

(Q1) (a) Feature extraction is the process of transforming the raw input data into some reduced representation. The representation thus reflects some measurable property or subset of the raw data - preferably chosen so as to facilitate discrimination between known classes.

— desirable properties

- Invariance (rotation, scaling, etc).
- Good discrimination / sep. between classes
- Compact / low variance within class

(b) Generalization \leftrightarrow Overfitting. TRADEOFF

ability for classifier to perform well on unseen / novel patterns

ability for classifier to perform well on training data - if highly fitted, may do well in classifying training samples at the expense of unseen novel samples.

(c) BDT vs LDA.

In BDT we assume the FORM of the distribution of each class, through which we attain an implicit boundary between classes. In LDA we do not assume anything about the form of the distribution of each class, but rather we assume the explicit form of the boundary itself. In LDA for instance, the form used to model the boundary is linear $W^T X + w_0 = g(x)$. probability

$$(d) \mu_1 = \begin{pmatrix} -1 \\ 1 \end{pmatrix} \quad \mu_2 = \begin{pmatrix} 1 \\ 1 \end{pmatrix} \quad \Sigma_1 = \begin{pmatrix} 2 & 3 \\ 3 & 2 \end{pmatrix} \quad x_1 = \begin{pmatrix} 0 \\ -1 \end{pmatrix}$$

* decision rule: choose w_1 if $g_1(x) > g_2(x)$
otherwise choose w_2 .

$$g_i(x) = -\frac{1}{2}(x - \mu_i)^T \Sigma_i^{-1} (x - \mu_i)$$

$$- \frac{d}{2} \ln 2\pi - \frac{1}{2} \ln |\Sigma_i| + \ln P(w_i)$$

constant.

since $\Sigma_i = \Sigma_j = \Sigma_1$ and $P(w_1) = P(w_2)$

$$\therefore g_i(x) = -\frac{1}{2} (x - \mu_i)^T \Sigma_1^{-1} (x - \mu_i)$$

$$|\Sigma_1| = 2(2) - 3(3) = -5$$

$$\Sigma_1^{-1} = -\frac{1}{5} \begin{pmatrix} 2 & -3 \\ -3 & 2 \end{pmatrix} = \begin{pmatrix} -2/5 & 3/5 \\ 3/5 & -2/5 \end{pmatrix}$$

$$(x_1 - \mu_1) = \begin{pmatrix} 0 \\ -1 \end{pmatrix} - \begin{pmatrix} -1 \\ 1 \end{pmatrix} = \begin{pmatrix} 1 \\ -2 \end{pmatrix}$$

$$(x_1 - \mu_2) = \begin{pmatrix} 0 \\ -1 \end{pmatrix} - \begin{pmatrix} 1 \\ 1 \end{pmatrix} = \begin{pmatrix} -1 \\ -2 \end{pmatrix}$$

$$\therefore g_1(x_1) = -\frac{1}{2} (1 - 2) \begin{pmatrix} -2/5 & 3/5 \\ 3/5 & -2/5 \end{pmatrix} \begin{pmatrix} 1 \\ -2 \end{pmatrix}$$

$$= -\frac{1}{2} \left(\begin{pmatrix} -2/5 & -6/5 \end{pmatrix} \begin{pmatrix} 3/5 & 4/5 \end{pmatrix} \right) \begin{pmatrix} 1 \\ -2 \end{pmatrix} = -\frac{1}{2} \begin{pmatrix} -8/5 & 7/5 \end{pmatrix} \begin{pmatrix} 1 \\ -2 \end{pmatrix}$$

