

Package ‘ReGenesees’

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Type Package

Title R Evolved Generalized Software for Sampling Estimates and Errors
in Surveys

Description Design-Based and Model-Assisted analysis of complex sample surveys.
Multistage, stratified, clustered, unequally weighted survey designs.
Calibration of survey weights. Horvitz-Thompson and Calibration Estimators.
Variance Estimation for nonlinear smooth estimators by Taylor-series
linearization. Estimates, standard errors, confidence intervals and design
effects for: Totals, Means, absolute and relative Frequency Distributions
(marginal, conditional, and joint), Ratios, Shares and Ratios of Shares,
Multiple Regression Coefficients, and Quantiles. Automated Linearization
of user-defined Complex Estimators. Design Covariance and Correlation.
Estimates and sampling errors of user-defined complex Measures of Change
derived from two not necessarily independent samples. Estimates and sampling
errors for subpopulations. Consistent trimming of calibration weights.
Calibration on complex population parameters, e.g. multiple regression
coefficients. Generalized Variance Functions (GVF) method for predicting
variance estimates. Sample size requirements and power calculations.

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Author Diego Zardetto [aut, cre]

Maintainer Diego Zardetto <zardetto@istat.it>

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<https://github.com/DiegoZardetto/ReGenesees/>

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ReGenesees-package	<i>ReGenesees: a Package for Design-Based and Model-Assisted Analysis of Complex Sample Surveys</i>
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Description

ReGenesees is an R package for design-based and model-assisted analysis of complex sample surveys. It handles multistage, stratified, clustered, unequally weighted survey designs. Sampling variance estimation for nonlinear (smooth) estimators is obtained by Taylor-series linearization. Sampling variance estimation for multistage designs can be obtained both under the Ultimate Cluster approximation or by means of an actual multistage computation. **ReGenesees** offers comprehensive and advanced functionalities for calibration of survey weights. Estimates, standard errors, confidence intervals and design effects are provided for Horvitz-Thompson and Calibration estimators of: Totals, Means, absolute and relative Frequency Distributions (marginal, conditional and joint), Ratios, Shares and Ratios of Shares, Multiple Regression Coefficients and Quantiles (variance via the Woodruff method). **ReGenesees** also handles Complex Estimators, i.e. any user-defined estimator that can be expressed as an analytic function of Horvitz-Thompson or Calibration estimators of Totals or Means, by automatically linearizing them. The Design Covariance and Correlation between Complex Estimators is also provided. Moreover, the package can compute estimates and sampling errors of complex Measures of Change derived from two not necessarily independent samples. All the analyses above can be carried out for arbitrary subpopulations. In addition, **ReGenesees** can trim calibration weights while preserving all the calibration constraints, and perform ‘special purpose calibration’ tasks, i.e. can calibrate on complex population parameters like Multiple Regression Coefficients. **ReGenesees** also offers a Generalized Variance Functions (GVF) infrastructure, i.e. facilities for defining, fitting, testing and plotting GVF models, and to exploit them to predict variance estimates. Lastly, the package offers simple survey planning tools to estimate sample size requirements and perform power calculations.

The **ReGenesees** package is the fundamental building block of a full-fledged R-based software system: the **ReGenesees System**. The latter has a clear-cut two-layer architecture. The application layer of the system is embedded into package **ReGenesees**. A second R package, called **ReGenesees.GUI**, implements the presentation layer of the system, namely a user-friendly Tcl/Tk GUI.

A Quick Reading Guide to the Reference Manual

This reference manual reports a documentation entry for each (user visible) function of package **ReGenesees**. As you may have noticed by reading section ‘R topics documented’ (page 1 of the pdf manual), these documentation entries are automatically sorted according to the alphabetic ordering of the names of the functions. Such an ordering doesn’t provide any clue about where should a user start reading, nor on the best way to proceed further.

In section ‘Table of Contents’, I tried to cluster the most important topics documented in the reference manual into few broad groups, based on both the statistical goals and on the software design of the underlying functions.

Moreover, I provided a *relevance code* for each documented topic/function. The meaning of such codes, along with the corresponding *reading suggestions*, are reported in the following table:

Relevance Codes Legend

CODE	RELEVANCE	READING SUGGESTION
***	Very Important.....	Read these topics as soon as possible. A clear understanding of these functions is mandatory in order to start using profitably the package.
**	Important.....	Read these topics once you have been experiencing for a while with (at least some of) the 'Very Important' functions.
*	Useful.....	These functions are ancillary (albeit in different ways) to the 'Very Important' and 'Important' ones (and their usage is generally simpler).
.	Advanced.....	These topics are very relevant but, unfortunately quite difficult. As they involve technical details, you should postpone their reading until you become familiar with the package.

Important Notice

It goes without saying that the **'Examples'** sections at the end of each documented topic **represent a crucial part of this reference manual**.

TABLE OF CONTENTS

Survey Design:

***	e.svydesign.....	Specification of a Complex Survey Design
*	weights.....	Retrieve Sampling Units Weights
*	find.lon.strata.....	Find Strata with Lonely PSUs
**	collapse.strata.....	Collapse Strata Technique for Eliminating Lonely PSUs
*	des.addvars.....	Add Variables to Design Objects
*	des.merge.....	Merge New Survey Data into Design Objects
**	smooth.strat.jump....	Smooth Weights to Cope with Stratum Jumpers

Calibration:

**	pop.template.....	Template Data Frame for Known Population Totals
*	population.check.....	Compliance Test for Known Totals Data Frames
*	pop.desc.....	Natural Language Description of Known Totals Templates
**	fill.template.....	Fill the Known Totals Template for a Calibration Task
*	pop.plot.....	Plot Calibration Control Totals vs Current Estimates
*	bounds.hint.....	A Hint for Range Restricted Calibration

```

*** e.calibrate.....Calibration of Survey Weights
*   check.cal.....Calibration Convergence Check
**  trimcal.....Trim Calibration Weights while Preserving
      Calibration Constraints
*   g.range.....Range of g-Weights
.   get.residuals.....Calibration Residuals of Interest Variables
.   get.linvar.....Linearized Variable(s) of Complex Estimators
      by Domains
*   ext.calibrated.....Make ReGenesees Digest Externally Calibrated
      Weights
.   contrasts.RG.....Set, Reset or Switch Off Contrasts for
      Calibration Models
.   %into%.....Compress Nested Factors

```

Special Purpose Calibration:

```

.   prep.calBeta.....Prepare a Survey Design to Calibration on
      Multiple Regression Coefficients
.   pop.calBeta.....Prepare Control Totals for Calibration on
      Multiple Regression Coefficients
.   pop.fuse.....Fuse Control Totals Data Frames for Special
      Purpose and Ordinary Calibration Tasks

```

Estimates and Sampling Errors:

```

*** svystatTM.....Estimation of Totals and Means in
      Subpopulations
*** svystatR.....Estimation of Ratios in Subpopulations
*** svystatS.....Estimation of Shares in Subpopulations
*** svystatSR.....Estimation of Share Ratios in Subpopulations
*** svystatB.....Estimation of Population Regression Coefficients in
      Subpopulations
*** svystatQ.....Estimation of Quantiles in Subpopulations
*** svystatL.....Estimation of Complex Estimators in
      Subpopulations
*** svySigma.....Estimation of the Population Standard Deviation of
      a Variable
*** svySigma2.....Estimation of the Population Variance of a Variable
*** svyDelta.....Estimation of a Measure of Change from Two
      Not Necessarily Independent Samples
*   details.....Details on svyDelta results
**  aux.estimates.....Quick Estimates of Auxiliary Variables Totals
**  CoV, Corr.....Design Covariance and Correlation of Complex
      Estimators in Subpopulations
*   write.svystat.....Export Survey Statistics
*   extractors.....Extractor Functions for Variability Statistics
.   ReGenesees.options...Variance Estimation Options for the ReGenesees
      Package

```

Generalized Variance Functions Method:

```

*** GVF.db.....Archive of Registered GVF Models
*** gvf.input.....Prepare Input Data to Fit GVF Models
*** svystat.....Compute Many Estimates and Errors in Just a
      Single Shot

```

```

*** fit.gvf.....Fit GVF Models
** plot.gvf.fit.....Diagnostic Plots for Fitted GVF Models
** drop.gvf.points.....Drop Outliers and Refit a GVF Model
* getR2, AIC, BIC.....Quality Measures on Fitted GVF Models
* getBest.....Identify the Best Fit GVF Model
*** predictCV.....Predict CV Values via Fitted GVF Models
* gvf.misc.....Miscellanea: Methods for Fitted GVF Models
* estimator.kind.....Which Estimator Did Generate these
                        Survey Statistics?

```

Sample Size and Power:

```

** n.prop.....Sample Size Requirements for the Estimation
                of a Proportion
** prec.prop.....Expected Precision Level in the Estimation
                of a Proportion
** n.comp2prop.....Power Calculations for a Test that Compares
                Two Estimated Proportions: Sample Size
** pow.comp2prop.....Power Calculations for a Test that Compares
                Two Estimated Proportions: Expected Power
** mde.comp2prop.....Power Calculations for a Test that Compares
                Two Estimated Proportions: Expected Minimum
                Detectable Effect
** n.mean.....Sample Size Requirements for the Estimation
                of a Mean
** prec.mean.....Expected Precision Level in the Estimation
                of a Mean
** n.comp2mean.....Power Calculations for a Test that Compares
                Two Estimated Means: Sample Size
** pow.comp2mean.....Power Calculations for a Test that Compares
                Two Estimated Means: Expected Power
** mde.comp2mean.....Power Calculations for a Test that Compares
                Two Estimated Means: Expected Minimum
                Detectable Effect

```

Diagnostics and Utilities:

```

* UWE.....Unequal Weighting Effect
* Zapsmall.....Zapsmall Data Frame Columns and Numeric Vectors

```

Data Sets:

```

** data.examples.....Artificial Household Survey Data
** fpcdat.....A Small But Not Trivial Artificial Sample
                Data Set
** sbs.....Artificial Structural Business Statistics Data
** Delta.el.....Two Artificial Samples of Elementary Units for
                Estimation of Change
** Delta.clus.....Two Artificial Cluster Samples for Estimation
                of Change
** AF.gvf.....Example Data for GVF Model Fitting

```

The ordering of the above ‘Table of Contents’ reflects only loosely the procedural sequence in which functions could be used. For instance, while you cannot apply function [e.calibrate](#) unless you have previously built a design object by using [e.svydesign](#), you can exploit, e.g., function

`collapse.strata` also after calibration. As a further example, all functions in group ‘Estimates and Sampling Errors’ can be used on objects created by `e.svydesign` (yielding estimates and sampling errors for functions of Horvitz-Thompson estimators), as well as on objects created by `e.calibrate` (yielding estimates and sampling errors for functions of Calibration estimators).

References

Zardetto, D. (2015) “*ReGenesees: an Advanced R System for Calibration, Estimation and Sampling Error Assessment in Complex Sample Surveys*”. Journal of Official Statistics, 31(2), 177-203. doi: <https://doi.org/10.1515/jos-2015-0013>.

AF.gvf

Example Data for GVF Model Fitting

Description

File AF.gvf contains a set of summary statistics that can be used to illustrate **ReGenesees** facilities for fitting Generalized Variance Functions models. These summary statistics have kind ‘Absolute Frequency’ (see function `estimator.kind`), i.e. involve estimates and errors of counts.

Usage

```
data(AF.gvf)
```

Format

Each row of the `ee.AF` data frame represents an estimated absolute frequency along with its estimated sampling error (expressed in terms of standard error, coefficient of variation and variance). The data frame has 349 rows, and the following 5 columns:

`name` The name of the original estimate, factor with 349 levels.
`Y` The value of the original estimate (an absolute frequency), numeric.
`SE` The standard error of the original estimate, numeric.
`CV` The coefficient of variation of the original estimate, numeric.
`VAR` The variance of the original estimate, numeric.

Details

Object `AF` is a list storing estimates and errors of counts (namely, summary statistics of kind ‘Absolute Frequency’) computed on survey design object `exdes`. The names of the slots of list `AF` indicate the nature of the corresponding estimates, e.g. element `AF[["sex.marstat"]]` stores estimates and errors of the joint absolute frequency distribution of variables `sex` and `marstat` (see ‘Examples’).

Object `ee.AF` is the `gvf.input` object built upon all such summary statistics, via function `gvf.input` (see ‘Examples’).

See Also

`estimator.kind` to assess what kind of estimates are stored inside a survey statistic object, `GVF.db` to manage **ReGenesees** archive of registered GVF models, `gvf.input` and `svystat` to prepare the input for GVF model fitting, `fit.gvf` to fit GVF models, `plot.gvf.fit` to get diagnostic plots for fitted GVF models, `drop.gvf.points` to drop alleged outliers from a fitted GVF model and simultaneously refit it, and `predictCV` to predict CV values via fitted GVF models.

Examples

```
data(AF.gvf)

# Inspect object AF
class(AF)
length(AF)
names(AF)
AF$sex.marstat
class(AF$sex.marstat)

# Inspect gvf.input object ee.AF
head(ee.AF)
str(ee.AF)
plot(ee.AF)

# The design object used to compute ee.AF is the following:
exdes

# How has object ee.AF been built?
foo <- gvf.input(exdes, stats = AF)
identical(ee.AF, foo)
```

aux.estimate

Quick Estimates of Auxiliary Variables Totals

Description

Quickly estimates the totals of the auxiliary variables of a calibration model.

Usage

```
aux.estimate(design,
             calmodel = if (inherits(template, "pop.totals"))
                           attr(template, "calmodel"),
             partition = if (inherits(template, "pop.totals"))
                           attr(template, "partition") else FALSE,
             template = NULL)
```

Arguments

design	Object of class analytic (or inheriting from it) containing survey data and sampling design metadata.
calmodel	Formula defining the linear structure of the calibration model.
partition	Formula specifying the variables that define the "calibration domains" for the model (see 'Details'); FALSE (the default) implies no calibration domains.
template	An object of class pop.totals, be it a template or the actual known totals data frame for the calibration task.

Details

The main purpose of function `aux.estimate` is to make easy the task of estimating the totals of *all* the auxiliary variables involved in a calibration model (separately inside distinct calibration domains, if specified). Even if such totals can be estimated also by repeatedly invoking function `svyestat`, this may reveal very tricky in practice, because real-world calibration tasks (e.g. in the field of Official Statistics) can simultaneously involve hundreds of auxiliary variables. Moreover, total estimates provided by function `svyestat` are always complemented by sampling errors, whose estimation is very computationally demanding.

Function `aux.estimate`, on the contrary, *only* provides estimates of totals (i.e. without associated sampling errors), thus being very quick to be executed. Moreover, `aux.estimate` is able to compute, *in just a single shot*, all the totals of the auxiliary variables of a calibration model, no matter how complex the model is. Lastly, as a third strong point, the totals estimated by `aux.estimate` will be returned exactly in the same *standard format* in which the known population totals for the related calibration task need to be represented (see `pop.template`, `population.check`, `fill.template`).

It may be useful to point out that, besides having been designed to handle auxiliary variables involved in calibration models, function `aux.estimate` could be also used for computing *general* estimates of totals inside subpopulations in a very effective way (see ‘Examples’).

Value

An object of class `pop.totals`, thus inheriting from class `data.frame` storing the estimated totals in a standard format.

Author(s)

Diego Zardetto

See Also

`e.svydesign` to bind survey data and sampling design metadata, `svyestat` for calculating estimates and standard errors of totals, `e.calibrate` for calibrating weights, `pop.template` for constructing known totals data frames in compliance with the standard required by `e.calibrate`, `population.check` to check that the known totals data frame satisfies that standard, `fill.template` to automatically fill the template when a sampling frame is available.

Examples

```
# Load sbs data:
data(sbs)

# Build a design object:
sbsdes<-e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,fpc=~fpc)

# Now suppose you have to perform a calibration process which
# exploits as auxiliary information:
# i) the total number of employees (emp.num)
#    by class of number of employees (emp.cl) crossed with nace.macro;
# ii) the total number of enterprises (ent)
#    by region crossed with nace.macro;

# Build a template for the known totals:
pop<-pop.template(sbsdes,
  calmodel=~emp.num:emp.cl + region -1,
  partition=~nace.macro)
```

```

# Use the fill.template function to automatically compute
# the totals from the universe (sbs.frame) and safely fill
# the template:
pop<-fill.template(sbs.frame,template=pop)
pop

# You can now use aux.estimates to verify how much difference
# exists between the target totals and the initial HT estimates:
aux.HT<-aux.estimates(sbsdes,template=pop)
aux.HT

# If you calibrate, ...
sbscal<-e.calibrate(sbsdes,pop)

# ... you can verify that CAL estimates exactly match the known totals:
aux.CAL<-aux.estimates(sbscal,template=pop)
aux.CAL

# Recall that you can also use aux.estimates for computing
# general estimates of totals inside subpopulations (even
# not related to any calibration task).
# E.g. estimate the total of value added inside areas:
aux.estimates(sbsdes,~va.imp2-1,~area)

# ...and compare to svstatTM (notice also
# the increased execution time):
svstatTM(sbsdes,~va.imp2,~area)

```

bounds.hint

A Hint for Range Restricted Calibration

Description

Suggests a sound bounds value for which `e.calibrate` is likely to converge.

Usage

```

bounds.hint(design, df.population,
  calmodel = if (inherits(df.population, "pop.totals"))
    attr(df.population, "calmodel"),
  partition = if (inherits(df.population, "pop.totals"))
    attr(df.population, "partition") else FALSE,
  msg = TRUE)

```

Arguments

<code>design</code>	Object of class <code>analytic</code> (or inheriting from it) containing survey data and sampling design metadata.
<code>df.population</code>	Data frame containing the known population totals for the auxiliary variables.
<code>calmodel</code>	Formula defining the linear structure of the calibration model.
<code>partition</code>	Formula specifying the variables that define the "calibration domains" for the model; <code>FALSE</code> (the default) implies no calibration domains.
<code>msg</code>	Enables printing of a summary description of the result (the default is <code>TRUE</code>).

Details

Function `bounds.hint` returns a bounds value for which `e.calibrate` is *likely* to converge. This interval is just a sound hint, *not* an exact result (see ‘Note’).

The mandatory argument `design` identifies the analytic object on which the calibration problem is defined.

The mandatory argument `df.population` identifies the known totals data frame.

The argument `calmodel` symbolically defines the calibration model you want to use: it identifies the auxiliary variables and the constraints for the calibration problem. The design variables referenced by `calmodel` must be numeric or factor and must not contain any missing value (NA). The argument can be omitted provided `df.population` is an object of class `pop.totals` (see [population.check](#)).

The optional argument `partition` specifies the variables that define the calibration domains for the model. The default value (FALSE) means either that there are not calibration domains or that you want to solve the problem globally (even though it could be factorized). The design variables referenced by `partition` (if any) must be factor and must not contain any missing value (NA). The argument can be omitted provided `df.population` is an object of class `pop.totals` (see [population.check](#)).

The optional argument `msg` enables/disables printing of a summary description of the achieved result.

Value

A numeric vector of length 2, representing the *suggested* value for the bounds argument of `e.calibrate`. The attributes of that vector store additional information, which can lead to better understand why a given calibration problem is (un)feasible (see ‘Examples’).

Note

Assessing the feasibility of an arbitrary calibration problem is not an easy task. The problem is even more difficult whenever additional “*range restrictions*” are imposed. Indeed, even if one assumes that the calibration constraints define a consistent system, one also has to choose the bounds such that the feasible region is non-empty.

One can argue that there must exist a minimum-length interval $I = [L, U]$ such that, if it is covered by bounds, the specified calibration problem is feasible. Unfortunately in order to compute exactly that minimum-length interval I one should solve a big linear programming problem [Vanderhoeft 01]. As an alternative, a trial and error procedure has been frequently proposed [Deville et al. 1993; Sautory 1993]: (i) start with a very large interval `bounds.0`; (ii) if convergence is achieved, shrink it so as to obtain a new interval `bounds.1`; (iii) repeat until you get a sufficiently tight feasible interval `bounds.n`. The drawback is that this procedure can cost a lot of computer time since, for each choice of the bounds, the full calibration problem has to be solved.

However, when both the benchmark population totals and the corresponding Horvitz-Thompson estimates are *all non-negative*, it is easy to find at least a given specific interval $I^* = [L^*, U^*]$ such that, if it is *not* covered by bounds, the current calibration problem is *surely unfeasible*. This means that any feasible bounds value must necessarily contain the I^* interval. Function `bounds.hint`: (i) first identifies such an I^* interval (by computing the range of the ratios between known population totals and corresponding direct Horvitz-Thompson estimates), (ii) then builds a new interval I^{sugg} with same midpoint and double length. The latter is the *suggested* value for the bounds argument of `e.calibrate`. The return value of `bounds.hint` should be understood as a useful starting guess for bounds, even though there is definitely no warranty that the calibration algorithm will actually converge.

Author(s)

Diego Zardetto

References

Vanderhoeft, C. (2001) “*Generalized Calibration at Statistic Belgium*”, Statistics Belgium Working Paper n. 3.

Deville, J.C., Sarndal, C.E. and Sautory, O. (1993) “*Generalized Raking Procedures in Survey Sampling*”, Journal of the American Statistical Association, Vol. 88, No. 423, pp.1013-1020.

Sautory, O. (1993) “*La macro CALMAR: Redressement d'un Echantillon par Calage sur Marges*”, Document de travail de la Direction des Statistiques Demographiques et Sociales, no. F9310.

See Also

[e.calibrate](#) for calibrating weights, [pop.template](#) for constructing known totals data frames in compliance with the standard required by [e.calibrate](#), [population.check](#) to check that the known totals data frame satisfies that standard, [g.range](#) to compute the range of the obtained g-weights, and [check.cal](#) to check if calibration constraints have been fulfilled.

Examples

```
# Creation of the object to be calibrated:
data(data.examples)
des<-e.svydesign(data=example,ids=~towcod+famcod,strata=~SUPERSTRATUM,
  weights=~weight)

# Calibration (partitioned solution) on the marginal distribution
# of age in 5 classes (age5c) inside provinces (procod)
# (totals in pop06p). Get a hint for feasible bounds:
hint<-bounds.hint(des,pop06p,~age5c-1,~procod)

# Let's verify if calibration converges with the suggested
# value for the bounds argument (i.e. c(0.219, 1.786) ):
descal06p<-e.calibrate(design=des,df.population=pop06p,
  calmodel=~age5c-1,partition=~procod,calfun="logit",
  bounds=hint,aggregate.stage=2)

# Now let's verify that calibration fails, if bounds don't cover
# the interval [0.611, 1.394]:
## Not run:
descal06p<-e.calibrate(design=des,df.population=pop06p,
  calmodel=~age5c-1,partition=~procod,calfun="logit",
  bounds=c(0.62,1.50),aggregate.stage=2,force=FALSE)

## End(Not run)
# The warning message raised by e.calibrate tells that
# the population total of variable age5c5 (i.e. the fifth
# age class frequency) was not matched.

# By analysing ecal.status one understands that calibration
# failed due to the sub-task identified by procod 30:
ecal.status

# this is easily explained by inspecting the "bounds"
# attribute of the bounds.hint output object:
```

```

attr(hint,"bounds")

# indeed the specified lower bound (0.62) was too high
# for procod 30, where instead a value ~0.61 was required.

# Recall that you can always "force" a calibration task that
# would not converge:
descal06p.forced<-e.calibrate(design=des,df.population=pop06p,
                             calmodel=~age5c-1,partition=~procod,calfun="logit",
                             bounds=c(0.62,1.50),aggregate.stage=2,force=TRUE)

# Notice, also, that forced sub-tasks can be tracked down by
# directly looking at ecal.status...
ecal.status

# ...or by using function check.cal:
check.cal(descal06p.forced)

```

check.cal

Calibration Convergence Check

Description

Checks whether Calibration Constraints are fulfilled; if not, assesses constraints violation degree.

Usage

```
check.cal(cal.design)
```

Arguments

cal.design Object of class cal.analytic.

Details

The function verifies if all the imposed Calibration Constraints are actually fulfilled by object cal.design. If it is not the case, the function evaluates the degree of violation of the constraints and prints a summary of the mismatches between population totals and achieved estimates (see also Section 'Calibration process diagnostics' in the help page of [e.calibrate](#)).

Value

The main purpose of the function is to print on screen; anyway a list is invisibly returned, which summarizes the results of the check.

Author(s)

Diego Zardetto

See Also

[e.calibrate](#) for calibrating weights (in particular, Section 'Calibration process diagnostics').

Examples

```
# Load sbs data:
data(sbs)

# Build a design object:
sbsdes<-e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,fpc=~fpc)

## Example 1
# Build template...
pop<-pop.template(sbsdes,~emp.num:emp.cl+ent-1,~region)
# Fill template...
pop<-fill.template(sbs.frame,pop)
# Calibrate...
sbscal<-e.calibrate(sbsdes,pop,sigma2=~emp.num)
# Check calibration...
check.cal(sbscal)

## Example 2
# Build template...
pop<-pop.template(sbsdes,~emp.num+ent-1,~area)
# Fill template...
pop<-fill.template(sbs.frame,pop)
# Calibrate with tight bounds...
sbscal<-e.calibrate(sbsdes,pop,sigma2=~emp.num,bounds=c(0.8,1.2))
# Check calibration...
check.cal(sbscal)

# Now try to calibrate with suggested bounds...
hint <- bounds.hint(sbsdes,pop)
sbscal<-e.calibrate(sbsdes,pop,sigma2=~emp.num,bounds=hint)
# Check calibration...
check.cal(sbscal)
```

collapse.strata

Collapse Strata Technique for Eliminating Lonely PSUs

Description

Modifies a stratified design containing lonely PSUs by collapsing its design strata into superstrata.

Usage

```
collapse.strata(design, block.vars = NULL, sim.score = NULL)
```

Arguments

design	Object of class <code>analytic</code> (or inheriting from it) containing survey data and sampling design metadata.
block.vars	Formula specifying blocking variables: only strata belonging to the same block will be aggregated (see ‘Details’). If <code>NULL</code> (the default option) no constraints will be imposed.
sim.score	Formula specifying a similarity score for strata: lonely strata will be paired with the most similar stratum in each block (see ‘Details’). If <code>NULL</code> (the default option) random pairs will be formed.

Details

Lonely PSUs (i.e. PSUs which are alone inside a not self-representing stratum) are a concern from the viewpoint of variance estimation. As a general solution, the **ReGenesees** package can handle the lonely PSUs problem by setting proper variance estimation options (see [ReGenesees.options](#)). The `collapse.strata` function implements a widely used alternative: the so called collapsed strata technique. The basic idea is to build artificial “*superstrata*” by aggregating strata containing lonely PSUs to other strata, and then to use such superstrata for variance estimation (see e.g. [Wolter 85] and [Rust, Kalton 87]).

The optional argument `block.vars` identifies “*blocking variables*” that can be used to constrain the way lonely strata are collapsed to form superstrata. More specifically: first, blocking variables are used to partition sample data in “*blocks*” via factor crossing, then, only lonely strata belonging to the same block are aggregated. If `block.vars=NULL` (the default option), no constraint will act on collapsing. The design variables referenced by `block.vars` (if any) should be of type factor. Errors will be raised if (i) blocks cut across strata, or (ii) `block.vars` generate any non-aggregable strata (i.e. lonely strata which are a singleton inside a block).

The optional argument `sim.score` can be used to specify a similarity score for strata aggregation. This means that each lonely stratum will be collapsed with the stratum that has the most similar value of variable `sim.score` inside the block. Thus the similarity of two strata is actually measured by the (absolute value of the) difference among the corresponding `sim.score` values. Only one design variable can be referenced by the `sim.score` formula: (i) it must be of type numeric, (ii) it must be constant inside each stratum, and (iii) it should be positive (otherwise its `abs()` will be silently used). Note that if no similarity score is specified (i.e. `sim.score=NULL`), the achieved strata aggregation will depend on the ordering of input sample data in design.

The collapsing algorithm will, whenever possible, build superstrata by pairing a lonely stratum to another not-yet-aggregated stratum. Therefore, in general, superstrata will contain only two design strata. Rare exceptions can arise, e.g. due to constraints, with at most three design strata inside a superstratum. The choice to collapse strata in pairs has been taken because it is known to be appropriate for large-scale surveys with many strata (at least for national level estimates, see e.g. [Rust, Kalton 87]).

The `collapse.strata` function handles correctly finite population corrections. If design has been built by passing strata sampling fractions via the `fpc` argument, the function re-computes sampling fractions inside superstrata by exploiting the achieved mapping of strata to superstrata and the `fpc` slot of design.

Value

An object of the same class as `design`, without strata containing lonely PSUs.

Strata Collapse Process Diagnostics

As already observed in the ‘Details’ Section, there are three non trivial reasons why function `collapse.strata` can run into errors: (1) the blocks cut across strata, (2) some blocks contain a stratum needing to be aggregated while this stratum happens to be the only one inside the block, (3) the similarity score for strata aggregation varies inside strata. In order to help the user to identify such data anomalies, hence taking a step forward to eliminate them, every call to `collapse.strata` generates, by side effect, a diagnostics data structure named `clps.strata.status` into the `.GlobalEnv` (see ‘Examples’).

The `clps.strata.status` list has three components: the first reports the error message, the second stores a vector identifying the data subsets that have been hit by the anomaly, the third reports the call to `collapse.strata` that generated the list. For instance, when error condition (1) holds, the second element of `clps.strata.status` identifies the strata that are cut by blocks; if, instead, error

condition (2) holds, the second element of the list identifies the blocks containing non-aggregable strata.

It must be stressed that *every call* to `collapse.strata` generates the `clps.strata.status` list, *even* when the strata collapsing process ends *successfully*. In such cases, the first element of the list reports the number of lonely strata that have undergone aggregation, whereas the second is a useful data frame (named `clps.table`) mapping collapsed strata to superstrata. To be more specific: each row of `clps.table` identifies a stratum that has been mapped to a superstratum, while the columns of `clps.table` give: (i) the block to which the stratum belongs, (ii) the stratum name, (iii) a flag indicating if the stratum was lonely or not, (iv) the name of the superstratum to which it has been mapped.

Methodological Warning

A warning must be emphasized: strata similarity score `sim.score` should be based on prior knowledge and/or on expectations on *true* values of stratum means for the variable(s) to be estimated, not on current sample data. Indeed, building `sim.score` by estimating stratum means with the current sample can lead to severe *underestimation* of sampling variance, i.e. to too tight confidence intervals.

Author(s)

Diego Zardetto

References

- Wolter, K.M. (2007) “*Introduction to Variance Estimation*”, Second Edition, Springer-Verlag, New York.
- Rust, K., Kalton, G. (1987) “*Strategies for Collapsing Strata for Variance Estimation*”, Journal of Official Statistics, Vol. 3, No. 1, pp. 69-81.

See Also

[ReGenesees.options](#) for a different way to handle the lonely PSUs problem (namely by setting variance estimation options).

Examples

```
#####
# Explore alternative collapsing strategies. #
#####

# Build a survey design with lonely PSU strata:
data(data.examples)
exdes <- e.svydesign(data= example, ids= ~ towcod+famcod,
                   strata= ~ stratum, weights= ~ weight)
exdes

# Explore 3 possible collapsing strategies:
# 1) Aggregate lonely strata by forming random pairs
exdes.clps1 <- collapse.strata(exdes)
exdes.clps1

# 2) Aggregate lonely strata in pairs under constraints:
#   i. aggregated strata must be both not self-representing
```



```

# ii. aggregated strata must belong to the same province (which
# is appropriate if e.g. provinces are planned estimation domains)
exdes.clps2 <- collapse.strata(exdes, ~sr:procod)
exdes.clps2

# 3) A WRONG strategy: compute strata similarity score by using
# sample estimates of the interest variable (y1) inside strata:
old.op <- options("RG.lonely.psu"="remove")
stat.score <- svystatTM(design= exdes, ~y1, by= ~ stratum)
options(old.op)
exdes2<-des.addvars(exdes,
                    sim.score=stat.score[match(stratum,stat.score$stratum),2])
exdes.clps3 <- collapse.strata(exdes2,~sr:procod,~sim.score)
exdes.clps3

# Compute total estimates of y1 at the province level
# for all 3 designs with collapsed strata:
stat.clps1 <- svystatTM(design= exdes.clps1, y= ~ y1, by= ~ procod,
                      estimator= "Total", vartype= "cvpct")
stat.clps2 <- svystatTM(design= exdes.clps2, y= ~ y1, by= ~ procod,
                      estimator= "Total", vartype= "cvpct")
stat.clps3 <- svystatTM(design= exdes.clps3, y= ~ y1, by= ~ procod,
                      estimator= "Total", vartype= "cvpct")

# Compute the same estimates by using two alternatives
# to handle lonely PSUs:
# "adjust" option
old.op <- options("RG.lonely.psu"="adjust")
stat.adj <- svystatTM(design= exdes, y= ~ y1, by= ~ procod,
                    estimator= "Total", vartype= "cvpct")
options(old.op)
# "average" option
old.op <- options("RG.lonely.psu"="average")
stat.ave <- svystatTM(design= exdes, y= ~ y1, by= ~ procod,
                    estimator= "Total", vartype= "cvpct")
options(old.op)

# Lastly, compare achieved estimates for CV percentages:
stat.clps1
stat.clps2
stat.clps3
stat.adj
stat.ave

# Thus the qualitative features are as expected: the "adjust" option
# tends to give conservative sampling variance estimates, the WRONG collapsing
# strategy 3) tends to underestimate sampling variance, while other methods
# give results in-between those extrema.

#####
# A simple way for defining the strata similarity scores. #
#####
# Suppose that strata have been clustered in groups of similar
# strata. You can, then, use the integer codes of the factor
# variable identifying the clusters as a similarity score.
# You can do as follows:

```

```

# Load some data:
data(fpcdat)

# Build a design object:
fpcdes<-e.svydesign(data=fpcdat,ids=~psu+ssu,strata=~stratum,weights=~w)
fpcdes

# As we deliberately omitted to specify fpcs, this design
# has 2 lonely strata out of 5:
find.lon.strata(fpcdes)

# Now, suppose that factor variable pl.domain identifies clusters of
# similar strata...
table(fpcdat$stratum,fpcdat$pl.domain)

# ...hence, the similarity score can be obtained simply...
fpcdes<-des.addvars(fpcdes,score=unclass(pl.domain))

# ...and readily be used to drive the strata collapsing:
fpcdes.clps<-collapse.strata(fpcdes,sim.score=~score)
fpcdes.clps
clps.strata.status

# As we expected from the groups defined by pl.domain, lonely stratum S.2
# has been paired to S.3, and lonely stratum S.5 to S.4.

# Should we have omitted to specify a similarity score, we would have
# obtained different superstrata:
fpcdes.clps2<-collapse.strata(fpcdes)
fpcdes.clps2
clps.strata.status

#####
# Few examples to inspect the clps.strata.status list generated #
# for diagnostics purposes.                                     #
#####

# 1) Ill defined blocks: cutting across strata:
## Not run:
clps.err1 <- collapse.strata(exdes,~sex)

## End(Not run)
clps.strata.status

# 2) Ill defined blocks: generating non-aggregable strata
## Not run:
clps.err2 <- collapse.strata(exdes,~regcod:stratum)

## End(Not run)
clps.strata.status

# 3) Successful collapsing: explore strata to superstrata mapping
exdes.ok <- collapse.strata(exdes, ~sr:regcod:procod)
clps.strata.status

```

Description

These functions control the way **ReGenesees** translates a symbolic calibration model (as specified by the `calmodel` formula in `e.calibrate`, `pop.template`, `fill.template`, `aux.estimate`s, ...) to its numeric encoding (i.e. the model-matrix used by the internal algorithms to perform actual computations).

Usage

```
contrasts.RG()
contrasts.off()
contrasts.reset()
contr.off(n, base = 1, contrasts = TRUE, sparse = FALSE)
```

Arguments

<code>n</code>	Formally as in function <code>contr.treatment</code> (see ‘Details’).
<code>base</code>	Formally as in function <code>contr.treatment</code> (see ‘Details’).
<code>contrasts</code>	Fictitious, but formally as in function <code>contr.treatment</code> . (see ‘Details’)
<code>sparse</code>	Formally as in function <code>contr.treatment</code> . (see ‘Details’)

Details

All the calibration facilities in package **ReGenesees** transform symbolic calibration models (as specified by the user via `calmodel`) into numeric model-matrices. Factor variables occurring in `calmodel` play a special role in such transformations, as the encoding of a factor can (and, by default, do) *depend* on the *structure* of the formula in which it occurs. The **ReGenesees** functions documented below control the way factor levels are translated into auxiliary variables and mapped to columns of population totals data frames. The underlying technical tools are `contrasts` handling functions (see Section ‘Technical Remarks and Warnings’ for further details).

Under the calibration perspective, ordered and unordered factors appearing in `calmodel` must be treated the same way. This obvious constraint defines the **ReGenesees** default for contrasts handling. Such a default is silently set when loading the package. Moreover, you can set it also by calling `contrasts.RG()`. As can be understood by reading Section ‘Technical Remarks and Warnings’ below, the default setup can be seen as **“efficient-but-slightly-risky”**.

A call to `contrasts.off()` simply disables all contrasts and imposes a complete dummy coding of factors. Under this setup, all levels of factors occurring in `calmodel` generate a distinct model-matrix column, *even if some of these columns can be linearly dependent*. To be very concise, the `contrasts.off()` setup can be seen as **“safe-but-less-efficient”** as compared to the default one (read Section ‘Technical Remarks and Warnings’ for more details).

Function `contr.off` is not meant to be called directly by users: it serves only the purpose of enabling the `contrasts.off()` setup.

A call to `contrasts.reset()` restores R factory-fresh defaults for contrasts (which do distinguish ordered and unordered factors). Users may want to use this function after having completed a **ReGenesees** session, e.g. before switching to other R functions relying on contrasts (such as `lm`, `glm`, ...).

Technical Remarks and Warnings

“[...] the corner cases of `model.matrix` and `friends` is some of the more impenetrable code in the R sources.”

Peter Dalgaard

Contrasts handling functions tell R how to encode the model-matrix associated to a given model-formula on specific data (see, e.g., `contr.treatment`, `contrasts`, `model.matrix`, `formula`, and references therein). More specifically, contrasts control the way factor-terms and interaction-terms occurring in formulae get actually represented in the model matrix. For instance, R (by default) avoids the complete dummy coding of a factor whenever it is able to understand, on the basis of the structure of the model-formula, that some of the factor levels would generate linearly dependent (i.e. redundant) columns in the model-matrix (see Section ‘Examples’).

The usage of contrasts to build smaller, full-rank calibration model-matrices would be a good opportunity for **ReGenesees**, provided it comes *without any information loss*. Indeed, smaller model-matrices mean less population totals to be provided by users, and higher efficiency in computations.

Unfortunately, few controversial cases have been signalled in which R ability to “simplify” a model-matrix on the basis of the structure of the related model-formula seems to lead to strange, unexpected results (see, e.g., [this R-help thread](#)). No matter whether such R behaviour is or not an actual bug with respect to its impact on R linear model fitting or ANOVA facilities, it surely represents a concern for **ReGenesees** with respect to calibration (see Section ‘Examples’). The risk is the following: there could be rare cases in which exploiting R contrasts handling functions inside **ReGenesees** ends up with a *wrong* (i.e. incomplete) population totals template, and (eventually) with *wrong* calibration results.

Though one could adopt several ad-hoc countermeasures to sterilize the risk described above while still taking advantage of contrasts (see Section ‘Examples’), the choice of completely disabling contrasts via `contrasts.off()` would result in a **100% safety guarantee**. If computational efficiency is not a serious concern for you, switching off contrasts may determine the best **ReGenesees** setup for your analyses.

Author(s)

Diego Zardetto

References

Chambers, J. M. and Hastie, T. J. (1992) *Statistical models*. Chapter 2 of *Statistical Models in S* eds J. M. Chambers and T. J. Hastie, Wadsworth & Brooks/Cole.

["Why does the order of terms in a formula translate into different models/model matrices?"](#), R-help thread.

See Also

`e.calibrate`, `pop.template`, `fill.template`, and `aux.estimates` for the meaning and the usage of `calmodel` in **ReGenesees**. `formula`, `model.matrix`, `contrasts`, and `contr.treatment` to understand the role of contrasts in R.

Examples

```
#####
# Easy things first: #
#####
```

```

# 1) When ReGenesees is loaded, its standard way of handling contrasts
#      (i.e. no ordered-unordered factor distinction) is silently set:
options("contrasts")

# 2) To switch off contrasts (i.e. apply always dummy coding to factors),
#      simply type:
contrasts.off()

# 3) To restore R factory-fresh defaults for contrasts, simply type:
contrasts.reset()

# 4) To switch on again standard ReGenesees contrasts, simply type:
contrasts.RG()

#####
# A simple calibration example to understand the effects of #
# switching off contrasts.                                     #
#####

# Load sbs data:
data(sbs)

# Create a design object:
sbsdes<-e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,fpc=~fpc)

# Suppose you want to calibrate on the marginals of 'region' (a factor
# with 3 levels: "North", "Center", and "South") and 'dom3' (a factor
# with 4 levels: "A", "B", "C", and "D").
# Let's see how things go under the 'contrast on' (default) and 'contrasts off'
# setups:

#####
# 1) ReGenesees default: contrasts ON. #
#####
# As you see contrasts are ON:
options("contrasts")

# Build and fill the population totals template:
temp1<-pop.template(data=sbsdes,calmodel=~region+dom3-1)
pop1<-fill.template(universe=sbs.frame,template=temp1)

# Now inspect the obtained known totals data.frame:
pop1

# As you see: (i) it has only 6 columns, and (ii) the "A" level of
# factor 'dom3' is missing. This is because contrasts are ON, so that
# R is able to understand that only 6 out of the 3 + 4 marginal counts
# are actually independent. Indeed, the "A" counts...
sum(sbs.frame$dom3=="A")

# ...are actually redundant, since they can be deduced by pop1:
sum(pop1[,1:3])-sum(pop1[,4:6])

# Now calibrate:
cal1<-e.calibrate(sbsdes,pop1)

```

```
#####
# 2) Switch OFF contrasts: dummy coding for all! #
#####
# To switch off contrasts simply call:
contrasts.off()

# Build and fill the population totals template:
temp2<-pop.template(data=sbsdes,calmodel=~region+dom3-1)
pop2<-fill.template(universe=sbs.frame,template=temp2)

# Now inspect the obtained known totals data.frame:
pop2

# As you see: (1) it has now 7 columns, and (2) the "A" level of factor
# 'dom3' has been resurrected. This is because contrasts are OFF,
# so that each level of factors in calmodel are coded to dummies.

# Now calibrate. Since only 6 out of 7 dummy auxiliary variables are
# actually independent, the model.matrix computed by e.calibrate will not be
# full-rank. As a consequence, e.calibrate would use the Moore-Penrose
# generalized inverse (in practice, this could depend on the machine R
# is running on):
cal2<-e.calibrate(sbsdes,pop2)

# Compare the calibration weights generated under setups 1) and 2):
all.equal(weights(cal2),weights(cal1))

# Lastly set back contrasts to ReGenesees default:
contrasts.RG()

#####
# Weird results, risks and countermeasures. #
# ("When the going gets tough...")          #
#####

# Suppose you want to calibrate on: (A) the joint distribution of 'region' (a
# factor with 3 levels: "North", "Center", and "South") and 'nace.macro' (a
# factor with 4 levels: "Agriculture", "Industry", "Commerce", and "Services")
# and, at the same time, on (B) the total number of employees ('emp.num', a
# numeric variable) by 'nace.macro'.
#
# You rightly expect that  $3 \times 4 + 4 = 16$  population totals are needed for such a
# calibration task. Indeed, knowing the enterprise counts for the  $3 \times 4$  cells of
# the joint distribution (A) doesn't tell anything on the number of employees
# working in the 4 nace macrosectors (B), and vice-versa.
#
# Moreover, you might expect that calibration models:
# (i) calmodel = ~region:nace.macro + emp.num:nace.macro - 1
# (ii) calmodel = ~emp.num:nace.macro + region:nace.macro - 1
#
# should produce the same results.
# Unfortunately, WHEN CONTRASTS ARE ON, this is not the case: only model (i)
# leads to the expected, right results. Let's see.

#####
```

```

# A strange result when contrasts are ON: #
# the order of terms in calmodel matters! #
#####
# As you see contrasts are ON:
options("contrasts")

# Start with (i) calmodel = ~region:nace.macro + emp.num:nace.macro - 1
# Build and fill the population totals template:
temp1<-pop.template(data=sbsdes,~region:nace.macro+emp.num:nace.macro-1)
pop1<-fill.template(universe=sbs.frame,template=temp1)

# Now inspect the obtained known totals data.frame:
pop1

# and verify it stores the right, expected number of totals (i.e. 16):
dim(pop1)

# Now calibrate:
cal1<-e.calibrate(sbsdes,pop1)

# Now compare with (ii) calmodel = ~emp.num:nace.macro + region:nace.macro - 1
# Build and fill the population totals template:
temp2<-pop.template(data=sbsdes,~emp.num:nace.macro+region:nace.macro-1)
pop2<-fill.template(universe=sbs.frame,template=temp2)

# First check if it stores the right, expected number of totals (i.e. 16):
dim(pop2)

# Apparently 4 totals are missing; let's inspect the known totals data.frame
# to understand which ones:
pop2

# Thus we are missing the 4 'nace.macro' totals for 'region' level "North".
# Everything goes as if R contrasts functions mistakenly treated the term
# emp.num:nace.macro as a factor-factor interaction (i.e. a 2 way joint
# distribution), which would have justified to eliminate the 4 missing totals
# as redundant.

# Notice that calibrating on pop2 would generate wrong results...
cal2<-e.calibrate(sbsdes,pop2)

# ...indeed the 4 estimates of 'nace.macro' for 'region' level "North" are not
# actually calibrated (look at the magnitude of SE estimates):
svstatTM(cal2,~region,~nace.macro)

#####
# A possible countermeasure (still working with contrasts ON). #
#####
# Empirical evidence tells that the weird case above is extremely rare
# and that it manifests whenever a numeric (say X) and a factor (say F) both
# interact with the same factor (say D), i.e. calmodel=~(X+F):D-1.
#
# The risky order-dependent nature of such models can be sterilized (while
# still taking advantage of contrasts-driven simplifications for large,
# complex calibrations) by using a numeric variable with values 1 for

```

```

# all sample units.
#
# For instance, one could use variable 'ent' in the sbs data.frame, to
# handle the (A) part of the calibration constraints. Indeed you may easily
# verify that both the calmodel formulae below:
# (i) calmodel = ~ent:region:nace.macro + emp.num:nace.macro - 1
# (ii) calmodel = ~emp.num:nace.macro + ent:region:nace.macro - 1
#
# produce exactly the same, right results.

#####
# THE ULTIMATE, 100% SAFE, COUNTERMEASURE: switch contrasts OFF! #
#####
# No contrasts means no model-matrix simplifications at all, hence
# also no unwanted, wrong simplifications. Let's see:

# To switch off contrasts simply call:
contrasts.off()

# Compare again, with contrasts OFF, the calibration models:
# (i) calmodel = ~region:nace.macro + emp.num:nace.macro - 1
# (ii) calmodel = ~emp.num:nace.macro + region:nace.macro - 1

# Build and fill the population totals templates:
temp1<-pop.template(data=sbsdes,~region:nace.macro+emp.num:nace.macro-1)
pop1<-fill.template(universe=sbs.frame,template=temp1)
pop1

temp2<-pop.template(data=sbsdes,~emp.num:nace.macro+region:nace.macro-1)
pop2<-fill.template(universe=sbs.frame,template=temp2)
pop2

# Verify they store the same, right number of totals (i.e. 16):
dim(pop1)
dim(pop2)

# Verify they lead to right calibrated objects...
cal1<-e.calibrate(sbsdes,pop1)
cal2<-e.calibrate(sbsdes,pop2)

# ...with the same calibrated weights:
all.equal(weights(cal2),weights(cal1))

# Lastly set back contrasts to ReGenesees default:
contrasts.RG()

```

Corr

Design Covariance and Correlation of Complex Estimators in Sub-populations

Description

Estimates the covariance and the correlation of Complex Estimators in subpopulations. A Complex Estimator can be any analytic function of (Horvitz-Thompson or Calibration) estimators of Totals and Means.

Usage

```
CoV(design, expr1, expr2,
    by = NULL, na.rm = FALSE)
Corr(design, expr1, expr2,
    by = NULL, na.rm = FALSE)
```

Arguments

design	Object of class <code>analytic</code> (or inheriting from it) containing survey data and sampling design metadata.
expr1	R expression defining the first Complex Estimator (see ‘Details’).
expr2	R expression defining the second Complex Estimator (see ‘Details’).
by	Formula specifying the variables that define the "estimation domains". If <code>NULL</code> (the default option) estimates refer to the whole population.
na.rm	Should missing values (if any) be removed from the variables of interest? The default is <code>FALSE</code> (see ‘Details’).

Details

This function allows to estimate the covariance and the correlation of two arbitrary Complex Estimators. Estimates are calculated using the Taylor linearization technique.

The mandatory arguments `expr1` and `expr2` identify the Complex Estimators: both must be of class `expression`. For further details on the syntax and the semantics of such expressions, see [svystatL](#).

The optional argument `by` specifies the variables that define the "estimation domains", that is the subpopulations for which the estimates are to be calculated. If `by=NULL` (the default option), the estimates produced by `CoV` (`Corr`) refer to the whole population. Estimation domains must be defined by a formula: for example the statement `by=~B1:B2` selects as estimation domains the subpopulations determined by crossing the modalities of variables `B1` and `B2`. Notice that a formula like `by=~B1+B2` will be automatically translated into the factor-crossing formula `by=~B1:B2`: if you need to compute estimates for domains `B1` and `B2` *separately*, you have to call `CoV` (`Corr`) twice. The design variables referenced by `by` (if any) should be of type `factor`, otherwise they will be coerced.

Missing values (NA) in interest variables should be avoided. If `na.rm=FALSE` (the default) they generate NAs in estimates (or even an error, if `design` is calibrated). If `na.rm=TRUE`, observations containing NAs are dropped, and estimates get computed on non missing values only. This implicitly assumes that missing values hit interest variables *completely at random*: should this not be the case, computed estimates would be *biased*.

Value

An object inheriting from the `data.frame` class, whose detailed structure depends on input parameters' values.

Author(s)

Diego Zardetto

References

Sarndal, C.E., Swensson, B., Wretman, J. (1992) *“Model Assisted Survey Sampling”*, Springer Verlag.

See Also

Estimators of Totals and Means [svystatTM](#), Ratios between Totals [svystatR](#), Shares [svystatS](#), Ratios between Shares [svystatSR](#), Multiple Regression Coefficients [svystatB](#), Quantiles [svystatQ](#), and Complex Analytic Functions of Totals and/or Means [svystatL](#).

Examples

```
#####
# Some checks and some simple examples #
# to illustrate the syntax.             #
#####
# Load survey data:
data(data.examples)

# Creation of a design object:
des<-e.svydesign(data=example,ids=~towcod+famcod,strata=~SUPERSTRATUM,
               weights=~weight)

# Let's start with some natural checks:
## The covariance of any estimator with itself is its variance
## (use mean income as an example):
CoV(des,expression(income/ones),expression(income/ones))
VAR(svystatL(des,expression(income/ones)))
VAR(svystatTM(des,~income,estimator="Mean"))

## The correlation of any estimator with itself is 1
## (use mean income as an example):
Corr(des,expression(income/ones),expression(income/ones))

# Switch to non trivial examples:
## Correlation of mean income with population size:
Corr(des,expression(income/ones),expression(ones))

## Correlation of mean income with total income:
# at population level:
Corr(des,expression(income/ones),expression(income))
# for regions:
Corr(des,expression(income/ones),expression(income),by=~regcod)

## Correlation of a product of two totals and a ratio of two totals:
# at population level:
Corr(des,expression(y1*y2),expression(x1/x2))
# for provinces:
Corr(des,expression(income/ones),expression(income),by=~procod)

#####
# A more meaningful and complex example: correlation #
# between Geometric, Harmonic and Arithmetic Means. #
#####
# Creation of another design object:
data(sbs)
sbsdes<-e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,
                  fpc=~fpc)
```

```

# Let's use variable emp.num, which is ok as it is always strictly positive:
## Add a convenience variable for estimating the harmonic mean (see ?svstatL
## for details) and prepare the formal estimator expression:
sbsdes<-des.addvars(sbsdes,emp.num.m1=1/emp.num)
h<-expression(ones/emp.num.m1)

## Add a convenience variable for estimating the geometric mean (see ?svstatL
## for details) and prepare the formal estimator expression:
sbsdes<-des.addvars(sbsdes,log.emp.num=log(emp.num))
g<-expression(exp(log.emp.num/ones))

## prepare the formal estimator expression for the arithmetic mean:
m<-expression(emp.num/ones)

# Now compute correlations:
## Harmonic with Arithmetic:
Corr(sbsdes,h,m)

## Geometric with Arithmetic:
Corr(sbsdes,g,m)

## Harmonic with Geometric:
Corr(sbsdes,h,g)

## Hence, while correlations g-m and g-h are high, correlation h-m is low.

#####
# Another example: is a ratio estimator of a total #
# expected to be more efficient than an HT one?    #
#####

# Let's recall that the ratio estimator of a total is
# expected to be more efficient than HT, if the
# correlation of numerator and denominator exceeds
# half of the ratio between the CVs of denominator
# and numerator.

# Compute the HT estimate of the total of value added (variable va.imp2):
VA<-svstatTM(sbsdes,~va.imp2)
VA

# Compute the HT estimate of the total of emp.num:
EMP<-svstatTM(sbsdes,~emp.num)
EMP

# Now estimate the correlation of the numerator
# and denominator totals:
corr <- Corr(sbsdes,expression(va.imp2),expression(emp.num))
corr

# and compare it with  $(1/2) * (CV(den)/CV(num))$ 
stopifnot( corr > 0.5*cv(EMP)/cv(VA) )

# As the comparison holds TRUE, we expect an efficiency gain
# of the ratio estimator of the total compared to HT.
# Let's check...:

```

```

# Compute the ratio estimate of the total of value added using
# as auxiliary variable the number of employees, whose total
# is 984394:
TOT.emp.num <- sum(sbs.frame$emp.num)
TOT.emp.num

VA.ratio<-svystatL(sbsdes, expression(TOT.emp.num * (va.imp2/emp.num)))
VA.ratio

# Compare standard errors sizes:
SE(VA.ratio)
SE(VA)
stopifnot( SE(VA.ratio) < SE(VA) )

# ...as expected.

```

data.examples

Artificial Household Survey Data

Description

Example data frames. Allow to run R code contained in the ‘Examples’ section of the **ReGenesees** package help pages.

Usage

```
data(data.examples)
```

Format

The main data frame, named `example`, contains (artificial) data from a two stage stratified cluster sampling design. The sample is made up of 3000 final units, for which the following 21 variables were observed:

`towcod` Code identifying "variance PSUs": towns (PSUs) in not-self-representing (NSR) strata, families (SSUs) in self-representing (SR) strata, numeric

`famcod` Code identifying families (SSUs), numeric

`key` Key identifying final units (individuals), numeric

`weight` Initial weights, numeric

`stratum` Stratification variable, factor with levels 801 802 803 901 902 903 904 905 906 907 908 1001 1002 1003 1004 1005 1006 1007 1008 1009 1101 1102 1103 1104 3001 3002 3003 3004 3005 3006 3007 3008 3009 3010 3011 3012 3101 3102 3103 3104 3105 3106 3107 3108 3201 3202 3203 3204 5401 5402 5403 5404 5405 5406 5407 5408 5409 5410 5411 5412 5413 5414 5415 5416 5501 5502 5503 5504 9301 9302 9303 9304 9305 9306 9307 9308 9309 9310 9311 9312

`SUPERSTRATUM` Collapsed strata variable (eliminates lonely PSUs), factor with levels 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55

`sr` Strata type, integer with values 0 (NSR strata) and 1 (SR strata)

`regcod` Code identifying regions, factor with levels 6 7 10

```

procod Code identifying provinces, factor with levels 8 9 10 11 30 31 32 54 55 93
x1 Indicator variable (integer), numeric
x2 Indicator variable (integer), numeric
x3 Indicator variable (integer), numeric
y1 Indicator variable (integer), numeric
y2 Indicator variable (integer), numeric
y3 Indicator variable (integer), numeric
age5c Age variable with 5 classes, factor with levels 1 2 3 4 5
age10c Age variable with 10 classes, factor with levels 1 2 3 4 5 6 7 8 9 10
sex Sex variable, factor with levels f m
marstat Marital status variable, factor with levels married unmarried widowed
z A continuous quantitative variable, numeric
income Income variable, numeric

```

Details

Objects `pop01`, ..., `pop07pp` contain known population totals for various calibration models. Object pairs with names differing in the 'p' suffix (such as `pop03` and `pop03p`) refer to the *same* calibration problem but pertain to *different* solution methods (global and partitioned respectively, see [e.calibrate](#)). The two-component numeric vector `bounds` expresses a possible choice for the allowed range for the ratios between calibrated weights and direct weights in the aforementioned calibration problems.

Warning

Data in the example data frame are artificial. The *structure* of `example` intentionally resembles the one of typical household survey data, but the *values* it stores are unreliable. The only purpose of such data is that they can be fruitfully exploited to illustrate the syntax and the working mechanism of the functions provided by the **ReGenesees** package.

