Package 'coRanking'

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Title Co-Ranking Matrix

Version 0.2.3

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Description Calculates the co-ranking matrix to assess the quality of a dimensionality reduction.

URL https://www.guido-kraemer.com/software/coranking/

BugReports https://github.com/gdkrmr/coRanking/issues

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Encoding UTF-8

Imports methods, graphics, stats

RoxygenNote 7.1.2

Collate 'coranking-package.R' 'coranking.R' 'coranking_internals.R' 'lcmc.R' 'criteria.R' 'image.R' 'rankmatrix.R' 'submatrix.R' 'r_nx.R'

Suggests testthat, knitr, rmarkdown, Rtsne, scatterplot3d

VignetteBuilder knitr

NeedsCompilation yes

Repository CRAN

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R topics documented:

`coRanking-package` *Methods for the co-ranking matrix*

Description

coRanking provides methods for the calculation of the co-ranking matrix and derived measures to assess the quality of a dimensionality reduction

Details

This package provides functions for calculating the co-ranking matrix, plotitng functions and some derived measures for quality assessment of dimensionality reductions.

Funding provided by the Department for Biogeochemical Integration, Empirical Inference of the Earth System Group, at the Max Plack Institute for Biogeochemistry, Jena.

References

Chen, L., Buja, A., 2006. Local Multidimensional Scaling for Nonlinear Dimension Reduction, Graph Layout and Proximity Analysis.

Lee, J.A., Lee, J.A., Verleysen, M., 2009. Quality assessment of dimensionality reduction: Rank-based criteria. Neurocomputing 72.

Lueks, W., Mokbel, B., Biehl, M., & Hammer, B. (2011). How to Evaluate Dimensionality Reduction? - Improving the Co-ranking Matrix. ArXiv:1110.3917 [Cs]. http://arxiv.org/abs/1110.3917

Lee, J. A., Peluffo-Ordóñez, D. H., & Verleysen, M., 2015. Multi-scale similarities in stochastic neighbour embedding: Reducing dimensionality while preserving both local and global structure. Neurocomputing, 169, 246–261. https://doi.org/10.1016/j.neucom.2014.12.095

See Also

Useful links:

- https://www.guido-kraemer.com/software/coranking/
- Report bugs at https://github.com/gdkrmr/coRanking/issues

AUC_ln_K *Area under the* RN_X *curve*

Description

Area under the $R_{NX}(K)$ curve when K is put on a logarithmic scale.

Usage

```
AUC_ln_K(R_NX)
```

Arguments

R_NX	The R_NX curve, a vector of values

Details

It is calculated as:

$$AUC_{\ln K}(R_{NX}(K)) = \left(\sum_{K=1}^{N-2} R_{NX}(K)/K\right) / \left(\sum_{K=1}^{N-2} 1/K\right)$$

Value

A value, the area under the curve.

Author(s)

Guido Kraemer

References

Lee, J. A., Peluffo-Ordóñez, D. H., & Verleysen, M., 2015. Multi-scale similarities in stochastic neighbour embedding: Reducing dimensionality while preserving both local and global structure. Neurocomputing, 169, 246–261. https://doi.org/10.1016/j.neucom.2014.12.095

`coranking` *Co-Ranking Matrix*

Description

Calculate the co-ranking matrix to assess the quality of a diminsionality reduction.

Usage

```
coranking(
  Xi,
  X,
  input_Xi = c("data", "dist", "rank"),
  input_X = input_Xi,
  use = "C"
)
```

Arguments

`Xi`	high dimensional data
`X`	low dimensional data
`input_Xi`	type of input of Xi (see. details)
`input_X`	type of input of X (see. details)
`use`	`R` or `C` backend

Details

Calculate the coranking matrix, to assess the quality of a dimensionality reduction. `Xi` is input in high dimensions, `X` is input in low dimensions the type of input is given in `input_Xi` and `input_X`, they can be one of `c('data','dist','rank')`.

Value

a matrix of class `'coranking'`

Author(s)

Guido Kraemer

See Also

`rankmatrix`

imageplot *Image function for the co-ranking matrix*

Description

Plots the co-ranking matrix nicely

Usage

```
imageplot(
  Q,
  lwd = 2,
  bty = "n",
  main = "co-ranking matrix",
  xlab = expression(R),
  ylab = expression(Ro),
 col = colorRampPalette(colors = c("gray85", "red", "yellow", "green", "blue"))(100),
  axes = FALSE,
  legend = TRUE,
  ...
)
```

Arguments

Q	of class coranking.
lwd	linewidth in legend
bty	boxtype of legend
main	title of plot
xlab	label of the x axis
ylab	label of the y axis
col	a palette for coloring
axes	ligical draw axes
legend	if T plot a legend.
...	parameters for the image function.

