

Package ‘symbolicDA’

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Title Analysis of Symbolic Data

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Depends R(>= 3.6.0), clusterSim,XML

Imports shapes, e1071, ade4, cluster, RSDA

Description Symbolic data analysis methods: importing/exporting data from ASSO XML Files, distance calculation for symbolic data (Ichino-Yaguchi, de Carvalho measure), zoom star plot, 3d interval plot, multidimensional scaling for symbolic interval data, dynamic clustering based on distance matrix, HINoV method for symbolic data, Ichino's feature selection method, principal component analysis for symbolic interval data, decision trees for symbolic data based on optimal split with bagging, boosting and random forest approach (+visualization), kernel discriminant analysis for symbolic data, Kohonen's self-organizing maps for symbolic data, replication and profiling, artificial symbolic data generation.
(Milligan, G.W., Cooper, M.C. (1985) <[doi:10.1007/BF02294245](https://doi.org/10.1007/BF02294245)>, Breiman, L. (1996), <[doi:10.1007/BF00058655](https://doi.org/10.1007/BF00058655)>, Hubert, L., Arabie, P. (1985), <[doi:10.1007/BF01908075](https://doi.org/10.1007/BF01908075)>, Ichino, M., & Yaguchi, H. (1994), <[doi:10.1109/21.286391](https://doi.org/10.1109/21.286391)>, Rand, W.M. (1971) <[doi:10.1080/01621459.1971.10482356](https://doi.org/10.1080/01621459.1971.10482356)>, Breckenridge, J.N. (2000) <[doi:10.1207/S15327906MBR3502_5](https://doi.org/10.1207/S15327906MBR3502_5)>, Groenen, P.J.F, Winsberg, S., Rodriguez, O., Diday, E. (2006) <[doi:10.1016/j.csda.2006.04.003](https://doi.org/10.1016/j.csda.2006.04.003)>, Dudek, A. (2007), <[doi:10.1007/978-3-540-70981-7_4](https://doi.org/10.1007/978-3-540-70981-7_4)>).

License GPL (>= 2)

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Contents

bagging.SDA	2
boosting.SDA	4
cars	5
cluster.Description.SDA	6
data_symbolic	8
DClust	8
decisionTree.SDA	9
dist_SDA	11
draw.decisionTree.SDA	13
generate.SO	14
HINoV.SDA	15
IchinoFS.SDA	17
index.G1d	18
interscal.SDA	20
iscal.SDA	21
kernel.SDA	23
kohonen.SDA	24
parse.SO	25
PCA.centers.SDA	26
PCA.mrpca.SDA	27
PCA.spaghetti.SDA	28
PCA.spca.SDA	29
PCA.vertices.SDA	30
random.forest.SDA	31
replication.SDA	33
RSDA2SymbolicDA	34
save.SO	37
SCLust	38
simple2SO	39
SO2Simple	40
subsdt.SDA	41
symbolic.object	42
symscal.SDA	45
zoomStar	46

Index	49
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bagging.SDA	<i>Bagging algorithm for optimal split based on decision tree for symbolic objects</i>
-------------	--

Description

Bagging algorithm for optimal split based on decision (classification) tree for symbolic objects

Usage

```
bagging.SDA(sdt, formula, testSet, mfinal=20, rf=FALSE, ...)
```

Arguments

sdt	Symbolic data table
formula	formula as in <code>lm</code> function
testSet	a vector of integers indicating classes to which each objects are allocated in learning set
mfinal	number of partial models generated
rf	random forest like drawing of variables in partial models
...	arguments passed to <code>decisionTree.SDA</code> function

Details

The bagging, which stands for bootstrap aggregating, was introduced by Breiman in 1996. The diversity of classifiers in bagging is obtained by using bootstrapped replicas of the training data. Different training data subsets are randomly drawn with replacement from the entire training data set. Then each training data subset is used to train a decision tree (classifier). Individual classifiers are then combined by taking a simple majority vote of their decisions. For any given instance, the class chosen by most number of classifiers is the ensemble decision.

Value

An object of class `bagging.SDA`, which is a list with the following components:

predclass	the class predicted by the ensemble classifier
confusion	the confusion matrix for ensemble classifier
error	the classification error
pred	?
classfinal	final class memberships

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References

- Billard L., Diday E. (eds.) (2006), *Symbolic Data Analysis, Conceptual Statistics and Data Mining*, John Wiley & Sons, Chichester.
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- Diday E., Noirhomme-Fraiture M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

See Also

[boosting.SDA](#), [random.forest.SDA](#), [decisionTree.SDA](#)

Examples

```
#Example will be available in next version of package, thank You for your patience :-)
```

boosting.SDA	<i>Boosting algorithm for optimal split based decision tree for symbolic objects</i>
--------------	--

Description

Boosting algorithm for optimal split based decision tree for symbolic objects, "symbolic" version of adabag.M1 algorithm

Usage

```
boosting.SDA(sdt,formula,testSet, mfinal = 20,...)
```

Arguments

sdt	Symbolic data table
formula	formula as in <code>lm</code> function
testSet	a vector of integers indicating classes to which each objects are allocated in learning set
mfinal	number of partial models generated
...	arguments passed to <code>decisionTree.SDA</code> function

Details

Boosting, similar to bagging, also creates an ensemble of classifiers by resampling the data. The results are then combined by majority voting. Resampling in boosting provides the most informative training data for each consecutive classifier. In each iteration of boosting three weak classifiers are created: the first classifier C1 is trained with a random subset of the training data. The training data subset for the next classifier C2 is chosen as the most informative subset, given C1. C2 is trained on a training data only half of which is correctly classified by C1 and the other half is misclassified. The third classifier C3 is trained with instances on which C1 and C2 disagree. Then the three classifiers are combined through a three-way majority vote.

Value

formula	a symbolic description of the model that was used
trees	trees built while making the ensemble
weights	weights for each object from test set
votes	final consensus clustering
class	predicted class memberships
error	error rate of the ensemble clustering

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References

Billard L., Diday E. (eds.) (2006), *Symbolic Data Analysis, Conceptual Statistics and Data Mining*, John Wiley & Sons, Chichester.
 Bock H.H., Diday E. (eds.) (2000), *Analysis of symbolic data. Explanatory methods for extracting statistical information from complex data*, Springer-Verlag, Berlin.
 Diday E., Noirhomme-Fraiture M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

See Also

[bagging.SDA](#), [random.forest.SDA](#), [decisionTree.SDA](#)

Examples

#Example will be available in next version of package, thank You for your patience :-)

cars	<i>real data set in symbolic form - selected car models described by a set of symbolic variables</i>
------	--

Description

symbolic data set: 30 observations on 12 symbolic variables - 9 interval-valued and 3 multinomial variables, third dimension represents the beginning and the end of intervals for interval-valued variable's implementation or a set of categories for multinomial variable's implementation

Format

symbolic data table (see `(link{symbolic.object})`)

Source

the original data on 30 selected car models and their prices, chasis and engine types were collected from the websites of authorized car dealers. Then the data were converted (aggregated) to symbolic format (second order symbolic objects). Each symbolic object - e.g. "Seat Leon", "Citroen C4" - represents all chasis, engine types and price range of this kind of car model available on the Polish market in 2010. For example the price range [54,900; 96,190] PLN, hatchback and saloon body style, petrol and diesel engine, acceleration 0-100 kph range [10.00; 11.90] seconds are, in general, the characteristics of "Toyota Corolla".

Examples

```
# LONG RUNNING - UNCOMMENT TO RUN
#data("cars",package="symbolicDA")
#sdt<-cars
#r<- HINoV.SDA(sdt, u=5, distance="U_3")
#print(r$stopri)
#plot(r$stopri[,2], xlab="Variable number", ylab="topri",
#xaxt="n", type="b")
#axis(1,at=c(1:max(r$stopri[,1])),labels=r$stopri[,1])
```

```
cluster.Description.SDA
```

description of clusters of symbolic objects

Description

description of clusters of symbolic objects is obtained by a generalisation operation using in most cases descriptive statistics calculated separately for each cluster and each symbolic variable.

Usage

```
cluster.Description.SDA(table.Symbolic, clusters, precission=3)
```

Arguments

<code>table.Symbolic</code>	Symbolic data table
<code>clusters</code>	a vector of integers indicating the cluster to which each object is allocated
<code>precission</code>	Number of digits to round the results

Value

A List of cluster numbers, variable number and labels.

