Relaxed calibration of sampling weights

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Keywords:

Adjustment of sampling weights; auxiliary information; calibration (benchmarking); population (national) surveys.

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Literature

Deville and Särndal (1992) — Särndal (2007) Lohr and Raghunathan (2017), Devaud and Tillé (2019)

Monograph by Tillé (2020)

Haziza and Beaumont (2017) — model-based approaches

Chambers (1996); Guggemos and Tillé (2010) — ridge regression

Some adaptations:

Cardot, Goga and Shehzad (2017); Dagdoug, Goga and Haziza (2023)

!! A similar problem in causal analysis (matching/balancing)

Calibration

A long-standing problem in population surveys & official statistics

Auxiliary information: known population totals of some variables

Calibration: adjusting the sampling weights so that:

- weighted sample totals agree with the known population totals
- total of the sample weights stays the same
- the weights are changed as little as possible
- the weights are not too dispersed (efficiency)

Hard calibration: no leeway for any discrepancies Soft calibration: thresholds for the discrepancies

Solutions; old and new

Raking for discrete variables:

— Iteratively adjust the weights for one variable at a time Quadratic programming: optimisation constrained by the thresholds

Problem: solution may not exist or may be unsatisfactory
 Solution: discard some variables, change some thresholds
 improvise with a black box

Proposal: replace *tresholds/constraints* with *penalties*

- *simplicity:* noniterative solution/algorithm
- *transparency:* properties are easy to study/explore
- *optimality* in a well-defined sense

Notation and formalities

A realised population survey:

- focal variable y (values \mathbf{y}), weights \mathbf{w} (estimator $\hat{\theta} = \mathbf{w}^{\top} \mathbf{y}$) - other variables, vector $\mathbf{x} = (x_0 = 1, x_1, \dots, x_K)$; - data matrix \mathbf{X} $[n \times (K+1)]$ - population totals, vector $\mathbf{t} = (t_0 = N, t_1, \dots, t_K)$;

Calibration: adjusted weights
$$\mathbf{u} = C(\mathbf{w}; \mathbf{X}, \mathbf{t}),$$

 $[\boldsymbol{\delta} =] \mathbf{X}^{\top}\mathbf{u} - \mathbf{t} \doteq \mathbf{0}, \quad \text{i.e.}, \quad \boldsymbol{\delta}_k = \mathbf{X}_k^{\top}\mathbf{u} - t_k \doteq 0, \quad 0 \le k \le K$
subject to small $||\mathbf{u} - \mathbf{w}||$
small $\operatorname{var}(u)$

E.g., thresholds $D_k \ge 0$ on the discrepancies; $|\delta_k| \le D_k$

Motivation. Thresholds \rightarrow penalties

Replace the constraints $\delta_k^2 \leq D_k^2$ with a single constraint $\delta_0^2 + \delta_1^2 + \cdots + \delta_K^2 \leq D$. Minimise

$$\sum_{k=0}^{K} p_k \delta_k^2 \quad \left(= \boldsymbol{\delta}^\top \mathbf{P} \boldsymbol{\delta} \right)$$

subject to constraints on efficiency and small change $(\mathbf{u} - \mathbf{w})^{\top}(\mathbf{u} - \mathbf{w})$ *Priorities* $p_k, 0 \le k \le K$ to be set.

Next: minimise

$$F(\mathbf{u};\mathbf{w}) = \sum_{k=0}^{K} p_k \delta_k^2 + R \left(\mathbf{u} - \mathbf{w}\right)^\top \left(\mathbf{u} - \mathbf{w}\right) + S \left(\mathbf{u}^\top \mathbf{u} - \frac{1}{n} \mathbf{u}^\top \mathbf{1} \mathbf{1}^\top \mathbf{u}\right)$$

Unconstrained optimisation

Invariance ... we can assume that R + S = 1.

