

## CHAPTER 9

ESTIMATION OF THE PARAMETERS OF DOUBLY TRUNCATED  
NORMAL DISTRIBUTION FROM FIRST FOUR SAMPLE MOMENTS

## 9.1 Introduction

A.G. Cohen [11] has estimated the parameters of singly and doubly truncated normal distributions by the method of maximum likelihood. Using the method of moments, he [12] has also obtained the estimators of singly truncated normal distribution from first three sample moments. In this chapter, the method of moments has been applied to estimate the parameters of doubly truncated normal distribution. The estimators are obtained from the first four sample moments. Further, comparison of these estimators has been made with the maximum likelihood estimators. The study reveals that the method of moments provides simple estimators of the parameters of doubly truncated normal distribution without much loss of efficiency, while the maximum

likelihood estimators are complicated and laborious.

## 9.2 Doubly truncated normal distribution

The density function of doubly truncated normal distribution is given by

$$(9.2.1) \quad f(x) = \phi\left(\frac{x-u}{\sigma}\right) / \sigma [\bar{\phi}(x_1) - \bar{\phi}(x_0)],$$

$$x_0 < x < x_1,$$

where  $\phi(t) = (\sqrt{2\pi})^{-1} e^{-t^2/2}$  and  $\bar{\phi}(t) = \int_{-\infty}^t \phi(x) dx$ .

Let  $(x_0 - \mu)/\sigma = k_0$  and  $(x_1 - \mu)/\sigma = k_1$ . Change the origin to  $x_0$  and put  $x - x_0 = y$ . Then, the density function of  $y$  is

$$(9.2.2) \quad g(y) = \phi\left(\frac{y}{\sigma} + k_0\right) / G \sigma, \quad 0 < y < d$$

where  $G = \bar{\phi}(k_1) - \bar{\phi}(k_0)$  and  $d = x_1 - x_0$ . The moments  $m_r$  of the distribution of  $y$  about its origin are given by

$$(9.2.3) \quad m_1 = \sigma(z_0 - z_1) - \sigma k_0$$

$$(9.2.4) \quad m_r = -\sigma d^{r-1} z_1 + (r-1)\sigma^2 m_{r-2} - k_0 \sigma m_{r-1},$$

$$r = 2, 3, \dots$$

where  $z_0 = \phi(k_0)/G$  and  $z_1 = \phi(k_1)/G$ .

### 9.3 Estimators of the parameters

From (9.2.4), by taking  $r = 2, 3$  and  $4$ , we obtain

$$(9.3.1) \quad m_2 = -\sigma d z_1 + \sigma^2 - \sigma k_0 m_1 ,$$

$$(9.3.2) \quad m_3 = -\sigma d^2 z_1 + 2 \sigma^2 m_1 - \sigma k_0 m_2 ,$$

$$(9.3.3) \quad m_4 = -\sigma d^3 z_1 + 3 \sigma^2 m_2 - \sigma k_0 m_3 .$$

It should be observed that equations (9.3.1), (9.3.2), (9.3.3) are the same as equations (19) obtained by Cohen([13], p. 259) for the case of doubly truncated normal population when  $b_1 = b_2 = 0$ . Considering equations (9.3.1), (9.3.2), (9.3.3) in three unknowns  $\sigma z_1$ ,  $\sigma^2$ , and  $h = \sigma k_0$  and solving them, we see that the solutions for  $h$  and  $\sigma^2$  are

$$(9.3.4) \quad h = [(3m_2 m_3 - 2m_1 m_4) + d(m_4 - 3m_2^2) + d^2(2m_1 m_2 - m_3)]/P,$$

$$(9.3.5) \quad \sigma^2 = [(m_3^2 - m_2 m_4) + d(m_1 m_4 - m_2 m_3) + d^2(m_2^2 - m_1 m_3)]/P,$$

$$\text{where } P = (2m_1 m_3 - 3m_2^2) + d(3m_1 m_2 - m_3) + d^2(m_2 - 2m_1^2).$$

This suggests that we can obtain estimators  $h^*$  and  $\sigma^{2*}$  of  $h$  and  $\sigma^2$  from (9.3.4) and (9.3.5) by substituting for  $m_r$  the corresponding sample moments  $v_r = \Sigma(x - x_0)^r/N$ . The estimator  $\mu^*$  of  $\mu$  is then given by  $\mu^* = x_0 - h^*$ . Thus, we have

$$(9.3.6) \quad h^* = [(3v_2v_3 - 2v_1v_4) + d(v_4 - 3v_2^2) + d^2(2v_1v_2 - v_3)]/P^*,$$

$$(9.3.7) \quad \sigma^{2*} = [(v_3^2 - v_2v_4) + d(v_1v_4 - v_2v_3) + d^2(v_2^2 - v_1v_3)]/P^*,$$

where  $P^*$  is the value of  $P$  obtained by substituting for  $m_r$  the corresponding sample moments  $v_r$  in it.