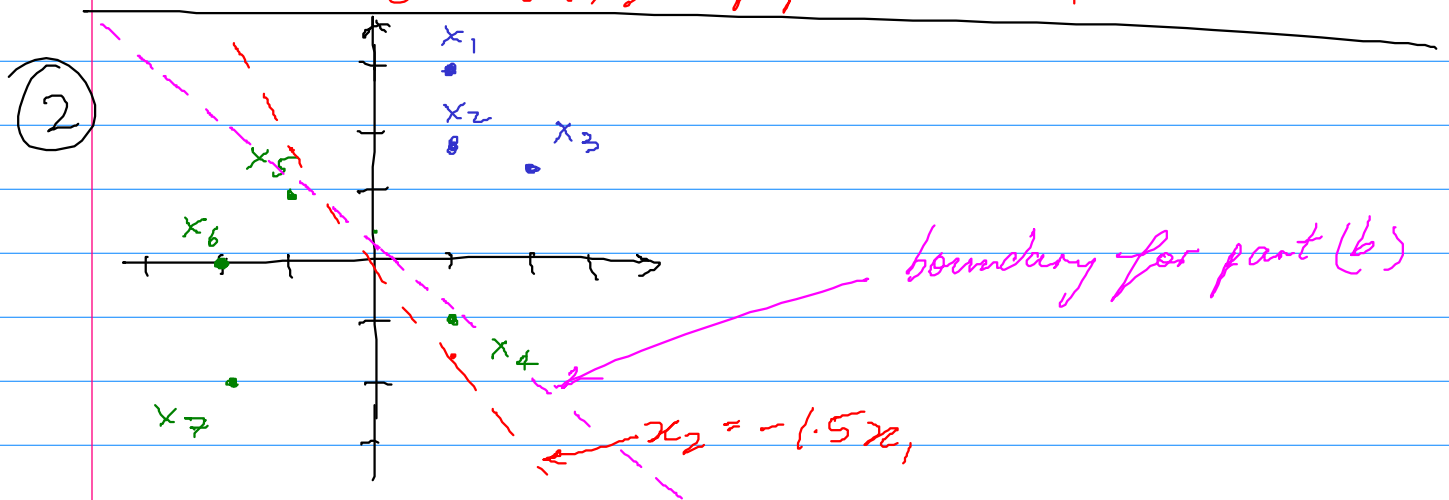
$$= -\frac{1}{2} \left(\frac{-22}{5} \right) = \frac{11}{5}$$

$$\begin{aligned}
 g_2(x_1) &= \frac{-1}{2} \begin{pmatrix} -1 & -2 \end{pmatrix} \begin{pmatrix} -\frac{2}{5} & \frac{3}{5} \\ \frac{3}{5} & -\frac{2}{5} \end{pmatrix} \begin{pmatrix} -1 \\ -2 \end{pmatrix} \\
 &= \frac{-1}{2} \begin{pmatrix} \frac{2}{5} - \frac{6}{5} & \frac{-3}{5} + \frac{4}{5} \end{pmatrix} \begin{pmatrix} -1 \\ -2 \end{pmatrix} \\
 &= \frac{-1}{2} \begin{pmatrix} -\frac{4}{5} & \frac{1}{5} \end{pmatrix} \begin{pmatrix} -1 \\ -2 \end{pmatrix} = \frac{-1}{2} \left(\frac{2}{5} \right) = -\frac{1}{5}
 \end{aligned}$$

since $g_1(x_1) > g_2(x_1)$

$$\Rightarrow \boxed{x_1 \in w_1}$$

* $g_2(x_1) > g_1(x_1)$ for paper B $\rightarrow x_1 \in w_2$



(a)

$$\begin{aligned}
 x_1 &= \begin{pmatrix} 1 & 3 \end{pmatrix} \rightarrow w_1 & g(x_1) &= 4.5 \\
 x_7 &= \begin{pmatrix} -2 & -2 \end{pmatrix} \rightarrow w_2 & g(x_7) &= -5 \\
 & & g(0) &= 0.
 \end{aligned}$$

$$g(x) = w_0 + w_1 x_1 + w_2 x_2$$

$$g(0) = w_0 = 0$$

$$\therefore g(x_1) = w_1(1) + 3w_2 = 4.5 \rightarrow w_1 = -3w_2 + 4.5$$

$$g(x_7) = -2w_1 - 2w_2 = -5$$

$$-2(-3w_2 + 4.5) - 2w_2 = -5$$

$$\begin{aligned}
 4w_2 &= 4 \Rightarrow w_1 = -3 + 4.5 \\
 w_2 &= 1 & &= 1.5
 \end{aligned}$$

$$\therefore a = \begin{bmatrix} w_0 \\ w_1 \\ w_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 1.5 \\ 1 \end{bmatrix}$$

$$\therefore g(x) = a^T y = \begin{bmatrix} 0 & 1.5 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ x_1 \\ x_2 \end{bmatrix}$$

$$= 1.5x_1 + x_2$$

$$1.5x_1 + x_2 = 0$$

$$x_2 = -1.5x_1$$

\Rightarrow boundary classifies x_4 incorrectly $x_4 = (1 \ -1)$
 $1.5(+1) + -1 = 0.5$ should be negative!