Examples

```

data(data.examples)
head(example)
str(example)

```

Delta.clus

Two Artificial Cluster Samples for Estimation of Change

Description

Two small, partially overlapping datasets, built to mimick non-independent PSU samples selected with a one- or multi-stage, stratified, cluster sampling design (but identifiers of SSUs etc. are not reported). Allow to run R code contained in the 'Examples' section of **ReGenesees** function [svyDelta](#).

Usage

```
data(Delta.clus)
```

Format

Two data frames, `sclus1` and `sclus2`, with 6 PSUs each (and 20 and 22 final units, respectively), and the following 5 variables.

- For both samples `sclus1` and `sclus2`:

`id` Identifier of sample PSUs, numeric

`strata` Stratification variable, a factor with 2 levels: A, and B

`w` Sampling weights of final units, numeric

`y` A numeric variable

`x` A numeric variable, correlated with `y`

Details

The two samples, `sclus1` and `sclus2`, have 3 PSUs in common, resulting in an overlap rate of $3 / 6 = 0.5$ at PSU-level. One could think of them as, e.g., two consecutive waves of a rotating panel with a 50% overlap at PSU-level.

Common PSUs are unambiguously identified by variable `id`.

The stratification is *static*: (1) `sclus1` and `sclus2` use the same strata (i.e. levels A, and B), and (2) no common PSUs changed stratum from `sclus1` to `sclus2`.

The ‘Examples’ section of [svyDelta](#) will illustrate the effect of *dynamic* stratification by injecting new strata and stratum-changer units in the samples.

See Also

[svyDelta](#) for calculating estimates and sampling errors of Measures of Change from two not necessarily independent samples, and [Delta.el](#) for 2 artificial overlapping samples of elementary units.

Examples

```
data(Delta.clus)
# Have a look:
sclus1
sclus2

# Have a look at the overlap subsample of 3 PSUs (36 final units):
sc <- merge(sclus1, sclus2, by = "id", suffixes = c("1", "2"))
sc

# Have a look at the full rotation structure (50% PSUs overlap in each stratum):
s <- merge(sclus1, sclus2, by = "id", all = TRUE, suffixes = c("1", "2"))
s <- s[order(s$strata1, s$strata2), ]
s

# As anticipated, strata are static:
with(s, table(strata1, strata2, useNA = "ifany"))
```

Delta.el

Two Artificial Samples of Elementary Units for Estimation of Change

Description

Two small, partially overlapping datasets, built to mimick non-independent samples selected with a one-stage, stratified, element sampling design. Allow to run R code contained in the ‘Examples’ section of **ReGenesees** function [svyDelta](#).

Usage

```
data(Delta.el)
```

Format

Two data frames, `s1` and `s2`, with 20 observations each and the following 5 variables.

- For both samples `s1` and `s2`:

`id` Identifier of sample units, numeric

`strata` Stratification variable, a factor with 2 levels: A, and B

`w` Sampling weights, numeric

`y` A numeric variable

`x` A numeric variable, correlated with `y`

Details

The two samples, `s1` and `s2`, have 8 units in common, resulting in an overlap rate of $8 / 20 = 0.4$. One could think of them as, e.g., two consecutive waves of a rotating panel with a 40% overlap.

Common units are unambiguously identified by variable `id`.

The stratification is *static*: (1) `s1` and `s2` use the same strata (i.e. levels A, and B), and (2) no common units changed stratum from `s1` to `s2`.

The ‘Examples’ section of [svyDelta](#) will illustrate the effect of *dynamic* stratification by injecting new strata and stratum-changer units in the samples.

See Also

[svyDelta](#) for calculating estimates and sampling errors of Measures of Change from two not necessarily independent samples, and [Delta.clus](#) for 2 artificial overlapping samples of clusters.

Examples

```
data(Delta.el)
# Have a look:
s1
s2

# Have a look at the overlap subsample of 8 units:
sc <- merge(s1, s2, by = "id", suffixes = c("1", "2"))
sc
```

```
# Have a look at the full rotation structure (40% overlap in each stratum):
s <- merge(s1, s2, by = "id", all = TRUE, suffixes = c("1", "2"))
s <- s[order(s$strata1, s$strata2), ]
s

# As anticipated, strata are static:
with(s, table(strata1, strata2, useNA = "ifany"))
```

des.addvars

Add Variables to Design Objects

Description

Modifies an analytic object by adding new variables to it.

Usage

```
des.addvars(design, ...)
```

Arguments

design	Object of class <code>analytic</code> (or inheriting from it) containing survey data and sampling design metadata.
...	tag = expr arguments defining columns to be added to design.

Details

This function adds to the data frame contained in `design` the *new* variables defined by the `tag = expr` arguments. A `tag` can be specified either by means of an identifier or by a character string; `expr` can be any expression that it makes sense to evaluate in the design environment.

For each argument `tag = expr` bound to the formal argument `...` the added column will have *name* given by the `tag` value and *values* obtained by evaluating the `expr` expression on `design`. Any input expression not supplied with a `tag` will be ignored and will therefore have no effect on the `des.addvars` return value.

Variables to be added to the input object have to be *new*: namely it is not possible to use `des.addvars` to modify the values in a pre-existing design column. This is an intentional feature meant to safeguard the integrity of the relations between survey data and sampling design metadata stored in `design`.

Value

An object of the same class of `design`, containing new variables but supplied with exactly the same metadata.

Author(s)

Diego Zardetto

References

Zardetto, D. (2015) “*ReGenesees: an Advanced R System for Calibration, Estimation and Sampling Error Assessment in Complex Sample Surveys*”. Journal of Official Statistics, 31(2), 177-203. doi: <https://doi.org/10.1515/jos-2015-0013>.

See Also

[e.svydesign](#) to bind survey data and sampling design metadata, [e.calibrate](#) for calibrating weights.

Examples

```
data(data.examples)

# Creation of an analytic object:
des<-e.svydesign(data=example,ids=~towcod+famcod,strata=~SUPERSTRATUM,
  weights=~weight)

# Adding the new 'ones' variable to estimate the number
# of final units in the population:
des<-des.addvars(des,ones=1)
svystatTM(des,~ones)

# Recoding a qualitative variable:
des<-des.addvars(des,agerange=factor(ifelse(age5c==1,
  "young", "not-young")))
svystatTM(des,~agerange,estimator="Mean")
svystatTM(des,~income,~agerange,estimator="Mean",conf.int=TRUE)

# Algebraic operations on numeric variables:
des<-des.addvars(des,z2=z^2)
svystatTM(des,~z2,estimator="Mean")

# A more interesting example: estimating the
# percentage of population with income below
# the poverty threshold (defined as 0.6 times
# the median income for the whole population):
Median.Income <- coef(svystatQ(des, ~income,probs=0.5))
Median.Income
des <- des.addvars(des,
  status = factor(
    ifelse(income < (0.6 * Median.Income),
      "poor", "non-poor")
  )
)
svystatTM(des,~status,estimator="Mean")
# Mean income for poor and non-poor:
svystatTM(des,~income,~status,estimator="Mean")

### NOTE: Procedure above yields *correct point estimates* of the share of poor
### population and their average income, while *variance estimation is
### approximated* since we neglected the sampling variability of the
### estimated poverty threshold.
```

des.merge

*Merge New Survey Data into Design Objects***Description**

Modifies an analytic object by joining the original survey data with a new data frame via a common key.

Usage

```
des.merge(design, data, key)
```

Arguments

design	Object of class <code>analytic</code> (or inheriting from it) containing survey data and sampling design metadata.
data	Data frame containing a key variable, plus new variables to be merged to design data.
key	Formula identifying the common key variable to be used for merging.

Details

This function updates the survey variables contained into design (i.e. `design$variables`), by merging the original data with those contained into the data data frame. The merge operation exploits a *single* variable key, which must be common to both design and data.

The function preserves both the original *ordering* of the survey data stored into design, as well as all the original sampling design *metadata*.

The variable referenced by key must be a *valid* unique key for both design and data: it must not contain duplicated values, nor NAs. Moreover, the values of key in design and data must be in *1:1 correspondence*. These requirements are meant to ensure that the *new* survey data (that is the merged ones) will have exactly the same number of rows as the *old* survey data stored into design.

Should design and data contain further common variables besides the key, only their original design version will be retained. Thus, `des.merge` cannot modify any pre-existing design columns. This an intentional feature intended to safeguard the integrity of the relations between survey data and sampling design metadata stored in design.

Value

An object of the same class of design, containing additional survey data but supplied with exactly the same metadata.

Practical Purpose

In the field of Official Statistics, it is not infrequent that calibration weights must be computed even several months before the target variables of the survey are made available for estimation. Such a time lag follows from the fact that target variables typically undergo much more thorough editing and imputation procedures than auxiliary variables.

In such production scenarios, function `des.merge` allows to tackle the task of computing estimates and errors for the fresh-released target variables *without* any need of *repeating* the calibration step. Indeed, by using the function, one can join the data contained into an already calibrated design

object with new data made available only after the calibration step. The merge operation is made easy and safe, and preserves all the original calibration metadata (e.g. those needed for variance estimation).

Author(s)

Diego Zardetto

See Also

[e.svydesign](#) to bind survey data and sampling design metadata, [e.calibrate](#) for calibrating weights, [des.addvars](#) to add new variables to design objects.

Examples

```
data(data.examples)

# Create a design object:
des<-e.svydesign(data=example,ids=~towcod+famcod,strata=~SUPERSTRATUM,
  weights=~weight)

# Create a calibrated design object as well (e.g. using population totals
# stored inside pop03p):
cal<-e.calibrate(design=des,df.population=pop03p,
  calmodel=~marstat-1,partition=~sex,calfun="logit",
  bounds=bounds)

# Lastly create a new data frame to be merged into des and cal:
set.seed(12345) # RNG seed fixed for reproducibility
new.data<-example[,c("income","key")]
new.data$income <- 1000 + new.data$income # altered income values
new.data$NEW.f<-factor(sample(c("A","B"),nrow(new.data),rep=TRUE))
new.data$NEW.n<-rnorm(nrow(new.data),10,2)
new.data <- new.data[sample(1:nrow(new.data)), ] # rows ordering changed
head(new.data)

#####
# Example 1: merge new data into a non calibrated design. #
#####

# Merge new data inside des (note the warning on income):
des2<-des.merge(design=des,data=new.data,key=~key)

# Compare visually:
## before:
head(des$variables)
## after:
head(des2$variables)

# New data can be used as usual:
svystatTM(des2,~NEW.n,~NEW.f,vartype="cvpct")

# Old data are unaffected, as it must be:
svystatTM(des,~income,estimator="Mean",vartype="cvpct")
svystatTM(des2,~income,estimator="Mean",vartype="cvpct")

#####
```

```
# Example 2: merge new data into a calibrated design. #
#####

# Merge new data inside cal (note the warning on income):
cal2<-des.merge(design=cal,data=new.data,key=~key)

# Compare visually:
## before:
head(cal$variables)
## after:
head(cal2$variables)

# New data can be used as usual:
svystatTM(cal2,~NEW.n,~NEW.f,vartype="cvpct")

# Old data are unaffected, as it must be:
svystatTM(cal,~income,estimator="Mean",vartype="cvpct")
svystatTM(cal2,~income,estimator="Mean",vartype="cvpct")
```

drop.gvf.points

Drop Outliers and Refit a GVF Model

Description

This function drops observations (alleged outliers) from a fitted GVF model and simultaneously re-fits the model.

Usage

```
drop.gvf.points(x, method = c("pick", "cut"), which.plot = 1:2,
               res.type = c("standard", "student"), res.cut = 3,
               id.n = 3, labels.id = NULL,
               cex.id = 0.75, label.pos = c(4, 2),
               cex.caption = 1, col = NULL, drop.col = "red",
               ...)
```

Arguments

x	An object containing a <i>single</i> fitted GVF model (i.e. of class <code>gvf.fit</code> or <code>gvf.fit.gr</code>).
method	character specifying the method for identifying observations to be dropped (see ‘Details’); it may be either ‘pick’ (the default) or ‘cut’.
which.plot	integer controlling the nature of the plot(s) that are used to identify and/or visualize the observations to be dropped: 1 means ‘Observed vs Fitted’, 2 means ‘Residuals vs Fitted’ (see ‘Details’).
res.type	character specifying what kind of residuals must be used.
res.cut	A positive value: observations to be dropped will be those with residuals whose absolute value exceeds ‘res.cut’. Only meaningful if method is ‘cut’.
id.n	Number of points to be initially labelled in each plot, starting with the most extreme. Only meaningful if method is ‘pick’.
labels.id	Vector of labels, from which the labels for extreme points will be chosen. NULL uses observation numbers.

cex.id	Magnification of point labels.
label.pos	Positioning of labels, for the left half and right half of the graph(s) respectively.
cex.caption	Controls the size of caption.
col	Color to be used for the points in the plot(s).
drop.col	Color to be used to visualize and annotate the points to be dropped in the plot(s).
...	Other parameters to be passed through to plotting functions.

Details

This function drops observations (alleged outliers) from a *single* fitted GVF model and simultaneously re-fits the model. As a side effect, the function prints on screen the induced change for selected quality measures (see, e.g., [getR2](#)).

If method = "pick", observations to be dropped are identified interactively by clicking on points of a plot (see 'Note'). Argument which.plot determines the nature of the plot: value 1 is for 'Observed vs Fitted', value 2 is for 'Residuals vs Fitted'. In the latter case, argument res.type specifies what kind of residuals have to be plotted. Argument id.n specifies how many points have to be labelled initially, starting with the most extreme in terms of the selected residuals: this applies to both kinds of plots.

If method = "cut", observations to be dropped are those with residuals whose absolute value exceeds the value of argument res.cut. Again, argument res.type specifies what kind of residuals have to be used (and plotted). The points which have been cut will be highlighted on a plot, whose nature is again specified by argument which.plot. If which.plot = 1:2, dropped points will be visualized on both the 'Observed vs Fitted' and the 'Residuals vs Fitted' graphs simultaneously.

Argument drop.col controls the color to be used to visualize and annotate in the plot(s) the points to be dropped. All the other arguments have the same meaning as in function [plot.lm](#).

Value

An object of the same class as x (i.e. either `gvf.fit` or `gvf.fit.gr`), containing the original GVF model re-fitted after dropping (alleged) outliers.

Note

For method = "pick", function drop.gvf.points is only supported on those screen devices for which function [identify](#) is supported. The identification process can be terminated either by right-clicking the mouse and selecting 'Stop' from the menu, or from the 'Stop' menu on the graphics window.

Author(s)

Diego Zardetto

See Also

[GVF.db](#) to manage **ReGenesees** archive of registered GVF models, [gvf.input](#) and [svystat](#) to prepare the input for GVF model fitting, [fit.gvf](#) to fit GVF models, [plot.gvf.fit](#) to get diagnostic plots for fitted GVF models, and [predictCV](#) to predict CV values via fitted GVF models.

Examples

```

# Load example data:
data(AF.gvf)

# Inspect available estimates and errors of counts:
str(ee.AF)

# List available registered GVF models:
GVF.db

# Fit example data to registered GVF model number one:
m <- fit.gvf(ee.AF, model=1)
m
summary(m)

#####
# Method 'pick': identify outlier observations to be dropped #
# interactively by clicking on points of a plot.           #
#####
# Using the 'Observed vs Fitted' plot (the default):
## Not run:
m1 <- drop.gvf.points(m)
m1
summary(m1)

## End(Not run)

# Using the 'Residuals vs Fitted' plot with standardized
# residuals (the default) and increasing id.n to get more
# labelled points to guide your choices:
## Not run:
m1 <- drop.gvf.points(m, which.plot = 2, id.n = 10)
m1
summary(m1)

## End(Not run)

# The same as above, but with studentized residuals and
# playing with colors:
## Not run:
m1 <- drop.gvf.points(m, which.plot = 2, id.n = 10, res.type = "student",
                      col = "blue", drop.col = "green", pch = 20)
m1
summary(m1)

## End(Not run)

#####
# Method 'cut': identify outlier observations to be dropped #
# by specifying a threshold for the absolute values of the #
# residuals.                                               #
#####
# Using default threshold on standardized residuals and visualizing
# dropped observations on both 'Observed vs Fitted' and 'Residuals
# vs Fitted' plots:

```

```

m1 <- drop.gvf.points(m, method ="cut")
m1
summary(m1)

# Using a custom threshold on studentized residuals and visualizing
# dropped observations on the 'Observed vs Fitted' plot:
m1 <- drop.gvf.points(m, method ="cut", res.type = "student",
                      res.cut = 2.5, which.plot = 1)
m1
summary(m1)

# The same as above, but visualizing dropped observations on the
# 'Residuals vs Fitted' plot:
m1 <- drop.gvf.points(m, method ="cut", res.type = "student",
                      res.cut = 2.5, which.plot = 2)
m1
summary(m1)

# You can obviously "cut"/"pick" alleged outliers again from an already
# "cut"/"picked" fitted GVF model:
m2 <- drop.gvf.points(m1, method ="cut", res.type = "student",
                      res.cut = 2.5, col = "blue", pch = 20)
m2
summary(m2)

#####
# Identifying outlier observations to be dropped from "grouped" #
# GVF fitted models (i.e. x has class 'gvf.fit.gr').           #
#####
# Recall we have at our disposal the following survey design object
# defined on household data:
exdes

# Now use function svystat to prepare "grouped" estimates and errors
# of counts to be fitted separately (here groups are regions):
ee <- svystat(exdes, y=~ind, by=~age5c:marstat:sex, combo=3, group=~regcod)
ee
plot(ee)

# Fit registered GVF model number one separately inside groups:
m <- fit.gvf(ee, model=1)
m
summary(m)

# Now drop alleged outliers separately inside groups:

#####
# Method 'pick': work interactively group by group. #
#####
## Not run:
m1 <- drop.gvf.points(m, which.plot = 2, res.type = "student", col = "blue",
                      pch = 20)

m1
summary(m1)

## End(Not run)

```

```
#####
# Method 'cut': apply the same threshold to all groups. #
#####
m1 <- drop.gvf.points(m, method = "cut", res.type = "student", res.cut = 2)
m1
summary(m1)
```

e.calibrate

Calibration of Survey Weights

Description

Adds to an analytic object the calibrated weights column.

Usage

```
e.calibrate(design, df.population,
            calmodel = if (inherits(df.population, "pop.totals"))
                        attr(df.population, "calmodel"),
            partition = if (inherits(df.population, "pop.totals"))
                        attr(df.population, "partition") else FALSE,
            calfun = c("linear", "raking", "logit"),
            bounds = c(-Inf, Inf), aggregate.stage = NULL,
            sigma2 = NULL, maxit = 50, epsilon = 1e-07, force = TRUE)
```

Arguments

design	Object of class <code>analytic</code> (or inheriting from it) containing survey data and sampling design metadata.
df.population	Data frame containing the known population totals for the auxiliary variables.
calmodel	Formula defining the linear structure of the calibration model.
partition	Formula specifying the variables that define the "calibration domains" for the model (see 'Details'); FALSE (the default) implies no calibration domains.
calfun	character specifying the distance function for the calibration process; the default is 'linear'.
bounds	Allowed range for the ratios between calibrated and initial weights; the default is <code>c(-Inf, Inf)</code> .
aggregate.stage	An integer: if specified, causes the calibrated weights to be constant within sampling units at this stage.
sigma2	Formula specifying a possible heteroskedasticity effect in the calibration model; NULL (the default) implies homoskedasticity.
maxit	Maximum number of iterations for the Newton-Raphson algorithm; the default is 50.
epsilon	Tolerance for the absolute relative differences between the population totals and the corresponding estimates based on the calibrated weights; the default is 10^{-7} .
force	If TRUE, whenever the calibration algorithm does not converge, forces the function to return a value (see 'Details' and 'Calibration process diagnostics'); the default is TRUE.

Details

This function creates an object of class `cal.analytic`. A `cal.analytic` object makes it possible to compute estimates and standard errors of calibration estimators [Deville, Sarndal 92] [Deville, Sarndal, Sautory 93].

The mandatory argument `calmodel` symbolically defines the calibration model you intend to use, that is - in the language of the Generalized Regression Estimator - the assisting linear regression model underlying the calibration problem. More specifically, the `calmodel` formula identifies the auxiliary variables and the constraints for the calibration problem, with a notation inspired by [Wilkinson, Rogers 73]. For example, `calmodel=~(X+Z):C+(A+B):D-1` defines the calibration problem in which constraints are imposed: (i) on the totals of auxiliary (quantitative) variables *X* and *Z* within the subpopulations identified by the (qualitative) classification variable *C* and, at the same time, (ii) on the absolute frequency of the (qualitative) variables *A* and *B* within the subpopulations identified by the (qualitative) classification variable *D*.

The design variables referenced by `calmodel` must be numeric or factor and must not contain any missing value (NA).

Problems for which one or more qualitative variables can be “*factorized*” in the formula that specifies the calibration model, are particularly interesting. These variables split the population into non-overlapping subpopulations known as “*calibration domains*” for the model. An example is provided by the statement `calmodel=~(A+B+X+Z):D-1` in which the variable that identifies the calibration domains is *D*; similarly, the formula `calmodel=~(A+B+X+Z):D1:D2-1` identifies as calibration domains the subpopulations determined by crossing the modalities of *D1* and *D2*. The interest in models of this kind lies in the fact that the *global* calibration problem they describe can, actually, be broken down into *local* subproblems, one per calibration domain, which can be solved separately [Vanderhoeft 01]. Thus, for example, the global problem defined by `calmodel=~(A+B+X+Z):D-1` is equivalent to the sequence of problems defined by the “*reduced model*” `calmodel=~A+B+X+Z-1` in each of the domains identified by the modalities of *D*. The opportunity to separately solve the subproblems related to different calibration domains achieves a significant reduction in computation complexity: the gain increases with increasing survey data size and (most importantly) with increasing auxiliary variables number.

The optional argument `partition` makes it possible to choose, in cases in which the calibration problem can be factorized, whether to solve the problem globally or in a partitioned way (that is, separately for each calibration domain). The global solution (which is the default option) can be selected invoking the `e.calibrate` function with `partition=FALSE`. To request the partitioned solution - a strongly recommended option when dealing with a lot of auxiliary variables and big data sizes - it is necessary to specify via `partition` the variables defining the calibration domains for the model. If a formula is passed through the `partition` argument (for example: `partition=~D1:D2`), the program checks that `calmodel` actually describes a “reduced model” (for example: `calmodel=~A+B+X+Z-1`), that is it does *not* reference any of the partition variables; if this is not the case, the program stops and prints an error message. Notice that a formula like `partition=~D1+D2` will be automatically translated into the factor-crossing formula `partition=~D1:D2`.

The design variables referenced by `partition` (if any) must be factor and must not contain any missing value (NA).

The mandatory argument `df.population` is used to specify the known totals of the auxiliary variables referenced by `calmodel` within the subpopulations (if any) identified by `partition`. These known totals must be stored in a data frame whose structure (i) depends on the values of `calmodel` and `partition` and (ii) must conform to a standard. In order to facilitate understanding of and compliance with this standard, the **ReGeneseees** package provides the user with four functions: `pop.template`, `population.check`, `pop.desc` and `fill.template`. The `pop.template` function is able to guide the user in constructing the known totals data frame for a specific calibration problem, the `pop.desc` function provides a natural language description of the template structure, the

`fill.template` function can be exploited to automatically fill the template when a sampling frame is available, while the `population.check` function allows to check whether a known totals data frame conforms to the standard required by `e.calibrate`. In any case, if the `df.population` data frame does not comply with the standard, the `e.calibrate` function stops and prints an error message: the meaning of the message should help the user diagnose the cause of the problem.

The `calfun` argument identifies the distance function to be used in the calibration process. Three built-in functions are provided: "linear", "raking", and "logit" (see [Deville, Sarndal, Sautory 93]). The default is "linear", which corresponds to the euclidean metric and yields the Generalized Regression Estimator (provided that no range restrictions are imposed on the g-weights). The "raking" distance corresponds to the "*multiplicative method*" of [Deville, Sarndal, Sautory 93].

The `bounds` argument allows to add "*range constraints*" to the calibration problem. To be precise, the interval defined by `bounds` will contain the values of the ratios between final (calibrated) and initial (direct) weights. The default value is `c(-Inf, Inf)`, i.e. no range constraints are imposed. These constraints are optional unless the "logit" function is selected: in the latter case the range defined by `bounds` has to be finite (see, again, [Deville, Sarndal, Sautory 93]).

The value passed by the `aggregate.stage` argument must be an integer between 1 and the number of sampling stages of design. If specified, causes the calibrated weights to be constant within sampling units selected at the `aggregate.stage` stage (actually this is only allowed if the initial weights had already this property, as it is sometimes the case in multistage cluster sampling). If not specified, the calibrated weights may differ even for sampling units with identical initial weights. The same holds if some final units belonging to the same cluster selected at the stage `aggregate.stage` fall in distinct calibration domains (i.e. if the domains defined by partition "cut across" the `aggregate.stage`-stage clusters).

The argument `sigma2` can be used to take into account a possible heteroskedasticity effect in the (assisting linear regression model underlying the) calibration problem. In such cases, `sigma2` must identify some variable to which the variances of the error terms are believed to be proportional. Notice that `sigma2` can also be interpreted from a "purely calibration-based" point of view: it corresponds to the $1/q_k$ unit-weights appearing inside the distance measures of [Deville, Sarndal 92] [Deville, Sarndal, Sautory 93]. The final effect is, on average, that *calibrated weights associated to higher values of sigma2 tend to stay closer to their corresponding initial weights*.

Note that it is technically possible to exploit this behaviour in order to *prevent some subset of the initial weights from being altered by calibration*. The trick is simple: just build a convenience `sigma2` variable whose values are set to some very high value (e.g. $1E12$) for those units whose initial weight must be preserved, and to 1 otherwise (see 'Examples'). Nevertheless, this trick should be used sparingly and very carefully, as otherwise it may: (i) cause the calibration algorithm to not converge, (ii) result in introducing bias in calibration estimates. In particular, with respect to bias, one should not select the units whose weight must be preserved on the basis of the current sample.

The `sigma2` formula can reference just a single design variable: such variable must be numeric, strictly positive and must not contain NAs. If `aggregate.stage` is specified, `sigma2` must obviously be constant inside `aggregate.stage`-stage clusters (otherwise the function stops and prints an error message).

The `maxit` argument sets the maximum number of iteration for the Newton-Raphson algorithm that is used to solve the calibration problem (the only exception being *unbounded linear* calibration, i.e. `calfun='linear'` and `bounds=c(-Inf, Inf)`, which is actually handled by directly solving a linear problem). The default value of `maxit` is 50.

The `epsilon` argument determines the convergence criterion for the optimization algorithm: it fixes the maximum allowed absolute value for the relative differences between the population totals and the corresponding estimates based on the calibrated weights. The default value is 10^{-7} .

The calibrated weights computed by `e.calibrate` must ensure that the calibration estimators of the auxiliary variables *exactly* match the corresponding known population totals. It is, however,

possible (more likely when range constraints are imposed) that, for a specific calibration problem and for given values of `epsilon` and `maxit`, the solving algorithm does not converge. In this case, if `force = FALSE`, `e.calibrate` stops and prints an error message. If - on the contrary - `force = TRUE`, the function is forced to return the best approximation achieved for the calibrated weights, nevertheless signaling the calibration failure by a warning (see also Section 'Calibration process diagnostics').

Value

An object of class `cal.analytic`. The data frame it contains includes (in addition to the data already stored in `design`) the calibrated weights column. The name of this column is obtained by pasting the name of the initial weights column with the string `".cal"`.

Calibration Process Diagnostics

When, dealing with a factorizable calibration problem, the user selects the partitioned solution, the global calibration problem gets split into as many *sub-problems* as the number of subpopulations defined by partition. In turn, each one of these calibration sub-problems can end without convergence on any one of the involved auxiliary variables. A calibration process with such a complex structure needs some ad hoc tool for error diagnostics. For this purpose, every call to `e.calibrate` creates, by side effect, a dedicated data structure named `ecal.status` into the `.GlobalEnv`.

`ecal.status` is a list with up to three components: the first, `"call"`, identifies the call to `e.calibrate` that generated the list, the second, `return.code`, is a matrix each element of which identifies the return code of a specific calibration sub-problem. The meaning of the return codes is as follows:

CODE	MEANING
-1.....	not yet tackled sub-problem;
0.....	solved sub-problem (convergence achieved);
1.....	unsolved sub-problem (no convergence): output forced.

Recall that the latter return code (1) may only occur if `force = TRUE`.

If any `return.code` equal to 1 exists, the `ecal.status` list gains a third component named `"fail.diagnostics"` which is itself a list; its components correspond to sub-problems for which convergence was not achieved, and store useful information about the auxiliary variables for which calibration constraints are violated. Therefore, users can exploit `ecal.status` to identify sub-problems and variables from which errors stemmed, hence taking a step forward to eliminate them.

Notice, lastly, that the `ecal.status` list will also be persistently bound to the `e.calibrate` return object, stored inside a dedicated attribute. For the inspection of such diagnostics information the [check.cal](#) function is available.

Note

The `cal.analytic` class is a specialization of the [analytic](#) class; this means that an object created by `e.calibrate` inherits from the [analytic](#) class and you can use on it all methods defined on the latter class, e.g. `print`, `summary`, [weights](#). Moreover, a calibrated design can be passed again to `e.calibrate`, thus undergoing further calibration steps.

Author(s)

Diego Zardetto

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See Also

`e.svydesign` to bind survey data and sampling design metadata, `svystatTM`, `svystatR`, `svystatS`, `svystatSR`, `svystatB`, `svystatQ` and `svystatL` for calculating estimates and standard errors, `pop.template` for constructing known totals data frames in compliance with the standard required by e.calibrate, `population.check` to check that the known totals data frame satisfies that standard, `pop.desc` to provide a natural language description of the template structure, `fill.template` to automatically fill the template when a sampling frame is available, `bounds.hint` to obtain a hint for range restricted calibration, `g.range` to assess the variation of weights after calibration and `check.cal` to check if calibration constraints have been fulfilled.

Examples

```
#####
# Calibration of a design object according to different calibration #
# models (the known totals data frames pop01, \ldots, pop05p and the #
# bounds vector are all contained in the data.examples file).      #
# For the examples relating to calibration models that can be      #
# factorized both a global and a partitioned solution are given.  #
#####

# Load household data:
data(data.examples)

# Creation of the object to be calibrated:
des<-e.svydesign(data=example,ids=~towcod+famcod,strata=~SUPERSTRATUM,
  weights=~weight)

# 1) Calibration on the total number of units in the population
# (totals in pop01):
descal01<-e.calibrate(design=des,df.population=pop01,calmodel=~1,
  calfun="logit",bounds=bounds,aggregate.stage=2)
```

```

# Printing descal01 immediately recalls that it is a
# "calibrated" object:
descal01

# Use the summary() function if you need some additional details, e.g.:
summary(descal01)

# Use the 'variables' slot to extract survey data, e.g.:
head(descal01$variables)

# Use the weights() function to extract weights, e.g.:
summary(weights(descal01))

# Checking the result (first add the new 'ones' variable
# to estimate the number of final units in the population):
descal01<-des.addvars(descal01,ones=1)
svystatTM(descal01, ~ones)

# 2) Calibration on the marginal distributions of sex and marstat
# (totals in pop02):
descal02<-e.calibrate(design=des,df.population=pop02,
                      calmodel=~sex+marstat-1,calfun="logit",bounds=bounds,
                      aggregate.stage=2)

# Checking the result:
svystatTM(descal02,~sex+marstat)

# 3) Calibration (global solution) on the joint distribution of sex
# and marstat (totals in pop03):
descal03<-e.calibrate(design=des,df.population=pop03,
                      calmodel=~marstat:sex-1,calfun="logit",bounds=bounds)

# Checking the result:
svystatTM(descal03,~sex,~marstat) # or: svystatTM(descal03,~marstat,~sex)

# which, obviously, is not respected by descal02 (notice the size of SE):
svystatTM(descal02,~sex,~marstat)

# 3.1) Again a calibration on the joint distribution of sex and marstat
# but, this time, with the partitioned solution (partition=~sex,
# totals in pop03p):
descal03p<-e.calibrate(design=des,df.population=pop03p,
                      calmodel=~marstat-1,partition=~sex,calfun="logit",
                      bounds=bounds)

# Checking the result:
svystatTM(descal03p,~sex,~marstat)

# 4) Calibration (global solution) on the totals for the quantitative
# variables x1, x2 and x3 in the subpopulations defined by the
# regcod variable (totals in pop04):
descal04<-e.calibrate(design=des,df.population=pop04,
                      calmodel=~(x1+x2+x3):regcod-1,calfun="logit",

```

```

        bounds=bounds, aggregate.stage=2)

# Checking the result:
svystatTM(descal04, ~x1+x2+x3, ~regcod)

# 4.1) Same problem with the partitioned solution (partition=~regcod,
#       totals in pop04p):
descal04p<-e.calibrate(design=des, df.population=pop04p,
                      calmodel=~x1+x2+x3-1, partition=~regcod, calfun="logit",
                      bounds=bounds, aggregate.stage=2)

# Checking the result:
svystatTM(descal04p, ~x1+x2+x3, ~regcod)

# 5) Calibration (global solution) on the total for the quantitative
#   variable x1 and on the marginal distribution of the qualitative
#   variable age5c, in the subpopulations defined by crossing sex
#   and marstat (totals in pop05):
descal05<-e.calibrate(design=des, df.population=pop05,
                    calmodel=~(age5c+x1):sex:marstat-1, calfun="logit",
                    bounds=bounds)

# Checking the result:
svystatTM(descal05, ~age5c+x1, ~sex:marstat)

# 5.1) Same problem with the partitioned solution (partition=~sex:marstat,
#       totals in pop05p):
descal05p<-e.calibrate(design=des, df.population=pop05p,
                    calmodel=~age5c+x1-1, partition=~sex:marstat,
                    calfun="logit", bounds=bounds)

# Checking the result:
svystatTM(descal05p, ~age5c+x1, ~sex:marstat)

# Notice that 3.1 and 5.1) 5.2) do not impose the aggregate.stage=2
# condition. This condition cannot, in fact, be fulfilled because
# in both cases the domains defined by partition "cut across"
# the des second stage clusters (households). To compare the results,
# the same choice was also made for 3) and 5).

# 5.2) Just a single example to inspect the ecal.status list generated
#       for diagnostics purposes.
#       Let's shrink the bounds in order to prevent perfect convergence
#       (recall that force=TRUE by default):
approx.cal<-e.calibrate(design=des, df.population=pop05p,
                    calmodel=~age5c+x1-1, partition=~sex:marstat,
                    calfun="logit", bounds=c(0.95, 1.05))

# ...now use check.cal function to assess the amount of calibration
# constraints violation:
check.cal(approx.cal)

# ...or (equivalently) inspect directly ecal.status:

```

ecal.status

```
#####
# Some examples illustrating how calibration    #
# can be exploited to reduce nonresponse bias  #
# (see, e.g. [Sarndal, Lundstrom 05]).        #
#####

# Load sbs data:
data(sbs)

#####
# Full-response case. #
#####

# Create a full-response design object:
sbsdes<-e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,fpc=~fpc)

# Now estimate the average value added and its 95% confidence interval:
mean.VA<-svystatTM(design=sbsdes,y=~va.imp2,estimator="Mean",vartype="cvpct",
  conf.int=TRUE,conf.lev=0.95)
mean.VA

# Compare the obtained estimate with the true population parameter:
MEAN.VA<-mean(sbs.frame$va.imp2)
MEAN.VA

# We get a small overestimation of about 4%...
100*(coef(mean.VA)-MEAN.VA)/MEAN.VA

# which, anyway, doesn't indicate a significant bias for the
# full-response sample, because the 95% confidence interval
# covers the true value.

#####
# Nonresponse case: assume a response propensity #
# which increases with enterprise size.          #
#####

# Set bigger response probabilities for bigger firms,
# e.g. exploiting available information about the
# number of employees (emp.cl):
levels(sbs$emp.cl)
p.resp <- c(.4,.6,.8,.95,.99)

# Tie response probabilities to sample observations:
pr<-p.resp[unclass(sbs$emp.cl)]

# Now, randomly select a subsample of responding units from sbs:
set.seed(12345)      # (fix the RNG seed for reproducibility)
rand<-runif(1:nrow(sbs))
sbs.nr<-sbs[rand<pr,]

# This implies an overall response rate of about 73%:
nrow(sbs.nr)/nrow(sbs)
```

```

# Treat the non-response sample as it was complete: this should
# lead to biased estimates of value added, as the latter is
# positively correlated with firms size...
sbsdes.nr<-e.svydesign(data=sbs.nr,ids=~id,strata=~strata,weights=~weight)

#...indeed:
old.op <- options("RG.lonely.psu"="adjust") # (prevent lonely-PSUs troubles)
mean.VA.nr<-svystatTM(design=sbsdes.nr,y=~va.imp2,estimator="Mean",
                      vartype= "cvpct",conf.int=TRUE,conf.lev=0.95)
mean.VA.nr

# and, comparing with the true population average, we see a
# significant overestimation effect, with the 95% confidence
# interval not even covering the parameter:
MEAN.VA

# Nonresponse bias can be effectively reduced by calibrating
# on variables explaining the response propensity: e.g., in
# the present example, on the population distribution of emp.cl:
# Prepare the known totals template...
N.emp.cl<-pop.template(data=sbs.nr,calmodel=~emp.cl-1)
N.emp.cl

# Fill it by using the sampling frame...
N.emp.cl<-fill.template(sbs.frame,N.emp.cl)
N.emp.cl

# Lastly calibrate:
# Get a hint on the calibration bounds:
hint<-bounds.hint(sbsdes.nr,N.emp.cl)
sbscal.nr<-e.calibrate(design=sbsdes.nr,df.population=N.emp.cl,
                      bounds=hint)
sbscal.nr

# Now estimate the average value added on the calibrated design:
mean.VA.cal.nr<-svystatTM(design=sbscal.nr,y=~va.imp2,estimator="Mean",
                          vartype= "cvpct",conf.int=TRUE,conf.lev=0.95)

# options(old.op) # (reset variance estimation options)

# As expected, we see a significant bias reduction:
MEAN.VA
mean.VA.nr
mean.VA.cal.nr

# Even if the 95% confidence interval still doesn't cover the
# true value, by calibration we passed from an initial overestimation
# of about 33% to a 7% one:
100*(coef(mean.VA.nr)-MEAN.VA)/MEAN.VA
100*(coef(mean.VA.cal.nr)-MEAN.VA)/MEAN.VA

#####
# A multi-step calibration example showing that #
# a calibrated object can be calibrated again #
# (this can be sometimes useful in practice): #

```



```

# Step 1: calibrate to reduce nonresponse bias; #
# Step 2: calibrate again to gain efficiency.   #
#####

# Suppose you already performed a first calibration step,
# as shown in the example above, with the aim of softening
# nonresponse bias:
sbscal.nr

# Now you may want to calibrate again in order to reduce
# estimators variance, by using further available auxiliary
# information, e.g. the total number of employees (emp.num)
# and enterprises (ent) inside the domains obtained
# by crossing nace.macro and region:

# Build the second step population totals template:
pop2<-pop.template(sbscal.nr,
  calmodel=~emp.num+ent-1,
  partition=~nace.macro:region)

# Use the fill.template function to (i) automatically compute
# the totals from the universe (sbs.frame) and (ii) safely fill
# the template:
pop2<-fill.template(universe=sbs.frame,template=pop2)

# Now perform the second calibration step:
# Get a hint on the calibration bounds:
hint2<-bounds.hint(sbscal.nr,pop2)
sbscal.nr2<-e.calibrate(design=sbscal.nr,df.population=pop2,
  bounds=hint2)

# Notice that printing sbscal.nr2 you immediately understand
# that it is a "twice-calibrated" object:
sbscal.nr2

# Notice also that, even if the second calibration step causes
# sbscal.nr2 to be no more exactly calibrated with respect to
# emp.cl (look at the cvpct values)...
old.op <- options("RG.lonely.psu"="adjust") # (prevent lonely-PSUs troubles)
svyestatTM(design=sbscal.nr2,y=~emp.cl,vartype="cvpct")

# ...the nonresponse bias has not been resurrected (i.e. it gets stuck
# to its previous 7%):
mean.VA.cal.nr2<-svyestatTM(design=sbscal.nr2,y=~va.imp2,estimator="Mean",
  vartype= "cvpct",conf.int=TRUE,conf.lev=0.95)

options(old.op) # (reset variance estimation options)

mean.VA.cal.nr2
100*(coef(mean.VA.cal.nr2)-MEAN.VA)/MEAN.VA

#####
# Provided the auxiliary variables are chosen in a smart way #
# a single calibration step can simultaneously succeed in:  #
# (i) softening nonresponse bias;                             #
# (ii) reducing estimators variance.                          #

```

```
#####

# Let's come back to the original design with nonresponse:
sbsdes.nr

# Now, let's try to calibrate simultaneously on (see examples above):
# (i) the population distribution of emp.cl;
# (ii) the total number of employees (emp.num) and enterprises (ent)
#     inside the domains obtained by crossing nace.macro and region:

# Build the population totals template (notice that we are now forced
# to a global calibration, as we are assuming to ignore emp.cl counts
# inside domains obtained by crossing nace.macro and region):
pop1<-pop.template(sbs.nr,
  calmodel=~emp.cl+(emp.num+ent):nace.macro:region-1)

# Use the fill.template function to (i) automatically compute
# the totals from the universe (sbs.frame) and (ii) safely fill
# the template:
pop1<-fill.template(universe=sbs.frame,template=pop1)

# Now perform the single calibration step:
# Get a hint on the calibration bounds:
hint1<-bounds.hint(sbsdes.nr,pop1)
sbscal.nr1<-e.calibrate(design=sbsdes.nr,df.population=pop1,
  bounds=hint1)

sbscal.nr1

# Now:
# (i) verify the nonresponse bias reduction effect:
old.op <- options("RG.lonely.psu"="adjust") #(prevent lonely-PSUs troubles)
mean.VA.cal.nr1<-svystatTM(design=sbscal.nr1,y=~va.imp2,estimator="Mean",
  vartype= "cvpct",conf.int=TRUE,conf.lev=0.95)
options(old.op)

mean.VA.cal.nr1
100*(coef(mean.VA.cal.nr1)-MEAN.VA)/MEAN.VA

# thus we are back to ~7%, as for the previous 2-step calibration example.

# (ii) compare cvpct with the previous 2-step calibration example:
mean.VA.cal.nr1
mean.VA.cal.nr2

# hence, both bias reduction and efficiency are almost the same in 2-step and
# single step calibration (auxiliary information being equal): the choice
# will often depend on practical considerations (e.g. convergence, computation
# time).

#####
# Example with heteroskedastic assisting linear model: shows how to obtain #
# the ratio estimator of a total by calibration. #
#####

# Load sbs data:
```

```

data(sbs)

# Create the design object to be calibrated:
sbsdes<-e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,fpc=~fpc)

# Suppose you have to calibrate on the total amount of employees:
# Prepare the template:
pop<-pop.template(data=sbsdes,calmodel=~emp.num-1)
pop

# Fill it by using the sampling frame (sbs.frame)...
pop<-fill.template(sbs.frame,pop)
pop

# ... thus the total number of employees is 984394.
# Now calibrate assuming that error terms variances are proportional
# to emp.num:
sbscal<-e.calibrate(design=sbsdes,df.population=pop,sigma2=~emp.num)

# Now compute the calibration estimator of the total
# of value added (i.e. variable va.imp2)...
VA.tot.cal<-svystatTM(design=sbscal,y=~va.imp2)
VA.tot.cal

#... and observe that this is identical to the ratio estimator of the total...
TOT.emp.num <- pop[1, 1]
VA.ratio<-svystatL(design=sbsdes, expression(TOT.emp.num * (va.imp2/emp.num)))
VA.ratio

# ...as it must be.

# Recall that, for the calibration problem above, one must expect, by virtue of
# simple theoretical arguments, that the g-weights are constant and equal to the
# ratio between the known total of emp.num (984394) and its HT estimate.
# This property is exactly satisfied by our numerical results, see below:
pop[1, 1]/coef(svystatTM(sbsdes, ~emp.num))
g.range(sbscal)

# ...as it must be.

#####
# A second example of calibration with heteroskedastic assisting linear #
# model. Shows that calibrated weights associated to higher values of   #
# sigma2 tend to stay closer to their corresponding initial weights.    #
#####

# Perform a calibration process which exploits as auxiliary
# information the total number of employees (emp.num)
# and enterprises (ent) inside the domains obtained by:
# i) crossing nace2 and region;
# ii) crossing emp.cl, region and nace.macro;

# Build the population totals template:
pop<-pop.template(sbsdes,
  calmodel=~(emp.num+ent):(nace2+emp.cl:nace.macro)-1,
  partition=~region)

```

```

# Use the fill.template function to (i) automatically compute
# the totals from the universe (sbs.frame) and (ii) safely fill
# the template:
pop<-fill.template(universe=sbs.frame,template=pop)

# Now calibrate:
# 1) First, without any heteroskedasticity effect
sbscal1<-e.calibrate(sbsdes,pop,calfun="linear",bounds = c(0.01, 3),
  sigma2=NULL)

# 2) Then, with heteroskedastic effect proportional to emp.num:
sbscal2<-e.calibrate(sbsdes,pop,calfun="linear",bounds = c(0.01, 3),
  sigma2=~emp.num)

# Compute the g-weights for both the calibrated objects:
g1<-weights(sbscal1)/weights(sbsdes)
g2<-weights(sbscal2)/weights(sbsdes)

# Now visually compare the absolute deviations from 1 of the g-weights
# as a function of emp.num:
plot(log10(sbs$emp.num),abs(g1-1), col="blue", pch=19, cex=0.5)
points(log10(sbs$emp.num),abs(g2-1), col="red", pch=19, cex=0.5)

#...as emp.num grows red points clearly tend to stay closer to
# the horizontal axis than blue ones, as expected.

#####
# A third example. Shows how to exploit the sigma2 argument to prevent #
# some initial weights from being altered by calibration. #
#####

# Let's refer again to object sbsdes:
sbsdes

# Let's assume that for some reason we want to prevent the *highest* initial
# weights from being altered by calibration:
dmax <- max(weights(sbsdes))
dmax

# The relevant units are the following 4:
to.keep <- which(weights(sbsdes) == dmax)
to.keep

# Now, let's prepare a convenience variable (to be later bound to the 'sigma2'
# argument of e.calibrate) whose values are set to a very high value (say 1E12)
# for those units whose initial weight must be preserved, and to 1 otherwise.
# For definiteness, let's call such variable 'fixed':
sbsdes <- des.addvars(sbsdes, fixed = ifelse(weights(sbsdes) == dmax, 1E12, 1))

# Now, let's perform a calibration process which exploits as auxiliary
# information the total number of employees (emp.num)
# and enterprises (ent) inside the domains obtained by:
# i) crossing region and emp.cl;
# ii) crossing region and nace.macro;

```

```

# Build the population totals template:
pop<-pop.template(sbsdes,
  calmodel = ~(emp.num + ent):(emp.cl + nace.macro) - 1,
  partition = ~region)

# Use the fill.template function to (i) automatically compute
# the totals from the universe (sbs.frame) and (ii) safely fill
# the template:
pop<-fill.template(universe=sbs.frame,template=pop)

# Now calibrate:
# 1) First, *without* any heteroskedasticity effect:
sbscal1 <- e.calibrate(sbsdes, pop, calfun = "linear", sigma2 = NULL)
g.range(sbscal1)

## As expected, calibration weights of the 4 units to.keep *differ* from
## the corresponding initial weights:
weights(sbsdes)[to.keep]
weights(sbscal1)[to.keep]

# 2) Then, *with* heteroskedasticity effect given by our convenience variable
# 'fixed':
sbscal2 <- e.calibrate(sbsdes, pop, calfun = "linear", sigma2 = ~fixed)
g.range(sbscal2)

## Let's verify that calibration weights of the 4 units to.keep are now
## *equal* to the corresponding initial weights:
weights(sbsdes)[to.keep]
weights(sbscal2)[to.keep]

## ...as it must be.

# NOTE: It should be clear that the additional request to hold some weights
#       fixed while calibrating will - all other things being equal - increase
#       the probability of non-convergence of the calibration algorithm.

#####
# Calibrating simultaneously on unit-level and cluster-level #
# auxiliary information: an household survey example.        #
#####

# Load household data:
data(data.examples)

# Define the survey design:
exdes<-e.svydesign(data=example,ids=~towcod+famcod,strata=~stratum,
  weights=~weight)

# Collapse strata to eliminate lonely PSUs:
exdes<-collapse.strata(design=exdes,block.vars=~sr:procod)

# Now add new convenience variables to the design object:
## 'houdensity': to estimate households counts
## 'ones':      to estimate individuals counts
exdes<-des.addvars(exdes,
  houdensity=ave(famcod,famcod,FUN = function(x) 1/length(x)),

```

```

ones=1)

# Let's see how it's possible to calibrate *simultaneously* on:
# 1. the number of *individuals* crossclassified by sex, 5 age classes,
#    and province;
# 2. the number of *households* by region.

# First, for the purpose of running the example, let's generate some
# artificial population totals. We have only to get HT estimates for
# the auxiliary variables and perturb them randomly:
# Get HT estimates of auxiliary variables:
xx<-aux.estimates(design=exdes,calmodel=~houdensity+sex:age5c:procod-1,
                  partition=~regcod)

# Add a random uniform perturbation to these numbers:
set.seed(12345) # Fix the RNG seed for reproducibility
xx[, -1]<-round(xx[, -1]*runif(prod(dim(xx[, -1])), 0.8, 1.2))

# Now we have at hand our artificial population totals, and
# we can proceed with the calibration task:
excal<-e.calibrate(design=exdes, df.population=xx, calfun= "linear",
                  bounds=c(0,3), aggregate.stage=2)

# To perceive the effect of calibration, let's e.g. compare the HT and
# calibrated estimates of the average number of individuals per household
# at population level:
svystatR(exdes, ~ones, ~houdensity, vartype="cvpct")
svystatR(excal, ~ones, ~houdensity, vartype="cvpct")

#####
# Calibrating on different patterns of #
# "incomplete" auxiliary information. #
#####

# Usually calibration constraints involve "complete auxiliary information",
# i.e. totals which are known either:
# (i) for the target population as a whole (e.g. total number of
#      employees working in italian active enterprises at a given date);
# or:
# (ii) for each subpopulation belonging to a complete partition of
#      the target population (e.g. number of male and female people
#      residing in Italy at a given date).
#
# Anyway, it may happen sometimes that the available auxiliary information
# is actually "incomplete", i.e. one doesn't know all the totals for all the
# subpopulations in a partition, but rather only for some of them. As an
# example, suppose marital status has categories "married", "unmarried",
# and "widowed" and that one only knows the number of "unmarried" people.
#
# In what follows I show how you can use ReGenesees to handle a calibration
# task on "incomplete" auxiliary information.

#####
# A simple example. #
#####

```

```

# Load household data:
data(data.examples)

# Define the survey design:
des<-e.svydesign(data=example,ids=~towcod+famcod,strata=~SUPERSTRATUM,
  weights=~weight)

# Suppose you only know the number of "unmarried" people (let's say 398240)
# but you ignore "married" and "widowed" totals, and you want to calibrate
# on this incomplete information.

# First, add to the survey design a new numeric variable with value 1
# for unmarried people and 0 otherwise:
des<-des.addvars(des,unmarried=as.numeric(marstat=="unmarried"))

# Second, prepare a template to store the known "unmarried" people count:
pop<-pop.template(des,calmodel=~unmarried-1)

# Third, fill the template with the known total:
pop[1,1] <- 398240

# Fourth, calibrate:
descal<-e.calibrate(des,pop)

# Now test that only "unmarried" estimated total has 0 percent CV:
Zapsmall(svystatTM(descal,~marstat,vartype="cvpct"))

# ...as it must be.

#####
# A more complicated example. #
#####

# Load sbs data:
data(sbs)

# Define the survey design:
sbsdes<-e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,fpc=~fpc)

# Suppose you want to calibrate on the following "incomplete" known totals:
# 1. enterprises counts by nace.macro
# 2. enterprises counts by dom3 ONLY inside nace.macro 'Industry'
# 3. total of y by emp.cl ONLY inside nace.macro 'Commerce'

# First, add to the survey design new variables identifying the domains
# where "incomplete" totals 2. and 3. are known:
## 2. -> nace.macro = 'Industry'
sbsdes<-des.addvars(sbsdes,Industry=as.numeric(nace.macro=="Industry"))
## 3. -> nace.macro = 'Commerce'
sbsdes<-des.addvars(sbsdes,Commerce=as.numeric(nace.macro=="Commerce"))

# Do the same for the sampling frame:
## 2. -> nace.macro = 'Industry'
sbs.frame$Industry=as.numeric(sbs.frame$nace.macro=="Industry")
## 3. -> nace.macro = 'Commerce'
sbs.frame$Commerce=as.numeric(sbs.frame$nace.macro=="Commerce")

```

```

# Second, prepare a template to store the totals listed in 1., 2. and 3.;
# to this purpose one can e.g. compute HT estimates of the involved auxiliary
# variables:
Xht<-aux.estimates(design=sbsdes,
                  calmodel=~nace.macro+Industry:dom3+Commerce:y:emp.cl-1)

Xht

# Third, use the structure above to compute actual population totals
# from the sampling frame:
pop <- fill.template(universe=sbs.frame,template=Xht)
pop

# Fourth, calibrate:
sbscal <- e.calibrate(design=sbsdes,df.population=pop)

# Test1: nace.macro counts have 0 CVs:
test1<-svystatTM(design=sbscal,y=~nace.macro,vartype="cvpct")
test1

# Test2: only 'Industry' macrosector has 0 CVs for dom3 counts:
test2<-svystatTM(design=sbscal,y=~dom3,by=~nace.macro,vartype="cvpct")
Zapsmall(test2)

# Test3: only 'Commerce' macrosector has 0 CVs for y total by emp.cl:
test3<-svystatTM(design=sbscal,y=~y,by=~emp.cl:nace.macro,vartype="cvpct")
Zapsmall(test3)

```

e.svydesign

*Specification of a Complex Survey Design***Description**

Binds survey data and sampling design metadata.

Usage

```
e.svydesign(data, ids, strata = NULL, weights,
           fpc = NULL, self.rep.str = NULL, check.data = TRUE)
```

```
## S3 method for class 'analytic'
summary(object, ...)
```

Arguments

data	Data frame of survey data.
ids	Formula identifying clusters selected at subsequent sampling stages (PSUs, SSUs, ...).
strata	Formula identifying the stratification variable; NULL (the default) implies no stratification.
weights	Formula identifying the initial weights for the sampling units.
fpc	Formula identifying finite population corrections at subsequent sampling stages (see ‘Details’).

<code>self.rep.str</code>	Triggers an approximate variance estimation method for multistage designs (see ‘Details’). If not NULL (the default), must be a formula identifying self-representing strata (SR), if any.
<code>check.data</code>	Check out the correct nesting of data clusters? The default is TRUE.
<code>object</code>	An object of class <code>analytic</code> , as returned by <code>e.svydesign</code> .
<code>...</code>	Arguments for future extensions.

Details

This function has the purpose of binding in an effective and persistent way the survey data to the metadata describing the adopted sampling design. Both kinds of information are stored in a complex object of class `analytic`, which extends the `survey.design2` class from the **survey** package. The sampling design metadata are then used to enable and guide processing and analyses provided by other functions in the **ReGenesees** package (such as `e.calibrate`, `svystatTM`, ...).

The `data`, `ids` and `weights` arguments are mandatory, while `strata`, `fpc`, `self.rep.str` and `check.data` arguments are optional. The data variables that are referenced by `ids`, `weights` and, if specified, by `strata`, `fpc`, `self.rep.str` must not contain any missing value (NA). Should empty levels be present in any factor variable belonging to `data`, they would be dropped.

The `ids` argument specifies the cluster identifiers. It is possible to specify a multistage sampling design by simply using a formula which involves the identifiers of clusters selected at subsequent sampling stages. For example, `ids=~id.PSU + id.SSU` declares a two-stage sampling in which the first stage units are identified by the `id.PSU` variable and second stage ones by the `id.SSU` variable.

The `strata` argument identifies the stratification variable. The data variable referenced by `strata` (if specified) must be a factor. By default the sample is assumed to be non-stratified.

The `weights` argument identifies the initial (or direct) weights for the units included in the sample. The data variable referenced by `weights` must be numeric. Direct weights must be strictly positive.

The `fpc` formula serves the purpose of specifying the finite population corrections at subsequent sampling stages. By default `fpc=NULL`, which implies with-replacement sampling.

If the survey has only one stage, then the `fpc`s can be given either as the total population size in each stratum or as the fraction of the total population that has been sampled. In either case the relevant population size must be expressed in terms of sampling units (be they elementary units or clusters). That is, sampling 100 units from a population stratum of size 500 can be specified as 500 or as $100/500=0.2$. Thus, passing to `fpc` a column of zeros, means again with-replacement sampling.

