Package ‘fastICA’

Version 1.2-4
Date 2023-11-27
Title FastICA Algorithms to Perform ICA and Projection Pursuit
Author J L Marchini, C Heaton and B D Ripley <ripley@stats.ox.ac.uk>
Maintainer Brian Ripley <ripley@stats.ox.ac.uk>
Depends R (>= 4.0.0)
Suggests MASS
Description Implementation of FastICA algorithm to perform Independent Component Analysis (ICA) and Projection Pursuit.
License GPL-2 | GPL-3
NeedsCompilation yes
Repository CRAN
Date/Publication 2023-11-27 08:34:50 UTC

R topics documented:

<table>
<thead>
<tr>
<th>fastICA</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>ica.R.def</td>
<td>5</td>
</tr>
<tr>
<td>ica.R.par</td>
<td>6</td>
</tr>
</tbody>
</table>

Index 7

Description

This is an R and C code implementation of the FastICA algorithm of Aapo Hyvarinen et al. (https://www.cs.helsinki.fi/u/ahyvarin/) to perform Independent Component Analysis (ICA) and Projection Pursuit.
Usage

fastICA(X, n.comp, alg.typ = c("parallel","deflation"),
        fun = c("logcosh","exp"), alpha = 1.0, method = c("R","C"),
        row.norm = FALSE, maxit = 200, tol = 1e-04, verbose = FALSE,
        w.init = NULL)

Arguments

X a data matrix with n rows representing observations and p columns representing variables.

n.comp number of components to be extracted

alg.typ if alg.typ == "parallel" the components are extracted simultaneously (the default). if alg.typ == "deflation" the components are extracted one at a time.

fun the functional form of the $G$ function used in the approximation to neg-entropy (see 'details').

alpha constant in range $[1, 2]$ used in approximation to neg-entropy when fun == "logcosh"

method if method == "R" then computations are done exclusively in R (default). The code allows the interested R user to see exactly what the algorithm does. if method == "C" then C code is used to perform most of the computations, which makes the algorithm run faster. During compilation the C code is linked to an optimized BLAS library if present, otherwise stand-alone BLAS routines are compiled.

row.norm a logical value indicating whether rows of the data matrix X should be standardized beforehand.

maxit maximum number of iterations to perform.

tol a positive scalar giving the tolerance at which the un-mixing matrix is considered to have converged.

verbose a logical value indicating the level of output as the algorithm runs.

w.init Initial un-mixing matrix of dimension c(n.comp, n.comp). If NULL (default) then a matrix of normal r.v.'s is used.

Details

Independent Component Analysis (ICA)

The data matrix X is considered to be a linear combination of non-Gaussian (independent) components i.e. $X = SA$ where columns of S contain the independent components and A is a linear mixing matrix. In short ICA attempts to 'un-mix' the data by estimating an un-mixing matrix W where $XW = S$.

Under this generative model the measured 'signals' in X will tend to be 'more Gaussian' than the source components (in S) due to the Central Limit Theorem. Thus, in order to extract the independent components/sources we search for an un-mixing matrix W that maximizes the non-gaussianity of the sources.
In FastICA, non-gaussianity is measured using approximations to neg-entropy \((J)\) which are more robust than kurtosis-based measures and fast to compute.

The approximation takes the form

\[
J(y) = |\mathbb{E}\{G(y)\} - \mathbb{E}\{G(v)\}|^2
\]

where \(v\) is a \(N(0,1)\) r.v.

The following choices of \(G\) are included as options \(G(u) = \frac{1}{\alpha} \log \cosh(\alpha u)\) and \(G(u) = -\exp(u^2/2)\).

**Algorithm**

First, the data are centered by subtracting the mean of each column of the data matrix \(X\).

The data matrix is then ‘whitened’ by projecting the data onto its principal component directions i.e. \(X \rightarrow XK\) where \(K\) is a pre-whitening matrix. The number of components can be specified by the user.

The ICA algorithm then estimates a matrix \(W\) s.t \(XKW = S\). \(W\) is chosen to maximize the neg-entropy approximation under the constraints that \(W\) is an orthonormal matrix. This constraint ensures that the estimated components are uncorrelated. The algorithm is based on a fixed-point iteration scheme for maximizing the neg-entropy.

**Projection Pursuit**

In the absence of a generative model for the data the algorithm can be used to find the projection pursuit directions. Projection pursuit is a technique for finding ‘interesting’ directions in multi-dimensional datasets. These projections and are useful for visualizing the dataset and in density estimation and regression. Interesting directions are those which show the least Gaussian distribution, which is what the FastICA algorithm does.

