# ON ESTIMATING THE SIZE OF A POPULATION AND ITS INVERSE BY CAPTURE MARK METHOD

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SUMMARY. The problem of estimating the size of a population and its inverse is considered here on the basis of several independent simple readom (without replacement) samples selected from the population. New estimates of the population size and its reciprocal are given. The estimate of the reciprocal of the population size is the unbiased minimum variance estimate. The estimate of the population size is unbiased and neminimum variance only if the total sample size is not less than the population size. Variance estimates of these estimates are also given.

### 1. INTRODUCTION

The problem of estimating the size of a population is known to be of great importance in biological and other related problems, e.g., well-known problems of this kind are the estimation of the total number of fish in a lake and the estimation of the total number of wild animals in a forest, etc. Several authors have already considered this problem in the past and have devised methods of sampling (see references). In this paper simple random sampling (without replacement) at several stages has been considered for this purpose. Czen Pin and Dzan Dzo (1981) have also considered this method and termed it as capture-mark method. Here, this method is also referred to as capture-mark method. Bailey (1951) mentions that in certain ecological problems one is more interested in estimating the reciprocal of the population size itself; the problem of estimating the reciprocal of the population size itself; the problem of estimating the reciprocal of the population size is therefore also considered here.

To begin with, the following lemma is given which will be found useful later.

Lomma 1.1: Let  $A_1, ..., A_n$  be m events defined on a probability space. Let  $A = \bigcup_{i=1}^n A_i$  and  $B_i = (A - A_i)$  i = 1, ..., m. Then

$$P\left[\bigcap_{i=1}^{n} A_{i}\right] = P(A) - \Sigma'P(B_{1}) + \Sigma'P(B_{1} \cap B_{2})... \qquad ... \quad (1.1)$$

where the summation  $\Sigma'$  is taken over all combinations of B's chosen from  $B_1, ..., B_m$ .

The proof is omitted.

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#### 2. CAPTURE-MARK METHOD

The capture-mark method of sampling from a finite population of size N is as follows: k simple random (without replacement) subsamples of size  $n_1, n_2, \dots n_k$  respectively are drawn independently of each other and the number, M, of distinct population units is noted. The random variable M is used to get estimates of the population size and its reciprocal.

To got the probability distribution of M, it can be verified on letting  $A_i = \{i \cdot \text{th population unit is selected in the sample}\}$  (i = 1, ..., m) in Lemma 1.1 that the probability of getting any preassigned m distinct units, in this sampling scheme, is given by

$$P_{1} = \frac{\prod_{i=1}^{n} \binom{m_{i}}{n_{i}} - \binom{m}{n_{1}} \prod_{i=1}^{n} \binom{m-1}{n_{i}} + \dots (-)^{m-\max n_{i}} \binom{m}{m-\max n_{i}} \prod_{i=1}^{n} \binom{\max n_{i}}{n_{i}}}{\prod_{i=1}^{n} \binom{N}{n_{i}}}.$$
(2.1)

The probability distribution of M is immediately obtained from (2.1) as given below

$$P[M = m] = \frac{\binom{N}{m} \binom{\frac{1}{m}}{\binom{m}{l-1}} \binom{m}{n_l} \binom{m}{1} \binom{m-1}{n_l} + \dots}{\prod_{i=1}^{n} \binom{N}{n_i}} \dots (2.2)$$

A useful equality follows from (2.2)

$$\min_{\substack{m \text{ in } (n,N) \\ m = \max n_i}} {N \choose m} \left\{ \prod_{i=1}^k {m \choose n_i} - {m \choose 1} \prod_{i=1}^k {m-1 \choose n_i} + \ldots \right\} = \prod_{i=1}^k {N \choose n_i}. \dots (2.3)$$

It is worthwhile to mention here that Czen Pin and Dzen Dze (1961) have proved that if  $n = \sum_{i=1}^k n_i \to \infty$  in such a manner that  $n^* \mid \left( \sum_{i>j} n_i n_j \right)$  remains bounded, then

$$P[M = m] = e^{-\lambda} \frac{\lambda^{n-m}}{(n-m)!} \left[ 1 + 0 \left( \frac{n}{N} \right) \right]$$
 ... (2.4)

where  $\lambda = \left(\sum_{i=1}^{N} n_i n_j\right)/N$ .

