

Section exam 2 Numerical Analysis: Linear Algebra

9:30am – 10:45am, October 24, 2024.

Instructions:

- *This is a closed books exam.* No books or calculators are allowed. However, you are allowed to bring one hand written, single sided formula sheet.
- Try to answer the questions within the space given. If you must use more space, you *can* attach extra pages, but try to avoid it. If you do need extra space, then please mark this very clearly on the exam.
- If a question does not specifically ask for a motivation, then the correct answer alone will give full points. You are welcome to enter a brief explanation of how you arrived at the answer — this might yield partial credit in case the given answer is incorrect.
- Use your time strategically. Note in particular that Question 6 is only worth 10 points.
- In this exam, the default is that for a vector \mathbf{x} , the notation $\|\mathbf{x}\|$ denotes the Euclidean norm. For a matrix \mathbf{A} , the notation $\|\mathbf{A}\|$ refers to the operator norm with respect to the Euclidean vector norm, and $\|\mathbf{A}\|_F$ refers to the Frobenius norm. If \mathbf{A} is a matrix, then \mathbf{A}^* refers to the complex conjugate of the transpose of \mathbf{A} (or merely the transpose when \mathbf{A} is real).

Name: _____

Section: _____

Question	Max points	Scored points
1	20	
2	20	
3	15	
4	15	
5	20	
6	10	
Total:		

Question 1: (20p) Set $\mathbf{A} = \begin{bmatrix} 1 & 2 & -1 & 1 \\ 2 & 6 & -1 & 5 \\ -1 & 0 & 3 & 1 \\ -3 & -12 & -1 & -9 \end{bmatrix}$. In the first two steps of the LU factorization of

\mathbf{A} , we form $\mathbf{A}_1 = \mathbf{L}_1\mathbf{A} = \begin{bmatrix} 1 & 2 & -1 & 1 \\ 0 & 2 & 1 & 3 \\ 0 & 2 & 2 & 2 \\ 0 & -6 & -4 & -6 \end{bmatrix}$ and $\mathbf{A}_2 = \mathbf{L}_2\mathbf{A}_1 = \begin{bmatrix} 1 & 2 & -1 & 1 \\ 0 & 2 & 1 & 3 \\ 0 & 0 & 1 & -1 \\ 0 & 0 & -1 & 3 \end{bmatrix}$.

Please provide only answers to these questions. (Motivations will not be graded.)

(a) (7p) Specify the following matrices:

$$\mathbf{L}_1 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ -2 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 3 & 0 & 0 & 1 \end{bmatrix} \quad \mathbf{L}_2 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & -1 & 1 & 0 \\ 0 & 3 & 0 & 1 \end{bmatrix} \quad \mathbf{L}_2^{-1} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & -3 & 0 & 1 \end{bmatrix} \quad \mathbf{L}_1^{-1}\mathbf{L}_2^{-1} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 2 & 1 & 0 & 0 \\ -1 & 1 & 1 & 0 \\ -3 & -3 & 0 & 1 \end{bmatrix}$$

(b) (7p) Complete the LU factorization of \mathbf{A} so that $\mathbf{A} = \mathbf{LU}$. Specify:

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

(c) (6p) Specify the determinants of the matrices involved:

$$\det(\mathbf{L}) = 1 \quad \det(\mathbf{U}) = 4 \quad \det(\mathbf{A}) = 4$$

Question 2: (20p) For a given matrix \mathbf{X} , let $\sigma_{\max}(\mathbf{X})$ and $\sigma_{\min}(\mathbf{X})$ denote the largest and the smallest singular values of \mathbf{X} , respectively. Let m and n be positive integers such that $m > n$. You know that the $m \times n$ matrix \mathbf{A} has the largest and smallest singular values $\sigma_{\max}(\mathbf{A}) = 6$ and $\sigma_{\min}(\mathbf{A}) = 2$. In this question, let \mathbf{A}^\dagger denote the pseudo inverse of \mathbf{A} , let $\kappa(\mathbf{A})$ denote the condition number of \mathbf{A} , and let $\mathbf{Q} \in \mathbb{R}^{m \times n}$ and $\mathbf{R} \in \mathbb{R}^{n \times n}$ denote the factors in the QR factorization $\mathbf{A} = \mathbf{QR}$. Specify the following quantities without motivation:

$$\begin{aligned} \kappa(\mathbf{A}) &= 3 & \sigma_{\max}(\mathbf{R}) &= 6 & \sigma_{\max}(\mathbf{A}^*\mathbf{A}) &= 36 & \sigma_{\max}(\mathbf{A}\mathbf{A}^*) &= 36 & \sigma_{\max}(\mathbf{A}^\dagger) &= 1/2 \\ \kappa(\mathbf{A}^*\mathbf{A}) &= 9 & \sigma_{\min}(\mathbf{R}) &= 2 & \sigma_{\min}(\mathbf{A}^*\mathbf{A}) &= 4 & \sigma_{\min}(\mathbf{A}\mathbf{A}^*) &= 0 & \sigma_{\min}(\mathbf{A}^\dagger) &= 1/6 \end{aligned}$$