**Value**

A list containing the following components

\(X\)   pre-processed data matrix
\(K\)   pre-whitening matrix that projects data onto the first \(n\).comp principal components.
\(W\)   estimated un-mixing matrix (see definition in details)
\(A\)   estimated mixing matrix
\(S\)   estimated source matrix

**Author(s)**

J L Marchini and C Heaton

**References**


**See Also**

ica.R.def, ica.R.par
Examples

#---------------------------------------------------
#Example 1: un-mixing two mixed independent uniforms
#---------------------------------------------------

S <- matrix(runif(10000), 5000, 2)
A <- matrix(c(1, 1, -1, 3), 2, 2, byrow = TRUE)
X <- S %*% A

a <- fastICA(X, 2, alg.typ = "parallel", fun = "logcosh", alpha = 1,
             method = "C", row.norm = FALSE, maxit = 200,
             tol = 0.0001, verbose = TRUE)

par(mfrow = c(1, 3))
plot(a$X, main = "Pre-processed data")
plot(a$X %*% a$K, main = "PCA components")
plot(a$S, main = "ICA components")

#------------------------------------------------------------
#Example 2: un-mixing two independent signals
#------------------------------------------------------------

S <- cbind(sin((1:1000)/20), rep(((1:200)-100)/100, 5))
A <- matrix(c(0.291, 0.6557, -0.5439, 0.5572), 2, 2)
X <- S %*% A

a <- fastICA(X, 2, alg.typ = "parallel", fun = "logcosh", alpha = 1,
             method = "R", row.norm = FALSE, maxit = 200,
             tol = 0.0001, verbose = TRUE)

par(mfcol = c(2, 3))
plot(1:1000, S[,1], type = "l", main = "Original Signals",
     xlab = "", ylab = "")
plot(1:1000, S[,2], type = "l", xlab = "", ylab = "")
plot(1:1000, X[,1], type = "l", main = "Mixed Signals",
     xlab = "", ylab = "")
plot(1:1000, X[,2], type = "l", xlab = "", ylab = "")
plot(1:1000, a$S[,1], type = "l", main = "ICA source estimates",
     xlab = "", ylab = "")
plot(1:1000, a$S[,2], type = "l", xlab = "", ylab = "")

#------------------------------------------------------------
#Example 3: using FastICA to perform projection pursuit on a
#mixture of bivariate normal distributions
#------------------------------------------------------------

if(require(MASS)){
x <- mvrnorm(n = 1000, mu = c(0, 0), Sigma = matrix(c(10, 3, 3, 1), 2, 2))
x1 <- mvrnorm(n = 1000, mu = c(-1, 2), Sigma = matrix(c(10, 3, 3, 1), 2, 2))
X <- rbind(x, x1)
a <- fastICA(X, 2, alg.typ = "deflation", fun = "logcosh", alpha = 1,
\begin{verbatim}
method = "R", row.norm = FALSE, maxit = 200,
tol = 0.0001, verbose = TRUE)
par(mfrow = c(1, 3))
plot(a$X, main = "Pre-processed data")
plot(a$X %*% a$K, main = "PCA components")
plot(a$S, main = "ICA components")
}\end{verbatim}

\textit{Description} \\
\textit{R code for FastICA using a deflation scheme in which the components are estimated one by one. This function is called by the \texttt{fastICA} function.}

\textit{Usage} \\
ica.R.def(X, n.comp, tol, fun, alpha, maxit, verbose, w.init)

\textit{Arguments} \\
X data matrix  
n.comp number of components to be extracted  
tol a positive scalar giving the tolerance at which the un-mixing matrix is considered to have converged.  
fun the functional form of the $G$ function used in the approximation to negentropy.  
alpha constant in range $[1,2]$ used in approximation to negentropy when \texttt{fun} == \texttt{"logcosh"}  
maxit maximum number of iterations to perform  
verbose a logical value indicating the level of output as the algorithm runs.  
w.init Initial value of un-mixing matrix.

\textit{Details} \\
See the help on \texttt{fastICA} for details.

\textit{Value} \\
The estimated un-mixing matrix W.

\textit{Author(s)} \\
J L Marchini and C Heaton

\textit{See Also} \\
\texttt{fastICA,ica.R.par}
R code for FastICA using a parallel scheme

Description

R code for FastICA using a parallel scheme in which the components are estimated simultaneously. This function is called by the fastICA function.

Usage

ica.R.par(X, n.comp, tol, fun, alpha, maxit, verbose, w.init)

Arguments

- **X**: data matrix.
- **n.comp**: number of components to be extracted.
- **tol**: a positive scalar giving the tolerance at which the un-mixing matrix is considered to have converged.
- **fun**: the functional form of the $G$ function used in the approximation to negentropy.
- **alpha**: constant in range $[1,2]$ used in approximation to negentropy when fun == "logcosh".
- **maxit**: maximum number of iterations to perform.
- **verbose**: a logical value indicating the level of output as the algorithm runs.
- **w.init**: Initial value of un-mixing matrix.

Details

See the help on fastICA for details.

Value

The estimated un-mixing matrix W.

Author(s)

J L Marchini and C Heaton

See Also

fastICA, ica.R.def
Index

* multivariate
  fastICA, 1

* utilities
  ica.R.def, 5
  ica.R.par, 6

fastICA, 1, 5, 6

ica.R.def, 3, 5, 6
ica.R.par, 3, 5, 6