From (2.2) it can be seen by induction over N that M is a complete sufficient statistic for the parameter space  $\{N \geq \max_{1 \leq i \leq k} n_i\}$ . It thus follows that if minimum variance unbiased estimates of the population size and its inverse exist, they must be functions of M.

In the next two sections, the problem of estimating the population size and its inverse is considered in reverse order for some simplicity in the expesition.

$$\binom{r}{k}$$
 is to be regarded as zero for  $k > r$ .

#### ESTIMATES OF POPULATION SIZE AND ITS INVERSE

#### 3. ESTIMATION OF THE INVERSE OF THE POPULATION SIZE

The following theorem gives the unbiased minimum variance estimate of  $\frac{1}{N}$ 

Theorem 1: The unbiased minimum variance estimate of 1/N is given by

$$I_{-1}(m) = \frac{\left[\frac{1}{m}\prod_{i=1}^{m}\binom{m}{n_i} - \frac{\binom{m}{1}}{(m-1)}\prod_{i=1}^{k}\binom{m-1}{n_i} + \frac{\binom{m}{2}}{(m-2)}\prod_{i=1}^{k}\binom{m-2}{n_i} - \cdots\right]}{\left[\frac{1}{n}\binom{m}{n_i} - \binom{m}{1}\prod_{i=1}^{k}\binom{m-1}{n_i} + \binom{m}{2}\prod_{i=1}^{k}\binom{m-2}{n_i} - \cdots\right]}.$$

**Proof:** Let  $u_{11}$  and  $u_{11}$  be the first sample units respectively of the first two subsamples. Since  $P(u_{11} = u_{11}) = 1/N$ , an unbiased estimate of 1/N is given by

$$t_{-1} = \begin{cases} 1 & \text{if } u_{11} = u_{21} \\ 0 & \text{otherwise.} \end{cases}$$
 ... (3.2)

Further, since M is a complete sufficient statistic, the unbiased minimum variance estimate of  $\frac{1}{W}$  is given by

$$t_{-1}(m) = E[t_{-1} | M = m] = \frac{P[u_{11} = u_{21} \cap M = m]}{P[M = m]}.$$
 ... (3.3)

In order to be able to express (3.3) as a function of  $m, n_1, ..., n_k$ , let  $u_{(1)}, ..., u_{(m)}$  be the m distinct population units selected in the sample. Then on letting  $A_j = [u_{11} = u_{11} = u_{10} = n \text{d} u_{10}]$  is selected in the sample j = 1, ..., m in Lemma 1.1, it can be seen that the probability of getting a sample with  $u_{(1)}, ..., u_{(m)}$  and  $u_{11} = u_{11} = u_{10}$  is given by

$$P[u_{11} = u_{21} = u_{10} \bigcap u_{(1)}, ..., u_{(m)}]$$

$$=\frac{\binom{m-1}{n_1-1}\binom{m-1}{n_2-1}\binom{n}{1}\binom{m}{n_1}-\binom{m-1}{1}\binom{m-2}{n_1-1}\binom{m-2}{n_2-1}\binom{m-2}{1}\binom{n}{n_2-1}}{N\cdot N\cdot \binom{N-1}{1}\binom{N-1}{1}\binom{N-1}{1}\binom{N}{1}}\prod\binom{N}{1}}$$

$$= \frac{-\frac{1}{m!} \prod_{i=1}^{n} {m \choose n_i} - \frac{{m \choose 1}}{m(m-1)} \prod_{i=1}^{n} {m \choose n_i} + \dots}{\prod_{i=1}^{n} {N \choose n_i}} \dots (3.4)$$

