Survey Sampling Theory

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1 The population total, population mean, and population variance of a population characteristic

Let $n, N \in \mathbb{N}$, with $n \leq N$. Let $\mathcal{U} = \{1, 2, \ldots, N\}$, which represents the finite population, or universe, of N elements.

Definition 1.1 *A* population characteristic *is an $\mathbb{R}$-valued function $y : \mathcal{U} \longrightarrow \mathbb{R}$ defined on the population $\mathcal{U}$. We denote the value of y evaluated at $i \in \mathcal{U}$ by y_i. The population total, denoted by t, of y is defined:*

$$t \;:=\; \sum_{i=1}^{N} y_i \in \mathbb{R}\,.$$

The population mean*, denoted by $\overline{y}$, of y is defined by:*

$$\overline{y} \;:=\; \frac{1}{N}\sum_{i=1}^{N} y_i \in \mathbb{R}\,.$$

The population variance*, denoted by S^2, of y is defined by:*

$$S^2 \;:=\; \frac{1}{N-1}\sum_{i=1}^{N}\left(y_i - \overline{y}\right)^2 \;=\; \frac{1}{N-1}\left\{\left(\sum_{i=1}^{N} y_i^2\right) - N\cdot\overline{y}^2\right\} \in \mathbb{R}\,.$$

In survey sampling, we seek to estimate population total t and population mean $\overline{y}$ of a population characteristic $y : \mathcal{U} \longrightarrow \mathbb{R}$ by making observations of values of y on only a (usually proper) subset of $\mathcal{U}$, and extrapolate from these observations. The subset on which observations of values of y are made is called a *sample*.

2 Simple Random Sampling (SRS)

Definition 2.1 *Let $\mathcal{U}$ be a nonempty finite set, $N := \#(\mathcal{U}) \in \mathbb{N}$, and let $n \in \{1, 2\ldots, N\}$ be given. We define the probability space $\Omega_{\mathrm{SRS}}(\mathcal{U}, n)$ as follows: Let $\Omega(\mathcal{U}, n)$ be the set of all subsets of $\mathcal{U}$ with n elements, i.e.*

$$\Omega(\mathcal{U}, n) \;:=\; \{\, \omega \subset \mathcal{U} \mid \#(\omega) = n \,\}\,.$$

Note that $\#(\Omega(\mathcal{U}, n)) = \begin{pmatrix} N \\ n \end{pmatrix}$. Let $\mathcal{P}(\Omega(\mathcal{U}, n))$ be the power set of $\Omega(\mathcal{U}, n)$. Define $\mu : \Omega \longrightarrow \mathbb{R}$ to be the "uniform" probability measure on the (finite) σ-algebra $\mathcal{P}(\Omega(\mathcal{U}, n))$ determined by:

$$\mu(\omega) \;=\; \frac{1}{\begin{pmatrix} N \\ n \end{pmatrix}} \;=\; \frac{n!(N-n)!}{N!}\,, \quad \text{for each } \omega \in \Omega(\mathcal{U}, n).$$

Then, $\Omega_{\mathrm{SRS}}(\mathcal{U}, n)$ is defined to be the probability space $(\,\Omega(\mathcal{U}, n)\,,\,\mathcal{P}(\Omega(\mathcal{U}, n))\,,\,\mu\,)$.

Definition 2.2 *The* simple-random-sampling sample total $\widehat{t}_{\mathrm{SRS}}$ *of the population characteristic y is, by definition, the random variable $\widehat{t}_{\mathrm{SRS}} : \Omega_{\mathrm{SRS}}(\mathcal{U}, n) \longrightarrow \mathbb{R}$ defined by*

$$\widehat{t}_{\mathrm{SRS}}(\omega) \;:=\; \frac{N}{n}\sum_{i\in\omega} y_i\,, \quad \text{for each } \omega \in \Omega.$$

The simple-random-sampling sample mean $\widehat{\overline{y}}_{\mathrm{SRS}}$ *of the population characteristic y is, by definition, the random variable $\widehat{\overline{y}}_{\mathrm{SRS}} : \Omega_{\mathrm{SRS}}(\mathcal{U}, n) \longrightarrow \mathbb{R}$ defined by*

$$\widehat{\overline{y}}_{\mathrm{SRS}}(\omega) \;:=\; \frac{1}{n}\sum_{i\in\omega} y_i\,, \quad \text{for each } \omega \in \Omega.$$

The simple-random-sampling sample variance $\widehat{s^2}_{\text{SRS}}$ *of the population characteristic y is, by definition, the random variable $\widehat{s^2}_{\text{SRS}} : \Omega_{\text{SRS}}(\mathcal{U}, n) \longrightarrow \mathbb{R}$ defined by*

$$\widehat{s^2}_{\text{SRS}}(\omega) \;:=\; \frac{1}{n-1} \sum_{i \in \omega} \left(y_i - \widehat{\overline{y}}_{\text{SRS}}(\omega) \right)^2 \,, \quad \text{for each } \; \omega \in \Omega.$$

Proposition 2.3

1. *$\widehat{\overline{y}}_{\text{SRS}}$ is an unbiased estimator of the population mean $\overline{y}$, and* $\operatorname{Var}\!\left[\, \widehat{\overline{y}}_{\text{SRS}} \,\right] = \left(1 - \dfrac{n}{N}\right) \dfrac{S^2}{n}$.
2. *$\widehat{t}_{\text{SRS}}$ is an unbiased estimator of the population total t, and* $\operatorname{Var}\!\left[\, \widehat{t}_{\text{SRS}} \,\right] = N^2 \left(1 - \dfrac{n}{N}\right) \dfrac{S^2}{n}$.
3. *$\widehat{s^2}_{\text{SRS}}$ is an unbiased estimator of the population variance S^2.*
4. $\widehat{\operatorname{Var}}\!\left[\, \widehat{\overline{y}}_{\text{SRS}} \,\right] := \left(1 - \dfrac{n}{N}\right) \dfrac{\widehat{s^2}_{\text{SRS}}}{n}$ *is an unbiased estimator of* $\operatorname{Var}\!\left[\, \widehat{\overline{y}}_{\text{SRS}} \,\right]$.
5. $\widehat{\operatorname{Var}}\!\left[\, \widehat{t}_{\text{SRS}} \,\right] := N^2 \left(1 - \dfrac{n}{N}\right) \dfrac{\widehat{s^2}_{\text{SRS}}}{n}$ *is an unbiased estimator of* $\operatorname{Var}\!\left[\, \widehat{t}_{\text{SRS}} \,\right]$.

A quote from Lohr [3], p.37: *Hájek [2] proves a central limit theorem for simple random sampling without replacement. In practical terms, Hájek's theorem says that if certain technical conditions hold, and if n, N, and $N - n$ are all "sufficiently large," then the sampling distribution of*

$$\frac{\widehat{\overline{y}}_{\text{SRS}} - \overline{y}}{\sqrt{\left(1 - \dfrac{n}{N}\right) \dfrac{S^2}{n}}}$$

is "approximately" normal (Gaussian) with mean 0 *and variance* 1.

