# Algorithms for Optimal Integration of Two or Three Surveys 

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#### Abstract

Let $\mathscr{S}=\{1,2, \ldots, N\}$ and for each $i, 1 \leqslant i \leqslant k$, let $\mathscr{P}_{i}=\left\{P_{i j}, 1 \leqslant j \leqslant N\right\}$ denote a probability distribution on $\mathscr{S}$. Let $X_{i}$ denote a random variable with the distribution $\mathscr{P}_{i}$. For $k=2$ and 3, we present here simple algorithms which yield a joint probability distribution for random variables ( $X_{1}, \ldots, X_{k}$ ) with the prescribed marginal distributions such that the expectation of the number of distinct values among ( $X_{1}, X_{2}, \ldots, X_{k}$ ) is minimized.


Key words: multiple surveys, joint probability distribution, algorithm, optimal integrated surveys

## 1. Introduction

The problem of optimal integration of surveys has its origin in multiple surveys, sampling over successive occasions and to a lesser extent in certain problems of controlled selection in stratified sampling. For two surveys, this problem has been studied in some detail by Keyfitz (1951), Lahiri (1954), Raj (1957) and others, while Pathak \& Maczynski (1980) have recently studied the more general problem of integration of $k$ surveys with $k \geqslant 2$. The object of this paper is to furnish an algorithm which provides a complete solution of the problem of optimal integration of $k=2$ or 3 surveys.

Briefly the problem of optimal integration of surveys can be described as follows. At the outset, we have a population consisting of $N$ units serially numbered $1,2, \ldots, N$. Let $\mathscr{S}$ denote the set of the first $N$ integers. It is proposed to carry out $k$ separate surveys on this population. The $i$ th survey corresponds to a random variable $X_{i}$ having a preassigned probability distribution $\mathscr{P}_{i}=\left\{P_{i j}, 1 \leqslant j \leqslant N\right\}$ on $\mathscr{S}, 1 \leqslant i \leqslant k$. (Thus for each $i, 1 \leqslant i \leqslant k$, $P\left(X_{i}=j\right)=P_{i j}, 1 \leqslant j \leqslant N$, with $\Sigma_{j} P_{i j}=1$.) An integrated survey with marginals $\mathscr{P}_{1}, \ldots, \mathscr{P}_{k}$ is a joint probability distribution $\mathscr{P}$ on the $k$ th cartesian power of $\mathscr{S}$ which realizes for each $i$ the marginal distribution $\mathscr{P}_{i}$. Let $\mathbf{x}=\left(x_{1}, x_{2}, \ldots, x_{k}\right)$ be the observed sample in the integrated survey and $\nu=\nu(\mathbf{x})$ denote the number of distinct units represented in the sample $\mathbf{x}$. An integrated survey is called optimal (for the given marginals) if it minimizes $E[v(\mathbf{X})]$. For any given marginal surveys $\mathscr{P}_{i}, 1 \leqslant i \leqslant k$, an optimal integrated survey always exists, it is, however, not unique (cf. Maczynski \& Pathak (1980)). We shall describe here algorithms for deriving optimal integrated surveys for $k=2$ and 3.

To begin with consider the $k \times N$ array of the $P_{i j}$ 's, which will be called a configuration. A configuration in general is an arrangement of $k N$ nonnegative numbers in $k$ rows and $N$ columns such that the row totals are all equal. Consider the initial configuration of the $P_{i j}$ 's and let the smallest entry in Column $j$ be denoted by $P_{(1) j}$, the next smallest by $P_{(2) j}$ and so on. We let

$$
\begin{equation*}
\theta_{i}=\Sigma_{j} P_{(i) j} . \tag{1.1}
\end{equation*}
$$

We consider a partition of the $N^{k}$ points in $\mathscr{S}^{k}$ as follows. Let

$$
\begin{equation*}
\mathscr{S}_{u}=\{\mathbf{x}: v(\mathbf{x})=u\}, \quad 1 \leqslant u \leqslant k . \tag{1.2}
\end{equation*}
$$

Clearly the $\mathscr{S}_{u}$ 's are disjoint sets and

$$
\begin{equation*}
\mathscr{S}_{1} \cup \mathscr{S}_{2} \ldots \cup \mathscr{S}_{k}=\mathscr{S}^{k} \tag{1.3}
\end{equation*}
$$

