

Linear Discrimination

Classification $\Rightarrow \mathcal{X} = \{ (x_i, y_i) \}_{i=1}^N$

$y_i \in \{1, 2, \dots, K\}$

$\left. \begin{matrix} g_1(x) \\ g_2(x) \\ \vdots \\ g_K(x) \end{matrix} \right\}$ score functions

$$c^* = \arg \max_{c=1}^K \underline{g_c(x)}$$

$$g_c(x) = p(x|y=c) \Pr(y=c)$$

univariate
 $(x_i \in \mathbb{R})$

class conditional density

$$\downarrow \\ N(\mu_c, \sigma_c^2)$$

$$\Downarrow \\ \hat{\mu}_c, \hat{\sigma}_c^2 \\ \hookrightarrow 1 \times 1 \quad \hookrightarrow 1 \times 1$$

multivariate
 $(x_i \in \mathbb{R}^D)$

class conditional density

$$\downarrow \\ N(\mu_c, \Sigma_c)$$

$$\Downarrow \\ \hat{\mu}_c, \hat{\Sigma}_c \hookrightarrow D \times D \\ \hookrightarrow D \times 1$$

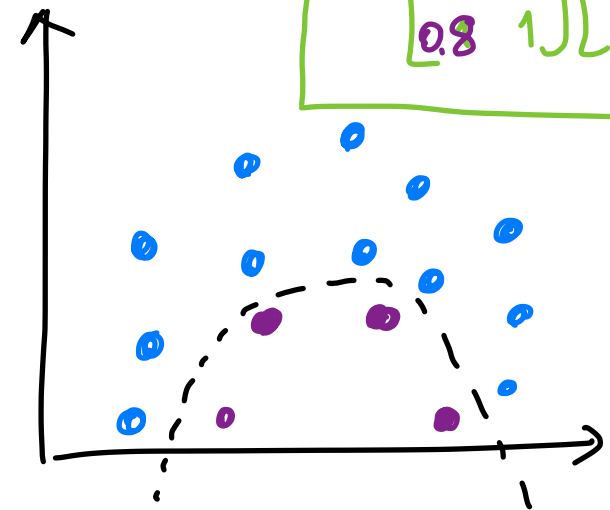
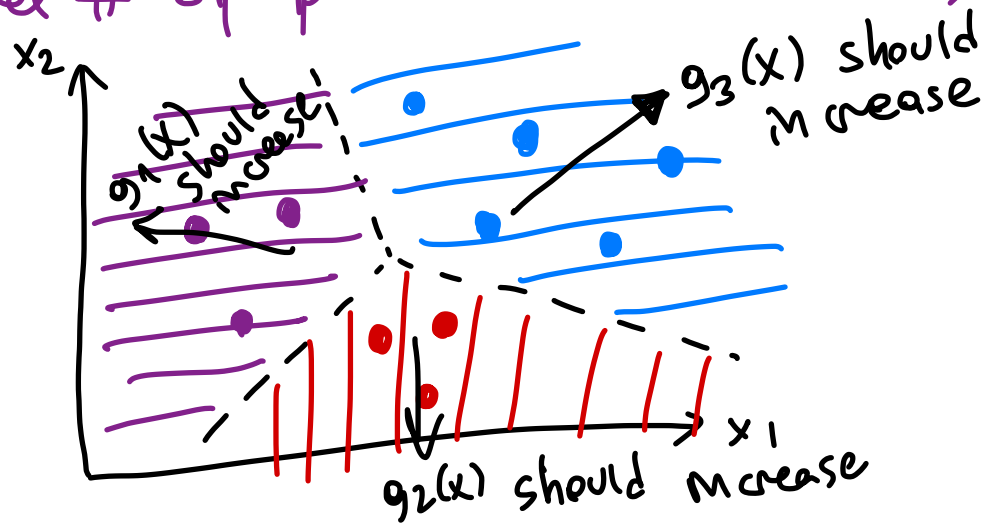
$$\frac{N_c}{N} = \frac{\text{\# of data points in class } c}{\text{total \# of data points}}$$

