

- In the following discussion of this topic, we consider the without-replacement case, but neglect the finite population correction. Actually, this is equivalent to the with-replacement case. $n_l \ll N_l$ assume $n_l's \in \mathbb{R}$

Theorem 24 (optimal allocation of the sample size n in a stratified random sampling)

Neglecting the finite population correction, the subsample sizes n_1, \dots, n_L that minimize $Var(\bar{X}_S)$ subject to the constraint $n_1 + n_2 + \dots + n_L = n$ are

$$n_l \propto \frac{W_l \sigma_l}{\bar{\sigma}} \quad \text{where } \bar{\sigma} = \sum_{l'=1}^L W_{l'} \sigma_{l'} \text{ is a weighted average of } \sigma_1, \dots, \sigma_L.$$

sum over $l \Rightarrow$ equal 1 $l = 1, 2, \dots, L$

minimize $Var(\bar{X}_S)$ subject to $(n_1 + \dots + n_L) - n = 0$

Proof. Introduce a Lagrange multiplier λ , and minimize

$$L(n_1, \dots, n_L, \lambda) = Var(\bar{X}_S) + \lambda \left(\sum_{l'=1}^L n_{l'} - n \right) = \sum_{l'=1}^L \frac{W_{l'}^2 \sigma_{l'}^2}{n_{l'}} + \lambda \left(\sum_{l'=1}^L n_{l'} - n \right).$$

target function

Setting the partial derivatives equal to zero

$$0 = \frac{\partial L}{\partial n_l} = -\frac{W_l^2 \sigma_l^2}{n_l^2} + \lambda, \quad l = 1, \dots, L, \quad \text{and} \quad \frac{\partial L}{\partial \lambda} = \sum_{l'=1}^L n_{l'} - n = 0$$

we have

$$n_l = \frac{W_l \sigma_l}{\sqrt{\lambda}}, \quad l = 1, \dots, L \Rightarrow n = \sum_{l'=1}^L n_{l'} = \frac{1}{\sqrt{\lambda}} \sum_{l'=1}^L W_{l'} \sigma_{l'}$$

Thus,

$$\frac{1}{\sqrt{\lambda}} = \frac{n}{\sum_{l'=1}^L W_{l'} \sigma_{l'}} \Rightarrow n_l = n \times \frac{W_l \sigma_l}{\sum_{l'=1}^L W_{l'} \sigma_{l'}}$$

proportion of the sample size n allocated to S_l

Note 18 (Some notes about the optimal allocation scheme)

- This theorem shows that those strata with large $W_l \sigma_l$ should be sampled heavily. This makes sense intuitively because
 - W_l is large $\Rightarrow S_l$ contains a large fraction of $\Omega \Rightarrow$ sample more
 - σ_l is large $\Rightarrow x_{i,l}$'s in S_l are quite variable \Rightarrow a relatively large n_l is required to obtain a good determination of $\mu_l \leftarrow Var(\bar{X}_l) \propto \sigma_l^2/n_l$
- This optimal allocation scheme depends on the within-stratum variances $\sigma_1^2, \dots, \sigma_L^2$, which generally is unknown before sampling.
- If a survey measures several attributes, it is usually impossible to find an allocation optimal for all attributes. $x_i's, y_i's, z_i's, \dots \Rightarrow \sigma_{l,x} \neq \sigma_{l,y} \neq \sigma_{l,z} \neq \dots$

Definition 23 (optimal stratified estimator)

- This optimal allocation scheme is called **Neyman allocation**.

- Denote the stratified estimator under this optimal allocation scheme by

$$\text{Data from scheme 1} \rightarrow \sum_l W_l \bar{X}_l \rightarrow \bar{X}_{S,o}$$

Theorem 25 (variance of the optimal stratified estimator)

Neglecting the finite population correction, and substituting the optimal values of n_l 's in Thm. 24 (LNp.69) for the variance of the stratified estimator \bar{X}_S of μ presented in Thm. 22 (LNp.65) gives us

$$Var(\bar{X}_{S,o}) \approx \sum_{l=1}^L W_l^2 \left(\frac{\sigma_l^2}{n_l} \right) = \sum_{l=1}^L \frac{W_l^2 \sigma_l^2}{n(W_l \sigma_l) / \bar{\sigma}} = \frac{\bar{\sigma}^2}{n} = \frac{1}{n} \left(\sum_{l=1}^L W_l \sigma_l \right)^2$$

$[E(Z_6)]^2$ (Z_6 : check LNp.69)

