

# Numerical Methods I

## Exam #2 Tips

Jonathan Henrique Maia de Moraes (ID: 1620855)

10/29/2015

# Quiz #2

## 1 Inverse of a Matrix

$$AA^{-1} = I \quad (1)$$

### 1.1 Using Determinant

$$A^{-1} = \frac{A^T}{\det(A)} \quad (2)$$

For  $A = 2 \times 2$ :

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix}^{-1} = \frac{1}{ad - bc} \begin{bmatrix} a & c \\ b & d \end{bmatrix} \quad (3)$$

For  $A = 3 \times 3$ :

$$\begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix}^{-1} = \frac{1}{(aei + bfg + cdh) - (ceg + bdi + afh)} \begin{bmatrix} a & d & g \\ b & e & h \\ c & f & i \end{bmatrix} \quad (4)$$

## 2 LU Factorizations

Purpose:

$$A = LU \quad (5)$$

$$\begin{aligned} A\vec{x} &= (LU)\vec{x} = L(U\vec{x}) = b & U\vec{x} &= \vec{y} \\ L\vec{y} &= b & & \end{aligned} \quad (6)$$

Procedure ( $3 \times 3$  matrix):

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} = \begin{bmatrix} l_{11} & 0 & 0 \\ l_{21} & l_{22} & 0 \\ l_{31} & l_{32} & l_{33} \end{bmatrix} \begin{bmatrix} u_{11} & u_{12} & u_{13} \\ 0 & u_{22} & u_{23} \\ 0 & 0 & u_{33} \end{bmatrix} \quad (7)$$

$$= \begin{bmatrix} l_{11}u_{11} & l_{11}u_{12} & l_{11}u_{13} \\ l_{21}u_{11} & l_{21}u_{12} + l_{22}u_{22} & l_{21}u_{13} + l_{22}u_{23} \\ l_{31}u_{11} & l_{31}u_{12} + l_{32}u_{22} & l_{31}u_{13} + l_{32}u_{23} + l_{33}u_{33} \end{bmatrix} \quad (8)$$

Types of equations:

$$i < j \quad l_{i1} + u_{1j} + l_{i2}u_{2j} + \cdots + l_{ii}u_{ij} = a_{ij} \quad (9)$$

$$i = j \quad l_{i1} + u_{1j} + l_{i2}u_{2j} + \cdots + l_{ii}u_{jj} = a_{ij} \quad (10)$$

$$i > j \quad l_{i1} + u_{1j} + l_{i2}u_{2j} + \cdots + l_{ij}u_{jj} = a_{ij} \quad (11)$$

## 2.1 Doolittle

$A = 3 \times 3$  matrix:

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ l_{21} & 1 & 0 \\ l_{31} & l_{32} & 1 \end{bmatrix} \begin{bmatrix} u_{11} & u_{12} & u_{13} \\ 0 & u_{22} & u_{23} \\ 0 & 0 & u_{33} \end{bmatrix} \quad (12)$$

$$= \begin{bmatrix} (1)u_{11} & (1)u_{12} & (1)u_{13} \\ l_{21}u_{11} & l_{21}u_{12} + (1)u_{22} & l_{21}u_{13} + (1)u_{23} \\ l_{31}u_{11} & l_{31}u_{12} + l_{32}u_{22} & l_{31}u_{13} + l_{32}u_{23} + (1)u_{33} \end{bmatrix} \quad (13)$$

## 2.2 Crout

$A = 3 \times 3$  matrix:

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} = \begin{bmatrix} l_{11} & 0 & 0 \\ l_{21} & l_{22} & 0 \\ l_{31} & l_{32} & l_{33} \end{bmatrix} \begin{bmatrix} 1 & u_{12} & u_{13} \\ 0 & 1 & u_{23} \\ 0 & 0 & 1 \end{bmatrix} \quad (14)$$

$$= \begin{bmatrix} l_{11}(1) & l_{11}u_{12} & l_{11}u_{13} \\ l_{21}(1) & l_{21}u_{12} + l_{22}(1) & l_{21}u_{13} + l_{22}u_{23} \\ l_{31}(1) & l_{31}u_{12} + l_{32}(1) & l_{31}u_{13} + l_{32}u_{23} + l_{33}(1) \end{bmatrix} \quad (15)$$

