

## CX 4640 Homework 2

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### 2.7

(a)

$$\begin{aligned}\det A &= \det \begin{bmatrix} 1 & 1 + \epsilon \\ 1 - \epsilon & 1 \end{bmatrix} \\ &= 1 - (1 - \epsilon)(1 + \epsilon) \\ &= 1 - (1 - \epsilon^2) \\ &= \epsilon^2\end{aligned}$$

(b)

The smallest non-negative number representable in a normalized single-precision system is  $1 \times 2^{-126}$ . Therefore the computed result for determinant would be zero if

$$\begin{aligned}\epsilon^2 &< 2^{-126} \\ |\epsilon| &< 2^{-63} \\ -2^{-63} &< \epsilon < 2^{63}\end{aligned}$$

In a double-precision system,

$$\begin{aligned}\epsilon^2 &< 2^{-1022} \\ -2^{-511} &< \epsilon < 2^{511}\end{aligned}$$

(c)

$$A = \begin{bmatrix} 1 & 1 + \epsilon \\ 1 - \epsilon & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 - \epsilon & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 + \epsilon \\ 0 & \epsilon^2 \end{bmatrix}$$

(d)

$$\det U = 1 \cdot \epsilon^2 = \epsilon^2$$

The matrix is singular when the computed value of  $\epsilon^2$  equals zero, that is,  $\epsilon^2$  is smaller than the smallest representable number. So the answer is the same as (b).

## 2.21

$$\begin{aligned}\mathbf{x} &= B^{-1}(2A + I)(C^{-1} + A)\mathbf{b} \\ B\mathbf{x} &= (2A + I)(C^{-1} + A)\mathbf{b} \\ &= 2AC^{-1}\mathbf{b} + 2A^2\mathbf{b} + C^{-1}\mathbf{b} + A\mathbf{b}\end{aligned}$$

Let  $\mathbf{y} = C^{-1}\mathbf{b}$ , then

$$\begin{aligned}C\mathbf{y} &= \mathbf{b} \\ B\mathbf{x} &= 2A\mathbf{y} + 2A^2\mathbf{b} + \mathbf{y} + A\mathbf{b}\end{aligned}$$

Using Gaussian Elimination, one can solve the first equation for  $\mathbf{y}$ , and then solve the second one for  $\mathbf{x}$  without computing the inverses of  $B$  and  $C$ .

The MATLAB code is included in `SolveForX.m`

## 2.26

(a)

One can compute the inverse of  $A$  using Sherman-Morrison formula:

$$\begin{aligned}A^{-1} &= (I - uv^T)^{-1} \\ &= I^{-1} + I^{-1}u(1 - v^T I^{-1}u)^{-1}v^T I^{-1} \\ &= I + u(1 - v^T u)^{-1}v^T,\end{aligned}$$

provided that  $1 - v^T u$  is invertible, that is,

$$v^T u \neq 1$$

(b)

From (a),  $\sigma = -(1 - v^T u)^{-1}$

(c)

Yes.

$$M_k = \begin{bmatrix} 1 & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 1 & 0 & \cdots & 0 \\ 0 & \cdots & -m_{k+1} & 1 & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & -m_n & 0 & \cdots & 1 \end{bmatrix} = I - \begin{bmatrix} 0 \\ \vdots \\ m_{k+1} \\ \vdots \\ m_n \end{bmatrix} \mathbf{e}_k^T,$$

$$u = \begin{bmatrix} 0 \\ \vdots \\ m_{k+1} \\ \vdots \\ m_n \end{bmatrix}, \quad v = e_k, \quad \sigma = - \left( 1 - e_k^T \begin{bmatrix} 0 \\ \vdots \\ m_{k+1} \\ \vdots \\ m_n \end{bmatrix} \right)^{-1} = -(1-0)^{-1} = -1$$

## 2.4

$$\|A_1^{-1}\| = 0.7097, \quad \text{cond}(A_1) = 12.7742, \quad \|A_2^{-1}\| = 1.6393e+04, \quad \text{cond}(A_2) = 4.0163e+06$$

Using the first approach, the estimations are:

$$\|A_1^{-1}\| = 0.6226, \quad \text{cond}(A_1) = 11.2071, \quad \|A_2^{-1}\| = 1.3082e+04, \quad \text{cond}(A_2) = 3.2051e+06$$

Using the second approach (The values might vary):

$$\|A_1^{-1}\| = 0.6013, \quad \text{cond}(A_1) = 11.1528, \quad \|A_2^{-1}\| = 4.4131e+03, \quad \text{cond}(A_2) = 1.9666e+06$$

Apparently, the first approach is more accurate.

## 5

(Run `CreateTable` to reproduce the result.)

n	relative error	condition number
2	2.8951e-16	19.281
3	3.4571e-15	524.06
4	9.1928e-14	15514
5	8.4248e-14	4.7661e+05
6	1.0052e-10	1.4951e+07
7	3.3589e-09	4.7537e+08
8	1.1118e-08	1.5258e+10
9	3.2899e-06	4.9315e+11
10	0.00010306	1.6025e+13
11	0.0024921	5.2202e+14
12	0.068797	1.6212e+16