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Class: EE-559

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Assignment : Homework 2

① Num Classes  $C = 3$

Method to be used, One v/s One

Discriminant Functions  $\rightarrow g_{12}(x) = -x_1 - x_2 + 5$

$$g_{13}(x) = -x_1 + 3$$

$$g_{23}(x) = -x_1 + x_2 - 1$$

$$g_{ij}(x) = -g_{ji}(x)$$

Decision Rule  $\rightarrow$

$x \in \Gamma_k$  iff  $g_j(x) > 0$  for all  $j \neq k$

A lie  $g_{kj}(x) = 0$  is Decision Boundary.

Boundary  $H_{12} \rightarrow g_{12}(x) = 0 \Rightarrow -x_1 - x_2 + 5 = 0$

$$\Rightarrow x_1 + x_2 = 5$$

$$x_1 = 0 \Rightarrow x_2 = 5 \rightarrow (0, 5)$$

$$x_2 = 0 \Rightarrow x_1 = 5 \rightarrow (5, 0)$$

line joining  
will be  $H_{12}$

$$H_{13} \rightarrow g_{13}(x) = 0 \Rightarrow -x_1 + 3 \Rightarrow x_1 = 3$$

$$H_{23} \rightarrow g_{23}(x) = 0 \Rightarrow -x_1 + x_2 - 1 = 0 \Rightarrow x_2 - x_1 = 1$$

$$x_1 = 0 \Rightarrow x_2 = 1 \rightarrow (0, 1)$$

$$x_2 = 0 \Rightarrow x_1 = -1 \rightarrow (-1, 0)$$

line joining  
will be  
 $H_{23}$

Points

- $\underline{(2, 4)} \rightarrow$

$$g_{12}([2, 4]) = -2 - 4 + 5 = -1 ; g_{21}([2, 4]) = 1$$

$$g_{13}([2, 4]) = -2 + 3 = 1 ; g_{31}([2, 4]) = -1$$

$$g_{23}([2, 4]) = -2 + 4 - 1 = 1 ; g_{32}([2, 4]) = -1$$

For  $\Gamma_1$ ,  $g_{12}([2, 4]) < 0 ; g_{13}([2, 4]) > 0$

For  $\Gamma_2$ ,  $g_{21}([2, 4]) > 0 ; g_{23}([2, 4]) > 0$

For  $\Gamma_3$ ,  $g_{31}([2, 4]) < 0 ; g_{32}([2, 4]) < 0$

$\therefore g_{2j}([2, 4]) > 0 \text{ for } j \in \{1, 3\}$

$$[2, 4] \in \Gamma_2$$

- $\underline{(4, 3)} \rightarrow$

$$g_{12}([4, 3]) = -4 - 3 + 5 = -2 ; g_{21}([4, 3]) = 2$$

$$g_{13}([4, 3]) = -4 + 3 = -1 ; g_{31}([4, 3]) = 1$$

$$g_{23}([4, 3]) = -4 + 3 - 1 = -2 ; g_{32}([4, 3]) = 2$$

For  $\Gamma_1$ ,  $g_{12}(3) < 0 , g_{13}(3) < 0$

For  $\Gamma_2$ ,  $g_{21}(3) > 0 , g_{23}(3) < 0$

For  $\Gamma_3$ ,  $g_{31}(3) > 0 ; g_{32}(3) > 0$

$\therefore g_{3j}([4, 3]) > 0 \text{ for } j \in \{1, 2\}$

$$[4, 3] \in \Gamma_3$$

•  $\overset{(1,2)}{\underset{g_{12}}{\text{for } \{1,2\}}} \Rightarrow g_{12}(\{1,2\}) = -1 - 2 + 5 = 2 ; g_{21}(\underline{x}) = -2$

$g_{13}(\{1,2\}) = -1 + 3 = 2 ; g_{31}(\underline{x}) = -2$

$g_{23}(\{1,2\}) = -1 + 2 - 1 = 0 ; g_{32}(\underline{x}) = 0$

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For  $T_1$ ,  $g_{12}(\{1,2\}) > 0 ; g_{23}(\{1,2\}) < 0$

