

## ESTIMATING FUTURE FROM PAST IN LIFE TESTING

BY JOHN E. WALSH

*Military Operations Research Division, Lockheed Aircraft Corp., Burbank, Calif.*

**1. Summary.** Let  $\theta_p$  represent the unique 100 $p$  per cent point of a continuous statistical population, while  $x_r$  is the  $r$ th largest value of a sample of size  $n$  from this population ( $r = 1, \dots, n$ ). This paper considers estimation of  $\theta_p$  on the basis of  $x_{r(1)}, \dots, x_{r(m)}$ , where the  $r(i)$  differ by  $O(\sqrt{n+1})$  and do not necessarily have values near  $(n+1)p$ . Also considered is estimation of  $x_R$  on the basis of  $x_{r(1)}, \dots, x_{r(m)}$ , where the  $r(i)$  differ by  $O(\sqrt{n+1})$  and do not necessarily have values near  $R$ . The results are of a nonparametric nature and based on expected value considerations. These estimation procedures may be useful for life-testing situations where time to failure is the variable and some of the items tested have not yet failed when observation is discontinued. Then  $\theta_p$  and  $x_R$  can be estimated for  $p$  and  $R$  values which extend a moderate way into the region where sample data is not available. Estimation of the  $x_R$  value which would be obtained by continuing to observe the experiment represents a prediction of the future from the past. The results of this paper may be of value in the actuarial, population statistics, operations research, and other fields.

**2. Introduction.** Let us consider a sampling situation where  $n$  items are simultaneously life tested to determine their times to failure. Then the time to failure for the first item which fails is the smallest value for this sample of size  $n$ . The value for the second item to fail is the next to smallest sample value; etc. Thus life-testing situations have the property that the  $r$  smallest order statistics of a sample are determined in advance of the remaining values of the sample. Moreover, the first  $r$  items to fail furnish the  $r$  smallest values of the sample of size  $n$ , even if some or all of the remaining sample values are never determined. Jacobson called attention to these valuable properties of life-testing situations in [1]. A descriptive outline of the life-testing field is given in [2].

The property that the  $r$  smallest order statistics of a lifetesting sample can be obtained without the necessity of determining the remaining sample values can be exploited in many ways. The basis for this exploitation is that substantial time and/or cost can often be saved by stopping a life-testing experiment at some convenient time before all the items have failed. The situation of this type considered here is the estimation of  $\theta_p$  on the basis of  $x_1, \dots, x_r$  when  $(n+1)p > r$ —that is, estimation of population percentage points in the region not covered by the available data.

The life-testing property that the  $r$  smallest order statistics are determined in advance of the remaining sample values furnishes an opportunity for estimating the future from the past. Suppose that  $r$  items have failed up to the present time and it is desired to predict the future time at which the  $R$ th item of this set will

Received June 20, 1956; revised September 14, 1956.

fail ( $R > r$ ). That is,  $x_1, \dots, x_r$  are known and estimation of  $x_R$  in an expected value sense is desired. This paper derives such an estimate for the case where  $r$  and  $R$  do not differ too much.

The purpose of this paper is to derive nonparametric expected value estimates which are approximately valid for nearly all continuous statistical populations of practical interest. These estimates are not intended to be competitive with those which can be obtained on the basis of additional information about the population sampled. Instead, the nonparametric estimates presented are for use when more specialized estimation methods are not warranted.

