

Probability Review

1 Concepts

$$\Omega = \{w_1, \dots, w_n\} \quad S_i \subseteq \Omega$$

\swarrow Sample space \downarrow possible outcomes \downarrow event

Axioms

① $\Pr\{S_j\} \geq 0$ ② $\Pr\{\Omega\} = 1$ ③ if $S_i \cap S_j = \emptyset$,
 $\Pr\{S_i \cup S_j\} = \Pr\{S_i\} + \Pr\{S_j\}$

Random variable is a function/mapping $X(w): \Omega \rightarrow \mathbb{R}$

① Cumulative density function $F(x) = \Pr\{X \leq x\}$

② Probability density function $p(x) = \frac{dF(x)}{dx}$ $\Pr(a \leq X \leq b) = \int_a^b p(x) dx$

③ Mean: $m_X = E(X) = \int_{-\infty}^{\infty} x p_X(x) dx$

④ Variance: ~~$\text{Var}[X] = E[(X - m_X)^2]$~~

$$\text{Var}[X] = E[(X - m_X)^2] = \int_{-\infty}^{\infty} (x - m_X)^2 p_X(x) dx$$

Prove $\text{Var}[X] = E[X^2] - (E[X])^2$

$$\text{Var}[X] = \int_{-\infty}^{\infty} (x - m_X)^2 p_X(x) dx$$

$$= \int_{-\infty}^{\infty} x^2 p_X(x) dx - 2m_X \int_{-\infty}^{\infty} x p_X(x) dx$$

$$+ m_X^2$$

$$= E[X^2] - (E[X])^2$$

Multiple random variable

joint : Probability : $\Pr(X=x, Y=y)$

Cdf : $F(x, y) = \Pr(X \leq x, Y \leq y)$

pdf : $P(x, y) = \frac{\partial^2}{\partial x \partial y} F(x, y)$

* Covariance : $\sum XY = E[(X - m_X)(Y - m_Y)]$

Uncorrelated : $\sum XY = 0$ independent $P(x, y) = P(x)P(y)$

* independent \Rightarrow uncorrelated ;
uncorrelated \nRightarrow independent

Condition : Probability : $P_X(x|y_i) = P_X(x|Y=y_i) = \frac{P(x, y_i)}{P_Y(y_i)}$

independent : $P_X(x|y_i) = P_X(x)$

Gaussian :

Single variable :

$$P_X(x) = \frac{1}{\sigma_x \sqrt{2\pi}} \exp\left(-\frac{(x - m_x)^2}{2\sigma_x^2}\right)$$

vector

$$x \in \mathbb{R}^n \quad P_X(x) = \frac{1}{(\sqrt{2\pi})^n \sqrt{\det \Sigma}} \exp\left\{-\frac{1}{2} [x - m_x]^T \Sigma^{-1} [x - m_x]\right\}$$

$$\Sigma = E[(x - m_x)(x - m_x)^T]$$

Gaussian properties:

- The pdf is only determined by mean & Variance/co-matrix.
- Uncorrelation \Leftrightarrow independence.
- Invariant under linear transform (test LTI system)
- If X_1 and X_2 are jointly Gaussian, then $X_1 | X_2$ & $X_2 | X_1$ are Gaussian.

$$\frac{P(x|y)}{P_X(y)}$$

$$m_{X|Y} = m_X + \Sigma_{XY} \Sigma_{YY}^{-1} (y - m_Y)$$

$$\Sigma_{X|Y} = \Sigma_{XX} - \Sigma_{XY} \Sigma_{YY}^{-1} \Sigma_{YX}$$

Random Process

- Auto covariance

$$\Sigma_{xx}(j, k) = E[(X(j) - m_x(j))(X(k) - m_x(k))^T]$$

- Cross covariance

$$\Sigma_{xy}(j, k) = E[(X(j) - m_x(j))(Y(k) - m_y(k))^T]$$

- ergodic (for all moments) $E[X(k)] = \lim_{N \rightarrow \infty} \frac{1}{2N+1} \sum_{j=-N}^N X(j) \triangleq \overline{X(k)}$

$$\Sigma_{xx}(j, k) = \frac{(X(j) - m_x)(X(k) - m_k)}{(X(j) - m_x)(X(k) - m_k)}$$

- Stationary, tells whether a process changes its statistical properties w.r.t. time

– Strict-sense Stationary: probability distribution does not change w.r.t time.

– Weak-sense, mean & auto-covariance does depend on time

Ergodic \Rightarrow Stationary

Ergodic \Rightarrow Stationary

$$\left\{ \begin{array}{l} \text{Stationary: } E[X(k)] = m_x = \text{constant} \\ \text{auto-covariance} \\ \Sigma_{xx}(k, j) = E[(X(k) - m_x)(X(j) - m_x)] = E[(X(k+j) - m_x)(X(j) - m_x)] \\ = \Sigma_{xx}(j-k) \end{array} \right.$$

- White noise: $\Sigma_{xx}(l) = \begin{cases} 0 & l \neq 0 \\ \sigma_{xx}^2 & l = 0 \end{cases}$

In ME233, Stationary & ergodicity is assumed

Auto Covariance $\Sigma_{xy}(l) = \overbrace{(x(k) - m_x)(y(k+l) - m_y)}^{\text{}} = \Sigma_{yx}(-l)$.

Spectral density:

$$\Phi_{xx}(\omega) = \sum_{-\infty}^{+\infty} (\Sigma_{xx}(l)) e^{j\omega l}$$

Why?

$$\Sigma_{yy}(l) = g(l) * \Sigma_{yu}(l)$$

$$\Sigma_{uy}(l) = g(l) * \Sigma_{uu}(l)$$

↑
hard to operate

$$\phi_{yy}(\omega) = G(e^{j\omega}) G(e^{j\omega})^T \phi_{uu}(\omega)$$

$$\begin{aligned} \Sigma_{uy}(l) &= E[(u(k) - m_x)(y(k+l) - m_y)] \quad \text{Zero-mean assumed} \\ &= E[u(k) \cdot \sum_{i=-\infty}^{+\infty} g(i) u(k+l-i)] \\ &= \overline{u(k) \cdot \sum_{i=-\infty}^{+\infty} g(i) u(k+l-i)} = \sum_{i=-\infty}^{+\infty} X_{uu}(l-i) g(i) \\ &= g(l) * X_{uu}(l) \end{aligned}$$

In vector sense $\phi_{yy}(e^{j\omega}) = G(e^{j\omega}) \cdot \phi_{uu}(e^{j\omega}) \cdot G^T(e^{j\omega})$