Package ‘fnets’

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Type Package

Title Factor-adjusted Network Estimation and Forecasting for High-dimensional Time Series

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Description Implements methods for network estimation and forecasting of high-dimensional time series exhibiting strong serial and cross-sectional correlations under a factor-adjusted vector autoregressive model.

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R topics documented:

`common.predict` *Forecasting the factor-driven common component*

Description

Produces forecasts of the common component for a given forecasting horizon by estimating the best linear predictors

Usage

```
common.predict(
  object,
  x,
  h = 1,
  common.method = c("restricted", "unrestricted"),
  r = NULL
)
```

Arguments

`object`	`fnets` object
`x`	input time series matrix, with each row representing a variable
`h`	forecasting horizon
`common.method`	a string specifying the method for common component forecasting; possible values are: • `"restricted"` performs forecasting under a restrictive static factor model • `"unrestricted"` performs forecasting under an unrestrictive, blockwise VAR representation of the common component
`r`	number of static factors; if `common.method = "restricted"` and `r = NULL`, it is estimated as the maximiser of the ratio of the successive eigenvalues of the estimate of the common component covariance matrix, see Ahn and Horenstein (2013)

Value

a list containing

`is`	in-sample estimator of the common component
`fc`	forecasts of the common component for a given forecasting horizon `h`
`r`	static factor number
`h`	forecast horizon

References

Barigozzi, M., Cho, H. & Owens, D. (2021) FNETS: Factor-adjusted network analysis for high-dimensional time series.

Ahn, S. C. & Horenstein, A. R. (2013) Eigenvalue ratio test for the number of factors. Econometrica, 81(3), 1203–1227.

Forni, M., Hallin, M., Lippi, M. & Reichlin, L. (2005). The generalized dynamic factor model: one-sided estimation and forecasting. Journal of the American Statistical Association, 100(471), 830–840.

Forni, M., Hallin, M., Lippi, M. & Zaffaroni, P. (2017). Dynamic factor models with infinite-dimensional factor space: Asymptotic analysis. Journal of Econometrics, 199(1), 74–92.

Examples

```
set.seed(123)
n <- 500
p <- 50
common <- sim.common1(n, p)
idio <- sim.var(n, p)
x <- common$data + idio$data
out <- fnets(x, q = NULL, idio.var.order = 1, idio.method = "lasso", lrpc.method = "none")
cpre <- common.predict(out, x, h = 1, common.method = 'restricted', r = NULL)
ipre <- idio.predict(out, x, cpre, h = 1)
```

---

fnets *Factor-adjusted network estimation*

Description

Operating under factor-adjusted vector autoregressive (VAR) model, the function estimates the spectral density and autocovariance matrices of the factor-driven common component and the idiosyncratic VAR process, the impulse response functions and common shocks for the common component, and VAR parameters, innovation covariance matrix and long-run partial correlations for the idiosyncratic component.

Usage

```
fnets(
  x,
  center = TRUE,
  q = NULL,
  ic.op = 5,
  kern.const = 4,
 common.args = list(var.order = NULL, max.var.order = NULL, trunc.lags = 20, n.perm =
    10),
  idio.var.order = 1,
  idio.method = c("lasso", "ds"),
  lrpc.method = c("par", "npar", "none"),
  cv.args = list(n.folds = 1, path.length = 10, do.plot = FALSE)
)
```

Arguments

x	input time series matrix, with each row representing a variable
center	whether to de-mean the input x row-wise
q	number of factors. If q = NULL, the factor number is estimated by an information criterion-based approach of Hallin and Liška (2007), see hl.factor.number for further details

