

## 2201-MTL106: ASSIGNMENT-5

**✓Q1.** Let  $g : [0, \infty) \mapsto (0, \infty)$  be a function such that  $g(x) \geq b > 0$  for  $x \geq a$ . Let  $X$  be a non-negative random variable such that  $\mathbb{E}[g(X)]$  exists. Show that

$$\mathbb{P}(X \geq a) \leq \frac{\mathbb{E}[g(X)]}{b}.$$

**✓Q2.** Let  $X$  be a Binomial  $B(n, p)$  random variable defined on a given probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ . Then show the followings:

- a) For  $\lambda > 0$  and  $b > 0$ ,  $\mathbb{P}(X - np > nb) \leq \mathbb{E}[\exp(\lambda(X - np - nb))]$ .
- b) For any  $\epsilon > 0$ ,  $\mathbb{P}(X \geq np + \epsilon \sqrt{np(1-p)}) \leq \frac{1}{1+\epsilon^2}$ .
- c) For all  $\epsilon > 0$ ,  $\mathbb{P}(|X - np| \leq n\epsilon)$  tends to 1.

*Read ~ Q3.* Show that  $X_n \xrightarrow{\mathbb{P}} X$  if and only if  $\lim_{n \rightarrow \infty} \mathbb{E}(1 \wedge |X_n - X|) = 0$ .

**✓Q4.** Let  $\{X_n\}$  be a sequence of random variables defined on a given probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ , given by

$$X_n := \sqrt{n} \mathbf{1}_{(0, \frac{1}{n})}(U), \quad U \sim \mathcal{U}(0, 1).$$

Show that  $X_n \xrightarrow{\mathbb{P}} 0$  but  $X_n \not\xrightarrow{2} 0$ .

**✓Q5.** Prove or disprove:  $X_n \xrightarrow{\mathbb{P}} 0 \implies \mathbb{E}(X_n) \rightarrow 0$  and  $\text{Var}(X_n) \rightarrow 0$ .

**✓Q6.** Let  $\{X_n\}$  be a sequence of random variables that is monotonically increasing, i.e.,  $X_n(\omega) \leq X_{n+1}(\omega)$  for all  $\omega \in \Omega, n \in \mathbb{N}$ . If  $X_n \xrightarrow{\mathbb{P}} X$ , then show that  $X_n \xrightarrow{a.s.} X$ .

**✓Q7.** Let  $X_n \xrightarrow{d} X$  with  $X = a$  a.e. Then show that  $X_n \xrightarrow{\mathbb{P}} a$ .

**✓Q8.** Prove or disprove:

$$X_n \xrightarrow{d} X, \quad Y_n \xrightarrow{\mathbb{P}} c, \quad c \in \mathbb{R}, \implies X_n + Y_n \xrightarrow{d} X + c, \quad X_n Y_n \xrightarrow{d} cX.$$

**✓Q9.** Let  $Y, \{X_n\}$  be random variables such that for each fixed  $\tau > 0$ ,  $X_n + \tau Y \xrightarrow{d} X + \tau Y$ . Show that  $X_n \xrightarrow{d} X$ .

**✓Q10.** Let  $\{X_j\}$  be a sequence of i.i.d. random variables with  $X_j$  in  $L^1$ . Let  $Y_j = e^{X_j}$ . Show that  $\left(\prod_{i=1}^n Y_i\right)^{\frac{1}{n}}$  converges to a constant  $\alpha = e^{\mathbb{E}[X_1]}$ .

**✓Q11.** Let  $\{X_j\}$  be a sequence of i.i.d. non-negative random variables with  $\mathbb{E}[X_1] = 1$  and  $\text{Var}(X_1) = \sigma^2 \in (0, \infty)$ . Show that

$$\frac{2}{\sigma} (\sqrt{S_n} - \sqrt{n}) \xrightarrow{d} Y, \quad Y \sim \mathcal{N}(0, 1).$$

**✓Q12.** Use CLT to show that

$$\lim_{n \rightarrow \infty} e^{-n} \sum_{k=0}^n \frac{n^k}{k!} = \frac{1}{2}.$$

✓ **Q13.** Let  $\{X_i\}$  be a sequence of i.i.d. random variables with  $\mathbb{P}(X_i = 1) = \frac{3}{4}$  and  $\mathbb{P}(X_i = 0) = \frac{1}{4}$ . Let  $Y_i = X_i + X_i^2$ . Use CLT to evaluate  $\mathbb{P}\left(\sum_{i=1}^{80} Y_i > 100\right)$ .

✓ **Q14.** Let  $\{X_i\}$  be a sequence of **i.i.d** non-negative random variables with mean 4 and variance 16. Calculate:

$$\lim_{n \rightarrow \infty} \mathbb{E}\left[\cos(\sqrt{S_n} - 2\sqrt{n})\right],$$

where  $S_n := \sum_{i=1}^n X_i$ .

✗ **Q15.** Let  $\{X_n\}$  be a sequence of **i.i.d** random variables, defined on a given probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ , with uniform distribution on  $(-1, 1)$ . Let

$$Y_n = \frac{\sum_{i=1}^n X_i}{\sum_{i=1}^n X_i^2 + X_i^3}.$$

Show that  $\sqrt{n}Y_n$  converges in distribution as  $n \rightarrow \infty$ . Let  $\phi_n(t)$  be the characteristic function of  $\sqrt{n}Y_n$ . Calculate  $\lim_{n \rightarrow \infty} \phi_n(2)$ .

✓ **Q16.** Let  $X_n \xrightarrow{\mathbb{P}} X$ . Show that the characteristic function  $\phi_{X_n}$  converges pointwise to  $\phi_X$ .

Q1. Let  $g : [0, \infty) \rightarrow (0, \infty)$  be a function such that  $g(x) \geq b > 0$  for  $x \geq a$ . Let  $X$  be a non-negative random variable such that  $\mathbb{E}[g(X)]$  exists. Show that

$$\mathbb{P}(X \geq a) \leq \frac{\mathbb{E}[g(X)]}{b}$$

$$g(x) \geq b > 0 \text{ for } x \geq a$$

$$\mathbb{P}(X \geq a) \leq \underbrace{\mathbb{P}(g(X) \geq b)}_{\substack{\text{true for} \\ x \geq a \text{ atleast}}} \leq \frac{\mathbb{E}[g(X)]}{b}$$

Q2. Let  $X$  be a Binomial  $B(n, p)$  random variable defined on a given probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ . Then show the followings:

- a) For  $\lambda > 0$  and  $b > 0$ ,  $\mathbb{P}(X - np > nb) \leq \mathbb{E}[\exp(\lambda(X - np - nb))]$ .
- b) For any  $\epsilon > 0$ ,  $\mathbb{P}(X \geq np + \epsilon \sqrt{np(1-p)}) \leq \frac{1}{1+\epsilon^2}$ .
- c) For all  $\epsilon > 0$ ,  $\mathbb{P}(|X - np| \leq n\epsilon)$  tends to 1.

