# Package ‘R2BEAT’

January 13, 2020

**Type** Package

**Title** Multistage Allocation

**Description** Multivariate optimal allocation for different domains in one and two stages stratified sample design. R2BEAT extends the Neyman (1934) <doi:10.2307/2342192> – Tschuprow (1923) allocation method to the case of several variables, adopting a generalization of the Bethel’s proposal (1989). R2BEAT develops this methodology but, moreover, it allows to determine the sample allocation in the multivariate and multi-domains case of estimates for two-stage stratified samples.

**Version** 1.0.1

**Depends** R (>= 3.5.0)

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**License** EUPL

**Encoding** UTF-8

**LazyData** true

**RoxygenNote** 6.1.1

**NeedsCompilation** no

**Repository** CRAN

**Date/Publication** 2020-01-13 10:20:02 UTC

## R topics documented:

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`allocation` *Sample sizes for each stratum*

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## Description

Example data frame containing a given allocation.

## Usage

```
data(beat.example)
allocation
```

## Format

The Strata data frame contains a row per each stratum with the following variables:

**SIZE** Stratum sample size (numeric)

## Details

Note: the names of the variables must be the ones indicated above.

## Examples

```
# Load example data
data(beat.example)
allocation
str(allocation)
```

---

`beat.1st` *Compute one stage multivariate optimal allocation.*

---

## Description

Compute multivariate optimal allocation for different domains in one stage stratified sample design

## Usage

```
beat.1st(stratif, errors, minnumstrat=2, maxiter=200, maxiter1=25, epsilon=10^(-11))
```

### Arguments

`stratif` Data frame of survey strata, for more details see, e.g.,strata.

`errors` Data frame of expected coefficients of variation (CV) for each domain, for more details see, e.g.,errors.

`minnumstrat` Minimum number of elementary units per strata (default=2).

`maxiter` Maximum number of iterations (default=200) of the general procedure. This kind of iteration may be required by the fact that when in a stratum the number of allocated units is greater or equal to its population, that stratum is set as "census stratum", and the whole procedure is re-initialised.

`maxiter1` Maximum number of iterations in Chromy algorithm (default=25).

`epsilon` Tollerance for the maximum absolute differences between the expected CV and the realised CV with the allocation obtained in the last iteraction for all domains. The default is 10^(-11).

### Details

The methodology is a generalization of Bethel multivariate allocation (1989) that extended the Neyman (1959) - Tchuprov (1923) allocation for multi-purpose and multi-domains surveys. The generalized Bethel's algorithm allows to determine the optimal sample size for each stratum in a stratified sample design. The overall sample size and the allocation among the different strata is determined starting from the accuracy constraints imposed in the survey on interest estimates.

### Value

Object of class `list`. The list contains 4 objects:

`n` Vector with the optimal sample size for each stratum.

`file_strata` Data frame corresponding to the input data.frame `stratif` with the `n` optimal sample size column added.

`alloc` Data frame with optimal (`ALLOC`), proportional (`PROP`), equal (`EQUAL`) sample size allocation.

`sensitivity` Data frame with a summary of expected coefficients of variation (`Planned CV`), realized coefficients of variation with the given optimal allocation (`Actual CV`) and the sensitivity at 10% for each domain and each variable. Sensitivity can be a useful tool to help in finding the best allocation, because it provides a hint of the expected sample size variation for a 10% change in planned CVs.

### Author(s)

Developed by Stefano Falorsi, Andrea Fasulo, Alessio Guandalini, Daniela Pagliuca, Marco D. Terribili.

### References

Bethel, J. (1989) *Sample allocation in multivariate surveys.* Survey methodology, 15.1: 47-57.

Cochran, W. (1977) *Sampling Techniques.* John Wiley & Sons, Inc., New York

Neyman, J. (1934). On the two different aspects of the representative method: the method of stratified sampling and the method of purposive selection. *Journal of the Royal Statistical Society*, 97(4): 558-625.

Tschuprow, A. A. (1923). On the mathematical expectation of the moments of frequency distributions in the case of correlated observation. (Chapters 4-6). *Metron*, 2: 646-683.