The description of clusters of symbolic objects which differs according to the symbolic variable type:

- for interval-valued variable:

"min value" - minimum value of the lower-bounds of intervals observed for objects belonging to the cluster

"max value" - maximum value of the upper-bounds of intervals observed for objects belonging to the cluster

- for multinominal variable:

"categories" - list of all categories of the variable observed for symbolic belonging to the cluster

- for multinominal with weights variable:

"min probabilities" - minimum weight of each category of the variable observed for objects belonging to the cluster

"max probabilities" - maximum weight of each category of the variable observed for objects belonging to the cluster

"avg probabilities" - average weight of each category of the variable calculated for objects belonging to the cluster

"sum probabilities" - sum of weights of each category of the variable calculated for objects belonging to the cluster

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References

Billard, L., Diday, E. (eds.) (2006), *Symbolic Data Analysis. Conceptual Statistics and Data Mining*, Wiley, Chichester.

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Diday E., Noirhomme-Fraiture, M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

See Also

[SClust](#), [DClust](#); [hclust](#) in stats library; [pam](#) in cluster library

Examples

```
# LONG RUNNING - UNCOMMENT TO RUN
#data("cars", package="symbolicDA")
#y<-cars
#cl<-SClust(y, 4, iter=150)
#print(cl)
#o<-cluster.Description.SDA(y, cl)
#print(o)
```

data_symbolic	<i>Symbolic interval data</i>
---------------	-------------------------------

Description

Artificially generated symbolic interval data

Format

3-dimensional array: 125 objects, 6 variables, third dimension represents beginning and end of interval, 5-class structure

Source

Artificially generated data

DClust	<i>Dynamical clustering based on distance matrix</i>
--------	--

Description

Dynamical clustering of objects described by symbolic and/or classic (metric, non-metric) variables based on distance matrix

Usage

```
DClust(dist, cl, iter=100)
```

Arguments

dist	distance matrix
cl	number of clusters or vector with initial prototypes of clusters
iter	maximum number of iterations

Details

See file [../doc/DClust_details.pdf](#) for further details

Value

a vector of integers indicating the cluster to which each object is allocated

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References

Bock, H.H., Diday, E. (eds.) (2000), *Analysis of Symbolic Data. Explanatory Methods for Extracting Statistical Information from Complex Data*, Springer-Verlag, Berlin.

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See Also

[SClust](#), [dist_SDA](#); dist in stats library; dist.GDM in clusterSim library; pam in cluster library

Examples

```
# LONG RUNNING - UNCOMMENT TO RUN
#data("cars",package="symbolicDA")
#sdt<-cars
#dist<-dist_SDA(sdt, type="U_3")
#clust<-DClust(dist, cl=5, iter=100)
#print(clust)
```

decisionTree.SDA	<i>Decison tree for symbolic data</i>
------------------	---------------------------------------

Description

Optimal split based decision tree for symbolic objects

Usage

```
decisionTree.SDA(sdt,formula,testSet,treshMin=0.0001,treshW=-1e10,
tNodes=NULL,minSize=2,epsilon=1e-4,useEM=FALSE,
multiNominalType="ordinal",rf=FALSE,rf.size,objectSelection)
```

Arguments

sdt	Symbolic data table
formula	formula as in ln function
testSet	a vector of integers indicating classes to which each objects are allocated in learnig set
treshMin	parameter for tree creation algorithm

treshW	parameter for tree creation algorithm
tNodes	parameter for tree creation algorithm
minSize	parameter for tree creation algorithm
epsilon	parameter for tree creation algorithm
useEM	use Expectation Optimalization algorithm for estimating conditional probabilities
multiNominalType	"ordinal" - functione treats multi-nominal data as ordered or "nominal" functione treats multi-nomianal data as unordered (longer performance times)
rf	if TRUE symbolic variables for tree creation are randomly chosen like in random forest algorithm
rf.size	the number of variables chosen for tree creation if rf is true
objectSelection	optional, vector with symbolic object numbers for tree creation

Details

For futher details see [../doc/decisionTree_SDA.pdf](#)

Value

nodes	nodes in tree
nodeObjects	contribution of each objects nodes in tree
conditionalProbab	conditional probability of belonginess of nodes te classes
prediction	predicted classes for objects from testSet

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References

- Billard L., Diday E. (eds.) (2006), *Symbolic Data Analysis, Conceptual Statistics and Data Mining*, John Wiley & Sons, Chichester.
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- Diday E., Noirhomme-Fraiture M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

See Also

[bagging.SDA](#), [boosting.SDA](#), [random.forest.SDA](#), [draw.decisionTree.SDA](#)

Examples

```
# Example 1
# LONG RUNNING - UNCOMMENT TO RUN
# File samochody.xml needed in this example
# can be found in /inst/xml library of package
#sda<-parse.SO("samochody")
#tree<-decisionTree.SDA(sda, "Typ_samochodu~.", testSet=1:33)
#summary(tree) # a very gernerall information
#tree # summary information
```

dist_SDA	<i>distance measurement for symbolic data</i>
----------	---

Description

calculates distances between symbolic objects described by interval-valued, multinominal and multinominal with weights variables

Usage

```
dist_SDA(table.Symbolic,type="U_2",subType=NULL,gamma=0.5,power=2,probType="J",
probAggregation="P_1",s=0.5,p=2,variableSelection=NULL,weights=NULL)
```

Arguments

table.Symbolic	symbolic data table
type	distance measure for boolean symbolic objects: H, U_2, U_3, U_4, C_1, SO_1, SO_2, SO_3, SO_4, SO_5; mixed symbolic objects: L_1, L_2
subType	comparison function for C_1 and SO_1: D_1, D_2, D_3, D_4, D_5
gamma	gamma parameter for U_2 and U_3, gamma [0, 0.5]
power	power parameter for U_2 and U_3; power [1, 2, 3, ..]
probType	distance measure for probabilistic symbolic objects: J, CHI, REN, CHER, LP
probAggregation	agregation function for J, CHI, REN, CHER, LP: P_1, P_2
s	parameter for Renyi (REN) and Chernoff (CHE) distance, s [0, 1)
p	parameter for Minkowski (LP) metric; p=1 - manhattan distance, p=2 - euclidean distance
variableSelection	numbers of variables used for calculation or NULL for all variables
weights	weights of variables for Minkowski (LP) metrics

Details

Distance measures for boolean symbolic objects:

H - Hausdorff's distance for objects described by interval-valued variables, U_2, U_3, U_4 - Ichino-Yaguchi's distance measures for objects described by interval-valued and/or multinominal variables, C_1, SO_1, SO_2, SO_3, SO_4, SO_5 - de Carvalho's distance measures for objects described by interval-valued and/or multinominal variables.

Distance measurement for probabilistic symbolic objects consists of two steps: 1. Calculation of distance between objects for each variable using componentwise distance measures: J (Kullback-Leibler divergence), CHI (Chi-2 divergence), REN (Renyi's divergence), CHER (Chernoff's distance), LP (modified Minkowski metrics). 2. Calculation of aggregative distance between objects based on componentwise distance measures using objectwise distance measure: P_1 (manhattan distance), P_2 (euclidean distance).

Distance measures for mixed symbolic objects - modified Minkowski metrics: L_1 (manhattan distance), L_2 (euclidean distance).

See file [../doc/dist_SDA.pdf](#) for further details

NOTE !!!: In previous version of package this function has been called dist.SDA.

Value

distance matrix of symbolic objects

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References

- Billard L., Diday E. (eds.) (2006), *Symbolic Data Analysis, Conceptual Statistics and Data Mining*, John Wiley & Sons, Chichester.
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See Also

[DClust](#), [index.G1d](#); dist.Symbolic in clusterSim library

Examples

```
# LONG RUNNING - UNCOMMENT TO RUN
#data("cars",package="symbolicDA")
#dist<-dist_SDA(cars, type="U_3", gamma=0.3, power=2)
#print(dist)
```

draw.decisionTree.SDA *Draws optimal split based decision tree for symbolic objects*

Description

Draws optimal split based decision tree for symbolic objects

Usage

```
draw.decisionTree.SDA(decisionTree.SDA,boxWidth=1,boxHeight=3)
```

Arguments

decisionTree.SDA	optimal split based decision tree for symbolic objects (result of decisionTree.SDA function)
boxWidth	width of single box in drawing
boxHeight	height of single box in drawing

Details

Draws optimal split based decision (classification) tree for symbolic objects.

Value

A draw of optimal split based decision (classification) tree for symbolic objects.

