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Maintainer Ines Wilms <i.wilms@maastrichtuniversity.nl>

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Author Ines Wilms [cre, aut], David S. Matteson [aut], Jacob Bien [aut], Sumanta Basu [aut], Will Nicholson [aut], Enrico Wegner [aut]

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`bigtime` *bigtime: A package for obtaining sparse estimates of large time series models.*

Description

The bigtime package provides sparse estimators for three large time series models: Vector AutoRegressive Models, Vector AutoRegressive Models with Exogenous variables, and Vector AutoRegressive Moving Average Models. The univariate cases are also supported.

Details

To use the facilities of this package, start with a T by k time series matrix Y (for the VAR and VARMA), and an exogenous time series matrix X (for the VARX). Run sparseVAR, sparseVARX or sparseVARMA to get the estimated model. The function lagmatrix returns the lag matrix of estimated coefficients of the estimated model. The function directforecast gives h-step ahead forecasts based on the estimated model. The function recursiveforecast can be used to recursively forecast a VAR model. The function is.stable returns whether an estimated VAR model is stable. The function diagnostics_plot returns a plot of the fitted vs. observed values as well as of the residuals. The functions fitted and residuals return the fitted, respectively the residuals of the estimated model. The function simVAR can be used to simulate a VAR model with various sparsity patterns.

Author(s)

Ines Wilms <i.wilms@maastrichtuniversity.nl>, Jacob Bien, David S. Matteson, Sumanta Basu, Will Nicholson, Enrico Wegner

References

Nicholson William B., Wilms Ines, Bien Jacob and Matteson David S. (2020), "High-dimensional forecasting via interpretable vector autoregression", Journal of Machine Learning Research, 21(166), 1-52.

Wilms Ines, Sumanta Basu, Bien Jacob and Matteson David S. (2021), "Sparse Identification and Estimation of Large-Scale Vector AutoRegressive Moving Averages", Journal of the American Statistical Association, doi: 10.1080/01621459.2021.1942013.

Examples

```
# Fit a sparse VAR model
data(var.example)
VARfit <- sparseVAR(Y=scale(Y.var), selection = "cv") # using time series cross-validation
Lhat <- lagmatrix(fit=VARfit) # get estimated lagmatrix
VARforecast <- directforecast(fit=VARfit, h=1) # get one-step ahead forecasts
```

---

create_rand_coef_mat *Creates a random coefficient matrix*

Description

Creates a random coefficient matrix

Usage

```
create_rand_coef_mat(
  k,
  p,
  max_abs_eigval = 0.8,
  sparsity_pattern = c("none", "lasso", "hvar"),
```

```
  sparsity_options = NULL,
  decay = 0.5,
  ...
)
```

Arguments

k	Number of time series
p	Number of lags
max_abs_eigval	if < 1, then the VAR will be stable
sparsity_pattern	The sparsity pattern that should be simulated. Options are: "none" for a dense VAR, "lasso" for a VAR with random zeroes, and "hvar" for an elementwise hierarchical sparsity pattern
sparsity_options	Named list of additional options for when sparsity pattern is lasso or hvar. For lasso the option num_zero determines the number of zeros. For hvar, the options zero_min (zero_max) give the minimum (maximum) of zeroes for each variable in each equation, and the option zeroes_in_self (boolean) determines if any of the coefficients of a variable on itself should be zero.
decay	How fast should coefficients shrink when the lag increases.
...	Not currently used

Value

Returns a coefficient matrix in companion form of dimension kpxkp.

---

diagnostics_plot *Creates a Diagnostic Plot*

Description

Creates a Diagnostic Plot

Usage

```
diagnostics_plot(mod, variable = 1, dates = NULL)
```

Arguments

mod	VAR model estimated using sparseVAR, sparseVARMA, or sparseVARX
variable	Variable to show. Either numeric (which column) or character (variable name)
dates	Optional Date vector.

Value

Returns a ggplot2 plot

Examples

```
# VAR example
dat <- simVAR(periods=200, k=2, p=5, decay = 0.1, seed = 6150533,
                       sparsity_pattern = "hvar")
mod <- sparseVAR(Y=scale(dat$Y), selection = "bic", h = 1)
diagnostics_plot(mod, variable = 1) # Plotting the first variable
## Not run:
# VARMA example
data(varma.example)
varma <- sparseVARMA(Y=scale(Y.varma), VARMAselection="cv")
diagnostics_plot(varma, variable = 2) # Plotting the second variable

## End(Not run)
## Not run:
# VARX example
data(varx.example)
varx <- sparseVARX(Y=scale(Y.varx), X=scale(X.varx), selection="cv")
diagnostics_plot(varx, variable = 1) # Plotting the first variable

## End(Not run)
```

---

diagnostics_plot.bigtime.VAR

diagnostics_plot function for VAR models

Description

Not supposed to be called directly. Rather call diagnostics_plot

Usage

```
## S3 method for class 'bigtime.VAR'
diagnostics_plot(mod, variable = 1, dates = NULL)
```

Arguments

mod	VAR model estimated using sparseVAR
variable	Variable to show. Either numeric (which column) or character (variable name)
dates	Optional Date vector.

