

# Package ‘tensorBSS’

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**Type** Package

**Title** Blind Source Separation Methods for Tensor-Valued Observations

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**Description** Contains several utility functions for manipulating tensor-valued data (centering, multiplication from a single mode etc.) and the implementations of the following blind source separation methods for tensor-valued data: 'tPCA', 'tFOBI', 'tJADE', 'k-tJADE', 'tgFOBI', 'tg-JADE', 'tSOBI', 'tNSS.SD', 'tNSS.JD', 'tNSS.TD.JD', 'tPP' and 'tTUCKER'.

**License** GPL (>= 2)

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## R topics documented:

tensorBSS-package . . . . .	2
ggtladleplot . . . . .	3
k_tJADE . . . . .	5
mModeAutoCovariance . . . . .	7
mModeCovariance . . . . .	8
plot.tbss . . . . .	9
print.tladle . . . . .	11
selectComponents . . . . .	11
tensorBoot . . . . .	12
tensorCentering . . . . .	13

tensorStandardize . . . . .	14
tensorTransform . . . . .	15
tensorTransform2 . . . . .	17
tensorVectorize . . . . .	18
tFOBI . . . . .	19
tgFOBI . . . . .	21
tgJADE . . . . .	23
tJADE . . . . .	24
tMD . . . . .	26
tNSS.JD . . . . .	28
tNSS.SD . . . . .	29
tNSS.TD.JD . . . . .	32
tPCA . . . . .	34
tPCAladle . . . . .	36
tPP . . . . .	38
tSIR . . . . .	39
tSOBI . . . . .	41
tTUCKER . . . . .	42
<b>Index</b>	<b>45</b>

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tensorBSS-package

*Blind Source Separation Methods for Tensor-Valued Observations*

---

## Description

Contains several utility functions for manipulating tensor-valued data (centering, multiplication from a single mode etc.) and the implementations of the following blind source separation methods for tensor-valued data: ‘tPCA’, ‘tFOBI’, ‘tJADE’, ‘k-tJADE’, ‘tgFOBI’, ‘tgJADE’, ‘tSOBI’, ‘tNSS.SD’, ‘tNSS.JD’, ‘tNSS.TD.JD’, ‘tPP’ and ‘tTUCKER’.

## Details

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 Type: Package  
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 License: GPL (>= 2)

## Author(s)

Joni Virta, Christoph Koesner, Bing Li, Klaus Nordhausen and Hannu Oja

Maintainer: Joni Virta <joni.virta@outlook.com>

## References

- Virta, J., Taskinen, S. and Nordhausen, K. (2016), Applying fully tensorial ICA to fMRI data, *Signal Processing in Medicine and Biology Symposium (SPMB)*, 2016 IEEE, doi: [10.1109/SPMB.2016.7846858](https://doi.org/10.1109/SPMB.2016.7846858)
- Virta, J., Li, B., Nordhausen, K. and Oja, H., (2017), Independent component analysis for tensor-valued data, *Journal of Multivariate Analysis*, doi: [10.1016/j.jmva.2017.09.008](https://doi.org/10.1016/j.jmva.2017.09.008)
- Virta, J. and Nordhausen, K., (2017), Blind source separation of tensor-valued time series. *Signal Processing* 141, 204-216, doi: [10.1016/j.sigpro.2017.06.008](https://doi.org/10.1016/j.sigpro.2017.06.008)
- Virta J., Nordhausen K. (2017): Blind source separation for nonstationary tensor-valued time series, *2017 IEEE 27th International Workshop on Machine Learning for Signal Processing (MLSP)*, doi: [10.1109/MLSP.2017.8168122](https://doi.org/10.1109/MLSP.2017.8168122)
- Virta J., Li B., Nordhausen K., Oja H. (2018): JADE for tensor-valued observations, *Journal of Computational and Graphical Statistics*, Volume 27, p. 628 - 637, doi: [10.1080/10618600.2017.1407324](https://doi.org/10.1080/10618600.2017.1407324)
- Virta J., Lietzen N., Ilmonen P., Nordhausen K., (2018), Asymptotically and computationally efficient tensorial JADE, preprint available on arXiv <https://arxiv.org/abs/1808.00791>.
- Koesner, C, Nordhausen, K. and Virta, J. (2019), Estimating the signal tensor dimension using tensorial PCA. *Manuscript*.

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ggtladleplot

*Ladle plot for each mode of an object of class tladle using ggplot2*


---

## Description

The ladle plot is a measure for deciding about the number of interesting components. Of interest for the ladle criterion is the minimum. The function here offers however also to plot other criterion values which are part of the actual ladle criterion.

## Usage

```
ggtladleplot(x, crit = "gn", type="l", ylab = crit,
             xlab = "component", main = deparse(substitute(x)), ...)
```

## Arguments

x	an object of class ladle.
crit	the criterion to be plotted, options are "gn", "fn", "phin" and "lambda".
type	plotting type, either lines l or points p.
ylab	default ylab value.
xlab	default xlab value.
main	default title.
...	other arguments for the plotting functions.

## Details

The main criterion of the ladle is the scaled sum of the eigenvalues and the measure of variation of the eigenvectors up to the component of interest.

The sum is denoted "gn" and the individual parts are "fn" for the measure of the eigenvector variation and "phin" for the scaled eigenvalues. The last option "lambda" corresponds to the unscaled eigenvalues yielding then a screeplot.

The plot is drawn separately for each mode of the data.

## Author(s)

Klaus Nordhausen, Joni Virta

## References

*Koesner, C, Nordhausen, K. and Virta, J. (2019), Estimating the signal tensor dimension using tensorial PCA. Manuscript.*

*Luo, W. and Li, B. (2016), Combining Eigenvalues and Variation of Eigenvectors for Order Determination, Biometrika, 103. 875–887. <doi:10.1093/biomet/asw051>*

## See Also

[tPCAladle](#)

## Examples

```
library(ICtest)
n <- 500
sig <- 0.6

Z <- rbind(sqrt(0.7)*rt(n,df=5)*sqrt(3/5),
           sqrt(0.3)*runif(n,-sqrt(3),sqrt(3)),
           sqrt(0.3)*(rchisq(n,df=3)-3)/sqrt(6),
           sqrt(0.9)*(rexp(n)-1),
           sqrt(0.1)*rlogis(n,0,sqrt(3)/pi),
           sqrt(0.5)*(rbeta(n,2,2)-0.5)*sqrt(20)
)

dim(Z) <- c(3, 2, n)

U1 <- rorth(12)[,1:3]
U2 <- rorth(8)[,1:2]
U <- list(U1=U1, U2=U2)
Y <- tensorTransform2(Z,U,1:2)
EPS <- array(rnorm(12*8*n, mean=0, sd=sig), dim=c(12,8,n))
X <- Y + EPS

TEST <- tPCAladle(X, n.boot = 100)
TEST
ggtladleplot(TEST, crit = "gn")
```

```

ggtladleplot(TEST, crit = "fn")
ggtladleplot(TEST, crit = "phin")
ggtladleplot(TEST, crit = "lambda")

```

k\_tJADE

*k-tJADE for Tensor-Valued Observations***Description**

Computes the faster “k”-version of tensorial JADE in an independent component model.

**Usage**

```
k_tJADE(x, k = NULL, maxiter = 100, eps = 1e-06)
```

**Arguments**

x	Numeric array of an order at least two. It is assumed that the last dimension corresponds to the sampling units.
k	A vector with one less element than dimensions in x. The elements of k give upper bounds for cumulant matrix indices we diagonalize in each mode. Lower values mean faster computation times. The default value NULL puts k equal to 1 in each mode (the fastest choice).
maxiter	Maximum number of iterations. Passed on to <a href="#">rjd</a> .
eps	Convergence tolerance. Passed on to <a href="#">rjd</a> .

**Details**

It is assumed that  $S$  is a tensor (array) of size  $p_1 \times p_2 \times \dots \times p_r$  with mutually independent elements and measured on  $N$  units. The tensor independent component model further assumes that the tensors  $S$  are mixed from each mode  $m$  by the mixing matrix  $A_m$ ,  $m = 1, \dots, r$ , yielding the observed data  $X$ . In R the sample of  $X$  is saved as an [array](#) of dimensions  $p_1, p_2, \dots, p_r, N$ .

k\_tJADE recovers then based on x the underlying independent components  $S$  by estimating the  $r$  unmixing matrices  $W_1, \dots, W_r$  using fourth joint moments at the same time in a more efficient way than [tFOBI](#) but also in fewer numbers than [tJADE](#). k\_tJADE diagonalizes in each mode only those cumulant matrices  $C^{ij}$  for which  $|i - j| < k_m$ .

If x is a matrix, that is,  $r = 1$ , the method reduces to JADE and the function calls [k\\_JADE](#).

**Value**

A list with class 'tbss', inheriting from class 'bss', containing the following components:

S	Array of the same size as x containing the independent components.
W	List containing all the unmixing matrices
Xmu	The data location.
k	The used vector of $k$ -values.
datatype	Character string with value "iid". Relevant for <a href="#">plot.tbss</a> .

**Author(s)**

Joni Virta

**References**

Miettinen, J., Nordhausen, K., Oja, H. and Taskinen, S. (2013), *Fast Equivariant JADE*, In the *Proceedings of 38th IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP 2013)*, 6153–6157, doi: [10.1109/ICASSP.2013.6638847](https://doi.org/10.1109/ICASSP.2013.6638847)

Virta J., Li B., Nordhausen K., Oja H. (2018): *JADE for tensor-valued observations*, *Journal of Computational and Graphical Statistics*, Volume 27, p. 628 - 637, doi: [10.1080/10618600.2017.1407324](https://doi.org/10.1080/10618600.2017.1407324)

Virta J., Lietzen N., Ilmonen P., Nordhausen K., (2018), *Asymptotically and computationally efficient tensorial JADE*, preprint available on arXiv <https://arxiv.org/abs/1808.00791>.

