

1 LDA-Derivation from the LS Error

decision boundary in LDA given by D-1 dim. hyperplane:

$$\hat{w}^T x + \hat{b} = 0 \quad (\text{here } w \& x \text{ are column vectors!})$$

normal vector scalar

decision rule: $\hat{y} = \text{sign}(\hat{w}^T x + \hat{b}) = \begin{cases} 1 & \hat{w}^T x + \hat{b} > 0 \\ -1 & \text{---} < 0 \end{cases}$

training phase: N datapoints $\{x_i\}_{i=1}^N, x_i \in \mathbb{R}^D$ given
plus $\{y_i\}_{i=1}^N, y_i \in \{-1, 1\}$ labels.

(*) Assumption: balanced training set $N_1 = N_{-1} = \frac{N}{2}$

$$\hat{w}, \hat{b} = \underset{w, b}{\text{argmin}} \sum_{i=1}^N (w^T x_i + b - y_i)^2$$

a) Compute \hat{b} from $\frac{\partial}{\partial b} \sum_{i=1}^N (w^T x_i + b - y_i)^2 = 0$.

$$\rightarrow \frac{\partial}{\partial b} \sum_{i=1}^N (w^T x_i + b - y_i)^2 = \sum_{i=1}^N 2(w^T x_i + b - y_i) \stackrel{!}{=} 0$$

$$\Rightarrow Nb = - \sum_{i=1}^N w^T x_i - y_i$$

$$\Rightarrow \hat{b} = \frac{\sum_{i=1}^N y_i - w^T x_i}{N}$$

b) Show that $\frac{\partial}{\partial w} \sum_{i=1}^N (w^T x_i + \hat{b} - y_i)^2 = 0 \Leftrightarrow (S_w + \frac{1}{4} S_B) \hat{w} = (\mu_1 - \mu_{-1})$

with $a := \mu_1 = \frac{1}{N_1} \sum_{i: y_i=1} x_i$, $b := \mu_{-1} = \frac{1}{N_{-1}} \sum_{i: y_i=-1} x_i$

and $S_B = (a-b)(a-b)^T$ between class

$S_w = \frac{1}{N} \sum_{i=1}^N (x_i - \mu_{y_i})(x_i - \mu_{y_i})^T$ within-class.

$$\frac{\partial}{\partial w} \sum_{i=1}^N (w^T x_i + \hat{b} - y_i)^2 = 0 \quad \leftarrow \hat{y}_i = 0 \text{ wegen } *$$

Ans a) $\Leftrightarrow \sum_{i=1}^N (x_i - \frac{\sum x_i}{N}) \cdot (w^T x_i + \frac{1}{N} (\sum_{i=1}^N y_i - w^T x_i) - y_i) = 0$

$= \frac{Nb}{2}$ because $a+b = \frac{2}{N} (\sum_{i=1}^N x_i + \sum_{i=-1}^N x_i) = \frac{2}{N} \sum x_i$

$$\Leftrightarrow \sum_{i=1}^N (x_i - \frac{a+b}{2}) (w^T x_i - w^T \frac{a+b}{2} - y_i) = 0$$

$$= \sum_{i=1}^N x_i w^T x_i - x_i w^T \frac{a+b}{2} - x_i y_i - \frac{a+b}{2} w^T x_i + \frac{a+b}{2} w^T \frac{a+b}{2} + \frac{a+b}{2} y_i$$

$$\stackrel{(*)}{=} \sum_{i=1}^N \left(x_i x_i^T - x_i \left(\frac{a+b}{2} \right)^T - \frac{a+b}{2} x_i^T + \frac{a+b}{2} \left(\frac{a+b}{2} \right)^T \right) w - x_i y_i$$

$$\Leftrightarrow \sum_{i=1}^N \left[x_i x_i^T - \frac{x_i b^T}{2} - \frac{a x_i^T}{2} - \frac{b x_i^T}{2} + \frac{a a^T}{4} + \frac{a b^T}{4} + \frac{b a^T}{4} + \frac{b b^T}{4} \right] w = \sum_{i=1}^N x_i y_i$$

$$\Leftrightarrow \frac{1}{N} \sum_{i=1}^N \left[2 x_i x_i^T - x_i a^T - x_i b^T - a x_i^T - b x_i^T + \frac{a a^T + a b^T + b a^T + b b^T}{2} \right] w = a - b$$

$$\stackrel{?}{=} S_w + \frac{1}{4} S_B = \frac{1}{N} \sum_{i=1}^N [x_i - \mu_{y_i}][x_i - \mu_{y_i}]^T + \frac{1}{4} (a a^T - b a^T - a b^T + b b^T)$$

c) Show: $\hat{w} = \tau S_w^{-1} (a-b) \Leftrightarrow (S_w + \frac{1}{4} S_B) \hat{w} = a-b$

$$(S_w \tau^{-1}) \hat{w} = a-b$$

$$\Leftrightarrow S_w \tau^{-1} = S_w + \frac{1}{4} S_B$$

$$\Leftrightarrow \tau = \frac{S_w}{S_w + \frac{S_B}{4}} \text{ pos. const.}$$