## Examples

```
# Load example data
data(beat.example)

## Example 1
# Allocate the sample
allocation_1 <- beat.1st(stratif=strata, errors=errors)

# The total sample size is
sum(allocation_1$n)

## Example 2
# Assume 5700 units is the maximum sample size to stick to our budget.
# Looking at allocation_1$sensitivity we can see that most of the
# sensitivity is in DOM1 for REG1 and REG2 due to V1.
allocation_1$sensitivity
# We can relax the constraints increasing the expected coefficients of variation for X1 by 10%
errors1 <- errors
errors1[1,2] <- errors[1,2]+errors[1,2]*0.1

# Try the new allocation
allocation_2 <- beat.1st(stratif=strata, errors=errors1)
sum(allocation_2$n)

## Example 3
# On the contrary, if we tighten the constraints decreasing the expected coefficients of variation
# for X1 by 10%
errors2 <- errors
errors2[1,2] <- errors[1,2]-errors[1,2]*0.1

# The new allocation leads to a larger sample than the first example
allocation_3 <- beat.1st(stratif=strata, errors=errors2)
sum(allocation_3$n)
```

---

`beat.2st` *Multivariate optimal allocation for different domains in two stage stratified sample design*

---

## Description

Compute multivariate optimal allocation for different domains corrected considering stratified two stages design

## Usage

```
beat.2st(stratif, errors, des_file, psu_file, rho, deft_start = NULL,
    effst = NULL, epsilon1 = 5, mmdiff_deft = 1,maxi = 20,
    epsilon = 10^(-11), minnumstrat = 2, maxiter = 200, maxiter1 = 25)
```

## Arguments

| | |
|---|---|
| stratif | Data frame of survey strata, for more details see, e.g.,strata. |
| errors | Data frame of coefficients of variation for each domain, for more details see, e.g.,errors. |
| des_file | Data frame containing information on sampling design variables, for more details see, e.g.,design. |
| psu_file | Data frame containing information on primary stage units stratification, for more details see, e.g.,PSU_strat. |
| rho | Data frame of survey strata, for more details see, e.g.,rho. |
| deft_start | Data frame of survey strata, for taking into account the initial design effect on each variable, for more details see, e.g.,deft_start. |
| effst | Data frame of survey strata, for taking into account the estimator effect on each variable, for more details see, e.g.,effst. |
| epsilon1 | First stop condition: sample sizes differences beetween two iterations; iteration continues until the maximum of sample sizes differences is greater than the default value. The default is 5. |
| mmdiff_deft | Second stop condition: defts differences beetween two iterations; iteration continues until the maximum of defts largest differences is greater than the default value. The default is 0.06. |
| maxi | Third stop condition: maximum number of allowed iterations. The default is 20. |
| epsilon | The same as in function beat.1st. |
| minnumstrat | The same as in function beat.1st. |
| maxiter | The same as in function beat.1st. |
| maxiter1 | The same as in function beat.1st. |

## Details

The methodology is a generalization of Bethel multivariate allocation (1989) that extended the Neyman (1959) - Tchuprov (1923) allocation for multi-purpose and multi-domains surveys. The generalized Bethel's algorithm allows to determine the optimal sample size for each stratum in a stratified sample design. The overall sample size and the allocation among the different strata is determined starting from the accuracy constraints imposed in the survey on interest estimates. The optimal allocation is obtained throught a procedure that converge in few iteractions:

The first iteration is a computation of an initial allocation with the multivariate optimal allocation for different domains in one stages statified sample design (the methodology is a generalization for multidomains and multistages designs of Bethel multivariate allocation, 1989).

The correction of the initial allocation is based on an iterative method calculating new allocations and is based on an inflaction of strata variances using the design effect (Ganninger, 2010).

## Value

Object of class `list`. The list contains 8 objects:

- `iteractions` Data frame that for each iteraction provides a summary with the number of Primary Stage Units (`PSU_Total`) distinguish between Self-Representative (`PSU_SR`) from Non-Self-Representative (`PSU_NSR`) and the number of Secondary Stage Units (`SSU`). This output is also printed to the screen.
- `file_strata` Input data frame in `stratif` with the design effect for each variables in each stratum (`DEFT1 -DEFTn`) and the optimal sample size columns.
- `alloc` Data frame with optimal (`ALLOC`), proportional (`PROP`), equal (`EQUAL`) sample size allocation.
- `planned` Data frame with a summary of expected coefficients of variation for each variable in each domain.
- `expected` Data frame with a summary of realized coefficients of variation with the given optimal allocation for each variable in each domain.
- `sensitivity` Data frame with a summary of the sensitivity at 10% for each domain and each variable. Sensitivity can be a useful tool to help in finding the best allocation, because it provides a hint of the expected sample size variation for a 10% change in planned CVs.
- `deft_c` Data frame with the design effect for each variable in each domain in each iteraction. Note that `DEFT1_0 -DEFTn_0` is always equal to 1 if `deft_start` is `NULL`. Instead is equal to `deft_start`. While `DEFT1 -DEFTn` are the final design effect related to the given allocation.
- `param_alloc` A vector with a resume of all the parameter given for the allocation.

## Author(s)

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## References

Cochran, W. (1977) *Sampling Techniques.* John Wiley & Sons, Inc., New York

Ganninger, M. (2010). *Design effects: model-based versus design-based approach.* Vol. 3, p. 174. DEU.

Neyman, J. (1934). On the two different aspects of the representative method: the method of stratified sampling and the method of purposive selection. *Journal of the Royal Statistical Society*, 97(4), 558-625.

Tschuprow, A. A. (1923). On the mathematical expectation of the moments of frequency distributions in the case of correlated observation. (Chapters 4-6). *Metron*, 1923, 2: 646-683.

## Examples

```
# Load example data
data(beat.example)
```

```
## Example 1
# Allocate the sample
allocation2st_1 <- beat.2st(stratif=strata, errors=errors,
des_file=design, psu_file=PSU_strat,rho=rho)
# The total ammount of sample size is 191 PSU (36 SR + 155 NSR) and 15147 SSU.

## Example 2
# Assume 13000 SSUs is the maximum sample size to stick to our budget.
# Look at the sensitivity is in DOM1 for REG1 and REG2 due to V1.
allocation2st_1$sensitivity
# We can relax the constraints increasing the expected coefficients of variation for X1 by 10%
errors1 <- errors
errors1[1,2] <- errors[1,2]+errors[1,2]*0.1

# Try the new allocation
allocation2st_2 <- beat.2st(stratif=strata, errors=errors1,
des_file=design, psu_file=PSU_strat,rho=rho)

## Example 3
# On the contrary, if we tighten the constraints decreasing the expected coefficients of variation
# for X1 by 10%
errors2 <- errors
errors2[1,2] <- errors[1,2]-errors[1,2]*0.1

# The new allocation leads to a larger sample than the first example (around 18000)
allocation2st_3 <- beat.2st(stratif=strata, errors=errors2,
des_file=design, psu_file=PSU_strat,rho=rho)

## Example 4
# Sometimes some budget constraints concern the number of PSU involved in the survey.
# Tuning the PSUs number is possible modyfing the MINIMUM in des_file.
# Assume to increase the MINIMUM from 48 to 60
design1 <- design
design1[,4] <- 60
allocation2st_4 <- beat.2st(stratif=strata, errors=errors2,
des_file=design1, psu_file=PSU_strat, rho=rho)

# The PSUs numer is decreased, while the SSUs number increased
# due to cluster intra-correlation effect.
# Under the same expected errors, to offset a slight reduction of PSUs (from 221 to 207)
# an increase of SSUs involved is observed.
allocation2st_3$expected
allocation2st_4$expected

## Example 5
# On the contrary, assume to decrease the MINIMUM from 48 to 24.
# The SSUs number strongly decrease in the face of an increase of PSUs,
# always under the same expected errors.
design2 <- design
design2[,4] <- 24
allocation2st_5 <- beat.2st(stratif=strata, errors=errors2,
des_file=design2, psu_file=PSU_strat, rho=rho)
allocation2st_4$expected
```

```
allocation2st_5$expected

# Note that MINIMUM can be different for each stratum.

## Example 6
# Assume that the SSUs are in turn clusters, for instance households composed by individuals.
# In the previous examples we always derived optimal allocations
# for sample of SSUs (i.e. households, because
# DELTA = 1).
design
design1
design2
# For obtaining a sample in terms of the elements composing SSUs
# (i.e., individuals) is just sufficient to
# modify the DELTA in des_file.
design3 <- design
design3$DELTA <- 2.31
# DELTA_IND=2.31, the average size of household in Italy.
allocation2st_6 <- beat.2st(stratif=strata, errors=errors,
des_file=design3, psu_file=PSU_strat, rho=rho)
```

---

beat.cv *Computation of coefficient of variation (CV) for a given multivariate multiple allocation*

---

## Description

Compute the coefficients of variation considering a given multivariate optimal allocation.

