

# Package: smacof (via r-universe)

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**Type** Package

**Title** Multidimensional Scaling

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**Description** Implements the following approaches for multidimensional scaling (MDS) based on stress minimization using majorization (smacof): ratio/interval/ordinal/spline MDS on symmetric dissimilarity matrices, MDS with external constraints on the configuration, individual differences scaling (idioscal, indscal), MDS with spherical restrictions, and ratio/interval/ordinal/spline unfolding (circular restrictions, row-conditional). Various tools and extensions like jackknife MDS, bootstrap MDS, permutation tests, MDS biplots, gravity models, unidimensional scaling, drift vectors (asymmetric MDS), classical scaling, and Procrustes are implemented as well.

**Imports** graphics, stats, polynom, Hmisc, nnls, grDevices, MASS, weights, ellipse, wordcloud, candisc, parallel, foreach, doParallel

**Depends** R (>= 3.5.0), plotrix, colorspace, e1071

**License** GPL-3

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biplotmds *MDS Biplots*

**Description**

Regresses external variables on a MDS configuration which results in a MDS biplot.

**Usage**

```
## S3 method for class 'smacof'
biplotmds(object, extvar, scale = TRUE)
## S3 method for class 'mdsbi'
plot(x, vecscale = NULL, plot.dim = c(1,2), sphere = TRUE, col = 1,
      label.conf = list(label = TRUE, pos = 3, col = 1, cex = 0.8),
      vec.conf = list(col = 1, cex = 0.8, length = 0.1),
      identify = FALSE, type = "p", pch = 20,
      asp = 1, main, xlab, ylab, xlim, ylim, ...)
```

**Arguments**

- object      Object of class "smacof" or "smacofID".
- extvar      Data frame with external variables.
- scale       If TRUE, external variables are standardized internally.
- x            Object of class "mdsbi".

<code>vecscale</code>	Scaling factor for regression coefficients, either a single number or NULL (see details).
<code>plot.dim</code>	Vector with dimensions to be plotted.
<code>main</code>	Plot title.
<code>xlab</code>	Label of x-axis.
<code>ylab</code>	Label of y-axis.
<code>xlim</code>	Scale x-axis.
<code>ylim</code>	Scale y-axis.
<code>pch</code>	Plot symbol.
<code>asp</code>	Aspect ratio.
<code>col</code>	Point color.
<code>type</code>	What type of plot should be drawn.
<code>sphere</code>	In case of spherical smacof, whether sphere should be plotted or not.
<code>label.conf</code>	List with arguments for plotting the labels of the configurations in a configuration plot (logical value whether to plot labels or not, label position, label color).
<code>vec.conf</code>	List with arguments for arrows and arrow labels of the external variables.
<code>identify</code>	If TRUE, the <code>identify()</code> function is called internally that allows to add configuration labels by mouse click.
<code>...</code>	Further plot arguments passed: see <a href="#">plot</a> for detailed information.

### Details

If a model for individual differences is provided, the external variables are regressed on the group stimulus space configurations. In the biplot only the relative length of the vectors and their direction matters. Using the scale argument the user can control for the relative length of the vectors. If `vecscale = NULL`, the `vecscale()` function from the **candisc** package is used which tries to automatically calculate the scale factor so that the vectors approximately fill the same space as the configuration.

### Value

Returns an object belonging to classes "mlm" and "mdsbi". See [lm](#) for details.

`R2vec`            Vector containing the R2 values.

### References

- Greenacre, M. (2010). *Biplots in Practice*. Fundacion BBVA, Bilbao, Spain.
- Mair, P., Groenen, P. J. F., De Leeuw, J. (2022). More on multidimensional scaling in R: smacof version 2, *Journal of Statistical Software*, 102(10), 1-47. [doi:10.18637/jss.v102.i10](https://doi.org/10.18637/jss.v102.i10)

### See Also

[plot.smacof](#)

## Examples

```
## morse code data with external scales
res <- mds(morse)
fitbi <- biplotmds(res, morsescales[,2:3])
plot(fitbi, main = "MDS Biplot", vecscale = 0.5)

## wish data with external economic development factor
diss <- sim2diss(wish, method = 7)
res <- mds(diss, type = "ordinal")
ecdev <- data.frame(ecdev = c(3,1,3,3,8,3,7,9,4,7,10,6))
fitbi <- biplotmds(res, ecdev)
plot(fitbi, main = "MDS Biplot", vecscale = 1)
plot(fitbi, main = "MDS Biplot", vecscale = 0.5, xlim = c(-1, 1),
vec.conf = list(col = "red", length = 0.05))

## Ekman's color data (by Michael Friendly)
require(colorspace)
wavelengths <- attr(ekman, "Labels")
colors <- c("#2600F0", "#0028FF", "#0092FF", "#00B2FF", "#00FFFF", "#00FF61", "#77FF00", "#B3FF00",
"#FFF200", "#FFBE00", "#FF9B00", "#FF5700", "#F60000", "#D60000")
ekmanD <- sim2diss(ekman)
res <- mds(ekmanD, type = "ordinal")
RGB <- t(col2rgb(colors)) / 255
HCL <- as(hex2RGB(colors), "polarLUV")
HCL <- slot(HCL, "coords")
fit <- biplotmds(res, cbind(RGB, HCL))
fit
plot(fit, vecscale = 0.5, cex = 6, col = colors,
label.conf=list(cex = 1, pos = ifelse(wavelengths < 560, 2, 4)),
vec.conf = list(cex = 1.2), main = "Ekman configuration and color properties" )
```

---

bootmds

*SMACOF Bootstrap*


---

## Description

Performs a bootstrap on a SMACOF solution. It works for derived dissimilarities only. The original data matrix needs to be provided, as well as the type of dissimilarity measure used to compute the input dissimilarities.

## Usage

```
## S3 method for class 'smacofB'
bootmds(object, data, method.dat = "pearson", nrep = 100,
alpha = 0.05, verbose = FALSE, ...)

## S3 method for class 'smacofboot'
plot(x, plot.dim = c(1,2), col = 1,
```

```
label.conf = list(label = TRUE, pos = 3, cex = 0.8),
ell = list(lty = 1, lwd = 1, col = "gray"), main, xlab, ylab, xlim, ylim,
asp = 1, type = "p", pch = 20, ...)
```

### Arguments

object	Object of class "smacofB", i.e., an MDS solution from <code>mds()</code> .
data	Initial data (before dissimilarity computation).
method.dat	Dissimilarity computation used as MDS input. This must be one of "pearson", "spearman", "kendall", "euclidean", "maximum", "manhattan", "canberra", "binary". For unfolding models it is either "full" for full permutations or "rows" for permutations within rows.
nrep	Number of bootstrap replications.
alpha	Alpha level for confidence ellipsoids.
verbose	If TRUE, bootstrap index is printed out.
...	Additional arguments needed for dissimilarity computation as specified in <code>sim2diss()</code> .
x	Object of class "smacofboot"
plot.dim	Vector with dimensions to be plotted.
col	Color for points.
label.conf	List with arguments for plotting the labels of the configurations in a configuration plot (logical value whether to plot labels or not, label position). If <code>pos = 5</code> labels are placed away from the nearest point.
ell	List with arguments for plotting ellipses: line type, line width, color.
main	Plot title.
xlab	Label of x-axis.
ylab	Label of y-axis.
xlim	Scale x-axis.
ylim	Scale y-axis.
asp	Aspect ratio.
pch	Plotting symbol for object point.
type	Type of plot.

### Details

In order to examine the stability solution of an MDS, a bootstrap on the raw data can be performed. This results in confidence ellipses in the configuration plot. The ellipses are returned as list which allows users to produce (and further customize) the plot by hand.

### Value

cov	Covariances for ellipse computation
bootconf	Configurations bootstrap samples
stressvec	Bootstrap stress values
bootci	Stress bootstrap percentile confidence interval
stab	Stability coefficient

## References

Jacoby, W. G., & Armstrong, D. A. (2014). Bootstrap confidence regions for multidimensional scaling solutions. *American Journal of Political Science*, 58, 264-278.

Mair, P., Groenen, P. J. F., De Leeuw, J. (2022). More on multidimensional scaling in R: smacof version 2, *Journal of Statistical Software*, 102(10), 1-47. doi:10.18637/jss.v102.i10

## See Also

[jackmds](#)

## Examples

```
## Example using Euclidean distances
data <- na.omit(PVQ40[,1:5])
diss <- dist(t(data)) ## Euclidean distances
fit <- mds(diss)      ## 2D interval MDS

set.seed(123)
resboot <- bootmds(fit, data, method.dat = "euclidean", nrep = 50)
resboot
plot(resboot)

## Example using Pearson correlations
sim <- cor(data)
diss <- sim2diss(sim, method = 1) ## subtract from 1 (method needs to be passed to bootmds)
fit <- mds(diss, type = "ratio", ndim = 3)      ## 3D ratio MDS

set.seed(123)
resboot <- bootmds(fit, data, method.dat = "pearson", nrep = 50, alpha = 0.1, method = 1)
resboot
## plot 1st against 3rd dimension
ellipses <- plot(resboot, plot.dim = c(1,3), ell = list(lty = 2, col = "gray", lwd = 0.8))
str(ellipses) ## list of ellipse coordinates for each object
```

---

bread

*Breakfast preferences*

---

## Description

The data set is described in Bro (1998). The raw data consist of ratings of 10 breads on 11 different attributes carried out by 8 raters. Note that the bread samples are pairwise replications: Each of the 5 different breads, which have a different salt content, was presented twice for rating.

## Usage

```
data(bread)
```

**Format**

A list of length 8 with elements of class "dist". The attributes are bread odor, yeast odor, off-flavor, color, moisture, dough, salt taste, sweet taste, yeast taste, other taste, and total taste.

**References**

Bro, R. (1998). Multi-way Analysis in the Food Industry: Models, Algorithms, and Applications. Ph.D. thesis, University of Amsterdam (NL) & Royal Veterinary and Agricultural University (DK).

**Examples**

bread

---

breakfast	<i>Breakfast preferences</i>
-----------	------------------------------

---

**Description**

42 individuals were asked to order 15 breakfast items due to their preference.

**Usage**

data(breakfast)

**Format**

Data frame with students in the rows and breakfast items in the columns.

toast: toast pop-up

butoast: buttered toast

engmuff: English muffin and margarine

jdonut: jelly donut

cintoast: cinnamon toast

bluemuff: blueberry muffin and margarine

hrolls: hard rolls and butter

toastmarm: toast and marmalade

butoastj: buttered toast and jelly

toastmarg: toast and margarine

cinbun: cinnamon bun

danpastry: Danish pastry

gdonut: glazed donut

cofcake: coffee cake

cornmuff: corn muffin and butter



**References**

Green, P. E. & Rao, V. (1972). Applied multidimensional scaling. Hinsdale, IL: Dryden.

**Examples**

```
breakfast
```

---

```
CanadaNews
```

```
Canadian Newspapers
```

---

**Description**

We took Canadian newspapers that appeared in the time period between June and September 2009 and searched for articles that contained the word "aboriginal". A total of 92 articles was found. In these articles, we determined the frequencies of other meaningful words (e.g., tribal, moose, arctic, and health). The data are organized as word co-occurrence matrix.

**Usage**

```
data(CanadaNews)
```

**Format**

Matrix with word co-occurrence counts.

**References**

Borg, I., Groenen, P. J. F., & Mair, P. (2017). Applied Multidimensional Scaling and Unfolding. New York: Springer.

**Examples**

```
str(CanadaNews)
```

---

```
confEllipse
```

```
Pseudo Confidence Ellipses
```

---

**Description**

Computes pseudo-confidence ellipses for symmetric and individual difference MDS fits.

**Usage**

```
## S3 method for class 'smacofID'
confEllipse(object)

## S3 method for class 'confell'
plot(x, eps = 0.05, plot.dim = c(1,2), col = 1,
      label.conf = list(label = TRUE, pos = 3, cex = 0.8),
      ell = list(lty = 1, lwd = 1, col = 1), main, xlab, ylab, xlim, ylim,
      asp = 1, type = "p", pch = 20, ...)
```

**Arguments**

object	Object of class "smacofB" or "smacofID".
x	Object of class "confell"
eps	Perturbation region (e.g. 0.05 means that we look at a perturbation region where stress is at most 5% larger than the minimum we have found).
plot.dim	Vector with dimensions to be plotted.
col	Color for points.
label.conf	List with arguments for plotting the labels of the configurations in a configuration plot (logical value whether to plot labels or not, label position). If pos = 5 labels are placed away from the nearest point.
ell	List with arguments for plotting ellipses: line type, line width, color.
main	Plot title.
xlab	Label of x-axis.
ylab	Label of y-axis.
xlim	Scale x-axis.
ylim	Scale y-axis.
asp	Aspect ratio.
pch	Plotting symbol for object point.
type	Type of plot.
...	Additional plotting arguments.

**Details**

The confEllipse function normalizes the dissimilarities and performs a few more iterations to optimize the configuration and the individual difference weights. This result is then passed to a function that computes the stress derivatives which are the basis of the ellipses in the plot function. This function works for ratio scaled versions only.

**Value**

Returns an object belonging to classes "confell".

X	Configuration (group stimulus space for individual difference models)
h	Stress derivatives
s	Optimized stress (raw value)

## References

Mair, P., Groenen, P. J. F., De Leeuw, J. (2022). More on multidimensional scaling in R: smacof version 2, *Journal of Statistical Software*, 102(10), 1-47. doi:10.18637/jss.v102.i10

## See Also

[plot.smacofboot](#)

## Examples

```
## Simple ratio MDS fit
delta <- sim2diss(cor(PVQ40agg))
res <- mds(delta, ndim = 3)
cres <- confEllipse(res)
plot(cres, plot.dim = c(1,2))
plot(cres, plot.dim = c(1,3))
plot(cres, plot.dim = c(2,3))

## INDSCAL on Helm data
fit1 <- indscal(helm)
cfit1 <- confEllipse(fit1)
plot(cfit1, ell = list(col = "gray", lty = 2), ylim = c(-0.04, 0.04))

## IDIOSCAL on Helm data
fit2 <- idioscal(helm)
cfit2 <- confEllipse(fit2)
plot(cfit2, ell = list(col = "gray", lty = 2), ylim = c(-0.04, 0.04))
```

---

crimes

*Crime Correlations*

---

## Description

Correlations of crime rates in 50 US states.

