8.2.2 Point Estimators for Mean and Variance

The above discussion suggests the sample mean, \overline{X} , is often a reasonable point estimator for the mean. Now, suppose that we would like to estimate the variance of a distribution σ^2 . Assuming $0 < \sigma^2 < \infty$, by definition

$$\sigma^2 = E[(X - \mu)^2].$$

Thus, the variance itself is the mean of the random variable $Y=(X-\mu)^2$. This suggests the following estimator for the variance

$$\hat{\sigma}^2 = rac{1}{n} \sum_{k=1}^n (X_k - \mu)^2.$$

By linearity of expectation, $\hat{\sigma}^2$ is an unbiased estimator of σ^2 . Also, by the weak law of large numbers, $\hat{\sigma}^2$ is also a consistent estimator of σ^2 . However, in practice we often do not know the value of μ . Thus, we may replace μ by our estimate of the μ , the sample mean, to obtain the following estimator for σ^2 :

$$\overline{S}^2 = rac{1}{n} \sum_{k=1}^n (X_k - \overline{X})^2.$$

Using a little algebra, you can show that

$$\overline{S}^2 = rac{1}{n} \Biggl(\sum_{k=1}^n X_k^2 - n \overline{X}^2 \Biggr) \,.$$

Example 8.5

Let $X_1, X_2, X_3, ..., X_n$ be a random sample with mean $EX_i = \mu$, and variance $Var(X_i) = \sigma^2$. Suppose that we use

$$\overline{S}^2 = rac{1}{n} \sum_{k=1}^n (X_k - \overline{X})^2 = rac{1}{n} \Biggl(\sum_{k=1}^n X_k^2 - n \overline{X}^2 \Biggr)$$

to estimate σ^2 . Find the bias of this estimator

$$B(\overline{S}^2) = E[\overline{S}^2] - \sigma^2.$$

Solution

First note that

$$egin{aligned} E\overline{X}^2 &= ig(E\overline{X}ig)^2 + \mathrm{Var}(\overline{X}ig) \ &= \mu^2 + rac{\sigma^2}{n}. \end{aligned}$$

Thus,

$$egin{align} E[\overline{S}^2] &= rac{1}{n} \Biggl(\sum_{k=1}^n E X_k^2 - n E \overline{X}^2 \Biggr) \ &= rac{1}{n} \Biggl(n (\mu^2 + \sigma^2) - n \left(\mu^2 + rac{\sigma^2}{n}
ight) \Biggr) \ &= rac{n-1}{n} \sigma^2. \end{split}$$

Therefore,

$$B(\overline{S}^{2}) = E[\overline{S}^{2}] - \sigma^{2}$$
$$= -\frac{\sigma^{2}}{n}.$$

We conclude that \overline{S}^2 is a biased estimator of the variance. Nevertheless, note that if n is relatively large, the bias is very small. Since $E[\overline{S}^2] = \frac{n-1}{n}\sigma^2$, we can obtain an unbiased estimator of σ^2 by multiplying \overline{S}^2 by $\frac{n}{n-1}$. Thus, we define

$$S^2 = rac{1}{n-1} \sum_{k=1}^n (X_k - \overline{X})^2 = rac{1}{n-1} \Biggl(\sum_{k=1}^n X_k^2 - n \overline{X}^2 \Biggr) \, .$$

By the above discussion, S^2 is an unbiased estimator of the variance. We call it the **sample variance**. We should note that if n is large, the difference between S^2 and \overline{S}^2 is very small. We also define the **sample standard deviation** as

$$S = \sqrt{S^2}$$
.

Although the sample standard deviation is usually used as an estimator for the standard deviation, it is a biased estimator. To see this, note that S is random, so Var(S) > 0. Thus,

$$0 < Var(S) = ES^2 - (ES)^2$$

= $\sigma^2 - (ES)^2$.

Therefore, $ES < \sigma$, which means that S is a biased estimator of σ .

Let $X_1, X_2, X_3, \ldots, X_n$ be a random sample with mean $EX_i = \mu < \infty$, and variance $0 < \operatorname{Var}(X_i) = \sigma^2 < \infty$. The **sample variance** of this random sample is defined as

$$S^2 = rac{1}{n-1} \sum_{k=1}^n (X_k - \overline{X})^2 = rac{1}{n-1} \Biggl(\sum_{k=1}^n X_k^2 - n \overline{X}^2 \Biggr) \, .$$

The sample variance is an unbiased estimator of σ^2 . The **sample standard deviation** is defined as

$$S = \sqrt{S^2}$$
,

and is commonly used as an estimator for σ . Nevertheless, S is a biased estimator of σ .

You can use the mean command in MATLAB to compute the sample mean for a given sample. More specifically, for a given vector $x = [x_1, x_2, \dots, x_n]$, mean(x) returns the sample average

$$\frac{x_1+x_2+\cdots+x_n}{n}.$$

Also, the functions var and std can be used to compute the sample variance and the sample standard deviation respectively.

Example 8.6

Let T be the time that is needed for a specific task in a factory to be completed. In order to estimate the mean and variance of T, we observe a random sample T_1, T_2, \cdots , T_6 . Thus, T_i 's are i.i.d. and have the same distribution as T. We obtain the following values (in minutes):

Find the values of the sample mean, the sample variance, and the sample standard deviation for the observed sample.

Solution

The sample mean is

$$\overline{T} = rac{T_1 + T_2 + T_3 + T_4 + T_5 + T_6}{6} \ = rac{18 + 21 + 17 + 16 + 24 + 20}{6} \ = 19.33$$

The sample variance is given by

$$S^2 = rac{1}{6-1} \sum_{k=1}^6 (T_k - 19.333)^2 = 8.67$$

Finally, the sample standard deviation is given by

$$S = \sqrt{S^2} = 2.94$$

You can use the following MATLAB code to compute the above values:

```
t = [18, 21, 17, 16, 24, 20];
m = mean(t);
v = var(t);
s = std(t);
```