

CS475/CS675

Lecture 1: May 3, 2016

Basic Theory of Linear Algebra
Reading: [TB] chapt 1 (p. 1-10),
chapt 20 (p. 147-152)

Range

- Definition: the range of A is defined as
 - $range(A) = \{y: y = Ax \text{ for some } x\}$
- Theorem:
 - $range(A) =$ space spanned by
 - the columns of $A = [a_1 \ a_2 \ \dots \ a_n]$
 - $= \{y = x_1 a_1 + x_2 a_2 + \dots + x_n a_n = \sum_{j=1}^n a_j x_j\}$
- Thus $range(A)$ is also called the column space of A

Rank

- Definition:
 - Column rank = dimension of column space
 - Row rank = dimension of row space
- Theorem: column rank = row rank
- Thus we simply call it the rank of A , $rank(A)$

Full Rank

- Definition: An $m \times n$ matrix is of full rank if
$$\text{rank}(A) = \min\{m, n\}$$
- Thus, if $m \geq n$, ($A = \square$), then a full rank matrix has n independent column vectors
- Definition: A nonsingular (invertible) matrix is a square matrix of full rank
- Definition: The null space of A , $\text{null}(A)$ is defined as
$$\text{null}(A) = \{x: Ax = 0\}$$

Matrix inverse

- Matrix inverse

$$(AB)^{-1} = B^{-1}A^{-1}$$

$$(A^{-1})^T = (A^T)^{-1} = A^{-T}$$

- Interesting identity:

$$B^{-1} = A^{-1} - B^{-1}(B - A)A^{-1}$$

$$\text{Proof: } B(A^{-1} - B^{-1}(B - A)A^{-1})$$

$$= BA^{-1} - (B - A)A^{-1}$$

$$= BA^{-1} - BA^{-1} + I$$

$$= I$$

Updating Matrix Inverses

- Sherman-Morrison-Woodbury formula

$$(A + UV^T)^{-1} = A^{-1} - A^{-1}U(I + V^T A^{-1}U)^{-1}V^T A^{-1}$$

where $U, V \in \mathfrak{R}^{n \times k}$ ($U = \begin{matrix} \square & n \\ & k \end{matrix}$).

- Thus a rank k correction to A results in a rank k correction of the inverse

Example

How to compute $x = A^{-1}b$?

- In numerical linear algebra, NEVER compute A^{-1} and then $A^{-1}b$.

- We always consider x as the solution of the eqn:

$$Ax = b$$

- We compute x by solving the equation by Gaussian Elimination

Gaussian Elimination (GE)

- Big picture of GE:

GE algorithm

For $i = 1, 2, \dots, n - 1$

For $k = i + 1, \dots, n$

$$mult = a_{ki}/a_{ii} \quad (a_{ki} = mult)$$

for $j = i + 1, \dots, n$

$$a_{kj} = a_{kj} - mult \times a_{ij}$$

end

$$b_k = b_k - mult \times b_i$$

end

End

At the end, $A^{(n-1)}x = b^{(n-1)}$ is solved by back substitution

} Update $row(k)$
} Update RHS

LU Factorization

- Theorem: $A = LU$ where

$$L = \text{lower } \Delta, \text{ unit diagonal} = \begin{bmatrix} 1 & & 0 \\ & \ddots & \\ \text{mult} & & 1 \end{bmatrix}$$

$$U = \text{upper } \Delta = A^{(n-1)}$$

Solve $Ax = b$

- $Ax = b \rightarrow L U x = b$
- Let $y = Ux$, then we have $Ly = b$
 - Solve $Ly = b$ by forward solve
 - Solve $Ux = y$ by back solve

Forward solve algorithm

For $i = 1, 2, \dots, n$

$$y_i = b_i$$

For $j = 1, 2, \dots, i - 1$

$$y_i = y_i - l_{ij} \times y_j$$

end

$$\left. \begin{array}{l} \\ \\ \end{array} \right\} y_i = b_i - \sum_{j=1}^{i-1} l_{ij} y_j$$

end

Complexity

- 1 flop = + / - / x / ÷
- Consider forward solve
 - For each i , the j -loop performs $2(i - 1)$ flops
 - Total flops = $\sum_{i=1}^n (2i - 2)$
$$= 2 \sum_{i=1}^n i - \sum_{i=1}^n 2$$
$$= 2 \frac{n(n+1)}{2} - 2n$$
$$= n^2 - n$$
$$= O(n^2)$$

Complexity (continued)

- flops(back solve) = n^2 (exercise)
- flops(LU) = $\frac{2}{3}n^3 + O(n^2)$
- For large n , factorization is more expensive than forward or backward solves