**See Also**

[k\\_JADE](#), [tJADE](#), [JADE](#)

**Examples**

```
n <- 1000
S <- t(cbind(rexp(n)-1,
            rnorm(n),
            runif(n, -sqrt(3), sqrt(3)),
            rt(n,5)*sqrt(0.6),
            (rchisq(n,1)-1)/sqrt(2),
            (rchisq(n,2)-2)/sqrt(4)))
```

```
dim(S) <- c(3, 2, n)
```

```
A1 <- matrix(rnorm(9), 3, 3)
```

```
A2 <- matrix(rnorm(4), 2, 2)
```

```
X <- tensorTransform(S, A1, 1)
```

```
X <- tensorTransform(X, A2, 2)
```

```
k_tjade <- k_tJADE(X)
```

```
MD(k_tjade$W[[1]], A1)
```

```
MD(k_tjade$W[[2]], A2)
```

```
tMD(k_tjade$W, list(A1, A2))
```

```
k_tjade <- k_tJADE(X, k = c(2, 1))
```

```
MD(k_tjade$W[[1]], A1)
```

```
MD(k_tjade$W[[2]], A2)
```

```
tMD(k_tjade$W, list(A1, A2))
```

---

mModeAutoCovariance     *The m-Mode Autocovariance Matrix*


---

### Description

Estimates the m-mode autocovariance matrix from an array of array-valued observations with the specified lag.

### Usage

```
mModeAutoCovariance(x, m, lag, center = TRUE)
```

### Arguments

x	Array of order higher than two with the last dimension corresponding to the sampling units.
m	The mode with respect to which the autocovariance matrix is to be computed.
lag	The lag with respect to which the autocovariance matrix is to be computed.
center	Logical, indicating whether the observations should be centered prior to computing the autocovariance matrix. Default is TRUE.

### Details

The m-mode autocovariance matrix provides a higher order analogy for the ordinary autocovariance matrix of a random vector and is computed for a random tensor  $X_t$  of size  $p_1 \times p_2 \times \dots \times p_r$  as  $Cov_{m\tau}(X_t) = E(X_t^{(m)} X_{t+\tau}^{(m)T}) / (p_1 \dots p_{m-1} p_{m+1} \dots p_r)$ , where  $X_t^{(m)}$  is the centered  $m$ -flattening of  $X_t$  and  $\tau$  is the desired lag. The algorithm computes the estimate of this based on the sample  $x$ .

### Value

The m-mode autocovariance matrix of  $x$  with respect to  $lag$  having the size  $p_m \times p_m$ .

### Author(s)

Joni Virta

### References

Virta, J. and Nordhausen, K., (2017), *Blind source separation of tensor-valued time series*, *Signal Processing*, 141, 204-216, doi: [10.1016/j.sigpro.2017.06.008](https://doi.org/10.1016/j.sigpro.2017.06.008)

### See Also

[mModeCovariance](#)

**Examples**

```

n <- 1000
S <- t(cbind(as.vector(arima.sim(n = n, list(ar = 0.9))),
            as.vector(arima.sim(n = n, list(ar = -0.9))),
            as.vector(arima.sim(n = n, list(ma = c(0.5, -0.5)))),
            as.vector(arima.sim(n = n, list(ar = c(-0.5, -0.3)))),
            as.vector(arima.sim(n = n, list(ar = c(0.5, -0.3, 0.1, -0.1), ma=c(0.7, -0.3)))),
            as.vector(arima.sim(n = n, list(ar = c(-0.7, 0.1), ma = c(0.9, 0.3, 0.1, -0.1))))))
dim(S) <- c(3, 2, n)

mModeAutoCovariance(S, m = 1, lag = 1)
mModeAutoCovariance(S, m = 1, lag = 4)

```

---

mModeCovariance

*The m-Mode Covariance Matrix*


---

**Description**

Estimates the m-mode covariance matrix from an array of array-valued observations.

**Usage**

```
mModeCovariance(x, m, center = TRUE)
```

**Arguments**

x	Array of order higher than two with the last dimension corresponding to the sampling units.
m	The mode with respect to which the covariance matrix is to be computed.
center	Logical, indicating whether the observations should be centered prior to computing the covariance matrix. Default is TRUE.

**Details**

The m-mode covariance matrix provides a higher order analogy for the ordinary covariance matrix of a random vector and is computed for a random tensor  $X$  of size  $p_1 \times p_2 \times \dots \times p_r$  as  $Cov_m(X) = E(X^{(m)} X^{(m)T}) / (p_1 \dots p_{m-1} p_{m+1} \dots p_r)$ , where  $X^{(m)}$  is the centered  $m$ -flattening of  $X$ . The algorithm computes the estimate of this based on the sample  $x$ .

**Value**

The m-mode covariance matrix of  $x$  having the size  $p_m \times p_m$ .

**Author(s)**

Joni Virta



## References

Virta, J., Li, B., Nordhausen, K. and Oja, H., (2017), *Independent component analysis for tensor-valued data*, *Journal of Multivariate Analysis*, doi: [10.1016/j.jmva.2017.09.008](https://doi.org/10.1016/j.jmva.2017.09.008)

## See Also

[mModeAutoCovariance](#)

## Examples

```
## Generate sample data.
n <- 100
x <- t(cbind(rnorm(n, mean = 0),
            rnorm(n, mean = 1),
            rnorm(n, mean = 2),
            rnorm(n, mean = 3),
            rnorm(n, mean = 4),
            rnorm(n, mean = 5)))

dim(x) <- c(3, 2, n)

# The m-mode covariance matrices of the first and second modes
mModeCovariance(x, 1)
mModeCovariance(x, 2)
```

---

plot.tbss

*Plot an Object of the Class tbss*

---

## Description

Plots the most interesting components (in the sense of extreme kurtosis) obtained by a tensor blind source separation method.

## Usage

```
## S3 method for class 'tbss'
plot(x, first = 2, last = 2, datatype = NULL,
     main = "The components with most extreme kurtoses", ...)
```

## Arguments

x	Object of class tbss.
first	Number of components with maximal kurtosis to be selected. See <a href="#">selectComponents</a> for details.
last	Number of components with minimal kurtosis to be selected. See <a href="#">selectComponents</a> for details.
main	The title of the plot.

datatype      Parameter for choosing the type of plot, either NULL, "iid" or "ts". The default NULL means the value from the tbss object x is taken.

...            Further arguments to be passed to the plotting functions, see details.

### Details

The function `plot.tbss` first selects the most interesting components using `selectComponents` and then plots them either as a matrix of scatter plots using `pairs` (`datatype = "iid"`) or as a time series plot using `plot.ts` (`datatype = "ts"`). Note that for `tSOBI` this criterion might not necessarily be meaningful as the method is based on second moments only.

### Author(s)

Joni Virta

### Examples

```
library(ElemStatLearn)
x <- zip.train

rows <- which(x[, 1] == 0 | x[, 1] == 1)
x0 <- x[rows, 2:257]
y0 <- x[rows, 1] + 1

x0 <- t(x0)
dim(x0) <- c(16, 16, 2199)

tfobi <- tFOBI(x0)
plot(tfobi, col=y0)

library("stochvol")
n <- 1000
S <- t(cbind(svsim(n, mu = -10, phi = 0.98, sigma = 0.2, nu = Inf)$y,
            svsim(n, mu = -5, phi = -0.98, sigma = 0.2, nu = 10)$y,
            svsim(n, mu = -10, phi = 0.70, sigma = 0.7, nu = Inf)$y,
            svsim(n, mu = -5, phi = -0.70, sigma = 0.7, nu = 10)$y,
            svsim(n, mu = -9, phi = 0.20, sigma = 0.01, nu = Inf)$y,
            svsim(n, mu = -9, phi = -0.20, sigma = 0.01, nu = 10)$y))
dim(S) <- c(3, 2, n)

A1 <- matrix(rnorm(9), 3, 3)
A2 <- matrix(rnorm(4), 2, 2)

X <- tensorTransform(S, A1, 1)
X <- tensorTransform(X, A2, 2)

tgfobi <- tgFOBI(X)
plot(tgfobi, 1, 1)
```

---

print.tladle	<i>Printing an object of class tladle</i>
--------------	---

---

**Description**

Prints an object of class tladle.

**Usage**

```
## S3 method for class 'tladle'  
## S3 method for class 'tladle'  
print(x, ...)
```

**Arguments**

x	object of class tladle.
...	further arguments to be passed to or from methods.

**Author(s)**

Klaus Nordhausen

---

selectComponents	<i>Select the Most Informative Components</i>
------------------	---

---

**Description**

Takes an array of observations as an input and outputs a subset of the components having the most extreme kurtoses.

**Usage**

```
selectComponents(x, first = 2, last = 2)
```

**Arguments**

x	Numeric array of an order at least two. It is assumed that the last dimension corresponds to the sampling units.
first	Number of components with maximal kurtosis to be selected. Can equal zero but the total number of components selected must be at least two.
last	Number of components with minimal kurtosis to be selected. Can equal zero but the total number of components selected must be at least two.

**Details**

In independent component analysis (ICA) the components having the most extreme kurtoses are often thought to be also the most informative. With this viewpoint in mind the function `selectComponents` selects from `x` first components having the highest kurtosis and last components having the lowest kurtoses and outputs them as a standard data matrix for further analysis.

