



Bucharest, 13 December 2023 The Use of R in Official Statistics - uRos2023

Assessing coherence between estimated distributions in R O Coherence of statistics

- Assessing coherence between estimated distributions: **categorical** variables
- Assessing coherence between estimated distributions: **continuous** variables



## **Coherence of statistics**

• Coherence, jointly with comparability, is part of the ESS definition of quality of statistics.

#### • Coherence:

"assessing the extent to which the outputs from different statistical processes have the potential to be reliably used in combination"

**Incoherence** and **non-comparability** can affect statistics originating from different sources. Causes may be:

- Differences in concepts (a household could be defined in a number of ways...)
- <u>Differences in methods</u> (e.g. employment estimated from a household survey Vs. employment estimated from administrative data)

ESS, Handbook for Quality and Metadata Report, 2021 re-edition

 Assessing coherence becomes crucial in modern statistical production processes involving integration of data from different sources (exploitation of variables shared by the sources)



SIMS	Concept Name	Definition	Summary Guidelines			
S.15.3	Coherence- cross domain	The extent to which statistics are reconcilable with those obtained through other data sources or statistical domains.	An analysis of incoherence should be provided, where this is an issue of importance Reporting under 15.3 is for coherence problems that are not reported under 15.3.1, 15.3.2 or 15.4			
S.15.3.1	Coherence - subannual and annual statistics (P)	The extent to which statistics of different frequencies are reconcilable.	For producer reports only. Coherence between subannual and annual statistical outputs is a natural expectation but the statistical processes producing them are often quite different. Compare subannual and annual estimates and, eventually, describe reasons for lack of coherence between subannual and annual statistical outputs.			
S.15.3.2	Coherence- National Accounts (P)	The extent to which statistics are reconcilable with National Accounts.	For producer reports only. Where relevant, the results of comparisons with the National Account framework and			

"Where possible, a quantitative analysis of any lack of coherence should be presented"



## **Coherence Assessment**

Currently assessment is based on comparison of estimates:

- Occurrence of given categories of a <u>categorical</u> variable
- Average, totals, percentiles for <u>continuous</u> variables

It is preferable to assess coherence between estimated marginal distributions

#### Different scenarios depending on the type of data source:

- Estimates from two independent random samples (complex sampling design)
- Estimate from a sample survey and an estimate from a nonprobabilistic data source (non-prob. sample, admin. data, big data, etc.)

Is it available a "reference" estimate? I.e. an estimate considered reliable and therefore the reference one



# **Coherence Between distributions: categorical variables (1/3)**

Category	Source_1	Source_2		
1	$\hat{p}_{11}$	$\hat{p}_{12}$		
2	$\hat{p}_{21}$	$\hat{p}_{22}$		
j	$\hat{p}_{j1}$	$\hat{p}_{j2}$		
		•••		
J	$\hat{p}_{J1}$	$\hat{p}_{J2}$		
Total	1.00	1.00		

$$\hat{p}_{ji} = \widehat{N}_{ji} / \widehat{N}_i$$
 ,  $i = 1,2$ 

In probabilistic sample surveys:

$$\hat{p}_{ji} = \sum_{k=1}^{n_i} w_{ki} I(y_{ki} = j)$$

Total Variation Distance (TVD)  $\Delta_{12} = \frac{1}{2} \sum_{j=1}^{J} |\hat{p}_{j1} - \hat{p}_{j2}| \quad 0 \le \Delta_{12} \le 1$  $O_{12} = 1 - \Delta_{12}$  $0 \le 0_{12} \le 1$ Overlapping coefficient  $B_{12} = \sum_{i=1}^{J} \sqrt{\hat{p}_{j1} \times \hat{p}_{j2}} \quad 0 \le B_{12} \le 1$ Bhattacharyya coefficient  $d_{H,12} = \sqrt{1 - B_{12}}$  $0 \le d_{H,12} \le 1$ Hellinger distance  $d_{H,AB}^2 \leq \Delta_{AB} \leq d_{H,AB}(\sqrt{2})$ **Rule of thumbs**: if  $\hat{p}_{i2}$  is the <u>reference</u>:  $\hat{p}_{j1}$  is «close» to  $\hat{p}_{j2}$  when  $\Delta_{12} \leq 0.03$  (Agresti, 2002)  $\hat{p}_{j1}$  is «close» to  $\hat{p}_{j2}$  when  $d_{H,12} \le 0.05$  (??)  $d_{H\,12} \leq 0.0212$ Istat