## Usage

```
data(crimes)
```

## Format

Crime correlation matrix.

## References

Borg, I., Groenen, P. J. F., & Mair, P. (2017). *Applied Multidimensional Scaling and Unfolding*. New York: Springer.

**Examples**

```
crimes
```

---

```
csrranking
```

```
CSR activities
```

---

**Description**

This dataset collects rankings of 100 individual on 5 topics that reflect social responsibilities on corporations.

**Usage**

```
data(csrranking)
```

**Format**

A data frame where each individual ranked prevention of environmental pollution (Environment), waste prevention (Waste Prevention), selling organic products (Organic Products), participating on charity programs (Charity), and fair treatment of employees (Employee) according to its own preferences. A value of 1 corresponds to highest importance, 5 to lowest importance.

**Examples**

```
csrranking
```

---

```
dissWeights
```

```
Create Weights for Uniform Weighted Distribution
```

---

**Description**

Compute weights as a function of the dissimilarities.

**Usage**

```
dissWeights(delta, type = c("unif", "knn", "power", "unifpower"),
             k = NULL, power = 0)
```

**Arguments**

delta	Either a symmetric dissimilarity matrix or an object of class "dist"
type	One of "unif" (default), "knn", "power", "unifpower". See details for a description of the various options.
k	The number of smallest dissimilarities per row for which the weights need to be set to 1. The default k = NULL makes k to be set to use the 25% smallest dissimilarities per row.
power	power to which the dissimilarities need to be raised as weights. Default is 0, so that all weights are 1.

**Details**

The weights are computed as a function of the dissimilarities depending on type.

- "unif" Compute weights such that the weighted empirical distribution (histogram) of the dissimilarities is uniform. Particularly if the number of objects is large, the dissimilarities that occur most often will start to dominate the solution. This option de-emphasizes often occurring dissimilarities such that the weighted empirical distribution (the weighted histogram) becomes approximately uniform.
- "knn" Per row of the dissimilarity matrix the k smallest dissimilarities obtain a weight of 1 and the others a 0.
- "power" The weights are set to the  $\text{delta}^{\text{power}}$ . If power is small (e.g., power = -5) then the smaller dissimilarities will be better fitted. If power is large (e.g., power = 5) then the larger dissimilarities will be better fitted.
- "unifpower" First weights are determined by the "unif" option and then multiplied by the weights obtained by the "power" option. If the dissimilarity matrix is large, then this option is needed to see an effect of the "power" option on the MDS solution.

**Value**

weightmat      the weight matrix

**Author(s)**

Patrick Groenen

**Examples**

```
## mds solution for kinship data with uniform weights
res <- mds(kinshipdelta, weightmat = dissWeights(kinshipdelta, type = "unif"))
par(mfrow = c(2,2))
plot(res, main = "uniform weights")
plot(res, plot.type = "Shepard")
plot(res, plot.type = "histogram")

## mds solution for kinship data with knn weights
res <- mds(kinshipdelta, weightmat = dissWeights(kinshipdelta, type = "knn", k = 5))
par(mfrow = c(1,2))
plot(res, main = "knn weights with k=5")
```

```

plot(res, plot.type = "Shepard")

## mds solution for kinship data with power weights emphasizing large dissimilarities
res <- mds(kinshipdelta, weightmat = dissWeights(kinshipdelta, type = "power", power = 5))
par(mfrow = c(2,2))
plot(res, main = "Power = 5 weights")
plot(res, plot.type = "Shepard")
plot(res, plot.type = "histogram")

## mds solution for kinship data with power weights emphasizing small dissimilarities
res <- mds(kinshipdelta, weightmat = dissWeights(kinshipdelta, type = "power", power = -5))
par(mfrow = c(2,2))
plot(res, main = "Power = -5 weights")
plot(res, plot.type = "Shepard")
plot(res, plot.type = "histogram")

## mds solution for kinship data with power weights emphasizing large dissimilarities
## while correcting for nonuniform dissimilarities
res <- mds(kinshipdelta, weightmat = dissWeights(kinshipdelta, type = "unifpower", power = 5))
par(mfrow = c(2,2))
plot(res, main = "Uniform power = 5 weights")
plot(res, plot.type = "Shepard")
plot(res, plot.type = "histogram")

## mds solution for kinship data with power weights emphasizing small dissimilarities
## while correcting for nonuniform dissimilarities
res <- mds(kinshipdelta, weightmat = dissWeights(kinshipdelta, type = "unifpower", power = -5))
par(mfrow = c(2,2))
plot(res, main = "Uniform power = -5 weights")
plot(res, plot.type = "Shepard")
plot(res, plot.type = "histogram")

```

---

driftVectors

*Asymmetric MDS: Drift Vectors*


---

## Description

Takes an asymmetric dissimilarity matrix and decomposes it into a symmetric and a skew-symmetric part. Fits an MDS on the symmetric part and computes drift vectors for the skew-symmetric portion. This model makes it possible to see how these two components are related to each other. It is limited to two dimensions only.

## Usage

```

driftVectors(data, type = c("ratio", "interval", "ordinal", "mspline"),
             weightmat = NULL, init = "torgerson", ties = "primary", verbose = FALSE,
             relax = FALSE, modulus = 1, itmax = 1000, eps = 1e-6,
             spline.degree = 2, spline.intKnots = 2)

```

```
## S3 method for class 'driftvec'
plot(x, adjust = 1, main, xlim, ylim,
      xlab = "Dimension 1", ylab = "Dimension 2", pch = 20, asp = 1,
      col.conf = "black", col.drift = "lightgray",
      label.conf = list(label = TRUE, pos = 3, col = "black",
                        cex = 0.8), ...)
```

## Arguments

<code>data</code>	Asymmetric dissimilarity matrix
<code>weightmat</code>	Optional matrix with dissimilarity weights
<code>init</code>	Either "torgerson" (classical scaling starting solution), "random" (random configuration), or a user-defined matrix
<code>type</code>	MDS type: "interval", "ratio", "ordinal" (nonmetric MDS), or "mspline"
<code>ties</code>	Tie specification for ordinal MDS only: "primary", "secondary", or "tertiary"
<code>verbose</code>	If TRUE, intermediate stress is printed out
<code>relax</code>	If TRUE, block relaxation is used for majorization
<code>modulus</code>	Number of smacof iterations per monotone regression call
<code>itmax</code>	Maximum number of iterations
<code>eps</code>	Convergence criterion
<code>spline.degree</code>	Degree of the spline for "mspline" MDS type
<code>spline.intKnots</code>	Number of interior knots of the spline for "mspline" MDS type
<code>x</code>	Object of class "driftvec"
<code>adjust</code>	Scaling factor for drift vectors (value larger than 1 increases the length)
<code>main</code>	Plot title
<code>xlab</code>	Label of x-axis
<code>ylab</code>	Label of y-axis
<code>xlim</code>	Scale x-axis
<code>ylim</code>	Scale y-axis
<code>pch</code>	Plot symbol
<code>asp</code>	Aspect ratio
<code>col.conf</code>	Point color (MDS configurations)
<code>col.drift</code>	Color for drift vectors (arrows)
<code>label.conf</code>	Settings for plotting labels
<code>...</code>	Additional plotting arguments

## Details

The skew-symmetric values are embedded into the MDS representation of the symmetrized data by drawing errors (drift vectors) from each point  $i$  to each point  $j$  in the configuration so that these vectors correspond in length and direction to the values of row  $i$  of the skew-symmetric matrix.

**Value**

fitsym	MDS output for symmetric portion
sym	Symmetric matrix
skewsym	Skew-symmetric matrix
driftcoor	Drift vector coordinates
stress	Stress-1 value
niter	Number of iterations
nobj	Number of objects

**Author(s)**

Patrick Mair

**References**

Borg, I., & Groenen, P. J. F. (2005). *Modern Multidimensional Scaling* (2nd ed.). Springer.

**See Also**

[smacofSym](#)

**Examples**

```
## simple example
P <- matrix(c(0, 4, 6, 13,
             5, 0, 37, 21,
             4, 38, 0, 16,
             8, 31, 18, 0), nrow = 4, ncol = 4, byrow = TRUE)
D <- sim2diss(P, method = 40)
res <- driftVectors(D, type = "interval")
plot(res)
plot(res, adjust = 0.1) ## shorten drift vectors

## Morse code data
fit.drift <- driftVectors(morse2, type = "ordinal")
fit.drift
plot(fit.drift)
```

---

Duration

*Facets of the subjective duration of imagined situations*

---

**Description**

The `DurationRaw` dataset contains the duration rating of 76 subjects on 24 situations. Subjects were asked to rate the duration on a 7 point scale (1 ... substantially shorter, 7 ... substantially longer). The `Duration` data file contains the corresponding correlations between the 24 situations including some information about the facets.



**Usage**

```
data(Duration)
data(DurationRaw)
```

**Format**

Data frame 24 correlations based on duration ratings:

S1-S24: situation

F1: pleasant (1), neutral (2), unpleasant (3)

F2: variable (1), monotonous (2)

F3: difficult (1), easy (2)

F3: many (1), few (2)

structuple: the facet structure written as a tuple

**References**

Borg, I., & Groenen, P. J. F. (2005). *Modern Multidimensional Scaling* (2nd ed.). Springer.

**Examples**

```
ddiss <- sim2diss(Duration[,paste0("S", 1:24)])
fit <- mds(ddiss, type = "ordinal", ndim = 4)
plot(fit)
```

---

ekman

*Ekman data set*

---

**Description**

Ekman dissimilarities

**Usage**

```
data(ekman)
```

**Format**

Object of class `dist`

**Details**

Ekman presents similarities for 14 colors which are based on a rating by 31 subjects where each pair of colors was rated on a 5-point scale (0 = no similarity up to 4 = identical). After averaging, the similarities were divided by 4 such that they are within the unit interval. Similarities of colors with wavelengths from 434 to 674 nm.

**References**

Ekman, G. (1954). Dimensions of color vision. *Journal of Psychology*, 38, 467-474.

**Examples**

```
ekman
```

---

EW\_ger

*Work values*

---

**Description**

Intercorrelations of 13 working values for former West (first list element) and East Germany.

**Usage**

```
data(EW_eng)
```

**Format**

Object of class `dist`

**Details**

Note that in `EW_ger` the labels are given in German. For `smacof`, the data must be converted into a dissimilarity matrix by applying the `sim2diss()` function to each list element.

**References**

ALLBUS 1991, German General Social Survey.

Borg, I., Groenen, P. J. F., & Mair, P. (2010). *Multidimensionale Skalierung*. Muenchen: Hampp Verlag.

Borg, I., Groenen, P. J. F., & Mair, P. (2012). *Multidimensional Scaling*. New York: Springer, forthcoming.

**Examples**

```
data(EW_eng)  
data(EW_ger)
```

---

FaceExp

*Facial Expression Data*

---

### Description

Dissimilarity matrix of 13 facial expressions (Abelson & Sermat, 1962). The external scales are taken from Engen et al. (1958) reflecting the following three perceptual dimensions: pleasant-unpleasant (PU), attention-rejection (AR), and tension-sleep (TS).

### Usage

```
data(FaceExp)
data(FaceScale)
```

### Format

Symmetric dissimilarity matrix and data frame with 3 perceptual dimensions

### References

Abelson, R. P., & Sermat, V. (1962). Multidimensional scaling of facial expressions. *Journal of Experimental Psychology*, 63, 546-554.

Engen, B., Levy, N., & Schlossberg, H. (1958). The dimensional analysis of a new series of facial expressions. *Journal of Experimental Psychology*, 55, 454-458.

### Examples

```
str(FaceExp)
str(FaceScale)
```

---

fitCircle

*Fitting circle into point configuration*

---

### Description

Utility function for fitting a circle into 2D point configurations.

### Usage

```
fitCircle(x, y)
```

### Arguments

x	Vector with x-coordinates
y	Vector with y-coordinates

**Value**

cx	x-coordinate center
cy	y-coordinate center
radius	circle radius

**References**

Pratt, V. (1987). Direct least-squares fitting of algebraic surfaces. *Computer Graphics*, Vol. 21, pages 145-152.

**Examples**

```
## Dataset on Schwartz values:
require(plotrix)
valsD <- 1 - cor(indvalues)
fit <- mds(valsD)
plot(fit, main = "MDS Value Circle")
circle <- fitCircle(fit$conf[,1], fit$conf[,2])
draw.circle(circle$cx, circle$cy, radius = circle$radius, border = "gray")
```

---

GOPdtm

*Republican Statements*

---

**Description**

Document-term matrix based on statements by Republican voters.

**Usage**

```
data(GOPdtm)
```

**Format**

Document-term matrix with statements in the rows and terms (keywords) in the columns

**Details**

This dataset emerges from statements of Republican voters scraped from the official GOP website. They were asked to complete the sentence "I am a Republican because ...". We have selected the 37 most frequent words and created a document-term matrix.

**References**

air, P., Rusch, T. & Hornik, K. (2014). The Grand Old Party - A party of values? *SpringerPlus*, 3(697), <https://springerplus.springeropen.com/articles/10.1186/2193-1801-3-697>

**Examples**

```
data(GOPdtm)
GOPdtm
```

---

gravity	<i>Gravity dissimilarities</i>
---------	--------------------------------

---

**Description**

Computes the dissimilarities using a gravity model based on co-occurrences.

**Usage**

```
gravity(X, lambda = 1)
```

**Arguments**

X	numeric matrix
lambda	tuning parameter

**Details**

The first step in this function is to compute the co-occurrences. Based on the binarized data matrix  $Y$  we compute  $Y'Y$  which leads to the co-occurrence matrix. We then use the gravity model to compute the gravity dissimilarities. In order to give more (or less) structure to the MDS solution, the tuning parameter (which defines a power transformation) can be increased (or decreased). In addition, a weight matrix is created that sets cells with no co-occurrences to 0. The corresponding weight matrix for blanking out these cells is established automatically in `mds()`.