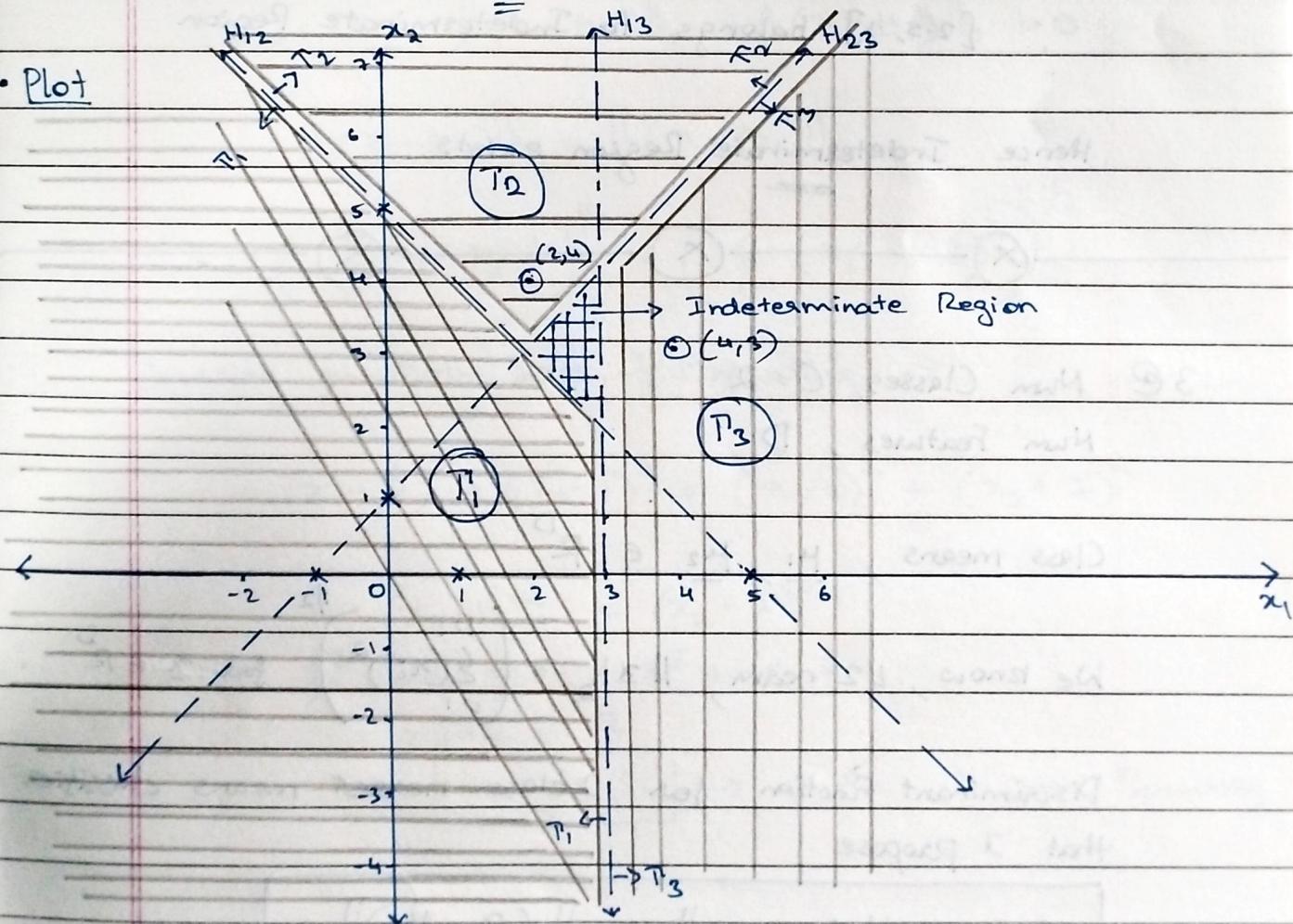
For  $T_2$ ,  $g_{21}(\{1,2\}) < 0 ; g_{23}(\{1,2\}) = 0$

