

Package ‘MTS’

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Type Package

Title All-Purpose Toolkit for Analyzing Multivariate Time Series (MTS)
and Estimating Multivariate Volatility Models

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Description Multivariate Time Series (MTS) is a general package for analyzing multivariate linear time series and estimating multivariate volatility models. It also handles factor models, constrained factor models, asymptotic principal component analysis commonly used in finance and econometrics, and principal volatility component analysis. (a) For the multivariate linear time series analysis, the package performs model specification, estimation, model checking, and prediction for many widely used models, including vector AR models, vector MA models, vector ARMA models, seasonal vector ARMA models, VAR models with exogenous variables, multivariate regression models with time series errors, augmented VAR models, and Error-correction VAR models for co-integrated time series. For model specification, the package performs structural specification to overcome the difficulties of identifiability of VARMA models. The methods used for structural specification include Kronecker indices and Scalar Component Models. (b) For multivariate volatility modeling, the MTS package handles several commonly used models, including multivariate exponentially weighted moving-average volatility, Cholesky decomposition volatility models, dynamic conditional correlation (DCC) models, copula-based volatility models, and low-dimensional BEKK models. The package also considers multiple tests for conditional heteroscedasticity, including rank-based statistics. (c) Finally, the MTS package also performs forecasting using diffusion index, transfer function analysis, Bayesian estimation of VAR models, and multivariate time series analysis with missing values. Users can also use the package to simulate VARMA models, to compute impulse response functions of a fitted VARMA model, and to calculate theoretical cross-covariance matrices of a given VARMA model.

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Description

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Details

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Author(s)

Ruey S. Tsay Maintainer: Ruey S. Tsay <ruey.tsay@chicagobooth.edu>

Description

Perform asymptotic PCA for a data set. Typically for cases in which the number of variables is greater than the number of data points.

Usage

```
apca(da, m)
```

Arguments

da	A T-by-k data set matrix, where T is the sample size and k is the dimension
m	The number of common factors

Details

Perform the PCA analysis of interchanging the roles of variables and observations.

Value

sdev	Square root of the eigenvalues
factors	The common factors
loadings	The loading matrix

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 6). Multivariate Time Series Analysis with R and Financial Applications. John Wiley. Hoboken, NJ.

Examples

```
rtn=matrix(rnorm(1200),12,100)
sp100=apca(rtn,3)
```

archTest

ARCH test for univariate time series

Description

Perform tests to check the conditional heteroscedasticity in a time series. The Ljung-Box statistics of squared series and a rank-based Ljung-Box test are used.

Usage

```
archTest(rt, lag = 10)
```

Arguments

`rt` A scalar time series. If `rt` is a matrix, only the first column is used.

`lag` The number of lags of ACF used in the Ljung-Box statistics. The default is 10.

Details

The Ljung-Box statistics based on the squared series are computed first. The rank series of the squared time series is then used to test the conditional heteroscedasticity.

Value

The Q-statistic and its p-value. Also, the rank-based Q statistic and its p-value.

Author(s)

Ruey Tsay

See Also

`MarchTest`

Examples

```
rt=rnorm(200)
archTest(rt)
```

BEKK11

BEKK Model

Description

Estimation of a BEKK(1,1) Model for a k-dimensional time series. Only $k = 2$ or 3 is available

Usage

```
BEKK11(rt, include.mean = T, cond.dist = "normal")
```

Arguments

`rt` A T-by-k data matrix of k-dimensional asset returns

`include.mean` A logical switch to include a constant vector in the mean equation. Default is with a constant vector.

`cond.dist` Conditional innovation distribution. Only Gaussian innovations are used in the current version.

Value

estimates	Parameter estimates
HessianMtx	Hessian matrix of the estimates
Sigma.t	The multivariate volatilities, each row contains k-by-k elements of the volatility matrix $\Sigma(t)$

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 7)

Examples

```
#data("mts-examples", package="MTS")
#da=ibmspko
#rtn=log(da[,2:3]+1)
#m1=BEKK11(rtn)
```

Btfm2

Back-Test of a Transfer Function Model with Two Input Variables

Description

Perform back-test of transfer function model with 2 input variable. For a specified tfm2 model and a given forecast origin, the command iterated between estimation and 1-step ahead prediction starting at the forecast origin until the (T-1)th observation, where T is the sample size.

Usage

```
Btfm2(y, x, x2=NULL, wt=NULL, ct=NULL, orderN=c(1, 0, 0), orderS=c(0, 0, 0), sea=12,
order1=c(0, 1, 0), order2=c(0, -1, 0), orig=(length(y)-1))
```

Arguments

y	Data vector of dependent variable
x	Data vector of the first input (or independent) variable
x2	Data vector of the second input variable if any
ct	Data vector of a given deterministic variable such as time trend, if any
wt	Data vector of co-integrated series between input and output variables if any
orderN	Order (p,d,q) of the regular ARMA part of the disturbance component
orderS	Order (P,D,Q) of the seasonal ARMA part of the disturbance component
sea	Seasonality, default is 12 for monthly data

order1	Order (r,s,b) of the transfer function model of the first input variable, where r and s are the degrees of denominator and numerator polynomials and b is the delay
order2	Order (r2,s2,b2) of the transfer function model of the second input variable, where 2r and s2 are the degrees of denominator and numerator polynomials and b2 is the delay
orig	Forecast origin with default being T-1, where T is the sample size

Details

Perform out-of-sample 1-step ahead prediction to evaluate a fitted tfm2 model

Value

ferror	1-step ahead forecast errors, starting at the given forecast origin
mse	out-of-sample mean squared forecast errors
rmse	root mean squared forecast errors
mae	out-of-sample mean absolute forecast errors
nobf	The number of 1-step ahead forecast errors computed
rAR	Regular AR coefficients

Author(s)

Ruey S. Tsay

References

Box, G. E. P., Jenkins, G. M., and Reinsel, G. C. (1994). *Time Series Analysis: Forecasting and Control*, 3rd edition, Prentice Hall, Englewood Cliffs, NJ.

See Also

tfm2

BVAR

Bayesian Vector Autoregression

Description

Estimate a VAR(p) model using Bayesian approach, including the use of Minnesota prior

Usage

BVAR(z, p=1, C, V0, n0=5, Phi0=NULL, include.mean=T)

Arguments

<code>z</code>	A matrix of vector time series, each column represents a series.
<code>p</code>	The AR order. Default is <code>p=1</code> .
<code>C</code>	The precision matrix of the coefficient matrix. With constant, the dimension of <code>C</code> is $(kp+1)$ -by- $(kp+1)$. The covariance matrix of the prior for the parameter <code>vec(Beta)</code> is <code>Kronecker(Sigma_a,C-inverse)</code> .
<code>V0</code>	A k -by- k covariance matrix to be used as prior for the <code>Sigma_a</code> matrix
<code>n0</code>	The degrees of freedom used for prior of the <code>Sigma_a</code> matrix, the covariance matrix of the innovations. Default is <code>n0=5</code> .
<code>Phi0</code>	The prior mean for the parameters. Default is set to <code>NULL</code> , implying that the prior means are zero.
<code>include.mean</code>	A logical switch controls the constant term in the VAR model. Default is to include the constant term.

Details

for a given prior, the program provide the posterior estimates of a VAR(p) model.

Value

<code>est</code>	Posterior means of the parameters
<code>Sigma</code>	Residual covariance matrix

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 2).

Examples

```
data("mts-examples",package="MTS")
z=log(qgdp[,3:5])
zt=diffM(z)*100
C=0.1*diag(rep(1,7))
V0=diag(rep(1,3))
BVAR(zt,p=2,C,V0)
```

`ccm`*Cross-Correlation Matrices*

Description

Computes sample cross-correlation matrices of a multivariate time series, including simplified ccm matrix and p-value plot of Ljung-Box statistics.

Usage

```
ccm(x, lags = 12, level = FALSE, output = T)
```

Arguments

<code>x</code>	A matrix of vector time series, each column represents a series.
<code>lags</code>	The number of lags of CCM to be computed. Default is 12.
<code>level</code>	A logical switch. When <code>level=T</code> , numerical values of CCM is printed. Default is no printing of CCM.
<code>output</code>	A logical switch. If <code>output=F</code> , no output is given. Default is with output.

Details

The p-value of Ljung-Box statistics does not include any adjustment in degrees of freedom.

Value

<code>ccm</code>	Sample cross-correlation matrices
<code>pvalue</code>	p-values for each lag of CCM being a zero matrix

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 1). Multivariate Time Series Analysis with R and Financial Applications. John Wiley. Hoboken, NJ.

Examples

```
xt=matrix(rnorm(1500),500,3)
ccm(xt)
ccm(xt,lag=20)
```

comVol	<i>Common Volatility</i>
--------	--------------------------

Description

Compute the principal volatility components based on the residuals of a VAR(p) model.

Usage

```
comVol(rtn, m = 10, p = 1, stand = FALSE)
```

Arguments

rtn	A T-by-k data matrix of k-dimensional asset returns
m	The number of lags used to compute generalized cross-Kurtosis matrix
p	VAR order for the mean equation
stand	A logical switch to standardize the returns

Details

Perform a VAR(p) fit, if any. Then, use the residual series to perform principal volatility component analysis. The ARCH test statistics are also computed for the sample principal components

Value

residuals	The residuals of a VAR(p) fit
values	Eigenvalues of the principal volatility component analysis
vectors	Eigenvectors of the principal volatility component analysis
M	The transformation matrix

Author(s)

Ruey S. Tsay and Y.B. Hu

References

Tsay (2014, Chapter 7)

Examples

```
data("mts-examples", package="MTS")
zt=diffM(log(qgdp[, 3:5]))
m1=comVol(zt, p=2)
names(m1)
```

 dccFit

Dynamic Cross-Correlation Model Fitting

Description

Fits a DCC model using either multivariate Gaussian or multivariate Student-t innovations. Two types of DCC models are available. The first type is proposed by Engle and the other is by Tse and Tsui. Both models appear in the Journal of Business and Economic Statistics, 2002.

Usage

```

dccFit(rt, type = "TseTsui", theta = c(0.9, 0.02),
       ub = c(0.92, 0.079999), lb = c(0.4, 1e-04),
       cond.dist = "std", df = 7, m = 0)

```

Arguments

rt	The T-by-k data matrix of k-dimensional standardized asset returns. Typically, they are the standardized residuals of the command dccPre.
type	A logical switch to specify the type of DCC model. Type="TseTsui" for Tse and Tsui's DCC model. Type = "Engle" for Engle's DCC model. Default is Tse-Tsui model.
theta	The initial parameter values for theta1 and theta2
ub	Upper bound of parameters
lb	Lower bound of parameters
cond.dist	Conditional innovation distribution with std for multivariate Student-t innovations.
df	degrees of freedom of the multivariate Student-t innovations.
m	For Tse and Tsui method only, m denotes the number of returns used in local correlation matrix estimation

Value

estimates	Parameter estimates
Hessian	Hessian marix of the estimates
rho.t	Time-varying correlation matrices. Each row contains elements of a cross-correlation matrix.

