

7. a. Using  $A = \begin{bmatrix} 0.007 & -0.8 \\ -0.1 & 10 \end{bmatrix}$  and  $b = (0.7, 10)^T$  from Eq. (2.3), find the solution of  $Ax = b$  in ~~MATLAB~~ (use  $y=A \setminus b$ ).
- b. Find the residual vector  $r$ , the norm of the residual, and the absolute error (recall that the true solution is  $x_1 = -1500, x_2 = -14$ ).
- c. Compute the ratio of the absolute error to the norm of the residual  $\|y - x\|/\|r\|$ .

7a.

```
julia> A=[0.007 -0.8; -0.1 10]
2x2 Matrix{Float64}:
 0.007  -0.8
 -0.1    10.0

julia> b=[0.7,10]
2-element Vector{Float64}:
 0.7
 10.0

julia> y=A\b
2-element Vector{Float64}:
-1500.000000000000002
 -14.000000000000002
```

7b.

```
julia> using LinearAlgebra

julia> r=A*y-b
2-element Vector{Float64}:
 1.1102230246251565e-15
 0.0

julia> norm(r)
1.1102230246251565e-15

julia> x=[-1500,-14]
2-element Vector{Int32}:
 -1500
  -14

julia> norm(y-x)
2.273806142312601e-13
```

7c.

```
julia> norm(y-x)/norm(r)
204.80624990463548
```

8. a. Solve  $Ax = b$  with  $A = \begin{bmatrix} 0.0002 & 2 \\ 2 & 2 \end{bmatrix}$  and  $b = (2, 4)^T$  using three-digit arithmetic and naive Gaussian elimination. Compare this to the solution found using exact arithmetic.
- b. Repeat part (a) using Gaussian elimination with partial pivoting.

8a. The augmented matrix is

$$\left[ \begin{array}{cc|c} 0.0002 & 2 & 2 \\ 2 & 2 & 4 \end{array} \right]$$

Gaussian elimination with 3-digit rounding yields

$$\left[ \begin{array}{cc|c} 0.0002 & 2 & 2 \\ 2 & 2 & 4 \end{array} \right]$$

$$r_2 \leftarrow r_2 - \frac{2}{0.0002} r_1$$

$$\begin{aligned} 2 - 20000 &= -19998 \approx -20000 \\ 4 - 20000 &= -19996 \approx -20000 \end{aligned}$$

$$\left[ \begin{array}{cc|c} 0.0002 & 2 & 2 \\ 0 & -20000 & -20000 \end{array} \right]$$

$$r_1 \leftarrow r_1 + \frac{2}{20000} r_2$$

$$\left[ \begin{array}{cc|c} 0.0002 & 0 & 0 \\ 0 & -20000 & -20000 \end{array} \right]$$

$$\text{Solution is } x = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

Exact solution

$$\left[ \begin{array}{cc|c} 0.0002 & 2 & 2 \\ 0 & -19998 & -19996 \end{array} \right]$$

$$r_1 \leftarrow r_1 + \frac{2}{19998} r_2$$

$$2 - 2 \left( \frac{19996}{19998} \right) = 2 \left( \frac{2}{19998} \right)$$

$$\left[ \begin{array}{cc|c} 0.0002 & 0 & \frac{4}{19998} \\ 0 & -19998 & -19996 \end{array} \right]$$

$$\text{Solution is } x =$$

$$\begin{bmatrix} \frac{20000}{19998} \\ \frac{19996}{19998} \end{bmatrix} = \begin{bmatrix} \frac{10000}{9999} \\ \frac{9998}{9999} \end{bmatrix}$$

In Julia the exact solution can be calculated using fractions as

```

julia> A=[2//10000 2; 2 2]
2x2 Matrix{Rational{Int32}}:
 1//5000  2//1
 2//1    2//1

julia> b=[2,4]
2-element Vector{Int32}:
 2
 4

julia> A\b
2-element Vector{Rational{Int32}}:
 10000//9999
 9998//9999

```

8b. Using partial pivoting one has

$$\left[ \begin{array}{cc|c} 0.0002 & 2 & 2 \\ 2 & 2 & 4 \end{array} \right] \quad r_1 \leftrightarrow r_2$$

$$\left[ \begin{array}{cc|c} 2 & 2 & 4 \\ 0.0002 & 2 & 2 \end{array} \right] \quad \begin{array}{l} r_2 \leftarrow r_2 - 0.0001 r_1 \\ 2 - 0.0002 = 1.9998 \approx 2 \\ 4 - 0.0004 = 3.9996 \approx 4 \end{array}$$

$$\left[ \begin{array}{cc|c} 2 & 2 & 4 \\ 0 & 2 & 2 \end{array} \right] \quad r_1 \leftarrow r_1 - r_2$$

$$\left[ \begin{array}{cc|c} 2 & 0 & 2 \\ 0 & 2 & 2 \end{array} \right] \quad \text{Solution} \quad x = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

Note that the solution with partial pivoting is much closer to the exact solution.