For multistage sampling the population size (or the sampling fraction) for each sampling stage should also be specified in `fpc`. For instance, when `ids=~id.PSU + id.SSU` the `fpc` formula should look like `fpc=~fpc.PSU + fpc.SSU`, with variable `fpc.PSU` giving the population sizes (or sampling fractions) in each stratum for the first stage units, while variable `fpc.SSU` gives population sizes (or sampling fractions) for the second stage units in each sampled PSU. Notice that if you choose to pass to `fpc` population totals (rather than sampling rates) at a given stage, then you must do the same for all stages (and vice versa).

If `fpc` is specified but for fewer stages than `ids`, sampling is assumed to be *complete* for subsequent stages. The function will check that `fpc`s values at each sampling stage do not vary within strata.

When dealing with a two-stage (multistage) stratified sampling design that includes *self-representing (SR) strata* (i.e. strata containing only one PSU selected with probability 1), the only (leading) contribution to the variance of SR strata arises from the second stage units (“*variance PSUs*”).

When `options("RG.ultimate.cluster")` is FALSE (which is the default for **ReGenesees**), variance estimation for SR strata is correctly handled provided the survey `fpc`s have been properly specified. In particular, if `fpc=~fpc.PSU + fpc.SSU` and one specifies `fpc`s in terms of sampling fractions, then, inside SR strata, `fpc.PSU` must be always equal to one. When, on the contrary, the

“*Ultimate Cluster Approximation*” holds (i.e. `options("RG.ultimate.cluster")` has been set to `TRUE`) the SR strata give no contribution at all to the sampling variance.

A compromise solution (adopted by former existing survey software) is the one of retaining, for both SR and not-SR strata, only the leading contribution to the sampling variance. This means that only the SSUs are relevant for SR strata, whereby only the PSUs matter in not-SR strata. This compromise solution can be achieved by using the `self.rep.str` argument. If this argument is actually specified (as a formula referencing the data variable that identifies the SR strata), a warning is generated in order to remind the user that an approximate variance estimation method will be adopted on that design. Notice that, when choosing the `self.rep.str` option, the user must ensure that the variable referenced by `self.rep.str` is logical (with value `TRUE` for SR strata and `FALSE` otherwise) or numeric (with value 1 for SR strata and 0 otherwise) or factor (with levels "1" for SR strata and "0" otherwise).

The optional argument `check.data` allows to check out the correct nesting of data clusters (PSUs, SSUs, ...). If `check.data=TRUE` the function checks that every unit selected at stage $k+1$ is associated to one and only one unit selected at stage k . For a stratified design the function checks also the correct nesting of clusters within strata.

Value

An object of class `analytic`. The `print` method for that class gives a concise description of the sampling design. The `summary` method provides further details. Objects of class `analytic` persistently store input survey data inside their `variables` component. Weights can be accessed by using the `weights` function.

PPS Sampling Designs

Probability proportional to size sampling *with replacement* does not pose any problem: one must simply specify `fpc=NULL` and pass the right weights. This holds also for multistage designs, where PSUs are selected with replacement with PPS inside strata. Moreover, when the PSUs are sampled with replacement, the only contribution to the variance arises from the estimated PSU totals, and one can simply ignore any available information about subsequent sampling stages.

For unequal probability sampling *without replacement*, on the contrary, in order to get correct variance estimates, one should know the second-order inclusion probabilities under the sampling design at hand. Unluckily, these probabilities cannot generally be computed, thus one has to resort to some viable approximation. The easier one rests on pretending that PSUs were sampled with replacement, even if this is not actually the case. It is worth stressing that this approach will result in conservative estimates. Moreover, the variance overestimation is expected to be negligible as long as the actual sampling fractions of PSUs are close to zero. Notice that this "with replacement" approximation can be achieved by either not specifying `fpc`, or by passing to the PSUs term of `fpc` a column of zeros.

Note

The `analytic` class is a specialization of the `survey.design2` class from the **survey** package [Lumley 06]; this means that an object created by `e.svydesign` inherits from the `survey.design2` class and you can use on it every method defined on the latter class.

Author(s)

Diego Zardetto.

References

- Sarndal, C.E., Swensson, B., Wretman, J. (1992) “*Model Assisted Survey Sampling*”, Springer Verlag.
- Lumley, T. (2006) “*survey: analysis of complex survey samples*”, <https://CRAN.R-project.org/package=survey>.
- Zardetto, D. (2015) “*ReGenesees: an Advanced R System for Calibration, Estimation and Sampling Error Assessment in Complex Sample Surveys*”. Journal of Official Statistics, 31(2), 177-203. doi: <https://doi.org/10.1515/jos-2015-0013>.

See Also

[svystatTM](#), [svystatR](#), [svystatS](#), [svystatSR](#), [svystatB](#), [svystatQ](#), [svystatL](#) for calculating estimates and standard errors, [e.calibrate](#) for calibrating weights, [ReGenesees.options](#) for setting/changing variance estimation options, [collapse.strata](#) for the suggested way of handling lonely PSUs, [weights](#) to extract weights.

Examples

```
#####
# The following examples illustrate how to create objects  #
# (of class 'analytic') defining different sampling designs. #
# Note: sometimes the same survey data will be used to    #
# define more than one design: this serves only the purpose #
# of illustrating e.svydesign syntax.                        #
#####

data(data.examples)
# Two-stage stratified cluster sampling design (notice that
# the design contains lonely PSUs):
des<-e.svydesign(data=example,ids=~towcod+famcod,strata=~stratum,
  weights=~weight)
des

# Use the summary() function if you need some additional details, e.g.:
summary(des)

# Use the 'variables' slot to extract survey data, e.g.:
head(des$variables)

# Use the weights() function to extract weights, e.g.:
summary(weights(des))

# Again the same design, but using collapsed strata (SUPERSTRATUM variable)
# to remove lonely PSUs:
des<-e.svydesign(data=example,ids=~towcod+famcod,strata=~SUPERSTRATUM,
  weights=~weight)
des

# Two stage cluster sampling (no stratification):
des<-e.svydesign(data=example,ids=~towcod+famcod,weights=~weight)
des

# Stratified unit sampling design:
des<-e.svydesign(data=example,ids=~key,strata=~SUPERSTRATUM,
  weights=~weight)
```

```

des

data(sbs)
# One-stage stratified unit sampling without replacement
# (notice the presence of the fpc argument):
des<-e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,
               fpc=~fpc)
des

# Same design as above but ignoring the finite population corrections:
des<-e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight)
des

data(fpcdat)
# Two-stage stratified cluster sampling without replacement
# (notice that the fpcs are specified for both stages):
des<-e.svydesign(data=fpcdat,ids=~psu+ssu,strata=~stratum,weights=~w,
               fpc=~fpc1+fpc2)
des

# Same design as above but assuming complete sampling for the
# second stage units (notice fpcs have been passed only for the
# first stage):
des<-e.svydesign(data=fpcdat,ids=~psu+ssu,strata=~stratum,weights=~w,
               fpc=~fpc1)
des

# Again a two-stage stratified cluster sampling without replacement but
# specified in such a way as to retain, in the estimation phase, only
# the leading contribution to the sampling variance (i.e. the one arising
# from SSUs in SR strata and PSUs in not-SR strata). Notice that the
# self.rep.str argument is used:
des<-e.svydesign(data=fpcdat,ids=~psu+ssu,strata=~stratum,weights=~w,
               fpc=~fpc1+fpc2, self.rep.str=~sr)
des

```

estimator.kind

Which Estimator Did Generate these Survey Statistics?

Description

Identifies what kind of estimator has been used to compute a (set of) survey static(s).

Usage

```
estimator.kind(stat, design)
```

Arguments

stat	An object containing survey statistics.
design	Object of class <code>analytic</code> (or inheriting from it) containing survey data and sampling design metadata.

Details

Given a survey statistic object `stat` and a survey design object `design` from which `stat` is supposed to have been derived, this function returns the “precise kind” of the corresponding estimator, as a textual description.

Argument `stat` can be any object which have been returned by calling a survey statistics function (e.g. `svyestatTM`, `svyestatR`, `svyestatS`, `svyestatSR`, `svyestatB`, `svyestatQ`, `svyestatL`, `svySigma`, and `svySigma2`) on survey design object `design`. It can also be a collection of survey statistics as generated by protean function `svyestat`, provided that function is invoked with `forGVF = FALSE`.

Should `stat` be a survey statistic derived from a design object *other than* `design`, the function would raise an error.

Note that function `estimator.kind` is smart enough to recognize that estimates of totals/means of *dummy variables* are actually estimates of absolute/relative frequencies, despite such variables are of class `numeric` (see Section ‘Examples’).

Value

A character string describing the estimator kind.

Currently, possible return values (i.e. estimator kinds) are the following:

- (1) 'Total'
- (2) 'Absolute Frequency'
- (3) 'Mix of Totals and Absolute Frequencies'
- (4) 'Mean'
- (5) 'Relative Frequency'
- (6) 'Mix of Means and Relative Frequencies'
- (7) 'Ratio'
- (8) 'Share'
- (9) 'Share Ratio'
- (10) 'Regression Coefficient'
- (11) 'Quantile'
- (12) 'Complex Estimator'
- (13) 'Population Variance'
- (14) 'Population Standard Deviation'

Author(s)

Diego Zardetto

See Also

`gvf.input` and `svyestat` to prepare the input for GVF model fitting, `fit.gvf` to fit GVF models, and `GVF.db` to manage **ReGenesees** archive of registered GVF models.

Examples

```
# Create a design object:
data(sbs)
des<-e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,
  fpc=~fpc)

# Compute some statistics and ask the corresponding estimator kind:
```

```

stat<-svystatTM(des,~emp.num)
stat
estimator.kind(stat,des)

stat<-svystatTM(des,~emp.num,estimator="Mean")
stat
estimator.kind(stat,des)

stat<-svystatTM(des,~emp.num+emp.c1)
stat
estimator.kind(stat,des)

stat<-svystatR(des,num=~va.imp2,den=~emp.num,by=~region)
stat
estimator.kind(stat,des)

stat<-svystatQ(des,y=~va.imp2,ties="rounded")
stat
estimator.kind(stat,des)

# Using protean function svystat to get many statistics in a single shot:
## ungrouped summary statistics:
stat<-svystat(des,kind="R",num=~va.imp2,den=~emp.num,by=~emp.c1:nace.macro,
             combo=2,forGVF=FALSE)
stat
estimator.kind(stat,des)

## grouped summary statistics:
stat<-svystat(des,kind="R",num=~va.imp2,den=~emp.num,by=~emp.c1:nace.macro,
             group=~region,forGVF=FALSE)
stat
estimator.kind(stat,des)

# Behaviour with dummy variables:
## 1. convenience variable 'ent' (whose values are always 1, so that its
#   estimated total actually estimates how many enterprises are there in the
#   target population)
class(des$variables$ent)
range(des$variables$ent)
# The estimated total is correctly recognized as a count
stat<-svystatTM(des,~ent)
stat
estimator.kind(stat,des)

## 2. an actual dummy variable (built on the fly) which indicates if the
#   enterprise has more than 29 employees or not:
des<-des.addvars(des,emp.gt.29=as.numeric(emp.num > 29))
class(des$variables$emp.gt.29)
range(des$variables$emp.gt.29)
# The estimated total is correctly recognized as an absolute frequency
stat<-svystatTM(des,~emp.gt.29)
stat
estimator.kind(stat,des)
# The estimated mean is correctly recognized as a relative frequency
stat<-svystatTM(des,~emp.gt.29,estimator="Mean")
stat

```

```
estimator.kind(stat,des)
```

ext.calibrated	<i>Make ReGenesees Digest Externally Calibrated Weights</i>
----------------	---

Description

Enables **ReGenesees** to provide correct variance estimates of (functions of) calibration estimators, even if the survey weights have not been calibrated by **ReGenesees**.

Usage

```
ext.calibrated(data, ids, strata = NULL, weights,
               fpc = NULL, self.rep.str = NULL, check.data = TRUE,
               weights.cal, calmodel, partition = FALSE, sigma2 = NULL)
```

Arguments

data	The same as in function e.svydesign .
ids	The same as in function e.svydesign .
strata	The same as in function e.svydesign .
weights	The same as in function e.svydesign .
fpc	The same as in function e.svydesign .
self.rep.str	The same as in function e.svydesign .
check.data	The same as in function e.svydesign .
weights.cal	Formula identifying the externally calibrated weights.
calmodel	The same as in function e.calibrate .
partition	The same as in function e.calibrate .
sigma2	The same as in function e.calibrate .

Details

Owing to **ReGenesees**'s ability to provide proper variance estimates for (complex functions of) calibration estimators, some users may be tempted to exploit **ReGenesees** in the estimation phase *even if* they did *not* use **ReGenesees** for calibration.

This result *cannot* be achieved naively, by simply passing to **ReGenesees** function [e.svydesign](#) the survey data and supplying the externally calibrated weights through its `weights` argument.

Indeed, variance estimation methods of **ReGenesees**'s summary statistics functions ([svystatTM](#), [svystatR](#), [svystatS](#), [svystatSR](#), [svystatB](#), [svystatQ](#), [svystatL](#) and [svystat](#)) are dispatched according to the class of the input design object:

1. If the design object is un-calibrated (i.e. its class is 'analytic'), variance formulas are appropriate to Horvitz-Thompson estimators (and functions of them).
2. If the design object is calibrated (i.e. its class is 'cal.analytic'), variance formulas are appropriate to Calibration estimators (and functions of them).

Therefore, the naive approach of passing the externally calibrated weights `weights.cal` to `e.svydesign` as if they were initial or design weights cannot succeed, since it would result in HT-like variance estimates, leading generally to *variance overestimation* (with bigger upward bias for variables that are better explained by the calibration model).

Function `ext.calibrated` has been designed exactly to avoid the aforementioned pitfalls and to allow **ReGenesees** provide correct variance estimates of (functions of) calibration estimators, even if the survey weights have been calibrated externally by other software.

Argument `weights.cal` identifies the externally calibrated weights of the units included in the sample. The data variable referenced by `weights.cal` must be numeric. Currently, only *positive* externally calibrated weights can be handled (see the dedicated section below).

Other arguments to `ext.calibrated` derive either from function `e.svydesign` or from function `e.calibrate`. The former serve the purpose of passing the survey data and the corresponding sampling design metadata, the latter are meant to tell `ext.calibrated` how the externally calibrated weights have been obtained.

Value

An object of class `cal.analytic`, storing the original survey data *plus* all the sampling design and calibration metadata needed for proper variance estimation.

What if externally calibrated weights happen to be negative?

From a methodological perspective, negative calibration weights are legitimate. However, owing to software implementation details whose modification would not be trivial, function `ext.calibrated` is *not* yet able to cope with this case. Note that the problem is actually due to the *external* origin of the negative calibration weights. In fact, **ReGenesees** calibration and estimation facilities are entirely able to cope with possibly negative calibration weights, provided they were computed *internally*.

Note

Exactly as **ReGenesees**'s base functions `e.svydesign` and `e.calibrate` would do, `ext.calibrated` too will wrap inside its return value a local copy of data. As usual, this copy will be stored inside the variables slot of the output list. As usual, again, the calibrated weights will be accessible by using the `weights` function.

Author(s)

Diego Zardetto.

See Also

`e.svydesign` to bind survey data and sampling design metadata, and `e.calibrate` for calibrating survey weights within **ReGenesees**.

Examples

```
# Load data sbs data
data(sbs)

#####
# Simulate an external calibration procedure and compute some benchmark #
# estimates and errors to test function ext.calibrated                    #
```



```
#####
# Define a survey design
sbsdes <- e.svydesign(data= sbs, ids= ~id, strata= ~strata, weights= ~weight,
                    fpc= ~fpc)

# Build a template for population totals
pop <- pop.template(data= sbsdes, calmodel= ~y:nace.macro + emp.cl + emp.num - 1,
                    partition= ~dom3)

# Have a look at the template structure
pop.desc(pop)

# Fill the template
pop <- fill.template(universe= sbs.frame, template= pop)

# Calibrate
sbscal <- e.calibrate(design= sbsdes, df.population= pop, calfun= "logit",
                     bounds= c(0.8, 1.3), sigma2= ~emp.num)

# Compute benchmark estimates and errors (average value added per employee by
# region) to be later compared with those obtained by using ext.calibrated
benchmark <- svystatR(design= sbscal, num= ~va.imp2, den= ~emp.num, by= ~region)
benchmark

# Extract the 'externally' calibrated weights...
w <- weights(sbscal)

#...and add these 'externally' calibrated weights to the original survey data
sbs.ext <- data.frame(sbs, w.ext = w)

# NOTE: Now sbs.ext is just a data frame, without any knowledge of the
#       calibration metadata formerly stored inside sbscal (i.e. the object
#       calibrated by ReGenesees)

#####
# Let ReGenesees digest the 'externally' calibrated weights, #
# then re-compute benchmark estimates and errors for testing #
#####
# Simply pass survey data along with sampling design and calibration model
# metadata
sbscal.ext <- ext.calibrated(data= sbs.ext, ids= ~id, strata= ~strata,
                            weights= ~weight, fpc = ~fpc,
                            weights.cal= ~w.ext,
                            calmodel= ~y:nace.macro + emp.cl + emp.num - 1,
                            partition= ~dom3, sigma2= ~emp.num)

# Have a look at the output
sbscal.ext

# Now re-compute benchmark estimates and errors by means of new object
# ext.sbscal
test <- svystatR(design= sbscal.ext, num= ~va.imp2, den= ~emp.num, by= ~region)
test

#####
# Compare benchmark estimates and errors to those derived from #
```

```
# ext.calibrated return object #
#####
benchmark
test

# ...and they are identical, as it must be.

# NOTE: All utility tools yield exactly the same results, e.g.
identical(weights(sbscal), weights(sbscal.ext))
identical(g.range(sbscal), g.range(sbscal.ext))

#####
# Show that the naive idea of directly passing the externally calibrated #
# weights to e.svydesign does NOT work properly for variance estimation #
#####
naive <- e.svydesign(data= sbs.ext, ids= ~id, strata= ~strata,
                    weights= ~w.ext, fpc = ~fpc)

# Estimated sampling errors derived by this naive design object...
svystatR(design= naive, num= ~va.imp2, den= ~emp.num, by= ~region)

#...do NOT match benchmark values, overestimating them:
benchmark
```

extractors

Extractor Functions for Variability Statistics

Description

These functions extract standard errors (SE), variances (VAR), coefficients of variation (cv) and design effects (deff) from an object which has been returned by a survey statistic function (e.g. [svystatTM](#), [svystatR](#), [svystatS](#), [svystatSR](#), [svystatB](#), [svystatQ](#), [svystatL](#), [svystat](#), ...).

Usage

```
SE(object, ...)
VAR(object, ...)
cv(object, ...)
deff(object, ...)
```

Arguments

object	An object containing survey statistics.
...	Arguments for future expansion.

Details

With the exception of deff, all extractor functions can be used on any object returned by a survey statistic function: the correct answer will be obtained whatever the call that generated the object. For getting the design effect, object must have been built with option deff = TRUE or deff = "replace".

Value

A data structure (typically inheriting from classes `matrix` or `data.frame`) storing the requested information.

Note

Package **ReGenesees** provides extensions of methods `coef` and `confint` (originally from package **stats**) that can be used to extract estimates and confidence intervals respectively.

Author(s)

Diego Zardetto

See Also

Function `coef` to extract estimates and function `confint` to extract confidence intervals. Estimators of Totals and Means `svystatTM`, Ratios between Totals `svystatR`, Shares `svystatS`, Ratios between Shares `svystatSR`, Multiple Regression Coefficients `svystatB`, Quantiles `svystatQ`, Complex Analytic Functions of Totals and/or Means `svystatL`, and all of the above `svystat`.

Examples

```
# Creation of a design object:
data(sbs)
des<-e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,
  fpc=~fpc)

# Estimation of the average value added at the
# nation level (by default one gets the SE):
VA.avg <- svystatTM(des,~va.imp2,estimator="Mean")
VA.avg

# Extractions of some variance statistics from the
# object above:
## 1) SE
SE(VA.avg)
## 2) CV
cv(VA.avg)
## 3) VAR
VAR(VA.avg)

# Design effects have to be requested in advance,
# i.e. the following invocation produces an error:
## Not run:
deff(VA.avg)

## End(Not run)
# ...while the following works:
VA.avg <- svystatTM(des,~va.imp2,estimator="Mean",deff=TRUE)
deff(VA.avg)

# Further examples:
## Extract the statistic:
coef(VA.avg)
## Extract the confidence interval at 90%
## confidence level (the default would be 95%):
```

```
confint(VA.avg, level=0.9)
## note the argument 'level', which comes from confint function in package stats
```

fill.template

Fill the Known Totals Template for a Calibration Task

Description

Given a template prepared to store the totals of the auxiliary variables for a specific calibration task, computes the actual values of such totals from a sampling frame.

Usage

```
fill.template(universe, template, mem.frac = 10)
```

Arguments

universe	Data frame containing the complete list of the units belonging to the target population, along with the corresponding values of the auxiliary variables (the sampling frame).
template	The template for the calibration task, an object of class <code>pop.totals</code> .
mem.frac	A numeric and non-negative value (the default is 10). It triggers a memory-efficient algorithm when universe is really huge (see ‘Details’ and ‘Performance’).

Details

Recall that a `template` object returned by function `pop.template` has a structure that complies with the standard required by `e.calibrate`, but is *empty*, in the sense that all the known totals it must be able to store are missing (NA). Whenever these totals are available to the user as such, that is in the form of already computed aggregated values (e.g. because they come from an external source, like a Population Census), the **ReGeneseees** package cannot automatically fill the template. Stated more explicitly: the user himself has to bear the responsibility of putting the *right values* in the *right slots* of the prepared template data frame. To this end, function `pop.desc` could be very helpful.

A lucky alternative arises when a “*sampling frame*” (that is a data frame containing the complete list of the units belonging to the target population, along with the corresponding values of the auxiliary variables) is available. In such cases, indeed, the `fill.template` function is able to: (i) automatically compute the totals of the auxiliary variables from the universe data frame, (ii) safely arrange and format these values according to the template structure.

Notice that `fill.template` will perform a complete coherence check between universe and template. If this check fails, the program stops and prints an error message: the meaning of the message should help the user diagnose the cause of the problem. Should empty levels be present in any factor variable belonging to universe, they would be dropped.

Argument `mem.frac` (whose value must be numeric and non-negative) triggers a memory-efficient algorithm when universe is *really huge*. The *only* sound reason to ever change the value of this argument from its default (`mem.frac=10`) is that an invocation of `fill.template` caused a memory-failure (i.e. a messages beginning cannot allocate vector of size ...) on your machine. In such a case, *increasing* the value of `mem.frac` (e.g. `mem.frac=20`) will provide a better chance of succeeding (for more details, see ‘Performance’ section below).

Value

An object of class `pop.totals` storing the *actual* values of the population totals for the specified calibration task, ready to be safely passed to [e.calibrate](#).

Performance

Real-world calibration tasks (e.g. in the field of Official Statistics) can simultaneously involve hundreds of auxiliary variables and refer to target populations of several million units. In such circumstances, the naive aggregation of the calibration `model.matrix` of universe may turn out to be too memory-demanding (at least in ordinary PC environments) and determine a memory-failure error.

The alternative implemented in `fill.template` is to: (i) split universe in chunks, (ii) compute partial sums of auxiliary variables chunk-by-chunk, (iii) update `template` by adding progressively such partial sums. This alternative is triggered by parameter `mem.frac`, which also implicitly controls the number of chunks. The function estimates the memory that would be used to store the *full* `model.matrix` of universe and compares it to 4 GB: if the resulting ratio is bigger than $1/\text{mem.frac}$, the memory-efficient algorithm starts; the number of chunks in which universe will then be split is determined in such a way that the memory needed to store the `model.matrix` of *each* chunk does not exceed a fraction $1/\text{mem.frac}$ of 4 GB.

Whenever `fill.template` switches to the memory-efficient "chunking" algorithm, a warning message will signal it and will specify as well the number of chunks that are being processed.

Author(s)

Diego Zardetto

References

Zardetto, D. (2015) "*ReGenesees: an Advanced R System for Calibration, Estimation and Sampling Error Assessment in Complex Sample Surveys*". Journal of Official Statistics, 31(2), 177-203. doi: <https://doi.org/10.1515/jos-2015-0013>.

See Also

[e.calibrate](#) for calibrating weights, [pop.template](#) for the definition of the class `pop.totals` and to build a "template" data frame for known population totals, [pop.desc](#) to provide a natural language description of the template structure, and [%into%](#) for the compression operator for nested factors.

Examples

```
# Load sbs data:
data(sbs)

# Build a design object:
sbsdes<-e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,fpc=~fpc)

#####
# A simple example first. #
#####

# Suppose you want to calibrate on the enterprise counts inside areas
```

```

# 1) Build the population totals template:
pop<-pop.template(sbsdes, calmodel=~area-1)

# Note: given the dimension of the obtained template...
dim(pop)

# ...the number of known totals to be stored is 24 (one for each area).

# 2) Use the fill.template function to (i) automatically compute
#     such 24 totals from the universe (sbs.frame) and (ii) safely fill
#     the template:
pop<-fill.template(universe=sbs.frame,template=pop)
pop

# 3) Lastly calibrate, e.g. with the unbounded linear distance and
#     heteroskedastic effects proportional to emp.num:
sbscal<-e.calibrate(sbsdes,pop,sigma2=~emp.num,bounds=c(-Inf,Inf))

#####
# A more involved (two-sided) example. #
#####

# Now suppose you have to perform a calibration process which
# exploits as auxiliary information the total number of employees (emp.num)
# and enterprises (ent) inside the domains obtained by:
# i) crossing nace2 and region;
# ii) crossing emp.cl, region and nace.macro;

# Due to the fact that nace2 is nested into nace.macro,
# the calibration model can be efficiently factorized as follows:
## 1) Add to the design object and universe the new compressed
#     factor variable involving nested factors, namely:
sbsdes<-des.addvars(sbsdes,nace2.in.nace.macro=nace2 %into% nace.macro)
sbs.frame$nace2.in.nace.macro<-sbs.frame$nace2 %into% sbs.frame$nace.macro

# 2) Build the template exploiting the new variable:
pop<-pop.template(sbsdes,
  calmodel=~(emp.num+ent):(nace2.in.nace.macro + emp.cl)-1,
  partition=~nace.macro:region)

# Note: given the dimension of the obtained template...
dim(pop)

# ...the number of known totals to be stored is 792.

# 3) Use the fill.template function to (i) automatically compute
#     such 792 totals from the universe (sbs.frame) and (ii) safely fill
#     the template:
pop<-fill.template(universe=sbs.frame,template=pop)

# Note: out of the 792 known totals in pop, only non-zero entries are actually
# relevant

# 4) Lastly calibrate, e.g. with the unbounded linear distance and
#     heteroskedastic effects proportional to emp.num:
sbscal<-e.calibrate(sbsdes,pop,sigma2=~emp.num,bounds=c(-Inf,Inf))

```

```

# Note: a global calibration task would have led to identical calibrated
# weights, but in a more memory-hungry and time-consuming way, as you can
# verify:
# 1) Build template:
pop.g<-pop.template(sbsdes,
  calmodel=~(emp.num+ent):(nace2:region + emp.cl:nace.macro:region)-1)
dim(pop.g)

# 2) Fill template:
pop.g <- fill.template(sbs.frame,pop.g)

# 3) Calibrate globally:
## Not run:
sbscal.g<-e.calibrate(sbsdes,pop.g,sigma2=~emp.num,bounds=c(-1E6,1E6))

# 4) Compare calibrated weights (factorized vs. global solution):
range(weights(sbscal)/weights(sbscal.g))

# ... they are equal.

## End(Not run)

#####
# Just a single example of the memory-efficient algorithm #
# triggered by argument 'mem.frac'.                        #
#####
## Not run:
# First artificially increase the size of the sampling frame (e.g.
# up to 5 million rows):
sbs.frame.HUGE<-sbs.frame[sample(1:nrow(sbs.frame),5000000,rep=TRUE),]
dim(sbs.frame.HUGE)

# Build the template:
pop<-pop.template(sbsdes,
  calmodel=~(emp.num+ent):(nace2.in.nace.macro + emp.cl)-1,
  partition=~nace.macro:region)
dim(pop)

# Fill the template by using the HUGE universe:
pop<-fill.template(universe=sbs.frame.HUGE,template=pop)

## End(Not run)

```

find.lon.strata

Find Strata with Lonely PSUs

Description

Checks whether a stratified design object contains lonely PSUs: if this is the case, returns the lonely strata levels.

Usage

```
find.lon.strata(design)
```

Arguments

design Object of class `analytic` (or inheriting from it) containing survey data and sampling design metadata.

Details

Lonely PSUs (i.e. PSUs which are alone inside a not self-representing stratum) are a concern from the viewpoint of variance estimation. The suggested **ReGenesees** facility to handle the lonely PSUs problem is the strata aggregation technique provided in function `collapse.strata` (for further alternatives, see also `ReGenesees.options`).

Function `find.lon.strata` (originally a private function intended to be called only by `collapse.strata`) is a simple diagnostic tool whose purpose is to identify the levels of the strata containing lonely PSUs (lonely strata for short).

Value

The lonely strata levels, if `design` actually contains lonely PSUs; `invisible(NULL)` otherwise.

Author(s)

Diego Zardetto

See Also

`collapse.strata` for the suggested way of handling lonely PSUs, `ReGenesees.options` for a different way to face the same problem (namely by setting variance estimation options), and `fpcdat` for useful data examples.

Examples

```
# Load sbs data:
data(fpcdat)

# A negative example first:

# Build a design object:
fpcdes<-e.svydesign(data=fpcdat,ids=~psu+ssu,strata=~stratum,weights=~w,
  fpc=~fpc1+fpc2)
fpcdes

# Find lonely strata:
find.lon.strata(fpcdes)

# Recall that the difference between certainty PSUs (those sampled with
# probability 1, contained inside self-representing strata) and lonely PSUs
# rests on the fpc information passed to e.svydesign, e.g.:

# Build a new design object with the same data, now IGNORING fpcs:
fpcdes.nofpc<-e.svydesign(data=fpcdat,ids=~psu+ssu,strata=~stratum,
  weights=~w)
fpcdes.nofpc

# Find lonely strata:
find.lon.strata(fpcdes.nofpc)
```



```
# A trivial check: collapsing strata eliminates lonely PSUs

# Apply the collapse strata technique:
fpcdes.nofpc.clps<-collapse.strata(fpcdes.nofpc)
fpcdes.nofpc.clps
clps.strata.status

# Find lonely strata:
find.lon.strata(fpcdes.nofpc.clps)

# ...as it must be.
```

fit.gvf

Fit GVF Models

Description

This function fits one or more GVF models to a set of survey statistics.

Usage

```
fit.gvf(gvf.input, model = NULL, weights = NULL)

## S3 method for class 'gvf.fit'
print(x, digits = max(3L, getOption("digits") - 3L), ...)
## S3 method for class 'gvf.fits'
print(x, digits = max(3L, getOption("digits") - 3L), ...)
## S3 method for class 'gvf.fit.gr'
print(x, digits = max(3L, getOption("digits") - 3L), ...)
## S3 method for class 'gvf.fits.gr'
print(x, digits = max(3L, getOption("digits") - 3L), ...)

## S3 method for class 'gvf.fits'
x[...]
## S3 method for class 'gvf.fits'
x[[...]]

## S3 method for class 'gvf.fit'
summary(object, correlation = FALSE, symbolic.cor = FALSE, ...)
## S3 method for class 'gvf.fits'
summary(object, correlation = FALSE, symbolic.cor = FALSE, ...)
## S3 method for class 'gvf.fit.gr'
summary(object, correlation = FALSE, symbolic.cor = FALSE, ...)
## S3 method for class 'gvf.fits.gr'
summary(object, correlation = FALSE, symbolic.cor = FALSE, ...)
```

Arguments

`gvf.input` An object of class `gvf.input` (or `gvf.input.gr`), containing the data to fit.

<code>model</code>	The GVF model(s) to be fitted (see ‘Details’). NULL (the default) requires to fit <i>all</i> the registered GVF models currently available in GVF.db .
<code>weights</code>	Formula specifying the weights to be used for fitting (via weighted least squares), if any. NULL (the default) means that ordinary least squares will be used. See also ‘Details’.
<code>x</code>	An object of class <code>gvf.fits</code> , storing fitted GVF models.
<code>digits</code>	Minimal number of significant digits, see print.default .
<code>object</code>	Any output of <code>fit.gvf</code> , storing one (more than one) fitted GVF model(s).
<code>correlation</code>	Should the correlation matrix of the estimated parameters be returned and printed? Logical, with default FALSE.
<code>symbolic.cor</code>	Should the correlations be printed in symbolic form (see symnum) rather than as numbers. Logical, with default FALSE.
<code>...</code>	Further arguments passed to or from other methods.

Details

Function `fit.gvf` fits one or more GVF models to a set of survey statistics. The rationale for fitting multiple models to the same data is primarily for comparison purposes: the user is expected to eventually choose his preferred model, in order to obtain sampling errors predictions.

Argument `gvf.input` specifies the set of (pre computed) estimates and errors to which GVF models are to be fitted, as prepared by functions [gvf.input](#) and/or [svystat](#).

One or more GVF models can be fitted *simultaneously* to the same data, depending on the way argument `model` is passed.

Argument `model` can be either:

- (1) NULL (the default) meaning *all* the registered models currently available in [GVF.db](#);
- (2) any sub-vector of `GVF.db$Model.id`, i.e. an integer vector identifying an arbitrary selection of registered models;
- (3) an arbitrary (single) formula, i.e. any custom, user-defined GVF model.

When `model` is passed via options (1) or (2), function `fit.gvf` can take advantage of any additional information available inside `GVF.db`, e.g. to warn the user in case a GVF model is not deemed to be appropriate for the kind of estimates contained into `gvf.input` (see ‘Examples’).

Argument `weights` enables fitting the specified GVF model(s) via weighted least squares. By default `weights = NULL` and ordinary least squares are used. The weights must be passed by a formula referencing variables belonging to `gvf.input`. For instance, to weight observations according to reciprocals of squared CVs, one can use `weights = ~I(CV^~2)`.

Value

An object containing one or more fitted GVF models, depending on the way argument `model` was passed.

Let’s first focus on input objects of class `gvf.input`.

If `model` specifies a single GVF model, the output object will be of class `gvf.fit` and inherit from class [lm](#).

If `model` specifies many GVF models, the output object will be of class `gvf.fits` and inherit from class [list](#). Hence, it will be possible to subset `gvf.fits` objects via methods `[` and `[[`. Note, moreover, that each component (in the sense of class [list](#)) of a `gvf.fits` object will be of class `gvf.fit`.

When, instead, the input object has class `gvf.input.gr`, i.e. it stores “grouped” estimates and errors, model fitting is performed *separately* for different groups. Therefore, applying `fit.gvf` *always* results in *many* fitted GVF models.

If `model` specifies a single GVF model, the output object will be of class `gvf.fit.gr` and inherit from class `list`. Each slot of the list will contain the same GVF model fitted to a specific group.

If `model` specifies many GVF models, the output object will be of class `gvf.fits.gr` and again inherit from class `list`. Each slot of the list will now contain *a second list* storing different GVF models fitted to a specific group.

Author(s)

Diego Zardetto

See Also

`estimator.kind` to assess what kind of estimates are stored inside a survey statistic object, `GVF.db` to manage **ReGenesees** archive of registered GVF models, `gvf.input` and `svystat` to prepare the input for GVF model fitting, `fit.gvf` to fit GVF models, `plot.gvf.fit` to get diagnostic plots for fitted GVF models, `drop.gvf.points` to drop alleged outliers from a fitted GVF model and simultaneously refit it, and `predictCV` to predict CV values via fitted GVF models.

Examples

```
# Load example data:
data(AF.gvf)

# Now we have at our disposal a set of estimates and errors
# of Absolute Frequencies:
str(ee.AF)

# And the available registered GVF models are listed below:
GVF.db

#####
# How to specify the GVF model(s) to fit? #
#####

## (A) How to specify a *single* GVF model ##

#### (A.1) Select one registered model using its 'Model.id' as reported in
####       the GVF.db archive
# Let's fit, for instance, the GVF model with Model.id = 1:
m <- fit.gvf(ee.AF, model = 1)

# Inspect the result:
class(m)
m
summary(m)

# Now let's fit GVF model with Model.id = 4
m <- fit.gvf(ee.AF, model = 4)
# Beware of the NOTE reported when printing or summarizing this fitted model:
m
summary(m)
```

```
#### (A.2) Specify the GVF model to fit by providing its formula directly, e.g.
####      because it is not available in GVF.db (yet):
m <- fit.gvf(ee.AF, model = CV ~ I(1/Y^2) + I(1/Y) + Y + I(Y^2))
m
summary(m)

## (B) How to specify a *many* GVF models simultaneously ##

#### (B.1) Use a subset of column 'Model.id' of GVF.db
# Let's, for instance, fit all the available GVF models which are appropriate
# to Frequencies, as reported in column 'Estimator.kind' of GVF.db
mm <- fit.gvf(ee.AF, model = 1:3)

# Inspect the result:
class(mm)
length(mm)
mm
summary(mm)

# Note that you can subset the output fitted models as a list:
mm.31 <- mm[c(3,1)]
class(mm.31)
mm.31

# and:
mm.2 <- mm[[2]]
class(mm.2)
mm.2

#### (B.2) Not specifying any GVF model, or specifying model = NULL, causes
####      *all* the available models in GVF.db to be fitted simultaneously:
mm <- fit.gvf(ee.AF)

# Inspect the result:
class(mm)
length(mm)
mm
summary(mm)

#####
# How to fit GVF model(s) via *weighted* least squares? #
#####
# Weights can be specified by a formula. Of course, the 'weights' formula must
# reference variables belonging to gvf.input.

# Let's use the built-in GVF model with Model.id = 1 and weight observations
# according to reciprocals of squared CVs:
mw <- fit.gvf(ee.AF, model = 1, weights = ~I(CV^-2))
mw

# Compute ordinary least squares fit:
m <- fit.gvf(ee.AF, model = 1)
```

```

m

# Compare the results:
summary(mw)
summary(m)

#####
# Fitting GVF model(s) to "grouped" estimates and errors: a quick ride. #
#####
# Recall we have at our disposal the following survey design object
# defined on household data:
exdes

# Now use function svystat to prepare "grouped" estimates and errors
# of counts to be fitted separately (here groups are regions):
ee.g <- svystat(exdes, y=~ind, by=~age5c:marstat:sex, combo=3, group=~regcod)
class(ee.g)
ee.g

## Fit a *single* registered GVF model separately inside groups ##
m.g <- fit.gvf(ee.g, model = 1)

# Inspect the result:
class(m.g)
length(m.g)
m.g
summary(m.g)

# Can subset the result as a list, e.g. to get the fitted model of region '7':
m.g7 <- m.g[["7"]]
class(m.g7)
summary(m.g7)

## Fit *many* registered GVF models separately inside groups ##
mm.g <- fit.gvf(ee.g, model = 1:3)

# Inspect the result:
class(mm.g)
length(mm.g)
mm.g
summary(mm.g)

# Still can subset the result as a list, but now each component is a list
# itself. To get the fitted models of region '7', simply:
mm.g7 <- mm.g[["7"]]
class(mm.g7)
summary(mm.g7)

# And to isolate GVF fitted model number 2 for region '7', simply:
mm.g7.2 <- mm.g7[[2]]
class(mm.g7.2)
summary(mm.g7.2)

```

fpcdat

*A Small But Not Trivial Artificial Sample Data Set***Description**

A small dataset mimicking sample data selected with a 2-stage, stratified, cluster sampling without replacement. Allows to run R code contained in the ‘Examples’ section of the **ReGenesees** package help pages.

Usage

```
data(fpcdat)
```

Format

A data frame with 28 observations on the following 12 variables.

psu Identifier of the primary sampling units, numeric

ssu Identifier of the second stage sampling units, numeric

stratum Stratification Variable, a factor with 5 levels: S.1, S.2, S.3, S.4, S.5

sr Strata type, integer with values 0 (NSR strata) and 1 (SR strata)

fpc1 First stage finite population corrections, given as population sizes (in terms of psu clusters) inside strata, numeric

fpc2 Second stage finite population corrections, given as population sizes (in terms of ssu clusters) inside the corresponding sampled psu, numeric

x A numeric variable

y A numeric variable

dom1 A variable defining unplanned estimation domains, factor with 3 levels: A, B, C

dom2 A variable defining unplanned estimation domains, factor with 6 levels: a, b, c, d, e, f

w Direct weights, numeric

z A numeric variable

pl.domain A variable defining planned estimation domains, factor with 3 levels: pd.1, pd.2, pd.3

Details

Though very small, the fpcdat dataset concentrates a lot of interesting features. The sampling design is a complex one, with both self-representing (SR) and not-self-representing (NSR) strata. Sampling fractions are deliberately not negligible, in order to stress the effects of finite population corrections on variance estimation. Moreover, being the observations so few, performing computations on the fpcdat dataset allows to check and understand easily all the effects of setting/changing the global variance estimation options of the **ReGenesees** package (see e.g. [ReGenesees.options](#)).

See Also

[ReGenesees.options](#) for setting/changing variance estimation options.

Examples

```
data(fpcdat)
head(fpcdat)
str(fpcdat)
```

g.range	<i>Range of g-Weights</i>
---------	---------------------------

Description

Computes the range of the ratios between calibrated weights and initial weights (*g-weights*).

Usage

```
g.range(cal.design)
```

Arguments

cal.design Object of class cal.analytic.

Details

This function computes the smallest interval which contains the ratios between calibrated weights and initial weights.

Value

A numeric vector of length 2.

Note

If cal.design has undergone k subsequent calibration steps (with $k \geq 2$), the function will return the range of the ratios between the output weights of calibration steps k and k - 1.

Author(s)

Diego Zardetto

See Also

[weights](#) to extract the weights from a design object, [e.calibrate](#) for calibrating weights and [bounds.hint](#) to obtain a hint for calibration problems where range restrictions are imposed on the *g-weights*.

Examples

```
# Creation of the object to be calibrated:
data(data.examples)
des<-e.svydesign(data=example,ids=~towcod+famcod,strata=~SUPERSTRATUM,
  weights=~weight)

# Calibration (partitioned solution) on the marginal distribution
# of age in 5 classes (age5c) inside provinces (procod)
# (totals in pop06p) with bounds=c(0.5, 1.5):
descal06p<-e.calibrate(design=des,df.population=pop06p,
  calmodel=~age5c-1,partition=~procod,calfun="logit",
  bounds=c(0.5, 1.5),aggregate.stage=2)

# Now let's verify the actual range of the obtained g-weights:
g.range(descal06p)

# which indeed is covered by c(0.5, 1.5), as required.

# Now calibrate once again, this time on the joint distribution of sex
# and marstat (totals in pop03) with the global solution:
descal2<-e.calibrate(design=descal06p,df.population=pop03,
  calmodel=~marstat:sex-1,calfun="linear",bounds=bounds)

# Notice that the print method correctly takes the calibration chain
# into account:
descal2

# The range of the g-weights for the twice calibrated object is:
g.range(descal2)

#... which is equal to:
range(weights(descal2)/weights(descal06p))

#... and must not be confused with:
range(weights(descal2)/weights(des))
```

get.linvar

Linearized Variable(s) of Complex Estimators by Domains

Description

Computes the linearized variable(s) of a Complex Estimator in subpopulations (domains). The Complex Estimator can be any analytic function of Horvitz-Thompson or Calibration estimators.

Usage

```
get.linvar(design, expr, by = NULL, stack = FALSE, na.rm = FALSE)
```

Arguments

design	Object of class <code>analytic</code> (or inheriting from it) containing survey data and sampling design metadata. Can be either uncalibrated or calibrated.
expr	R expression defining the Complex Estimator (see svystatL for the basic syntax; see also section ‘Details’).

by	Formula specifying the variables that define the "estimation domains". If NULL (the default option) the estimator refers to the whole population.
stack	If FALSE (the default), the function will return a matrix of domain-specific linearized variables, with one column per domain. If TRUE, the domain-specific linearized variables will be stacked without information loss and returned as a single column. The <i>stacked</i> output format is only possible for <i>uncalibrated</i> designs (see 'Details').
na.rm	Allow missing values in the variables entering the estimator expression? The default is FALSE.

Details

This function has been designed mainly for programmers or advanced users willing to build upon **ReGenesee**s: typical users are not expected to feel much need of it.

The **ReGenesee**s package adopts the Taylor-series linearization technique to estimate the sampling variance of nonlinear (smooth) estimators. Using this technique, it can handle any Complex Estimator that can be expressed as an analytic function of Horvitz-Thompson or Calibration estimators. This includes even user-defined estimators, through function [svystatL](#) [Zardetto, 15].

In the Taylor-series linearization approach, estimating the sampling variance of a Complex Estimator amounts to estimating the sampling variance of the Horvitz-Thompson estimator of the total of the *linearized variable* of the Complex Estimator under the sampling design at hand. Function `get.linvar` computes that linearized variable. If one is interested in estimating the sampling variance of a Complex Estimator by *domains* (i.e. for subpopulations), then - owing to the Taylor linearization technique - a different linearized variable has to be calculated for each domain. Therefore, in the most general case, the output of function `get.linvar` will be a matrix of linearized variables, with one column per domain.

If the input object `design` is calibrated, then the linearized variable produced by function `get.linvar` correctly takes into account the theoretical properties of Calibration estimators (see, e.g., [Deville, 1999]). In particular, `get.linvar` computes the needed g-weighted residuals (see, e.g., equations (8) and (9) of [Zardetto, 15]) by leveraging function [get.residuals](#).

The mandatory argument `expr`, which identifies the Complex Estimator, must be an object of class `expression`. You can specify just a single Complex Estimator at a time, i.e. `length(expr)` must be equal to 1. Any analytic function of estimators of Totals and Means derived from the input design object `design` is allowed.

The basic syntax follows the same rules described for function [svystatL](#). Inside `expr`, the estimator of the Total of a variable is simply represented by the *name* of the variable itself. The reserved name `ones` can be used to reference an artificial variable (which will be created on-the-fly, if not already present) whose value is 1 for each sampling unit, so that its Total estimator actually estimates the size of the population in terms of elementary units. Therefore, e.g., expression `y/ones` represents the estimator of the Mean of variable `y`. Variables referenced inside `expr` must be numeric and belong to `design`.

The optional argument `by` specifies the variables that define the "estimation domains", that is the subpopulations for which the estimates are to be calculated. If `by=NULL` (the default option), the estimates produced by `svystatL` refer to the whole population. Estimation domains must be defined by a formula: for example the statement `by=~B1:B2` selects as estimation domains the subpopulations determined by crossing the modalities of variables `B1` and `B2`. Notice that a formula like `by=~B1+B2` will be automatically translated into the factor-crossing formula `by=~B1:B2`: if you need to compute estimates for domains `B1` and `B2` *separately*, you have to call `svystatL` twice. The design variables referenced by `by` (if any) should be of type `factor`, otherwise they will be coerced.

As already noted, in the most general case, the output of function `get.linvar` will be a matrix of linearized variables, with one column per domain. However, the linearized variable of any *domain estimator* that is a function of Horvitz-Thompson estimators is identically equal to zero outside the domain. Thanks to this property, and only for functions of HT estimators, the columns of the output matrix can be stacked into one single column without information loss. Users may request this convenient output format by specifying `stack = TRUE`. Unfortunately, the same result cannot be obtained for functions of Calibration estimators, because the g-weighted residuals are generally non-zero outside the active estimation domain. Therefore, argument `stack` does nothing if design is calibrated.

Value

A matrix of linearized variables.

Author(s)

Diego Zardetto

References

Deville, J. C. (1999) “*Variance Estimation for Complex Statistics and Estimators: Linearization and Residual Techniques*.”. Survey Methodology 25: 193-203.

Zardetto, D. (2015) “*ReGenesees: an Advanced R System for Calibration, Estimation and Sampling Error Assessment in Complex Sample Surveys*”. Journal of Official Statistics, 31(2), 177-203. doi: <https://doi.org/10.1515/jos-2015-0013>.

See Also

`svystatL` to calculate estimates and sampling errors of Complex Estimators, `get.residuals` to compute residuals of interest variables w.r.t. the calibration model adopted to build a calibrated object.

Examples

```
# Load sbs data:
data(sbs)

# Create a design object to be calibrated:
sbsdes<-e.svydesign(data= sbs, ids= ~id, strata= ~strata, weights= ~weight, fpc= ~fpc)

#####
# Just some checks on the consistency of the numerical results #
# obtained by ReGenesees with well known theoretical properties. #
#####

## In the Taylor-series linearization approach, estimating the sampling variance of a
## Complex Estimator amounts to estimating the sampling variance of the Horvitz-Thompson
## estimator of the total of the linearized variable of the Complex Estimator under the
## sampling design at hand.

#####
## Check 1 ##
#####
# Global estimate (i.e., no domains) of a nonlinear function of HT estimators:
# - Average value added per employee
```

```

# Compute the linearized variable of the estimator:
z <- get.linvar(sbsdes, expression(va.imp2/emp.num))

# Have a look:
head(z)

# Now add that variable to the input design object:
sbsdes <- des.addvars(sbsdes, z = z)

# Now compute the estimated standard error of the HT total of the linearized variable:
svystatTM(sbsdes, ~z)

# And compare it to the estimated standard error of the complex estimator:
svystatL(sbsdes, expression(va.imp2/emp.num))

# ...which - in this case - can equivalently be obtained exploiting its ratio nature:
svystatR(sbsdes, num = ~va.imp2, den= ~emp.num)

# Test the equality of the results:
all.equal(svystatTM(sbsdes, ~z)$SE,
          svystatL(sbsdes, expression(va.imp2/emp.num))$SE)
# OK

#####
## Check 2 ##
#####
# Domain estimates of a nonlinear function of HT estimators:
# - Average value added per employee by NACE macro-sectors

# Compute the linearized variable(s) of the domain estimator(s):
z.dom <- get.linvar(sbsdes, expression(va.imp2/emp.num), by = ~nace.macro)

# Have a look:
head(z.dom)
tail(z.dom)

# Note the staggered matrix-format of the result. Since you are dealing with HT estimators
# (namely sbsdes is not calibrated), you can opt for the more convenient (but equivalent)
# stacked format:
z.dom <- get.linvar(sbsdes, expression(va.imp2/emp.num), by = ~nace.macro, stack = TRUE)

# Have a look:
head(z.dom)
tail(z.dom)

# Now add that variable to the input design object:
sbsdes <- des.addvars(sbsdes, z.dom = z.dom)

# Now compute the estimated standard error of the HT total of the linearized variable by
# domains:
svystatTM(sbsdes, ~z.dom, by= ~nace.macro)

# And compare it to the estimated standard error of the complex estimator:
svystatL(sbsdes, expression(va.imp2/emp.num), by= ~nace.macro)

# ...which - in this case - can equivalently be obtained exploiting its ratio nature:

```

```

svystatR(sbsdes, num = ~va.imp2, den= ~emp.num, by= ~nace.macro)

# Test the equality of the results:
all.equal(svystatTM(sbsdes, ~z.dom, by= ~nace.macro)$SE,
          svystatL(sbsdes, expression(va.imp2/emp.num), by= ~nace.macro)$SE)
# OK

#####
# Now run the same checks for functions of Calibration Estimators #
#####

# Build a population totals template and fill it with actual known totals computed from
# the sampling frame (sbs.frame):
pop <- pop.template(sbsdes, calmodel= ~ent:emp.cl + y:nace.macro-1, partition= ~region)
pop <- fill.template(sbs.frame, pop)

# Calibrate the weights:
sbscal <- e.calibrate(sbsdes, pop)
g.range(sbscal)

#####
## Check 3 ##
#####
# Global estimate (i.e., no domains) of a nonlinear function of CAL estimators:
# - Average value added per employee

# Compute the linearized variable of the estimator (the name gez should remind you of
# the g-weighted residuals of the HT linearized variable w.r.t. the calibration model):
gez <- get.linvar(sbscal, expression(va.imp2/emp.num))

# Have a look:
head(gez)

# Now add that variable to the initial *uncalibrated* design object:
sbsdes <- des.addvars(sbsdes, gez = gez)

# Now compute the estimated standard error of the *HT total* of the linearized variable:
svystatTM(sbsdes, ~gez)

# And compare it to the estimated standard error of the complex *calibration* estimator:
svystatL(sbscal, expression(va.imp2/emp.num))

# ...which - in this case - can equivalently be obtained exploiting its ratio nature:
svystatR(sbscal, num = ~va.imp2, den= ~emp.num)

# Test the equality of the results:
all.equal(svystatTM(sbsdes, ~gez)$SE,
          svystatL(sbscal, expression(va.imp2/emp.num))$SE)
# OK

#####
## Check 4 ##
#####
# Domain estimates of a nonlinear function of CAL estimators:
# - Average value added per employee by NACE macro-sectors

# Compute the linearized variable(s) of the domain estimator(s):

```

```

gez.dom <- get.linvar(sbscal, expression(va.imp2/emp.num), by = ~nace.macro)

# Have a look:
head(gez.dom)
tail(gez.dom)

# As you see the matrix no longer has the staggered structure of the HT case. In fact, the
# calibration residuals are in general not 0 outside the active domain. Therefore, you
# cannot opt for the more convenient stacked format!

# Let's thus add all the column of the linearized variable(s) matrix to the initial
# *uncalibrated* design object:
sbsdes$variables <- cbind(sbsdes$variables, gez.dom)

# Now compute the estimated standard error of the *HT totals* of the *domain-specific*
# linearized variables:
svystatTM(sbsdes, ~gez_Agriculture + gez_Industry + gez_Commerce + gez_Services)

# And compare it to the estimated standard errors of the complex *calibration* estimator
# by domains:
svystatL(sbscal, expression(va.imp2/emp.num), by= ~nace.macro)

# ...which - in this case - can equivalently be obtained exploiting its ratio nature:
svystatR(sbscal, num = ~va.imp2, den= ~emp.num, by= ~nace.macro)

# Test the equality of the results:
all.equal(
  svystatTM(sbsdes, ~gez_Agriculture + gez_Industry + gez_Commerce + gez_Services)$SE,
  svystatL(sbscal, expression(va.imp2/emp.num), by= ~nace.macro)$SE)
# OK

```

get.residuals

*Calibration Residuals of Interest Variables***Description**

Computes (scaled) residuals of a set of interest variables w.r.t. the calibration model adopted to build a calibrated object.

Usage

```
get.residuals(cal.design, y, scale = c("no", "w", "d", "g"))
```

Arguments

cal.design	Object of class <code>cal.analytic</code> .
y	Formula defining the variables of interest.
scale	character specifying how to scale the residuals, can be one of: 'no' (the default), 'w', 'd', 'g' (see 'Details').

Details

This function has been designed mainly for programmers or advanced users willing to build upon **ReGenesees**: typical users are not expected to feel much need of it.

The residuals of an interest variable w.r.t. the linear model defined by the auxiliary variables used for calibration play a central role in estimating the variance of Calibration Estimators (see, e.g., [Deville, 1999]). Notice that if object `cal.design` has been generated by running a *partitioned* calibration task (see [e.calibrate](#)), the residuals will be correctly computed using the different estimated regression coefficients pertaining to the different domains belonging to the partition.

The mandatory argument `y` behaves exactly the same way as it does in function [svystatTM](#).

The scale argument allows to scale the computed residuals by multiplying them by different factors. By default `scale="no"`, that is *unscaled* residuals are returned. Value `"w"` returns the residuals times the calibrated weights; value `"d"` returns the residuals times the initial weights; finally, value `"g"` returns the residuals times the *g-weights* (i.e. the ratios between calibrated and initial weights). Notice that the semantics of argument `scale` are slightly modified when the input object `cal.design` has been obtained by a multi-step calibration procedure (see Section 'Note' below).

Value

A matrix of residuals.

Note

If `cal.design` has undergone `k` subsequent calibration steps (with `k >= 1`), the function will return the residuals computed w.r.t. the linear assisting model underlying the *last* (i.e. `k`-th) calibration step. If `k >= 2`, the scale parameter will be interpreted as follows:

SCALE	MEANING
"no"no scale;
"w"last calibration weight (i.e. at step <code>k</code>);
"d"second to last calibration weight (i.e. at step <code>k - 1</code>);
"g"ratio between last and second to last calibration weights.

Author(s)

Diego Zardetto

References

Deville, J. C. (1999) "*Variance Estimation for Complex Statistics and Estimators: Linearization and Residual Techniques*". Survey Methodology 25: 193-203.

See Also

[weights](#) to extract the weights from a design object, [e.calibrate](#) for calibrating weights and [g.range](#) to get the range of the *g-weights*.

