

## Solutions 11

1. (a) Convergence in distribution for  $X_n$ :  $\lim_{n \rightarrow \infty} \mathcal{N}\left(\mu + \frac{1}{n}, \frac{n\sigma^2 + 2}{n}\right) = \mathcal{N}(\mu, \sigma^2)$   
 Convergence in distribution for  $Y_n$ :  $\lim_{n \rightarrow \infty} \mathcal{N}\left(\mu, \frac{1}{n}\right) = \mathcal{N}(\mu, 0)$  (degenerate distribution)

- (b) Convergence in probability for  $Y_n$ :

Using Chebyshevs inequality  $P(|Y_n - E(Y_n)| < \epsilon) \geq 1 - \frac{\text{Var}(Y_n)}{\epsilon^2}$  yields:

$$\lim_{n \rightarrow \infty} P(|Y_n - \mu| < \epsilon) \geq \lim_{n \rightarrow \infty} 1 - \frac{\frac{1}{n}}{\epsilon^2} = 1$$

Thus  $Y_n \xrightarrow{p} \mu$

- (c) Using Slutsky's theorems

$$A_n = X_n \cdot Y_n \xrightarrow{d} N(\mu^2, \sigma^2 \mu^2)$$

$$B_n = X_n - Y_n \xrightarrow{d} N(0, \sigma^2)$$

2. (a) Since  $X_i$  only shows up in the indicator function  $\mathcal{I}_{(-\infty, t]}(X_i) \equiv Y_i$ , we have that  $Y_i$  is Bernoulli distributed with the probability of observing  $Y_i$  being the probability that  $X_i \in (-\infty, t]$  which is given by the cdf of  $X$  evaluated at  $t$ . Thus  $p = F(t)$ . Because  $Y_n = \sum_{i=1}^n Y_i$  and each  $Y_i$  is iid Bernoulli distributed,  $Y_n$  is Binomial distributed with size  $n$  and probability of "success"  $p = F(t)$ .

$$E(Z_n) = E\left(\frac{1}{n}Y_n\right) = \frac{1}{n}E(Y_n) = \frac{1}{n}nF(t) = F(t)$$

$$\text{Var}(Z_n) = \text{Var}\left(\frac{1}{n}Y_n\right) = \frac{1}{n^2}\text{Var}(Y_n) = \frac{1}{n^2}nF(t)(1 - F(t)) = \frac{F(t)(1 - F(t))}{n}$$

- (b) Convergence in mean-square:

$$\lim_{n \rightarrow \infty} E(Z_n) = \lim_{n \rightarrow \infty} F(t) = F(t)$$

$$\lim_{n \rightarrow \infty} \text{Var}(Z_n) = \lim_{n \rightarrow \infty} \frac{1}{n^2}nF(t)(1 - F(t)) = 0$$

Thus  $Z_n \xrightarrow{m} F(t)$  (Corollary 5.1) which implies convergence in probability.

- (c) Note that  $Z_n = \frac{1}{n} \sum_{i=1}^n \mathcal{I}_{(-\infty, t]}(X_i) = \frac{1}{n} \sum_{i=1}^n Y_i$  is an average, thus by CLT

$$\sqrt{n}(Z_n - E(Y_i)) \xrightarrow{d} N(0, \text{Var}(Y_i))$$

$$\sqrt{n}(Z_n - F(t)) \xrightarrow{d} N(0, F(t)(1 - F(t)))$$

3. For a simple fair die it holds:

$$E(X_i) = \mu = 3.5; \text{Var}(X_i) = \sigma^2 = \frac{35}{12}$$

Examine the average of  $X_i$  after 200 tosses:

Lindberg-Levy CLT

$$\frac{(\bar{X} - \mu)}{\sigma/\sqrt{n}} \xrightarrow{d} N(0,1); \bar{X} \overset{\text{asy.}}{\sim} N(\mu, \sigma^2/n)$$

$$\Rightarrow \bar{X} \overset{\text{asy.}}{\sim} N\left(3.5, \frac{35/12}{200}\right)$$

$$P(\bar{X} \leq 3.6) = P\left(\frac{\bar{X} - 3.5}{\sqrt{\frac{1}{200} \frac{35}{12}}} \leq \frac{0.1}{\sqrt{\frac{1}{200} \frac{35}{12}}}\right) = \Phi\left(\frac{0.1}{\sqrt{\frac{1}{200} \frac{35}{12}}}\right) \approx 0.7967$$

4. (a) Due to Lindeberg-Levy CLT:

$$\sqrt{n}(\bar{X}_n - E(X_i)) \xrightarrow{d} \mathcal{N}(0, \text{Var}(X_i))$$

$$\sqrt{n}(\bar{X}_n - \nu) \xrightarrow{d} \mathcal{N}(0, 2\nu)$$

$$\bar{X}_n \xrightarrow{a} \mathcal{N}\left(\nu, \frac{2\nu}{n}\right)$$

(b) With the help of theorems 4.2 and 4.3 (Chi Square is a special case of Gamma), we find

$$\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i \sim \text{Gamma}\left(\frac{n\nu}{2}, \frac{2}{n}\right)$$

(c) Apply the Delta-Method:

$$\sqrt{n}(g(\bar{X}_n) - g(\mu)) \xrightarrow{d} \mathcal{N}(0, G^2 \text{Var}(X_i)), \text{ where}$$

$$G = \frac{\partial g(\bar{X}_n)}{\partial \bar{X}_n} \Big|_{\bar{X}_n = \mu = \nu} = 2\bar{X}_n \Big|_{\bar{X}_n = \nu} = 2\nu$$

$$\sqrt{n}(\bar{X}_n^2 - \nu^2) \xrightarrow{d} \mathcal{N}(0, 8\nu^3)$$

$$\bar{X}_n^2 \xrightarrow{a} \mathcal{N}\left(\nu^2, \frac{8\nu^3}{n}\right)$$

(d) Again use the Delta-Method with  $G = \frac{\partial g(\bar{X}_n)}{\partial \bar{X}_n} \Big|_{\bar{X}_n = \nu} = 3\bar{X}_n^2 \exp(\bar{X}_n^3) \Big|_{\bar{X}_n = \nu} = 3\nu^2 \exp(\nu^3)$ :

$$\begin{aligned} \sqrt{n}(\exp(\bar{X}_n^3) - \exp(\nu^3)) &\xrightarrow{d} \mathcal{N}(0, 18\nu^5 \exp(2\nu^3)) \\ \exp(\bar{X}_n^3) &\xrightarrow{a} \mathcal{N}\left(\exp(\nu^3), \frac{18\nu^5 \exp(2\nu^3)}{n}\right) \end{aligned}$$

(e) We have

$$\begin{aligned} \mathbb{E}(X_i^2) &= \text{Var}(X_i) + \mathbb{E}(X_i)^2 = 2\nu + \nu^2 = \nu(\nu + 2) \\ \mathbb{E}(X_i^4) &= \nu(\nu + 2)(\nu + 4)(\nu + 6) \\ \text{Var}(X_i^2) &= \mathbb{E}(X_i^4) - \mathbb{E}(X_i^2)^2 = 8\nu(\nu + 2)(\nu + 3) \end{aligned}$$

Due to Lindeberg-Levy CLT:

$$\begin{aligned} \sqrt{n}(\bar{X}_n^2 - \mathbb{E}(X_i^2)) &\xrightarrow{d} \mathcal{N}(0, \text{Var}(X_i^2)) \\ \sqrt{n}(\bar{X}_n^2 - \nu(\nu + 2)) &\xrightarrow{d} \mathcal{N}(0, 8\nu(\nu + 2)(\nu + 3)) \\ \bar{X}_n^2 &\xrightarrow{a} \mathcal{N}\left(\nu(\nu + 2), \frac{8\nu(\nu + 2)(\nu + 3)}{n}\right) \end{aligned}$$