When the upper truncation point  $x_1$  is infinity, i.e.,  $d = \infty$ , then we obtain the estimators as

$$h^* = (2v_1v_2 - v_3)/(v_2 - 2v_1^2),$$

$$\sigma^{2*} = (v_2^2 - v_1v_3)/(v_2 - 2v_1^2),$$

which are the same as obtained by Cohen [12] for singly truncated normal distribution.

In practical situation, rather computing  $h^*$  and  $\sigma^{2*}$  from (9.3.6) and (9.3.7), it might be easier to

solve some pair of linear equations obtained from (9.3.1), (9.3.2) and (9.3.3).

#### 9.4 Comparison with the maximum likelihood estimators

The maximum likelihood estimators  $\hat{h}$  and  $\hat{\sigma}$  of the parameters  $h$  and  $\sigma$  of doubly truncated normal distribution were obtained by Cohen [11]. In the present notation, they are given as

$$(9.4.1) \quad v_1 = \hat{\sigma}(z_0 - z_1) - \hat{h} ,$$

$$(9.4.2) \quad v_2 = -\hat{\sigma}dz_1 + \hat{\sigma}^2 - \hat{h}v_1 .$$

It should be noted that  $z_0$  and  $z_1$  depend on  $\hat{h}$  and  $\hat{\sigma}$  and hence the estimators  $\hat{h}$  and  $\hat{\sigma}$  are to be found by numerical methods. As can be seen from (9.2.3) and (9.3.1), these estimators are the usual moment estimators using only first two moments. The asymptotic variances of  $\hat{h}$  and  $\hat{\sigma}$  are given below.

$$(9.4.3) \quad (N/\sigma^2)\text{Var}(\hat{h}) = F_3/(F_1F_3 - F_2^2),$$

$$(9.4.4) \quad (N/\sigma^2)\text{Var}(\hat{\sigma}) = F_1/(F_1F_3 - F_2^2),$$

where

$$F_1 = [-(z_1 - z_0)^2 - k_1 z_1 + k_0 z_0 + 1],$$

$$F_2 = [(k_1^2 z_1 - k_0^2 z_0) + (z_1 - z_0)(k_1 z_1 - k_0 z_0 + 1)],$$

$$F_3 = [-3(k_1 z_1 - k_0 z_0 - 1) - (k_1 z_1 - k_0 z_0 - 1)^2 - (k_1^3 z_1 - k_0^3 z_0)]$$

and  $N$  = size of the truncated sample.

The asymptotic variances of  $h^*$  and  $\sigma^*$  have been obtained by the  $\delta$ -method (Kendall and Stuart [23], §10.6). Let

$$A_j = \left. \frac{\partial h^*}{\partial v_j} \right|_{(v_1, v_2, v_3, v_4) = (m_1, m_2, m_3, m_4)}, \quad (j=1, 2, 3, 4),$$

$$B_j = \left. \frac{\partial \sigma^*}{\partial v_j} \right|_{(v_1, v_2, v_3, v_4) = (m_1, m_2, m_3, m_4)}, \quad (j=1, 2, 3, 4).$$

Then, the asymptotic variances of  $h^*$  and  $\sigma^*$  are given by

$$(9.4.5) \quad \text{Var}(h^*) = \sum_i^4 \sum_{j=1}^4 A_i A_j \text{Cov}(v_i, v_j),$$

$$(9.4.6) \quad \text{Var}(\sigma^*) = \sum_i^4 \sum_{j=1}^4 B_i B_j \text{Cov}(v_i, v_j),$$

where it is to be understood that  $\text{Cov}(v_i, v_i) = \text{Var}(v_i)$ .

