

7-4.  $X_i \sim N(100, 10^2) \quad n = 25$

$$\mu_{\bar{X}} = 100 \quad \sigma_{\bar{X}} = \frac{\sigma}{\sqrt{n}} = \frac{10}{\sqrt{25}} = 2$$

$$\begin{aligned} P[(100 - 1.8(2)) \leq \bar{X} \leq (100 + 2)] &= P(96.4 \leq \bar{X} \leq 102) = P\left(\frac{96.4 - 100}{\frac{\bar{X} - \mu}{\sigma/\sqrt{n}}} \leq \frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \leq \frac{102 - 100}{2}\right) \\ &= P(-1.8 \leq Z \leq 1) = P(Z \leq 1) - P(Z \leq -1.8) = 0.8413 - 0.0359 = 0.8054 \end{aligned}$$

7-11.  $n = 36$

$$\mu_X = \frac{a+b}{2} = \frac{(3+1)}{2} = 2$$

$$\sigma_X = \sqrt{\frac{1^2 + 0^2 + 1^2}{3}} = \sqrt{\frac{2}{3}}$$

$$\mu_{\bar{X}} = 2, \sigma_{\bar{X}} = \frac{\sqrt{2/3}}{\sqrt{36}} = \frac{\sqrt{2/3}}{6}$$

$$z = \frac{\bar{X} - \mu}{\sigma/\sqrt{n}}$$

Using the central limit theorem:

$$\begin{aligned} P(2.1 < \bar{X} < 2.5) &= P\left(\frac{2.1 - 2}{\frac{\sqrt{2/3}}{6}} < Z < \frac{2.5 - 2}{\frac{\sqrt{2/3}}{6}}\right) = P(0.7348 < Z < 3.6742) \\ &= P(Z < 3.6742) - P(Z < 0.7348) = 1 - 0.7688 = 0.2312 \end{aligned}$$

7-23. a)  $\frac{s}{\sqrt{N}} = \text{SE Mean} \rightarrow \frac{10.25}{\sqrt{N}} = 2.05 \rightarrow N = 25$

$$\text{Mean} = \frac{3761.70}{25} = 150.468, \text{Variance} = S^2 = 10.25^2 = 105.0625$$

$$\text{Variance} = \frac{\text{Sum of Squares}}{n-1} \rightarrow 105.0625 = \frac{SS}{25-1} \rightarrow SS = 2521.5$$

b) Estimate of population mean = sample mean = 150.468

7-26. 
$$E(\bar{X}_1) = E\left(\frac{\sum_{i=1}^{2n} X_i}{2n}\right) = \frac{1}{2n} E\left(\sum_{i=1}^{2n} X_i\right) = \frac{1}{2n} (2n\mu) = \mu$$

$$E(\bar{X}_2) = E\left(\frac{\sum_{i=1}^n X_i}{n}\right) = \frac{1}{n} E\left(\sum_{i=1}^n X_i\right) = \frac{1}{n} (n\mu) = \mu$$

$\bar{X}_1$  and  $\bar{X}_2$  are unbiased estimators of  $\mu$ .

The variances are  $V(\bar{X}_1) = \frac{\sigma^2}{2n}$  and  $V(\bar{X}_2) = \frac{\sigma^2}{n}$ ; compare the MSE (variance in this case),

$$\frac{MSE(\hat{\Theta}_1)}{MSE(\hat{\Theta}_2)} = \frac{\sigma^2 / 2n}{\sigma^2 / n} = \frac{n}{2n} = \frac{1}{2}$$

Because both estimators are unbiased, one concludes that  $\bar{X}_1$  is the “better” estimator with the smaller variance.

7-35. **Descriptive Statistics**

Variable	N	Mean	Median	TrMean	StDev	SE Mean
Oxide Thickness	24	423.33	424.00	423.36	9.08	1.85

- The mean oxide thickness, as estimated by Minitab from the sample, is 423.33 Angstroms.
- The standard deviation for the population can be estimated by the sample standard deviation, or 9.08 Angstroms.
- The standard error of the mean is 1.85 Angstroms.
- Our estimate for the median is 424 Angstroms.
- Seven of the measurements exceed 430 Angstroms, so our estimate of the proportion requested is  $7/24 = 0.2917$

7-46.  $f(x) = (\theta + 1)x^\theta$

$$L(\theta) = \prod_{i=1}^n (\theta + 1)x_i^\theta = (\theta + 1)x_1^\theta \times (\theta + 1)x_2^\theta \times \dots = (\theta + 1)^n \prod_{i=1}^n x_i^\theta$$

$$\ln L(\theta) = n \ln(\theta + 1) + \theta \ln x_1 + \theta \ln x_2 + \dots = n \ln(\theta + 1) + \theta \sum_{i=1}^n \ln x_i$$

$$\frac{\partial \ln L(\theta)}{\partial \theta} = \frac{n}{\theta + 1} + \sum_{i=1}^n \ln x_i = 0$$

$$\frac{n}{\theta + 1} = -\sum_{i=1}^n \ln x_i$$

$$\hat{\theta} = \frac{n}{-\sum_{i=1}^n \ln x_i} - 1$$

7-48.

$$L(\theta) = \prod_{i=1}^n \frac{x_i e^{-x_i/\theta}}{\theta^2} \quad \ln L(\theta) = \sum \ln(x_i) - \sum \frac{x_i}{\theta} - 2n \ln \theta$$

$$\frac{\partial \ln L(\theta)}{\partial \theta} = \frac{1}{\theta^2} \sum x_i - \frac{2n}{\theta}$$

Setting the last equation equal to zero and solving for theta yields

$$\hat{\theta} = \frac{\sum_{i=1}^n x_i}{2n}$$

7-52. a)  $\hat{a}$  cannot be unbiased since it will always be less than  $a$ .

$$\text{b) bias} = \frac{na}{n+1} - \frac{a(n+1)}{n+1} = -\frac{a}{n+1} \xrightarrow{n \rightarrow \infty} 0.$$

$$\text{c) } 2\bar{X}$$

$$\text{d) } P(Y \leq y) = P(X_1, \dots, X_n \leq y) = [P(X_1 \leq y)]^n = \left(\frac{y}{a}\right)^n. \text{ Thus, } f(y) \text{ is as given. Thus,}$$

$$\text{bias} = E(Y) - a = \frac{an}{n+1} - a = -\frac{a}{n+1}.$$

e) For any  $n > 1$ ,  $n(n+2) > 3n$  so the variance of  $\hat{a}_2$  is less than that of  $\hat{a}_1$ . It is in this sense that the second estimator is better than the first.