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References

- Billard L., Diday E. (eds.) (2006), *Symbolic Data Analysis, Conceptual Statistics and Data Mining*, John Wiley & Sons, Chichester.
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- Diday E., Noirhomme-Fraiture M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

See Also

[decisionTree.SDA](#)

Examples

```
# LONG RUNNING - UNCOMMENT TO RUN
# Files samochody.xml and wave.xml needed in this example
# can be found in /inst/xml library of package

# Example 1
#sda<-parse.SO("samochody")
#tree<-decisionTree.SDA(sda, "Typ_samochodu~.", testSet=26:33)
#draw.decisionTree.SDA(tree,boxWidth=1,boxHeight=3)

# Example 2
#sda<-parse.SO("wave")
#tree<-decisionTree.SDA(sda, "WaveForm~.", testSet=1:30)
#draw.decisionTree.SDA(tree,boxWidth=2,boxHeight=3)
```

generate.SO	<i>generation of artificial symbolic data table with given cluster structure</i>
-------------	--

Description

generation of artificial symbolic data table with given cluster structure

Usage

```
generate.SO(numObjects,numClusters,numIntervalVariables,numMultivaluedVariables)
```

Arguments

numObjects	number of objects in each cluster
numClusters	number of objects
numIntervalVariables	Number of symbolic interval variables in generated data table
numMultivaluedVariables	Number of symbolic multi-valued variables in generated data table

Value

data	symbolic data table with given cluster structure
clusters	vector with cluster numbers for each object

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References

Billard L., Diday E. (eds.) (2006), *Symbolic Data Analysis, Conceptual Statistics and Data Mining*, John Wiley & Sons, Chichester.

Bock H.H., Diday E. (eds.) (2000), *Analysis of symbolic data. Explanatory methods for extracting statistical information from complex data*, Springer-Verlag, Berlin.

Diday E., Noirhomme-Fraiture M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

User manual for SODAS 2 software, Software Report, Analysis System of Symbolic Official Data, Project no. IST-2000-25161, Paris.

See Also

see [symbolic.object](#) for symbolic data table R structure representation

Examples

```
# Example will be available in next version of package, thank You for your patience :-)
```

HINoV.SDA

Modification of HINoV method for symbolic data

Description

Carmone, Kara and Maxwell's Heuristic Identification of Noisy Variables (HINoV) method for symbolic data

Usage

```
HINoV.SDA(table.Symbolic, u=NULL, distance="H", Index="cRAND",method="pam",...)
```

Arguments

table.Symbolic	symbolic data table
u	number of clusters
distance	symbolic distance measure as parameter type in dist_SDA
method	clustering method: "single", "ward", "complete", "average", "mcquitty", "median", "centroid", "pam" (default), "SClust", "DClust"
Index	"cRAND" - adjusted Rand index (default); "RAND" - Rand index
...	additional argument passed to dist_SDA function

Details

For HINoV in symbolic data analysis there can be used methods based on distance matrix such as hierarchical ("single", "ward", "complete", "average", "mcquitty", "median", "centroid") and optimization methods ("pam", "DClust") and also methods based on symbolic data table ("SClust").

See file [../doc/HINoVSDA_details.pdf](#) for further details

Value

parim	$m \times m$ symmetric matrix (m - number of variables). Matrix contains pairwise adjusted Rand (or Rand) indices for partitions formed by the j -th variable with partitions formed by the l -th variable
topri	sum of rows of parim
stopri	ranked values of topri in decreasing order

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References

- Bock, H.H., Diday, E. (eds.) (2000), *Analysis of Symbolic Data. Explanatory Methods for Extracting Statistical Information from Complex Data*, Springer-Verlag, Berlin.
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See Also

DClust, SClust, dist_SDA; HINoV.Symbolic, dist.Symbolic in clusterSim library; hclust in stats library; pam in cluster library

Examples

```
# LONG RUNNING - UNCOMMENT TO RUN
#data("cars",package="symbolicDA")
#r<- HINoV.SDA(cars, u=3, distance="U_2")
#print(r$stopri)
#plot(r$stopri[,2], xlab="Variable number", ylab="topri",
#xaxt="n", type="b")
#axis(1,at=c(1:max(r$stopri[,1])),labels=r$stopri[,1])
```

IchinoFS.SDA	<i>Ichino's feature selection method for symbolic data</i>
--------------	--

Description

Ichino's method for identifying non-noisy variables in symbolic data set

Usage

```
IchinoFS.SDA(table.Symbolic)
```

Arguments

table.Symbolic symbolic data table

Details

See file [../doc/IchinoFSSDA_details.pdf](#) for further details

Value

- plot plot of the gradient illustrating combinations of variables, in which the axis of ordinates (Y) represents the maximum number of mutual neighbor pairs and the axis of the abscissae (X) corresponds to the number of features (m)
- combination the best combination of variables, i.e. the combination most differentiating the set of objects
- maximum results step-by-step combinations of variables up to m variables
- calculation results

Author(s)

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References

Ichino, M. (1994), *Feature selection for symbolic data classification*, In: E. Diday, Y. Lechevallier, P.B. Schader, B. Burtschy (Eds.), *New Approaches in Classification and data analysis*, Springer-Verlag, pp. 423-429.

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Diday, E., Noirhomme-Fraiture, M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

See Also

[HINoV.SDA](#); HINoV.Symbolic in clusterSim library

Examples

```
# LONG RUNNING - UNCOMMENT TO RUN
#data("cars",package="symbolicDA")
#sdt<-cars
#ichino<-IchinoFS.SDA(sdt)
#print(ichino)
```

index.G1d

Calinski-Harabasz pseudo F-statistic based on distance matrix

Description

Calculates Calinski-Harabasz pseudo F-statistic based on distance matrix

Usage

```
index.G1d (d,cl)
```

Arguments

d	distance matrix (see dist_SDA)
cl	a vector of integers indicating the cluster to which each object is allocated

Details

See file [../doc/indexG1d_details.pdf](#) for further details

Value

value of Calinski-Harabasz pseudo F-statistic based on distance matrix

Author(s)

Andrzej Dudek <andrzej.dudek@ue.wroc.pl>, Justyna Wilk Department of Econometrics and Computer Science, Wrocław University of Economics, Poland

References

Calinski, T., Harabasz, J. (1974), *A dendrite method for cluster analysis*, "Communications in Statistics", vol. 3, 1-27.

Everitt, B.S., Landau, E., Leese, M. (2001), *Cluster analysis*, Arnold, London, p. 103. ISBN 9780340761199.

Gordon, A.D. (1999), *Classification*, Chapman & Hall/CRC, London, p. 62. ISBN 9781584880134.

Milligan, G.W., Cooper, M.C. (1985), *An examination of procedures of determining the number of cluster in a data set*, "Psychometrika", vol. 50, no. 2, 159-179. Available at: [doi:10.1007/BF02294245](https://doi.org/10.1007/BF02294245).

Diday, E., Noirhomme-Fraiture, M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester, pp. 236-262.

Dudek, A. (2007), *Cluster Quality Indexes for Symbolic Classification. An Examination*, In: H.H.-J. Lenz, R. Decker (Eds.), *Advances in Data Analysis*, Springer-Verlag, Berlin, pp. 31-38. Available at: [doi:10.1007/9783540709817_4](https://doi.org/10.1007/9783540709817_4).

See Also

[DClust](#), [SClust](#); [index.G2](#), [index.G3](#), [index.S](#), [index.H](#), [index.KL](#), [index.Gap](#), [index.DB](#) in [clusterSim](#) library

Examples

```
# LONG RUNNING - UNCOMMENT TO RUN
# Example 1
#library(stats)
#data("cars",package="symbolicDA")
#x<-cars
#d<-dist_SDA(x, type="U_2")
#wynik<-hclust(d, method="ward", members=NULL)
#clusters<-cutree(wynik, 4)
#G1d<-index.G1d(d, clusters)
#print(G1d)

# Example 2

#data("cars",package="symbolicDA")
#md <- dist_SDA(cars, type="U_3", gamma=0.5, power=2)
# nc - number_of_clusters
#min_nc=2
```

```

#max_nc=10
#res <- array(0,c(max_nc-min_nc+1,2))
#res[,1] <- min_nc:max_nc
#clusters <- NULL
#for (nc in min_nc:max_nc)
#{
#cl2 <- pam(md, nc, diss=TRUE)
#res[nc-min_nc+1,2] <- G1d <- index.G1d(md,cl2$clustering)
#clusters <- rbind(clusters, cl2$clustering)
#}
#print(paste("max G1d for", (min_nc:max_nc)[which.max(res[,2])], "clusters=", max(res[,2])))
#print("clustering for max G1d")
#print(clusters[which.max(res[,2]),])
#write.table(res, file="G1d_res.csv", sep=";", dec=".", row.names=TRUE, col.names=FALSE)
#plot(res, type="p", pch=0, xlab="Number of clusters", ylab="G1d", xaxt="n")
#axis(1, c(min_nc:max_nc))

