

Q<sub>1</sub> Consider the following function

$$f(x) = \frac{1}{2}x_1^2 + x_1x_2 + \frac{1}{2}x_2^2, \quad g(x) = \frac{1}{2}x_1^3 + x_1x_2 + \frac{1}{2}x_2^2$$

a) Is  $f, g$  coercive?

b) Is  $x = (10, -10)$  a critical point of  $f$ ? Is it a global minimizer?

A<sub>1</sub>: a)  $f(x) = \frac{1}{2}(x_1 + x_2)^2$ , whenever  $x_1 = -x_2$ ,  $f(x) = 0$

So when  $\|x\| = \sqrt{x_1^2 + x_2^2} \rightarrow \infty$ ,  $f(x)$  doesn't go to  $+\infty$

So no

$g(x) = \frac{1}{2}x_1^3 + x_1x_2 + \frac{1}{2}x_2^2$ , to see this we set  $x_2 = 0$

$\Rightarrow g(x, 0) = \frac{1}{2}x_1^3$  when  $x_1 < 0$  and  $\|x\| = \sqrt{x_1^2 + 0} = |x_1| \rightarrow \infty$

$g(x) = \frac{1}{2}x_1^3 \rightarrow -\infty$ , So no

b). We compute the gradient

$$\nabla f(x) = \begin{bmatrix} x_1 + x_2 \\ x_1 + x_2 \end{bmatrix} = 0 \Rightarrow x_1 + x_2 = 0 \Rightarrow (10, -10)$$

$\therefore \nabla f((10, -10)) = \begin{bmatrix} 0 \\ 0 \end{bmatrix} = 0 \Rightarrow (10, -10)$  is a critical point.

$Hf(x) = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \Rightarrow \Delta_1 > 0 \quad \Delta_2 = 0 \Rightarrow Hf(x) \geq 0$  for  $\forall x \in \mathbb{R}^n$ .

$\Rightarrow x = (10, -10)$  is a global minimizer of  $f$ .

(To see this, we can also refer to the property of function  $f = \frac{1}{2}(x_1^2 + x_2^2) \geq 0$ )

Q.2 let  $A \in \mathbb{R}^{n \times n}$  be a symmetric matrix

a) show that if  $A$  is positive definite, then  $A^{-1}$  is symmetric and positive definite.

b) Classify the following matrices according to whether they are positive or negative definite, semidefinite, or indefinite.

$$(i) \begin{bmatrix} 2 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0.1 \end{bmatrix}$$

$$(ii) \begin{bmatrix} 3 & 1 & 2 \\ 1 & 5 & 3 \\ 2 & 3 & 7 \end{bmatrix}$$

$$(iii) \begin{bmatrix} 2 & -4 & 0 \\ -4 & 8 & 0 \\ 0 & 0 & -3 \end{bmatrix}$$

$$(iiii) \begin{bmatrix} 2 & -4 & 3 \\ -4 & 0 & 6 \\ 3 & 6 & 5 \end{bmatrix}$$



$A_2 = (a)$ .

① symmetric

$A$  is symmetric  $\Rightarrow A = A^T$

We want to prove  $(A^{-1})^T = A^{-1}$  (\*)

that is to prove  $(A^{-1})^T \cdot A = (A^{-1})^T A^T = (A A^{-1})^T = I$

So (\*) is proved, which means  $A^{-1}$  is symmetric

②  $A > 0$

We want to prove  $x^T A^{-1} x > 0$  for  $\forall x$

We have that  $y^T A y > 0$  for  $\forall y$

$\Rightarrow \forall x$ ,  $x$  can be represented as  $x = Ay$

$$x^T A^{-1} x = (Ay)^T A^{-1} Ay = y^T A^T A^{-1} Ay = y^T A^T y = y^T A y > 0$$

$\therefore A^{-1} > 0$

(Note this can also be seen from the eigenvalue view:

$\because A > 0 \Rightarrow \lambda_i > 0$  for all  $i \in [1, \dots, n]$ ,

$\therefore$  all the eigenvalues of  $A^{-1}$  are  $1/\lambda_i > 0 \Rightarrow A^{-1} > 0$ )

(b) (i) all eigenvalues  $\lambda_1 = 2, \lambda_2 = 1, \lambda_3 = 0.1 > 0 \Rightarrow A > 0$

(also  $\Delta_1 = 2 > 0, \Delta_2 = 1 > 0, \Delta_3 = 0.1 > 0$ )

$$(ii) \Delta_1 = 3 > 0 \quad \Delta_2 = \det \begin{bmatrix} 3 & 1 \\ 1 & 5 \end{bmatrix} = 15 - 1 = 14 > 0$$

$$\Delta_3 = 3 \times (35 - 9) - 1 \times (7 - 6) + 2(3 - 10) = 63 > 0$$

$\therefore A > 0$

$$(iii) \Delta_1 = 2 > 0 \quad \Delta_2 = 16 + 16 = 32 > 0 \quad \Delta_3 = -3 \times 32 = -96 < 0$$