a)  $\lambda > 0$  and  $b > 0$

$$\mathbb{P}(X - np > nb) \leq \mathbb{E}[e^{\lambda(X - np - nb)}]$$

$$\begin{aligned} \mathbb{P}(e^{\lambda(X - np - nb)} > 1) &\leq \frac{\mathbb{E}[e^{\lambda(X - np - nb)}]}{1} && \text{Markov's Inequality} \\ \downarrow \\ &= \mathbb{P}(\lambda(X - np - nb) > 0) \\ &= \mathbb{P}(X - np > nb) \end{aligned}$$

b)  $\epsilon > 0$ ,  $\mathbb{P}(X \geq np + \epsilon \sqrt{np(1-p)}) \leq \frac{1}{1+\epsilon^2}$

$$\mathbb{P}\left(\frac{X - np}{\sqrt{np(1-p)}} \geq \epsilon\right) = \mathbb{P}(|Z - 0| \geq \epsilon) \leq \frac{1}{\epsilon^2}$$

or using one sided Chebyshev's

$$\begin{aligned} \mathbb{P} &\leq \frac{\sigma^2}{\sigma^2 + \alpha^2} \\ &= \frac{1}{1+\epsilon^2} \therefore \text{Proved} \end{aligned}$$

c)  $\epsilon > 0$ ,  $\mathbb{P}(|X - np| \leq n\epsilon) \rightarrow 1$

$$\begin{aligned} &\equiv \mathbb{P}(|X - np| > n\epsilon) \rightarrow 0 \\ &\leq \frac{n\epsilon(1-p)}{n^2\epsilon^2} \rightarrow 0 \end{aligned}$$

Q3. Show that  $X_n \xrightarrow{\mathbb{P}} X$  if and only if  $\lim_{n \rightarrow \infty} \mathbb{E}(1 \wedge |X_n - X|) = 0$ .

$$X_n \xrightarrow{\mathbb{P}} X \quad : \quad \forall \epsilon > 0, \quad \lim_{n \rightarrow \infty} \mathbb{P}(|X_n - X| > \epsilon) = 0$$

$$\begin{aligned} \mathbb{E}(1 \wedge |X_n - X|) &= \mathbb{E}\left(\mathbf{1}_{|X_n - X| > 1} + |X_n - X| \mathbf{1}_{|X_n - X| \leq 1}\right) \\ &= E\left(\mathbf{1}_{|X_n - X| > 1}\right) + |X_n - X| \mathbb{P}(|X_n - X| \leq 1) \\ &= 1 \cdot \mathbb{P}(|X_n - X| > 1) + \mathbb{E}(|X_n - X|) \mathbb{P}(|X_n - X| \leq 1) \end{aligned}$$

$$X_n := \begin{cases} \sqrt{n} & \text{if } (0, 1/n) \\ 0 & \text{otherwise} \end{cases}$$

$$X_n := \begin{cases} \sqrt{n} & \text{if } (0, 1/n) \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbb{P}(|X_n| > \epsilon) = \mathbb{P}(X_n > \epsilon) = \mathbb{P}(X_n = \sqrt{n})$$

Q4. Let  $\{X_n\}$  be a sequence of random variables defined on a given probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ , given by

$$X_n := \sqrt{n} \mathbf{1}_{(0, \frac{1}{n})}(U), \quad U \sim \mathcal{U}(0, 1).$$

Show that  $X_n \xrightarrow{\mathbb{P}} 0$  but  $X_n \not\xrightarrow{d} 0$ .

$$X_n = \sqrt{n} \mathbf{1}_{(0, \frac{1}{n})}(U)$$

$$X_n = \begin{cases} \sqrt{n} U_{(0,1)}, & 0 < U < \frac{1}{n} \\ 0, & \text{else} \end{cases}$$

$$\lim_{n \rightarrow \infty} \mathbb{P}\{|X_n - 0| > \epsilon\} \begin{cases} \text{if } \epsilon > \sqrt{n}, \mathbb{P} = 0 \\ \epsilon < \sqrt{n}, \mathbb{P} = \sqrt{n} \times \frac{1}{n} \rightarrow 0 \text{ as } n \rightarrow \infty \end{cases} \therefore X_n \xrightarrow{\mathbb{P}} 0$$

$$\lim_{n \rightarrow \infty} \mathbb{E}(|X_n - 0|^2) = 0.$$

$$\mathbb{E}(|X_n|^2) = n \times \frac{1}{n} = 1 \neq 0$$

Q5. Prove or disprove:  $X_n \xrightarrow{\mathbb{P}} 0 \implies \mathbb{E}(X_n) \rightarrow 0$  and  $\text{Var}(X_n) \rightarrow 0$ .

$$X_n \xrightarrow{\mathbb{P}} 0 \Rightarrow \begin{aligned} \mathbb{E}(X_n) &\rightarrow 0 \\ \& \text{Var}(X_n) \rightarrow 0 \end{aligned}$$

$$\lim_{n \rightarrow \infty} \mathbb{P}(|X_n| > \epsilon) = 0 \leq \frac{\mathbb{E}(X_n)}{\epsilon}$$

The statements are not true

• Counterexample:

$$\begin{aligned} \mathbb{P}(X_n = 0) &= 1 - 1/n \\ \mathbb{P}(X_n = n) &= 1/n \end{aligned}$$

$$X_n \xrightarrow{\mathbb{P}} 0$$

$$\begin{aligned} \text{But } \lim_{n \rightarrow \infty} \mathbb{E}[X] &= 1 \\ \lim_{n \rightarrow \infty} \text{Var}(X) &= n - 1 \end{aligned} \} \neq 0$$

Q6. Let  $\{X_n\}$  be a sequence of random variables that is monotonically increasing, i.e.,  $X_n(\omega) \leq X_{n+1}(\omega)$  for all  $\omega \in \Omega, n \in \mathbb{N}$ . If  $X_n \xrightarrow{\mathbb{P}} X$ , then show that  $X_n \xrightarrow{a.s.} X$ .

$$X_n(\omega) \leq X_{n+1}(\omega) \quad \forall \omega \in \Omega$$

$$X_n \xrightarrow{\mathbb{P}} X$$

$$\lim_{n \rightarrow \infty} \mathbb{P}(|X_n - X| > \epsilon) = 0$$

$$\begin{aligned}
 & \text{PROOF: } \lim_{n \rightarrow \infty} \mathbb{P}(|X_n - a| > \epsilon) \\
 &= \lim_{n \rightarrow \infty} \mathbb{P}(a - \epsilon \leq X_n \leq a + \epsilon) \\
 &= \lim_{n \rightarrow \infty} [F_{X_n}(a + \epsilon) - F_{X_n}(a - \epsilon)] \\
 &= 1 - \lim_{n \rightarrow \infty} [1 - F_{X_n}(a - \epsilon)] = 0 \\
 & \quad \text{Case 1: } t < a \quad \mathbb{P}(X \leq t) = 0 \\
 & \quad \text{Case 2: } t \geq a \quad \mathbb{P}(X \leq t) = 1 \\
 & \quad \lim_{n \rightarrow \infty} \mathbb{P}(X_n \leq t) = 0 \quad \lim_{n \rightarrow \infty} \mathbb{P}(X_n \leq t) = 1
 \end{aligned}$$