```

interscal.SDA

Multidimensional scaling for symbolic interval data - InterScal algorithm

Description

Multidimensional scaling for symbolic interval data - InterScal algorithm

Usage

```
interscal.SDA(x, d=2, calculateDist=FALSE)
```

Arguments

x	symbolic interval data: a 3-dimensional table, first dimension represents object number, second dimension - variable number, and third dimension contains lower- and upper-bounds of intervals (Simple form of symbolic data table)
d	Dimensionality of reduced space
calculateDist	if TRUE x are treated as raw data and min-max dist matrix is calculated. See details

Details

InterScal is the adaptation of well-known classical multidimensional scaling for symbolic data. The input for InterScal is the interval-valued dissimilarity matrix. Such dissimilarity matrix can be obtained from symbolic data matrix (that contains only interval-valued variables), judgements obtained from experts, respondents. See Lechevallier Y. (2001) for details on calculating interval-valued distance. See file [../doc/Symbolic_MDS.pdf](#) for further details

Value

xprim	coordinates of rectangles
stress.sym	final STRESSSym value

Author(s)

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References

Billard L., Diday E. (eds.) (2006), *Symbolic Data Analysis, Conceptual Statistics and Data Mining*, John Wiley & Sons, Chichester.

Bock H.H., Diday E. (eds.) (2000), *Analysis of symbolic data. Explanatory methods for extracting statistical information from complex data*, Springer-Verlag, Berlin.

Diday E., Noirhomme-Fraiture M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

Lechevallier Y. (ed.), *Scientific report for unsupervised classification, validation and cluster analysis*, Analysis System of Symbolic Official Data - Project Number IST-2000-25161, project report.

See Also

[iscal.SDA](#), [symscal.SDA](#)

Examples

```
# LONG RUNNING - UNCOMMENT TO RUN
#sda<-parse.SO("samochoy")
#data<-sda$indivIC
#mds<-interscal.SDA(data, d=2, calculateDist=TRUE)
```

iscal.SDA

Multidimensional scaling for symbolic interval data - IScal algorithm

Description

Multidimensional scaling for symbolic interval data - IScal algorithm

Usage

```
iscal.SDA(x,d=2,calculateDist=FALSE)
```

Arguments

x	symbolic interval data: a 3-dimensional table, first dimension represents object number, second dimension - variable number, and third dimension contains lower- and upper-bounds of intervals (Simple form of symbolic data table)
d	Dimensionality of reduced space
calculateDist	if TRUE x are treated as raw data and min-max dist matrix is calculated. See details

Details

IScal, which was proposed by Groenen et. al. (2006), is an adaptation of well-known nonmetric multidimensional scaling for symbolic data. It is an iterative algorithm that uses I-STRESS objective function. This function is normalized within the range [0; 1] and can be interpreted like classical STRESS values. IScal, like Interscal and SymScal, requires interval-valued dissimilarity matrix. Such dissimilarity matrix can be obtained from symbolic data matrix (that contains only interval-valued variables), judgements obtained from experts, respondents. See Lechevallier Y. (2001) for details on calculating interval-valued distance. See file [../doc/Symbolic_MDS.pdf](#) for further details

Value

xprim	coordinates of rectangles
STRESSSym	final STRESSSym value

Author(s)

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References

- Billard L., Diday E. (red.) (2006), *Symbolic Data Analysis, Conceptual Statistics and Data Mining*, John Wiley & Sons, Chichester.
- Bock H.H., Diday E. (eds.) (2000), *Analysis of symbolic data. Explanatory methods for extracting statistical information from complex data*, Springer-Verlag, Berlin.
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- Lechevallier Y. (ed.), *Scientific report for unsupervised classification, validation and cluster analysis*, Analysis System of Symbolic Official Data - Project Number IST-2000-25161, project report.

See Also

[interscal.SDA](#), [symscal.SDA](#)

Examples

```
# Example will be available in next version of package, thank You for your patience :-)
```

kernel.SDA	<i>Kernel discriminant analysis for symbolic data</i>
------------	---

Description

Kernel discriminant analysis for symbolic data

Usage

```
kernel.SDA(sdt, formula, testSet, h, ...)
```

Arguments

sdt	symbolic data table
formula	a formula, as in the <code>lm</code> function
testSet	vector with numbers objects <code>ij</code> test set
h	kernel bandwidth size
...	arguments passed to <code>dist_SDA</code> function

Details

Kernel discriminant analysis for symbolic data is based on the intensity estimator (that is based on dissimilarity measure for symbolic data) due to the fact that classical well-known density estimator can not be applied. Density estimator can not be applied due to the fact that symbolic objects are not object of euclidean space and the integral operator for symbolic data is not applicable.

For further details see [../doc/Kernel_SDA.pdf.pdf](#)

Value

vector of class belongings of each object in test set

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References

- Billard L., Diday E. (eds.) (2006), *Symbolic Data Analysis, Conceptual Statistics and Data Mining*, John Wiley & Sons, Chichester.
- Bock H.H., Diday E. (eds.) (2000), *Analysis of symbolic data. Explanatory methods for extracting statistical information from complex data*, Springer-Verlag, Berlin.
- Diday E., Noirhomme-Fraiture M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

See Also[dist_SDA](#)**Examples**

```
# Example 1
# LONG RUNNING - UNCOMMENT TO RUN
#sda<-parse.SO("samochody")
#model<-kernel.SDA(sda, "Typ_samochodu~.", testSet=6:16, h=0.75)
#print(model)
```

kohonen.SDA

*Kohonen's self-organizing maps for symbolic interval-valued data***Description**

Kohonen's self-organizing maps for a set of symbolic objects described by interval-valued variables

Usage

```
kohonen.SDA(data, rlen=100, alpha=c(0.05,0.01))
```

Arguments

data	symbolic data table in simple form (see S02Simple)
rlen	number of iterations (the number of times the complete data set will be presented to the network)
alpha	learning rate, determining the size of the adjustments during training. Default is to decline linearly from 0.05 to 0.01 over rlen updates

Details

See file [../doc/kohonenSDA_details.pdf](#) for further details

Value

clas	vector of mini-class belonginers in a test set
prot	prototypes

Author(s)

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References

- Kohonen, T. (1995), *Self-Organizing Maps*, Springer, Berlin-Heidelberg.
- Bock, H.H. (2001), *Clustering Algorithms and Kohonen Maps for Symbolic Data*, International Conference on New Trends in Computational Statistics with Biomedical Applications, ICNCB Proceedings, Osaka, pp. 203-215.
- Bock, H.H., Diday, E. (eds.) (2000), *Analysis of Symbolic Data. Explanatory Methods for Extracting Statistical Information from Complex Data*, Springer-Verlag, Berlin.
- Diday, E., Noirhomme-Fraiture, M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester, pp. 373-392.

See Also

SO2Simple; som in kohonen library

Examples

```
# Example will be available in next version of package, thank You for your patience :-)
```

parse.SO

Reading symbolic data table from ASSO-format XML file

Description

Kohonen self organizing maps for symbolic data with interval variables

Usage

```
parse.SO(file)
```

Arguments

file file name without xml extension

Details

see [symbolic.object](#) for symbolic data table R structure representation

Value

Symbolic data table parsed from XML file

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References

- Billard L., Diday E. (eds.) (2006), *Symbolic Data Analysis, Conceptual Statistics and Data Mining*, John Wiley & Sons, Chichester.
- Bock H.H., Diday E. (eds.) (2000), *Analysis of symbolic data. Explanatory methods for extracting statistical information from complex data*, Springer-Verlag, Berlin.
- Diday E., Noirhomme-Fraiture M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

See Also

[save.S0,generate.S0](#)

Examples

```
#cars<-parse.S0("cars")
```

PCA.centers.SDA	<i>principal component analysis for symbolic objects described by symbolic interval variables. Centers algorithm</i>
-----------------	--

Description

principal component analysis for symbolic objects described by symbolic interval variables. *Centers* algorithm

Usage

```
PCA.centers.SDA(t,pc.number=2)
```

Arguments

t	symbolic interval data: a 3-dimensional table, first dimension represents object number, second dimension - variable number, and third dimension contains lower- and upper-bounds of intervals (Simple form of symbolic data table)
pc.number	number of principal components

Details

See file [../doc/PCA_SDA.pdf](#) for further details

Value

Data in reduced space (symbolic interval data: a 3-dimensional table)

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References

Billard L., Diday E. (eds.) (2006), *Symbolic Data Analysis, Conceptual Statistics and Data Mining*, John Wiley & Sons, Chichester.

