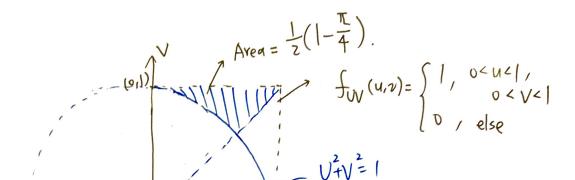
## Problem





Therefore, 
$$P(U^2V^2)$$
,  $U \leq V$ 

$$= \frac{1}{2}(1 - \frac{\pi}{4})$$

Markov's inequality is applicable only to non-negative vandom variables.

Since 
$$X_1, X_2$$
 are Bernoulli and  $E[X_1^2] = \frac{1}{2}$ ,  $E[X_2^2] = \frac{1}{2}$ , then  $X_1 = \begin{cases} 1 & \text{w.p.} \frac{1}{2} \\ 0 & \text{w.p.} \frac{1}{2} \end{cases}$ ,  $X_2 = \begin{cases} 1 & \text{w.p.} \frac{1}{2} \\ 0 & \text{w.p.} \frac{1}{2} \end{cases}$ 

One possible case is that Xz= 1-X1.

Then, 
$$E[X_1X_2]=0$$
,  $Cov(X_1,X_2)=E[X_1X_2]-E[X_1]E[X_2]$   
=  $0-\frac{1}{2}\times\frac{1}{2}$ 

Therefore, it is possible that  $\chi_1,\chi_2$  are negatively correlated.

$$P(\left\{\omega : \lim_{n \to \infty} Y_n(\omega) \ge \xi\right\}) = 0 \quad \text{for all } \xi > 0.$$
Hence, 
$$P(\left\{\omega : \lim_{n \to \infty} Y_n(\omega) = 0\right\}) = 1, \text{ i.e., } Y_n \xrightarrow{a.s.} 0$$

$$P(\theta=0.3)P(THT|\theta=0.3) = \frac{P(\theta=0.3)P(THT|\theta=0.3)}{P(THT)} = \frac{O.4 \times (0.7)^2 \times (0.3)}{P(THT)}$$

$$P(\theta=0.7|THT) = \frac{P(\theta=0.7) \cdot P(THT|\theta=0.7)}{P(THT)} = \frac{O.6 \times (0.3)^2 \times (0.7)}{P(THT)}$$

$$Therefore, P(\theta=0.3|THT) > P(\theta=0.7|THT).$$

(a) 
$$\frac{\text{For } t \neq 0}{\text{M}_{X}(t)} = \text{E[e]} = \begin{cases} t \\ -\infty \end{cases} e^{tx} \int_{x}^{x} (x) dx$$

$$= \int_{-1}^{3} e^{tx} \frac{1}{4} dx = \frac{1}{4t} e^{tx} \Big|_{-1}^{3} = \frac{1}{4t} \left(e^{3t} - e^{t}\right)$$

For 
$$t=0$$
:
$$M_{X}(t) = \int_{-1}^{3} e^{0} \frac{1}{4} dx = 1$$

Therefore, 
$$M_X(t) = \begin{cases} \frac{1}{4t} (e^{3t} - e^{-t}), & t \neq 0 \\ 1, & t = 0. \end{cases}$$

$$E[X] = M_{X}(0) = \lim_{h \to 0} \frac{M_{X}(h) - M_{X}(0)}{h}$$

$$= \lim_{h \to 0} \frac{\frac{1}{4h}(\frac{3^{h} - e^{h}}{-e^{h}}) - 1}{h}$$

$$= \lim_{h \to 0} \frac{\frac{2^{h} - e^{h} - 4h}{h}}{\frac{4h^{2}}{-e^{h}}}$$

$$= \lim_{h \to 0} \frac{3e^{h} - e^{h} - 4h}{\frac{8h}{-e^{h}}}$$

$$= \lim_{h \to 0} \frac{9e^{3h} - e^{h}}{\frac{8h}{-e^{h}}}$$

(Cont.)
$$E[X^{2}] = M_{X}'(0) = \lim_{h \to 0} \frac{M_{X}(h) - M_{X}(0)}{h}$$

$$= \lim_{h \to 0} \frac{-\frac{1}{4h^{2}}(e^{3h} - h^{2}) + \frac{1}{4h}(3e^{3h} - h^{2}) - \frac{1}{4h^{2}}}{h}$$