Details

Plots the co-ranking matrix nicely for visual inspection. uses the image function internaly, ... is passed down to the image function. The values in the co-ranking matrix are logscaled for better contrast.

Author(s)

Guido Kramer

LCMC *The local continuity meta-criterion*

Description

Calculate the local continuity meta-criterion from a co-ranking matrix.

Usage

```
LCMC(Q, K = 1:nrow(Q))
```

Arguments

Q	a co-ranking matrix
K	vector of integers describing neighborhood size

Details

The local continuity meta-criterion (Chen and Buja, 2006) is defined as

$$LCMC = \frac{K}{1-N} + \frac{1}{NK} \sum_{(k,l) \in UL_K} q_{kl}$$

Higher values mean a better performance of the dimensionality reduction.

Value

A number, the local continuity meta-criterion

Author(s)

Guido Kraemer

plot_R_NX *Plot the $R\_NX(K)$ curve*

Description

Produces a plot with the $R_{NX}(K)$ curves from the arguments

Usage

```
plot_R_NX(R_NXs, pal = grDevices::palette(), ylim = c(0, 0.9), ...)
```

Arguments

R_NXs	A list of R_NX curves, names from the list will appear in the legend
pal	a vector of colors
ylim	set the y-axis limits of the plot
...	options for the plotting function

Value

Nothing, produces a plot.

Author(s)

Guido Kraemer

References

Lee, J. A., Peluffo-Ordóñez, D. H., & Verleysen, M., 2015. Multi-scale similarities in stochastic neighbour embedding: Reducing dimensionality while preserving both local and global structure. Neurocomputing, 169, 246–261. https://doi.org/10.1016/j.neucom.2014.12.095

Q_NX *The $Q\_NX(K)$ criterion*

Description

A curve indicating the percentage of points that are mild in- and extrusions or keep their rank.

Usage

```
Q_NX(Q)
```

Arguments

Q	a co-ranking matrix

Details

$$Q_{NX}(K) = \frac{1}{KN} \sum_{k=1}^{K} \sum_{l=1}^{K} Q_{kl}$$

Value

A vector with the values for Q_NX(K)

Author(s)

Guido Kraemer

References

Lueks, W., Mokbel, B., Biehl, M., & Hammer, B. (2011). How to Evaluate Dimensionality Reduction? - Improving the Co-ranking Matrix. ArXiv:1110.3917 [Cs]. http://arxiv.org/abs/1110.3917

`rankmatrix` *Rank matrix*

Description

Replaces the elements of X with their rank in the column vector of the distance matrix

Usage

```
rankmatrix(X, input = c("data", "dist"), use = "C")
```

Arguments

`X`	data, dist object, or distance matrix
`input`	type of input
`use`	if 'C' uses the compiled library, else uses the native R code

Details

Each column vector in the distance matrix (or the distance matrix computed from the input) is replaced by a vector indicating the rank of the distance inside that vector.

This is a computation step necessary for the co-ranking matrix and provided mainly so that the user has the possibility to save computation time.

Value

returns a matrix of class `'rankmatrix'`

Author(s)

Guido Kraemer

R_NX *The $R\_NX(K)$ criterion*

Description

A curve indicating the improvement of the embedding over a random embedding for the neighborhood size K. Values range from 0, for a random embedding, to 1 for a perfect embedding.

Usage

```
R_NX(Q)
```

Arguments

Q	a co-ranking matrix

Details

$R_{NX}(K)$ is calculated as follows:

$$Q_{NX}(K) = \sum_{1 \leq k \leq K} \sum_{1 \leq l \leq K} \frac{q_{kl}}{KN}$$

Counts the upper left K-by-K block of Q, i.e. it considers the preserved ranks on the diagonal and the permutations within a neighborhood.

$$R_{NX}(K) = \frac{(N-1)Q_{NX}(K) - K}{N - 1 - K}$$

A resulting vale of 0 corresponds to a random embedding, a value of 1 to a perfect embedding of the K-ary neighborhood.

Value

A vector with the values for R_NX(K)

Author(s)

Guido Kraemer

References

Lee, J.A., Lee, J.A., Verleysen, M., 2009. Quality assessment of dimensionality reduction: Rank-based criteria. Neurocomputing 72.

Lee, J. A., Peluffo-Ordóñez, D. H., & Verleysen, M., 2015. Multi-scale similarities in stochastic neighbour embedding: Reducing dimensionality while preserving both local and global structure. Neurocomputing, 169, 246–261. https://doi.org/10.1016/j.neucom.2014.12.095

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