Bock H.H., Diday E. (eds.) (2000), *Analysis of symbolic data. Explanatory methods for extracting statistical information from complex data*, Springer-Verlag, Berlin.

Diday E., Noirhomme-Fraiture M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

See Also

[PCA.mrpca.SDA](#), [PCA.spaghetti.SDA](#), [PCA.spca.SDA](#), [PCA.vertices.SDA](#)

Examples

```
# Example will be available in next version of package, thank You for your patience :-)
```

PCA.mrpca.SDA	<i>principal component analysis for symbolic objects described by symbolic interval variables. Midpoints and radii algorithm</i>
---------------	--

Description

principal component analysis for symbolic objects described by symbolic interval variables. *Midpoints and radii* algorithm

Usage

```
PCA.mrpca.SDA(t, pc.number=2)
```

Arguments

t	symbolic interval data: a 3-dimensional table, first dimension represents object number, second dimension - variable number, and third dimension contains lower- and upper-bounds of intervals (Simple form of symbolic data table)
pc.number	number of principal components

Details

See file [../doc/PCA_SDA.pdf](#) for further details

Value

Data in reduced space (symbolic interval data: a 3-dimensional table)

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References

Billard L., Diday E. (eds.) (2006), *Symbolic Data Analysis, Conceptual Statistics and Data Mining*, John Wiley & Sons, Chichester.

Bock H.H., Diday E. (eds.) (2000), *Analysis of symbolic data. Explanatory methods for extracting statistical information from complex data*, Springer-Verlag, Berlin.

Diday E., Noirhomme-Fraiture M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

See Also

[PCA.centers.SDA](#), [PCA.spaghetti.SDA](#), [PCA.spca.SDA](#), [PCA.vertices.SDA](#)

Examples

```
# Example will be available in next version of package, thank You for your patience :-)
```

PCA.spaghetti.SDA	<i>principal component analysis for symbolic objects described by symbolic interval variables. Spaghetti algorithm</i>
-------------------	--

Description

principal component analysis for symbolic objects described by symbolic interval variables. *Spaghetti* algorithm

Usage

```
PCA.spaghetti.SDA(t,pc.number=2)
```

Arguments

t	symbolic interval data: a 3-dimensional table, first dimension represents object number, second dimension - variable number, and third dimension contains lower- and upper-bounds of intervals (Simple form of symbolic data table)
pc.number	number of principal components

Details

See file [../doc/PCA_SDA.pdf](#) for further details

Value

Data in reduced space (symbolic interval data: a 3-dimensional table)

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References

Billard L., Diday E. (eds.) (2006), *Symbolic Data Analysis, Conceptual Statistics and Data Mining*, John Wiley & Sons, Chichester.

Bock H.H., Diday E. (eds.) (2000), *Analysis of symbolic data. Explanatory methods for extracting statistical information from complex data*, Springer-Verlag, Berlin.

Diday E., Noirhomme-Fraiture M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

See Also

[PCA.centers.SDA](#), [PCA.mrpca.SDA](#), [PCA.spca.SDA](#), [PCA.vertices.SDA](#)

Examples

```
# Example will be available in next version of package, thank You for your patience :-)
```

PCA.spca.SDA	<i>principal component analysis for symbolic objects described by symbolic interval variables. 'Symbolic' PCA algorithm</i>
--------------	---

Description

principal component analysis for symbolic objects described by symbolic interval variables. 'Symbolic' PCA algorithm

Usage

```
PCA.spca.SDA(t, pc.number=2)
```

Arguments

t	symbolic interval data: a 3-dimensional table, first dimension represents object number, second dimension - variable number, and third dimension contains lower- and upper-bounds of intervals (Simple form of symbolic data table)
pc.number	number of principal components

Details

See file [../doc/PCA_SDA.pdf](#) for further details

Value

Data in reduced space (symbolic interval data: a 3-dimensional table)

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References

Billard L., Diday E. (eds.) (2006), *Symbolic Data Analysis, Conceptual Statistics and Data Mining*, John Wiley & Sons, Chichester.

Bock H.H., Diday E. (eds.) (2000), *Analysis of symbolic data. Explanatory methods for extracting statistical information from complex data*, Springer-Verlag, Berlin.

Diday E., Noirhomme-Fraiture M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

See Also

[PCA.centers.SDA](#), [PCA.mrpca.SDA](#), [PCA.spaghetti.SDA](#), [PCA.vertices.SDA](#)

Examples

```
# Example will be available in next version of package, thank You for your patience :-)
```

PCA.vertices.SDA	<i>principal component analysis for symbolic objects described by symbolic interval variables. Vertices algorithm</i>
------------------	---

Description

principal component analysis for symbolic objects described by symbolic interval variables. *Vertices* algorithm

Usage

```
PCA.vertices.SDA(t,pc.number=2)
```

Arguments

t	symbolic interval data: a 3-dimensional table, first dimension represents object number, second dimension - variable number, and third dimension contains lower- and upper-bounds of intervals (Simple form of symbolic data table)
pc.number	number of principal components

Details

See file [../doc/PCA_SDA.pdf](#) for further details

Value

Data in reduced space (symbolic interval data: a 3-dimensional table)

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References

Billard L., Diday E. (eds.) (2006), *Symbolic Data Analysis, Conceptual Statistics and Data Mining*, John Wiley & Sons, Chichester.

Bock H.H., Diday E. (eds.) (2000), *Analysis of symbolic data. Explanatory methods for extracting statistical information from complex data*, Springer-Verlag, Berlin.

Diday E., Noirhomme-Fraiture M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

See Also

[PCA.centers.SDA](#), [PCA.mrpca.SDA](#), [PCA.spaghetti.SDA](#), [PCA.spca.SDA](#)

Examples

```
# Example will be available in next version of package, thank You for your patience :-)
```

random.forest.SDA	<i>Random forest algorithm for optimal split based decision tree for symbolic objects</i>
-------------------	---

Description

Random forest algorithm for optimal split based decision tree for symbolic objects

Usage

```
random.forest.SDA(sdt, formula, testSet, mfinal = 100, ...)
```

Arguments

sdt	Symbolic data table
formula	formula as in <code>lm</code> function
testSet	a vector of integers indicating classes to which each objects are allocated in learning set
mfinal	number of partial models generated
...	arguments passed to <code>decisionTree.SDA</code> function

Details

`random.forest.SDA` implements Breiman's random forest algorithm for classification of symbolic data set.

Value

Section details goes here

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References

- Billard L., Diday E. (eds.) (2006), *Symbolic Data Analysis, Conceptual Statistics and Data Mining*, John Wiley & Sons, Chichester.
- Bock H.H., Diday E. (eds.) (2000), *Analysis of symbolic data. Explanatory methods for extracting statistical information from complex data*, Springer-Verlag, Berlin.
- Diday E., Noirhomme-Fraiture M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

See Also

[bagging.SDA](#), [boosting.SDA](#), [decisionTree.SDA](#)

Examples

```
# Example will be available in next version of package, thank You for your patience :-)
```

replication.SDA	<i>Modification of replication analysis for cluster validation of symbolic data</i>
-----------------	---

Description

Replication analysis for cluster validation of symbolic data

Usage

```
replication.SDA(table.Symbolic, u=2, method="SClust", S=10, fixedAsample=NULL, ...)
```

Arguments

table.Symbolic	symbolic data table
u	number of clusters given arbitrarily
method	clustering method: "SClust" (default), "DClust", "single", "complete", "average", "mcquitty", "median", "centroid", "ward", "pam", "diana"
S	the number of simulations used to compute average adjusted Rand index
fixedAsample	if NULL A sample is generated randomly, otherwise this parameter contains object numbers arbitrarily assigned to A sample
...	additional argument passed to dist_SDA function