For  $T_3$ ,  $g_{31}(\{1,2\}) < 0 ; g_{32}(\{1,2\}) = 0$

$\therefore g_{ij}(\{1,2\}) > 0 \text{ for } j \in \{2,3\}$

$\therefore [1,2] \in T_1$

• Plot



• (2.5, 3)

$$g_{12}([2.5, 3]) = -2.5 - 3 + 5 = -0.5; g_{21}(3) = 0.5$$

$$g_{13}([2.5, 3]) = -2.5 + 3 = 0.5; g_{31}(3) = -0.5$$

$$g_{23}([2.5, 3]) = -2.5 + 3 - 1 = -0.5; g_{32}(3) = 0.5$$

$$\text{For } T_1 \rightarrow g_{12}(3) < 0; g_{13}(3) > 0$$

$$\text{For } T_2 \rightarrow g_{21}(3) > 0; g_{23}(3) < 0$$

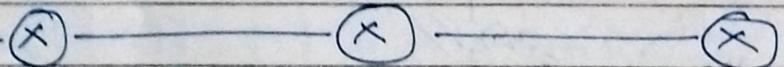
$$\text{For } T_3 \rightarrow g_{31}(3) < 0; g_{32}(3) > 0$$

~~For~~ none  $[2.5, 3]$  doesn't satisfy the rule

$$g_{Rj}(3) > 0 \text{ for all } j \neq 2$$

$[2.5, 3]$  belongs to Indeterminate Region

Hence Indeterminate Region exists.



3@ Num Classes,  $C = 2$

Num Features,  $D$

Class means,  $\underline{\mu}_1, \underline{\mu}_2 \in \mathbb{R}^D$

$$\text{We know, L2 norm, } \|\underline{x}\|_2 = \left( \sum_{i=1}^D (x_i)^2 \right)^{1/2} \text{ for } \underline{x} \in \mathbb{R}^D$$

Discriminant Function for 2 class nearest means classifier  
that I propose

$$g(\underline{x}) = \|\underline{x} - \underline{\mu}_2\|_2 - \|\underline{x} - \underline{\mu}_1\|_2$$

with a Decision Rule,

$$g(\underline{x}) \geq 0$$

Design Boundary,

$$\|\underline{x} - \underline{\mu}_1\|_2 - \|\underline{x} - \underline{\mu}_2\|_2$$

It is a Linear Classifier.

①  $\underline{\mu}_1 = \begin{bmatrix} 0 \\ -2 \end{bmatrix}, \quad \underline{\mu}_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$

To get Design Boundary,  $g(\underline{x}) = 0$

$$g(\underline{x}) = 0 \Rightarrow \|\underline{x} - \underline{\mu}_2\|_2 - \|\underline{x} - \underline{\mu}_1\|_2 = 0$$

$$\|\underline{x} - \underline{\mu}_2\|_2 = \|\underline{x} - \underline{\mu}_1\|_2$$

$$\left( \sum_{i=1}^2 (x_i - \mu_{2i})^2 \right)^{1/2} = \left( \sum_{i=1}^2 (x_i - \mu_{1i})^2 \right)^{1/2}$$

Squaring on Both Sides & Expanding  $\Rightarrow$

$$(x_1 - 0)^2 + (x_2 - 1)^2 = (x_1 - 0)^2 + (x_2 + 2)^2$$

$$(x_2 - 1)^2 = (x_2 + 2)^2$$

$$x_2^2 - 2x_2 + 1 = x_2^2 + 4x_2 + 4$$

$$-6x_2 = 3$$

$$x_2 = -0.5$$

$\rightarrow$  is the Decision Boundary

$$\cdot \underline{(0,0)} = 2$$

$$g([0,0]) = \|z - \mu_2\|_2 - \|z - \mu_1\|_2$$

$$= \left( (0-0)^2 + (0-1)^2 \right)^{1/2} - \left( (0-0)^2 + (0+2)^2 \right)^{1/2}$$

