# Homework 3: Report

#### Dante Buhl

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All example code outputs are in stored in a text file, "output.txt", within the fortran tar-ball.

### 1 Warming-Up Fortran Routines

1. Write a function which computes the trace of a square matrix A.

This was not all too difficult, in fact it only used one loop. On first inspection it also seems to be accurally calculating the trace of matrix A from Amat.dat.

- $2.\,$  Write a function which computes the two norm of a (column) vector.
  - This was also not very difficult, besides defining my variables, this took 1 line of code.
- 3. Write a function which prints a matrix and its dimensions to a screen.
  - This was slightly more complex, in that I like to format my print statements in fortran for matrices. So I chose an arbitrary amount of digits to keep and added a small routine for turning integers in string formats.
- 4. Write a driver routine which reads in a matrix from Amat, and then computes its trace, prints it to the terminal, and then computes the norm of each of its column vectors.

This was very simple. I decided to use one driver file for all 3 of the main programing questions. I simply called the routines from my module, and made sure to use all of the routines I had placed in my module at the top of the file.

```
Question 2: Basic Fortran Routines
Matrix A from Amat.dat
        4 by
matrix.
              1.000
    4.000
                        3.000
                                   1.000
    6.000
                                   8.000
Trace of the matrix is
                          22.0000000000000000
                          10.954451150103322
                          10.392304845413264
                          13.114877048604001
Norm of 3th column is
                          9.4868329805051381
```

#### 2 Gaussian Elimination with Pivoting

1. Write a subroutine which performs Gaussian Elimination with Pivoting to on a Matrix A and a rhsmatrix B.

This was tricky and I realized about midway through that storing the permutation matrix was a little crazy (especially for very large scale problems which I don't necessarily have to care about right now). So I changed the method I was pivoting and now it seems to work very well.

- 2. Write a subroutine which performs backsubstitution to solve the linear system UX = B. This was a fairly short routine and not very difficult. It can be easily scaled so that it computes the solutions for all columns of B at once, so I programmed it to do so.
- 3. Write a driver routine which calls your GE subroutine and backsub subroutine, and prints the matrices, before GE, after GE but before backsubstitution, the solution matrix X, and the error matrix  $E = B_s A_s X$ , and the 2-norms of the column vectors of E.

The code runs very well except for the fact that there is a small artifact of error for the one very odd, 5th column of B in Bmat.dat. The error for that specific column in of order  $10^{-13}$  rather than  $10^{-16}$  which we all know and love to be machine double precision. I'm going to double check the backsub routine to see if there is any large gleaming issue with it (I've triple checked the GE and LU routines and there is no error there). Below is the found solution and error.

```
Matrix X1
matrix.
    0.000
               3.500
    1.000
                         -0.500
              -6.000
                                   33.400
                                           -1234.360
    2.000
              -1.000
                         1.000
                                   -28.490
                                             515.920
                                                          4.207
   -3.000
               5.000
                         -1.500
                                    3.690
                                             223.040
                                                          7.125
        4 by
matrix.
    0.000
              0.000
                         0.000
                                    -0.000
                                              -0.000
                                                          0.000
    0.000
               0.000
                         0.000
                                    -0.000
                                              -0.000
                                                          0.000
    0.000
              -0.000
                          0.000
                                    0.000
                                              -0.000
                                                          0.000
    0.000
                                   -0.000
                                                          0.000
              -0.000
                          0.000
                                              -0.000
Norm of 1th
                           1.8310267194088950E-015
                           3.9720546451956370E-015
                           0.000000000000000000
        3th column is
Norm of 4th column is
                           1.6890356739932773E-014
Norm of 5th column is
                           1.3111789431856821E-012
Norm of 6th column is
                           1.5203165631859585E-014
```

## 3 LU Decomposition with Pivoting

- 1. Write a subroutine which performs LU Decomposition with Pivoting to on a Matrix A.
  - This routine was very similar to my GE routine except that it doesn't do any computations for the matrix B. The permutation matrix was also very easy to return. I did the actual calculation manually and found the same matrices that my decomposition yields.
- 2. Write a subroutine which performs forward substitution and backwards substitution to solve the linear system UX = Y, LY = B for X.
  - This was also very straight forward and easily scalable for rhs matrices. I used the same backsub routine from GE to solve, UX = Y and wrote a forward subroutine to solve LY = PB.
- 3. Write a driver routine which calls your LU subroutine and LU solver routine, and prints A before LU decompition, A, L, and U after the decomposition, the solution matrix X after solving, and the error matrix  $E = B_s A_s X$ , and the 2-norms of the column vectors of E.

This method goes as planned and has the same exact solution you find in GE. With nearly the same error norms as in GE. It has the same artifact of error as the GE method.