## 2. Algorithm for $\boldsymbol{k}=\mathbf{2}$

Stage 1. Assign a probability of $P_{(1) j}$ to the pair $(j, j)$ in $\mathscr{S}_{1}, 1 \leqslant j \leqslant N$, and replace $P_{i j}$ by $\bar{P}_{i j}=P_{i j}-P_{(1) j}$. In the resulting configuration of the $\bar{P}_{i j}$ 's, at least one entry in each column is equal to zero, and the two row sums are equal to $1-\theta_{1}$, where $\theta_{1}=\Sigma_{j} P_{(1) j}$.
Stage 2. Assume without any loss of generality that $\bar{P}_{i j}$ 's have the following configuration

$$
\begin{array}{lllllll}
0 & 0 & \ldots & 0 & \bar{P}_{1, M+1} & \ldots & \bar{P}_{1 N} \\
\bar{P}_{21} & \bar{P}_{22} & \ldots & \bar{P}_{2 M} & 0 & \ldots & 0 . \tag{2.1}
\end{array}
$$

We also assume without any loss of generality that $\bar{P}_{1, M+1}$ is the smallest positive entry in the configuration of the $\bar{P}_{i j}$ 's. (If necessary this can be achieved by permuting the rows and the columns of the configuration in (2.1).) Clearly $\bar{P}_{1, M+1} \leqslant \bar{P}_{21}$. Assign a probability of $\bar{P}_{1, M+1}$ to the pair $(M+1,1)$ in $\mathscr{S}_{2}$ and replace $\bar{P}_{1, M+1}$ by zero and $\bar{P}_{21}$ by $\overline{\bar{P}}_{21}=\bar{P}_{21}-\bar{P}_{1, M+1}$. The resulting configuration has one less positive entry and at most ( $N-1$ ) repetitions of this step may be necessary to zero out all the entries in (2.1) and thus reach the complete specification of an integrated survey, which in fact is optimal.

Note that for the suggested survey a probability of $\theta_{1}$ is assigned to $\mathscr{S}_{1}$ and $\left(1-\theta_{1}\right)$ to $\mathscr{S}_{2}$. Hence

$$
\begin{equation*}
E v=1 \cdot \theta_{1}+2\left(1-\theta_{1}\right)=\theta_{2} \tag{2.2}
\end{equation*}
$$

since in this case $\theta_{1}+\theta_{2}=2$.
Proof of optimality: Let $I_{j}$ be the indicator variable which assumes the value 1 if unit $j$ is included in the survey and the value zero otherwise. Then $v=I_{1}+\ldots+I_{N}$, so that

$$
\begin{align*}
E v & =\Sigma_{j} \mathscr{P}\left(I_{j}=1\right)=\Sigma_{j} \mathscr{P}\left(\bigcup_{i=1}^{k}\left\{X_{i}=j\right\}\right) \\
& \geqslant \Sigma_{j} \max P_{i j}=\Sigma_{j} P_{(k) j}=\theta_{k} . \tag{2.3}
\end{align*}
$$

The optimality of our algorithm clearly follows from (2.3). Observe that in our case $k=2$.

## 3. Algorithm for $\boldsymbol{k}=3$

Stage 1. This is parallel to that for the case $k=2$ in that a probability of $P_{(1) j}=\min \left(P_{1 j}, P_{2 j}, P_{3 j}\right)$ is assigned to the point $(j, j, j)$ in $\mathscr{S}_{1}$ and $P_{i j}$ is replaced by $\bar{P}_{i j}=P_{i j}-P_{(1) j}$ for each $j, 1 \leqslant j \leqslant N$.