Whether  $\theta_p$  or  $x_R$  is estimated, the arithmetical problem consists in determining the values of  $c_1, \dots, c_m$  for a linear function of the form

$$\sum_{i=1}^m c_i x_{r(i)},$$

where  $m, r(1), \dots, r(m)$  are given integers. The procedure for obtaining the values of the  $c_i$  consists in solving  $m$  specified linear equations in  $m$  unknowns. Although the emphasis of the paper is on life-testing situations, the results derived are valid for more general types of situations than those where only  $x_1, \dots, x_r$  are available and  $r < (n+1)p, R$ . For estimation of  $\theta_p$ , knowledge of the values of order statistics  $x_{r(1)}, \dots, x_{r(m)}$  such that  $r(i) = r(j) + O(\sqrt{n+1})$  and none of the  $r(i)$  differ too much from  $(n+1)p$  is sufficient. In estimating  $x_R$ , it is sufficient that  $x_{r(1)}, \dots, x_{r(m)}$  are available with  $r(i) = r(j) + O(\sqrt{n+1})$  and none of the  $r(i)$  differing too much from  $R$ . Thus the results of this paper can also be used to estimate the past from the present for life-testing situations where the data for the past was lost or not recorded.

Life-testing situations where population properties are of greater interest than sample properties usually involve inanimate objects such as automobile tires, light bulbs, etc. Often a considerable savings in time and/or expense can be obtained by deliberately stopping a life test of this type when 80 to 90 per cent rather than all of the items have failed. Through use of the method given in this paper, many of the upper population percentage points of interest can be estimated even though the upper 10 per cent to 20 per cent of the data is truncated.

The future mortality occurrences among the now-surviving members of a given set of items can be of interest for some types of life-testing situations. The future mortality among the survivors of a specified group of persons which have already been observed for some time represents a situation of this nature. Estimates of the future mortality among the survivors of such a group of persons can be valuable in actuarial science, population statistics, and other fields. This paper presents a rather widely applicable procedure for estimating the first time at which a specified number of additional individuals will have died on the basis of the times to death for the individuals which have already died.

An investigation is made of the variances for the derived estimates. Every estimate considered has an estimate of the form

$$p_i(1 - p_i)/n[f(\theta_{p_i})]^2 + O(n^{-3/2}),$$

where  $t$  is a specified number which differs from the  $r(i)$  by  $O(\sqrt{n+1})$ ,  $p_i = t/(n+1)$ , and  $f(x)$  is the probability density function (*pdf*) of the statistical population sampled. Thus all the estimates presented are consistent, having standard deviations which are  $O(1/\sqrt{n})$ .

If all the sample values were available, the corresponding sample percentage point might appear to be the most suitable nonparametric expected value estimate for  $\theta_p$ . In many cases, however, an estimate for  $\theta_p$  of the type given in this paper may have a higher efficiency (i.e., smaller variance) than the corresponding sample percentage point. The variance for the sample percentage point corresponding to  $\theta_p$  is

$$p(1-p)/n[f(\theta_p)]^2 + O(n^{-2}).$$

If  $n$  is large and

$$p_i(1-p_i)/f(\theta_{p_i})^2 < p(1-p)/f(\theta_p)^2,$$

the sample percentage point corresponding to  $\theta_p$  usually has a lower efficiency than an estimate of the type presented here. This inequality is frequently satisfied for unimodal populations where  $\theta_{p_i}$  is more toward the central part of the probability distribution than  $\theta_p$ .

In deriving the results,  $f(x)$  is assumed to exist, be positive, and of an analytical nature for all  $x$  of interest. Such strong restrictions on  $f(x)$  are not necessary for the validity of the results presented. However, little generality is gained for practical cases by using weaker restrictions on  $f(x)$ . There are limitations on the accuracy to which measurements on continuous observations can be made for all applied situations. This data-accuracy limitation indicates that the conditions imposed on  $f(x)$  should be acceptable for virtually all practical situations of a continuous type where  $\theta_p$  is unique for all  $p$ .

Section 3 contains a statement of the estimates for  $\theta_p$  and  $x_R$  along with some restrictions on their use. A numerical example of the application of each type of estimate is given in Section 4. Assuming a standard normal population, the approximate properties stated for these estimates are compared with their exact properties. Section 5 contains the derivations and motivation for the material given in Section 3.