Question 3: (15p) Let m be a positive integer, and let $\{x_i\}_{i=1}^m$ and $\{y_i\}_{i=1}^m$ be two sets of real numbers. We seek to fit the pairs $\{x_i, y_i\}$ to a function

$$y = f(x) = c_1 + c_2 \sin(x) + c_3 x^2.$$

To be precise, we seek to determine c_1, c_2, c_3 such that the mean square error

$$E = \sum_{i=1}^m |(c_1 + c_2 \sin(x_i) + c_3 x_i^2) - y_i|^2$$

is minimized. As we saw in class, minimizing E is equivalent to solving a linear system $\mathbf{Ac} = \mathbf{b}$ for the vector $\mathbf{c} = [c_1, c_2, c_3]^*$ in a least squares sense. Specify (without motivation) \mathbf{A} and \mathbf{b} :

$$\mathbf{A} = \begin{bmatrix} 1 & \sin(x_1) & x_1^2 \\ 1 & \sin(x_2) & x_2^2 \\ \vdots & \vdots & \vdots \\ 1 & \sin(x_m) & x_m^2 \end{bmatrix} \quad \mathbf{b} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix}$$

Question 4: (15p) Let \mathbf{B} denote the 10×10 "Hilbert matrix". In other words, $\mathbf{B}(i, j) = \frac{1}{i+j-1}$. Set

$$\mathbf{A} = \frac{1}{\|\mathbf{B}\|} \mathbf{B}.$$

The matrix \mathbf{A} has 10 distinct positive eigenvalues $\{\lambda_j\}_{j=1}^{10}$. Suppose that these are ordered so that

$$0 < \lambda_{10} < \lambda_9 < \dots < \lambda_1.$$

(a) (6p) Let k be a positive integer. Specify the eigenvalues of \mathbf{A}^k . (Express the eigenvalues of \mathbf{A}^k in terms of the quantities introduced. It is not recommended to try to compute them directly!) What is the (exact) rank of \mathbf{A}^k ?

$$\lambda_1(\mathbf{A}^k) = 1 \quad \lambda_j(\mathbf{A}^k) = \lambda_j^k \quad \text{for } j = 2, 3, \dots, 10$$

(b) (9p) Consider the code snippet:

```
A=(1/norm(hilb(10)))*hilb(10); C=A; for i=1:10; disp(rank(C)); C=A*C; end;
```

(The function $r = \text{rank}(\mathbf{A})$ outputs an estimate for the *numerical* rank r of \mathbf{A} . When answering this problem, you may take r to be the largest number r such that $\sigma_r/\sigma_1 > \epsilon_{\text{mach}}$ where $\{\sigma_j\}_j$ are the singular values of \mathbf{A} .) When executed in Matlab, the output is:

```
10
7
5
4
4
3
3
3
2
2
```

Based on this, provide estimated bounds for λ_2 , λ_5 , and λ_{10} , expressed in terms of ϵ_{mach} .

Observe that an eigenmode gets lost when $\lambda_j^k < \epsilon$.

λ_2 This mode never drops, so

$$\lambda_2^{10} > \epsilon \quad \Leftrightarrow \quad \lambda_2 > \epsilon^{1/10}$$

0.196 0.025

λ_5 This mode lives in \mathbf{A}^3 but is dead in \mathbf{A}^4 , so

$$\lambda_5^3 > \epsilon \quad \& \quad \lambda_5^4 < \epsilon \quad \Leftrightarrow \quad \epsilon^{1/3} < \lambda_5 < \epsilon^{1/4}$$

5×10^{-6} 7×10^{-5} 10^{-4}

λ_{10} This mode is dropped in \mathbf{A}^2 , so

$$\lambda_{10}^2 < \epsilon \quad \Leftrightarrow \quad \lambda_{10} < \epsilon^{1/2}$$

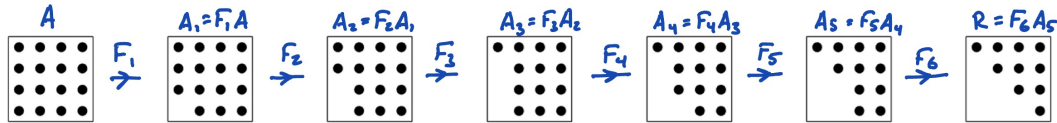
6×10^{-14} 10^{-8}

NOTE: Blue text is just for fun!
Not expected in actual answer, of course!

