

Numerical Methods

5633

Lecture 5

Michaelmas Term 2017

Marina Krstic Marinkovic
mmarina@maths.tcd.ie

School of Mathematics
Trinity College Dublin

Organisational (Michaelmas Term 2018)

- Make up for the lost lecture: 2nd week of Nov. (12.11: 11am-1pm)

	To appear	Submission DL
• Assignment 1	online (start early!)	<u>2.11</u>
• Assignment 2	14.11	30.11

Solving linear algebraic equations

- ➔ How is the matrix solution process affected by the changes of the problem?
- ➔ If the small change in the problem produces the large change in the solution:
 - is it due to small perturbation of the problem?
 - or due to the instability in the computational scheme?
- ➔ Recall some linear algebra
 - Vector and Matrix norms
 - Perturbations, conditioning, stability

Vector and matrix norms

Definition 1: A **vector norm** on \mathbf{R}^n is any mapping $\|\cdot\|$, defined on \mathbf{R}^n , defined on with values in $[0, \infty)$, which satisfies the conditions:

1. $\|x\| > 0$ for any vector $x \neq 0$;
2. $\|ax\| = |a| \|x\|$ for any scalar a ;
3. $\|x + y\| \leq \|x\| + \|y\|$ for any two vectors x and y ;

→ Examples of vector norms:

- Infinity norm:

$$\|x\|_{\infty} = \max_{1 \leq i \leq n} |x_i|$$

- Euclidean 2-norm:

$$\|x\|_2 = \left(\sum_{i=1}^n x_i^2 \right)^{\frac{1}{2}}$$

Vector and matrix norms

Definiton 2: Let $\|\cdot\|$ be a given vector norm on \mathbf{R}^n . A corresponding **matrix norm** for matrices $\mathbf{A} \in \mathbf{R}^{n \times n}$ is defined by:

$$\|A\| = \max_{x \neq 0} \frac{\|Ax\|}{\|x\|}$$

→ Consequences of this definition of operator (matrix) norm:

$$\|AB\| \leq \|A\| \|B\| \quad \text{and} \quad \|Ax\| \leq \|A\| \|x\|$$

→ Not necessary to associate matrix norm with a particular vector one

- Matrix infinity norm:

$$\|A\|_{\infty} = \max_{1 \leq i \leq n} \sum_{j=1}^n |a_{ij}|$$

- Matrix 2-norm:

$$\|A\|_2 = \sqrt{\Lambda(A^T A)}$$

$\Lambda(B)$ is the largest (in abs. value) eigenvalue of the matrix B

Condition number

Definiton 3: For a given matrix $\mathbf{A} \in \mathbf{R}^{n \times n}$ and a given matrix norm $\|\cdot\|$, the **condition number** with respect to the given norm is defined by:

$$\kappa(A) = \|A\| \|A^{-1}\|$$

If A is singular, then we take $\kappa(A) = \infty$.

Theorem 1: Let $\mathbf{A} \in \mathbf{R}^{n \times n}$ be a given nonsingular matrix. Then, for any singular matrix $\mathbf{B} \in \mathbf{R}^{n \times n}$ holds:

$$\frac{1}{\kappa(A)} \leq \frac{\|A - B\|}{\|A\|}$$

Effects of perturbations

→ in **b**:

Theorem 2: Let $\mathbf{A} \in \mathbf{R}^{n \times n}$ be a given nonsingular matrix and $\mathbf{b} \in \mathbf{R}^n$. Let us also define $\mathbf{x} \in \mathbf{R}^n$ as the solution of the linear system $\mathbf{Ax}=\mathbf{b}$ and let $\delta\mathbf{b} \in \mathbf{R}^n$ be a small perturbation of \mathbf{b} . If we define $\mathbf{x}+\delta\mathbf{x} \in \mathbf{R}^n$ as the solution of the system $\mathbf{A}(\mathbf{x}+\delta\mathbf{x})=\mathbf{b}+\delta\mathbf{b}$ then

$$\frac{\|\delta x\|}{\|x\|} \leq \kappa(A) \frac{\|\delta b\|}{\|b\|}$$

→ in **A**:

Theorem 3: Let $\mathbf{A} \in \mathbf{R}^{n \times n}$ be a given nonsingular matrix and let $\mathbf{E} \in \mathbf{R}^{n \times n}$ be a perturbation of \mathbf{A} . Let $\mathbf{x} \in \mathbf{R}^n$ be a unique solution of $\mathbf{Ax}=\mathbf{b}$. If then the perturbed system $(\mathbf{A}+\mathbf{E})\mathbf{x}=\mathbf{b}$ has a unique solution and

$$\frac{\|x - x_c\|}{\|x\|} \leq \frac{\theta}{1 - \theta}, \quad \text{where } \theta = \kappa(A) \frac{\|E\|}{\|A\|}.$$

Estimating the condition number

- ➔ If the solution to a linear system changes a great deal when the problem changes only very slightly, then we suspect that the matrix is ill-conditioned
- ➔ Recall the definition (infinity norm):

$$\kappa(A) = \|A\|_{\infty} \|A^{-1}\|_{\infty}$$

- ➔ Computing $\|A\|_{\infty}$ not hard, computing $\|A^{-1}\|_{\infty}$ is! (if A is ill-conditioned, computing A^{-1} will be unreliable)

Estimating condition number

- ➔ Algorithm for estimating the condition number, given LU factorisation of A

1. Compute $\alpha = \|A\|_\infty$
2. Take a random initial guess $y^{(0)}$
3. Compute $y^{(5)}$ in the sequence defined by

$$y^{(i+1)} = \frac{A^{-1}y^{(i)}}{\|y^{(i)}\|_\infty}, \quad i = 0, 1, \dots, 4$$

by solving the systems using the exact factorisation of A, and set $v = \|y^{(5)}\|_\infty$.

4. Set $K^* = \alpha v$.

➔ Homework: write an R code determining the condition number

➔ Check with predefined R routine: `library('Matrix'); condnr <- 1/(rcond(a, norm = c("I")))`