**3. Statement of estimates.** Let us consider an explicit statement of the method for obtaining estimates of  $\theta_p$  and  $x_R$ . The additional notation used is

$$t = \frac{1}{m} \sum_{i=1}^m r(i),$$

$$r = \max_{1 \leq i \leq m} r(i),$$

$$d(i) = t - r(i) = \text{quantity which is } O(\sqrt{n+1}), \quad (i = 1, \dots, m);$$

$$d(i) \neq d(k) \text{ if } i \neq k$$

$$p_i = t/(n+1), \quad q_i = 1 - p_i,$$

$$p_R = R/(n + 1), \quad q_R = 1 - p_R,$$

$$A_j = [\frac{1}{2}(p - p_i)]^{j-1}/(j - 1)!,$$

$$B_j = \frac{[\frac{1}{2}(p_R - p_i)]^{j-1}}{(j - 1)!} + \frac{p_R q_R (j - 1)(j - 2)}{2(n + 2)(j - 1)!} [\frac{1}{2}(p_R - p_i)]^{j-2},$$

$$\begin{aligned} C_j[d(i), \delta] &= \frac{(-\delta)^{j-1}}{(j - 1)!} - \frac{(j - 1)(-\delta)^{j-2} d(i)}{(n + 1)(j - 1)!} \\ &\quad + \frac{(j - 1)(j - 2)(-\delta)^{j-3}}{2(n + 1)(n + 2)(j - 1)!} [(n + 1)p_i q_i + (p_i - q_i)d(i) + d(i)^2] \\ &\quad - \frac{(j - 1)(j - 2)(j - 3)(-\delta)^{j-4} d(i)}{2(n + 1)^2(n + 2)(j - 1)!} [(n + 1)p_i q_i + \frac{1}{3}d(i)^2], \end{aligned}$$

$$C(j, i) = C_j[d(i), \frac{1}{2}(p - p_i)],$$

$$C'(j, i) = C_j[d(i), \frac{1}{2}(p_R - p_i)],$$

where  $j = 1, \dots, m$ .

For specified  $n, m, r(1), \dots, r(m), p, R$ , the estimates considered and their principal expected value properties are given by

$$E \left[ \sum_{i=1}^m a_i x_{r(i)} \right] = \theta_p + O(n^{-3/2}) + O[|\frac{1}{2}(p - p_i)|^m],$$

$$E \left[ \sum_{i=1}^m b_i x_{r(i)} \right] = E(x_R) + O(n^{-3/2}) + O[|\frac{1}{2}(p_R - p_i)|^m].$$

If  $m \geq 4$ ,  $O(n^{-3/2})$  is replaced by  $O(n^{-2})$  in these expressions. The sets of linear equations used to determine the values of the  $a_i$  and the  $b_i$  are

$$\sum_{i=1}^m a_i C(j, i) = A_j, \quad \sum_{i=1}^m b_i C'(j, i) = B_j, \quad j = 1, \dots, m.$$

The values for the  $a_i$  and the  $b_i$  can be conveniently expressed in the form of determinants. This form is especially useful for small values of  $m$ . Explicitly,

$$a_i = \frac{\text{determinant of the } C(u, v), \text{ with } C(j, i) \text{ replaced by } A_j \text{ for } j = 1, \dots, m}{\text{determinant of the } C(u, v)},$$

$$b_i = \frac{\text{determinant of the } C'(u, v) \text{ with } C'(j, i) \text{ replaced by } B_j \text{ for } j = 1, \dots, m}{\text{determinant of the } C'(u, v)}.$$

If the determinant of the  $C(u, v)$  is zero or near zero, a change in the values for the  $r(i)$  may be required to assure that none of the  $a_i$  are of too large a magnitude. Usually a change of one value is enough to eliminate this difficulty. The same will be true if the determinant of the  $C'(u, v)$  is zero or near zero.