**Value**

gravdiss	Gravity dissimilarities
weightmat	Weight matrix for subsequent smacof computation
co.occ	Matrix with co-occurrences

**Author(s)**

Patrick Mair

**References**

Mair, P., Rusch, T. & Hornik, K. (2014). The Grand Old Party - A party of values? SpringerPlus, 3(697), <https://springerplus.springeropen.com/articles/10.1186/2193-1801-3-697>

**See Also**

[mds](#)

**Examples**

```
data(GOPdtm)
gravD <- gravity(GOPdtm, lambda = 2)
res <- mds(gravD$gravdiss)
res$weightmat ## NA's were blanked out when fitting the model
plot(res)
```

---

Guerry

*Map Dataset France 1830*

---

**Description**

Distances (in km) among French Departments in 1830.

**Usage**

```
data(Guerry)
```

**Format**

Symmetric matrix with distances.

**References**

Friendly, M. (2007). A. M. Guerry's Moral Statistics of France: Challenges for Multivariate Spatial Analysis, *Statistical Science*, 2007, 22(3), 368-399.

**Examples**

```
Guerry
```

---

Guttman1991

*Guttman's Intelligence Facets*

---

**Description**

The first dataset (Guttman1991) contains similarities and facets for Guttman's 3D cylindrical intelligence structure as published in Guttman (1991). The second dataset (Guttman1965) contains similarities and structural intelligence facets from Guttman (1965).

**Usage**

```
data(Guttman1991)
data(Guttman1965)
```

**Format**

List with two elements: The first element contains the similarity matrix, the second element the facets labels.

**References**

Guttman, L. & Levy, S. (1991). Two structural laws for intelligence tests. *Intelligence*, 15, 79-103.

Guttman, L. (1965). The structure of interrelations among intelligence tests. In C. W. Harris (Ed.), *Proceedings of the 1964 Invitational Conference on Testing Problems* (pp. 23-36). Princeton: ETS.

**Examples**

```
Guttman1991[[1]]      ## similarity matrix
Guttman1991[[2]]      ## facets

Guttman1965[[1]]      ## similarity matrix
Guttman1965[[2]]      ## facets
```

---

helm

*Helm's color data*


---

**Description**

Contains dissimilarity data for individual difference scaling from an experiment carried out by Helm (1959).

**Usage**

```
data(helm)
```

**Format**

List containing objects of class `dist`

**Details**

A detailed description of the experiment can be found in Borg and Groenen (2005, p. 451) with the corresponding Table 21.1. containing distance estimates for color pairs. There were 14 subjects that rated the similarity of colors, 2 of whom replicated the experiment. 10 subjects have a normal color vision (labelled by N1 to N10 in our list object), 4 of them are red-green deficient in varying degrees. In this dataset we give the dissimilarity matrices for each of the subjects, including the replications. They are organized as a list of length 16 suited for `smacofIndDiff` computations.

The authors thank Michael Friendly and Phil Spector for data preparation.

## References

- Helm, C. E. (1959). A multidimensional ratio scaling analysis of color relations. Technical Report, Princeton University and Educational Testing Service. Princeton, NJ.
- Borg, I., & Groenen, P. J. F. (2005). Modern Multidimensional Scaling: Theory and Applications (2nd edition). New York: Springer.

## Examples

```
helm
```

---

icExplore

*Exploring Initial Configurations*

---

## Description

Allows to user to explore the effect of various random starting configurations when fitting an MDS model.

## Usage

```
icExplore(delta, nrep = 100, returnfit = FALSE, ndim = 2,
  type = c("ratio", "interval", "ordinal", "mspline"), weightmat = NULL, ties = "primary",
  verbose = FALSE, relax = FALSE, modulus = 1, itmax = 1000, eps = 1e-6,
  spline.degree = 2, spline.intKnots = 2)
```

## Arguments

delta	Either a symmetric dissimilarity matrix or an object of class "dist"
nrep	Number of initial random configurations
returnfit	If TRUE all fitted models are returned.
ndim	Number of dimensions
weightmat	Optional matrix with dissimilarity weights
type	MDS type: "interval", "ratio", "ordinal" (nonmetric MDS), or "mspline"
ties	Tie specification (ordinal MDS only): "primary", "secondary", or "tertiary"
verbose	If TRUE, replication number is printed
relax	If TRUE, block relaxation is used for majorization
modulus	Number of smacof iterations per monotone regression call
itmax	Maximum number of iterations
eps	Convergence criterion
spline.degree	Degree of the spline for "mspline" MDS type
spline.intKnots	Number of interior knots of the spline for "mspline" MDS type



**Details**

This function generates a large set of MDS solutions using random initial configurations, matches them all by Procrustean fittings, computes the inter-correlations of their point coordinates, and finally runs an interval MDS of these inter-correlations. It can be used to explore local minima.

In the plot function the number reflects the index of corresponding MDS fit, the size reflects the stress value: the larger the font, the larger the stress (i.e., the worse the solution). The size is associated with a corresponding color shading (the smaller the size the darker the color).

**Value**

mdsfit	Fitted MDS objects (NULL if returnfit = FALSE)
conf	Configuration based on multiple random starts
stressvec	Vector with stress values

**References**

Borg, I. and Mair, P. (2017). The choice of initial configurations in multidimensional scaling: local minima, fit, and interpretability. *Austrian Journal of Statistics*, 46, 19-32. doi:10.17713/ajs.v46i2.561

**See Also**

[mds](#)

**Examples**

```
## simple example with 20 random starts
diss <- sim2diss(wish, method = 7)
set.seed(123)
res <- icExplore(diss, type = "ordinal", nrep = 20, returnfit = TRUE)
res
plot(res)

res$mdsfit[[14]] ## bad fitting solution
res$mdsfit[[3]]  ## better fitting solution
```

---

indvalues

*Schwartz Value Survey*


---

**Description**

Responses from a sample in Britain were collected varying in value measures of the Schwartz value theory. The instrument used was the Schwartz Value Survey (SVS).

**Usage**

```
data(indvalues)
```

**Format**

Data frame with 327 persons in the rows and psychological values in the columns.

**Details**

The data were centered (row-wise) and converted from preferences into dissimilarities.

**References**

Borg, I., Bardi, A., & Schwartz, S. H. (2017). Does the value circle exist within persons or only across persons? *Journal of Personality*, 85(2), 151-162.

**See Also**

[PVQ40](#)

**Examples**

```
str(indvalues)
```

---

intelligence

*Intelligence Tests*

---

**Description**

Contains intercorrelations of 8 intelligence tests, together with two facets. In addition, a hypothesized restriction matrix for the intercorrelations is provided. The proximities for items with the same structuples, such as p(NA1,NA2) and p(GA1,GA3), all are set to the value 5. The proximities that correspond to the immediate neighborhood relations are set to the value 4, since none of these distances should be larger than any distance between definitionally equivalent items. Finally, the large distances between the groups NI, GA and the groups NA, GI are set to 3. The intelligence tests are coded on the following facets: format (N = numerical, G = geometrical) and requirement (A = application, I - inference).

**Usage**

```
data(intelligence)
```

**Format**

Data frame of 8 intelligence tests: facets, intercorrelations, and restrictions

Test: Test number

Language: numerical, geometrical

Requirement: application, inference

T1-T8: intercorrelations

R1-R8: restrictions

## References

Borg, I., & Groenen, P. J. F. (2005). *Modern Multidimensional Scaling* (2nd ed.). Springer.

## Examples

```
idiss <- sim2diss(intelligence[,paste0("T", 1:8)])
fit <- mds(idiss)
plot(fit)
```

---

jackmds

*SMACOF Jackknife*

---

## Description

These methods perform a SMACOF Jackknife and plot the corresponding solution.

## Usage

```
## S3 method for class 'smacofB'
jackmds(object, eps = 1e-6, itmax = 100, verbose = FALSE)

## S3 method for class 'smacofJK'
plot(x, plot.dim = c(1,2), hclpar = list(c = 50, l = 70),
     col.p, col.l, plot.lines = TRUE, legend = FALSE, inset = c(-0.2, 0), cex.legend = 0.7,
     main, xlab, ylab, xlim, ylim, asp = 1, ...)
```

## Arguments

object	Object of class "smacofB", i.e., an MDS solution from smacofSym()
itmax	Maximum number of iterations
eps	Convergence criterion
verbose	If TRUE, intermediate stress is printed out
x	Object of class "smacofJK"
plot.dim	Vector with dimensions to be plotted.
hclpar	Chroma and luminance to be used for HCL colors (further details see <a href="#">rainbow_hcl</a> )
col.p	Point color. If omitted, hcl colors will be used; if specified, the corresponding (single) color will be used for plotting.
col.l	Line color. If omitted, hcl colors will be used; if specified, the corresponding (single) color will be used for plotting.
plot.lines	If TRUE, the Jackknife configurations are plotted are connected with their centroid.
legend	If TRUE, the centroid labels are added as legend.

<code>inset</code>	Inset distance from the margins as a fraction of the plot region when legend is placed by keyword.
<code>cex.legend</code>	Character expansion factor for legend.
<code>main</code>	Plot title.
<code>xlab</code>	Label of x-axis.
<code>ylab</code>	Label of y-axis.
<code>xlim</code>	Scale x-axis.
<code>ylim</code>	Scale y-axis.
<code>asp</code>	Aspect ratio.
<code>...</code>	Further plot arguments passed: see <a href="#">plot</a> for detailed information.

### Details

In order to examine the stability solution of an MDS, a Jackknife on the configurations can be performed (see de Leeuw & Meulman, 1986) and plotted. The plot shows the jackknife configurations which are connected to their centroid. In addition, the original smacof configuration (transformed through Procrustes) is plotted. The Jackknife function itself returns also a stability measure (as ratio of between and total variance), a measure for cross validity, and the dispersion around the original smacof solution.

### Value

<code>smacof.conf</code>	SMACOF configurations
<code>jackknife.conf</code>	An array of n-1 configuration matrices for each Jackknife MDS solution
<code>comparison.conf</code>	Centroid Jackknife configurations (comparison matrix)
<code>stab</code>	Stability measure
<code>cross</code>	Cross validity
<code>disp</code>	Dispersion
<code>loss</code>	Value of the loss function
<code>ndim</code>	Number of dimensions
<code>call</code>	Model call
<code>niter</code>	Number of iterations
<code>nobj</code>	Number of objects

### Author(s)

Jan de Leeuw and Patrick Mair

### References

- De Leeuw, J., & Meulman, J. (1986). A special jackknife for multidimensional scaling. *Journal of Classification*, 3, 97-112.
- Mair, P., Groenen, P. J. F., De Leeuw, J. (2022). More on multidimensional scaling in R: smacof version 2, *Journal of Statistical Software*, 102(10), 1-47. [doi:10.18637/jss.v102.i10](https://doi.org/10.18637/jss.v102.i10)

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

```
## symmetric smacof
data <- na.omit(PVQ40[,1:5])
diss <- dist(t(data)) ## Euclidean distances
fit <- mds(diss)
res.jk <- jackmds(fit)

plot(res.jk, col.p = "black", col.l = "gray")
plot(res.jk, hclpar = list(c = 80, l = 40))
plot(res.jk, hclpar = list(c = 80, l = 40), plot.lines = FALSE)
```

---

kinshipdelta

*Kinship Terms*

---

**Description**

Percentages of how often 15 kinship terms were not grouped together by college students including three external scales.

**Usage**

```
data(kinshipdelta)

data(kinshipscales)
```

**Format**

Dissimilarity matrix of 15 kinship terms and data frame with the following external scales:  
Gender (1 = male, 2 = female)  
Generation (-2 = two back, -1 = one back, 0 = same generation, 1 = one ahead, 2 = two ahead)  
Degree (1 = first, 2 = second, 3 = third, 4 = fourth)

**References**

Rosenberg, S. & Kim, M. P. (1975). The method of sorting as a data gathering procedure in multivariate research. *Multivariate Behavioral Research*, 10, 489-502.

**Examples**

```
kinshipdelta
kinshipscales
```

---

KIPT

*Kennedy Institute Phonics Test*

---

### **Description**

Contains correlations of eight test items of the Kennedy Institute Phonics Test (KIPT), a test for reading skills.

### **Usage**

data(KIPT)

### **Format**

An 8 times 8 correlation matrix. Items:

Nonsense word production: NP

Long vowel production: LVP

Short vowel production: SVP

Consonant cluster production: CCP

Nonsense word recognition: NR

Single letter production: SLP

Consonant cluster recognition: CCR

Initial letter recognition: ILR

### **References**

Guthrie, J. T. (1973). Models of reading and reading disability. *Journal of Educational Psychology*, 65, 9-18.

### **Examples**

```
KIPT  
sim2diss(KIPT)
```

---

LawLer

*Management Performance Data*

---

**Description**

Performance of managers: 3 criteria ("traits") and 3 methods. Traits: T1 = Quality of output, T2 = Ability to generate output, T3 = Demonstrated effort to perform. Methods: M1 = Rating by superior, M2 = Peer rating, M3 = Self-rating.

**Usage**

```
data(Lawler)
```

**Format**

Symmetric matrix (trait-method combinations) with inter-correlations.

**References**

Lawler, E. E. (1967). Management performance as seen from above, below, and within. In Evaluation of executive performance. Princeton, New Jersey. Educational Testing Service.

**Examples**

```
Lawler
```

---

morse

*Morse Code Confusion Data*

---

**Description**

Confusion percentages between Morse code signals. The scores are derived from confusion rates on 36 Morse code signals (26 for the alphabet; 10 for the numbers 0,...,9). Each Morse code signal is a sequence of up to five 'beeps'. The beeps can be short (0.05 sec) or long (0.15 sec), and, when there are two or more beeps in a signal, they are separated by periods of silence (0.05 sec).

Rothkopf asked 598 subjects to judge whether two signals, presented acoustically one after another, were the same or not. The values are the average percentages with which the answer 'Same!' was given in each combination of row stimulus  $i$  and column stimulus  $j$ , where either  $i$  or  $j$  was the first signal presented. The values are 1 minus the symmetrized confusion rates and are thus dissimilarities.

