

Solution 1. Given  $X_1, X_2, \dots, X_n$  are iid

$$f(x) = \begin{cases} 1/2 & \text{for } -1 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

ie.  $X_i \forall i$  is uniform distribution ( $X_i \sim U(-1, 1)$ )

$$m_{X_i} = \frac{-1+1}{2} = 0 \text{ (expected value)} \Rightarrow E[X_i] = 0$$

$$\text{Variance, } \sigma_{X_i}^2 = \frac{(1+1)^2}{12} = \frac{4}{12} = \frac{1}{3}$$

$$S_n = X_1 + X_2 + \dots + X_n$$

$$E[S_n] = E[X_1] + E[X_2] + \dots + E[X_n] = 0$$

$$E\left[\frac{S_n}{n}\right] = \frac{0}{n} = 0$$

$$\begin{aligned} \sigma^2(S_n) &= E[S_n^2] - [E(S_n)]^2 && \{ \text{here } \sigma^2(S_n) = \text{Var}(S_n) \} \\ &= E[X_1^2] + E[X_2^2] + \dots + E[X_n^2] \\ &= \sigma_{X_1}^2 + 0 + \sigma_{X_2}^2 + 0 + \dots + \sigma_{X_n}^2 + 0 \\ &= \frac{1}{3} + \frac{1}{3} + \dots + \frac{1}{3} = \frac{n}{3} \end{aligned}$$

$$\sigma^2\left(\frac{S_n}{n}\right) = \frac{1}{n^2} \sigma^2(S_n) = \frac{1}{n^2} \frac{n}{3} = \frac{1}{3n} \quad \{ \text{here } \sigma^2\left(\frac{S_n}{n}\right) = \text{Var}\left(\frac{S_n}{n}\right) \}$$

According to Chebyshev inequality,

$$P[|X - m_X| \geq a] \leq \frac{\sigma_X^2}{a^2}$$

now put  $X = \frac{S_n}{n}$ ,  $m_X = 0$ ,  $a = \epsilon$ , we get

$$P\left[\left|\frac{S_n}{n}\right| \geq \epsilon\right] \leq \frac{\sigma^2\left(\frac{S_n}{n}\right)}{\epsilon^2} = \frac{1}{3n\epsilon^2}$$

Hence, proved.

(2)

Solution 2. Given  $X_1, X_2, \dots, X_n$  with mean  $\mu$  &  $\text{Cov}(X_i, X_j) = \sigma^2 \rho^{|i-j|}$  &  $|\rho| < 1$

(a)  $S_n = X_1 + X_2 + \dots + X_n$

$$E[S_n] = E[X_1] + E[X_2] + \dots + E[X_n]$$

$$= \mu + \mu + \dots + \mu = n\mu$$

$$\text{Cov}(X_i, X_j) = \sigma^2 \rho^{|i-j|} = E[(X_i - \mu)(X_j - \mu)]$$

$$= E[X_i X_j] - 2\mu^2 + \mu^2 = E[X_i X_j] - \mu^2$$

$$E[X_i X_j] = \sigma^2 \rho^{|i-j|} + \mu^2$$

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

$$= E\left[\sum_{i=1}^n X_i (X_1 + X_2 + \dots + X_n)\right] - \mu^2 n^2$$

$$= \sum_{i=1}^n E[X_i (X_1 + X_2 + \dots + X_n)] - n^2 \mu^2$$

$$= n\sigma^2 + 2\sigma^2 \sum_{i=1}^{n-1} (\rho + \rho^2 + \dots + \rho^i) + n^2 \mu^2 - n^2 \mu^2$$

$$= n\sigma^2 + 2\sigma^2 \rho \sum_{i=1}^{n-1} \left(\frac{1-\rho^i}{1-\rho}\right) = n\sigma^2 + 2\sigma^2 \rho \left[\frac{n-1}{1-\rho} - \frac{\rho}{1-\rho} \sum_{i=1}^{n-1} \frac{\rho^{i-1}}{1-\rho}\right]$$

$$\text{Var}[S_n] = n\sigma^2 + 2\sigma^2 \rho \left[\frac{n-1}{1-\rho} - \left(\frac{\rho}{1-\rho}\right)\left(\frac{1-\rho^{n-1}}{1-\rho}\right)\right]$$