$$\sum_{i=1}^N x_i \cdot 1 = [x_1 \ x_2 \ \dots \ x_N] \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} \\ \text{np.sum}()$$

$$g_c(x | w_c, w_{co}) = w_c^T \cdot x + w_{co}$$

$$= \underbrace{[w_{c1} \ w_{c2} \ \dots \ w_{cD}]}_{\text{weights}} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_D \end{bmatrix} + \underbrace{w_{co}}_{\text{bias}} = \sum_{d=1}^D (w_{cd} \cdot x_d) + w_{co}$$

total # of parameters = $K(D+1)$



$$a^2 + 2ab + b^2$$

$$[a, b] \begin{bmatrix} 1 & 1.2 \\ 0.8 & 1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix}$$

$$g_c(x | W_c, w_c, w_{co}) = x^T \cdot \underbrace{W_c}_D x + \underbrace{w_c^T \cdot x}_{D} + \underbrace{w_{co}}_1$$

total # of parameters = $K \left(\frac{D(D+1)}{2} + D + 1 \right)$

$$[a \ b] \begin{bmatrix} a+b \\ a+b \end{bmatrix} =$$

$$a^2 + ab + ba + b^2 = a^2 + 2ab + b^2$$

Binary Classification (K=2)

$$\left. \begin{array}{l} g_1(x) \\ g_2(x) \end{array} \right\} \begin{array}{l} \text{if } g_1(x) > g_2(x) \\ \text{if } g_2(x) > g_1(x) \end{array} \Rightarrow \begin{array}{l} \hat{y} = 1 \\ \hat{y} = 2 \end{array}$$

$$\text{if } g_1(x) - g_2(x) > 0 \Rightarrow \hat{y} = 1$$

$$\text{if } g_1(x) - g_2(x) < 0 \Rightarrow \hat{y} = 2$$

$$\text{if } g(x) > 0 \Rightarrow \hat{y} = 1$$

$$\text{if } g(x) < 0 \Rightarrow \hat{y} = 2$$

$$g_1(x) = w_1^T \cdot x + w_{10}$$

$$g_2(x) = w_2^T \cdot x + w_{20}$$

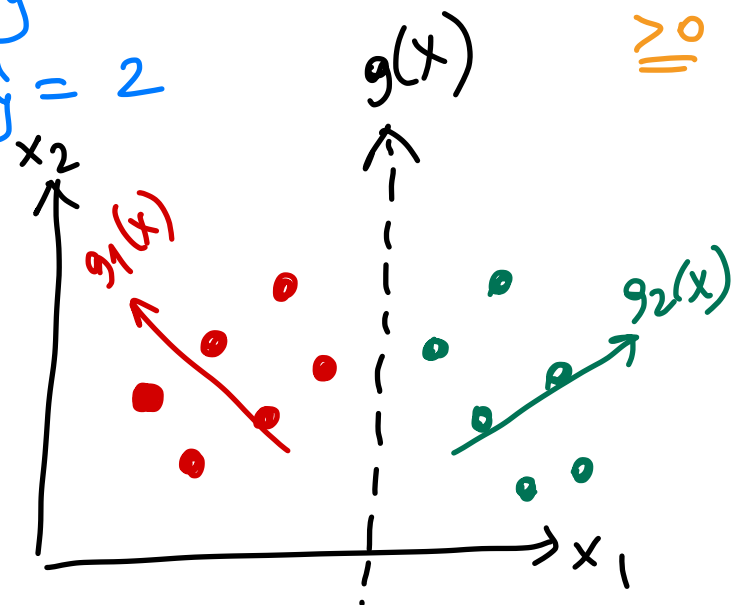
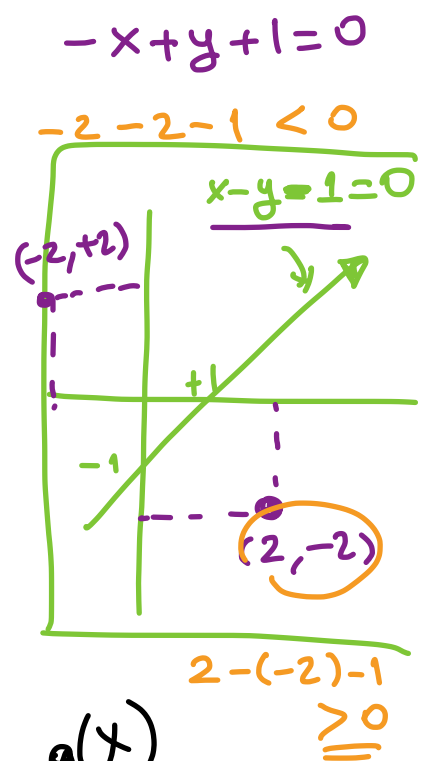
$$g_1(x) - g_2(x) = (w_1 - w_2)^T \cdot x + (w_{10} - w_{20})$$