**Value**

Data matrix with rows corresponding to the observations and the columns corresponding to the first + last selected components in decreasing order with respect to kurtosis. The names of the components in the output matrix correspond to the indices of the components in the original array `x`.

**Author(s)**

Joni Virta

**Examples**

```
library(ElemStatLearn)
x <- zip.train

rows <- which(x[, 1] == 0 | x[, 1] == 1)
x0 <- x[rows, 2:257]

x0 <- t(x0)
dim(x0) <- c(16, 16, 2199)

tfobi <- tFOBI(x0)
comp <- selectComponents(tfobi$S)
head(comp)
```

---

tensorBoot

*Bootstrapping or Permuting a Data Tensor*

---

**Description**

The function takes bootstrap samples or permutes its content along the last dimension of the tensor.

**Usage**

```
tensorBoot(x, replace = TRUE)
```

**Arguments**

<code>x</code>	Array of an order of at least two with the last dimension corresponding to the sampling units.
<code>replace</code>	Logical. Should sampling be performed with or without replacement.

**Details**

Assume an array of dimension  $r + 1$ , where the last dimension represents the  $n$  sampling units and the first  $r$  dimensions the data per unit. The function then returns an array of the same dimension as  $x$  where either  $n$  bootstraps samples are selected or the units are permuted.

**Value**

The bootstrapped or permuted samples in an array with the same dimension as  $x$ .

**Author(s)**

Christoph Koesner

**Examples**

```
x <- array(1:50, c(2, 5, 5))
x
tensorBoot(x)
tensorBoot(x, replace = FALSE)

x <- array(1:100, c(2, 5, 2, 5))
x
tensorBoot(x)
```

---

tensorCentering	<i>Center an Array of Observations</i>
-----------------	--

---

**Description**

Centers an array of array-valued observations by subtracting a location array (the mean array by default) from each observation.

**Usage**

```
tensorCentering(x, location = NULL)
```

**Arguments**

$x$	Array of order at least two with the last dimension corresponding to the sampling units.
location	The location to be used in the centering. Either NULL, defaulting to the mean array, or a user-specified $p_1 \times p_2 \times \dots \times p_r$ -dimensional array.

**Details**

Centers a  $p_1 \times p_2 \times \dots \times p_r \times n$ -dimensional array by subtracting the  $p_1 \times p_2 \times \dots \times p_r$ -dimensional location from each of the observed arrays.

**Value**

Array of centered observations with the same dimensions as the input array. The used location is returned as attribute "location".

**Author(s)**

Joni Virta

**Examples**

```
## Generate sample data.
n <- 1000
x <- t(cbind(rnorm(n, mean = 0),
            rnorm(n, mean = 1),
            rnorm(n, mean = 2),
            rnorm(n, mean = 3),
            rnorm(n, mean = 4),
            rnorm(n, mean = 5)))

dim(x) <- c(3, 2, n)

## Centered data
xcen <- tensorCentering(x)

## Check the means of individual cells
apply(xcen, 1:2, mean)
```

---

tensorStandardize      *Standardize an Observation Array*

---

**Description**

Standardizes an array of array-valued observations simultaneously from each mode. The method can be seen as a higher-order analogy for the regular multivariate standardization of random vectors.

**Usage**

```
tensorStandardize(x, location = NULL, scatter = NULL)
```

**Arguments**

x	Array of an order higher than two with the last dimension corresponding to the sampling units.
location	The location to be used in the standardizing. Either NULL, defaulting to the mean array, or a user-specified $p_1 \times p_2 \times \dots \times p_r$ -dimensional array.
scatter	The scatter matrices to be used in the standardizing. Either NULL, defaulting to the m-mode covariance matrices, or a user-specified list of length r of $p_1 \times p_1, \dots, p_r \times p_r$ -dimensional symmetric positive definite matrices.

**Details**

The algorithm first centers the  $n$  observed tensors  $X_i$  using location (either the sample mean, or a user-specified location). Then, if `scatter = NULL`, it estimates the  $m$ th mode covariance matrix  $Cov_m(X) = E(X^{(m)}X^{(m)T})/(p_1 \dots p_{m-1}p_{m+1} \dots p_r)$ , where  $X^{(m)}$  is the centered  $m$ -flattening of  $X$ , for each mode, and transforms the observations with the inverse square roots of the covariance matrices from the corresponding modes. If, instead, the user has specified a non-NULL value for `scatter`, the inverse square roots of those matrices are used to transform the centered data.

**Value**

A list containing the following components:

- `x`                    Array of the same size as `x` containing the standardized observations. The used location and scatters are returned as attributes "location" and "scatter".
- `S`                    List containing inverse square roots of the covariance matrices of different modes.

**Author(s)**

Joni Virta

**Examples**

```
# Generate sample data.
n <- 100
x <- t(cbind(rnorm(n, mean = 0),
            rnorm(n, mean = 1),
            rnorm(n, mean = 2),
            rnorm(n, mean = 3),
            rnorm(n, mean = 4),
            rnorm(n, mean = 5)))

dim(x) <- c(3, 2, n)

# Standardize
z <- tensorStandardize(x)$x

# The m-mode covariance matrices of the standardized tensors
mModeCovariance(z, 1)
mModeCovariance(z, 2)
```

---

tensorTransform

*Linear Transformation of Tensors from mth Mode*

---

**Description**

Applies a linear transformation to the  $m$ th mode of each individual tensor in an array of tensors.

**Usage**

```
tensorTransform(x, A, m)
```

**Arguments**

x	Array of an order at least two with the last dimension corresponding to the sampling units.
A	Matrix corresponding to the desired linear transformation with the number of columns equal to the size of the $m$ th dimension of $x$ .
m	The mode from which the linear transform is to be applied.

**Details**

Applies the linear transformation given by the matrix  $A$  of size  $q_m \times p_m$  to the  $m$ th mode of each of the  $n$  observed tensors  $X_i$  in the given  $p_1 \times p_2 \times \dots \times p_r \times n$ -dimensional array  $x$ . This is equivalent to separately applying the linear transformation given by  $A$  to each  $m$ -mode vector of each  $X_i$ .

**Value**

Array of size  $p_1 \times p_2 \times \dots \times p_{m-1} \times q_m \times p_{m+1} \times \dots \times p_r \times n$

**Author(s)**

Joni Virta

**Examples**

```
# Generate sample data.
n <- 10
x <- t(cbind(rnorm(n, mean = 0),
            rnorm(n, mean = 1),
            rnorm(n, mean = 2),
            rnorm(n, mean = 3),
            rnorm(n, mean = 4),
            rnorm(n, mean = 5)))

dim(x) <- c(3, 2, n)

# Transform from the second mode
A <- matrix(c(2, 1, 0, 3), 2, 2)
z <- tensorTransform(x, A, 2)

# Compare
z[, , 1]
x[, , 1]%*%t(A)
```



**Description**

Applies a linear transformation to user selected modes of each individual tensor in an array of tensors. The function is a generalization of [tensorTransform](#) which only transforms one specific mode.

**Usage**

```
tensorTransform2(x, A, mode, transpose = FALSE)
```

**Arguments**

x	Array of order $r+1 \geq 2$ where the last dimension corresponds to the sampling units.
A	A list of $r$ matrices to apply linearly to the corresponding mode.
mode	subsetting vector indicating which modes should be linearly transformed by multiplying them with the corresponding matrices from A.
transpose	logical. Should the matrices in A be transposed before the mode wise transformations or not.

**Details**

For the modes  $i_1, \dots, i_k$ , specified via mode, the function applies the linear transformation given by the matrix  $A^{i_j}$  of size  $q_{i_j} \times p_{i_j}$  to the  $i_j$ th mode of each of the  $n$  observed tensors  $X_{i_j}$  in the given  $p_1 \times p_2 \times \dots \times p_r \times n$ -dimensional array x.

**Value**

Array with  $r+1$  dimensions where the dimensions specified via mode are transformed.

**Author(s)**

Klaus Nordhausen

**See Also**

[tensorTransform](#)

**Examples**

```

n <- 5
x <- array(rnorm(5*6*7), dim = c(7, 6, 5))
A1 <- matrix(runif(14), ncol = 7)
A2 <- matrix(rexp(18), ncol = 6)
A <- list(A1 = A1, A2 = A2)
At <- list(tA1 = t(A1), tA2 = t(A2))

x1 <- tensorTransform2(x, A, 1)
x2 <- tensorTransform2(x, A, -2)
x3 <- tensorTransform(x, A1, 1)
x1 == x2
x1 == x3
x4 <- tensorTransform2(x, At, -2, TRUE)
x1 == x4
x5 <- tensorTransform2(x, A, 1:2)

```

---

tensorVectorize

*Vectorize an Observation Tensor*


---

**Description**

Vectorizes an array of array-valued observations into a matrix so that each column of the matrix corresponds to a single observational unit.

**Usage**

```
tensorVectorize(x)
```

**Arguments**

**x** Array of an order at least two with the last dimension corresponding to the sampling units.

**Details**

Vectorizes a  $p_1 \times p_2 \times \dots \times p_r \times n$ -dimensional array into a  $p_1 p_2 \dots p_r \times n$ -dimensional matrix, each column of which then corresponds to a single observational unit. The vectorization is done so that the  $r$ th index goes through its cycle the fastest and the first index the slowest.

Note that the output is a matrix of the size "number of variables" x "number of observations", that is, a transpose of the standard format for a data matrix.

**Value**

Matrix whose columns contain the vectorized observed tensors.