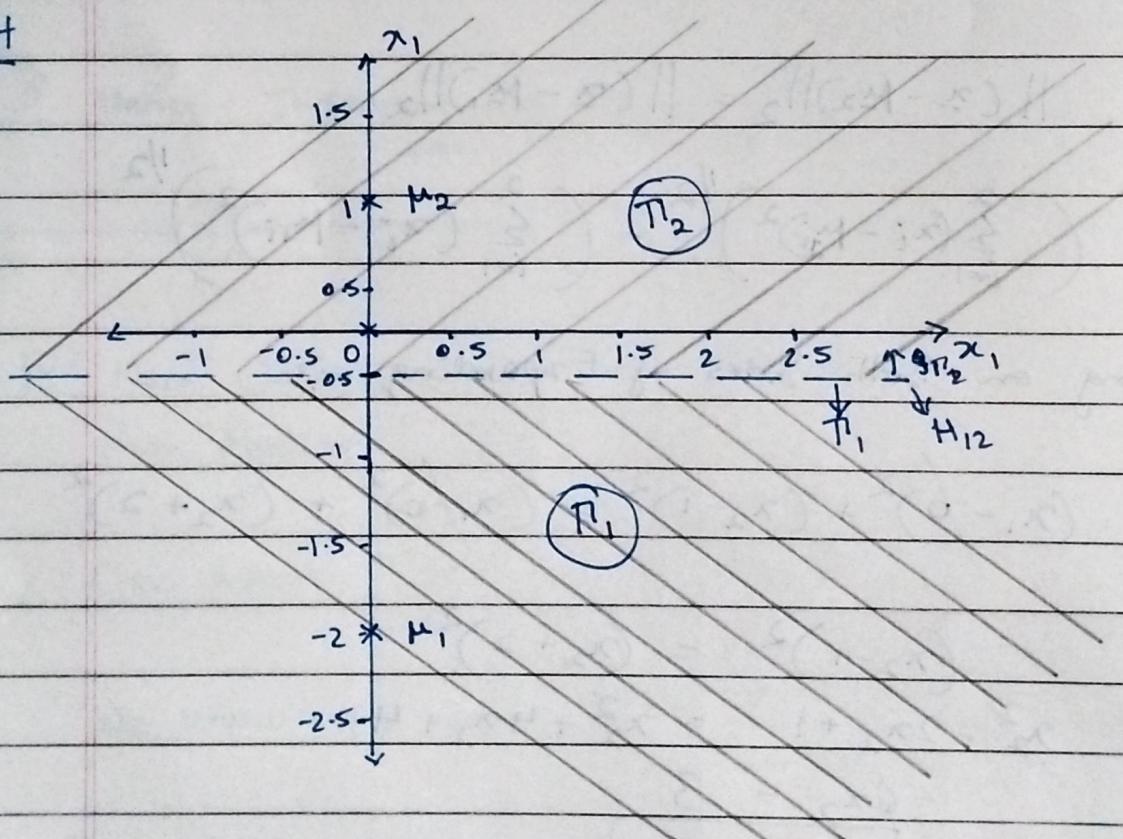
$$= (1^2)^{1/2} - (-2^2)^{1/2}$$

$$= 1 - 2$$

$$g([0,0]) = -1 \text{ which is less than } 0.$$

$$\therefore [0,0] \in T_2$$

Plot



3(c) Num Classes,  $C=3$   
Num Features, D

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Method  $\rightarrow$  Maximal Value Method

Class Means  $\rightarrow \underline{\mu}_1, \underline{\mu}_2, \underline{\mu}_3$

I choose the following discriminant functions,

$$g_1(\underline{x}) = -\|\underline{x} - \underline{\mu}_1\|_2$$

$$g_2(\underline{x}) = -\|\underline{x} - \underline{\mu}_2\|_2$$

$$g_3(\underline{x}) = -\|\underline{x} - \underline{\mu}_3\|_2$$

Decision Rule:  $g_k(\underline{x}) > g_j(\underline{x}) \quad \forall j \neq k$   
 $\Rightarrow \underline{x} \in \Gamma_k$

Decision Boundary b/w  $\Gamma_k$  &  $\Gamma_j$  is

$$g_k(\underline{x}) = g_j(\underline{x})$$

$$\Rightarrow -\|\underline{x} - \underline{\mu}_k\|_2 = -\|\underline{x} - \underline{\mu}_j\|_2$$

$$\|\underline{x} - \underline{\mu}_k\|_2 = \|\underline{x} - \underline{\mu}_j\|_2$$

which is same as the  $C=2$  class case.

Hence the classified is Linear.

