

# Statistical Theory II: Chapter 9 - Properties of Point Estimators and Methods of Estimation

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## Problem 9.20.

We know that  $\frac{Y}{n}$  is an unbiased estimator of  $p$  with  $V(\frac{Y}{n}) = \frac{pq}{n}$  from Ch. 8.

Since  $pq$  is a constant,

$$\lim_{n \rightarrow \infty} \frac{pq}{n} = pq \lim_{n \rightarrow \infty} \frac{1}{n} = pq(0) = 0$$

By Theorem 9.1,  $\frac{Y}{n}$  is thus a consistent estimator of  $p$ .

## Problem 9.46.

We know that an exponential distribution has the following pdf:

$$f(x; \beta) = \begin{cases} \frac{1}{\beta} e^{-\frac{x}{\beta}} & x \geq 0 \\ 0 & x < 0 \end{cases}$$

Thus,

$$\begin{aligned} L(y_1, y_2, \dots, y_n | \beta) &= f(y_1, y_2, \dots, y_n | \beta) \\ &= f(y_1 | \beta) * f(y_2 | \beta) * \dots * f(y_n | \beta) \\ &= \frac{1}{\beta} e^{-\frac{y_1}{\beta}} * \dots * \frac{1}{\beta} e^{-\frac{y_n}{\beta}} \\ &= \left(\frac{1}{\beta}\right)^n e^{-\sum y_i / \beta} \\ &= \left(\frac{1}{\beta}\right)^n e^{-n\bar{y} / \beta} \end{aligned}$$

If we let  $g(\bar{y}, \beta) = \left(\frac{1}{\beta}\right)^n e^{-n\bar{y} / \beta}$  and  $h(y_1, y_2, \dots, y_n) = 1$ , we can see that,

$$L(y_1, \dots, y_n | \beta) = g(\bar{y}, \beta) * h(y_1, \dots, y_n)$$

This satisfies Theorem 9.4, and thus  $\bar{Y}$  is a sufficient statistic for the parameter  $\beta$ .

**Problem 9.56.**

We know from Exercise 9.38(b) that  $\Sigma(Y_i - \mu)^2$  is sufficient for  $\sigma^2$ .

We also know that  $\hat{\sigma}^2 = \frac{1}{n-1}\Sigma(y_i - \mu)^2$  is an unbiased estimator for  $\sigma^2$  from Ch. 8.4. Since  $\hat{\sigma}^2$  is unbiased and is a function of the sufficient statistic, it is an MVUE for  $\sigma^2$ .

**Problem 9.70.**

We need to estimate one parameter,  $\lambda$ , so we only need to find  $\mu'_1 = m'_1$ .

The value of  $\mu'_1$  for a Poisson random variable is,

$$\mu'_1 = \mu = \lambda$$

The first sample moment is,

$$m'_1 = \frac{1}{n}\Sigma Y_i = \bar{Y}$$

Thus,

$$\mu'_1 = \lambda = \bar{Y}$$

**Problem 9.82.**

a) By Theorem 9.4, a sufficient statistic for  $\theta$  is  $\Sigma Y_i^r$ .

b)  $\ln(L(\theta)) = -n\ln(\theta) + n\ln(r) + (r-1)\ln(\Pi y_i) - \Sigma y_i^r/\theta$

After taking the derivative with regards to  $\theta$  and setting the equation equal to 0, we get:

$$\hat{\theta} = \frac{1}{n}\Sigma Y_i^r$$

c) We know that  $\hat{\theta}$  is a function of the sufficient statistic.

$E(Y^r) = \theta$ , so  $\hat{\theta}$  is unbiased and, by Theorem 9.5,  $\hat{\theta}$  is the MVUE for  $\theta$ .