Corollary 2.4 (to Hájek's theorem) *For a simple random sampling procedure, an approximate $(1-\alpha)$-confidence interval, $0 < \alpha < 1$, for the population mean $\overline{y}$ is given by:*

$$\widehat{\overline{y}}_{\text{SRS}} \,\pm\, z_{\alpha/2} \cdot \sqrt{\left(1 - \frac{n}{N}\right) \frac{S^2}{n}}$$

For sufficiently large samples, the above approximate confidence interval can itself be estimated from observations by:

$$\widehat{\overline{y}}_{\text{SRS}} \pm \operatorname{SE}\!\left[\, \widehat{\overline{y}}_{\text{SRS}} \,\right] \;=\; \widehat{\overline{y}}_{\text{SRS}} \pm \sqrt{\left(1 - \frac{n}{N}\right) \frac{\widehat{s^2}_{\text{SRS}}}{n}}$$

where

$$\operatorname{SE}\!\left[\, \widehat{\overline{y}}_{\text{SRS}} \,\right] \;:=\; \sqrt{\widehat{\operatorname{Var}}\!\left[\, \widehat{\overline{y}}_{\text{SRS}} \,\right]} \;=\; \sqrt{\left(1 - \frac{n}{N}\right) \frac{\widehat{s^2}_{\text{SRS}}}{n}}$$

In order to prove Proposition 2.3, we introduce some auxiliary random variables:

Definition 2.5 *Let $n, N \in \mathbb{N}$, with $n < N$, $\mathcal{U} := \{\, 1, 2, \ldots, N \,\}$, and $\Omega := \{\, \omega \subset \mathcal{U} \mid \#(\omega) = n \,\}$. For each $i \in \mathcal{U} = \{\, 1, 2, \ldots, N \,\}$, we define the random variable $Z_i : \Omega \longrightarrow \{0, 1\}$ as follows:*

$$Z_i(\omega) \;=\; \begin{cases} 1, & \text{if } \; i \in \omega \,, \\ 0, & \text{if } \; i \notin \omega \end{cases} \,.$$

Immediate observations:

- $\widehat{t}_{\mathrm{SRS}} = \dfrac{N}{n}\sum_{i=1}^{N} Z_i\, y_i,$, as random variables on (Ω, P), i.e.

$$\widehat{t}_{\mathrm{SRS}}(\omega) \;=\; \frac{N}{n}\sum_{i=1}^{N} Z_i(\omega)\, y_i, \quad \text{for each } \;\omega \in \Omega.$$

- $\widehat{\overline{y}}_{\mathrm{SRS}} = \dfrac{1}{n}\sum_{i=1}^{N} Z_i\, y_i$, as random variables on (Ω, P), i.e.

$$\widehat{\overline{y}}_{\mathrm{SRS}}(\omega) \;=\; \frac{1}{n}\sum_{i=1}^{N} Z_i(\omega)\, y_i, \quad \text{for each } \;\omega \in \Omega.$$

- $E[\, Z_i \,] = \dfrac{n}{N}$. Indeed,

$$E[\, Z_i \,] = 1\cdot P(Z_i = 1) + 0 \cdot P(Z_i = 0) = P(Z_i = 1) = \frac{\text{number of samples containing } i}{\text{number of all possible samples}} = \frac{\begin{pmatrix} N-1 \\ n-1 \end{pmatrix}}{\begin{pmatrix} N \\ n \end{pmatrix}} = \frac{n}{N}$$

- $Z_i^2 = Z_i$, since $\mathrm{range}(Z_i) = \{\, 0, 1 \,\}$. Consequently,

$$E[\, Z_i^2 \,] \;=\; E[\, Z_i \,] \;=\; \frac{n}{N}\,.$$

- $\mathrm{Var}[\, Z_i \,] = \dfrac{n}{N}\left(1 - \dfrac{n}{N}\right)$. Indeed,

$$\begin{aligned}
\mathrm{Var}[\, Z_i \,] \;&:=\; E\left[\, (Z_i - E[\, Z_i \,])^2 \,\right] \;=\; E\left[Z_i^2\right] - (E[\, Z_i \,])^2 \\
&=\; E[\, Z_i \,] - \left(\frac{n}{N}\right)^2 \;=\; \frac{n}{N} - \left(\frac{n}{N}\right)^2 \\
&=\; \frac{n}{N}\left(1 - \frac{n}{N}\right).
\end{aligned}$$

- For $i \neq j$, we have $E[\, Z_i \cdot Z_j \,] = \left(\dfrac{n-1}{N-1}\right)\cdot\left(\dfrac{n}{N}\right)$. Indeed,

$$\begin{aligned}
E[\, Z_i \cdot Z_j \,] \;&=\; 1 \cdot P(Z_i = 1 \;\text{ and }\; Z_j = 1) + 0 \cdot P(Z_i = 0 \;\text{ or }\; Z_j = 0) \\
&=\; P(Z_i = 1 \;\text{ and }\; Z_j = 1) \;=\; P(Z_j = 1 | Z_i = 1)\cdot P(Z_i = 1) \\
&=\; \left(\frac{n-1}{N-1}\right)\cdot\left(\frac{n}{N}\right)
\end{aligned}$$

- For $i \neq j$, we have $\mathrm{Cov}\,(Z_i, Z_j) = -\dfrac{1}{N-1}\left(1 - \dfrac{n}{N}\right)\left(\dfrac{n}{N}\right) \leq 0$. Indeed,

$$\begin{aligned}
\mathrm{Cov}\,(Z_i, Z_j) \;&:=\; E\,[\, (Z_i - E[\, Z_i \,])\cdot(Z_j - E[\, Z_j \,])\,] \;=\; E\,[\, Z_i\, Z_j \,] - E[\, Z_i \,]\cdot E[\, Z_j \,] \\
&=\; \left(\frac{n-1}{N-1}\right)\cdot\left(\frac{n}{N}\right) - \left(\frac{n}{N}\right)^2 \;=\; \frac{n}{N}\left(\frac{nN - N - nN + n}{N(N-1)}\right) \\
&=\; -\frac{1}{N-1}\left(1 - \frac{n}{N}\right)\left(\frac{n}{N}\right)
\end{aligned}$$

PROOF OF Proposition 2.3

1.