## 2.3 Cholesky

$A = 3 \times 3$  matrix:

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} = \begin{bmatrix} x_{11} & 0 & 0 \\ l_{21} & x_{22} & 0 \\ l_{31} & l_{32} & x_{33} \end{bmatrix} \begin{bmatrix} x_{11} & u_{12} & u_{13} \\ 0 & x_{22} & u_{23} \\ 0 & 0 & x_{33} \end{bmatrix} \quad (16)$$

$$\begin{aligned} &= \begin{bmatrix} x_{11}x_{11} & x_{11}u_{12} & x_{11}u_{13} \\ l_{21}x_{11} & l_{21}u_{12} + x_{22}x_{22} & l_{21}u_{13} + x_{22}u_{23} \\ l_{31}x_{11} & l_{31}u_{12} + l_{32}x_{22} & l_{31}u_{13} + l_{32}u_{23} + x_{33}x_{33} \end{bmatrix} \\ &= \begin{bmatrix} x_{11}^2 & x_{11}u_{12} & x_{11}u_{13} \\ l_{21}x_{11} & l_{21}u_{12} + x_{22}^2 & l_{21}u_{13} + x_{22}u_{23} \\ l_{31}x_{11} & l_{31}u_{12} + l_{32}x_{22} & l_{31}u_{13} + l_{32}u_{23} + x_{33}^2 \end{bmatrix} \end{aligned} \quad (17)$$

## 3 Identifying Matrices

### 3.1 Strictly Diagonally Dominant (SDD)

A matrix  $A_{n \times n}$  is strictly diagonally dominant if:

$$|a_{ii}| > \sum_{j=1, j \neq i}^n |a_{ij}|, \quad \forall i \quad (18)$$

### 3.2 Symmetric Positive Definite (SPD)

A symmetric matrix  $A_{n \times n}$  is positive definite if:

$$\vec{x}^T A \vec{x} > 0 \quad (19)$$

$$\vec{x}_{ij} \in \mathbb{R}_{\neq 0} \quad (20)$$

Or if:

1. All the eigenvalues of  $A$  are positive;
2. And only if, the determinant of each leading submatrix is positive.

### 3.3 Coefficient Matrix (A) Significance

If  $A$  is either SDD or SPD:

- $A$  is invertible, and  $A\vec{x} = b$  has a unique solution;
- Both Gaussian elimination and LU factorization may be performed with any pivoting technique;
- Both Gaussian elimination and LU factorization are stable with regard to round-off error.

## 4 Matrix Norms

### 4.1 1- Norm

The maximum absolute column sum norm:

$$\|A\|_1 = \max_j \sum_{i=1}^n |a_{ij}| \quad (21)$$

### 4.2 2- Norm

The spectral norm (or simply: matrix norm) is determined as follow:

$$\|A\|_2 = p(A^T A) \quad (22)$$

Which  $p$  is the maximum eigenvalue (in absolute mode). For  $A = 2 \times 2$  matrix:

$$\|A\|_2 = p \left( \begin{bmatrix} a & b \\ c & d \end{bmatrix}^T \begin{bmatrix} a & b \\ c & d \end{bmatrix} \right) \quad (23)$$

$$= p \left( \begin{bmatrix} a & c \\ b & d \end{bmatrix} \begin{bmatrix} a & b \\ c & d \end{bmatrix} \right) \quad (24)$$

$$= p \left( \begin{bmatrix} a^2 + c^2 & ab + cd \\ ca + dc & cb + d^2 \end{bmatrix} \right) \quad (25)$$

$$= \sqrt{\max \det \left( \begin{bmatrix} a^2 + c^2 - \lambda & ab + cd \\ ba + dc & b^2 + d^2 - \lambda \end{bmatrix} \right)} \quad (26)$$

$$= \sqrt{\max (|(a^2 + c^2 - \lambda)(b^2 + d^2 - \lambda) - (ab + cd)^2|)} \quad (27)$$