## Usage

```
beat.cv(n_file, stratif, errors, des_file, psu_file, rho, epsilon)
```

## Arguments

| | |
|---|---|
| n_file | Data frame containing the sample size allocated in each stratum, for more details, e.g.,allocation. |
| stratif | Data frame of survey strata, for more details see, e.g.,strata. |
| errors | Data frame of expected coefficients of variation (CV) for each domain, for more details see, e.g.,errors. |
| des_file | Data frame containing information on sampling design variables, for more details see, e.g.,design. |
| psu_file | Data frame containing information on primary stage units stratification, for more details see, e.g.,PSU_strat. |
| rho | Data frame of survey strata, for more details see, e.g.,rho. |
| epsilon | The same as in function beat.1st. |

## Details

This function enables to derive the expected coefficient of variation (CV) from a given allocation. The function `beat.cv` returns the estimates expected accuracy in terms of coefficient of variation, for several variables in different domains, given a certain allocation among the different strata.

## Value

Object of class `list`. The list contains a set of `data.frame`, as many of the cross product between domain and interest variables, containing total estimates, population, variance and expected coefficient of variation for every domain modality. For each domain and each variable is defined

| | |
|---|---|
| `Tot1` | Total estimate |
| `N` | Measure of size |
| `Varfin` | The sample variance of the total estimate |
| `CV` | The coefficient of variation of the |

## Author(s)

Developed by Stefano Falorsi, Andrea Fasulo, Alessio Guandalini, Daniela Pagliuca, Marco D. Terribili.

## Examples

```
# Load example data
data(beat.example)

## Example 1
# Calculate coefficients of variation, for two variables in two domains,
# given an allocation among the different strata.
allocation
cv1<-beat.cv( n_file=allocation, stratif=strata, errors=errors,
des_file=design, psu_file=PSU_strat, rho=rho)

## Example 2
# Take the example 1 in beat.2st.
allocation2st_1 <- beat.2st(stratif=strata, errors=errors,
des_file=design, psu_file=PSU_strat,rho=rho)
# The allocation obtained is
allocation2st_1$alloc
# with these precision constraints
errors
# and these expacted coefficient of variaction
allocation2st_1$expected

# Now, fit the output of beat.2st to allocation, that is
SIZE <- allocation2st_1$alloc[-18,c(2)]
allocation1 <- data.frame(SIZE)
# If apply beat.cv the same error in allocation2st_1$expected should be obtained.
# In fact
```

```
cv2<-beat.cv( n_file=allocation1, stratif=strata, errors=errors,
des_file=design, psu_file=PSU_strat, rho=rho)
cv2

# Please, note that some very slightly differences may occur.
```

---

deft_start *Starting values for the Design Effect ($deft$)*

---

## Description

Example data frame containing the starting values for the Design Effect ($deft$) .

## Usage

```
data(beat.example)
deft_start
```

## Format

The Design Effect data frame contains a row per each stratum with the following variables:

**STRATUM** Identifier of the stratum (numeric).

**DEFT1** Starting values for the Design Effect in the stratum of the first variable (numeric).

**DEFTj** Starting values for the Design Effect in the stratum of the j-th variable (numeric).

**DEFTn** Starting values for the Design Effect in the stratum of the last variable (numeric).

## Details

Note: the names of the variables must be the ones indicated above.

This is an optional input. The function `beat.2st` independently computes and updates the design effect. However, it is possible to set the starting values of design effect for each variable in each stratum. The design effect is the square root of the ratio of the actual sampling variance to the variance expected with the simple random sampling (SRS), on equal sample size.

Under SRS the desing effect is equal to 1. Usually, as increasing the stages of selection the design effect increases because it takes into account the "clusterization" of sampling units and the sample size in Self Representative (SR) and Non Self Representative (NSR) strata.

In practice, higher is the intraclass correlation, higher will be the design effect and much more sample size for satisfying the precision constraints is needed with respect to SRS.