(d)  $\underline{\mu}_1 = \begin{bmatrix} 0 \\ -2 \end{bmatrix}, \underline{\mu}_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \underline{\mu}_3 = \begin{bmatrix} 2 \\ 0 \end{bmatrix}$

## Decision Boundaries

$$H_{12} \rightarrow g_1(\mathbf{z}) = g_2(\mathbf{z})$$

$$\|\mathbf{z}_i - \mathbf{\mu}_1\|_2 = \|\mathbf{z} - \mathbf{\mu}_2\|_2$$

$$\left( \sum_{i=1}^2 (x_i - \mu_{1i})^2 \right)^{1/2} = \left( \sum_{i=1}^2 (x_i - \mu_{2i})^2 \right)^{1/2}$$

Squaring and Expanding

$$\left( (x_1 - 0)^2 + (x_2 + 2)^2 \right)^{1/2} = (x_1 - 0)^2 + (x_2 - 1)^2$$

$$x_1^2 + 4x_2 + 4 = x_1^2 - 2x_2 + 1$$

$$6x_2 = -3$$

$$\boxed{x_2 = -0.5} \rightarrow H_{12}$$

$$H_{13} \rightarrow g_1(\mathbf{z}) = g_3(\mathbf{z})$$

$$\|\mathbf{z} - \mathbf{\mu}_1\|_2 = \|\mathbf{z} - \mathbf{\mu}_3\|_2$$

Squaring and Expanding  $\rightarrow$

$$(x_1 - 0)^2 + (x_2 + 2)^2 = (x_1 - 2)^2 + (x_2 - 0)^2$$

$$\pm(x_2 + 2) = \pm(x_1 - 2)$$

$$\Rightarrow x_2 + 2 = x_1 - 2 \quad | \quad x_2 + 2 = -x_1 + 2$$

$$\boxed{x_2 - x_1 = -4}$$

$$\boxed{x_2 = -x_1}$$

$$x_2 = 0 \Rightarrow x_1 = 4 \Rightarrow (4, 0)$$

$$x_2 = 0 \Rightarrow x_1 = 0 \rightarrow (0, 0)$$

$$x_1 = 0 \Rightarrow x_2 = -4 \Rightarrow (0, -4)$$

$$x_2 = 1 \Rightarrow x_1 = -1 \Rightarrow (-1, 1)$$

$$H_{23} \rightarrow g_2(z) = g_3(z)$$

$$\|z - \mu_2\|_2 = \|z - \mu_3\|_2$$

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Squaring & Expanding  $\rightarrow$

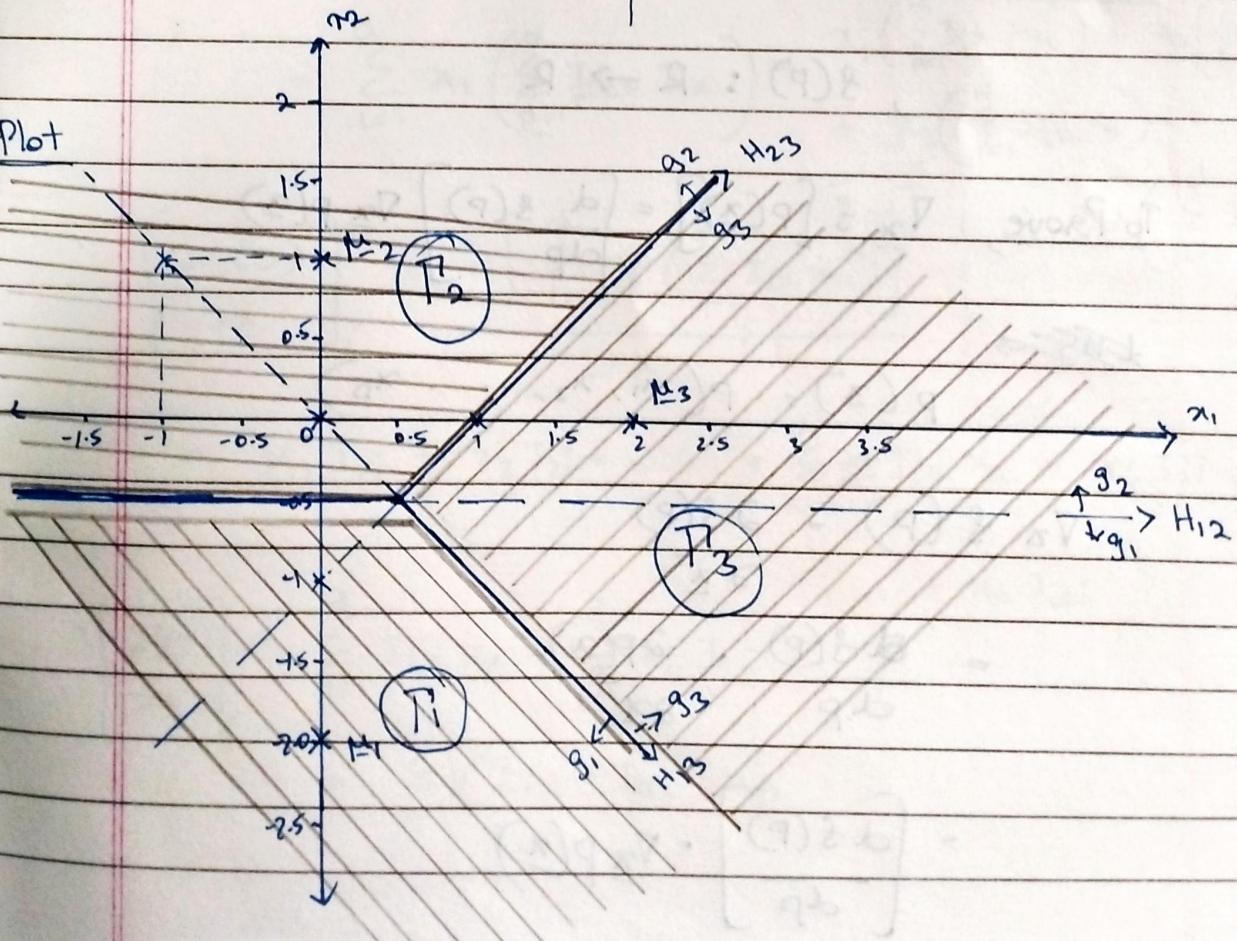
$$(x_1 - 0)^2 + (x_2 - 1)^2 = (x_1 - 2)^2 + (x_2 - 0)^2$$