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 7). Multivariate Time Series Analysis with R and Financial Applications. John Wiley. Hoboken, NJ.

See Also

dccPre

dccPre

Preliminary Fitting of DCC Models

Description

This program fits marginal GARCH models to each component of a vector return series and returns the standardized return series for further analysis. The garchFit command of fGarch package is used.

Usage

```
dccPre(rtn, include.mean = T, p = 0, cond.dist = "norm")
```

Arguments

rtn	A T-by-k data matrix of k-dimensional asset returns
include.mean	A logical switch to include a mean vector. Default is to include the mean.
p	VAR order for the mean equation
cond.dist	The conditional distribution of the innovations. Default is Gaussian.

Details

The program uses fGarch package to estimate univariate GARCH model for each residual series after a VAR(p) fitting, if any.

Value

marVol	A matrix of the volatility series for each return series
sresi	Standardized residual series
est	Parameter estimates for each marginal volatility model
se.est	Standard errors for parameter estimates of marginal volatility models

Note

fGarch package is used

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 7). Multivariate Time Series Analysis with R and Financial Applications. John Wiley. Hoboken, NJ.

See Also

dccFit

`diffM`*Difference of multivariate time series*

Description

Performs the difference operation of a vector time series

Usage

```
diffM(zt, d = 1)
```

Arguments

`zt` A vector time series (T by k, with sample size T and dimension k)
`d` Order of differencing. Default is d=1.

Details

When $d = 1$, the command is equivalent to `apply(zt,2,diff)`

Value

The differenced time series

Author(s)

Ruey S Tsay

Examples

```
data("mts-examples", package="MTS")
zt=log(qgdp[,3:5])
xt=diffM(zt)
```

Eccm

*Extended Cross-Correlation Matrices***Description**

Compute the extended cross-correlation matrices and the associated two-way table of p-values of multivariate Ljung-Box statistics of a vector time series.

Usage

```
Eccm(zt, maxp = 5, maxq = 6, include.mean = FALSE, rev = TRUE)
```

Arguments

zt	Data matrix (T-by-k) of a vector time series, where T is the sample size and k is the dimension.
maxp	Maximum AR order entertained. Default is 5.
maxq	Maximum MA order entertained. Default is 6.
include.mean	A logical switch controlling the mean vector in estimation. Default assumes zero mean.
rev	A logical switch to control the cross-correlation matrices used to compute the multivariate Ljung-Box statistics. Traditional way is to compute test statistics from lag-1 to lag-m. If rev = TRUE, then the test statistics are compute from lag-(m-1) to lag-m, from lag-(m-2) to lag-m, etc.

Value

pEccm	A two-way table of the p-values of extended cross-correlation matrices
vEccm	The sample extended cross-correlation matrices
ARcoef	AR coefficient marices of iterated VAR fitting

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 3). Multivariate Time Series Analysis with R and Financial Applications. John Wiley. Hoboken, NJ.

Examples

```
zt=matrix(rnorm(900),300,3)
m1=Eccm(zt)
```

ECMvar

*Error-Correction VAR Models***Description**

Performs estimation of an Error-Correction VAR(p) model using the Quasi Maximum Likelihood Method.

Usage

```
ECMvar(x, p, ibeta, include.const = FALSE, fixed = NULL,
       alpha = NULL, se.alpha = NULL, se.beta = NULL, phip =
       NULL, se.phip = NULL)
```

Arguments

x	A T-by-k data matrix of a k-dimensional co-integrated VAR process
p	VAR order
ibeta	Initial estimate of the co-integrating matrix. The number of columns of ibeta is the number of co-integrating series
include.const	A logical switch to include a constant term in the model. The default is no constant
fixed	A logical matrix to set zero parameter constraints.
alpha	Initial estimate of alpha, if any
se.alpha	Initial estimate of the standard error of alpha, if any
se.beta	Initial estimate of the standard error of beta, if any
phip	Initial estimate of the VAR coefficients, if any
se.phip	Initial estimate of the stanard error of the VAR coefficients, if any

Value

data	The vector time series
ncoint	The number of co-integrating series
arorder	VAR order
include.const	Logical switch to include constant
alpha, se.alpha	Estimates and their standard errors of the alpha matrix
beta, se.beta	Estimates and their standard errors of the beta matrix
aic, bic	Information criteria of the fitted model
residuals	The residual series
Sigma	Residual covariance matrix
Phip, se.Phip	Estimates and their standard errors of VAR coefficients

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 5)

See Also

ECMvar1

Examples

```

phi=matrix(c(0.5,-0.25,-1.0,0.5),2,2); theta=matrix(c(0.2,-0.1,-0.4,0.2),2,2)
Sig=diag(2)
mm=VARMAsim(300,arlags=c(1),malags=c(1),phi=phi,theta=theta,sigma=Sig)
zt=mm$series[,c(2,1)]
beta=matrix(c(1,0.5),2,1)
m1=ECMvar(zt,3,ibeta=beta)
names(m1)

```

 ECMvar1

Error-Correction VAR Model 1

Description

Perform least-squares estimation of an ECM VAR(p) model with known co-integrating processes

Usage

```
ECMvar1(x, p, wt, include.const = FALSE, fixed = NULL, output = TRUE)
```

Arguments

x	A T-by-k data matrix of a k-dimensional co-integrated VAR process
p	VAR order
wt	A T-by-m data matrix of m-dimensional co-integrated process
include.const	A logical switch to include a constant term. Default is no constant.
fixed	A logical matrix to set zero parameter constraints
output	A logical switch to control output

Value

data	The vector time series
wt	The co-integrated series
arorder	VAR order
include.const	Logical switch to include constant
coef	Parameter estimates
aic,bic	Information criteria of the fitted model
residuals	The residual series
Sigma	Residual covariance matrix

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 5). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

See Also

ECMvar

Examples

```
phi=matrix(c(0.5,-0.25,-1.0,0.5),2,2); theta=matrix(c(0.2,-0.1,-0.4,0.2),2,2)
Sig=diag(2)
mm=VARMAsim(300,arlags=c(1),malags=c(1),phi=phi,theta=theta,sigma=Sig)
zt=mm$series
wt=0.5*zt[,1]+zt[,2]
m1=ECMvar1(zt,3,wt)
names(m1)
```

EWMAvol

Exponentially Weighted Moving-Average Volatility

Description

Use exponentially weighted moving-average method to compute the volatility matrix

Usage

```
EWMAvol(rtn, lambda = 0.96)
```

Arguments

rtn	A T-by-k data matrix of k-dimensional asset returns, assuming the mean is zero
lambda	Smoothing parameter. The default is 0.96. If lambda is negative, then the multivariate Gaussian likelihood is used to estimate the smoothing parameter.

Value

Sigma.t	The volatility matrix with each row representing a volatility matrix
return	The data
lambda	The smoothing parameter lambda used

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 7). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

Examples

```
data("mts-examples", package="MTS")
rtn=log(ibmspko[,2:4]+1)
m1=EWMAvol(rtn)
```

FEVdec

Forecast Error Variance Decomposition

Description

Computes the forecast error variance decomposition of a VARMA model

Usage

```
FEVdec(Phi, Theta, Sig, lag = 4)
```

Arguments

Phi	VAR coefficient matrices in the form $\text{Phi}=[\text{Phi}_1, \text{Phi}_2, \dots, \text{Phi}_p]$, a k-by-kp matrix.
Theta	VMA coefficient matrices in form $\text{Theta}=[\text{Theta}_1, \text{Theta}_2, \dots, \text{Theta}_q]$, a k-by-kq matrix.
Sig	The residual covariance matrix Sigma, a k-by-k positive definite matrix.
lag	The number of lags of forecast errors variance to be computed. Default is 4.

Details

Use the psi-weight matrices to compute the forecast error covariance and use Cholesky decomposition to perform the decomposition

Value

irf	Impulse response matrices
orthirf	Orthogonal impulse response matrices
Omega	Forecast error variance matrices
OmegaR	Forecast error variance decomposition

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 3)

Examples

```
p1=matrix(c(0.2,-0.6,0.3,1.1),2,2)
theta1=matrix(c(-0.5,0,0,-0.6),2,2)
Sig=matrix(c(3,1,1,1),2,2)
m1=FEVdec(p1,theta1,Sig)
names(m1)
```

GrangerTest

Granger Causality Test

Description

Performs Granger causality test using a vector autoregressive model

Usage

```
GrangerTest(X,p=1,include.mean=T,locInput=c(1))
```

Arguments

X	a T-by-p data matrix with T denoting sample size and p the number of variables
p	vector AR order.
include.mean	Indicator for including a constant in the model. Default is TRUE.
locInput	Locators for the input variables in the data matrix. Deafult is the first column being the input variable. Multiple inputs are allowed.

Details

Perform VAR(p) and constrained VAR(p) estimations to test the Granger causality. It uses likelihood ratio and asymptotic chi-square.

Value

data	Original data matrix
cnst	logical variable to include a constant in the model
order	order of VAR model used
coef	Coefficient estimates
constraints	Implied constraints of Granger causality
aic, bic, hq	values of information criteria
residuals	residual vector
secoef	standard errors of coefficient estimates
Sigma	Residual covariance matrix
Phi	Matrix of VAR coefficients
Ph0	constant vector
omega	Estimates of constrained coefficients
covomega	covariance matrix of constrained parameters
locInput	Locator vector for input variables

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 2)

hfactor

Constrained Factor Model

Description

Performs factor model analysis with a given constrained matrix

Usage

hfactor(X, H, r)

Arguments

X	A T-by-k data matrix of an observed k-dimensional time series
H	The constrained matrix with each column representing a constraint
r	The number of common factor

Value

Results of the traditional PCA and constrained factor models are given

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 6). Tsai and Tsay (2010, JASA)

Examples

```
data("mts-examples", package="MTS")
rtn=log(tenstocks[,2:11]+1) # compute log returns
h1=c(1,1,1,1,rep(0,6)) # specify the constraints
h2=c(0,0,0,0,1,1,1,0,0,0)
h3=c(rep(0,7),1,1,1)
H=cbind(h1,h2,h3)
m1=hfactor(rtn,H,3)
```

ibmspko

Monthly simple returns of the stocks of International Business Machines (IBM) and Coca Cola (KO) and the S&P Composite index (SP)

Description

Monthly simple returns of the stocks of International Business Machines (IBM) and Coca Cola (KO) and the S&P Composite index (SP). The sample period is from January 1961 to December 2011. The original data were from the Center for Research in Security Prices (CRSP) of the University of Chicago. The files has four columns. They are dates, IBM, SP, and KO.

Usage

ibmspko

Format

A 2-d list containing 612x4 observations. The files has four columns. They are dates, IBM, SP, and KO.