`diagnostics_plot.bigtime.VARMA` *diagnostics_plot function for VARMA models*

Description

Not supposed to be called directly. Rather call `diagnostics_plot`

Usage

```
## S3 method for class 'bigtime.VARMA'
diagnostics_plot(mod, variable = 1, dates = NULL)
```

Arguments

`mod`	VAR model estimated using `sparseVARMA`
`variable`	Variable to show. Either numeric (which column) or character (variable name)
`dates`	Optional Date vector.

`diagnostics_plot.bigtime.VARX` *diagnostics_plot function for VARX models*

Description

Not supposed to be called directly. Rather call `diagnostics_plot`

Usage

```
## S3 method for class 'bigtime.VARX'
diagnostics_plot(mod, variable = 1, dates = NULL)
```

Arguments

`mod`	VARX model estimated using `sparseVARX`
`variable`	Variable to show. Either numeric (which column) or character (variable name)
`dates`	Optional Date vector.

directforecast *Function to obtain h-step ahead direct forecast based on estimated VAR, VARX or VARMA model*

Description

Function to obtain h-step ahead direct forecast based on estimated VAR, VARX or VARMA model

Usage

```
directforecast(fit, h = 1)
```

Arguments

fit	Fitted sparse VAR, VARX or VARMA model.
h	Desired forecast horizon. Default is h=1.

Value

Vector of length k containing the h-step ahead forecasts for the k time series.

Examples

```
data(var.example)
VARfit <- sparseVAR(Y=scale(Y.var), selection = "cv") # sparse VAR
VARforecast <- directforecast(fit=VARfit, h=1)
```

fitted.bigtime.VAR *Gives the fitted values of a model estimated using* sparseVAR

Description

Gives the fitted values of a model estimated using sparseVAR

Usage

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

Arguments

object	Model estimated using sparseVAR
...	Not currently used

Value

Returns a matrix of fitted values

Examples

```
dat <- simVAR(periods=200, k=2, p=5, decay = 0.001, seed = 6150533)
mod <- sparseVAR(Y=scale(dat$Y))
f <- fitted(mod)
```

`fitted.bigtime.VARMA` *Gives the fitted values of a model estimated using* `sparseVARMA`

Description

Gives the fitted values of a model estimated using `sparseVARMA`

Usage

```
## S3 method for class 'bigtime.VARMA'
fitted(object, ...)
```

Arguments

`object`	Model estimated using `sparseVARMA`
`...`	Not currently used

Value

Returns a matrix of fitted values data(varma.example) varma <- sparseVARMA(Y = scale(Y.varma), VARMAselection="cv") f <- fitted(varma)

`fitted.bigtime.VARX` *Gives the fitted values of a model estimated using* `sparseVARX`

Description

Gives the fitted values of a model estimated using `sparseVARX`

Usage

```
## S3 method for class 'bigtime.VARX'
fitted(object, ...)
```

Arguments

object	Model estimated using sparseVARX
...	Not currently used

Value

Returns a matrix of fitted values data(varx.example) varx <- sparseVARX(Y=scale(Y.varx), X=scale(X.varx), selection="cv") fit <- fitted(varx)

---

get_ic_vals *Calculates the Information Criteria for a VAR, VARX, VARMA model*

Description

The number of non-zero coefficients are taken as the degrees of freedom. Use with care for VARMA.

Usage

```
get_ic_vals(mod, verbose = TRUE)
```

Arguments

mod	Model estimated Model estimated using sparseVAR, sparseVARX, or sparseVARMA
verbose	Should information about the optimal selection be printed?

Examples

```
dat <- simVAR(periods=200, k=2, p=5, decay = 0.01)
mod <- sparseVAR(Y=scale(dat$Y))
ics <- get_ic_vals(mod)
```

---

get_ic_vals.bigtime.VAR *Calculates the Information Criteria for a model estimated using sparseVAR*

Description

The number of non-zero coefficients are taken as the degrees of freedom.