(b).

$$\begin{array}{llll} x_1 & \rightarrow & 1 & 3 & w_1 \\ x_2 & \rightarrow & 1 & 2 & w_1 \\ x_5 & \rightarrow & -1 & 1 & w_2 \\ x_4 & \rightarrow & 1 & -1 & w_2 \end{array}$$

$\Rightarrow \hat{Y} =$
 Augment
 & normalize

$$\begin{array}{cccc} x_1 & x_2 & x_5 & x_4 \\ \hat{y}_1 & \hat{y}_2 & \hat{y}_3 & \hat{y}_4 \\ \downarrow & \downarrow & \downarrow & \downarrow \\ \begin{bmatrix} 1 & 1 & -1 & -1 \\ 1 & 1 & 1 & -1 \\ 3 & 2 & -1 & 1 \end{bmatrix} \end{array}$$

single sample criterion

$$\text{if } a^T \hat{y}_k < 0$$

$$a(k+1) \leftarrow a(k) + \eta \hat{y}_k$$

else $a(k+1) \leftarrow a(k)$

$$a(0) = \begin{pmatrix} -0.1 \\ -0.1 \\ -0.1 \end{pmatrix} \quad \eta(\cdot) = 1$$

step 1: $a(0)^T \hat{y}_1$

$$= (-0.1 \ -0.1 \ -0.1) \begin{pmatrix} 1 \\ 1 \\ 3 \end{pmatrix}$$

$$= -0.5 < 0$$

missclassified \therefore update

$$\Rightarrow a(1) = \begin{pmatrix} -0.1 \\ -0.1 \\ -0.1 \end{pmatrix} + \begin{pmatrix} 1 \\ 1 \\ 3 \end{pmatrix} = \begin{pmatrix} 0.9 \\ 0.9 \\ 2.9 \end{pmatrix}$$

step 2

$$a(1)^T y_2 = (0.9 \ 0.9 \ 2.9) \begin{pmatrix} 1 \\ 1 \\ 2 \end{pmatrix}$$

$$= 0.9 + 0.9 + 5.8$$

$$= 7.6 > 0 \quad \Rightarrow \text{correctly classified} \therefore \text{no change}$$

$$\therefore a(2)^T = (0.9 \ 0.9 \ 2.9)$$

step 3 $a(2)^T y_3 = (0.9 \ 0.9 \ 2.9) \begin{pmatrix} -1 \\ 1 \\ -1 \end{pmatrix}$

$$= -2.9 < 0 \quad \Rightarrow \text{missclassified} \therefore \text{update}$$

$$\therefore a(3) = \begin{pmatrix} 0.9 \\ 0.9 \\ 2.9 \end{pmatrix} + \begin{pmatrix} -1 \\ 1 \\ -1 \end{pmatrix} = \begin{pmatrix} -0.1 \\ 1.9 \\ 1.9 \end{pmatrix}$$

Step 4 $\alpha(3)^T y_4 = \begin{pmatrix} -0.1 & 1.9 & 1.9 \end{pmatrix} \begin{pmatrix} -1 \\ -1 \\ 1 \end{pmatrix}$

$= 0.1 - 1.9 + 1.9 > 0 \Rightarrow$ classified correctly \therefore no update.

$\therefore \alpha(4) = \begin{pmatrix} -0.1 \\ 1.9 \\ 1.9 \end{pmatrix}$

** when you draw boundary \rightarrow all samples correctly classified \therefore would expect no further iterations to cause updates.

$g(x) = \alpha^T y = \begin{pmatrix} -0.1 & 1.9 & 1.9 \end{pmatrix} \begin{pmatrix} 1 \\ x_1 \\ x_2 \end{pmatrix}$
 $= -0.1 + 1.9x_1 + 1.9x_2 \Rightarrow x_2 = \frac{-1.9x_1 + 0.1}{1.9}$

* same approach for paper B, just different order for presenting & testing \hat{y}_k 's

(c) Single sample perceptron vs LMS.