Examples

```
#####
# Just some checks on the consistency of the numerical results #
# obtained by ReGenesees with well known theoretical properties. #
#####
```

```

# Load sbs data:
data(sbs)

# Create a design object to be calibrated:
sbsdes<-e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,fpc=~fpc)

#####
## Property 1 ##
#####
## If the calibration model has (implicitly or explicitly) an intercept
## the weighted sum of residuals must be zero.

# Suppose you calibrate on enterprise counts inside areas, i.e. a calibration
# model WITH intercept (though implicitly):
# calmodel= ~ area - 1

# First, build and fill the known totals template:
pop<-pop.template(sbsdes, calmodel= ~ area - 1)
pop<-fill.template(pop, universe=sbs.frame)

# Then, calibrate:
sbscal<-e.calibrate(sbsdes, pop)

# Now, get the residuals of any variable (e.g. y and emp.num) scaled with the
# direct weights:
de <- get.residuals(sbscal, ~ y + emp.num, scale="d")

# Lastly, compute the column sums...
colSums(de)

#...which is (numerically) zero, as it must be.

#####
## Property 2 ##
#####
## If the calibration model does not have (implicitly or explicitly) an
## intercept term the weighted sum of residuals is generally different from zero.

# Suppose you calibrate on employees counts inside areas, i.e. a calibration
# model WITHOUT intercept:
# calmodel= ~ emp.num:area - 1

# First, build and fill the known totals template:
pop<-pop.template(sbsdes, calmodel= ~ emp.num:area - 1)
pop<-fill.template(pop, universe=sbs.frame)

# Then, calibrate:
sbscal<-e.calibrate(sbsdes, pop)

# Now, get the residuals of any variable (e.g. y and region) scaled with the
# direct weights:
de <- get.residuals(sbscal, ~ y + region, scale="d")

# Lastly, compute the column sums...
colSums(de)

```

```

#...which is far from zero, as expected.

#####
## Property 3 ##
#####
## In the Taylor linearization approach, estimating the variance of a
## Calibration Estimator amounts to estimating the variance of the HT total
## of its linearized variable (i.e. the g-scaled residual), under the sampling
## design at hand.

# Suppose you calibrate on the total number of employees and enterprises
# inside the domains obtained by:
# i) crossing nace.macro and region;
# ii) crossing emp.cl and region;

# First, build and fill the population totals template:
pop<-pop.template(sbsdes,
  calmodel=~(emp.num+ent):(nace.macro+emp.cl)-1,
  partition=~region)
pop<-fill.template(universe=sbs.frame,template=pop)

# Then, calibrate:
sbscal<-e.calibrate(sbsdes,pop)

# Now, compute the linearized variable of the Calibration Estimator of the
# total of any variable (e.g. va.imp2):
z_va.imp2 <- get.residuals(sbscal, ~ va.imp2, scale="g")

# Now, treat z_va.imp2 as an ordinary variable and compute the standard error
# of its HT total:
sbsdes<-des.addvars(sbsdes, z_va.imp2 = z_va.imp2)
SE(svystatTM(sbsdes, ~z_va.imp2))

# Lastly, compute directly the standard error of the Calibration Estimator...
SE(svystatTM(sbscal, ~va.imp2))

#...and they are identical, as it must be.

# Obviously the same result would hold for domain estimates (e.g. the total
# of va.imp2 for the "Agriculture" nace.macro).

# Compute the linearized variable of the Calibration Estimator of the domain
# total:
z_va.imp2.Agr <- get.residuals(sbscal, ~ I(va.imp2*(nace.macro=="Agriculture")),
  scale="g")

# Now, treat z_va.imp2.Agr as an ordinary variable and compute the standard
# error of its HT total:
sbsdes<-des.addvars(sbsdes, z_va.imp2.Agr = z_va.imp2.Agr)
SE(svystatTM(sbsdes, ~z_va.imp2.Agr))

# Lastly, compute directly the standard error of the Calibration Estimator
# by domain...
SE(svystatTM(sbscal, ~va.imp2, ~nace.macro))

```



```
#...and the "Agriculture" SEs are identical, as it must be.
```

getBest

Identify the Best Fit GVF Model

Description

Given a set of competing fitted GVF models, this function selects the best model according to a given criterion.

Usage

```
getBest(object,
        criterion = c("R2", "adj.R2", "AIC", "BIC"), ...)
```

Arguments

object	Typically, an object containing <i>many</i> fitted GVF models (i.e. of class <code>gvf.fits</code> or <code>gvf.fits.gr</code>).
criterion	The quality criterion to be used for model selection. Default is R^2 .
...	Further arguments passed to or from other methods.

Details

Given a set of competing fitted GVF models, this function selects the best model according to a given criterion.

Four goodness-of-fit criteria are available: R^2 , adjusted R^2 , AIC, and BIC (see [getR2](#)).

If object is a *set* of GVF models fitted to *grouped* data (i.e. of class `gvf.fits.gr`), the function will return the fitted GVF model with best *average score* in the given criterion *over the groups*.

Value

A single GVF fitted model.

Methodological Warning

Each one of the available criteria has its own specificities and limitations (e.g. it is senseless to use AIC to compare two GVF models with different response variables). It is up to the user to select the measure which is appropriate to his goals.

Author(s)

Diego Zardetto

See Also

[GVF.db](#) to manage **ReGenesees** archive of registered GVF models, [gvf.input](#) and [svystat](#) to prepare the input for GVF model fitting, [fit.gvf](#) to fit GVF models, [plot.gvf.fit](#) to get diagnostic plots for fitted GVF models, [drop.gvf.points](#) to drop alleged outliers from a fitted GVF model and simultaneously refit it, and [predictCV](#) to predict CV values via fitted GVF models.

Examples

```
# Load example data:
data(AF.gvf)

# Inspect available estimates and errors of counts:
str(ee.AF)

# List available registered GVF models:
GVF.db

## (A) A *set* of GVF models fitted to the same data ##
# Fit example data to all registered GVF models:
mm <- fit.gvf(ee.AF)
summary(mm)

# Get the best model according to adjusted R^2:
mm.best <- getBest(mm, criterion = "adj.R2")
mm.best

# NOTE: The *first* model has been selected. A thorough model comparison
#       by means of diagnostic plots would have led to the same result:
plot(mm, 1:3)

## (B) a *set of* GVF models fitted to *grouped* data ##
# We have at our disposal the following survey design object on household data:
exdes

# Use function svystat to prepare *grouped* estimates and errors of counts
# to be fitted separately (here groups are regions):
ee.g <- svystat(exdes, y=~ind, by=~age5c:marstat:sex, combo=3, group=~regcod)
str(ee.g)

# Fit all registered GVF model number separately inside groups:
mm.g <- fit.gvf(ee.g)
summary(mm.g)

# Get the best model according to R^2:
mm.g.best <- getBest(mm.g)
mm.g.best

# NOTE: Again, the *first* model has been selected. A thorough model comparison
#       by means of diagnostic plots would have led to the same result:
plot(mm.g, 1:3)
```

Description

These functions extract goodness-of-fit measures from fitted GVF models.

Usage

```
getR2(object, adjusted = FALSE, ...)

## S3 method for class 'gvf.fits'
AIC(object, ...)

## S3 method for class 'gvf.fits'
BIC(object, ...)
```

Arguments

<code>object</code>	An object containing one or more fitted GVF models.
<code>adjusted</code>	Should the <i>adjusted</i> R^2 be computed? The default is FALSE
<code>...</code>	Further arguments passed to or from other methods.

Details

These functions compute three goodness-of-fit measures on fitted GVF models: R^2 , [AIC](#), and [BIC](#). Such measures can help compare the relative quality of competing GVF models, hence facilitating model selection (see also function [getBest](#)).

Though `object` can also be a *single* fitted GVF model, these functions are principally meant to compare *different* GVF models fitted to the same data (i.e. the same estimates and errors).

To request the *adjusted* R^2 , use function `getR2` and specify `adjusted = TRUE`.

Value

If `object` is a single GVF model (class `gvf.fit`), the requested quality measure.

If `object` is a set of GVF models fitted to the same data (class `gvf.fits`), a vector whose elements store the requested quality measure for each GVF model.

If `object` is a single GVF model fitted to "grouped" data (class `gvf.fit.gr`), a list whose components store the requested quality measure for the corresponding groups.

If `object` is a set of GVF models fitted to "grouped" data (class `gvf.fits.gr`), a list whose components store vectors whose elements report the requested quality measure for each GVF model of each group.

Methodological Warning

Each one of the provided quality measures has its own specificities and limitations (e.g. it is senseless to use AIC to compare two GVF models with different response variables). It is up to the user to select the measure which is appropriate to his goals.

Author(s)

Diego Zardetto

See Also

[GVF.db](#) to manage **ReGenesees** archive of registered GVF models, [gvf.input](#) and [svystat](#) to prepare the input for GVF model fitting, [fit.gvf](#) to fit GVF models, [plot.gvf.fit](#) to get diagnostic plots for fitted GVF models, [drop.gvf.points](#) to drop alleged outliers from a fitted GVF model and simultaneously refit it, and [predictCV](#) to predict CV values via fitted GVF models.

Examples

```

# Load example data:
data(AF.gvf)

# Inspect available estimates and errors of counts:
str(ee.AF)

# List available registered GVF models:
GVF.db

## (A) A *single* fitted GVF model ##
# Fit example data to registered GVF model number one:
m <- fit.gvf(ee.AF, 1)

# Compute some goodness-of-fit measures:
getR2(m)
AIC(m)

## (B) A *a set* of GVF models fitted to the same data ##
# Fit example data to all registered GVF models:
mm <- fit.gvf(ee.AF)

# Compute some goodness-of-fit measures:
getR2(mm, adjusted = TRUE)
BIC(mm)

## (C) a *single* GVF model fitted to *grouped* data ##
# We have at our disposal the following survey design object on household data:
exdes

# Use function svystat to prepare *grouped* estimates and errors of counts
# to be fitted separately (here groups are regions):
ee.g <- svystat(exdes, y=~ind, by=~age5c:marstat:sex, combo=3, group=~regcod)
str(ee.g)

# Fit registered GVF model number one separately inside groups:
m.g <- fit.gvf(ee.g, 1)

# Compute some goodness-of-fit measures:
getR2(mm)
AIC(mm)

## (D) a *set of* GVF models fitted to *grouped* data ##
# Fit all registered GVF model number separately inside groups:
mm.g <- fit.gvf(ee.g)

# Compute some goodness-of-fit measures:
getR2(mm.g, adjusted = TRUE)
BIC(mm.g)

```

Description

GVF.db is the archive of *registered* (i.e. built-in and/or user-defined) Generalized Variance Functions models supported by **ReGene-sees**. Special accessor functions allow to customize, maintain, extend, update, save and reset such archive.

Usage

```
GVF.db
```

```
GVF.db$insert(GVF.model, Estimator.kind = NA, Resp.to.CV = NA, verbose = TRUE)
```

```
GVF.db$delete(Model.id, verbose = TRUE)
```

```
GVF.db$get(verbose = TRUE)
```

```
GVF.db$assign(value, verbose = TRUE)
```

```
GVF.db$reset(verbose = TRUE)
```

Arguments

GVF.model	A GVF model, expressed as a formula object or as a character string (see ‘Details’).
Estimator.kind	Character string identifying the kind of estimators for which the GVF model is deemed to be appropriate (see ‘Details’).
Resp.to.CV	Character string representing the function which maps the response of the GVF model (namely: variable ‘resp’) to the coefficient of variation (namely: variable ‘CV’), see ‘Details’.
Model.id	Unique integer key identifying the GVF model.
value	An exported copy of GVF.db, as returned by GVF.db\$get().
verbose	Enables printing of a summary description of the result (the default is TRUE).

Format

Each row of the GVF.db data frame represents a registered GVF model, with relevant information on the following 4 variables:

Model.id A unique integer key identifying the GVF model, integer.

GVF.model A character string specifying the GVF model formula, character. See also ‘Details’.

Estimator.kind A character string identifying the kind of estimators for which the GVF model is deemed to be appropriate, character. See also ‘Details’.

Resp.to.CV A character string which represents the function mapping the response of the GVF model (namely: variable ‘resp’) to the coefficient of variation (namely: variable ‘CV’), character. See also ‘Details’.

Details

GVF.db stores information about Generalized Variance Functions models supported by **ReGene-sees**. When starting a new work session with **ReGene-sees**, GVF.db contains few built-in GVF models (currently 5, see sections ‘Source’ and ‘Examples’). The content of GVF.db can be customized by means of special accessor functions:

ACCESSOR FUNCTION	PURPOSE
GVF.db\$insert.....	Register a new GVF model by adding a new row to the GVF.db archive
GVF.db\$delete.....	Unregister a GVF model by deleting the corresponding row from GVF.db
GVF.db\$get.....	Get the current version of GVF.db (e.g. to copy/save a customized archive for later usage)
GVF.db\$assign.....	Overwrite the current version of GVF.db (e.g. to use a customized archive which was exported in a previous ReGenesees session)
GVF.db\$reset.....	Reset GVF.db to its default version (i.e. the one with built-in GVF models only)

Information about registered GVF models stored inside GVF.db will be accessed and used by **Re-Genesees** Generalized Variance Functions facilities, e.g. functions [fit.gvf](#) or [predictCV](#).

GVF.db\$insert()

Function GVF.db\$insert has just a single mandatory argument: GVF.model. This can be either a two-sided formula or a character string which would be transformed into a (well formed) two-sided formula by function [as.formula](#).

The GVF.model formula to be inserted into GVF.db must be *new* (i.e. not already present into the archive) and can involve only variables contained inside [gvf.input](#) objects, namely:

- (1) 'Y'
- (2) 'SE'
- (3) 'CV'
- (4) 'VAR'
- (5) 'DEFF'

Moreover, since GVF models are intended to model variances in terms of estimates, the response term of GVF.model must involve some of 'SE', 'CV', 'VAR', and the linear predictor must involve 'Y'.

Optional argument Estimator.kind can be used to specify the kind of estimators for which the GVF.model is deemed to be appropriate. There are currently only 11 valid values for Estimator.kind, namely:

- (1) 'Total'
- (2) 'Mean'
- (3) 'Frequency'
- (4) 'Absolute Frequency'
- (5) 'Relative Frequency'
- (6) 'Ratio'
- (7) 'Share'
- (8) 'Share Ratio'
- (9) 'Regression Coefficient'
- (10) 'Quantile'
- (11) 'Complex Estimator'

Note that category 'Frequency' has to be understood as an aggregation of categories 'Absolute Frequency' and 'Relative Frequency', thus being appropriate for GVF models which are deemed to work well for estimators of *both* kind of frequencies.

One of the primary motivations for building and fitting a GVF model is to exploit the fitted model to *predict* the sampling error associated to a given estimate, instead of having to *compute* directly an estimate of such sampling error. Optional argument `Resp.to.CV` is relevant to that scope.

Indeed, different GVF models can actually specify as response term (call it 'resp' for definiteness) different functions of variables 'SE', 'CV', and 'VAR', but **ReGenesees** will always adopt variable 'CV' as a *pivot*. Thus, when registering a new GVF model, the user can provide via argument `Resp.to.CV` the function which transforms the response of the model, 'resp', into the pivot measure of variability, 'CV'. A look to the default content of `GVF.db` should make the latter statement clear (see 'Examples').

Note that while `Resp.to.CV` is passed as a character string, that string is expected to represent a well-formed mathematical expression (otherwise function `predictCV` would not work). Moreover, only variables 'resp' and 'Y' are allowed to appear inside `Resp.to.CV` (which is enough, since 'VAR' and 'SE' can be expressed in terms of 'CV' and 'Y').

If the user does not specify `Resp.to.CV` when registering a new GVF model, he will be not able to use function `predictCV` for predicting CV values based on the fitted GVF model.

Lastly, note that the `Model.id` of a newly inserted GVF model will automatically be set, by adding 1 to the previous maximum of `Model.id`.

GVF.db\$delete()

Function `GVF.db$delete` has just a single mandatory argument: `Model.id`. It must match the integer key of the (already existing) GVF model you want to drop from `GVF.db`.

Note that, after deleting a GVF model from `GVF.db`, values of column `Model.id` will be automatically renumbered, so as to range always from 1 to `nrow(GVF.db)`.

GVF.db\$get()

Function `GVF.db$get` has no mandatory arguments. When invoked, the function returns the *current* content of `GVF.db`, so that it can be assigned and saved/exported for later usage (see 'Examples'). Should the *current* content of `GVF.db` happen to be empty, the function would inform the user and return `NULL`. The return value of `GVF.db$get` has class "`GVF.db_exported`", and inherits from class "`data.frame`".

GVF.db\$assign()

Function `GVF.db$assign` has just a single mandatory argument: `value`. The object passed to argument `value` can only be a previously exported copy of `GVF.db`, i.e. an object of class `GVF.db_exported`. The function overwrites the *current* version of `GVF.db` with `value`. As a result, after invoking `GVF.db$assign`, the content of `GVF.db` is `value`.

GVF.db\$reset()

Function `GVF.db$reset` has no mandatory arguments and simply restores the default version of `GVF.db` (i.e. the one containing built-in GVF models only).

Author(s)

Diego Zardetto

Source

Built-in GVF models for frequencies (i.e. those with `Model.id` 1, 2, and 3) are discussed in Chapter 7 of [Wolter 07], along with their theoretical justification. Built-in GVF models for totals (i.e. those with `Model.id` 4, and 5) lack a rigorous justification, but have sometimes been used successfully on a purely empirical basis. For instance, Istat surveys on structural business statistics adopted models of that kind to summarize standard errors in publications and to allow their approximate evaluation on a custom basis.

References

Wolter, K.M. (2007) “*Introduction to Variance Estimation*”, Second Edition, Springer-Verlag, New York.

See Also

`estimator.kind` to assess what kind of estimates are stored inside a survey statistic object, `gvf.input` and `svystat` to prepare the input for GVF model fitting, `fit.gvf` to fit GVF models, `plot.gvf.fit` to get diagnostic plots for fitted GVF models, `drop.gvf.points` to drop alleged outliers from a fitted GVF model and simultaneously refit it, and `predictCV` to predict CV values via fitted GVF models.

Examples

```
# Print the current content of GVF.db (invoking
# print(GVF.db) would do the same):
GVF.db

# Inspect the structure of the GVF.db data frame:
data.class(GVF.db)
str(GVF.db)
dim(GVF.db)
nrow(GVF.db)

#####
# Accessor functions #
#####

# Delete the 3rd model:
GVF.db$delete(3)
# Print GVF.db (note that Model.id has been renumbered,
# so as to range always from 1 to nrow(GVF.db))
GVF.db

# Now delete the 1st model:
GVF.db$delete(1)
GVF.db

# Reset GVF.db to its default values:
GVF.db$reset()
GVF.db
```



```

# Insert a new tentative GVF model for Totals:
GVF.db$insert(CV ~ I(1/Y^2) + I(1/Y) + Y + I(Y^2), "Total", "resp")
GVF.db
# (notice that invoking GVF.db$insert() with first argument of type character,
# i.e. GVF.model="CV~I(1/Y^2)+I(1/Y)+Y+I(Y^2)", would have obtained exactly the
# same result)

# Now suppose you have somehow validated your newly added model,
# and you want to save your current, enhanced GVF.db in order to
# be able to use it later in a subsequent ReGenesees session.
### This can be achieved as follows:
### START
# 1. You must first get a copy of it, by using accessor function
#   GVF.db$get:
myGVF.db <- GVF.db$get()
myGVF.db
data.class(myGVF.db)

# 2. Then, you must save the copy to a .RData workspace, in order
#   to be able to load it later when needed, e.g.:
## Not run:
save(myGVF.db, file="custom.GVF.Archive.RData")

## End(Not run)

# 3. Starting a new ReGenesees session will set the default GVF.db,
#   which we can simulate in this example as follows:
GVF.db$reset()
GVF.db

# 4. Now you can load your previously saved customized GVF.db...
## Not run:
load("custom.GVF.Archive.RData")

## End(Not run)
# ...so that myGVF.db is back into your .GlobalEnv:
myGVF.db

# 5. Lastly, you must overwrite GVF.db with your custom
#   GVF archive myGVF.db via function GVF.db$assign:
GVF.db$assign(myGVF.db)
GVF.db

### Now your custom GVF archive is ready to be used by ReGenesees.
### STOP

# Illustrate some GVF.db$insert checks by trying crazy models
# or ill-specified attributes

# Examples start: reset GVF.db to its default values
GVF.db$reset()
GVF.db

# GVF model must be "syntactically new"...
## Not run:
GVF.db$insert(log(CV^2) ~ log(Y))

```

```
## End(Not run)
# ...if this is the case, it can even be "equivalent" to old ones: e.g.
# the following is identical to model number 5 and will produces identical
# estimates and predictions (as you may want to check):
GVF.db$insert(I(sqrt(VAR)/Y) ~ I(1/Y) + Y, "Total", Resp.to.CV = "resp")
GVF.db

# GVF model must have a response term
## Not run:
GVF.db$insert(~ log(Y))

## End(Not run)

# GVF model response must involve some of 'SE', 'CV', 'VAR'
## Not run:
GVF.db$insert(DEFF ~ log(Y))

## End(Not run)

# GVF model predictor must involve 'Y'
## Not run:
GVF.db$insert(VAR ~ SE)

## End(Not run)

# If passed, Resp.to.CV can only involve 'resp' and 'Y'
## Not run:
GVF.db$insert(I(sqrt(VAR)/Y) ~ I(1/Y) + Y + I(Y^2), Resp.to.CV = "sqrt(VAR)/Y")

## End(Not run)

# Examples end: reset GVF.db to its default values:
GVF.db$reset()
```

gvf.input

Prepare Input Data to Fit GVF Models

Description

Transforms a set of computed survey statistics into a suitable (data.frame-like) data structure, in order to fit a Generalized Variance Function model.

Usage

```
gvf.input(design, ..., stats = list(...))
```

```
## S3 method for class 'gvf.input'
plot(x, ...)
```

Arguments

design	The design object (of class <code>analytic</code> or inheriting from it) from which the input survey statics are supposed to have been derived.
--------	---

...	For function <code>gvf.input</code> , objects containing survey statistics. For plot, further arguments passed to or from other methods.
stats	A list storing survey statistic objects (see ‘Details’).
x	The object of class <code>gvf.input</code> to plot.

Details

Given a set of survey statistic objects (via arguments ‘...’ or `stats`) and a design object (`design`) from which those statics are supposed to have been derived, function `gvf.input` builds a data structure that can be fed to **ReGenesees** GVF model fitting function `fit.gvf`.

Argument ‘...’ can be bound to an arbitrary number of objects. These objects must be output of survey statistics functions, i.e. `svystatTM`, `svystatR`, `svystatS`, `svystatSR`, `svystatB`, `svystatQ`, `svystatL`, `svySigma`, and `svySigma2`.

All input objects passed to ‘...’ must derive from estimators of the *same* kind (as returned by function `estimator.kind`). For the same reason, objects of *mixed* kind (see `estimator.kind`) are not allowed. Since function `svystatL` can actually handle estimators of *different* kinds, objects of kind ‘Complex Estimator’ are the only exception to the rule.

Argument `stats` can be used as an alternative to argument ‘...’: one has only to store the survey statistic objects into a list and bind such list to `stats`. Note that, if both are passed, argument `stats` will prevail on ‘...’ (see ‘Examples’).

Should *any* input object be a survey statistic derived from a design object *other than* `design`, the function would raise an error.

The plot method for `gvf.input` objects produces a matrix of scatterplots with polynomial smoothers.

Value

An object of class `gvf.input`, inheriting from class `data.frame`: basically a data frame supplied with appropriate attributes.

Each row of the data frame contains an *estimate* along with its estimated sampling error, expressed in terms of *standard error*, *coefficient of variation*, *variance*, and - whenever available - *design effect*.

The data frame has the following structure:

name	The name of the original estimate, factor.
Y	The value of the original estimate, numeric.
SE	The standard error of the original estimate, numeric.
CV	The coefficient of variation of the original estimate, numeric.
VAR	The variance of the original estimate, numeric.
DEFF	The design effect of the original estimate (if available), numeric.

Note that by inspecting the *attributes* of a `gvf.input` object, one can always identify which design object and which kind of estimator generated that object (see ‘Examples’).

Author(s)

Diego Zardetto

See Also

[estimator.kind](#) to assess what kind of estimates are stored inside a survey statistic object, [svystat](#) as a useful alternative to prepare the input for GVF model fitting, [GVF.db](#) to manage **ReGenesees** archive of registered GVF models, [fit.gvf](#) to fit GVF models, [plot.gvf.fit](#) to get diagnostic plots for fitted GVF models, [drop.gvf.points](#) to drop alleged outliers from a fitted GVF model and simultaneously refit it, and [predictCV](#) to predict CV values via fitted GVF models.

Examples

```
# Load sbs data:
data(sbs)

# Create a design object...
sbsdes<-e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,fpc=~fpc)

# ...and use it to compute some survey statistics:
va<-svystatTM(sbsdes,~va.imp2)
va.reg<-svystatTM(sbsdes,~va.imp2,~region)
va.area<-svystatTM(sbsdes,~va.imp2,~area)

# Now suppose you want to fit a GVF model on the estimates and errors computed
# above: you must prepare your input as follows:
ee<-gvf.input(sbsdes,va,va.reg,va.area)

# Inspect the obtained data structure:
ee
str(ee)  # Note the "design" and "stats.kind" attributes
plot(ee)

# Note that, instead of argument '...', you could have used argument 'stats'
# as follows:
va.list<-list(va,va.reg,va.area)
ee2<-gvf.input(sbsdes,stats=va.list)

# ...obtaining exactly the same result:
identical(ee,ee2)

# Note also that, if both are passed, argument 'stats' prevails on '...':
# indeed, while:
gvf.input(sbsdes,va.reg)
# we would get again:
gvf.input(sbsdes,va.reg,stats=va.list)
```

Description

These methods extract information from fitted GVF model(s).

Usage

```
## S3 method for class 'gvf.fit'
coef(object, ...)
## S3 method for class 'gvf.fits'
coef(object, ...)
## S3 method for class 'gvf.fit.gr'
coef(object, ...)
## S3 method for class 'gvf.fits.gr'
coef(object, ...)

## S3 method for class 'gvf.fit'
residuals(object, ...)
## S3 method for class 'gvf.fits'
residuals(object, ...)
## S3 method for class 'gvf.fit.gr'
residuals(object, ...)
## S3 method for class 'gvf.fits.gr'
residuals(object, ...)

## S3 method for class 'gvf.fit'
fitted(object, ...)
## S3 method for class 'gvf.fits'
fitted(object, ...)
## S3 method for class 'gvf.fit.gr'
fitted(object, ...)
## S3 method for class 'gvf.fits.gr'
fitted(object, ...)

## S3 method for class 'gvf.fit'
predict(object, ...)
## S3 method for class 'gvf.fits'
predict(object, ...)
## S3 method for class 'gvf.fit.gr'
predict(object, ...)
## S3 method for class 'gvf.fits.gr'
predict(object, ...)

## S3 method for class 'gvf.fit'
effects(object, ...)
## S3 method for class 'gvf.fits'
effects(object, ...)
## S3 method for class 'gvf.fit.gr'
effects(object, ...)
## S3 method for class 'gvf.fits.gr'
effects(object, ...)

## S3 method for class 'gvf.fit'
rstandard(model, ...)
## S3 method for class 'gvf.fits'
rstandard(model, ...)
## S3 method for class 'gvf.fit.gr'
rstandard(model, ...)
```

```
## S3 method for class 'gvf.fits.gr'
rstandard(model, ...)

## S3 method for class 'gvf.fit'
rstudent(model, ...)
## S3 method for class 'gvf.fits'
rstudent(model, ...)
## S3 method for class 'gvf.fit.gr'
rstudent(model, ...)
## S3 method for class 'gvf.fits.gr'
rstudent(model, ...)

## S3 method for class 'gvf.fit'
anova(object, ...)
## S3 method for class 'gvf.fits'
anova(object, ...)
## S3 method for class 'gvf.fit.gr'
anova(object, ...)
## S3 method for class 'gvf.fits.gr'
anova(object, ...)

## S3 method for class 'gvf.fit'
vcov(object, ...)
## S3 method for class 'gvf.fits'
vcov(object, ...)
## S3 method for class 'gvf.fit.gr'
vcov(object, ...)
## S3 method for class 'gvf.fits.gr'
vcov(object, ...)
```

Arguments

<code>object</code>	An object containing one or more fitted GVF models (see ‘Usage’ for the allowed classes).
<code>model</code>	An object containing one or more fitted GVF models (see ‘Usage’ for the allowed classes).
<code>...</code>	Further arguments passed to or from other methods (see corresponding <code>.lm</code> methods).

Details

These methods can be used to extract information from fitted GVF model(s).

For more details on their usage, please read the help pages of the methods with same name defined on class `.lm` by package **stats** (e.g. `coef`, `fitted`, etc.).

Value

The requested information, wrapped into an R object whose structure depends on the class of the input fitted GVF model(s) (i.e. arguments `object` and/or `model`).

Author(s)

Diego Zardetto

See Also

[GVF.db](#) to manage **ReGenesees** archive of registered GVF models, [gvf.input](#) and [svystat](#) to prepare the input for GVF model fitting, [fit.gvf](#) to fit GVF models, [plot.gvf.fit](#) to get diagnostic plots for fitted GVF models, [drop.gvf.points](#) to drop alleged outliers from a fitted GVF model and simultaneously refit it, and [predictCV](#) to predict CV values via fitted GVF models.

Examples

```
# Load example data:
data(AF.gvf)

# Inspect available estimates and errors of counts:
head(ee.AF)
summary(ee.AF)

# List available registered GVF models:
GVF.db

## (A) A *single* fitted GVF model ##
# Fit example data to registered GVF model number one:
m <- fit.gvf(ee.AF, 1)

# Extract some information:
coef(m)
fitted(m)

## (B) A *a set* of GVF models fitted to the same data ##
# Fit example data to registered GVF models for frequencies (i.e. number 1:3):
mm <- fit.gvf(ee.AF, 1:3)

# Extract some information:
r.mod <- residuals(mm)
lapply(r.mod, head)

r.sta <- rstandard(mm)
lapply(r.sta, head)

r.stu <- rstudent(mm)
lapply(r.stu, head)

## (C) a *single* GVF model fitted to *grouped* data ##
# We have at our disposal the following survey design object on household data:
exdes

# Use function svystat to prepare *grouped* estimates and errors of counts
# to be fitted separately (here groups are regions):
ee.g <- svystat(exdes, y=~ind, by=~age5c:marstat:sex, combo=3, group=~regcod)
str(ee.g)

# Fit registered GVF model number one separately inside groups:
m.g <- fit.gvf(ee.g, 1)

# Extract some information:
coef(m.g)
```

```
fitted(m.g)
```

```
## (D) a *set of* GVF models fitted to *grouped* data ##
# Fit all registered GVF models for frequencies (i.e. number 1:3) separately
# inside groups:
mm.g <- fit.gvf(ee.g, 1:3)
# Extract some information:
coef(mm.g)
fitted(mm.g)
```

n.mean

Sample Size Requirements and Power Calculations for Means

Description

These functions estimate the minimum sample size required to (i) satisfy specific precision constraints in the estimation of means and to (ii) attain specified levels of significance and power in a statistical test that compares two means. The inverse problems of finding, given a specified sample size, (iii) the expected precision of the estimator of the mean and (iv) the expected power or (v) minimum detectable effect for the test that compares two means are also addressed.

Usage

```
n.mean(prec, prec.ind = c("ME", "RME", "SE", "CV"), sigmaY, muY = NULL,
        DEFF = 1, RR = 1,
        F = 1, hhSize = 1, AVEhh = F * hhSize,
        old.clus.size = NULL, new.clus.size = NULL,
        N = NULL, alpha = 0.05, verbose = TRUE)

prec.mean(n, prec.ind = c("ME", "RME", "SE", "CV"), sigmaY, muY = NULL,
          DEFF = 1, RR = 1,
          F = 1, hhSize = 1, AVEhh = F * hhSize,
          old.clus.size = NULL, new.clus.size = NULL,
          N = NULL, alpha = 0.05, verbose = TRUE)

n.comp2mean(sigmaY, MDE, K1 = 1/2,
            alpha = 0.05, beta = 0.2, sides = c("two-tailed", "one-tailed"),
            DEFF = 1, RR = 1,
            F = 1, hhSize = 1, AVEhh = F * hhSize,
            old.clus.size = NULL, new.clus.size = NULL,
            verbose = TRUE)

pow.comp2mean(n, sigmaY, MDE, K1 = 1/2,
            alpha = 0.05, sides = c("two-tailed", "one-tailed"),
            DEFF = 1, RR = 1,
            F = 1, hhSize = 1, AVEhh = F * hhSize,
            old.clus.size = NULL, new.clus.size = NULL,
            verbose = TRUE)

mde.comp2mean(n, sigmaY, K1 = 1/2,
            alpha = 0.05, beta = 0.2, sides = c("two-tailed", "one-tailed"),
```



```

DEFF = 1, RR = 1,
F = 1, hhSize = 1, AVEhh = F * hhSize,
old.clus.size = NULL, new.clus.size = NULL,
verbose = TRUE)

```

Arguments

prec	The precision level you want to attain in estimation.
prec.ind	The precision indicator for which the specified precision level prec has to be attained. The following uncertainty measures can be used as precision indicators: Margin of Error ('ME', the default), Relative Margin of Error ('RME'), Standard Error ('SE'), and Coefficient of Variation ('CV', also known as Relative Standard Error).
sigmaY	Anticipated estimate of the standard deviation of interest variable Y for your target (sub)population.
muY	Anticipated estimate of the mean of interest variable Y for your target (sub)population.
DEFF	Anticipated estimate of the design effect of the estimator of the mean.
RR	Anticipated estimate of the response rate.
F	Anticipated estimate of the proportion of your target subpopulation in the general population that will be sampled.
hhSize	Anticipated estimate of the average household size.
AVEhh	Anticipated estimate of the average number of individuals belonging to the target subpopulation per household.
old.clus.size	Average number of households sampled per PSU in the survey you have used to compute the input value for the DEFF argument.
new.clus.size	Average number of households to be sampled per PSU in the survey you are planning.
N	The size of your target (sub)population. Only needed if you don't want to neglect finite population corrections (which is the default behaviour if N = NULL).
alpha	Significance level used to build confidence intervals (with confidence level equal to 1 - alpha) or probability of Type I error (False Positive) for hypothesis testing.
verbose	Print on screen some description or just return the results?
n	The sample size for which the expected precision or power or MDE must be calculated (see 'Details').
MDE	Minimum Detectable Effect for the difference between means.
K1	Ratio between the sample size of group 1 and the total sample size of groups 1 and 2 (defaults to 1/2, i.e. equal sized groups).
beta	Probability of Type II error (False Negative) for hypothesis testing (so that Power = 1 - beta).
sides	Do you want a 'two-tailed' test (the default) or a 'one-tailed' test?

Details

These functions are intended as simple everyday tools for basic sampling design decisions and survey planning. They address sample size requirements and power calculations for *means* in surveys (typically household surveys) adopting one- or two-stage sampling designs. The means acting as

estimation targets can be defined either in terms of individuals or in terms of households. Specific arguments (such as `hhSize`, `AVEhh`, `old.clus.size`, and `new.clus.size`) can be tweaked to cover different designs (one or two stages) and target populations (individual-level or household-level means), see the ‘Examples’ section.

The formulas needed to guesstimate the minimum sample size required to satisfy specific precision constraints in the estimation of a mean (function `n.mean`) or the expected precision of the estimator of the mean given a specified sample size (function `prec.mean`) are available in many textbooks and spreadsheet templates (see, e.g., [Rosner 2006], [Lance, Hattori 2016], [ILO 2014a], [ILO 2014b]).

The formula needed to guesstimate the minimum sample size required to attain specified levels of significance and power in a statistical test that compares two means (function `n.comp2mean`) can be derived from equation 8.27 on page 302 of [Rosner 2006], by extending it to real-world complex sampling designs (see, e.g., arguments `RR` and `DEFF`). Functions `pow.comp2mean` and `mde.comp2mean` solve the resulting equation for Power ($= 1 - \text{beta}$) and MDE given a specified *total* sample size, `n`.

NOTE: For both `pow.comp2mean` and `mde.comp2mean`, argument `n` must be the *total* sample size, namely the sum of the sample sizes of the two groups (group 1 and group 2) whose estimated means need to be compared. The way the total sample size is allocated to the two groups is controlled by argument `K1`.

NOTE: Despite most of the arguments to the above five functions come with default values, those defaults must not be considered as suggested values: in general, users will need to specify actual values that suit their specific design needs. For instance, the default value `muY = NULL` is not valid when relative measures of precision are used (`'RME'` and `'CV'`).

NOTE: Arguments `F`, `hhSize`, and `AVEhh` are necessarily related to each other, as it is illustrated by the expression of the default of `AVEhh`, thus it is not required to specify all of them. If all are explicitly passed, the function will check that they comply with the identity $\text{AVEhh} = F * \text{hhSize}$.

NOTE: Most of the arguments to the above five functions are vectorized, meaning that users can pass numeric vectors to them to investigate multiple design scenarios in a single shot (e.g. via `MDE = c(750, 1000, 1250)`). When vectors of length greater than 1 are passed to multiple arguments, R recycling rule will kick in.

NOTE: Input values for sample size, `n`, and population size (if any), `N`, should be positive integers. The functions will silently make them so, by using their `round(abs())` values. When both `n` and `N` are specified, an error will be raised if $n > N$.

NOTE: Since, as shown in the ‘Examples’ section, the functions can be tweaked to cover different designs (one or two stages) and target populations (*individual-level* or *household-level* means), users who do not want to neglect finite population corrections must specify the population size `N` in terms of the *analytical units* that are relevant to their analysis.

NOTE: Both functions `n.mean` and `n.comp2mean` return the *ceiling* of the analytically calculated minimum sample sizes (which are not integers in general). This is conservative and will result in slightly better sampling performances than the nominally requested ones (e.g. higher precision or power, and smaller confidence intervals or MDEs).

Value

For `n.mean`, `prec.mean`, `pow.comp2mean`, and `mde.comp2mean`, a numeric vector whose length depends on the length of the numeric inputs passed to the function (under R recycling rule).

For `n.comp2mean`, a list of length 3 with names `n1`, `n2`, and `n`, providing the required sample sizes for group 1, group 2, and the overall sample. Each of the elements of the list is a numeric vector whose length depends on the length of the numeric inputs passed to the function (under R recycling rule).

Author(s)

Diego Zardetto

References

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ILO (2014b) ILO-IPEC TOOLS USER GUIDE. URL: https://www.ilo.org/sites/default/files/2024-09/Child_labour_Sampling_Tools_Tool_01_Sample_Size_and_Margin_of_Error_Guidelines_2014.pdf.

Rosner, B. (2006) Fundamentals of biostatistics (7th ed.). Boston, MA: Brooks/Cole.

Lance, P., Hattori, A. (2016) Sampling and evaluation. Chapel Hill, North Carolina: MEASURE Evaluation, University of North Carolina (2016).

See Also

Functions [n.prop](#), [prec.prop](#), [n.comp2prop](#), [pow.comp2prop](#), and [mde.comp2prop](#) provide the same functionalities documented here, when the statistics of interest are *proportions* rather than means.

Examples

```
#####
# Reproducible example #
#####
# Solve the problem used as illustrating example in Diagram 1b on page 12 of the ILO-IPEC
# TOOLS USER GUIDE (which can be freely downloaded from ILO-IPEC TOOLS USER GUIDE URL in
# the References section above).
# This is the only example provided by the document for the estimate of a *mean* (which
# the document, somewhat oddly, refers to as an <<indicator of amount>>):

n.mean(prec= 20, prec.ind= "ME", sigmaY= 250, muY= 400, DEFF= 4.0, AVEhh= 0.75, RR= 0.9)

# NOTE: We get 3557. The result of the ILO-IPEC template is a bit larger: 3704. This is
# simply because the ILO-IPEC template approximates the 1 - 0.05/2 quantile of the
# standard normal distribution with 2. Indeed, one can see that 3704 is exactly
# equal to:
round( 3557 * (2 / 1.96)^2 )

#####
# Impact of Finite Population Corrections (fpc). #
#####
# The sample size above was obtained by neglecting finite population corrections. Now let's
# assume we know the population size is in the ballpark of 100 thousand households. If we
# correctly factor in the fpc terms, then the required sample size is reduced as follows:
n.mean(prec= 20, prec.ind= "ME", sigmaY= 250, muY= 400, DEFF= 4.0, AVEhh= 0.75, RR= 0.9,
      N= 100000)

#####
# Power calculations for the comparison of two means #
#####
```

```
# A new national assistance policy aims to increase by 7% the average monthly household
# consumption, which was estimated to be equal to 362000 (in the country currency) by an
# household survey conducted two years before. The DEFF of that estimate was reported to
# be 3.5, and the same survey estimated the population standard deviation of the monthly
# household consumption to be 461000. To evaluate the impact of the intervention, two
# household surveys with the same sample sizes will be conducted before (T0) and after
# (T1) the implementation of the policy. Assuming that (i) the average monthly household
# consumption at T0 will still be close to 362000 and (ii) the new policy will be the only
# driver of changes, success of the policy would require a value of at least 387340 at T1
# ( $387340 = 362000 * 1.07$ ), namely an increase of 25340. However, the government would like
# the study to be able to detect a possibly *smaller* consumption increase of 20000.
# Moreover, the government is confident the new policy cannot result in harming household
# consumption (so a one-tailed test is deemed appropriate). Assuming 20 households per EA
# will be sampled as it was the case for the survey conducted two years before, and
# anticipating a response rate of 0.9, and how many households must be selected to achieve
# 80% power for the detection of the sought-after consumption increase at significance
# level 5%?
```

```
n.comp2mean(sigmaY = 362000, MDE = 20000, sides = "one-tailed", DEFF = 3.5, RR = 0.9,
             old.clus.size= 20, new.clus.size= 20)
```

```
# NOTE: The required sample size is 31520 households, 15760 at baseline (T0) and 15760 at
#       endpoint (T1). The EAs to be visited are  $15760 / 20 = 788$  per round.
```

```
# What would be the implications of using designs with 15 or 12 households per EA, instead
# of 20?
```

```
n.comp2mean(sigmaY = 362000, MDE = 20000, sides = "one-tailed", DEFF = 3.5, RR = 0.9,
             old.clus.size= 20, new.clus.size= c(15, 12))
```

```
# NOTE: When going from 20 to 15 or 12 households per EA, the required sample size is
#       expected to decrease to 25590 households (12795 per round) and 22032 households
#       (11016 per round), respectively. Conversely, the EAs to be visited are expected to
#       increase to  $12795 / 15 = 853$  and  $11016 / 12 = 918$  per round, respectively.
```

```
# How much sample size could be saved if the government resorts to detecting as significant
# a larger consumption increase of 25000, which is much closer to the actually intended
# goal of the policy?
```

```
n.comp2mean(sigmaY = 362000, MDE = 25000, sides = "one-tailed", DEFF = 3.5, RR = 0.9,
             old.clus.size= 20, new.clus.size= 20)
```

```
# NOTE: The required sample size would become 20200 households, 10100 per round. Therefore,
#        $31520 - 20200 = 11320$  households would be saved, 5660 per round.
```

```
# The above reduced sample size would, of course, imply a lower statistical power (i.e.
# smaller than the ideally desired 80%) for the detection of an increase of 20000 that
# might actually be induced by the policy. What would actually be the expected power for
# the detection of an effect of 20000 for  $n = 20200$ ?
```

```
pow.comp2mean(n = 20200, sigmaY = 362000, MDE = 20000, sides = "one-tailed", DEFF = 3.5,
              RR = 0.9, old.clus.size= 20, new.clus.size= 20)
```

```
# NOTE: The power would be reduced to about 63.5%.
```

Description

These functions estimate the minimum sample size required to (i) satisfy specific precision constraints in the estimation of proportions and to (ii) attain specified levels of significance and power in a statistical test that compares two proportions. The inverse problems of finding, given a specified sample size, (iii) the expected precision of the estimator of the proportion, and (iv) the expected power or (v) minimum detectable effect for the test that compares two proportions are also addressed.

Usage

```
n.prop(prec, prec.ind = c("ME", "RME", "SE", "CV"), P = 0.5,
      DEFF = 1, RR = 1,
      F = 1, hhSize = 1, AVEhh = F * hhSize,
      old.clus.size = NULL, new.clus.size = NULL,
      N = NULL, alpha = 0.05, verbose = TRUE)

prec.prop(n, prec.ind = c("ME", "RME", "SE", "CV"), P = 0.5,
      DEFF = 1, RR = 1,
      F = 1, hhSize = 1, AVEhh = F * hhSize,
      old.clus.size = NULL, new.clus.size = NULL,
      N = NULL, alpha = 0.05, verbose = TRUE)

n.comp2prop(P1, P2 = P1, MDE = abs(P2 - P1), K1 = 1/2,
      alpha = 0.05, beta = 0.2, sides = c("two-tailed", "one-tailed"),
      pooled.variance = TRUE,
      DEFF = 1, RR = 1,
      F = 1, hhSize = 1, AVEhh = F * hhSize,
      old.clus.size = NULL, new.clus.size = NULL,
      verbose = TRUE)

pow.comp2prop(n, P1, P2 = P1, MDE = abs(P2 - P1), K1 = 1/2,
      alpha = 0.05, sides = c("two-tailed", "one-tailed"),
      pooled.variance = TRUE,
      DEFF = 1, RR = 1,
      F = 1, hhSize = 1, AVEhh = F * hhSize,
      old.clus.size = NULL, new.clus.size = NULL,
      verbose = TRUE)

mde.comp2prop(n, P1, P2 = P1, K1 = 1/2,
      alpha = 0.05, beta = 0.2, sides = c("two-tailed", "one-tailed"),
      pooled.variance = TRUE,
      DEFF = 1, RR = 1,
      F = 1, hhSize = 1, AVEhh = F * hhSize,
      old.clus.size = NULL, new.clus.size = NULL,
      verbose = TRUE)
```

Arguments

prec	The precision level you want to attain in estimation.
prec.ind	The precision indicator for which the specified precision level prec has to be attained. The following uncertainty measures can be used as precision indicators: Margin of Error ('ME', the default), Relative Margin of Error ('RME'), Standard Error ('SE'), and Coefficient of Variation ('CV', also known as Relative Standard Error).
P	Anticipated estimate of the proportion for your target (sub)population.
DEFF	Anticipated estimate of the design effect of the estimator of the proportion.
RR	Anticipated estimate of the response rate.
F	Anticipated estimate of the proportion of your target subpopulation in the general population that will be sampled.
hhSize	Anticipated estimate of the average household size.
AVEhh	Anticipated estimate of the average number of individuals belonging to the target subpopulation per household.
old.clus.size	Average number of households sampled per PSU in the survey you have used to compute the input value for the DEFF argument.
new.clus.size	Average number of households to be sampled per PSU in the survey you are planning.
N	The size of your target (sub)population. Only needed if you don't want to neglect finite population corrections (which is the default behaviour if N = NULL).
alpha	Significance level used to build confidence intervals (with confidence level equal to 1 - alpha) or probability of Type I error (False Positive) for hypothesis testing.
verbose	Print on screen some description or just return the results?
n	The sample size for which the expected precision or power or MDE must be calculated (see 'Details').
P1	Anticipated estimate of the proportion for group 1.
P2	Anticipated estimate of the proportion for group 2 (only needed when it differs from P1).
MDE	Minimum Detectable Effect for the difference between proportions.
K1	Ratio between the sample size of group 1 and the total sample size of groups 1 and 2 (defaults to 1/2, i.e. equal sized groups).
beta	Probability of Type II error (False Negative) for hypothesis testing (so that Power = 1 - beta).
sides	Do you want a 'two-tailed' test (the default) or a 'one-tailed' test?
pooled.variance	Do you want to use the pooled estimator of the variance (the default) or the unpooled one?

Details

These functions are intended as simple everyday tools for basic sampling design decisions and survey planning. They address sample size requirements and power calculations for *proportions* in surveys (typically household surveys) adopting one- or two-stage sampling designs. The proportions acting as estimation targets can be defined either in terms of individuals or in terms of

households. Specific arguments (such as `hhSize`, `AVEhh`, `old.clus.size`, and `new.clus.size`) can be tweaked to cover different designs (one or two stages) and target populations (proportions of individuals or households), see the ‘Examples’ section.

The formulas needed to guesstimate the minimum sample size required to satisfy specific precision constraints in the estimation of a proportion (function `n.prop`) or the expected precision of the estimator of the proportion given a specified sample size (function `prec.prop`) are available in many textbooks and spreadsheet templates (see, e.g., [Rosner 2006], [Lance, Hattori 2016], [ILO 2014], [UNICEF 2023]).

The formula needed to guesstimate the minimum sample size required to attain specified levels of significance and power in a statistical test that compares two proportions (function `n.comp2prop`) can be derived from equation 10.14 on page 381 of [Rosner 2006], by extending it to real-world complex sampling designs (see, e.g., arguments `RR` and `DEFF`). Functions `pow.comp2prop` and `mde.comp2prop` solve the resulting equation for Power ($= 1 - \beta$) and MDE given a specified *total* sample size, `n`.

NOTE: For both `pow.comp2prop` and `mde.comp2prop`, argument `n` must be the *total* sample size, namely the sum of the sample sizes of the two groups (group 1 and group 2) whose estimated proportions need to be compared. The way the total sample size is allocated to the two groups is controlled by argument `K1`.

NOTE: Despite most of the arguments to the above five functions come with default values, those defaults must not be considered as suggested values: in general, users will need to specify actual values that suit their specific design needs. For instance, as illustrated in the ‘Examples’ section, the Minimum Detectable Effect does not necessarily need to be equal to its default expression ($MDE = \text{abs}(P2 - P1)$).

NOTE: Arguments `F`, `hhSize`, and `AVEhh` are necessarily related to each other, as it is illustrated by the expression of the default of `AVEhh`, thus it is not required to specify all of them. If all are explicitly passed, the function will check that they comply with the identity $AVEhh = F * hhSize$.

NOTE: Most of the arguments to the above five functions are vectorized, meaning that users can pass numeric vectors to them to investigate multiple design scenarios in a single shot (e.g. via $MDE = c(0.06, 0.08, 0.10)$). When vectors of length greater than 1 are passed to multiple arguments, R recycling rule will kick in.

NOTE: Input values for sample size, `n`, and population size (if any), `N`, should be positive integers. The functions will silently make them so, by using their `round(abs())` values. When both `n` and `N` are specified, an error will be raised if $n > N$.

NOTE: Since, as shown in the ‘Examples’ section, the functions can be tweaked to cover different designs (one or two stages) and target populations (proportions of *individuals* or *households*), users who do not want to neglect finite population corrections must specify the population size `N` in terms of the *analytical units* that are relevant to their analysis.

NOTE: Both functions `n.prop` and `n.comp2prop` return the *ceiling* of the analytically calculated minimum sample sizes (which are not integers in general). This is conservative and will result in slightly better sampling performances than the nominally requested ones (e.g. higher precision or power, and smaller confidence intervals or MDEs).

Value

For `n.prop`, `prec.prop`, `pow.comp2prop`, and `mde.comp2prop`, a numeric vector whose length depends on the length of the numeric inputs passed to the function (under R recycling rule).

For `n.comp2prop`, a list of length 3 with names `n1`, `n2`, and `n`, providing the required sample sizes for group 1, group 2, and the overall sample. Each of the elements of the list is a numeric vector whose length depends on the length of the numeric inputs passed to the function (under R recycling rule).

Author(s)

Diego Zardetto

References

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See Also

Functions `n.mean`, `prec.mean`, `n.comp2mean`, `pow.comp2mean`, and `mde.comp2mean` provide the same functionalities documented here, when the statistics of interest are *means* rather than proportions.

Examples

```
#####
# Reproducible example 1 #
#####
# Solve the illustrating example problem stored in sheet 'Sample Size(SS) for one domain'
# of the MICS7 Excel template (which can be freely downloaded from:
# https://mics.unicef.org/tools?round=mics7):

n.prop(prec= 0.12, prec.ind= "RME", P= 0.2, DEFF= 1.5, F= 0.09, hhSize= 5.0, RR= 0.9)

# NOTE: We get 3953. The result of the MICS7 template is a bit larger: 4115. This is
# simply because the MICS7 template approximates the 1 - 0.05/2 quantile of the
# standard normal distribution with 2. Indeed, one can see that 4115 is exactly
# equal to:
floor( 3953 * (2 / 1.96)^2 )

#####
# Reproducible example 2 #
#####
# Sheet 'RME and Expected Cases given SS' of the MICS7 Excel template contains one example
# of the reverse problem of finding the expected standard error for a given sample size.
# You can solve it as follows:

prec.prop(n= 4000, prec.ind= "SE", P= 0.2, DEFF= 1.5, F= 0.09, hhSize= 5.0, RR= 0.9)

# NOTE: This time, the result of the MICS7 template (0.01217) is exactly the same, since
# the standard error is a measure of precision that does not depend on the
# confidence level (so that MICS' approximation  $qnorm(1 - 0.05/2) = 2$  plays no role
# here).
```



```
#####
# Reproducible example 3 #
#####

# Solve the problem stored as illustrating example in the ILO-IPEC Excel template (which
# can be freely downloaded from the ILO-IPEC TEMPLATE URL in the References section
# above):

n.prop(prec= 0.03, prec.ind= "ME", P= 0.1, DEFF= 4, F= 0.15, hhSize= 5.0, RR= 0.9)

# NOTE: We get 2277. The result of the ILO-IPEC template is a bit larger: 2370. This
#       simply because the ILO-IPEC template too approximates the 1 - 0.05/2 quantile of
#       the standard normal distribution with 2. Indeed, one can see that 2370 is exactly
#       equal to:
floor( 2277 * (2 / 1.96)^2 )

# By using the additional input that the number of households per PSU was 16 for the
# survey that generated the pre-estimates reported above, the ILO-IPEC template also
# returns the estimated intraclass correlation coefficient (ICC) of the binary indicator
# variable underlying the proportion: 27.3%.

# To obtain the same result, just use the arguments 'old.clus.size' and 'new.clus.size'
# as follows:
n.prop(prec= 0.03, prec.ind= "ME", P= 0.1, DEFF= 4, F= 0.15, hhSize= 5.0, RR= 0.9,
       old.clus.size= 16, new.clus.size= 16)

# NOTE: Once more, the result is in agreement with the ILO-IPEC template.

# NOTE: By making explicit the cluster size, we obtained a slightly larger sample size
#       than before (2288 vs 2277). This is because, when the user specifies a value for
#       'new.clus.size', the function returns a sample size that is guaranteed to be an
#       integer multiple of it.

# NOTE: Following Kish's naming convention, ReGenesee uses the label 'ROH' (which stands
#       for 'rate of homogeneity') for the ICC.

#####
# Impact of adjusting the survey design to accommodate a different #
# number of households per sampled PSU.                               #
#####
# More generally, the argument 'new.clus.size' can be used to predict the impact on sample
# size requirements of changing the number of households per PSU. This is performed by
# leveraging the so-called *ICC portability assumption*.

# Suppose the survey you are designing will use 20 households per PSU, rather than the 16
# used by the survey from which you obtained the anticipated estimates used so far. Since
# this setting is expected to increase the DEFF, a larger sample size will be needed to
# meet the previous precision constraint of ME = 0.03:
n.prop(prec= 0.03, prec.ind= "ME", P= 0.1, DEFF= 4, F= 0.15, hhSize= 5.0, RR= 0.9,
       old.clus.size= 16, new.clus.size= 20)

# NOTE: As can be seen, when going from 16 to 20 households per PSU, the DEFF is expected
#       to increase from 4 to 4.8, thus bringing the sample size required to achieve the
#       desired margin of error from 2288 to 2760 households.
```

```
#####
# Impact of Finite Population Corrections (fpc). #
#####
# The sample size above was obtained by neglecting finite population corrections. Now let's
# assume we know the population size is in the ballpark of 100 thousand households. If we
# correctly factor in the fpc terms, then the required sample size is reduced as follows:
n.prop(prec= 0.03, prec.ind= "ME", P= 0.1, DEFF= 4, F= 0.15, hhSize= 5.0, RR= 0.9,
      old.clus.size= 16, new.clus.size= 20, N= 100000)
```

```
#####
# Power calculations for the comparison of two proportions: example 1 #
#####
# Suppose one wants to plan two household surveys to evaluate whether a proposed new
# targeting strategy will increase the proportion of beneficiaries of a social assistance
# program that are poor. The surveys will be conducted before (T0) and after (T1) the
# implementation of the new strategy. From a previous assessment (T < T0, with a response
# rate of 0.9), it is known that the proportion of poor households among beneficiaries was
# around 73% and that the DEFF of this estimated proportion was 1.4. The new strategy
# would be considered successful if, after the implementation of the new targeting
# strategy, the proportion of poor households among beneficiaries equals or exceeds 80%.
# Households will be selected from the list of beneficiaries (so F = 1) with the same
# one-stage sampling design as the previous assessment, and the baseline and endline
# surveys will have equal sample sizes (so K1 = 1/2). Moreover, it is believed that the new
# strategy cannot result in harming the targeting performance (so a one-tailed test is
# deemed appropriate). How many households must be sampled to achieve 80% power for the
# detection of the sought-after effect at significance level 5%?
```

```
n.comp2prop(P1 = 0.73, P2 = 0.80, sides = "one-tailed", DEFF = 1.4, RR = 0.9)
```

```
# NOTE: The required sample size is 1410 households, 705 at baseline (T0) and 705 at
#       endline (T1).
```

```
# NOTE: The default value hhSize = 1 (which implies AVEhh = F = 1) was used because the
#       target proportion was defined in terms of households, rather than in terms of
#       individuals.
```

```
# Suppose the available budget is not enough to survey the required 705 households per
# round, whereas a sample of 600 households per round (i.e. 1200 overall) would be feasible.
# What would be the expected power in that case?
```

```
pow.comp2prop(n = 1200, P1 = 0.73, P2 = 0.80, sides = "one-tailed", DEFF = 1.4, RR = 0.9)
```

```
# NOTE: The power would be reduced to about 74.2%.
```

```
#####
# Power calculations for the comparison of two proportions: example 2 #
#####
# An assistance program aims to reduce by 20% the prevalence of stunted children under age
# 5 in a given target area. The historical prevalence before the intervention is estimated
# at 35%, so bringing it down to 28% (a 20% reduction, resulting in a 7 percentage points
# decrease) would be considered a full success. To evaluate the impact of the intervention,
# two household surveys will be conducted before (T0) and after (T1) the implementation.
# The surveys will have the same sample sizes, and it is desired that the study manages to
```

```

# detect a possible reduction effect of 5 percentage points (thus somewhat *smaller* than
# the official target). In the target area, the proportion of children under age 5 in the
# general population is estimated to be 15% and the average household size to be 5.6. The
# latest household survey that estimated the prevalence of stunted children under age 5
# reported a DEFF of 2.70, used a two-stage stratified cluster sampling design with 20
# households per each sampled EA, and had a response rate of 92%. If the same sampling
# design were adopted, how many households would be needed to achieve 80% power for the
# detection of the sought-after minimum effect at significance level 5%?

n.comp2prop(P1 = 0.35, MDE = 0.05, sides = "one-tailed", DEFF = 2.7, RR = 0.92,
            F = 0.15, hhSize = 5.6, old.clus.size = 20, new.clus.size = 20)

# NOTE: The required sample size is 7880 households, 3940 at baseline (T0) and 3940 at
#       endpoint (T1). The EAs to be visited are 3940 / 20 = 197 per round.

# What would be the implications of using a design with 15 households per EA, instead of
# 20?

n.comp2prop(P1 = 0.35, MDE = 0.05, sides = "one-tailed", DEFF = 2.7, RR = 0.92,
            F = 0.15, hhSize = 5.6, old.clus.size = 20, new.clus.size = 15)

# NOTE: When going from 20 to 15 households per EA, the DEFF is expected to decrease from
#       2.70 to 2.25. As a result, the required sample size would become 6570 households,
#       3285 at baseline (T0) and 3285 at endpoint (T1). The EAs to be visited would become
#       3285 / 15 = 219 per round.
#       Therefore, the proposed design would save 655 (= 3940 - 3285) households per round,
#       but would require visiting 22 (= 219 - 197) additional EAs per round.

# Suppose that the available budget only allows to survey 5000 households, 2500 per round,
# and that logistic constraints dictate to survey 15 households per EA. What would be the
# expected MDE of the study in that case, if a 80% power is desired?

mde.comp2prop(n = 5000, P1 = 0.35, sides = "one-tailed", DEFF = 2.7, RR = 0.92,
            F = 0.15, hhSize = 5.6, old.clus.size = 20, new.clus.size = 15)

# NOTE: The MDE would be about 5.7 percentage points. This means that, if the assistance
#       program actually results in the hoped-for 7 percentage points reduction, the study
#       will detect its effect as statistically significant with high probability (>= 80%).
#       However, should the program result in a smaller, yet not negligible, impact (e.g.
#       a reduction of 5 percentage points), the study will have less than 80% probability
#       to detect it, because of the sample size constraint.