Definition 24 (Proportional allocation and its stratified estimator)

• **Proportional allocation.** A simple and popular alternative method of allocation is to use the same sampling fraction in each stratum, i.e.,

$$\frac{n_1}{N_1} = \frac{n_2}{N_2} = \dots = \frac{n_L}{N_L} = p \left(= \frac{n}{N} \right), \quad n_l = p N_l, \quad l = 1, \dots, L$$

which holds iff $n_l = n(N_l/N) = n W_l$ for $l = 1, \dots, L$. $\Rightarrow p = n/N$

optimal allocation
 $n_l \propto W_l \sigma_l$

$W_l = \frac{N_l}{N}$
 $= N_l/N$

• Denote the stratified estimator under the proportional allocation scheme by

Data from scheme 2 $\rightarrow \sum_l W_l \bar{X}_l \rightarrow \bar{X}_{S,p}$

(Note. $\bar{X}_{S,o}$ and $\bar{X}_{S,p}$ are the estimator \bar{X}_S under two different allocation schemes (different n_l 's, different possible samples (LNp.62), different joint distribution of data (LNp.64)). They are not different estimators.)

Note 13, LNp.55

Note 19 (Some notes about the proportional allocation)

based on same data, eg.

- Compared to the optimal allocation schemes, the proportional allocation neglects the difference in within-stratum variances σ_l 's. \leftarrow same n_l 's
- If $\sigma_1 = \sigma_2 = \dots = \sigma_L = \bar{\sigma}$, proportional allocation = optimal allocation, and $\bar{X}_{S,p}$ and $\bar{X}_{S,o}$ have same variance (accuracy).
- Under the proportional allocation,

$$\bar{X}_{S,p} = \sum_{l=1}^L W_l \bar{X}_l = \sum_{l=1}^L \left(\frac{n_l}{n} \right) \left(\frac{1}{n_l} \sum_{k=1}^{n_l} X_{k,l} \right) = \frac{1}{n} \sum_{l=1}^L \sum_{k=1}^{n_l} X_{k,l}$$

which is the unweighted mean of the sampled data. \leftarrow equal weights

Example 21 (optimal and proportional allocations, cont. Ex.20 in LNp.68)

Ch7, p.72

Consider the population of 393 hospitals. The sampling fractions of the 4 strata are

Stratum	A	B	C	D	
optimal allocation	0.106	0.210	0.250	0.434	$\leftarrow W_l \sigma_l / (\sum_l W_l \sigma_l)$
proportional allocation	0.249	0.249	0.249	0.252	$\leftarrow W_l$

Theorem 26 (variance of the stratified estimator under proportional allocation)

Ignoring the finite population correction, and substituting the proportional allocation, $n_l = n W_l$, for the variance of the stratified estimator \bar{X}_S of μ presented in Thm. 22 (LNp.65) gives us

$$Var(\bar{X}_{S,p}) \approx \sum_{l=1}^L W_l^2 \left(\frac{\sigma_l^2}{n_l} \right) = \sum_{l=1}^L \frac{W_l^2 \sigma_l^2}{n W_l} = \frac{1}{n} \left(\sum_{l=1}^L W_l \sigma_l^2 \right)$$

$n_l \ll N_l$

Theorem 27 (variance difference between the optimal and proportional allocations)

Ignoring the finite population correction, from Thm.25 (LNp.70) and Thm.26,

$$Var(\bar{X}_{S,p}) - Var(\bar{X}_{S,o}) \approx \frac{1}{n} \left(\sum_{l=1}^L W_l \sigma_l^2 \right) - \frac{1}{n} \bar{\sigma}^2 = \frac{1}{n} \sum_{l=1}^L W_l (\sigma_l - \bar{\sigma})^2 \geq 0$$

Note that

more accurate

$E(Z_\sigma^2)$

$- [E(Z_\sigma)]^2$

$Var(Z_\sigma)$

- If $\sigma_1 = \sigma_2 = \dots = \sigma_L$, then $Var(\bar{X}_{S,p}) = Var(\bar{X}_{S,o})$.