$$E\left[\,\widehat{\overline{y}}_{\mathrm{SRS}}\,\right] \;=\; E\left[\,\frac{1}{n}\sum_{i=1}^{N} Z_i\,y_i\,\right] \;=\; \frac{1}{n}\sum_{i=1}^{N} E[\,Z_i\,]\cdot y_i \;=\; \frac{1}{n}\sum_{i=1}^{N}\left(\frac{n}{N}\right)\cdot y_i \;=\; \frac{1}{N}\sum_{i=1}^{N} y_i \;=:\; \overline{y}.$$

$$\begin{aligned}
\mathrm{Var}\left[\,\widehat{\overline{y}}_{\mathrm{SRS}}\,\right] &= \mathrm{Var}\left[\,\frac{1}{n}\sum_{i=1}^{N} Z_i\,y_i\,\right] \;=\; \frac{1}{n^2}\,\mathrm{Var}\left[\,\sum_{i=1}^{N} Z_i\,y_i\,\right] \;=\; \frac{1}{n^2}\,\mathrm{Cov}\left[\,\sum_{i=1}^{N} Z_i\,y_i\;,\;\sum_{j=1}^{N} Z_j\,y_j\,\right] \\
&= \frac{1}{n^2}\left\{\,\sum_{i=1}^{N} y_i^2\,\mathrm{Var}(Z_i) + \sum_{i=1}^{N}\sum_{i\neq j=1}^{N} y_i y_j\,\mathrm{Cov}(Z_i, Z_j)\,\right\} \\
&= \frac{1}{n^2}\left\{\,\sum_{i=1}^{N} y_i^2\,\frac{n}{N}\left(1-\frac{n}{N}\right) - \sum_{i=1}^{N}\sum_{i\neq j=1}^{N} y_i y_j\,\frac{1}{N-1}\left(1-\frac{n}{N}\right)\left(\frac{n}{N}\right)\,\right\} \\
&= \frac{1}{n^2}\,\frac{n}{N}\left(1-\frac{n}{N}\right)\left\{\,\sum_{i=1}^{N} y_i^2 - \frac{1}{N-1}\sum_{i=1}^{N}\sum_{i\neq j=1}^{N} y_i y_j\,\right\} \\
&= \frac{1}{n}\left(1-\frac{n}{N}\right)\frac{1}{N(N-1)}\left\{\,(N-1)\sum_{i=1}^{N} y_i^2 - \sum_{i=1}^{N}\sum_{i\neq j=1}^{N} y_i y_j\,\right\} \\
&= \frac{1}{n}\left(1-\frac{n}{N}\right)\frac{1}{N(N-1)}\left\{\,(N-1)\sum_{i=1}^{N} y_i^2 - \sum_{i=1}^{N}\sum_{j=1}^{N} y_i y_j + \sum_{i=1}^{N} y_i^2\,\right\} \\
&= \frac{1}{n}\left(1-\frac{n}{N}\right)\frac{1}{N(N-1)}\left\{\,N\sum_{i=1}^{N} y_i^2 - \left(\sum_{i=1}^{N} y_i\right)\left(\sum_{j=1}^{N} y_j\right)\,\right\} \\
&= \frac{1}{n}\left(1-\frac{n}{N}\right)\frac{1}{N-1}\left\{\,\sum_{i=1}^{N} y_i^2 - N\left(\frac{1}{N}\sum_{i=1}^{N} y_i\right)^2\,\right\} \\
&= \frac{1}{n}\left(1-\frac{n}{N}\right)\frac{1}{N-1}\left\{\,\sum_{i=1}^{N} y_i^2 - N\cdot\overline{y}^2\,\right\} \\
&= \left(1-\frac{n}{N}\right)\frac{S^2}{n}
\end{aligned}$$

2.

$$E\left[\,\widehat{t}_{\mathrm{SRS}}\,\right] \;=\; E\left[\,N\cdot\widehat{\overline{y}}_{\mathrm{SRS}}\,\right] \;=\; N\cdot E\left[\,\widehat{\overline{y}}_{\mathrm{SRS}}\,\right] \;=\; N\cdot\overline{y} \;=\; N\cdot\left(\frac{1}{N}\sum_{i=1}^{N} y_i\right) \;=\; \sum_{i=1}^{N} y_i \;=:\; t.$$

$$\mathrm{Var}\left[\,\widehat{t}_{\mathrm{SRS}}\,\right] \;=\; \mathrm{Var}\left[\,N\cdot\widehat{\overline{y}}_{\mathrm{SRS}}\,\right] \;=\; N^2\cdot\mathrm{Var}\left[\,\widehat{\overline{y}}_{\mathrm{SRS}}\,\right] \;=\; N^2\left(1-\frac{n}{N}\right)\frac{S^2}{n}$$

3.

$$\begin{aligned}
E\left[\, \widehat{s^2}_{\mathrm{SRS}} \,\right] &= E\left[\, \frac{1}{n-1}\sum_{i\in\omega}\left(y_i - \widehat{\overline{y}}_{\mathrm{SRS}}\right)^2 \,\right] \;=\; \frac{1}{n-1}\,E\left[\, \sum_{i\in\omega}\left((y_i-\overline{y}) - (\widehat{\overline{y}}_{\mathrm{SRS}}-\overline{y})\right)^2 \,\right] \\
&= \frac{1}{n-1}\,E\left[\, \left(\sum_{i\in\omega}(y_i-\overline{y})^2\right) - n\left(\widehat{\overline{y}}_{\mathrm{SRS}}-\overline{y}\right)^2 \,\right] \\
&= \frac{1}{n-1}\left\{\, E\left[\, \sum_{i=1}^{N} Z_i(y_i-\overline{y})^2 \,\right] - n\,\mathrm{Var}\left[\, \widehat{\overline{y}}_{\mathrm{SRS}} \,\right] \right\} \\
&= \frac{1}{n-1}\left\{\, \sum_{i=1}^{N} E[\, Z_i \,]\,(y_i-\overline{y})^2 - n\left(1-\frac{n}{N}\right)\frac{S^2}{n} \,\right\} \\
&= \frac{1}{n-1}\left\{\, \sum_{i=1}^{N} \frac{n}{N}(y_i-\overline{y})^2 - \left(1-\frac{n}{N}\right)S^2 \,\right\} \\
&= \frac{1}{n-1}\left\{\, \frac{n(N-1)}{N}\,\frac{1}{N-1}\sum_{i=1}^{N}(y_i-\overline{y})^2 - \left(1-\frac{n}{N}\right)S^2 \,\right\} \\
&= \frac{1}{n-1}\left\{\, \frac{n(N-1)}{N} - \left(1-\frac{n}{N}\right) \,\right\}S^2 \\
&= \frac{1}{n-1}\left\{\, \frac{nN-n-N+n}{N} \,\right\}S^2 \;=\; S^2
\end{aligned}$$

4. Immediate from preceding statements.

5. Immediate from preceding statements. □

3 Stratified Simple Random Sampling

Let $\mathcal{U} = \{\,1,2,\ldots,N\,\}$ be the population, as before. Let

$$\mathcal{U} \;=\; \bigsqcup_{h=1}^{H} \mathcal{U}_h$$

be a partition of $\mathcal{U}$. Such a partition is called a *stratification* of the population $\mathcal{U}$. Each of $\mathcal{U}_1,\mathcal{U}_2,\ldots,\mathcal{U}_H$ is called a *stratum*. Let $N_h := \#(\mathcal{U}_h)$, for $h=1,2,\ldots,H$. Note that $N_1+N_2+\cdots+N_H = N$.