```

plot.gvf.fit

*Diagnostic Plots for Fitted GVF Models***Description**

This function provides basic diagnostic plots for fitted GVF model(s).

Usage

```

## S3 method for class 'gvf.fit'
plot(x, which.more = 1:3, id.n = 3, labels.id = names(residuals(x)),
     cex.id = 0.75, label.pos = c(4, 2), cex.caption = 1, Main = NULL, ...)

```

```
## S3 method for class 'gvf.fits'
plot(x, which.more = NULL, id.n = 3, labels.id = names(residuals(x)),
     cex.id = 0.75, label.pos = c(4, 2), cex.caption = 1, Main = NULL, ...)

## S3 method for class 'gvf.fit.gr'
plot(x, which.more = 1:3, id.n = 3, labels.id = NULL,
     cex.id = 0.75, label.pos = c(4, 2), cex.caption = 1, ...)

## S3 method for class 'gvf.fits.gr'
plot(x, which.more = NULL, id.n = 3, labels.id = NULL,
     cex.id = 0.75, label.pos = c(4, 2), cex.caption = 1, ...)
```

Arguments

<code>x</code>	An object containing one or more fitted GVF models (see ‘Usage’ for the allowed classes).
<code>which.more</code>	Select additional plots beyond the default one (‘Observed vs Fitted’). Can be any subset of vector 1:6 with up to three elements.
<code>id.n</code>	Number of points to be initially labelled in each plot, starting with the most extreme.
<code>labels.id</code>	Vector of labels, from which the labels for extreme points will be chosen. NULL uses observation numbers.
<code>cex.id</code>	Magnification of point labels.
<code>label.pos</code>	Positioning of labels, for the left half and right half of the graph(s) respectively.
<code>cex.caption</code>	Controls the size of caption.
<code>Main</code>	Optional string to be added to automatic plot titles.
<code>...</code>	Other parameters to be passed through to plotting functions.

Details

Diagnostic plots can be useful both for assessing the goodness of a GVF model fit qualitatively, and for selecting the “best” GVF model among different alternatives.

This function can provide any of the following 7 plots:

- (0) 'Observed vs Fitted'
- (1) 'Residuals vs Fitted'
- (2) 'Normal Q-Q'
- (3) 'Scale-Location'
- (4) 'Cook's distance'
- (5) 'Residuals vs Leverage'
- (6) 'Cook's distances vs Leverage/(1-Leverage)'

The ‘*Residuals vs Fitted*’ plot is special in that it will be always provided: this explains its zeroth order in the list above. The rest of the list, namely plots 1:6, exactly matches the numbering convention of function [plot.lm](#).

Additional plots - beyond ‘*Residuals vs Fitted*’ - can be requested through argument `which.more`. Any subset of 1:6 is allowed, provided its length does not exceed 3. Therefore, at most 4 plots will be generated simultaneously.

Note that the *default* behaviour of this function do depend on whether input object `x` stores *one* or *more than one* fitted GVF models. In the first case, plots 0:3 will be returned in a multiple plot with a 2x2 layout. In the second case, only the default plot number 0 will be returned, opening a new graphics frame for each different GVF model.

Argument `id.n` specifies how many points have to be labelled, starting with the most extreme in terms of residuals: this applies to all plots.

Argument `Main` is expected to be seldom (if ever) useful: its main purpose is programming consistency at a deeper level.

All the other arguments have the same meaning as in function [plot.lm](#).

Author(s)

Diego Zardetto

References

See [plot.lm](#) and references therein.

See Also

[GVF.db](#) to manage **ReGenesees** archive of registered GVF models, [gvf.input](#) and [svystat](#) to prepare the input for GVF model fitting, [fit.gvf](#) to fit GVF models, [drop.gvf.points](#) to drop alleged outliers from a fitted GVF model and simultaneously refit it, and [predictCV](#) to predict CV values via fitted GVF models.

Examples

```
# Load example data:
data(AF.gvf)

# Inspect available estimates and errors of counts:
str(ee.AF)

# List available registered GVF models:
GVF.db

#####
# Diagnostic plots for fitted GVF model(s) #
#####

## (A) Plots of a *single* fitted GVF model ##
# Fit example data to registered GVF model number one:
m <- fit.gvf(ee.AF, 1)

## Default call yields 4 plots:
plot(m)

# Play with argument 'which.more':
## which.more = NULL yields the "Observed vs Fitted" plot only:
plot(m, which.more = NULL)

## which.more = 1 adds the "Residuals vs Fitted" plot:
plot(m, which.more = 1)
```

```

## subsets of 1:6 with length <= 3 are allowed:
plot(m, which.more = c(1:2,4))

# Just for illustration, play with other parameters:
plot(m, id.n = 6, col = "blue", pch = 20)

## (B) Plots of *many* fitted GVF models ##
# Fit example data to registered GVF models for frequencies (i.e. number 1:3):
mm <- fit.gvf(ee.AF, 1:3)

## Default call yields the "Observed vs Fitted" plot reported separately for
## each model in subsequent graphics frames:
plot(mm)

# Play with argument 'which.more':
## which.more = 1:3 yields subsequent 2x2 plots:
plot(mm, which.more = 1:3)

## again, subsets of 1:6 are allowed:
plot(mm, which.more = 1)

#####
# Diagnostic plots for "grouped" fitted GVF model(s) #
#####
# We have at our disposal the following survey design object on household data:
exdes

# Use function svystat to prepare "grouped" estimates and errors of counts
# to be fitted separately (here groups are regions):
ee <- svystat(exdes, y=~ind, by=~age5c:marstat:sex, combo=3, group=~regcod)
lapply(ee, head)

## (C) Plots of a *single* GVF model fitted to different groups ##
# Fit registered GVF model number one separately inside groups:
m.g <- fit.gvf(ee, 1)

## Default call yields 4 plots reported separately for each group
## in subsequent graphics frames:
plot(m.g)

## Play with argument 'which.more' to select different plots:
plot(m.g, which.more = c(1:2,4))

## (D) Plots of *many* GVF model fitted to different groups ##
# Fit all registered GVF models for frequencies separately inside groups:
mm.g <- fit.gvf(ee, 1:3)

## Default call yields the "Residuals vs Fitted" plot reported separately
## for each group in subsequent graphics frames:
plot(mm.g)

## Play with argument 'which.more' to add more plots:
plot(mm.g, which.more = 1:3, id.n = 6, col = "blue", pch = 20)

```

pop.desc

*Natural Language Description of Known Totals Templates***Description**

Provides a natural language description of a known totals data frame to be used for a calibration task.

Usage

```
pop.desc(pop.totals, ...)

## S3 method for class 'pop.totals'
pop.desc(pop.totals, ...)

## S3 method for class 'spc.pop'
pop.desc(pop.totals, verbose = FALSE, ...)
```

Arguments

pop.totals	An object of class pop.totals, be it a template or the actual known totals data frame for the calibration task.
verbose	Fully describe the control totals of a special purpose calibration task?
...	Parameters for future extensions (currently unused).

Details

Function `pop.template` generates a *template* (i.e. *empty*) data frame of class `pop.totals`, which is appropriate to store the known totals of a given calibration task. Afterwards, the template data frame must be filled with actual figures.

When the sampling frame of the survey is available and the actual population totals can be calculated from this source, function `fill.template` (i) automatically computes the totals of the auxiliary variables from the sampling frame, (ii) safely arranges and formats these values according to the template structure. Therefore, function `fill.template` avoids any need for the user to understand, comply with, or even be aware of, the structure of the template that is being filled.

On the contrary, when the population totals are available to the user as such, that is in the form of already computed aggregated values (e.g. because they come from an external source, like a Population Census), it is up to the user to correctly fill the template, that is to put the *right values* in the *right slots* of the prepared template.

Function `pop.desc` has been designed for users who cannot take advantage of function `fill.template`, to help them understand the structure of the known totals template, in order to safely fill it with actual figures.

Invoking `pop.desc` will print on screen a detailed natural language description of the structure of the input `pop.totals` object. Such description will clarify how known totals are organized inside the template slots.

Value

The main purpose of the function is to print on screen, anyway it returns invisibly the input `pop.totals` object (as `print` would do).

Author(s)

Diego Zardetto

See Also

[e.calibrate](#) for calibrating weights, [pop.template](#) for the definition of the class `pop.totals` and to build a template data frame for known population totals, [fill.template](#) to automatically fill the template when a sampling frame is available.

Examples

```
## First prepare some design objects to work with:

# Load household data:
data(data.examples)
# Build a design object:
exdes<-e.svydesign(data=example,ids=~towcod+famcod,strata=~SUPERSTRATUM,
                  weights=~weight)

# Load sbs data:
data(sbs)
# Build a design object:
sbsdes<-e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,fpc=~fpc)

## Now build some known totals templates that (after having been filled by
## actual figures) could be used to calibrate the design objects above,
## and explore the corresponding natural language description:

#####
## Some simple and small examples ##
#####
expop<-pop.template(exdes,calmodel=~1)
expop
pop.desc(expop)

expop<-pop.template(exdes,calmodel=~sex)
expop
pop.desc(expop)

# equivalent to the one above
expop<-pop.template(exdes,calmodel=~sex-1)
expop
pop.desc(expop)

expop<-pop.template(exdes,calmodel=~x1+x2+x3,partition=~procod)
expop
pop.desc(expop)

expop<-pop.template(exdes,calmodel=~sex:marstat-1)
expop
pop.desc(expop)

# equivalent to the one above
expop<-pop.template(exdes,calmodel=~sex*marstat-1)
expop
pop.desc(expop)
```



```

# equivalent to the one above
expop<-pop.template(exdes,calmodel=~1,partition=~sex:marstat)
expop
pop.desc(expop)

expop<-pop.template(exdes,calmodel=~x1+age5c:marstat-1,partition=~regcod:sex)
expop
pop.desc(expop)

#####
## Some more involved and bigger examples ##
#####
expop<-pop.template(exdes,calmodel=~sex:age10c:regcod + sex:age5c:procod - 1)
expop
pop.desc(expop)

# equivalent to the one above (because procod is nested into regcod and
# age10c is nested into age5c)
expop<-pop.template(exdes,calmodel=~age10c+procod-1,
                    partition=~regcod:sex:age5c)
expop
pop.desc(expop)
# NOTE: Most of the entries of the template above will be structural zeros,
#       as can be seen in what follows:
expop.HT<-aux.estimate(exdes, template=expop)
expop.HT
sum(expop.HT==0)

# Switch to sbs data
sbspop<-pop.template(sbsdes,
                    calmodel=~(emp.num + ent):(nace.macro + emp.cl) - 1, partition=~region)

# Can fill the template using the sampling frame...
sbspop<-fill.template(universe=sbs.frame,template=sbspop)
sbspop

# ...and invoke function pop.desc on the filled known totals data frame:
pop.desc(sbspop)

sbspop <- pop.template(data=sbsdes,
                      calmodel=~((emp.num + ent):(nace2 + emp.cl:nace.macro))-1,
                      partition=~region:public)

sbspop
pop.desc(sbspop)

```

Description

Allows to solve jointly a special purpose calibration task and an ordinary calibration task by fusing their respective control totals.

Usage

```
pop.fuse(spc.pop, pop, design)
```

Arguments

spc.pop	A control totals data frame prepared for a <i>special purpose calibration</i> task. Must be of class <code>spc.pop</code> .
pop	A known totals data frame for an <i>ordinary calibration</i> task. Must be of class <code>pop.totals</code> .
design	A design object <i>prepared</i> for a special purpose calibration task.

Details

ReGenesees 2.1 introduced support for ‘*special purpose calibration*’ tasks, i.e. facilities to calibrate survey weights so as to match complex, non-linear population parameters, instead of ordinary population totals.

Currently, **ReGenesees**’ support for special purpose calibration tasks is limited to Multiple Regression Coefficients (see [prep.calBeta](#) and [pop.calBeta](#)), which includes calibration on Means as a notable special case. Further support will likely be provided in future extensions.

Function `pop.fuse` allows you to run a calibration task that *simultaneously* involves as benchmarks:

- Complex population parameters (e.g. multiple regression coefficients).
- Ordinary population totals.

To achieve this goal, `pop.fuse` simply “*fuses*” the corresponding control totals data frames. The resulting fused control totals data frame is indeed enough to automatically instruct function [e.calibrate](#) to run the joint calibration task.

Argument `spc.pop` must be an object of class `spc.pop`, namely a control totals data frame prepared for a special purpose calibration task (e.g. via function [pop.calBeta](#) for the case of calibration on multiple regression coefficients).

Argument `pop` must be an object of class `pop.totals`, namely a known totals data frame for an ordinary calibration task (e.g. generated using functions [pop.template](#) and [fill.template](#)).

Argument `design` must be the survey design object that:

- was already *prepared* for the special purpose calibration task at hand, and
- you want to calibrate simultaneously also on the ordinary population totals at hand.

Note that condition (i) requires that object `design` has actually been used to build object `spc.pop` (see the ‘Examples’ section). Note, moreover, that condition (ii) requires that you eventually run [e.calibrate](#) on object `design` (see the ‘Examples’ section).

Value

A *fused* data frame, with class `spc.pop`, encompassing control totals for both the special purpose calibration task and the ordinary calibration task.

Note that printing this control totals data frame might not be very telling: to better understand its structure you should instead leverage function [pop.desc](#), for which a method dedicated to class `spc.pop` is available.

Author(s)

Diego Zardetto

See Also

[e.calibrate](#) to calibrate weights, functions [prep.calBeta](#) and [pop.calBeta](#) to prepare survey data and control totals for calibration on multiple regression coefficients, functions [pop.template](#) and [fill.template](#) to generate and fill population totals templates for ordinary calibration tasks, [pop.desc](#) to obtain a natural language description of control totals data frames.

Examples

```
# Function pop.fuse allows you to run a calibration task that simultaneously
# involves as benchmarks:
# (A) complex population parameters (e.g. multiple regression coefficients)
# (B) ordinary population totals
# You just have to:
## 1) prepare the survey design and control totals data frame for (A)
## 2) create and fill the known totals data frame for (B)
## 3) fuse the control totals data frames produced in steps 1) and 2)!

# Load sbs data:
data(sbs)
# Create a design object:
sbsdes <- e.svydesign(data = sbs, ids = ~id, strata = ~strata,
                    weights = ~weight, fpc = ~fpc)

# (A) Suppose you know with satisfactory accuracy from some external source
#       the regression coefficients of the following model:
model <- va.imp2 ~ emp.num + emp.cl

# Here, use the sbs sampling frame available in ReGenesees to simulate the
# external source and compute the values of the regression coefficients:
Beta <- coef(lm(model, data = sbs.frame))
Beta

## 1) Prepare the survey design and control totals for calibration (A):
sbsdes.A <- prep.calBeta(sbsdes, model, Beta)
pop.A <- pop.calBeta(sbsdes.A)

# (B) Suppose you know the number of enterprises and employees by economic
#       activity macro sectors
## 2) Create and fill the known totals data frame for calibration (B)
pop.B <- pop.template(sbsdes.A, calmodel = ~(ent + emp.num):nace.macro - 1)
# Note that, to create the template above, you could have used equally well
# the original object sbsdes.
pop.B <- fill.template(pop.B, universe = sbs.frame)

## 3) Lastly, fuse the control totals data frames produced in steps 1) and 2)
pop.AB <- pop.fuse(pop.A, pop.B, sbsdes.A)
# Note that, to create the fused control totals data frame above, you *MUST USE*
# the *PREPARED* design object sbsdes.A

# Have a look:
pop.desc(pop.AB)
# ...and recall you can set verbose = TRUE to see the full structure
```

```
# pop.desc(pop.AB, verbose = TRUE)

# Now you are ready to calibrate simultaneously on (A) and (B)
sbscal.AB <- e.calibrate(sbsdes.A, pop.AB)
# Note again that, to run the calibration on the *fused* control totals, you
# *MUST USE* the *PREPARED* design object sbsdes.A

# Now, check that all the benchmarks are indeed matched:
# (A) Multiple regression coefficients:
svyestatB(sbscal.AB, model)
Beta

# (B) Ordinary population totals:
svyestatTM(sbscal.AB, ~ent + emp.num, ~nace.macro)
pop.B
# OK
```

pop.plot

*Plot Calibration Control Totals vs Current Estimates***Description**

Draw a scatter plot of calibration control totals vs current estimates.

Usage

```
pop.plot(pop.totals, ...)

## S3 method for class 'pop.totals'
pop.plot(pop.totals, design,
         xlab = "Current Estimates",
         ylab = "Calibration Control Totals",
         lcol = c("red", "green", "blue"),
         lwd = c(1, 1, 1),
         lty = c(2, 1, 2),
         verbose = TRUE, ...)

## S3 method for class 'spc.pop'
pop.plot(pop.totals, design,
         xlab = "Current Estimates",
         ylab = "Calibration Control Totals",
         lcol = c("red", "green", "blue"),
         lwd = c(1, 1, 1),
         lty = c(2, 1, 2),
         verbose = TRUE, ...)
```

Arguments

pop.totals	A known totals data frame for a calibration task. Must be of class pop.totals (for ordinary calibration tasks) or spc.pop (for special purpose calibration tasks).
design	A design object to compute estimates of the calibration control totals. Must be of class of class analytic (or inheriting from it).

xlab	A suggested label for the x axis. See also plot .
ylab	A suggested label for the y axis. See also plot .
lcol	Colors of reference lines, see ‘Details’. See also par .
lwd	Width of reference lines, see ‘Details’. See also par .
lty	Type of reference lines, see ‘Details’. See also par .
verbose	Print on screen minimum and maximum slopes?
...	Other parameters to be passed through to plotting functions.

Details

Function [pop.plot](#) draws a scatter plot of calibration control totals vs current estimates derived from object design. This plot is sometimes very telling and may provide a first-level, rough assessment of how hard the calibration problem at hand will turn out to be in terms of constrained optimization.

A trivial calibration problem would correspond to points lying exactly on the $y = x$ bisector line. A moderate spread around the bisector line without evident and anomalous patterns is usually a sign of a well behaved calibration task. Larger spreads signal increasing calibration complexity. The maximum and minimum slopes of lines connecting the origin to the points in the scatter plot provide often a reasonable clue about the minimum possible range for the calibration bounds $[L, U]$, see [bounds.hint](#). Evident and anomalous patterns emerging from the scatter plot not only generally imply harder calibration tasks, but can even reveal signs of underlying biases in the auxiliary variables. For instance, an extremely imbalanced pattern, with the overwhelming majority of points lying below (or above) the $y = x$ line would be a striking symptom of upward (or downward) bias of the current estimates with respect to the true population totals.

In addition to the scatter plot of calibration control totals vs current estimates, function [pop.plot](#) draws three useful reference lines: (1) the maximum slope line connecting the origin to the points, (2) the $y = x$ bisector line, and (3) the minimum slope line connecting the origin to the points.

If `verbose = TRUE`, the minimum and maximum slopes get printed on screen.

When the calibration control totals in `pop.totals` span different orders of magnitude (as it often happens in enterprise surveys) it is beneficial to look at the plot in logarithmic scale, which can be achieved by setting `log = "xy"` via argument ...

If `pop.totals` is of class `spc.pop`, i.e. it stores known totals for a special purpose calibration tasks, which are all zero (see [prep.calBeta](#)), then just one reference vertical line at $x = 0$ is added to the scatter plot.

If `pop.totals` is of class `spc.pop` but it is a *fused* data frame, encompassing simultaneous control totals for a special purpose calibration task and an ordinary calibration task (see [pop.fuse](#)), then two separate scatter plots are drawn.

Note that you can also pass to argument `design` the calibrated object obtained using `pop.totals` as known totals data frame: if calibration perfectly converged, points will lie on the $y = x$ bisector line, otherwise the spread around the bisector line will provide a visual assessment of how significantly the calibration task failed.

Value

The main purpose of the function is to draw a plot, anyway it returns invisibly the minimum and maximum slopes whenever it is meaningful to do so (thus excluding non-fused special purpose calibration task).

Author(s)

Diego Zardetto

See Also

[e.calibrate](#) for calibrating weights, [pop.template](#) for the definition of the class `pop.totals` and to build a template data frame for known population totals, [fill.template](#) to automatically fill the template when a sampling frame is available, [pop.desc](#) to obtain a natural language description of control totals data frames.

Examples

```
## First prepare some design objects to work with:
# Load household data:
data(data.examples)

# Build a design object:
exdes<-e.svydesign(data=example,ids=~towcod+famcod,strata=~SUPERSTRATUM,
                  weights=~weight)

# Now suppose the known population totals for the calibration task
# are stored in object pop07p:
class(pop07p)
dim(pop07p)

# These totals refer to the
# 1) Joint distribution of sex and age10c (age in 10 classes)
#    at the region level;
# 2) Joint distribution of sex and age5c (age in 5 classes)
#    at the province level;

# For a natural language description, run:
# pop.desc(pop07p)

## Here is the totals vs estimates scatter plot:
pop.plot(pop07p, exdes, pch = 20)

# ...or with a log-log scale:
pop.plot(pop07p, exdes, pch = 20, log = "xy")

# Now calibrate (e.g. with the unbounded linear function):
excal07p <- e.calibrate(exdes, pop07p)

# As calibration converged...
check.cal(excal07p)

# ...the points now lie on the y = x bisector:
pop.plot(pop07p, excal07p, pch = 20)

## You are encouraged to try the function on control totals for special
## purpose calibration tasks (both simple and fused, see ?prep.calBeta,
## ?pop.calBeta, and ?pop.fuse). It might be interesting.
```

pop.template

*Template Data Frame for Known Population Totals***Description**

Constructs a “*template*” data frame to store known population totals for a calibration problem.

Usage

```
pop.template(data, calmodel, partition = FALSE)
```

Arguments

data	Data frame of survey data (or an object inheriting from class <code>analytic</code>).
calmodel	Formula defining the linear structure of the calibration model.
partition	Formula specifying the variables that define the "calibration domains" for the model. FALSE (the default) implies no calibration domains.

Details

This function creates an object of class `pop.totals`. A `pop.totals` object is made up by the union of a data frame (whose structure conforms to the standard required by `e.calibrate` for the known totals) and the metadata describing the calibration problem.

The mandatory argument `data` must identify the survey data frame on which the calibration problem is defined (or, as an alternative, an `analytic` object built upon that data frame). Should empty levels be present in any factor variable belonging to `data`, they would be dropped.

The mandatory argument `calmodel` symbolically defines the calibration model you intend to use: it identifies the auxiliary variables and the constraints for the calibration problem. The data variables referenced by `calmodel` must be numeric or factor and must not contain any missing value (NA).

The optional argument `partition` specifies the variables that define the calibration domains for the model. The default value (FALSE) means either that there are not calibration domains or that you want to solve the problem globally (even though it could be factorized). If a formula is passed through the `partition` argument the program checks that `calmodel` actually describes a "reduced model", that is it does not reference any of the partition variables; if this is not the case, the program stops and prints an error message. Notice that a formula like `by=~D1+D2` will be automatically translated into the factor-crossing formula `by=~D1:D2`. The data variables referenced by `partition` (if any) must be factor and must not contain any missing value (NA). Note that, if the `partition` formula involves two or more factors, their crossed levels will be ordered according to operator : (that is, those from the *rightmost* variable will vary fastest).

Value

An object of class `pop.totals`. The data frame it contains is a “*template*” in the sense that all the known totals it must be able to store are missing (NA). However, this data frame has a structure that complies with the standard required by `e.calibrate` (provided the latter is invoked with the same `calmodel` and `partition` values used to create the template).

The operation of filling the template’s NAs with the actual values of the corresponding population totals has, obviously, to be done by the user. If the user has access to a “*sampling frame*” (that is a data frame containing the complete list of the units belonging to the target population along with

the corresponding values of the auxiliary variables), then he can exploit function `fill.template` to automatically fill the template.

The `pop.totals` class is a specialization of the `data.frame` class; this means that an object built by `pop.template` inherits from the `data.frame` class and you can use on it every method defined on that class.

Author(s)

Diego Zardetto

References

Zardetto, D. (2015) “*ReGenesees: an Advanced R System for Calibration, Estimation and Sampling Error Assessment in Complex Sample Surveys*”. *Journal of Official Statistics*, 31(2), 177-203. doi: <https://doi.org/10.1515/jos-2015-0013>.

See Also

`e.calibrate` for calibrating weights, `population.check` to check that the known totals data frame satisfies the standard required by `e.calibrate`, `pop.desc` to provide a natural language description of the template structure, and `fill.template` to automatically fill the template when a sampling frame is available.

Examples

```
# Creation of population totals template data frames for different
# calibration problems (if the calibration models can be factorized
# both a global and a partitioned solution are given):

data(data.examples)

# 1) Calibration on the total number of units in the population:
pop.template(data=example,calmodel=~1)

# 2) Calibration on the total number of units in the population
# and on the marginal distribution of marstat (notice that the
# total for the first level "married" of the marstat factor
# variable is missing because it can be deduced from
# the remaining totals):
pop.template(data=example,calmodel=~marstat)

# 3) Calibration on the marginal distribution of marstat (you
# must explicitly remove the intercept term in the
# calibration model adding -1 to the calmodel formula):
pop.template(data=example,calmodel=~marstat-1)

# 4) Calibration (global solution) on the joint distribution of sex
# and marstat:
pop.template(data=example,calmodel=~sex:marstat-1)

# 4.1) Calibration (partitioned solution) on the joint distribution
# of sex and marstat:
# 4.1.1) Using sex to define calibration domains:
```



```

pop.template(data=example,calmodel=~marstat-1,partition=~sex)

#      4.1.2) Using marstat to define calibration domains:
pop.template(data=example,calmodel=~sex-1,partition=~marstat)

#      4.1.3) Using sex and marstat to define calibration domains:
pop.template(data=example,calmodel=~1,partition=~sex:marstat)

# 5) Calibration (global solution) on the total for the quantitative
#     variable x1 and on the marginal distribution of the qualitative
#     variable age5c, in the subpopulations defined by crossing sex
#     and marstat:
pop.template(data=example,calmodel=~(age5c+x1-1):sex:marstat)

# 5.1) The same problem with partitioned solutions:
#     5.1.1) Using sex to define calibration domains:
pop.template(data=example,calmodel=~(age5c+x1-1):marstat,partition=~sex)

#     5.1.2) Using marstat to define calibration domains:
pop.template(data=example,calmodel=~(age5c+x1-1):sex,partition=~marstat)

#     5.1.3) Using sex and marstat to define calibration domains:
pop.template(data=example,calmodel=~age5c+x1-1,partition=~sex:marstat)

```

population.check

Compliance Test for Known Totals Data Frames

Description

Checks whether a known population totals data frame conforms to the standard required by `e.calibrate` for a specific calibration problem.

Usage

```
population.check(df.population, data, calmodel, partition = FALSE)
```

Arguments

<code>df.population</code>	Data frame of known population totals.
<code>data</code>	Data frame of survey data (or an object inheriting from class <code>analytic</code>).
<code>calmodel</code>	Formula defining the linear structure of the calibration model.
<code>partition</code>	Formula specifying the variables that define the "calibration domains" for the model. <code>FALSE</code> (the default) implies no calibration domains.

Details

The behaviour of this function depends on the outcome of the test. If `df.population` is found to conform to the standard, the function first converts it into an object of class `pop.totals` and then invisibly returns it. Failing this, the function stops and prints an error message: the meaning of the message should help the user diagnose the cause of the problem.

The mandatory argument `df.population` identifies the known totals data frame for which compliance with the standard is to be checked.

The mandatory argument `data` identifies the survey data frame on which the calibration problem is defined (or, as an alternative, an analytic object built upon that data frame).

The mandatory argument `calmodel` symbolically defines the calibration model you intend to use: it identifies the auxiliary variables and the constraints for the calibration problem. The data variables referenced by `calmodel` must be numeric or factor and must not contain any missing value (NA).

The optional argument `partition` specifies the variables that define the calibration domains for the model. The default value (FALSE) means either that there are not calibration domains or that you want to solve the problem globally (even though it could be factorized). If a formula is passed through the `partition` argument the program checks that `calmodel` actually describes a "reduced model", that is it does not reference any of the partition variables; if this is not the case, the program stops and prints an error message. Notice that a formula like `by=~D1+D2` will be automatically translated into the factor-crossing formula `by=~D1:D2`. The data variables referenced by `partition` (if any) must be factor and must not contain any missing value (NA). Note that, if the `partition` formula involves two or more factors, their crossed levels will be ordered according to operator : (that is, those from the *rightmost* variable will vary fastest).

Value

An invisible object of class `pop.totals`. The `pop.totals` class is a specialization of the `data.frame` class; this means that an object built by `pop.template` inherits from the `data.frame` class and you can use on it every method defined on that class.

Note

The `population.check` function can be used to convert a known totals data frame that conforms to the standard required by `e.calibrate` into an object of class `pop.totals`. The usefulness of this conversion lies in the fact that, once you have known totals with this "certified format", you can invoke `e.calibrate` without specifying the values for the `calmodel` and `partition` arguments (this means that the function is able to extract them directly from the attributes of the `pop.totals` object).

Author(s)

Diego Zardetto

References

Zardetto, D. (2015) "*ReGenesees: an Advanced R System for Calibration, Estimation and Sampling Error Assessment in Complex Sample Surveys*". Journal of Official Statistics, 31(2), 177-203. doi: <https://doi.org/10.1515/jos-2015-0013>.

See Also

`e.calibrate` for calibrating weights, `pop.template` for the definition of the class `pop.totals` and to build a "template" data frame for known population totals, `fill.template` to automatically fill the template when a sampling frame is available.

Examples

```

data(data.examples)

# Suppose you have to calibrate the example survey data frame
# on the totals of x1 by sex and you want the partitioned solution.
# Start creating a design object:
des<-e.svydesign(data=example,ids=~towcod+famcod,strata=~SUPERSTRATUM,
  weights=~weight)

# Then build a template data frame for the known totals:
pop<-pop.template(data=example,calmodel=~x1-1,partition=~sex)
pop
class(pop)

# Now fill NAs with the actual values for the population
# totals (suppose 123 for sex="f" and 456 for sex="m"):
pop[, "x1"]<-c(123,456)
pop
class(pop)

# Finally check if pop complies with the e.calibrate standard:
population.check(df.population=pop,data=example,calmodel=~x1-1,
  partition=~sex)

# If, despite keeping the content unchanged, we altered the
# structure of the data frame (for example, by changing the
# order of its rows)...
pop.mod<-pop ; pop.mod[1,]<-pop[2,] ; pop.mod[2,]<-pop[1,]
pop
pop.mod

# ...we would obtain an error:
## Not run:
population.check(df.population=pop.mod,data=example,calmodel=~x1-1,
  partition=~sex)

## End(Not run)

# Remember that, if the known totals have been converted
# into the pop.totals "format" by means of population.check,
# it is possible to invoke e.calibrate without specifying
# calmodel and partition:

class(pop04p)
pop04p
descal04p<-e.calibrate(design=des,df.population=pop04p,
  calfun="logit",bounds=bounds,aggregate.stage=2)

# ...this option is not allowed if the known totals
# are not of class 'pop.totals' even if they conform to the
# standard:

pop04p.mod<-data.frame(pop04p)

```

```

class(pop04p.mod)
pop04p.mod
## Not run:
e.calibrate(design=des,df.population=pop04p.mod,calfun="logit",
            bounds=bounds,aggregate.stage=2)

## End(Not run)

```

predictCV

Predict CV Values via Fitted GVF Models

Description

This function predicts the CV values associated to given estimates, based on fitted GVF model(s).

Usage

```

predictCV(object, new.Y = NULL, scale = NULL, df = Inf,
          interval = c("none", "confidence", "prediction"), level = 0.95,
          na.action = na.pass, pred.var = NULL, weights = 1)

```

Arguments

object	An object containing one or more fitted GVF models.
new.Y	A data frame storing new estimates whose CVs have to be predicted. If omitted or NULL, CVs arising from the fitted GVF model(s) will be returned.
scale	Scale parameter for standard error calculation. See also predict.lm .
df	Degrees of freedom for scale. See also predict.lm .
interval	Type of interval calculation. Can be abbreviated. See also predict.lm .
level	Confidence (or tolerance) level for intervals. See also predict.lm .
na.action	Function determining what should be done with missing values in new.Y. The default is to predict NA. See also predict.lm .
pred.var	The variance(s) for future observations to be assumed for prediction intervals. See also predict.lm .
weights	Variance weights for prediction. This can be a numeric vector or a one-sided model formula. In the latter case, it is interpreted as an expression evaluated in new.Y. See also predict.lm .

Details

The main motivation for building and fitting a GVF model is to exploit the fitted model to *predict* the sampling error associated to a given estimate, instead of having to *compute* directly an estimate of such sampling error. Function predictCV is relevant to that scope.

Despite different GVF models can specify as response term (call it 'resp') different functions of variables 'SE', 'CV', and 'VAR' (see e.g. [Wolter 07]), function predictCV adopts variable 'CV' as a universal *pivot*. This means that predictCV can handle *only* fitted GVF models which are *registered* (that is already stored inside [GVF.db](#)), and for which variable Resp.to.CV is *not* NA. Indeed, it is variable Resp.to.CV of data frame GVF.db which tells predictCV how to transform the response of an arbitrary GVF model ('resp') into the pivot measure of variability ('CV').

By default `new.Y = NULL` and CVs (and intervals, if any) obtained by transforming fitted response values will be returned. If passed, argument `new.Y` must be a data frame storing new estimates for which CVs have to be predicted. Such input estimates have to be stored in column `Y` of data frame `new.Y`. Moreover, if object stores GVF model(s) fitted to *grouped* data (namely, it has class `gvf.fit.gr` or `gvf.fits.gr`), then `new.Y` should also have columns identifying the *groups* to which input estimates are referred (see ‘Examples’). The *only exception* is the following: if the `new.Y` data frame has just the `Y` column, then CVs will be predicted for *all groups* (see ‘Examples’). The function will check for consistency between groups available in object and in `new.Y` (see ‘Examples’).

If `interval = "none"` (the default), the function will return predicted CVs only. Otherwise, lower and upper bounds of confidence (or prediction) intervals around predicted CVs will be also provided. Use argument `level` to specify the desired confidence (or tolerance) level for those intervals.

All the other arguments have the same meaning as in function [predict.lm](#).

Value

If object is a single GVF model (classes `gvf.fit` and `gvf.fit.gr`), a data frame.

If object is a set of GVF models fitted to the same data (classes `gvf.fits` and `gvf.fits.gr`), a list of data frames, one for each input GVF model.

The output data frame(s) will store input estimates `new.Y` plus additional columns:

`CV.fit` Predicted CV value, numeric.

`CV.lwr` Lower bound of requested interval (if any), numeric.

`CV.upr` Upper bound of requested interval (if any), numeric.

Of course, lower and upper bounds for CVs will be reported only when `interval != "none"`.

Note

Please read the ‘Note’ section of [predict.lm](#).

Author(s)

Diego Zardetto

References

Wolter, K.M. (2007) “*Introduction to Variance Estimation*”, Second Edition, Springer-Verlag, New York.

See Also

[GVF.db](#) to manage **ReGenesees** archive of registered GVF models, [gvf.input](#) and [svystat](#) to prepare the input for GVF model fitting, [fit.gvf](#) to fit GVF models, [plot.gvf.fit](#) to get diagnostic plots for fitted GVF models, and [drop.gvf.points](#) to drop alleged outliers from a fitted GVF model and simultaneously refit it.

Examples

```
#####
# Simple examples to illustrate the syntax #
#####
# Load example data:
data(AF.gvf)

# Inspect available estimates and errors of counts:
head(ee.AF)
summary(ee.AF)

# List available registered GVF models:
GVF.db

## (A) A *single* fitted GVF model ##
# Fit example data to registered GVF model number one:
m <- fit.gvf(ee.AF, 1)

# Not passing 'new.Y' yield CVs from fitted response values:
p <- predictCV(m)

# Take a look:
head(p)
with(p, plot(CV, CV.fit, col = "blue", pch = 20))

# Now let's predict CV values for new estimates of counts
# e.g. Y = c(1000, 5000, 10000, 50000, 100000)
# First, put these values into a data frame:
new.Y <- data.frame(Y = c(1000, 5000, 10000, 50000, 100000))
new.Y

# Then, compute predicted values and confidence intervals:
p <- predictCV(m, new.Y, interval = "confidence")
p

# NOTE: Should we ever need it, we could also use function predict
#       to predict *response* values instead of CVs:
predict(m, new.Y, interval = "confidence")

## (B) A *a set* of GVF models fitted to the same data ##
# Fit example data to registered GVF models for frequencies (i.e. number 1:3):
mm <- fit.gvf(ee.AF, 1:3)

# Let's predict CV values for the same new estimates of counts used above,
# i.e. Y = c(1000, 5000, 10000, 50000, 100000).

# Separate predictions will be obtained from the three fitted GVF models
pp <- predictCV(mm, new.Y, interval = "confidence")
pp

# NOTE: The WARNING above arises from the third fitted GVF model and explains
#       the appearance of NaN at the lower bound of the CV confidence interval
#       for input Y = 100000. Indeed, the response of the third model is the
#       squared CV (which ought to be *positive*), but the prediction for the
#       lower endpoint of the confidence interval happens to be *negative*:
```

```

predict(mm, new.Y, interval = "confidence")

## (C) a *single* GVF model fitted to *grouped* data ##
# We have at our disposal the following survey design object on household data:
exdes

# Use function svstat to prepare *grouped* estimates and errors of counts
# to be fitted separately (here groups are regions):
ee.g <- svstat(exdes, y=~ind, by=~age5c:marstat:sex, combo=3, group=~regcod)

# Inspect these grouped estimates and errors of counts:
lapply(ee.g, head)
lapply(ee.g, summary)

# Fit registered GVF model number one, separately inside regions '6', '7',
# and '10':
m.g <- fit.gvf(ee.g, 1)

# Suppose we want to predict CV values for the same new estimates of counts used
# above, i.e. Y = c(1000, 5000, 10000, 50000, 100000).
# Obviously, we need tell to what groups (i.e. regions) should these Y values
# be referred. Therefore, input data frame new.Y should have columns identifying
# the groups (i.e. regions).

# Case 1: all known regions (i.e. regions '6', '7', and '10')
#           Here we can exploit the exception described in section 'Details' and
#           avoid building group variables explicitly:

# Predict:
p.g <- predictCV(m.g, new.Y, interval = "confidence")
p.g

# Case 2: a subset of known regions (e.g. region '7' only)
#           Here we must build group variables explicitly:
new.Y.g <- data.frame(Y = c(1000, 5000, 10000, 50000, 100000),
                      regcod = 7)
new.Y.g

# Predict:
p.g <- predictCV(m.g, new.Y.g, interval = "confidence")
p.g

# Case 3: a subset of known regions (e.g. region '7') *plus* some *unknown*
#           region (e.g. region '11').
#           Unknown groups will be tacitly *discarded*:
new.Y.g <- data.frame(Y = c(1000, 5000, 10000, 50000, 100000),
                      regcod = rep(c(7, 11), each = 5))
new.Y.g

# Predict:
p.g <- predictCV(m.g, new.Y.g, interval = "confidence")
p.g

```

```

# Case 4: only *unknown* regions (e.g. regions '11' and '12').
#       This will raise an *error*:
new.Y.g <- data.frame(Y = c(1000, 5000, 10000, 50000, 100000),
                      regcod = rep(c(11, 12), each = 5))
new.Y.g

## Not run:
# Predict:
p.g <- predictCV(m.g, new.Y.g, interval = "confidence")

## End(Not run)

# Case 5: *unknown* group variables (e.g. 'region' instead of 'regcod').
#       This will raise an *error*:
new.Y.g <- data.frame(Y = c(1000, 5000, 10000, 50000, 100000),
                      region = rep(c(11, 12), each = 5))
new.Y.g

## Not run:
# Predict:
p.g <- predictCV(m.g, new.Y.g, interval = "confidence")

## End(Not run)

## (D) a *set of* GVF models fitted to *grouped* data ##
# Fit all registered GVF models for frequencies (i.e. number 1:3) separately
# inside groups:
mm.g <- fit.gvf(ee.g, 1:3)

# Predict CV values for the same new estimates of counts used above,
# i.e. Y = c(1000, 5000, 10000, 50000, 100000), for all the regions:
# Again, here we can exploit the exception described in section 'Details'
# and avoid building group variables explicitly:

# Predict:
pp.g <- predictCV(mm.g, new.Y)
pp.g

# NOTE: The WARNING above explains the appearance of NaN for some predicted
#       CV values stemming from the third GVF model. The reason causing this
#       behaviour is exactly the same as discussed in previous example (B).

#####
# Estimating CVs: Prediction vs Direct Calculation #
#####
# Load example data:
data(AF.gvf)

# Fit available registered GVF models for frequencies:
mm <- fit.gvf(ee.AF, model=1:3)

# Get the best fitted model:
mbest <- getBest(mm, criterion="adj.R2")

```



```

mbest
# Note: adjusted R^2 used as a 'quick and dirty' criterion, as a thorough model
#       comparison via diagnostic plots would have given the same result.

# Compute directly the estimates and errors of a set of absolute frequencies
# which did not belong to the previously fitted data ee.AF, e.g. the joint
# distribution of marstat and regcod:
marstat.regcod <- svstatTM(exdes, ~I(marstat:regcod))
marstat.regcod

# Predict CVs of the joint distribution of marstat and regcod
# by means of the selected GVF model:
# First, prepare data with which to predict:
newdata <- gvf.input(exdes, marstat.regcod)
# Then, compute CV predictions:
p.marstat.regcod <- predictCV(mbest, new.Y = newdata, interval="prediction")

# Inspect the results:
p.marstat.regcod

# Plot of computed and predicted CVs with prediction error bars:
# plot starts #
plot(p.marstat.regcod$Y, p.marstat.regcod$CV.fit, pch=19, col="red",
     ylim=range(p.marstat.regcod$CV.lwr, p.marstat.regcod$CV.upr, p.marstat.regcod$CV),
     xlab="Absolute Frequency Estimate", ylab="Coefficient of Variation",
     main="Estimated and GVF Predicted CVs\n(joint distribution of marstat and regcod)")
segments(x0=p.marstat.regcod$Y, y0=p.marstat.regcod$CV.lwr, y1=p.marstat.regcod$CV.upr,
         col="red")
points(p.marstat.regcod$Y, p.marstat.regcod$CV, pch=0)
legend("topright", title="CV Estimation Method",
      legend=c("Direct Estimate", "GVF Predicted Value", "GVF Prediction Interval"),
      pch=c(0,19,124), col=c("black", "red", "red"), inset=rep(0.05, 2))
# plot ends #

```

prep.calBeta

Calibration on Multiple Regression Coefficients

Description

Prepare survey data and control totals to run a calibration task on multiple regression coefficients.

Usage

```

prep.calBeta(design, model, Beta,
             by = NULL, partition = FALSE, drop.z = TRUE)

pop.calBeta(design)

```

Arguments

design	Object of class <code>analytic</code> (or inheriting from it) containing survey data and sampling design metadata. For function <code>pop.calBeta</code> , a <i>prepared</i> design object as returned by function <code>prep.calBeta</code> .
--------	--

model	Formula (or list of formulas) specifying the linear model(s) whose regression coefficients will be used as calibration benchmarks (see ‘Details’).
Beta	Numeric vector (or list of numeric vectors) of regression coefficients to be used as calibration benchmarks (see ‘Details’).
by	If regression coefficients are known at domain level (i.e. within subpopulations), a formula specifying the domains (see ‘Details’). Specify NULL (the default option) if the regression coefficients are known at the overall population level.
partition	In case domains have been specified through argument by, should a partitioned calibration task be performed? The default is FALSE, which selects a global calibration task.
drop.z	Can the prepared calibration variables (see ‘Details’) be dropped upon completion of the calibration task? Specify TRUE (the default) if you want to save memory space.

Details

Special Purpose Calibration tasks

ReGenesees 2.1 introduced support for ‘*special purpose calibration*’ tasks, i.e. facilities to calibrate survey weights so as to match complex population parameters, instead of ordinary population totals.

When calibration benchmarks come in the form of population parameters that are complex, *non-linear* functions of auxiliary variables (like, in the present case, multiple regression coefficients), calibration constraints have to be linearized first. This generates *synthetic linearized variables* z , which are the *actual calibration variables* the calibration algorithm will eventually work on. Typically, *control totals* for these synthetic linearized variables z will *all* be *zero*. See, e.g. [Lesage, 2011].

Put briefly:

- Function `prep.calBeta` generates and binds to design the *synthetic linearized variables* z needed for the calibration task.
- Then, given the *prepared* design object returned by `prep.calBeta`, function `pop.calBeta` generates the *control totals* data frame for those z variables.

Of course, once prepared, survey data and control totals returned by the above functions will be fed in input to function `e.calibrate`, which will run the calibration task.

Function `prep.calBeta()`

Function `prep.calBeta` makes it possible to:

1. Calibrate on regression coefficients of *different linear models*, each known at the *overall population level*.
2. Calibrate on regression coefficients of a *single linear model*, known possibly for *different subpopulations*.

Note that, as detailed below, the key argument to switch from case 1. to case 2. is `by`. For extensive illustration of both the above cases 1. and 2., please see the ‘Examples’ section.

The mandatory argument `model` specifies the linear model(s) whose regression coefficients will be used as calibration benchmarks. Use a formula object to specify a *single* linear model, or a list of formula objects to specify *several* different linear models. For details on model specification, see e.g. [1m](#).

The design variables referenced by model formula(s) must be numeric or factor and must not contain any missing value (NA).

The mandatory argument Beta specifies the vector(s) of regression coefficients that will be used as calibration benchmarks. Use a numeric vector to specify regression coefficients of a *single* linear model, or a list of numeric vectors to specify regression coefficients of *several* different linear models. The Beta vector(s) must not contain any missing value (NA).

If argument model is passed as a list, argument Beta must be passed as a list too, and the length of both must be the same. If this is the case, Beta vectors will be *positionally* tied to linear model formulas contained in model.

Each vector of regression coefficients specified through Beta must be *consistent* with the corresponding model, namely match its model matrix columns (as generated using actual design data). Function prep.calBeta will check for this consistency and raise an informative error message in case of failure.

Note that, in order to ensure consistency with model, not only the length, but also the *order* of Beta elements *matters*. If in doubt, you can easily learn about the *right* ordering of Beta coefficients, given model, by calling function `svystatB` as follows: `svystatB(design, model)`. This will, of course, return the estimated regression coefficients of model *before* calibration.

Note that each Beta vector can have names or not. If a Beta vector has *names* that match the expected ones (given the corresponding model formula), but appear in a *different order*, then function prep.calBeta will suitably re-order them and inform you with a warning message.

As anticipated, argument by can be used to enable calibration on regression coefficients known at *domain level* (i.e. within subpopulations).

If passed, by must be a formula: for example, the statement `by=~B1:B2` defines as domains the subpopulations determined by crossing the modalities of variables B1 and B2. Notice that a formula like `by=~B1+B2` will be automatically translated into the factor-crossing formula `by=~B1:B2`. The design variables referenced by by (if any) should be of type factor, otherwise they will be coerced. Note that, to prevent obvious collinearity issues, the variables referenced by argument by must *not* appear in the input model formula: otherwise, the program will stop and print an error message.

If you specify domains through argument by, you will be allowed to specify *just a single* linear model through argument model. Instead, through argument Beta, you will have to specify domain-level vectors of regression coefficients. Therefore, Beta will be necessarily passed as a *list*. Note that, in this case, the Beta list must have as many components as the domains defined through argument by, and the two will be matched *positionally* by function prep.calBeta. Therefore, the *order* of elements in the Beta list *matters*. Specifically, Beta vectors must appear in the same order as the domains specified by argument by. You can easily learn about the *right* ordering of by domains (and hence Beta elements) by calling function `svystatB` as follows: `svystatB(design, model, by)`. This will, of course, return the estimated regression coefficients of model within by domains *before* calibration.

Lastly, if you specify domains through argument by, you will be allowed to decide whether design should be prepared for a *global* or a *partitioned* calibration task (see [e.calibrate](#)). Recall that partitioned calibration tasks are computationally more efficient, but produce exactly the same results. Note that, if you select `partition = TRUE`, then the *calibration domains* used to split the global calibration task will be the same domains specified via argument by. More explicitly: function [e.calibrate](#) will eventually be called on prep.calBeta's output object silently assuming `partition = by`.

The synthetic linearized variables `z` prepared by prep.calBeta will eventually be used by function [e.calibrate](#) to solve the calibration task. Argument `drop.z` allows you to instruct [e.calibrate](#) to drop these variables from its output object - or rather keep them within it - upon completion of the calibration task. The default has been set to `TRUE` to reduce memory usage. In case you want to be able to consistently trim weights after calibration via function [trimcal](#), you *must* specify `drop.z =`

FALSE.

Function pop.calBeta()

Given the *prepared* design object returned by `prep.calBeta`, function `pop.calBeta` generates the *control totals* data frame needed to run the calibration task. This dataframe suitably accomodates the control totals of the *synthetic linearized variables* `z` prepared by `prep.calBeta`.

Note that the data frame object returned by `pop.calBeta` is *already filled*, with control totals that are *all zero*, and it is ready to be directly passed to function `e.calibrate` (see the ‘Examples’ section).

Note, lastly, that printing this control totals data frame might not be very telling: to better understand its structure you should instead leverage function `pop.desc`, for which a method dedicated to ‘*special purpose calibration*’ tasks is available (see the ‘Examples’ section).

Value

- For function `pop.calBeta`, an object of the same class as `design`, storing the freshly created *synthetic linearized variables* `z` as columns of its `$variables` slot (see the ‘Examples’ section).
- For function `pop.calBeta`, a *control totals* data frame for those `z` variables, with class `spc.pop` (see the ‘Examples’ section).

Linear Algebra Remark

Contrary to ordinary calibration tasks, the control totals of a ‘special purpose calibration’ task are typically all zero. Therefore, calibration constraints of such tasks - unlike ordinary ones - define a system of linear equations that is *homogeneous*. Homogeneous systems always admit the trivial zero solution, which, in calibration terms, would mean output weights that are identically zero (and thus statistically unacceptable). For this reason, the possibility that function `e.calibrate` ends up with a *false convergence* of the special purpose calibration task cannot, in general, be ruled out. Note that functions `e.calibrate` and `check.cal` are able to detect such false convergence events and warn the user about it.

A satisfactory countermeasure to this issue is to set calibration bounds to any interval that does not include zero (see argument `bounds` of `e.calibrate`).

A second, very attractive alternative would be to run the special purpose calibration task *jointly* with some ordinary calibration task, as the joint calibration constraints would then define a *non-homogeneous* system. This solution can be obtained straightforwardly using function `pop.fuse`.

Author(s)

Diego Zardetto

References

Lesage, E. (2011). “The use of estimating equations to perform a calibration on complex parameters”. *Survey Methodology*. 37.

See Also

`e.calibrate` to calibrate weights, `svystatB` to compute estimates and sampling errors of Multiple Regression Coefficients, `pop.desc` to obtain a natural language description of control totals (including those for *special purpose calibration* tasks), `pop.fuse` to fuse population totals prepared for ordinary and special purpose calibration tasks.