Let us consider determination of a value for  $m$  which seems large enough to assure that the unstated higher order expected value terms can be neglected. Accuracy to terms of order  $n^{-3/2}$  implies that  $m \geq 3$ . The value used is also re-

quired to satisfy the condition

$$m \geq \begin{cases} \frac{\log [\max (n^{-3/2}, 10^{-4})]}{\log |\frac{1}{2}(p - p_i)|}, & \text{if } \theta_p \text{ estimated,} \\ \frac{\log [\max (n^{-3/2}, 10^{-4})]}{\log |\frac{1}{2}(p_R - p_i)|}, & \text{if } x_R \text{ estimated.} \end{cases}$$

This second condition for determining  $m$  is based on the requirement that

$$\max(n^{-3/2}, 10^{-4}) \geq \begin{cases} |\frac{1}{2}(p - p_i)|^m, & \text{if } \theta_p \text{ estimated,} \\ |\frac{1}{2}(p_R - p_i)|^m, & \text{if } x_R \text{ estimated.} \end{cases}$$

These two conditions assure that the expected value error of an estimate is  $O[\max(n^{-3/2}, 10^{-4})]$ . The minimum value of  $m = 3$  is acceptable for many of the cases encountered. From a computational viewpoint, the method probably should not be used if the value of  $m$  obtained by this procedure exceeds 10.

The convergence rates of the expansions used in obtaining estimates for  $\theta_p$  depend on  $\frac{1}{2}(p - p_i)$ , the  $d(i)/(n + 1)$ , and the properties of the underlying statistical population. In practice, the underlying population properties are usually such that convergence is more rapid for  $p_i$  and  $p$  near the center of the distribution. On this basis, both  $|d(i)|/(n + 1)p_i q_i$  and  $\frac{1}{2}|p - p_i|/[\min(pq, p_i q_i)]$  should not be too large. The maximum allowable value for these quantities is taken to be  $\frac{2}{3}$  for the type of situations considered. This value is not overly small but should be satisfactory for a large majority of the practical applications. Hence, the method given in this paper for estimating  $\theta_p$  should not be used if either

$$\max_{1 \leq i \leq m} |d(i)| > \frac{2}{3} p_i q_i (n + 1),$$

or

$$|p - p_i| > \frac{4}{3} \min(pq, p_i q_i).$$

On a similar basis, the method for estimating  $x_R$  should not be used if either

$$\max_{1 \leq i \leq m} |d(i)| > \frac{2}{3} p_i q_i (n + 1),$$

or

$$|p_R - p_i| > \frac{4}{3} \min(p_R q_R, p_i q_i).$$

Sometimes the inequality involving the  $d(i)$  can be changed from unacceptable to acceptable by using a different value for  $m$  which allows a decrease in  $\max |d(i)|$ .

When  $x_1, \dots, x_r$  are given and  $r > (n + 1)p$ ,  $R$ , a recommended selection for the values of the  $r(i)$  in both types of estimates is

$$r(i) = r - (m - i)K, \quad (i = 1, \dots, m),$$

where

$$K = \max [1, \text{largest integer contained in } \frac{1}{m} \sqrt{n+1}].$$

The resulting  $r(i)$  differ by  $O(\sqrt{n+1})$ , are equally spaced, and have desirable properties with respect to the expansions used in deriving the estimates.

Every estimate of the two types considered has approximately the same variance. For all estimates derived, the variances are of the form

$$p_i q_i / n [f(\theta_{p_i})]^2 + O(n^{-3/2}).$$

Thus, each estimate has a standard deviation which is  $O(n^{-1/2})$ . The order of the standard deviation for an estimate is the reason for neglecting all terms involving  $n$  to orders  $n^{-3/2}$  and higher in the expected value expressions for these estimates.