**Usage**

```
data(morse)
data(morse2)
```

**Format**

Symmetric and asymmetric dissimilarity matrices of 36 morse codes

**Details**

The first dataset (`morse`) contains a symmetric version, the second dataset (`morse2`) the original asymmetric version.

**References**

Rothkopf, E. Z. (1957). A measure of stimulus similarity and errors in some paired-associate learning. *Journal of Experimental Psychology*, 53, 94-101.

**Examples**

```
morse  
morse2
```

---

`morsescapes`*Morse Code Confusion Scales*

---

**Description**

Two properties of Morse code signals. Each Morse code signal is a sequence of up to five 'beeps'. The beeps can be short (0.05 sec) or long (0.15 sec), and, when there are two or more beeps in a signal, they are separated by periods of silence (0.05 sec). The two external variables are: Signal type (1 = all short beeps, 2 = more short than long beeps, 3 = same short and long beeps, 4 = more long than short beeps, 5 = all long beeps) and Signal length (in seconds; 1 = .05, 2 = .15, 3 = .25, 4 = .35, 5 = .45, 6 = .55, 7 = .65, 8 = .85, 9 = .95).

**Usage**

```
data(morsescapes)
```

**Format**

Matrix of 36 morse codes by 2 properties. The first column contains the morse code letters.

**References**

Rothkopf, E. Z. (1957). A measure of stimulus similarity and errors in some paired-associate learning. *Journal of Experimental Psychology*, 53, 94-101.

**Examples**

```
morsescapes
```



---

OCP	<i>Organizational Culture Profile</i>
-----	---------------------------------------

---

**Description**

Contains similarities (correlations) of 54 OCP (see O'Reilly, Chatman, and Caldwell, 1991) items. The last three columns contain the facet assigned by Bilsky and Jehn (2002) as well as the external variables for regional restrictions.

**Usage**

```
data(OCP)
```

**Format**

Data frame with OCP item correlations and facet:

i1-i54: OCP item correlations

facet: factor with facets

z1, z2: external constraints

**References**

Bilsky, W. & Jehn, K. (2002). Organizational Culture and Individual Values: Evidence for a Common Structure. In M. Myrtek (Ed.), *The Person in Biological and Social Context*, pp. 211-228. Goettingen, Germany: Hogrefe Press.

**Examples**

```
ocpD <- sim2diss(OCP[,1:54])
fit <- mds(ocpD, type = "ordinal")
plot(fit)
```

---

partypref	<i>Party preferences</i>
-----------	--------------------------

---

**Description**

Artificial dataset containing the judges in the rows and the parties in the columns.

**Usage**

```
data(partypref)
```

**Format**

Matrix of party preferences.

**References**

Borg, I., Groenen, P. J. F., & Mair, P. (2010). *Multidimensionale Skalierung*. Muenchen: Hampp Verlag.

**Examples**

partypref

---

perception

*Rectangle Perception Data*

---

**Description**

42 subjects are assigned to two groups of 21 persons. 120 stimulus pairs of rectangles are presented. For the first group (width-height; WH), the rectangles were constructed according to a design as given in `rect_constr`. For the second group (size-shape; SS) the rectangles were constructed according to a grid design, which is orthogonal in the dimensional system reflecting area (size), and width/height (shape). All subjects had to judge the similarity of the rectangles on a scale from 0 to 9.

**Usage**

```
data(perception)
```

**Format**

List of subject dissimilarities for WH (first element) and SS group (second element).

**References**

Borg, I. & Leutner, D. (1983). Dimensional models for the perception of rectangles. *Perception and Psychophysics*, 34, 257-269.

**See Also**

[rectangles](#)

**Examples**

```
perception  
rect_constr
```

---

permtest                      *SMACOF Permutation*

---

### Description

These methods perform a permutation test for a symmetric or an unfolding SMACOF model.

### Usage

```
## S3 method for class 'smacof'
permtest(object, data, method.dat = "pearson", nrep = 100, verbose = TRUE, ...)
## S3 method for class 'smacofR'
permtest(object, data = NULL, method.dat = "rows", nrep = 100, verbose = TRUE, ...)
## S3 method for class 'smacofPerm'
plot(x, alpha = 0.05, main, xlab, ylab, ...)
```

### Arguments

object	Object of class "smacofB", i.e., an MDS solution from smacofSym()
data	Optional argument; if provided permutations are performed on the data matrix (see details; ignored for unfolding models)
method.dat	If data are provided, this must be one of "pearson", "spearman", "kendall", "euclidean", "maximum", "manhattan", "canberra", "binary". For unfolding models it is either "full" for full permutations or "rows" for permutations within rows.
nrep	Number of permutations
verbose	If TRUE, permutation index is printed out
x	Object of class "smacofPerm"
alpha	Alpha level
main	Plot title.
xlab	Label of x-axis.
ylab	Label of y-axis.
...	additional plot arguments for plot function; additional arguments to be passed to sim2diss in permutation functions.

### Details

This routine permutes  $m$  dissimilarity values, where  $m$  is the number of lower diagonal elements in the corresponding dissimilarity matrix. For each sample a symmetric, nonmetric SMACOF of dimension  $ndim$  is computed and the stress values are stored in `stressvec`. Using the fitted stress value, the p-value is computed. Subsequently, the empirical cumulative distribution function can be plotted using the plot method.

If the MDS fit provided on derived proximities of a data matrix, this matrix can be passed to the `permtest` function. Consequently, the data matrix is subject to permutations. The proximity measure used for MDS fit has to match the one used for the permutation test. If a correlation similarity is provided, it is converted internally into a dissimilarity using `sim2diss` with corresponding arguments passed to the `...` argument.

### Value

<code>stressvec</code>	Vector containing the stress values of the permutation samples
<code>stress.obs</code>	Stress (observed sample)
<code>pval</code>	Resulting p-value
<code>call</code>	Model call
<code>nrep</code>	Number of permutations
<code>nobj</code>	Number of objects

### Author(s)

Patrick Mair and Ingwer Borg

### References

Mair, P., Borg, I., and Rusch, T. (2016). Goodness-of-fit assessment in multidimensional scaling and unfolding. *Multivariate Behavioral Research*, 51, 772-789.

Mair, P., Groenen, P. J. F., De Leeuw, J. (2022). More on multidimensional scaling in R: smacof version 2, *Journal of Statistical Software*, 102(10), 1-47. doi:10.18637/jss.v102.i10

### See Also

[jackmds](#), [bootmds](#)

### Examples

```
## permuting the dissimilarity matrix (full)
data(kinshipdelta)
fitkin <- mds(kinshipdelta, ndim = 2, type = "interval")
set.seed(222)
res.perm <- permtest(fitkin)
res.perm
plot(res.perm)

## permuting the data matrix
GOPdtm[GOPdtm > 1] <- 1 ## use binary version
diss1 <- dist(t(GOPdtm[,1:10]), method = "binary") ## Jaccard distance
fitgop1 <- mds(diss1, type = "ordinal")
fitgop1
set.seed(123)
permtest(fitgop1, GOPdtm[,1:10], nrep = 10, method.dat = "binary")

rmat <- cor(GOPdtm[,1:10], method = "kendall") ## Kendall correlation
```

```
diss2 <- sim2diss(rmat, method = 1)
fitgop2 <- mds(diss2, type = "ordinal")
fitgop2
set.seed(123)
permtest(fitgop2, GOPdtm[,1:10], nrep = 10, method.dat = "kendall", method = 1)

## unfolding permutation
data(breakfast)
res.unfolding <- unfolding(breakfast, ndim = 2)
set.seed(123)
permtest(res.unfolding, nrep = 20, method.dat = "rows")
```

---

Plato7

*Plato's Seven Works*

---

## Description

This dataset contains statistical information about Plato's seven works. The underlying problem to this dataset is the fact that the chronological order of Plato's works is unknown. Scholars only know that Republic was his first work, and Laws his last work. For each work, Cox and Brandwood (1959) extracted the last five syllables of each sentence. Each syllable is classified as long or short which gives 32 types. Consequently, we obtain a percentage distribution across the 32 scenarios for each of the seven works.

## Usage

```
data(Plato7)
```

## Format

Data frame containing syllable percentages of Plato's 7 works.

## References

Cox, D. R. & Brandwood, L. (1959). On a discriminatory problem connected with the work of Plato. *Journal of the Royal Statistical Society (Series B)*, 21, 195-200.

## Examples

```
Plato7
```

plot.smacof

2D SMACOF plots

**Description**

These methods provide various 2D plots for SMACOF models.

**Usage**

```
## S3 method for class 'smacof'
plot(x, plot.type = "confplot", plot.dim = c(1,2), sphere = TRUE,
      bubscale = 1, col = 1, label.conf = list(label = TRUE, pos = 3,
      col = 1, cex = 0.8), hull.conf = list(hull = FALSE, col = 1,
      lwd = 1, ind = NULL), shepard.x = NULL, identify = FALSE,
      type = "p", pch = 20, cex = 0.5, asp = 1, main, xlab, ylab,
      xlim, ylim, col.hist = NULL, ...)

## S3 method for class 'smacofR'
plot(x, plot.type = "confplot", what = c("both", "columns", "rows"),
      plot.dim = c(1,2), col.rows = hcl(0), col.columns = hcl(240),
      label.conf.rows = list(label = TRUE, pos = 3,
      col = hcl(0, l = 50), cex = 0.8),
      label.conf.columns = list(label = TRUE, pos = 3,
      col = hcl(240, l = 50), cex = 0.8),
      shepard.x = NULL, col.dhat = NULL, type = "p", pch = 20,
      cex = 0.5, asp = 1, main, xlab, ylab, xlim, ylim, ...)

## S3 method for class 'smacofID'
plot(x, plot.type = "confplot", plot.dim = c(1,2), bubscale = 1,
      col = 1, label.conf = list(label = TRUE, pos = 3, col = 1,
      cex = 0.8), identify = FALSE, type = "p", pch = 20, cex = 0.5,
      asp = 1, plot.array, main, xlab, ylab, xlim, ylim, ...)
```

**Arguments**

x	Object of class "smacof", "smacofR", and "smacofID" (see details)
plot.type	String indicating which type of plot to be produced: "confplot", "resplot", "Shepard", "stressplot", "bubbleplot", "histogram" (see details)
plot.dim	Vector with dimensions to be plotted.
main	Plot title.
xlab	Label of x-axis.
ylab	Label of y-axis.
xlim	Scale x-axis.
ylim	Scale y-axis.
type	What type of plot should be drawn (see also <a href="#">plot</a> ).

pch	Plot symbol.
cex	Symbol size.
asp	Aspect ratio.
col	Point color.
sphere	In case of spherical smacof, whether sphere should be plotted or not.
bubscale	Scaling factor (size) for the bubble plot.
label.conf	List with arguments for plotting the labels of the configurations in a configuration plot (logical value whether to plot labels or not, label position, label color). If pos = 5 labels are placed away from the nearest point.
hull.conf	Option to add convex hulls to a configuration plot. Hull index needs to be provided.
shepard.x	Shepard plot only: original data (e.g. correlation matrix) can be provided for plotting on x-axis.
identify	If TRUE, the identify() function is called internally that allows to add configuration labels by mouse click.
what	For unfolding only: Whether row coordinates, column coordinates, or both should be plotted.
col.rows	Row colors in unfolding configuration plot.
col.columns	Column colors in unfolding configuration plot.
col.dhat	Shepard plot only: color specification of the dhats. For row conditional transformations in unfolding a vector of the length of the number of rows should be specified.
label.conf.rows	List with arguments for plotting the labels of the row configurations in an unfolding configuration plot (logical value whether to plot labels or not, label position, label color).
label.conf.columns	List with arguments for plotting the labels of the columns configurations in an unfolding configuration plot (logical value whether to plot labels or not, label position, label color).
col.hist	Color of the borders of the histogram.
plot.array	Array arrangements of plots for individual difference models (see details).
...	Further plot arguments passed: see <a href="#">plot</a> for detailed information.

## Details

mds() and smacofSym() create an object of class "smacof", unfolding(), prefscal(), and smacofRect() produce "smacofR", and smacofIndDiff() generates "smacofID".

Plot description:

- Configuration plot (plot.type = "confplot"): Plots the MDS configuration.
- Residual plot (plot.type = "resplot"): Plots the disparities (d-hats) distances against the fitted distances.

- Shepard diagram (`plot.type = "Shepard"`): Diagram with the observed dissimilarities against the fitted distances including (isotonic) regression line.
- Stress decomposition plot (`plot.type = "stressplot"`): Plots the stress contribution in of each observation. Note that it rescales the stress-per-point (SPP) from the corresponding smacof function to percentages (sum is 100). The higher the contribution, the worse the fit.
- Bubble plot (`plot.type = "bubbleplot"`, not available for rectangular SMACOF): Combines the configuration plot with the point stress contribution. The larger the bubbles, the worse the fit.
- Histogram (`plot.type = "histogram"`: gives a weighted histogram of the dissimilarities. For optional arguments, see [wtd.hist](#).

For `smacofIndDiff()` the residual plot, Shepard diagram, and stress plot are based on the sum of the residuals across individuals/ways. The configuration plot represents the group stimulus space (i.e., joint configuration). If `plot.array` is not specified, it produces a Shepard plot of the distances summed across subjects, if `plot.array = 0` it produces a  $\sqrt{\text{nsubjects}}$  times  $\sqrt{\text{nsubjects}}$  array of graph panels, if `plot.array = 3` it produces 3x3 arrays of graph panels, if `plot.array = c(2, 3)` it produces 2x3 arrays of graph panels, and if `plot.array = c(3, 2, 5)` produces 3x2 arrays of panels (only the first two values are used).