Matrix X2					
This is 4 l	by 6				
matrix.					
0.000	3.500	0.250	-2.005	360.270	10.631
1.000	-6.000	-0.500	33.400	-1234.360	-22.328
2.000	-1.000	1.000	-28.490	515.920	4.207
-3.000	5.000	-1.500	3.690	223.040	7.125
Matrix E2					
This is 4 by 6					
matrix.					
0.000	0.000	0.000	-0.000	-0.000	0.000
0.000	0.000	0.000	-0.000	-0.000	0.000
-0.000	-0.000	0.000	0.000	-0.000	0.000
0.000	-0.000	0.000	-0.000	-0.000	0.000
Norm of 1th	column is	1.7763568394002505E-015			
Norm of 2th	column is	3.9720546451956370E-015			
Norm of 3th	column is	0.000000000000000			
Norm of 4th column is 1.6890356739932773E-014					
Norm of 5th column is 1.6977670504095128E-012					
Norm of 6th	column is	2.4948	3171360229	9557E-014	

#### 4 Theory Problems

1. The Schur decomposition theorem states that if  $A \in C^{m \times m}$ , then there exist a unitary matrix Q and an upper triangular matrix U such that  $A = QUQ^{-1}$ . Use the Schur decomposition theorem to show that a real symmetric matrix A is diagonalizable by an orthogonal matrix, i.e.,  $\exists$  an orthogonal matrix Q such that  $Q^TAQ = D$ , where D is a diagonal matrix with its eigenvalues in the diagonal.

*Proof.* We begin with the Schur Decomposition Theorm for real symmetric matrix A. We have,

$$A = QUQ^{-1} = QUQ^*$$

By the property that A is real and symmetric, we have that  $A^* = A$ .

$$A^* = A = QUQ^*$$

$$Q^*A^*Q = U^* = Q^*AQ = U$$

So we have,  $U = U^*$ . Since we have that U is upper triangular, that means that  $U^*$  is lower triangular. However, since they are equal to one another, we must have that they are both diagonal. Thereby we have that A is diagonalizable by an othorgonal matrix Q (a property of unitary matrices).

$$A = QUQ^* \implies Q^{-1}AQ = U = D$$

Since we have this property, we have that Q contains the eigenvectors of A and U is a diagonal matrix contianing its eigenvalues.

2. Consider the following system

$$\left(\begin{array}{cc} 1 & 1 \\ \epsilon & 1 \end{array}\right) \left(\begin{array}{c} x \\ y \end{array}\right) = \left(\begin{array}{c} 2 \\ 1 \end{array}\right)$$

Multiply the last row of the matrix and the right-hand side vector by a large constant c such that  $c\epsilon \gg 1$ . Perform Gaussian elimination with partial pivoting to the modified row-scaled system and discuss what happens. If solving the resulting system has numerical issues, identify the issues and discuss how to improve the method.

$$\begin{pmatrix} 1 & 1 \\ c\epsilon & c \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} 2 \\ c \end{pmatrix}$$

$$\begin{pmatrix} 1 & 1 \\ 0 & c(1-\epsilon) \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} 2 \\ c(1-2\epsilon) \end{pmatrix}$$

$$y = \frac{1-2\epsilon}{1-\epsilon} \approx 1$$

$$x = \frac{1}{1-\epsilon} \approx 1$$

This method actually does a decent job computing x and y within machine precision.

3. What can you say about the diagonal entries of a symmetric positive definite matrix? Justify your assertion.

Claim: All diagonal entries of a symmetric pos. def. matrix are positive.

*Proof.* Take A to be a symmetric positive definite square matrix,  $A \in \mathbb{C}^{m \times m}$ . We have that for all vectors  $x \in \mathbb{C}^m$ , that the inner product is greater than zero, (i.e. (x, Ax) > 0). We can now chose vectors x to demonstrate that the diagonal elements are positive. Let us chose  $x = \hat{e}_1$ .

$$(\hat{e}_1, A\hat{e}_1) = \hat{e}_1^* A \hat{e}_1 = \hat{e}_1^* \vec{a}_1$$

Where  $\vec{a}_i$  is the ith column vector of A.

$$(\hat{e}_1, A\hat{e}_1) = \hat{e}_1^* \vec{a}_1 = a_{11}$$

$$(\hat{e}_1, A\hat{e}_1) > 0 \implies a_{11} > 0$$

This argument can be repeated for unit basis vectors,  $\hat{e}_i, \forall i \in 1, \dots, m$ . Thus we have, that  $a_{ii} > 0 \forall i \in 1, \dots, m$ .

4. Suppose  $A \in \mathbb{C}^{m \times m}$  is written in the block form

$$A = \left( \begin{array}{cc} A_{11} & A_{12} \\ A_{21} & A_{22} \end{array} \right)$$

where  $A_{11} \in \mathbb{C}^{n \times n}$  and  $A_{22} \in \mathbb{C}^{(m-n) \times (m-n)}$ . Assume that A satisfies the condition: A has an LU decomposition if and only if the upper-left  $k \times k$  block matrix  $A_{1:k,1:k}$  is nonsingular for each k with  $1 \le k \le m$ .

