

Probability:

$$P[A | B] = \frac{P[A \cap B]}{P[B]} \text{ for } P[B] > 0 \text{ ; Conditional probability}$$

$$P[\omega_j | x] = \frac{P[x | \omega_j] \cdot P[\omega_j]}{\sum_{k=1}^N P[x | \omega_k] \cdot P[\omega_k]} = \frac{P[x | \omega_j] \cdot P[\omega_j]}{P[x]} \text{ ; Bayes theorem}$$

$P[\omega_j]$: **Prior probability** ; $P[\omega_j | x]$: **Posterior Probability** ; $P[x | \omega_j]$: **Likelihood** ;
 $P[x]$: A normalization constant that does not affect the decision

Random variable:

$$F_X(x) = P[X \leq x] \text{ for } -\infty < x < +\infty \text{ ; cdf}$$

$$f_X(x) = \frac{\Delta F_X(x)}{\Delta x} \text{ ; pmf}$$

$$E[X] = \mu = \int_{-\infty}^{+\infty} x f_X(x) dx$$

$$VAR[X] = E[(X - E[X])^2] = \int_{-\infty}^{+\infty} (x - \mu)^2 f_X(x) dx$$

$$STD[X] = VAR[X]^{1/2}$$

$$E[X^N] = \int_{-\infty}^{+\infty} x^N f_X(x) dx$$

Random vectors:

$$F_{\underline{X}}(\underline{x}) = P_{\underline{X}}[\{X_1 \leq x_1\} \cap \{X_2 \leq x_2\} \cap \dots \cap \{X_N \leq x_N\}] \text{ ; joint cdf}$$

$$f_{\underline{X}}(\underline{x}) = \frac{\partial^N F_{\underline{X}}(\underline{x})}{\partial x_1 \partial x_2 \dots \partial x_N} \text{ ; joint pdf}$$

$$f_{X_1}(x_1) = \int_{x_2=-\infty}^{x_2=+\infty} f_{X_1 X_2}(x_1 x_2) dx_2 \text{ ; marginal pdf}$$

$$E[X] = [E[X_1] E[X_2] \dots E[X_N]]^T = [\mu_1 \mu_2 \dots \mu_N] = \mu \text{ ; Mean vector}$$

$\text{COV}[X] = \Sigma = E[(X - \mu)(X - \mu)^T]$; Covariance matrix

$$= \begin{bmatrix} E[(x_1 - \mu_1)(x_1 - \mu_1)] & \dots & E[(x_1 - \mu_1)(x_N - \mu_N)] \\ \dots & \dots & \dots \\ E[(x_N - \mu_N)(x_1 - \mu_1)] & \dots & E[(x_N - \mu_N)(x_N - \mu_N)] \end{bmatrix} = \begin{bmatrix} \sigma_1^2 & \dots & c_{1N} \\ \dots & \dots & \dots \\ c_{1N} & \dots & \sigma_N^2 \end{bmatrix}$$

$$f_x(x) = \frac{1}{(2\pi)^{n/2} |\Sigma|^{1/2}} \exp\left[-\frac{1}{2}(X - \mu)^T \Sigma^{-1}(X - \mu)\right] ; \text{Normal distribution}$$

Linear algebra:

$$\langle x, y \rangle = x^T y = y^T x = \sum_{k=1}^d x_k y_k ; \text{Dot product}$$

$$|x| = \sqrt{x^T x} = \left[\sum_{k=1}^d x_k x_k \right]^{1/2} ; \text{Vector magnitude}$$

$$\langle y^T u_x \rangle u_x ; \text{Orthogonal projection}$$

$$\cos \theta = \frac{\langle x, y \rangle}{|x| \cdot |y|} ; \text{Angle between } x \text{ and } y$$

$$|A| = \sum_{k=1}^d a_{kk} |A_k| (-1)^{k+i} ; \text{Determinant of } A_{d \times d}$$

$$\text{tr}(A) = \sum_{k=1}^d a_{kk} ; \text{Trace of } A_{d \times d}$$

Bayesian decision theory:

$$\Lambda(x) = \frac{P(x | \omega_1)}{P(x | \omega_2)} \underset{\omega_2}{\overset{\omega_1}{\gtrless}} \frac{P(\omega_2)}{P(\omega_1)} ; \text{Likelihood ratio}$$

$$P[\text{error}] = \sum_{i=1}^C P[\text{error} | \omega_i] P[\omega_i]$$

$$P[\text{error} | \omega_i] = P[\text{choose } \omega_j | \omega_i] = \int_{R_j} P(x | \omega_i) dx$$

$$\mathfrak{R} = \int_{R_1} [C_{11} \cdot P[\omega_1] \cdot P(x | \omega_1) + C_{12} \cdot P[\omega_2] \cdot P(x | \omega_2)] dx + \int_{R_2} [C_{21} \cdot P[\omega_1] \cdot P(x | \omega_1) + C_{22} \cdot P[\omega_2] \cdot P(x | \omega_2)] dx ; \text{Bayes risk}$$

$$\Lambda(x) = \frac{P(x | \omega_1) > (C_{12} - C_{22}) \frac{P(\omega_2)}{P(\omega_1)}}{P(x | \omega_2) < (C_{21} - C_{11}) \frac{P(\omega_1)}{P(\omega_2)}} \quad \text{Bayes criterion}$$

$$C_{ij} = \begin{cases} 0 & i = j \\ 1 & i \neq j \end{cases} \Rightarrow \Lambda(x) = \frac{P(x | \omega_1) > \frac{P(\omega_2)}{P(\omega_1)}}{P(x | \omega_2) < \frac{P(\omega_1)}{P(\omega_2)}} \Leftrightarrow \frac{P(\omega_1 | x) > \frac{P(\omega_2 | x)}{P(\omega_1 | x)}}{P(\omega_2 | x) < \frac{P(\omega_1 | x)}{P(\omega_2 | x)}} \quad \text{Maximum A Posteriori (MAP) Criterion}$$

$$C_{ij} = \begin{cases} 0 & i = j \\ 1 & i \neq j \end{cases} \Rightarrow \Lambda(x) = \frac{P(x | \omega_1) > \frac{P(\omega_2)}{P(\omega_1)}}{P(x | \omega_2) < \frac{P(\omega_1)}{P(\omega_2)}} \quad \text{Maximum Likelihood (ML) Criterion}$$

$$P[\text{correct}] = \sum_{i=1}^C P(\omega_i) \int_{R_i} P(x | \omega_i) dx = \sum_{i=1}^C \int_{R_i} P(x | \omega_i) P(\omega_i) dx = \sum_{i=1}^C \underbrace{\int_{R_i} P(\omega_i | x) P(x) dx}_{\mathfrak{A}_i}$$

Optical sensors:

$$C = \lambda \cdot f \quad ; \quad C : \text{light speed} = 3 \times 10^8 \text{ m/s} ; \quad \lambda : \text{wavelength} ; \quad f : \text{frequency}$$

$$\Theta = 2 \arctan \left(\frac{D_f - D_i}{2l} \right) \quad ; \text{Divergence of a beam}$$

$$P_{\text{net}} = A \sigma \varepsilon (T^4 - T_0^4) \quad ; \text{Stefan Boltzmann law} ; \sigma = 5.67 \times 10^{-8} \text{ W m}^{-2} \text{ K}^{-4}$$