

## Chapter 7: Sums of Random Variables and Long-Term Averages

### 7.1 Sums of Random Variables

7.1  $\mathcal{E}[X + Y + Z] = \mathcal{E}[X] + \mathcal{E}[Y] + \mathcal{E}[Z] = 0$

a) From Eqn. 5.3 we have

$$\begin{aligned} \text{VAR}(X + Y + Z) &= \text{VAR}(X) + \text{VAR}(Y) + \text{VAR}(Z) \\ &\quad + 2\text{COV}(X, Y) + 2\text{COV}(X, Z) + 2\text{COV}(Y, Z) \\ &= 1 + 1 + 1 + 2\left(\frac{1}{4}\right) + 2(0) + 2\left(-\frac{1}{4}\right) = 3 \end{aligned}$$

b) From Eqn. 5.3 we have

$$\text{VAR}(X + Y + Z) = \text{VAR}(X) + \text{VAR}(Y) + \text{VAR}(Z) = 3$$

7.2  $\mathcal{E}[S_n] = \mathcal{E}\left[\sum_{i=1}^n X_i\right] = \sum_{i=1}^n \mathcal{E}[X_i] = n\mu$

$$\text{VAR}(S_n) = \underbrace{\sum_{k=1}^n \text{VAR}(X_k)}_{\substack{\text{sum of diag.} \\ \text{elements of} \\ \text{covariance matrix } K}} + \underbrace{\sum_{j=1}^n \sum_{k=1, k \neq j}^n \text{COV}(X_j, X_k)}_{\substack{\text{sum of off-diag.} \\ \text{element of } K}}$$

$$K = \begin{bmatrix} \sigma^2 & \rho\sigma^2 & 0 & \dots & 0 \\ \rho\sigma^2 & \sigma^2 & \rho\sigma^2 & 0 & \dots & 0 \\ & & \ddots & \ddots & \ddots & 0 \\ & & & \rho\sigma^2 & & \rho\sigma^2 \\ & & & & & \sigma^2 \end{bmatrix}$$

$$\therefore \text{VAR}(S_n) = n\sigma^2 + 2(n-1)\rho\sigma^2$$

7.18 For  $n = 16$ , Eqn. 7.20 gives

$$\sigma_x^2 = 1$$

$$P[|M_{16} - 0| < \epsilon] \geq 1 - \frac{1^2}{16\epsilon^2} = 1 - \frac{1}{16\epsilon^2}$$

Since  $M_{16}$  is Gaussian with mean 0 and variance  $\frac{1}{16}$

$$\begin{aligned} P[|M_{16} - 0| < \epsilon] &= P[-\epsilon < M_{16} < \epsilon] = 1 - 2Q(\sqrt{16}\epsilon) \\ &= 1 - 2Q(4\epsilon) \end{aligned}$$

Similarly for  $n = 100$  we obtain

$$\begin{aligned} P[|M_{100} - 0| < \epsilon] &\geq 1 - \frac{1}{100\epsilon^2} \\ P[|M_{100} - 0| < \epsilon] &= 1 - 2Q(10\epsilon) \end{aligned}$$

For example if  $\epsilon = \frac{1}{2}$

$$\begin{aligned} P[|M_{16}| < \frac{1}{2}] &\geq 1 - \frac{1}{16/4} = .75 \\ P[|M_{16}| < \frac{1}{2}] &= 1 - 2Q(2) = 1 - 2(5.44 \times 10^{-2}) = .8912 \\ P[|M_{100}| < \frac{1}{2}] &\geq 1 - \frac{1}{100/4} = .96 \\ P[|M_{100}| < \frac{1}{2}] &= 1 - 2Q(5) = 1 - 2(2.87 \times 10^{-6}) = .9999944 \end{aligned}$$

Note the significant discrepancies between the bounds and the exact values.

7.19

$$\begin{aligned} P\left[\left|\frac{1}{n}S_n - \mu\right| > \epsilon\right] &\leq \frac{\text{VAR}\left(\frac{1}{n}S_n\right)}{\epsilon^2} = \frac{\text{VAR}(S_n)}{n^2\epsilon^2} \\ &= \frac{n\sigma^2 + 2(n-1)\rho\sigma^2}{n^2\epsilon^2} \rightarrow 0 \quad \text{as } n \rightarrow \infty \end{aligned}$$

⇒ Weak Law of Large Numbers holds.