### See Also

[plot.procr](#)

### Examples

```
## 2D plots for simple MDS
data(trading)
res <- mds(trading)
plot(res, plot.type = "confplot")
plot(res, plot.type = "confplot", label.conf = list(pos = 5)) ## avoid overlapping labels
plot(res, plot.type = "Shepard")
plot(res, plot.type = "stressplot")
plot(res, plot.type = "resplot")
plot(res, plot.type = "bubbleplot")
plot(res, plot.type = "histogram")

## Add convex hulls to configuration plot
r <- cor(PVQ40, use = "pairwise.complete.obs")
diss <- sim2diss(r, method = "corr")
res <- mds(delta = diss, type = "ordinal")
codes <- substring(colnames(PVQ40), 1, 2) ## supplementary variable
plot(res, hull.conf = list(hull = TRUE, ind = codes, col = "coral1", lwd = 2))

## Shepard plots
ekmanD <- sim2diss(ekman)
fit1 <- mds(ekmanD, type = "ordinal")
plot(fit1, plot.type = "Shepard")
plot(fit1, plot.type = "Shepard", shepard.x = ekman) ## original data on x-axis

## Joint configuration plot and row/column stressplots for unfolding
data(breakfast)
res <- unfolding(breakfast)
```



```
plot(res, plot.type = "confplot")
plot(res, plot.type = "stressplot")
```

---

Procrustes

*Procrustean Similarity Transformations*


---

### Description

Solves the Procrustean problem of fitting one (MDS) configuration (testee) to another (target) MDS configuration.

### Usage

```
Procrustes(X, Y)
```

```
## S3 method for class 'procr'
plot(x, plot.type = "jointplot", plot.dim = c(1,2), main, xlab, ylab,
      xlim, ylim, asp = 1, pch = 20, col.X = "cadetblue",
      col.Y = "gray", col.Yhat = "coral1",
      label.conf = list(label = TRUE, pos = 3, cex = 0.8),
      arrows = TRUE, length = 0.10,
      legend = list(plot = TRUE, labels = c("Target", "Testee"),
                    pos = "bottomright"), ...)
```

### Arguments

X	Target configuration
Y	Testee configuration
x	Object of class procr
plot.type	Either "jointplot" or "transplot"
plot.dim	Vector with dimensions to be plotted.
main	Plot title.
xlab	Label of x-axis.
ylab	Label of y-axis.
xlim	Scale x-axis.
ylim	Scale y-axis.
pch	Plot symbol.
asp	Aspect ratio.
col.X	Color target configuration.
col.Y	Color testee configuration.
col.Yhat	Color transformed configuration.
label.conf	List with arguments for plotting the labels of the configurations in a configuration plot (logical value whether to plot labels or not, label position, label color).

length	length of the edges of the arrow head (in inches).
arrows	For "transplot" only, whether arrows should be plotted or not.
legend	List with arguments for plotting the legend.
...	Additional plot arguments.

### Details

Y is going to be modified by finding an optimal dilation factor, an optimal translation and rotation for Y such that it is as similar as possible to X. X remains untouched.

### Value

Returns an object of class `procr` with:

X	Input target configuration
Y	Input testee configuration
Yhat	Procrustes transformed (fitted) configuration
translation	Translation vector
dilation	Dilation factor
rotation	Rotation-reflection matrix
confdistX	Configuration distances X
confdistY	Configuration distances Y
confdistYhat	Configuration distances of fitted configuration
congcoef	Congruence coefficient
aliencoef	Alienation coefficient
r	Correlation coefficient between X and Y-hat (shrinkage ratio)
pairdist	Pairwise object distances (sorted)

### References

- Borg, I., & Groenen, P. J. F. (2005). *Modern Multidimensional Scaling and Unfolding* (2nd ed.). Springer.
- Mair, P., Groenen, P. J. F., De Leeuw, J. (2022). More on multidimensional scaling in R: `smacof` version 2, *Journal of Statistical Software*, 102(10), 1-47. [doi:10.18637/jss.v102.i10](https://doi.org/10.18637/jss.v102.i10)
- Borg, I. and Mair, P. (2022). A note on Procrustean fittings of noisy configurations. *Austrian Journal of Statistics*, 51, 1-9. [doi:10.17713/ajs.v51i4.1423](https://doi.org/10.17713/ajs.v51i4.1423)

### Examples

```
## artificial example:
X <- matrix(c(1, -1, -1, 1, 2, 2, -2, -2), ncol = 2)
Y <- matrix(c(0.07, 0.93, 1.93, 1.07, 2.62, 3.12, 1.38, 0.88), ncol = 2)
op <- par(mfrow = c(1,2))
plot(X[,1], X[,2], xlim = c(-3, 3), ylim = c(-2, 3.5), asp = 1, xlab = "", ylab = "")
rect(-1, -2, 1, 2)
```

```

points(Y[,1], Y[,2], xlim = c(-3, 3), col = "gray")
polygon(Y[,1], Y[,2], border = "gray")
fitp <- Procrustes(X, Y)
plot(fitp$Yhat[,1], fitp$Yhat[,2], col = "red", xlim = c(-3, 3), ylim = c(-2, 3.5),
     asp = 1, xlab = "", ylab = "")
polygon(fitp$Yhat[,1], fitp$Yhat[,2], border = "red")
par(op)

## MDS example:
eastD <- sim2diss(EW_eng$east)
attr(eastD, "Labels") <- abbreviate(attr(eastD, "Labels"))
fit.east <- mds(eastD, type = "ordinal")
westD <- sim2diss(EW_eng$west)
attr(westD, "Labels") <- abbreviate(attr(westD, "Labels"))
fit.west <- mds(westD, type = "ordinal", init = torgerson(eastD))

fit.proc <- Procrustes(fit.east$conf, fit.west$conf)
fit.proc

## Configuration plots; Procrustes plots.
plot(fit.east, main = "MDS East Germany") ## MDS plot East Germany
plot(fit.west, main = "MDS West Germany") ## MDS plot West Germany

## Procrustes configurations (X and Yhat)
plot(fit.proc, ylim = c(-1, 1), col.X = "cadetblue", col.Yhat = "brown", pch = 19,
     legend = list(pos = "topleft", labels = c("East Germany", "West Germany")))

## Procrustes transformations (Y and Yhat)
plot(fit.proc, plot.type = "transplot", length = 0.05, ylim = c(-1,1),
     legend = list(pos = "bottomright",
     labels = c("West Germany (untransformed)", "West Germany (transformed)")))

```

---

PVQ40

*Portrait Value Questionnaire*


---

## Description

The PVQ40 (Schwartz et al., 1999) consists of 40 items, each a short portrait of one person. For example, to measure power, the PVQ includes two portraits (male/female versions): It is important to him to be rich. He wants to have a lot of money and expensive things. It is important to him to get respect from others. He wants people to do what he says. Respondents indicate on 6-point bipolar rating scale (1 ... not at all like me, 6 ... very much like me) the degree to which the description also fits himself/herself. Gender and age of the participants are added as attributes.

## Usage

```
data(PVQ40)
```

**Format**

PVQ40 data of 151 adults from various states in the USA:

sd1-sd4: self-direction

po1-po3: power

un1-un6: universalism

ac1-ac4: achievement

se1-se5: security

st1-st3: stimulation

co1-co4: conformity

tr1-tr4: tradition

he1-he3: hedonism

be1-be4: benevolence

Age and Gender are added as attributes.

**Details**

PVQ40agg is an aggregated version of PVQ40 where the item scores belonging to the same value are averaged. Abbreviations: power (PO), achievement (AC), hedonism (HE), stimulation (ST), self-direction (SD), universalism (UN), benevolence (BE), tradition (TR), conformity (CO), security (SE).

**References**

Borg, I., Bardi, A., & Schwartz, S. H. (2017). Does the value circle exist within persons or only across persons? *Journal of Personality*, 85(2), 151-162.

**See Also**

[indvalues](#)

**Examples**

```
str(PVQ40)
head(PVQ40)
attr(PVQ40, "Gender")
attr(PVQ40, "Age")
str(PVQ40agg)
```

---

randomstress                      *Stress Calculation for Random Dissimilarities*

---

### Description

Creates random dissimilarity matrices (n objects), fits an MDS, and returns the stress values of each MDS fit.

### Usage

```
randomstress(n, ndim, nrep = 100, type = c("ratio", "interval", "ordinal", "mspline"))
```

### Arguments

n	Number of objects
ndim	Number of dimensions for MDS
nrep	Number of random samples
type	MDS type

### Details

The random dissimilarities are drawn from a  $U(0,1)$  distribution.

### Value

Returns a vector with stress values.

### References

Spence I., Ogilvie, J.C. (1973). A table of expected stress values for random rankings in nonmetric multidimensional scaling. *Multivariate Behavioral Research*, 8, 511-517.

Mair, P., Groenen, P. J. F., De Leeuw, J. (2022). More on multidimensional scaling in R: smacof version 2. *Journal of Statistical Software*, 102(10), 1-47. [doi:10.18637/jss.v102.i10](https://doi.org/10.18637/jss.v102.i10)

### Examples

```
## 8 objects, 2 dimensions, interval MDS (50 replications)
stressvec <- randomstress(n = 8, ndim = 2, nrep = 50, type = "interval")
mean(stressvec)
```

---

`rectangles`*Rectangles*

---

**Description**

These data are based on an experiment by Borg and Leutner (1983). They constructed rectangles on the basis of the grid design (see `rect_constr`). Each point in this grid defines a rectangle. Rectangle 16, for example, had a width of 4.25 cm and a height of 1.25 cm; rectangle 4 was 3.00 cm wide and 2.75 cm tall. A total of 21 persons rated (twice) the similarity of each pair of these 16 rectangles (on a 10-point scale ranging from 0 = equal/identical to 9 = very different) The means of these ratings over persons and replications are given in `rectangles`. A second dataset (`rectangles2`) is constructed based on area and shape of the rectangles.

**Usage**

```
data(rectangles)
data(rect_constr)
data(rectangles2)
```

**Format**

The rectangles are object of class `dist`, the constraints are given as matrix

**References**

Borg, I., & Leutner, D. (1983). Dimensional models for the perception of rectangles. *Perception and Psychophysics*, 34, 257-269.

Borg, I., Groenen, P. J. F., & Mair, P. (2017). *Applied Multidimensional Scaling and Unfolding*. New York, Springer.

**Examples**

```
rectangles
rect_constr
rectangles2
```

---

`residuals.smacof`*Residuals*

---

**Description**

Computes the residuals by subtracting the configuration dissimilarities from the observed dissimilarities.

**Usage**

```
## S3 method for class 'smacof'  
residuals(object, ...)  
## S3 method for class 'smacofR'  
residuals(object, ...)  
## S3 method for class 'smacofID'  
residuals(object, ...)
```

**Arguments**

object	Object of class smacof, smacofR (rectangular), or smacofID (individual differences)
...	Ignored

**Examples**

```
res <- mds(kinshipdelta)  
residuals(res)
```

---

RockHard

*RockHard Ratings*

---

**Description**

Data from RockHard Magazine: In this German Heavy Metal Magazine around 50 records are rated by the writers on a scale from (0 ... worst to 10 ... best) each month. The dataset contains all ratings from 2013.

**Usage**

```
data(RockHard)
```

**Format**

Data frame with raters in the columns, bands/albums in the rows.

**References**

Mair, P., de Leeuw, J., & Wurzer, M. (2015). Multidimensional Unfolding. Wiley StatsRef: Statistics Reference Online. New York: Wiley.

**Examples**

```
head(RockHard)
```

---

sim2diss	<i>Converts similarites to dissimilarities</i>
----------	--

---

### Description

Utility function for converting similarities into dissimilarities. Different methods are provided.

### Usage

```
sim2diss(s, method = "corr", to.dist = FALSE)
```

### Arguments

s	Similarity matrix (not necessarily symmetric, nor square)
method	Various methods for converting similarities into dissimilarities: "corr", "reverse", "reciprocal", "ranks", "exp", "Gaussian", "cooccurrence", "gravity", "confusion", "transition", "membership", "probability", or an integer value from which the similarity is subtracted
to.dist	If TRUE, object of class dist is produced

### Details

The conversion formulas for the various methods can be found in the package vignette.

### Value

Returns dissimilarities either as matrix or as dist object.

### References

Mair, P., Groenen, P. J. F., De Leeuw, J. (2022). More on multidimensional scaling in R: smacof version 2. *Journal of Statistical Software*, 102(10), 1-47. doi:10.18637/jss.v102.i10

### Examples

```
## Convert crimes data (correlations)
data(crimes)
crimeD <- sim2diss(crimes, method = "corr", to.dist = TRUE)

## Convert Wish data (similarities) by subtracting from 7
data(wish)
wishD <- sim2diss(wish, method = 7, to.dist = TRUE)

## Convert Ekman data (similarities) into dissimilarities
data(ekman)
ekmanD <- sim2diss(ekman, method = "confusion", to.dist = TRUE)

## Convert album ratings (rectangular similarities) by reversing the ratings
```



```
data(RockHard)
rockD1 <- sim2diss(RockHard[,5:18], method = "reverse")
```

---

smacofConstraint      *SMACOF Constraint*

---

## Description

SMACOF with internal constraints on the configurations.

## Usage

```
smacofConstraint(delta, constraint = "unrestricted", external, ndim = 2,
  type = c("ratio", "interval", "ordinal", "mspline"), weightmat = NULL,
  init = NULL, ties = "primary", verbose = FALSE, modulus = 1,
  itmax = 1000, eps = 1e-6, spline.intKnots = 4, spline.degree = 2,
  constraint.type = c("ratio", "interval", "ordinal", "spline",
    "mspline"), constraint.ties = "primary",
  constraint.spline.intKnots = 2, constraint.spline.degree = 2)
```

## Arguments

delta	Either a symmetric dissimilarity matrix or an object of class "dist"
constraint	Type of constraint: "unrestricted", "unique", "diagonal", or a user-specified function (see details)
external	Data frame or matrix with external covariates, or list for simplex and circumplex (see details)
ndim	Number of dimensions
type	MDS type: "interval", "ratio", "ordinal" (nonmetric MDS), or "mspline"
weightmat	Optional matrix with dissimilarity weights
init	Optional matrix with starting values for configurations. If NULL random starts are used (see details).
ties	Tie specification for non-metric MDS only: "primary", "secondary", or "tertiary"
verbose	If TRUE, intermediate stress is printed out
modulus	Number of smacof iterations per monotone regression call
itmax	Maximum number of iterations
eps	Convergence criterion
spline.degree	Degree of the spline for "mspline" MDS type
spline.intKnots	Number of interior knots of the spline for "mspline" MDS type
constraint.type	Transformation for external covariates: "ratio", "interval", "ordinal", "spline", or "mspline")

```

constraint.ties
    Tie specification for external covariates with constraint.type = "ordinal":
    "primary", "secondary", or "tertiary"
constraint.spline.intKnots
    Number of interior knots for external covariates with constraint.type =
    "spline" or "mspline"
constraint.spline.degree
    Degree of the spline for external covariates with constraint.type = "spline"
    or "mspline"

```

## Details

The argument `external` is mandatory to specify and requires a data frame (or matrix) of dimension  $(n \times q)$ . Alternatively, for simplex fitting the user can specify a list of the following structure: `external = list("simplex", dim2)` with `dim2` denoting the dimension of the simplex with  $\text{dim2} < n$ . For a circumplex fitting, the list has to be of the following form: `external = list("circumplex", dim2, k1, k2)` with  $1 \leq k1 \leq k2 \leq n$  (see also examples section). `k1` and `k2` denote the circumplex width.

