

C.1 Parameter Estimation



C.1.1 Estimator Basics

Basic Ideas

Examples of Estimators

Mean and Variance of Estimators

Exercises

Sources



This lesson comes from Hogg McKean & Craig (7th Ed.) section 4.1 and Wackerly sections 8.1-8.3.



Functions of Samples

The number of customers entering a store between 9 and 10 A.M. is recorded on 3 days to be 9, 15, and 11.

X = the number of customers on a day $\sim F(x) = P[X \leq x]$

What we can learn about F depends on what we assume.

1. No assumption $\rightarrow$ nonparametric statistics (later)
2. Assume some shape, and maybe some parameter values.

Examples: $X \sim \text{Poisson}(\lambda)$, $N(\mu, \sigma^2)$, $N(\mu, 25)$

A random sample of size 3 (Independent): $\mathbb{X} = (X_1, X_2, X_3)$, $X_i \sim X$.

A realization of the sample: $(9, 15, 11)$, (x_1, x_2, x_3)

$T(\mathbb{X}) = \frac{X_1 + X_2 + X_3}{3}$ is a statistic

$T(\mathbb{X} = (9, 15, 11)) = \frac{9+15+11}{3} = \frac{35}{3} = t$ is a realization of T .



Estimators

The number of customers entering a store between 9 and 10 A.M. is recorded on 3 days to be 9, 15, and 11.

Suppose $\mathbb{X} = (X_1, \dots, X_n)$ with $X_i \sim \text{Poisson}(\lambda)$

$\hat{\lambda} = T$ is an estimator of λ

$\hat{\lambda}(\mathbb{X}) = T(\mathbb{X})$ is random. $\hat{\lambda}(\mathbb{X} = (x_1, \dots, x_n))$ is a number.

$\hat{\lambda}$ is notationally tricky. Sometimes a function, sometimes a number.

Possible choices for estimators:

$$\hat{\lambda}_1 = \bar{X}, \quad \hat{\lambda}_2 = X_1, \quad \hat{\lambda}_3 = 12, \quad \hat{\lambda}_4 = \bar{X} + 1/n$$

For this data set,

$$\hat{\lambda}_1 = 35/3, \quad \hat{\lambda}_2 = 9, \quad \hat{\lambda}_3 = 12, \quad \hat{\lambda}_4 = 35/3 + 1/3 = 12.$$



Expected Value of an Estimator

$$\hat{\lambda}_1 = \bar{X} \quad \hat{\lambda}_2 = X_1, \quad \hat{\lambda}_3 = 12, \quad \hat{\lambda}_4 = \bar{X} + 1/n$$

$$E[\hat{\lambda}]?$$

$$E[\hat{\lambda}] = \sum_{\mathbb{X}=(x_1, \dots, x_n)} \hat{\lambda}(\mathbb{X}) P[\mathbb{X} = (x_1, \dots, x_n)]$$

$$\begin{aligned} E[\hat{\lambda}_3] &= \sum 12 P[\mathbb{X} = (x_1, \dots, x_n)] \\ &= 12 \sum P[\mathbb{X} = (x_1, \dots, x_n)] = 12 \cdot 1 \end{aligned}$$

$$E[\hat{\lambda}_2] = E[X_1] = \lambda$$

$$E[\hat{\lambda}_1] = E\left[\left(\sum X_i\right)/n\right] = (1/n) \sum E[X_i] = n\lambda/n = \lambda$$

$$E[\hat{\lambda}_4] = E\left[\left(\sum X_i\right)/n + 1/n\right] = \lambda + 1/n$$