Stage 2. Assume without any loss of generality that $P_{11}=\min \left(P_{11}, P_{21}, P_{31}\right)$, so that $\bar{P}_{11}=0$, and let $\bar{P}_{(2) j}=P_{(2) j}-P_{(1) j}$ be the second smallest entry in Column $j$. Assume further that it is possible to remove nonnegative reals $\delta_{1}, \delta_{2}, \ldots, \delta_{N}$ from $\bar{P}_{11}, \bar{P}_{12}, \ldots, \bar{P}_{1 N}$ respectively without affecting the numerical values of the second smallest entries in the respective columns and that the $\delta$ 's add up to $\bar{P}_{(2) 1}$. (Note that in this case $\delta_{1}=0$.) Assign a probability $\delta_{j}$ to the point $(j, 1,1), j=1,2, \ldots, N$, and replace $\bar{P}_{i 1}$ by $\overline{\bar{P}}_{i 1}=\bar{P}_{i 1}-\bar{P}_{(2) 1}, i=2,3, \bar{P}_{1 \mathrm{j}}$ by $\overline{\bar{P}}_{1 j}=\bar{P}_{1 j}-\delta_{j}, 1 \leqslant j \leqslant N$, and $\bar{P}_{i j}=\bar{P}_{i j}$ for all other pairs $(i, j)$. The object of this operation is to "zero out" the second smallest entry, $\bar{P}_{(2) 1}$, from

Column 1 without affecting the second smallest entries in other columns. Thus after this operation Column 1 has at most one nonzero entry. Carry out analogous operations of zeroing out second smallest entries as far as possible for all the $N$ columns. A systematic way of doing this would be to first zero out all columns of the form $(0, b, c)$, then all columns of the form ( $a, 0, c$ ), and finally all columns of the form $(a, b, 0)$. For example if Column 2 has the configuration $(a, b, 0)$, then this operation would involve assigning probabilities $\delta_{k}^{*}$ to points of the form $(2,2, k)$, where $k=1,3, \ldots, N$.

If in the configuration $\left\{P_{i j}^{*}\right\}$ that will finally emerge, each column has at most one nonzero entry then go to Stage 3, otherwise we are in Stage 2* described below.

Stage 3. The nonzero entries in $\left\{P_{i j}^{*}\right\}$ can be zeroed out through steps similar to Stage 2 for the case $k=2$ by putting the remaining probability on $\mathscr{S}_{3}$.

The constructed survey assigns a probability of $\theta_{1}$ to $\mathscr{S}_{1}$, a probability of $\theta_{2}-\theta_{1}$ to $\mathscr{S}_{2}$ and thus a probability of $\left(1-\theta_{2}\right)$ to $\mathscr{S}_{3}$. Hence

$$
\begin{equation*}
E v=1 \cdot \theta_{1}+2\left(\theta_{2}-\theta_{1}\right)+3\left(1-\theta_{2}\right)=3-\theta_{1}-\theta_{2}=\theta_{3} . \tag{3.1}
\end{equation*}
$$

From (2.3) it follows that the suggested algorithm then does yield an optimal integrated survey.

Note that the possibility of carrying out the above construction entails that $\theta_{2} \leqslant 1$.

Stage 2*. If the required operations get blocked during Stage 2, it will be because either all the nonzero entries in one of the rows are also the second smallest column entries in their respective columns, or that it is not possible to remove the stipulated amount of probability from this row without lowering the magnitude of the second smallest column entries. For example, if it is the first row which reaches this configuration during Stage 2, then either each nonzero entry in the first row is the second smallest column entry in the respective column, or zeroing out of the second smallest entry from any column of the form ( $0, b, c$ ) cannot be accomplished without affecting the magnitude of the second smallest entries in other columns; if so, then we can and do zero out a column of the form $(0, b, c)$ in such a way that all nonzero entries in the first row turn into second smallest column entries. From this stage go to Stage 3*.

Stage 3*. In Stage 3*, the positive entries in the configuration are zeroed out by distributing the probability mass suitably in $\mathscr{S}_{2}$. We assume without any loss of generality that the configuration at this stage has the appearance of Table 1 , in which $a_{t+1} \leqslant b_{t+1}, \ldots, a_{u} \leqslant b_{u}$, $a_{u+1} \leqslant c_{u+1}, \ldots, a_{N} \leqslant c_{N}$.

It is important to note here that for reasons of notational simplicity we now denote the entries in any configuration by generic symbols $a, b$ and $c$ in the three rows respectively. Thus entries in a new configuration are not necessarily the same as that of the preceding tables from which they may have been derived, and their meanings depend very much on the context in which they are being used; the only exception to this rule is when a given entry has been zeroed out.