5. a. The matrix  $A = [0 \ 0 \ 1; 0 \ 2 \ 3; 1 \ 4 \ -4]$  can't be row-reduced without row interchanges, so our LU decomposition method does not apply. Show that if  $P = [0 \ 0 \ 1; 0 \ 1 \ 0; 1 \ 0 \ 0]$ , then  $PA$  has an LU decomposition. Identify  $L$  and  $U$  explicitly, and then write them in the form of Example 2.2.4.
- b. Repeat with  $A = [0 \ 1 \ 1; 0 \ 2 \ 3; 1 \ 4 \ -4]$  and the same  $P$ .

5a.

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

amazingly  $PA$  is already upper-triangular. Therefore

$$L = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad \text{and} \quad U = \begin{bmatrix} 1 & 4 & -4 \\ 0 & 2 & 3 \\ 0 & 0 & 1 \end{bmatrix}$$

Therefore the compact form of the LU factorization discussed in example 2.2.4 is

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

5b.

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

Now reduce  $PA$  using elimination steps

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

$$r_3 \leftarrow r_3 - \frac{1}{2}r_2 \quad 1 - \frac{3}{2} = -\frac{1}{2}$$

place  $\frac{1}{2}$  in the  $3/2$  position

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

$$L = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & \frac{1}{2} & 1 \end{bmatrix}$$

Therefore the compact form of the LU factorization discussed in example 2.2.4 is

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

15. Use ~~MATLAB~~ to find the LU decomposition of ones(10,10). Explain why L, U, and P have the form they do in terms of the Gaussian elimination with partial pivoting algorithm.

```

julia> A=ones(10,10)
10×10 Matrix{Float64}:
 1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0
 1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0
 1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0
 1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0
 1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0
 1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0
 1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0
 1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0
 1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0
 1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0

julia> L,U=lu(A,check=false)
Failed factorization of type LU{Float64, Matrix{Float64}}

julia> L
10×10 Matrix{Float64}:
 1.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 1.0  1.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 1.0  0.0  1.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 1.0  0.0  0.0  1.0  0.0  0.0  0.0  0.0  0.0  0.0
 1.0  0.0  0.0  0.0  1.0  0.0  0.0  0.0  0.0  0.0
 1.0  0.0  0.0  0.0  0.0  1.0  0.0  0.0  0.0  0.0
 1.0  0.0  0.0  0.0  0.0  0.0  1.0  0.0  0.0  0.0
 1.0  0.0  0.0  0.0  0.0  0.0  0.0  1.0  0.0  0.0
 1.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  1.0  0.0
 1.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  1.0

```

*To allow Julia to factor a singular matrix.*

```

julia> U
10×10 Matrix{Float64}:
 1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
 0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0

julia> L*U
10×10 Matrix{Float64}:
 1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0
 1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0
 1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0
 1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0
 1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0
 1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0
 1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0
 1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0
 1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0
 1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0  1.0

```

6. a. Use the Cholesky Decomposition Algorithm to find the Cholesky decomposition of the cross-product matrix  $A^T A$ , where  $A = [1 \ 0 \ 1; 1 \ 0 \ -1; 1 \ 1 \ 0; 1 \ 1 \ 1]$ .
- b. Use your Cholesky decomposition from part (a) to solve  $A^T A x = A^T b$ , where  $b = (1, -1, 1, -1)^T$ .

6a.

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

### Cholesky Decomposition Algorithm:

1. Set  $R_1 = \sqrt{a_{11}}$ .
2. Begin loop ( $p = 2$  to  $n$ ):
3. Solve  $R_{p-1}^T \gamma_{p-1} = c_{p-1}$  for  $\gamma_{p-1}$  by forward substitution.
4. Set  $r_{pp} = \sqrt{a_{pp} - \gamma_{p-1}^T \gamma_{p-1}}$ .
5. Set  $R_p = \begin{pmatrix} R_{p-1} & \gamma_{p-1} \\ 0 & r_{pp} \end{pmatrix}$ .
6. End loop.
7. Set  $L = R_n^T$ .