Examples

```

# Load sbs data:
data(sbs)
# Create a design object:
sbsdes <- e.svydesign(data = sbs, ids = ~id, strata = ~strata,
                    weights = ~weight, fpc = ~fpc)

#####
# Calibrate on the regression coefficients of a *single model* known at the #
# *overall population level*                                           #
#####
# Suppose you know the coefficients of the following linear model, which you
# obtained fitting the model on some external source (e.g. Census or register
# data):
model0 <- y ~ emp.num*emp.cl

# Here, use the sbs sampling frame available in ReGenesees to simulate the
# external source and compute the values of the regression coefficients:
B0 <- coef(lm(model0, data = sbs.frame))
B0

# Now, prepare the survey design for calibration:
sbsdes0 <- prep.calBeta(design = sbsdes, model = model0, Beta = B0)

# Have a look at the freshly created *synthetic* auxiliary variables:
head(sbsdes0$variables)

# Then, prepare the control totals dataframe for the calibration task:
pop0 <- pop.calBeta(sbsdes0)

# Have a look...
class(pop0)
pop.desc(pop0)
# ...and note that all the control totals are zero!
pop0

# Lastly, calibrate:
sbscal0 <- e.calibrate(sbsdes0, pop0)

# Check that calibration estimates of regression coefficients now match the
# input B0 values derived from the external source:
svystatB(sbscal0, model0)
B0
# OK

#####
# Calibrate simultaneously on the regression coefficients of *different #
# models* known at the *overall population level*                       #
#####
# Suppose you know the coefficients of the following linear models, which you
# obtained fitting the models on some external sources
model1 <- va.imp2 ~ emp.num:emp.cl + nace.macro - 1
model2 <- y ~ dom3 - 1

# Here, use the sbs sampling frame available in ReGenesees to simulate the

```

```

# external sources and compute the values of the regression coefficients:
B1 <- coef(lm(model1, data = sbs.frame))
B2 <- coef(lm(model2, data = sbs.frame))

## First, just for illustration, calibrate only on B1 regression coefficients:
sbsdes1 <- prep.calBeta(sbsdes, model = model1, Beta = B1)
pop1 <- pop.calBeta(sbsdes1)
sbscal1 <- e.calibrate(sbsdes1, pop1)

# Check that calibration estimates of regression coefficients now match the
# input B1 values derived from the external source...
svystatB(sbscal1, model1)
B1
# ...but, of course, do *not* match those of B2:
svystatB(sbscal1, model2)
B2
# OK

## Second, just for illustration, calibrate only on B2 regression coefficients:
sbsdes2 <- prep.calBeta(sbsdes, model = model2, Beta = B2)
pop2 <- pop.calBeta(sbsdes2)
sbscal2 <- e.calibrate(sbsdes2, pop2)

# Check that calibration estimates of regression coefficients now match the
# input B2 values derived from the external source...
svystatB(sbscal2, model2)
B2
# ...but, of course, do *not* match those of B1:
svystatB(sbscal2, model1)
B1
# OK

## Now, calibrate *simultaneously* on *B1 and B2* regression coefficients
# Prepare the survey design for the joint calibration task:
sbsdes1_2 <- prep.calBeta(sbsdes, model = list(model1, model2), Beta = list(B1, B2))

# Prepare the control totals dataframe for the joint calibration task:
pop1_2 <- pop.calBeta(sbsdes1_2)

# Have a look to the control totals (note the presence of two models and
# Beta vectors):
pop.desc(pop1_2)
pop1_2

# Lastly, run the calibration:
sbscal1_2 <- e.calibrate(sbsdes1_2, pop1_2)

# Check that calibration estimates of regression coefficients now match *both*
# the B1 and B2 values derived from the external sources:
svystatB(sbscal1_2, model1)
B1
svystatB(sbscal1_2, model2)
B2
# OK

```

```
#####
```

```

# Calibrate simultaneously on the regression coefficients of a *single model* #
# known for *different subpopulations* #
#####
# NOTE: In this case, both *global* and *partitioned* calibration tasks are
#       possible, and both will be illustrated below.

# Suppose you know the coefficients of the following linear model, which you
# obtained fitting the model on some external source (e.g. Census or register
# data) *within subpopulations* defined by some factor variable(s):
model <- va.imp2 ~ emp.num:emp.cl + nace.macro - 1

# Here, use the sbs sampling frame available in ReGenesees to simulate the
# external source and suppose the subpopulations are defined by variable 'dom3'.
# Thus, compute the values of the regression coefficients as follows:
B <- by(sbs.frame, sbs.frame$dom3, function(df) coef(lm(model, data = df)))
B

## Let's start with the *global* solution
# Prepare the survey design for the calibration task (note that the 'by'
# argument is used):
sbsdes.g <- prep.calBeta(sbsdes, model, Beta = B, by = ~dom3)

# Prepare the control totals for the calibration task:
pop.g <- pop.calBeta(sbsdes.g)

# Have a look to the control totals (note the presence of one Beta vector *for
# each domain*):
pop.desc(pop.g)
pop.g

# Run the calibration:
sbscal.g <- e.calibrate(sbsdes.g, pop.g)

# Check that calibration estimates of regression coefficients now match the
# input B values derived from the external source *for each domain*:
svystatB(sbscal.g, model, ~dom3)
B
# OK

## Let's proceed with the *partitioned* solution
# Prepare the survey design for the calibration task (note that 'by' and
# 'partition' arguments are used):
sbsdes.p <- prep.calBeta(sbsdes, model, Beta = B, by = ~dom3, partition = TRUE)

# Prepare the control totals for the calibration task:
pop.p <- pop.calBeta(sbsdes.p)

# Have a look to the control totals (note the presence of one Beta vector *for
# each domain*):
pop.desc(pop.p)
pop.p

# Run the calibration:
sbscal.p <- e.calibrate(sbsdes.p, pop.p)

# Check that calibration estimates of regression coefficients now match the
# input B values derived from the external source *for each domain*:

```

```

svystatB(sbscal.p, model, ~dom3)
B
# OK

## Lastly, check that calibration weights obtained using the *global* and
## *partitioned* solution are the same:
g.range(sbscal.g)
g.range(sbscal.p)
all.equal(weights(sbscal.g), weights(sbscal.p))
# OK

#####
# BONUS TIP: Calibration on the mean (or on domain means) #
#           of one variable or multiple variables.      #
#####
# Since the domain mean of a numeric variable can be thought as a
# regression coefficient (see the 'Examples' section of ?svystatB),
# you can use the ReGenesees facilities documented above to
# *calibrate on the mean (or on domain means)* of *one variable
# or multiple variables*.
# NOTE: The examples below cover the following cases of calibration on:
#       (i) The overall mean of a single variable.
#       (ii) The means of a single variable within domains of just
#           one type.
#       (iii) The domain means of several variables, with multiple
#           and different domain types.

# Load artificial household survey data and define a survey design:
data(data.examples)
exdes <- e.svydesign(data = example, ids = ~towcod + famcod,
                   strata = ~SUPERSTRATUM, weights = ~weight)
exdes <- des.addvars(exdes, ones = 1)

## CASE (i): Calibrate on the overall mean of a single variable
# Suppose you know with satisfactory accuracy the *average income* of your
# target population (but you do *not* have reliable information on the
# *total income*, nor on the *total number of individuals*):
income.AVG <- 1270

# You can calibrate on *average income* as follows:
exdes.new <- prep.calBeta(exdes, income ~ 1, Beta = income.AVG)
pop.new <- pop.calBeta(exdes.new)
excal.new <- e.calibrate(exdes.new, pop.new)

# Now, check that calibration estimate of average income now match the known
# value derived from the external source *without residual uncertainty*:
svystatTM(excal.new, ~income, estimator = "Mean")
income.AVG

# ...while there is *residual uncertainty* in the estimates of the numerator and
# denominator totals:
svystatTM(excal.new, ~income + ones, estimator = "Total")
# OK

## CASE (ii): Calibrate on the means of a single variable within domains
#             of just one kind

```



```

# You can calibrate on *domain means* along the lines illustrated above (note,
# however, that argument 'by' would provide an alternative way to achieve
# the same result).
# Suppose you know with satisfactory accuracy the *average income* by the
# crossclassification of sex and marital status:
income.AVG.sex.marstat <- c(f.married = 1310, m.married = 1260,
                           f.unmarried = 1150, m.unmarried = 1200,
                           f.widowed = 1380, m.widowed = 1300)

# Run the calibration on *average income by sex:marstat* as follows:
exdes.new <- prep.calBeta(exdes, income ~ sex:marstat -1,
                        Beta = income.AVG.sex.marstat)
pop.new <- pop.calBeta(exdes.new)
excal.new <- e.calibrate(exdes.new, pop.new)

# Now, check that calibration estimates of average income by domains now match
# the known values derived from the external source *without residual
# uncertainty*:
svystatTM(excal.new, ~income, ~sex:marstat, estimator = "Mean")
income.AVG.sex.marstat

# ...while there is *residual uncertainty* in the estimates of the numerator and
# denominator totals:
svystatTM(excal.new, ~income + ones, ~sex:marstat, estimator = "Total")
# OK

## CASE (iii): Calibrate on the domain means of several variables, with multiple
#               and different domain types.
# Suppose you know with satisfactory accuracy:
# - the average income by sex:
# - the average income by marstat:
# - the average of variable z by age (variable 'age5c', 5 classes):
income.AVG.sex <- c("f" = 1245, "m" = 1250)
income.AVG.marstat <- c("married" = 1260, "unmarried" = 1230, "widowed" = 1290)
z.AVG.age5c <- c("1" = 125, "2" = 130, "3" = 135, "4" = 125, "5" = 140)

# Run the calibration as follows:
exdes.new <- prep.calBeta(exdes, model = list(income ~ sex -1,
                                             income ~ marstat -1,
                                             z ~ age5c -1),
                        Beta = list(income.AVG.sex,
                                   income.AVG.marstat,
                                   z.AVG.age5c)
                                )
pop.new <- pop.calBeta(exdes.new)
excal.new <- e.calibrate(exdes.new, pop.new)

# Now, check that calibration estimates match the known domain means derived
# from the external source:
svystatTM(excal.new, ~income, ~sex, estimator = "Mean")
income.AVG.sex
svystatTM(excal.new, ~income, ~marstat, estimator = "Mean")
income.AVG.marstat
svystatTM(excal.new, ~z, ~age5c, estimator = "Mean")
z.AVG.age5c
# OK

```

ReGenesees.options *Variance Estimation Options for the ReGenesees Package*

Description

This help page documents the options that control the behaviour of the **ReGenesees** package with respect to standard error estimation.

Details

The **ReGenesees** package provides four options for variance estimations which can be freely set and modified by the user:

- RG.ultimate.cluster
- RG.lonely.psu
- RG.adjust.domain.lonely
- RG.warn.domain.lonely

When `options("RG.ultimate.cluster")` is TRUE, the **ReGenesees** package adopts the so called “*Ultimate Cluster Approximation*” [Kalton 79]. Under this approximation, the overall sampling variance for a multistage sampling design is estimated by taking into account only the contribution arising from the estimated PSU totals (thus simply ignoring any available information about subsequent sampling stages). For without replacement sampling designs, this approach is known to underestimate the true multistage variance, while - at the same time - overestimating its true first-stage component. Anyway, the underestimation error becomes negligible if the PSUs’ sampling fractions across strata are very small. When sampling with replacement, the Ultimate Cluster approach is no longer an approximation, but rather an exact result. Hence, be `options("RG.ultimate.cluster")` TRUE or FALSE, if one does not specify first-stage finite population corrections, **ReGenesees** will produce exactly the same variance estimates.

When `options("RG.ultimate.cluster")` is FALSE, each sampling stage contributes and variances get estimated by means of a recursive algorithm [Bellhouse, 85] inherited and adapted from package **survey** [Lumley 06]. Notice that the results obtained by choosing this option can differ from the one that would be obtained under the “Ultimate Cluster Approximation” *only if* first-stage finite population corrections are specified.

Lonely PSUs (i.e. PSUs which are alone inside a not self-representing stratum) are a concern from the viewpoint of variance estimation. The suggested **ReGenesees** facility to handle the lonely PSUs problem is the strata aggregation technique (see e.g. [Wolter 07] and [Rust, Kalton 87]) provided in function `collapse.strata`. As a possible alternative, you can get rid of lonely PSUs also by setting proper variance estimation options via `options("RG.lonely.psu")`. The default setting is “fail”, which raises an error if a lonely PSU is met. Option “remove” simply causes the software to ignore lonely PSUs for variance computation purposes. Option “adjust” means that deviations from the *population mean* will be used in variance estimation formulae, instead of deviations from the stratum mean (a conservative choice). Finally, option “average” causes the software to replace the variance contribution of the stratum by the average variance contribution across strata (this can be appropriate e.g. when one believes that lonely PSU strata occur at random due to uniform nonresponse among strata).

The variance formulae for domain estimation give well-defined, positive results when a stratum contains only a single PSU with observations falling in the domain, but are not unbiased.

If `options("RG.adjust.domain.lonely")` is TRUE and `options("RG.lonely.psu")` is “average”

or "adjust" the same adjustment for lonely PSUs will be used within a domain. Note that this adjustment is not available for calibrated designs.

If `options("RG.warn.domain.lonely")` is set to TRUE, a warning message is raised whenever an estimation domain happens to contain just a single PSU belonging to a stratum. The default is FALSE.

References

- Kalton, G. (1979). "Ultimate cluster sampling", *Journal of the Royal Statistical Society, Series A*, 142, pp. 210-222.
- Bellhouse, D. R. (1985). "Computing Methods for Variance Estimation in Complex Surveys". *Journal of Official Statistics*, Vol. 1, No. 3, pp. 323-329.
- Lumley, T. (2006) "survey: analysis of complex survey samples", <https://CRAN.R-project.org/package=survey>.
- Wolter, K.M. (2007) "Introduction to Variance Estimation", Second Edition, Springer-Verlag, New York.
- Rust, K., Kalton, G. (1987) "Strategies for Collapsing Strata for Variance Estimation", *Journal of Official Statistics*, Vol. 3, No. 1, pp. 69-81.

See Also

[e.svydesign](#) and its `self.rep.str` argument for a "compromise solution" that can be adopted when the sampling design involves self-representing (SR) strata, [collapse.strata](#) for the suggested way of handling lonely PSUs, and [fpcdat](#) for useful data examples.

Examples

```
# Define a two-stage stratified cluster sampling without
# replacement:
data(fpcdat)
des<-e.svydesign(data=fpcdat,ids=~psu+ssu,strata=~stratum,weights=~w,
  fpc=~fpc1+fpc2)

# Now compare SE (or CV%) sizes under different settings:

## 1) Default setting, i.e. Ultimate Cluster Approximation is off
svystatTM(des,~x+y+z,vartype=c("se","cvpct"))

## 2) Turn on the Ultimate Cluster Approximation, thus missing
##    the variance contribution from the second stage
##    (hence SR strata give no contribution at all):
old.op <- options("RG.ultimate.cluster"=TRUE)
svystatTM(des,~x+y+z,vartype=c("se","cvpct"))
options(old.op)

## 3) The "compromise solution" (see ?e.svydesign) i.e. retaining
##    only the leading contribution to the sampling variance (namely
##    the one arising from SSUs in SR strata and PSUs in not-SR strata):
des2<-e.svydesign(data=fpcdat,ids=~psu+ssu,strata=~stratum,weights=~w,
  fpc=~fpc1+fpc2, self.rep.str=~sr)
svystatTM(des2,~x+y+z,vartype=c("se","cvpct"))

# Therefore, sampling variances come out in the expected
# hierarchy: 1) > 3) > 2).
```

```
# Under default settings lonely PSUs produce errors in standard
# errors estimation (notice we didn't pass the fpcs):
data(fpcdat)
des.lpsu<-e.svydesign(data=fpcdat,ids=~psu+ssu,strata=~stratum,
                    weights=~w)
## Not run:
svystatTM(des.lpsu,~x+y+z,vartype=c("se","cvpct"))

## End(Not run)

# This can be circumvented in different ways, namely:
old.op <- options("RG.lonely.psu"="adjust")
svystatTM(des.lpsu,~x+y+z,vartype=c("se","cvpct"))
options(old.op)

# or:
old.op <- options("RG.lonely.psu"="average")
svystatTM(des.lpsu,~x+y+z,vartype=c("se","cvpct"))
options(old.op)

# or otherwise by collapsing strata inside planned
# estimation domains:
des.clps<-collapse.strata(design=des.lpsu,block.vars=~pl.domain)
svystatTM(des.clps,~x+y+z,vartype=c("se","cvpct"))
```

sbs

Artificial Structural Business Statistics Data

Description

The `sbs` data frame stores artificial sbs-like sampling data, while `sbs.frame` is the artificial sampling frame from which the `sbs` units have been drawn. They allow to run R code contained in the ‘Examples’ section of the **ReGenesees** package help pages.

Usage

```
data(sbs)
```

Format

The `sbs` data frame mimics data observed in a Structural Business Statistics survey, under a one-stage stratified unit sampling design. The sample is made up of 6909 units, for which the following 22 variables were observed:

`id` Identifier of the sampling units (enterprises), numeric
`public` Does the enterprise belong to the Public Sector? factor with levels 0 (No) and 1 (Yes)
`emp.num` Number of employees, numeric
`emp.c1` Number of employees classified into 5 categories, factor with levels [6, 9] (9, 19] (19, 49] (49, 99] (99, Inf] (notice that small enterprises with less than 6 employees fell outside the scope of the survey)

nace5 Economic Activity code with 5 digits, factor with 596 levels
 nace2 Economic Activity code with 2 digits, factor with 57 levels
 area Territorial Division, factor with 24 levels
 cens Flag identifying statistical units to be censused (hence defining take-all strata), factor with levels 0 (No) and 1 (Yes)
 region Macroregion, factor with levels North Center South
 va.cl Class of Value Added, factor with 27 levels
 va Value Added, numeric (contains NAs)
 dom1 A planned estimation domain, factor with 261 levels (dom1 crosses nace2 and emp.cl)
 nace.macro Economic Activity Macrosector, factor with levels Agriculture Industry Commerce Services
 dom2 A planned estimation domain, factor with 12 levels (dom2 crosses nace.macro and region)
 strata Stratification Variable, a factor with 664 levels (obtained by crossing variables region, nace2, emp.cl and cens)
 va.imp1 Value Added Imputed1, numeric (NAs were replaced with average values computed inside imputation strata obtained by crossing region, nace.macro, emp.cl)
 va.imp2 Value Added Imputed2, numeric (NAs were replaced with median values computed inside imputation strata obtained by crossing region, nace.macro, emp.cl)
 y A numeric variable correlated with va
 weight Direct weights, numeric
 fpc Finite Population Corrections (given as sampling fractions inside strata), numeric
 ent Convenience numeric variable identically equal to 1 (sometimes useful, e.g. to estimate the total number of enterprises)
 dom3 An unplanned estimation domain, factor with 4 levels

The sbs.frame sampling frame (from which sbs units have been drawn) contains 17318 units.

Examples

```
data(sbs)
head(sbs)
str(sbs)
str(sbs.frame)
```

smooth.strat.jump

Smooth Weights to Cope with Stratum Jumpers

Description

Given a stratified one-stage unit sampling design object, this function smooths survey weights to mitigate estimation issues that may arise from stratum jumpers.

Usage

```
smooth.strat.jump(design, curr.strata, method = c("MinChange", "Beaumont"))
```

Arguments

design	Object of class <code>analytic</code> containing the weights to be smoothed. It must be a one-stage unit sampling design object. Moreover, it must be a non-calibrated object. See ‘Details’.
curr.strata	Formula identifying the <i>current</i> strata variable, as observed at survey-time (see ‘Details’).
method	The smoothing method (see ‘Details’). The default method ‘MinChange’ smooths the weight of stratum jumpers almost without affecting the weights of other units. Method ‘Beaumont’ adopts a much more aggressive smoothing strategy, which may result in significant modifications of the weights also for units that are <i>not</i> stratum jumpers (see ‘Examples’).

Details

In business surveys, stratum jumpers are sampling units (e.g. firms or establishments) whose stratum information observed at survey-time happens to differ from the stratum information that was available in the sampling frame at design-time.

If the current value of the strata variable (i.e. the one observed at survey-time) is reliable, stratum jumpers are evidence of frame imperfections (typically, the frame was not up-to-date). Empirically, stratum jumpers are often units that underwent a fast growth in size from sampling-time to survey-time.

In most enterprise surveys the sampling design is such that smaller firms receive a smaller inclusion probability (and hence a larger design weight). Therefore, stratum jumpers often have a “too large” weight, in the sense that they would have received a smaller weight had their actual size been known at sampling-time. When these units also happen to have a large value of interest variable y , they may become influential in estimation. Even though stratum jumpers may exist in household surveys too, business surveys are much more exposed to the risk that stratum jumpers unduly influence estimation, as their target populations are typically highly skewed with respect to many interest variables. As a consequence, in business surveys, stratum jumpers can result in inefficient (and, under some circumstances, even biased) design-based estimators.

Despite stratum jumpers are actually a concern only when both their design weight w and their y value (as measured at survey-time) conspire to yield an influential value of $w * y$, function `smooth.strat.jump` tries to mitigate their potential adverse impact by smoothing the weights *without* using any information on y . Such a choice is driven by two major aims. First, the methodology must preserve the universality of the weights (i.e. the same weights must be used to compute estimates for whatever interest variables y). Second, the methodology should not require explicit modeling efforts and be easy enough to scale to production settings that need automated and replicable procedures.

Argument `design` identifies the survey design object that is (possibly) affected by stratum jumpers and contains the weights that will be smoothed. In case no stratum jumpers are found, the function will raise an error. Object `design` can only be a one-stage unit sampling design. Moreover, it must be a non-calibrated object. Should any of these conditions be false, the function would raise an error. Note, lastly, that function `smooth.strat.jump` will not smooth further weights that have already been smoothed. This is a deliberate design choice, devised to discourage over-smoothing and cosmetic adjustments of the survey weights.

Formula `curr.strata` defines the *current* strata variable, as observed at survey-time. This is different from the *design* strata variable used to build object `design` using function `e.svydesign`, as the latter was measured at sampling-time. Function `smooth.strat.jump` will flag as stratum jumpers all the units whose *current* stratum differs from the *design* one. Note that the function will handle properly even design objects whose strata were collapsed for variance estimation purposes (via `collapse.strata`), by accessing and using the original *non-collapsed* design strata. Note that, in

case *current* strata become available only after object design was created, you may use function `des.addvars` to add this new column to the old object.

The weight smoothing process entails two steps:

1. The weights are smoothed according to a given method (see below): $w \rightarrow w_1$
2. The weights w_1 of all units are scaled by a global factor so as to preserve the initial overall sum of weights: $w_1 \rightarrow w_2 = \text{scale} * w_1$ with $\text{scale} = \text{sum}(w) / \text{sum}(w_1)$

Argument `method` controls the smoothing algorithm. Two methods can be selected: 'MinChange' (the default) and 'Beaumont' (which implements the proposal of [Beaumont, Rivest 09]). Note that the methods only differ with respect to step 1., as step 2. is identical for both of them.

The step 1 working mechanism of these methods can be summarized as follows:

- **'MinChange'**

Only the weights of stratum jumpers are smoothed, by setting their value to the average weight of units belonging to the same *current* stratum. Weights of all other units are left unchanged.

- **'Beaumont'**

The weights of all units are smoothed, by setting their value to the average weight of units belonging to the same *current* stratum, with the exception of *minimum weight* units, whose weights are left unchanged. Therefore all weights, excluding only minimum weights within each current stratum, are smoothed. Note that this smoothing affects all current strata, even those that do *not* include any stratum jumper.

In summary, both methods often lead to very similar smoothed weights for units that are stratum jumpers. However method 'Beaumont' smooths the weights of all other (i.e. *non* stratum jumpers) units much more aggressively than method 'MinChange' (which only minimally alters them in step 2. to preserve the overall sum of weights). Moreover, method 'MinChange' treats stratum jumpers that grew in size and those that decreased in size on the same footing, whereas method 'Beaumont' typically smooths the weights of the former more than those of the latter (owing to its minimum weight preservation constraint, see 'Examples').

Note that every call to `smooth.strat.jump` generates, by side effect, a diagnostics data structure named `strat.jump.status` into the `.GlobalEnv` (see 'Examples'). This is a data frame with one row for each stratum jumper unit, with the following columns:

Column	Meaning
IDS.....	Unit identifier
W.....	Initial weight
DES_STR.....	Design stratum
DES_STR_W_AVG.....	Average of initial weights within the design stratum
CURR_STR.....	Current stratum
CURR_STR_W_AVG.....	Average of initial weights within the current stratum
N_JUMP_DES_CURR_STR....	Number of stratum jumpers that jumped between the design stratum and the current stratum (NOTE: in any direction)
W_SMOOTH_UNSC.....	Unscaled smoothed weight (as obtained after step 1)
W_SMOOTH.....	Smoothed weight (scaled, as obtained after step 2)

Value

An object of the same class as `design`. The data frame it contains (stored in its `$variables` slot) includes the smoothed weights columns and a column that flags the stratum jumpers. The name of the smoothed weights column is obtained by pasting the name of the initial weights column with the string `".smooth"`. Stratum jumpers are identified by a new (logical) column named `is.jumper`.

Methodological Remark

Smoothing survey weights is a model-based approach, see [Beaumont 08] (e.g. `method = 'Beaumont'` basically models the smoothed weights as a function of the current strata using a one-way ANOVA model plus constraints). Therefore Horvitz-Thompson-like estimators that use smoothed weights - instead of design weights - cannot be guaranteed to be design-unbiased. Of course, the need to smooth the weights arises precisely because the existence of stratum jumpers already signals a departure from the ideal conditions of design-based inference.

As the design-unbiasedness of Horvitz-Thompson estimators in probability sampling rests on using design weights that are reciprocals of inclusion probabilities, smoothing methods that change the design weights the least appear preferable in a design-based perspective. For this reason, function `smooth.strat.jump` adopts the `'MinChange'` method by default. One could, nonetheless, argue that the `'Beaumont'` method could sometimes perform better (e.g. lead to more efficient estimates) from a model-based perspective.

Regardless the choice of argument `method`, in order to reduce any possible design-bias introduced by smoothing the weights, users are advised to *calibrate the smoothed weights* using any auxiliary information available from external sources that are *more up-to-date* than the sampling frame.

Author(s)

Diego Zardetto

References

- Beaumont, J. F. (2008). A new approach to weighting and inference in sample surveys. *Biometrika*, 95(3), 539-553.
- Beaumont, J. F., Rivest, L. P. (2009). Dealing with outliers in survey data. In *Handbook of statistics* (Vol. 29, pp. 247-279). Elsevier.

See Also

[e.svydesign](#) to bind survey data and sampling design metadata and [e.calibrate](#) for calibrating smoothed survey weights by leveraging auxiliary information that is more up-to-date than the sampling frame (a warmly suggested option).

Examples

```
#####
# Build [Beaumont, Rivest 09] example dataset, containing: #
# - a first stratum 'A' that, at survey time, contains one large weight stratum #
#   jumper received from design-stratum 'B' #
# - a second stratum 'B' that, at survey time, does not contain stratum jumpers #
# #
# and enhance it with: #
# - a third stratum 'C' that, at survey time, does not contain stratum jumpers #
# - a fourth stratum 'D' that, at survey time, does not contain stratum jumpers #
# - a fifth stratum 'E' that, at survey time, contains two stratum jumpers, both #
```



```

# received from design-stratum 'D', one with small and one with medium weight #
#####
BR <- data.frame(
  id = 1:90,
  des.strata = factor(rep(c("A", "B", "C", "D", "E"), c(9, 41, 10, 20, 10))),
  curr.strata = factor(rep(c("A", "B", "C", "D", "E"), c(10, 40, 10, 19, 11))),
  w = c(rep(c(1, 31), c(9, 41)), c(27, 28, 22, 26, 11, 12, 13, 30, 17, 21), 2:21, 11:2)
)
BR$curr.strata[61] <- "E"

# Have a look at the data:
BR

# Have a look at the jumps:
with(BR, table(des.strata, curr.strata))

# Use the BR data frame to build a one stage stratified unit sampling design:
BRdes <- e.svydesign(data=BR, ids=~id, strata=~des.strata, weights=~w)

## Now smooth the weights:
## Method: MinChange (the default)
M.smooth <- smooth.strat.jump(BRdes, ~curr.strata)
M.smooth

# Have a look at the new columns:
head(M.smooth$variables)

# Inspect the effects of smoothing on the stratum jumpers:
strat.jump.status

## Method: Beaumont
B.smooth <- smooth.strat.jump(BRdes, ~curr.strata, method = "Beaumont")
B.smooth

# Inspect the effects of smoothing on the stratum jumpers:
strat.jump.status

## As anticipated, smoothed weights of stratum jumpers are mostly similar for
## both methods. However the methods differ significantly when it comes to non
## stratum jumpers. This is clearly shown in the following plots.

## Plot 1 - START
opar <- par("mfcol" = c(1, 2))

# M.smooth
with(M.smooth$variables, plot(w, w.smooth, pch = c(19, 15)[1 + is.jumper],
  col = c("black", "red")[1 + is.jumper], cex = c(1,1.2)[1 + is.jumper],
  xlab = "Original Weights", ylab = "Smoothed Weights",
  main = "method: MinChange"))
abline(0:1, col = "limegreen", lwd = 2, lty = 2)

legend("topleft",
  legend = c("Stratum Jumper", "Non Stratum Jumper"),
  col = c("red", "black"),
  pch = c(15, 19),
  bty = "n",

```

```

text.col = "black",
inset = c(0.05, 0.05)
)

# B.smooth
with(B.smooth$variables, plot(w, w.smooth, pch = c(19, 15)[1 + is.jumper],
  col = c("black", "red")[1 + is.jumper], cex = c(1,1.2)[1 + is.jumper],
  xlab = "Original Weights", ylab = "Smoothed Weights",
  main = "method: Beaumont"))
abline(0:1, col = "limegreen", lwd = 2, lty = 2)

legend("topleft",
  legend = c("Stratum Jumper", "Non Stratum Jumper"),
  col = c("red", "black"),
  pch = c(15, 19),
  bty = "n",
  text.col = "black",
  inset = c(0.05, 0.05)
)

par(opar)
## Plot 1 - END

## Plot 2 - START
# M.smooth
with(M.smooth$variables, plot(w, pch = 20, col = curr.strata,
  ylab = "Original and Smoothed Weights",
  main = "method: MinChange \n(colors identify different current strata)"))
with(M.smooth$variables, points(w.smooth, pch = 0, col = curr.strata))

legend("topright",
  legend = c("Original Weight", "Smoothed Weight"),
  col = rep("grey", 2),
  pch = c(20, 0),
  text.col = "black",
  inset = c(0.01, 0.01)
)

# B.smooth
with(B.smooth$variables, plot(w, pch = 20, col = curr.strata,
  ylab = "Original and Smoothed Weights",
  main = "method: Beaumont \n(colors identify different current strata)"))
with(B.smooth$variables, points(w.smooth, pch = 0, col = curr.strata))

legend("topright",
  legend = c("Original Weight", "Smoothed Weight"),
  col = rep("grey", 2),
  pch = c(20, 0),
  text.col = "black",
  inset = c(0.01, 0.01)
)
## Plot 2 - END

# Although, as seen above, non-negligible differences in smoothed weights exist
# at unit level, both methods perform similarly in terms of strata averages...
## Initial weights, design strata:
with(BR, tapply(w, des.strata, mean))

```

```
## Initial weights, current strata:
with(BR, tapply(w, curr.strata, mean))

## Smoothed weights, current strata, method MinChange:
with(M.smooth$variables, tapply(w.smooth, curr.strata, mean))

## Smoothed weights, current strata, method Beaumont:
with(B.smooth$variables, tapply(w.smooth, curr.strata, mean))

# ...as expected
```

svyDelta

Estimation of a Measure of Change from Two Not Necessarily Independent Samples

Description

Computes estimates and sampling errors of a Measure of Change from two not necessarily independent samples. The Measure of Change can be any analytic function of Horvitz-Thompson or Calibration estimators derived from the two samples.

Usage

```
svyDelta(expr, design1, design2, by = NULL,
         des.INDEP = FALSE, rho.STRAT = c("Full", "noJump", "noStrat"),
         vartype = c("se", "cv", "cvpct", "var"),
         conf.int = FALSE, conf.lev = 0.95)
```

```
details(object, print.call = TRUE, ...)
```

```
## S3 method for class 'svyDelta'
coef(object, ...)
## S3 method for class 'svyDelta'
SE(object, ...)
## S3 method for class 'svyDelta'
VAR(object, ...)
## S3 method for class 'svyDelta'
cv(object, ...)
## S3 method for class 'svyDelta'
confint(object, ...)
```

Arguments

expr	R expression defining the Measure of Change (see svystatL for the basic syntax; see also section ‘Details’).
design1	Object of class <code>analytic</code> (or inheriting from it) containing survey data and sampling design metadata related to the first sample. See ‘Details’.
design2	Object of class <code>analytic</code> (or inheriting from it) containing survey data and sampling design metadata related to the second sample. See ‘Details’.

<code>by</code>	Formula specifying the variables that define the "estimation domains". If NULL (the default option) estimates refer to the whole population. See 'Details'.
<code>des.INDEP</code>	Have the samples in <code>design1</code> and <code>design2</code> been selected independently? The default is FALSE. See 'Details'.
<code>rho.STRAT</code>	To which extent should stratification be considered when estimating correlations? The default is "Full", which accommodates even <i>dynamic stratification</i> but can sometimes be too computationally demanding. See 'Details' and 'Methodological and Computational Remarks' for alternatives.
<code>vartype</code>	character vector specifying the desired variability estimators. It is possible to choose one or more of: standard error ('se', the default), coefficient of variation ('cv'), percent coefficient of variation ('cvpct'), or variance ('var').
<code>conf.int</code>	Compute confidence intervals for the estimates? The default is FALSE.
<code>conf.lev</code>	Probability specifying the desired confidence level: the default value is 0.95.
<code>object</code>	An object created by invoking function <code>svyDelta</code> , about which details are sought.
<code>print.call</code>	Print on screen the call of <code>svyDelta</code> that generated the input object?
<code>...</code>	Additional arguments to <code>coef</code> , ..., <code>confint</code> methods (if any). For function details, arguments for future extensions (currently unused).

Details

Function `svyDelta` computes estimates and sampling errors of a Measure of Change from two not necessarily independent samples.

For 'Measure of Change' we mean here any function that can be used to compare cross-sectional estimates of two population parameters derived from two samples. The easiest Measure of Change is the simple difference between the estimators of the same population parameter referred to two distinct survey occasions. Estimating this difference and its sampling variance is central to hypothesis testing (e.g. for impact evaluation). More complex Measures of Change can of course be considered, for instance nonlinear ones, like the relative difference between two estimators. In addition, the cross-sectional estimators being compared in the Measure of Change can themselves be complex (i.e. expressed as nonlinear functions of Horvitz-Thompson or Calibration estimators).

Function `svyDelta` can accommodate all the cases sketched above.

When the two samples being analyzed are independent, estimating the sampling variance of a simple Measure of Change is fairly straightforward: one just has to add variance estimates derived from the two samples. The problem becomes non-trivial when the two samples are not independent, because sampling covariance terms come into play. Yet, the analysis of non-independent samples is often required in concrete applications, including panel studies (with or without sample rotation), repeated cross-sectional surveys making use of coordinated samples, quasi-experimental designs in which control and treatment groups share some level of sampling information (e.g. observations are taken within same PSUs), etc.

If the samples in `design1` and `design2` are not independent, function `svyDelta` estimates the needed sampling covariance terms following the method of [Berger, Priam 16]. Note that this method derives design-based covariance estimates from estimates of *correlation* (`rho`), which are computed in the first place.

If the Measure of Change is *complex*, `svyDelta` automatically linearizes it. Automatic linearization is performed as function `svystatL` would do, along the lines illustrated in [Zardetto, 15], see also section 'Methodological and Computational Remarks' below.

The mandatory argument `expr`, which identifies the Measure of Change, must be an object of class expression. You can specify just a single Measure of Change at a time, i.e. `length(expr)` must

be equal to 1. Any analytic function of estimators of Totals and Means derived from the two input design objects `design1` and `design2` is allowed.

The basic syntax follows the same rules described for function `svystatL`. Inside `expr`, the estimator of the Total of a variable is simply represented by the *name* of the variable itself. The reserved name `ones` can be used to reference an artificial variable (which will be created on-the-fly, if not already present) whose value is 1 for each sampling unit, so that its Total estimator actually estimates the size of the population in terms of elementary units. Therefore, expression `y/ones` represents the estimator of the Mean of variable `y`. Variables referenced inside `expr` must be numeric and belong to `design1` and/or `design2`.

To unequivocally associate each variable either to `design1` or to `design2`, suffixes `'.1'` and `'.2'` must always be used. This makes it possible to reuse the same variable names across the two samples. For instance, expression `(y.1 - y.2)`, represents the difference between the Totals of `y` estimated from `design1` and `design2`, respectively. Similarly, expression `((y.1 - y.2) / y.1)` represents the relative difference of the same Totals (using the estimate derived from the first sample as reference value). Along the same vein, the difference between the Means of `y` estimated from `design1` and `design2` can be specified as expression `(y.1/ones.1 - y.2/ones.2)`. Likewise, expression `(y.1/x.1 - y.2/x.2)` represents the difference between estimates of a Ratio derived from `design1` and `design2`.

The mathematical expression of the Measure of Change, as specified by argument `expr`, can involve 'parameters', that is *symbols* representing given, non-random, scalar, numeric *values*. For each parameter appearing in `expr`, the value corresponding to its symbol will be searched following R standard scoping rules.

Although function `svyDelta` is very general and flexible, when the samples are *non-independent* (i.e. `des.INDEP = FALSE`, see below), some restrictions exist on arguments `design1` and `design2`:

1. Objects `design1` and `design2` must be either both stratified or both unstratified: mixed cases are not allowed.
2. Objects `design1` and `design2` must be either both element sampling designs or both cluster sampling designs: mixed cases are not allowed.
3. Objects `design1` and `design2` can be both uncalibrated, both calibrated, or even one uncalibrated and the other calibrated (i.e. mixed cases are allowed).

The method of [Berger, Priam 16] can handle non-independent samples with fixed (i.e. non-random) overlap (including the limiting cases of no overlap and full overlap, for which it reproduces "classical" covariance estimates). Therefore, in order for function `svyDelta` to work properly, it is a fundamental requirement that the overlapping portion of `design1` and `design2` can be unequivocally identified. To this end, **the identifiers of sampling units originally used by function `e.svydesign` to define objects `design1` and `design2` (or, if they are calibrated, their uncalibrated counterparts) must be consistent**. Note that function `svyDelta` will use those same identifiers as keys to merge the survey data of `design1` and `design2` and thereby identify their overlapping subsample. Since, for multi-stage designs, the method of [Berger, Priam 16] resorts to the ultimate cluster approximation, in those cases the fundamental piece of information actually concerns the identifier of the PSUs of `design1` and `design2`: it is crucial that the latter can be used to identify PSUs that are common to both samples.

The optional argument `by` specifies the variables that define the "estimation domains", that is the subpopulations for which the estimates are to be calculated. If `by=NULL` (the default option), the estimates produced by `svyDelta` refer to the whole population. If specified, estimation domains must be defined by a formula, following the usual syntactic and semantic rules (see e.g. `svystatL`). Variables referenced in `by` must be common to both `design1` and `design2`, and suffixes `'.1'` and `'.2'` must not be used for them.

Concerning domain estimation, a methodological caveat is in order. Since the method of [Berger, Priam 16] handles non-independent samples assuming their overlap is fixed, in case design1 and design2 are not independent one should use svyDelta only for *planned* estimation domains, namely domains that can be obtained by aggregation of sampling strata. In any case, even considering unplanned estimation domains, point estimates produced by svyDelta will still be correct.

Argument `des.INDEP` must be used to tell svyDelta whether the samples in design1 and design2 were selected independently or not (the default is FALSE). Note that this argument is indeed necessary, because in *finite population sampling* there is always a chance that two independent samples have a non-null overlap. Therefore, in case of any overlap in design1 and design2, function svyDelta will behave differently depending on the value you specify for `des.INDEP`:

- If `des.INDEP = FALSE`, then any overlap will be regarded as non-accidental and intended by design, thereby triggering the method of [Berger, Priam 16] for calculating the correlation terms needed to estimate the sampling variance of the Measure of Change.
- If `des.INDEP = TRUE`, then any overlap will be regarded as accidental and not intended by design, thereby leading to the sampling variance estimate of the Measure of Change that is appropriate for independent samples.

Note that, when the samples are declared to be *independent* by setting `des.INDEP = TRUE`, even the above restrictions 1. and 2. on objects design1 and design2 are obviously lifted, and function svyDelta can be used to compare estimators coming from arbitrarily mixed sampling designs (e.g. stratified element vs. unstratified cluster).

When non-independent samples with sizable overlap are concerned (e.g. for rotating panel surveys), the method of [Berger and Priam 2016] may become *computationally demanding*, especially for highly stratified unit sampling designs (see section ‘Methodological and Computational Remarks’). In such cases, if the invocation of svyDelta with the default setting `rho.STRAT = "Full"` resulted in unaffordable computation time or memory-failure on your machine, you might want to resort to lighter, but approximate, alternatives:

- If `rho.STRAT = "noJump"`, then function svyDelta will disregard the contribution of units that changed stratum from design1 to design2 (if any) when estimating correlation terms (`rho`). Note that, in case no such units actually exist, the result will be the *same* that would be obtained with the default setting `rho.STRAT = "Full"`, only it will be achieved *using much less computing time and memory*.
- If `rho.STRAT = "noStrat"`, then function svyDelta will entirely disregard stratification when estimating correlation terms (`rho`). This sometimes results in *huge computing time and memory savings*.

In the light of the above, setting `rho.STRAT = "noJump"` seems a *very sound option* in many concrete large-scale applications (see section ‘Methodological and Computational Remarks’).

Note, in any case, that both the approximations `rho.STRAT = "noJump"` and `rho.STRAT = "noStrat"` are restricted to *correlation* terms only: all the other terms involved in the estimator of the sampling variance of the Measure of Change will still be calculated by properly and fully taking into account the stratification of design1 and design2.

The `conf.int` argument allows to request the confidence intervals for the estimates. By default `conf.int=FALSE`, that is the confidence intervals are not provided.

Whenever confidence intervals are requested (i.e. `conf.int=TRUE`), the desired confidence level can be specified by means of the `conf.lev` argument. The `conf.lev` value must represent a probability ($0 \leq \text{conf.lev} \leq 1$) and its default is chosen to be 0.95.

Function `details` provides more details about the results of function svyDelta. It takes in input an object returned by svyDelta, and prints on screen that object together with additional diagnostic

information. This additional information (see also section ‘Methodological and Computational Remarks’) is stored in a data frame with one row and the following columns:

Column	Meaning
n1.....	Sample size of design1 (in terms of elements or PSUs, depending on the sampling design)
n2.....	Sample size of design2 (in terms of elements or PSUs, depending on the sampling design)
nc.....	Size of the overlapping sample between design1 and design2
overlap...	Rate of overlap: $nc / ((n1 + n2) / 2)$
V1.....	Estimated sampling variance of the linearized Measure of Change, arranged in standard difference form, w.r.t. design1: $V1(L.1)$
V2.....	Estimated sampling variance of the linearized Measure of Change, arranged in standard difference form, w.r.t. design2: $V2(L.2)$
Vind.....	Estimated sampling variance of the linearized Measure of Change, as would be obtained if design1 and design2 were independent: $V1 + V2$
rho.....	Estimated sampling correlation between L.1 and L.2
CoV.....	Estimated sampling covariance between L.1 and L.2: $\rho * \sqrt{V1} * \sqrt{V2}$
V.....	Estimated sampling variance of the linearized Measure of Change w.r.t. design1 and design2 jointly: $V1 + V2 - 2 * CoV$

Note that the same data frame is also invisibly returned by function details.

Value

An object inheriting from the `data.frame` class, whose detailed structure depends on input parameters’ values.

Methodological and Computational Remarks

The method proposed by [Berger and Priam 2016] estimates correlations (ρ) using the estimated residual variance-covariance matrix of a suitable multivariate regression model. The explanatory variables of this multivariate regression model encode information about stratification, and overlap of the two samples. However, the estimation approach remains fully design-based (i.e. not model-based), because the multivariate regression model is exploited only to make calculations easier, whereas its validity is never assumed, nor used, for inferential purposes.

As already mentioned, the method of [Berger and Priam 2016] assumes instead that (i) the size of both samples and, importantly, of their overlapping subsample is fixed, and that (ii) sampling fractions are negligible in both samples. For multi-stage designs, both conditions (i) and (ii) should be fulfilled at the PSU-level.

When stratified designs are concerned, the method is flexible enough to handle *dynamic stratification*. More explicitly, the sample at time 2 can include new strata that were not present at time 1, and sampling units that are common to both samples can belong to different strata at time 1 and 2. However, as already mentioned, this flexibility comes with a computational cost, which can become prohibitive for highly stratified sampling designs.

If no units exist that changed stratum from design1 to design2, then correlations can be estimated exactly using a more parsimonious multivariate regression model than the one of [Berger and Priam 2016] (i.e. a model with less interaction terms). This is triggered by `rho.STRAT = "noJump"`. This option allows for remarkable savings in computing time and memory usage, and typically results in a very good approximation when a moderate number of units actually changed stratum.

In extreme cases, the option of entirely disregarding stratification when estimating correlations (triggered by setting `rho.STRAT = "noStrat"`) can sometimes be the only viable solution, at least in ordinary computing environments. Unfortunately, however, the inferential effect of this approximation (e.g. whether it leads to over-estimation or under-estimation) is unclear.

Complex Measures of Change, expressed as nonlinear functions of Horvitz-Thompson or Calibration estimators derived from the two samples, are inherently challenging, and would still be so even for independent samples. To estimate the sampling variance of a *complex* Measure of Change, `svyDelta` automatically linearizes the estimator specified by argument expression, call it **Delta**. Automatic linearization is performed as in function `svystatL`, along the lines illustrated in [Zardetto, 15]. Put briefly:

1. Woodruff transforms of the estimator **Delta** are derived with respect to `design1` and `design2`, respectively.
2. In case any of the two input designs is calibrated, the Woodruff transform associated to it and computed in step 1. includes the appropriate residuals of the involved variables with respect to the calibration model.
3. The linearized expression of the Measure of Change **Delta** is re-arranged in standard difference form, $\mathbf{L.Delta} = \mathbf{L.1} - \mathbf{L.2}$, where **L.1** and **L.2** are linear functions of the previously computed Woodruff transforms with suitable signs.
4. The method of [Berger and Priam 2016] is applied to **L.Delta** to derive the estimate of the correlation between **L.1** and **L.2** (this is the `rho` value that can be extracted using function `details`).
5. The other terms of the variance of **L.Delta** are estimated using the respective sampling designs separately.
6. The overall estimate of the variance of **L.Delta** is re-constructed using the terms computed in steps 4. and 5.

Author(s)

Diego Zardetto

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- Sarndal, C.E., Swensson, B., Wretman, J. (1992) "*Model Assisted Survey Sampling*", Springer Verlag.

See Also

Estimators of Complex Analytic Functions of Totals and/or Means `svystatL`. Estimators of Totals and Means `svystatTM`, Ratios between Totals `svystatR`, Shares `svystatS`, Ratios between Shares `svystatSR`, Multiple Regression Coefficients `svystatB`, Quantiles `svystatQ`, and all of the above `svystat`.

Examples

```
#####
# Basic usage and trivial consistency checks. #
#####
## Load two non-independent stratified samples of *elementary units*, s1 and s2,
## with 40% overlap (see ?Delta.el)
data(Delta.el)

# Define the design objects
# s1
des1 <- e.svydesign(ids = ~id, strata = ~strata, weights = ~w, data = s1)
des1

# s2
des2 <- e.svydesign(ids = ~id, strata = ~strata, weights = ~w, data = s2)
des2

# Estimate the difference between cross-sectional estimates of the Total of
# variable y
d <- svyDelta(expression(y.2 - y.1), des1, des2)
d

# Now, to know if the difference is statistically significant at alpha = 0.05,
# just see whether the confidence interval covers 0
confint(d)
# it does not, thus the difference is significant

# Have a look at the details, e.g. the estimated correlation rho
details(d)
# ...so rho ~ 0.2

# Can check some of that figures in the details above:
Y1 <- svystatTM(des1, ~y)
Y1
VAR(Y1) # Equal to V1 in details above

Y2 <- svystatTM(des2, ~y)
Y2
VAR(Y2) # Equal to V2 in details above

coef(d)
coef(Y2) - coef(Y1) # Exactly matched, as it must be

## Function svyDelta handles *cluster samples* essentially the same way. The key
## is this time the identifier of PSUs.
## Load two non-independent stratified *cluster samples*, sclus1 and sclus2,
## with 50% overlap at the PSU-level (see ?Delta.clus)
data(Delta.clus)

# Define the design objects
# sclus1
dclus1 <- e.svydesign(ids = ~id, strata = ~strata, weights = ~w, data = sclus1)
dclus1

# sclus2
```

```

dclus2 <- e.svydesign(ids = ~id, strata = ~strata, weights = ~w, data = sclus2)
dclus2

# Estimate the difference between cross-sectional estimates of the Total of
# variable y
d <- svyDelta(expression(y.2 - y.1), dclus1, dclus2)
d

# Check statistical significance at alpha = 0.05
confint(d)
# strongly significant (would be so at alpha = 0.01 too)

# Have a look at the details, e.g. the estimated correlation rho
details(d)
# ...so, this time, rho ~ 0.9

# NOTE: If one compared the estimates assuming independence, i.e. disregarding
#       sampling correlations, the difference would be wrongly considered
#       statistically not significant (see the size of Vind above).
#       In fact:
d <- svyDelta(expression(y.2 - y.1), dclus1, dclus2, des.INDEP = TRUE)
details(d)

# Check statistical significance at alpha = 0.05
confint(d)
# non-significant, as anticipated.

#####
# Complex Measures of Change. #
#####

## Relative difference (percent) between Totals of y at time 2 and time 1:
d <- svyDelta(expression( 100 * (y.2 - y.1) / y.1 ), des1, des2)
details(d, print.call = FALSE)

## Difference between Means of y at time 2 and time 1:
d <- svyDelta(expression( y.2/ones.2 - y.1/ones.1 ), des1, des2)
details(d, print.call = FALSE)

## Relative difference between Ratios Y/X at time 2 and time 1:
d <- svyDelta(expression( (y.2/x.2 - y.1/x.1) / (y.1/x.1) ), des1, des2)
details(d, print.call = FALSE)

# NOTE: For the cases above, you may want to perform the same checks illustrated
#       for the simple difference between Totals, using suitable ReGenesees
#       functions

#####
# Examples with calibrated objects. #
#####
# Suppose that:
# (1) Population size was N = 500 at time 1, and N = 501 at time 2
# (2) Total of x was X = 1810 at time 1, and X = 1770 at time 2

# Calibrate on the auxiliary information (1) and (2) above:

```

```

# design1
des1 <- des.addvars(des1, ones = 1)
pop1 <- pop.template(des1, calmodel = ~ ones + x - 1)
pop1[,] <- c(500, 1810)
pop1
descal1 <- e.calibrate(des1, pop1)

# design2
des2 <- des.addvars(des2, ones = 1)
pop2 <- pop.template(des2, calmodel = ~ ones + x - 1)
pop2[,] <- c(501, 1770)
pop2
descal2 <- e.calibrate(des2, pop2)

# Compare the estimates of change:
## Calibration estimators
d <- svyDelta(expression(y.2 - y.1), descal1, descal2)
details(d, print.call = FALSE)

## Horvitz-Thompson estimators
d <- svyDelta(expression(y.2 - y.1), des1, des2)
details(d, print.call = FALSE)

# Technically, you can estimate changes in mixed situations, comparing e.g.
# Horvitz-Thompson estimators at time 1 with Calibration estimators at time 2:
## Mix HT and CAL
d <- svyDelta(expression(y.2 - y.1), des1, descal2)
details(d, print.call = FALSE)

#####
# Dynamic stratification and computational efficiency. #
#####
## Stratification of s1 and s2 is static (see ?Delta.el).
# Therefore the full complexity setting (rho.STRAT = "Full", the default), and
# the alternative and *much more efficient setting* which disregards stratum-
# changer units (if any) in estimating correlations (rho.STRAT = "noJump") will
# yield identical results:

## rho.STRAT = "Full"
d <- svyDelta(expression(y.2 - y.1), des1, des2)
details(d, print.call = FALSE)

## rho.STRAT = "noJump"
d <- svyDelta(expression(y.2 - y.1), des1, des2, rho.STRAT = "noJump")
details(d, print.call = FALSE)

## identical results, as it must be.

## Now check the implications of dynamic stratification.
# Simulate new strata at time 2 (new level "C"):
levels(s2$strata) <- c("A", "B", "C")
# and stratum-changer units from s1 to s2:
s2$strata[4] <- "C"
s2$strata[14] <- "A"
s2$strata[16] <- "C"
s2$strata[20] <- "C"

```

```

# Have a look at the resulting rotation structure of s1 and s2:
s <- merge(s1, s2, by = "id", all = TRUE, suffixes = c("1", "2"))
s <- s[order(s$strata1, s$strata2), ]
s

# Check that strata are dynamic: one unit jumped from "A" to "C", one from "B"
# to "A", and one from "B" to "C":
with(s, table(strata1, strata2, useNA = "ifany"))

# Now recreate object des2 using the updated s2 data
des2 <- e.svydesign(ids = ~id, strata = ~strata, weights = ~w, data = s2)

# And re-do the comparison:
## rho.STRAT = "Full"
d <- svyDelta(expression(y.2 - y.1), des1, des2)
details(d, print.call = FALSE)

## rho.STRAT = "noJump"
d <- svyDelta(expression(y.2 - y.1), des1, des2, rho.STRAT = "noJump")
details(d, print.call = FALSE)

## The results are slightly different, as expected.

## However, the approximation obtained adopting option rho.STRAT = "noJump"
## is *very good*, and - importantly - *far more efficient* (computation is way
## less memory-hungry and remarkably faster).

## You may want to run the same comparison using real-world stratified samples
## to really appreciate the efficiency gain.

```

svySigma

Estimation of the Population Standard Deviation of a Variable

Description

Computes estimates and sampling errors of the Population Standard Deviation of a numeric variable (in subpopulations too).

Usage

```

svySigma(design, y, by = NULL,
         fin.pop = TRUE,
         vartype = c("se", "cv", "cvpct", "var"),
         conf.int = FALSE, conf.lev = 0.95, deff = FALSE,
         na.rm = FALSE)

## S3 method for class 'svySigma'
coef(object, ...)
## S3 method for class 'svySigma'
SE(object, ...)
## S3 method for class 'svySigma'
VAR(object, ...)

```

```
## S3 method for class 'svySigma'
cv(object, ...)
## S3 method for class 'svySigma'
confint(object, ...)
```

Arguments

<code>design</code>	Object of class <code>analytic</code> (or inheriting from it) containing survey data and sampling design metadata.
<code>y</code>	Formula identifying the <i>numeric</i> interest variable.
<code>by</code>	Formula specifying the variables that define the "estimation domains". If <code>NULL</code> (the default option) estimates refer to the whole population.
<code>fin.pop</code>	If <code>TRUE</code> (the default) the estimation target is the <i>finite</i> population formula of the standard deviation, i.e. the one with $N - 1$ at denominator in the expression of the variance. If <code>FALSE</code> the estimation target is the standard deviation with N at denominator in the expression of the variance.
<code>vartype</code>	character vector specifying the desired variability estimators. It is possible to choose one or more of: standard error ('se', the default), coefficient of variation ('cv'), percent coefficient of variation ('cvpct'), or variance ('var').
<code>conf.int</code>	Compute confidence intervals for the estimates? The default is <code>FALSE</code> .
<code>conf.lev</code>	Probability specifying the desired confidence level: the default value is 0.95.
<code>deff</code>	Should the design effect be computed? The default is <code>FALSE</code> (see 'Details').
<code>na.rm</code>	Should missing values (if any) be removed from the variable of interest? The default is <code>FALSE</code> (see 'Details').
<code>object</code>	An object of class <code>svySigma</code> .
<code>...</code>	Additional arguments to <code>coef</code> , ..., <code>confint</code> methods (if any).

Details

Function `svySigma` computes estimates and sampling errors of the Population Standard Deviation of a numeric variable. These estimates play an important role in many contexts, including sample size guesstimation and power calculations.

As the Population Standard Deviation is a *complex* estimator, `svySigma` automatically linearizes it to estimate its sampling variance. Automatic linearization is performed as function `svystatL` would do, along the lines illustrated in [Zardetto, 15]. This, of course, also entails the usage of the residuals technique when the input design object is calibrated (i.e. of class `cal.analytic`).

The mandatory argument `y` identifies the variable of interest. The design variable referenced by `y` must be *numeric*.

If variable `y` is binary (i.e. has only values 0 and 1), the estimated Population Standard Deviation coincides with the classical Bernoulli expression $\sqrt{p(1 - p)}$, where p is the estimated proportion of population units with $y = 1$ (see 'Examples').

The optional argument `by` specifies the variables that define the "estimation domains", that is the subpopulations for which the estimates are to be calculated. If `by=NULL` (the default option), the estimates produced by `svySigma` refer to the whole population. If specified, estimation domains must be defined by a formula, following the usual syntactic and semantic rules (see e.g. `svystatTM`).

Argument `fin.pop` allows the users to select which standard deviation formula they prefer as estimation target. If `fin.pop = TRUE` (the default) the *finite* population version of the standard deviation formula will be used, namely the one with $N - 1$ at denominator in the expression of the variance

[Sarndal, Swensson, Wretman 92]. If `fin.pop = FALSE` the standard deviation formula with `N` at denominator in the expression of the variance will be used.

The `conf.int` argument allows to request the confidence intervals for the estimates. By default `conf.int=FALSE`, that is the confidence intervals are not provided.

Whenever confidence intervals are requested (i.e. `conf.int=TRUE`), the desired confidence level can be specified by means of the `conf.lev` argument. The `conf.lev` value must represent a probability ($0 \leq \text{conf.lev} \leq 1$) and its default is chosen to be `0.95`.

The optional argument `deff` allows to request the design effect [Kish 1995] for the estimates. By default `deff=FALSE`, that is the design effect is not provided. The design effect of an estimator is defined as the ratio between the sampling variance of the estimator under the actual sampling design and the sampling variance that would be obtained for an 'equivalent' estimator under a hypothetical simple random sampling without replacement of the same size. To obtain an estimate of the design effect comparing to simple random sampling "*with replacement*", one must use `deff="replace"`. See [svystatTM](#) for further details.

Missing values (NA) in interest variables should be avoided. If `na.rm=FALSE` (the default) they generate NAs in estimates (or even an error, if design is calibrated). If `na.rm=TRUE`, observations containing NAs are dropped, and estimates get computed on non missing values only. This implicitly assumes that missing values hit interest variables *completely at random*: should this not be the case, computed estimates would be *biased*.

Value

An object inheriting from the `data.frame` class, whose detailed structure depends on input parameters' values.

Author(s)

Diego Zardetto

References

- Sarndal, C.E., Swensson, B., Wretman, J. (1992) "*Model Assisted Survey Sampling*", Springer Verlag.
- Kish, L. (1995). "*Methods for design effects*". Journal of Official Statistics, Vol. 11, pp. 55-77.
- Zardetto, D. (2015) "*ReGenesees: an Advanced R System for Calibration, Estimation and Sampling Error Assessment in Complex Sample Surveys*". Journal of Official Statistics, 31(2), 177-203. doi: <https://doi.org/10.1515/jos-2015-0013>.

See Also

Function [svySigma2](#) to estimate the Population Variance of a numeric variable. Estimators of Complex Analytic Functions of Totals and/or Means [svystatL](#). Estimators of Totals and Means [svystatTM](#), Ratios between Totals [svystatR](#), Shares [svystatS](#), Ratios between Shares [svystatSR](#), Multiple Regression Coefficients [svystatB](#), Quantiles [svystatQ](#), and all of the above [svystat](#).