In *stratified simple random sampling*, an SRS is taken within each stratum $\mathcal{U}_h$, $h=1,2,\ldots,H$. Let n_h, $h = 1,2,\ldots,H$, be the number elements in the simple random sample taken in the stratum $\mathcal{U}_h$. In other words, a stratified simple random sample ω of the stratified population $\mathcal{U} = \bigsqcup_{h=1}^{H}\mathcal{U}_h$ has the form:

$$\omega \;=\; \bigsqcup_{h=1}^{H} \omega_h\,, \quad \text{where } \omega_h \in \Omega_{\mathrm{SRS}}(\mathcal{U}_h, n_h)\,, \quad \text{for each } h = 1,2,\ldots,h\,.$$

Note that $n_1+n_2+\cdots+n_H =: n = \#(\omega)$.

We now give unbiased estimators, and their variances, of the population total and population mean of a population characteristic under stratified simple random sampling. Let $y : \mathcal{U} \longrightarrow \mathbb{R}$ be a population characteristic. Define:

$$\widehat{t}_{\mathrm{Str}} \;:=\; \sum_{h=1}^{H} N_h \cdot \widehat{\overline{y}}_{h,\mathrm{SRS}}$$

$$\widehat{\overline{y}}_{\mathrm{Str}} \;:=\; \frac{1}{N}\cdot\widehat{t}_{\mathrm{Str}} \;=\; \sum_{h=1}^{H} \frac{N_h}{N}\cdot\widehat{\overline{y}}_{h,\mathrm{SRS}}$$

Here,

$$\widehat{\overline{y}}_{h,\mathrm{SRS}} \;:\; \Omega_{\mathrm{SRS}}(\mathcal{U}_h, n_h) \longrightarrow \mathbb{R} \;:\; \omega_h \;\longmapsto\; \frac{1}{n_h}\sum_{i\in\omega_h} y_i$$

is the SRS estimator of

$$\overline{y}_h \;:=\; \overline{y|_{\mathcal{U}_h}} \;=\; \frac{1}{N_h}\sum_{i\in\mathcal{U}_h} y_i \in \mathbb{R},$$

the "stratum mean" of the "stratum characteristic" $y|_{\mathcal{U}_h} : \mathcal{U}_h \longrightarrow \mathbb{R}$, the restriction of the population characteristic $y : \mathcal{U} \longrightarrow \mathbb{R}$ to the stratum $\mathcal{U}_h$. Then,

$$E\left[\,\widehat{t}_{\mathrm{Str}}\,\right] \;=\; t \;:=\; \sum_{i=1}^{N} y_i, \quad \text{and} \quad E\left[\,\widehat{\overline{y}}_{\mathrm{Str}}\,\right] \;=\; \overline{y} \;:=\; \frac{1}{N}\sum_{i=1}^{N} y_i.$$

In other words, $\widehat{t}_{\mathrm{Str}}$ and $\widehat{\overline{y}}_{\mathrm{Str}}$ are unbiased estimators of the population total t and population mean $\overline{y}$ of the population characteristic $y : \mathcal{U} \longrightarrow \mathbb{R}$, respectively. Indeed,

$$\begin{aligned}
E\left[\,\widehat{t}_{\mathrm{Str}}\,\right] &= E\left[\sum_{h=1}^{H} N_h\cdot\widehat{\overline{y}}_{h,\mathrm{SRS}}\right] \;=\; \sum_{h=1}^{H} N_h\, E\left[\,\widehat{\overline{y}}_{h,\mathrm{SRS}}\,\right] \;=\; \sum_{h=1}^{H} N_h\,\overline{y}_h \\
&= \sum_{h=1}^{H} N_h\left(\frac{1}{N_h}\sum_{i\in\mathcal{U}_h} y_i\right) \;=\; \sum_{h=1}^{H}\left(\sum_{i\in\mathcal{U}_h} y_i\right) \;=\; \sum_{i=1}^{N} y_i \;=:\; t\,.
\end{aligned}$$

And,

$$E\left[\,\widehat{\overline{y}}_{\mathrm{Str}}\,\right] \;=\; E\left[\,\frac{1}{N}\cdot\widehat{t}_{\mathrm{Str}}\,\right] \;=\; \frac{1}{N}\,E\left[\,\widehat{t}_{\mathrm{Str}}\,\right] \;=\; \frac{1}{N}\sum_{i=1}^{N} y_i \;=:\; \overline{y}\,.$$

Furthermore,

$$\mathrm{Var}\left[\,\widehat{t}_{\mathrm{Str}}\,\right] \;=\; \mathrm{Var}\left[\sum_{h=1}^{H} N_h\cdot\widehat{\overline{y}}_{h,\mathrm{SRS}}\right] \;=\; \sum_{h=1}^{H} N_h^2\cdot\mathrm{Var}\left[\,\widehat{\overline{y}}_{h,\mathrm{SRS}}\,\right] \;=\; \sum_{h=1}^{H} N_h^2\left(1-\frac{n_h}{N_h}\right)\frac{S_h^2}{n_h}.$$

$$\mathrm{Var}\left[\,\widehat{\overline{y}}_{\mathrm{Str}}\,\right] \;=\; \mathrm{Var}\left[\,\frac{1}{N}\cdot\widehat{t}_{\mathrm{Str}}\,\right] \;=\; \frac{1}{N^2}\cdot\mathrm{Var}\left[\,\widehat{t}_{\mathrm{Str}}\,\right] \;=\; \sum_{h=1}^{H}\left(\frac{N_h}{N}\right)^2\left(1-\frac{n_h}{N_h}\right)\frac{S_h^2}{n_h}.$$

Comparing variances of SRS and stratified simple random sampling with proportional allocation via ANOVA (analysis of variance):

By definition, in stratified simple random sampling with proportional allocation, the stratum sample size n_h, for each $h = 1, 2, \ldots, H$, is chosen such that $n_h/N_h = n/N$. Consequently,

$$\begin{aligned}
\mathrm{Var}\left[\,\widehat{t}_{\mathrm{PropStr}}\,\right] &= \sum_{h=1}^{H} N_h^2\left(1-\frac{n_h}{N_h}\right)\frac{S_h^2}{n_h} \;=\; \frac{N}{n}\left(1-\frac{n}{N}\right)\sum_{h=1}^{H} N_h\,S_h^2 \\
&= \frac{N}{n}\left(1-\frac{n}{N}\right)\left\{\,\sum_{h=1}^{H}(N_h-1)\,S_h^2 + \sum_{h=1}^{H} S_h^2\,\right\} \\
&= \frac{N}{n}\left(1-\frac{n}{N}\right)\left\{\,\mathrm{SSW} + \sum_{h=1}^{H} S_h^2\,\right\},
\end{aligned}$$