(b) Sample mean,  $M_n = \frac{S_n}{n}$

Expected value,  $E[M_n] = E\left[\frac{S_n}{n}\right] = \frac{E[S_n]}{n} = \frac{n\mu}{n} = \mu = E[X_i]$  — (i)

Variance,  $\text{Var}[M_n] = \text{Var}\left[\frac{S_n}{n}\right] = \frac{\text{Var}[S_n]}{n^2}$

$$= \frac{\sigma^2}{n} + \frac{2\sigma^2 \rho}{n} \left[\frac{1-\rho^{n-1}}{1-\rho} - \frac{1}{n} \frac{\rho(1-\rho^{n-1})}{(1-\rho)^2}\right]$$

$\lim_{n \rightarrow \infty} \text{Var}[M_n] = 0$  — (ii)

Hence, weak law of large no. holds true for sample mean.

from (i) & (ii) we conclude that



Solution 3. Given  $X_1, X_2, \dots, X_n$  are iid

$$f(x) = \begin{cases} 1/2a & \text{for } |x| \leq a \\ 0 & \text{otherwise} \end{cases}$$

ie.  $X_i \sim U(-a, a)$  is uniform distribution

(a) let  $S_n = \frac{X_1 + X_2 + \dots + X_n}{\sqrt{n}}$  & Notation:  $\exp\{x\} = e^x$

$$\begin{aligned} \text{Characteristic function, } \Phi_{S_n}(j\omega) &= E[\exp\{-j\omega S_n\}] \\ &= E\left[\exp\left\{-j\omega \left(\frac{X_1 + X_2 + \dots + X_n}{\sqrt{n}}\right)\right\}\right] \end{aligned}$$

as given  $X_1, X_2, \dots, X_n$  are iid

$$\Phi_{S_n}(j\omega) = \left[ E\left[\exp\left\{-j\omega \frac{X_1}{\sqrt{n}}\right\}\right] \right]^n$$

$$\begin{aligned} E\left[\exp\left\{-j\omega \frac{X_1}{\sqrt{n}}\right\}\right] &= \int_{-\infty}^{\infty} f_{X_1}(x) \exp\left\{\frac{-j\omega x}{\sqrt{n}}\right\} dx = \int_{-a}^a \frac{1}{2a} \exp\left\{\frac{-j\omega x}{\sqrt{n}}\right\} dx \\ &= \left[ \frac{\sqrt{n}}{-2aj\omega} \exp\left\{\frac{-j\omega x}{\sqrt{n}}\right\} \right]_{-a}^a = \frac{\sqrt{n}}{2aj\omega} \left[ \exp\left\{\frac{j\omega a}{\sqrt{n}}\right\} - \exp\left\{\frac{-j\omega a}{\sqrt{n}}\right\} \right] \end{aligned}$$

$$\therefore \text{Characteristic function, } \Phi_{S_n}(j\omega) = \left[ \frac{\sqrt{n}}{2aj\omega} \left[ \exp\left\{\frac{j\omega a}{\sqrt{n}}\right\} - \exp\left\{\frac{-j\omega a}{\sqrt{n}}\right\} \right] \right]^n$$

(b) As we know,  $e^x - e^{-x} = 2 \left[ x + \frac{x^3}{3!} + \frac{x^5}{5!} + \dots \right]$

put  $x = \frac{j\omega a}{\sqrt{n}}$  & substitute value of  $e^x - e^{-x}$  in  $\Phi_{S_n}(j\omega)$  we get,

$$\Phi_{S_n}(j\omega) = \left[ 1 + \frac{(j\omega a)^2}{3! n} + \frac{(j\omega a)^4}{5! n^2} + \dots \right]^n = \left[ 1 + \sum_{i=1}^{\infty} \frac{(j\omega a)^{2i}}{(2i+1)! n^i} \right]^n$$

Now assume  $k = j\omega a$  & put limit  $n \rightarrow \infty$  on both sides we get,

$$\lim_{n \rightarrow \infty} \Phi_{S_n}(j\omega) = \exp \left\{ \lim_{n \rightarrow \infty} n \log \left[ 1 + \frac{k^2}{3! n} + \frac{k^4}{5! n^2} + \dots \right] \right\}$$

apply change of variable  $t = 1/n$ , (as  $n \rightarrow \infty$  we get  $t \rightarrow 0$ )

$$= \exp \left\{ \lim_{t \rightarrow 0} \frac{1}{t} \log \left[ 1 + \frac{k^2 t}{3!} + \frac{k^4 t^2}{5!} + \dots \right] \right\}$$