Quadratic objective function

$$F(\mathbf{u}; \mathbf{w}) = \mathbf{u}^{\top} \mathbf{H} \mathbf{u} - 2\mathbf{u}^{\top} \mathbf{s} + E,$$

where

$$\begin{split} \mathbf{H} &= \mathbf{I}_n + \mathbf{X} \mathbf{P} \mathbf{X}^\top \\ \mathbf{s} &= R \mathbf{w} + (1 - R) \frac{t_0}{n} \mathbf{1}_n + \mathbf{X} \mathbf{P} \mathbf{t} \,. \end{split} \\ \end{split}$$

Minimum: $\mathbf{u}^* = \mathbf{H}^{-1} \mathbf{s}; \quad F(\mathbf{u}^*; \mathbf{w}) \,= \, E - \mathbf{s}^\top \mathbf{H}^{-1} \mathbf{s}. \end{split}$

Minimum *always* exists and has a closed form. ... setting $\mathbf{P} = \text{diag}(p_k)$ and R (*tuning* parameters)

\mathbf{H}^{-1} and a link to ridge regression

$$\begin{split} \mathbf{H} &= \mathbf{I} + \mathbf{L}, \text{ where } \mathbf{I} \text{ is easy to invert and } \operatorname{rank}(\mathbf{L}) \leq K + 1 \\ & \left(\mathbf{I} + \mathbf{X} \mathbf{P} \mathbf{X}^{\top}\right)^{-1} = \mathbf{I} - \mathbf{X} \left(\mathbf{P}^{-1} + \mathbf{X}^{\top} \mathbf{X}\right)^{-1} \mathbf{X}^{\top} \\ & \left[\hat{\boldsymbol{\beta}} =\right] \left(\mathbf{P}^{-1} + \mathbf{X}^{\top} \mathbf{X}\right)^{-1} \mathbf{X}^{\top} \mathbf{y} \\ & - \text{ affinity with (generalised) } ridge \ regression \end{split}$$

Alternative: A recursive algorithm for evaluating $\mathbf{H}^{-1}\mathbf{s}$, — operating only with vectors of length n

Estimator of the population total:

$$\hat{\theta}(\mathbf{u};R) = (1-R) \left\{ \frac{t_0 \bar{y}}{1+np_0} + \mathbf{t}^{\top} \hat{\boldsymbol{\beta}} \right\} + R \mathbf{w} \left(\mathbf{y} - \mathbf{X} \hat{\boldsymbol{\beta}} \right)$$

Properties of $\delta_k(\mathbf{P}, R)$

$$\frac{\partial \delta_k^2}{\partial p_k} = -2\delta_k^2 \mathbf{X}_k^{\mathsf{T}} \mathbf{H}^{-1} \mathbf{X}_k < 0$$

 $\begin{array}{l} - \text{ large } \delta_k^2 \text{ is easy to reduce; small } \delta_k^2 \text{ is difficult to reduce} \\ - \text{ do not try to wipe out the last bit of discrepancy} \end{array}$

$$\frac{\partial \delta_k}{\partial R} = \mathbf{X}_k^{\top} \mathbf{H}^{-1} \left(\mathbf{w} - \frac{t_0}{n} \mathbf{1}_n \right)$$

— linear dependence on R

Simple *micro-management* of individual δ_k

Examples and simulations:

— easy control of the discrepancies δ_k

Summary

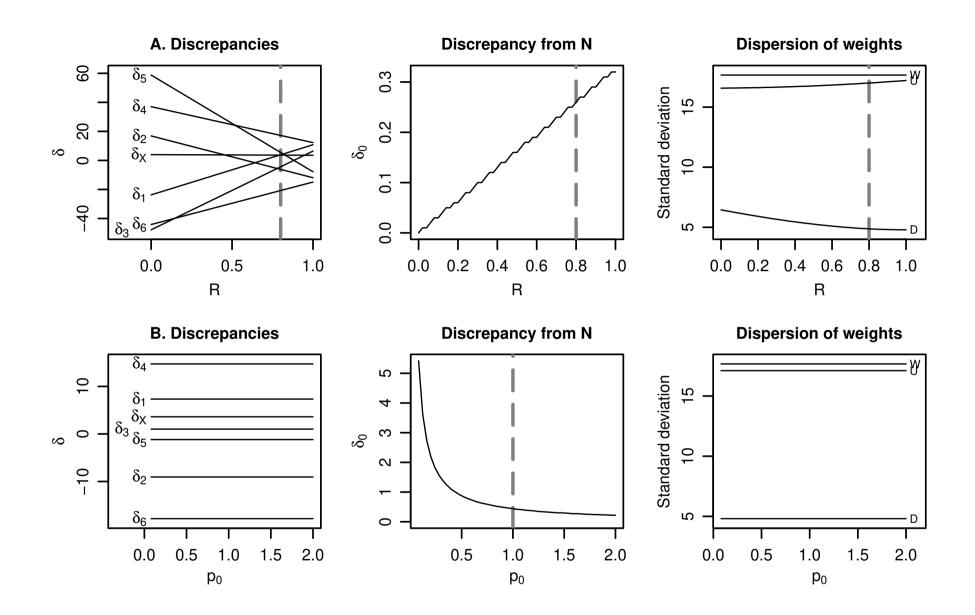
Calibration as a routine operation

- with a unique closed-form solution
- that reflects the perspectives, judgements and priorities
 easy control of the discrepancies
- *Old:* Include/exclude in calibration
- New: Set priorities for calibration; use all available information

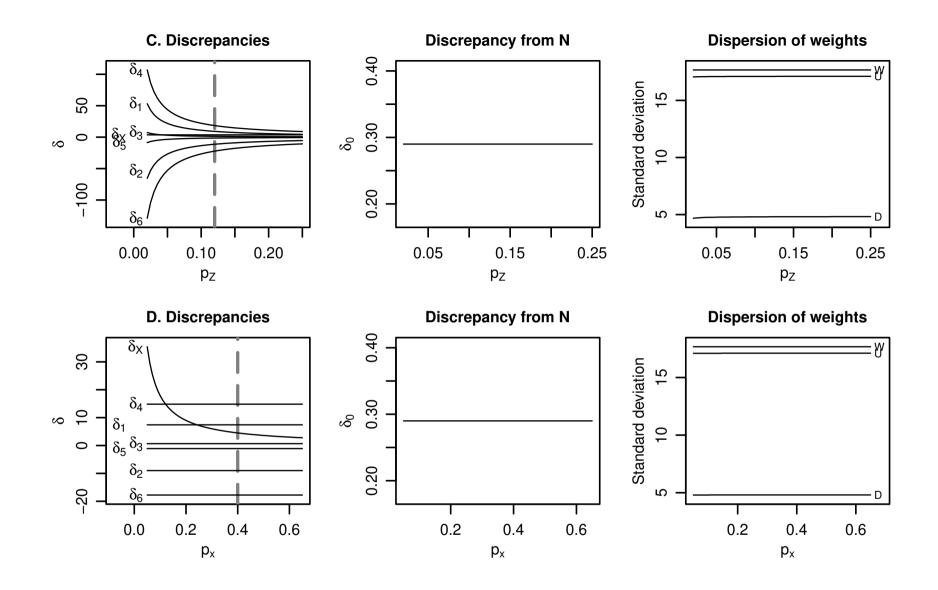
Analytical connection with balancing in causal analysis:

— matching the means of group A with weighted means of group B

Thank you — Dziękuję bardzo. Questions? — Pytania?



Dependence of $\boldsymbol{\delta}$, var(u), var(u-w) and R and p_0 .



Dependence of $\boldsymbol{\delta}$, var(u), var(u-w) and p_k , $k = 1, \ldots, K-1$ (for categories) and p_K (for a cont. variable).