where

$$\mathrm{SSW} \;:=\; \sum_{h=1}^{H}\sum_{i\in\mathcal{U}_h}\left(y_i - \overline{y}_{\mathcal{U}_h}\right)^2 \;=\; \sum_{h=1}^{H}(N_h-1)\,S_h^2.$$

is called the *inter-strata squared deviation* (or *within-strata squared deviation*), and

$$S_h^2 \;:=\; \frac{1}{N_h - 1}\sum_{i\in\mathcal{U}_h}\left(y_i - \overline{y}_{\mathcal{U}_h}\right)^2$$

is the stratum variance of the population characteristic $y : \mathcal{U} \longrightarrow \mathbb{R}$ over the stratum $\mathcal{U}_h$. The following relation between $\textnormal{Var}\left[\,\widehat{t}_{\textnormal{SRS}}\,\right]$ and $\textnormal{Var}\left[\,\widehat{t}_{\textnormal{PropStr}}\,\right]$ always holds (see [3], p.106):

$$\textnormal{Var}\left[\,\widehat{t}_{\textnormal{SRS}}\,\right] \;=\; \textnormal{Var}\left[\,\widehat{t}_{\textnormal{PropStr}}\,\right] + \left(1 - \frac{n}{N}\right)\frac{N}{n}\,\frac{N}{N-1}\left\{\,\textnormal{SSB} - \sum_{h=1}^{H}\left(1 - \frac{N_h}{N}\right)S_h^2\,\right\},$$

where

$$\textnormal{SSB} \;:=\; \sum_{h=1}^{H} N_h\left(\overline{y}_{\mathcal{U}_h} - \overline{y}_{\mathcal{U}}\right)^2 \;=\; \sum_{h=1}^{H}\sum_{i\in\mathcal{U}_h}\left(\overline{y}_{\mathcal{U}_h} - \overline{y}_{\mathcal{U}}\right)^2$$

is the *inter-strata squared deviation* (or *between-strata squared deviation*). It is also an easily established fact that the sum of the inter-strata squared deviation SSB and the intra-strata squared deviation SSW is always the total population squared deviation SSTO:

$$\textnormal{SSTO} \;:=\; \sum_{i=1}^{N}\left(y_i - \overline{y}_{\mathcal{U}}\right)^2 \;=\; \sum_{h=1}^{H}\sum_{i\in\mathcal{U}_h}\left(y_i - \overline{y}_{\mathcal{U}}\right)^2\,.$$

Most importantly, we see from above that, for stratified simple random sampling with proportional allocation, the following implication holds:

$$\sum_{h=1}^{H}\left(1 - \frac{N_h}{N}\right)S_h^2 \;\leq\; \textnormal{SSB} \quad\Longrightarrow\quad \textnormal{Var}\left[\,\widehat{t}_{\textnormal{PropStr}}\,\right] \leq \textnormal{Var}\left[\,\widehat{t}_{\textnormal{SRS}}\,\right]\,.$$

In heuristic terms, in proportional-allocation stratification for which each stratum is relatively homogeneous and the strata are relatively dissimilar to each other (intra-strata variation being smaller than inter-strata variation), then the unbiased estimator for the population total from the proportional-allocation stratified simple random sampling is more precise than that from SRS.

4 Two-stage Cluster Sampling

The universe $\mathcal{U} = \displaystyle\bigsqcup_{i=1}^{N}\mathcal{C}_i$ of observation units is partitioned into N *clusters* (or *primary sampling units*, psu's) $\mathcal{C}_i$. In two-stage cluster sampling, the *secondary sampling units* (or ssu's) are the observation units. Let M_i be the number of ssu's in the ith psu; in other words, $M_i := \#(\mathcal{C}_i)$.

First Stage: Select a simple random sample (SRS) $\omega_1 = \{\,\mathcal{C}_{i_1}, \mathcal{C}_{i_2}, \ldots, \mathcal{C}_{i_n}\,\}$ of n psu's from the collection of N psu's.

Second Stage: From each psu $\mathcal{C} \in \omega_1$ selected in the First Stage, select a simple random sample (SRS) $\omega_{\mathcal{C}}$ of m_i secondary sampling units (ssu's) from the collection of M_i ssu's in $\mathcal{C}$.

The sample is then $\omega := \displaystyle\bigsqcup_{\mathcal{C}\in\omega_1}\omega_{\mathcal{C}}$. In other words, the sample ω consists of all the secondary sampling units (or observation units) selected (during the Second Stage) from all the primary sampling units selected in the First Stage.

The Horvitz-Thompson estimator $\widehat{t}_{\textnormal{HT}}$, as defined below, is an unbiased estimator for the total of an $\mathbb{R}$-valued population characteristic $y : \mathcal{U} \longrightarrow \mathbb{R}$.

$$\widehat{t}_{\textnormal{HT}} \;\;:=\;\; \sum_{k\in\omega}\left(\frac{N}{n}\frac{M_{y_k}}{m_{y_k}}\right)y_k \;\;=\;\; \sum_{k\in\omega}\left(\frac{1}{\pi_k}\right)y_k \;\;=\;\; \sum_{\mathcal{C}\in\omega_1}\sum_{k\in\omega_{\mathcal{C}}}\left(\frac{N}{n}\frac{M_{y_k}}{m_{y_k}}\right)y_k,$$

where $M_{y_k} := M_i := \#(\mathcal{C}_i)$ and $m_{y_k} := m_i := \#(\omega_{\mathcal{C}_i})$ such that $\mathcal{C}_i$ is the unique psu containing the ssu $k \in \mathcal{U} = \bigsqcup_{i}^{N} \mathcal{C}_i$.

The variance of the Horvitz-Thompson estimator $\widehat{t}_{\mathrm{HT}}$ is given by:

$$\mathrm{Var}\big(\,\widehat{t}_{\mathrm{HT}}\,\big) \;=\; N^2\left(1-\frac{n}{N}\right)\frac{S_t^2}{n} \;+\; \sum_{i=1}^{N}\frac{N}{n}\cdot M_i^2\left(1-\frac{m_i}{M_i}\right)\frac{S_i^2}{m_i},$$

where

$$S_t^2 \;:=\; \frac{1}{N-1}\sum_{i=1}^{N}\left(t_i-\frac{t}{N}\right)^2, \quad S_i^2 \;:=\; \frac{1}{M_i-1}\sum_{j=1}^{M_i}\left(y_j-\frac{t_i}{M_i}\right)^2, \quad t \;:=\; \sum_{k\in\mathcal{U}} y_k\,, \quad \text{and} \quad t_i \;:=\; \sum_{k\in\mathcal{C}_i} y_k$$

IMPORTANT OBSERVATION: The first summand in the expression of $\mathrm{Var}\big(\,\widehat{t}_{\mathrm{HT}}\,\big)$ is due to variability in the First-Stage sampling, whereas the second summand is due to variability in the Second-Stage sampling.

