Package ‘nets’

October 27, 2020

Type Package
Title Network Estimation for Time Series
Version 0.9.1
Date 2020-10-27
Author Christian Brownlees
Maintainer Christian Brownlees <christian.brownlees@upf.edu>
Imports stats, igraph
Description Sparse VAR estimation based on LASSO.
License GPL
LazyLoad yes
URL https://github.com/ctbrownlees/R-Package-nets
Repository CRAN
NeedsCompilation yes
Date/Publication 2020-10-27 18:30:02 UTC

R topics documented:

<table>
<thead>
<tr>
<th>nets-package</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>nets</td>
<td>2</td>
</tr>
</tbody>
</table>

Index

---

nets-package

Network Estimator for Time Series

Description

The NETS package provides routines for the estimation of sparse VAR models.

Details
Author(s)

Christian Brownlees
Maintainer: Christian Brownlees

References


nets
Network Estimation for Time Series

description

'nets' is used to fit sparse VARs using the NETS algorithm.

Usage

nets(y, GN=TRUE, CN=TRUE, p=1, lambda, alpha.init=NULL, rho.init=NULL, 
algorithm='activeshooting', weights='adaptive', 
iter.in=100, iter.out=2, verbose=FALSE)

Arguments

y data, an T x N matrix, each column being a time series.
GN Estimate the Autoregressive VAR matrices (default true)
CN Estimate the Concentration matrix of the VAR innovations (default true)
p VAR order (default 1)
lambda shrinkage parameter either a scalar or a vector of size two 
alpha.init initial value of the alpha parameter
**nets**

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>rho.init</td>
<td>initial value of the rho parameter</td>
</tr>
<tr>
<td>algorithm</td>
<td>lasso optimization algorithm ‘shooting’ or ‘activeshooting’ (default)</td>
</tr>
<tr>
<td>weights</td>
<td>lasso weights: ‘none’ or ‘adaptive’ (default)</td>
</tr>
<tr>
<td>iter.in</td>
<td>maximum number of in iterations (default 100)</td>
</tr>
<tr>
<td>iter.out</td>
<td>maximum number of out iterations (default 2)</td>
</tr>
<tr>
<td>verbose</td>
<td>extra output messages</td>
</tr>
</tbody>
</table>

**Details**

The `nets` procedure estimates sparse Vector Autoregression (VAR) models by LASSO. In particular, the routine can be used to estimate: (i) the autoregressive matrices of the VAR model and the concentration matrix of the VAR innovations via the nets algorithm (GN=TRUE and CN=TRUE) (ii) the autoregressive matrices of the VAR model via the LASSO algorithm (GN=TRUE and CN=FALSE), (iii) the concentration matrix of data via the space algorithm of Peng et al. (2009) (GN=FALSE and CN=TRUE). Notice that in this last case the order \( p \) of the VAR is automatically set to zero.

In case (i) the penalty parameter lambda can be either set to a single scalar or two a vector of size two. In the former case all the parameters of the model are penalized using the single value of lambda provided while in the latter the first entry is the vector used to penalize the autoregressive coefficients and the second entry for the contemporaneous correlation coefficients. In case (ii) and (iii) the penalty parameter lambda has to be a single scalar.

Two variants of the LASSO algorithm are implemented: "shooting" and "activeshooting". The second can be significantly faster when the model is sparse.

If the weights variable is set to 'none' the model is estimated using the standard lasso. If the weights variable is set to 'adaptive' the model is estimated using the 'adaptive' lasso.

The iter.in variable sets the maximum number of lasso iterations. The iter.out variable sets the number of times the lasso algorithm is reiterated. This is only relevant for the space and nets algorithms. See Peng et al. (2009) and Barigozzi and Brownlees (2016) for details.

The `nets` procedure returns an object of class "nets"

The function "print" is used to print a summary of the estimation results of a "nets" object.

The function "predict" is used to predict the future realizations of the VAR using a "nets" object and a sample of new observation.

**Value**

An object of class "nets" is a list containing at least the following components:

A.hat: an \( N \times N \times P \) array containing the estimated autoregressive matrices

C.hat: an \( N \times N \) matrix containing the estimated concentration matrix

alpha.hat: \( (N^2 \times P) \times 1 \) vector of autoregressive parameters stacked in a vector

rho.hat: \( (N^2(N+1)/2) \times 1 \) vector of partial correlations associated with the concentration matrix of the var innovations stacked in a vector

c.hat: \( N \times 1 \) vector of diagonal entries of the diagonal entries of the concentration matrix of the var innovations
nets

g.adj: Adjacency matrix associated with the Granger network implied by the VAR autoregressive matrices

c.adj: Adjacency matrix associated with the contemporaneous network implied by the VAR innovation concentration matrix

Author(s)
Christian Brownlees

References


Examples

```r
N <- 5
P <- 3
T <- 1000

A <- array(0,dim=c(N,N,P))
C <- matrix(0,N,N)

A[,1] <- 0.7 * diag(N)
A[,2] <- 0.2 * diag(N)
A[1,2,1] <- 0.2
A[4,3,2] <- 0.2

C <- diag(N)
C[1,1] <- 2
C[4,2] <- -0.2
C[2,4] <- -0.2
C[1,3] <- -0.1
C[1,3] <- -0.1

Sig <- solve(C)
L <- t(chol(Sig))

y <- matrix(0,T,N)
eps <- rep(0,N)

for( t in (P+1):T ){
  z <- rnorm(N)
  for( i in 1:N ){
    eps[i] <- sum( L[i,] * z )
    y[i,] <- sum( L[i,] * z )
  }
}
```
nets

for( l in 1:P ){
  for( i in 1:N ){
    y[t,i] <- y[t,i] + sum(A[i,,l] * y[t-l,])
  }
}

y[t,] <- y[t,] + eps

lambda <- c(1,2)

system.time( mdl <- nets(y,P,lambda=lambda*T,verbose=TRUE) )

mdl
Index

* multivariate timeseries
  nets, 2
* network
  nets, 2
* package
  nets-package, 1

nets, 2
nets-package, 1

predict.nets (nets), 2
print.nets (nets), 2