### 4.3 $\infty$ - Norm

The maximum absolute row sum norm:

$$\|A\|_{\infty} = \max_i \sum_{j=1}^n |a_{ij}| \quad (28)$$

## 5 Linear System Root Approximations

### 5.1 Jacobi Method

$$x_i = \frac{b_i - \sum_{j=1}^{i-1} a_{ij}x_j - \sum_{j=i+1}^n a_{ij}x_j}{a_{ii}}, a_{ii} \neq 0 \quad (29)$$

$$\vec{x} = -D^{-1}(L + U)\vec{x} + D^{-1}\vec{b} \quad (30)$$

$$T = -D^{-1}(L + U) \quad (31)$$

$$\vec{c} = D^{-1}\vec{b} \quad (32)$$

$$\vec{x} = T\vec{x} + \vec{c} \quad (33)$$

### 5.2 Gauss-Seidel

$$x_i^{(k+1)} = \frac{b_i - \sum_{j=1}^{i-1} a_{ij}x_j^{k+1} - \sum_{j=i+1}^n a_{ij}x_j^{(k)}}{a_{ii}}, a_{ii} \neq 0 \quad (34)$$

$$\vec{x} = -(L + D)^{-1}U\vec{x} + (L + D)^{-1}\vec{b} \quad (35)$$

$$T = (L + D)^{-1}U \quad (36)$$

$$\vec{c} = (L + D)^{-1}\vec{b} \quad (37)$$

$$\vec{x} = T\vec{x} + \vec{c} \quad (38)$$

### 5.3 Criteria for Convergence

$$\vec{x}^{(k+1)} = T\vec{x}^{(k)} + \vec{c}, \|T\| < 1 \quad (39)$$

## 5.4 Error-Bound for Absolute Error

$$\|\vec{x} - \vec{x}^{(k)}\| \leq \|T\|^k \|\vec{x}^{(0)} - \vec{x}\| \quad (40)$$

$$\frac{\|\vec{x} - \vec{x}^{(k)}\|}{\|\vec{x}^{(0)} - \vec{x}\|} \leq \|T\|^k$$

$$\log \left( \frac{\|\vec{x} - \vec{x}^{(k)}\|}{\|\vec{x}^{(0)} - \vec{x}\|} \right) \leq k \log (\|T\|)$$

$$k \geq \frac{\log \left( \frac{\|\vec{x} - \vec{x}^{(k)}\|}{\|\vec{x}^{(0)} - \vec{x}\|} \right)}{\log (\|T\|)}$$

$$\lceil k \rceil = \frac{\log \left( \frac{\|\vec{x} - \vec{x}^{(k)}\|}{\|\vec{x}^{(0)} - \vec{x}\|} \right)}{\log (\|T\|)} \quad (41)$$

$$\|\vec{x} - \vec{x}^{(k)}\| \leq \frac{\|T\|^k}{1 - \|T\|} \|\vec{x}^{(1)} - \vec{x}^{(0)}\| \quad (42)$$

$$\frac{\|\vec{x} - \vec{x}^{(k)}\| (1 - \|T\|)}{\|\vec{x}^{(1)} - \vec{x}^{(0)}\|} \leq \|T\|^k$$

$$\log \left( \frac{\|\vec{x} - \vec{x}^{(k)}\| (1 - \|T\|)}{\|\vec{x}^{(1)} - \vec{x}^{(0)}\|} \right) \leq k \log (\|T\|)$$

$$k \geq \frac{\log \left( \frac{\|\vec{x} - \vec{x}^{(k)}\| (1 - \|T\|)}{\|\vec{x}^{(1)} - \vec{x}^{(0)}\|} \right)}{\log (\|T\|)}$$

$$\lceil k \rceil = \frac{\log \left( \frac{\|\vec{x} - \vec{x}^{(k)}\| (1 - \|T\|)}{\|\vec{x}^{(1)} - \vec{x}^{(0)}\|} \right)}{\log (\|T\|)}$$

(43)

## 6 Matrix Condition

### 6.1 Condition Number of a Matrix

$$K(A) = \|A\| \|A^{-1}\| \quad (44)$$

## 6.2 Ill-Conditioned Matrices

A matrix  $A$  is ill-conditioned if:

$$K(A) \gg 1 \quad (45)$$