

$$\textcircled{1} \quad P(X_k = \sqrt{k}) = P(X_k = -\sqrt{k}) = \frac{1}{2} \quad Y_n = \frac{1}{n} \sum_{k=1}^n X_k$$

$$\phi(t) = E(e^{itX}) = \sum_k e^{itk} P(X_k = \sqrt{k})$$

$$a) \quad \phi_{X_k}(t) = E(e^{itX_k}) = \frac{1}{2} e^{it\sqrt{k}} + \frac{1}{2} e^{-it\sqrt{k}}$$

For  $Y_n$ : Sum of independent random variables are being multiplied with their characteristic functions

$$\begin{aligned} \phi_{Y_n}(t) &= \left( \phi_{X_k}\left(\frac{t}{n}\right) \right)^n = \left( \frac{1}{2} e^{i\frac{t}{n}\sqrt{k}} + \frac{1}{2} e^{-i\frac{t}{n}\sqrt{k}} \right)^n \\ &= \left( \frac{1}{2} \left( e^{i\frac{t}{n}\sqrt{k}} + e^{-i\frac{t}{n}\sqrt{k}} \right) \right)^n \\ &= \left( \cos\left(\frac{t}{n}\sqrt{k}\right) \right)^n \end{aligned}$$

$$b) \quad \phi_{X_k}(t) = E(e^{itX_k}) \quad F_X(x) = P(X \leq x) = \sum p(x_i)$$

$$\phi_{Y_n}(t) \xrightarrow{n \rightarrow \infty} \phi_Y(t) : \cos\left(\frac{t}{n}\sqrt{k}\right)^n \xrightarrow{n \rightarrow \infty} 1$$

↓ Continuity theorem

$$X_n \xrightarrow{d} X$$

$$\lim_{n \rightarrow \infty} F_n(x) = \delta(x) ?$$

IFFY ↗

②  $S_n = \sum_{i=1}^n a_i X_i$      $M_n = \frac{S_n}{\sum_{i=1}^n a_i}$      $a_1 = k$   
 $a_n = a_{n-1} + k \quad n > 1$   
 $a_i = k;$

a) mean and variance of  $S_n$  and  $M_n$ :

$S_n$ :  $E[S_n] = \sum_{i=1}^n a_i E[X_i] = \sum_{i=1}^n a_i \cdot m = \sum_{i=1}^n ik \cdot m = mk \cdot \sum_{i=1}^n i = mk \cdot \frac{n(n+1)}{2}$   
 $Var[S_n] = \sum_{i=1}^n a_i^2 Var[X_i] = \sum_{i=1}^n a_i^2 \cdot \sigma^2 = \sigma^2 k^2 \cdot \left( \frac{n(n+1)(2n+1)}{6} \right)$

$M_n$ :  $E[M_n] = \frac{E[S_n]}{E[\sum_{i=1}^n a_i]} = \frac{\sum_{i=1}^n a_i m}{\sum_{i=1}^n a_i} = m$

$Var[M_n] = \frac{Var[S_n]}{(\sum_{i=1}^n a_i)^2} = \frac{\sigma^2 \cdot \sum_{i=1}^n a_i^2}{(\sum_{i=1}^n a_i)^2} = \frac{\sigma^2 \cdot \sum_{i=1}^n a_i^2}{mk^2 \left( \frac{n(n+1)}{2} \right)^2} = \frac{\sigma^2 \cdot k^2 \left( \frac{n(n+1)(2n+1)}{6} \right)}{mk^2 \left( \frac{n(n+1)}{2} \right)^2}$   
 $= \frac{\sigma^2}{m} \cdot \frac{(2n+1)^2}{n(n+1) \cdot 3}$

b)  $X_n \xrightarrow{P} X$   
 if  $P(|X_n - X| > \varepsilon) \rightarrow 0$  as  $n \rightarrow \infty$  for all  $\varepsilon > 0$

$P(|M_n - m| \geq \varepsilon) \leq \frac{\sigma_m}{\varepsilon}$  Chebyshev

$\sigma_m = \sqrt{Var} = \sqrt{\frac{\sigma^2}{m} \cdot \frac{(2n+1)^2}{n(n+1) \cdot 3}} = \frac{\sigma}{\varepsilon} \cdot \sqrt{\frac{2}{3m} \cdot \frac{(2n+1)}{(n^2+n)}} \xrightarrow{n \rightarrow \infty} 0$

$\rightarrow$  therefore  $M_n \xrightarrow{P} m$

c)  $\frac{S_n - E(S_n)}{\sqrt{\text{Var}(S_n)}} \xrightarrow{D} Z$   $Z$  is an  $N(0,1)$  c.v.

