Problem Set 8 Solution

Problem 1

$$E(\mathcal{H}_{S}(X) \leq \mathcal{H}_{S}(X) \leq \mathcal{H}_{S}) = F_{n_{n}(x)}(\mathcal{H}_{S}) - F_{n_{n}(x)}(\mathcal{H}_{S})$$

$$L_{S}(X) = \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{j=1}^{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{j=1}^{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{j=1}^{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{j=1}^{N} \sum_{j=1}^{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{j=1}^{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{j=1}^{$$

$$R(H \subseteq H_{\Lambda} \bowtie E H) = \overline{\Phi}\left(\frac{46-\mu}{6}\right) - \overline{\Phi}\left(\frac{44-\mu}{6}\right)$$

$$= \overline{\Phi}\left(\frac{46-\mu}{15}\right) - \overline{\Phi}\left(\frac{44-\mu}{15}\right)$$

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$$= 2\overline{\Phi}\left(\frac{15}{15}\right) - 1 = 0.99$$

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Note that we can write Y_k as

$$Y_k = \left(\frac{X_{2k-1} - X_{2k}}{2}\right)^2 + \left(\frac{X_{2k} - X_{2k-1}}{2}\right)^2 = \frac{(X_{2k} - X_{2k-1})^2}{2}$$
(1)

Hence,

$$E[Y_k] = \frac{1}{2}E[X_{2k}^2 - 2X_{2k}X_{2k-1} + X_{2k-1}^2] = E[X^2] - (E[X])^2 = Var[X]$$
 (2)

Next we observe that Y_1,Y_2,\ldots is an iid random sequence. If this independence is not obvious, consider that Y_1 is a function of X_1 and X_2, Y_2 is a function of X_3 and X_4 , and so on. Since X_1,X_2,\ldots is an idd sequence, Y_1,Y_2,\ldots is an iid sequence. Hence, $E[M_n(Y)]=E[Y]=\operatorname{Var}[X]$, implying $M_n(Y)$ is an unbiased estimator of $\operatorname{Var}[X]$. We can use Theorem 7.5 to prove that $M_n(Y)$ is consistent if we show that $\operatorname{Var}[Y]$ is finite. Since $\operatorname{Var}[Y] \leq E[Y^2]$, it is sufficient to prove that $E[Y^2] < \infty$. Note that

$$Y_k^2 = \frac{X_{2k}^4 - 4X_{2k}^3 X_{2k-1} + 6X_{2k}^2 X_{2k-1}^2 - 4X_{2k} X_{2k-1}^3 + X_{2k-1}^4}{4}$$
(3)

Taking expectations yields

$$E[Y_k^2] = \frac{1}{2}E[X^4] - 2E[X^3]E[X] + \frac{3}{2}(E[X^2])^2$$
(4)

Hence, if the first four moments of X are finite, then $Var[Y] \leq E[Y^2] < \infty$. By Theorem 7.5, the sequence $M_n(Y)$ is consistent.

$$P_X(x) = \begin{cases} 0.1 & x = 0 \\ 0.9 & x = 1 \\ 0 & \text{otherwise} \end{cases}$$
(1)

- (a) E[X] is in fact the same as $P_X(1)$ because X is a Bernoulli random variable.
- (b) We can use the Chebyshev inequality to find

$$P[|M_{90}(X) - P_X(1)| \ge .05] = P[|M_{90}(X) - E[X]| \ge .05] \le \alpha$$
(2)

In particular, the Chebyshev inequality states that

$$\alpha = \frac{\sigma_X^2}{90(.05)^2} = \frac{.09}{90(.05)^2} = 0.4 \tag{3}$$

(c) Now we wish to find the value of n such that $P[|M_n(X) - P_X(1)| \ge .03] \le .01$. From the Chebyshev inequality, we write

$$0.1 = \frac{\sigma_X^2}{n(.03)^2}.$$
 (4)

Since $\sigma_X^2 = 0.09$, solving for n yields n = 100.

