Package: tsDyn (via r-universe)

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Suggests sm, scatterplot3d, rgl, rugarch, broom, dplyr, stringr, purrr, tibble, tidyr, testthat (>= 3.0.0)

Maintainer Matthieu Stigler <Matthieu.Stigler@gmail.com>

Description Implements nonlinear autoregressive (AR) time series models. For univariate series, a non-parametric approach is available through additive nonlinear AR. Parametric modeling and testing for regime switching dynamics is available when the transition is either direct (TAR: threshold AR) or smooth (STAR: smooth transition AR, LSTAR). For multivariate series, one can estimate a range of TVAR or threshold cointegration TVECM models with two or three regimes. Tests can be conducted for TVAR as well as for TVECM (Hansen and Seo 2002 and Seo 2006).

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Author Antonio Fabio Di Narzo [aut] (ORCID:
<https://orcid.org/0000-0002-4033-5038>), Jose Luis Aznarte
[ctb] (ORCID: <https://orcid.org/0000-0002-1636-244X>),
Matthieu Stigler [aut, cre] (ORCID:
<https://orcid.org/0000-0002-6802-4290>)

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`tsDyn-package` *Getting started with the tsDyn package*

Description

Getting started with the tsDyn package

Details

This package provide some tools inspired by nonlinear dynamics for the analysis-modelling of observed time series.
For loading the package, type:
`library(tsDyn)`
A good place to start learning the package usage, is the vignette. It contains a more detailed guide on package contents, and an applied case study. At the R prompt, write:
`vignette("tsDyn")`
For a full list of functions exported by the package, type:
`ls("package:tsDyn")`

There is also an experimental GUI for built-in NLAR models. Call it with:
`nlarDialog(timeSeries)`
where `timeSeries` is an available time series object.

Each exported function has a corresponding man page (some man pages are in common to more functions). Display it by typing
`help(functionName)`

Author(s)

Antonio, Fabio Di Narzo

See Also

`availableModels` for listing all currently available NLAR models

`autopairs`,`autotriples`,`autotriples.rgl` for graphical exploratory functions

`llar`, `delta`, `delta.lin` for nonlinearity checking tools

---

aar *Additive nonlinear autoregressive model*

Description

Additive nonlinear autoregressive model.

Usage

```
aar(x, m, d=1, steps=d, series)
```

Arguments

`x`	time series
`m`, `d`, `steps`	embedding dimension, time delay, forecasting steps
`series`	time series name (optional)

Details

Nonparametric additive autoregressive model of the form:

$$x_{t+s} = \mu + \sum_{j=1}^{m} s_j(x_{t-(j-1)d})$$

where s_j are nonparametric univariate functions of lagged time series values. They are represented by cubic regression splines. s_j are estimated together with their level of smoothing using routines in the **mgcv** package (see references).

Value

An object of class `nlar`, subclass `aar`, i.e. a list with mostly internal structures for the fitted `gam` object.

Author(s)

Antonio, Fabio Di Narzo

References

Wood, mgcv:GAMs and Generalized Ridge Regression for R. R News 1(2):20-25 (2001)

Wood and Augustin, GAMs with integrated model selection using penalized regression splines and applications to environmental modelling. Ecological Modelling 157:157-177 (2002)

Examples

```
#fit an AAR model:
mod <- aar(log(lynx), m=3)
#Summary informations:
summary(mod)
#Diagnostic plots:
plot(mod)
```

`accuracy_stat` *Forecasting accuracy measures.*

Description

Compute forecasting accuracies. This is very similar to the `accuracy` method form **forecast**.

Usage

```
accuracy_stat(object, ...)

## Default S3 method:
accuracy_stat(object, true, ...)

## S3 method for class 'pred_roll'
accuracy_stat(object, w, ...)
```

Arguments

object	A data-frame, matrix, or object of class pred_roll
...	Not used currently.
true	If object is just a matrix or data-frame, true values to be compared to should be supplied
w	Optional. For objects of class pred_roll containing multiple variables, user can specify the way to aggregate the specific x-step-ahead into the 'all' category

Details

The function works either for a simple data.frame or for objects pred_roll. For simple data.frames, the argument true, i.e. a data frame containing the true values, has to be provided. For pred_roll objects, the true values are contained in the object, so no need (nor possibility) to provide the true values.

Value

A data-frame containing the forecasting accuracy measures.

Author(s)

Matthieu Stigler

Examples

```
## univariate:
mod_ar <- linear(lynx[1:100], m=1)
mod_ar_pred <- predict_rolling(mod_ar, newdata=lynx[101:114])
accuracy_stat(object=mod_ar_pred$pred, true=mod_ar_pred$true)

## multivariate
data(barry)
mod_var <- lineVar(barry, lag=1)

mod_var_pred <-predict_rolling(object=mod_var, nroll=10, n.ahead=1:3)
accuracy_stat(object=mod_var_pred)
accuracy_stat(object=mod_var_pred, w=c(0.7, 0.2, 0.1))
```

---

addRegime *addRegime test*

Description

addRegime test

Usage

```
addRegime(object, ...)
```

Arguments

object	fitted model object with at least 2 regimes
...	arguments to and from other methods

Value

A list containing the p-value of the F statistic and a boolean, true if there is some remaining nonlinearity and false otherwise.

Author(s)

J. L. Aznarte

References

TODO

See Also

star

Examples

```
##TODO
```

---

ar_mean *Long-term mean of an AR(p) process*

Description

Computes the long term mean of an AR process

Usage

```
ar_mean(object, ...)

## S3 method for class 'linear'
ar_mean(object, ...)

## S3 method for class 'setar'
ar_mean(object, ...)

## S3 method for class 'lstar'
ar_mean(object, ...)
```

Arguments

object	an object of class linear, setar or lstar
...	unused argument

Details

The function computes the long-term mean of an AR(p) process, or of the corresponding sub-regimes in SETAR or LSTAR model. There are three possible cases:

No constant nor trend The LT mean is 0

constant The LT mean is given by const/(1-sum(AR coefs))

Trend The LT mean is not defined

Examples

```
## estimate a (linear) AR, a SETAR and a LSTAR
lin_cst_l1 <-  linear(lh, m = 1, include = "const")
set_cst_l1 <-  setar(lh, m = 1, include = "const")
lst_cst_l1 <-  lstar(lh, m = 1, include = "const", trace = FALSE)

ar_mean(lin_cst_l1)
ar_mean(set_cst_l1)
ar_mean(lst_cst_l1)
```

---

autopairs *Bivariate time series plots*

Description

Bivariate time series plots: scatterplots, directed lines and kernel density estimations using functions in the **sm** package.

Usage

```
autopairs(
  x,
  lag = 1,
  h,
  type = c("levels", "persp", "image", "lines", "points", "regression")
)
```

Arguments

x	time series
lag	time lag
h	kernel window (useful only for kernel estimations)
type	type of plot: contour levels, perspective plots, image, directed lines, points or points with superposed kernel regression

Details

Bivariate time series plots: scatterplots, directed lines and kernel density and regression functions estimations using functions in the package **sm**. In particular, for kernel density estimation `sm.density` is used, with smoothing parameter `h` defaulting to `hnorm`. For kernel regression, `sm.regression` is used.

Value

None. Plots are produced on the default graphical device.

Author(s)

Wrappers to **sm** by Antonio, Fabio Di Narzo

See Also

For finer control on density estimation, consider using directly `sm.density` and, especially, `sm.ts.pdf` from package **sm**.

Examples

```
x <- log10(lynx)
autopairs(x, lag=2, type="lines")
```

---

autotriples *Trivariate time series plots*

Description

Trivariate time series plots: kernel autoregression using functions in the **sm** package

Usage

```
autotriples(
  x,
  lags = 1:2,
  h,
  type = c("levels", "persp", "image", "lines", "points")
)
```

Arguments

`x`	time series
`lags`	vector of regressors lags
`h`	kernel window
`type`	type of plot: contour levels, perspective plots, image

Details

This function displays trivariate time series plots, i.e. kernel regression of $x[t - lags[1]], x[t - lags[2]]$ against $x[t]$ using functions in the package **sm**. In particular, `sm.regression` is used, with smoothing parameter defaulting to `hnorm(x)`.

Value

None. Plots are produced on the default graphical device.

Author(s)

Wrappers to **sm** by Antonio, Fabio Di Narzo

See Also

For finer control on kernel regression, consider using directly `sm.regression` and, especially, `sm.autoregression` in package `sm`.

Examples

```
autotriples(log(lynx))
autotriples(log(lynx), type="persp")
autotriples(log(lynx), type="image")
```

---

autotriples.rgl *Interactive trivariate time series plots*

Description

Interactive trivariate time series plots

Usage

```
autotriples.rgl(x, lags = 1:2, type = c("lines", "points"))
```

Arguments

`x`	time series
`lags`	vector of regressors lags
`type`	type of plot: contour levels, perspective plots, image

Details

This function displays interactive trivariate time series plots `x[t-lags[1]]`, `x[t-lags[2]]` against `x[t]` using the interactive `rgl` device.

Value

None. A plot is produced on the current `rgl` device.

Author(s)

Wrapper to 'sm' and GUI by Antonio, Fabio Di Narzo

See Also

`autotriples` for 3d visualization via **scatterplot3d** package and for kernel post-processing of the cloud for nonparametric autoregression functions estimates.

Examples

```
if(interactive())
autotriples.rgl(log(lynx))
```

---

availableModels *Available models*

Description

Available built-in time series models

Usage

```
availableModels()
```

Details

Return the list of built-in available 'nlar' time series models

Value

A character vector containing built-in time series models. For help on a specific model, type: `help(modelName)`.

Author(s)

Antonio, Fabio Di Narzo

Examples

```
availableModels()
```

barry *Time series of PPI used as example in Bierens and Martins (2010)*

Description

This data set contains the series used by *Bierens and Martins* for testing for PPI between Canada and US.

Usage

```
data(barry)
```

Format

A data frame with 324 monthly observations, ranging from 1973:M1 until 1999:M12.

`dolcan`	Exchange rate US/Can dollar.
`cpiUSA`	US Consumer Price Index.
`cpiCAN`	Canada Consumer Price Index.

Author(s)

Matthieu Stigler

Source

Bierens, H. and Martins, L. (2010), Time Varying Cointegration,

BBCTest *Test of unit root against SETAR alternative*

Description

Test of unit root against a stationnary three regime SETAR alternative

Usage

```
BBCTest(
  x,
  m,
  series,
  testStat = c("LR", "Wald", "LM"),
  trim = 0.1,
  grid = c("minPerc", "minObs")
)
```

Arguments

x	time series
m	Number of lags under the alternative
series	time series name (optional)
testStat	Type of test statistic to use
trim	trimming parameter indicating the minimal percentage of observations in each regime
grid	Whether a minimal number of percentage or observations should be imposed. See details

Details

TODO

Value

A object of class "BBC2004Test" containing:

-The value of the sup Test

-The version of test used (either Wald, LM or LR).

Author(s)

Matthieu Stigler

References

Bec, Ben Salem and Carrasco (2004) Tests for Unit-Root versus Threshold Specification With an Application to the Purchasing Power Parity Relationship, Journal of Business and Economic Statistics; 22:4

See Also

setarTest for a test with stationarity as a null.

Examples

```
BBCTest(lynx, m=3, test="Wald", grid="minPerc")
```

charac_root *Characteristic roots of the AR coefficients*

Description

Computes the (inverse) characteristic roots of the auto-regressive coefficients. To be stationary, the values should be outside the unit circle. The function here returns the modulus of the roots.

Usage

```
charac_root(object, ...)

## S3 method for class 'nlar'
charac_root(object, ...)
```

Arguments

object	object of class nlar
...	currently unused

Details

Computes the roots of the polynomial (1, -phi) using function polyroot

Value

a data.frame, with the modulus of the roots. For models with multiple regimes (setar, lstar, star), one column per regime.

Examples

```
mod.ar <-  linear(lh, m = 5, include = "const")
mod.setar <-  setar(lh, m = 5, include = "const")

charac_root(mod.ar)
charac_root(mod.setar)
```

coefB *Extract cointegration parameters A, B and PI*

Description

Extract parameters in VECM: adjustment coefficients A, cointegrating coefficients B , or the composite matrix PI

Usage

```
coefB(object, ...)

## S3 method for class 'VECM'
coefB(object, ...)

## S3 method for class 'ca.jo'
coefB(object, r = 1, normalize = TRUE, ...)

coefA(object, ...)

## S3 method for class 'VECM'
coefA(object, ...)

## S3 method for class 'ca.jo'
coefA(object, r = 1, normalize = TRUE, ...)

coefPI(object, ...)
```

Arguments

object	An object of class VECM, ca.jo
r	The cointegrating rank
normalize	Whether to normalize the A/B coefficients. See details
...	Further arguments passed to methods

Details

The functions extract the parameters from a VECM with K variables and rank r:

A Adjustment coefficients, of dim $K \times r$

B Cointegrating coefficients, of dim $K \times r$

Pi Matrix $\Pi = AB^{'}$, of dim $K \times K$

Coefficients are extracted from a VECM in package tsDyn, or from a VECM obtained in package urca from ca.jo or cajorls.

Note that by default, the A and B coefficients returned are normalized (see below). This is the case for results obtained from VECM/lineVar and cajorls, while for ca.jo, the user has the choice (but normalize=TRUE by default), in which case the rank r is also to be specified. The normalization is the Phillips triangular representation, as suggested by Johansen (1995, p. 72), standardising the first $r \times r$ coefficients to I_r:

B $B_{norm} = B(c^{'}B)^{-1}$ with $c = (I_r, 0_{K-r,r})^{'}$

A $A_{norm} = AB^{'}c$

Finally, note that the function also apply to objects obtained from tests of class ca.jo.test (from blrtest etc...). Care should be taken however, since the normalization might override the restrictions imposed.

Value

A matrix containing the coefficients

Author(s)

Matthieu Stigler

References

Johansen, Soren, (1995), Likelihood-Based Inference in Cointegrated Vector Autoregressive Models, Oxford University Press

Examples

```
data(barry)
vecm <- VECM(barry,  lag=1, estim="ML")
vecm_r2 <- VECM(barry,  lag=1, estim="ML", r=2)

## extract coefficients:
coefA(vecm)
coefB(vecm)
coefPI(vecm)
coefB(vecm_r2)
coefPI(vecm_r2)

## Beta-Restricted VECM:
beta_vecm2 <- coefB(vecm_r2)
beta_vecm2[3,2] <- 0.02
vecm_r2_rest <- VECM(barry,  lag=1, estim="ML", r=2, beta=beta_vecm2)
round(coefB(vecm_r2_rest),5)

## Package vars/urca
if(require(urca)){
 vecm_ur <- ca.jo(barry, K=2)
 coefB(vecm_ur)
 coefB(vecm_ur,r=2)
 coefB(cajorls(vecm_ur, r=2))
 all.equal(coefB(vecm), coefB(vecm_ur), check.attributes=FALSE)
 all.equal(coefB(vecm_r2), coefB(vecm_ur, r=2), check.attributes=FALSE)
}
```

`delta` *delta test of conditional independence*

Description

delta statistic of conditional independence and associated bootstrap test

Usage

```
delta(x, m, d = 1, eps)

delta.test(
  x,
  m = 2:3,
  d = 1,
  eps = seq(0.5 * sd(x), 2 * sd(x), length = 4),
  B = 49
)
```

Arguments

x	time series
m	vector of embedding dimensions
d	time delay
eps	vector of length scales
B	number of bootstrap replications

Details

delta statistic of conditional independence and associated bootstrap test. For details, see Manzan(2003).

Value

`delta` returns the computed delta statistic. `delta.test` returns the bootstrap based 1-sided p-value.

Warning

Results are sensible to the choice of the window `eps`. So, try the test for a grid of `m` and `eps` values. Also, be aware of the course of dimensionality: m can't be too high for relatively small time series. See references for further details.

Author(s)

Antonio, Fabio Di Narzo

References

Sebastiano Manzan, Essays in Nonlinear Economic Dynamics, Thela Thesis (2003)

See Also

BDS marginal independence test: `bds.test` in package **tseries**

Teraesvirta's neural network test for nonlinearity: `terasvirta.test` in package **tseries**

delta test for nonlinearity: `delta.lin.test`

Examples

```
delta(log10(lynx), m=3, eps=sd(log10(lynx)))
```

`delta.lin` *delta test of linearity*

Description

delta test of linearity based on conditional mutual information

Usage

```
delta.lin(x, m, d = 1)

delta.lin.test(
  x,
  m = 2:3,
  d = 1,
  eps = seq(0.5 * sd(x), 2 * sd(x), length = 4),
  B = 49
)
```

Arguments

`x`	time series
`m`	vector of embedding dimensions
`d`	time delay
`eps`	vector of length scales
`B`	number of bootstrap replications

Details

delta test of linearity based on conditional mutual information

Value

`delta.lin` returns the parametrically estimated delta statistic for the given time series (assuming linearity). `delta.lin.test` returns the bootstrap based 1-sided p-value. The test statistic is the difference between the parametric and nonparametric delta estimators.