Source

World Almanac and Book of Facts, 1975, page 406.

Kronfit

Fitting a VARMA Model via Kronecker Index

Description

Perform estimation of a VARMA model specified by the Kronecker indices

Usage

```
Kronfit(da, kidx, include.mean = T, fixed = NULL, Kpar=NULL,
        seKpar=NULL, prelim = F, details = F, thres = 1)
```

Arguments

da	Data matrix (T-by-k) of a k-dimensional time series
kidx	The vector consisting of Kronecker indices
include.mean	A logical switch for including the mean vector in estimation. Default is to include the mean vector.
fixed	A logical matrix used to set zero parameter constraints. This is used mainly in the command refKronfit.
Kpar	Parameter vectors for use in model simplification
seKpar	Standard errors of the parameter estimates for use in model simplification
prelim	A logical switch for a preliminary estimation.
details	A logical switch to control output.
thres	A threshold for t-ratios in setting parameter to zero. Default is 1.

Value

data	The observed time series data
Kindex	Kronecker indices
ARid	Specification of AR parameters: 0 denotes fixing to zero, 1 denotes fixing to 1, and 2 denoting estimation
MAid	Specification of MA parameters
cnst	A logical variable: include.mean
coef	Parameter estimates
se.coef	Standard errors of the estimates
residuals	Residual series
Sigma	Residual covariance matrix
aic,bic	Information criteria of the fitted model
Ph0	Constant vector
Phi	AR coefficient matrices
Theta	MA coefficient matrices

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 4). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

See Also

refKronfit, Kronspect

Kronid

*Kronecker Index Identification***Description**

Find the Kronecker indices of a k-dimensional time series

Usage

```
Kronid(x, plag = 5, crit = 0.05)
```

Arguments

x	Data matrix (T-by-k) of a k-dimensional time series
plag	The number of lags used to represent the past vector. Default is 5.
crit	Type-I error used in testing for zero canonical correlations. Default is 0.05.

Value

index	Kronecker indices
tests	Chi-square test statistics

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 4). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

Examples

```
phi=matrix(c(0.2,-0.6,.3,1.1),2,2); sigma=diag(2); theta=-0.5*sigma
m1=VARMAsim(300,arlags=c(1),malags=c(1),phi=phi,theta=theta,sigma=sigma)
zt=m1$series
Kronid(zt)
```

Kronspec	<i>Kronecker Index Specification</i>
----------	--------------------------------------

Description

For a given set of Kronecker indices, the program specifies a VARMA model. It gives details of parameter specification.

Usage

```
Kronspec(kdx, output = TRUE)
```

Arguments

kdx	A vector of Kronecker indices
output	A logical switch to control output. Default is with output.

Value

PhiID	Specification of the AR matrix polynomial. 0 denotes zero parameter, 1 denotes fixing parameter to 1, and 2 denotes the parameter requires estimation
ThetaID	Specification of the MA matrix polynomial

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 4)

Examples

```
kdx=c(2,1,1)
m1=Kronspec(kdx)
names(m1)
```

MarchTest *Multivariate ARCH test*

Description

Perform tests to check the conditional heteroscedasticity in a vector time series

Usage

```
MarchTest(zt, lag = 10)
```

Arguments

zt	a nT-by-k data matrix of a k-dimensional financial time series, each column contains a series.
lag	The number of lags of cross-correlation matrices used in the tests

Details

Several tests are used. First, the vector series z_t is transformed into $r_t = [t(z_t)]$ perform the test. The second test is based on the ranks of the transformed r_t series. The third test is the multivariate Ljung-Box statistics for the squared vector series z_t^2 . The fourth test is the multivariate Ljung-Box statistics applied to the 5-percent trimmed series of the transformed series r_t .

Value

Various test statistics and their p-values

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 7). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

Examples

```
zt=matrix(rnorm(600),200,3)
MarchTest(zt)
function (zt, lag = 10)
{
  if (!is.matrix(zt))
    zt = as.matrix(zt)
  nT = dim(zt)[1]
  k = dim(zt)[2]
  C0 = cov(zt)
  zt1 = scale(zt, center = TRUE, scale = FALSE)
```

```

C0iv = solve(C0)
wk = zt1 %*% C0iv
wk = wk * zt1
rt2 = apply(wk, 1, sum) - k
m1 = acf(rt2, lag.max = lag, plot = F)
acf = m1$acf[2:(lag + 1)]
c1 = c(1:lag)
deno = rep(nT, lag) - c1
Q = sum(acf^2/deno) * nT * (nT + 2)
pv1 = 1 - pchisq(Q, lag)
cat("Q(m) of squared series(LM test): ", "\n")
cat("Test statistic: ", Q, " p-value: ", pv1, "\n")
rk = rank(rt2)
m2 = acf(rk, lag.max = lag, plot = F)
acf = m2$acf[2:(lag + 1)]
mu = -(rep(nT, lag) - c(1:lag))/(nT * (nT - 1))
v1 = rep(5 * nT^4, lag) - (5 * c(1:lag) + 9) * nT^3 + 9 *
      (c(1:lag) - 2) * nT^2 + 2 * c(1:lag) * (5 * c(1:lag) +
      8) * nT + 16 * c(1:lag)^2
v1 = v1/(5 * (nT - 1)^2 * nT^2 * (nT + 1))
QR = sum((acf - mu)^2/v1)
pv2 = 1 - pchisq(QR, lag)
cat("Rank-based Test: ", "\n")
cat("Test statistic: ", QR, " p-value: ", pv2, "\n")
cat("Q_k(m) of squared series: ", "\n")
x = zt^2
g0 = var(x)
ginv = solve(g0)
qm = 0
df = 0
for (i in 1:lag) {
  x1 = x[(i + 1):nT, ]
  x2 = x[1:(nT - i), ]
  g = cov(x1, x2)
  g = g * (nT - i - 1)/(nT - 1)
  h = t(g) %*% ginv %*% g %*% ginv
  qm = qm + nT * nT * sum(diag(h))/(nT - i)
  df = df + k * k
}
pv3 = 1 - pchisq(qm, df)
cat("Test statistic: ", qm, " p-value: ", pv3, "\n")
cut1 = quantile(rt2, 0.95)
idx = c(1:nT)[rt2 <= cut1]
x = zt[idx, ]^2
eT = length(idx)
g0 = var(x)
ginv = solve(g0)
qm = 0
df = 0
for (i in 1:lag) {
  x1 = x[(i + 1):eT, ]
  x2 = x[1:(eT - i), ]
  g = cov(x1, x2)

```

```

g = g * (eT - i - 1)/(eT - 1)
h = t(g) %*% ginv %*% g %*% ginv
qm = qm + eT * eT * sum(diag(h))/(eT - i)
df = df + k * k
}
pv4 = 1 - pchisq(qm, df)
cat("Robust Test(5%) : ", qm, " p-value: ", pv4, "\n")
}

```

MCHdiag

Multivariate Conditional Heteroscedastic Model Cheking

Description

Apply four portmanteau test statistics to check the validity of a fitted multivariate volatility model

Usage

```
MCHdiag(at, Sigma.t, m = 10)
```

Arguments

at	A T-by-k matrix of residuals for a k-dimensional asset return series
Sigma.t	The fitted volatility matrices. The dimension is T-by-k ² matrix
m	The number of lags used in the tests. Default is 10.

Details

The four test statistics are given in Tsay (2014, Chapter 7)

Value

Four test statistics and their p-values

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 7). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

MCholV

Multivariate Cholesky Volatility Model

Description

Use Cholesky decomposition to obtain multivariate volatility models

Usage

```
MCholV(rtn, size = 36, lambda = 0.96, p = 0)
```

Arguments

rtn	A T-by-k data matrix of a k-dimensional asset return series.
size	The initial sample size used to start recursive least squares estimation
lambda	The exponential smoothing parameter. Default is 0.96.
p	VAR order for the mean equation. Default is 0.

Details

Use recursive least squares to perform the time-varying Cholesky decomposition. The least squares estimates are then smoothed via the exponentially weighted moving-average method with decaying rate 0.96. University GARCH(1,1) model is used for the innovations of each linear regression.

Value

betat	Recursive least squares estimates of the linear transformations in Cholesky decomposition
bt	The transformation residual series
Vol	The volatility series of individual innovations
Sigma.t	Volatility matrices

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 7)

See Also

fGarch

 Mlm

Multivariate Linear Model

Description

Fit a multivariate multiple linear regression model via the least squares method

Usage

```
Mlm(y, z, constant=TRUE, output=TRUE)
```

Arguments

y	data matrix of dependent variable. Each column contains one variable.
z	data matrix of the explanatory variables. Each column contains one variable.
constant	A logical switch for including the constant term
output	A logical switch to print the output

Value

beta	coefficient matrix
se.beta	standard errors of the coefficient matrix
residuals	The residual series
sigma	Residual covariance matrix

Author(s)

Ruey S. Tsay

 mq

Multivariate Ljung-Box Q Statistics

Description

Computes the multivariate Ljung-Box statistics for cross-correlation matrices

Usage

```
mq(x, lag = 24, adj = 0)
```

Arguments

x	The data matrix of a vector time series or residual series of a fitted multivariate model.
lag	The number of cross-correlation matrices used. Default is 24.
adj	Adjustment for the degrees of freedom for the Ljung-Box statistics. This is used for residual series. Default is zero.

Details

Computes the multivariate Ljung-Box statistics and their p-values. For model checking, the sub-command adj can be used to adjust the degrees of freedom of the Chi-square statistics.

Value

The multivariate Q-statistics and their p-values. Also, it provides a plot of the p-values.

Author(s)

Ruey S. Tsay

References

Tsay (2014). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley, Hoboken, NJ.

Examples

```
x=matrix(rnorm(1500),500,3)
mq(x)
```

msqrt

Square Root Matrix

Description

Compute the symmetric square root of a positive definite matrix

Usage

```
msqrt(M)
```

Arguments

M	A positive definite matrix
---	----------------------------

Details

Use spectral decomposition to compute the square root of a positive definite matrix

Value

mtxsqrt	The square root matrix
invsqrt	The inverse of the square root matrix

Note

This command is used in some of the MTS functions.

Author(s)

Ruey S. Tsay

Examples

```
m=matrix(c(1,0.2,0.2,1),2,2)
m1=msqrt(m)
names(m1)
```

mtCopula

Multivariate t-Copula Volatility Model

Description

Fits a t-copula to a k-dimensional standardized return series. The correlation matrices are parameterized by angles and the angles evolve over time via a DCC-type equation.

Usage

```
mtCopula(rt, g1, g2, grp = NULL, th0 = NULL, m = 0, include.th0 = TRUE)
```

Arguments

rt	A T-by-k data matrix of k standardized time series (after univariate volatility modeling)
g1	lambda1 parameter, nonnegative and less than 1
g2	lambda2 parameter, nonnegative and satisfying lambda1+lambda2 < 1.
grp	a vector to indicate the number of assets divided into groups. Default means each individual asset forms a group.
th0	initial estimate of theta0
m	number of lags used to estimate the local theta-angles
include.th0	A logical switch to include theta0 in estimation. Default is to include.