Usage

```
## S3 method for class 'bigtime.VAR'
get_ic_vals(mod, verbose = TRUE)
```

Arguments

mod	Model estimated using sparseVAR
verbose	Should information about the optimal selection be printed?

Value

Returns a list containing

ics	Values of the ICs for all lambdas
mins	Which IC lead to the minimum (the row number)
selected_lambdas	Which lambdas were selected

Examples

```
dat <- simVAR(periods = 200, k=2, p=5, decay = 0.01)
mod <- sparseVAR(Y=scale(dat$Y))
ics <- get_ic_vals(mod)
```

---

get_ic_vals.bigtime.VARX

Calculates the Information Criteria for a model estimated using sparseVARX

Description

The number of non-zero coefficients in both the Phihat and Bhat matrix are taken as the degrees of freedom.

Usage

```
## S3 method for class 'bigtime.VARX'
get_ic_vals(mod, verbose = TRUE)
```

Arguments

mod	Model estimated using sparseVARX
verbose	Should information about the optimal selection be printed?

Value

Returns a list containing

ics	Values of the ICs for all lambdas
mins	Which IC lead to the minimum (the row number)
selected_lamPhi	Which lambda Phi were selected
selected_lamB	Which lambda B were selected

ic_selection *Selects the optimal penalty parameter using information criteria*

Description

Selects the optimal penalty parameter using information criteria

Usage

```
ic_selection(mod, ic = c("bic", "aic", "hq"), verbose = FALSE)
```

Arguments

mod	Model estimated Model estimated using sparseVAR, sparseVARX, or sparseVARMA
ic	Which information criteria should be used. Must be one of "bic", "aic" or "hq"
verbose	If true, some useful information will be printed during the process

Value

Returns a model that uses the optimal penalty

is.stable *Checks whether a VAR is stable*

Description

Using a model estimated by sparseVAR, this function checks whether the resulting VAR is stable. This is the case, whenever the maximum absolute eigenvalue of the companion matrix corresponding to the VAR is less than one. This is sometimes also referred to as that the root lies outside the unit circle.

Usage

```
is.stable(mod, verbose = FALSE)
```

Arguments

mod	Model estimated using sparseVAR. Can only be a model with one coefficient vector. Hence, the model must be estimated using a selection method. See sparseVAR for more details.
verbose	If TRUE, then the actual maximum absolute eigenvalue of the companion matrix will be printed to the console. Default is FALSE

Value

Returns TRUE if the VAR is stable and FALSE otherwise

lagmatrix *Creates Lagmatrix of Estimated Coefficients*

Description

Creates Lagmatrix of Estimated Coefficients

Usage

```
lagmatrix(fit, returnplot = F)
```

Arguments

fit	Fitted VAR, VARX or VARMA model.
returnplot	TRUE or FALSE: return plot of lag matrix or not.

Value

A list with estimated lag matrix of the VAR model, or lag matrices of the VARX or VARMA model. The rows contain the responses, the columns contain the predictors.

Examples

```
data(var.example)
mod <- sparseVAR(Y=scale(Y.var), selection="cv")
Lhat <- lagmatrix(fit=mod)
```

plot.bigtime.recursiveforecast *Plots Recursive Forecasts*

Description

Plots the recursive forecast obtained using recursiveforecast When forecasts were made for multiple lambdas and lmbda is not a single number, then a ribbon will be plotted that reaches from the minimum estimate of all lambdas to the maximum.

Usage

```
## S3 method for class 'bigtime.recursiveforecast'
plot(x, series = NULL, lmbda = NULL, last_n = floor(nrow(fcst$Y) * 0.1), ...)
```

Arguments

x	Recursive Forecast obtained using recursiveforecast
series	Series name. If original data has no names, then use Y1 for the first series, Y2 for the second, and so on.
lmbda	Lambdas to be used for plotting. If forecast was done using only one lambda, then this will be ignored.
last_n	Last n observations of the original data to include in the plot
...	Not currently used

Details

If lmbda is of length one or forecasts were made using only one lambda, then only a line will be plotted.

Default names for series are Y1, Y2, ... if the original data does not have any column names.