Author(s)

Antonio, Fabio Di Narzo

References

Sebastiano Manzan, Essays in Nonlinear Economic Dynamics, Thela Thesis (2003)

Examples

```
delta.lin(log10(lynx), m=3)
```

`fevd.nlVar` *Forecast Error Variance Decomposition*

Description

Use the `fevd` function from package **vars** to compute the forecast error variance decomposition of a VAR(p) or VECM for `n.ahead` steps.

Usage

```
## S3 method for class 'nlVar'
fevd(x, n.ahead = 10, ...)
```

Arguments

`x`	Object of class '`VAR`' generated by `lineVar()`, or an object of class '`VECM`' generated by `VECM()`
`n.ahead`	Integer specifying the number of steps.
`...`	Currently not used.

Details

The function converts the VAR or VECM computed by package tsDyn into an object of class '`vec2var`', on which then the `fevd` method is applied. For details, see package **vars**.

Value

A list with class attribute '`varfevd`' of length `K` holding the forecast error variances as matrices.

Author(s)

Bernhard Pfaff

References

Hamilton, J. (1994), *Time Series Analysis*, Princeton University Press, Princeton.

Lutkepohl, H. (2006), *New Introduction to Multiple Time Series Analysis*, Springer, New York.

See Also

plot for the plot method. lineVar, VECM for the models.

Examples

```
data(zeroyld)
mod_vecm <- VECM(zeroyld, lag = 2)
fevd(mod_vecm, n.ahead = 5)
```

`fitted.nlVar` *fitted method for objects of class nlVar, i.e. VAR and VECM models.*

Description

Returns the fitted values of the model, either as computed in the model, or back to the original series level.

Usage

```
## S3 method for class 'nlVar'
fitted(object, level = c("model", "original"), ...)
```

Arguments

`object`	An object of class 'nlVar'; generated by VECM or lineVar.
`level`	How to return the fitted values. See below.
`...`	Currently not used.

Details

In case of a VAR in differences, in ADF specification, or a VECM, the fitted values are actually in differences. With the option `level="original"`, the function returns the series in the original level.

For VAR in levels, the two arguments are evidently the same and hence it is not taken into account, returning a warning.

Value

A matrix.

Author(s)

Matthieu Stigler

Examples

```
## estimate models
data(barry)

ve <- VECM(barry, lag=2)
va <- lineVar(barry, lag=1)
va_diff <- lineVar(barry, lag=1, I="diff")
va_ADF <- lineVar(barry, lag=1, I="ADF")


## get fitted values:
tail(fitted(ve))
tail(fitted(ve, level="original"))

tail(fitted(va))
tail(fitted(object=va, level="original"))

tail(fitted(va_diff))
tail(fitted(object=va_diff, level="original"))

tail(fitted(va_ADF))
tail(fitted(object=va_ADF, level="original"))
```

`getTh` *Extract threshold(s) coefficient*

Description

Extract threshold coefficient(s)

Usage

```
getTh(object, ...)

## Default S3 method:
getTh(object, ...)
```

Arguments

`object`	object of class `setar`, `summary.setar`, `nlVar`
`...`	additional arguments to `getTh`

Value

Threshold value.

Author(s)

Matthieu Stigler

Examples

```
set<-setar(lynx, m=3)
getTh(set)
getTh(summary(set))
```

GIRF *Generalized Impulse response Function (GIRF)*

Description

Generates a GIRF for multiple innovations and histories

Usage

```
GIRF(object, n.ahead, seed = NULL, ...)

## S3 method for class 'setar'
GIRF(
  object,
  n.ahead = 10,
  seed = NULL,
  n.hist = 20,
  n.shock = 20,
  R = 10,
  hist_li = NULL,
  shock_li = NULL,
  ...
)

## S3 method for class 'linear'
GIRF(
  object,
  n.ahead = 10,
  seed = NULL,
  n.hist = 20,
  n.shock = 20,
  R = 10,
  hist_li = NULL,
  shock_li = NULL,
  ...
)
```

```
## S3 method for class 'nlVar'
GIRF(
  object,
  n.ahead = 10,
  seed = NULL,
  n.hist = 20,
  n.shock = 20,
  R = 10,
  hist_li = NULL,
  shock_li = NULL,
  ...
)

## S3 method for class 'GIRF_df'
plot(
  x,
  plot_type = c("density", "line"),
  n.ahead = c(1, 5, 10),
  var = unique(x$var)[1],
  n_simu = c(1, 2),
  ...
)
```

Arguments

object	An object of class linear, setar or nlVar (TVAR, TVECM)
n.ahead	The number of steps ahead to compute
seed	optional, the seed for the random numbers
n.hist	The number of past histories to consider. Should be high, ideally size of data (minus lags).
n.shock	The number of actual shocks to consider
R	the number of draws to use for the n.ahead innovations
hist_li	optional, a list of histories (each of same length as lags in the model). If not provided, n.hist histories will be randomly drawn for the original series.
shock_li	optional, a list of innovations. If not provided, n.shock shocks will be randomly drawn from the estimated residuals.
x	output of girf
plot_type	plot: density (for each n.ahead), or line (for multipe n_simu)?
var	plot: which variable to plot?
n_simu	line plot: which simulation to plot?
...	Further arguments passed to specific methods.

Details

In a nonlinear model, the Impulse response Function (IRF) is not time-, scale- and sign-invariant as in linear models. To address this, Koop et al (1996) introduced the Generalized Impulse response

Function (GIRF):

$$GIRF(h, \delta, \omega_{t-1}) = E[y_{t+h}|\epsilon_t = \delta, \epsilon_{t+h} = 0, \omega_{t-1}] - E[y_{t+h}|\epsilon_t = 0, \epsilon_{t+h} = 0, \omega_{t-1}]$$

It is the difference between two conditional expectations, one containing the shock of interest, the second one averaging it out. The averaging-out is done by comparing against random innovations (unlike the IRF, which compares against innovation 0), The parameter `R` corresponds to the number of times this is done.

The GIRF as defined here depends on the particular shock, as well as on the history. Koop et al (1996) suggest to draw multiple combinations of histories and innovations. This is done with arguments `n.hist` and `n.shock` (or, alternatively, provide one of, or both, `hist_li` and `hist_li` as list of histories and shocks).

The output is a data-frame containing the two average paths for each combinations of shocks and histories.

Value

A data-frame, with:

n_simu: Id for the simulation (total number is n.hist times n.shock)

hist, shock History and shock used in the nth simulation

n.ahead: The forecasting horizon. Note the shocks happens at time 0

var: The variable (on which the shock happens, corresponds hence to the `response` argument in `irf`)

sim_1, sim_2 The average (over R times) simulation with the specific shock (sim_1) or with random shocks (sim_2).

girf The difference between sim_1 and sim_2

Author(s)

Matthieu Stigler

References

Koop, G, Pesaran, M. H. & Potter, S. M. (1996) Impulse response analysis in nonlinear multivariate models. Journal of Econometrics, 74, 119-147

See Also

`irf.nlVar` for the IRF, for linear models, or in case of non-linear models, for each regime.

Examples

```
## simulate a SETAR for the example. Higher regime more persistent (AR coef 0.5 instead of 0.2)
set <- setar.sim(B = c(0.5, 0.2, 0.5, 0.5), lag = 1, Thresh = 0.5, n = 500)
set_estim <- setar(set, m = 1)

## regime-specific IRF:
```

```
plot(irf(set_estim, regime = "L", boot = FALSE))
plot(irf(set_estim, regime = "H", boot = FALSE))

## GIRF
girf_out <- GIRF(set_estim, n.hist = 10, n.shock = 10) # smaller number for example only

## the GIRF shows a very fast convergence (the shock at n.ahead = 4 is already very close to 0)
plot(girf_out, n.ahead = 1:4)
## investigate a few specific GIRFS:
plot(girf_out, plot_type = "line", n_simu  = 1:5)
```

`IIPUs` *US monthly industrial production from Hansen (1999)*

Description

This data, used as example in Hansen (1999), contains the US monthly industrial production.

Usage

```
IIPUs
```

Format

A monthly time series of class ts starting in January 1960 and ending in September 1997. Note that the series ends at 1997 and not 1998 as in the paper of Hansen, even if the data was taken from hi site and the graph is exactly the same.

Source

Hansen (1999) Testing for linearity, Journal of Economic Surveys, Volume 13, Number 5, December 1999 , pp. 551-576(26) available at: https://www.ssc.wisc.edu/~bhansen/papers/cv.htm

Examples

```
data(IIPUs)
end(IIPUs) #not same date as in the paper

## Figure 2 in paper (p. 555)
plot(IIPUs)

## Table 1 in paper (p. 556)
ar_1 <- linear(IIPUs, m=16)
coef(summary(ar_1))[, 1:2]
deviance(ar_1)

## Table 2 in paper (p. 559)
set_1 <- setar(IIPUs, m=16, thDelay=5, trim=0.1)
## tsDyn finds another threshold, with a better SSR:
getTh(set_1)
```

```
deviance(set_1)

## estimate with Hansen threshold:
set_1_han <- setar(IIPUs, m=16, thDelay=5, trim=0.1, th = 0.23)
deviance(set_1_han)
set_1_CO <- coef(summary(set_1_han))[, 1:2]
cbind(set_1_CO[1:17,], set_1_CO[18:34,])


## Table 4 in paper (p. 561)
set_2 <- setar(IIPUs, m=16, thDelay=5, trim=0.1, nthresh =2)
getTh(set_2)
deviance(set_2)

##most of the results agree, except constant in the low regime which has opposed signs!
set_2_CO <- coef(summary(set_2))[, 1:2]
cbind(set_2_CO[1:17,], set_1_CO[18:34,])

#this is obviously a error in Hansen, see:
XX<-embed(IIPUs, 17)
Y<-XX[,1]
X<-XX[,-1]
dummyDown<-ifelse(X[,6]<= -2.5, 1,0)
sum(dummyDown)
M<-cbind(1*dummyDown,X*dummyDown )
lm(Y~M-1)

## setar test (takes long to compute, even with small nboot)
## Not run:
  test_1 <- setarTest(IIPUs, m=16, thDelay=5, nboot=10)
  #because of the discrepency. test1vs2 does not correspond, test 1vs3 conforms
  test_1$Ftests ## compare with Table 2 (F12)  and Table 4 (F13, F23)
  summary(test_1)

  setarTest(IIPUs, m=16, thDelay=5, nboot=10, test="2vs3")
  #test 2vs3 is also different of the version in the article (27)

## End(Not run)

## results from the test is stored in: setarTest_IIPUs_results
data(setarTest_IIPUs_results)

## Table 5 and 6
test_1vs <- setarTest_IIPUs_results$test_1
test_1vs

## Table 7
test_2vs <- setarTest_IIPUs_results$test_2
test_2vs
plot(test_2vs)
```

`irf.linear` *Impulse response function*

Description

Compute the impulse response coefficients (IRF) of a VAR(p) (or transformed VECM to VAR(p)) for `n.ahead` steps. For TVECM and TVAR model, argument `regime` offers regime-specific IRF.

Usage

```
## S3 method for class 'linear'
irf(
  x,
  impulse = NULL,
  response = NULL,
  n.ahead = 10,
  ortho = TRUE,
  cumulative = FALSE,
  boot = TRUE,
  ci = 0.95,
  runs = 100,
  seed = NULL,
  ...
)

## S3 method for class 'setar'
irf(
  x,
  impulse = NULL,
  response = NULL,
  n.ahead = 10,
  ortho = TRUE,
  cumulative = FALSE,
  boot = TRUE,
  ci = 0.95,
  runs = 100,
  seed = NULL,
  regime = c("L", "M", "H"),
  ...
)

## S3 method for class 'ar'
irf(
  x,
  impulse = NULL,
  response = NULL,
  n.ahead = 10,
```

```
  ortho = TRUE,
  cumulative = FALSE,
  boot = TRUE,
  ci = 0.95,
  runs = 100,
  seed = NULL,
  ...
)

## S3 method for class 'VAR'
irf(
  x,
  impulse = NULL,
  response = NULL,
  n.ahead = 10,
  ortho = TRUE,
  cumulative = FALSE,
  boot = TRUE,
  ci = 0.95,
  runs = 100,
  seed = NULL,
  ...
)

## S3 method for class 'VECM'
irf(
  x,
  impulse = NULL,
  response = NULL,
  n.ahead = 10,
  ortho = TRUE,
  cumulative = FALSE,
  boot = TRUE,
  ci = 0.95,
  runs = 100,
  seed = NULL,
  ...
)

## S3 method for class 'TVAR'
irf(
  x,
  impulse = NULL,
  response = NULL,
  n.ahead = 10,
  ortho = TRUE,
  cumulative = FALSE,
  boot = TRUE,
```

```
  ci = 0.95,
  runs = 100,
  seed = NULL,
  regime = c("L", "M", "H"),
  ...
)

## S3 method for class 'TVECM'
irf(
  x,
  impulse = NULL,
  response = NULL,
  n.ahead = 10,
  ortho = TRUE,
  cumulative = FALSE,
  boot = TRUE,
  ci = 0.95,
  runs = 100,
  seed = NULL,
  regime = c("L", "M", "H"),
  ...
)
```

Arguments

x	Object of class 'VAR'; generated by lineVar(), or object of class 'VECM'; generated byVECM().
impulse, response	Not used!
n.ahead	Integer specifying the steps.
ortho	Logical, if TRUE (the default) the orthogonalised impulse response coefficients are computed .
cumulative	Logical, if TRUE the cumulated impulse response coefficients are computed. The default value is false.
boot, ci, runs, seed	Arguments for the bootstrap, see irf.varest
...	Currently not used.
regime	For a setar model, which regime (L, M or H) to produce IRF for?

Value

A list of class 'varirf' see irf.varest

Author(s)

Matthieu Stigler

See Also

plot for the plot method. lineVar, VECM for the models. Hamilton, J. (1994), *Time Series Analysis*, Princeton University Press, Princeton.

Lutkepohl, H. (2006), *New Introduction to Multiple Time Series Analysis*, Springer, New York.

Examples

```
data(barry)

## For VAR
mod_var <- lineVar(barry, lag = 2)
irf(mod_var, impulse = "dolcan", response = c("dolcan", "cpiUSA", "cpiCAN"), boot =
FALSE)

## For VECM
mod_VECM <- VECM(barry, lag = 2, estim="ML", r=2)
irf(mod_VECM, impulse = "dolcan", response = c("dolcan", "cpiUSA", "cpiCAN"), boot =
FALSE)
```

---

isLinear *isLinear*

Description

Generic NLAR linearity test

Usage

```
isLinear(object, ...)
```

Arguments

object	fitted time series model
...	arguments to and from other methods

Author(s)

A. F. Di Narzo

KapShinTest *Test of unit root against SETAR alternative with*

Description

Test of unit root against a stationnary 3 regime SETAR alternative with random walk in the inner regime

Usage

```
KapShinTest(x, m=1, series, include = c("none","const", "trend", "both"),
 c=3, delta=0.5, points=NULL,minObsMid=10,
 trick=c("for", "apply", "mapply"), trace=FALSE)
```

Arguments

x	time series
m	Number of lags under the alternative
series	time series name (optional)
include	Whether data should be raw, de-meaned or de-meaned and de-trended
c	Argument for the grid search. See details
delta	Argument for the grid search. See details
points	Points for the grid search. See details
minObsMid	Minimal number of observations in the inner regime
trick	type of internal function used
trace	should additional infos be printed? (logical)

Details

This function is currently spurious.

Value

A object of class KapShin2006Test containing:

statistic	The three (SupW, AvgW, ExpW) test statistics computed
case	Whether the data was transformed, corresponds to input argument include
series	The name of the series

Author(s)

Matthieu Stigler

See Also

BBCTest for a similar test. setarTest for a test with stationarity as a null.

Examples

```
KapShinTest(lynx, m=1, trace=FALSE, include="none", points=10)
```

---

lags.select *Selection of the lag with Information criterion.*

Description

Selection of the cointegrating rank and the lags with Information criterion (AIC, BIC).

Usage

```
lags.select(
  data,
  lag.max = 10,
  include = c("const", "trend", "none", "both"),
  fitMeasure = c("SSR", "LL"),
  sameSample = TRUE
)
```

Arguments

data	multivariate time series.
lag.max	Maximum number of lags to investigate.
include	Type of deterministic regressors to include.
fitMeasure	Whether the AIC/BIC should be based on the full likelihood, or just the SSR. See explanations in logLik.VECM.
sameSample	Logical. Whether the data should be shortened so that the AIC/BIC are estimated on the same sample. Default to TRUE.

Details

This function selects the lag according to AIC, BIC and Hannan-Quinn.

Value

An object of class rank.select, with 'print' and 'summary methods', containing among other the matrices of AIC/BIC/HQ.

Author(s)

Matthieu Stigler

See Also

rank.select, the underlying function, to estimate the rank also.

VARselect in package **vars**, does basically the same.

Examples

```
data(barry)

#
rk_sel <- lags.select(barry)
rk_sel
summary(rk_sel)
```

LINEAR *Linear AutoRegressive models*

Description

AR(m) model

Usage

```
linear(x, m, d=1, steps=d, series, include = c( "const", "trend","none", "both"),
       type=c("level", "diff", "ADF"), warn_root=TRUE)
```

Arguments

x	time series
m, d, steps	embedding dimension, time delay, forecasting steps
series	time series name (optional)
include	Type of deterministic regressors to include
type	Whether the variable is taken is level, difference or a mix (diff y= y-1, diff lags) as in the ADF test
warn_root	Whether to check (and warn) for roots outside the unit circle?