In constraint `smacof`, the configuration matrix  $X$  is subject to a constraint based on the external scales (predictors  $Z$  specified using `external`) of the following linear form:  $X = ZC$ . The type of constraint in  $C$  can be specified using the `constraint` argument. We provide the following standard setting:

For `constraint = "unrestricted"`,  $C$  is unrestricted. Note that "linear" still works as well for backward compatibility.

The same for `constraint = "diagonal"` where  $X$  needs to be of dimension  $(n \times q)$  where  $q$  is the number of columns of the external scale matrix (and thus number of dimensions). Here,  $C$  is restricted to be diagonal.

For `constraint = "unrestricted"` or "diagonal", the external covariates  $Z$  can be optimally transformed as specified by `constraint.type`. Choosing the number of covariates equal to the number of dimensions together with `constraint.type = "ordinal"`, `constraint.ties = "primary"` will effectively restrict the configuration to parallel regions defined by the categories of the covariates. Note that missing values of the covariates are estimated by the model.

For `constraint = "unique"` we get the Bentler-Weeks uniqueness model. Hence  $X$  is of dimension  $(n \times (n + p))$ . This implies that we fit a certain number of dimensions  $p$  and, in addition we extract  $n$  additional dimensions where each object is scored on a separate dimension. More technical details can be found in the corresponding JSS article (reference see below).

In addition, the user can specify his own constraint function with the following arguments: configuration matrix with starting values (`init`) (mandatory in this case), matrix  $V$  (`weightmat`; based on the weight matrix, see package vignette), external scale matrix (`external`). The function must return a matrix of resulting configurations.

If no starting configuration is provided, a random starting solution is used. In most applications, this is not a good idea in order to find a well fitting model. The user can fit an exploratory MDS using `mds()` first, and use the resulting configurations as starting configuration for `smacofConstraint()`. Alternatively, if the user has starting configurations determined by some underlying theory, they can be used as well.

**Value**

delta	Observed dissimilarities
obsdiss	Observed dissimilarities, normalized
confdist	Configuration dissimilarities
conf	Matrix of final configurations
C	Matrix with restrictions
stress	Stress-1 value
spp	Stress per point
resmat	Matrix with squared residuals
rss	Residual sum-of-squares
weightmat	Weight matrix
ndim	Number of dimensions
extvars	List for each external covariate with a list of class "optscal"
init	Starting configuration
model	Type of smacof model
niter	Number of iterations
nobj	Number of objects

**References**

- De Leeuw, J. & Mair, P. (2009). Multidimensional scaling using majorization: The R package smacof. *Journal of Statistical Software*, 31(3), 1-30. [doi:10.18637/jss.v031.i03](https://doi.org/10.18637/jss.v031.i03)
- Mair, P., Groenen, P. J. F., De Leeuw, J. (2022). More on multidimensional scaling in R: smacof version 2. *Journal of Statistical Software*, 102(10), 1-47. [doi:10.18637/jss.v102.i10](https://doi.org/10.18637/jss.v102.i10)
- De Leeuw, J., & Heiser, W. (1980). Multidimensional scaling with restrictions on the configurations. In P. R. Krishnaiah (eds.), *Multivariate Analysis V*, pp. 501-522. North-Holland.
- Borg, I., & Lingoes, J. C. (1980). A model and algorithm for multidimensional scaling with external constraints on the distances. *Psychometrika*, 45, 25-38.

**See Also**

[smacofSym](#), [smacofRect](#), [smacofIndDiff](#), [smacofSphere](#)

**Examples**

```
## theoretical grid restrictions (rectangles; keep covariate ties tied)
fit.rect1 <- mds(rectangles, type = "ordinal", init = rect_constr)
fit.rect2 <- smacofConstraint(rectangles, type = "ordinal", ties = "secondary",
                             constraint = "diagonal", init = fit.rect1$conf,
                             external = rect_constr, constraint.type = "ordinal")

plot(fit.rect2)

## regional restrictions morse code data (signal length, strength)
```

```

fitMorse1 <- mds(morse, type = "ordinal")
fitMorse1
fitMorse2 <- smacofConstraint(morse, type = "ordinal", constraint = "unrestricted",
                             external = morsescales[,2:3],
                             constraint.type = "ordinal",
                             init = fitMorse1$conf)

fitMorse2
plot(fitMorse2)

## facial expression data I (axial restriction, C diagonal)
Delta <- FaceExp
attr(Delta, "Labels") <- NULL
fitFace <- mds(Delta, type = "ordinal") ## starting solution
Z <- FaceScale[, c(1,3)] ## external variables
fitFaceC1 <- smacofConstraint(Delta, type = "ordinal",
                              constraint = "diagonal", external = Z, constraint.type = "ordinal",
                              init = fitFace$conf)
fitFaceC1$C
plot(fitFaceC1, xlab = "Pleasant-Unpleasant", ylab = "Tension-Sleep",
     main = "Face Expression (Diagonal Restriction)")

## facial expression data II (C unrestricted)
fitFaceC3 <- smacofConstraint(Delta, type = "ordinal",
                              constraint = "unrestricted", external = Z, constraint.type = "ordinal",
                              init = fitFace$conf)
fitFaceC3$C
plot(fitFaceC3, main = "Face Expression (C Unrestricted, Ordinal Transformation)")

```

---

smacofIndDiff

*SMACOF for Individual Differences*


---

## Description

Performs smacof for individual differences also known as Three-Way smacof on a list of dissimilarity matrices. Various restrictions decompositions and restrictions on the weight matrix are provided. The most prominent models are INDSCAL and IDIOSCAL.

## Usage

```

smacofIndDiff(delta, ndim = 2, type = c("ratio", "interval", "ordinal", "mspline"),
              constraint = c("indscal", "idioscal", "identity"),
              weightmat = NULL, init = "torgerson", ties = "primary",
              verbose = FALSE, modulus = 1, itmax = 1000, eps = 1e-6,
              spline.degree = 2, spline.intKnots = 2)

indscal(delta, ndim = 2, type = c("ratio", "interval", "ordinal", "mspline"),
        weightmat = NULL, init = "torgerson", ties = "primary",
        verbose = FALSE, modulus = 1, itmax = 1000, eps = 1e-6,
        spline.degree = 2, spline.intKnots = 2)

```

```

idioscal(delta, ndim = 2, type = c("ratio", "interval", "ordinal", "mspline"),
         weightmat = NULL, init = "torgerson", ties = "primary",
         verbose = FALSE, modulus = 1, itmax = 1000, eps = 1e-6,
         spline.degree = 2, spline.intKnots = 2)

```

### Arguments

<code>delta</code>	A list of dissimilarity matrices or a list objects of class <code>dist</code>
<code>ndim</code>	Number of dimensions
<code>type</code>	MDS type: "interval", "ratio", "ordinal" (nonmetric MDS), or "mspline"
<code>weightmat</code>	Optional matrix with dissimilarity weights
<code>init</code>	Matrix with starting values for configurations (optional)
<code>ties</code>	Tie specification for non-metric MDS
<code>constraint</code>	Either "indscal", "idioscal", or "identity" (see details)
<code>verbose</code>	If TRUE, intermediate stress is printed out
<code>modulus</code>	Number of smacof iterations per monotone regression call
<code>itmax</code>	Maximum number of iterations
<code>eps</code>	Convergence criterion
<code>spline.degree</code>	Degree of the spline for "mspline" MDS type
<code>spline.intKnots</code>	Number of interior knots of the spline for "mspline" MDS type

### Details

If the constraint is "indscal", INDSCAL is performed with configuration weight matrices restricted to be diagonal. `indscal()` is a corresponding wrapper function that can be used instead of `smacofIndDiff()` with "indscal" constraints.

IDIOSCAL can be computed using the "idioscal" argument. The weight matrices are then unconstrained. `idioscal()` is a corresponding wrapper function that can be used instead of `smacofIndDiff()` with "idioscal" constraints.

Additional weight restrictions can be imposed with "identity" which restricts the configurations across individuals/replications/ways to be equal.

### Value

<code>delta</code>	Observed dissimilarities
<code>obsdiss</code>	List of observed dissimilarities, normalized
<code>confdist</code>	List of configuration dissimilarities
<code>conf</code>	List of matrices of final configurations
<code>gspace</code>	Joint configuration aka group stimulus space
<code>cweights</code>	Individual weights

stress	Stress-1 value
resmat	Matrix with squared residuals
rss	Residual sum-of-squares
spp	Stress per point (in percent)
spps	Stress per point per subject (in percent, conditional on subject)
sps	Stress per subject (in percent)
ndim	Number of dimensions
model	Type of smacof model
niter	Number of iterations
nobj	Number of objects

**Author(s)**

Jan de Leeuw and Patrick Mair

**References**

De Leeuw, J., & Mair, P. (2009). Multidimensional scaling using majorization: The R package smacof. *Journal of Statistical Software*, 31(3), 1-30, [doi:10.18637/jss.v031.i03](https://doi.org/10.18637/jss.v031.i03)

**See Also**

[smacofConstraint](#), [smacofSym](#), [smacofRect](#), [smacofSphere](#)

**Examples**

```
## Example 1: rectangle perception data
res.diag <- indscal(perception, type = "ordinal")      ## INDSCAL
res.diag$weights
plot(res.diag)
plot(res.diag, type = "p", pch = 25, col = 4, label.conf = list(label = TRUE, pos = 3, col = 4))

res.idio <- idioscal(perception, type = "ordinal")    ## IDIOSCAL
Wk <- res.idio$weights
G <- res.idio$gspace
G
G

## identity restricted weights
res.id <- smacofIndDiff(perception, type = "ordinal", constraint = "identity")
summary(res.id)
res.id$weights
plot(res.id)
plot(res.id, type = "p", pch = 25, col = 4, label.conf = list(label = TRUE, pos = 3, col = 4))

## Example 2: Helm's color data
res.helm <- indscal(helm, type = "interval")
```

```

plot(res.helm, plot.type = "confplot")
barplot(sort(res.helm$sps, decreasing = TRUE), main = "Stress per Subject", cex.names = 0.8)
plot(res.helm, plot.type = "bubbleplot")
plot(res.helm, plot.type = "stressplot")
plot(res.helm, plot.type = "Shepard")

## idioscal and indscal with random starting configuration:
set.seed(123)
startconf <- matrix(rnorm(20), 10, 2)
idioscal(helm, init = startconf, type = "interval")
indscal(helm, init = startconf, type = "interval")

```

---

smacofSphere

*Spherical SMACOF*


---

## Description

Dual and primal approach for spherical SMACOF.

## Usage

```

smacofSphere(delta, ndim = 2, type = c("ratio", "interval", "ordinal", "mspline"),
  algorithm = c("dual", "primal"), weightmat = NULL,
  init = "torgerson", ties = "primary", verbose = FALSE, penalty = 100,
  relax = FALSE, modulus = 1, itmax = 1000, eps = 1e-6,
  spline.degree = 2, spline.intKnots = 2)

```

## Arguments

delta	Either a symmetric dissimilarity matrix or an object of class <code>dist</code>
ndim	Number of dimensions
type	MDS type: "interval", "ratio", or "ordinal" (nonmetric MDS)
algorithm	Algorithm type (see details)
weightmat	Optional matrix with dissimilarity weights
init	Either "torgerson" (classical scaling starting solution), "random" (random configuration), or a user-defined matrix
ties	Tie specification for non-metric MDS only
verbose	If TRUE, intermediate stress is printed out
penalty	Penalty parameter for dual algorithm (larger 0), see details
relax	If TRUE, block relaxation is used for majorization (dual algorithm)
modulus	Number of smacof iterations per monotone regression call
itmax	Maximum number of iterations
eps	Convergence criterion
spline.degree	Degree of the spline for "mspline" MDS type
spline.intKnots	Number of interior knots of the spline for "mspline" MDS type

**Details**

For large scale problems it is suggested to use the dual algorithm. Using the penalty parameter (dual algorithm), the user allow for slight point deviations from the circle (the higher the penalty, the stricter the algorithm is in terms of placing points in the sphere, see examples section below).

**Value**

delta	Observed dissimilarities
obsdiss	Observed dissimilarities, normalized
obsdiss1	Dual SMACOF: Observed dissimilarities
obsdiss2	Dual SMACOF: Restriction matrix
confdist	Configuration dissimilarities
conf	Matrix with fitted configurations
spp	Stress per point
resmat	Matrix with squared residuals
rss	Residual sum-of-squares
stress	Stress-1 value
init	Starting configurations
ndim	Number of dimensions
dummyvec	Dummy vector of restriction matrix
model	Type of smacof model
niter	Number of iterations
nobj	Number of objects

**Author(s)**

Jan de Leeuw and Patrick Mair

**References**

De Leeuw, J. & Mair, P. (2009). Multidimensional scaling using majorization: The R package smacof. *Journal of Statistical Software*, 31(3), 1-30, [doi:10.18637/jss.v031.i03](https://doi.org/10.18637/jss.v031.i03)

**See Also**

[smacofRect](#), [smacofIndDiff](#), [smacofSym](#), [smacofConstraint](#)

**Examples**

```
## spherical SMACOF solution for trading data
## dual algorithm
res <- smacofSphere(trading, type = "ordinal")
res
plot(res)
```



```
## lower penalty
res <- smacofSphere(trading, penalty = 20, type = "ordinal")
res
plot(res)

## primal algorithm, interval
res <- smacofSphere(trading, type = "interval", algorithm = "primal")
res
```

---

smacofSym

*Symmetric smacof*


---

## Description

Multidimensional scaling on a symmetric dissimilarity matrix using SMACOF.