It follows from (3.4) that

$$P[u_{11}=u_{11}\cap M=m]$$

$$= \frac{\binom{N}{m} \left\lceil \frac{1}{m} \prod_{i=1}^{k} \binom{m}{n_{i}} - \frac{\binom{m}{i}}{(m-1)} \prod_{i=1}^{k} \binom{m-1}{n_{i}} + \frac{\binom{m}{2}}{(m-2)} \prod_{i=1}^{k} \binom{m-2}{n_{i}} - \dots \right]}{\prod_{i=1}^{k} \binom{N}{n_{i}}} ... (3.5)$$

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The theorem is proved on combining (2.2), (3.3) and (3.5),

Corollary 1: In the particular case when  $n_1 = n_2 = ... = n_k = 1$ , the unbiased minimum variance estimate of  $\frac{1}{N}$  is given by

$$t_{-1}(m) = \frac{C_{n}(k-1)}{C_{-}(k)}$$
 ... (3.6)

where  $C_n(k) = m^2 - {m \choose 1}(m-1)^2 + \dots + {m \choose m-1}C_n(k)$  is are called the differences of zeroes.

The author (1961) has tabulated the values of  $\frac{O_m(k-1)}{O_m(k)}$  for all m and k=1 to 50.

It can be shown in a similar manner that the best unbiased estimate of  $V[t_{-1}(m)]$  is given by

$$v[t_{-1}(m)] = t_{-1}^{*}(m) - t_{-2}(m)$$
 ... (3.7)

whore

$$l_{-1}(m) = \frac{\left[\frac{1}{m^2} \prod_{i=1}^{n} {m \choose n_i} - \frac{{n \choose 1}}{(m-1)^2} \prod_{i=1}^{n} {m-1 \choose n_i} + \dots \right]}{\left[\prod_{i=1}^{n} {n \choose n_i} - \prod_{i=1}^{n} {m-1 \choose m_i} + \dots \right]}.$$

## 4. ESTIMATION OF THE POPULATION SIZE

The search for an unbiased estimate of N leads to the following theorem.

Theorem 2: The unbiased minimum variance estimate of N exists if and only if the sample size  $n = \sum_{i=1}^{N} n_i > N$  in which case the required estimate is given by

$$t_{\lambda}(m) = \frac{\left[\begin{array}{ccc} \frac{1}{m} \prod_{i=1}^{k} {m \choose n_i} - (m-1) {m \choose 1} \prod_{i=1}^{k} {m-1 \choose n_i} + \ldots \right]}{\left[\begin{array}{ccc} \prod_{i=1}^{k} {m \choose n_i} - {m \choose 1} \prod_{i=1}^{k} {m-1 \choose n_i} + \ldots \right]}. \dots (4.1)$$

Proof: Suppose that there exists such an estimate. Let it be  $t_1(m)$ . Then we have from the condition of unbiasedness

$$\frac{\min (n, N)}{\sum\limits_{m=\max n_i} t_i(m) \binom{N}{m}} \frac{\prod\limits_{i=1}^{k} \binom{m}{n_i} - \binom{m}{i} \prod\limits_{i=1}^{k} \binom{m-1}{n_i} + \dots}{\prod \binom{N}{m}} = N \quad \dots \quad (4.2)$$

for all  $N > \max_i n_i$ .

#### ESTIMATES OF POPULATION SIZE AND ITS INVERSE

Putting auccessively  $N = \max n_t$ ,  $\max n_t + 1, ...,$  we get the only possible estimate,  $t_t(m)$ , as defined above. It is found on taking the expectation of  $t_t(m)$ , with the help of (2.3), that  $t_t(m)$  is an unbiased estimate of N if and only if  $n \ge N$ ; otherwise

$$E[t_i(m)] = \begin{bmatrix} N - \frac{\binom{N}{n+1} \binom{1}{i} \binom{1}{n-0} \binom{n+1}{n_i} - \prod_{i=0}^{i} \binom{n}{n_i} + \dots}{\prod_{i=0}^{N} \binom{N}{n_i}} & \dots & (4.3) \end{bmatrix}$$

where  $n_0 = 1$ .

