

Calculate μ and Σ

$$1. \mu = \frac{\sum_{i=1}^I X_i}{I}$$

$$2. I \cdot \Sigma = \sum_{i=1}^I (X_i - \mu)(X_i - \mu)^T$$

$$\Sigma_{D \times D} = \frac{\sum_{i=1}^I \underbrace{(X_i - \hat{\mu})}_{D \times 1} \underbrace{(X_i - \hat{\mu})^T}_{1 \times D}}{I} \quad \begin{matrix} \hookrightarrow \# \text{ of images} \\ \text{of face/bg} \end{matrix}$$

$$\begin{bmatrix} \quad \end{bmatrix} = \begin{bmatrix} \quad \end{bmatrix} \cdot \begin{bmatrix} \quad \end{bmatrix}$$

Training

$$\begin{aligned} \circ \bar{X}_{\text{face}} &= \{X_1, \dots, X_I\}_{\text{face}} \\ \Rightarrow \hat{\mu}_{\text{face}}, \hat{\Sigma}_{\text{face}} &\left\{ \begin{array}{l} \mu_{\text{face}} = \frac{\sum}{I} \\ \Sigma_{\text{face}} = \frac{\sum}{I} \end{array} \right. \end{aligned}$$

$$\begin{aligned} \circ \bar{X}_{\text{bg}} &= \{X_1, \dots, X_I\}_{\text{bg}} \\ \Rightarrow \hat{\mu}_{\text{bg}}, \hat{\Sigma}_{\text{bg}} &\left\{ \begin{array}{l} \mu_{\text{bg}} = \frac{\sum}{J} \\ \Sigma_{\text{bg}} = \frac{\sum}{J} \end{array} \right. \end{aligned}$$

Testing

$$\Theta = \{\mu, \Sigma\}$$

Given a new testing image X^* , $\Pr(Y|X^*) = \frac{\Pr(X^*|Y)\Pr(Y)}{\Pr(X^*)}$

Assume $\Pr(Y)$ is uniform, $\Pr(Y|X^*) \sim \Pr(X^*|Y)$

$$\Pr(Y=1|X^*) \stackrel{?}{>} \Pr(Y=0|X^*)$$

$$\Rightarrow \frac{\Pr(X^*|Y=1)\cancel{\Pr(Y=1)}}{\cancel{\Pr(X^*)}} > \frac{\Pr(X^*|Y=0)\cancel{\Pr(Y=0)}}{\cancel{\Pr(X^*)}}$$

$$\Rightarrow \Pr(X^*|Y=1) > \Pr(X^*|Y=0)$$

$$\text{Norm}_{X^*} [\mu_{\text{face}}, \Sigma_{\text{face}}] \stackrel{?}{>} \text{Norm}_{X^*} [\mu_{\text{bg}}, \Sigma_{\text{bg}}]$$

$$\text{Norm}_X(\mu, \Sigma) = \frac{1}{(2\pi)^{D/2} |\Sigma|^{1/2}} e^{-\frac{1}{2}(X-\mu)^T \Sigma^{-1}(X-\mu)}$$

X^* : a test image (vector, $X^* \in \mathbb{R}^{D \times 1}$)

μ : mean ($\mu \in \mathbb{R}^{D \times 1}$)

Σ : variance ($\Sigma \in \mathbb{R}^{D \times D}$)

$|\Sigma|$: determinant of Σ ($|\Sigma| \in \mathbb{R}$)

Simplify the expression

$$\Pr(X^* | Y=1) \stackrel{?}{>} \Pr(X^* | Y=0)$$

\Rightarrow

$$\frac{1}{(2\pi)^{D/2} \left(\frac{D}{D-1} (\sigma_{dd}^2)_{Y=1} \right)^{1/2}} e^{-\frac{\sum_{d=1}^D (X_d - (\mu_d)_{Y=1})^2}{2 (\sigma_{dd}^2)_{Y=1}}} \stackrel{?}{>} \frac{1}{(2\pi)^{D/2} \left(\frac{D}{D-1} (\sigma_{dd}^2)_{Y=0} \right)^{1/2}} e^{-\frac{\sum_{d=1}^D (X_d - (\mu_d)_{Y=0})^2}{2 (\sigma_{dd}^2)_{Y=0}}}$$

take logarithm

\Rightarrow

A

B

$$-\frac{1}{2} \sum_{d=1}^D \lg(\sigma_{dd}^2)_{Y=1} - \sum_{d=1}^D \frac{(X_d - (\mu_d)_{Y=1})^2}{2 (\sigma_{dd}^2)_{Y=1}} \stackrel{?}{>} -\frac{1}{2} \sum_{d=1}^D \lg(\sigma_{dd}^2)_{Y=0} - \sum_{d=1}^D \frac{(X_d - (\mu_d)_{Y=0})^2}{2 (\sigma_{dd}^2)_{Y=0}}$$

\downarrow \downarrow \downarrow \downarrow
 $- d_1$ $- Y_1$ $- d_0$ $- Y_0$

$A > B \Rightarrow$ face

$A < B \Rightarrow$ background.

(in my codes)