**Author(s)**

Joni Virta

**Examples**

```
# Generate sample data.
n <- 100
x <- t(cbind(rnorm(n, mean = 0),
            rnorm(n, mean = 1),
            rnorm(n, mean = 2),
            rnorm(n, mean = 3),
            rnorm(n, mean = 4),
            rnorm(n, mean = 5)))

dim(x) <- c(3, 2, n)

# Matrix of vectorized observations.
vecx <- tensorVectorize(x)

# The covariance matrix of individual tensor elements
cov(t(vecx))
```

tFOBI

*FOBI for Tensor-Valued Observations***Description**

Computes the tensorial FOBI in an independent component model.

**Usage**

```
tFOBI(x, norm = NULL)
```

**Arguments**

x	Numeric array of an order at least two. It is assumed that the last dimension corresponds to the sampling units.
norm	A Boolean vector with number of entries equal to the number of modes in a single observation. The elements tell which modes use the “normed” version of tensorial FOBI. If NULL then all modes use the non-normed version.

**Details**

It is assumed that  $S$  is a tensor (array) of size  $p_1 \times p_2 \times \dots \times p_r$  with mutually independent elements and measured on  $N$  units. The tensor independent component model further assumes that the tensors  $S$  are mixed from each mode  $m$  by the mixing matrix  $A_m$ ,  $m = 1, \dots, r$ , yielding the observed data  $X$ . In R the sample of  $X$  is saved as an [array](#) of dimensions  $p_1, p_2, \dots, p_r, N$ .

tFOBI recovers then based on  $x$  the underlying independent components  $S$  by estimating the  $r$  unmixing matrices  $W_1, \dots, W_r$  using fourth joint moments.

The unmixing can in each mode be done in two ways, using a “non-normed” or “normed” method and this is controlled by the argument `norm`. The authors advocate the general use of non-normed version, see the reference below for their comparison.

If  $x$  is a matrix, that is,  $r = 1$ , the method reduces to FOBI and the function calls `FOBI`.  
For a generalization for tensor-valued time series see `tgFOBI`.

### Value

A list with class 'tbss', inheriting from class 'bss', containing the following components:

<code>S</code>	Array of the same size as $x$ containing the independent components.
<code>W</code>	List containing all the unmixing matrices.
<code>norm</code>	The vector indicating which modes used the "normed" version.
<code>Xmu</code>	The data location.
<code>datatype</code>	Character string with value "iid". Relevant for <code>plot.tbss</code> .

### Author(s)

Joni Virta

### References

Virta, J., Li, B., Nordhausen, K. and Oja, H., (2017), *Independent component analysis for tensor-valued data*, *Journal of Multivariate Analysis*, doi: [10.1016/j.jmva.2017.09.008](https://doi.org/10.1016/j.jmva.2017.09.008)

### See Also

`FOBI`, `tgFOBI`

### Examples

```
n <- 1000
S <- t(cbind(rexp(n)-1,
             rnorm(n),
             runif(n, -sqrt(3), sqrt(3)),
             rt(n,5)*sqrt(0.6),
             (rchisq(n,1)-1)/sqrt(2),
             (rchisq(n,2)-2)/sqrt(4)))

dim(S) <- c(3, 2, n)

A1 <- matrix(rnorm(9), 3, 3)
A2 <- matrix(rnorm(4), 2, 2)

X <- tensorTransform(S, A1, 1)
X <- tensorTransform(X, A2, 2)

tfobi <- tFOBI(X)

MD(tfobi$W[[1]], A1)
MD(tfobi$W[[2]], A2)
tMD(tfobi$W, list(A1, A2))
```

```

# Digit data example

library(ElemStatLearn)
x <- zip.train

rows <- which(x[, 1] == 0 | x[, 1] == 1)
x0 <- x[rows, 2:257]
y0 <- x[rows, 1] + 1

x0 <- t(x0)
dim(x0) <- c(16, 16, 2199)

tfobi <- tFOBI(x0)
plot(tfobi, col=y0)

```

tgFOBI

*gFOBI for Tensor-Valued Time Series***Description**

Computes the tensorial gFOBI for time series where at each time point a tensor of order  $r$  is observed.

**Usage**

```
tgFOBI(x, lags = 0:12, maxiter = 100, eps = 1e-06)
```

**Arguments**

<code>x</code>	Numeric array of an order at least two. It is assumed that the last dimension corresponds to the time.
<code>lags</code>	Vector of integers. Defines the lags used for the computations of the autocovariances.
<code>maxiter</code>	Maximum number of iterations. Passed on to <a href="#">rjd</a> .
<code>eps</code>	Convergence tolerance. Passed on to <a href="#">rjd</a> .

**Details**

It is assumed that  $S$  is a tensor (array) of size  $p_1 \times p_2 \times \dots \times p_r$  measured at time points  $1, \dots, T$ . The assumption is that the elements of  $S$  are mutually independent, centered and weakly stationary time series and are mixed from each mode  $m$  by the mixing matrix  $A_m$ ,  $m = 1, \dots, r$ , yielding the observed time series  $X$ . In R the sample of  $X$  is saved as an [array](#) of dimensions  $p_1, p_2, \dots, p_r, T$ . tgFOBI recovers then based on  $x$  the underlying independent time series  $S$  by estimating the  $r$  unmixing matrices  $W_1, \dots, W_r$  using the lagged fourth joint moments specified by `lags`. This reliance on higher order moments makes the method especially suited for stochastic volatility models. If  $x$  is a matrix, that is,  $r = 1$ , the method reduces to gFOBI and the function calls [gFOBI](#). If `lags = 0` the method reduces to [tFOBI](#).

**Value**

A list with class 'tbss', inheriting from class 'bss', containing the following components:

S	Array of the same size as x containing the estimated uncorrelated sources.
W	List containing all the unmixing matrices
Xmu	The data location.
datatype	Character string with value "ts". Relevant for <code>plot.tbss</code> .

**Author(s)**

Joni Virta

**References**

Virta, J. and Nordhausen, K., (2017), *Blind source separation of tensor-valued time series*. *Signal Processing* 141, 204-216, doi: [10.1016/j.sigpro.2017.06.008](https://doi.org/10.1016/j.sigpro.2017.06.008)

**See Also**

[gFOBI](#), [rjd](#), [tFOBI](#)

**Examples**

```
library("stochvol")
n <- 1000
S <- t(cbind(svsim(n, mu = -10, phi = 0.98, sigma = 0.2, nu = Inf)$y,
            svsim(n, mu = -5, phi = -0.98, sigma = 0.2, nu = 10)$y,
            svsim(n, mu = -10, phi = 0.70, sigma = 0.7, nu = Inf)$y,
            svsim(n, mu = -5, phi = -0.70, sigma = 0.7, nu = 10)$y,
            svsim(n, mu = -9, phi = 0.20, sigma = 0.01, nu = Inf)$y,
            svsim(n, mu = -9, phi = -0.20, sigma = 0.01, nu = 10)$y))
dim(S) <- c(3, 2, n)

A1 <- matrix(rnorm(9), 3, 3)
A2 <- matrix(rnorm(4), 2, 2)

X <- tensorTransform(S, A1, 1)
X <- tensorTransform(X, A2, 2)

tgfobi <- tgFOBI(X)

MD(tgfobi$W[[1]], A1)
MD(tgfobi$W[[2]], A2)
tMD(tgfobi$W, list(A1, A2))
```

tgJADE

*gJADE for Tensor-Valued Time Series***Description**

Computes the tensorial gJADE for time series where at each time point a tensor of order  $r$  is observed.

**Usage**

```
tgJADE(x, lags = 0:12, maxiter = 100, eps = 1e-06)
```

**Arguments**

x	Numeric array of an order at least two. It is assumed that the last dimension corresponds to the time.
lags	Vector of integers. Defines the lags used for the computations of the autocovariances.
maxiter	Maximum number of iterations. Passed on to <a href="#">rjd</a> .
eps	Convergence tolerance. Passed on to <a href="#">rjd</a> .

**Details**

It is assumed that  $S$  is a tensor (array) of size  $p_1 \times p_2 \times \dots \times p_r$  measured at time points  $1, \dots, T$ . The assumption is that the elements of  $S$  are mutually independent, centered and weakly stationary time series and are mixed from each mode  $m$  by the mixing matrix  $A_m$ ,  $m = 1, \dots, r$ , yielding the observed time series  $X$ . In R the sample of  $X$  is saved as an [array](#) of dimensions  $p_1, p_2, \dots, p_r, T$ .

tgJADE recovers then based on  $x$  the underlying independent time series  $S$  by estimating the  $r$  unmixing matrices  $W_1, \dots, W_r$  using the lagged fourth joint moments specified by `lags`. This reliance on higher order moments makes the method especially suited for stochastic volatility models.

If  $x$  is a matrix, that is,  $r = 1$ , the method reduces to gJADE and the function calls [gJADE](#).

If `lags = 0` the method reduces to [tJADE](#).

**Value**

A list with class 'tbss', inheriting from class 'bss', containing the following components:

S	Array of the same size as $x$ containing the estimated uncorrelated sources.
W	List containing all the unmixing matrices
Xmu	The data location.
datatype	Character string with value "ts". Relevant for <a href="#">plot.tbss</a> .