`ic.op`	choice of the information criterion, see hl.factor.number for further details
`kern.const`	constant multiplied to `floor((dim(x)[2]/log(dim(x)[2]))^(1/3)))` which determines the kernel bandwidth for dynamic PCA
`common.args`	a list specifying the tuning parameters required for estimating the impulse response functions and common shocks. It contains: • `var.order` order of the blockwise VAR representation of the common component. If `var.order = NULL`, it is selected blockwise by Schwarz criterion • `max.var.order` maximum blockwise VAR order for the Schwarz criterion • `trunc.lags` truncation lag for impulse response function estimation • `n.perm` number of cross-sectional permutations involved in impluse response function estimation
`idio.var.order`	order of the idiosyncratic VAR process; if a vector of integers is supplied, the order is chosen via cross validation
`idio.method`	a string specifying the method to be adopted for idiosyncratic VAR process estimation; possible values are: • `"lasso"` Lasso-type `l1`-regularised `M`-estimation • `"ds"` Dantzig Selector-type constrained `l1`-minimisation
`lrpc.method`	a string specifying the type of estimator for long-run partial correlation matrix estimation; possible values are: • `"par"` parametric estimator based on the VAR model assumption • `"npar"` nonparametric estimator from inverting the long-run covariance matrix of the idiosyncratic component via constrained `l1`-minimisation • `"none"` do not estimate the long-run partial correlation matrix
`cv.args`	a list specifying arguments for the cross validation procedures for selecting the tuning parameters involved in VAR parameter and (long-run) partial correlation matrix estimation. It contains: • `n.folds` number of folds • `path.length` number of regularisation parameter values to consider; a sequence is generated automatically based in this value • `do.plot` whether to plot the output of the cross validation step

Details

See Barigozzi, Cho and Owens (2021) for further details.

Value

an S3 object of class `fnets`, which contains the following fields:

`q`	number of factors
`spec`	a list containing estimates of the spectral density matrices for `x`, common and idiosyncratic components
`acv`	a list containing estimates of the autocovariance matrices for `x`, common and idiosyncratic components
`common.irf`	if `q >= 1`, a list containing estimators of the impulse response functions (as an array of dimension `(p,q,trunc.lags + 2)`) and common shocks (an array of dimension `(q,n)`) for the common component
`idio.var`	a list containing the following fields:

- `beta` estimate of VAR parameter matrix; each column contains parameter estimates for the regression model for a given variable
- `Gamma` estimate of the innovation covariance matrix
- `lambda` regularisation parameter
- `var.order` VAR order

`lrpc` see the output of par.lrpc if `lrpc.method = 'par'` and that of npar.lrpc if `lrpc.method = 'npar'`

`mean.x` if `center = TRUE`, returns a vector containing row-wise sample means of `x`; if `center = FALSE`, returns a vector of zeros

`idio.method` input parameter

`lrpc.method` input parameter

`kern.const` input parameter

References

Barigozzi, M., Cho, H. & Owens, D. (2021) FNETS: Factor-adjusted network analysis for high-dimensional time series.

Hallin, M. & Liška, R. (2007) Determining the number of factors in the general dynamic factor model. Journal of the American Statistical Association, 102(478), 603–617.

See Also

predict.fnets, plot.fnets

Examples

```
## Not run:
set.seed(123)
n <- 500
p <- 50
common <- sim.common1(n, p)
idio <- sim.var(n, p)
x <- common$data + idio$data
out <- fnets(x, q = NULL, idio.var.order = 1, idio.method = "lasso",
lrpc.method = "par", cv.args = list(n.folds = 1, path.length = 10, do.plot = TRUE))
pre <- predict(out, x, h = 1, common.method = 'unrestricted')
plot(out, type = 'granger', display = 'network', threshold = .05)
plot(out, type = 'lrpc', display = 'heatmap', threshold = .05)

## End(Not run)
```

`fnets.var` *`l1`-regularised Yule-Walker estimation for VAR processes*

Description

Estimates the VAR parameter matrices via `l1`-regularised Yule-Walker estimation and innovation covariance matrix via constrained `l1`-minimisation.

