Probability and Stochastic Processes: A Friendly Introduction for Electrical and Computer Engineers Roy D. Yates and David J. Goodman

Problem Solutions : Yates and Goodman, 8.1.3 8.2.4 8.2.5 8.2.7 8.2.8 8.3.3 8.4.2 8.4.3 and 8.4.4

Problem 8.1.3

- $X_1, X_2...X_n$ are independent uniform random variables with mean value $\mu_X = 7$ and $\sigma_X^2 = 3$
- (a) Since X_1 is a uniform random variable, it must have a uniform PDF over an interval [a,b]. From Appendix A, we can look up that $\mu_X = (a+b)/2$ and that $\operatorname{Var}[X] = (b-a)^2/12$. Hence, given the mean and variance, we obtain the following equations for *a* and *b*.

$$(b-a)^2/12 = 3$$
 $(a+b)/2 = 7$

Solving these equations yields a = 4 and b = 10 from which we can state the distribution of *X*.

$$f_X(x) = \begin{cases} 1/6 & 4 \le x \le 10\\ 0 & \text{otherwise} \end{cases}$$

(b) From Theorem 8.1, we know that

$$\operatorname{Var}[M_{16}(X)] = \frac{\operatorname{Var}[X]}{16} = \frac{3}{16}$$

(c)

$$P[X_1 \ge 9] = \int_9^\infty f_{X_1}(x) \, dx = \int_9^{10} (1/6) \, dx = 1/6$$

(d) The variance of $M_{16}(X)$ is much less than Var $[X_1]$. Hence, the PDF of $M_{16}(X)$ should be much more concentrated about E[X] than the PDF of X_1 . Thus we should expect $P[M_{16}(X) > 9]$ to be much less than $P[X_1 > 9]$.

$$P[M_{16}(X) > 9] = 1 - P[M_{16}(X) \le 9] = 1 - P[(X_1 + \dots + X_{16}) \le 144]$$

By a Central Limit Theorem approximation,

$$P[M_{16}(X) > 9] \approx 1 - \Phi\left(\frac{144 - 16\mu_X}{\sqrt{16}\sigma_X}\right) = 1 - \Phi(2.66) = 0.0039$$

As we predicted, $P[M_{16}(X) > 9] \ll P[X_1 > 9]$.

Problem 8.2.4

The N[0,1] random variable Z has MGF $\phi_Z(s) = e^{s^2/2}$. Hence the Chernoff bound for Z is

$$P[Z \ge c] \le \min_{s \ge 0} e^{-sc} e^{s^2/2} = \min_{s \ge 0} e^{s^2/2 - sc}$$

We can minimize $e^{s^2/2-sc}$ by minimizing the exponent $s^2/2-sc$. By setting

$$\frac{d}{ds}\left(s^2/2 - sc\right) = 2s - c = 0$$

we obtain s = c. At s = c, the upper bound is $P[Z \ge c] \le e^{-c^2/2}$. The table below compares this upper bound to the true probability. Note that for c = 1, 2 we use Table 4.1 and the fact that $Q(c) = 1 - \Phi(c)$.

	c = 1	c = 2	<i>c</i> = 3	c = 4	<i>c</i> = 5
Chernoff bound	0.606	0.135	0.011	3.35×10^{-4}	3.73×10^{-6}
Q(c)	0.1587	0.0228	0.0013	3.17×10^{-5}	2.87×10^{-7}

We see that in this caase, the Chernoff bound typically overestimates the true probability by roughly a factor of 10.

Problem 8.2.5

For an $N[\mu, \sigma^2]$ random variable *X*, we can write

$$P[X \ge c] = P[(X - \mu)/\sigma \ge (c - \mu)/\sigma] = P[Z \ge (c - \mu)/\sigma]$$

Since Z is N[0, 1], we can apply the result of Problem 8.2.4 with c replaced by $(c - \mu)/\sigma$. This yields

$$P[X \ge c] = P[Z \ge (c - \mu)/\sigma] \le e^{-(c - \mu)^2/2\sigma^2}$$

Problem 8.2.7

process of rate $\lambda = 1/2$ trains/minute, *N*, the number of trains in the first 30 minutes, is a Poisson random variable with parameter $\alpha = 30\lambda = 15$. The PMF of *N* is

$$P_N(n) = \begin{cases} 15^n e^{-15}/n! & n = 0, 1, 2, \dots \\ 0 & \text{otherwise} \end{cases}$$

Since *X* is the arrival time of the third train, $X \ge 30$ if and only if there were $N \le 2$ trains in the first 30 minutes. That is,

$$P[X \ge 30] = P[N \le 2] = P_N(0) + P_N(1) + P_N(2)$$

= (1+15+15²/2!)e⁻¹⁵
= 241e⁻¹⁵ = 7.37 × 10⁻⁵

In Quiz 8.2, we found the following bounds:

$$P[X \ge 30] \le \frac{E[X]}{30} = 0.20 \qquad \text{Markov}$$
$$P[X \ge 30] \le 0.021 \qquad \text{Chebyshev}$$
$$P[X \ge 30] \le 7.68 \times 10^{-4}$$

Comparing the exact probability to the bounds, we see that the Markov inequaland Chebyshev inequalities were extremely weak. On the other hand, the Chernoff bound worked reasonably well.

