

For XOR data set

$x_1$	$x_2$	$y$
0	0	-1
0	1	1
1	0	1
1	1	-1

Here we are using the kernel function

~~we are~~ for  $x = \begin{pmatrix} u_1 \\ u_2 \end{pmatrix}$   $x' = \begin{pmatrix} v_1 \\ v_2 \end{pmatrix}$

$$K(x, x') = \frac{(x^T x' + 1)^2}{(u_1 v_1 + u_2 v_2 + 1)^2}$$

$$= 1 + (u_1 v_1 + u_2 v_2)^2 + 2(u_1 v_1 + u_2 v_2)$$

$$= 1 + u_1^2 v_1^2 + u_2^2 v_2^2 + 2u_1 v_1 + 2u_2 v_2$$

So the equivalent transformation

$x \Rightarrow [1, \sqrt{2}u_1, \sqrt{2}u_2, u_1^2, u_2^2, \sqrt{2}u_1 u_2]^T$

for  $(x_1, x_2) = (0, 0)$

$$\Phi([0, 0]) = [1, 0, 0, 0, 0, 0]^T$$

$$\Phi([0, 1]) = [1, 0, \sqrt{2}, 0, 1, 0]^T$$

$$\Phi([1, 0]) = [1, \sqrt{2}, 0, 1, 0, 0]^T$$

$$\Phi([1, 1]) = [1, \sqrt{2}, \sqrt{2}, 1, 1, \sqrt{2}]^T$$

$$L(\alpha) = \alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 - \frac{1}{2} \sum_{i=1}^4 \sum_{j=1}^4 \alpha_i \alpha_j y_i y_j K_{ij}$$

s.t  $\alpha_i y_i = 0 \Rightarrow \alpha_1 + \alpha_4 = \alpha_2 + \alpha_3$   
 $\alpha_i \geq 0$

inner product = K

$$\begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 4 & 1 & 4 \\ 1 & 1 & 4 & 4 \\ 1 & 4 & 4 & 9 \end{bmatrix}$$

Our Lagrange equation =

$$\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 - \frac{1}{2} (\alpha_1^2 + 4\alpha_2^2 + 4\alpha_3^2 + 9\alpha_4^2 +$$

$$- \alpha_1\alpha_2 - \alpha_1\alpha_3 + \alpha_1\alpha_4$$

$$- \alpha_1\alpha_2 - \alpha_1\alpha_3 + \alpha_1\alpha_4$$

$$+ \alpha_2\alpha_3 + \alpha_2\alpha_4 - 4\alpha_2\alpha_4 - 4\alpha_4\alpha_2 - 4\alpha_3\alpha_4 - 4\alpha_4\alpha_3)$$

$$= \alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 + \frac{\alpha_1^2}{2} + \frac{2\alpha_2^2}{2} + \frac{2\alpha_3^2}{2} + \frac{9\alpha_4^2}{2} - \alpha_1\alpha_2$$

$$- \alpha_1\alpha_3 + \alpha_1\alpha_4 + \alpha_2\alpha_3 - 4\alpha_2\alpha_4 - 4\alpha_3\alpha_4$$

$$\frac{\partial L}{\partial \alpha_1} = 0 \Rightarrow \alpha_1 - \alpha_2 - \alpha_3 + \alpha_4 = 1 \quad (i)$$

$$\frac{\partial L}{\partial \alpha_2} = 0 \Rightarrow 4\alpha_2 - \alpha_1 + \alpha_3 - 4\alpha_4 = 1 \quad (ii)$$

$$\frac{\partial L}{\partial \alpha_3} = 0 \Rightarrow 4\alpha_3 - \alpha_1 + \alpha_2 - 4\alpha_4 = 1 \quad (iii)$$

$$\frac{\partial L}{\partial \alpha_4} = 0 \Rightarrow \alpha_1\alpha_4 + \alpha_1 - 4\alpha_2 - 4\alpha_3 = 1 \quad (iv)$$

from the following equations

$$\alpha_1 = \frac{13}{3} \quad \alpha_2 = \frac{8}{3} \quad \alpha_3 = \frac{8}{3} \quad \alpha_4 = 2$$

as we know

$$w = \sum_{i=1}^4 \alpha_i y_i \phi(x_i)$$



$$-\frac{13}{3} \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \frac{8}{3} \begin{bmatrix} 1 \\ 0 \\ \sqrt{2} \\ 0 \\ 1 \\ 0 \end{bmatrix} + \frac{8}{3} \begin{bmatrix} 1 \\ \sqrt{2} \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} - 2 \begin{bmatrix} 1 \\ \sqrt{2} \\ \sqrt{2} \\ 1 \\ 1 \\ \sqrt{2} \end{bmatrix}$$

$$2 \begin{bmatrix} -1 \\ \frac{2\sqrt{2}}{3} \\ \frac{2\sqrt{2}}{3} \\ -2\sqrt{2} \\ \frac{2}{3} \\ 2 \end{bmatrix}$$

$$g(x_1, x_2) = \omega^T \Phi(x)$$

$$2 \left[ \begin{array}{ccc|ccc} -1 & \frac{2\sqrt{2}}{3} & \frac{2\sqrt{2}}{3} & \frac{2\sqrt{2}}{3} & \frac{2}{3} & 2 \\ \hline & & & & & \end{array} \right] \begin{bmatrix} 1 \\ \sqrt{2}x_1 \\ \sqrt{2}x_2 \\ x_1^2 \\ x_2^2 \\ \sqrt{2}x_1x_2 \end{bmatrix}$$

• decision boundary

$$-1 + \frac{4}{3}x_1 + \frac{4}{3}x_2 + \frac{2}{3}x_1^2 + \frac{2}{3}x_2^2 - 4x_1x_2 \geq 0$$



Q Bayes classifier means classification of datapoints into 2 or more classes based on the probability of occurrence of their attributes in Class<sub>1</sub> or Class<sub>2</sub>.