- The more variable these σ_l 's are, the better it is to use (if feasible) the optimal allocation.

the impact of total sample size Z_σ (r.v.) $\in \{\sigma_1, \dots, \sigma_L\}$
 $E(Z_\sigma) = \bar{\sigma}, E(Z_\sigma^2) = ?, Var(Z_\sigma) = ?$

σ_l 's are more distinct, not they are large

- $$\frac{\text{Var}(\bar{X}_{S,o}) + \text{Var}(\bar{X}_{S,p}) - \text{Var}(\bar{X}_{S,o})}{\text{Var}(\bar{X}_{S,p})} = 1 + \frac{\sum_l W_l (\sigma_l - \bar{\sigma})^2}{\bar{\sigma}^2} = 1 + 0.218.$$
- CV² of Z_σ (check Def. 16, LN p. 56)

- **Q: When** can a stratified random sample based on proportional allocation perform better than a simple random sample? Note that

But, not every stratified random sampling can successfully exclude biased samples

- under proportional allocation, $\bar{X}_{s,p}$ and \bar{X} , where \bar{X} is the sample mean of the data from a s.r.s., have the same functional form, **← Note 19 (LNp.71)**
 - a s.r.s. has more possible samples than a stratified random sample (check Thm. 21, LNp.62).
- S.R.S. = same estimator \bar{y} (= $\bar{y}_{s,p}$)**

- Recall. proportional allocation $\xrightarrow{\text{same estimator } \hat{\mu}(\cdot, S; E)} \mu$
- Under a s.r.s. without replacement, neglecting the finite population correction, we have $\text{Var}(\bar{X}) \approx \sigma^2/n$ (check Thm.3, LNp.18).
 - From Thm.20 (LNp.61), $n \ll N$ $\leftarrow n \times \text{Var}(\bar{X}_{s,p})$ $\boxed{Z\mu}$ $\boxed{\text{Var}[E(x|z)]}$

$$E[\text{Var}(x|Z)] = \sigma^2 = \sum_{l=1}^L W_l \sigma_l^2 + \sum_{l=1}^L W_l (\mu_l - \mu)^2.$$

Theorem 28 (variance difference between s.r.s. and proportional allocation)

Ignoring the finite population correction, from Thm.26 (LNp.71), we have

$$\underbrace{Var(\bar{X}) - Var(\bar{X}_{S,p})}_{\text{variance reduction}} \approx \underbrace{\frac{\sigma^2}{n}}_{\text{variance of sample mean}} - \underbrace{\frac{1}{n} \left(\sum_{l=1}^L W_l \sigma_l^2 \right)}_{E[Var(x|Z)]} = \underbrace{\frac{1}{n} \left[\sum_{l=1}^L W_l (\mu_l - \mu)^2 \right]}_{Var[E(x|z)]} \geq 0.$$

Note 20 (Some notes about s.r.s., proportional allocation, and optimal allocation)

- Stratified random sampling with proportional allocation is better than s.r.s., which is a result of excluding some unwanted simple random samples.

Comparing the equations for the variances under s.r.s., proportional allocation, and optimal allocation, we see that

The diagram illustrates the proof of Theorem 26, showing the decomposition of the variance of the sample mean. It starts with the definition of the sample mean \bar{X} and its variance $\frac{\sigma^2}{n}$. The proof then uses the law of total variance to decompose the variance into the variance of the conditional means and the conditional variances. The conditional means are shown to be the sample means of the individual data points, and the conditional variances are shown to be the variances of the individual data points. The final result is the variance of the sample mean, which is the variance of the individual data points divided by the sample size.

$$\begin{aligned} \frac{\sigma^2}{n} &= \frac{1}{n} \sum_{l=1}^L \frac{W_l \sigma_l^2}{n} + \frac{1}{n} \sum_{l=1}^L \frac{W_l (\mu_l - \mu)^2}{n} \\ &= \frac{\bar{\sigma}^2}{n} + \frac{1}{n} \sum_{l=1}^L \frac{W_l (\sigma_l - \bar{\sigma})^2}{n} + \frac{1}{n} \sum_{l=1}^L \frac{W_l (\mu_l - \mu)^2}{n} \end{aligned}$$