Details

See file [../doc/replicationSDA_details.pdf](#) for further details

Value

A	3-dimensional array containing data matrices for A sample of objects in each simulation (first dimension represents simulation number, second - object number, third - variable number)
B	3-dimensional array containing data matrices for B sample of objects in each simulation (first dimension represents simulation number, second - object number, third - variable number)
medoids	3-dimensional array containing matrices of observations on u representative objects (medoids) for A sample of objects in each simulation (first dimension represents simulation number, second - cluster number, third - variable number)
clusteringA	2-dimensional array containing cluster numbers for A sample of objects in each simulation (first dimension represents simulation number, second - object number)
clusteringB	2-dimensional array containing cluster numbers for B sample of objects in each simulation (first dimension represents simulation number, second - object number)

clusteringBB	2-dimensional array containing cluster numbers for B sample of objects in each simulation according to 4 step of replication analysis procedure (first dimension represents simulation number, second - object number)
cRand	value of average adjusted Rand index for S simulations

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References

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- Bock H.H., Diday E. (eds.) (2000), *Analysis of Symbolic Data. Explanatory methods for extracting statistical information from complex data*, Springer-Verlag, Berlin.
- Diday E., Noirhomme-Fraiture M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

See Also

[dist_SDA](#), [SClust](#), [DClust](#); hclust in stats library; pam in cluster library; replication.Mod in clusterSim library

Examples

```
#data("cars", package="symbolicDA")
#set.seed(123)
#w<-replication.SDA(cars, u=3, method="SClust", S=10)
#print(w)
```

RSDA2SymbolicDA

Read a Symbolic Table from

Description

It reads a symbolic data table from a CSV file or converts RSDA object to SymbolicDA "symbolic" class type object

Usage

```
RSDA2SymbolicDA(rsda.object=NULL,from.csv=F,file=NULL
, header = TRUE, sep, dec, row.names = NULL)
```

Arguments

<code>rsda.object</code>	object of class "symb.data.table" from (former) RSDA package)
<code>from.csv</code>	object of class "symb.data.table" from (former) RSDA package)
<code>file</code>	optional, The name of the CSV file in RSDA format (see details)
<code>header</code>	As in R function <code>read.table</code>
<code>sep</code>	As in R function <code>read.table</code>
<code>dec</code>	As in R function <code>read.table</code>
<code>row.names</code>	As in R function <code>read.table</code>

Details

(as in (former) RSDA package) The labels \$C means that follows a continuous variable, \$I means an interval variable, \$H means a histogram variables and \$S means set variable. In the first row each labels should be follow of a name to variable and to the case of histogram a set variables types the names of the modalities (categories) . In data rows for continuous variables we have just one value, for interval variables we have the minimum and the maximum of the interval, for histogram variables we have the number of modalities and then the probability of each modality and for set variables we have the cardinality of the set and next the elements of the set.

The format is the CSV file should be like:

```
$C F1 $I F2 F2 $H F3 M1 M2 M3 $S F4 E1 E2 E3 E4
```

```
Case1 $C 2.8 $I 1 2 $H 3 0.1 0.7 0.2 $S 4 e g k i
```

```
Case2 $C 1.4 $I 3 9 $H 3 0.6 0.3 0.1 $S 4 a b c d
```

```
Case3 $C 3.2 $I -1 4 $H 3 0.2 0.2 0.6 $S 4 2 1 b c
```

```
Case4 $C -2.1 $I 0 2 $H 3 0.9 0.0 0.1 $S 4 3 4 c a
```

```
Case5 $C -3.0 $I -4 -2 $H 3 0.6 0.0 0.4 $S 4 e i g k
```

The internal format is:

```
$N
```

```
[1] 5
```

```
$M
```

```
[1] 4
```

```
$sym.obj.names
```

```
[1] 'Case1' 'Case2' 'Case3' 'Case4' 'Case5'
```

```
$sym.var.names
```

```

[1] 'F1' 'F2' 'F3' 'F4'
$sym.var.types
[1] '$C' '$I' '$H' '$S'
$sym.var.length
[1] 1 2 3 4
$sym.var.starts
[1] 2 4 8 13
$meta
$C F1 $I F2 F2 $H F3 M1 M2 M3 $S F4 E1 E2 E3 E4
Case1 $C 2.8 $I 1 2 $H 3 0.1 0.7 0.2 $S 4 e g k i
Case2 $C 1.4 $I 3 9 $H 3 0.6 0.3 0.1 $S 4 a b c d
Case3 $C 3.2 $I -1 4 $H 3 0.2 0.2 0.6 $S 4 2 1 b c
Case4 $C -2.1 $I 0 2 $H 3 0.9 0.0 0.1 $S 4 3 4 c a
Case5 $C -3.0 $I -4 -2 $H 3 0.6 0.0 0.4 $S 4 e i g k
$data
F1 F2 F2.1 M1 M2 M3 E1 E2 E3 E4
Case1 2.8 1 2 0.1 0.7 0.2 e g k i
Case2 1.4 3 9 0.6 0.3 0.1 a b c d
Case3 3.2 -1 4 0.2 0.2 0.6 2 1 b c
Case4 -2.1 0 2 0.9 0.0 0.1 3 4 c a
Case5 -3.0 -4 -2 0.6 0.0 0.4 e i g k

```

Value

Return a symbolic data table in form of SymbolicDA "symbolic" class type object.

Author(s)

Andrzej Dudek

With ideas from RSDA package by Oldemar Rodriguez Rojas

References

Bock H.H., Diday E. (eds.) (2000), *Analysis of Symbolic Data. Explanatory methods for extracting statistical information from complex data*, Springer-Verlag, Berlin.

See Also

display.sym.table

Examples

```
# Example will be available in next version of package, thank You for your patience :-)
```

save.S0	<i>saves symbolic data table of 'symbolic' class to xml file</i>
---------	--

Description

saves symbolic data table of 'symbolic' class to xml file (ASSO format)

Usage

```
save.S0(sdt, file)
```

Arguments

sdt	Symbolic data table
file	file name with extension

Details

see [symbolic.object](#) for symbolic data table R structure representation

Value

No value returned

Author(s)

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Department of Econometrics and Computer Science, University of Economics, Wroclaw, Poland

References

Billard L., Diday E. (eds.) (2006), *Symbolic Data Analysis, Conceptual Statistics and Data Mining*, John Wiley & Sons, Chichester.

Bock H.H., Diday E. (eds.) (2000), *Analysis of symbolic data. Explanatory methods for extracting statistical information from complex data*, Springer-Verlag, Berlin.

Diday E., Noirhomme-Fraiture M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

See Also

[generate.S0](#), [subsdt.SDA](#), [parse.S0](#)

Examples

```
#data("cars", package="symbolicDA")
#save.S0(cars, file="cars_backup.xml")
```

SClust

Dynamical clustering of symbolic data

Description

Dynamical clustering of symbolic data based on symbolic data table

Usage

```
SClust(table.Symbolic, cl, iter=100, variableSelection=NULL, objectSelection=NULL)
```

Arguments

<code>table.Symbolic</code>	symbolic data table
<code>cl</code>	number of clusters or vector with initial prototypes of clusters
<code>iter</code>	maximum number of iterations
<code>variableSelection</code>	vector of numbers of variables to use in clustering procedure or NULL for all variables
<code>objectSelection</code>	vector of numbers of objects to use in clustering procedure or NULL for all objects

Details

See file [../doc/SClust_details.pdf](#) for further details

Value

a vector of integers indicating the cluster to which each object is allocated

Author(s)

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References

Bock, H.H., Diday, E. (eds.) (2000), *Analysis of Symbolic Data. Explanatory Methods for Extracting Statistical Information from Complex Data*, Springer-Verlag, Berlin.

Diday, E., Noirhomme-Fraiture, M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester, pp. 185-191.

Verde, R. (2004), *Clustering Methods in Symbolic Data Analysis*, In: D. Banks, L. House, E. R. McMorris, P. Arabie, W. Gaul (Eds.), *Classification, clustering and Data mining applications*, Springer-Verlag, Heidelberg, pp. 299-317.

Diday, E. (1971), *La methode des Nuees dynamiques*, Revue de Statistique Appliquee, Vol. 19-2, pp. 19-34.

Celeux, G., Diday, E., Govaert, G., Lechevallier, Y., Ralambondrainy, H. (1988), *Classification Automatique des Donnees*, Environnement Statistique et Informatique - Dunod, Gauthier-Villards, Paris.