Value

estimates	Parameter estimates
Hessian	Hessian matrix
rho.t	Cross-correlation matrices
theta.t	Time-varying angel mtrices

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 7). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

MTS-internal	<i>MTS Internal Functions</i>
--------------	-------------------------------

Description

MTS Internal Functions

Details

These are not to be called by the user.

MTSdiag	<i>Multivariate Time Series Diagnostic Checking</i>
---------	---

Description

Performs model checking for a fitted multivariate time series model, including residual cross-correlation matrices, multivariate Ljung-Box tests for residuals, and residual plots

Usage

```
MTSdiag(model, gof = 24, adj = 0, level = F)
```

Arguments

model	A fitted multivariate time series model
gof	The number of lags of residual cross-correlation matrices used in the tests
adj	The adjustment for degrees of freedom of Ljung-Box statistics. Typically, the number of fitted coefficients of the model. Default is zero.
level	Logical switch for printing residual cross-correlation matrices

Value

Various test statistics, their p-values, and residual plots.

Author(s)

Ruey S Tsay

Examples

```
phi=matrix(c(0.2,-0.6,0.3,1.1),2,2); sigma=diag(2)
m1=VARMAsim(200,arlags=c(1),phi=phi,sigma=sigma)
zt=m1$series
m2=VAR(zt,1,include.mean=FALSE)
MTSdiag(m2)
```

MTSplot

Multivariate Time Series Plot

Description

Provides time plots of a vector time series

Usage

```
MTSplot(data, caltime = NULL)
```

Arguments

data	data matrix of a vector time series
caltime	Calendar time. Default is NULL, that is, using time index

Details

Provides time plots of a vector time series. The output frame depends on the dimension of the time series

Value

Time plots of vector time series

Author(s)

Ruey S. Tsay

Examples

```
xt=matrix(rnorm(1500),500,3)
MTSplot(xt)
```

Mtxprod	<i>Polynomial Matrix Product</i>
---------	----------------------------------

Description

Compute the product of two polynomial matrices

Usage

Mtxprod(Mtx, sMtx, p, P)

Arguments

Mtx	The coefficient matrix of a regular polynomial matrix
sMtx	The coefficient matrix of a seasonal polynomial matrix
p	Degree of the regular polynomial matrix
P	Degree of the seasonal polynomial matrix

Value

Coefficient matrix of the product. The product is in the form reg-AR * sAR, etc.

Author(s)

Ruey S. Tsay

Mtxprod1	<i>Alternative Ploynomial Matrix Product</i>
----------	--

Description

Compute the product of two polynomial matrices

Usage

Mtxprod1(Mtx, sMtx, p, P)

Arguments

Mtx	The coefficient matrix of a regular polynomial matrix
sMtx	The coefficient matrix of a seasonal polynomial matrix
p	Degree of the regular polynomial matrix. p is less than P.
P	Degree of the seasonal polynomial matrix

Details

This polynomial product is used in seasonal VARMA modeling to check the multiplicative nature between the regular and seasonal polynomial matrices

Value

Coefficient matrix of the product. The product matrix is in the form sAR * reg-AR, etc.

Author(s)

Ruey S. Tsay

 PIwgt

Pi Weight Matrices

Description

Compute the Pi-weight matrices of a VARMA model

Usage

```
PIwgt(Phi = NULL, Theta = NULL, lag = 12, plot = TRUE)
```

Arguments

Phi	A k-by-kp matrix of VAR coefficients in the form [Phi1, Phi2, Phi3, ..., Phip]
Theta	A k-by-kq matrix of VMA coefficients in the form [Theta1, Theta2, ..., Thetaq]
lag	The number of Pi-weight matrices to be computed.
plot	A logical switch to plot the Pi-weight matrices

Details

The Pi-weight matrices for a VARMA model is $Pi(B) = \text{inverse}(\text{Theta}(B)) \text{ times } \text{Phi}(B)$.

Value

pi.weight The matrix of Pi-weight coefficient

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapters 2 and 3). Multivariate Time Series Analysis with R and Financial Applications. John Wiley. Hoboken, NJ.

See Also

PSIwgt

Examples

```
Phi1=matrix(0,2,2); Phi2=matrix(c(0.2,-0.6,0.3,1.1),2,2)
Theta1=diag(c(-0.5,-0.4))
Phi=cbind(Phi1,Phi2)
m1=PSIwgt(Phi=Phi,Theta=Theta1)
names(m1)
```

PSIwgt

*Psi Wights Matrices***Description**

Computes the psi-weight matrices of a VARMA model

Usage

```
PSIwgt(Phi = NULL, Theta = NULL, lag = 12, plot = TRUE, output = FALSE)
```

Arguments

Phi	A k-by-kp matrix of VAR coefficient matrix. Phi=[Phi1, Phi1, ..., Phip]
Theta	A k-by-kq matrix of VMA coefficient matrix. Theta=[Theta1, Theta2, ..., Thetaq]
lag	The number of psi-weight matrices to be computed. Deafult is 12.
plot	A lofical switch to control plotting of the psi-weights.
output	A logical switch to control the output.

Value

psi.weight	Psi-weight matrices
irf	Impulse response cofficient matrices

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 3). Multivariate Time Series Analysis with R and Financial Applications. John Wiley. Hoboken, NJ.

Examples

```
phi=matrix(c(0.2,-0.6,0.3,1.1),2,2)
theta=matrix(c(-0.5,0.2,0.0,-0.6),2,2)
m1=PSIwgt(Phi=phi,Theta=theta)
```

qgdp	<i>Quarterly real gross domestic products of United Kingdom, Canada, and the United States</i>
------	--

Description

Quarterly real gross domestic products of United Kingdom, Canada, and the United States from the first quarter of 1980 to the second quarter of 2011. The UK and CA data were originally from OECD and the US data from the Federal Reserve Bank of St Louis.

Usage

qgdp

Format

A 2-d list containing 126x5 observations. The data set consists of 5 columns, namey year, month, UK, CA, and US.

Source

The data were downloaded from the FRED of the Federal Reserve Bank of St Louis. The UK data were in millions of chained 2006 Pounds, the CA data were in millions of chained 2002 Canadian dollars, and the US data were in millions of chained 2005 dollars.

refECMvar	<i>Refining Error-Correction Model for VAR series</i>
-----------	---

Description

Refining an estimated ECM VAR model by setting insignificant estimates to zero

Usage

```
refECMvar(m1, thres = 1)
```

Arguments

m1	An object of the ECMvar command or the refECMvar command
thres	Threshold for individual t-ratio. The default is 1.

Details

Set simultaneously all estimates with t-ratio less than the threshold to zero (in modulus).

Value

Constrained estimation results of a ECM VAR model

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 5). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

 refECMvar1

Refining ECM for a VAR process

Description

Performs constrained least squares estimation of a ECM VAR model with known co-integrated processes

Usage

```
refECMvar1(m1, thres = 1)
```

Arguments

m1	An object of the ECMvar1 command or the refECMvar1 command
thres	Threshold for individual t-ratio. Default is 1.

Details

Setting all estimates with t-ration less than the threshold, in absolute value, to zero simultaneously.

Value

Constrained estimation results of an ECM VAR model

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 5). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

See Also

ECMvar1, refECMvar

`refKronfit`*Refining VARMA Estimation via Kronecker Index Approach*

Description

This program performs model simplification of a fitted VARMA model via the Kronecker index approach

Usage

```
refKronfit(model, thres = 1)
```

Arguments

<code>model</code>	The name of a model from the command <code>Kronfit</code> or <code>refKronfit</code>
<code>thres</code>	A threshold for t-ratio of individual parameter estimate. The default is 1.

Details

For a given threshold, the program sets a parameter to zero if its t-ratio (in modulus) is less than the threshold.

Value

Same as those of the command `Kronfit`.

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 4). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

See Also

`Kronfit`

`refREGts`*Refining a Regression Model with Time Series Errors*

Description

Refines a fitted REGts by setting simultaneously parameters with t-ratios less than the threshold (in modulus) to zero

Usage

```
refREGts(m1, thres = 1)
```

Arguments

<code>m1</code>	An output object from the REGts command or refREGts command
<code>thres</code>	Threshold value for individual t-ratio. Default is 1.

Value

The same as those of the command REGts.

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 6). Multivariate Time Series Analysis with R and Financial Applications. John Wiley. Hoboken, NJ.

See Also

refVAR, refVARMA

`refSCMfit`*Refining Estimation of VARMA Model via SCM Approach*

Description

Refine estimation of a VARMA model specified via the SCM approach by removing insignificant parameters

Usage

```
refSCMfit(model, thres = 1)
```

Arguments

model	Name of the model from the SCMfit command or the refSCMfit command
thres	Threshold for the t-ratio of individual coefficient. Default is 1.

Value

The same as those of the command SCMfit.

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 4)

See Also

SCMfit

refsVARMA

Refining a Seasonal VARMA Model

Description

Refines a fitted seasonal VARMA model by setting insignificant estimates to zero

Usage

```
refsVARMA(model, thres = 0.8)
```

Arguments

model	An output object of the sVARMA command or the refsVARMA command
thres	Threshold for individual t-ratio. Default is 0.8.

Details

The command removes simultaneously all parameters with t-ratio less than the threshold in modulus.

Value

The same as those of the command sVARMA

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 6)

See Also

sVARMA

refVAR

Refining a VAR Model

Description

Refine a fitted VAR model by removing simultaneously insignificant parameters

Usage

```
refVAR(model, fixed = NULL, thres = 1)
```

Arguments

model	An output object of the command VAR or the refVAR command
fixed	A logical matrix for VAR polynomial structure
thres	Threshold used to set parameter to zero. Default is 1.

Details

Refine a VAR fitting by setting all estimates with t-ratio less than the threshold (in modulus) to zero.

Value

The same as those of the command VAR

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 2)

See Also

VAR

Examples

```
data("mts-examples", package="MTS")
gdp=log(qgdp[,3:5])
zt=diffM(gdp)
m1=VAR(zt,3)
m2=refVAR(m1, thres=1.0)
names(m2)
```

refVARMA

Refining VARMA Estimation

Description

Refines a fitted VARMA model by setting insignificant estimates to zero

Usage

```
refVARMA(model, thres = 1.5)
```

Arguments

model	An output object from the command VARMA or the command refVARMA
thres	A threshold value for individual t-ratio of the estimates.

Details

The program simultaneously sets estimates with t-ratios less than the threshold (in modulus) to zero.

Value

The same as those of the command VARMA.