$\Rightarrow A \not> 0 \quad A \not> 0 \quad A \not> 0 \quad A \not> 0$

We check by one more step with eigenvalues:

$$Ax = \lambda x$$

$$\Rightarrow (A - \lambda I)x = 0$$

$$A - \lambda I = \begin{bmatrix} 2 & -4 & 0 \\ -4 & 8 & 0 \\ 0 & 0 & -3 \end{bmatrix} - \begin{bmatrix} \lambda & & \\ & \lambda & \\ & & \lambda \end{bmatrix} = \begin{bmatrix} 2-\lambda & -4 & 0 \\ -4 & 8-\lambda & 0 \\ 0 & 0 & -3-\lambda \end{bmatrix}$$

$$\det(A - \lambda I) = (-3 - \lambda) [(8 - \lambda)(2 - \lambda) - 16]$$

$$= -(3 + \lambda)(\lambda^2 - 10\lambda)$$

$$= -(3 + \lambda)(\lambda - 10)\lambda$$

by taking  $\det(A - \lambda I) = 0 \Rightarrow \lambda_1 = 10, \lambda_2 = 0, \lambda_3 = -3$ .  
Since there is a positive and a negative eigenvalue,  
the matrix is indefinite.

(iii) It is not symmetric.



Q3: Compute the gradient of the following functions.

①  $f(x) = y^T x$

②  $f(x) = x^T y$

$x, y \in \mathbb{R}^n$

③  $f(x) = x^T A x$

$A \in \mathbb{R}^{n \times n}$

④  $f(x) = \frac{1}{2} \|Ax - y\|^2$

A: ①  $f(x) = y^T x = \sum_{i=1}^n y_i x_i$   
 $\Rightarrow \nabla f(x) = \begin{bmatrix} \frac{\partial f(x)}{\partial x_1} \\ \vdots \\ \frac{\partial f(x)}{\partial x_i} \\ \vdots \\ \frac{\partial f(x)}{\partial x_n} \end{bmatrix} = \begin{bmatrix} \frac{\partial f(x)}{\partial x_1}, \dots, \frac{\partial f(x)}{\partial x_i}, \dots, \frac{\partial f(x)}{\partial x_n} \end{bmatrix}^T = \begin{bmatrix} y_1, \dots, y_i, \dots, y_n \end{bmatrix}^T = y$

②  $f(x) = x^T y = \sum_{i=1}^n y_i x_i$

Similarly  $\nabla f(x) = y$

③  $f(x) = x^T A x$

$= [x_1 \dots x_i \dots x_n] \cdot \begin{bmatrix} \vec{a}_1 \\ \vec{a}_2 \\ \vdots \\ \vec{a}_n \end{bmatrix} \cdot \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$

$= \left( \sum_{i=1}^n x_i \vec{a}_i \right) \cdot x = \sum_{i=1}^n (x_i \vec{a}_i \cdot x) = \sum_{i=1}^n x_i (\vec{a}_i^T x)$

$= \sum_{i=1}^n x_i \sum_{j=1}^n a_{ij} x_j = \sum_{i=1}^n \sum_{j=1}^n a_{ij} x_i x_j$

$\Rightarrow \frac{\partial f(x)}{\partial x_k} = \sum_{j=1}^n a_{kj} x_j + \sum_{i=1}^n a_{ik} x_i = \vec{a}_k^T x + \vec{a}_k^T x$

$\Rightarrow \nabla f(x) = A x + A^T x = (A + A^T) x$  if  $A$  is symmetric  $\Rightarrow \nabla f(x) = 2Ax$

④ :  $f(x) = \frac{1}{2} \|Ax - y\|^2 + \frac{1}{2} \|x\|^2, \quad x, y \in \mathbb{R}^n$

(compute the expression for the gradient of  $f$ )

$$\begin{aligned} f(x) &= \frac{1}{2} \|Ax - y\|^2 + \frac{1}{2} \|x\|^2 \\ &= \frac{1}{2} (Ax - y)^T (Ax - y) + \frac{1}{2} x^T x \\ &= \frac{1}{2} (x^T A^T - y^T) (Ax - y) + \frac{1}{2} x^T x \\ &= \frac{1}{2} [x^T A^T A x - x^T A^T y - y^T A x + y^T y] \end{aligned}$$

$$\begin{aligned} \nabla f(x) &= \frac{1}{2} [2A^T A \cdot x - A^T y - (y^T A)^T] \\ &= A^T A x - A^T y \\ &= A^T (Ax - y) \end{aligned}$$