See Also

[DClust](#); [kmeans](#) in stats library

Examples

```
# LONG RUNNING - UNCOMMENT TO RUN
#data("cars", package="symbolicDA")
#sdt<-cars
#clust<-SClust(sdt, cl=3, iter=50)
#print(clust)
```

simple2S0	<i>Change of representation of symbolic data from simple form to symbolic data table</i>
-----------	--

Description

Change of representation of symbolic data from simple form to symbolic data table

Usage

```
simple2S0(x)
```

Arguments

x	symbolic interval data: a 3-dimensional table, first dimension represents object number, second dimension - variable number, and third dimension contains lower- and upper-bounds of intervals
---	--

Details

see [symbolic.object](#) for symbolic data table R structure representation

Value

Symbolic data table in full form

Author(s)

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References

- Billard L., Diday E. (eds.) (2006), *Symbolic Data Analysis, Conceptual Statistics and Data Mining*, John Wiley & Sons, Chichester.
- Bock H.H., Diday E. (eds.) (2000), *Analysis of symbolic data. Explanatory methods for extracting statistical information from complex data*, Springer-Verlag, Berlin.
- Diday E., Noirhomme-Fraiture M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

See Also

`link{SO2Simple}`

Examples

```
# Example will be available in next version of package, thank You for your patience :-)
```

SO2Simple	<i>Change of representation of symbolic data from symbolic data table to simple form</i>
-----------	--

Description

Change of representation of symbolic data from symbolic data table to simple form

Usage

```
SO2Simple(sd)
```

Arguments

<code>sd</code>	Symbolic data table in full form
-----------------	----------------------------------

Details

see [symbolic.object](#) for symbolic data table R structure representation

Value

symbolic interval data: a 3-dimensional table, first dimension represents object number, second dimension - variable number, and third dimension contains lower- and upper-bounds of intervals

Author(s)

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References

- Billard L., Diday E. (eds.) (2006), *Symbolic Data Analysis, Conceptual Statistics and Data Mining*, John Wiley & Sons, Chichester.
- Bock H.H., Diday E. (eds.) (2000), *Analysis of symbolic data. Explanatory methods for extracting statistical information from complex data*, Springer-Verlag, Berlin.
- Diday E., Noirhomme-Fraiture M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

See Also

`link{simple2S0}`

Examples

```
# Example will be available in next version of package, thank You for your patience :-)
```

subsdt.SDA	<i>Subset of symbolic data table</i>
------------	--------------------------------------

Description

This method creates symbolic data table containing only objects, whose indices are given in second argument

Usage

```
subsdt.SDA(sdt,objectSelection)
```

Arguments

sdt	Symbolic data table
objectSelection	vector containing symbolic object numbers, default value - all objects from sdt

Details

see [symbolic.object](#) for symbolic data table R structure representation

Value

Symbolic data table containing only objects, whose indices are given in second argument. The result is of 'symbolic' class

Author(s)

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References

- Billard L., Diday E. (eds.) (2006), *Symbolic Data Analysis, Conceptual Statistics and Data Mining*, John Wiley & Sons, Chichester.
- Bock H.H., Diday E. (eds.) (2000), *Analysis of symbolic data. Explanatory methods for extracting statistical information from complex data*, Springer-Verlag, Berlin.
- Diday E., Noirhomme-Fraiture M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

See Also

[generate.S0](#), [save.S0](#), [parse.S0](#)

Examples

```
# Example will be available in next version of package, thank You for your patience :-)
```

symbolic.object	<i>Symbolic data table Object</i>
-----------------	-----------------------------------

Description

These are objects representing symbolic data table structure

Details

For all fields symbol N.A. means not available value.

For futher details see [../doc/SDA.pdf](#)

Value

individuals	data frame with one row for each row in symbolic data table with following columns: num - symbolic object (described by symbolic data table row) ordering number , usually from 1 to numebr of symbolic objects; name - short name of symbolic object with no spaces; label - full descriptive name of symbolic object.
variables	data frame with one row for each column in symbolic data table with following columns: num - symbolic variable (adequate to symbolic data table column) ordering number, usually from 1 to number of symbolic variables; name - short name of symbolic variable with no spaces; label - full descriptive name of symbolic variable; type - type of symbolic variable: IC (InterContinous) - Symbolic interval variable type, every realization of symbolic variable of this type on symbolic object takes form of numerical interval; C (Continous) - Symbolic interval variable

type, every realization of symbolic variable of this type on symbolic object takes form of numerical interval for which beginning is equal to end (equivalent to simple "numeric" value); MN (MultiNominal) - every realization of multi nominal symbolic variable on symbolic objects takes form of set of nominal values; NM ((Multi) Nominal Modif) - every realization of nominal symbolic variable on symbolic objects takes form of distribution of probabilities (set of nominal values with weights summing to one) N (Nominal) - every realization of nominal symbolic variable on symbolic objects is one value (or N.A.)

details - id of this variable in details table appropriate for this kind of variable (*detailsN* for nominal and multi nominal variables, *detailsIC* for symbolic interval variables, *detailsC* for continuous (metric single-valued) variables, *detailsNM* of multi nominal with weights variables).

detailsC	data frame describing symbolic continuous (metric, single-valued) variables details with following columns: na - number of N.A. (not available) variables realization; nu - not used, left for compatibility with ASSO-XML specification; min - beginning of interval representing symbolic interval variable domain (minimal value of all realizations of this variable on all symbolic objects); max - end of interval representing symbolic interval variable domain (maximal value of all realizations of this variable on all symbolic objects).
detailsIC	data frame describing symbolic inter-continuous (symbolic interval) variables details with following columns: na - number of N.A. (not available) variables realizations; nu - not used, left for compatibility with ASSO-XML specification; min - beginning of interval representing symbolic interval variable domain (minimal value of all beginnings of interval realizations of this variable on all symbolic objects); max - end of interval representing symbolic interval variable domain (maximal value of all ends of interval realizations of this variable on all symbolic objects).
detailsN	data frame describing symbolic nominal and multi nominal variables details with following columns: na - number of N.A. variables realizations; nu - not used, left for compatibility with ASSO-XML specification; modals - number of categories in symbolic variable domain. Each categorie is described in <i>detailsListNom</i>.
detailsListNom	data frame describing every category of symbolic nominal and multi nominal variables, with following columns: details_no - number of variable in <i>detailsN</i> to which domain belongs category; num - number of category within variable domain; name - category short name label - category full name
detailsNM	data frame describing symbolic multi nominal modiff (categories sets with weights) variables details with following columns: na number of N.A. (not available) variables realizations.

	nu not used, left for compatibility with ASSO-XML specification modals number of categories in symbolic variable domain. Each categorie is described in <i>detailsListNomModiff</i>
detailsListNomModif	data frame describing every category of symbolic multi nominal modiff variables, with following columns details_no - number of variable in <i>detailsNM</i> to which domain belongs category num - number of category within variable domain name - category short name label - category full name
indivIC	array of symbolic interval variables realizations, with dimensions nr_of_objects X nr_of_variables X 2 containing beginnings and ends of intervals for given object and variable. For values different type than symbolic interval array contains zeros
indivC	array of symbolic continues variables realizations, with dimensions nr_of_objects X nr_of_variables X 1 containing single values - realizations of variable on symbolic object. For values different type than symbolic continous array contains zeros
indivN	data frame describing symbolic nominal and multi nonimal variables realizations with folowing columns: indiv - id of symbolic object from <i>individuals</i>; variable - id of symbolic object from <i>variables</i>; value - id of category object from <i>detailsListNom</i>; When this data frame contains line i,j,k it means that category k belongs to set that is realization of j-th symbolic variable on i-th symbolic object.
indivNM	data frame describing symbolic multi nonimal modiff variables realizations with folowing columns: indiv - id of symbolic object from <i>individuals</i>; variable - id of symbolic object from <i>variables</i>; value - id of category object from <i>detailsListNom</i>; frequency - wiught of category; When this data frame contains line i,j,k,w it means that category k belongs to set that is realization of j-th symbolic variable on i-th symbolic object with weight(probability) w.

Structure

The following components must be included in a legitimate symbolic object.

See Also

[dist_SDA](#).

symscal.SDA	<i>Multidimensional scaling for symbolic interval data - SymScal algorithm</i>
-------------	--

Description

Multidimensional scaling for symbolic interval data - symScal algorithm

Usage

```
symscal.SDA(x,d=2,calculateDist=FALSE)
```

Arguments

x	symbolic interval data: a 3-dimensional table, first dimension represents object number, second dimension - variable number, and third dimension contains lower- and upper-bounds of intervals (Simple form of symbolic data table)
d	Dimensionality of reduced space
calculateDist	if TRUE x are treated as raw data and min-max dist matrix is calculated. See details

Details

SymScal, which was proposed by Groenen et. al. (2005), is an adaptation of well-known non-metric multidimensional scaling for symbolic data. It is an iterative algorithm that uses STRESS objective function. This function is unnormalized. IScal, like Interscal and SymScal, requires interval-valued dissimilarity matrix. Such dissimilarity matrix can be obtained from symbolic data matrix (that contains only interval-valued variables), judgements obtained from experts, respondents. See Lechevallier Y. (2001) for details on calculating interval-valued distance. See file [../doc/Symbolic_MDS.pdf](#) for further details

Value

xprim	coordinates of rectangles
STRESSSym	final STRESSSym value

Author(s)

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References

Billard L., Diday E. (eds.) (2006), *Symbolic Data Analysis, Conceptual Statistics and Data Mining*, John Wiley & Sons, Chichester.

