

# Homework - 2

## Problem - 1

$$f = 2x_1^2 - 4x_1x_2 + 1.5x_2^2 + x_2$$

$$\frac{\partial f}{\partial x_1} = 4x_1 - 4x_2$$

$$\frac{\partial f}{\partial x_2} = -4x_1 + 3x_2 + 1$$

$$\frac{\partial^2 f}{\partial x_1^2} = 4, \quad \frac{\partial^2 f}{\partial x_2^2} = 3, \quad \frac{\partial^2 f}{\partial x_1 \partial x_2} = -4$$

$$4x_1 - 4x_2 = 0 \Rightarrow x_1 = x_2$$

$$1 - 4x_1 + 3x_2 = 0$$

$$1 - 4x_1 + 3x_1 = 0$$

$$1 - x_1 = 0$$

$$\Rightarrow \boxed{x_1 = 1 = x_2}$$

$$D(1,1) = 4 \times 3 - (-4)^2 = 12 - 16 = -4 < 0$$

$\Rightarrow (1,1)$  is a saddle point

$$\text{Hessian Matrix } H = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} \\ \frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} \end{bmatrix} = \begin{bmatrix} 4 & -4 \\ -4 & 3 \end{bmatrix}$$

Eigen values of  $H$

$$\begin{aligned} \det |H - \lambda I| &= \begin{vmatrix} 4-\lambda & -4 \\ -4 & 3-\lambda \end{vmatrix} \\ &= (4-\lambda)(3-\lambda) - (-4)(-4) \\ &= 12 - 4\lambda - 3\lambda + \lambda^2 - 16 \\ &= \lambda^2 - 7\lambda - 4 \end{aligned}$$

$$\Rightarrow \lambda = \frac{7 \pm \sqrt{49 - (4 \times 1 \times -4)}}{2} = \frac{7 \pm \sqrt{65}}{2}$$

$$\lambda_1 = 7.531 \quad \text{and} \quad \lambda_2 = -0.531$$

Eigen vector of H

$$\text{For } \lambda_1 \quad \begin{bmatrix} \frac{-1 + \sqrt{65}}{8} \\ 1 \end{bmatrix} \approx \begin{bmatrix} 0.8827 \\ 1 \end{bmatrix} \quad \text{for } \lambda_2 \quad \begin{bmatrix} \frac{-1 - \sqrt{65}}{8} \\ 1 \end{bmatrix} \approx \begin{bmatrix} -1.327 \\ 1 \end{bmatrix}$$

Hessian matrix H has one +ve and one -ve eigen values  
 $\Rightarrow$  H is an indefinite matrix

Taylor's expansion at  $[x_1, x_2] = [1, 1]$

$$g_0 = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad H_0 = \begin{bmatrix} 4 & -4 \\ -4 & 3 \end{bmatrix} \quad f_0 = 0.5$$

$$f(x) = f_0 + g_0^T (x - x_0) + \frac{1}{2} (x - x_0)^T H (x - x_0)$$

$$f(x) = 0.5 + 0 + \frac{1}{2} [x_1 \ x_2] \begin{bmatrix} 4 & -4 \\ -4 & 3 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$\Rightarrow \frac{1}{2} [x_1 \ x_2] \begin{bmatrix} 4 & -4 \\ -4 & 3 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = f(x) - 0.5 < 0$$

$$\frac{1}{2} (4x_1^2 - 8x_1x_2 + 3x_2^2) < 0$$

$$0.5 (2x_1 - x_2)(2x_2 - 3x_1) < 0$$

$$\Rightarrow \quad 2x_1 - x_2 < 0 \quad \text{AND} \quad 2x_2 - 3x_1 > 0$$

OR

$$2x_1 - x_2 > 0 \quad \text{AND} \quad 2x_2 - 3x_1 < 0$$

## Problem 2

Let assume the point on the plane be  $(x_1, x_2, x_3)$

distance b/w  $(x_1, x_2, x_3)$  and  $(-1, 0, 1)$

$$= \sqrt{(x_1+1)^2 + x_2^2 + (x_3-1)^2}$$

we know if  $\min(f(x)) \Rightarrow \min(\sqrt{f(x)})$

$\Rightarrow$  we have to minimise

$$\min [(x_1+1)^2 + x_2^2 + (x_3-1)^2] \quad - (1)$$

which is s.t

$$x_1 + 2x_2 + 3x_3 = 1$$

$$\Rightarrow x_1 = 1 - 2x_2 - 3x_3 \quad - (2)$$

put the value of  $x_1$  in eq<sup>n</sup> (1)

$$\Rightarrow \min [(1 - 2x_2 - 3x_3 + 1)^2 + x_2^2 + (x_3 - 1)^2]$$

$$\Rightarrow f(x, y) = (2 - 2x - 3y)^2 + x^2 + (y - 1)^2$$

$$\text{Gradient } g = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} = \begin{bmatrix} 10x + 12y - 8 \\ 20y + 12x - 14 \end{bmatrix}$$

$$\text{Hessian } H = \begin{bmatrix} \frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial y \partial x} \\ \frac{\partial^2 f}{\partial x \partial y} & \frac{\partial^2 f}{\partial y^2} \end{bmatrix} = \begin{bmatrix} 10 & 12 \\ 12 & 20 \end{bmatrix}$$