Examples

```
## Load sbs data and create a design object:
data(sbs)
sbsdes <- e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,
                    fpc=~fpc)
```

```

# Estimation of the population standard deviation of value added (variable
# 'va.imp2'):
svySigma(sbsdes, ~va.imp2, vartype = "cvpct", conf.int = TRUE, deff = TRUE)

# Compare with the true value computed from the sampling frame ('sbs.frame'):
sqrt(var(sbs.frame$va.imp2))

# The same as above, by classes of macro-class of economic activity ('nace.macro'):
svySigma(sbsdes, ~va.imp2, ~nace.macro, vartype = "cvpct", conf.int = TRUE)

# Compare with the true value computed from the sampling frame ('sbs.frame'):
sqrt(tapply(sbs.frame$va.imp2, sbs.frame$nace.macro, var))

## An example with a binary variable
# Load household data and create a design object:
data(data.examples)
des<-e.svydesign(data=example,ids=~towcod+famcod,strata=~SUPERSTRATUM,
  weights=~weight)

# Build the indicator variable of the 'widowed' marital status:
des<-des.addvars(des, is.widowed = as.numeric(marstat == "widowed"))

# Estimate and store the population proportion of widowed people:
svystatTM(des, ~is.widowed, estimator = "Mean")
# which of course is equal to what one would get directly:
svystatTM(des, ~marstat, estimator = "Mean")

# Store only the estimated proportion
p.widowed <- coef(svystatTM(des, ~is.widowed, estimator = "Mean"))

# Now estimate the population variance of the binary variable 'is.widowed' *with
# fin.pop = FALSE*, and verify that it *exactly* equals the Bernoulli expression
# sqrt(p.widowed * (1 - p.widowed))
svySigma(des, ~is.widowed, fin.pop = FALSE, conf.int = TRUE)
sqrt(p.widowed * (1 - p.widowed))

# ...as it must be.

```

svySigma2

*Estimation of the Population Variance of a Variable***Description**

Computes estimates and sampling errors of the Population Variance of a numeric variable (in sub-populations too).

Usage

```

svySigma2(design, y, by = NULL,
  fin.pop = TRUE,
  vartype = c("se", "cv", "cvpct", "var"),
  conf.int = FALSE, conf.lev = 0.95, deff = FALSE,
  na.rm = FALSE)

```

```
## S3 method for class 'svySigma2'
coef(object, ...)
## S3 method for class 'svySigma2'
SE(object, ...)
## S3 method for class 'svySigma2'
VAR(object, ...)
## S3 method for class 'svySigma2'
cv(object, ...)
## S3 method for class 'svySigma2'
confint(object, ...)
```

Arguments

<code>design</code>	Object of class <code>analytic</code> (or inheriting from it) containing survey data and sampling design metadata.
<code>y</code>	Formula identifying the <i>numeric</i> interest variable.
<code>by</code>	Formula specifying the variables that define the "estimation domains". If <code>NULL</code> (the default option) estimates refer to the whole population.
<code>fin.pop</code>	If <code>TRUE</code> (the default) the estimation target is the <i>finite</i> population formula of the variance, i.e. the one with the N - 1 denominator. If <code>FALSE</code> the estimation target is the population variance with the N denominator.
<code>vartype</code>	character vector specifying the desired variability estimators. It is possible to choose one or more of: standard error (' <code>se</code> '), the default, coefficient of variation (' <code>cv</code> '), percent coefficient of variation (' <code>cvpct</code> '), or variance (' <code>var</code> ').
<code>conf.int</code>	Compute confidence intervals for the estimates? The default is <code>FALSE</code> .
<code>conf.lev</code>	Probability specifying the desired confidence level: the default value is <code>0.95</code> .
<code>deff</code>	Should the design effect be computed? The default is <code>FALSE</code> (see 'Details').
<code>na.rm</code>	Should missing values (if any) be removed from the variable of interest? The default is <code>FALSE</code> (see 'Details').
<code>object</code>	An object of class <code>svySigma2</code> .
<code>...</code>	Additional arguments to <code>coef</code> , ..., <code>confint</code> methods (if any).

Details

Function `svySigma2` computes estimates and sampling errors of the Population Variance of a numeric variable. These estimates play an important role in many contexts, including sample size guesstimation and power calculations.

As the Population Variance is a *complex* estimator, `svySigma2` automatically linearizes it to estimate its sampling variance. Automatic linearization is performed as function `svyestatL` would do, along the lines illustrated in [Zardetto, 15]. This, of course, also entails the usage of the residuals technique when the input design object is calibrated (i.e. of class `cal.analytic`).

The mandatory argument `y` identifies the variable of interest. The design variable referenced by `y` must be `numeric`.

If variable `y` is binary (i.e. has only values 0 and 1), the estimated Population Variance coincides with the classical Bernoulli expression $p \cdot (1 - p)$, where p is the estimated proportion of population units with $y = 1$ (see 'Examples').

The optional argument `by` specifies the variables that define the "estimation domains", that is the subpopulations for which the estimates are to be calculated. If `by=NULL` (the default option), the

estimates produced by `svySigma2` refer to the whole population. If specified, estimation domains must be defined by a formula, following the usual syntactic and semantic rules (see e.g. [svystatTM](#)).

Argument `fin.pop` allows the users to select which population variance formula they prefer as estimation target. If `fin.pop = TRUE` (the default) the *finite* population version of the variance formula will be used, namely the one with the $N - 1$ denominator [Sarndal, Swensson, Wretman 92]. If `fin.pop = FALSE` the population variance formula with the N denominator will be used.

The `conf.int` argument allows to request the confidence intervals for the estimates. By default `conf.int=FALSE`, that is the confidence intervals are not provided.

Whenever confidence intervals are requested (i.e. `conf.int=TRUE`), the desired confidence level can be specified by means of the `conf.lev` argument. The `conf.lev` value must represent a probability ($0 \leq \text{conf.lev} \leq 1$) and its default is chosen to be 0.95.

The optional argument `deff` allows to request the design effect [Kish 1995] for the estimates. By default `deff=FALSE`, that is the design effect is not provided. The design effect of an estimator is defined as the ratio between the sampling variance of the estimator under the actual sampling design and the sampling variance that would be obtained for an 'equivalent' estimator under a hypothetical simple random sampling without replacement of the same size. To obtain an estimate of the design effect comparing to simple random sampling "*with replacement*", one must use `deff="replace"`. See [svystatTM](#) for further details.

Missing values (NA) in interest variables should be avoided. If `na.rm=FALSE` (the default) they generate NAs in estimates (or even an error, if design is calibrated). If `na.rm=TRUE`, observations containing NAs are dropped, and estimates get computed on non missing values only. This implicitly assumes that missing values hit interest variables *completely at random*: should this not be the case, computed estimates would be *biased*.

Value

An object inheriting from the `data.frame` class, whose detailed structure depends on input parameters' values.

Author(s)

Diego Zardetto

References

- Sarndal, C.E., Swensson, B., Wretman, J. (1992) "*Model Assisted Survey Sampling*", Springer Verlag.
- Kish, L. (1995). "*Methods for design effects*". Journal of Official Statistics, Vol. 11, pp. 55-77.
- Zardetto, D. (2015) "*ReGenesees: an Advanced R System for Calibration, Estimation and Sampling Error Assessment in Complex Sample Surveys*". Journal of Official Statistics, 31(2), 177-203. doi: <https://doi.org/10.1515/jos-2015-0013>.

See Also

Function [svySigma](#) to estimate the Population Standard Deviation of a numeric variable. Estimators of Complex Analytic Functions of Totals and/or Means [svystatL](#). Estimators of Totals and Means [svystatTM](#), Ratios between Totals [svystatR](#), Shares [svystatsS](#), Ratios between Shares [svystatSR](#), Multiple Regression Coefficients [svystatB](#), Quantiles [svystatQ](#), and all of the above [svystat](#).

Examples

```
## Load sbs data and create a design object:
data(sbs)
sbsdes <- e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,
                    fpc=~fpc)

# Estimation of the population variance of value added (variable 'va.imp2'):
svySigma2(sbsdes, ~va.imp2, vartype = "cvpct", conf.int = TRUE, deff = TRUE)

# Compare with the true value computed from the sampling frame ('sbs.frame'):
var(sbs.frame$va.imp2)

# The same as above, by classes of macro-class of economic activity ('nace.macro'):
svySigma2(sbsdes, ~va.imp2, ~nace.macro, vartype = "cvpct", conf.int = TRUE)

# Compare with the true value computed from the sampling frame ('sbs.frame'):
tapply(sbs.frame$va.imp2, sbs.frame$nace.macro, var)

## An example with a binary variable
# Load household data and create a design object:
data(data.examples)
des<-e.svydesign(data=example,ids=~towcod+famcod,strata=~SUPERSTRATUM,
                weights=~weight)

# Build the indicator variable of the 'widowed' marital status:
des<-des.addvars(des, is.widowed = as.numeric(marstat == "widowed"))

# Estimate and store the population proportion of widowed people:
svystatTM(des, ~is.widowed, estimator = "Mean")
# which of course is equal to what one would get directly:
svystatTM(des, ~marstat, estimator = "Mean")

# Store only the estimated proportion
p.widowed <- coef(svystatTM(des, ~is.widowed, estimator = "Mean"))

# Now estimate the population variance of the binary variable 'is.widowed' *with
# fin.pop = FALSE*, and verify that it *exactly* equals the Bernoulli expression
# p.widowed * (1 - p.widowed)
svySigma2(des, ~is.widowed, fin.pop = FALSE, conf.int = TRUE)
p.widowed * (1 - p.widowed)

# ...as it must be.
```

svystat

Compute Many Estimates and Errors in Just a Single Shot

Description

Computes many estimates and errors (e.g. for disparate estimation domains) in just a single shot, primarily to use them in fitting GVF models. Can handle estimators of all kinds.

Usage

```
svystat(design, kind = c("TM", "R", "S", "SR", "B", "Q", "L", "Sigma", "Sigma2"),
```

```

        by = NULL, group = NULL, forGVF = TRUE,
        combo = -1, ...)

## S3 method for class 'gvf.input.gr'
plot(x, ...)

## S3 method for class 'svystat.gr'
coef(object, ...)
## S3 method for class 'svystat.gr'
SE(object, ...)
## S3 method for class 'svystat.gr'
VAR(object, ...)
## S3 method for class 'svystat.gr'
cv(object, ...)
## S3 method for class 'svystat.gr'
deff(object, ...)
## S3 method for class 'svystat.gr'
confint(object, ...)

```

Arguments

design	Object of class <code>analytic</code> (or inheriting from it) containing survey data and sampling design metadata.
kind	character specifying the summary statistics function to call: it may be 'TM' (i.e. <code>svystatTM</code> , the default), 'R' (i.e. <code>svystatR</code>), 'S' (i.e. <code>svystatS</code>), 'SR' (i.e. <code>svystatSR</code>), 'B' (i.e. <code>svystatB</code>), 'Q' (i.e. <code>svystatQ</code>), 'L' (i.e. <code>svystatL</code>), 'Sigma' (i.e. <code>svySigma</code>), and 'Sigma2' (i.e. <code>svySigma2</code>).
by	Formula specifying the variables that define the "estimation domains". If <code>NULL</code> (the default option) estimates refer to the whole population.
group	Formula specifying a partition of the population into "groups": the output will be returned separately for each group. If <code>NULL</code> (the default option) the output is returned as a whole.
forGVF	Select <code>TRUE</code> (the default) if you want to use the output to fit a GVF model. Otherwise, the output will be simply a set of summary statistics objects.
combo	An integer which is only meaningful if <code>by</code> is passed. Requests to compute outputs for all the domains determined by crossing the <code>by</code> variables <i>up to</i> a given order (see 'Details').
...	For function <code>svystat</code> , additional arguments to the summary statistic function implied by <code>kind</code> . Otherwise, further arguments passed to or from other methods.
x	The object of class <code>gvf.input.gr</code> to plot.
object	An object of class <code>svystat.gr</code> containing survey statistics.

Details

This function can compute *all* the summary statistics provided by **ReGenesees**, and is principally meant to return a lot of them in just a single shot.

If `forGVF = TRUE` the output will be ready to feed **ReGenesees** GVF fitting infrastructure, otherwise it will consist simply of a set of summary statistic objects.

Use argument `kind` to specify the summary statistic you need. The default value 'TM' selects function `svystatTM`, which yields Totals and Means. All the arguments needed by the summary

statistic function implied by `kind` (e.g. argument `y` for `svystatTM` when `kind = 'TM'`) will be passed on through argument `'...'`.

As usual in summary statistics, argument `by` can be used to request domain estimates.

The group formula (if any) specifies a way of partitioning the population into groups: the output will be reported separately for each group. In the GVF context, a “*grouped*” output will permit to fit *separate* GVF models inside different groups (and hence to compute separate variance predictions for different groups).

Note that `group` and `by` share identical syntax and semantics as model formulae, despite they have different purposes in function `svystat` (as explained above).

Parameter `combo` is *only* meaningful if `by` is passed. Its purpose is to allow computing estimates and errors simultaneously for many estimation domains.

If the `by` formula involves `n` variables, specifying `combo = m` requests to compute outputs for all the domains determined by all the interactions of `by` variables *up to* order `m` (with $-1 \leq m \leq n$), as follows:

COMBO	MEANING
<code>m = -1.....</code>	'no combo', i.e. treat 'by' formula as usual (the default);
<code>m = 0.....</code>	'order zero' combination, i.e. just a single domain: the whole population;
<code>m = 1.....</code>	'order zero' plus 'order one' combinations, the latter being all the marginal domains defined by 'by' variables;
<code>m = n.....</code>	combinations of any order, the maximum being the one with all 'by' variables interacting simultaneously.

The `plot` method can be used *only* when `forGVF = TRUE` and produces a matrix (or many matrices, if `group` is passed) of scatterplots with polynomial smoothers.

Methods `coef`, `SE`, `VAR`, `cv`, `deff`, and `confint` can be used *only* when `forGVF = FALSE`, to extract estimates and variability statistics.

Value

An object storing estimates and errors, whose detailed structure depends on input parameters' values.

If `forGVF = FALSE`, a set of summary statistics possibly stored into a list (with class `svystat.gr` in the most general case).

If `forGVF = TRUE` and argument `group` is *not* passed, an object of class `gvf.input`.

If `forGVF = TRUE` and argument `group` is passed, an object of class `gvf.input.gr`. This is a list of objects of class `gvf.input`, each one pertaining to a different population group.

Author(s)

Diego Zardetto

See Also

`estimator.kind` to assess what kind of estimates are stored inside a survey statistic object, `gvf.input` as an alternative to prepare the input for GVF model fitting, `GVF.db` to manage **ReGenesees** archive of registered GVF models, `fit.gvf` to fit GVF models, `plot.gvf.fit` to get diagnostic plots for fitted GVF models, `drop.gvf.points` to drop alleged outliers from a fitted GVF model and simultaneously refit it, and `predictCV` to predict CV values via fitted GVF models.

Examples

```
# Load sbs data:
data(sbs)

# Create a design object:
sbsdes<-e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,fpc=~fpc)

#####
# svystat as an alternative way to compute 'ordinary' summary statistics #
#####
## Total number of employees
svystat(sbsdes,y=~emp.num,forGVF=FALSE)
# equivalent to:
svystatTM(sbsdes,y=~emp.num)

## Average number of employees per enterprise
svystat(sbsdes,y=~emp.num,estimator="Mean",forGVF=FALSE)
# equivalent to:
svystatTM(sbsdes,y=~emp.num,estimator="Mean")

## Average value added per employee by economic activity macro-sector
## (nace.macro):
svystat(sbsdes,kind="R",num=~va.imp2,den=~emp.num,by=~nace.macro,forGVF=FALSE)
# equivalent to:
svystatR(sbsdes,num=~va.imp2,den=~emp.num,by=~nace.macro)

## Counts of employees by classes of number of employees (emp.cl) crossed
## with economic activity macro-sector (nace.macro):
svystat(sbsdes,y=~emp.num,by=~emp.cl:nace.macro,forGVF=FALSE)
# equivalent to:
svystatTM(sbsdes,y=~emp.num,by=~emp.cl:nace.macro)

## Provided forGVF = FALSE, you can use estimator.kind on svystat output:
stat<-svystat(sbsdes,kind="R",num=~va.imp2,den=~emp.num,by=~emp.cl:nace.macro,
              group=~region,forGVF=FALSE)
stat
estimator.kind(stat,sbsdes)

#####
# Understanding syntax and semantics of argument 'combo' #
#####
# Load household data:
data(data.examples)

# Create a design object:
houdes<-e.svydesign(data=example,ids=~towcod+famcod,strata=~SUPERSTRATUM,
                  weights=~weight)

# Add convenience variable 'ones' to estimate counts:
houdes<-des.addvars(houdes,ones=1)

## To facilitate understanding, let's for the moment keep forGVF = FALSE.
## Let's use estimates and errors of counts of individuals by sex and
## five age classes (age5c):
```

```

svystat(houdes,y=~ones,by=~age5c:sex,forGVF=FALSE)

## Now let's play with argument 'combo':
# combo = -1
# -> 'no combo', i.e. treat 'by' formula as usual
svystat(houdes,y=~ones,by=~age5c:sex,forGVF=FALSE,combo=-1)

# combo = 0
# -> 'order zero' combination, i.e. just a single domain: the whole population
svystat(houdes,y=~ones,by=~age5c:sex,forGVF=FALSE,combo=0)

# combo = 1
# -> 'order zero' plus 'order one' combinations, the latter being all the
#     marginal domains defined by 'by' variables
svystat(houdes,y=~ones,by=~age5c:sex,forGVF=FALSE,combo=1)

# combo = 2
# -> since 'by' has 2 variables, this means combinations of any order up to
#     the maximum
svystat(houdes,y=~ones,by=~age5c:sex,forGVF=FALSE,combo=2)

# combo = 3
# -> yields an error, as 'combo' cannot exceed the number of 'by' variables
#     (2 in this example)
## Not run:
svystat(houdes,y=~ones,by=~age5c:sex,forGVF=FALSE,combo=3)

## End(Not run)

#####
# svystat as an alternative way to prepare input data for GVF models #
#####
## The same estimates and errors of the last example above, now with
## forGVF = TRUE: note the different output data format
svystat(houdes,y=~ones,by=~age5c:sex,combo=2)

## Note that the agile command above is indeed equivalent to the following
## lengthier, cumbersome statement:
gvf.input(houdes,
          svystatTM(houdes,y=~ones),
          svystatTM(houdes,y=~ones,by=~age5c),
          svystatTM(houdes,y=~ones,by=~sex),
          svystatTM(houdes,y=~ones,by=~age5c:sex)
          )

#####
# Using argument 'group' to prepare input data #
# for separate GVF models #
#####
## The same estimates and errors of the last example above, now prepared
## separately for different regions (regcod):
svystat(houdes,y=~ones,by=~age5c:sex,combo=2,group=~regcod)

## Again the same estimates and errors, prepared separately for groups
## defined crossing marital status (marstat) and region:

```

```

svystat(houdes,y=~ones,by=~age5c:sex,combo=2,group=~marstat:regcod)

## NOTE: Output has class "gvf.input.gr". This will tell ReGenesees' GVF
##       fitting facilities to handle estimates and errors pertaining to
##       different groups independently of each other.

## NOTE: Parameter combo allows svystat to gather a huge amount of estimates and
##       errors in just a single slot, as the number of estimation domains grows
##       exponentially with the number of by variables.
##       See, for instance, the following example:
out <- svystat(houdes,y=~ones,by=~age5c:marstat:sex:regcod,combo=4)
dim(out)
head(out)
plot(out)

#####
# Minor details: accessor functions and plotting #
#####
## Accessor functions work only when forGVF = FALSE
# Average value added per employee by nace.macro:
out <- svystat(sbsdes,kind="R",num=~va.imp2,den=~emp.num,by=~nace.macro,forGVF=FALSE)
out
# Access CV values and confidence intervals:
cv(out)
confint(out)

# The same as above, separately for regions:
out <- svystat(sbsdes,kind="R",num=~va.imp2,den=~emp.num,by=~nace.macro,group=~region,forGVF=FALSE)
out
# Access CV values and confidence intervals:
cv(out)
confint(out)

## Plot function works only when forGVF = TRUE
# Counts of individuals by sex, marstat and age5c, and all their interactions:
out <- svystat(houdes,y=~ones,by=~age5c:marstat:sex,combo=3)
# Plot GVF input:
plot(out)

# The same as above, grouped by region:
out <- svystat(houdes,y=~ones,by=~age5c:marstat:sex,combo=3,group=~regcod)
# Plot GVF inputs, separately by groups (regions):
plot(out)

```

Description

Computes estimates, standard errors and confidence intervals for Multiple Regression Coefficients in subpopulations.

Usage

```
svystatB(design, model, by = NULL,
         vartype = c("se", "cv", "cvpct", "var"),
         conf.int = FALSE, conf.lev = 0.95, deff = FALSE,
         na.rm = FALSE)

## S3 method for class 'svystatB'
coef(object, ...)
## S3 method for class 'svystatB'
SE(object, ...)
## S3 method for class 'svystatB'
VAR(object, ...)
## S3 method for class 'svystatB'
cv(object, ...)
## S3 method for class 'svystatB'
deff(object, ...)
## S3 method for class 'svystatB'
confint(object, ...)
## S3 method for class 'svystatB'
summary(object, ...)
```

Arguments

<code>design</code>	Object of class <code>analytic</code> (or inheriting from it) containing survey data and sampling design metadata.
<code>model</code>	Formula specifying the linear model whose coefficients have to be estimated.
<code>by</code>	Formula specifying the variables that define the "estimation domains" (see 'Details'). If <code>NULL</code> (the default option) estimates refer to the whole population.
<code>vartype</code>	character vector specifying the desired variability estimators. It is possible to choose one or more of: standard error ('se', the default), coefficient of variation ('cv'), percent coefficient of variation ('cvpct'), or variance ('var').
<code>conf.int</code>	Compute confidence intervals for the estimates? The default is <code>FALSE</code> .
<code>conf.lev</code>	Probability specifying the desired confidence level: the default value is 0.95.
<code>deff</code>	Should the design effect be computed? The default is <code>FALSE</code> (see 'Details').
<code>na.rm</code>	Should missing values (if any) be removed from the variables of interest? The default is <code>FALSE</code> (see 'Details').
<code>object</code>	An object of class <code>svystatB</code> .
<code>...</code>	Additional arguments to <code>coef</code> , ..., <code>confint</code> methods (if any).

Details

This function computes weighted estimates for Multiple Regression Coefficients using suitable weights depending on the class of `design`: calibrated weights for class `cal.analytic` and direct weights otherwise. Standard errors are calculated using the Taylor linearization technique.

The mandatory argument `model` identifies the regression model whose population coefficients have to be estimated (for details on model specification, see e.g. [lm](#)). The design variables referenced by `model` should be numeric or factor (variables of other types - e.g. character - will need to be converted in advance, e.g. using function [des.addvars](#)).

The optional argument `by` specifies the variables that define the "estimation domains", that is the subpopulations for which the estimates are to be calculated. If `by=NULL` (the default option), the estimates produced by `svystatB` refer to the whole population. Estimation domains must be defined by a formula: for example the statement `by=~B1:B2` selects as estimation domains the subpopulations determined by crossing the modalities of variables `B1` and `B2`. Notice that a formula like `by=~B1+B2` will be automatically translated into the factor-crossing formula `by=~B1:B2`: if you need to compute estimates for domains `B1` and `B2` *separately*, you have to call `svystatQ` twice. The design variables referenced by `by` (if any) should be of type factor, otherwise they will be coerced. Note that, to prevent obvious collinearity issues, the variables referenced by argument `by` must *not* appear in the input `model` formula: otherwise, the program will stop and print an error message.

The `conf.int` argument allows to request the confidence intervals for the estimates. By default `conf.int=FALSE`, that is the confidence intervals are not provided.

Whenever confidence intervals are requested (i.e. `conf.int=TRUE`), the desired confidence level can be specified by means of the `conf.lev` argument. The `conf.lev` value must represent a probability ($0 \leq \text{conf.lev} \leq 1$) and its default is chosen to be 0.95 .

The optional argument `deff` allows to request the design effect [Kish 1995] for the estimates. By default `deff=FALSE`, that is the design effect is not provided. The design effect of an estimator is defined as the ratio between the variance of the estimator under the actual sampling design and the variance that would be obtained for an 'equivalent' estimator under a hypothetical simple random sampling without replacement of the same size. To obtain an estimate of the design effect comparing to simple random sampling "*with replacement*", one must use `deff="replace"`.

For nonlinear estimators, the design effect is estimated on the linearized version of the estimator (that is for the estimator of the total of the linearized variable, aka "Woodruff transform").

When dealing with domain estimation, the design effects referring to a given subpopulation are currently computed by taking the ratios between the actual variance estimates and those that would have been obtained if a simple random sampling were carried out *within* that subpopulation. This is the same as the `srssubpop` option for Stata's function `estat`.

Missing values (NA) in model variables should be avoided. If `na.rm=FALSE` (the default) they generate an error. If `na.rm=TRUE`, observations containing NAs in model variables are dropped, and estimates get computed on non missing values only. This implicitly assumes that missing values hit interest variables *completely at random*: should this not be the case, computed estimates would be *biased*.

The summary method invoked on regression coefficients (say `b`) estimated via `svystatB`, gives *p*-values and significance codes for the component-wise test $b = 0$. Such values are computed assuming that the distribution of the regression coefficients estimators is normal (which is asymptotically true for large scale surveys). This assumption has the advantage of overcoming the problem of choosing the "right" statistic and assessing its "right" number of degrees of freedom when using data from a complex survey (see e.g. [Korn, Graubard 1990]).

Value

An object inheriting from the `data.frame` class, whose detailed structure depends on input parameters' values. In special cases (see Section 'Collinearity, Aliasing and Impacts in Domain Estimation'), a *list* object.

Collinearity, Aliasing and Impacts in Domain Estimation

Function `svystatB` overcomes problems arising from exact collinearity between model variables via '*aliasing*' (see the 'Examples' Section). Put simply, aliasing discards redundant (i.e. collinear) regressors, yielding exact estimates and standard errors for non-aliased regression coefficients (namely, the same results that would be obtained with a reduced - no collinearity - model). Note that for the way aliasing works, the order of the terms in the linear model formula definitely matters.

Collinearity between variables may manifest itself in subsets of the sample, and with different patterns across subsets. In domain estimation, this phenomenon can have an impact on the structure of svystatB's output. In fact, owing to aliasing, the estimable regression coefficients - for the same input linear model - can be different across domains. In such cases, the domain estimates produced by svystatB can no longer be stored in a `data.frame`, and the output object will instead be a *list* (see the 'Examples' Section). Note that for these svystatB's return objects (whose class is `svystatB.by.list`) no variance [extractors](#) are currently available.

Note also that, for the reasons above, the usage of svystatB via function [svystat](#) is restricted: it is not allowed to specify [svystat](#)'s arguments by and group when `kind == "B"`.

Author(s)

Diego Zardetto

References

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- Korn, E.L., Graubard, B.I. (1990) *"Simultaneous testing of regression coefficients with complex survey data: Use of Bonferroni t statistics"*. The American Statistician, 44, 270-276.

See Also

Estimators of Totals and Means [svystatTM](#), Ratios between Totals [svystatR](#), Shares [svystatS](#), Ratios between Shares [svystatSR](#), Quantiles [svystatQ](#), Complex Analytic Functions of Totals and/or Means [svystatL](#), and all of the above [svystat](#).

Examples

```
#####
# A simple regression model with a single predictor. #
# Let's compare the estimated regression coefficient #
# to its true value computed on the sampling frame. #
#####

# Load sbs data:
data(sbs)

# Create a design object:
sbsdes<-e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,
  fpc=~fpc)

# The population scatterplot of y vs emp.num reveals a linear
# behaviour:
plot(sbs.frame$emp.num,sbs.frame$y,
  col=rgb(50,205,50,100,maxColorValue=255),pch=16)

# Compute the population fit of the linear regression
# model y~emp.num-1 (no intercept):
pop.fit<-lm(y~emp.num-1,data=sbs.frame)
abline(pop.fit,col="red",lwd=2,lty=2)
```

```

# The obtained population R-squared is quite significant
# (greater than 0.7):
pop.R2<-summary(pop.fit)$r.squared
pop.R2

# The population regression coefficient is:
B<-coef(pop.fit)
B

# Now let's estimate B on the basis of the sbs sample and
# let's build a 95% confidence interval for the obtained estimate:
svystatB(sbsdes,y~emp.num-1,conf.int=TRUE)

# Thus, the confidence interval covers the true value of B.

# Notice that using ReGenesees Complex Estimators function
# svystatL, you would have obtained exactly the same results:
sbsdes<-des.addvars(sbsdes,y4emp.num=y*emp.num,
                    emp.num.sq=emp.num^2)
svystatL(sbsdes,expression(y4emp.num/emp.num.sq),
          conf.int=TRUE)

#####
# A multiple regression example. #
#####

# Let's estimate the coefficients of a model describing
# value added (variable va.imp2) as a linear function
# of number of employees by region and of nace.macro:
b <- svystatB(sbsdes,va.imp2~emp.num:region+nace.macro,vartype="cvpct")
b

# To obtain p-values and significance codes for the
# component-wise test  $t=0$ , you can exploit the
# summary method:
summary(b)

# Notice that estimators normality is assumed.

#####
# Obtaining domain means via regression. #
#####

# The domain mean of a numeric variable can be thought
# as a regression coefficient. Suppose you need the
# average number of employees by macro-sector, you can
# do as follows:
svystatB(sbsdes,emp.num~nace.macro-1)

# ...which, indeed, gives exactly the same results of:
svystatTM(sbsdes,y=~emp.num,by=~nace.macro,estimator="Mean")

#####

```

```

# Handling collinearity. #
#####

# Function svystatB overcomes problems arising from exact
# collinearity between model variables via 'aliasing'.
# To understand how aliasing works, let's build a manifestly
# redundant linear model:
svystatB(sbsdes,y~emp.num+I(2*emp.num)+I(3*va.imp2)+va.imp2-1)

# The obtained warning message shows that order definitely matters
# in aliasing, indeed:
svystatB(sbsdes,y~emp.num+I(2*emp.num)+va.imp2+I(3*va.imp2)-1)

# Notice also that aliasing gives exact estimates and standard errors
# for non-aliased regression coefficients (i.e. the same results that
# would be obtained with a reduced - no collinearity - model):
svystatB(sbsdes,y~emp.num+va.imp2-1)

#####
# Handling missing values in model variables. #
#####

# Load fpcdat:
data(fpcdat)

# Now, let's introduce some NAs in survey data:
fpcdat$y[c(1,3)]<-NA
fpcdat$x[c(3,5)]<-NA

# Create a design object:
fpcdes<-e.svydesign(data=fpcdat,ids=~psu+ssu,strata=~stratum,weights=~w,
  fpc=~fpc1+fpc2)

# Let's estimate regression coefficients of model z~y+x
# na.rm=FALSE (the default) leads to an error:
## Not run:
svystatB(fpcdes,z~y+x)

## End(Not run)

# whereas na.rm=TRUE simply drops all the cases
# with missing data in model variables:
svystatB(fpcdes,z~y+x,na.rm=TRUE)

#####
# Handling non positive weights. #
#####

# Non positive direct weights are not allowed, anyway some
# calibrated weights can sometimes turn out to be <= 0. The
# corresponding observations would be dropped by svystatB.

# Prepare a template for population totals:
pop<-pop.template(fpcdes,~z+pl.domain-1)

```

```

# Fill it with silly values in order to obtain some negative g-weights:
pop[1,]<-c(20000,90,10,90)

# Calibrate:
fpccal<-e.calibrate(fpcdes,pop)

# We got 2 negative calibrated weights:
g.range(fpccal)
sum(weights(fpccal)<=0)

# Now, let's estimate regression coefficients of model z~y+x
# and pay attention to the warnings:
svystatB(fpccal,z~y+x,na.rm=TRUE)

#####
# Domain estimates of simple and multiple regression coefficients. #
#####

# Estimate the coefficients of the simple regression y ~ emp.num by domains
# obtained crossing region and nace.macro:
bb <- svystatB(sbsdes, model= va.imp2 ~emp.num, by= ~region:nace.macro)
bb

# Obtain p-values and significance codes via the summary method:
summary(bb)

# You have yet another method to estimate domain means of numeric variables.
# Suppose you need the average number of employees by macro-sector, you can
# do as follows:
svystatB(sbsdes, model= emp.num ~1, by= ~nace.macro)

# ...which gives exactly the same results of:
svystatB(sbsdes, model= emp.num ~nace.macro -1)

# ...and, of course, of:
svystatTM(sbsdes, y= ~emp.num, by= ~nace.macro, estimator= "Mean")

# One multiple regression example:
svystatB(sbsdes, model = y ~ va.imp2 + emp.num, by = ~region:nace.macro)

# A case of differential aliasing across domain (note the warning messages).
# A list-like object is returned:
svystatB(sbsdes, va.imp2 ~emp.num:emp.cl + nace.macro, by= ~region:public)

```

Description

Computes estimates, standard errors and confidence intervals for Complex Estimators in subpopulations. A Complex Estimator can be any analytic function of (Horvitz-Thompson or Calibration) estimators of Totals and Means.

Usage

```
svystatL(design, expr, by = NULL,
         vartype = c("se", "cv", "cvpct", "var"),
         conf.int = FALSE, conf.lev = 0.95, deff = FALSE,
         na.rm = FALSE)

## S3 method for class 'svystatL'
coef(object, ...)
## S3 method for class 'svystatL'
SE(object, ...)
## S3 method for class 'svystatL'
VAR(object, ...)
## S3 method for class 'svystatL'
cv(object, ...)
## S3 method for class 'svystatL'
deff(object, ...)
## S3 method for class 'svystatL'
confint(object, ...)
```

Arguments

<code>design</code>	Object of class <code>analytic</code> (or inheriting from it) containing survey data and sampling design metadata.
<code>expr</code>	R expression defining the Complex Estimator (see ‘Details’).
<code>by</code>	Formula specifying the variables that define the "estimation domains". If <code>NULL</code> (the default option) estimates refer to the whole population.
<code>vartype</code>	character vector specifying the desired variability estimators. It is possible to choose one or more of: standard error ('se', the default), coefficient of variation ('cv'), percent coefficient of variation ('cvpct'), or variance ('var').
<code>conf.int</code>	Compute confidence intervals for the estimates? The default is <code>FALSE</code> .
<code>conf.lev</code>	Probability specifying the desired confidence level: the default value is 0.95.
<code>deff</code>	Should the design effect be computed? The default is <code>FALSE</code> (see ‘Details’).
<code>na.rm</code>	Should missing values (if any) be removed from the variables of interest? The default is <code>FALSE</code> (see ‘Details’).
<code>object</code>	An object of class <code>svystatL</code> .
<code>...</code>	Additional arguments to <code>coef</code> , ..., <code>confint</code> methods (if any).

Details

This function computes weighted estimates for Complex Estimators using suitable weights depending on the class of `design`: calibrated weights for class `cal.analytic` and direct weights otherwise. Standard errors are calculated using the Taylor linearization technique.

Function `svystatL` can handle any user-defined estimator that can be expressed as an analytic function of Horvitz-Thompson or Calibration estimators of Totals or Means, by automatically linearizing them (see [Zardetto, 15] for details).

The mandatory argument `expr`, which identifies the Complex Estimator, must be an object of class `expression`. It can be specified just a single Complex Estimator at a time, i.e. `length(expr)` must be equal to 1. Any analytic function of estimators of Totals and Means is allowed.

Inside `expr` the estimator of the Total of a variable is simply represented by the *name* of the variable

itself. To represent the estimator of the Mean of a variable y , the expression y/ones has to be used (ones being the convenience name of an artificial variable - created on-the-fly - whose value is 1 for each elementary sampling unit, so that its Total estimator actually estimates the size of the population). Variables referenced inside `expr` must obviously belong to `design` and must be numeric. At a minimal level, `svyestatL` can be used to estimate Totals, Means, Ratios, etc., thus reproducing the same results achieved by using the corresponding dedicated functions `svyestatTM`, `svyestatR`, etc. For instance, calling `svyestatL(design, expression(y/x))` is equivalent to invoking `svyestatR(design, ~y, ~x)`, while using `svyestatL(design, expression(y/ones))` or `svyestatTM(design, ~y, estimator = "Mean")` achieves an identical result.

The mathematical expression of a Complex Estimator, as specified by argument `expr`, can involve '*parameters*', that is *symbols* representing given, non-random, scalar, numeric *values*. For each parameter appearing in `expr`, the value corresponding to its symbol will be searched following R standard scoping rules, see e.g. the first example in Section 'Examples' for a practical illustration.

The optional argument `by` specifies the variables that define the "estimation domains", that is the subpopulations for which the estimates are to be calculated. If `by=NULL` (the default option), the estimates produced by `svyestatL` refer to the whole population. Estimation domains must be defined by a formula: for example the statement `by=~B1:B2` selects as estimation domains the subpopulations determined by crossing the modalities of variables `B1` and `B2`. Notice that a formula like `by=~B1+B2` will be automatically translated into the factor-crossing formula `by=~B1:B2`: if you need to compute estimates for domains `B1` and `B2` *separately*, you have to call `svyestatL` twice. The design variables referenced by `by` (if any) should be of type `factor`, otherwise they will be coerced.

The `conf.int` argument allows to request the confidence intervals for the estimates. By default `conf.int=FALSE`, that is the confidence intervals are not provided.

Whenever confidence intervals are requested (i.e. `conf.int=TRUE`), the desired confidence level can be specified by means of the `conf.lev` argument. The `conf.lev` value must represent a probability ($0 \leq \text{conf.lev} \leq 1$) and its default is chosen to be 0.95.

The optional argument `deff` allows to request the design effect [Kish 1995] for the estimates. By default `deff=FALSE`, that is the design effect is not provided. The design effect of an estimator is defined as the ratio between the variance of the estimator under the actual sampling design and the variance that would be obtained for an 'equivalent' estimator under a hypothetical simple random sampling without replacement of the same size. To obtain an estimate of the design effect comparing to simple random sampling "*with replacement*", one must use `deff="replace"`.

For nonlinear estimators, the design effect is estimated on the linearized version of the estimator (that is for the estimator of the total of the linearized variable, aka "Woodruff transform").

When dealing with domain estimation, the design effects referring to a given subpopulation are currently computed by taking the ratios between the actual variance estimates and those that would have been obtained if a simple random sampling were carried out *within* that subpopulation. This is the same as the `srssubpop` option for Stata's function `estat`.

Missing values (NA) in interest variables should be avoided. If `na.rm=FALSE` (the default) they generate NAs in estimates (or even an error, if `design` is calibrated). If `na.rm=TRUE`, observations containing NAs are dropped, and estimates get computed on non missing values only. This implicitly assumes that missing values hit interest variables *completely at random*: should this not be the case, computed estimates would be *biased*.

Value

An object inheriting from the `data.frame` class, whose detailed structure depends on input parameters' values.

Warning

When the linearized variable corresponding to a Complex Estimator is ill defined (because the estimator gradient is singular at the Taylor series expansion point), SE estimates returned by `svystatL` are NaN.

Author(s)

Diego Zardetto

References

- Sarndal, C.E., Swensson, B., Wretman, J. (1992) *“Model Assisted Survey Sampling”*, Springer Verlag.
- Zardetto, D. (2015) *“ReGenesees: an Advanced R System for Calibration, Estimation and Sampling Error Assessment in Complex Sample Surveys”*. Journal of Official Statistics, 31(2), 177-203. doi: <https://doi.org/10.1515/jos-2015-0013>.
- Kish, L. (1995). *“Methods for design effects”*. Journal of Official Statistics, Vol. 11, pp. 55-77.
- European Commission, Eurostat, (2013). *“Handbook on precision requirements and variance estimation for ESS households surveys: 2013 edition”*, Publications Office. doi: 10.2785/13579

See Also

Estimators of Totals and Means [svystatTM](#), Ratios between Totals [svystatR](#), Shares [svystatS](#), Ratios between Shares [svystatSR](#), Multiple Regression Coefficients [svystatB](#), Quantiles [svystatQ](#), and all of the above [svystat](#).

Examples

```
#####
# A first example: the Ratio Estimator of a Total. #
#####

# Creation of a design object:
data(data.examples)
des<-e.svydesign(data=example,ids=~towcod+famcod,strata=~SUPERSTRATUM,
  weights=~weight)

# Recall that ratio estimators of Totals rely on auxiliary
# information. Thus, suppose you want to estimate the total
# of income and suppose you know from an external source that
# the population size is, say, 1E6:
pop <- 1E6

# To obtain the ratio estimator of total income, you can do as follows:
## A) Directly plug the numeric value of pop into expr
svystatL(des, expression(1E6 * (income/ones)), vartype = "cvpct")

## B) Treat pop as a parameter and let R find its actual value (1E6) inside
## the calling environment of svystatL (the .GlobalEnv)
svystatL(des, expression(pop * (income/ones)), vartype = "cvpct")

# NOTE: Method B) can be very useful for simulation purposes, as it avoids
# having to directly type in numbers when invoking svystatL (something
# that only a human in an interactive R session could do).
```



```

# By comparing the latter result with the ordinary estimator of the mean...
svystatTM(des,~income,vartype="cvpct")

# ...one can appreciate the variance reduction stemming from the correlation
# between numerator and denominator:
Corr(des, expression(income), expression(ones))

#####
# A complex example: estimation of the Population Standard #
# Deviation of a variable.                                     #
#####

# Creation of another design object:
data(sbs)
sbsdes<-e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,
                    fpc=~fpc)

# Suppose you want to estimate the standard deviation of the
# population distribution of value added (va.imp2):
sbsdes<-des.addvars(sbsdes,va.imp2.sq=va.imp2^2)
svystatL(sbsdes,expression( sqrt( (ones/(ones-1))*
                                ( (va.imp2.sq/ones)-(va.imp2/ones)^2 )
                                ), conf.int=TRUE)

# The estimate above and the associated confidence interval (which
# involves the estimate of the sampling variance of the complex
# estimator) turn out to be very sound: indeed the TRUE value of the
# parameter is:
sd(sbs.frame$va.imp2)

#####
# Estimation of Geometric and Harmonic Means. #
#####

## 1. Harmonic Mean
# Recall that the the harmonic mean of a positive variable,
# say z, can be computed as 1/mean(1/z). Thus, for instance,
# to get a survey estimate of the harmonic mean of emp.num,
# you can do as follows:
sbsdes<-des.addvars(sbsdes,emp.num.m1=1/emp.num)
h<-svystatL(sbsdes,expression( ones/emp.num.m1 ),
            conf.int=TRUE)
h

# You can easily verify that the obtained estimate is close
# to the true value (as computed from the sampling frame) and
# covered by the 95% confidence interval:
1/mean(1/sbs.frame$emp.num)

## 2. Geometric Mean
# Recall that the the geometric mean of a non negative variable,
# say z, can be computed as exp(mean(log(z))). Thus, for instance,
# to get a survey estimate of the geometric mean of emp.num,

```

```

# you can do as follows:
sbsdes<-des.addvars(sbsdes,log.emp.num=log(emp.num))
g<-svystatL(sbsdes,expression( exp(log.emp.num/ones) ),
            conf.int=TRUE)
g

# You can easily verify that the obtained estimate is close
# to the true value (as computed from the sampling frame) and
# covered by the 95% confidence interval:
exp(mean(log(sbs.frame$emp.num)))

## 3. Comparison with the arithmetic mean
# If you compute the arithmetic mean estimate:
a<-svystatTM(sbsdes,~emp.num,estimator="Mean")
a

#...you easily verify the expected hierachy,
# i.e. harmonic <= geometric <= arithmetic:
H<-coef(h)
G<-coef(g)
A<-coef(a)
stopifnot(H <= G && G <= A)

#####
# Further complex examples: estimation of Population Regression #
# Coefficients (for a model with a single predictor).          #
#####

# Suppose you want to estimate of the slope of the population
# regression y vs. emp.num. You can do as follows:

## 1. No intercept model: y ~ emp.num - 1
# Get survey estimate:
sbsdes<-des.addvars(sbsdes,y4emp.num=y*emp.num,
                    emp.num.sq=emp.num^2)
svystatL(sbsdes,expression(y4emp.num/emp.num.sq),
        conf.int=TRUE)

# Compare with the actual slope from the population fit:
pop.fit<-lm(y~emp.num-1,data=sbs.frame)
coef(pop.fit)

# ...a very good agreement.

## 2. The model with intercept: y ~ emp.num
# Get survey estimate:
svystatL(sbsdes,expression( (ones*y4emp.num - y*emp.num)/
                            (ones*emp.num.sq - emp.num^2)
                            ),
        conf.int=TRUE)

# Compare with the actual slope from the population fit:
pop.fit<-lm(y~emp.num,data=sbs.frame)
coef(pop.fit)

# ...again a very good agreement.

```

```
# Notice that both results above could be obtained also
# by using ReGenesees specialized function svystatB:

## 1.
svystatB(sbsdes,y~emp.num-1,conf.int=TRUE)

## 2.
svystatB(sbsdes,y~emp.num,conf.int=TRUE)

# Notice also - incidentally - that the estimate of the intercept
# turns out to be less accurate than the one we obtained for the slope,
# with about a 6% overestimation.
```

svystatQ

*Estimation of Quantiles in Subpopulations***Description**

Calculates estimates, standard errors and confidence intervals for Quantiles of numeric variables in subpopulations.

Usage

```
svystatQ(design, y, probs = c(0.25, 0.5, 0.75), by = NULL,
         vartype = c("se", "cv", "cvpct", "var"),
         conf.lev = 0.95, na.rm = FALSE,
         ties=c("discrete", "rounded"))

## S3 method for class 'svystatQ'
coef(object, ...)
## S3 method for class 'svystatQ'
SE(object, ...)
## S3 method for class 'svystatQ'
VAR(object, ...)
## S3 method for class 'svystatQ'
cv(object, ...)
## S3 method for class 'svystatQ'
confint(object, ...)
```

Arguments

design	Object of class <code>analytic</code> (or inheriting from it) containing survey data and sampling design metadata.
y	Formula defining the interest variable.
probs	Vector of probability values to be used to calculate the quantiles estimates. The default value selects estimates of quartiles.
by	Formula specifying the variables that define the "estimation domains". If <code>NULL</code> (the default option) estimates refer to the whole population.
vartype	character vector specifying the desired variability estimators. It is possible to choose one or more of: standard error ('se', the default), coefficient of variation ('cv'), percent coefficient of variation ('cvpct'), or variance ('var').

<code>conf.lev</code>	Probability specifying the desired confidence level: the default value is 0.95.
<code>na.rm</code>	Should missing values (if any) be removed from the variable of interest? The default is FALSE (see 'Details').
<code>ties</code>	How should duplicated observed values be treated? Select 'discrete' for a genuinely discrete interest variable and 'rounded' for a continuous one.
<code>object</code>	An object of class <code>svystatQ</code> .
<code>...</code>	Additional arguments to <code>coef</code> , ..., <code>confint</code> methods (if any).

Details

This function calculates weighted estimates for the Quantiles of a quantitative variable using suitable weights depending on the class of design: calibrated weights for class `cal.analytic` and direct weights otherwise.

Standard errors are calculated using the so-called "Woodruff method" [Woodruff 52][Sarndal, Swensson, Wretman 92]: (i) first a confidence interval (at a given confidence level $1-\alpha$) is constructed for the relative frequency of units with values below the estimated quantile, (ii) then the inverse of the estimated cumulative relative frequency distribution (ECDF) is used to map this interval to a confidence interval for the quantile, (iii) lastly the desired standard error is estimated by dividing the length of the obtained confidence interval by the value $2 \cdot qnorm(1-\alpha/2)$. Notice that the procedure above builds, in general, asymmetric confidence intervals around the estimated quantiles.

The mandatory argument `y` identifies the variable of interest, that is the variable for which estimates of quantiles have to be calculated. The design variable referenced by `y` must be numeric.

The optional argument `probs` specifies the probability values ($0.001 \leq \text{probs}[i] \leq 0.999$) corresponding to the quantiles one wants to estimate; the default option selects quartiles.

The optional argument `by` specifies the variables that define the "estimation domains", that is the subpopulations for which the estimates are to be calculated. If `by=NULL` (the default option), the estimates produced by `svystatQ` refer to the whole population. Estimation domains must be defined by a formula: for example the statement `by=~B1:B2` selects as estimation domains the subpopulations determined by crossing the modalities of variables `B1` and `B2`. Notice that a formula like `by=~B1+B2` will be automatically translated into the factor-crossing formula `by=~B1:B2`: if you need to compute estimates for domains `B1` and `B2` *separately*, you have to call `svystatQ` twice. The design variables referenced by `by` (if any) should be of type factor, otherwise they will be coerced.

The `conf.int` argument allows to request the confidence intervals for the estimates. By default `conf.int=FALSE`, that is the confidence intervals are not provided.

Whenever confidence intervals are requested (i.e. `conf.int=TRUE`), the desired confidence level can be specified by means of the `conf.lev` argument. The `conf.lev` value must represent a probability ($0 \leq \text{conf.lev} \leq 1$) and its default is chosen to be 0.95.

Missing values (NA) in interest variables should be avoided. If `na.rm=FALSE` (the default) they generate NAs in estimates (or even an error, if design is calibrated). If `na.rm=TRUE`, observations containing NAs are dropped, and estimates get computed on non missing values only. This implicitly assumes that missing values hit interest variables *completely at random*: should this not be the case, computed estimates would be *biased*.

Argument `ties` addresses the problem of how to treat duplicated observed values (if any) when computing the ECDF. Option 'discrete' (the default) is appropriate when the variable of interest is genuinely discrete, while 'rounded' is a better choice for a continuous variable, i.e. when duplicates stem from rounding. In the first case the ECDF will show a vertical step corresponding to a duplicated value, in the second a smoother shape will be achieved by linear interpolation.

Value

An object inheriting from the `data.frame` class, whose detailed structure depends on input parameters' values.

Author(s)

Diego Zardetto

References

Woodruff, R.S. (1952) “*Confidence Intervals for Medians and Other Position Measures*”, Journal of the American Statistical Association, Vol. 47, No. 260, pp. 635-646.

Sarndal, C.E., Swensson, B., Wretman, J. (1992) “*Model Assisted Survey Sampling*”, Springer Verlag.

See Also

Estimators of Totals and Means [svystatTM](#), Ratios between Totals [svystatR](#), Shares [svystatS](#), Ratios between Shares [svystatSR](#), Multiple Regression Coefficients [svystatB](#), Complex Analytic Functions of Totals and/or Means [svystatL](#), and all of the above [svystat](#).

Examples

```
# Creation of a design object:
data(data.examples)
des<-e.svydesign(data=example,ids=~towcod+famcod,strata=~SUPERSTRATUM,
  weights=~weight)

# Estimate of the deciles of the income variable for
# the whole population:
svystatQ(des,~income,probs=seq(0.1,0.9,0.1),ties="rounded")

# Another design object:
data(sbs)
des<-e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,
  fpc=~fpc)

# Estimation of the median value added
# for economic activity macro-sectors:
svystatQ(des,~va.imp2,probs=0.5,by=~nace.macro,
  ties="rounded",vartype="cvpct")

# Estimation of the Interquartile Range (IQR) of the number
# of employees for economic activity macro-sectors:
apply(svystatQ(des,~emp.num,probs=c(0.25,0.75),by=~nace.macro)[,2:3],1,diff)
```

Description

Calculates estimates, standard errors and confidence intervals for Ratios between Totals in subpopulations.

Usage

```
svystatR(design, num, den, by = NULL, cross = FALSE,
          vartype = c("se", "cv", "cvpct", "var"),
          conf.int = FALSE, conf.lev = 0.95, deff = FALSE,
          na.rm = FALSE)
```

```
## S3 method for class 'svystatR'
coef(object, ...)
## S3 method for class 'svystatR'
SE(object, ...)
## S3 method for class 'svystatR'
VAR(object, ...)
## S3 method for class 'svystatR'
cv(object, ...)
## S3 method for class 'svystatR'
deff(object, ...)
## S3 method for class 'svystatR'
confint(object, ...)
```

Arguments

design	Object of class <code>analytic</code> (or inheriting from it) containing survey data and sampling design metadata.
num	Formula defining the numerator variables for the ratios.
den	Formula defining the denominator variables for the ratios.
by	Formula specifying the variables that define the "estimation domains". If <code>NULL</code> (the default option) estimates refer to the whole population.
cross	Should ratios be estimated for all the pairs of variables in 'num' and 'den'? The default is <code>FALSE</code> , meaning that ratios get estimated parallel-wise (see 'Details').
vartype	character vector specifying the desired variability estimators. It is possible to choose one or more of: standard error ('se', the default), coefficient of variation ('cv'), percent coefficient of variation ('cvpct'), or variance ('var').
conf.int	Compute confidence intervals for the estimates? The default is <code>FALSE</code> .
conf.lev	Probability specifying the desired confidence level: the default value is 0.95.
deff	Should the design effect be computed? The default is <code>FALSE</code> (see 'Details').
na.rm	Should missing values (if any) be removed from the variables of interest? The default is <code>FALSE</code> (see 'Details').
object	An object of class <code>svystatR</code> .
...	Additional arguments to <code>coef</code> , ..., <code>confint</code> methods (if any).

Details

This function computes weighted estimates for Ratios between Totals using suitable weights depending on the class of design: calibrated weights for class `cal.analytic` and direct weights otherwise. Standard errors are calculated using the Taylor linearization technique.

The mandatory argument `num (den)` identifies the variables whose totals appear as numerators (denominators) in the Ratios: the corresponding formula must be of the type `num = ~num.1 + ... + num.k` (`den = ~den.1 + ... + den.l`). The design variables referenced by `num (den)` must be numeric.

If `cross=TRUE`, the function computes estimates for *all* the Ratios between pairs of variables coming from `num` and `den` (that is $k \times l$ estimates for the formulae above). If, on the contrary, `cross=FALSE` (the default), Ratios get estimated parallel-wise and R recycling rule is applied whenever $k \neq l$: for the formulae above, this generates r Ratios, where $r = \max(k, l)$.

The optional argument `by` specifies the variables that define the "estimation domains", that is the subpopulations for which the estimates are to be calculated. If `by=NULL` (the default option), the estimates produced by `svystatR` refer to the whole population. Estimation domains must be defined by a formula: for example the statement `by=~B1:B2` selects as estimation domains the subpopulations determined by crossing the modalities of variables `B1` and `B2`. Notice that a formula like `by=~B1+B2` will be automatically translated into the factor-crossing formula `by=~B1:B2`: if you need to compute estimates for domains `B1` and `B2` *separately*, you have to call `svystatR` twice. The design variables referenced by `by` (if any) should be of type `factor`, otherwise they will be coerced.

The `conf.int` argument allows to request the confidence intervals for the estimates. By default `conf.int=FALSE`, that is the confidence intervals are not provided.

Whenever confidence intervals are requested (i.e. `conf.int=TRUE`), the desired confidence level can be specified by means of the `conf.lev` argument. The `conf.lev` value must represent a probability ($0 \leq \text{conf.lev} \leq 1$) and its default is chosen to be `0.95`.

The optional argument `deff` allows to request the design effect [Kish 1995] for the estimates. By default `deff=FALSE`, that is the design effect is not provided. The design effect of an estimator is defined as the ratio between the variance of the estimator under the actual sampling design and the variance that would be obtained for an 'equivalent' estimator under a hypothetical simple random sampling without replacement of the same size. To obtain an estimate of the design effect comparing to simple random sampling "*with replacement*", one must use `deff="replace"`.

Being Ratios nonlinear estimators, the design effect is estimated on the linearized version of the estimator (that is: for the estimator of the total of the linearized variable, aka "Woodruff transform"). When dealing with domain estimation, the design effects referring to a given subpopulation are currently computed by taking the ratios between the actual variance estimates and those that would have been obtained if a simple random sampling were carried out *within* that subpopulation. This is the same as the `srssubpop` option for Stata's function `estat`.

Missing values (NA) in interest variables should be avoided. If `na.rm=FALSE` (the default) they generate NAs in estimates (or even an error, if design is calibrated). If `na.rm=TRUE`, observations containing NAs are dropped, and estimates get computed on non missing values only. This implicitly assumes that missing values hit interest variables *completely at random*: should this not be the case, computed estimates would be *biased*. Notice that the `na.rm=TRUE` option is only allowed for a single Ratio, i.e. if `num` and `den` reference a *single* interest variable.

Value

An object inheriting from the `data.frame` class, whose detailed structure depends on input parameters' values.

Warning

It can happen that, in some subpopulations, the estimate of the Total of some den variables turns out to be zero. In such cases svystatR estimates are either NaN or Inf, and NaN is returned for the corresponding SE estimates.

Author(s)

Diego Zardetto

References

- Sarndal, C.E., Swensson, B., Wretman, J. (1992) *“Model Assisted Survey Sampling”*, Springer Verlag.
- Kish, L. (1995). *“Methods for design effects”*. Journal of Official Statistics, Vol. 11, pp. 55-77.
- European Commission, Eurostat, (2013). *“Handbook on precision requirements and variance estimation for ESS households surveys: 2013 edition”*, Publications Office. doi: 10.2785/13579

See Also

Estimators of Totals and Means [svystatTM](#), Shares [svystatS](#), Ratios between Shares [svystatSR](#), Multiple Regression Coefficients [svystatB](#), Quantiles [svystatQ](#), Complex Analytic Functions of Totals and/or Means [svystatL](#), and all of the above [svystat](#).