Details

AR(m) model:

$$x_{t+s} = \phi_0 + \phi_1 x_t + \phi_2 x_{t-d} + \cdots + \phi_m x_{t-(m-1)d} + \epsilon_{t+s}$$

Value

A nlar object, linear subclass.

Author(s)

Antonio, Fabio Di Narzo

See Also

nlar for fitting this and other models to time series data

Examples

```
#fit an AR(2) model
mod.linear <- linear(log(lynx), m=2)
mod.linear
summary(mod.linear)
```

---

lineVar *Multivariate linear models: VAR and VECM*

Description

Estimate either a VAR or a VECM.

Usage

```
lineVar(
  data,
  lag,
  r = 1,
  include = c("const", "trend", "none", "both"),
  model = c("VAR", "VECM"),
  I = c("level", "diff", "ADF"),
  beta = NULL,
  estim = c("2OLS", "ML"),
  LRinclude = c("none", "const", "trend", "both"),
  exogen = NULL
)
```

Arguments

data	multivariate time series (first row being first=oldest value)
lag	Number of lags to include in each regime
r	Number of cointegrating relationships
include	Type of deterministic regressors to include
model	Model to estimate. Either a VAR or a VECM
I	For VAR only: whether in the VAR the variables are to be taken in levels (original series) or in difference, or similarly to the univariate ADF case.

beta	for VECM only: user-specified cointegrating value. If NULL, will be estimated using the estimator specified in estim
estim	Type of estimator for the VECM: '2OLS' for the two-step approach or 'ML' for Johansen MLE
LRinclude	For VECM: type of deterministic regressor(s) to include in the long-term relationship. Can also be a matrix with exogeneous regressors (2OLS only).
exogen	Inclusion of exogenous variables (first row being first=oldest value). Is either of same size than data (then automatically cut) or than end-sample.

Details

This function provides basic functionalities for VAR and VECM models. More comprehensive functions are in package **vars**. A few differences appear in the VECM estimation:

Engle-Granger estimator The Engle-Granger estimator is available

Presentation Results are printed in a different ways, using a matrix form

lateX export The matrix of coefficients can be exported to latex, with or without standard-values and significance stars

Two estimators are available: the Engle-Granger two-steps approach (2OLS) or the Johansen (ML). For the 2OLS, deterministic regressors (or external variables if LRinclude is of class numeric) can be added for the estimation of the cointegrating value and for the ECT. This is only working when the beta value is not pre-specified.

The argument beta is only for VECM, look at the specific help page for more details.

Value

Fitted model data

Author(s)

Matthieu Stigler

See Also

VECM which is just a wrapper for lineVar(..., model="VECM"). Methods predict.VAR, VARrep, regime, irf and toLatex.

TVAR and TVECM for the corresponding threshold models. linear for the univariate AR model.

Examples

```
data(zeroyld)

#Fit a VAR
VAR <- lineVar(zeroyld, lag=1)
VAR
summary(VAR)

#compare results with package vars:
```

```
if(require(vars)) {
a<-VAR(zeroyld, p=1)
coef_vars <- t(sapply(coef(a), function(x) x[c(3,1,2),1]))
all.equal(coef(VAR),coef_vars, check.attributes=FALSE)
}

###VECM
VECM.EG <- lineVar(zeroyld, lag=2, model="VECM")
VECM.EG
summary(VECM.EG)

VECM.ML <- lineVar(zeroyld, lag=2, model="VECM", estim="ML")
VECM.ML
summary(VECM.ML)


###Check Johansen MLE
myVECM <- lineVar(zeroyld, lag=1, include="const", model="VECM", estim="ML")
summary(myVECM, digits=7)
#comparing with vars package
if(require(vars)){
a<-ca.jo(zeroyld, spec="trans")
summary(a)
#same answer also!
}

##export to Latex
toLatex(VECM.EG)
toLatex(summary(VECM.EG))
options("show.signif.stars"=FALSE)
toLatex(summary(VECM.EG), parenthese="Pvalue")
options("show.signif.stars"=TRUE)
```

`llar` *Locally linear model*

Description

Casdagli test of nonlinearity via locally linear forecasts

Usage

```
llar(x, m, d = 1, steps = d, series, eps.min = sd(x)/2,
 eps.max = diff(range(x)), neps = 30, trace = 0)

llar.predict(x, m, d=1, steps=d, series, n.ahead=1,
eps=stop("you must specify a window value"),
```

```
onvoid=c("fail","enlarge"), r = 20, trace=1)

llar.fitted(x, m, d=1, steps=d, series, eps, trace=0)
```

Arguments

x	time series
m, d, steps	embedding dimension, time delay, forecasting steps
series	time series name (optional)
n.ahead	n. of steps ahead to forecast
eps.min, eps.max	min and max neighbourhood size
neps	number of neighbourhood levels along which iterate
eps	neighbourhood size
onvoid	what to do in case of an isolated point: stop or enlarge neighbourhood size by an r%
r	if an isolated point is found, enlarge neighbourhood window by r%
trace	tracing level: 0, 1 or more than 1 for llar, 0 or 1 for llar.forecast

Details

llar does the Casdagli test of non-linearity. Given the embedding state-space (of dimension m and time delay d) obtained from time series series, for a sequence of distance values eps, the relative error made by forecasting time series values with a linear autoregressive model estimated on points closer than eps is computed. If minimum error is reached at relatively small length scales, a global linear model may be inappropriate (using current embedding parameters). This was suggested by Casdagli(1991) as a test for non-linearity.

llar.predict tries to extend the given time series by n.ahead points by iteratively fitting locally (in the embedding space of dimension m and time delay d) a linear model. If the spatial neighbourhood window is too small, your time series last point would be probably isolated. You can ask to automatically enlarge the window eps by a factor of r% sequentially, until enough neighbours are found for fitting the linear model.

llar.fitted gives out-of-sample fitted values from locally linear models.

Value

llar gives an object of class 'llar'. I.e., a list of components:

RMSE	vector of relative errors
eps	vector of neighbourhood sizes (in the same order of RMSE)
frac	vector of fractions of the time series used for RMSE computation
avfound	vector of average number of neighbours for each point in the time series which can be plotted using the plot method, and transformed to a regular data.frame with the as.data.frame function.

Function llar.forecast gives the vector of n steps ahead locally linear iterated forecasts.

Function llar.fitted gives out-of-sample fitted values from locally linear models.

Warning

For long time series, this can be slow, especially for relatively big neighbourhood sizes.

Note

The C implementation was re-adapted from that in the TISEAN package ("ll-ar" routine, see references). However, here the euclidean norm is used, in place of the max-norm.

Author(s)

Antonio, Fabio Di Narzo

References

M. Casdagli, Chaos and deterministic versus stochastic nonlinear modelling, J. Roy. Stat. Soc. 54, 303 (1991)

Hegger, R., Kantz, H., Schreiber, T., Practical implementation of nonlinear time series methods: The TISEAN package; CHAOS 9, 413-435 (1999)

Examples

```
res <- llar(log(lynx), m=3, neps=7)
plot(res)

x.new <- llar.predict(log(lynx),n.ahead=20, m=3, eps=1, onvoid="enlarge", r=5)
lag.plot(x.new, labels=FALSE)

x.fitted <-  llar.fitted(log(lynx), m=3, eps=1)
lag.plot(x.fitted, labels=FALSE)
```

---

logLik.nlVar *Extract Log-Likelihood*

Description

Log-Likelihood method for VAR and VECM models.

Usage

```
## S3 method for class 'nlVar'
logLik(object, ...)

## S3 method for class 'VECM'
logLik(object, r, ...)
```

Arguments

`object`	object of class `VAR` computed by `lineVar`, or class `VECM` computed by `VECM`.
`...`	additional arguments to `logLik`.
`r`	The cointegrating rank. By default the rank specified in the call to `VECM`, but can be set differently by user.

Details

For a VAR, the Log-Likelihood is computed as in Luetkepohl (2006) equ. 3.4.5 (p. 89) and Juselius (2006) p. 56:

$$LL = -(TK/2)\log(2\pi) - (T/2)\log|\Sigma| - (1/2)\sum^{T}\left[(y_t - A^{'}x_t)^{'}\Sigma^{-1}(y_t - A^{'}x_t)\right]$$

Where Σ is the Variance matrix of residuals, and x_t is the matrix stacking the regressors (lags and deterministic).

However, we use a computationally simpler version:

$$LL = -(TK/2)\log(2\pi) - (T/2)\log|\Sigma| - (TK/2)$$

See Juselius (2006), p. 57.

(Note that Hamilton (1994) 11.1.10, p. 293 gives $+(T/2)\log|\Sigma^{-1}|$, which is the same as $-(T/2)\log|\Sigma|$).

For VECM, the Log-Likelihood is computed in two different ways, depending on whether the `VECM` was estimated with ML (Johansen) or 2OLS (Engle and Granger).

When the model is estimated with ML, the LL is computed as in Hamilton (1994) 20.2.10 (p. 637):

$$LL = -(TK/2)\log(2\pi) - (TK/2) - (T/2)\log|\hat{\Sigma}_{UU}| - (T/2)\sum_{i=1}^{r}\log(1-\hat{\lambda}_i)$$

Where Σ_{UU} is the variance matrix of residuals from the first auxiliary regression, i.e. regressing Δy_t on a constant and lags, $\Delta y_{t-1}, \ldots, \Delta y_{t-p}$. λ_i are the eigenvalues from the $\Sigma_{VV}^{-1}\Sigma_{VU}\Sigma_{UU}^{-1}\Sigma_{UV}$, see 20.2.9 in Hamilton (1994).

When the model is estimated with 2OLS, the LL is computed as:

$$LL = \log|\Sigma|$$

Where Σ is the variance matrix of residuals from the the VECM model. There is hence no correspondence between the LL from the VECM computed with 2OLS or ML.

Value

Log-Likelihood value.

Author(s)

Matthieu Stigler

References

Hamilton (1994) *Time Series Analysis*, Princeton University Press

Juselius (2006) *The Cointegrated VAR model: methodology and Applications*, Oxford Univesity Press

Luetkepohl (2006) *New Introduction to Multiple Time Series Analysis*, Springer

Examples

```
data(zeroyld)

#Fit a VAR
VAR <- lineVar(zeroyld, lag=1)
logLik(VAR)

#'#Fit a VECM
vecm <- VECM(zeroyld, lag=1, r=1, estim="ML")
logLik(vecm)
```

LSTAR *Logistic Smooth Transition AutoRegressive model*

Description

Logistic Smooth Transition AutoRegressive model.

Usage

```
lstar(x, m, d=1, steps=d, series, mL, mH, mTh, thDelay,
       thVar, th, gamma, trace=TRUE, include = c("const", "trend","none", "both"),
          control=list(), starting.control=list())
```

Arguments

x	time series
m, d, steps	embedding dimension, time delay, forecasting steps
series	time series name (optional)
mL	autoregressive order for 'low' regime (default: m). Must be <=m
mH	autoregressive order for 'high' regime (default: m). Must be <=m
thDelay	'time delay' for the threshold variable (as multiple of embedding time delay d)
mTh	coefficients for the lagged time series, to obtain the threshold variable
thVar	external threshold variable
th, gamma	starting values for coefficients in the LSTAR model. If missing, a grid search is performed

`trace`	should additional infos be printed? (logical)
`include`	Type of deterministic regressors to include
`control`	further arguments to be passed as `control` list to `optim`
`starting.control`	further arguments for the grid search (dimension, bounds). See details below.

Details

$$x_{t+s} = (\phi_{1,0}+\phi_{1,1}x_t+\phi_{1,2}x_{t-d}+\cdots+\phi_{1,mL}x_{t-(mL-1)d})G(z_t,th,\gamma)+(\phi_{2,0}+\phi_{2,1}x_t+\phi_{2,2}x_{t-d}+\cdots+\phi_{2,mH}x_{t-(mH-1)d}$$

with z the threshold variable, and G the logistic function, computed as `plogis(q, location = th, scale = 1/gamma)`, so see `plogis` documentation for details on the logistic function formulation and parameters meanings. The threshold variable can alternatively be specified by:

mTh $z[t] = x[t]mTh[1] + x[t-d]mTh[2] + \cdots + x[t-(m-1)d]mTh[m]$

thDelay $z[t] = x[t - thDelay * d]$

thVar $z[t] = thVar[t]$

Note that if starting values for phi1 and phi2 are provided, isn't necessary to specify `mL` and `mH`. Further, the user has to specify only one parameter between `mTh`, `thDelay` and `thVar` for indicating the threshold variable.

Estimation of the transition parameters *th* and *gamma*, as well as the regression parameters *phi1* and *phi2*, is done using concentrated least squares, as suggested in *Leybourne et al. (1996)*.

Given *th* and *gamma*, the model is linear, so regression coefficients can be obtained as usual by OLS. So the nonlinear numerical search needs only to be done for *th* and *gamma*; the regression parameters are then recovered by OLS again from the optimal *th* and *gamma*.

For the nonlinear estimation of the parameters *th* and *gamma*, the program uses the `optim` function, with optimization method BFGS using the analytical gradient. For the estimation of standard values, `optim` is re-run using the complete Least Squares objective function, and the standard errors are obtained by inverting the hessian. You can pass further arguments to optim directly with the `control` list argument. For instance, the option `maxit` maybe useful when there are convergence issues (see examples).

Starting parameters are obtained doing a simple two-dimensional grid-search over *th* and *gamma*. Parameters of the grid (interval for the values, dimension of the grid) can be passed to `starting.control`.

`nTh` The number of threshold values (*th*) in the grid. Defaults to 200

`nGamma` The number of smoothing values (*gamma*) in the grid. Defaults to 40

`trim` The minimal percentage of observations in each regime. Defaults to 10% (possible threshold values are between the 0.1 and 0.9 quantile)

`gammaInt` The lower and higher smoothing values of the grid. Defaults to c(1,40)

`thInt` The lower and higher threshold values of the grid. When not specified (default, i.e NA), the interval are the `trim` quantiles above.

Value

An object of class `nlar`, subclass `lstar`, i.e. a list with fitted model informations.

Author(s)

Antonio, Fabio Di Narzo

References

Non-linear time series models in empirical finance, Philip Hans Franses and Dick van Dijk, Cambridge: Cambridge University Press (2000).

Non-Linear Time Series: A Dynamical Systems Approach, Tong, H., Oxford: Oxford University Press (1990).

Leybourne, S., Newbold, P., Vougas, D. (1998) Unit roots and smooth transitions, Journal of Time Series Analysis, 19: 83-97

See Also

`plot.lstar` for details on plots produced for this model from the `plot` generic.

Examples

```
#fit a LSTAR model. Note 'maxit': slow convergence
mod.lstar <- lstar(log10(lynx), m=2, mTh=c(0,1), control=list(maxit=3000))
mod.lstar

#fit a LSTAR model without a constant in both regimes.
mod.lstar2 <- lstar(log10(lynx), m=1,  include="none")
mod.lstar2

#Note in example below that the initial grid search seems to be to narrow.
# Extend it, and evaluate more values (slow!):
controls <- list(gammaInt=c(1,2000), nGamma=50)
mod.lstar3 <- lstar(log10(lynx), m=1,  include="none", starting.control=controls)
mod.lstar3

# a few methods for lstar:
summary(mod.lstar)
residuals(mod.lstar)
AIC(mod.lstar)
BIC(mod.lstar)
plot(mod.lstar)
predict(mod.lstar, n.ahead=5)
```

m.unrate *Monthly US unemployment*

Description

Monthly US civilian unemployment rate from 1948 through 2004. Used in the book financial time series for Tsay (2005, chapter 4)

Usage

```
data(m.unrate)
```

Format

zoo object

Source

'https://faculty.chicagobooth.edu/ruey-s-tsay/research/analysis-of-financial-time-series-2nd-editior

References

Ruey Tsay (2005) Analysis of Financial Time Series, 2nd ed. (Wiley, ch. 4)

MakeThSpec *Specification of the threshold search*

Description

This optional function allows the user to set different restrictions for the threshold grid search in function selectSETAR.

Usage

```
MakeThSpec(
  ngrid = c("All", "Half", "Third", "Quarter"),
  exact = NULL,
  int = c("from", "to"),
  around = "val",
  ...
)
```

Arguments

ngrid	The number of values to search for
exact	The user give an exact threshold value
int	The user gives an interval to search inside
around	The user gives an point to search around
...	currently unused

Details

This function is just to check the inputs for the specification of the grid search. If not provided, the search will be in the biggest interval (`ngrid ="All"`) between the minimum and maximum values. The user can reduce it by giving setting "Half" (only every two points is taken) and so on, or setting a number.

The search can also be made around a point, or between two points. When between a point, the argument `ngrid` is still used, whereas for around, a value of 30 is taken as default value if `ngrid` is not specified by user.

Value

The input values are given as output after checking for consistency (only one of exact/int/around should be given).