$$= \underbrace{w^T}_{x \cdot a \cdot x} \cdot x + \underbrace{w_0}_{x \cdot b \cdot x}$$

$$x \cdot a \cdot x \quad x \cdot b \cdot x$$

$$\text{tr}[x^T \cdot w_1 \cdot x] = \text{tr}[w_1 \cdot x \cdot x^T]$$

$$\text{tr}(ABC) = \text{tr}(BCA)$$



Multiclass Classification ($K > 2$)

$$\left. \begin{array}{l} g_1(x) \\ g_2(x) \\ \vdots \\ g_K(x) \end{array} \right\}$$

assume $K=3$

if $g_1(x) > g_2(x)$ & $g_1(x) > g_3(x) \Rightarrow \hat{y} = 1$

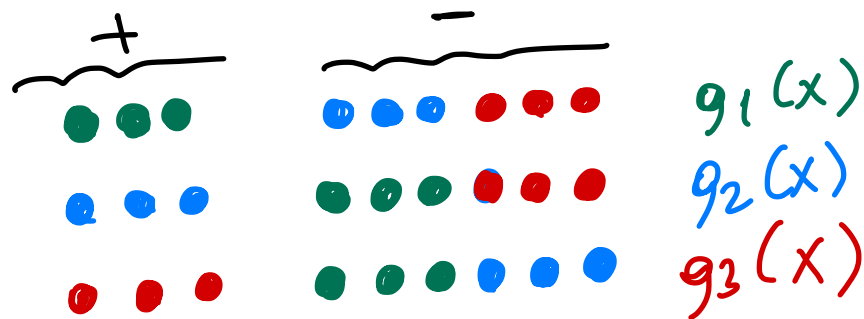
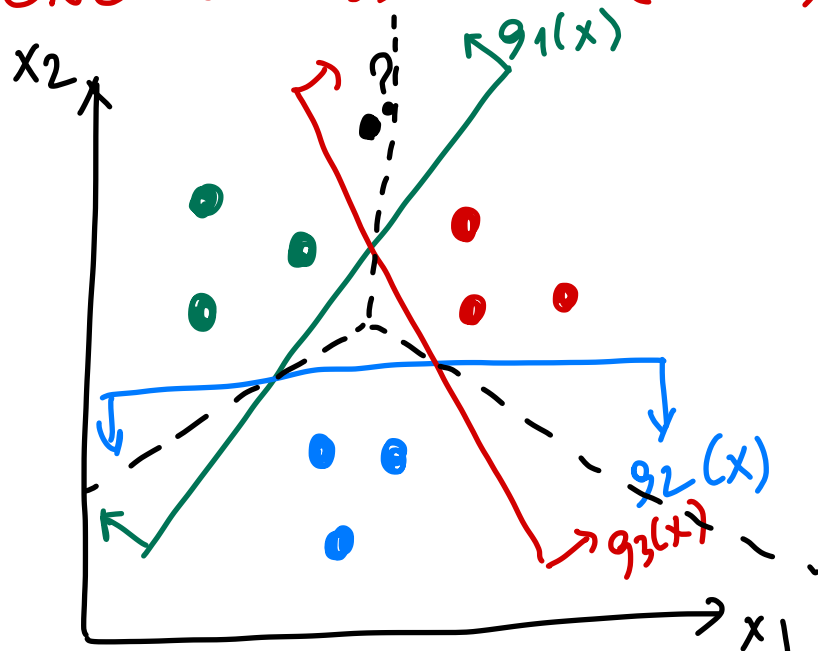
if $g_2(x) > g_1(x)$ & $g_2(x) > g_3(x) \Rightarrow \hat{y} = 2$