Value

Returns a ggplot

---

plot.bigtime.simVAR *Plots a simulated VAR*

Description

Plots a simulated VAR

Usage

```
## S3 method for class 'bigtime.simVAR'
plot(x, ...)
```

Arguments

x	Simulated data of class bigtime.simVAR obtained from the simVAR function
...	Not currently used

Value

Returns a ggplot2 plot

plot_cv *Plot the Cross Validation Error Curve for a Sparse VAR or VARX*

Description

Plot the Cross Validation Error Curve for a Sparse VAR or VARX

Usage

```
plot_cv(fit, ...)
```

Arguments

fit	Fitted VAR, VARMA or VARX model. returned by sparseVAR, sparseVARMA or sparseVARX.
...	Not currently used

recursiveforecast *Recursively Forecasts a VAR*

Description

Recursively forecasts a VAR estimated using sparseVAR. lambda can either be NULL, in which case all lambdas that were used for model estimation are used for forecasting, or a single value, in which case only the model using this lambda will be used for forecasting.

Usage

```
recursiveforecast(mod, h = 1, lambda = NULL)
```

Arguments

mod	VAR model estimated using sparseVAR
h	Desired forecast horizon. Default is h=1.
lambda	Either NULL in which case a forecast will be made for all lambdas for which the model was estimated, or a single value in which case a forecast will only be made for the model using this lambda. Choice is redundant if the model was estimated using a selection procedure.

Value

Returns an object of S3 class bigtime.recursiveforecast containing

fcst	Matrix or 3D array of forecasts
h	Selected forecast horizon
lambda	List of lambdas for which the forecasts were made
Y	Data used for recursive forecasting

Examples

```
sim_data <- simVAR(periods=200, k=5, p=5, seed = 12345)
summary(sim_data)
mod <- sparseVAR(Y=scale(sim_data$Y), selection = "bic")
is.stable(mod)
fcst_recursive <- recursiveforecast(mod, h = 4)
plot(fcst_recursive, series = "Y1")
fcst_direct <- directforecast(mod)
fcst_direct
fcst_recursive$fcst
```

`residuals.bigtime.VAR` *Gives the residuals for VAR models estimated using* `sparseVAR`

Description

Gives the residuals for VAR models estimated using `sparseVAR`

Usage

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

Arguments

`object`	Model estimated using `sparseVAR`
`...`	Not currently used

Value

Returns a matrix of residuals.

Examples

```
dat <- simVAR(periods=200, k=2, p=5, decay = 0.001, seed = 6150533)
mod <- sparseVAR(Y=scale(dat$Y))
res <- resid(mod)
```

residuals.bigtime.VARMA

Gives the residuals for VARMA models estimated using sparseVARMA

Description

Gives the residuals for VARMA models estimated using sparseVARMA

Usage

```
## S3 method for class 'bigtime.VARMA'
residuals(object, ...)
```

Arguments

object	Model estimated using sparseVARMA
...	Not currently used

Value

Returns a matrix of residuals.

Examples

```
## Not run:
data(varma.example)
varma <- sparseVARMA(Y = scale(Y.varma), VARMAselection="cv")
res <- residuals(varma)

## End(Not run)
```

residuals.bigtime.VARX

Gives the residuals for VARX models estimated using sparseVARX

Description

Gives the residuals for VARX models estimated using sparseVARX

Usage

```
## S3 method for class 'bigtime.VARX'
residuals(object, ...)
```

Arguments

object	Model estimated using sparseVARX
...	Not currently used

Value

Returns a matrix of residuals.

Examples

```
## Not run:
data(varx.example)
varx <- sparseVARX(Y=scale(Y.varx), X=scale(X.varx), selection="cv")
res <- residuals(varx)

## End(Not run)
```

---

simVAR *Simulates a VAR(p) with various sparsity patterns*

Description

Simulates a VAR(p) with various sparsity patterns

Usage

```
simVAR(
  periods,
  k,
  p,
  coef_mat = NULL,
  const = rep(0, k),
  e_dist = rnorm,
  init_y = rep(0, k * p),
  max_abs_eigval = 0.8,
  burnin = periods,
  sparsity_pattern = c("none", "lasso", "L1", "hvar", "HLag"),
  sparsity_options = NULL,
  decay = 1/p,
  seed = NULL,
  ...
)
```