**Author(s)**

Joni Virta

## References

Virta, J. and Nordhausen, K., (2017), *Blind source separation of tensor-valued time series*. *Signal Processing* 141, 204-216, doi: [10.1016/j.sigpro.2017.06.008](https://doi.org/10.1016/j.sigpro.2017.06.008)

## See Also

[gJADE](#), [rjd](#), [tJADE](#)

## Examples

```
library("stochvol")
n <- 1000
S <- t(cbind(svsim(n, mu = -10, phi = 0.98, sigma = 0.2, nu = Inf)$y,
             svsim(n, mu = -5, phi = -0.98, sigma = 0.2, nu = 10)$y,
             svsim(n, mu = -10, phi = 0.70, sigma = 0.7, nu = Inf)$y,
             svsim(n, mu = -5, phi = -0.70, sigma = 0.7, nu = 10)$y,
             svsim(n, mu = -9, phi = 0.20, sigma = 0.01, nu = Inf)$y,
             svsim(n, mu = -9, phi = -0.20, sigma = 0.01, nu = 10)$y))
dim(S) <- c(3, 2, n)

A1 <- matrix(rnorm(9), 3, 3)
A2 <- matrix(rnorm(4), 2, 2)

X <- tensorTransform(S, A1, 1)
X <- tensorTransform(X, A2, 2)

tgjade <- tgJADE(X)

MD(tgjade$W[[1]], A1)
MD(tgjade$W[[2]], A2)
tMD(tgjade$W, list(A1, A2))
```

---

tJADE

*tJADE for Tensor-Valued Observations*

---

## Description

Computes the tensorial JADE in an independent component model.

## Usage

```
tJADE(x, maxiter = 100, eps = 1e-06)
```

## Arguments

x	Numeric array of an order at least two. It is assumed that the last dimension corresponds to the sampling units.
maxiter	Maximum number of iterations. Passed on to <a href="#">rjd</a> .
eps	Convergence tolerance. Passed on to <a href="#">rjd</a> .



## Details

It is assumed that  $S$  is a tensor (array) of size  $p_1 \times p_2 \times \dots \times p_r$  with mutually independent elements and measured on  $N$  units. The tensor independent component model further assumes that the tensors  $S$  are mixed from each mode  $m$  by the mixing matrix  $A_m$ ,  $m = 1, \dots, r$ , yielding the observed data  $X$ . In R the sample of  $X$  is saved as an [array](#) of dimensions  $p_1, p_2, \dots, p_r, N$ .

tJADE recovers then based on  $x$  the underlying independent components  $S$  by estimating the  $r$  unmixing matrices  $W_1, \dots, W_r$  using fourth joint moments in a more efficient way than [tFOBI](#).

If  $x$  is a matrix, that is,  $r = 1$ , the method reduces to JADE and the function calls [JADE](#).

For a generalization for tensor-valued time series see [tgJADE](#).

## Value

A list with class 'tbss', inheriting from class 'bss', containing the following components:

S	Array of the same size as $x$ containing the independent components.
W	List containing all the unmixing matrices
Xmu	The data location.
datatype	Character string with value "iid". Relevant for <a href="#">plot.tbss</a> .

## Author(s)

Joni Virta

## References

Virta J., Li B., Nordhausen K., Oja H. (2018): JADE for tensor-valued observations, *Journal of Computational and Graphical Statistics*, Volume 27, p. 628 - 637, doi: [10.1080/10618600.2017.1407324](https://doi.org/10.1080/10618600.2017.1407324)

## See Also

[JADE](#), [tgJADE](#)

## Examples

```
n <- 1000
S <- t(cbind(rexp(n)-1,
            rnorm(n),
            runif(n, -sqrt(3), sqrt(3)),
            rt(n,5)*sqrt(0.6),
            (rchisq(n,1)-1)/sqrt(2),
            (rchisq(n,2)-2)/sqrt(4)))

dim(S) <- c(3, 2, n)

A1 <- matrix(rnorm(9), 3, 3)
A2 <- matrix(rnorm(4), 2, 2)

X <- tensorTransform(S, A1, 1)
X <- tensorTransform(X, A2, 2)
```

```

tjade <- tJADE(X)

MD(tjade$W[[1]], A1)
MD(tjade$W[[2]], A2)
tMD(tjade$W, list(A1, A2))

## Not run:
# Digit data example
# Running will take a few minutes

library(ElemStatLearn)
x <- zip.train

rows <- which(x[, 1] == 0 | x[, 1] == 1)
x0 <- x[rows, 2:257]
y0 <- x[rows, 1] + 1

x0 <- t(x0)
dim(x0) <- c(16, 16, 2199)

tjade <- tJADE(x0)
plot(tjade, col=y0)

## End(Not run)

```

---

tMD

*Minimum Distance Index of a Kronecker Product*


---

## Description

A shortcut function for computing the minimum distance index of a tensorial ICA estimate on the Kronecker product “scale” (the vectorized space).

## Usage

```
tMD(W.hat, A)
```

## Arguments

W.hat	A list of $r$ unmixing matrix estimates, $W_1, W_2, \dots, W_r$ .
A	A list of $r$ mixing matrices, $A_1, A_2, \dots, A_r$ .

## Details

The function computes the minimum distance index between  $W.hat[[r]] \%x\% \dots \%x\% W.hat[[1]]$  and  $A[[r]] \%x\% \dots \%x\% A[[1]]$ . The index is useful for comparing the performance of a tensor-valued ICA method to that of a method using first vectorization and then some vector-valued ICA method.

**Value**

The value of the MD index of the Kronecker product.

**Author(s)**

Joni Virta

**References**

*Ilmonen, P., Nordhausen, K., Oja, H. and Ollila, E. (2010), A New Performance Index for ICA: Properties, Computation and Asymptotic Analysis. In Vigneron, V., Zarzoso, V., Moreau, E., Gribonval, R. and Vincent, E. (editors) Latent Variable Analysis and Signal Separation, 229-236, Springer.*

*Virta, J., Li, B., Nordhausen, K. and Oja, H., (2017), Independent component analysis for tensor-valued data, Journal of Multivariate Analysis, doi: [10.1016/j.jmva.2017.09.008](https://doi.org/10.1016/j.jmva.2017.09.008)*

**See Also**

[MD](#)

**Examples**

```
n <- 1000
S <- t(cbind(rexp(n)-1,
            rnorm(n),
            runif(n, -sqrt(3), sqrt(3)),
            rt(n,5)*sqrt(0.6),
            (rchisq(n,1)-1)/sqrt(2),
            (rchisq(n,2)-2)/sqrt(4)))

dim(S) <- c(3, 2, n)

A1 <- matrix(rnorm(9), 3, 3)
A2 <- matrix(rnorm(4), 2, 2)

X <- tensorTransform(S, A1, 1)
X <- tensorTransform(X, A2, 2)

tfobi <- tFOBI(X)

MD(tfobi$W[[2]] %x% tfobi$W[[1]], A2 %x% A1)
tMD(list(tfobi$W[[2]]), list(A2))
```

tNSS.JD

*NSS-JD Method for Tensor-Valued Time Series***Description**

Estimates the non-stationary sources of a tensor-valued time series using separation information contained in several time intervals.

**Usage**

```
tNSS.JD(x, K = 12, n.cuts = NULL, eps = 1e-06, maxiter = 100, ...)
```

**Arguments**

x	Numeric array of an order at least two. It is assumed that the last dimension corresponds to the sampling units.
K	The number of equisized intervals into which the time range is divided. If the parameter n.cuts is non-NULL it takes preference over this argument.
n.cuts	Either a interval cutoffs (the cutoffs are used to define the two intervals that are open below and closed above, e.g. $(a, b]$ ) or NULL (the parameter K is used to define the the amount of intervals).
eps	Convergence tolerance for <a href="#">rjd</a> .
maxiter	Maximum number of iterations for <a href="#">rjd</a> .
...	Further arguments to be passed to or from methods.

**Details**

Assume that the observed tensor-valued time series comes from a tensorial BSS model where the sources have constant means over time but the component variances change in time. Then TNSS-JD first standardizes the series from all modes and then estimates the non-stationary sources by dividing the time scale into K intervals and jointly diagonalizing the covariance matrices of the K intervals within each mode.

**Value**

A list with class 'tbss', inheriting from class 'bss', containing the following components:

S	Array of the same size as x containing the independent components.
W	List containing all the unmixing matrices.
K	The number of intervals.
n.cuts	The interval cutoffs.
Xmu	The data location.
datatype	Character string with value "ts". Relevant for <a href="#">plot.tbss</a> .

**Author(s)**

Joni Virta

**References**

Virta J., Nordhausen K. (2017): *Blind source separation for nonstationary tensor-valued time series*, 2017 IEEE 27th International Workshop on Machine Learning for Signal Processing (MLSP), doi: [10.1109/MLSP.2017.8168122](https://doi.org/10.1109/MLSP.2017.8168122)

**See Also**

[NSS.SD](#), [NSS.JD](#), [NSS.TD.JD](#), [tNSS.SD](#), [tNSS.TD.JD](#)

**Examples**

```
# Create innovation series with block-wise changing variances
n1 <- 200
n2 <- 500
n3 <- 300
n <- n1 + n2 + n3
innov1 <- c(rnorm(n1, 0, 1), rnorm(n2, 0, 3), rnorm(n3, 0, 5))
innov2 <- c(rnorm(n1, 0, 1), rnorm(n2, 0, 5), rnorm(n3, 0, 3))
innov3 <- c(rnorm(n1, 0, 5), rnorm(n2, 0, 3), rnorm(n3, 0, 1))
innov4 <- c(rnorm(n1, 0, 5), rnorm(n2, 0, 1), rnorm(n3, 0, 3))

# Generate the observations
vecx <- cbind(as.vector(arima.sim(n = n, list(ar = 0.8), innov = innov1)),
             as.vector(arima.sim(n = n, list(ar = c(0.5, 0.1)), innov = innov2)),
             as.vector(arima.sim(n = n, list(ma = -0.7), innov = innov3)),
             as.vector(arima.sim(n = n, list(ar = 0.5, ma = -0.5), innov = innov4)))

# Vector to tensor
tenx <- t(vecx)
dim(tenx) <- c(2, 2, n)

# Run TNSS-JD
res <- tNSS.JD(tenx, K = 6)
res$W

res <- tNSS.JD(tenx, K = 12)
res$W
```

**Description**

Estimates the non-stationary sources of a tensor-valued time series using separation information contained in two time intervals.