Q7. Let  $X_n \xrightarrow{d} X$  with  $X = a$  a.e. Then show that  $X_n \xrightarrow{\mathbb{P}} a$ .

$$X_n \xrightarrow{d} X \quad X = a \quad (\text{a.e.})$$

$$\lim_{n \rightarrow \infty} \phi_{X_n} = \phi_X \quad \mathbb{P}(X = a) = 1$$

$$\begin{aligned}
 \mathbb{P}(|X_n - X| > \epsilon) &= \mathbb{P}(|X_n - a| > \epsilon) \\
 &= 1 - \mathbb{P}(|X_n - a| \leq \epsilon) \\
 &= 1 - \mathbb{P}(a - \epsilon \leq X_n \leq a + \epsilon) \\
 &= 1 - (F_{X_n}(a + \epsilon) - F_{X_n}(a - \epsilon)) \\
 &= 1 - F_{X_n}(a + \epsilon) + F_{X_n}(a - \epsilon)
 \end{aligned}$$

$$\lim_{n \rightarrow \infty} \mathbb{P}(|X_n - X| > \epsilon) = 1 - \underbrace{F_X(a + \epsilon)}_{1} + \underbrace{F_X(a - \epsilon)}_{0} \quad (\because X_n \xrightarrow{d} X) \\
 (\because X = a \text{ a.e.})$$

$$= 0 \quad \therefore \text{Hence proved} \quad X_n \xrightarrow{\mathbb{P}} X$$

Q8. Prove or disprove:

$$X_n \xrightarrow{d} X, Y_n \xrightarrow{\mathbb{P}} c, c \in \mathbb{R}, \Rightarrow X_n + Y_n \xrightarrow{d} X + c, X_n Y_n \xrightarrow{d} cX.$$

$$X_n \xrightarrow{d} X, Y_n \xrightarrow{\mathbb{P}} c \Rightarrow X_n + Y_n \xrightarrow{d} X + c$$

$$\lim_{n \rightarrow \infty} P(|Y_n - c| > \epsilon) = 0 \quad X_n Y_n \xrightarrow{d} cX$$

$$\begin{aligned} & P(X_n Y_n \leq t) \\ & \sum P(X_n Y_n \leq t) \times P(Y_n = y) \\ & \lim_{n \rightarrow \infty} P(|Y_n - c| > \epsilon) = 0 \end{aligned}$$

$$\begin{aligned} P(X_n + Y_n \leq t) &= P(X_n + Y_n \leq t, |Y_n - c| \leq \epsilon) + P(X_n + Y_n \leq t, |Y_n - c| \geq \epsilon) \\ &= \underbrace{P(X_n + Y_n \leq t, c - \epsilon \leq Y_n \leq c + \epsilon)}_A \end{aligned}$$

$$\Rightarrow A \geq P(X_n + c + \epsilon \leq t) \quad \textcircled{1}$$

$$\text{and } A \leq P(X_n + c - \epsilon \leq t) \quad \textcircled{2}$$

$$\text{From } \textcircled{1}, \textcircled{2}, \text{ take } \epsilon = 0, \quad A = P(X_n + c \leq t) = F_{X_n}(t - c)$$

Now take  $\lim_{n \rightarrow \infty}$

$$\begin{aligned} \lim_{n \rightarrow \infty} P(X_n + Y_n \leq t) &= \lim_{n \rightarrow \infty} A + \lim_{n \rightarrow \infty} \underbrace{P(X_n + Y_n \leq t, |Y_n - c| \geq \epsilon)}_{\rightarrow 0 \text{ as } Y_n \xrightarrow{\mathbb{P}} c} \\ &= \lim_{n \rightarrow \infty} F_{X_n}(t - c) \\ &= F_X(t - c) = P(X \leq t - c) \\ &= P(X + c \leq t) \quad \therefore \text{Proved} \end{aligned}$$

Q9. Let  $Y, \{X_n\}$  be random variables such that for each fixed  $\tau > 0$ ,  $X_n + \tau Y \xrightarrow{d} X + \tau Y$ . Show that

$$X_n \xrightarrow{d} X$$

$$X_n + \gamma Y \xrightarrow{d} X + \gamma Y$$

$$\text{Let } \gamma = 1/m$$

$$\begin{aligned} \lim_{n \rightarrow \infty} P(X_n + \gamma Y \leq t) &= P(X + \gamma Y \leq t) \\ &= P(X + \frac{1}{m} Y \leq t) \end{aligned}$$

$$\text{Apply } \lim_{m \rightarrow \infty} \cdot \frac{1}{m} \rightarrow 0$$

$$\Rightarrow \lim_{n \rightarrow \infty} P(X_n \leq t) = P(X \leq t) \quad \therefore \text{Proved}$$

**Q10.** Let  $\{X_j\}$  be a sequence of i.i.d. random variables with  $X_j$  in  $L^1$ . Let  $Y_j = e^{X_j}$ . Show that

$(\prod_{i=1}^n Y_i)^{\frac{1}{n}}$  converges to a constant  $\alpha = e^{\mathbb{E}[X_1]}$ .

$$\lim_{j \rightarrow \infty} \mathbb{E}(|X_j - X|) = 0 \Rightarrow \lim_{n \rightarrow \infty} \mathbb{E}(|X_n|) < \infty$$

$$Y_j = e^{X_j}$$

$$\text{T.P. } (\prod_{i=1}^n Y_i)^{\frac{1}{n}} \rightarrow K = e^{\mathbb{E}[X]}$$

$$(\prod_{j=1}^n Y_j)^{\frac{1}{n}} = e^{\frac{\sum_{j=1}^n X_j}{n}}$$

$$e^{\lim_{n \rightarrow \infty} \frac{\sum X_j}{n}} = \lim_{n \rightarrow \infty} (\prod_{j=1}^n Y_j)^{\frac{1}{n}}$$

Using the strong law of large nos.

$$\lim_{n \rightarrow \infty} \frac{\sum X_j}{n} = \mathbb{E}[X]$$

Now, using the continuity mapping theorem,  $e^x$  is continuous

$$\text{So, } \frac{\sum X_j}{n} \xrightarrow{\text{a.s.}} \mathbb{E}[X] \Rightarrow e^{\frac{\sum X_j}{n}} \xrightarrow{\text{a.s.}} e^{\mathbb{E}[X]}$$

Hence proved

### The theorem

Here is a statement of the multivariate version of the Continuous Mapping theorem.