Problem 8.2.8

Let $W_n = X_1 + \cdots + X_n$. Since $M_n(X) = W_n/n$, we can write

$$P[M_n(X) \ge c] = P[W_n \ge nc]$$

Since $\phi_{W_n}(s) = (\phi_X(s))^n$, applying the Chernoff bound to W_n yields

$$P[W_n \ge nc] \le \min_{s \ge 0} e^{-snc} \phi_{W_n}(s) = \min_{s \ge 0} \left(e^{-sc} \phi_X(s) \right)^n$$

For $y \ge 0$, y^n is a nondecreasing function of y. This implies that the value of s that minimizes $e^{-sc}\phi_X(s)$ also minimizes $(e^{-sc}\phi_X(s))^n$. Hence

$$P[M_n(X) \ge c] = P[W_n \ge nc] \le \left(\min_{s \ge 0} e^{-sc} \phi_X(s)\right)^n$$

Problem 8.3.3

Both questions can be answered using the following equation from Example 8.8:

$$P[|R_n - P[A]| \ge c] \le \frac{P[A](1 - P[A])}{nc^2}$$

The unusual part of this problem is that we are given the true value of P[A]. Since P[A] = 0.01, we can write

$$P[|R_n - P[A]| \ge c] \le \frac{0.0099}{nc^2}$$

(a) In this part, we meet the requirement by choosing c = 0.001 yielding

$$P[|R_n - P[A]| \ge 0.001] \le \frac{9900}{n}$$

Thus to have confidence level 0.01, we require that $9900/n \le 0.01$. This requires $n \ge 990,000$.

(b) In this case, we meet the requirement by choosing $c = 10^{-3}P[A] = 10^{-5}$. This implies

$$P[|R_n - P[A]| \ge c] \le \frac{P[A](1 - P[A])}{nc^2} = \frac{0.0099}{n10^{-10}} = \frac{9.9 \times 10^7}{n}$$

The confidence level 0.01 is met if $9.9 \times 10^7/n = 0.01$ or $n = 9.9 \times 10^9$.

Problem 8.4.2

(a) From Theorem 7.2, we have

$$\operatorname{Var}[X_1 + \dots + X_n] = \sum_{i=1}^n \operatorname{Var}[X_i] + 2\sum_{i=1}^{n-1} \sum_{j=i+1}^n \operatorname{Cov}[X_i, X_j]$$

Note that $\operatorname{Var}[X_i] = \sigma^2$ and for j > i, $\sigma_{X_i,X_j} = \sigma^2 a^{j-i}$. This implies

$$\operatorname{Var} [X_1 + \dots + X_n] = n\sigma^2 + 2\sigma^2 \sum_{i=1}^{n-1} \sum_{j=i+1}^n a^{j-i}$$

= $n\sigma^2 + 2\sigma^2 \sum_{i=1}^{n-1} (a + a^2 + \dots + a^{n-i})$
= $n\sigma^2 + \frac{2a\sigma^2}{1-a} \sum_{i=1}^{n-1} (1-a^{n-i})$
= $n\sigma^2 + \frac{2a\sigma^2}{1-a} (n-1) - \frac{2a}{1-a} (a + a^2 + \dots + a^{n-1})$
= $\left(\frac{n(1+a)\sigma^2}{1-a}\right) - \frac{2a\sigma^2}{1-a} - 2\sigma^2 \left(\frac{a}{1-a}\right)^2 (1-a^{n-1})$

Since a/(1-a) and $1-a^{n-1}$ are both nonnegative,

$$\operatorname{Var}\left[X_1+\cdots+X_n\right] \leq n\sigma^2\left(\frac{1+a}{1-a}\right)$$

(b) Since the expected value of a sum equals the sum of the expected values,

$$E[M(X_1,\ldots,X_n)] = \frac{E[X_1] + \cdots + E[X_n]}{n} = \mu$$

The variance of $M(X_1, \ldots, X_n)$ is

$$\operatorname{Var}\left[M(X_1,\ldots,X_n)\right] = \frac{\operatorname{Var}\left[X_1+\cdots+X_n\right]}{n^2} \leq \frac{\sigma^2(1+a)}{n(1-a)}$$

Applying the Chebyshev inequality to $M(X_1, \ldots, X_n)$ yields

$$P[|M(X_1,...,X_n) - \mu| \ge c] \le \frac{\operatorname{Var}[M(X_1,...,X_n)]}{c^2} \le \frac{\sigma^2(1+a)}{n(1-a)c^2}$$

(c) Taking the limit as *n* approaches infinity of the bound derived in part (b) yields

$$\lim_{n\to\infty} P[|M(X_1,\ldots,X_n)-\mu|\geq c]\leq \lim_{n\to\infty}\frac{\sigma^2(1+a)}{n(1-a)c^2}=0$$