Arguments

periods	Scalar indicating the desired time series length
k	Number of time series
p	Maximum lag number. In case of sparsity_patter="none" this will be the actual number of lags for all variables
coef_mat	Coefficient matrix in companion form. If not provided, one will be simulated
const	Constant term of VAR. Default is zero. Must be either a scalar, in which case it will be broadcasted to a k-vector, or a k-vector
e_dist	Either a function taking argument n indicating the number of variables in the system, or a matrix of dimensions k x (periods+burnin)
init_y	Initial values. Defaults to zero. Expects either a scalar or a vector of length (k*p)
max_abs_eigval	Maximum allowed eigenvalue of companion matrix. Only applicable if coefficient matrix is being simulated
burnin	Number of time points to be used for burnin
sparsity_pattern	The sparsity pattern that should be simulated. Options are: "none" for a dense VAR, "lasso" (or "L1") for a VAR with random zeroes, and "hvar" (or "HLag") for an elementwise hierarchical sparsity pattern
sparsity_options	Named list of additional options for when sparsity pattern is lasso (L1) or hvar (HLag). For lasso (L1) the option num_zero determines the number of zeros. For hvar (HLag), the options zero_min (zero_max) give the minimum (maximum) of zeroes for each variable in each equation, and the option zeroes_in_self (boolean) determines if any of the coefficients of a variable on itself should be zero.
decay	How much smaller should parameters for later lags be. The smaller, the larger will early parameters be w.r.t. later ones.
seed	Seed to be used for the simulation
...	Additional arguments passed to e_dist

Value

Returns an object of S3 class bigtime.simVAR containing the following

Y	Simulated Data
periods	Time series length
k	Number of endogenous variables
p	Maximum lag length; effective lag length might be shorter due to sparsity patterns
coef_mat	Companion form of the coefficient matrix. Will be of dimensions (kp)x(kp). First k rows correspond to the actual coefficient matrix.
is_coef_mat_simulated	TRUE if the coef_mat was simulated, FALSE if it was user provided

const	Constant term
e_dist	Errors used in the construction of the data
init_y	Initial conditions
max_abs_eigval	Maximum eigenvalue to which the companion matrix was constraint
burnin	Burnin period used
sparsity_pattern	Sparsity pattern used
sparsity_options	Extra options for the sparsity patterns used
seed	Seed used for the simulation

Examples

```
periods <- 200 # time series length
k <- 5 # number of variables
p <- 10 # maximum lag
sparsity_pattern <- "HLag" # HLag sparsity structure
sparsity_options <- list(zero_min = 0, # variables can be included with all lags
                         zero_max = 10, # but some could also include no lags
                         zeroes_in_self = TRUE)
sim <- simVAR(periods=periods, k=k, p=p, sparsity_pattern=sparsity_pattern,
              sparsity_options=sparsity_options, seed = 12345)
summary(sim)
```

---

sparseVAR *Sparse Estimation of the Vector AutoRegressive (VAR) Model*

Description

Sparse Estimation of the Vector AutoRegressive (VAR) Model

Usage

```
sparseVAR(
  Y,
  p = NULL,
  VARpen = "HLag",
  VARlseq = NULL,
  VARgran = NULL,
  selection = c("none", "cv", "bic", "aic", "hq"),
  cvcut = 0.9,
  h = 1,
  eps = 0.001,
  check_std = TRUE,
  verbose = FALSE
)
```

Arguments

Y	A T by k matrix of time series. If k=1, a univariate autoregressive model is estimated.
p	User-specified maximum autoregressive lag order of the VAR. Typical usage is to have the program compute its own maximum lag order based on the time series length.
VARpen	"HLag" (hierarchical sparse penalty) or "L1" (standard lasso penalty) penalization.
VARlseq	User-specified grid of values for regularization parameter corresponding to sparse penalty. Typical usage is to have the program compute its own grid. Supplying a grid of values overrides this. WARNING: use with care.
VARgran	User-specified vector of granularity specifications for the penalty parameter grid: First element specifies how deep the grid should be constructed. Second element specifies how many values the grid should contain.
selection	One of "none" (default), "cv" (Time Series Cross-Validation), "bic", "aic", "hq". Used to select the optimal penalization.
cvcut	Proportion of observations used for model estimation in the time series cross-validation procedure. The remainder is used for forecast evaluation. Redundant if selection is not "cv".
h	Desired forecast horizon in time-series cross-validation procedure.
eps	a small positive numeric value giving the tolerance for convergence in the proximal gradient algorithm.
check_std	Check whether data is standardised. Default is TRUE and is not recommended to be changed
verbose	Logical to print value of information criteria for each lambda together with selection. Default is FALSE

Value

A list with the following components

Y	T by k matrix of time series.
k	Number of time series.
p	Maximum autoregressive lag order of the VAR.
Phihat	Matrix of estimated autoregressive coefficients of the VAR.
phi0hat	vector of VAR intercepts.
series_names	names of time series
lambdas	sparsity parameter grid
MSFEcv	MSFE cross-validation scores for each value of the sparsity parameter in the considered grid
MSFEcv_all	MSFE cross-validation full output
lambda_opt	Optimal value of the sparsity parameter as selected by the time-series cross-validation procedure

lambda_SEopt	Optimal value of the sparsity parameter as selected by the time-series cross-validation procedure and after applying the one-standard-error rule. This is the value used.
h	Forecast horizon h

References

Nicholson William B., Wilms Ines, Bien Jacob and Matteson David S. (2020), "High-dimensional forecasting via interpretable vector autoregression", Journal of Machine Learning Research, 21(166), 1-52.

