

# NOTE ON SAMPLING FROM A SOCIOMETRIC PATTERN

By CHIKIO HAYASHI

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Usual sampling theory, treats mainly the universe in which the label of an element is a function of only that element itself, although the label is sometimes regarded as a random variable. Here in this note some remark will be made on this point.

We take up a universe consisting of people or things and of size  $N$ . Suppose that the relation between  $i$  element and  $j$  element ( $i, j = 1, 2, \dots, N, i \neq j$ ) is represented by  $e_{ij}$  (a numerical value) which is measured by a survey. We want to estimate some statistic made by  $e_{ij}$ 's in the universe, for example  $I = \sum_{i \neq j}^N \frac{e_{ij}}{N(N-1)}$ , by the sampling method with the equal sampling probability  $1/N$  for each element of the universe.

In those cases, it is not valid in the light of sociometry-technique to use this sampling method, where the value  $e_{ij}$  in the universe, which we use to make the required statistic, is a function of both  $i, j$  and of the universe, but  $e_{ij}$  in a probability sample is determined in the very sample set including fixed  $i$  and  $j$ , and so  $e_{ij}$  varies according to what elements else than  $i, j$  are sampled, that is to say,  $e_{ij}$  is a function of not only  $i$  and  $j$  but also of the sample set. In many socio-psychological surveys, we encounter this situation.

However, this sampling method is effective in cases where  $e_{ij}$  is a function of only  $i$  and  $j$ , and the size  $N$  is large. These conditions are fulfilled in some kinds of socio-psychological surveys and surveys of factual relations between elements.

In the present note, a problem of sampling from a sociometric pattern is treated as an example of some sampling estimation in a correlated pattern.

## 1. In-Group Choice.

Suppose each element of the universe concerned chooses positive, neutral or negative relation to all elements excluding itself, and element

$i$  has a numerical value  $e_{ij}$  in relation to  $j$  ( $j=1, 2, \dots, N, i \neq j$ ) which describes the directive relation of  $i$  to  $j$ .

For example, let  $e_{ij} > 0$  if  $i$  likes  $j$  and  $e_{ji} < 0$  if  $j$  dislikes  $i$ .  $j$  does not always like  $i$  though  $i$  likes  $j$ . In this case we call the relation directive, because the relation of  $i$  to  $j$  is not same as that of  $j$  to  $i$ .

	1	2	3	.....	$N$
1	×	$e_{12}$	$e_{13}$	.....	$e_{1N}$
2	$e_{21}$	×	$e_{23}$	.....	$e_{2N}$
3	$e_{31}$	$e_{32}$	×	.....	$e_{3N}$
⋮	⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮	⋮
$N$	$e_{N1}$	$e_{N2}$	$e_{N3}$	.....	×

Fig. 1

Generally  $e_{ij} \neq e_{ji}$ . We take a sample of size say,  $n$ , by equal probability sampling without replacement, in order to estimate the so-called index of cohesion in the universe  $I = \sum_{i \neq j}^N \sum \frac{e_{ij}}{N(N-1)}$ .

This idea leads to probability sampling of correlated lines in a grid.

In the first step, we assume that  $e_{ij} = 1$  or  $0$  and that  $e_{ij} = 1$  represents positive relation,  $e_{ij} = 0$  non-positive relation. In this case  $I$  represents the proportion of positive choices to total choices.

It is natural to take  $\bar{x} = \frac{1}{n(n-1)} \sum_{k \neq l}^n x_{kl}$  as an estimate of  $I$ , where  $x_{kl}$  is the label to describe the relation of  $k$  to  $l$  in a probability sample of size  $n$  ( $k, l = 1, 2, \dots, n, k \neq l$ ).  $\bar{x}$  is clearly an unbiased estimate of  $I$ .  $\sigma_{\bar{x}}^2$ , the variance of  $\bar{x}$ , is calculated as below.

$$\begin{aligned} \sigma_{\bar{x}}^2 = & \frac{1}{n(n-1)} \left[ R + \frac{N-n}{N} (n-2) \left\{ \frac{1}{(N-1)(N-2)(N-3)} \sum_{i=1}^N N_i^2 \right. \right. \\ & + 2 \frac{1}{(N-1)(N-2)(N-3)} \sum_{i=1}^N N_i M_i + \frac{1}{(N-1)(N-2)(N-3)} \sum_{i \neq j}^N S_i \\ & \left. \left. + \frac{1}{(N-1)(N-2)} \left( \frac{1}{n-2} - \frac{1}{N-3} \right) \sum_{i \neq j}^N \delta_{ij} \right] \right] \end{aligned}$$

where

$$N_i = \sum_{j=1, j \neq i}^N e_{ij}$$

$$M_i = \sum_{j=1, j \neq i}^N e_{ji}$$

$$S_{ij} = \sum_{g=1, g \neq i, j}^N e_{ig} e_{jg}$$

$$\delta_{ij} = \sum_{k \neq j}^N \sum_{l \neq i}^N e_{ik} e_{jl}$$

$$R = \left[ \frac{N-n}{N-2} I + N(N-1) \left\{ \frac{(n-2)(n-3)}{(N-2)(N-3)} - \frac{n(n-1)}{N(N-1)} \right\} I^2 \right]$$