## Examples

```
# Load example data
data(beat.example)
deft_start
str(deft_start)
```

`design` *Sampling design variables*

## Description

Example data frame containing variables for describing the sampling design.

## Usage

```
data(beat.example)
design
```

## Format

The design data frame contains a row per each stratum with the following variables:

**STRATUM** Identifier of the stratum (numeric)

**STRAT_MOS** Measure of size of the stratum (numeric)

**DELTA** The average size of Secondary Stage Units (SSU) in the strata. With respect to the sample on which we are interested in, it could be equal or greater than 1 (numeric). See details for a depth explanation.

**MINIMUM** the minimum number of SSU to be selected in each PSU. It could be different in each stratum (numeric)

## Details

Note: the names of the variables must be the ones indicated above.

The sample design can be defined through a measure of size of the stratum, the average size of each SSU (>=1) and the minimum number of SSU to be selected in each PSU. In particular, if SSU are not cluster DELTA=1 and the sample size determined will be given in term of SSU. Instead, when SSUs are, in turn, clusters (for instance, households composed by individuals), defining DELTA equal to the average size of SSUs, enables to derive a sample in term of individuals.

Furthermore, modifying the MINIMUM it is possible to tune the number of PSU in the sample (see the example in beat.1st). In fact, considering the same sample size, increasing the MINIMUM, less PSU will be involved in the sample, but worst estimates in term of expected coefficient of variations will be provided. On the contrary, decreasing the MINIMUM, more PSU will be involved in the sample and better estimates will be obtained. Instead, increasing the MINIMUM for obtaining the same expected errors, requests less PSU, but much more SSU. The contrary occurs decreasing the MINIMUM.

## Examples

```
# Load example data
data(beat.example)
design
str(design)
```

effst *Estimator effect*

## Description

Example data frame containing estimator effect, $(effst)$, in each stratum for each variable.

## Usage

```
data(beat.example)
effst
```

## Format

The estimator effect data frame contains a row per each stratum with the following variables:

**STRATUM** Identifier of the stratum (numeric).

**EFFST1** Estimator effect in the stratum of the first variable (numeric).

**EFFSTj** Estimator effect in the stratum of the j-th variable (numeric).

**EFFSTn** Estimator effect in the stratum of the last variable (numeric).

## Details

Note: the names of the variables must be the ones indicated above.

The estimator effect, $(effst)$, provides a measure of the variance inflaction or reduction due to the use of a different estimator from the HT (Horvitz and Thompson, 1952). It is equal to the ratio between the sampling variance of the estimator planned to be used and the sampling variance of the HT.

Then, when the HT is used, $(effst)$ is equal to 1. However, always more often, different estimators, such as calibration estimator (Deville and Särndal, 1992) or generalized regression estimator GREG (Fuller, 2002 and references therein), are used. Usually this kind of estimators take into account auxiliary variables that enables to increase the accuracy of the estimates, that is, they reduce their errors (CV). Then, their $effst$ is usually lower than 1.

Therefore, taking into account the estimator effect when planning the survey can help in saving sample size or at least to more properly evatuate the allocation.

## References

Deville, J.C., Särndal, C.E. (1992). Calibration estimators in survey sampling. *Journal of the American statistical Association*, 87(418): 376-38.

Fuller, W.A.. (2002). Regression estimation for survey samples. Survey Methodology 28(1): 5-23.

Horvitz, D.G., Thompson, D.J. (1952) A generalization of sampling without replacement from a finite universe. *Journal of the American statistical Association*, 47(260): 663-685.

## Examples

```
# Load example data
data(beat.example)
effst
str(effst)
```

---

errors *Precision constraints (maximum CVs) as input for Bethel allocation*

---

## Description

Example data frame containing precision levels (expressed in terms of acceptable CV's).

## Usage

```
data(beat.example)
errors
```

## Format

The constraint data frame (errors) contains a row per each type of domain with the following variables:

**DOM** Type of domain code (factor).

**CV1** Planned coefficient of variation for first variable (numeric).

**CVj** Planned coefficient of variation for j-th variable (numeric).

**CVn** Planned coefficient of variation for last variable (numeric).

## Details

Note: the names of the variables must be the ones indicated above.

The coefficient of variation (CV) is a standardized measure of variance. It is often expressed as a percentage and is defined as the ratio between the standard deviation of the estimate and the estimate (or its absolute value).