## Usage

```
smacofSym(delta, ndim = 2, type = c("ratio", "interval", "ordinal", "mspline"),
  weightmat = NULL, init = "torgerson", ties = "primary", principal = FALSE,
  verbose = FALSE, relax = FALSE, modulus = 1, itmax = 1000, eps = 1e-06,
  spline.degree = 2, spline.intKnots = 2)
```

```
mds(delta, ndim = 2, type = c("ratio", "interval", "ordinal", "mspline"),
  weightmat = NULL, init = "torgerson", ties = "primary", principal = FALSE,
  verbose = FALSE, relax = FALSE, modulus = 1, itmax = 1000, eps = 1e-06,
  spline.degree = 2, spline.intKnots = 2)
```

## Arguments

delta	Either a symmetric dissimilarity matrix or an object of class "dist"
ndim	Number of dimensions
weightmat	Optional matrix with dissimilarity weights
init	Either "torgerson" (classical scaling starting solution), "random" (random configuration), or a user-defined matrix
type	MDS type: "interval", "ratio", "ordinal" (nonmetric MDS), or "mspline"
ties	Tie specification (ordinal MDS only): "primary", "secondary", or "tertiary"
principal	If TRUE, principal axis transformation is applied to the final configuration
verbose	If TRUE, intermediate stress is printed out
relax	If TRUE, block relaxation is used for majorization
modulus	Number of smacof iterations per monotone regression call
itmax	Maximum number of iterations
eps	Convergence criterion
spline.degree	Degree of the spline for "mspline" MDS type
spline.intKnots	Number of interior knots of the spline for "mspline" MDS type

## Details

The function `mds()` is a wrapper function and can be used instead of `smacofSym()`. It reports the Stress-1 value (normalized). The main output are the coordinates in the low-dimensional space (configuration; `conf`; see also `plot.smacof`).

Four types of MDS can be fitted: ratio MDS (no dissimilarity transformation), interval MDS (linear transformation), ordinal MDS (ordinal transformation with various options for handling ties), and spline MDS (monotone spline transformation). Shepard plots in `plot.smacof` give insight into this transformation.

Setting `principal = TRUE` is useful for interpretability of the dimensions, or to check hypotheses about the dimensions.

In case of missing input dissimilarities, the `weightmat` is computed internally so that missings are blanked out during optimization.

## Value

<code>delta</code>	Observed dissimilarities, not normalized
<code>dhat</code>	Disparities (transformed proximities, approximated distances, d-hats)
<code>confdist</code>	Configuration distances
<code>conf</code>	Matrix of fitted configurations
<code>stress</code>	Stress-1 value
<code>spp</code>	Stress per point (stress contribution of each point on a percentage scale)
<code>resmat</code>	Matrix with squared residuals
<code>rss</code>	Residual sum-of-squares
<code>weightmat</code>	Weight matrix
<code>ndim</code>	Number of dimensions
<code>init</code>	Starting configuration
<code>model</code>	Name of smacof model
<code>niter</code>	Number of iterations
<code>nobj</code>	Number of objects
<code>type</code>	Type of MDS model

## Author(s)

Jan de Leeuw, Patrick Mair, and Patrick Groenen

## References

- De Leeuw, J. & Mair, P. (2009). Multidimensional scaling using majorization: The R package `smacof`. *Journal of Statistical Software*, 31(3), 1-30. doi:10.18637/jss.v031.i03
- Mair, P, Groenen, P. J. F., De Leeuw, J. (2022). More on multidimensional scaling in R: `smacof` version 2. *Journal of Statistical Software*, 102(10), 1-47. doi:10.18637/jss.v102.i10
- Borg, I., & Groenen, P. J. F. (2005). *Modern Multidimensional Scaling* (2nd ed.). Springer.
- Borg, I., Groenen, P. J. F., & Mair, P. (2018). *Applied Multidimensional Scaling and Unfolding* (2nd ed.). Springer.

**See Also**

[smacofConstraint](#), [smacofRect](#), [smacofIndDiff](#), [smacofSphere](#), [plot.smacof](#)

**Examples**

```
## simple SMACOF solution (interval MDS) for kinship data
res <- mds(kinshipdelta, type = "interval")
res
summary(res)
plot(res)
plot(res, type = "p", label.conf = list(label = TRUE, col = "darkgray"), pch = 25, col = "red")

## ratio MDS, random starts
set.seed(123)
res <- mds(kinshipdelta, init = "random")
res

## 3D ordinal SMACOF solution for trading data (secondary approach to ties)
data(trading)
res <- mds(trading, ndim = 3, type = "ordinal", ties = "secondary")
res

## spline MDS
delta <- sim2diss(cor(PVQ40agg))
res <- mds(delta, type = "mspline", spline.degree = 3, spline.intKnots = 4)
res
plot(res, "Shepard")
```

---

stardist

*Distances among stars in zodiac signs*


---

**Description**

A distance matrix for the 10 brightest stars in each of the 12 zodiac signs was computed. Astronomers measure the projected positions of objects on the celestial sphere in two angles, i.e. right ascension  $\alpha$  and declination  $\delta$ . For every zodiac sign, the projected distances on the sky between individual stars  $S_i$  and  $S_j$  have been calculated in decimal degrees by means of the Pythagorean theorem

$$d_{i,j} = \sqrt{(\alpha_i - \alpha_j)^2 + (\delta_i - \delta_j)^2}$$

assuming planar geometry. Since the zodiac signs are relatively small compared to the whole celestial sphere and the computation is only done for illustrative purposes, such a simplified assumption is appropriate.

**Usage**

```
data(stardist)
```

**Format**

A dist object containing the star distances.

**Note**

Thanks to Paul Eigenthaler, Department of Astronomy, University of Vienna for calculating the distances.

**Examples**

```
stardist
```

---

stress0	<i>Zero-Iterations Stress</i>
---------	-------------------------------

---

**Description**

Computes the stress for 0 iterations based on a starting configuration provided by the user.

**Usage**

```
stress0(delta, init, type = c("interval", "ratio", "ordinal", "mspline"),
        weightmat = NULL, ties = "primary", spline.degree = 2, spline.intKnots = 2)
```

**Arguments**

delta	Either a symmetric dissimilarity matrix or an object of class "dist"
init	An initial configuration provided by the user
weightmat	Optional matrix with dissimilarity weights
type	MDS type: "interval", "ratio", "ordinal" (nonmetric MDS), or "mspline"
ties	Tie specification (ordinal MDS only): "primary", "secondary", or "tertiary"
spline.degree	Degree of the spline for "mspline" MDS type
spline.intKnots	Number of interior knots of the spline for "mspline" MDS type

**Details**

Computes stress-1 for a particular starting configuration the user needs to provide. It can also be helpful if the user wants to force a particular theoretical configuration (as specified in `inits`) on the data.

**Value**

delta	Observed dissimilarities, not normalized
dhat	Disparities (transformed proximities, approximated distances, d-hats)
confdist	Configuration distances
conf	Matrix of fitted configurations
stress	Stress-1 value
spp	Stress per point (stress contribution in percentages)
resmat	Matrix with squared residuals
rss	Residual sum-of-squares
weightmat	Weight matrix
ndim	Number of dimensions
init	Starting configuration
model	Name of smacof model
niter	Number of iterations
nobj	Number of objects
type	Type of MDS model

**See Also**

[mds](#)

**Examples**

```
## rectangle starting solution
rect_constr
stress0(rectangles, init = rect_constr)

## torgerson starting solution
tstart <- torgerson(rectangles)
stress0(rectangles, init = tstart)
```

---

summary.smacofB

*S3 methods for smacof*


---

**Description**

Print and summary methods for objects of class smacofB, smacofR (rectangular), and smacofID (individual differences).

**Usage**

```
## S3 method for class 'smacofB'
summary(object, ...)
## S3 method for class 'smacofB'
print(x, ...)
## S3 method for class 'smacofR'
summary(object, ...)
## S3 method for class 'smacofR'
print(x, ...)
## S3 method for class 'smacofID'
summary(object, ...)
## S3 method for class 'smacofID'
print(x, ...)
```

**Arguments**

object	Object of class smacofB, smacofR, smacofID
x	Object of class smacofB, smacofR, smacofID
...	Ignored

**Examples**

```
data(kinshipdelta)
res <- smacofSym(kinshipdelta)
res
summary(res)
```

---

svm\_mdsplo

*Support Vector Machine MDS*


---

**Description**

Plots 2D MDS configuration including facets as determined by an SVM.

**Usage**

```
svm_mdsplo(mds_object, svm_object, class, legend1 = TRUE, legend2 = TRUE,
           inset = c(-0.2, 0.5), plot.dim = c(1,2), by = 0.01,
           main, xlab, ylab, xlim, ylim, ...)
```

**Arguments**

mds_object	Object of class "smacofB", i.e., an MDS solution from smacofSym() or smacofConstraint.
svm_object	Object of class "svm", i.e., an SVM solution from svm or tune.svm
class	Vector of class assignments (facets) for each object.
legend1	If TRUE, facet legend is added.
legend2	If TRUE, class legend is added.
inset	Inset distance from the margins for both legends as a fraction of the plot region when legend is placed by keyword.
plot.dim	Vector with dimensions to be plotted.
by	Scaling factor for resolution (the smaller, the higher the resolution).
main	Plot title.
xlab	Label of x-axis.
ylab	Label of y-axis.
xlim	Scale x-axis.
ylim	Scale y-axis.
...	Further plot arguments passed: see <a href="#">image</a> for detailed information.

**Details**

Using the SVM implementation of e1071 one can determine facets in an MDS configuration based on an SVM fit. This function plots the resulting facets on top of the 2D MDS configuration. Note that this function is work in progress.

**References**

Mair, P., Cetron, J. S., and Borg, I. (2022). Using support vector machines for facet partitioning in multidimensional scaling. *Multivariate Behavioral Research*. Forthcoming; [doi:10.1080/00273171.2022.2035207](https://doi.org/10.1080/00273171.2022.2035207)

**See Also**

[svm](#), [tune.svm](#)

**Examples**

```
## Guttman intelligence data
Delta <- sim2diss(Guttman1965[[1]])
class <- Guttman1965[[2]]

## ordinal MDS fit
mds_gut <- mds(Delta, ndim = 2, type = "ordinal")
mds_gut
cols <- rainbow_hcl(4)[as.numeric(class)]
plot(mds_gut, col = cols, label.conf = list(col = cols))
legend("bottomright", legend = levels(class), cex = 0.7, col = rainbow_hcl(4), pch = 19)
```

```
## radial SVM fit
X <- mds_gut$conf          ## extract configuration
dat <- data.frame(class = class, X) ## merge with class vector
costvec <- 2^seq(-4, 4)    ## tuning parameter grid
gamma <- seq(0.01, 0.5, 10)

set.seed(111)
svm_gut <- tune.svm(class ~ D1 + D2, data = dat, kernel = "radial",
                   cross = 10, cost = costvec)$best.model

svm_gut
preds <- predict(svm_gut, data = dat) ## predicted classes
table(obs = class, pred = preds)     ## confusion matrix

svm_mdspplot(mds_gut, svm_gut, dat$class, inset = c(-0.3, 0.5))
```

---

symdecomp

*Proximity Matrix Decomposition*


---

## Description

Additive decomposition of an asymmetric, square proximity matrix into a symmetric matrix and an skew-symmetric matrix

## Usage

```
symdecomp(P)
```

## Arguments

P                      Square proximity matrix

## Details

Performs the decomposition  $P = M + N$  (M and N are orthogonal).

## Value

Returns the following matrices:

M                      symmetric component  
N                      skew-symmetric component

## References

Borg, I., & Groenen, P. J. F. (2005). *Modern Multidimensional Scaling* (2nd ed.). Springer.

## Examples

```
P <- matrix(c(92,5,4,8,4,84,38,62,6,37,87,17,13,31,17,88), ncol = 4)
symdecomp(P)
```



---

torgerson	<i>Torgerson Scaling</i>
-----------	--------------------------

---

**Description**

Classical MDS aka Torgerson Scaling

**Usage**

```
torgerson(delta, p)
```

**Arguments**

delta	Dissimilarity matrix
p	Number of dimensions

**Value**

Returns an  $n \times p$  matrix of configurations

**References**

Borg, I., & Groenen, P. J. F. (2005). *Modern Multidimensional Scaling* (2nd ed.). Springer.

**Examples**

```
fit <- torgerson(Guerry)
```

---

trading	<i>Trading data</i>
---------	---------------------

---

**Description**

Data from the *New Geographical Digest* (1986) analyzed in Cox and Cox (2001). For 20 countries their main trading partners were dichotomously scored (1 = trade performed, 0 = trade not performed). Based on this dichotomous matrix the dissimilarities were computed using the Jaccard coefficient.

**Usage**

```
data(trading)
```

**Format**

Object of class "dist" with dissimilarities of the following countries:

Arge: Argentina

Aust: Australia

Braz: Brazil

Cana: Canada

Chin: China

Czec: Czechoslovakia

Egyp: Egypt

E.Ge: East Germany

Fran: France

Hung: Hungary

Indi: India

Ital: Italy

Japa: Japan

N.Ze: New Zealand

Pola: Poland

Swed: Sweden

USA

USSR: Soviet Union

U.K.: United Kingdom

W.Ge: West Germany

**References**

Cox, T.F., Cox, M.A.A. (1991). Multidimensional scaling on a sphere. *Communications in Statistics: Theory and Methods*, 20, 2943-2953.