Examples

```
# Creation of a design object:
data(sbs)
des<-e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,
  fpc=~fpc)

# Estimation of the average value added per employee
# at the nation level:
svystatR(des,~va.imp2,~emp.num)

# The same as above by economic activity macro-sector:
svystatR(des,~va.imp2,~emp.num,~nace.macro,vartype="cvpct")

# Another design object:
data(data.examples)
des<-e.svydesign(data=example,ids=~towcod+famcod,strata=~SUPERSTRATUM,
  weights=~weight)

# Estimation of the ratios y1/x1, y1/x2, y2/x1 and y2/x2 by region,
# notice the use of argument cross:
svystatR(des,~y1+y2,~x1+x2,by=~regcod,cross=TRUE)

# ... compare the latter with the default (i.e. cross=FALSE)
svystatR(des,~y1+y2,~x1+x2,by=~regcod)

# Estimation of the ratios z/x1, z/x2 e z/x3
# for the whole population (notice the recycling rule):
svystatR(des,~z,~x1+x2+x3,conf.int=TRUE)
```



```

# Estimators of means can be thought as
# estimators of ratios:
svystatTM(des,~income,estimator="Mean")
svystatR(des.addvars(des,ones=1),num=~income,den=~ones)

#####
# Household-level averages in household surveys. #
#####

# For an introduction on this topic, see ?svystatTM examples.

# Load survey data:
data(data.examples)

# Define the survey design (variable famcod identifies households)
exdes<-e.svydesign(data=example,ids=~towcod+famcod,strata=~stratum,
  weights=~weight)

# Collapse strata to eliminate lonely PSUs
exdes<-collapse.strata(design=exdes,block.vars=~sr:procod)

# Now add new convenience variables to the design object:
## 'ones':      to estimate individuals counts
## 'housize':   to classify individuals by household size
## 'houdensity': to estimate households counts
exdes<-des.addvars(exdes,
  ones=1,
  housize=factor(ave(famcod,famcod,FUN = length)),
  houdensity=ave(famcod,famcod,FUN = function(x) 1/length(x))
)

# Estimate the average number of household components by region:
svystatR(exdes,num=~ones,den=~houdensity,by=~regcod,
  vartype="cvpct",conf.int=TRUE)

# Estimate the average household income for the whole population:
svystatR(exdes,num=~income,den=~houdensity,vartype="cvpct",
  conf.int=TRUE)

# ...for household size categories:
svystatR(exdes,num=~income,den=~houdensity,by=~housize,
  vartype="cvpct",conf.int=TRUE)

# ...and for province and household size:
svystatR(exdes,num=~income,den=~houdensity,by=~housize:procod,
  vartype="cvpct")

```

svystatS

Estimation of Shares in Subpopulations

Description

Calculates estimates, standard errors and confidence intervals for Shares of a numeric variable within subpopulations.

Usage

```
svystatS(design, y, classes, by = NULL,
         vartype = c("se", "cv", "cvpct", "var"),
         conf.int = FALSE, conf.lev = 0.95, deff = FALSE,
         na.rm = FALSE)

## S3 method for class 'svystatS'
coef(object, ...)
## S3 method for class 'svystatS'
SE(object, ...)
## S3 method for class 'svystatS'
VAR(object, ...)
## S3 method for class 'svystatS'
cv(object, ...)
## S3 method for class 'svystatS'
deff(object, ...)
## S3 method for class 'svystatS'
confint(object, ...)
```

Arguments

<code>design</code>	Object of class <code>analytic</code> (or inheriting from it) containing survey data and sampling design metadata.
<code>y</code>	Formula defining the interest variable.
<code>classes</code>	Formula defining the population groups whose <code>y</code> shares must be estimated.
<code>by</code>	Formula specifying the variables that define the "estimation domains". If <code>NULL</code> (the default option) estimates refer to the whole population.
<code>vartype</code>	character vector specifying the desired variability estimators. It is possible to choose one or more of: standard error (<code>'se'</code> , the default), coefficient of variation (<code>'cv'</code>), percent coefficient of variation (<code>'cvpct'</code>), or variance (<code>'var'</code>).
<code>conf.int</code>	Compute confidence intervals for the estimates? The default is <code>FALSE</code> .
<code>conf.lev</code>	Probability specifying the desired confidence level: the default value is <code>0.95</code> .
<code>deff</code>	Should the design effect be computed? The default is <code>FALSE</code> (see 'Details').
<code>na.rm</code>	Should missing values (if any) be removed from the variables of interest? The default is <code>FALSE</code> (see 'Details').
<code>object</code>	An object of class <code>svystatS</code> .
<code>...</code>	Additional arguments to <code>coef</code> , <code>...</code> , <code>confint</code> methods (if any).

Details

This function computes weighted estimates for Shares of a numeric variable, using suitable weights depending on the class of `design`: calibrated weights for class `cal.analytic` and direct weights otherwise. Standard errors are calculated using the Taylor linearization technique.

Shares are a special case of Ratios. Therefore, at the price of some additional (and possibly heavy) data preparation effort, shares could also be estimated using function `svystatR`. However, `svystatS` makes estimation by far easier, in particular when shares have to be estimated for many population groups and/or within many domains.

The mandatory argument `y` identifies the variable of interest, that is the variable for which estimates of shares have to be calculated. The design variable referenced by `y` must be numeric.

The mandatory argument `classes` identifies population groups whose shares of `y` have to be estimated. The design variables referenced by `classes` must be of class `factor`. Groups can be identified by crossing factors, e.g. `statement classes = ~C1:C2` selects as groups the subpopulations determined by crossing the levels of factors `C1` and `C2`.

The optional argument `by` specifies the variables defining the "estimation domains", that is the subpopulations within which shares of `y` by `classes` must be estimated. If `by=NULL` (the default option), the estimates produced by `svystatS` refer to the whole population. Estimation domains must be defined by a formula: for instance the statement `by=~B1:B2` selects as estimation domains the subpopulations determined by crossing the modalities of variables `B1` and `B2`. Notice that a formula like `by=~B1+B2` will be automatically translated into the factor-crossing formula `by=~B1:B2`: if you need to compute estimates for domains `B1` and `B2` *separately*, you have to call `svystatS` twice. The design variables referenced by `by` (if any) should be of type `factor`, otherwise they will be coerced.

The `conf.int` argument allows to request the confidence intervals for the estimates. By default `conf.int=FALSE`, that is the confidence intervals are not provided.

Whenever confidence intervals are requested (i.e. `conf.int=TRUE`), the desired confidence level can be specified by means of the `conf.lev` argument. The `conf.lev` value must represent a probability ($0 \leq \text{conf.lev} \leq 1$) and its default is chosen to be `0.95`.

The optional argument `deff` allows to request the design effect [Kish 1995] for the estimates. By default `deff=FALSE`, that is the design effect is not provided. The design effect of an estimator is defined as the ratio between the variance of the estimator under the actual sampling design and the variance that would be obtained for an 'equivalent' estimator under a hypothetical simple random sampling without replacement of the same size. To obtain an estimate of the design effect comparing to simple random sampling "*with replacement*", one must use `deff="replace"`.

Being Ratios nonlinear estimators, the design effect is estimated on the linearized version of the estimator (that is: for the estimator of the total of the linearized variable, aka "Woodruff transform"). When dealing with domain estimation, the design effects referring to a given subpopulation are currently computed by taking the ratios between the actual variance estimates and those that would have been obtained if a simple random sampling were carried out *within* that subpopulation. This is the same as the `srssubpop` option for Stata's function `estat`.

Missing values (NA) in interest variables should be avoided. If `na.rm=FALSE` (the default) they generate NAs in estimates (or even an error, if design is calibrated). If `na.rm=TRUE`, observations containing NAs are dropped, and estimates get computed on non missing values only. This implicitly assumes that missing values hit interest variables *completely at random*: should this not be the case, computed estimates would be *biased*.

Value

An object inheriting from the `data.frame` class, whose detailed structure depends on input parameters' values.

Author(s)

Diego Zardetto

References

- Sarndal, C.E., Swensson, B., Wretman, J. (1992) "*Model Assisted Survey Sampling*", Springer Verlag.
- Kish, L. (1995). "*Methods for design effects*". Journal of Official Statistics, Vol. 11, pp. 55-77.


```
# Third: estimate income shares by income quintiles
svystatS(des, y=~income, classes=~quintile, vartype="cvpct")

### NOTE: Procedure above yields *correct point estimates* of income shares by
###       income quintiles, while *variance estimation is approximated* since
###       we neglected the sampling variability of the estimated quintiles.
```

svystatSR

Estimation of Share Ratios in Subpopulations

Description

Calculates estimates, standard errors and confidence intervals for Ratios between Shares of a numeric variables in subpopulations.

Usage

```
svystatSR(design, y, classes, by = NULL,
          vartype = c("se", "cv", "cvpct", "var"),
          conf.int = FALSE, conf.lev = 0.95, deff = FALSE,
          na.rm = FALSE)
```

```
## S3 method for class 'svystatSR'
coef(object, ...)
## S3 method for class 'svystatSR'
SE(object, ...)
## S3 method for class 'svystatSR'
VAR(object, ...)
## S3 method for class 'svystatSR'
cv(object, ...)
## S3 method for class 'svystatSR'
deff(object, ...)
## S3 method for class 'svystatSR'
confint(object, ...)
```

Arguments

design	Object of class <code>analytic</code> (or inheriting from it) containing survey data and sampling design metadata.
y	Formula defining the interest variable.
classes	Formula defining the population groups among which ratios of y shares must be estimated.
by	Formula specifying the variables that define the "estimation domains". If <code>NULL</code> (the default option) estimates refer to the whole population.
vartype	character vector specifying the desired variability estimators. It is possible to choose one or more of: standard error (<code>'se'</code> , the default), coefficient of variation (<code>'cv'</code>), percent coefficient of variation (<code>'cvpct'</code>), or variance (<code>'var'</code>).
conf.int	Compute confidence intervals for the estimates? The default is <code>FALSE</code> .
conf.lev	Probability specifying the desired confidence level: the default value is <code>0.95</code> .

<code>deff</code>	Should the design effect be computed? The default is FALSE (see 'Details').
<code>na.rm</code>	Should missing values (if any) be removed from the variables of interest? The default is FALSE (see 'Details').
<code>object</code>	An object of class <code>svystatSR</code> .
<code>...</code>	Additional arguments to <code>coef</code> , <code>...</code> , <code>confint</code> methods (if any).

Details

This function computes weighted estimates for Ratios between Shares of a numeric variable, using suitable weights depending on the class of design: calibrated weights for class `cal.analytic` and direct weights otherwise. Standard errors are calculated using the Taylor linearization technique.

Ratios of Shares are a special case of Ratios. Therefore, at the price of some additional and heavy data preparation effort, ratios of shares could also be estimated using function `svyestatR`. However, `svystatSR` makes estimation by far easier, in particular when share ratios have to be estimated for many population groups and/or within many domains.

The mandatory argument `classes` identifies population groups whose ratios of y shares have to be estimated. Note that ratios of shares will be estimated and returned *for all the ordered pairs of population groups* defined by `classes`. Therefore, if `classes` defines G groups, `svystatSR` will have to compute estimates and sampling errors for $G * (G - 1)$ share ratios. To prevent combinatorial explosions (e.g. $G = 20$ would generate 380 share ratios), `classes` formula can reference just a *single* design variable, which must be a factor.

The optional argument `by` specifies the variables that define the "estimation domains", that is the subpopulations for which the estimates are to be calculated. If `by=NULL` (the default option), the estimates produced by `svystatSR` refer to the whole population. Estimation domains must be defined by a formula: for example the statement `by=~B1:B2` selects as estimation domains the subpopulations determined by crossing the modalities of variables `B1` and `B2`. Notice that a formula like `by=~B1+B2` will be automatically translated into the factor-crossing formula `by=~B1:B2`: if you need to compute estimates for domains `B1` and `B2` *separately*, you have to call `svystatSR` twice. The design variables referenced by `by` (if any) should be of type factor, otherwise they will be coerced.

The `conf.int` argument allows to request the confidence intervals for the estimates. By default `conf.int=FALSE`, that is the confidence intervals are not provided.

Whenever confidence intervals are requested (i.e. `conf.int=TRUE`), the desired confidence level can be specified by means of the `conf.lev` argument. The `conf.lev` value must represent a probability ($0 \leq \text{conf.lev} \leq 1$) and its default is chosen to be 0.95.

The optional argument `deff` allows to request the design effect [Kish 1995] for the estimates. By default `deff=FALSE`, that is the design effect is not provided. The design effect of an estimator is defined as the ratio between the variance of the estimator under the actual sampling design and the variance that would be obtained for an 'equivalent' estimator under a hypothetical simple random sampling without replacement of the same size. To obtain an estimate of the design effect comparing to simple random sampling "*with replacement*", one must use `deff="replace"`.

Being Ratios nonlinear estimators, the design effect is estimated on the linearized version of the estimator (that is: for the estimator of the total of the linearized variable, aka "Woodruff transform"). When dealing with domain estimation, the design effects referring to a given subpopulation are currently computed by taking the ratios between the actual variance estimates and those that would have been obtained if a simple random sampling were carried out *within* that subpopulation. This is the same as the `srssubpop` option for Stata's function `estat`.

Missing values (NA) in interest variables should be avoided. If `na.rm=FALSE` (the default) they generate NAs in estimates (or even an error, if design is calibrated). If `na.rm=TRUE`, observations

containing NAs are dropped, and estimates get computed on non missing values only. This implicitly assumes that missing values hit interest variables *completely at random*: should this not be the case, computed estimates would be *biased*.

Value

An object inheriting from the `data.frame` class, whose detailed structure depends on input parameters' values.

Author(s)

Diego Zardetto

References

- Sarndal, C.E., Swensson, B., Wretman, J. (1992) *“Model Assisted Survey Sampling”*, Springer Verlag.
- Kish, L. (1995). *“Methods for design effects”*. Journal of Official Statistics, Vol. 11, pp. 55-77.
- European Commission, Eurostat, (2013). *“Handbook on precision requirements and variance estimation for ESS households surveys: 2013 edition”*, Publications Office. doi: 10.2785/13579

See Also

Estimators of Totals and Means [svystatTM](#), Ratios between Totals [svystatR](#), Shares [svystatS](#), Multiple Regression Coefficients [svystatB](#), Quantiles [svystatQ](#), Complex Analytic Functions of Totals and/or Means [svystatL](#), and all of the above [svystat](#).

Examples

```
# Load household data:
data(data.examples)

# Create a design object:
des<-e.svydesign(data=example,ids=~towcod+famcod,strata=~SUPERSTRATUM,
  weights=~weight)

# Add convenience variable 'ones' to estimate counts:
des<-des.addvars(des,ones=1)

### Simple examples to illustrate the syntax:
# Population sex ratios:
svystatSR(des, y=~ones, classes=~sex, vartype="cvpct")

# Population sex ratios within provinces:
svystatSR(des, y=~ones, classes=~sex, by=~procod, vartype="cvpct")

# Ratios of population shares for 5 age classes:
# NOTE: This yields 5*(5-1)=20 ratios
svystatSR(des, y=~ones, classes=~age5c, vartype="cvpct")

### One more complicated example:
#####
# Ratios between shares of income held by people for income quintiles #
#####
```

```

# First: estimate income quintiles
inc.Q5 <- svystatQ(des, y=~income, probs=seq(0.2, 0.8, 0.2), ties="rounded")
inc.Q5

# Second: add a convenience factor variable classifying people by income
# quintiles
des<-des.addvars(des, quintile = cut(income, breaks = c(0, coef(inc.Q5), Inf),
                                   labels = 1:5, include.lowest=TRUE)
)

# Third: estimate income shares by income quintiles
QS5 <- svystatSR(des, y=~income, classes=~quintile, vartype="cvpct")
QS5

### Therefore, for instance, the *S80/S20 income quintile share ratio* is:
S80.20 <- QS5["quintile5/quintile1",]
S80.20

### NOTE: Procedure above yields *correct point estimates* of income quintile
###       share ratios, while *variance estimation is approximated* since
###       we neglected the sampling variability of the estimated quintiles.

```

svystatTM

Estimation of Totals and Means in Subpopulations

Description

Computes estimates, standard errors and confidence intervals for Totals and Means in subpopulations.

Usage

```

svystatTM(design, y, by = NULL, estimator = c("Total", "Mean"),
          vartype = c("se", "cv", "cvpct", "var"),
          conf.int = FALSE, conf.lev = 0.95, deff = FALSE,
          na.rm = FALSE)

## S3 method for class 'svystatTM'
coef(object, ...)
## S3 method for class 'svystatTM'
SE(object, ...)
## S3 method for class 'svystatTM'
VAR(object, ...)
## S3 method for class 'svystatTM'
cv(object, ...)
## S3 method for class 'svystatTM'
deff(object, ...)
## S3 method for class 'svystatTM'
confint(object, ...)

```


Arguments

<code>design</code>	Object of class <code>analytic</code> (or inheriting from it) containing survey data and sampling design metadata.
<code>y</code>	Formula defining the variables of interest. Only numeric or factor variables are allowed.
<code>by</code>	Formula specifying the variables that define the "estimation domains". If <code>NULL</code> (the default option) estimates refer to the whole population.
<code>estimator</code>	character specifying the desired estimator: it may be <code>'Total'</code> (the default) or <code>'Mean'</code> .
<code>vartype</code>	character vector specifying the desired variability estimators. It is possible to choose one or more of: standard error (<code>'se'</code> , the default), coefficient of variation (<code>'cv'</code>), percent coefficient of variation (<code>'cvpct'</code>), or variance (<code>'var'</code>).
<code>conf.int</code>	Compute confidence intervals for the estimates? The default is <code>FALSE</code> .
<code>conf.lev</code>	Probability specifying the desired confidence level: the default value is <code>0.95</code> .
<code>deff</code>	Should the design effect be computed? The default is <code>FALSE</code> (see 'Details').
<code>na.rm</code>	Should missing values (if any) be removed from the variables of interest? The default is <code>FALSE</code> (see 'Details').
<code>object</code>	An object of class <code>svystatTM</code> .
<code>...</code>	Additional arguments to <code>coef</code> , <code>...</code> , <code>confint</code> methods (if any).

Details

This function computes weighted estimates for Totals and Means using suitable weights depending on the class of `design`: calibrated weights for class `cal.analytic` and direct weights otherwise. Standard errors for nonlinear estimators (e.g. calibration estimators) are calculated using the Taylor linearization technique.

The mandatory argument `y` identifies the variables of interest, that is the variables for which estimates are to be calculated. The corresponding formula should be of the type `y=~var1+...+varn`. The design variables referenced by `y` should be numeric or factor (variables of other types - e.g. character - will generate an error). It is admissible to specify for `y` "mixed" formulae that simultaneously contain quantitative (numeric) variables and qualitative (factor) variables.

To override the restriction to formulae of the type `y=~var1+...+varn`, the `AsIs` operator `I()` can be used (see 'Examples'). Though the latter opportunity could appear quite useful in some occasion, actually it should be almost always possible to find a work-around by using other functions of the **ReGenesees** package.

The optional argument `by` specifies the variables that define the "estimation domains", that is the subpopulations for which the estimates are to be calculated. If `by=NULL` (the default option), the estimates produced by `svystatTM` refer to the whole population. Estimation domains must be defined by a formula: for example the statement `by=~B1:B2` selects as estimation domains the subpopulations determined by crossing the modalities of variables `B1` and `B2`. Notice that a formula like `by=~B1+B2` will be automatically translated into the factor-crossing formula `by=~B1:B2`: if you need to compute estimates for domains `B1` and `B2` *separately*, you have to call `svystatTM` twice. The design variables referenced by `by` (if any) should be of type factor, otherwise they will be coerced.

The optional argument `estimator` makes it possible to select the desired estimator. If `estimator="Total"` (the default option), `svystatTM` calculates, for a given variable of interest `vark`, the estimate of the total (when `vark` is numeric) or the estimate of the absolute frequency

distribution (when `vark` is factor). Similarly, if `estimator="Mean"`, the function calculates the estimate of the mean (when `vark` is numeric) or the estimate of the relative frequency distribution (when `vark` is factor).

The `conf.int` argument allows to request the confidence intervals for the estimates. By default `conf.int=FALSE`, that is the confidence intervals are not provided.

Whenever confidence intervals are requested (i.e. `conf.int=TRUE`), the desired confidence level can be specified by means of the `conf.lev` argument. The `conf.lev` value must represent a probability ($0 \leq \text{conf.lev} \leq 1$) and its default is chosen to be 0.95.

The optional argument `deff` allows to request the design effect [Kish 1995] for the estimates. By default `deff=FALSE`, that is the design effect is not provided. The design effect of an estimator is defined as the ratio between the variance of the estimator under the actual sampling design and the variance that would be obtained for an 'equivalent' estimator under a hypothetical simple random sampling without replacement of the same size. To obtain an estimate of the design effect comparing to simple random sampling "*with replacement*", one must use `deff="replace"`.

Understanding what 'equivalent' estimator actually means is straightforward when dealing with Horvitz-Thompson estimators of Totals and Means. This is not the case when, on the contrary, the estimator to which the `deff` refers is a nonlinear estimator (e.g. for Calibration estimators of Totals and Means). In such cases, the standard approach is to use as 'equivalent' estimator the linearized version of the original estimator (that is: the estimator of the total of the linearized variable, aka "Woodruff transform").

When dealing with domain estimation, the design effects referring to a given subpopulation are currently computed by taking the ratios between the actual variance estimates and those that would have been obtained if a simple random sampling were carried out *within* that subpopulation. This is the same as the `srssubpop` option for Stata's function `estat`.

Missing values (NA) in interest variables should be avoided. If `na.rm=FALSE` (the default) they generate NAs in estimates (or even an error, if design is calibrated). If `na.rm=TRUE` and `estimator="Mean"`, observations containing NAs are dropped, and estimates get computed on non-missing values only. This implicitly assumes that missing values hit interest variables *completely at random* (MCAR): should this not be the case, computed estimates would be *biased*. Since, even under the MCAR assumption, estimates of totals and counts solely based on complete cases would be biased, function `svystatTM` adopts a model-based ratio estimator when `na.rm=TRUE` and `estimator="Total"`. This is obtained by (i) first estimating the mean or proportion based on complete cases only, and (ii) then multiplying the result by the estimated population size based on all observations (i.e. both missing and non-missing). This model-based ratio estimator is asymptotically design-unbiased under the MCAR assumption. Notice that the `na.rm=TRUE` option is only allowed if `y` references a *single* interest variable.

Value

An object inheriting from the `data.frame` class, whose detailed structure depends on input parameters' values.

Author(s)

Diego Zardetto

References

- Sarndal, C.E., Swensson, B., Wretman, J. (1992) "*Model Assisted Survey Sampling*", Springer Verlag.
- Kish, L. (1995). "*Methods for design effects*". Journal of Official Statistics, Vol. 11, pp. 55-77.

European Commission, Eurostat, (2013). *“Handbook on precision requirements and variance estimation for ESS households surveys: 2013 edition”*, Publications Office. doi: 10.2785/13579

See Also

Estimators of Ratios between Totals [svystatR](#), Shares [svystatS](#), Ratios between Shares [svystatSR](#), Quantiles [svystatQ](#), Multiple Regression Coefficients [svystatB](#), Complex Analytic Functions of Totals and/or Means [svystatL](#), and all of the above [svystat](#).

Examples

```
# Load survey data:
data(data.examples)

# Creation of a design object:
des<-e.svydesign(data=example,ids=~towcod+famcod,strata=~SUPERSTRATUM,
  weights=~weight)

# Estimation of the total of 3 quantitative variables for the whole
# population:
svystatTM(des,~y1+y2+y3)

# Estimation of the total of the same 3 variables by region, with SE
# and CV%:
svystatTM(des,~y1+y2+y3,~regcod,vartype=c("se","cvpct"))

# Estimation of the mean of the same 3 variables by marstat and sex:
svystatTM(des,~y1+y2+y3,~marstat:sex,estimator="Mean")

# Estimation of the absolute frequency distribution of the qualitative
# variable age5c for the whole population, with the design effect:
svystatTM(des,~age5c,deff=TRUE)

# MARGINAL relative frequency distributions
# Estimation of the relative frequency distribution of the qualitative
# variable age5c for the whole population:
svystatTM(des,~age5c,estimator="Mean")

# CONDITIONAL relative frequency distributions
# Estimation of the relative frequency distribution of the qualitative
# variable marstat by sex:
svystatTM(des,~marstat,~sex,estimator="Mean")

# JOINT relative frequency distributions
# Estimation of the relative frequency of the joint distribution of sex
# and marstat:
# *First Solution* (using the AsIs operator I()):
svystatTM(des,~I(sex:marstat),estimator="Mean")
# *Second Solution* (adding a new variable to des):
des2 <- des.addvars(des, sex.marstat=sex:marstat)
svystatTM(des2,~sex.marstat,estimator="Mean")
# *Third Solution* (exploiting estimators of Shares, see also ?svystatS):
# Add new variable 'ones' to estimate counts of final units (individuals)
```

```

# and estimate the share of people for classes of sex and marstat
des2 <- des.addvars(des, ones=1)
svystatS(des2,~ones,classes=~sex:marstat)

# Estimation of the mean income inside provinces, with confidence intervals
# at a confidence level of 0.9:
svystatTM(des,~income,~procd,estimator="Mean",conf.int=TRUE,conf.lev=0.9)

# Quantitative and qualitative variables together: estimation of the
# total of income and of the absolute frequency distribution of sex,
# by marstat:
svystatTM(des,~income+sex,~marstat)

# Estimating totals in domains for "incomplete" partitions: more on
# the AsIs operator I()

# Estimation of the total income (plus cvpct) ONLY in region 7:
svystatTM(des,~I(income*(regcod=="7")),vartype="cvpct")
# Alternative solution (adding a new variable to des):
des2 <- des.addvars(des, inc_reg7=I(income*(regcod=="7")))
svystatTM(des2,~inc_reg7,vartype="cvpct")

# Estimation of the total income (plus cvpct) ONLY in regions 6 and 10:
svystatTM(des,~I(income*as.numeric(regcod %in% c("6","10"))),vartype="cvpct")
# Alternative solution (adding a new variable to des):
des2 <- des.addvars(des, inc_reg6.10=I(income*(regcod %in% c("6","10"))))
svystatTM(des2,~inc_reg6.10,vartype="cvpct")

# Compare with the corresponding estimates for the "complete" partition,
# i.e. for regions:
svystatTM(des,~income,~regcod,vartype="cvpct")

# Under default settings lonely PSUs produce errors in standard
# errors estimation (notice we didn't pass the fpcs):
data(fpcdat)
des.lpsu<-e.svydesign(data=fpcdat,ids=~psu+ssu,strata=~stratum,
                     weights=~w)
## Not run:
svystatTM(des.lpsu,~x+y+z,vartype=c("se","cvpct"))

## End(Not run)

# This can be circumvented in different ways, namely:
old.op <- options("RG.lonely.psu"="adjust")
svystatTM(des.lpsu,~x+y+z,vartype=c("se","cvpct"))
options(old.op)

# or otherwise:
old.op <- options("RG.lonely.psu"="average")
svystatTM(des.lpsu,~x+y+z,vartype=c("se","cvpct"))
options(old.op)

# but see also ?collapse.strata for a better alternative.

```

```
#####
# Household-level estimation in household surveys. #
#####

# Large scale household surveys typically adopt a 2-stage sampling
# design with municipalities as PSUs and households as SSUs, in order
# to eventually collect information on each individual belonging to
# sampled SSUs. In such a framework (up to possible total nonresponse
# effects), each individual inside a sampled household shares the
# same direct weight, which, in turn, equals the household weight.
# This implies that it is very easy to build estimates referred to
# SSU-level (households) information, despite estimators actually
# involve only individual values. Some examples are given below.

# Load survey data:
data(data.examples)

# Define the survey design (variable famcod identifies households)
exdes<-e.svydesign(data=example,ids=~towcod+famcod,strata=~stratum,
  weights=~weight)

# Collapse strata to eliminate lonely PSUs
exdes<-collapse.strata(design=exdes,block.vars=~sr:procod)

# Now add new convenience variables to the design object:
## 'ones':      to estimate individuals counts
## 'houseize':  to classify individuals by household size
## 'houdensity': to estimate households counts
exdes<-des.addvars(exdes,
  ones=1,
  houseize=factor(ave(famcod,famcod,FUN = length)),
  houdensity=ave(famcod,famcod,FUN = function(x) 1/length(x))
)

# Estimate the total number of households:
nhou<-svystatTM(exdes,~houdensity,vartype="cvpct")
nhou

# Estimate the total number of individuals:
nind<-svystatTM(exdes,~ones,vartype="cvpct")
nind

# Thus the average number of individuals per household is:
coef(nind)/coef(nhou)

# ...which can be obtained also as a ratio (along with
# its estimated sampling variability):
svystatR(exdes,~ones,~houdensity,vartype="cvpct")

# Estimate the number and proportion of individuals living in households
# of given sizes:
nind.by.houseize<-svystatTM(exdes,~houseize,vartype="cvpct")
nind.by.houseize

pind.by.houseize<-svystatTM(exdes,~houseize,estimator="Mean",var="cvpct")
```

```

pind.by.housize

# Estimate the number of households by household size:
nhou.by.housize<-svystatTM(exdes,~houdensity,~housize,vartype="cvpct")
nhou.by.housize

# Notice that estimates of individuals and household counts are consistent,
# indeed:
coef(nind.by.housize)/coef(nhou.by.housize)

```

trimcal

Trim Calibration Weights while Preserving Calibration Constraints

Description

This function trims calibration weights to a bounded interval, while preserving all the calibration constraints.

Usage

```

trimcal(cal.design, w.range = c(-Inf, Inf),
        maxit = 50, epsilon = 1e-07, force = TRUE)

```

Arguments

<code>cal.design</code>	Object of class <code>cal.analytic</code> containing the calibration weights to be trimmed.
<code>w.range</code>	The interval to which trimmed calibration weights must be bound (see ‘Details’). The default is <code>c(-Inf, Inf)</code> , which would leave the calibration weights <i>unchanged</i> .
<code>maxit</code>	The same as in function e.calibrate .
<code>epsilon</code>	The same as in function e.calibrate .
<code>force</code>	The same as in function e.calibrate .

Details

Extreme calibration weights might determine unstable estimates and inflate sampling error estimates. To avoid this risk, extreme weights may be *trimmed* by using some suitable procedure (see e.g. [Potter 90], [Valliant, Dever, Kreuter 13]). Despite no rigorous justifications exist for any proposed trimming method, sometimes practitioners are (or feel) compelled to apply a trimming step before estimation. This happens more frequently when interest variables are highly skewed at the population level, like in business surveys or in social surveys with a focus on economic variables (e.g. income, see [Verma, Betti, Ghellini 07], [EUROSTAT 16]).

Unfortunately, the most common trimming techniques do *not* preserve the calibration constraints: if the input weights to the trimming algorithm are calibrated, typically the trimmed weights will *not* reproduce the calibration totals. As a consequence, users have to calibrate again the weights after trimming and iterate through the trimming and calibration steps, until a set of weights is obtained that respects both the trimming bounds and the calibration controls.

Function `trimcal` overcomes this limitation: it allows to trim calibration weights to a specific interval while *simultaneously* preserving all the calibration totals. To achieve this result, a *constrained trimming algorithm* is used, which is similar in spirit to the GEM (Generalized Exponential Method)

of [Folsom, Singh 2000], but adopts the range restricted *euclidean* distance - instead of the *logit* - for numerical stability considerations.

When `w.range` is passed, *both* the trimming limits it defines must be *positive*. In other words, all calibration weights have to be positive after trimming. The purpose of this condition is to enable sound variance estimation on the trimmed object (see also below).

Note that `trimcal` is allowed to trim only *already calibrated* weights, i.e. the input object `cal.design` must be of class `cal.analytic`. This is a deliberate design choice, as trimming design (or initial) weights is methodologically unsound.

Note also that, in case the original calibration weights were asked to be constant within clusters selected at a given sampling stage (via argument `aggregate.stage` of `e.calibrate`), `trimcal` will *preserve* that property (see ‘Examples’).

Note lastly that `trimcal` will not trim further weights that have *just* been trimmed. This is again a deliberate design choice, devised to discourage over-trimming and cosmetic adjustments of the survey weights. Of course, it is instead entirely legitimate to calibrate again a trimmed object: after that, a further trimming step will be allowed.

From a variance estimation perspective, the trimmed object returned by function `trimcal` is treated as an ordinary calibrated object. More precisely, the trimming step is regarded as a “*finalization*” of the weight adjustment procedure which generated `cal.design`, i.e. as a completion of the previous calibration step. Call `w`, `w.cal` and `w.cal.trim` the starting weights, the calibrated weights of `cal.design` and the trimmed calibration weights as computed by function `trimcal`, respectively. Variance estimates computed on the trimmed object will pretend that one passed from `w` to `w.cal.trim` *directly* (`w -> w.cal.trim`), rather than in two steps (`w -> w.cal -> w.cal.trim`). Note incidentally that function `get.residuals`, when invoked on a trimmed object, will behave consistently with the variance estimation approach documented here.

Value

A calibrated object of class `cal.analytic`, storing *trimmed* calibration weights.

Trimming Process Diagnostics

Function `trimcal` exploits a *constrained* trimming algorithm to adjust the calibration weights so that (i) they fall within a bounded interval but (ii) still preserve all the calibration totals. *When this task is unfeasible, the algorithm will fail*. As a consequence, the adjusted weights returned in the output object will respect the range restrictions set by `w.range`, but some of the calibration constraints will be broken. Exactly as for function `e.calibrate`, in order to assess the degree of violation of the calibration constraints introduced by trimming, the user can exploit function `check.cal` (or, equivalently, the diagnostic data structure `ecal.status` available in the `.GlobalEnv`).

Methodological Warning

Trimming the calibration weights can result in introducing a *bias* in calibration estimates. Of course, one must hope that this *unknown* bias will turn out to be small compared to the *unknown* gain in precision obtained by trimming. In any case - since the actual effect of trimming weights on the MSE of the estimators is unclear - function `trimcal` should be used sparingly and carefully.

Author(s)

Diego Zardetto

References

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- Folsom, R.E., Singh, A.C. (2000) “The generalized exponential model for sampling weight calibration for extreme values, nonresponse, and poststratification”. Proceedings of the Section on Survey Research Methods, American Statistical Association, pp. 598-603.
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See Also

[e.calibrate](#) for calibrating survey weights within **ReGenesees** and [check.cal](#) to check if calibration constraints have been fulfilled.

Examples

```
#####
## Data preparation ##
#####
# Load sbs data:
data(sbs)
# Build a design object:
sbsdes<-e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,fpc=~fpc)
# Build a population totals template and fill it with actual known totals:
pop<-pop.template(sbsdes, calmodel=~(emp.num+ent):emp.cl:nace.macro-1, ~region)
pop <- fill.template(sbs.frame, pop)
# Calibrate:
sbscal <- e.calibrate(sbsdes, pop)
# Have a look at the calibration weights distribution:
summary(weights(sbscal))

#####
## Trimming examples ##
#####
## Example 1
# Now suppose we want to trim these calibration weights to, say, the bounded
# interval [0.5, 20]. Let's use our trimcal() function:
sbstrim <- trimcal(sbscal, c(0.5, 20))

# Have a look at the trimmed object:
sbstrim

# Let's first verify that the trimmed calibration weights actually obey the
# imposed range restrictions...
summary(weights(sbstrim))
# ...ok, as it must be.

# Second, let's verify that the trimmed object still preserves all the
```



```

# calibration constraints:
check.cal(sbstrim)

# or, more explicitly:
all.equal(aux.estimates(sbscal, template=pop),
          aux.estimates(sbstrim, template=pop))
# ...ok, as it must be.

# Let's have a look at the scatterplots of calibrated and trimmed weights:
plot(weights(sbsdes), weights(sbscal), pch = 20, col = "red",
      xlab = "Direct weights", ylab = "Calibration (red) and Trimmed (blue) weights")
points(weights(sbsdes), weights(sbstrim), pch = 20, col = "blue")
abline(h = c(0.5, 20), col = "green")

# Last, compute estimates and estimated sampling errors on the trimmed object
# as you would do on ordinary calibrated objects, e.g.
# before trimming:
svystatTM(sbscal, y = ~va.imp2, by = ~nace.macro, estimator = "Mean")
# after trimming:
svystatTM(sbstrim, y = ~va.imp2, by = ~nace.macro, estimator = "Mean")

## Example 2
# If w.range is too tight, constrained trimming can fail:
sbstrim2 <- trimcal(sbscal, c(1, 20))

# As a consequence, the trimmed weights will respect the range restrictions...
summary(weights(sbstrim2))

# ...but some of the calibration constraints will be broken:
check.cal(sbstrim2)

## Example 3
# If calibration weights were asked to be constant within clusters, the same
# will hold true for the trimmed calibration weights.

# Load household data:
data(data.examples)

# Define a survey design object:
des <- e.svydesign(data=example, ids=~towcod+famcod, strata=~SUPERSTRATUM,
                  weights=~weight)

# Calibrate asking that all individuals within any household share the same
# calibration weight (re-use an example from ?e.calibrate):
descal <- e.calibrate(design=des, df.population=pop04p,
                     calmodel=~x1+x2+x3-1, partition=~regcod, calfun="logit",
                     bounds=bounds, aggregate.stage=2)

# Have a look at the calibration weights distribution:
summary(weights(descal))

# Trim the calibration weights to, say, the bounded interval [150, 850]
destrim <- trimcal(descal, c(150, 850))

# Do trimmed calibration weights obey the imposed range restrictions?

```

```

summary(weights(destrim))

# Verify that trimmed weights are still equal within households:
any( tapply( weights(destrim), destrim$variables$famcod,
              function(x) {length(unique(x)) > 1} ) ) )

# FALSE, as it must be.

#####
## Allowed and forbidden trimming policies ##
#####
# Let's illustrate some design restrictions on function trimcal():
# 1) Trimming limits must be both positive:
## Not run:
trimcal(sbscal, c(-0.05, 18))

## End(Not run)

# 2) Trimming design (or direct, or initial) weights is not allowed, you can
#    only trim calibration weights:
## Not run:
trimcal(sbsdes, c(1, 18))

## End(Not run)

# 3) You cannot trim further weights that have just been trimmed:
## Not run:
trimcal(sbsttrim, c(1, 18))

## End(Not run)

# 4) You can calibrate again trimmed weights...
pop2<-pop.template(sbsdes, calmodel=~(emp.num+ent):area-1)
pop2<-fill.template(sbs.frame,pop2)
sbscal2<-e.calibrate(sbsttrim, pop2)
summary(weights(sbscal2))

# ...after that, a further trimming step is allowed:
sbstrim2 <- trimcal(sbscal2, c(0.6, 19))
sbstrim2
summary(weights(sbstrim2))

```

Description

Computes the Unequal Weighting Effect for the current and initial weights of a design object.

Usage

```
UWE(design, by = NULL)
```

Arguments

design	Object of class <code>analytic</code> (or inheriting from it).
by	Formula specifying variables that define "estimation domains". If <code>NULL</code> (the default option) the UWE refer to the whole sample.

Details

Function `UWE` computes the Unequal Weighting Effect for the current (w) and initial (w_0) weights of a design object, plus the corresponding variance inflation (or deflation) factor ($UWE(w) / UWE(w_0)$) induced by changing the weights from w_0 to w ($w_0 \rightarrow w$).

Following Kish's definition [Kish 92], the UWE is calculated as 1 plus the relative sample variance of the weights: $UWE(w) = 1 + RelVar(w)$.

The *current* weights, w , of design are the weights that would be returned by `weights(design)` and would be used for estimation purposes by functions `svyestatTM`, `svyestatR`, etc.

The *initial* weights, w_0 , of design depend on the nature of object design:

- If design is the outcome of a '**weight-changing pipeline**', $w_0 \rightarrow w_1 \rightarrow \dots \rightarrow w$, i.e. it was obtained by the application of an arbitrary *chain* of **ReGenesees** functions that *modify the weights* (e.g. `smooth.strat.jump`, `e.calibrate`, `ext.calibrated`, `trimcal`, ...), then the initial weights, w_0 , are the weights of the starting design object in the pipeline.
- If design is an initial design object generated by function `e.svydesign`, then the initial weights, w_0 , are taken as equal to current weights, $w_0 = w$.

Note that, when design is the outcome of a 'weight-changing pipeline', function `UWE` provides a measure of the overall, cumulative impact of all the adjustments the weights underwent throughout the pipeline.

To assess the effect, in terms of UWE and variance inflation, of just a single processing step of the pipeline, you can call function `UWE` on the input and output designs of that step and compare the results (basically, by taking suitable ratios).

Value

A data.frame, with one single row (if `by = NULL`) or one row for each domain (if `by` is passed), and the following columns:

Column	Meaning
<code>UWE.curr.....</code>	Current Unequal Weighting Effect
<code>UWE.ini.....</code>	Initial Unequal Weighting Effect
<code>VAR.infl.....</code>	Variance Inflation Factor (<code>UWE.curr / UWE.ini</code>)

Methodological Remark

Kish's UWE is a model-based tool that can be useful for diagnostic purposes. However, its values must be interpreted with some caution, exactly as it is necessary to do for model-based estimates of Kish's Deff.

In particular, UWE is - by construction - only sensitive to variations of the *sample* variance of the weights. Therefore, it is unable to discriminate weight adjustments which, despite adding variability to the weights at sample level, might result in reductions of the *sampling* variance for some estimators. This is often the case of calibration, which may well make survey weights more unequal, but nonetheless cause their reciprocals to become more correlated to some interest variables. Similar

considerations hold for stratified sampling, to the extent that, with respect to the interest variables, units tend to be more similar within strata than between strata.

In any case, the UWE can turn out handy when comparing the potential outcomes of performing the same kind of weight adjustment under slightly different settings (e.g. calibration with different bounds or distance functions, trimming with different thresholds, etc.).

Author(s)

Diego Zardetto

References

Kish, L. (1992). Weighting for unequal π . *Journal of Official Statistics*, 8, 183-200.

See Also

ReGensees functions which define survey weights ([e.svydesign](#)), or modify survey weights (e.g. [smooth.strat.jump](#), [e.calibrate](#), [ext.calibrated](#), [trimcal](#), ...).

Examples

```
#####
# Compute the UWE along the following example #
# of weight-changing pipeline:                #
# 1) Smooth for stratum jumpers                #
# 2) Adjust for nonresponse                    #
# 3) Calibrate to known population totals      #
# 4) Consistently trim calibration weights     #
#                                              #
# NOTE: To perform 1) and 2) I will first      #
#       A) simulate some stratum jumpers.     #
#       B) simulate some nonresponse.         #
#####

## Load sbs data:
data(sbs)

## -- A) Simulate stratum jumpers
# Create the strata variable observed at survey time by cloning the
# strata variable at sampling time
sbs$curr.strata <- sbs$strata

# Now inject some (say ~250) random stratum jumpers
set.seed(12345)          # (fix the RNG seed for reproducibility)
sbs$curr.strata[sample(1:nrow(sbs), 250)] <- sbs$curr.strata[sample(1:nrow(sbs), 250)]

# Resulting number of stratum jumpers:
tt <- table(sbs$strata, sbs$curr.strata)
sum(tt[row(tt) != col(tt)])

## -- B) Simulate nonresponse
# Assume a response propensity that increases with enterprise size (as
# measured by number of employees)
levels(sbs$emp.cl)
p.resp <- c(.4, .6, .8, .95, .99)
```

```

# Tie response probabilities to sample observations:
pr <- p.resp[unclass(sbs$emp.cl)]

# Now, randomly select a subsample of responding units from sbs:
set.seed(12345)          # (fix the RNG seed for reproducibility)
rand <- runif(1:nrow(sbs))
sbs.r <- sbs[rand < pr, ]

# This implies an overall response rate of about 73%:
nrow(sbs.r) / nrow(sbs)

## -- 0) Create the respondent design object
# NOTE: I'll keep using the original fpc column for the sake of the examples,
#       but they should be recomputed in real applications...
sbsdes<-e.svydesign(data=sbs.r,ids=~id,strata=~strata,weights=~weight,fpc=~fpc)

## -- 1) Smooth for stratum jumpers
# Use method 'MinChange'
sbssmooth <- smooth.strat.jump(sbsdes, ~curr.strata)

# Have a look
sbssmooth

## -- 2) Adjust for nonresponse
# Use a simple Response Homogeneity Model approach, with size classes
# as RHGs. Perform the RHG weight adjustment via calibration

# Compute enterprise counts by size classes from the frame
N.RHG <- pop.template(sbssmooth, calmodel= ~emp.cl - 1)
N.RHG <- fill.template(sbs.frame, N.RHG)

# Calibrate to achieve the RHG adjustment
sbsRHG <- e.calibrate(sbssmooth, N.RHG)

# Have a look
sbsRHG

## -- 3) Calibrate to known population totals
# Now calibrate again in order to reduce estimators variance, by using further
# available auxiliary information, e.g. the total number of employees (emp.num)
# and enterprises (ent) inside the domains obtained by crossing nace.macro
# and region:
pop <- pop.template(sbsRHG, calmodel = ~emp.num + ent-1,
                   partition = ~nace.macro:region)
pop <- fill.template(sbs.frame, pop)

# Calibrate to improve estimation efficiency
sbscal <- e.calibrate(sbsRHG, pop)

# Have a look
sbscal

## -- 4) Consistently trim calibration weights
# Say one wants to avoid weights that are less than 1 and above 50:
sbstrim <- trimcal(sbscal, c(1, 50))

# Have a look

```

```

sbstrim

## -- UWE calculation along the weights-changing pipeline
# Object sbstrim is the output of the weights-changing pipeline, as
# one easily recognizes when printing it:
sbstrim

# UWE of initial object
UWE(sbsdes)

# UWE at step 1), i.e. smoothing for stratum jumpers
UWE(sbssmooth)

# UWE of step 2), i.e. nonresponse RHG adjustment
UWE(sbsRHG)

# UWE at step 3), i.e. calibration for efficiency improvement
UWE(sbscal)

# UWE at step 4), i.e. consistent trimming of calibration weights
UWE(sbstrim)

# End

```

weights

Retrieve Sampling Units Weights

Description

Extracts the *current* weights of units belonging to a survey design object.

Usage

```
weights(object, ...)
```

Arguments

object	Object of class <code>analytic</code> (or inheriting from it) containing survey data and sampling design metadata.
...	Arguments for future expansion.

Details

The *current* weights of object are, by definition, those weights that would be used for estimation purposes on that object (e.g. by functions [svystatTM](#), [svystatR](#), [svystatS](#), [svystatSR](#), [svystatQ](#), [svystatB](#), [svystatL](#), ...). The nature of such weights depends on the class of object: calibrated weights for class `cal.analytic` and direct weights otherwise.

Value

A vector of weights, whose components are positionally tied to the sampling units belonging to object.

Note

If object has undergone multiple, subsequent calibration steps, the function will return the output weights generated by the *last* calibration step.

Author(s)

Diego Zardetto

See Also

Function [g.range](#) to assess the range of the g-weights of a calibrated design object.

Examples

```
# Creation of the object to be calibrated:
data(data.examples)
exdes<-e.svydesign(data=example,ids=~towcod+famcod,strata=~SUPERSTRATUM,
  weights=~weight)

# Retrieve the weights and summarize their distribution:
summary(weights(exdes))

# Now calibrate (global solution) on the joint distribution of sex
# and marstat (totals in pop03):
excal.1st<-e.calibrate(design=exdes,df.population=pop03,
  calmodel=~marstat:sex-1,calfun="linear",bounds=bounds)

# Retrieve the current weights (i.e. the calibrated ones) and
# summarize their distribution:
summary(weights(excal.1st))

# Now calibrate once again, this time on the marginal distribution
# of age in 5 classes (age5c) inside provinces (procod) (totals in pop06p)
# with the partitioned solution, the logit distance and bounds=c(0.5, 1.5):
excal.2nd<-e.calibrate(design=excal.1st,df.population=pop06p,
  calmodel=~age5c-1,partition=~procod,calfun="logit",
  bounds=c(0.5, 1.5))

# Notice that the print method correctly takes the calibration chain
# into account:
excal.2nd

# Now retrieve the current weights (i.e. the ones generated by the second
# calibration step) and summarize their distribution:
summary(weights(excal.2nd))
```

write.svystat

Export Survey Statistics

Description

Prints survey statistics to a file or connection.

Usage

```
write.svystat(x, ...)
```

Arguments

```
x                An object containing survey statistics.
...              Arguments to write.table
```

Details

This function is just a convenience wrapper to [write.table](#), designed to export objects which have been returned by survey statistics functions (e.g. [svystatTM](#), [svystatR](#), [svystatS](#), [svystatSR](#), [svystatB](#), [svystatQ](#), [svystatL](#), [svySigma](#), [svySigma2](#)).

Author(s)

Diego Zardetto

See Also

[write.table](#) and the 'R Data Import/Export' manual.

Examples

```
# Creation of a design object:
data(sbs)
des<-e.svydesign(data=sbs,ids=~id,strata=~strata,weights=~weight,
  fpc=~fpc)

# Estimation of the average value added per employee
# for economic activity region and macro-sectors,
# with SE, CV% and standard confidence intervals:
stat <- svystatR(des,~va.imp2,~emp.num,by=~region:nace.macro,
  vartype=c("se","cvpct"),conf.int=TRUE)
stat

# In order to export the summary statistics above
# into a CSV file for input to Excel one can use:
## Not run:
write.svystat(stat,file="stat.csv",sep=";")

## End(Not run)

# ...and to read this file back into R one needs
## Not run:
stat.back <- read.table("stat.csv",header=TRUE,sep=";",
  check.names=FALSE)
stat.back

## End(Not run)

# Notice, however, that the latter object has
# lost a lot of meta-data as compared to the
# original one, so that e.g.:
## Not run:
```



```

confint(stat.back)

## End(Not run)

# ...while, on the contrary:
confint(stat)

```

Zapsmall

*Zapsmall Data Frame Columns and Numeric Vectors***Description**

Put to zero values "close" to zero.

Usage

```

## Default S3 method:
Zapsmall(x, digits = getOption("digits"), ...)
## S3 method for class 'data.frame'
Zapsmall(x, digits = getOption("digits"), except = NULL, ...)

```

Arguments

<code>x</code>	A <code>data.frame</code> with numeric columns or a numeric vector.
<code>digits</code>	Integer indicating the precision to be used.
<code>except</code>	Indices of columns not to be zapped (if any).
<code>...</code>	Arguments for future expansion.

Details

This function "extends" to `data.frame` objects function [zapsmall](#) from the package **base**. The method for class `data.frame` 'zaps' values close to zero occurring in columns of `x`. Argument `except` can be used to prevent specific columns from being zapped. The default method is a bare copy of the original function from package **base**.

Value

An object of the same class of `x`, with values "close" to zero zapped to zero.

Author(s)

Diego Zardetto

See Also

The original function [zapsmall](#) from package **base**.

Examples

```
# Create a test data frame with columns containing
# values of different orders of magnitude:
data <- data.frame(a = pi*10^(-8:1), b = c(rep(1000,8), c(1E-5, 1E-6)))

# Print on screen the test data frame:
data

# Compare with its zapped version:
Zapsmall(data)
```

%into%

Compress Nested Factors

Description

The special binary operator %into% transforms nested factors in such a way as to reduce the dimension and/or the sparsity of the model matrix of a calibration problem.

Usage

```
inner %into% outer
"%into%"(inner, outer)
```

Arguments

inner	Factor with levels nested into outer (see ‘Details’).
outer	Factor whose levels are an aggregation of those in inner (see ‘Details’).

Details

Arguments inner and outer must be both factors and must have the same length. Moreover, inner has to be *strictly nested* into outer. Nesting is defined by treating elements in inner and outer as if they were positionally tied (i.e. as if they belonged to columns of a given data frame). The definition is as follows:

inner and outer are strictly nested if, and only if, 1) every set of equal elements in inner correspond to a set of equal elements in outer, and 2) inner has *more* non-empty levels than outer.

If inner and outer do not fulfill the conditions above, evaluating inner %into% outer gives an error.

Suppose inner is actually nested into outer and define inner.in.outer <- inner %into% outer. The output factor inner.in.outer is built by recoding inner levels in such a way that each of them is mapped into the integer which represents its order inside the corresponding level of outer (see ‘Examples’). As a consequence, the levels of inner.in.outer will be 1:n.max, being n.max the *maximum* number of levels of inner tied to a level of outer. Since this number is generally considerably smaller than the number of levels of inner, inner.in.outer can be seen as a *compressed* representation of inner. Obviously, compression comes at a price: indeed inner.in.outer can now be used to identify a level of inner only *inside* a given level of outer (see ‘Examples’).

The usefulness of the %into% operator emerges in the calibration context. As we already documented in [e.calibrate](#), factorizing a calibration problem (i.e. exploiting the partition argument

of `e.calibrate`) determines a significant reduction in computation complexity, especially for big surveys. Now, it is sometimes the case that a calibration model is actually factorizable, even if this property is not self-apparent, due to factor nesting. In such cases, anyway, trying naively to factorize the outer variable(s) typically leads to very big and sparse model matrices (as well as population totals data frames), with the net result of washing-out the expected efficiency gain. A better alternative is to exploit the `%into%` operator in order to *compress* the inner variable in such a way that the outer variable can be actually factorized *without* giving rise to huge and sparse matrices. Section ‘Examples’ reports some practical illustration of the above line of reasoning.

Value

A factor with levels `1:n.max`, being `n.max` the *maximum* number of levels of inner tied to a level of outer.

Author(s)

Diego Zardetto

See Also

Further examples can be found in the [fill.template](#) help page.

Examples

```
#####
## General properties of the %into% operator.  #
#####
# First build a small data frame with 2 nested factors representing
# regions and provinces:
dd <- data.frame(
  reg = factor( rep(LETTERS[1:3], c(6, 3, 1)) ),
  prov = factor( rep(letters[1:6], c(3, 2, 1, 2, 1, 1)) )
)

dd

# Since prov is strictly nested into reg we can compute:
prov.in.reg <- dd$prov %into% dd$reg
prov.in.reg

# Note that prov.in.reg has 3 levels because, as can be seen from dd,
# the maximum number of provinces inside regions is 3. Thus prov.in.reg
# is actually a compressed version of dd$prov (whose levels were 6)
# but, obviously, it can now be used to identify a province only inside
# a given region. This means that the the two factors below are identical (up
# to levels' labels):
dd$prov
interaction(prov.in.reg, dd$reg, drop=TRUE)

# Note that all the statements below generate errors:
## Not run:
dd$reg %into% dd$prov
dd$reg %into% dd$reg
dd$prov %into% dd$prov

## End(Not run)
```

```
#####
## A more useful (and complex) example from the calibration context. #
#####
# First define a design object:
data(data.examples)
exdes <- e.svydesign(data=example,ids=~towcod+famcod,strata=~SUPERSTRATUM,
weights=~weight)

# Now suppose you have to perform a calibration process which
# exploits the following known population totals:
# 1) Joint distribution of sex and age10c (age in 10 classes)
#    at the region level;
# 2) Joint distribution of sex and age5c (age in 5 classes)
#    at the province level;
#
# The auxiliary variables corresponding to the population totals above
# can be symbolically represented by a calibration model like the following:
# ~(procod:age5c + regcod:age10c - 1):sex
#
# At first sight it seems that only the sex variable can be factorized
# in the model above. However if one observe that regions are an aggregation
# of provinces, one realizes that also the regcod variable can be factorized.
# Similarly, since categories of age5c are an aggregation of categories of
# age10c, age5c can be factorized too. In both cases, using the %into%
# operator will save computation time and memory usage.
# Let us see it in practice:
#
## 1) Global calibration (i.e. calmodel=~(procod:age5c + regcod:age10c - 1):sex,
# no partition variable, known totals stored in pop07):
t<-system.time(
  cal07<-e.calibrate(design=exdes,df.population=pop07,
    calmodel=~(procod:age5c + regcod:age10c - 1):sex,
    calfun="logit",bounds=c(0.2,1.8))
)

## 2) Partitioned calibration on the self evident variable sex only
# (i.e. calmodel=~procod:age5c + regcod:age10c - 1, partition=~sex,
# known totals stored in pop07p):
tp<-system.time(
  cal07p<-e.calibrate(design=exdes,df.population=pop07p,
    calmodel=~procod:age5c + regcod:age10c - 1,partition=~sex,
    calfun="logit",bounds=c(0.2,1.8))
)

## 3) Full partitioned calibration on variables sex, regcod and age5c
# by exploiting %into%.
# First add to the design object the new compressed factor variables
# involving nested factors, namely provinces inside regions...
exdes<-des.addvars(exdes,procod.in.regcod=procod %into% regcod)

# ...and age10c inside age5c:
exdes<-des.addvars(exdes,age10c.in.age5c=age10c %into% age5c)

# Now calibrate exploiting the new variables
# (i.e. calmodel=~procod.in.regcod + age10c.in.age5c - 1,
# partition=~sex:regcod:age5c, known totals stored inside cal07pp)
tpp<-system.time(
```

```
cal07pp<-e.calibrate(design=exdes,df.population=pop07pp,
  calmodel=~procod.in.regcod + age10c.in.age5c - 1,
  partition=~sex:regcod:age5c,
  calfun="logit",bounds=c(0.2,1.8))
)

# Now compare execution times:
t
tp
tpp

# thus, tpp < tp < t, as expected.
# Notice also that we obtained identical calibrated weights:
all.equal(weights(cal07),weights(cal07p))
all.equal(weights(cal07),weights(cal07pp))

# as it must be.
```

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