Bock H.H., Diday E. (eds.) (2000), *Analysis of symbolic data. Explanatory methods for extracting statistical information from complex data*, Springer-Verlag, Berlin.

Diday E., Noirhomme-Fraiture M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

Groenen P.J.F, Winsberg S., Rodriguez O., Diday E. (2006), I-Scal: multidimensional scaling of interval dissimilarities, *Computational Statistics and Data Analysis*, 51, pp. 360-378. Available at: [doi:10.1016/j.csda.2006.04.003](https://doi.org/10.1016/j.csda.2006.04.003).

See Also

[iscal.SDA](#), [interscal.SDA](#)

Examples

```
# Example will be available in next version of package, thank You for your patience :-)
```

zoomStar

zoom star chart for symbolic data

Description

plot in a form of zoom star chart for symbolic object described by interval-valued, multivalued and modal variables

Usage

```
zoomStar(table.Symbolic, j, variableSelection=NULL, offset=0.2,
firstTick=0.2, labelCex=.8, labelOffset=.7, tickLength=.3, histWidth=0.04,
histHeight=2, rotateLabels=TRUE, variableCex=NULL)
```

Arguments

table.Symbolic	symbolic data table
j	symbolic object number in symbolic data table used to create the chart
variableSelection	numbers of symbolic variables describing symbolic object used to create the chart, if NULL all variables are used
offset	relational offset of chart (margin size)
firstTick	place of first tick (relational to lenght of axis)
labelCex	labels cex parameter of labels
labelOffset	relational offset of labels

tickLength	relational length of single tick of axis
histWidth	histogram (for modal variables) relational width
histHeight	histogram (for modal variables) relational height
rotateLabels	if TRUE labels are rotated due to rotation of axes
variableCex	cex parameter of names of variables

Value

zoom star chart for selected symbolic object in which each axis represents a symbolic variable. Depending on the type of symbolic variable their implementations are presented as:

- a) rectangle - interval range of interval-valued variable),
 - b) circles - categories of multinominal (or multinominal with weights) variable from among coloured circles means categories of the variable observed for the selected symbolic object
- bar chart - additional chart for multinominal with weights variable in which each bar represents a weight (percentage share) of a category of the variable

Author(s)

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References

- Bock, H.H., Diday, E. (eds.) (2000), *Analysis of symbolic data. Explanatory methods for extracting statistical information from complex data*, Springer-Verlag, Berlin.
- Diday, E., Noirhomme-Fraiture, M. (eds.) (2008), *Symbolic Data Analysis with SODAS Software*, John Wiley & Sons, Chichester.

See Also

plotInterval in clusterSim

Examples

```
# LONG RUNNING - UNCOMMENT TO RUN
# Example 1
#data("cars", package="symbolicDA")
#sdt<-cars
#zoomStar(sdt, j=12)

# Example 2
#data("cars", package="symbolicDA")
#sdt<-cars
#variables<-as.matrix(sdt$variables)
#indivN<-as.matrix(sdt$indivN)
#dist<-as.matrix(dist_SDA(sdt))
#classes<-DClust(dist, cl=5, iter=100)
#for(i in 1:max(classes)){
```

```
#getOption("device")()  
#zoomStar(sdt, .medoid2(dist, classes, i))}
```


Index

- * **MDS**
 - interscal.SDA, [20](#)
 - iscal.SDA, [21](#)
 - symscal.SDA, [45](#)
- * **Multidimensional**
 - interscal.SDA, [20](#)
 - iscal.SDA, [21](#)
 - symscal.SDA, [45](#)
- * **PCA**
 - PCA.centers.SDA, [26](#)
 - PCA.mrpca.SDA, [27](#)
 - PCA.spaghetti.SDA, [28](#)
 - PCA.spca.SDA, [29](#)
 - PCA.vertices.SDA, [30](#)
- * **Principal components analysis**
 - PCA.centers.SDA, [26](#)
 - PCA.mrpca.SDA, [27](#)
 - PCA.spaghetti.SDA, [28](#)
 - PCA.spca.SDA, [29](#)
 - PCA.vertices.SDA, [30](#)
- * **RSDA**
 - RSDA2SymbolicDA, [34](#)
- * **SDA**
 - decisionTree.SDA, [9](#)
 - dist_SDA, [11](#)
 - generate.SO, [14](#)
 - RSDA2SymbolicDA, [34](#)
 - symbolic.object, [42](#)
- * **SymbolicDA**
 - RSDA2SymbolicDA, [34](#)
- * **Symbolic**
 - RSDA2SymbolicDA, [34](#)
- * **Table**
 - RSDA2SymbolicDA, [34](#)
- * **cluster**
 - bagging.SDA, [2](#)
 - boosting.SDA, [4](#)
 - cluster.Description.SDA, [6](#)
 - DClust, [8](#)
 - HINoV.SDA, [15](#)
 - IchinoFS.SDA, [17](#)
 - index.G1d, [18](#)
 - kernel.SDA, [23](#)
 - kohonen.SDA, [24](#)
 - parse.SO, [25](#)
 - replication.SDA, [33](#)
 - save.SO, [37](#)
 - SClust, [38](#)
 - simple2SO, [39](#)
 - SO2Simple, [40](#)
 - subsdt.SDA, [41](#)
 - zoomStar, [46](#)
- * **datasets**
 - cars, [5](#)
 - data_symbolic, [8](#)
- * **decision tree**
 - draw.decisionTree.SDA, [13](#)
 - random.forest.SDA, [31](#)
- * **multivariate**
 - replication.SDA, [33](#)
- * **scaling**
 - interscal.SDA, [20](#)
 - iscal.SDA, [21](#)
 - symscal.SDA, [45](#)
- * **symbolic**
 - decisionTree.SDA, [9](#)
 - dist_SDA, [11](#)
 - generate.SO, [14](#)
 - symbolic.object, [42](#)
- bagging.SDA, [2](#), [5](#), [10](#), [32](#)
- boosting.SDA, [4](#), [4](#), [10](#), [32](#)
- cars, [5](#)
- cluster.Description.SDA, [6](#)
- data_symbolic, [8](#)
- DClust, [7](#), [8](#), [13](#), [19](#), [34](#), [39](#)
- decisionTree.SDA, [4](#), [5](#), [9](#), [14](#), [32](#)

`dist_SDA`, [9](#), [11](#), [16](#), [18](#), [24](#), [33](#), [34](#), [44](#)
`draw.decisionTree.SDA`, [10](#), [13](#)

`generate.S0`, [14](#), [26](#), [37](#), [42](#)

`hclust`, [7](#)
`HINoV.SDA`, [15](#), [18](#)

`IchinoFS.SDA`, [17](#)
`index.G1d`, [13](#), [18](#)
`interscal.SDA`, [20](#), [22](#), [46](#)
`iscal.SDA`, [21](#), [21](#), [46](#)

`kernel.SDA`, [23](#)
`kmeans`, [39](#)
`kohonen.SDA`, [24](#)

`parse.S0`, [25](#), [37](#), [42](#)
`PCA.centers.SDA`, [26](#), [28–31](#)
`PCA.mrpca.SDA`, [27](#), [27](#), [29–31](#)
`PCA.spaghetti.SDA`, [27](#), [28](#), [28](#), [30](#), [31](#)
`PCA.spca.SDA`, [27–29](#), [29](#), [31](#)
`PCA.vertices.SDA`, [27–30](#), [30](#)

`random.forest.SDA`, [4](#), [5](#), [10](#), [31](#)
`replication.SDA`, [33](#)
`RSDA2SymbolicDA`, [34](#)

`save.S0`, [26](#), [37](#), [42](#)
`SClust`, [7](#), [9](#), [19](#), [34](#), [38](#)
`simple2S0`, [39](#)
`S02Simple`, [24](#), [40](#)
`subsdt.SDA`, [37](#), [41](#)
`symbolic.object`, [15](#), [25](#), [37](#), [39–41](#), [42](#)
`symscal.SDA`, [21](#), [22](#), [45](#)

`zoomStar`, [46](#)