Usage

```
fnets.var(
  x,
  center = TRUE,
  method = c("lasso", "ds"),
  lambda = NULL,
  var.order = 1,
  cv.args = list(n.folds = 1, path.length = 10, do.plot = FALSE),
  n.iter = 100,
  tol = 0,
  n.cores = min(parallel::detectCores() - 1, 3)
)
```

Arguments

`x`	input time series matrix, with each row representing a variable
`center`	whether to de-mean the input `x` row-wise
`method`	a string specifying the method to be adopted for VAR process estimation; possible values are: • `"lasso"` Lasso-type `l1`-regularised `M`-estimation • `"ds"` Dantzig Selector-type constrained `l1`-minimisation
`lambda`	regularisation parameter; if `lambda = NULL`, cross validation is employed to select the parameter
`var.order`	order of the VAR process; if a vector of integers is supplied, the order is chosen via cross validation
`cv.args`	a list specifying arguments for the cross validation procedure for selecting the regularisation parameter (and VAR order). It contains: • `n.folds` number of folds • `path.length` number of regularisation parameter values to consider; a sequence is generated automatically based in this value • `do.plot` whether to plot the output of the cross validation step
`n.iter`	maximum number of descent steps; applicable when `method = "lasso"`
`tol`	numerical tolerance for increases in the loss function; applicable when `method = "lasso"`
`n.cores`	number of cores to use for parallel computing, see makePSOCKcluster; applicable when `method = "ds"`

Details

Further information can be found in Barigozzi, Cho and Owens (2021).

Value

a list which contains the following fields:

`beta`	estimate of VAR parameter matrix; each column contains parameter estimates for the regression model for a given variable
`Gamma`	estimate of the innovation covariance matrix
`lambda`	regularisation parameter

`var.order`	VAR order
`mean.x`	if `center = TRUE`, returns a vector containing row-wise sample means of `x`; if `center = FALSE`, returns a vector of zeros

References

Barigozzi, M., Cho, H. & Owens, D. (2021) FNETS: Factor-adjusted network analysis for high-dimensional time series.

Examples

```
library(fnets)

set.seed(123)
n <- 500
p <- 50
idio <- sim.var(n, p)
x <- idio$data

fv <- fnets.var(x, center = TRUE, method = 'lasso', var.order = 1,
                cv.args = list(n.folds = 1, path.length = 10, do.plot = TRUE))
norm(fv$beta - t(idio$A), 'F')/norm(t(idio$A), 'F')
```

`hl.factor.number` *Factor number estimator of Hallin and Liška (2007)*

Description

Estimates the number of factors by minimising an information criterion over sub-samples of the data. Currently the three information criteria proposed in Hallin and Liška (2007) (`ic.op = 1,2` or `3`) and their variations with logarithm taken on the cost (`ic.op = 4,5` or `6`) are implemented, with `ic.op = 5` recommended as a default choice based on numerical experiments.

Usage

```
hl.factor.number(x, q.max = NULL, mm, w = NULL, do.plot = FALSE, center = TRUE)
```

Arguments

`x`	input time series matrix, with each row representing a variable
`q.max`	maximum number of factors; if `q.max = NULL`, a default value is selected as `min(50,floor(sqrt(min(dim(x)[2] -1,dim(x)[1]))))`
`mm`	integer representing the kernel bandwidth
`w`	vector of length `2 * mm + 1` containing symmetric weights; if `w = NULL`, default weights are generated using the Bartlett kernel and `mm`
`do.plot`	whether to plot the values of six information criteria
`center`	whether to de-mean the input `x` row-wise

Details

See Hallin and Liška (2007) for further details.

Value

a list containing

q.hat	a vector containing minimisers of the six information criteria
Gamma_x	an array containing the estimates of the autocovariance matrices of x at 2 * mm + 1 lags
Sigma_x	an array containing the estimates of the spectral density matrices of x at 2 * mm + 1 Fourier frequencies
sv	a list containing the singular value decomposition of Sigma_x

References

Hallin, M. & Liška, R. (2007) Determining the number of factors in the general dynamic factor model. Journal of the American Statistical Association, 102(478), 603–617.