Problem 4

Since the relative frequency of the error event E is $\hat{P}_n(E) = M_n(X_E)$ and $E[M_n(X_E)] = P[E]$, we can use Theorem 7.12(a) to write

$$P\left[\left|\hat{P}_n(A) - P\left[E\right]\right| \ge c\right] \le \frac{\operatorname{Var}[X_E]}{nc^2}.$$
 (1)

Note that $\mathrm{Var}[X_E] = P[E](1-P[E])$ since X_E is a Bernoulli (p=P[E]) random variable. Using the additional fact that $P[E] \leq \epsilon$ and the fairly trivial fact that $1-P[E] \leq 1$, we can conclude that

$$Var[X_E] = P[E](1 - P[E]) \le P[E] \le \epsilon. \tag{2}$$

Thus

$$P\left[\left|\hat{P}_{n}(A) - P\left[E\right]\right| \ge c\right] \le \frac{\text{Var}[X_{E}]}{nc^{2}} \le \frac{\epsilon}{nc^{2}}.$$
 (3)

Both questions can be answered using the following equation from Example 7.6:

$$P\left[\left|\hat{P}_{n}(A) - P\left[A\right]\right| \ge c\right] \le \frac{P\left[A\right]\left(1 - P\left[A\right]\right)}{nc^{2}} \tag{1}$$

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

$$P\left[\left|\hat{P}_{n}(A) - P[A]\right| \ge c\right] \le \frac{0.0099}{nc^{2}}$$
 (2)

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

$$P\left[\left|\hat{P}_{n}(A) - P[A]\right| \ge 0.001\right] \le \frac{9900}{n}$$
 (3)

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

$$P\left[\left|\hat{P}_{n}(A) - P\left[A\right]\right| \ge c\right] \le \frac{P\left[A\right]\left(1 - P\left[A\right]\right)}{nc^{2}} = \frac{0.0099}{n10^{-10}} = \frac{9.9 \times 10^{7}}{n} \tag{4}$$

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

(1)
$$E[M_{10}] = E[\frac{1}{10}\sum_{i=1}^{5}X_{i}] = \frac{1}{10}E[\sum_{i=1}^{5}X_{i}] = \frac{1}{10}\sum_{i=1}^{5}X_{i}] = \frac{1}{10}$$

$$= 1 - P \left[-36_{M_{10}} < M_{10} - 1 < 36_{M_{10}} \right]$$

$$= 1 - P \left[-36_{M_{10}} + 1 < M_{10} < 36_{M_{10}} + 1 \right]$$

$$= 1 - P \left[-36_{M_{10}} + 1 < M_{10} < \frac{3}{15} + 1 \right]$$

$$= 1 - P \left[-36_{M_{10}} < M_{10} < 1.95 \right]$$

$$= 1 - \left[-\frac{1.95}{15} - \frac{1}{15} - \frac{1}{15} - \frac{0.05}{15} - \frac{1}{15} \right]$$

$$= 1 - \left[-\frac{1.95}{15} - \frac{1}{15} - \frac$$

Recall that $X_1, X_2 ... X_n$ are independent exponential random variables with mean value $\mu_X = 5$ so that for $x \ge 0$, $F_X(x) = 1 - e^{-x/5}$.