See Also

lagmatrix and directforecast

Examples

```
data(var.example)
VARfit <- sparseVAR(Y = scale(Y.var)) # sparse VAR
ARfit <- sparseVAR(Y=scale(Y.var[,2])) # sparse AR
```

---

sparseVARMA *Sparse Estimation of the Vector AutoRegressive Moving Average (VARMA) Model*

Description

Sparse Estimation of the Vector AutoRegressive Moving Average (VARMA) Model

Usage

```
sparseVARMA(
  Y,
  U = NULL,
  VARp = NULL,
  VARpen = "HLag",
  VARlseq = NULL,
  VARgran = NULL,
  VARselection = c("cv", "bic", "aic", "hq"),
  VARMAp = NULL,
  VARMAq = NULL,
  VARMApen = "HLag",
  VARMAlPhiseq = NULL,
  VARMAPhigran = NULL,
  VARMAlThetaseq = NULL,
  VARMAThetagran = NULL,
  VARMAalpha = 0,
  VARMAselection = c("none", "cv", "bic", "aic", "hq"),
```

```
  h = 1,
  cvcut = 0.9,
  eps = 10^-3,
  check_std = TRUE
)
```

Arguments

Y	A T by k matrix of time series. If k=1, a univariate autoregressive moving average model is estimated.
U	A T by k matrix of (approximated) error terms. Typical usage is to have the program estimate a high-order VAR model (Phase I) to get approximated error terms U.
VARp	User-specified maximum autoregressive lag order of the PhaseI VAR. Typical usage is to have the program compute its own maximum lag order based on the time series length.
VARpen	"HLag" (hierarchical sparse penalty) or "L1" (standard lasso penalty) penalization in PhaseI VAR.
VARlseq	User-specified grid of values for regularization parameter in the PhaseI VAR. Typical usage is to have the program compute its own grid. Supplying a grid of values overrides this. WARNING: use with care.
VARgran	User-specified vector of granularity specifications for the penalty parameter grid of the PhaseI VAR: First element specifies how deep the grid should be constructed. Second element specifies how many values the grid should contain.
VARselection	Selection procedure for the first stage. Default is time series Cross-Validation. Alternatives are BIC, AIC, HQ
VARMAp	User-specified maximum autoregressive lag order of the VARMA. Typical usage is to have the program compute its own maximum lag order based on the time series length.
VARMAq	User-specified maximum moving average lag order of the VARMA. Typical usage is to have the program compute its own maximum lag order based on the time series length.
VARMApen	"HLag" (hierarchical sparse penalty) or "L1" (standard lasso penalty) penalization in the VARMA.
VARMAlPhiseq	User-specified grid of values for regularization parameter corresponding to the autoregressive coefficients in the VARMA. Typical usage is to have the program compute its own grid. Supplying a grid of values overrides this. WARNING: use with care.
VARMAPhigran	User-specified vector of granularity specifications for the penalty parameter grid corresponding to the autoregressive coefficients in the VARMA: First element specifies how deep the grid should be constructed. Second element specifies how many values the grid should contain.
VARMAlThetaseq	User-specified grid of values for regularization parameter corresponding to the moving average coefficients in the VARMA. Typical usage is to have the program compute its own grid. Supplying a grid of values overrides this. WARNING: use with care.

VARMAThetagran	User-specified vector of granularity specifications for the penalty parameter grid corresponding to the moving average coefficients in the VARMA: First element specifies how deep the grid should be constructed. Second element specifies how many values the grid should contain.
VARMAalpha	a small positive regularization parameter value corresponding to squared Frobenius penalty in VARMA. The default is zero.
VARMAselection	selection procedure in the second stage. Default is "none"; Alternatives are cv, bic, aic, hq
h	Desired forecast horizon in time-series cross-validation procedure.
cvcut	Proportion of observations used for model estimation in the time series cross-validation procedure. The remainder is used for forecast evaluation.
eps	a small positive numeric value giving the tolerance for convergence in the proximal gradient algorithms.
check_std	Check whether data is standardised. Default is TRUE and is not recommended to be changed