Now if we write

$$m_j = \sigma^j w_j, \quad (j = 1, 2, 3, \dots, 8),$$

then we get

$$w_1 = z_0 - z_1 - k_0,$$

$$w_2 = -z_1 (k_1 - k_0)^{+1 - k_0} w_1,$$

$$w_j = -z_1 (k_1 - k_0)^{j-1} + (j-1) w_{j-2} - k_0 w_{j-1}, \quad (j=3, 4, \dots, 8).$$

From the definitions of  $A_i$  and  $B_j$  we obtain

$$A_1 = [-2(w_4 + k_0 w_3) - 3k_0 w_2 (k_1 - k_0) + 2(k_1 - k_0)^2 (2k_0 w_1 + w_2)] / \Delta,$$

$$A_2 = [3(w_3 + 2k_0 w_2) - 3(k_1 - k_0)(2w_2 + k_0 w_1) + (k_1 - k_0)^2 (2w_1 - k_0)] / \sigma \Delta,$$

$$A_3 = [(3w_2 - 2k_0 w_1) + k_0 (k_1 - k_0) - (k_1 - k_0)^2] / \sigma^2 \Delta,$$

$$A_4 = [-2w_1 + (k_1 - k_0)] / \sigma^3 \Delta,$$

$$B_1 = [-2w_3 + (k_1 - k_0)(w_4 - 3w_2) + (k_1 - k_0)^2 (4w_1 - w_3)] / 2 \Delta,$$

$$B_2 = [(6w_2 - w_4) - (k_1 - k_0)(w_3 + 3w_1) + (k_1 - k_0)^2 (2w_2 - 1)] / 2 \sigma \Delta,$$

$$B_3 = [2(w_3 - w_1) + (k_1 - k_0)(1 - w_2) - w_1(k_1 - k_0)^2] / 2 \sigma^2 \Delta ,$$

$$B_4 = [-w_2 + w_1(k_1 - k_0)] / 2 \sigma^3 \Delta ,$$

where

$$\Delta = (2w_1w_3 - 3w_2^2) + (3w_1w_2 - w_3)(k_1 - k_0) + (w_2 - 2w_1^2)(k_1 - k_0)^2.$$

If we put  $A_j = a_j / \sigma^{j-1}$  and  $B_j = b_j / \sigma^{j-1}$ , then from

(9.4.5) and (9.4.6), observing that  $\text{Var}(v_r) = \sigma^{2r}(w_{2r} -$

$w_r^2)/N$ , and  $\text{Cov}(v_r, v_s) = \sigma^{r+s}(w_{r+s} - w_r \cdot w_s)/N$ , we

obtain

$$(9.4.7) \quad (N/\sigma^2)\text{Var}(h^*) = \sum_{i,j=1}^4 (w_{i+j} - w_i w_j) a_i a_j,$$

$$(9.4.8) \quad (N/\sigma^2)\text{Var}(\sigma^*) = \sum_{i,j=1}^4 (w_{i+j} - w_i w_j) b_i b_j.$$

The asymptotic efficiencies of  $h^*$  and  $\sigma^*$  are then obtained by dividing expressions in (9.4.3) and (9.4.4) respectively by (9.4.7) and (9.4.8). It should be noted that the asymptotic efficiencies of the estimators depend on  $k_0$  and  $k_1$ , the lower and the upper points of truncation in standard units.



## 9.5 Example

To illustrate the foregoing results, a truncated sample of size 35 from a normal population with  $\mu = 0$  and  $\sigma = 1$  was selected from Mahalanobis' tables [26] by discarding observations less than  $x_0 = -1$  and greater than  $x_1 = 2$ . The first four sample moments about  $x_0 = -1$  were found to be  $v_1 = 1.26508$ ,  $v_2 = 2.18548$ ,  $v_3 = 4.46599$ ,  $v_4 = 10.000867$ . Substituting these values in equations (9.3.6) and (9.3.7), we obtain  $h^* = -0.834$  and  $\sigma^{2*} = 1.591$ . These give us  $\mu^* = -0.166$  and  $\sigma^* = 1.261$ . The maximum likelihood estimates of  $\mu$  and  $\sigma$  were obtained by numerical methods from equations (9.4.1) and (9.4.2). They are  $\hat{\mu} = -0.052$  and  $\hat{\sigma} = 1.192$ .

Applying formulas (9.4.3), (9.4.4), (9.4.7) and (9.4.8), we find that

$$\begin{aligned} (N/\sigma^{*2})\text{Var}(h^*) &= 3.49372, & (N/\sigma^{*2})\text{Var}(\hat{h}) &= 3.42971 \\ (N/\sigma^{*2})\text{Var}(\sigma^*) &= 3.25404, & (N/\sigma^{*2})\text{Var}(\hat{\sigma}) &= 3.14663. \end{aligned}$$

Hence, the estimated asymptotic efficiencies of  $h^*$  and  $\sigma^*$  are respectively 98 % and 97 %.