Examples

```
library(fnets)

set.seed(123)
n <- 500
p <- 50
common <- sim.common2(n, p)
idio <- sim.var(n, p)
x <- common$data * apply(idio$data, 1, sd)/apply(common$data, 1, sd) + idio$data

hl <- hl.factor.number(x, q.max = NULL, mm = floor(4 * (n/log(n))^(1/3)), do.plot = TRUE)
hl$q
```

---

idio.predict — *Forecasting idiosyncratic VAR process*

Description

Produces forecasts of the idiosyncratic VAR process for a given forecasting horizon by estimating the best linear predictors

Usage

```
idio.predict(object, x, cpre, h = 1)
```

Arguments

object	fnets object
x	input time series matrix, with each row representing a variable
cpre	output of common.predict
h	forecast horizon

Value

a list containing

`is`	in-sample estimator of the idiosyncratic component
`fc`	forecasts of the idiosyncratic component for a given forecasting horizon `h`
`h`	forecast horizon

References

Barigozzi, M., Cho, H. & Owens, D. (2021) FNETS: Factor-adjusted network analysis for high-dimensional time series.

Examples

```
set.seed(123)
n <- 500
p <- 50
common <- sim.common1(n, p)
idio <- sim.var(n, p)
x <- common$data + idio$data
out <- fnets(x, q = NULL, idio.var.order = 1, idio.method = "lasso", lrpc.method = "none")
cpre <- common.predict(out, x, h = 1, common.method = 'restricted', r = NULL)
ipre <- idio.predict(out, x, cpre, h = 1)
```

`npar.lrpc` *Nonparametric estimation of long-run partial correlations of factor-adjusted VAR processes*

Description

Returns a nonparametric estimate of long-run partial correlations of the VAR process from the inverse of long-run covariance matrix obtained via constrained `l1`-minimisation.

Usage

```
npar.lrpc(
  object,
  x,
  eta = NULL,
  cv.args = list(n.folds = 1, path.length = 10, do.plot = FALSE),
  do.correct = TRUE,
  n.cores = min(parallel::detectCores() - 1, 3)
)
```

Arguments

`object`	`fnets` object
`x`	input time series matrix; with each row representing a variable
`eta`	regularisation parameter; if `eta = NULL`, it is selected by cross validation

`cv.args` a list specifying arguments for the cross validation procedure for selecting the tuning parameter involved in long-run partial correlation matrix estimation. It contains:

- `n.folds` number of folds
- `path.length` number of regularisation parameter values to consider; a sequence is generated automatically based in this value
- `do.plot` whether to plot the output of the cross validation step

`do.correct` whether to correct for any negative entries in the diagonals of the inverse of long-run covariance matrix

`n.cores` number of cores to use for parallel computing, see makePSOCKcluster

Value

a list containing

`Omega` estimated inverse of the long-run covariance matrix

`lrpc` estimated long-run partial correlation matrix

`eta` regularisation parameter

Examples

```
## Not run:
set.seed(123)
n <- 500
p <- 50
common <- sim.common1(n, p)
idio <- sim.var(n, p)
x <- common$data + idio$data
out <- fnets(x, q = NULL, idio.method = 'lasso', lrpc.method = 'none')
nlrpc <- npar.lrpc(out, x, cv.args = list(n.folds = 1, path.length = 10, do.plot = TRUE))
out$lrpc <- nlrpc
out$lrpc.method <- 'npar'
plot(out, type = 'lrpc', display = 'heatmap', threshold = .05)

## End(Not run)
```

`par.lrpc` *Parametric estimation of long-run partial correlations of factor-adjusted VAR processes*

Description

Returns a parametric estimate of long-run partial correlations of the VAR process from the VAR parameter estimates and the inverse of innovation covariance matrix obtained via constrained `l1`-minimisation.