\rightarrow LMS uses every sample to update α . (updates at every step)
 \leftarrow SSP only uses sample if it is misclassified by the current α .

\rightarrow LMS imposes a margin into the update process
 \leftarrow SSP has no margin

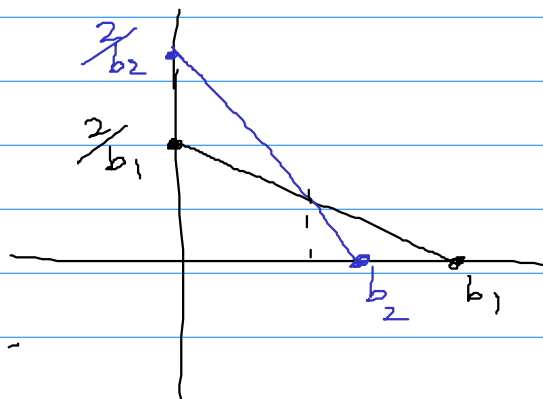
(these are the main diffs)

$$(3) \quad p(x/w_i) = \begin{cases} 0 & x \leq 0 \\ \frac{2}{b_i} \left(1 - \frac{x}{b_i}\right) & 0 \leq x \leq b_i \\ 0 & \text{otherwise} \end{cases}$$

(a) $b_1 > b_2$.

$$w_1 \rightarrow p(x/w_1) = \frac{2}{b_1} \left(1 - \frac{x}{b_1}\right)$$

$$w_2 \rightarrow p(x/w_2) = \frac{2}{b_2} \left(1 - \frac{x}{b_2}\right)$$



likelihood $\rightarrow \frac{p(x/w_1)}{p(x/w_2)} = \frac{\frac{2}{b_1} \left(1 - \frac{x}{b_1}\right)}{\frac{2}{b_2} \left(1 - \frac{x}{b_2}\right)}$

$$= \frac{b_2^2 (b_1 - x)}{b_1^2 (b_2 - x)}$$

(b) min error rate classifier

\rightarrow zero-one loss

$$\lambda_{11} = \lambda_{22} = 0$$

$$\lambda_{12} = \lambda_{21} = 1$$

assumptions

\rightarrow assume equal priors

$$P(w_1) = P(w_2) = 0.5$$

$$\therefore \text{likelihood} \cdot \frac{p(x/w_1)}{p(x/w_2)} > \frac{\lambda_{21} - \lambda_{11}}{\lambda_{12} - \lambda_{22}} \frac{P(w_1)}{P(w_2)}$$

decision
boundary
@

$$\frac{b_2^2 (b_1 - x)}{b_1^2 (b_2 - x)} > 1$$

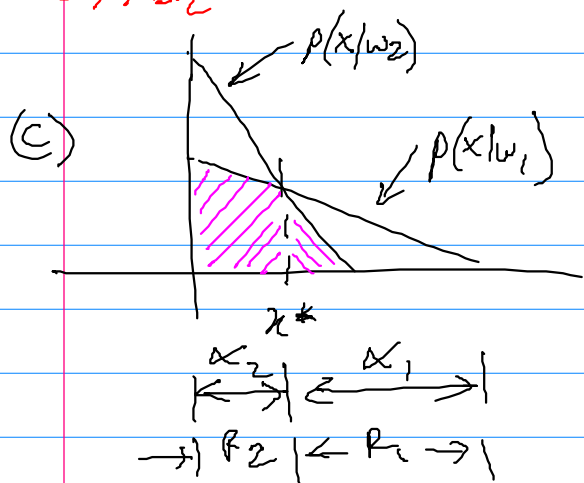
$$b_2^2 (b_1 - x) > b_1^2 (b_2 - x)$$

$$x(b_1^2 - b_2^2) > b_1 b_2 (b_1 - b_2)$$



$$x > \frac{b_1 b_2 (b_1 - b_2)}{b_1^2 - b_2^2} = (b_1 + b_2)(b_1 - b_2)$$

$$x > \frac{b_1 b_2}{b_1 + b_2}$$



$$P_E = P(\text{error}) = P(\alpha_2, x \in w_1) + P(\alpha_1, x \in w_2)$$

$$= \int_{R_2} p(x/w_1) p(w_1) dx + \int_{R_1} p(x/w_2) p(w_2) dx$$

$$P_E = \int_0^{x^*} \frac{2}{b_1} \left(\frac{b_1 - x}{b_1} \right) \cdot \frac{1}{2} dx + \int_{x^*}^{b_2} \frac{2}{b_2} \left(\frac{b_2 - x}{b_2} \right) \cdot \frac{1}{2} dx$$