$$(x_2 - 1)^2 = (x_1 - 2)^2$$

$$\Rightarrow x_2 - 1 = x_1 - 2 \quad | \quad x_2 - 1 = -x_1 + 2$$
$$\boxed{x_2 - x_1 = -1} \quad | \quad \boxed{x_2 + x_1 = 3}$$

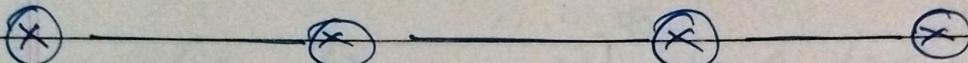
$$x_2 = 0 \Rightarrow x_1 = 1 \rightarrow (1, 0) \quad | \quad x_2 = 0 \Rightarrow x_1 = 3 \rightarrow (3, 0)$$
$$x_1 = 0 \Rightarrow x_2 = -1 \rightarrow (0, -1) \quad | \quad x_1 = 0 \Rightarrow x_2 = 3 \rightarrow (0, 3)$$

Plot



We chose points  $\{(0,0), (-1,1)\}$  for  $H_{13}$   
 and points  $\{(1,0), (0,-1)\}$  for  $H_{23}$  instead of  
 because they satisfied the discriminant funct<sup>n</sup> of its  
 decision rule.

Points  $\{(4,0), (0,-4)\}$  for  $H_{13}$  &  $\{(3,0), (0,3)\}$  for  
 $H_{23}$  didn't satisfy the constraints.



4 @ Given,  
 $\underline{x} \in \mathbb{R}^D$

Scalar function,  $P(\underline{x}) : \mathbb{R}^D \rightarrow \mathbb{R}$

,  $f(P) : \mathbb{R} \rightarrow \mathbb{R}$

To Prove,  $\nabla_{\underline{x}} f[P(\underline{x})] = \left[ \frac{d}{dp} f(p) \right] \nabla_{\underline{x}} P(\underline{x})$

~~LHS~~  $\Rightarrow$

$$P(\underline{x}) = P(x_1, x_2, \dots, x_D)$$

$$\nabla_{\underline{x}} f(P) = \frac{\partial f(P)}{\partial \underline{x}}$$

$$= \frac{\partial f(P)}{\partial p} \cdot \frac{\partial P(\underline{x})}{\partial \underline{x}}$$

$$= \left[ \frac{\partial f(P)}{\partial p} \right] \cdot \nabla_{\underline{x}} P(\underline{x})$$

