DN2222 Applied Numerical Methods - part 2: Numerical Linear Algebra

Lecture 2: Error Analysis & Gaussian Elimination

2012 - 10 - 24

Register for the course!

- Go to https://rapp.csc.kth.se/ and activate your-self!
- Go to *Mina Sidor* and activate yourself!
- ... or you cannot register for the written exam Dec $10^{th}!$
- On-line registration for the exam is done using *Mina Sidor*. It is **only open** from (about) November 9th to (about) November 23rd.
- Exam registration only open mid November.
- No late registration for the exam allowed.

Norm

- A norm is a function mapping from \mathbb{R}^n to \mathbb{R} fulfilling the following three conditions:
- $f(x) \ge 0$ and f(x) = 0 if and only if x = 0.
- $f(\alpha x) = |\alpha| f(x)$ for all $\alpha \epsilon R$ and all $x \epsilon R^n$
- $f(x+y) \le f(x) + f(y)$ for all x and $y \in \mathbb{R}^n$
- A norm is often denoted by $|| \cdot ||$ (avoid $| \cdot | !!!$)

Famous Norms

- Euclidian norm, $||x||_2 = \sqrt{\sum_{i=1}^n x_i^2}$
- Infimum norm (or max norm), $||x||_{\infty} = \max_{i=1:n} |x_i|$
- Maximum norm (or 1-norm), $||x||_1 = \sum_{i=1}^n |x_i|$
- ℓ_p -norm, $||x||_p = (\sum_{i=1}^n x_i^p)^{(1/p)}$

Equivalent Norms

• Two norms $||\cdot||_{\alpha}$ and $||\cdot||_{\beta}$ in \mathbb{R}^n are *equivalent* if there exists two constants m > 0 and M > 0 such that for all $x \in \mathbb{R}$

 $m||x||_{\alpha} \le ||x||_{\beta} \le M||x||_{\alpha}$

• All vector norms in \mathbb{R}^n are equivalent

Equivalent Norms (cont.)

The following relations are useful when converting error bounds in terms of one norm to error bounds in terms of another norm.

$$\begin{split} ||x||_2 &\leq ||x||_1 \leq \sqrt{n} ||x||_2 \\ ||x||_{\infty} \leq ||x||_2 \leq \sqrt{n} ||x||_{\infty} \\ ||x||_{\infty} \leq ||x||_1 \leq n ||x||_{\infty} \\ \text{(D p21: Lemma 1.5)} \end{split}$$

Quiz

- Find an array for which $||x||_{\infty} < ||x||_{1}$
- Find an array for which $||x||_{\infty} = ||x||_{1}$
- Find an array for which $||x||_1 = n||x||_{\infty}$

Quiz

• If $||x||_2 < ||y||_2$ what about the relation between $||x||_{\infty}$ and $||y||_{\infty}$?

Quiz' answer

- If $||x||_2 < ||y||_2$ what about the relation between $||x||_{\infty}$ and $||y||_{\infty}$?
- \star Nothing! Since:
- $\begin{array}{l} \circ \ \mbox{Ex2: If $x=(10,1)$ and $y=(8,9)$ then} \\ ||x||_2 < ||y||_2 \ \ \mbox{but} \ \ ||x||_\infty > ||y||_\infty \end{array}$

Inner product

Let B be a complex linear space. $\langle \cdot, \cdot \rangle : B \times B \to R$ is an inner product if all of the following apply:

- $\begin{array}{l} 1) < x, y > = < y, \overline{x} > \\ 2) < x, y + z > = < x, y > + < x, z > \\ 3) < \alpha x, y > = |\alpha| < x, y > \\ 4) < x, x > \ge 0 \text{ with } < x, x > = 0 \text{ iff } x = 0 \end{array}$
- x and y are orthogonal if $\langle x, y \rangle = 0$
- $\sqrt{\langle x, x \rangle}$ is a norm.

Cauchy-Schwartz' inequality

 $\bullet \ | < x,y > | \leq \sqrt{< x,x > \cdot < y,y >}$

Induced matrix norm

Let A be $m \times n$, $|| \cdot ||_{\hat{m}}$ be a norm on R^m and $|| \cdot ||_{\hat{n}}$ be a norm on R^n . Then

$$||A||_{\hat{m}\hat{n}} = \max_{x \neq 0} \frac{||Ax||_{\hat{m}}}{||x||_{\hat{n}}}$$

is called an operator norm or *induced norm* or subordinate norm.

• For operator norms we have $||AB|| \le ||A|| \cdot ||B||$.

Special matrix norms

- $||A||_1 = ||A^T||_{\infty} = \max_j \sum_i |a_{ij}| = \text{maximum column sum.}$
- $||A||_{\infty} = ||A^T||_1 = \max_i \sum_j |a_{ij}| =$ maximum row sum.
- $||A||_2 = \sqrt{\lambda_{max}(A * A)}$
- $||A||_2 = ||A^T||_2$
- $||A||_F = ||A^T||_F = \sqrt{\sum_i \sum_j |a_{ij}|^2}$, the Frobenius norm.