$$= \lim_{h \to 0} \frac{-(e^{3h} - h^{2}) + h(3e^{3h} - h^{2}) - 4h^{2}}{4h^{3}}$$

$$= \lim_{h \to 0} \frac{-(e^{3h} - h^{2}) + h(3e^{3h} - h^{2}) + h(9e^{3h} - h^{2}) - 8h}{12h^{2}}$$

$$= \lim_{h \to 0} \frac{(qe^{3h} - h^{2}) + h(2ne^{3h} - h^{2}) - 8h}{24h}$$

$$= \lim_{h \to 0} \frac{(2ne^{3h} + e^{-h}) + h(8e^{3h} - e^{-h})}{24h}$$

$$= \frac{(2ne^{3h} + e^{-h}) + (2ne^{3h} - e^{-h}) + h(8e^{3h} - e^{-h})}{24}$$

$$= \frac{n}{3}$$

Therefore, 
$$Var[X] = E[X^2] - (E[X])^2$$

$$= \frac{7}{3} - 1^2$$

$$= \frac{4}{3}$$

X1, Xz, ..., Xn are i.i.d. standard normal.

Then, X1, X2, ..., Xn are also i.i.d. with:

$$E[X_i^2] = V_{av}[X_i] + (E[X_i])^2 = 1$$

$$E[\chi_{\overline{t}}^{+}] = \frac{dM_{\chi_{\overline{t}}}(t)}{dt^{+}}\Big|_{t=0} = 3.$$

Var[xi] = E[xi4] - (E[xi3]) = 3-1=2

Accordingly, by CLT, we can approximate

Sn=X1+ ... + Xn as follows: For any a EIR,

$$M_{x_{i}}(t) = Q^{2}$$

$$M_{x_{i}}(t) = t \cdot Q^{2}$$

$$M_{x_{i}}(t) = Q^{2} + t^{2} \cdot Q^{2}$$

$$+ t^{2} \cdot Q^{2} + t^{2} \cdot Q^{2}$$

$$+ 3t^{2}Q^{2} + t^{2}Q^{2}$$

$$P\left(\frac{S_{n}-n.E[X_{i}^{2}]}{\sqrt{n.Var[X_{i}^{2}]}} \leq a\right) = P\left(\frac{S_{n}-n}{\sqrt{2n}} \leq a\right) \approx \overline{\Phi}(a)$$

Therefore, we have 
$$P(S_n \le n + \sqrt{2n}) = P(\frac{S_n - n}{\sqrt{2n}} \le 1) \approx \overline{\Phi}(1)$$
.

(a). 
$$P(Z \le t) = P(U = 1 \text{ and } X \le t) + P(U = 0 \text{ and } X \ge -t)$$

by the independence
$$= P(U = 1) \cdot P(X \le t) + P(U = 0) \cdot P(X \ge -t)$$

$$= \frac{1}{2} \cdot \overline{P(t)} + \frac{1}{2} \left( 1 - \overline{P(-t)} \right) = \overline{\Phi(t)} \text{ by the symmetry of } \overline{\Phi(c)}$$

$$= \overline{Q(t)}.$$

(b) 
$$C_{OV}(X,Z) = E[XZ] - (E[X])E[Z]$$

$$= E[XZ]$$

$$= P(U=0) \cdot E[XZ|U=0] + P(U=1) \cdot E[XZ|U=1]$$

$$= P(U=0) \cdot E[-X^2|U=0] + P(U=1) \cdot E[X^2|U=1]$$

$$= D$$

(c). Recall that two Yandom Variables  $X_1, X_2$  are independent if for arbitrary sets of real numbers A, B, we have  $P(X \in A, Y \in B) = P(X \in A) \cdot P(X \in B)$ . It is easy to check that  $P(X \in [H, I], Z \in [2,3]) = 0$ , but  $P(X \in [H, I]) > 0$ . Hence, X and Z are not independent. D