## Examples

```
# Load example data
data(beat.example)
errors
str(errors)
```

## PSU_strat — *Information on Primary Stage Units (PSUs) stratification*

### Description

Example data frame containing information on Primary Stage Units (PSUs) stratification.

### Usage

```
data(beat.example)
PSU_strat
```

### Format

The PSU_strat data frame contains a row for each Primary Stage Units (PSUs) with the following variables:

**STRATUM** Identifier of the stratum (numeric)

**PSU_MOS** Measure of size of the primary stage unit (numeric)

**PSU_ID** Identifier of the primary stage unit (numeric)

### Details

Note: the names of the variables must be the ones indicated above.

### Examples

```
# Load example data
data(beat.example)
PSU_strat
str(PSU_strat)
```

## rho — *Intraclass correlation coefficients for self and non self representative in the strata*

### Description

Example data frame containing intraclass correlation $\rho$ in Self Representative (SR) and Non Self Representative (NSR) strata.

### Usage

```
data(beat.example)
rho
```

## Format

The intraclass correlation coefficienta ($\rho$) data frame contains a row per each stratum with the following variables:

**STRATUM** Identifier of the stratum (numeric)

**RHO_AR1** intraclass correlation of the elementary units for each primary stage unit of the self representing area belonging to the stratum for the first variable.

**RHO_ARj** intraclass correlation of the elementary units for each primary stage unit of the self representing area belonging to the stratum for the j-th variable.

**RHO_ARn** intraclass correlation of the elementary units for each primary stage unit of the self representing area belonging to the stratum for the n-th variable.

**RHO_NAR1** intraclass correlation of the elementary units for each primary stage unit of the non self representing area belonging to the stratum for the first variable.

**RHO_NARj** intraclass correlation of the elementary units for each primary stage unit of the non self representing area belonging to the stratum for the j-th variable.

**RHO_NARn** intraclass correlation of the elementary units for each primary stage unit of the non self representing area belonging to the stratum for the n-th variable.

## Details

Note: the names of the variables must be the ones indicated above.

Intraclass correlation, $\rho$, provide a measure of the cluster heterogeneity and they have a direct impact on the design effect (design). It can be indirectly computed from the design effect and the average minimum number of interviews in the Primary Stage Units (PSUs).

The ideal situation is when all the clusters in which the population is divided are more heterogeneous possible within them. At the limit, if each cluster were a reduced copy of the population then it would be sufficient to extract one just to have the same information that would be obtained from a complete survey. Then, more similar the units in the cluster are, higher the sample size must be (Cochran, 1977, Chapter 8).

By definition, in SR strata $\rho$, is equal to 1, because there is just a single PSU in SR strata. In NSR strata usually, $\rho$ is usual higher than 1, because a double stage of selection is needed.

## References

Cochran, W. (1977) *Sampling Techniques.* John Wiley & Sons, Inc., New York.

## Examples

```
# Load example data
data(beat.example)
rho
str(rho)
```

strata *Strata characteristics*

## Description

Example data frame containing information on strata characteristics.

## Usage

```
data(beat.example)
strata
```

## Format

The Strata data frame contains a row per each stratum with the following variables:

**STRATUM** Identifier of the stratum (numeric).

**N** Stratum population size (numeric).

**M1** Mean in the stratum of the first variable (numeric).

**Mj** Mean in the stratum of the j-th variable (numeric).

**Mn** Mean in the stratum of the last variable (numeric).

**S1** Standard deviation in the stratum of the first variable (numeric).

**Sj** Standard deviation in the stratum of the j-th variable (numeric).

**Sn** Standard deviation in the stratum of the last variable (numeric).

**CENS** flag (1 indicates a take all stratum, 0 a sampling stratum, usually 0 ) (numeric).

**COST** Cost per interview in each stratum, usually 0 (numeric).

**DOM1** Domain value to which the stratum belongs for the first type of domain (factor or numeric).

**DOMa** Domain value to which the stratum belongs for the a-th type of domain (factor or numeric).

**DOMk** Domain value to which the stratum belongs for the k-th type of domain (factor or numeric).

## Details

Note: the names of the variables must be the ones indicated above.

## Examples

```
# Load example data
data(beat.example)
strata
str(strata)
```

# Index