

CSE Exercises - week 7

① Let X_1, \dots, X_n be independent and identically distributed random variables with $E(X_1) < \infty$ and $V(X_1) < \infty$. Let \bar{X}_n denote the sample mean. We know, by the WLLN, that \bar{X}_n is asymptotically consistent for $E(X_1)$. Verify this using Proposition 95 (page 199) by showing that

(a) \bar{X}_n is an unbiased estimator for $E(X_1)$;
and

(b) $V(\bar{X}_n) \rightarrow 0$ as $n \rightarrow \infty$.

② Let $X_1, \dots, X_n \stackrel{iid}{\sim} \text{Bernoulli}(\theta^*)$ and let $S_n = X_1 + \dots + X_n$. Consider the following estimator for θ^* :

$$\hat{\theta}_n := (S_n + 1) / (n + 2).$$

(a) Is $\hat{\theta}_n$ a biased or unbiased estimator for θ^* ? If biased, find the bias.

(b) Show clearly whether $\hat{\theta}_n$ is asymptotically consistent.

- ③ Recall from Exercise 1 in week 2's exercises that for X_1, \dots, X_n IID with $E(X_1) < \infty$ and $V(X_1) < \infty$, the usual sample variance,

$$S_n^2 := \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X}_n)^2,$$

is an unbiased estimator for $V(X_1)$.

In this exercise, we will discover by simulation that the property of unbiasedness is generally not preserved under transformations. Specifically, we will see that S_n is not an unbiased estimator of the population standard deviation, $\sqrt{V(X_1)}$. Do the following:

- (i) Generate $n=10$ Uniform(0,1) random values.
- (ii) Compute S_n^2 and S_n and store the answers.
- (iii) Repeat steps (i) and (ii) 10,000 times.
- (iv) Use the 10,000 S_n^2 values to obtain a 95% confidence interval for $E(S_n^2)$. Compare this with the Uniform(0,1) population variance and comment on your result.
- (v) Use the 10,000 S_n values to obtain a 95% confidence interval for $E(S_n)$. Compare this with the Uniform(0,1) population standard deviation and comment on your result.

④ Let X be a continuous random variable with PDF,

$$f(x; c) = \begin{cases} cx^{c-1} & , \quad 0 \leq x \leq 1 \\ 0 & , \quad \text{otherwise} \end{cases}$$

where $c > 0$ is a parameter.

(a) Suppose that $X = 0.25$ is observed. Write down the likelihood function and log-likelihood function and plot them.

(b) Suppose that $X_1, X_2 \stackrel{\text{iid}}{\sim} f(x; c)$, and $X_1 = 0.7$ and $X_2 = 0.9$ are observed. Write down the likelihood function and log-likelihood function and plot them.

(c) If $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} f(x; c)$, write down the likelihood function and log-likelihood function.

Solutions

$$\begin{aligned}
 \textcircled{1} \quad (a) \quad \bar{X}_n &:= \frac{1}{n} \sum_{i=1}^n X_i \\
 E(\bar{X}_n) &= E\left(\frac{1}{n} \sum_{i=1}^n X_i\right) \\
 &= \frac{1}{n} \sum_{i=1}^n E(X_i) \\
 &= \frac{1}{n} \cdot n E(X_1) = E(X_1).
 \end{aligned}$$

Hence, \bar{X}_n is unbiased for $E(X_1)$.

$$\begin{aligned}
 (b) \quad V(\bar{X}_n) &= V\left(\frac{1}{n} \sum_{i=1}^n X_i\right) \\
 &= \frac{1}{n^2} \sum_{i=1}^n V(X_i) \\
 &= \frac{1}{n^2} \cdot n V(X_1) \\
 &= \frac{V(X_1)}{n} \rightarrow 0 \quad \text{as } n \rightarrow \infty.
 \end{aligned}$$

$$\textcircled{2} \quad X_1, \dots, X_n \stackrel{i.i.d.}{\sim} \text{Bernoulli}(\theta^*), \quad S_n = X_1 + \dots + X_n,$$

$$\hat{\theta}_n := \frac{S_n + 1}{n + 2}$$

$$(a) \quad \text{Since } \bar{X}_n = S_n / n,$$

$$\hat{\theta}_n = \frac{n \bar{X}_n + 1}{n + 2}$$

$$E(\hat{\theta}_n) = E\left(\frac{n \bar{X}_n + 1}{n + 2}\right)$$

$$\begin{aligned}
&= \frac{n E(\bar{X}_n) + 1}{n+2} \\
&= \frac{n \theta^* + 1}{n+2} \quad \left(\text{since } \bar{X}_n \text{ is unbiased for } \theta^* \right) \\
&\neq \theta^*
\end{aligned}$$

and so $\hat{\theta}_n$ is a biased estimator for θ^* .

