

Lecture 19

Last time we studied about size of error in solving linear system $Ax=b$

If \hat{x} is computed solution of $Ax=b$

Then error $e = x - \hat{x}$ is not known

to us. However we can calculate the residual

$$\bar{r} = A\bar{e} = Ax - A\hat{x} = b - A\hat{x}$$

Condition number

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

Then

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

If Condition number is high then we say that the system $Ax=b$ is ill-conditioned

note that if condition number is high we cannot compute A^{-1} (and so $\|A^{-1}\|$) accurately.

So we need indirect method to compute condition number

$$\kappa_{\text{thm}} = \frac{1}{\text{Cond}(A)} = \min \left\{ \frac{\|A-B\|}{\|A\|} \mid B \text{ is not invertible} \right\}$$

we proved \leq

i.e. we proved $\frac{1}{\|A^{-1}\|} \leq \|A-B\|$ if B is not invertible

Then we studied "perturbed linear system".

In applications the coeff matrix A is known upto some error.

So instead of solving $Ax = b$ we are in effect solving $\hat{A}\hat{x} = b$

$$A = \hat{A} + E$$

E = matrix containing errors in coefficient

$$\frac{\|x - \hat{x}\|}{\|\hat{x}\|} \leq \text{cond}(A) \frac{\|E\|}{\|\hat{A}\|}$$

We also did iterative improvement of a solution to a linear system

$Ax = b$ has app solⁿ $\hat{x}^{(1)}$

$e = x - \hat{x}^{(1)}$ is unknown

We solve $Ae = r = b - A\hat{x}^{(1)}$

to find $\hat{e}^{(1)}$ approximation to e

$\hat{x}^{(2)} = \hat{x}^{(1)} + e^{(1)}$ is usually a better approximation to x than $\hat{x}^{(1)}$.

If necessary we can compute the new residual $r = b - A\hat{x}^{(2)}$

and solve $Ac = r$ again to obtain

a new correction $e^{(2)}$

$$\hat{x}^{(3)} = \hat{x}^{(2)} + e^{(2)}$$

and so on.

Today we study determinants.

If $A = (a_{ij})$ is a $n \times n$ matrix

$$\det(A) = \sum_p \sigma_p a_{1,p_1} a_{2,p_2} \cdots a_{n,p_n}$$

where the sum is taken over all

$n!$ permutations of degree n and

$\sigma_p = 1$ or -1 depending on whether p is even or odd

This defⁿ is not good for practical purpose as $n!$ grows very large with n

However one can derive some rules from this defⁿ and then get a simpler rule to calculate determinants.

The determinant of a matrix is of importance because of the following thm.

Theorem :- Let A be an $n \times n$ matrix.

Then A is invertible if and only if $\det(A) \neq 0$

Rule 1 If A is an upper (or lower) triangular matrix then

$$\det(A) = a_{11} a_{22} \dots a_{nn}$$

i.e the det is just the product of the diagonal entries

Pf Assume A is upper-triangular.

If p is any permutation other than the identity then for some i $p_i < i$

$$\Rightarrow a_{i,p_i} = 0$$

$$\therefore a_{1,p_1} \dots a_{n,p_n} = 0$$

$$\therefore \det A = \sum \sigma_p a_{1,p_1} \dots a_{n,p_n} = a_{11} a_{22} \dots a_{nn}$$

Rule 2)

If P is a $n \times n$ - permutation matrix
given by $P_{ij} = \delta_{ip_j}$ $j=1, 2, \dots, n$
for some permutation P

$$\text{Then } \det(P) = \begin{cases} 1 & \text{if } P \text{ is even} \\ -1 & \text{if } P \text{ is odd} \end{cases}$$

Rule 3

If the matrix B results from the matrix
 A by the interchange of two columns
(rows) of A then

$$\det(B) = -\det(A)$$

Rule 4)

If the matrix B is formed by
multiplying all entries of one column (row)
of A by the same number α then

$$\det B = \alpha \det A$$

Rule 5

Suppose 3 matrices A_1, A_2, A_3 differ only in one column (row) say the j^{th} and the j^{th} column (row) of A_3 is the vector sum of the j^{th} columns of A_1 and A_2 then $\det(A_1) + \det(A_2) = \det(A_3)$

Theorem If A and B are $n \times n$ matrices then $\det(AB) = \det A \cdot \det B$

Practical method to find determinant

factor A into PLU

P permutation matrix

L Lower triangular with 1's in the diagonal

U upper triangular matrix

$$A = PLU$$

$$\det A = \det P \cdot \det L \cdot \det U$$

$$= (-1)^i \cdot 1 \cdot u_{11} \cdots u_{nn}$$

$i = \#$ number of row-interchanges in GE

Exercise Let A be a $n \times n$ invertible matrix such that $A = LU$ where L is unit lower triangular matrix and U is upper triangular matrix. Let A_k denote the principal submatrix of A formed by the first k -rows and the first k columns of A .