If  $N \gg n$ ,  $N \gg 1$ ,  $n \gg 1$ , we obtain,

$$\sigma_{\bar{x}}^2 \doteq \frac{I}{n^2} + \frac{1}{n} \left\{ \frac{1}{N(N-1)^2} \sum_{i=1}^N N_i^2 + 2 \frac{1}{N(N-1)^2} \sum_{i=1}^N N_i M_i + \right. \\ \left. + \frac{1}{N(N-1)(N-2)} \sum_{i \neq j}^N S_{ij} + \frac{1}{n} \frac{1}{N(N-1)} \sum_{i \neq j}^N \delta_{ij} \right\}.$$

The estimates of various sociometric indices will be obtained by various definitions of  $e_{ij}$ . Suppose that element  $i$  has a numerical value  $e_{ij}$  in relation to  $j$  ( $i=1, 2, \dots, n$ ,  $j=1, 2, \dots, N$ ,  $i \neq j$ ), i.e. element  $i$  in a probability sample is asked for the relations to all elements in the universe. In this case,

$$\bar{x} = \frac{\sum_{i=1}^n \sum_{j=1, j \neq i}^N x_{ij}}{n(N-1)}$$

is an unbiased estimate of  $I$ . The variance of  $\bar{x}$  can easily be obtained by the usual formulae of sampling theory.

## 2. Out-Group Choice.

Suppose that there are two groups  $A$ ,  $B$  in the universe, the sizes of which are  $N_A$ ,  $N_B$ , respectively,  $N_A + N_B = N$ . We take a sample of size  $n_\alpha$  from the sub-universe  $\alpha$  by equal probability sampling without replacement ( $\alpha = A, B$ ). We want to estimate the statistics

$$O_{AB} = \frac{1}{N_A N_B} \sum_{i_A=1}^{N_A} \sum_{j_B=1}^{N_B} g_{i_A j_B} \quad \text{or} \quad O_{BA} = \frac{1}{N_A N_B} \sum_{j_B=1}^{N_B} \sum_{i_A=1}^{N_A} g_{j_B i_A},$$

by the sampling above mentioned, where  $g_{i_A j_B}$  represents the relation of  $i_A$  element in group  $A$  to  $j_B$  element in group  $B$ ,  $g_{j_B i_A}$  vice versa, and generally  $g_{i_A j_B} \neq g_{j_B i_A}$ .

In sociometric research it is desirable in analyzing a group structure

of the universe to use not only  $I_A, I_B$  (cohesion index in sub-universes  $A, B$ ) but also these  $O_{AB}$  and  $O_{BA}$  simultaneously.

If we define  $g_{i_A j_B}(g_{j_B i_A})=1$  or 0 as in the previous section, the following results are easily obtained by the idea of two stage sampling method. As to a further generalization it will be not necessary to describe it here.

We use  $\bar{y}_{AB} = \frac{1}{n_A n_B} \sum_{k_A=1}^{n_A} \sum_{l_B=1}^{n_B} y_{k_A l_B}$  to estimate  $O_{AB}$ , where  $y_{k_A l_B}$  is the label to describe the relation of  $k_A$  in a probability sample of  $A$  to  $l_B$  in that of  $B$ ,  $\bar{y}_{AB}$  is clearly an unbiased estimate of  $O_{AB}$ . The variance of  $\bar{y}_{AB}$ ,  $\sigma_{\bar{y}_{AB}}^2$ , is

$$\frac{N_B - n_B}{N_B - 1} \frac{\bar{\sigma}_{AB}^2}{n_A n_B} + \frac{N_A - n_A}{N_A - 1} \frac{\sigma_{P_{AB}}^2}{n_A} + \frac{N_A - n_B}{N_B - 1} \frac{1}{n_B} \frac{n_A - 1}{n_A} \frac{1}{N_A (N_A - 1)} \sum_{r_A}^{N_A} \sum_{s_A}^{N_A} C_{r_A s_A}$$

where

$$P_{k_B} = \frac{1}{N_B} \sum_{l_B=1}^{N_B} g_{k l_B}, \quad k=1, 2, \dots, N_A$$

$$\bar{P}_{AB} = \frac{1}{N_A} \sum_{k=1}^{N_A} P_{k_B}$$

$$\sigma_{P_{AB}}^2 = \frac{1}{N_A} \sum_{k=1}^{N_A} (P_{k_B} - \bar{P}_{AB})^2$$

$$\tau_{k_B}^2 = P_{k_B}(1 - P_{k_B}), \quad k=1, 2, \dots, N_A$$

$$\bar{\sigma}_{AB}^2 = \frac{1}{N_A} \sum_{k=1}^{N_A} \tau_{k_B}^2$$

$$C_{r_A s_A} = \frac{1}{N_B} \sum_{j_B=1}^{N_B} (g_{r_A j_B} - P_{r_A B})(g_{s_A j_B} - P_{s_A B}).$$

It will be possible to design a sampling survey by using the ideas mentioned above.

THE INSTITUTE OF STATISTICAL MATHEMATICS

#### REFERENCES

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