# **Coherence Between distributions: categorical variables (2/3)**

New R function **comp.tables()**, derived from **comp.prop()** in **StatMatch** (D'Orazio, 2022)

```
> data(samp.A, package = "StatMatch")
> data(samp.B, package = "StatMatch")
> t.edu.A <- xtabs(ww~edu7, data=samp.A)</pre>
> t.edu.B <- xtabs(ww~edu7, data=samp.B)</pre>
> t.edu.B
edu7
        0
                  1 2
                                       3
                                                  4
                                                            5
                                                                       6
149580,43 997271,57 1604170,80 1687398,23 141106,95 564485,98 13568,23
> comp.tables(p1 = t.edu.A, p2 = t.edu.B,
        ref = TRUE) # t.edu.B is the reference one
+
      tvd overlap
                         Bhatt
                                    Hell
0.01048456 0.98951544 0.99986854 0.01146559
```



Estimates from two independent sample surveys referred to the same target population and no reference

 Reference estimate obtained by «pooling» (Sarndal et al 1992; Korn & Graubard, 1999):

$$\hat{p}_{j,r} = \lambda_1 \hat{p}_{j1} + (1 - \lambda_1) \hat{p}_{j2}$$

$$\lambda_1 = \frac{n_1}{n_1 + n_2} \, \backslash$$

 Alternative ways for estimating λ<sub>1</sub> (O'Muirchertaigh & Pedlow, 2002)

$$\lambda_1 = \frac{n_1/d_{w1}}{n_1/d_{w1} + n_2/d_{w2}}, \quad d_{wi} = 1 + CV_{w_1}^2$$

 These and other options implemented in the a new R function opt.lambda()

```
> data(samp.A, package = "StatMatch")
> data(samp.B, package = "StatMatch")
> opt.lambda(w1 = samp.A$ww, w2 = samp.B$ww)
$summaries.w
                 s1
                               s2
       3.009000e+03 6.686000e+03
n
       5.094952e+06 5.157582e+06
N
       1.006146e+00 9.939283e-01
NC
mean.w 1.693238e+03 7.714003e+02
       1.203468e+03 5.339756e+02
sd.w
CV.w
       7.107498e-01 6.922160e-01
deff.w 1.505165e+00 1.479163e+00
$lambdas
```

	s1	s2	tot
kg1	0.3085334	0.6891416	0.9976750
kg2a	0.3122738	0.6854466	0.9977204
kg2b	0.3066486	0.6933514	1.0000000
kg3	0.3103662	0.6896338	1.0000000
<b>→</b> omp	0.3066486	0.6933514	1.0000000

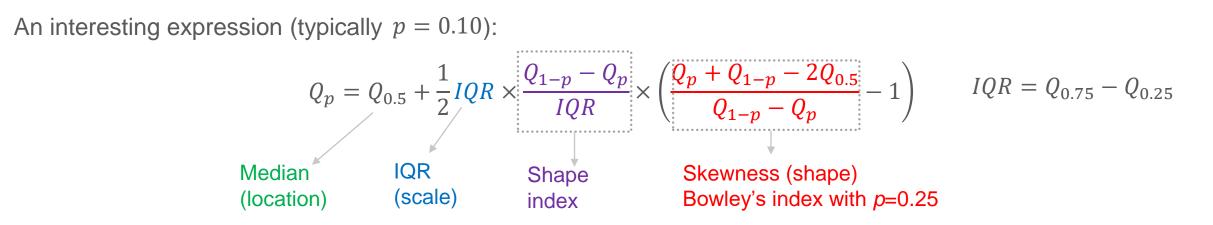


Two approximate approaches:

- Comparison of percentiles (Q-Q)
- Categorization and estimation of indicators for categorical variables (TVD, Hellinger's distance, etc.)