**Examples**

```
data(trading)
```

---

transform	<i>Internal Dissimilarity Transformation</i>
-----------	--

---

### Description

Utility functions for optimal scaling calls (used internally)

### Usage

```
transPrep(x, trans = "ordinals", spline.intKnots = 4, spline.degree = 2, missing = "none")
transform(Target, x, w = rep(1,length(x$x)), normq = 0)
```

### Arguments

Target	unconstrained vector of target values
x	object of type optScal
w	vector non-negative weights
normq	sum of squares normalization
trans	type of transformation
spline.intKnots	interior spline knots
spline.degree	spline degree
missing	missing treatment

---

unfolding	<i>Nonmetric unfolding</i>
-----------	----------------------------

---

### Description

Variant of smacof for rectangular matrices (typically ratings, preferences) that allows for nonmetric transformations. Also known as nonmetric unfolding.

### Usage

```
unfolding(delta, ndim = 2, type = c("ratio", "interval", "ordinal", "mspline"),
  conditionality = "unconditional", lambda = 0.5, omega = 1,
  circle = c("none", "row", "column"), weightmat = NULL, init = NULL,
  fixed = c("none", "row", "column"), fixed.coord = NULL,
  ties = c("primary", "secondary"), verbose = FALSE, relax = TRUE,
  itmax = 10000, eps = 1e-6, spline.degree = 2, spline.intKnots = 2,
  parallelize = FALSE)

smacofRect(delta, ndim = 2, type = c("ratio", "interval", "ordinal", "mspline"),
```

```

conditionality = "unconditional", lambda = 0.5, omega = 1,
circle = c("none", "row", "column"), weightmat = NULL, init = NULL,
fixed = c("none", "row", "column"), fixed.coord = NULL,
ties = c("primary", "secondary"), verbose = FALSE, relax = TRUE,
itmax = 10000, eps = 1e-6, spline.degree = 2, spline.intKnots = 2,
parallelize = FALSE)

```

```

prefscal(delta, ndim = 2, type = c("ratio", "interval", "ordinal", "mspline"),
conditionality = "unconditional", lambda = 0.5, omega = 1,
circle = c("none", "row", "column"), weightmat = NULL, init = NULL,
fixed = c("none", "row", "column"), fixed.coord = NULL,
ties = c("primary", "secondary"), verbose = FALSE, relax = TRUE,
itmax = 10000, eps = 1e-6, spline.degree = 2, spline.intKnots = 2,
parallelize = FALSE)

```

### Arguments

<code>delta</code>	Data frame or matrix of preferences, ratings, dissimilarities.
<code>ndim</code>	Number of dimensions.
<code>type</code>	MDS type: "interval", "ratio", "ordinal", or "mspline".
<code>conditionality</code>	A single transformations are applied for the entire matrix "unconditional", or for each row separately "row".
<code>lambda</code>	Penalty strength balancing the loss contribution of stress and the penalty (see details).
<code>omega</code>	Penalty width determines for what values of the variation coefficient the penalty should become active (see details).
<code>circle</code>	If "column", the column configurations are restricted to be on a circle, if "row", row configurations are on a circle, if "none", there are no restrictions on row and column configurations
<code>weightmat</code>	Optional matrix with dissimilarity weights.
<code>init</code>	Optional list of length two with starting values for the row coordinates (first element) and column coordinates (second element).
<code>fixed</code>	Do external unfolding by fixing the row coordinates, column coordinate, or choose none (default) to do normal unfolding. Even fixed coordinates are uniformly scaled by a constant to fit the loss function.
<code>fixed.coord</code>	Matrix with fixed coordinates of the appropriate size.
<code>ties</code>	Tie specification for ordinal transformations: primary unties the ties and secondary keeps the ties tied.
<code>verbose</code>	If TRUE, intermediate stress is printed out.
<code>relax</code>	If TRUE, block relaxation is used for majorization after 100 iterations. It tends to reduce the number of iterations by a factor 2.
<code>itmax</code>	Maximum number of iterations.
<code>eps</code>	Convergence criterion.
<code>spline.degree</code>	Degree of the spline for an "mspline" transformation.

spline.intKnots	Number of interior knots of the spline for a "mspline" transformation.
parallelize	Tries to parallelize the computations when conditionality = "row".

### Details

Unfolding tries to match a rectangular matrix  $\delta$  of dissimilarities between row and column objects by Euclidean distances between row and column points. Badness of fit is measured by raw Stress as the sum of squared differences between  $\delta$  and the Euclidean distances. Instead of dissimilarities optimal transformations ( $\hat{d}$ ) can be found. The  $\hat{d}$  should be a function of the original  $\delta$  restricted to be "ratio", "interval", "ordinal", or "mspline". These transformations can be the same for the entire matrix (conditionality = "unconditional") of data, or different per row (conditionality = "row"). To avoid a degenerate solution with all  $\hat{d}$ s and distances equal to 1, the prefscal penalty is used.

A penalty is added based on the variation coefficient of the  $\hat{d}$ s (mean  $\hat{d}$  divided by the standard deviation of the  $\hat{d}$ s). The penalty width ( $\omega$ ) weights the penalty and determines from what value of the variation coefficient of the  $\hat{d}$ s the penalty should become active. The penalty strength ( $\lambda$ ) is needed to ensure that the penalty can be strong enough. Busing et al. (2005) suggest to use  $\lambda = 0.5$  and  $\omega = 1.0$  (for unconditional solutions  $\omega$  can be lowered to a value as low as 0.1).

External unfolding can be done by specifying fixed = "row" or "column" and providing the fixed coordinates in fixed.coord. Then, either the rows or columns are fixed up to a uniform constant.

Creates an object of class smacofR.

### Value

obsdiss	Observed dissimilarities, corresponds to $\delta$
confdist	Configuration dissimilarities
dhat	Matrix with optimal transformation of size $\delta$
iord	List of size 1 for matrix conditional and size $nrow(\delta)$ for row conditional with the index that orders the $\hat{d}$ s. Needed for the Shepard plot
conf.row	Matrix of final row configurations
conf.col	Matrix of final column configurations
stress	Final, normalized stress value
pstress	Penalized stress value (the criterion that is minimized)
spp.row	Stress per point, rows
spp.col	Stress per point, columns
congvec	Vector of congruency coefficients
ndim	Number of dimensions
model	Type of smacof model
niter	Number of iterations
nind	Number of individuals (rows)
trans	Transformation
conditionality	Conditionality of the transformation
nobj	Number of objects (columns)

**Author(s)**

Patrick Groenen, Jan de Leeuw and Patrick Mair

**References**

De Leeuw, J. & Mair, P. (2009). Multidimensional scaling using majorization: The R package smacof. *Journal of Statistical Software*, 31(3), 1-30, doi:10.18637/jss.v031.i03

Mair, P., Groenen, P. J. F., De Leeuw, J. (2022). More on multidimensional scaling in R: smacof version 2. *Journal of Statistical Software*, 102(10), 1-47. doi:10.18637/jss.v102.i10

Busing, F. M. T. A., Groenen, P. J. F., & Heiser, W. J. (2005). Avoiding degeneracy in multidimensional unfolding by penalizing on the coefficient of variation. *Psychometrika*, 70, 71-98.

**See Also**

[plot.smacof](#), [smacofConstraint](#), [smacofSym](#), [smacofIndDiff](#), [smacofSphere](#)

**Examples**

```
## Ratio unfolding
res <- unfolding(breakfast)
res

## various configuration plots
plot(res)
plot(res, type = "p", pch = 25)
plot(res, type = "p", pch = 25, col.columns = 3,
      label.conf.columns = list(label = TRUE, pos = 3, col = 3),
      col.rows = 8, label.conf.rows = list(label = TRUE, pos = 3, col = 8))

## Shepard plot
plot(res, "Shepard")

## Stress decomposition chart
plot(res, "stressplot")

## Not run:
## Ordinal unfolding, row-conditional
## Note that ordinal unfolding may need many iterations (several thousands)
res <- unfolding(breakfast, type = "ordinal", conditionality = "row", omega = 0.1, itmax = 3000)
res
plot(res, "Shepard")      ## Shepard plot
plot(res)

## End(Not run)
```

---

uniscale	<i>Unidimensional Scaling</i>
----------	-------------------------------

---

**Description**

Simple implementation where all dissimilarity permutations are subject to a 1D MDS fit and the one which leads to a minimal stress values is returned.

**Usage**

```
uniscale(delta, weightmat = NULL, verbose = TRUE)
```

**Arguments**

delta	Either a symmetric dissimilarity matrix or an object of class "dist"
weightmat	Optional matrix with dissimilarity weights
verbose	Permutation printout

**Value**

delta	Observed dissimilarities, not normalized
confdist	Configuration distances
conf	Vector with fitted configurations
stress	Stress-1 value
weightmat	Weight matrix
nobj	Number of objects
npermtot	Total number of permutations (factorial)
npermscale	Number of accepted permutations (monotonicity check)

**References**

Mair P., De Leeuw J. (2015). Unidimensional scaling. In Wiley StatsRef: Statistics Reference Online, Wiley, New York.

**See Also**

[mds](#)

**Examples**

```
## unidimensional scaling of Plato's 7 works
PlatoD <- dist(t(Plato7))
fit.uni <- uniscale(PlatoD)
fit.uni
plot(fit.uni)
```

---

VaziriXu

*Visual Object Representations*

---

### **Description**

Contains two similarity matrices related to an experiment on visual object representations.

similarities (correlations) of 54 OCP (see O'Reilly, Chatman, and Caldwell, 1991) items. The last three columns contain the facet assigned by Bilsky and Jehn (2002) as well as the external variables for regional restrictions.

### **Usage**

```
data(VaziriXu)
```

### **Format**

List of two similarity matrices from two experimental conditions: artificial and real object categories.

V1-V4: early visual areas

LO: lateral occipital regions

VOT: ventral occipitotemporal regions

V3A, V3B, IPS0-IPS4: topographic regions along the intraparietal sulcus

Inferior IPS: inferior intraparietal sulcus

Superior IPS: superior intraparietal sulcus

### **References**

Vaziri-Pashkam M, Xu Y (2018). An information-driven two-pathway characterization of occipitotemporal and posterior parietal visual object representations. *Cerebral Cortex*, forthcoming.

### **Examples**

```
vx1 <- sim2diss(VaziriXu[[1]])  
vx2 <- sim2diss(VaziriXu[[2]])
```



---

 vmu *Vector Model of Unfolding*


---

**Description**

Computes the metric vector model of unfolding (VMU) on rectangular input data (preferences, ratings) with the individuals (rows) represented as vectors in the biplot. There is also the option to fix the column coordinates.

**Usage**

```
vmu(delta, ndim = 2, center = TRUE, scale = FALSE, col.coord = NULL)
```

```
## S3 method for class 'vmu'
plot(x, ...)
```

**Arguments**

delta	Data frame or matrix of preferences, ratings, dissimilarities
ndim	Number of dimensions
center	If TRUE input data are centered row-wise.
scale	If TRUE input data are scaled row-wise.
col.coord	Optional fixed coordinates for the column objects in delta.
x	Object of class "vmu".
...	Additional arguments passed to biplot in stats.

**Value**

conf.row	Row coordinates
conf.col	Column coordinates
VAF	variance accounted for

**Author(s)**

Ingwer Borg and Patrick Mair

**References**

- Borg, I., & Groenen, P. J. F. (2005). *Modern Multidimensional Scaling* (2nd ed.). Springer.
- Borg, I., Groenen, P. J. F., & Mair, P. (2018). *Applied Multidimensional Scaling and Unfolding* (2nd ed.). Springer.
- Tucker, L. R. (1960). Intra-individual and inter-individual multidimensionality. In H. Gulliksen & S. Messick (Eds.), *Psychological scaling: Theory and applications* (pp. 155-167). Wiley.
- Mair, P., Groenen, P. J. F., De Leeuw, J. (2022). More on multidimensional scaling in R: smacof version 2. *Journal of Statistical Software*, 102(10), 1-47. doi:10.18637/jss.v102.i10

**See Also**

[biplot, unfolding](#)

**Examples**

```
## VMU on portrait value questionnaire ratings
fit_vmu <- vmu(PVQ40agg)      ## fit 2D VMU
fit_vmu
plot(fit_vmu, cex = c(1, 0.7))  ## call biplot from stats

## VMU with fixed column coordinates (circular)
tuv <- matrix(0, nrow = 10, ncol = 2)
alpha <- -360/10
for (i in 1:10){
  alpha <- alpha+360/10
  tuv[i, 1]<- cos(alpha*pi/180)
  tuv[i, 2] <- sin(alpha*pi/180)
}
fit_vmu2 <- vmu(PVQ40agg, col.coord = tuv)  ## fit 2D circular VMU
fit_vmu2
plot(fit_vmu2, cex = c(1, 0.7))
```

---

winedat

*Wine tasting*

---

**Description**

This dataset collects dissimilarity matrices of 10 raters of 6 different wines.

**Usage**

```
data(winedat)
```

**Format**

A list of dissimilarity matrices reflecting the rating of 10 judges on 6 different wines (Ziniel Chardonnay, Markowitsch Chardonnay, Krems Chardonnay, Castel Nova Chardonnay, Ritinitis Noble Retsina, RetsinaCriteria). The attributes color, smell, taste, fun, and overall impression were rated on a scale from 1 (very good) to 5. Based on these ratings the distances were computed.

**Examples**

```
winedat
```

---

wish

*Wish dataset*

---

**Description**

Similarity ratings for 12 countries. There were no instructions concerning the characteristics on which these similarity judgements were to be made, this was information to discover rather than to impose.

**Usage**

```
data(wish)
```

**Format**

Object of class `dist`

**Details**

For `smacof`, the data must be converted into a dissimilarity matrix (see examples).

**References**

Borg, I., Groenen, P. J. F., & Mair, P. (2010). *Multidimensionale Skalierung*. Muenchen: Hampp Verlag.

Borg, I., Groenen, P. J. F., & Mair, P. (2012). *Multidimensional Scaling*. New York: Springer, forthcoming.

Wish, M. (1971). Individual differences in perceptions and preferences among nations. In C. W. King and D. Tigert (Eds.), *Attitude research reaches new heights*, pp. 312-328. Chicago: American Marketing Association.

**Examples**

```
data(wish)
sim2diss(wish, method = max(wish))
```

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