Author(s)

Matthieu Stigler

See Also

selectSETAR

Examples

```
sun<-(sqrt(sunspot.year+1)-1)*2
selectSETAR(sun, m=3, th=MakeThSpec(exact=10.40967),criterion="SSR", d=1, thDelay=0:2,
           plot=FALSE, nthresh=1)
#when pre-sepcified value does not correspond, function will search nearest value
selectSETAR(sun, m=3, th=MakeThSpec(exact=10.4),criterion="SSR", d=1, thDelay=0:2,
           plot=FALSE, nthresh=1)
#search around:
selectSETAR(sun, m=3, th=MakeThSpec(around=10.40967, ngrid=20),criterion="SSR", d=1, thDelay=0:2,
           plot=FALSE, nthresh=1)
#search in an interval
selectSETAR(sun, m=3, th=MakeThSpec(int=c(10, 11), ngrid=20),criterion="SSR", d=1, thDelay=0:2,
           plot=FALSE, nthresh=1)
#reduce size of the grid:
selectSETAR(sun, m=3, th=MakeThSpec(ngrid="Half"),criterion="SSR", d=1, thDelay=0:2,
           plot=FALSE, nthresh=1)
```

```
# 2 thresholds:
selectSETAR(sun, m=3, th=MakeThSpec(ngrid="Half"),criterion="SSR", d=1, thDelay=0:2,
           plot=FALSE, nthresh=2)
```

MAPE *Mean Absolute Percent Error*

Description

Generic function to compute the Mean Absolute Percent Error of a fitted model.

Usage

```
MAPE(object, ...)

## Default S3 method:
MAPE(object, ...)
```

Arguments

object	object of class nlar.fit
...	additional arguments to MAPE

Value

Computed Mean Absolute Percent Error for the fitted model.

Author(s)

Antonio, Fabio Di Narzo

---

mse *Mean Square Error*

Description

Generic function to compute the Mean Squared Error of a fitted model.

Usage

```
mse(object, ...)

## Default S3 method:
mse(object, ...)
```

Arguments

object	object of class nlar.fit
...	additional arguments to mse

Value

Computed MSE for the fitted model.

Author(s)

Antonio, Fabio Di Narzo

---

nlar-methods *NLAR methods*

Description

Generic 'nlar' methods. Method 'nlar' is described in a separate page: nlar

Usage

```
## S3 method for class 'nlar'
coef(object, ...)

## S3 method for class 'nlar'
fitted(object, ...)

## S3 method for class 'nlar'
residuals(object, initVal = TRUE, timeAttr = TRUE, ...)

## S3 method for class 'nlar'
deviance(object, ...)

## S3 method for class 'nlar'
mse(object, ...)

## S3 method for class 'nlar'
AIC(object, k = 2, ...)

## S3 method for class 'nlar'
BIC(object, ...)

## S3 method for class 'nlar'
MAPE(object, ...)

## S3 method for class 'nlar'
summary(object, ...)
```

```
## S3 method for class 'nlar'
plot(x, ask = interactive(), ...)

## S3 method for class 'nlar'
toLatex(object, digits, label, ...)
```

Arguments

...	further arguments to be passed to and from other methods
initVal	Whether to return NA for initial values in residuals/predicitons etc
timeAttr	Whether the time attributes should be returned in the output
k	numeric, the penalty per parameter to be used for AIC/BIC; the default k = 2 is the classical AIC
x, object	fitted 'nlar' object
ask	graphical option. See par
digits	For print method, see printCoefmat.
label	LaTeX label passed to the equation

Details

MAPE Mean Absolute Percent Error

mse Mean Square Error

plot Diagnostic plots

Author(s)

Antonio, Fabio Di Narzo

See Also

availableModels for listing all currently available models.

Examples

```
x <- log10(lynx)
mod.setar <- setar(x, m=2, thDelay=1, th=3.25)
mod.setar
AIC(mod.setar)
mse(mod.setar)
MAPE(mod.setar)
coef(mod.setar)
summary(mod.setar)

e <- residuals(mod.setar)
e <- e[!is.na(e)]
plot(e)
acf(e)
```

```
plot(x)
lines(fitted(mod.setar), lty=2)
legend(x=1910, y=3.9,lty=c(1,2), legend=c("observed","fitted"))

plot(mod.setar)
```

NNET *Neural Network nonlinear autoregressive model*

Description

Neural Network nonlinear autoregressive model.

Usage

```
nnetTs(x, m, d = 1, steps = d, series, size,
 control = list(trace = FALSE))
```

Arguments

x	time series
m, d, steps	embedding dimension, time delay, forecasting steps
series	time series name (optional)
size	number of hidden units in the neural network
control	control list to be passed to nnet::nnet optimizer

Details

Neural network model with 1 hidden layer and linear output:

$$x_{t+s} = \beta_0 + \sum_{j=1}^{D} \beta_j g(\gamma_{0j} + \sum_{i=1}^{m} \gamma_{ij} x_{t-(i-1)d})$$

Model is estimated using the nnet function in **nnet** package. Optimization is done via the BFGS method of optim. Note that for this model, no additional model-specific summary and plot methods are made available from this package.

Value

An object of class nlar, subclass nnetTs, i.e. a list with mostly nnet::nnet internal structures.

Author(s)

Antonio, Fabio Di Narzo

References

Non-linear time series models in empirical finance, Philip Hans Franses and Dick van Dijk, Cambridge: Cambridge University Press (2000).

Non-Linear Time Series: A Dynamical Systems Approach, Tong, H., Oxford: Oxford University Press (1990).

Chaos: A Statistical Perspective, Chan, K., Tong, H., New York: Springer-Verlag (2001).

Examples

```
#fit a Neural Network model
mod.nnet <- nnetTs(log(lynx), m=2, size=3)
mod.nnet
```

`plot methods` *Plotting methods for SETAR and LSTAR subclasses*

Description

Plotting methods 'setar' and 'lstar' subclasses

Usage

```
## S3 method for class 'setar'
plot(x, ask=interactive(), legend=FALSE, regSwStart, regSwStop, ...)
## S3 method for class 'lstar'
plot(x, ask=interactive(), legend=FALSE, regSwStart, regSwStop, ...)
```

Arguments

`x`	fitted 'setar' or 'lstar' object
`ask`	graphical option. See `par`
`legend`	Should a legend be plotted? (logical)
`regSwStart, regSwStop`	optional starting and stopping time indices for regime switching plot
`...`	further arguments to be passed to and from other methods

Details

These plot methods produce a plot which gives to you an idea of the behaviour of the fitted model.

Firstly, if embedding dimension is, say, m, m scatterplots are produced. On the x axis you have the lagged time series values. On the y axis the 'response' time series values. Observed points are represented with different colors-symbols depending on the level of the threshold variable. Specifically, for the setar model, black means 'low regime', red means 'high regime'. For the lstar model, where the self-threshold variable is continuous, threshold values are grouped in 5 different zones with the same number of points in each. Note that if more than 300 points are to be plotted, they all

share the same symbol, and regimes can be distinguished only by color. If you want, by specifying `legend=TRUE` a legend is added at the upper-left corner of each scatterplot. To each scatterplot, a dashed line is superposed, which links subsequent fitted values.

Finally, a new time series plot is produced, with lines segments coloured depending on the regime (colors meanings are the same of those in the preceding scatterplots). Optionally, you can specify a starting and ending time indices, for zooming on a particular segment of the time series.

Author(s)

Antonio, Fabio Di Narzo

See Also

`setar`, `lstar`

nlar-methods for other generic available methods for this kind of objects.

Examples

```
##
##See 'setar' examples
##
```

`plot_ECT` *Plot the Error Correct Term (ECT) response*

Description

This plot shows how variables in a (T)VECM respond to deviations from the long-term equilibrium

Usage

```
plot_ECT(x, add.legend = TRUE, legend.location = "topright", ...)
```

Arguments

`x`	object of class `VECM` or `TVECM`
`add.legend`	logical. Whether to add a legend?
`legend.location`	character. Location of the legend, see `legend`
`...`	arguments passed to the initial `plot` call, see `plot`

Value

a plot, and invisibly the underlying data.frame, containing the ECT and the response for each variable

Examples

```
data(zeroyld)
vec_l1 <- VECM(zeroyldMeta[, c("long.run", "short.run")], lag =1)
tvec_l1 <- TVECM(zeroyldMeta[, c("long.run", "short.run")], lag =1,
                 plot  = FALSE, trace = FALSE, th1 = list(exact = -1.263))

plot_ECT(vec_l1)
plot_ECT(tvec_l1, legend.location = "bottomright")
```

`predict.nlar` *Predict method for objects of class* '`nlar`'.

Description

Forecasting a non-linear model object of general class '`nlar`', including '`setar`' and '`star`'.

Usage

```
## S3 method for class 'nlar'
predict(
  object,
  newdata,
  n.ahead = 1,
  type = c("naive", "MC", "bootstrap", "block-bootstrap"),
  nboot = 100,
  ci = 0.95,
  block.size = 3,
  boot1Zero = TRUE,
  seed = NULL,
  ...
)
```

Arguments

`object`	An object of class '`nlar`'; generated by `setar()` or `lstar()`.
`newdata`	Optional. A new data frame to predict from.
`n.ahead`	An integer specifying the number of forecast steps.
`type`	Type of forecasting method used. See details.
`nboot`	The number of replications for type MC or bootstrap.
`ci`	The forecast confidence interval (available only with types MC and bootstrap).
`block.size`	The block size when the block-bootstrap is used.
`boot1Zero`	Whether the first innovation for MC/bootstrap should be set to zero.
`seed`	optional, the seed for the random generation.
`...`	Further arguments passed to the internal '`oneStep`' function. Mainly argument '`thVar`' if an external threshold variable was provided

Details

The forecasts are obtained recursively from the estimated model. Given that the models are non-linear, ignoring the residuals in the 2- and more steps ahead forecasts leads to biased forecasts (so-called naive). Different resampling methods, averaging `n.boot` times over future residuals, are available:

naive No residuals

MC Monte-Carlo method, where residuals are taken from a normal distribution, with a standard deviation equal to the residuals sd.

bootstrap Residuals are resampled from the empirical residuals from the model.

block-bootstrap Same as bootstrap, but residuals are resampled in block, with size `block.size`

The `MC` and `bootstrap` methods correspond to equations 3.90 and 3.91 of Franses and van Dijk (2000, p. 121). The bootstrap/MC is initiated either from the first forecast, `n.ahead=1` (set with `boot1zero` to TRUE), or from the second only.

When the forecast method is based on resampling, forecast intervals are available. These are obtained simply as empirical `ci` quantiles of the resampled forecasts (cf Method 2 in Franses and van Dijk, 2000, p. 122).

Value

A '`ts`' object, or, in the case of MC/bootstrap, a list containing the prediction (pred) and the forecast standard errors (`se`).

Author(s)

Matthieu Stigler

References

Non-linear time series models in empirical finance, Philip Hans Franses and Dick van Dijk, Cambridge: Cambridge University Press (2000).

See Also

The model fitting functions `setar`, `lstar`.

A more sophisticated predict function, allowing to do sub-sample rolling predictions: `predict_rolling`.

Examples

```
x.train <- window(log10(lynx), end = 1924)
x.test <- window(log10(lynx), start = 1925)


### Use different forecasting methods:
mod.set <- setar(x.train, m=2, thDelay=0)
pred_setar_naive <- predict(mod.set, n.ahead=10)
pred_setar_boot <- predict(mod.set, n.ahead=10, type="bootstrap", n.boot=200)
```

```
pred_setar_Bboot <- predict(mod.set, n.ahead=10, type="block-bootstrap", n.boot=200)
pred_setar_MC <- predict(mod.set, n.ahead=10, type="bootstrap", n.boot=200)

## Plot to compare results:
pred_range <- range(pred_setar_naive, pred_setar_boot$pred, pred_setar_MC$pred, na.rm=TRUE)
plot(x.test, ylim=pred_range, main="Comparison of forecasts methods from same SETAR")
lines(pred_setar_naive, lty=2, col=2)
lines(pred_setar_boot$pred, lty=3, col=3)
lines(pred_setar_Bboot$pred, lty=4, col=4)
lines(pred_setar_MC$pred, lty=5, col=5)

legLabels <- c("Observed", "Naive F", "Bootstrap F","Block-Bootstrap F", "MC F")
legend("bottomleft", leg=legLabels, lty=1:5, col=1:5)
```

`predict.TVAR` *Predict method for objects of class* '`VAR`', '`VECM`' *or* '`TVAR`'

Description

Forecasting the **level** of a series estimated by '`VAR`' / '`VECM`' or '`TVAR`'

Usage

```
## S3 method for class 'TVAR'
predict(object, newdata, n.ahead = 5, newdataTrendStart, ...)

## S3 method for class 'VAR'
predict(object, newdata, n.ahead = 5, newdataTrendStart, exoPred = NULL, ...)
```

Arguments

`object`	An object of class '`VAR`', '`VECM`' or '`TVAR`'
`newdata`	Optional. A new data frame to predict from. This should contain lags of the level of the original series. See Details.
`n.ahead`	An integer specifying the number of forecast steps.
`newdataTrendStart`	If '`newdata`' is provided by the user, and the estimated model includes a trend, this argument specifies where the trend should start
`...`	Arguments passed to the unexported '`VAR.gen`' or '`TVAR.gen`' function
`exoPred`	vector/matrix of predictions for the exogeneous variable(s) (with '`n.ahead`' rows). Only for '`VAR`'/'`VECM`', not for '`TVAR`'.

Details

The forecasts are obtained recursively, and are for the levels of the series.

When providing newdata, newdata has to be ordered chronologically, so that the first row/element is the earliest value.

For VECM, the forecasts are obtained by transforming the VECM to a VAR (using function VARrep). Note that a VECM(lag=p) corresponds to a VAR(lag=p+1), so that if the user provides newdata for a VECM(lag=p), newdata should actually contain p+1 rows.

Value

A matrix of predicted values.

Author(s)

Matthieu Stigler

See Also

lineVar and VECM. VARrep

A more sophisticated predict function, allowing to do sub-sample rolling predictions: predict_rolling.

Examples

```
data(barry)
barry_in <- head(barry, -5)
barry_out <- tail(barry, 5)

mod_vecm <- VECM(barry_in, lag=2)
mod_var <- lineVar(barry_in, lag=3)
mod_tvar <- TVAR(barry_in, lag=3, nthresh=1, thDelay=1)

pred_vecm <- predict(mod_vecm)
pred_var  <- predict(mod_var)
pred_tvar <- predict(mod_tvar)


## compare forecasts on a plot
n <- 30
plot(1:n, tail(barry[,1], n), type="l", xlim=c(0,n))
lines((n-5+1):n, pred_var[,1], lty=2, col=2)
lines((n-5+1):n, pred_vecm[,1], lty=2, col=3)
lines((n-5+1):n, pred_tvar[,1], lty=2, col=4)
legend("bottomright", lty=c(1,2,2,2), col=1:4, legend=c("true", "var", "vecm", "tvar"))

## example for newdata:
all.equal(predict(mod_vecm), predict(mod_vecm, newdata=barry[c(317, 318, 319),]))
```

predict_rolling *Rolling forecasts*

Description

Forecasts a VAR or VECM by discarding a part of the sample, and recursively generating a series of updated forecasts.

Usage

```
predict_rolling(object, ...)

## S3 method for class 'nlVar'
predict_rolling(object, nroll = 10, n.ahead = 1, refit.every, newdata, ...)
```

Arguments

object	A linear object of class 'nlVar'; generated by lineVar or VECM.
...	Currently not used.
nroll	The number of rolling forecasts
n.ahead	An integer specifying the number of forecast steps.
refit.every	Determines every how many periods the model is re-estimated.
newdata	In case the given model is already estimated on the sub-sample, the out-of-sample data can be provided with this argument. Note it should contain observations to predict the first values, that are also contained in the in-sample.

Details

This function allows to check the out-of sample forecasting accuracy by estimating the model on a sub-sample of the original, then making nroll forecasts of horizon n.ahead, each time by updating the sample. In other words, with a given model estimated on 100 observations, the function will estimate it on say 90 first obs (nroll=10), generate a say 1 step-ahead (n.ahead=1) from obs 90, then using true value 91 for to predict value at 92, etc, till the full sample is used.

Unlike with usual predict() methods, specifiying n.ahead=2 will not generate a 1 step-ahead and a 2 step-ahead forecasts, but only nroll 2 step-ahead forecasts.

Note that while the forecasts are updated with new values, the model estimation is (by default) not updated. This can however be done with the argument fit.every, specifiying at which frequency the model should be re-estimated. By setting it to 1 for example, each time a new observation is taken, the model is reestimated. This is similar to the ugarchroll in package **rugarch**.

Value

A matrix containing the forecasts.

Author(s)

Matthieu Stigler

See Also

predict.nlar for the standard predict function.

Examples

```
data(barry)

## model estimated on full sample:
mod_vec <- VECM(barry, lag=2)

## generate 10 1-step-ahead forecasts:
preds_roll <- predict_rolling(mod_vec, nroll=10)

## plot the results:
plot(window(barry[,"dolcan"],start=1998), type="l", ylab="barry: dolcan")
preds_roll_ts <- ts(preds_roll$pred, start=time(barry)[nrow(barry)-10], freq=12)
lines(preds_roll_ts[,"dolcan"], col=2, lty=2)
legend("bottomright", lty=c(1,2), col=1:2, leg=c("True", "Fitted"))
title("Comparison of true and rolling 1-ahead forecasts\n")
```

---

rank.select *Selection of the cointegrating rank with Information criterion.*

Description

Selection of the cointegrating rank and the lags with Information criterion (AIC, BIC).