Table 1

| 0 | 0 | $\ldots$ | 0 | 0 | 0 | $\ldots$ | 0 | 0 | $\ldots$ | 0 | $a_{t+1}$ | $\ldots$ | $a_{u}$ | $a_{u+1}$ | $\ldots$ | $a_{N}$ |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| $b_{1}$ | $b_{2}$ | $\ldots$ | $b_{r}$ | 0 | 0 | $\ldots$ | 0 | $b_{s+1}$ | $\ldots$ | $b_{t}$ | $b_{t+1}$ | $\ldots$ | $b_{u}$ | 0 | $\ldots$ | 0 |
| 0 | 0 | $\ldots$ | 0 | $c_{r+1}$ | $c_{r+2}$ | $\ldots$ | $c_{s}$ | $c_{s+1}$ | $\ldots$ | $c_{t}$ | 0 | $\ldots$ | 0 | $c_{u+1}$ | $\ldots$ | $c_{N}$ |

Since $\sum_{t+1}^{N} a_{j}=\sum_{1}^{t} b_{j}+\sum_{t+1}^{u} b_{j}$ and $a_{j} \leqslant b_{j}$ for $j=t+1, \ldots, u$, we have

$$
\begin{equation*}
\sum_{u+1}^{N} a_{j} \geqslant \sum_{1}^{t} b_{j} \tag{3.2}
\end{equation*}
$$

Consequently we can choose nonnegative numbers $\delta_{u+1} \leqslant a_{u+1}, \ldots, \delta_{N} \leqslant a_{N}$ such that $\sum_{u+1}^{N} \delta_{j}=b_{1}$. Since $a_{j} \leqslant c_{j}$ for $j=u+1, \ldots, N$, it follows that $\delta_{u+1} \leqslant c_{u+1}, \ldots, \delta_{N} \leqslant c_{N}$. Now define $\mathscr{P}\left(X_{1}=j, X_{2}=1, X_{3}=j\right)=\delta_{j}$ for $j=u+1, \ldots, N$. Removing the probability mass $b_{1}=\Sigma \delta_{j}$ from this assignment, zeroes out the first cell in the second row, the entries $a_{j}$ in the first row are replaced by $\bar{a}_{j}=a_{j}-\delta_{j}$ and the entries in the third row are replaced by $\bar{c}_{j}=c_{j}-\delta_{j}$ for $j=u+1, \ldots, N$. Note that this operation leaves the structure of the configuration intact in that the new $a_{j}$ 's continue to be the second smallest entries in their respective columns. The new configuration now has the appearance of Table 2 . The entries $b_{2}, \ldots, b_{t}$ in Table 2 are zeroed out in a similar fashion by assigning suitable probabilities to the cells $(j, k, j)$ for $k=2, \ldots, r, s+1, \ldots, t$ and $j=u+1, \ldots, N$ and keeping the structure of the first row intact. After these operations, the configuration assumes the appearance of Table 3. The entries $c_{r+1}, \ldots, c_{t}$ in Table 3 are now zeroed out one-by-one in a similar fashion by assigning suitable probabilities to the cells $(j, j, k)$ for $j=t+1, \ldots, u$ and $k=r+1, \ldots, t$. As a result of this operation, the configuration that emerges has the appearance of Table 4.

We now zero out the entry $a_{t+1}$ in the first row of Table 4. We note that $\Sigma_{t+1}^{u} a_{j}=\sum_{u+1}^{N}\left(c_{j}-a_{j}\right)$. Therefore

$$
\begin{equation*}
a_{t+1} \leqslant \sum_{u+1}^{N}\left(c_{j}-a_{j}\right) \tag{3.3}
\end{equation*}
$$

Consequently there exist nonnegative numbers $\delta_{j} \leqslant\left(c_{j}-a_{j}\right), j=u+1, \ldots, N$, such that

$$
\begin{equation*}
a_{t+1}=\sum_{u+1}^{N} \delta_{j} \tag{3.4}
\end{equation*}
$$