apply L'Hopital's we get, (because it is  $\frac{0}{0}$  form)

$$= \exp \left\{ \lim_{t \rightarrow 0} \frac{\left[ \frac{k^2}{3!} + 2 \frac{k^4 t}{5!} + \dots \right]}{\left[ 1 + \frac{k^2 t}{3!} + \frac{k^4 t^2}{5!} + \dots \right]} \right\} = \exp \left\{ \frac{k^2}{3!} \right\}$$

$$\lim_{n \rightarrow \infty} \Phi_{S_n}(j\omega) = \exp \left\{ \frac{k^2}{3!} \right\} = \exp \left\{ \frac{j^2 \omega^2 a^2}{6} \right\} = e^{-\omega^2 a^2 / 6}$$



Solution 4. Given  $U_0, U_1, \dots \sim N(0, 1)$  are iid

$$X_n = \frac{(U_n + U_{n-1})}{2} \text{ \& } Y_n = \frac{(U_n - U_{n-1})}{2}$$

(a)  $X_n$  &  $X_{n-1}$  can be written in matrix form as,

$$\begin{bmatrix} X_{n-1} \\ X_n \end{bmatrix} = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 0 & 1/2 & 1/2 \end{bmatrix} \begin{bmatrix} U_{n-2} \\ U_{n-1} \\ U_n \end{bmatrix}$$

here it is equivalent to  $X = AU$

$$\mu_X = A\mu_U = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 0 & 1/2 & 1/2 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\text{Covariance matrix, } C_X = AC_UA^T = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 0 & 1/2 & 1/2 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1/2 & 0 \\ 1/2 & 1/2 \\ 0 & 1/2 \end{bmatrix} = \begin{bmatrix} 1/2 & 1/4 \\ 1/4 & 1/2 \end{bmatrix}$$

$$|C_X| = \frac{1}{4} - \frac{1}{16} = \frac{3}{16} \text{ \& } C_X^{-1} = \frac{16}{3} \begin{bmatrix} 1/2 & -1/4 \\ -1/4 & 1/2 \end{bmatrix}$$

$$(x - \mu_X)^T C_X^{-1} (x - \mu_X) = \begin{bmatrix} x_{n-1} & x_n \end{bmatrix} \begin{bmatrix} 1/2 & -1/4 \\ -1/4 & 1/2 \end{bmatrix} \begin{bmatrix} x_{n-1} \\ x_n \end{bmatrix} \frac{16}{3} = \frac{8}{3} (x_n^2 + x_{n-1}^2 - x_n x_{n-1})$$

So, joint pdf of  $X_n$  &  $X_{n-1}$  can be written as,

$$\begin{aligned} f_{X_n, X_{n-1}}(x_n, x_{n-1}) &= \frac{1}{2\pi \sqrt{|C_X|}} \exp \left\{ -\frac{1}{2} (x - \mu_X)^T C_X^{-1} (x - \mu_X) \right\} \\ &= \frac{2}{\pi \sqrt{3}} \exp \left\{ -\frac{4}{3} (x_n^2 + x_{n-1}^2 - x_n x_{n-1}) \right\} \end{aligned}$$

(b)  $Y_n$  &  $Y_{n+m}$  can be written in matrix form as,

$$\begin{bmatrix} Y_n \\ Y_{n+m} \end{bmatrix} = \begin{bmatrix} -1/2 & 1/2 & \dots & 0 & 0 \\ 0 & 0 & \dots & -1/2 & 1/2 \end{bmatrix} \begin{bmatrix} U_{n-1} \\ U_n \\ \vdots \\ U_{n+m-1} \\ U_{n+m} \end{bmatrix}$$

for  $m > 1$  i.e.  $m = 2, 3, \dots$

here it is equivalent to  $Y = AU$

$$\mu_Y = A\mu_U = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$C_Y = AC_UA^T = \begin{bmatrix} 1/2 & 0 \\ 0 & 1/2 \end{bmatrix} = \frac{1}{2} I \text{ \& } |C_Y| = \frac{1}{4} \text{ \& } C_Y^{-1} = 2I$$

$$(y - \mu_Y)^T C_Y^{-1} (y - \mu_Y) = 2 (y_n^2 + y_{n+m}^2)$$

So, joint pdf of  $Y_n$  &  $Y_{n+m}$  can be written as,

$$\begin{aligned} f_{Y_n, Y_{n+m}}(y_n, y_{n+m}) &= \frac{1}{2\pi \sqrt{|C_Y|}} \exp \left\{ -\frac{1}{2} (y - \mu_Y)^T C_Y^{-1} (y - \mu_Y) \right\} \\ &= \frac{1}{\pi} \exp \left\{ -y_n^2 - y_{n+m}^2 \right\} \end{aligned}$$