Step 1:  $R_1 = \sqrt{4} = 2$

Step 2:  $p = 2$

Step 3:  $2\gamma_1 = 2, \quad \gamma_1 = 1$

Step 4:  $r_{22} = \sqrt{2 - 1} = 1$

Step 5:  $R_2 = \begin{bmatrix} 2 & 1 \\ 0 & 1 \end{bmatrix}$

Step 2:  $p = 3$

Step 3:  $\begin{bmatrix} 2 & 0 \\ 1 & 1 \end{bmatrix} \gamma_2 = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad \gamma_2 = \begin{bmatrix} 1/2 \\ 1/2 \end{bmatrix}$

Step 4:  $r_{33} = \sqrt{3 - \begin{bmatrix} 1/2 & 1/2 \end{bmatrix} \begin{bmatrix} 1/2 \\ 1/2 \end{bmatrix}} = \sqrt{3 - 1/2} = \sqrt{5/2}$

Step 5:  $R = R_3 = \begin{bmatrix} 2 & 1 & 1/2 \\ 0 & 1 & 1/2 \\ 0 & 0 & \sqrt{5/2} \end{bmatrix}$

$$\frac{16}{\frac{3}{48}}$$

Check that  $A^T A = R_3^T R_3$

```

julia> R=[2 1 1/2; 0 1 1/2; 0 0 sqrt(5/2)]
3x3 Matrix{Float64}:
 2.0  1.0  0.5
 0.0  1.0  0.5
 0.0  0.0  1.58114

julia> R'*R
3x3 Matrix{Float64}:
 4.0  2.0  1.0
 2.0  2.0  1.0  = A
 1.0  1.0  3.0
    
```

6b.

$$A^T b = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 \\ 1 & -1 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \\ 1 \\ -1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

$$A^T A x = R^T \underbrace{R x}_y = A^T b$$

$$\begin{cases} R^T y = A^T b \\ R x = y \end{cases}$$

$$R^T = \begin{bmatrix} 2 & 0 & 0 \\ 1 & 1 & 0 \\ 1/2 & 1/2 & \sqrt{5/2} \end{bmatrix}$$

$$R = \begin{bmatrix} 2 & 1 & 1/2 \\ 0 & 1 & 1/2 \\ 0 & 0 & \sqrt{5/2} \end{bmatrix}$$

$$\begin{bmatrix} 2 & 0 & 0 \\ 1 & 1 & 0 \\ 1/2 & 1/2 & \sqrt{5/2} \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

$$\begin{aligned} y_1 &= 0 \\ y_2 &= 0 \\ y_3 &= \sqrt{2/5} \end{aligned}$$

$$\begin{bmatrix} 2 & 1 & 1/2 \\ 0 & 1 & 1/2 \\ 0 & 0 & \sqrt{5/2} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \sqrt{2/5} \end{bmatrix}$$

$$\begin{aligned} x_1 &= 0 \\ x_2 &= -1/5 \\ x_3 &= 2/5 \end{aligned}$$

Solution  $x = \begin{bmatrix} 0 \\ -1/5 \\ 2/5 \end{bmatrix}$



10. a. Prove that if every leading principal minor of a symmetric matrix  $A$  is positive definite, then  $A$  is positive definite.
- b. Prove that the diagonal elements of a positive definite matrix are positive.
- c. Prove that every leading principal minor of a positive definite matrix has a positive determinant.

10a. The leading principal minors  $A_p$  are the  $p \times p$  submatrices in the northwest corner of the matrix. If  $A$  is symmetric then it's square, in which case  $A$  is an  $n \times n$  matrix for some  $n$ . In this case  $A = A_n$  for  $p = n$ . Now since  $A_n$  is positive definite then so is  $A$ .

10b. Since  $A$  is positive definite it has a Cholesky factorization given as  $A = R^T R$  moreover, since  $A$  is invertible, then no column of  $R$  could be identically zero. It follows that

$$a_{kk} = (R^T R)_{kk} = \sum_{i=1}^n (R^T)_{ki} R_{ik} = \sum_{i=1}^n (R_{ik})^2 > 0$$

since this is a sum of non-negative terms at least one of which is not zero.

10c. Since a matrix  $A$  is positive definite if and only if all leading principle minor submatrices are also positive definite, it is enough to show the determinant of a positive definite matrix is positive. Let  $R$  be the Cholesky factorization such that  $A = R^T R$ . Then

$$\det A = \det R^T R = (\det R^T)(\det R) = (\det R)^2 > 0$$

Since  $A$  is invertible then  $\det A \neq 0$ .

It follows that  $\det A > 0$ .