Usage

```
par.lrpc(
  object,
  x,
  eta = NULL,
  cv.args = list(n.folds = 1, path.length = 10, do.plot = FALSE),
  do.correct = TRUE,
  n.cores = min(parallel::detectCores() - 1, 3)
)
```

Arguments

`object`	`fnets` object
`x`	input time series matrix; with each row representing a variable
`eta`	regularisation parameter; if `eta = NULL`, it is selected by cross validation
`cv.args`	a list specifying arguments for the cross validation procedure for selecting the tuning parameter involved in long-run partial correlation matrix estimation. It contains: • `n.folds` number of folds • `path.length` number of regularisation parameter values to consider; a sequence is generated automatically based in this value • `do.plot` whether to plot the output of the cross validation step
`do.correct`	whether to correct for any negative entries in the diagonals of the inverse of long-run covariance matrix
`n.cores`	number of cores to use for parallel computing, see makePSOCKcluster

Details

See Barigozzi, Cho and Owens (2021) for further details.

Value

a list containing

`Delta`	estimated inverse of the innovation covariance matrix
`Omega`	estimated inverse of the long-run covariance matrix
`pc`	estimated innovation partial correlation matrix
`lrpc`	estimated long-run partial correlation matrix
`eta`	regularisation parameter

References

Barigozzi, M., Cho, H. & Owens, D. (2021) FNETS: Factor-adjusted network analysis for high-dimensional time series.

Examples

```
## Not run:
set.seed(123)
n <- 500
p <- 50
common <- sim.common1(n, p)
idio <- sim.var(n, p)
x <- common$data + idio$data
out <- fnets(x, q = NULL, idio.method = 'lasso', lrpc.method = 'none')
plrpc <- par.lrpc(out, x, cv.args = list(n.folds = 1, path.length = 10, do.plot = TRUE))
out$lrpc <- plrpc
out$lrpc.method <- 'par'
plot(out, type = 'pc', display = 'network', threshold = .05)
plot(out, type = 'lrpc', display = 'heatmap', threshold = .05)

## End(Not run)
```

`plot.fnets` *Plotting the networks estimated by fnets*

Description

Plotting method for S3 objects of class `fnets`. Produces a plot visualising three networks underlying factor-adjusted VAR processes: (i) directed network representing Granger causal linkages, as given by estimated VAR transition matrices aggregated across the lags, (ii) undirected network representing contemporaneous linkages after accounting for lead-lag dependence, as given by partial correlations of VAR innovations, (iii) undirected network summarising (i) and (ii) as given by long-run partial correlations of VAR processes.

Usage

```
## S3 method for class 'fnets'
plot(
  x,
  type = c("granger", "pc", "lrpc"),
  display = c("network", "heatmap"),
  names = NA,
  groups = NA,
  threshold = 0,
  ...
)
```

Arguments

`x` `fnets` object

`type` a string specifying which of the above three networks (i)–(iii) to visualise; possible values are

- `"granger"` directed network representing Granger causal linkages
- `"pc"` undirected network representing contemporaneous linkages; available when `x$lrpc.method` = `"par"`

	• `"lrpc"` undirected network summarising Granger causal and contemporaneous linkages; available when `x$lrpc.method = "par"` or `x$lrpc.method = "npar"`
`display`	a string specifying how to visualise the network; possible values are: • `"network"` as an `igraph` object, see plot.igraph • `"heatmap"` as a heatmap, see imagePlot
`names`	a character vector containing the names of the vertices
`groups`	an integer vector denoting any group structure of the vertices
`threshold`	if `threshold > 0`, hard thresholding is performed on the matrix giving rise to the network of interest
`...`	additional arguments

Details

See Barigozzi, Cho and Owens (2021) for further details.

References

Barigozzi, M., Cho, H. & Owens, D. (2021) FNETS: Factor-adjusted network analysis for high-dimensional time series.