Thus

$$\lim_{n\to\infty} P[|M(X_1,\ldots,X_n)-\mu|\geq c]=0$$

Problem 8.4.3

The solution to this problem generalizes the solution of Problem 8.4.1. As a preliminary step, first we find the CDF of $Y_n = \min \{X_1, \dots, X_n\}$.

$$P[Y_n \le y] = 1 - P[Y_n > y] = 1 - P[X_1 > y, X_2 > y, \cdots, X_n > y]$$

Since X_1, X_2, \ldots is an iid sequence,

$$P[X_1 > y, X_2 > y, \cdots, X_n > y] = P[X_1 > y] \cdots P[X_n > y] = (1 - F_X(y))^n$$

This implies

$$P[Y_n \le y] = 1 - (1 - F_X(y))^n$$

Now we use Theorem 8.7 to prove w.p.1 convergence. Since $F_{X_i}(0) = 0$, we know that each X_i and thus each Y_i is nonnegative. This implies

$$S_n(\varepsilon) = \{|Y_n| < \varepsilon\} = \{Y_n < \varepsilon\}$$

Since $Y_n = \min \{X_1, \ldots, X_n\}$, we observe that $Y_n = \min \{X_n, Y_{n-1}\}$. Hence $Y_n \le Y_{n-1}$ for all *n* so that if $Y_n \le \varepsilon$, then $Y_k \le \varepsilon$ for all $k \ge n$. Hence,

$$P[\bigcap_{k\geq n}S_k(\varepsilon)] = P[Y_n \leq \varepsilon, Y_{n+1} \leq \varepsilon, \ldots] = P[Y_n \leq \varepsilon] = 1 - (1 - F_X(\varepsilon))^n$$

Thus,

$$\lim_{n\to\infty} P[\cap_{k\geq n} S_k(\varepsilon)] = \lim_{n\to\infty} 1 - (1 - F_X(\varepsilon))^n = 1$$

Note that if there were an ε_0 such that $F_X(\varepsilon_0) = 0$, then

$$\lim_{n \to \infty} 1 - (1 - F_X(\varepsilon_0))^n = \lim_{n \to \infty} 1 - (1 - 0)^n = 0$$

and the Y_n sequence would not converge to zero.

Problem 8.4.4

For n = 1, 2, ..., let $W_n = (X_{3n-2} + X_{3n-1} + X_{3n})/3$. That is, $W_1 = (X_1 + X_2 + X_3)/3$, $W_2 = (X_4 + X_5 + X_6)/3$ and so on. Note that $W_1, W_2, ...$ is an iid random sequence. In addition, since $E[X_{3n}] = 0$ for all n,

$$E[W_n] = \frac{E[X_{3n-2}] + E[X_{3n-1}] + E[X_{3n}]}{3} = 1/3$$

By the construction of W_n , we can write

$$Y_{3n} = \frac{X_1 + \dots + X_{3n}}{3n} = \frac{W_1 + \dots + W_n}{n}$$

Since W_1, W_2, \ldots is an iid sequence with E[W] = 1/3, the strong law of large numbers says that

$$\lim_{k\to\infty}Y_{3k}=1/3 \qquad \text{w.p. 1}$$

At this point it may seem that we are done. However, we have not quite shown that the sequence Y_n converges w.p. 1. Given Y_{3k} , we need to find upper and lower bounds to Y_j . When $3k \le j \le 3k+2$,

$$Y_j = \frac{X_1 + \dots + X_{3k}}{j} + \frac{X_{3k+1} + \dots + X_j}{j}$$

Since $X_{3k+1} + \cdots + X_j \ge 0$,

$$Y_j \ge \frac{X_1 + \dots + X_{3k}}{j} = \frac{3k}{j} Y_{3k} = \left(1 - \frac{j - 3k}{j}\right) Y_{3k}$$

Since $0 \le j - 3k \le 2$ and since $Y_{3k} \le 1$, we see that

$$Y_j \ge Y_{3k} - \frac{2}{j} Y_{3k} \ge Y_{3k} - \frac{2}{j}$$

In addition, since $j \leq 3k+2$,

$$X_{3k+1} + \dots + X_j \le X_{3k+1} + X_{3k+2} \le 2$$

This implies

$$Y_j \le \frac{3k}{j} \frac{X_1 + \dots + X_{3k}}{3k} + \frac{2}{j} \le Y_{3k} + \frac{2}{j}$$

Combining these results, we have for $3k \le j \le 3k+2$,

$$Y_{3k} - 2/j \le Y_j \le Y_{3k} + 2/j$$

We can rewrite this result using the floor function as

$$Y_{3\lfloor j/3\rfloor} - 2/j \le Y_j \le Y_{3\lfloor j/3\rfloor} + 2/j$$

Taking limits, we obtain with probability 1 that

$$\lim_{j\to\infty} Y_{3\lfloor j/3\rfloor} - 2/j \leq \lim_{j\to\infty} Y_j \leq \lim_{j\to\infty} Y_{3\lfloor j/3\rfloor} + 2/j$$

which implies

$$1/3 \le \lim_{j \to \infty} Y_j \le 1/3 \qquad \text{w.p. 1}$$