**4. Numerical Example.** To illustrate use of the methods of this paper, let us consider the case where  $n = 20$ ,  $x_1, \dots, x_{15}$  are given,  $p = 0.84$ , and  $R = 17$ . The value of  $m$  is determined first. This value is the smallest integer which is at least 3 and such that

$$m \cong \begin{cases} \frac{\log [\max (n^{-3/2}, 10^{-4})]}{\log |\frac{1}{2}(p - p_i)|} \doteq 1.84, & \text{if } \theta_p \text{ estimated,} \\ \frac{\log [\max (n^{-3/2}, 10^{-4})]}{\log |\frac{1}{2}(p_R - p_i)|} \doteq 1.71, & \text{if } x_R \text{ estimated.} \end{cases}$$

Thus  $m = 3$  for both types of estimates.

Next let us evaluate  $r(1)$ ,  $r(2)$ , and  $r(3)$ . The value of  $K$  is given by

$$K = \max [1, \text{largest integer contained in } \frac{1}{m} \sqrt{n+1}] = 1.$$

Hence, for both types of estimates

$$r(1) = 13, \quad r(2) = 14, \quad r(3) = 15,$$

since  $r(i) = r - (m - i)K$ . Thus  $t = 14$  and

$$d(1) = 1, \quad d(2) = 0, \quad d(3) = -1.$$

Also the relations

$$\begin{aligned} \max_{1 \leq i \leq m} |d(i)| &\leq \frac{2}{3} p_i q_i (n+1), \\ |p - p_i| &\leq \frac{4}{3} \min(pq, p_i q_i), \\ |p_R - p_i| &\leq \frac{4}{3} \min(p_R q_R, p_i q_i) \end{aligned}$$

are easily verified so that the methods of the paper are applicable for the case considered.

By direct substitution, the values of the  $A_j$  and  $B_j$  are found to be

$$\begin{aligned} A_1 &= 1.0000, & A_2 &= 0.0867, & A_3 &= 0.0038, \\ B_1 &= 1.0000, & B_2 &= 0.0715, & B_3 &= 0.0028. \end{aligned}$$

Thus

$$\begin{aligned} C(1, 1) &= 1.0000, & C(1, 2) &= 1.0000, & C(1, 3) &= 1.0000, \\ C(2, 1) &= -0.0390 & C(2, 2) &= -0.0867 & C(2, 3) &= -0.1344, \\ C(3, 1) &= 0.0054 & C(3, 2) &= 0.0088 & C(3, 3) &= 0.0144, \end{aligned}$$

and

$$\begin{aligned} C'(1, 1) &= 1.0000, & C'(1, 2) &= 1.000, & C'(1, 3) &= 1.0000, \\ C'(2, 1) &= -0.0238 & C'(2, 2) &= -0.0715 & C'(2, 3) &= -0.1192, \\ C'(3, 1) &= 0.0049 & C'(3, 2) &= 0.0076 & C'(3, 3) &= 0.0125. \end{aligned}$$

Consequently,

$$a_1 = \begin{vmatrix} 1.0000 & 1.0000 & 1.0000 \\ 0.0867 & -0.0867 & -0.0390 \\ 0.0038 & 0.0088 & 0.0054 \end{vmatrix} / \begin{vmatrix} 1.0000 & 1.0000 & 1.0000 \\ -0.1344 & -0.0867 & -0.0390 \\ 0.0144 & 0.0088 & 0.0054 \end{vmatrix} = 3.38.$$

Similarly,  $a_2 = -9.41$  and  $a_3 = 7.03$ . Also

$$b_1 = \begin{vmatrix} 1.0000 & 1.0000 & 1.0000 \\ 0.0715 & -0.0715 & -0.0238 \\ 0.0028 & 0.0076 & 0.0049 \end{vmatrix} / \begin{vmatrix} 1.0000 & 1.0000 & 1.0000 \\ -0.1192 & -0.0715 & -0.0238 \\ 0.0125 & 0.0076 & 0.0049 \end{vmatrix} = 1.49.$$

In a like fashion,  $b_2 = -4.99$  and  $b_3 = 4.50$ .