**Proposition** Let  $\{X_n\}$  be a sequence of  $K$ -dimensional random vectors. Let  $g : \mathbb{R}^K \rightarrow \mathbb{R}^L$  be a continuous function. Then,

$$\begin{aligned} X_n &\xrightarrow{P} X \Rightarrow g(X_n) \xrightarrow{P} g(X) \\ X_n &\xrightarrow{\text{a.s.}} X \Rightarrow g(X_n) \xrightarrow{\text{a.s.}} g(X) \\ X_n &\xrightarrow{d} X \Rightarrow g(X_n) \xrightarrow{d} g(X) \end{aligned}$$

where  $\xrightarrow{P}$  denotes convergence in probability,  $\xrightarrow{\text{a.s.}}$  denotes almost sure convergence and  $\xrightarrow{d}$  denotes convergence in distribution.

### Sums and products of sequences converging in probability

An important implication of the Continuous Mapping theorem is that arithmetic operations preserve convergence in probability.

**Proposition** If  $X_n \xrightarrow{P} X$  and  $Y_n \xrightarrow{P} Y$ . Then,

$$\begin{aligned} X_n + Y_n &\xrightarrow{P} X + Y \\ X_n Y_n &\xrightarrow{P} XY \end{aligned}$$

### Sums and products of sequences converging in distribution

For convergence almost surely and convergence in probability, the convergence of  $\{X_n\}$  and  $\{Y_n\}$  individually implies their joint convergence as a vector (see the previous two proofs), but this is not the case for convergence in distribution. Therefore, to obtain preservation of convergence in distribution under arithmetic operations, we need the stronger assumption of joint convergence in distribution.

**Proposition** If

$$[X_n \ Y_n] \xrightarrow{d} [X \ Y]$$

then

$$\begin{aligned} X_n + Y_n &\xrightarrow{d} X + Y \\ X_n Y_n &\xrightarrow{d} XY \end{aligned}$$

### Sums and products of sequences converging almost surely

Everything that was said in the previous subsection applies, with obvious modifications, also to almost surely convergent sequences.

**Proposition** If  $X_n \xrightarrow{\text{a.s.}} X$  and  $Y_n \xrightarrow{\text{a.s.}} Y$ , then

$$\begin{aligned} X_n + Y_n &\xrightarrow{\text{a.s.}} X + Y \\ X_n Y_n &\xrightarrow{\text{a.s.}} XY \end{aligned}$$

**Q11.** Let  $\{X_j\}$  be a sequence of i.i.d. non-negative random variables with  $E[X_1] = 1$  and  $\text{Var}(X_1) = \sigma^2 \in (0, \infty)$ . Show that

$$\frac{2}{\sigma}(\sqrt{S_n} - \sqrt{n}) \xrightarrow{d} Y, \quad Y \sim \mathcal{N}(0, 1).$$

$$\begin{aligned} P\left(\frac{2}{\sigma}(\sqrt{S_n} - \sqrt{n}) \leq t\right) &= P\left(\sqrt{S_n} \leq \frac{\sigma t}{2} + \sqrt{n}\right) \\ &= P\left(S_n \leq \frac{\sigma^2 t^2}{4} + n + t\sqrt{n}\right) \\ &= P\left(\frac{S_n - n}{\sigma\sqrt{n}} \leq \frac{\sigma t^2 + t}{4\sqrt{n}}\right) \end{aligned}$$

$E[S_n] = n$

$$\lim_{n \rightarrow \infty} P\left(\frac{2}{\sigma}(\sqrt{S_n} - \sqrt{n}) \leq t\right) = P(Z \leq t) \quad (\text{using CLT})$$

$\therefore \text{Proved}$

**Q12.** Use CLT to show that

$$\lim_{n \rightarrow \infty} e^{-n} \sum_{k=0}^n \frac{n^k}{k!} = \frac{1}{2}.$$

$$X_i \sim P(1), \quad E[X_i] = 1$$

$$\sum X_i \sim P(n), \quad E[\sum X_i] = n, \quad \text{Var}[\sum X_i] = n$$

$$P(S_n \leq n) = \sum_{k=0}^n \frac{e^{-n} n^k}{k!}$$

$$\begin{aligned} P\left(\frac{S_n - n}{\sqrt{n}} \leq 0\right) &= " = \phi(0) \quad (\text{using CLT}) \\ &= \frac{1}{2} \end{aligned}$$

**Q13.** Let  $\{X_i\}$  be a sequence of i.i.d. random variables with  $P(X_i = 1) = \frac{3}{4}$  and  $P(X_i = 0) = \frac{1}{4}$ . Let  $Y_i = X_i + X_i^2$ . Use CLT to evaluate  $P(\sum_{i=1}^{80} Y_i > 100)$ .

$$P(X_i = 1) = \frac{3}{4}, \quad P(X_i = 0) = \frac{1}{4}, \quad \text{Var}(X_i) = \frac{3}{4} - \frac{9}{16} = \frac{3}{16}, \quad \text{Var}(X_i^2) = \frac{3}{16}$$

$$Y_i = X_i + X_i^2$$

$$Y_i = X_i + X_i^2 = \{0, 2\}$$

$$P(Y_i = 0) = \frac{1}{4}, \quad P(Y_i = 2) = \frac{3}{4}$$

$$E[Y_i] = \frac{3}{2}$$

$$E[Y_i^2] = 3$$

$$\text{Var}[Y_i] = 3 - \frac{9}{4} = \frac{3}{4}$$

$$E[\sum Y_i] = \frac{3}{2} \times 80 = 120$$

$$\text{Var}[\sum Y_i] = \frac{3}{4} \times 80 = 60$$

$$\begin{aligned} P(S_i > 100) &= 1 - P(S_i \leq 100) = 1 - P\left(\frac{S_i - 120}{\sqrt{60}} \leq \frac{100 - 120}{\sqrt{60}}\right) \\ &= 1 - \Phi(-) \end{aligned}$$

Q14. Let  $\{X_i\}$  be a sequence of **i.i.d** non-negative random variables with mean 4 and variance 16.

Calculate:

$$\lim_{n \rightarrow \infty} \mathbb{E} [\cos(\sqrt{S_n} - 2\sqrt{n})],$$

where  $S_n := \sum_{i=1}^n X_i$ .

$$\mathbb{E}[X_i] = 4$$

$$\text{Var}[X_i] = 16$$

$$\begin{aligned} P(\sqrt{S_n} - 2\sqrt{n} \leq t) &= P(\sqrt{S_n} \leq t + 2\sqrt{n}) = P(S_n \leq t^2 + 4n + 4t\sqrt{n}) \\ &= P\left(\frac{S_n - 4n}{\sqrt{16n}} \leq \frac{t^2 + t}{4\sqrt{n}}\right) \end{aligned}$$

$$\lim_{n \rightarrow \infty} P(\sqrt{S_n} - 2\sqrt{n} \leq t) = \lim_{n \rightarrow \infty} P\left(\frac{S_n - 4n}{\sqrt{16n}} \leq \frac{t^2 + t}{4\sqrt{n}}\right)$$

$$= \phi(t) \quad (\text{CLT})$$

$$\therefore \sqrt{S_n} - 2\sqrt{n} \xrightarrow{d} Z \sim N(0, 1)$$

$$\begin{aligned} \lim_{n \rightarrow \infty} \mathbb{E}[\cos(\sqrt{S_n} - 2\sqrt{n})] &= \mathbb{E}[\cos Z] \\ &= \int_{-\infty}^{\infty} \cos z \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz \\ &= e^{-1/2} \end{aligned}$$

