Statistical Disclosure Control of Microdata at Statistics Netherlands

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Contents:

1. Statistical Disclosure Control (SDC)

Objective:

Protecting the privacy of respondents when data are released to external users.

Procedure:

1. Detecting unsafe information in data.

2. Processing the data to make the data safe.

Methods for *microdata* differ from methods for *tabular data*.

2. Microdata

Series of records, each containing information on an individual unit (≡ data matrix).

(Tabular data: aggregated microdata)

Availability of microdata:

1. **On site: researchers come to Statistic Netherlands.**
2. **Remote access: using the internet.**
3. **Release under contract: data are made safe against spontaneous recognition.**

Making microdata safe

Identifying variables: variables that can be used to identify a respondent.

- **Direct identifiers (name, address etc.) are deleted from the microdata.**
- **Indirect identifiers.**

Example:

Variables: Place of Residence,
Gender,
Profession.

In the microdata one combination of the scores:

$$\textit{Volendam} \times \textit{female} \times \textit{notary}$$

3. Global Recoding and Local Suppression

Currently used at Statistics Netherlands
(Software: μ-Argus)

Global recoding

Replace *Volendam* by the name of the district:

$$\textit{Noord-Holland} \times \textit{female} \times \textit{notary}$$

Local Suppression

Replace *Volendam* by a missing:

$$\times\, \textit{female} \times \textit{notary}$$

Current practice: first recoding, then suppression

4. Post RAndomisation Method (PRAM)

PRAM is applied to microdata

PRAM concerns the identifying variables in unsafe combinations

Description:

Conditional on the original scores of the variable, the scores are re-classified using a prescribed probability mechanism that allows of misclasssification.

The probability mechanism is provided along with the released microdata.

References:
Kooiman et al. (1997), Warner (1965), and Rosenberg (1979)

Example of PRAM

A file with 100 respondents, several variables, and the binary variable A.

Assume, there is exactly one respondent with score $a = 2$.

Misclassification on purpose:

$a = 1$	→	$a^* = 1$:	90%
$a = 1$	→	$a^* = 2$:	10%
$a = 2$	→	$a^* = 2$:	80%
$a = 2$	→	$a^* = 1$:	20%.

The PRAM matrix $P = (p_{kl})$ where $p_{kl} = \mathrm{P}(A^* = l \mid A = k)$ is given by:

$$P = \begin{pmatrix} 9/10 & 1/10 \\ 2/10 & 8/10 \end{pmatrix}.$$

After applying PRAM, the file is safe (in a certain sense):

$$\mathbf{P}\ (A = 2 \mid A^{*} = 2) \cong 0.075.$$

The identity of the respondent with score 2 is protected by possible misclassification of the score 2 as score 1 *and* by possible misclassification of scores 1 as scores 2.

In general: protection by “outflow” en “inflow”.

<u>Analysis</u>: estimation of frequencies

Let

$$T = \begin{pmatrix} T_1 \\ T_2 \end{pmatrix} = \begin{pmatrix} \#\,\text{scores with value 1} \\ \#\,\text{scores with value 2} \end{pmatrix}$$

and

$$T^* = \begin{pmatrix} \#\,\text{scores with value 1 after PRAM} \\ \#\,\text{scores with value 2 after PRAM} \end{pmatrix}.$$

Then

$$E[T^*{}_1] = p_{11}T_1 + p_{21}T_2$$

$$E[T^*{}_2] = p_{12}T_1 + p_{22}T_2.$$

In matrix notation:

$$E[T^*] = (\mathbf{P})^t\, T.$$

The equality

$$E\left[T^*\right] = \left(\mathbf{P}\right)^t T,$$

provides a unbiased *moment estimator*:

$$\hat{T} = \left(\mathbf{P}^{-1}\right)^t T^*.$$

(Kooiman et al. , 1997)

Variances can be computed.

The estimation of tables is possible with this method

5. Conclusion

Regarding PRAM:

- Complex data analysis demands complex adjustment.

- It is statistically sound.

- It is an alternative to recoding and suppression (not a substitution).

- More detail, but same safety level.