The bias is $E(\hat{\theta}_n) - \theta^*$

$$\begin{aligned}
&= \frac{n \theta^* + 1}{n+2} - \theta^* \\
&= \frac{1 - 2\theta^*}{n+2} .
\end{aligned}$$

(b) Bias of $\hat{\theta}_n = \frac{1 - 2\theta^*}{n+2} \rightarrow 0$ as $n \rightarrow \infty$.

$$\begin{aligned}
V(\hat{\theta}_n) &= V\left(\frac{n\bar{X}_n + 1}{n+2}\right) \\
&= \left(\frac{n}{n+2}\right)^2 V(\bar{X}_n) \\
&= \left(\frac{n}{n+2}\right)^2 \frac{\theta^*(1-\theta^*)}{n} \\
&= \frac{n \theta^*(1-\theta^*)}{(n+2)^2} \rightarrow 0 \text{ as } n \rightarrow \infty .
\end{aligned}$$

$\therefore \hat{\theta}_n$ is asymptotically consistent.

③ Results for my generated values are as follows:

(iv) Let $\overline{S_N^2}$ denote the sample mean of my $N = 10,000$ S_n^2 values (here $n = 10$). Then

$$\overline{S_N^2} = 0.0836$$

$$\begin{aligned} \text{SE}_N(\overline{S_N^2}) &= \sqrt{\frac{\text{sample variance of } 10,000 \text{ } S_n^2 \text{ values}}{N}} \\ &= 0.000264 \end{aligned}$$

95% confidence interval for $E(\overline{S_N^2})$ is

$$\begin{aligned} &\overline{S_N^2} \pm 1.96 \text{SE}_N(\overline{S_N^2}) \\ &= 0.0836 \pm 1.96 \times 0.000264 \\ &= (0.0830, 0.0841). \end{aligned}$$

The Uniform $(0,1)$ variance is $\frac{1}{12} = 0.0833$, which lies within the confidence interval.

Thus, we are 95% confident that $E(S_n^2)$ is equal to the population variance, i.e. that S_n^2 is an unbiased estimator for the population variance.

(v) Let \bar{S}_N denote the sample mean of my $N = 10,000$ S_n values (here $n = 10$). Then

$$\bar{S}_N = 0.2852$$

$$\begin{aligned} \text{SE}_N(\bar{S}_N) &= \sqrt{\frac{\text{sample variance of 10,000 } S_n \text{ values}}{N}} \\ &= 0.000469 \end{aligned}$$

95% confidence interval for $E(\bar{S}_N)$ is

$$\bar{S}_N \pm 1.96 \text{SE}_N(\bar{S}_N)$$

$$= 0.2852 \pm 1.96 \times 0.000469$$

$$= (0.2843, 0.2862).$$

The Uniform $(0,1)$ standard deviation is $\frac{1}{\sqrt{12}} = 0.2887$, which lies outside the confidence interval.

Thus, we are 95% confident that $E(S_n)$ is not equal to the population standard deviation, i.e. that S_n is a biased estimator for the population standard deviation.

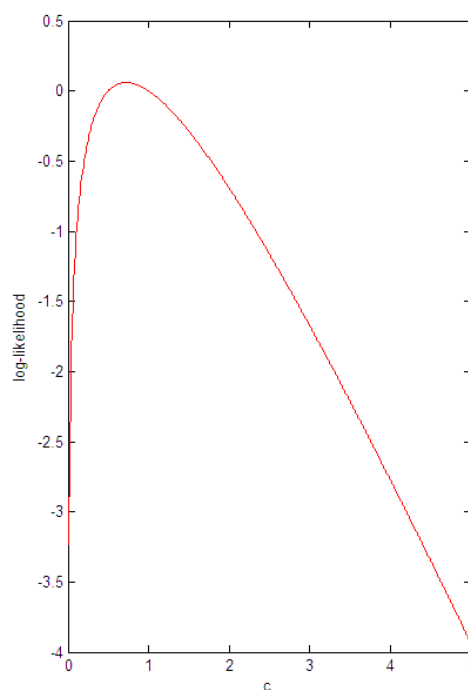
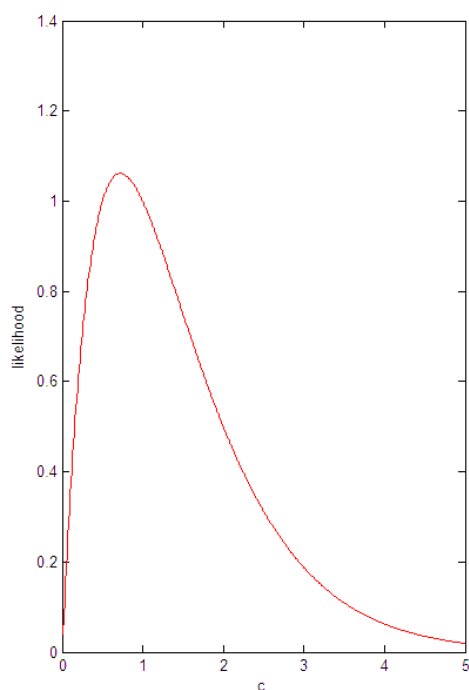
④

$$f(x; c) = \begin{cases} c x^{c-1}, & 0 \leq x \leq 1 \\ 0, & \text{otherwise} \end{cases}$$