Central limit theorem:

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

$X_1, X_2, \dots$  iid  
 $\mu, \sigma^2 \neq 0$

$$\rightarrow \frac{S_n - n\mu}{\sqrt{n\sigma^2}} \xrightarrow{D} N(0,1)$$

$$E[S_n] = mk \cdot \frac{n(n+1)}{2}$$

$$\text{Var}[S_n] = \sum_{i=1}^n a_i^2 \text{Var}[X_i] = \sum_{i=1}^n a_i^2 \cdot \sigma^2 = \sigma^2 \cdot \sum_{i=1}^n (ik)^2 = \sigma^2 k^2 \cdot \left( \frac{n(n+1)(2n+1)}{6} \right)$$

$$\frac{S_n - mk \cdot \frac{n(n+1)}{2}}{\sqrt{\sigma^2 k^2 \cdot \left( \frac{n(n+1)(2n+1)}{6} \right)}} = \frac{\sum_{i=1}^n iX_i - m \cdot \frac{n(n+1)}{2}}{\sqrt{\sigma^2 \cdot \left( \frac{n(n+1)(2n+1)}{6} \right)}} \xrightarrow{n \rightarrow \infty} \frac{n \sum_{i=1}^n X_i - m n^2}{\sqrt{\sigma^2 \cdot n^3}}$$

$$= \frac{\sum_{i=1}^n X_i - mn}{\sqrt{\sigma^2 \cdot n}} \xrightarrow{D} Z$$

c) Theorems  $X_1, X_2, \dots$  independent  $E[X_i] = 0$   $\text{Var}(X_i) = \sigma_i^2$ ,  $E[X_j^3] < \infty$

$$\frac{1}{\sigma(n)^3} \sum_{j=1}^n E[X_j^3] \rightarrow 0 \quad \text{as } n \rightarrow \infty$$

$$(\sigma(n)^2 = \text{var}(\sum_{j=1}^n X_j) = \sum \sigma_j^2)$$

$$\Rightarrow \frac{1}{\sigma(n)} \sum_{j=1}^n X_j \xrightarrow{D} N(0, 1)$$

$$Z_i = f(X_i) = \frac{1}{n} a_i \cdot X_i - a_i \quad E[Z_i] = \frac{1}{n} a_i - a_i = 0 \quad \frac{S_n - E(S_n)}{\sqrt{\text{Var}(S_n)}} \xrightarrow{D} Z$$

$$E[Z_i^3] = \frac{a_i^3}{n} \cdot E[X_i^3] - a_i \quad \text{and as defined all moments of } X_i \text{ are finite, therefore: } E[Z_i^3] < \infty$$

$$\text{Var}(Z_i) = \text{Var}\left(\frac{1}{n} a_i X_i - 1\right) = \left(\frac{a_i}{n}\right)^2 \cdot \text{Var}(X_i) = \frac{\sigma_i^2}{n^2} a_i^2$$

$$\sigma(n)^2 = \text{Var}\left(\sum_{j=1}^n Z_j\right) = \sum_{j=1}^n \frac{a_j^2 \sigma_j^2}{n^2} = \frac{\sigma^2}{n^2} \cdot k^2 \cdot \left(\frac{n(n+1)(2n+1)}{6}\right)$$

$$\frac{1}{(\sigma(n))^3} \cdot \sum_{j=1}^n E[Z_j^3] \leq \frac{n^4}{\left(\frac{\sigma^2}{n^2} \cdot k^2 \cdot \left(\frac{n(n+1)(2n+1)}{6}\right)\right)^{\frac{3}{2}}} \xrightarrow{n \rightarrow \infty} 0$$

$$\sum_{j=1}^n a_j^3 = k^3 \cdot \frac{n^2(n+1)^2}{4} \quad \text{because numerator bigger than denominator}$$

$$\Rightarrow \frac{1}{\sigma(n)} \cdot \sum_{j=1}^n Z_j \xrightarrow{D} N(0, 1)$$

and if  $Z_j \sim N(0, 1)$  then  $S_n$  is as well?

$$(3) \quad f(x) = \frac{1}{2} e^{-|x|} \quad S_n = \sum_{i=1}^n X_i$$

$$a) \quad \lim_{n \rightarrow \infty} P(S_n^2 > n)$$

Chebyshev's inequality,  $a > 0$   
 $\mu, \sigma^2$

$$\rightarrow P(|X - \mu| > a) \leq \frac{\sigma^2}{a^2}$$

Markov's inequality:  $P(|X| \geq a) \leq \frac{E(|X|)}{a}$

$$\begin{aligned} P((S_n - \mu_n)^2 > n) &= P(S_n^2 > n) = P(S_n > \sqrt{n}) + P(S_n < -\sqrt{n}) \quad \frac{0}{\sqrt{n}} \\ &= P(S_n > \sqrt{n}) + 1 - P(S_n \geq -\sqrt{n}) = P(S_n > \sqrt{n}) + 1 - P(S_{n-1} \geq -\sqrt{n-1}) \\ &\leq \frac{\sigma}{\sqrt{n}} + 1 - \frac{\sigma}{\sqrt{n-1}} = \sqrt{2} + 1 - \sqrt{2} = \underline{\underline{1}} \end{aligned}$$