This completes the proof.

The bias of  $t_1(m)$  decreases as n increases and would be negligible if n is large. Moreover, if in practice some approximation for N is available in advance, a correction for the bias can be made.

In the particular case when  $n_1 = n_2 = ... = n_k = 1$ .  $t_1(m)$  may be expressed in terms of the differences of zeroes as

$$t_1(m) = \frac{O_m(k+1)}{O_m(k)}$$
 ... (4.4)

An estimate of  $V[t_1(m)]$  (unbiased if  $\sum_{i=1}^{k} n_i \ge N$ ) is given by

$$v[t_1(m)] = t_1^2(m) - t_2(m)$$
 ... (4.5)

whore

$$l_{\mathbf{I}}(m) = \frac{\left[\begin{array}{cc} m^2 & \prod\limits_{l=1}^{n} {m \choose n_l} - (m-1)^2 {m \choose 1} \prod\limits_{l=1}^{n} {m-1 \choose n_l} + \ldots \right]}{\left[\begin{array}{cc} \prod\limits_{l=1}^{n} {m \choose n_l} - {m \choose 1} \prod\limits_{l=1}^{n} {m-1 \choose n_l} + \ldots \right]}.$$

# 5. CONCLUDING REMARK

The estimates suggested in the preceding sections are difficult to compute in practice except when  $n_1=n_2=\ldots=n_k=1$  and  $k\leqslant 50$ . However, if the subsampling fractions  $\frac{n_\ell}{N}$   $(i=1,\ldots,k)$  are negligible so that subsampling may be assumed with replacement, the above described estimates may be approximated by

$$t_{-1}(m) \doteq \frac{C_m (\sum n_i - 1)}{C_m (\sum n_i)}$$
 ... (4.6)

$$v[t_{-1}(m)] \doteq t_1^2(m) - \frac{C_m(\Sigma n_i - 2)}{C_m(\Sigma n_i)}$$
 ... (4.7)

$$t_1(m) \doteq \frac{O_m\left(\sum n_t + 1\right)}{C_m\left(\sum n_t\right)} \qquad \dots (4.8)$$

$$v[t_1(m)] \doteq t_1^2(m) - \frac{C_m(\Sigma n_1 + 2)}{C_-(\Sigma n_1)}$$
... (4.9)

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These approximations are good only for  $\Sigma n_i \leq 50$  as tables of the ratio  $\frac{C_m(r-1)}{C_m(r)}$  are not yet available in the literature beyond r=50.

As a further approximation to these estimates, it is of interest to point out that if  $n = \sum_{i=1}^k n_i$  is large and if  $\frac{n^k}{\sum_i n_i n_i}$  is bounded so that (2.4) may be used to approxi-

mate the numerators and denominators of these estimates, the asymptotic expressions for these estimates are given by

$$t_{-1}(m) \doteq \frac{(n-m)}{\sum_{i \in I} n_i n_j} \qquad \dots \tag{4.10}$$

$$v[\ell_{-1}(m)] \doteq i_{-1}^2(m) - \frac{(n-m)(n-m-1)}{\binom{\sum\limits_{i>j} n_i n_j}{\binom{i}{i>j}}^4} \dots (4.11)$$

$$t_1(m) \doteq \frac{\left(\sum_{i > j} n_i n_j\right)}{(n - m + 1)} \qquad \dots \quad (4.12)$$

$$v(t_1(m)) \doteq t_1^2(m) - \frac{\left(\sum_{l \ge j} n_l n_j\right)^6}{(n-m+1)(n-m+2)}$$
 ... (4.13)

The estimate (4.12) has been suggested for estimating N by Czon Pin and Dzan Dzo (1961). An interesting discussion on the bias and variance of (4.12) and on other related problems like confidence interval estimation of N may be found in their paper. It has been proved by them that (4.12) attains least variance when  $n_1 = n_2 = \dots = n_n = 1$ .

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