Perturbation Theory

Suppose Ax = b and $(A + \delta A)\hat{x} = b + \delta b$. Our goal is to bound the norm of $\delta x = \hat{x} - x$.

$$(A + \delta A)(x + \delta x) = b + \delta b$$
$$Ax = b$$
$$\delta Ax + (A + \delta A)\delta x = \delta b$$

 $\longrightarrow \quad \delta Ax + (A +$ giving $\delta x = A^{-1}(\delta b - \delta A\hat{x})$ and

$$||\delta x|| \le ||A^{-1}||(||\delta b|| + ||\delta A|| \cdot ||\hat{x}||)$$

We can also derive

$$\begin{aligned} &\frac{||\delta x||}{||\hat{x}||} \le ||A^{-1}|| \cdot ||A|| \cdot \left(\frac{||\delta A||}{||A||} + \frac{||\delta b||}{||A|| \cdot ||\hat{x}||}\right) \\ &= \{ \mathbf{D} \ \mathbf{p33} \} = \le \frac{\kappa(A)}{1 - \kappa(A)\frac{||\delta A||}{||A||}} \left(\frac{||\delta A||}{||A||} + \frac{||\delta b||}{||b||}\right) \end{aligned}$$

• The quantity $\kappa(A) = ||A^{-1}|| \cdot ||A||$ is the condition number.

Condition number,

• Theorem 2.1 (p33) Let A be non-singular then

$$\min\{||\delta A||_2 : A + \delta A \text{ is singular}\} = \frac{1}{||A^{-1}|| \cdot ||A||} = \frac{1}{\kappa(A)}$$

• The distance from a non-singular matrix A to the nearest singular matrix is $\frac{1}{\kappa(A)}$.

Use the residual

$$Ax = b$$

$$A\hat{x} = \hat{b}$$

$$A(x - \hat{x}) = b - \hat{b}$$

$$x - \hat{x} = A^{-1}(b - \hat{b})$$

$$x - \hat{x} = A^{-1}(b - A\hat{x})$$

$$x - \hat{x} = A^{-1}r$$

 $||x - \hat{x}|| \le ||A^{-1}|| \cdot ||r||$

LU-decomposition

- There exists a unique unit lower triangular matrix Land a non-singular upper triangular matrix U such that A = LU.
- D: Thm 2.5 If A is non-singular, there exist permutations P_1 and P_2 , a unit lower matrix L, and a nonsingular upper triangular matrix U such that $P_1AP_2 = LU$.
- Only one of the permutation matrices is neccessary. P_1A reorders the rows of A, AP_2 reorders the columns of A.

Permutation matrix

- A permutation matrix is the identity-matrix with permuted rows.
- PX is the same as X with its rows permuted.
- XP is the same as X with its columns permuted.
- $P^{-1} = P^T$
- $det(P) = \pm 1$

Quiz

• If P_1 and P_2 are permutation matrices. Let $P = P_1 \cdot P_2$. Is P a permutation matrix?

Quiz

- If P_1 and P_2 are permutation matrices. Let $P = P_1 \cdot P_2$. Is P a permutation matrix?
- \star Yes:
- If P_1 and P_2 are permutation matrices. $P = \pm P_1 \cdot P_2$ is also a permutation matrix.

Floating Point Arithmetic

 $fl(a \circ b) = (a \circ b) \cdot (1 + \delta)$

 δ is bounded by $\epsilon,$ the machine epsilon or machine precision.

- Example
- Calculate z = a + b + c
- Step 1: $w = fl(a + b) = (a + b) \cdot (1 + \delta_1)$
- Step 2: $z = fl(w+c) = (w+c) \cdot (1+\delta_2)$ = $((a+b) \cdot (1+\delta_1) + c) \cdot (1+\delta_2)$

$$= ((a+b) \cdot (1+\delta_1) \cdot (1+\delta_2) + c \cdot (1+\delta_2))$$

= { $\delta_i \leq \epsilon$ }
= $(a+b) \cdot (1+\epsilon)^2 + c \cdot (1+\epsilon)$

• Note that the error does not depend equally on all *a*, *b*, and *c*!!!

Gaussian Elimination

on the blackboard...

Pivoting

on the blackboard...

GEPP

- The main empirical observation, justified by decades of experience, is that GEPP almost always keeps $||L|| \cdot ||U|| \approx ||A||.$
- We define the pivot growth factor for GEPP as $g_{pp} = ||U||_{\infty}/||A||_{\infty}$

Some practical error estimates: (D p54)

$$\operatorname{error} = \frac{||\hat{x} - x||_{\infty}}{||\hat{x}||} \le ||A^{-1}|| \cdot \frac{||r||}{||\hat{x}||}$$
$$\operatorname{error} = \frac{||\hat{x} - x||_{\infty}}{||\hat{x}||} \le ||\frac{|A^{-1}| \cdot |r|}{||\hat{x}||}||$$

Some review questions:

- Q21. Define the condition number of a matrix.
- Q22. Describe what happens with the solution x of a linear system Ax = b when the right hand side b is perturbed into $b + \delta b$.
- Q25. What is meant with pivoting for stability?
- **Q28.** How many arithmetic operations are needed for computing the Gaussian elimination *LU*-factorization of an *n* × *n*-matrix A?
- **Q29.** How many arithmetic operations are needed to solve a linear system by forward and backward substitution, once the triangular factors *L* and *U* are computed?
- Q31. How many arithmetic operations are needed to multiply a $m \times n$ matrix by a $n \times p$ matrix? Compare with the count for Gaussian elimination!