Using the values determined for the  $a_i$  and  $b_i$ , approximate expected value estimates are obtained for  $\theta_{0.84}$  and  $x_{17}$ . These estimates and their properties are given by

$$\begin{aligned} E(3.38 x_{13} - 9.41 x_{14} + 7.03 x_{15}) &= \theta_{0.84} + O(n^{-3/2}) + O\left[\frac{1}{2}(p - p_t)^m\right] \\ &= \theta_{0.84} + O(0.011) + O(0.00065), \end{aligned}$$

$$\begin{aligned} E(1.49 x_{13} - 4.99 x_{14} + 4.50 x_{15}) &= E(x_{17}) + O(n^{-3/2}) + O\left[\frac{1}{2}(p_R - p_t)^m\right] \\ &= E(x_{17}) + O(0.011) + O(0.00036). \end{aligned}$$

Here the contribution of order  $n^{-3/2}$  seems to be much more important than the contribution of order  $|\frac{1}{2}(p - p_t)^m|$  or the contribution of order  $|\frac{1}{2}(p_R - p_t)^m|$ .

To check the expected value accuracy of these estimates, let us consider the special case of a normal distribution with zero mean and unit variance. Using a table of the standardized normal distribution and the results of [3],

$$E(3.38 x_{13} - 9.41 x_{14} + 7.03 x_{15}) = 0.995, \quad \theta_{0.84} = 0.996,$$

$$E(1.49 x_{13} - 4.99 x_{14} + 4.50 x_{15}) = 0.888, \quad E(x_{17}) = 0.921$$

Thus the expected values of these two estimates are in rather close agreement with the true values for the case of normality. This expected value agreement is much closer than is required on the basis of the standard deviations of these estimates. For the standardized normal case,

$$\text{s.d. of } (3.38 x_{13} - 9.41 x_{14} + 7.03 x_{15}) \doteq 1.03$$

$$\text{s.d. of } (1.49 x_{13} - 4.99 x_{14} + 4.50 x_{15}) \doteq 0.72.$$

Due to the moderately small value of  $n$ , these standard deviation values do not agree very closely with the asymptotic value of

$$\sqrt{p_i q_i} / \sqrt{n} f(\theta_{p_i}) \doteq 0.33.$$

The moderately small value of  $n = 20$  was selected for the example in order that the results of [3] could be used.

**5. Derivations.** Here verification is presented for the expected value and variance results stated in Section 3. This verification is based on the material presented by David and Johnson in [4].

Let  $s$  be a number such that  $1 \leq s \leq n$  while  $f(x)$  has derivatives of all orders at all points where it is defined and is non-zero at all points considered. Some additional notation is used

$$F(X) = \int_{-\infty}^X f(x) dx, \quad F(X_s) = p_s, \quad X_s^{(u)} = \left. \frac{d^u X}{dF^u} \right|_{X=X_s},$$

$u = 1, 2, \dots$ . Here  $X_s^{(0)} = X_s$  while  $X_{(n+1)p} = \theta_p$ , whether  $(n + 1)p$  is an integer or not. On the basis of [4],

$$E[x_{r(i)}]$$

$$= X_{r(i)} + \frac{p_{r(i)} q_{r(i)}}{2(n+2)} X_{r(i)}^{(2)} + \frac{p_{r(i)} q_{r(i)}}{(n+2)^2} \left[ \frac{1}{3}(q_{r(i)} - p_{r(i)}) X_{r(i)}^{(3)} \right. \\ \left. + \frac{1}{6} p_{r(i)} q_{r(i)} X_{r(i)}^{(4)} \right]$$

to terms of order  $n^{-3}$ , where  $p_{r(i)} = r(i)/(n + 1)$ , and  $q_{r(i)} = 1 - p_{r(i)}$ . Also

$$E(x_R) = X_R + \frac{p_R q_R}{2(n+2)} X_R^{(2)} + O(n^{-2}),$$

on the basis of [4].