Q15. Let  $\{X_n\}$  be a sequence of **i.i.d** random variables, defined on a given probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ , with uniform distribution on  $(-1, 1)$ . Let

$$Y_n = \frac{\sum_{i=1}^n X_i}{\sum_{i=1}^n X_i^2 + X_i^3}.$$

Show that  $\sqrt{n}Y_n$  converges in distribution as  $n \rightarrow \infty$ . Let  $\phi_n(t)$  be the characteristic function of  $\sqrt{n}Y_n$ . Calculate  $\lim_{n \rightarrow \infty} \phi_n(2)$ .

$$Y_n = \frac{\sum_{i=1}^n X_i}{\sum_{i=1}^n X_i^2 + X_i^3} \quad \text{d.}$$

$$X_i \sim U(-1, 1)$$

$$\{X_n\} \text{ is i.i.d r.v } (-1, 1)$$

$$f_{X_n}(x) = \begin{cases} \frac{1}{2} & -1 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbb{E}[X_i] = 0, \text{Var}[X_i] = \frac{1}{3}.$$

$$\mathbb{E}[X_i] = 0$$

$$\mathbb{E}[X_i^2] = \int_0^1 u^2 \frac{1}{2} du = \frac{1}{3}$$

$$\text{Var}[X_i] = \frac{1}{3}$$

$$Y_n = \frac{\sum_{i=1}^n X_i}{n/3} \times \frac{n}{3}$$

$$\begin{aligned} \lim_{n \rightarrow \infty} P(Y_n \leq t) &= P\left(\frac{\sum_{i=1}^n X_i}{n/3} \leq t\right) \\ &\xrightarrow{n \rightarrow \infty} P\left(\frac{\sum_{i=1}^n X_i/n}{\frac{1}{3} \sum_{i=1}^n X_i^2 + \frac{1}{3} \sum_{i=1}^n X_i^3} \leq t\right) \end{aligned}$$

$$\left[ \sum_{i=1}^n \frac{X_i}{n} \xrightarrow{a.s.} u \text{ iff } \mathbb{E}[X_i] = u \right]$$

Q16. Let  $X_n \xrightarrow{\mathbb{P}} X$ . Show that the characteristic function  $\phi_{X_n}$  converges pointwise to  $\phi_X$ .

$$\lim_{n \rightarrow \infty} \mathbb{P}(|X_n - X| > \epsilon) = 0 \quad = \quad \mathbb{P}(X_n > X + \epsilon, X_n < X - \epsilon)$$

$$\begin{aligned}\phi_{X_n}(t) &= \mathbb{P}(X_n \leq t, |X_n - X| > \epsilon) + \mathbb{P}(X_n \leq t, |X_n - X| \leq \epsilon) \\ &\stackrel{\epsilon \rightarrow 0}{=} \mathbb{P}(X_n \leq t, |X_n - X| \leq \epsilon) \\ &= \mathbb{P}(X_n \leq t, X - \epsilon \leq X_n \leq X + \epsilon) = A\end{aligned}$$

$$A \leq \mathbb{P}(X - \epsilon \leq t)$$

$$A \geq \mathbb{P}(X + \epsilon \leq t)$$

$$\mathbb{P}(X + \epsilon \geq t) \leq A \leq \mathbb{P}(X - \epsilon \leq t)$$

$$\text{Take } \epsilon \rightarrow 0, \quad A = \mathbb{P}(X \leq t) = \phi_X(t)$$

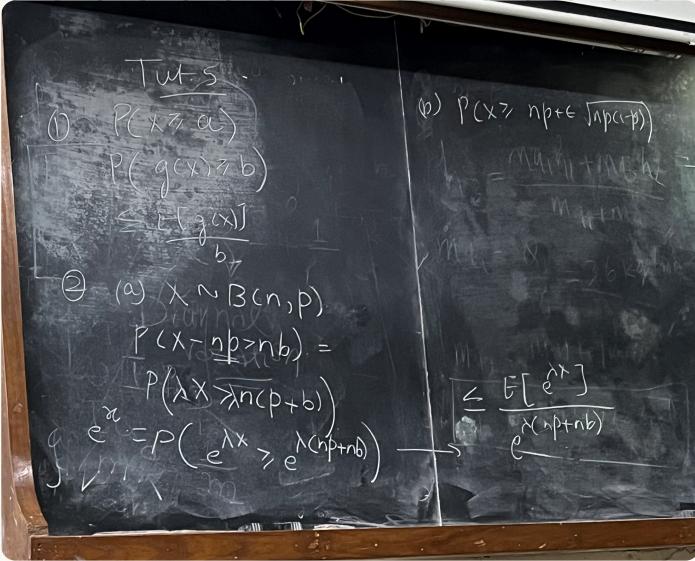
$$\begin{array}{c} X_n \xrightarrow{\mathbb{P}} X \\ \Rightarrow X_n \xrightarrow{d} X \end{array}$$

$$\Leftrightarrow E[g(X_n)] \rightarrow E[g(X)]$$

$\downarrow$  bounded ct.  $f^n$

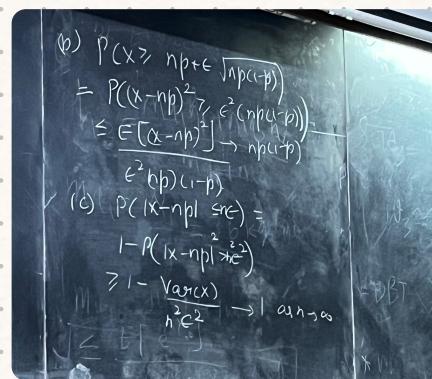
$$\begin{aligned}E(e^{itX_n}) g(n) &= e^{itn} \\ &= \cos tu + i \sin tu\end{aligned}$$

# Class



Q2. Let  $X$  be a Binomial  $B(n, p)$  random variable defined on a given probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ . Then show the followings:

- For  $\lambda > 0$  and  $b > 0$ ,  $\mathbb{P}(X - np > nb) \leq \mathbb{E}[\exp(\lambda(X - np - nb))]$ .
- For any  $\epsilon > 0$ ,  $\mathbb{P}(X \geq np + \epsilon \sqrt{np(1-p)}) \leq \frac{1}{1+\epsilon^2}$ .
- For all  $\epsilon > 0$ ,  $\mathbb{P}(|X - np| \leq n\epsilon)$  tends to 1.



b)  $P(X \geq np + \epsilon \sqrt{np(1-p)})$

$$= P((X-np)^2 \geq \epsilon^2(np(1-p))) \leq \frac{E[(X-np)^2]}{\epsilon^2 np(1-p)} \xrightarrow{\text{Variance of binomial}} np(1-p)$$