(a) Using Theorem 7.1, $\sigma_{M_n(x)}^2 = \sigma_X^2/n$. Realizing that $\sigma_X^2 = 25$, we obtain

$$Var[M_9(X)] = \frac{\sigma_X^2}{9} = \frac{25}{9}$$
 (1)

(b)

$$P[X_1 \ge 7] = 1 - P[X_1 \le 7] = 1 - F_X(7) = 1 - (1 - e^{-7/5}) = e^{-7/5} \approx 0.247$$
 (2)

(c) First we express $P[M_9(X) > 7]$ in terms of X_1, \ldots, X_9 .

$$P[M_9(X) > 7] = 1 - P[M_9(X) \le 7] = 1 - P[(X_1 + \ldots + X_9) \le 63]$$
(3)

Now the probability that $M_9(X) > 7$ can be approximated using the Central Limit Theorem (CLT).

$$P[M_9(X) > 7] = 1 - P[(X_1 + ... + X_9) \le 63] \approx 1 - \Phi(\frac{63 - 9\mu_X}{\sqrt{9}\alpha_X}) = 1 - \Phi(6/5)$$
 (4)

Consulting with Table 3.1 yields $P[M_9(X) > 7] \approx 0.1151$.

Problem 8

Form the sample mean

$$M_{12}(x) = \frac{69.71 + 27.31 + ... + 71.36}{27.55} = \frac{71.55}{5}$$

Since we have 12 samples we can use "Gaussian"

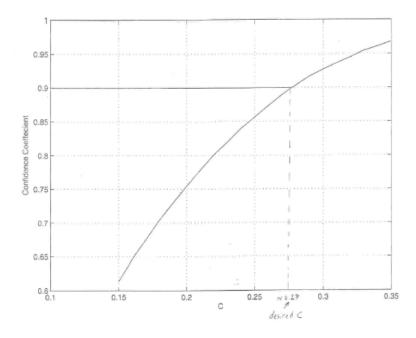
Approximation

 $P[M_{12}(x) = d < N_x \leq M_n(x) + d] = 1 - 2Q(\frac{d\sqrt{12}}{6x})$

so $1 = 2Q(\frac{d\sqrt{12}}{\sqrt{13.7}}) = 0.95$
 $Q(\frac{d\sqrt{12}}{13.7}) = 0.05 = 0.025$

```
I = \overline{\Phi}(d \ 0.9359) = 0.025
\overline{\Phi}(d \ 0.9359) = 0.975
I = \rho \ 142 + Text = K
d \ (0.9359) = 1.96 = 7 d = 2.09
\boxed{P[69.46 < \mu_{x} \leq 73.64] = 95\%}
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```
for i=1:10000
     sample_mean(i)=mean(rand(1,3));
end
C=0.15;
mean(0.5 > sample_mean - C & 0.5 < sample_mean + C)
% We get 0.6112
for i=1:10000
     sample_mean(i)=mean(rand(1,3));
C=0.35;
mean(0.5 > sample_mean - C & 0.5 < sample_mean + C)
% We get 0.9692
% So the desired C is between 0.15 and 0.35. % Let us search for the desired C in that range
C=.15:0.01:0.35
for i=1:length(C)
    confidence(i)=mean(0.5 > sample_mean - C(i) & 0.5 < sample_mean + C(i));
end
plot(C, confidence)
grid;
xlabel('C');
ylabel('Confidence Coeffecient');
% So we see from the plot (below) that the desired C to get % a confidence coeffecient of 90 % is C \sim 0.27.
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First we observe that the interval estimate can be expressed as

$$\left| \hat{P}_n(A) - P[A] \right| < 0.05.$$
 (1)

Since $\hat{P}_n(A) = M_n(X_A)$ and $E[M_n(X_A)] = P[A]$, we can use Theorem 7.12(b) to write

$$P\left[\left|\hat{P}_{n}(A) - P\left[A\right]\right| < 0.05\right] \ge 1 - \frac{\operatorname{Var}[X_{A}]}{n(0.05)^{2}}.$$
 (2)

Note that $\text{Var}[X_A] = P[A](1 - P[A]) \le 0.25$. Thus for confidence coefficient 0.9, we require that

$$1 - \frac{\text{Var}[X_A]}{n(0.05)^2} \ge 1 - \frac{0.25}{n(0.05)^2} \ge 0.9.$$
 (3)

This implies $n \ge 1,000$ samples are needed.