$$\mu_X = \int_{-\infty}^{\infty} \frac{1}{2} e^{-|x|} \cdot x \, dx = 0$$

$$\mu_{S_n} = E\left(\sum_{i=1}^n X_i\right) = 0$$

$$\sigma_X^2 = \int_{-\infty}^{\infty} x^2 \cdot \frac{1}{2} e^{-|x|} \, dx = 2$$

$$\sigma_{S_n}^2 = \text{Var}\left(\sum_{i=1}^n X_i\right) = \sum_{i=1}^n \text{Var}(X_i) = 2 \cdot n$$

$$\sigma_{S_{n-1}}^2 = 2 \cdot (n-1)$$

$$\lim_{n \rightarrow \infty} P(S_n > \sqrt{n}) \leq \frac{\sqrt{2n}}{\sqrt{n}} = \sqrt{2}$$

$$a) \quad P(|S_n - \mu_n|^2 > n) = P(S_n^2 > n) = P(S_n > \sqrt{n}) + P(S_n < -\sqrt{n})$$

Chebyshev bounds:

$$\leq M(t) \cdot e^{-t\sqrt{n}} \quad t > 0 \quad + \quad M(t) e^{+t\sqrt{n}} \quad t < 0$$

$$M_{S_n(t)} = (M_{X_1(t)})^n = \left( \frac{1}{1-t^2} \right)^n$$

$$= \left( \frac{1}{1-t^2} \right)^n \cdot e^{-t\sqrt{n}} \quad t > 0 \quad + \quad \left( \frac{1}{1-t^2} \right)^n e^{+t\sqrt{n}} \quad t < 0$$

$$\lim_{n \rightarrow \infty} = 0$$

$$b) \lim_{n \rightarrow \infty} P(S_n^2 > n^2)^{\frac{1}{2}} = \lim_{n \rightarrow \infty} P(S_n > n)^{\frac{1}{n}}$$

$$= \lim_{n \rightarrow \infty} \left( P(S_n > n)^{\frac{1}{n}} + P(S_n < -n)^{\frac{1}{n}} \right)$$

Chernoff bounds:

$$\leq \inf_{t > 0} \left( M(t) \cdot e^{-tn} \right)^{\frac{1}{n}} \quad (t > 0) + \inf_{t < 0} \left( M(t) e^{+tn} \right)^{\frac{1}{n}} \quad (t < 0)$$

$$\left( \begin{array}{l} \text{MGF of } f: \\ M_{x_i}(t) = \frac{1}{2} \left( \frac{1}{1-t} + \frac{1}{1+t} \right) = \frac{1}{2} \left( \frac{1+t+1-t}{1-t^2} \right) = \frac{1}{1-t^2} \\ \\ M_{S_n}(t) = (M_{x_i}(t))^n = \left( \frac{1}{1-t^2} \right)^n \end{array} \right)$$

$$= \inf_{t > 0} \left( \frac{1}{1-t^2} \right)^{\frac{n}{n}} \cdot e^{-\frac{tn}{n}} + \inf_{t < 0} \left( \frac{1}{1-t^2} \right)^{\frac{n}{n}} \cdot e^{\frac{tn}{n}}$$

$$= \circ$$

(4)

# visits:

$$V_j = |\{n \geq 1 : X_n = j\}|$$

$$\nu_{ij} = P(V_j = \infty | X_0 = i)$$

a) 
$$\nu_{ii} = \begin{cases} 1 & i \text{ persistent} \\ 0 & i \text{ transient} \end{cases}$$

Definition of persistent:  $P(X_n = i \text{ for some } n \geq 1 | X_0 = i) = 1$

the probability of eventual return to  $i$ , having started in  $i$ , is 1.  
if this is less than 1, the state is called transient

$$\nu_{ii} = P(V_i = \infty | X_0 = i)$$

since  $V_i$  are the number of visits, if  $P(V_i = 1 | X_0 = i) = 1$  then the state is persistent, since the return is eventual, and if one visit is eventual then  $\infty$  are eventual as well therefore  $\nu_{ii}$  is persistent

if  $P(V_i = 1 | X_0 = i) = 0$  that means there is no eventual return for some  $n \geq 1$  steps and  $P(V_i = \infty | X_0 = i)$  is also 0 if we can't even get back once, then we also can't get back more than once therefore  $\nu_{ii} = 0$



$$b) \quad N_{ij} = \begin{cases} P(T_j < \infty | X_0 = i) & \text{if } j \text{ is persistent} \\ 0 & \text{if } j \text{ is transient} \end{cases}$$

$T_j = \min \{ n \geq 1 \mid X_n = j \} \rightarrow$  the first time the MC reaches state  $j$   
the number of steps

so if  $j$  is persistent, that means that an eventual return/reach of state  $j$  is certain, therefore the number of steps is finite and

$$N_{ij} = P(T_j < \infty | X_0 = i)$$

if  $j$  is transient on the other hand means that the chain may never reach state  $j$  therefore

$$N_{ij} = 0$$