Usage

```
rank.select(
  data,
  lag.max = 10,
  r.max = ncol(data) - 1,
  include = c("const", "trend", "none", "both"),
  fitMeasure = c("SSR", "LL"),
  sameSample = TRUE,
  returnModels = FALSE
)

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

```
## S3 method for class 'rank.select'
as.data.frame(x, ...)

## S3 method for class 'rank.select'
summary(object, ...)
```

Arguments

data	multivariate time series.
lag.max	Maximum number of lags to investigate.
r.max	Maximum rank to investigate.
include	Type of deterministic regressors to include. See VECM or lineVar.
fitMeasure	Whether the AIC/BIC should be based on the full likelihood, or just the SSR. See explanations in logLik.VECM.
sameSample	Logical. Whether the data should be shortened so that the AIC/BIC are estimated on the same sample. Default to TRUE.
returnModels	Logical, default to FALSE. Whether the output should also contain the list of each model computed.
x	The output from rank.select for the print method.
...	Unused.
object	The output from rank.select for the summary method.

Details

This function estimates the AIC, BIC and Hannan-Quinn for each rank (up to lags.max) and lags (up to lags.max). This method has been shown to be useful to select simultaneously the rank and the lags, see references.

Value

An object of class 'rank.select', with 'print' and 'summary methods', containing among other the matrices of AIC/BIC/HQ, the Likelihood, and best ranks according to each criterion.

Author(s)

Matthieu Stigler

References

- Aznar A and Salvador M (2002). Selecting The Rank Of The Cointegration Space And The Form Of The Intercept Using An Information Criterion. Econometric Theory, *18*(04), pp. 926-947. <URL: http://ideas.repec.org/a/cup/etheor/v18y2002i04p926-947_18.html>.

-Cheng X and Phillips PCB (2009). Semiparametric cointegrating rank selection. Econometrics Journal , *12*(s1), pp. S83-S104. <URL: http://ideas.repec.org/a/ect/emjrnl/v12y2009is1ps83-s104.html>.

- Gonzalo J and Pitarakis J (1998). Specification via model selection in vector error correction models. Economics Letters, *60*(3), pp. 321 - 328. ISSN 0165-1765, <URL: http://dx.doi.org/DOI: 10.1016/S0165-1765(98)00129-3>.

- Kapetanios G (2004). The Asymptotic Distribution Of The Cointegration Rank Estimator Under The Akaike Information Criterion. Econometric Theory, *20*(04), pp. 735-742. <URL: http://ideas.repec.org/a/cup/etheor/v20y2004i04p735-742_20.html>.

- Wang Z and Bessler DA (2005). A Monte Carlo Study On The Selection Of Cointegrating Rank Using Information Criteria. Econometric Theory, *21*(03), pp. 593-620. <URL: http://ideas.repec.org/a/cup/etheor/v21y200 620_05.html>.

See Also

VECM for estimating a VECM. rank.test (or ca.jo in package **urca**) for the classical Johansen cointegration test.

Examples

```
data(barry)

#
rk_sel <- rank.select(barry)
rk_sel
summary(rk_sel)
```

---

rank.test *Test of the cointegrating rank*

Description

Maximum-likelihood test of the cointegrating rank.

Usage

```
rank.test(vecm, type = c("eigen", "trace"), r_null, cval = 0.05)

## S3 method for class 'rank.test'
print(x, ...)

## S3 method for class 'rank.test'
summary(object, digits = max(1, getOption("digits") - 3), ...)
```

Arguments

vecm	'VECM' object computed with the function VECM.
type	Type of test, either 'trace' or 'eigenvalue'. See details below.
r_null	Rank to test specifically.
cval	Critical value level for the automatic test.
x	The output from rank.test for the print method.
...	Unused.
object	The output from rank.test for the summary method.
digits	The number of digits to use in format.pval

Details

This function computes the two maximum-likelihood tests for the cointegration rank from Johansen (1996). Tests are:

trace Test the hypothesis of rank 'h' against rank 'K', i.e. against the alternative that the system is stationary.

eigenvalue Test the hypothesis of rank 'h' against rank 'h+1'.

The test works for five specifications of the deterministic terms as in Doornik et al (1998), to be specified in the previous call to VECM:

H_ql Unrestricted constant and trend: use include="both"

H_l Unrestricted constant and restricted trend: use include="const"and LRinclude="trend"

H_lc Unrestricted constant and no trend: use include="const"

H_c Restricted constant and no trend: use LRinclude="const"

H_z No constant nor trend: use include="none"

Two testing procedures can be used:

Specific test By specifying a value for 'r_null'. The 'pval' value returned gives the speciifc p-value.

Automatic test If not value is specified for 'r_null', the function makes a simple automatic test: returns the rank (slot 'r') of the first test not rejected (level specified by arg cval) as recommend i.a. in Doornik et al (1998, p. 544).

A full table with both test statistics ad their respective p-values is given in the summary method.

P-values are obtained from the gamma approximation from Doornik (1998, 1999). Small sample values adjusted for the sample site are also available in the summary method. Note that the 'effective sample size' for the these values is different from output in gretl for example.

Value

An object of class 'rank.test', with 'print' and 'summary methods'.

Comparison with urca

While ca.jo in package **urca** and rank.test both implement Johansen tests, there are a few differences:

- rank.test gives p-values, while ca.jo gives only critical values.
- rank.test allows for five different specifications of deterministic terms (see above), ca.jo for only three.
- ca.jo allows for seasonal and exogenous regressors, which is not available in rank.test.
- The lag is specified differently: K from ca.jo corresponds to lag+1 in rank.test.

Author(s)

Matthieu Stigler

References

- Doornik, J. A. (1998) Approximations to the Asymptotic Distributions of Cointegration Tests, Journal of Economic Surveys, 12, 573-93

- Doornik, J. A. (1999) Erratum [Approximations to the Asymptotic Distribution of Cointegration Tests], Journal of Economic Surveys, 13, i

- Doornik, Hendry and Nielsen (1998) Inference in Cointegrating Models: UK M1 Revisited, Journal of Economic Surveys, 12, 533-72

- Johansen, S. (1996) Likelihood-based inference in cointegrated Vector Autoregressive Models, Oxford University Press

See Also

VECM for estimating a VECM. rank.select to estimate the rank based on information criteria.

ca.jo in package **urca** for another implementation of Johansen cointegration test (see section 'Comparison with urca' for more infos).

Examples

```
data(barry)

## estimate the VECM with Johansen!
ve <- VECM(barry, lag=1, estim="ML")

## specific test:
ve_test_spec <- rank.test(ve, r_null=1)
ve_test_spec_tr <- rank.test(ve, r_null=1, type="trace")

ve_test_spec
ve_test_spec_tr

## No specific test: automatic method
ve_test_unspec <- rank.test(ve)
```

```
ve_test_unspec_tr <- rank.test(ve, type="trace")

ve_test_unspec
ve_test_unspec_tr

## summary method: output will be same for all types/test procedure:
summary(ve_test_unspec_tr)

## The function works for many specification of the VECM(), try:
rank.test(VECM(barry, lag=3, estim="ML"))
rank.test(VECM(barry, lag=3, include="both",estim="ML"))
rank.test(VECM(barry, lag=3, LRinclude="const",estim="ML"))

## Note that the tests are simple likelihood ratio, and hence can be obtained also manually:
-2*(logLik(ve, r=1)-logLik(ve, r=2)) # eigen test, 1 against 2
-2*(logLik(ve, r=1)-logLik(ve, r=3)) # eigen test, 1 against 3
```

`regime` *Extract a variable showing the regime*

Description

This function allows to extract the indicator variable specifying the regime in which the process is at time t.

Usage

```
regime(object, initVal = TRUE, timeAttr = TRUE, series = NULL, ...)

## S3 method for class 'lstar'
regime(object, initVal = TRUE, timeAttr = TRUE, series, discretize = TRUE, ...)
```

Arguments

`object`	object of class `setar` or `nlVar`
`initVal`	Logical. Whether the initial NA values should be returned. Default to TRUE.
`timeAttr`	Logical. Whether the time attributes should be returned. Default to TRUE.
`series`	Optional. A numeric vector to classify according to the model.
`...`	additional arguments to `regime`
`discretize`	logical (default TRUE) whether the series are discretized to {1,2}, or whether regime probabilities are returned.

Value

Time series of same attributes as input to setar.

Author(s)

Matthieu Stigler

Examples

```
set<-setar(lynx, m=3)
regime(set)
regime(set, time=FALSE, initVal=FALSE)

plot(regime(set))
```

`resample_vec` *Resampling schemes*

Description

Bootstrap a vector according to multiple resampling schemes: resampling, block resampling, Wild bootstrap.

Usage

```
resample_vec(
  x,
  boot.scheme = c("resample", "resample_block", "wild1", "wild2", "check"),
  seed = NULL,
  block.size = 2
)
```

Arguments

`x`	A numeric vector
`boot.scheme`	The type of resampling scheme used, see Details
`seed`	the seed used, see `set.seed`
`block.size`	for the `resample_block` scheme, the size of the blocks.

Details

This function offers various bootstrap/resampling schemes:

resample Resampling with replacement

resample_block Resampling contiguous observations (blocks) with replacement. Use argument `block.size`

wild1 Wild bootstrap: do not resample, but add a N(0,1) distribution to each value

wild12 Wild bootstrap: same, but add instead -1 or 1.

resVar *Residual variance*

Description

Extracts the global and regime-dependent variance of the residuals

Usage

```
resVar(x, adj=c("OLS", "ML"))
```

Arguments

x	setar object
adj	Degrees of freedom adjustment for the variance

Details

The degree of freedom adjustment in the formula for the variance is the number of parameters when adj="OLS" or zero when adj="ML".

Value

A vector containing:

Total	The residual variance of the full sample
L, (M), H	The residual variance of the lower (L), middle (if two thresholds) (M) and higher (H) regimes

Author(s)

Matthieu Stigler

References

Non-Linear Time Series: A Dynamical Systems Approach, Tong, H., Oxford: Oxford University Press (1990).

Examples

```
#Lynx model as in Tong (1980, p. 387)
mod.setar <- setar(log10(lynx), mL=7,mH=2, thDelay=1, th=3.116)
summary(mod.setar)
#coefficients are same for lower regime but differ for higer

resVar(mod.setar, adj="ML")
#variance or the residuals is same for lower regime but differ for higer regime and hence for total

#Lynx model as in Tong (1980, p. 405)
```

```
mod.setar2 <- setar(log10(lynx), mL=1,mM=7,mH=2, thDelay=1, nthresh=2,th=c(2.373, 3.154))
round(coefficients(mod.setar2),3)

resVar(mod.setar2, adj="ML")
```

`selectHyperParms` *Automatic selection of model hyper-parameters*

Description

Automatic selection of model hyper-parameters

Usage

```
selectLSTAR(x, m, d=1, steps=d, mL = 1:m, mH = 1:m, thDelay=0:(m-1),
            fast=TRUE, trace=FALSE)
selectNNET(x, m, d=1, steps=d, size=1:(m+1), maxit=1e3, trace=FALSE)
```

Arguments

`x`	time series
`m`, `d`, `steps`	embedding parameters. For their meanings, see help about `nlar`
`mL`, `mH`	Vector of 'low' and 'high' regimes autoregressive orders
`thDelay`	Vector of 'threshold delay' values
`size`	Vector of numbers of hidden units in the nnet model
`maxit`	Max. number of iterations for each model estimation
`fast`	For LSTAR selection, whether a fast algorithm using starting values fro previous models should be used
`trace`	Logical. Whether informations from each model should be returned.

Details

Functions for automatic selection of LSTAR and NNET models hyper parameters. An exhaustive search over all possible combinations of values of specified hyper-parameters is performed. Embedding parameters `m`,`d`,`steps` are kept fixed.

Selection criterion is the usual AIC.

For the LSTAR model, two methods are offered:

fast=FALSE Each model is run separately, each time using the full grid search for starting values.

fast=TRUE Only the first model is run with a full grid search, while the subsequent use the first model results for their starting values.

Value

A data-frame, with columns giving hyper-parameter values and the computed AIC for each row (only the best 10s are returned)

Author(s)

Antonio, Fabio Di Narzo

Examples

```
llynx <- log10(lynx)
selectLSTAR(llynx, m=2)
selectNNET(llynx, m=3, size=1:5)
```

---

selectSETAR *Automatic selection of SETAR hyper-parameters*

Description

Automatic selection of SETAR hyper-parameters

Usage

```
selectSETAR(x, m, d=1, steps=d, series, mL, mH,mM, thDelay=0, mTh, thVar,
     th=MakeThSpec(), trace=TRUE, include = c("const", "trend","none", "both"),
     common=c("none", "include","lags", "both"), model=c("TAR", "MTAR"),
     ML=seq_len(mL), MH=seq_len(mH), MM=seq_len(mM), nthresh=1, trim=0.15,
     criterion = c("pooled-AIC", "AIC","BIC", "SSR"),  plot=TRUE,
     max.iter=2, type=c("level", "diff", "ADF"), same.lags=FALSE,
   restriction=c("none","OuterSymAll","OuterSymTh"), hpc=c("none", "foreach") )
```

Arguments

x	time series
m, d, steps	embedding parameters. For their meanings, see help about nlar
series	time series name (optional)
mL, mH, mM	autoregressive order for 'low' (mL) 'middle' (mM, only useful if nthresh=2) and 'high' (mH) regime (default values: m). Must be <=m. Alternatively, you can specify ML
thDelay	Vector of possible 'threshold delay' values to check for
mTh	coefficients for the lagged time series, to obtain the threshold variable
thVar	external threshold variable
th	Different specifications of the grid search, to pre-specify a value or set the number of points to search. SeeMakeThSpec
trace	should additional infos be printed? (logical)

include	Type of deterministic regressors to include
common	Indicates which elements are common to all regimes: no, only the include variables, the lags or both
model	Currently not implemented
ML, MM, MH	vector of lags for order for 'low' (ML) 'middle' (MM, only useful if nthresh=2) and 'high' (MH)regime. Max must be <=m
nthresh	Number of threshold of the model
trim	trimming parameter indicating the minimal percentage of observations in each regime. Default to 0.15
criterion	Model selection criterion
plot	Should a plot showing the criterion values be printed? (logical)
max.iter	Number of iterations for the algorithm
type	Whether the variable is taken is level, difference or a mix (diff y= y-1, diff lags) as in the ADF test
same.lags	Logical. When AIC or pooled-AIC is used and arg m is given, should it search for same number of lags in each regime (TRUE) or allow for different (FALSE) lags in each regime. Different lags involves more computation
restriction	Restriction on the threshold. OuterSymAll will take a symmetric threshold and symmetric coefficients for outer regimes. OuterSymTh currently unavailable
hpc	Possibility to run the bootstrap on parallel core. See details

Details

Routine for automatic selection of SETAR models hyper parameters.

An exhaustive search over all possible combinations of values of specified hyper-parameters is performed. Thus the threshold delay, the number of lags in each regime and the threshold value are computed.

Embedding parameters d, steps are kept fixed.

Possible criteria are the usual SSR, AIC and a pooled AIC formula: $AIC(lowregimemodel) + AIC(highregimemodel)$. The default criterion is the pooled AIC formula. SSR criterion can't be used to compare models with different lags.

When two thresholds(nthresh=2) have to be computed, the search for the second is made conditional on results for first threshold as suggested in Gonzalo and Pittarakis (2002). Refinements can be obtained by using max.iter (first threshold being re-estimated based on the second one). If SSR is used, the number of lags in the inner regime is either the same if only arg m was given, otherwise it has to be pre-specified. Criterion AIC can be used to determine the number of lags in the nner regime, whereas pooled-AIC is currently not implemented for nthresh=2.

By default, all threshold values excluding the upper and lower trim of the threshold values are taken as potential threshold. restriction can be made with arg th. See function MakeThSpec.

With the argument hpc, the heavy grid search can be run on parallel cores, thus alleviating the time of computation. Preliminary results indicate however that the length of the series must be very considerable in order that the parallel code becomes advantageous. To use it, the user needs simply to choose a package (among doMC, doMPI, doSNOW or doRedis) and register the backend. See the vignette for more details.

Value

An object of class `selectSETAR` (print and plot methods) with:

`res`	A data-frame, with columns giving hyper-parameter values and the computed AIC for each row (only the best 10/5s are returned)
`res2`	Same as res, returned if nthresh=2 otherwise set to NULL
`bests`	estimated hyper-parameters
`th`, `firstBests`, `bests2th`, `ML`, `MM`, `MH`	estimated parameters, from first and conditional search
`criterion`, `nthresh`, `same.lags`	returns args given by user
`allTh`	all threshold values and corresponding criterion from first search

Author(s)

Antonio, Fabio Di Narzo and Stigler, Matthieu

References

Gonzalo, J. & Pitarakis, J. (2002) Estimation and model selection based inference in single and multiple threshold models, Journal of Econometrics, 110, 319 - 352

See Also

`selectLSTAR`, `selectNNET`, MakeThSpec

Examples