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 3). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

See Also

VARMA

`refVARX`*Refining a VARX Model*

Description

Refine a fitted VARX model by setting insignificant parameters to zero

Usage

```
refVARX(m1, thres = 1)
```

Arguments

<code>m1</code>	An output object of the VARX command or the refVARX command
<code>thres</code>	A threshold for the individual t-ratio. Default is 1.

Details

The program sets simultaneously all estimates with t-ratio less than threshold (in modulus) to zero and re-estimate the VARX model.

Value

The same as those of the command VARX.

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 6). Multivariate Time Series Analysis with R and Financial Applications. John Wiley. Hoboken, NJ.

See Also

VARX

`refVMA`*Refining VMA Models*

Description

Refines a fitted VMA model by setting insignificant parameters to zero

Usage

```
refVMA(model, thres = 1)
```

Arguments

<code>model</code>	An output object from the command <code>VMA</code> or the <code>refVMA</code> command
<code>thres</code>	A threshold for individual t-ratio of parameter estimate. Default is 1.

Details

The program simultaneously sets all estimates with t-ratios less than the threshold (in modulus) to zero.

Value

The same as those of the command `VMA`.

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 3). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

See Also

`VMA`

`refVMAe`*Refining VMA Estimation via the Exact Likelihood Method*

Description

Refines a fitted VMA model via the VMAe command by setting insignificant parameters to zero

Usage

```
refVMAe(model, thres = 1)
```

Arguments

<code>model</code>	An output object of the command VMAe or the command refVMAe itself
<code>thres</code>	A threshold for individual t-ratio of parameter estimates. Deafult is 1.

Details

The program sets simultaneously all estimates with t-ratios less than the threshold (in modulus) to zero.

Value

The same as those of the command VMAe.

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 3). Multivariate Time Series Analysis with R and Financial Applications. John Wiley. Hoboken, NJ.

See Also

VMAe, refVMA

REGts

*Regression Model with Time Series Errors***Description**

Perform the maximum likelihood estimation of a multivariate linear regression model with time-series errors

Usage

```
REGts(zt, p, xt, include.mean = T, fixed = NULL, par = NULL, se.par = NULL, details = F)
```

Arguments

zt	A T-by-k data matrix of a k-dimensional time series
p	The VAR order
xt	A T-by-v data matrix of independent variables, where v denotes the number of independent variables (excluding constant 1).
include.mean	A logical switch to include the constant term. Default is to include the constant term.
fixed	A logical matrix used to set parameters to zero
par	Initial parameter estimates of the beta coefficients, if any.
se.par	Standard errors of the parameters in par, if any.
details	A logical switch to control the output

Details

Perform the maximum likelihood estimation of a multivariate linear regression model with time series errors. Use multivariate linear regression to obtain initial estimates of regression coefficients if not provided

Value

data	The observed k-dimensional time series
xt	The data matrix of independent variables
aror	VAR order
include.mean	Logical switch for the constant vector
Phi	The VAR coefficients
se.Phi	The standard errors of Phi coefficients
beta	The regression coefficients
se.beta	The standard errors of beta
residuals	The residual series
Sigma	Residual covariance matrix
coef	Parameter estimates, to be used in model simplification.
se.coef	Standard errors of parameter estimates

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 6). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken NJ.

RLS

Recursive Least Squares

Description

Compute recursive least squares estimation

Usage

```
RLS(y, x, ist = 30, xpxi = NULL, xpy0 = NULL)
```

Arguments

y	data of dependent variable
x	data matrix of regressors
ist	initial number of data points used to start the estimation
xpxi	Inverse of the $X'X$ matrix
xpy0	Initial value of $X'y$.

Value

beta	Time-varying regression coefficient estimates
resi	The residual series of recursive least squares estimation

Note

This function is used internally, but can also be used as a command.

Author(s)

Ruey S. Tsay

SCCor

Sample Constrained Correlations

Description

Compute the sample constrained correlation matrices

Usage

```
SCCor(rt, end, span, grp)
```

Arguments

rt	A T-by-k data matrix of a k-dimensional time series
end	The time index of the last data point to be used in computing the sample correlations.
span	The size of the data span used to compute the correlations.
grp	A vector of group sizes. The time series in the same group are pooled to compute the correlation matrix.

Value

unconCor	Un-constrained sample correlation matrix
conCor	Constrained sample correlation matrix

Note

This is an internal function, not intended to be a general command

Author(s)

Ruey S. Tsay

Examples

```
rt=matrix(rnorm(1000),200,5)
grp=c(3,2)
m1=SCCor(rt,200,200,grp)
m1$unconCor
m1$conCor
```

 SCMfit *Scalar Component Model Fitting*

Description

Perform estimation of a VARMA model specified via the SCM approach

Usage

```
SCMfit(da, scms, Tdx, include.mean = T, fixed = NULL,
       prelim = F, details = F, thres = 1, ref = 0,
       SCMpar=NULL, seSCMpar=NULL)
```

Arguments

da	The T-by-k data matrix of a k-dimensional time series
scms	A k-by-2 matrix of the orders of SCMs
Tdx	A k-dimensional vector for locating "1" of each row in the transformation matrix.
include.mean	A logical switch to include the mean vector. Default is to include mean vector.
fixed	A logical matrix to set parameters to zero
prelim	A logical switch for preliminary estimation. Default is false.
details	A logical switch to control details of output
thres	Threshold for individual t-ratio when setting parameters to zero. Default is 1.
ref	A switch to use SCMmod in model specification.
SCMpar	Parameter estimates of the SCM model, to be used in model refinement
seSCMpar	Standard errors of the parameter estimates in SCMpar

Details

Perform conditional maximum likelihood estimation of a VARMA model specified by the scalar component model approach, including the transformation matrix.

Value

data	Observed time series
SCMs	The specified SCMs
Tdx	Indicator vector for the transformation matrix. The length of Tdx is k.
locTmtx	Specification of estimable parameters of the transformation matrix
locAR	Locators for the estimable parameters of the VAR coefficients
locMA	Locators for the estimable parameters of the VMA coefficients
cnst	A logical switch to include the constant vector in the model

coef	The parameter estimates
secoef	Standard errors of the parameter estimates
residuals	Residual series
Sigma	Residual covariance matrix
aic,bic	Information criteria of the fitted model
Ph0	Estimates of the constant vector, if any
Phi	Estimates of the VAR coefficients
Theta	Estimates of the VMA coefficients

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 4). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

SCMid

Scalar Component Identification

Description

Find the overall order of a VARMA process via the scalar component model approach

Usage

```
SCMid(zt, maxp = 5, maxq = 5, h = 0, crit = 0.05, output = FALSE)
```

Arguments

zt	The T-by-k data matrix of a k-dimensional time series
maxp	Maximum AR order entertained. Default is 5.
maxq	Maximum MA order entertained. Default is 5.
h	The additional past lags used in canonical correlation analysis. Default is 0.
crit	Type-I error of the chi-square tests used.
output	A logical switch to control the output.

Value

Nmtx	The table of the numbers of zero canonical correlations
DDmtx	The diagonal difference table of the number of zero canonical correlations

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 4). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

Examples

```
phi=matrix(c(0.2,-0.6,0.3,1.1),2,2); sigma=diag(2)
m1=VARMAsim(300,arlags=c(1),phi=phi,sigma=sigma)
zt=m1$series
m2=SCMid(zt)
```

SCMid2

*Scalar Component Model Specification II***Description**

Provides detailed analysis of scalar component models for a specified VARMA model. The overall model is specified by SCMid.

Usage

```
SCMid2(zt, maxp = 2, maxq = 2, h = 0, crit = 0.05, sseq = NULL)
```

Arguments

zt	The T-by-k data matrix of a k-dimensional time series
maxp	Maximum AR order specified. Default is 2.
maxq	Maximum MA order specified. Default is 2.
h	The additional past lags used in canonical correlation analysis. Default is zero.
crit	Type-I error used in testing. Default is 0.05.
sseq	The search sequence for SCM components. Default sequence starts with AR order.

Value

Tmatrix	The transformation matrix T
SCMorder	The orders of SCM components

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 4). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

See Also

SCMid

Examples

```
phi=matrix(c(0.2,-0.6,0.3,1.1),2,2); sigma=diag(2)
m1=VARMAsim(300,arlags=c(1),phi=phi,sigma=sigma)
zt=m1$series
m2=SCMid2(zt)
names(m2)
```

SCMmod

Scalar Component Model specification

Description

For a given set of SCMs and locator of transformation matrix, the program specifies a VARMA model via SCM approach for estimation

Usage

SCMmod(order, Ivor, output)

Arguments

order	A k-by-2 matrix of the orders of SCM
Ivor	A k-dimensioal vector indicating the location of "1" for each component in the transformation matrix.
output	A logical switch to control output.

Details

The command specified estimable parameters for a VARMA model via the SCM components. In the output, "2" denotes estimation, "1" denotes fixing the value to 1, and "0" means fixing the parameter to zero.

Value

Tmtx	Specification of the transformation matrix T
ARpar	Specification of the VAR parameters
MApar	Specification of the VMA parameters

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 4). Multivariate Time Series Analysis with R and Financial Applications. John Wiley. Hoboken, NJ.

Examples

```
ord=matrix(c(0,1,1,0,0,1),3,2)
Ivor=c(3,1,2)
m1=SCMmod(ord,Ivor,TRUE)
```

sVARMA

*Seasonal VARMA Model Estimation***Description**

Performs conditional maximum likelihood estimation of a seasonal VARMA model

Usage

```
sVARMA(da, order, sorder, s, include.mean = T, fixed = NULL, details = F, switch = F)
```

Arguments

da	A T-by-k data matrix of a k-dimensional seasonal time series
order	Regular order (p,d,q) of the model
sorder	Seasonal order (P,D,Q) of the model
s	Seasonality. s=4 for quarterly data and s=12 for monthly series
include.mean	A logical switch to include the mean vector. Default is to include the mean
fixed	A logical matrix to set zero parameter constraints
details	A logical switch for output
switch	A logical switch to exchange the ordering of the regular and seasonal VMA factors. Default is $\theta(B)*\Theta(B)$.

Details

Estimation of a seasonal VARMA model

Value

data	The data matrix of the observed k-dimensional time series
order	The regular order (p,d,q)
sorder	The seasonal order (P,D,Q)
period	Seasonality
cnst	A logical switch for the constant term
ceof	Parameter estimates for use in model simplification
secoef	Standard errors of the parameter estimates
residuals	Residual series
Sigma	Residual covariance matrix
aic,bic	Information criteria of the fitted model
regPhi	Regular AR coefficients, if any
seaPhi	Seasonal AR coefficients
regTheta	Regular MA coefficients
seaTheta	Seasonal MA coefficients
Ph0	The constant vector, if any
switch	The logical switch to change the ordering of matrix product

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 6). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

sVARMACpp

Seasonal VARMA Model Estimation (C++)

Description

Performs conditional maximum likelihood estimation of a seasonal VARMA model. This is the same function as sVARMA, with the likelihood function implemented in C++ for efficiency.