Value

A list with the following components

Y	T by k matrix of time series.
U	Matrix of (approximated) error terms.
k	Number of time series.
VARp	Maximum autoregressive lag order of the PhaseI VAR.
VARPhihat	Matrix of estimated autoregressive coefficients of the Phase I VAR.
VARphi0hat	Vector of Phase I VAR intercepts.
VARMAp	Maximum autoregressive lag order of the VARMA.
VARMAq	Maximum moving average lag order of the VARMA.
Phihat	Matrix of estimated autoregressive coefficients of the VARMA.
Thetahat	Matrix of estimated moving average coefficients of the VARMA.
phi0hat	Vector of VARMA intercepts.
series_names	names of time series
PhaseI_lambas	Phase I sparsity parameter grid
PhaseI_MSFEcv	MSFE cross-validation scores for each value of the sparsity parameter in the considered grid
PhaseI_lambda_opt	Phase I Optimal value of the sparsity parameter as selected by the time-series cross-validation procedure
PhaseI_lambda_SEopt	Phase I Optimal value of the sparsity parameter as selected by the time-series cross-validation procedure and after applying the one-standard-error rule
PhaseII_lambdaPhi	Phase II sparsity parameter grid corresponding to Phi parameters

`PhaseII_lambdaTheta`
: Phase II sparsity parameter grid corresponding to Theta parameters

`PhaseII_lambdaPhi_opt`
: Phase II Optimal value of the sparsity parameter (corresponding to Phi parameters) as selected by the time-series cross-validation procedure

`PhaseII_lambdaPhi_SEopt`
: Phase II Optimal value of the sparsity parameter (corresponding to Theta parameters) as selected by the time-series cross-validation procedure and after applying the one-standard-error rule

`PhaseII_lambdaTheta_opt`
: Phase II Optimal value of the sparsity parameter (corresponding to Phi parameters) as selected by the time-series cross-validation procedure

`PhaseII_lambdaTheta_SEopt`
: Phase II Optimal value of the sparsity parameter (corresponding to Theta parameters) as selected by the time-series cross-validation procedure and after applying the one-standard-error rule

`PhaseII_MSFEcv`
: Phase II MSFE cross-validation scores for each value in the two-dimensional sparsity grid

`h`
: Forecast horizon h

References

Wilms Ines, Sumanta Basu, Bien Jacob and Matteson David S. (2021), "Sparse Identification and Estimation of Large-Scale Vector AutoRegressive Moving Averages", Journal of the American Statistical Association, doi: 10.1080/01621459.2021.1942013.

See Also

lagmatrix and directforecast

Examples

```
data(varma.example)
VARMAfit <- sparseVARMA(Y = scale(Y.varma)) # sparse VARMA
y <- matrix(Y.varma[,1], ncol=1)
ARMAfit <- sparseVARMA(Y=scale(y)) # sparse ARMA
```

`sparseVARX` *Sparse Estimation of the Vector AutoRegressive with Exogenous Variables X (VARX) Model*

Description

Sparse Estimation of the Vector AutoRegressive with Exogenous Variables X (VARX) Model

Usage

```
sparseVARX(
  Y,
  X,
  p = NULL,
  s = NULL,
  VARXpen = "HLag",
  VARXlPhiseq = NULL,
  VARXPhigran = NULL,
  VARXlBseq = NULL,
  VARXBgran = NULL,
  VARXalpha = 0,
  h = 1,
  cvcut = 0.9,
  eps = 10^-3,
  selection = c("none", "cv", "bic", "aic", "hq"),
  check_std = TRUE,
  verbose = FALSE
)
```

Arguments

Y	A T by k matrix of time series. If k=1, a univariate autoregressive model is estimated.
X	A T by m matrix of time series.
p	User-specified maximum endogenous autoregressive lag order. Typical usage is to have the program compute its own maximum lag order based on the time series length.
s	User-specified maximum exogenous autoregressive lag order. Typical usage is to have the program compute its own maximum lag order based on the time series length.
VARXpen	"HLag" (hierarchical sparse penalty) or "L1" (standard lasso penalty) penalization in VARX.
VARXlPhiseq	User-specified grid of values for regularization parameter corresponding to the endogenous autoregressive coefficients in the VARX. Typical usage is to have the program compute its own grid. Supplying a grid of values overrides this. WARNING: use with care.
VARXPhigran	User-specified vector of granularity specifications for the penalty parameter grid corresponding to the endogenous autoregressive coefficients in the VARX: First element specifies how deep the grid should be constructed. Second element specifies how many values the grid should contain.
VARXlBseq	User-specified grid of values for regularization parameter corresponding to the exogenous autoregressive coefficients in the VARX. Typical usage is to have the program compute its own grid. Supplying a grid of values overrides this. WARNING: use with care.

