

Package ‘semDs’

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Title Structural Equation Multidimensional Scaling

Imports graphics, stats, pracma, minpack.lm

Depends R (>= 3.0.0)

Suggests MASS

Description Fits a structural equation multidimensional scaling (SEMDS) model for asymmetric and three-way input dissimilarities. It assumes that the dissimilarities are measured with errors. The latent dissimilarities are estimated as factor scores within an SEM framework while the objects are represented in a low-dimensional space as in MDS.

License GPL (>= 2)

LazyData yes

LazyLoad yes

ByteCompile yes

NeedsCompilation no

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AvaRegions

Avalanche Problems Across Canadian Mountain Regions

Description

Contains dissimilarity matrices across mountain regions in British Columbia and BC for each of the 13 avalanche problems. The extended Dice coefficient was used on problem prevalences in order to compute the dissimilarities. This computation was carried out for each elevation band (alpine, treeline, below treeline) separately.

Usage

```
data(AvaRegions)
```

Format

For each elevation band a list of dissimilarity matrices is provided for the following avalanche problems:

DeepP Deep persistent slab

Ldry Loose dry avalanche

Lwet Loose wet & persistent slab

NoProbs No avalanche problems

Pers Persistent slab

PersPlus Persistent slab plus

Spring Spring-like

Storm Storm slab

StormDeepP Storm & deep persistent slab

StormPers Storm & persistent slab

StormWind Storm & wind slab

StormWindPers Storm, wind, & persistent slab

Wind Wind slab

Note

Thanks to Pascal Haegeli from SFU for sharing this dataset.

References

Shandro, B., & Haegeli, P. (2018). Characterizing the nature and variability of avalanche hazard in western Canada. *Natural Hazards and Earth System Sciences*, 18, 1141-1158.

Examples

```
data(AvaRegions)
str(alpD)          ## alpine
str(tlD)           ## treeline
str(btld)          ## below treeline
```

BrahmsNorm

Brahms Compositions

Description

A few seconds from recordings of 15 musical compositions by Brahms were the stimuli for a study involving 10 McGill undergraduates. The 105 possible unordered pairs of these pieces of music were transcribed to tape and each student was required to judge the dissimilarity for each pair. The judgements were ratings on an ordered category rating scale having 25 numbered categories with the lowest category labelled "extremely similar" and the largest category labelled "extremely different". Thus each judgement was transcribed as an integer from 1 to 25. Here we give a normalized version of the data.

Usage

```
data(BrahmsNorm)
```

Format

A list of length 10 (10 students). Each list element contains a lower triangular matrix with entries reflecting dissimilarities of 15 compositions by Brahms: Violin C (V), Clarinet Quintet (Cl5), Symphony 1 (S1), Piano Trio (P3), Piano C (P), Requiem (R), Variants (V), Symphony 4 (S4), Piano Quintet (P5), Viola S (Vi), Valse (Val), Serenata (Ser), Horn Trio (HT), Rhapsody (RH), Violin S (Vs).

References

Ramsay, J. O. (1982). Some statistical approaches to multidimensional scaling data. *Journal of the Royal Statistical Society, Series A*, 145, 285–312.

Examples

```
data(BrahmsNorm)
```

Miller

Perceptual Confusion Data

Description

Miller and Nicely (1955) data of perceptual confusions between 16 English consonant phonemes. In this test, female subjects listened to female speakers reading consonant-vowel syllables formed by pairing the consonants with the vowel "a" (as in father), and the subjects were required to write down the consonant they heard after each syllable was spoken. The confusions or errors of identification matrices were compiled under 17 different experimental conditions. The first four 16 x 16 tables given summarize the data obtained when noise-masking conditions produced varying speech-to-noise (S/N) ratios, with the addition of random noise at different levels. The original similarities were transformed into dissimilarities by considering the normalization procedure described by Hubert (1972) for this data set.

Usage

`data(Miller)`

Format

An asymmetric dissimilarity matrix. "th1" refers to the "th" as in "thy"; "th2" to the "th" as in "thigh"; "ti" refers to the "ti" as in "dilution".

References

Miller, G. A., & Nicely, P. E. (1955). An analysis of perceptual confusions among some English consonants. *The Journal of the Acoustic Society of America*, 27, 338–352.

Hubert, L. (1972). Some extensions of Johnson's hierarchical clustering algorithms. *Psychometrika*, 37, 261–274.

Vera, J. F. & Rivera, C. D. (2014). A structural equation multidimensional scaling model for one-mode asymmetric dissimilarity data. *Structural Equation Modeling: A Multidisciplinary Journal*, 21(1), 54–62.