5 One-stage Cluster Sampling

One-stage cluster sampling is a special form of two-stage cluster sampling in which all second-stage samples are censuses. In other words, following the notation introduced for two-stage cluster sampling, in one-stage cluster sampling, we have $\omega_{\mathcal{C}} = \mathcal{C}$, for each first-stage-selected $\mathcal{C} \in \omega_1$. This also implies $m_i = M_i$ for each $i = 1, 2, \ldots, N$.

Then, the Horvitz-Thompson estimator $\widehat{t}_{\mathrm{HT}}$ and its variance reduces to:

$$\begin{aligned}
\widehat{t}_{\mathrm{HT}} \;&:=\; \sum_{\mathcal{C}\in\omega_1}\sum_{k\in\mathcal{C}}\left(\frac{N}{n}\frac{M_{y_k}}{m_{y_k}}\right)y_k \;=\; \frac{N}{n}\cdot\sum_{\mathcal{C}\in\omega_1}\sum_{k\in\mathcal{C}} y_k \;=\; \frac{N}{n}\cdot\sum_{\mathcal{C}\in\omega_1} t_{\mathcal{C}}\,, \quad \text{where } t_{\mathcal{C}} := \sum_{k\in\mathcal{C}} y_k \\
\mathrm{Var}\big(\,\widehat{t}_{\mathrm{HT}}\,\big) \;&=\; N^2\left(1-\frac{n}{N}\right)\frac{S_t^2}{n} \;+\; \sum_{i=1}^{N}\frac{N}{n}\cdot M_i^2\left(1-\frac{m_i}{M_i}\right)\frac{S_i^2}{m_i} \\
&=\; N^2\left(1-\frac{n}{N}\right)\frac{S_t^2}{n} \;+\; \sum_{i=1}^{N}\frac{N}{n}\cdot M_i^2\,(1-1)\,\frac{S_i^2}{m_i} \;=\; N^2\left(1-\frac{n}{N}\right)\frac{S_t^2}{n}
\end{aligned}$$

6 Stratified Simple Random Sampling as a special case of Two-stage Cluster Sampling

Stratified simple random sampling is a special case of two-stage cluster sampling in which the first-stage sampling is a census. In other words, if $\mathcal{U} = \bigsqcup_{i=1}^{N} \mathcal{C}_i$, then $\omega_1 = \{\,\mathcal{C}_1, \mathcal{C}_2, \ldots, \mathcal{C}_N\,\}$. In particular, $n = N$.

Then, the Horvitz-Thompson estimator $\widehat{t}_{\mathrm{HT}}$ and its variance reduces to:

$$\begin{aligned}
\widehat{t}_{\mathrm{HT}} \;&:=\; \sum_{\mathcal{C}\in\omega_1}\sum_{k\in\omega_{\mathcal{C}}}\left(\frac{N}{n}\frac{M_{y_k}}{m_{y_k}}\right)y_k \;=\; \sum_{i=1}^{N} M_i\left(\frac{1}{m_i}\sum_{k\in\omega_{\mathcal{C}_i}} y_k\right) \;=\; \sum_{i=1}^{N} M_i\,\overline{y}_{\omega_{\mathcal{C}_i}} \\
\mathrm{Var}\big(\,\widehat{t}_{\mathrm{HT}}\,\big) \;&=\; N^2\left(1-\frac{n}{N}\right)\frac{S_t^2}{n} \;+\; \sum_{i=1}^{N}\frac{N}{n}\cdot M_i^2\left(1-\frac{m_i}{M_i}\right)\frac{S_i^2}{m_i} \\
&=\; N^2\,(1-1)\,\frac{S_t^2}{n} \;+\; \sum_{i=1}^{N} 1\cdot M_i^2\left(1-\frac{m_i}{M_i}\right)\frac{S_i^2}{m_i} \;=\; \sum_{i=1}^{N} M_i^2\left(1-\frac{m_i}{M_i}\right)\frac{S_i^2}{m_i}
\end{aligned}$$

The above formula agree exactly with those derived earlier for stratified simple random sampling (apart from obvious notational changes).

7 Generalized Regression Estimator as a special case of Calibration Estimators

This is a summary of [1].

Let $U = \{1, 2, \ldots, N\}$ be a finite population. Let $y : U \longrightarrow \mathbb{R}$ be an $\mathbb{R}$-valued function defined on U (commonly called a "population parameter"). We will use the common notation y_i for $y(i)$. We wish to estimate $T_y := \sum_{i \in U} y_i$ via survey sampling. Let $p : \mathcal{S} \longrightarrow (0, 1]$ be our chosen sampling design, where $\mathcal{S} \subseteq \mathcal{P}(U)$ is the set of all possible samples in the design, and $\mathcal{P}(U)$ is the power set of U. For each $k \in U$, let $\pi_k := \sum_{s \ni k} p(s)$ be the inclusion probability of k under the sampling design p. We assume $\pi_k > 0$ for each $k \in U$. Then, the Horvitz-Thompson estimator

$$\widehat{T}_y^{\mathrm{HT}}(s) \;:=\; \sum_{k \in s} \frac{y_k}{\pi_k} \;=\; \sum_{k \in s} d_k y_k \;=\; \sum_{k \in U} I_{ks} \frac{y_k}{\pi_k}, \quad \text{where } d_k := \frac{1}{\pi_k} \text{ and } I_{ks} \;:=\; \begin{cases} 1, & \text{if } k \in s \\ 0, & \text{otherwise} \end{cases}$$

is well-defined and is known to be a design-unbiased estimator of T_y; in other words,

$$E_p\!\left[\, \widehat{T}_y^{\mathrm{HT}} \,\right] \;=\; \sum_{s \in \mathcal{S}} p(s) \cdot \widehat{T}_y^{\mathrm{HT}}(s) \;=\; \sum_{s \in \mathcal{S}} p(s) \cdot \left(\sum_{k \in U} I_{ks} \frac{y_k}{\pi_k} \right) \;=\; \sum_{k \in U} \frac{y_k}{\pi_k} \left(\sum_{s \in \mathcal{S}} p(s) I_{ks} \right) \;=\; \sum_{k \in U} \frac{y_k}{\pi_k} \pi_k \;=\; T_y.$$

We will call the d_k's above the *Horvitz-Thompson weights.*

Roughly, the generalized regression estimator for T_y is an estimator of the form:

$$\widehat{T}_y^{\mathrm{GREG}}(s) \;:=\; \sum_{k \in s} w_k(s) y_k,$$

where the sample-dependent "calibrated" weights $w_k(s)$ are the solution of a certain constrained minimization problem (see below) where the objective function depends on the $w_k(s)$'s and the Horvitz-Thompson weights d_k's, while the constraints involve the $w_k(s)$'s and auxiliary information. More precisely, the calibrated weights $w_k(s)$ solve the following constrained minimization problem:

Constrained Minimization Problem for the GREG calibrated weights

Conceptual framework: Let $\mathbf{x} : U \longrightarrow \mathbb{R}^{1 \times J}$ be an $\mathbb{R}^{1 \times J}$-valued function defined on U. We use the common notation $\mathbf{x}_k$ for $\mathbf{x}(k)$, for each $k \in U$.