VARXBgran	User-specified vector of granularity specifications for the penalty parameter grid corresponding to the exogenous autoregressive coefficients in the VARX: First element specifies how deep the grid should be constructed. Second element specifies how many values the grid should contain.
VARXalpha	a small positive regularization parameter value corresponding to squared Frobenius penalty. The default is zero.
h	Desired forecast horizon in time-series cross-validation procedure.
cvcut	Proportion of observations used for model estimation in the time series cross-validation procedure. The remainder is used for forecast evaluation.
eps	a small positive numeric value giving the tolerance for convergence in the proximal gradient algorithm.
selection	Model selection method to be used. Default is none, which will return all values for all penalisations.
check_std	Check whether data is standardised. Default is TRUE and is not recommended to be changed
verbose	Logical to print value of information criteria for each lambda together with selection. Default is FALSE

Value

A list with the following components

Y	T by k matrix of endogenous time series.
X	T by m matrix of exogenous time series.
k	Number of endogenous time series.
m	Number of exogenous time series.
p	Maximum endogenous autoregressive lag order of the VARX.
s	Maximum exogenouss autoregressive lag order of the VARX.
Phihat	Matrix of estimated endogenous autoregressive coefficients.
Bhat	Matrix of estimated exogenous autoregressive coefficients.
phi0hat	vector of VARX intercepts.
exogenous_series_names	names of the exogenous time series
endogenous_series_names	names of the endogenous time series
lambdaPhi	sparsity parameter grid corresponding to endogenous autoregressive parameters
lambdaB	sparsity parameter grid corresponding to exogenous autoregressive parameters
lambdaPhi_opt	Optimal value of the sparsity parameter (corresponding to the endogenous autoregressive parameters) as selected by the time-series cross-validation procedure
lambdaPhi_SEopt	Optimal value of the sparsity parameter (corresponding to the endogenous autoregressive parameters) as selected by the time-series cross-validation procedure and after applying the one-standard-error rule

lambdaB_opt	Optimal value of the sparsity parameter (corresponding to the exogenous autoregressive parameters) as selected by the time-series cross-validation procedure
lambdaB_SEopt	Optimal value of the sparsity parameter (corresponding to the exogenous autoregressive parameters) as selected by the time-series cross-validation procedure and after applying the one-standard-error rule
MSFEcv	MSFE cross-validation scores for each value in the two-dimensional sparsity grid
h	Forecast horizon h

References

Wilms Ines, Sumanta Basu, Bien Jacob and Matteson David S. (2017), "Interpretable vector autoregressions with exogenous time series", NIPS 2017 Symposium on Interpretable Machine Learning, arXiv:1711.03623.

See Also

lagmatrix and directforecast

Examples

```
data(varx.example)
VARXfit <- sparseVARX(Y=scale(Y.varx), X=scale(X.varx)) # sparse VARX
y <- matrix(Y.varx[,1], ncol=1)
ARXfit <- sparseVARX(Y=y, X=X.varx) # sparse ARX
```

---

summary.bigtime.simVAR

Gives a small summary of a VAR simulation

Description

Gives a small summary of a VAR simulation

Usage

```
## S3 method for class 'bigtime.simVAR'
summary(object, plot = TRUE, ...)
```

Arguments

object	Simulated data of class bigtime.simVAR obtained from the simVAR function
plot	Should the VAR be plotted. Default is TRUE
...	Not currently used

Value

If 'plot=TRUE', then a ggplot2 plot will be returned

X.varx *VARX Time Series Example (*varx.example*)*

Description

The data consists of a 200x3 matrix of endogenous variables, Y.varx, and a 200x3 matrix of exogenous variables, X.varx.

Usage

```
X.varx
```

Format

Two matrices, X.varx and Y.varx, both of dimension 200x3

Y.var *VAR Time Series Example (*var.example*)*

Description

The data consists of a 200x5 data matrix, Y.var, and was simulated from a sparse VAR model with HLag sparsity pattern.

Usage

```
Y.var
```

Format

A matrix of dimension 200x5

Y.varma *VARMA Time Series Example (*varma.example*)*

Description

The data consists of a 200x3 data matrix, Y.varma, and was simulated from a sparse VARMA model.

Usage

```
Y.varma
```

Format

A matrix of dimension 200x3

Y.varx *VARX Time Series Example (*varx.example*)*

Description

The data consists of a 200x3 matrix of endogenous variables, Y.varx, and a 200x3 matrix of exogenous variables, X.varx.

Usage

```
Y.varx
```

Format

Two matrices, X.varx and Y.varx, both of dimension 200x3

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