

Solutions to Chapter 7 Exercises

Problem 7.3

Since the N_i are Gaussian, $\hat{\mu}$ is also Gaussian with

$$\begin{aligned} E[\hat{\mu}] &= \mu_N = 0 \\ \text{Var}(\hat{\mu}) &= \frac{\sigma_N^2}{n} = \frac{0.01}{100} = 10^{-4}. \\ \Rightarrow \hat{\mu} &\sim N(0, 10^{-4}). \end{aligned}$$

Problem 7.8

Given x_1, x_2, \dots, x_N are observed, we want to minimize

$$\epsilon^2 = \frac{1}{N} \sum_{n=1}^N (x_n - a - bn)^2.$$

Taking derivatives with respect to a and b and setting equal to zero produces

$$\begin{aligned} \frac{\partial \epsilon^2}{\partial a} &= \frac{1}{N} \sum_{n=1}^N (-2)(x_n - a - bn) = 0 \\ \Rightarrow \frac{1}{N} \sum_{n=1}^N x_n &= a \left(\frac{1}{N} \sum_{n=1}^N 1 \right) + b \left(\frac{1}{N} \sum_{n=1}^N n \right) \\ \frac{\partial \epsilon^2}{\partial b} &= \frac{1}{N} \sum_{n=1}^N (-2n)(x_n - a - bn) = 0 \\ \Rightarrow \frac{1}{N} \sum_{n=1}^N nx_n &= a \left(\frac{1}{N} \sum_{n=1}^N n \right) + b \left(\frac{1}{N} \sum_{n=1}^N n^2 \right) \end{aligned}$$

To simplify the notation, define the following:

$$\begin{aligned}\bar{n} &= \frac{1}{N} \sum_{n=1}^N n, \\ \overline{n^2} &= \frac{1}{N} \sum_{n=1}^N n^2, \\ \bar{x}_n &= \frac{1}{N} \sum_{n=1}^N x_n, \\ \overline{nx_n} &= \frac{1}{N} \sum_{n=1}^N nx_n.\end{aligned}$$

Then, the optimum values of a and b will satisfy the following matrix equation:

$$\begin{bmatrix} 1 & \bar{n} \\ \bar{n} & \overline{n^2} \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} \bar{x}_n \\ \overline{nx_n} \end{bmatrix}$$

. The solution is

$$\begin{bmatrix} a \\ b \end{bmatrix} = \frac{\begin{bmatrix} \overline{n^2} \cdot \bar{x}_n - \bar{n} \cdot \overline{nx_n} \\ \overline{nx_n} - \bar{n} \cdot \bar{x}_n \end{bmatrix}}{\overline{n^2} - (\bar{n})^2}.$$

Problem 7.11

(a) Because X_i is a Bernoulli RV

$$\begin{aligned}\sigma_X^2 &= p_A(1 - p_A) \\ \hat{p}_A &= \frac{1}{n} \sum_{i=1}^n X_i \\ E[\hat{p}_A] &= p_A \\ Var(\hat{p}_A) &= \frac{\sigma_X^2}{n} = \frac{p_A(1 - p_A)}{n}\end{aligned}$$

By virtue of the central limit theorem, we can write

$$\begin{aligned}\hat{p}_A &\sim \left(p_A, \frac{p_A(1 - p_A)}{n}\right) \\ Pr(|\hat{p}_A - p_A| < \varepsilon) &= 1 - 2Q\left(\frac{p_A + \varepsilon - p_A}{\sqrt{p_A(1 - p_A)/n}}\right) \\ &= 1 - 2Q\left(\sqrt{\frac{n\varepsilon^2}{p_A(1 - p_A)}}\right)\end{aligned}$$

(b)

$$\Pr(|\hat{p}_A - p_A| < 0.1p_A) = 0.95$$

Using the result from (a) we get

$$\begin{aligned} 1 - 2Q\left(\sqrt{\frac{n(0.1p_A)^2}{p_A(1-p_A)}}\right) &= 0.95 \\ \Rightarrow Q\left(\sqrt{\frac{0.01p_An}{(1-p_A)}}\right) &\leq 0.025 \\ \Rightarrow \sqrt{\frac{0.01p_An}{(1-p_A)}} &\geq 1.9597 \approx 1.96 \end{aligned}$$

Note in the last step, the inequality is reversed since $Q(x)$ is a decreasing function of x .

$$\Rightarrow n \geq 19.6^2 \frac{1-p_A}{p_A}$$

(c)

$$\begin{aligned} Y_n &= \sum_{i=1}^n X_i = n\hat{p}_A \\ E[Y_n] &= np_A \end{aligned}$$

Since the value of n was chosen to satisfy the constraints of (b), we can write

$$E[Y_n] = 19.6^2 \frac{1-p_A}{p_A} p_A = 19.6^2(1-p_A).$$

Strictly speaking we will have

$$E[Y_n] \geq 19.6^2(1-p_A).$$

If we assume that $p_A \ll 1$ we can approximate it as

$$E[Y_n] \geq 19.6^2 \approx 384.$$

Problem 7.14

$$\mu_X = 5\text{volts}, \sigma_X = 0.25\text{volts}.$$

For $n = 100$ samples, the sample mean will have

$$E[\hat{\mu}] = 5\text{volts}, \sigma_{\hat{\mu}} = \frac{1}{40}\text{volts}.$$

The 99% confidence interval will be $(\mu_X - \epsilon, \mu_X + \epsilon)$ where

$$\epsilon = c_{0.99}\sigma_{\hat{\mu}} = 2.58 \cdot \frac{1}{40} = 0.0645\text{volts}.$$

Hence, the 99% confidence interval is (4.9355,5.0645) volts. None of the estimates in (a)-(c) fall in this range.