**Usage**

```
tNSS.SD(x, n.cuts = NULL)
```

**Arguments**

x	Numeric array of an order at least two. It is assumed that the last dimension corresponds to the sampling units.
n.cuts	Either a 3-vector of interval cutoffs (the cutoffs are used to define the two intervals that are open below and closed above, e.g. $(a, b]$ ) or NULL (the time range is sliced into two parts of equal size).

**Details**

Assume that the observed tensor-valued time series comes from a tensorial BSS model where the sources have constant means over time but the component variances change in time. Then TNSS-SD estimates the non-stationary sources by dividing the time scale into two intervals and jointly diagonalizing the covariance matrices of the two intervals within each mode.

**Value**

A list with class 'tbss', inheriting from class 'bss', containing the following components:

S	Array of the same size as x containing the independent components.
W	List containing all the unmixing matrices.
EV	Eigenvalues obtained from the joint diagonalization.
n.cuts	The interval cutoffs.
Xmu	The data location.
datatype	Character string with value "ts". Relevant for <code>plot.tbss</code> .

**Author(s)**

Joni Virta

**References**

Virta J., Nordhausen K. (2017): *Blind source separation for nonstationary tensor-valued time series*, 2017 IEEE 27th International Workshop on Machine Learning for Signal Processing (MLSP), doi: [10.1109/MLSP.2017.8168122](https://doi.org/10.1109/MLSP.2017.8168122)

**See Also**

[NSS.SD](#), [NSS.JD](#), [NSS.TD.JD](#), [tNSS.JD](#), [tNSS.TD.JD](#)

**Examples**

```

# Create innovation series with block-wise changing variances

# 9 smooth variance structures
var_1 <- function(n){
  t <- 1:n
  return(1 + cos((2*pi*t)/n)*sin((2*150*t)/(n*pi)))
}

var_2 <- function(n){
  t <- 1:n
  return(1 + sin((2*pi*t)/n)*cos((2*150*t)/(n*pi)))
}

var_3 <- function(n){
  t <- 1:n
  return(0.5 + 8*exp((n+1)^2/(4*t*(t - n - 1))))
}

var_4 <- function(n){
  t <- 1:n
  return(3.443 - 8*exp((n+1)^2/(4*t*(t - n - 1))))
}

var_5 <- function(n){
  t <- 1:n
  return(0.5 + 0.5*gamma(10)/(gamma(7)*gamma(3))*(t/(n + 1))^(7 - 1)*(1 - t/(n + 1))^(3 - 1))
}

var_6 <- function(n){
  t <- 1:n
  res <- var_5(n)
  return(rev(res))
}

var_7 <- function(n){
  t <- 1:n
  return(0.2+2*t/(n + 1))
}

var_8 <- function(n){
  t <- 1:n
  return(0.2+2*(n + 1 - t)/(n + 1))
}

var_9 <- function(n){
  t <- 1:n
  return(1.5 + cos(4*pi*t/n))
}

# Innovation series

```

```

n <- 1000

innov1 <- c(rnorm(n, 0, sqrt(var_1(n))))
innov2 <- c(rnorm(n, 0, sqrt(var_2(n))))
innov3 <- c(rnorm(n, 0, sqrt(var_3(n))))
innov4 <- c(rnorm(n, 0, sqrt(var_4(n))))
innov5 <- c(rnorm(n, 0, sqrt(var_5(n))))
innov6 <- c(rnorm(n, 0, sqrt(var_6(n))))
innov7 <- c(rnorm(n, 0, sqrt(var_7(n))))
innov8 <- c(rnorm(n, 0, sqrt(var_8(n))))
innov9 <- c(rnorm(n, 0, sqrt(var_9(n))))

# Generate the observations
vecx <- cbind(as.vector(arima.sim(n = n, list(ar = 0.9), innov = innov1)),
              as.vector(arima.sim(n = n, list(ar = c(0, 0.2, 0.1, -0.1, 0.7)),
              innov = innov2)),
              as.vector(arima.sim(n = n, list(ar = c(0.5, 0.3, -0.2, 0.1)),
              innov = innov3)),
              as.vector(arima.sim(n = n, list(ma = -0.5), innov = innov4)),
              as.vector(arima.sim(n = n, list(ma = c(0.1, 0.1, 0.3, 0.5, 0.8)),
              innov = innov5)),
              as.vector(arima.sim(n = n, list(ma = c(0.5, -0.5, 0.5)), innov = innov6)),
              as.vector(arima.sim(n = n, list(ar = c(-0.5, -0.3), ma = c(-0.2, 0.1)),
              innov = innov7)),
              as.vector(arima.sim(n = n, list(ar = c(0, -0.1, -0.2, 0.5), ma = c(0, 0.1, 0.1, 0.6)),
              innov = innov8)),
              as.vector(arima.sim(n = n, list(ar = c(0.8), ma = c(0.7, 0.6, 0.5, 0.1)),
              innov = innov9)))

# Vector to tensor
tenx <- t(vecx)
dim(tenx) <- c(3, 3, n)

# Run TNSS-SD
res <- tNSS.SD(tenx)
res$W

```

---

tNSS.TD.JD

*TNSS-TD-JD Method for Tensor-Valued Time Series*


---

## Description

Estimates the non-stationary sources of a tensor-valued time series using separation information contained in several time intervals and lags.

## Usage

```
tNSS.TD.JD(x, K = 12, lags = 0:12, n.cuts = NULL, eps = 1e-06, maxiter = 100, ...)
```



**Arguments**

x	Numeric array of an order at least two. It is assumed that the last dimension corresponds to the sampling units.
K	The number of equisized intervals into which the time range is divided. If the parameter <code>n.cuts</code> is non-NULL it takes preference over this argument.
lags	The lag set for the autocovariance matrices.
n.cuts	Either a interval cutoffs (the cutoffs are used to define the two intervals that are open below and closed above, e.g. $(a, b]$ ) or NULL (the parameter K is used to define the the amount of intervals).
eps	Convergence tolerance for <code>rjd</code> .
maxiter	Maximum number of iterations for <code>rjd</code> .
...	Further arguments to be passed to or from methods.

**Details**

Assume that the observed tensor-valued time series comes from a tensorial BSS model where the sources have constant means over time but the component variances change in time. Then TNSS-TD-JD first standardizes the series from all modes and then estimates the non-stationary sources by dividing the time scale into K intervals and jointly diagonalizing the autocovariance matrices (specified by `lags`) of the K intervals within each mode.

**Value**

A list with class `'tbss'`, inheriting from class `'bss'`, containing the following components:

S	Array of the same size as <code>x</code> containing the independent components.
W	List containing all the unmixing matrices.
K	The number of intervals.
lags	The lag set.
n.cuts	The interval cutoffs.
Xmu	The data location.
datatype	Character string with value "ts". Relevant for <code>plot.tbss</code> .

**Author(s)**

Joni Virta

**References**

Virta J., Nordhausen K. (2017): *Blind source separation for nonstationary tensor-valued time series*, 2017 IEEE 27th International Workshop on Machine Learning for Signal Processing (MLSP), doi: [10.1109/MLSP.2017.8168122](https://doi.org/10.1109/MLSP.2017.8168122)

**See Also**

[NSS.SD](#), [NSS.JD](#), [NSS.TD.JD](#), [tNSS.SD](#), [tNSS.JD](#)

**Examples**

```

# Create innovation series with block-wise changing variances
n1 <- 200
n2 <- 500
n3 <- 300
n <- n1 + n2 + n3
innov1 <- c(rnorm(n1, 0, 1), rnorm(n2, 0, 3), rnorm(n3, 0, 5))
innov2 <- c(rnorm(n1, 0, 1), rnorm(n2, 0, 5), rnorm(n3, 0, 3))
innov3 <- c(rnorm(n1, 0, 5), rnorm(n2, 0, 3), rnorm(n3, 0, 1))
innov4 <- c(rnorm(n1, 0, 5), rnorm(n2, 0, 1), rnorm(n3, 0, 3))

# Generate the observations
vecx <- cbind(as.vector(arima.sim(n = n, list(ar = 0.8), innov = innov1)),
              as.vector(arima.sim(n = n, list(ar = c(0.5, 0.1)), innov = innov2)),
              as.vector(arima.sim(n = n, list(ma = -0.7), innov = innov3)),
              as.vector(arima.sim(n = n, list(ar = 0.5, ma = -0.5), innov = innov4)))

# Vector to tensor
tenx <- t(vecx)
dim(tenx) <- c(2, 2, n)

# Run TNSS-TD-JD
res <- tNSS.TD.JD(tenx)
res$W

res <- tNSS.TD.JD(tenx, K = 6, lags = 0:6)
res$W

```

tPCA

*PCA for Tensor-Valued Observations***Description**

Computes the tensorial principal components.