if $g_3(x) > g_1(x)$ & $g_3(x) > g_2(x) \Rightarrow \hat{y} = 3$

$$\hat{y} = \arg \max_{c=1}^K g_c(x)$$

$$\begin{array}{l} 1x^2 + 0y^2 = 9 \\ 0x^2 + 1y^2 = 16 \end{array}$$

ONE-VERSUS-ALL (OVA) APPROACH

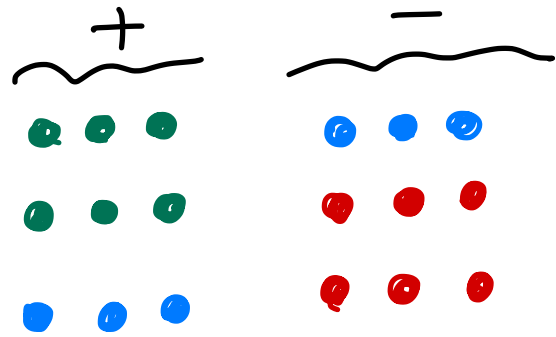


of parameters = $K(D+1)$

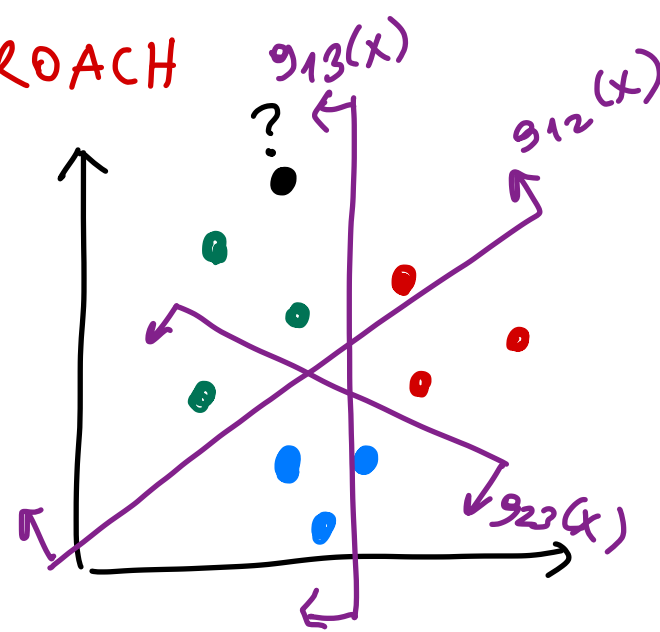
data set size = N
for each problem

of score functions = K

ONE-VERSUS-OTHER (OVO) APPROACH



$g_{12}(x)$
 $g_{13}(x)$
 $g_{23}(x)$



$$\binom{K}{2} = \frac{K!}{(K-2)!2!} = \frac{K \cdot (K-1)}{2}$$

?

x	1	2	3
$g_{12}(x)$	1	0	0
$g_{13}(x)$	1	0	0
$g_{23}(x)$	0	0	1
# of wins	2	0	1

↓
overall winner

of parameter = $\frac{K(K-1)}{2} (D+1)$

data set size for each problem = $\frac{2N}{K}$

of score functions = $\frac{K(K-1)}{2}$

$K=2$

$$\Pr(y=1|x) = \delta$$

$$\Pr(y=2|x) = 1-\delta$$

$$\begin{cases} \text{if } \delta > 0.5 \Rightarrow \hat{y} = 1 \\ \text{if } \frac{\delta}{1-\delta} > 1 \Rightarrow \hat{y} = 1 \\ \text{if } \log\left[\frac{\delta}{1-\delta}\right] > 0 \Rightarrow \hat{y} = 1 \end{cases}$$