Assumptions:

- The population total of $\mathbf{x}$
$$T_{\mathbf{x}} \;:=\; \sum_{k \in U} \mathbf{x}_k \in \mathbb{R}^{1 \times J}$$
is known.
- For each $s \in \mathcal{S}$, the value $(y_k, \mathbf{x}_k)$ can be observed for each $k \in s$ via the sampling procedure.

Constrained Minimization Problem: For each $k \in U$, let $q_k > 0$ be chosen. For each $s \in \mathcal{S}$, the calibrated weights $w_k(s)$, for $k \in s$, are obtained by minimizing the following objective function:

$$f_s(w_k(s)\,;\,d_k, q_k) \;:=\; \sum_{k \in s} \frac{(w_k(s) - d_k)^2}{d_k q_k}$$

subject to the (vectorial) constraint on $w_k(s)$:

$$\mathbf{h}(w_k(s)\,;\,\mathbf{x}_k, T_{\mathbf{x}}) \;:=\; -T_{\mathbf{x}} + \sum_{k \in s} w_k(s)\,\mathbf{x}_k \;=\; 0$$

The above constrained minimization problem for the calibrated weights can be solved by the method of Lagrange Multipliers.

Solution of the Constrained Minimization Problem for the Generalized Regression Estimator calibrated weights:
Let $s \in \mathcal{S}$ be fixed. We write the objective function as

$$f(\{w_k(s)\,:\,k \in s\}) \;=\; \sum_{k\in s} \frac{(w_k(s) - d_k)^2}{d_k q_k},$$

and we write the constraints on $w_k(s)$ as:

$$h_j(\{w_k(s)\,:\,k \in s\}) \;=\; \sum_{k\in s} w_k(s)\,x_{kj} - T_{x_j} = 0, \quad j = 1,2,\ldots,J.$$

By the Method of Lagrange Multipliers, if $\mathbf{w}_0 = \{w_k(s)\,:\,k \in s\}$ is a solution to the constrained minimization problem, then $\mathbf{w}_0$ satisfies:

$$\nabla_w f(\mathbf{w}_0) \;\in\; \text{span}\{\,\nabla_w h_j(\mathbf{w}_0)\,:\, j = 1,2,\ldots,J\,\}\,.$$

Now,

$$\frac{\partial f}{\partial w_k(s)} \;=\; \frac{2(w_k(s) - d_k)}{d_k q_k} \quad\text{and}\quad \frac{\partial h_j}{\partial w_k(s)} \;=\; x_{kj}.$$

Thus, we seek $\lambda_1, \lambda_2, \ldots, \lambda_J$ such that

$$\frac{2(w_k(s) - d_k)}{d_k q_k} \;=\; \frac{\partial f}{\partial w_k(s)} \;=\; \sum_{j=1}^{J} 2\,\lambda_j\,\frac{\partial h_j}{\partial w_k(s)} \;=\; \sum_{j=1}^{J} 2\,\lambda_j\,x_{kj},$$

which immediately implies:

$$w_k(s) \;=\; d_k\left(1 + q_k \sum_{j=1}^{J} \lambda_j x_{kj}\right).$$

Substituting the above expression for $w_k(s)$ back into the constraints yields, for each $i = 1,2,\ldots,J$:

$$-T_{x_i} + \sum_{k\in s} d_k\left(1 + q_k\sum_{j=1}^{J}\lambda_j x_{kj}\right)x_{ki} = 0,$$

which can be rearranged to be:

$$\sum_{k\in s} d_k\,x_{ki} + \sum_{j=1}^{J}\left(\sum_{k\in s} d_k q_k x_{ki} x_{kj}\right)\lambda_j = T_{x_i}$$

The preceding equation can be rewritten in vectorial form:

$$\widehat{T}^{\text{HT}}_{\mathbf{x}}(s) + \mathbf{A}(s)\cdot\lambda \;=\; T_{\mathbf{x}},$$

where $\mathbf{A}(s) \in \mathbb{R}^{J\times J}$ is the symmetric matrix with entries:

$$\mathbf{A}(s)_{ij} = \sum_{k\in s} d_k q_k x_{ki} x_{kj}.$$

Assuming the matrix $\mathbf{A}(s)$ is invertible, the vector λ of Lagrange multipliers is given by:

$$\lambda \;=\; \mathbf{A}(s)^{-1}\left(T_{\mathbf{x}} - \widehat{T}^{\text{HT}}_{x}(s)\right).$$

Hence, the generalized regression estimator $\widehat{T}_y^{\text{GREG}}(s)$ is given by:

$$\begin{aligned}
\widehat{T}_y^{\text{GREG}}(s) &= \sum_{k\in s} w_k(s)y_k \;=\; \sum_{k\in s} d_k(1+q_k\,\mathbf{x}_k^T\,\lambda)\,y_k \;=\; \sum_{k\in s} d_k y_k + \sum_{k\in s} d_k q_k(\mathbf{x}_k^T\cdot\lambda)\,y_k \\
&= \widehat{T}_y^{\text{HT}}(s) + \left(\sum_{k\in s} d_k q_k y_k\cdot\mathbf{x}_k^T\right)\cdot\lambda \\
&= \widehat{T}_y^{\text{HT}}(s) + \left(\sum_{k\in s} d_k q_k y_k\cdot\mathbf{x}_k^T\right)\cdot\mathbf{A}(s)^{-1}\cdot\Big(T_{\mathbf{x}} - \widehat{T}_x^{\text{HT}}(s)\Big)\,.
\end{aligned}$$

□

8 Conditional inference in finite-population sampling

In this section, we give a justification for making inference conditional on the observed sample size for sampling designs with random sample size.

Observation ("mixture" of experiments) [see [4], p.15.]
Consider a population $\mathcal{U}$ of 1000 units. We wish to estimate the total T_y of a certain population characteristic $\mathbf{y} = (y_1, y_2, \ldots, y_{1000})$. Suppose we use the following two-step sampling scheme:

- Step 1: We first flip a fair coin.
  Define the random variable X by letting $X = 1$ if the coin lands heads, and $X = 0$ if it lands tails.
- Step 2: If $X = 1$, we select an SRS from $\mathcal{U}$ of size 100. If $X = 0$, we take a census on all of $\mathcal{U}$.