Usage

```
sVARMACpp(da, order, sorder, s, include.mean = T, fixed = NULL, details = F, switch = F)
```


Arguments

da	A T-by-k data matrix of a k-dimensional seasonal time series
order	Regular order (p,d,q) of the model
sorder	Seasonal order (P,D,Q) of the model
s	Seasonality. s=4 for quarterly data and s=12 for monthly series
include.mean	A logical switch to include the mean vector. Default is to include the mean
fixed	A logical matrix to set zero parameter constraints
details	A logical switch for output
switch	A logical switch to exchange the ordering of the regular and seasonal VMA factors. Default is $\theta(B)*\Theta(B)$.

Details

Estimation of a seasonal VARMA model

Value

data	The data matrix of the observed k-dimensional time series
order	The regular order (p,d,q)
sorder	The seasonal order (P,D,Q)
period	Seasonality
cnst	A logical switch for the constant term
coef	Parameter estimates for use in model simplification
secoef	Standard errors of the parameter estimates
residuals	Residual series
Sigma	Residual covariance matrix
aic,bic	Information criteria of the fitted model
regPhi	Regular AR coefficients, if any
seaPhi	Seasonal AR coefficients
regTheta	Regular MA coefficients
seaTheta	Seasonal MA coefficients
Ph0	The constant vector, if any
switch	The logical switch to change the ordering of matrix product

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 6). Multivariate Time Series Analysis with R and Financial Applications. John Wiley. Hoboken, NJ.

See Also

sVARMA

SWfore

*Stock-Watson Diffusion Index Forecasts***Description**

Uses the diffusion index approach of Stock and Watson to compute out-of-sample forecasts

Usage

```
SWfore(y, x, orig, m)
```

Arguments

y	The scalar variable of interest
x	The data matrix (T-by-k) of the observed explanatory variables
orig	Forecast origin
m	The number of diffusion index used

Details

Performs PCA on X at the forecast origin. Then, fit a linear regression model to obtain the coefficients of prediction equation. Use the prediction equation to produce forecasts and compute forecast errors, if any. No recursive estimation is used.

Value

coef	Regression coefficients of the prediction equation
yhat	Predictions at the forecast origin
MSE	Mean squared errors, if available
loadings	Loading matrix
DFindex	Diffusion indices

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 6). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

tenstocks	<i>Monthly simple returns of ten U.S. stocks</i>
-----------	--

Description

Monthly simple returns of ten U.S. stocks. The sample period is from January 2001 to December 2011. Tick symbols of the ten stocks are used as column names for the returns.

Usage

tenstocks

Format

A 2-d list containing 132x11 observations.

Source

The original data were from Center for Research in Security Prices (CRSP) of the University of Chicago. The first column denotes the dates.

tfm	<i>Transfer Function Model</i>
-----	--------------------------------

Description

Estimates a transform function model. This program does not allow rational transfer function model. It is a special case of tfm1 and tfm2.

Usage

$\text{tfm}(y, x, b = 0, s = 1, p = 0, q = 0)$

Arguments

y	Data vector of dependent (output) variable
x	Data vector of independent variable
b	deadtime or delay
s	The order of the transfer function polynomial
p	AR order of the disturbance
q	MA order of the disturbance

Details

The model entertained is $y_t = c_0 + v(B)x_t + n_t$. $v(B) = 1 - v_1*B - \dots - v_s*B^s$, and n_t is an ARMA(p,q) process.

Value

coef	Coefficient estimates of the transfer function
se.coef	Standard errors of the transfer function coefficients
coef.arma	Coefficient estimates of ARMA models
se.arma	Standard errors of ARMA coefficients
nt	The disturbance series
residuals	The residual series

Author(s)

Ruey S. Tsay

References

Box, G. E. P., Jenkins, G. M., and Reinsel, G. C. (1994). Time Series Analysis: Forecasting and Control, 3rd edition, Prentice Hall, Englewood Cliffs, NJ.

 tfm1

Transfer Function Model with One Input

Description

Estimation of a general transfer function model. The model can only handle one input and one output.

Usage

tfm1(y, x, orderN, orderX)

Arguments

y	Data vector of dependent variable
x	Data vector of input (or independent) variable
orderN	Order (p,d,q) of the disturbance component
orderX	Order (r,s,b) of the transfer function model, where r and s are the degrees of denominator and numerator polynomials and b is the delay

Details

Perform estimation of a general transfer function model

Value

estimate	Coefficient estimates
sigma2	Residual variance sigma-square
residuals	Residual series
varcoef	Variance of the estimates
Nt	The disturbance series

Author(s)

Ruey S. Tsay

References

Box, G. E. P., Jenkins, G. M., and Reinsel, G. C. (1994). *Time Series Analysis: Forecasting and Control*, 3rd edition, Prentice Hall, Englewood Cliffs, NJ.

See Also

tfm

Examples

```
##da=read.table("gasfur.txt")
##y=da[,2]; x=da[,1]
##m1=tfm1(y,x,orderX=c(1,2,3),orderN=c(2,0,0))
```

tfm2

Transfer Function Model with Two Input Variables

Description

Estimation of a general transfer function model with two input variables. The model can handle one output and up-to 2 input variables. The time series noise can assume multiplicative seasonal ARMA models.

Usage

```
tfm2(y,x,x2=NULL,ct=NULL,wt=NULL,orderN=c(1,0,0),orderS=c(0,0,0),
sea=12,order1=c(0,1,0),order2=c(0,-1,0))
```

Arguments

y	Data vector of dependent variable
x	Data vector of the first input (or independent) variable
x2	Data vector of the second input variable if any
ct	Data vector of a given deterministic variable such as time trend, if any
wt	Data vector of co-integrated series between input and output variables if any
orderN	Order (p,d,q) of the regular ARMA part of the disturbance component
orderS	Order (P,D,Q) of the seasonal ARMA part of the disturbance component
sea	Seasonality, default is 12 for monthly data
order1	Order (r,s,b) of the transfer function model of the first input variable, where r and s are the degrees of denominator and numerator polynomials and b is the delay
order2	Order (r2,s2,b2) of the transfer function model of the second input variable, where 2r and s2 are the degrees of denominator and numerator polynomials and b2 is the delay

Details

Perform estimation of a general transfer function model with two input variables

Value

estimate	Coefficient estimates
sigma2	Residual variance sigma-square
residuals	Residual series
varcoef	Variance of the estimates
Nt	The disturbance series
rAR	Regular AR coefficients
rMA	Regular MA coefficients
sAR	Seasonal AR coefficients
sMA	Seasonal MA coefficients
omega	Numerator coefficients of the first transfer function
delta	Denominator coefficients of the first transfer function
omega2	Numerator coefficients of the 2nd transfer function
delta2	Denominator coefficients of the 2nd transfer function

Author(s)

Ruey S. Tsay

References

Box, G. E. P., Jenkins, G. M., and Reinsel, G. C. (1994). Time Series Analysis: Forecasting and Control, 3rd edition, Prentice Hall, Englewood Cliffs, NJ.

See Also

tfm, tfm1

 VAR

Vector Autoregressive Model

Description

Perform least squares estimation of a VAR model

Usage

```
VAR(x, p = 1, output = T, include.mean = T, fixed = NULL)
```

Arguments

x	A T-by-k matrix of k-dimensional time series
p	Order of VAR model. Default is 1.
output	A logical switch to control output. Default is with output.
include.mean	A logical switch. It is true if mean vector is estimated.
fixed	A logical matrix used in constrained estimation. It is used mainly in model simplification, e.g., removing insignificant estimates.

Details

To remove insignificant estimates, one specifies a threshold for individual t-ratio. The fixed matrix is then defined automatically to identify those parameters for removal.

Value

data	Observed data
cnst	A logical switch to include the mean constant vector
order	VAR order
coef	Coefficient matrix
aic,bic,hq	Information criteria of the fitted model
residuals	Residuals
secoef	Standard errors of the coefficients to be used in model refinement
Sigma	Residual covariance matrix
Phi	AR coefficient polynomial
Ph0	The constant vector

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 3). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

See Also

refVAR command

Examples

```
data("mts-examples", package="MTS")
gdp=log(qgdp[,3:5])
zt=diffM(gdp)
m1=VAR(zt, p=2)
```

VARMA

*Vector Autoregressive Moving-Average Models***Description**

Performs conditional maximum likelihood estimation of a VARMA model. Multivariate Gaussian likelihood function is used.

Usage

```
VARMA(da, p = 0, q = 0, include.mean = T,
      fixed = NULL, beta=NULL, sebeta=NULL,
      prelim = F, details = F, thres = 2)
```

Arguments

da	Data matrix (T-by-k) of a k-dimensional time series with sample size T.
p	AR order
q	MA order
include.mean	A logical switch to control estimation of the mean vector. Default is to include the mean in estimation.
fixed	A logical matrix to control zero coefficients in estimation. It is mainly used by the command refVARMA.
beta	Parameter estimates to be used in model simplification, if needed
sebeta	Standard errors of parameter estimates for use in model simplification
prelim	A logical switch to control preliminary estimation. Default is none.
details	A logical switch to control the amount of output.
thres	A threshold used to set zero parameter constraints based on individual t-ratio. Default is 2.

Details

The fixed command is used for model refinement

Value

data	Observed data matrix
ARorder	VAR order
MAorder	VMA order
cnst	A logical switch to include the mean vector
coef	Parameter estimates
secoef	Standard errors of the estimates
residuals	Residual matrix
Sigma	Residual covariance matrix
aic,bic	Information criteria of the fitted model
Phi	VAR coefficients
Theta	VMA coefficients
Ph0	The constant vector

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 3). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

See Also

refVARMA

Examples

```
phi=matrix(c(0.2,-0.6,0.3,1.1),2,2); theta=matrix(c(-0.5,0,0,-0.5),2,2)
sigma=diag(2)
m1=VARMAsim(300,arlags=c(1),malags=c(1),phi=phi,theta=theta,sigma=sigma)
zt=m1$series
m2=VARMA(zt,p=1,q=1,include.mean=FALSE)
```

VARMAcov

*Autocovariance Matrices of a VARMA Model***Description**

Uses psi-weights to compute the autocovariance matrices of a VARMA model

Usage

```
VARMAcov(Phi = NULL, Theta = NULL, Sigma = NULL, lag = 12, trun = 120)
```

Arguments

Phi	A k-by-kp matrix consisting of VAR coefficient matrices, Phi = [Phi1, Phi2, ..., Phip].
Theta	A k-by-kq matrix consisting of VMA coefficient matrices, Theta = [Theta1, Theta2, ..., Thetaq]
Sigma	Covariance matrix of the innovations (k-by-k).
lag	Number of cross-covariance matrices to be computed. Default is 12.
trun	The lags of psi-weights used in calculation. Default is 120.