Q4. Let  $\{X_n\}$  be a sequence of random variables defined on a given probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ , given by

$$X_n := \sqrt{n} \mathbf{1}_{(0, \frac{1}{n})}(U), \quad U \sim \mathcal{U}(0, 1).$$

Show that  $X_n \xrightarrow{\mathbb{P}} 0$  but  $X_n \not\xrightarrow{a.s.} 0$ .

$$X_n = \sqrt{n} (\mathbf{1}_{(0, 1/n)} \cup)$$

$$\mathbf{1}_{(0, 1/n)} \cup \{\omega\} = \begin{cases} 1, & \omega \in (0, 1/n) \\ 0, & \text{else} \end{cases}$$

i) T.S.  $X_n \xrightarrow{P} 0$

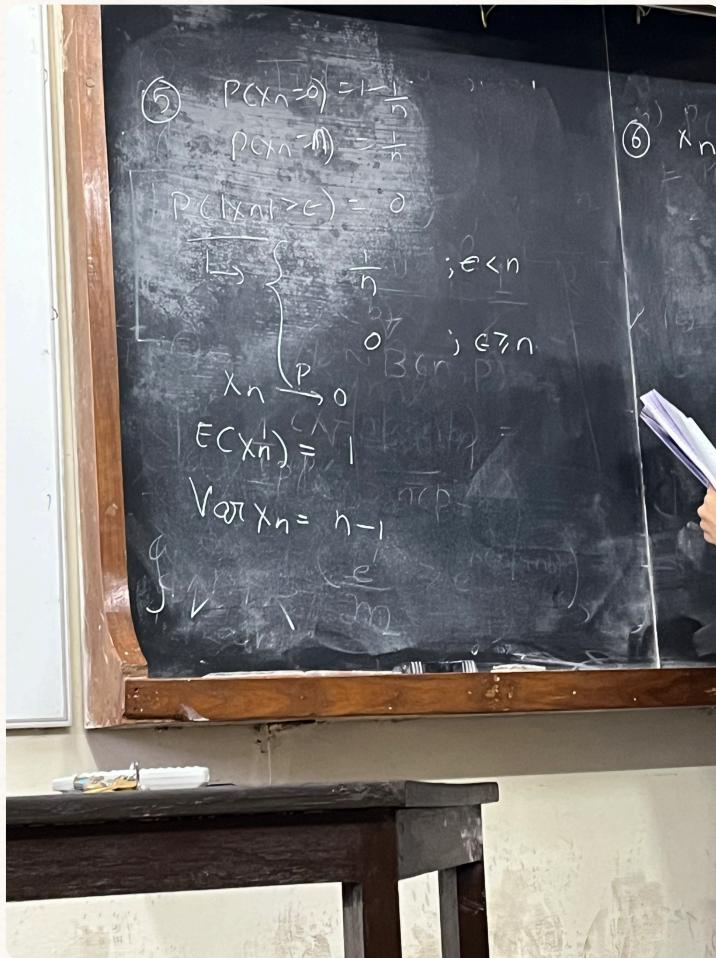
$$\begin{aligned} P(|X_n| > \epsilon) &= 1 - P(|X_n| \leq \epsilon) \\ &= 1 - P(\mathbf{1}_{(0, 1/n)} \cup \{\omega\} \leq \epsilon / \sqrt{n}) \\ &= 1 - P(\omega \in (\frac{1}{n}, 1)) \end{aligned}$$

$$= 1 - \left(1 - \frac{1}{n}\right) \rightarrow 0$$

(ii)  $X_n \xrightarrow{2} 0$

$$\begin{aligned} E(X_n^2) &= n \cdot E\left(\left(1_{(0, \frac{1}{n})} \cup\right)^2\right) \\ &= n \left\{ 1 \cdot P\left(\cup(\omega) \in (0, \frac{1}{n})\right) \right\} \\ &= n \cdot \frac{1}{n} = 1 \not\rightarrow 0 \end{aligned}$$

Q5. Prove or disprove:  $X_n \xrightarrow{\mathbb{P}} 0 \implies E(X_n) \rightarrow 0$  and  $\text{Var}(X_n) \rightarrow 0$ .



Q6. Let  $\{X_n\}$  be a sequence of random variables that is monotonically increasing, i.e.,  $X_n(\omega) \leq X_{n+1}(\omega)$  for all  $\omega \in \Omega, n \in \mathbb{N}$ . If  $X_n \xrightarrow{\mathbb{P}} X$ , then show that  $X_n \xrightarrow{a.s.} X$ .

$$\Rightarrow \exists X_n \xrightarrow{\mathbb{P}} X \quad \xrightarrow{a.s.} X - \textcircled{1}$$

$$\lim_{n \rightarrow \infty} P(|X_n - X| > \epsilon) = 0$$

$$\Rightarrow \exists n_1 > 0 \text{ s.t. } P(|X_n - X| > \frac{1}{2}) < \frac{1}{2} \quad \forall n \geq n_1 \quad \text{BASE CASE}$$

Assume:  $n_1 < n_2 \dots < n_{k-1}$

$$\text{so. } \forall n \geq n_j, P\left(|X_n - X| > \frac{1}{2^j}\right) < \frac{1}{2^j}, \quad j \in \{1, \dots, k-1\}$$

$$P\left(|X_n - X| > \frac{1}{2^k}\right) = 0 \text{ as } n \rightarrow \infty$$

$$\Rightarrow \exists n_k > n_{k-1} \text{ s.t. } \forall n \geq n_k, P\left(|X_{n_k} - X| > \frac{1}{2^k}\right) < \frac{1}{2^k}$$

$$E_k = \{w \in \Omega, |X_{n_k}(w) - X(w)| > \frac{1}{2^k}\}$$

$$\sum_{k=1}^{\infty} P(E_k) < \sum_{k=1}^{\infty} \frac{1}{2^k} < \infty$$

$$\Rightarrow P(\limsup E_k) = 0 \quad (\text{from Borel-Cantelli lemma})$$

$$\Rightarrow P\left(\limsup |X_{n_k} - X| > \frac{1}{2^k}\right) = 0$$

$$\Rightarrow P(\limsup |X_{n_k} - X| \neq 0) = 0$$

$$\Rightarrow X_{n_k} \xrightarrow{a.s.} X$$

Q7. Let  $X_n \xrightarrow{d} X$  with  $X = a$  a.e. Then show that  $X_n \xrightarrow{\mathbb{P}} a$ .

