# Numerical Linear Algebra

Yashas.N

if a matrix is in triangular form one can easy calculate its inverse by making note that inverse of a triangular matrix is of the same triangular type i.e. for example $A$ is upper triangular non-singular matrix then $A^{-1}$ is also an upper triangular matrix.

## LU Decomposition

■ From previous point we have if any non singular matrix $A$ can be written as $A = LU$ for lower triangular $L$ and upper triangular $U$ then $A^{-1} = U^{-1}L^{-1}$ thus inverse can be easily calculated.
■ This Decomposition may not be unique
■ To decompose in a easy way we take diagonal elements of $U$ or $L$ as 1. (only in one of the factors) and compute the coefficients by writing $A = LU$ and solving some equations in a linear order.
■ Now in addition if principal minors $(\Delta_k)$ of matrix $A$ are not zero then the above decomposition is unique.

## Gauss elimination

if $A = [a_{ij}]$ be a $n \times n$ non singular matrix then for linear system $Ax = b$ then we can use elementary operations:
exchange of rows, addition of rows and multiplication by a non zero constant to a row to transform the linear system$A'x = b'$ such that $a'_{11} \neq 0$ and $a'_{i1} = 0$ for $i < 1$ and continuing this process to get for $i = 2, 3, .., n$ we get a system $Gx = \tilde{b}$ where $G$ is upper triangular and has same solutions as original system.

## Gauss-Jordan method

this method is similar to Gauss elimination but $Ax = b$ for non singular square $A$ is transformed to $G_J x = \tilde{b}$ where $G_J$ is diagonal i.e. for $A = [a_{ij}]$, $a_{ii}$ is made non zero and all other $a_{ij}$ is made zero with elementary transformations.

## General Iterative methods

■ iterative methods can be generalised as $x^{(k)} = Tx^{(k-1)} + c$
■ this method converges to a unique solution for any initial approximation $x^{(0)}$ iff $(\iff)$ $\rho(T) < 1$ where $\rho(T) = \max(|\lambda|)$ for $\lambda$ eigenvalue of $T$.

## Jacobi's Method

■ if $Ax = b$ is a system such that for $n$-square $A = [a_{ij}]$ we have $a_{ii} \neq 0$ (if not is made by rearranging rows or equations if possible) then for $x = [x_i]^T$ we can transform $x_i = \left[\sum_{\substack{j=1 \\ j\neq i}}^{n} (-a_{ij}x_j/a_{ii}) + b_i/a_{ii}\right]$ from which we get the iterative method i.e. $x^{(0)}$ is initial approximation and for $k^{th}$ approximation $x^{(k)}$ we have the iteration using $x^{(k-1)}$ given by

$$x_i^{(k)} = \frac{1}{a_{ii}} \left[\sum_{\substack{j=1 \\ j\neq i}}^{n} (-a_{ij}x_j^{(k-1)}) + b_i\right].$$

■ Now for matrix representation if $A = D + L + U$ where $D$ is diagonal $L$ is lower diagonal with diagonal entries 0 and $U$ is upper diagonal with diagonal entries 0 then for Jacobi method we have

$$(D + L + U)x = b$$
$$\implies Dx* = -(L + U)x + b.$$
$$\implies x = -D^{-1}(L + U)x + D^{-1}b.$$
$$\text{i.e.} \quad x^{(k)} = -D^{-1}(L + U)x^{(k-1)} + D^{-1}b.$$

so we get $T = -D^{-1}(L + U), c = D^{-1}b$ for general form.

## Gauss-Seidel Method

■ This is similar to Gauss method but here we use the previous $k^{th}$ iterated variables for the next $k^{th}$ one i.e. for in $x_i^{(k)}$ iteration we can replace $x_j^{(k-1)}$ for $j < i$ with $x_j^{(k)}$ as these are already found i.e.

$x_i^{(k)} =$

$$\frac{1}{a_{ii}} \left[ -\sum_{j=1}^{i-1} a_{ij} x_j^{(k)} - \sum_{j=i+1}^{n} a_{ij} x_j^{(k-1)} + b_i \right].$$

■ for matrix representation we rewrite the iterative formula as

$$\sum_{j=1}^{i} a_{ij} x_j^{(k)} = -\sum_{j=i+1}^{n} a_{ij} x_j^{(k-1)} + b_i$$

similar to Jacobi's case if $A = D + L + U$ by above formula we have

$$(D + L)x^{(k)} = -Ux^{(k-1)} + b.$$
$$\text{i.e.} x^{(k)} = -(D + L)^{-1}Ux^{(k-1)} + (D + L)^{-1}b.$$

so we get $T = -(D + L^{-1})U, c = (D + L)^{-1}b$.

for system $Ax = b$ , $A = D + L + U$

■ if A is strictly diagonal then both Jacobi and Gauss-Seidel methods converge for every initial approximation $x^{(0)}$.

■ Gauss-Seidel method is twice as fast as Jacobi's method for convergence

now from general iterative methods we have

■ sufficient condition for convergence of Jacobi's method is that

$$||T|| = || - D^{-1}(L + U)|| < 1 \quad \text{i.e.} \rho(T) < 1.$$

■ similarly sufficient condition for convergence of Gauss-Seidel method is that

$$||T|| = || - (D + L)^{-1}U|| < 1.$$

■ Both these method also converge if $A = [a_{ij}]$ is such that

$\sum_{\substack{j=1 \\ j \neq i}}^{n} |a_{ij}| \leqslant |a_{ii}|$ for $i = 1, 2, . . , n$ and strict inequality holds for at least one $i$.

# 0 References


[1] Burden R. L., Faires D. J., Burden A. M.: Numerical Analysis, Cengage Learning,(2016).

[2] S. S. Sastry: Introductory Methods of Numerical Analysis, PHI Learning,(2012).