① Find  $\nabla_{\underline{x}} (\underline{x}^T \underline{x})$

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$$f(\underline{x}) = \underline{x}^T \underline{x}$$

$$= \underline{x}^T \underline{\underline{I}} \underline{x}$$

$$\nabla_{\underline{x}} f(\underline{x}) = \frac{\partial f(\underline{x})}{\partial \underline{x}}$$

$$= (\underline{\underline{I}} + \underline{\underline{I}}^T) \underline{x}$$

$$\nabla_{\underline{x}} f(\underline{x}) = 2\underline{\underline{I}} \underline{x} = 2\underline{x}$$

② Prove  $\nabla_{\underline{x}} [\underline{x}^T \underline{x}] = 2\underline{x}$

$$f(\underline{x}) = \underline{x}^T \underline{x} = \underline{x}^T \underline{\underline{I}} \underline{x}$$

$$= \sum_{l=1}^d x_l \left( \sum_{n=1}^d I_{ln} x_n \right) = x_1 \left( \sum_{n=1}^d I_{1n} x_n \right) + x_2 \left( \sum_{n=1}^d I_{2n} x_n \right)$$

$$+ x_3 \left( \sum_{n=1}^d I_{3n} x_n \right) + \dots$$

$$\left[ \frac{\partial f(\underline{x})}{\partial \underline{x}} \right]_i = \frac{\partial \left[ \sum_{l=1}^d x_l \left( \sum_{n=1}^d I_{ln} x_n \right) \right]}{\partial x_i} = x_1 I_{1i} + x_2 I_{2i} + \dots + x_d I_{di}$$

$$= x_1 I_{1i} + x_2 I_{2i} + \dots + \sum_{n=1}^d I_{ni} x_n + x_i I_{ii} + \dots$$

$$\dots + x_d I_{di}$$

$$\left[ \frac{\partial f(\underline{x})}{\partial \underline{x}} \right]_i = \sum_{n=1}^d I_{ni} x_n + \sum_{l=1}^d x_l I_{li}$$

$$= \sum_{n=1}^d (I_{ni} + I_{ni}) x_n$$

$$\left[ \frac{\partial f(\underline{x})}{\partial x_i} \right]_i = (I_{ii} + I_{1i}^o) x_1 + (I_{i2} + I_{2i}^o) x_2 + \dots + (I_{ii}^o + I_{ii}^o) x_i + \dots + (I_{id} + I_{di}^o) x_d$$

$$= 2x_i$$

$$\nabla_{\underline{x}} f(\underline{x}) = \begin{bmatrix} \left( \frac{\partial f(\underline{x})}{\partial x_1} \right)_1 \\ \left( \frac{\partial f(\underline{x})}{\partial x_2} \right)_2 \\ \vdots \\ \left( \frac{\partial f(\underline{x})}{\partial x_d} \right)_d \end{bmatrix} = \begin{bmatrix} 2x_1 \\ 2x_2 \\ \vdots \\ 2x_d \end{bmatrix} = 2 \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_d \end{bmatrix}$$

$$\boxed{\nabla_{\underline{x}} f(\underline{x}) = 2\underline{x}}$$

Hence Proved

@  $\nabla_{\underline{x}} \left[ (\underline{x}^T \underline{x})^3 \right]$  ; Let  $p(\underline{x}) = \underline{x}^T \cdot \underline{x}$

$\downarrow$  Let  $f(p) = p^3$

$$\nabla_{\underline{x}} [f(p)] = \left[ \frac{df(p)}{dp} \right] \nabla_{\underline{x}} p(\underline{x})$$

$$\frac{df(p)}{dp} = 3p^2$$

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$$\nabla_{\underline{x}} P(\underline{x}) = \nabla_{\underline{x}} (\underline{x}^T \cdot \underline{x}) = 2 \underline{x}$$

$$\therefore \nabla_{\underline{x}} \left[ (\underline{x}^T \cdot \underline{x})^3 \right] = 3 (\underline{x}^T \cdot \underline{x})^2 \cdot 2 \underline{x} = 6 (\underline{x}^T \cdot \underline{x})^2 \cdot \underline{x}$$