Table 2

| 0 | 0 | $\ldots$ | 0 | 0 | $\ldots$ | 0 | 0 | $\ldots$ | 0 | $a_{t+1}$ | $\ldots$ | $a_{u}$ | $\bar{a}_{u+1}$ | $\ldots$ | $\bar{a}_{N}$ |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 0 | $b_{2}$ | $\ldots$ | $b_{r}$ | 0 | $\ldots$ | 0 | $b_{s+1}$ | $\ldots$ | $b_{t}$ | $b_{t+1}$ | $\ldots$ | $b_{u}$ | 0 | $\ldots$ | 0 |
| 0 | 0 | $\ldots$ | 0 | $c_{r+1}$ | $\ldots$ | $c_{s}$ | $c_{s+1}$ | $\ldots$ | $c_{t}$ | 0 | $\ldots$ | 0 | $\bar{c}_{u+1}$ | $\ldots$ | $\bar{c}_{N}$ |

Table 3

| 0 | 0 | $\ldots$ | 0 | 0 | $\ldots$ | 0 | $a_{t+1}$ | $\ldots$ | $a_{u}$ | $a_{u+1}$ | $\ldots$ | $a_{N}$ |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 0 | 0 | $\ldots$ | 0 | 0 | $\ldots$ | 0 | $b_{t+1}$ | $\ldots$ | $b_{u}$ | 0 | $\ldots$ | 0 |
| 0 | 0 | $\ldots$ | 0 | $c_{r+1}$ | $\ldots$ | $c_{t}$ | 0 | $\ldots$ | 0 | $c_{u+1}$ | $\ldots$ | $c_{N}$ |

Table 4

| 0 | $\ldots$ | 0 | $a_{t+1}$ | $\ldots$ | $a_{u}$ | $a_{u+1}$ | $\ldots$ | $a_{N}$ |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 0 | $\ldots$ | 0 | $b_{t+1}$ | $\ldots$ | $b_{u}$ | 0 | $\ldots$ | 0 |
| 0 | $\ldots$ | 0 | 0 | $\ldots$ | 0 | $c_{u+1}$ | $\ldots$ | $c_{N}$ |

Now define $\mathscr{P}\left(X_{1}=t+1, X_{2}=t+1, X_{3}=j\right)=\delta_{j}$ for $j=u+1, \ldots, N$. Removing these probabilities leads to the configuration given by Table 5 in which $\bar{b}_{t+1}=b_{t+1}-a_{t+1}$ and $\bar{c}_{j}=c_{j}-\delta_{j}$ for $j=u+1, \ldots, N$.
Table 5 is easily seen to have the structure of Table 3. The entry $\bar{b}_{t+1}$ of Table 5 can be zeroed in a manner similar to that of Table 3. The configuration that emerges now is like that of Table 4 in which the $(t+1)$ st column has now been zeroed out. We repeat this procedure until all the entries in Columns $(t+1)$ through $u$ have been zeroed out. The final configuration that now emerges must necessarily be of the form of Table 6. By assumption the three row sums of Table 6 are all equal and so all the $a$ 's and $c$ 's in the final configuration must be zero.
It is easily seen that in this case, our algorithm assigns a probability of $\theta_{1}$ to $\mathscr{S}_{1}$, a probability of $1-\theta_{1}$ to $\mathscr{S}_{2}$ and zero probability to $\mathscr{S}_{3}$. Hence

$$
\begin{equation*}
E v=1 \cdot \theta_{1}+2\left(1-\theta_{1}\right)=2-\theta_{1} . \tag{3.5}
\end{equation*}
$$

Proof of optimality. To prove the optimality in this last case, we observe that for any integrated survey

$$
\begin{equation*}
E v \geqslant \mathscr{P}\left(\mathscr{S}_{1}\right)+2\left[1-\mathscr{P}\left(\mathscr{S}_{1}\right)\right]=2-\mathscr{P}\left(\mathscr{\mathscr { C }}_{1}\right) . \tag{3.6}
\end{equation*}
$$

Since $\mathscr{P}\left(\mathscr{S}_{1}\right) \leqslant \theta_{1}$, it follows that we must always have

$$
\begin{equation*}
E v \geqslant 2-\theta_{1} \tag{3.7}
\end{equation*}
$$

Since for our algorithm the equality in (3.7) is attained, it is necessarily optimal.
It is worth noting that the quantity $\theta_{2}$ plays a crucial role in the preceding algorithm. The algorithm shows that if $\theta_{2}>1$ then the given algorithm must get blocked at Stage 2 so that the achieved optimal solution must have its support in $\mathscr{S}_{1} \cup \mathscr{S}_{2}$.