(a) When $X = 0.25$,

$$L(c) = c (0.25)^{c-1}, \quad c > 0.$$

$$\begin{aligned} l(c) &= \log L(c) \\ &= \log c + (c-1) \log 0.25, \quad c > 0. \end{aligned}$$



(b) Let $X_1, X_2 \stackrel{i.i.d}{\sim} f(x; c)$. Then

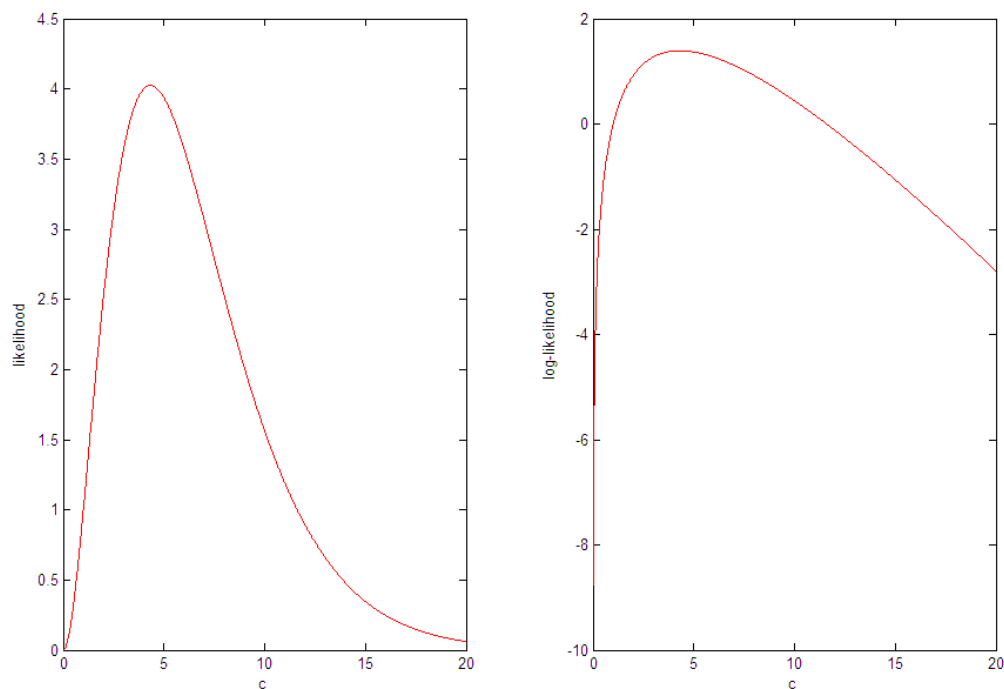
$$\begin{aligned}
 L_2(c) &= f(x_1, x_2; c) \\
 &= f(x_1; c) f(x_2; c) \\
 &= (c x_1^{c-1})(c x_2^{c-1}) \\
 &= c^2 (x_1 x_2)^{c-1}, \quad c > 0.
 \end{aligned}$$

$$\begin{aligned}
 l_2(c) &= \log L_2(c) \\
 &= 2 \log c + (c-1) \log(x_1 x_2), \quad c > 0.
 \end{aligned}$$

When $X_1 = 0.7$ and $X_2 = 0.9$,

$$L_2(c) = c^2 (0.63)^{c-1}, \quad c > 0.$$

$$l_2(c) = 2 \log c + (c-1) \log(0.63), \quad c > 0.$$



(c) Let $X_1, \dots, X_n \stackrel{iid}{\sim} f(x; c)$. Then

$$\begin{aligned}
 L_n(c) &= f(x_1, \dots, x_n; c) \\
 &= \prod_{i=1}^n f(x_i; c) \\
 &= c^n \left(\prod_{i=1}^n x_i \right)^{c-1}, \quad c > 0,
 \end{aligned}$$

and

$$\begin{aligned}
 \ln(c) &= \log L_n(c) \\
 &= n \log c + (c-1) \log \left(\prod_{i=1}^n x_i \right) \\
 &= n \log c + (c-1) \sum_{i=1}^n \log x_i, \quad c > 0.
 \end{aligned}$$