See Also

fnets

`predict.fnets` *Forecasting by fnets*

Description

Produces forecasts of the data for a given forecasting horizon by separately estimating the best linear predictors of common and idiosyncratic components

Usage

```
## S3 method for class 'fnets'
predict(
  object,
  x,
  h = 1,
  common.method = c("restricted", "unrestricted"),
  r = NULL,
  ...
)
```

Arguments

`object`	`fnets` object
`x`	input time series matrix, with each row representing a variable
`h`	forecasting horizon
`common.method`	a string specifying the method for common component forecasting; possible values are: • `"restricted"` performs forecasting under a restrictive static factor model • `"unrestricted"` performs forecasting under an unrestrictive, blockwise VAR representation of the common component
`r`	number of static factors; if `common.method = "restricted"` and `r = NULL`, it is estimated as the maximiser of the ratio of the successive eigenvalues of the estimate of the common component covariance matrix, see Ahn and Horenstein (2013)
`...`	not used

Value

a list containing

`forecast`	forecasts for the given forecasting horizon
`common.pred`	a list containing forecasting results for the common component
`idio.pred`	a list containing forecasting results for the idiosyncratic component
`mean.x`	`mean.x` argument from `object`

References

Barigozzi, M., Cho, H. & Owens, D. (2021) FNETS: Factor-adjusted network analysis for high-dimensional time series.

Ahn, S. C. & Horenstein, A. R. (2013) Eigenvalue ratio test for the number of factors. Econometrica, 81(3), 1203–1227.

See Also

fnets, common.predict, idio.predict

`sim.common1` *Simulate data from a dynamic factor model*

Description

Simulate the common component following a dynamic factor model that does not admit a static representation; see the model (C1) in the reference.

Usage

```
sim.common1(n, p, q = 2, heavy = FALSE)
```

Arguments

`n`	sample size
`p`	dimension
`q`	number of dynamic factors
`heavy`	if `heavy = FALSE`, common shocks are generated from `rnorm` whereas if `heavy = TRUE`, from `rt` with `df = 5` and then scaled by `sqrt(3 / 5)`

Value

a list containing

`data`	generated series
`q`	number of factors

References

Barigozzi, M., Cho, H. & Owens, D. (2021) FNETS: Factor-adjusted network analysis for high-dimensional time series.

Examples

```
common <- sim.common1(500, 50)
```

`sim.common2` *Simulate data from a static factor model*

Description

Simulate the common component following a dynamic factor model that admits a static representation; see the model (C2) in the reference.

Usage

```
sim.common2(n, p, q = 2, heavy = FALSE)
```

Arguments

`n`	sample size
`p`	dimension
`q`	number of dynamic factors; number of static factors is given by `2 * q`
`heavy`	if `heavy = FALSE`, common shocks are generated from `rnorm` whereas if `heavy = TRUE`, from `rt` with `df = 5` and then scaled by `sqrt(3 / 5)`

Value

a list containing

`data`	generated series
`q`	number of factors
`r`	number of static factors

References

Barigozzi, M., Cho, H. & Owens, D. (2021) FNETS: Factor-adjusted network analysis for high-dimensional time series.

Examples

```
common <- sim.common2(500, 50)
```

`sim.var` *Simulate a VAR(1) process*

Description

Simulate a VAR(1) process; see the reference for the generation of the transition matrix.

Usage

```
sim.var(n, p, Gamma = diag(1, p), heavy = FALSE)
```

Arguments

`n`	sample size
`p`	dimension
`Gamma`	innovation covariance matrix; ignored if `heavy = TRUE`
`heavy`	if `heavy = FALSE`, common shocks are generated from `rnorm` whereas if `heavy = TRUE`, from `rt` with `df = 5` and then scaled by `sqrt(3 / 5)`

Value

a list containing

`data`	generated series
`A`	transition matrix
`Gamma`	innovation covariance matrix

References

Barigozzi, M., Cho, H. & Owens, D. (2021) FNETS: Factor-adjusted network analysis for high-dimensional time series.

Examples

```
idio <- sim.var(500, 50)
```

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