The first step of the procedure used for developing the estimate of  $\theta_p$  consists



in expanding the  $E[x_{r(i)}]$  and  $\theta_p$  about a probability value which is halfway between  $p_i$  and  $p$ . The value  $p_i$  is considered because of the relation

$$E[x_{r(i)}] = \theta_{i/(n+1)} + O(1/\sqrt{n}), \quad (i = 1, \dots, m).$$

Taylor series expansion about the midway probability value of  $\frac{1}{2}(p + p_i)$  yields desirable convergence properties for both the  $E[x_{r(i)}]$  and  $\theta_p$ . In particular, these expansions have about the same rate of convergence. Similarly, the first step in developing the estimate for  $x_R$  consists in expanding the  $E[x_{r(i)}]$  and  $E(x_R)$  about the midway probability value of  $\frac{1}{2}(p_R + p_i)$ . Here the probability  $p_R$  is considered because of the relation  $E(x_R) = \theta_{R/(n+1)} + O(n^{-1})$ .

Next let us consider the expansion of  $E[x_{r(i)}]$  about the general probability value of  $\frac{1}{2}(Q + p_i)$ . By use of Taylor series,

$$X_{r(i)}^{(u)} = \sum_{v=0}^{\infty} \frac{(-1)^v}{v!} \left[ \frac{\frac{1}{2}(n+1)(Q - p_i) + d(i)}{n+1} \right]^v X_{\frac{1}{2}[(n+1)Q+i]}^{(u+v)},$$

( $u = 0, 1, \dots$ ), since

$$\frac{d^v X_s^{(u)}}{ds^v} = \frac{X_s^{(u+v)}}{(n+1)^v}, \quad (v = 1, 2, \dots).$$

Substitution of these relations into the expression given for  $E[x_{r(i)}]$  shows that

$$\begin{aligned} E[x_{r(i)}] &= \sum_{j=1}^m C_j [d(i), \frac{1}{2}(Q - p_i)] X_{\frac{1}{2}[(n+1)Q+i]}^{(j-1)} + O(n^{-2}) \\ &\quad + \sum_{j=m-3}^m O\{n^{-(m-j)/2} |\frac{1}{2}(Q - p_i)|^j\}. \end{aligned}$$

Here the  $O(n^{-2})$  and/or the  $O[|\frac{1}{2}(Q - p_i)|^m]$  terms are the most important of those which are not explicitly stated.

Now the expansions for  $\theta_p$  and  $E(x_R)$  are considered. The Taylor series expansion of  $\theta_p$  about the probability value of  $\frac{1}{2}(p + p_i)$  is

$$\theta_p = \sum_{u=0}^{\infty} \frac{1}{u!} [\frac{1}{2}p - p_i]^u X_{\frac{1}{2}[(n+1)p+i]}^{(u)}.$$

To obtain the expansion of  $E(x_R)$  to  $O(n^{-2})$ , the Taylor series expansion of the  $X_R^{(u)}$  about the probability value of  $\frac{1}{2}(p_R + p_i)$  is needed. This is given by

$$X_R^{(u)} = \sum_{v=0}^{\infty} \frac{1}{v!} [\frac{1}{2}(p_R - p_i)]^v X_{\frac{1}{2}(R+i)}^{(u+v)}, \quad (u = 0, 1, \dots).$$

Substitution of these relations into the expression given for  $E(x_R)$  shows that

$$E(x_R) = \sum_{u=0}^{\infty} \left\{ \frac{[\frac{1}{2}(p_R - p_i)]^u}{u!} + \frac{p_R q_R u(u-1)}{2(n+2)u!} [\frac{1}{2}(p_R - p_i)]^{u-1} \right\} X_{\frac{1}{2}(R+i)}^{(u)}$$

plus terms of order  $n^{-2}$ .