(c) Here 5 cases arise for  $X_n$  &  $Y_m$

Case I:  $n=m$

$$\begin{bmatrix} X_n \\ Y_n \end{bmatrix} = \begin{bmatrix} 1/2 & 1/2 \\ -1/2 & 1/2 \end{bmatrix} \begin{bmatrix} U_{n-1} \\ U_n \end{bmatrix} \approx B = AU$$

$$\mu_B = A\mu_U = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$C_B = A^T C_U A = \begin{bmatrix} 0 & 1/2 \\ -1/2 & 0 \end{bmatrix} \quad \& \quad |C_B| = \frac{1}{4} \quad \& \quad C_B^{-1} = 4 \begin{bmatrix} 0 & -1/2 \\ 1/2 & 0 \end{bmatrix}$$

$$(B - \mu_B)^T C_B^{-1} (B - \mu_B) = 0$$

So, joint pdf of  $X_n$  &  $Y_n$  can be written as,

$$f_{X_n Y_n}(x_n, y_n) = \frac{1}{\pi}$$

Case II:  $n=m+1$

$$\begin{bmatrix} X_{n-1} \\ X_n \end{bmatrix} = \begin{bmatrix} -1/2 & 1/2 & 0 \\ 0 & 1/2 & 1/2 \end{bmatrix} \begin{bmatrix} U_{n-2} \\ U_{n-1} \\ U_n \end{bmatrix} \approx B = AU$$

$$\mu_B = A\mu_U = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$C_B = A^T C_U A = \begin{bmatrix} 1/2 & 1/4 \\ 1/4 & 1/2 \end{bmatrix} \quad \& \quad |C_B| = \frac{3}{16} \quad \& \quad C_B^{-1} = \frac{16}{3} \begin{bmatrix} 1/2 & -1/4 \\ -1/4 & 1/2 \end{bmatrix}$$

$$(B - \mu_B)^T C_B^{-1} (B - \mu_B) = \frac{8}{3} (x_n^2 + y_{n-1}^2 - x_n y_{n-1})$$

So, joint pdf of  $X_n$  &  $Y_{n-1}$  can be written as,

$$f_{X_n Y_{n-1}}(x_n, y_{n-1}) = \frac{2}{\pi \sqrt{3}} \exp \left\{ -\frac{4}{3} (x_n^2 + y_{n-1}^2 - x_n y_{n-1}) \right\}$$

Case III:  $m=n+1$

$$\begin{bmatrix} X_n \\ Y_{n+1} \end{bmatrix} = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 0 & -1/2 & 1/2 \end{bmatrix} \begin{bmatrix} U_{n-1} \\ U_n \\ U_{n+1} \end{bmatrix} \approx B = AU$$

$$\mu_B = A\mu_U = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$C_B = A^T C_U A = \begin{bmatrix} 1/2 & -1/4 \\ -1/4 & 1/2 \end{bmatrix} \quad \& \quad |C_B| = \frac{3}{16} \quad \& \quad C_B^{-1} = \frac{16}{3} \begin{bmatrix} 1/2 & 1/4 \\ 1/4 & 1/2 \end{bmatrix}$$

$$(B - \mu_B)^T C_B^{-1} (B - \mu_B) = \frac{8}{3} (x_n^2 + y_{n+1}^2 + x_n y_{n+1})$$

So, joint pdf of  $X_n$  &  $Y_{n+1}$  can be written as,

$$f_{X_n Y_{n+1}}(x_n, y_{n+1}) = \frac{2}{\pi \sqrt{3}} \exp \left\{ -\frac{4}{3} (x_n^2 + y_{n+1}^2 + x_n y_{n+1}) \right\}$$