```
llynx <- log10(lynx)
selectSETAR(llynx, m=2)
#Suggested model is the following:
setar(llynx, m=2, thDelay=1, th=3.4)
```

SETAR *Self Threshold Autoregressive model*

Description

Self Exciting Threshold AutoRegressive model.

Usage

```
setar(x, m, d=1, steps=d, series, mL, mM, mH, thDelay=0, mTh, thVar, th, trace=FALSE,
      nested=FALSE, include = c( "const", "trend","none", "both"),
    common=c("none", "include","lags", "both"), model=c("TAR", "MTAR"), ML=seq_len(mL),
    MM=seq_len(mM), MH=seq_len(mH),nthresh=1,trim=0.15, type=c("level", "diff", "ADF"),
      restriction=c("none","OuterSymAll","OuterSymTh") )
```

Arguments

x	time series
m, d, steps	embedding dimension, time delay, forecasting steps
series	time series name (optional)
mL, mM, mH	autoregressive order for 'low' (mL) 'middle' (mM, only useful if nthresh=2) and 'high' (mH)regime (default values: m). Must be <=m. Alternatively, you can specify ML
thDelay	'time delay' for the threshold variable (as multiple of embedding time delay d)
mTh	coefficients for the lagged time series, to obtain the threshold variable
thVar	external threshold variable
th	threshold value (if missing, a search over a reasonable grid is tried)
trace	should additional infos be printed? (logical)
include	Type of deterministic regressors to include
common	Indicates which elements are common to all regimes: no, only the include variables, the lags or both
ML, MM, MH	vector of lags for order for 'low' (ML) 'middle' (MM, only useful if nthresh=2) and 'high' (MH)regime. Max must be <=m
model	Whether the threshold variable is taken in levels (TAR) or differences (MTAR)
nthresh	Number of threshold of the model
trim	trimming parameter indicating the minimal percentage of observations in each regime. Default to 0.15
type	Whether the variable is taken is level, difference or a mix (diff y= y-1, diff lags) as in the ADF test
restriction	Restriction on the threshold. OuterSymAll will take a symmetric threshold and symmetric coefficients for outer regimes. OuterSymTh currently unavailable
nested	Whether is this a nested call? (useful for correcting final model df)

Details

Self Exciting Threshold AutoRegressive model.

$$X_{t+s} = x_{t+s} = (\phi_{1,0}+\phi_{1,1}x_t+\phi_{1,2}x_{t-d}+\cdots+\phi_{1,mL}x_{t-(mL-1)d})I(z_t \leq th)+(\phi_{2,0}+\phi_{2,1}x_t+\phi_{2,2}x_{t-d}+\cdots+\phi_{2,mH}x_{t-(}$$

with *z* the threshold variable. The threshold variable can alternatively be specified by (in that order):

thDelay `z[t] = x[t - thDelay*d ]`

mTh `z[t] = x[t] mTh[1] + x[t-d] mTh[2] + ... + x[t-(m-1)d] mTh[m]`

thVar `z[t] = thVar[t]`

For fixed th and threshold variable, the model is linear, so phi1 and phi2 estimation can be done directly by CLS (Conditional Least Squares). Standard errors for phi1 and phi2 coefficients provided by the summary method for this model are taken from the linear regression theory, and are to be considered asymptotical.

Value

An object of class `nlar`, subclass `setar`

Author(s)

Antonio, Fabio Di Narzo

References

Non-linear time series models in empirical finance, Philip Hans Franses and Dick van Dijk, Cambridge: Cambridge University Press (2000).

Non-Linear Time Series: A Dynamical Systems Approach, Tong, H., Oxford: Oxford University Press (1990).

See Also

`plot.setar` for details on plots produced for this model from the `plot` generic.

Examples

```
#fit a SETAR model, with threshold as suggested in Tong(1990, p 377)
mod.setar <- setar(log10(lynx), m=2, thDelay=1, th=3.25)
mod.setar
summary(mod.setar)

## example in Tsay (2005)
data(m.unrate)
setar(diff(m.unrate), ML=c(2,3,4,12), MH=c(2,4,12), th=0.1, include="none")
```

---

setar.sim *Simulation and bootstrap of Threshold Autoregressive model (SETAR)*

Description

Simulate or bootstrap a Threshold AR (SETAR) The `setar.sim` function allows to simulate a SETAR model from scratch. The most important argument is the `B` argument, which should be a one row matrix, with first the constant/trend arguments, then the slope coefficients, and this for each regime (lower, middle, high). Other arguments such as `lag`, `nthresh` indicate the dimension of this matrix. As an example, a SETAR with 2 lags, 1 threshold, a constant, would have coefficient in the order: `c(const_L, phi_1_L, phi_2_L, const_H, phi_1_H, phi_2_H)` where L is for Lower regime, H for Higher.

`setar.boot` on the other side resample/bootstraps an existing setar output. It uses a recursive approach, reconstructing the series. Residuals from the original model are resampled using different bootstrap schemes, see `resample_vec`.

Usage

```
setar.boot(
  setarObject,
  boot.scheme = c("resample", "resample_block", "wild1", "wild2", "check"),
  seed = NULL,
  ...
)

linear.boot(
  linearObject,
  boot.scheme = c("resample", "resample_block", "wild1", "wild2", "check"),
  seed = NULL,
  ...
)

setar.sim(
  B,
  n = 200,
  lag = 1,
  include = c("const", "trend", "none", "both"),
  nthresh = 1,
  Thresh,
  starting = NULL,
  innov = rnorm(n),
  ...
)

linear.sim(
  B,
  n = 200,
  lag = 1,
  include = c("const", "trend", "none", "both"),
  starting = NULL,
  innov = rnorm(n),
  ...
)
```

Arguments

setarObject	Bootstrap: the setar object to resample data from.
boot.scheme	Bootstrap: which resampling scheme to use for the residuals. See resample_vec.
seed	Bootstrap: seed used in the resampling
...	additional arguments for the unexported setar.gen.
linearObject	Bootstrap: the linear object to resample data from.
B	Simulation: vector of coefficients to simulate from.
n	Simulation: Number of observations to simulate.

`Thresh`, `nthresh`, `lag`, `include`
: Simulation: parameters for the SETAR to simulate. See `setar` for their description.

`starting`
: Simulation: Starting values (same length as lag)

`innov`
: Simulation: time series of innovations/residuals.

Value

a list with the simulated/bootstrapped data and the parameter matrix used.

Author(s)

Matthieu Stigler

See Also

`SETAR` to estimate a SETAR, `arima.sim` to simulate an ARMA.

Examples

```
##Simulation of a TAR with 1 threshold
TvarMat <- c(2.9,-0.4,-0.1,-1.5, 0.2,0.3)
sim<-setar.sim(B=TvarMat,lag=2, type="simul", nthresh=1, Thresh=2, starting=c(2.8,2.2))
mean(ifelse(sim>2,1,0)) #approximation of values over the threshold

#check the result
selectSETAR(sim, m=2)

##Bootstrap a TAR with two threshold (three regimes)
sun <- (sqrt(sunspot.year+1)-1)*2
sun_est <- setar(sun, nthresh=2, m=2)
sun_est_boot <- setar.boot(sun_est)
head(sun_est_boot)

##Check the bootstrap: with no resampling, is it the same series?
sun_est_boot <- setar.boot(sun_est, boot.scheme = "check")
all.equal(as.numeric(sun), sun_est_boot)
```

---

setarTest *Test of linearity against threshold (SETAR)*

Description

Test of linearity against threshold of Hansen (1999) with bootstrap distribution

Usage

```
setarTest(
  x,
  m,
  thDelay = 0,
  trim = 0.1,
  include = c("const", "trend", "none", "both"),
  nboot = 10,
  test = c("1vs", "2vs3"),
  hpc = c("none", "foreach"),
  boot.scheme = c("resample", "resample_block", "wild1", "wild2", "check"),
  seed = NULL
)
```

Arguments

x	time series
m, thDelay	lag and 'time delay' for the threshold variable
trim	trimming parameter indicating the minimal percentage of observations in each regime
include	Type of deterministic regressors to include: none, a constant, a trend, or constant and trend (both).
nboot	number of bootstrap replications
test	whether to test AR against SETAR, or SETAR(1 reg) against SETAR(2 reg)
hpc	Possibility to run the bootstrap on parallel core. See details in
boot.scheme	Type of resampling scheme to use for the residuals. See resample_vec.
seed	Seed used in the bootstrap resampling TVECM.HStest

Details

Estimation of the first threshold parameter is made with CLS, a conditional search with one iteration is made for the second threshold. The Ftest comparing the residual sum of squares (SSR) of each model is computed.

$$F_{ij} = T((S_i - S_j)/S_j)$$

where S_i is the SSR of the model with i regimes (and so i-1 thresholds).

Three test are available. The both first can be seen as linearity test, whereas the third can be seen as a specification test: once the 1vs2 or/and 1vs3 rejected the linearity and henceforth accepted the presence of a threshold, is a model with one or two thresholds preferable?

Test **1vs**2: Linear AR versus 1 threshold TAR

Test **1vs**3: Linear AR versus 2 thresholds TAR

Test **2vs3**: 1 threshold TAR versus 2 thresholds TAR

The two first tests are computed together and available with test="1vs". The third test is available with test="2vs3".

The homoskedastic bootstrap distribution is based on resampling the residuals from H0 model (ar for test 1vs, and setar(1) for test 2vs3), estimating the threshold parameter and then computing the Ftest, so it involves many computations and is pretty slow.

Value

A object of class "Hansen99Test" containing:

`SSRs`	The residual Sum of squares of model AR, 1 threshold TAR and 2 thresholds TAR
`Ftests`	The Ftest statistic for the test
`PvalBoot`	The bootstrap p-values for the test selected
`CriticalValBoot`	The critical values for the test selected
`Ftestboot`	All the F-test computed
`firstBests`, `secBests`	The thresholds for the original series, obtained from search for 1 thresh (`firstBests`) and conditional search for 2 thresh (secBests)
`nboot`, `m`	The number of bootstrap replications (`nboot`), the lags used (`m`)

Author(s)

Matthieu Stigler

References

Hansen (1999) Testing for linearity, Journal of Economic Surveys, Volume 13, Number 5, December 1999 , pp. 551-576(26) available at: https://www.ssc.wisc.edu/~bhansen/papers/cv.htm

See Also

`TVAR.LRtest` for the multivariate version. `SETAR` for estimation of the model.

Examples

```
#Data used by Hansen
sun <- (sqrt(sunspot.year + 1) - 1) * 2

#Test 1vs2 and 1vs3
#setarTest(sun, m=11, thDelay=0:1, nboot=5,trim=0.1, test="1vs")
```

setarTest_IIPUs_results *Results from the setarTest, applied on Hansen (1999) data*

Description

Saved objects

Usage

```
setarTest_IIPUs_results
```

Format

A list containing output from two tests

See Also

Example in IIPUs

Examples

```
library(tsDyn)
data(IIPUs)
B <-  1000
## Not run:
  test_1 <- setarTest(IIPUs, m=16, thDelay=5, nboot=B)
  test_2 <- setarTest(IIPUs, m=16, thDelay=5, nboot=B, test = "2vs3")

## End(Not run)
```

sigmoid *sigmoid functions*

Description

Some sigmoid functions. See R sources for their definition

Usage

```
sigmoid(x)

dsigmoid(x)
```

Arguments

x	numeric vector

Author(s)

J. L. Aznarte

STAR *STAR model*

Description

STAR model fitting with automatic selection of the number of regimes based on LM tests.

Usage

```
star(x, m=2, noRegimes, d = 1, steps = d, series, rob = FALSE,
                mTh, thDelay, thVar, sig=0.05, trace=TRUE, control=list(), ...)
```

Arguments

x	time series
m, d, steps	embedding dimension, time delay, forecasting steps
noRegimes	max number of regimes
series	time series name (optional)
rob	perform robust test (not implemented)
thDelay	'time delay' for the threshold variable (as multiple of embedding time delay d)
mTh	coefficients for the lagged time series, to obtain the threshold variable
thVar	external threshold variable
sig	significance level for the tests to select the number of regimes.
control	further arguments to be passed as control list to optim
trace	should additional infos be printed out?
...	currently unused

Details

The function star implements the iterative building strategy described in [1] to identify and estimate Smooth Transition Autoregressive models.

[1] T. Terasvirta, "Specification, estimation and evaluation of smooth transition autoregressive models", J. Am. Stat. Assoc. 89 (1994): 208-218.

Value

star returns an object of class nlar, subclass star, i.e. a list with informations about the fitted model.

Author(s)

J. L. Aznarte M.

See Also

addRegime

Examples

```
mod.star <- star(log10(lynx), mTh=c(0,1), control=list(maxit=3000))
mod.star

addRegime(mod.star)
```

---

toLatex.setar *Latex representation of fitted setar models*

Description

Produce LaTeX output of the SETAR model.

Usage

```
## S3 method for class 'setar'
toLatex(object, digits = 3, label, ...)
```

Arguments

object	fitted setar model (using nlar)
digits	options to be passed to format for formatting numbers
label	LaTeX label passed to the equation
...	Not used

Author(s)

Antonio, Fabio Di Narzo

See Also

setar, nlar-methods

Examples

```
mod.setar <- setar(log10(lynx), m=2, thDelay=1, th=3.25)
toLatex(mod.setar)
```

TVAR *Multivariate Threshold Vector Autoregressive model*

Description

Estimate a multivariate Threshold VAR (TVAR), either using lags as transition variable (default), or specifying an external variable.

Usage

```
TVAR(
  data,
  lag,
  include = c("const", "trend", "none", "both"),
  model = c("TAR", "MTAR"),
  commonInter = FALSE,
  nthresh = 1,
  thDelay = 1,
  mTh = 1,
  thVar,
  trim = 0.1,
  ngrid,
  gamma = NULL,
  around,
  plot = FALSE,
  dummyToBothRegimes = TRUE,
  trace = TRUE,
  trick = "for",
  max.iter = 2
)
```

Arguments

data	time series
lag	Number of lags to include in each regime
include	Type of deterministic regressors to include
model	Whether the transition variable is taken in levels (TAR) or difference (MTAR)
commonInter	Whether the deterministic regressors are regime specific (commonInter=FALSE) or not.
nthresh	Number of thresholds
thDelay	'time delay' for the threshold variable (as multiple of embedding time delay d) PLEASE NOTE that the notation is currently different to univariate models in tsDyn. The left side variable is taken at time t, and not t+1 as in univariate cases.
mTh	combination of variables with same lag order for the transition variable. Either a single value (indicating which variable to take) or a combination

thVar	Optional. External transition variable.
trim	trimming parameter indicating the minimal percentage of observations in each regime
ngrid	number of elements of the grid, especially for nthresh=3
gamma	prespecified threshold values
around	The grid search is restricted to *ngrid* values around this point. Especially useful for nthresh=3.
plot	Whether a plot showing the results of the grid search should be printed
dummyToBothRegimes	Whether the dummy in the one threshold model is applied to each regime or not.
trace	should additional infos be printed out?
trick	type of R function called: for or mapply
max.iter	Number of iterations for the algorithm

Details

For fixed th and threshold variable, the model is linear, so estimation can be done directly by CLS (Conditional Least Squares). The search of the parameters values is made upon a grid of potential values. So it is pretty slow.

nthresh=1: estimation of one threshold model (two regimes) upon a grid of *ngrid* values (default to ALL) possible thresholds and delays values.

nthresh=2: estimation of two thresholds model (three regimes) Conditional on the threshold found in model where nthresh=1, the second threshold is searched. When both are found, a second grid search is made with 30 values around each threshold.

nthresh=3: DOES NOT estimate a 3 thresholds model, but a 2 thresholds model with a whole grid over the thresholds parameters (so is really slow) with a given delay, is there rather to check the consistency of the method nthresh=2

Value

An object of class TVAR, with standard methods.

Author(s)

Matthieu Stigler

References

Lo and Zivot (2001) "Threshold Cointegration and Nonlinear Adjustment to the Law of One Price," Macroeconomic Dynamics, Cambridge University Press, vol. 5(4), pages 533-76, September.

See Also

lineVar for the linear VAR/VECM, TVAR.LRtest to test for TVAR, TVAR.sim to simulate/bootstrap a TVAR.

Examples

```
data(zeroyld)

tv <- TVAR(zeroyld, lag=2, nthresh=2, thDelay=1, trim=0.1, mTh=1, plot=FALSE)

print(tv)
summary(tv)

# a few useful methods:
plot(tv)
predict(tv)
c(AIC(tv), BIC(tv), logLik(tv))
```

TVAR.LRtest *Test of linearity*

Description

Multivariate extension of the linearity against threshold test from Hansen (1999) with bootstrap distribution

Usage