## **Coherence Between distributions: percentiles of continuous variables (1/2)**



 $Q_p$  should estimated using survey weights, when available (see e.g. Korn & Graubard, 1999) -> wtd.qs()

In alternative compare percentiles (quartiles; quintiles, deciles,...)

$$\hat{Q}_{pi} - \hat{Q}_{pr} \qquad \frac{(\hat{Q}_{pi} - \hat{Q}_{pr})}{\hat{Q}_{pr}} \qquad i = 1,2; \qquad p = 0.25, 0.50, 0.75 \quad \text{in the case of quartiles, and so on...}$$

If there are no reference  $\hat{Q}_{pr}$  and the data come from two independent sample surveys referred to the same target population, then  $\hat{Q}_{pr}$  should be estimated on the concatenated sample with weights

$$\widetilde{w}_{ki} = \lambda_i w_{ki}, \qquad k = 1, 2, \dots, n_i, \qquad i = 1, 2$$



## Coherence Between distributions: percentiles of continuous variables (2/2)

The Median, IQR, shape and skewness based on Quantiles are returned by the R function smrs()

<pre>&gt; smrs(x=samp.A\$n.income, weights = samp.A\$ww, p = 0.10)</pre>									
Şsummary									
Min	P10	Q1	Median	Mean	Q3	P90	Max		
-15000.000	0.000	3977.326	12497.762	13978.449	19825.173	28185.414	276750.000		
\$qq.based									
P	:	IQR	shape s	kewness					
1.000000e-01 1.584785e+04 1.778501e+00 1.131752e-01									

While comparison of quantiles is performed by the R function **comp.quantiles()** 

>	comp.quantiles(x1 = samp.A\$age, x2 = samp.B\$age, w1 = samp.A\$ww, w2 = samp.B\$ww,										
+	pctp = seq(0.1, 0.9, 0.1), ref = TRUE)										
	Pct	qqs.1	qqs.2	qqs.ref	diff	rel.diff					
1	P10	24	25	25	-1	-0.0400000					
2	P20	32	33	33	-1	-0.03030303					
	•										
8	P80	68	68	68	0	0.0000000					
9	P90	77	77	77	0	0.0000000					

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#### **Discretization**

Freedman & Diaconis (1981) rule for histogram bin width:

$$b = 2 \times \frac{IQR}{\sqrt[3]{n_0}}$$

No. of bins:

$$m = \left[\frac{x_u - x_l}{b}\right] + 1 \qquad x_l \le x_{min} \quad x_u \ge x_{max}$$

Instead of min and max it is possible to consider bounds for detection of outliers (see functions **boxB()** or **LocScaleB()** in **univOutl**)

$$n_0 = \min(n_1, n_2)$$

In case of sample surveys, replace  $n_i$  with  $n_i/d_{wi}$ 

IQR should be estimated on the <u>reference</u> data source (using weights if data come from a prob. sample survey)

When data are from two independent sample surveys and there's NOT a reference then concatenate the samples and use new weights:

$$\widetilde{w}_{ki} = \lambda_i w_{ki}, \qquad k = 1, 2, \dots, n_i, \qquad i = 1, 2$$

to estimate IQR



In R two new functions:

#### wtd.qs (x, w, prb, ties=FALSE)

to estimate quantiles using survey weights (considers possibility of tied values)

(many alternative functions exist in R packages with different estimation methods)

```
hist.bks(x, w = NULL, neff = NULL,
    robust=0,...)
```

to get the breaks to categorize  $\mathbf{x}$ 

In case of sample surveys replace  $n_i$  with  $n_i/d_{wi}$ 

IQR should be estimated on the <u>reference</u> data source (using weights if data come from a prob. sample survey)