## 4. Remark

It is perhaps natural to speculate that the optimality of the integrated surveys worked out in Section 3 would go through if apart from possibly a constant term, the cost instead of being proportional to the number of distinct units, is actually a monotonic increasing function thereof. The following counterexample for $N=3$ sets at rest any such speculation.

Table 5

```
0
0
0
```

Table 6

```
0
0
0
```

Example 4.1. Let $N=3$ and consider the problem of integrating three surveys. Let $C(v)$ denote the cost of selecting an integrated sample with $v$ distinct units and suppose that $C(1)=1, C(2)=2$ and $C(3)=10$. Further suppose that the marginal probabilities of selection for the three surveys are given by the entries in Table 7.

An optimally integrated survey based on the algorithm of Section 3 is given in Table 8. The integrated survey of Table 8 yields the following distribution for the number of distinct units in the sample: $\mathscr{P}(v=1)=0.6, \mathscr{P}(v=2)=0.3, \mathscr{P}(v=3)=0.1$ so that $E C(v)=2.2$. On the other hand the integrated survey given in Table 9 assigns all the probability exclusively to $\mathscr{S}_{2}$ and therefore has a lower expected cost $E C(v)=2.0$.

## 5. Integrating four or more surveys

The algorithm described in this paper cannot be extended to four or more surveys in a routine manner. Consider the marginal probabilities of selection for four units in four surveys as given by the entries in Table 10. Applying a routine extension of the algorithm in Section 3, one arrives at the following plan for an integrated survey

Table 7. Stochastic matrix for three surveys

| $i$ | $P_{i 1}$ | $P_{i 2}$ | $P_{i 3}$ |
| :--- | :--- | :--- | :--- |
| 1 | .2 | .3 | .5 |
| 2 | .5 | .2 | .3 |
| 3 | .3 | .5 | .2 |

Table 8. Plan for an optimally integrated survey (Section 3): values of $P_{i j k}$

| ( $j, k$ ) | $P_{1 j k}$ |  |  | $P_{2 j k}$ |  |  | $P_{3 j k}$ |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| 1 | . 2 | 0 | 0 | . 1 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | 0 | 0 | . 2 | 0 | 0 | 0 | 0 |
| 3 | 0 | 0 | 0 | . 1 | . 1 | 0 | . 1 | 0 | . 2 |

Table 9. Plan for an alternative integrated survey: values of $P_{i j k}$

| ( $j, k$ ) | $150 P_{1 j k}$ |  |  | $150 P_{2 j k}$ |  |  | ${ }^{150 P_{3 j k}}$ |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| 1 | 0 | 9 | 0 | 17 | 5 | 0 | 5 | 0 | 9 |
| 2 | 2 | 0 | 0 | 17 | 0 | 2 | 0 | 9 | 0 |
| 3 | 17 | 0 | 2 | 0 | 17 | 17 | 17 | 5 | 0 |

Table 10. Stochastic matrix for four surveys

| $i$ | $P_{i 1}$ | $P_{i 2}$ | $P_{i 3}$ | $P_{i 4}$ |
| :--- | :--- | :--- | :--- | :--- |
| 1 | $1 / 3$ | 0 | $1 / 3$ | $1 / 3$ |
| 2 | 1 | 0 | 0 | 0 |
| 3 | $1 / 3$ | $1 / 3$ | 0 | $1 / 3$ |
| 4 | $1 / 3$ | $1 / 3$ | $1 / 3$ | 0 |

$$
p_{1111}=1 / 3, \quad p_{3122}=1 / 3, \quad p_{4143}=1 / 3
$$

with an expected number of distinct units $E(v)=1 / 3$. The following alternative plan however assigns probability 1 to sample points with two distinct units

$$
p_{1122}=1 / 3, \quad p_{3113}=1 / 3, \quad p_{4141}=7 / 3
$$

which points out the nonoptimality of the plan arrived via Section 3. One also faces difficulty of another type. Sample points in $\mathscr{S}_{2}$ are seen to have two different structures of the type $(1,1,2,2)$ or $(1,2,2,2)$. In Stage 2 one is thus occasionally unable to decide which path to proceed to eliminate the second largest entry in each column.

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## Dedication

This paper is dedicated to Professor D. Basu on the occasion of his sixtieth birthday.

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