```
TVAR.LRtest(
  data,
  lag = 1,
  trend = TRUE,
  series,
  thDelay = 1:m,
  mTh = 1,
  thVar,
  nboot = 10,
  plot = FALSE,
  trim = 0.1,
  test = c("1vs", "2vs3"),
  model = c("TAR", "MTAR"),
  hpc = c("none", "foreach"),
  trace = FALSE,
  check = FALSE
)
```

Arguments

data	multivariate time series
lag	Number of lags to include in each regime
trend	whether a trend should be added
series	name of the series

thDelay	'time delay' for the threshold variable (as multiple of embedding time delay d) PLEASE NOTE that the notation is currently different to univariate models in tsDyn. The left side variable is taken at time t, and not t+1 as in univariate cases.
mTh	combination of variables with same lag order for the transition variable. Either a single value (indicating which variable to take) or a combination
thVar	external transition variable
nboot	Number of bootstrap replications
plot	Whether a plot showing the results of the grid search should be printed
trim	trimming parameter indicating the minimal percentage of observations in each regime
test	Type of usual and alternative hypothesis. See details
model	Whether the threshold variable is taken in level (TAR) or difference (MTAR)
hpc	Possibility to run the bootstrap on parallel core. See details in TVECM.HStest
trace	should additional infos be printed? (logical)
check	Possibility to check the function by no sampling: the test value should be the same as in the original data

Details

This test is just the multivariate extension proposed by Lo and Zivot of the linearity test of Hansen (1999). As in univariate case, estimation of the first threshold parameter is made with CLS, for the second threshold a conditional search with one iteration is made. Instead of a Ftest comparing the SSR for the univariate case, a Likelihood Ratio (LR) test comparing the covariance matrix of each model is computed.

$$LR_{ij} = T(ln(\det \hat{\Sigma}_i) - ln(\det \hat{\Sigma}_j))$$

where $\hat{\Sigma}_i$ is the estimated covariance matrix of the model with i regimes (and so i-1 thresholds).

Three test are available. The both first can be seen as linearity test, whereas the third can be seen as a specification test: once the 1vs2 or/and 1vs3 rejected the linearity and henceforth accepted the presence of a threshold, is a model with one or two thresholds preferable?

Test **1vs**2: Linear VAR versus 1 threshold TVAR

Test **1vs**3: Linear VAR versus 2 threshold2 TVAR

Test **2vs3**: 1 threshold TAR versus 2 threshold2 TAR

The both first are computed together and available with test="1vs". The third test is available with test="2vs3".

The homoskedastik bootstrap distribution is based on resampling the residuals from H0 model, estimating the threshold parameter and then computing the Ftest, so it involves many computations and is pretty slow.

Value

A list containing:

-The values of each LR test

-The bootstrap Pvalues and critical values for the test selected

Author(s)

Matthieu Stigler

References

Hansen (1999) Testing for linearity, Journal of Economic Surveys, Volume 13, Number 5, December 1999 , pp. 551-576(26) available at: https://www.ssc.wisc.edu/~bhansen/papers/cv.htm

Lo and Zivot (2001) "Threshold Cointegration and Nonlinear Adjustment to the Law of One Price," Macroeconomic Dynamics, Cambridge University Press, vol. 5(4), pages 533-76, September.

See Also

`setarTest` for the univariate version. `OlsTVAR` for estimation of the model.

Examples

```
data(zeroyld)
data<-zeroyld

TVAR.LRtest(data, lag=2, mTh=1,thDelay=1:2, nboot=3, plot=FALSE, trim=0.1, test="1vs")
```

TVAR.sim *Simulation of a multivariate Threshold Autoregressive model (TVAR)*

Description

Simulate a multivariate Threshold VAR (TVAR)

Usage

```
TVAR.sim(
  B,
  Thresh,
  nthresh = 1,
  n = 200,
  lag = 1,
  include = c("const", "trend", "none", "both"),
  thDelay = 1,
  mTh = 1,
  starting = NULL,
  innov = rmnorm(n, varcov = varcov),
  varcov = diag(1, nrow(B)),
  show.parMat = FALSE,
  ...
)
```

```
TVAR.boot(
  TVARobject,
  innov,
  seed,
  boot.scheme = c("resample", "wild1", "wild2", "check"),
  ...
)
```

Arguments

B	Matrix of coefficients to simulate
Thresh	The threshold value(s). Vector of length nthresh
nthresh	number of threshold (see details)
n	Number of observations to create when type="simul"
lag	Number of lags to include in each regime
include	Type of deterministic regressors to include. NOT WORKING PROPERLY CURRENTLY if not const
thDelay	'time delay' for the threshold variable (as multiple of embedding time delay d) PLEASE NOTE that the notation is currently different to univariate models in tsDyn. The left side variable is taken at time t, and not t+1 as in univariate cases.
mTh	combination of variables with same lag order for the transition variable. Either a single value (indicating which variable to take) or a combination
starting	Starting values (matrix of dimension lag x k). If not given, set to zero.
innov	Innovations used for simulation. Should be matrix of dim n x k. By default multivariate normal. For the bootstrap case TVAR.boot, residuals are resampled if argument is missing.
varcov	Variance-covariance matrix for the innovations. By default identity matrix.
show.parMat	Logical. Should the parameter matrix be shown? Useful to understand how to give right input
...	Further arguments passed to the underlying (un-exported) TVAR.gen function
TVARobject	Object of class TVAR generated by function TVAR
seed	Optional. Seed for the random resampling function.
boot.scheme	The bootstrap scheme.

Details

This function offers the possibility to generate series following a TVAR.

By giving a matrix of coefficients, on can only simulate a VAR (nthresh=0) or TVAR (nthresh=1 or 2). One can have a specification with constant (default), trend, both or none (see arg include). Order in parameters is include/lags (VECM) and include/lags/include/lags for TVECM, hence, a matrix for a TVECM with 3 regimes, a const and a 2 lags would have 2 lines and 2*(1+4) columns. The innovations can be given by the user (a matrix of dim nxk, here n does not include the starting values!), by default it uses a multivariate normal distribution, with covariance matrix specified by

varcov. The starting values (of dim lags x k) can be given. The user should take care for their choice, since it is not sure that the simulated values will cross the threshold even once.

The matrix 'B' has to be in the form: constant, trend, lags, then repeated if many regimes. In case of uncertainty, using `who.parMat=TRUE` will print the matrix as interpreted by the function, helping the user to feed the right input.

For the bootstrap, the function resamples data from a given TVAR model generated by `TVAR`, returning the resampled data. A residual recursive bootstrap is used, where one uses either a simple resampling, or the Wild bootstrap, either with a normal distribution (wild1) or inverting the sign randomly (wild2)

Value

A matrix with the simulated/bootstrapped series.

Author(s)

Matthieu Stigler

See Also

`TVAR` to estimate the TVAR. Similar `TVECM.sim` and `TVECM.boot` for `TVECM`, `VAR.sim` and `VAR.boot` for VAR models estimated with `lineVar`.

Examples

```
## TVAR.sim: Simulation of a TVAR with 1 threshold
B <- rbind(c(0.11928245, 1.00880447, -0.009974585, -0.089316, 0.95425564, 0.02592617),
        c(0.25283578, 0.09182279,  0.914763741, -0.0530613, 0.02248586, 0.94309347))
colnames(B) <- paste(rep(c("Const", "Lag_1_var1", "Lag_1_var2"), 2), c("Low", "High"), sep="_")
sim <- TVAR.sim(B=B,nthresh=1,n=500, mTh=1, Thresh=5, starting=matrix(c(5.2, 5.5), nrow=1))

#estimate the new serie
TVAR(sim, lag=1, dummyToBothRegimes=TRUE)




## TVAR.boot: Bootstrap a TVAR with two threshold (three regimes)
data(zeroyld)
serie <- zeroyld
mod <- TVAR(data=serie,lag=1, nthresh=1)
TVAR.boot(mod)
```

TVECM *Threshold Vector Error Correction model (VECM)*

Description

Estimate a Threshold Vector Error Correction model (VECM)

Usage

```
TVECM(
  data,
  lag = 1,
  nthresh = 1,
  trim = 0.05,
  ngridBeta = 50,
  ngridTh = 50,
  plot = TRUE,
  th1 = list(exact = NULL, int = c("from", "to"), around = "val"),
  th2 = list(exact = NULL, int = c("from", "to"), around = "val"),
  beta = list(exact = NULL, int = c("from", "to"), around = c("val", "by")),
  restr = c("none", "equal", "signOp"),
  common = c("All", "only_ECT"),
  include = c("const", "trend", "none", "both"),
  dummyToBothRegimes = TRUE,
  beta0 = 0,
  methodMapply = FALSE,
  trace = TRUE
)
```

Arguments

data	time series
lag	Number of lags to include in each regime
nthresh	number of threshold (see details)
trim	trimming parameter indicating the minimal percentage of observations in each regime
ngridBeta	number of elements to search for the cointegrating value
ngridTh	number of elements to search for the threshold value
plot	Whether the grid with the SSR of each threshold should be plotted.
th1	different possibilities to pre-specify an exact value, an interval or a central point for the search of the threshold (or first threshold if nthresh=2)
th2	different possibilities to pre-specify an exact value or a central point for the search of the second threshold (used only if nthresh=2)
beta	different possibilities to pre-specify an exact value, an interval or a central point for the search of the cointegrating value

`restr`	Currently not available
`common`	Whether the regime-specific dynamics are only for the ECT or for the ECT and the lags
`include`	Type of deterministic regressors to include
`dummyToBothRegimes`	Whether the dummy in the one threshold model is applied to each regime or not.
`beta0`	Additional regressors to include in the cointegrating relation
`methodMapply`	only for programming. Is to make the choice between a for loop or `mapply` implementation
`trace`	should additional infos be printed? (logical)

Details

For fixed threshold and cointegrating vector, the model is linear, so estimation of the regression parameters can be done directly by CLS (Conditional Least Squares). The search of the threshold and cointegrating parameters values which minimize the residual sum of squares (SSR) is made on a grid of potential values. For specification of the grids, see below.

The function can estimate one as well as two thresholds:

nthresh=1: estimation of one threshold model (two regimes) upon a grid of *ngridTh* values (default to ALL) possible thresholds and delays values.

nthresh=2: estimation of two thresholds model (three regimes). Conditional on the threshold found in model where nthresh=1, the second threshold is searched. When both are found, a second grid search is made with 30 values around each threshold.

The model can be either with a threshold effect on all variables ("All") or only on the error correction term (ECT) (argument "only ECT"). In the second case, the value for the middle threshold is taken a null, as in Balke and Fomby (1997).

The grid for the threshold parameters can be set in different ways, through the argument *th1*, *th2* and *beta*:

exact: Pre-specified value (for beta: cointegrating vector will be c(1,`-beta`))

int: Specify an interval (of length *ngridTh*) in which to search.

around: Specify to take *ngridTh* points around the value given.

The default is to do an interval search. Interval bounds for the threshold interval are simply the *trim* and 1-*trim* percents of the sorted error correction term. For the cointegrating parameter, bounds of the interval are obtained from the (OLS) confidence interval of the linear cointegration case. It is often found however that this interval is too tight. It is hence recommended to inspect the plot of the grid search.

Value

Fitted model data

Author(s)

Matthieu Stigler

References

Hansen, B. and Seo, B. (2002), Testing for two-regime threshold cointegration in vector error-correction models, Journal of Econometrics, 110, pages 293 - 318

Seo, M. H. (2009) Estimation of non linear error-correction models, Working paper

See Also

VECM for the linear VECM, TVAR for the threshold VAR, TVECM.SeoTest to test for TVECM, TVECM.sim to simulate/bootstrap a TVECM.

Examples

```
data(zeroyld)

##Estimate a TVECM (we use here minimal grid, it should be usually much bigger!)

tvec <- TVECM(zeroyld, nthresh=2,lag=1, ngridBeta=20, ngridTh=30, plot=TRUE,trim=0.05, common="All")

print(tvec)
summary(tvec)

#Obtain diverse infos:
AIC(tvec)
BIC(tvec)

res.tvec<-residuals(tvec)

#export the equations as Latex:
toLatex(tvec)
```

TVECM.HStest *Test of linear cointegration vs threshold cointegration*

Description

Tests the null of linear cointegration against threshold cointegration following Hansen and Seo (2002). Fixed regressor and residual bootstrap are available.

Usage

```
TVECM.HStest(data, lag=1, ngridTh=300, trim=0.05,
 nboot=100, fixed.beta=NULL,  intercept=TRUE,
 boot.type=c("FixedReg", "ResBoot"),
 hpc=c("none", "foreach"))
```

Arguments

data	Time series
lag	Number of lags to include in each regime
ngridTh	Number of threshold grid points to evaluate the optimal threshold.
trim	Trimming parameter indicating the minimal percentage of observations in each regime
nboot	Number of bootstrap replications
fixed.beta	Numeric. User pre-specified cointegrating value, as in VECM (i.e. cointegrating vector will be c(1, -beta.fixed)). When NULL (default), the value is estimated from the linear VECM.
intercept	Logical. Whether an intercept has to be included in the VECM
boot.type	Character. Type of bootstrap simulation (only if nboot>0)
hpc	Possibility to run the bootstrap on parallel core. See details

Details

This test follows the implementation done by Hansen and Seo (2002). The cointegrating value is estimated from the linear VECM. Then, conditional on this value, the LM test is run for a range of different threshold values. The maximum of those LM test values is reported.

Two bootstrap are available: a fixed regressor, as well as a usual residual bootstrap (using the function TVECM.sim).

Available methods are print(), summary() and plot().

With the argument hpc, the burdensome bootstrap replication can be run on parallel cores, thus alleviating the time of computation. The user needs simply to choose a package (among doMC, doMPI, doSNOW or doRedis) and register the backend. See the vignette for more details.

Value

A list containing diverse values:

stat	The sup-LM statistic.
values	The whole LM values.
PvalBoot	The bootstrap p-value
CriticalValBoot	The bootstrap critical values
allBoots	The boot sup-LM values
args	Some user given args (nboot, boot.type)

Reproducibility

Comparison with original paper is made difficult as values of the test are not shown in the paper, only their critical values, which depend on random bootstrap.

Comparison is done with the GAUSS code available on the page of Bruce Hansen. Running tar_ci, we have the same sup-LM value when lags=1 and lags=2, a higher value with lag=3. When the test is run with pre-specified beta values, we have different results, sometimes higher but also smaller sup-LM value.

Author(s)

Matthieu Stigler

References

Hansen, B. and Seo, B. (2002), Testing for two-regime threshold cointegration in vector error-correction models, Journal of Econometrics, 110, pages 293 - 318

See Also

zeroyld: data used in the original paper of Hansen and Seo.

TVECM.SeoTest: a similar test, but with null hypothesis of no-cointegration.

TVECM for estimating a TVECM, TVECM.sim for simulating/bootstrap a TVECM,

Examples

```
#Use original data from paper:
data(zeroyld)
dataPaper<-zeroyld
# Test: nboot, number of bootstrap replications, should be high
## Not run:
test1<-TVECM.HStest(dataPaper, lag=1, intercept=TRUE, nboot=1000)

## End(Not run)

#we use here for the example a much smaller number of bootstrap:
test1<-TVECM.HStest(dataPaper, lag=1, intercept=TRUE, nboot=10)

test1
summary(test1)
plot(test1)

#can have only specific plots:
plot(test1, which="LM values")
plot(test1, which="Density")

## Run the function in parallel:
## Not run:
#we show here the use with package doMC
library(doMC)
registerDoMC(2) #Number of cores
test1<-TVECM.HStest(dataPaper, lag=1, intercept=TRUE, nboot=1000, hpc="foreach")

## End(Not run)
```

TVECM.SeoTest *No cointegration vs threshold cointegration test*

Description

Test the null of no cointegration against threshold cointegration with bootstrap distribution of Seo (2006)

Usage

```
TVECM.SeoTest(
  data,
  lag,
  beta,
  trim = 0.1,
  nboot,
  plot = FALSE,
  hpc = c("none", "foreach"),
  check = FALSE
)
```

Arguments

data	time series
lag	Number of lags to include in each regime
beta	Pre-specified cointegrating value (i.e. cointegrating vector will be c(1, -beta))
trim	trimming parameter indicating the minimal percentage of observations in each regime
nboot	Number of bootstrap replications
plot	Whether a grid with the SSR of each threshold should be printed
hpc	Possibility to run the bootstrap on parallel core. See details in TVECM.HStest
check	Possibility to check the function by no sampling: the test value should be the same as in the original data

Details

For this test, the cointegrating value has to be specified by the user.

The model used is one where the threshold effect concerns only the cointegrating vector, and only in the outer regimes.

Due to the presence of parameters unidentified under the null hypothesis, the test employed is a Sup-Wald test, that means that for each combination of the thresholds, a Wald Test is computed and the supremum of all tests is taken. For each bootstrap replication, this approach is taken, so that the test is really slow.

Value

A list containing diverse informations:

Estimated threshold parameters and usual slope parameters.

Value of the test.

Critical and Pvalue from bootstrap distribution.

Author(s)

Matthieu Stigler

References

Seo, Myunghwan, 2006. "Bootstrap testing for the null of no cointegration in a threshold vector error correction model," Journal of Econometrics, vol. 127(1), pages 129-150, September.

See Also

TVECM for estimating a TVECM, TVECM.sim for simulating/bootstrap a TVECM,

Examples

```
# As the function takes long long time to be executed, we show in in don't run environement
## Not run:
data(zeroyld)

#can be useful to check whether the bootstrap is working:
#without sampling, results of boot should be same as original
#this is indeed not always the case duye to floating point algorithm
TVECM.SeoTest(zeroyld,lag=2, beta=1, trim=0.1,nboot=2, plot=FALSE,check=TRUE)

#then run the function:
TVECM.SeoTest(zeroyld,lag=2, beta=1, trim=0.1,nboot=100, plot=FALSE,check=FALSE)