Problem 5 
$$\times \sim \text{Exp}(\lambda=1)$$
  
 $Y_n = \{1, \text{ if } \times \times n\}$   
 $Y_n = \{0, \text{ else}\}$   
For any  $\{0, \text{ else}\}$   
For any  $\{0, \text{ else}\}$   
 $Y_n(\omega) = 0 > \{0, \text{ for all } n \in \mathbb{N}\}$   
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 $Y_n(\omega) = \{0, \text{ else}\}$ 

D

Therefore, we know that for any 
$$\varepsilon > 0$$
,
$$\lim_{h \to \infty} \mathbb{P}\left\{\left\{\omega: \left| Y_n(\omega) - 0\right| > \varepsilon^2\right\}\right\} = 0$$

$$P\left(\left|\frac{X_{A,N}}{N} - E\left[\frac{X_{A,N}}{N}\right] > \delta\right) \leq \frac{\sqrt{\alpha_{Y}\left[\frac{X_{A,N}}{N}\right]}}{\delta^{2}}$$

Moreover, we know 
$$E\left[\frac{X_{A,N}}{N}\right] = \theta_{A}$$
.

Then, we conclude that for any \$>0,

$$P\left(\frac{\chi_{A,N}}{N} \leq \theta_{\alpha} - \delta\right) \leq P\left(\left|\frac{\chi_{A,N}}{N} - \theta_{\alpha}\right| > \delta\right) \leq \frac{\theta_{\alpha} \cdot (1 - \theta_{\alpha})}{N \delta^{2}}$$

(b). 
$$P\left(\left\{\frac{\chi_{A,N}}{N} > \frac{\chi_{B,N}}{N}\right\}\right) > P\left(\left\{\frac{\chi_{A,N}}{N} > \theta_{\alpha} - \frac{\Delta}{2}\right\} \cap \left\{\frac{\chi_{B,N}}{N} \leq \theta_{0} + \frac{\Delta}{2}\right\}\right)$$

by independence = 
$$P\left(\left\{\frac{X_{A,N}}{N} > \theta_{\alpha} - \frac{\Delta^{2}}{2}\right\}\right) \cdot P\left(\left\{\frac{X_{B,N}}{N} \leq \theta_{b} + \frac{\Delta^{2}}{2}\right\}\right)$$
of  $X_{A,N}$  and  $X_{B,N}$ 

$$= \left[ \left| - P\left( \left\{ \frac{\lambda^{N}}{N} \leq \theta^{N} - \frac{\sigma}{2} \right\} \right) \right| \left[ \left| - P\left( \left\{ \frac{\lambda^{N}}{N} > \theta^{P} + \frac{\sigma}{2} \right\} \right) \right]$$

$$P\left(\left\{\frac{X^{B'N}}{N} > \theta^{P} + \frac{\nabla}{S}\right\}\right) \leq P\left(\left[\frac{X^{B'N}}{N} - \theta^{P}\right] > \frac{\nabla}{S}\right) \leq \frac{\theta^{P}(1 - \theta^{P})}{N \cdot \left(\frac{\nabla}{S}\right)^{2}}$$
 (\*)

Therefore, we have 
$$P\left(\left\{\frac{X_{A,N}}{N}>\frac{X_{B,N}}{N}\right\}\right) > \left(1-\frac{\theta_a(1-\theta_a)}{N(\frac{\Delta}{2})^2}\right) \cdot \left(1-\frac{\theta_b(1-\theta_b)}{N\cdot(\frac{\Delta}{2})^2}\right)$$
.