

Bayes Theorem :-

$$P(\omega_j | x) = \frac{P(x | \omega_j) P(\omega_j)}{p(x)}, \quad \text{where } P(x) = \sum_{k=1}^N P(x | \omega_k) \cdot P(\omega_k)$$

where ω_j is the j^{th} class and x is the feature vector.

$P(\omega_j) \rightarrow$ A priori probability of class ω_j

$P(\omega_j | x) \rightarrow$ Posterior prob. of class ω_j given the observation x .

$P(x | \omega_j) \rightarrow$ likelihood (Class conditional prob. of x given Class ω_j)

$P(x) \rightarrow$ A normalization Constant that does not affect the decision.

Discrete Random variable

PMF (Prob. Mass function) $\rightarrow P_x(x) = P(X=x)$

CDF (Cumulative distribution funⁿ) $\rightarrow F_x(x) = P(X \leq x)$

Continuous Random variable

$$P(a < x < b) = F(a < x < b) = \int_a^b f(x) dx = F(b) - F(a)$$

where $F(x)$ is cumulative distribution function

& $f(x)$ " prob. density function.

$$(i) f(x) = \frac{d}{dx} F(x)$$

$$(ii) f(x) \geq 0$$

$$(iii) F(x) = \int_{-\infty}^x f(x) dx = 1$$

Expectation or mean of Prob. distribution

$$\mu = E[x] = \sum x f[x]$$

For discrete variables

$$\mu = E[x] = \int x f(x) dx$$

Continuous variables.

Variance For discrete variables

$$\begin{aligned}\text{Var}[X] &= \sigma^2 = E[(X - \mu)^2] \\ &= E[X^2 + \mu^2 - 2X\mu] \\ &= E[X^2] + E[\mu^2] - E[2X\mu] \\ &= E[X^2] + \mu^2 - 2\mu E[X] \\ &= E[X^2] + \mu^2 - 2\mu \cdot \mu\end{aligned}$$

$$\boxed{\text{Var}[X] = E[X^2] - \mu^2}$$

For continuous variables

$$\text{Var}[X] = \sigma^2(X) = \int_a^b x^2 f(x) dx - \mu^2$$

Standard deviation

$$\begin{aligned}\sigma &= \text{Sqrt}(\text{variance}) \\ &= \sqrt{E[X^2] - \mu^2}\end{aligned}$$

Covariance

$$\text{Cov}(X, Y) = E(XY) - E(X)E(Y)$$

OR

$$\text{Cov}(X, Y) = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{n}$$

Correlation: - Karl Pearson's Product moment method

$$-1 \leq \rho \leq 1$$

$-1 \leq \rho \leq 0 \rightarrow$ -ve Correlation.

$0 < \rho \leq 1 \rightarrow$ +ve Correlation.

$$\boxed{\rho = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y}}$$

\rightarrow Use when directly Cov. & Std. deviation are given

$$\sigma_X = \sqrt{\frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n}}, \quad \sigma_Y = \sqrt{\frac{\sum_{i=1}^n (y_i - \bar{y})^2}{n}}$$

OR

$$\sigma_X = \sqrt{E(X^2) - E(X)^2}, \quad \sigma_Y = \sqrt{E(Y^2) - E(Y)^2}$$