## End(Not run)
```

TVECM.sim *Simulation and bootstrap a VECM or bivariate TVECM*

Description

Estimate or bootstraps a multivariate Threshold VAR

Usage

```
TVECM.sim(
  B,
  n = 200,
  lag = 1,
  include = c("const", "trend", "none", "both"),
  beta,
  nthresh = 1,
  Thresh,
  starting = NULL,
  innov = rmnorm(n, varcov = diag(1, nrow(B))),
  show.parMat = FALSE,
  returnStarting = FALSE,
  ...
)

VECM.sim(
  B,
  n = 200,
  lag = 1,
  include = c("const", "trend", "none", "both"),
  beta,
  starting = NULL,
  innov = rmnorm(n, varcov = diag(1, nrow(B))),
  show.parMat = FALSE,
  returnStarting = FALSE,
  ...
)

VECM.boot(
  object,
  boot.scheme = c("resample", "resample_block", "wild1", "wild2", "check"),
  seed = NULL,
  ...
)

TVECM.boot(
  object,
  boot.scheme = c("resample", "resample_block", "wild1", "wild2", "check"),
  seed = NULL,
  ...
)
```

Arguments

B	Simulation: Matrix of coefficients to simulate
n	Simulation: Number of observations to simulate.
beta	The cointegrating value

Thresh, nthresh, lag, include	Simulation: parameters for the VECM/TVECM to simulate. See TVECM for their description.
starting	Simulation: Starting values (same length as lag = 1)
innov	Simulation: time series of innovations/residuals.
show.parMat	Logical. Whether to show how the parameter matrix B is interpreted.
returnStarting	Logical. Whether to return the starting values.
...	additional arguments for the unexported TVECM.gen.
object	Object computed by function TVECM or linear VECM
boot.scheme	Bootstrap: which resampling scheme to use for the residuals. See resample_vec.
seed	Bootstrap: seed used in the resampling

Details

This function offers the possibility to generate series following a VECM/TVECM from two approaches: bootstrap or simulation. VECM.sim is just a wrapper for TVECM.sim.

When the argument matrix is given, on can only simulate a VECM (nthresh=0) or TVECM (nthresh=1 or 2). One can have a specification with constant ("const"), "trend", "both" or "none" (see argument include). Order for the parameters is ECT/include/lags for VECM and ECT1/include1/lags1/ECT2/include2/lags2 for TVECM. To be sure that once is using it correctly, setting show.parMat = TRUE will show the matrix of parameters together with their values and names.

The argument beta is the cointegrating value on the right side of the long-run relationship, and hence the function use the vector (1,-beta). The innov argument specifies the innovations. It should be given as a matrix of dim nxk, (here *n* does not include the starting values!), by default it uses a multivariate normal distribution, with covariance matrix specified by varcov.

The starting values (of dim lags x k) can be given through argument starting. The user should take care for their choice, since it is not sure that the simulated values will cross the threshold even once. Notice that only one cointegrating value is allowed. User interested in simulating a VECM with more cointegrating values should do use the VAR representation and use TVAR.sim.

The second possibility is to bootstrap series. This is done on a object generated by TVECM (or VECM). A simple residual bootstrap is done, or one can simulate a series with the same parameter matrix and with normal distributed residuals (with variance pre-specified), corresponding to Monte-carlo simulations.

One can alternatively give only the series, and then the function will call internally TVECM.

Value

A matrix with the simulated/bootstrapped series.

Author(s)

Matthieu Stigler

See Also

VECM or TVECM to estimate the VECM or TVECM. Similar TVAR.sim and TVAR.boot for TVAR, VAR.sim and VAR.boot for VAR models estimated with lineVar models.

Examples

```
###reproduce example in Enders (2004, 2 edition) p. 350,
# (similar example in Enders (2010, 3 edition) 301-302).

if(require(mnormt)){
#see that the full "VAR" coefficient matrix is:
 A <- matrix(c(-0.2, 0.2, 0.2, -0.2), byrow=TRUE, ncol=2)

# but this is not the input of VECM.sim. You should decompose into the a and b matrix:
 a<-matrix(c(-0.2, 0.2), ncol=1)
 b<-matrix(c(1,-1), nrow=1)

# so that:
 a%*%b

# The a matrix is the input under argument B, while the b matrix is under argument beta:
# (the other zeros in B are for the not-specified lags)
 innov<-rmnorm(100, varcov=diag(2))
 Bvecm <- rbind(c(-0.2, 0,0), c(0.2, 0,0))
 vecm1 <- VECM.sim(B=Bvecm, beta=1,n=100, lag=1,include="none", innov=innov)
 ECT <- vecm1[,1]-vecm1[,2]

#add an intercept as in panel B
 Bvecm2 <- rbind(c(-0.2, 0.1,0,0), c(0.2,0.4, 0,0))
 vecm2 <- VECM.sim(B=Bvecm2,  n=100,beta=1, lag=1,include="const", innov=innov)

 par(mfrow=c(2,1))
 plot(vecm1[,1], type="l", main="Panel a: no drift or intercept", ylab="", xlab="")
 lines(vecm1[,2], lty=2)
 plot(vecm2[,1], type="l", main="Panel b: drift terms (0.1)", ylab="", xlab="")
 lines(vecm2[,2], lty=2)
}
##Bootstrap a TVAR with 1 threshold (two regimes)
data(zeroyld)
TVECMobject <- TVECM(zeroyld, nthresh=1, lag=1, ngridBeta=20, ngridTh=20, plot=FALSE, trace = FALSE)
TVECM.boot(TVECMobject)

##Check the bootstrap: do we get original series, when not resampling residuals?
TVECM.boot.check <- TVECM.boot(TVECMobject, boot.scheme = "check")
all.equal(as.data.frame(TVECM.boot.check), zeroyld)
```

UsUnemp *US unemployment series used in Caner and Hansen (2001)*

Description

This data, used as example in *Caner and Hansen (2001)*, contains the monthly US adult male unemployment from 1956 to 1999.

Usage

```
data(UsUnemp)
```

Format

A monthly time series of class `ts` starting in January 1956 and ending in August 1999.

Source

Caner and Hansen,Threshold autoregression with a unit root Econometrica, 2001, 69, 1555-1596 available at: https://www.ssc.wisc.edu/~bhansen/papers/cv.htm

---

`VAR.sim` *Simulate or bootstrap a VAR model*

Description

Allow to either simulate from scratch (by providing coefficients) or bootstrap from an estimated VAR model,

Usage

```
VAR.sim(
  B,
  n = 200,
  lag = 1,
  include = c("const", "trend", "none", "both"),
  starting = NULL,
  innov = rmnorm(n, varcov = varcov),
  varcov = diag(1, nrow(B)),
  show.parMat = FALSE,
  returnStarting = FALSE,
  ...
)

VAR.boot(
  VARobject,
  boot.scheme = c("resample", "wild1", "wild2", "check"),
  seed,
  ...
)
```

Arguments

B	Matrix of coefficients.
n	Number of observations to simulate
lag	Number of lags of the VAR to simulate
include	Type of deterministic regressors to include in the VAR to simulate
starting	Starting values (matrix of dimension lag x k) for the VAR to simulate. If not given, set to zero.
innov	Innovations used for in the VAR to simulate. Should be matrix of dim n x k. By default multivariate normal.
varcov	Variance-covariance matrix for the innovations. By default identity matrix.
show.parMat	Logical. Should the parameter matrix be shown? Useful to understand how to give right input
returnStarting	Whether starting values are returned. Default to FALSE
...	Further arguments passed to the underlying (un-exported) VAR.gen function
VARobject	Object of class VAR generated by function lineVar
boot.scheme	The bootstrap scheme. See details.
seed	Optional. Seed for the random resampling function.

Details

For the bootstrap, the function resamples data from a given VAR model generated by lineVar, returning the resampled data. A residual recursive bootstrap is used, where one uses either a simple resampling, or the Wild bootstrap, either with a normal distribution (wild1) or inverting the sign randomly (wild2)

Value

A matrix with the resampled series.

Author(s)

Matthieu Stigler

See Also

lineVar to estimate the VAR. Similar TVECM.sim and TVECM.boot for TVECM, TVAR.sim and TVAR.boot for TVAR models.

Examples

```
## VAR.sim: simulate VAR as in Enders 2004, p 268
B1<-matrix(c(0.7, 0.2, 0.2, 0.7), 2)
var1 <- VAR.sim(B=B1, n=100, include="none")
ts.plot(var1, type="l", col=c(1,2))
```

```
B2<-rbind(c(0.5, 0.5, 0.5), c(0, 0.5, 0.5))
varcov<-matrix(c(1,0.2, 0.3, 1),2)
var2 <- VAR.sim(B=B2, n=100, include="const", varcov=varcov)
ts.plot(var2, type="l", col=c(1,2))

## VAR.boot: Bootstrap a VAR
data(zeroyld)
mod <- lineVar(data=zeroyld,lag=1)
VAR.boot(mod)
```

VARrep *VAR representation*

Description

Show the VAR representation of a VECM

Usage

```
VARrep(object, ...)

## S3 method for class 'VECM'
VARrep(object, ...)

## S3 method for class 'VAR'
VARrep(object, ...)
```

Arguments

object	An object of class 'VECM' created by VECM, or of class 'VAR' created by lineVar
...	Currently not used

Value

A matrix containing the parameters of the VECM under their VAR representation.

Author(s)

Matthieu Stigler

References

Hamilton (1994) *Time Series Analysis*, Princeton University Press

Examples

```
data(barry)

# VECM model:
mod_vecm <- VECM(barry, lag=2, estim="ML")
VARrep(mod_vecm)

# VAR model:
mod_var <- lineVar(barry, lag=2, I="diff")
VARrep(mod_var)
```

VECM *Estimation of Vector error correction model (VECM)*

Description

Estimate a VECM by either Engle-Granger (2OLS) or Johansen (MLE) method.

Usage

```
VECM(
  data,
  lag,
  r = 1,
  include = c("const", "trend", "none", "both"),
  beta = NULL,
  estim = c("2OLS", "ML"),
  LRinclude = c("none", "const", "trend", "both"),
  exogen = NULL
)
```

Arguments

data	multivariate time series (first row being first=oldest value)
lag	Number of lags (in the VECM representation, see Details)
r	Number of cointegrating relationships
include	Type of deterministic regressors to include
beta	for VECM only: user-specified cointegrating values, the cointegrating vector will be taken as: (1, -beta) If NULL, will be estimated using the estimator specified in estim
estim	Type of estimator: 2OLS for the two-step approach or ML for Johansen MLE
LRinclude	Type of deterministic regressor(s) to include in the long-term relationship. Can also be a matrix with exogeneous regressors (2OLS only).
exogen	Inclusion of exogenous variables (first row being first=oldest value). Is either of same size than data (then automatically cut) or than end-sample.

Details

This function is just a wrapper for the `lineVar`, with model="VECM".

More comprehensive functions for VECM are in package **vars**. Differences with that package are:

Engle-Granger estimator The Engle-Granger estimator is available

Presentation Results are printed in a different ways, using a matrix form

lateX export The matrix of coefficients can be exported to latex, with or without standard-values and significance stars

Prediction The `predict` method contains a `newdata` argument allowing to compute rolling forecasts.

Two estimators are available: the Engle-Granger two step approach (`2OLS`) or the Johansen (`ML`). For the 2OLS, deterministic regressors (or external variables if `LRinclude` is of class numeric) can be added for the estimation of the cointegrating value and for the ECT. This is only working when the beta value is not pre-specified.

The arg beta is the cointegrating value, the cointegrating vector will be taken as: (1, -beta).

Note that the lag specification corresponds to the lags in the VECM representation, not in the VAR (as is done in package vars or software GRETL). Basically, a VAR with 2 lags corresponds here to a VECM with 1 lag. The lag can be set to 0, although some methods (irf, fevd) won't work for this case.

#'The arg `beta` allows to specify constrained cointegrating values, leading to $ECT = \beta' X_{t-1}$. It should be specified as a $K \times r$ matrix. In case of $r = 1$, can also be specified as a vector. Note that the vector should be normalised, with the first value to 1, and the next values showing the opposite sign in the long-run relationship $-\beta$. In case the vector has $K - 1$ values, this is what `lineVar` is doing, setting $(1, -\beta)$. Note finally one should provide values for all the coefficients (eventually except for special case of r=1 and k-1), if you want to provide only part of the parameters, and let the others be estimated, look at the functions in package urca.

The eigenvector matrix β is normalised using the Phillips triangular representation, see Hamilton (1994, p. 576) and Juselius (2006, p. 216), see `coefA` for more details.

Value

An object of class `VECM` (and higher classes `VAR` and `nlVar`) with methods:

Usual methods: Print, summary, residuals, fitted, vcov

Fit criteria: AIC, BIC, `MAPE`, `mse`, `logLik` (the latter only for models estimated with MLE)

Prediction: predict and `predict_rolling`

coef extraction: Extract cointegrating/adjustment coefficients, `coefA`, `coefB` `coefPI`

VAR/VECM methods: Impulse response function (`irf.VECM`) and forecast error variance decomposition (`fevd`)

LaTeX: toLatex

Author(s)

Matthieu Stigler

References

Hamilton (1994) Time Series Analysis, Princeton University Press

Juselius (2006) The Cointegrated VAR model, Oxford University Press

See Also

coefA, coefB and coefPI to extract the relevant parameter matrices.

lineVar TVAR and TVECM for the corresponding threshold models. linear for the univariate AR model.

Examples

```
data(zeroyld)
data<-zeroyld

#Fit a VECM with Engle-Granger 2OLS estimator:
vecm.eg<-VECM(zeroyld, lag=2)

#Fit a VECM with Johansen MLE estimator:
vecm.jo<-VECM(zeroyld, lag=2, estim="ML")

#compare results with package vars:
if(require(vars)) {
 data(finland)
 #check long coint values
   all.equal(VECM(finland, lag=2, estim="ML", r=2)$model.specific$beta,
         cajorls(ca.jo(finland, K=3, spec="transitory"), r=2)  $beta, check.attributes=FALSE)
# check OLS parameters
  all.equal(t(coefficients(VECM(finland, lag=2, estim="ML", r=2))),
   coefficients(cajorls(ca.jo(finland, K=3, spec="transitory"), r=2)$rlm), check.attributes=FALSE)

}


##export to Latex
toLatex(vecm.eg)
toLatex(summary(vecm.eg))
options("show.signif.stars"=FALSE)
toLatex(summary(vecm.eg), parenthese="Pvalue")
options("show.signif.stars"=TRUE)
```

VECM_symbolic *Virtual VECM model*

Description

Pedagogical tool to create a symbolic VECM model, i.e. just for representation purpose.

Usage

```
VECM_symbolic(
  alpha,
  beta,
  lags,
  inc,
  include = c("none", "const", "trend", "both")
)
```

Arguments

alpha	Matrix of alpha speed adjustment coefficients.
beta	Matrix of alpha, cointegrating coefficients.
lags	Matrix containing the lags coefficients.
inc	Matrix containing the include (see following arg.) coefficients.
include	Character indicating the type of deterministic term included, if any.

Value

An object of class 'VECM', without however any data.

Examples

```
a<-matrix(c(-0.4, 0.1), ncol=1)
b<-matrix(c(1, -2), ncol=2)

# VECM_symb(alpha=a, beta=t(b))
d<- VECM_symbolic(alpha=a, beta=t(b))
VARrep(d)
d<- VECM_symbolic(alpha=a, beta=t(b), lags=matrix(0, ncol=2, nrow=2))
VARrep(d)
LagMat <- matrix(c(0.1, 0.3, 0.1, 0.2), ncol=2, nrow=2)
incMat <- matrix(c(0.5, 0.1), ncol=1)
d3<- VECM_symbolic(alpha=a, beta=t(b), lags=LagMat, inc=incMat, include="const")
VARrep(d3)
```

`zeroyld` *zeroyld time series*

Description

U.S. Term Structure Data, 1951-1991. Dataset used by Hansen and Seo (2002). The data contains the 12 month short rate and 120 month long rate.

Usage

```
zeroyld
zeroyldMeta
```

Format

`zeroyld` contains two variables, while `zeryldMeta` contains also `Year` and `Month` columns.

`zeroyld` is a data frame with 482 observations and 2 variables:

`short.run`	numeric	Short term, 12 month
`long.run`	numeric	Long term, 120 month

Source

Hansen, B. and Seo, B. (2002), Testing for two-regime threshold cointegration in vector error-correction models, Journal of Econometrics, 110, pages 293 - 318

The data can be downloaded from: https://www.ssc.wisc.edu/~bhansen/progs/joe_02r.zip.

The authors themselves took the data from the webpage of Huston McCulloch: https://www.asc.ohio-state.edu/mcculloch.2/ts/mcckwon/mccull.htm

See Also

`TVECM.HStest`: Hansen and Seo test.

`TVECM` for estimating a TVECM.

Examples

```
data(zeroyldMeta)
plot(zeroyldMeta$Date, zeroyldMeta$short.run, type = "l", xlab = "Date", ylab ="Rate")
lines(zeroyldMeta$Date, zeroyldMeta$long.run, lty = 2)
legend("topleft", lty = c(1, 2), legend = c("Short rate: 12 months", "Long rate: 120 months"))
```

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