Show $\det(A_k) \neq 0$ for $k = 1, 2, \dots, n$

Ans

$$A = LU$$

$$A_k = L_k U_k$$

note that L_k and U_k are invertible

so A_k is invertible

so $\det(A) \neq 0$

$$\begin{bmatrix} A \end{bmatrix} = \begin{bmatrix} \diagup & & \\ L & \diagdown & \\ & & \ddots \end{bmatrix} \begin{bmatrix} \diagup & & \\ & \diagdown & \\ & & U \end{bmatrix}$$

$$\begin{bmatrix} \diagup & & \\ & \diagdown & \\ & & \ddots \end{bmatrix}_k = \begin{bmatrix} \diagup & & \\ & \diagdown & \\ & & \ddots \end{bmatrix}_k \begin{bmatrix} \diagup & & \\ & \diagdown & \\ & & \ddots \end{bmatrix}_k$$

Remark A the definite matrix can be factored into LU .

One can prove a symmetric matrix A
is the definite iff $\det(A_k) > 0$ for
 $k = 1, 2, \dots, n$.

Recall Cholesky decomposition

$$A = LL^t \quad \text{if } A \text{ is true definite.}$$

Exercise Let M be a non-singular matrix.

Let $A = MM^t$. Show A is true definite

Pf

$$A = MM^t$$

$$A^t = (MM^t)^t$$

$$= (M^t)^t M^t$$

$$= MM^t$$

$$= A$$

Ans Let \bar{x} be non-zero

$$\bar{x}^t A \bar{x} = \bar{x}^t M M^t \bar{x}$$

$$\text{let } \bar{y} = M^t \bar{x} \Rightarrow \bar{y}^t = \bar{x}^t M$$

note that $\bar{y} \neq 0$ $\because M^t$ is non-singular

$$\text{then } \bar{x}^t A \bar{x} = \bar{y}^t \bar{y} = \|\bar{y}\|_2^2 > 0$$

Computing A^{-1}

There is usually no good reason for ever calculating the inverse

However if one has to calculate A^{-1} then one does the following

- Factor A into PLU

- Solve $Ax = e_j$

e_j j^{th} unit column vector

to obtain j^{th} column of the inverse
(by back substitution)

Example

$$A = \begin{bmatrix} 2 & 1 & 0 & 0 \\ -1 & 3 & 3 & 0 \\ 2 & -2 & 1 & 4 \\ -2 & 2 & 2 & 5 \end{bmatrix}$$

Find LU dec.
of A and
then find A^{-1}

$R_2 + \frac{1}{2} R_1$, $R_3 - R_1$, $R_4 + R_1$ gives

$$\begin{bmatrix} 2 & 1 & 0 & 0 \\ 0 & 3\frac{1}{2} & 3 & 0 \\ 0 & -3 & 1 & 4 \\ 0 & 3 & 2 & 5 \end{bmatrix}$$

$$R_3 + \frac{6}{7} R_2$$

$$R_4 - \frac{6}{7} R_2$$

$$\begin{bmatrix} 2 & 1 & 0 & 0 \\ 0 & 3\frac{1}{2} & 3 & 0 \\ 0 & 0 & \frac{25}{7} & 4 \\ 0 & 0 & -\frac{4}{7} & 5 \end{bmatrix}$$

$$R_4 + \frac{4}{25} R_3 \text{ yields}$$



$$U = \begin{bmatrix} 2 & 1 & 0 & 0 \\ 0 & 3\frac{1}{2} & 3 & 0 \\ 0 & 0 & \frac{25}{7} & 4 \\ 0 & 0 & 0 & \frac{141}{25} \end{bmatrix}$$

$$L = \begin{bmatrix} 1 & 0 & 0 & 0 \\ -\frac{1}{2} & 1 & 0 & 0 \\ 1 & -\frac{6}{7} & 1 & 0 \\ -1 & \frac{6}{7} & -\frac{4}{25} & 1 \end{bmatrix}$$

$$L U x = e_1$$

$$U x = y$$

$$L y = e_1$$

$$1 y_1 = 1$$

$$\Rightarrow y_1 = 1$$

$$-\frac{1}{2} y_1 + y_2 = 0$$

$$y_2 = \frac{1}{2}$$

$$y_1 - \frac{6}{7} y_2 + y_3 = 0$$

$$y_3 = -1 + \frac{6}{7} \cdot \frac{1}{2} = -\frac{4}{7}$$

$$-y_1 + \frac{6}{7} y_2 - \frac{4}{25} y_3 + y_4 = 0$$

$$y_4 = +1 + \frac{3}{7} - \frac{4}{175}$$

$$y_4 = \frac{175 - 75 - 4}{175} = \frac{96}{175}$$

$$UX = y$$

$$\frac{141}{25} x_4 = y_4 = \frac{96}{175}$$

$$x_4 = \frac{96}{7} \frac{1}{141} = \frac{32}{7 \cdot 47} = \frac{32}{327}$$