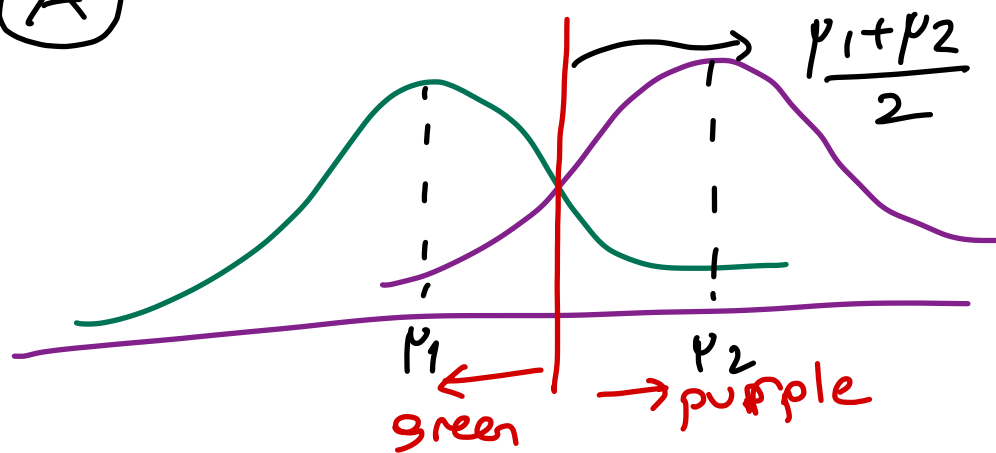
$$\log \left[\frac{\Pr(y=1|x)}{\Pr(y=2|x)} \right] = \log \left[\frac{\frac{p(x|y=1) \Pr(y=1)}{\cancel{p(x)}}}{\frac{p(x|y=2) \Pr(y=2)}{\cancel{p(x)}}} \right]$$

$$= \log \left[\frac{p(x|y=1)}{p(x|y=2)} \right] + \log \left[\frac{\Pr(y=1)}{\Pr(y=2)} \right]$$

(A) $\rightarrow N(x; \mu_1, \Sigma_1)$ (B) $\rightarrow N(x; \mu_2, \Sigma_2)$

assuming

$$\Sigma_1 = \Sigma_2 = \Sigma$$



$$\frac{1}{\sqrt{(2\pi)^p |\Sigma|}} \cdot \exp\left[-\frac{1}{2} (x-\mu)^T \Sigma^{-1} (x-\mu)\right] = N(x; \mu, \Sigma)$$

$$= \underbrace{\log \left[\frac{\frac{1}{\sqrt{(2\pi)^p |\Sigma|}} \cdot \exp\left[-\frac{1}{2} (x-\mu_1)^T \Sigma^{-1} (x-\mu_1)\right]}{\frac{1}{\sqrt{(2\pi)^p |\Sigma|}} \cdot \exp\left[-\frac{1}{2} (x-\mu_2)^T \Sigma^{-1} (x-\mu_2)\right]} \right]}_{(A)} + \underbrace{\log \left[\frac{Pr(y=1)}{Pr(y=2)} \right]}_{(B)}$$

$$= -\frac{1}{2} (x-\mu_1)^T \Sigma^{-1} (x-\mu_1) + \frac{1}{2} (x-\mu_2)^T \Sigma^{-1} (x-\mu_2) + (B)$$

$$= \cancel{-\frac{1}{2} x^T \Sigma^{-1} x} + \mu_1^T \Sigma^{-1} x - \frac{1}{2} \mu_1^T \Sigma^{-1} \mu_1 + \cancel{\frac{1}{2} x^T \Sigma^{-1} x} - \mu_2^T \Sigma^{-1} x + \frac{1}{2} \mu_2^T \Sigma^{-1} \mu_2 + (B)$$

$$= \underbrace{(\hat{\mu}_1 - \hat{\mu}_2)^T \cdot \hat{\Sigma}^{-1} \cdot x}_{W^T} + \underbrace{\left[-\frac{1}{2} (\hat{\mu}_1 + \hat{\mu}_2)^T \cdot \hat{\Sigma}^{-1} (\hat{\mu}_1 - \hat{\mu}_2) \right]}_{W_0} + \log \left[\frac{\hat{Pr}(y=1)}{\hat{Pr}(y=2)} \right]$$