Details

Use psi-weight matrices to compute approximate autocovariance matrices of a VARMA model.

Value

autocov	Autocovariance matrices
ccm	Auto correlation matrices

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 3). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

Examples

```
Phi=matrix(c(0.2,-0.6,0.3,1.1),2,2)
Sig=matrix(c(4,1,1,1),2,2)
VARMAcov(Phi=Phi,Sigma=Sig)
```

Description

Performs conditional maximum likelihood estimation of a VARMA model. Multivariate Gaussian likelihood function is used. This is the same function as VARMA, with the likelihood function implemented in C++ for efficiency.

Usage

```
VARMACpp(da, p = 0, q = 0, include.mean = T,
         fixed = NULL, beta=NULL, sebeta=NULL,
         prelim = F, details = F, thres = 2)
```

Arguments

da	Data matrix (T-by-k) of a k-dimensional time series with sample size T.
p	AR order
q	MA order
include.mean	A logical switch to control estimation of the mean vector. Default is to include the mean in estimation.
fixed	A logical matrix to control zero coefficients in estimation. It is mainly used by the command refVARMA.
beta	Parameter estimates to be used in model simplification, if needed
sebeta	Standard errors of parameter estimates for use in model simplification
prelim	A logical switch to control preliminary estimation. Default is none.
details	A logical switch to control the amount of output.
thres	A threshold used to set zero parameter constraints based on individual t-ratio. Default is 2.

Details

The fixed command is used for model refinement

Value

data	Observed data matrix
ARorder	VAR order
MAorder	VMA order
cnst	A logical switch to include the mean vector
coef	Parameter estimates
secoef	Standard errors of the estimates

residuals	Residual matrix
Sigma	Residual covariance matrix
aic,bic	Information criteria of the fitted model
Phi	VAR coefficients
Theta	VMA coefficients
Ph0	The constant vector

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 3). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

See Also

VARMA

Examples

```
phi=matrix(c(0.2,-0.6,0.3,1.1),2,2); theta=matrix(c(-0.5,0,0,-0.5),2,2)
sigma=diag(2)
m1=VARMAsim(300,arlags=c(1),malags=c(1),phi=phi,theta=theta,sigma=sigma)
zt=m1$series
m2=VARMA(zt,p=1,q=1,include.mean=FALSE)
```

VARMAirf

Impulse Response Functions of a VARMA Model

Description

Compute and plot the impulse response function of a given VARMA model

Usage

```
VARMAirf(Phi = NULL, Theta = NULL, Sigma = NULL, lag = 12, orth = TRUE)
```

Arguments

Phi	A k-by-kp matrix of VAR coefficients in the form $\text{Phi}=[\text{Phi1}, \text{Phi2}, \dots, \text{Phi}p]$.
Theta	A k-by-kq matrix of VMA coefficients in the form $\text{Theta}=[\text{Theta1}, \text{Theta2}, \dots, \text{Theta}q]$
Sigma	Covariance matrix (k-by-k) of the innovations.
lag	Number of lags of impulse response functions to be computed
orth	A logical switch to use orthogonal innovations. Default is to perform orthogonalization of the innovations.

Value

psi	The Psi-weight matrices
irf	Impulse response functions

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 3). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

See Also

VARMApsi command

Examples

```
p1=matrix(c(0.2,-0.6,0.3,1.1),2,2)
th1=matrix(c(-0.5,0.2,0.0,-0.6),2,2)
Sig=matrix(c(4,1,1,1),2,2)
m1=VARMAirf(Phi=p1,Theta=th1,Sigma=Sig)
```

 VARMApred

VARMA Prediction

Description

Compute forecasts and their associate forecast error covariances of a VARMA model

Usage

```
VARMApred(model, h = 1, orig = 0)
```

Arguments

model	A fitted VARMA model
h	Number of steps of frecasts, i.e., forecast horizon.
orig	Forecast origin. Default is the end of the sample.

Value

pred	Predictions
se.err	Standard errors of forecasts
orig	Forecast origin

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 3). Multivariate Time Series Analysis with R and Financial Applications. John Wiley. Hoboken, NJ.

VARMAsim

*Generating a VARMA Process***Description**

Performs simulation of a given VARMA model

Usage

```
VARMAsim(nobs, arlags = NULL, malags = NULL,
         cnst = NULL, phi = NULL, theta = NULL,
         skip = 200, sigma)
```

Arguments

nobs	Sample size
arlags	The exact lags of the VAR matrix polynomial.
malags	The exact lags of the VMA matrix polynomial.
cnst	Constant vector, Phi0
phi	Matrix of VAR coefficient matrices in the order of the given arlags.
theta	Matrix of VMA coefficient matrices in the order of the given malags.
skip	The number of initial data to be omitted. Deafult is 200.
sigma	Covariance matrix (k-by-k, positive definite) of the innovations

Details

Use multivariate Gaussian distribution to generate random shocks. Then, generate a given VARMA model. The first skip data points were discarded.

Value

series	Generated series
noises	The noise series

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 3). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

Examples

```
p1=matrix(c(0.2,-0.6,0.3,1,1),2,2)
sig=matrix(c(4,0.8,0.8,1),2,2)
th1=matrix(c(-0.5,0,0,-0.6),2,2)
m1=VARMAsim(300,arlags=c(1),malags=c(1),phi=p1,theta=th1,sigma=sig)
zt=m1$series
```

VARorder	<i>VAR Order Specification</i>
----------	--------------------------------

Description

Computes information criteria and the sequential Chi-square statistics for a vector autoregressive process

Usage

```
VARorder(x, maxp = 13, output = T)
```

Arguments

x	Data matrix of dimension T-by-k with T being the sample size and k the number of time series
maxp	The maximum VAR order entertained. Default is 13.
output	A logical switch to control the output. Default is to provide output

Details

For a given maxp, the command computes Akaike, Bayesian and Hannan-Quinn information criteria for various VAR models using the data from $t=\text{maxp}+1$ to T. It also computes the Tiao-Box sequential Chi-square statistics and their p-values.

Value

aic	Akaike information criterion
bic	Bayesian information criterion
hq	Hannan and Quinn information criterion
aicor, bicor, hqor	Orders selected by various criteria
Mstat	Chi-square test statistics
Mpv	p-values of the Mstat

Author(s)

Ruey S. Tsay

References

Tsay (2014). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley, Hoboken, NJ.

See Also

VARorderI

Examples

```
data("mts-examples", package="MTS")
zt=diffM(log(qgdp[, 3:5]))
VARorder(zt, maxp=8)
```

VARorderI

VAR order specification I

Description

This program is similar to VARorder, but it uses observations from $t=p+1$ to T to compute the information criteria for a given VAR(p) model.

Usage

```
VARorderI(x, maxp = 13, output = T)
```

Arguments

x	A T-by-k data matrix of vector time series
maxp	The maximum VAR order entertained
output	A logical switch to control output

Details

For a given VAR(p) model, the program uses observations from $t=p+1$ to T to compute the information criteria. Therefore, different numbers of data points are used to estimate different VAR models.

Value

aic	Akaike information criterion
aicor	Order selected by AIC
bic	Bayesian information criterion
bicor	Order selected by BIC
hq	Hannan and Quinn information criterion
hqor	Order selected by hq
Mstat	Step-wise Chi-square statistics
Mpv	p-values of the M-statistics

Author(s)

Ruey S Tsay

References

Tsay (2014)

See Also

VARorder

VARpred

VAR Prediction

Description

Computes the forecasts of a VAR model, the associated standard errors of forecasts and the mean squared errors of forecasts

Usage

```
VARpred(model, h = 1, orig = 0, Out.level = F)
```

Arguments

model	An output object of a VAR or refVAR command
h	Forecast horizon, a positive integer
orig	Forecast origin. Default is zero meaning the forecast origin is the last data point
Out.level	A logical switch to control output

Details

Computes point forecasts and the associated variances of forecast errors

Value

pred	Point predictions
se.err	Standard errors of the predictions
mse	Mean-square errors of the predictions

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 2). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

Examples

```
data("mts-examples", package="MTS")
gdp=log(qgdp[,3:5])
zt=diffM(gdp)
m1=VAR(zt,p=2)
VARpred(m1,4)
```

 VARpsi

VAR Psi-weights

Description

Computes the psi-weight matrices of a VAR model

Usage

```
VARpsi(Phi, lag = 5)
```

Arguments

Phi	A k-by-kp matrix of VAR coefficients in the form $\text{Phi}=[\text{Phi}_1, \text{Phi}_2, \dots, \text{Phi}_p]$
lag	Number of psi-weight lags

Value

Psi-weights of a VAR model

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 2). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

Examples

```
p1=matrix(c(0.2,-0.6,0.3,1.1),2,2)
m1=VARpsi(p1,4)
names(m1)
```

 VARs

VAR Model with Selected Lags

Description

This is a modified version of VAR command by allowing the users to specify which AR lags to be included in the model.

Usage

```
VARs(x, lags, include.mean = T, output = T, fixed = NULL)
```

Arguments

x	A T-by-k data matrix of k-dimensional time series with T observations
lags	A vector of non-zero AR lags. For instance, lags=c(1,3) denotes a VAR(3) model with $\Phi_2 = 0$.
include.mean	A logical switch to include the mean vector
output	A logical switch to control output
fixed	A logical matrix to fix parameters to zero.

Details

Performs VAR estimation by allowing certain lag coefficient matrices being zero.

Value

data	Observed time series data
lags	The selected VAR lags
order	The VAR order
cnst	A logical switch to include the mean vector
coef	Parameter estimates
aic,bic	Information criteria of the fitted model
residuals	Residual series

secoef	Standard errors of the estimates
Sigma	Residual covariance matrix
Phi	VAR coefficient matrix
Ph0	A constant vector

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 2). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

See Also

VAR command

Examples

```
data("mts-examples", package="MTS")
zt=log(qgdp[, 3:5])
m1=VARs(zt, lags=c(1, 2, 4))
```

 VARX

VAR Model with Exogenous Variables

Description

Estimation of a VARX model

Usage

```
VARX(zt, p, xt = NULL, m = 0, include.mean = T, fixed = NULL, output = T)
```

Arguments

zt	A T-by-k data matrix of a k-dimensional time series
p	The VAR order
xt	A T-by-kx data matrix of kx exogenous variables
m	The number of lags of exogenous variables
include.mean	A logical switch to include the constant vector. Default is to include the constant.
fixed	A logical matrix for setting parameters to zero.
output	A logical switch to control output

Details

Performs least squares estimation of a VARX(p,s) model

Value

data	The observed time series
xt	The data matrix of explanatory variables
aror	VAR order
m	The number of lags of explanatory variables used
Ph0	The constant vector
Phi	VAR coefficient matrix
beta	The regression coefficient matrix
residuals	Residual series
coef	The parameter estimates to be used in model simplification
se.coef	Standard errors of the parameter estimates
include.mean	A logical switch to include the mean vector

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 6). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

VARXorder

VARX Order Specification

Description

Specifies the orders of a VARX model, including AR order and the number of lags of exogenous variables

Usage

```
VARXorder(x, exog, maxp = 13, maxm = 3, output = T)
```

Arguments

x	A T-by-k data matrix of a k-dimensional time series
exog	A T-by-v data matrix of exogenous variables
maxp	The maximum VAR order entertained
maxm	The maximum lags of exogenous variables entertained
output	A logical switch to control output

Details

Computes the information criteria of a VARX process

Value

aic	Akaike information criterion
aicor	Order selected by AIC
bic	Bayesian information criterion
bicor	Order selected by BIC
hq	Hannan and Quinn information criterion
hqor	Order selected by hq

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 6). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

 VARXpred

VARX Model Prediction

Description

Computes point forecasts of a VARX model. The values of exogenous variables must be given.