Examples

`data(Miller)`

Recreation

Recreation Data

Description

Ten subjects were asked to judge differences, in terms of his/her own preference, between 15 forms of recreations. Each particular subject judged every one of 105 pairs of forms of recreation in a dissimilarity scale of 25 categories (numbered from 1 to 25). In this data set, only the lower right triangle excluding the diagonal was originally considered for each dissimilarity matrix because the natural asymmetry in judgements. Recreations forms were Concert (Ct), Museum (M), Theater (T), Movie (Mv), Television (TV), Conference (Cf), Reading (R), Hockey (H), Ballet (B), Debate (D), Fashion (F), Doc-film (Df), Exhibition (E), Shopping (S) and Restaurant (Re).

Usage

```
data(Miller)
```

Format

A list of dissimilarity matrices.

References

Ramsay, J. O. (1978). MULTISCALE: Four programs for multidimensional scaling by the method of maximum likelihood. Chicago: National Educational Resources, Inc.

Examples

```
data(Recreation)
```

SBanks2008D

Spanish Bank Crisis

Description

Data are taken from Sagarra et al. (2018) involving 15 Spanish Banks in 2008 and 2012. Dissimilarities are computed by a reverse transformation of Chen's commonality index for studying branch rivalry. The rows reflect the recipients of competitive pressure, the columns the creators of rivalry. The larger a dissimilarity value, the lower the competition.

Usage

```
data(SBanks2008D)  
data(SBanks2012D)
```

Format

Two asymmetric dissimilarity matrices (2008 and 2012) with 15 Spanish banks in the rows and columns.

References

Sagarra, M., Busing, F. M. T. A., Mar-Molinero, C., & Rialp, J. (2018). Assessing the asymmetric effects on branch rivalry of spanish financial sector restructuring. *Advances in Data Analysis and Classification*, 12 , 131-153.

Examples

```
data(SBanks2008D)
str(SBanks2008D)
```

```
data(SBanks2012D)
str(SBanks2012D)
```

 semDs

Structural Equation Multidimensional Scaling

Description

Fits a multidimensional scaling (MDS) model on asymmetric dissimilarity data and three-way data. It uses an alternating estimation procedure in which the unknown symmetric dissimilarity matrix is estimated in a structural equation modeling (SEM) framework while the objects are represented in a low-dimensional space.

Usage

```
semDs(D, dim = 2, saturated = FALSE, theta0 = NULL, maxiter = 1000, eps = 1e-06)
```

Arguments

| | |
|-----------|-----------------------------------------------------------------------------------------------------------------------------------------------------------|
| D | A list of input dissimilarity matrices for the general multiway case. For the special 2-way case it can also be a single asymmetric dissimilarity matrix. |
| dim | Number of dimensions for MDS solution. |
| saturated | For the 2-way case only: whether the model is saturated (TRUE) or not (FALSE; default). |
| theta0 | Starting values for SEM parameter vector. |
| maxiter | Maximum number of iterations. |
| eps | Convergence criterion for difference of subsequent stress values. |

Details

Add details

Value

Returns an object of class "semDs" containing the following elements.

| | |
|------------|-----------------------------------------|
| stressnorm | Normalized stress value. |
| stressraw | Raw stress value. |
| Delta | Disparity matrix. |
| theta | SEM parameter vector. |
| conf | MDS configurations. |
| dist | Distance matrix based on configurations |
| niter | Number of iterations. |
| thetatab | Parameter table. |
| call | Function call. |

Author(s)

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References

Vera, J. F. & Rivera, C. D. (2014). A structural equation multidimensional scaling model for one-mode asymmetric dissimilarity data. *Structural Equation Modeling: A Multidisciplinary Journal*, 21(1), 54–62.

Examples

```
## asymmetric model
fit2way <- semDs(Miller)
fit2way
summary(fit2way)
plot(fit2way)

## asymmetric model (saturated)
fit2wayS <- semDs(Miller, saturated = TRUE)
fit2wayS
fit2wayS$theta

## general three-way model
fitmway <- semDs(BrahmsNorm)
fitmway
summary(fitmway)
plot(fitmway)
```

Wang

Consonant Confusions in Noise

Description

In this data set by Wang and Bilger (1973), the same consonant phonemes considered as in Miller & Nicely (1955), except that "m" and "n" are substituted for "tS" as in "cheap", and "d3" as in "jeep", were combined with each of the three vowels /i,a,u/ under six speech-to-noise ratios. To obtain dissimilarities, the normalization approach proposed in Hubert (1972) was applied.

Usage

`data(Wang)`

Format

An asymmetric dissimilarity matrix.

References

Wang, M. D., & Bilger, R. C. (1973). Consonant confusions in noise: A study of perceptual features. *The Journal of the Acoustical Society of America*, 54(5), 1248–1266.

Miller, G. A., & Nicely, P. E. (1955). An analysis of perceptual confusions among some English consonants. *The Journal of the Acoustic Society of America*, 27, 338–352.

Hubert, L. (1972). Some extensions of Johnson's hierarchical clustering algorithms. *Psychometrika*, 37, 261–274.

See Also

[Miller](#)

Examples

`data(Wang)`

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