $\|I - AB\| < 1$, then A and B are invertible. Furthermore,

$A^{-1} = B \sum_{k=0}^{\infty} (I - AB)^k$ and $B^{-1} = \sum_{k=0}^{\infty} (I - AB)^k A$

Pf By the prev. thm, $I - (I - AB) = AB$ is invertible and

$(AB)^{-1} = \sum_{k=0}^{\infty} (I - AB)^k$ Since $(AB)^{-1} = B^{-1}A^{-1}$,

we have $B^{-1}A^{-1} = \sum_{k=0}^{\infty} (I - AB)^k$. The desired equalities are easy to obtain from here.

Iterative Refinement

Say $x^{(0)}$ is an approximate sol.ⁿ to $Ax = b$

(for example the solution obtained numerically using Gaussian elimination)

Q) How to improve the accuracy of the solution?

- A) Define
- $r^{(k)} = b - Ax^{(k)}$ the residual vector corresponding to $x^{(k)}$
 - $Ae^{(k)} = r^{(k)}$ the error vector
 - $x^{(k+1)} = x^{(k)} + e^{(k)}$ for $k \geq 0$

Then $x^{(k)} \rightarrow x$: the exact solution as $k \rightarrow \infty$.

Here's why:

Say B is an approximate inverse to A . More precisely, B is a matrix that satisfies $\|I - BA\| < 1$. $Ax = b$

We have $x^{(0)} = Bb$ then combining steps 1, 2, 3 we have

$x^{(k+1)} = x^{(k)} + B(b - Ax^{(k)})$

Thus $x^{(k+1)} - x = x^{(k)} - x + B(b - Ax^{(k)})$

$= x^{(k)} - x + B(Ax - Ax^{(k)})$

$= (I - BA)(x^{(k)} - x)$

Therefore, $\|x^{(k+1)} - x\| = \|(I - BA)(x^{(k)} - x)\|$
 $\leq \|I - BA\| \|x^{(k)} - x\|$
 $\leq \|I - BA\|^2 \|x^{(k-1)} - x\|$
 \vdots
 $\leq \|I - BA\|^k \|x^{(0)} - x\|$

Since $\|I - BA\| < 1$, $\|x^{(k)} - x\| \rightarrow 0$ as $k \rightarrow \infty$.

Note that Thm 2 gives us a way to compute A^{-1} very accurately starting with an initial approximation, that is, B with $\|I - AB\| < 1$

Then $A^{-1} = B \sum_{k=0}^{\infty} (I - AB)^k$

That is, $A_0 = B$ and $A_{n+1} = B + A_n(I - AB)$

gives $A_n \rightarrow A^{-1}$ as $n \rightarrow \infty$

$Ax = b \Rightarrow x = A^{-1}b = B \sum_{k=0}^{\infty} (I - AB)^k b$