When data are from **two independent sample surveys** and **there's NOT a reference** then concatenate the samples and use new weights:

$$\widetilde{w}_{ki} = \lambda_i w_{ki}, \qquad k = 1, 2, \dots, n_i, \qquad i = 1, 2$$

to estimate IQR



#### **Coherence Between distributions: categorize continuous variables (3/4)**

```
> source("wtd.qs.R")
> source("hist.bks.R")
> bk.0 <- hist.bks(x = samp.A$n.income, w = samp.A$ww, neff = NULL, robust = 0)
n and eff_n: 3009 1999.339
width: 2515.966
min & max: -15000 276750
mod low & up bounds: -15051.04 276801
bins: 116</pre>
```



### Coherence Between distributions: categorize continuous variables (4/4)

 $h_{\rm R}$ : bandwidth (rule of thumb  $h_{\rm R} = b/1.25$ )

Categorization based on histograms permits estimating the density (Bellhouse & Stafford, 1999):

```
\hat{f}_B(x) = \frac{1}{h_B} \sum_{l=1}^m \hat{p}_l K_B\left(\frac{x - \tilde{x}_l}{h_B}\right)
                                           \hat{p}_l: estimated prop. of obs. (weighted) in the bin l
                                           K_B(\cdot): kernel function
                                           \tilde{x}_l: midpoint of the bin l
> bk.0 <- hist.bks(x = samp.A$n.income, w = samp.A$ww, neff = NULL, robust = 1)</pre>
> oo <- discr.sum(x=samp.A$n.income, w=samp.A$ww, breaks = bk.0$breaks, density = TRUE)</pre>
> head(oo$binned.sum, 4)
                                          relFreq low.b
                                                                    midpoint
                                 Freq
                                                                                      up.b
                       CXX
1 [-1.51e+04,-1.26e+04] 2002.5312 3.930422e-04 -15147.506 -13889.523 -12631.5395
2(-1.26e+04, -1.01e+04)
                              0.0000 \ 0.000000e+00 \ -12631.539 \ -11373.556 \ -10115.5733
3 (-1.01e+04,-7.6e+03]
                            401.9409 7.889002e-05 -10115.573
                                                                   -8857.590 -7599.6072
4 (-7.6e+03,-5.08e+03] 649.5610 1.274911e-04 -7599.607 -6341.624 -5083.6411
> head(oo$est.dens, 4)
                   dens
        x
1 - 15000 6.705574e - 08
2 -9000 3.036892e-08
```

- 3 -7000 4.574928e-08
- 4 -1672 1.615645e-05



Future:

- Introduce comparison of estimated empirical cumulative distribution function (P-P) for continuous variables
- evaluate whether to create a new R package

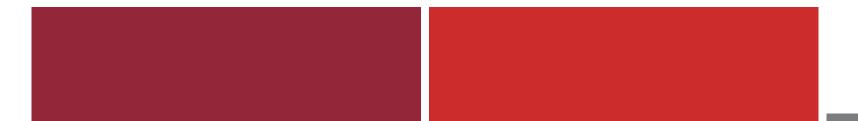
Repository with R code and supporting material

https://github.com/marcellodo/coherenceD



# Thank You

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# **Main References**

Agresti A. (2002) Categorical Data Analysis. Second Edition. Wiley, New York.

Bellhouse D.R., Stafford J. E. (1999) "Density Estimation From Complex Surveys". Statistica Sinica, 9,

pp. 407-424

D'Orazio M (2022). *StatMatch: Statistical Matching or Data Fusion.* R package version 1.4.1, <u>https://CRAN.R-project.org/package=StatMatch</u>

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Korn E.I., Graubard B.I. (1999) Analysis of Health Surveys. Wiley, New York.

- O'Muircheataigh C., Pedlow S. (2002) "Combining samples vs. cumulating cases: a comparison of two weighting strategies in NLS97". *American Statistical Association Proceedings of the Joint Statistical Meetings*, pp. 2557-2562.
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