

Question 1

$$a) \begin{bmatrix} I & A^T \\ A^T & 0 \end{bmatrix} \begin{bmatrix} r \\ x \end{bmatrix} = \begin{bmatrix} b \\ 0 \end{bmatrix} \quad - (1)$$

We apply Gaussian elimination on (1) and obtain

$$\begin{bmatrix} I & A \\ 0 & A^T A \end{bmatrix} \begin{bmatrix} r \\ x \end{bmatrix} = \begin{bmatrix} b \\ A^T b \end{bmatrix} \quad - (2)$$

From (2) we obtain the following results;

$$r + Ax = b$$

$$A^T Ax = A^T b$$

$$x = (A^T A)^{-1} A^T b$$

Thus x minimizes $\|Ax - b\|_2$.

$r = b - Ax$, which is the residual.

(b)

$$A = \begin{bmatrix} I & u\bar{z}v^T \\ v\bar{z}^T u^T & 0 \end{bmatrix}$$

Next, let $P = \begin{bmatrix} u & 0 \\ 0 & v \end{bmatrix}$

and $P^T A P = \underbrace{\begin{bmatrix} I & \bar{z} \\ \bar{z}^T & 0 \end{bmatrix}}_{\tilde{A}} ; \bar{z}^T = \bar{z}$

Expressing \tilde{A} as blocks of 2×2 matrices have;

$$\tilde{A}_1 = \begin{bmatrix} 1 & \sigma_1 \\ \sigma_1 & 0 \end{bmatrix}, \tilde{A}_2 = \begin{bmatrix} 1 & \sigma_2 \\ \sigma_2 & 0 \end{bmatrix}, \dots, \tilde{A}_n = \begin{bmatrix} 1 & \sigma_n \\ \sigma_n & 0 \end{bmatrix}$$

If $A \in \mathbb{R}^{m \times n}$ and $m \geq n$, we shall have some extra term expressed as

$$\tilde{A}_{m-n} = I_{m-n}.$$

In general, we can express $\tilde{A}_i, i=1, 2, \dots, n$ in a compact form as:

$$\tilde{A}_i = \begin{bmatrix} 1 & \sigma_i \\ \sigma_i & 0 \end{bmatrix}$$

we now compute the determinant of \tilde{A}_i

$$\begin{vmatrix} 1 - \lambda_i & \sigma_i \\ \sigma_i & -\lambda_i \end{vmatrix} = 0$$

$$\lambda_i^2 - \lambda_i - \sigma_i^2 = 0 \Rightarrow \lambda_i = \frac{1 \pm \sqrt{1 + 4\sigma_i^2}}{2}, i=1, 2, \dots, n$$

$$\tilde{A}_{m-n} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

determinant of \tilde{A}_{m-n} :

$$\begin{bmatrix} 1-\lambda & 0 \\ 0 & 1-\lambda \end{bmatrix} = 0 \Rightarrow \lambda = 1$$

The 2-norm condition number of A is given by

$$\kappa(A) = \frac{|\text{eigenvalue max}(A)|}{|\text{eigenvalue min}(A)|}$$

$$\begin{aligned} \text{maximum eigenvalue of } A &= \lambda_1 = \frac{1 + \sqrt{1 + 4\sigma_1^2}}{2} \\ \text{minimum eigenvalue of } A &= \lambda_n = \frac{1 - \sqrt{1 + 4\sigma_n^2}}{2} \end{aligned}$$

$$\kappa(A) = \frac{|1 + \sqrt{1 + 4\sigma_1^2}|}{|1 - \sqrt{1 + 4\sigma_n^2}|}$$

Since $1 - \sqrt{1 + 4\sigma_n^2} < 1$, we can rearrange terms to incorporate the absolute sign.

$$\kappa(A) = \frac{1 + \sqrt{1 + 4\sigma_1^2}}{\sqrt{1 + 4\sigma_n^2} - 1}$$

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$$\kappa(A) = \frac{1 + \sqrt{1 + 4\sigma_1^2}}{\sqrt{1 + 4\sigma_n^2} - 1} \quad - (1)$$

$$\kappa(A^T A) = \frac{\sigma_1^2}{\sigma_n^2} \quad - (2)$$

By comparing (1) and (2), we can observe that (2) will always be bigger for a given σ_1 and σ_n .

From (2), It follows that $L_k^{-1} = (I + L_k L_k)$.

For (1) to hold, then $L_k L_k^{-1} = I$.

$$\begin{aligned} L_k L_k^{-1} &= (I - L_k L_k)(I + L_k L_k) \\ &= I + L_k L_k - L_k L_k - \underbrace{L_k L_k L_k L_k}_{=0} \\ &= I - L_k L_k L_k L_k \end{aligned}$$

But the inner product $L_k L_k = 0$ because the non-zero term in L_k get multiplied with a zero term in L_k . The non-zero terms of L_k begins from index $k+1$. Hence $L_k L_k = 0$.

Therefore:

$$L_k L_k^{-1} = I - 0 = I$$

Question 4

We apply induction to show that the growth factor of A is exactly: $g_n(A) = 2^{n-1}$ i.e. for $A \in \mathbb{R}^{n \times n}$. $g_n(A) = \frac{\max_{i,j} |u_{ij}|}{\max_{i,j} |a_{ij}|}$.

Let us consider a few base cases that are easy to visualize.

When $n=2$.

$$A = \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix} \xrightarrow{\text{LU Decomposition}} U = \begin{bmatrix} 1 & 1 \\ 0 & 2 \end{bmatrix}, L = \begin{bmatrix} 1 & 0 \\ -1 & 1 \end{bmatrix}.$$

$$g_2(A) = \frac{2^1}{1} = 2.$$

When $n=3$.

$$A = \begin{bmatrix} 1 & 0 & 1 \\ -1 & 1 & 1 \\ -1 & -1 & 1 \end{bmatrix} \xrightarrow{\text{LU Decomposition}} U = \begin{bmatrix} 1 & 0 & 2^0 \\ -1 & 1 & 2^1 \\ -1 & -1 & 2^2 \end{bmatrix}, L = \begin{bmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ -1 & -1 & 1 \end{bmatrix}$$

$$g_3(A) = \frac{2^2}{1} = 2^2$$

Let us assume that the growth factor holds for $A \in \mathbb{R}^{n \times n}$ where $n=k$.

That is, $g_k(A) = 2^{k-1}$

Now we shall show that it is true for $n=k+1$.

Let $A \in \mathbb{R}^{n \times n}$ for $n=k+1$.

$$A = \begin{bmatrix} 1 & & & & 1 \\ -1 & 1 & & & \\ \vdots & & \ddots & & \\ \vdots & & & \ddots & \\ \vdots & & & & \ddots \\ -1 & & & & -1 \end{bmatrix} \xrightarrow{\text{LU Decomposition}} U = \begin{bmatrix} 1 & & & & 2^0 \\ -1 & 1 & & & 2^1 \\ \vdots & & \ddots & & 2^2 \\ \vdots & & & \ddots & \\ -1 & \dots & -1 & 2^{(k+1)-1} \end{bmatrix}$$

$$L = \begin{bmatrix} 1 & & & & \\ -1 & 1 & & & \\ \vdots & & \ddots & & \\ -1 & \dots & -1 & 1 \end{bmatrix}$$

$$g_{k+1}^{(A)} = \frac{2^{(k+1)-1}}{1} = 2^{(k-1)+1} = g_k^{(A)} \cdot 2 = 2^k.$$

Therefore $g_n^{(A)} = 2^{n-1}.$