To determine the equations which are used to evaluate  $a_1, \dots, a_m$ , first

set  $Q$  equal to  $p$ . Then the coefficient of  $X_{\frac{1}{2}[(n+1)p+i]}^{(u)}$  in the expansion for

$$E\left(\sum a_i x_{r(i)}\right)$$

is required to be the same as the coefficient of this quantity in the expansion of  $\theta_p$ , ( $u = 0, 1, \dots, m - 1$ ), to terms of the prescribed order. Examination of the expansions for  $E[x_{r(i)}]$  and  $\theta_p$  shows that the  $m$  linear equations in  $m$  unknowns given in Section 3 for evaluating the  $a_i$  satisfy this requirement when  $m \geq 3$ . If  $m \geq 4$ , the terms of order  $n^{-3/2}$  are also cancelled out.

To determine the equations used to evaluate  $b_1, \dots, b_m$ , set  $Q$  equal to  $p_R$ . Then the coefficient of  $X_{\frac{1}{2}(R+i)}^{(u)}$  in the expansion for  $E\left(\sum b_i x_{r(i)}\right)$  is required to be the same as the coefficient of this quantity in the expansion for  $E(x_R)$ , ( $u = 0, 1, \dots, m - 1$ ), to terms of the prescribed order. Examination of the expansions for  $E[x_{r(i)}]$  and  $E(x_R)$  shows that the equations given in Section 3 for evaluating the  $b_i$  satisfy this requirement when  $m \geq 3$ . If  $m \geq 4$ , the terms of order  $n^{-3/2}$  also cancel out.

Finally let us consider the variance expressions for the type of estimates considered. Let the  $d(i)$  be numbered so that  $d(1) > d(2) > \dots > d(m)$ . Then, using the variance results presented in [4] and the general notation  $c_i$  to represent either the  $a_i$  or the  $b_i$ ,

$$\begin{aligned} \text{var} \left[ \sum_{i=1}^m c_i x_{r(i)} \right] &= \sum_{i=1}^m \frac{c_i^2}{n} \left[ p_i q_i + \frac{(p_i - q_i) d(i)}{n + 1} \right] \left[ X_t^{(1)} - \frac{d(i)}{n + 1} X_t^{(2)} \right]^2 \\ &+ 2 \sum_{i>j=1}^m \frac{c_i c_j}{n} \left[ p_i q_i + \frac{p_i d(i) - q_i d(j)}{n + 1} \right] \left[ X_t^{(1)} - \frac{d(i)}{n + 1} X_t^{(2)} \right] \\ &\quad \cdot \left[ X_t^{(1)} - \frac{d(j)}{n + 1} X_t^{(2)} \right] + O(n^{-2}). \end{aligned}$$

This follows from the fact that all of the  $a_i$ ,  $b_i$ , and  $d(i)/\sqrt{n + 1}$  are  $O(1)$  with respect to  $n$ . Using the condition  $\sum_i c_i = 1$ , which holds in all cases for the estimates derived, it is easily verified that

$$\text{var} \left[ \sum_{i=1}^m c_i x_{r(i)} \right] = \frac{p_i q_i}{n[f(\theta_{p_i})]^2} + O(n^{-3/2});$$

here the relation  $X_i^{(1)} = 1/f(\theta_{p_i})$  is used.

REFERENCES

[1] PAUL H. JACOBSON, "The relative power of three statistics," *Jour. Amer. Stat. Assoc.*, Vol. 42 (1947), pp. 575-84.  
 [2] B. EPSTEIN AND M. SOBEL, "Life testing," *Jour. Amer. Stat. Assoc.*, Vol. 48 (1953), pp. 486-502.  
 [3] D. TEICHROEW, "Tables of expected values of order statistics and products of order statistics for samples of size twenty or less from the normal distribution," *Ann. Math. Stat.*, Vol. 27 (1955), pp. 410-26.  
 [4] F. N. DAVID AND N. L. JOHNSON, "Statistical treatment of censored data. Part I—fundamental formulae," *Biometrika*, Vol. 41 (1954), pp. 228-40.