Case IV:  $n > m+1$ 

$$\begin{bmatrix} y_m \\ x_n \end{bmatrix} = \begin{bmatrix} -1/2 & 1/2 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & 1/2 & 1/2 \end{bmatrix} \begin{bmatrix} u_{m-1} \\ u_m \\ \vdots \\ u_{n-1} \\ u_n \end{bmatrix} \approx B = AU$$

$$\mu_B = A\mu_U = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$C_B = A^T C_U A = \begin{bmatrix} 1/2 & 0 \\ 0 & 1/2 \end{bmatrix} \text{ \& } |C_B| = \frac{1}{4} \text{ \& } C_B^{-1} = 2I$$

$$(B - \mu_B)^T C_B^{-1} (B - \mu_B) = 2(x_n^2 + y_m^2)$$

So, joint pdf of  $x_n$  &  $y_m$  can be written as,

$$f_{x_n y_m}(x_n, y_m) = \frac{1}{\pi} \exp \{-x_n^2 - y_m^2\}$$

Case V:  $m > n+1$ 

$$\begin{bmatrix} x_n \\ y_m \end{bmatrix} = \begin{bmatrix} 1/2 & 1/2 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & -1/2 & 1/2 \end{bmatrix} \begin{bmatrix} u_{n-1} \\ u_n \\ \vdots \\ u_{m-1} \\ u_m \end{bmatrix} \approx B = AU$$

$$\mu_B = A\mu_U = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$C_B = A^T C_U A = \begin{bmatrix} 1/2 & 0 \\ 0 & 1/2 \end{bmatrix} \text{ \& } |C_B| = \frac{1}{4} \text{ \& } C_B^{-1} = 2I$$

$$(B - \mu_B)^T C_B^{-1} (B - \mu_B) = 2(x_n^2 + y_m^2)$$

So, joint pdf of  $x_n$  &  $y_m$  can be written as,

$$f_{x_n y_m}(x_n, y_m) = \frac{1}{\pi} \exp \{-x_n^2 - y_m^2\}$$



(d) Mean square convergence means/implies

$$\lim_{n \rightarrow \infty} E[|X_n - X|^2] = 0 \sim \text{converges to } X$$

Now here we don't have  $X$ , hence we use Cauchy criteria

$$\lim_{i, j \rightarrow \infty} E[|X_i - X_j|^2] = 0$$

$$\text{we have } X_i = \frac{U_i + U_{i-1}}{2} \text{ \& } X_j = \frac{U_j + U_{j-1}}{2}$$

$$\begin{aligned} |X_i - X_j|^2 &= \frac{1}{4} (U_i + U_{i-1} - U_j - U_{j-1})^2 \\ &= \frac{1}{4} [U_i^2 + U_{i-1}^2 + U_j^2 + U_{j-1}^2 + 2(-U_i U_j + U_i U_{j-1} - U_i U_{j-1} - U_{i-1} U_j - U_{i-1} U_{j-1} + U_j U_{j-1})] \end{aligned}$$

As we know  $U_i$  are iid &  $\sim N(0, 1)$  & hence we get,

$$E(|X_i - X_j|^2) = \frac{1}{4} (1 + 1 + 1 + 1) = \frac{4}{4} = 1 \neq 0$$

$$\lim_{i, j \rightarrow \infty} E(|X_i - X_j|^2) \neq 0$$

Hence,  $X_n$  do not converge in mean square sense.

$$(e) \quad X_n = \frac{(U_n + U_{n-1})}{2} \Rightarrow X_n = \begin{bmatrix} 1/2 & 1/2 \end{bmatrix} \begin{bmatrix} U_{n-1} \\ U_n \end{bmatrix} \approx X_n = AU$$

$$\mu_X = A\mu_U = 0$$

$$C_X = AC_U A^T = \begin{bmatrix} 1/2 & 1/2 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1/2 \\ 1/2 \end{bmatrix} = \frac{1}{2}$$

$$C_X^{-1} = 2 \text{ \& } |C_X| = \frac{1}{2}$$

$$(x - \mu_X)^T C_X^{-1} (x - \mu_X) = 2x^2$$

$$f_{X_n}(x_n) = \frac{1}{\sqrt{\pi}} e^{-x^2} \text{ which is pdf for } X_n$$

ie.  $X_n \sim N(0, 1/2)$  & also do not depend on  $n$

$$\therefore \lim_{n \rightarrow \infty} F_{X_n}(x) = F_{X^*}(x) \quad \forall x$$

$\sim N(0, 1/2)$

ie. same distribution

$\therefore X_n$  converges in distribution.