Hessian of this function is +ve

$\Rightarrow f(x, y)$  is a convex function

### Problem 3

a)

to proof  $af(x) + bg(x)$  is convex s.t.  $a \geq 0$  and  $b \geq 0$

For any point  $x_1$  and  $x_2$  which belong to  $\mathcal{X}$

$\lambda x_1 + (1-\lambda)x_2$  is a convex function

If  $\mathcal{X}$  is a convex set and ' $\lambda$ ' belongs to  $[0,1]$

$$f(\lambda x_1 + (1-\lambda)x_2) \leq \lambda f(x_1) + (1-\lambda)f(x_2)$$

Similarly

$$g(\lambda x_1 + (1-\lambda)x_2) \leq \lambda g(x_1) + (1-\lambda)g(x_2)$$

with  $a$  and  $b$  variables

$$a f(\lambda x_1 + (1-\lambda)x_2) + b g(\lambda x_1 + (1-\lambda)x_2) \leq a \lambda f(x_1) + a (1-\lambda) f(x_2) + b \lambda g(x_1) + b (1-\lambda) g(x_2)$$

$$a f(\lambda x_1 + (1-\lambda)x_2) + b g(\lambda x_1 + (1-\lambda)x_2) \leq \lambda [a f(x_1) + b g(x_1)] + (1-\lambda) [a f(x_2) + b g(x_2)]$$

As the above statement is a convex function

$\Rightarrow af(x) + bg(x)$  is a convex function

b)

Condition for which  $f(g(x))$  will be convex

$$\text{Let } h(x) = f(g(x))$$

$$\text{dom } h = \{x \in \text{dom } g \mid g(x) \in \text{dom } f\}$$

The second derivative of  $h = f \circ g$

$$h''(x) = f''(g(x))g'(x)^2 + f'(g(x))g''(x)$$

Now if  $g$  is convex ( $g'' \geq 0$ )

$f$  is convex and increasing ( $f'' \geq 0$  and  $f' \geq 0$ )

$$h'' \geq 0$$

$\Rightarrow h$  is convex

Similarly

$h$  is convex when

- $f$  is convex and increasing, and  $g$  is convex
- $f$  is convex and increasing, and  $g$  is concave

## Problem 4

To show  $f(x_1) \geq f(x_0) + g_{x_0}^T (x_1 - x_0)$  for a convex function

$f(x) : \mathcal{X} \rightarrow \mathbb{R}$  and for  $x_0, x_1 \in \mathcal{X}$

As  $f$  is a convex function, and  $x, y \in \text{dom } f$ .

Since  $\text{dom } f$  is convex

$$\Rightarrow 0 < d \leq 1, \quad x + d(y - x) \in \text{dom } f$$

$$\Rightarrow f(x + d(y - x)) \leq (1 - d)f(x) + df(y)$$

Divide both sides by  $d$

we get,

$$f(y) \geq f(x) + \underbrace{f'(x+d(y-x))}_{\downarrow} - f(x) \quad \text{--- (1)}$$

as  $d \rightarrow 0$

$$\text{let } z = \theta x + (1-\theta)y$$

Applying (1) twice yield

$$f(x) \geq f(z) + f'(z)(x-z) \quad , \quad f(y) \geq f(z) + f'(z)(y-z)$$

Multiply first inequality by  $\theta$  and second by  $1-\theta$

$$\theta f(x) \geq \theta f(z) + \theta f'(z)(x-z) \quad \text{--- (2)}$$

$$(1-\theta) f(y) \geq (1-\theta) f(z) + (1-\theta) f'(z)(y-z) \quad \text{--- (3)}$$

Add (2) and (3), we get

$$\theta f(x) + (1-\theta) f(y) \geq f(z)$$

$$g(t) = f(dy + (1-d)x)$$

$$g'(t) = \nabla f(dy + (1-d)x)^T (y-x)$$

As  $f$  is convex which implies  $g$  is convex

$$\Rightarrow g(1) \geq g(0) + g'(0)$$

$$\Rightarrow f(y) \geq f(x) + \nabla f(x)^T (y-x)$$

$$\Rightarrow \boxed{f(x_1) \geq f(x_0) + g_{x_0}^T (x_1 - x_0)}$$

## Problem 5

a)

For optimality function we have to minimize the error b/w the intensity level  $a_k^T p$  and the target intensity  $I_t$

$$\text{intensity level on } k^{\text{th}} \text{ mirror} = a_k^T p$$

where  $p \rightarrow$  power output

$a \rightarrow$  distance b/w lamp and mirror

$$(I_k) \quad \text{Total intensity} = \sum_{j=1}^n a_{kj} p_j$$

$$\begin{aligned} \min \quad f(p_i)_{j=1}^n &= \sum_{i=1}^m (I_k - I_t)^2 \\ &= \sum_{i=1}^n \sum_{j=1}^n (a_{ij} p_j - I_t)^2 \end{aligned}$$

b)

$$g = 2(a^T p - I) a$$

$$H = 2a a^T$$

$$\text{Here } H \geq 0$$

We know

$$d^T H d \geq 0$$

$$\text{Here } d \neq 0$$

This means that  $H$  is p.s.d

$\Rightarrow$  The function is a convex problem

c)

Yes there will be a unique sol<sup>n</sup> if the overall power output is  $P^*$

d)

If only half of the lamp switched on then the function should not have a unique sol<sup>n</sup>