$$\begin{aligned} \text{I. } X_n &\xrightarrow{d} X \\ X &= a \quad a.s. \\ \Rightarrow P(X=a) &= 1 \end{aligned}$$

$$\text{II. } \lim P(|X_n - a| > \epsilon) = 0$$

$$\begin{aligned} &= 1 - P(|X_n - a| \leq \epsilon) \\ &= 1 - P(a - \epsilon \leq X_n \leq a + \epsilon) \end{aligned}$$

$$= 1 - [P(X_n \leq a + \epsilon) - P(X_n \leq a - \epsilon)]$$

$$= 1 - \frac{F(a+\epsilon)}{1} + \frac{F(a-\epsilon)}{0}$$

$$= 0$$

Q8. Prove or disprove:

$$X_n \xrightarrow{d} X, Y_n \xrightarrow{\mathbb{P}} c, c \in \mathbb{R}, \implies X_n + Y_n \xrightarrow{d} X + c, X_n Y_n \xrightarrow{d} cX.$$

$$(1) P(X_n + Y_n \leq t)$$

$$= P(X_n + Y_n \leq t, |Y_n - c| \leq \epsilon) + P(X_n + Y_n \leq t, |Y_n - c| \geq \epsilon)$$

$$= P(X_n + Y_n \leq t, c - \epsilon \leq Y_n \leq c + \epsilon) + P(|Y_n - c| \geq \epsilon)$$

$$\{X_n + Y_n \leq t\} \subseteq \{X_n + c - \epsilon \leq t\}$$

$$0 \leq P(X_n \leq t - c + \epsilon) + P(|Y_n - c| \geq \epsilon)$$

$$P(X_n + Y_n \leq t) \geq P(X_n \leq t - c + \epsilon) - P(|Y_n - c| \geq \epsilon)$$

$$P(X_n \leq t - c + \epsilon) \leq P(X_n + Y_n \leq t) \leq P(X_n \leq t - c + \epsilon)$$

$$\epsilon \rightarrow 0$$

$$\Rightarrow P(X_n + Y_n \leq t) = F_{X_n}(t - c)$$

The chalkboard contains the following text and symbols:

- $P(X_n + Y_n \leq t - c) \leq P(X_n + Y_n \leq t) \leq P(|Y_n - c| > \epsilon R) \xrightarrow{R \rightarrow 0}$
- $\epsilon \rightarrow 0$
- $\Rightarrow P(X_n + Y_n \leq t) = F_{X_n}(t - c) \leq P(|Y_n - c| > R) + P(|Y_n - c| \leq R) \xrightarrow{n \rightarrow \infty}$
- $(i) c X_n \xrightarrow{d} 0$
- $(ii) X_n(Y_n - c) \xrightarrow{P} 0$

Q10. Let  $\{X_j\}$  be a sequence of i.i.d. random variables with  $X_j$  in  $L^1$ . Let  $Y_j = e^{X_j}$ . Show that

$$\left( \prod_{i=1}^n Y_i \right)^{\frac{1}{n}}$$

$$x_i \in L^1$$

$$\Rightarrow E(|X_i|) < \infty$$

$$\frac{\sum_{i=1}^n X_i}{n} \xrightarrow{\text{a.s.}} E(X_i)$$

$$g(x) = e^x$$

cts. mapping then

$$X_n \xrightarrow{\text{a.s.}} X \Rightarrow g(X_n) \xrightarrow{\text{a.s.}} g(X)$$

$$(e^{\sum X_i})^{\frac{1}{n}} \xrightarrow{\text{a.s.}} e^{E(X_i)}$$

$$\prod_{i=1}^n e^{X_i}$$

**Q11.** Let  $\{X_j\}$  be a sequence of i.i.d. non-negative random variables with  $\mathbb{E}[X_1] = 1$  and  $\text{Var}(X_1) = \sigma^2 \in (0, \infty)$ . Show that

$$\frac{2}{\sigma}(\sqrt{S_n} - \sqrt{n}) \xrightarrow{d} Y, \quad Y \sim \mathcal{N}(0, 1).$$

$$\begin{aligned} E(X_i) &= 1 \\ \text{Var}(X_i) &= \sigma^2 \end{aligned}$$

$$S_n = \sum_{i=1}^n X_i$$

$$E(S_n) = n$$

$$\text{Var}(S_n) = \sigma^2 n$$

$$\text{CLT} \quad S_n \xrightarrow{d} N(n, \sigma^2 n)$$

$$\begin{aligned} P\left(\frac{2}{\sigma}(\sqrt{S_n} - \sqrt{n}) \leq t\right) &\rightarrow 0 \\ &= P(S_n \leq n + \frac{t^2 \sigma^2}{2} + \sigma \sqrt{n}) \\ &= P\left(\frac{S_n - n}{\sqrt{\sigma^2 n}} \leq \frac{\frac{t^2 \sigma^2}{4} + \sigma \sqrt{n}}{\sqrt{\sigma^2 n}}\right) \\ &\quad \underbrace{\qquad}_{\frac{t^2 \sigma^2}{4 \sigma \sqrt{n}} + t} \\ &\quad \xrightarrow{\rightarrow 0} \end{aligned}$$

$$= P\left(\frac{S_n - n}{\sigma \sqrt{n}} \leq t\right) \text{ as } n \rightarrow \infty$$

$$\begin{aligned} &= F_{N(0, 1)}(t) \\ &\frac{2}{\sigma}(\sqrt{S_n} - \sqrt{n}) \xrightarrow{d} N(0, 1) \end{aligned}$$

**Q12.** Use CLT to show that

$$\lim_{n \rightarrow \infty} e^{-n} \sum_{k=0}^n \frac{n^k}{k!} = \frac{1}{2}.$$

$$\lim_{n \rightarrow \infty} e^{-n} \sum_{k=0}^n \frac{n^k}{k!} = \frac{1}{2}$$

$$\begin{aligned} \langle X_i \rangle &\rightarrow \text{i.i.d.} \\ X_i &\sim P(1) \end{aligned}$$

$$= \sum_{i=1}^n X_i \sim P(n)$$

$$P(S_n \leq n) = \sum_{i=0}^n \frac{e^{-n} n^i}{i!}$$

$$P(S_n \leq n) = P\left(\frac{S_n - n}{\sqrt{n}} \leq 0\right) \text{ as } n \rightarrow \infty$$

$$= F_{N(0,1)}(0) = \frac{1}{2}$$

**Q13.** Let  $\{X_i\}$  be a sequence of i.i.d. random variables with  $P(X_i = 1) = \frac{3}{4}$  and  $P(X_i = 0) = \frac{1}{4}$ . Let  $Y_i = X_i + X_i^2$ . Use CLT to evaluate  $P\left(\sum_{i=1}^{80} Y_i > 100\right)$ .

$$P(X_i = 1) = 3/4$$

$$P(X_i = 0) = 1/4$$

$$Y_i = X_i + X_i^2 \in \{0, 2\}$$

$$P(Y_i = 0) = P(X_i = 0)$$

$$2 \quad 1$$

$$E(Y_i) = \frac{3}{2} \text{ on calc}$$

$$\text{Var}(Y_i) = \frac{3}{4} \text{ on calc}$$

$$E\left(\sum_{i=1}^{80} Y_i\right) = 80\left(\frac{3}{2}\right) = 120$$

$$\text{Var}(Y_i) = 60$$

$$\begin{aligned} P\left(\sum_{i=1}^{80} Y_i > 100\right) &= 1 - P\left(\sum_{i=1}^{80} Y_i \leq 100\right) \\ &= 1 - P\left(Z \leq \frac{100 - 120}{\sqrt{60}}\right) \\ &= 1 - \Phi(-2.582) \end{aligned}$$