Variance of an Estimator

$$\hat{\lambda}_1 = \bar{X} \quad \hat{\lambda}_2 = X_1, \quad \hat{\lambda}_3 = 12, \quad \hat{\lambda}_4 = \bar{X} + 1/n$$

$$\text{Var}[\hat{\lambda}] = E[\hat{\lambda}^2] - E[\hat{\lambda}]^2, \text{ but sometimes } \dots$$

$$\text{Var}[\hat{\lambda}_3] = \text{Var}[12] = 0$$

$$\text{Var}[\hat{\lambda}_2] = \text{Var}[X_1] = \lambda$$

$$\text{Var}[\hat{\lambda}_1] = \text{Var}\left[(1/n) \sum X_i\right] = (1/n)^2 \sum \text{Var}(X_i) = n\lambda/n^2 = \lambda/n.$$

$$\text{Var}(X_1 + X_2) = \text{Var}(X_1) + \text{Var}(X_2) + 2(\text{Cov}(X_1, X_2) = 0).$$

$$\text{Var}[\hat{\lambda}_4] = \text{Var}\left[(1/n) \sum X_i + 1/n\right] = \lambda/n$$



Exercise 1

Suppose that $X_1, \dots, X_n$ is a random sample, and $X_i \sim N(\mu, \sigma^2)$.

With $\hat{\mu} = \bar{X} + 1/n$ as the estimator for μ , what is the variance of $\hat{\mu}$?



Exercise 1

Suppose that $X_1, \dots, X_n$ is a random sample, and $X_i \sim N(\mu, \sigma^2)$.

With $\hat{\mu} = \bar{X} + 1/n$ as the estimator for μ , what is the variance of $\hat{\mu}$?

$$\begin{aligned} \text{Var}(\hat{\mu}) &= \text{Var}\left(\frac{1}{n} \sum X_i + \frac{1}{n}\right) \\ &= \left(\frac{1}{n}\right)^2 \sum \text{Var}(X_i) + 0 \\ &= \left(\frac{1}{n}\right)^2 n \sigma^2 \\ &= \boxed{\sigma^2/n} \end{aligned}$$



Exercise 2

Suppose that $X_1, \dots, X_n$ is a random sample, and $X_i \sim N(\mu, \sigma^2)$.

Using $\hat{\sigma}^2 = \frac{\sum (X_i - \bar{X})^2}{n}$ as the estimator for σ^2 , compute $E[\hat{\sigma}^2]$.



Exercise 2

Suppose that $X_1, \dots, X_n$ is a random sample, and $X_i \sim N(\mu, \sigma^2)$.

Using $\hat{\sigma}^2 = \frac{\sum (X_i - \bar{X})^2}{n}$ as the estimator for σ^2 , compute $E[\hat{\sigma}^2]$.

$$\begin{aligned} E[\hat{\sigma}^2] &= E\left[\frac{\sum (X_i - \bar{X})^2}{n}\right] \\ &= \frac{1}{n} E\left[\sum (X_i^2 - 2X_i\bar{X} + \bar{X}^2)\right] \\ &= \frac{1}{n} E\left[\left(\sum X_i^2\right) - 2n\bar{X}\frac{\sum X_i}{n} + n\bar{X}^2\right] \\ &= \frac{1}{n} \left(\sum E[X_i^2] - E[n\bar{X}^2] \right) \end{aligned}$$

$$\frac{1}{n} \left(\sum E[X_i^2] - E[n\bar{X}^2] \right) \quad \begin{array}{l} X_i \sim \mathcal{N}(\mu, \sigma^2) \\ E[X_i^2] = \sigma^2 + \mu^2 \end{array}$$

$$\frac{1}{n} \left(n(\sigma^2 + \mu^2) - n(\text{Var } \bar{X} + (E[\bar{X}])^2) \right) \quad E[\bar{X}^2] = \text{Var}(\bar{X}) + (E[\bar{X}])^2$$

$$\cancel{\sigma^2 + \mu^2} - \cancel{\sigma^2/n} - \cancel{\mu^2}$$

$$E[\hat{\sigma}^2] = \frac{n\sigma^2}{n} - \frac{1\sigma^2}{n} = \boxed{\left(\frac{n-1}{n}\right)\sigma^2}$$