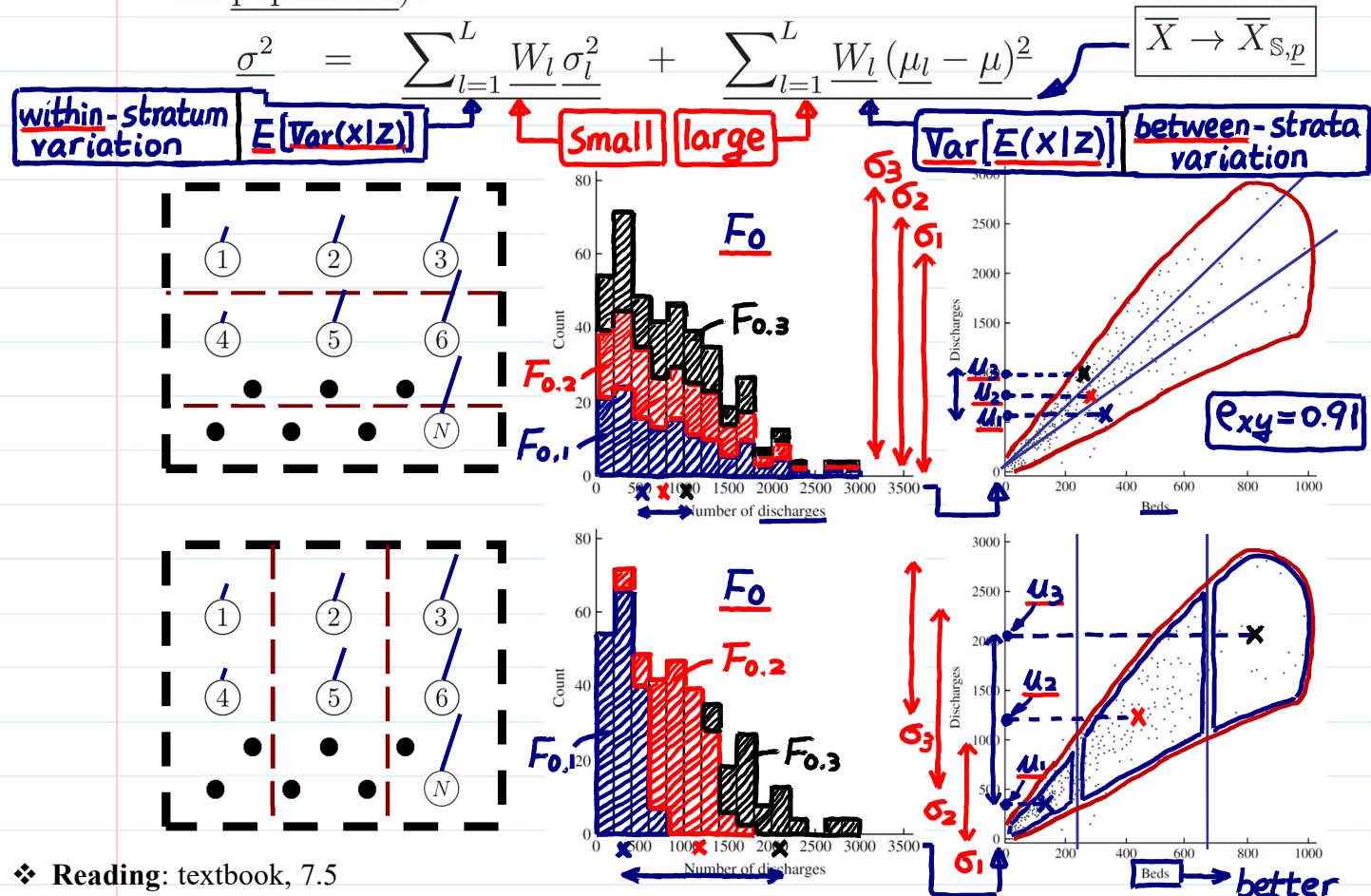
The diagram also shows the relationship between the sample mean and the conditional means, and the relationship between the variance of the sample mean and the variance of the individual data points.

depends on the construction of strata

- $\boxed{\overline{X} \rightarrow \overline{X}_{\mathbb{S}, \underline{p}}}$: $\overline{X}_{\mathbb{S}, \underline{p}}$ much better than \overline{X} if $\underline{\mu}_l$'s are quite variable
- $\boxed{\overline{X}_{\mathbb{S}, p} \rightarrow \overline{X}_{\mathbb{S}, \underline{o}}}$: $\overline{X}_{\mathbb{S}, \underline{o}}$ much better $\overline{X}_{\mathbb{S}, p}$ if $\underline{\sigma}_l$'s are quite variable

• The gain from $\overline{X} \rightarrow \overline{X}_{S,p}$ is often greater than the gain from $\overline{X}_{S,p} \rightarrow \overline{X}_{S,o}$.

- **Q:** Which one is a better way to form strata (i.e., to partition the population)?



❖ Reading: textbook, 7.5

❖ Further reading: textbook, 7.6 (**systematic sampling, cluster sampling, practical difficult**)