**Q3.** Show that  $X_n \xrightarrow{\mathbb{P}} X$  if and only if  $\lim_{n \rightarrow \infty} \mathbb{E}(1 \wedge |X_n - X|) = 0$ .

$$\lim_{n \rightarrow \infty} P(|X_n - X| > \epsilon) = 0 \quad \downarrow \min\{1, |X_n - X|\}$$

$$\begin{aligned} \{w \in \Omega : P(\min\{1, |X_n - X|\} \geq n) \geq \delta\} \\ \leq \{w \in \Omega : |X_n - X| \geq \epsilon\} \end{aligned}$$

$$\Rightarrow E(X) = \int P(X \geq x) dx \quad \text{1 to } \infty \text{ is 0}$$

$$E(\min\{1, |X_n - X|\}) = \int_0^\infty \underbrace{P(\min\{1, |X_n - X|\} \geq x)}_A dx$$

$$= \int_0^\epsilon A dx + \int_\epsilon^\infty A dx \leq \epsilon + \int_\epsilon^\infty \underbrace{P(\min\{1, |X_n - X|\} \geq \epsilon)}_{\text{constant} = A_\epsilon} dx$$

$$= \epsilon + A_\epsilon(1 - \epsilon) \rightarrow 0 \text{ as } n \rightarrow \infty$$

goes to 0  
check!

$$\Leftarrow \forall \epsilon > 0, \liminf_{n \rightarrow \infty} P(|X_n - X| > \epsilon) = 0$$

$$\{ \omega \in \Omega, |X_n(\omega) - X(\omega)| > \epsilon \} \subseteq \{ \omega \in \Omega, \min\{L, |X_n(\omega) - X(\omega)|\} \geq \min\{L, \epsilon\} \}$$

$$P(|X_n - X| \geq \epsilon) \leq P(\min\{L, |X_n - X|\} \geq \min\{L, \epsilon\}) \leq \frac{E(\min\{L, |X_n - X|\})}{\min(L, \epsilon)} \xrightarrow{\epsilon \rightarrow 0} 0 \quad (\text{Markov})$$

Q9. Let  $Y, \{X_n\}$  be random variables such that for each fixed  $\tau > 0$ ,  $X_n + \tau Y \xrightarrow{d} X + \tau Y$ . Show that  $X_n \xrightarrow{d} X$ .

$$X_n + \gamma Y \xrightarrow{d} X + \gamma Y$$

$$\Rightarrow \lim_{n \rightarrow \infty} P(X_n + \gamma Y \leq u) = \lim_{n \rightarrow \infty} P(X_n \leq u) \text{ for } m \rightarrow \infty$$

$\downarrow \frac{1}{m}$

Q14. Let  $\{X_i\}$  be a sequence of i.i.d non-negative random variables with mean 4 and variance 16. Calculate:

$$\lim_{n \rightarrow \infty} E[\cos(\sqrt{S_n} - 2\sqrt{n})],$$

where  $S_n := \sum_{i=1}^n X_i$ .

$$S_n = \sum X_i$$

$$E(S_n) = \sum E(X_i) = 4n$$

$$\text{Var}(S_n) = \sum \text{Var}(X_i) = 16n$$

$$\begin{aligned} P(\sqrt{S_n} - 2\sqrt{n} \leq t) &= P(S_n \leq (t + 2\sqrt{n})^2) \\ &= P(S_n \leq t^2 + 4n + 4t\sqrt{n}) \\ &= P\left(\frac{S_n - 4n}{4\sqrt{n}} \leq \frac{t^2 + 4t\sqrt{n}}{4\sqrt{n}}\right) \xrightarrow{t^2 \rightarrow 0} 0 \\ &\rightarrow P(Z \leq t) \end{aligned}$$

$\uparrow$   
Std Normal

$$\sqrt{S_n} - 2\sqrt{n} \xrightarrow{d} Z = N(0, 1)$$

$g \rightarrow$  bdd cts function

$$g(\sqrt{S_n} - 2\sqrt{n}) \xrightarrow{d} g(Z)$$

$$E[g(\sqrt{S_n} - 2\sqrt{n})] \rightarrow E[g(Z)]$$

Portmanteau lemma  $E[\cos(z)] = \int_{-\infty}^{\infty} \cos z \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz = e^{-1/2}$

**Q15.** Let  $\{X_n\}$  be a sequence of i.i.d random variables, defined on a given probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ , with uniform distribution on  $(-1, 1)$ . Let

$$Y_n = \frac{\sum_{i=1}^n X_i}{\sum_{i=1}^n X_i^2 + X_i^3}.$$

$$Y_n = \frac{\sum X_i}{\sum (X_i^2 + X_i^3)} \quad X_i \sim U(-1, 1)$$

$$S_n = \sum_{i=1}^n X_i$$

$$E(S_n) = 0$$

$$\text{Var}(S_n) = \frac{n}{3}$$

$$\frac{S_n - nE(X_n)}{\sqrt{n\text{Var}(X_n)}} = \frac{S_n}{\sqrt{n/3}} \xrightarrow{d} Z \sim N(0, 1)$$

$$\frac{S_n}{\sqrt{n}} \xrightarrow{d} \frac{1}{\sqrt{3}} Z$$

$$f(x) = x^2 + x^3 \rightarrow \text{measurable}$$

$$\Rightarrow f(x_i) \rightarrow \text{iid}$$

$$E(f(x_i)) = 1/3$$

$$\text{Var}(f(x_i)) < \infty$$

$$\text{WLLN: } \frac{\sum f(x_i)}{n} \xrightarrow{P} \frac{1}{3}$$

$$Y_n^{-1} \xrightarrow{P} C^{-1} \quad (\text{Remember})$$

$$\frac{n}{\sum f(x_i)} \xrightarrow{P} 3$$

$$\text{Q8: } \underbrace{\frac{S_n}{\sqrt{n}} \frac{n}{\sum f(x_i)}}_{n Y_n} \xrightarrow{d} \sqrt{3} Z$$

$$X_n \xrightarrow{d} X \text{ iff } \phi_{X_n}(t) \rightarrow \phi_X(t)$$

$$E(e^{it\sqrt{n}Y_n}) \rightarrow E(e^{it\sqrt{3}Z}) = E(e^{i(t+\sqrt{3}z)}) = e^{-\frac{3t^2}{2}}$$

Q16. Let  $X_n \xrightarrow{\mathbb{P}} X$ . Show that the characteristic function  $\phi_{X_n}$  converges pointwise to  $\phi_X$ .

$$\begin{array}{c} X_n \xrightarrow{\mathbb{P}} X \\ \Rightarrow X_n \xrightarrow{d} X \end{array}$$

$$\Leftrightarrow E[g(X_n)] \rightarrow E[g(X)]$$

↳ bounded cf.  $f^n$

$$E(e^{itX_n}) g(n) = e^{itn} \\ = \cos tu + i \sin tu$$