$$= \frac{1}{b_1^2} \int_0^{x^*} (b_1 - x) dx + \frac{1}{b_2^2} \int_{x^*}^{b_2} (b_2 - x) dx$$

$$= \frac{1}{b_1^2} \left[b_1 x - \frac{x^2}{2} \right]_0^{x^*} + \frac{1}{b_2^2} \left[b_2 x - \frac{x^2}{2} \right]_{x^*}^{b_2}$$

$$= \frac{1}{b_1^2} \left[b_1 x^* - \frac{x^{*2}}{2} \right] + \frac{1}{b_2^2} \left[\left(b_2^2 - \frac{b_2^2}{2} \right) - \left(b_2 x^* - \frac{x^{*2}}{2} \right) \right]$$

$$= \left(\frac{1}{b_1} - \frac{1}{b_2} \right) x^* - \frac{1}{2} \left(\frac{1}{b_1^2} - \frac{1}{b_2^2} \right) x^{*2} + \frac{1}{2}$$

$$\frac{dP_E}{dx^*} = \left(\frac{1}{b_1} - \frac{1}{b_2} \right) - \frac{2}{2} \left(\frac{1}{b_1^2} - \frac{1}{b_2^2} \right) x^* = 0$$

$$\frac{b_2 - b_1}{b_1 b_2} - \left[\frac{b_2^2 - b_1^2}{(b_1 b_2)^2} \right] x^* = 0$$

$$x^* = \frac{(b_1 b_2)^2 (b_2 - b_1)}{(b_1 b_2) (b_2^2 - b_1^2)}$$

$$= \frac{b_1 b_2}{(b_2 + b_1)} \rightarrow \text{same as part (b)}$$

$$(d) P_E = \left(\frac{1}{b_1} - \frac{1}{b_2} \right) x^* - \frac{1}{2} \left(\frac{1}{b_1^2} - \frac{1}{b_2^2} \right) x^{*2} + \frac{1}{2}$$

$$\left[\begin{array}{l} b_1 = 10 \\ b_2 = 3 \end{array} \right] = \left(\frac{1}{10} - \frac{1}{3} \right) \left(\frac{30}{13} \right) - \frac{1}{2} \left(\frac{1}{100} - \frac{1}{9} \right) \left(\frac{30}{13} \right)^2 + \frac{1}{2}$$

$$\frac{b_1 b_2}{b_2 + b_1} = \frac{30}{13}$$

$$P_E = 0.2308$$

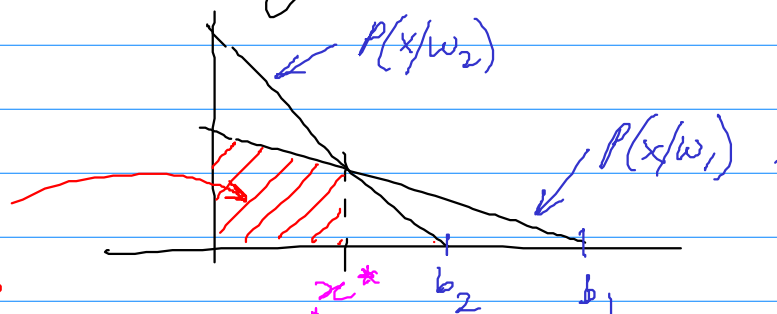
* for paper B \rightarrow insert $\left[\begin{array}{l} b_1 = 5 \\ b_2 = 3 \end{array} \right]$

$$(e) \lambda_1 > \lambda_2$$

\Rightarrow classifying w_1 incorrectly more costly

* move RIGHT for paper B

error in classifying x as w_2 if $x \in w_1$



α_1 classify $x \in w_1$

to REDUCE overall error, move x^* LEFT (toward origin)