Q3 Let  $N$  be equal to the total number of data points and  $N_1$  be the data points for ~~test~~ <sup>Class 1</sup> and  $N_2$  for ~~test~~ <sup>Class 2</sup>

We label  $t$  as  $\frac{N}{N_1}$  for  $C_1$  and  $-\frac{N}{N_2}$  for  $C_2$

Then the Sum of Square error function

$$E = \frac{1}{2} \sum_{n=1}^N (\omega^T x_n + \omega_0 t_n)^2$$

$$\frac{\partial E}{\partial \omega} = 0 \Rightarrow \sum_{n=1}^N (\omega^T x_n + \omega_0 t_n) x_n = 0 \quad (I)$$

$$\frac{\partial E}{\partial \omega_0} = 0 \Rightarrow \sum_{n=1}^N (\omega^T x_n + \omega_0 t_n) t_n = 0 \quad (II)$$

from II we can compute

$$\omega_0 = -\omega^T \bar{m}$$

here  $\bar{m} = \frac{1}{N} \sum_{n=1}^N x_n$

$$\text{i.e. } \bar{m} = \frac{1}{N} (N_1 \bar{m}_1 + N_2 \bar{m}_2)$$

Here  $\bar{m}_1$  and  $\bar{m}_2$  are corresponding mean of dataset belong to class  $C_1$  and  $C_2$

and we can see

$$\sum_{n=1}^N t_n = N_1 \frac{N}{N_1} - N_2 \frac{N}{N_2} = 0$$



Equation (4) can also be written as

$$\left( S_W + \frac{N_1 N_2}{N} S_B \right) \omega = N (\bar{m}_1 - \bar{m}_2)$$

$$\text{Here } S_W = \sum_{n \in C_1} (x_n - \bar{m}_1)(x_n - \bar{m}_1)^T + \sum_{n \in C_2} (x_n - \bar{m}_2)(x_n - \bar{m}_2)^T$$

$$S_B = (\bar{m}_2 - \bar{m}_1)(\bar{m}_2 - \bar{m}_1)^T$$

To get the direction of  $\omega$

We can see  $S_B \omega$  is always in the direction of  $(\bar{m}_2 - \bar{m}_1)$

$$\omega \propto S_W^{-1} (\bar{m}_2 - \bar{m}_1)$$

which is the same solution for Fisher linear discriminant analysis



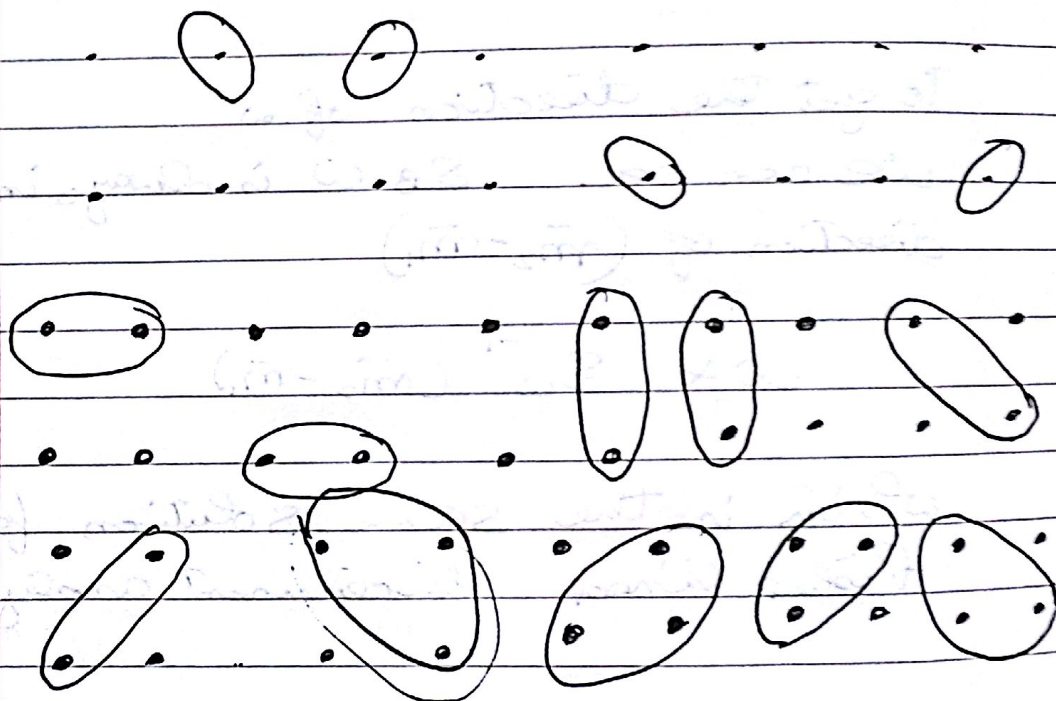
Q5

Data points

$\alpha_1 (-1, -1)$   $\alpha_2 (-1, 1)$

$\alpha_3 (+1, -1)$   $\alpha_4 (+1, 1)$

- a) Linear kernel cannot shatter this  
 b) Polynomial kernel of degree 2 can shatter this. We take here ~~a parallel~~ an ellipse to show shattering



c) Gaussian kernel can shatter it