2. a. The matrix norm induced by the  $l_1$  vector norm is  $\|A\|_1 = \max_{j=1}^n \{\sum_{i=1}^n |a_{ij}|\}$ , the maximum column sum. The matrix norm induced by the  $l_\infty$  vector norm is  $\|A\|_\infty = \max_{i=1}^n \{\sum_{j=1}^n |a_{ij}|\}$ , the maximum row sum. For  $A = [1 \ 2 \ 3; 4 \ 5 \ 6; 7 \ 8 \ 9]$ , find (by hand)  $\|A\|_F$ ,  $\|A\|_1$ ,  $\|A\|_\infty$ .
- b. Find  $\|A\|_2$  by finding the largest eigenvalue of  $A^T A$  (use  $\max(\text{eig}(A^T * A))$ ).  
*maximum (eigvals (A' \* A))*

2a.

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix}$$

By definition

$$\begin{aligned} \|A\|_1 &= \max \left\{ \sum_{i=1}^n |a_{ij}| : j=1, 2, \dots, n \right\} \\ &= \max \{ 1+4+7, 2+5+8, 3+6+9 \} \\ &= \max \{ 12, 15, 18 \} = 18 \end{aligned}$$

$$\begin{aligned} \|A\|_\infty &= \max \left\{ \sum_{j=1}^n |a_{ij}| : i=1, 2, \dots, n \right\} \\ &= \max \{ 1+2+3, 4+5+6, 7+8+9 \} \\ &= \max \{ 6, 15, 24 \} = 24 \end{aligned}$$

$$\|A\|_F = \sqrt{\sum_{i,j=1}^n |a_{ij}|^2} = \sqrt{1^2+2^2+3^2+4^2+5^2+6^2+7^2+8^2+9^2}$$

$$= \sqrt{1+4+9+16+25+36+49+64+81} = \sqrt{285} \approx 16.88194$$

```
julia> A=[1 2 3; 4 5 6; 7 8 9]
3x3 Matrix{Int64}:
 1  2  3
 4  5  6
 7  8  9

julia> A.*A
3x3 Matrix{Int64}:
 1  4  9
16 25 36
49 64 81

julia> sum(A.*A)
285

julia> sqrt(sum(A.*A))
16.881943016134134
```

ab.  $\|A\|_5 = \sqrt{\max\{\lambda : \lambda \text{ is an eigenvalue of } A^T A\}}$

Using Julia we have

```
julia> A=[1 2 3;4 5 6;7 8 9]
3×3 Matrix{Int32}:
 1  2  3
 4  5  6
 7  8  9
```

```
julia> B=A'*A
3×3 Matrix{Int32}:
 66  78  90
 78  93  108
 90  108  126
```

```
julia> using LinearAlgebra
```

```
julia> lambda=eigvals(B)
3-element Vector{Float64}:
 -1.516797508290897e-14
  1.1414134196298527
 283.8585865803701
```

thus

$$\|A\|_5 = \sqrt{283.8586} \approx 16.84810$$

```
julia> maximum(lambda)
283.8585865803701
```

```
julia> sqrt(maximum(lambda))
16.848103352614206
```

10. a. An orthogonal matrix satisfies  $U^T U = I$ . Show that  $\|Ux\|_2 = \|x\|_2$  for all  $x$  if  $U$  is orthogonal. (Hint: Consider the quadratic form  $x^T A x$  with  $A = U^T U$ .)
- b. Show that an orthogonal matrix  $U$  has  $\|U\|_2 = 1$  and  $\kappa_s(U) = 1$ .

$$\begin{aligned} \underline{10a.} \quad \|Ux\|_2 &= \sqrt{Ux \cdot Ux} = \sqrt{(Ux)^T Ux} = \sqrt{x^T U^T U x} = \sqrt{x^T I x} \\ &= \sqrt{x^T x} = \sqrt{x \cdot x} = \|x\|_2 \end{aligned}$$

$$\underline{10b.} \quad \|U\|_2 = \max \{ \|Ux\|_2 : \|x\|_2 = 1 \} = \max \{ \|x\|_2 : \|x\|_2 = 1 \} = 1.$$

Since orthogonal matrices are square and  $U^T U = I$ , then  $U^T = U^{-1}$ . Consequently  $U U^T = U U^{-1} = I$  implies that  $U^T$  is also an orthogonal matrix. Thus

$$\|U^{-1}\|_2 = \|U^T\|_2 = 1.$$

It follows that

$$\kappa_s(U) = \|U\|_2 \|U^{-1}\|_2 = 1.$$