Solution 5.  $M_n = \frac{X_1 + X_2 + \dots + X_n}{n}$  where  $X_i$  are iid

$$(a) E[M_n] = \frac{1}{n} E[X_1 + X_2 + \dots + X_n] = \frac{n}{n} E[X] = E[X] = \mu \text{ (let)}$$

$$\text{let } \text{Var}(X) = \sigma^2$$

$$E[X_i^2] = \sigma^2 + \mu^2$$

$$E[X_i X_j] = E[X_i] E[X_j] = \mu^2 \text{ (iid samples for } i \neq j)$$

$$\text{Var}[M_n] = \frac{1}{n^2} \text{Var}[X_1 + X_2 + \dots + X_n] = \frac{n\sigma^2}{n^2} = \frac{\sigma^2}{n}$$

$$\begin{aligned} \text{Covariance, } \text{Cov}(M_n, M_k) &= E[(M_n - \mu)(M_k - \mu)] = E[M_n M_k] - \mu^2 + \mu^2 - \mu^2 \\ &= \frac{\min\{n, k\} (E(X^2) - \mu^2) + n k \mu^2}{n k} - \mu^2 \\ &= \min\{n, k\} \frac{\sigma^2}{n k} \quad (\text{because } E(X^2) - \mu^2 = \sigma^2) \end{aligned}$$

$$(b) M_{n+1} - M_n = \frac{X_1 + X_2 + \dots + X_n + X_{n+1}}{n+1} - \frac{X_1 + X_2 + \dots + X_n}{n} = -\frac{M_n}{n+1} + \frac{X_{n+1}}{n+1}$$

$$\text{ie. } M_{n+1} - M_n = \frac{X_{n+1} - M_n}{n+1}$$

here it is clear that  $M_{n+1} - M_n$  depends on  $M_n$  & hence not independent increment  
 $\therefore M_n$  does not have independent increments.

$$\begin{aligned} \text{NOTE: } \text{Cov}((M_{n+2} - M_{n+1}), (M_{n+1} - M_n)) &= E((M_{n+2} - M_{n+1})(M_{n+1} - M_n)) \\ &\text{because } E[M_{n+m} - M_n] = \mu - \mu = 0 \end{aligned}$$

$$\begin{aligned} \text{Cov}((M_{n+2} - M_{n+1}), (M_{n+1} - M_n)) &= E[M_{n+2} M_{n+1}] - E[M_{n+2} M_n] - E[M_{n+1}^2] + E[M_{n+1} M_n] \\ &= \frac{\sigma^2}{n+2} - \frac{\sigma^2}{n+2} - \frac{\sigma^2}{n+1} + \frac{\sigma^2}{n+1} = 0 \end{aligned}$$

here we get covariance = 0 but not independent ie.  
 covariance does not imply independence

(c) For stationary increments,  $M_{n+1} - M_n$  and  $M_1$  have same distribution

$$E[M_{n+1} - M_n] = \mu - \mu = 0 \quad \text{--- (i)}$$

$$E[M_1] = E[X_1] = \mu \quad \text{--- (ii)}$$

$$\begin{aligned} \text{Var}[M_{n+1} - M_n] &= \text{Var}(M_{n+1}) + \text{Var}(M_n) - 2 \text{Cov}(M_{n+1}, M_n) \\ &= \frac{\sigma^2}{n+1} + \frac{\sigma^2}{n} - \frac{2\sigma^2}{n+1} = \frac{\sigma^2}{n(n+1)} \quad \text{--- (iii)} \end{aligned}$$

$$\text{Var}[M_1] = \text{Var}[X_1] = \sigma^2 \quad \text{--- (iv)}$$

from (i), (ii), (iii) & (iv) we conclude that,  
 $M_n$  does not have stationary increments.



Solution 6. Probability distribution for  $X_n$  can be given as

$$P_n[X(n)=x] = \begin{cases} 1/2, & x=1 \text{ (heads)} \\ 1/2, & x=-1 \text{ (tails)} \end{cases}$$

As events doesnot depend on previous. So, independent events.

(a) Expected value,  $m_{x(n)} = \frac{1}{2} - \frac{1}{2} = 0 \quad \forall n$

$$\begin{aligned} \text{Covariance, } C_x(n_1, n_2) &= E[(X(n_1) - m_{x(n_1)})(X(n_2) - m_{x(n_2)})] && \text{identical (not depend on } n) \\ &= E[X(n_1)X(n_2)] = E[X(n_1)]E[X(n_2)] && (\text{independent events}) \\ &\quad \& R_x(n_1, n_2) \quad R_x(n_1, n_2) = 0 = 0(n_1 - n_2) \end{aligned}$$

As  $C_x(n_1, n_2)$  is function of  $n_1 - n_2$ .