Question 5: (20p) Given any vector $\mathbf{v} = [a, b]^* \in \mathbb{R}^2$, there exist real numbers c and s such that the matrix $\mathbf{G} = \begin{bmatrix} c & -s \\ s & c \end{bmatrix}$ is unitary, and satisfies

$$(1) \quad \mathbf{G}\mathbf{v} = \begin{bmatrix} c & -s \\ s & c \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} \sqrt{a^2 + b^2} \\ 0 \end{bmatrix}.$$

Such a matrix is called a ‘‘Givens rotation’’ and can be used to compute the QR factorization of a given $m \times m$ matrix \mathbf{A} . The idea is similar to Householder QR, in that we apply transformations from the left that successively drive \mathbf{A} to upper triangular form. The first step of the process is to apply a Givens rotation to the bottom two rows of \mathbf{A} to create a zero in the $(m, 1)$ slot. Then continue to work upwards in the first column to successively introduce additional zeros. Then proceed with the second column, and so on. For a 4×4 matrix, the process involves six steps:



(a) (6p) Given a and b , provide formulas for c and s that result in a Givens rotation satisfying (1):

$$c = \frac{a}{\sqrt{a^2 + b^2}} \quad s = \frac{-b}{\sqrt{a^2 + b^2}}$$

(b) (6p) Specify a matrix \mathbf{F}_1 that contains a Givens rotation as a submatrix such that

$$\mathbf{F}_1 \begin{bmatrix} \times & \times & \times & \times \\ \times & \times & \times & \times \\ a & \times & \times & \times \\ b & \times & \times & \times \end{bmatrix} = \begin{bmatrix} \times & \times & \times & \times \\ \times & \times & \times & \times \\ \sqrt{a^2 + b^2} & \times & \times & \times \\ 0 & \times & \times & \times \end{bmatrix} \quad \text{where} \quad \mathbf{F}_1 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & c & -s \\ 0 & 0 & s & c \end{bmatrix} \quad \begin{matrix} c = \frac{a}{\sqrt{a^2 + b^2}} \\ s = -\frac{b}{\sqrt{a^2 + b^2}} \end{matrix}$$

(c) (8p) The figure shows Matlab code that drives a given matrix \mathbf{A} to the factor \mathbf{R} in a QR factorization $\mathbf{A} = \mathbf{QR}$, with \mathbf{Q} unitary. Fill in the missing lines so that the code builds the required Givens matrix \mathbf{G} using `mygivens`, and then applies it to the two relevant rows of \mathbf{R} :

```
function R = computer(A)
m = size(A,1);
R = A;
for j = 1:(m-1)
    for i = (m-1):(-1):j
        I = [i: i+1];
        G = mygivens(R(I,j));
        R(I,:) = G R(I,:);
    end
end
return
```

CODE MISSING HERE!

```
function G = mygivens(v)
c = v(1) / sqrt(v(1)*v(1) + v(2)*v(2));
s = -v(2) / sqrt(v(1)*v(1) + v(2)*v(2));
G = [c, -s; s, c];
return
```

INSERT MISSING CODE

Question 6: (10p) Let \mathbf{A} be a matrix of size $m \times n$. Suppose that $m < n$ and that $\text{rank}(\mathbf{A}) = m$. Given a vector $\mathbf{b} \in \mathbb{R}^m$, we seek to solve

$$\mathbf{Ax} = \mathbf{b} \quad (*)$$

for \mathbf{x} in a least squares sense. We covered in class how to do this using the SVD. Suppose that you are working in a software environment where you do not have access to a routine for computing the SVD, but you do have access to a routine for computing QR factorizations. Could you use this to construct the solution \mathbf{x} ? If yes, then write down a formula for \mathbf{x} , and motivate why it is the unique least squares solution. If no, then motivate why the problem cannot be solved using QR factorization.

Compute QR factorization of \mathbf{A}^* , so that

$$\mathbf{A}^* = \mathbf{QR}$$

$$\text{Then } (*) \Leftrightarrow \mathbf{R}^* \mathbf{Q}^* \mathbf{x} = \mathbf{b} \Leftrightarrow \mathbf{Q}^* \mathbf{x} = \mathbf{R}^{-*} \mathbf{b}$$

The obvious exact solⁿ is $\hat{\mathbf{x}} = \mathbf{QR}^{-*} \mathbf{b}$.

Is $\hat{\mathbf{x}}$ the minimal norm solⁿ?

Suppose $\mathbf{y} = \hat{\mathbf{x}} + \mathbf{z}$ is another solⁿ.

$$\mathbf{b} = \mathbf{Ay} = \mathbf{A}\hat{\mathbf{x}} + \mathbf{Az} = \mathbf{b} + \mathbf{Az} \Leftrightarrow \mathbf{Az} = \mathbf{0} \Leftrightarrow \mathbf{RQ}^* \mathbf{z} = \mathbf{0} \Leftrightarrow \mathbf{Q}^* \mathbf{z} = \mathbf{0}$$

Since $\hat{\mathbf{x}} \in \text{col}(\mathbf{Q})$, it follows that $\hat{\mathbf{x}} \perp \mathbf{z}$.

$$\text{Consequently } \|\mathbf{y}\|^2 = \|\hat{\mathbf{x}} + \mathbf{z}\|^2 = \|\hat{\mathbf{x}}\|^2 + \|\mathbf{z}\|^2$$

So if $\mathbf{z} \neq \mathbf{0}$, then $\|\mathbf{y}\| > \|\hat{\mathbf{x}}\|$.