(a) Verify the formula

$$\begin{pmatrix} I & 0 \\ -A_{21}A_{11}^{-1} & I \end{pmatrix} \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix} = \begin{pmatrix} A_{11} & A_{12} \\ 0 & A_{22} - A_{21}A_{11}^{-1}A_{12} \end{pmatrix}$$

which "eliminate" the block  $A_{21}$  from A. The matrix  $A_{22} - A_{21}A_{11}^{-1}A_{12}$  is known as the Schur complement of  $A_{11}$  in A, denoted as  $A/A_{11}$ .

Proof.

$$\begin{pmatrix} \mathbf{I} & 0 \\ -A_{21}A_{11}^{-1} & \mathbf{I} \end{pmatrix} \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix} = \begin{pmatrix} \mathbf{I}A_{11} & \mathbf{I}A_{12} \\ \mathbf{I}A_{21} - A_{21}A_{11}^{-1}A_{11} & \mathbf{I}A_{22} - A_{21}A_{11}^{-1}A_{12} \end{pmatrix}$$
$$= \begin{pmatrix} A_{11} & A_{12} \\ A_{21} - A_{21} & A_{22} - A_{21}A_{11}^{-1}A_{12} \end{pmatrix} = \begin{pmatrix} A_{11} & A_{12} \\ 0 & A_{22} - A_{21}A_{11}^{-1}A_{12} \end{pmatrix}$$

(b) Suppose that after applying n steps of Gaussian elimination on the matrix A in (2),  $A_{21}$  is eliminated row by row, resulting in a matrix

$$\left(\begin{array}{cc} A_{11} & C \\ 0 & D \end{array}\right)$$

Show that the bottom-right  $(m-n) \times (m-n)$  block matrix D is again  $A_{22} - A_{21}A_{11}^{-1}A_{12}$ . Note: Part (b) is separate from Part (a)).

*Proof.* We start by looking at the process of gaussian elimination. We have that we progress by devloping these L matrices, so as to eliminate the entries below the diagonal element in each column. We look at  $L_1$ .

$$L_1 = \left( egin{array}{cccc} 1 & 0 & \cdots & \mathbf{0} \ -rac{a_{21}}{a_{11}} & \ddots & \cdots & \mathbf{0} \ dots & 0 & \ddots & \mathbf{0} \ -rac{a_{\overline{21}}^1}{a_{11}} & dots & \cdots & \mathbf{I} \end{array} 
ight)$$

Where  $a_{21}^{\vec{i}}$  denotes the ith column vector of  $A_{21}$ . We will ultimately have,

$$D(i,j) = A_{22}(i,j) - \sum_{k=1}^{n} \frac{1}{a_{kk}} (\vec{a_{21}}^{k}(i) \cdot \vec{a_{12}}^{k}(j))$$

with  $a_{kk}$  are the diagonal elements of  $A_{11}$ , and  $\vec{a_{12}}^k$  is the kth column vector of  $A_{12}$ . Note that if  $A_{11}$  is a diagonal block matrix, then this exactly gives,

$$D = A_{22} - A_{21} A_{11}^{-1} A_{12}$$

5. Consider solving Ax = b, with A and b are complex-valued of order m, i.e.,  $A \in \mathbb{C}^{m \times m}, b \in \mathbb{C}^m$ .

(a) Modify this problem to a problem where you only solve a real square system of order 2m. (Hint: Decompose  $A = A_1 + iA_2$ , where  $A_1 = Re(A)$  and  $A_2 = Im(A)$ , and similarly for b and x. Determine equations to be satisfied by  $x_1 = Re(x)$  and  $x_2 = Im(x)$ .

$$(A_1 + iA_2)(x_1 + ix_2) = b_1 + ib_2$$

$$A_1x_1 - A_2x_2 = b_1, \quad A_1x_2 + A_2x_1 = b_2$$

$$\begin{pmatrix} A_1 & -A_2 \\ A_2 & A_1 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} b_1 \\ b_2 \end{pmatrix}$$

(b) Determine the storage requirement and the number of floating-point operations for the real-valued method in (a) of solving the original complex-valued system Ax = b. Compare these results with those based on directly solving the original complex-valued system using Gaussian elimination (without pivoting) and complex arithmetic. Use the fact that the operation count of Gaussian elimination is  $O\left(\frac{m^3}{3}\right)$  for an  $m \times m$  real-valued system with one right-hand side vector. Pay close attention to the greater expense of complex arithmetic operations. Make your conclusion by quantifying the storage requirement and the operating expense of each method. Draw your conclusion on which method is computationally advantageous.