Hence,  $X_n$  is Wide Sense Stationary random process.

(b)  $P_n[X(n_1)=a_1, X(n_2)=a_2, \dots, X(n_k)=a_k] = P_n[X(n_1)=a_1] P_n[X(n_2)=a_2] \dots P_n[X(n_k)=a_k] \quad \text{--- (i)}$

because independent events for  $a_i \in \{-1, 1\} \forall i$

As  $P_n$  value will not depend on  $n$  & hence,

$$P_n[X(n_i + T) = a_i] = P_n[X(n_i) = a_i]$$

$$\begin{aligned} P_n[X(n_1 + T) = a_1, X(n_2 + T) = a_2, \dots, X(n_k + T) = a_k] &= P_n[X(n_1 + T) = a_1] \dots P_n[X(n_k + T) = a_k] \\ &= P_n[X(n_1) = a_1] P_n[X(n_2) = a_2] \dots P_n[X(n_k) = a_k] \quad \text{--- (ii)} \end{aligned}$$

from (i) & (ii) we conclude that,

$$P_n[X(n_1 + T) = a_1, X(n_2 + T) = a_2, \dots, X(n_k + T) = a_k] = P_n[X(n_1) = a_1, X(n_2) = a_2, \dots, X(n_k) = a_k]$$

Hence,  $X_n$  is stationary random process.

(c) if coin is biased then probability distribution for  $X_n$  can be given as

$$P_n[X(n)=x] = \begin{cases} p, & x=1 \text{ (heads)} \\ 1-p, & x=-1 \text{ (tails)} \end{cases}$$

As events neither depend on previous nor on  $n$ . So, identical & independent events.

$$m_{x(n)} = p - (1-p) = 2p-1 \quad \forall n \quad (\text{let } \mu = 2p-1)$$

$$\begin{aligned} C_x(n_1, n_2) &= E[(X(n_1) - m_{x(n_1)})(X(n_2) - m_{x(n_2)})] \\ &= E[X(n_1)X(n_2)] - \mu^2 + \cancel{\mu^2} - \cancel{\mu^2} \\ &= E[X(n_1)]E[X(n_2)] - \mu^2 = \mu^2 - \mu^2 = 0 = 0(n_1 - n_2) \\ &\quad \& R_x(n_1, n_2) \end{aligned}$$

As  $C_x(n_1, n_2)$  is function of  $n_1 - n_2$

Hence,  $X_n$  is WSS random process here also (in biased coin case).

$$P_{\mathcal{H}}[X(n_1)=a_1, X(n_2)=a_2, \dots, X(n_k)=a_k] = P_{\mathcal{H}}[X(n_1)=a_1] P_{\mathcal{H}}[X(n_2)=a_2] \dots P_{\mathcal{H}}[X(n_k)=a_k] \quad \text{--- ii}$$

because independent events for  $a_i \in \{-1, 1\} \forall i$

As  $P_{\mathcal{H}}$  value will not depend on  $n$  & hence,

$$P_{\mathcal{H}}[X(n_i + \tau) = a_i] = P_{\mathcal{H}}[X(n_i) = a_i]$$

$$\begin{aligned} P_{\mathcal{H}}[X(n_1 + \tau) = a_1, X(n_2 + \tau) = a_2, \dots, X(n_k + \tau) = a_k] &= P_{\mathcal{H}}[X(n_1 + \tau) = a_1] \dots P_{\mathcal{H}}[X(n_k + \tau) = a_k] \\ &= P_{\mathcal{H}}[X(n_1) = a_1] P_{\mathcal{H}}[X(n_2) = a_2] \dots P_{\mathcal{H}}[X(n_k) = a_k] \quad \text{--- iii} \end{aligned}$$

from ii & iii we conclude that,

$$P_{\mathcal{H}}[X(n_1 + \tau) = a_1, X(n_2 + \tau) = a_2, \dots, X(n_k + \tau) = a_k] = P[X(n_1) = a_1, X(n_2) = a_2, \dots, X(n_k) = a_k]$$

Hence,  $X_n$  is stationary random process here also (in biased coin case)