7.20

$$\begin{aligned}
 P \left[ \left| \frac{1}{n} S_n - \mu \right| > \varepsilon \right] &\leq \frac{\text{VAR}(S_n)}{n^2 \varepsilon^2} \\
 &= \frac{1}{n^2 \varepsilon^2} \left[ n\sigma^2 + 2\rho\sigma^2 \left( \frac{n-1}{1-\rho} - \frac{\rho}{1-\rho} \frac{1-\rho^{n-1}}{1-\rho} \right) \right] \\
 &= \frac{\sigma^2}{n\varepsilon^2} + \frac{2\rho\sigma^2}{\varepsilon^2} \left( \frac{n-\frac{1}{n}}{n(1-\rho)} - \frac{1}{n^2} \frac{\rho(1-\rho^{n-1})}{(1-\rho)^2} \right) \\
 &\rightarrow 0 \text{ as } n \rightarrow \infty \text{ (assuming } \rho < 1)
 \end{aligned}$$

⇒ Weak Law of Large Numbers holds.

7.21 a)

$$\begin{aligned}
 LHS &= \sum_{j=1}^n (X_j^2 - 2\mu X_j + \mu^2) = \sum_{j=1}^n X_j^2 - 2\mu(nM_n) + n\mu^2 \\
 RHS &= \sum_{j=1}^n (X_j^2 - 2M_n X_j + M_n^2) + n(M_n - \mu)^2 \\
 &= \sum_{j=1}^n X_j^2 - 2M_n(nM_n) + nM_n^2 + nM_n^2 - 2n\mu M_n + n\mu^2 \\
 &= \sum_{j=1}^n X_j^2 - 2n\mu M_n + n\mu^2 = LHS \quad \checkmark
 \end{aligned}$$

b)

$$\begin{aligned}
 \mathcal{E} \left[ k \sum_{j=1}^n (X_j - M_n)^2 \right] &= k \mathcal{E} \left[ \underbrace{\sum_{j=1}^n (X_j - \mu)^2 - n(M_n - \mu)^2}_{\text{from part a}} \right] \\
 &= k \sum_{j=1}^n \mathcal{E}[(X_j - \mu)^2] - kn \mathcal{E}[(M_n - \mu)^2] \\
 &= kn\sigma^2 - kn \frac{\sigma^2}{n} \\
 &= k(n-1)\sigma^2 \quad \text{since } \text{VAR}[M_n] = \frac{\sigma^2}{n}.
 \end{aligned}$$

c) If  $k = \frac{1}{n-1}$  then  $\mathcal{E}[V_n^2] = \sigma^2$

d) if  $k = \frac{1}{n}$  then

$$\mathcal{E} \left[ \frac{1}{n} \sum_{j=1}^n (X_j - M_n)^2 \right] = \left( 1 - \frac{1}{n} \right) \sigma^2 = \sigma^2 - \underbrace{\frac{1}{n} \sigma^2}_{\text{bias}}$$

### 7.3 The Central Limit Theorem

7.22

The relevant parameters are  $n = 100$ ,  $m = np = 50$ ,  $\sigma^2 = npq = 25$ . The Central Limit Theorem then gives:

$$P[40 \leq N \leq 60] = P\left[\frac{40 - 50}{\sqrt{25}} \leq \frac{N - m}{\sigma} \leq \frac{60 - 50}{\sqrt{25}}\right]$$

$$\approx Q(-2) - Q(2) = 1 - 2Q(2) = 1 - 2 \cdot 0.0540 = 0.912$$

$$P[50 \leq N \leq 55] \approx Q(0) - Q(1) = \frac{1}{2} - 0.2420 = 0.258$$

7.23

The relative frequency  $f_A(n)$  has mean  $\frac{2}{10}$  and variance  $\frac{1}{n}p(1-p) = \frac{0.16}{n}$

$$P[|f_A(n) - 0.2| < 0.02] = P[0.18 < f_A(n) < 0.22]$$

$$= P\left[\frac{0.18 - 0.20}{\sqrt{\frac{0.16}{n}}} < \frac{f_A(n) - 0.2}{\sqrt{\frac{0.16}{n}}} < \frac{0.22 - 0.20}{\sqrt{\frac{0.16}{n}}}\right]$$

$$\approx 1 - 2Q\left(\frac{0.02}{\sqrt{\frac{0.16}{n}}}\right) = 0.95$$

$$\Rightarrow Q\left(\frac{\sqrt{n}}{20}\right) = 0.025 \Rightarrow \frac{\sqrt{n}}{20} = 1.95 \Rightarrow n = 780.1$$

7.24

$$S = \sum_{i=1}^{20} X_i \Rightarrow E[S] = 20 \cdot E[X] = 20 \times 3.5 = 70$$

$$\text{VAR}[S] = 20 \text{VAR}[X] = 20 \times 2.92 = 58.4$$

Using CLT we have:  $S \sim N(70, \sqrt{58.4})$

$$P\{60 < S < 80\} = P\left\{\frac{60-70}{7.64} < \frac{S-70}{7.64} < \frac{80-70}{7.64}\right\}$$

$$= 1 - 2Q(1.3089) = 0.8094$$