Usage

```
VARXpred(m1, newxt = NULL, hstep = 1, orig = 0)
```

Arguments

m1	An output object of VARX or refVARX command
newxt	The data matrix of exogenous variables needed in forecasts.
hstep	Forecast horizon
orig	Forecast origin. Default is 0, meaning the last data point.

Details

Uses the provided exogenous variables and the model to compute forecasts

Value

Point forecasts and their standard errors

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 6). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley, Hoboken, NJ.

Vech

Half-Stacking Vector of a Symmetric Matrix

Description

Obtain the half-stacking vector of a symmetric matrix

Usage

Vech(mtx)

Arguments

mtx A symmetric matrix

Details

Stacking a matrix into a vector using data on and below the diagonal.

Value

a vector consisting of stacked elements of a symmetric matrix

Author(s)

Ruey S. Tsay

Examples

```
m1=matrix(c(1:9),3,3)
m2=(m1+t(m1))/2
v1=Vech(m2)
```

VechM	<i>Matrix constructed from output of the Vech Command. In other words, restore the original symmetric matrix from its half-stacking vector.</i>
-------	---

Description

Restores the symmetric matrix from the Vech command

Usage

VechM(vec)

Arguments

vec A vector representing the half-stacking of a symmetric matrix

Details

This command re-construct a symmetric matrix from output of the Vech command

Value

A symmetric matrix

Author(s)

Ruey S. Tsay

References

Tsay (2014, Appendix A)

See Also

Vech

Examples

```
v1=c(2,1,3)
m1=VechM(v1)
m1
```

VMA *Vector Moving Average Model*

Description

Performs VMA estimation using the conditional multivariate Gaussian likelihood function

Usage

```
VMA(da, q = 1, include.mean = T, fixed = NULL,
     beta=NULL, sebeta=NULL, prelim = F,
     details = F, thres = 2)
```

Arguments

da	Data matrix of a k-dimensional VMA process with each column containing one time series
q	The order of VMA model
include.mean	A logical switch to include the mean vector. The default is to include the mean vector in estimation.
fixed	A logical matrix used to fix parameter to zero
beta	Parameter estimates for use in model simplification
sebeta	Standard errors of parameter estimates for use in model simplification
prelim	A logical switch to select parameters to be included in estimation
details	A logical switch to control the amount of output
thres	Threshold for t-ratio used to fix parameter to zero. Default is 2.

Value

data	The data of the observed time series
MAorder	The VMA order
cnst	A logical switch to include the mean vector
coef	Parameter estimates
secoef	Standard errors of the parameter estimates
residuals	Residual series
Sigma	Residual covariance matrix
Theta	The VAR coefficient matrix
mu	The constant vector
aic,bic	The information criteria of the fitted model

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 3).

Examples

```
theta=matrix(c(0.5,0.4,0,0.6),2,2); sigma=diag(2)
m1=VARMAsim(200,malags=c(1),theta=theta,sigma=sigma)
zt=m1$series
m2=VMA(zt,q=1,include.mean=FALSE)
```

VMACpp

Vector Moving Average Model (Cpp)

Description

Performs VMA estimation using the conditional multivariate Gaussian likelihood function. This is the same function as VMA, with the likelihood function implemented in C++ for efficiency.

Usage

```
VMACpp(da, q = 1, include.mean = T, fixed = NULL,
        beta=NULL, sebeta=NULL, prelim = F,
        details = F, thres = 2)
```

Arguments

da	Data matrix of a k-dimensional VMA process with each column containing one time series
q	The order of VMA model
include.mean	A logical switch to include the mean vector. The default is to include the mean vector in estimation.
fixed	A logical matrix used to fix parameter to zero
beta	Parameter estimates for use in model simplification
sebeta	Standard errors of parameter estimates for use in model simplification
prelim	A logical switch to select parameters to be included in estimation
details	A logical switch to control the amount of output
thres	Threshold for t-ratio used to fix parameter to zero. Default is 2.

Value

data	The data of the observed time series
MAorder	The VMA order
cnst	A logical switch to include the mean vector
coef	Parameter estimates
secoef	Standard errors of the parameter estimates
residuals	Residual series
Sigma	Residual covariance matrix
Theta	The VAR coefficient matrix
mu	The constant vector
aic,bic	The information criteria of the fitted model

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 3).

See Also

VMA

Examples

```
theta=matrix(c(0.5,0.4,0,0.6),2,2); sigma=diag(2)
m1=VARMAsim(200,malags=c(1),theta=theta,sigma=sigma)
zt=m1$series
m2=VMACpp(zt,q=1,include.mean=FALSE)
```

VMAe

VMA Estimation with Exact likelihood

Description

Estimation of a VMA(q) model using the exact likelihood method. Multivariate Gaussian likelihood function is used.

Usage

```
VMAe(da, q = 1, include.mean = T, coef0 = NULL,
      secoef0 = NULL, fixed = NULL, prelim = F,
      details = F, thres = 2)
```

Arguments

da	Data matrix (T-by-k) for a k-dimensional VMA process
q	The order of a VMA model
include.mean	A logical switch to include the mean vector in estimation. Default is to include the mean vector.
coef0	Initial estimates of the coefficients used mainly in model refinement
secoef0	Standard errors of the initial estimates
fixed	A logical matrix to put zero parameter constraints
prelim	A logical switch for preliminary estimation
details	A logical switch to control output in estimation
thres	The threshold value for zero parameter constraints

Value

data	The observed time series
MAorder	The VMA order
cnst	A logical switch to include the mean vector
coef	Parameter estimates
secoef	Standard errors of parameter estimates
residuals	Residual series
Sigma	Residual covariance matrix
Theta	VMA coefficient matrix
mu	The mean vector
aic,bic	The information criteria of the fitted model

Author(s)

Ruey S. Tsay

References

Tsay (2014). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

See Also

VMA

Description

Performs multivariate Ljung-Box tests to specify the order of a VMA process

Usage

```
VMAorder(x, lag = 20)
```

Arguments

x	Data matrix of the observed k-dimensional time series. Each column represents a time series.
lag	The maximum VMA order entertained. Default is 20.

Details

For a given lag, the command computes the Ljung-Box statistic for testing $\rho_j = \dots = \rho_{\text{lag}} = 0$, where $j = 1, 2, \dots, \text{lag}$. For a VMA(q) process, the Ljung-Box statistics should be significant for the first q lags, and insignificant thereafter.

Value

The Q-statistics and p-value plot

Author(s)

Ruey S. Tsay

References

Tsay (2014). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley, Hoboken, NJ.

Examples

```
zt=matrix(rnorm(600),200,3)
VMAorder(zt)
```

 VMAs

VMA Model with Selected Lags

Description

Performs the conditional maximum likelihood estimation of a VMA model with selected lags in the model

Usage

```
VMAs(da, malags, include.mean = T, fixed = NULL, prelim = F, details = F, thres = 2)
```

Arguments

da	A T-by-k matrix of a k-dimensional time series with T observations
malags	A vector consisting of non-zero MA lags
include.mean	A logical switch to include the mean vector
fixed	A logical matrix to fix coefficients to zero
prelim	A logical switch concerning initial estimation
details	A logical switch to control output level
thres	A threshold value for setting coefficient estimates to zero

Details

A modified version of VMA model by allowing the user to select non-zero MA lags

Value

data	The observed time series
MAlags	The VMA lags
cnst	A logical switch to include the mean vector
coef	The parameter estimates
secoef	The standard errors of the estimates
residuals	Residual series
aic,bic	The information criteria of the fitted model
Sigma	Residual covariance matrix
Theta	The VMA matrix polynomial
mu	The mean vector
MAorder	The VMA order

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 3). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

See Also

VMA

Vmiss

VARMA Model with Missing Value

Description

Assuming that the model is known, this program estimates the value of a missing data point. The whole data point is missing.

Usage

```
Vmiss(zt, piwgt, sigma, tmiss, cnst = NULL, output = T)
```

Arguments

zt	A T-by-k data matrix of a k-dimensional time series
piwgt	The pi-weights of a VARMA model defined as piwgt=[pi0, pi1, pi2,]
sigma	Positive definite covariance matrix of the innovations
tmiss	Time index of the missing data point
cnst	Constant term of the model
output	A logical switch to control output

Details

Use the least squares method to estimate a missing data point. The missing is random.

Value

Estimates of the missing values

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 6). *Multivariate Time Series Analysis with R and Financial Applications*. John Wiley. Hoboken, NJ.

See Also

Vpmiss

Examples

```
data("mts-examples", package="MTS")
gdp=log(qgdp[,3:5])
m1=VAR(gdp,3)
piwgt=m1$Phi; Sig=m1$Sigma; cnst=m1$Ph0
m2=Vmiss(gdp,piwgt,Sig,50,cnst)
```

Vpmiss

*Partial Missing Value of a VARMA Series***Description**

Assuming that the data is only partially missing, this program estimates those missing values. The model is assumed to be known.

Usage

```
Vpmiss(zt, piwgt, sigma, tmiss, mdx, cnst = NULL, output = T)
```

Arguments

zt	A T-by-k data matrix of a k-dimensional time series
piwgt	pi-weights of the model in the form piwgt[pi0, pi1, pi2,]
sigma	Residual covariance matrix
tmiss	Time index of the partilly missing data point
mdx	A k-dimensional indicator with "0" denoting missing component and "1" denoting observed value.
cnst	Constant term of the model
output	values of the partially missing data

Value

Estimates of the missing values

Author(s)

Ruey S. Tsay

References

Tsay (2014, Chapter 6). Multivariate Time Series Analysis with R and Financial Applications. John Wiley. Hoboken, NJ.

See Also

Vmiss

Examples

```
#data("mts-examples",package="MTS")
#gdp=log(qgdp[,3:5])
#m1=VAR(gdp,1)
#piwgt=m1$Phi; cnst=m1$Ph0; Sig=m1$Sigma
#mdx=c(0,1,1)
#m2=Vpmiss(gdp,piwgt,Sig,50,mdx,cnst)
```

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