Let $\mathcal{S} \subset \mathcal{P}(\mathcal{U})$ denote the probability space of all possible samples induced by the (two-step) sampling design above. Note that $\mathcal{S} = \mathcal{S}_0 \sqcup \mathcal{S}_1$, where $\mathcal{S}_0 = \{\,\mathcal{U}\,\}$ and $\mathcal{S}_1$ is the set of all subsets of $\mathcal{U}$ of size 100. The sampling design is determined by the following probability distribution on $\mathcal{S}$:

$$P(\,\mathcal{U}\,) = \frac{1}{2} \quad\text{and}\quad P(\,s\,) = \frac{1}{2\left(\begin{array}{c}1000\\100\end{array}\right)}, \quad\text{for each } s\in\mathcal{S}_1.$$

Let $\widehat{T}_y : \mathcal{S} \longrightarrow \mathbb{R}$ denote our chosen estimator for T_y. Then the (unconditional) probability distribution of $\widehat{T}_y$ can be "decomposed" as follows:

$$\begin{aligned}
P\left(\widehat{T}_y = t\,\middle|\,\mathbf{y}\right) &= P\left(\widehat{T}_y = t,\, X=0\,\middle|\,\mathbf{y}\right) + P\left(\widehat{T}_y = t,\, X=1\,\middle|\,\mathbf{y}\right) \\
&= P\left(\widehat{T}_y = t\,\middle|\,X=0,\,\mathbf{y}\right)\cdot P(\,X=0\mid\mathbf{y}\,) + P\left(\widehat{T}_y = t\,\middle|\,X=1,\,\mathbf{y}\right)\cdot P(\,X=1\mid\mathbf{y}\,) \\
&= P\left(\widehat{T}_y = t\,\middle|\,X=0,\,\mathbf{y}\right)\cdot P(\,X=0\,) + P\left(\widehat{T}_y = t\,\middle|\,X=1,\,\mathbf{y}\right)\cdot P(\,X=1\,)\,,
\end{aligned}$$

where the last equality follows because the distribution of X is independent of $\mathbf{y}$. Suppose the observation we make consists of $\left(\widehat{T}_y\,,\,X\right)$. The unconditional probability distribution of $\widehat{T}_y$, given by $P\left(\widehat{T}_y = t\,\middle|\,\mathbf{y}\right)$ above, describes of course the randomness of the estimator $\widehat{T}_y$ as induced by both the randomness of the sample $s \in \mathcal{S} = \mathcal{S}_0 \sqcup \mathcal{S}_1$ as well as that of X (the outcome of the coin flip in Step 1). Now, suppose we have indeed carried out the sampling procedure and have obtained an observation of $\left(\widehat{T}_y\,,\,X\right)$. Suppose it happened that $X = 1$. Hence, we know that the estimate $\widehat{T}_y(s)$ we actually obtained was generated from an SRS of size 100 (rather than a census). Note also that the probability distribution of X is independent of $\mathbf{y}$ and the observation of X gives no information about $\mathbf{y}$. One school of thought therefore argues that downstream inferences about $\mathbf{y}$ should be carried out using the conditional probability $P\left(\widehat{T}_y = t\,\middle|\,X=1\,,\,\mathbf{y}\right)$, rather than the unconditional probability $P\left(\widehat{T}_y = t\,\middle|\,\mathbf{y}\right)$. In other words, in the present example, as far as making inferences about $\mathbf{y}$ is concerned, only the randomness in Step 2 is relevant, and the randomness in Step 1 (i.e. the randomness of X, the outcome of the coin flip) is irrelevant to any inference about $\mathbf{y}$. Consequently randomness of X "should" be removed in any inference procedure for $\mathbf{y}$, and this is achieved by conditioning on the observed value of X. □

Conditioning on obtained sample size for sample designs with random sample size

Suppose $\mathcal{U}$ is a finite population. We wish to estimate the total $T_y = \sum_{i\in\mathcal{U}} y_i$ of a population characteristic $\mathbf{y} : \mathcal{U} \longrightarrow \mathbb{R}$, using a sample design $p : \mathcal{S} \longrightarrow [\,0\,,1\,]$ and a estimator $\widehat{T} : \mathcal{S} \longrightarrow \mathbb{R}$. We make the assumption that the sampling design p is independent of $\mathbf{y}$. Let $N : \mathcal{S} \longrightarrow \mathbb{N} \cup \{\,0\,\}$ be the random variable of sample size, i.e. $N(s)$ = number of elements in s, for each possible sample $s \in \mathcal{S}$. Then,

$$\begin{aligned} P\left(\widehat{T}=t \,\middle|\, \mathbf{y}\right) &= \sum_n P\left(\widehat{T}=t,\, N=n \,\middle|\, \mathbf{y}\right) \\ &= \sum_n P\left(\widehat{T}=t \,\middle|\, N=n,\, \mathbf{y}\right)\cdot P\left(\,N=n \,|\, \mathbf{y}\,\right) \\ &= \sum_n P\left(\widehat{T}=t \,\middle|\, N=n,\, \mathbf{y}\right)\cdot P\left(N=n\right), \end{aligned}$$

where the last equality follows from the assumed independence of the probability distribution $p : \mathcal{S} \longrightarrow [\,0\,,\,1\,]$ (hence that of N) from $\mathbf{y}$. The key observation to make now is that: Although the actual sampling procedure operationally may or may not have been a two-step procedure, the independence of p from $\mathbf{y}$ makes it probabilistically equivalent to a two-step procedure, as shown by the above decomposition of $P\left(\widehat{T}=t \,\middle|\, \mathbf{y}\right)$ — Step (1): randomly select a sample size $N = n$ according to the distribution $P(N = n)$, and then Step (2): randomly select a sample s of size n chosen in Step (1) according to the distribution $P(\,s \mid N = n\,)$. By the statistical reasoning explained in the preceding observation, it follows that post-sampling inference about $\mathbf{y}$ should be made based on the conditional distribution $P\left(\widehat{T}=t \,\middle|\, N=n\,,\,\mathbf{y}\right)$, rather than the unconditional distribution $P\left(\widehat{T}=t \,\middle|\, \mathbf{y}\right)$. This is because the sampling scheme is probabilistically equivalent to a two-step procedure, with the probability distribution of the first step (choosing a sample size) independent of the parameters of interest (T_y), and thus only the probability distribution of the second step (choosing a sample of the size chosen in first step) should be used to make inference about T_y. □

Caution

In more formal parlance, the random variable $N : \mathcal{S} \longrightarrow \mathbb{N} \cup \{\,0\,\}$ is ancillary to the parameter $\mathbf{y}$. Thus, conditioning on sample size, for finite-population sampling schemes with random sample size, *partially* conforms to the **Conditionality Principle**, which states that statistical inference about a parameter should be made conditioned on observed values of statistics ancillary to that parameter. The conformance is only partial due to the (obvious) fact that it is the sample s itself which is ancillary to the parameter of interest $\mathbf{y}$, not just its sample size $N(s)$. Thus, full conformance to the Conditionality Principle would require inference about $\mathbf{y}$ be made conditioned on the observed sample s itself (rather than its size $N(s)$). However, if we did condition on the obtained sample s itself, the domain of the estimator $\widehat{T}$ would be restricted to the singleton $\{\,s\,\}$, and $\widehat{T}$ could then attain only one value under conditioning on s, and no randomization-based (i.e. design-based) inference — apart from the observed value of $\widehat{T}(s)$ — could be made any longer.

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