5@ Find  $\nabla_{\underline{w}} \|\underline{w}\|_2$ ; We know

$$\|\underline{w}\|_2 = (\underline{w}^T \cdot \underline{w})^{1/2}$$

$$\nabla_{\underline{w}} \left[ (\underline{w}^T \cdot \underline{w})^{1/2} \right] ; \text{ Let } p(\underline{w}) = \underline{w}^T \cdot \underline{w}$$

$$\text{Let } f(p) = p^{1/2}$$

$$\nabla_{\underline{w}} f(p) = \left[ \frac{df(p)}{dp} \right] \cdot \nabla_{\underline{w}} p(\underline{w})$$

$$\frac{df(p)}{dp} = \frac{1}{2} p^{-1/2} ; \nabla_{\underline{w}} (\underline{w}^T \cdot \underline{w}) = 2 \underline{w}$$

$$\therefore \nabla_{\underline{w}} \|\underline{w}\|_2 = \frac{1}{2} (\underline{w}^T \cdot \underline{w})^{-1/2} \cdot 2 \underline{w} = (\underline{w}^T \cdot \underline{w})^{-1/2} \underline{w}$$

(b) Find,  $\nabla_{\underline{w}} \|\underline{M}\underline{w} - \underline{b}\|_2$ ;  $\|\underline{w}\|_2 = (\underline{w}^T \cdot \underline{w})^{1/2}$

$$\Rightarrow \nabla_{\underline{w}} \left[ (\underline{M}\underline{w} - \underline{b})^T \cdot (\underline{M}\underline{w} - \underline{b}) \right]^{1/2}$$

$$\text{Let } P(\underline{\omega}) = (\underline{\underline{M}} \underline{\omega} - \underline{b})^T \cdot (\underline{\underline{M}} \underline{\omega} - \underline{b})$$

$$\text{Let } f(P) = P^{1/2}$$

$$\nabla_{\underline{\omega}} f(P) = \left[ \frac{df(P)}{dP} \right] \cdot \nabla_{\underline{\omega}} P$$

$$\nabla_{\underline{\omega}} P = \frac{\partial P(\underline{\omega})}{\partial \underline{\omega}} = \frac{\partial}{\partial \underline{\omega}} \left[ \left\{ (\underline{\underline{M}} \underline{\omega})^T - \underline{b}^T \right\} (\underline{\underline{M}} \underline{\omega} - \underline{b}) \right]$$

$$= \frac{\partial}{\partial \underline{\omega}} \left[ (\underline{\underline{M}} \underline{\omega})^T (\underline{\underline{M}} \underline{\omega}) - (\underline{\underline{M}} \underline{\omega})^T \underline{b} - \underline{b}^T \underline{\underline{M}} \underline{\omega} + \underline{b}^T \underline{b} \right]$$

$$= \frac{\partial}{\partial \underline{\omega}} \left[ \underline{\omega}^T (\underline{\underline{M}}^T \underline{\underline{M}} \underline{\omega}) - \underline{\omega}^T (\underline{\underline{M}}^T \underline{b}) - (\underline{b}^T \underline{\underline{M}}) \underline{\omega} + \underline{b}^T \underline{b} \right]$$

$$= \frac{\partial}{\partial \underline{\omega}} \left[ \underline{\omega}^T (\underline{\underline{M}}^T \underline{\underline{M}} \underline{\omega}) - \underline{\omega}^T (\underline{\underline{M}}^T \underline{b}) - (\underline{\underline{M}}^T \underline{b})^T \underline{\omega} + \underline{b}^T \underline{b} \right]$$

$$\text{We know if } f(x) = \underline{y}^T \underline{x} = \underline{x}^T \underline{y} \rightarrow \frac{\partial f(x)}{\partial \underline{x}} = \underline{y}$$

$$\Rightarrow \nabla_{\underline{\omega}} P = \underline{\underline{M}}^T \underline{\underline{M}} \underline{\omega} - \underline{\underline{M}}^T \underline{b} - \underline{\underline{M}}^T \underline{b}$$

$$= \underline{\underline{M}}^T \underline{\underline{M}} \underline{\omega} - 2 \underline{\underline{M}}^T \underline{b}$$

$$\nabla_{\underline{w}} \|\underline{\underline{M}} \underline{w} - \underline{b}\|_2 = \left[ (\underline{\underline{M}} \underline{w} - \underline{b})^T \cdot (\underline{\underline{M}} \underline{w} - \underline{b}) \right] \circ$$
$$\left( \underline{\underline{M}}^T \underline{\underline{M}} \underline{w} - 2 \underline{\underline{M}}^T \underline{b} \right)$$

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