**Usage**

```
tPCA(x, p = NULL, d = NULL)
```

**Arguments**

- |   |  |
|---|--|
| x | Numeric array of an order at least three. It is assumed that the last dimension corresponds to the sampling units.                   |
| p | A vector of the percentages of variation per each mode the principal components should explain.                                      |
| d | A vector of the exact number of components retained per each mode. At most one of this and the previous argument should be supplied. |

## Details

The observed tensors (array)  $X$  of size  $p_1 \times p_2 \times \dots \times p_r$  measured on  $N$  units are projected from each mode on the eigenspaces of the  $m$ -mode covariance matrices of the corresponding modes. As in regular PCA, by retaining only some subsets of these projections (indices) with respective sizes  $d_1, d_2, \dots, d_r$ , a dimension reduction can be carried out, resulting into observations tensors of size  $d_1 \times d_2 \times \dots \times d_r$ . In R the sample of  $X$  is saved as an `array` of dimensions  $p_1, p_2, \dots, p_r, N$ .

## Value

A list containing the following components:

S	Array of the same size as x containing the principal components.
U	List containing the rotation matrices
D	List containing the amounts of variance explained by each index in each mode.
p_comp	The percentages of variation per each mode that the principal components explain.
Xmu	The data location.

## Author(s)

Joni Virta

## References

Virta, J., Taskinen, S. and Nordhausen, K. (2016), *Applying fully tensorial ICA to fMRI data*, *Signal Processing in Medicine and Biology Symposium (SPMB), 2016 IEEE*, doi: [10.1109/SPMB.2016.7846858](https://doi.org/10.1109/SPMB.2016.7846858)

## Examples

```
# Digit data example

library(ElemStatLearn)
x <- zip.train

rows <- which(x[, 1] == 0 | x[, 1] == 1)
x0 <- x[rows, 2:257]
y0 <- x[rows, 1] + 1

x0 <- t(x0)
dim(x0) <- c(16, 16, 2199)

tpca <- tPCA(x0, d = c(2, 2))
pairs(t(apply(tpca$S, 3, c)), col=y0)
```

tPCAladle

*Ladle Estimate for tPCA***Description**

For r-dimensional tensors, the Ladle estimate for tPCA assumes that for a given mode  $m$ , the last  $p_m - k_m$  modewise eigenvalues are equal. Combining information from the eigenvalues and eigenvectors of the m-mode covariance matrix the ladle estimator yields estimates for  $k_1, \dots, k_r$ .

**Usage**

```
tPCAladle(x, n.boot = 200, ncomp = NULL)
```

**Arguments**

x	array of an order at least two with the last dimension corresponding to the sampling units.
n.boot	number of bootstrapping samples to be used.
ncomp	vector giving the number of components among which the ladle estimator is to be searched for each mode. The default follows the recommendation of Luo and Li 2016.

**Details**

The model here assumes that the eigenvalues of the m-mode covariance matrix are of the form  $\lambda_{1,m} \geq \dots \geq \lambda_{k_m,m} > \lambda_{k_m+1,m} = \dots = \lambda_{p_m,m}$  and the goal is to estimate the value of  $k_m$  for all modes. The ladle estimate for this purpose combines the values of the scaled eigenvalues and the variation of the eigenvectors based on bootstrapping. The idea there is that for distinct eigenvalues the variation of the eigenvectors is small and for equal eigenvalues the corresponding eigenvectors have large variation.

This measure is then computed assuming  $k_m=0, \dots, ncomp[m]$  and the ladle estimate for  $k_m$  is the value where the measure takes its minimum.

**Value**

A list of class 'tladle' containing:

U	list containing the modewise rotation matrices.
D	list containing the modewise eigenvalues.
S	array of the same size as x containing the principal components.
ResMode	a list with the modewise results which are lists containing: <ul style="list-style-type: none"> <li><b>mode</b> label for the mode.</li> <li><b>k</b> the estimated value of k.</li> <li><b>fn</b> vector giving the measures of variation of the eigenvectors using the bootstrapped eigenvectors for the different number of components.</li> </ul>

	<b>phin</b> normalized eigenvalues.
	<b>lambda</b> the unnormalized eigenvalues used to compute phin.
	<b>gn</b> the main criterion for the ladle estimate - the sum of fn and phin. k is the value where gn takes its minimum.
	<b>comp</b> vector from 0 to the number of dimensions to be evaluated.
xmu	the data location
data.name	string with the name of the input data
method	string tPCA.

**Author(s)**

Klaus Nordhausen

**References**

Koesner, C, Nordhausen, K. and Virta, J. (2019), *Estimating the signal tensor dimension using tensorial PCA*. Manuscript.

Luo, W. and Li, B. (2016), *Combining Eigenvalues and Variation of Eigenvectors for Order Determination*, *Biometrika*, 103, 875–887. <doi:10.1093/biomet/asw051>

**See Also**

[tPCA](#), [ggtladleplot](#)

**Examples**

```
library(ICtest)
n <- 500
sig <- 0.6

Z <- rbind(sqrt(0.7)*rt(n,df=5)*sqrt(3/5),
           sqrt(0.3)*runif(n,-sqrt(3),sqrt(3)),
           sqrt(0.3)*(rchisq(n,df=3)-3)/sqrt(6),
           sqrt(0.9)*(rexp(n)-1),
           sqrt(0.1)*rlogis(n,0,sqrt(3)/pi),
           sqrt(0.5)*(rbeta(n,2,2)-0.5)*sqrt(20)
)

dim(Z) <- c(3, 2, n)

U1 <- rorth(12)[,1:3]
U2 <- rorth(8)[,1:2]
U <- list(U1=U1, U2=U2)
Y <- tensorTransform2(Z,U,1:2)
EPS <- array(rnorm(12*8*n, mean=0, sd=sig), dim=c(12,8,n))
X <- Y + EPS

TEST <- tPCAladle(X)
TEST
```

```
ggtheadleplot(TEST)
```

---

tPP

*Projection pursuit for Tensor-Valued Observations*


---

### Description

Applies mode-wise projection pursuit to tensorial data with respect to the chosen measure of interestingness.

### Usage

```
tPP(x, nl = "pow3", eps = 1e-6, maxiter = 100)
```

### Arguments

x	Numeric array of an order at least three. It is assumed that the last dimension corresponds to the sampling units.
nl	The chosen measure of interestingness/objective function. Current choices include pow3 (default) and skew, see the details below
eps	The convergence tolerance of the iterative algorithm.
maxiter	The maximum number of iterations.

### Details

The observed tensors (arrays)  $X$  of size  $p_1 \times p_2 \times \dots \times p_r$  measured on  $N$  units are standardized from each mode and then projected mode-wise onto the directions that maximize the  $L_2$ -norm of the vector of the values  $E[G(u_k^T X X^T u_k)] - E[G(c^2)]$ , where  $G$  is the chosen objective function and  $c^2$  obeys the chi-squared distribution with  $q$  degrees of freedom. Currently the function allows the choices  $G(x) = x^2$  (pow3) and  $G(x) = x\sqrt{x}$  (skew), which correspond roughly to the maximization of kurtosis and skewness, respectively. The algorithm is the multilinear extension of FastICA, where the names of the objective functions also come from.

### Value

A list with class 'tbss', inheriting from class 'bss', containing the following components:

S	Array of the same size as x containing the estimated components.
W	List containing all the unmixing matrices.
iter	The numbers of iteration used per mode.
Xmu	The data location.
datatype	Character string with value "iid". Relevant for <code>plot.tbss</code> .

### Author(s)

Joni Virta

## References

- Nordhausen, K. and Virta, J. (2018), *Tensorial projection pursuit*, Manuscript in preparation.
- Hyvarinen, A. (1999) *Fast and robust fixed-point algorithms for independent component analysis*, *IEEE transactions on Neural Networks* 10.3: 626-634.

## See Also

[fICA](#), [NGPP](#)

## Examples

```
n <- 1000
S <- t(cbind(rexp(n)-1,
            rnorm(n),
            runif(n, -sqrt(3), sqrt(3)),
            rt(n,5)*sqrt(0.6),
            (rchisq(n,1)-1)/sqrt(2),
            (rchisq(n,2)-2)/sqrt(4)))

dim(S) <- c(3, 2, n)

A1 <- matrix(rnorm(9), 3, 3)
A2 <- matrix(rnorm(4), 2, 2)

X <- tensorTransform(S, A1, 1)
X <- tensorTransform(X, A2, 2)

tpp <- tPP(X)

MD(tpp$W[[1]], A1)
MD(tpp$W[[2]], A2)
tMD(tpp$W, list(A1, A2))
```

---

tSIR

*SIR for Tensor-Valued Observations*


---

## Description

Computes the tensorial SIR.

## Usage

```
tSIR(x, y, h = 10, ...)
```

**Arguments**

x	Numeric array of an order at least three. It is assumed that the last dimension corresponds to the sampling units.
y	A numeric or factor response vector.
h	The number of slices. If y is a factor the number of factor levels is automatically used as the number of slices.
...	Arguments passed on to <a href="#">quantile</a> .

**Details**

Computes the mode-wise sliced inverse regression (SIR) estimators for a tensor-valued data set and a univariate response variable.

**Value**

A list with class 'tbss', inheriting from class 'bss', containing the following components:

S	Array of the same size as x containing the predictors.
W	List containing all the unmixing matrices.
Xmu	The data location.
datatype	Character string with value "iid". Relevant for <a href="#">plot.tbss</a> .

**Author(s)**

Joni Virta, Klaus Nordhausen

**Examples**

```
library(ElemStatLearn)
x <- zip.train

rows <- which(x[, 1] == 0 | x[, 1] == 3)
x0 <- x[rows, 2:257]
y0 <- as.factor(x[rows, 1])

x0 <- t(x0)
dim(x0) <- c(16, 16, length(y0))

res <- tSIR(x0, y0)
plot(res$S[1, 1, ], res$S[1, 2, ], col = y0)
```



tSOBI

*SOBI for Tensor-Valued Time Series***Description**

Computes the tensorial SOBI for time series where at each time point a tensor of order  $r$  is observed.

**Usage**

```
tSOBI(x, lags = 1:12, maxiter = 100, eps = 1e-06)
```

**Arguments**

x	Numeric array of an order at least two. It is assumed that the last dimension corresponds to the time.
lags	Vector of integers. Defines the lags used for the computations of the autocovariances.
maxiter	Maximum number of iterations. Passed on to <a href="#">rjd</a> .
eps	Convergence tolerance. Passed on to <a href="#">rjd</a> .

**Details**

It is assumed that  $S$  is a tensor (array) of size  $p_1 \times p_2 \times \dots \times p_r$  measured at time points  $1, \dots, T$ . The assumption is that the elements of  $S$  are uncorrelated, centered and weakly stationary time series and are mixed from each mode  $m$  by the mixing matrix  $A_m$ ,  $m = 1, \dots, r$ , yielding the observed time series  $X$ . In R the sample of  $X$  is saved as an [array](#) of dimensions  $p_1, p_2, \dots, p_r, T$ .

tSOBI recovers then based on  $x$  the underlying uncorrelated time series  $S$  by estimating the  $r$  unmixing matrices  $W_1, \dots, W_r$  using the lagged joint autocovariances specified by `lags`.

If  $x$  is a matrix, that is,  $r = 1$ , the method reduces to SOBI and the function calls [SOBI](#).

**Value**

A list with class 'tbss', inheriting from class 'bss', containing the following components:

S	Array of the same size as $x$ containing the estimated uncorrelated sources.
W	List containing all the unmixing matrices
Xmu	The data location.
datatype	Character string with value "ts". Relevant for <a href="#">plot.tbss</a> .

**Author(s)**

Joni Virta

**References**

Virta, J. and Nordhausen, K., (2017), *Blind source separation of tensor-valued time series*. *Signal Processing* 141, 204-216, doi: [10.1016/j.sigpro.2017.06.008](https://doi.org/10.1016/j.sigpro.2017.06.008)

**See Also**

[SOBI](#), [rjd](#)

**Examples**

```
n <- 1000
S <- t(cbind(as.vector(arima.sim(n = n, list(ar = 0.9))),
            as.vector(arima.sim(n = n, list(ar = -0.9))),
            as.vector(arima.sim(n = n, list(ma = c(0.5, -0.5)))),
            as.vector(arima.sim(n = n, list(ar = c(-0.5, -0.3)))),
            as.vector(arima.sim(n = n, list(ar = c(0.5, -0.3, 0.1, -0.1), ma=c(0.7, -0.3)))),
            as.vector(arima.sim(n = n, list(ar = c(-0.7, 0.1), ma = c(0.9, 0.3, 0.1, -0.1))))))
dim(S) <- c(3, 2, n)

A1 <- matrix(rnorm(9), 3, 3)
A2 <- matrix(rnorm(4), 2, 2)

X <- tensorTransform(S, A1, 1)
X <- tensorTransform(X, A2, 2)

tsobi <- tSOBI(X)

MD(tsobi$W[[1]], A1)
MD(tsobi$W[[2]], A2)
tMD(tsobi$W, list(A1, A2))
```

---

tTUCKER

*Tucker (2) Transformation for a Tensor*


---

**Description**

This is a Tucker (2) transformation of a data tensor where the sampling dimension is uncompressed. The transformation is known also under many different names like multilinear principal components analysis or generalized low rank approximation of matrices if the tensorial data is matrixvalued.

**Usage**

```
tTUCKER(x, ranks, maxiter = 1000, eps = 1e-06)
```

**Arguments**

x	array with $r + 1$ dimensions where the last dimension corresponds to the sampling units.
ranks	vector of length $r$ giving the dimensions of the compressed core tensor.
maxiter	maximum number of iterations for the algorithm.
eps	convergence tolerance.

**Details**

As initial solution tPCA is used and iterated using an alternating least squares (ALS) approach, known also as higher order orthogonal iteration (HOOI).

**Value**

A list containing the following components:

S	array of the compressed tensor.
U	list containing the rotation matrices.
Xmu	the data location.
norm2xc	squared norm of the original data tensor after centering.
norm2rxc	squared norm of the reconstructed (centered) data tensor.
norm2ratio	the ratio $\text{norm2rxc}/\text{norm2xc}$ .
mEV	list containing the eigenvalues from the m-mode covariance matrix when all but the relevant mode have be compressed.
tPCA	The output from tPCA which was used as initial value.

**Author(s)**

Klaus Nordhausen

**References**

Lu, H., Plataniotis, K. and Venetsanopoulos, A. (2008), *MPCA: Multilinear principal component analysis of tensor objects*, *IEEE Transactions on Neural Networks*, 19, 18-39. doi: [10.1109/TNN.2007.901277](https://doi.org/10.1109/TNN.2007.901277)

Lietzen, N., Nordhausen, K. and Virta, J. (2019), *Statistical analysis of second-order tensor decompositions*, *manuscript*.

**See Also**

tPCA

**Examples**

```
library(ElemStatLearn)
x <- zip.train

rows <- which(x[, 1] == 0 | x[, 1] == 1)
x0 <- x[rows, 2:257]
y0 <- x[rows, 1] + 1

x0 <- t(x0)
dim(x0) <- c(16, 16, 2199)

tucker <- tTUCKER(x0, ranks = c(2, 2), eps=1e-03)
pairs(t(apply(tucker$S, 3, c)), col=y0)

# To approximate the original data one uses then
x0r <- tensorTransform2(tucker$S, tucker$U)
```

# Index

## \*Topic **array**

- k\_tJADE, 5
- mModeAutoCovariance, 7
- mModeCovariance, 8
- print.tladle, 11
- tensorBoot, 12
- tensorBSS-package, 2
- tensorCentering, 13
- tensorStandardize, 14
- tensorTransform, 15
- tensorTransform2, 17
- tensorVectorize, 18
- tFOBI, 19
- tgFOBI, 21
- tgJADE, 23
- tJADE, 24
- tMD, 26
- tNSS.JD, 28
- tNSS.SD, 29
- tNSS.TD.JD, 32
- tPCA, 34
- tPCAladle, 36
- tPP, 38
- tSIR, 39
- tSOBI, 41
- tTUCKER, 42

## \*Topic **hplot**

- ggtladleplot, 3

## \*Topic **methods**

- plot.tbss, 9

## \*Topic **multivariate**

- k\_tJADE, 5
- print.tladle, 11
- tensorBSS-package, 2
- tFOBI, 19
- tgFOBI, 21
- tgJADE, 23
- tJADE, 24
- tMD, 26

- tNSS.JD, 28
- tNSS.SD, 29
- tNSS.TD.JD, 32
- tPCA, 34
- tPCAladle, 36
- tPP, 38
- tSIR, 39
- tSOBI, 41
- tTUCKER, 42

## \*Topic **package**

- tensorBSS-package, 2

## \*Topic **ts**

- tensorBSS-package, 2
- tgFOBI, 21
- tgJADE, 23
- tSOBI, 41

## \*Topic **utilities**

- mModeAutoCovariance, 7
- mModeCovariance, 8
- selectComponents, 11
- tensorBoot, 12
- tensorCentering, 13
- tensorStandardize, 14
- tensorTransform, 15
- tensorTransform2, 17
- tensorVectorize, 18

array, 5, 19, 21, 23, 25, 35, 41

fICA, 39

FOBI, 20

gFOBI, 21, 22

ggtladleplot, 3, 37

gJADE, 23, 24

JADE, 6, 25

k\_JADE, 5, 6

k\_tJADE, 5

MD, [27](#)  
mModeAutoCovariance, [7](#), [9](#)  
mModeCovariance, [7](#), [8](#)

NGPP, [39](#)  
NSS.JD, [29](#), [30](#), [33](#)  
NSS.SD, [29](#), [30](#), [33](#)  
NSS.TD.JD, [29](#), [30](#), [33](#)

pairs, [10](#)  
plot.tbss, [5](#), [9](#), [20](#), [22](#), [23](#), [25](#), [28](#), [30](#), [33](#), [38](#),  
[40](#), [41](#)  
plot.ts, [10](#)  
print.tladle, [11](#)

quantile, [40](#)

rjd, [5](#), [21–24](#), [28](#), [33](#), [41](#), [42](#)

selectComponents, [9](#), [10](#), [11](#)  
SOBI, [41](#), [42](#)

tensorBoot, [12](#)  
tensorBSS (tensorBSS-package), [2](#)  
tensorBSS-package, [2](#)  
tensorCentering, [13](#)  
tensorStandardize, [14](#)  
tensorTransform, [15](#), [17](#)  
tensorTransform2, [17](#)  
tensorVectorize, [18](#)  
tFOBI, [5](#), [19](#), [21](#), [22](#), [25](#)  
tgFOBI, [20](#), [21](#)  
tgJADE, [23](#), [25](#)  
tJADE, [5](#), [6](#), [23](#), [24](#), [24](#)  
tMD, [26](#)  
tNSS.JD, [28](#)  
tNSS.SD, [29](#)  
tNSS.TD.JD, [32](#)  
tPCA, [34](#), [37](#), [43](#)  
tPCAladle, [4](#), [36](#)  
tPP, [38](#)  
tSIR, [39](#)  
tSOBI, [10](#), [41](#)  
tTUCKER, [42](#)